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Rare events in random geometric graphs

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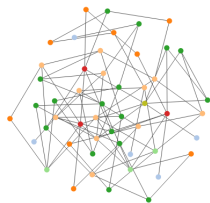
joint work with S. B. Moka, T. Taimre & D. P. Kroese

Projet ANR GrHyDy - Kickoff meeting, 20 Oct 2021

Spatial random
networks



Rare events in
random graphs



$G(n, p)$ = ER graph on n nodes and prob p

$T(G(n, p)) = \#\Delta$ in $G(n, p)$

$$\mathbb{P}\left(T(G(n, p)) \geq \binom{n}{3} t^3\right) \rightsquigarrow ??$$

<http://www.networkpages.nl>

Bhamidi, Hanning, Lee & Nolen (2015) \rightsquigarrow **Importance sampling (IS)**

- ▷ Generate graph samples G_1, \dots, G_K under IS distribution \mathbb{Q}
- ▷ Compute $M_K := \frac{1}{K} \sum_{i \leq K} \mathbb{1}\{T(G_i) \geq \binom{n}{3} t^3\} \frac{d\mathbb{P}}{d\mathbb{Q}}(G_i)$.

How to choose \mathbb{Q} ?

- ▷ **Edge tilt.** $\mathbb{Q}^h(G) := c \exp(hE(G))$, $E(G) = \#\text{edges}$
- ▷ **Triangle tilt.** $\mathbb{Q}^{h, \beta, \alpha}(G) := c \exp\left(hE(G) + \frac{\beta}{n}(n^3/6)^{1-\alpha} T(G)^\alpha\right)$

\rightsquigarrow **# Edges in random geometric graphs??**

- 1 Motivation
- 2 Conditional Monte Carlo in 1D**
- 3 Conditional Monte Carlo in 2D
- 4 Importance sampling
- 5 Outlook

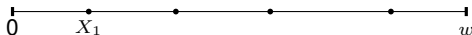
- ▷ $X = \{X_i\}_i = \text{PPP on } [0, \infty) \text{ with intensity } \lambda$
- ▷ $G(X \cap W) = \text{edges in RGG at level 1 in window } W = [0, w], w \geq 1$

Few edges. $\mathbb{P}(E_{\leq k}) := \mathbb{P}(|G(X \cap W)| \leq k) = ?$

$k = 0.$

▷ $X_1^* := X_1; X_{m+1}^* := \inf\{X_i \in X : X_i \geq X_m^* + 1\}$

▷ $X_* := X_{I_*}; I_* := \sup\{i \geq 1 : X_i^* \in W\}$



Theorem

$\mathbb{P}(E_0 | \mathcal{F}^*) = e^{-\lambda((I_*-1)_+ + (w-X_*) \wedge 1)}$, where $\mathcal{F}^* := \sigma(X_1^*, X_2^*, \dots)$.

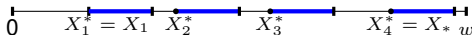
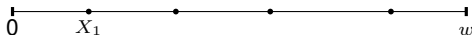
- ▷ $X = \{X_i\}_i = \text{PPP on } [0, \infty) \text{ with intensity } \lambda$
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Theorem

$\mathbb{P}(E_0 | \mathcal{F}^*) = e^{-\lambda((I_*-1)_+ + (w-X_*) \wedge 1)}$, where $\mathcal{F}^* := \sigma(X_1^*, X_2^*, \dots)$.

$k = 1.$

$$\triangleright I^+ := \inf\{i \geq 2 : X_i - X_{i-1} \leq 1\}$$

$$\triangleright X^+ := (X - X_{I^+}) \cap [1, \infty)$$



Theorem ($k = 1$)

$$\mathbb{P}(E_{\leq 1} | \mathcal{F}^+) = e^{-\lambda((w - X_{I^+}) + \wedge 1)} \mathbb{1}\{G(X^+ \cap [1, w - X_{I^+}]) = \emptyset\},$$

where $\mathcal{F}^+ := \sigma(X_1, X_2, \dots, X_{I^+}, X^+)$

- ▷ $p_{\leq i} := \mathbb{P}(E_{\leq i})$
- ▷ $w \in \{5, 7.5, 10\}$, $\lambda = 2$, $N = 10^6$ simulations

$$\triangleright p_{\leq k}^{\text{CMC}} := \frac{1}{N} \sum_{i \leq N} \mathbb{1}\{|G(X^{(i)} \cap [0, w])| \leq k\}$$

w	p_0^{CMC}	$p_{<1}^{\text{CMC}}$
5	$4.056 \times 10^{-3} \pm 6.36 \times 10^{-5}$	$1.676 \times 10^{-2} \pm 1.28 \times 10^{-4}$
7.5	$2.410 \times 10^{-4} \pm 1.55 \times 10^{-5}$	$1.354 \times 10^{-4} \pm 3.68 \times 10^{-5}$
10	$1.100 \times 10^{-5} \pm 3.32 \times 10^{-6}$	$8.500 \times 10^{-5} \pm 9.23 \times 10^{-6}$

$$\triangleright p_{\leq k}^{\text{Cond}} := \frac{1}{N} \sum_{i \leq N} P^{(i)}$$

w	p_0^{Cond}	$p_{<1}^{\text{Cond}}$
5	$4.148 \times 10^{-3} \pm 1.41 \times 10^{-5}$ (20.30)	$1.670 \times 10^{-2} \pm 7.63 \times 10^{-4}$ (2.8)
7.5	$2.244 \times 10^{-4} \pm 1.06 \times 10^{-6}$ (216.3)	$1.304 \times 10^{-4} \pm 1.87 \times 10^{-5}$ (3.9)
10	$1.296 \times 10^{-5} \pm 1.06 \times 10^{-7}$ (984.9)	$9.637 \times 10^{-5} \pm 4.56 \times 10^{-6}$ (4.1)

Few missing edges.

▷ $M_w := \binom{|X \cap [0, w]|}{2} - |G(X \cap [0, w])| =$ number of missing edges.

Theorem (No missing edges)

$$\mathbb{P}(M_w = 0) = e^{-\lambda(w-1)} + (w-1)\lambda e^{-\lambda(w-1)}.$$



Theorem (At most one missing edge)

$$\mathbb{P}(M_w = 1) = \frac{\lambda^2(w-2)^2}{2} e^{-\lambda w} + (w-3/2)\lambda^2 e^{-\lambda(w-1)}$$

▷ $X'_1 :=$ first Poisson point to the left of w



Case 1. $X'_1 \in [X_1 + 2, w] \rightsquigarrow X \cap (X_1, w] = \{X'_1\}$

Case 2. $X'_1 \in [X_1 + 1, X_1 + 2] \rightsquigarrow X \cap ((X_1, X'_1 - 1] \cup [X_1 + 1, X'_1)) = \emptyset$

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W = full-dimensional sampling window in \mathbb{R}^d

Rare event. $F_{<a} := \{|G(X \cap W)| < (1 - a)\mu\}$

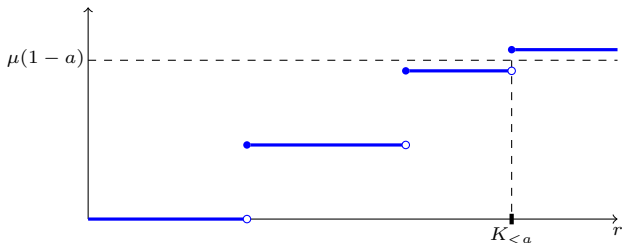
Idea. $X = \{X_n\}_{n \leq K}$, where

- ▷ $X_\infty := \{X_n\}_{n \geq 1}$ iid $X_i \sim \text{Unif}(W)$
- ▷ $K \sim \text{Poi}(\lambda|W|)$

$$\mathbb{P}(F_{<a}) = \mathbb{E}[\mathbb{P}(F_{<a} | X_\infty)] = \mathbb{E}[\text{Poi}(K_{<a}(X_\infty) - 1)],$$

where $K_{<a}(X_\infty) := \inf\{k \geq 1 : |G(\{X_1, \dots, X_k\} \cap W)| \geq (1 - a)\mu\}$

$|G(\{X_1, \dots, X_{\lfloor r \rfloor}\} \cap W)|$





▷ $W = [0, w]^2$, $w \in \{20, 25, 30\}$

▷ $\lambda = 2$

▷ $N = 10^5$ simulations

▷ $p_{<0.2}^{\text{Cond}} := \frac{1}{N} \sum_{i \leq N} \text{Poi}(K_{<a}(X_\infty(i)) - 1)$,

	$p_{<0.2}^{\text{Cond}}$	$p_{>0.2}^{\text{Cond}}$
X^S	$2.02 \times 10^{-3} \pm 6.98 \times 10^{-6}$ (414.8)	$5.12 \times 10^{-3} \pm 1.63 \times 10^{-5}$ (193.7)
X^M	$1.54 \times 10^{-4} \pm 7.05 \times 10^{-7}$ (3, 106.4)	$6.76 \times 10^{-4} \pm 2.77 \times 10^{-6}$ (878.6)
X^L	$6.91 \times 10^{-6} \pm 4.19 \times 10^{-8}$ (39, 415.8)	$6.24 \times 10^{-5} \pm 3.24 \times 10^{-7}$ (5, 911.1)

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Refined estimator by *importance sampling* of X_∞ ?

Lower tail

Idea. Find point-process law \mathbb{Q} such that

- ▷ Rare event is typical under \mathbb{Q} and $h(\mathbb{Q}|\text{Poi})$ is minimal

↪ *Edge-tilt/Strauss process*

Sequential algorithm.

- ▷ *Initialize.* $X = \{X_1, \dots, X_{n_0}\}$ iid points $n_0 \approx \lambda|W|$
- ▷ *Iterate.* Remove point X_i from X with prob. $\propto \gamma^{\deg(X_i)}$, $\gamma > 1$
- ▷ *Likelihood ratio per step.*

$$\frac{|X| \gamma^{\deg(X_i)}}{\sum_j \gamma^{\deg(X_j)}}.$$

- ▷ *Stop.* If $|G(X \cap W)| \leq \mu(1 - a)$

Algorithm 4.1: Importance sampling estimator $q_{<a}^{\text{IS}}$ for $q < a$

input: Number $N \geq 1$ of MC runs; parameter γ ; Poisson intensity λ ; sampling window W .

output: Importance sampling estimator $q_{<a}^{\text{IS}}$ for $q < a$.

```

1  $n_0 \leftarrow \lfloor \lambda |W| \rfloor$ 
2  $\text{sum} \leftarrow 0$ 
3 for  $i \leq N$  do
4    $X \leftarrow \{X_1, \dots, X_{n_0}\}$  iid uniform in  $W$ 
5    $\rho \leftarrow 1$ 
6   while  $|G(X \cap W)| \geq \mu(1 - a)$  do
7      $\left[ \begin{array}{l} \text{draw } X_i \in X \text{ with probability } r_i = \gamma^{\deg(X_i)} / \sum_{X_j \in X} \gamma^{\deg(X_j)} \\ \rho \leftarrow \rho / (|X| r_i) \quad X \leftarrow X \setminus \{X_i\} \end{array} \right.$ 
8    $\text{sum} \leftarrow \text{sum} + \rho \text{Poi}(|X|)$ 
9 return  $\text{sum}/N$ 

```



Upper tail

Sequential algorithm.

- ▷ **Initialize.** $X = \{X_1, \dots, X_{n_0}\}$ iid points $n_0 \approx \lambda|W|$
- ▷ **Discretize** W into bins W_i
- ▷ **Iterate.** Add point in W_i prob. $\propto \gamma^{n(W_i)}$,
 - ▷ $n(W_i) = \#$ points in adjacent bins
- ▷ **Likelihood ratio per step.**

$$\frac{\gamma^{n(W_i)} \cdot \# \text{bins}}{\sum_j \gamma^{n(W_j)}}.$$

- ▷ **Stop.** If $|G(X \cap W)| \geq \mu(1 - a)$



- ▷ $W = [0, w]^2, w \in \{20, 25, 30\}$
- ▷ $\lambda = 2$
- ▷ $N = 10^5$ simulations

	$q_{<0.2}^{\text{IS}}$	$q_{>0.2}^{\text{IS}}$
X^S	$2.02 \times 10^{-3} \pm 6.22 \times 10^{-6} (523.3)$	$5.12 \times 10^{-3} \pm 1.57 \times 10^{-5} (207.9)$
X^M	$1.54 \times 10^{-4} \pm 6.16 \times 10^{-7} (4,071.0)$	$6.74 \times 10^{-4} \pm 2.66 \times 10^{-6} (951.8)$
X^L	$6.93 \times 10^{-6} \pm 3.63 \times 10^{-8} (52,665.8)$	$6.24 \times 10^{-5} \pm 3.09 \times 10^{-7} (6,537.22)$

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- ▷ **1D.** Probabilities of few edges/few missing edges ✓
- ▷ **2D.** Conditional MC ✓
- ▷ **2D.** Sequential importance sampling ✓
- ▷ ***Rigorous results in 2D !***
- ▷ ***Optimality !***
- ▷ ***Triangles, edge length, ... !***

Thanks!





- [1] S. Chatterjee and M. Harel.
Localization in random geometric graphs with too many edges.
Ann. Probab., 48(1):574–621, 2020.

- [2] C. Hirsch, S. B. Moka, D. Taimre, and D. P. Kroese.
Rare events in random geometric graphs.
Methodol. Comput. Appl. Probab., 2021+.

