Towards Optimal Teams in Big Networks

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Teams Are Everywhere

1. Film Crew

2. Sports Team

3. Sales Team

4. Research Team

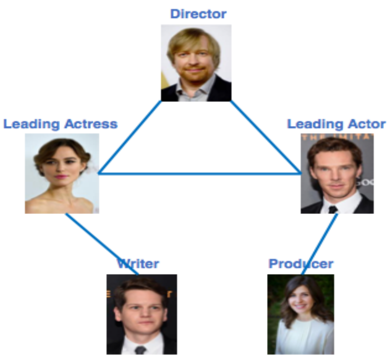
5. Military Team

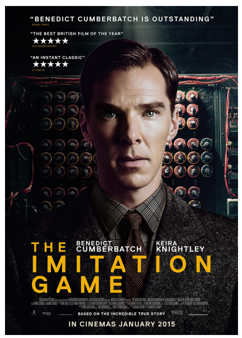
6. Development Team

- Wuchty, Stefan, Ben Jones, and Brian Uzzi. "The Increasing Dominance of Teams in the Production of Knowledge," Science, May 2007, 316:1036-1039.

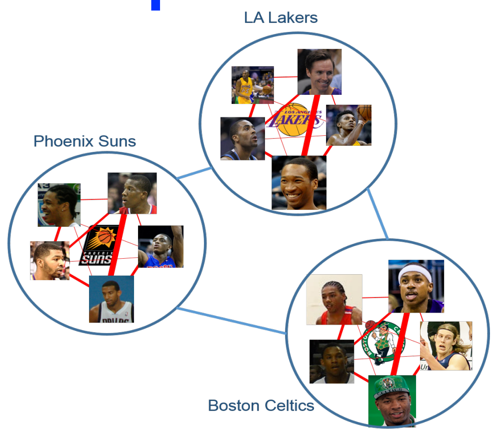
Networks Are Everywhere in Teams

1. Film Crew





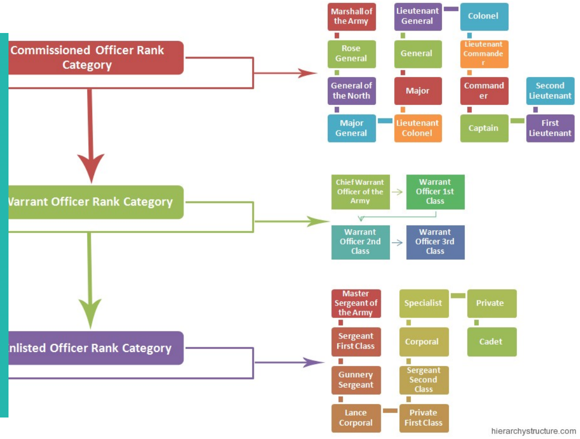
2. Sports Team



3. Sales Team

4. Research Team

5. Military Team

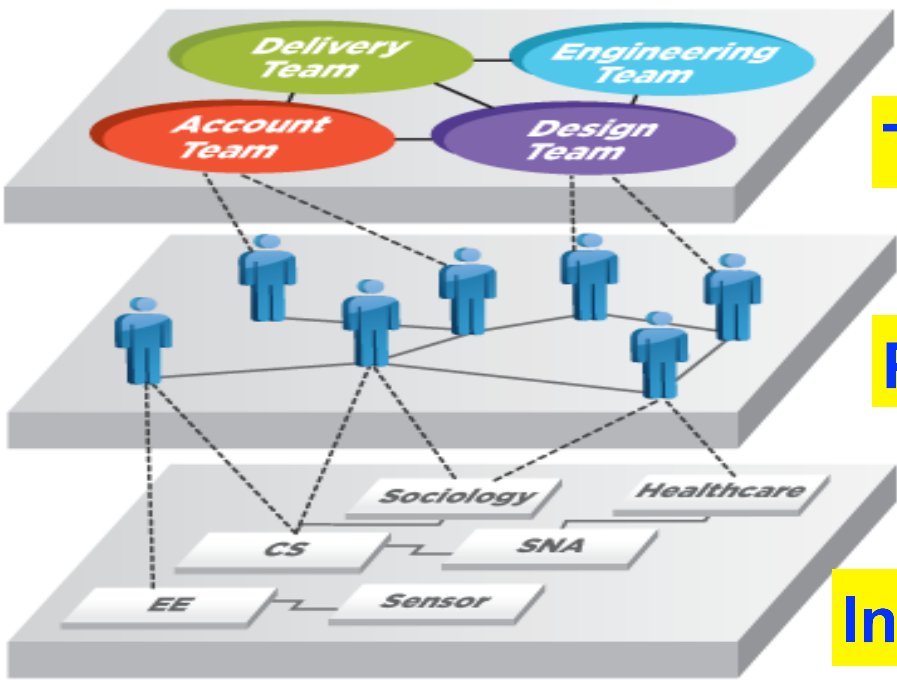


6. Development Team

- Wuchty, Stefan, Ben Jones, and Brian Uzzi. "The Increasing Dominance of Teams in the Production of Knowledge," Science, May 2007, 316:1036-1039.

Network Science of Teams

People collaborate as a team to collectively perform some complex tasks



Team Level Network

Person Level Network

Information Topic Level Network

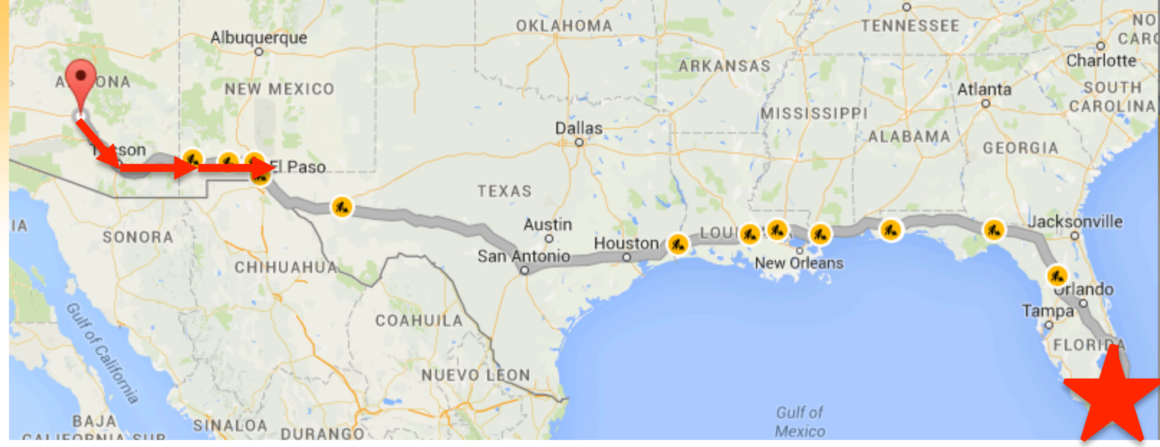
- Wuchty, Stefan, Ben Jones, and Brian Uzzi. "The Increasing Dominance of Teams in the Production of Knowledge," Science, May 2007, 316:1036-1039.

Research Questions

- Q1: What do high-performing teams share in common? [Uzzi+Science13]
- Q2: How to foresee the success at an early stage? [Wang+Science13]
- Q3: What's the optimal design for a team in the context of networks?[Lappas+KDD09, Rangapuram+WWW13]

- S. Wuchty, B. Jones, and B. Uzzi. The Increasing Dominance of Teams in the Production of Knowledge, Science, 2007
- D. Wang, C. Song, and A.-L. Barabasi. Quantifying long-term scientific impact. Science, 342(6154): 127-132, 2013.
- T. Lappas, K. Liu, and E. Terzi. Finding a team of experts in social networks. In KDD, pages 467–476, 2009.
- S. S. Rangapuram, T. Buhler, and M. Hein. Towards realistic team formation in social networks based on densest subgraphs. WWW 2013.

Roadmap



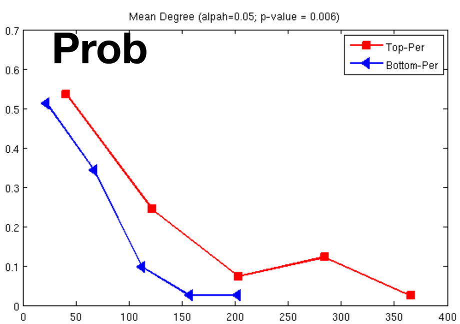
- Motivations
- Q1: Team Performance Characterization
- Q2: Team Performance Prediction
- Q3: Team Performance Optimization
- Open Challenges

Degrees, Forwarding, Tie Skewness and Sociability

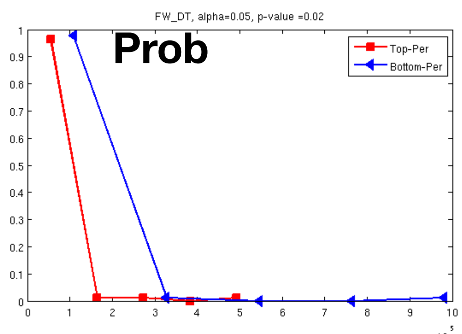
Empirical Findings:

- The average degree 
- The maximum tie skewness of team members 
- The sociability of team members 
- The information forwarding efficiency. 

Network metrics	T-Statistic	P-value
Mean degree	1.739	0.084
Min sociability	-1.907	0.058
Max sociability	-2.165	0.031
Max tie skewness	3.305	0.0001



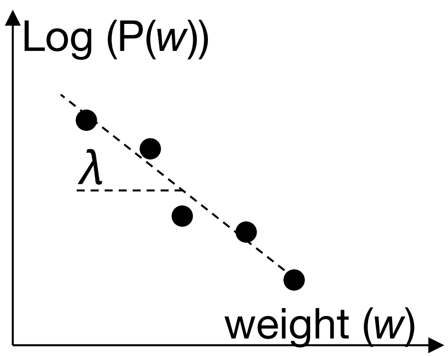
ave degree



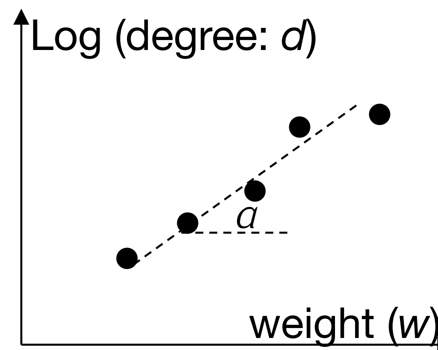
ave forwarding delay

Red: top-teams; Blue: bottom-teams

For a given person:



$P(w) \propto w^{-\lambda}$; λ: tie skewness

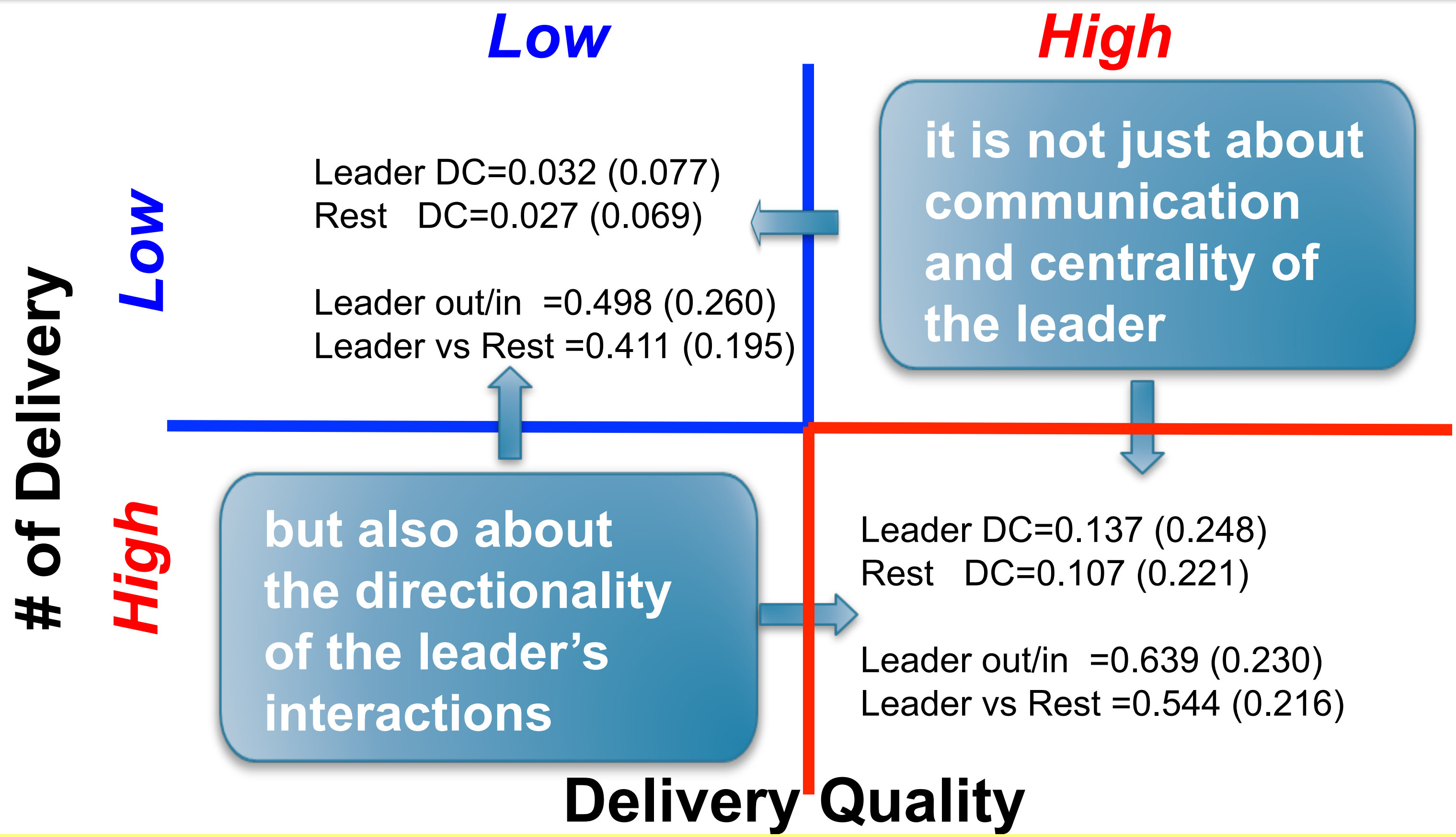


$d \propto w^{a}$; a: sociability

A **focused** team with **larger reachability** performs better

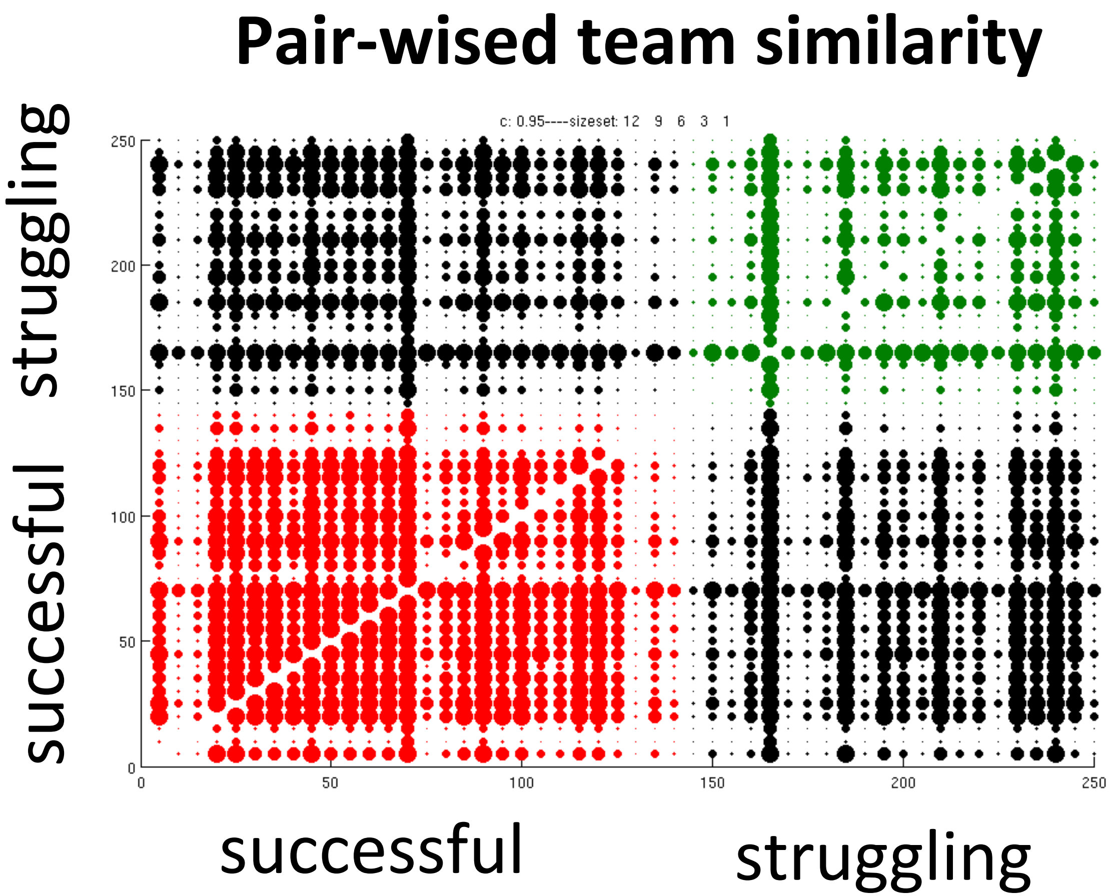
The Effect of Team Leaders

Result initially found with sales teams and replicated in 2 independent studies with software teams showing measurable effects on productivity and quality even after taking into account team-level communication structure. Accounts for > 55% variance



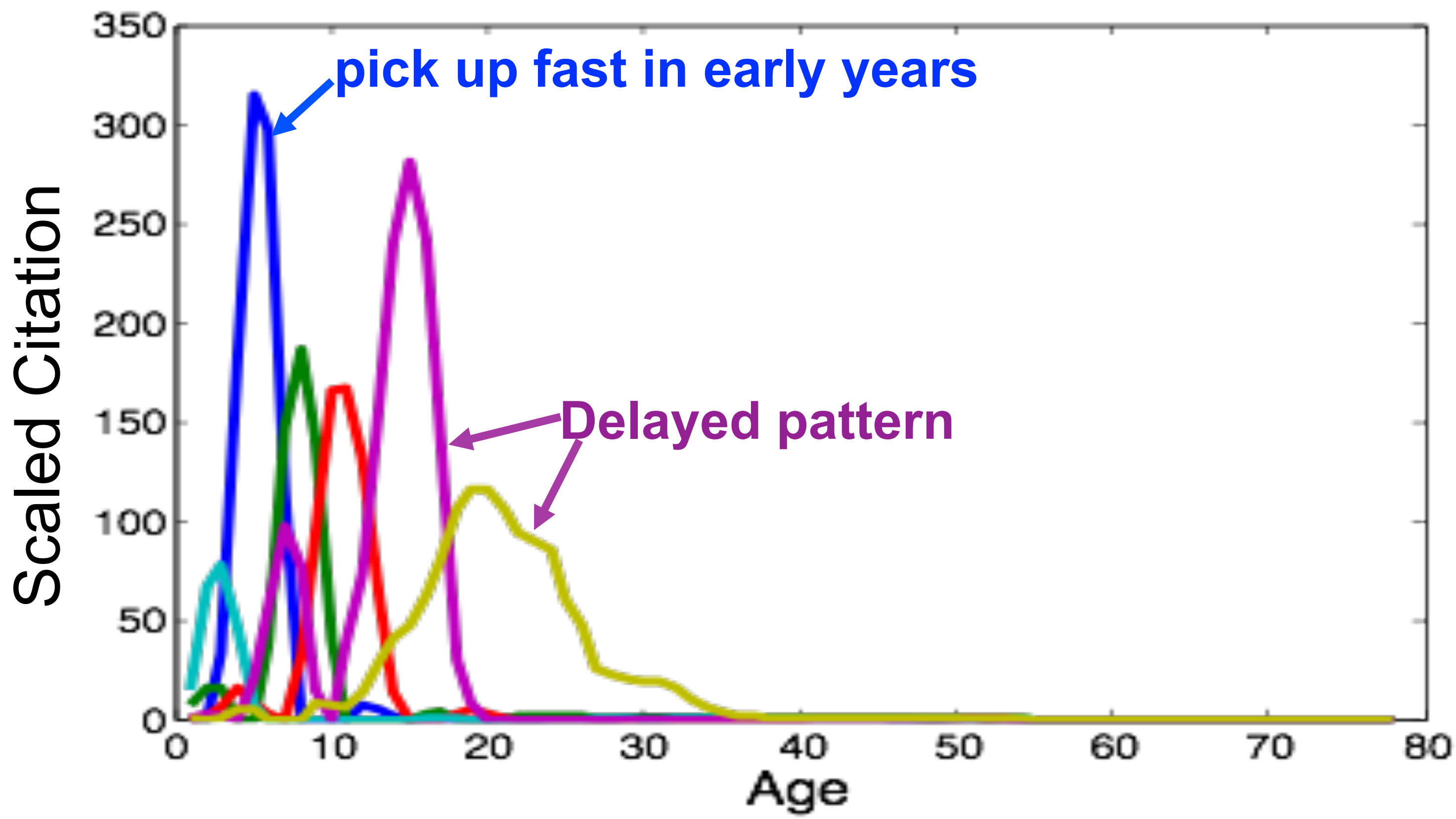
Teams perform better when (formal) leader is central in communication **out-flow** but not in-flow [Ehrlich & Tong WIDS12]

The Effect of Team Network Connectivity



"Happy families are all alike; every unhappy family is unhappy in its own way."
- Leo Tolstoy

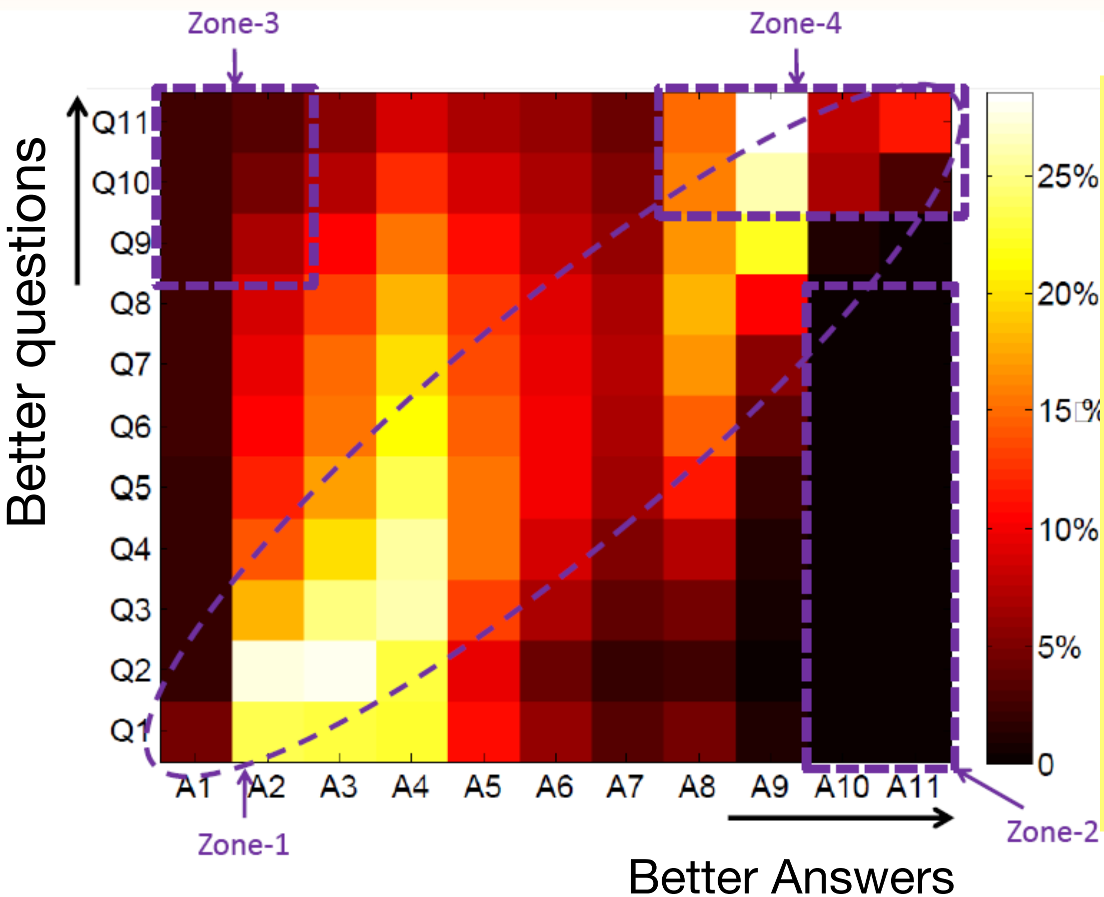
Performance Dynamics
(metric: long-term citation counts)



Impact of scientific work from different domains behaves differently

- L. Li, and H. Tong: The Child is Father of the Man: Foresee the Success at the Early Stage. KDD 2015: 655-664

Performance/Impact Coupling



Zone 1: strong positive correlation, *r=0.67, p-value < 0.0001*

Zone 2: want a good A? Ask a good Q first!

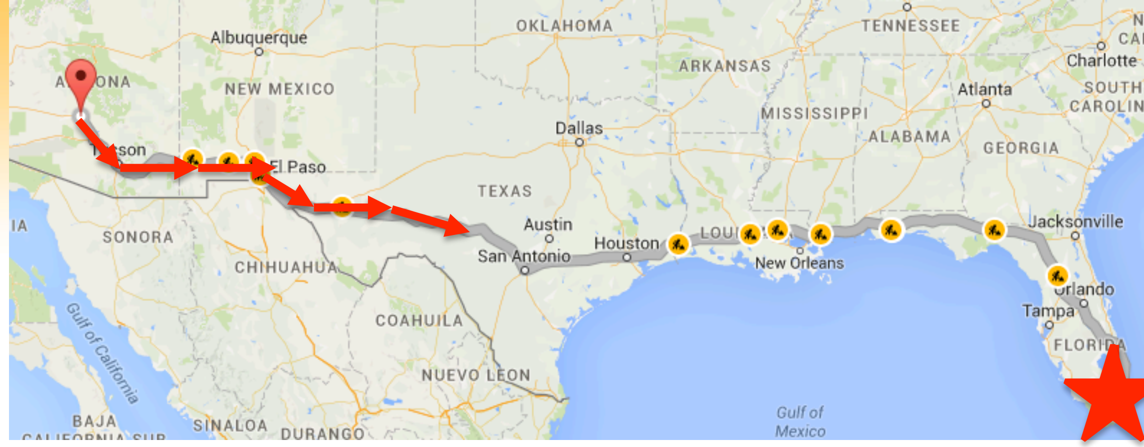
Zone 3: harder Qs

Zone 4: high Q ←→ high A

- Analysis conducted on stack overflow,
- independently verified on another CQA: math overflow

- Y. Yao, H. Tong, F. Xu, J. Lu: Predicting long-term impact of CQA posts: a comprehensive viewpoint. KDD 2014
- “Data Mining Reveals the Secret to Getting Good Answers”, MIT Technology Review, 2013

Roadmap



- Motivations
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- Q2: Team Performance Prediction
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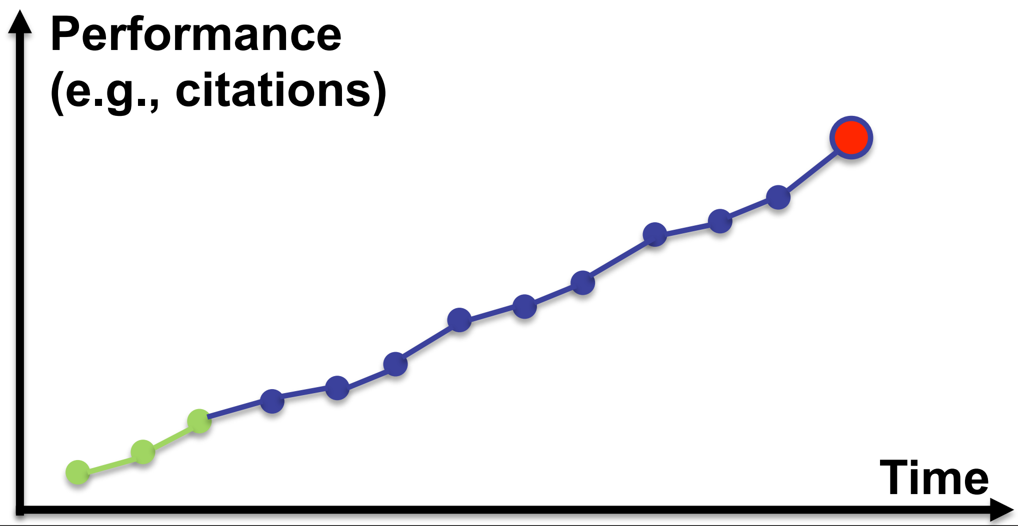
Performance Prediction: Setup

- **Given:** Initial Performance of a team
- **Predict:**
  - (1) Long-Term Performance [KDD15]
  - (2) Performance Trajectory [SDM16]



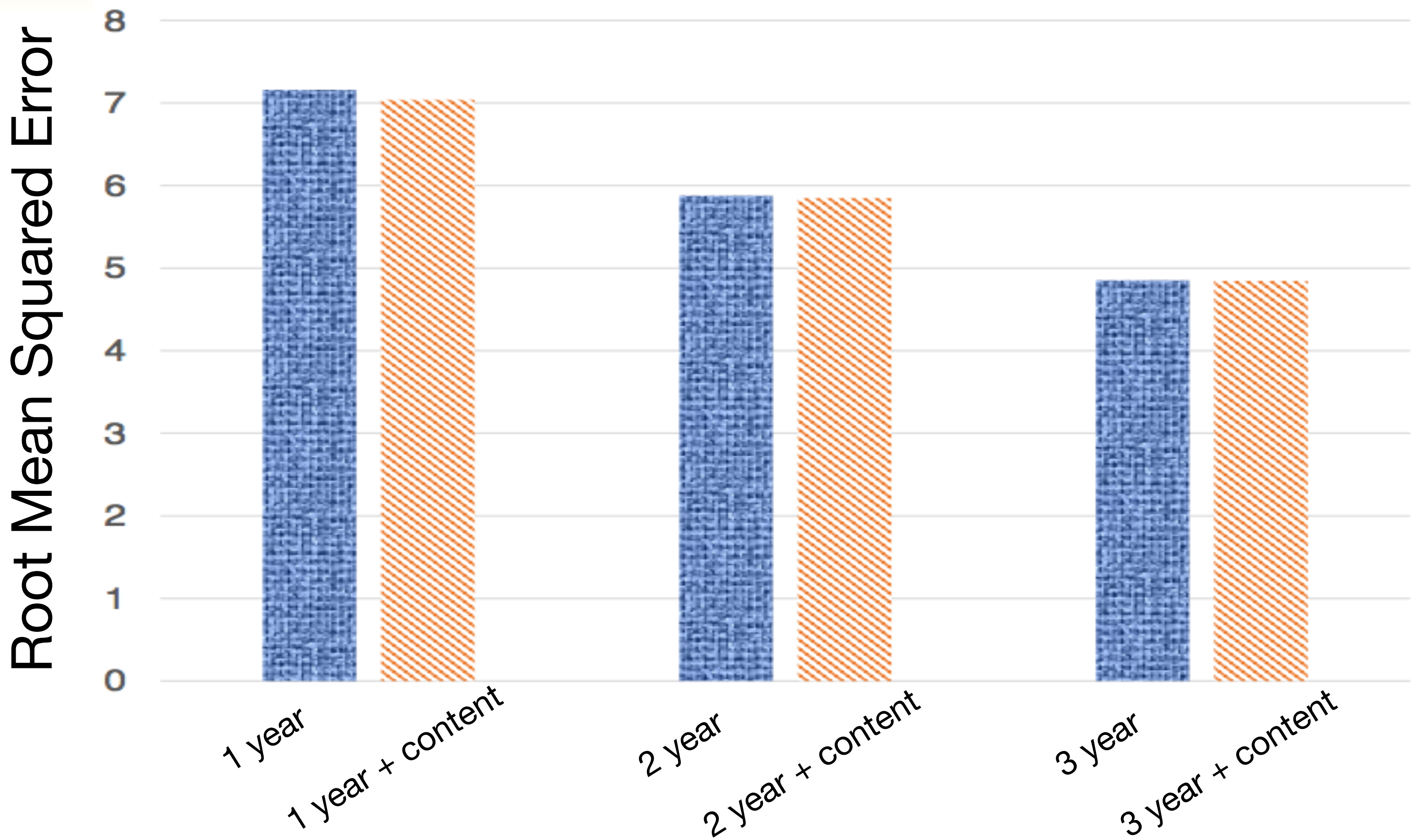
- L. Li, and H. Tong: The Child is Father of the Man: Foresee the Success at the Early Stage. KDD 2015: 655-664
- L. Li, *H. Tong*, J. Tang and W. Fan: "iPath: Forecasting the Pathway to Impact". SDM 2016

Performance Prediction: Challenges

- C1: Scholarly feature design
- C2: Non-linearity
- C3: Domain heterogeneity
- C4: Dynamics

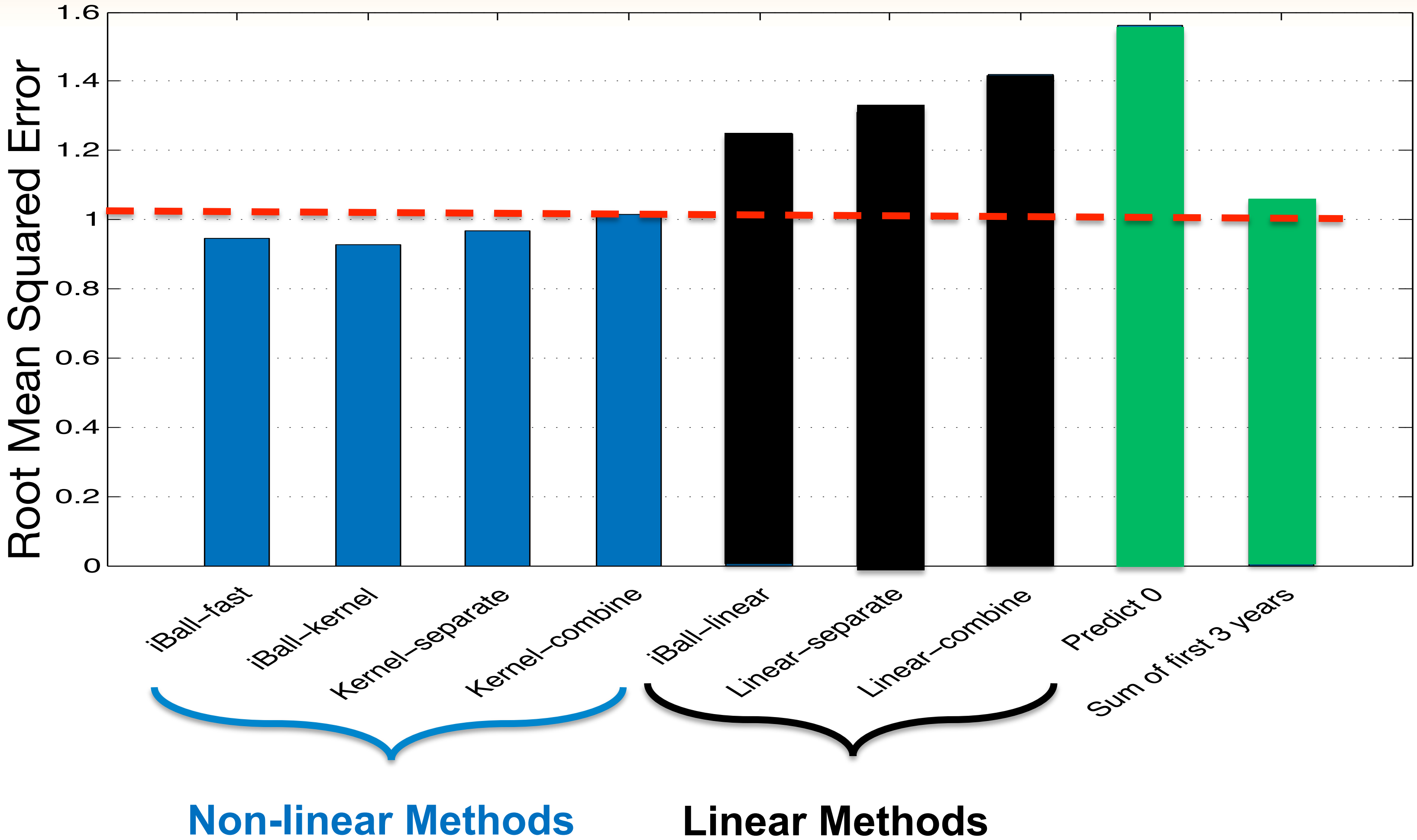
- L. Li, and H. Tong: The Child is Father of the Man: Foresee the Success at the Early Stage. KDD 2015: 655-664

C1: Scholarly Feature Design



Obs.: Adding content features brings little improvement

C2: Non-linearity



Obs.: Non-linear methods > linear ones

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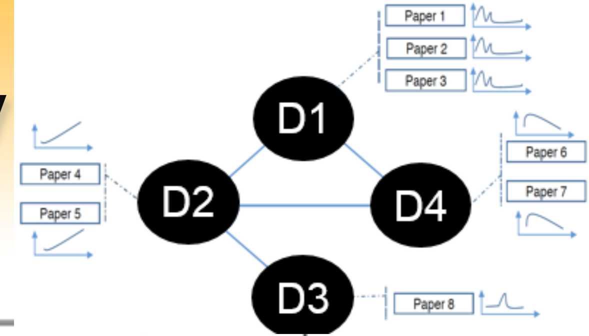
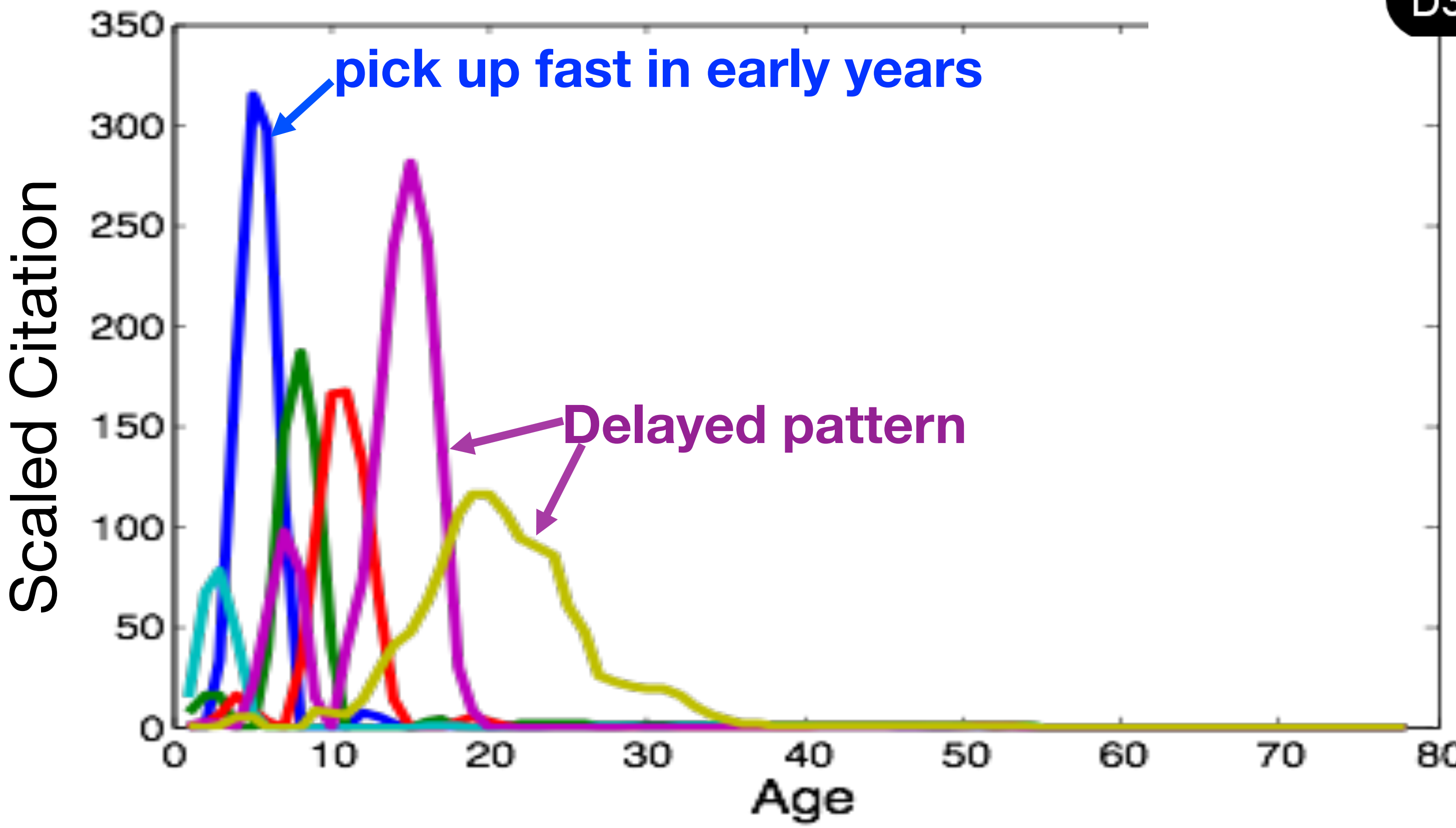
C3: Domain heterogeneity





Obs.: Impact of scientific work from different domains behaves differently

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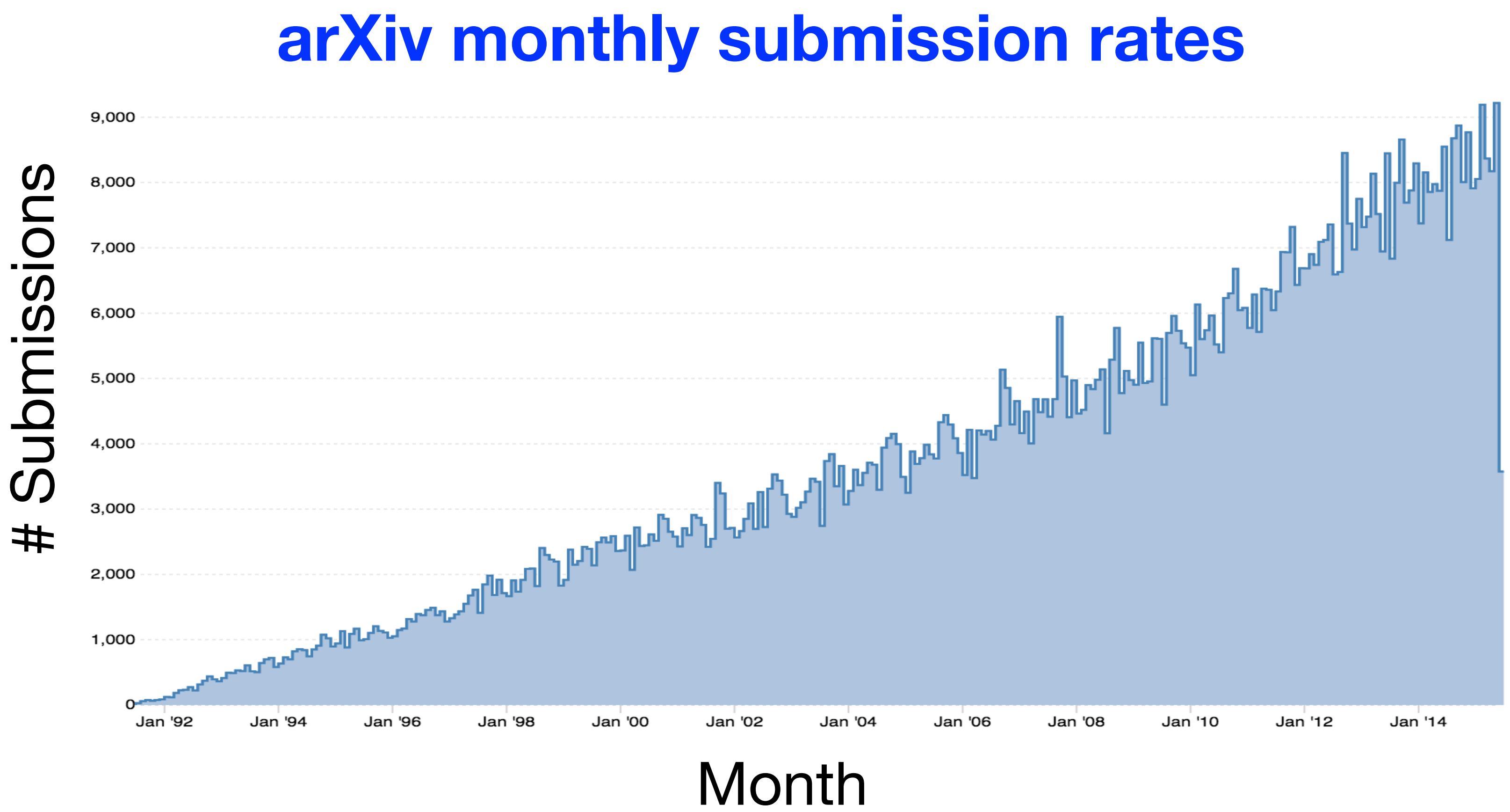
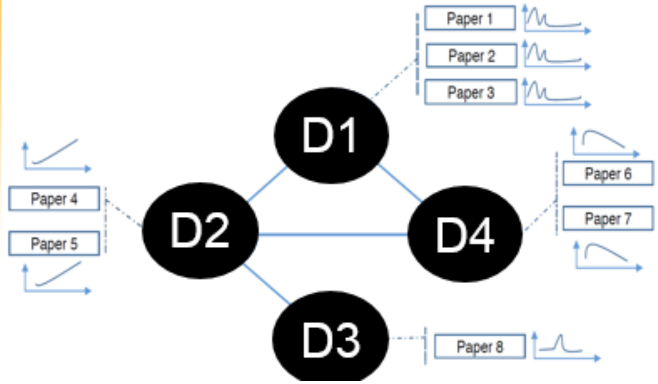
C4: Dynamics



Q: How to quickly update the predictive model?

iBall — Formulations



- Optimization Formulation

$$\min_{\mathbf{w}^{(\mathrm{i})}, i=1,\ldots,n_d} \sum_{i=1}^{n_d} \overbrace{\mathcal{L}[f(\mathbf{X}^{(\mathrm{i})}, \mathbf{w}^{(\mathrm{i})}), \mathbf{Y}^{(\mathrm{i})}] + \lambda \sum_{i=1}^{n_d} \Omega(\mathbf{w}^{(\mathrm{i})})}^{\text{Within-Domain Model}}$$

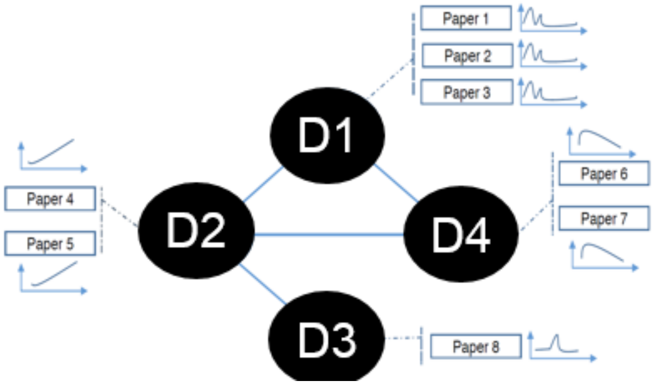
$$+\theta \sum_{i=1}^{n_d} \sum_{j=1}^{n_d} \mathbf{A}_{\mathrm{ij}} \underbrace{g(\mathbf{w}^{(\mathrm{i})}, \mathbf{w}^{(\mathrm{j})})}_{\text{Cross-Domain Consistency}}$$

- Remarks
  - **Within-Domain Model**: regression/classification, linear/non-linear
  - **Cross-Domain Consistency**: similar domains have similar models

Question: how to instantiate such consistency?

- L. Li, and H. Tong: The Child is Father of the Man: Foresee the Success at the Early Stage. KDD 2015: 655-664

iBall — linear formulation



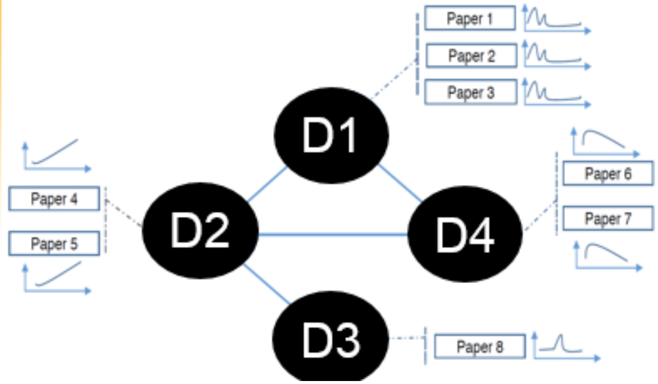
Details:

$$\min_{\mathbf{w}^{(\mathrm{i})}, i=1,\ldots,n_d} \sum_{i=1}^{n_d} \|\mathbf{X}^{(\mathrm{i})}\mathbf{w}^{(\mathrm{i})} - \mathbf{Y}^{(\mathrm{i})}\|_2^2 + \lambda \sum_{i=1}^{n_d} \|\mathbf{w}^{(\mathrm{i})}\|_2^2 + \theta \sum_{i=1}^{n_d} \sum_{j=1}^{n_d} \underbrace{\mathbf{A}_{\mathrm{ij}} \|\mathbf{w}^{(\mathrm{i})} - \mathbf{w}^{(\mathrm{j})}\|_2^2}$$

Intuitions: similar domains (large $\mathbf{A}_{ij}$)

→ same feature has similar effect (small $\|\mathbf{w}^{(\mathrm{i})} - \mathbf{w}^{(\mathrm{j})}\|_2^2$)

iBall — non-linear formulation



Details:

$$\min_{\mathbf{w}^{(\mathbf{i})}, i=1,\ldots,n_d} \sum_{i=1}^{n_d} \|\mathbf{K}^{(\mathbf{i})}\mathbf{w}^{(\mathbf{i})} - \mathbf{Y}^{(\mathbf{i})}\|_2^2 + \lambda \sum_{i=1}^{n_d} \mathbf{w}^{(\mathbf{i})'}\mathbf{K}^{(\mathbf{i})}\mathbf{w}^{(\mathbf{i})}$$
$$+\theta \sum_{i=1}^{n_d}\sum_{j=1}^{n_d} \mathbf{A_{ij}} \|\mathbf{K}^{(\mathbf{i})}\mathbf{w}^{(\mathbf{i})} - \mathbf{K}^{(\mathbf{ij})}\mathbf{w}^{(\mathbf{j})}\|_2^2$$

Predicted output (domain *i* → domain *i*)

Predicted output (domain *j* → domain *i*)

Intuitions: similar domains (large $\mathbf{A}_{ij}$)

→ similar predicted outputs (small $\|\mathbf{K}^{(\mathbf{i})}\mathbf{w}^{(\mathbf{i})} - \mathbf{K}^{(\mathbf{ij})}\mathbf{w}^{(\mathbf{j})}\|_2^2$)

iBall — Closed-form Solutions

- Closed-form Solution

$$\mathbf{w} = \mathbf{S}^{-1}\mathbf{Y}$$

  - iBall — linear:

$$\mathbf{w} = [\mathbf{w}^{(1)}; \ldots; \mathbf{w}^{(k)}] \quad \mathbf{Y} = [\mathbf{X}^{(1)\prime}\mathbf{Y}^{(1)}; \ldots; \mathbf{X}^{(k)\prime}\mathbf{Y}^{(k)}]$$

$$\mathbf{S} = \begin{array}{c} \\ \end{array}\begin{array}{cc} \begin{array}{ccc} & \text{i-th block column} & \text{j-th block column} \end{array} & \\ \begin{bmatrix} \cdots & \cdots & \cdots \\ \cdots & \mathbf{X}^{(\mathbf{i})\prime}\mathbf{X}^{(\mathbf{i})} + (\theta \sum_{j=1}^{k} \mathbf{A}_{\mathbf{ij}} + \lambda)\mathbf{I} & -\theta\mathbf{A}_{\mathbf{ij}}\mathbf{I} \\ \cdots & \cdots & \cdots \end{bmatrix} & \begin{array}{l} \text{i-th block} \\ \text{row} \end{array} \end{array}$$

Time Complexity: *$O(dk)^3$*

d: # of features; k: # of domains
(*dk:* in the order of 10 or 100)

iBall — Closed-form Solutions

- Closed-form Solution

$$\mathbf{w} = \mathbf{S}^{-1}\mathbf{Y}$$

  - iBall — non-linear:

$$\mathbf{w} = [\mathbf{w}^{(1)}; \ldots; \mathbf{w}^{(k)}] \qquad \mathbf{Y} = [\mathbf{Y}^{(1)}; \ldots; \mathbf{Y}^{(k)}]$$

$$\mathbf{S} = \begin{array}{c c} \begin{array}{ccc} & \text{i-th block column} & \text{j-th block column} \end{array} & \\ \begin{bmatrix} \cdots & \cdots & \cdots \\ \cdots & (1+\theta\sum_{j=1}^{k}\mathbf{A_{ij}})\mathbf{K}^{(\mathbf{i})} + \lambda\mathbf{I} & -\theta\mathbf{A_{ij}}\mathbf{K}^{(\mathbf{ij})} \\ \cdots & \cdots & \cdots \end{bmatrix} & \begin{array}{c} \\ \text{i-th block row} \\ \\ \end{array} \end{array}$$

Time Complexity: $O(n^3)$

n: total # of training examples
(in the order of millions)

iBall — Scale-up with Dynamic Update

- **Key idea #1**: Approx ***S*** by low-rank approx
- **Details:**

$$\mathbf{S}_{t+1} \approx \mathbf{U}_{t+1}\mathbf{\Lambda}_{t+1}\mathbf{U}'_{t+1} \rightarrow \mathbf{w}_{t+1} = \mathbf{S}_{t+1}^{-1}\mathbf{Y}_{t+1} = \mathbf{U}_{t+1}\mathbf{\Lambda}_{t+1}^{-1}\mathbf{U}'_{t+1}\mathbf{Y}_{t+1}$$

(Overall: $O(n^2 r)$) (Overall: $O(nr)$)

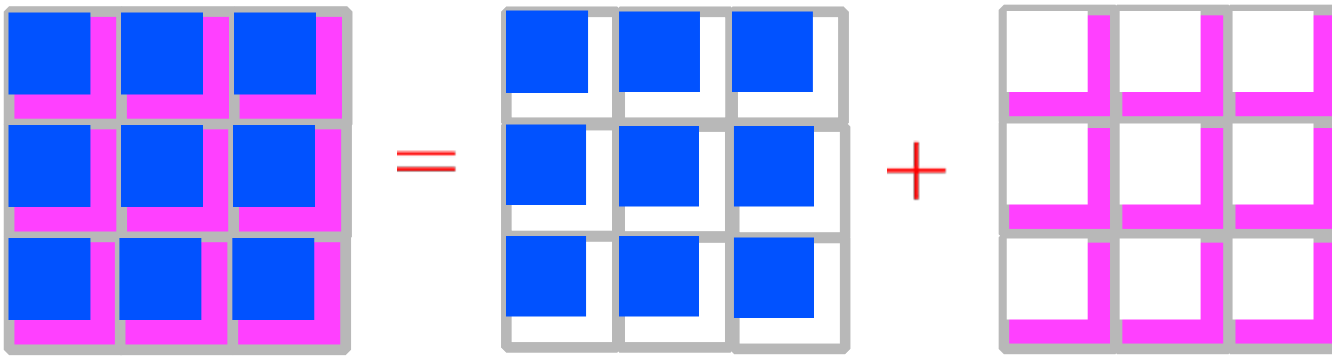
- **Complexity:** $O(n^3) \rightarrow O(n^2 r + nr)$
- **Benefit:** avoid matrix inverse

Question: how to avoid re-computing low-rank approx at each time step?

iBall — Scale-up with Dynamic Update

- **Key idea #2:** Incrementally update the low rank structure of **S**
- **Details:**

white: zeros
blue: old at *t*
pink: new at *t+1*



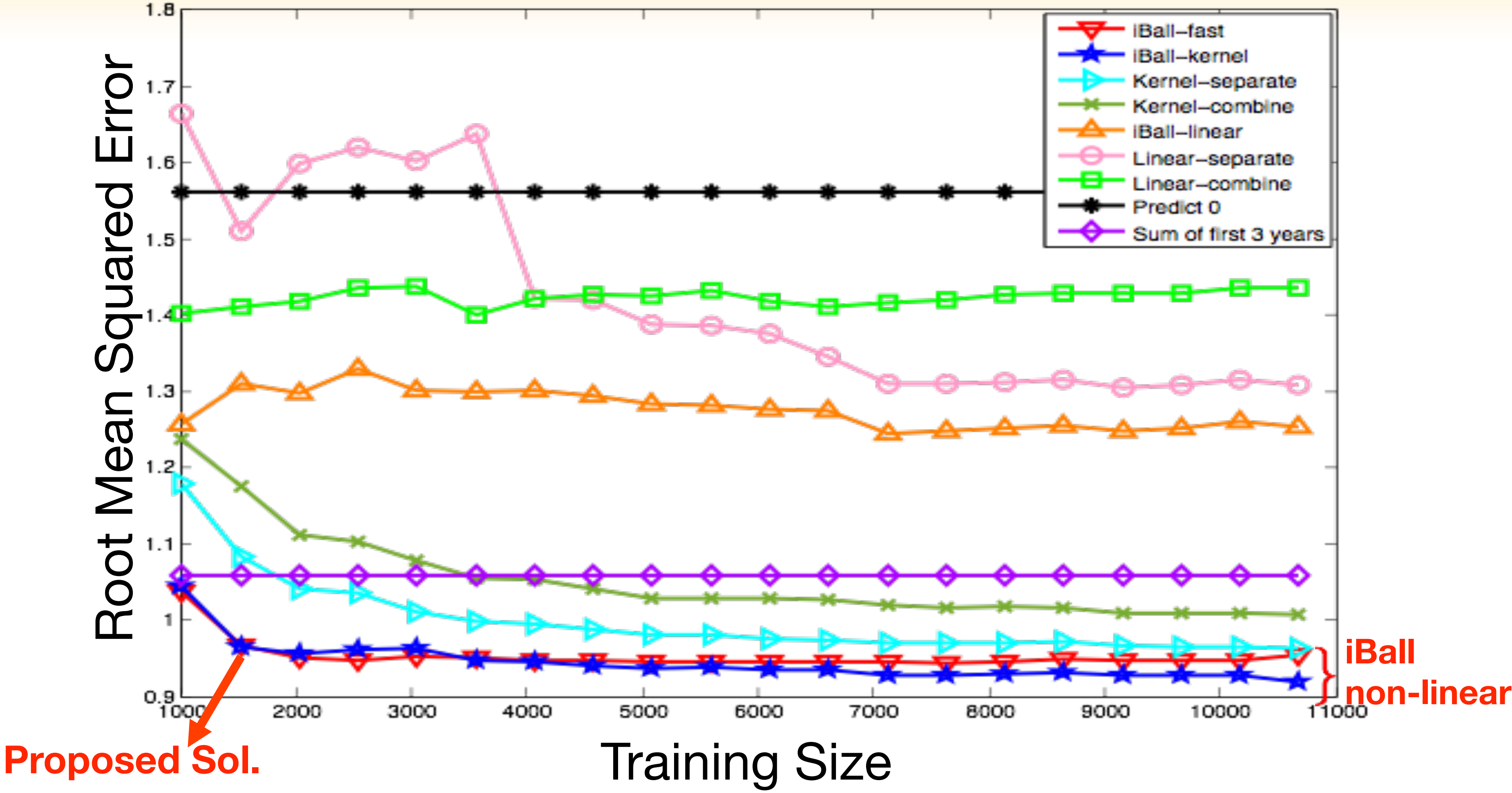
$\mathbf{S}_{t+1}$ $\tilde{\mathbf{S}}_t$ $\Delta\mathbf{S}$

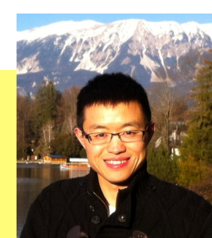
(low rank, sparse)

- **Complexity:** $O(n^2 r) \rightarrow O((n+m)(r^2 + r'^2)), r \ll n$
- **Benefit:** avoid re-computing low-rank approx

• L. Li, H. Tong, Y. Xiao, W. Fan. Cheetah: Fast Graph Kernel Tracking on Dynamic Graphs. SDM 2015.

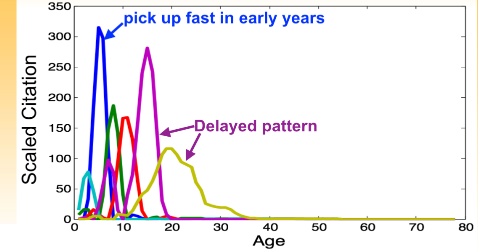
Paper Citation Prediction Performance

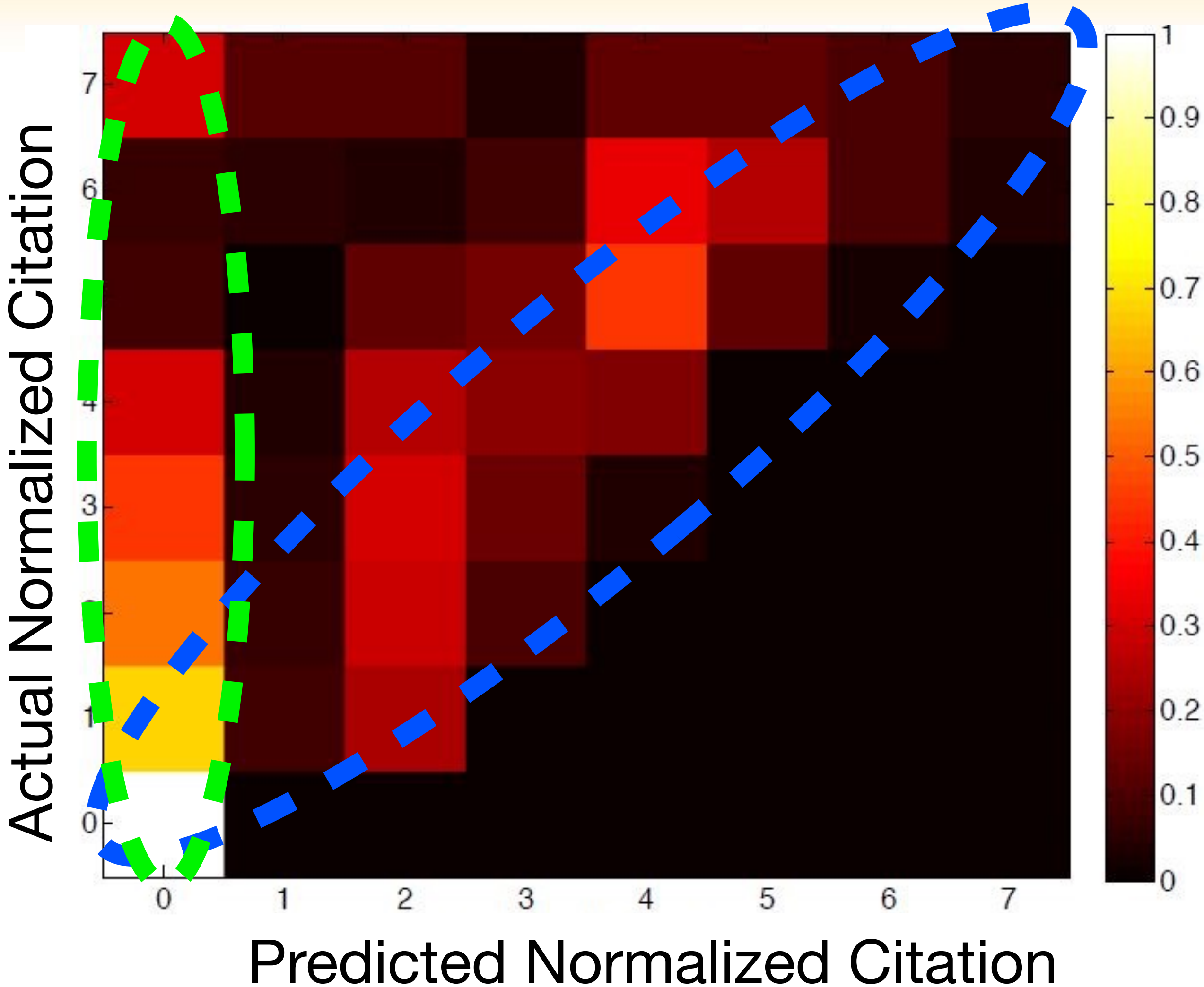




Datasets: AMiner (2,243,976 papers, 1,274,360 authors, 8,882 venues)

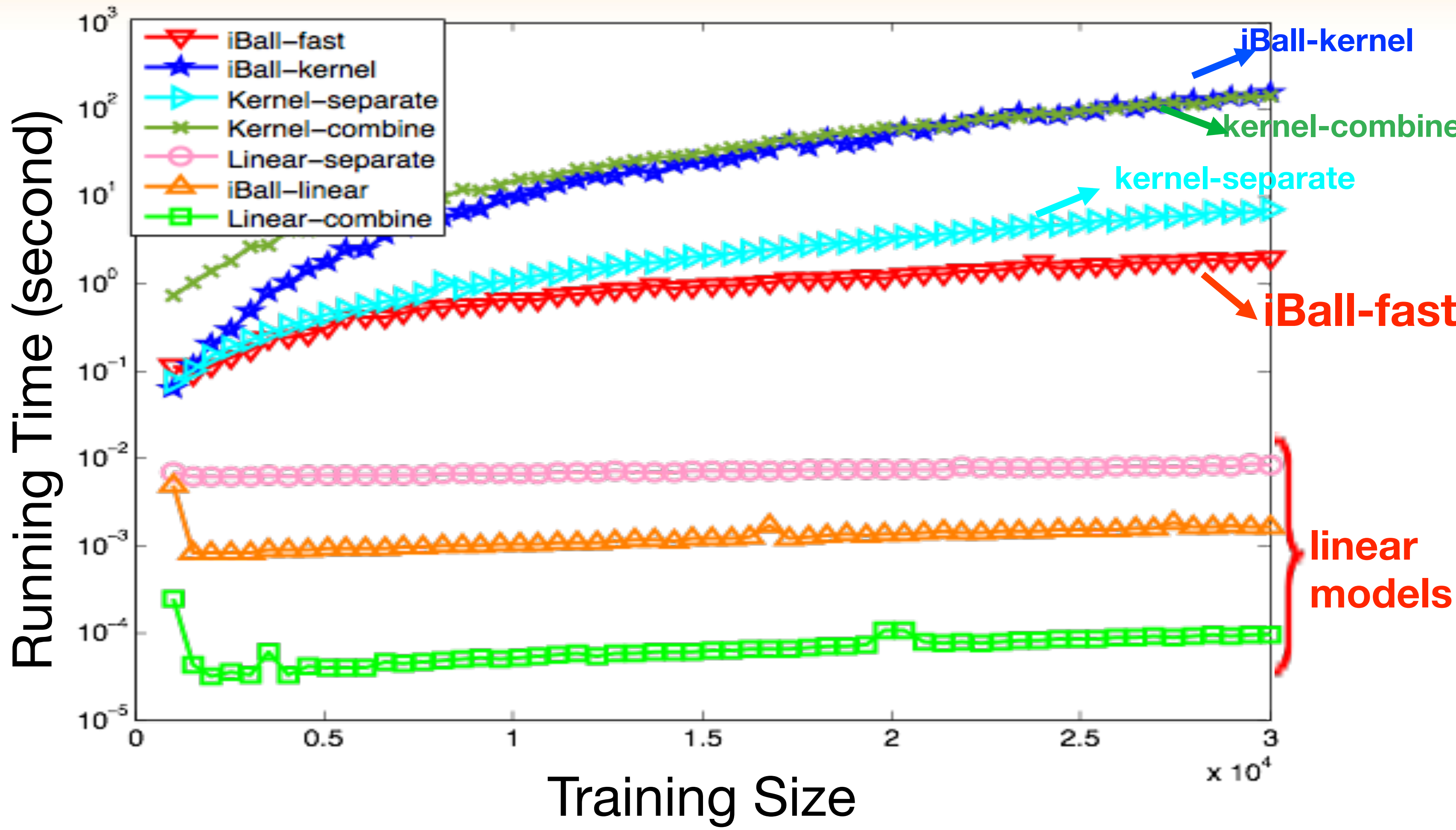
Error Analysis





Obs.: bright region at x = y

Running Time Comparison



Obs.: iBall-fast outperforms other non-linear methods

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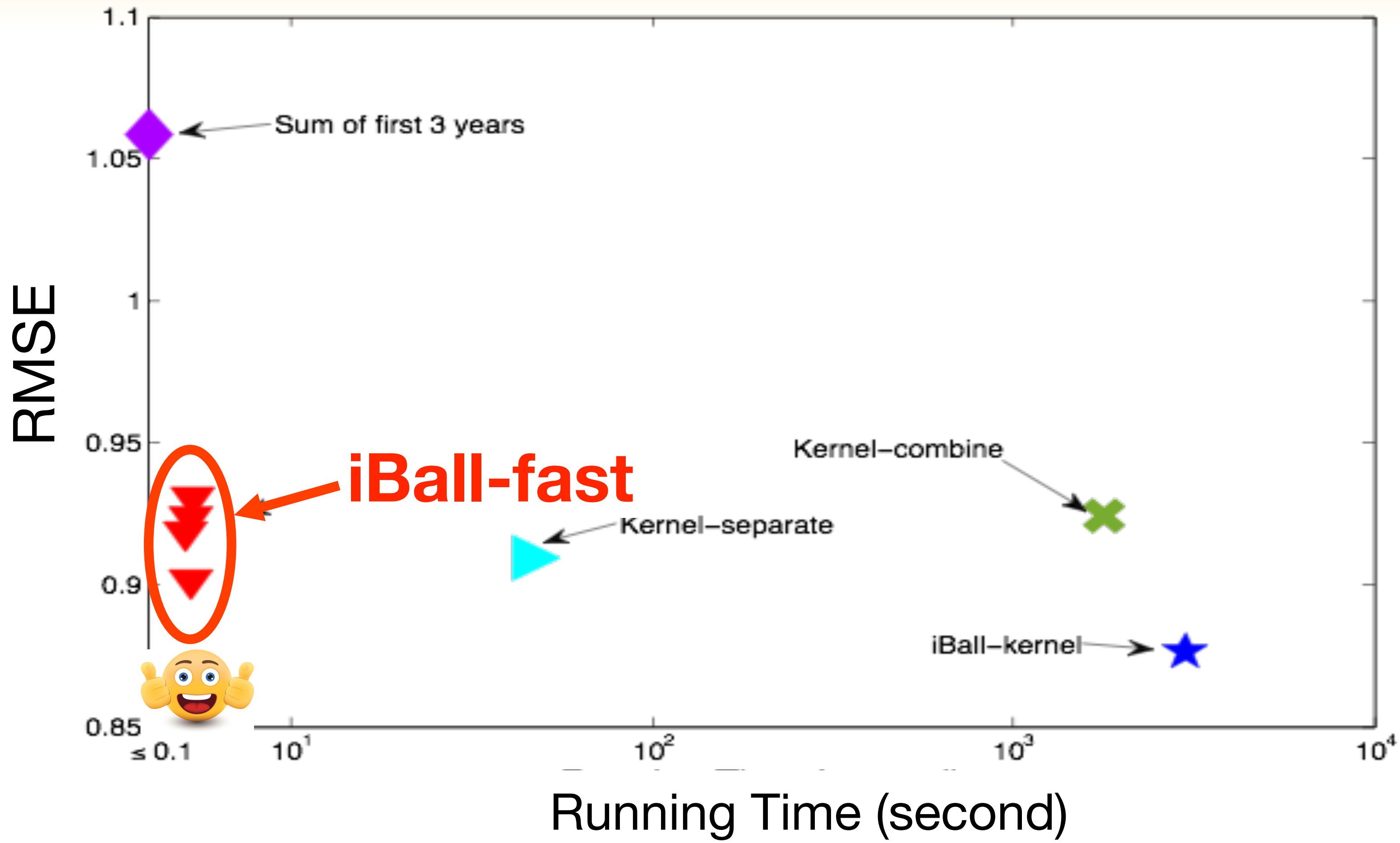
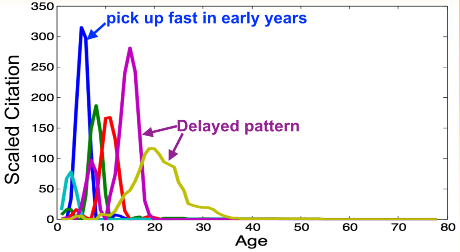
Quality vs. Speed



Obs.: iBall-fast: good trade-off between quality and speed

iBall: Summary



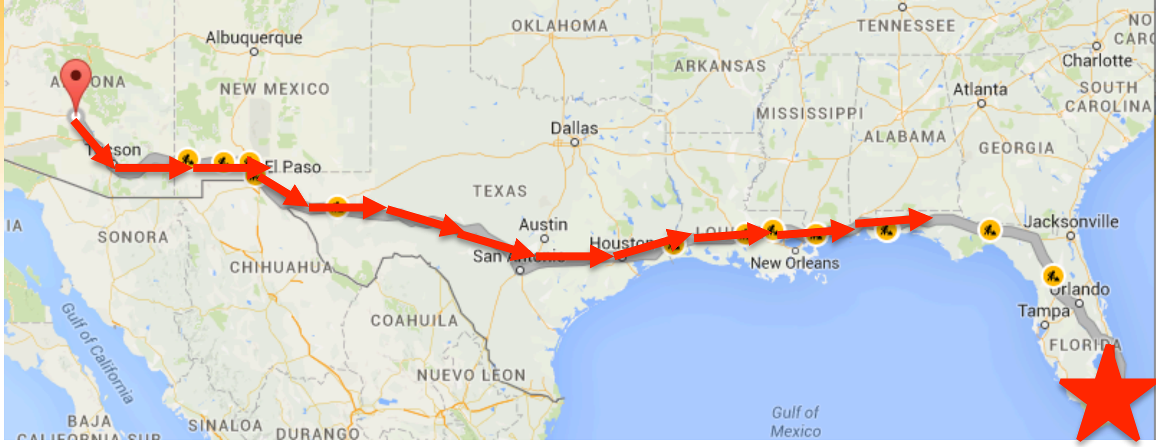
- **Goal**: predict long-term impact of scholarly entities
- **Solutions**: joint predictive model (**iBall**)

Challenges	C1 ***feature design***	C2 ***non-linearity***	C3 ***domain-heterogeneity***	C4 ***dynamics***
Tactics	***first 3 years' citation***	***kernel trick***	***domain consistency***	***low-rank approximation***

- **Results:**
  - iBall joint models better than separate versions
  - iBall-fast updates efficiently and accurately

- L. Li, and H. Tong: The Child is Father of the Man: Foresee the Success at the Early Stage. KDD 2015: 655-664

Roadmap



- Motivations
- Q1: Team Performance Characterization
- Q2: Team Performance Prediction
- Q3: Team Performance Optimization
  - Team Replacement
  - Team Enhancement
- Open Challenges

Churn of A Team Member

- **Case 1:** Employee resigns in a sales team
- **Case 2:** Task force down in a SWAT team
- **Case 3:** Rotation tactic between benches in NBA team

Q: How to find the best alternative when a team member leaves?

- L. Li, H. Tong, N. Cao, K. Ehrlich, Y.-R. Lin and N. Buchler: Replacing the Irreplaceable: Fast Algorithms for Team Member Recommendation, WWW 2015
- N. Cao, Y.-R. Lin, L. Li, H. Tong: g-Miner: Interactive Visual Group Mining on Multivariate Graphs, ACM CHI 2015
- System prototype & video demo: http://team-net-work.org

Team Member Replacement

Problem Definition:

Given: (1) A labelled social network $G := \{A, L\}$

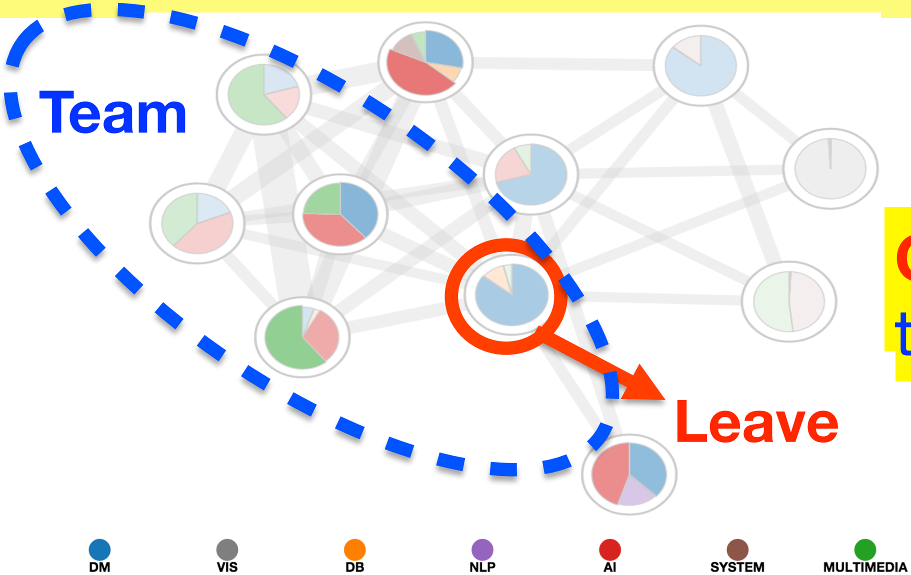
Adj. Matrix

Skill Indicator

(2) A team $G(\mathcal{T})$

(3) A team member $p \in \mathcal{T}$

Recommend: A "best" alternative $q \notin \mathcal{T}$ to replace the person *p's* role in the team $G(\mathcal{T})$



Q: who is a good candidate to replace the person to leave

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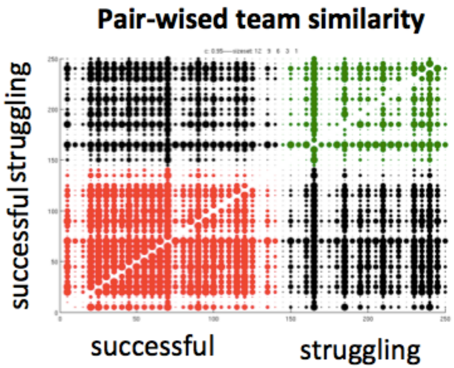
Social Science Literature

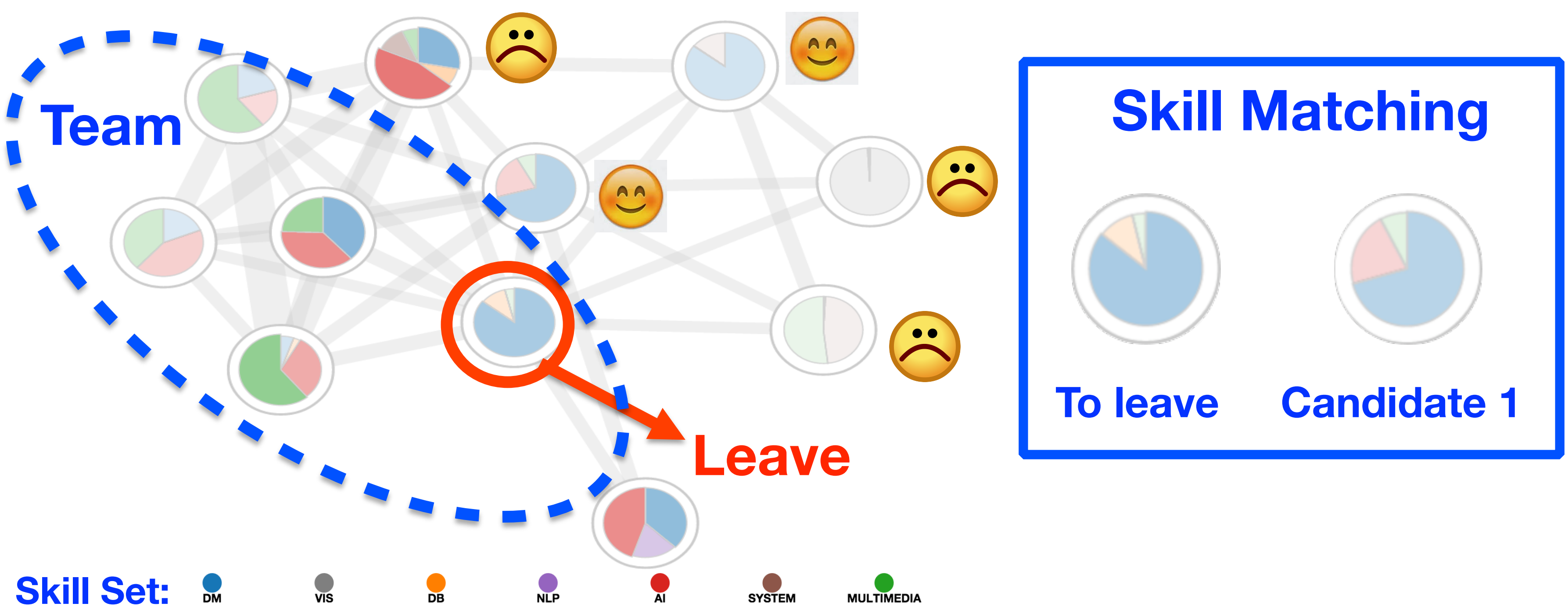


- Team members prefer to work with people they have worked before [Hinds+OBHDP00]
- Distributed teams perform better when members know each other [Cummings+CSCW08]
- Specific communication patterns amongst team members are critical for performance [Cataldo+CHI12]

Conjecture: The similarity should be measured in the **context of the team itself**

Design Objectives

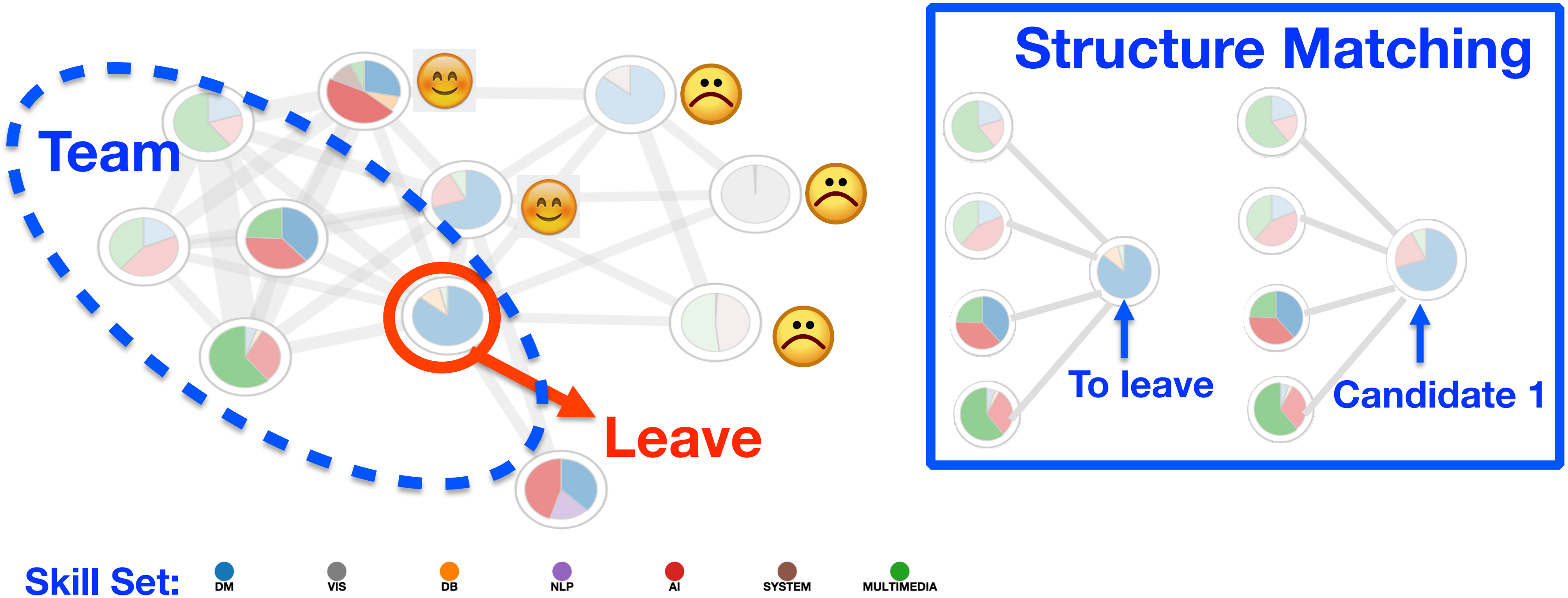
Objective 1: A good candidate should have a similar skill set



New team would have a similar skill set as the old team to continue to complete the task

Design Objectives

Objective 2: A good candidate should have a similar network structure



New team would have a similar network structure as the old team to collaborate effectively

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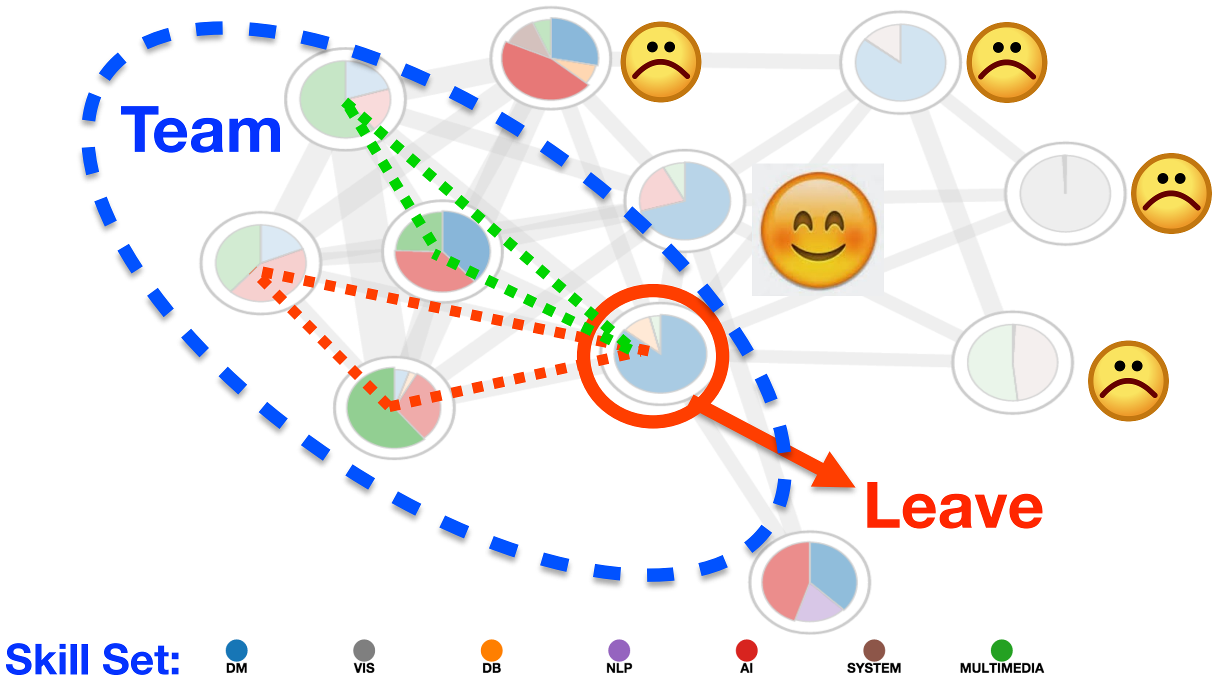
Design Objectives

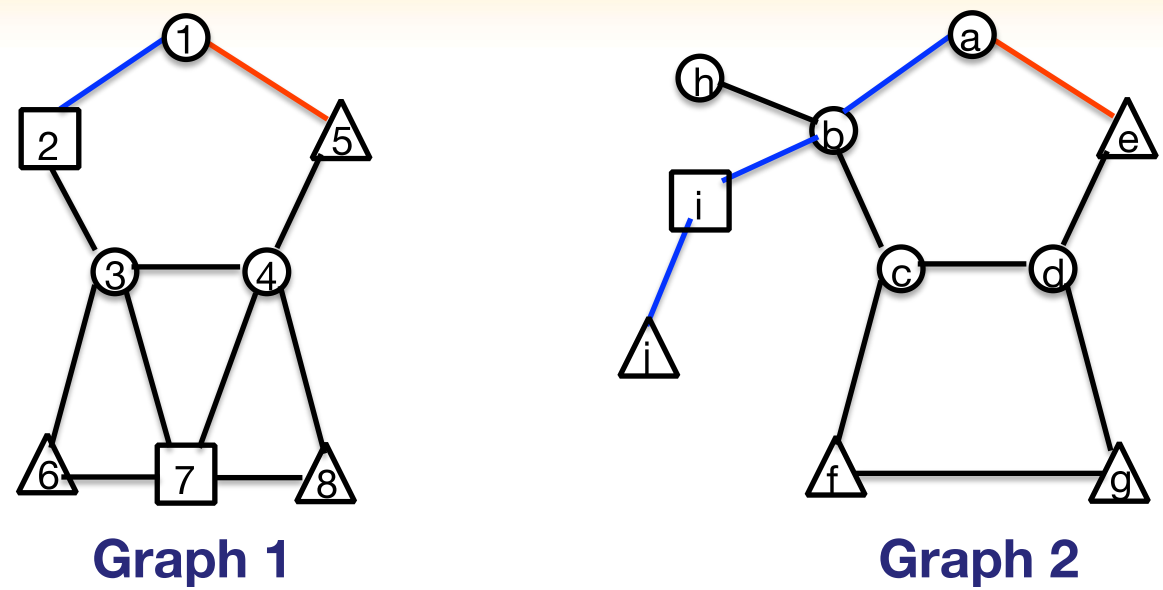
The skill and structure match should be fulfilled simultaneously!



New team would have similar skill and communication configuration for each sub-task

- L. Li, H. Tong, N. Cao, K. Ehrlich, Y.-R. Lin and N. Buchler: Replacing the Irreplaceable: Fast Algorithms for Team Member Recommendation, WWW 2015

Random Walk based Graph Kernel



Details:

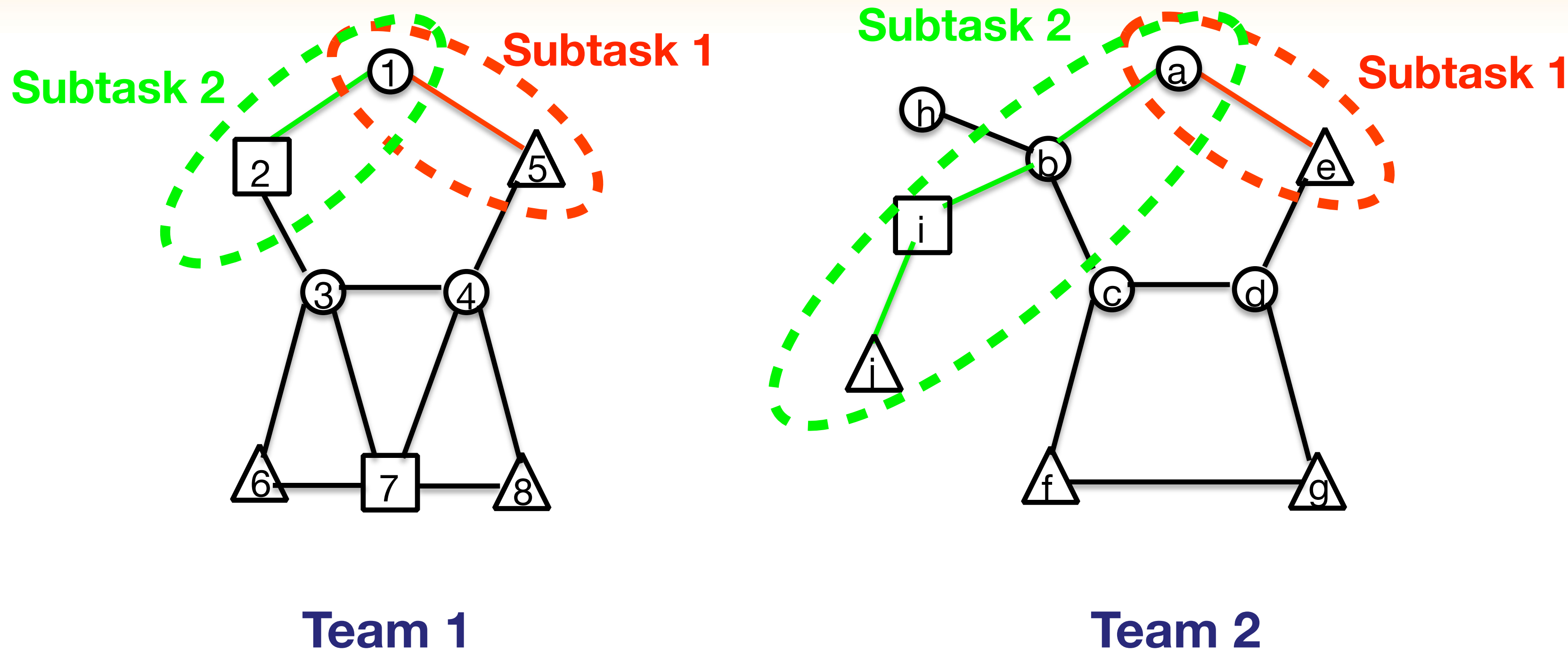
1. Compare similarity of every pair of nodes from each graph

— Eg: (1,2) vs (a, j) $\longrightarrow$ less similar

(1,5) vs (a,e) $\longrightarrow$ more similar

2. Node pair similarity is measured by random walks
3. Two graphs are similar if they share many similar node pairs

Random Walk based Graph Kernel

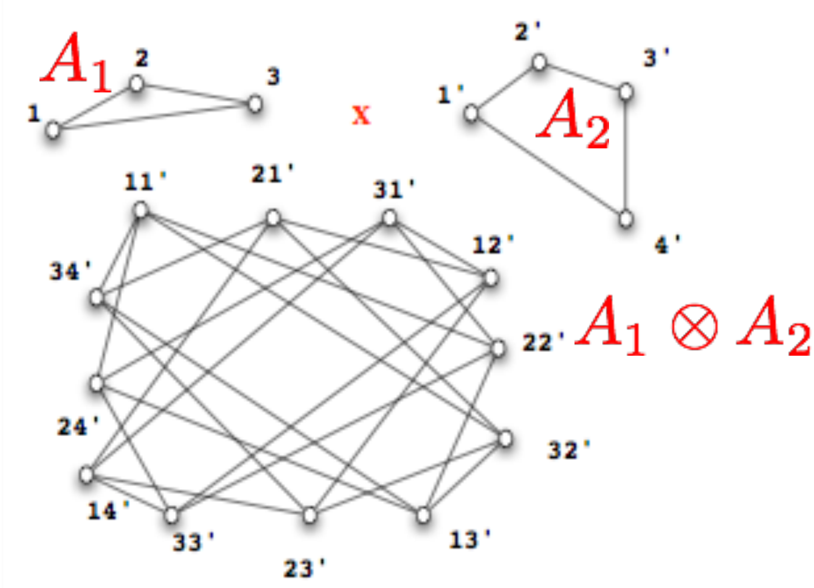


Remarks:

- Incorporates both **attributes** and **structures** similarity
- Ideal fit for our two design objectives **simultaneously**

Kronecker Product Graph w/o Attribute

Graph Illustration



Matrix Description

$$A_1 = \begin{bmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \end{bmatrix} \qquad A_2 = \begin{bmatrix} 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 1 & 0 & 1 & 0 \end{bmatrix}$$

$$A_1 \otimes A_2 = \begin{bmatrix} 0&0&0&0&0&1&0&1&0&1&0&1 \\ 0&0&0&0&1&0&1&0&1&0&1&0 \\ 0&0&0&0&0&1&0&1&0&1&0&1 \\ 0&0&0&0&1&0&1&0&1&0&1&0 \\ 0&1&0&1&0&0&0&0&0&1&0&1 \\ 1&0&1&0&0&0&0&0&1&0&1&0 \\ 0&1&0&1&0&0&0&0&0&1&0&1 \\ 1&0&1&0&0&0&0&0&1&0&1&0 \\ 0&1&0&1&0&1&0&1&0&0&0&0 \\ 1&0&1&0&1&0&1&0&0&0&0&0 \\ 0&1&0&1&0&1&0&1&0&0&0&0 \\ 1&0&1&0&1&0&1&0&0&0&0&0 \end{bmatrix}$$

Kronecker product

One Random Walk on A_1

$+$

One Random Walk on A_2

$=$ One Random Walk on $A_1 \otimes A_2 = A_\times$

- S. V. N. Vishwanathan, Nicol N. Schraudolph, Imre Risi Kondor, and Karsten M. Borgwardt. Graph Kernels. Journal of Machine Learning Research, 11:1201–1242, April 2010.

RW Graph Kernel — Formulation

Taking expectations instead of summing

$$\begin{aligned}\mathrm{Ker}(G_1, G_2) &= \sum_k c^k q'_\times (L_\times A_\times)^k L_\times p_\times \\ &= q'_\times (I - c\underset{\uparrow}{L_\times} A_\times)^{-1} L_\times p_\times\end{aligned}$$

Attribute Indicator

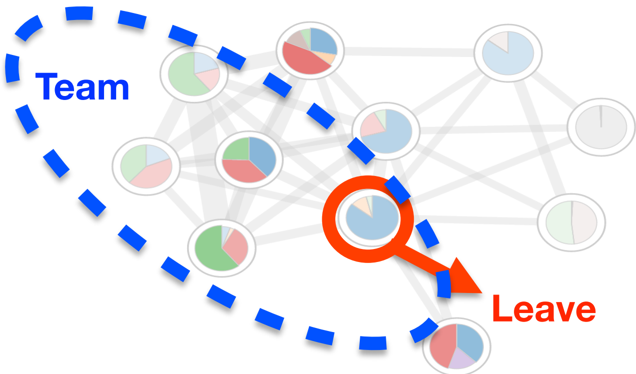
- **Computational cost** (A_x: t^2 x t^2)
  - *Exact methods:* [Vishwanathan+JMLR2010]
    - $O(t^6)$ - Direct computation
    - $O(t^3)$ - Sylvester equation
  - *Approx methods:* $O(t^2r^4+mr+r^6)$ [Kang+SDM12]

- U. Kang, Hanghang Tong, Jimeng Sun. Fast Random Walk Graph Kernel. SDM 2012
- S. V. N. Vishwanathan, N. N. Schraudolph, I. Kondor, and K. M. Borgwardt. Graph Kernels. JMLR 2010.

TEAMREP-BASIC

Find a new member *q* not in the current team that satisfies:

$$q = \arg\max_{j, j \notin \mathcal{T}} \mathrm{Ker}(G(\mathcal{T}), G(\mathcal{T}_{p \to j}))$$



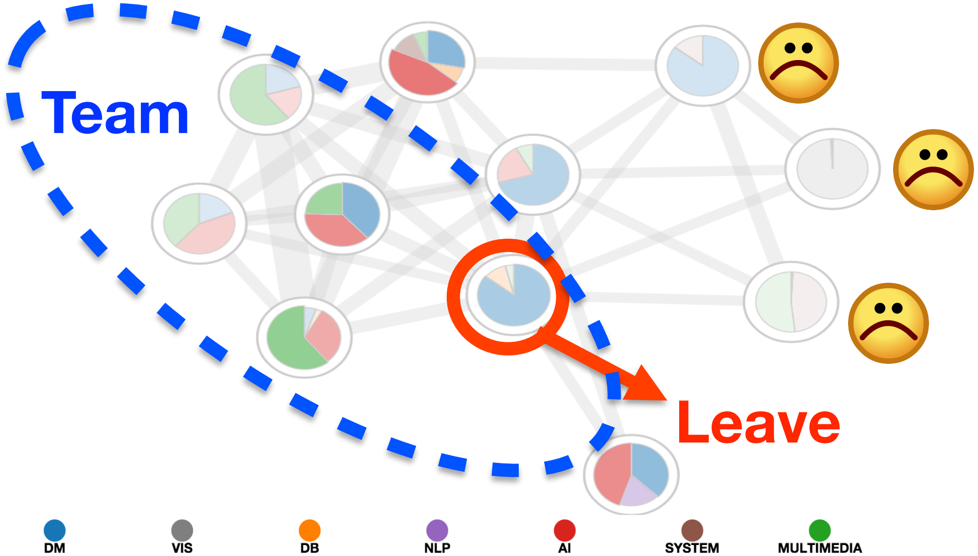
One graph kernel computation for every possible candidate

- **Challenge:** need to compute many graph kernel
  overall complexity: ***O(nt³)***
- **Questions:**
  - **Q1:** how to reduce the number of graph kernels
  - **Q2:** how to speed up the computation for each graph kernel

• L. Li, H. Tong, N. Cao, K. Ehrlich, Y.-R. Lin and N. Buchler: Replacing the Irreplaceable: Fast Algorithms for Team Member Recommendation, WWW 2015

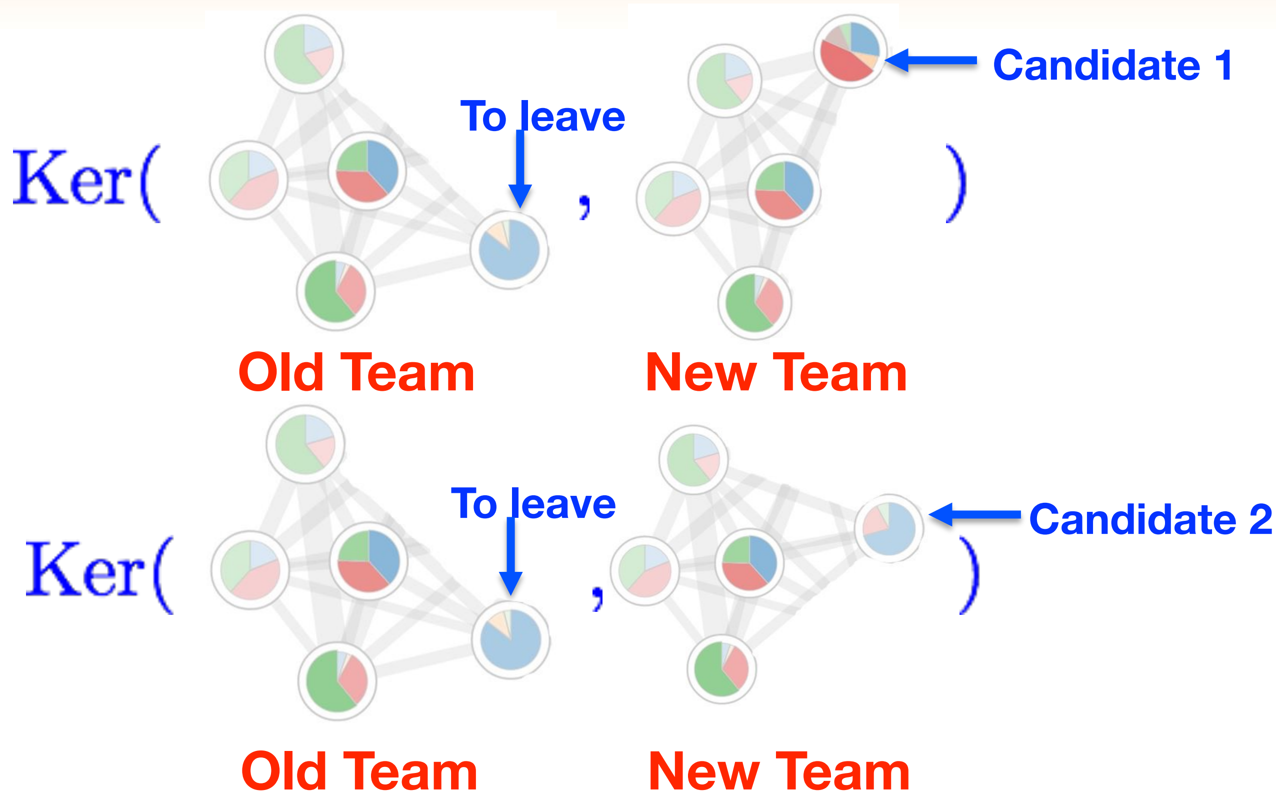
Scale-up: Candidate Filtering

***Pruning Strategy*:** Filter out all the candidates w/o any connections to any of the rest team members.



- **Theorem:** The pruning is safe: wont' miss any potentially good replacement
- **Benefit:** The number of graph kernel computations is reduced to O(size of the neighborhood of T) $O(\sum_{i \in \mathcal{T}/p} d_i)$

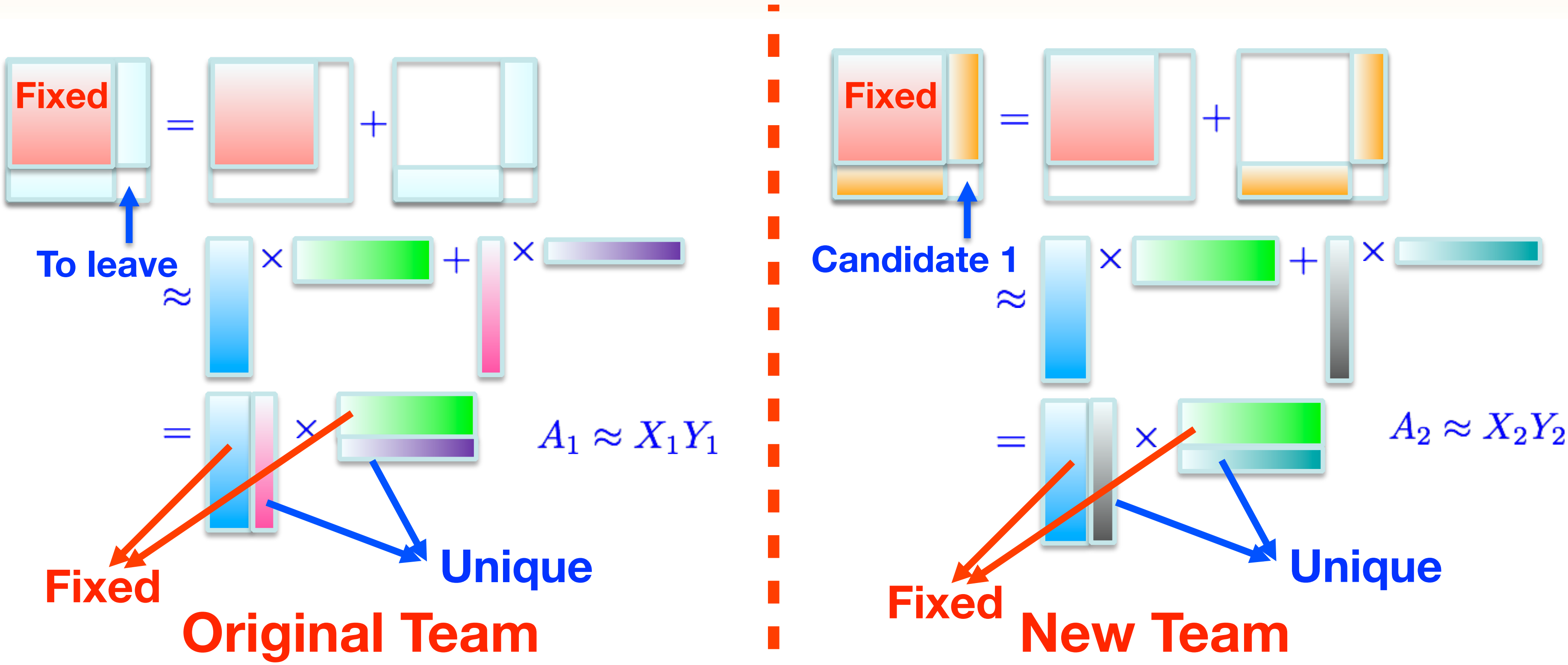
Speedup — Observation



Observation:

Many redundancies — *the nodes and edges within the rest team members remain the same*

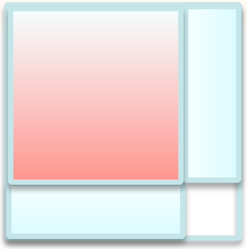
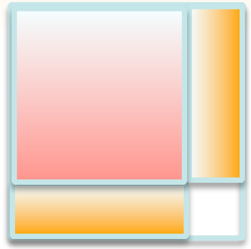
Speedup — Approx Approach



The common part is the adjacency matrix of the rest team members

Speedup — Approx Approach

Details

Ker( , )

$$\approx y'(1 - cL_\times (X_1Y_1)\otimes(X_2Y_2))^{-1}L_\times x$$

$$= y'L_\times x + cy'L_\times (X_1 \otimes X_2)\boxed{M}(Y_1 \otimes Y_2))L_\times x$$

$$M = (I - c(\sum_{j=1}^{l} Y_1 L_1^{(j)} X_1 \otimes Y_2 L_2^{(j)} X_2))^{-1}$$

M is of size $(r+2)^2 \times (r+2)^2$

Time Complexity: $O((\sum_{i\in\mathcal{T}/p} d_i)(lt^2r + r^6))$

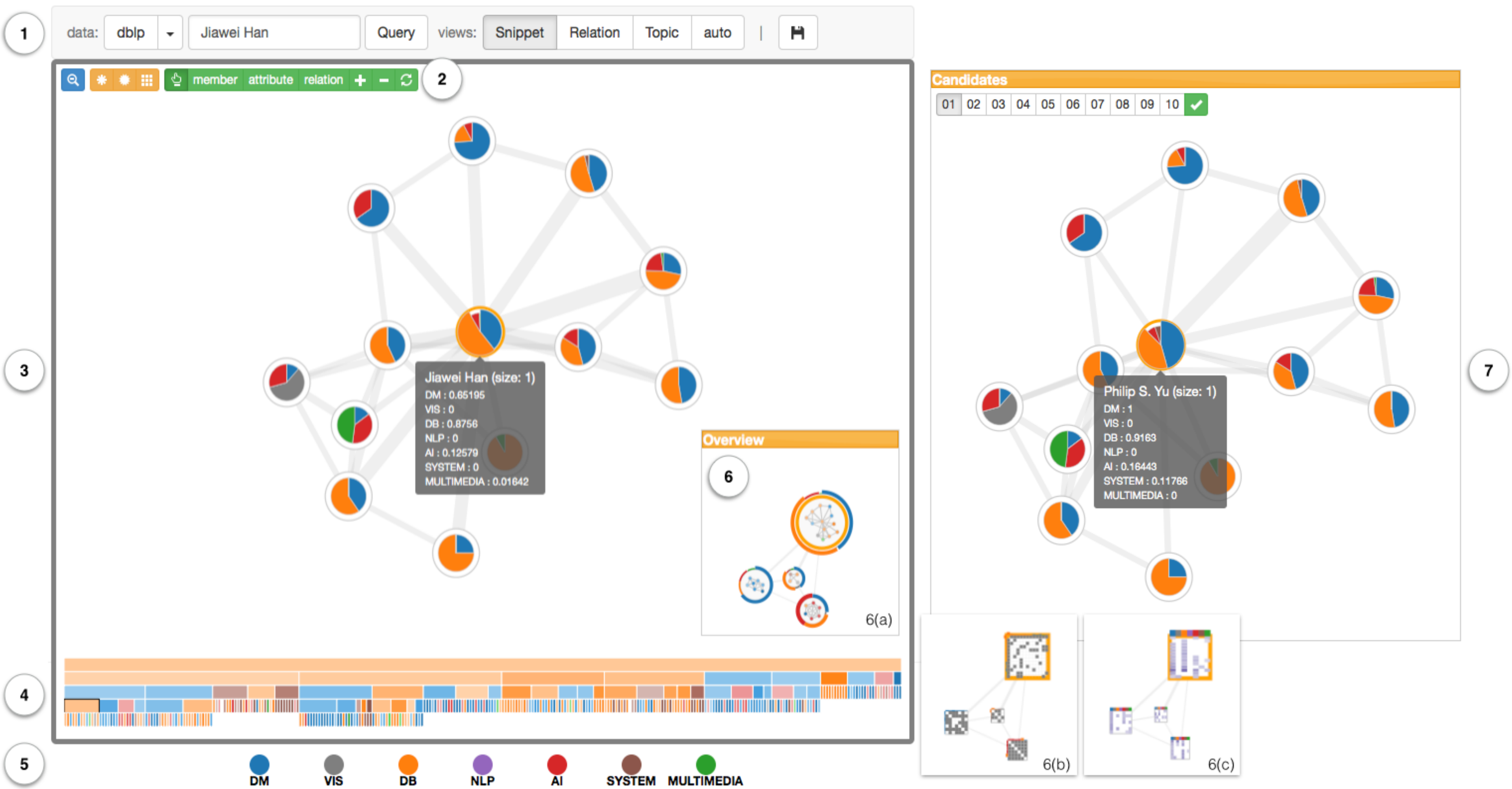
$[\sum_{i\in\mathcal{T}/p} d_i \ll n, r \ll t]$

Original Complexity: $O(nt^3)$

Prototype Systems

Questions

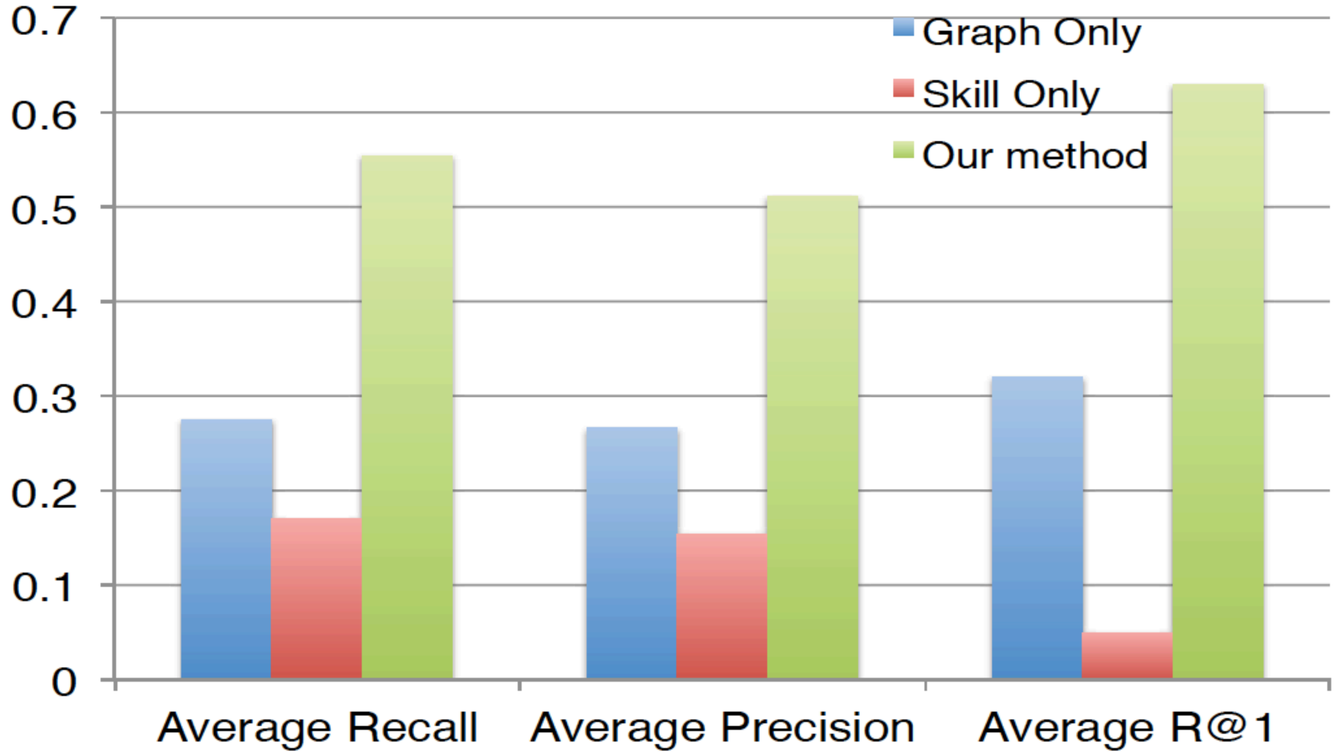
- **Q1: How effective is skill + structure?**
- **Q2**: How fast is pruning?
- **Q3:** How fast is proposed solution?
- **Q4**: How is the scalability?



prototype: http://team-net-work.org

- Nan Cao, Yu-Ru Lin, Liangyue Li, Hanghang Tong."g-Miner: Interactive Visual Group Mining on Multivariate Graphs", ACM **CHI** 2015.

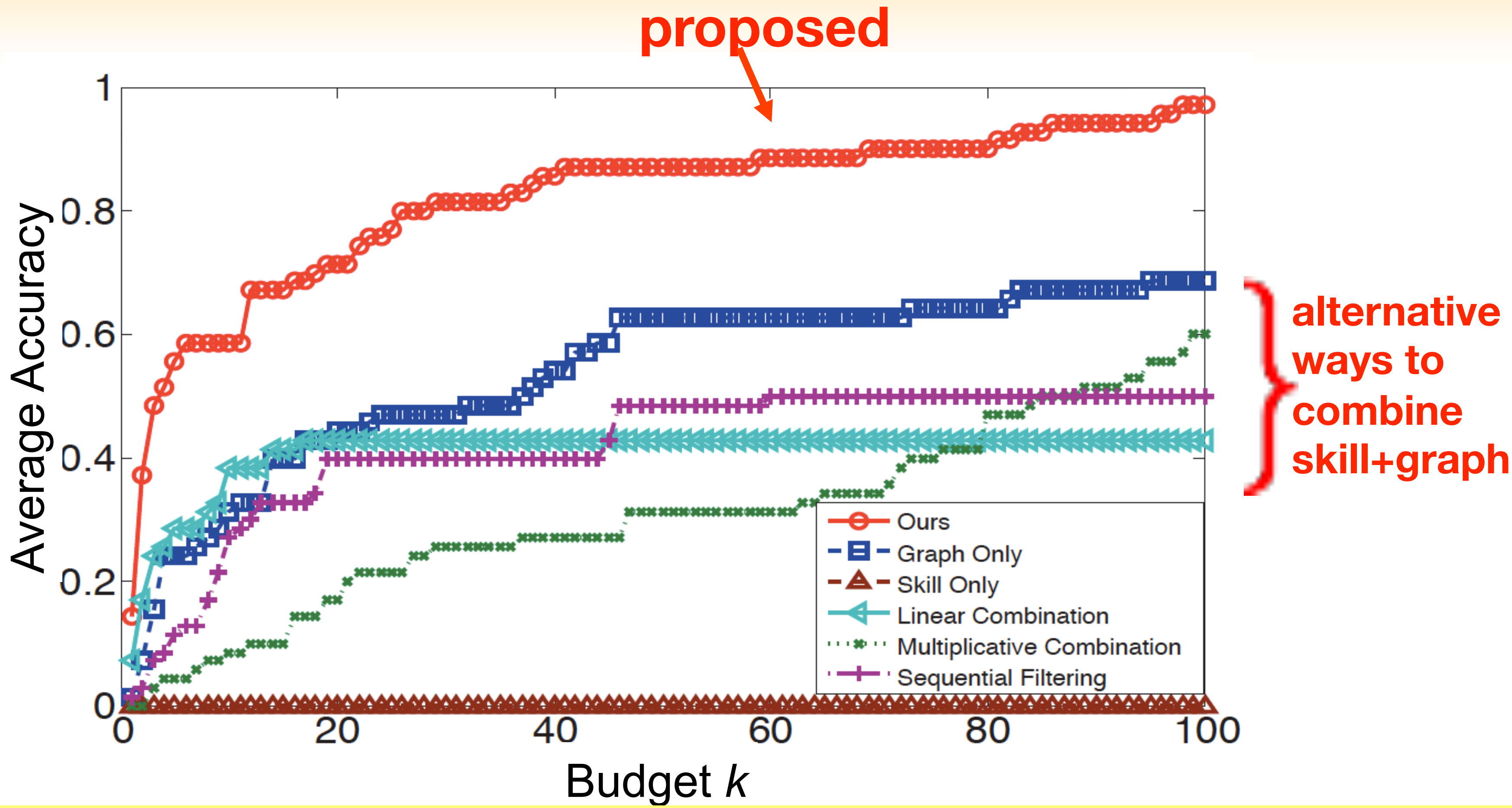
User Studies



Our method achieves the best average recall, precision and R@1

- L. Li, H. Tong, N. Cao, K. Ehrlich, Y.-R. Lin and N. Buchler: Replacing the Irreplaceable: Fast Algorithms for Team Member Recommendation, WWW 2015

Application in Author Alias Prediction

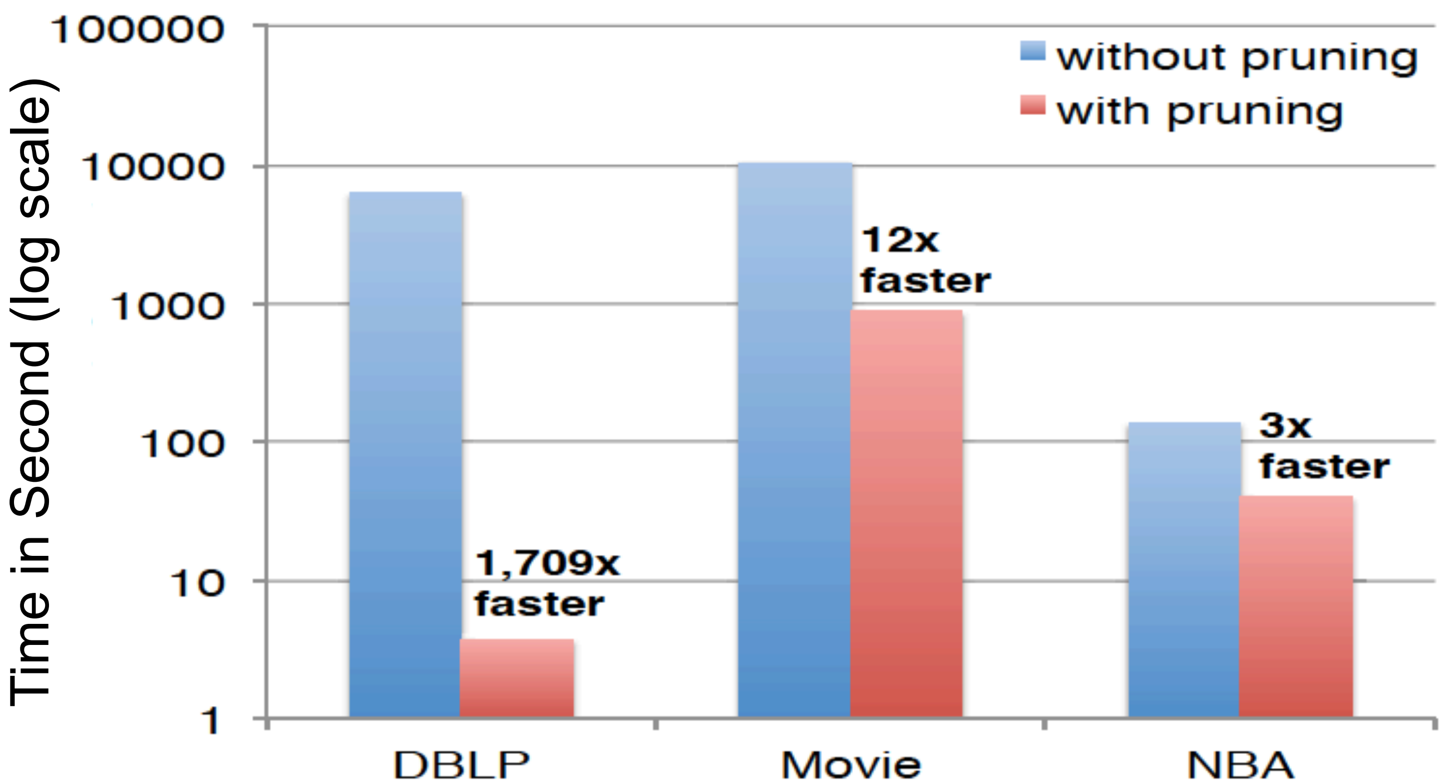


Our method achieves the highest accuracy

Author Alias: *Alexander J. Smola* vs. *Alex J. Smola*

Speed-up by Pruning

Questions
- **Q1**: How effective is skill + structure?
- **Q2: How fast is pruning?**
- **Q3:** How fast is proposed solution?
- **Q4**: How is the scalability?

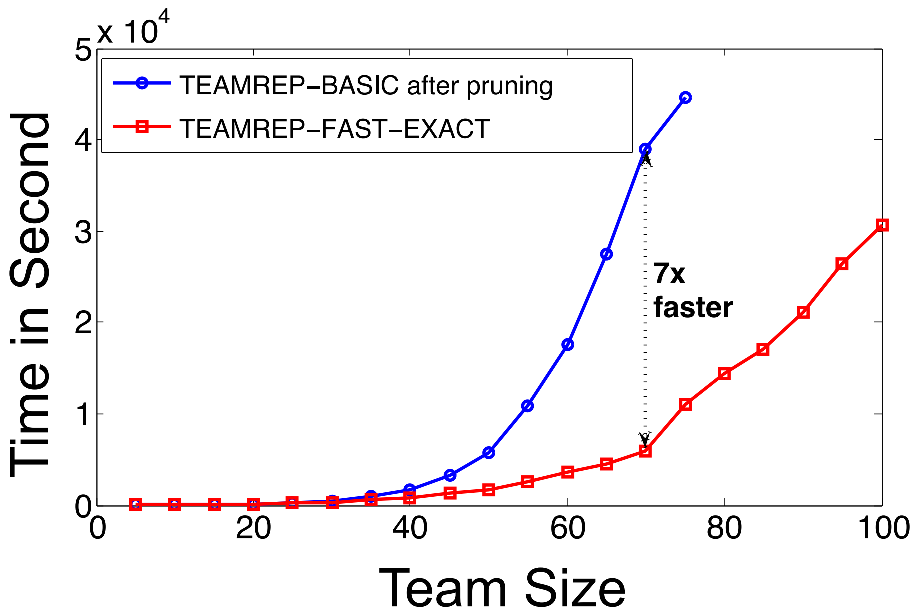


Pruning has dramatic speed improvement

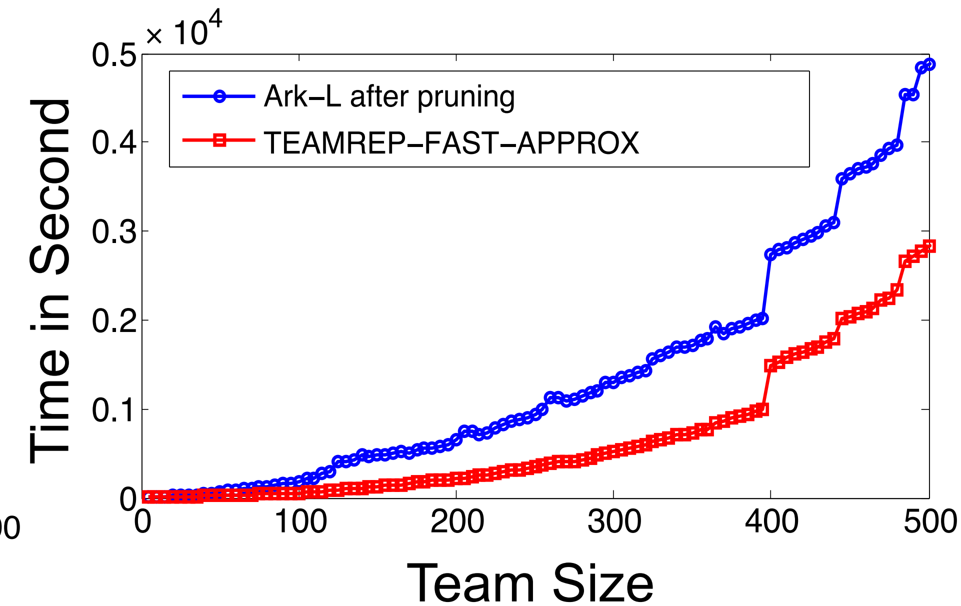
Further Speed-up

Questions

- **Q1**: How effective is skill + structure?
- **Q2**: How fast is pruning?
- **Q3: How fast is proposed solution?**
- **Q4**: How is the scalability?



Exact methods



Approximate methods

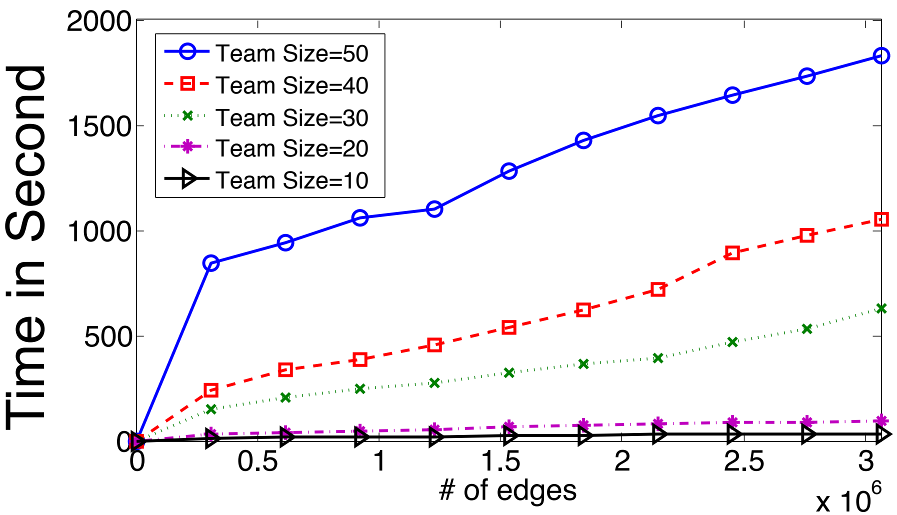
Exploiting redundancy leads to additional speed-up!

DATA Lab

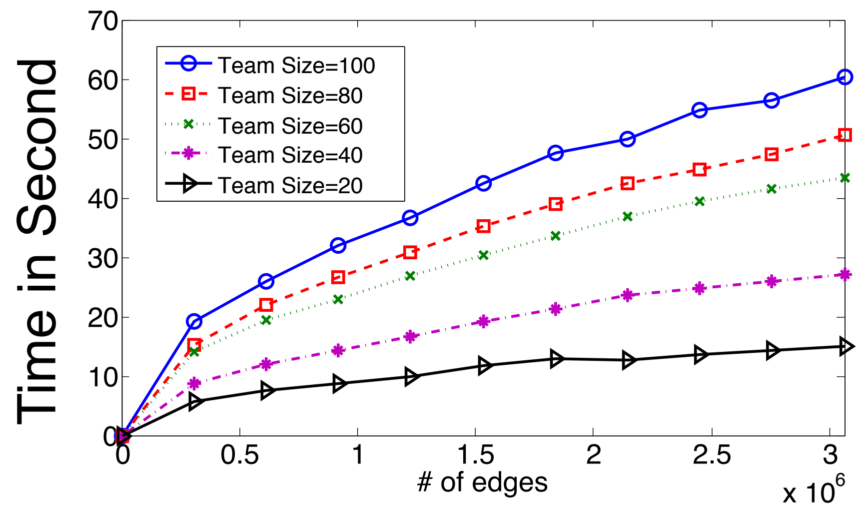
Scalability

Questions

- **Q1**: How effective is skill + structure?
- **Q2**: How fast is pruning?
- **Q3:** How fast is proposed solution?
- **Q4**: **How is the scalability?**



TEAMREP-FAST-EXACT

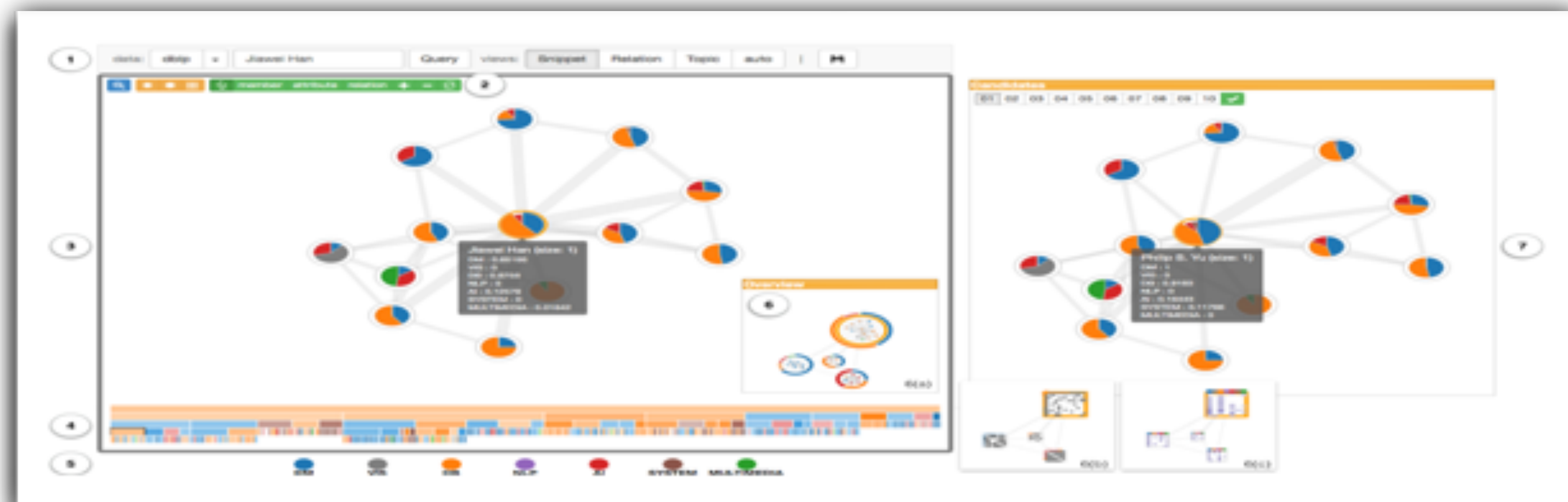


TEAMREP-FAST-APPROX

Our fast solutions scale sub-linearly

Team Member Replacement - Summary

- **Problem Def**: Team Member Replacement
- **Design Objectives**: skill + structural matching
- **Solutions**: graph kernel and fast algorithms
- **Prototype Systems:** http://team-net-work.org/



- L. Li, H. Tong, N. Cao, K. Ehrlich, Y.-R. Lin and N. Buchler: Replacing the Irreplaceable: Fast Algorithms for Team Member Recommendation, WWW 2015
- N. Cao, Y.-R. Lin, L. Li, H. Tong: g-Miner: Interactive Visual Group Mining on Multivariate Graphs, ACM CHI 2015

Beyond Team Member Replacement

- **Team Shrinkage**
  - If we need to reduce the size of an existing team (e.g., for the purpose of cost reduction), who shall leave the team?
- **Team Expansion**
  - If the team leader perceives the need to enhance certain expertise of the entire team, who shall we bring into the team?
- **Team Conflict Resolution**
  - If the team leader sees a conflict between certain team members, how shall we resolve it?

Key Idea: Solve all these team enhancement scenarios by team member replacement !

- L. Li, H. Tong, N. Cao, K. Ehrlich, Y.-R. Lin and N. Buchler: Enhancing Team Composition in Professional Networks: Problem Definitions and Fast Solutions, 2016

Open Challenges

- Team Performance Characterization
  - Correlation → Causality
  - When does “1+1 < 2” ?
- Team Performance Prediction
  - Joint Content-Individual-Team Prediction
  - Prediction→ Attribution
- Team Performance Optimization
  - Predictive Optimization
  - Team Optimization → Network Optimization

Acknowledgement

Norbou Buchler, Tina Eliassi-Rad, Nan Cao, Kate Erhlich, Wei Fan, Liangyue Li, Yuru Lin, Jie Tang, Brian Uzzi, Dashun Wang

Project website: http://team-net-work.org (for data, paper, slides and systems, etc)