

intermediacy of publications

“pomembnost prispevkov za razvoj znanstvene tematike”

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AI seminar '19

summer research visits



CWTS in Leiden, Vincent, Ludo & Nees

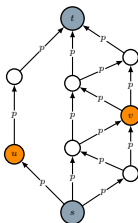


Tjaša, Nevi & Mažo, biking, boating & skating etc.

introduction & motivation

algorithmic historiography for evolution of field (**Garfield, 1964–**)

relying on **citations** between scientific **publications** from **WoS** & **Scopus**



existing approaches include **main paths** (**Hummon & Doreian, 1989**)
(**longest/shortest paths**) many **irrelevant**/miss **relevant** publications
(**intermediacy**) important publications should only be **well-connected**

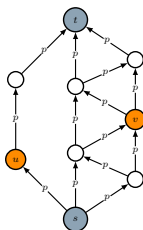
intermediacy measure

(**input**) selected **source** & **target** publications **s** & **t**

(**method**) each citation is relevant/active with **probability p**

(**measure**) importance of **publication u** called **intermediacy** ϕ_u

$$\phi_u = \Pr(X_{st}^u) = \Pr(X_{su}) \Pr(X_{ut})$$

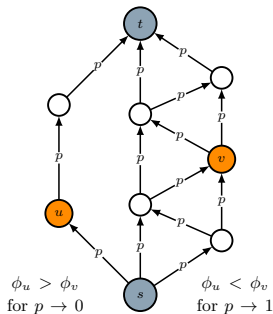


X_{st} exists path **from s to t** & X_{st}^u exists path **through u**

intermediacy for $p \rightarrow 0$

for $p \rightarrow 0$ intermediacy ϕ governed by ℓ (**proof**)

for $p \rightarrow 0$ if $\ell_u < \ell_v$ then $\phi_u > \phi_v$

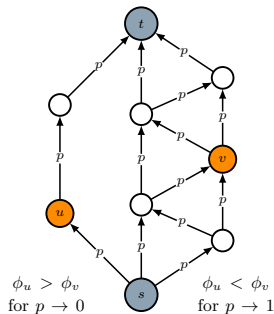


ℓ_u is **length** of **shortest paths** from s to t through u

intermediacy for $p \rightarrow 1$

for $p \rightarrow 1$ intermediacy ϕ governed by σ (**proof**)

for $p \rightarrow 1$ if $\sigma_u < \sigma_v$ then $\phi_u < \phi_v$

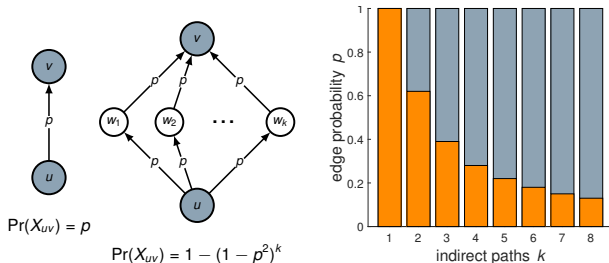


σ_u is **number** of **edge-disjoint paths** from s to t through u

intuition for p

for what p is **direct citation** equivalent to k **indirect citations**

$$\Pr(X_{uv}) = p = 1 - (1 - p^2)^k$$

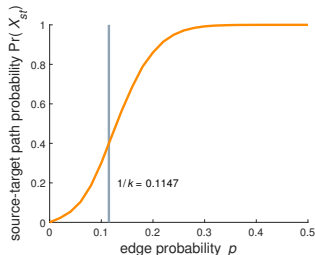
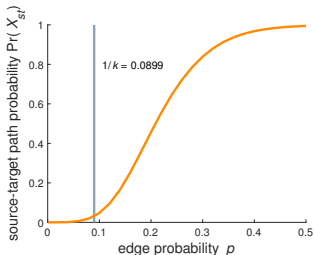


k is **number** of **indirect paths** from u to v

p phase transition

for what p source-target path $\Pr(\mathbf{X}_{st}) > 0$ & intermediacy $\exists \mathbf{u} : \phi_{\mathbf{u}} > 0$

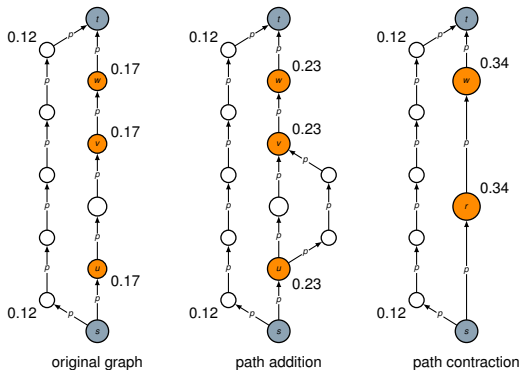
$$p \geq n/2m = 1/k$$



k is **average** number of **citations/references**

properties of intermediacy

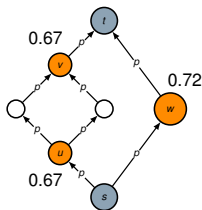
path **addition** & **contraction** increase intermediacy (**proof**)



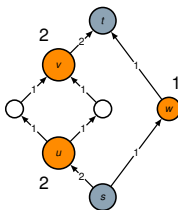
path from source to target becomes **“easier”** (**intuition**)

alternatives to intermediacy

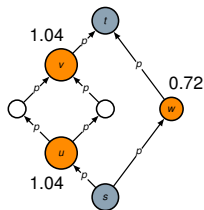
alternatives are **main paths** & **expected paths** (state of the art)



intermediacy



main path analysis



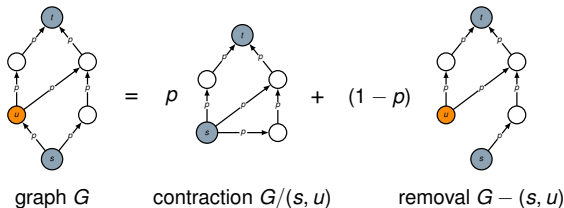
expected path count

alternatives **violate** path contraction property (**example**)

exact algorithm

decomposition algorithm by edge **contraction** & **removal** (Ball, 1979)

$$\Pr(X_{st} \mid G) = p \Pr(X_{st} \mid G/(s, u)) + (1 - p) \Pr(X_{st} \mid G - (s, u))$$

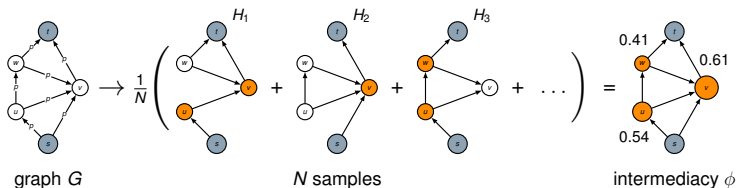


runs in **exponential time** since NP-hard even in DAG (Johnson, 1984)

approximate algorithm

simple **Monte Carlo** simulation algorithm by edge **sampling**

$$\phi_u = \Pr(X_{st}^u \mid G) = \frac{1}{N} \sum_{k=1}^N I(X_{st}^u \mid H_k)$$



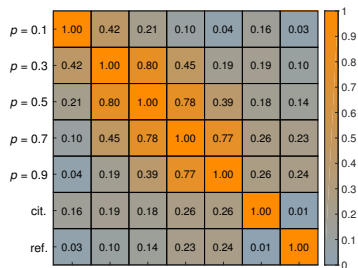
runs in quasi **linear time** using probabilistic DFS over say **10^6 samples**

intermediacy $\neq$ centrality

correlation coefficient between **intermediacies** ϕ & **citations/references**



Pearson correlation



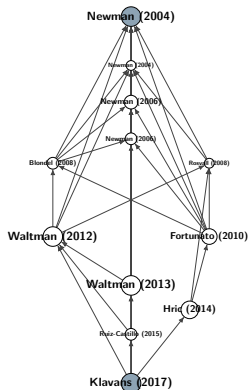
Pearson correlation

intermediacy ϕ **uncorrelated** with standard **centrality measures**

modularity example

(**target**) Newman & Girvan (2004), **Finding and evaluating community...**, *Phys. Rev. E* **69**(2), 026113.

(**source**) Klavans & Boyack (2017), **Which type of citation analysis generates...**, *JASIST* **68**(4), 984-998.

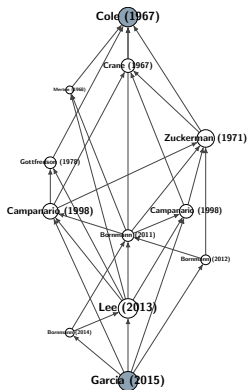


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peer review example

(**target**) Cole & Cole (1967), **Scientific output and recognition**, *Am. Sociol. Rev.* **32**(3), 377-390.

(**source**) Garcia et al. (2015), **The author-editor game**, *Scientometrics* **104**(1), 361-380.



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- 3 Campanario (1998), Peer review for journals as it stands today: Part 1, *Sci. Commun.* **19**(3), 181-211.
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sensing example

(**target**) Eagle & Pentland (2006), **Reality mining: Sensing complex social systems**, *Pers. Ubiquit. Comp.* **10**(4), 255-268.

(**source**) Mohr et al. (2017), **Personal sensing: Understanding mental health using ubiquitous sensors and machine learning**, *Annu. Rev. Clin. Psychol.* **13**, 23-47.

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- 10 Piwek et al. (2016), The rise of consumer health wearables: Promises and barriers, *PLoS Med.* **13**(2), e1001953.

rendering example

(**target**) Wenger et al. (2004), **Interactive volume rendering of thin thread structures within multivalued scientific data sets**, *IEEE T. Vis. Comput. Gr.* **10**(6), 664-672.

(**source**) Eid et al. (2017), **Cinematic rendering in CT: A novel, lifelike 3D visualization technique**, *Am. J. Roentgenol.* **209**(2), 370-379.

- 1 Zhang et al. (2011), Volume visualization: A technical overview with a focus on medical applications, *J. Digit. Imaging* **24**(4), 640-664.
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chess example

(**target**) Guid & Bratko (2006), **Computer analysis of world chess champions**,
ICGA J. **29**(2), 65-73.

(**source**) Mohr et al. (2017), **Personal sensing: Understanding mental health using
ubiquitous sensors and machine learning**, *Annu. Rev. Clin. Psychol.* **13**, 23-47.

- 1 Guid & Bratko (2011), Using heuristic-search based engines for estimating human skill at chess, *ICGA J.* **34**(2), 71-81.
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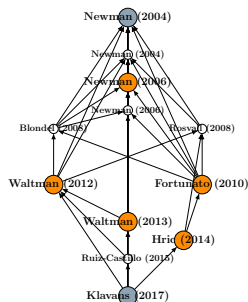
conclusions & future work

(**proposal**) measure of importance of publications called **intermediacy**

(**theory**) conceptually clear & provable behavior in **extreme cases**

(**practice**) intermediacy shows promising results in **case studies**

(**future**) online **research app**! applicability to **other networks**?



(**paper**) arxiv.org/abs/1812.08259
(**code**) github.com/lovre/intermediacy

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