



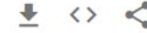
Dynamics in Youtube Recommendation: Are there filter-bubbles?

Presenter: Manqing Ma
10/24/2022
FNS Class Presentation

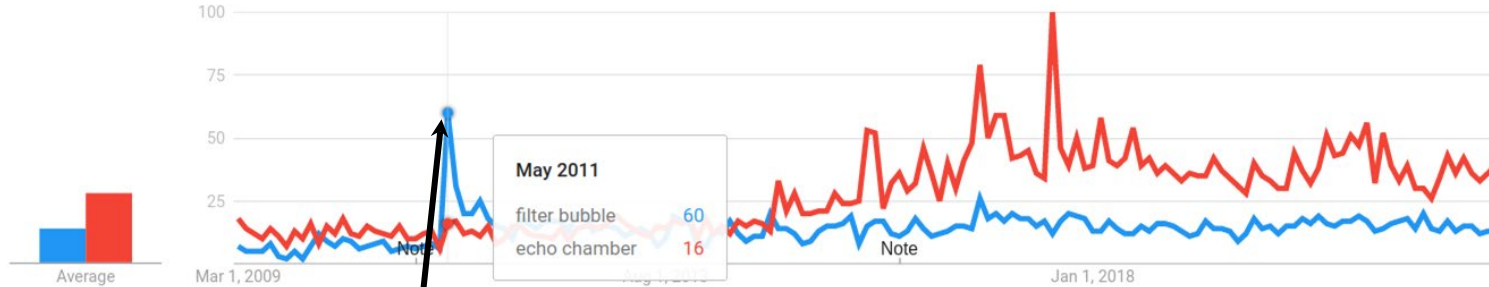
Initiatives, dataset and some related works

How the notion of “Filter bubble”/“Echo chamber” got the public attention

Interest over time ?



Filter bubble / Echo chamber

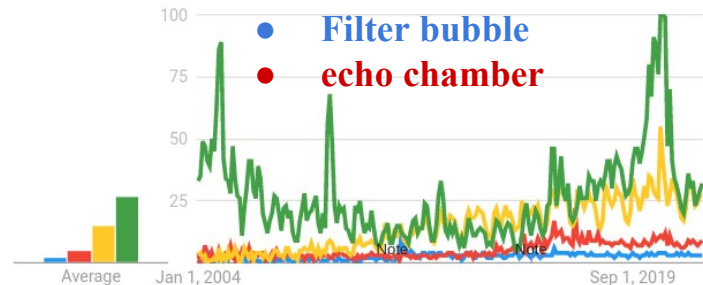


Interest over time

Google Trends

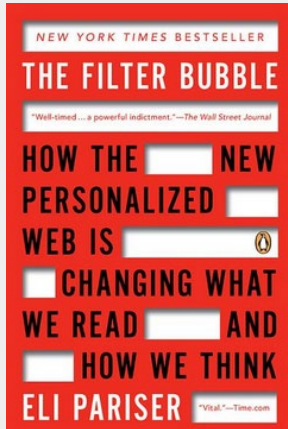
● filter bubble ● echo chamber ● confirmation bias ● media bias

- Media bias
- Confirmation bias
- Filter bubble
- echo chamber

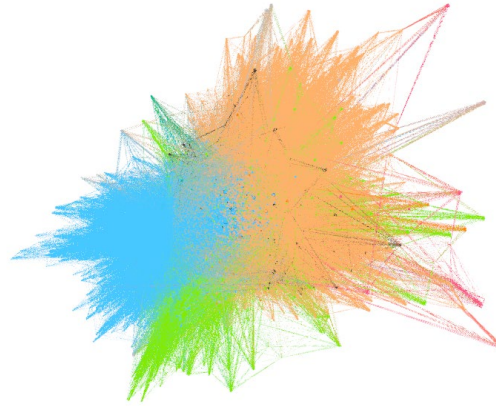
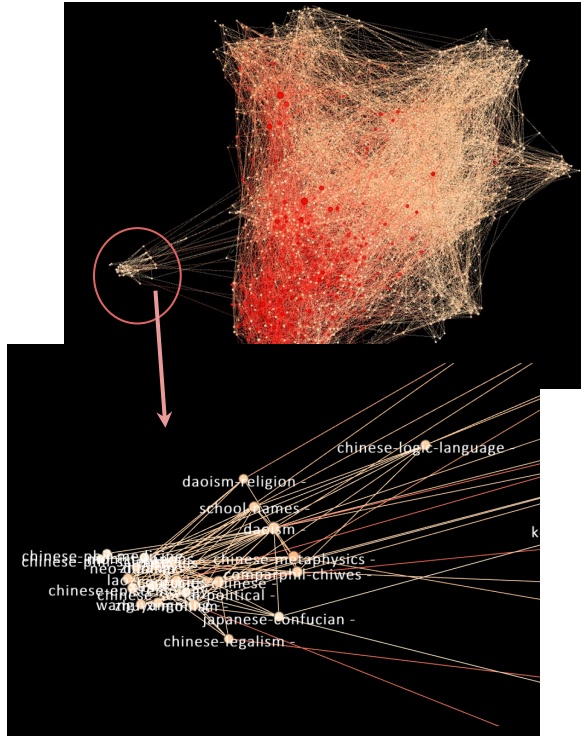


“...In December 2009, Google began customizing its search results for each user. Instead of giving you the most broadly popular result, Google now tries to predict what you are most likely to click on.”

– “The Filter Bubble: How the New Personalized Web Is Changing What We Read and How We Think”, May 2011, Eli Pariser



“Filter bubble” is naturally ubiquitous in content and preferences



Literature writer – readers’ preferences network communities: Nodes - Writers, Edges - “reader who likes xx also likes xx”

(Data: Literature-map.com – Random walk from a single author and merging the nearest-neighbors networks. ~12000 writers. Two giant communities detected.)

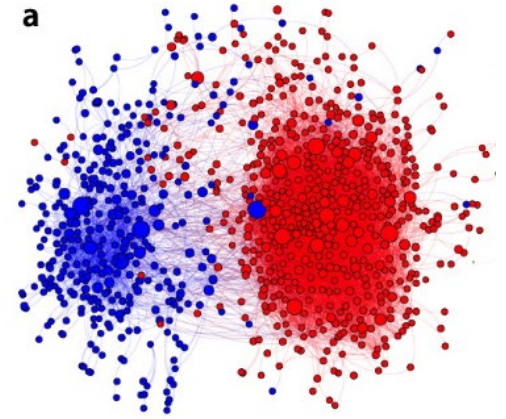


Fig. 1 (a) Visualization of the co-purchase network among 583 liberal (blue) and 673 conservative (red) books

Shi, Feng, et al. "Millions of online book co-purchases reveal partisan differences in the consumption of science." *Nature Human Behaviour* 1.4 (2017): 1-9.

[Stanford Encyclopedia of Philosophy\(SEP\)](https://plato.stanford.edu/)
network: Nodes - entries, Edges – hyperlinks

Literature review: Filter bubble/echo-chamber induced by recommendation systems (RS)

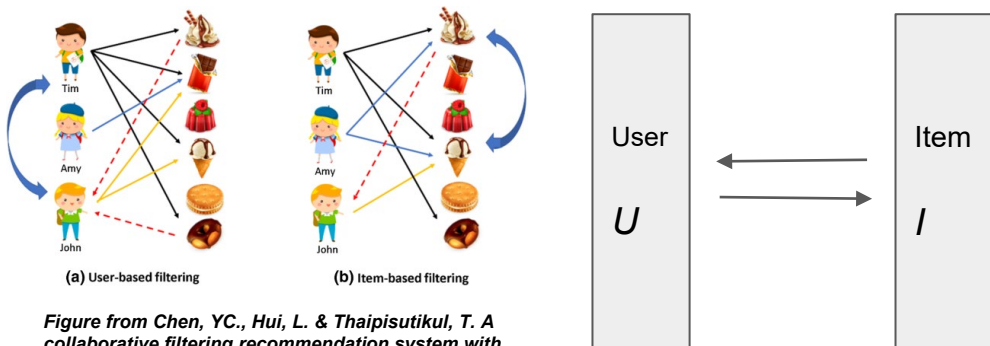


Figure from Chen, YC., Hui, L. & Thaipisutikul, T. A collaborative filtering recommendation system with dynamic time decay. *J Supercomput* 77, 244–262 (2021). <https://doi.org/10.1007/s11227-020-03266-2>

Collaborative-filtering propagates similarities of items through the choices of the users:

$$\text{Sim}((i1, i2), t) \leftarrow \text{Sim}((U(i1), U(i2))), t-1)$$

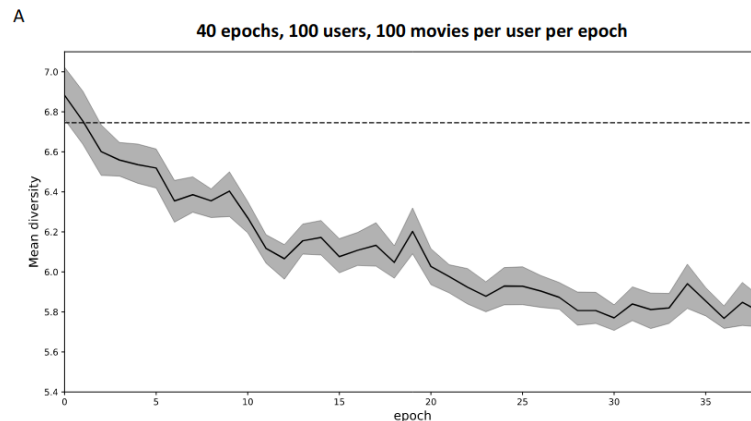
$$\text{Sim}((u1, u2), t-1) \leftarrow \text{Sim}((I(u1), I(u2)), t-2)$$

The recommendation is a map $R: (u, t) \rightarrow I^*$. Where the strategy could be expressed as

$$R(u, t) = I^*, \text{ s.t. } \max \text{Sim}(I(u, [t-1, t-2, \dots, t-n]), I^*)$$

The role of RS in the echo-chamber effect:

“The collaborative-filtering mechanism captures the users’ preference by creating feedback loops, leading to system degeneracy.”



The mean diversity of movie recommendations as the number of epochs increase. E. Noordeh, R. Levin, R. Jiang, and H. Shadmany, “Echo chambers in collaborative filtering based recommendation systems,” *arXiv preprint arXiv:2011.03890*, 2020.

A brief history

AlgoTransparency,

Chaslot (ex-youtube-engineer), et. al.

“AlgoTransparency has been providing more transparency on which Youtube videos are the most recommended.

...our work illicit a positive reaction from YouTube. First it put wikipedia snippets under debated. Then, they took more than 30 measures to **decrease the propagation of harmful disinformation, which resulted in a decrease of it by 70%.**”

Jan. 25 2019

Reducing recommendations of borderline content

YOUTUBE OFFICIAL BLOG

May 2020

Managing harmful conspiracy theories on YouTube

YOUTUBE OFFICIAL BLOG

Nov. 03 2020

YouTube Cut Down Misinformation. Then It Boosted Fox News.

THE NEW YORK TIMES

Dec. 9 2020

Supporting the 2020 U.S. election

YOUTUBE OFFICIAL BLOG

Youtube bans new videos about voter fraud.

2018

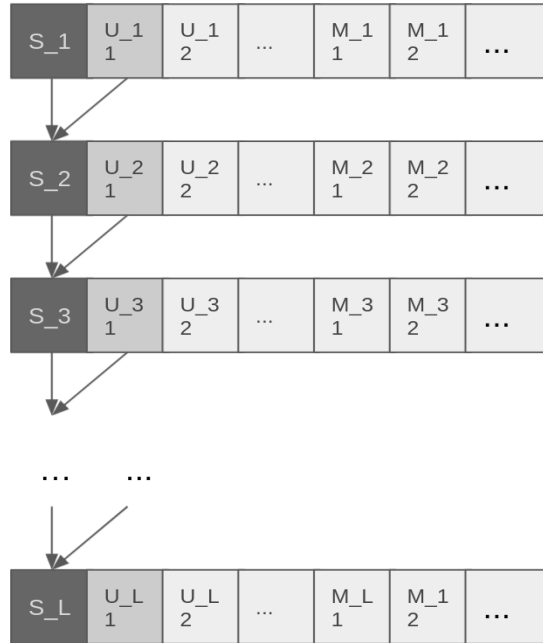
2020.11

Our impact on YouTube

Since 2018, YouTube started to fix their algorithms to address the issues we raised.

>. Our data collection began

Our data collection



(Up Next Recom.)

(Main Page Recom.)

- An anonymous user start from a channel S_1
- The user click on the most recent video the channel published
- Get recommendations as $[U_{11}, U_{12} \dots, M_{11}, \dots]$ from “up next” recommendations and main page recommendations
- Click on the first recommendation video and go to $S_2 = U_{11}$
- Get recommendations as $[U_{21}, U_{22} \dots, M_{21}, \dots]$
- ...

Analogies with human mobility problems

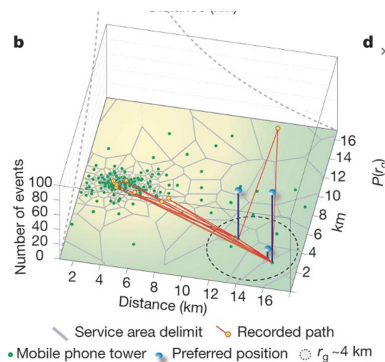
Comparison between the human mobility and the recommendation problem

to time t (Fig. 1b). Next, we determined the radius of gyration distribution $P(r_g)$ by calculating r_g for all users in samples D_1 and D_2 , finding that they also can be approximated with a truncated power-law:

$$P(r_g) = (r_g + r_g^0)^{-\beta_r} \exp(-r_g/\kappa) \quad (2)$$

with $r_g^0 = 5.8$ km, $\beta_r = 1.65 \pm 0.15$ and $\kappa = 350$ km

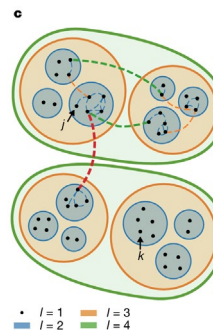
08, Marta et. al.



depends on the level distance between them. For an agent located in j , we model the probability of moving to k as the product of two factors:

$$P(j \rightarrow k) = p_{d(j,k), d(j,h)} \prod_{l \leq d(j,k)} a(k_l) \quad (1)$$

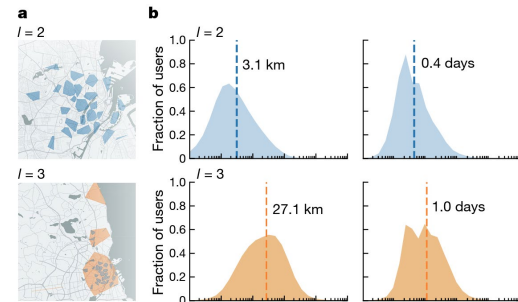
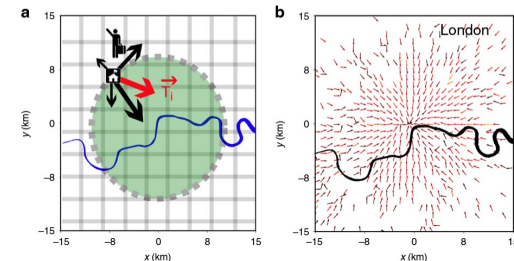
20, Laura et. al



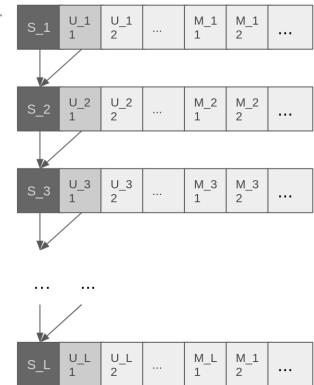
Drawing a parallel with classical field theories, \vec{T}_i can be divided by the “mass” of the origin cell i (home-place) to define the vector field

$$\vec{W}_i = \frac{\vec{T}_i}{m_i} = \sum_{j \neq i} \frac{T_{ij}}{m_i} \vec{u}_{ij} \quad (1)$$

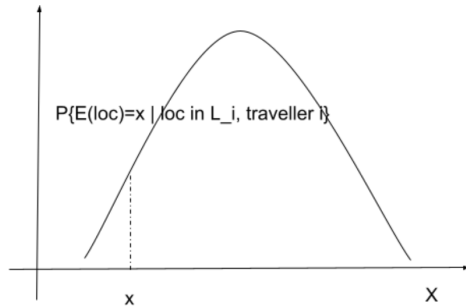
19, Mattia, et. al



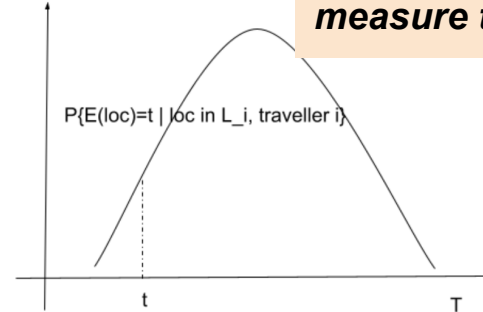
Mobility problem	Youtube Recommendation problem
Known distance space: 2-d, 3-d space, fixed location, or easily determined location	Unknown distance space: unknown dimensionality, location hard to determine
Locations all observed	Unobserved locations existed
Low magnitude of no. of locations (~100-1000)	High magnitude of no. of locations (> 10,000)



An analogy with the human mobility problem



Human mobility; traveller's location distribution at X



Youtube recommendation; traveller's location distribution at T

One simple way to measure the "distance"

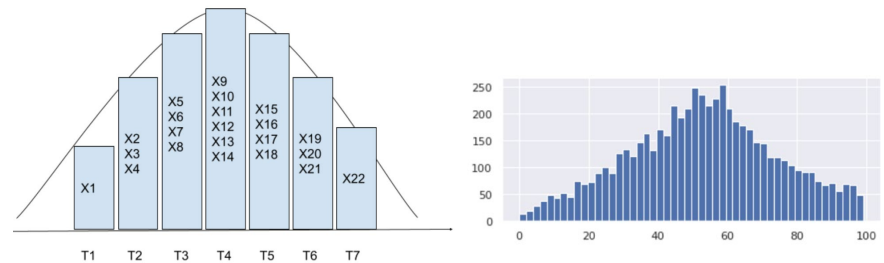
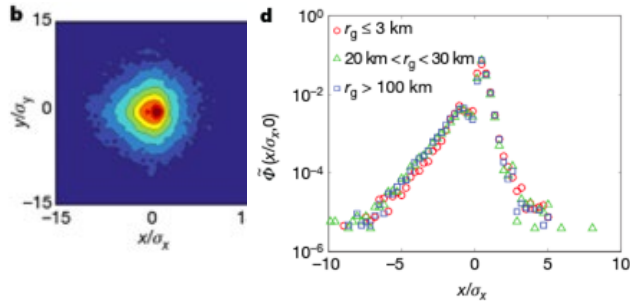
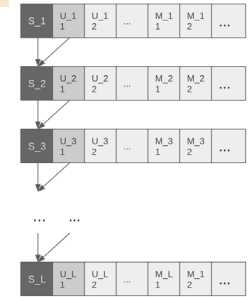
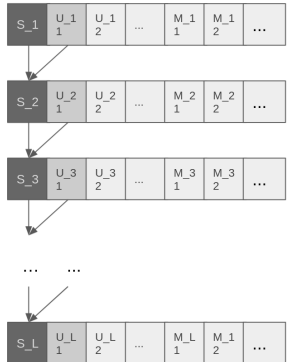
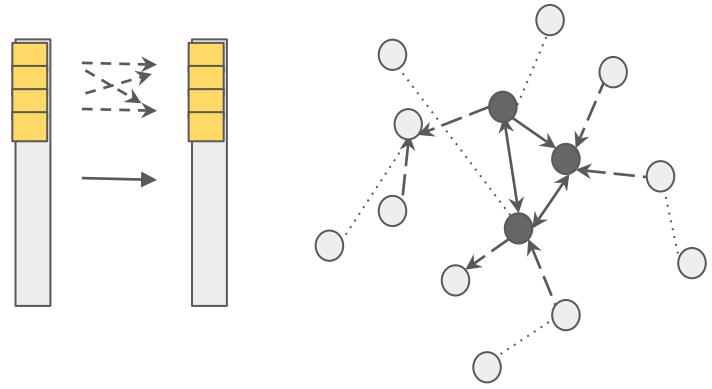


Fig 3. (d) Gonzalez, Marta C., Cesar A. Hidalgo, and Albert-Laszlo Barabasi. "Understanding individual human mobility patterns." *nature* 453.7196 (2008): 779-782.

Data: The traveller starts from Fox news

Perspective Universe

- From each seed, get its perspective universe



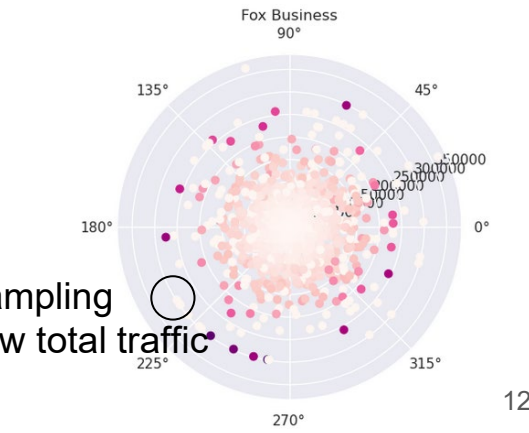
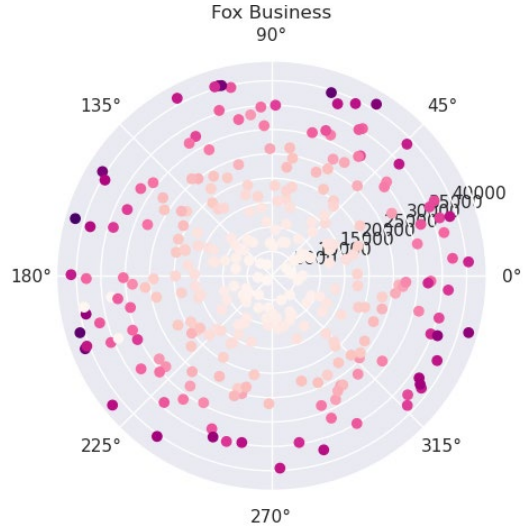
For each node n in the *universe*:

- Def.
- 'in-traffic': # of $n \rightarrow m$, where m in *core|seed*
 - 'Out-traffic': # of $n \rightarrow m$, where m not in *core|seed*

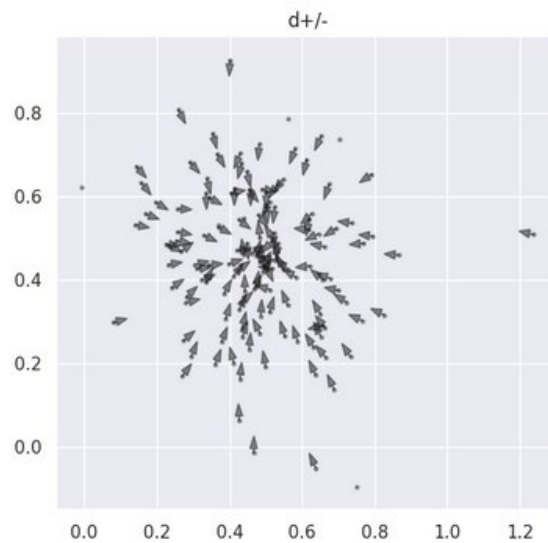
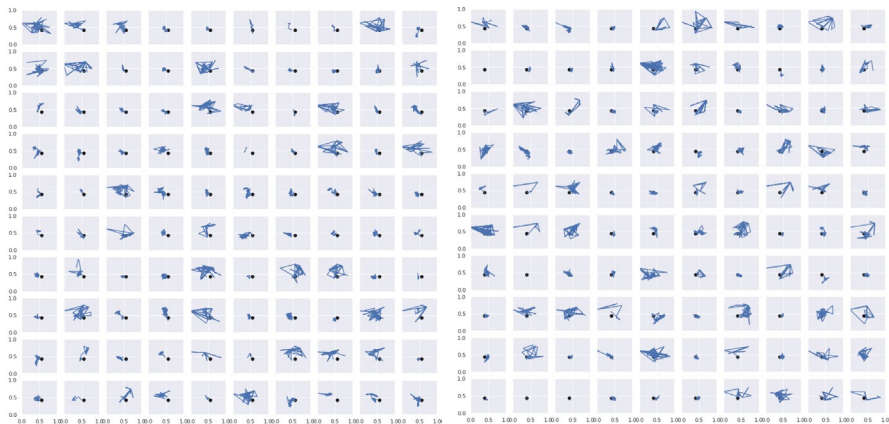
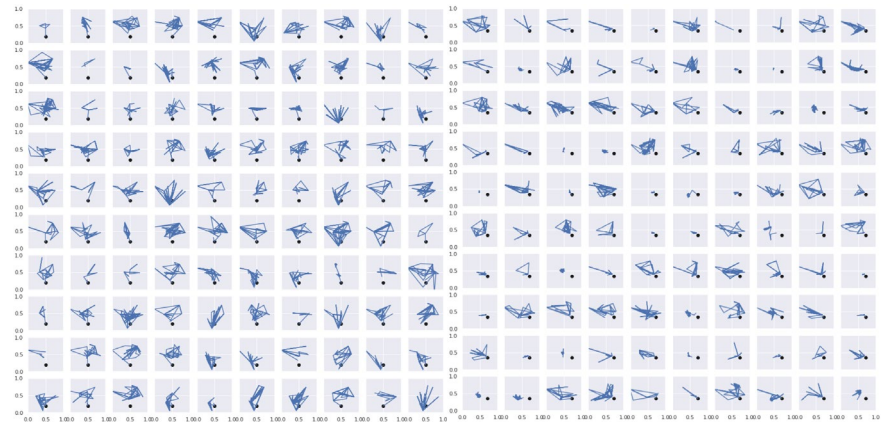
(Noise reduction:

Only keep the nodes where $total_traffic > N$, to reduce the small sampling noise

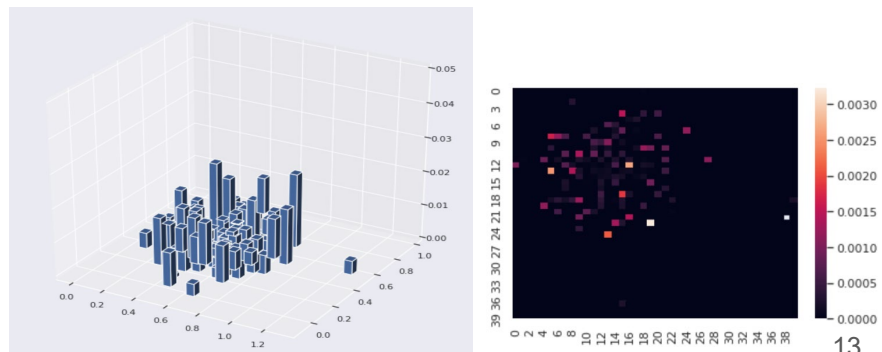
)



Trajectory Visualization (on 2-d embedding)



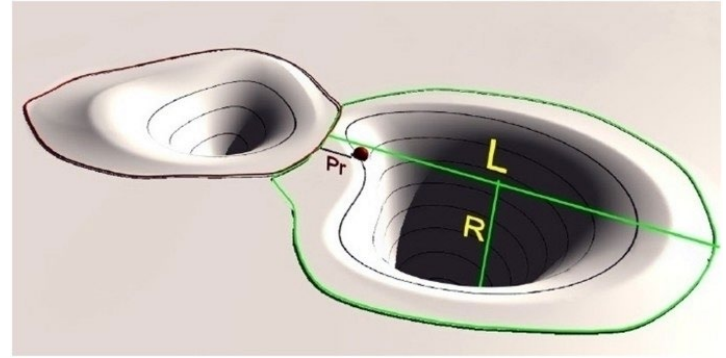
Distribution of the avg. trajectory std. starting from some seeds at (x, y);



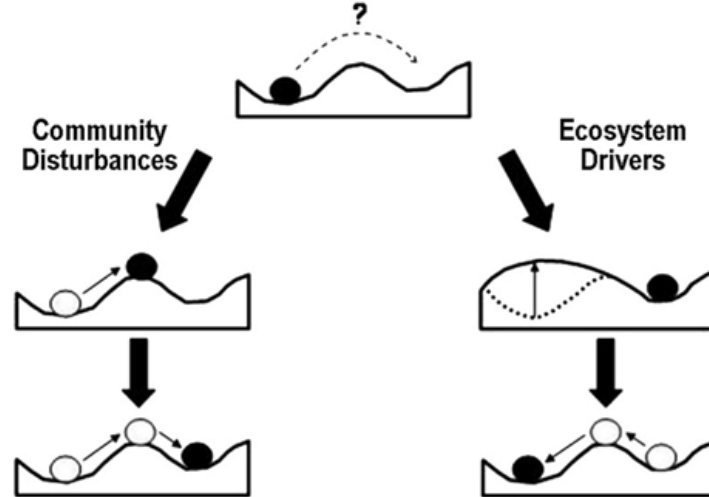
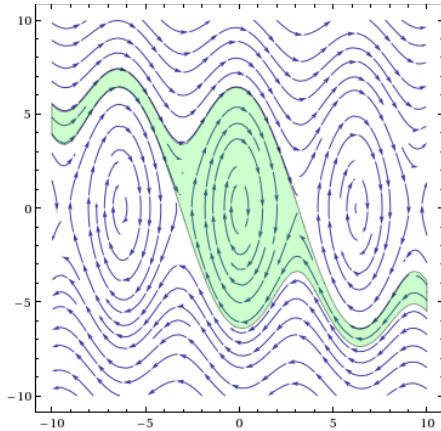
Looking into possible filter-bubbles

Resilience Problem Formation

According to the preliminary experiments, we would model the event of the user interacting with the RS as **traversing the space of multiple basins of attraction**

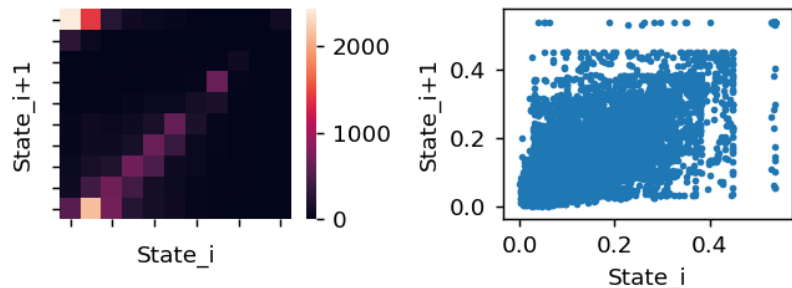


Mitra, C., Kurths, J. & Donner, R. An integrative quantifier of multistability in complex systems based on ecological resilience. *Sci Rep* 5, 16196 (2015).
<https://doi.org/10.1038/srep16196>



Single potential well hypothesis:

2-d embedding



Hessian LLE

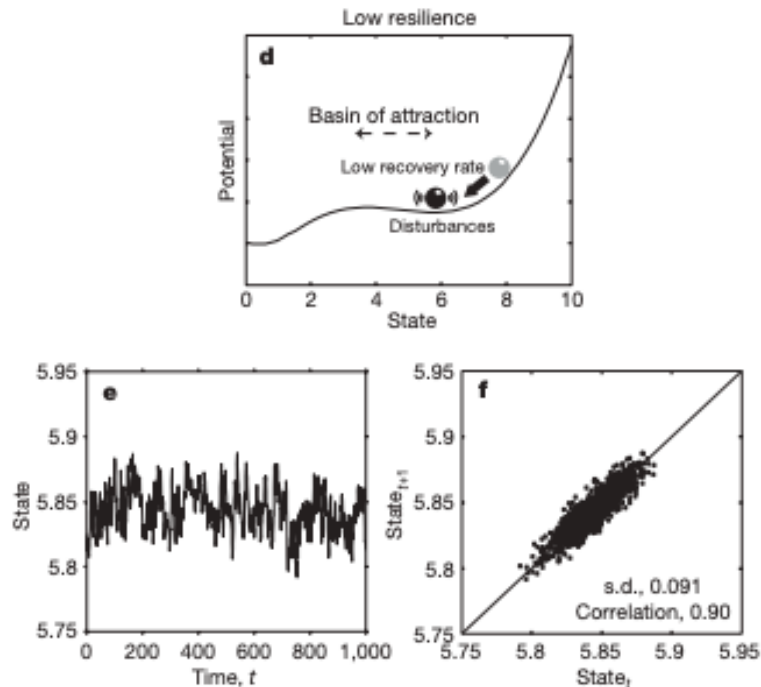
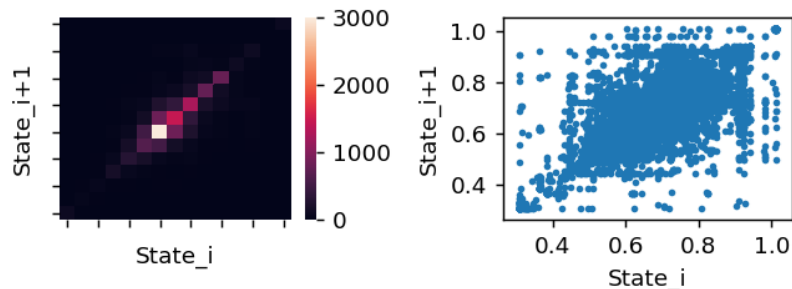
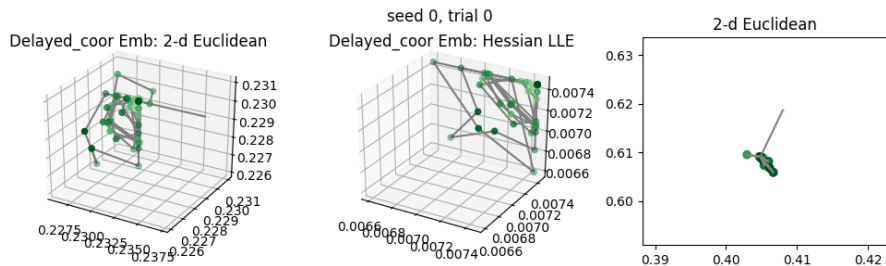


Figure 1 | Some characteristic changes in non-equilibrium dynamics as a system approaches a catastrophic bifurcation (such as F_1 or F_2 , Box 1).

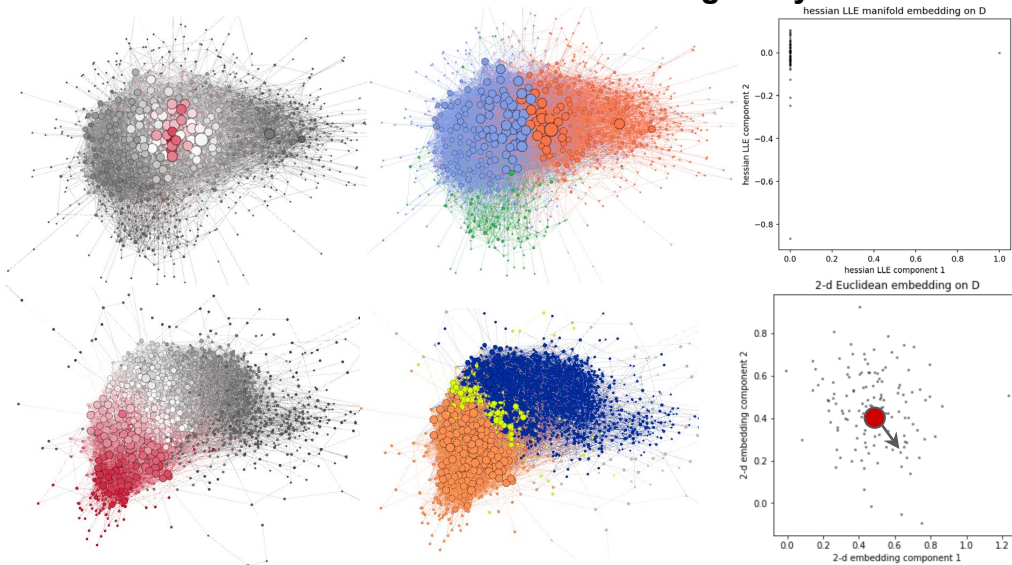
2009, Nature, “Early Warning Signals for critical transitions”

Trajectories in a reconstructed state-space



- For 2-d Eucl. The 1-d sensor is set as $\| \cdot \|_2$ distance from center (.5, .4)

loc-shift transition network clustering analysis

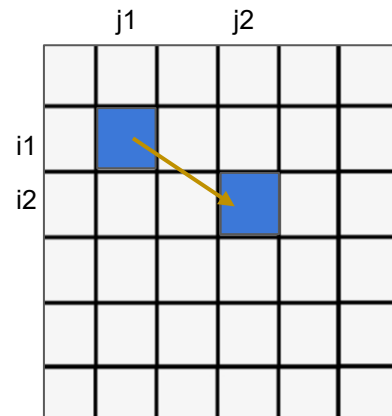


Delayed-Coordination Embedding [Takens, 1980]

For a state-space of E state variables, it suffices to create $d_E = 2 * E + 1$ dimensional Delayed-Coord. Embed from the 1-d sensor observation, and the reconstructed trajectory are topological equivalent to the original one.

From preliminary analysis, our data behaves like 1-d, therefore we set $d_E = 3 = 2 * 1 + 1$, and create the following Delayed-Coord. Embed.: $X(t) = (x(t), x(t+1), x(t+2))$, where $x(t)$ is the value at time step t in the 1-d time series

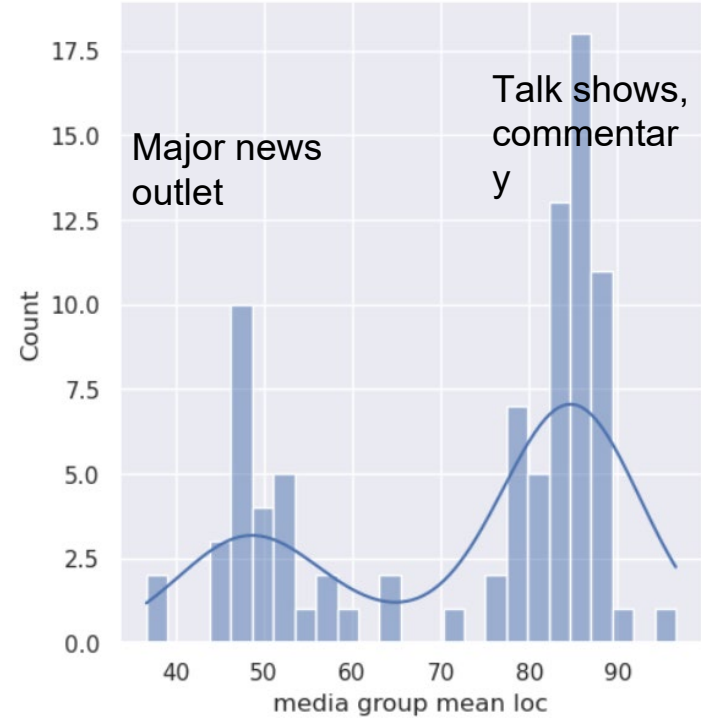
Demo: Grids in the embedding space as nodes in the transition network

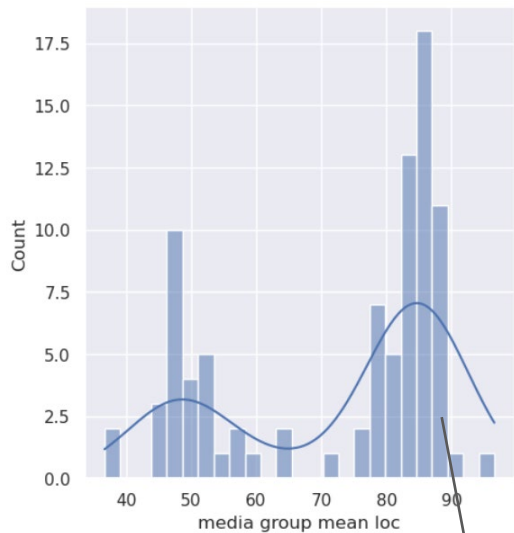


Media coverage data projected onto the embedding space

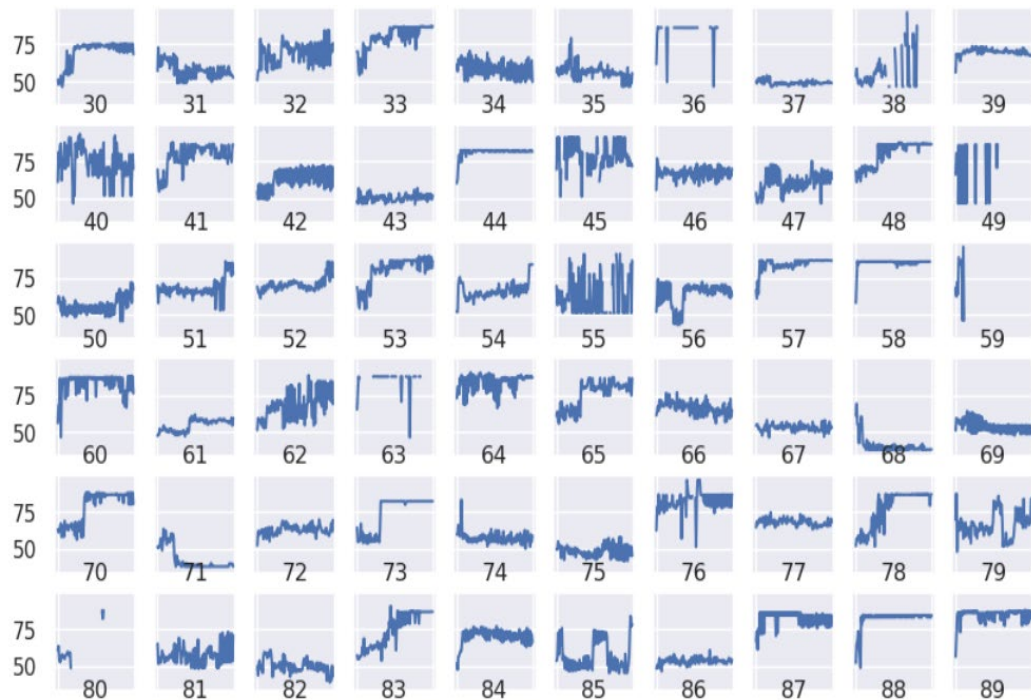
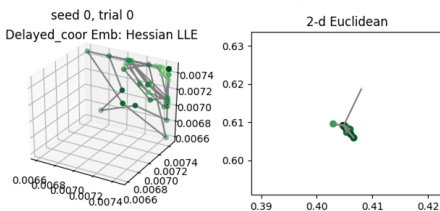
```
[[1, 1, 1, 0, ...],  
 [1, 0, 1, 1, ...],  
 ...]
```

media coverage data
-> channel encoding matrix





Demo of a trajectory in the embedding space



Still exploring... To be continued!