Identifying Decision Makers from Professional Social Networks

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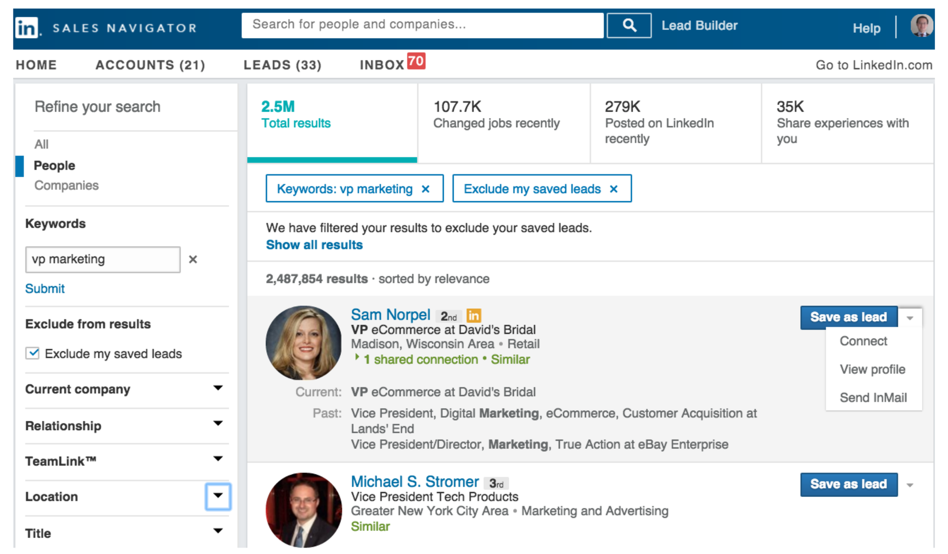
Contributions

LinkedIn Decision Maker Score (LDMS)

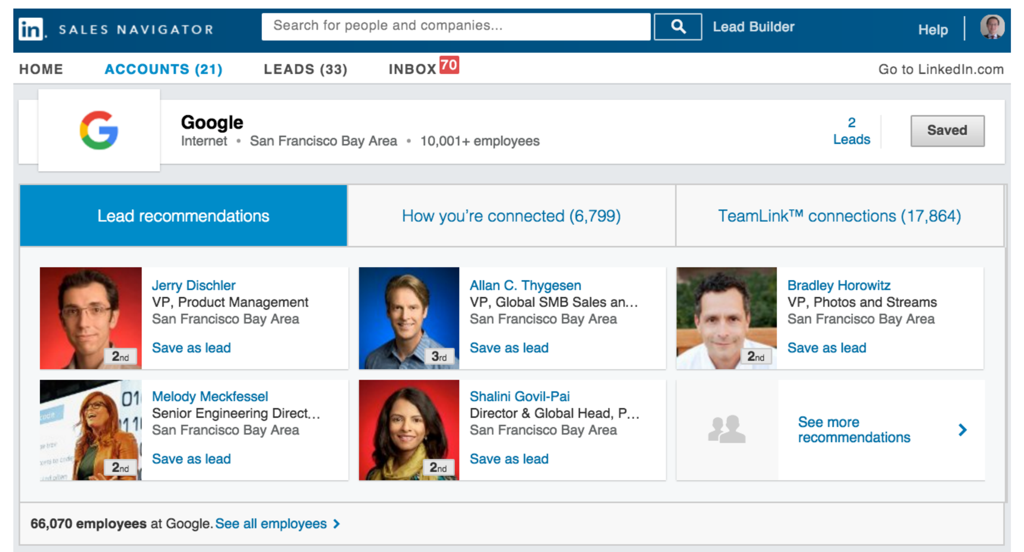
for each of the 400M+ Million Members

- We present LDMS score, the LinkedIn Decision Maker score, to capture the ability to make/influence a sales decision for each of the 400M+ LinkedIn member.
- We propose 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
  - handle heterogeneous graphs

Applications



Sales Navigator Search



Lead Recommendation

Groundtruth Challenge

Who are the Decision Makers?

- We do not have definite answer!
- No explicit labels from LinkedIn ecosystem.
- Our solution: Use surrogate signals!

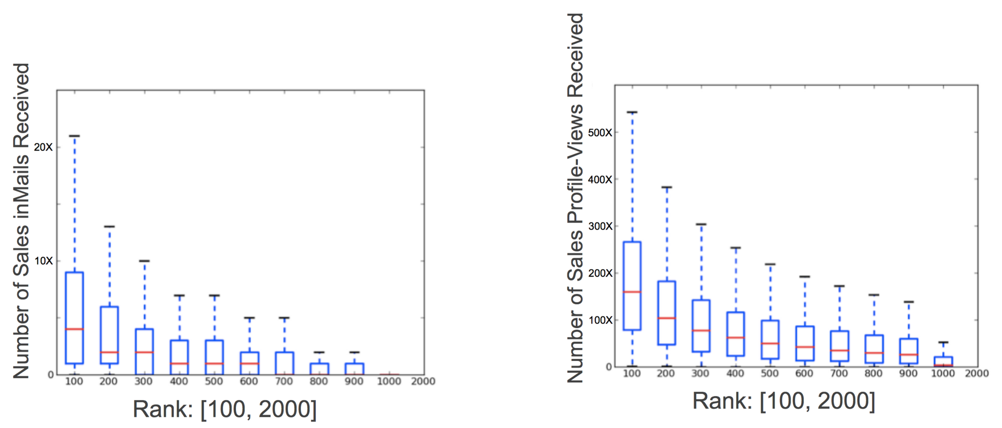
  #incoming sales-inMails within time T

  - High outgoing inMails discount
  - Peer comparison discount

Do we still need to learn LDMS?

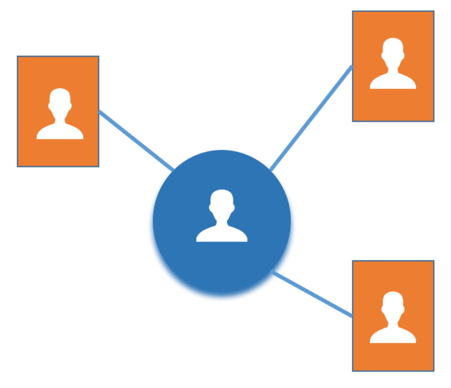
Yes! Because of sparsity!

#inmails << #profile views!



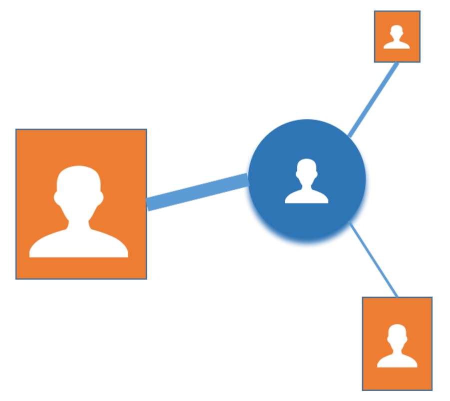
Learning Approaches

Graph Summarization



- Every sales professional has equal weight.
- Using only LDMS.

Bipartite Learning



- Every sales professional is weighted based on competency.
- Using LDMS & LSCS (LinkedIn Sales Competency Score).

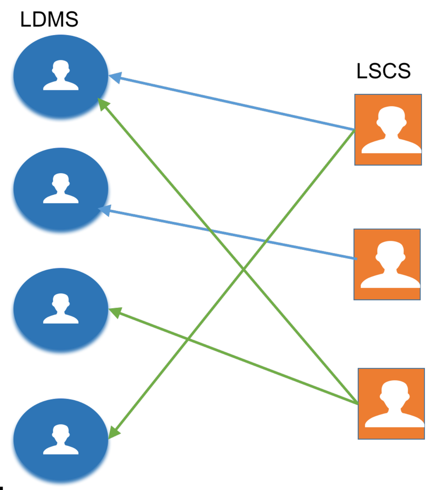
Bipartite Learning Approach

Contextual features

Graph features

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

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



Condition	Connection to other methods
$q_j = 1$ (equal weight for sales professionals)	Graph Summarization approach
$K = 1$ (one graph) & $x_i = z_i = 0$ (no content features)	Label Propagation for bipartite graphs
No ground truth labels	HITS for bipartite graphs

Features

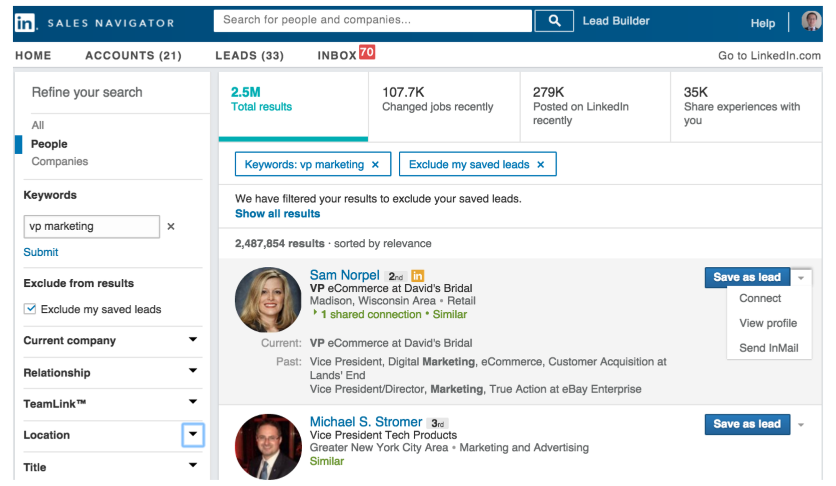
Contextual Information	Graph Information
Title	Connection Graph
Position	InvitationIn Graph
Seniority	Profile View Graph
Related Working Experience	Lead Save Graph
	InMail Graph

Features extracted from the graphs include:

- Degree/Indegree/Outdegree of the member in the graph from all/only sales professionals and ratios.

Online A/B test for search ranking

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



Results for Graph Summarization & Bipartite Graph Learning

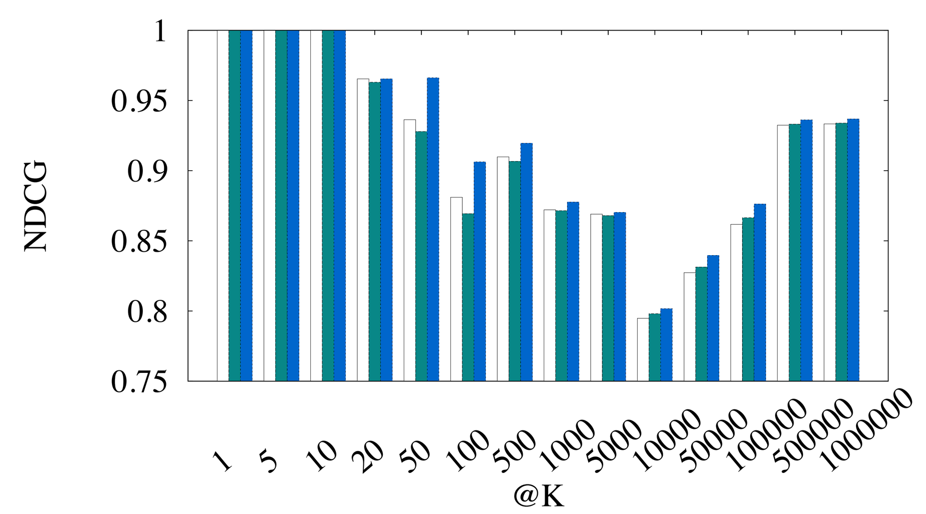
NDCG Results

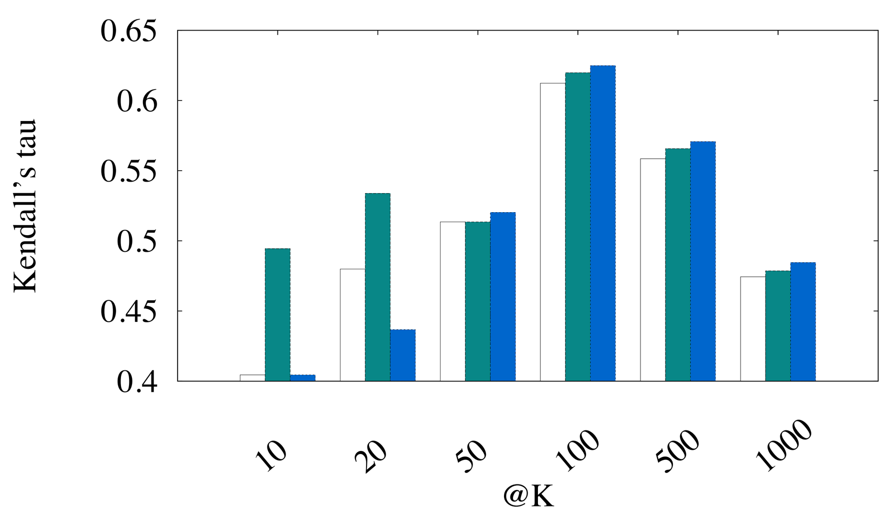
NDCG@K	10	20	50	100	500	1,000	5,000	10,000	50,000	100,000	500,000	1,000,000
Summarization	**1**	0.963	0.9084	0.8593	0.9039	0.8684	0.8682	0.7987	0.8339	0.8701	0.9336	0.9344
Bipartite	**1**	**0.9664**	**0.9665**	**0.9063**	**0.9183**	**0.878**	**0.871**	**0.8043**	**0.8412**	**0.8778**	**0.9367**	**0.9373**

Kendall's τ Results

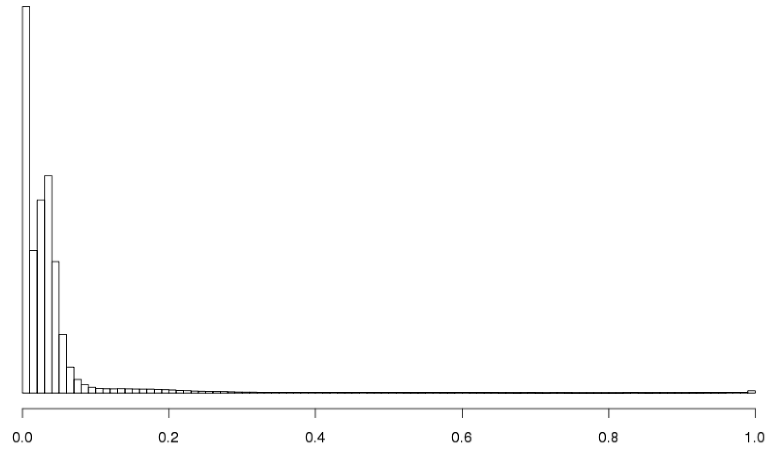
Kendall's τ@K	10	20	50	100	500	1,000	5,000	10,000
Summarization	**0.5394**	**0.5769**	**0.5185**	**0.6365**	**0.5681**	0.4829	0.4717	0.4956
Bipartite	0.4045	0.4476	0.5135	0.6253	0.5605	**0.4855**	**0.4746**	**0.5043**

Leveraging Different Social Graphs

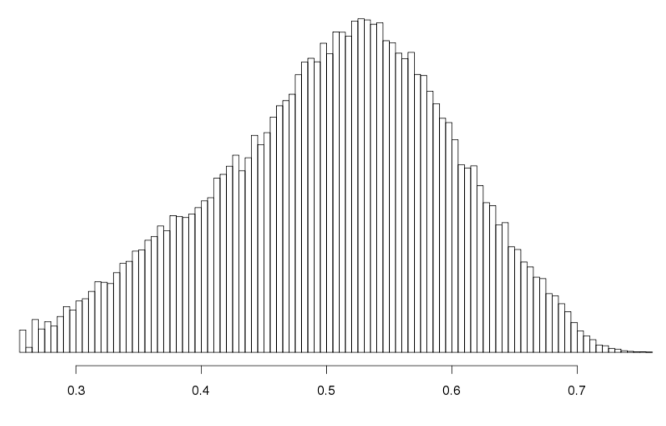




Score Distributions



LDMS Scores



LSCS Scores

Decision Makers scores follow a power law distribution, while Sales Professionals scores have a gaussian distribution.