Identifying Decision Makers from Professional Social Networks

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Outline

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- Social Network Environment
- Applications
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- Features
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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

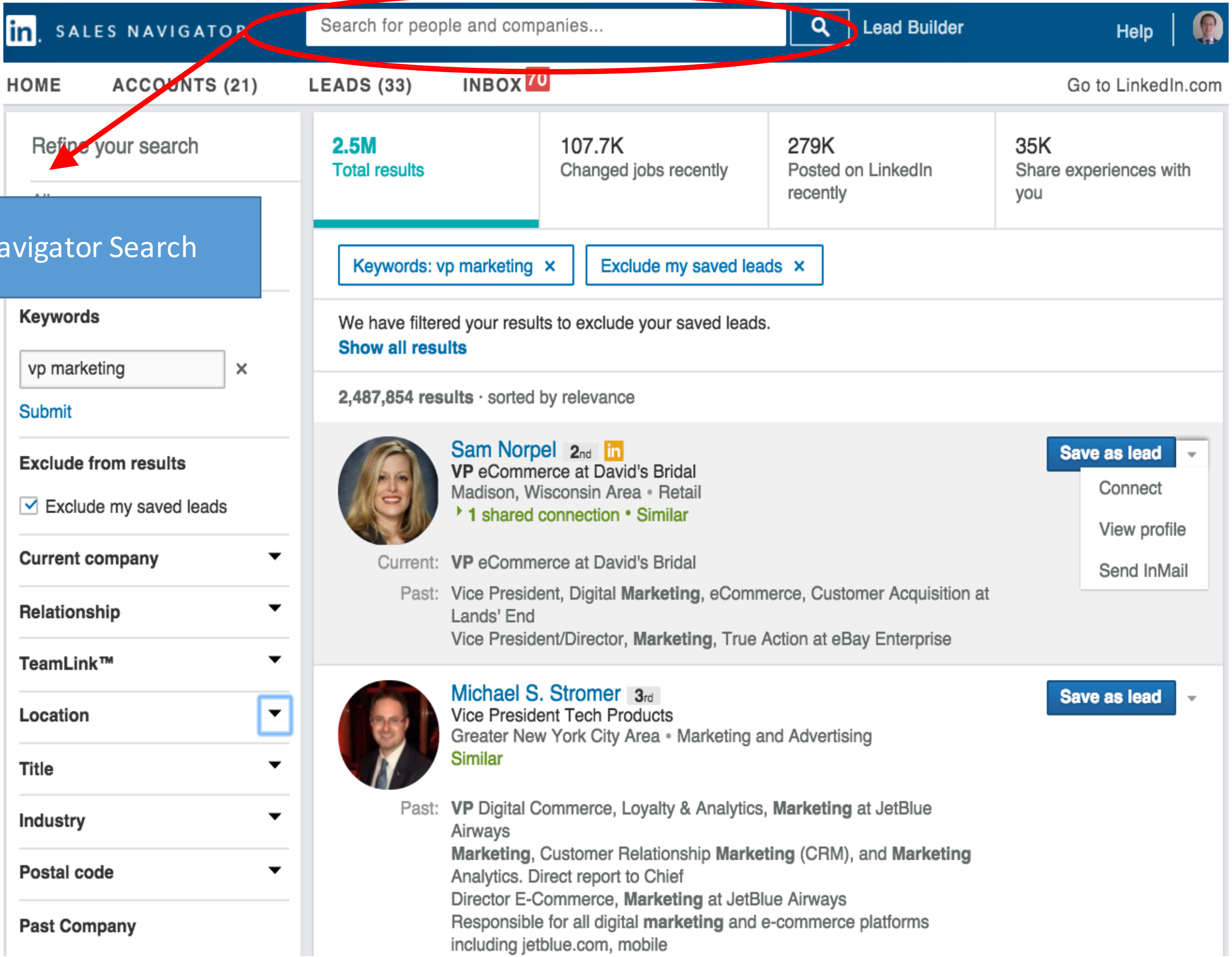

SALES NAVIGATOR
Welcome to the social selling era.

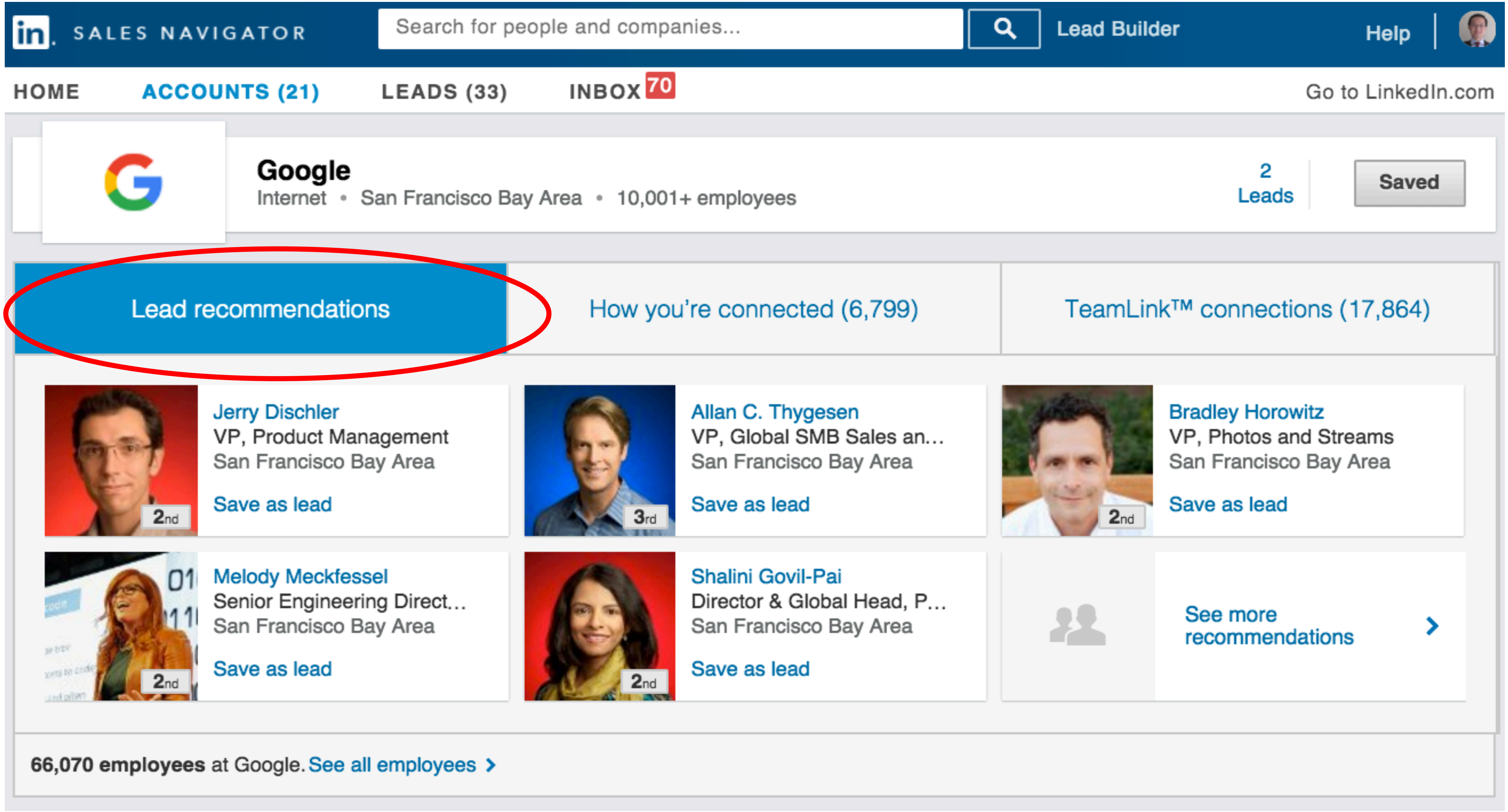
Unique Characteristics of Sales Navigator

- 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

Sales Navigator Search




in. SALES NAVIGATOR
Search for people and companies...
Lead Builder
Help
HOME
ACCOUNTS (21)
LEADS (33)
INBOX 70
Go to LinkedIn.com
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

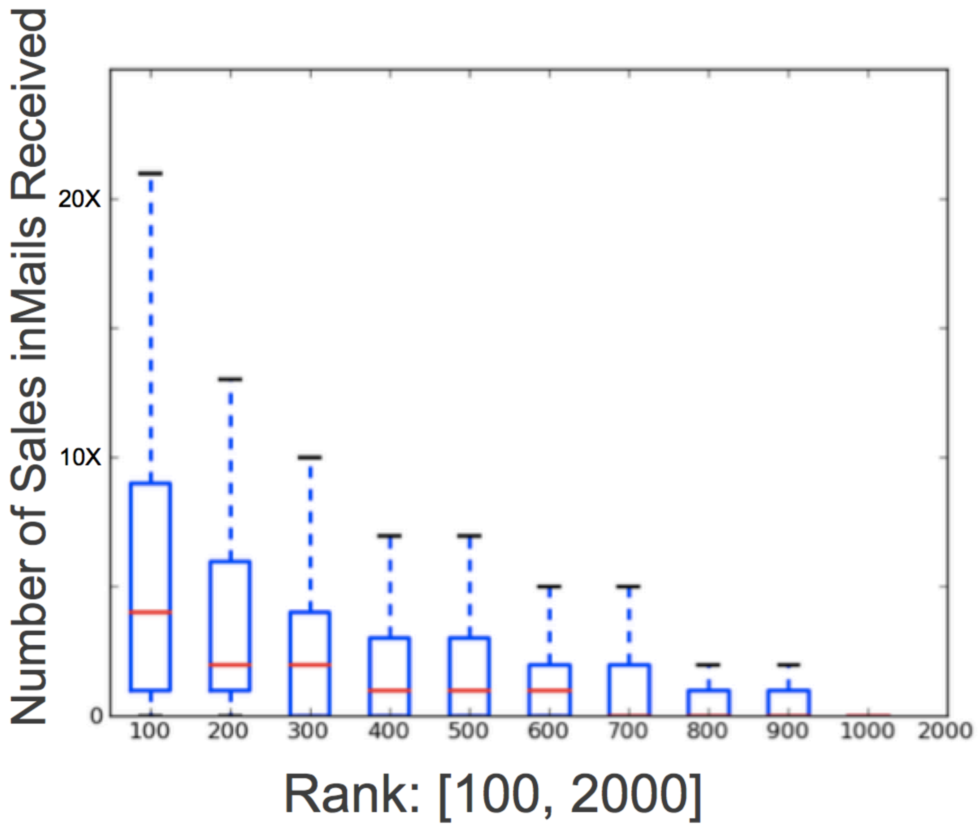
Unavailability of Ground Truth

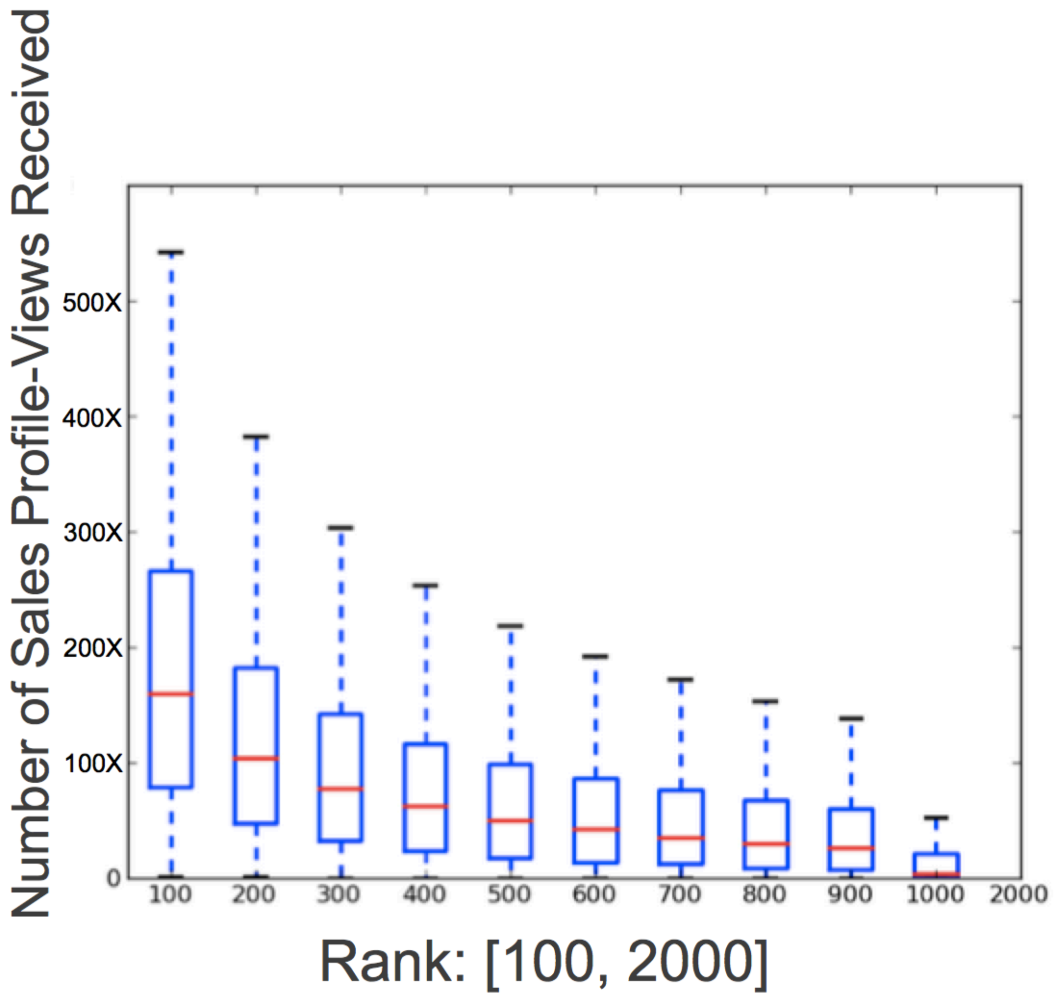
We do not have a definite answer
on who is and who is not
a decision maker.

Signal for Ground Truth Definition

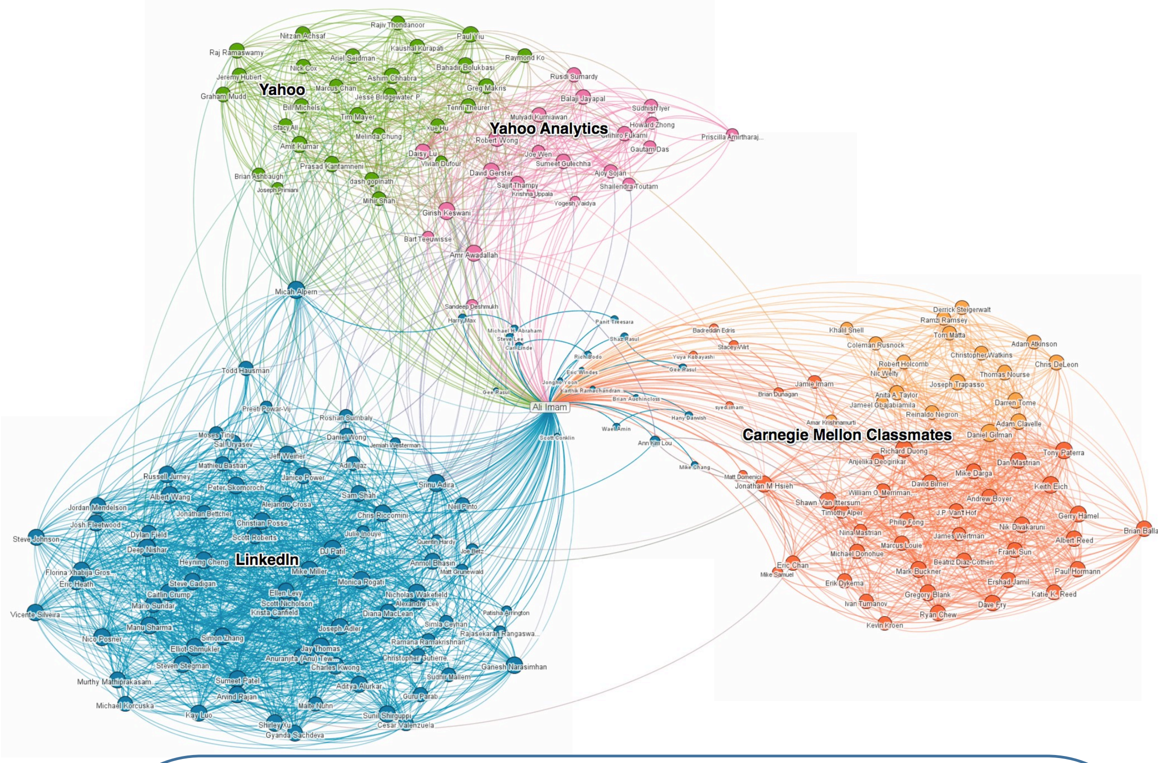
The number of inMails
from distinct Sales Professionals
within a specified time frame.

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

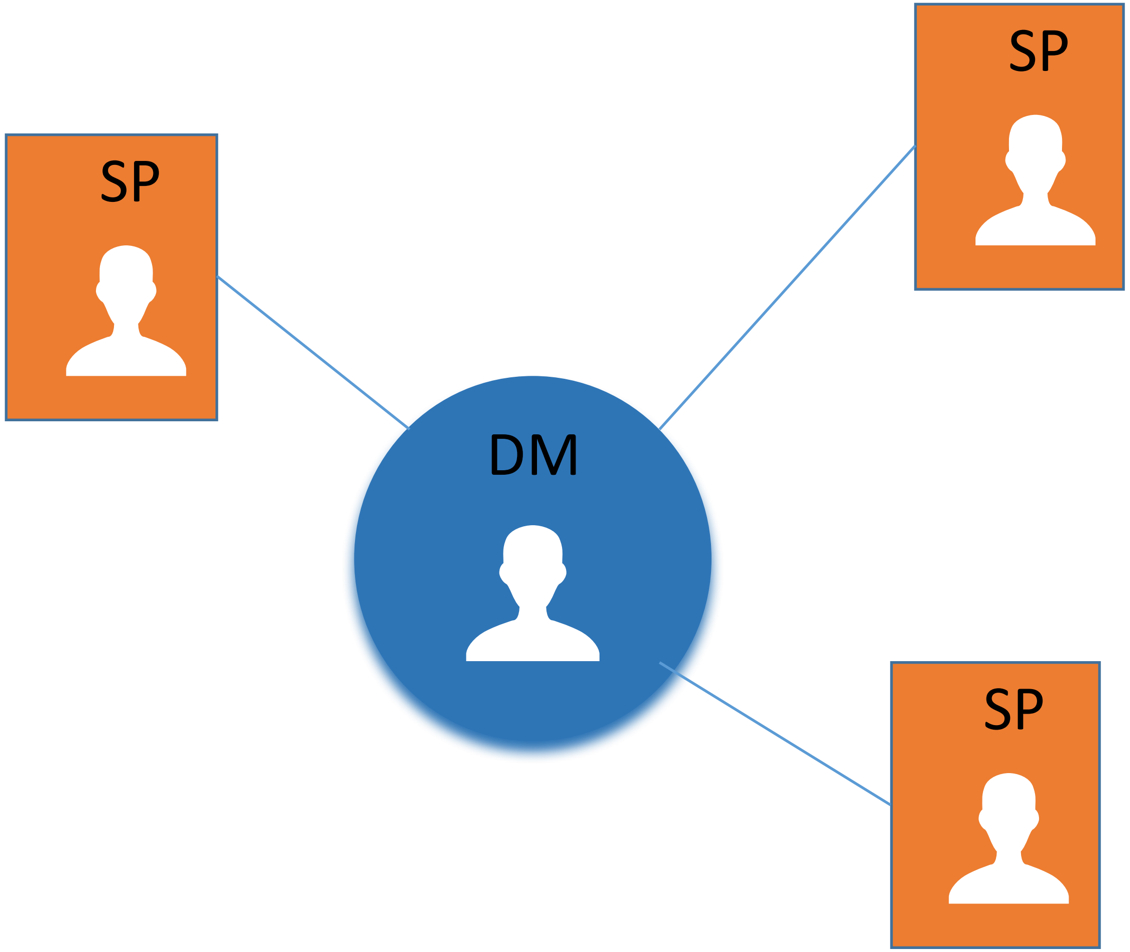
Undirected Graphs (e.g. Connection Graph)	
All-Degree	Degree of the member in the graph
Sales-Degree	Degree of the member considering only neighbors who are sales professionals
Ratio-Sales-All	Sales-Degree / All-Degree

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	Sales-In / All-In
Ratio-In-Out	All-In / All-Out

Learning Approaches

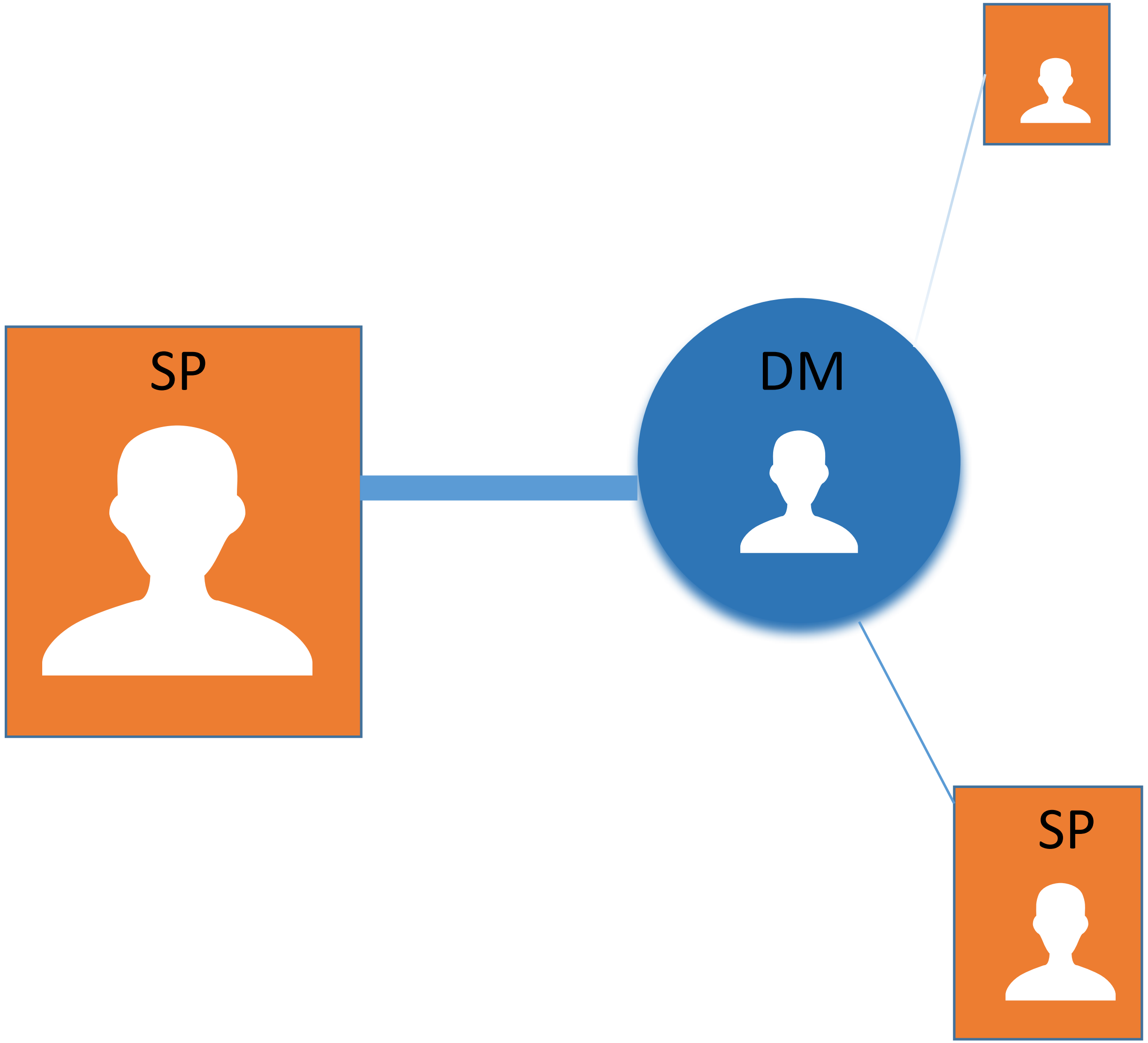
Graph Summarization

Every sales professional has equal weight!



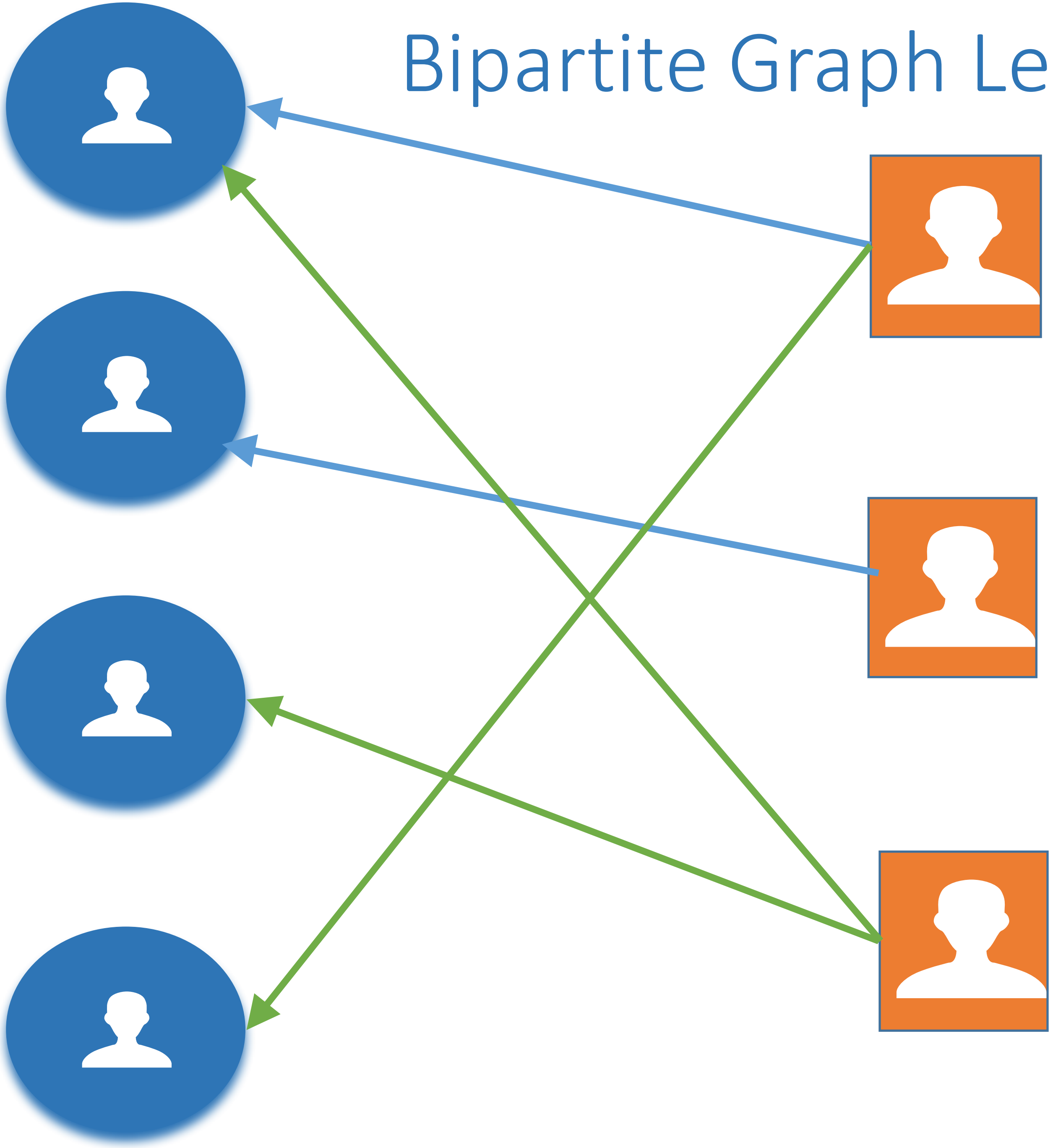
Bipartite Graph Learning

Every sales professional is weighted based on their competency.

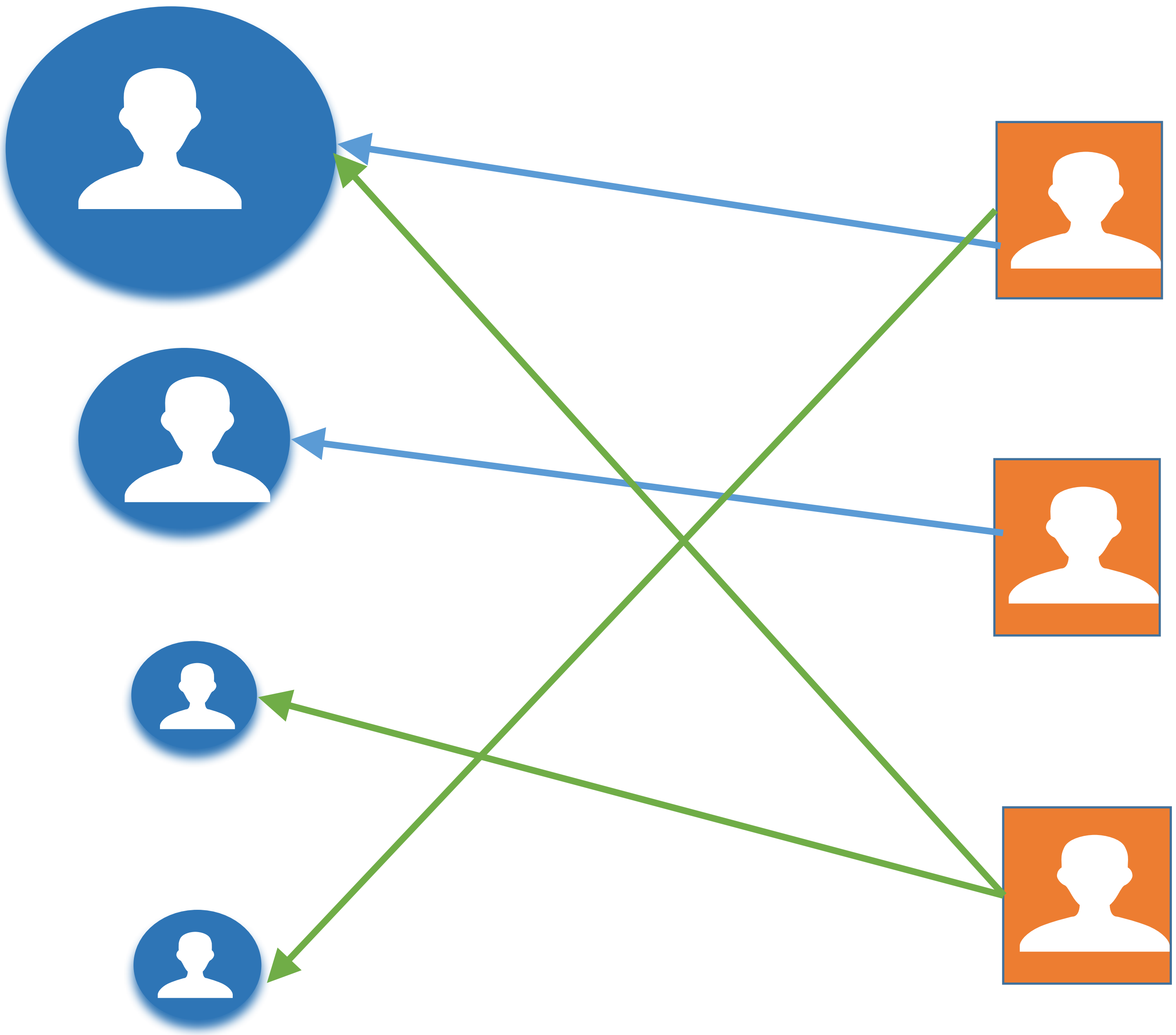


The Bipartite Graph Learning approach explicitly takes into account the LDMS for each member and the LSCS (LinkedIn Sales Competency Score) for each sales professional!

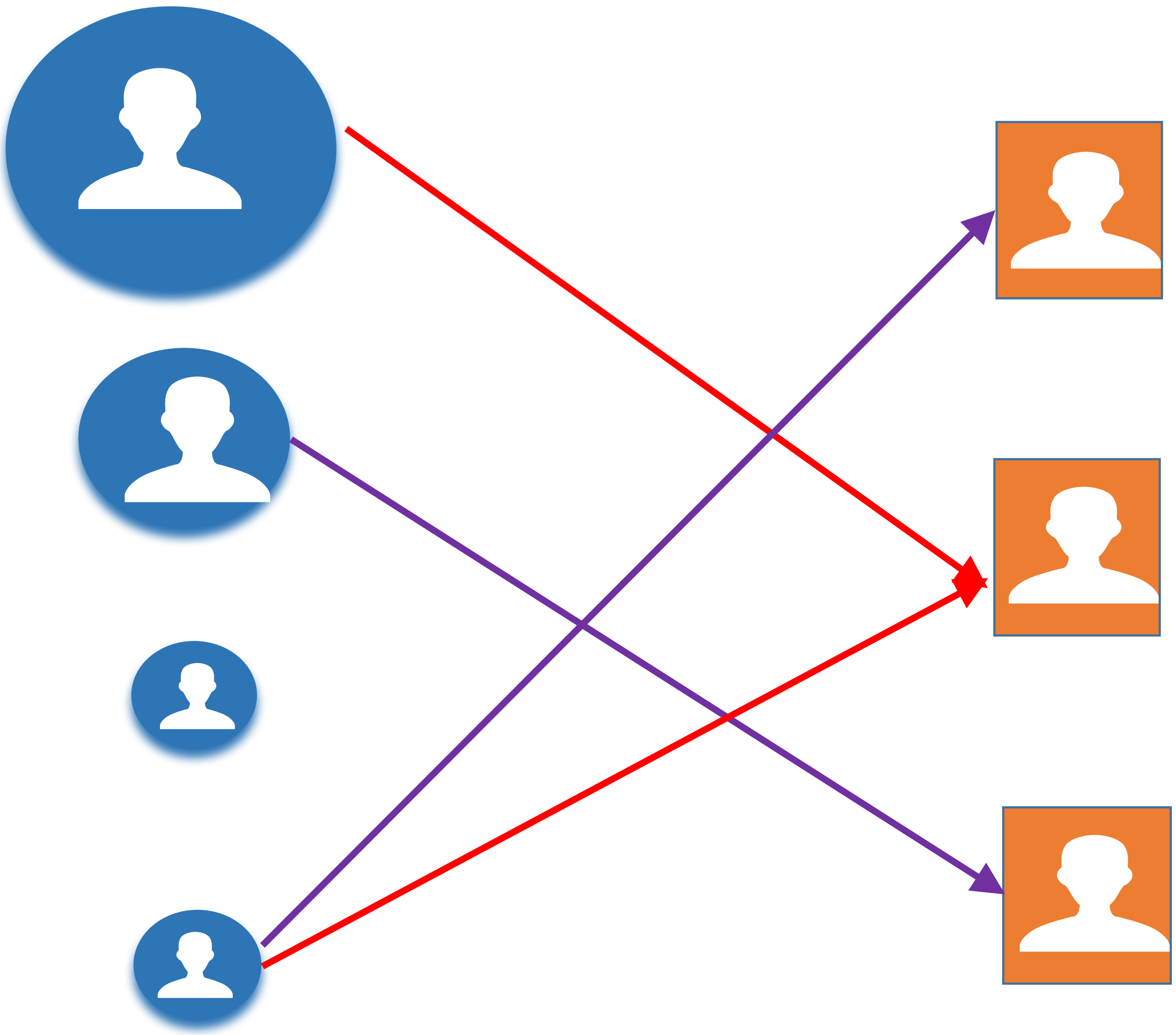
Bipartite Graph Learning - Algorithm



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

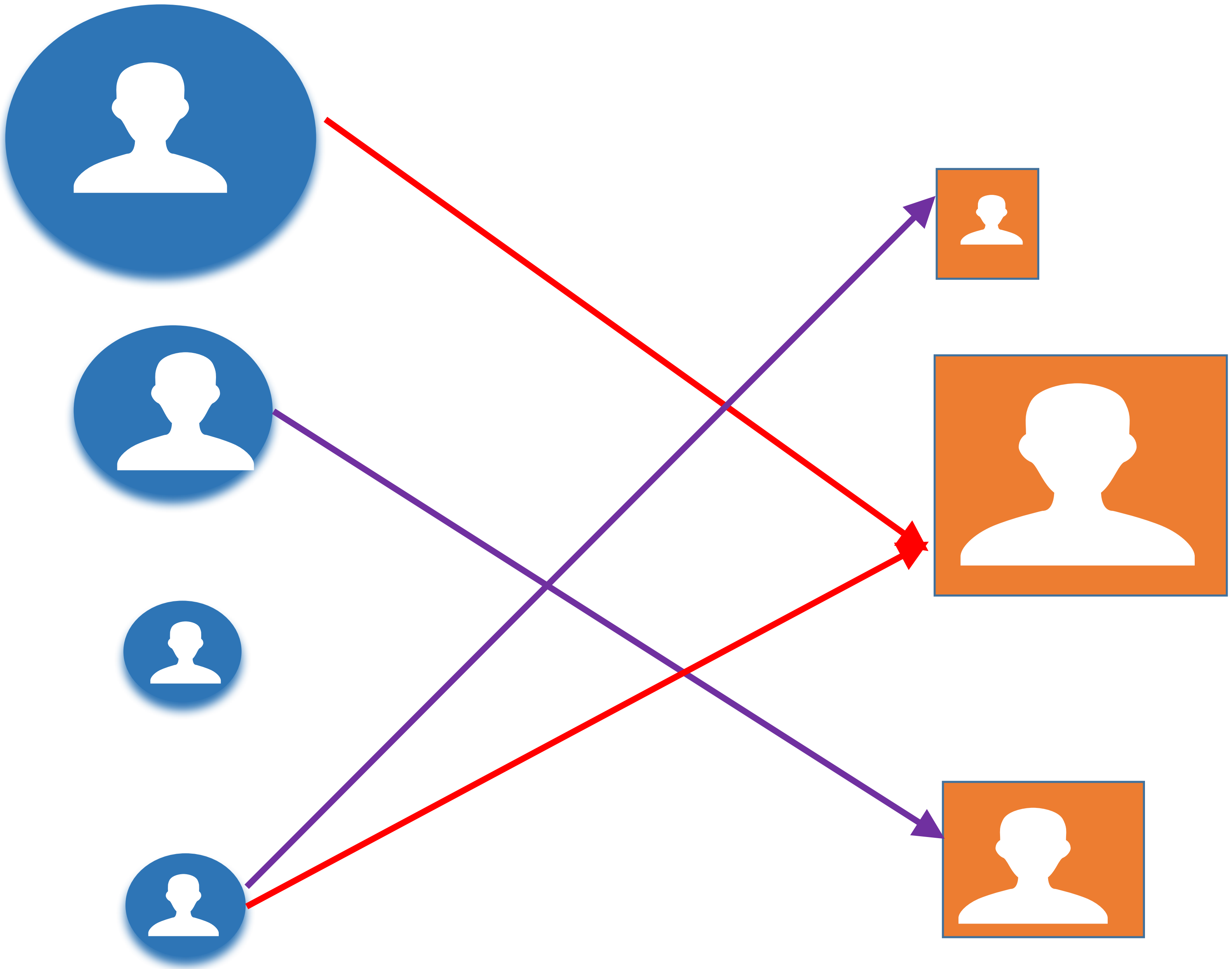


Based on the LDMS score, some DMs are more important than others!



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 *iterative*ly, solving the elastic net problems for the decision makers and the sales people until the weights converge!

The algorithm typically converges within *twenty* iterations.

$$p_i = f(w_{pc}x_i + \sum_{k=1}^{K} w_{pk} \sum_{j:e_{k(j->i)} \in E_k} q_j t(j,i))$$

$$q_j = g(w_{qc}z_j + \sum_{k=1}^{K} w_{qk} \sum_{i:e_{k(i->j)} \in E_k} p_i t(i,j))$$

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: Tpos and Tneg.

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

- 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

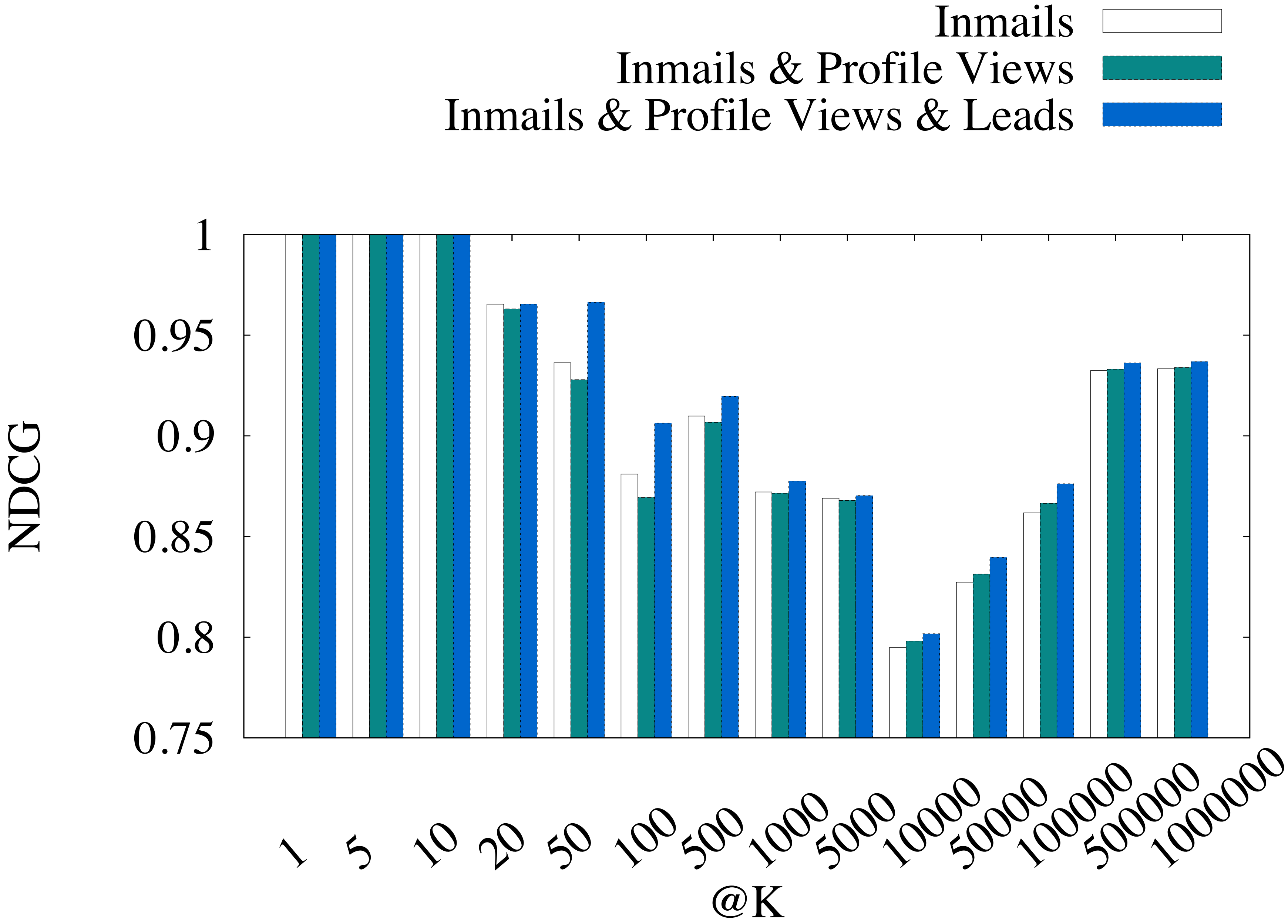
Offline Results

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**

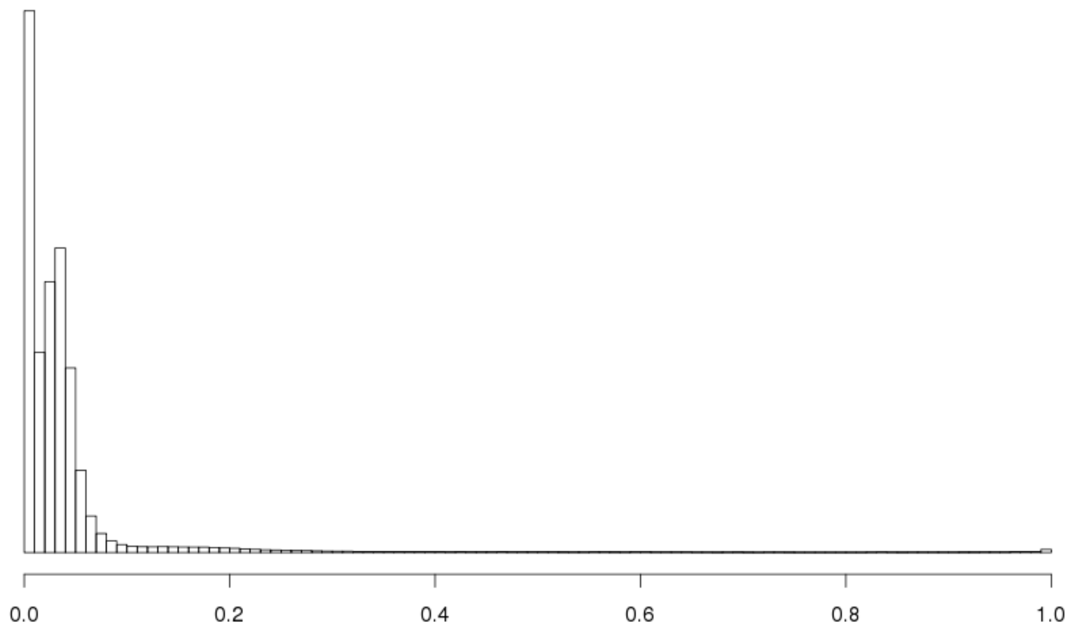
Kendall's τ@K	10	20	50	100	500	1,000	5,000	10,000
Summarization	**0.5394**	**0.5769**	**0.5185**	**0.6365**	**0.5681**	0.4829	0.4717	0.4956
Bipartite	0.4045	0.4476	0.5135	0.6253	0.5605	**0.4855**	**0.4746**	**0.5043**

Leveraging Different Social Graphs



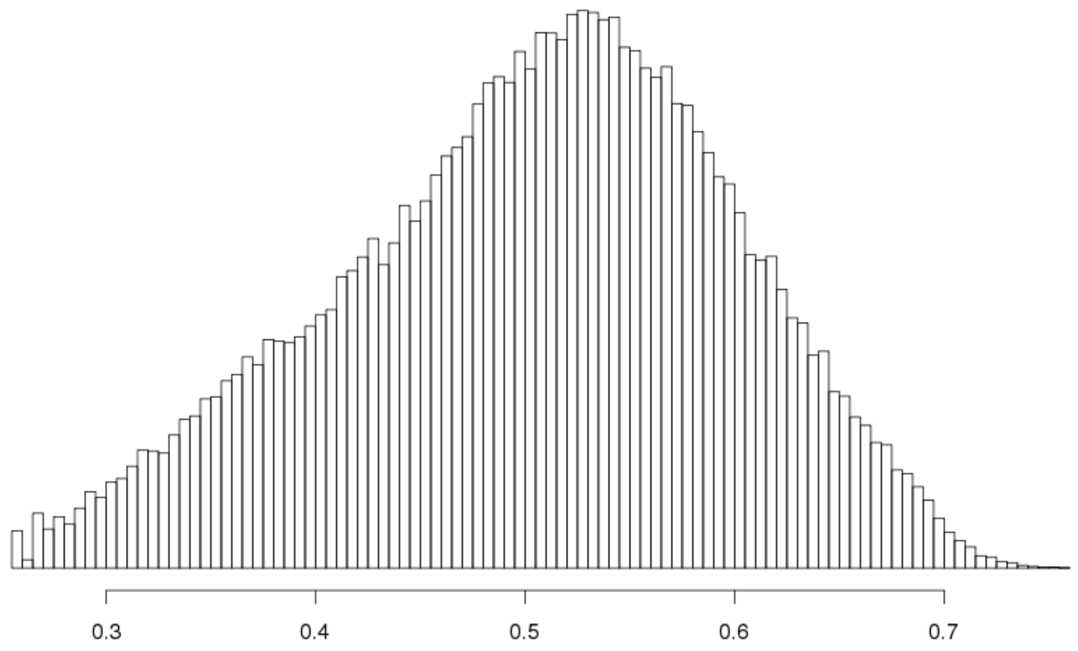
Score Distributions

LDMS scores



Power Law Distribution

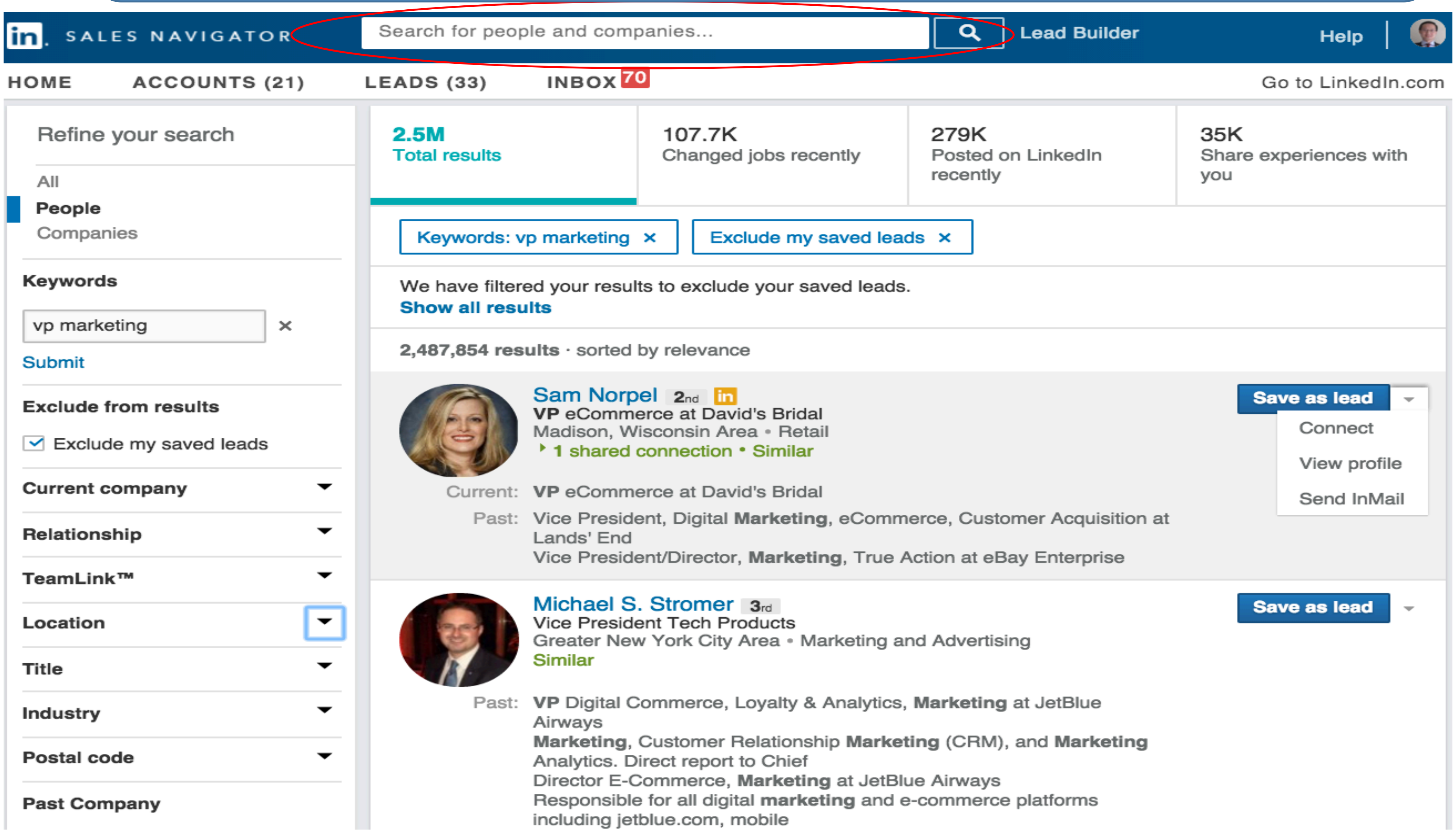
LSCS scores



Normal Distribution

Online Results

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



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? ☺