FASCINATE: Fast Cross-Layer Dependency Inference on Multi-Layered Networks

Presented by Chen Chen


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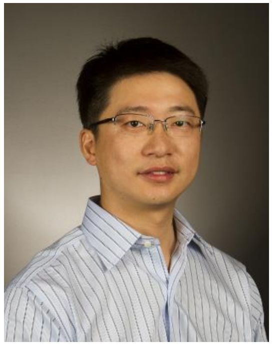
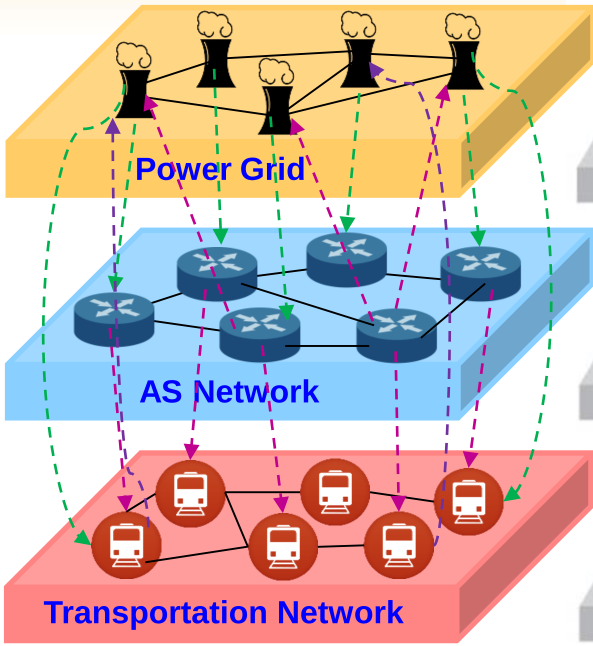
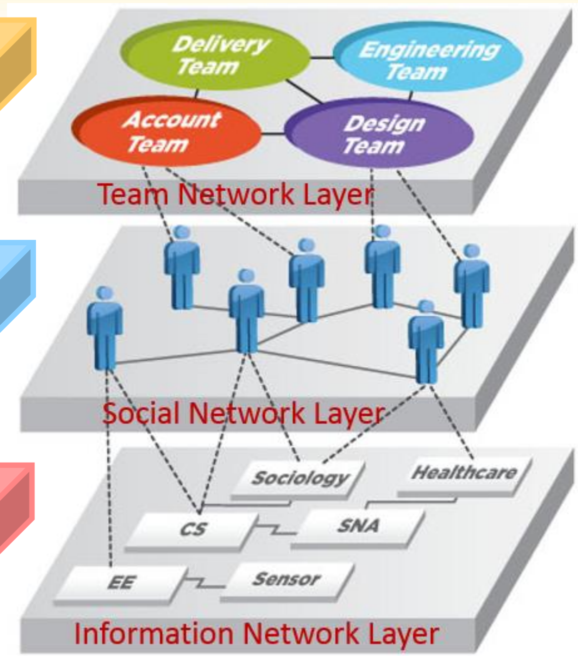
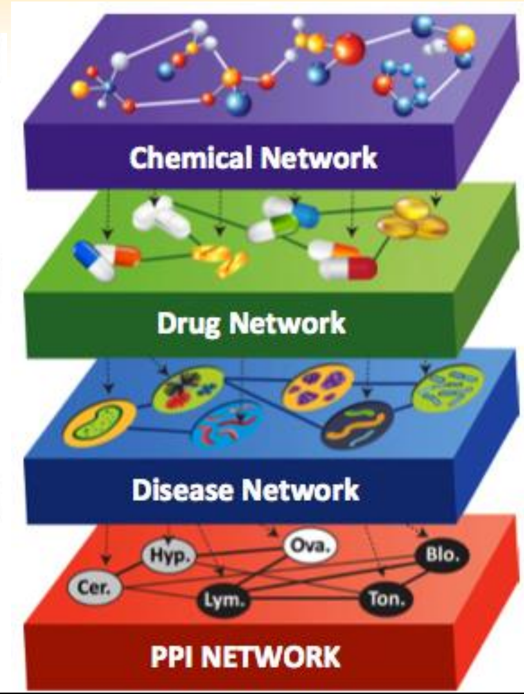

Lei Ying


Qing He

Multi-Layered Networks are Everywhere!



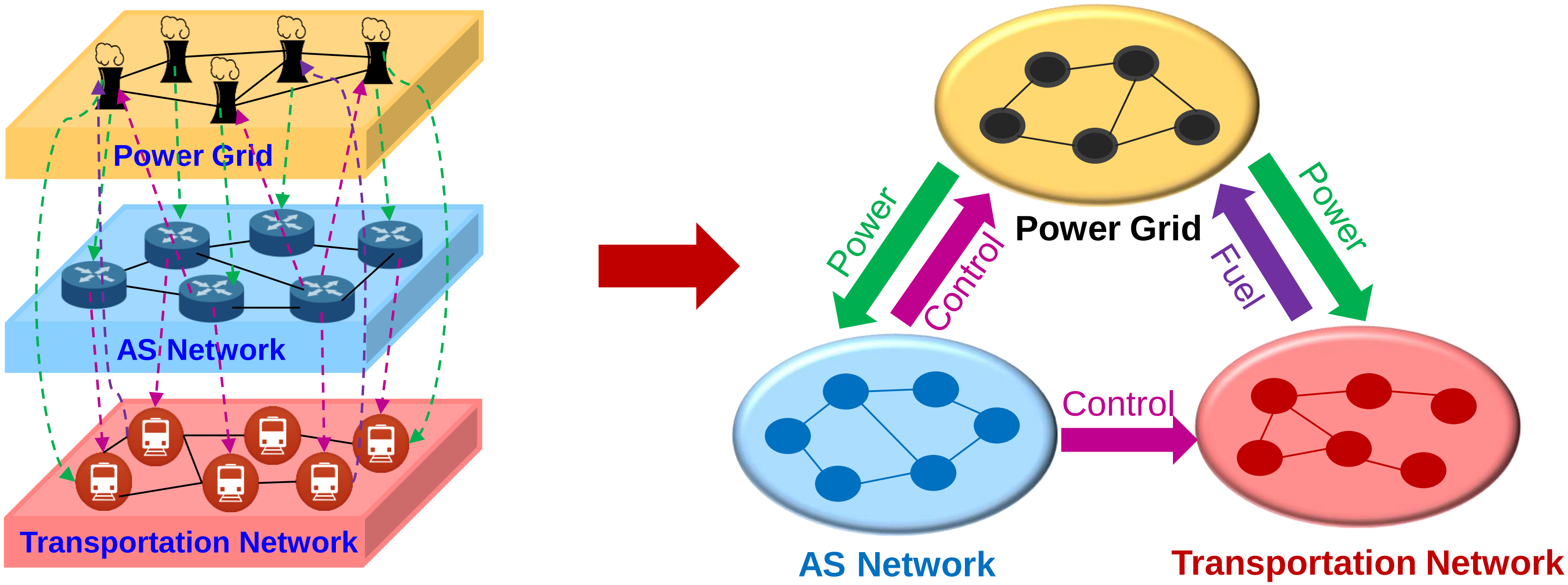




	Infrastructure Networks	Collaboration Platforms	Bio Systems
Intra-Layer	Power Grid AS Network Transportation Network	Team Network Social Network Information Network	Chemical Network Drug Network Disease Network PPI Network
Cross-Layer	**Power Supply**, **Control** (Power Station↔ Routers) **Power Supply**, **Fuel Supply** (Power Station↔Transportation) **Control** (Routers→Transportation)	**Membership** (Team→Employees) **Specialization** Employee→Information	**Composition** (Chemical→Drug) **Treatment** (Drug→Disease) **Association** (Disease→PPI)

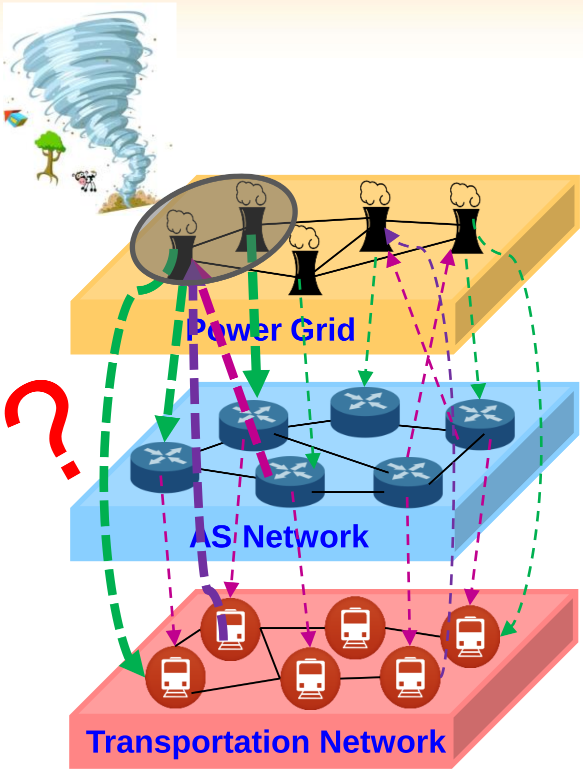
Cross-Layer Dependency

- **Role:** Unique topology characteristic of multi-layered networks

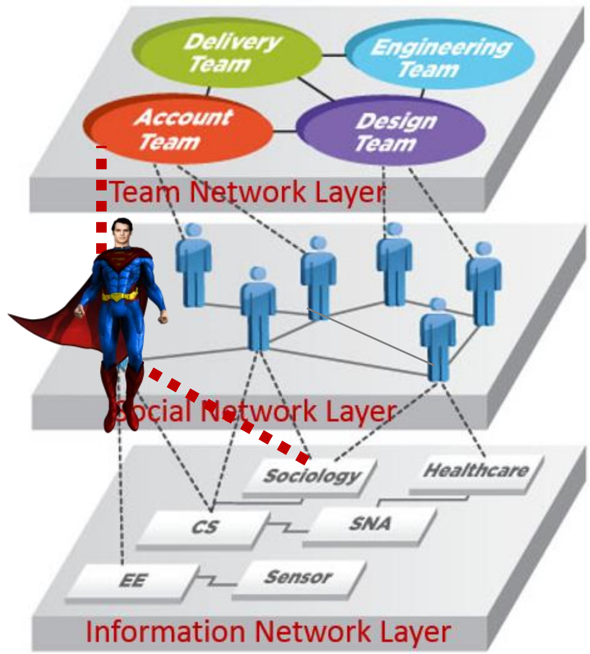


- **Importance:** Key to multi-layered network mining tasks (e.g. connectivity control, robustness analysis)
- **Challenge:** Incomplete cross-layer dependencies

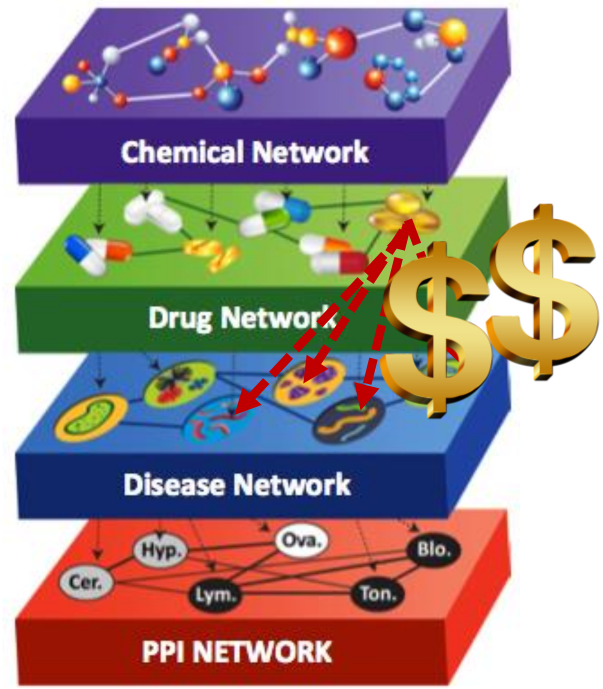
Infer Cross-Layer Dependency



Network Dynamics



Incomplete Record

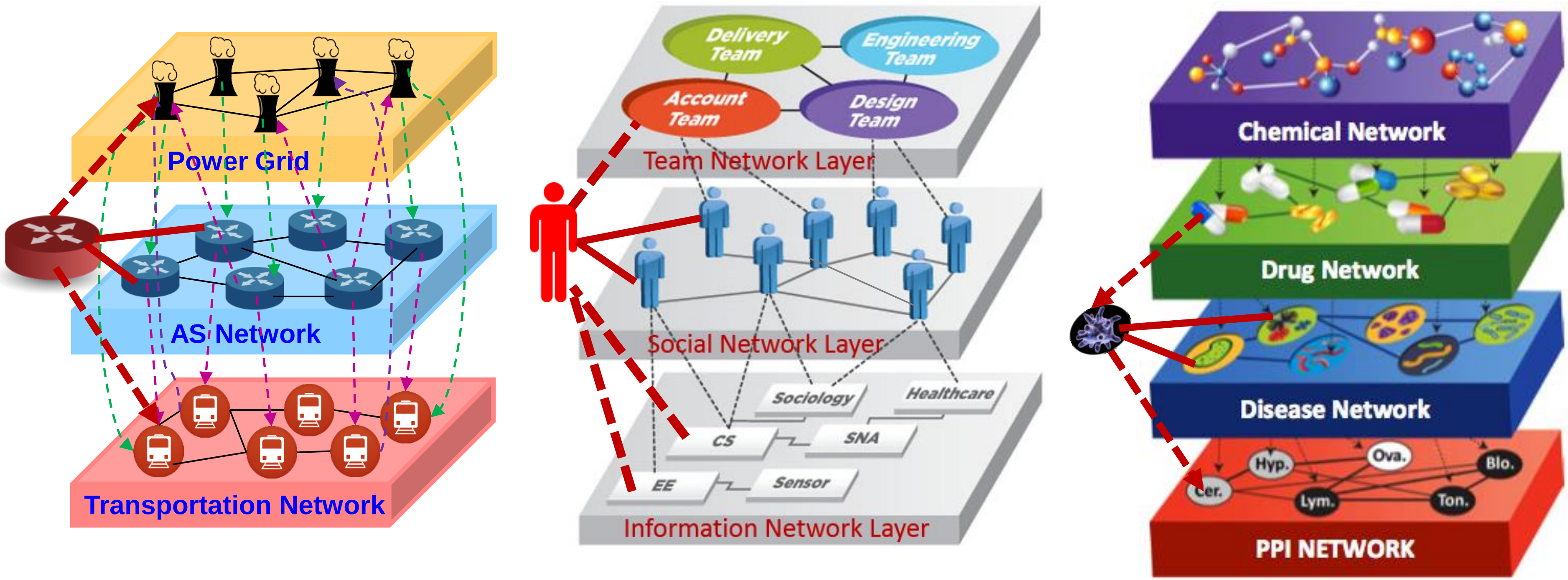


Limited Accessibility

- **Q1:** How to infer the hidden cross-layer dependencies?

Dependencies of Zero-Start nodes

- **Obs.:** New nodes are emerging over time

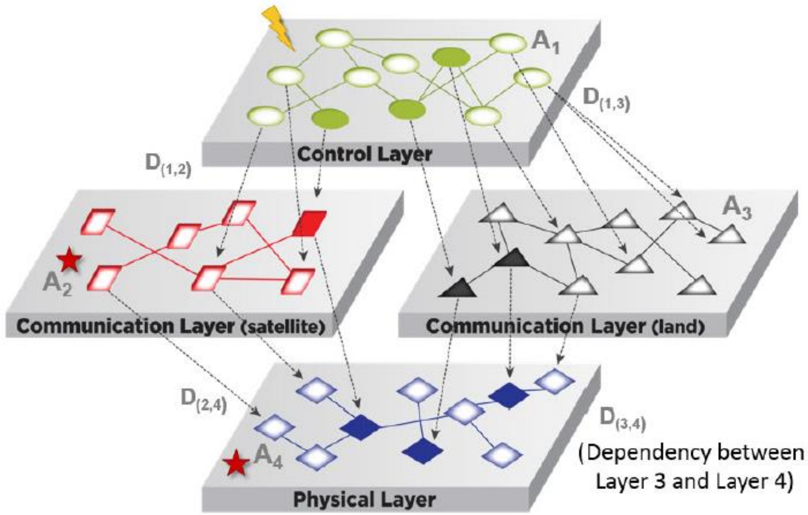


- **Q2:** How to efficiently infer the dependencies of zero-start nodes?

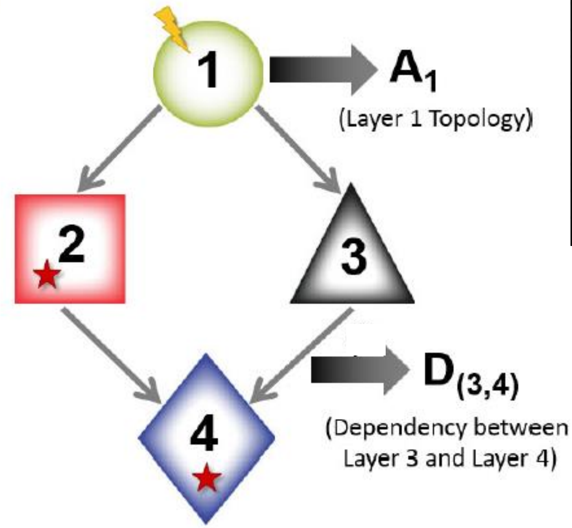
Roadmap

- Motivation
- Q1: Cross-Layer Dependency Inference
- Q2: Dependencies for Zero-Start Nodes
- Evaluations
- Conclusions

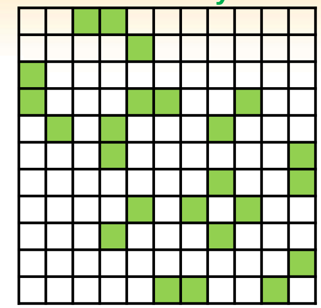
Background: A (Simplified) Multi-layered Network Model

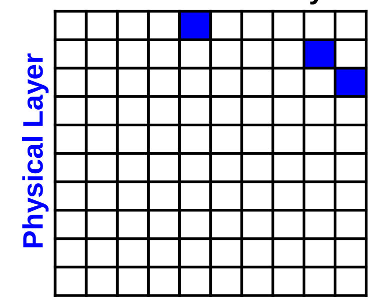


A four-layered network



layer-layer dependency network



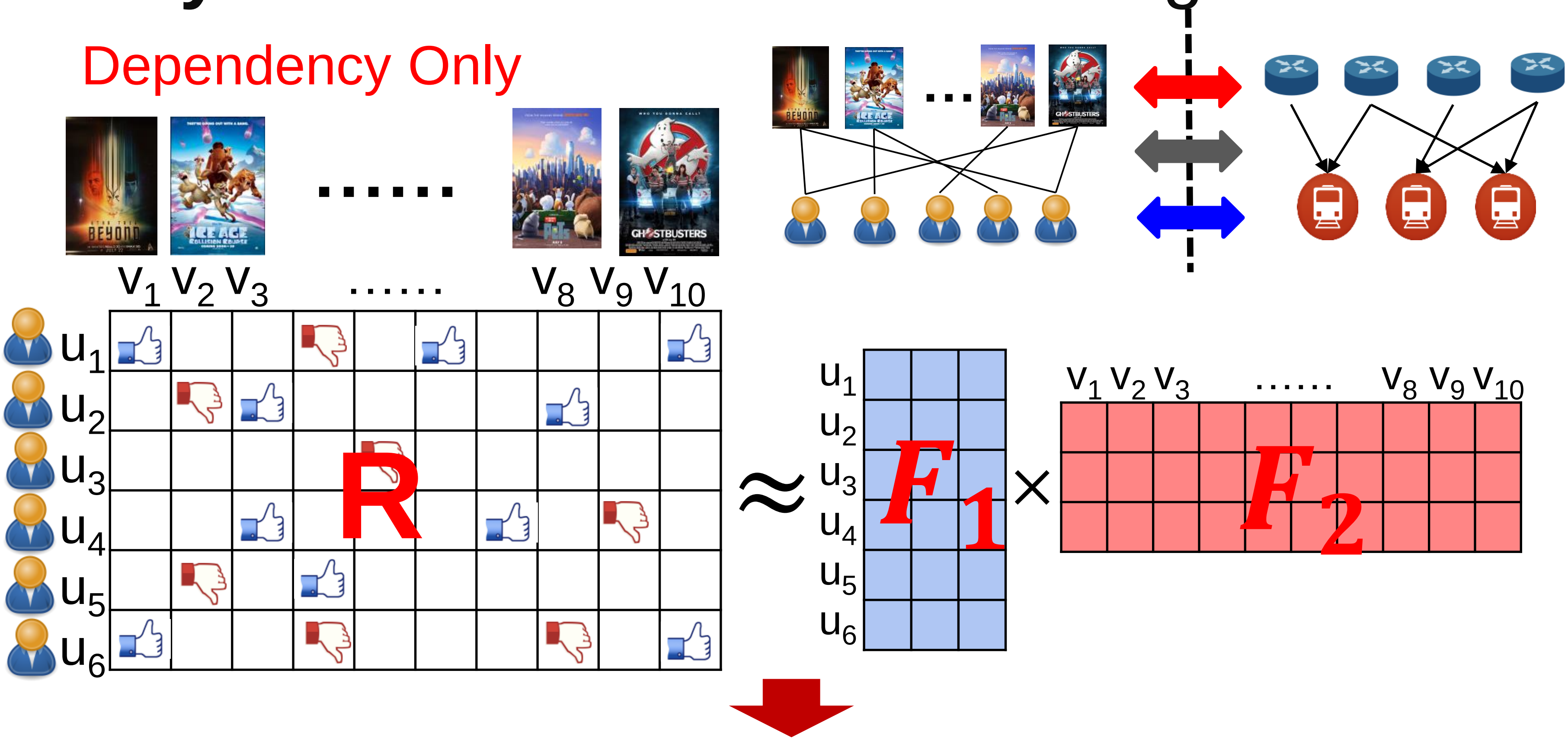


- **A tuple** $\Gamma = < G, A, D >$
  - *G:* layer-layer dependency network
  - ***A***: intra-layer connectivity
  - ***D***: cross-layer dependence

Chen Chen, Jingrui He, Nadya Bliss, Hanghang Tong: **On the Connectivity of Multi-layered Networks: Models, Measures and Optimal Control.** ICDM 2015: 715-720

Q1: Dependency Inference

- **Key Idea 1**: Collaborative Filtering

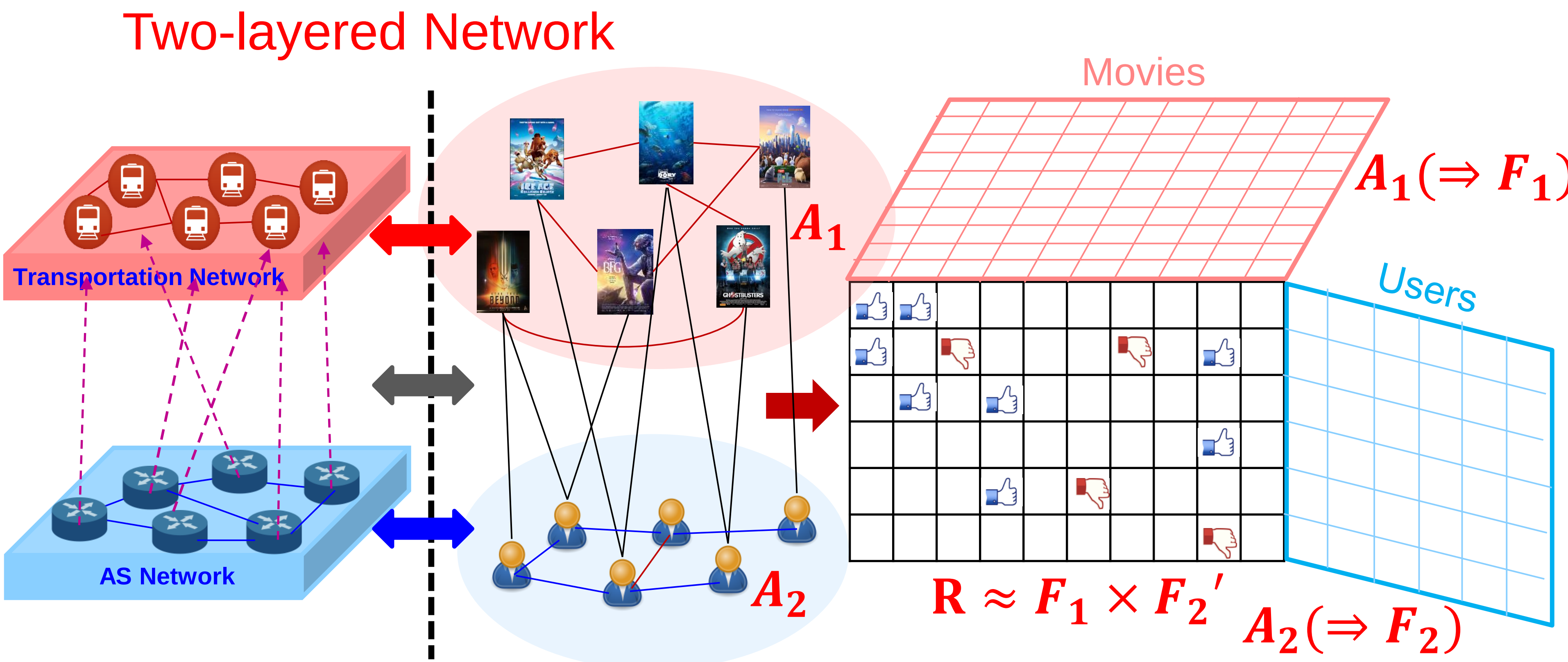


$$\mathbf{R} \approx F_1 \times F_2'$$

Users ≈ Routers| Movies ≈ Transportation | Known Ratings ≈ Observed Cross-Layer Dependency

Q1: Dependency Inference

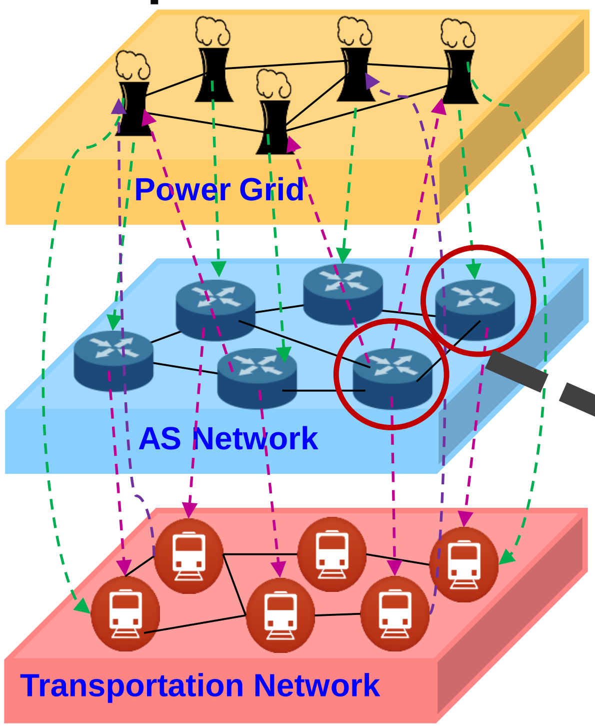
- **Key Idea 2:** Collaborative Filtering with Side Information

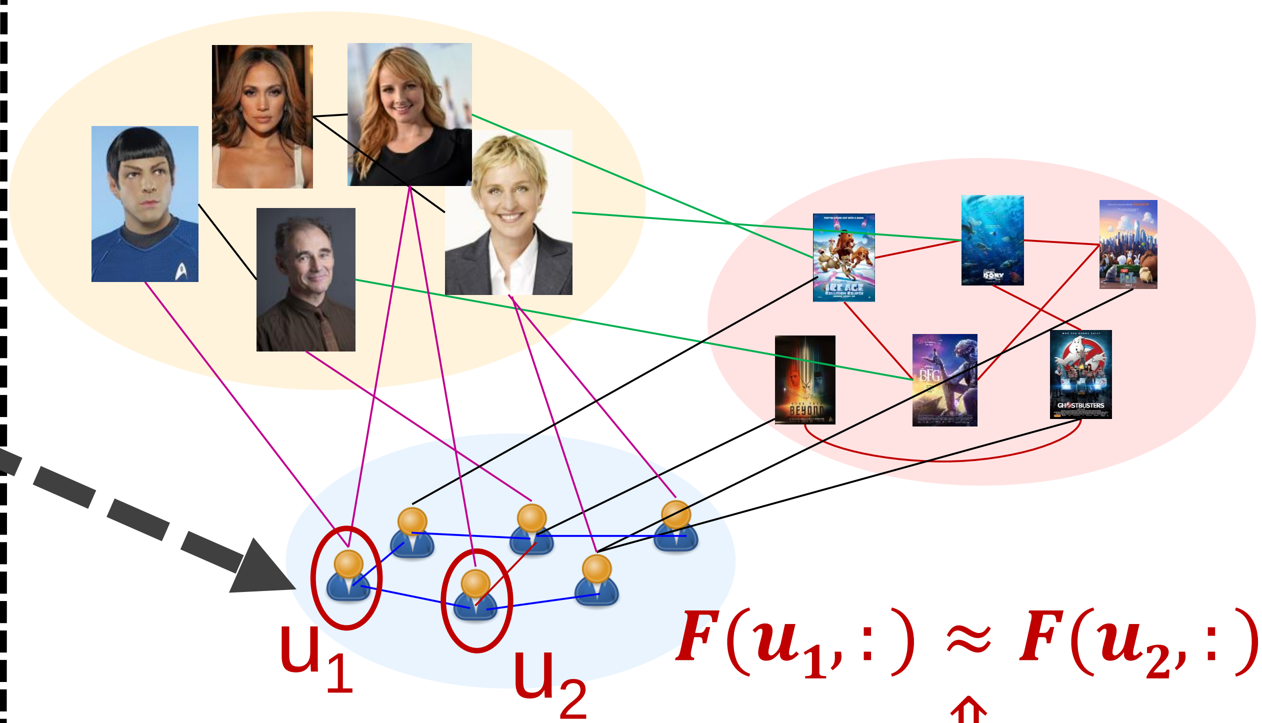


Movie-Movie Similarity ≈ Transportation Network | Social Network ≈ AS Network
Known Ratings ≈ Support from Routers to Transportation Network

Node Homophily

- **Assumption**: closely connected entities within each layer tend to have similar latent profiles





$$\boldsymbol{F(u_1,:) \approx F(u_2,:)}$$

$$\Updownarrow$$

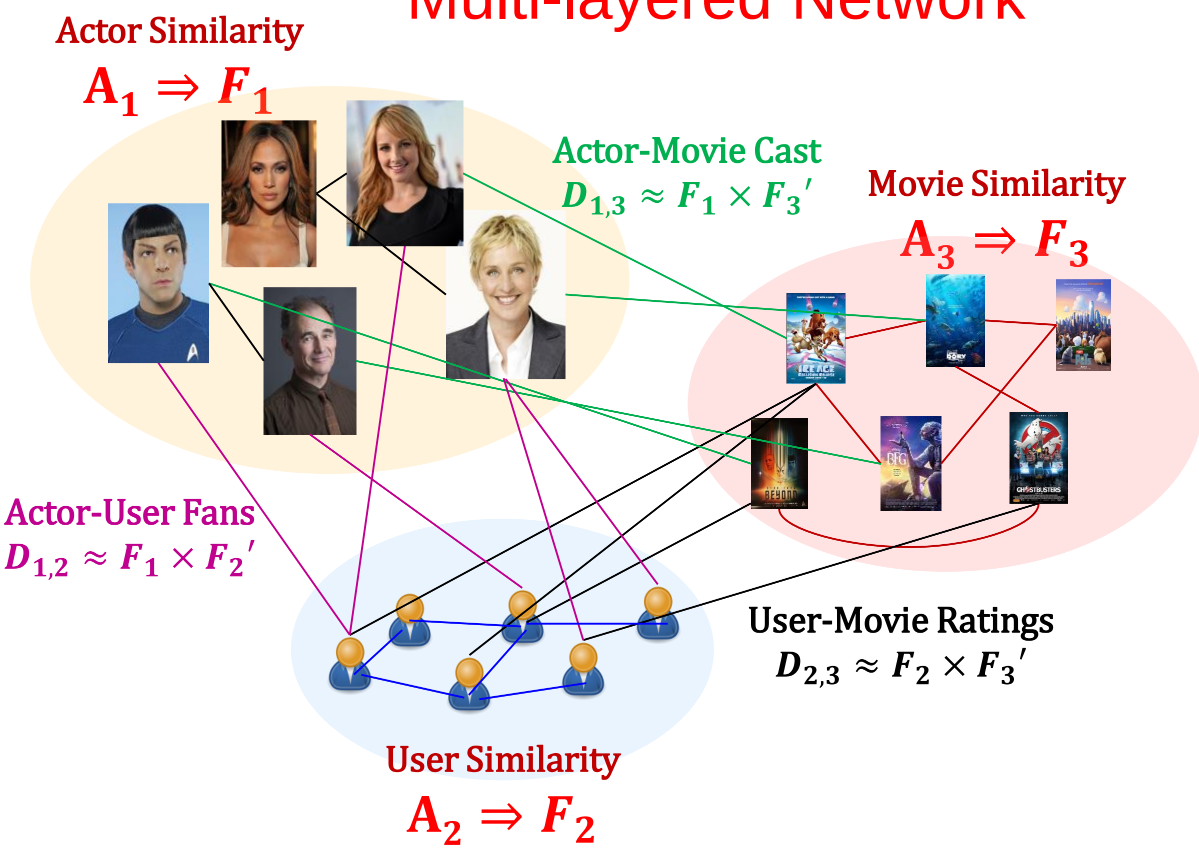
$$(\min \boldsymbol{tr(F'(D_U - U)F)})$$

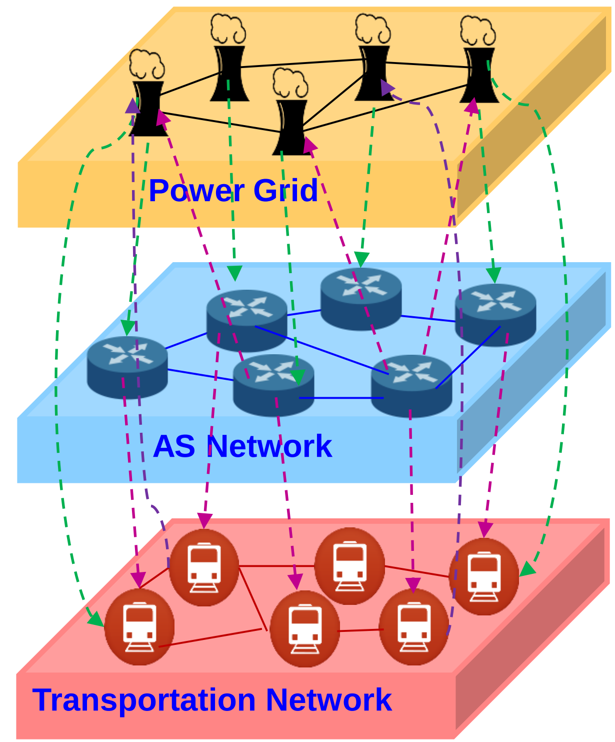
Celebrities ≈ Power Plants | Users ≈ Routers | Movies ≈ Transportation
Known Ratings, Movie Cast, Fans ≈ Observed Cross-Layer Dependencies

Q1: Dependency Inference

- **Key Idea 3:** Collective Collaborative Filtering

Multi-layered Network





Celebrities ≈ Power Plants | Users ≈ Routers | Movies ≈ Transportation
Known Ratings, Movie Cast, Fans ≈ Observed Cross-Layer Dependencies

Optimization Problem

- **Objective Function:**

$$\min_{F_i \geq 0 (i=1,\dots,g)} J = \sum_{i,j:G(i,j)=1} \underbrace{\| W_{i,j} \odot (D_{i,j} - F_i F_j{}') \|_F^2}_{\text{Matching observed cross-layer dependencies}} +$$

$$\alpha \sum_i \underbrace{tr(F_i{}'(T_i - A_i)F_i)}_{\text{Node homophily}} + \beta \sum_i \underbrace{\| F_i \|_F^2}_{\text{Regularization}}$$

- **Challenge**: Not jointly convex w.r.t. $F_{i(i=1,\dots,g)}$!

Hard to find **global** optimal solution!

- **Q:** How to find a **local** optimal?

FACINATE: Proposed Solution

- **Obs.: J** becomes convex if we fix all but one (e.g. $\mathbf{F_i}$) latent matrices
- **Method:** Block coordinate descent

Fixing all other $F_{j(j \neq i)}$, the objective function w.r.t. F_i is

$$\min_{F_i \geq 0} J_i = \sum_{j:G(i,j)=1} \underbrace{\| W_{i,j} \odot (D_{i,j} - F_i F_j') \|_F^2}_{\text{Cross-layer dependencies that involve layer } i} + \underbrace{\alpha tr(F_i'(T_i - A_i)F_i)}_{\text{Homophily in layer } i} + \underbrace{\beta \| F_i \|_F^2}_{\text{Layer regularization}}$$

$\boxed{\mathbf{J_i} \text{ is convex w.r.t. } \mathbf{F_i}}$

- **Multiplicative Update Rules:**

$$F_i(u,v) \leftarrow F_i(u,v) \sqrt{\frac{X(u,v)}{Y(u,v)}} \quad \begin{cases} X = \sum_{j:G(i,j)=1} (W_{i,j} \odot W_{i,j} \odot D_{i,j}) F_j + \alpha A_i F_i \\ Y = \sum_{j:G(i,j)=1} (W_{i,j} \odot W_{i,j} \odot (F_i F_j')) F_j + \alpha T_i F_i + \beta \end{cases}$$

Roadmap

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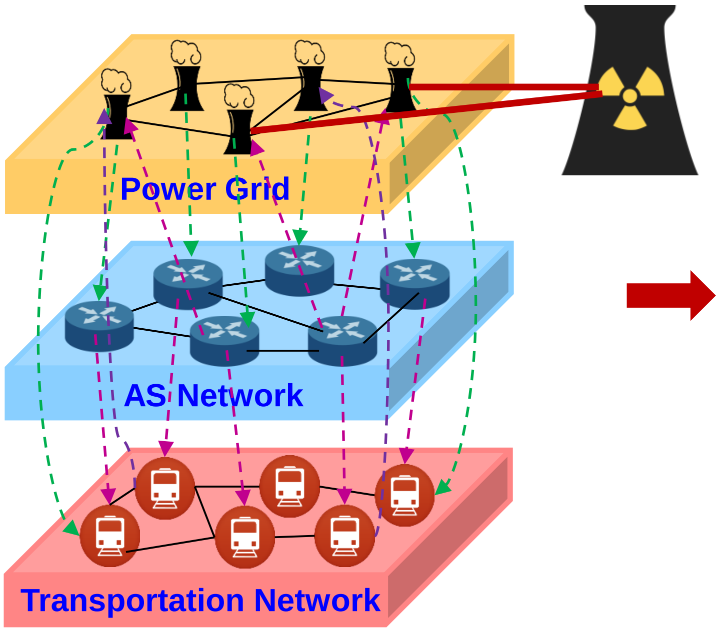
Q2: Dependencies for zero-start nodes



$$\begin{array}{c c} & A_1 \\ \mathbf{s} & \end{array}$$

$$\hat{A}_1 = \begin{bmatrix} A_1 & s' \\ s & 0 \end{bmatrix}$$

$F_i \rightarrow \hat{F}_i \quad (i \neq 1)$

$F_1 \rightarrow \hat{F}_1 = [\hat{F}_{1(n1 \times r)}, f]$

Existing Nodes **New Node**

Decompose Objective Function

$$\hat{J} = J + J^1$$

J: objective function without zero-start node

J^1: $\alpha \sum_{v=1}^{n_1} \mathbf{s}(v) \parallel f - \hat{F}_1(v,:) \parallel_2^2 + \parallel f \parallel_2^2$

Local Neighbors

DATA Lab

Q2: Dependencies for zero-start nodes

- **Objective Function with Zero-Start Node:**

$$min_{\hat{F}_i \geq 0}\ \hat{J} = J + J^1 \qquad \begin{cases} J\text{: objective function without zero-start node} \\ J^1\text{: } \alpha \sum_{v=1}^{n_1} \boldsymbol{s}(v) \parallel f - \hat{F}_1(v,:) \parallel_2^2 + \parallel f \parallel_2^2 \end{cases}$$

- **Local Search Assumption:**

$$\hat{F}_{1(n_1 \times r)} \approx F_1 \qquad \hat{F}_i \approx F_i \ (i \neq 1)$$

- **Solution:**

$$min_{\hat{F}_i \geq 0}\ \hat{J} = J + J^1 \Rightarrow min_{f \geq 0}\ J^1 \text{ sub. to } \hat{F}_{1(n_1 \times r)} = F_1^*$$

$$f = \frac{\alpha \boldsymbol{s} F_1^*}{\beta + \alpha \sum_{v=1}^{n_1} \boldsymbol{s}(v)}$$

Only related to zero-start node's local neighbors!

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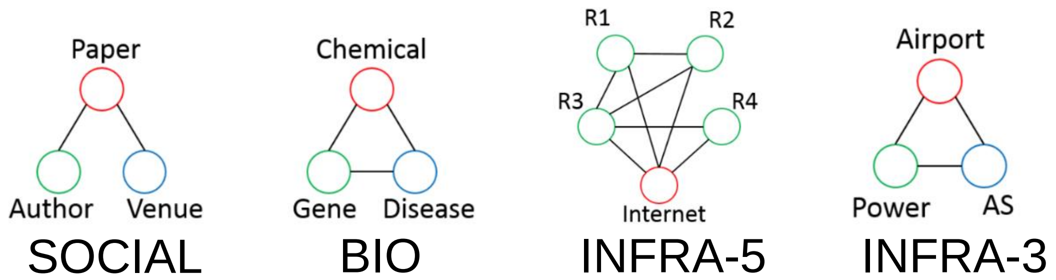
Experimental Set-up

- **Datasets:**



Datasets	#Layers	#Nodes	#Links	#CrossLinks
SOCIAL	3	125,344	214,181	188,844
BIO	3	35,631	253,827	75,456
INFRA-5	5	349	379	565
INFRA-3	3	15,126	29,861	28,023,500

- **Evaluation Objectives:**
  - Effectiveness: How accurate is FACSINATE?
  - Efficiency: How fast is FACSINATE?

Effectiveness of FASCINATE (Q1)

Cross-layer dependency inference on BIO dataset

Methods	MAP	R-MPR	HLU	AUC	Prec@10
FASCINATE	**0.3979**	**0.4066**	**45.1001**	**0.9369**	**0.1039**
FASCINATE-CLUST	0.3189	0.3898	37.4089	0.9176	0.0857
MulCol	0.3676	0.3954	42.8687	0.9286	0.0986
PairSid	0.3623	0.3403	40.4048	0.8682	0.0941
PairCol	0.3493	0.3153	38.4364	0.8462	0.0889
PairNMF	0.1154	0.1963	15.8486	0.6865	0.0393
PairRec	0.0290	0.2330	3.6179	0.7105	0.0118
FlatNMF	0.2245	0.2900	26.1010	0.8475	0.0615
FlatRec	0.0613	0.3112	8.4858	0.8759	0.0254

FASCINATE performs best!

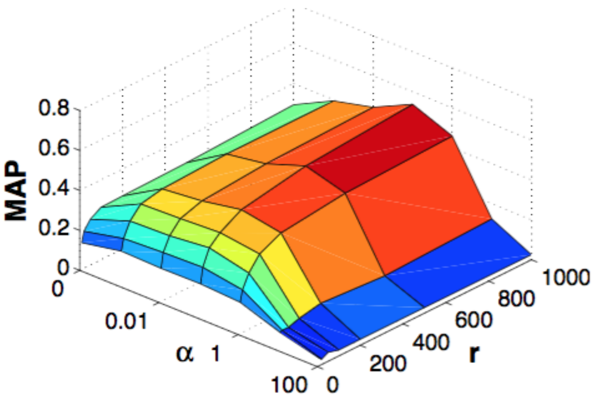
MAP: Mean Average Precision **R-MPR**: Reverse Mean Percentage Ranking
HLU: Half-Life Utility **AUC**: Area Under ROC Curve **Prec@K**: Precision at K

Parameter Studies

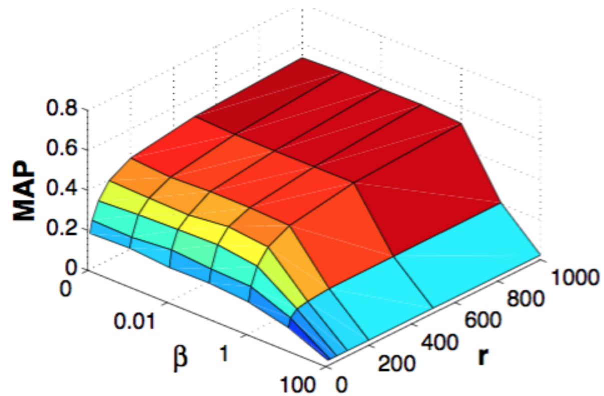
- Parameters: α, β, r

$$\min_{F_i \geq 0} J = \sum_{i,j:G(i,j)=1} \| W_{i,j} \odot (D_{i,j} - F_i F_j') \|_F^2 + \boldsymbol{\alpha} \sum_i tr(F_i'(T_i - A_i)F_i) + \boldsymbol{\beta} \sum_i \| F_i \|_F^2$$

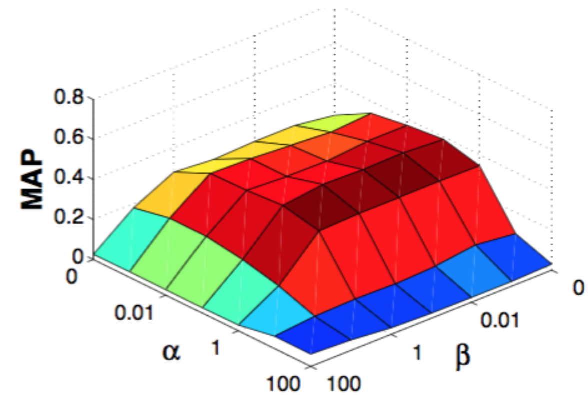
($\boldsymbol{r}$: rank of $F_{i\ (i=1,\ldots,g)}$)



Impact of α and r



Impact of β and r

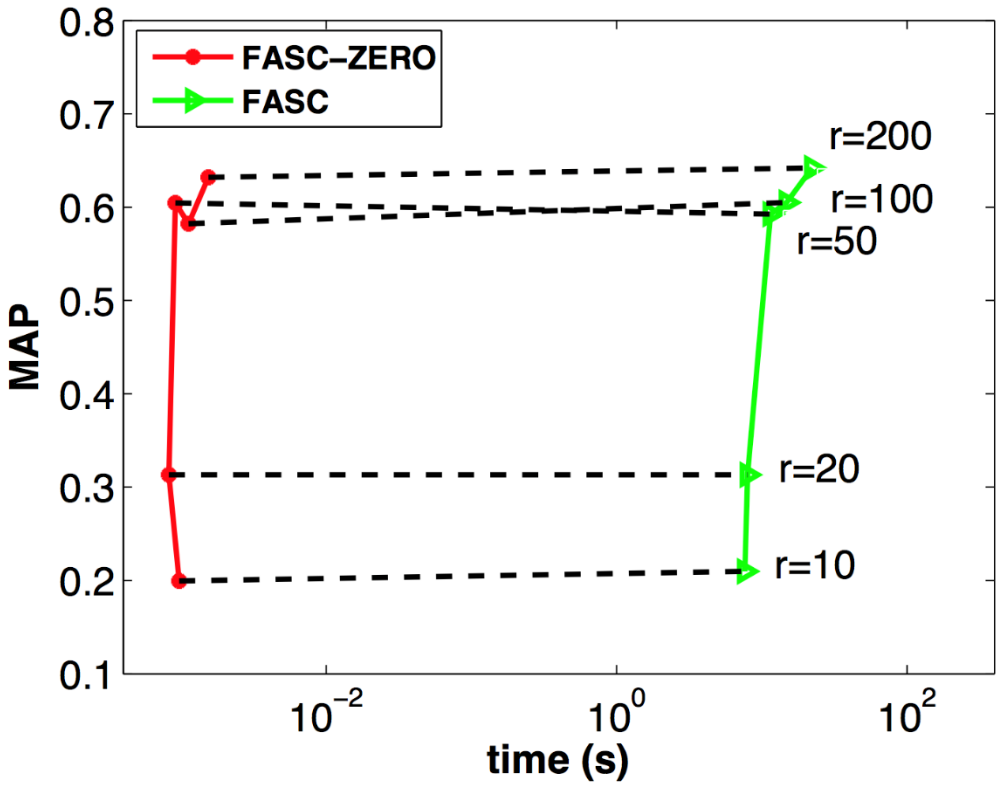


Impact of α and β

FASCINATE is stable in wide range of parameter settings!

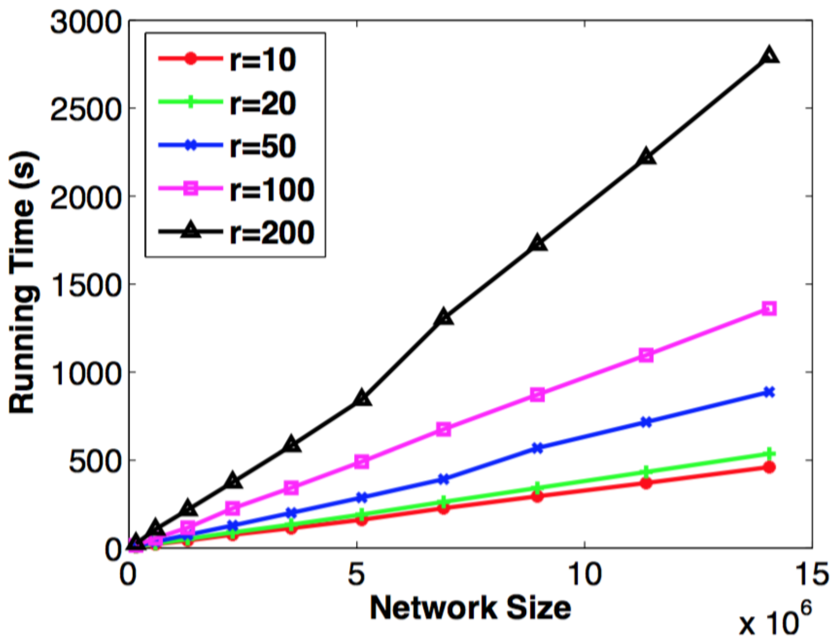
Effectiveness of FASCINATE-ZERO (Q2)

- FASCINATE-ZERO vs. FASCINATE



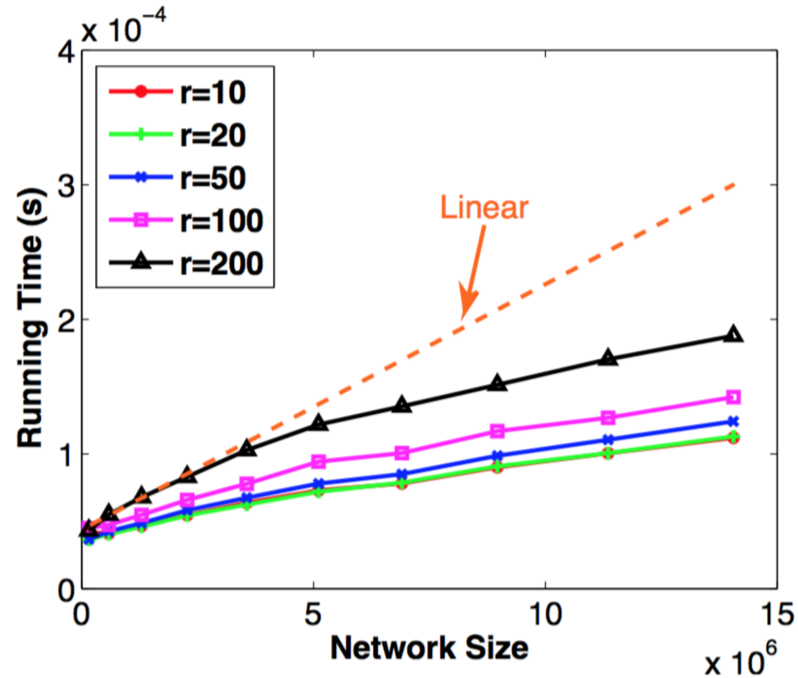
FASCINATE-ZERO: similar performance, faster speed!

Scalability



FASCINATE (Q1)

Linear



FASCINATE-ZERO (Q2)

Sub-linear

Roadmap

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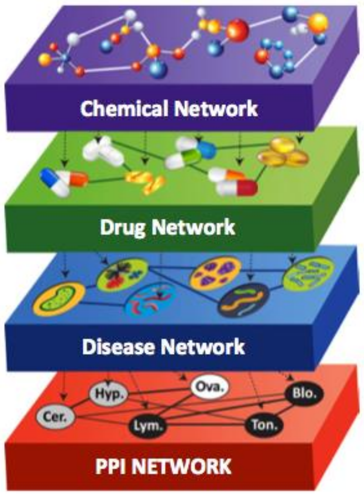
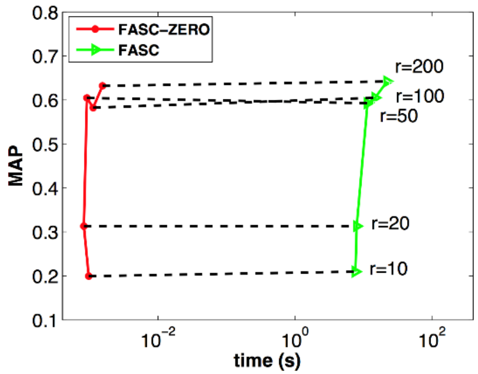
Conclusions

- **Cross-Layer Dependency Inference**
  - **Key Ideas**:
    - Collective Collaborative Filtering + Node Homophily
    - Local Search (for zero-start nodes)
  - **Methods**: FASCINATE & FASCINATE-ZERO



- **Results**
  - **Effectiveness**: 8.2%-41.9% over best competitors
  - **Efficiency**: linear (FASCINATE), sublinear (FASCINATE-ZERO)



- **More in paper**
  - Variants
  - Convergence analysis & Effectiveness results
- **Code:** [http://www.public.asu.edu/~cchen211]