## Accessible paths on the hypercube

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In collaboration with Julien Berestycki and Zhan Shi (LPMA UPMC)

- The model we consider
- 2 Results
- Outline of proofs

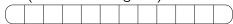
• A genome with L loci ( = location of genes)



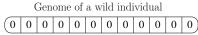
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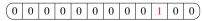
• There are two viable types (alleles) for each gene: the **wild type** (0) and the **mutated type** (1)

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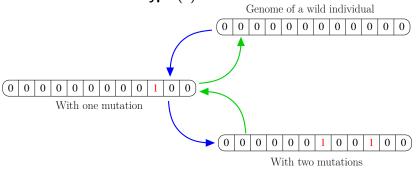
With one mutation



With two mutations

• A genome with L loci ( = location of genes)

• There are two viable types (alleles) for each gene: the **wild type** (0) and the **mutated type** (1)

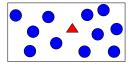


 During reproduction, when a mutation occurs, only one gene is affected.

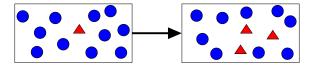
 $0 \longrightarrow 1$ : forward mutation

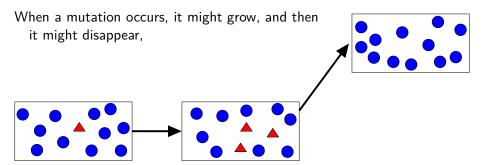
 $1 \longrightarrow 0$ : backward mutation

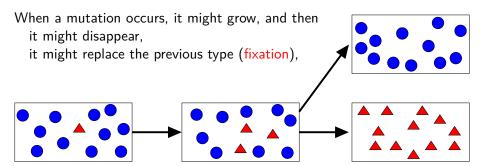
When a mutation occurs,

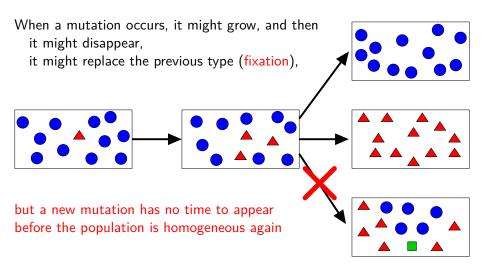


When a mutation occurs, it might grow, and then









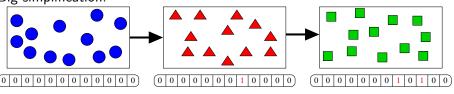
#### Evolutionary paths and Hypercube

Big simplification:

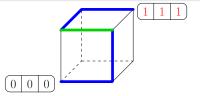
Gillespie 1983, Kauffman Levin 1987

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# $\label{eq:energy} \mbox{Evolutionary path} = \mbox{walk on the hypercube}$



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#### Fitness and selection

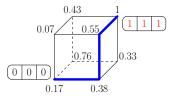
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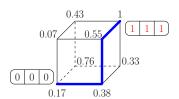
#### Evolutionary path = walk on the hypercube

- $\bullet$  To each of the  $2^L$  genomes one associates a fitness value
- Assume strong selection
- A transition (= a mutation fixates) may occur only if the fitness value increases

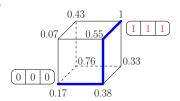


Open or accessible evolutionary path = walk on the hypercube such that fitness values increase along the walk

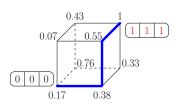
- Flat landscape: fitness value proportional to number of mutations. All forward paths are accessible.
- Rough landscape: no clear relationship between fitness value and number of mutations. Lots of local extrema, valleys and dead ends.



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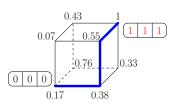


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the House of Cards model Fitness values are independent random numbers

Kingman 1978

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The question: can the population reach the fittest possible state?

- asexual population
- low mutation rate
- high selection
- House of Cards fitnesses

Is there an accessible path to the fittest site? How many are there?

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- Consider a *L*-hypercube.
- Each site is assigned an independent random value, its fitness.

- A path is said to be accessible if the fitness values increase along it.
- One starts from site  $(0,0,0,\ldots,0)$ .

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- Consider a *L*-hypercube.
- Each site is assigned an independent random value, its fitness.
- Choose location of the fittest site; give it a fitness value 1
- The other sites get independent uniform fitness values between 0 and 1
- A path is said to be accessible if the fitness values increase along it.
- One starts from site  $(0,0,0,\ldots,0)$ .

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#### Results

- When one allows only forward mutations
- When one allows both forward and backward mutations

- No backward mutation, only  $0 \rightarrow 1$  and never  $1 \rightarrow 0$ , path length is L.
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$$\boxed{\mathbb{E}^{x}(\mathsf{nb}\;\mathsf{of}\;\mathsf{open}\;\mathsf{paths}) = L(1-x)^{L-1}} \quad \begin{cases} \propto L & \mathsf{lf}\;x \lessapprox \frac{1}{L} \\ \propto 1 & \mathsf{lf}\;x \approx \frac{\mathsf{ln}\;L}{L} \\ \ll 1 & \mathsf{lf}\;x \gg \frac{\mathsf{ln}\;L}{L} \end{cases}$$

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$$\mathbb{P}(\mathsf{nb}\;\mathsf{of}\;\mathsf{open}\;\mathsf{paths}\neq 0) \leq \frac{\mathsf{ln}\;\! L + \mathsf{Cste}}{L}$$

Nowak Krug 2013, Hegarty Martinsson 2012

Assume fittest site is  $(1, 1, 1, \dots, 1)$ .

#### Theorem (Hegarty-Martinsson 2012)

As  $L \to \infty$ ,

$$\mathbb{P}(\mathsf{nb}\;\mathsf{of}\;\mathsf{open}\;\mathsf{paths}\neq 0)\sim \frac{\mathsf{ln}\;L}{L},$$

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If 
$$a(L) \to \infty$$
 (but, typically,  $a(L) \ll \ln L$ ),

$$\mathbb{P}^{\frac{\ln L - a(L)}{L}} \text{(nb of open paths} \neq 0) \to 1 \qquad \left( \begin{array}{c} \text{If starting position has a fitness below} \\ (\ln L)/L \text{, there are some open paths.} \end{array} \right)$$

$$\mathbb{P}^{\frac{\ln L + a(L)}{L}} (\text{nb of open paths} \neq 0) \to 0 \qquad \left( \begin{array}{c} \text{If starting position has a fitness above} \\ (\ln L)/L, \text{ there are no open paths.} \end{array} \right)$$

# Only forward mutations — summary

Assume fittest site is  $(1, 1, 1, \dots, 1)$ .

$$\mathbb{E}(\text{nb of open paths}) = 1 \qquad \qquad \text{(a lie: typical nb of open paths} \neq 1)$$
 
$$\mathbb{E}^x(\text{nb of open paths}) = L(1-x)^{L-1} \qquad \text{(truth: correct order of magnitude)}$$
 
$$\mathbb{P}(\text{nb of open paths} \neq 0) \sim \frac{\ln L}{L} \qquad \text{(value of } x \text{ for which } \mathbb{E}^x(\ldots) \approx 1)$$

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# Theorem (Berestycki-Brunet-Shi 2013)

If 
$$x = \frac{X}{L}$$
, as  $L \to \infty$ ,

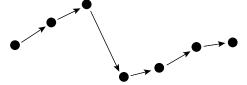
$$\frac{\text{nb of open paths}}{L} \xrightarrow{\text{in law}} e^{-X} \times \mathcal{E} \times \mathcal{E}'$$

where  $\mathcal{E}$  and  $\mathcal{E}'$  are two independent exponential numbers.

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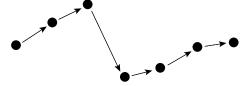
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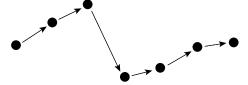
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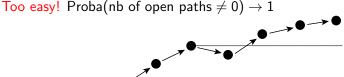


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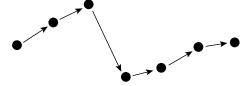


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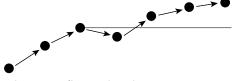


The less fit mutant does not fixate, but has time to mutate to a higher fitness

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Small chance that a mutant fixates at a lower fitness Too easy! Proba(nb of open paths  $\neq$  0)  $\rightarrow$  1



The less fit mutant does not fixate, but has time to mutate to a higher fitness Helps a bit: Proba(nb of open paths  $\neq 0$ )  $\sim (p+1)\frac{\ln L}{L}$  (p= number of "tunnels" allowed)

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### For large L, when the location of the fittest site is at $(1, 1, 1, \ldots, 1)$

- There are no open paths is starting fitness is larger than 0.11863....
- There are open paths otherwise. (Not our result...)

#### For large L, when the location of the fittest site is random

- There are no open paths is starting fitness is larger than 0.27818....
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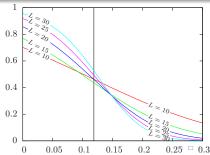
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We allow paths to do  $0 \to 1$  or  $1 \to 0$ . Assume fittest site is  $(1, 1, 1, \dots, 1)$ .

```
0 backstep length L
1 backstep length L+2
2 backsteps length L+4
p backsteps length L+2p
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We allow paths to do 0  $\rightarrow$  1 or 1  $\rightarrow$  0. Assume fittest site is (1,1,1,...,1). nb of self-avoiding paths

```
0 backstep length L a_{L,0} = L!
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$$L$$
  $a_{L,0}=L!$   
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2 backsteps length  $L+4$   $a_{L,2} = L! \times \frac{(L-1)(L-2)(5L^4+3L^3+34L^2-264L+180)}{360}$   
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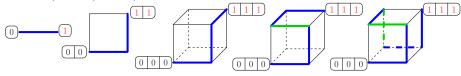
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```

$$a_L = a_{L,0} + a_{L,1} + a_{L,2} + \cdots = \text{total nb of self-avoiding paths}.$$

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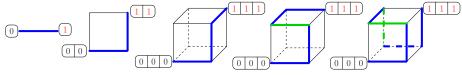


$$a_1 = 1$$
,  $a_2 = 2$ ,  $a_3 = 18$ 

We allow paths to do 0  $\rightarrow$  1 or 1  $\rightarrow$  0. Assume fittest site is (1,1,1,...,1). nb of self-avoiding paths

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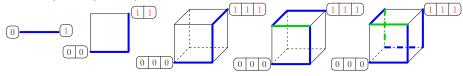


$$a_1 = 1$$
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 $\begin{array}{lll} 0 \; \text{backstep} & \text{length } L & a_{L,0} = L! \\ 1 \; \text{backstep} & \text{length } L+2 & a_{L,1} = L! \times \frac{L(L-1)(L-2)}{6} \\ 2 \; \text{backsteps} & \text{length } L+4 & a_{L,2} = L! \times \frac{(L-1)(L-2)(5L^4+3L^3+34L^2-264L+180)}{360} \\ p \; \text{backsteps} & \text{length } L+2p & a_{L,p} \sim L! \times \frac{L^{3p}}{6^p p!} \; \; (p \; \text{fixed}, \; L \; \text{large}) \end{array}$ 

 $a_L = a_{L,0} + a_{L,1} + a_{L,2} + \cdots = \text{total nb of self-avoiding paths}.$ 



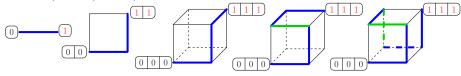
$$a_1 = 1$$
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Asymptotically,  $e^{c \times 2^L} \le a_L \le e^{c' \times (\ln L) 2^L}$ 

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How many are open ?

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Fittest site is  $(1, 1, 1, \ldots, 1)$ 

$$\mathbb{E}(\mathsf{nb}\;\mathsf{of}\;\mathsf{open}\;\mathsf{paths}) = \sum_{p} a_{L,p} \frac{1}{(L+2p)!}$$

But...

Fittest site is  $(1,1,1,\ldots,1)$ 

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$$\mathbb{E}^{\times}(\mathsf{nb} \mathsf{ of open paths}) = \sum_{p} a_{L,p} \frac{(1-x)^{L+2p-1}}{(L+2p-1)!}$$

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## Theorem (Berestycki-Brunet-Shi 2013)

$$\left[\mathbb{E}^x(\mathsf{nb}\ \mathsf{of}\ \mathsf{open}\ \mathsf{paths})\right]^{1/L} \xrightarrow[L \to \infty]{} \mathsf{sinh}(1-x).$$

Corollary: if  $x > \underbrace{1 - \sinh^{-1}(1)}_{0.11863}$ ,  $\mathbb{P}^x(\text{nb of open paths} \neq 0) \to 0$ .

Fittest site is 
$$(1,1,1,\ldots,1)$$
:  $\left[\mathbb{E}^x(\mathsf{nb}\;\mathsf{of}\;\mathsf{open}\;\mathsf{paths})\right]^{\frac{1}{L}} \to \mathsf{sinh}(1-x)$   
No open path if  $x>x^*(1)=\underbrace{1-\mathsf{sinh}^{-1}(1)}_{0.11863...}$ 

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Fittest site at distance  $\alpha L$  from  $(0,0,0,\ldots,0)$ :

$$\left[\mathbb{E}^x(\mathsf{nb}\;\mathsf{of}\;\mathsf{open}\;\mathsf{paths})
ight]^{rac{1}{L}} o \mathsf{sinh}(1-x)^lpha\,\mathsf{cosh}(1-x)^{1-lpha}$$

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Fittest site is randomly chosen:  $\left[\mathbb{E}^x(\text{nb of open paths})\right]^{\frac{1}{L}} \to \sqrt{\frac{\sinh(2-2x)}{2}}$ 

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### Theorem (Martinsson 2015 and Li 2015)

Expectations are telling the truth.  $\mathbb{P}^x(\mathsf{nb}\ \mathsf{of}\ \mathsf{open}\ \mathsf{paths} \neq 0) \to 1$  if  $x < x^*$  with  $x^*$  given above. Furthermore,  $\mathbb{P}(\mathsf{nb}\ \mathsf{of}\ \mathsf{open}\ \mathsf{paths} \neq 0) \to x^*$ 

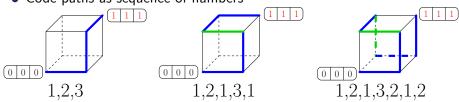
Forward and backward mutations, fittest is  $(1, 1, 1, \dots, 1)$ .

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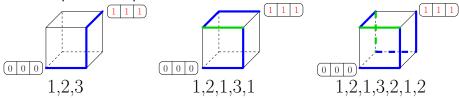
Code paths as sequence of numbers



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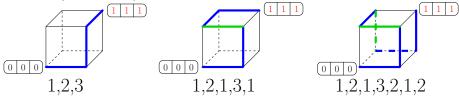


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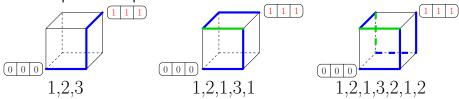
- A path in  $a_{L,p}$  has a sequence of length L+2p
- A path reaches (1, 1, 1, ..., 1) if each number between 1 and L appears oddly many times in the sequence

4□ > 4□ > 4 = > 4 = > = 90

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Code paths as sequence of numbers



- A path in  $a_{L,p}$  has a sequence of length L + 2p
- A path reaches (1,1,1,...,1) if each number between 1 and L
  appears oddly many times in the sequence
- A path is self-avoiding if in any non-empty substring, at least one number appears oddly many times

Strategy:  $m_{L,p} \leq a_{L,p} \leq M_{L,p}$ 

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#### Example

$m_{3,0}$ :	123	132	213	231	312	321
a <sub>3,0</sub> :	123	132	213	231	312	321
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#### Example

```
m_{3,0}: 123 132 213 231 312 321 a_{3,0}: 123 132 213 231 312 321 M_{3,0}: 123 132 213 231 312 321
```

```
      m_{3,1}:
      31323 32313

      a_{3,1}:
      12131 13121 21232 23212 31323 32313

      M_{3,1}:
      12131 13121 21232 23212 31323 32313 11123 12113 ...
```

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```

 $(M_{3,1}=60, M_{3,2}=4920...)$ 

Strategy:  $m_{L,p} \leq a_{L,p} \leq M_{L,p}$ 

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$$\begin{bmatrix}
N \\
P
\end{bmatrix} := \begin{pmatrix}
\text{nb of ways of choosing } P \text{ items out of } N \\
\text{without taking two consecutive items}
\end{pmatrix}$$

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$$\mathbb{E}^x(\mathsf{nb} \mathsf{ of open paths}) \leq -\partial_x[\mathsf{sinh}^L(1-x)] \xrightarrow[L \to \infty]{} \mathsf{if } x \leq 1 - \mathsf{sinh}^{-1}(1)$$

Generalization: if fittest at distance H:

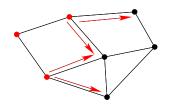
$$\mathbb{E}^{x}$$
(nb of open paths)  $\leq -\partial_{x} \Big[ \sinh(1-x)^{H} \cosh(1-x)^{L-H} \Big].$ 

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First passage percolation



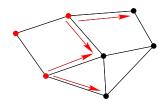
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#### First passage percolation

[Time to infect 
$$(1,1,\ldots)$$
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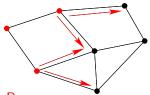
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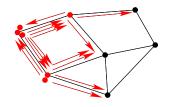
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#### First passage percolation

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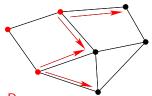
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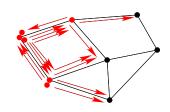
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#### First passage percolation

Hypercube started with one  $\bullet$  at  $(0,0,\ldots,0)$ :

[Time to infect 
$$(1,1,\ldots)$$
]  $\xrightarrow[L\to\infty]{} \sinh^{-1}(1)$ 





#### **Branching Translation Process**

$$n_t(V) = \mathbb{E}(\mathsf{nb} \ \mathsf{of} ullet \mathsf{at} \ V) \ \partial_t n_t(V) = \sum_{U \wedge V} n_t(U)$$

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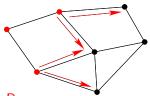
Generalization: if fittest at distance H:

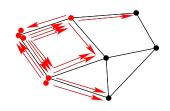
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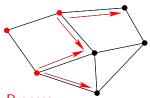
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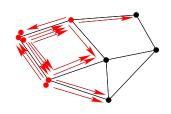
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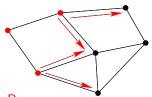
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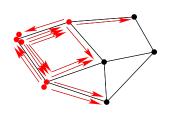
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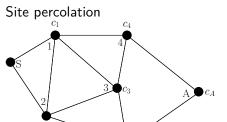
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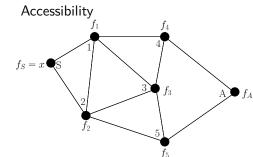
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$$n_t(H) = \sinh(t)^H \cosh(t)^{L-H}$$

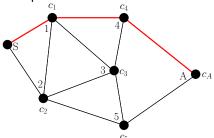
# Martinsson's result for any graph





# Martinsson's result for any graph

#### Site percolation



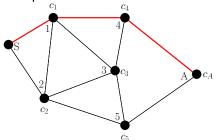
Time (or cost) =  $c_1 + c_4 + c_A$  $T_A$  =minimal time to reach A

# Accessibility $f_1 \qquad f_4$ $f_5 = x \bullet S$ 2 $3 \quad f_3$ $A \quad f$

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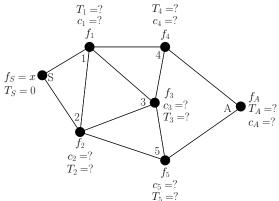
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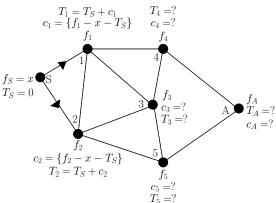
# (Martinsson 2015)

$$\mathbb{P}(T_A < 1 - x) = \mathbb{P}^x(A \text{ is accessible})$$

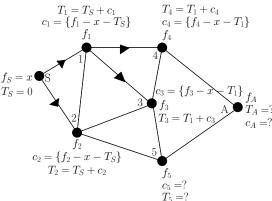
But no relation betwen the number of paths with a time smaller than 1-x and the number of accessible paths!



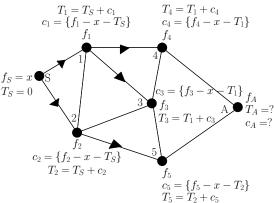
• At first, we choose the  $f_i$ 



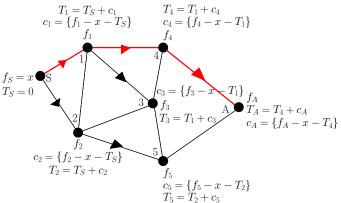
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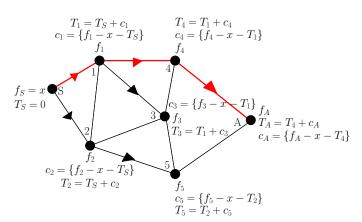


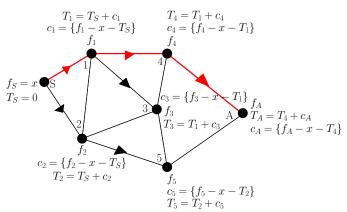
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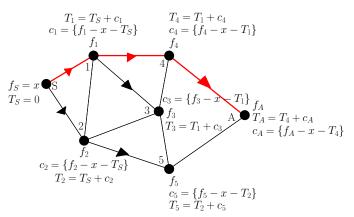
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- Assume  $T_4 < T_5$ . We compute  $c_A$  and  $T_A$

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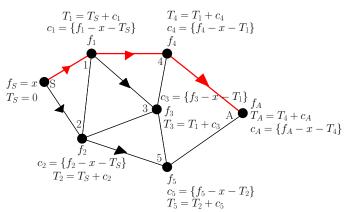




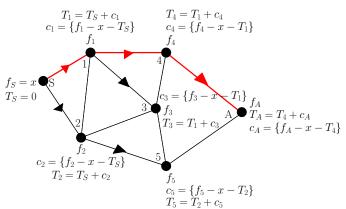
Notice that  $f_i = \{x + T_i\}$  and  $T_A = c_1 + c_4 + c_A$ 



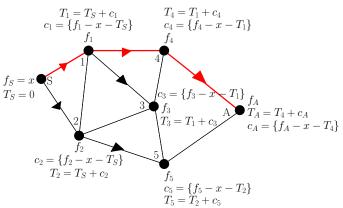
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# When only forward steps are allowed

- Forward steps only are allowed
- Fittest site is  $(1,1,1,\ldots,1)$
- Starting site  $(0,0,0,\ldots,0)$  has fitness x=X/L
- $L \to \infty$

$$\frac{1}{L}\left(\text{nb of open paths if starting fitness is } x = \frac{X}{L}\right) \to \mathrm{e}^{-X} \times \mathcal{E} \times \mathcal{E}'$$

with  ${\mathcal E}$  and  ${\mathcal E}'$  two independent exponential variables

One already knows that

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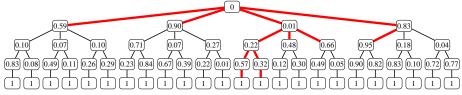
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- ullet There are indeed typically  $\propto L$  open paths



```
Hypercube is hard; try a tree! 1^{st} step: L choices; 2^{nd} step: L-1 choices; 3^{rd} step: L-2 choices; ...
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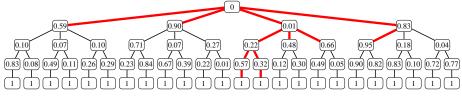
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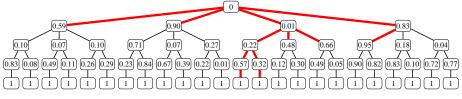


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ight.$$

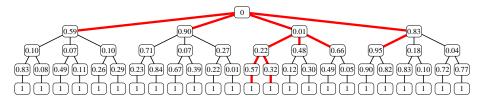
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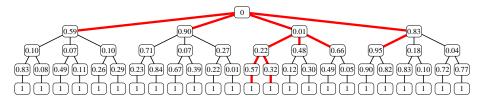


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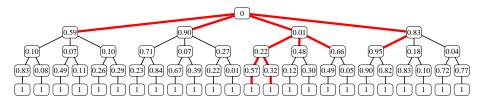


(Nb of open paths) = 
$$\sum_{|\sigma|=1}$$
 (nb of open paths going through  $\sigma$ )



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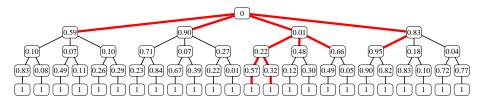
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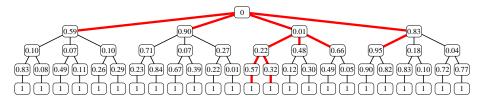
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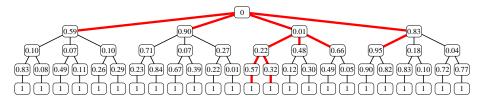
$$G(\lambda, x, L) = \left[x + \frac{1}{2}\right]^{L}$$



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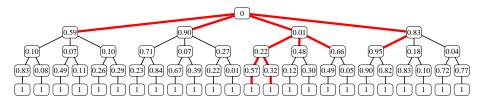
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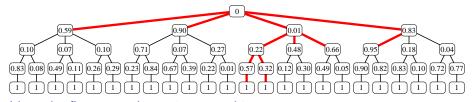
Sum of uncorrelated terms (because it is a tree), generating function

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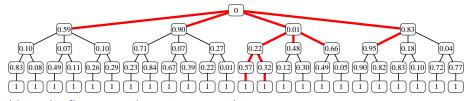
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$$\lim_{L\to\infty}G\left(\frac{\mu}{L},\frac{X}{L},L\right)=?$$

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Idea: the first steps determine everything

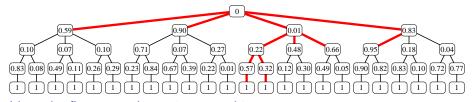


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$$\Theta = (\mathsf{nb} \; \mathsf{of} \; \mathsf{open} \; \mathsf{paths}), \qquad \Theta_k = \mathbb{E}(\Theta|\mathcal{F}_k), \qquad \mathcal{F}_k = (\mathsf{info} \; \mathsf{up} \; \mathsf{to} \; \mathsf{level} \; k)$$

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$$\Theta_k = \sum_{|\sigma|=k} \mathbb{1}_{\{\sigma \text{ open}\}} \underbrace{(L-k)(1-x_\sigma)^{L-k-1}}_{\text{expected nb of open paths through } \sigma}$$

$$\Theta_1 = 3(1 - 0.59)^2 + 3(1 - 0.90)^2 + 3(1 - 0.01)^2 + 3(1 - 0.83)^2 = 3.5613$$
  

$$\Theta_2 = 2(1 - 0.22)^1 + 2(1 - 0.48)^1 + 2(1 - 0.66)^1 + 2(1 - 0.95)^1 = 3.38$$

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But (sum over pairs of paths):

$$\lim_{L \to \infty} \mathbb{E}^{\frac{X}{L}} \left[ \mathsf{Var} \left[ \frac{\Theta}{L} \middle| \mathcal{F}_k \right] \right] = \frac{e^{-2X}}{2^k}$$

In the  $L \to \infty$ ,  $k \to \infty$  limit,  $\Theta/L$  and  $\Theta_k/L$  have the same distribution

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One can then prove that  $F_k(\mu, X) = \lim_{L \to \infty} G_k(\frac{\mu}{L}, \frac{X}{L}, L)$  exists and

$$F_k(\mu, X) = \exp\left[-\int_X^\infty dY (1 - F_{k-1}(\mu, Y))\right], \quad F_0(\mu, X) = \exp\left(-\mu e^{-X}\right)$$

 $F_k$  is the generating function of  $\lim_{L\to\infty} \frac{\Theta_k}{L}$  when starting fron  $\frac{X}{L}$ .

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On the tree, starting from  $x = \frac{X}{L}$ ,  $\frac{\Theta}{L} = \frac{\ln \text{law}}{L \times \Omega} e^{-X} \times \mathcal{E}$ 

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$$\Theta_k = \mathbb{E}(\Theta|\mathcal{F}_k), \qquad \mathcal{F}_k = (\text{info in the } k \text{ first and } k \text{ last levels})$$

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The expectation of the conditional variance can be computed and it works.

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$$\Theta_k = \sum_{|\sigma| = k} \sum_{|\tau| = L - k} n_\sigma m_\tau \mathbb{1}_{\{\tau \text{ reachable from } \sigma\}} \mathbb{1}_{\{x_\sigma < x_\tau\}} (L - 2k) (x_\tau - x_\sigma)^{L - 2k - 1}$$

 $n_{\sigma}=$ nb of open paths from (0,...,0) to  $\sigma$ ;  $m_{ au}=$ nb from au to (1,...,1)

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$$\tilde{\Theta}_k > \Theta_k \text{, but not that much: } \lim_{L \to \infty} \mathbb{E}^{\frac{X}{L}} \big[ \frac{\Theta_k}{L} \big] = \lim_{L \to \infty} \mathbb{E}^{\frac{X}{L}} \big[ \frac{\tilde{\Theta}_k}{L} \big]$$

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 $\Theta_k/L$  and  $\Theta_k/L$  have the same distribution for large L

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First factor: beginning of the hypercube. Second factor: end of the hypercube. Terms are independent and symmetrical if X = 0.

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First factor: beginning of the hypercube. Second factor: end of the hypercube. Terms are independent and symmetrical if X=0. Last step: prove that

$$\phi_k := \sum_{|\sigma|=k} n_{\sigma} (1-x_{\sigma})^{L-2k-1} \xrightarrow[L\to\infty \text{ then } k\to\infty]{\text{in law}} e^{-X} \mathcal{E}$$

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Intuition: with k fixed and  $L\to\infty$ , loops become negligible, and the beginning of the hypercube looks like the beginning of the tree. So  $\phi_k$  and  $\Theta_k^{\rm tree}/L$  have the same large L distribution.

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Thank you!