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## **Strong amplifiers of natural selection**

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Technical Report No. IST-2016-728-v1+1  
Deposited at 30 Dec 2016 09:00  
<https://repository.ist.ac.at/728/1/main.pdf>

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# Supplementary Information: Strong amplifiers of natural selection

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## 1 Organization

Before presenting our proofs we first present detailed description of our model and the results. We then present the formal notations, then our negative results, and finally the positive results.

## 2 Model and Summary of Results

### 2.1 Model

*The birth-death Moran process.* The *Moran process* considers a population of  $n$  individuals, which undergoes reproduction and death, and each individual is either a resident or a mutant [21]. The residents and the mutants have constant fitness 1 and  $r$ , respectively. The Moran process is a discrete-time stochastic process defined as follows: in the initial step, a single mutant is introduced into a homogeneous resident population. At each step, an individual is chosen randomly for reproduction with probability proportional to its fitness; another individual is chosen uniformly at random for death and is replaced by a new individual of the same type as the reproducing individual. Eventually, this Markovian process ends when all individuals become of one of the two types. The probability of the event that all individuals become mutants is called the *fixation* probability.

*The Moran process on graphs.* In general, the Moran process takes place on a population structure, which is represented as a graph. The vertices of the graph represent individuals and edges represent interactions between individuals [17, 22]. Formally, let  $G_n = (V_n, E_n, W_n)$  be a weighted, directed graph, where  $V_n = \{1, 2, \dots, n\}$  is the vertex set,  $E_n$  is the Boolean edge matrix, and  $W_n$  is a stochastic weight matrix. An edge is a pair of vertices  $(i, j)$  which is indicated by  $E_n[i, j] = 1$  and denotes that there is an interaction from  $i$  to  $j$  (whereas we have  $E_n[i, j] = 0$  if there is no interaction from  $i$  to  $j$ ). The stochastic weight matrix  $W_n$  assigns weights to interactions, i.e.,  $W_n[i, j]$  is positive iff  $E_n[i, j] = 1$ , and for all  $i$  we have  $\sum_j W_n[i, j] = 1$ . For a vertex  $i$ , we denote by  $\text{In}(i) = \{j \mid E_n[j, i] = 1\}$  (resp.,  $\text{Out}(i) = \{j \mid E_n[i, j] = 1\}$ ) the set of vertices that have incoming (resp., outgoing) interaction or edge to (resp., from)  $i$ . Similarly to the Moran process, at each step an individual is chosen randomly for reproduction with probability proportional to its fitness. An edge originating from the reproducing vertex is selected randomly with probability equal to its weight. The terminal vertex of the chosen edge takes on the type of the vertex at the origin of the edge. In other words, the stochastic matrix  $W_n$  is the weight matrix that represents the choice probability of the edges. We only

consider graphs which are *connected*, i.e., every pair of vertices is connected by a path. This is a sufficient condition to ensure that in the long run, the Moran process reaches a homogeneous state (i.e., the population consists entirely of individuals of a single type). See Figure S1 for an illustration. The well-mixed population is represented by a complete graph where all edges have equal weight of  $1/n$ .

*Classification of graphs.* We consider the following classification of graphs:

1. *Directed vs undirected graphs.* A graph  $G_n = (V_n, E_n, W_n)$  is called *undirected* if for all  $1 \leq i, j \leq n$  we have  $E_n[i, j] = E_n[j, i]$ . In other words, there is an edge from  $i$  to  $j$  iff there is an edge from  $j$  to  $i$ , which represents symmetric interaction. If a graph is not undirected, then it is called a *directed* graph.
2. *Self-loop free graphs.* A graph  $G_n = (V_n, E_n, W_n)$  is called a *self-loop free* graph iff for all  $1 \leq i \leq n$  we have  $E_n[i, i] = W_n[i, i] = 0$ .
3. *Weighted vs unweighted graphs.* A graph  $G_n = (V_n, E_n, W_n)$  is called an *unweighted* graph if for all  $1 \leq i \leq n$  we have

$$W_n[i, j] = \begin{cases} \frac{1}{|\text{Out}(i)|} & j \in \text{Out}(i); \\ 0 & j \notin \text{Out}(i) \end{cases}$$

In other words, in unweighted graphs for every vertex the edges are chosen uniformly at random. Note that for unweighted graphs the weight matrix is not relevant, and can be specified simply by the graph structure  $(V_n, E_n)$ . In the sequel, we will represent unweighted graphs as  $G_n = (V_n, E_n)$ .

4. *Bounded degree graphs.* The degree of a graph  $G_n = (V_n, E_n, W_n)$ , denoted  $\deg(G_n)$ , is  $\max\{\text{In}(i), \text{Out}(i) \mid 1 \leq i \leq n\}$ , i.e., the maximum in-degree or out-degree. For a family of graphs  $(G_n)_{n>0}$  we say that the family has bounded degree, if there exists a constant  $c$  such that the degree of all graphs in the family is at most  $c$ , i.e., for all  $n$  we have  $\deg(G_n) \leq c$ .

*Initialization of the mutant.* The fixation probability is affected by many different factors [23]. In a well-mixed population, the fixation probability depends on the population size  $n$  and the relative fitness advantage  $r$  of mutants [18, 22]. For the Moran process on graphs, the fixation probability also depends on the population structure, which breaks the symmetry and homogeneity of the well-mixed population [16, 15, 7, 17, 5, 8, 4, 24, 11]. Finally, for general population structures, the fixation probability typically depends on the initial location of the mutant [2, 3], unlike the well-mixed population where the probability of the mutant fixing is independent of where the mutant arises [18, 22]. There are two standard ways mutants may arise in a population [17, 1]. First, mutants may arise spontaneously and with equal probability at any vertex of the population structure. In this case we consider that the mutant arise at any vertex uniformly at random and we call this *uniform initialization*. Second, mutants may be introduced through reproduction, and thus arise at a vertex with rate proportional to the incoming edge weights of the vertex. We call this *temperature initialization*. In general, uniform and temperature initialization result in different fixation probabilities.

*Amplifiers, quadratic amplifiers, and strong amplifiers.* Depending on the initialization, a population structure can distort fitness differences [17, 22, 5], where the well-mixed population serves as a canonical point of comparison. Intuitively, amplifiers of selection exaggerate variations in fitness by increasing (respectively decreasing) the chance of fitter (respectively weaker) mutants fixing compared to their chance of fixing in the well-mixed population. In a well-mixed population of size  $n$ , the fixation probability is

$$\frac{1 - 1/r}{1 - (1/r)^n}.$$

Thus, in the limit of large population (i.e., as  $n \rightarrow \infty$ ) the fixation probability in a well-mixed population is  $1 - 1/r$ . We focus on two particular classes of amplifiers that are of special interest. A family of graphs  $(G_n)_{n>0}$  is a *quadratic amplifier* if in the limit of large population the fixation probability is  $1 - 1/r^2$ . Thus, a mutant with a 10% fitness advantage over the resident has approximately the same chance of fixing in quadratic amplifiers as a mutant with a 21% fitness advantage in the well-mixed population. A family of graphs  $(G_n)_{n>0}$  is an *arbitrarily strong amplifier* (hereinafter called simply a strong amplifier) if for any constant  $r > 1$  the fixation probability approaches 1 at the

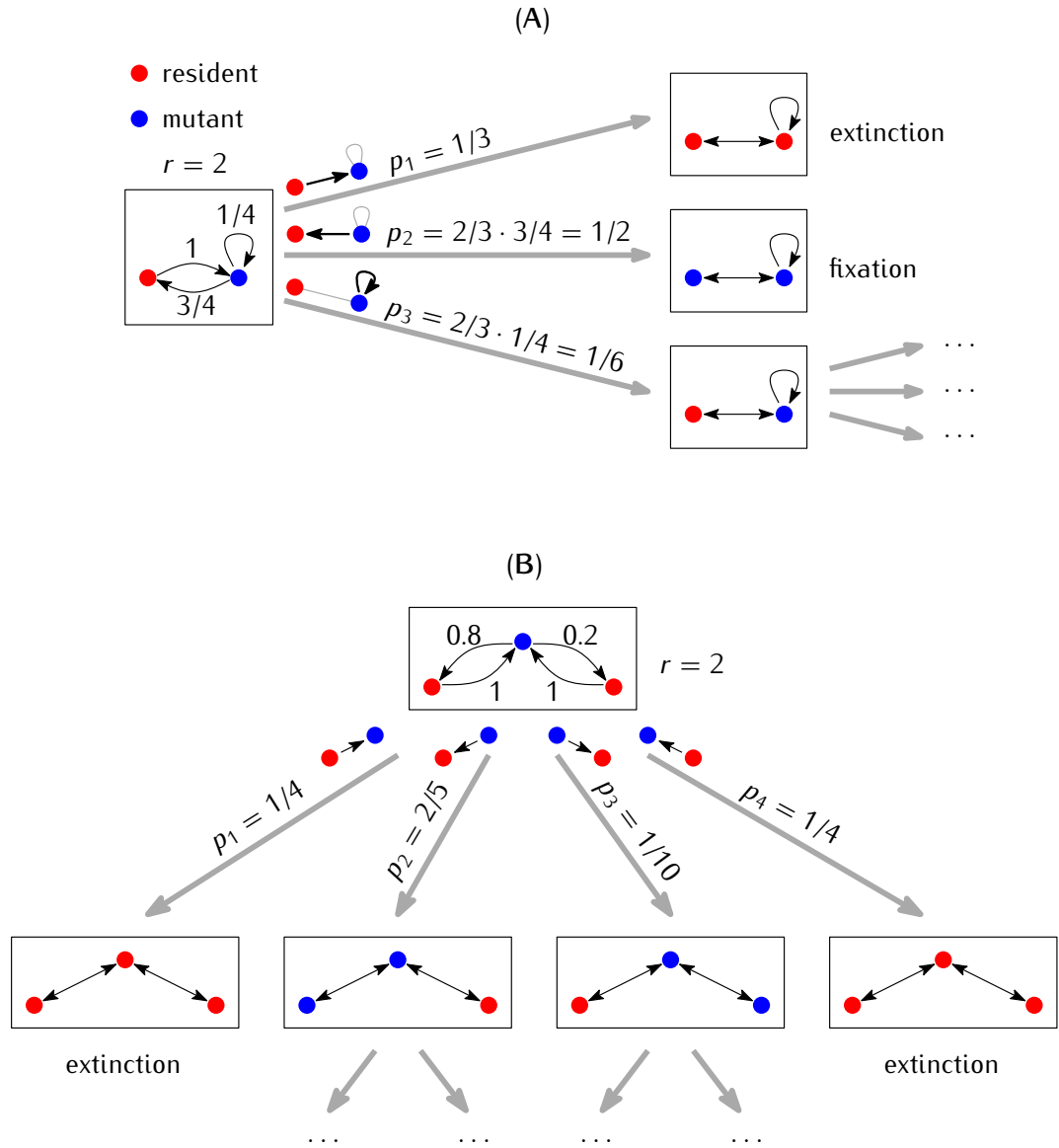


Figure S1: Illustration of one step of the Moran process on a weighted graph with self-loops. Residents are depicted as red vertices, and mutants as blue vertices. As a concrete example, we consider the relative fitness of the mutants is  $r = 2$ . In Figure S1(A), the total fitness of the population is  $\mathcal{F} = 1 + 2 = 3$ , and hence the probability of selecting resident (resp., mutant) for reproduction equals  $1/3$  (resp.,  $2/3$ ). The mutant reproduces along an edge, and the edge is chosen randomly proportional to the edge weight. Figure S1(B) shows that different reproduction events might lead to the same outcome.

limit of large population sizes, whereas when  $r < 1$ , the fixation probability approaches 0. There is a much finer classification of amplifiers presented in [1]. For other amplifiers (such as cubic, polynomial amplifiers) see [1]. We focus on quadratic amplifiers which are the most well-known among polynomial amplifiers, and strong amplifiers which represents the strongest form of amplification.

*Existing results.* We summarize the main existing results in terms of uniform and temperature initialization.

1. *Uniform initialization.* First, consider the family of Star graphs, which consist of one central vertex and  $n-1$  leaf vertices, with each leaf being connected to and from the central vertex. Star graphs are unweighted, undirected, self-loop free graphs, whose degree is linear in the population size. Under uniform initialization, the family of Star graphs is a quadratic amplifier [17, 22]. A generalization of Star graphs, called Superstars [17, 22, 12, 6], are known to be strong amplifiers under uniform initialization [9]. The Superstar family consists of unweighted, self-loop free, but directed graphs where the degree is linear in the population size. Another family of directed graphs with strong amplification properties, called Megastars, was recently introduced in [9]. The Megastars are stronger amplifiers than the Superstars, as the fixation probability on the former is approximately  $1 - n^{-1/2}$  (ignoring logarithmic factors), and is asymptotically optimal (again, ignoring logarithmic factors). In contrast, the fixation probability on the Superstars is approximately  $1 - n^{-1/2}$ . In the limit of  $n \rightarrow \infty$ , both families approach the fixation probability 1.
2. *Temperature initialization.* While the family of Star graphs is a quadratic amplifier under uniform initialization, it is not even an amplifier under temperature initialization [1]. It was shown in [1] that by adding self-loops and weights to the edges of the Star graph, a graph family, namely the family of Looping Stars, can be constructed, which is a quadratic amplifier simultaneously under temperature and uniform initialization. Note that in contrast to Star graphs, the Looping Star graphs are weighted and also have self-loops.

*Open questions.* Despite several important existing results on amplifiers of selection, several basic questions have remained open:

1. *Question 1.* Does there exist a family of self-loop free graphs (weighted or unweighted) that is a quadratic amplifier under temperature initialization?
2. *Question 2.* Does there exist a family of unweighted graphs (with or without self-loops) that is a quadratic amplifier under temperature initialization?
3. *Question 3.* Does there exist a family of bounded degree self-loop free (weighted or unweighted) graphs that is a strong amplifier under uniform initialization?
4. *Question 4.* Does there exist a family of bounded degree unweighted graphs (with or without self-loops) that is a strong amplifier under uniform initialization?
5. *Question 5.* Does there exist a family of graphs that is a strong amplifier under temperature initialization? More generally, does there exist a family of graphs that is a strong amplifier both under temperature and uniform initialization?

To summarize, the open questions ask for (i) the existence of quadratic amplifiers under temperature initialization without the use of self-loops, or weights (Questions 1 and 2); (ii) the existence of strong amplifiers under uniform initialization without the use of self-loops, or weights, and while the degree of the graph is small; and (iii) the existence of strong amplifiers under temperature initialization. While the answers to Question 1 and Question 2 are positive under uniform initialization, they have remained open under temperature initialization. Questions 3 and 4 are similar to 1 and 2, but focus on uniform rather than temperature initialization. The restriction on graphs of bounded degree is natural: large degree means that some individuals must have a lot of interactions, whereas graphs of bounded degree represent simple structures. Question 5 was mentioned as an open problem in [1]. Note that under temperature initialization, even the existence of a cubic amplifier, that achieves fixation probability at least  $1 - (1/r^3)$  in the limit of large population, has been open [1].

## 2.2 Results

In this work we present several negative as well as positive results that answer the open questions (Questions 1-5) mentioned above. We first present our negative results.

*Negative results.* Our main negative results are as follows:

1. Our first result (Theorem 1) shows that for any self-loop free weighted graph  $G_n = (V_n, E_n, W_n)$ , for any  $r \geq 1$ , under temperature initialization the fixation probability is at most  $1 - 1/(r + 1)$ . The implication of the above result is that it answers Question 1 in negative.
2. Our second result (Theorem 2) shows that for any unweighted (with or without self-loops) graph  $G_n = (V_n, E_n)$ , for any  $r \geq 1$ , under temperature initialization the fixation probability is at most  $1 - 1/(4r + 4)$ . The implication of the above result is that it answers Question 2 in negative.
3. Our third result (Theorem 3) shows that for any bounded degree self-loop free graph (possibly weighted)  $G_n = (V_n, E_n, W_n)$ , for any  $r \geq 1$ , under uniform initialization the fixation probability is at most  $1 - 1/(c + c^2r)$ , where  $c$  is the bound on the degree, i.e.,  $\deg(G_n) \leq c$ . The implication of the above result is that it answers Question 3 in negative.
4. Our fourth result (Theorem 4) shows that for any unweighted, bounded degree graph (with or without self-loops)  $G_n = (V_n, E_n)$ , for any  $r \geq 1$ , under uniform initialization the fixation probability is at most  $1 - 1/(1 + rc)$ , where  $c$  is the bound on the degree, i.e.,  $\deg(G_n) \leq c$ . The implication of the above result is that it answers Question 4 in negative.

*Significance of the negative results.* We now discuss the significance of the above results.

1. The first two negative results show that in order to obtain quadratic amplifiers under temperature initialization, self-loops and weights are inevitable, complementing the existing results of [1]. More importantly, it shows a sharp contrast between temperature and uniform initialization: while self-loop free, unweighted graphs (namely, Star graphs) are quadratic amplifiers under uniform initialization, no such graph families are quadratic amplifiers under temperature initialization.
2. The third and fourth results show that without using self-loops and weights, bounded degree graphs cannot be made strong amplifiers even under uniform initialization. See also Remark 1.

*Positive result.* Our main positive result shows the following:

1. For any constant  $\epsilon > 0$ , consider any connected unweighted graph  $G_n = (V_n, E_n)$  of  $n$  vertices with self-loops and which has *diameter* at most  $n^{1-\epsilon}$ . The diameter of a connected graph is the maximum, among all pairs of vertices, of the length of the shortest path between that pair. We establish (Theorem 5) that there is a stochastic weight matrix  $W_n$  such that for any  $r > 1$  the fixation probability both under uniform and temperature initialization is at least  $1 - \frac{1}{n^{\epsilon/3}}$ . An immediate consequence of our result is the following: for any family of connected unweighted graphs  $(G_n = (V_n, E_n))_{n>0}$  graphs with self-loops such that the diameter of  $G_n$  is at most  $n^{1-\epsilon}$ , for a constant  $\epsilon > 0$ , one can construct a stochastic weight matrix  $W_n$  such that the resulting family  $(G_n = (V_n, E_n, W_n))_{n>0}$  of weighted graphs is a strong amplifier simultaneously under uniform and temperature initialization. Thus we answer Question 5 in affirmative.

Our results are summarized in Table 1.

*Significance of the positive result.* We highlight some important aspects of the results established in this work.

1. First, note that for the fixation probability of the Moran process on graphs to be well defined, a necessary and sufficient condition is that the graph is connected. A uniformly chosen random connected unweighted graph of  $n$  vertices has diameter at most  $O(\log n)$ , with high probability. Hence, within the family of connected, unweighted graphs, the family of graphs of diameter at most  $O(n^{1-\epsilon})$ , for any constant  $0 < \epsilon < 1$ , has

	Temperature		Uniform*	
	Loops	No Loops	Loops	No Loops
Weights	✓	×	✓	×
No Weights	×	×	×	×

Table 1: Summary of our results on existence of strong amplifiers for different initialization schemes (temperature initialization or uniform initialization) and graph families (presence or absence of loops and/or weights). The “✓” symbol marks that for given choice of initialization scheme and graph family, almost all graphs admit a weight function that makes them strong amplifiers. The “×” symbol marks that for given choice of initialization scheme and graph family, no strong amplifiers exist (under any weight function). The asterisk signifies that the negative results under uniform initialization only hold for bounded degree graphs.

probability measure 1. Our results establish a strong dichotomy: (a) the negative results state that without self-loops and/or without weights, *no* family of graphs can be a quadratic amplifier (even more so a strong amplifier) even for only temperature initialization; and (b) in contrast, for *almost all* families of connected graphs with self-loops, there exist weight functions such that the resulting family of weighted graphs is a strong amplifier both under temperature and uniform initialization.

2. Second, with the use of self-loops and weights, even simple graph structures, such as Star graphs, Grids, and well-mixed structures (i.e., complete graphs) can be made strong amplifiers.
3. Third, our positive result is constructive, rather than existential. In other words, we not only show the existence of strong amplifiers, but present a construction of them.
4. Finally, note that in using weights, edges can be effectively removed by assigning to their weight a small value. However, edges cannot be created. Thus, for complete graphs, desired sub-graphs can be created easily using weights. Our positive result states that for almost all graphs, one can use weights to create sub-graphs which are strong amplifiers both under uniform and temperature initialization.

### 3 Preliminaries: Formal Notations

#### 3.1 The Moran Process on Weighted Structured Populations

We consider a population of  $n$  individuals on a graph  $G_n = (V_n, E_n, W_n)$ . Each individual of the population is either a *resident*, or a *mutant*. Mutants are associated with a *reproductive rate* (or *fitness*)  $r$ , whereas the reproductive rate of residents is normalized to 1. Typically we consider the case where  $r > 1$ , i.e., mutants are *advantageous*, whereas when  $r < 1$  we call the mutants *disadvantageous*. We now introduce formal notations related to the process.

*Configuration.* A *configuration* of  $G_n$  is a subset  $S \subseteq V$  which specifies the vertices of  $G_n$  that are occupied by mutants and thus the remaining vertices  $V \setminus S$  are occupied by residents. For a configuration  $S$ , we denote by  $F(S) = r \cdot |S| + n - |S|$  the total fitness of the population in configuration  $S$ , and by  $|S|$  the number of mutants in the configuration.

*The Moran process.* The birth-death Moran process on  $G_n$  is a discrete-time Markovian random process. We denote by  $X_i$  the random variable for a configuration at time step  $i$ , and  $F(X_i)$  and  $|X_i|$  denote the total fitness and the number of mutants of the corresponding configuration, respectively. The probability distribution for the next configuration  $X_{i+1}$  at time  $i + 1$  is determined by the following two events in succession:

**Birth:** One individual is chosen at random to reproduce, with probability proportional to its fitness. That is, the probability to reproduce is  $r/F(X_i)$  for a mutant, and  $1/F(X_i)$  for a resident. Let  $u$  be the vertex occupied by the reproducing individual.



**Death:** A neighboring vertex  $v \in \text{Out}(u)$  is chosen randomly with probability  $W_n[u, v]$ . The individual occupying  $v$  dies, and the reproducing individual places a copy of its own on  $v$ . Hence, if  $u \in X_i$ , then  $X_{i+1} = X_i \cup \{v\}$ , otherwise  $X_{i+1} = X_i \setminus \{v\}$ .

The above process is known as the *birth-death* Moran process, where the death event is conditioned on the birth event, and the dying individual is a neighbor of the reproducing one.

*Probability measure.* Given a graph  $G_n$  and the fitness  $r$ , the birth-death Moran process defines a probability measure on sequences of configurations, which we denote as  $\mathbb{P}^{G_n, r}[\cdot]$ . If the initial configuration is  $\{u\}$ , then we define the probability measure as  $\mathbb{P}_u^{G_n, r}[\cdot]$ , and if the graph and fitness  $r$  is clear from the context, then we drop the superscript.

*Fixation event.* The fixation event, denoted  $\mathcal{E}$ , represents that all vertices are mutants, i.e.,  $X_i = V$  for some  $i$ . In particular,  $\mathbb{P}_u^{G_n, r}[\mathcal{E}]$  denotes the fixation probability in  $G_n$  for fitness  $r$  of the mutant, when the initial mutant is placed on vertex  $u$ . We will denote this fixation probability as  $\rho(G_n, r, u) = \mathbb{P}_u^{G_n, r}[\mathcal{E}]$ .

### 3.2 Initialization and Fixation Probabilities

We will consider three types of initialization, namely, (a) uniform initialization, where the mutant arises at vertices with uniform probability, (b) temperature initialization, where the mutant arises at vertices proportional to the temperature, and (c) convex combination of the above two.

*Temperature.* For a weighted graph  $G_n = (V_n, E_n, W_n)$ , the temperature of a vertex  $u$ , denoted  $T(u)$ , is  $\sum_{v \in \text{In}(u)} W_n[v, u]$ , i.e., the sum of the incoming weights. Note that  $\sum_{u \in V_n} T(u) = n$ , and a graph is *isothermal* iff  $T(u) = 1$  for all vertices  $u$ .

*Fixation probabilities.* We now define the fixation probabilities under different initialization.

1. *Uniform initialization.* The fixation probability under uniform initialization is

$$\rho(G_n, r, \text{U}) = \sum_{u \in V_n} \frac{1}{n} \cdot \rho(G_n, r, u).$$

2. *Temperature initialization.* The fixation probability under temperature initialization is

$$\rho(G_n, r, \text{T}) = \sum_{u \in V_n} \frac{T(u)}{n} \cdot \rho(G_n, r, u).$$

3. *Convex initialization.* In  $\eta$ -convex initialization, where  $\eta \in [0, 1]$ , the initial mutant arises with probability  $(1 - \eta)$  via uniform initialization, and with probability  $\eta$  via temperature initialization. The fixation probability is then

$$\rho(G_n, r, \eta) = (1 - \eta) \cdot \rho(G_n, r, \text{U}) + \eta \cdot \rho(G_n, r, \text{T}).$$

### 3.3 Strong Amplifier Graph Families

A *family* of graphs  $\mathcal{G}$  is an infinite sequence of weighted graphs  $\mathcal{G} = (G_n)_{n \in \mathbb{N}^+}$ .

- *Strong amplifiers.* A family of graphs  $\mathcal{G}$  is a *strong uniform amplifier* (resp. *strong temperature amplifier*, *strong convex amplifier*) if for every fixed  $r_1 > 1$  and  $r_2 < 1$  we have that

$$\liminf_{n \rightarrow \infty} \rho(G_n, r_1, Z) = 1 \quad \text{and} \quad \limsup_{n \rightarrow \infty} \rho(G_n, r_2, Z) = 0;$$

where  $Z = \text{U}$  (resp.,  $Z = \text{T}$ ,  $Z = \eta$ ).

Intuitively, strong amplifiers ensures (a) fixation of advantageous mutants with probability 1 and (b) extinction of disadvantageous mutants with probability 1. In other words, strong amplifiers represent the strongest form of amplifiers possible.

## 4 Negative Results

In the current section we present our negative results, which show the nonexistence of strong amplifiers in the absence of either self-loops or weights. In our proofs, we consider weighted graph  $G_n = (V_n, E_n, W_n)$ , and for notational simplicity we drop the subscripts from vertices, edges and weights, i.e., we write  $G_n = (V, E, W)$ . We also consider that  $G_n$  is connected and  $n \geq 2$ . Throughout this section we will use a technical lemma, which we present below. Given a configuration  $\mathsf{X}_i = \{u\}$  with one mutant, let  $x$  and  $y$  be the probability that in the next configuration the mutants increase and go extinct, respectively. The following lemma bounds the fixation probability  $\rho(G_n, r, u)$  as a function of  $x$  and  $y$ .

**Lemma 1.** *Consider a vertex  $u$  and the initial configuration  $\mathsf{X}_0 = \{u\}$  where the initial mutant arises at vertex  $u$ . For any configuration  $\mathsf{X}_i = \{u\}$ , let*

$$x = \mathbb{P}^{G_n, r}[|\mathsf{X}_{i+1}| = 2 \mid \mathsf{X}_i = \{u\}] \quad \text{and} \quad y = \mathbb{P}^{G_n, r}[|\mathsf{X}_{i+1}| = 0 \mid \mathsf{X}_i = \{u\}].$$

Then the fixation probability from  $u$  is at most  $x/(x + y)$ , i.e.,

$$\rho(G_n, r, u) \leq \frac{x}{x + y} = 1 - \frac{y}{x + y}.$$

*Proof.* We upperbound the fixation probability  $\rho(G_n, r, u)$  starting from  $u$  by the probability that a configuration  $\mathsf{X}_t$  is reached with  $|\mathsf{X}_t| = 2$ . Note that to reach fixation the Moran process must first reach a configuration with at least two mutants. We now analyze the probability to reach at least two mutants. This is represented by a three-state one dimensional random walk, where two states are absorbing, one absorbing state represents a configuration with two mutants, and the other absorbing state represents the extinction of the mutants, and the bias towards the absorbing state representing two mutants is  $x/y$ . See Figure S2 for an illustration. Using the formulas for absorption probability in one-dimensional three-state Markov chains (see, e.g., [13], [22, Section 6.3]), we have the probability that a configuration with two mutants is reached is

$$\frac{1 - (x/y)^{-1}}{1 - (x/y)^{-2}} = \frac{1}{1 + (x/y)^{-1}} = \frac{x}{x + y}.$$

Hence it follows that  $\rho(G_n, r, u) \leq 1 - \frac{y}{x+y}$ . □

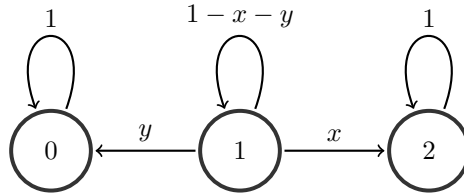


Figure S2: Illustration of the Markov chain of Lemma 1.

### 4.1 Negative Result 1

We now prove our negative result 1.

**Theorem 1.** *For all self-loop free graphs  $G_n$  and for every  $r \geq 1$  we have  $\rho(G_n, r, \mathsf{T}) \leq 1 - 1/(r + 1)$ .*

*Proof.* Since  $G_n$  is self-loop free, for all  $u$  we have  $W[u, u] = 0$ . Hence  $\mathsf{T}(u) = \sum_{v \in \ln(u) \setminus \{u\}} W[v, u]$ . Consider the case where the initial mutant is placed on vertex  $u$ , i.e.,  $\mathsf{X}_0 = \{u\}$ . For any configuration  $\mathsf{X}_i = \{u\}$ , we have the following:

$$x = \mathbb{P}^{G_n, r}[|\mathsf{X}_{i+1}| = 2 \mid \mathsf{X}_i = \{u\}] = \frac{r}{F(\mathsf{X}_i)}$$

$$y = \mathbb{P}^{G_n, r} [ |X_{i+1}| = 0 \mid X_i = \{u\} ] = \frac{1}{F(X_i)} \cdot \sum_{v \in \ln(u) \setminus \{u\}} W[v, u] = \frac{1}{F(X_i)} \cdot T(u).$$

Thus  $x/y = r/T(u)$ . Hence by Lemma 1 we have

$$\rho(G_n, r, u) \leq 1 - \frac{T(u)}{T(u) + r}.$$

Summing over all  $u$ , we obtain

$$\rho(G_n, r, T) = \sum_u \frac{T(u)}{n} \cdot \rho(G_n, r, u) \leq \frac{1}{n} \cdot \sum_u T(u) \cdot \left(1 - \frac{T(u)}{T(u) + r}\right) = 1 - \frac{1}{n} \cdot \sum_u \frac{T(u)^2}{T(u) + r}; \quad (1)$$

since  $\sum_u T(u) = n$ . Using the Cauchy-Schwarz inequality, we obtain

$$\sum_u \frac{T(u)^2}{T(u) + r} \geq \frac{(\sum_u T(u))^2}{\sum_u (T(u) + r)} = \frac{n^2}{n + n \cdot r} = \frac{n}{r + 1};$$

and thus Eq. (1) becomes

$$\rho(G_n, r, T) \leq 1 - \frac{1}{n} \cdot \frac{n}{r + 1} = 1 - \frac{1}{r + 1}$$

as desired.  $\square$

We thus arrive at the following corollary.

**Corollary 1.** *There exists no self-loop free family of graphs which is a strong temperature amplifier.*

## 4.2 Negative Result 2

We now prove our negative result 2.

**Theorem 2.** *For all unweighted graphs  $G_n$  and for every  $r \geq 1$  we have  $\rho(G_n, r, T) \leq 1 - 1/(4 \cdot (r + 1))$ .*

*Proof.* For every vertex  $u \in V$ , let

$$T'(u) = \sum_{v \in \ln(u) \setminus \{u\}} \frac{1}{|\text{Out}(v)|}.$$

We establish two inequalities related to  $T'$ . Since  $G_n$  is unweighted, we have

$$T(u) = \sum_{v \in \ln(u)} \frac{1}{|\text{Out}(v)|} \geq T'(u).$$

For a vertex  $u$ , let  $\text{sl}(u) = 1$  if  $u$  has a self-loop and  $\text{sl}(u) = 0$  otherwise. Since  $G_n$  is connected, each vertex  $u$  has at least one neighbor other than itself. Thus for every vertex  $u$  with  $\text{sl}(u) = 1$  we have that  $|\text{Out}(u)| \geq 2$ . Hence

$$\begin{aligned} \sum_u T'(u) &= \sum_u \left( \sum_{v \in \ln(u)} \frac{1}{|\text{Out}(v)|} - \text{sl}(u) \frac{1}{|\text{Out}(u)|} \right) = \sum_u \left( \sum_{v \in \ln(u)} \frac{1}{|\text{Out}(v)|} \right) - \sum_{u: \text{sl}(u)=1} \left( \frac{1}{|\text{Out}(u)|} \right) \\ &\geq \sum_u T(u) - \sum_u \frac{1}{2} = n - \frac{n}{2} = \frac{n}{2}. \end{aligned} \quad (2)$$

Similarly to the proof of Theorem 1, the fixation probability given that a mutant is initially placed on vertex  $u$  is at most

$$\rho(G_n, r, u) \leq 1 - \frac{\Gamma'(u)}{\Gamma'(u) + r}$$

Summing over all  $u$ , we obtain

$$\rho(G_n, r, \Gamma) = \frac{1}{n} \cdot \sum_u \Gamma(u) \cdot \rho(G_n, r, u) \leq \frac{1}{n} \cdot \sum_u \Gamma(u) \cdot \left(1 - \frac{\Gamma'(u)}{\Gamma'(u) + r}\right) \leq 1 - \frac{1}{n} \cdot \sum_u \frac{\Gamma'(u)^2}{\Gamma'(u) + r}; \quad (3)$$

since  $\Gamma(u) \geq \Gamma'(u)$ , and  $\sum_u \Gamma(u) = n$ . Using the Cauchy-Schwarz inequality and Eq. (2), we obtain

$$\sum_u \frac{\Gamma'(u)^2}{\Gamma'(u) + r} \geq \frac{(\sum_u \Gamma'(u))^2}{\sum_u (\Gamma'(u) + r)} \geq \frac{(n/2)^2}{n + n \cdot r} = \frac{n}{4 \cdot (r + 1)}$$

and thus Eq. (3) becomes

$$\rho(G_n, r, \Gamma) \leq 1 - \frac{1}{n} \cdot \frac{n}{4 \cdot (r + 1)} = 1 - \frac{1}{4 \cdot (r + 1)};$$

as desired.  $\square$

We thus arrive at the following corollary.

**Corollary 2.** *There exists no unweighted family of graphs which is a strong temperature amplifier.*

### 4.3 Negative Result 3

We now prove our negative result 3.

**Theorem 3.** *For all self-loop free graphs  $G_n$  with  $c = \deg(G_n)$ , and for every  $r \geq 1$  we have  $\rho(G_n, r, \mathbf{U}) \leq 1 - 1/(c + r \cdot c^2)$ .*

*Proof.* Let  $G_n = (V, E, W)$  and  $\gamma = 1/c$ . For a vertex  $u$ , denote by  $\text{Out}^\gamma(u) = \{v \in \text{Out}(u) : W[u, v] \geq \gamma\}$ . Observe that since  $\deg(G_n) = c$ , every vertex  $u$  has an outgoing edge of weight at least  $1/c$ , and thus  $\text{Out}^\gamma(u) \neq \emptyset$  for all  $u \in V$ . Let  $V^h = \bigcup_u \text{Out}^\gamma(u)$ . Intuitively, the set  $V^h$  contains ‘‘hot’’ vertices, since each vertex  $u \in V^h$  is replaced frequently (with rate at least  $\gamma$ ) by at least one neighbor  $v$ .

*Bound on size of  $V^h$ .* We first obtain a bound on the size of  $V^h$ . Consider a vertex  $u \in V$  and a vertex  $v \in \text{Out}^\gamma(u)$  (i.e.,  $v \in V^h$ ). For every vertex  $w \in \text{In}(v)$  such that  $v \in \text{Out}^\gamma(w)$  we can count  $v \in V^h$  and to avoid multiple counting, we consider for each count of  $v$  a contribution of  $\frac{1}{|\{w \in \text{In}(v) : v \in \text{Out}^\gamma(w)\}|}$ , which is at least  $\frac{1}{c}$  due to the degree bound. Hence we have

$$|V^h| = \sum_{u \in V} \sum_{v \in \text{Out}^\gamma(u)} \frac{1}{|\{w \in \text{In}(v) : v \in \text{Out}^\gamma(w)\}|} \geq \sum_{u \in V} \sum_{v \in \text{Out}^\gamma(u)} \frac{1}{c} \geq \sum_{u \in V} \frac{1}{c} = \frac{n}{c};$$

where the last inequality follows from the fact that  $\text{Out}^\gamma(u) \neq \emptyset$  for all  $u \in V$ . Hence the probability that the initial mutant is a vertex in  $V^h$  has probability at least  $1/c$  according to the uniform initialization.

*Bound on probability.* Consider that the initial mutant is a vertex  $u \in V^h$ . Consider any configuration  $\mathbf{X}_i = \{u\}$ , we have the following:

$$x = \mathbb{P}^{G_n, r}[|\mathbf{X}_{i+1}| = 2 \mid \mathbf{X}_i = \{u\}] = \frac{r}{F(\mathbf{X}_i)}$$

$$y = \mathbb{P}^{G_n, r}[|\mathbf{X}_{i+1}| = 0 \mid \mathbf{X}_i = \{u\}] = \frac{1}{F(\mathbf{X}_i)} \cdot \sum_{(v, u) \in E} W[v, u] \geq \frac{1}{F(\mathbf{X}_i)} \cdot \sum_{v: u \in \text{Out}^\gamma(v)} \gamma \geq \frac{1}{F(\mathbf{X}_i)} \cdot \gamma.$$

Thus  $x/y \leq r/\gamma$ . Hence by Lemma 1 we have

$$\rho(G_n, r, u) \leq \frac{r \cdot c}{1 + r \cdot c}.$$

Finally, we have

$$\begin{aligned} \rho(G_n, r, \mathbf{U}) &= \sum_{u \in V^h} \frac{1}{n} \cdot \rho(G_n, r, u) + \sum_{u \in V \setminus V^h} \frac{1}{n} \cdot \rho(G_n, r, u) \\ &\leq \frac{1}{c} \cdot \frac{r \cdot c}{1 + r \cdot c} + \frac{c-1}{c} \cdot 1 = 1 - \frac{1}{c} \cdot \left(1 - \frac{r \cdot c}{1 + r \cdot c}\right) = 1 - \frac{1}{c + r \cdot c^2}. \end{aligned}$$

The desired result follows.  $\square$

We thus arrive at the following corollary.

**Corollary 3.** *There exists no self-loop free, bounded-degree family of graphs which is a strong uniform amplifier.*

#### 4.4 Negative Result 4

We now prove our negative result 4.

**Theorem 4.** *For all unweighted graphs  $G_n$  with  $c = \deg(G_n)$ , and for every  $r \geq 1$  we have  $\rho(G_n, r, \mathbf{U}) \leq 1 - 1/(1 + r \cdot c)$ .*

*Proof.* Let  $G_n = (V, E, W)$  and consider that  $X_0 = u$  for some  $u \in V$ . Consider any configuration  $X_i = \{u\}$ , we have the following:

$$\begin{aligned} x &= \mathbb{P}^{G_n, r}[|X_{i+1}| = 2 \mid X_i = \{u\}] \leq \frac{r}{F(X_i)}. \\ y &= \mathbb{P}^{G_n, r}[|X_{i+1}| = 0 \mid X_i = \{u\}] = \frac{1}{F(X_i)} \cdot \sum_{v \in \ln(u) \setminus \{u\}} W[v, u] \geq \frac{1}{F(X_i)} \cdot \frac{1}{c}. \end{aligned}$$

Thus  $x/y \leq r \cdot c$ . By Lemma 1 we have

$$\rho(G_n, r, u) \leq \frac{r \cdot c}{1 + r \cdot c}.$$

Finally, we have

$$\rho(G_n, r, \mathbf{U}) = \frac{1}{n} \cdot \sum_u \rho(G_n, r, u) \leq \frac{r \cdot c}{1 + r \cdot c} = 1 - \frac{1}{1 + r \cdot c}.$$

The desired result follows.  $\square$

We thus arrive at the following corollary.

**Corollary 4.** *There exists no unweighted, bounded-degree family of graphs which is a strong uniform amplifier.*

*Remark 1.* Theorems 3 and 4 establish the nonexistence of strong amplification with bounded degree graphs. A relevant result can be found in [19], which establishes an upperbound of the fixation probability of mutants under uniform initialization on unweighted, undirected graphs. If the bounded degree restriction is relaxed to average bounded degree, then recent results show that strong amplifiers (called *sparse incubators*) exist [10].

## 5 Positive Result

In the previous section we showed that self-loops and weights are necessary for the existence of strong amplifiers. In this section we present our positive result, namely that every family of undirected graphs with self-loops and whose diameter is not “too large” can be made a strong amplifier by using appropriate weight functions. Our result relies on several novel conceptual steps, therefore the proof is structured in three parts.

1. First, we introduce some formal notation that will help with the exposition of the ideas that follow.
2. Second, we describe an algorithm which takes as input an undirected graph  $G_n = (V_n, E_n)$  of  $n$  vertices, and constructs a weight matrix  $W_n$  to obtain the weighted graph  $G_n^w = (V_n, E_n, W_n)$ .
3. Lastly, we prove that  $G_n^w$  is a strong amplifier both for uniform and temperature initialization.

Before presenting the details we introduce some notations to be used in this section.

### 5.1 Undirected Graphs and Notation

We first present some additional notation required for the exposition of the results of this section.

*Undirected graphs.* Our input is an unweighted undirected graph  $G_n = (V_n, E_n)$  with self loops. For ease of notation, we drop the subscript  $n$  and refer to the graph  $G = (V, E)$  instead. Since  $G$  is undirected, for all vertices  $u$  we have  $\text{In}(u) = \text{Out}(u)$ , and we denote by  $\text{Nh}(u) = \text{In}(u) = \text{Out}(u)$  the set of neighbors of vertex  $u$ . Hence,  $v \in \text{Nh}(u)$  iff  $u \in \text{Nh}(v)$ . Moreover, since  $G$  has self-loops, we have  $u \in \text{Nh}(u)$ . Also we consider that  $G$  is connected, i.e., for every pair of vertices  $u, v$ , there is a path from  $u$  to  $v$ .

*Symmetric weight function.* So far we have used a stochastic weight matrix  $W$ , where for every  $u$  we have  $\sum_v W[u, v] = 1$ . In this section, we will consider a weight function  $w : E \rightarrow \mathbb{R}_{\geq 0}$ , and given a vertex  $u \in V$  we denote by  $w(u) = \sum_{v \in \text{Nh}(u)} w(u, v)$ . Our construction will not only assign weights, but also ensure symmetry. In other words, we we construct *symmetric* weights such that for all  $u, v$  we have  $w(u, v) = w(v, u)$ . Given such a weight function  $w$ , the corresponding stochastic weight matrix  $W$  is defined as  $W[u, v] = w(u, v)/w(u)$  for all pairs of vertices  $u, v$ . Given an unweighted graph  $G$  and weight function  $w$ , we denote by  $G^w$  the corresponding weighted graph.

*Vertex-induced subgraphs.* Given a set of vertices  $X \subseteq V$ , we denote by  $G^w[X] = (X, E[X], w[X])$  the subgraph of  $G$  induced by  $X$ , where  $E[X] = E \cap (X \times X)$ , and the weight function  $w[X] : E[X] \rightarrow \mathbb{R}_{\geq 0}$  defined as

$$w[X](u, v) = \begin{cases} w(u, u) + \sum_{(u, w) \in E \setminus E[X]} w(u, w) & \text{if } u = v \\ w(u, v) & \text{otherwise} \end{cases}$$

In words, the weights on the edges of  $u$  to vertices that do not belong to  $X$  are added to the self-loop weight of  $u$ . Since the sum of all weights does not change, we have  $w[X](u) = w(u)$  for all  $u$ . The temperature of  $u$  in  $G[X]$  is

$$\text{T}[X](u) = \sum_{v \in \text{Nh}(u) \cap X} \frac{w[X](v, u)}{w[X](v)}.$$

### 5.2 Algorithm for Weight Assignment on $G$

We start with the construction of the weight function  $w$  on  $G$ . Since we consider arbitrary input graphs,  $w$  is constructed by an algorithm. The time complexity of the algorithm is  $O(n \cdot \log n)$ . Since our focus is on the properties of the resulting weighted graph, we do not explicitly analyze the time complexity.

**Steps of the construction.** Consider a connected graph  $G$  with diameter  $\text{diam}(G) \leq n^{1-\varepsilon}$ , where  $\varepsilon > 0$  is a constant independent of  $n$ . We construct a weight function  $w$  such that whp an initial mutant arising under uniform or temperature initialization, eventually fixates on  $G^w$ . The weight assignment consists of the following conceptual steps.

1. *Spanning tree construction and partition.* First, we construct a *spanning tree*  $\mathcal{T}_n^x$  of  $G$  rooted on some arbitrary vertex  $x$ . In words, a spanning tree of an undirected graph is a connected subgraph that is a tree and includes all of the vertices of the graph. Then we partition the tree into a number of component trees of appropriate sizes.
2. *Sink construction.* Second, we construct the *sink* of  $G$ , which consists of the vertices  $x_i$  that are roots of the component trees, together with all vertices in the paths that connect each  $x_i$  to the root  $x$  of  $\mathcal{T}_n^x$ . All vertices that do not belong to the sink belong to the *branches* of  $G$ .
3. *Weight assignment.* Finally, we assign weights to the edges of  $G$ , such that the following properties hold:
  - (a) The sink is an isothermal graph, and evolves exponentially faster than the branches.
  - (b) All edges between vertices in different branches are effectively cut-out (by being assigned weight 0).

In the following we describe the above steps formally.

**Spanning tree  $\mathcal{T}_n^x$  construction and partition.** Given the graph  $G$ , we first construct a spanning tree using the standard breadth-first-search (BFS) algorithm. Let  $\mathcal{T}_n^x$  be such a spanning tree of  $G$ , rooted at some arbitrary vertex  $x$ . We now construct the partitioning as follows: We choose a constant  $c = 2\varepsilon/3$ , and pick a set  $S \subset V$  such that

1.  $|S| \leq n^c$ , and
2. the removal of  $S$  splits  $\mathcal{T}_n^x$  into  $k$  trees  $T_{n_1}^{x_1}, \dots, T_{n_k}^{x_k}$ , each  $T_{n_i}^{x_i}$  rooted at vertex  $x_i$  and of size  $n_i$ , with the property that  $n_i \leq n^{1-c}$  for all  $1 \leq i \leq k$ .

The set  $S$  is constructed by a simple bottom-up traversal of  $\mathcal{T}_n^x$  in which we keep track of the size  $\text{size}(u)$  of the subtree marked by the current vertex  $u$  and the vertices already in  $S$ . Once  $\text{size}(u) > n^{1-c}$ , we add  $u$  to  $S$  and proceed as before. Since every time we add a vertex  $u$  to  $S$  we have  $\text{size}(u) > n^{1-c}$ , it follows that  $|S| \leq n^c$ . Additionally, the subtree rooted in every child of  $u$  has size at most  $n^{1-c}$ , otherwise that child of  $u$  would have been chosen to be included in  $S$  instead of  $u$ .

**Sink construction: sink  $S$ .** Given the set of vertices  $S$  constructed during the spanning tree partitioning, we construct the set of vertices  $S \subset V$  called the *sink*, as follows:

1. We choose a constant  $\gamma = \varepsilon/3$ .
2. For every vertex  $u \in S$ , we add in  $S$  every vertex  $v$  that lies in the unique simple path  $P_u : x \rightsquigarrow u$  between the root  $x$  of  $\mathcal{T}_n^x$  and  $u$  (including  $x$  and  $u$ ). Since  $\text{diam}(G) \leq n^{1-\varepsilon}$  and  $|S| \leq n^c$ , we have that  $|S| \leq n^{1-\varepsilon+c} \leq n^{1-\gamma}$ .
3. We add  $n^{1-\gamma} - |S|$  extra vertices to  $S$ , such that in the end, the vertices of  $S$  form a connected subtree of  $\mathcal{T}_n^x$  (rooted in  $x$ ). This is simply done by choosing a vertex  $u \in S$  and a neighbor  $v$  of  $u$  with  $v \notin S$ , and adding  $v$  to  $S$ , until  $S$  contains  $n^{1-\gamma}$  vertices.

**Branches  $B_j = T_{m_j}^{y_j}$ .** The sink  $S$  defines a number of trees  $B_j = T_{m_j}^{y_j}$ , where each tree is rooted at a vertex  $y_j \notin S$  adjacent to  $S$ , and has  $m_j$  vertices. We will refer to these trees as *branches* (see Figure S3).

**Proposition 1.** *Note that by construction, we have  $m_j \leq n^{1-2/3\varepsilon}$  for every  $j$ , and  $|S| = n^{1-\varepsilon/3}$ , and  $\sum_j m_j = n - n^{1-\varepsilon/3}$ .*

*Remark 2.* By Proposition 1, the size of each branch is much smaller than the size of the sink; but the sum of the sizes of all branches is much larger than the size of the sink.

**Notation.** To make the exposition of the ideas clear, we rely on the following notation.

1. *Parent  $\text{par}(u)$  and ancestors  $\text{anc}(u)$ .* Given a vertex  $u \neq x$ , we denote by  $\text{par}(u)$  the parent of  $u$  in  $\mathcal{T}_n^x$  and by  $\text{anc}(u)$  the set of ancestors of  $u$ .

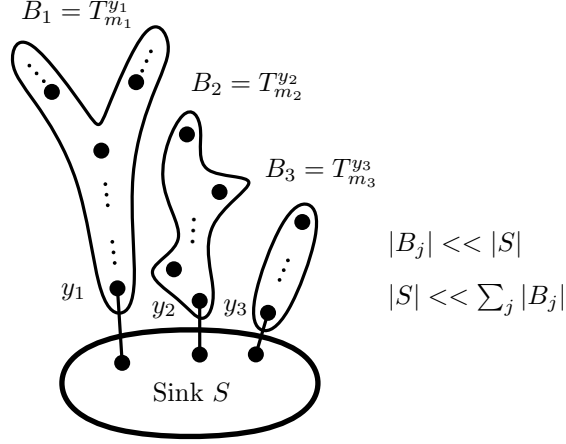


Figure S3: Illustration of the Sink  $\mathcal{S}$  and the branches  $T_{m_j}^{y_j}$ .

2. *Children*  $\text{chl}(u)$  and *descendants*  $\text{des}(u)$ . Given a vertex  $u$  that is not a leaf in  $\mathcal{T}_n^x$ , we denote by  $\text{chl}(u)$  the children of  $u$  in  $\mathcal{T}_n^x$  that do not belong to the sink  $\mathcal{S}$ , and by  $\text{des}(u)$  the set of descendants of  $u$  in  $\mathcal{T}_n^x$  that do not belong to the sink  $\mathcal{S}$ .

**Frontier, distance, and branches.** We present few notions required for the weight assignment:

1. *Frontier*  $\mathcal{F}$ . Given the sink  $\mathcal{S}$ , the *frontier* of  $\mathcal{S}$  is the set of vertices  $\mathcal{F} \subseteq \mathcal{S}$  defined as

$$\mathcal{F} = \bigcup_{u \in V \setminus \mathcal{S}} \text{Nh}(u) \cap \mathcal{S}.$$

In words,  $\mathcal{F}$  contains all vertices of  $\mathcal{S}$  that have a neighbor not in  $\mathcal{S}$ .

2. *Distance function*  $\lambda$ . For every vertex  $u$ , we define its *distance*  $\lambda(u)$  to be the length of the shortest path  $P : u \rightsquigarrow v$  in  $\mathcal{T}_n^x$  to some vertex  $v \in \mathcal{F}$  (e.g., if  $u \in \mathcal{F}$ , we have (i)  $\lambda(u) = 0$ , and (ii) for every  $v \in \text{Nh}(u) \setminus \mathcal{S}$  we have  $\lambda(v) = 1$ ).
3. *Values*  $\mu$  and  $\nu$ . For every vertex  $u \in \mathcal{S}$ , we define  $\text{deg}(u) = |(\text{Nh}(u) \cap \mathcal{S}) \setminus \{u\}|$  i.e.,  $\text{deg}(u)$  is the number of neighbors of  $u$  that belong to the sink (excluding  $u$  itself). Let

$$\mu = \max_{u \in \mathcal{F}} |\text{chl}(u)| \quad \text{and} \quad \nu = \max_{u \in \mathcal{S}} \text{deg}(u).$$

**Weight assignment.** We are now ready to define the weight function  $w : E \rightarrow \mathbb{R}_{\geq 0}$ .

1. For every edge  $(u, v)$  such that  $u \neq v$  and  $u, v \notin \mathcal{S}$  and  $u$  and  $v$  are not neighbors in  $\mathcal{T}_n^x$ , we assign  $w(u, v) = 0$ .
2. For every vertex  $u \in \mathcal{F}$  we assign  $w(u, u) = (\mu - |\text{chl}(u)|) \cdot 2^{-n} + \nu - \text{deg}(u)$ .
3. For every vertex  $u \in \mathcal{S} \setminus \mathcal{F}$  we assign  $w(u, u) = \mu \cdot 2^{-n} + \nu - \text{deg}(u)$ .
4. For every vertex  $u \notin \mathcal{S}$  we assign  $w(u, u) = n^{-2 \cdot \lambda(u)}$ .
5. For every edge  $(u, v) \in E$  such that  $u \neq v$  and  $u, v \in \mathcal{S}$  we assign  $w(u, v) = 1$ .
6. For every remaining edge  $(u, v) \in E$  such that  $u = \text{par}(v)$  we assign  $w(u, v) = 2^{-n} \cdot n^{-4 \cdot \lambda(u)}$ .

Figure S4 illustrates the assignment of the symmetric weights  $w$  on the Star graph.

The following lemma is straightforward from the weight assignment, and captures that every vertex in the sink has the same weight.

**Lemma 2.** For every vertex  $u \in \mathcal{S}$  we have  $w(u) = \sum_{v \in \text{Nh}(u)} w(u, v) = \mu \cdot 2^{-n} + \nu$ .



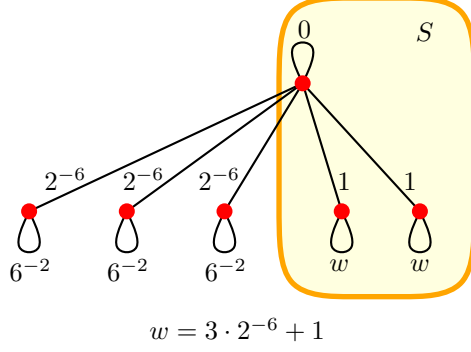


Figure S4: Illustration of the weight assignment on a Star graph of 6 vertices. The spanning tree is rooted on the central vertex of the Star, and the sink consists of the central vertex together with two leaf vertices.

*Proof.* Consider any vertex  $u \in \mathcal{S} \setminus \mathcal{F}$ . We have

$$\begin{aligned}
 w(u) &= w(u, u) + \sum_{v \in \text{Nh}(u) \setminus \{u\}} w(u, v) \\
 &= \mu \cdot 2^{-n} + \nu - \text{deg}(u) + \sum_{v \in \text{Nh}(u) \setminus \{u\}} 1 \\
 &= \mu \cdot 2^{-n} + \nu - \text{deg}(u) + \text{deg}(u) \\
 &= \mu \cdot 2^{-n} + \nu
 \end{aligned} \tag{4}$$

Similarly, consider any  $u \in \mathcal{F}$ . We have

$$\begin{aligned}
 w(u) &= w(u, u) + \sum_{v \in (\text{Nh}(u) \cap \mathcal{S}) \setminus \{u\}} w(u, v) + \sum_{v \in \text{chl}(u)} w(u, v) \\
 &= (\mu - |\text{chl}(u)|) \cdot 2^{-n} + \nu - \text{deg}(u) + \sum_{v \in (\text{Nh}(u) \cap \mathcal{S}) \setminus \{u\}} 1 + \sum_{v \in \text{chl}(u)} 2^{-n} \\
 &= \mu \cdot 2^{-n} - |\text{chl}(u)| \cdot 2^{-n} + \nu - \text{deg}(u) + \text{deg}(u) + |\text{chl}(u)| \cdot 2^{-n} \\
 &= \mu \cdot 2^{-n} + \nu
 \end{aligned} \tag{5}$$

□

### 5.3 Analysis of Fixation Probability

In this section we present detailed analysis of the fixation probability and we start with the outline of the proof.

#### 5.3.1 Outline of the proof

Recall Figure 1 of the main article (and also an illustration VIDEO), which illustrates the four stages to fixation, which we outline here.

- (A) In stage 1 we consider the event  $\mathcal{E}_1$  that a mutant arises in one of the branches (i.e., outside the sink  $\mathcal{S}$ ). We show that event  $\mathcal{E}_1$  happens whp.
- (B) In stage 2 we consider the event  $\mathcal{E}_2$  that a mutant occupies a vertex  $v$  of the branches which is a neighbor to the sink. We show that given event  $\mathcal{E}_1$  the event  $\mathcal{E}_2$  happens whp.

- (C) In stage 3 we consider the event  $\mathcal{E}_3$  that the mutants fixate in the sink. We show that given  $\mathcal{E}_2$  the event  $\mathcal{E}_3$  happens whp.
- (D) In stage 4 we consider the event  $\mathcal{E}_4$  that the mutants fixate in all the branches. We show that given  $\mathcal{E}_3$  the event  $\mathcal{E}_4$  happens whp.

**Crux of the proof.** Before the details of the proof we present the main crux of the proof. We say a vertex  $v \notin \mathcal{S}$  hits the sink when it places an offspring to the sink. First, our construction ensures that the sink is isothermal. Second, our construction ensures that a mutant appearing in a branch reaches to a vertex adjacent to the sink, and hits the sink with a mutant polynomially many times. Third, our construction also ensures that the sink reaches a homogeneous configuration whp between any two hits to the sink. We now describe two crucial events.

- Consider that a mutant is adjacent to a sink of residents. Every time a mutant is introduced in the sink it has a constant probability (around  $1 - 1/r$  for large population) of fixation since the sink is isothermal. The polynomially many hits of the sink by mutants ensure that the sink becomes mutants whp.
- In contrast consider that a resident is adjacent to a sink. Every time a resident is introduced in the sink it has exponentially small probability (around  $(r-1)/(r^{|\mathcal{S}|}-1)$ ) of fixation.

Hence, given a sink of mutants, the probability (say,  $\eta_1 = 2^{-\Omega(|\mathcal{S}|)}$ ) that the residents win over the sink is exponentially small. Given a sink of mutant, the probability that the sink wins over a branch  $B_j$  is also exponentially small (say,  $\eta_2 = 2^{-O(|B_j|)}$ ). More importantly the ratio of  $\eta_1/\eta_2$  is also exponentially small (by Proposition 1 regarding the sizes of the sink and branches). Using this property, we show that fixation the mutants reach fixation whp. We now analyze each stage in detail.

### 5.3.2 Analysis of Stage 1: Event $\mathcal{E}_1$

**Lemma 3.** Consider the event  $\mathcal{E}_1$  that the initial mutant is placed at a vertex outside the sink. Formally, the event  $\mathcal{E}_1$  is that  $X_0 \cap \mathcal{S} = \emptyset$ . The event  $\mathcal{E}_1$  happens with probability at least  $1 - O(n^{-\varepsilon/3})$ , i.e., the event  $\mathcal{E}_1$  happens whp.

*Proof.* We examine the uniform and temperature initialization schemes separately.

- (*Uniform initialization*): The initial mutant is placed on a vertex  $u \notin \mathcal{S}$  with probability

$$\sum_{u \notin \mathcal{S}} \frac{1}{n} = \frac{|V \setminus \mathcal{S}|}{n} = \frac{n - n^{1-\gamma}}{n} = 1 - \frac{n^{1-\gamma}}{n} = 1 - O(n^{-\varepsilon/3});$$

since  $\gamma = \varepsilon/3$ .

- (*Temperature initialization*): For any vertex  $u \notin \mathcal{S}$ , we have

$$\sum_{v \in \text{Nh}(u) \setminus \{u\}} w(u, v) \leq \sum_{v \in \text{Nh}(u) \setminus \{u\}} 2^{-n} = 2^{-\Omega(n)};$$

whereas since  $\text{diam}(G) \leq n^{1-\varepsilon}$  we have

$$w(u, u) = n^{-2 \cdot \lambda(u)} \geq n^{-2 \cdot \text{diam}(G)} \geq n^{-O(n^{1-\varepsilon})}.$$

Note that

$$n^{-O(n^{1-\varepsilon})} = 2^{-O(n^{1-\varepsilon} \cdot \log n)} \gg 2^{-O(n)}.$$

Let  $A = w(u, u)$  and  $B = \sum_{v \in \text{Nh}(u) \setminus \{u\}} w(u, v)$ , and we have

$$\frac{w(u, u)}{w(u)} = \frac{A}{A+B} = 1 - \frac{B}{A+B} = 1 - \frac{2^{-\Omega(n)}}{n^{-O(n^{1-\varepsilon})} + 2^{-\Omega(n)}} = 1 - \frac{2^{-\Omega(n)}}{n^{-O(n^{1-\varepsilon})}} = 1 - 2^{-\Omega(n)}.$$

Then the desired event happens with probability at least

$$\begin{aligned} \sum_{u \notin \mathcal{S}} \mathbb{P}^\top[\mathcal{X}_0 = \{u\}] &= \sum_{u \notin \mathcal{S}} \frac{\mathbb{T}(u)}{n} = \frac{1}{n} \cdot \sum_{u \notin \mathcal{S}} \sum_{v \in \text{Nh}(u)} \frac{w(u, v)}{w(v)} \geq \frac{1}{n} \cdot \sum_{u \notin \mathcal{S}} \frac{w(u, u)}{w(u)} \geq \frac{1}{n} \cdot \sum_{u \notin \mathcal{S}} (1 - 2^{-\Omega(n)}) \\ &= \frac{|V \setminus \mathcal{S}|}{n} \cdot (1 - 2^{-\Omega(n)}) = \frac{n - n^{1-\gamma}}{n} \cdot (1 - 2^{-\Omega(n)}) = (1 - n^{-\gamma}) \cdot (1 - 2^{-\Omega(n)}) \\ &= 1 - O(n^{-\varepsilon/3}) \end{aligned}$$

since  $\gamma = \varepsilon/3$ . The desired result follows. □

### 5.3.3 Analysis of Stage 2: Event $\mathcal{E}_2$

The following lemma states that if a mutant is placed on a vertex  $w$  outside the sink, then whp the mutant will propagate to the ancestor  $v$  of  $w$  at distance  $\lambda(v) = 1$  from the sink (i.e., the parent of  $v$  belongs to the sink). This is a direct consequence of the weight assignment, which guarantees that for every vertex  $u \notin \mathcal{S}$ , the individual occupying  $u$  will place an offspring on the parent of  $u$  before some neighbor of  $u$  places an offspring on  $u$ , and this event happens with probability at least  $1 - O(n^{-1})$ .

**Lemma 4.** *Consider that at some time  $j$  the configuration of the Moran process on  $G^w$  is  $\mathcal{X}_j = \{w\}$  with  $w \notin \mathcal{S}$ . Let  $v \in \text{anc}(w)$  with  $\lambda(v) = 1$ , i.e.,  $v$  is the ancestor of  $w$  and  $v$  is adjacent to the sink. Then a subsequent configuration  $\mathcal{X}_t$  with  $v \in \mathcal{X}_t$  is reached with probability  $1 - O(n^{-1})$ , i.e., given event  $\mathcal{E}_1$ , the event  $\mathcal{E}_2$  happens whp.*

*Proof.* Let  $t$  be the first time such that  $v \in \mathcal{X}_t$  (possibly  $t = \infty$ , denoting that  $v$  never becomes mutant). Let  $s_i$  be the random variable such that

$$s_i = \begin{cases} |\mathcal{X}_i \cap \text{anc}(w)| & \text{if } i < t \\ |\text{anc}(w)| & \text{if } i \geq t \end{cases}$$

In words,  $s_i$  counts the number of mutant ancestors of  $u$  until time  $t$ . Given the current configuration  $\mathcal{X}_i$  with  $0 < s_i < |\text{anc}(w)|$ , let  $u = \arg \min_{z \in \mathcal{X}_i \cap \text{anc}(w)} \lambda(z)$ . The probability that  $s_{i+1} = s_i + 1$  is lowerbounded by the probability that  $u$  reproduces and places an offspring on  $\text{par}(u)$ . Similarly, the probability that  $s_{i+1} = s_i - 1$  is upperbounded by the probability that (i)  $\text{par}(u)$  reproduces and places an offspring on  $u$ , plus (ii) the probability that some  $z \in \text{des}(u) \setminus \mathcal{X}_i$  reproduces and places an offspring on  $\text{par}(z)$ .

We now proceed to compute the above probabilities. Consider any configuration  $\mathcal{X}_i$ , and let  $z$  be any child of  $u$  and  $z'$  any child of  $z$ . The above probabilities crucially depend on the following quantities:

$$\frac{w(u, \text{par}(u))}{w(u)}; \quad \frac{w(u, \text{par}(u))}{w(\text{par}(u))}; \quad \sum_{z_i \in \text{des}(u)} \frac{w(\text{par}(z_i), z_i)}{w(z_i)}.$$

Recall that

- $w(u, \text{par}(u)) = 2^{-n} \cdot n^{-4 \cdot \lambda(\text{par}(u))}$
- $w(u, x) = 2^{-n} \cdot n^{-4 \cdot \lambda(x)}$
- $w(z, z') = 2^{-n} \cdot n^{-4 \cdot \lambda(z)}$
- $w(\text{par}(u), \text{par}(\text{par}(u))) = 2^{-n} \cdot n^{-4 \cdot \lambda(\text{par}(\text{par}(u)))}$
- $w(u, u) = n^{-2 \cdot \lambda(u)}$
- $w(\text{par}(u), \text{par}(u)) = n^{-2 \cdot \lambda(\text{par}(u))}$
- $w(z, z) = n^{-2 \cdot \lambda(z)}$

Thus, we have

$$\begin{aligned}\frac{w(u, \text{par}(u))}{w(u)} &= \frac{w(u, \text{par}(u))}{w(u, u) + w(u, \text{par}(u)) + |\text{chl}(u)| \cdot w(u, x)} = \frac{2^{-n} \cdot n^{-4 \cdot (\lambda(u)-1)}}{O(n^{-2 \cdot \lambda(u)})} \\ &= \Omega(2^{-n} \cdot n^{-2 \cdot (\lambda(u)-2)})\end{aligned}\quad (6)$$

$$\begin{aligned}\frac{w(u, \text{par}(u))}{w(\text{par}(u))} &= \frac{w(u, \text{par}(u))}{w(\text{par}(u), \text{par}(u)) + w(\text{par}(u), \text{par}(\text{par}(u))) + |\text{chl}(\text{par}(u))| \cdot w(u, \text{par}(u))} \\ &= \frac{2^{-n} \cdot n^{-4 \cdot (\lambda(u)-1)}}{\Omega(n^{-2 \cdot (\lambda(u)-1)})} = O(2^{-n} \cdot n^{-2 \cdot (\lambda(u)-1)})\end{aligned}\quad (7)$$

$$\begin{aligned}\sum_{z_i \in \text{des}(u)} \frac{w(\text{par}(z_i), z_i)}{w(z_i)} &= |\text{des}(u)| \cdot \frac{w(u, z)}{w(z, z) + w(u, z) + |\text{chl}(z)| \cdot w(z, z')} \\ &\leq |\text{des}(u)| \cdot \frac{2^{-n} \cdot n^{-4 \cdot \lambda(u)}}{\Omega(n^{-2 \cdot (\lambda(u)+1)})} = n \cdot O(2^{-n} \cdot n^{-2 \cdot (\lambda(u)-1)}) \\ &= O(2^{-n} \cdot n^{-2 \cdot \lambda(u)+3})\end{aligned}\quad (8)$$

Thus, using Eq. (6), Eq. (7) and Eq. (8), we obtain

$$\begin{aligned}\frac{\mathbb{P}[s_{i+1} = s_i + 1]}{\mathbb{P}[s_{i+1} = s_i - 1]} &\geq \frac{\frac{r}{F(X')} \cdot \frac{w(u, \text{par}(u))}{w(u)}}{\frac{1}{F(X')} \cdot \left( \frac{w(u, \text{par}(u))}{w(\text{par}(u))} + \sum_{z_i \in \text{des}(u)} \frac{w(\text{par}(z_i), z_i)}{w(z_i)} \right)} \\ &= \frac{\Omega(2^{-n} \cdot n^{-2 \cdot (\lambda(u)-2)})}{O(2^{-n} \cdot n^{-2 \cdot (\lambda(u)-1)}) + O(2^{-n} \cdot n^{-2 \cdot \lambda(u)+3})} = \Omega(n)\end{aligned}\quad (9)$$

Let  $\alpha(n) = 1 - O(n^{-1})$  and consider a one-dimensional random walk  $P : s'_0, s'_1, \dots$  on states  $0 \leq i \leq |\text{anc}(w)|$ , with transition probabilities

$$\mathbb{P}[s'_{i+1} = \ell | s'_i] = \begin{cases} \alpha(n) & \text{if } 0 < s'_i < |\mathcal{S}| \text{ and } \ell = s'_i + 1 \\ 1 - \alpha(n) & \text{if } 0 < s'_i < |\mathcal{S}| \text{ and } \ell = s'_i - 1 \\ 0 & \text{otherwise} \end{cases}\quad (10)$$

Using Eq. (9), we have that

$$\frac{\mathbb{P}[s'_{i+1} = s'_i + 1]}{\mathbb{P}[s'_{i+1} = s'_i - 1]} = \frac{\alpha(n)}{1 - \alpha(n)} = \Omega(n) \leq \frac{\mathbb{P}[s_{i+1} = s_i + 1]}{\mathbb{P}[s_{i+1} = s_i - 1]}.$$

Hence the probability that  $s_\infty = |\text{anc}(w)|$  is lowerbounded by the probability that  $s'_\infty = |\text{anc}(w)|$ . The latter event occurs with probability  $1 - O(n^{-1})$  (see e.g., [13], [22, Section 6.3]), as desired.  $\square$

### 5.3.4 Analysis of Stage 3: Event $\mathcal{E}_3$

We now focus on the evolution on the sink  $\mathcal{S}$ , and establish several useful results.

1. First, we show that  $G^w[\mathcal{S}]$  is isothermal (Lemma 5)
2. Second, the above result implies that the sink behaves as a well-mixed population. Considering advantageous mutants ( $r > 1$ ) this implies the following (Lemma 6).
  - (a) Every time a mutant hits a sink of only residents, then the mutant has at least a *constant* probability of fixating in the sink.
  - (b) In contrast, every time a resident hits a sink of only mutants, then the resident has *exponentially small* probability of fixating in the sink.
3. Third, we show that an initial mutant adjacent to the sink, hits the sink a polynomial number of times (Lemma 7).
4. Finally, we show that an initial mutant adjacent to the sink ensures fixating in the sink whp (Lemma 8), i.e., we show given event  $\mathcal{E}_2$  the event  $\mathcal{E}_3$  happens whp.

We start with observing that the sink is isothermal, which follows by a direct application of the definition of isothermal (sub)graphs [17].

**Lemma 5.** *The graph  $G^w[\mathcal{S}]$  is isothermal.*

*Proof.* Consider any vertex  $u \in \mathcal{S} \setminus \mathcal{F}$ . We have

$$\begin{aligned}
\mathbb{T}[X](u) &= \sum_{v \in \text{Nh}(u) \cap \mathcal{S}} \frac{w[\mathcal{S}](v, u)}{w[\mathcal{S}](v)} = \frac{w[\mathcal{S}](u, u)}{w[\mathcal{S}](u)} + \sum_{v \in (\text{Nh}(u) \setminus \{u\}) \cap \mathcal{S}} \frac{w[\mathcal{S}](v, u)}{w[\mathcal{S}](v)} \\
&= \frac{w(u, u)}{w(u)} + \sum_{v \in (\text{Nh}(u) \setminus \{u\}) \cap \mathcal{S}} \frac{w(v, u)}{w(v)} \\
&= \frac{1}{\mu \cdot 2^{-n} + \nu} \cdot \left( w(u, u) + \sum_{v \in (\text{Nh}(u) \setminus \{u\}) \cap \mathcal{S}} 1 \right) \\
&= \frac{1}{\mu \cdot 2^{-n} + \nu} \cdot (\mu \cdot 2^{-n} + \nu - \deg(u) + \deg(u)) \\
&= 1
\end{aligned}$$

since by Lemma 2 we have  $w(u) = \mu \cdot 2^{-n} + \nu$ . Similarly, consider any  $u \in \mathcal{F}$ . We have

$$\begin{aligned}
\mathbb{T}[X](u) &= \sum_{v \in \text{Nh}(u) \cap \mathcal{S}} \frac{w[\mathcal{S}](v, u)}{w[\mathcal{S}](v)} = \frac{w[\mathcal{S}](u, u)}{w[\mathcal{S}](u)} + \sum_{v \in (\text{Nh}(u) \setminus \{u\}) \cap \mathcal{S}} \frac{w[\mathcal{S}](v, u)}{w[\mathcal{S}](v)} \\
&= \frac{w(u, u) + \sum_{v \in \text{Nh}(u) \setminus \mathcal{S}} w(u, v)}{w(u)} + \sum_{v \in (\text{Nh}(u) \setminus \{u\}) \cap \mathcal{S}} \frac{w(v, u)}{w(v)} \\
&= \frac{1}{\mu \cdot 2^{-n} + \nu} \cdot \left( w(u, u) + \sum_{v \in \text{Nh}(u) \setminus \mathcal{S}} 2^{-n} + \sum_{v \in (\text{Nh}(u) \setminus \{u\}) \cap \mathcal{S}} 1 \right) \\
&= \frac{1}{\mu \cdot 2^{-n} + \nu} \cdot ((\mu - |\text{chl}(u)|) \cdot 2^{-n} + \nu - \deg(u) + |\text{chl}(u)| \cdot 2^{-n} + \deg(u)) \\
&= 1
\end{aligned}$$

Thus for all  $u \in \mathcal{S}$  we have  $\mathbb{T}[X](u) = 1$ , as desired. □

**Lemma 6.** *Consider that at some time  $j$  the configuration of the Moran process on  $G^w$  is  $X_j$ .*

1. If with  $|\mathcal{S} \cap X_j| \geq 1$ , i.e., at least one mutant in the sink, then a subsequent configuration  $X_t$  with  $\mathcal{S} \subseteq X_t$  will be reached with probability at least  $1 - r^{-1} - 2^{-\Omega(n)}$  (mutants fixate in the sink with constant probability).
2. If  $|\mathcal{S} \setminus X_j| = 1$ , i.e., exactly one resident in the sink, then a subsequent configuration  $X_t$  with  $\mathcal{S} \subseteq X_t$  will be reached with probability at least  $1 - 2^{-\Omega(m)}$ , where  $m = n^{1-\gamma}$  (mutants fixate in the sink with probability exponentially close to 1).

*Proof.* Given a configuration  $X_i$ , denote by  $s_i = |\mathcal{S} \cap X_i|$ . Let  $X_i$  be any configuration of the Moran process with  $0 < s_i < |X_i|$ ,  $u$  be the random variable that indicates the vertex that is chosen for reproduction in  $X_i$ , and  $X_{i+1}$  be the random variable that indicates the configuration of the population in the next step. By Lemma 5, the subgraph  $G^w[\mathcal{S}]$  induced by the sink  $\mathcal{S}$  is isothermal, thus

$$\frac{\mathbb{P}[s_{i+1} = s_i - 1 | u \in \mathcal{S}]}{\mathbb{P}[s_{i+1} = s_i + 1 | u \in \mathcal{S}]} = \frac{1}{r}. \quad (11)$$

Additionally,

$$\begin{aligned} \mathbb{P}[s_{i+1} = s_i - 1 | u \notin \mathcal{S}] &\leq \sum_{\substack{v \in \mathcal{F} \\ u \in \text{chl}(v)}} \left( \frac{1}{F(X_i)} \cdot \frac{w(u, v)}{w(u)} \right) \leq n^{-1} \cdot \sum_{\substack{v \in \mathcal{F} \\ u \in \text{chl}(v)}} \frac{2^{-n}}{n^{-2}} \\ &\leq n^{-1} \cdot n \cdot 2^{-n} \cdot n^2 = O(n^2 \cdot 2^{-n}) \end{aligned} \quad (12)$$

since  $1/F(X_i) \leq n^{-1}$ ,  $w(u, v) = 2^{-n}$  and  $w(u, u) = n^{-2}$ . Moreover, as  $\mathcal{S}$  is heterogeneous, it contains at least a mutant vertex  $v$  and a resident vertex  $w \in \text{Nh}(v)$ , and  $v$  reproduces with probability  $r/F(X_i) \geq n^{-1}$ , and replaces the individual  $v \in \mathcal{S}$  with probability at least  $1/w(v)$ . Hence we have

$$\mathbb{P}[s_{i+1} = s_i + 1 | u \in \mathcal{S}] \cdot \mathbb{P}[u \in \mathcal{S}] \geq \frac{1}{w(u)} \cdot \frac{r}{F(X_i)} \geq \frac{1}{\mu \cdot 2^{-n} + \nu} \cdot n^{-1} \geq \frac{1}{n \cdot 2^{-n} + n} \cdot n^{-1} = \Omega(n^{-2}) \quad (13)$$

since by Lemma 2 we have  $w(v) = \mu \cdot 2^{-n} + \nu$ . Using Eq. (11), Eq. (12) and Eq. (13), we have

$$\begin{aligned} \frac{\mathbb{P}[s_{i+1} = s_i - 1]}{\mathbb{P}[s_{i+1} = s_i + 1]} &= \frac{\mathbb{P}[s_{i+1} = s_i - 1 | u \in \mathcal{S}] \cdot \mathbb{P}[u \in \mathcal{S}] + \mathbb{P}[s_{i+1} = s_i - 1 | u \notin \mathcal{S}] \cdot \mathbb{P}[u \notin \mathcal{S}]}{\mathbb{P}[s_{i+1} = s_i + 1 | u \in \mathcal{S}] \cdot \mathbb{P}[u \in \mathcal{S}] + \mathbb{P}[s_{i+1} = s_i + 1 | u \notin \mathcal{S}] \cdot \mathbb{P}[u \notin \mathcal{S}]} \\ &\leq \frac{\mathbb{P}[s_{i+1} = s_i - 1 | u \in \mathcal{S}] \cdot \mathbb{P}[u \in \mathcal{S}] + \mathbb{P}[s_{i+1} = s_i - 1 | u \notin \mathcal{S}] \cdot \mathbb{P}[u \notin \mathcal{S}]}{\mathbb{P}[s_{i+1} = s_i + 1 | u \in \mathcal{S}] \cdot \mathbb{P}[u \in \mathcal{S}]} \\ &\leq \frac{\mathbb{P}[s_{i+1} = s_i - 1 | u \in \mathcal{S}]}{\mathbb{P}[s_{i+1} = s_i + 1 | u \in \mathcal{S}]} + O(n^2) \cdot \mathbb{P}[s_{i+1} = s_i - 1 | u \notin \mathcal{S}] = \frac{1}{r} + 2^{-\Omega(n)} \end{aligned} \quad (14)$$

Hence,  $s_j, s_{j+1}, \dots$  performs a one-dimensional random walk on the states  $0 \leq i \leq |\mathcal{S}|$ , with the ratio of transition probabilities given by Eq. (14). Let  $\alpha(n) = r/(r + 1 + 2^{-\Omega(n)})$  and consider the one-dimensional random walk  $\rho : s'_j, s'_{j+1}, \dots$  on states  $0 \leq i \leq |\mathcal{S}|$ , with transition probabilities

$$\mathbb{P}[s'_{i+1} = \ell | s'_i] = \begin{cases} \alpha(n) & \text{if } 0 < s'_i < |\mathcal{S}| \text{ and } \ell = s'_i + 1 \\ 1 - \alpha(n) & \text{if } 0 < s'_i < |\mathcal{S}| \text{ and } \ell = s'_i - 1 \\ 0 & \text{otherwise} \end{cases} \quad (15)$$

Using Eq. (14) we have that

$$\frac{\mathbb{P}[s'_{i+1} = s'_i - 1]}{\mathbb{P}[s'_{i+1} = s'_i + 1]} = \frac{1 - \alpha(n)}{\alpha(n)} = \frac{1}{r} + 2^{-\Omega(n)} \geq \frac{\mathbb{P}[s_{i+1} = s_i - 1]}{\mathbb{P}[s_{i+1} = s_i + 1]}.$$

Let  $\rho_1$  (resp.  $\rho_2$ ) be the probability that the Moran process starting on configuration  $X_j$  with  $|\mathcal{S} \cap X_j| \geq 1$  (resp.  $|\mathcal{S} \setminus X_j| = 1$ ) will reach a configuration  $X_t$  with  $\mathcal{S} \subseteq X_t$ . We have that  $\rho_1$  (resp.  $\rho_2$ ) is lowerbounded by the probability that  $\rho$  gets absorbed in  $s'_\infty = |\mathcal{S}|$  when it starts from  $s'_j = 1$  (resp.  $s'_j = |\mathcal{S}| - 1$ ). Let

$$\beta = \frac{\mathbb{P}[s'_{i+1} = s'_i - 1]}{\mathbb{P}[s'_{i+1} = s'_i + 1]} = \frac{1}{r} + 2^{-\Omega(n)} < 1;$$

and we have (see e.g., [13], [22, Section 6.3])

$$\rho_1 \geq \frac{1 - \beta}{1 - \beta^{|\mathcal{S}|}} \geq 1 - \beta = 1 - \frac{1}{r} - 2^{-\Omega(n)};$$

and

$$\rho_2 \geq 1 - \frac{1 - \beta^{-1}}{1 - \beta^{-|\mathcal{S}|}} \geq 1 - \frac{\beta^{-1}}{\beta^{-|\mathcal{S}|}} = 1 - \beta^{|\mathcal{S}|-1} = 1 - \left(\frac{1}{r} + 2^{-\Omega(n)}\right)^{n^{1-\gamma}-1} = 1 - 2^{-\Omega(n^{1-\gamma})};$$

since  $\beta^{-|\mathcal{S}|} > \beta^{-1}$  and thus  $(\beta^{-1} - 1)/(\beta^{-|\mathcal{S}|} - 1) \leq \beta^{-1}/\beta^{-|\mathcal{S}|}$ . The desired result follows.  $\square$

**Lemma 7.** Consider that at some time  $j$  the configuration of the Moran process on  $G^w$  is  $X_j$  such that  $v \in X_j$  for some  $v \notin \mathcal{S}$  that is adjacent to the sink ( $\lambda(v) = 1$ ). Then a mutant hits the sink at least  $n^{1/3}$  times with probability  $1 - O(n^{-1/3})$ .

*Proof.* For any configuration  $X_i$  occurring after  $X_j$ , let

1.  $A$  be the event that  $v$  places an offspring on  $\text{par}(v)$  in  $X_{i+1}$ , and
2.  $B$  be the event that a neighbor of  $v$  places an offspring on  $v$  in  $X_{i+1}$ ,

and let  $\rho_A$  and  $\rho_B$  be the corresponding probabilities. Using Eq. (6), we have

$$\rho_A = \frac{r}{F(X_i)} \cdot \frac{w(v, \text{par}(v))}{w(v)} = \Omega(n \cdot 2^{-n}); \quad (16)$$

and using Eq. (7) and Eq. (8)

$$\rho_B \leq \frac{r}{F(X_i)} \cdot \left( \frac{w(v, \text{par}(v))}{w(\text{par}(u))} + \sum_{z \in \text{chl}(v)} \frac{w(v, z)}{w(z)} \right) \leq \frac{r}{n} \cdot (2^{-n} + O(n \cdot 2^{-n})) = 2^{-\Omega(n)}. \quad (17)$$

since  $\text{par}(u) \in \mathcal{S}$  and by Lemma 2 we have  $w(\text{par}(u)) \geq 1$ . Let  $X$  be the random variable that counts the time required until event  $A$  occurs  $n^{1/3}$  times. Then, for all  $\ell \in \mathbb{N}$  we have  $\mathbb{P}[X \geq \ell] \leq \mathbb{P}[X' \geq \ell]$  where  $X'$  is a random variable that follows the negative binomial distribution on  $n^{1/3}$  failures with success rate  $\rho_{X'} = 1 - O(n \cdot 2^{-n}) \leq \rho_A$  (using Eq. (16)). The expected value of  $X'$  is

$$\mathbb{E}[X'] = \frac{\rho_{X'} \cdot n^{1/3}}{1 - \rho_{X'}} = O\left(\frac{1 - n \cdot 2^{-n}}{n^{2/3} \cdot 2^{-n}}\right).$$

Let  $\alpha = 2^n \cdot n^{-1/3}$ , and by Markov's inequality, we have

$$\mathbb{P}[X' \geq \alpha] \leq \frac{\mathbb{E}[X']}{\alpha} = \frac{O\left(\frac{1 - n \cdot 2^{-n}}{n^{2/3} \cdot 2^{-n}}\right)}{2^n \cdot n^{-1/3}} = O(n^{-1/3}).$$

Similarly, let  $Y$  be the random variable that counts the time required until event  $B$  occurs. Then, for all  $\ell \in \mathbb{N}$ , we have  $\mathbb{P}[Y \leq \ell] \leq \mathbb{P}[Y' \leq \ell]$ , where  $Y'$  is a geometrically distributed variable with rate  $\rho_{Y'} = 2^{-\Omega(n)} \geq \rho_B$  (using Eq. (17)). Then

$$\mathbb{P}[Y' \leq \alpha] = 1 - (1 - \rho_{Y'})^\alpha = O(n^{-1/3});$$

and thus

$$\mathbb{P}[Y \leq X] \leq \mathbb{P}[Y \leq \alpha] + \mathbb{P}[X \geq \alpha] \leq \mathbb{P}[Y' \leq \alpha] + \mathbb{P}[X' \geq \alpha] = O(n^{-1/3}). \quad (18)$$

Hence, with probability at least  $1 - O(n^{-1/3})$ , the vertex  $v$  places an offspring on  $\text{par}(v)$  at least  $n^{1/3}$  times before it is replaced by a neighbor. The desired result follows.  $\square$

**Lemma 8.** *Consider that at some time  $j$  the configuration of the Moran process on  $G^w$  is  $X_j$  with  $v \in X_j$  for some  $v \notin \mathcal{S}$  that is adjacent to the sink ( $\lambda(v) = 1$ ). Then a subsequent configuration  $X_t$  with  $\mathcal{S} \subseteq X_t$  (mutants fixating in the sink) is reached with probability  $1 - O(n^{-1/3})$ , i.e., given event  $\mathcal{E}_2$ , the event  $\mathcal{E}_3$  happens whp.*

*Proof.* By Lemma 7, we have that with probability at least  $\Omega(n^{1/3})$ , the vertex  $v$  places an offspring on  $\text{par}(v)$  at least  $n^{1/3}$  times before it is replaced by a neighbor. Let  $t_i$  be the time that  $v$  places its  $i$ -th offspring on  $\text{par}(v)$ , with  $1 \leq i \leq n^{1/3}$ . Let  $A_i$  be the event that a configuration  $X_t$  is reached, where  $t \geq t_i$  and such that  $\mathcal{S} \subseteq X_t$ . By Lemma 6, we have  $\mathbb{P}[A_i] \geq 1 - r^{-1} - 2^{-\Omega(n)}$ . Moreover, with probability  $1 - 2^{-\Omega(n)}$ , at each time  $t_i$  the sink is in a homogeneous state, i.e., either  $\mathcal{S} \subseteq X_{t_i}$  or  $\mathcal{S} \cap X_{t_i} = \emptyset$ . The proof is similar to that of Lemma 9, and is based on the fact that every edge which has one end on the sink and the other outside the sink has exponentially small weight (i.e.,  $2^{-n}$ ), whereas the sink  $G^w[\mathcal{S}]$  resolves to a homogeneous state in polynomial time with probability exponentially close to 1. It follows that with probability at least  $p = 1 - 2^{-\Omega(n)}$ , the events  $\bar{A}_i$  are pairwise independent, and thus

$$\mathbb{P}[\bar{A}_1 \cap \bar{A}_2 \cdots \cap \bar{A}_{n^{1/3}}] \leq p \cdot \prod_{i=1}^{n^{1/3}} \mathbb{P}[\bar{A}_i] + (1-p) \leq \prod_{i=1}^{n^{1/3}} (1 - \mathbb{P}[A_i]) + 2^{-\Omega(n)} \leq \left(r^{-1} + 2^{-\Omega(n)}\right)^{n^{1/3}} + 2^{-\Omega(n)}. \quad (19)$$

Finally, starting from  $X_0 = \{u\}$ , the probability that a configuration  $X_t$  is reached such that  $\mathcal{S} \subseteq X_t$  is lowerbounded by the probability of the events that

1. the ancestor  $v$  of  $u$  is eventually occupied by a mutant, and
2.  $v$  places at least  $n^{1/3}$  offsprings to  $\text{par}(v) \in \mathcal{S}$  before a neighbor of  $v$  places an offspring on  $v$ , and
3. the event  $\bar{A}_1 \cap \bar{A}_2 \cdots \cap \bar{A}_{n^{1/3}}$  does not occur.

Combining Lemma 4, Eq. (18) and Eq. (19), we obtain that the goal configuration  $X_t$  is reached with probability at least

$$(1 - O(n^{-1})) \cdot (1 - O(n^{-1/3})) \cdot (1 - \mathbb{P}[\bar{A}_1 \cap \bar{A}_2 \cdots \cap \bar{A}_{n^{1/3}}]) = 1 - O(n^{-1/3});$$

as desired.  $\square$

### 5.3.5 Analysis of Stage 4: Event $\mathcal{E}_4$

In this section we present the last stage to fixation. This is established in four intermediate steps.

1. First, we consider the event of some vertex in the sink placing an offspring in one of the branches, while the sink is heterogeneous. We show that this event has exponentially small probability of occurring (Lemma 9).
2. We introduce the *modified* Moran process which favors residents when certain events occur, more than the conventional Moran process. This modification underapproximates the fixation probability of mutants, but simplifies the analysis.
3. We define a set of simple Markov chains  $\mathcal{M}_j$  and show that the fixation of mutants on the  $j$ -th branch  $T_{m_j}^{y_j}$  is captured by the absorption probability to a specific state of  $\mathcal{M}_j$  (Lemma 11). This absorption probability is computed in Lemma 10.
4. Finally we combine the above steps in Lemma 12 to show that if the sink is occupied by mutants (i.e., given that event  $\mathcal{E}_3$  holds), the mutants eventually fixate in the graph (i.e., event  $\mathcal{E}_4$  holds) whp.

We start with an intermediate lemma, which states that while the sink is heterogeneous, the probability that a node from the sink places an offspring to one of the branches is exponentially small.



**Lemma 9.** For any configuration  $X_j$  with  $|\mathcal{S} \setminus X_j| = 1$ , let  $t_1 \geq j$  be the first time such that  $\mathcal{S} \subseteq X_{t_1}$  (possibly  $t_1 = \infty$ ), and  $t_2 \geq j$  the first time in which a vertex  $u \in \mathcal{F}$  places an offspring on some vertex  $v \in \text{Nh}(u) \setminus \mathcal{S}$ . We have that  $\mathbb{P}[t_2 < t_1] = 2^{-\Omega(m)}$ , where  $m = n^{1-\gamma}$ .

*Proof.* Given a configuration  $X_i$ , denote by  $s_i = |\mathcal{S} \cap X_i|$ . Recall from the proof of Lemma 8 that  $s_j, s_{j+1}, \dots$  performs a one-dimensional random walk on the states  $0 \leq i \leq |\mathcal{S}|$ , with the ratio of transition probabilities given by Eq. (14). Observe that in each  $s_i$ , the random walk changes state with probability at least  $n^{-2}$ , which is a lowerbound on the probability that the walk progresses to  $s_{i+1} = s_i + 1$  (i.e., the mutants increase by one). Consider that the walk starts from  $s_j$ , and let  $H_a$  be the expected absorption time,  $H_f$  the expected fixation time on state  $|\mathcal{S}|$ , and  $H_e$  the expected extinction time on state 0 of the random walk, respectively. The unlooped variant of the random walk  $\rho = s_i, s_{i+1}, \dots$  has expected absorption time  $O(n)$  [14], hence the random walk  $s_j, s_{j+1}, \dots$  has expected absorption time

$$H_a \leq n^2 \cdot O(n) = O(n^3);$$

and since by Lemma 6 for large enough  $n$  we have  $\mathbb{P}[s_\infty = |\mathcal{S}|] \geq \mathbb{P}[s_\infty = 0]$ , we have

$$H_a = \mathbb{P}[s_\infty = |\mathcal{S}|] \cdot H_f + \mathbb{P}[s_\infty = 0] \cdot H_e \implies H_f \leq 2 \cdot H_a = O(n^3).$$

Let  $t'_1$  be the random variable defined as  $t'_1 = t_1 - j$ , and we have

$$\mathbb{E}[t'_1 | t'_1 < \infty] = H_f = O(n^3);$$

i.e., given that a configuration  $X_{t_1}$  with  $\mathcal{S} \subseteq X_{t_1}$  is reached (thus  $t_1 < \infty$  and  $t'_1 < \infty$ ), the expected time we have to wait after time  $j$  for this event to happen equals the expected fixation time  $H_f$  of the random walk  $s_j, s_{j+1}, \dots$ . Let  $\alpha = 2^{\frac{n}{2}}$ , and by Markov's inequality, we have

$$\mathbb{P}[t'_1 > \alpha | t'_1 < \infty] \leq \frac{\mathbb{E}[t'_1 | t'_1 < \infty]}{\alpha} = n^3 \cdot 2^{-\frac{n}{2}}. \quad (20)$$

Consider any configuration  $X_i$ . The probability  $p$  that a vertex  $u \in \mathcal{F}$  places an offspring on some vertex  $v \in \text{Nh}(u) \setminus \mathcal{S}$  is at most

$$p \leq \frac{r}{F(X_i)} \cdot \sum_{u \in \mathcal{F}} \sum_{v \in \text{Nh}(u) \setminus \mathcal{S}} \frac{w(u, v)}{w(u)} \leq r \cdot n^{-1} \cdot n^{1-\gamma} \cdot 2^{-n} \leq r \cdot n^2 \cdot 2^{-n}.$$

since  $w(u, v) = 2^{-n}$  and by Lemma 2 we have  $w(u) > 1$ . Let  $t'_2 = t_2 - i$ , and we have  $\mathbb{P}[t'_2 \leq \alpha] \leq \mathbb{P}[X \leq \alpha]$ , where  $X$  is a geometrically distributed random variable with rate  $\rho = r \cdot n^2 \cdot 2^{-n}$ . Since  $\mathbb{P}[t_2 < t_1] = \mathbb{P}[t'_2 < t'_1]$ , we have

$$\begin{aligned} \mathbb{P}[t_2 < t_1] &= \mathbb{P}[t'_2 < t'_1 | t'_1 < \infty] \cdot \mathbb{P}[t'_1 < \infty] + \mathbb{P}[t'_2 < t'_1 | t'_1 = \infty] \cdot \mathbb{P}[t'_1 = \infty] \\ &\leq \mathbb{P}[t'_2 < t'_1 | t'_1 < \infty] + \mathbb{P}[t'_1 = \infty] \\ &\leq \mathbb{P}[t'_2 < t'_1 | t_1 < \infty] + 2^{-\Omega(n^{1-\gamma})} \\ &\leq \mathbb{P}[t'_2 \leq \alpha | t'_1 < \infty] + \mathbb{P}[t'_1 > \alpha | t'_1 < \infty] + 2^{-\Omega(n^{1-\gamma})} \\ &\leq \mathbb{P}[t'_2 \leq \alpha | t'_1 < \infty] + n^3 \cdot 2^{-\frac{n}{2}} + 2^{-\Omega(n^{1-\gamma})} \\ &\leq \mathbb{P}[X \leq \alpha] + 2^{-\Omega(n^{1-\gamma})} \\ &\leq 1 - (1 - \rho)^\alpha + 2^{-\Omega(n^{1-\gamma})} \\ &\leq 1 - (1 - r \cdot n^2 \cdot 2^{-n})^{2^{n/2}} + 2^{-\Omega(n^{1-\gamma})} \\ &= 2^{-\Omega(n^{1-\gamma})} \end{aligned}$$

The second inequality holds since by Lemma 6 we have  $\mathbb{P}[t'_1 = \infty] = 2^{-\Omega(n^{1-\gamma})}$ . The fourth inequality comes from Eq. (20).  $\square$

To simplify the analysis, we replace the Moran process with a *modified* Moran process, which favors the residents (hence it is conservative) and allows for rigorous derivation of the fixation probability of the mutants.

**The modified Moran process.** Consider the Moran process on  $G^w$ , and assume there exists a first time  $t^* < \infty$  when a configuration  $X_{t^*}$  is reached such that  $\mathcal{S} \subseteq X_{t^*}$ . We underapproximate the fixation probability of the Moran process starting from  $X_{t^*}$  by the fixation probability of the *modified* Moran process  $\bar{X}_{t^*}, \bar{X}_{t^*+1}, \dots$ , which behaves as follows. Recall that for every vertex  $y_j$  with  $\lambda(y_j) = 1$ , we denote by  $T_{m_j}^{y_j}$  the subtree of  $\mathcal{T}_n^x$  rooted at  $y_j$ , which has  $m_j$  vertices. Let  $V_i$  be the set of vertices of  $T_{m_i}^{y_i}$ , and note that by construction  $m_i \leq n^{1-c}$ , while there are at most  $n$  such trees. The *modified* Moran process is identical to the Moran process, except for the following modifications.

1. Initially,  $\bar{X}_{t^*} = \mathcal{S}$ .
2. At any configuration  $\bar{X}_i$  with  $\mathcal{S} \subseteq \bar{X}_i$ , for all trees  $T_{m_j}^{y_j}$ , if a resident vertex  $u \in V_j$  places an offspring on some vertex  $v$  with  $u \neq v$ , then  $\bar{X}_{i+1} = \bar{X}_i \setminus V_j$  and  $|\mathcal{S} \setminus \bar{X}_{i+1}| = 1$  i.e., all vertices of  $T_{m_j}^{y_j}$  become residents and the sink is invaded by a single resident.
3. If the modified process reaches a configuration  $\bar{X}_i$  with  $\bar{X}_i \cap \mathcal{S} = \emptyset$ , the process instead transitions to configuration  $\bar{X}_i = \emptyset$ , i.e., if the sink becomes resident, then all mutants go extinct.
4. At any configuration  $\bar{X}_i$  with  $\mathcal{S} \setminus \bar{X}_i \neq \emptyset$ , if some vertex  $u \in \mathcal{F}$  places an offspring on some vertex  $v \in \text{Nh}(u) \setminus \mathcal{S}$ , then the process instead transitions to configuration  $\bar{X}_i = \emptyset$ , i.e., if while the sink is heterogeneous, an offspring is placed from the sink to a vertex outside the sink, the mutants go extinct.

Note that any time a case of Item 1-Item 4 applies, the Moran and modified Moran processes transition to configurations  $X_i$  and  $\bar{X}_i$  respectively, with  $\bar{X}_i \subseteq X_i$ . Thus, the fixation probability of the Moran process on  $G_n^w$  is underapproximated by the fixation probability of the modified Moran process (i.e., we have  $\mathbb{P}[X_\infty = V | t^* < \infty] \geq \mathbb{P}[\bar{X}_\infty = V]$ ). It is easy to see that Lemma 6 and Lemma 9 directly apply to the modified Moran process.

**The Markov chain  $\mathcal{M}_j$ .** Recall that  $T_{m_j}^{y_j}$  refers to the  $j$ -th branch of the weighted graph  $G^w$ , rooted at the vertex  $y_j$  and consisting of  $m_j$  vertices. We associate  $T_{m_j}^{y_j}$  with a Markov chain  $\mathcal{M}_j$  of  $m_j + 3$  vertices, which captures the number of mutants in  $T_{m_j}^{y_j}$ , and whether the state of the sink. Intuitively, a state  $0 \leq i \leq m_j$  of  $\mathcal{M}_j$  represents a configuration where the sink is homogeneous and consists only of mutants, and there are  $i$  mutants in the branch  $T_{m_j}^{y_j}$ . The state  $\mathcal{H}$  represents a configuration where the sink is heterogeneous, whereas the state  $\mathcal{D}$  represents a configuration where the mutants have gone extinct in the sink, and thus the modified Moran process has terminated. We first present formally the Markov chain  $\mathcal{M}_j$ , and later (in Lemma 11) we couple  $\mathcal{M}_j$  with the modified Moran process.

Consider any tree  $T_{m_j}^{y_j}$ , and let  $\alpha = 1/(n^3 + 1)$ . We define the Markov chain  $\mathcal{M}_j = (\mathcal{X}_j, \delta_j)$  as follows:

1. The set of states is  $\mathcal{X}_j = \{\mathcal{H}, \mathcal{D}\} \cup \{0, 1, \dots, m_j\}$
2. The transition probability matrix  $\delta_j : \mathcal{X}_j \times \mathcal{X}_j \rightarrow [0, 1]$  is defined as follows:
  - (a)  $\delta_j[i, i+1] = \alpha$  for  $0 \leq i < m_j$ ,
  - (b)  $\delta_j[i, 0] = 1 - \alpha$  for  $1 < i < m_j$ ,
  - (c)  $\delta_j[0, \mathcal{H}] = 1 - \alpha$ ,
  - (d)  $\delta_j[\mathcal{H}, 0] = 1 - 2^{-\Omega(m)}$ , and  $\delta_j[\mathcal{H}, \mathcal{D}] = 2^{-\Omega(m)}$ , where  $m = n^{1-\gamma}$ ,
  - (e)  $\delta_j[m_j, m_j] = \delta_j[\mathcal{D}, \mathcal{D}] = 1$ ,
  - (f)  $\delta_j[x, y] = 0$  for all other pairs  $x, y \in \mathcal{X}_j$

See Figure S5 for an illustration. The Markov chain  $\mathcal{M}_j$  has two absorbing states,  $\mathcal{D}$  and  $m_j$ . We denote by  $\rho_j$  the probability that a random walk on  $\mathcal{M}_j$  starting from state 0 will be absorbed in state  $m_j$ . The following lemma lowerbounds  $\rho_j$ , and comes from a straightforward analysis of  $\mathcal{M}_j$ .

**Lemma 10.** *For all Markov chains  $\mathcal{M}_j$ , we have  $\rho_j = 1 - 2^{-\Omega(m)}$ , where  $m = n^{1-\gamma}$ .*

*Proof.* Given a state  $a \in \mathcal{X}_j$ , we denote by  $x_a$  the probability that a random walk starting from state  $a$  will be absorbed in state  $m_j$ . Then  $\rho_j = x_0$ , and we have the following linear system

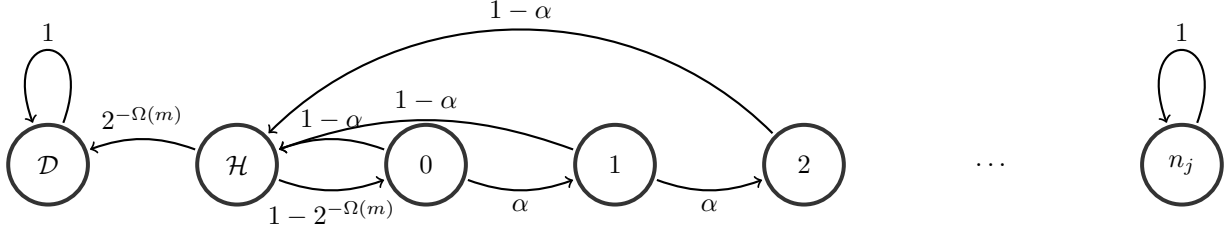


Figure S5: The Markov chain  $\mathcal{M}_j$  given a tree  $T_{n_j}^{x_j}$ .

$$\begin{aligned}
x_{\mathcal{H}} &= \delta[\mathcal{H}, 0] \cdot x_0 = \left(1 - 2^{-\Omega(n^{1-\gamma})}\right) \cdot x_0 \\
x_i &= \delta[i, \mathcal{H}] \cdot x_{\mathcal{H}} + \delta[i, i+1] \cdot x_{i+1} = (1 - \alpha) \cdot x_{\mathcal{H}} + \alpha \cdot x_{i+1} \quad \text{for } 0 \leq i < m_j \\
x_{m_j} &= 1
\end{aligned}$$

and thus

$$\begin{aligned}
x_{\mathcal{H}} &= \left(1 - 2^{-\Omega(n^{1-\gamma})}\right) \cdot \left(x_{\mathcal{H}} \cdot (1 - \alpha) \cdot \sum_{i=0}^{m_j} a^i + a^{m_j}\right) \\
\Rightarrow x_{\mathcal{H}} &= \left(1 - 2^{-\Omega(n^{1-\gamma})}\right) \cdot \left(x_{\mathcal{H}} \cdot (1 - a^{m_j-1}) + a^{m_j}\right) \\
\Rightarrow x_{\mathcal{H}} \left(1 - \left(1 - 2^{-\Omega(n^{1-\gamma})}\right) \cdot (1 - a^{m_j-1})\right) &= a^{m_j} \tag{21}
\end{aligned}$$

Note that

$$1 - \left(1 - 2^{-\Omega(n^{1-\gamma})}\right) \cdot (1 - a^{n_j-1}) \leq 2^{-\Omega(n^{1-\gamma})} + a^{n_j};$$

and from Eq. (21) we obtain

$$x_{\mathcal{H}} \geq \frac{\alpha^{n_j}}{2^{-\Omega(n^{1-\gamma})} + \alpha^{n_j}} = 1 - \frac{2^{-\Omega(n^{1-\gamma})}}{2^{-\Omega(n^{1-\gamma})} + \alpha^{n_j}} \geq 1 - 2^{-\Omega(n^{1-\gamma})} \cdot \alpha^{-n_j} = 1 - 2^{-\Omega(n^{1-\gamma})} \cdot (n^3 + 1)^{n^{1-c}} = 1 - 2^{-\Omega(n^{1-\gamma})};$$

since  $a = 1/(n^3 + 1)$  and by construction  $n_j \leq n^{1-c}$  and  $\gamma = \varepsilon/3 < \varepsilon/2 = c$ . Finally, we have that  $\rho_j = x_0 \geq x_{\mathcal{H}} = 1 - 2^{-\Omega(n^{1-\gamma})}$ , as desired.  $\square$

Given a configuration  $\bar{X}_k$  of the modified Moran process, we denote by  $\bar{\rho}_j(\bar{X}_k)$  the probability that the process reaches a configuration  $\bar{X}_\ell$  with  $\mathcal{S} \cup V_j \subseteq \bar{X}_\ell$ . The following lemma states that the probability  $\bar{\rho}_j(\bar{X}_\ell)$  is underapproximated by the probability  $\rho_j$ . The proof is by a coupling argument, which ensures that

1. every time the run on  $\mathcal{M}_j$  is on a state  $0 \leq i \leq m_j$ , there are at least  $i$  mutants placed on  $T_{m_j}^{y_j}$ , and
2. every time the modified Moran process transitions to a configuration where sink is heterogeneous (i.e., we reach a configuration  $X$  with  $\mathcal{S} \setminus X \neq \emptyset$ ), the run on  $\mathcal{M}_j$  transitions to state  $\mathcal{H}$ .

**Lemma 11.** Consider any configuration  $\bar{X}_\ell$  of the modified Moran process, with  $\mathcal{S} \subseteq \bar{X}_\ell$ , and any tree  $T_{m_j}^{y_j}$ . We have  $\bar{\rho}_j(\bar{X}_\ell) \geq \rho_j$ .

*Proof.* The proof is by coupling the modified Moran process and the Markov chain  $\mathcal{M}_j$ . To do so, we let the modified Moran process execute, and use certain events of that process as the source of randomness for a run in  $\mathcal{M}_j$ . We describe the coupling process in high level. Intuitively, every time the run on  $\mathcal{M}_j$  is on a state  $0 \leq i \leq m_j$ , there are

at least  $i$  mutants placed on  $T_{m_j}^{y_j}$ . Additionally, every time the modified Moran process transitions to a configuration where sink is heterogeneous (i.e., we reach a configuration  $X$  with  $\mathcal{S} \setminus X \neq \emptyset$ ), then the run on  $\mathcal{M}_j$  transitions to state  $\mathcal{H}$ . Finally, if the modified Moran process ends on a configuration  $X = \emptyset$ , then the run on  $\mathcal{M}_j$  gets absorbed to state  $\mathcal{D}$ . The coupling works based on the following two facts.

1. For every state  $0 < i < m_j$ , the ratio  $\delta_j[i, i+1]/\delta_j[i, i-1]$  is upperbounded by the ratio of the probabilities of increasing the number of mutant vertices in  $T_{m_j}^{y_j}$  by one, over decreasing that number by one and having the sink being invaded by a resident. Indeed, we have

$$\frac{\delta_j[i, i+1]}{\delta_j[i, i-1]} = \frac{\alpha}{1-\alpha} = \frac{1}{n^3};$$

while for every mutant vertex  $x$  of  $G$  with at last one resident neighbor, the probability that  $x$  becomes mutant in the next step of the modified Moran process over the probability that  $x$  becomes resident is at least  $1/n^3$  (this ratio is at least  $1/n^2$  for every resident neighbor  $y$  of  $x$ , and there are at most  $n$  such resident neighbors). The same holds for the ratio  $\delta_j[0, 1]/\delta_j[0, \mathcal{H}]$ .

2. The probability of transitioning from state  $\mathcal{H}$  to state  $0$  is upperbounded by the probability that once the mutant sink gets invaded by a resident the modified Moran process reaches a configuration where the sink consists of only mutants (using Lemma 6 and Lemma 9).

□

The following lemma captures the probability that the modified Moran process reaches fixation whp. That is, whp a configuration  $\bar{X}_i$  is reached which contains all vertices of  $G^w$ . The proof is based on repeated applications of Lemma 11 and Lemma 10, one for each subtree  $T_{m_j}^{y_j}$ .

**Lemma 12.** *Consider that at some time  $t^*$  the configuration of the Moran process on  $G^w$  is  $X_{t^*}$  with  $\mathcal{S} \subseteq X_{t^*}$ . Then, a subsequent configuration  $X_t$  with  $X_t = V$  is reached with probability at least  $1 - 2^{-\Omega(m)}$  where  $m = n^{1-\gamma}$ , i.e., given event  $\mathcal{E}_3$ , the event  $\mathcal{E}_4$  happens whp.*

*Proof.* It suffices to consider the modified Moran process on  $G$  starting from configuration  $\bar{X}_{t^*} = \mathcal{S}$ , and showing that whp we eventually reach a configuration  $\bar{X}_t = V$ . First note that if there exists a configuration  $\bar{X}_{t'}$  with  $V_i \subseteq \bar{X}_{t'}$  for any  $V_i$ , then for all  $t'' \geq t'$  with  $\bar{X}_{t''} \neq \emptyset$  we have  $V_i \subseteq \bar{X}_{t''}$ . Let  $t_1 = t^*$ . Since  $\mathcal{S} \subseteq \bar{X}_{t_1}$ , by Lemma 11, with probability  $\bar{\rho}_1(\bar{X}_{t_1}) \geq \rho_1$  there exists a time  $t_2 \geq t_1$  such that  $\mathcal{S} \cup V_1 \subseteq \bar{X}_{t_2}$ . Inductively, given the configuration  $\bar{X}_{t_i}$ , with probability  $\bar{\rho}_i(\bar{X}_{t_i}) \geq \rho_i$  there exists a time  $t_{i+1} \geq t_i$  such that  $\mathcal{S} \cup V_1 \cup \dots \cup V_i \subseteq \bar{X}_{t_{i+1}}$ . Since  $V = \mathcal{S} \cup (\bigcup_{i=1}^k V_i)$ , we obtain

$$\mathbb{P}[\bar{X}_\infty = V] \geq \prod_{i=1}^n \rho_i = \prod_{i=1}^n \left(1 - 2^{-\Omega(n^{1-\gamma})}\right) \geq \left(1 - 2^{-\Omega(n^{1-\gamma})}\right)^n = 1 - 2^{-\Omega(m)};$$

as by Lemma 10 we have that  $\rho_i = 1 - 2^{-\Omega(m)}$  for all  $i$ . The desired result follows. □

### 5.3.6 Main Positive Result

We are now ready to prove the main theorem of this section. First, combining Lemma 3, Lemma 4, Lemma 8 and Lemma 12, we obtain that if  $r > 1$ , then the mutants fixate  $G_n$  whp.

**Lemma 13.** *For any fixed  $\varepsilon > 0$ , for any graph  $G_n$  of  $n$  vertices and diameter  $\text{diam}(G_n) \leq n^{1-\varepsilon}$ , there exists a weight function  $w$  such that for all  $r > 1$ , we have  $\rho(G_n^w, r, U) = 1 - O(n^{-\varepsilon/3})$  and  $\rho(G_n^w, r, T) = 1 - O(n^{-\varepsilon/3})$ .*

It now remains to show that if  $r < 1$ , then the mutants go extinct whp. This is a direct consequence of the following lemma, which states that for any  $r > 1$ , the fixation probability of a mutant with relative fitness  $1/r$  is upperbounded by one minus the fixation probability of a mutant with relative fitness  $r$ , in the same population.

**Lemma 14.** *For any graph  $G_n$  and any weight function  $w$ , for all  $r \geq 1$ , we have that  $\rho(G_n^w, 1/r, U) \leq 1 - \rho(G_n^w, r, U)$ .*

*Proof.* Let  $\sigma$  be any irreflexive permutation of  $V$  (i.e.,  $\sigma(u) \neq u$  for all  $u \in V$ ), and observe that for every vertex  $u$ , the probability that a mutant of fitness  $1/r$  arising at  $u$  fixates in  $G_n$  is upperbounded by one minus the probability that a mutant of fitness  $r$  arising in  $\sigma(u)$  fixates in  $G_n$ . We have

$$\begin{aligned} \rho(G_n^w, 1/r, U) &= \frac{1}{n} \sum_u \rho(G_n^w, 1/r, u) \\ &\leq \frac{1}{n} \cdot \sum_u (1 - \rho(G_n^w, r, \sigma(u))) \\ &= 1 - \frac{1}{n} \cdot \sum_{\sigma(u)} \rho(G_n^w, r, u) \\ &= 1 - \rho(G_n^w, r, U) \end{aligned}$$

□

A direct consequence of the above lemma is that under uniform initialization, for any graph family where the fixation probability of advantageous mutants ( $r > 1$ ) approaches 1, the fixation probability of disadvantageous mutants ( $r < 1$ ) approaches zero. Since under our weight function  $w$  temperature initialization coincides with uniform initialization whp, Lemma 13 and Lemma 14 lead to the following corollary, which is our positive result.

**Theorem 5.** *Let  $\varepsilon > 0$  and  $n_0 > 0$  be any two fixed constants, and consider any sequence of unweighted, undirected graphs  $(G_n)_{n>0}$  such that  $\text{diam}(G_n) \leq n^{1-\varepsilon}$  for all  $n > n_0$ . There exists a sequence of weight functions  $(w_n)_{n>0}$  such that the graph family  $\mathcal{G} = (G_n^{w_n})$  is a (i) strong uniform, (ii) strong temperature, and (iii) strong convex amplifier.*

## 6 Simulation Results

In this section we present the details of computer simulation results.

### 6.1 Figure 3 of Main article

Figure 3 of main article shows how simple structures can be turned into strong amplifiers under uniform initialization by assigning weights according to our algorithm. Unless stated otherwise, the values plotted are obtained by simulating the process 10 000 times. For completeness, in Figure S7 we also present analogous comparisons for temperature initialization.

**Figure 3(A).** A Star on  $N$  vertices, denoted  $S_N$ , consists of a single vertex in the center and  $N - 1$  so-called *leaf* vertices connected to it. We consider  $N = 10, 20, \dots, 500$ .

1. Unweighted star: Exact fixation probability for a star under both uniform and temperature initialization follows from formula in [20].
2. Weighted star: The sink consists of the center vertex and  $\lfloor \sqrt{N} \rfloor$  other leaf vertices called sink-leaves. We use the following weights:

$$w(u, u) = \begin{cases} 0 & \text{if } u \text{ is the center,} \\ (N - |\mathcal{S}|) \cdot 2^{-N} + |\mathcal{S}| - 2 & \text{if } u \text{ is a sink-leaf,} \\ N^{-2} & \text{if } u \text{ is outside the sink,} \end{cases} \quad w(u, v) = \begin{cases} 1 & \text{if } u, v \in \mathcal{S}, \\ 2^{-N} & \text{otherwise.} \end{cases}$$

See Figure S6(a) for illustration.

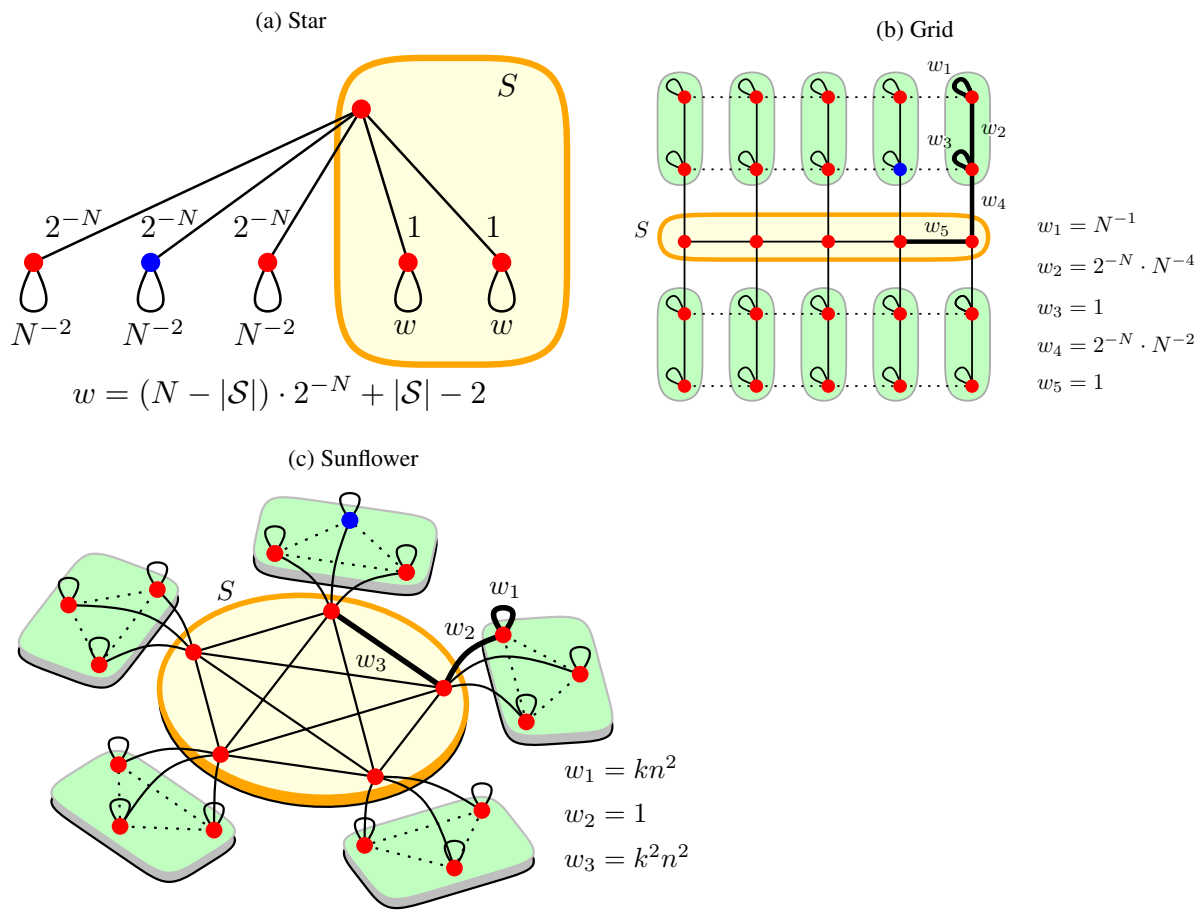


Figure S6

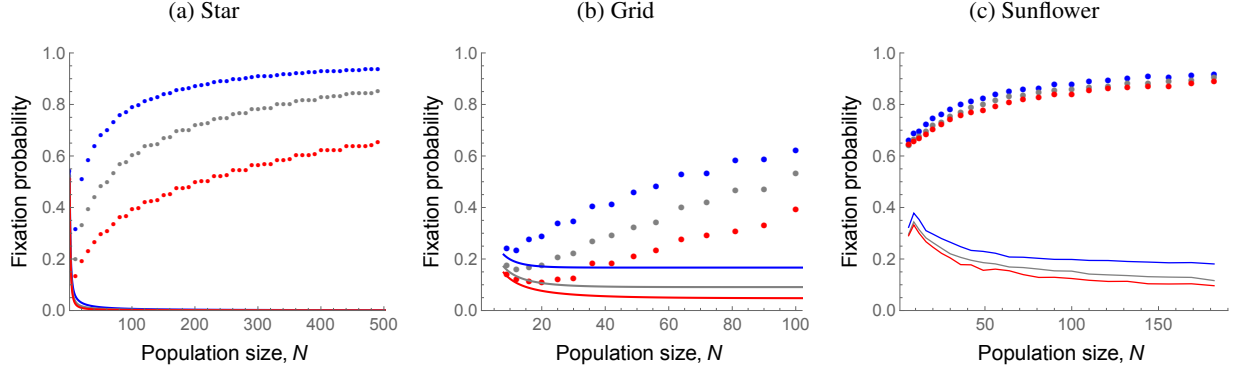


Figure S7

**Figure 3(B).** An  $a \times b$  Grid graph, denoted by  $G_{a,b}$ , is a graph on  $N = a \cdot b$  vertices aligned in a grid fashion with  $a$  rows and  $b$  columns where each vertex is connected to four other vertices (one above, below, to the left, and to the right). In order to avoid boundary conditions, the grid “wraps around”, i.e. the vertices in the first row are connected to the vertices in the last row and the same holds for columns. We consider  $n \times n$  and  $n \times (n + 1)$  Grid graphs of sizes  $N = 9, 12, 16, 20, \dots, 100$ .

1. Unweighted grid: Unweighted grid is isothermal so the fixation probability under both uniform and temperature initialization is given by  $\rho(G_{a,b}, r, \mathcal{U}) = \rho(G_{a,b}, r, \mathcal{T}) = (1 - 1/r)/(1 - 1/r^{ab})$ .
2. Weighted grid: For odd  $n$  the sink consists of vertices in the middle row and the rest is split into branches by assigning weight 0 to all the remaining horizontal edges. For even  $n$  we choose either of the two middle rows and proceed analogously. The weights on the remaining edges are defined as follows (recall that  $\lambda(u)$  is the distance from vertex  $u$  to the sink):

$$w(u, u) = \begin{cases} 0 & \text{if } u \in \mathcal{S}, \\ N^{-(l-1)} & \text{if } \lambda(u) = l, \end{cases} \quad w(u, v) = \begin{cases} 1 & \text{if } u, v \in \mathcal{S}, \\ 2^{-N} \cdot N^{-2l} & \text{if } \lambda(u) + 1 = \lambda(v) = l. \end{cases}$$

See Figure S6(b) for illustration.

**Figure 3(C).** An  $(n, k)$ -Sunflower graph is a graph on  $N = n(k + 1)$  vertices: a complete graph of size  $n$  in the center, and  $n$  surrounding *petals* which are complete graphs of size  $k$  each. Each petal is connected with all its vertices to a unique vertex from the center. We consider  $(n, n - 1)$  and  $(n, n - 2)$ -Sunflower graphs of sizes  $N = 6, 9, 12, 16, \dots, 182$ .

1. Unweighted sunflower: The values plotted are computed by simulating the process 10 000 times.
2. Weighted sunflower: We define sink  $\mathcal{S}$  as the complete graph in the center and assign zero weights to all edges within petals. We define the weights of the remaining edges as follows:

$$w(u, u) = \begin{cases} 0 & \text{if } u \in \mathcal{S}, \\ kn^2 & \text{otherwise,} \end{cases} \quad w(u, v) = \begin{cases} k^2n^2 & \text{if } u, v \in \mathcal{S}, \\ 1 & \text{otherwise.} \end{cases}$$

See Figure S6(c) for illustration.

## 6.2 Figure 4 of Main article

In Figure 4(A),(B),(C) we compare two realistic structures: the Mainland-island graph and the classical Well-mixed population modelled by a complete graph.

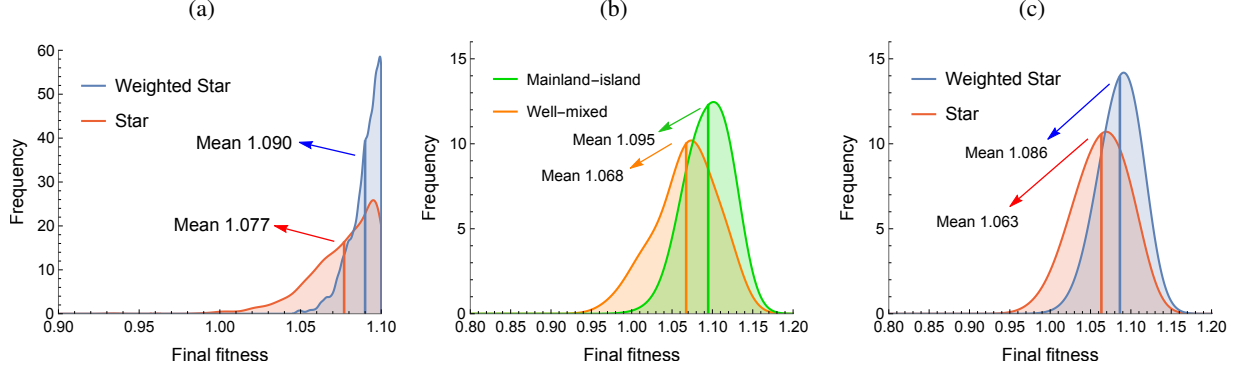


Figure S8

A complete graph on  $N$  vertices, denoted by  $K_N$ , consists of  $N$  vertices, all possible edges, and all possible self-loops.

An  $(n, k)$ -Mainland-island graph is a weighted graph on  $N = n(k + 1)$  vertices: a complete graph of size  $n$  in the center (“mainland”, denoted  $\mathcal{M}$ ), and  $n$  surrounding complete graphs of size  $k$  each (“islands”). Every vertex from the mainland is connected to every vertex of every island and no two vertices from different islands are connected.

In order to ensure that most of the time the offspring stays in the same land, the edge-weights on  $(n, k)$ -Mainland-island are defined as follows:

$$w(u, u) = 0, \quad w(u, v) = \begin{cases} k^2 n^4 & \text{if } u, v \in \mathcal{M}, \\ n^3 & \text{if } u \notin \mathcal{M}, v \notin \mathcal{M}, \\ 1 & \text{otherwise.} \end{cases}$$

Note that  $(n, k)$ -Mainland-island graph is not a strong amplifier – since it is self-loop free, this follows, for example, from Theorem 1.

**Figure 4(A).** We consider  $(n, 3)$ -Mainland-island graphs of sizes  $N = 4, 8, 12, \dots, 88$ . The values plotted are computed by simulating Moran process 1 000 times with the mutant being initialized uniformly at random to one of the islands.

For complete graphs  $K_N$ ,  $N = 4, 8, 12, \dots, 88$ , the fixation probability is given by  $(1 - 1/r)/(1 - 1/r^N)$ .

Note that even though Mainland-island graphs are not strong amplifiers, still they provide significant improvement over the well-mixed population.

**Figure 4(B).** In experiment *Selection of initial diversity*, given a range  $[r_1, r_2]$  of relative fitness values and a population of  $N$  individuals, we first select  $N$  values  $r_1 = \alpha_1 < \alpha_2 < \dots < \alpha_N = r_2$  uniformly spaced in the range  $[r_1, r_2]$  (i.e.  $\alpha_i = r_1 + (i - 1)(r_2 - r_1)/(N - 1)$ ). In each run, these values are randomly shuffled, assigned to the  $N$  individuals and the Moran process is executed until one individual fixates. Its fitness value is recorded. Figure 4(B) shows the distribution of this final fitness value as a probability density function over 1 000 trials. We consider  $N = 60$ , the range  $[r_1, r_2] = [0.9, 1.1]$  and two different graphs: the  $(15, 3)$ -Mainland-island graph (green) and the complete graph  $K_{60}$  (orange). The vertical line is the mean.

Here we present additional computer simulation data. Figure S8 shows the distribution of the fixating fitness value as a probability density function over 1 000 trials for different regimes and structures with  $N = 60$ . In (a) we compare the Weighted Star (blue) and the Star Graph (red). We again set  $[r_1, r_2] = [0.9, 1.1]$ . In (b) and (c) we compare the Well-mixed population (orange), Mainland-island graph (green), Weighted Star (blue) and Star Graph (red) under a different initialization scheme – the starting fitness values are selected independently at random from a normal distribution with mean  $\mu = 1$  and standard deviation  $\sigma = 0.05$ .



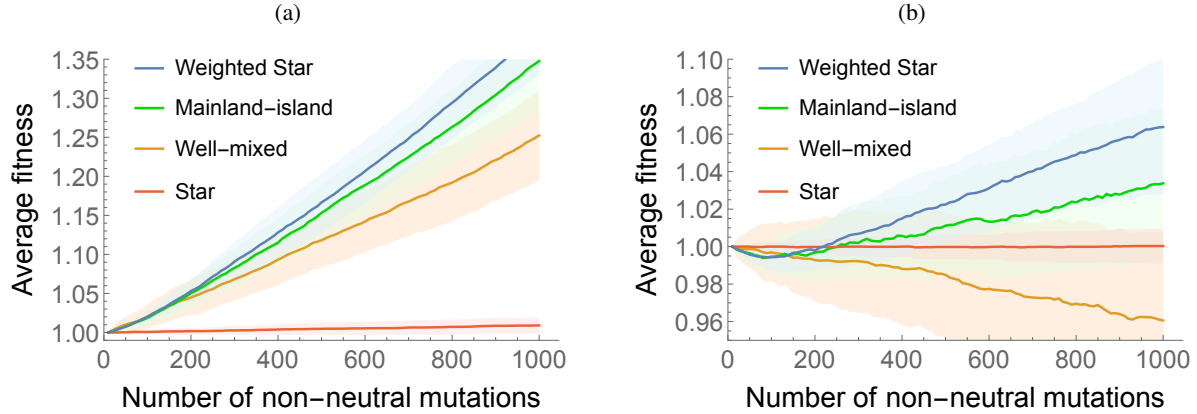


Figure S9

**Figure 4(C).** In experiment *Accumulation of mutants*, we investigate how average fitness of a population evolves over time if the Moran process is enriched by mutations. We start with a population of individuals with fitness 1 each. The simple case is characterized by a pair  $(u, x)$ , where  $u$  is a mutation rate  $x$  is the relative advantage. During each reproduction event, a mutation happens with probability  $u$ . If it does, the fitness of the offspring produced by the event equals  $(1 + x)$ -times the fitness of the parent. Note that  $x > 0$  corresponds to advantageous mutations and  $x < 0$  to disadvantageous mutations. The general case is characterized by pair  $(u, X)$  where  $X$  is a probability distribution over values of  $x$ , hence different relative advantages can appear with different rates that add up to  $u$ . Figure 4(C) presents the results of mutation-accumulation experiment for  $u = 10^{-6}$  and  $\mathbb{P}[x = 0.01] = \mathbb{P}[x = -0.01] = 0.5$ . The experiment is run on Weighted  $(15, 3)$ -Mainland-island graph and on the complete graph  $K_{60}$  ( $N = 60$ ), and averaged over 100 trials.

Here we present additional computer simulation data. Figure S9 shows results of the mutation-accumulation experiment for four different structures of size  $N = 60$  and different probability distributions  $X_1, X_2$ . The four structures we compare are: Complete graph  $K_{60}$  (orange),  $(15, 3)$ -Mainland-island graph (green), Star graph  $S_{60}$  (red), and the Weighted Star (blue). Figure S9(a) shows results for distribution  $X_1$  given by  $\mathbb{P}[x = 0.01] = 1$  (i.e. only positive mutations). Figure S9(b) shows results for distribution  $X_2$  given by  $\mathbb{P}[x = 0.01] = 1/3, \mathbb{P}[x = -0.02] = 2/3$  (i.e. fewer relatively weaker advantageous mutations and more relatively stronger disadvantageous mutations).

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