

The OSSS inequality and its consequences in percolation

Rahul Roy

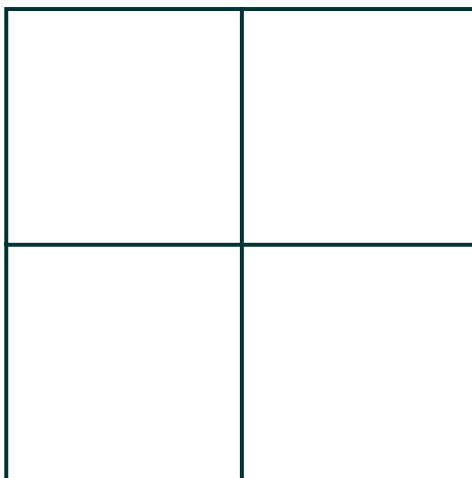
Indian Statistical Institute, New Delhi.

# OSSS setup

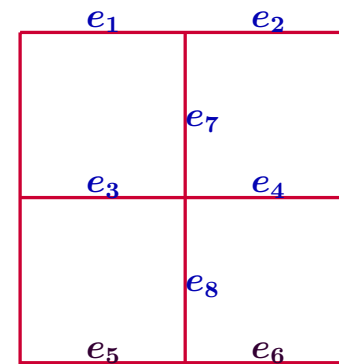
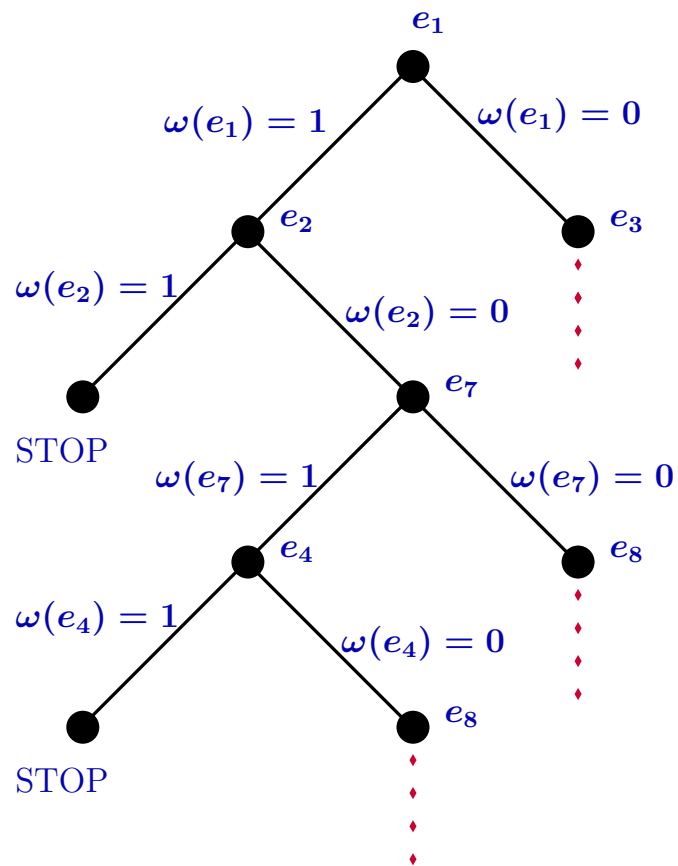
So we need to obtain the Duminil-Copin inequality, and it is here we need the OSSS inequality.

Let  $\{(\Omega_i, \mathcal{F}_i, \mu_i) : 1 \leq i \leq n\}$  be a finite collection of measure spaces and  $(\Omega, \mathcal{F}, \mu)$  be the product space.

Suppose we want to find whether there is a Left-Right open crossing of the following rectangle.



# Decision tree



$A := \{\exists \text{ a L-R open crossing of the box}\}$

$$f := 1_A$$

$$f : \{0, 1\}^8 \rightarrow [0, 1]$$

Let  $\{(\Omega_i := \{0, 1\}, \mathcal{F}_i, \mu_i) : 1 \leq i \leq n\}$  and  $(\Omega, \mathcal{F}, \mu)$  be the product probability space.

Let  $f : \Omega \rightarrow [0, 1]$  be a measurable function (random variable) and fix a configuration  $\omega$ . We want an algorithm  $T$  (decision tree) which opens (samples), one at a time, an  $\omega(e_i)$  to determine the function.

We start with a root index  $i_1$  and a family of decision rules  $(\phi_j) : 1 \leq j \leq n - 1$ . The index  $i_{j+1}$  is chosen as

$$i_{j+1} := \phi_j(i_1, \dots, i_j; \omega(e_{i_1}), \dots, \omega(e_{i_j})).$$

In our example, we chose  $i_1 = 1$  and

$$i_2 = \phi_1(i_1, \omega(e_{i_1})) = \begin{cases} 2 & \text{if } \omega(e_1) = 1 \\ 3 & \text{if } \omega(e_1) = 0. \end{cases}$$

The algorithm T stops at step  $\tau$  if the value of the function is determined at time  $\tau$ , i.e.,  $i_1, \dots, i_\tau$  and  $\omega(e_{i_1}), \dots, \omega(e_{i_\tau})$  determine the function f.

Of course,  $\tau$  depends on the choice of the root index and the family of decision rules  $(\phi_j) : 1 \leq j \leq n - 1$ .

In our example, if we observe

$$\begin{aligned} i_1 = 1, \omega(e_{i_1}) = 1; & \quad i_2 = 2, \omega(e_{i_2}) = 0; \\ i_3 = 7, \omega(e_{i_3}) = 1; & \quad i_4 = 4, \omega(e_{i_4}) = 1 \end{aligned}$$

then we stop at the 4th step, so  $\tau = 4$ .

## Definition

The algorithm  $T$  **reveals** edge  $e_j$  if  $j \in \{i_1, \dots, i_\tau\}$

Clearly the event  $\{T \text{ reveals } e_j\}$  depends on the configuration  $\omega(e_{i_1}), \dots$  and we define the **revelment** of  $j$  as

$$\delta_{e_j}(T) := \mu\{T \text{ reveals } e_j\}.$$

We also define the influence of an edge  $e_i$  as

$$\text{Inf}_{e_j} := \mu\{f(\omega) \neq f(\omega')\} \text{ where } \omega'(e_j) = \begin{cases} \omega(e_j) & \text{if } j \neq i \\ 1 - \omega(e_i) & \text{if } j = i. \end{cases}$$

# The OSSS inequality

The first result we have is useful for bond/site percolation on the lattice, later we state and prove the result useful for continuum models.

## Theorem

(OSSS Inequality) Let  $f$  and  $(\Omega, \mathcal{F}, \mu)$  be as above. In addition suppose that  $f$  is an increasing function. Then we have

$$\text{Var}(f) \leq 2 \sum_{j=1}^n \delta_{e_j}(T) \text{Cov}(\omega_{e_j}, f).$$

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R. O'Donnell, M. Saks, O. Schramm and R. Servedio (2005)

# Proof

First note that because  $f$  takes values in  $[0, 1]$ , we have

$$\text{Var}(f) = \mathbb{E} \left( (f - \mathbb{E}(f))^2 \right) \leq \mathbb{E} (|f - \mathbb{E}f|) .$$

Now let  $\omega$  and  $\omega'$  be two i.i.d. realizations from  $\Omega$ .

$$\mathbb{E}(f - \mathbb{E}(f)) = \mathbb{E} (f(\omega) - f(\omega')) ,$$

where  $\mathbb{E}$  is w.r.t. the product measure  $\mu \times \mu$ . And so

$$\text{Var}(f) \leq \mathbb{E} (|f - \mathbb{E}(f)|) \leq \mathbb{E} (|f(\omega) - f(\omega')|) . \quad (1)$$



For the realisation  $\omega$  suppose the algorithm checks the edges  $e_{i_1}, \dots, e_{i_\tau}$  before stopping.

Note that  $\tau$ , as well as, the order of the edges  $e_{i_1}, e_{i_2}, \dots$  depend on the realisation  $\omega$ . Let

$$J_t := \{t + 1, t + 2, \dots, \tau\}$$

and, define the configuration  $\omega^t$ , as

$$\omega^t(e_{i_j}) := \begin{cases} \omega(e_{i_j}) & \text{for } j \in J_t \\ \omega'(e_{i_j}) & \text{for } j \notin J_t \end{cases}$$

Clearly  $f(\omega^\tau) = f(\omega')$  and, the stopping time  $\tau$  ensures that  $f(\omega^0) = f(\omega)$ , so that from (1) we have

$$\begin{aligned}
 \text{Var}(f) &\leq \mathbb{E}(|f - \mathbb{E}(f)|) \\
 &= \cancel{\mathbb{E}} \mathbb{E} (|f(\omega) - f(\omega')|) \\
 &= \mathbb{E} \left( \sum_{t=1}^{\tau} |f(\omega^{t-1}) - f(\omega^t)| \right) \\
 &\leq \sum_{t=1}^n \mathbb{E} (|f(\omega^{t-1}) - f(\omega^t)| 1_{\{t \leq \tau\}}) \\
 &\leq \sum_{j=1}^n \sum_{t=1}^n \mathbb{E} (|f(\omega^{t-1}) - f(\omega^t)| 1_{\{t=j\}}) \tag{2}
 \end{aligned}$$

To study the term  $f(\omega^{t-1}) - f(\omega^t)$ , we note that since  $f$  is increasing, on the event  $\{i_t = j\}$  we have

$$\begin{aligned}
& |f(\omega^{t-1}) - f(\omega^t)| \\
&= (f(\omega^{t-1}) - f(\omega^t)) (\omega^{t-1}(e_j) - \omega^t(e_j)) \\
&= f(\omega^{t-1})\omega^{t-1}(e_j) + f(\omega^t)\omega^t(e_j) - f(\omega^{t-1})\omega^t(e_j) - f(\omega^t)\omega^{t-1}(e_j)
\end{aligned} \tag{3}$$

We will study each of the four terms above.

Let  $X_t := (\omega(e_{i_1}), \dots, \omega(e_{i_t \wedge \tau}))$ .

Observe that  $i_t$  is  $X_{t-1}$  measurable.

On the event  $\{i_t = j\}$  we have

$$\begin{aligned} & \mathbb{E} \left( f(\omega^{t-1}) \omega^{t-1}(e_j) \mid X_{t-1} \right) \\ &= \mathbb{E} (f(\omega) \omega(e_j)) \text{ by independence} \\ &= \mathbb{E} \left( f(\omega^t) \omega^t(e_j) \mid X_t \right) \text{ by independence} \end{aligned} \tag{4}$$

?

Next, since  $f$  is increasing, so fixing the first few co-ordinates of  $\omega$ ,  $f(\omega^{t-1})\omega^t(e_j)$  is increasing in  $\omega'$ . So, by the FKG inequality,

$$\mathbb{E} \left( f(\omega^{t-1})\omega^t(e_j) \mid X_n \right) \geq \mathbb{E} \left( f(\omega^{t-1}) \mid X_n \right) \mathbb{E} \left( \omega^t(e_j) \mid X_n \right)$$

and

$$\begin{aligned} & \mathbb{E} \left( \mathbb{E} \left( f(\omega^{t-1})\omega^t(e_j) \mid X_n \right) \mid X_{t-1} \right) \\ & \geq \mathbb{E} \left( \mathbb{E}(\omega^t(e_j) \mid X_n) (\mathbb{E}(f(\omega^{t-1}) \mid X_n)) \mid X_{t-1} \right) \\ & = \mathbb{E} \left( \mathbb{E}(\omega^t(e_j) \mid X_{t-1}) \left[ \mathbb{E}(f(\omega^{t-1} \mid X_n)) \mid X_{t-1} \right] \right) \end{aligned}$$

because  $i_t$  is determined by  $i_1, \dots, i_{t-1}$  and so

$$\begin{aligned} & \mathbb{E} \left( \omega^t(e_j) \mid X_n \right) \text{ is } X_{t-1} \text{ measurable} \\ & = \mathbb{E} \left( \mathbb{E}(\omega^t(e_j) \mid X_{t-1}) (\mathbb{E}(f(\omega^{t-1}) \mid X_{t-1})) \right) \\ & = \mathbb{E}(\omega(e_j))\mathbb{E}(f) \end{aligned}$$

because  $\omega^t$  and  $\omega^{t-1}$  are independent of  $X_{t-1}$

Thus we have

$$\mathbb{E} \left( f(\boldsymbol{\omega}^{t-1}) \boldsymbol{\omega}^t(e_j) \mid X_{t-1} \right) \geq \mathbb{E}(\boldsymbol{\omega}(e_j)) \mathbb{E}(f) \quad (5)$$

Similarly, we obtain

$$\mathbb{E} \left( f(\boldsymbol{\omega}^t) \boldsymbol{\omega}^{t-1}(e_j) \mid X_t \right) \geq \mathbb{E}(\boldsymbol{\omega}(e_j)) \mathbb{E}(f) \quad (6)$$

Now combining everything from (2) and (3) we have

$$\begin{aligned} & \text{Var}(f) \\ & \leq \sum_{j=1}^n \sum_{t=1}^n \left( \mathbb{E}(f(\omega^{t-1})\omega^{t-1}(e_j)1_{\{t=j\}}) + \mathbb{E}(f(\omega^t)\omega^t(e_j)1_{\{t=j\}}) \right. \\ & \quad \left. - \mathbb{E}(f(\omega^{t-1})\omega^t(e_j)1_{\{t=j\}}) - \mathbb{E}(f(\omega^t)\omega^{t-1}(e_j)1_{\{t=j\}}) \right) \end{aligned}$$

taking conditional expectations appropriately w.r.t.  $X_{t-1}$  and  $X_t$  and then unconditioning and using (5) and (6)

$$\begin{aligned} & \leq \sum_{j=1}^n \sum_{t=1}^n \mathbb{E} \left( (2\mathbb{E}(f(\omega)\omega(e_j)) - 2\mathbb{E}f(\omega)\mathbb{E}\omega(e_j))1_{\{t=j\}} \right) \\ & = \sum_{j=1}^n 2\text{Cov}(f, \omega(e_j)) \sum_{t=1}^n \mathbb{E}(1_{\{t=j\}}) \\ & = 2 \sum_{j=1}^n \delta_{e_j}(T) \text{Cov}(f, \omega(e_j)) \end{aligned}$$

□

# The algorithm

So now we have to find a ‘good’ algorithm  $T$  which gives a good bound on  $\delta_{ej}(T)$ .

A natural algorithm would be to first enumerate the edges  $E$  in  $B_n = [-n, n]^d$ . Note that for the event  $\{0 \leftrightarrow \partial B_n\}$ , we do not need to include the edges of  $\partial B_n$ .

So take  $V_0 = 0$ , the origin, and  $E_0 = \emptyset$ .

Let  $e = \langle 0, v \rangle$  (say) be the edge adjacent to the origin which is ‘earliest’ in the enumeration of  $E$ .

Take

$$E_1 = \{e\} \text{ and } V_1 = \begin{cases} V_0 & \text{if } \omega(e) = 0 \\ V_0 \cup \{v\} & \text{if } \omega(e) = 1 \end{cases}$$



For the next step get the edge  $f = \langle x, y \rangle \notin E_1$  with  $x \in V_1$  and  $y \notin V_1$ , which is ‘earliest’ in the enumeration of  $E \setminus E_1$ .

Take

$$E_2 = E_1 \cup \{f\} \text{ and } V_2 = \begin{cases} V_1 & \text{if } \omega(f) = 0 \\ V_1 \cup \{y\} & \text{if } \omega(f) = 1 \end{cases}$$

Continue in this fashion until one of the following two happen for the first time.

$$V_t \cap \partial B_n \neq \emptyset$$

in this case, you have found the open path from  $\{0\}$  to  $\partial B_n$

there is no edge in  $E \setminus E_t$  incident to  $V_t$

in this case, there is no open path from  $\{0\}$  to  $\partial B_n$

Here  $\tau = t$

Unfortunately, this algorithm does not give a good bound on  $\delta_{e_j}(T)$ .

Duminil-Copin's work is to get an 'averaging' algorithm which gives a better bound.

We want an algorithm to obtain all the open connected components of  $B_n$  which intersect the square  $\delta(B_k)$  for each  $k \in \{1, \dots, n\}$ .

The algorithm T we define below starts with

$$V_0 = \{v : v \in \delta(B_k)\} \text{ and } E_0 = \emptyset.$$

Having defined  $V_0 \subseteq V_1 \subseteq \dots \subseteq V_s$  and  $E_0 \subseteq E_1 \subseteq \dots \subseteq E_s$

(Step 1) if there exists an edge  $e = \langle x, y \rangle \notin E_s$  with  $x \in V_s$  and  $y \notin V_s$ , choose the one 'earliest' in the enumeration of  $E \setminus E_s$ .

With a slight abuse of notation let  $e = \langle x, y \rangle$  be this edge.

The decision rule  $\phi_t$  chooses this edge  $e$  and set

$$E_{s+1} = E_s \cup \{e\} \text{ and } V_{s+1} = \begin{cases} V_s & \text{if } \omega(e) = 0 \\ V_s \cup \{y\} & \text{if } \omega(e) = 1. \end{cases}$$

(Step 2) if no such edge exists then take  $E_{s+1} = E_s \cup \{e\}$ , where  $e$  is the ‘earliest’ in the enumeration of  $E$ , with  $e \notin E_s$  and  $V_{s+1} = V_s$ .

We note that in the first step we are still exploring whether an edge belongs to the connected open component of  $\delta(B_k)$ . When this step stops, we are in exactly one of two situations

Situation 1. we have found a connected open component admitting a path from the origin  $\{0\}$  to  $\delta(B_n)$

Situation 2. (i) we have found closed edges surrounding the origin  $\{0\}$  in  $B_k$  which does not allow any open path from the origin  $\{0\}$  to  $\delta(B_k)$  or

(ii) we have found closed edges surrounding  $\delta(B_k)$  in  $B_n \setminus B_k$  which does not allow any open path from the origin  $\delta(B_k)$  to  $\delta(B_n)$ .

In either case our goal has been achieved.

More importantly note that the stop time  $\tau$  is smaller than the time when the first step stops. Also  $\tau$  may be strictly smaller because Situation 1 or 2 may have been obtained even before all the connected open components of  $\delta(B_k)$  are found.

Thus for any edge  $e = \langle u, v \rangle \in E$  we see that the revealment of  $e$  for the algorithm to study  $1_{\{0 \leftrightarrow \partial B_n\}}$  is smaller than that for the above algorithm. Hence

$$\delta_e(T) \leq P_p\{u \leftrightarrow \delta(B_k)\} + P_p\{v \leftrightarrow \delta(B_k)\}.$$

W.l.o.g. assume that  $u \notin \partial B_n$  and  $v \neq 0$ .

Taking  $d_u = \max\{u_1, \dots, u_d\}$ , where  $u = (u_1, \dots, u_d)$ , we see that

$$\begin{aligned} \sum_{k=1}^n P_p\{u \leftrightarrow \delta(B_k)\} &\leq \sum_{k=1}^n P_p\{u \leftrightarrow (u + \delta(B_{k-d_u}))\} \\ &\leq 2 \sum_{k=0}^{n-1} \theta_k. \end{aligned} \tag{7}$$

Combining everything we have

$$\begin{aligned}
& n\theta_n(p)(1 - \theta_n(p)) \\
&= n\text{Var}(1_{\{0 \leftrightarrow \partial B_n\}}) \text{ direct calculation} \\
&\leq 2 \sum_{k=1}^n \sum_{e \in E} \delta_e(T) \text{Cov}(1_{\{0 \leftrightarrow \partial B_n\}}, \omega(e)) \text{ OSSS} \\
&\leq 8 \sum_{k=0}^{n-1} \theta_k \sum_{e \in E} \text{Cov}(1_{\{0 \leftrightarrow \partial B_n\}}, \omega(e)) \text{ from (7)} \\
&= 8p(1 - p)\theta'_n(p) \sum_{k=0}^{n-1} \theta_k \text{ Russo's formula} \\
&\leq 2\theta'_n(p) \sum_{k=0}^{n-1} \theta_k(p)
\end{aligned}$$

Finally,  $\theta_n(p)$  being a polynomial in  $p$  with  $\theta_p < 1$  for  $p < 1$ , we can get  $\epsilon > 0$  and a constant  $c > 0$  such that  $1 - \theta(1 - \epsilon) = c > 0$ , which gives us

$$\theta'_n(p) \geq c \frac{n\theta_n(p)}{\sum_{k=0}^{n-1} \theta_k(p)}$$

as required.

For  $p < p_c$

$$\mathbb{P}_p \left( \boxed{\text{Diagram}}_{B_n} \right) \leq C_1 e^{-C_2 n}$$

For  $p > p_c$

$$\mathbb{P}_p \left( \boxed{\text{Diagram}} \right) \geq \frac{p - p_c}{2}$$