Recent Algorithmic Developments in NetworKit

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Agenda

Since last NetworKit Day:

- numerous algorithmic additions to NetworKit
- and lots of refactoring (see previous talk)

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In this talk: new algorithms and features since ND'17

(Brief tour through various modules . . .)

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Use cases:

- Null-model for network analytics (e.g., modularity)
- Benchmarking graph algorithms

Randomization: Curveball algorithm

[SNBFS14], [CHMPTW18], code contributed by Manuel Penschuck

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In NetworKit: Curveball and GlobalCurveball (pick many trades at a time)

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  (More related electrical centralities in the pipeline [APvdGM20])

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  Considers graph as electrical network, measures resistance of edges
  (More related electrical centralities in the pipeline [APvdGM20])
- Top-k (harmonic) closeness [BBCMM16]
  Computes k vertices with highest closeness w/o computing all scores

Network Centrality: KADABRA

Let $G = (V, E)$ be a graph. $s, t \in V$.

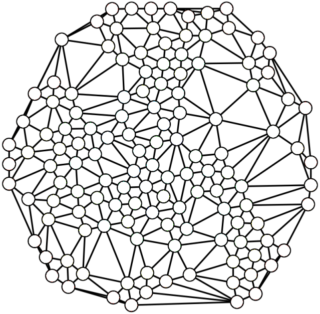

Image by Claudio Rocchini (CC-BY). Taken from `wikipedia.org/wiki/Betweenness_centrality`.

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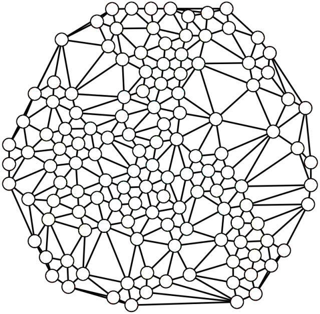
Network Centrality: KADABRA

Let $G = (V, E)$ be a graph. $s, t \in V$.

σ_{st}: number of shortest s-t paths
$\sigma_{st}(x)$: number of shortest s-t paths over vertex $x \in V$



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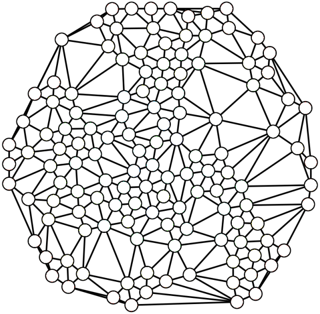
of a vertex $x \in V$:

$$\mathrm{BC}(x) = \sum_{s,t \in V \setminus \{x\}} \frac{\sigma_{st}(x)}{\sigma_{st}}$$



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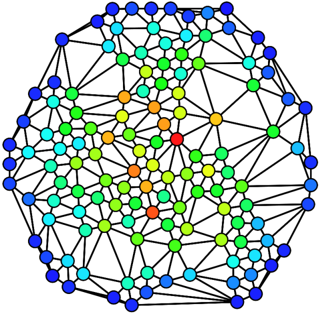

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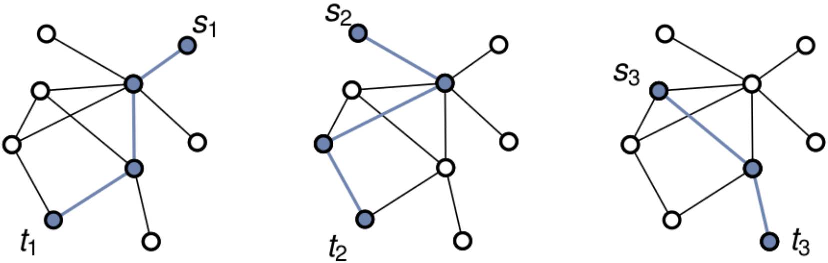

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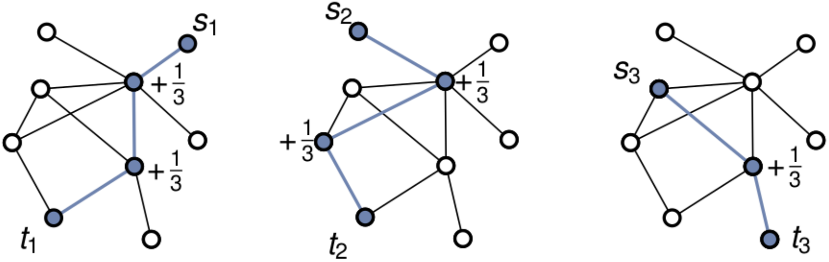

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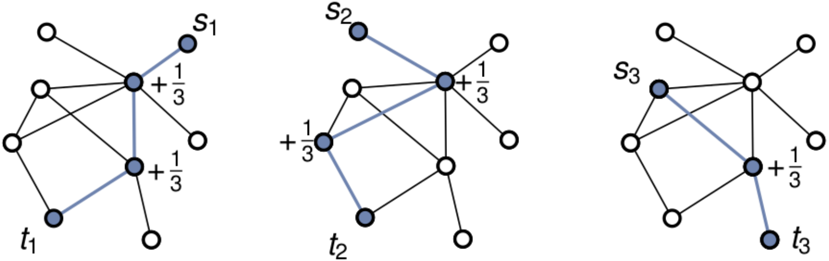

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In NETWORKIT: fastest available betweenness approximation

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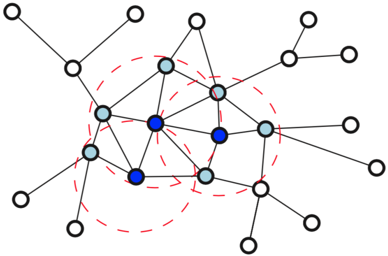

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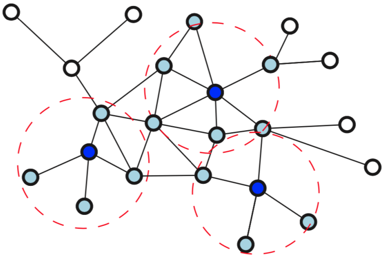

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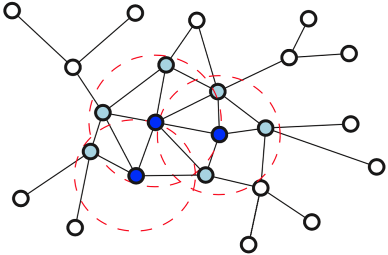

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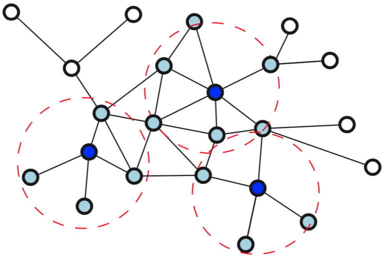

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Support for group centralities recently added to NetworKit.

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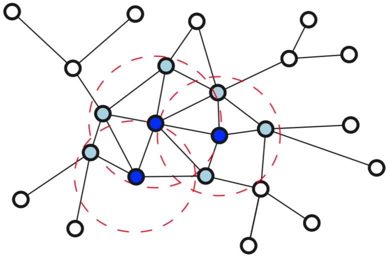

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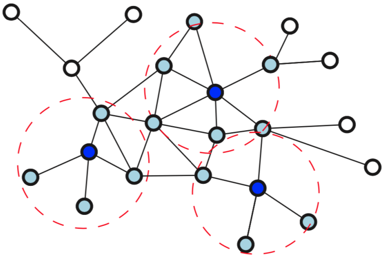

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- Finding groups with maximal centrality (usually a hard problem)

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- GED-Walk [AvdGBZGM19]
  Similar to Katz centrality:
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- Upcoming: Group closeness [AvdGM19]
  Fast local-search algorithm

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- Goal: represent all data available in NetworKit(weights, IDs, . . .) in a compact format

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a.k.a. Representation Learning

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Other embedding algorithms in the future?

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  Classical graph problem; useful building block for other algorithms
- Graph generator by F.-B. Mocnik [M18]
  Models spacial graphs

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Available from: `https://github.com/hu-macsy/simexpal`

Thank You!