

# Crossing Numbers and Stress of Random Graphs

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Stochastics

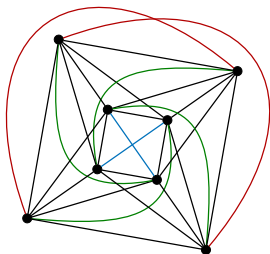
Matthias Reitzner

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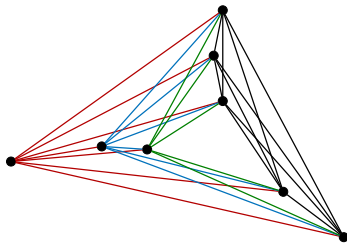
# Crossing Numbers

Crossing Number  
 $cr(G)$



$$cr(K_8) = 18$$

Rectilinear Crossing Number  
 $\overline{cr}(G)$



$$\overline{cr}(K_8) = 19$$

**Observation.**  $cr(G) \leq \overline{cr}(G)$

# Crossing Number Approximations

There is no PTAS [Cabello 13]

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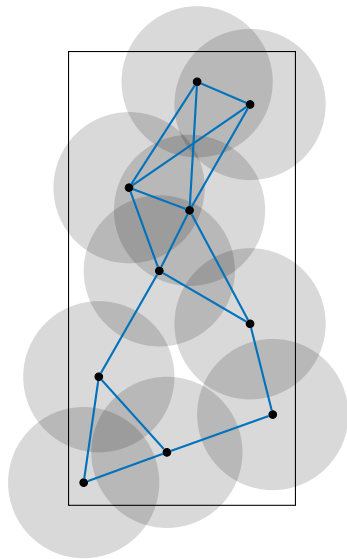
## Known approximations:

graph class	bounded $\Delta$	ratio
general	✓	$\mathcal{O}(n^{9/10} \cdot \text{polylog } n)$
$m = \Theta(n^2)$	–	$\mathcal{O}(1)$
bounded <b>genus</b>	✓	$\mathcal{O}(1)$
bounded number of graph elements away from planarity	✓	$\mathcal{O}(1)$
bounded <b>pathwidth</b>	–	$\mathcal{O}(1)$

# Random Geometric Graphs

## Geometric Graph (unit-disc/-ball graph):

Given: points  $V \subset \mathbb{R}^d$ , threshold  $\delta$ . Connect points iff their Euclidean distance is at most  $\delta$ .

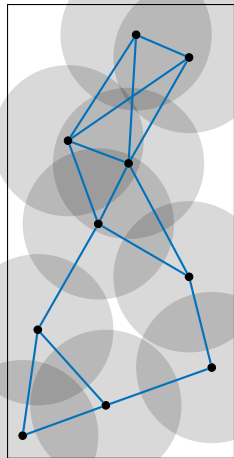


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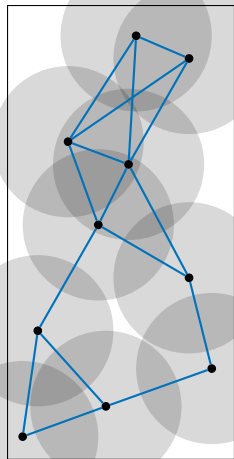
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### More formally:

- ▶ Convex set  $W \subset \mathbb{R}^d$  with  $\text{vol}_d(W) = 1$
- ▶ Poisson process of intensity  $t \rightarrow \mathbb{E}n = t$ .
- ▶ Choose  $n$  points  $V \subset W$  independently according to uniform distribution.
- ▶ Simpler:  $W$  is a ball  $\rightarrow V$  is rotation invariant
- ▶ Consider threshold  $\delta$  dependent on  $t \rightarrow \delta_t$



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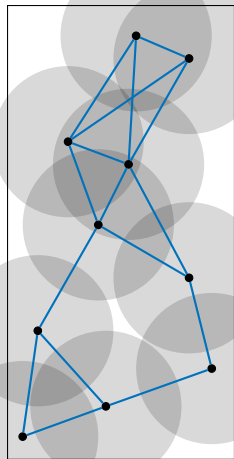
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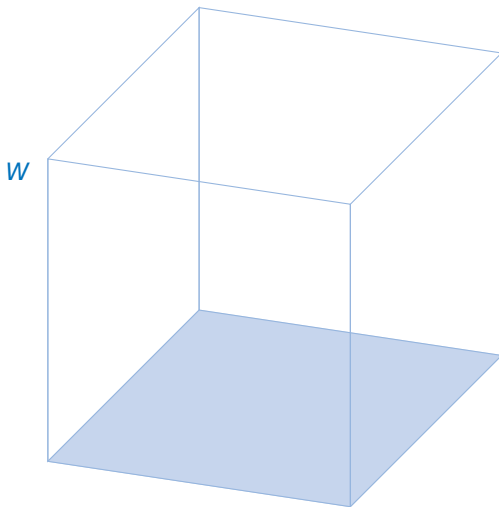
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**Remark:** Poisson simplifies formulae. We can de-Poissonize: simply pick  $n$  uniform random independent points in  $W$ .

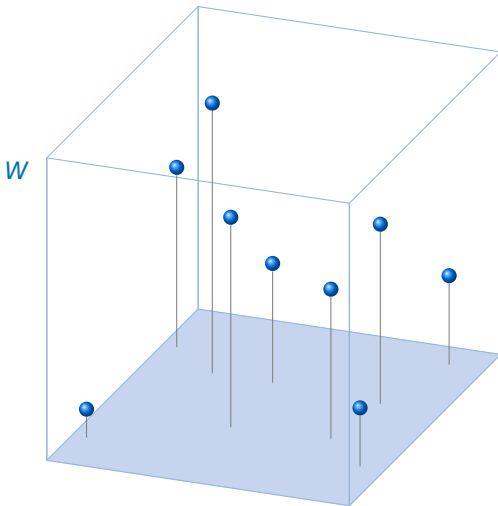




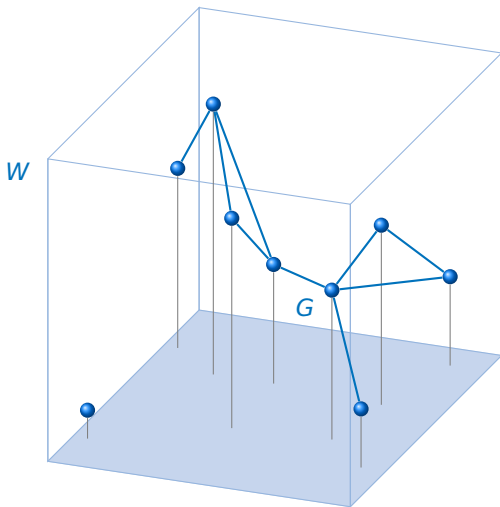
# Projection Algorithm



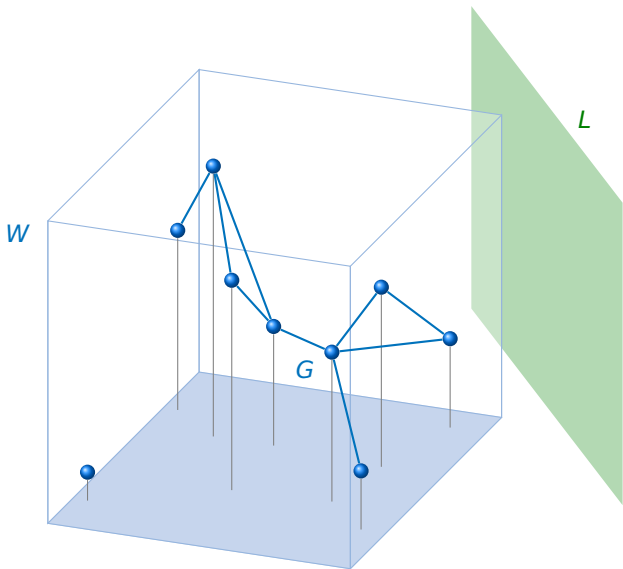
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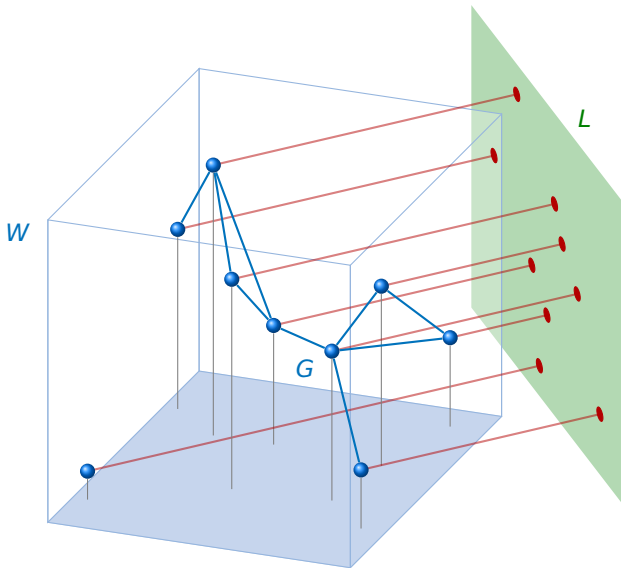
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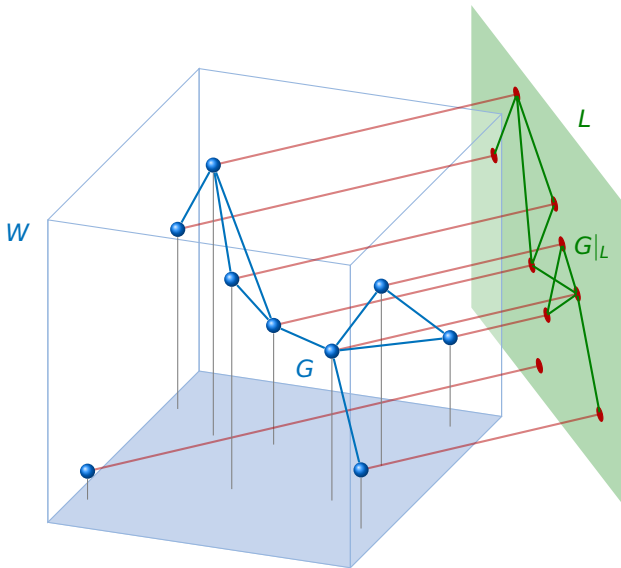
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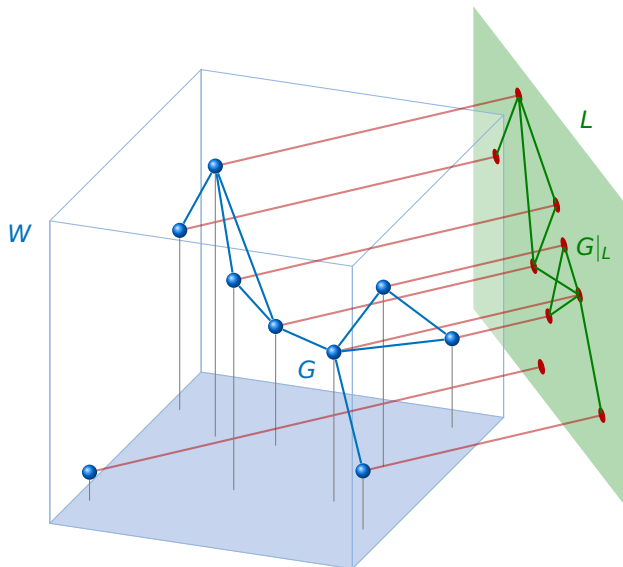
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$G_0$  = abstract graph of  $G$ : Relation between  $\overline{cr}(G_0)$  and  $\overline{cr}(G|_L)$ ?

# Stochastic Tools: U-Statistics

measurable, non-negative, real-valued, independent of other points

$$\mathbf{U}\text{-statistic} = \text{measure } U(k, f) := \sum_{\mathbf{v} \in V_{\neq}^k} f(\mathbf{v})$$

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- ▶ of order  $k = 4$ : Number of crossings in  $G$  after projecting onto  $L$

line segment after projection on  $L$

$$\bar{c}r(G|_L) = \sum_{(v_1, v_2, v_3, v_4) \in V_{\neq}^4} \mathbb{1}([v_1, v_2]|_L \cap [v_3, v_4]|_L \neq \emptyset) / 8$$

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**Variance** of  $f$ : Malliavin calculus for Poisson point processes

Wiener-Itô chaos expansion, assuming  $f$  is  $L^2$ -integrable

$$t \int_W (\mathbb{E}_V D_v f(V))^2 dv \leq \text{Var}_V f(V) \leq t \int_W \mathbb{E}_V (D_v f(V))^2 dv.$$

Poincaré inequality

where  $D_v f(V) := f(V \cup \{v\}) - f(V)$  is an operator measuring the difference when adding a point.

## after some calculations... **Stochastic Results**

Let  $G_0$  be the abstract graph (=no coordinates) of  $G$ .

For **any** projection plane  $L$  we have:

$$\text{cr}(G_0) \leq \overline{\text{cr}}(G_0) \leq \mathbb{E}_V \overline{\text{cr}}(G|_L) = \Theta\left(\frac{m^3}{n^2} \cdot \left(\frac{m}{n^2}\right)^{\frac{2-d}{d}}\right)$$

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- ▶ A random geometric graph  $G$  in  $\mathbb{R}^2$  is an **expected constant-factor** approximation for  $\text{cr}(G_0)$  and  $\overline{\text{cr}}(G_0)$ .
- ▶ Let  $d$  and density  $m/n^2$  fixed. Picking **any** projection plane  $L$  for a random geometric graph in  $\mathbb{R}^d$  yields an **expected constant-factor** approximation for  $\text{cr}(G_0)$  and  $\overline{\text{cr}}(G_0)$ .

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Details in the paper...

- ▶  $\text{Var} \ll \mathbb{E}$  by several orders + Law-of-Large-Numbers  $\rightarrow$   
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- ▶ We pick  $L$  not arbitrary but **random** (uniform): compute  $\mathbb{E}_{L,V} \bar{cr}(G|_L)$ ,  $\text{Var}_{L,V} \bar{cr}(G|_L)$ , LLN
- ▶ This is „simpler“ if  $W$  is rotation invariant:  
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- ▶ The probability of finding „optimum“  $L$  is only in  $\mathcal{O}(t^{-1})$ ... expensive!  $\rightarrow$  How to find a good  $L$ ?

# Stress

$$\text{stress}(G) := \sum_{\substack{v_1, v_2 \in V(G), \\ v_1 \neq v_2}} w(v_1, v_2) \cdot (d_0(v_1, v_2) - d_1(v_1, v_2))^2$$

often  $\frac{1}{d_0(v_1, v_2)^2}$  distance in drawing

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Based on **experimental** data, low-stress drawings **seem** to have small crossing number... **Can we prove this?**

Find low-stress drawings via **Multidimensional Scaling (MDS)**:

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**If** stress and crossing number positively correlated

→ MDS yields crossing number approximations?!

Not really (graph-theoretic != our geometric distances), but close.



# Stress vs. Crossings

## Details in the paper...

- ▶ Stress is a **U-statistic!**
- ▶ Project a random geometric graph  $G$  onto  $L$ 
  - Consider stress w.r.t.  $\mathbb{R}^d$ -distances as desired distances
  - we compute  $\mathbb{E}$ ,  $\text{Var}$ , LLN

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  - we compute  $\mathbb{E}$ ,  $\text{Var}$ , LLN
- ▶ **Furthermore** we show:  
strictly **positive correlation** between  $\mathbb{E}_V \bar{c}_r$  and  $\mathbb{E}_V \text{stress}$

**Yes**, in some sense a stress-minimum drawing **is** a crossing number approximation!

## Wrapping up...

**Summary.** For a **random geometric graph**,...

- 1** ...a trivial projection yields an **expected** crossing number approximation **with high probability**.
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- ▶ What about other random graph models?

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