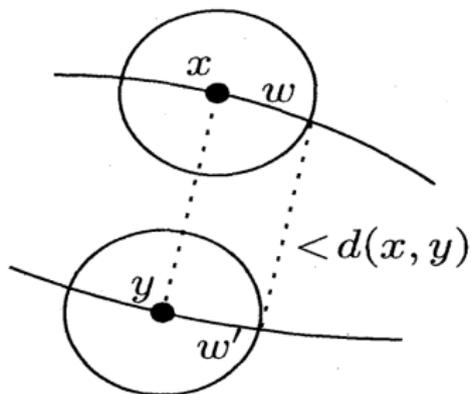


Sparse expanders have negative curvature

JUSTIN SALEZ

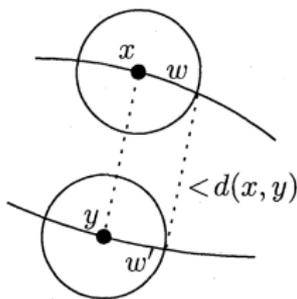


UNIVERSITÉ PARIS-DAUPHINE & PSL

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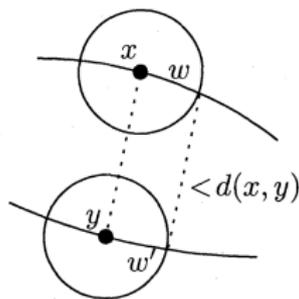
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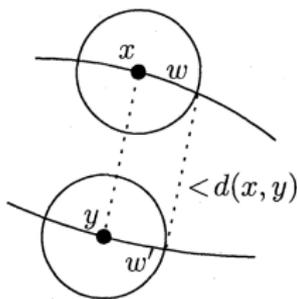
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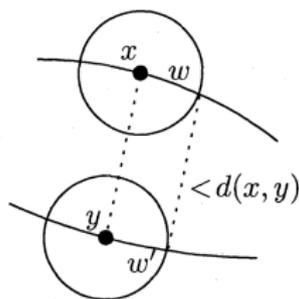
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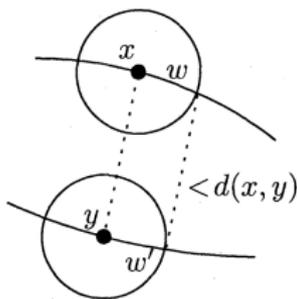
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Question: can expanders have non-negative curvature?

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- ▶ P is the **transition matrix** of lazy simple random walk:

$$P(x, y) := \begin{cases} \frac{1}{2 \deg(x)} & \text{if } \{x, y\} \in E; \\ \frac{1}{2} & \text{if } x = y; \\ 0 & \text{else.} \end{cases}$$

Online Graph Curvature Calculator (Stagg-Cushing)

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Graph curvature calculator

Written by George Stagg and David Cushing

Graph viz with [cytoscape.js](#)

v0.6.2

Controls

Add new vertex - Click vertex, then click empty space

Connect vertices - Click vertex, then click another

Remove vertex - Right click (tap-and-hold) a vertex

Remove edge - Right click (tap-and-hold) an edge

Zoom in/out - Scroll wheel (pinch-and-zoom)

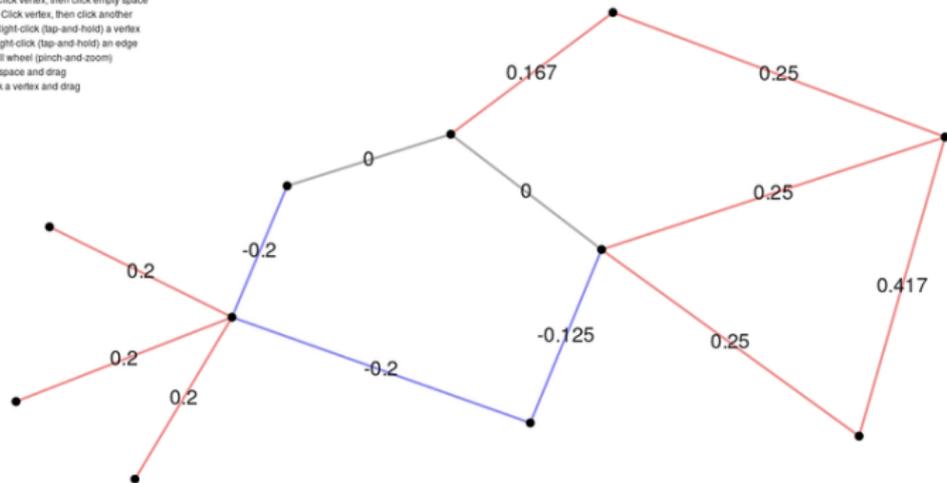
Pan - Click empty space and drag

Move vertex - Click a vertex and drag

[\[Hide\]](#)

[\[Toggle Labels\]](#)

[\[Autolayout\]](#)



Ollivier-Ricci Curvature with Idleness

0.5

Adjacency Matrix [\[Hide\]](#)

```
[[0,1,0,1,1,1,0,0,0,0,0],[1,0,1,0,0,0,0,0,1,0,0,0],[1,0,1,0,1,0,0,0,0,0,0,0],[1,0,0,1,0,0,0,0,0,0,0,0],[1,0,0,0,0,0,0,0,1,0,0,0],[0,0,0,0,0,0,1,0,0,1,1,1],[0,1,0,0,0,0,0,1,0,0,0,0],[0,0,0,0,0,0,1,0,0,0,0,1],[0,0,0,0,0,0,1,0,0,0,0,1],[0,0,0,0,0,0,1,0,0,0,0,1]]
```

[\[Undo\]](#) [\[Load\]](#)

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- ▶ Intimately related to the **cutoff phenomenon** (S.'21)

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Far-reaching applications... (Hoory-Linial-Wigderson'06)

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▷ Sparse graphs either have a macroscopic fraction of edges with negative curvature or a macroscopic fraction of eigenvalues near 1

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- curvature and expansion (this talk !)

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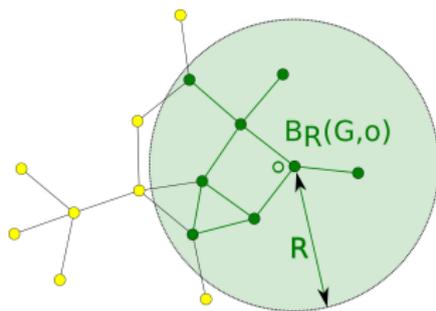
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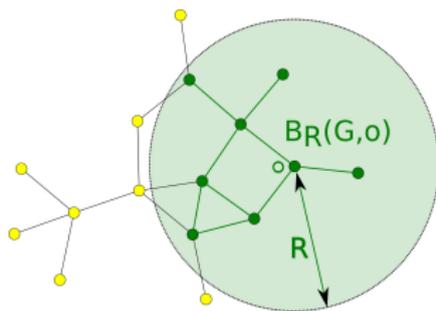
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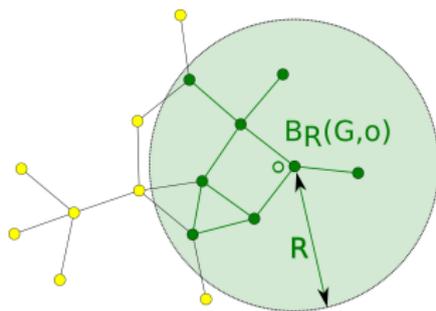
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▷ $\mathcal{G}_\bullet := \{\text{loc. finite, connected rooted graphs}\}$ is a Polish space.

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Intuition: (\mathbb{G}, o) describes how G_n looks **from a random vertex**.

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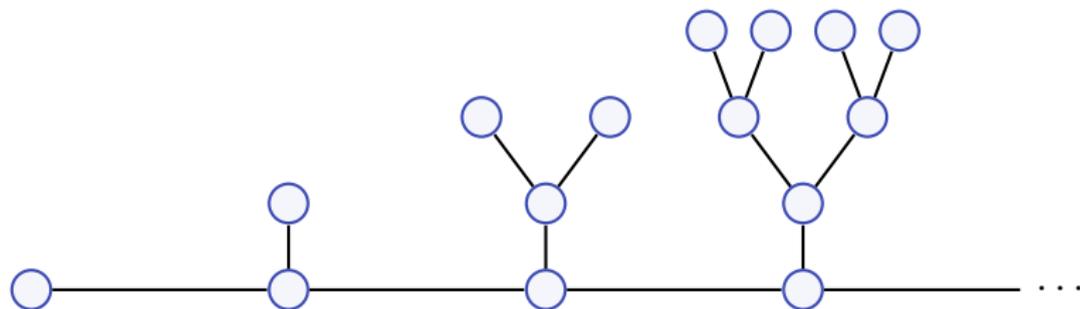
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Theorem (Benjamini-Lyons-Schramm'15) For a sequence (G_n) to admit **subsequential limits**, it is enough that it satisfies

$$\sup_{n \geq 1} \left\{ \frac{1}{|V_n|} \sum_{x \in V_n} \deg(x) 1_{\deg(x) > \Delta} \right\} \xrightarrow{\Delta \rightarrow \infty} 0.$$

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Theorem (S.'21). No limit (\mathbb{G}, o) can satisfy these 3 properties.

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$$h_G := \lim_{t \rightarrow \infty} \frac{1}{t} \sum_{x \in V} P_G^t(o, x) \log \frac{1}{P_G^t(o, x)}.$$

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Warning: false without unimodularity... (Benjamini-Kozma'10)

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