intermediacy of publications

uncovering important publications for the development of a field

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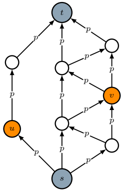
problem & motivation

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

relying on **citations between publications** from **WoS/Scopus**



existing approaches include **main paths** (**Hummon & Doreian, 1989**)

(**longest/shortest paths**) many **irrelevant**/miss **relevant** publications

(**however**) important publications should only be **well-connected**

"...citations are valid and valuable means of creating accurate historical descriptions of scientific fields."

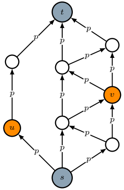
measure of intermediacy

(**setting**) select **source** & **target** publications **s** & **t**

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

(**result**) importance of **publication u** as **intermediacy** $\phi_{\mathbf{u}}$

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



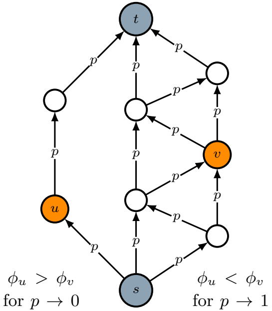
$\mathbf{X_{st}}$ – exists path **from s to t** & $\mathbf{X_{st}^u}$ – exists such path **through u**

$\phi_u = 2\phi_v \not\equiv$ publication u is "twice" as important as publication v

limit case $p \to 0$

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

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

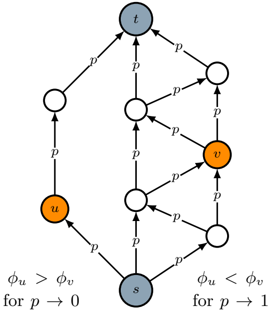


ℓ_u – **length** of **shortest paths** from s to t through u

limit case $p \to 1$

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

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

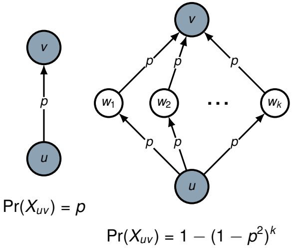


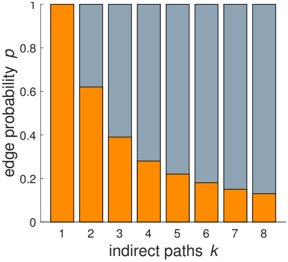
σ_u – **number** of **edge-disjoint paths** from s to t through u

intuition for parameter p

for what p is **direct citation** $\equiv$ k **indirect citations**

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





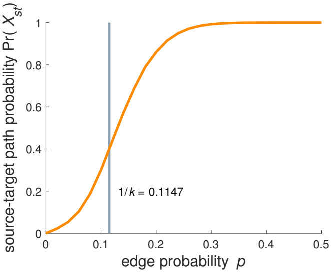
k – **number** of **indirect paths** from u to v

$p = 0.22 \equiv k = 5$ & $p = 0.11 \equiv k = 10$

choice of parameter p

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

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



k – **average** number of **citations** & **references**

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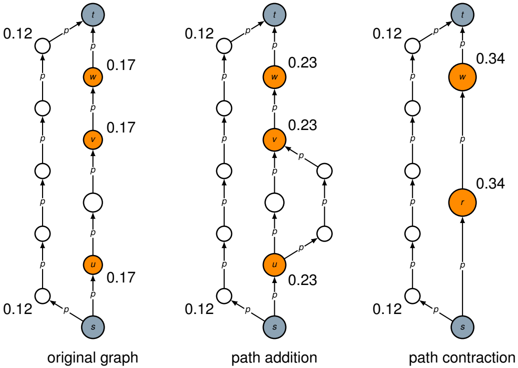
percolation theory suggests that for $k > 1$ probability $\Pr(X_{st})$ is non-negligible

properties of intermediacy

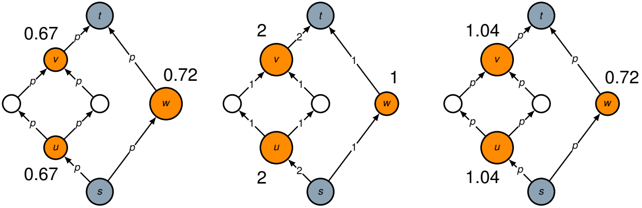
path addition & **contraction** increase intermediacy (**proof**)



path from source to target becomes **"easier"** (**intuition**)

alternatives to intermediacy

alternatives include **main paths** & **resistance** (**state of the art**)



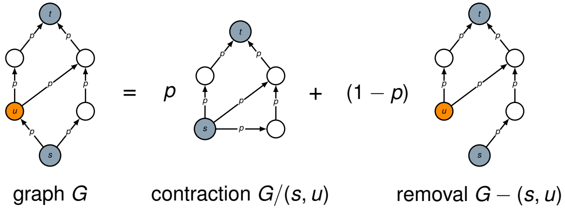
intermediacy | main path analysis | expected path count

alternatives **violate** path addition/contraction property (**examples**)

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**)

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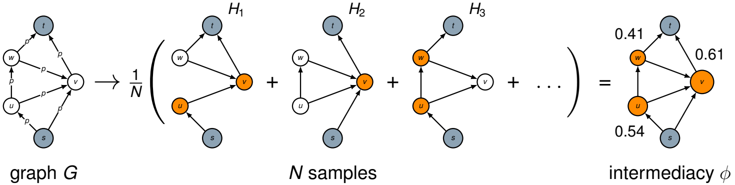
decomposition algorithm is cute & elegant, but useless in practice :(

approximate algorithm

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

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



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

$\ll$ 30 min for network with 9 145 771 nodes and 81 771 723 edges :)

intermediacy $\neq$ centrality

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

p = 0.1	1.00	0.33	0.28	0.28	0.26	0.09	0.12
p = 0.3	0.33	1.00	0.82	0.79	0.71	0.26	0.29
p = 0.5	0.28	0.82	1.00	0.98	0.91	0.38	0.41
p = 0.7	0.28	0.79	0.98	1.00	0.96	0.44	0.43
p = 0.9	0.26	0.71	0.91	0.96	1.00	0.51	0.40
cit.	0.09	0.26	0.38	0.44	0.51	1.00	0.00
ref.	0.12	0.29	0.41	0.43	0.40	0.00	1.00

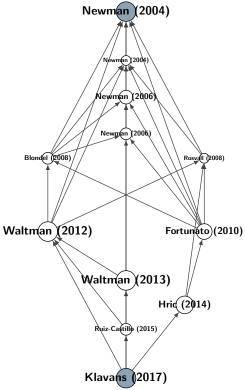
intermediacy **not correlated** with standard **centrality measures**

intermediacy most useful from ordinal perspective $\equiv$ Pearson $<$ Spearman correlation

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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5. Newman (2006), Modularity and community structure in networks, *PNAS* **103**(23), 8577-8582.
6. Ruiz-Castillo & Waltman (2015), Field-normalized citation impact indicators using algorithmically..., *J. Informetr.* **9**(1), 102-117.
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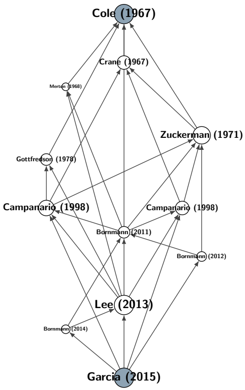
we set $p = 0.1$ & use in-house version of **Scopus** database at **CWTS**

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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6. Gottfredson (1978), Evaluating psychological research reports: Dimensions, reliability, and correlates. . . , *Am. Psychol.* **33**(10), 920-934.
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9. Bornmann (2014), Do we still need peer review? An argument for change, *JASIST* **65**(1), 209-213.
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we set $p = 0.1$ & use snapshot of **WoS** collected by (**Batagelj et al., 2017**)

small-world example

(**target**) Watts & Strogatz (1998), **Collective dynamics of 'small-world' networks**, *Nature* **393**(6684), 440-442.

(**source**) Backstrom et al. (2012), **Four degrees of separation**, In: *Proceedings of the WebSci '12*, pp. 45-54.

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9 Ye et al. (2010), Distance distribution and average shortest path length estimation in real-world networks, In: *Proceedings of the ADMA '10*, pp. 322-333.

10 Lattanzi et al. (2011), Milgram-routing in social networks, In: *Proceedings of the WWW '11*, pp. 725-734.

we set $p = 0.1$ & use in-house version of **Scopus** database at **CWTS**

scale-free example

(**target**) Barabási & Albert (1999), **Emergence of scaling in random networks**, *Science* **286**(5439), 509-512.

(**source**) Liu et al. (2011), **Controllability of complex networks**, *Nature* **473**(7346), 167-173.

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9 Pastor-Satorras et al. (2001), Dynamical and correlation properties of the Internet, *Phys. Rev. Lett.* **87**(25), 258701.

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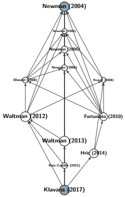
conclusions & future

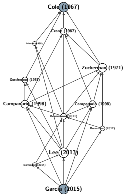
(**proposal**) measure of **importance of publications** called intermediacy

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

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

(**extensions**) multiple sources & targets, weighted networks





(**future**) **online app**! other networks, axiomatic foundation etc.

(paper) arxiv.org/abs/**1812.08259**

(code) github.com/lovre/**intermediacy**

Šubelj, Waltman, Traag & Van Eck (2020) Intermediacy of publications, *Royal Society Open Science*, **7**(1), 190207.

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