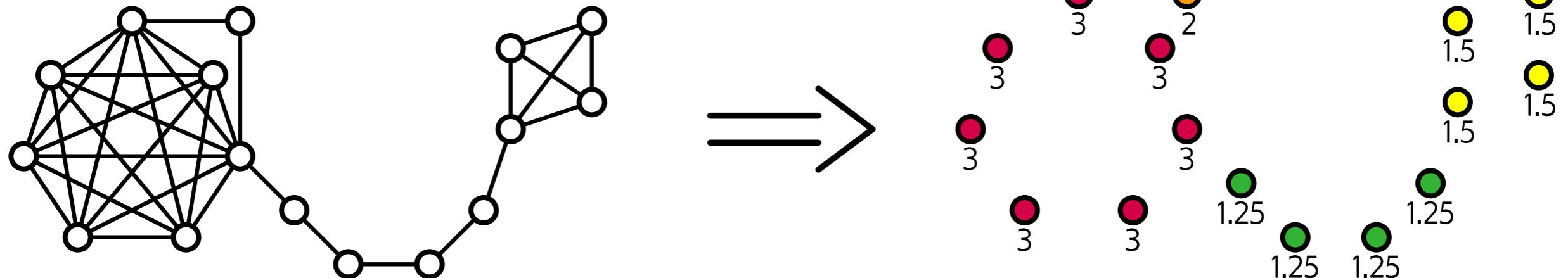


Local Density and its Distributed Approximation



Aleksander B. Christiansen

Ivor van der Hoog

Eva Rotenberg

Maximum Subgraph Density

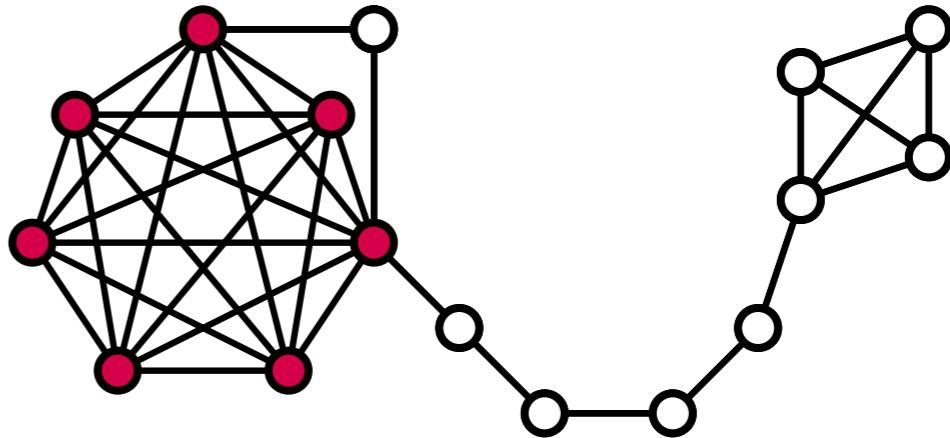
Input: graph $G = (\textcolor{blue}{V}, \textcolor{blue}{E})$.

Given any subset $X \subset \textcolor{blue}{V}$:

$$E[X] := \{(u, v) \in \textcolor{blue}{E} \mid u, v \in X\}.$$

$$G[X] := (X, E[X]).$$

$$\rho(G[X]) := \frac{|E[X]|}{|X|} = \frac{21}{7} = 3.$$



Maximum Subgraph Density

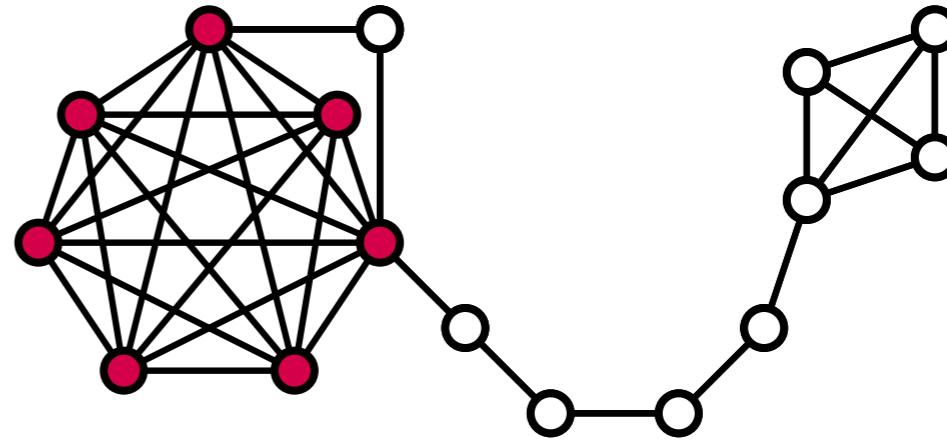
Input: graph $G = (\mathcal{V}, \mathcal{E})$.

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$$G[X] := (X, \mathcal{E}[X]).$$

$$\rho(G[X]) := \frac{|\mathcal{E}[X]|}{|X|} = \frac{21}{7} = 3.$$



We define the **maximum subgraph density** as:

$$\rho^{\max}(G) := \max_{X \subset \mathcal{V}} \rho(G[X])$$

There exist **many** papers that either compute or dynamically maintain $\rho^{\max}(G)$.

Why care about Maximum Subgraph Density?

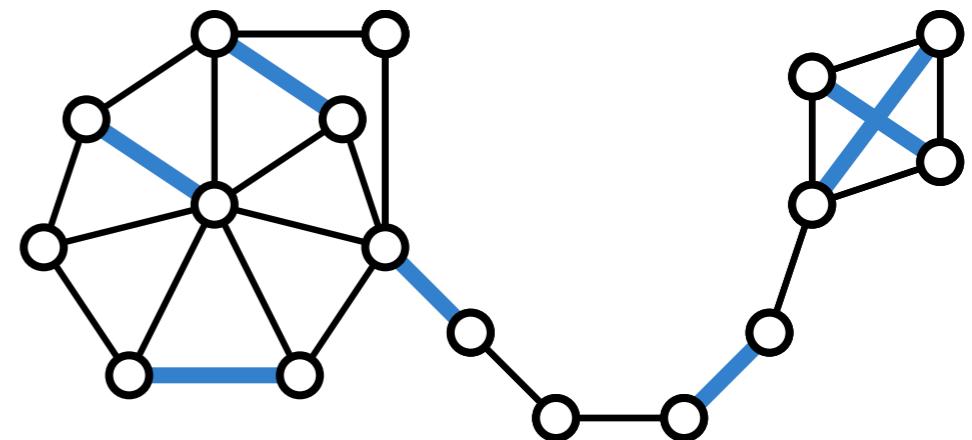
Many algorithms can have their running time be parametrized by $\rho^{\max}(G)$.

E.g., dynamic maximal matching.

Input: dynamic graph $G = (V, E)$.

Edge insertion + deletion.

Maintain a maximal matching.



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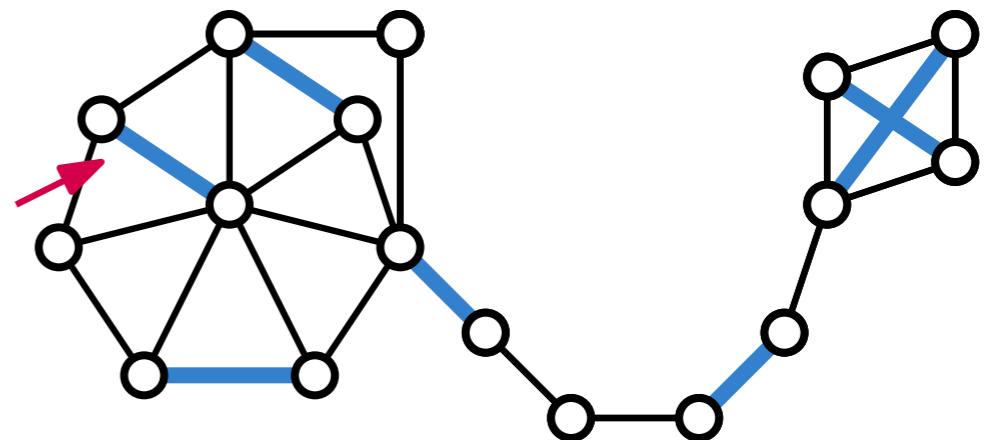
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Naive algorithm:

Upon a deletion (u, v) , check the neighborhood of u and v



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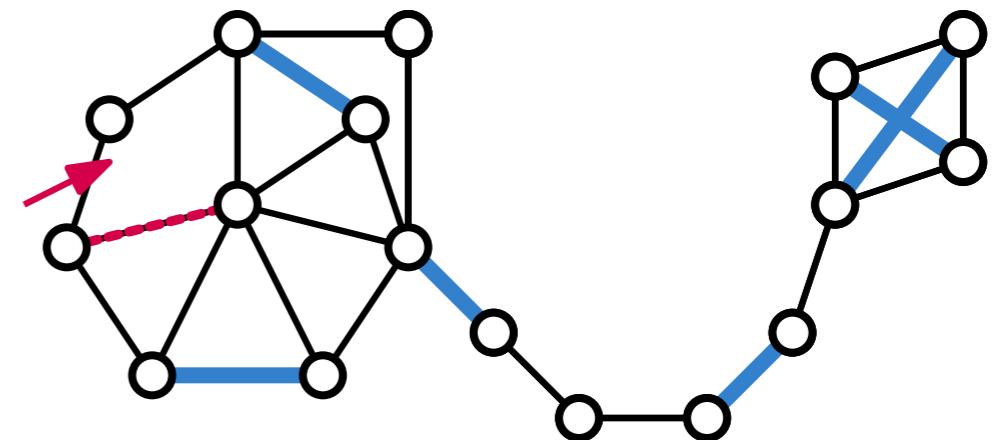
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Runtime: $O(\Delta)$

Runtime can be parametrized by $\rho^{\max}(G)$ instead!

Duality: fractional orientations

Input: dynamic graph $G = (\mathcal{V}, \mathcal{E})$.

Maximum subgraph density: $\rho^{\max}(G) := \max_{X \subset \mathcal{V}} \rho(G[X]).$

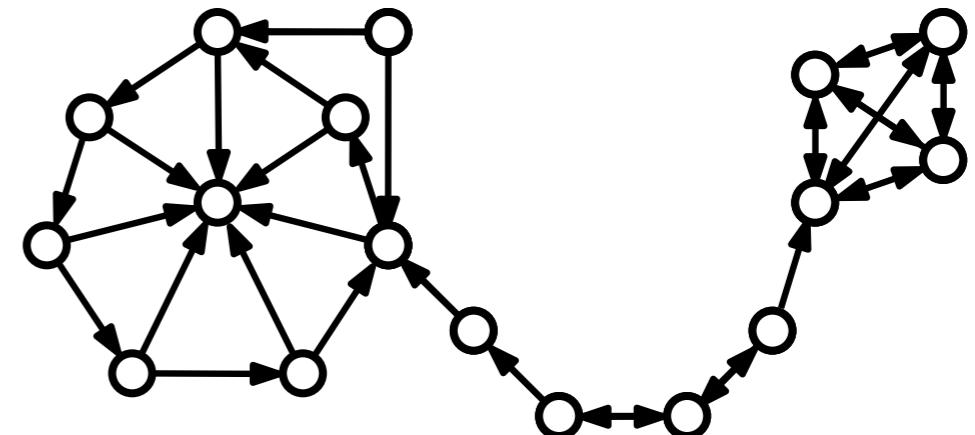
Minimum out-degree $\Delta^{\min}(\overrightarrow{G}) := \min_{\overrightarrow{G}} \max_{v \in \mathcal{V}} \Delta(v).$

Fractional orientation \overrightarrow{G} :

$\forall (u, v) \in \mathcal{E}$, define: $g(u \rightarrow v), g(v \rightarrow u) \in [0, 1].$

$\forall (u, v) \in \mathcal{E}$, require: $g(u \rightarrow v) + g(v \rightarrow u) = 1.$

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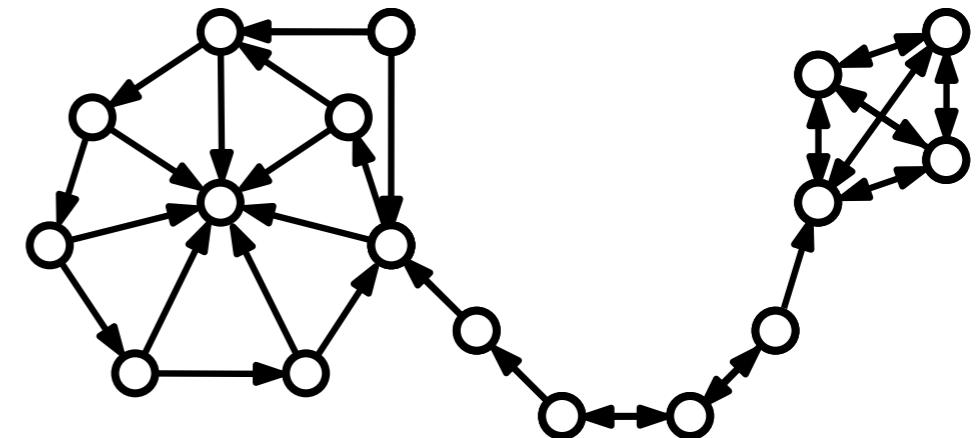
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Minimum out-degree $\Delta^{\min}(G)$:

Minimum over all fractional orientations, of
the maximum out-degree $\Delta(v)$ over all $v \in \mathcal{V}$.



Duality of linear programs:

$$\rho^{\max}(G) = \Delta^{\min}(G)$$

Why care about Maximum Subgraph Density?

E.g., dynamic maximal matching.

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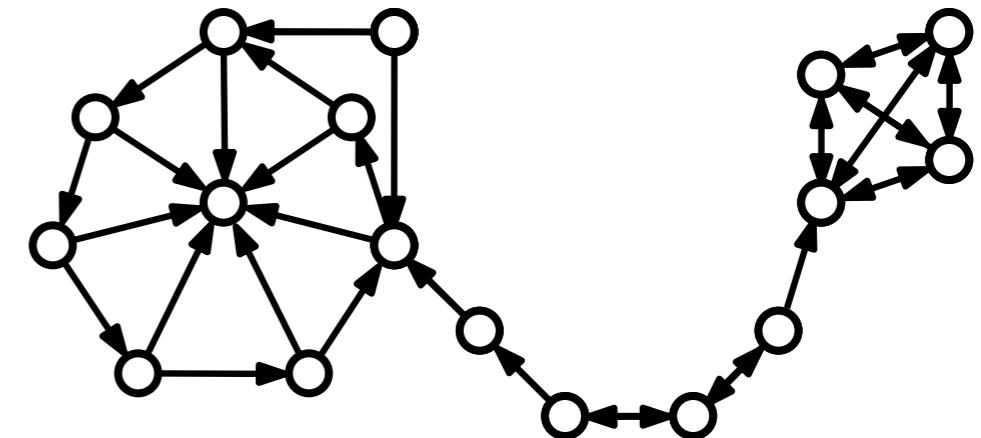
Edge insertion + deletion.

Maintain a maximal matching.

Smart algorithm:

Maintain an orientation with minimum out-degree.

Each node v maintains a list of all un-matched in-neighbors.



Runtime: $O(\rho^{\max}(G) + \text{polylog } n)$

Delete (u, v) :

The vertices u, v inform their out-neighbors.

If unmatched, u checks its outneighbors.

If still unmatched, u checks whether its in-neighbor list is empty.

This paper: Local density

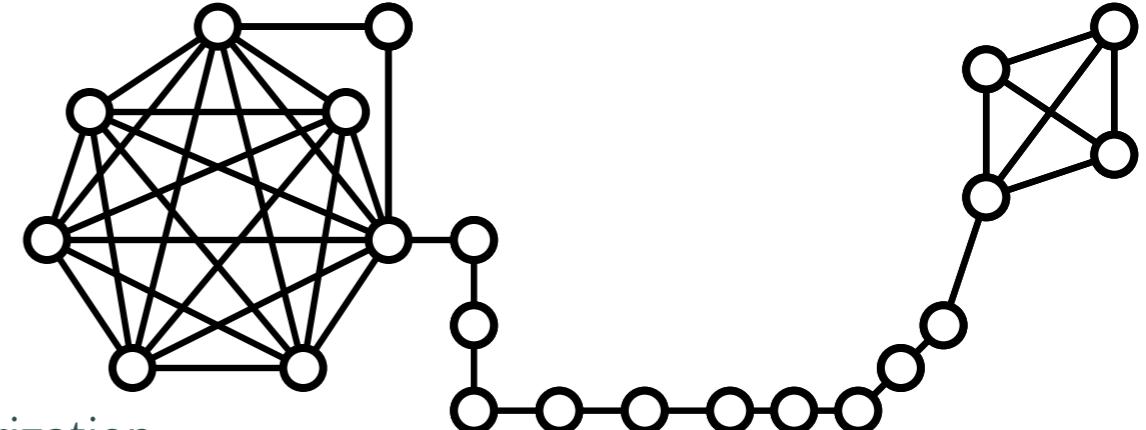
Danisch, Chan, and Sozio. [WWW, 2017].

Maximum subgraph density has downsides:

- It is a global measure, not a local one.

- Distributed lower bound: $\Omega(D)$ where D is the diameter.

- Dynamic algorithms get a very crude running time parametrization.



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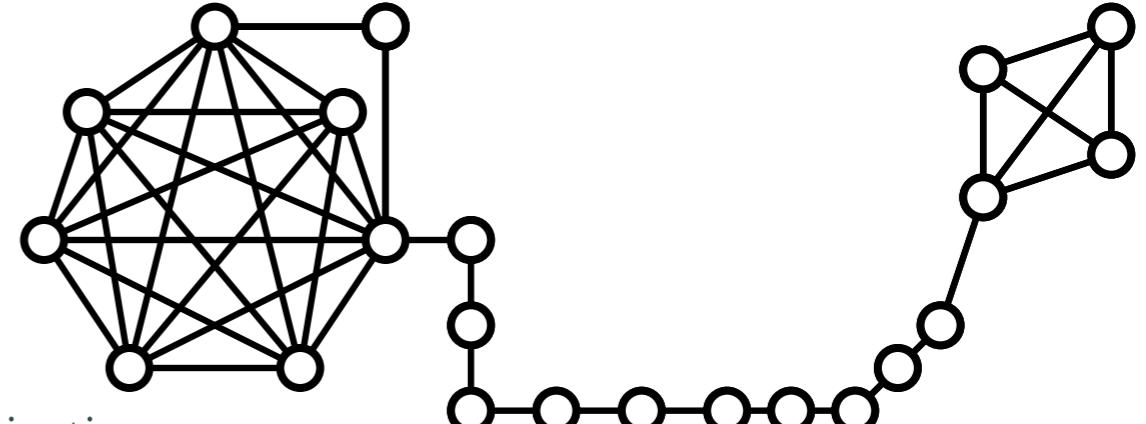
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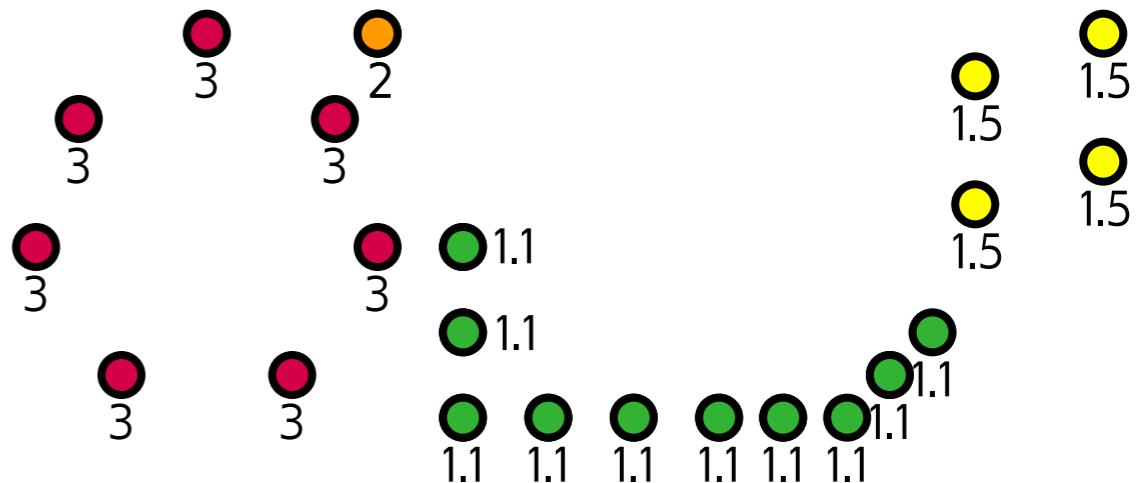
Their idea:

Define a measure to measure how ‘locally dense’ the graph is around a vertex v .

Local density assigns to each vertex $v \in V$ a value $\rho^*(v)$,

Experimental paper.

They approach $\rho^*(v)$ with no guarantees.

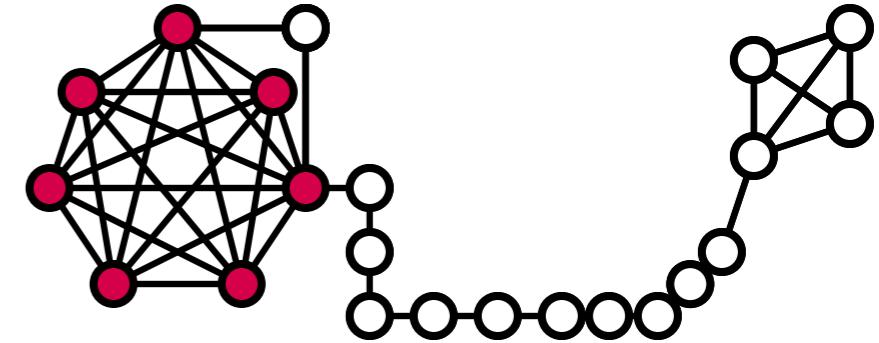


Definition: Local Density

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Iterative definition:

- 1: find $X \subseteq V$ that maximizes $\rho(G[X])$.
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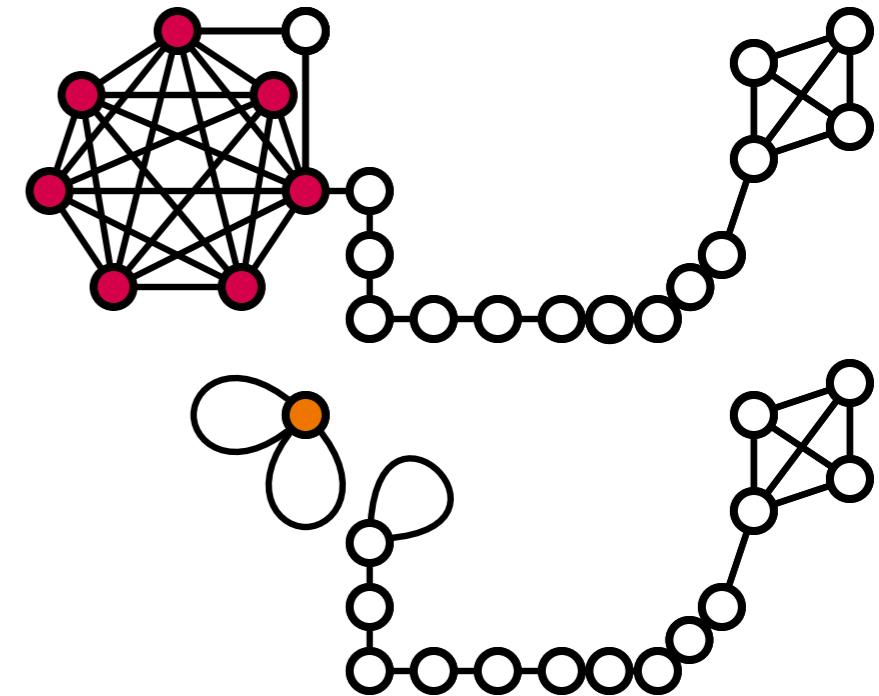


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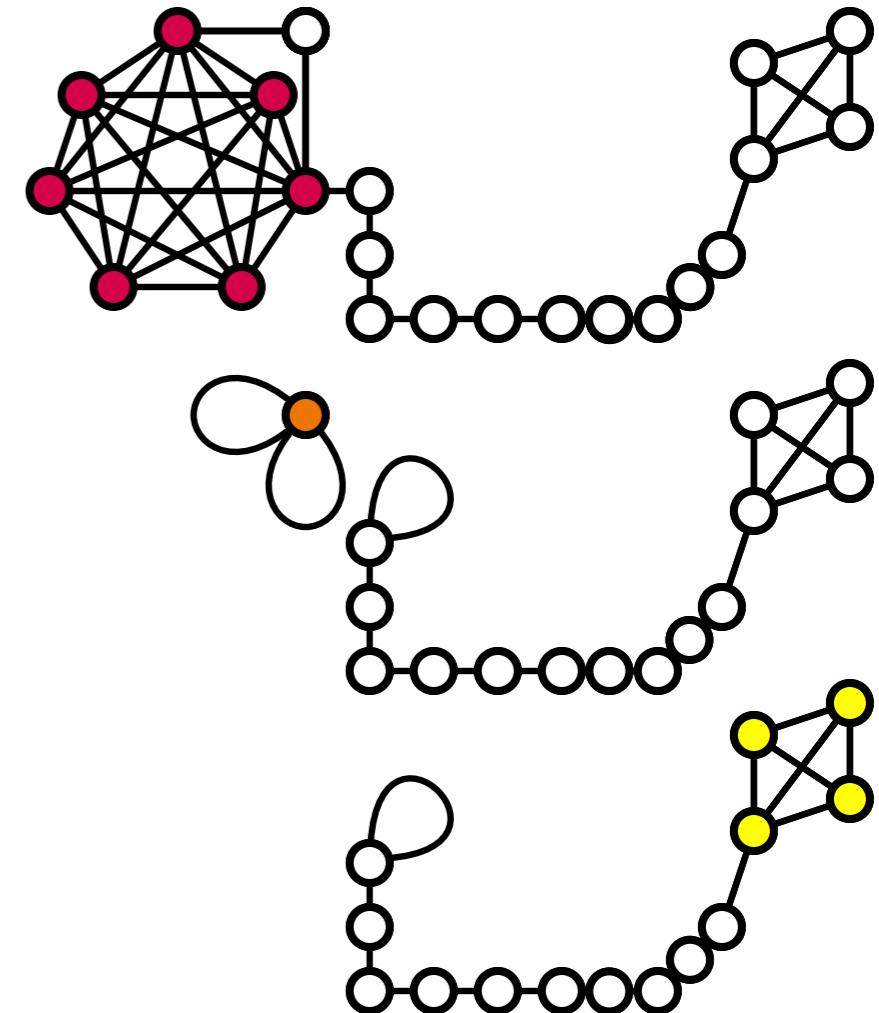


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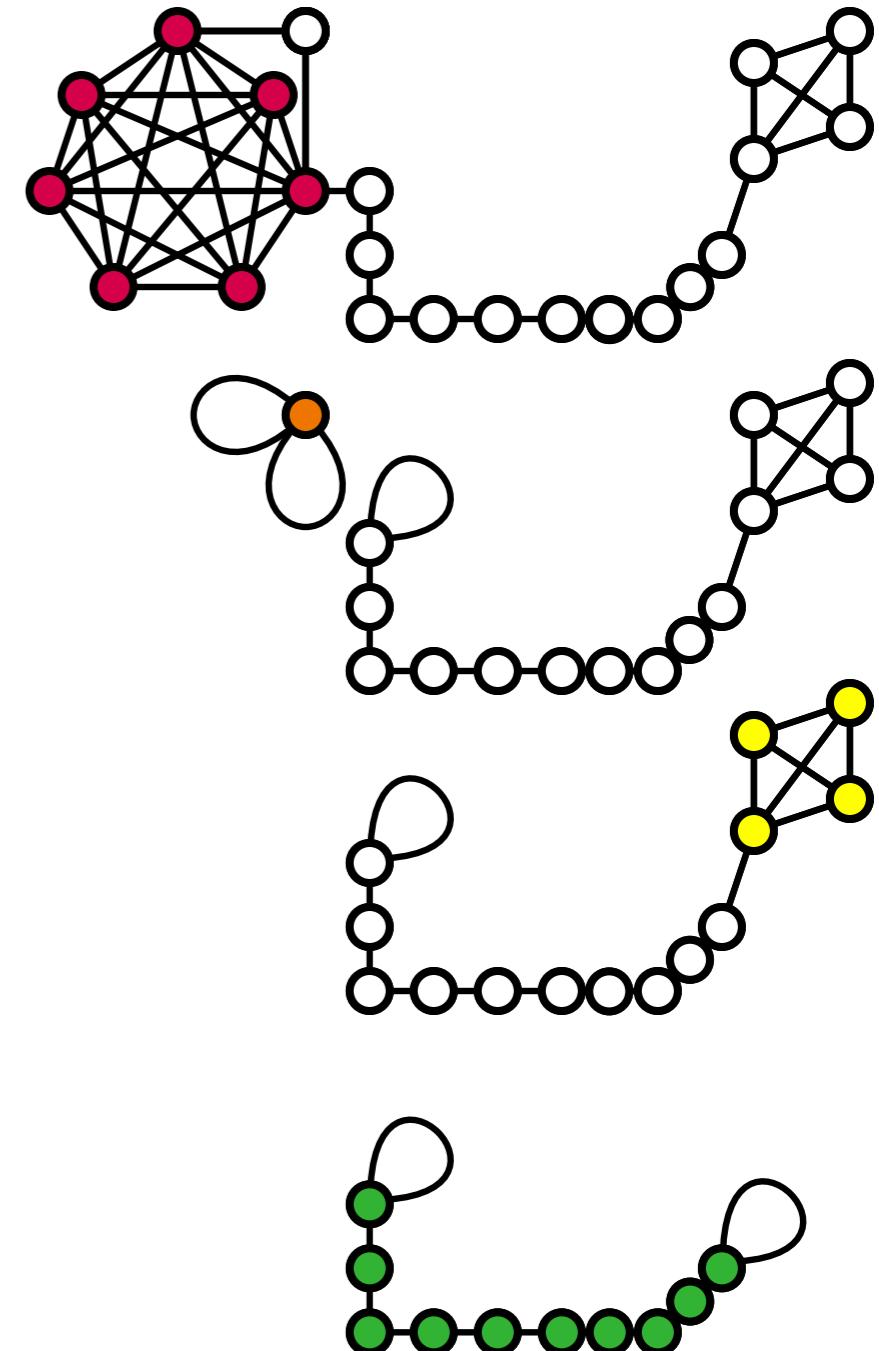


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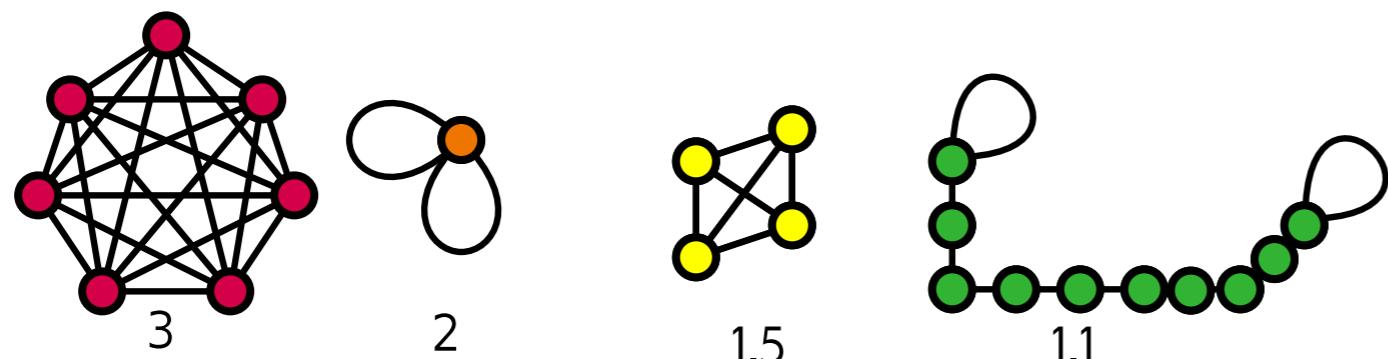
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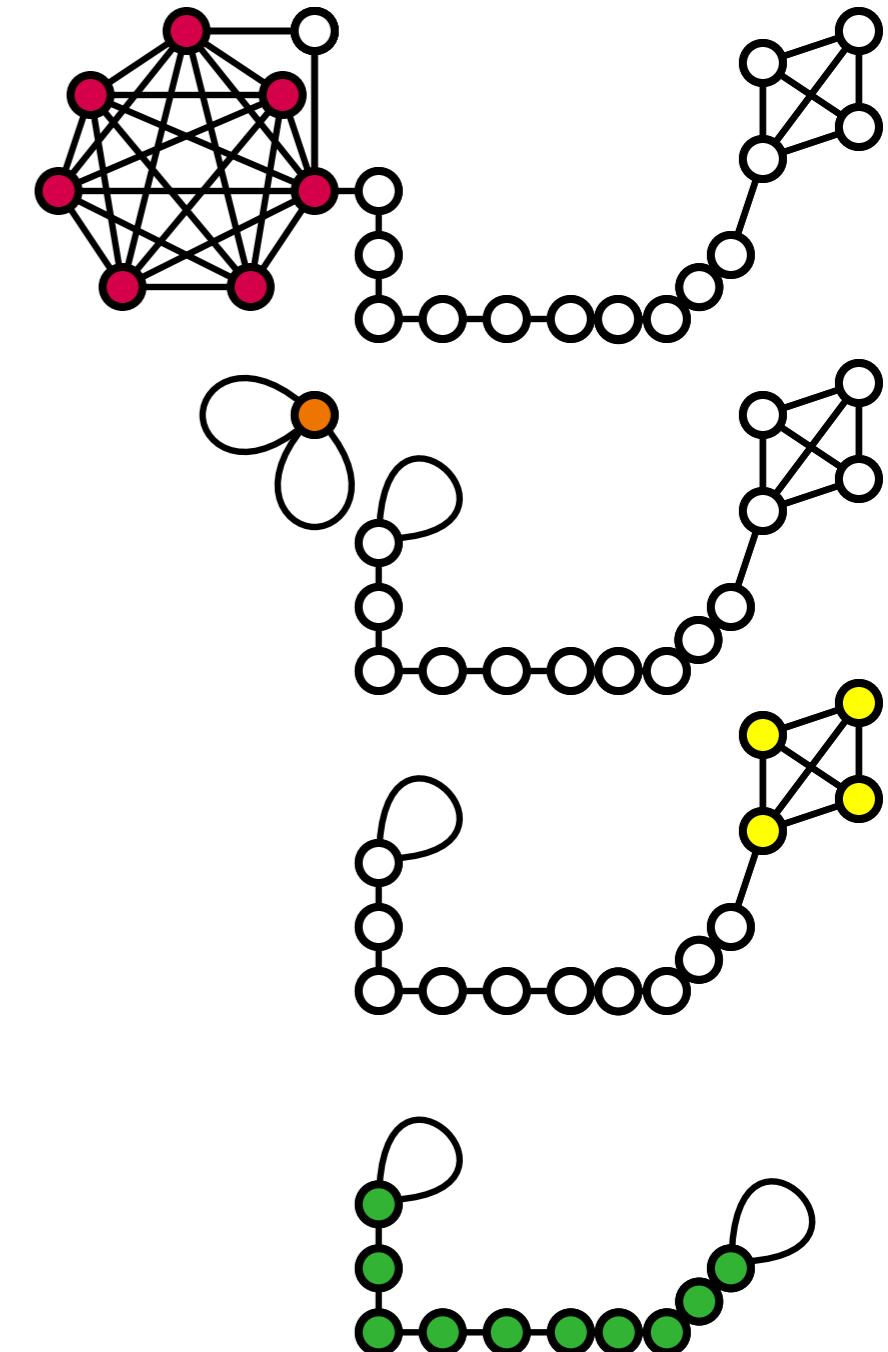
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This gives a partition into graphs (with loops).



If $v \in H_i$ then $\rho^*(v) = \rho(H_i) = \frac{|\text{Edges}(H_i)|}{|\text{Vertices}(H_i)|}$.



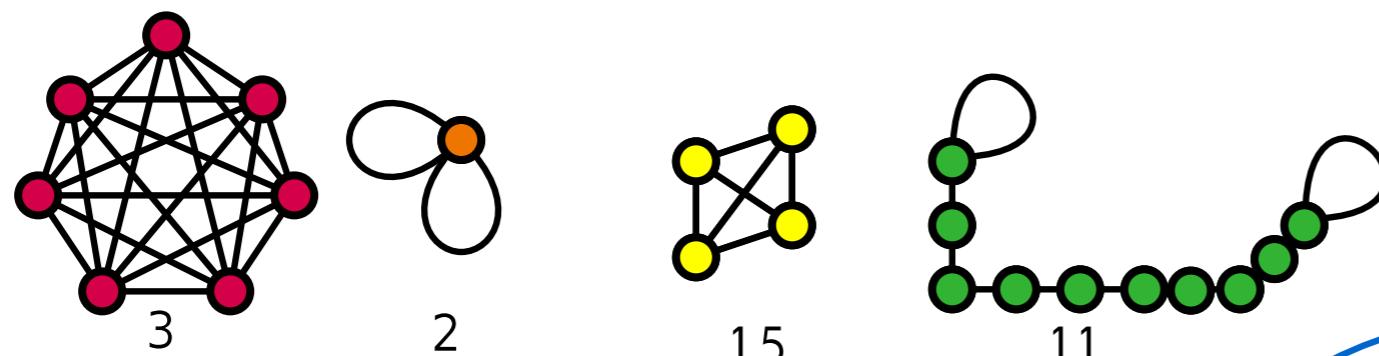
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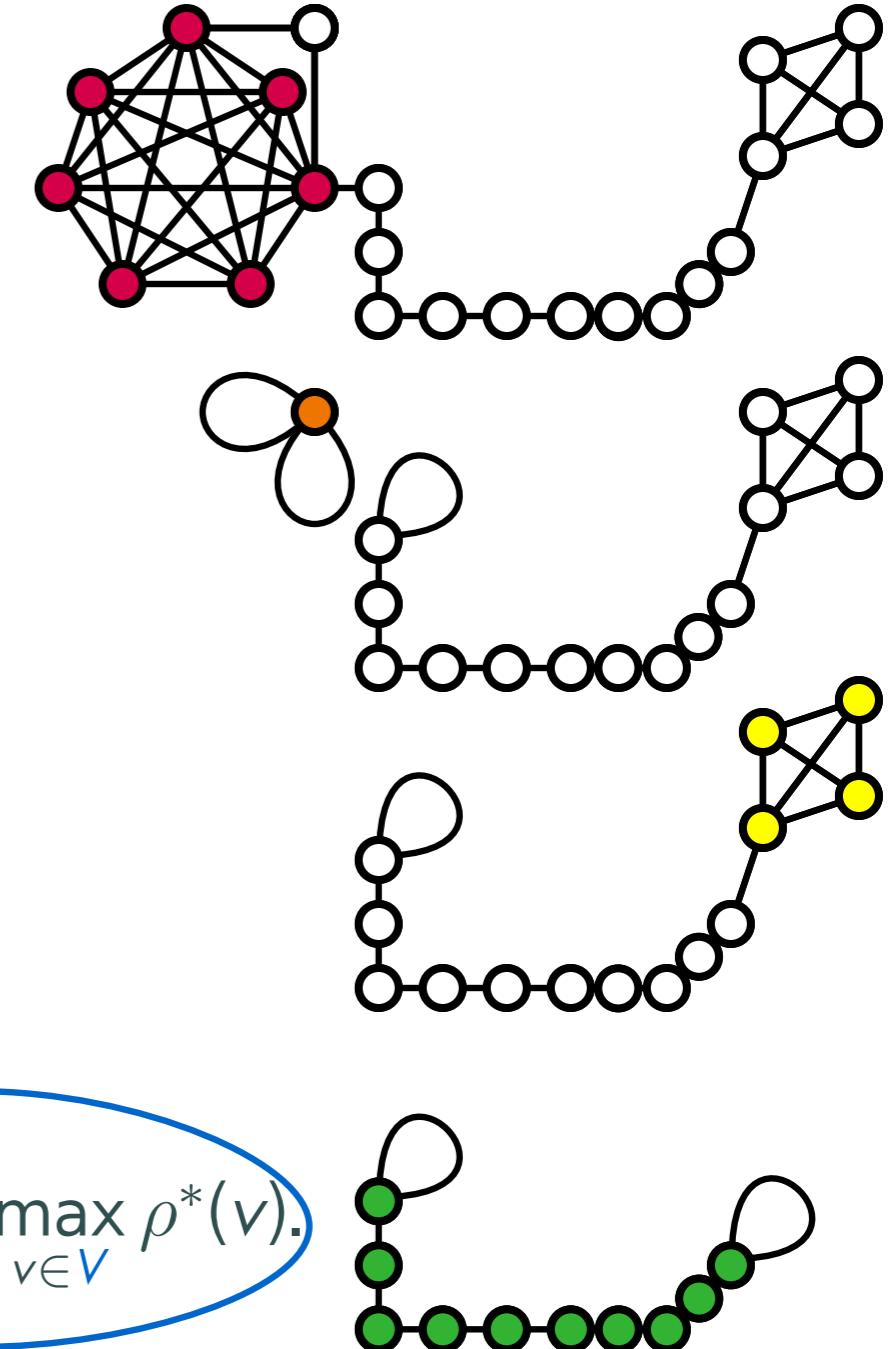
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This paper:

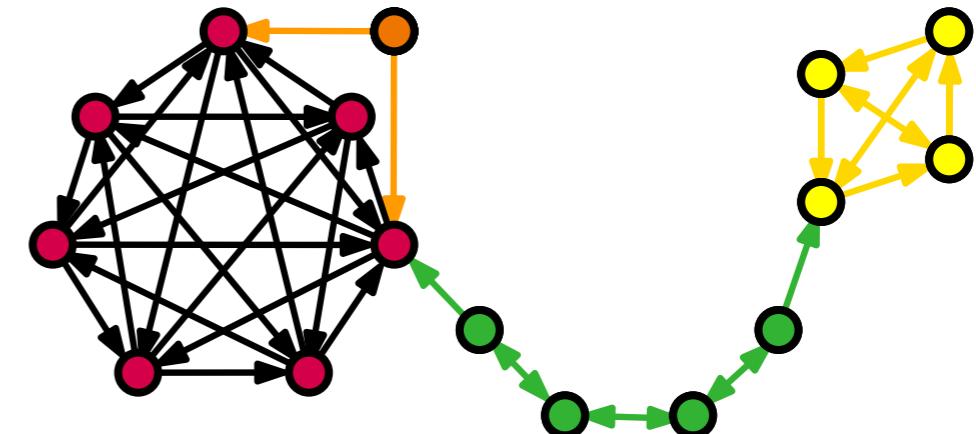
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$$\forall(u, v) \in E, \text{ require: } g(u \rightarrow v) + g(v \rightarrow u) = 1.$$

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Locally fair orientation \vec{G} :

$$g(u \rightarrow v) > 0 \Rightarrow \Delta(u) \leq \Delta(v).$$



This paper:

Local out-degree $\Delta^*(v)$.

Fix any locally fair orientation \vec{G} ,

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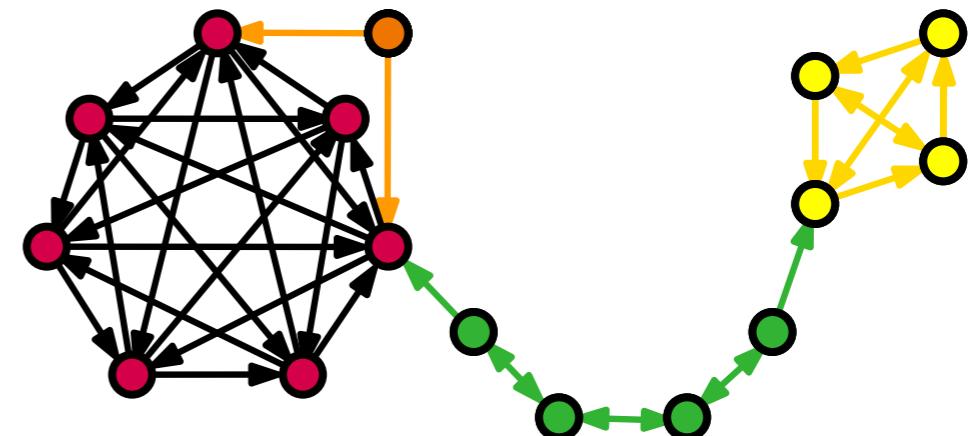
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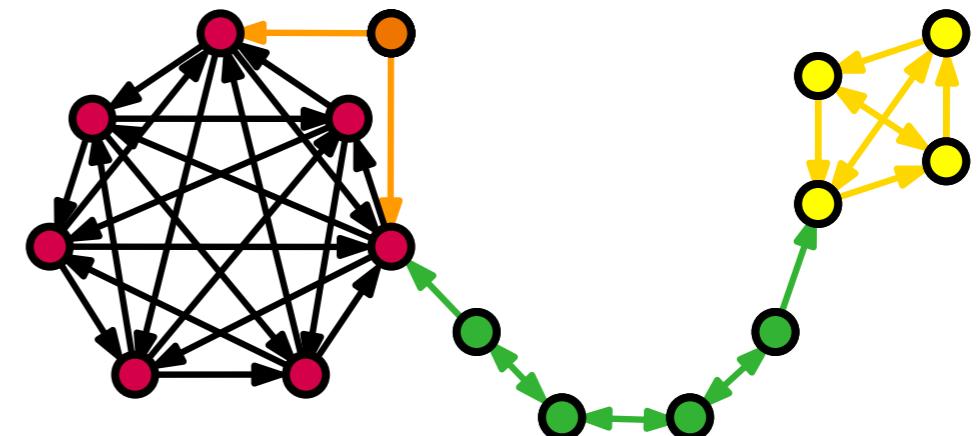
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η -fair orientations $(1 + \varepsilon)$ -approximate $\rho^*(v)$ for all vertices v .

Cor.: \exists dynamic algorithms to $(1 + \varepsilon)$ -approximate $\rho^*(v)$!

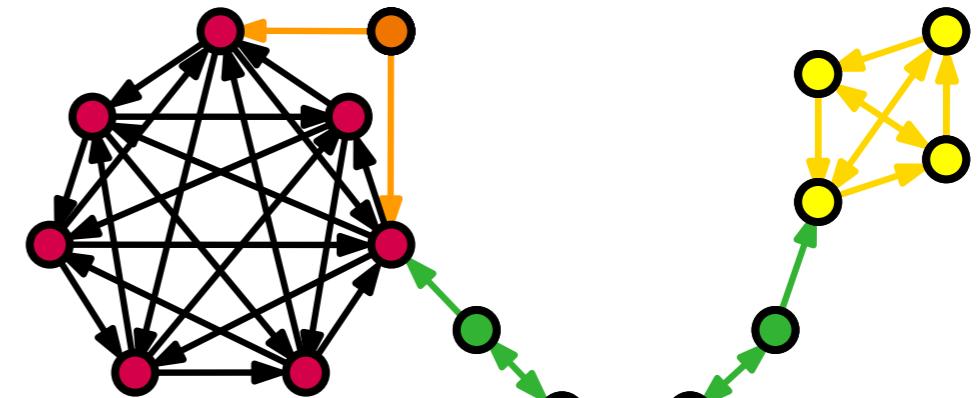
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Result 3:

$O(\varepsilon^{-2} \log^2 n)$ rounds in LOCAL.

Sublinear rounds in CONGEST.

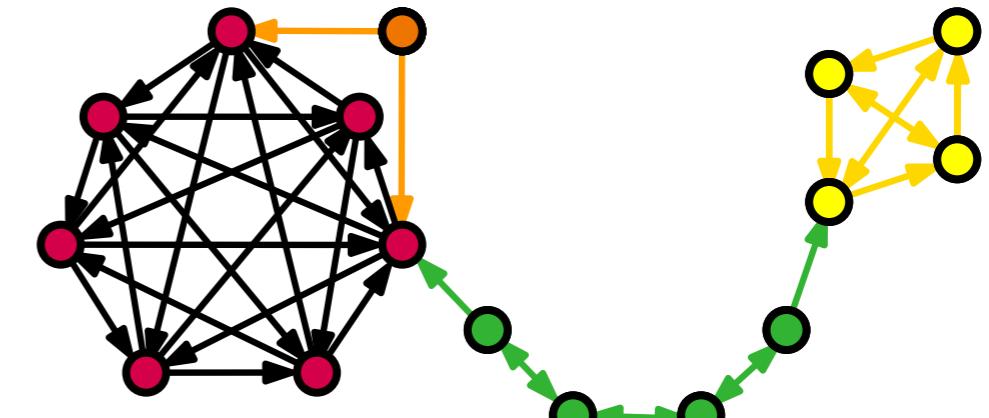
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Dynamic $(1 + \varepsilon)$ -minimum out-orientation:

Chekuri, Christiansen, Holm, van der Hoog, Quanrud, Rotenberg, and Schwiegelshohn [SODA, 2024].

$(1 + \varepsilon)$ -approximate $\rho^{\max}(G)$ in $O(\varepsilon^{-6} \log^4 n)$ time.

Result 1: local density is well-defined

Quadratic program FO^2 :

Domain: space of all fractional orientations \vec{G} .

Cost function: minimize $\sum_{v \in V} (\Delta(v))^2$

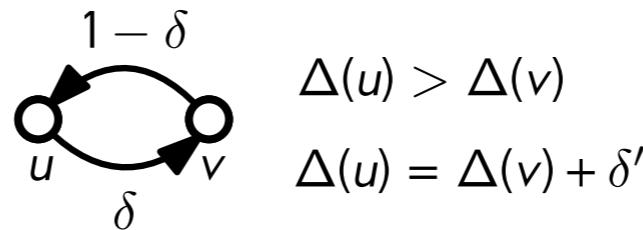
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For contradiction: fix OPT, and suppose that $\exists u, v \in V$ with $\Delta(u) > \Delta(v) + \delta'$ and $g(u \rightarrow v) = \delta$ for $\delta, \delta' > 0$.



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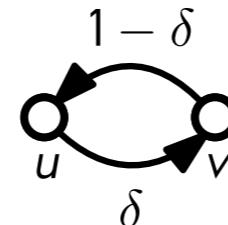
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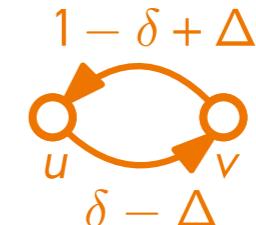
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Create a new orientation \vec{G}' ,
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$$\begin{aligned}\Delta(u) &> \Delta(v) \\ \Delta(u) &= \Delta(v) + \delta'\end{aligned}$$



$$\begin{aligned}\Delta(u) &\leq \Delta(v) \\ \Delta(u) &= \Delta(v) + \delta'\end{aligned}$$

$\Delta(u)^2 + \Delta(v)^2 > (\Delta(u) - \Delta)^2 + (\Delta(v) + \Delta)^2 \Rightarrow$ contradiction.

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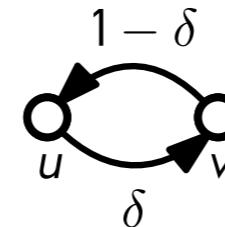
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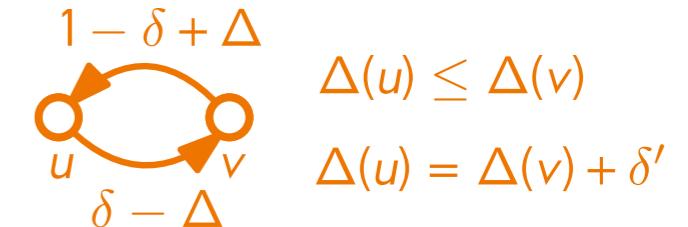
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Cor: $\Delta^*(v)$ is well-defined.

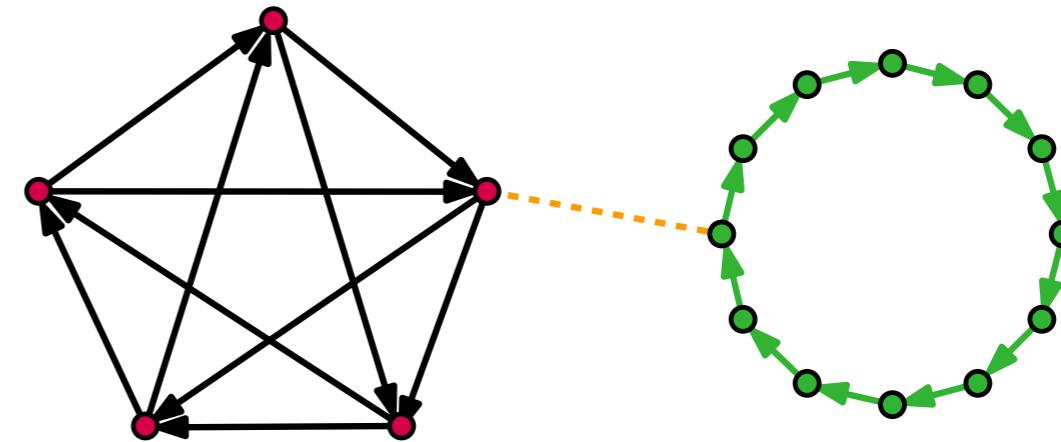
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Local density is a stricter measure than global minimum density.

Result 2: η -fairness \Rightarrow density

Fair orientation \vec{G} :

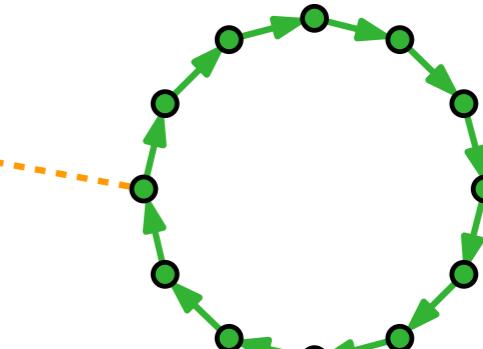
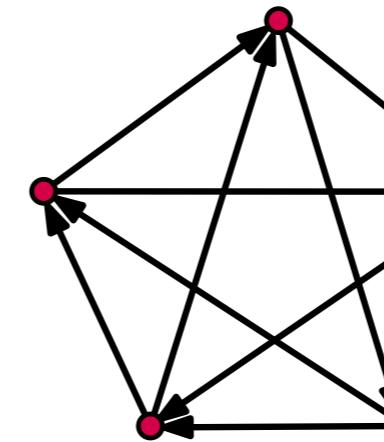
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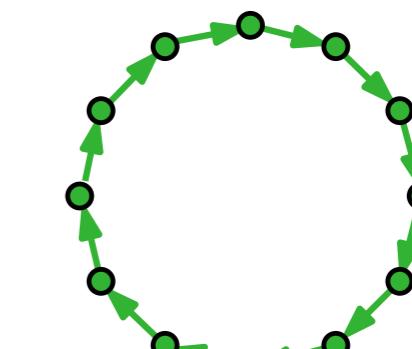
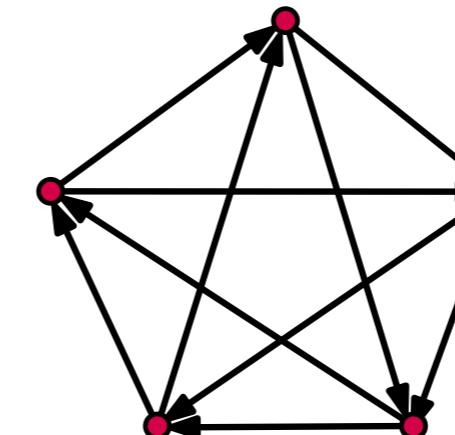
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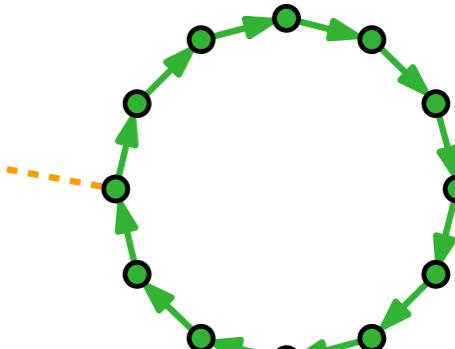
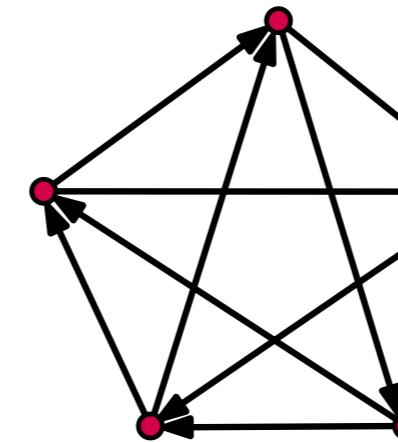
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Result 2: η -fairness \Rightarrow density

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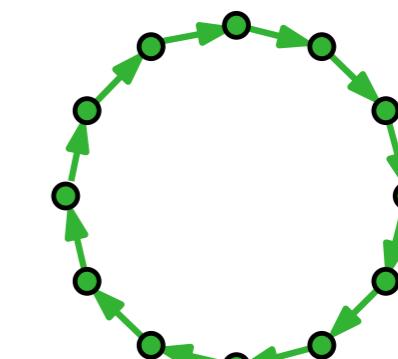
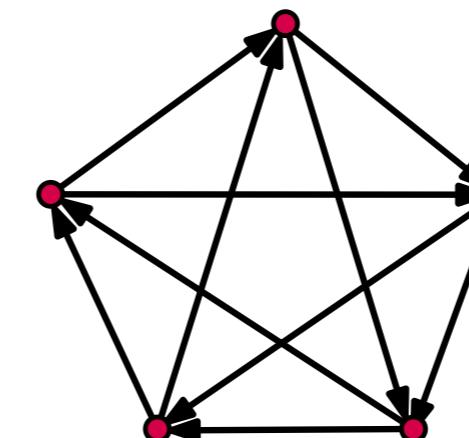
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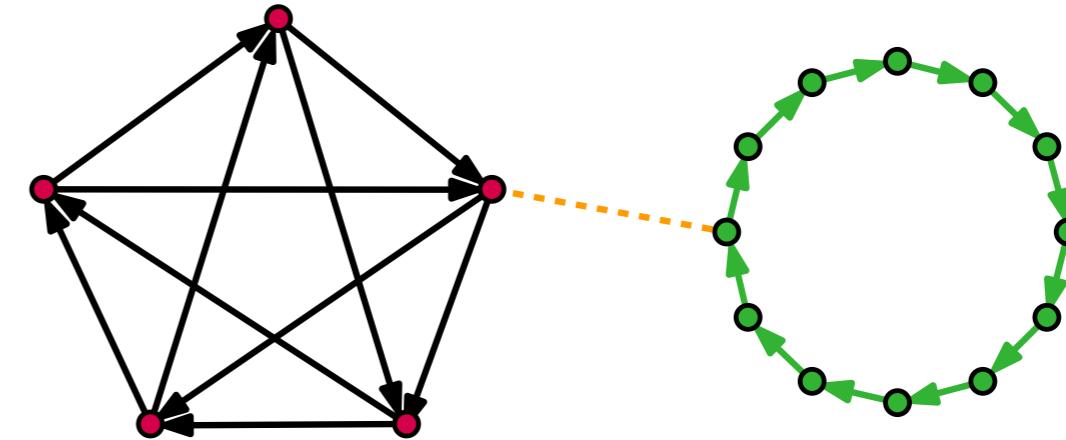
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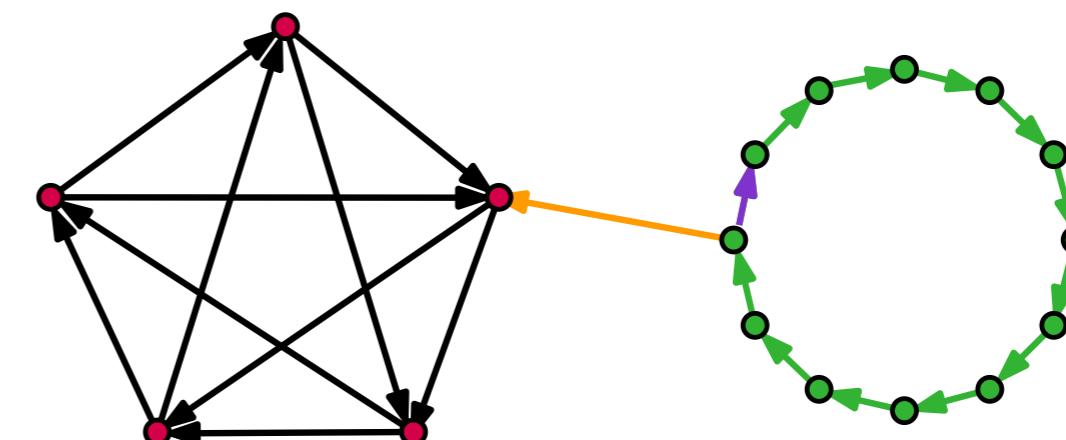
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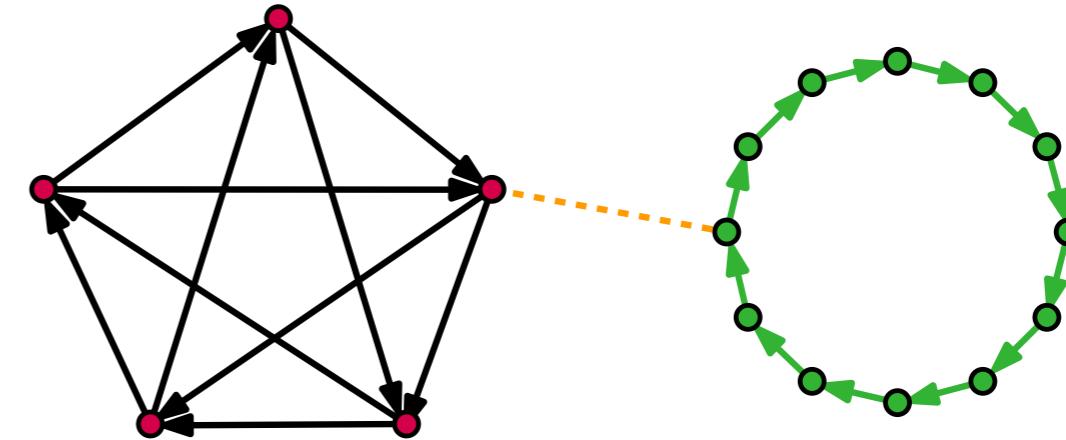
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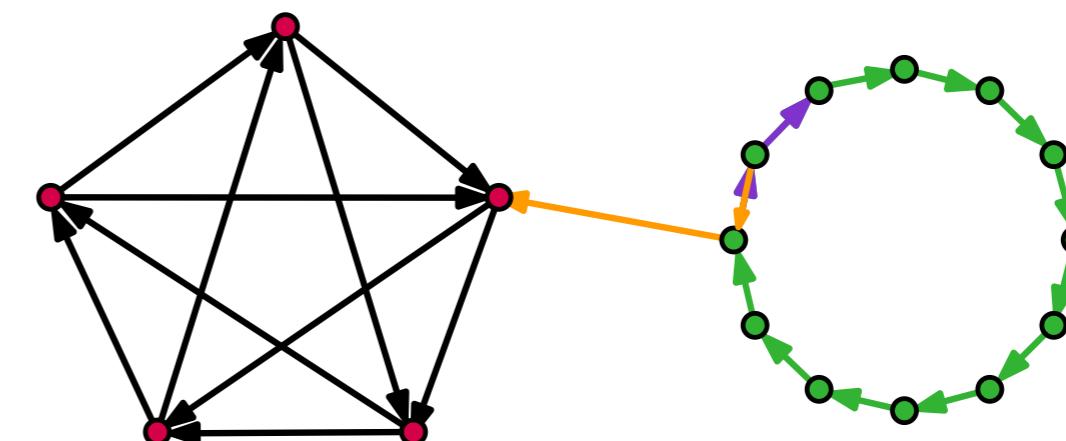
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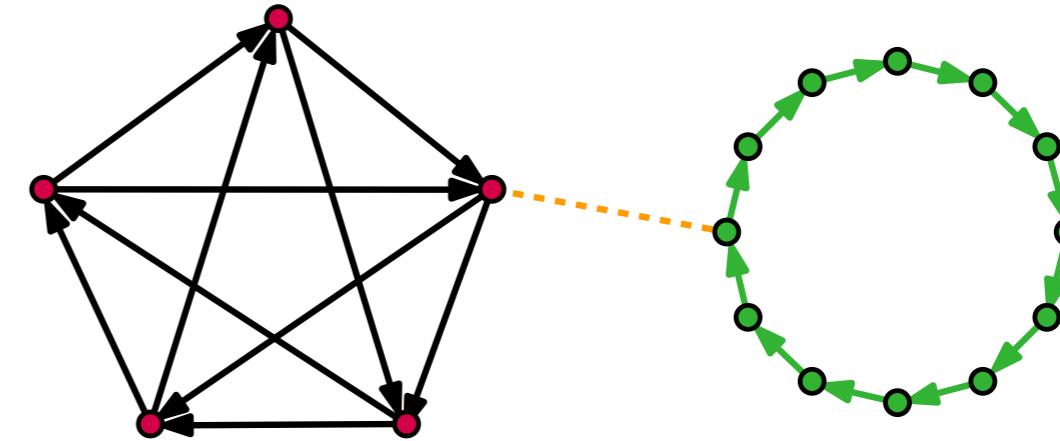
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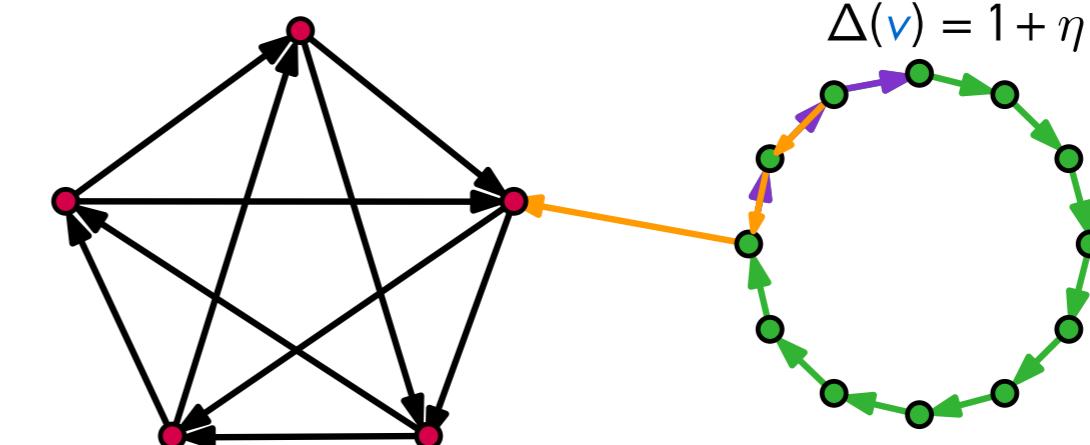
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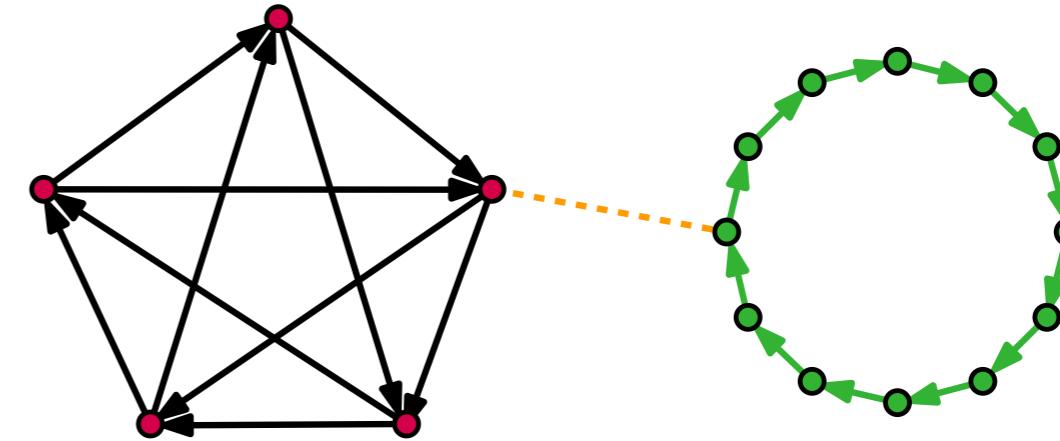
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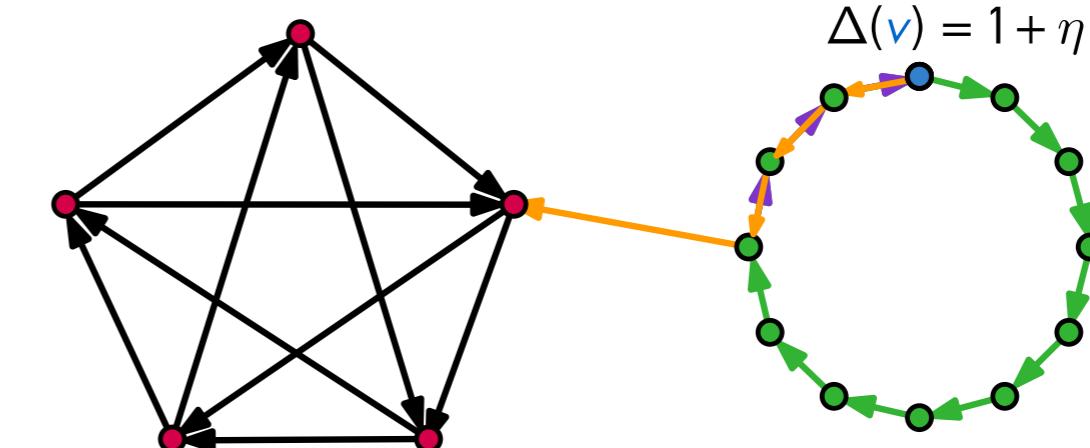
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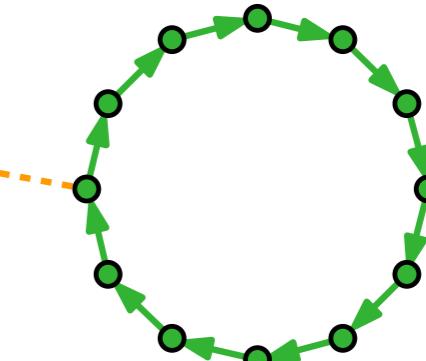
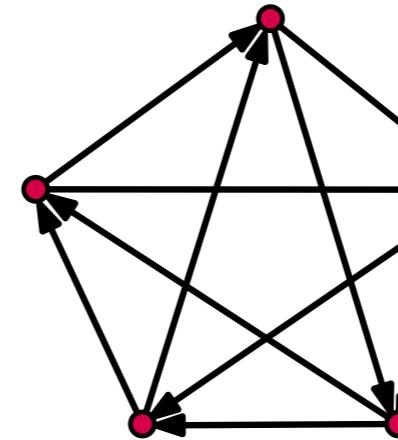
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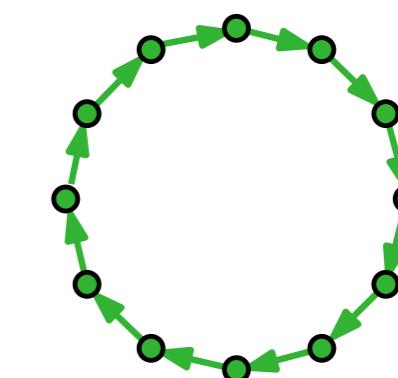
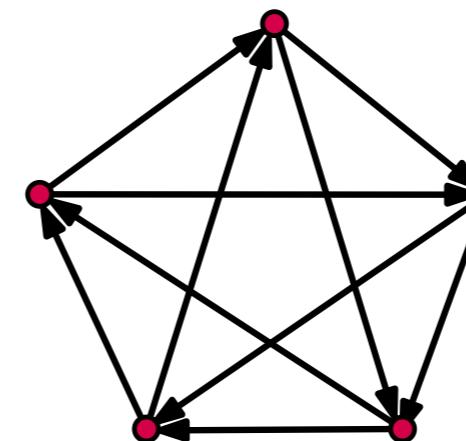
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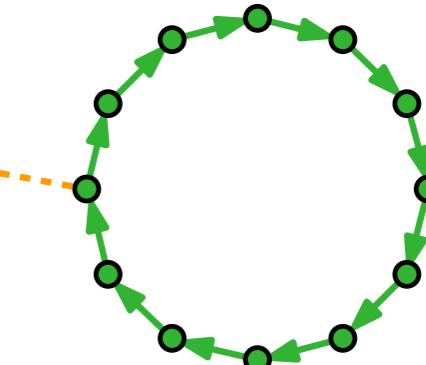
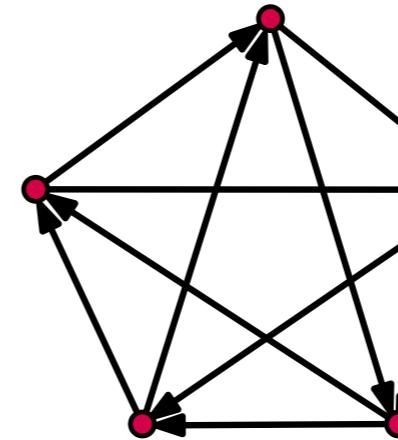
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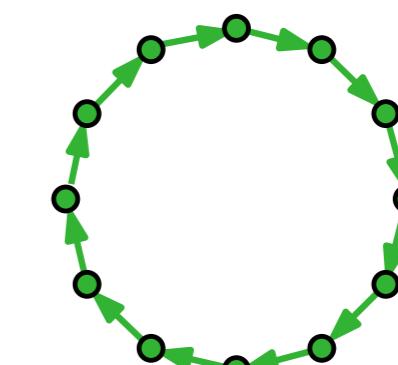
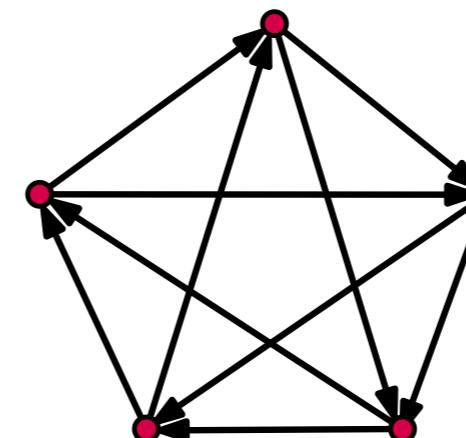
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$(1 + \varepsilon)$ -approximate $\rho^*(v)$ from [WWW, 2017] in $O(\varepsilon^{-6} \log^4 n)$ time.

Result 2: fairness \Rightarrow density

Main Theorem:

Let \vec{G} be an η -fair fractional orientation for $\eta \leq \frac{\varepsilon^2}{128 \cdot \log n}$.

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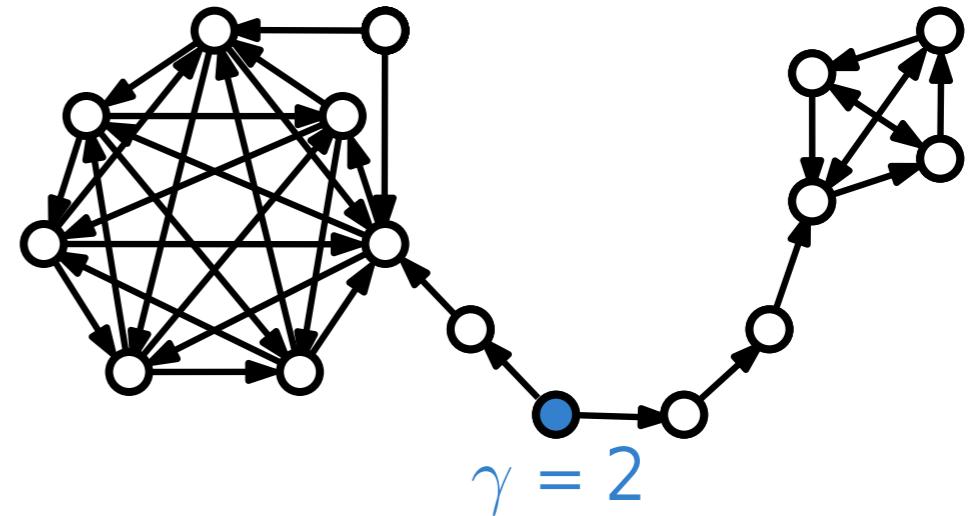
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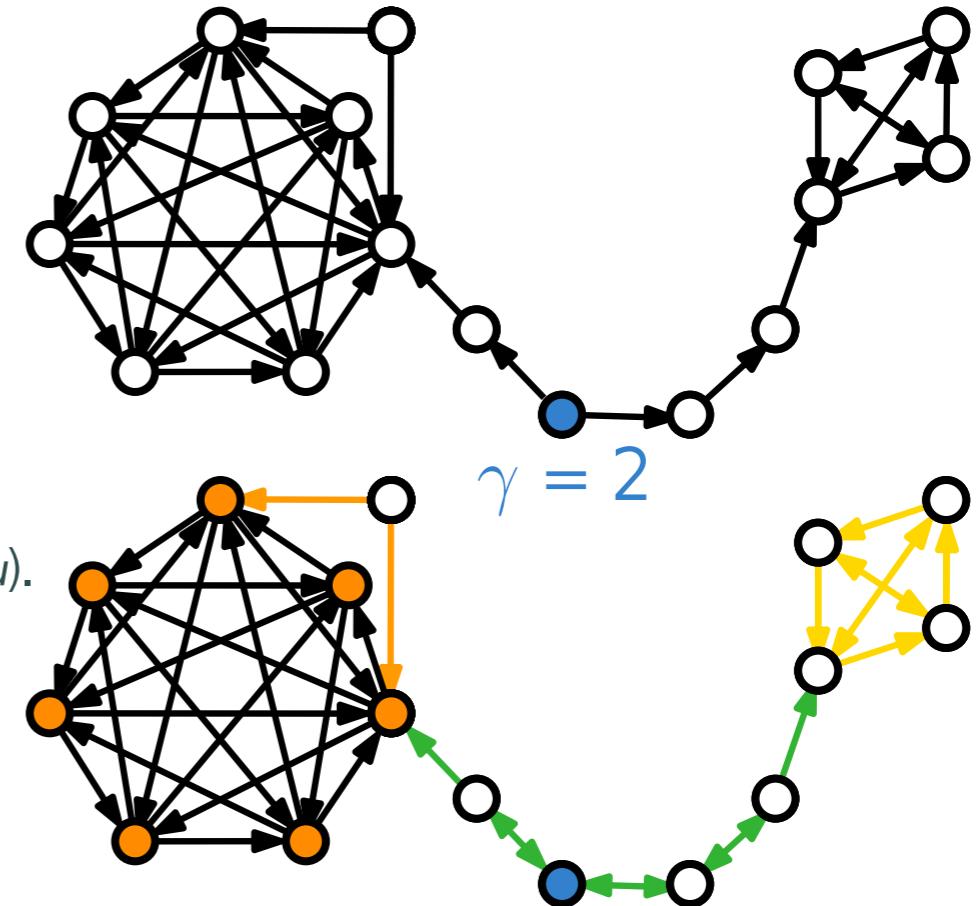
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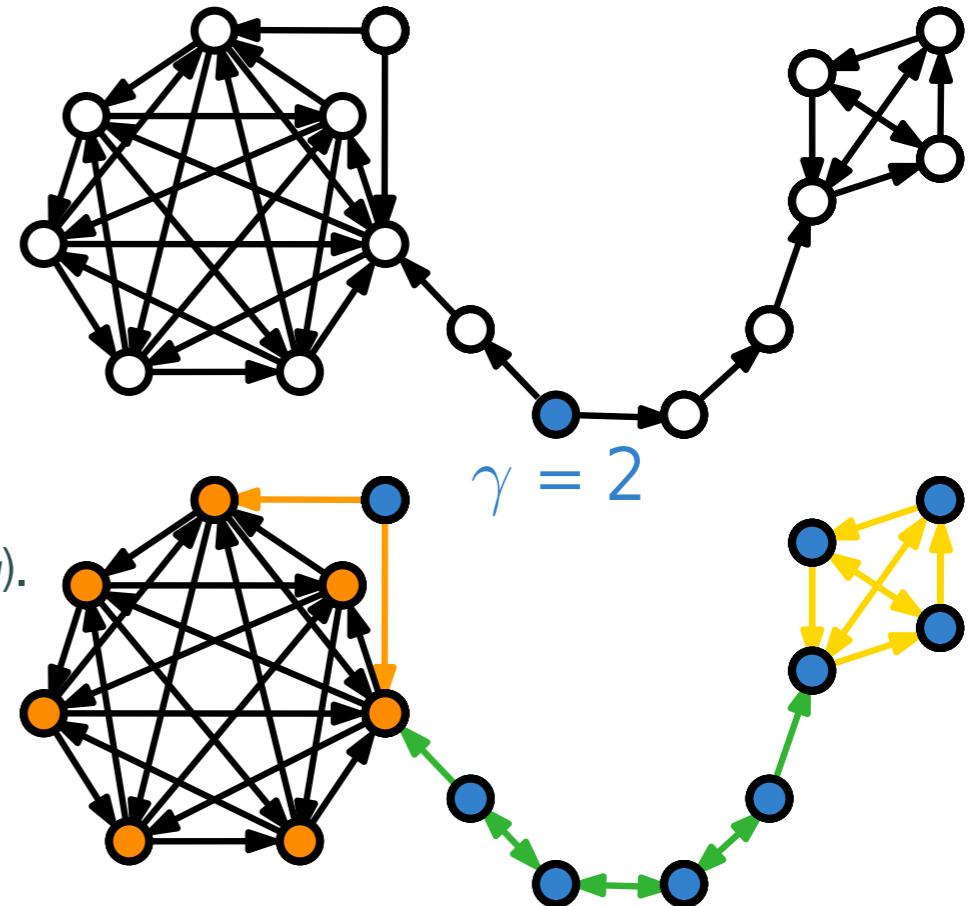
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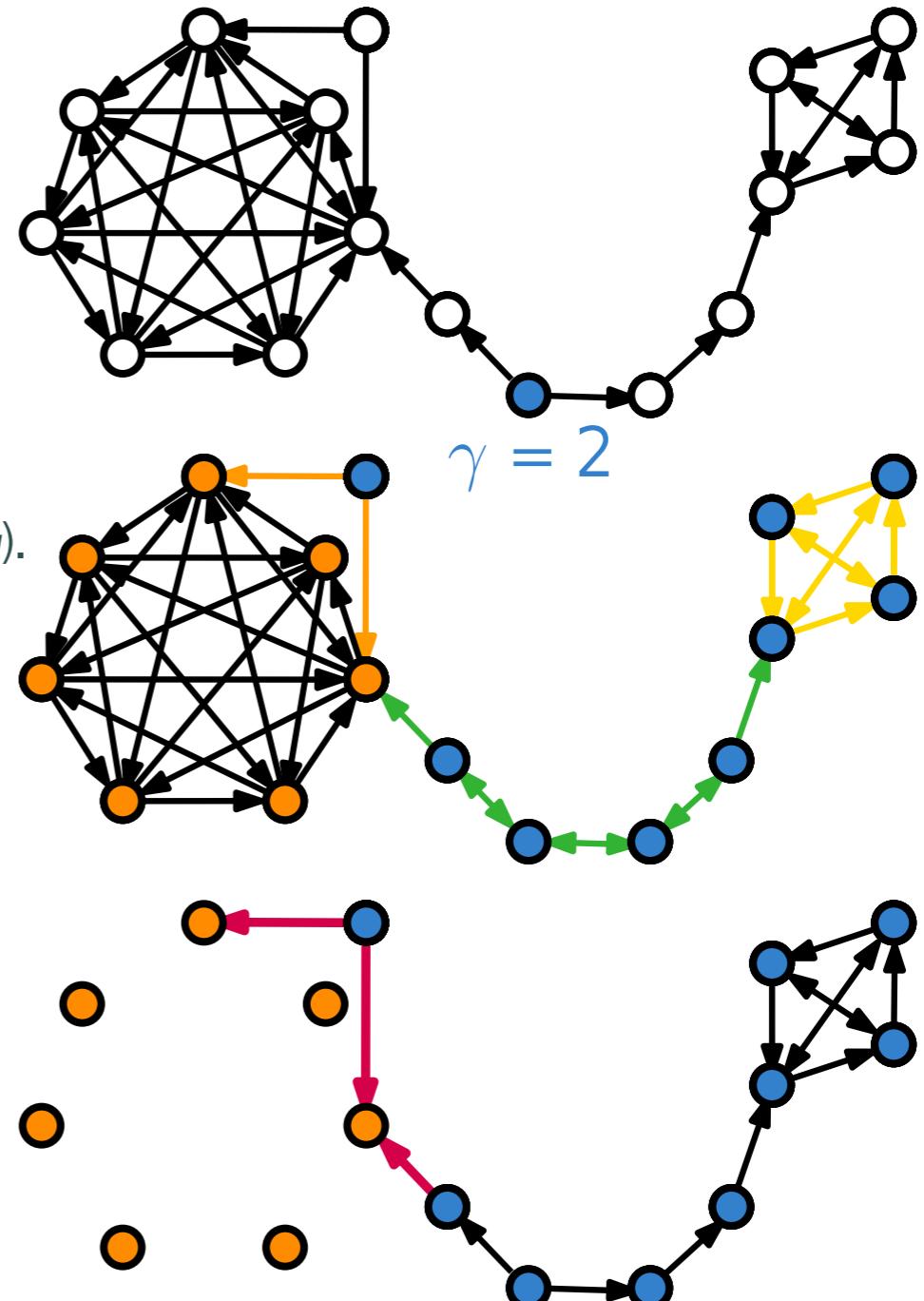
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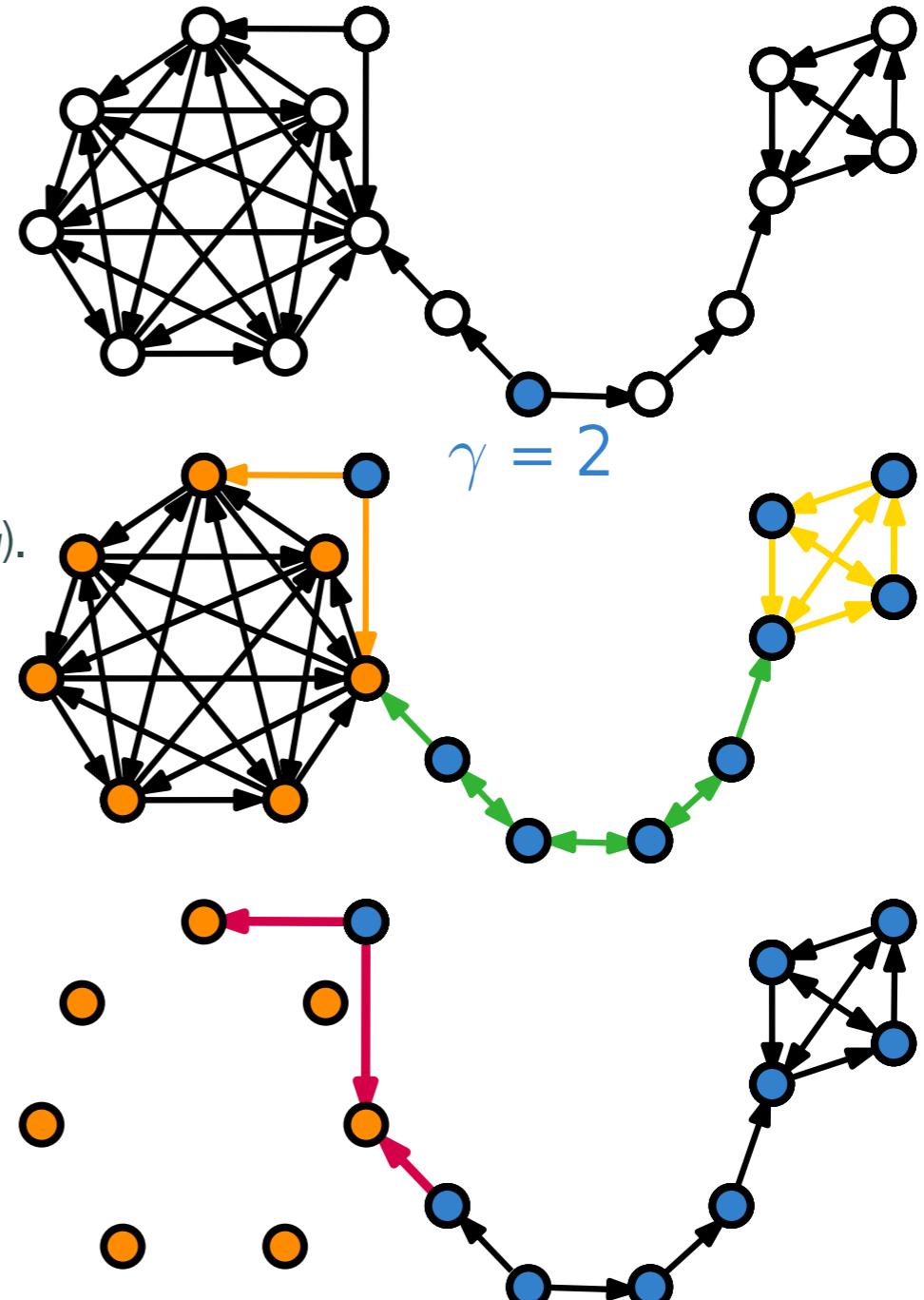
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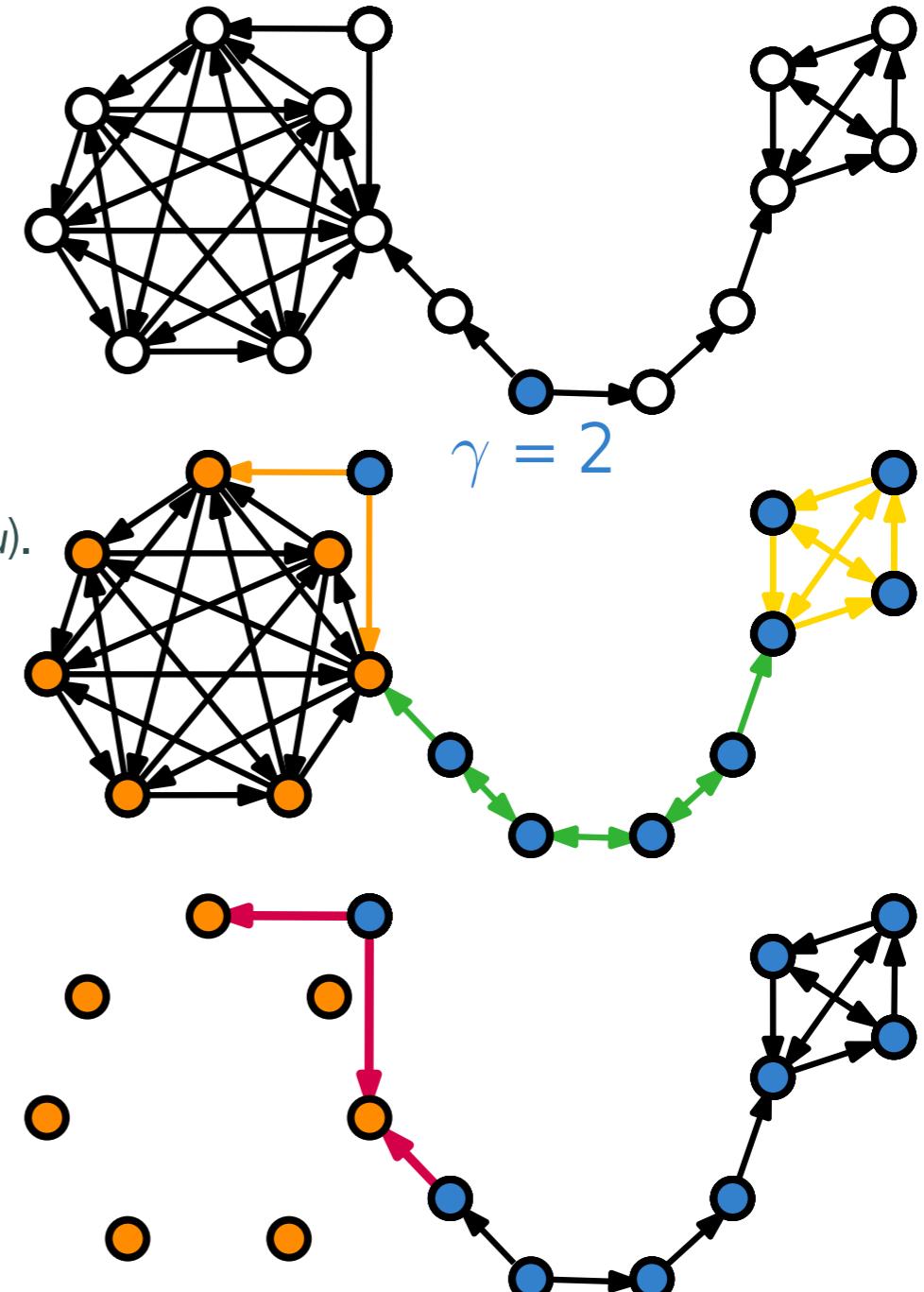
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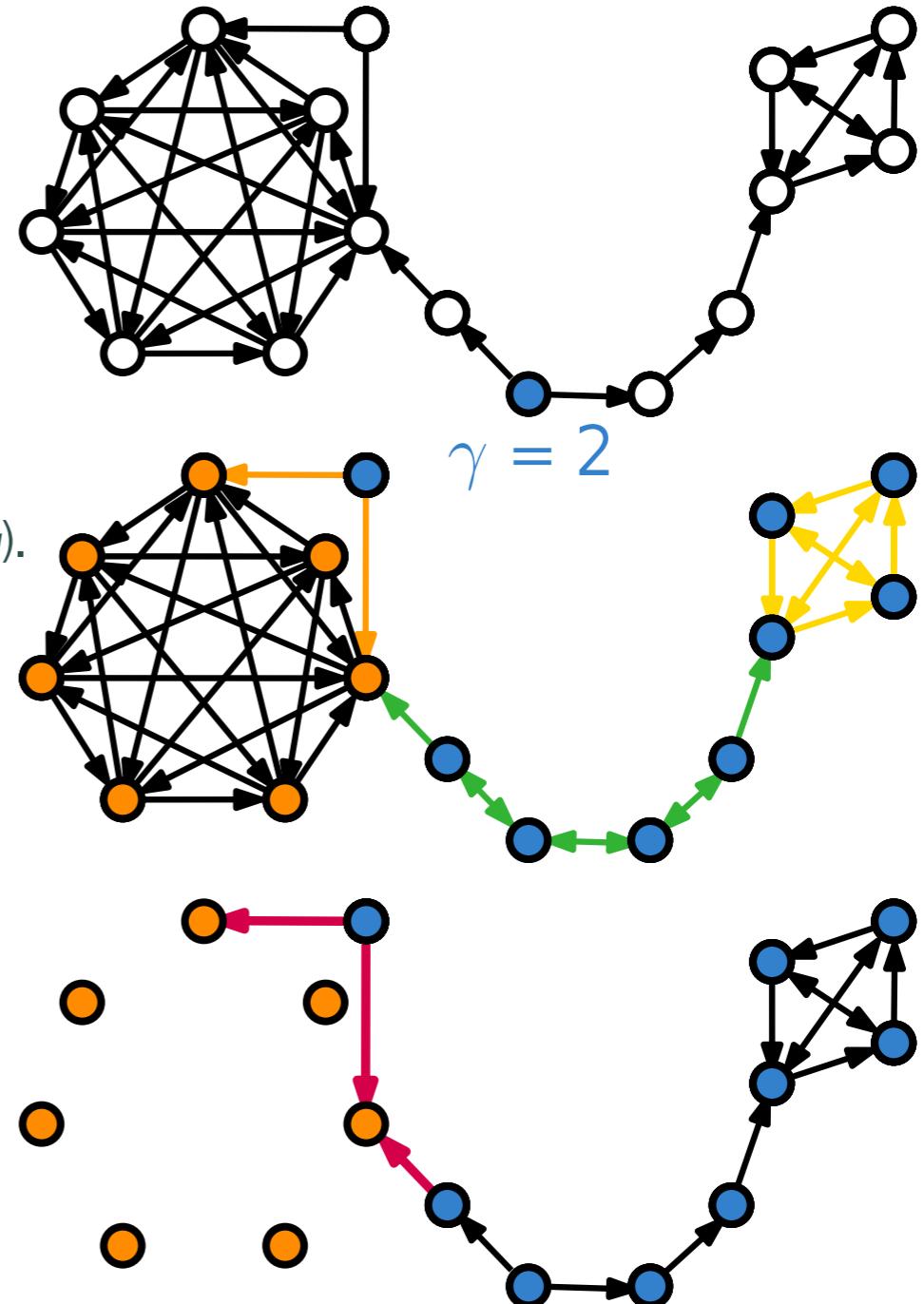
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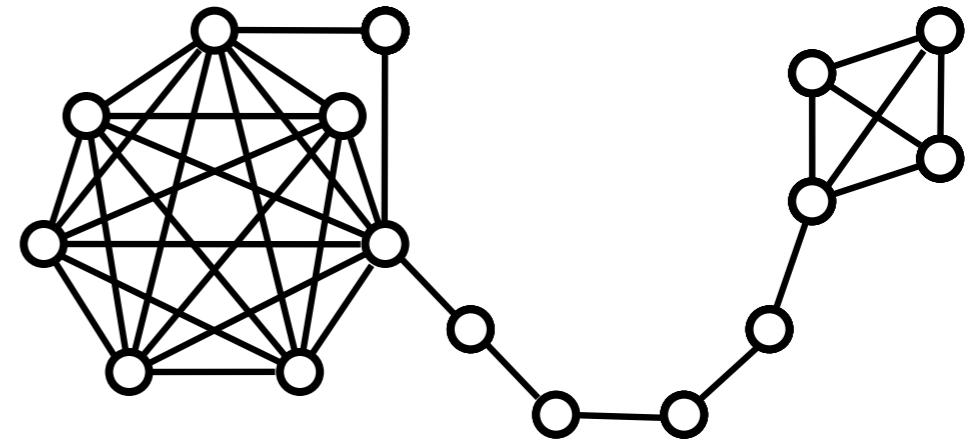
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Result 3: Distributed algorithms

This talk:

Compute $\rho^*(v)$ for all v in LOCAL in $O(\varepsilon^{-2} \log^2 n)$ rounds.



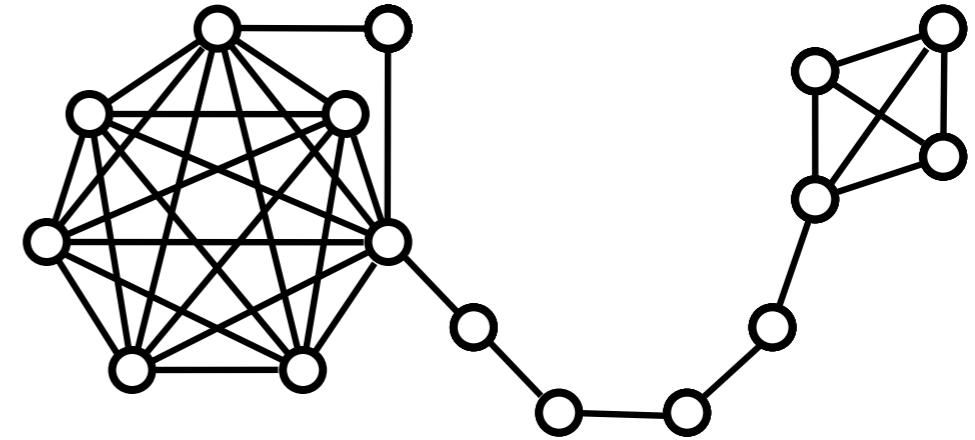
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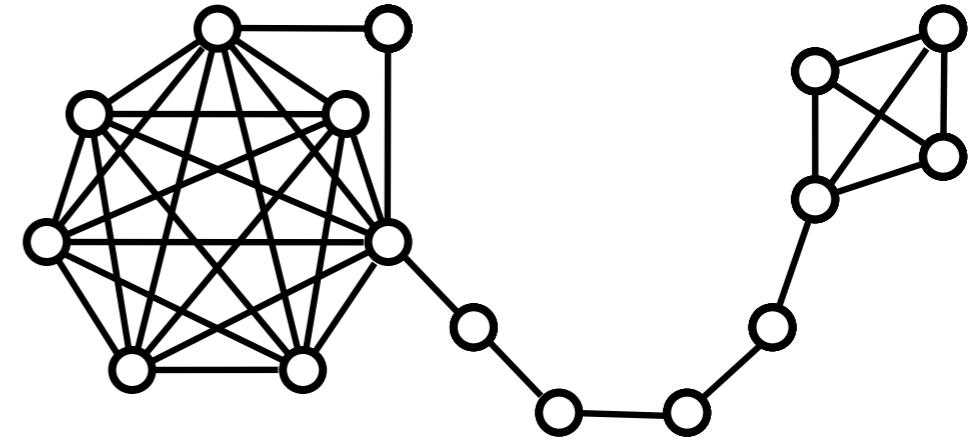
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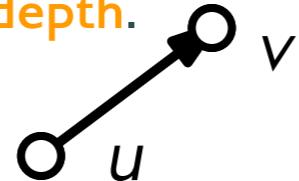
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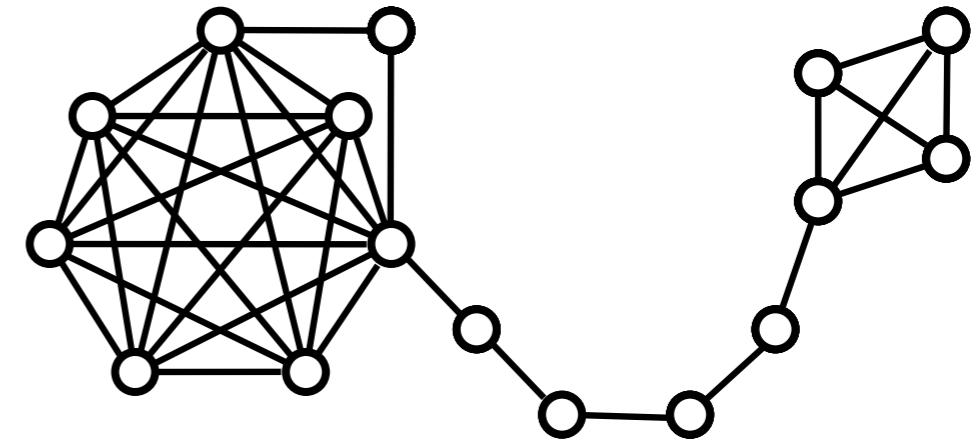
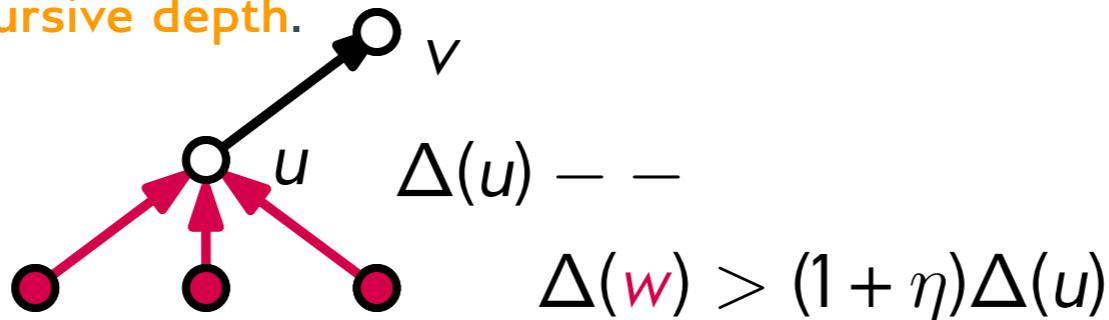
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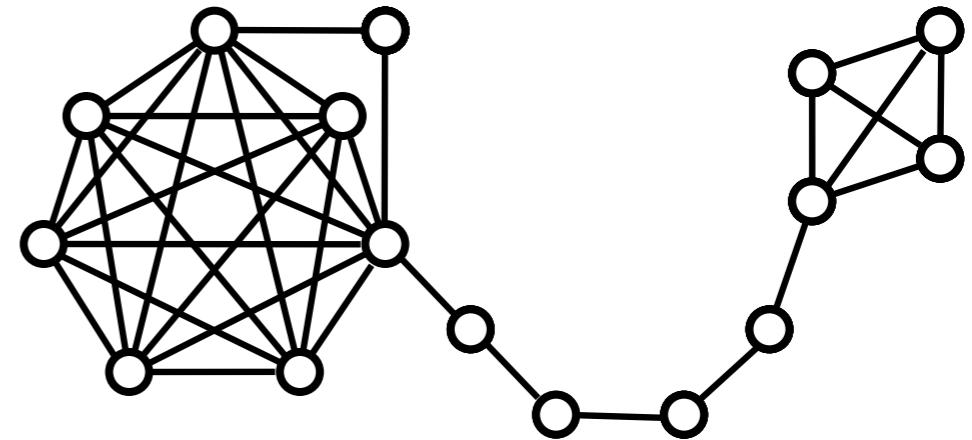
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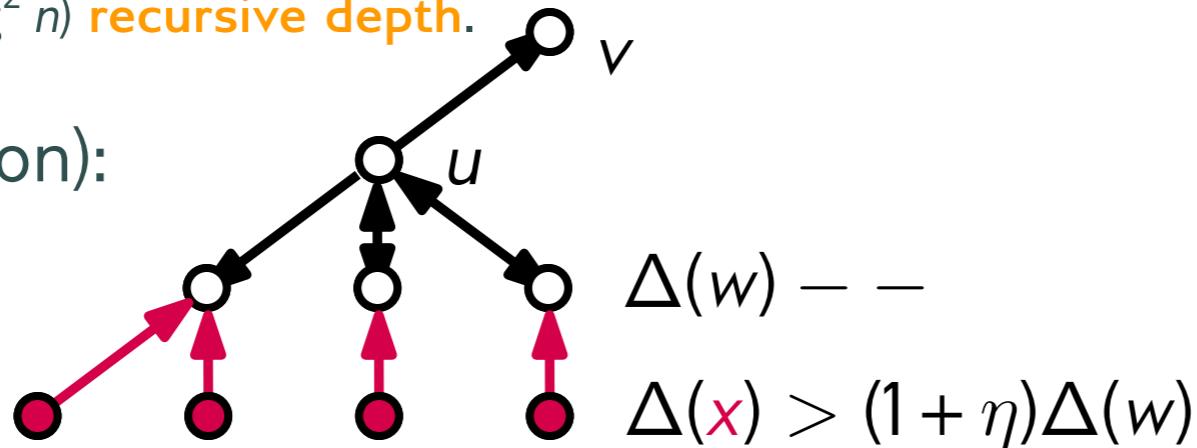
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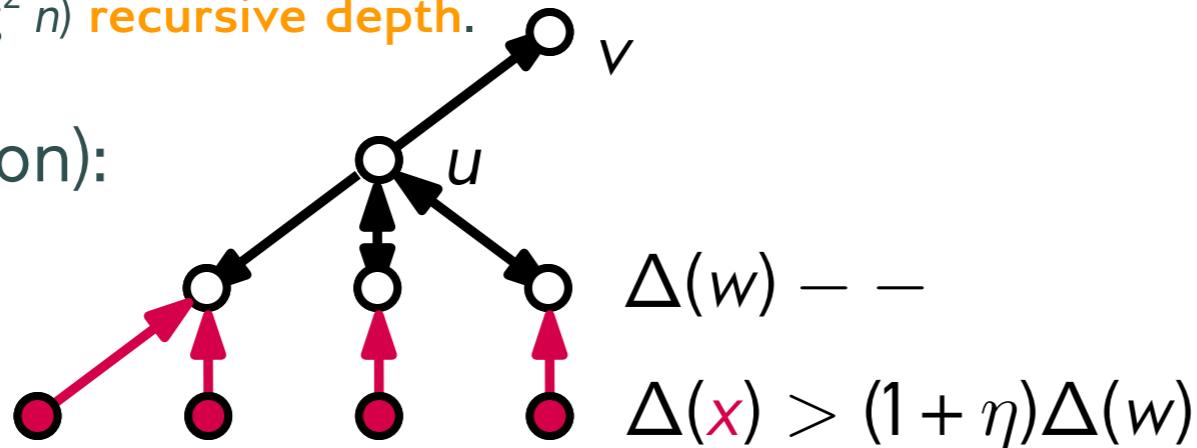
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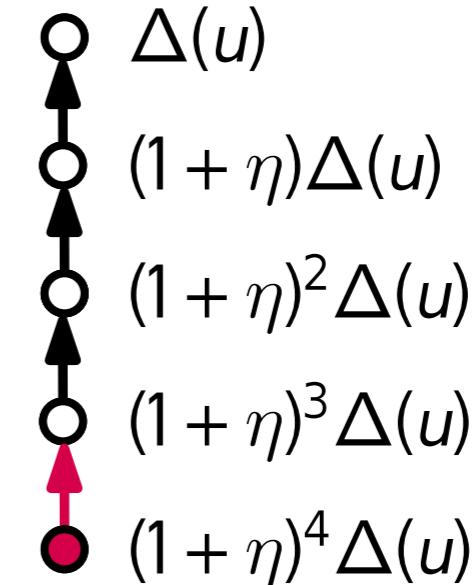
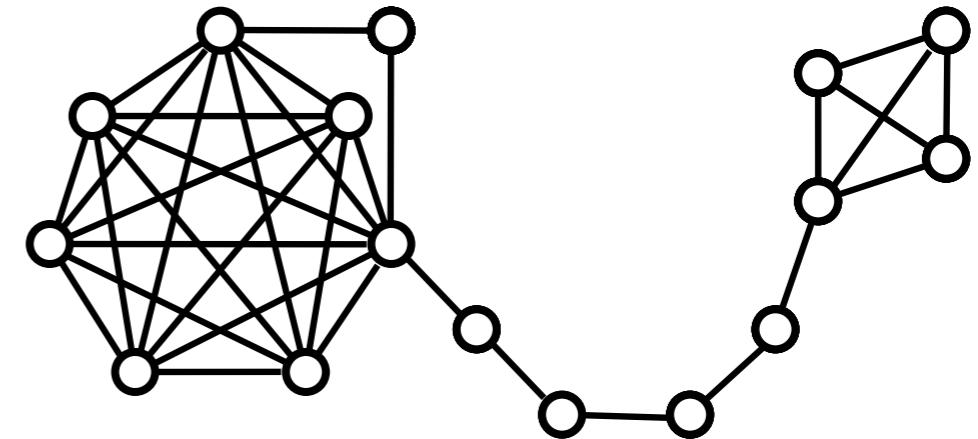
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Recursive Depth: $\frac{\log n}{\log(1+\eta)} \in O(\varepsilon^{-2} \log^2 n)$



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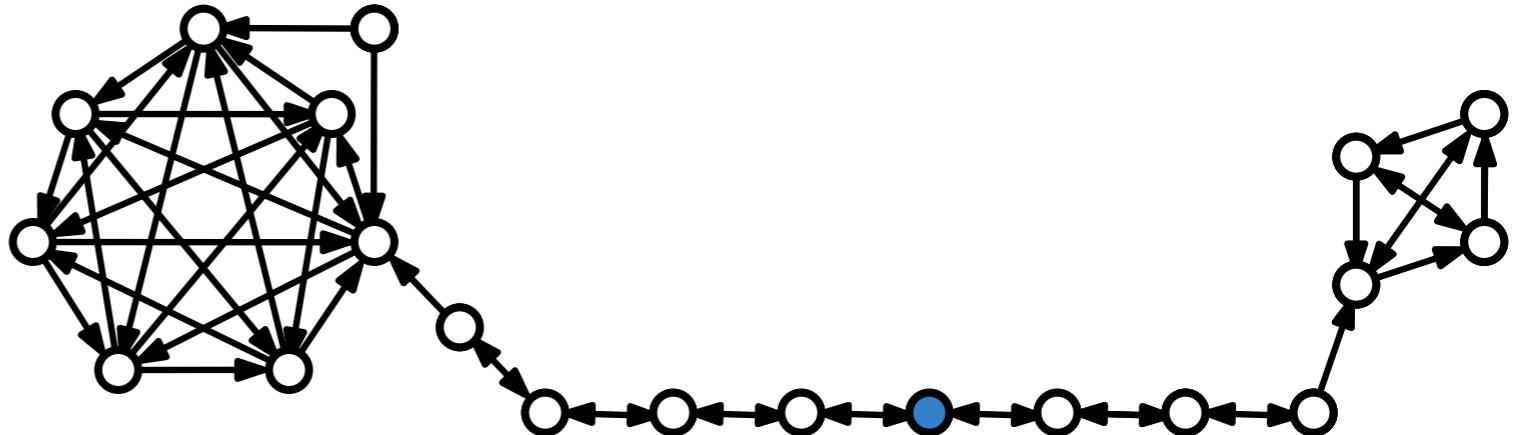
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Proof:

Fix a vertex v and a fair orientation.

$$\Delta(v) = \rho^*(v).$$



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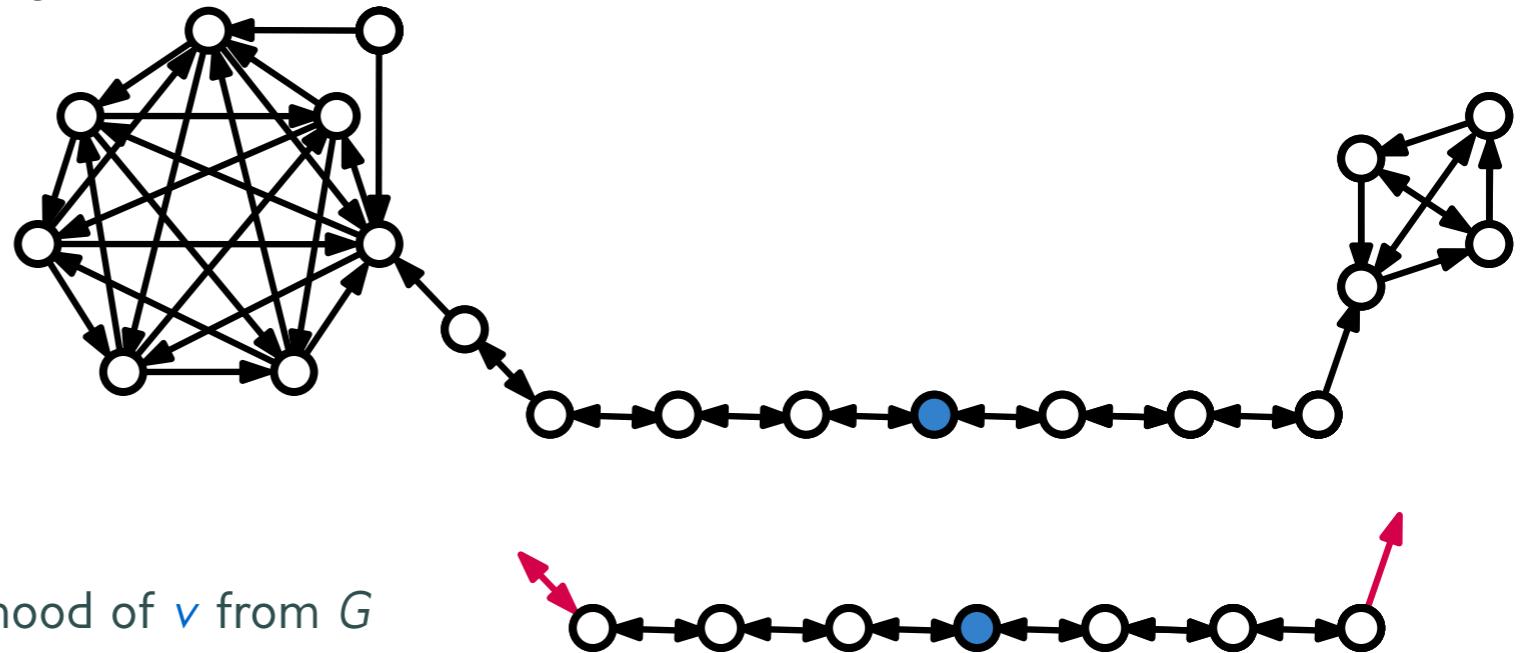
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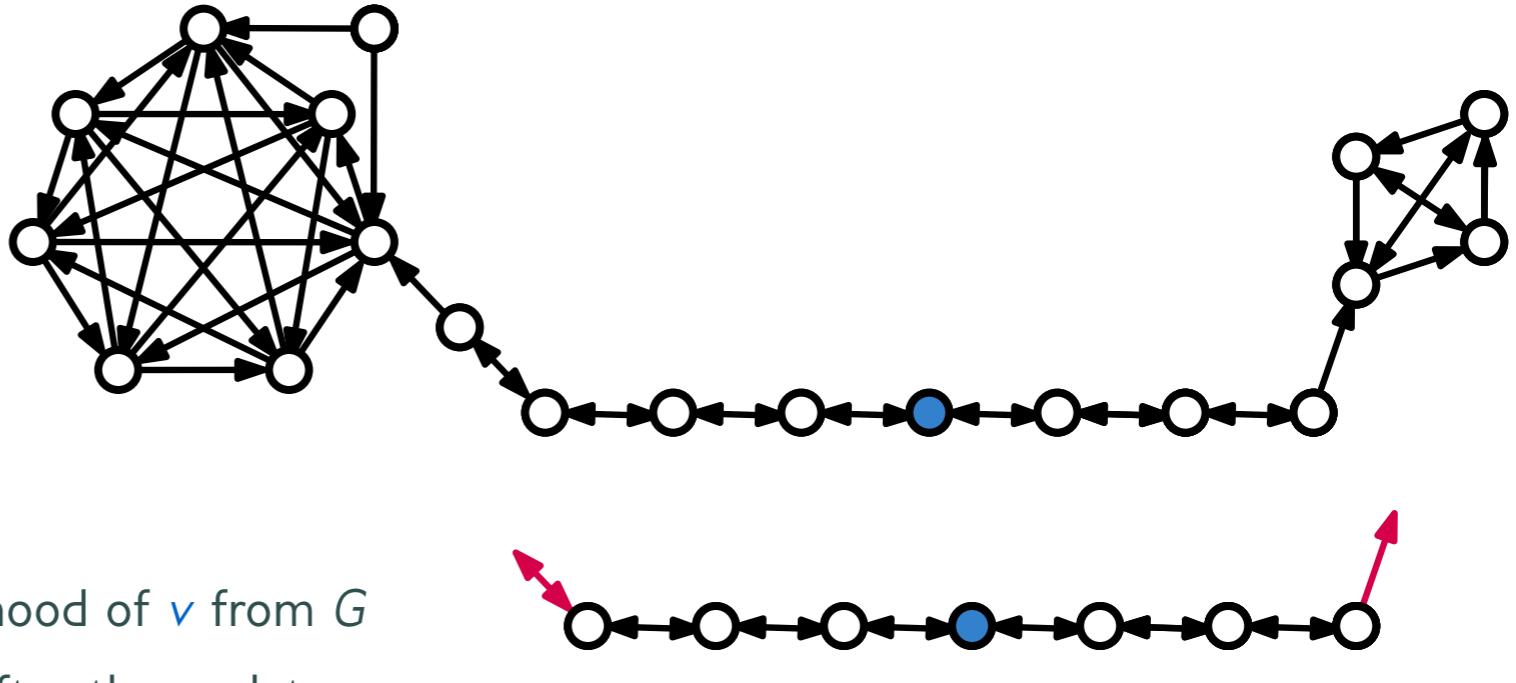
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The out-degree $\Delta(v)$ remains unchanged after the update.

$$\Delta(v) \approx_{1+\varepsilon} \rho_{G'}^*(v) \quad \Rightarrow \quad \rho_{G'}^*(v) \approx_{1+\varepsilon} \rho^*(v) \quad \square$$

This paper:

Local out-degree $\Delta^*(v)$.

Fix any locally fair orientation \vec{G} ,

We define $\forall v \in V$, $\Delta^*(v) := \Delta(v)$.

Result 1:

Local out-degree is well-defined.

Duality: $\Delta^*(v) = \rho^*(v)$.

Result 2:

η -fair orientations $(1 + \varepsilon)$ -approximate $\rho^*(v)$ for all vertices v .

Cor.: \exists dynamic algorithms to $(1 + \varepsilon)$ -approximate $\rho^*(v)$!

Result 3:

$O(\varepsilon^{-2} \log^2 n)$ rounds in LOCAL.

Sublinear rounds in CONGEST.

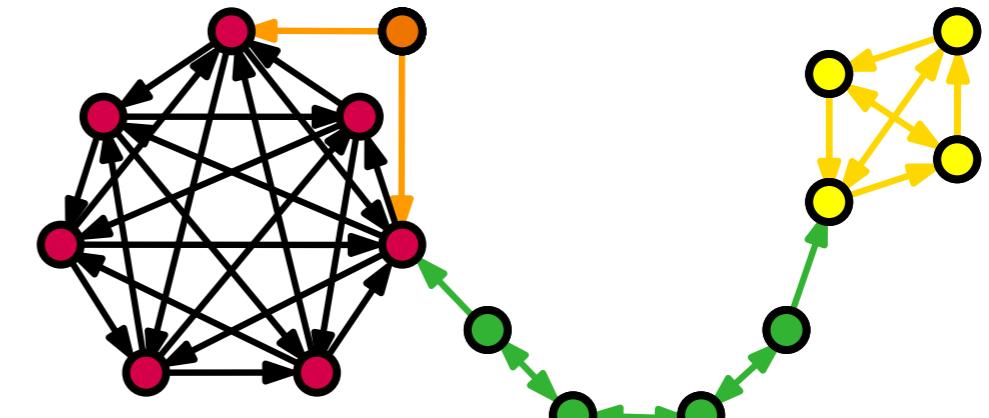
Fractional orientation \vec{G} :

$\forall (u, v) \in E$, require: $g(u \rightarrow v) + g(v \rightarrow u) = 1$.

$\forall v \in V$, define: $\Delta(u) = \sum_{(u,v) \in E} g(u \rightarrow v)$.

Locally fair orientation \vec{G} :

$g(u \rightarrow v) > 0 \Rightarrow \Delta(u) \leq \Delta(v)$.



η -fair orientation \vec{G} :

$g(u \rightarrow v) > 0 \Rightarrow \Delta(u) \leq (1 + \eta)\Delta(v)$.