

Uncovering the structure and dynamics of information flow on the Telegram network

Thomas Louf, Aurora Vindimian, Riccardo Gallotti

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Matematica



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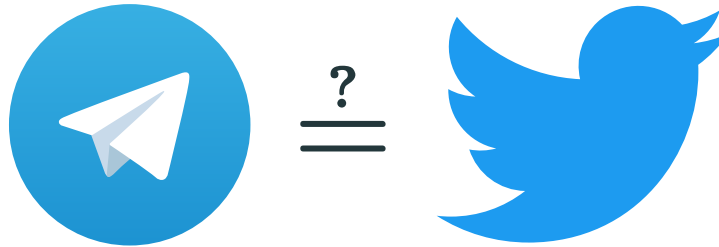
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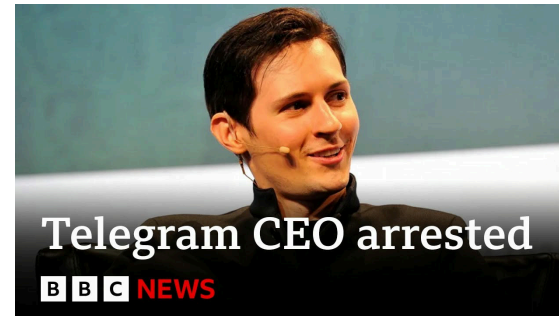
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→ Lots of work to be done



Is the network of Telegram channels anything like a social network?



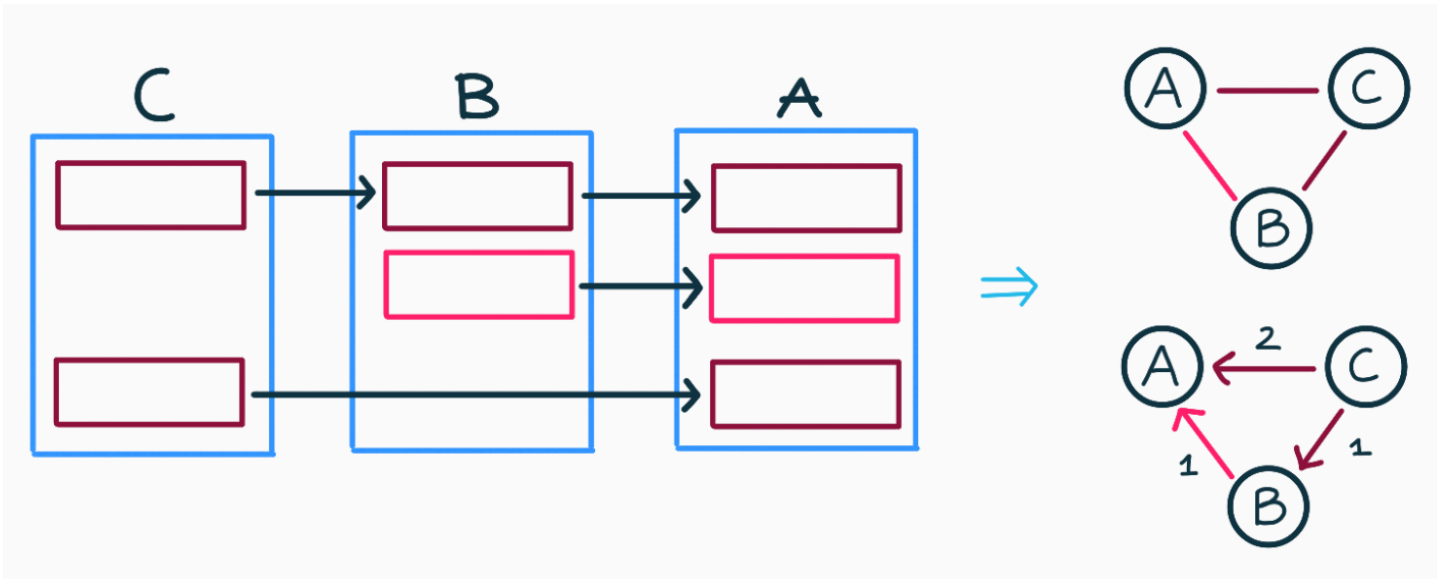
What are the main mechanisms giving rise to it?

→ Analysis of the Telegram network using the Pushshift dataset (Baumgartner et al., 2020)

→ Model that reproduces its *topological* and *temporal* features

Structural analysis > A forwarding network ✓

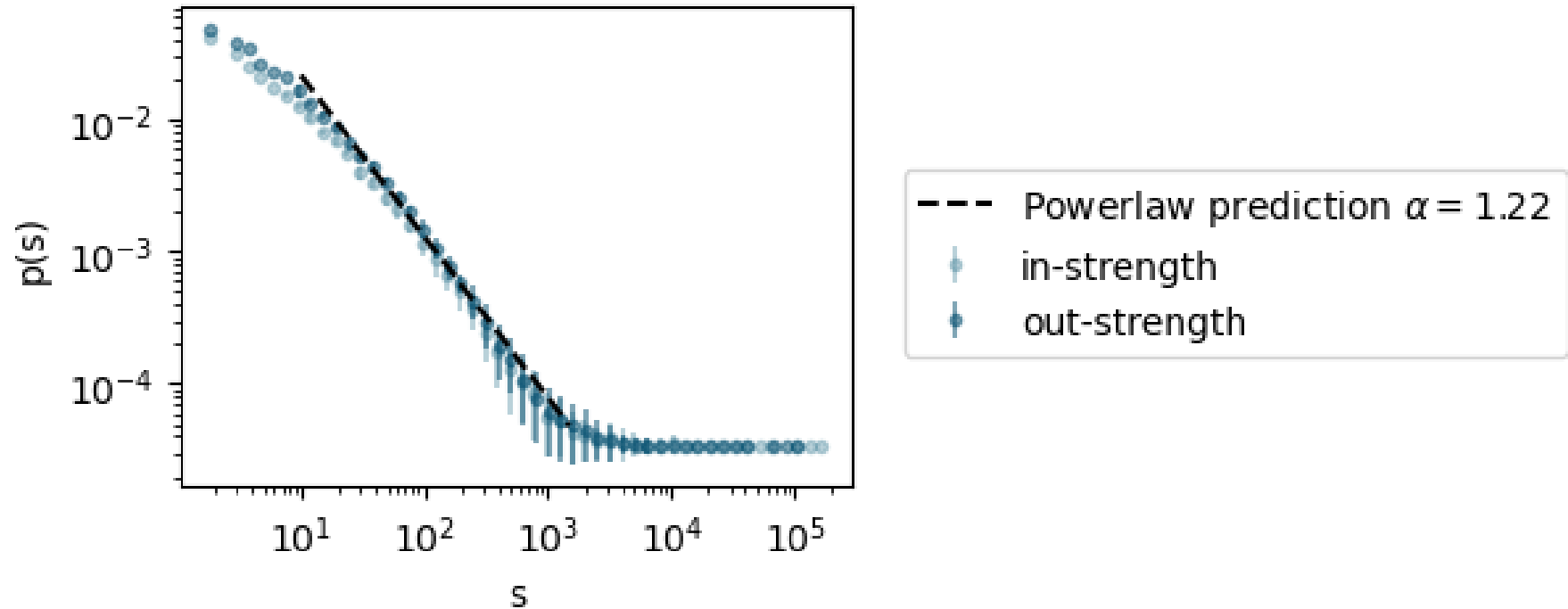
- Nodes: 29 609 channels
- Edge from B to A when A forwards a message from B → 501 897 directed edges



→ Network of information flow

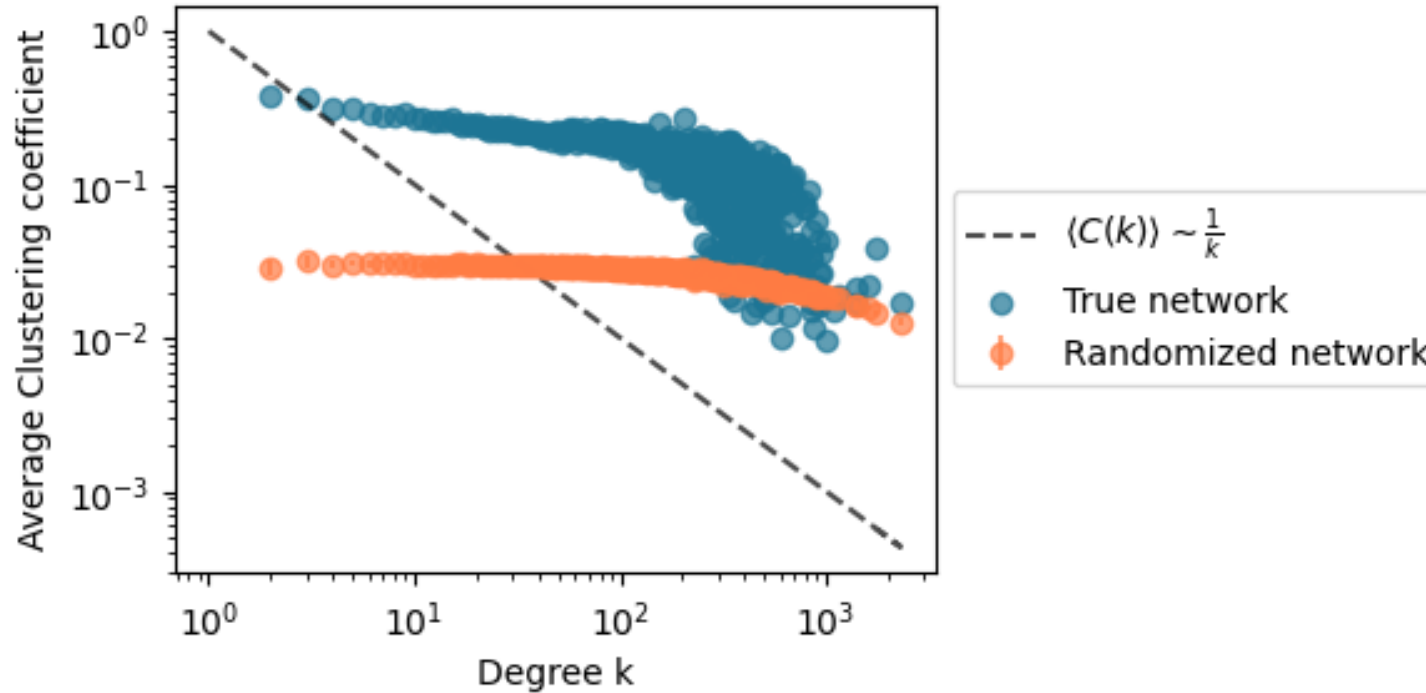
Structural analysis > Strength distributions ✓

Do we have the usual Pareto law?



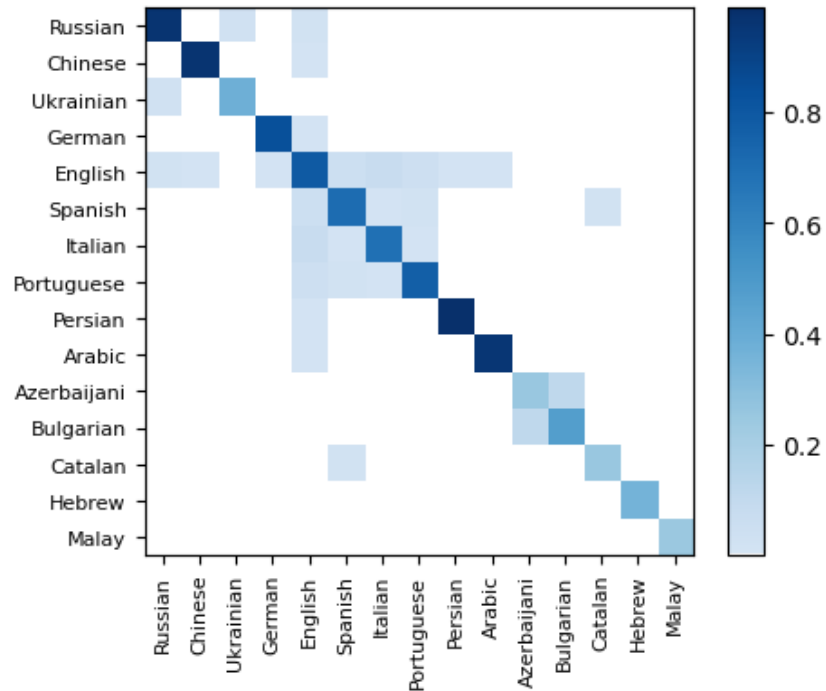
Structural analysis > Clustering ✓

Tendency to forward from friends of my friends?

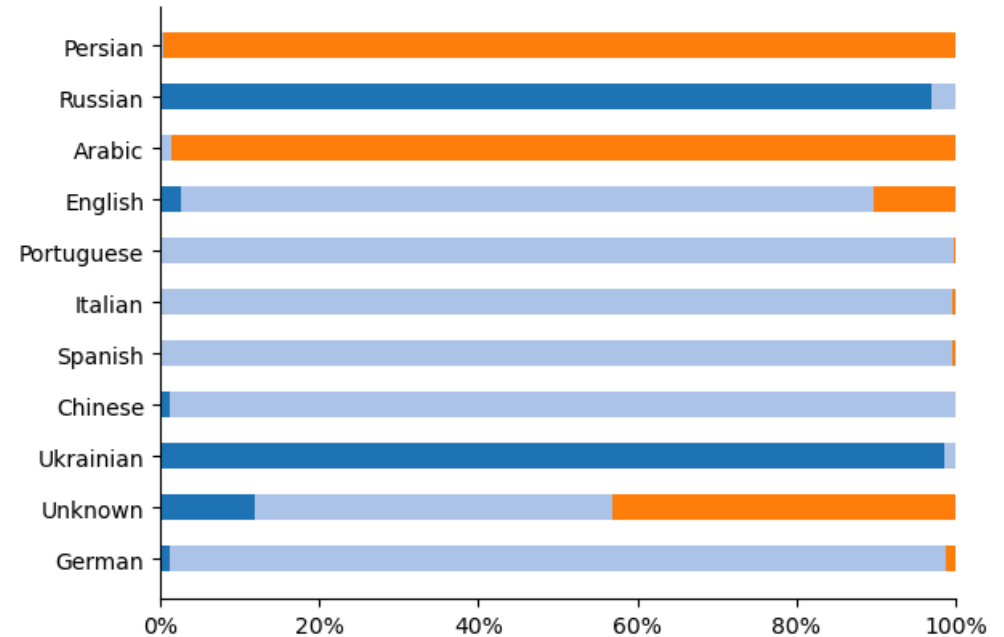


Structural analysis > Assortativity ✓

Ties formed preferably with same language...



...also reflected in community partition (SBM)

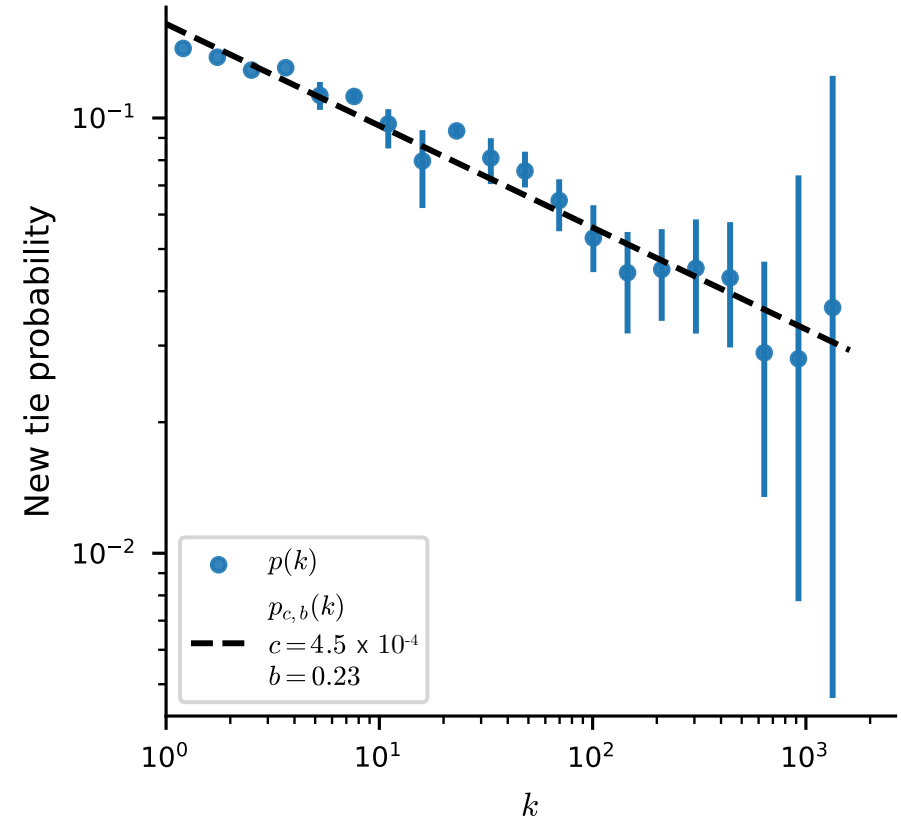


Aversion to form too many ties

→ probability to form new ties should decrease with in-degree k_{in} .

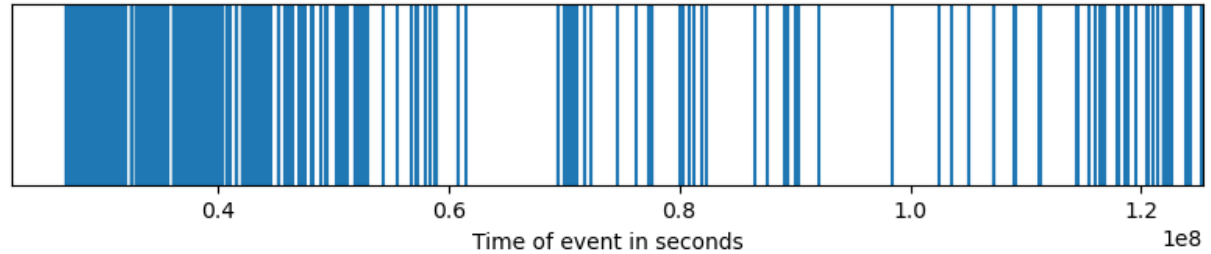
Model from (Ubaldi et al., 2016)

$$p_{\text{new}}(k_{\text{in}}) = \left(1 + \frac{k_{\text{in}}}{c}\right)^{-b}$$

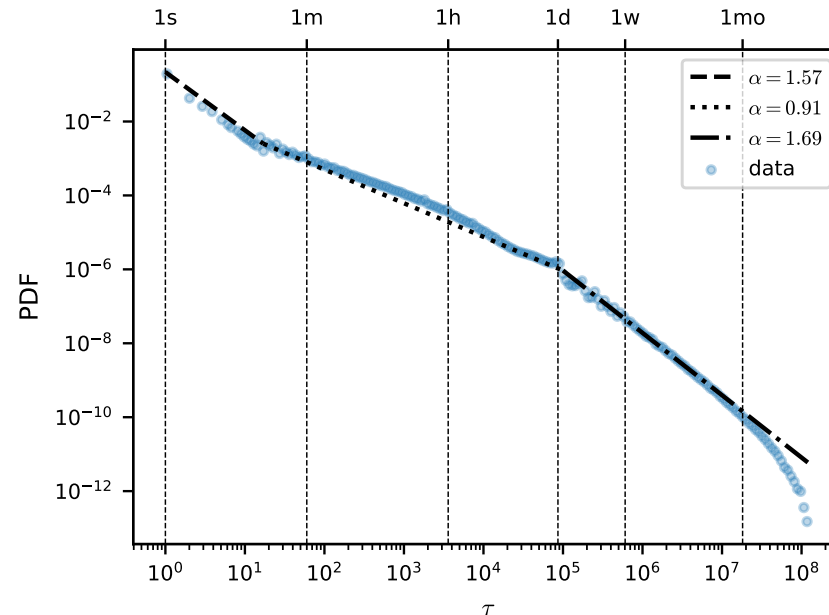


Temporal analysis > Inter-event times ✓

For all channels, get times between two forwarded messages = *inter-event times* τ

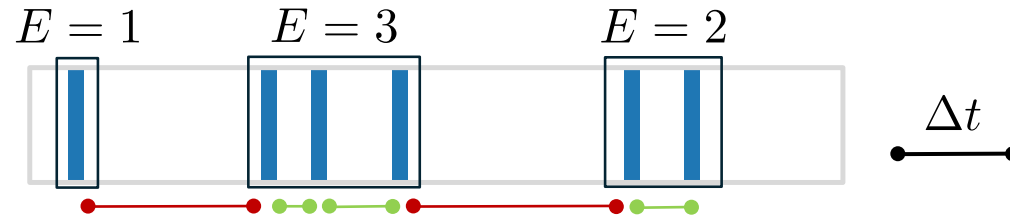


↪ $f(\tau)$ is piecewise power-law, with two main regimes separated by $\tau = 1$ day



Temporal analysis > Burstiness ✓

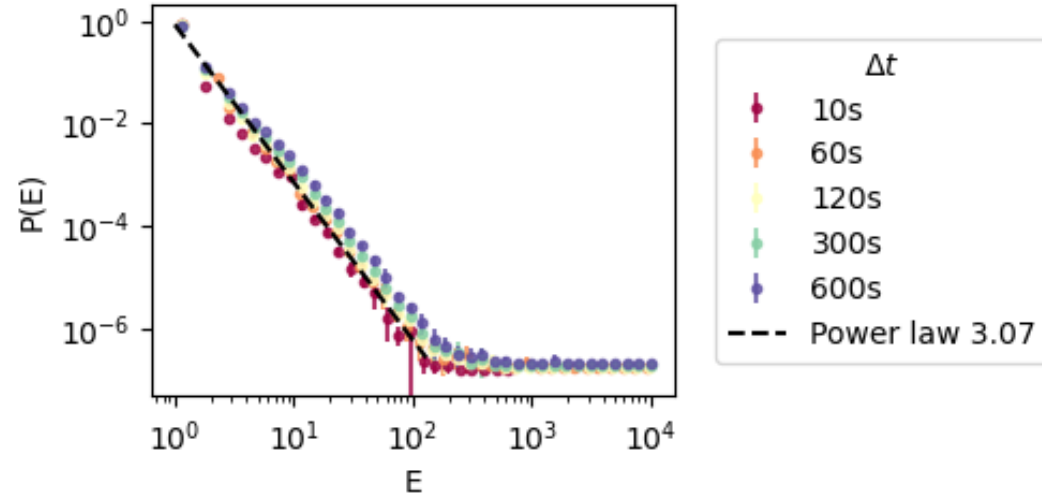
Investigate shape of distribution of *burst train sizes* E (Karsai et al., 2012):



We do have

$$p(E) \sim E^{-\beta}$$

➡ forwarding is bursty



Topology

- clustering
- power-law in/out-strength distributions
- language assortativity
- tendency to reinforce existing ties

Time

- two regimes
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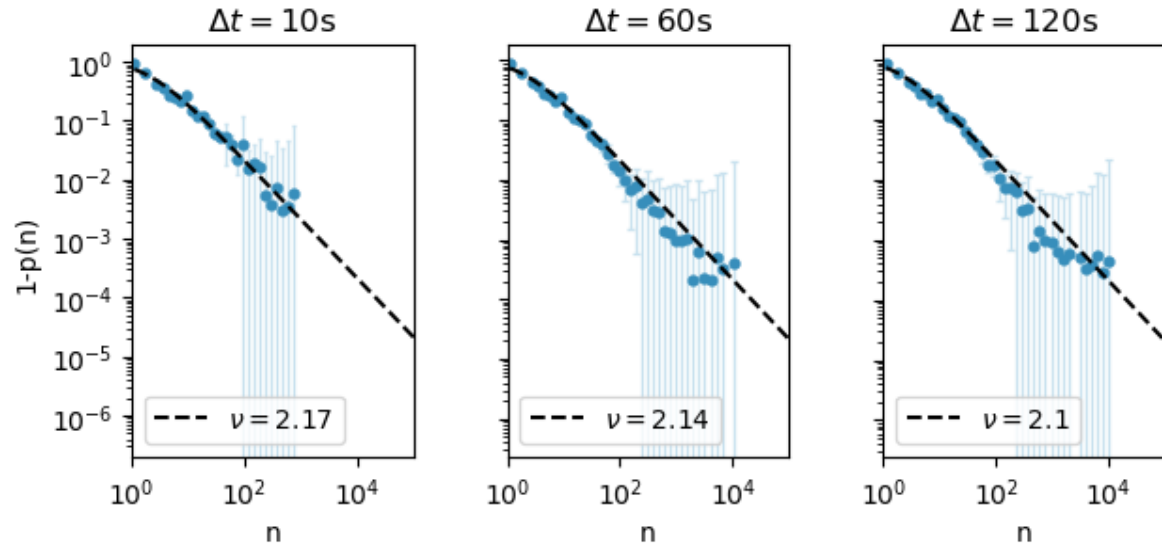
Time

- two regimes
- burstiness

Simple-enough model that can reproduce these features?

➡ Could help simulate contagion model or equivalent and test effect of interventions on synthetic networks

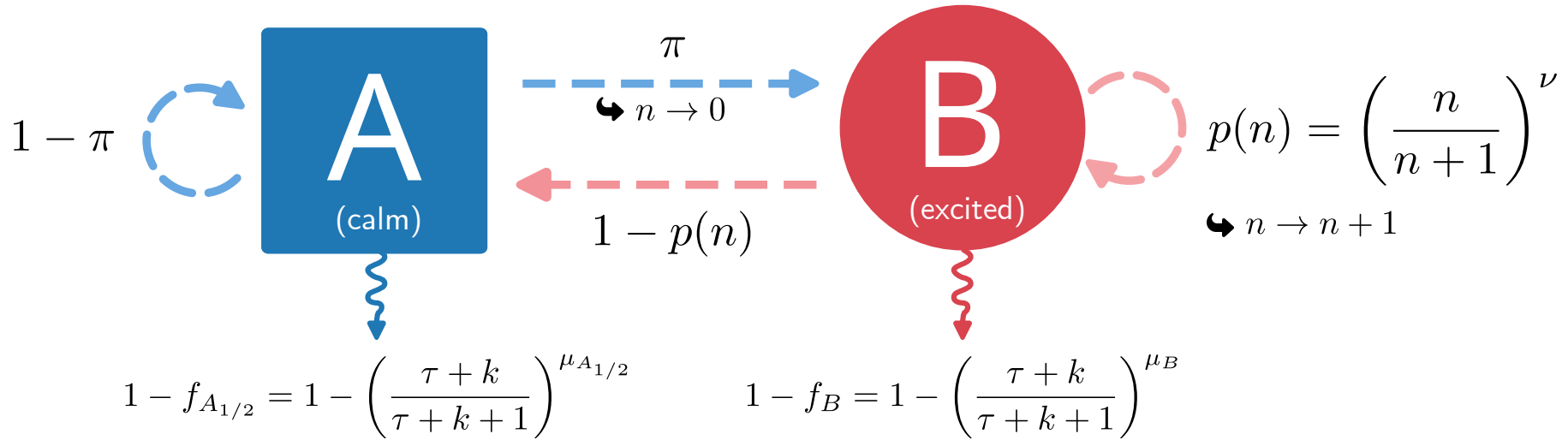
With already n events in a burst train, probability $p(n)$ to generate another within the same train?



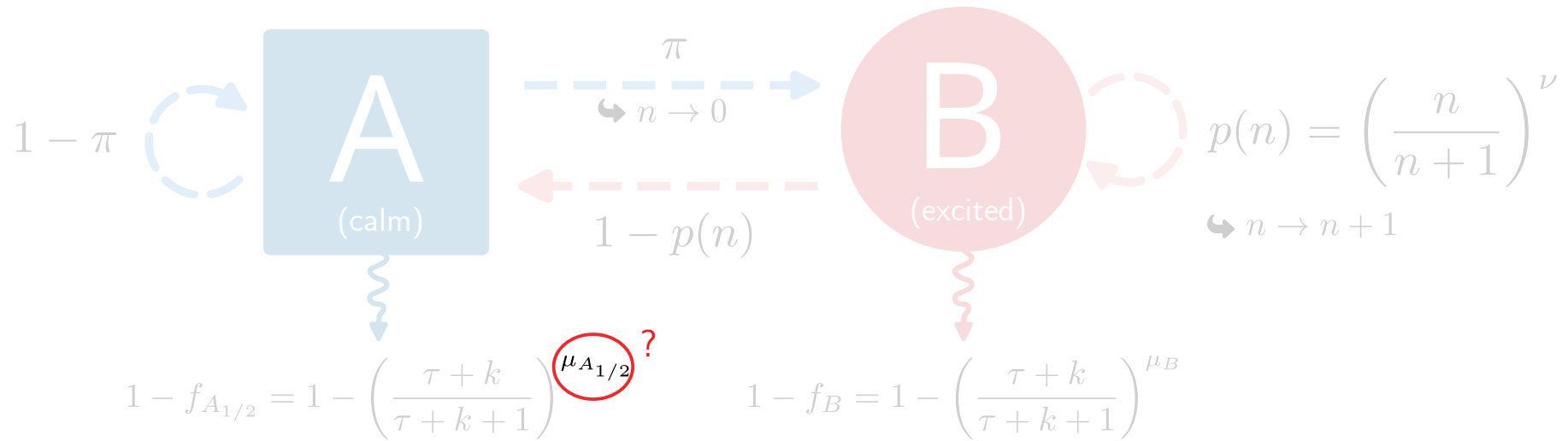
→ Train size distribution generated from memory process (Karsai et al., 2012)

$$p(E) \sim E^{-\beta} \Leftrightarrow p(n) = \left(\frac{n}{n+1} \right)^{\nu} \quad \text{with } \nu \approx \beta - 1$$

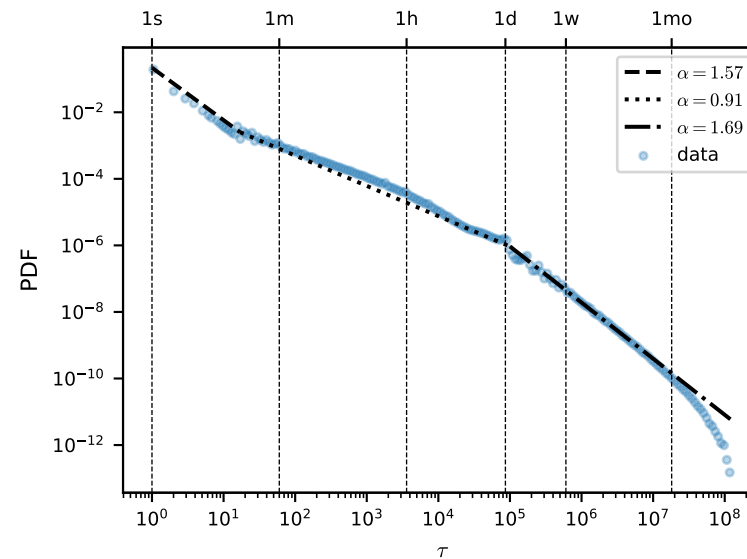
Generalisation from (Karsai et al., 2012)



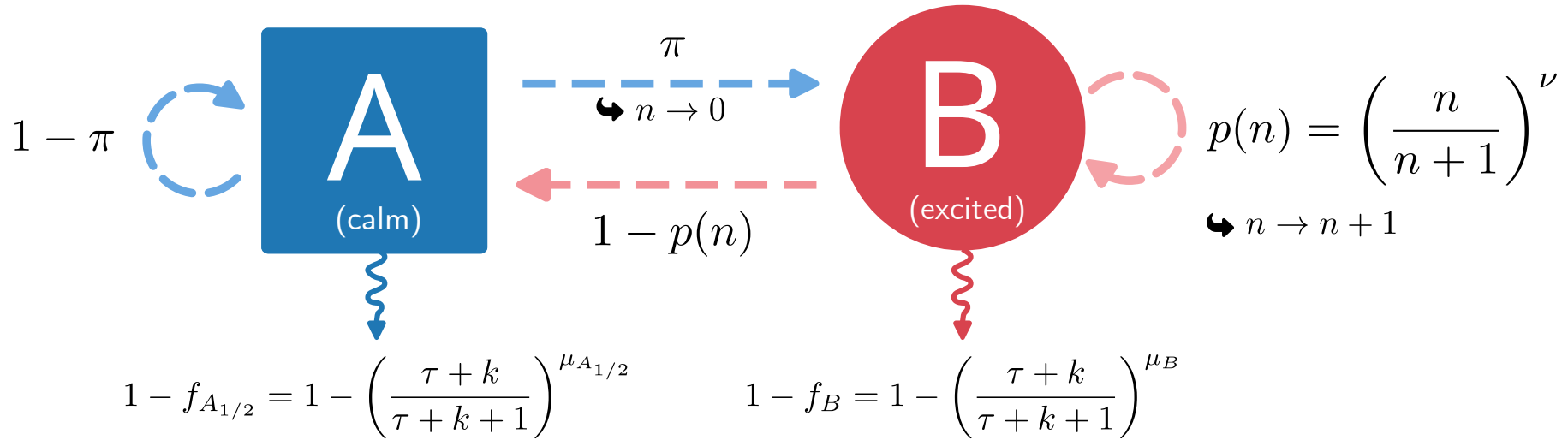
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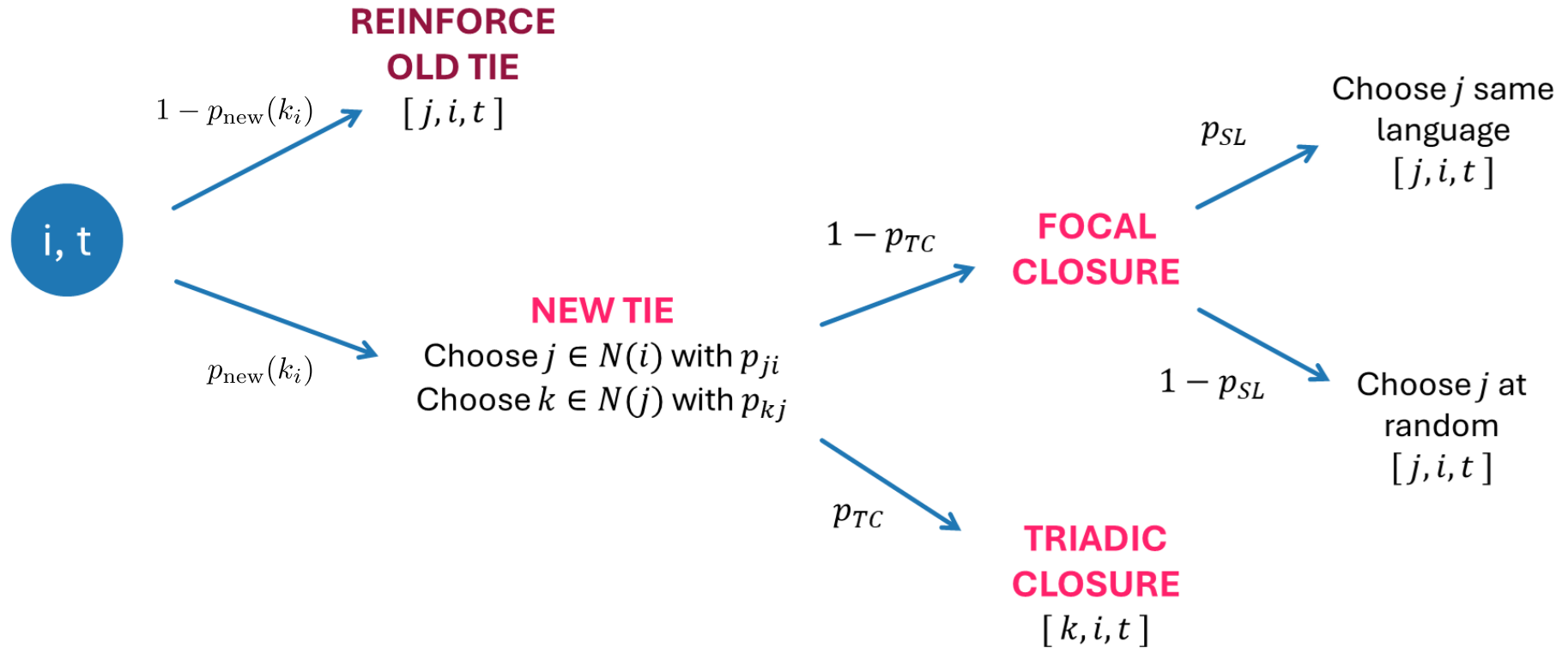
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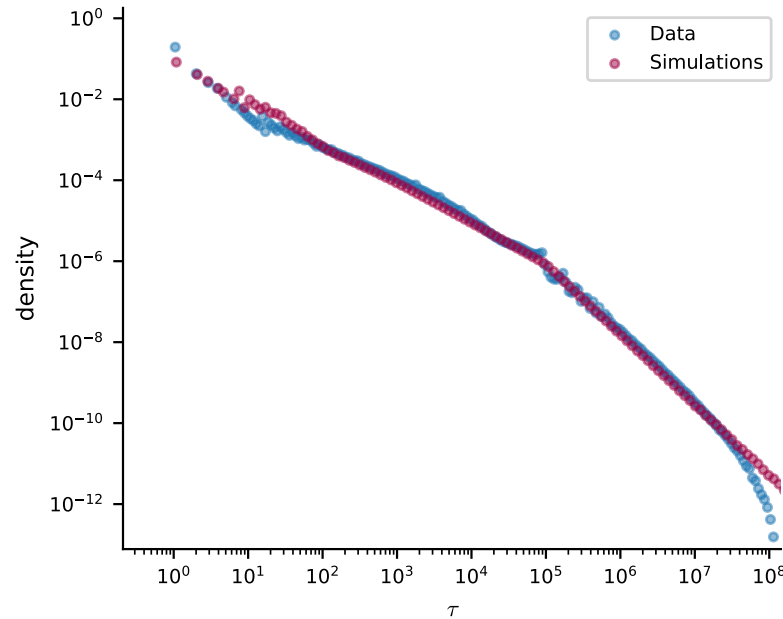
Generalisation from (Karsai et al., 2012)



Adapted from (Laurent et al., 2015)



Fitted time model $(\pi, \mu_{A_{1/2}}, \mu_B, k)$ to reproduce piecewise power-law $p(\tau)$



↪ It fits (+ it runs fast: $\sim 10s$) ($\pi \approx 0.20$, $\mu_{A_1} \approx 0.019$, $\mu_{A_2} \approx 0.74$, $\mu_B \approx 4.8$, $k = 81$)

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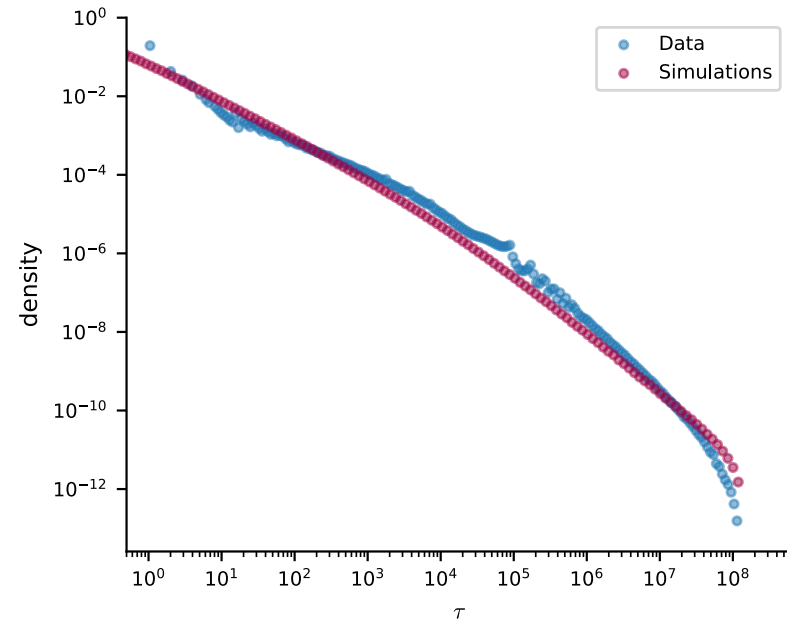
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→ What if we just contract/dilate time to fit event rates?

↪ slight deformation of $p(\tau)$



Modeling > Results ✓

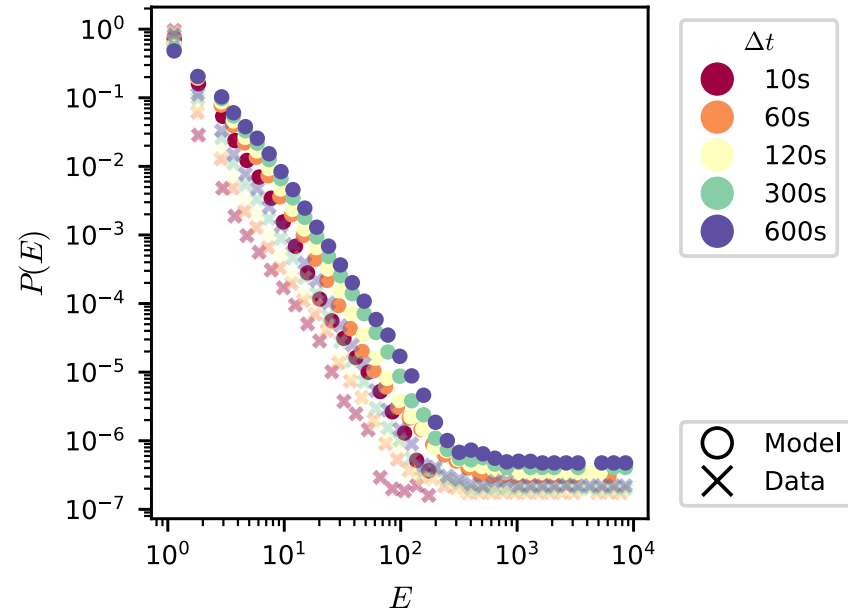
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↪ very similar β in $p(E) \sim E^{-\beta}$



What we've shown...

- Network of Telegram channels is very social-network-like
- Main mechanisms behind its emergence: tie reinforcement, clustering, language assortativity + memory process

...and what this leads to

- Model information propagation and effect of interventions
- Very global view of temporal process: what about local coordination?

and much more!

Thanks for your attention 🙌

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🐙 @TLouf

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Bibliography ✓

- Baumgartner, J., Zannettou, S., Squire, M., & Blackburn, J. (2020). The Pushshift Telegram Dataset. *Proceedings of the International AAAI Conference on Web and Social Media*, 14, 840–847. <https://doi.org/10.1609/icwsm.v14i1.7348>
- Karsai, M., Kaski, K., Barabási, A.-L., & Kertész, J. (2012). Universal Features of Correlated Bursty Behaviour. *Scientific Reports*, 2(1), 397. <https://doi.org/10.1038/srep00397>
- Laurent, G., Saramäki, J., & Karsai, M. (2015). From Calls to Communities: A Model for Time-Varying Social Networks. *The European Physical Journal B*, 88(11), 301. <https://doi.org/10.1140/epjb/e2015-60481-x>
- Ubaldi, E., Perra, N., Karsai, M., Vezzani, A., Burioni, R., & Vespignani, A. (2016). Asymptotic Theory of Time-Varying Social Networks with Heterogeneous Activity

Bibliography ✓

and Tie Allocation. *Scientific Reports*, 6(1), 35724. <https://doi.org/10.1038/srep35724>