Community evolution in dynamic networks

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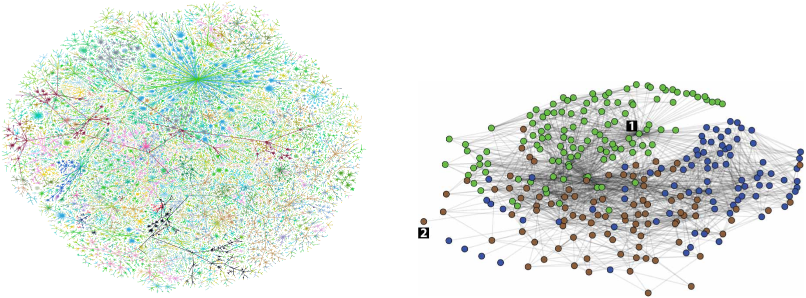
Contents

Networks are everywhere



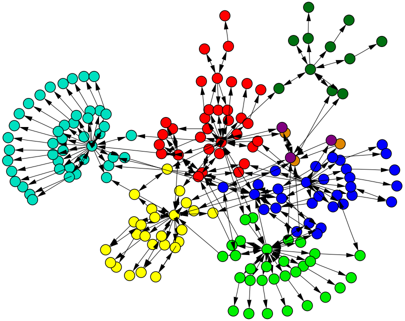
(a) internet at level of AS [5]

(b) neural network [2]

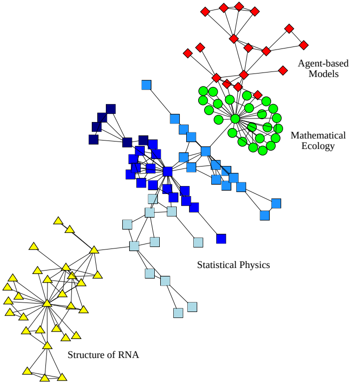
Figure 1: Technological and biological networks.

It's important to study communities because...

We want to understand why communities form, how to detect communities, and long-term behaviour of communities.



(a) links between web pages [6]



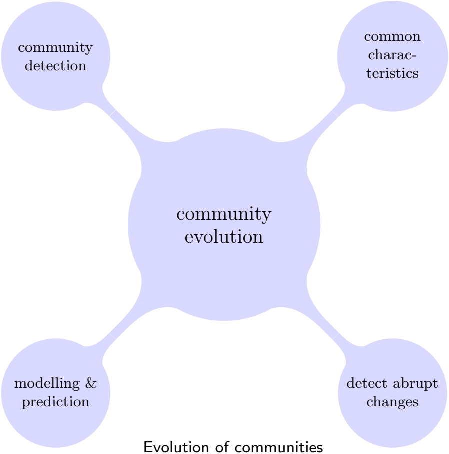
(b) scientific collaboration [3]

Figure 2: Community members have more in common with each other.

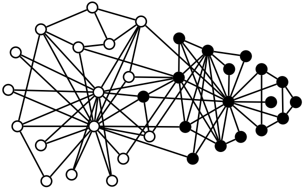
Research questions

1. What characteristics of community evolution are common across information, social, and technological networks?

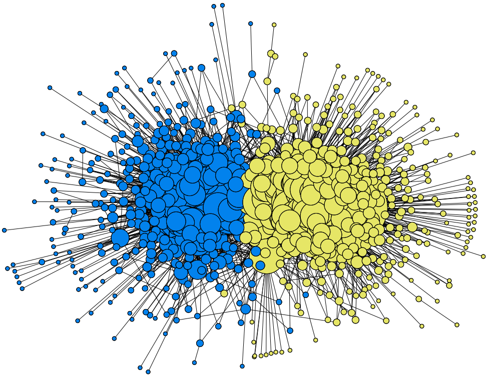
2. How do we model and make predictions about communities in real-world networks?



Communities are tightly connected nodes



(a) karate club [8]



(b) political blogs [4]

Figure 3: More connections between nodes within community than to nodes outside of community.

Community tracking as a problem of object matching

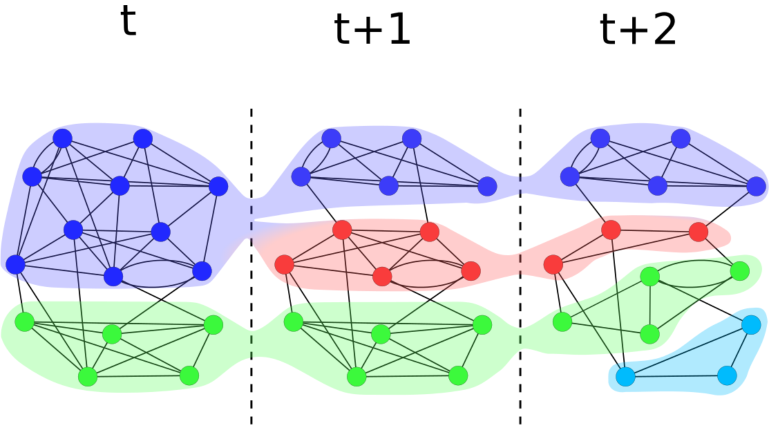


Figure 4: Infer communities across time [1].

Communities evolve according to a life-cycle

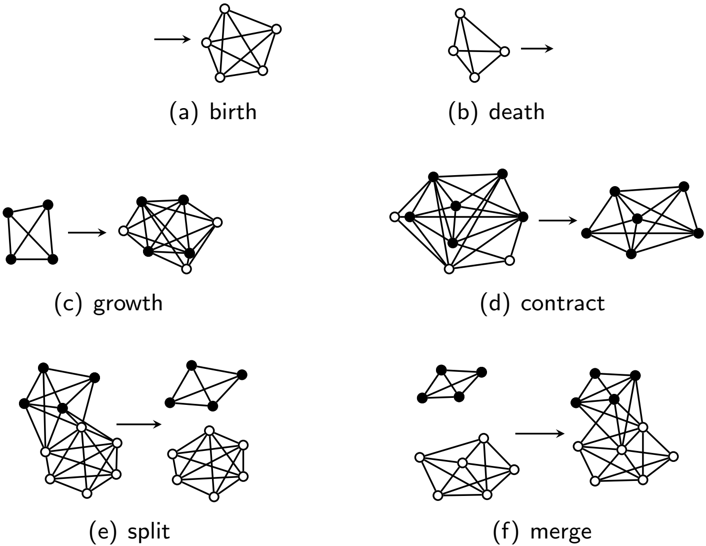


Figure 5: Events in the life-cycle of communities [7].

Datasets on real-world dynamic networks

Scientific collaboration

- arXiv — physics, computer science, maths
- GP — genetic programming

Autonomous systems of the internet

- DIMES — similar to RouteViews
- Katrina — subset of RouteViews around Hurricane Katrina

Communities mostly have power-law lifespan . . .

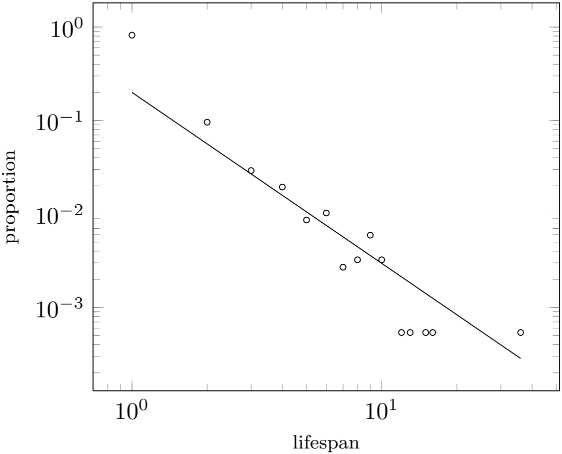


Figure 6: DIMES: lifespan follows a power-law of the form $\ell \sim k^{-\gamma}$.

. . . and sometimes exponential lifespan

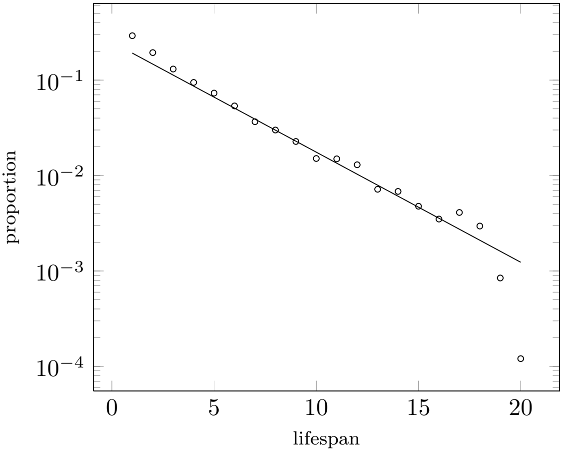
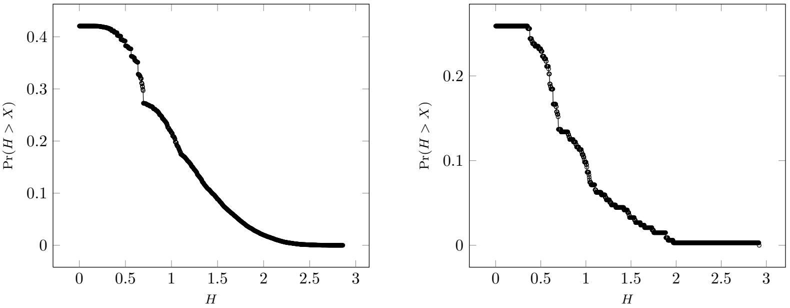


Figure 7: arXiv: lifespan follows an exponential law $\ell \sim \exp(-\lambda k)$.

Lifetime growth rates are non-uniform

$$\text{lifetime growth rate} = H = -\sum_k \Pr(k) \log \Pr(k)$$



(a) arXiv (b) DIMES

Figure 8: A stagnant majority and a tiny minority of "super attractors".

Simulate a network with split and merge events

- node represents a community
- start with c communities at time $t = 1$
- add m communities at each time $t \geq 2$
- p is probability of split or merge at time t

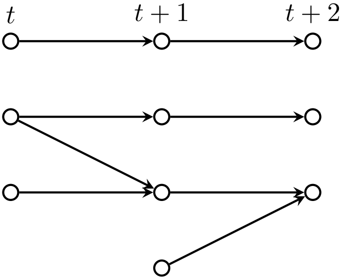


Figure 9: Communities in one time step split or merge with communities in the next time step.

Communities have small probability of split or merge

- window of interest is $p \in [0, 0.3]$

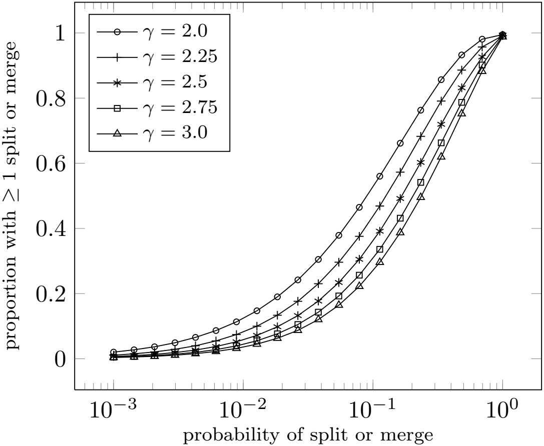
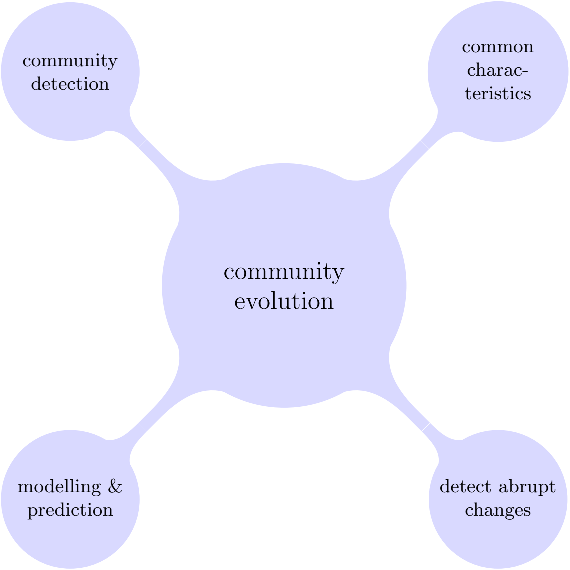


Figure 10: The proportion of communities with at least one split or merge as a function of p.

Future work


community detection
common charac- teristics
community evolution
modelling & prediction
detect abrupt changes

Thank you

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