Hidden Interactions of Social Populations & Epidemic Dynamics

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Outline

- **Brief review and motivation**
- **Familiar Stranger: overlooked social interactions**

  Familiar stranger classifier, location prediction, immunization strategies
- **Invasion pathways: inference before prediction**

  Invasion case, observability, identifiability
- **Outlook with extensions**

C.A.N. Fudan Univ.

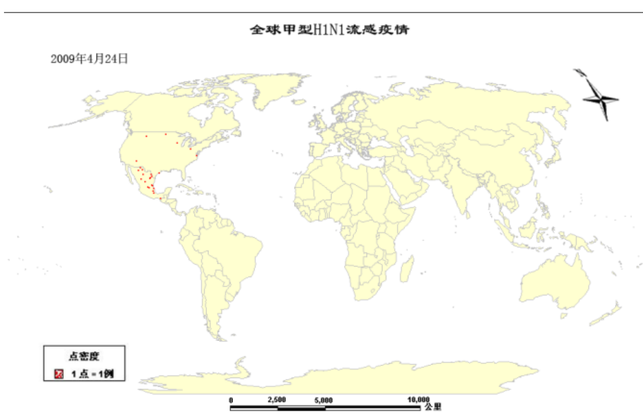
History repeats itself. ——Thucidides

- Smallpox, black-death,……, AIDS,……, SARS(2003), ……, A-H1N1(2009), ……*E.Coli*(2011),……Ebola/Zika,……?

- *The modern medical technology can save more patients before, while failed more effectively stopping a virus prevalence than before…*

<Science>, June 20, 2003:

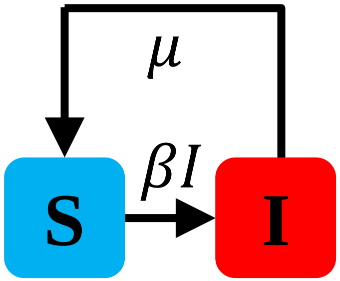
Modeling the SARS Epidemic Transmission Dynamics and Control of SARS



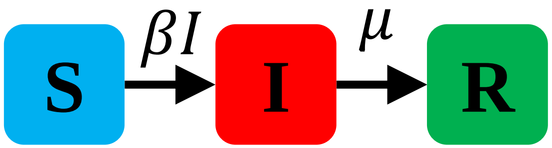
Epidemic models in a population

Daniel Bernoulli, *on smallpox inoculation,1766*

Prototype of compartment model



SIS



SIR

mass action principle

An incremental infection depends on the rate of contact between susceptible and infectious individuals.

$$\Delta I = \beta \cdot S \cdot I$$

William Heaton Hamer
(1862-1936)

Epidemics on complex network (single population)

- **Analytic thresholds**

R. Pastor-Satorras, A. Vespingnani (2001), Epidemic spreading in scale-free networks, *Physical Review Letters*, 86, 3200.

C. Castellano, R. Pastor-Satorras (2010), Thresholds for epidemic spreading in networks, *Physical Review Letters*, 105, 218701.

P. Van Mieghem and R. van de Bovenkamp (2013), Non-Markovian infection spread dramatically alters the SIS epidemic threshold, *Physical Review Letters*, 110, 108701.

……

- **Evolution dynamics**

T. Gross, C.J.D. D'Limma, B. Blasius (2006). Epidemic dynamics on an adaptive network. *Physical Review Letters*, 96: 208701.

X. Li, X.F. Wang (2006), Controlling the spreading in small-world evolving networks: stability, oscillation, and topology. *IEEE Trans. Automatic Control*, 51(3): 534-540.

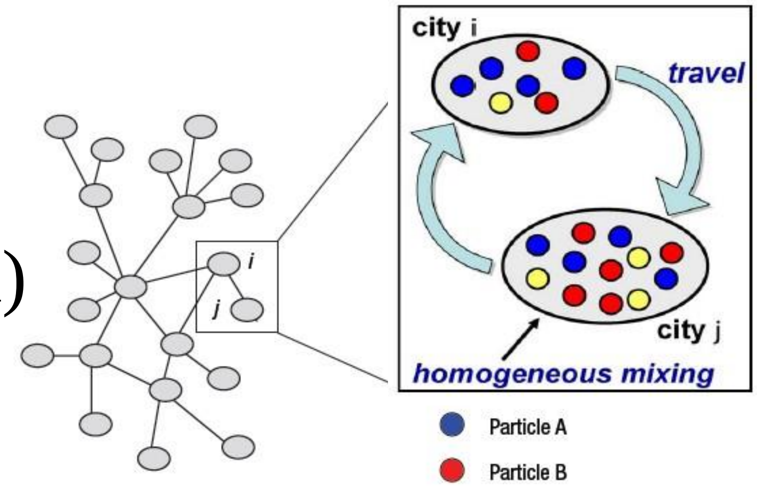
……

- **Latest survey**

R. Pastor-Satorras, C. Castellano, P. Van Mieghem and A. Vespignani (2015), Epidemic processes in complex networks, *Review of Modern Physics*, 87(3), 925-979.

From single population to meta-population

- Richard Levins (1969), Bull. Entomol. Soc. Am. 15, 237. (**Spatial ecology**)



- Metapopulation: Divide the whole population (country/world) into several sub-populations (cities), a subpopulation is connected with others via public transportation networks, e.g., the air-line web, high-way web.

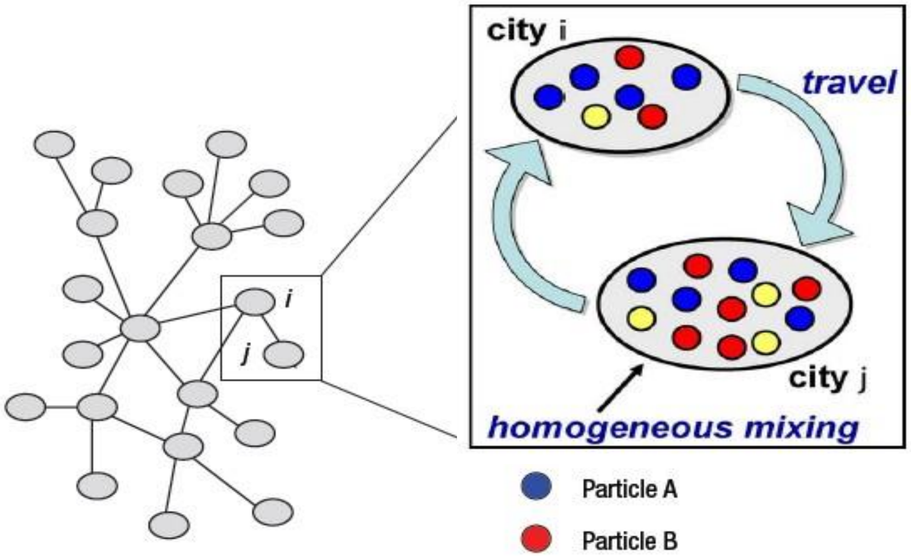
Figure 1 | Interconnected networks of human mobility in North America. The blue network represents short-range commuting flows by car, train and other means of transportation and transport infrastructures. Yellow-to-red lines denote airline flows for a few selected cities; red corresponds to greater traffic intensity. Population density is identified on the grey/white colour scale, with white corresponding to areas of higher density. All features in this map were obtained from real data[10].

V. Colizza, et al. The role of the airline transportation network in the prediction and predictability of global epidemic. PNAS 103(2006): 2015-2020.

Too many stories,
leave for a new book

☺

Spatial epidemics on meta-population



Computational models:
SI/SIS/SIR/SIRS/……

Infectious parameters:
R_0 /……

Assumptions and data-driven **availability**:

- Subpopulation (node): Homogeneous mixing, human resident structure, human interactive patterns, ……
- Path (edge): Human travel mobility, local commuting patterns, invasion tree, ……

Our continuous concerns

- Subpopulations (nodes):

How is the temporal effect of social interactive patterns on network epidemics?

- Paths (edges):

How to infer the invasion trees before predicting network epidemics?

Our continuous concerns

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How is the temporal effect of social interactive patterns on network epidemics?

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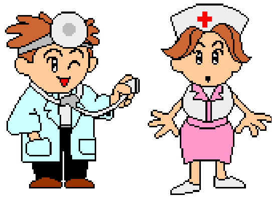
Towards Human Interactions

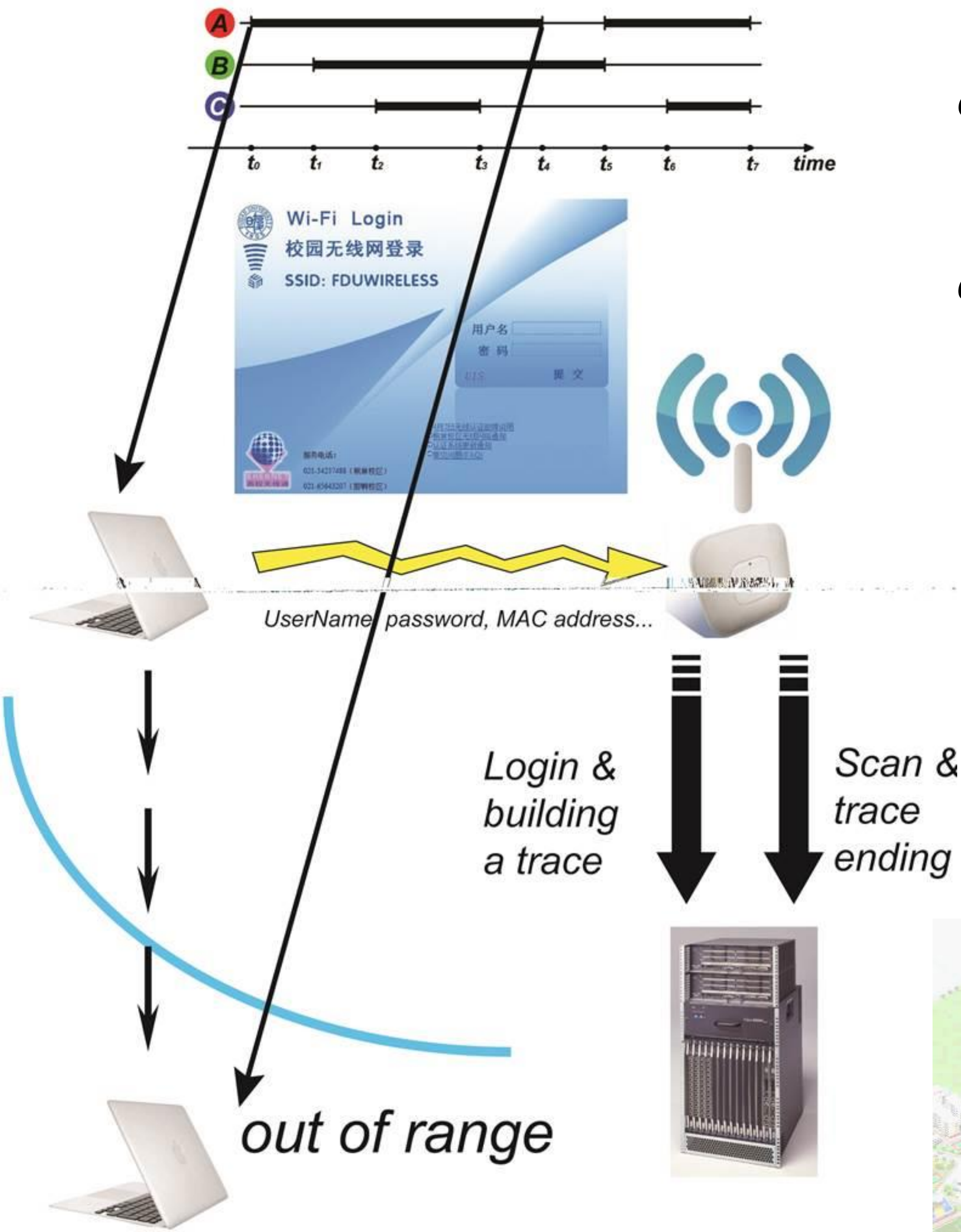


- **Data Proxy**: Cell phones (bluetooth), Wireless Sensors, RFIDs, **Wi-Fi**……
- **Temporal complexity**: interaction frequency, durations, intervals, time-stamps, ……
- **Temporal information**, more than 'time-varying', 'time-switching', 'time-evolving',……

Human Interactive Dynamics: Proxy Datasets

	RFID	**Wireless Sensor**	**Bluetooth**	**WiFi-Fudan**
Number of attendee	25~14000	788	100	18715(46669)
Experiment period(day)	2~69	18	270 (9 months)	84 (3 months)
Time accuracy(second)	20	20	300 (5 minutes)	60 (1 minute)
Space accuracy(meter)	1~5	3	25	20
Agent awareness (**Hawthorne effect**)	Y	Y	Y	N

- FudanWiFi09
- HT09
- SGInfectious
- SMS-1
- SMS-2
- Sex6yr



The individual trace begins at the time of login passed.

The individual trace ends at the time of access signal lost.

Contributed publications

- X. Li, Y.Q. Zhang, A. V. Vasilakos, Discovering and Predicting Temporal Patterns of WiFi-Interactive Social Populations, in **Opportunistic Mobile Social Networks**, CRC Press, 2015, 99-122.

- D. Liang, X. Li, Y.Q. Zhang, Identifying familiar strangers in human encounter networks, **EPL**, 2016, 116, 18006.
- Y.Q. Zhang, J. Cui, S. Zhang, Q. Zhang, X. Li, Modelling temporal networks of human face-to-face contacts with public activity and individual reachability, European Physical Journal B, 2016, 89:26
- Y.Q. Zhang, X. Li, D. Liang, J. Cui, Characterizing bursts of aggregate pairs with individual poissonian activity and preferential mobility. **IEEE Communication Letters**, 2015, 19(7), 1225-1228.
- Y.Q. Zhang, X. Li, J. Xu, A. V. Vasilakos, Human interactive patterns in temporal networks, **IEEE Trans. Systems, Man & Cybernetics: Systems**, 2015, 45(2), 214-222.
- Y. Zhang, X. Li, Temporal dynamics and impact of event interactions of cyber-social populations, ***Chaos***, 2013, 23, 013131.
- Y. Zhang, L. Wang, Y.Q. Zhang, X. Li, Towards a temporal network analysis of interactive WiFi users, ***EPL***, 2012, 98, 68002.

Social ties

Acquaintances

Strangers

Familiar strangers

friends, in-role, …



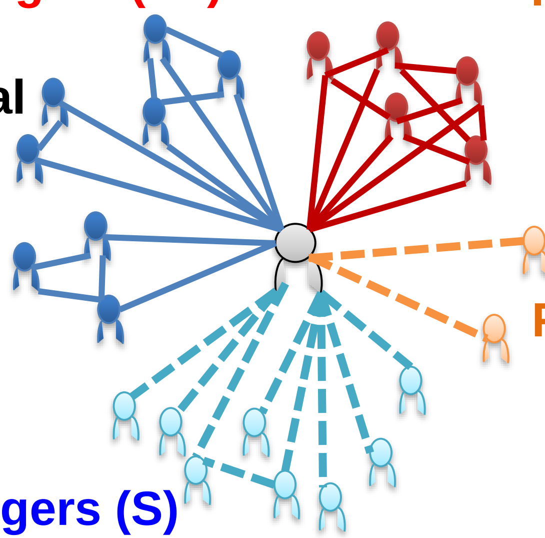






Familiar Stranger

- Milgram (1970): Familiar Strangers are two persons who have repeatedly encountered but might never have been acquainted with each other.



Encounters with 'familiar strangers' play overlooked role in human interactions

9 December 2016, by Lisa Zyga

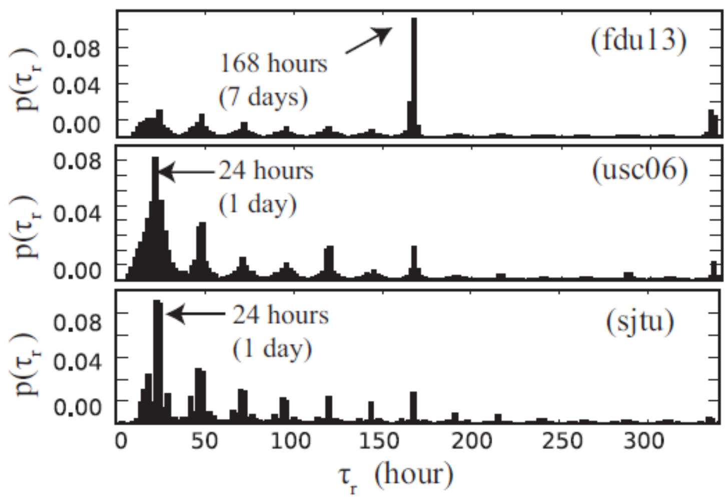
PHYS.ORG

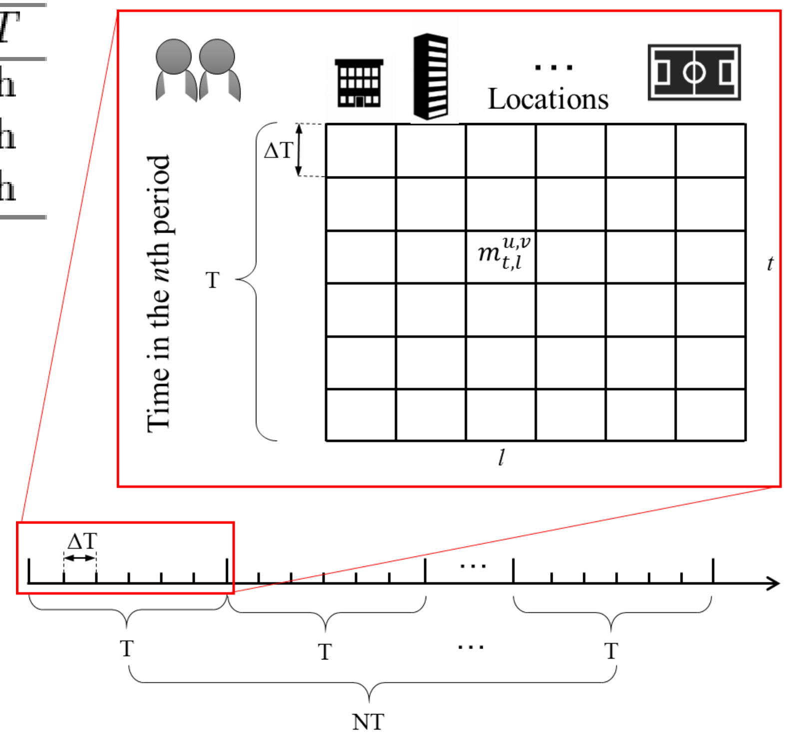
D. Liang, X. Li, Y.Q. Zhang, Identifying familiar strangers in human encounter networks, **<u>EPL</u>**, 2016, 116, 18006.

Data and Encounter network

Data	$\|U\|$	$\|L\|$	Records #	N	T	ΔT
fdu13	10,146	1,452	3,825,382	12	7 d	3 h
usc06	5,185	137	808,015	84	1 d	3 h
sjtu	14,755	85	4,050,267	92	1 d	6 h

|U|: Number of users
|L|: Number of locations
Records #: Total number of records
N: number of time cycles
T: length of one time cycle
ΔT: length of time step





$$m_{t,l}^{u,v} = (w_{t,l}^{u,v}, prop_{t,l}^{u,v})$$

$w_{t,l}^{u,v}$: **encounter weight.** The number of cycles that individual *u* and *v* encounter at location *l* and time step *t*.

$prop_{t,l}^{u,v}$: **encounter probability.** The empirical probability that individual *u* and *v* encounter at location *l* and time step *t*.

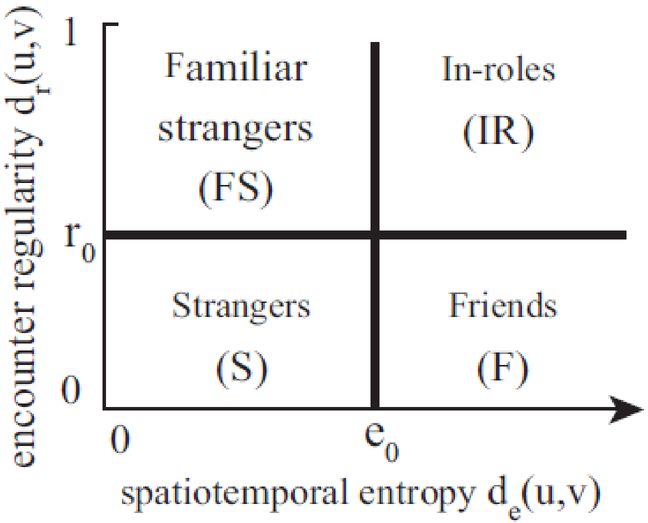
Social ties and Entropy

spatiotemporal entropy $$d_e(u,v) = log_2 \sum_l \sum_t \mathrm{sign}(w_{t,l}^{u,v})$$

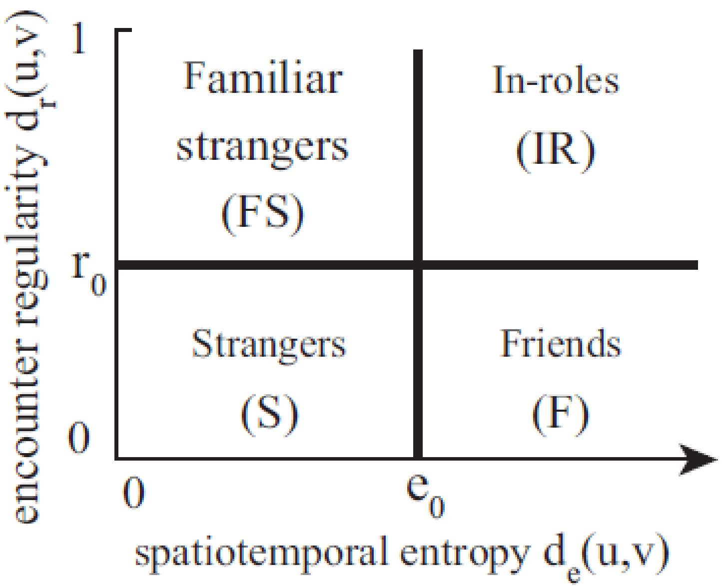
The spatiotemporal entropy measures **the degree of social similarity**. The spatiotemporal entropy between acquaintances will be larger than that of other pairs with random social similarity.

encounter regularity $$d_r(u,v) = \frac{\sum_l \sum_t (w_{t,l}^{u,v} \times prop_{t,l}^{u,v})}{\sum_l \sum_t w_{t,l}^{u,v}}$$

Encounter regularity measures to what degree the encounter events between a pair of users are generated obeying the periodic life routines



Familiar Stranger Classifier

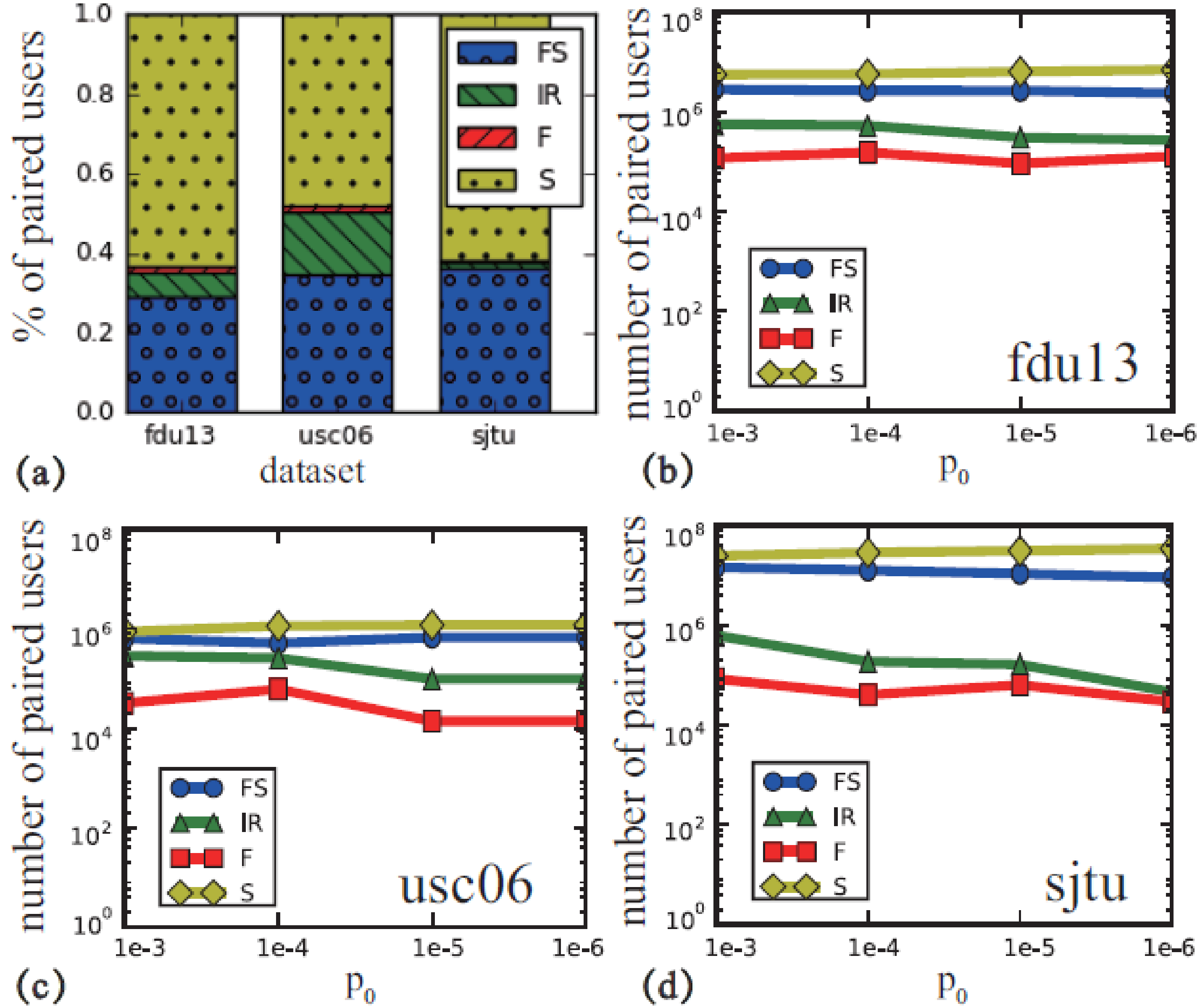


(1) Obtain encounter matrix $M_{u,v}$ and $M_{u,v}^{null}$ from the empirical dataset and the null model.

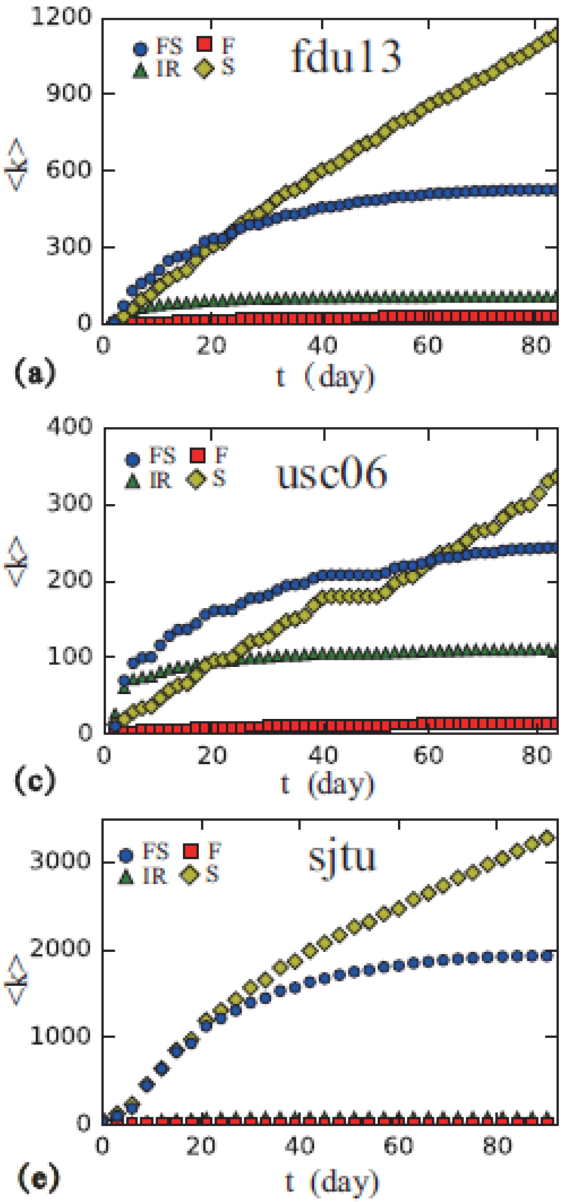
(2) Calculate $\mathrm{d_e}(u,v)$ and $\mathrm{d_r}(u,v)$ from $M_{u,v}$. Calculate $\mathrm{d_e^{null}}(u,v)$ and $\mathrm{d_r^{null}}(u,v)$ from $M_{u,v}^{null}$.

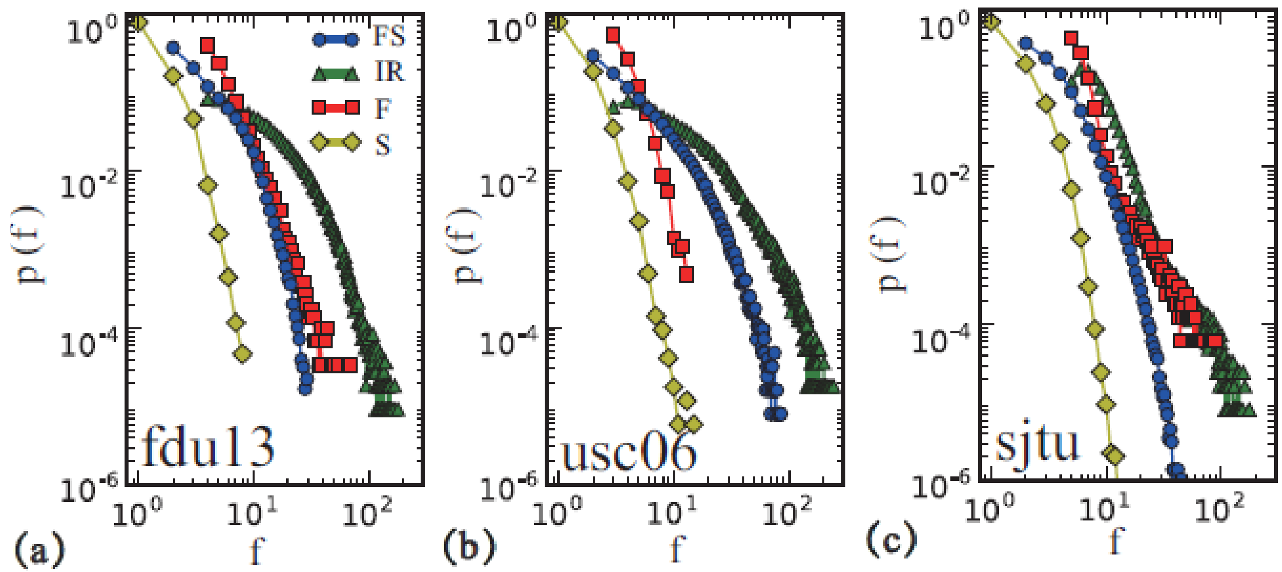
(3) Get $\boldsymbol{e_0}$ and $\boldsymbol{r_0}$, where $P\left(d_r^{null}(u,v) > r_0\right) = P\left(d_e^{\mathrm{null}}(u,v) > e_0\right) = \boldsymbol{p_0}$.

(4) Get pairwise relationship according to the diagram on the left.


1.0
0.8
0.6
0.4
0.2
0.0
% of paired users
FS
IR
F
S
fdu13
usc06
sjtu
(a)
dataset
10^8
10^6
10^4
10^2
10^0
number of paired users
fdu13
1e-3
1e-4
1e-5
1e-6
(b)
p_0
usc06
(c)
sjtu
(d)

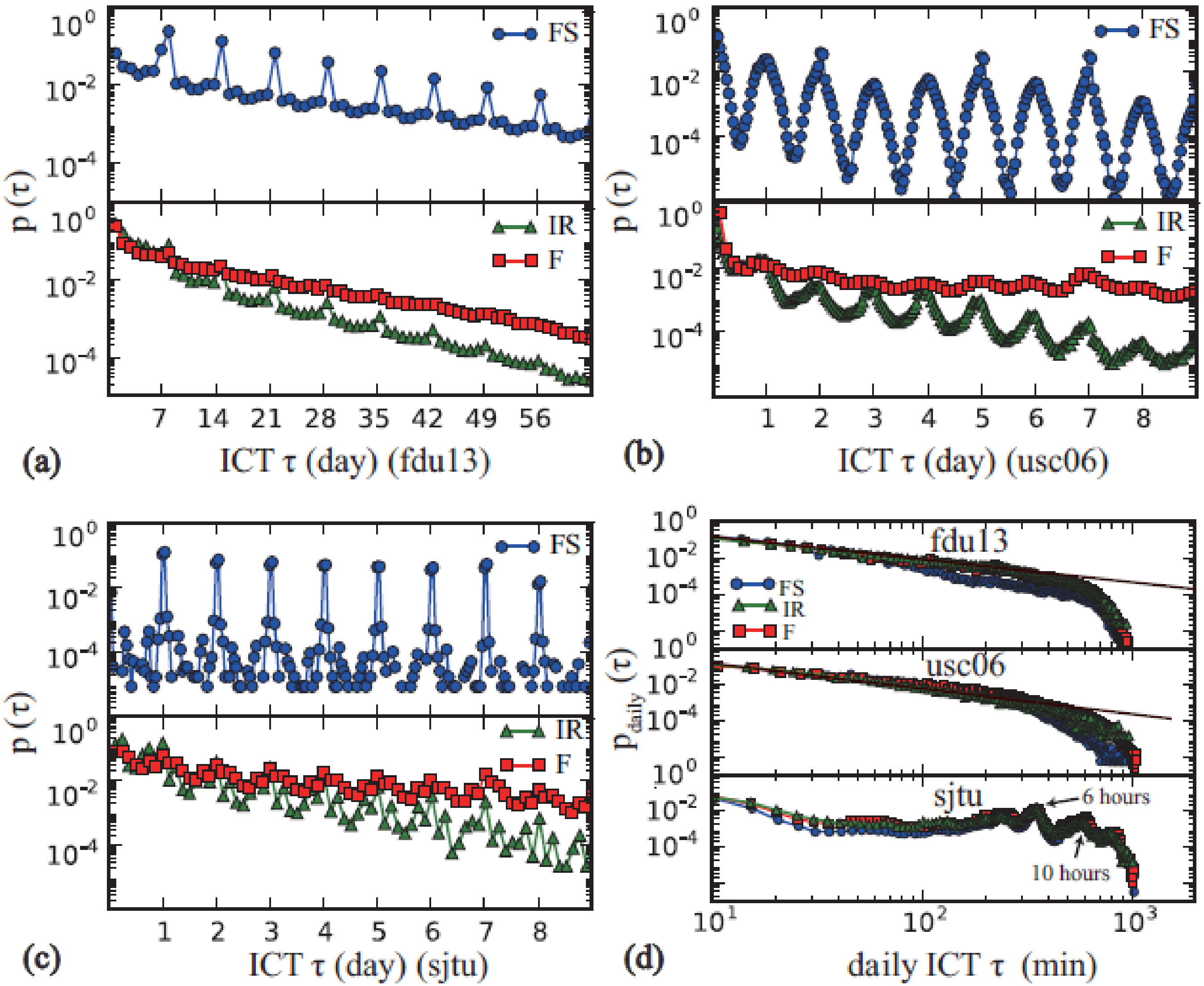
FS degree characteristics





- FS' average degree is finite but larger than the Dunbar Number (150).
- FS' encounters are structurally stable with higher encounter frequencies than those of strangers.

FS temporal (ICT) characteristics



Our continuous concerns

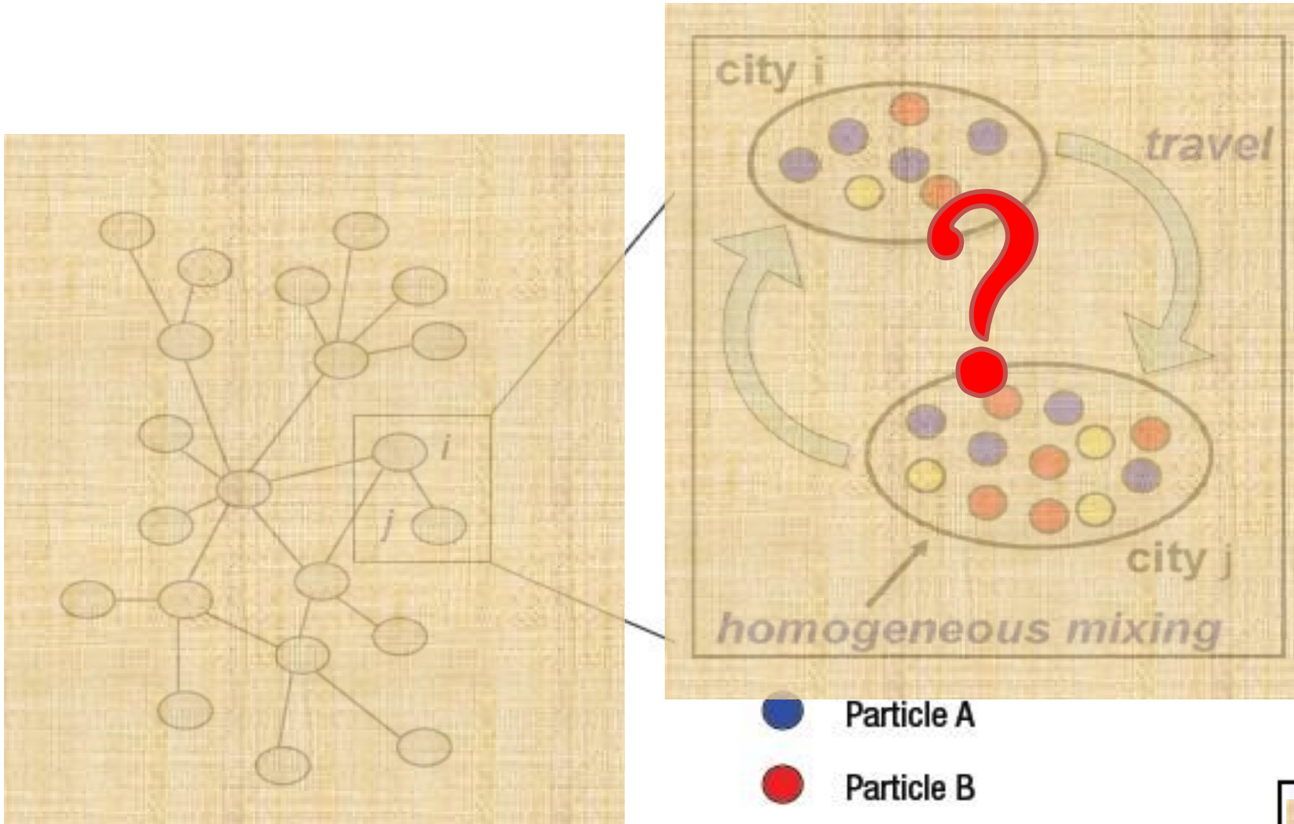
- Subpopulations (nodes):

    How is the temporal effect of social interactive patterns on network epidemics?

- Paths (edges):

    How to infer the invasion trees before predicting network epidemics?

To identify such epidemic processes?



Epidemic parameter?

Invasion trees?

……

when such epidemic processes are unknown with only (partial) observed data?

Contributed publications

- X. Li, J.B. Wang, and C. Li, “Towards identifying and predicting spatial epidemics on complex meta-population networks”, Springer, 2017, in press.
- J.B. Wang, L. Wang, and X. Li, “Identifying spatial invasion of pandemics on meta-population networks via anatomizing arrival history,” **IEEE Trans. Cybernetics**, 2016, 46(12), 2782-2795.

- X. J. Li, C. Li, and X. Li, “Vaccinating SIS epidemics in networks with zero-determinant
- strategy,” IEEE Int. Symposium on Circuits and Systems (ISCAS 2017), 2275-2278, 2017.
- X. Li, J.B. Wang, and C. Li, “Towards identifying epidemic processes with interplay between complex networks and human populations”, **2016 IEEE Conference on Norbert Wiener in the 21st Century**. 67-71, 2016.
- J.B. Wang, C. Li, and X. Li, “Predicting spatial transmission at the early stage of epidemics on a networked metapopulation,” 12th IEEE International Conference on Control & Automation (ICCA), 116-121, 2016.
- J.B. Wang, X. Li, and L. Wang, “Inferring spatial transmission of epidemics in networked metapopulations”, IEEE Int. Symposium on Circuits and Systems (ISCAS 2015), 906-909, 2015.
- J.B. Wang, L. Cao, and X. Li, “On estimating spatial epidemic parameters of a simplified metapopulation model,” 13th IFAC Symposium on Large Scale Complex Systems, 383–388, 2013.

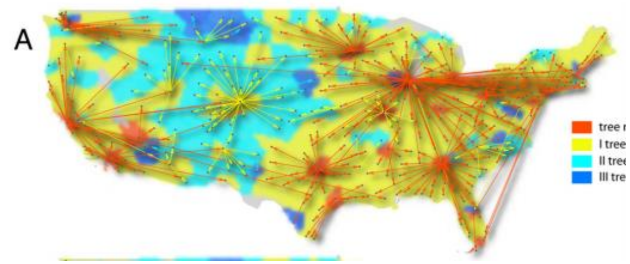
Exploring Epidemic Shortest Paths

Average-Arrival-Time (ARR)-Based Shortest Paths Tree (SPT) ***[1]***

Shortest path between subpopulation s, j

$$\lambda\langle t_j\rangle \approx \chi(j|s)$$
$$\equiv \min_{\{P_{s,j}\}} \sum_{(k,l)\in P_{s,j}} \left[\ln\left(\frac{N_k\lambda}{w_{kl}}\right) - \gamma\right]$$

Monte Carlo-Maximum-Likelihood (MCML)-Based Epidemic Invasion Tree ***[2]***



Distance between subpopulation i, j

$$d_{ij} = \sqrt{1 - T_{ij}}$$

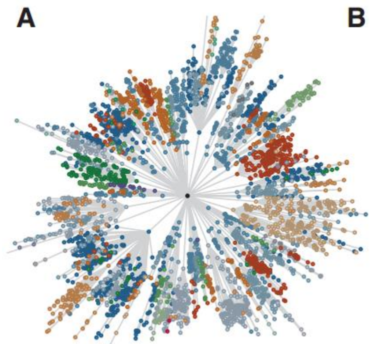
Effective (EFF)-Distance-Based Most Probable Paths Tree ***[3]***

Effective distance between subpopulation m, n

$$d_{mn} = (1 - \log P_{mn}) \geq 1$$

Shortest paths between subpopulation m, n

$$D_{mn} = \min_{\Gamma} \lambda(\Gamma)$$



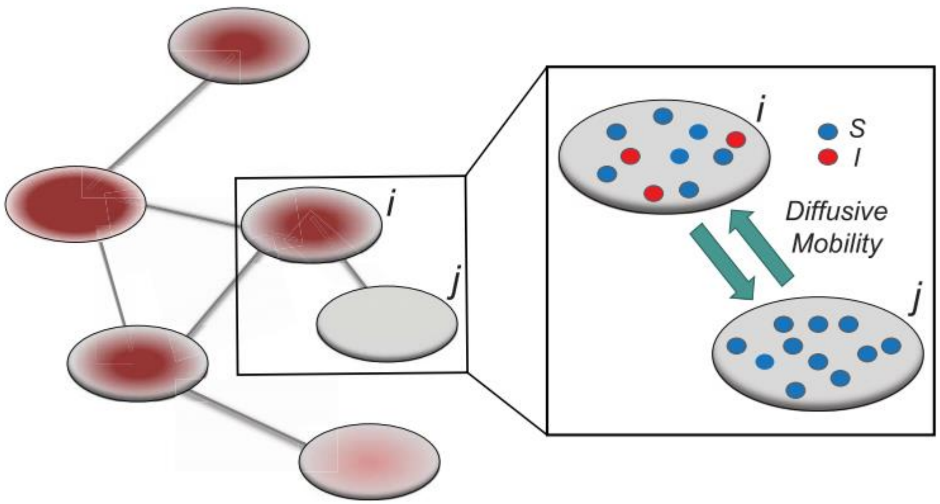
[1] A. Gautreau, A. Barrat, and M. Barthelemy. "Global disease spread: statistics and estimation of arrival times,"Journal of theoretical biology, vol. 251, no. 3, pp. 509–522, Apr. 2008.
[2] D. Balcan, V. Colizza, B. Gonc¸alves, H. Hu, J. J. Ramasco and A. Vespignani, "Multiscale mobility networks and the spatial spreading of infectious diseases." Proc. Natl. Acad. Sci., vol. 106 no. 51, pp. 21484–21489, Dec. 2009.
[3] D. Brockmann and D. Helbing, "The Hidden Geometry of Complex, Network-Driven Contagion Phenomena,"Science, vol. 342, no. 6164, pp. 1337–1342, Dec. 2013.

Q: is it possible to retrospect the stochastic pandemic spatial paths among a networked metapopulation?

Our answer:
Invasion Pathways Identification Algorithm Based on Dynamical Programming and Maximum Likelihood Estimation

J.-B. Wang, L. Wang, and X. Li, “Identifying spatial invasion of pandemics on meta-population networks via anatomizing arrival history,” IEEE Trans. Cybernetics, 2016, 46(12), 2782-2795.

Problem Statement with SI dynamics



(a) (b)

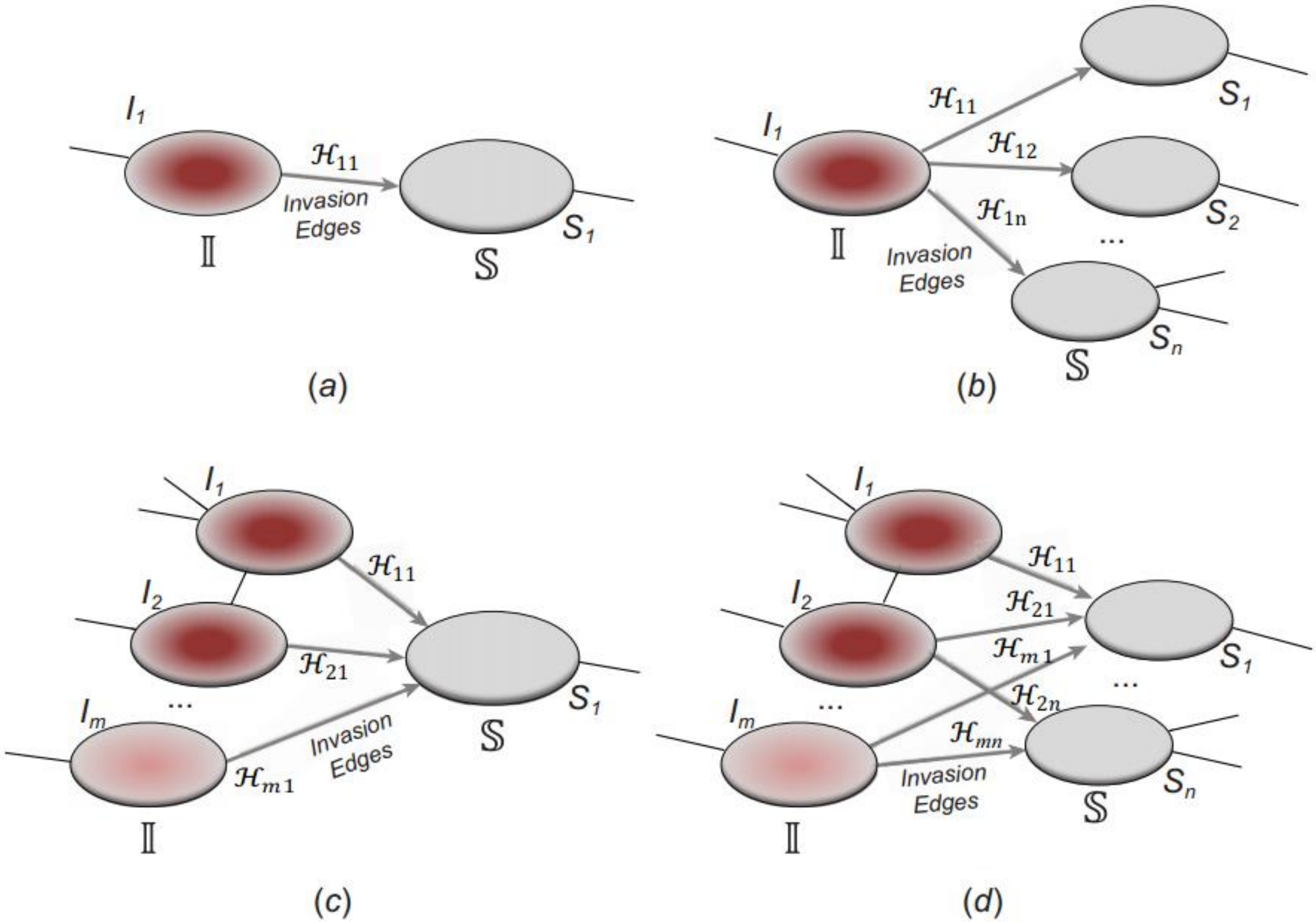
Reaction process $I + S \xrightarrow{\beta} 2I$

Diffusion process $\mathcal{X}_i \xrightarrow{p_{ij}} \mathcal{X}_j, \mathcal{X}$ represents S or I

[1] Hufnagel L, Brockmann D, Geisel T., PNAS, 101: 15124-15129, 2004.
[2] Colizza, V., Pastor-Satorras, R. & Vespignani A., Nature Phys.3, 276-282, 2007.

- Known:
  - Number of infected individuals of each infected subpopulation $I_i(t)$ at time step t, network topology(including diffusion rates)
- Unknown (to identify):
  - Spatial invasion pathways

Four Invasion Cases



Invasion Pathways Identification Algorithm

Algorithm steps:

1) **Invasion Partition (Dynamic Programming)**

The whole invasion pathway T is anatomized into (at each epidemic arrival time (EAT)) four classes of invasion cases with number of Λ :

$I \longmapsto S, I \longmapsto nS, mI \longmapsto S, mI \longmapsto nS$

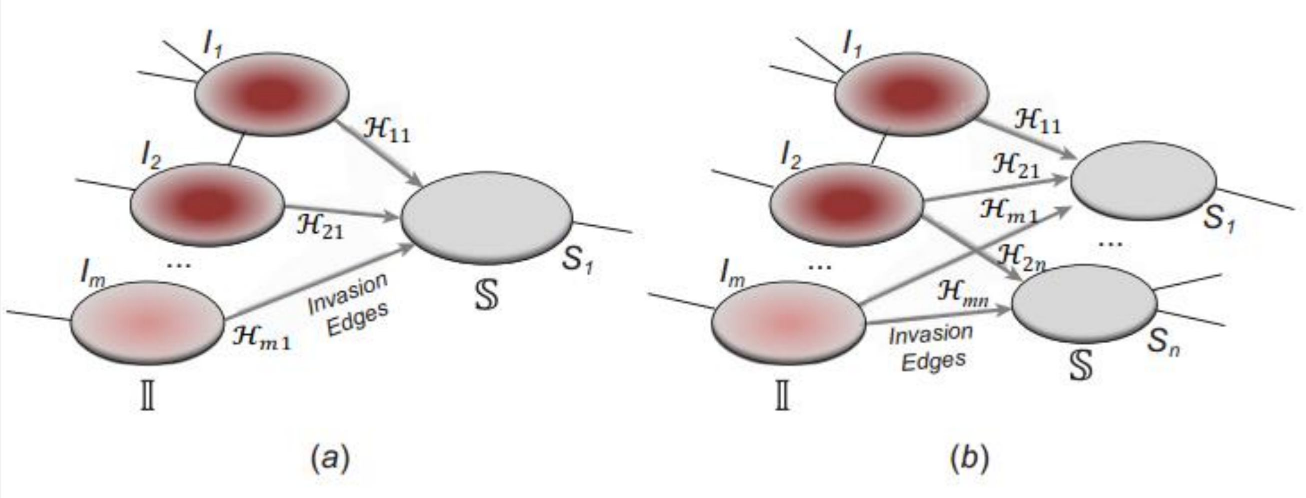
$$T_{whole\ invasion\ pathways} = opt \sum_{i=1}^{\Lambda} \hat{a}_i$$

2) **Identifying Each Invasion Case**

Accurate identification + optimal identification (Maximum Likelihood Estimation)

$$\hat{a}_i = \arg \max_{a_i \in G_{INC_i}} P(a_i | G_{INC_i})$$

Invasion Cases (INCs)



$mI \longmapsto S$ $\quad$ $mI \longmapsto nS$

Subpopulations' observability

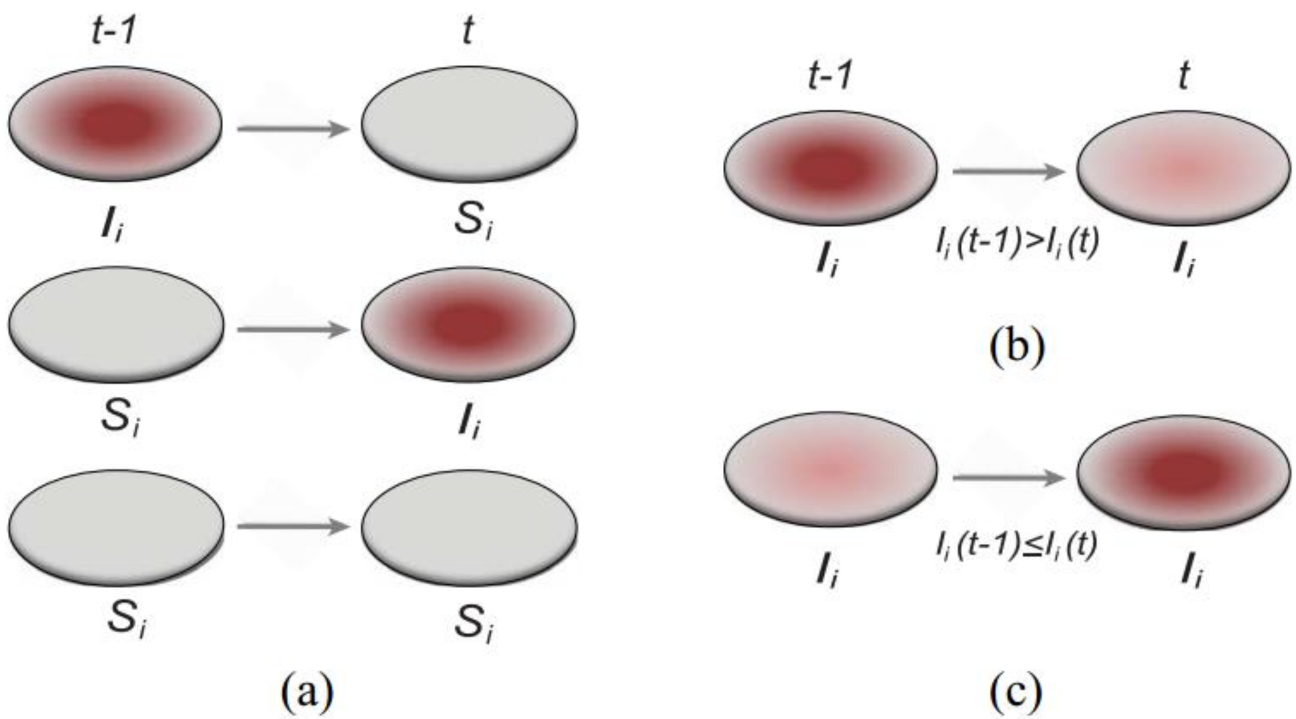
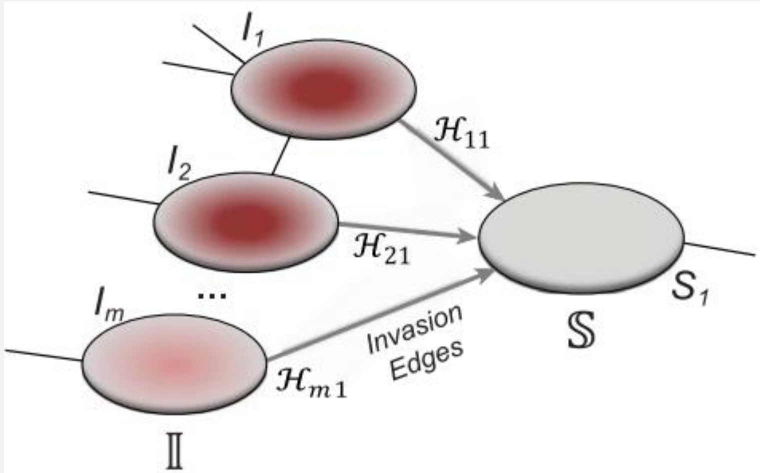


Illustration of neighbors subpopulation classification in terms of status transitions from $t-1$ to t:
(a) Observable subpopulation i. (b) Partially observable subpopulation i. (c) Unobservable subpopulation i.

Identification of $mI \mapsto S$



Step 1 Accurate Identification

Theorem 1 (Accurate Identification of Invasion Pathway): With the following conditions: 1) among m possible sources illustrated in set $\mathbb{I}$, there are only $m'(m' \leq m)$ partially observable subpopulations $\mathbb{I}'$, whose neighboring subpopulations (excluding the invasion destination S_1) only experience the transition S to S or I to S at that EAT and 2) $\sum_{i\in\mathbb{I}'}[I_i(t-1) - I_i(t)] = \mathcal{H}$, the invasion pathway of an INC $mI \mapsto S(m > 1)$ can be identified accurately.

Step 2 Optimal Identification

Decompose the number of first arrival infected individuals

$$\sum_{i=1}^{m} \mathcal{H}_{i1} = \mathcal{H}$$

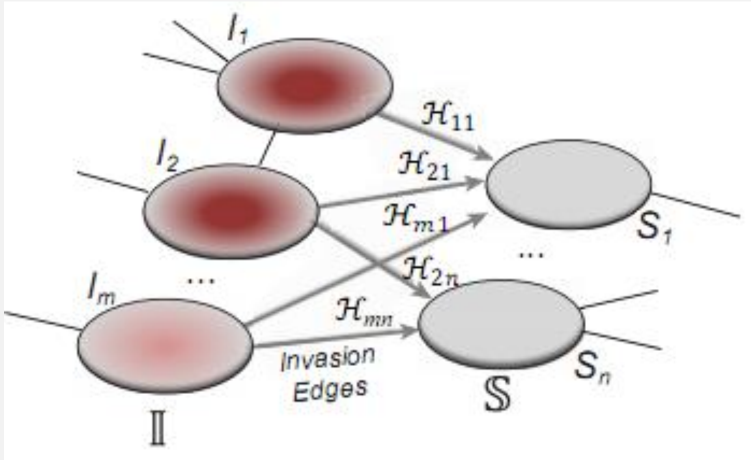
Compute the likelihood of each potential solution:

$$\begin{aligned} P(\sigma_j|\mathcal{E}_{mIS}) &= P(\mathcal{E}_{mIS}|\sigma_j)P(\sigma_j)/P(\mathcal{E}_{mIS}) \\ &= P(\mathcal{E}_{mIS}|\sigma_j)P(\sigma_j)\Big/\sum_{j=1}^{M}[P(\mathcal{E}_{mIS}|\sigma_j)P(\sigma_j)] \\ &= P(\sigma_j)\Big/\sum_{j=1}^{M}[P(\sigma_j)] \\ &= \prod_{k=1}^{m}\Omega\left(\mathcal{H}_{k1}^{(j)}\right)\Big/\sum_{i=1}^{M}\prod_{k=1}^{m}\Omega\left(\mathcal{H}_{k1}^{(i)}\right) \end{aligned}$$

Choose the maximal one

$$\begin{aligned} \hat{a}^{mIS} &= \arg\max_{\sigma_i} \; P(\sigma_i|\mathcal{E}_{mIS}) \\ &= \arg\max_{a_i} \; P(a_i|G_{mIS}) \end{aligned}$$

Identification of $mI \mapsto nS$



Step 1 Accurate Identification

Theorem 2 (Accurate Identification of Invasion Pathway): With the following conditions: 1) the number of invasion edges $E_{in} \leq n+m$; 2) the neighbor subpopulations of each subpopulation in set $\mathbb{I}$ are with the transition S to S or I to S except their neighbor subpopulations in set $\mathbb{S}$ during $t_{\mathrm{EAT}-1}$ to t_{EAT}; and 3) $\sum_{i=1}^{m} \Delta I_i(t) = \sum_{k=1}^{n} \mathcal{H}_k$, the invasion pathway of an INC $mI \mapsto nS(m, n > 1)$ can be identified accurately.

Step 2 Optimal Identification

Decompose the number of first arrival infected individuals

$$\sum_{i \in Y_k}^{m} \mathcal{H}_{ik} = \mathcal{H}_k$$

Compute the likelihood of each potential solution：

$$P(\sigma_j|\mathcal{E}_{mInS}) = \prod_{k=1}^{m} \Omega\left(\mathcal{H}_{kk_\hbar}^{(j)}\right) \Big/ \sum_{i=1}^{M} \prod_{k=1}^{m} \Omega\left(\mathcal{H}_{kk_\hbar}^{(i)}\right)$$

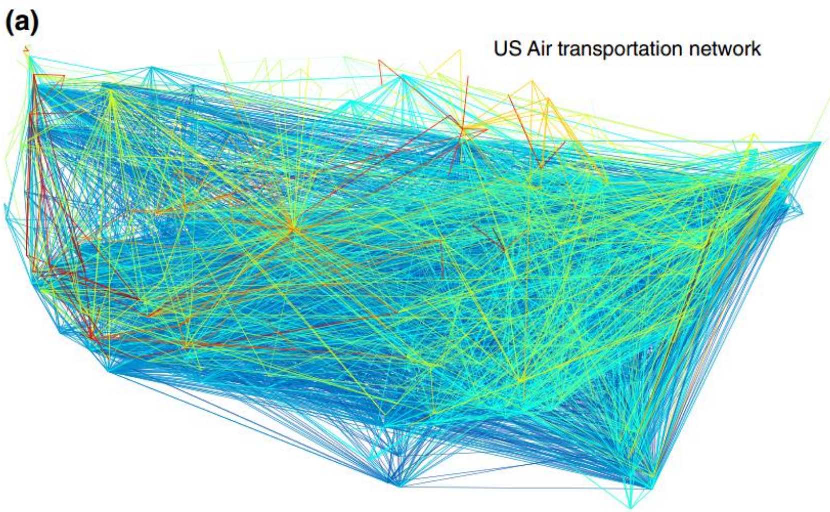
Choose the maximal one

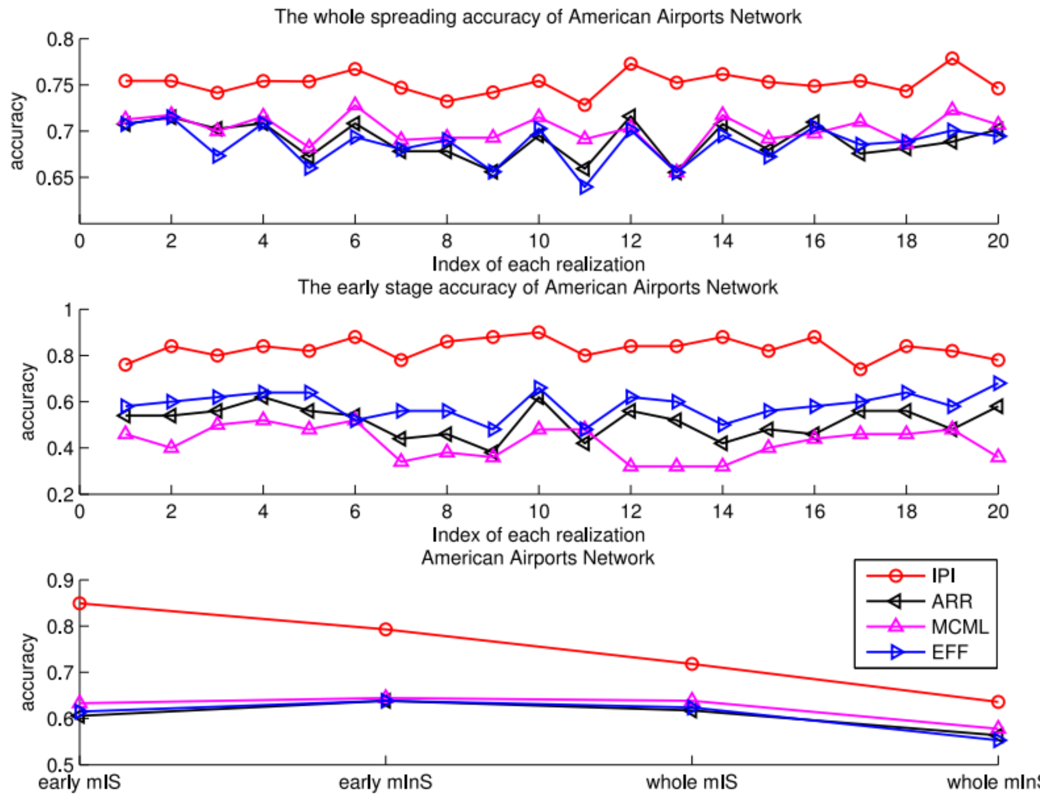
$$\hat{a}^{mInS} = \arg\max_{\sigma_i} P(\sigma_i|\mathcal{E}_{mInS}) = \arg\max_{a_i} P(a_i|G_{mInS})$$

Analysis	**Identifiability**
Denote π the probability corresponding to the most likely pathways for a given INC. Thus we have $\pi(\sigma) = \sup\{P(\sigma_i\|\mathcal{E})\}$. *Property 1*: Given an INC $mI \longmapsto S$ or $mI \longmapsto nS$, $P(\sigma_i\|\mathcal{E}) = \left(\prod_{k=1}^{m} \Omega / \sum_{i=1}^{M} \prod_{k=1}^{m} \Omega\right)$. there must exist P_{min} and P_{max} satisfying $$P_{min} \leq \pi(\sigma) \leq P_{max}$$	*Definition 1 (Entropy of Transferring Likelihoods of M Potential Solutions):* According to Shannon entropy, we define the normalized entropy of transferring likelihood $P(\sigma_1\|\mathcal{E}), \ldots, P(\sigma_M\|\mathcal{E})$ as $$\mathcal{S} = -\frac{1}{\log M}\sum_{i=1}^{M} P(\sigma_i\|\mathcal{E})\log P(\sigma_i\|\mathcal{E})$$ Define ***identifiability*** of invasion pathways to characterize the difficulty level an INC can be identified $\boldsymbol{\Pi} = \boldsymbol{\pi}(\boldsymbol{\sigma})(\mathbf{1} - \boldsymbol{\mathcal{S}})$. *Theorem 3*: Given an INC $mI \longmapsto S$ or $mI \longmapsto nS$, Π is the identifiability computed by the IPI algorithm. There exist a lower boundary $\Pi_{min} = {}^{1}/_{M}\,(1 - \mathcal{S}')$ and $\Pi_{max} = \pi - \mathcal{S}\big(\pi(\sigma)\big)$ that $$\Pi_{min} \leq \Pi \leq \Pi_{max},$$ where $\mathcal{S}' = -(\frac{1}{\log M})(\pi\log(\pi) + \sum\left(\frac{1-\pi}{M-1}\right)\log(\frac{1-\pi}{M-1})))$.

Example 1

American Airports Network (AAN)
N=404; total population=2.4×10^8 ,
$<k> = 16$.



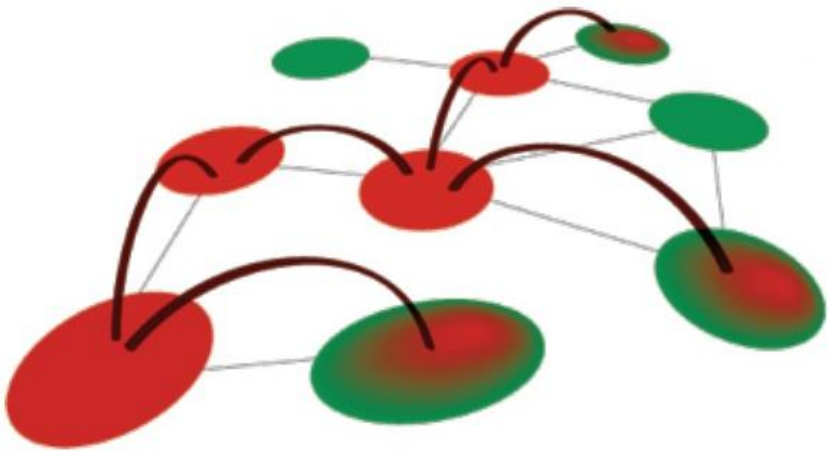


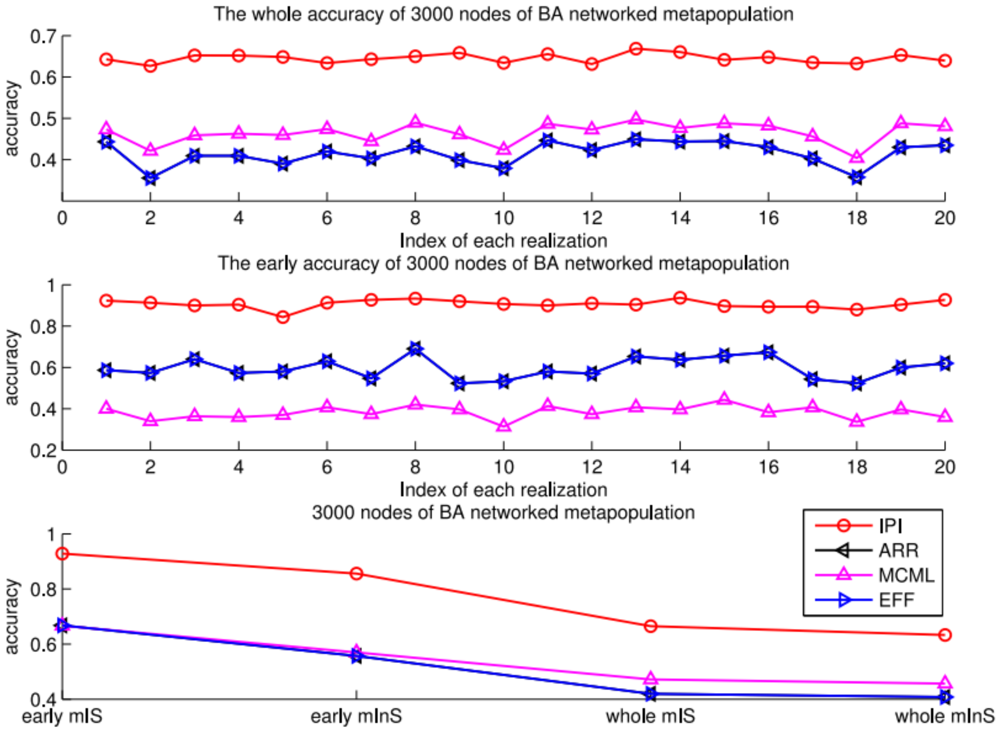
The figure shows various identified accuracy for the early stage and the whole invasion pathways on the AAN.

Example 2

Large-scale BA metapopulation network

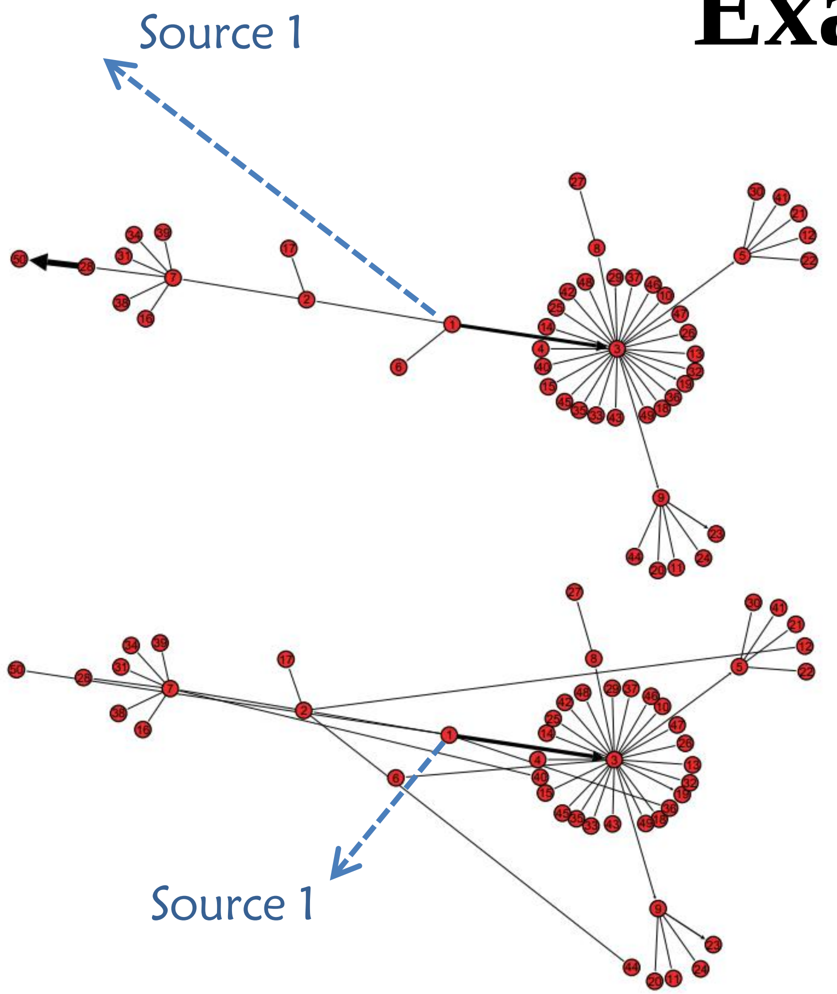
N=3000; N_i=6× 10^5; total population=$1.8 \times 10^9, < k > = 16$.





The figure shows various identified accuracy for the early stage and the whole invasion pathways on 3000 subpopulations of the BA networked metapopulation.

Example 3



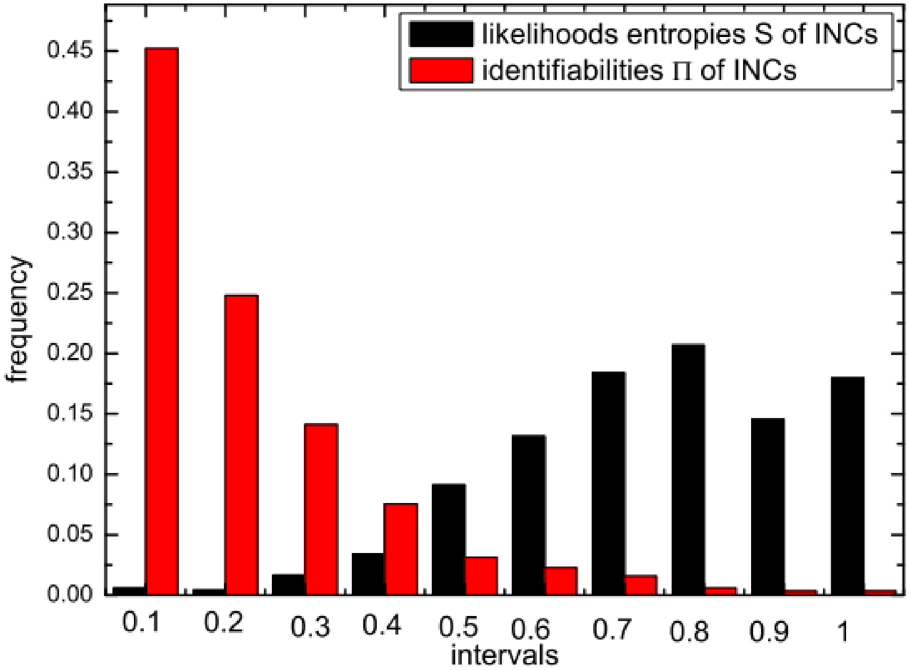


Illustration of the **actual** invasion pathways and the **most likely identified** invasion pathways on the AAN. Subpopulation 1 is the source.

Statistics analysis of the likelihoods entropy and identifiability of wrongly identified INCs on the AAN.

Extension to the SIR situation

Inferring SIR spatial invasion on meta-population networks, ready for submission.

Outlook with more extensions

- On reconstructing temporal networks **(null model)**

  Reconstruction of stochastic temporal networks through diffusive arrival times, ***Nature Communications***, 2017, 8, 15729.

- On optimizing vaccination social-cost **(ZD strategy)**

  Minimizing social-cost of vaccinating network SIS epidemics, ***IEEE Trans. Network Science and Engineering***, minor revision.

  Vaccinating SIS epidemics in networks with zero-determinant strategy, *ISCAS 2017*, Baltimore, 2275-2278.

- On Temporal epidemic thresholds **(non-markovian)**

  Spectral analysis of epidemic thresholds of temporal networks, ***IEEE Trans. Cybernetics***, 2017, in press.

Acknowledgment Contributions

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Su Causeway in Spring Dawn


Lotus Flowers in the Breezing Winding Courtyard


Autumn Moon over the Calm Lake


Lingering Snow on the Broken Bridge

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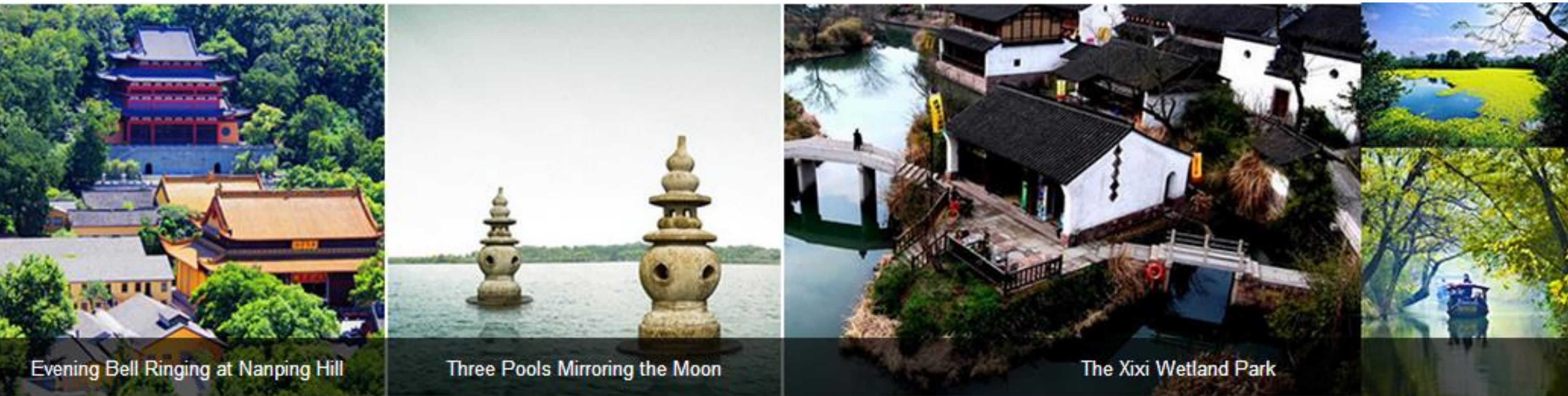

Thank you！

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