

# Fluctuations in first passage percolation

Thursday, 13 May 2021 13:09

On  $\mathbb{Z}^d$ , assign to every edge  $e$ , a random weight  $\eta_e$  with  $(\eta_e)$  IID with common dist.  $\nu$ .  
 The weight of a path  $P$  in  $\mathbb{Z}^d$  e.g. exponential, bernoulli( $p$ ), uniform, is defined as the sum of the  $\eta_e$  along the edges of  $P$ .

Get a random metric space with

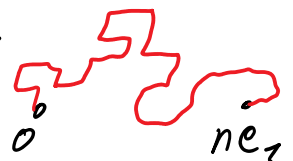
$$T(u, v) = \inf_{\text{paths } P \text{ from } u \text{ to } v} \text{weight of } P, \quad u, v \in \mathbb{Z}^d$$

Predictions: We saw that  $T(0, nx) = n\chi(x) + o(n)$  as  $n \rightarrow \infty$ , a.s. and in  $L^1$ , for each  $x \in \mathbb{Q}^d$ .  
 (under suitable assump. on  $\nu$ ).  
 Some number depending on  $x$ ,  $\downarrow$  the time constant.

$\exists \chi(d) \geq 0$  s.t.  $\text{Var}(T(0, nx)) \approx n$   
 Time fluctuat.  $\downarrow$  precise meaning not clear

$(n^\chi)$  is the st. dev. of the passage time.  
 Exponent  $\chi$  should be universal, the same for all  $\nu$  under mild assumptions, and the same for all  $x$ . Obviously, in  $d=1$ ,  $\chi = \frac{1}{2}$ .

In  $d=2$ , predicted  $\chi = \frac{1}{3}$ .  
 predicted that  $\chi(d) \leq \chi(d-1)$ .  
 disputed whether  $\chi(d) = 0$  for  $d$  large.



$e_1 = (1, 0, \dots, 0)$

In  $d=2$ ,  $\frac{T(0, ne_1) - n\chi(e_1)}{n^{1/3}} \xrightarrow[n \rightarrow \infty]{d}$  Tracy-Widom  $F_2$  dist. (Fluctuations)

For "solvable models" (all of them are directed last passage percolation) this has been shown. Moreover, a scaling limit "The directed landscape" was constructed in 2018 by Dauvergne-Ortmann-Dirag.  
 OF largest eigenvalue of a GUE random matrix.  
 Hermitian  $\rightarrow$  complex indep. Gaussian entries.  
 Gaussian unitary ensemble.

Transversal Fluctuations: weight minimizing paths  
 By how much do geodesics deviate from straight line? in  $d \geq 2$   
 maximal

By how much do geodesics deviate from the straight line? in  $d \geq 2$   
 It is predicted that there is a  $\xi(d) \geq \frac{1}{2}$  s.t. the deviation  $\approx n^\xi$ .  
 deviate more than simple random walk

maximal deviation from straight line.

In  $d=2$ , predicted  $\xi = \frac{2}{3}$ .

predicted relation: In every dimension  $\chi(d) = 2\xi(d) - 1$ .

Known (for non-solvable models. E.g., First-passage percolation with  $V(\{0\}) \in P_c(d)$  and having exponential moments):

$$c \leq \text{Var}(T(0, ne_1)) \leq \frac{Cn}{\text{Log } n} \quad \text{for every } d \geq 2.$$

Benjamini-Itai-Schramm (2003) and follow-up

In  $d=2$ :  $\text{Var}(T(0, ne_1)) \geq c \text{Log } n$ . Newman-Piza (1995)

(e.g.  $0 \leq \chi \leq \frac{1}{2}$ ).

Also,  $\xi \geq \frac{1}{d+1}$  for every  $d \geq 2$   
 For stronger def. of  $\xi$ ,  $\xi \geq \frac{1}{2}$  for every  $d \geq 2$   
 and  $\xi \geq \frac{3}{5}$  in  $d=2$ .

Licea-Newman-Piza (1996)

Open: Transversal Fluc. are  $o(n)$ .

There also exist conditional results.  
 E.g., conditioned on the limit shape being uniformly (strictly) convex.

Reference: Aufferinger-Damron-Hanson  
 50 years of FPP.

To explain the proofs of some of these results we take some detours.

Concentration inequalities - Efron-Stein Ineq.

Let  $X_1, \dots, X_n$  be RVS taking values in a meas. space  $\mathcal{X}$ . Let  $f: \mathcal{X}^n \rightarrow \mathbb{R}$  be s.t.

would like to bound  $\text{Var}(f)$  from above.

$$\mathbb{E}(f^2(X)) < \infty.$$

$$X = (X_1, \dots, X_n).$$

...  $\sigma$ -alg. =  $\xi \emptyset$ , full?

would like to bound var above.  $X = (X_1, \dots, X_n)$   
 Let  $\mathcal{F}_0 := \text{trivial } \sigma\text{-alg.} = \{\emptyset, \text{full}\}$

$\mathcal{F}_i := \sigma(X_1, \dots, X_i)$  for  $1 \leq i \leq n$ .

Doob Martingale:  $M_i := \mathbb{E}(F(X) | \mathcal{F}_i)$

Martingale difference:  $\Delta_i := M_i - M_{i-1}$

General Variance formula:  $\text{Var}[F(X)] = \sum_{i=1}^n \mathbb{E}(\Delta_i^2)$

Proof:  $F(X) - \mathbb{E}F(X) = \sum_{i=1}^n \Delta_i$

Note  $\mathbb{E}\Delta_i = 0$  by def, for each  $1 \leq i \leq n$ .

Additionally,  $\mathbb{E}\Delta_i \Delta_j = 0$  for  $i \neq j$ .

Since, for  $i > j$ ,  $\mathbb{E}\Delta_i \Delta_j = \mathbb{E}[\mathbb{E}(\Delta_i \Delta_j | \mathcal{F}_j)] =$   
 $= \mathbb{E}[\Delta_j \underbrace{\mathbb{E}(\Delta_i | \mathcal{F}_j)}_{=0, \text{ by mart. prop. of } M_i, \mathbb{E}(M_m | \mathcal{F}_j) = M_j \text{ when } m \geq j}]$

$\Rightarrow \text{var}(F(X)) = \mathbb{E}((F(X) - \mathbb{E}F(X))^2) =$   
 $= \mathbb{E}((\sum_{i=1}^n \Delta_i)^2) = \sum_{i=1}^n \mathbb{E}(\Delta_i^2)$

To proceed, we will assume that the  $(X_i)$  are independent.

Define the  $\sigma$ -alg.,  $\mathcal{G}_i = \sigma(X_1, \dots, X_{i-1}, X_{i+1}, \dots, X_n)$

One notion of influence:  $I_i := \mathbb{E}[\text{Var}(F(X) | \mathcal{G}_i)] =$   
 $= \mathbb{E}[(F(X) - \mathbb{E}F(X | \mathcal{G}_i))^2]$

Equivalent expressions: If  $X^i = (X_1, \dots, X_{i-1}, X', X_{i+1}, \dots, X_n)$   
 With  $X'_i$  indep. and dist. as  $X_i$ .

Then  $I_i = \frac{1}{2} \mathbb{E}[(F(X) - F(X^i))^2] = \mathbb{E}[(F(X) - F(X^i))_+^2] = \mathbb{E}[(F(X) - F(X^i))_-^2]$

(If  $z, z'$  are IID real-valued then  $\mathbb{E}[(z - z')^2] = \frac{1}{2} \mathbb{E}[(z - z')^2] = \mathbb{E}((z - z')_+^2) = \mathbb{E}((z - z')_-^2)$   
 $(z - z')^2 = (z - z')_+^2 + (z - z')_-^2$  IID

$$(z-z')^2 = (z-z')_+^2 + (z-z')_-^2 \quad \text{IID}$$

Lastly,  $I_i = \inf_{z_i \text{ RV meas. wrt. } G_i} \mathbb{E}[(F(X) - z_i)^2]$ .

(If  $z$  is real-valued then  $\text{Var}(z) = \inf_{a \in \mathbb{R}} \mathbb{E}[(z-a)^2]$ )

Thm. (Efron-Stein 1987, Steele 1986, Borel-Talagrand 1986): When  $X_1, \dots, X_n$

are indep.,  $\text{Var}(F(X)) \leq \sum_{i=1}^n I_i$ .

Proof:  $\text{Var}(F) = \sum_{i=1}^n \mathbb{E}(\Delta_i^2) = \sum_{i=1}^n \mathbb{E} \left[ \underbrace{(\mathbb{E}(F(X)|\mathcal{F}_i) - \mathbb{E}(F(X)|\mathcal{F}_{i-1}))^2}_{\text{independence}} \right]$

$$= \sum_{i=1}^n \mathbb{E} \left[ (\mathbb{E}[F(X) - \mathbb{E}(F(X)|G_i) | \mathcal{F}_i])^2 \right] \leq \mathbb{E} \left[ (F(X) - \mathbb{E}(F(X)|G_i))^2 \right] \leq \mathbb{E}[(z-a)^2] \leq \mathbb{E}(z^2)$$

$$\leq \sum_{i=1}^n \mathbb{E}[(F(X) - \mathbb{E}(F(X)|G_i))^2] = \sum_{i=1}^n I_i.$$

Corollary (bounded differences inequality):

Let  $X_1, \dots, X_n$  be indep. taking values in  $\mathcal{X}$ .  
Let  $f: \mathcal{X}^n \rightarrow \mathbb{R}$  be meas.,  $\mathbb{E}(f^2(X)) < \infty$  and

$\forall 1 \leq i \leq n, |f(x) - f(x')| \leq c_i$  when  $x, x'$  differ only in  $i$ th coord.

Then  $\text{Var}(f(X)) \leq \frac{1}{4} \sum_{i=1}^n c_i^2$ .

Proof: By Efron-Stein,  
 $\text{Var}(F(X)) \leq \sum_{i=1}^n I_i$

It is easy to see that  $I_i \leq c_i^2$ . To get the  $\frac{1}{4}$ ,  
write  $I_i = \inf_{z_i \text{ RV meas. wrt. } G_i} \mathbb{E}[(F(X) - z_i)^2] \leq \mathbb{E}[(\frac{1}{2}c_i)^2] \leq \frac{1}{4}c_i^2$ .

$z_i = \frac{1}{2}(\sup F(X) \text{ given } G_i - \inf F(X) \text{ given } G_i)$   
the diff. is at most  $c_i$

Application (Longest Common Subseq.):

## Application (Longest Common Subseq.):

$X_1, \dots, X_n, Y_1, \dots, Y_n$  indep. unifr. on  $\{0,1\}$ .

0 0 1 1 1 0 1 1  
 | / / / / | |  
 0 1 1 0 0 0 1 1

$X_1 \dots X_n$   
 0 1 1 1 1 1 0  
 $Y_1 \dots Y_n$

$F(X, Y) =$  Length of the longest common subseq.

We saw  $\frac{F(X, Y)}{n} \xrightarrow{n \rightarrow \infty} c$  a.s. and in  $L^1$ .  
 close to 80%.

Here, we note  $\text{Var}(F(X, Y)) \leq \frac{1}{2}n$ .

This is an immed. applic. of the bdd. diff. ineq. with  $c_i = 1$  for all  $i$ .

Open:  $\text{Var}(F(X, Y)) \xrightarrow{n \rightarrow \infty} \infty$ .

Cons.:  $\text{Var}(F(X, Y)) = \Theta(n)$ .

## Application (First passage percolation)



$\exists C = C(\nu), \text{Var}(T(o, ne_1)) \leq C \cdot n, \forall n$ .

This is known for a very general class of weight dist.  $\nu$ . We'll show it now when the weight takes values in  $[a, b], 0 < a \leq b < \infty$ .

Proof: Since the weight is bdd., the geodesic necessarily stays in a ball of radius  $Cn$  around  $o$ , so  $T(o, ne_1)$  is a fcn. of finitely many (indep.) edge weights.  
 (the length of the geodesic is  $\leq \frac{b}{a} \cdot n$ )

Thus  $\text{Var}(T(o, ne_1)) \leq \sum_e I_e$  Efron-Stein ineq.

for edges  $e$  in the ball.

$T = \mathbb{E}[\text{Var}(T(o, ne_1) / \text{cond. on all } \dots)]$

$$I_e = \mathbb{E} \left[ \text{Var} (T(0, ne_1) \mid \text{cond. on all but } \eta_e) \right]$$

Let  $\eta^e$  be another set of weights with  $\eta_f^e = \eta_f$  for all edges  $f$ , except  $f=e$  where  $\eta_e^e$  is an indep. copy of  $\eta_e$ .

Using an equiv. repr. of  $I_e$ ,

$$I_e = \mathbb{E} \left[ \underbrace{(T(0, ne_1)(\eta^e) - T(0, ne_1)(\eta))_+^2}_{\substack{\text{passage time} \\ \text{can only increase} \\ \text{if all geodesics from} \\ 0 \text{ to } ne_1 \text{ pass through } e.}} \right] \leq \underbrace{P(e \text{ is on all geodesics from } 0 \text{ to } ne_1)}_{\leq c} \cdot \underbrace{\mathbb{E}((\eta_e^e)^2)}_{\substack{\text{indep.} \\ \text{random variables}}}$$

$$= P(e \text{ is on all geodesics}) \cdot \mathbb{E}((\eta_e^e)^2) \leq c$$

$$\Rightarrow \text{Var}(T(0, ne_1)) \leq c \cdot \mathbb{E} \left( \underbrace{\text{length of the geodesic from } 0 \text{ to } ne_1}_{\substack{\text{as mentioned, } \leq \frac{b}{a}n}} \right) \leq c(v) \cdot n$$

Can put  $\mathbb{E}(\text{number of edges common to all geodesics}) \rightarrow$

## Improved upper bound on the variance

To improve the Efron-Stein upper bound on  $T(0, ne_1)$  we will discuss "improved influence ineq.". These go back to Talagrand (1994) and were extended, e.g., by Rossignol (2006) and Falik-Samorodnitsky (2007). We'll use the latter ineq.



the latter inequality.

Let  $X_1, \dots, X_n$  be indep. Let  $f$  be a real-valued fcn. of  $X$  with suitable moment assumption.

Define  $\text{Ent}(f(X)) := \mathbb{E}[f \log f] - \mathbb{E}(f) \log(\mathbb{E}f)$   
(we shorthand  $f(X)$  to  $f$ ).

Thm. (Falik-Samorodnitsky):

$$\text{Var}(f) \cdot \log \left[ \frac{\text{Var}(f)}{\sum_{k=1}^n (\mathbb{E}|\Delta_k|)^2} \right] \leq \sum_{k=1}^n \text{Ent}(\Delta_k^2)$$

Where  $\Delta_k = \mathbb{E}(f(X) | \mathcal{F}_k) - \mathbb{E}(f(X) | \mathcal{F}_{k-1})$

and  $\mathcal{F}_k = \sigma(X_1, \dots, X_k)$

(recall  $\text{Var} f = \sum_{k=1}^n \mathbb{E}(\Delta_k^2)$ ).