

Lecture 12

To prove sharpness of the phase transition in the FK percolation model, it remains to prove:

- OSSS inequality
- Lemma 3 (general lemma "good diff. req." \Rightarrow sharpness)

We start by the OSSS compared to Bernoulli percolation, we have dependencies,

To get closer to that setup: show how to sample any probability measure on $\{0, 1\}^E$ using iid random variables.

Recall in perc.:

let $U_1, \dots, U_n \sim U(0, 1)$, iid,
take $w_e = \begin{cases} 1 & \text{if } U_e \geq 1-p \\ 0 & \text{otherwise} \end{cases}$

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Lemma 2.14

Let $U_1, \dots, U_n \sim U[0, 1]$, iid

Let (e_1, \dots, e_n) be a random ordering of edges in E .

Assume that: U_1, \dots, U_{t-1}

U_t is indep. of $(e_1, \dots, e_t) \forall t$.

Let μ be a probab. meas. on $\{0, 1\}^E$.

Sample X - rand. var. on $\{0, 1\}^E$:

$$X_{e_t} := \begin{cases} 1 & \text{if } U_t \geq \mu(\omega_{e_t} = 0) \\ 0 & \text{otherwise} \end{cases}$$

$\omega = X$ on $e_{(t-1)}$

Then, $X \sim \mu$.

Rem:

Values of μ and U determine X

Rem:

This covers an algorithm given by a decision tree:

- start by e_1 and sample X_{e_1}
- take $e_2 = \gamma_2(e_1, X_{e_1})$
- sample X_{e_2}
- - - -

Proof:

Let $x \in \omega, \Omega \in \mathbb{F}$ and \bar{e} be the ordering of \mathbb{F} ,
 s, t . $\mathbb{P}(X=x, \bar{e}=\bar{e}) > 0$

Then:

$$\mathbb{P}(X=x, \bar{e}=\bar{e})$$

$$= \mathbb{P}(e_1 = e_1) \cdot \mathbb{P}(X_{e_1} = x_{e_1} | e_1 = e_1)$$

$$\cdot \mathbb{P}(e_2 = e_2 | e_1 = e_1, X_{e_1} = x_{e_1})$$

$$\cdot \mathbb{P}(X_{e_2} = x_{e_2} | e_{[2]} = e_{[2]}, X_{e_1} = x_{e_1})$$

$$= \prod_{t=1}^n \mathbb{P}(e_t = e_t | e_{[t-1]} = e_{[t-1]}, X_{e_{[t-1]}} = x_{e_{[t-1]}})$$

$$\cdot \prod_{t=1}^n \mathbb{P}(X_{e_t} = x_{e_t} | e_{[t]} = e_{[t]}, X_{e_{[t-1]}} = x_{e_{[t-1]}})$$

We know that U_t is indep.
of $e_{[t]}$ and $U_{[t-1]}$.
determine $X_{e_{[t-1]}}$

Hence \mathcal{E}_t and \mathcal{E}_{t-1} are indep.

Then:

$$\begin{aligned}
 & P(\mathcal{E}_t = 1 \mid \mathcal{E}_{[t]} = \mathcal{E}_{[t]}, \mathcal{E}_{[t-1]} = \mathcal{E}_{[t-1]}) \\
 &= P(\omega_t \geq \mu \mid \omega_{\mathcal{E}_t} = 0 \mid \omega_{\mathcal{E}_{[t-1]}} = \mathcal{E}_{[t-1]}) \\
 & \quad \mid \mathcal{E}_{[t]} = \mathcal{E}_{[t]}, \mathcal{E}_{[t-1]} = \mathcal{E}_{[t-1]}) \\
 &= P(\omega_{\mathcal{E}_t} = 1 \mid \omega_{\mathcal{E}_{[t-1]}} = \mathcal{E}_{[t-1]})
 \end{aligned}$$

Hence:

$$P(\mathcal{E}_t = \mathcal{E}_t \mid \omega) = \mu(\omega_{\mathcal{E}_t} = \mathcal{E}_t \mid \omega)$$

Taking the product over t , we get:

$$(*) = \mu(\omega = \mathcal{E})$$

This holds for any $\bar{\mathcal{E}}$ set.

$$P(\mathcal{E}_t = \mathcal{E}_t, \bar{\mathcal{E}} = \bar{\mathcal{E}}) > 0.$$

So we get:

$$P(\mathcal{E} = \mathcal{E}, \bar{\mathcal{E}} = \bar{\mathcal{E}}) = \mu(\omega = \mathcal{E})$$

$$\prod_{t=1}^T P(\mathcal{E}_t = \mathcal{E}_t \mid \mathcal{E}_{[t-1]} = \mathcal{E}_{[t-1]}, \mathcal{E}_{[t-1]} = \mathcal{E}_{[t-1]})$$

Fix $x \in \{0, 1\}^W$ and sum over all orderings \bar{e} , s, t . $\mathbb{P}(X = x, \bar{e} = \bar{e}) > 0$.

We want to show that the product equals to 1:

- for any $e_{[n-2]}$:

$$\sum_{e_{n-1}=r, f} \mathbb{P}(e_{n-1} = e_{n-1} \mid \text{---}) = 1,$$

since we have to choose some edge.

- continue by induction

Proof (OSSS ineq. for FK proc.)

Take $\mu = \varphi_{G, p, q}$

As in percolation, we will need two sequences of i.i.d. rand. var.:

u_1, \dots, u_n

$v_1, \dots, v_n \sim U[0, 1]$ i.i.d.

Write \mathbb{P} their joint law.

Use the decision tree

$$T = (e_1, \psi_t, t=1 \dots n)$$

to construct (\mathbf{e}, \mathbf{x}) as in **Lemma 2.14**:

- $\mathbf{e}_1 := e_1$

- $\mathbf{x}_{e_t} := \begin{cases} 1 & \text{if } U_t \geq \tau (w_{e_t} = 0) \\ 0 & \text{otherwise.} \end{cases}$ $w_{e_{t-1}} = \mathbf{x}_{e_{t-1}}$

- $\mathbf{e}_{t+1} = \psi_t(\mathbf{e}_t, \mathbf{x}_{e_t})$

As usually, we define

$$\tau := \min \{ t \geq 1 : \forall x \in \{0, 1\}^n$$

\uparrow $x_{e_{t+1}} = \mathbf{x}_{e_{t+1}} \Rightarrow f(x) = f(\mathbf{x})$
 time when t is computed.

Define also \mathbf{w}^s obtained by swapping some entries of \mathbf{u} be \mathbf{v} :

$$\mathbf{w}^s := (\mathbf{v}_1, \dots, \mathbf{v}_s, \mathbf{u}_{s+1}, \dots, \mathbf{u}_t, \mathbf{v}_{t+1}, \dots, \mathbf{v}_n)$$

Sample \mathbf{v}^s from \mathbf{w}^s using per a config. **Lemma 2.14** and the same \mathbf{e} .

$$Y_t^s := \begin{cases} 1 & \text{if } W_t^s \geq \mu (w_{e_t} = 0 | \tau) \\ 0 & \text{otherwise} \end{cases}$$

Note that:

- $X \sim \mu$ and is \mathcal{U} -meas.

- $f(X) = f(Y^0)$

Indeed $\bar{\mu}$ is the same

and for all $t \in T$

$$W_t^0 = U_t$$

hence $X_t = Y_t^0$ for all $t \in T$

Apply the def. of T .

- $Y^s \sim \mu$, for any s .

- Y^n is indep. of U .

Now, as in percolation:

$$\text{Var}(f) \leq \mu(|f - \mu(f)|)$$

$$\leq \mathbb{E}(|\mathbb{E}(f(X)|U) - \mathbb{E}(f(Y^n)|U)|)$$

$$= \mathbb{E}(|\mathbb{E}(f(Y^0)|U) - \mathbb{E}(f(Y^n)|U)|)$$

$$\leq \sum_{t=1}^T \mathbb{E}(\mathbb{E}(|H(Y^t) - f(Y^{t-1})|) | \mathcal{U}_{(t-1)})$$

$$\leq \sum_{e \in E} \sum_{t=1}^T \mathbb{E}(\mathbb{E}(|f(Y^t) - f(Y^{t-1})|) | \mathcal{U}_{(t-1)})$$

$$\stackrel{1}{e_t = e, t \in T}$$

Hence, it remains to show:

$$\mathbb{E}(|f(Y^t) - f(Y^{t-1})| | \mathcal{U}_{(t-1)})$$

$$\leq \frac{1}{\text{Var}(w_e)} \cdot \text{Cov}(f, w_e)$$

where $e_t = e, t \in T$.

Since e is FOG,

$$\mu(\cdot | w_e = 0) \leq \mu \leq \mu(\cdot | w_e = 1)$$

Now we sample weights.

using these measures

$$\begin{aligned} \mathbb{P}^{\mu(\cdot | w_e = 1)}(W^{t-1}) \leq Y^{t-1} &\leq \mathbb{P}^{\mu(\cdot | w_e = 0)}(W^{t-1}) \\ \mathbb{P}^{\mu(\cdot | w_e = 0)}(W^t) \leq Y^t &\leq \mathbb{P}^{\mu(\cdot | w_e = 1)}(W^t) \end{aligned}$$

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Then,

$$E(f(Y^t) - f(Y^{t-1}) | u_{(t-1)})$$

Since
we
are
independent
of $u_{(t-1)}$

$$= E(f(Z) - f(Z')) | u_{(t-1)}$$

$$= \underbrace{E(f(Z'))}_{\mu(f(w) | w_e = 1)} - \underbrace{E(f(Z))}_{\mu(f(w) | w_e = 0)}$$

$$= \frac{\text{Cov}(f, w_e)}{\mu(w_e) \cdot (1 - \mu(w_e))}$$

$$= \frac{\text{Cov}(f, w_e)}{\text{Var}(w_e)}$$