# Classical simulation of non-Gaussian fermionic circuits 

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We propose efficient algorithms for classically simulating fermionic linear optics operations applied to non-Gaussian initial states. By gadget constructions, this provides algorithms for fermionic linear optics with non-Gaussian operations. We argue that this problem is analogous to that of simulating Clifford circuits with non-stabilizer initial states: Algorithms for the latter problem immediately translate to the fermionic setting. Our construction is based on an extension of the covariance matrix formalism which permits to efficiently track relative phases in superpositions of Gaussian states. It yields simulation algorithms with polynomial complexity in the number of fermions, the desired accuracy, and certain quantities capturing the degree of non-Gaussianity of the initial state. We study one such quantity, the fermionic Gaussian extent, and show that it is multiplicative on tensor products when the so-called fermionic Gaussian fidelity is. We establish this property for the tensor product of two arbitrary pure states of four fermions with positive parity.

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## 1 Introduction

While universal polynomial-time quantum computation is believed to exceed the capabilities of efficient classical algorithms, restricted classes of quantum computations are amenable to efficient classical simulation. Identifying such models and corresponding simulation algorithms is a central goal in the study of quantum computing. On the one hand, a good characterization of the boundary between the computational power of classical and quantum computational models provides insight into potential quantum advantages. On the other hand, efficient classical simulation methods can be used to assess the merits and scalability of quantum information-processing proposals. For example, the resilience of certain quantum codes against restricted noise models has successfully been studied by means of classical simulation methods giving threshold estimates for large-scale systems, see e.g., [1-6] for an incomplete list of relevant references.

### 1.1 Efficiently simulable quantum computations

Most known examples of efficiently simulable quantum computations can be summarized by the following ingredients:
(i) A set $\mathcal{D}$ of states with the property that each element $\Psi \in \mathcal{D}$ has a succinct classical description $d_{\Psi}$. In the following, we will refer to $\mathcal{D}$ as a dictionary.
(ii) A set $\mathcal{E}$ of operations (unitary or non-unitary evolutions), again with the property that each element $E \in \mathcal{E}$ has a succinct classical description $d_{E}$. Following resourcetheoretic conventions, we call $\mathcal{E}$ the set of free operations.
(iii) A set $\mathcal{M}$ of measurements (quantum instruments) with an efficient classical descriptions $d_{M}$ for each $M \in \mathcal{M}$, and the property that every post-measurement state (associated with different measurement outcomes) obtained by applying $M \in \mathcal{M}$ to a state $\Psi \in \mathcal{D}$ belongs to $\mathcal{D}$.

A triple $(\mathcal{D}, \mathcal{E}, \mathcal{M})$ gives rise to a (generally restricted) quantum computational model by composing these ingredients. A typical (non-adaptive) computation proceeds by preparing an initial state $\Psi \in \mathcal{D}$, applying a sequence $\left\{E_{t}\right\}_{t=1}^{T} \subset \mathcal{E}$ of operations, and performing measurements $\left\{M_{k}\right\}_{k=1}^{L} \subset \mathcal{M}$ in succession. Assuming for simplicity that $\mathcal{E}$ consists of a set of unitaries, and that for each $k \in[L]=\{1, \ldots, L\}$, the measurement $M_{k}$ realizes a POVM $M_{k}=\left\{M_{m}^{(k)}\right\}_{m \in \mathcal{M}_{k}}$ with outcomes in a set $\mathcal{M}_{k}$, such a computation produces a sample $m=\left(m_{1}, \ldots, m_{L}\right) \in \mathcal{M}_{1} \times \cdots \times \mathcal{M}_{L}$ from the distribution

$$
\begin{equation*}
p\left(m_{1}, \ldots, m_{L}\right)=\left\langle\Psi_{T}, M_{m_{L}}^{(L)} \cdots M_{m_{1}}^{(1)} \Psi_{T}\right\rangle \quad \text { where } \quad \Psi_{T}=E_{T} \circ \cdots \circ E_{1}(\Psi) \tag{1}
\end{equation*}
$$

More generally, one may consider circuits where operations are chosen adaptively depending on intermediate measurement results, assuming that the dependence is given by an efficiently computable function.

The task of classically simulating the computational model associated with ( $\mathcal{D}, \mathcal{E}, \mathcal{M}$ ) comes in two flavors. The input in both cases is the collection $\left(d_{\Psi},\left\{d_{E_{t}}\right\}_{t=1}^{T},\left\{d_{M_{k}}\right\}_{k=1}^{L}\right)$ of descriptions of the initial state, the set of operations applied, and the measurements. The problem of weak simulation then consists in producing a sample $m \in \mathcal{M}_{1} \times \cdots \times \mathcal{M}_{L}$ drawn according to the (ideal) output distribution $p(m)$ of the circuit given by Eq. (1). In contrast, the problem of strong simulation consists of computing the output probability $p(m)$ for a given (potential) measurement outcome $m$.

Relaxing the requirements of weak and strong simulation, one may allow for an approximation error. For weak simulation, this is typically formalized by demanding that the (probabilistic) classical algorithm outputs a sample $m$ drawn from a distribution $\tilde{p}$ which is $\delta$-close in $L^{1}$-distance (for a chosen error parameter $\delta>0$ ) to the ideal output distribution $p$. Similarly, for strong simulation, the output $\tilde{p}$ is required to be close to the value $p(m)$ with a controlled (additive or multiplicative) error.

In cases where a computational model specified by $(\mathcal{D}, \mathcal{E}, \mathcal{M})$ is amenable to efficient classical simulation, associated classical simulation algorithms are typically constructed by considering evolution and measurement separately. The basic problem then consists in constructing efficient classical algorithms with the following functionalities:
(a) An algorithm evolve which, given classical descriptions $d_{\Psi}$ of a state $\Psi \in \mathcal{D}$ and $d_{E}$ of an evolution operation $E \in \mathcal{E}$, computes a classical description $d_{E(\Psi)}$ of the evolved state $E(\Psi)$.
(b) Given a classical description $d_{\Psi}$ of a state $\Psi \in \mathcal{D}$, a classical description $d_{M}$ of a measurement $M \in \mathcal{M}$ (with associated set of measurement outcomes $\mathcal{M}_{M}$ ) and a measurement outcome $m \in \mathcal{M}_{M}$,
(b1) an algorithm measureprob which outputs the probability $p(m)$ (determined by Born's rule) of obtaining measurement outcome $m$, and
(b2) an algorithm postmeasure which outputs a classical description of the postmeasurement state
when applying the measurement $M$ to $\Psi$.
It is clear that a triple (evolve, measureprob, postmeasure) of such algorithms immediately gives rise to an efficient algorithm for strong simulation of the model $(\mathcal{D}, \mathcal{E}, \mathcal{M})$, with a runtime

$$
T \cdot \text { time }(\text { evolve })+L \cdot(\text { time }(\text { measure } r o b)+\text { time }(\text { postmeasure }))
$$

which is linear in the number $T$ of operations applied, and linear in the number $L$ of measurements. Assuming that for any measurement $M \in \mathcal{M}$, the set of measurement outcomes $\mathcal{M}_{M}$ associated with $M$ is of constant cardinality, the triple (evolve, measureprob, postmeasure) also gives rise to a randomized algorithm for weak simulation: Such an algorithm is obtained by using measureprob to compute the entire distribution $\{p(m)\}_{m \in \mathcal{M}_{M}}$ of measurement outcomes (when applying a measurement $M$ ), and then drawing $m \in \mathcal{M}_{M}$ randomly according to this distribution. The runtime of this probabilistic algorithm is

$$
T \cdot \text { time }(\text { evolve })+L \cdot(\text { time }(\text { measureprob }) \cdot w+\text { time }(\text { postmeasure }))
$$

where $w=\max _{M \in \mathcal{M}}\left|\mathcal{M}_{M}\right|$ bounds the maximal cardinality of the set of measurement outcomes.

### 1.1.1 Clifford circuits / Stabilizer computations

Perhaps the most well-known example of a computational model ( $\mathcal{D}, \mathcal{E}, \mathcal{M}$ ) where efficient algorithms (evolve, measureprob, postmeasure) can be provided is the Gottesman-Knill-theorem for stabilizer computations on $n$ qubits. Here $\mathcal{D}$ is the set $\mathrm{STAB}_{n}$ of $n$-qubit stabilizer states (whose elements can be specified by their stabilizer generators, i.e., corresponding stabilizer tableaux), $\mathcal{E}$ is the set of Clifford unitaries (described by symplectic matrices), and $\mathcal{M}$ are measurements of single-qubit Pauli $Z$ operators (described by an index $j \in[n]$ ). In this case, there are efficient algorithms with runtimes given in Table 1.

| algorithm | time |
| :---: | :---: |
| evolve | $O(n)$ |
| measureprob | $O(n)$ |
| postmeasure | $O\left(n^{2}\right)$ |

Table 1: Runtimes of building blocks evolve, measureprob, postmeasure for classical simulation of $n$ qubit stabilizer circuits as given in [7]. Evolution corresponds to application of an $n$-qubit Clifford unitary, and each measurement is that of a Pauli observable $Z_{j}$ with $j \in[n]$.

### 1.1.2 Fermionic linear optics / Fermionic Gaussian computations

A different class of efficiently simulable computations - the one we are interested in here is that of fermionic linear optics on $n$ fermions. We focus on pure-state computations: Here the dictionary $\mathcal{D}$ consists of the set $\mathcal{G}_{n}$ of pure fermionic Gaussian states. An element $\Psi \in$ $\mathcal{G}_{n}$ in the dictionary can be described by its covariance matrix $\Gamma_{\Psi}$, an antisymmetric $2 n \times$ $2 n$ matrix with real entries. The set $\mathcal{E}=\mathcal{E}_{\text {Gauss }}$ can be taken as the set of Gaussian unitary operations. Each such unitary $U=U_{R}$ is fully determined by an element $R \in$ $O(2 n)$ of the orthogonal group on $\mathbb{R}^{2 n}$, where $R \mapsto U_{R}$ defines a (projective) unitary
representation of $O(2 n)$ on the space $\mathcal{H}^{n}$ of $n$ fermions. The set $\mathcal{M}=\mathcal{M}_{\text {number }}$ consists of all occupation number measurements. As in the case of stabilizer states, there are polynomial-time algorithms (evolve, measureprob, postmeasure) for classical simulation with runtimes summarized in Table 2. In particular, the covariance matrix $\Gamma_{U_{R} \Psi}$ of a Gaussian state $\Psi$ evolved under a Gaussian unitary $U_{R}$ can be computed in time $O\left(n^{3}\right)$ from $\Gamma_{\Psi}$ and $R$. The outcome probability of observing 0 (respectively 1 ) when performing an occupation number measurement can be computed in time $O(1)$, and the covariance matrix of the post-measurement state can be computed in time $O\left(n^{2}\right)[8-10]$ (see also [3]).

| algorithm | time |
| :---: | :---: |
| evolve | $O\left(n^{3}\right)$ |
| measureprob | $O(1)$ |
| postmeasure | $O\left(n^{2}\right)$ |

Table 2: Runtimes of building blocks evolve, measureprob, postmeasure for classical simulation of $n$ fermion linear optics circuits as proposed in [8-10], see also [3]. Evolution amounts to application of a fermionic Gaussian unitary. Measurement corresponds to measuring an observable $a_{j}^{\dagger} a_{j}$ (occupation number) for $j \in[n]$.

### 1.2 Classical simulation algorithms and measures of magic

A natural way of extending the power of a quantum computational model specified by $(\mathcal{D}, \mathcal{E}, \mathcal{M})$ consists in providing resources/capabilities that do not belong to the specified sets. "Magic states" are a prime example: Here a state $\Psi \notin \mathcal{D}$ not belonging to the dictionary is provided as an (initial) state in the quantum computation, thereby providing additional capabilities to the computational model. For example, non-Clifford unitaries can be realized by certain stabilizer-computations (sometimes referred to as "gadgets") applied to so-called magic states [11]. Similarly, non-Gaussian initial states can be combined with fermionic linear optics operations to realize non-Gaussian operations [12,13]. While such a magic state can even promote the computational model to universal quantum computation, this is generally not the case for all states $\Psi$. It is thus a natural question to quantify the degree of "magicness" provided by a state $\Psi \notin \mathcal{D}$. For the set STAB $_{n}$ of $n$-qubit stabilizer states, corresponding magic monotones considered in the literature include the robustness of magic [14,15], the exact and approximate stabilizer rank [16-18], the stabilizer extent [18,19], the stabilizer nullity [20], the generalized robustness [21] and the magic entropy [22].

The maximum overlap of a given state $\Psi$ with an element of the dictionary $\mathcal{D}$, i.e., the quantity

$$
\begin{equation*}
F_{\mathcal{D}}(\Psi)=\sup _{\varphi \in \mathcal{D}}|\langle\varphi, \Psi\rangle|^{2}, \tag{2}
\end{equation*}
$$

is arguably one of the most direct ways of quantifying how far $\Psi$ is from a "free" state, i.e., a state belonging to $\mathcal{D}$. Motivated by the analogously defined notion of stabilizer fidelity in Ref. [18], we call $F_{\mathcal{D}}(\Psi)$ the $\mathcal{D}$-fidelity of $\Psi$ in the following. This quantity plays an important role in our arguments when considering multiplicativity properties. However, the $\mathcal{D}$-fidelity $F_{\mathcal{D}}(\Psi)$ is not a good quantifier of hardness of classical simulation because simply replacing $\Psi$ by an element of $\mathcal{D}$ typically leads to a significant approximation error.

From the point of view of classical simulation, a relevant magicness measure for a state $\Psi \notin \mathcal{D}$ relates to the (added) complexity when trying to simulate a quantum computation with initial state $\Psi$, built from a triple ( $\mathcal{D}, \mathcal{E}, \mathcal{M}$ ) allowing for efficient classical simulation. One such measure, introduced in Ref. [16] for the case of stabilizer computations, is the $\mathcal{D}$-rank $\chi_{\mathcal{D}}(\Psi)$ of $\Psi$. (For $\mathcal{D}=\mathrm{STAB}_{n}$, this is called the stabilizer rank of $\Psi$.) It is defined as the minimum number of terms when decomposing $\Psi$ as a linear combination of elements of $\mathcal{D}$, i.e.,

$$
\begin{equation*}
\chi_{\mathcal{D}}(\Psi)=\min \left\{\chi \in \mathbb{N} \mid \exists\left\{\varphi_{j}\right\}_{j=1}^{\chi} \subset \mathcal{D},\left\{\gamma_{j}\right\}_{j=1}^{\chi} \subset \mathbb{C} \text { such that } \Psi=\sum_{j=1}^{\chi} \gamma_{j} \varphi_{j}\right\} . \tag{3}
\end{equation*}
$$

In the context of signal processing, the corresponding optimization problem is referred to as a sparse approximation problem. The $\mathcal{D}-\operatorname{rank} \chi_{\mathcal{D}}(\Psi)$ appears naturally when constructing and analyzing simulation algorithms, but it suffers from a number of shortcomings: On the one hand, the set of states $\Psi \in \mathcal{H}$ whose $\mathcal{D}$-rank is less than the dimension of the Hilbert space $\mathcal{H}$ is a set of zero Lebesgue measure [23, Proposition 4.1]. On the other hand, the quantity $\chi_{\mathcal{D}}(\Psi)$ relates to the classical simulation cost of exactly simulating dynamics involving the state $\Psi$. In practice, some approximation error is typically acceptable, and corresponding simulations can be achieved with lower cost. In other words, the quantity $\chi_{\mathcal{D}}(\Psi)$ does not accurately reflect the cost of approximate simulation.

A more operationally relevant quantity is the $\delta$-approximate $\mathcal{D}$-rank $\chi_{\mathcal{D}}^{\delta}(\Psi)$ of $\Psi$ introduced in Ref. [17], again for stabilizer computations. For a fixed approximation error $\delta>0$, this is given by the minimum $\mathcal{D}$-rank of any state $\Psi^{\prime}$ that is $\delta$-close to $\Psi$, i.e.,

$$
\begin{equation*}
\chi_{\mathcal{D}}^{\delta}(\Psi)=\min \left\{\chi_{\mathcal{D}}\left(\Psi^{\prime}\right) \mid \Psi^{\prime} \in \mathcal{H} \text { such that }\left\|\Psi-\Psi^{\prime}\right\| \leq \delta\right\} . \tag{4}
\end{equation*}
$$

An exact classical simulation algorithm whose complexity scales with the exact $\mathcal{D}$-rank $\chi_{\mathcal{D}}(\Psi)$ provides an approximate simulation at a cost with an identical scaling in the approximate (instead of exact) $\mathcal{D}$-rank $\chi_{\mathcal{D}}^{\delta}(\Psi)$ of $\Psi$. Here approximate weak simulation means that instead of sampling from the ideal output distribution $P$ of a circuit, the simulation samples from a distribution $P^{\prime}$ whose $L^{1}$-distance from $P$ is bounded by $O(\delta)$. Similarly, in approximate (strong) simulation, output probabilities are approximately computed with a controlled approximation error.

A different quantity of interest is obtained by replacing the ill-behaved rank function (i.e., size of the support) in the definition of the $\mathcal{D}$-rank $\chi_{\mathcal{D}}(\Psi)$ by the $L^{1}$-norm of the coefficients when representing $\Psi$ as a linear combination. In the context of stabilizer states the corresponding quantity was introduced by Bravyi et al. [18] under the term stabilizer extent: For a state $\Psi \in\left(\mathbb{C}^{2}\right)^{\otimes n}$ it is defined as

$$
\xi_{\operatorname{STAB}_{n}}(\Psi)=\inf \left\{\|\gamma\|_{1}^{2} \mid \gamma: \operatorname{STAB}_{n} \rightarrow \mathbb{C} \text { such that } \Psi=\sum_{\varphi \in \operatorname{STAB}_{n}} \gamma(\varphi) \varphi\right\}
$$

where $\|\gamma\|_{1}=\sum_{\varphi \in \text { STAB }_{n}}|\gamma(\varphi)|$ denotes the 1-norm of $\gamma$. The corresponding convex optimization problem is known as the basis pursuit problem [24] (when STAB $n$ is replaced by e.g., a finite dictionary $\mathcal{D}$ ). Sufficient conditions for when the basis pursuit problem yields a solution of the sparse approximation problem where investigated in a series of works culminating in Fuchs' condition [25] (see also [26]). More importantly for (approximate) simulation, feasible solutions of the basis pursuit problem provide upper bounds on the sparse approximation problem. For the stabilizer rank, a sparsification result (see [18, Theorem 1]) gives an upper bound on the $\delta$-approximate stabilizer $\operatorname{rank} \chi_{\operatorname{STAB}_{n}}(\Psi)$ in terms of the stabilizer extent $\xi_{\mathrm{STAB}_{n}}(\Psi)$, for any $\delta>0$ (see Section 4.2).

Building on earlier results [17], it was shown in Ref. [18] that a stabilizer circuit on $n$ qubits with $L$ Clifford gates initialized in a state $\Psi$ can be weakly simulated with error $\delta$ in a time scaling as $O\left(\xi_{\operatorname{STAB}_{n}}(\Psi) / \delta^{2} \cdot \operatorname{poly}(n, L)\right)$. The error $\delta$ expresses the $L^{1}$ norm distance of the distribution of simulated measurement outcomes from the output distribution of the actual quantum computation. Here we are not accounting for the time required to perform classical computations when adaptive quantum circuits are considered. In addition, Ref. [27] provided a classical algorithm for strong simulation of a circuit $U$ with $L$ Clifford gates and $t T$-gates initialized in a stabilizer state $\Psi$ with an additive error $\delta$. Their algorithm outputs an estimate of the probability $|\langle x, U \Psi\rangle|^{2}$ of obtaining measurement outcome $x \in\{0,1\}^{n}$ up to an additive error $\delta$, with success probability greater than $1-p_{f}$. It has runtime $O\left(\xi_{\text {STAB }_{n}}\left(|T\rangle^{\otimes t}\right) \log \left(1 / p_{f}\right) \cdot\right.$ poly $\left.\left(n, L, \delta^{-1}\right)\right)$, scaling linearly with the stabilizer extent $\xi_{\operatorname{STAB}_{n}}\left(|T\rangle^{\otimes t}\right)$ of $t$ copies of the single-qubit magic state $|T\rangle$ associated with a $T$-gate [11].

### 1.3 The fermionic Gaussian extent

In the following, we generalize the notion of the extent beyond stabilizer computations to any dictionary $\mathcal{D}$. We refer to the corresponding quantity as the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$ of $\Psi$. We assume throughout that we are interested in pure state quantum computations on a Hilbert space $\mathcal{H}$, and that the dictionary $\mathcal{D}$ is a subset of pure states on $\mathcal{H}$. Then the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$ of $\Psi \in \mathcal{H}$ is defined as

$$
\begin{equation*}
\xi_{\mathcal{D}}(\Psi)=\inf _{N \in \mathbb{N}} \inf _{\varphi_{1}, \ldots, \varphi_{N} \in \mathcal{D}}\left\{\|\gamma\|_{1}^{2} \mid \gamma \in \mathbb{C}^{N} \text { such that } \sum_{j=1}^{N} \gamma_{j} \varphi_{j}=\Psi\right\} \tag{5}
\end{equation*}
$$

Here $\|\gamma\|_{1}=\sum_{j=1}^{N}\left|\gamma_{j}\right|$ is the $L^{1}$-norm of the vector $\gamma$. That is, the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$ is the $L^{1}$-norm of the coefficients minimized over all decompositions of $\Psi$ into a finite linear combination of elements of the dictionary $\mathcal{D}$. As mentioned above, quantities of the form (5) are well-studied in the context of signal-processing.

When the dictionary $\mathcal{D}$ is a finite subset of a Hilbert space $\mathcal{H} \cong \mathbb{C}^{d}$, the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$ of a state $\Psi \in \mathcal{H}$ can be expressed as a second-order cone program [28] (see also e.g., [29]), as in Appendix A of Ref. [19]. Second-order cone programs can be solved in time polynomial in $\max (d,|\mathcal{D}|)$. We are typically interested in cases where $\mathcal{D}$ contains a basis of $\mathcal{H}$ (such that every state can indeed be represented as a linear combination of dictionary elements): Here this runtime is at least polynomial in $d$. For example, in the case $\mathcal{D}=\mathrm{STAB}_{n}$ of stabilizer states on $n$ qubits, this leads to an exponential scaling in $n^{2}$. Beyond algorithmic considerations related to the evaluation of the extent, the fact that $\xi_{\mathcal{D}}(\Psi)$ is given by a second-order cone program provides useful analytical insight by convex programming duality. Indeed, this fact has previously been exploited both for showing multiplicativity of the stabilizer extent for states of small dimension [18], as well as to show non-multiplicativity in high dimensions [19]. In Section 6, we also exploit this connection to relate the $\mathcal{D}$-fidelity $F_{\mathcal{D}}(\Psi)$ with the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$.

In contrast, the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$ for an infinite, i.e., continuously parameterized, dictionary $\mathcal{D}$ constitutes additional mathematical challenges as an optimization problem. This is the case of interest here as we are considering the dictionary $\mathcal{D}=\mathcal{G}_{n}$ consisting of all $n$-fermion Gaussian states in the following. We call the associated quantity $\xi_{\mathcal{G}_{n}}(\Psi)$ the (fermionic) Gaussian extent of an $n$-fermion state $\Psi$. Our focus here is on discussing the role of the quantity $\xi_{\mathcal{G}_{n}}(\Psi)$ in the context of classically simulating fermionic linear optics, and its behavior on tensor products. A detailed discussion of the algorithmic problem of computing $\xi_{\mathcal{G}_{n}}(\Psi)$ for an arbitrary state $\Psi$, and finding a corresponding optimal
decomposition of $\Psi$ into a linear combination of Gaussian states is beyond the scope of this work. We refer to e.g., [30] where semidefinite relaxations are given for the related atomic norm minimization problem in cases where the atomic set (corresponding to the dictionary) has algebraic structure. Similar techniques may be applicable to the fermionic Gaussian extent.

### 1.4 On the (sub)multiplicativity of the extent

Consider a situation where an operation $E \notin \mathcal{E}$ not belonging to the set $\mathcal{E}$ of efficiently simulable operations is implemented by using a "magic" resource state $\Psi \notin \mathcal{D}$. For example, if $\mathcal{D}=\operatorname{STAB}_{n}$ is the set of stabilizer states, $\mathcal{E}$ the set of Clifford unitaries and $\mathcal{M}$ the set of single-qubit Pauli- $Z$-measurements, then a non-Clifford gate (such as the $T$-gate) can be realized by an (adaptive) Clifford circuit at the cost of consuming a non-Clifford state (such as the state $|T\rangle$ ) [11]. Similar "gadget constructions" exist for fermionic linear optics, where non-Gaussian unitaries are realized by Gaussian unitaries and non-Gaussian states $[12,13]$. A natural question arising in this situation is to characterize the cost of simulating the application of two independent magic gates $E_{1}, E_{2} \notin \mathcal{E}$, each realized by efficiently simulable operations (belonging to $\mathcal{E}$ ) using magic states $\Psi_{1}, \Psi_{2}$. For any reasonable simulation algorithm, we expect the required simulation effort to increase at most multiplicatively. Indeed, this feature is reflected in the submultiplicativity property

$$
\begin{equation*}
\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right) \leq \xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{1} \in \mathcal{H}_{1} \text { and } \Psi_{2} \in \mathcal{H}_{2} \tag{6}
\end{equation*}
$$

of the $\mathcal{D}$-extent. In Eq. (6), we are considering Hilbert spaces $\mathcal{H}_{1}, \mathcal{H}_{2}$ and their tensor product $\mathcal{H}_{3}=\mathcal{H}_{1} \otimes \mathcal{H}_{2}$, as well as dictionaries $\mathcal{D}_{j} \subset \mathcal{H}_{j}$ for $j \in[3]$. The submultiplicativity property (6) follows immediately from the definition of the extent if the three dictionaries satisfy the inclusion property

$$
\begin{equation*}
\mathcal{D}_{1} \otimes \mathcal{D}_{2} \subset \mathcal{D}_{3} \tag{7}
\end{equation*}
$$

In particular, this is satisfied e.g., when the dictionary $\mathcal{D}_{j}=\operatorname{STAB}_{n_{j}} \subset\left(\mathbb{C}^{2}\right)^{\otimes n_{j}}$ is the set of $n_{j}$-qubit stabilizer states for $j \in[3]$, with $n_{3}=n_{1}+n_{2}$, or when considering the set of (even) Gaussian states (see below).

While the submultiplicativity property (6) is a trivial consequence of Eq. (7), the question of whether or not the stronger multiplicativity property

$$
\begin{equation*}
\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right)=\xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{1} \in \mathcal{H}_{1} \text { and } \Psi_{2} \in \mathcal{H}_{2} \tag{8}
\end{equation*}
$$

holds for the $\mathcal{D}$-extent is a much less trivial problem. If the multiplicativity property (8) is satisfied, then computing the extent of a product state can be broken down into several smaller optimization problems: It suffices to compute the extent of each factor in the tensor product. Furthermore, the classical simulation cost (with typical algorithms) when applying several non-free ("magic") gates constructed by gadgets increases at an exponential rate determined by the individual gates. In contrast, if the extent is not multiplicative (i.e., the equality in (8) is not satisfied for some states $\Psi_{j} \in \mathcal{H}_{j}, j \in[2]$ ), then such a simplification is not possible. More surprisingly, such a violation of multiplicativity implies that the classical simulation cost of applying certain non-free gates can be reduced by treating these jointly instead of individually. We note that in the slightly different context of so-called circuit knitting, similar savings in complexity have been shown to be significant [31].

Previous work established that the stabilizer extent is multiplicative even for multiple factors, that is,

$$
\xi_{\mathrm{STAB}_{n_{1}+\cdots+n_{r}}}\left(\Psi_{1} \otimes \cdots \otimes \Psi_{r}\right)=\prod_{j=1}^{r} \xi_{\mathrm{STAB}_{n_{j}}}\left(\Psi_{j}\right) \quad \text { for all } \quad \Psi_{j} \in\left(\mathbb{C}^{2}\right)^{\otimes n_{j}}, j \in[r]
$$

if the factors are single-qubit, 2 - or 3 -qubit states, i.e., $n_{j} \in[3]$, see Ref. [18]. An example is the stabilizer extent of a tensor product of $t$ copies of the magic (single-qubit) state $|T\rangle=\left(|0\rangle+e^{i \pi / 4}|1\rangle\right) / \sqrt{2}$ associated with the $T$-gate. Multiplicativity for qubit states gives $\xi_{\mathrm{STAB}_{1}}\left(|T\rangle^{\otimes t}\right)=\xi_{\mathrm{STAB}_{t}}(|T\rangle)^{t}$, where $\xi_{\mathrm{STAB}_{1}}(|T\rangle)$ is known to be approximately 1.17 [17]. This translates to an overhead exponential in $t$ in the runtime of stabilizer computations supplemented with $t T$-gates. Surprisingly, the stabilizer extent has been shown not to be multiplicative (for all pairs of states) in high dimensions [19].

For (pure) Gaussian states, the Gaussian extent of a 1-, 2- and 3-mode pure fermionic state is trivially one because any $1-, 2$ - and 3 -mode pure fermionic state is Gaussian [32] and is thus an element of the dictionary. Hence the Gaussian extent is (trivially) multiplicative if the factors are 1 -, 2 - or 3 -mode fermionic states. The simplest non-trivial case is that of $n=4$ fermionic modes in each factor.

### 1.5 Our contribution

Our results concern fermionic linear optics, the computational model introduced in Section 1.1.2 described by the triple $\left(\mathcal{G}_{n}, \mathcal{E}_{\text {Gauss }}, \mathcal{M}_{\text {number }}\right)$ of fermionic Gaussian pure states on $n$ fermions, Gaussian unitary operations and number state measurements. We propose classical simulation algorithms for the case where the initial state $\Psi \in \mathcal{H}_{n}$ is an arbitrary pure state in the $n$-fermion Hilbert space $\mathcal{H}_{n}$ (instead of belonging to the set $\mathcal{G}_{n} \subset \mathcal{H}_{n}$ of Gaussian states). Our results are two-fold:

New simulation algorithms. We give algorithms realizing the functionalities described in Section 1.1 exactly for the triple $\left(\mathcal{H}_{n}, \mathcal{E}_{\text {Gauss }}, \mathcal{M}_{\text {number }}\right)$. This immediately gives rise to efficient algorithms for weak and strong simulation of circuits with non-Gaussian initial states. The corresponding runtimes of these building blocks, which we refer to as ( $\chi$ evolve, $\chi$ measureprob, $\chi$ postmeasure), depend on the Gaussian rank $\chi=\chi_{\mathcal{G}_{n}}(\Psi)$ of the initial state $\Psi$ and are summarized in Table 3.

| algorithm | time |
| :---: | :---: |
| $\chi$ evolve | $O\left(\chi n^{3}\right)$ |
| $\chi$ measureprob | $O\left(\chi^{2} n^{3}\right)$ |
| $\chi$ postmeasure | $O\left(\chi n^{3}\right)$ |

Table 3: Runtimes of the building blocks $\chi$ evolve, $\chi$ measureprob, $\chi$ postmeasure for exact simulation of $n$-qubit fermionic linear optics circuits with a non-Gaussian initial state $\Psi$ of Gaussian rank $\chi=$ $\chi_{\mathcal{G}_{n}}(\Psi)$. Evolution corresponds to the application of a Gaussian unitary from a set $\mathcal{E}_{\text {Gauss }}$ of generators (specified below), and the set of measurements is given by occupation number measurements on each of the modes.

Key to the construction of these algorithms is a novel way of keeping track of relative phases in superpositions of Gaussian states, see Section 3. We argue that our techniques can be applied more generally to adapt simulation procedures developed, e.g., for Clifford circuits, to the setting of fermionic linear optics. In order to illustrate this procedure,
we apply it to the simulation algorithms of $[17,18]$ for efficient (approximate) classical simulation algorithms. In this way, we obtain new approximate simulation algorithms with runtimes depending linearly on the fermionic Gaussian extent $\xi=\xi_{\mathcal{G}_{n}}(\Psi)$ of the initial state $\Psi$, see Table 4 for a summary of the corresponding runtimes. They depend

| algorithm | time |
| :---: | :---: |
| approxevolve | $O\left(\xi \delta^{-2} n^{3}\right)$ |
| approxmeasureprob | $O\left(\xi \delta^{-2} \epsilon^{-2} p_{f}^{-1} n^{7 / 2}\right)$ |
| approxpostmeasure | $O\left(\xi \delta^{-2} n^{3}\right)$ |

Table 4: Runtimes of building blocks approxevolve, approxmeasureprob, approxpostmeasure for approximate simulation of $n$-qubit fermionic linear optics circuits with a non-Gaussian initial state $\Psi$ of Gaussian extent $\xi=\xi_{\mathcal{G}_{n}}(\Psi)$. The parameters $\left(\epsilon, \delta, p_{f}\right)$ determine the quality of the approximation.
inverse-polynomially on parameters $\left(\delta, \epsilon, p_{f}\right)$ determining the accuracy of the simulation. The error $\delta$ describes a certain "offset", i.e., a systematic error: Instead of simulating the dynamics of the circuit with the (ideal) initial state $\Psi$, the simulation algorithm emulates the dynamics when using a different starting state $\tilde{\Psi}$ which is $\delta$-close to $\Psi$, i.e., which satisfies $\|\Psi-\tilde{\Psi}\| \leq \delta$. The algorithm approxevolve computes evolution exactly on the state used in the simulation (i.e., it preserves the approximation error $\delta$ relative to the ideal initial state). In contrast, the procedure approxmeasureprob can fail with probability $p_{f}$, and both approxmeasureprob and approxpostmeasure introduce an additional error quantified by $\epsilon$ (if approxmeasureprob succeeds): Instead of returning the probability $p(0)$ of obtaining zero occupation number when measuring the state, the output of approxmeasureprob is a value $\tilde{p}$ which satisfies $|\tilde{p}-p(0)| \leq O(\epsilon)$. Similarly, the output of approxpostmeasure is a description of a state that is $O(\epsilon)$-close to the actual post-measurement state. These parameters and runtimes are analogous to those obtained in [18] for simulating Clifford circuits with non-stabilizer initial states. In particular, they imply that a circuit with initial state $\Psi$ involving $T$ Gaussian unitaries and $L$ occupation number measurements can be weakly simulated in time $\tilde{O}\left(\epsilon^{-2} \xi\right)$, such that the sampled measurement outcomes are $\epsilon$-close in $L^{1}$-distance to the ideal (joint) output distribution of all measurements. Here the notation $\tilde{O}(\cdot)$ suppresses a factor polynomial in $n, T, L$ and $\log \left(\epsilon^{-1}\right)$, see [17] for details.

On the multiplicativity of the Gaussian extent and the Gaussian fidelity. Motivated by the relevance of the Gaussian extent $\xi_{\mathcal{G}_{n}}(\Psi)$ for characterizing the complexity of classical simulation, we study multiplicativity properties of both the $\mathcal{D}$-fidelity $F_{\mathcal{D}}(\Psi)$ as we well as the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$ for a general infinite, i.e., continuously parameterized, dictionary $\mathcal{D}$. We show that multiplicativity of the $\mathcal{D}$-fidelity is closely related to that of the $\mathcal{D}$-extent: For a general family of (discrete or continuous) dictionaries $\mathcal{D}_{j} \subset \mathcal{H}_{j}$ for $j \in[3]$ with the property

$$
\mathcal{D}_{1} \otimes \mathcal{D}_{2} \subset \mathcal{D}_{3}
$$

multiplicativity of the $\mathcal{D}$-fidelity, i.e.,

$$
F_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right)=F_{\mathcal{D}_{1}}\left(\Psi_{1}\right) F_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{j} \in \mathcal{H}_{j} \text { for } j \in[2]
$$

implies multiplicativity of the $\mathcal{D}$-extent, i.e.

$$
\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right)=\xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{j} \in \mathcal{H}_{j} \text { for } j \in[2]
$$

We note that for stabilizer states $\mathcal{D}=$ STAB $_{n}$, a similar route was followed in Ref. [18] to show multiplicativity of the stabilizer extent $\xi_{\text {STAB }_{n}}$ with respect to the tensor product of 1-, 2- and 3-qubit states. Our main contribution is an extension of this connection to the case of infinite dictionaries by the use of nets. We expect this connection to be helpful in proving or disproving multiplicativity of the extent more generally.

We subsequently make use of this connection to the Gaussian fidelity to show that the fermionic Gaussian extent is multiplicative for the tensor product of any two 4-mode fermionic states with positive parity, i.e.,

$$
\begin{equation*}
\xi_{\mathcal{G}_{8}}\left(\Psi_{1} \otimes \Psi_{2}\right)=\xi_{\mathcal{G}_{4}}\left(\Psi_{1}\right) \xi_{\mathcal{G}_{4}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{1}, \Psi_{2} \in \mathcal{H}_{+}^{4} \tag{9}
\end{equation*}
$$

Here $\mathcal{H}_{+}^{4}$ denotes the set of 4-mode fermionic states with positive parity. The proof of (9) relies on the Schmidt decomposition of fermionic Gaussian states and specific properties of 4-mode (positive parity) fermionic states.

The result (9) gives the first non-trivial example of multiplicativity of the Gaussian extent. Multiplicativity for more general cases such as that of multiple 4-mode fermionic factors remains an open problem.

### 1.6 Prior and related work

The starting point of our work is the fact that fermionic Gaussian operations acting on Gaussian states can be efficiently simulated classically as shown in pioneering work by Terhal and DiVincenzo [9] and Knill [10]. The model and its simulability are closely related to that of matchgate computations introduced by Valiant [8], where so-called matchgates correspond to a certain certain subset of Gaussian operations (see also [33]). In analogy to the fermionic context, the efficient simulability of bosonic Gaussian circuits was recognized at around the same time [34,35]. In an effort to identify commonalities between simulation algorithms for a variety of quantum computational models, Somma et al. [36] provided a unifying Lie algebraic treatment which gives a counterpart to the Gottesman-Knill theorem for the simulability of Clifford circuits [7,37].

While matchgate circuits, fermionic and bosonic linear optics, and Clifford circuits provide rich classes of efficiently simulable models for the study of many-body dynamics associated with quantum circuits, it is desirable to extend the applicability of such simulation methods. There has been significant interest in this problem resulting in a range of approaches. We only briefly discuss these here to give an overview, without attempting to give an exhaustive treatment.

A first prominent approach is the use of quasi-probability distributions to describe states and corresponding dynamics. Such a description typically applies to a subset of density operators: For example, it has been shown in $[38,39]$ in the context of continuousvariable systems that circuits applying bosonic Gaussian operations to initial states with a positive Wigner function (a strict superset of the set of bosonic Gaussian states) can be simulated efficiently. Negativity of the Wigner function (both in the continuous-variable as well as the qubit context) thus serves as a resource for quantum computation, also see e.g., [40,41]. It is also closely related to contextuality, see [42], and thus connects contextuality to the complexity of classical simulation $[43,44]$. Not unlike the notorious sign problem in quantum Monte-Carlo methods applied in many-body physics, the runtimes of corresponding (randomized) simulation algorithms scale with certain measures of "negativity" of the initial state.

The concept of a convex-Gaussian state was introduced and studied in [32] to extend the range of fermionic linear optics simulation methods. This is related to quasi-probability
representations in the sense that initial states of a particular form are shown to lead to efficient simulability. Here a density operator is called convex-Gaussian if it is a convex combination of fermionic Gaussian states. The utility of this concept was illustrated in [32] by showing a converse to the fault-tolerance threshold theorem: Sufficiently noisy quantum circuits can be simulated classically because the corresponding states turn out to be convex-Gaussian. A detailed characteriziation of convex-Gaussianity is necessary to translate this into explicit (numerical) threshold estimates. An infinite hierarchy of semidefinite programs was constructed in [32] to detect convex-Gaussianity, and this was subsequently shown to be complete [45]. This hierarchy also provides a way of determining whether a state is close to being convex-Gaussian [45].

A second important class of approaches are rank-based methods. Here the non-free resource (either a state or an operation) is decomposed into a linear combination of free (i.e., efficiently simulable) resources. Our work follows this approach, which is detailed in Section 4.1 for pure states. For Clifford computations, this involves writing general states as superpositions of stabilizer states. The development of such simulators was pioneered by Bravyi, Smith, and Smolin [16] with subsequent work dealing with approximate stabilizer decompositions [17].

The concept of low-rank (approximate) decompositions of quantum states or operations into more easily treatable basic objects appears in a variety of forms: For example, the work [18] also discusses - in addition to state vector decompositions - decompositions of non-Clifford unitaries into sums of Clifford operations. In Ref. [46], a similar approach was taken to approximately decompose non-Gaussian fermionic unitary operations into linear combinations of Gaussian channels. In all these cases, the main challenge is to identify optimal (or simply good) decompositions (e.g., in terms of rank or an extent-like quantity).

In more recent work, Mocherla, Lao and Browne [47] study the problem of simulating matchgate circuits using universality-enabling gates. They provide a simulation algorithm and associated runtime estimates for estimating expectation values of single-qubit observables in output states obtained by applying a matchgate circuit to a product state. This problem is closely related to the problem considerd in this work as matchgate circuits efficiently describe evolution under a quadratic fermionic Hamiltonian. The approach taken in [47] is quite different from ours, however: The classical simulator keeps track of the density operator by tracking its coefficients in the Pauli (operator) basis, using the structure of corresponding linear maps associated with matchgates. The effect of a specific set of universality-enabling gates is then analyzed in detail. This extends the sparse simulation method for matchgate circuits to circuits augmented with such gates. The runtime estimates of [47] apply to certain universality-providing gates. In contrast, our constructions can in principle also be applied to (gadget-based) constructions of arbitrary gates and provide gate-specific information. For gates close to the identity, for example, this may provide additional resource savings (in terms of e.g., the rate of growth for several uses of such a gate).

Near the completion of our work, we became aware of concurrent independent work on fermionic circuits with non-Gaussian operations, see the papers [48, 49] which were posted simultaneously with our work to the arXiv. Reference [48] proposes an alternative classical simulation algorithm for such circuits whose basic building blocks have identical runtime as our algorithm. In particular, when applying a generator $\exp \left(\vartheta / 2 c_{j} c_{k}\right)$ of the Gaussian unitary group, the runtime of the corresponding state update routine is $O\left(n^{3}\right)$ as in our work. Specifying a circuit in terms of a sequence of generators is a common assumption when discussing restricted gate sets. If instead, a general Gaussian unitary
is specified by an element $R \in S O(2 n)$, the runtimes are different: By decomposing $R$ into $O\left(n^{2}\right)$ Givens rotations (generators), our techniques yield a runtime of order $O\left(n^{5}\right)$, whereas the algorithm of [48] runs in time $O\left(n^{4}\right)$ in this case. A more significant distinction is the underlying approach: While we rely on a minimal extension of the covariance matrix formalism, the approach of [48] involves an explicit decomposition of fermionic Gaussian unitaries inspired by a certain canonical form of Clifford circuits [18]. This decomposition of a Gaussian unitary $U$ is subsequently used to specify a Gaussian state $U|0\rangle$ including its global phase.

The work [49] analyses the set of fermionic Gaussian states to investigate properties of the (exact and approximate) Gaussian rank, the Gaussian fidelity and the Gaussian extent. A major result obtained in [49] is the multiplicativity of the extent for a tensor product state with any number of 4 -mode factors. This mirrors what is known for two-qubit and three-qubit factors in the stabilizer context [18]. The proof in Ref. [49] is inspired by Ref. [19] and makes use of tools from convex optimization. It involves the use of a net of Gaussian states to establish an upper bound on the Gaussian fidelity. While we only establish multiplicativity for two factors (i.e., a special case of their result), our approach is different and may be of independent interest: We use a net to show that multiplicativity of the Gaussian fidelity implies that of the Gaussian extent, and employ the Schmidt decomposition [50] of fermionic Gaussian states.

### 1.7 Outline

The paper is structured as follows. In Section 2, we give some background on fermionic linear optics, reviewing fermionic Gaussian operations and states, inner product formulas for Gaussian states and tensor products of fermionic systems. In Sections 3 and 4 we describe classical algorithms for simulation of Gaussian and non-Gaussian fermionic circuits, respectively. Specifically, in Section 3 we provide an algorithm overlap for computing the overlap of two Gaussian states, an algorithm evolve to simulate unitary evolution of a Gaussian state, and algorithms measureprob and postmeasure to simulate measurements of occupation numbers. All these algorithms keep track of the phase of the state. In Section 4 we extend the simulation described in Section 3 to allow for non-Gaussian input states. The remainder of this work is focused on the multiplicativity of the fermionic Gaussian extent. In Section 5, we prove the multiplicativity of the fermionic Gaussian fidelity for the tensor product of any two 4 -mode fermionic states with positive parity. Section 6 is devoted to showing that the multiplicativity of the $\mathcal{D}$-fidelity implies multiplicativity of the $\mathcal{D}$-extent for general (finite and infinite, i.e., continuously parameterized) dictionaries. Finally, the results from Sections 5 and 6 are used to prove the main result in Section 7, namely the multiplicativity of the fermionic Gaussian extent for the tensor product of any two 4-mode fermionic states with positive parity.

## 2 Background

In this section, we give some background on fermionic linear optics to fix notation.

### 2.1 Dirac and Majorana operators

Throughout, we consider fermionic systems composed of $n$ modes, with (Dirac) creationand annihilation operators $a_{j}^{\dagger}, a_{j}, j \in[n]$, satisfying the canonical anticommutation rela-
tions

$$
\left\{a_{j}, a_{k}^{\dagger}\right\}=\delta_{j, k} I \quad \text { and } \quad\left\{a_{j}, a_{k}\right\}=\left\{a_{j}^{\dagger}, a_{k}^{\dagger}\right\}=0 \quad \text { for all } \quad j, k \in[n] .
$$

The fermionic vacuum state $\left|0_{F}\right\rangle$ is the (up to a phase) unique unit vector satisfying $a_{j}\left|0_{F}\right\rangle=0$ for all $j \in[n]$. For $x=\left(x_{1}, \ldots, x_{n}\right) \in\{0,1\}^{n}$, we define the number state $|x\rangle$ by

$$
\begin{equation*}
|x\rangle=\left(a_{1}^{\dagger}\right)^{x_{1}} \cdots\left(a_{n}^{\dagger}\right)^{x_{n}}\left|0_{F}\right\rangle . \tag{10}
\end{equation*}
$$

The states $\{|x\rangle\}_{x \in\{0,1\}^{n}}$ are an orthonormal basis of the underlying Hilbert space $\mathcal{H}^{n} \cong$ $\left(\mathbb{C}^{2}\right)^{\otimes n}$. A state $|x\rangle$ is a simultaneous eigenstate of the occupation number operators $a_{j}^{\dagger} a_{j}$, $j \in[n]$, where $x_{j}$ is the eigenvalue of $a_{j}^{\dagger} a_{j}$. For later reference, we note that

$$
\begin{equation*}
a_{j}|x\rangle=(-1)^{\eta_{j}(x)} x_{j}\left|x \oplus e_{j}\right\rangle \quad \text { and } \quad a_{j}^{\dagger}|x\rangle=(-1)^{\eta_{j}(x)} \overline{x_{j}}\left|x \oplus e_{j}\right\rangle, \tag{11}
\end{equation*}
$$

with the definition

$$
\begin{equation*}
\eta_{j}(x)=\sum_{k=1}^{j-1} x_{k} \quad \text { for } \quad j \in[n], \tag{12}
\end{equation*}
$$

where we write $\overline{0}=1$ and $\overline{1}=0$, where $e_{j} \in\{0,1\}^{n}$ is given by $\left(e_{j}\right)_{k}=\delta_{j, k}$ for $k \in[n]$, and where $\oplus$ denotes bitwise addition modulo 2 .

It will be convenient to work with Majorana operators $\left\{c_{j}\right\}_{j=1}^{2 n}$ defined by

$$
\begin{equation*}
c_{2 j-1}=a_{j}+a_{j}^{\dagger} \quad \text { and } \quad c_{2 j}=i\left(a_{j}-a_{j}^{\dagger}\right) . \tag{13}
\end{equation*}
$$

Majorana operators are self-adjoint and satisfy the relations

$$
\left\{c_{j}, c_{k}\right\}=2 \delta_{j k} I \quad \text { and } \quad c_{j}^{2}=I \quad \text { for } \quad j, k \in[2 n] .
$$

For $\alpha \in\{0,1\}^{2 n}$, we call the self-adjoint operator

$$
c(\alpha)=i^{|\alpha| \cdot(|\alpha|-1) / 2} c_{1}^{\alpha_{1}} \cdots c_{2 n}^{\alpha_{2 n}}
$$

a Majorana monomial. Here $|\alpha|=\sum_{j=1}^{2 n} \alpha_{j}$ denotes the Hamming weight of $\alpha \in\{0,1\}^{2 n}$. The set $\{c(\alpha)\}_{\alpha \in\{0,1\}^{n}}$ constitutes an orthonormal basis of the real vector space of selfadjoint operators on $\mathcal{H}^{n}$ equipped with the (normalized) Hilbert-Schmidt inner product $\langle A, B\rangle=2^{-n} \operatorname{tr}\left(A^{\dagger} B\right)$. The Majorana monomials satisfy

$$
c(y) c(x)=(-1)^{|x| \cdot|y|+x \cdot y} c(x) c(y) \quad \text { with } \quad x, y \in\{0,1\}^{2 n},
$$

where $x \cdot y=\sum_{j=1}^{n} x_{j} y_{j}$. In particular, if either $x$ or $y$ have even Hamming weight then $c(x) c(y)=(-1)^{x \cdot y} c(y) c(x)$. In the following, we will denote the set of even- and odd-weight $2 n$-bit strings by $\{0,1\}_{+}^{2 n}$ and $\{0,1\}_{-}^{2 n}$, respectively.

The parity operator

$$
P=i^{n} c_{1} c_{2} \cdots c_{2 n}
$$

is the Majorana monomial associated with $\alpha=1^{2 n}=(1, \ldots, 1)$. The parity operator commutes with every even-weight Majorana monomial and anti-commutes with every odd-weight Majorana monomial, i.e., we have

$$
\begin{equation*}
P c(\alpha)=(-1)^{|\alpha|} c(\alpha) P \quad \text { for every } \quad \alpha \in\{0,1\}^{2 n} . \tag{14}
\end{equation*}
$$

The Hilbert space $\mathcal{H}^{n}=\mathcal{H}_{+}^{n} \oplus \mathcal{H}_{-}^{n}$ associated with $n$ fermions decomposes into a direct sum of positive- and negative-parity vectors

$$
\begin{aligned}
& \mathcal{H}_{+}^{n}=\left\{\Psi \in \mathcal{H}^{n} \mid P \Psi=\Psi\right\} \text { and } \\
& \mathcal{H}_{-}^{n}=\left\{\Psi \in \mathcal{H}^{n} \mid P \Psi=-\Psi\right\} .
\end{aligned}
$$

We call a state $\Psi \in \mathcal{H}^{n}$ of definite parity if either $\Psi \in \mathcal{H}_{+}^{n}$ or $\Psi \in \mathcal{H}_{-}^{n}$. An element $X \in$ $\mathcal{B}\left(\mathcal{H}^{n}\right)$ belonging to the set $\mathcal{B}\left(\mathcal{H}^{n}\right)$ of linear operators on $\mathcal{H}^{n}$ is called even (odd) if it is a linear combination of Majorana monomials $c(\alpha)$ with $\alpha \in\{0,1\}^{2 n}$ of even (odd) weight. An immediate consequence of these definitions is that a state $\Psi \in \mathcal{H}^{n}$ has definite parity if and only if $|\Psi\rangle\langle\Psi|$ is even (see e.g., [51, Proposition 1] for a proof).

### 2.2 Gaussian unitaries

A unitary operator $U$ on $\mathcal{H}^{n}$ is Gaussian if and only if it maps a Majorana operator $c_{j}$ to a linear combination of Majorana operators, i.e.

$$
\begin{equation*}
U c_{j} U^{\dagger}=\sum_{k=1}^{2 n} R_{j k} c_{k}, \tag{15}
\end{equation*}
$$

where $R \in O(2 n)$ is a real orthogonal matrix. Ignoring overall phases, the group of Gaussian unitary operators is generated by operators of the form

$$
U_{j, k}(\vartheta)=\exp \left(\vartheta / 2 c_{j} c_{k}\right) \quad \text { with } \quad \vartheta \in[0,2 \pi) \text { and } j<k \in[2 n]
$$

and by operators

$$
U_{j}=c_{j} \quad \text { with } \quad j \in[2 n] .
$$

The operator $U_{j, k}(\vartheta)$ implements the rotation

$$
\begin{array}{ll}
U_{j, k}(\vartheta) c_{j} U_{j, k}(\vartheta)^{\dagger}=\cos (\vartheta) c_{j}-\sin (\vartheta) c_{k} & \\
U_{j, k}(\vartheta) c_{k} U_{j, k}(\vartheta)^{\dagger}=\sin (\vartheta) c_{j}+\cos (\vartheta) c_{k} &  \tag{16}\\
U_{j, k}(\vartheta) c_{\ell} U_{j, k}(\vartheta)^{\dagger}=c_{\ell} \quad \text { for } \quad \ell \notin\{j, k\} .
\end{array}
$$

The operator $U_{j}=c_{j}$ leaves $c_{j}$ invariant and flips the sign of each $c_{k}$ with $k \neq j$, i.e., it implements the reflection

$$
\begin{align*}
U_{j} c_{j} U_{j}^{\dagger} & =c_{j} \\
U_{j} c_{k} U_{j}^{\dagger} & =-c_{k} \quad \text { for } \quad k \neq j . \tag{17}
\end{align*}
$$

We note that by relation (14), every generator $U_{j, k}(\vartheta)$ is parity-preserving, whereas every generator $U_{j}$ reverses the parity, i.e.,

$$
\begin{align*}
U_{j, k}(\vartheta) P U_{j, k}(\vartheta)^{\dagger} & =P & & \text { for all }
\end{align*} \begin{array}{ll} 
& k>j \in[n], \vartheta \in[0,2 \pi), \\
U_{j} P U_{j}^{\dagger} & =-P
\end{array} r \begin{array}{ll}
\text { for all } &  \tag{18}\\
j \in[n] .
\end{array}
$$

Every orthogonal matrix $R$ gives rise to a Gaussian unitary $U_{R}$ satisfying (15). The unitary $U_{R}$ is unique up to a global phase, and $R \mapsto U_{R}$ is called the metaplectic representation. We can fix the global phase of $U_{R}$ uniquely, e.g., by the following procedure. Every element $R \in O(2 n)$ can be uniquely decomposed into a product

$$
\begin{equation*}
R=S_{0} S_{1} \cdots S_{L} \tag{19}
\end{equation*}
$$

with $L \leq \frac{2 n(2 n-1)}{2}$ and where

$$
S_{0}=\left\{\begin{array}{lc}
I & \text { if } R \in S O(2 n) \\
R_{1} & \text { otherwise },
\end{array}\right.
$$

where for each $r \in[L]$, the matrix $S_{r}$ is of the form

$$
S_{r}=R_{j_{r}, k_{r}}\left(\vartheta_{r}\right) \quad \text { for some } \quad j_{r}<k_{r} \in[2 n], \vartheta_{r} \in[0,2 \pi) .
$$

Here $R_{1} \in O(2 n)$ is associated with the unitary $U_{1}$ by Eq. (17), whereas $R_{j, k}(\vartheta) \in S O(2 n)$ is associated with $U_{j, k}(\vartheta)$ according to Eq. (16). We note that $R_{j, k}(\vartheta) \in S O(2 n)$ is a so-called Givens rotation, introduced in Ref. [52], and a decomposition of the form (19) can be found by a deterministic algorithm with runtime $O\left(n^{3}\right)$ (see e.g., Section 5.2.3 in Ref. [53]). In particular, application of this algorithm defines a function taking an arbitrary element $R \in O(2 n)$ to a unique product of the form (19). Given the (unique) decomposition (19) of $R \in O(2 n)$, we can then define $U_{R}$ as the product

$$
U_{R}=U_{1} U_{j_{1}, k_{1}}\left(\vartheta_{1}\right) \cdots U_{j_{L}, k_{L}}\left(\vartheta_{L}\right) .
$$

Overall, this defines a function $R \mapsto U_{R}$ from $O(2 n)$ to the set of Gaussian unitaries, fixing the phase ambiguity. Throughout the remainder of this work, $U_{R}$ will denote the Gaussian unitary uniquely fixed by $R$.

### 2.3 Fermionic Gaussian (pure) states

The set of pure fermionic Gaussian states is the orbit of the vacuum state $\left|0_{F}\right\rangle$ under the action of $O(2 n)$ defined by the metaplectic representation, i.e., fermionic Gaussian states are of the form $U_{R}\left|0_{F}\right\rangle$ with $U_{R}$ a fermionic Gaussian unitary. In more detail, every fermionic Gaussian state $e^{i \theta} U_{R}\left|0_{F}\right\rangle$ is uniquely specified by a pair $(\theta, R)$ with $\theta \in[0,2 \pi)$ and $R \in O(2 n)$. We will denote the set of all fermionic Gaussian states by

$$
\mathcal{G}_{n}=\left\{e^{i \theta} U_{R}\left|0_{F}\right\rangle \mid \theta \in[0,2 \pi), R \in O(2 n)\right\} .
$$

By Eq. (18) and because $P\left|0_{F}\right\rangle=\left|0_{F}\right\rangle$, every pure fermionic Gaussian state $\Psi$ has a fixed parity, i.e., it is an eigenvector of the parity operator $P$. This defines a disjoint partition $\mathcal{G}_{n}=\mathcal{G}_{n}^{+} \cup \mathcal{G}_{n}^{-}$of the set of fermionic Gaussian states into positive- and negativeparity states.

### 2.4 Gaussianity condition

In Ref. [54] Bravyi established a necessary and sufficient condition to determine if a (possibly mixed) state $\rho \in \mathcal{B}\left(\mathcal{H}^{n}\right)$ is Gaussian (see Theorem 1 therein). Here Gaussianity of a density operator $\rho$ is defined by the condition that $\rho$ has the form

$$
\begin{equation*}
\rho=K \exp \left(i \sum_{j, k=1}^{2 n} A_{j, k} c_{j} c_{k}\right) \tag{20}
\end{equation*}
$$

for an antisymmetric matrix $A=-A^{T} \in \operatorname{Mat}_{2 n \times 2 n}(\mathbb{R})$ and a constant $K>0$. We note that a pure state $\Psi \in \mathcal{H}^{n}$ is Gaussian if and only if the associated density operator $\rho=$ $|\Psi\rangle\langle\Psi|$ is Gaussian. (This follows from the fact that $\left|0_{F}\right\rangle\left\langle 0_{F}\right|=\frac{1}{2^{n / 2}} \exp \left(i \frac{\pi}{4} \sum_{j=1}^{n} c_{2 j-1} c_{2 j}\right)$. Indeed, if $\rho=|\Psi\rangle\langle\Psi|$ is a rank-one projection of the form (20), then it follows from

Williamson's normal form for antisymmetric matrices that there is $R \in O(2 n)$ such that $R A R^{T}=\oplus_{j=1}^{n}\left(\begin{array}{cc}0 & 1 \\ -1 & 0\end{array}\right)$. This implies that $U_{R}|\Psi\rangle\langle\Psi| U_{R}^{\dagger}=\left|0_{F}\right\rangle\left\langle 0_{F}\right|$ and thus $|\Psi\rangle=$ $U_{R}^{\dagger}\left|0_{F}\right\rangle$. Conversely, for a Gaussian state $|\Psi\rangle=e^{i \theta} U_{R}\left|0_{F}\right\rangle \in \mathcal{G}_{n}$, we can use the expression for $\left|0_{F}\right\rangle\left\langle 0_{F}\right|$ to argue that $|\Psi\rangle\langle\Psi|$ is of the form (20), i.e., Gaussian.) The characterization of Gaussian density operators established in [54] is the following.

Theorem 2.1 (Theorem 1 in [54]). Define $\Lambda=\sum_{j=1}^{2 n} c_{j} \otimes c_{j}$. An even state $\rho \in \mathcal{B}\left(\mathcal{H}^{n}\right)$ is Gaussian if and only if $[\Lambda, \rho \otimes \rho]=0$.

Based on this characterization [54], the following was shown in [32].
Lemma 2.2 (Corollary 1 in [32]). Let $\rho \in \mathcal{B}\left(\mathcal{H}^{n}\right)$ be an even state. Then $\rho$ is a Gaussian pure state if and only if $\Lambda(\rho \otimes \rho)=0$.

In the following, we only use the statement of Lemma 2.2 applied to pure states in order to distinguish between Gaussian and non-Gaussian pure states. We formulate this as follows:

Lemma 2.3. Let $\Psi \in \mathcal{H}^{n}$ be a pure state with fixed parity. Then $\Psi$ is Gaussian if and only if

$$
\Lambda(|\Psi\rangle \otimes|\Psi\rangle)=0 .
$$

Proof. This follows immediately from the equivalence of the concepts of Gaussianity of pure states (vectors) and density operators because the density operator $|\Psi\rangle\langle\Psi|$ is even for any fixed-parity state $\Psi$.

We note that there is an elegant representation-theoretic interpretation of this characterization of Gaussianity [55]. It is derived from the fact that Gaussian states are the orbit of the vacuum state $\left|0_{F}\right\rangle$ (a highest weight state) under the action of the metaplectic group, cf. [56, Section IV] and [57]. We use a version of this reformulation for 4 fermions, see Lemma 5.1 below, that has first been obtained in [58].

### 2.5 Covariance matrices, Gaussian states and Wick's theorem

The covariance matrix $\Gamma=\Gamma(\Psi) \in \operatorname{Mat}_{2 n \times 2 n}(\mathbb{R})$ of a state $\Psi \in \mathcal{H}^{n}$ is the antisymmetric matrix with entries

$$
\Gamma_{j, k}(\Psi)= \begin{cases}\left\langle\Psi, i c_{j} c_{k} \Psi\right\rangle & \text { for } j \neq k  \tag{21}\\ 0 & \text { for } j=k\end{cases}
$$

with $j, k \in[2 n]$. It satisfies $\Gamma \Gamma^{T}=I$ for any state $\Psi \in \mathcal{H}^{n}$.
The expectation value of a Hermitian operator with respect to a Gaussian state $\Psi$ is fully determined by its covariance matrix $\Gamma=\Gamma(\Psi)$. This is because the expectation value of a Majorana monomial $c(\alpha), \alpha \in\{0,1\}^{2 n}$, is given by Wick's theorem

$$
\langle\Psi, c(\alpha) \Psi\rangle=\left\{\begin{array}{ll}
\operatorname{Pf}(\Gamma[\alpha]) & \text { if }|\alpha| \text { is even }  \tag{22}\\
0 & \text { otherwise }
\end{array} .\right.
$$

Here $\Gamma[\alpha] \in \operatorname{Mat}_{|\alpha| \times|\alpha|}(\mathbb{R})$ is the submatrix of $\Gamma$ which includes all rows and columns with index $j \in[2 n]$ such that $\alpha_{j}=1$. Evaluating such expectation values, i.e., computing Pfaffians of $|\alpha| \times|\alpha|$-matrices (with $|\alpha|$ even), takes time $O\left(|\alpha|^{3}\right)$. (Here and below we use the number of elementary arithmetic operations to quantify the time complexity of algorithms.)

### 2.6 Inner product formulas for Gaussian states

The modulus of the inner product of two Gaussian states $\Phi_{1}, \Phi_{2}$ with identical parity $\sigma \in$ $\{ \pm 1\}$ and covariance matrices $\Gamma_{1}, \Gamma_{2}$ is given by the expression [59]

$$
\begin{equation*}
\left|\left\langle\Phi_{1}, \Phi_{2}\right\rangle\right|^{2}=\sigma 2^{-n} \operatorname{Pf}\left(\Gamma_{1}+\Gamma_{2}\right) . \tag{23}
\end{equation*}
$$

For three Gaussian states $\Phi_{0}, \Phi_{1}, \Phi_{2}$, the expression $\left\langle\Phi_{0}, \Phi_{1}\right\rangle \cdot\left\langle\Phi_{1}, \Phi_{2}\right\rangle \cdot\left\langle\Phi_{2}, \Phi_{0}\right\rangle$ is invariant under a change of the global phase of any of the states, and can therefore be computed by the covariance matrix formalism. An explicit expression was derived by Löwdin in [59]. In Ref. [60] Bravyi and Gosset gave the formula

$$
\left\langle\Phi_{0}, \Phi_{1}\right\rangle \cdot\left\langle\Phi_{1}, \Phi_{2}\right\rangle \cdot\left\langle\Phi_{2}, \Phi_{0}\right\rangle=\sigma 4^{-n} i^{n} \operatorname{Pf}\left(\begin{array}{ccc}
i \Gamma_{0} & -I & I  \tag{24}\\
I & i \Gamma_{1} & -I \\
-I & I & i \Gamma_{2}
\end{array}\right)
$$

for three Gaussian states $\left\{\Phi_{j}\right\}_{j=0}^{2}$ of identical parity $\sigma \in\{ \pm 1\}$, where $\Gamma_{j}=\Gamma\left(\Phi_{j}\right)$ is the covariance matrix of $\Phi_{j}$ for $j=0,1,2$. More generally, they obtained the formula

$$
\begin{equation*}
\left\langle\Phi_{0}, \Phi_{1}\right\rangle \cdot\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle \cdot\left\langle\Phi_{2}, \Phi_{0}\right\rangle=\sigma 4^{-n} i^{n+|\alpha| \cdot(|\alpha|-1) / 2} \operatorname{Pf}\left(R_{\alpha}\right) \tag{25}
\end{equation*}
$$

for any even-weight Majorana monomial $c(\alpha), \alpha \in\{0,1\}_{+}^{2 n}$, where

$$
R_{\alpha}=\left(\begin{array}{cccc}
i \Gamma_{0} & -I & I & 0  \tag{26}\\
I & i \Gamma_{1} & -I & 0 \\
-I & I & i D_{\alpha} \Gamma_{2} D_{\alpha} & J_{\alpha}^{T}+i D_{\alpha} \Gamma_{2} J_{\alpha}^{T} \\
0 & 0 & -J_{\alpha}+i J_{\alpha} \Gamma_{2} D_{\alpha} & i J_{\alpha} \Gamma_{2} J_{\alpha}^{T}
\end{array}\right) \in \operatorname{Mat}_{(6 n+|\alpha|) \times(6 n+|\alpha|)}(\mathbb{R})
$$

Here $D_{\alpha}=\operatorname{diag}\left(\left\{1-\alpha_{j}\right\}_{j=1}^{2 n}\right)$ is a diagonal matrix, whereas $J_{\alpha} \in \operatorname{Mat}_{|\alpha| \times 2 n}(\mathbb{R})$ has entries defined in terms of the indices $\left\{i \in[2 n] \mid \alpha_{i} \neq 0\right\}=\left\{i_{1}<\cdots<i_{r}\right\}$ associated with non-zero entries of $\alpha$, that is,

$$
\left(J_{\alpha}\right)_{j, k}= \begin{cases}\delta_{i_{j}, k} & \text { if } j \leq r \\ 0 & \text { otherwise }\end{cases}
$$

In other words, $\left(J_{\alpha}\right)_{j, k}=1$ if and only if $k$ is the position of the $j$-th nonzero element of $\alpha$.
As argued in [60], expressions (24) and (25) determine the inner product $\left\langle\Phi_{1}, \Phi_{2}\right\rangle$ and an expression of the form $\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle$ entirely in terms of covariance matrices, assuming that the remaining two overlaps $\left\langle\Phi_{0}, \Phi_{1}\right\rangle,\left\langle\Phi_{2}, \Phi_{0}\right\rangle$ with a Gaussian reference state $\Phi_{0}$ are given and non-zero. In this situation, these quantities can be computed in time $O\left(n^{3}\right)$.

### 2.7 Gaussian evolution and occupation number measurement

Underlying the known classical simulation algorithms for fermionic linear optics is the fact that Gaussian unitaries and occupation number measurements preserve Gaussianity. Explicitly, this can be described as follows: Given a Gaussian state $\Psi$ with covariance matrix $\Gamma(\Psi)$
(i) the covariance matrix $\Gamma\left(U_{R} \Psi\right)$ of $\Psi$ evolved under the Gaussian unitary $U_{R}, R \in$ $O(2 n)$, is given by $\Gamma\left(U_{R} \Psi\right)=R \Gamma(\Psi) R^{T}$.
(ii) measurement of the observable $a_{j}^{\dagger} a_{j}$ for $j \in[n]$ gives the outcome $s \in\{0,1\}$ with probability

$$
\begin{align*}
P_{j}(s) & =\left\|\Pi_{j}(s) \Psi\right\|^{2}  \tag{27}\\
& =\left\langle\Psi, \Pi_{j}(s) \Psi\right\rangle \\
& =\frac{1}{2}\left(1+(-1)^{s}\left\langle\Psi, i c_{2 j-1} c_{2 j} \Psi\right\rangle\right) \\
& =\frac{1}{2}\left(1+(-1)^{s} \Gamma_{2 j-1,2 j}\right)
\end{align*}
$$

where the third identity follows from the definition

$$
\Pi_{j}(s)=\frac{1}{2}\left(1+(-1)^{s} i c_{2 j-1} c_{2 j}\right)
$$

and the last identity follows from the definition of the covariance matrix in Eq. (21). Given that the measurement outcome is $s \in\{0,1\}$, the post-measurement state

$$
\Psi(s)=\left(\Pi_{j}(s)|\Psi\rangle\right) / \sqrt{P_{j}(s)}
$$

is Gaussian with covariance matrix $\Gamma(\Psi(s))$ defined by the lower-diagonal entries (see e.g., [3, Proof of Lemma 4])

$$
\Gamma(\Psi(s))_{k, \ell}= \begin{cases}(-1)^{s} & \text { if }(k, \ell)=(2 j, 2 j-1)_{28)} \\ \Gamma_{k, \ell}+\frac{(-1)^{s}}{2 P_{j}(s)}\left(\Gamma_{2 j-1, \ell} \Gamma_{2 j, k}-\Gamma_{2 j-1, k} \Gamma_{2 j, \ell}\right) & \text { otherwise }\end{cases}
$$

for $k>\ell$.
In particular, the corresponding resulting covariance matrices can be computed in time $O\left(n^{3}\right)[8-10,54]$ and $O\left(n^{2}\right)$ [3] for unitary evolution and measurement, respectively.

### 2.8 The tensor product of two fermionic states

Two density operators $\rho_{j} \in \mathcal{B}\left(\mathcal{H}^{n_{j}}\right), j \in[2]$, have a joint extension if and only if there is an element $\rho \in \mathcal{B}\left(\mathcal{H}^{n_{1}+n_{2}}\right)$ such that

$$
\begin{equation*}
\operatorname{tr}\left(c\left(\alpha_{1} \| \alpha_{2}\right) \rho\right)=\operatorname{tr}\left(c\left(\alpha_{1}\right) \rho_{1}\right) \operatorname{tr}\left(c\left(\alpha_{2}\right) \rho_{2}\right) \quad \text { for all } \quad \alpha_{j} \in\{0,1\}^{2 n_{j}}, j \in[2] \tag{29}
\end{equation*}
$$

Here $\alpha_{1} \| \alpha_{2} \in\{0,1\}^{2\left(n_{1}+n_{2}\right)}$ denotes the concatenation of $\alpha_{1}$ and $\alpha_{2}$. Theorem 1 in [61] implies that if either $\rho_{1}$ or $\rho_{2}$ is even, then a unique joint extension $\rho$ of $\left(\rho_{1}, \rho_{2}\right)$ exists. Furthermore, this extension is even if and only if both $\rho_{1}$ and $\rho_{2}$ are even. Theorem 2 in [61] shows that if $\rho$ is even and $\rho_{1}$ and $\rho_{2}$ are pure, then $\rho$ is also pure.

In particular, this means that for states $\Psi_{1}, \Psi_{2}$ of definite parity, there is a unique joint pure extension $\rho=|\Psi\rangle\langle\Psi|$ of $\left(\left|\Psi_{1}\right\rangle\left\langle\Psi_{1}\right|,\left|\Psi_{2}\right\rangle\left\langle\Psi_{2}\right|\right)$. Since $\rho$ is pure, this also means that $\Psi$ is of definite parity. We will write $\Psi=\Psi_{1} \tilde{\otimes} \Psi_{2}$ for this state in the following, and we call $\tilde{\otimes}$ the fermionic tensor product. Note that $\Psi$ is only defined up to a global phase. It follows immediately from these definitions that

$$
\begin{equation*}
\left|\left\langle x, y \mid \Psi_{1} \tilde{\otimes} \Psi_{2}\right\rangle\right|=\left|\left\langle x, \Psi_{1}\right\rangle \cdot\left\langle y, \Psi_{2}\right\rangle\right| \quad \text { for all } \quad x \in\{0,1\}^{n_{1}} \text { and } y \in\{0,1\}^{n_{2}} \tag{30}
\end{equation*}
$$

Proof. Let $x \in\{0,1\}^{n_{1}}$ and $y \in\{0,1\}^{n_{2}}$ be arbitrary. By definition, we have

$$
\begin{aligned}
|x, y\rangle\langle x, y| & =\left(\prod_{j=1}^{n_{1}} \frac{1}{2}\left(I+(-1)^{x_{j}} i c_{2 j-1} c_{2 j}\right)\right)\left(\prod_{k=1}^{n_{2}} \frac{1}{2}\left(I+(-1)^{y_{k}} i c_{2 n_{1}+2 k-1} c_{2 n_{1}+2 k}\right)\right) \\
& =\left(\sum_{\alpha \in\{0,1\}_{+}^{2 n_{1}}} \gamma_{x}(\alpha) c\left(\alpha \| 0^{2 n_{2}}\right)\right)\left(\sum_{\beta \in\{0,1\}_{+}^{2 n_{2}}} \gamma_{y}(\beta) c\left(0^{2 n_{1}} \| \beta\right)\right) .
\end{aligned}
$$

for certain coefficients $\left\{\gamma_{x}(\alpha)\right\}_{\alpha \in\{0,1\}_{+}^{2 n_{1}}}$ and $\left\{\gamma_{y}(\beta)\right\}_{\beta \in\{0,1\}_{+}^{2 n_{2}}}$. Since $\rho=\left|\Psi_{1} \tilde{\otimes} \Psi_{2}\right\rangle\left\langle\Psi_{1} \tilde{\otimes} \Psi_{2}\right|$ is an extension of $\left(\left|\Psi_{1}\right\rangle\left\langle\Psi_{1}\right|,\left|\Psi_{2}\right\rangle\left\langle\Psi_{2}\right|\right)$ and $c\left(\alpha\left|\mid 0^{2 n_{2}}\right) c\left(0^{2 n_{1}}| | \beta\right)=i^{-|\alpha| \cdot|\beta|} c(\alpha \| \beta)=c(\alpha \| \beta)\right.$ for (even-weight) $\alpha \in\{0,1\}_{+}^{2 n_{1}}$ and $\beta \in\{0,1\}_{+}^{2 n_{2}}$, it follows that

$$
\begin{aligned}
\left|\left\langle x, y \mid \Psi_{1} \tilde{\otimes} \Psi_{2}\right\rangle\right|^{2} & =\sum_{\alpha \in\{0,1\}_{+}^{2 n_{1}}} \gamma_{x}(\alpha) \sum_{\beta \in\{0,1\}_{+}^{2 n_{2}}} \gamma_{y}(\beta) \operatorname{tr}(c(\alpha \| \beta) \rho) \\
& =\left\langle\Psi_{1},\left(\sum_{\alpha \in\{0,1\}_{+}^{2 n_{1}}} \gamma_{x}(\alpha) c(\alpha)\right) \Psi_{1}\right\rangle \cdot\left\langle\Psi_{2},\left(\sum_{\beta \in\{0,1\}_{+}^{2 n_{2}}} \gamma_{y}(\beta) c(\beta)\right) \Psi_{2}\right\rangle \\
& =\left|\left\langle x, \Psi_{1}\right\rangle\right|^{2} \cdot\left|\left\langle y, \Psi_{2}\right\rangle\right|^{2} .
\end{aligned}
$$

Refining Eq. (30), (relative) phase information between these matrix elements can be obtained from the explicit construction of $\Psi_{1} \tilde{\otimes} \Psi_{2}$ given in [61, Section 3.1] (see also [51, Proof of Theorem 1]): Consider the isometry

$$
U: \begin{array}{ccc}
U: & \mathcal{H}^{n_{1}+n_{2}} & \rightarrow \\
& \rightarrow & \mathcal{H}^{n_{1}} \otimes \mathcal{H}^{n_{2}} \\
& \left|x_{1}, \ldots, x_{n_{1}+n_{2}}\right\rangle & \mapsto
\end{array}\left|x_{1}, \ldots, x_{m}\right\rangle \otimes\left|x_{n_{1}+1}, \ldots, x_{n_{1}+n_{2}}\right\rangle
$$

whose action is given by

$$
U a_{j} U^{\dagger}= \begin{cases}a_{j} \otimes I & \text { if } j \in\left[n_{1}\right] \\ P_{1} \otimes a_{j-n_{1}} & \text { if } j \in\left\{n_{1}+1, \ldots, n_{1}+n_{2}\right\}\end{cases}
$$

where $P_{1}$, the parity operator acting on $\mathcal{H}_{n_{1}}$, introduces phases. Then

$$
\Psi_{1} \tilde{\otimes} \Psi_{2}=U^{\dagger}\left(\Psi_{1} \otimes \Psi_{2}\right) .
$$

It is straightforward from this definition to check that $\Psi_{1} \tilde{\otimes} \Psi_{2}$ is the extension of $\left(\Psi_{1}, \Psi_{2}\right)$ and

$$
\left\langle x, y \mid \Psi_{1} \tilde{\otimes} \Psi_{2}\right\rangle=(-1)^{|x|} \cdot\left\langle x, \Psi_{1}\right\rangle \cdot\left\langle y, \Psi_{2}\right\rangle \quad \text { for all } \quad x \in\{0,1\}^{n_{1}} \text { and } y \in\{0,1\}^{n}(31)
$$

We note that the fermionic tensor product preserves Gaussianity in the following sense.
Lemma 2.4. Let $\Psi_{j} \in \mathcal{G}_{n_{j}}^{+}$be positive-parity fermionic Gaussian states for $j \in[2]$. Then $\Psi_{1} \tilde{\otimes} \Psi_{2} \in \mathcal{G}_{n_{1}+n_{2}}^{+}$, i.e., it is an even fermionic Gaussian state.

Proof. By definition of an extension (see Eq. (29)) and Wick's theorem (Eq. (22)), the tensor product $\Psi=\Psi_{1} \tilde{\otimes} \Psi_{2}$ satisfies

$$
\left\langle\Psi, c\left(\alpha_{1} \| \alpha_{2}\right) \Psi\right\rangle= \begin{cases}\operatorname{Pf}\left(\Gamma_{1}\left[\alpha_{1}\right]\right) \operatorname{Pf}\left(\Gamma_{1}\left[\alpha_{1}\right]\right) & \text { if both }\left|\alpha_{1}\right| \text { and }\left|\alpha_{2}\right| \text { are even }  \tag{32}\\ 0 & \text { otherwise }\end{cases}
$$

for all $\alpha_{j} \in\{0,1\}^{2 n_{j}}$, where $\Gamma_{j}$ is the covariance matrix of $\Psi_{j}$ for $j \in[2]$. Because the Pfaffian satisfies

$$
\operatorname{Pf}\left(A_{1} \oplus A_{2}\right)=\operatorname{Pf}\left(\begin{array}{cc}
A_{1} & 0 \\
0 & A_{2}
\end{array}\right)=\operatorname{Pf}\left(A_{1}\right) \operatorname{Pf}\left(A_{2}\right)
$$

for block-matrices, it follows from (32) that the tensor product $\Psi$ satisfies Wick's theorem (22) with covariance matrix $\Gamma_{1} \oplus \Gamma_{2}$. In particular, it is Gaussian.

## 3 Tracking relative phases in fermionic linear optics

The covariance matrix $\Gamma(\Psi)$ of a fermionic Gaussian state $|\Psi\rangle=e^{i \theta} U_{R}\left|0_{F}\right\rangle \in \mathcal{G}_{n}$ fully determines expectation values by Wick's theorem, which is why Gaussian states and dynamics are amenable to efficient classical simulation (see Section 2.7). However, the description of $\Psi$ in terms of the covariance matrix $\Gamma(\Psi)$ does not capture information on the global phase $e^{i \theta}$ of the state. For processes involving non-Gaussian states expressed as superpositions of Gaussian states, such phase information needs to be available for computing norms, expectation values and overlaps.

Here we provide an extended (classical) description of fermionic Gaussian states that incorporates phase information. A central feature of our construction is the fact that this description permits to compute overlaps (including relative phases, i.e., not only the absolute value) of Gaussian states in an efficient manner.

Our construction is motivated by and relies on expression (24), which relates the inner product $\left\langle\Psi_{1}, \Psi_{2}\right\rangle$ of two Gaussian states $\Psi_{1}, \Psi_{2} \in \mathcal{G}_{n}$ to their inner products $\left\langle\Psi_{0}, \Psi_{1}\right\rangle$, $\left\langle\Psi_{0}, \Psi_{2}\right\rangle$ with a Gaussian reference state $\Psi_{0} \in \mathcal{G}_{n}$ and their covariance matrices $\Gamma_{0}, \Gamma_{1}, \Gamma_{2}$. This suggests fixing a reference state $\Psi_{0} \in \mathcal{G}_{n}$ and using the pair $\left(\Gamma(\Psi),\left\langle\Psi_{0}, \Psi\right\rangle\right)$ as a classical description of any state $|\Psi\rangle \in \mathcal{G}_{n}$ relevant in the computation. The problem with this idea is that $\left\langle\Psi_{0}, \Psi\right\rangle$ may vanish, preventing the application of (24). To avoid this problem, we use - instead of a single state $\Psi_{0}$ - a (potentially) different reference state for each state $\Psi$. Specifically, we will show that using number states, i.e., states of the form (10), suffices. This motivates the following definition.

Definition 3.1. Let $|\Psi\rangle=e^{i \theta} U_{R}\left|0_{F}\right\rangle \in \mathcal{G}_{n}$ be a Gaussian state. We call a tuple

$$
d=(\Gamma, x, r) \in \operatorname{Mat}_{2 n \times 2 n}(\mathbb{R}) \times\{0,1\}^{n} \times \mathbb{C}
$$

$a$ (valid) description of $|\Psi\rangle$ if the following three conditions hold:
(i) $\Gamma=\Gamma(\Psi)$ is the covariance matrix of $|\Psi\rangle$.
(ii) $x \in\{0,1\}^{n}$ is such that $\langle x, \Psi\rangle \neq 0$, where $|x\rangle$ is the number state defined by Eq. (10). In our algorithms we will in fact ensure that $|\langle x, \Psi\rangle|^{2} \geq 2^{-n}$, i.e., only a subset of valid descriptions is used. A description $d=(\Gamma, x, r)$ with this property, i.e., satisfying $|r|^{2} \geq 2^{-n}$, will be called a good description. The restriction to good descriptions is necessary to make our algorithms work with finite-precision arithmetic.
(iii) $r=\langle x, \Psi\rangle$.

More explicitly, necessary and sufficient conditions for $d=(\Gamma(\Psi), x, r)$ to constitute a description of $\Psi$ are that

$$
r \neq 0 \quad \text { and } \quad|r|^{4}=2^{-2 n} \operatorname{Det}(\Gamma(|x\rangle)+\Gamma(\Psi))
$$

because of formula (23) for the overlap of two states and because $\operatorname{Det}(\cdot)=\operatorname{Pf}^{2}(\cdot)$. Here

$$
\Gamma(|x\rangle)=\bigoplus_{j=1}^{n}\left(\begin{array}{cc}
0 & (-1)^{x_{j}}  \tag{33}\\
-(-1)^{x_{j}} & 0
\end{array}\right)
$$

is the covariance matrix of $|x\rangle$. Since a Gaussian state $\Psi$ generally has non-zero overlap with more than a single occupation number state $|x\rangle$, there are several distinct valid descriptions of $\Psi$. We will denote the set of descriptions of $|\Psi\rangle \in \mathcal{G}_{n}$ by $\operatorname{Desc}(\Psi)$.

We note that a description $d=(\Gamma, x, r)$ uniquely fixes a Gaussian state $\Psi \in \mathcal{G}_{n}$ : The covariance matrix $\Gamma$ determines all expectation values, and the global phase of $\Psi$ is fixed by the overlap $\langle x, \Psi\rangle$, i.e., by $r$. Denoting by $\operatorname{Desc}_{n}=\bigcup_{\Psi \in \mathcal{G}_{n}} \operatorname{Desc}(\Psi)$ the set of all descriptions of fermionic Gaussian $n$-mode states, this means that we have a function

$$
\begin{array}{cccc}
\Psi: \operatorname{Desc}_{n} & \rightarrow & \mathcal{G}_{n} \\
d & \mapsto & \Psi(d) \tag{34}
\end{array}
$$

The main result of this section shows that expectation values, overlaps, and matrix elements of (Majorana) operators with respect to Gaussian states can be efficiently computed from their classical descriptions. Furthermore, when evolving a Gaussian state under a Gaussian unitary, the description of the resulting state can be computed efficiently. The same is true for the post-measurement state when applying an occupation number measurement.

For evolution, we note that it suffices to consider Gaussian unitaries of the form $U_{R}$ where $R \in O(2 n)$ belongs to the set of generators $\operatorname{Gen}(O(2 n))$ introduced in Section 2.2, that is,

$$
\operatorname{Gen}(O(2 n))=\left\{R_{j, k}(\vartheta) \mid j<k \in[2 n], \vartheta \in[0,2 \pi)\right\} \cup\left\{R_{j}\right\}_{j=1}^{2 n}
$$

Here $R_{j, k}(\vartheta)$ is a Givens rotation and $R_{j}=-\operatorname{diag}\left(\left\{(-1)^{\delta_{j, k}}\right\}_{k=1}^{2 n}\right)$ a reflection. We note that each element of $\operatorname{Gen}(O(2 n))$ can be specified by a tuple $(j, k, \vartheta) \in[2 n] \times[2 n] \times[0,2 \pi)$ or an index $j \in[2 n]$, respectively. We assume that this parameterization is used in the following algorithms (but leave this implicit).

To state the properties of our (deterministic) algorithms, it is convenient to express these as functions.

Theorem 3.2 (Overlap, evolution, and measurement). Let $\Psi(d) \in \mathcal{G}_{n}$ be the Gaussian state associated with a description $d \in \operatorname{Desc}_{n}$, see Eq. (34). Then the following holds:
(i) The algorithm overlap : $\operatorname{Desc}_{n} \times \operatorname{Desc}_{n} \rightarrow \mathbb{C}$ given in Fig. 7 has runtime $O\left(n^{3}\right)$ and satisfies

$$
\text { overlap }\left(d_{1}, d_{2}\right)=\left\langle\Psi\left(d_{1}\right), \Psi\left(d_{2}\right)\right\rangle \quad \text { for all } \quad d_{1}, d_{2} \in \operatorname{Desc}_{n}
$$

(ii) The algorithm evolve : $\operatorname{Desc}_{n} \times \operatorname{Gen}(O(2 n)) \rightarrow$ Desc $_{n}$ given in Fig. 9 has runtime $O\left(n^{3}\right)$ and satisfies

$$
\Psi(\operatorname{evolve}(d, R))=U_{R} \Psi(d) \quad \text { for all } \quad d \in \operatorname{Desc}_{n} \text { and } R \in \operatorname{Gen}(O(2 n))
$$

where $U_{R}$ denotes the Gaussian unitary associated with $R \in O(2 n)$.
(iii) The algorithm measureprob: $\operatorname{Desc}_{n} \times[n] \times\{0,1\} \rightarrow \mathbb{R}$ given in Fig. 11 has runtime $O(1)$ and satisfies

$$
\text { measureprob }(d, j, s)=\left\|\Pi_{j}(s) \Psi(d)\right\|^{2} \quad \text { for all } \quad d \in \operatorname{Desc}_{n}, j \in[n], s \in\{0,1\}
$$

where $\Pi_{j}(s)=\frac{1}{2}\left(I+(-1)^{s} i c_{2 j-1} c_{2 j}\right)$ is the projection onto the eigenspace of $a_{j}^{\dagger} a_{j}$ with eigenvalue $s$.
(iv) The algorithm postmeasure : $\operatorname{Desc}_{n} \times[n] \times\{0,1\} \times[0,1] \rightarrow \operatorname{Desc}_{n}$ given in Fig. 12 has runtime $O\left(n^{3}\right)$. The algorithm satisfies

$$
\Psi(\operatorname{postmeasure}(d, j, s, p(d, j, s)))=\frac{\Pi_{j}(s) \Psi(d)}{\left\|\Pi_{j}(s) \Psi(d)\right\|}
$$

for all $d \in \operatorname{Desc}_{n}, j \in[n], s \in\{0,1\}$, with $p(d, j, s)=\left\|\Pi_{j}(s) \Psi(d)\right\|^{2}$.
The output of both evolve and postmeasure is a good description for any input.
We argue that descriptions of relevant initial states can be obtained efficiently. Clearly, this is the case for any state of the form $|\Psi\rangle=U_{R_{L}} \cdots U_{R_{1}}\left|0_{F}\right\rangle$ obtained by applying a sequence $\left\{R_{j}\right\}_{j \in[L]} \subset \operatorname{Gen}(O(2 n))$ of generators to the vacuum state $\left|0_{F}\right\rangle$ : Here we can use the algorithm evolve $L$ times, producing a description of $|\Psi\rangle$ in time $O\left(L n^{3}\right)$.

We we will at times need a description of a state $|\Psi\rangle$ but do not require fixing its global phase. This is the case for example when subsequent computational states only involve phase-insensitive expressions, e.g., terms of the form $|\langle\Psi, \Phi\rangle|^{2}$. Such a description can be found efficiently from the covariance matrix $\Gamma$ of $|\Psi\rangle$. Since the phase can be fixed arbitrarily, the problem here is to find $x \in\{0,1\}^{n}$ such that $\langle x, \Psi\rangle$ is non-zero.

Theorem 3.3. There is an algorithm describe : $\operatorname{Mat}_{2 n \times 2 n}(\mathbb{R}) \rightarrow \operatorname{Desc}_{n}$ with runtime $O\left(n^{3}\right)$ such that for any covariance matrix $\Gamma$, the state $\Psi(\operatorname{describe}(\Gamma))$ is a Gaussian state with covariance matrix $\Gamma$, and describe $(\Gamma)$ is a good description.

For example, consider states of the form $|\Phi(\pi, y)\rangle=U_{R_{\pi}}|y\rangle$, where $R_{\pi} \in O(2 n)$ is a permutation matrix specified by an element $\pi \in S_{2 n}$ and $y \in\{0,1\}^{n}$. (Such states are used in Ref. [60] to give a fast norm estimation algorithm, see Section 4.3.) The covariance matrix of this state is $\Gamma(\pi, y)=R_{\pi} \Gamma(|y\rangle) R_{\pi}^{T}$ (with $\Gamma(|y\rangle)$ defined by Eq. (33)). We thus conclude that $|\Psi(\operatorname{describe}(\Gamma(\pi, y)))\rangle$ is proportional to $|\Phi(\pi, y)\rangle$ with a global phase $e^{i \theta}$ possibly depending on the pair $(\pi, y)$.

The remainder of this section is devoted to the proofs of Theorem 3.2 and Theorem 3.3: We describe the algorithms evolve, overlap, measureprob, postmeasure and describe in detail, providing pseudocode, and verify that these satisfy the desired properties.

### 3.1 Subroutines

Our algorithms make use of subroutines called findsupport, relatebasiselements, overlaptriple and convert which we describe here.

```
Require: \(\Gamma \in \operatorname{Mat}_{2 n \times 2 n}(\mathbb{R})\) covariance matrix of a pure Gaussian state
    function findsupport( \(\Gamma\) )
        \(\Gamma^{(0)} \leftarrow \Gamma\)
        \(x \leftarrow 0^{n} \in\{0,1\}^{n}\).
        for \(j \leftarrow 1\) to \(n\) do \(\quad \triangleright\) simulate a measurement of \(a_{j}^{\dagger} a_{j}\)
            \(q_{j} \leftarrow \frac{1}{2}\left(I+\Gamma_{2 j-1,2 j}^{(j-1)}\right)\)
            if \(q_{j} \geq 1 / 2\) then \(\quad \triangleright\) choose the higher-probability outcome
                \(x_{j} \leftarrow 0\)
                \(p_{j} \leftarrow q_{j}\)
            else
                \(x_{j} \leftarrow 1\)
                \(p_{j} \leftarrow 1-q_{j}\)
            \(\Gamma^{(j)} \leftarrow 0 \in \operatorname{Mat}_{2 n \times 2 n}(\mathbb{R}) \quad \triangleright\) covariance matrix of the post-measurement
    state
            \(\Gamma_{2 j, 2 j-1}^{(j)} \leftarrow(-1)^{x_{j}}\)
            for \(\ell \leftarrow 1\) to \(n-1\) do
                for \(k \leftarrow \ell+1\) to \(n\) do
                    if \((k, \ell) \neq(2 j, 2 j-1)\) then
                    \(\Gamma_{k, \ell}^{(j)} \leftarrow \Gamma_{k, \ell}^{(j-1)}+\frac{(-1)^{x} j}{2 p_{j}}\left(\Gamma_{2 j-1, \ell}^{(j-1)} \Gamma_{2 j, k}^{(j-1)}-\Gamma_{2 j-1, k}^{(j-1)} \Gamma_{2 j, \ell}^{(j-1)}\right)\)
            \(\Gamma^{(j)} \leftarrow \Gamma^{(j)}-\left(\Gamma^{(j)}\right)^{T}\)
        return \(x\)
```

Figure 1: The algorithm findsupport: Given the covariance matrix $\Gamma$ of a Gaussian state $|\Psi\rangle$, it computes $x \in\{0,1\}^{n}$ such that $\langle x, \Psi\rangle \neq 0$.

The subroutine findsupport takes as input the covariance matrix $\Gamma$ of a Gaussian state $\Psi$ and produces a string $x \in\{0,1\}^{2 n}$ with the property that $\langle x, \Psi\rangle \neq 0$. It is given in Fig. 1. It has the following properties:

Lemma 3.4. The algorithm findsupport: $\operatorname{Mat}_{2 n \times 2 n}(\mathbb{R}) \rightarrow\{0,1\}^{n}$ runs in time $O\left(n^{3}\right)$. It satisfies

$$
\begin{equation*}
\mid\left.\langle\text { findsupport }(\Gamma(\Psi)), \Psi\rangle\right|^{2} \geq 2^{-n} \quad \text { for every } \quad \Psi \in \mathcal{G}_{n} \tag{35}
\end{equation*}
$$

where $\Gamma(\Psi)$ is the covariance matrix of $\Psi$.
Proof. The main idea of the algorithm is to mimic a measurement in the number state basis executed in a sequential manner. Consider the following process: Suppose we start with the state $\Psi^{(0)}=\Psi$, and then measure $a_{j}^{\dagger} a_{j}$ successively for $j=1, \ldots, n$. Let $P\left(x_{j} \mid x_{1} \cdots x_{j-1}\right)$ denote the conditional probability of observing the outcome $x_{j} \in\{0,1\}$ (when measuring $a_{j}^{\dagger} a_{j}$ ), given that the previous measurements yielded $\left(x_{1}, \ldots, x_{j-1}\right)$. According to Born's rule, this is given by

$$
P\left(x_{j} \mid x_{1} \cdots x_{j-1}\right)=\left\langle\Psi_{x_{1} \cdots x_{j-1}}^{(j-1)}, \Pi_{j}\left(x_{j}\right) \Psi_{x_{1} \cdots x_{j-1}}^{(j-1)}\right\rangle
$$

where $\Psi_{x_{1} \cdots x_{j-1}}^{(j-1)}$ is the post-measurement state after the first $(j-1)$ measurements. The probability of observing the sequence $x \in\{0,1\}^{n}$ of outcomes then is

$$
\begin{equation*}
|\langle x, \Psi\rangle|^{2}=\prod_{j=1}^{n} P\left(x_{j} \mid x_{1} \cdots x_{j-1}\right) \tag{36}
\end{equation*}
$$

by Bayes' rule.
The algorithm findsupport simulates this process: For each $j \in[n]$, the quantity $q_{j}$ computed in line 5 is equal to the conditional probability $P\left(0 \mid x_{1} \cdots x_{j-1}\right)$ that the $j$-th measurement results in the outcome 0 . Lines $6-11$ ensure that the outcome $x_{j} \in\{0,1\}$ with higher probability of occurrence is selected at each step, guaranteeing Property (35) (because of Eq. (36)). The matrix $\Gamma^{(j)}$ computed in steps $12-18$ is the covariance matrix of the post-measurement state $\Psi_{x_{1} \cdots x_{j}}^{(j)}$.

Each measurement is thus realized in time $O\left(n^{2}\right)$ yielding the overall complexity of $O\left(n^{3}\right)$.

The algorithm relatebasiselements is more straightforward: Given $x, y \in\{0,1\}^{n}$, it outputs $(\alpha, \vartheta) \in\{0,1\}^{2 n} \times \mathbb{R}$ such that $c(\alpha)|x\rangle=e^{i \vartheta}|y\rangle$. That is, it finds a Majorana monomial $c(\alpha)$ which maps the basis state $|x\rangle$ to $|y\rangle$ up to a phase and computes the corresponding phase. In Fig. 2 we give pseudocode for this algorithm.

```
Require: \(x \in\{0,1\}^{n}, y \in\{0,1\}^{n}\)
    function relatebasiselements \((x, y)\)
        \(\alpha \leftarrow 0^{2 n} \in\{0,1\}^{2 n}\).
        for \(j \leftarrow 1\) to \(n\) do
            \(\alpha_{2 j-1} \leftarrow x_{j} \oplus y_{j}\)
        \(\vartheta \leftarrow \frac{\pi}{4}|x \oplus y|+\pi \sum_{j=1}^{n}(x \oplus y)_{j} \eta_{j}(x)\)
```

        return \((\alpha, \vartheta) \quad \triangleright(\alpha, \vartheta)\) is such that \(c(\alpha)|x\rangle=e^{i \vartheta}|y\rangle\)
    Figure 2: Given $x, y \in\{0,1\}^{n}$, the algorithm relatebasiselements computes $\alpha \in\{0,1\}^{2 n}$ and $\vartheta \in \mathbb{R}$ such that $c(\alpha)|x\rangle=e^{i \vartheta}|y\rangle$. The expression $\eta_{j}(x)$ in line 5 is defined by Eq. (12), and $x \oplus y \in\{0,1\}^{n}$ denotes the bitwise addition modulo two for $x, y \in\{0,1\}^{n}$.

Lemma 3.5. The algorithm relatebasiselements : $\{0,1\}^{n} \rightarrow\{0,1\}^{2 n} \times \mathbb{C}$ runs in time $O(n)$ and satisfies

$$
c(\alpha)|x\rangle=e^{i \vartheta}|y\rangle \text { where }(\alpha, \vartheta)=\text { relatebasiselements }(x, y) \quad \text { for all } \quad x, y \in\{0,1\}^{n} .
$$

Proof. Let $x, y \in\{0,1\}^{n}$ be arbitrary. Define

$$
\alpha_{2 j-1}=x_{j} \oplus y_{j} \quad \text { and } \quad \alpha_{2 j}=0 \quad \text { for } \quad j \in[n],
$$

as in line 4 of algorithm relatebasiselements. Then

$$
\begin{aligned}
c(\alpha)|y\rangle & =i^{|\alpha| \cdot(|\alpha|-1) / 2} c_{1}^{x_{1} \oplus y_{1}} c_{3}^{x_{2} \oplus y_{2}} \cdots c_{2 n-1}^{x_{n} \oplus y_{n}}|y\rangle \\
& =i^{\left(\sum_{j=1}^{n} x_{j} \oplus y_{j}\right) \cdot\left(\left(\sum_{j=1}^{n} x_{j} \oplus y_{j}\right)-1\right) / 2}(-1)^{\sum_{j=1}^{n}\left(x_{j} \oplus y_{j}\right) \eta_{j}(x)}|y \oplus(x \oplus y)\rangle \\
& =i^{|x \oplus y| \cdot(|x \oplus y|-1) / 2}(-1)^{\sum_{j=1}^{n}(x \oplus y)_{j} \eta_{j}(x)}|x\rangle
\end{aligned}
$$

where in the second identity, we used that

$$
c_{2 j-1}|x\rangle=(-1)^{\eta_{j}(x)}\left|x \oplus e_{j}\right\rangle \quad \text { for all } \quad x \in\{0,1\}^{n} \text { and } j \in[n]
$$

because of Eq. (11). Because $i^{|x \oplus y| \cdot(|x \oplus y|-1) / 2}(-1)^{\sum_{j=1}^{n}(x \oplus y)_{j} \eta_{j}(x)}=e^{i \vartheta}$ for

$$
\vartheta=\frac{\pi}{4}|x \oplus y| \cdot(|x \oplus y|-1)+\pi \sum_{j=1}^{n}(x \oplus y)_{j} \eta_{j}(x),
$$

comparison with line 5 of the algorithm relatebasiselements gives the claim.

The algorithm overlaptriple takes covariance matrices $\Gamma_{0}, \Gamma_{1}, \Gamma_{2}$ of three Gaussian states $\Phi_{0}, \Phi_{1}, \Phi_{2}$ of the same parity $\sigma \in\{-1,1\}$ and $\alpha \in\{0,1\}_{+}^{n}$, as well as overlaps $u=\left\langle\Phi_{0}, \Phi_{1}\right\rangle$, $v=\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle$ (which both have to be non-zero), and computes the overlap $\left\langle\Phi_{2}, \Phi_{0}\right\rangle$. It is obtained by direct application of the formula (25). For completeness, we include pseudocode in Fig. 3. Since this algorithm involves computing Pfaffians of matrices that have size linear in $n$, its runtime is $O\left(n^{3}\right)$.

Require: $\Gamma_{j}$ covariance matrix of a Gaussian state $\Phi_{j}$ for $j=0,1,2$
Require: $\sigma=\operatorname{Pf}\left(\Gamma_{0}\right)=\operatorname{Pf}\left(\Gamma_{1}\right)=\operatorname{Pf}\left(\Gamma_{2}\right)$
Require: $\alpha \in\{0,1\}_{+}^{n}$ such that $\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle \neq 0$
Require: $\left\langle\Phi_{0}, \Phi_{1}\right\rangle \neq 0$
Require: $u=\left\langle\Phi_{0}, \Phi_{1}\right\rangle$ and $v=\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle$
function overlaptriple $\left(\Gamma_{0}, \Gamma_{1}, \Gamma_{2}, \alpha, u, v\right)$
$R_{\alpha} \in \operatorname{Mat}_{(6 n+|\alpha|) \times(6 n+|\alpha|)}(\mathbb{R})$
$R_{\alpha} \leftarrow$ evaluate Eq. (26)
$o \leftarrow u^{-1} \cdot v^{-1} \cdot \sigma \cdot 4^{-n} i^{n+|\alpha| \cdot(|\alpha|-1) / 2} \operatorname{Pf}\left(R_{\alpha}\right) \quad \triangleright$ compute the overlap $\left\langle\Phi_{2}, \Phi_{0}\right\rangle$ return $o$

Figure 3: The algorithm overlaptriple takes as input the covariance matrices $\Gamma_{j}$ of three Gaussian states $\Phi_{j}, j=0,1,2$ with identical parity, $\alpha \in\{0,1\}_{+}^{n}$ and the overlaps $\left\langle\Phi_{0}, \Phi_{1}\right\rangle,\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle$. The latter have to be non-zero. The algorithm computes the overlap $\left\langle\Phi_{2}, \Phi_{0}\right\rangle$ using Eq. (25).

Fig. 4 gives a graphical representation of what the algorithm overlaptriple achieves. These graphical representations will be helpful to construct and analyze other algorithmic building blocks.

(a) The input to the algorithm overlaptriple consists of (descriptions of) three Gaussian states $\Phi_{0}, \Phi_{1}, \Phi_{2}$ and $\alpha \in\{0,1\}^{2 n}$, together with overlaps $u=$ $\left\langle\Phi_{0}, \Phi_{1}\right\rangle$ and $v=\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle$ that are both nonzero.

(b) Applying overlaptriple provides the inner product $\left\langle\Phi_{0}, \Phi_{2}\right\rangle$. In this diagrammatic representation, this completes the triangle with vertices $\Phi_{0}, \Phi_{1}, \Phi_{2}$.

Figure 4: A graphical representation of the functionality provided by the algorithm overlaptriple. Solid lines represent inner products that are given / have been computed, and are non-zero. Inner products of the form $\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle$ are represented by arrows.

The algorithm convert takes a description $d=(\Gamma, x, r)$ of a Gaussian state $\Psi(d)$ and $y \in$ $\{0,1\}^{n}$ such that $\langle y, \Psi(d)\rangle \neq 0$, and outputs a description $d^{\prime}=(\Gamma, y, s)$ of the same state. In other words, it converts a description $d$ of the state involving the reference state $|x\rangle$ to a description $d^{\prime}$ of the same state but involving a different reference state $|y\rangle$. In Fig. 5 we give pseudocode for this algorithm.

```
Require: \(d=(\Gamma, x, r) \in \operatorname{Desc}_{n}, y \in\{0,1\}^{n}\) such that \(\langle y, \Psi(d)\rangle \neq 0\)
    function convert \((d, y)\)
        \((\alpha, \vartheta) \leftarrow \operatorname{relatebasiselements}(y, x) \quad \triangleright\) find \((\alpha, \vartheta)\) such that \(c(\alpha)|y\rangle=e^{i \vartheta}|x\rangle\)
        \(\Gamma_{0} \leftarrow \Gamma, \Gamma_{1} \leftarrow \Gamma(|x\rangle), \Gamma_{2} \leftarrow \Gamma(|y\rangle) \triangleright\) covariance matrices of \(\Psi(d),|x\rangle\) and \(|y\rangle\)
        \(u \leftarrow \bar{r} \quad \triangleright u=\langle\Psi(d), x\rangle\)
        \(v \leftarrow e^{i \vartheta} \quad \triangleright v=\langle x, c(\alpha) y\rangle\)
        \(w \leftarrow\) overlaptriple \(\left(\Gamma_{0}, \Gamma_{1}, \Gamma_{2}, \alpha, u, v\right) \quad \triangleright\) compute the overlap \(\langle y, \Psi(d)\rangle\)
        return \((\Gamma, y, w)\)
```

Figure 5: The algorithm convert takes a description $d \in \operatorname{Desc}_{n}$ and $y \in\{0,1\}^{n}$ such that $\langle y, \Psi(d)\rangle \neq 0$. It outputs a description $d^{\prime} \in \operatorname{Desc}_{n}$ of $\Psi(d)$ such that the second entry of $d^{\prime}$ is equal to $y$, i.e., $d^{\prime}=(\Gamma, y, s)$. It makes use of the subroutines relatebasiselements and overlaptriple. For $x \in\{0,1\}^{n}$, $\Gamma(|x\rangle)$ denotes the covariance matrix of the state $|x\rangle$, see Eq. (33).

The algorithm convert is illustrated in Fig. 6.

(a) The input to the algorithm convert specifies a Gaussian state $\Psi, x \in\{0,1\}^{n}$ such that $\langle x, \Psi\rangle \neq 0$, the value $r=$ $\langle x, \Psi\rangle$ and an element $y \in\{0,1\}^{n}$ such that $\langle y, \Psi\rangle \neq 0$. The value of $\langle y, \Psi\rangle$ is not given.

(b) The algorithm applies the subroutine relatebasiselements to find $(\alpha, \vartheta)$ such that $c(\alpha)|y\rangle=$ $e^{i \vartheta}|x\rangle$. In particular, after this step, the value $\langle x, c(\alpha) y\rangle=e^{i \vartheta}$ is known and it is non-zero.

(c) The algorithm then applies the subroutine overlaptriple to compute $w=\langle y, \Psi\rangle$. The triple $(\Gamma, y, w)$ is a valid description of $\Psi$.

Figure 6: An illustration of the algorithm convert. Dotted lines represent inner products that are nonzero, but that are not provided / have not yet been computed by the algorithm.

Lemma 3.6. The algorithm convert: $\operatorname{Desc}_{n} \times\{0,1\}^{n} \rightarrow$ Desc $_{n}$ given in Fig. 5 runs in time $O\left(n^{3}\right)$. Assume that $d \in \operatorname{Desc}_{n}$ and $y \in\{0,1\}^{n}$ satisfy $\langle y, \Psi(d)\rangle \neq 0$. Then

$$
\begin{equation*}
\Psi(\operatorname{convert}(d, y))=\Psi(d) \tag{37}
\end{equation*}
$$

Furthermore, denoting the output of convert $(d, y)$ by $d^{\prime}=\left(\Gamma^{\prime}, y^{\prime}, s^{\prime}\right)$ we have

$$
y^{\prime}=y
$$

as well as

$$
\begin{equation*}
\left|s^{\prime}\right|^{2}=\left|\left\langle y^{\prime}, \Psi(d)\right\rangle\right|^{2}=|\langle y, \Psi(d)\rangle|^{2} \tag{38}
\end{equation*}
$$

Proof. Let us denote the input to convert by $(d, y)$, where $d=(\Gamma, x, r) \in \operatorname{Desc}_{n}$ and $y \in$ $\{0,1\}^{n}$. Then

$$
\begin{equation*}
\langle x, \Psi(d)\rangle \neq 0 \tag{39}
\end{equation*}
$$

since $d$ is a description of $\Psi(d)$. Furthermore, for $(\alpha, \vartheta)$ as defined in line 2 we have

$$
\begin{equation*}
\langle x, c(\alpha) y\rangle=e^{i \vartheta} \neq 0 \tag{40}
\end{equation*}
$$

by definition of the algorithm relatebasiselements. In line 3 of convert, the matrices $\Gamma_{j}$, $j \in[3]$ are the covariance matrices of the states

$$
\left(\Phi_{0}, \Phi_{1}, \Phi_{2}\right)=(\Psi(d),|x\rangle,|y\rangle)
$$

We note that Eq. (39) and the assumption $\langle y, \Psi(d)\rangle \neq 0$ imply that these three states have identical parity. The value $w$ computed in line 6 using overlaptriple is equal to the overlap

$$
\begin{equation*}
w=\left\langle\Phi_{2}, \Phi_{0}\right\rangle=\langle y, \Psi(d)\rangle \tag{41}
\end{equation*}
$$

because

$$
\begin{aligned}
& u=\bar{r}=\overline{\langle x, \Psi(d)\rangle}=\langle\Psi(d), x\rangle=\left\langle\Phi_{0}, \Phi_{1}\right\rangle \neq 0 \\
& v=e^{i \vartheta}=\langle x, c(\alpha) y\rangle=\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle \neq 0
\end{aligned}
$$

by Eqs. (39) and (40). Eq. (41) together with the assumption $\langle y, \Psi(d)\rangle \neq 0$ show that the output $(\Gamma, y, w)$ is a description of $\Psi(d)$. This completes the proof of Eq. (37).

Eq. (38) is trivially satisfied because

$$
s^{\prime}=w=\langle y, \Psi(d)\rangle
$$

The complexity of the algorithm is dominated by overlaptriple, which takes time $O\left(n^{3}\right)$.

### 3.2 Computing overlaps and descriptions of evolved/measured states

Based on the subroutines findsupport, relatebasiselements, overlaptriple and convert, we can now describe our main algorithms overlap, evolve, measureprob and postmeasure for overlaps, Gaussian unitary evolution, to compute the outcome probability and the postmeasurement state when measuring the occupation number, respectively. We give pseudocode for each algorithm and establish the associated claims.

We give pseudocode for the algorithm overlap in Fig. 7 and we illustrate it in Fig. 8.

```
Require: \(d_{1}=\left(\Gamma_{1}, x_{1}, r_{1}\right), d_{2}=\left(\Gamma_{2}, x_{2}, r_{2}\right) \in \operatorname{Desc}_{n}\)
    function overlap \(\left(d_{1}, d_{2}\right)\)
        \(\sigma_{1} \leftarrow \operatorname{Pf}\left(\Gamma_{1}\right) \quad \triangleright\) compute the parity \(\sigma_{j}\) of \(\Psi\left(d_{j}\right)\)
        \(\sigma_{2} \leftarrow \operatorname{Pf}\left(\Gamma_{2}\right)\)
        if \(\sigma_{1} \neq \sigma_{2}\) then
            return \(0 \quad \triangleright\) states with different parities have zero overlap
        \((\alpha, \vartheta) \leftarrow\) relatebasiselements \(\left(x_{2}, x_{1}\right) \quad \triangleright(\alpha, \vartheta)\) satisfies \(c(\alpha)\left|x_{2}\right\rangle=e^{i \vartheta}\left|x_{1}\right\rangle\)
        \(\Gamma_{0}^{\prime} \leftarrow \Gamma_{1}, \Gamma_{1}^{\prime} \leftarrow \Gamma\left(\left|x_{1}\right\rangle\right), \Gamma_{2}^{\prime} \leftarrow \Gamma_{2} \quad \triangleright\) covariance matrices of \(\Psi\left(d_{1}\right),\left|x_{1}\right\rangle\)
    and \(\Psi\left(d_{2}\right)\)
        \(u \leftarrow \bar{r}_{1} \quad \triangleright u=\left\langle\Psi\left(d_{1}\right), x_{1}\right\rangle\)
        \(v \leftarrow e^{i \vartheta} r_{2} \quad \triangleright v=\left\langle x_{1}, c(\alpha) \Psi\left(d_{2}\right)\right\rangle\)
        \(w \leftarrow\) overlaptriple \(\left(\Gamma_{0}^{\prime}, \Gamma_{1}^{\prime}, \Gamma_{2}^{\prime}, \alpha, u, v\right) \quad \triangleright\) compute the overlap \(\left\langle\Psi\left(d_{2}\right), \Psi\left(d_{1}\right)\right\rangle\)
        return \(\bar{w}\)
```

Figure 7: The algorithm overlap takes descriptions $d_{1}, d_{2} \in \operatorname{Desc}_{n}$ and outputs the over$\operatorname{lap}\left\langle\Psi\left(d_{1}\right), \Psi\left(d_{2}\right)\right\rangle$.

(a) The input to the algorithm overlap consists of (descriptions of) two Gaussian $\Psi_{1}, \Psi_{2}$, $x_{1}, x_{2} \in\{0,1\}^{n}$ and the overlaps $r_{j}=\left\langle x_{j}, \Psi_{j}\right\rangle, j \in$ [2]. The latter are both assumed to be nonzero.

(b) The algorithm uses the subroutine relatebasiselements to find $(\alpha, \vartheta)$ such that $c(\alpha)\left|x_{2}\right\rangle=e^{i \vartheta}\left|x_{1}\right\rangle . \quad$ In particular, this means that the value $\left\langle x_{1}, c(\alpha) x_{2}\right\rangle=e^{i \vartheta}$ is computed, and it is non-zero. Furthermore, this implies that $\left\langle x_{1}, c(\alpha) \Psi_{2}\right\rangle=\left\langle c(\alpha) x_{1}, \Psi_{2}\right\rangle=$ $e^{i \vartheta}\left\langle x_{2}, \Psi_{2}\right\rangle=e^{i \vartheta} r_{2}$ is also known and non-zero

(c) In the last step of the algorithm, the subroutine overlaptriple is applied to complete a triangle: This amounts to computing $w=\left\langle\Psi_{2}, \Psi_{1}\right\rangle$. The algorithm returns the complex conjugate $\bar{w}=$ $\left\langle\Psi_{1}, \Psi_{2}\right\rangle$

Figure 8: An illustration of the algorithm overlap.

Lemma 3.7. The algorithm overlap : $\operatorname{Desc}_{n} \times$ Desc $_{n} \rightarrow \mathbb{C}$ given in Fig. 7 runs in time $O\left(n^{3}\right)$. It satisfies

$$
\begin{equation*}
\text { overlap }\left(d_{1}, d_{2}\right)=\left\langle\Psi\left(d_{1}\right), \Psi\left(d_{2}\right)\right\rangle \quad \text { for all } \quad d_{1}, d_{2} \in \operatorname{Desc}_{n} . \tag{42}
\end{equation*}
$$

Proof. Let $d_{j}=\left(\Gamma_{j}, x_{j}, r_{j}\right) \in \operatorname{Desc}_{n}$ for $j \in[2]$. Then

$$
\begin{equation*}
r_{j}=\left\langle x_{j}, \Psi\left(d_{j}\right)\right\rangle \neq 0 \quad \text { for } \quad j \in[2], \tag{43}
\end{equation*}
$$

by assumption.
Line 4 treats the case where $\Psi\left(d_{1}\right)$ and $\Psi\left(d_{2}\right)$ have different parity, and are thus orthogonal. Starting from line 6 , we can hence assume that the parities $\sigma_{1}, \sigma_{2}$ of $\Psi\left(d_{1}\right), \Psi\left(d_{2}\right)$ are identical, $\sigma=\sigma_{1}=\sigma_{2}$. By Eq. (43), this implies that both $\left|x_{1}\right\rangle$ and $\left|x_{2}\right\rangle$ also have parity $\sigma$, that is,

$$
\begin{equation*}
\sigma\left(\left|x_{1}\right\rangle\right)=\sigma\left(\left|x_{2}\right\rangle\right)=\sigma\left(\left|\Psi\left(d_{1}\right)\right\rangle\right)=\sigma\left(\left|\Psi\left(d_{2}\right)\right\rangle\right) . \tag{44}
\end{equation*}
$$

By definition of relatebasiselements, the pair $(\alpha, \vartheta)$ computed in line 6 satisfies

$$
\begin{equation*}
c(\alpha)\left|x_{2}\right\rangle=e^{i \vartheta}\left|x_{1}\right\rangle . \tag{45}
\end{equation*}
$$

Consider the triple of states

$$
\left(\Phi_{0}, \Phi_{1}, \Phi_{2}\right)=\left(\Psi\left(d_{1}\right),\left|x_{1}\right\rangle, \Psi\left(d_{2}\right)\right) .
$$

Then the matrices $\Gamma_{j}^{\prime}, j \in[3]$ defined in line 7 of the algorithm are the covariance matrices of $\Phi_{j}, j \in\{0,1,2\}$. We have

$$
u=\bar{r}_{1}=\overline{\left\langle x_{1}, \Psi\left(d_{1}\right)\right\rangle}=\left\langle\Psi\left(d_{1}\right), x_{1}\right\rangle=\left\langle\Phi_{0}, \Phi_{1}\right\rangle \neq 0,
$$

by Eq. (43), and similarly

$$
\begin{array}{rlr}
v & =e^{i \vartheta} r_{2} & \\
& =e^{i \vartheta}\left\langle x_{2}, \Psi\left(d_{2}\right)\right\rangle & \\
& =\left\langle e^{-i \vartheta} x_{2}, \Psi\left(d_{2}\right)\right\rangle & \\
& =\left\langle c(\alpha) x_{1}, \Psi\left(d_{2}\right)\right\rangle & \\
& \text { with }(45) \\
& =\left\langle x_{1}, c(\alpha) \Psi\left(d_{2}\right)\right\rangle & \\
& \text { because } c(\alpha) \text { is self-adjoint } \\
& \neq 0 & \\
\left.\hline \Phi_{1}, c(\alpha) \Phi_{2}\right\rangle & & \text { because } r_{2} \neq 0 \text { by Eq. (43). }
\end{array}
$$

Furthermore, by Eq. (44) the states $\left(\Phi_{0}, \Phi_{1}, \Phi_{2}\right)$ have identical parity. It thus follows from the properties of overlaptriple that the quantity $w$ computed in step line 10 is equal to

$$
w=\left\langle\Psi\left(d_{2}\right), \Psi\left(d_{1}\right)\right\rangle
$$

Since the output of the algorithm is the complex conjugate $\bar{w}=\left\langle\Psi\left(d_{1}\right), \Psi\left(d_{2}\right)\right\rangle$, this implies the claim (42).

The runtime of overlap is dominated by overlaptriple, hence it is of order $O\left(n^{3}\right)$.
We give pseudocode for the algorithm evolve in Fig. 9 and we illustrate it in Fig. 10.
Lemma 3.8. The algorithm evolve: $\operatorname{Gen}(O(2 n)) \times \operatorname{Desc}_{n} \rightarrow$ Desc $_{n}$ given in Fig. 9 runs in time $O\left(n^{3}\right)$. Consider an arbitrary generator $R \in \operatorname{Gen}(O(2 n))$ and a description $d \in$ Desc $_{n}$. Then

$$
\Psi(\operatorname{evolve}(R, d))=U_{R} \Psi(d)
$$

that is, the output of evolve is a description of the evolved state $U_{R} \Psi(d)$. Furthermore, denoting the output by $d^{\prime}=\left(\Gamma^{\prime}, x^{\prime}, r^{\prime}\right)=\operatorname{evolve}(R, d)$ we have

$$
\begin{equation*}
\left|r^{\prime}\right|^{2}=\left|\left\langle x^{\prime}, \Psi\left(d^{\prime}\right)\right\rangle\right|^{2} \geq 2^{-n} \tag{46}
\end{equation*}
$$

Proof. Let us denote the input of evolve by $(R, d)$ where $R \in \operatorname{Gen}(O(2 n))$ and $d=$ $(\Gamma, x, r) \in \operatorname{Desc}_{n}$. The state $U_{R} \Psi(d)$ has covariance matrix $\Gamma_{0}=R \Gamma R^{T}$ computed in line 2 (see Section 2.7). By the properties of findsupport (see Lemma 3.4), the state $|y\rangle$ with $y=$ findsupport $\left(\Gamma_{0}\right) \in\{0,1\}^{n}$ computed in line 3 is such that

$$
\begin{equation*}
\left|\left\langle y, U_{R} \Psi(d)\right\rangle\right|^{2} \geq 2^{-n} \tag{47}
\end{equation*}
$$

In particular, it is non-zero. The remainder of the algorithm computes $\left\langle y, U_{R} \Psi(d)\right\rangle$.
We first show the following:
Claim 3.9. Lines $4-15$ compute $(z, s) \in\{0,1\}^{n} \times \mathbb{C}$ such that

$$
\begin{equation*}
\left|\left\langle z, U_{R} x\right\rangle\right|^{2} \geq 1 / 2 \tag{48}
\end{equation*}
$$

and

$$
\begin{equation*}
s=\left\langle z, U_{R} x\right\rangle \tag{49}
\end{equation*}
$$

Proof. Here we are using the fact that for any generator $R \in \operatorname{Gen}(O(2 n))$, the associated Gaussian unitary $U_{R}$ has a local action on the mode operators. In particular, we can easily compute the image $U_{R}|x\rangle$ of a number state $|x\rangle$ under $U_{R}$. We distinguish two cases:

```
Require: \(R \in \operatorname{Gen}(O(2 n))\)
Require: \(d=(\Gamma, x, r) \in \operatorname{Desc}_{n}\)
    function evolve \((R, d)\)
    \(\Gamma_{0} \leftarrow R \Gamma R^{T} \quad \triangleright\) covariance matrix of \(U_{R} \Psi(d)\)
    \(y \leftarrow\) findsupport \(\left(\Gamma_{0}\right) \quad \triangleright\) gives \(y\) such that \(\left|\left\langle y, U_{R} \Psi(d)\right\rangle\right|^{2} \geq 2^{-n}\)
    if \(R=R_{j, k}(\vartheta)\) for \(j<k \in[2 n], \vartheta \in \mathbb{R}\) then \(\quad \triangleright R=R_{j, k}(\vartheta)\) is a Givens
    rotation
            if \(\cos ^{2}(\vartheta / 2) \geq 1 / 2\) then
                    \(z \leftarrow x\)
                    \(s \leftarrow \cos (\vartheta / 2)\)
            else
                    \(z \leftarrow x \oplus e_{j} \oplus e_{k}\)
                    \(\beta \leftarrow \beta_{j}(x)+\beta_{k}(x)\)
                \(s \leftarrow e^{i \pi \beta} \sin (\vartheta / 2)\)
        if \(R=R_{j}\) for \(j \in[2 n]\) then \(\quad \triangleright R=R_{j}\) is a reflection
            \(z \leftarrow x \oplus e_{j}\)
            \(\beta \leftarrow \beta_{j}(x)\)
            \(s \leftarrow e^{i \pi \beta}\)
        \((\alpha, \gamma) \leftarrow\) relatebasiselements \((y, z)\)
                            \(\triangleright(s, z)\) satisfies \(s=\left\langle z, U_{R} x\right\rangle,|s|^{2} \geq 1 / 2\)
        \((\alpha, \gamma) \leftarrow\) relatebasiselements \((y, z) \quad \triangleright(\alpha, \gamma)\) satisfies \(c(\alpha)|y\rangle=e^{i \gamma}|z\rangle\)
        \(\Gamma_{1} \leftarrow R \Gamma(|x\rangle) R^{T}, \Gamma_{2} \leftarrow \Gamma(|y\rangle) \quad \triangleright\) covariance matrices of \(U_{R}|x\rangle\) and \(|y\rangle\)
        \(u \leftarrow \bar{r} \quad \triangleright u=\left\langle U_{R} \Psi, U_{R} x\right\rangle\)
        \(v \leftarrow e^{i \gamma} \bar{s} \quad \triangleright v=\left\langle U_{R} x, c(\alpha) y\right\rangle\)
        \(w \leftarrow\) overlaptriple \(\left(\Gamma_{0}, \Gamma_{1}, \Gamma_{2}, \alpha, u, v\right) \quad \triangleright\) compute the overlap \(\left\langle y, U_{R} \Psi(d)\right\rangle\)
        return \(\left(\Gamma_{0}, y, w\right)\)
                                \(\triangleright\) return a description of \(U_{R}|\Psi(d)\rangle\)
```

Figure 9: The algorithm evolve takes a description $d \in \operatorname{Desc}_{n}$ and an orthogonal matrix $R \in \operatorname{Gen}(O(2 n))$ associated with the Gaussian unitary $U_{R}$ and computes a description for the state $U_{R} \Psi(d)$. In this algorithm, the functions $\beta_{s}:\{0,1\}^{n} \rightarrow \mathbb{R}$ for $s \in[n]$ are defined as $\beta_{s}(x)=\eta_{s}(x)+\left(x_{s}-\frac{1}{2}\right) \cdot(s+1)$, $x \in\{0,1\}^{n}$ with $\eta_{s}(x)$ given in Eq. (12).
(i) $R=R_{j, k}(\vartheta), j<k \in[2 n], \vartheta \in[0,2 \pi)$ is a Givens-rotation (see Lines 4-11): In this case, $R$ is associated with the unitary evolution operator

$$
U_{j, k}=\exp \left(\vartheta / 2 c_{j} c_{k}\right)=\cos (\vartheta / 2) I+\sin (\vartheta / 2) c_{j} c_{k} .
$$

It maps a basis state $|x\rangle, x \in\{0,1\}^{n}$, to

$$
\begin{equation*}
U_{j, k}(\vartheta)|x\rangle=\cos (\vartheta / 2)|x\rangle+e^{i \pi\left(\beta_{j}(x)+\beta_{k}(x)\right)} \sin (\vartheta / 2)\left|x \oplus e_{j} \oplus e_{k}\right\rangle \tag{50}
\end{equation*}
$$

where we introduced the quantities

$$
\beta_{s}(x)=\eta_{s}(x)+\left(x_{s}-\frac{1}{2}\right) \cdot(s+1) \quad \text { for any } \quad s \in[n],
$$

with $\eta_{s}(x)$ defined in Eq. (12). To obtain Eq. (50), we used that

$$
\begin{equation*}
c_{j}|x\rangle=e^{i \pi \beta_{j}(x)}\left|x \oplus e_{j}\right\rangle \quad \text { for all } \quad j \in[2 n] \quad \text { and } \quad x \in\{0,1\}^{n} \tag{51}
\end{equation*}
$$

because

$$
c_{2 j-1}|x\rangle=(-1)^{\eta_{j}(x)}\left|x \oplus e_{j}\right\rangle \quad \text { and } \quad c_{2 j}|x\rangle=-i(-1)^{\eta_{j}(x)+x_{j}}\left|x \oplus e_{j}\right\rangle .
$$

Eq. (50) motivates the following case distinction:

(a) The input to the algorithm evolve is (the description of) a Gaussian state $\Psi, x \in$ $\{0,1\}^{n}$ and the non-zero overlap $r=\langle x, \Psi\rangle$, as well as an element $R \in \operatorname{Gen}(O(2 n))$ associated with a Gaussian unitary $U_{R}$.

(d) Using the fact the action of $U_{R}$ for a generator $R \in \operatorname{Gen}(O(2 n))$ is local, the algorithm determines an element $z \in\{0,1\}^{n}$ such that $s=$ $\left\langle z, U_{R} x\right\rangle \neq 0$, and computes the value $s$.

$$
U_{R} \Psi
$$

(b) By unitarity of $U_{R}$, the input data also provides the inner product $\left\langle U_{R} x, U_{R} \Psi\right\rangle=\langle x, \Psi\rangle=r$, which is non-zero.

(e) The algorithm then uses the subroutine relatebasiselements to find $(\alpha, \gamma)$ such that $c(\alpha)|y\rangle=$ $e^{i \gamma}|z\rangle$. This means that the inner product $\langle z, c(\alpha) y\rangle=e^{i \gamma}$ is known and non-zero. Since $\left\langle z, U_{R} x\right\rangle$ is known and non-zero (as ensured by the previous step (10d)), the value $\left\langle U_{R} x, c(\alpha) y\right\rangle=e^{i \gamma} \overline{\left\langle z, U_{R} x\right\rangle}$ is also non-zero and can be computed.

(c) The algorithm invokes the subroutine findsupport applied to the covariance matrix $\Gamma_{0}$ of the evolved state $U_{R} \Psi$ in order to find an element $y \in\{0,1\}^{n}$ such that $\left\langle y, U_{R} \Psi\right\rangle \neq 0$. (The value of this inner product is not computed/available at this point.)

(f) In the last step, the subroutine overlaptriple is used to compute the quantity $w=\left\langle y, U_{R} \Psi\right\rangle$. It is non-zero by step (10c). Thus $\left(\Gamma_{0}, y, w\right)$ is a valid description of $U_{R} \Psi$.

Figure 10: An illustration of the algorithm evolve. Dotted lines correspond to inner products whose value is non-zero, but has not been computed at that stage of the algorithm.
(a) $\cos ^{2}(\vartheta / 2) \geq 1 / 2$ (see Lines $\left.6-7\right)$ : Here $|x\rangle$ has higher amplitude than $\left|x \oplus e_{j} \oplus e_{k}\right\rangle$ in the state $U_{j, k}(\vartheta)|x\rangle$. The algorithm picks $z=x$ (Line 6) and sets $s=\cos (\vartheta / 2)$ (line 7). In particular, comparing with (50), it follows immediately that the claims (48) and (49) are satisfied.
(b) $\cos ^{2}(\vartheta / 2)<1 / 2$ (see Lines $9-11$ ): In this case the algorithm ensures that

$$
\begin{array}{llrl}
z & =x \oplus e_{j} \oplus e_{k} & & \text { by Line } 9 \\
\beta & =\beta_{j}(x)+\beta_{k}(x) & & \text { by Line } 10 \\
s=e^{i \pi\left(\beta_{j}(x)+\beta_{k}(x)\right)} \sin (\vartheta / 2) & & \text { by Lines } 10 \text { and } 11 . \tag{53}
\end{array}
$$

Because $\cos ^{2}(\vartheta / 2)+\sin ^{2}(\vartheta / 2)=1$ we have

$$
|s|^{2} \geq \frac{1}{2}
$$

by the assumption that $\cos ^{2}(\theta / 2)<1 / 2$. To prove the claims (48) and (49), it thus suffices to show the second claim (49). But this again follows from (50) and the definitions (52) of $z$ and (53) of $s$, i.e., we have $s=\left\langle z, U_{j, k}(\vartheta) x\right\rangle$.
(ii) $R=R_{j}, j \in[2 n]$ is a reflection (see Lines $12-15$ ): Here $R$ is associated with the unitary evolution operator

$$
U_{j}=c_{j}
$$

Its action on $|x\rangle, x \in\{0,1\}^{n}$, is described by Eq. (51), i.e., we have

$$
U_{j}|x\rangle=e^{i \pi \beta_{j}(x)}\left|x \oplus e_{j}\right\rangle
$$

This state is proportional to $\left|x \oplus e_{j}\right\rangle$, showing that the choice

$$
\begin{array}{ll}
z=x \oplus e_{j} & \\
\beta=\beta_{j}(x) & \\
\text { Line 13) } \\
s=e^{i \pi \beta} & \\
(\text { Line } 14) \\
\text { Line 15) }
\end{array}
$$

indeed ensures that the claims (48) and (49) are satisfied.

Equipped with Claim 3.9, we can show that the algorithm evolve has the desired functionality. The matrix $\Gamma_{0}$ computed in Line 2 is the covariance matrix of the evolved state $U_{R} \Psi(d)$, whereas $\Gamma_{1}, \Gamma_{2}$ computed in Line 17 are the covariance matrices of $U_{R}|x\rangle$ and $|y\rangle$, respectively. Thus overlaptriple in Line 20 is invoked on the triple of states

$$
\left(\Phi_{0}, \Phi_{1}, \Phi_{2}\right)=\left(U_{R} \Psi(d), U_{R}|x\rangle,|y\rangle\right)
$$

To check that the requirements of overlaptriple are satisfied, first observe that

$$
\begin{aligned}
u & =\bar{r} & & \text { by Line } 18 \\
& =\langle\Psi(d), x\rangle & & \text { by definition of } r \\
& =\left\langle U_{R} \Psi(d), U_{R} x\right\rangle & & \text { by unitarity of } U_{R} \\
& =\left\langle\Phi_{0}, \Phi_{1}\right\rangle . & &
\end{aligned}
$$

Furthermore, this is non-zero because $r$ (part of the input) is non-zero by definition of the description $d=\left(\Gamma_{0}, x, r\right)$ of $\Psi(d)$.

By the defining property of the subroutine relatebasiselements, Line 16 of the algorithm computes $(\alpha, \gamma) \in\{0,1\}^{2 n} \times[0,2 \pi)$ such that

$$
\begin{equation*}
c(\alpha)|y\rangle=e^{i \gamma}|z\rangle \tag{54}
\end{equation*}
$$

We also have

$$
\begin{aligned}
v & =e^{i \gamma} \bar{s} & & \text { by line } 18 \\
& =e^{i \gamma} \overline{\left\langle z, U_{R} x\right\rangle} & & \text { by }(49) \\
& =\left\langle U_{R} x, c(\alpha) y\right\rangle & & \text { by }(54) \\
& =\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle . & &
\end{aligned}
$$

Because $|s|^{2} \geq 1 / 2$ (see Claim 3.9), this is non-zero.
We conclude from the the properties of overlaptriple that

$$
\begin{array}{rlr}
w & =\left\langle\Phi_{2}, \Phi_{0}\right\rangle \quad \text { see Line } 20 \\
& =\left\langle y, U_{R} \Psi(d)\right\rangle
\end{array}
$$

By construction of $y$ using findsupport, we have

$$
|w|^{2} \geq 2^{-n}
$$

see Eq. (47). In particular, we conclude that the triple $\left(\Gamma_{0}, y, w\right)$ is a valid description of $U_{R} \Psi(d)$ with the desired property (46). This is what the algorithm returns.

The runtime of the algorithm evolve is dominated by the runtime $O\left(n^{3}\right)$ of the algorithm overlaptriple.

We give pseudocode for the algorithm measureprob in Fig. 11.

```
Require: \(d=(\Gamma, x, r) \in \operatorname{Desc}_{n}\)
Require: \(j \in[n]\)
Require: \(s \in\{0,1\}\)
    function measureprob \((d, j, s)\)
        return \(\frac{1}{2}\left(1+(-1)^{s} \Gamma_{2 j-1,2 j}\right)\)
```

Figure 11: The subroutine measureprob takes as input a description $d=(\Gamma, x, r) \in \operatorname{Desc}_{n}$ of a Gaussian state $\Psi(d)$, an integer $j \in[n]$ and a bit $s \in\{0,1\}$. It outputs the probability of obtaining the measurement outcome $s$ when measuring the occupation number operator $a_{j}^{\dagger} a_{j}$. The outcome probability does not depends on the global phase of $\Psi(d)$ (which is determined by its reference state $x$ and the overlap $r$ ), but only on its covariance matrix $\Gamma$.

Lemma 3.10. The algorithm measureprob: $\operatorname{Desc}_{n} \times[n] \times\{0,1\} \rightarrow \mathbb{R}$ given in Fig. 11 runs in time $O(1)$. It satisfies

$$
\text { measureprob }(d, j, s)=\left\langle\Psi(d), \Pi_{j}(s) \Psi(d)\right\rangle \quad \text { for all } \quad d \in \operatorname{Desc}_{n}, j \in[n], s \in\{0,1\}
$$

where $\Pi_{j}(s)=\frac{1}{2}\left(I+(-1)^{s} i c_{2 j-1} c_{2 j}\right)$ is the projection onto the eigenvalue-s eigenspace of $a_{j}^{\dagger} a_{j}$.

Proof. We denote the input to measureprob by $(d, j, s)$ where $d=(\Gamma, x, r) \in \operatorname{Desc}_{n}$ is a description of a state $\Psi(d), j \in[n]$ and $s \in\{0,1\}$. Given the state $\Psi(d)$, the probability of obtaining measurement outcome $s$ when measuring the occupation number operator $a_{j}^{\dagger} a_{j}$ is given by Eq. (27). This is the output of the algorithm in line 2 and gives the claim. Computing line 2 requires a constant number of arithmetic operations, giving the runtime $O(1)$.

We give pseudocode for the algorithm postmeasure in Fig. 12 and we illustrate it in Fig. 13.

Lemma 3.11. The algorithm postmeasure : $\operatorname{Desc}_{n} \times[n] \times\{0,1\} \times[0,1] \rightarrow \operatorname{Desc}_{n}$ given in Fig. 12 runs in time $O\left(n^{3}\right)$. Let $d \in \operatorname{Desc}_{n}, j \in[n]$ and $s \in\{0,1\}$ be arbitrary. Let $\Pi_{j}(s)=\frac{1}{2}\left(I+(-1)^{s} i c_{2 j-1} c_{2 j}\right)$ be the projection onto the eigenvalue-s eigenspace of $a_{j}^{\dagger} a_{j}$ and let $p=\left\|\Pi_{j}(s) \Psi(d)\right\|^{2}$. Then

$$
\Psi\left(\text { postmeasure }(d, j, s, p)=\frac{\Pi_{j}(s) \Psi(d)}{\left\|\Pi_{j}(s) \Psi(d)\right\|}\right.
$$

```
Require: \(d=(\Gamma, x, r) \in \operatorname{Desc}_{n}\)
Require: \(j \in[n]\)
Require: \(s \in\{0,1\}\)
Require: \(p=\left\|\Pi_{j}(s) \Psi(d)\right\|^{2} \in[0,1] \triangleright\) probability of outcome \(s\) when measuring \(a_{j}^{\dagger} a_{j}\)
    function postmeasure \((d, j, s, p)\)
        \(\Gamma^{\prime} \leftarrow 0 \in \operatorname{Mat}_{2 n \times 2 n}(\mathbb{R}) \quad \triangleright\) compute covariance matrix of post-measurement
    state \(\Psi^{\prime}\)
        \(\Gamma_{2 j, 2 j-1}^{\prime} \leftarrow(-1)^{s}\)
        for \(\ell \leftarrow 1\) to \(n-1\) do
            for \(k \leftarrow \ell+1\) to \(n\) do
                if \((k, \ell) \neq(2 j, 2 j-1)\) then
                        \(\Gamma_{k, \ell}^{\prime} \leftarrow \Gamma_{k, \ell}+\frac{(-1)^{s}}{2 p}\left(\Gamma_{2 j-1, \ell} \Gamma_{2 j, k}-\Gamma_{2 j-1, k} \Gamma_{2 j, \ell}\right)\)
        \(\Gamma^{\prime} \leftarrow \Gamma^{\prime}-\left(\Gamma^{\prime}\right)^{T}\)
        \(y \leftarrow\) findsupport \(\left(\Gamma^{\prime}\right) \quad \triangleright\) find \(y\) such that \(\left|\left\langle y, \Psi^{\prime}\right\rangle\right|^{2} \geq 2^{-n}\)
        \((\alpha, \vartheta) \leftarrow \operatorname{relatebasiselements}(y, x) \quad \triangleright(\alpha, \vartheta)\) are such that \(c(\alpha)|y\rangle=e^{i \vartheta}|x\rangle\)
        \(\Gamma_{0} \leftarrow \Gamma, \Gamma_{1} \leftarrow \Gamma(|x\rangle), \Gamma_{2} \leftarrow \Gamma(|y\rangle) \triangleright\) covariance matrices of \(\Psi(d),|x\rangle\) and \(|y\rangle\)
        \(u \leftarrow \bar{r} \quad \triangleright u=\langle\Psi(d), x\rangle\)
        \(v \leftarrow e^{i \vartheta} \quad \triangleright v=\langle x, c(\alpha) y\rangle\)
        \(w \leftarrow\) overlaptriple \(\left(\Gamma_{0}, \Gamma_{1}, \Gamma_{2}, \alpha, u, v\right) \quad \triangleright w=\langle y, \Psi(d)\rangle\)
        return \(\left(\Gamma^{\prime}, y, w / \sqrt{p}\right) \quad \triangleright\) return a description of \(\Psi^{\prime}\)
```

Figure 12: The algorithm postmeasure takes as input a description $d \in \operatorname{Desc}_{n}$, an integer $j \in[n]$, a bit $s \in\{0,1\}$ and a real number $p \in[0,1]$. Assuming $p=\left\|\Pi_{j}(s) \Psi(d)\right\|^{2}$, the algorithm outputs a description of the post-measurement state $\Psi^{\prime}=\left(\Pi_{j}(s) \Psi(d)\right) /\left\|\Pi_{j}(s) \Psi(d)\right\|$ when measuring the number operator $a_{j}^{\dagger} a_{j}$ and obtaining the outcome $s$ where $s \in\{0,1\}$. Here, $\Pi_{j}(s)=\left(I+(-1)^{s} i c_{2 j-1} c_{2 j}\right) / 2$ is the projection onto the eigenvalue $s$ eigenspace of $a_{j}^{\dagger} a_{j}$.
that is, postmeasure computes a description of the post-measurement state when measuring $a_{j}^{\dagger} a_{j}$ and obtaining outcome s. Denoting the output of the algorithm by

$$
d^{\prime}=\left(\Gamma^{\prime}, x^{\prime}, r^{\prime}\right)=\text { postmeasure }(d, j, s, p),
$$

we further have

$$
\begin{equation*}
\left|r^{\prime}\right|^{2}=\left|\left\langle x^{\prime}, \Psi\left(d^{\prime}\right)\right\rangle\right|^{2} \geq 2^{-n} \tag{55}
\end{equation*}
$$

Proof. We denote the input to postmeasure by $(d, j, s, p)$, where $d \in \operatorname{Desc}_{n}, j \in[n]$, $s \in\{0,1\}$ and $p \in[0,1]$. For brevity, let us denote the post-measurement state when measuring the observable $a_{j}^{\dagger} a_{j}$ and obtaining outcome $s$ by

$$
\Psi^{\prime}=\frac{\Pi_{j}(s) \Psi(d)}{\left\|\Pi_{j}(s) \Psi(d)\right\|} .
$$

In lines $2-7$, the algorithm postmeasure computes the covariance matrix $\Gamma^{\prime}$ of $\Psi^{\prime}$ according to Eq. (28). In line 9 the algorithm uses findsupport to find $y \in\{0,1\}^{n}$ such that

$$
\begin{equation*}
\left|\left\langle y, \Psi^{\prime}\right\rangle\right|^{2} \geq 2^{-n} \tag{56}
\end{equation*}
$$


(a) The algorithm postmeasure is given the covariance matrix $\Gamma$ of a Gaussian state $\Psi, x \in\{0,1\}^{n}$ as well as the value $r=\langle x, \Psi\rangle$ (which is non-zero). It is additionally given the probability $p=$ $\left\|\Pi_{j}(s) \Psi\right\|^{2}$ of observing the outcome $s$.

(b) After computing the covariance matrix $\Gamma^{\prime}$ of the post-measurement state $\Psi^{\prime}$, the algorithm uses the subroutine findsupport to find an element $y \in\{0,1\}^{n}$ such that $\left\langle y, \Psi^{\prime}\right\rangle \neq 0$. (The value of this inner product is not computed at this point.)

(e) As argued in the proof of Lemma 3.11, the inner product $\left\langle y, \Psi^{\prime}\right\rangle$ can be computed
from $w$ and the probability $p$ : uct $\left\langle y, \Psi^{\prime}\right\rangle$ can be computed
from $w$ and the probability $p$ : it is equal to $\left\langle y, \Psi^{\prime}\right\rangle=w / \sqrt{p}$.
Thus $\left(\Gamma^{\prime}, y, w, \sqrt{p}\right)$ is a description it is equal to $\left\langle y, \Psi^{\prime}\right\rangle=w / \sqrt{p}$.
Thus $\left(\Gamma^{\prime}, y, w, \sqrt{p}\right)$ is a description of $\Psi^{\prime}$.
(d) The algorithm overlaptriple is used to compute the overlap $w=$ $\langle y, \Psi\rangle$.

(c) The subroutine relatebasiselements is then used to find $(\alpha, \vartheta)$ such that $c(\alpha)|y\rangle=e^{i \vartheta}|x\rangle$.



Figure 13: An illustration of the algorithm postmeasure, which computes a description of the postmeasurement state $\Psi^{\prime}=\frac{\Pi_{j}(s) \Psi}{\left\|\Pi_{j}(s) \Psi\right\|}$ given a description of $\Psi$.

Line 10 provides $(\alpha, \vartheta) \in\{0,1\}^{2 n} \times \mathbb{R}$ such that

$$
\begin{equation*}
c(\alpha)|y\rangle=e^{i \vartheta}|x\rangle \tag{57}
\end{equation*}
$$

Line 11 of the algorithm sets the matrices $\left(\Gamma_{0}, \Gamma_{1}, \Gamma_{2}\right)$ equal to the covariance matrices of the three states

$$
\left(\Phi_{0}, \Phi_{1}, \Phi_{2}\right)=(\Psi(d),|x\rangle,|y\rangle)
$$

We check that the conditions for applying overlaptriple in Line (14) are satisfied. We have

$$
\begin{aligned}
u & =\bar{r} & & \text { by Line } 12 \\
& =\langle\Psi(d), x\rangle & & \text { by definition of } r \\
& =\left\langle\Phi_{0}, \Phi_{1}\right\rangle, & &
\end{aligned}
$$

and this is non-zero because $d=(\Gamma, x, r)$ is a valid description (hence $r \neq 0$ ). Similarly as before, we also have

$$
\begin{aligned}
v & =e^{i \vartheta} & & \text { by Line } 13 \\
& =\langle x, c(\alpha) y\rangle & & \text { by Eq. (57) } \\
& =\left\langle\Phi_{1}, c(\alpha) \Phi_{2}\right\rangle . & &
\end{aligned}
$$

In particular, this is also non-zero. The requirements to run overlaptriple in Line 14 are therefore met, and Line 14 returns

$$
\begin{align*}
w & =\left\langle\Phi_{2}, \Phi_{0}\right\rangle \\
& =\langle y, \Psi(d)\rangle . \tag{58}
\end{align*}
$$

It remains to show that $\left(\Gamma^{\prime}, y, w / \sqrt{p}\right)$ (the expression returned by the algorithm) is a valid description of the post-measurement state $\Psi^{\prime}$, and to establish the bound

$$
\begin{equation*}
|w / \sqrt{p}|^{2} \geq 2^{-n} \tag{59}
\end{equation*}
$$

in order to prove Eq. (55).
Inserting $\Psi^{\prime}=\Pi_{j}(s) \Psi / \sqrt{p}$, Eq. (56) implies that

$$
\begin{equation*}
2^{-n} \leq\left|\left\langle y, \Psi^{\prime}\right\rangle\right|^{2}=\frac{1}{p}\left|\left\langle y, \Pi_{j}(s) \Psi\right\rangle\right|^{2}=\frac{1}{p}\left|\left\langle\Pi_{j}(s) y, \Psi\right\rangle\right|^{2} \leq \frac{1}{p}\left\|\Pi_{j}(s) y\right\|^{2} \cdot\|\Psi\|^{2} \tag{60}
\end{equation*}
$$

because $\Pi_{j}(s)$ is self-adjoint and with the Cauchy-Schwarz inequality. In particular, we have $\Pi_{j}(s) y \neq 0$ and thus

$$
\begin{equation*}
\Pi_{j}(s) y=y \tag{61}
\end{equation*}
$$

since any number state $|y\rangle$ is an eigenvector of the projection $\Pi_{j}(s)$. Inserting (61) into (60) and using (58) we obtain the bound

$$
2^{-n} \leq \frac{1}{p}|\langle y, \Psi\rangle|^{2}=\frac{|w|^{2}}{p},
$$

establishing (59). Eq. (61) and the self-adjointness of $\Pi_{j}(s)$ also imply that

$$
\left\langle y, \Psi^{\prime}\right\rangle=\frac{1}{\sqrt{p}}\left\langle y, \Pi_{j}(s) \Psi\right\rangle=\frac{1}{\sqrt{p}}\langle y, \Psi\rangle=\frac{w}{\sqrt{p}} .
$$

Since $\Gamma^{\prime}$ is the covariance matrix of $\Psi^{\prime}$ and $p=\left\|\Pi_{j}(s) \Psi(d)\right\|^{2}$ is the probability of obtaining outcome $s$ when measuring $a_{j}^{\dagger} a_{j}$, this shows that $\left(\Gamma^{\prime}, y, w / \sqrt{p}\right)$ is a valid description of $\Psi^{\prime}$ as claimed.

The complexity of the algorithm is dominated by overlaptriple, which takes time $O\left(n^{3}\right)$.

### 3.3 Initial states for computation

Using the algorithm evolve, it is straightforward to generate a description of a state that is obtained by applying a sequence of Gaussian unitaries (generators) to the vacuum state. This is all that is typically needed to describe initial states.

In cases where we do not need to fix the overall phase, we can generate a description from the covariance matrix. The algorithm describe takes as input the covariance matrix $\Gamma$ of a Gaussian state $\Psi$ and outputs a description $d \in \operatorname{Desc}_{n}$ of a Gaussian state which is equal to $\Psi$ up to a global phase. It is given in Fig. 14 and it simply uses the subroutine findsupport and Eq. (23).

```
Require: \(\Gamma \in \operatorname{Mat}_{n \times n}(\mathbb{R})\) covariance matrix of a pure Gaussian state \(\Psi\)
    function describe \((\Gamma)\)
        \(y \in\{0,1\}^{n}\)
        \(y \leftarrow\) findsupport \((\Gamma) \quad \triangleright\) find \(y\) such that \(|\langle y, \Psi\rangle|^{2} \geq 2^{-n}\)
        \(\sigma \leftarrow \operatorname{Pf}(\Gamma)\)
        \(r \leftarrow \sqrt{\sigma 2^{-n} \operatorname{Pf}(\Gamma(|y\rangle)+\Gamma)} \quad \triangleright\) compute \(|\langle y, \Psi\rangle|\)
        return \((\Gamma, y, r)\)
```

Figure 14: The algorithm describe: Given the covariance matrix $\Gamma$ of a Gaussian state $|\Psi\rangle$, it outputs $d \in$ Desc $_{n}$ such that $|\langle\Psi(d), \Psi\rangle|=1$.

Lemma 3.12. The algorithm describe : $\operatorname{Mat}_{2 n \times 2 n}(\mathbb{R}) \rightarrow \operatorname{Desc}_{n}$ runs in time $O\left(n^{3}\right)$. Its output is such that for every covariance matrix $\Gamma$, the state $\Psi(\operatorname{describe}(\Gamma))$ is a Gaussian state with covariance matrix $\Gamma$. We have

$$
\begin{equation*}
|r|^{2}=|\langle x, \Psi(d)\rangle|^{2} \geq 2^{-n} \tag{62}
\end{equation*}
$$

for $d=(\Gamma, x, r)=\Psi(\operatorname{describe}(\Gamma))$.
Proof. Let $\Gamma \in \operatorname{Mat}_{2 n \times 2 n}(\mathbb{R})$ be a covariance matrix and let $\Psi$ be a Gaussian state with covariance matrix $\Gamma$. By definition of the algorithm findsupport, the value $y \in\{0,1\}^{n}$ computed in line 3 satisfies

$$
|\langle y, \Psi\rangle|^{2} \geq 2^{-n}
$$

By Eq. (23), the value $r$ computed in Line 5 satisfies

$$
r=|\langle y, \Psi\rangle|
$$

In particular, there is an angle $\vartheta \in[0,2 \pi)$ such that

$$
r=\sqrt{\sigma 2^{-n} \operatorname{Pf}(\Gamma(|y\rangle)+\Gamma)}=\left\langle y, e^{i \vartheta} \Psi\right\rangle .
$$

It follows immediately that $d=(\Gamma, y, r)$ is a valid description of the Gaussian state $e^{i \vartheta} \Psi=$ $\Psi(d)$ with the required property (62).

## 4 Classical simulation of fermionic Gaussian circuits with non-Gaussian initial states

In this section, we argue that the techniques developed in Section 3 to describe fermionic Gaussian states (including relative phases) give rise to efficient classical simulation algorithms for computations composed of non-Gaussian initial states, Gaussian unitaries and occupation number measurements. Specifically, we argue that algorithms developed in the context of stabilizer circuits can immediately be translated to this fermionic setup. Furthermore, this translation maintains runtime bounds when the stabilizer extent is replaced by the fermionic Gaussian extent. Because of the generality of this adaptation procedure - it being applicable to a variety of simulation algorithms both for strong and weak simulation - we restrict our attention to the key substitutions.

Our algorithms apply to the efficient classical simulation of fermionic circuits of the following form, involving $n$ fermions.
(i) The initial state $\Psi^{(0)}=\Psi$ is a possibly non-Gaussian state $\Psi$. We assume that its fermionic Gaussian extent $\xi(\Psi)$ and a corresponding optimal decomposition into a superposition of Gaussian states is known. This is the case for example for any four-fermion state, or a tensor product of two four-fermion states, see Section 5. Alternatively, we may assume that an upper bound $\bar{\xi}(\Psi) \geq \xi(\Psi)$ and a corresponding decomposition of $\Psi$ achieving this value is known: In this case, runtime upper bounds will depend on $\bar{\xi}(\Psi)$ instead of $\xi(\Psi)$.
(ii) The computation proceeds in a sequence of timesteps. At each step $t \in[T]$, one of the following is performed:
(a) A Gaussian unitary $U_{R}, R \in \operatorname{Gen}(O(2 n))$ is applied to the state. Here the choice of $R$ may depend (in an efficiently computable manner) on measurement results obtained previously. We will leave this dependence implicit and do not take it into account in our runtime estimates, as it will typically depend heavily on the circuit considered.
(b) An occupation number measurement, i.e., measurement of the operator $a_{j}^{\dagger} a_{j}$ for some $j \in[n]$ is performed, yielding a measurement outcome $s \in\{0,1\}$ and a corresponding post-measurement state. The choice of the mode $j \in[n]$ to be measured may again depend (in an efficient manner) on the measurement outcomes already obtained.

We note that the restriction to the set of Gaussian unitaries associated with generators of $O(2 n)$ in (iia) incurs no loss of generality at the cost of possibly increasing $T$ by a factor of order $O\left(n^{2}\right)$ and an additive term in the runtime of order $O\left(n^{3}\right)$ since a decomposition of an arbitrary element $R \in O(2 n)$ of the form (19) as a product of $L \leq O\left(n^{2}\right)$ generators can be found in time $O\left(n^{3}\right)$, see the discussion below Theorem 3.2.

The use of arbitrary initial states $\Psi$ in (i) allows us to model, in particular, the application of certain "magic gates" using so-called gadgets. These can be realized by using non-Gaussian auxiliary states combined with Gaussian operations, see e.g., [12,13]. Since all 1-, 2 - and 3 -fermion states are Gaussian [32], 4 -fermion states provide the smallest nontrivial examples; these will also be our main focus in Section 5. We refer to e.g., [12, 13] for a discussion of these constructions.

We proceed as follows: In Section 4, we formulate in general terms how simulation algorithms for a model can be generalized to initial states that are superpositions: This follows known approaches for stabilizer circuits augmented by magic states. In Section 4.2 we review the relationship between the $\mathcal{D}$-extent and the $\mathcal{D}$-rank defined by a dictionary $\mathcal{D}$. In Section 4.3 we discuss fast algorithms for estimating norms of superpositions of dictionary states. In Section 4.4 we apply these constructions to our setup.

### 4.1 Extending simulation algorithms to superpositions

Here we discuss how to extend simulation algorithms for an efficiently simulable model $(\mathcal{D}, \mathcal{E}, \mathcal{M})$ in such a way that the resulting extended algorithms ( $\chi$ evolve, $\chi$ measureprob, $\chi$ postmeasure) work with any initial state $\Psi$ which is a superposition of $\chi$ elements of $\mathcal{D}$ (i.e., has $\mathcal{D}$-rank bounded by $\chi_{\mathcal{D}}(\Psi) \leq \chi$ ). Our discussion is standard and is included only for the reader's convenience: It follows that for stabilizer states as discussed in [18].

Recall that the dictionary $\mathcal{D}$ is a set of states, $\mathcal{E}$ a set of operations and $\mathcal{M}$ a set of measurements. In addition to the subroutines evolve, measureprob and postmeasure for evolution and measurement associated with $(\mathcal{D}, \mathcal{E}, \mathcal{M})$, the construction discussed here requires an efficient algorithm overlap which computes inner products $\left\langle\Psi\left(d_{1}\right), \Psi\left(d_{2}\right)\right\rangle$ from
descriptions $\left(d_{1}, d_{2}\right) \in \operatorname{Desc}_{n}^{2}$. This means that the description $d \in \operatorname{Desc}_{n}$ of a state $\Psi(d)$ must include phase information. For Gaussian states, the covariance matrix formalism has to be extended as discussed in Section 3.

Our goal is to find classical simulation algorithms for circuits of the following form:
(i) The initial state $\Psi^{(0)}=\Psi$ is a superposition of the form

$$
\Psi=\sum_{j=1}^{\chi} \gamma_{j} \varphi_{j}
$$

of $\chi$ states $\left\{\varphi_{j}\right\}_{j=1}^{\chi} \subset \mathcal{D}$ with complex coefficients $\left\{\gamma_{j}\right\}_{j=1}^{\chi}$. We assume that this decomposition is explicitly provided as an input to the classical algorithm in the form of a $\chi$-tuple $\left\{\left(\gamma_{j}, d_{j}\right)\right\}_{j=1}^{\mathcal{D}}$, where $d_{j}$ is an efficient classical descriptions of the state $\varphi_{j}$.
(ii) In each timestep $t \in[T]$,
(a) either an evolution operation $E \in \mathcal{E}$, or
(b) a measurement $M \in \mathcal{M}$
is applied to the state. We assume that corresponding efficient descriptions of $E$ respectively $M$ are given to the classical simulation algorithm.

The algorithms (evolve, measureprob, postmeasure, overlap) associated with the model $(\mathcal{D}, \mathcal{E}, \mathcal{M})$ then immediately give rise to algorithms ( $\chi$ evolve, $\chi$ measureprob, $\chi$ postmeasure) for simulating a more general circuit: At each time step $t \in[T]$, the resulting algorithm maintains the data $\left\{\gamma_{j}^{(t)}, d_{j}^{(t)}\right\}_{j=1}^{\mathcal{D}}$ describing the instantaneous state $\Psi^{(t)}$ after step $t$ as a linear combination

$$
\Psi^{(t)}=\sum_{j=1}^{\chi} \gamma_{j}^{(t)} \Psi\left(d_{j}^{(t)}\right)
$$

of vectors belonging to the dictionary $\mathcal{D}$, and the subroutines ( $\chi$ evolve, $\chi$ measureprob, $\chi$ postmeasure) are used to successively update this description (respectively sample from corresponding measurement outcomes).

Before describing the extended routines $\chi$ evolve, $\chi$ measureprob, $\chi$ postmeasure in more detail, it is convenient to introduce a subroutine $\chi$ norm which takes as input a tuple $\left\{\left(\gamma_{j}, d_{j}\right)\right\}_{j=1}^{\chi} \in\left(\mathbb{C} \times \operatorname{Desc}_{n}\right)^{\chi}$ and outputs the squared norm $\left\|\sum_{j=1}^{\chi} \gamma_{j} \Psi\left(d_{j}\right)\right\|^{2}$. It is clear that such a primitive can be realized naively by using the algorithm overlap for computing inner products. This naive implementation, which we refer to as $\chi$ naivenorm, requires time

$$
\operatorname{time}(\chi \text { naivenorm })=\chi^{2} \text { time }(\text { overlap })
$$

Let us now describe the procedures $\chi$ evolve, $\chi$ measureprob and $\chi$ postmeasure, building on a (general) norm computation subroutine $\chi$ norm.
(a) if an evolution operation $E \in E$ with description $d_{E}$ is applied at time $t$, then the description is updated by setting

$$
\gamma_{j}^{(t)}=\gamma_{j}^{(t-1)} \quad \text { and } \quad d_{j}^{(t)}=\operatorname{evolve}\left(d_{E}, d_{j}^{(t-1)}\right) \quad \text { for } \quad j \in[\chi]
$$

This defines the algorithm $\chi$ evolve. The runtime of this update is

$$
\operatorname{time}(\chi \text { evolve })=\chi \cdot \text { time }(\text { evolve })
$$

(b) if a (projective) measurement $M=\left\{M_{s}\right\}_{s \in \mathcal{M}} \in \mathcal{M}$ with description $d_{M}$ is applied to the state at time $t$, then the probability of obtaining $s \in \mathcal{M}$ is given by

$$
p\left(s \mid \Psi^{(t-1)}\right)=\left\|M_{s} \Psi^{(t-1)}\right\|^{2}=\left\|\sum_{j=1}^{\chi} \gamma_{j}^{(t-1)} \sqrt{p\left(s \mid \Psi_{j}^{(t-1)}\right)} \Psi_{j}^{(t-1)}(M, s)\right\|^{2} .
$$

Here the probability $p\left(s \mid \Psi_{j}^{(t-1)}\right)=\left\|M_{s} \Psi_{j}^{(t-1)}\right\|^{2}=\operatorname{measureprob}\left(d_{j}^{(t-1)}, d_{M}, s\right)$ of obtaining outcome $s$ when measuring $\Psi_{j}^{(t-1)}$ can be efficiently obtained from the description $d_{j}^{(t-1)}$ of $\Psi_{j}^{(t-1)}$ and the description $d_{M}$ of $M$. (Summands $j$ where the probability $p\left(s \mid \Psi_{j}^{(t-1)}\right)$ vanishes can be omitted from this sum.) Similarly, a description $d_{j}(s)=$ postmeasure $\left(d_{j}^{(t-1)}, d_{M}, s\right)$ of the (normalized) post-measurement state $\Psi_{j}^{(t-1)}(M, s)=\frac{1}{\sqrt{p\left(s \mid \Psi_{j}^{(t-1)}\right)}} M_{s} \Psi_{j}^{(t-1)}$ (when measuring $\Psi_{j}^{(t-1)}$ ) can be obtained efficiently. In particular, setting $\tilde{\gamma_{j}}=\gamma_{j}^{(t-1)} \sqrt{p\left(s \mid \Psi_{j}^{(t-1)}\right)}$, we conclude that the outcome probability

$$
\begin{equation*}
p\left(s \mid \Psi^{(t-1)}\right)=\left\|\sum_{j=1}^{\chi} \tilde{\gamma}_{j} \Psi\left(d_{j}(s)\right)\right\|^{2} \tag{63}
\end{equation*}
$$

is the squared norm of a superposition of elements from $\mathcal{D}$. This expression (together with the norm computation routine $\chi$ norm) defines the algorithm $\chi$ measureprob. In particular, given $\left\{\tilde{\gamma}_{j}, d_{j}(s), p\left(s \mid \Psi_{j}^{(t-1)}\right)\right\}_{j=1}^{\chi}$, the probability $p(s \mid \Psi)$ can be evaluated (exactly) in runtime time ( $\chi$ norm). Since $\chi$ measureprob first has to compute the descriptions $d_{j}(s)$ of the post-measurement states $\Psi_{j}^{(t-1)}(M, s)$ and the probabilities $\left\{p\left(s \mid \Psi_{j}^{(t-1)}\right)\right\}_{j=1}^{\chi}$, its runtime is

$$
\operatorname{time}(\chi \text { measureprob })=\operatorname{time}(\chi \text { norm })+\chi \cdot(\text { time }(\text { measureprob })+\text { time }(\text { postmeasure })) .
$$

One can easily verify that the post-measurement state after time step $t$ is given by

$$
\Psi^{(t)}=\sum_{j=1}^{\chi} \gamma_{j}^{(t)} \Psi\left(d_{j}^{(t)}\right),
$$

where

$$
\gamma_{j}^{(t)}=\frac{\tilde{\gamma}_{j}}{\sqrt{p\left(s \mid \Psi^{(t-1)}\right)}} \quad \text { and } \quad d_{j}^{(t)}=d_{j}(s)
$$

In particular, this means that (similarly as for $\chi$ measureprob) we have an algorithm $\chi$ postmeasure which given $\left\{\left(\gamma_{j}, d_{j}^{(t-1)}\right)\right\}_{j=1}^{\chi}$ and $p\left(s \mid \Psi^{(t-1)}\right)$, computes a description of the post-measurement state in time

$$
\text { time }(\chi \text { postmeasure })=\chi \cdot(\text { time }(\text { postmeasure })+\text { time }(\text { measureprob })) .
$$

Given the ability to compute $p(s \mid \Psi)$ and assuming, e.g., that the number $|\mathcal{M}|$ of measurement outcomes is constant, one can then sample from this distribution (when the goal is to perform weak simulation) to get an outcome $s \in \mathcal{M}$.

Using the naive algorithm $\chi$ naivenorm for $\chi$ norm gives runtimes

$$
\begin{align*}
\operatorname{time}(\chi \text { evolve }) & =\chi \cdot \text { time }(\text { evolve }) \\
\text { time }(\chi \text { measureprob }) & =\chi^{2} \cdot \text { time }(\text { overlap })+\chi \cdot(\text { time }(\text { postmeasure })+\text { time }(\text { measureprob })) \\
\text { time }(\chi \text { postmeasure }) & =\chi \cdot(\text { time }(\text { postmeasure })+\text { time }(\text { measureprob })) \tag{64}
\end{align*}
$$

As a function of $\chi$, this is dominated by the computation of the squared norm (63) in $\chi$ measureprob which takes time $O\left(\chi^{2}\right)$.

### 4.2 Sparsification: Relating $\mathcal{D}$-extent to approximate $\mathcal{D}$-rank

Algorithms whose complexity depends on the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$ instead of the (exact) $\mathcal{D}$ rank $\chi_{\mathcal{D}}(\Psi)$ (see Eq. (3)) of the initial state $\Psi$ can be obtained as follows. The idea consists in replacing $\Psi$ by a state $\tilde{\Psi}$ which is $\delta$-close to $\Psi$ and has bounded $\mathcal{D}$-rank. More precisely, it relies on the following result which connects the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$ to the approximate $\mathcal{D}$-rank $\chi_{\mathcal{D}}^{\delta}(\Psi)$ defined in Eq. (4).

Theorem 4.1 (Theorem 1 in [18]). Suppose $\Psi=\sum_{j=1}^{m} \gamma_{j} \varphi_{j}$ is a decomposition of a normalized vector $\Psi$ into a superposition of elements $\left\{\varphi_{j}\right\}_{j=1}^{m}$ belonging to the dictionary $\mathcal{D}$. Then

$$
\chi_{\mathcal{D}}^{\delta}(\Psi) \leq 1+\|\gamma\|_{1}^{2} / \delta^{2}
$$

where $\|\gamma\|_{1}=\sum_{j=1}^{m}\left|\gamma_{j}\right|$ is the 1 -norm of $\gamma$. In particular, we have the relationship

$$
\chi_{\mathcal{D}}^{\delta}(\Psi) \leq 1+\xi_{\mathcal{D}}(\Psi) / \delta^{2} .
$$

In [18], this result was established for the dictionary $\mathcal{D}=$ STAB $_{n}$ consisting of $n$ qubit stabilizer states. Inspection of the proof immediately shows that the statement is applicable to any dictionary $\mathcal{D}$ (independently of, e.g., whether or not it is finite). In particular, Theorem 4.1 implies that in runtime upper bounds, the quantity $\chi_{\mathcal{D}}$ can always be replaced by (the potentially much smaller quantity) $\xi_{\mathcal{D}}(\Psi) / \delta^{2}$, at the cost of introducing an $O(\delta)$-error in $L^{1}$-distance in the sampled distribution. For example, using the naive norm estimation algorithm (i.e., inserting into (64)), this gives a quadratic scaling (for computing output probabilities) in $\xi_{\mathcal{D}}(\Psi)$. Note that here we are assuming that a decomposition of $\Psi$ with squared $L^{1}$-norm $\|\gamma\|_{1}^{2}$ of coefficients achieving $\xi_{\mathcal{D}}(\Psi)$ is given.

### 4.3 Fast norm estimation and approximate simulation

In pioneering work, Bravyi and Gosset [17] improved upon the sketched algorithm in the case of stabilizer states. This was achieved by replacing the $O\left(\chi^{2}\right)$-runtime (naive) estimation algorithm $\chi$ naivenorm for the norm of a superposition of stabilizer states by a probabilistic algorithm $\chi$ fastnorm. With success probability at least $1-p_{f}$, the algorithm $\chi$ fastnorm provides an estimate $\hat{N}$ of the squared norm $N=\|\Psi\|^{2}$ of a superposition $\Psi=\sum_{j=1}^{\chi} \gamma_{j} \varphi_{j}$ of $n$-qubit stabilizer states $\left\{\varphi_{j}\right\}_{j=1}^{\chi}$ with multiplicative error $\epsilon$ (i.e., $\hat{N} \in[(1-\epsilon) N,(1+\epsilon) N])$, and has runtime $O\left(\chi \cdot n^{3} \epsilon^{-2} p_{f}^{-1}\right)$ The key observation underlying the algorithm is the fact that the norm of interest can be expressed as

$$
\begin{equation*}
N=2^{n} \mathbb{E}_{\Theta}\left[|\langle\Theta, \Psi\rangle|^{2}\right], \tag{65}
\end{equation*}
$$

i.e., it is proportional to the expected (squared) overlap of $\Psi$ with a state $|\Theta\rangle$ drawn uniformly at random from the set of $n$-qubit stabilizer states. Given $\left\{\gamma_{j}, \varphi_{j}\right\}_{j=1}^{\chi}$, this algorithm proceeds by taking $R=\left\lceil p_{f}^{-1} \epsilon^{-2}\right\rceil$ stabilizer states $\Theta_{1}, \ldots, \Theta_{R}$ chosen uniformly from the set of all stabilizer states, and producing the estimate

$$
\begin{equation*}
\hat{N}=\frac{2^{n}}{R} \sum_{k=1}^{R}\left|\left\langle\Theta_{k}, \Psi\right\rangle\right|^{2} \tag{66}
\end{equation*}
$$

of $N$. Importantly, expression (66) can be computed from (the descriptions of) $\left\{\Theta_{k}\right\}_{k=1}^{R}$, $\left\{\varphi_{j}\right\}_{j=1}^{\chi}$ and the coefficients $\left\{\gamma_{j}\right\}_{j=1}^{\chi}$, using $\chi \cdot R$ calls of a subroutine overlap which computes the overlap of two stabilizer states (including phases). This is because each summand in (66) can be written as a sum

$$
\begin{equation*}
\left|\left\langle\Theta_{k}, \Psi\right\rangle\right|=\left|\sum_{j=1}^{\chi} \gamma_{j}\left\langle\Theta_{k}, \varphi_{j}\right\rangle\right| \tag{67}
\end{equation*}
$$

of $\chi$ such products. The resulting runtime of this norm estimation algorithm is thus $O(\chi$. $R$.time(overlap)) which amounts to the claimed runtime $O\left(\chi \cdot n^{3} \epsilon^{-2} p_{f}^{-1}\right)$.

We note that a similar reasoning can be applied to any situation where the norm of a superposition of dictionary elements of interest can be expressed as in Eq. (65) as the expected overlap of the inner product of $\Psi$ with a state $\Theta$ randomly chosen according to a suitable distribution over dictionary states. Specifically, as derived in Appendix B of [60] and discussed below (see Section 4.4), this is the case for the set of fermionic Gaussian states. The corresponding norm estimation algorithm then has a runtime of the form

$$
\begin{align*}
\operatorname{time}(\chi \text { fastnorm }) & =O(\chi \cdot R \cdot \text { time }(\text { overlap })+R \cdot \text { time }(\text { samplestate })) \\
& =O\left(p_{f}^{-1} \epsilon^{-2}(\chi \text { time }(\text { overlap })+\text { time }(\text { samplestate }))\right. \tag{68}
\end{align*}
$$

where samplestate is an algorithm producing a description of a state $\Theta$ drawn randomly form the appropriate distribution. Importantly, the runtime (68) is linear in $\chi$, resulting in a linear dependence when replacing $\chi$ by the stabilizer extent $\xi_{\mathcal{D}}(\Psi)$ as discussed in Section 4.2.

Algorithms (approxevolve, approxmeasureprob, approxpostmeasure) can now be obtained by using $\chi$ fastnorm in place of $\chi$ norm. The algorithm approxevolve is identical to $\chi$ evolve since it does not involve norm computations. In contrast, approxmeasureprob is a probabilistic algorithm that can fail with probability $p_{f}$ and both approxmeasureprob and approxpostmeasure introduce an error (in the sampled distribution and the post-measurement state, respectively). This is because $\chi$ fastnorm only estimates the norm of a superposition.

Finally, replacing $\chi$ by the $\mathcal{D}$-extent $\xi_{\mathcal{D}}(\Psi)$, see Section 4.2 results in a triple of approximate algorithms (approxevolve, approxmeasureprob, approxpostmeasure) with parameters $\left(\epsilon, \delta, p_{f}\right)$ describing the quality of approximation and failure probability as discussed
in Section 1.5. By construction, the runtimes of these algorithms are

$$
\begin{align*}
\text { time(approxevolve) } & =O\left(\frac{\xi_{\mathcal{D}}(\Psi)}{\delta^{2}} \text { time }(\text { evolve })\right) \\
\text { time }(\text { approxmeasureprob }) & \left.=O\left(p_{f}^{-1} \epsilon^{-2}\left(\frac{\xi_{\mathcal{D}}(\Psi)}{\delta^{2}} \text { time }(\text { overlap })+\text { time (samplestate }\right)\right)\right) \\
& +O\left(\frac{\xi_{\mathcal{D}}(\Psi)}{\delta^{2}}(\text { time }(\text { postmeasure })+\text { time }(\text { measureprob }))\right) \\
\text { time }(\text { approxpostmeasure }) & =O\left(\frac{\xi_{\mathcal{D}}(\Psi)}{\delta^{2}}(\text { time }(\text { postmeasure })+\text { time }(\text { samplestate }))\right) \tag{69}
\end{align*}
$$

### 4.4 Fermionic linear optics with non-Gaussian initial states

The algorithms described above can be adapted in a straightforward manner to the problem of classically simulating fermionic linear optics with non-Gaussian initial states: We can simply use the efficient description of Gaussian states introduced in Section 3 and make use of the associated procedures overlap, evolve as well as measureprob and postmeasure. In particular, observe that combining Eq. (64) with the runtimes $O\left(n^{3}\right)$ for the algorithms evolve, postmeasure and overlap, and $O(1)$ for measureprob (see Section 3) results in the runtimes given in Table 3 for exact simulation.

To get a linear scaling in the Gaussian extent $\xi_{\mathcal{G}_{n}}(\Psi)$ of the initial state (for approximate simulation), the naive norm estimation needs to be replaced. A fast norm estimation scheme for superpositions of fermionic Gaussian has been described in Appendix C of Ref. [60]: Consider the following probabilistic process defined for a superposition $\Psi=\sum_{j=1}^{\chi} \gamma_{j} \varphi_{j}, \varphi_{j} \in \mathcal{G}_{n}, \gamma_{j} \in \mathbb{C}$ of $n$-mode fermionic Gaussian states:
(i) Sample $K$ random Gaussian states $\left\{\Theta_{k}\right\}_{k=1}^{K}$ independently and identically from the distribution induced by picking a permutation $\pi \in S_{2 n}$ and a string $y \in\{0,1\}^{n}$ uniformly at random and outputting

$$
|\Theta(\pi, y)\rangle=U_{R_{\pi}}|y\rangle
$$

Here $R_{\pi}=O(2 n)$ is a permutation matrix specified by an element $\pi \in S_{2 n}$ and $y \in$ $\{0,1\}^{n}$.
(ii) Set

$$
\begin{equation*}
\hat{N}=\frac{1}{K} \sum_{k=1}^{K} 2^{n}\left|\left\langle\Theta_{k}, \Psi\right\rangle\right|^{2} \tag{70}
\end{equation*}
$$

The following was shown in [60].
Lemma 4.2 (Lemma 10 in Ref. [60]). For any $p_{f} \in[0,1]$ and $\epsilon>0$, consider the probabilistic process described above with the choice $K=\left\lceil 2 \sqrt{n} \epsilon^{-2} p_{f}^{-1}\right\rceil$. Then the random variable $\hat{N}$ satisfies

$$
(1-\epsilon)\|\Psi\|^{2} \leq \hat{N} \leq(1+\epsilon)\|\Psi\|^{2}
$$

with probability at least $1-p_{f}$.

A description of a state proportional to $\Theta_{k}$ can be computed from the associated pair $\left(\pi_{k}, y_{k}\right) \in S_{2 n} \times\{0,1\}^{n}$ using the subroutine describe, for each $k \in[K]$, as follows (see Fig. 15 for pseudocode for the algorithm). The covariance matrix $\Gamma_{k}=R_{\pi_{k}} \Gamma(|y\rangle) R_{\pi_{k}}^{\dagger}$ of such a state can be computed in time $O\left(n^{3}\right)$ from $\left(\pi_{k}, y\right)$, and applying describe to $\Gamma_{k}$ gives the desired description. We note that any such state can be used in place of $\Theta_{k}$ since the expression (70) (and, in particular, (67)) does not depend on the global phase of $\Theta_{k}$. With the definition (70), it follows that the probabilistic process described here can be simulated in time given by Eq. (68) using $K$ calls to the subroutine samplestate shown in Fig. 15, and subsequent use of overlap to compute the empirical average (70).

```
function samplestate
    \(y \leftarrow\) uniform random string in \(\{0,1\}^{n}\)
    \(\pi \leftarrow\) uniform random permutation in \(S_{2 n}\)
    \(R_{\pi} \in O(2 n)\)
    for \(j \in[2 n]\) do \(\quad \triangleright\) compute the permutation matrix \(R_{\pi}\)
        \(R_{\pi}[j] \leftarrow e_{\pi(j)}\)
    \(\left.\left.\Gamma \leftarrow R_{\pi} \Gamma(\mid y]\right\rangle\right) R_{\pi}^{\dagger} \quad \triangleright\) compute the covariance matrix of \(|\Theta(\pi, y)\rangle=R_{\pi}|y\rangle\)
    return describe \((\Gamma) \quad \triangleright\) output a description of \(|\Theta(\pi, y)\rangle\)
```

Figure 15: The algorithm samplestate outputs a classical description of a state $|\Theta(\pi, y)\rangle=R_{\pi}|y\rangle$ where $\pi \in S_{2 n}$ and $y \in\{0,1\}^{n}$ are taken uniformly at random.

Because the runtimes of describe and overlap are both upper bounded by $O\left(n^{3}\right)$, this leads to an overall runtime of $O\left(n^{7 / 2} \epsilon^{-2} p_{f}^{-1} \chi\right)$ of this algorithm for computing the estimate $\hat{N}$ of $\|\Psi\|^{2}$. We note this conclusion about the runtime was also reached in Ref. [60], although the issue of a potential lack of a phase reference applicable throughout the computation was not considered there. This issue is resolved by our description of Gaussian states, see Section 3.

Combing this algorithm with the runtimes given in Eq. (69) and with the runtimes $O\left(n^{3}\right)$ for the algorithms evolve, postmeasure and overlap, and $O(1)$ for measureprob (see Section 3) gives runtimes claimed in Table 4 for the algorithms approxevolve, approxmeasureprob and approxpostmeasure.

To give an idea of the feasibility of running these algorithms, let us compare to [17], where Clifford circuits on $n=40$ qubits with up to $t=48 T$-gates were simulated by means of an algorithm relying on the stabilizer formalism augmented with stabilizerdecompositions of magic states. These simulations were performed using MATLAB on a laptop with a 2.6 GHz Intel i5 Dual Core CPU. Runtimes of individual building blocks are given in [17, Table I] and are of the order of tens of milliseconds even for 100 qubits. The algorithms of [17] have a scaling which is linear in the approximate (stabilizer) rank. Since this quantity scales exponentially in the number of copies of a single magic state, this dominates the runtime, which includes additional factors that are polynomial in the number of qubits and gates. In more detail, the authors of [17] consider the non-stabilizer state

$$
|A\rangle=\frac{1}{\sqrt{2}}\left(|0\rangle+e^{i \pi / 4}|1\rangle\right)
$$

A copy of this (magic) state can be used together with stabilizer operations to implement the (non-Clifford) $T$-gate [11]. The approximate stabilizer rank (which is defined in terms
of fidelity rather than distance in [17]) of $t$ copies of this state is shown to be bounded by

$$
\begin{equation*}
\tilde{\chi}^{\delta}\left(|A\rangle^{\otimes t}\right)=O\left(2^{\gamma t} \delta^{-1}\right) \quad \text { where } \quad \gamma \approx 0.228 \tag{71}
\end{equation*}
$$

Now consider our simulation procedure: Here the dependence of the runtime is linear in the Gaussian extent $\xi_{\mathcal{G}_{n}}$ and thus again essentially linear in the $\delta$-approximate Gaussian rank $\chi_{\mathcal{G}_{n}}^{\delta}$ (see Theorem 4.1), and this quantity dominates the runtime (which includes polynomial factors in the number of fermionic modes and gates). Thus our simulation algorithms have a runtime comparable to that of [17] when substituting the fermionic Gaussian extent of the initial state with the approximate stabilizer rank (respectively the stabilizer extent) of the initial state in the Clifford setting.

To make this more concrete, consider the state

$$
\begin{equation*}
\left|a_{8}\right\rangle=\frac{1}{\sqrt{2}}(|0000\rangle+|1111\rangle) \tag{72}
\end{equation*}
$$

which is a magic state for Gaussian computations: As shown in [12, Lemma 1], the nonGaussian unitary (magic gate) $U_{\text {magic }}=\exp \left(i \pi c_{1} c_{2} c_{3} c_{4}\right)$ can be implemented with Gaussian operations and a single copy of this state. The state $\left|a_{8}\right\rangle$ has Gaussian extent

$$
\begin{equation*}
\xi_{\mathcal{G}_{n}}\left(\left|a_{8}\right\rangle\right)=2 \tag{73}
\end{equation*}
$$

and thus we have

$$
\begin{equation*}
\xi_{\mathcal{G}_{n}}\left(\left|a_{8}\right\rangle^{\otimes t^{\prime}}\right) \leq 2^{t^{\prime}} \tag{74}
\end{equation*}
$$

for $t^{\prime}$ copies of $\left|a_{8}\right\rangle$. (We note that in fact, the results of [49] imply that equality holds in (74).) Eq. (73) can be shown as follows: The upper bound $\xi_{\mathcal{G}_{n}}\left(\left|a_{8}\right\rangle\right) \leq 2$ is a direct consequence of the decomposition given in (72) into a sum of the Gaussian states $|0000\rangle$ and $|1111\rangle$. The dual formulation of the extent implies that

$$
\begin{equation*}
\xi_{\mathcal{G}_{n}}(|\Psi\rangle) \geq \frac{1}{F_{\mathcal{G}_{n}}(|\Psi\rangle)} \quad \text { for any state } \Psi \in \mathcal{H}_{n} \tag{75}
\end{equation*}
$$

see (98) with the choice $y=|\Psi\rangle / \sqrt{F_{\mathcal{G}_{n}}(|\Psi\rangle)}$. Using the fact that $F_{\mathcal{G}_{n}}\left(\left|a_{8}\right\rangle\right)=1 / 2$ (see [50] - the inequality $F_{\mathcal{G}_{n}}\left(\left|a_{8}\right\rangle\right) \leq 1 / 2$ which is needed here was previously shown in [32]) and (75) gives the lower bound $\xi_{\mathcal{G}_{n}}\left(\left|a_{8}\right\rangle\right) \geq 2$, establishing (73).

Comparing the exponents in (71) and (74), we can give the following rough estimate: we expect that the cost (runtime) of simulating $t=48 T$-gates in the stabilizer framework is comparable with the cost of simulation of roughly $t^{\prime} \approx 10$ gates $U_{\text {magic }}$ in the fermionic context. Similar estimates apply to other non-Gaussian operations such that the SWAP gate, a magic gate in the context of fermionic Gaussian computation. The latter can be implemented using a certain non-Gaussian state as shown in [13].

### 4.5 Efficient additive-error strong simulation

In a different direction of generalization, building upon the work [17] and making innovative use of a concentration inequality by Hayes [62] for vector martingales, Ref. [27] gives a randomized algorithm which, for a state $\Psi$ obtained by applying $n$-qubit Clifford gates and $t$ (non-Clifford) $T$-gates to $|0\rangle^{\otimes n}$, provides an additive-error estimate $\hat{p}(x)$ for the probability $p(x)=\left\|\left(\langle x| \otimes I^{\otimes(n-a)}\right)|\Psi\rangle\right\|^{2}$ of observing $a$ qubits in the state $|x\rangle$, with $x \in\{0,1\}^{a}$. The algorithm is based on a procedure by which the probability $p(x)$ of
interest is expressed in terms of the squared norm $\left\|\left(\left\langle\left. 0\right|^{\otimes t-r} \otimes I^{\otimes r}\right) W|\Psi\rangle \|^{2}\right.\right.$ of a partially projected state, where $\Psi$ is a tensor product of $t$ non-stabilizer single-qubit states (arising from gadgetization), $W$ a certain Clifford unitary, and $r$ a circuit-dependent integer. The failure probability of the constructed algorithm is then upper bounded (see [27, Theorem 3]) by an expression depending on $p(x)$, the error $\epsilon$, the stabilizer rank $\xi_{\mathrm{STAB}_{n}}(\Psi)$ (taking the role of $\chi$ ) of the product state $\Psi$, as well as two additional parameters than be chosen freely, but enter into the (polynomial) runtime estimate.

The described method of adapting fast algorithms for simulating Clifford circuits with non-stabilizer initial states can be applied in a similar manner to this algorithm, since this also reduces to computing inner products (including phases) between Gaussian states.

## 5 Multiplicativity of the Gaussian fidelity for 4 fermions

The main result of this section is a proof that the fermionic Gaussian fidelity is multiplicative for the tensor product of any two positive-parity 4 -fermion states.

We begin in Section 5.1 by laying out some specific properties of 4 -fermion states. We discuss a Gaussianity condition specific to 4 -fermion states [58] and we write an explicit expression for any 4 -fermion state as a superposition of two orthogonal (Gaussian) states. This was first introduced in Refs. [56,58]. In Section 5.2 we establish properties of the fermionic Gaussian fidelity for 4 -fermion states which are subsequently used in Section 5.3 to prove that the fermionic Gaussian fidelity is multiplicative for the tensor product of any two 4 -fermion states.

### 5.1 Four-fermion Gaussian and non-Gaussian states

Key to our considerations is a certain antiunitary map $\theta$ acting on $\mathcal{H}_{+}^{4}$, the positive-parity subspace of 4 fermions spanned by $\{|x\rangle\}_{x \in\{0,1\}_{+}^{4}}$. It is defined by its action

$$
\begin{equation*}
\theta|x\rangle=(-1)^{\vartheta(x)}|\bar{x}\rangle \tag{76}
\end{equation*}
$$

for $x \in\{0,1\}_{+}^{4}$, on basis states (antilinearly extended to all of $\mathcal{H}_{+}^{4}$ ), where $\vartheta(x)=x_{1}+x_{3}$ $\bmod 2=x_{2}+x_{4} \bmod 2=\vartheta(\bar{x})$. Here $\bar{x}=\left(\bar{x}_{1}, \ldots, \bar{x}_{n}\right)$ is obtained by flipping each bit of $x$. The relevant properties of this map are the following. We note that the following statement has been given in [58, Eq. (9)], along with a negative-parity version.

Lemma 5.1 ([58]). A state $\Psi \in \mathcal{H}_{+}^{4}$ is Gaussian if and only if

$$
\langle\Psi, \theta \Psi\rangle=0
$$

Proof. This follows from the Gaussianity criterion given in Lemma 2.3. We give the proof in Appendix A.

Lemma 5.2. We have $\theta c_{j} c_{k}=c_{j} c_{k} \theta$ for all $j, k \in[8]$.
Proof. See Appendix B.
The following result was first shown in Ref. [56].
Lemma 5.3 ([56]). Let $\Psi \in \mathcal{H}_{+}^{4}$ be a unit vector. Then there are two orthogonal unit vectors $\Psi_{1}, \Psi_{2} \in \mathcal{H}_{+}^{4}, \varphi \in[0,2 \pi)$ and $a \in[0,1 / \sqrt{2}]$ such that

$$
\begin{equation*}
\theta \Psi_{j}=\Psi_{j} \quad \text { for } \quad j \in[2] \tag{77}
\end{equation*}
$$

and

$$
\begin{equation*}
\Psi=e^{i \varphi}\left(\sqrt{1-a^{2}} \Psi_{1}+i a \Psi_{2}\right) \tag{78}
\end{equation*}
$$

Proof. We first argue that it suffices to consider the case where $\Psi$ satisfies

$$
\begin{equation*}
\langle\Psi, \theta \Psi\rangle \in \mathbb{R} . \tag{79}
\end{equation*}
$$

This is because

$$
\left\langle\left(e^{i \varphi} \Psi\right), \theta\left(e^{i \varphi} \Psi\right)\right\rangle=e^{-2 i \varphi}\langle\Psi, \theta \Psi\rangle \quad \text { for every } \quad \varphi \in[0,2 \pi)
$$

which implies that (79) can be ensured by replacing $\Psi$ with $e^{i \varphi} \Psi$ for a suitably chosen $\varphi \in$ $[0,2 \pi)$.

Let $\Psi$ be such that (79) holds. We define "real" and "imaginary" parts of $\Psi$ by the expressions

$$
\begin{aligned}
\Psi_{R} & =\frac{1}{2}(\Psi+\theta \Psi) \\
\Psi_{I} & =\frac{1}{2 i}(\Psi-\theta \Psi)
\end{aligned}
$$

It follows immediately from this definition that

$$
\Psi=\Psi_{R}+i \Psi_{I}
$$

and

$$
\begin{aligned}
\theta \Psi_{R} & =\Psi_{R} \\
\theta \Psi_{I} & =\Psi_{I}
\end{aligned}
$$

because $\theta$ is antiunitary and an involution. Furthermore, Eq. (79) implies that the vectors $\Psi_{R}, \Psi_{I}$ are orthogonal: We have

$$
\begin{aligned}
4 i\left\langle\Psi_{R}, \Psi_{I}\right\rangle & =\langle\Psi+\theta \Psi, \Psi-\theta \Psi\rangle \\
& =\|\Psi\|^{2}-\|\theta \Psi\|^{2}+\langle\theta \Psi, \Psi\rangle-\langle\Psi, \theta \Psi\rangle \\
& =-2 i \operatorname{lm}\langle\Psi, \theta \Psi\rangle \\
& =0
\end{aligned}
$$

where we used that $\theta$ is an antiunitary in the first step, and assumption (79) in the last step. The claim now follows by setting

$$
\left(a, \Psi_{1}, \Psi_{2}\right)= \begin{cases}\left(\left\|\Psi_{I}\right\|, \frac{\Psi_{R}}{\left\|\Psi_{R}\right\|}, \frac{\Psi_{I}}{\left\|\Psi_{I}\right\|}\right) & \text { if } \quad\left\|\Psi_{I}\right\| \leq 1 / \sqrt{2} \\ \left(\left\|\Psi_{R}\right\|, \frac{\Psi_{I}}{\left\|\Psi_{I}\right\|}, \frac{\Psi_{R}}{\left\|\Psi_{R}\right\|}\right) & \text { otherwise } .\end{cases}
$$

Theorem 5.4 ([56,58]). Let $\Psi \in \mathcal{H}_{+}^{4}$ be an arbitrary unit vector. Then there are a Gaussian pure state $\Psi_{g} \in \mathcal{G}_{4}^{+}, \varphi \in[0,2 \pi)$ and $f \in[1 / 2,1]$ such that the state $\theta \Psi_{g}$ is Gaussian and orthogonal to $\Psi_{g}$ and

$$
\begin{equation*}
\Psi=e^{i \varphi}\left(\sqrt{f} \Psi_{g}+\sqrt{1-f} \theta \Psi_{g}\right) \tag{80}
\end{equation*}
$$

The triple $\left(\Psi_{g}, \varphi, f\right)$ is uniquely defined by $\Psi$, i.e., a function of $\Psi$. Furthermore, the quantity $f=f(\Psi)$ is invariant under the action of Gaussian unitaries associated with special orthogonal rotations: We have

$$
\begin{equation*}
f(U \Psi)=f(\Psi) \quad \text { for any Gaussian unitary } U=U_{R} \text { with } R \in S O(2 n) . \tag{81}
\end{equation*}
$$

Proof. Let $\Psi \in \mathcal{H}_{+}^{4}$ be an arbitrary unit vector. Let $\Psi_{1}, \Psi_{2} \in \mathcal{H}_{+}^{4}, \varphi \in[0,2 \pi)$ and $a \in[0,1]$ be as in Lemma 5.3. Define

$$
\Psi_{g}^{ \pm}=\frac{1}{\sqrt{2}}\left(\Psi_{1} \pm i \Psi_{2}\right)
$$

Then

$$
\begin{equation*}
\theta \Psi_{g}^{-}=\Psi_{g}^{+} \tag{82}
\end{equation*}
$$

because of property (77). It follows that

$$
\begin{aligned}
\left\langle\Psi_{g}^{-}, \Psi_{g}^{+}\right\rangle & =\left\langle\Psi_{g}^{-}, \theta \Psi_{g}^{-}\right\rangle \\
& =\frac{1}{2}\left(\left\|\Psi_{1}\right\|^{2}+2 i \operatorname{Re}\left\langle\Psi_{1}, \Psi_{2}\right\rangle-\left\|\Psi_{2}\right\|^{2}\right) \\
& =0
\end{aligned}
$$

since $\Psi_{1}$ and $\Psi_{2}$ are orthogonal unit vectors.
Using (82) and the orthogonality of $\Psi_{g}^{-}, \Psi_{g}^{+}$implies that

$$
\left\langle\Psi_{g}^{+}, \theta \Psi_{g}^{+}\right\rangle=\left\langle\Psi_{g}^{+}, \Psi_{g}^{-}\right\rangle=0
$$

and similarly (because $\theta$ is an involution)

$$
\left\langle\Psi_{g}^{-}, \theta \Psi_{g}^{-}\right\rangle=\left\langle\Psi_{g}^{-}, \Psi_{g}^{+}\right\rangle=0
$$

According to the Gaussianity criterion in Lemma 5.1, we conclude that both $\Psi_{g}^{+}$and $\Psi_{g}^{-}$ are Gaussian.

Rewriting Eq. (78) by expressing $\left(\Psi_{1}, \Psi_{2}\right)$ in terms of $\left(\Psi_{g}^{+}, \Psi_{g}^{-}\right)$gives

$$
\Psi=e^{i \varphi}\left(\sqrt{f} \Psi_{g}^{-}+\sqrt{1-f} \Psi_{g}^{+}\right) \quad \text { where } \quad f=\frac{1}{2}+a \sqrt{1-a^{2}}
$$

The claim (80) now follows with (82).
It remains to show property (81) of the function $f$. This follows immediately from the fact that the antiunitary $\theta$ commutes with all quadratic monomials $c_{j} c_{k}$ of Majorana operators (see Lemma 5.2), and hence with any Gaussian unitary $U=U_{R}$ with $R \in S O(2 n)$, i.e., $U \theta=\theta U$. Retracing the steps of the proof, it is easy to check that if $\left(\Psi_{1}, \Psi_{2}\right)$ are the states of Lemma 5.3, and $\Psi_{g}$ the state in expression (80) for $\Psi$, then the corresponding states $\left(\Psi_{1}^{\prime}, \Psi_{2}^{\prime}\right)$ and $\Psi_{g}^{\prime}$ for the state $\Psi^{\prime}=U \Psi$ are given by $\Psi_{j}^{\prime}=U \Psi_{j}$ for $j \in[2]$ and $\Psi_{g}^{\prime}=U \Psi_{g}$, respectively. This implies the claim.

### 5.2 The Gaussian fidelity for 4-fermion states

For a subset $E \subset\{0,1\}^{4}$, we define $\bar{E}=\{\bar{x} \mid x \in E\}$. We also write $\Pi_{E}=\sum_{x \in E}|x\rangle\langle x|$ for the projection onto the span of $\{|x\rangle\}_{x \in E}$.

Lemma 5.5. Let $E \subset\{0,1\}_{+}^{4},|E|=4$ be a subset of even-weight strings such that $E \cup \bar{E}=$ $\{0,1\}_{+}^{4}$. Let $f(\Psi) \in[1 / 2,1]$ be defined as in Theorem 5.4. Then

$$
\begin{equation*}
\left\|\Pi_{E} \Psi\right\|^{2} \leq f(\Psi) \quad \text { for any unit vector } \quad \Psi \in \mathcal{H}_{+}^{4} \tag{83}
\end{equation*}
$$

Proof. Let $f=f(\Psi) \in[1 / 2,1], \varphi \in[0,2 \pi)$ and $\Psi_{g} \in \mathcal{G}_{n}^{+}$be as in Theorem 5.4 such that

$$
\begin{equation*}
\Psi=e^{i \varphi}\left(\sqrt{f} \Psi_{g}+\sqrt{1-f} \theta \Psi_{g}\right) \tag{84}
\end{equation*}
$$

We define

$$
\begin{aligned}
& \alpha_{x}=\left\langle x, \Psi_{g}\right\rangle \\
& \beta_{x}=\left\langle x, \theta \Psi_{g}\right\rangle
\end{aligned} \quad \text { for every } \quad x \in E .
$$

We claim that we have the identities

$$
\begin{align*}
\sum_{x \in E}\left(\left|\alpha_{x}\right|^{2}+\left|\beta_{x}\right|^{2}\right) & =1  \tag{85}\\
\sum_{x \in E} \overline{\alpha_{x}} \beta_{x} & =0 . \tag{86}
\end{align*}
$$

Observe that these two identities immediately imply (83): Using expression (84), we have

$$
\begin{align*}
\left\|\Pi_{E} \Psi\right\|^{2} & =\sum_{x \in E}|\langle x, \Psi\rangle|^{2} \\
& =\sum_{x \in E}\left|\sqrt{f} \alpha_{x}+\sqrt{1-f} \beta_{x}\right|^{2} \\
& =\|\sqrt{f} \vec{\alpha}+\sqrt{1-f} \vec{\beta}\|^{2} \tag{87}
\end{align*}
$$

where we defined the vectors $\vec{\alpha}=\left(\alpha_{x}\right)_{x \in E}, \vec{\beta}=\left(\beta_{x}\right)_{x \in E} \in \mathbb{C}^{4}$. Since (85) and (86) are equivalent to the statement that

$$
\begin{align*}
\|\vec{\alpha}\|^{2}+\|\vec{\beta}\|^{2} & =1  \tag{88}\\
\langle\vec{\alpha}, \vec{\beta}\rangle & =0, \tag{89}
\end{align*}
$$

we obtain

$$
\begin{align*}
\|\sqrt{f} \vec{\alpha}+\sqrt{1-f} \vec{\beta}\|^{2} & =f\|\vec{\alpha}\|^{2}+(1-f)\|\vec{\beta}\|^{2} \\
& \leq \max \{f, 1-f\} \\
& =f \tag{90}
\end{align*}
$$

by the Pythagorean theorem in $\mathbb{C}^{4}$ (using (89)) and by maximizing over $(\alpha, \beta)$ satisfying (88). Inserting (90) into (87) results in the upper bound (83) on $\left\|\Pi_{E} \Psi\right\|^{2}$.

It remains to prove the claimed identities (85) and (86). We argue that these are a consequence of the fact that $\Psi_{g}$ is normalized and Gaussian, respectively.

Proof. Observe that by definition of the antiunitary $\theta$, we have

$$
\begin{aligned}
\beta_{x} & =\left\langle x, \theta \Psi_{g}\right\rangle \\
& =(-1)^{\vartheta(\bar{x})} \overline{\left\langle\bar{x}, \Psi_{g}\right\rangle} \quad \text { for all } \quad x \in E .
\end{aligned}
$$

In particular, this implies that

$$
\begin{equation*}
\left|\beta_{x}\right|^{2}=\left|\left\langle\bar{x}, \Psi_{g}\right\rangle\right|^{2} \quad \text { for every } \quad x \in E . \tag{91}
\end{equation*}
$$

Eq. (85) now follows from the fact that $\Psi_{g}$ is normalized and positive-parity: we have

$$
\begin{aligned}
\sum_{x \in E}\left(\left|\alpha_{x}\right|^{2}+\left|\beta_{x}\right|^{2}\right) & =\sum_{x \in E}\left(\left|\left\langle x, \Psi_{g}\right\rangle\right|^{2}+\left|\left\langle\bar{x}, \Psi_{g}\right\rangle\right|^{2}\right) \\
& =\left\|\Psi_{g}\right\|^{2} \\
& =1
\end{aligned}
$$

where we used the definition of $\alpha_{x}$ and (91) in the first step, and the assumption $E \cup \bar{E}=$ $\{0,1\}_{+}^{4}$ in the second identity.

Similarly, Eq. (86) is a consequence of the fact that $\Psi_{g}$ is Gaussian: we have

$$
\begin{aligned}
\sum_{x \in\{0,1\}_{+}^{4}} \overline{\alpha_{x}} \beta_{x} & =\sum_{x \in\{0,1\}_{+}^{4}}\left\langle\Psi_{g}, x\right\rangle\left\langle x, \theta \Psi_{g}\right\rangle \\
& =\left\langle\Psi_{g}, \theta \Psi_{g}\right\rangle \\
& =0
\end{aligned}
$$

where we used the definition of $\alpha_{x}$ and $\beta_{x}$ in the first step, the fact that $\Psi_{g} \in \mathcal{H}_{+}^{4}$ in the second step, and the characterization of Gaussianity from Lemma 5.1 in the last identity.

Lemma 5.5 immediately implies the following expression for the fermionic Gaussian fidelity. We note that a more general expression for the "Gaussian fidelity" of a mixed state has previously been obtained in [58]. The proof for pure states given here is more elementary and illustrates the use of Lemma 5.5.
Theorem 5.6 (Fermionic Gaussian fidelity for 4-mode pure states [56,58]). Let $\Psi \in \mathcal{H}_{+}^{4}$ be a unit vector. Let $f(\Psi) \in[1 / 2,1]$ be defined as in Theorem 5.4. Then

$$
F_{\mathcal{G}_{4}^{+}}(\Psi)=f(\Psi)
$$

Proof. Let $f=f(\Psi), \varphi \in[0,2 \pi)$ and $\Psi_{g} \in \mathcal{G}_{4}^{+}$be as in Theorem 5.4. Then we have

$$
\begin{aligned}
F_{\mathcal{G}_{4}^{+}}(\Psi) & \geq\left|\left\langle\Psi_{g}, e^{i \varphi}\left(\sqrt{f} \Psi_{g}+f \theta \Psi_{g}\right)\right\rangle\right|^{2} \\
& =f
\end{aligned}
$$

since $\theta \Psi_{g}$ is orthogonal to $\Psi_{g}$. It thus suffices to show the upper bound

$$
\begin{equation*}
F_{\mathcal{G}_{4}^{+}}(\Psi) \leq f \tag{92}
\end{equation*}
$$

Let $\Phi_{g} \in \mathcal{G}_{4}^{+}$be an arbitrary positive-parity Gaussian pure state. Then there is a Gaussian unitary $U=U_{R}$ with $R \in S O(2 n)$ and a phase $\mu \in[0,2 \pi)$ such that $\Phi_{g}=e^{i \mu} U\left|0_{F}\right\rangle$. We will use any subset $E \subset\{0,1\}_{+}^{4}$ of even-weight strings as in Lemma 5.5 with the additional property that $0000 \in E$, e.g., $E=\{0000,1100,1010,1001\}$. Then $\left|0_{F}\right\rangle=\Pi_{E}\left|0_{F}\right\rangle$ is in the image of $\Pi_{E}$. It follows that

$$
\begin{aligned}
\left|\left\langle\Phi_{g}, \Psi\right\rangle\right| & =\left|\left\langle 0_{F}, U^{\dagger} \Psi\right\rangle\right| \\
& =\left|\left\langle\Pi_{E} 0_{F}, U^{\dagger} \Psi\right\rangle\right| \\
& =\left|\left\langle 0_{F}, \Pi_{E} U^{\dagger} \Psi\right\rangle\right| \\
& \leq \| \Pi_{E} U^{\dagger} \Psi \mid \\
& \leq \sqrt{f\left(U^{\dagger} \Psi\right)}
\end{aligned}
$$

where we used the Cauchy-Schwarz inequality in the penultimate step, and Lemma 5.5 applied to the state $U^{\dagger} \Psi$. Since $\Phi_{g} \in \mathcal{G}_{4}^{+}$was arbitrary, the claimed inequality (92) follows by taking the square and using that $f\left(U^{\dagger} \Psi\right)=f(\Psi)$, see Eq. (81) of Theorem 5.4.

Combining Lemma 5.5 with Theorem 5.6 yields the following statement, which directly relates the weight of a state on certain subspaces to the fermionic Gaussian fidelity. It will be our main technical tool in the following.

Corollary 5.7. Let $E \subset\{0,1\}_{+}^{4},|E|=4$ be a subset of even-weight strings such that $E \cup$ $\bar{E}=\{0,1\}_{+}^{4}$. Then

$$
\left\|\Pi_{E} \Psi\right\|^{2} \leq F_{\mathcal{G}_{4}^{+}}(\Psi) \quad \text { for any unit vector } \quad \Psi \in \mathcal{H}_{+}^{4}
$$

### 5.3 Multiplicativity of the Gaussian fidelity for 4-fermion states

Here we prove that the fermionic Gaussian fidelity is multiplicative for 4 -fermion states (see Theorem 5.10). We use two intermediate results stated as Lemmas 5.8 and 5.9. In Lemma 5.8, we bound the overlap of a tensor product of two (arbitrary) positive-parity pure states $\Psi_{A}, \Psi_{B}$ with a state $\Phi$ written as a Schmidt decomposition of a bipartite fermionic pure state. In Theorem 5.10, this result is used to bound the fermionic Gaussian fidelity. More specifically, Lemma 5.9 is used to upper bound the Schmidt coefficients, giving the multiplicativity result for the Gaussian fidelity.

Lemma 5.8. Let $\left\{m_{x}\right\}_{x \in\{0,1\}^{4}} \subset \mathbb{C}$ be arbitrary. Define

$$
\begin{equation*}
|\Phi\rangle=\sum_{x \in\{0,1\}^{4}} m_{x}|x, x\rangle \in \mathcal{H}_{+}^{8} . \tag{93}
\end{equation*}
$$

Let $E \subset\{0,1\}_{+}^{4},|E|=4$ be a subset of even-weight strings such that $E \cup \bar{E}=\{0,1\}_{+}^{4}$. Then

$$
\left|\left\langle\Phi, \Psi_{A} \tilde{\otimes} \Psi_{B}\right\rangle\right|^{2} \leq F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)\left(\max _{x \in E}\left|m_{x}\right|+\max _{y \in \bar{E}}\left|m_{y}\right|\right)^{2}
$$

for all states $\Psi_{A}, \Psi_{B} \in \mathcal{H}_{+}^{4}$.
Proof. Because $\Psi_{A}$ and $\Psi_{B}$ are supported on $\mathcal{H}_{+}^{4}$ by assumption, we have by Eq. (31)

$$
\begin{align*}
\left\langle\Phi, \Psi_{A} \tilde{\otimes} \Psi_{B}\right\rangle & =\sum_{x \in\{0,1\}_{+}^{4}} m_{x}(-1)^{|x|}\left\langle x, \Psi_{A}\right\rangle\left\langle x, \Psi_{B}\right\rangle \\
& =\sum_{x \in\{0,1\}_{+}^{4}} m_{x} e^{i \nu_{x}}\left\langle\Psi_{A}, x\right\rangle\left\langle x, \Psi_{B}\right\rangle \tag{94}
\end{align*}
$$

where $\nu_{x}$ is defined by the identity

$$
(-1)^{|x|}\left\langle x, \Psi_{A}\right\rangle=e^{i \nu_{x}}\left\langle\Psi_{A}, x\right\rangle \quad \text { for } \quad x \in\{0,1\}_{+}^{4}
$$

Defining the operator

$$
M_{\Omega}=\sum_{x \in \Omega} m_{x} e^{i \nu_{x}}|x\rangle\langle x|
$$

for any subset $\Omega \subset\{0,1\}_{+}^{4}$, it follows from Eq. (94) that

$$
\begin{equation*}
\left\langle\Phi, \Psi_{A} \tilde{\otimes} \Psi_{B}\right\rangle=\left\langle\Psi_{A}, M_{E} \Psi_{B}\right\rangle+\left\langle\Psi_{A}, M_{\bar{E}} \Psi_{B}\right\rangle . \tag{95}
\end{equation*}
$$

Since $M_{E}$ is supported on span $\{|x\rangle\}_{x \in E}$, we have $\left\langle\Psi_{A}, M_{E} \Psi_{B}\right\rangle=\left\langle\Pi_{E} \Psi_{A}, M_{E} \Pi_{E} \Psi_{B}\right\rangle$. With the Cauchy-Schwarz inequality and the definition of the operator norm $\left\|M_{E}\right\|$ we thus get

$$
\begin{align*}
\left|\left\langle\Psi_{A}, M_{E} \Psi_{B}\right\rangle\right| & \leq\left\|\Pi_{E} \Psi_{A}\right\| \cdot\left\|\Psi_{E} \Psi_{B}\right\| \cdot\left\|M_{E}\right\| \\
& \leq \sqrt{F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right)} \cdot \sqrt{F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)} \cdot\left\|M_{E}\right\|, \tag{96}
\end{align*}
$$

where we applied Corollary 5.7. Identical reasoning applies to $\bar{E}$ and yields the inequality

$$
\begin{equation*}
\left|\left\langle\Psi_{A}, M_{\bar{E}} \Psi_{B}\right\rangle\right| \leq \sqrt{F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right)} \cdot \sqrt{F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)} \cdot\left\|M_{\bar{E}}\right\| . \tag{97}
\end{equation*}
$$

Combining Eqs. (96), (97) with Eq. (95), we conclude that

$$
\begin{aligned}
\left|\left\langle\Phi, \Psi_{A} \tilde{\otimes} \Psi_{B}\right\rangle\right| & \leq\left|\left\langle\Psi_{A}, M_{E} \Psi_{B}\right\rangle\right|+\left|\left\langle\Psi_{A}, M_{\bar{E}} \Psi_{B}\right\rangle\right| \\
& \leq \sqrt{F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)}\left(\left\|M_{E}\right\|+\left\|M_{\bar{E}}\right\|\right) .
\end{aligned}
$$

Taking the square and observing that

$$
\left\|M_{\Omega}\right\|=\max _{x \in \Omega}\left|m_{x} e^{i \nu_{x}}\right|=\max _{x \in \Omega}\left|m_{x}\right|
$$

gives the claim.
The following lemma will be useful to prove the main theorem.
Lemma 5.9. The function

$$
f(\theta, x)=\prod_{j=1}^{4}\left(\cos \theta_{j}\right)^{1-x_{j}}\left(\sin \theta_{j}\right)^{x_{j}} \quad \text { for } \quad \theta=\left(\theta_{1}, \ldots, \theta_{4}\right) \in \mathbb{R}^{4} \text { and } x \in\{0,1\}^{4}
$$

satisfies

$$
|f(\theta, x)|+|f(\theta, y)| \leq 1
$$

for all $\theta \in \mathbb{R}^{4}$ and $x, y \in\{0,1\}^{4}$ with $x, y$ even-weight and $x \neq y$.
Proof. Because $x, y$ have even and different weight, it suffices to consider two cases, namely with $|x-y| \in\{2,4\}$.

Consider first the case where $|x-y|=2$. Without loss of generality, assume that $\left(x_{1}, x_{2}\right)=\left(y_{1}, y_{2}\right), x_{3} \neq y_{3}, x_{4} \neq y_{4}$. Since translating $\theta$ by $-\pi / 2$ interchanges $|\sin \theta|$ and $|\cos \theta|$, it suffices to show the claim for $x=(0,0,0,0)$ and $y=(0,0,1,1)$. In this case we have

$$
\begin{aligned}
|f(\theta, x)|+|f(\theta, y)| & =\left|\cos \theta_{1} \cos \theta_{2} \cos \theta_{3} \cos \theta_{4}\right|+\left|\cos \theta_{1} \cos \theta_{2} \sin \theta_{3} \sin \theta_{4}\right| \\
& =\left|\cos \theta_{1} \cos \theta_{2}\right| \cdot\left(\left|\cos \theta_{3} \cos \theta_{4}\right|+\left|\sin \theta_{3} \sin \theta_{4}\right|\right) \\
& \leq\left|\cos \theta_{1} \cos \theta_{2}\right| \\
& \leq 1,
\end{aligned}
$$

where the first inequality follows from the Cauchy-Schwarz inequality in $\mathbb{R}^{2}$. Since $\theta \in \mathbb{R}^{4}$ was arbitrary, this concludes the proof for $|x-y|=2$.

The proof for $|x-y|=4$, i.e., $y=\bar{x}$ proceeds similarly. Again it suffices to show the claim for $x=(0,0,0,0)$. In this case

$$
\begin{aligned}
|f(\theta, x)|+|f(\theta, y)| & =\left|\cos \theta_{1} \cos \theta_{2} \cos \theta_{3} \cos \theta_{4}\right|+\left|\sin \theta_{1} \sin \theta_{2} \sin \theta_{3} \sin \theta_{4}\right| \\
& \leq\left|\cos \theta_{1} \cos \theta_{2}\right|+\left|\sin \theta_{1} \sin \theta_{2}\right| \\
& \leq 1
\end{aligned}
$$

where the first inequality follows from $\left|\cos \theta_{3} \cos \theta_{4}\right| \leq 1$ and $\left|\sin \theta_{3} \sin \theta_{4}\right| \leq 1$ and the second one from the Cauchy-Schwarz inequality.

Theorem 5.10 (Multiplicativity of the fermionic Gaussian fidelity for 4-mode pure states.). Let $\mathcal{H}_{+}^{n}$ be the set of pure $n$-fermion states with positive parity and let $\mathcal{G}_{n}^{+}$be the set of pure $n$-fermion Gaussian states with positive parity. We have that

$$
F_{\mathcal{G}_{8}}\left(\Psi_{A} \tilde{\otimes} \Psi_{B}\right)=F_{\mathcal{G}_{4}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}}\left(\Psi_{B}\right) \quad \text { for all } \quad \Psi_{A}, \Psi_{B} \in \mathcal{H}_{+}^{4}
$$

Proof. We first observe that $\mathcal{H}^{8}$ is a direct sum of the four spaces $\mathcal{H}_{+}^{4} \tilde{\otimes}^{4} \mathcal{H}_{+}^{4}, \mathcal{H}_{+}^{4} \tilde{\otimes} \mathcal{H}_{-}^{4}$, $\mathcal{H}_{-}^{4} \tilde{\otimes} \mathcal{H}_{+}^{4}$ and $\mathcal{H}_{-}^{4} \tilde{\otimes} \mathcal{H}_{-}^{4}$. This is because states in these subspaces have different eigenvalues with respect to the corresponding parity operators on the factors (interpreted as Majorana monomials on $\mathcal{H}^{8}$ these are the monomials $c\left(1^{8} 0^{8}\right)$ and $\left.c\left(0^{8} 1^{8}\right)\right)$. It follows immediately that the overlap with a state of the form $\Psi_{A} \tilde{\otimes} \Psi_{B} \in \mathcal{H}_{+}^{4} \tilde{\otimes} \mathcal{H}_{+}^{4}$ is maximized for a decomposition into states belonging to $\mathcal{H}_{+}^{4} \tilde{\otimes} \mathcal{H}_{+}^{4}$ only. In particular, it follows that

$$
F_{\mathcal{G}_{8}}\left(\Psi_{A} \tilde{\otimes} \Psi_{B}\right)=F_{\mathcal{G}_{8}^{+}}\left(\Psi_{A} \tilde{\otimes} \Psi_{B}\right) \quad \text { for all } \quad \Psi_{A}, \Psi_{B} \in \mathcal{H}_{+}^{4}
$$

and by the same reasoning, we have

$$
F_{\mathcal{G}_{4}}(\Psi)=F_{\mathcal{G}_{4}^{+}}(\Psi) \quad \text { for all } \quad \Psi \in \mathcal{H}_{+}^{4}
$$

We conclude that it suffices to show that

$$
F_{\mathcal{G}_{8}^{+}}\left(\Psi_{A} \tilde{\otimes} \Psi_{B}\right)=F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right) \quad \text { for all } \quad \Psi_{A}, \Psi_{B} \in \mathcal{H}_{+}^{4}
$$

Let $\Psi_{A}, \Psi_{B} \in \mathcal{H}_{+}^{4}$ be arbitrary. The inequality $F_{\mathcal{G}_{8}^{+}}\left(\Psi_{A} \tilde{\otimes} \Psi_{B}\right) \geq F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)$ follows trivially from the definition of fermionic Gaussian fidelity in Eq. (2), because $\mathcal{G}_{4}^{+} \tilde{\otimes}^{\mathcal{G}_{4}^{+} \subseteq}$ $\mathcal{G}_{8}^{+}$.

The inequality $F_{\mathcal{G}_{8}^{+}}\left(\Psi_{A} \tilde{\otimes} \Psi_{B}\right) \leq F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)$ is a consequence of the Schmidt decomposition for fermionic states put forward in Ref. [50] and of Lemmas 5.8 and 5.9. According to Ref. [50], an arbitrary pure fermionic state $\Phi \in \mathcal{H}^{n}$ admits a Schmidt decomposition of the form

$$
|\Phi\rangle=\sum_{x \in\{0,1\}^{n}} m_{x}|x, x\rangle
$$

with

$$
m_{x}=\prod_{j=1}^{n}\left(\cos \theta_{j}\right)^{1-x_{j}}\left(-\sin \theta_{j}\right)^{x_{j}} \quad \text { with } \quad \theta_{j} \in \mathbb{R} \text { for } j \in[n]
$$

With this definition of $m_{x}$ for $n=4$, an arbitrary state $\Phi \in \mathcal{G}_{8}^{+}$can be written as in Eq. (93) and the conditions for Lemma 5.8 apply. We have

$$
\begin{aligned}
F_{\mathcal{G}_{8}^{+}}\left(\Psi_{A} \tilde{\otimes} \Psi_{B}\right) & =\max _{\Phi \in \mathcal{G}_{8}^{+}}\left|\left\langle\Phi, \Psi_{A} \otimes \Psi_{B}\right\rangle\right| \\
& \leq F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)\left(\max _{x \in E}\left|m_{x}\right|+\max _{y \in \bar{E}}\left|m_{y}\right|\right)^{2}
\end{aligned}
$$

where $E \subset\{0,1\}_{+}^{4}$ with $|E|=4$ a subset of even weight strings such that $E \cup \bar{E}=\{0,1\}_{+}^{4}$. Notice that $x, y$ have even-weight and that $x \neq y$ because $E$ and $\bar{E}$ are disjoint sets. Identifying $m_{x}$ (whose dependence on $\theta \in \mathbb{R}^{4}$ is implicit) with $f(\theta, x)$ in Lemma 5.9 (apart from a minus sign that is not relevant because we take the absolute value) we have

$$
\begin{aligned}
F_{\mathcal{G}_{8}^{+}}\left(\Psi_{A} \tilde{\otimes} \Psi_{B}\right) & \leq F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)\left(\max _{x \in E}\left|m_{x}\right|+\max _{y \in \bar{E}}\left|m_{y}\right|\right)^{2} \\
& \leq F_{\mathcal{G}_{4}^{+}}\left(\Psi_{A}\right) F_{\mathcal{G}_{4}^{+}}\left(\Psi_{B}\right)
\end{aligned}
$$

giving the claim.

## 6 Multiplicativity of $\mathcal{D}$-fidelity implies that of $\mathcal{D}$-extent

In this section, we show that multiplicativity of the $\mathcal{D}$-fidelity implies multiplicativity of the $\mathcal{D}$-extent. In Section 6.1 we prove this for finite dictionaries: This follows immediately from the fact that $F_{\mathcal{D}}(\Psi)$ and $\xi_{\mathcal{D}}(\Psi)$ are related by (convex programming) duality. In Section 6.2 , we extend this results for infinite, i.e., continuously parameterized dictionaries. We achieve this extension by using (finite) $\epsilon$-nets for the set of Gaussian states. Similar approaches have been applied in the signal processing context, see e.g., the work [63], which shows how to approximately solve atomic norm minimization problems for sparse recovery when the parameters indexing the dictionary lie in a small-dimensional space.

### 6.1 Multiplicativity for finite dictionaries

We will restrict our attention to finite dictionaries in this section. For $|\mathcal{D}|<\infty$, the $\mathcal{D}$ fidelity is related to the dual formulation of the $\mathcal{D}$-extent as (see [19, Eq. (3.2)] and [18, Theorem 4])

$$
\begin{equation*}
\xi_{\mathcal{D}}(\Psi)=\max _{y \in \mathcal{H}: F_{\mathcal{D}}(y) \leq 1}|\langle\Psi, y\rangle|^{2} . \tag{98}
\end{equation*}
$$

Let $\mathcal{H}_{1}, \mathcal{H}_{2}$ and $\mathcal{H}_{3}$ be a triple of Hilbert spaces. Let $\left\{\mathcal{D}_{j}\right\}_{j \in[3]}$ be a family of dictionaries, where $\mathcal{D}_{j} \subset \mathcal{H}^{j}$ for $j \in[3]$. We assume that

$$
\begin{equation*}
\mathcal{D}_{1} \otimes \mathcal{D}_{2} \subseteq \mathcal{D}_{3} \tag{99}
\end{equation*}
$$

We are interested in the following two properties:

$$
\begin{array}{llll}
\operatorname{Mult}^{\xi}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right): & \xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right)=\xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{j} \in \mathcal{H}_{j} \text { for } j \in[2] \\
\operatorname{Mult}^{F}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right): & F_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right)=F_{\mathcal{D}_{1}}\left(\Psi_{1}\right) F_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{j} \in \mathcal{H}_{j} \text { for } j \in[2] .
\end{array}
$$

As an important example, let $n_{j} \in \mathbb{N}$ for $j \in[2], n_{3}=n_{1}+n_{2}, \mathcal{H}_{j}=\left(\mathbb{C}^{2}\right)^{\otimes n_{j}}$ and let STAB ${ }_{n}$ be the set of stabilizer states on $\left(\mathbb{C}^{2}\right)^{\otimes n}$. Then $\operatorname{Mult}^{\xi}\left(\right.$ STAB $_{n_{1}}$, STAB $_{n_{1}}$, STAB $\left._{n_{1}+n_{2}}\right)$ does
not hold for certain (large) choices of $n_{1}$ and $n_{2}$ [19]. On the other hand, for $n_{1}, n_{2} \leq$ 3 the multiplicativity property $\operatorname{Mult}^{\xi}\left(\mathrm{STAB}_{n_{1}}, \mathrm{STAB}_{n_{1}}, \mathrm{STAB}_{n_{1}+n_{2}}\right)$ holds (see Ref. [18, Proposition 1]). This was shown using that the stabilizer fidelity is multiplicative, i.e., Mult $^{F}\left(\right.$ STAB $_{n_{1}}$, STAB $_{n_{1}}$, STAB $\left._{n_{1}+n_{2}}\right)$.

We claim the property $\operatorname{Mult}^{F}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right)$ implies property $\operatorname{Mult}^{\xi}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right)$.
Theorem 6.1. Property $\operatorname{Mult}^{F}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right)$ implies property $\operatorname{Mult}^{\xi}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right)$.
Proof. We clearly have

$$
\begin{equation*}
\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right) \leq \xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \tag{100}
\end{equation*}
$$

for all $\Psi_{1} \in \mathcal{H}_{1}$ and $\Psi_{2} \in \mathcal{H}_{2}$ because of property (99) of the dictionaries $\left\{\mathcal{D}_{j}\right\}_{j=1}^{3}$ and the definition (5) of $\xi_{\mathcal{D}}$. To show the converse inequality, assume that $y_{1} \in \mathcal{H}_{1}, y_{2} \in \mathcal{H}_{2}$ are such that

$$
F_{\mathcal{D}_{j}}\left(y_{j}\right) \leq 1 \quad \text { and } \quad \xi_{\mathcal{D}_{j}}\left(\Psi_{j}\right)=\left|\left\langle\Psi_{j}, y_{j}\right\rangle\right|^{2} \quad \text { for } \quad j \in[2] .
$$

Then

$$
F_{\mathcal{D}_{3}}\left(y_{1} \otimes y_{2}\right)=F_{\mathcal{D}_{1}}\left(y_{1}\right) F_{\mathcal{D}_{2}}\left(y_{2}\right) \leq 1
$$

where we used the assumption that property $\operatorname{Mult}^{F}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right)$ holds to obtain the equality. This implies that $y_{1} \otimes y_{2}$ is a feasible point of the dual program for the quantity $\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right)$, see Eq. (98). Thus

$$
\begin{align*}
\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right) & \geq\left|\left\langle\Psi_{1} \otimes \Psi_{2}, y_{1} \otimes y_{2}\right\rangle\right|^{2} \\
& =\left|\left\langle\Psi_{1}, y_{1}\right\rangle\right|^{2} \cdot\left|\left\langle\Psi_{2}, y_{2}\right\rangle\right|^{2} \\
& =\xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) . \tag{101}
\end{align*}
$$

Expression (101) together with Eq. (100) gives the claim.

### 6.2 Multiplicativity for infinite dictionaries

In this section, we extend the results of Section 6.2 to dictionaries $\mathcal{D}$ that may contain infinitely many elements. Our strategy is to use an $\epsilon$-net for $\mathcal{D} \in \mathcal{H}$ with a finite number of elements, we denote by $\mathcal{D}^{\epsilon}$. We relate the extent and fidelity with respect to the dictionary $\mathcal{D}$ to the extent and fidelity with respect to its net $\mathcal{D}^{\epsilon}$ (see Lemmas 6.2 and 6.3 ) to prove that multiplicativity of the $\mathcal{D}$-fidelity implies multiplicativity of the $\mathcal{D}$-extent in Theorem 6.6. This result is a generalization of Theorem 6.1 (that considered finite dictionaries) for (possibly) infinite dictionaries.

We will make use of the notion of $\epsilon$-net to replace our infinite set $\mathcal{D}$ by a finite set $\mathcal{D}^{\epsilon}$. Let $\|\Psi\|=\sqrt{\langle\Psi, \Psi\rangle}$ for $\Psi \in \mathcal{H}$ denote the norm on $\mathcal{H}$. Let $\mathcal{D} \subset \mathcal{H}$ and let $\epsilon>0$. Then a set $\mathcal{D}^{\epsilon} \subset \mathcal{H}$ is called an $\epsilon$-net for $\mathcal{D}$ if for any $\Psi \in \mathcal{D}$ there is some $\Phi \in \mathcal{D}^{\epsilon}$ such that $\|\Phi-\Psi\| \leq \epsilon$.

We are interested in the case where for every $\epsilon>0$ there is a finite $\epsilon$-net $\mathcal{D}^{\epsilon}$ for $\mathcal{D}$, with the additional property that $\mathcal{D}^{\epsilon} \subset \mathcal{D}$, i.e., the net consists of elements of $\mathcal{D}$. A sufficient condition for this being the case is that the subset $\mathcal{D} \subset \mathcal{H}$ is compact.

Lemma 6.2. Let $\mathcal{D} \subset \mathcal{H}$ be a set of states. Assume that there is a finite $\epsilon$-net $\mathcal{D}^{\epsilon}$ for $\mathcal{D}$ such that $\mathcal{D}^{\epsilon} \subset \mathcal{D}$, for some $\epsilon>0$. Assume further that $\mathcal{D}^{\epsilon}$ contains an orthonormal basis of $\mathcal{H}$. Let $d$ be the dimension of $\mathcal{H}$. Then

$$
\xi_{\mathcal{D}}(\Psi) \leq \xi_{\mathcal{D}^{\epsilon}}(\Psi) \leq \xi_{\mathcal{D}}(\Psi)(1+\sqrt{d} \epsilon)^{2} \quad \text { for all } \quad \Psi \in \mathcal{H}
$$

Proof. The first inequality follows immediately from the definition of $\xi_{\mathcal{D}}$ and from the assumption that $\mathcal{D}^{\epsilon} \subset \mathcal{D}$.

To prove the second inequality, let $\Psi \in \mathcal{H}$ be arbitrary. By definition of $\xi_{\mathcal{D}}(\Psi)$ as an infimum, we have the following: For every $m \in \mathbb{N}$, there exist $N(m) \in \mathbb{N},\left\{\varphi_{j}(m)\right\}_{j=1}^{N(m)} \subset$ $\mathcal{D}$ and $\left\{c_{j}(m)\right\}_{j=1}^{N(m)} \subset \mathbb{C}$ such that

$$
\Psi=\sum_{j=1}^{N(m)} c_{j}(m) \varphi_{j}(m)
$$

and

$$
\begin{equation*}
\|c(m)\|_{1}<\sqrt{\xi_{\mathcal{D}}(\Psi)}+\frac{1}{m} \tag{102}
\end{equation*}
$$

Furthermore, we have

$$
\|c(m)\|_{1}^{2} \geq \xi_{\mathcal{D}}(\Psi) \quad \text { for any } \quad N(m) \in \mathbb{N},\left\{s_{j}\right\}_{j=1}^{N(m)} \subset \mathcal{D} \quad \text { and } \quad\left\{c_{j}(m)\right\}_{j=1}^{N(m)} \subset \mathbb{C}
$$

Fix such an $m \in \mathbb{N}$. Since $\mathcal{D}^{\epsilon}$ is an $\epsilon$-net for $\mathcal{D}$, there is, for every $j \in[N(m)]$, an element $\varphi_{j}^{\epsilon}(m) \in \mathcal{D}^{\epsilon}$ and $\delta_{j}(m) \in \mathcal{H}$ such that

$$
\varphi_{j}(m)=\varphi_{j}^{\epsilon}(m)+\delta_{j}(m) \quad \text { and } \quad\left\|\delta_{j}(m)\right\| \leq \epsilon
$$

It follows that

$$
\Psi=\left(\sum_{j=1}^{N(m)} c_{j}(m) \varphi_{j}^{\epsilon}(m)\right)+\delta(m) \quad \text { where } \quad \delta(m)=\sum_{j=1}^{N(m)} c_{j}(m) \delta_{j}(m)
$$

By the triangle inequality we have

$$
\begin{equation*}
\|\delta(m)\| \leq \epsilon \sum_{j=1}^{N(m)}\left|c_{j}(m)\right|=\epsilon\|c(m)\|_{1} \tag{103}
\end{equation*}
$$

Suppose $\left\{e_{k}\right\}_{k=1}^{d}$ is an orthonormal basis contained in $\mathcal{D}^{\epsilon}$. Then we can expand

$$
\delta(m)=\sum_{k=1}^{d} \alpha_{k}(m) e_{k}
$$

and it follows from (103) and the Cauchy-Schwarz inequality that

$$
\begin{aligned}
\|\alpha(m)\|_{1} & \leq \sqrt{d}\|\alpha(m)\|_{2} & & \\
& =\sqrt{d}\|\delta(m)\|_{2} & & \text { by the Cauchy-Schwarz inequality in } \mathbb{C}^{d} \\
& \leq \sqrt{d} \epsilon\|c(m)\|_{1} \quad & & \text { because of Eq. (103). }
\end{aligned}
$$

where $\|\cdot\|_{2}$ is the Euclidean norm in $\mathbb{C}^{d}$. In summary, we have

$$
\Psi=\sum_{j=1}^{N(m)} c_{j}(m) \varphi_{j}^{\epsilon}(m)+\sum_{k=1}^{d} \alpha_{k}(m) e_{k}
$$

with $(c, \alpha) \in \mathbb{C}^{N(m)+d}$ satisfying

$$
\begin{aligned}
\|(c, \alpha)\|_{1} & =\sum_{j=1}^{N(m)}\left|c_{j}(m)\right|+\sum_{k=1}^{d}\left|\alpha_{k}(m)\right| \\
& \leq\|c(m)\|_{1} \cdot(1+\sqrt{d} \epsilon) \\
& \leq\left(\sqrt{\xi_{\mathcal{D}}(\Psi)}+\frac{1}{m}\right) \cdot(1+\sqrt{d} \epsilon)
\end{aligned}
$$

by (102). Because $\varphi_{j}^{\epsilon}(m) \in \mathcal{D}^{\epsilon}$ for every $j \in[N(m)]$ and $e_{k} \in \mathcal{D}^{\epsilon}$ for every $k \in[d]$, this implies that

$$
\sqrt{\xi_{\mathcal{D}^{\epsilon}}(\Psi)} \leq\left(\sqrt{\xi_{\mathcal{D}}(\Psi)}+\frac{1}{m}\right) \cdot(1+\sqrt{d \epsilon}) .
$$

Since $m \in \mathbb{N}$ was arbitrary, we can take the limit $m \rightarrow \infty$ and obtain

$$
\sqrt{\xi_{\mathcal{D}^{\epsilon}}(\Psi)} \leq \sqrt{\xi_{\mathcal{D}}(\Psi)} \cdot(1+\sqrt{d \epsilon})
$$

This gives the claim.
Lemma 6.3. Let $\mathcal{D}^{\epsilon} \subset \mathcal{D} \subset \mathcal{H}$ be as in Lemma 6.2. Then we have

$$
\sqrt{F_{\mathcal{D}^{\epsilon}}(\Psi)} \leq \sqrt{F_{\mathcal{D}}(\Psi)} \leq \sqrt{F_{\mathcal{D}^{\epsilon}(\Psi)}}+\|\Psi\| \cdot \epsilon \quad \text { for all } \quad \Psi \in \mathcal{H} .
$$

Proof. The first inequality follows trivially from the definitions using $\mathcal{D}^{\epsilon} \subset \mathcal{D}$. For the second inequality, let $\Psi \in \mathcal{H}$ be arbitrary. Let $\varphi \in \mathcal{D}$ be such that

$$
F_{\mathcal{D}}(\Psi)=|\langle\varphi, \Psi\rangle|^{2}
$$

Then (by the fact that $\mathcal{D}^{\epsilon}$ is an $\epsilon$-net for $\mathcal{D}$ and $\varphi \in \mathcal{D}$ ) there is an element $\varphi^{\epsilon} \in \mathcal{D}^{\epsilon}$ and $\delta \in \mathcal{H}$ such that

$$
\varphi=\varphi^{\epsilon}+\delta \quad \text { where } \quad\|\delta\| \leq \epsilon
$$

It follows that

$$
\begin{aligned}
\sqrt{F_{\mathcal{D}}(\Psi)} & =|\langle\varphi, \Psi\rangle| \\
& \leq\left|\left\langle\varphi^{\epsilon}, \Psi\right\rangle\right|+|\langle\delta, \Psi\rangle| \\
& \leq \sqrt{F_{\mathcal{D}^{\epsilon}}(\Psi)}+|\langle\delta, \Psi\rangle| \\
& \leq \sqrt{F_{\mathcal{D}^{\epsilon}}(\Psi)}+\|\Psi\| \cdot\|\delta\| \\
& \leq \sqrt{F_{\mathcal{D}^{\epsilon}}(\Psi)}+\|\Psi\| \cdot \epsilon
\end{aligned}
$$

where we used the definition of $F_{\mathcal{D}^{\epsilon}}(\Psi)$ and the Cauchy-Schwarz inequality (in the penultimate step). The claim follows.

Lemma 6.4. We have

$$
\|y\|^{2} \leq d^{2} \cdot F_{\mathcal{D}^{\epsilon}}(y) \quad \text { for every } \quad y \in \mathcal{H}
$$

where $d=\operatorname{dim} \mathcal{H}$.

Proof. Let $\left\{e_{k}\right\}_{k=1}^{d}$ be an orthonormal basis contained in $\mathcal{D}^{\epsilon}$. Then

$$
\left|\left\langle e_{k}, y\right\rangle\right|^{2} \leq F_{\mathcal{D}^{\epsilon}}(y) \quad \text { for every } \quad k \in[d]
$$

because $e_{k} \in \mathcal{D}^{\epsilon}$ for every $k \in[n]$. We have

$$
\begin{aligned}
\|y\| & =\left(\sum_{k=1}^{d}\left|\left\langle e_{k}, y\right\rangle\right|^{2}\right)^{1 / 2} \\
& \leq \sum_{k=1}^{d}\left|\left\langle e_{k}, y\right\rangle\right| \\
& \leq d \cdot \sqrt{F_{\mathcal{D}^{\epsilon}}(y)}
\end{aligned}
$$

where we used that $\|v\|_{2} \leq\|v\|_{1}$ for $v \in \mathbb{C}^{d}$. The claim follows.
Lemma 6.5. Let $d_{j}=\operatorname{dim} \mathcal{H}_{j}$ for $j \in[2]$. Assuming that the property $\operatorname{Mult}{ }^{F}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right)$ holds, we have

$$
\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right) \geq g\left(d_{1}, d_{2}, d_{3}, \epsilon\right) \xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right)
$$

for a function $g$ which satisfies

$$
\lim _{\epsilon \rightarrow 0} g\left(d_{1}, d_{2}, d_{3}, \epsilon\right)=1 .
$$

Proof. Suppose $y_{j} \in \mathcal{H}_{j}$ for $j \in[2]$ is such that

$$
\begin{equation*}
F_{\mathcal{D}_{j}^{\epsilon}}\left(y_{j}\right) \leq 1 \tag{104}
\end{equation*}
$$

and

$$
\begin{equation*}
\xi_{\mathcal{D}_{j}^{\epsilon}}\left(\Psi_{j}\right)=\left|\left\langle y_{j}, \Psi_{j}\right\rangle\right|^{2} \tag{105}
\end{equation*}
$$

for $j \in[2]$. Such a pair $\left(y_{1}, y_{2}\right)$ exists since $\mathcal{D}_{1}^{\epsilon}$ and $\mathcal{D}_{2}^{\epsilon}$ are finite sets and the dual definition definition of the extent in terms of a maximum applies (see Eq. (98)). Equation (104) implies that

$$
\left\|y_{j}\right\| \leq d_{j} \quad \text { for } \quad j \in[2],
$$

see Lemma 6.4.
We have

$$
\begin{array}{rlr}
\sqrt{F_{\mathcal{D}_{3}^{\epsilon}}\left(y_{1} \otimes y_{2}\right)} & \leq \sqrt{F_{\mathcal{D}_{3}}\left(y_{1} \otimes y_{2}\right)} & \text { by Lemma } 6.3 \\
& =\sqrt{F_{\mathcal{D}_{1}}\left(y_{1}\right)} \cdot \sqrt{F_{\mathcal{D}_{2}}\left(y_{2}\right)} & \text { by the assumption that } \operatorname{Mult}^{F}\left(\mathcal{D}_{1}, \mathcal{D}_{2}, \mathcal{D}_{3}\right) \text { holds } \\
& \leq\left(\sqrt{F_{\mathcal{D}_{1}^{\epsilon}}\left(y_{1}\right)}+\left\|y_{1}\right\| \cdot \epsilon\right)\left(\sqrt{F_{\mathcal{D}_{2}^{\epsilon}}\left(y_{2}\right)}+\left\|y_{2}\right\| \cdot \epsilon\right) & \\
& \text { by Lemma } 6.3 \\
& \leq \sqrt{F_{\mathcal{D}_{1}^{\epsilon}}\left(y_{1}\right)} \cdot \sqrt{F_{\mathcal{D}_{2}^{\epsilon}}\left(y_{2}\right)} \cdot\left(1+d_{1} \cdot \epsilon\right)\left(1+d_{2} \cdot \epsilon\right) & \\
& \text { by Lemma } 6.4 \tag{106}
\end{array}
$$

Defining

$$
\tilde{y}_{j}=\left(1+d_{j} \epsilon\right)^{-1} y_{j} \quad \text { for } \quad j \in[2]
$$

it follows from Eq. (106) that

$$
F_{\mathcal{D}_{3}^{\epsilon}}\left(\tilde{y}_{1} \otimes \tilde{y}_{2}\right) \leq 1 .
$$

By the dual formulation (98) of the quantity $\xi_{\mathcal{D}_{3}^{\epsilon}}\left(\Psi_{1} \otimes \Psi_{2}\right)$ this implies that

$$
\begin{align*}
\xi_{\mathcal{D}_{3}^{\epsilon}}\left(\Psi_{1} \otimes \Psi_{2}\right) & \geq\left|\left\langle\tilde{y}_{1} \otimes \tilde{y}_{2}, \Psi_{1} \otimes \Psi_{2}\right\rangle\right|^{2} \\
& =\left(\prod_{j=1}^{2}\left(1+d_{j} \epsilon\right)^{-2}\left|\left\langle y_{j}, \Psi_{j}\right\rangle\right|^{2}\right) \\
& =\left(\prod_{j=1}^{2}\left(1+d_{j} \epsilon\right)^{-2}\right) \xi_{\mathcal{D}_{1}^{\epsilon}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}^{\epsilon}}\left(\Psi_{2}\right) \text { because of Eq. (105) }  \tag{105}\\
& \geq\left(\prod_{j=1}^{2}\left(1+d_{j} \epsilon\right)^{-2}\right) \xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \text { according to Lemma 6.2. } \tag{107}
\end{align*}
$$

Lemma 6.2 also implies that

$$
\begin{equation*}
\left(1+\sqrt{d_{3} \epsilon}\right)^{2} \xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right) \geq \xi_{\mathcal{D}_{3}^{\epsilon}}\left(\Psi_{1} \otimes \Psi_{2}\right) . \tag{108}
\end{equation*}
$$

Combining Eqs. (107) and (108) gives the claim, with

$$
g\left(d_{1}, d_{2}, d_{3} \epsilon\right)=\left(1+\sqrt{d_{3}} \epsilon\right)^{-2}\left(\prod_{j=1}^{2}\left(1+d_{j} \epsilon\right)^{-2}\right) .
$$

Theorem 6.6. Let $\mathcal{H}_{1}, \mathcal{H}_{2}$ and $\mathcal{H}_{3}$ be a triple of Hilbert spaces and let $\left\{\mathcal{D}_{j}\right\}_{j \in[3]}$ be a family of dictionaries, where $\mathcal{D}_{j} \subset \mathcal{H}_{j}$. Assume that $\mathcal{D}_{j}$ contains an orthonormal basis of $\mathcal{H}_{j}$, for $j \in[3]$, and that $\mathcal{D}_{1} \otimes \mathcal{D}_{2} \subset \mathcal{D}_{3}$. Assume further that for any $\epsilon>0$ there is an $\epsilon$-net $\mathcal{D}_{j}^{\epsilon}$ for $\mathcal{D}_{j}$ such that $\mathcal{D}_{j}^{\epsilon} \subset \mathcal{D}_{j}$, i.e., the net consists of elements of $\mathcal{D}_{j}$. Finally, assume that

$$
F_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right)=F_{\mathcal{D}_{1}}(\Psi) F_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{1} \in \mathcal{H}_{1}, \Psi_{2} \in \mathcal{H}_{2} .
$$

Then

$$
\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right)=\xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{1} \in \mathcal{H}_{1} \text { and } \Psi_{2} \in \mathcal{H}_{2} .
$$

Proof. By (if necessary) replacing $\mathcal{D}_{j}^{\epsilon}$ by $\mathcal{D}_{j}^{\epsilon} \cup\left\{e_{k}^{(j)}\right\}_{k=1}^{d}$, for $j \in[3]$, where $\left\{e_{k}^{(j)}\right\}_{k=1}^{d}$ is an orthonormal basis of $\mathcal{H}_{j}$ with $e_{k}^{(j)} \in \mathcal{D}_{j}$, for $n \in[3]$, we have that each $\mathcal{D}_{j}^{\epsilon}$ is finite and contains an orthonormal basis of the respective space. The inequality

$$
\xi_{\mathcal{D}_{3}}\left(\Psi_{1} \otimes \Psi_{2}\right) \geq \xi_{\mathcal{D}_{1}}\left(\Psi_{1}\right) \xi_{\mathcal{D}_{2}}\left(\Psi_{2}\right) \quad \text { for all } \quad \Psi_{1} \in \mathcal{H}_{1} \text { and } \Psi_{2} \in \mathcal{H}_{2}
$$

now follows immediately from Lemma 6.5 by taking the limit $\epsilon \rightarrow 0$. The converse inequality is trivial because $\mathcal{D}_{1} \otimes \mathcal{D}_{2} \subset \mathcal{D}_{3}$.

## 7 Multiplicativity of the Gaussian extent for four fermions

In this section we prove that the Gaussian extent is multiplicative for the tensor product of any two 4 -fermion pure states with positive parity.

Theorem 7.1 (Multiplicativity of the Gaussian extent for 4 -fermion pure states.). Let $\mathcal{H}_{+}^{4}$ be the set of pure 4 -fermion states with positive parity and let $\mathcal{G}_{n}$ be the set of Gaussian states on $n$ fermions. Then

$$
\xi_{\mathcal{G}_{8}}\left(\Psi_{A} \tilde{\left.\otimes \Psi_{B}\right)=\xi_{\mathcal{G}_{4}}\left(\Psi_{A}\right) \xi_{\mathcal{G}_{4}}\left(\Psi_{B}\right) \quad \text { for all } \quad \Psi_{A}, \Psi_{B} \in \mathcal{H}_{+}^{4} . . . . . . . . ~}\right.
$$

Proof. Since the metaplectic representation defines a surjective, continuous map

$$
\begin{aligned}
& f:[0,2 \pi] \times S O(2 n) \quad \rightarrow \quad \mathcal{G}_{n} \\
& (\varphi, R) \quad \mapsto e^{i \varphi} U_{R}\left|0_{F}\right\rangle
\end{aligned}
$$

from the compact set $[0,2 \pi] \times S O(2 n)$ to $\mathcal{G}_{n}$, the set $\mathcal{G}_{n} \subset \mathcal{H}^{n}$ is compact. We also observe that the occupation number states

$$
\left\{|x\rangle \mid x \in\{0,1\}^{n}\right\}
$$

form an orthonormal basis contained in $\mathcal{G}_{n}$. By compactness, we conclude that for any $\epsilon>0$, there is a finite $\epsilon$-net $\mathcal{G}_{n}^{\epsilon} \subset \mathcal{G}_{n}$ consisting of Gaussian states and containing an orthonormal basis of $\mathcal{H}^{n}$. Finally, we note that we also have the inclusion $\mathcal{G}_{n_{1}} \otimes \mathcal{G}_{n_{2}} \subset \mathcal{G}_{n_{1}+n_{2}}$ for $n_{1}, n_{2} \in \mathbb{N}$ arbitrary.

Let us now specialize to $n_{1}=n_{2}=4$. In this case, we have multiplicativity of the fermionic Gaussian fidelity by Theorem 5.10. In particular, the conditions for Theorem 6.6 apply and the claim follows.

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## A Alternative Gaussianity condition for 4 -fermion states

In the following, we prove Lemma 5.1.
Proof. Consider $\Psi \in \mathcal{H}_{+}^{4}$. We will show that $\langle\Psi, \theta \Psi\rangle=0$ is equivalent to $\Lambda(|\Psi\rangle \otimes|\Psi\rangle)=$ 0 . According to Lemma 2.3, this is a sufficient and necessary condition for $\Psi$ to be Gaussian.

Let $E \subset\{0,1\}_{+}^{4},|E|=4$ be a subset of even-weight strings such that $E \cup \bar{E}=\{0,1\}_{+}^{4}$.

We first compute $\langle\Psi, \theta \Psi\rangle$. We have

$$
\begin{aligned}
\langle\Psi, \theta \Psi\rangle & =\sum_{x, y \in\{0,1\}_{+}^{4}}\langle\Psi, x\rangle\langle x| \theta(|y\rangle\langle y, \Psi\rangle) \\
& =\sum_{x, y \in\{0,1\}_{+}^{4}}\langle\Psi, x\rangle\langle x, \theta y\rangle \overline{\langle y, \Psi\rangle} \\
& =\sum_{x, y \in\{0,1\}_{+}^{4}}(-1)^{\vartheta(y)}\langle x, \bar{y}\rangle\langle\Psi, x\rangle\langle\Psi, y\rangle \\
& =\sum_{x \in\{0,1\}_{+}^{4}}(-1)^{\vartheta(x)}\langle\Psi, x\rangle\langle\Psi, \bar{x}\rangle \\
& =\sum_{x \in E}(-1)^{\vartheta(x)}\langle\Psi, x\rangle\langle\Psi, \bar{x}\rangle+(-1)^{\vartheta(\bar{x})}\langle\Psi, \bar{x}\rangle\langle\Psi, x\rangle \\
& =2 \sum_{x \in E}(-1)^{\vartheta(x)}\langle\Psi, x\rangle\langle\Psi, \bar{x}\rangle
\end{aligned}
$$

where the second step follows from $\theta u=\bar{u} \theta$ for all $u \in \mathbb{C}$ due to the antiunitarity of $\theta$, the third step from Eq. (76) and the fourth and final steps from $\vartheta(\bar{x})=\vartheta(x)$ for $x \in\{0,1\}_{+}^{4}$. Thus,

$$
\begin{equation*}
\langle\Psi, \theta \Psi\rangle=0 \quad \text { if and only if } \quad \sum_{x \in\{0,1\}_{+}^{4}}(-1)^{\vartheta(x)}\langle\Psi, x\rangle\langle\Psi, \bar{x}\rangle=0 \tag{109}
\end{equation*}
$$

We proceed to prove that $\Lambda(|\Psi\rangle \otimes|\Psi\rangle)=0$ is equivalent to Eq. (109). We start by using Eq. (13) to write the operator $\Lambda$ in terms of creation and annihilation operators:

$$
\begin{aligned}
\Lambda & =\sum_{j=1}^{8} c_{j} \otimes c_{j} \\
& =\sum_{j=1}^{4}\left(c_{2 j-1} \otimes c_{2 j-1}+c_{2 j} \otimes c_{2 j}\right) \\
& =\sum_{j=1}^{4}\left(\left(a_{j}+a_{j}^{\dagger}\right) \otimes\left(a_{j}+a_{j}^{\dagger}\right)+i\left(a_{j}-a_{j}^{\dagger}\right) \otimes i\left(a_{j}-a_{j}^{\dagger}\right)\right) \\
& =2 \sum_{j=1}^{4}\left(a_{j} \otimes a_{j}^{\dagger}+a_{j}^{\dagger} \otimes a_{j}\right)
\end{aligned}
$$

Applying this expression to $|\Psi\rangle \otimes|\Psi\rangle$ and using Eq. (11) gives

$$
\begin{align*}
\Lambda(|\Psi\rangle \otimes|\Psi\rangle) & =2 \sum_{x, y \in\{0,1\}_{+}^{4}} \sum_{j=1}^{4}\left(a_{j} \otimes a_{j}^{\dagger}+a_{j}^{\dagger} \otimes a_{j}\right)(|x\rangle \otimes|y\rangle)\langle x, \Psi\rangle\langle y, \Psi\rangle \\
& =2 \sum_{x, y \in\{0,1\}_{+}^{4}} \sum_{j=1}^{4}(-1)^{\eta_{j}(x+y)}\left(x_{j} \overline{y_{j}}+\overline{x_{j}} y_{j}\right)\left(\left|x \oplus e_{j}\right\rangle \otimes\left|y \oplus e_{j}\right\rangle\right)\langle x, \Psi\rangle\langle y, \Psi\rangle \\
& =2 \sum_{x, y \in\{0,1\}_{+}^{4}} \sum_{j=1}^{4}(-1)^{\eta_{j}(x+y)}\left(y_{j} \oplus \overline{x_{j}}\right)\left(\left|x \oplus e_{j}\right\rangle \otimes\left|y \oplus e_{j}\right\rangle\right)\langle x, \Psi\rangle\langle y, \Psi\rangle \\
& =2 \sum_{x, y \in\{0,1\}_{-}^{4}}\left(\sum_{j=1}^{4}(-1)^{\eta_{j}(x+y)}\left(y_{j} \oplus \overline{x_{j}}\right)\left\langle x \oplus e_{j}, \Psi\right\rangle\left\langle y \oplus e_{j}, \Psi\right\rangle\right)(|x\rangle \otimes|y\rangle) \tag{110}
\end{align*}
$$

where in the third line we used $u \bar{v}+\bar{u} v=u \oplus \bar{v}$ for all $u, v \in\{0,1\}$ and in the last line we used $\left\{x \oplus e_{j} \mid x \in\{0,1\}_{+}^{4}\right\}=\{0,1\}_{-}^{4}, \eta_{j}\left(x \oplus e_{j}\right)=\eta_{j}(x)$ and $u \oplus v \oplus 2 e_{j}=u \oplus v$ valid for $x \in\{0,1\}_{+}^{4}, j \in[4]$ and $u, v \in\{0,1\}$. It follows that $\Lambda(|\Psi\rangle \otimes|\Psi\rangle)=0$ if and only if

$$
\begin{equation*}
\sum_{j=1}^{4}(-1)^{\eta_{j}(x+y)}\left(y_{j} \oplus \overline{x_{j}}\right)\left\langle x \oplus e_{j}, \Psi\right\rangle\left\langle y \oplus e_{j}, \Psi\right\rangle=0 \quad \text { for all } \quad x, y \in\{0,1\}_{+}^{4} \tag{111}
\end{equation*}
$$

Since $x$ and $y$ have the same parity, either $|x-y|=4$ (i.e., $y=\bar{x}$ ), $|x-y|=2$ or $|x-y|=0$ (i.e., $y=x$ ). The expression (111) is non-zero only if $|x-y|=4$ (we argue below why). For $|x-y|=4$ Eq. (111) becomes
$\sum_{j=1}^{4}(-1)^{\eta_{j}(x+\bar{x})}\left\langle x \oplus e_{j}, \Psi\right\rangle\left\langle\bar{x} \oplus e_{j}, \Psi\right\rangle=0 \quad$ if and only if $\quad \sum_{z \in E}^{4}(-1)^{\vartheta(z)}\langle z, \Psi\rangle\langle z, \Psi\rangle=0$,
where we used $\left\{x \oplus e_{j} \mid j \in[4]\right\}=E$ with $E \subset\{0,1\}_{+}^{4},|E|=4$ a subset of even-weight strings such that $E \cup \bar{E}=\{0,1\}_{+}^{4}$. We also used that $(-1)^{\eta_{j}(x+\bar{x})}=(-1)^{j-1}$ can be replaced by $(-1)^{\vartheta(x)+\vartheta(z)}$ upon changing the summation over $j \in[4]$ to a summation over $z \in E$. We recovered the right hand side of Eq. (109), proving the claim.

It remains to argue that Eq. (111) is zero for $|x-y| \in\{0,2\}$. For $|x-y|=0$, i.e., $x=y$, Eq. (111) is zero because $x_{j} \otimes \overline{x_{j}}=0$ for $j \in[4]$. We exemplify that terms $\propto|x\rangle \otimes|y\rangle$ with $|x-y|=2$ are zero by considering $x=1000$ and $y=0100$. Starting from Eq. (110) we obtain

$$
(\langle 1000| \otimes\langle 0100|) \Lambda(|\Psi\rangle \otimes|\Psi\rangle)=\left((-1)^{\eta_{1}(1100)}+(-1)^{\eta_{2}(1100)}\right)\langle 0000, \Psi\rangle\langle 1100, \Psi\rangle=0,
$$

where $\eta_{1}(1100)=0$ and $\eta_{2}(1100)=1$. The remaining cases with $|x-y|=2$ proceed similarly.

## B Commutativity of the map $\theta$ and quadratic Majorana monomials

In the following, we prove Lemma 5.2.
Proof. We start by showing that $\theta=c_{1} c_{3} c_{5} c_{7} K$, where $K$ denotes the antiunitary given by complex conjugation in the number state basis. For this, it suffices to show that $\theta$ is antiunitary, which directly follows from unitarity of $c_{1} c_{3} c_{5} c_{7}$, and that it satisfies Eq. (76). We show the later using Eqs. (13) and (11): We have

$$
\begin{aligned}
\theta|x\rangle & =c_{1} c_{3} c_{5} c_{7} K|x\rangle \\
& =\left(a_{1}+a_{1}^{\dagger}\right)\left(a_{2}+a_{2}^{\dagger}\right)\left(a_{3}+a_{3}^{\dagger}\right)\left(a_{4}+a_{4}^{\dagger}\right)|x\rangle \\
& =(-1)^{\eta_{4}(x)+\eta_{3}(x)+\eta_{2}(x)+\eta_{1}(x)}\left(x_{1}+\overline{x_{1}}\right)\left(x_{2}+\overline{x_{2}}\right)\left(x_{3}+\overline{x_{3}}\right)\left(x_{4}+\overline{x_{4}}\right)|\bar{x}\rangle \\
& =(-1)^{\vartheta(x)}|\bar{x}\rangle,
\end{aligned}
$$

where we used $(-1)^{\eta_{4}(x)+\eta_{3}(x)+\eta_{2}(x)+\eta_{1}(x)}=(-1)^{3 x_{1}+2 x_{2}+x_{3}}=(-1)^{x_{1}+x_{3}}=(-1)^{\vartheta(x)}$ and $x_{j}+\overline{x_{j}}=1$ for $j \in[4]$.

The result $\theta c_{j} c_{k}=c_{j} c_{k} \theta$ follows from simple algebra considering $c_{2 j} K=K c_{2 j}$ and $c_{2 j-1} K=-K c_{2 j-1}$. We show these last two equalities by explicitly computing their
action on $x \in\{0,1\}_{+}^{4}$ :

$$
\begin{aligned}
& K c_{2 j}|x\rangle=K\left(a_{j}+a_{j}^{\dagger}\right)|x\rangle=\left(x_{j}+\overline{x_{j}}\right)\left|x \oplus e_{j}\right\rangle=\left|x \oplus e_{j}\right\rangle, \\
& c_{2 j} K|x\rangle=\left(a_{j}+a_{j}^{\dagger}\right)|x\rangle=\left(x_{j}+\overline{x_{j}}\right)\left|x \oplus e_{j}\right\rangle=K c_{2 j}|x\rangle
\end{aligned}
$$

and

$$
\begin{aligned}
& K c_{2 j+1}|x\rangle=K i\left(a_{j}-a_{j}^{\dagger}\right)|x\rangle=-i\left(x_{j}-\overline{x_{j}}\right)\left|x \oplus e_{j}\right\rangle \\
& c_{2 j+1} K|x\rangle=i\left(a_{j}-a_{j}^{\dagger}\right)|x\rangle=i\left(x_{j}-\overline{x_{j}}\right)\left|x \oplus e_{j}\right\rangle=-K c_{2 j+1}|x\rangle .
\end{aligned}
$$

Proof. We will prove that $\theta c_{j}=-c_{j} \theta$ for $j \in[8]$, which implies the result.
We prove this for $j$ odd, the proof for $j$ even proceeds similarly. We use Eq. (13) to write the Majorana operators as creation and annihilation operators which act on basis states according to Eq. (11), and we apply $\theta$ according to Eq. (76):

$$
\begin{aligned}
\theta c_{2 j-1}|x\rangle & =\theta\left(a_{j}+a_{j}^{\dagger}\right)|x\rangle \\
& =\theta(-1)^{\eta_{j}(x)}\left(x_{j}+\overline{x_{j}}\right)\left|x \oplus e_{j}\right\rangle \\
& =(-1)^{\eta_{j}(x)}(-1)^{\vartheta\left(x \oplus e_{j}\right)}\left(x_{j}+\overline{x_{j}}\right)\left|\overline{x \oplus e_{j}}\right\rangle, \\
c_{2 j-1} \theta|x\rangle & =(-1)^{\vartheta(x)}\left(a_{j}+a_{j}^{\dagger}\right)|\bar{x}\rangle \\
& =(-1)^{\eta_{j}(\bar{x})}(-1)^{\vartheta(x)}\left(\overline{x_{j}}+x_{j}\right)\left|\bar{x} \oplus e_{j}\right\rangle .
\end{aligned}
$$

The equality $\theta c_{2 j-1}=-c_{2 j-1} \theta$ follows from $\left|\bar{x} \oplus e_{j}\right\rangle=\left|\overline{x \oplus e_{j}}\right\rangle$ for $j \in[4]$, from $(-1)^{\eta_{j}(\bar{x})}=$ $(-1)^{j+1}(-1)^{\eta_{j}(x)}$ and from $(-1)^{\vartheta(x)}=(-1)^{j}(-1)^{\vartheta\left(x \oplus e_{j}\right)}$.

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