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Limits of Multilayer Diffusion Network Inference in Social Media Research

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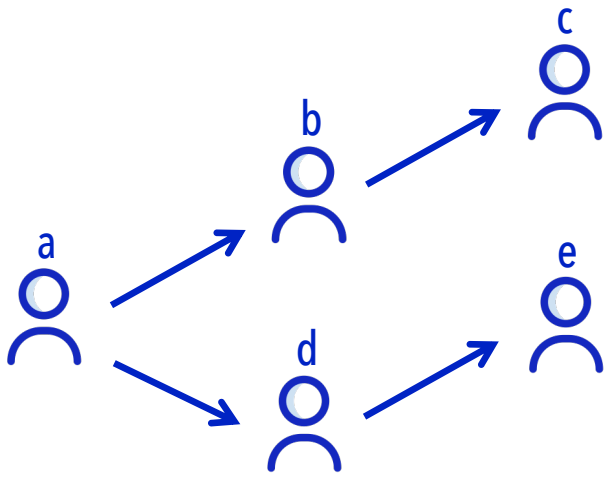
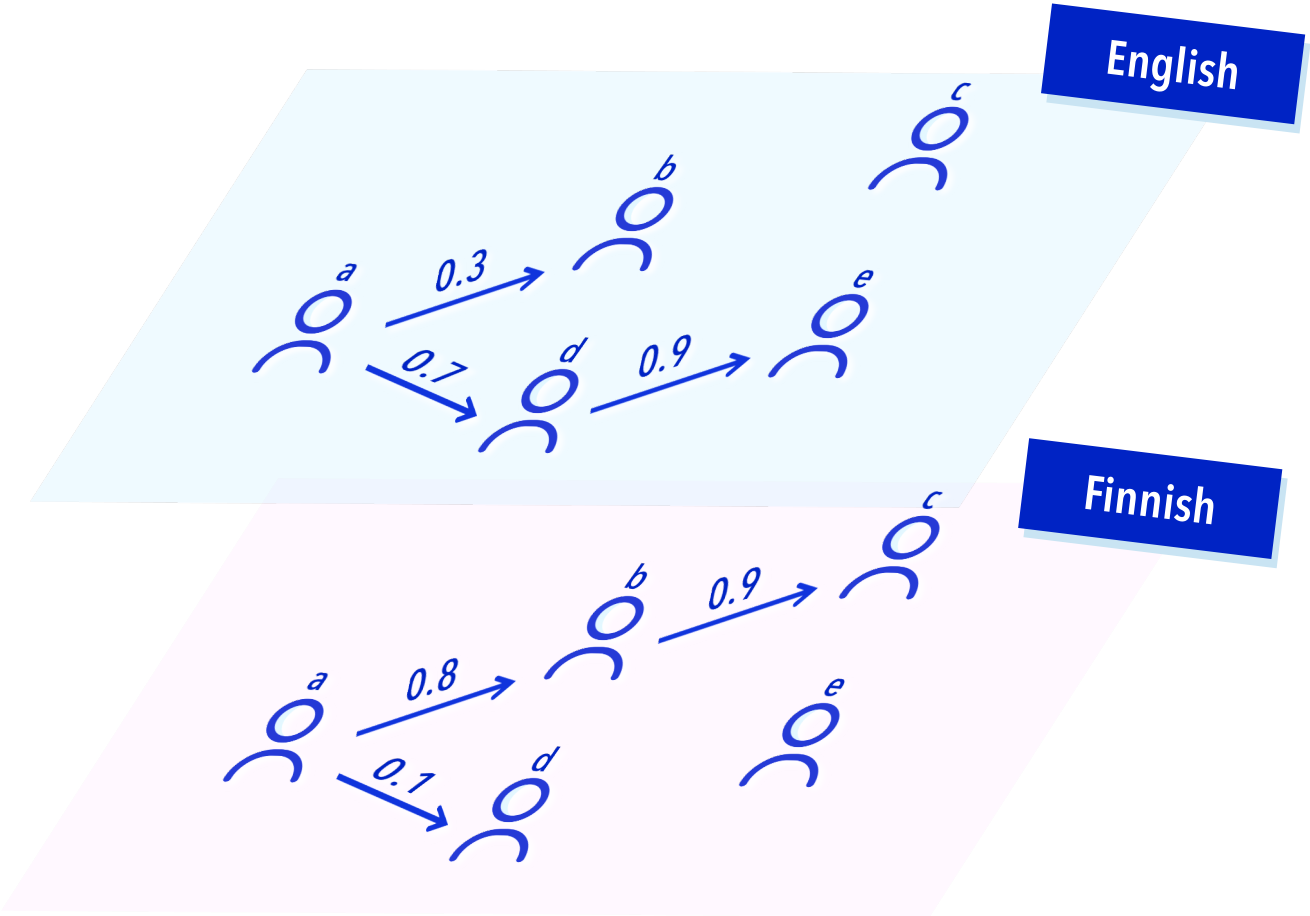
Motivation: Multilayer diffusion network

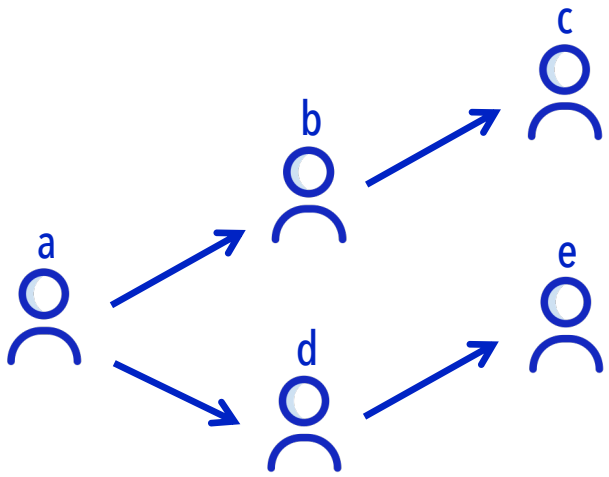


Single layer follower network



Multilayer diffusion network

Motivation: Multilayer diffusion network



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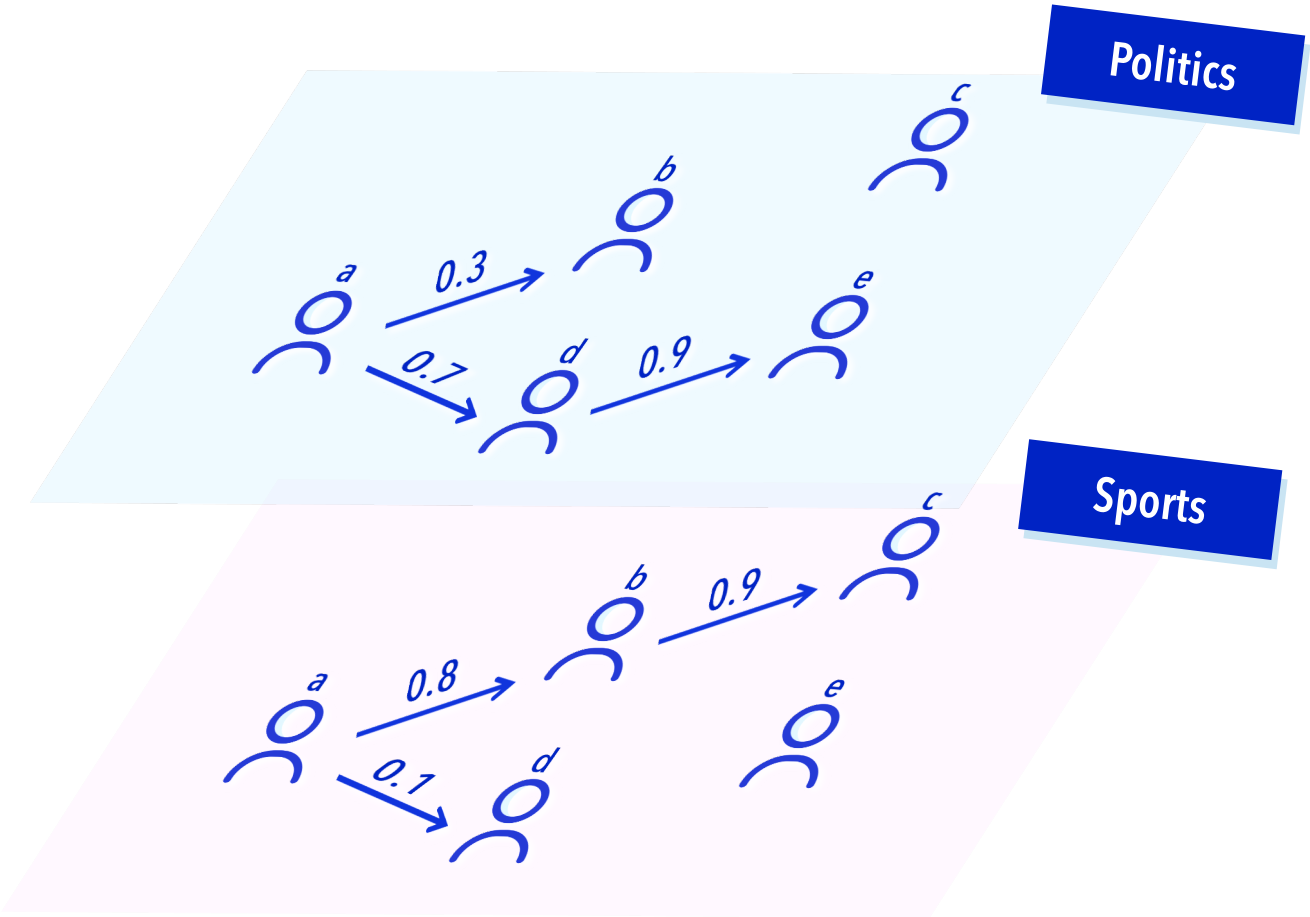

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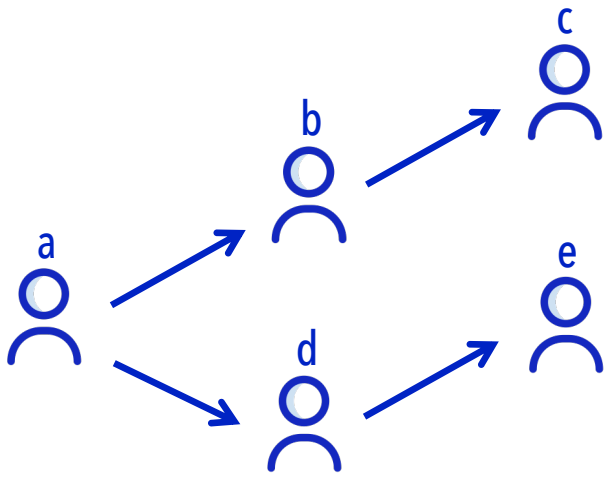

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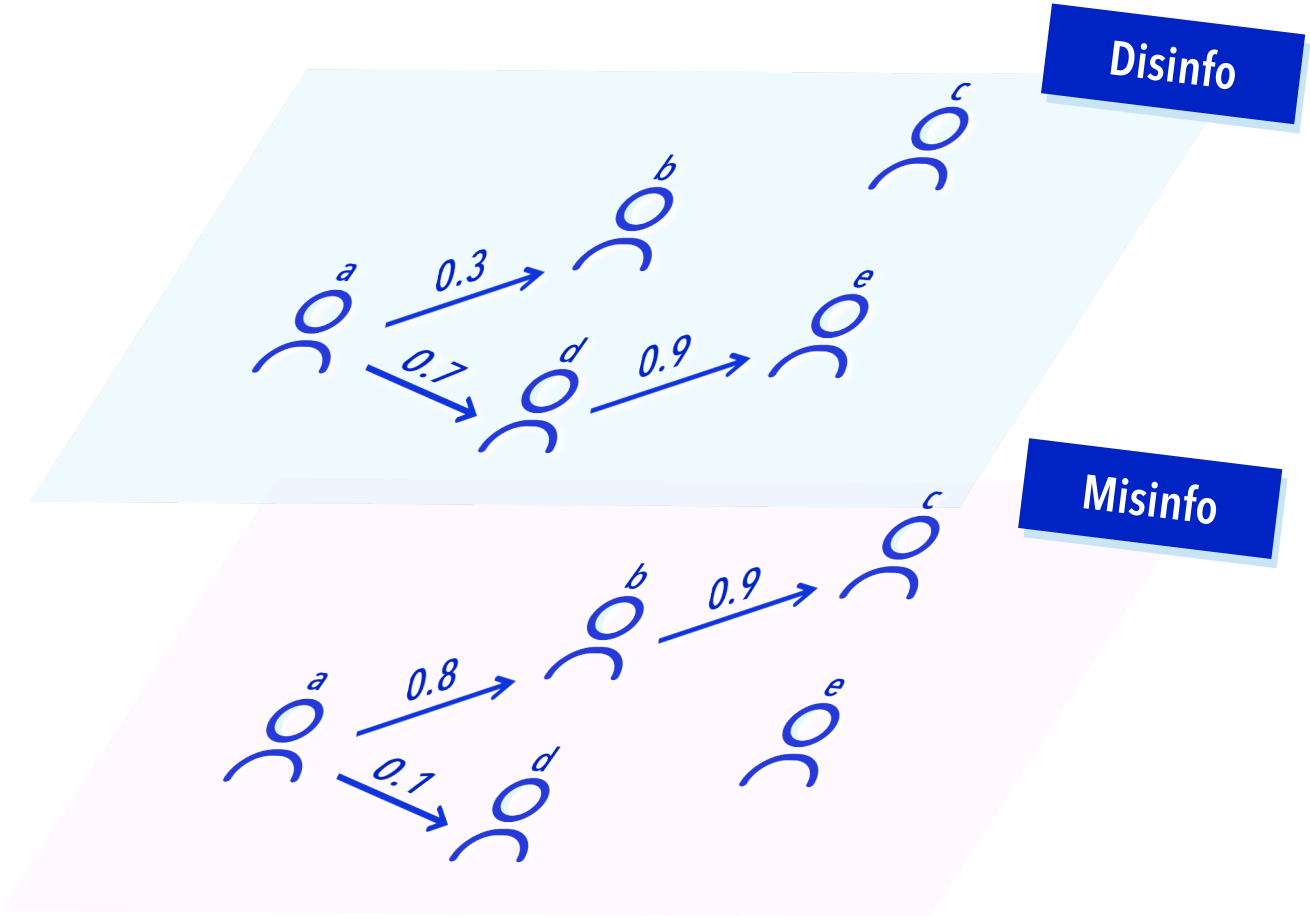

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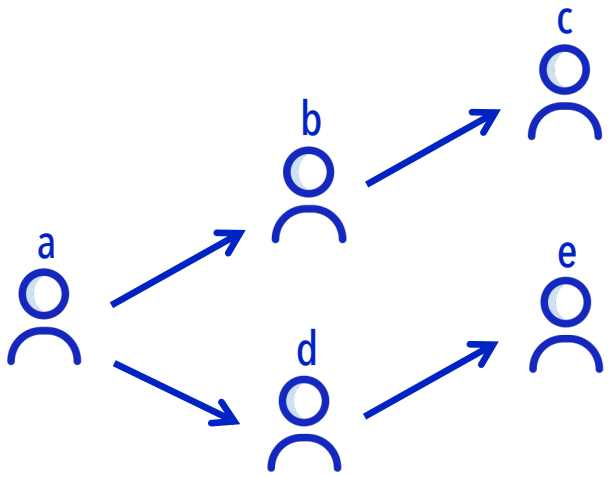

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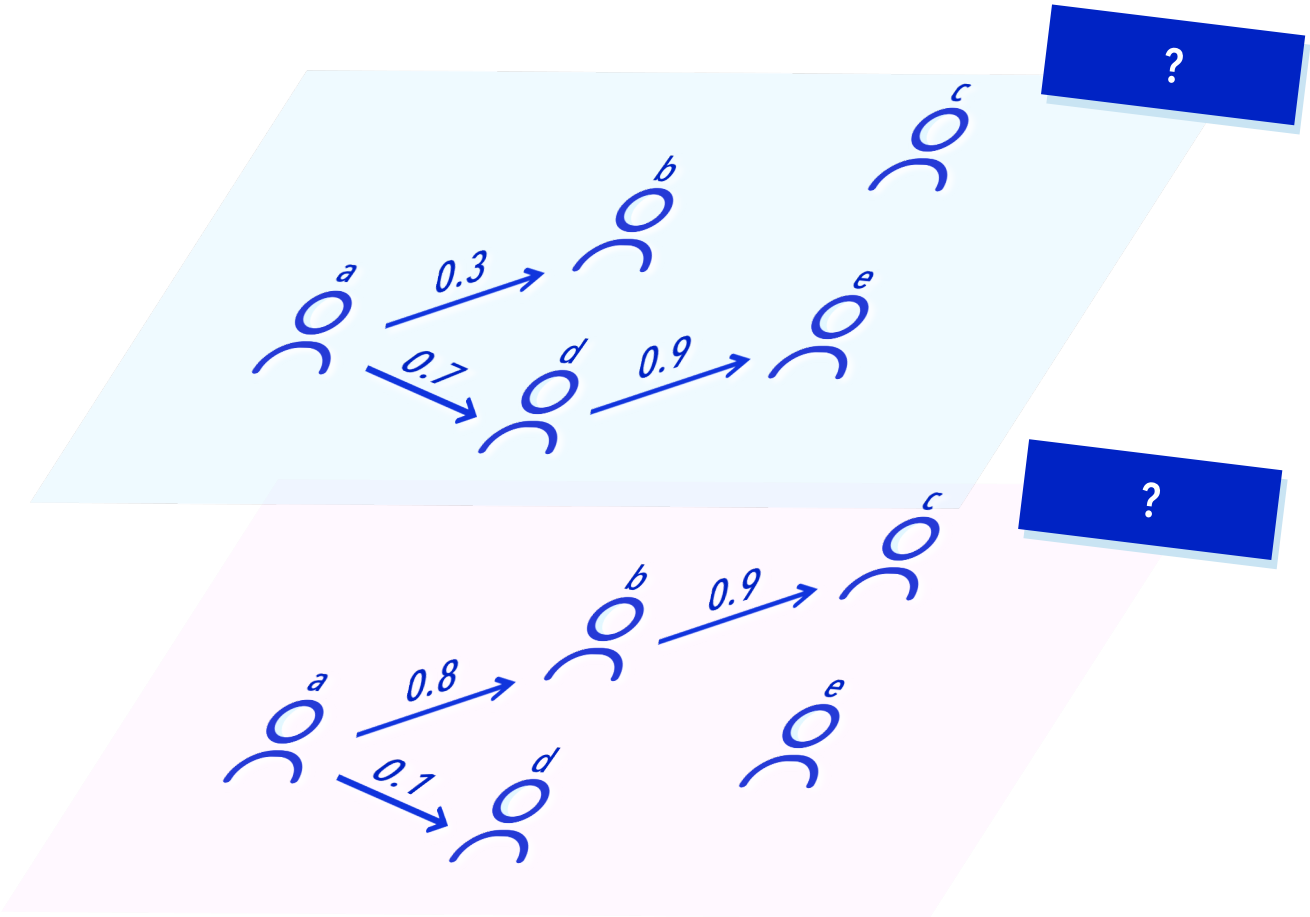

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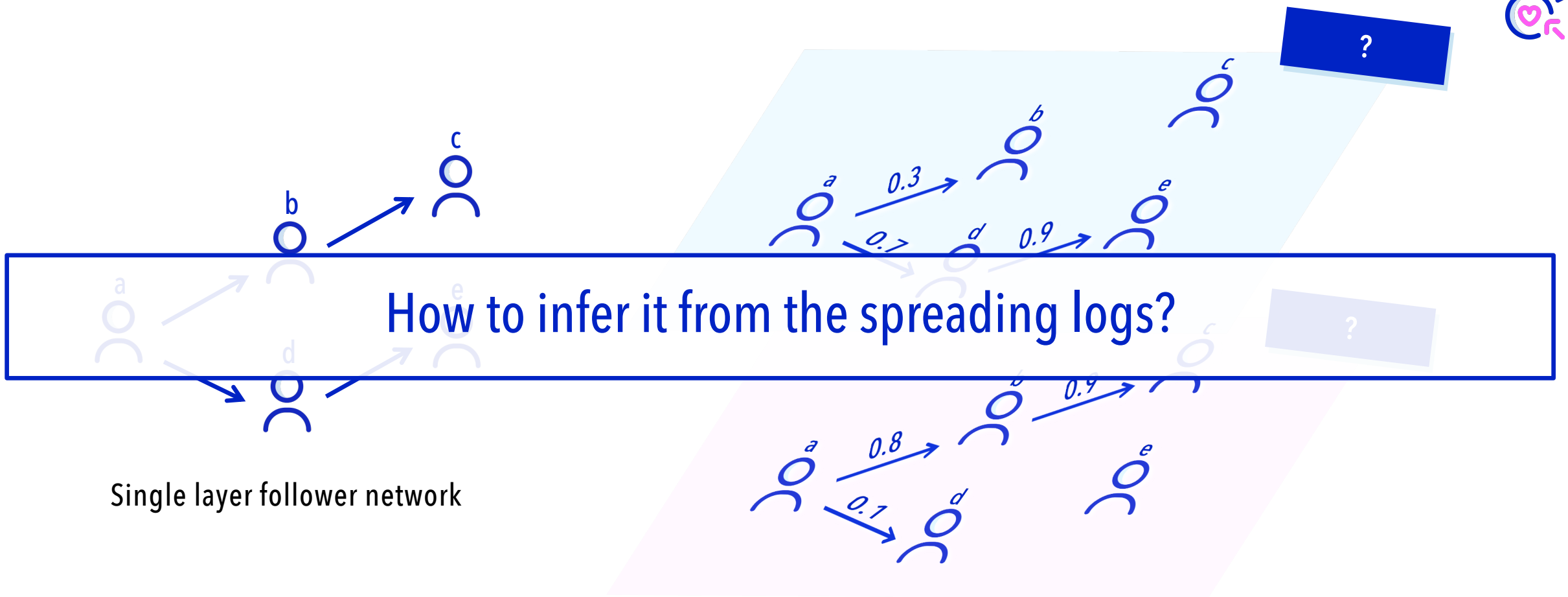


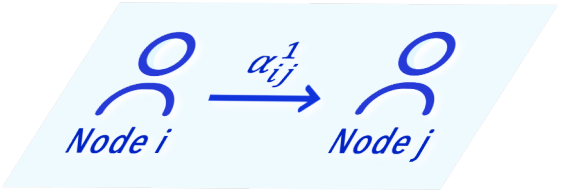
Generative spreading model [1]

Layer-wise edge weights α

Cascade membership π

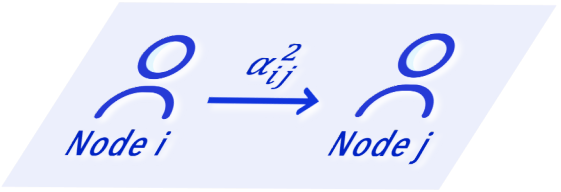
Cascade c

Layer 1



π_1^c

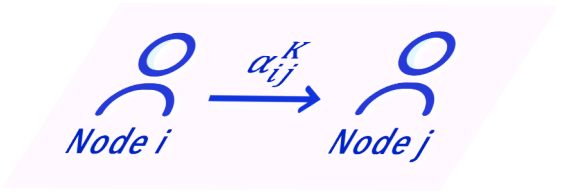
Layer 2



π_2^c

⋮ ⋮

Layer K



π_K^c

$\sum_{k=1}^{K} \pi_k^c = 1$

Transmission rate of cascade c from i to j

$$\lambda_{ij}^c = \sum_{k=1}^{K} \pi_k^c \alpha_{ij}^k$$

Transmission time of cascade c from i to j

$$\Delta t_{ij}^c \sim Exp(\lambda_{ij}^c)$$

Probability that i succeeds/fails to activate j on c

$$p_{ij}^c = f(\Delta t_{ij}^c; \lambda_{ij}^c) \qquad f(t) = P(T = t)$$

$$\overline{p_{ij}^c} = S(T - t_i^c; \lambda_{ij}^c) \qquad S(t) = P(T \geq t)$$

[1] Wang, S., Hu, X., Yu, P. S., & Li, Z. (2014, August). MMRate: inferring multi-aspect diffusion networks with multi-pattern cascades. In *Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining* (pp. 1246-1255).

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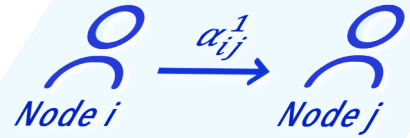

Cascade c

π_1^c

Transmission rate of cascade c from i to j

$$\lambda_{ij}^c = \sum_{k=1}^{K} \pi_k^c \alpha_{ij}^k$$

Minimize

$$-\log \mathcal{L}(\boldsymbol{\pi}, \boldsymbol{\alpha}) = \sum_c \sum_{j:t_j^c<T} \Big(\sum_{u:t_u^c<t_j^c} \Delta t_{uj}^c \sum_{k=1}^{K} \pi_k^c \alpha_{uj}^k - \log \sum_{i:t_i^c<t_j^c} \sum_{k=1}^{K} \pi_k^c \alpha_{ij}^k + \sum_{n:t_n^c>T} (T - t_n^c) \sum_{k=1}^{K} \pi_k^c \alpha_{jn}^k \Big)$$

Layer K

π_K^c

$$\sum_{k=1}^{K} \pi_k^c = 1$$

Probability that i succeeds/fails to activate j on c

$$p_{ij}^c = f(\Delta t_{ij}^c; \lambda_{ij}^c) \qquad f(t) = P(T = t)$$

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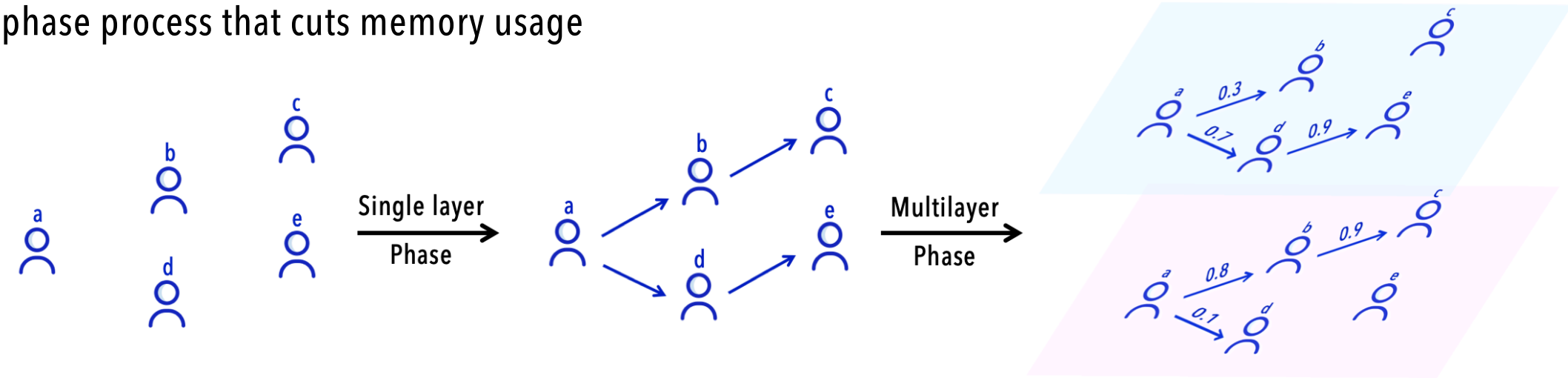
Implementation

Uses GPU computing for accelerating the optimization

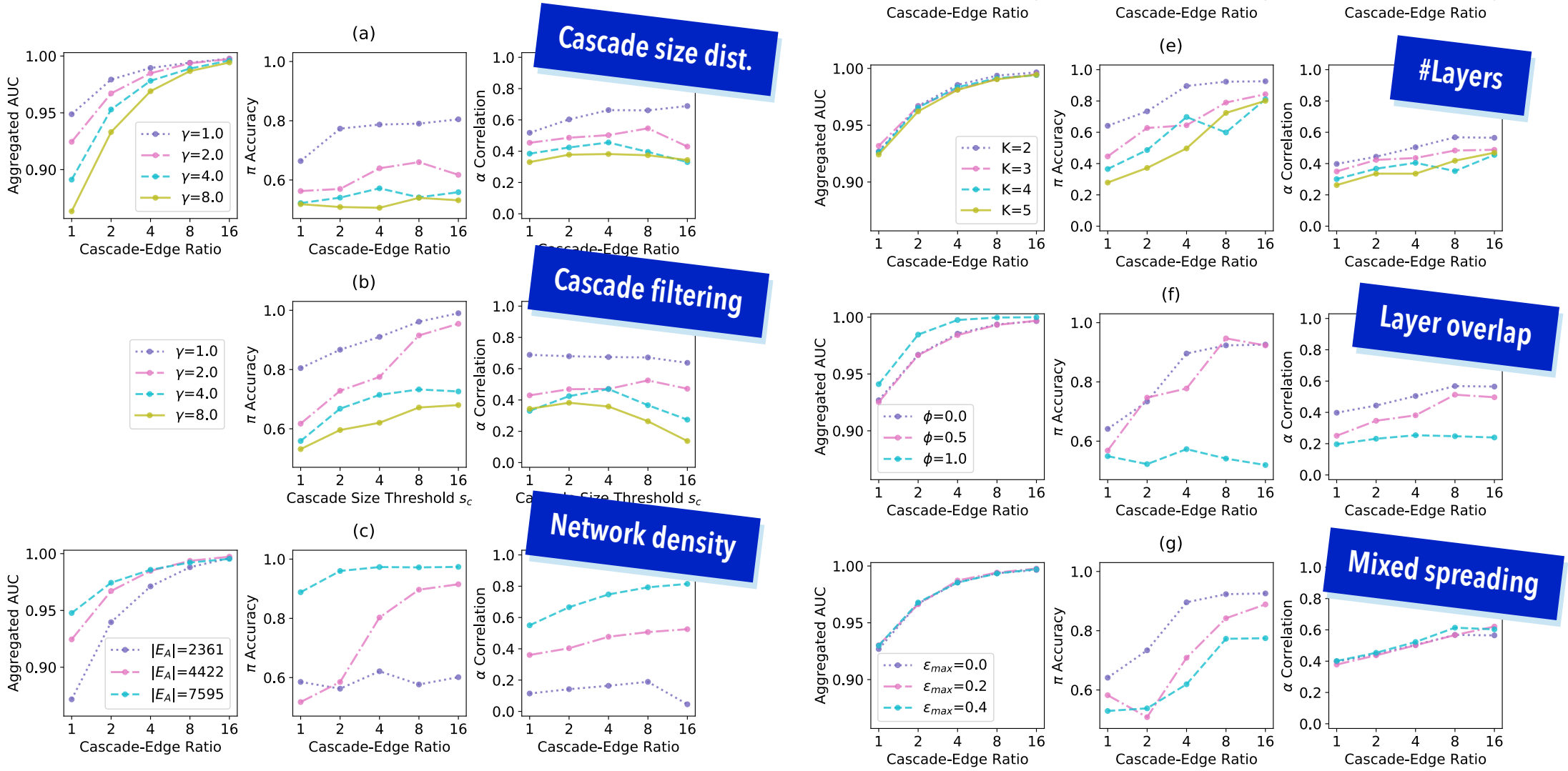
Two-phase process that cuts memory usage



Outperforms existing implementations in accuracy within comparable runtime

But realistic!

Synthetic data testing: Inference accuracy under varied …



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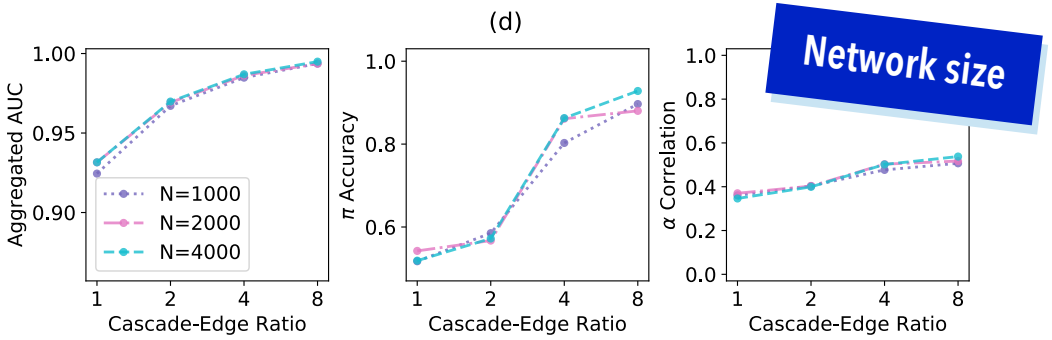

Takeaway 1: Excluding small cascades increases multilayer inference accuracy

Takeaway 2: The multilayer inference is still extremely inaccurate when
i) the proportion of large cascades is low OR
ii) the ground-truth network is sparse

Therefore:
i) We need to estimate the inference accuracy before applying the method to real data
ii) We need to develop a more real-data-applicable inference method

Thanks for listening!

Any question or comment?

Big thanks to: Aalto Scientific Computing and Barbara Keller

Code: https://github.com/ECANET-research/multic

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