

Random Degree Constrained Process: Local Limit, Its Applications and Some Open Questions

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Kutszem,
Rényi Institute

Joint work with Balázs Ráth and Lutz Warnke

1 Local limit of the RDCP

2 Critical time

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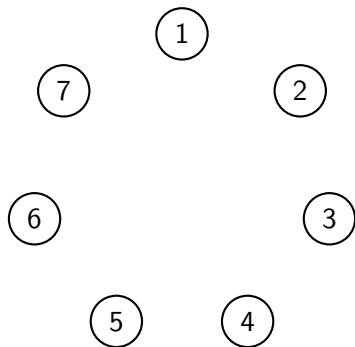
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- Vertex v is **saturated** at time t if its degree in $G_{\underline{p}}^n(t)$ is equal to $d(v)$

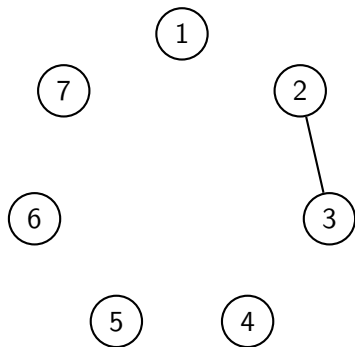
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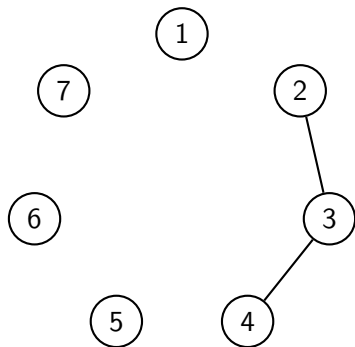
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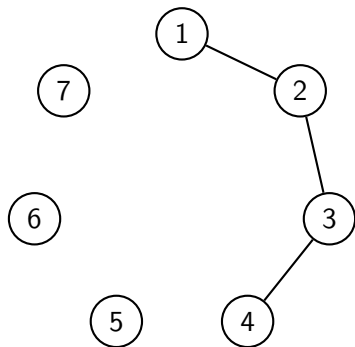
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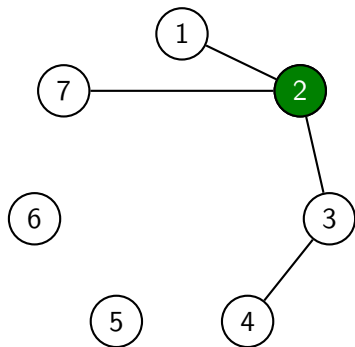
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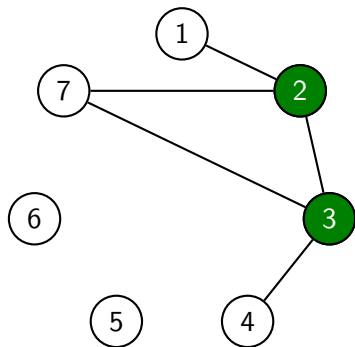
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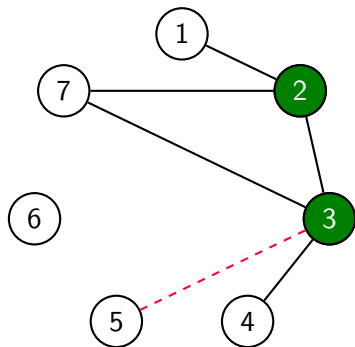
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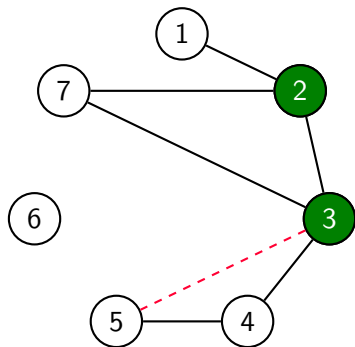
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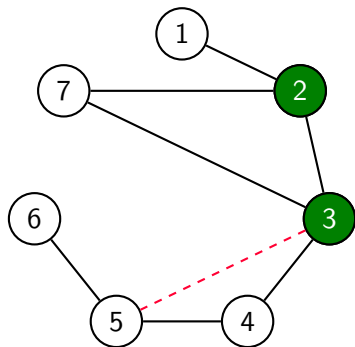
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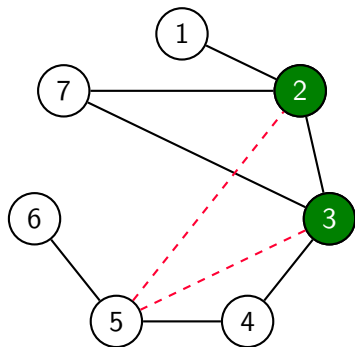
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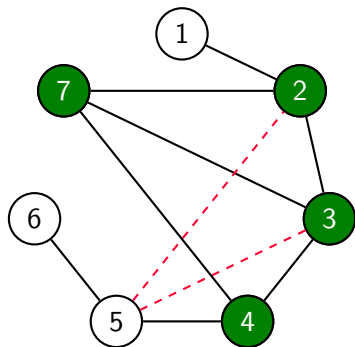
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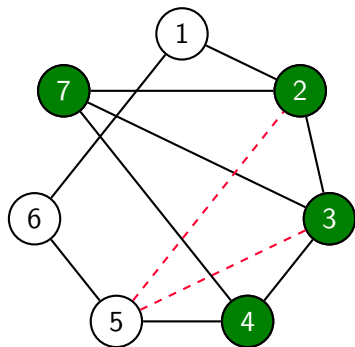
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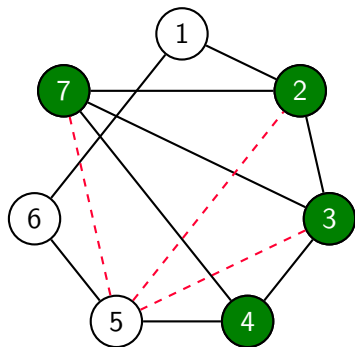
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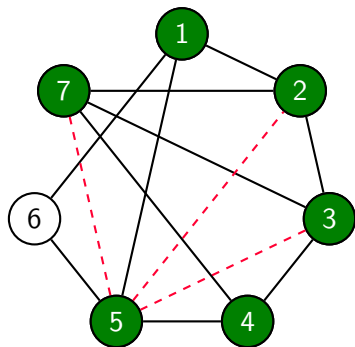
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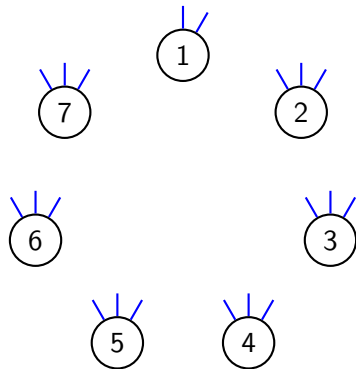
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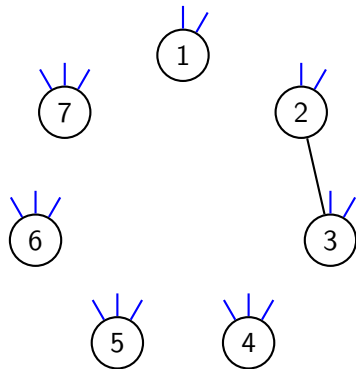
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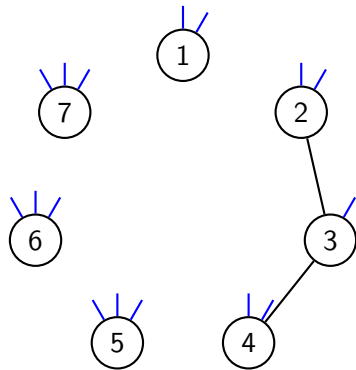
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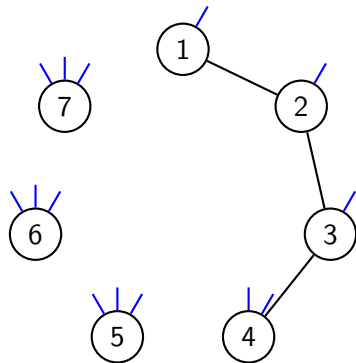
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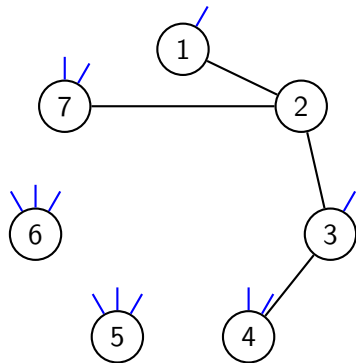
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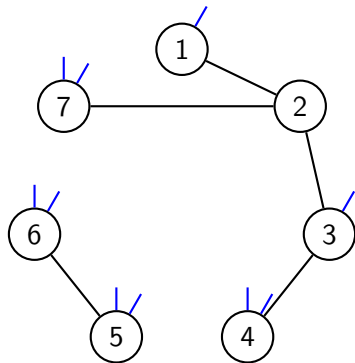
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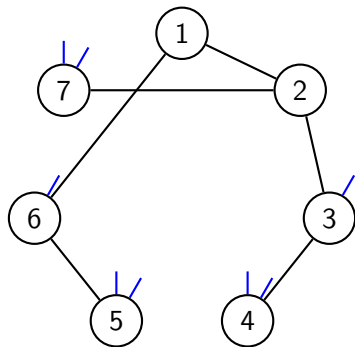
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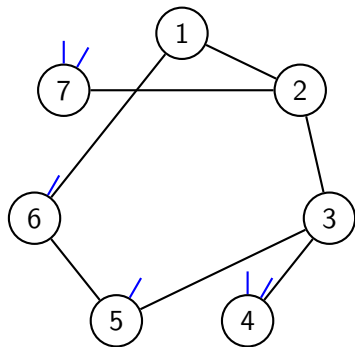
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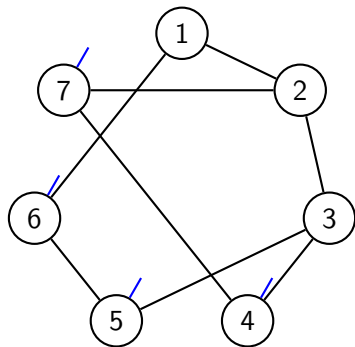
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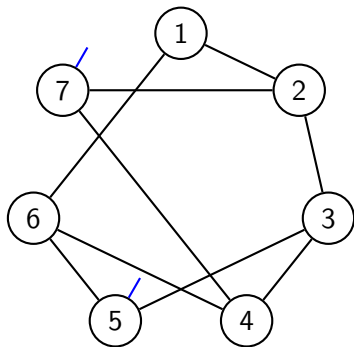
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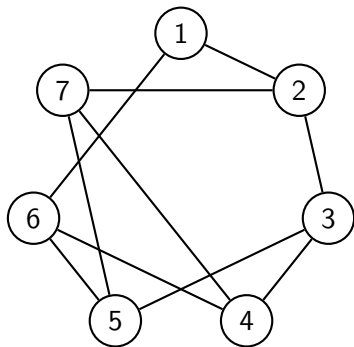
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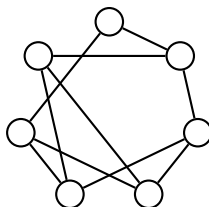
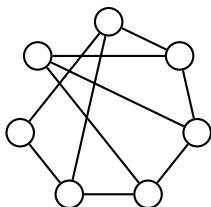
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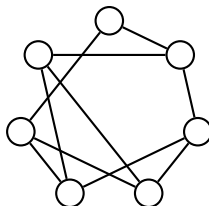
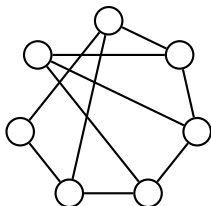
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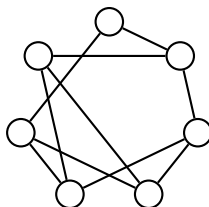
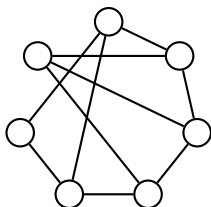
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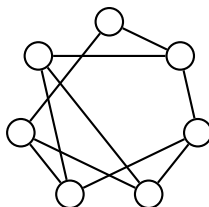
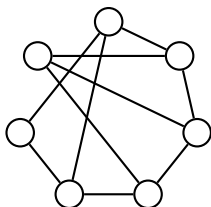
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- Open question (Wormald, 1999):** Does this hold for the regular case?

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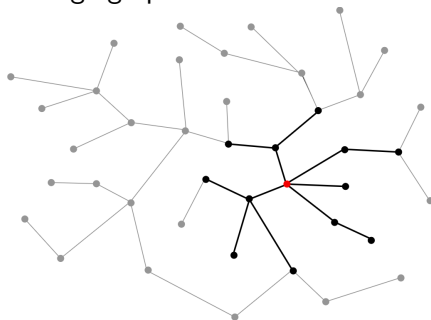
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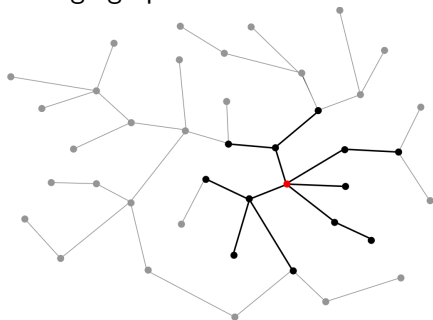
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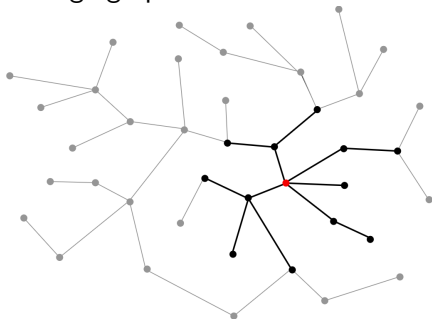


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- It can be used to investigate numerous graph properties, parameters
- The limiting objects (often branching processes) are much simpler to study than the original model

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In contrast to the configuration model, the **local weak limit of the RDCP was unknown** before our work

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Theorem (Local weak convergence of RDCP (Ráth, Sz., Warnke, 2024+))

Fix $t \in \mathbb{R}_+ \cup \{\infty\}$. Then the random degree constrained process on K_n at time t converges locally to a random rooted tree $(G_{\underline{p}}^\infty(t), \emptyset)$, i.e.,

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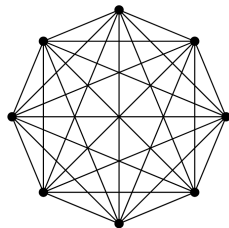
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Fix $t \in \mathbb{R}_+ \cup \{\infty\}$. Then the random degree constrained process on K_n at time t converges locally to a random rooted tree $(G_{\underline{p}}^\infty(t), \emptyset)$, i.e.,

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We even have a more general result:
Instead of K_n



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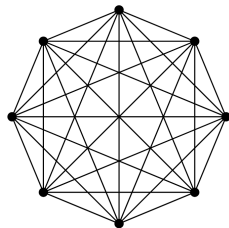
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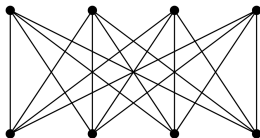
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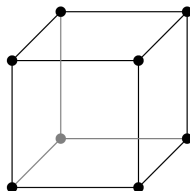
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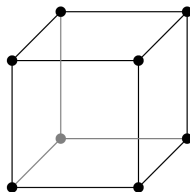
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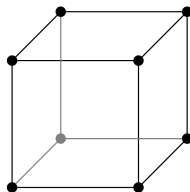
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Poisson weighted infinite tree

If we decorate K_n with i.i.d. exponentially distributed edge weights:

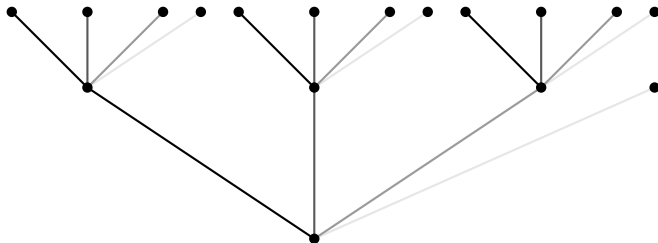
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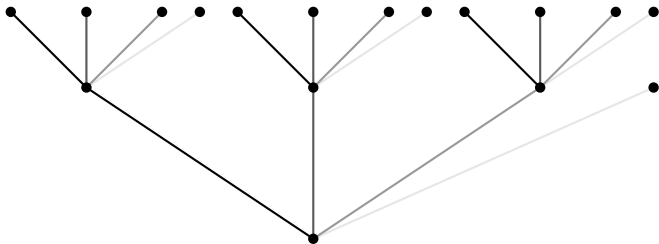
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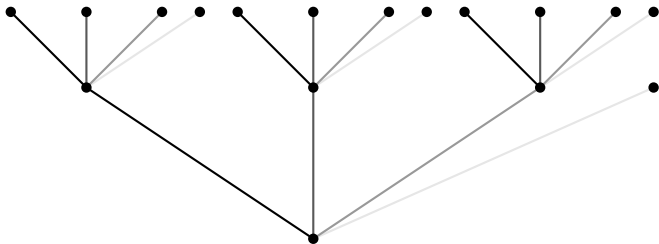
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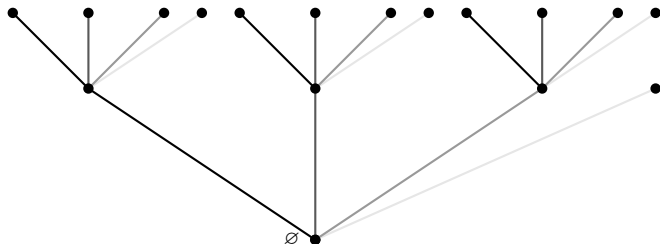
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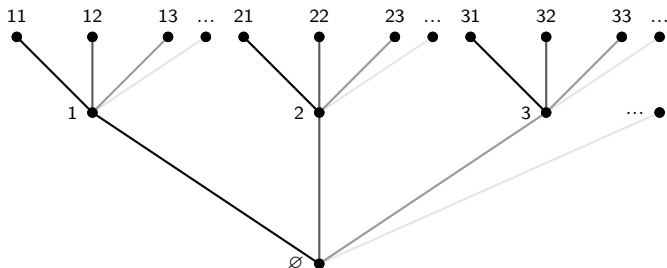
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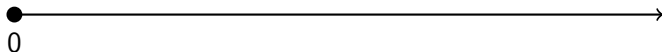


Poisson weighted infinite tree: edge labels

- For each vertex $\mathbf{i}$, take a unit intensity Poisson point process (PPP) $(\tau^{ij})_{j=1}^{\infty}$ on $[0, \infty)$

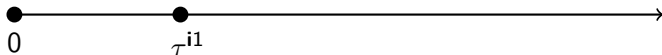
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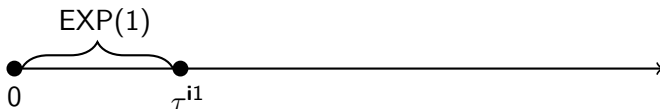
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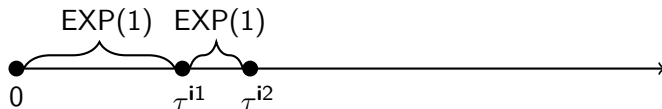
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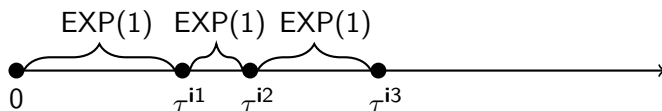
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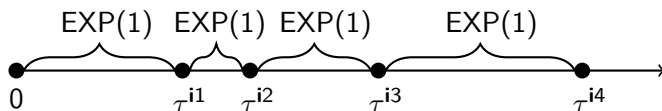
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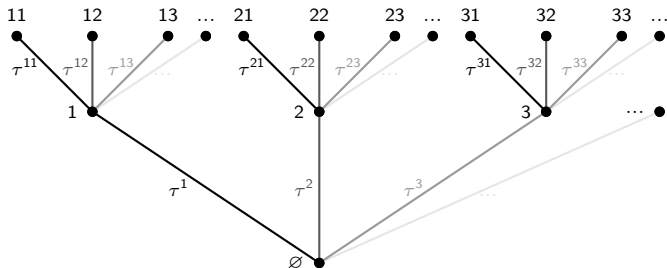


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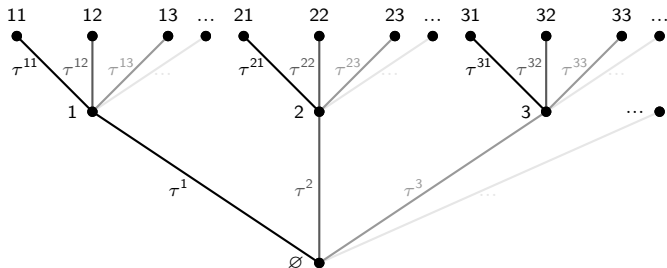
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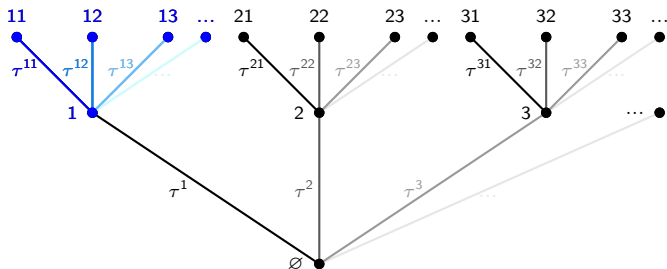
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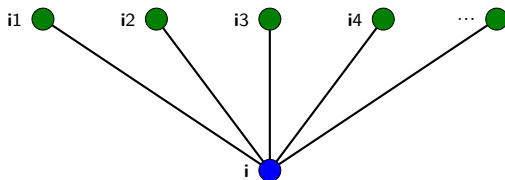
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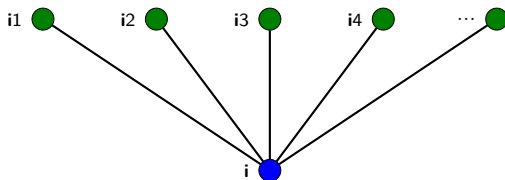
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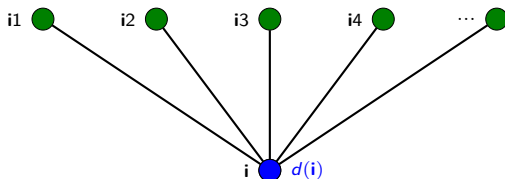
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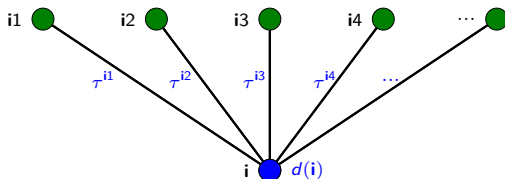
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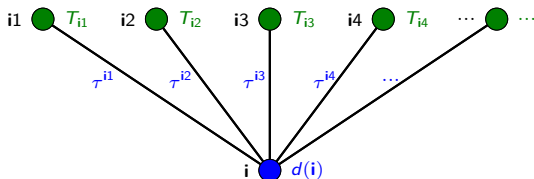
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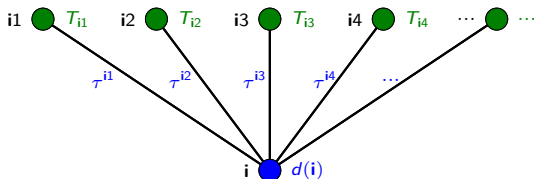
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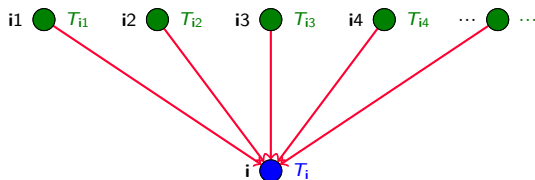
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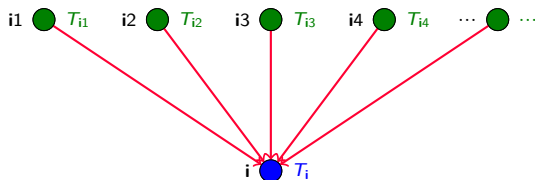
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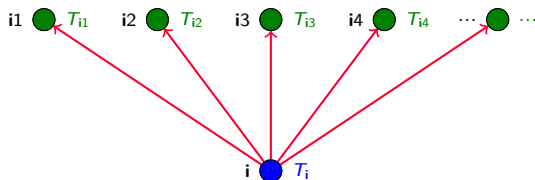
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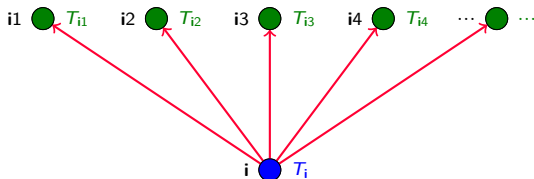


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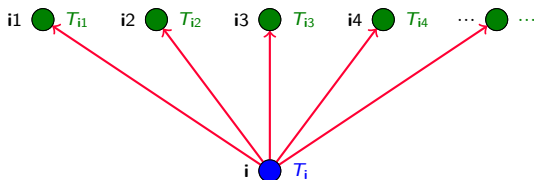


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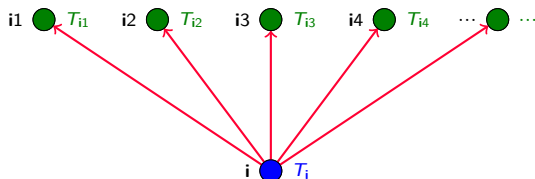


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1 Local limit of the RDCP

2 Critical time

Critical time $\hat{t}_c$

Theorem (Phase transition of the RDCP (Warnke, Wormald, 2022+))

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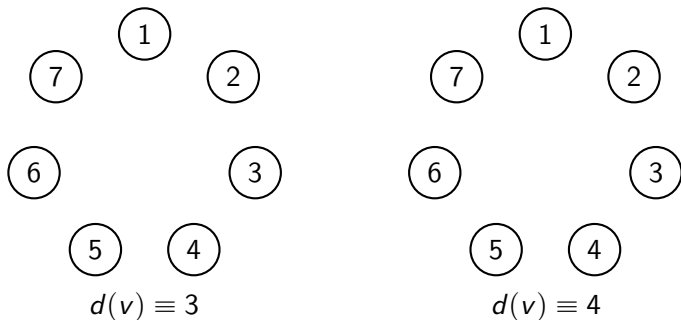
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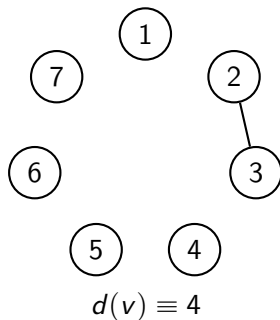
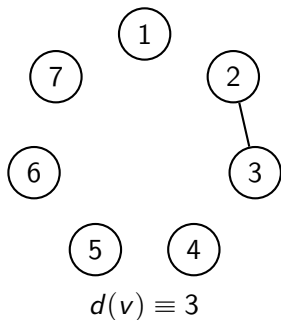


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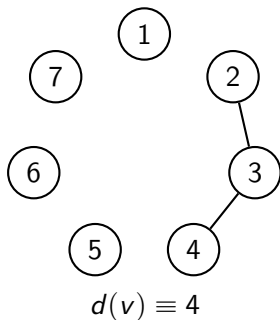
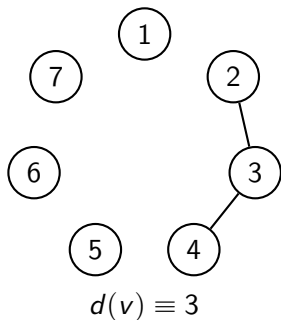


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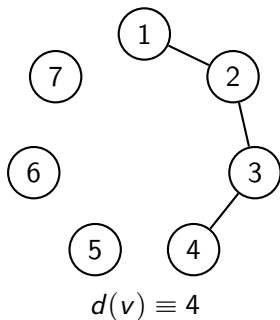
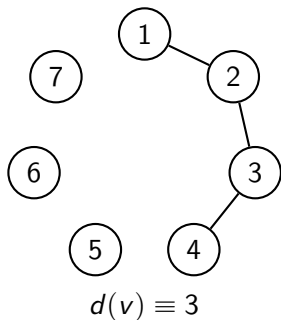


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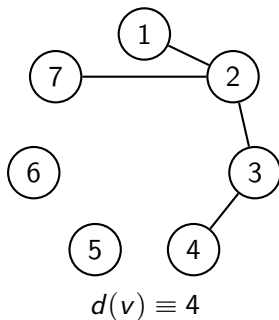
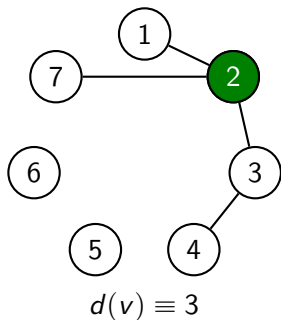


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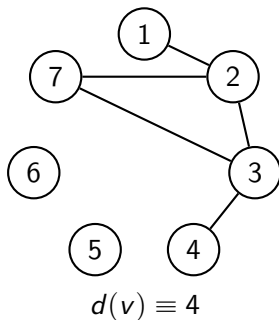
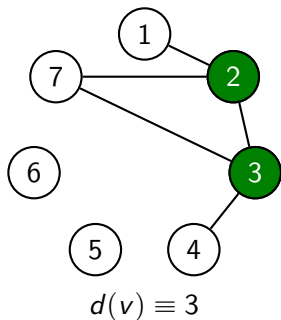


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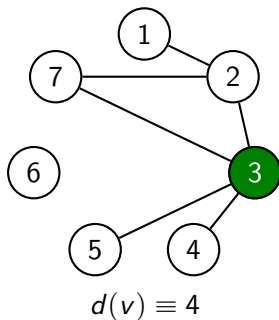
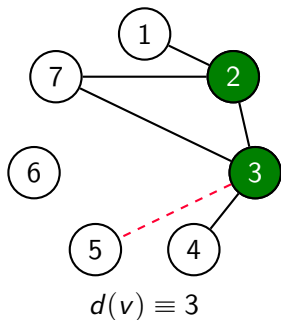


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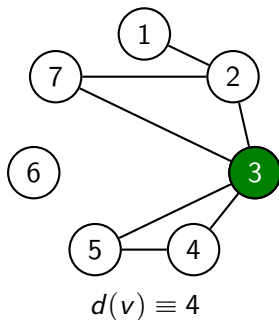
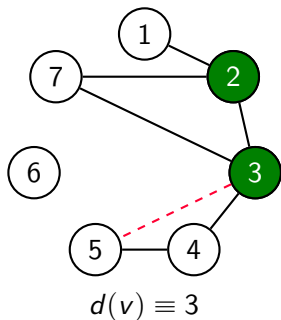


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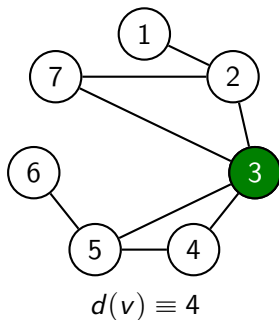
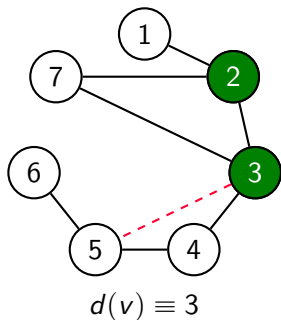


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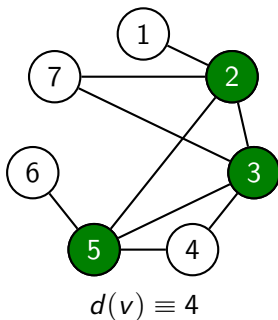
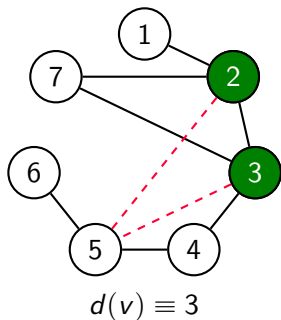


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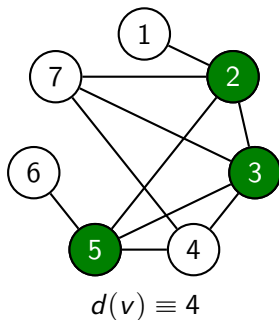
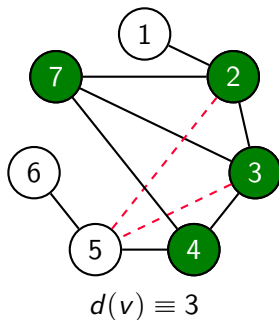


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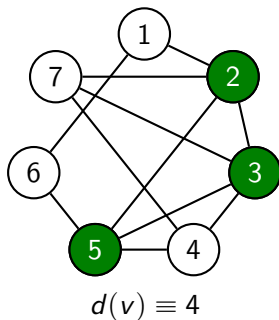
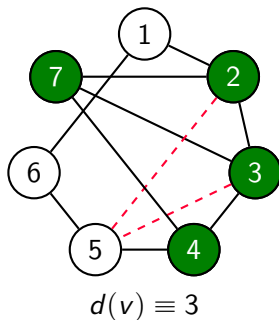


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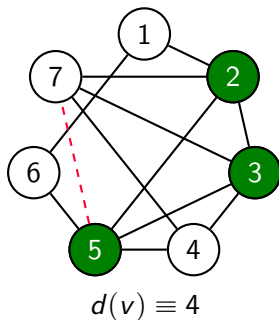
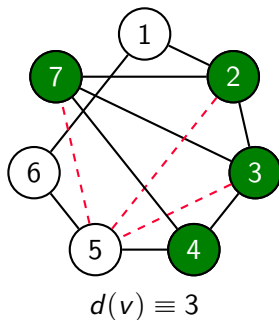


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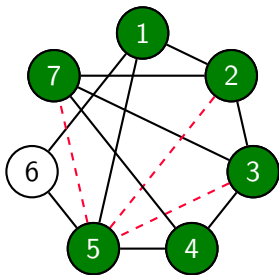


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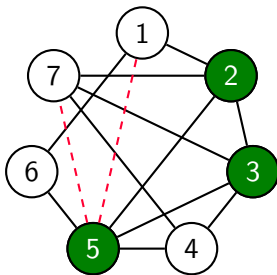
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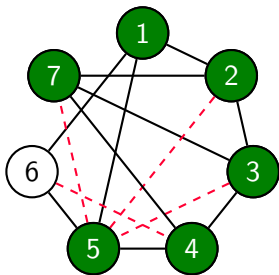
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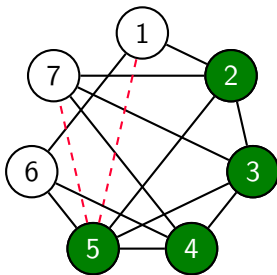
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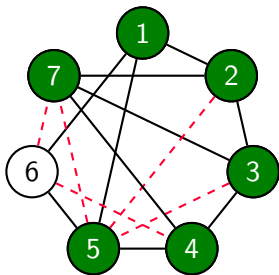
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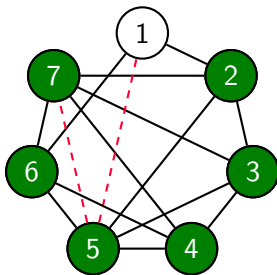
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Namely: $\hat{t}_c$ can be defined as the first time when the local weak limit has infinitely many vertices with positive probability:

$$\hat{t}_c(\underline{p}) := \sup \left\{ t \geq 0 : \mathbb{E} \left(\left| V(G_{\underline{p}}^{\infty}(t)) \right| \right) < \infty \right\} \quad (3)$$

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Open question: Does this hold for $d = 3, 4, \dots, d_0 - 1$?

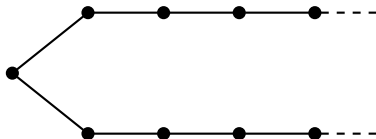
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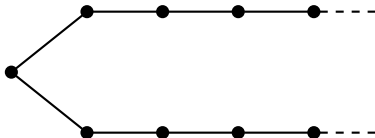


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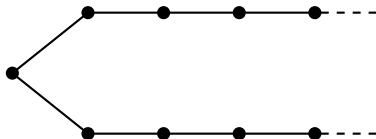
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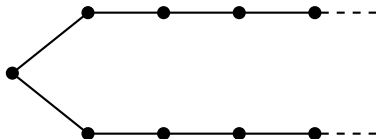
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where Δ is an upper bound on $\underline{p}$ and $D \sim \underline{p}$

Thank you for your attention!

szokemp@math.bme.hu

<https://arxiv.org/pdf/2409.11747>