

Identifying Decision Makers from Professional Social Networks

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Outline

- ❖ Motivation
- ❖ Social Network Environment
- ❖ Applications
- ❖ Challenges
- ❖ Features
- ❖ Learning Approaches
- ❖ Experimental Methodology
- ❖ Offline & Online Results
- ❖ Conclusion

Motivation



We learn a *global* scoring function to assign a **LinkedIn Decision Maker Score (LDMS)** to each of the 400+ Million Members.

- *Decision Makers* are the people who can make or influence a sales decision.

Social Network Environment



SALES NAVIGATOR

Welcome to the social selling era.

Unique Characteristics of Sales Navigator

- Most users are *sales professionals*.
- On top of LinkedIn.com actions, users can save potential prospects as *leads* for future follow-up.
- Users have *sales-focused* member and company search functionalities.

Applications



Refine your search

2.5M
Total results

107.7K
Changed jobs recently

279K
Posted on LinkedIn recently

35K
Share experiences with you

Keywords: vp marketing x

Exclude my saved leads x

We have filtered your results to exclude your saved leads.

Show all results

2,487,854 results · sorted by relevance



Sam Norpel 2nd



VP eCommerce at David's Bridal
Madison, Wisconsin Area · Retail
1 shared connection · Similar

Current: VP eCommerce at David's Bridal

Past: Vice President, Digital Marketing, eCommerce, Customer Acquisition at Lands' End

Vice President/Director, Marketing, True Action at eBay Enterprise

Save as lead

Connect

View profile

Send InMail



Michael S. Stromer 3rd

Vice President Tech Products
Greater New York City Area · Marketing and Advertising
Similar

Past: VP Digital Commerce, Loyalty & Analytics, Marketing at JetBlue Airways

Marketing, Customer Relationship Marketing (CRM), and Marketing Analytics. Direct report to Chief Director E-Commerce, Marketing at JetBlue Airways
Responsible for all digital marketing and e-commerce platforms including jetblue.com, mobile

Save as lead

Sales Navigator Search

Keywords

vp marketing x

Submit

Exclude from results

Exclude my saved leads

Current company

Relationship

TeamLink™

Location

Title

Industry

Postal code

Past Company



Google

Internet • San Francisco Bay Area • 10,001+ employees

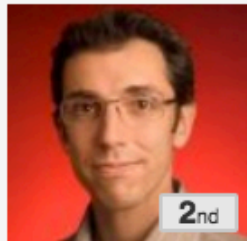
2 Leads

Saved

Lead recommendations

How you're connected (6,799)

TeamLink™ connections (17,864)



Jerry Dischler
VP, Product Management
San Francisco Bay Area

Save as lead

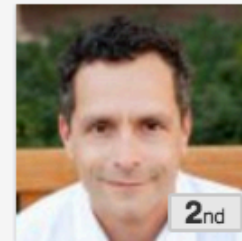
2nd



Allan C. Thygesen
VP, Global SMB Sales an...
San Francisco Bay Area

Save as lead

3rd



Bradley Horowitz
VP, Photos and Streams
San Francisco Bay Area

Save as lead

2nd



Melody Meckfessel
Senior Engineering Direct...
San Francisco Bay Area

Save as lead

2nd



Shalini Govil-Pai
Director & Global Head, P...
San Francisco Bay Area

Save as lead

2nd



See more recommendations



66,070 employees at Google. [See all employees >](#)

Challenges

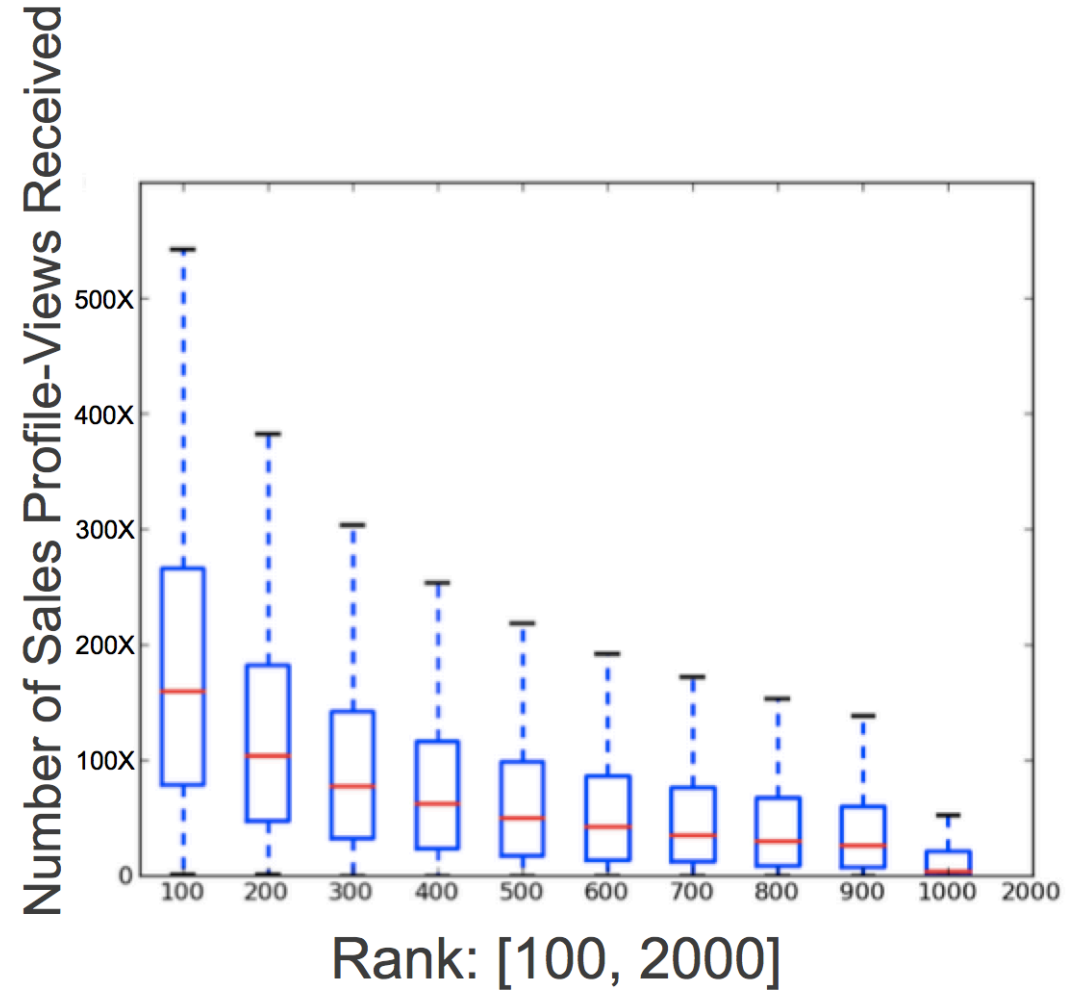
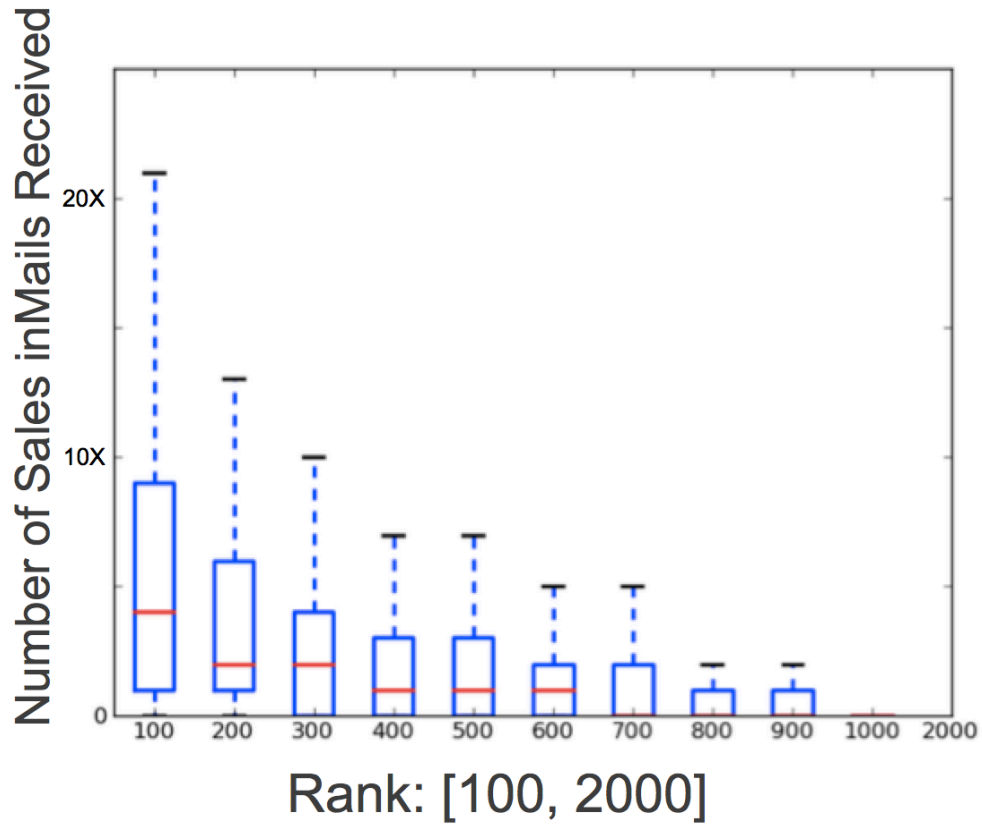
Unavailability of Ground Truth

We do not have a definite answer
on who is and who is not
a decision maker.

Signal for Ground Truth Definition

**The number of inMails
from distinct Sales Professionals
within a specified time frame.**

Why not choose the ground truth as LDMS score?

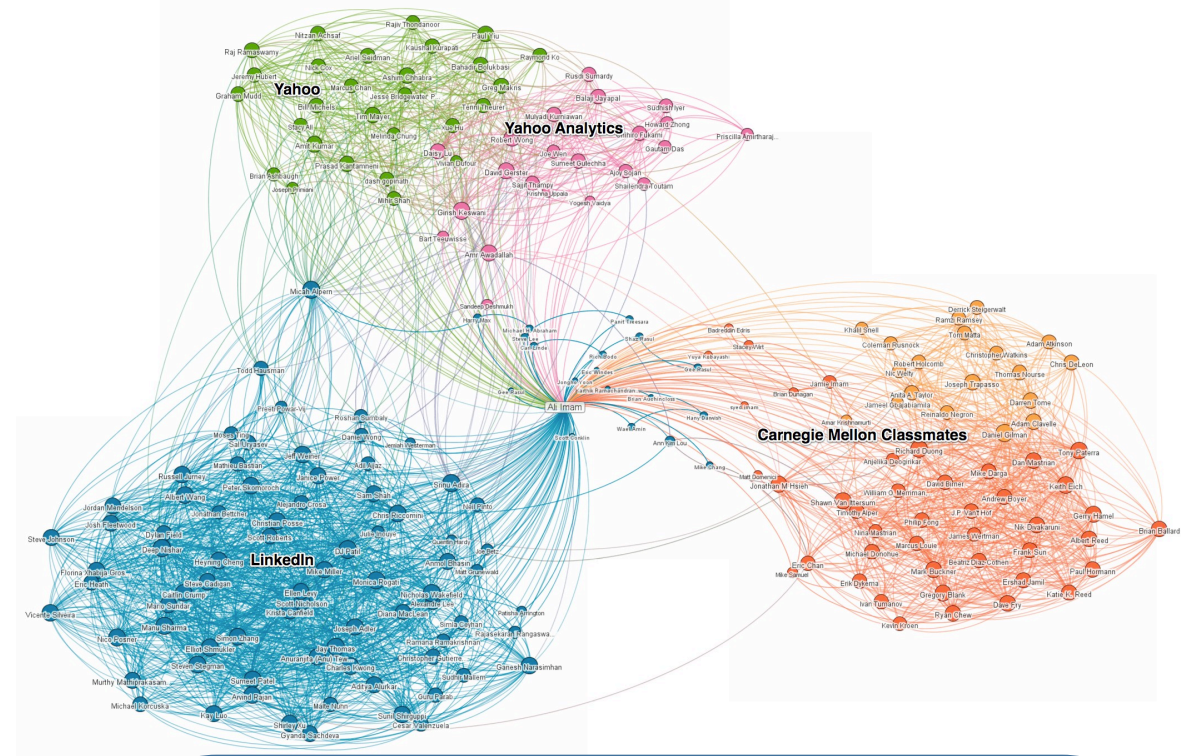


Features



Contextual Information (Member Profile)

- Title
- Position
- Seniority
- Related Working Experience of the member



Graph Information

- Connection Graph
- Invitation Graph
- Profile View Graph
- Lead Save Graph
- InMail Graph

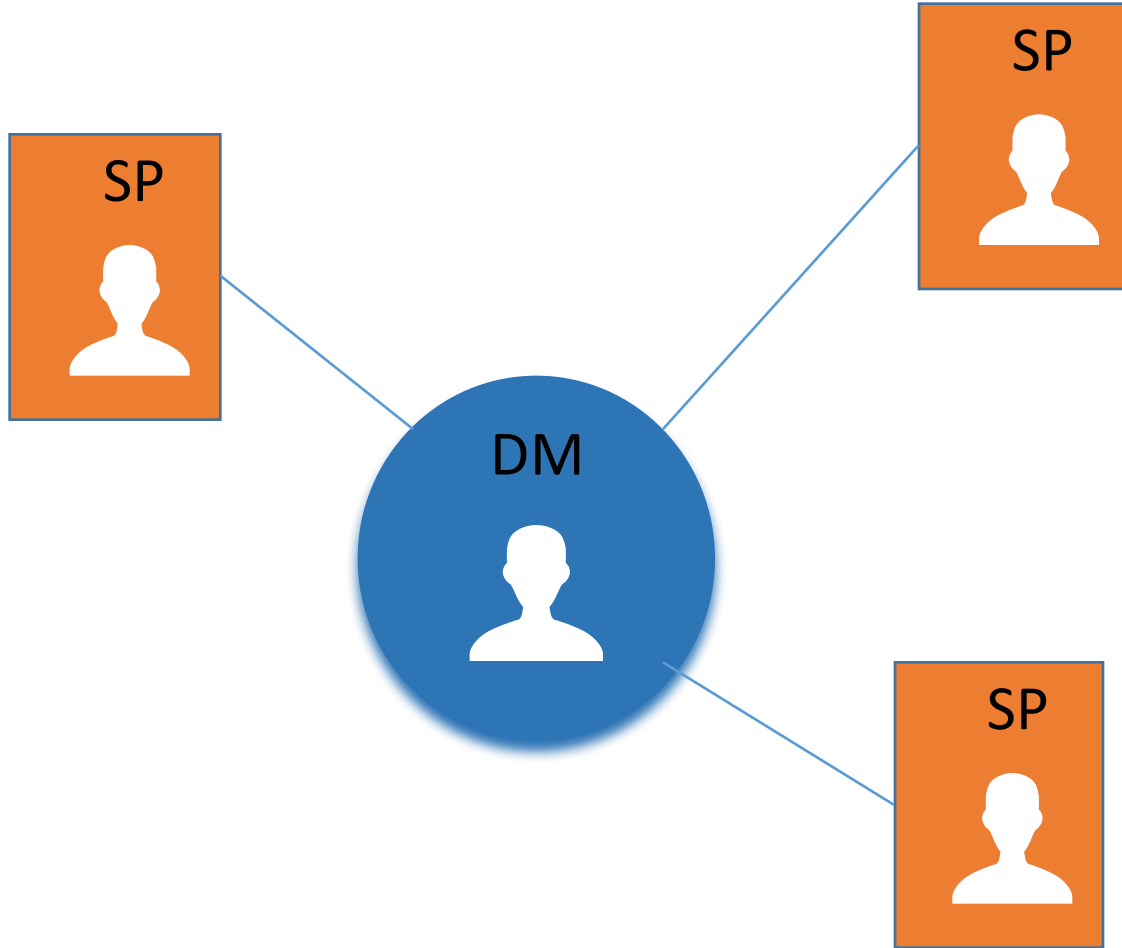
Graph Features Extracted

Undirected Graphs (e.g. Connection Graph)	
All-Degree	Degree of the member in the graph
Sales-Degree	Degree of the member considering only neighbors who are sales professionals
Ratio-Sales-All	$\text{Sales-Degree} / \text{All-Degree}$
Directed Graphs (e.g. Profile View graph, inMail graph)	
All-In	Indegree from all members
All-Out	Outdegree to all members
Sales-In	Indegree from sales professionals
Ratio-Sales-In	$\text{Sales-In} / \text{All-In}$
Ratio-In-Out	$\text{All-In} / \text{All-Out}$

Learning Approaches

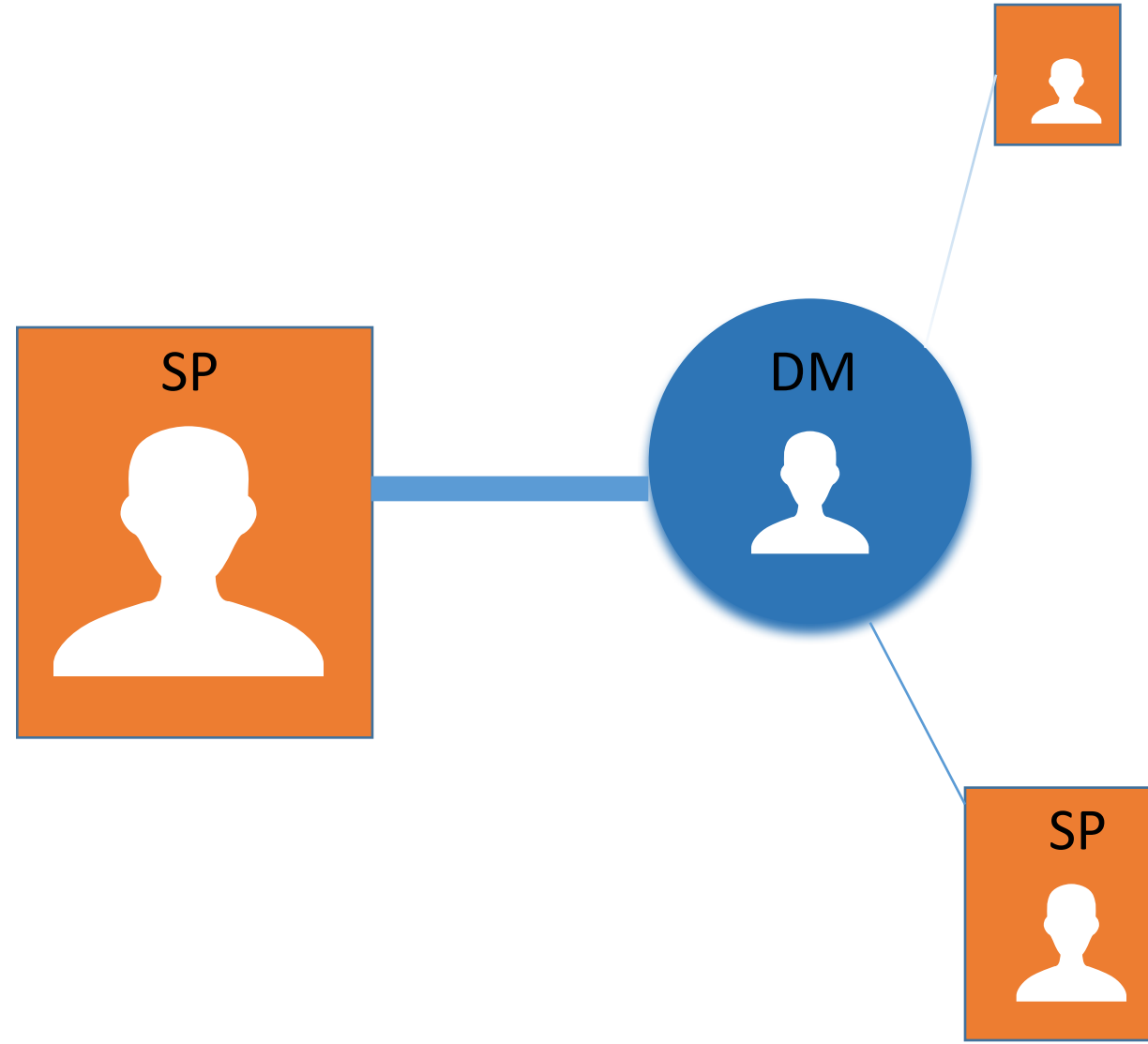
Graph Summarization

Every sales professional has equal weight!



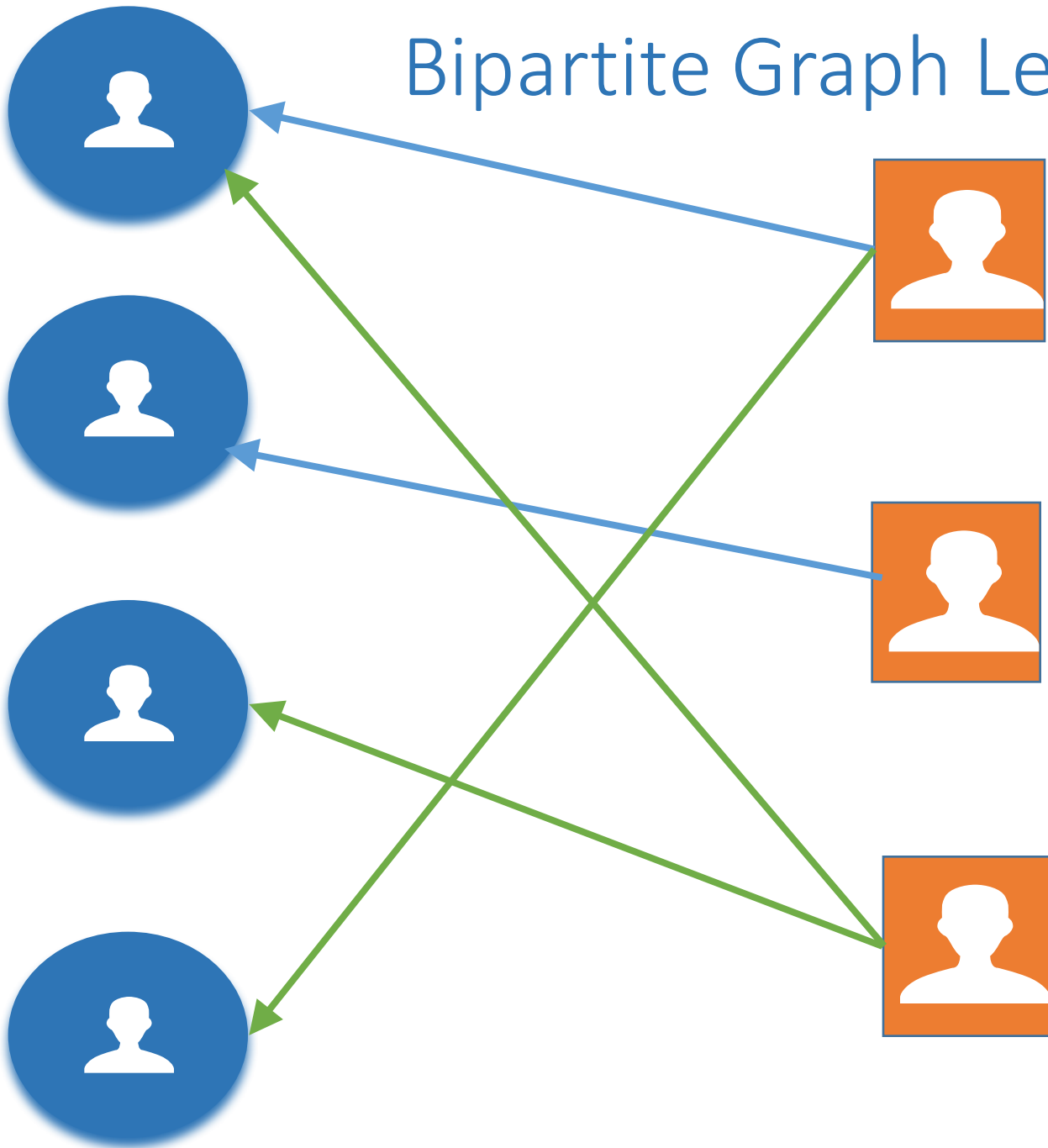
Bipartite Graph Learning

Every sales professional is weighted based on their competency.

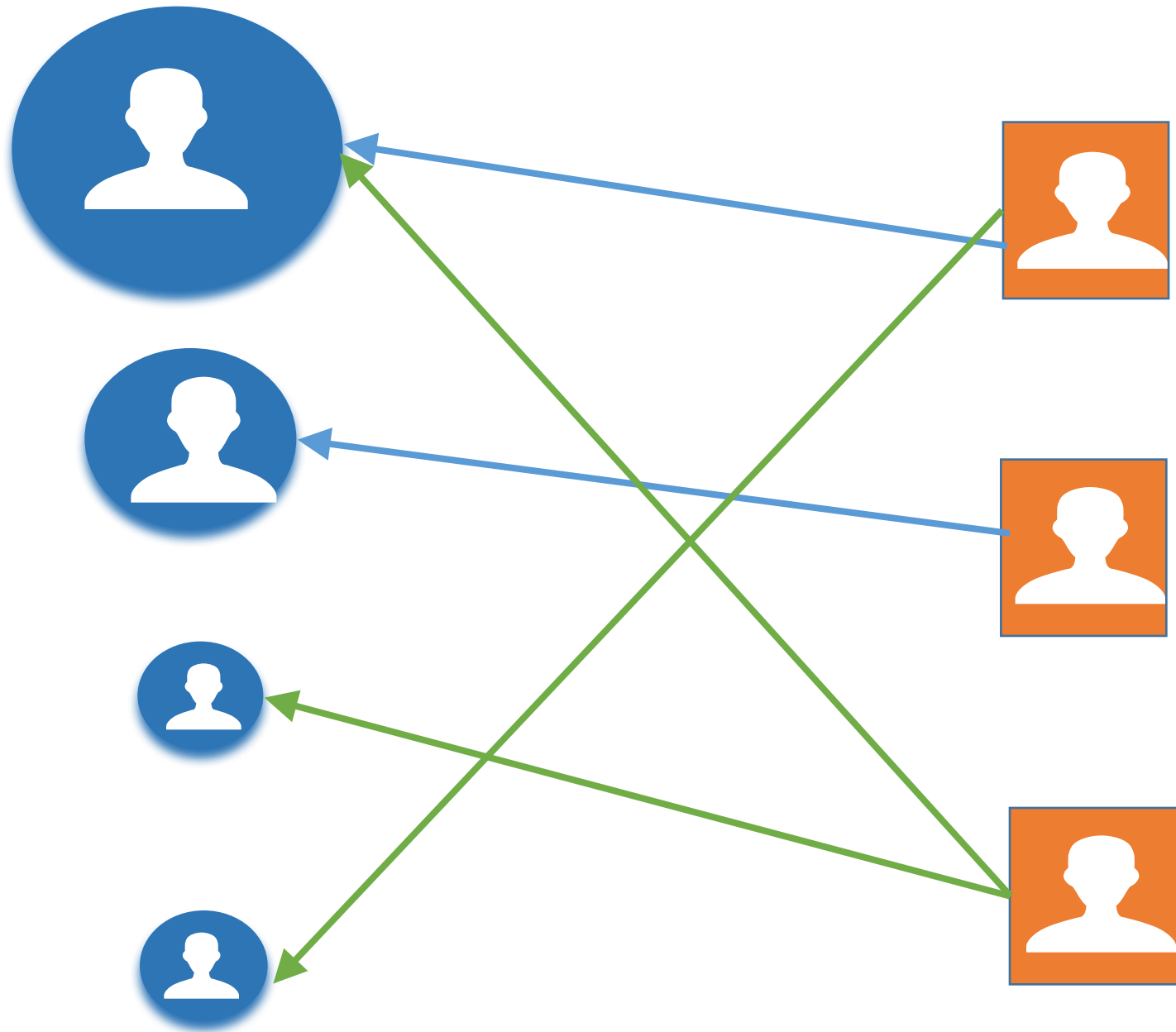


The Bipartite Graph Learning approach explicitly takes into account the LDMS for each member and the **LSCS (LinkedIn Sales Competency Score)** for each sales professional!

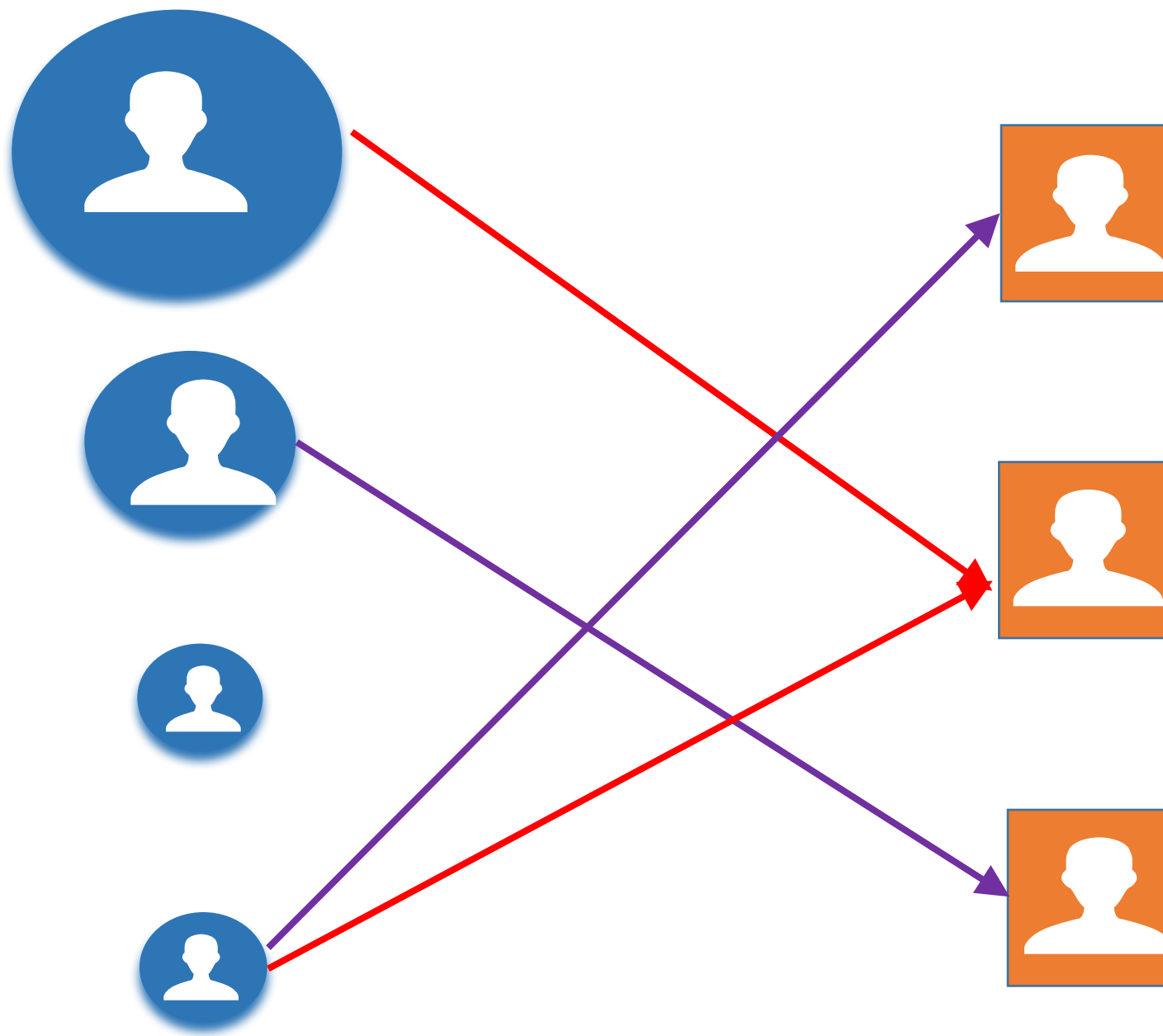
Bipartite Graph Learning - Algorithm



- First, all sales professionals are of equal weight .
- The direction SP -> DM is considered.
- The weights for decision makers are learned with elastic net.



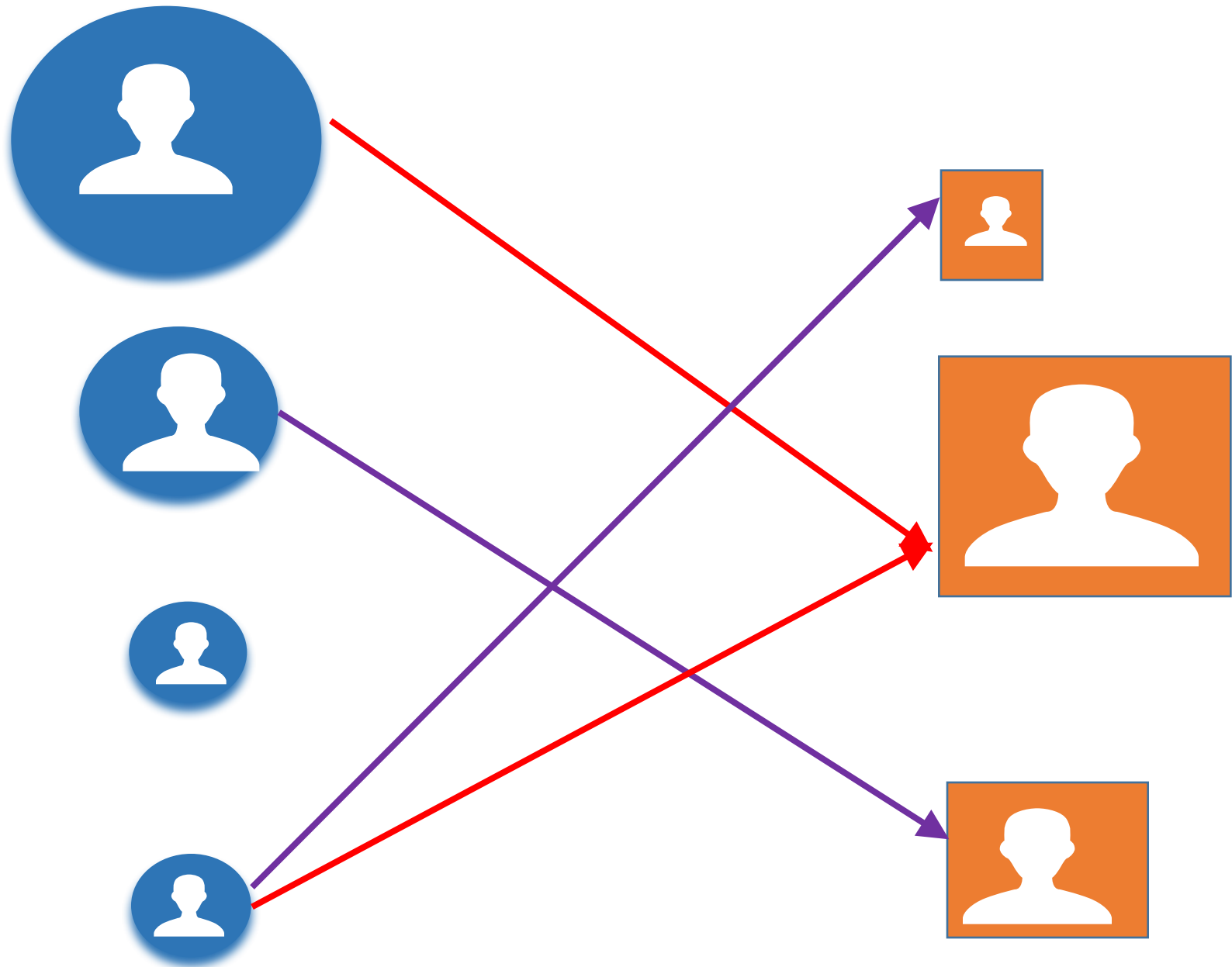
Based on the LDMS score, some DMs are more important than others!



The direction DM->SP is considered.

The elastic net is solved for the sales professionals.

As there is *no ground truth for sales professionals*, we take a heuristic approach and we label the top 20% as +1 and the bottom 20% as -1.



Based on the LSCS score learned, some sales professionals are more important than others!

The approach is continued *iteratively*, solving the elastic net problems for the decision makers and the sales people until the weights converge!

The algorithm typically converges within *twenty* iterations.

$$p_i = f\left(w_{pc}x_i + \sum_{k=1}^K w_{pk} \sum_{j: e_k(j \rightarrow i) \in E_k} q_j t(j, i)\right)$$

$$q_j = g\left(w_{qc}z_j + \sum_{k=1}^K w_{qk} \sum_{i: e_k(i \rightarrow j) \in E_k} p_i t(i, j)\right)$$

Condition under which	The Bipartite Learning Method is:
qj=1 (equal weight of sales professionals)	Graph summarization approach
K=1 & no constant features (xi=zj=0)	Extension of Label propagation
Removing ground truth labels	Extension of HITS to bipartite

Experimental Methodology

Training Methodology

- ❖ We collected all LinkedIn network data over the calendar year of 2015.
- ❖ The LinkedIn member base is randomly split into training (70%) and testing (30%).
- ❖ Each member x is assigned a label, based on their ground truth $GT(x)$ and two thresholds: T_{pos} and T_{neg} .

$$Label(x) = \begin{cases} +1, & \text{if } GT(x) \geq T_{pos} \\ -1, & \text{if } GT(x) < T_{neg} \\ 0, & \text{otherwise} \end{cases}$$

- ❖ The members with label 0 are ignored to remove noisy data.

Metrics

k: position

★ $NDCG@k = \frac{DCG@k}{Ideal\ DCG@k}$ where

$DCG@k = \sum_{r=1}^k \frac{2^{rel(r)} - 1}{\log_2(r + 1)}$ and Ideal DCG@k is obtained had the list been sorted by the ground truth label.

★ $\tau(k) = \frac{(\#concordant\ pairs) - (\#discordant\ pairs)}{\frac{1}{2}k(k - 1)}$

	NDCG	Kendall's tau
Range	[0,1]	[-1,1]
Weight of member pairs	Discount weighting scheme	same
Measures	Ranking Performance	Correlation

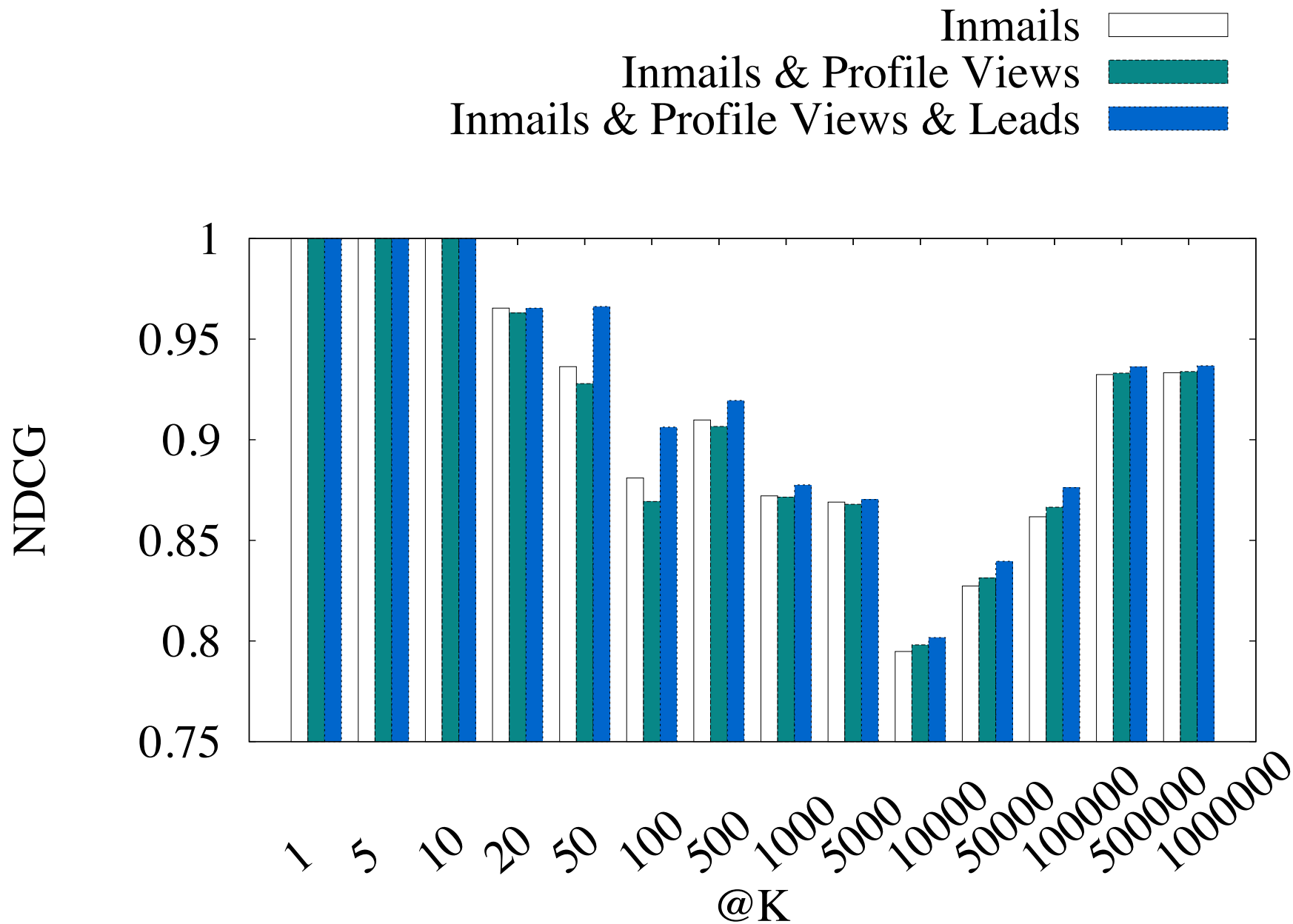
Offline Results

Results for Graph Summarization & Bipartite Graph Learning

NDCG@K	10	20	50	100	500	1,000	5,000	10,000	50,000	100,000	500,000	1,000,000
Summarization	1	0.963	0.9084	0.8593	0.9039	0.8684	0.8682	0.7987	0.8339	0.8701	0.9336	0.9344
Bipartite	1	0.9664	0.9665	0.9063	0.9183	0.878	0.871	0.8043	0.8412	0.8778	0.9367	0.9373

Kendall's τ @K	10	20	50	100	500	1,000	5,000	10,000
Summarization	0.5394	0.5769	0.5185	0.6365	0.5681	0.4829	0.4717	0.4956
Bipartite	0.4045	0.4476	0.5135	0.6253	0.5605	0.4855	0.4746	0.5043

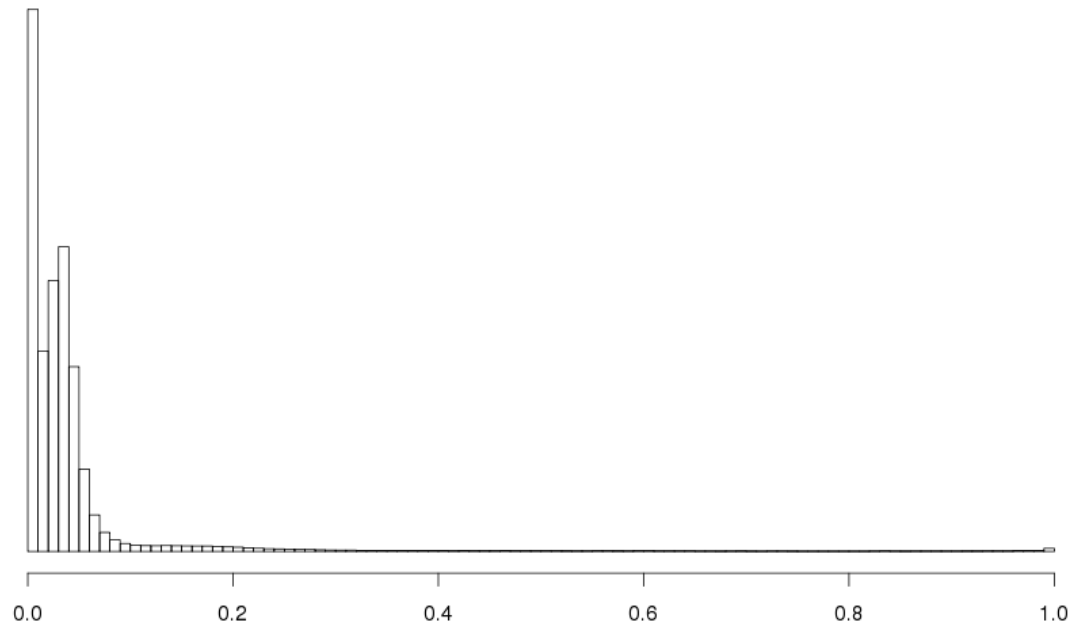
Leveraging Different Social Graphs



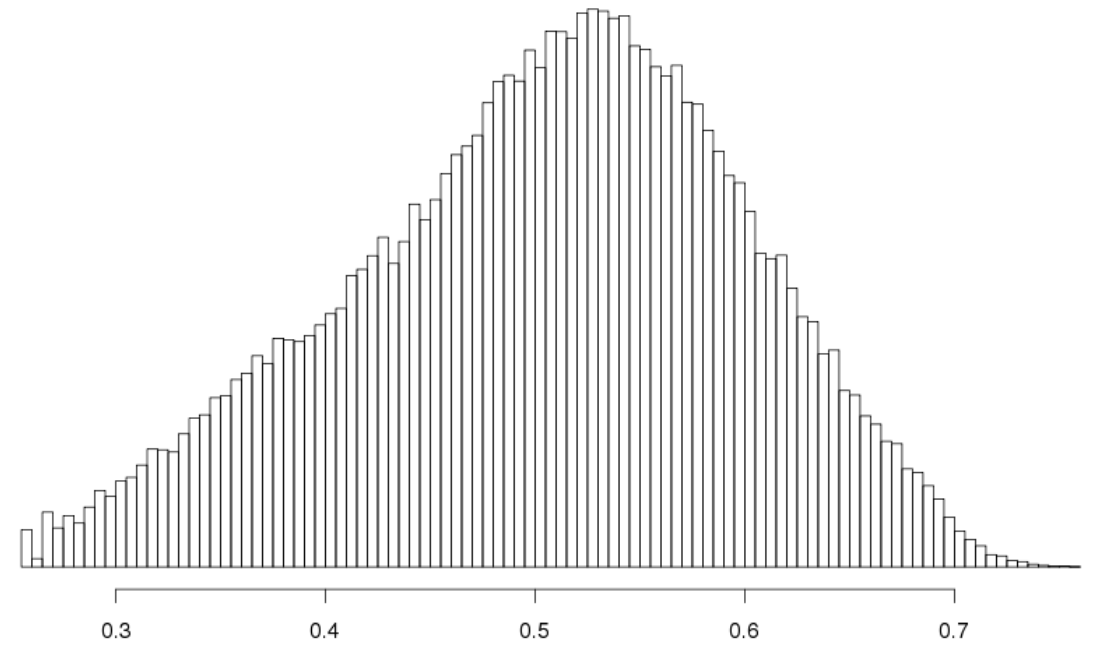
Score Distributions

LDMS scores

LSCS scores



Power Law Distribution



Normal Distribution

Online Results

A/B tests were performed on lead saves from search, which is the key metric for Sales Navigator Search.

The screenshot shows the LinkedIn Sales Navigator interface. At the top, the search bar contains the text "Search for people and companies..." and is circled in red. The navigation bar includes "HOME", "ACCOUNTS (21)", "LEADS (33)", and "INBOX 70". The main content area displays search results for "vp marketing".

Refine your search

- All
- People**
- Companies

Keywords

vp marketing x

Submit

Exclude from results

Exclude my saved leads

Current company ▾

Relationship ▾

TeamLink™ ▾

Location ▾

Title ▾

Industry ▾

Postal code ▾

Past Company

2.5M Total results

107.7K Changed jobs recently

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Sam Norpel 2nd
VP eCommerce at David's Bridal
Madison, Wisconsin Area · Retail
▶ 1 shared connection · [Similar](#)

Current: VP eCommerce at David's Bridal
Past: Vice President, Digital **Marketing**, eCommerce, Customer Acquisition at Lands' End
Vice President/Director, **Marketing**, True Action at eBay Enterprise

Save as lead ▾

- Connect
- View profile
- Send InMail

Michael S. Stromer 3rd
Vice President Tech Products
Greater New York City Area · Marketing and Advertising
[Similar](#)

Past: **VP** Digital Commerce, Loyalty & Analytics, **Marketing** at JetBlue Airways
Marketing, Customer Relationship **Marketing** (CRM), and **Marketing** Analytics. Direct report to Chief Director E-Commerce, **Marketing** at JetBlue Airways
Responsible for all digital **marketing** and e-commerce platforms including jetblue.com, mobile

Save as lead ▾

Results:

- A/B test for *graph summarization* approach has shown **4.5% improvement**.
- A/B test for *bipartite graph learning* approach has shown an **additional 10.6% improvement** on lead saves from search.

Conclusion

Contributions

- We presented **LDMS score**, the LinkedIn Decision Maker Score, to capture the ability to make/influence a sales decision for each of the 400M+ LinkedIn members.
- We proposed **two learning approaches**, which can be applied to other social network settings.
- The approaches are able to leverage graph and contextual information, deal with small amounts of labels on the graph, and handle heterogeneous graphs.

Thank you!

Questions? 😊