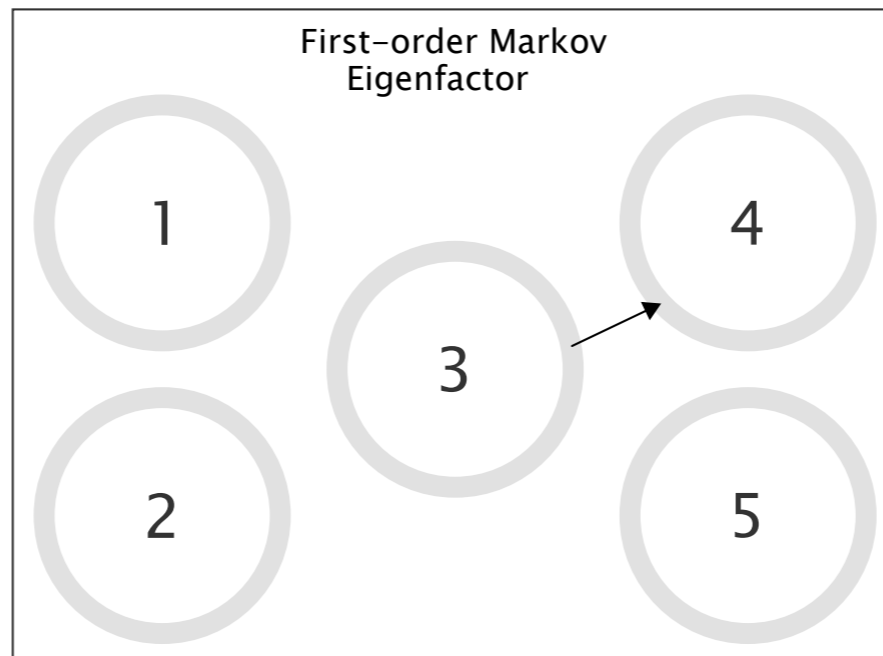
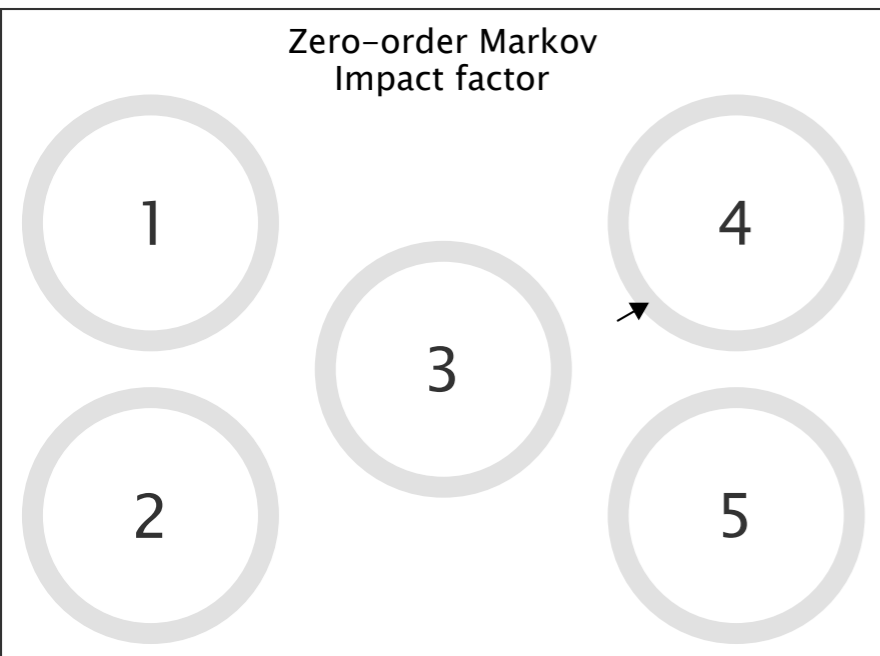
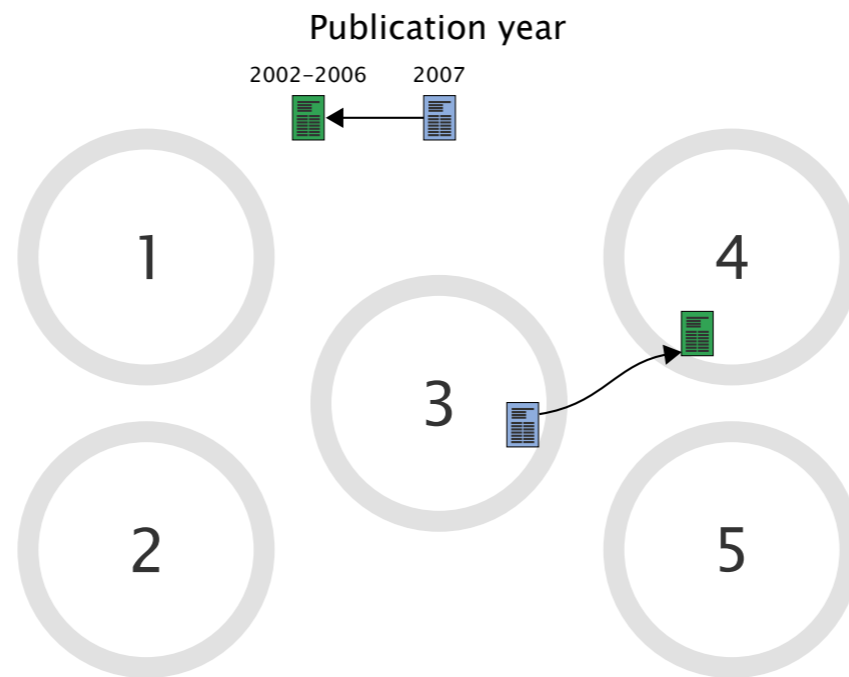


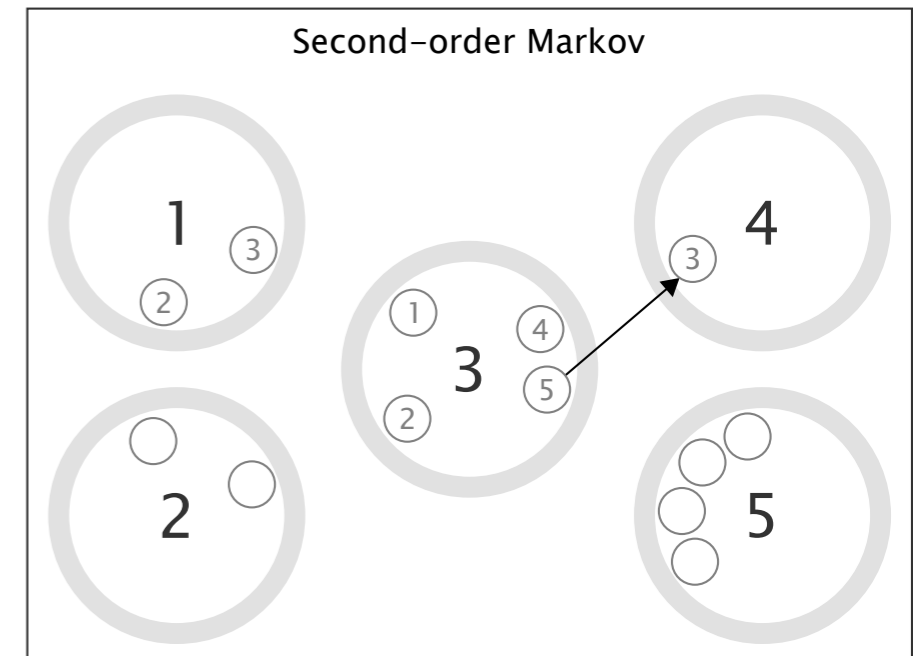
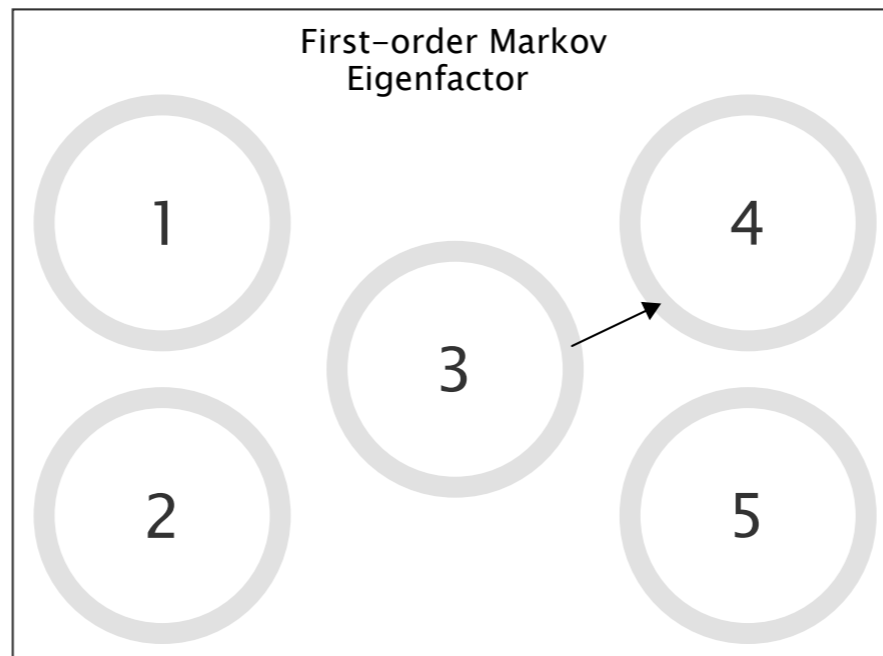
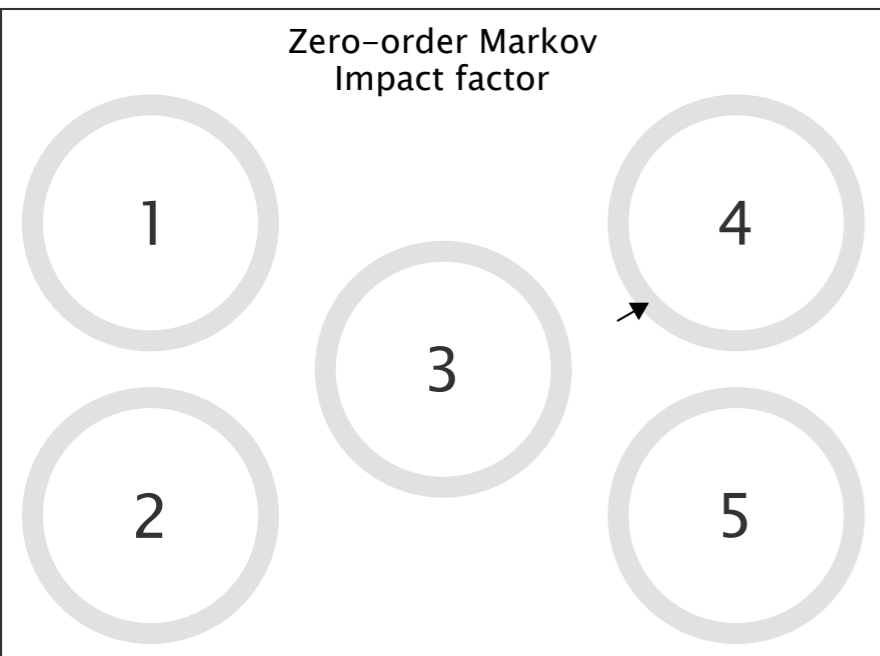
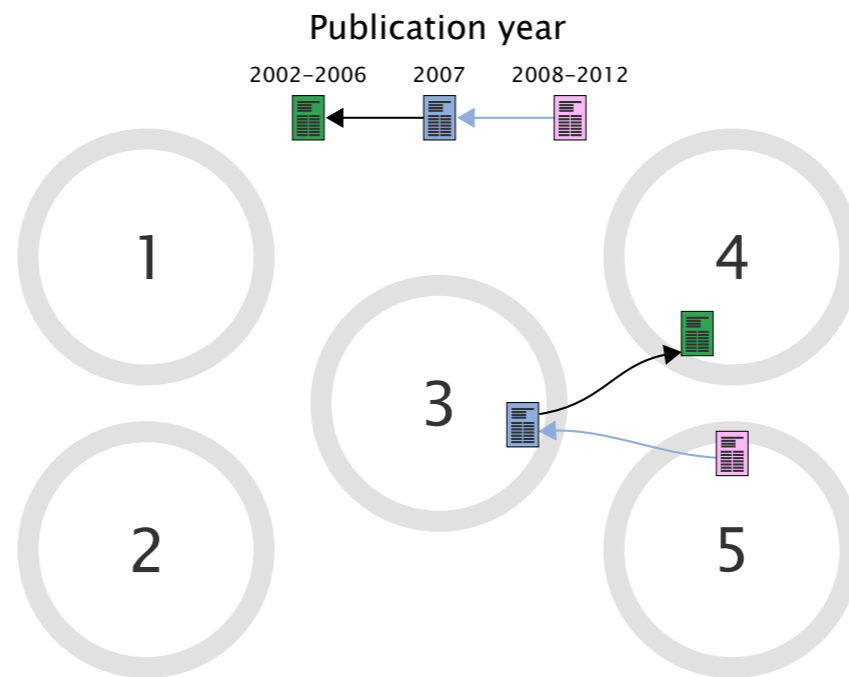
Machine learning for robust rankings

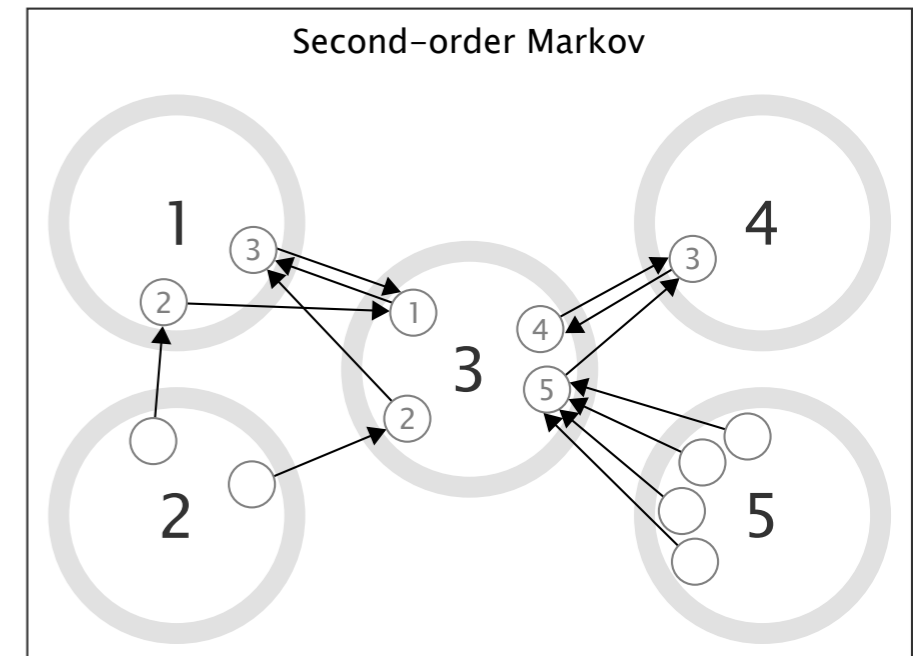
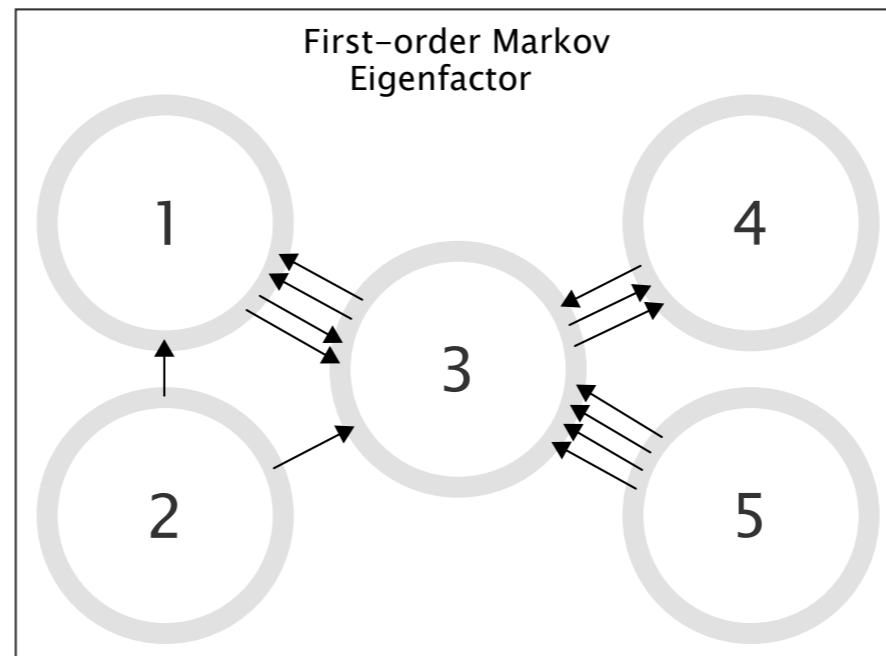
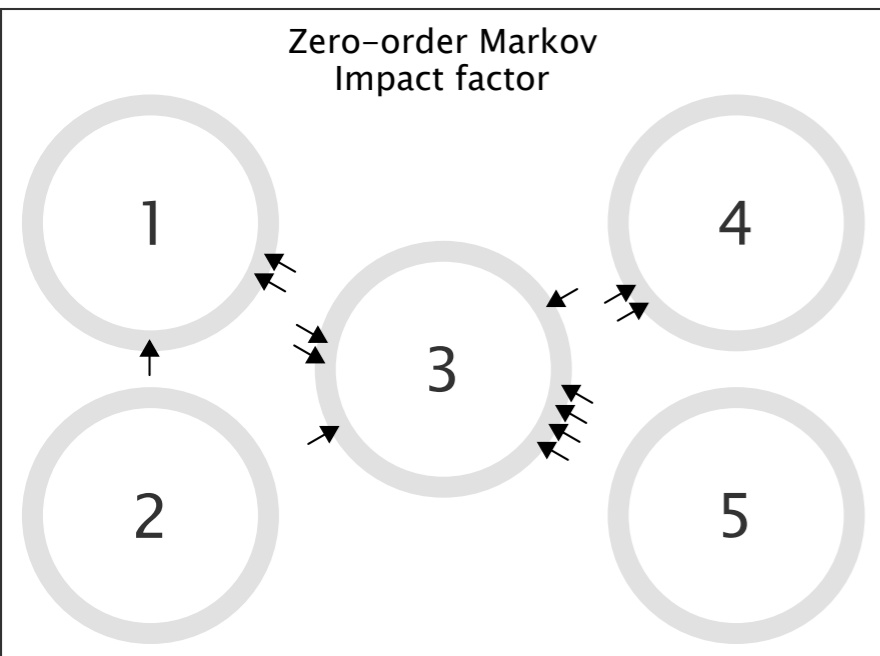
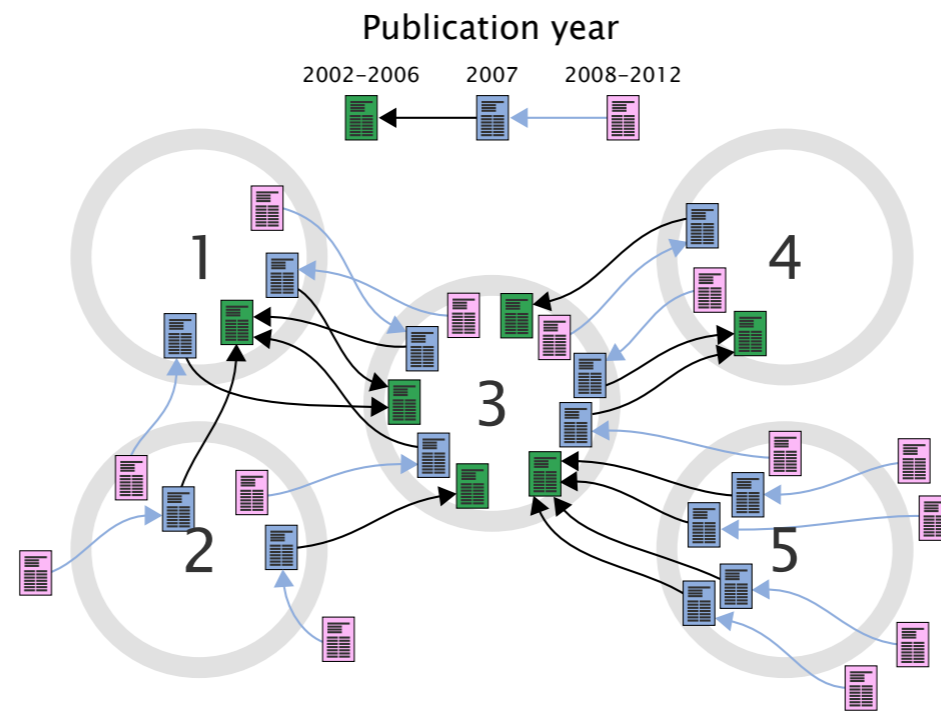
Martin Rosvall

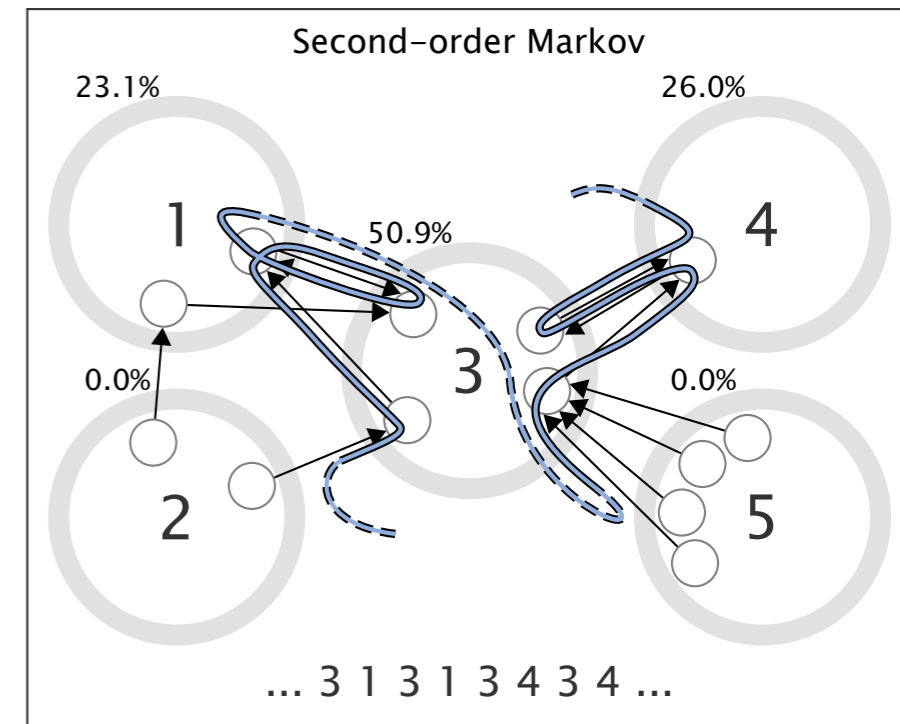
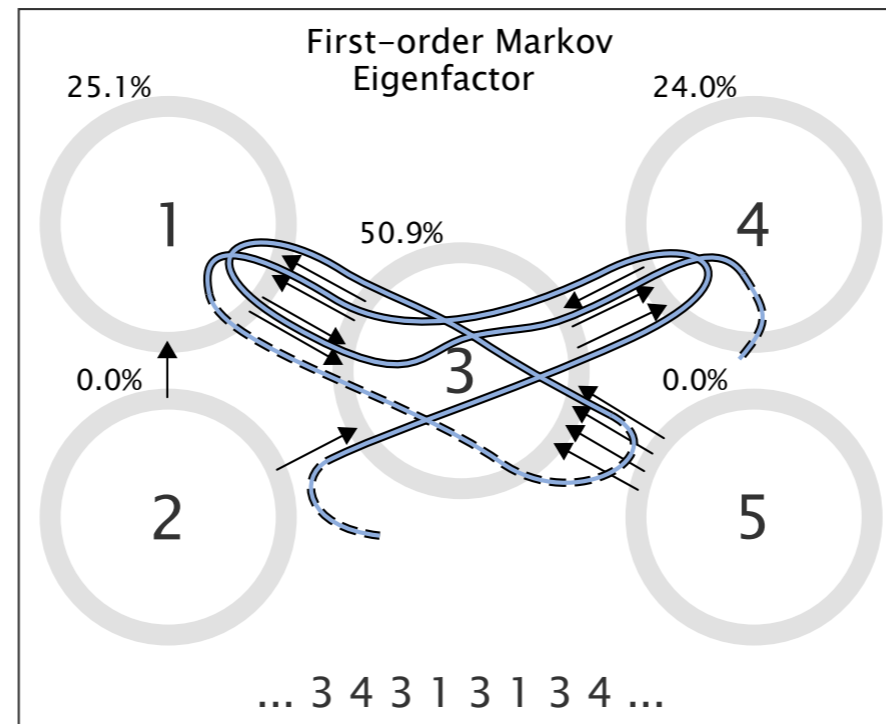
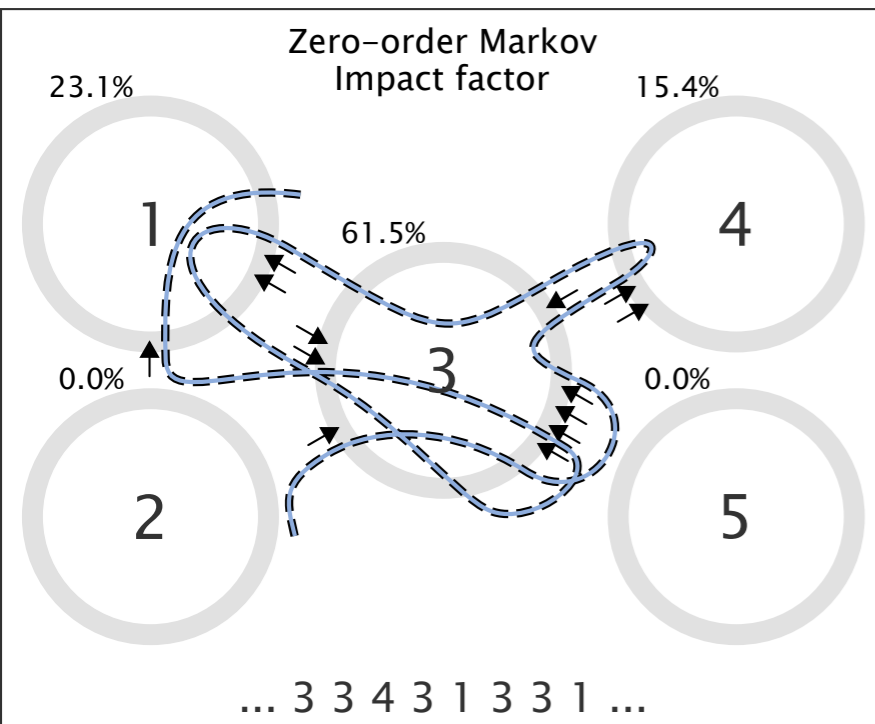
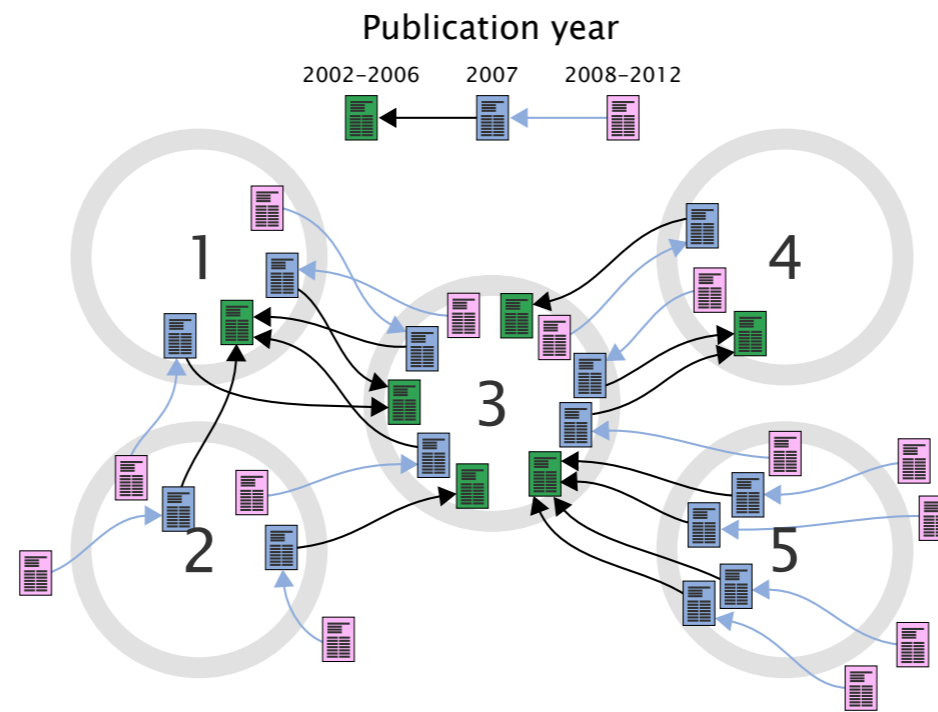
Ludvig Bohlin, Andrea Lancichinetti

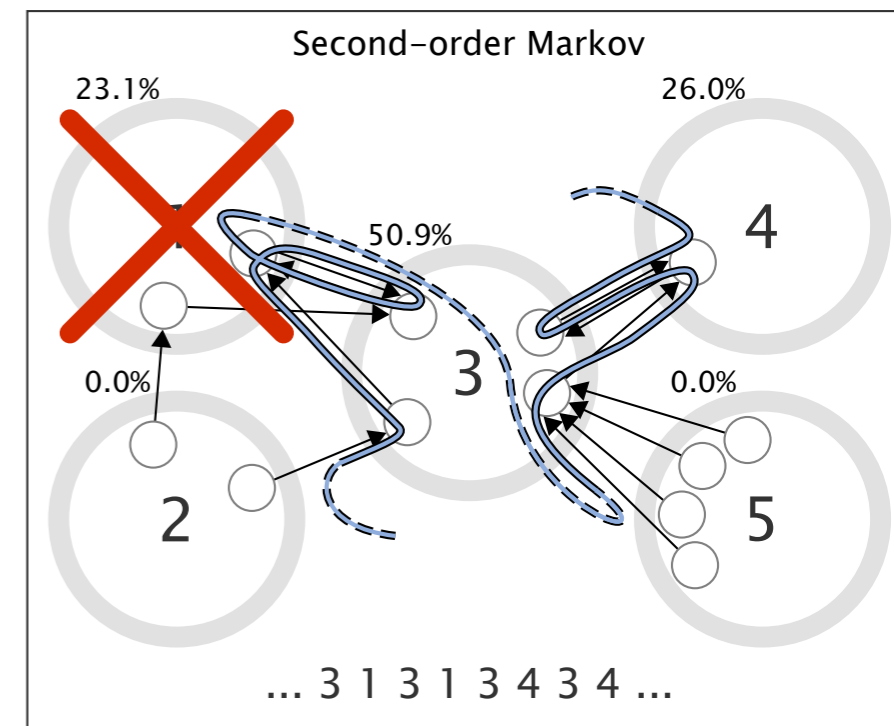
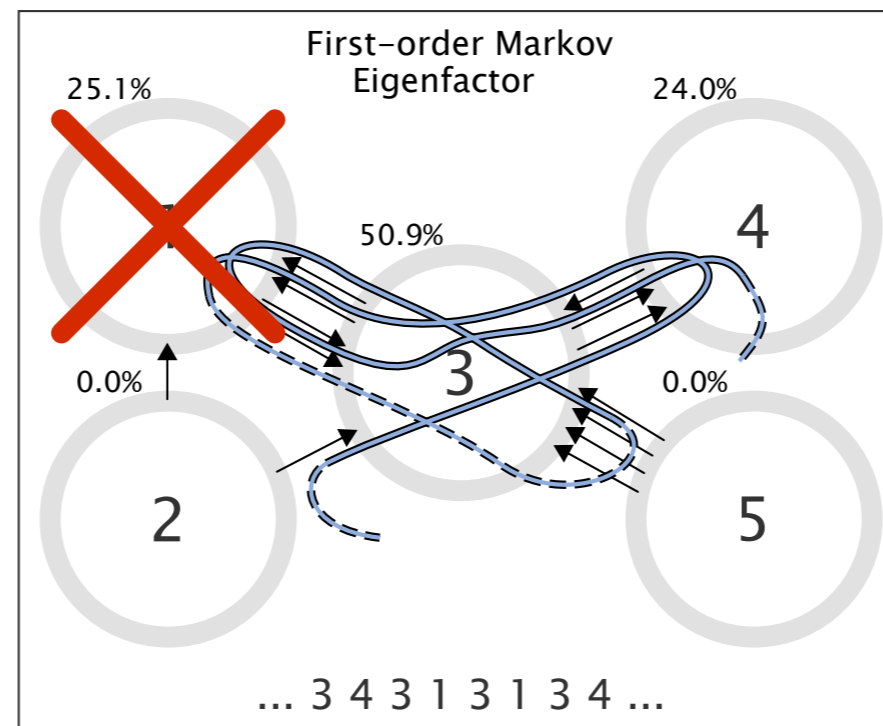
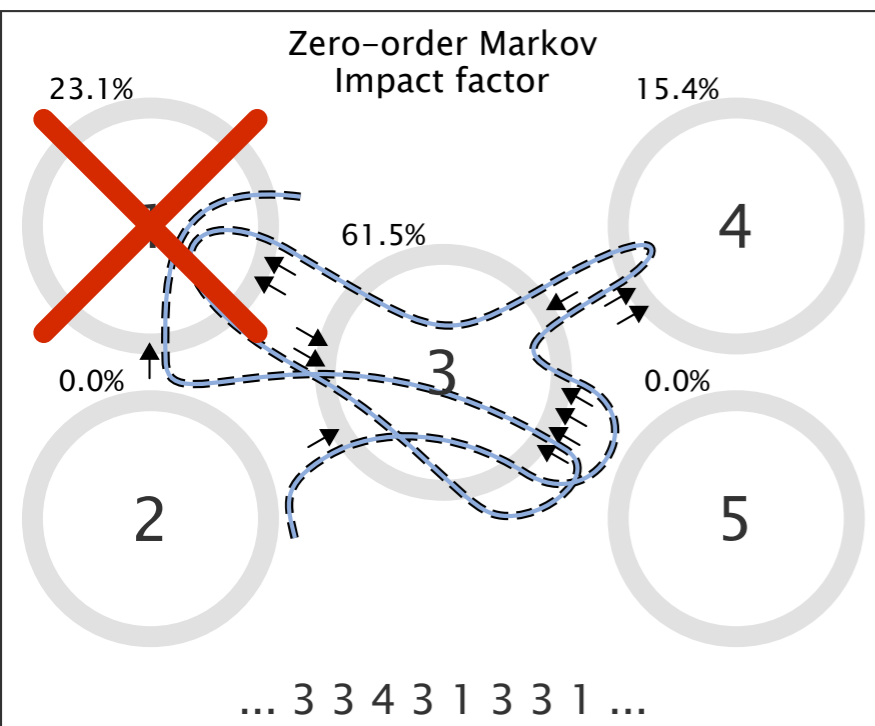
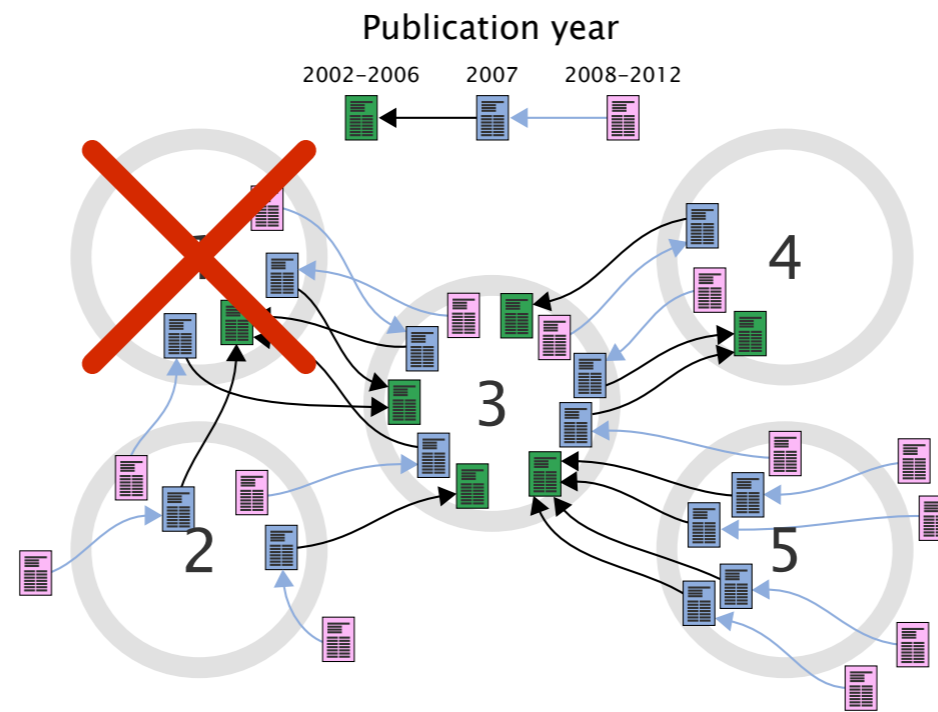
How robust are journal rankings
to the selection of journals?





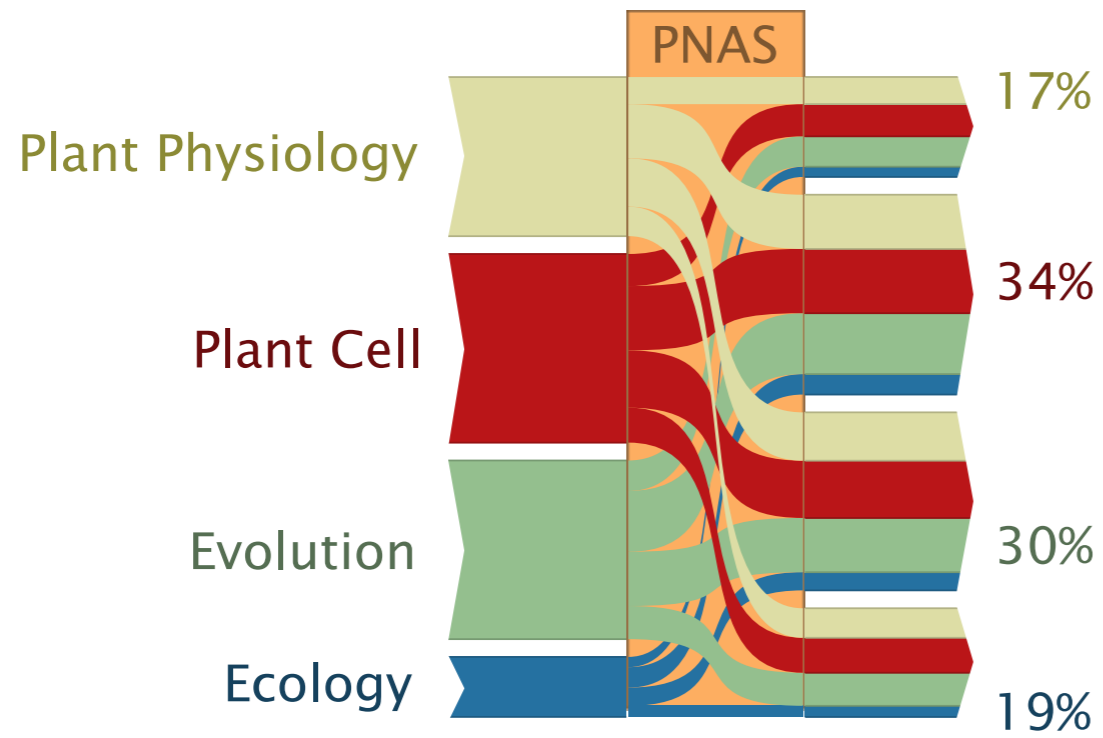




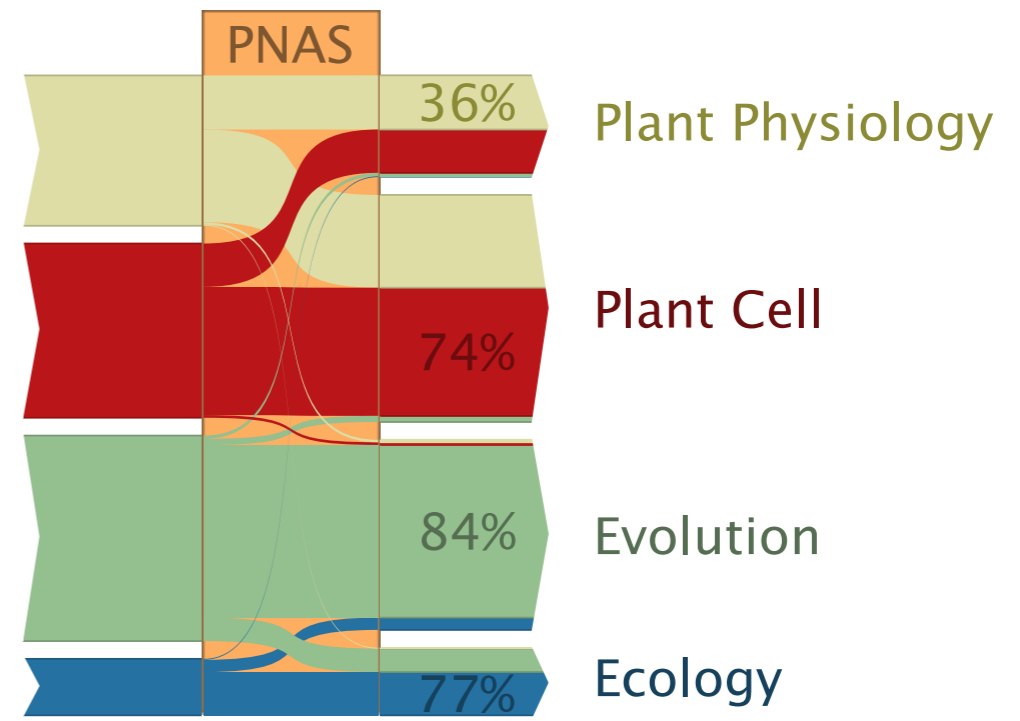


How does the Markov order
affect the robustness?

First-order Markov



Second-order Markov



Zero-order Markov

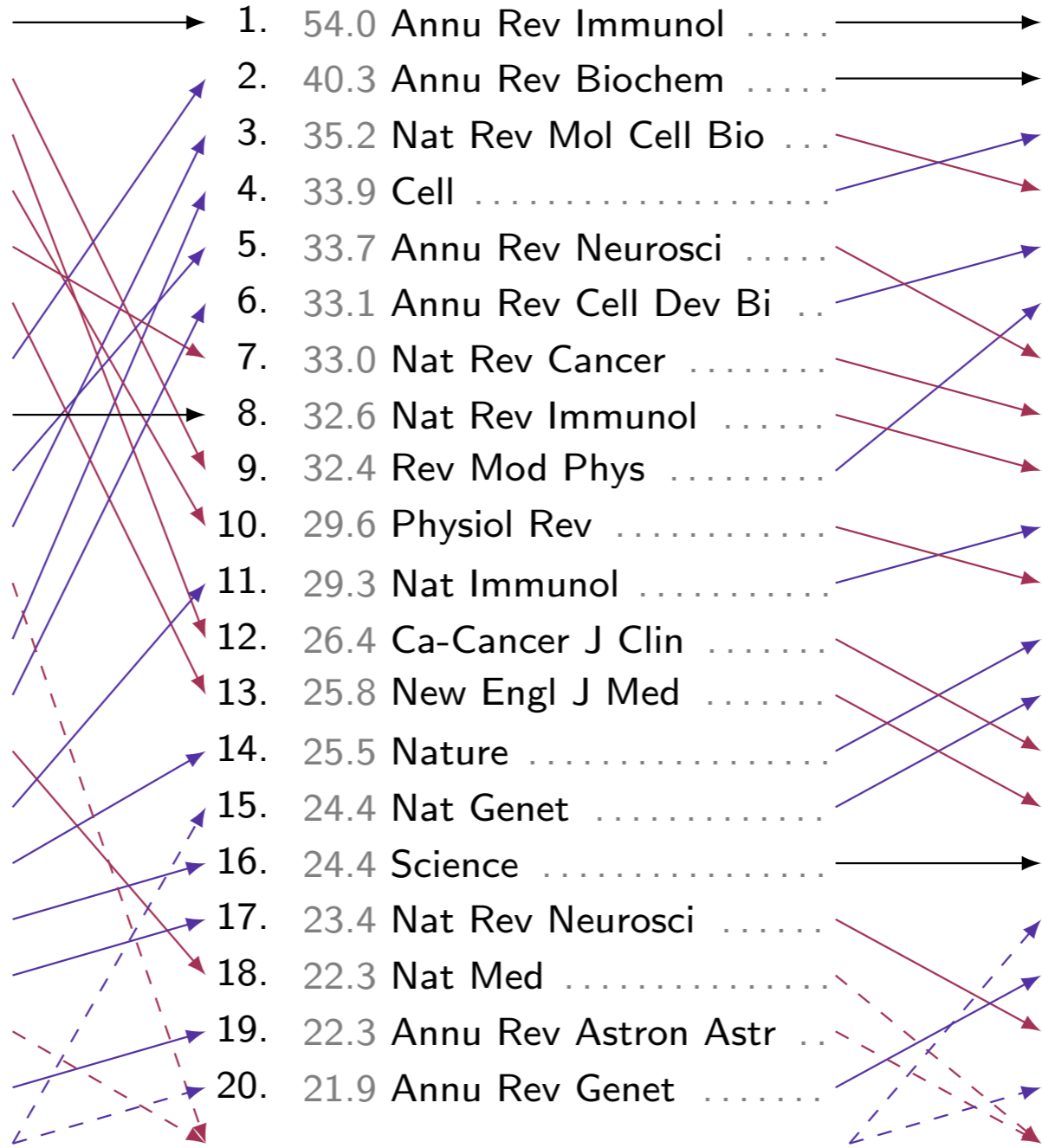
- 34.6 Annu Rev Immunol
- 27.8 Rev Mod Phys
- 25.8 Ca-Cancer J Clin
- 25.5 Physiol Rev
- 24.4 Nat Rev Cancer
- 23.7 New Engl J Med
- 23.2 Annu Rev Biochem
- 22.0 Nat Rev Immunol
- 21.1 Annu Rev Neurosci
- 20.4 Nat Rev Mol Cell Bio
- 18.4 Chem Rev
- 18.1 Cell
- 17.7 Annu Rev Cell Dev Bi
- 17.3 Nat Med
- 17.3 Nat Immunol
- 17.2 Nature
- 17.1 Science
- 16.7 Nat Rev Neurosci
- 16.3 Endocr Rev
- 15.5 Annu Rev Astron Astr

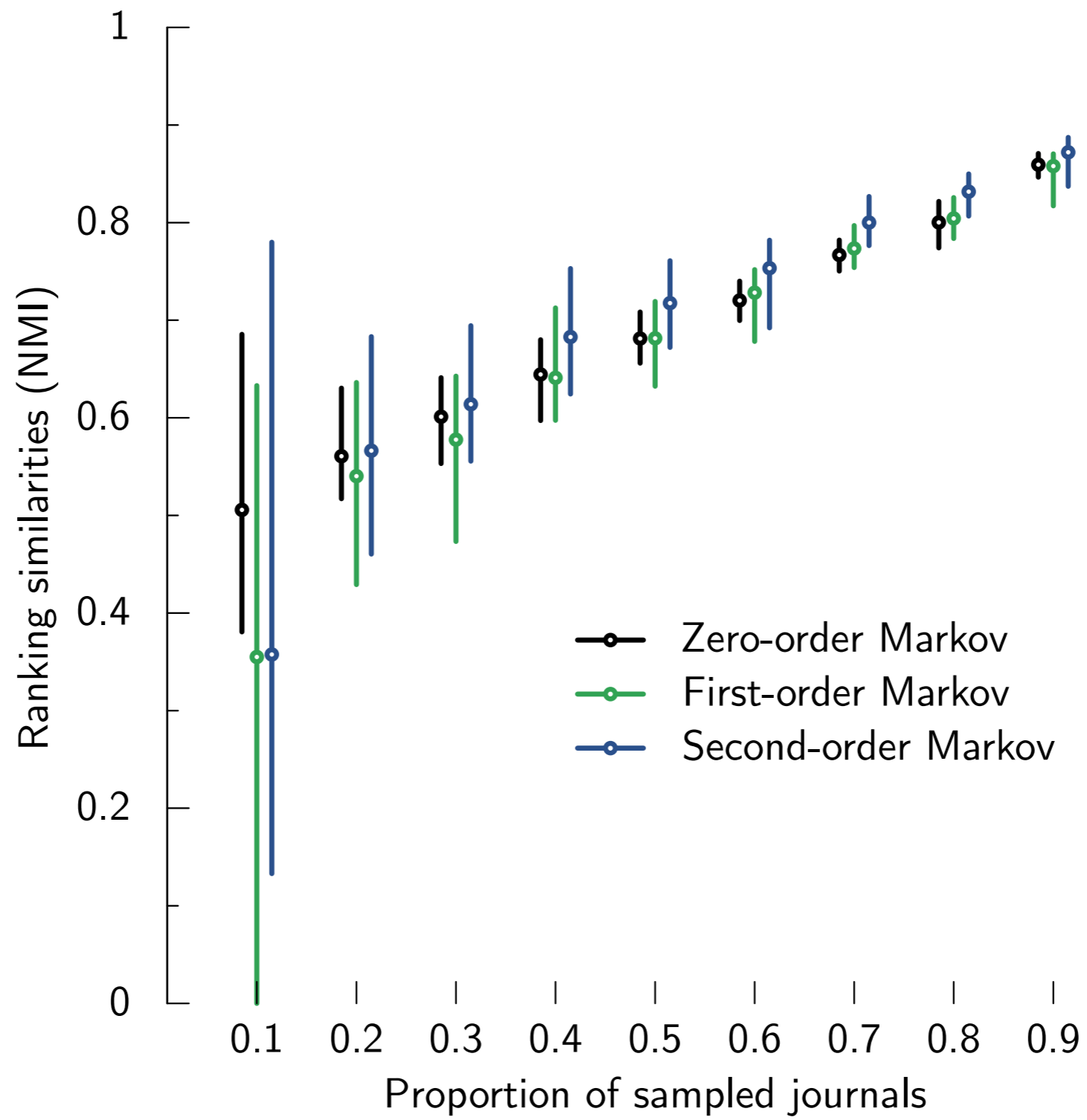
First-order Markov

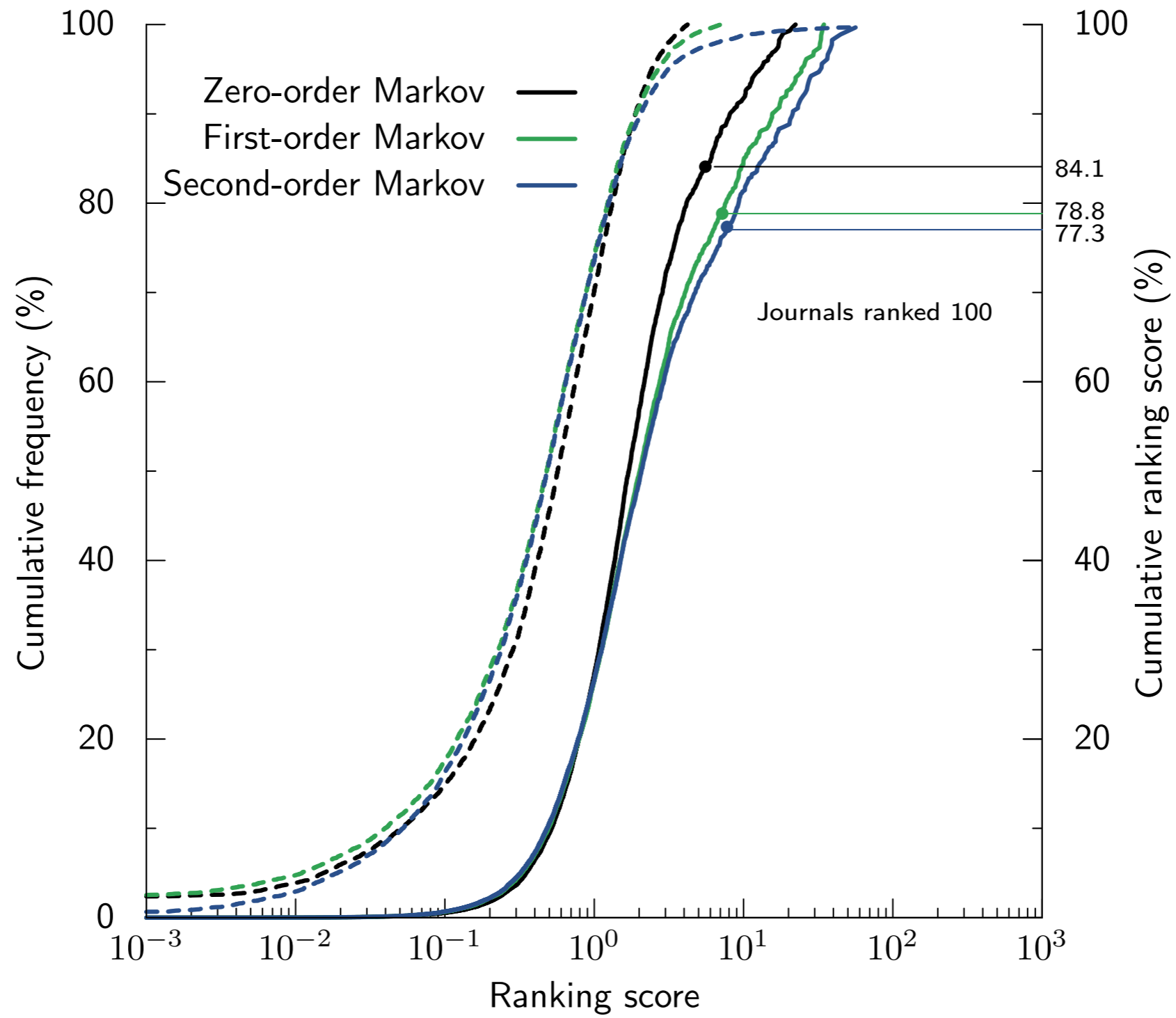
- 54.0 Annu Rev Immunol
- 40.3 Annu Rev Biochem
- 35.2 Nat Rev Mol Cell Bio
- 33.9 Cell
- 33.7 Annu Rev Neurosci
- 33.1 Annu Rev Cell Dev Bi
- 33.0 Nat Rev Cancer
- 32.6 Nat Rev Immunol
- 32.4 Rev Mod Phys
- 29.6 Physiol Rev
- 29.3 Nat Immunol
- 26.4 Ca-Cancer J Clin
- 25.8 New Engl J Med
- 25.5 Nature
- 24.4 Nat Genet
- 24.4 Science
- 23.4 Nat Rev Neurosci
- 22.3 Nat Med
- 22.3 Annu Rev Astron Astr
- 21.9 Annu Rev Genet

Second-order Markov

- 56.3 Annu Rev Immunol
- 44.6 Annu Rev Biochem
- 39.1 Cell
- 39.0 Nat Rev Mol Cell Bio
- 38.0 Annu Rev Cell Dev Bi
- 36.7 Rev Mod Phys
- 36.4 Annu Rev Neurosci
- 33.5 Nat Rev Cancer
- 33.3 Nat Rev Immunol
- 32.0 Nat Immunol
- 28.3 Physiol Rev
- 27.6 Nature
- 27.1 Nat Genet
- 26.8 Ca-Cancer J Clin
- 26.6 New Engl J Med
- 25.9 Science
- 25.0 Nat Cell Biol
- 24.1 Annu Rev Genet
- 23.6 Nat Rev Neurosci
- 23.2 Immunity







Conclusion

Higher orders give more robust rankings because

- + the range increases

- + citation weights depend on journal importance

- + perturbations remain local

- + higher predictability in cross-validation test

- at the cost of requiring more data

Remark

Second-order Markov dynamics are essential for identifying multidisciplinary journals

Field	PNAS		Science		Ecology		Plant Cell	
	M1	M2	M1	M2	M1	M2	M1	M2
Ecology	-	■ 13	-	■ 29	■ 100	■ 100	-	-
Cell biology	■ 100	■ 80	■ 100	■ 68	-	-	■ 100	■ 100
Mathematics	-	■ 4.6	-	-	-	-	-	-
Statistics	-	■ 1.5	-	-	-	-	-	-
Anthropology	-	-	-	■ 1.6	-	-	-	-
Others	-	■ 0.38 (1)	-	■ 1.4 (7)	-	-	-	-



Robustness of journal rankings by network flows with different amounts of memory

Ludvig Bohlin, Alcides Viamontes Esquivel, Andrea Lancichinetti, Martin Rosvall

(Submitted on 30 May 2014)

As the number of scientific journals has multiplied, journal rankings have become increasingly important for scientific decisions. From submissions and subscriptions to grants and hirings, researchers, policy makers, and funding agencies make important decisions with influence from journal rankings such as the ISI journal impact factor. Typically, the rankings are derived from the citation network between a selection of journals and unavoidably depend on this selection. However, little is known about how robust rankings are to the selection of included journals. Here we compare the robustness of three journal rankings based on network flows induced on citation networks. They model pathways of researchers navigating scholarly literature, stepping between journals and remembering their previous steps to different degree: zero-step memory as impact factor, one-step memory as Eigenfactor, and two-step memory, corresponding to zero-, first-, and second-order Markov models of citation flow between journals. We conclude that a second-order Markov model is slightly more robust, because it combines the advantages of the lower-order models: perturbations that remain local and citation weights that depend on journal importance. However, the robustness gain comes at the cost of requiring more data, because the second-order Markov model requires citation data from twice as long a period.

Comments: 8 pages, 5 figures

Subjects: **Physics and Society (physics.soc-ph)**; Digital Libraries (cs.DL)

Cite as: **arXiv:1405.7832 [physics.soc-ph]**

(or **arXiv:1405.7832v1 [physics.soc-ph]** for this version)

Submission history

From: Ludvig Bohlin [[view email](#)]

[v1] Fri, 30 May 2014 12:09:58 GMT (408kb,D)

[Which authors of this paper are endorsers?](#) | [Disable MathJax](#) ([What is MathJax?](#))

ARTICLE

Received 18 Mar 2014 | Accepted 9 Jul 2014 | Published 11 Aug 2014

DOI: [10.1038/ncomms5630](https://doi.org/10.1038/ncomms5630)

Memory in network flows and its effects on spreading dynamics and community detection

Martin Rosvall¹, Alcides V. Esquivel¹, Andrea Lancichinetti^{1,2}, Jevin D. West^{1,3} & Renaud Lambiotte⁴

Random walks on networks is the standard tool for modelling spreading processes in social and biological systems. This first-order Markov approach is used in conventional community detection, ranking and spreading analysis, although it ignores a potentially important feature of the dynamics: where flow moves to may depend on where it comes from. Here we analyse pathways from different systems, and although we only observe marginal consequences for disease spreading, we show that ignoring the effects of second-order Markov dynamics has important consequences for community detection, ranking and information spreading. For example, capturing dynamics with a second-order Markov model allows us to reveal actual travel patterns in air traffic and to uncover multidisciplinary journals in scientific communication. These findings were achieved only by using more available data and making no additional assumptions, and therefore suggest that accounting for higher-order memory in network flows can help us better understand how real systems are organized and function.