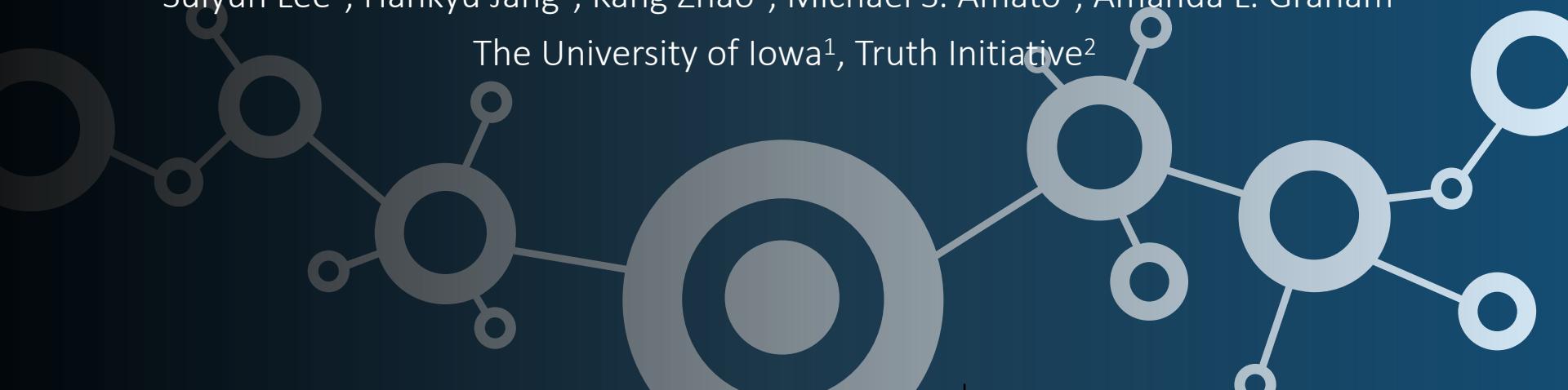


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Link Predictions for Social Networks in Online Health Communities

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Motivation

Online Health Community (OHC)

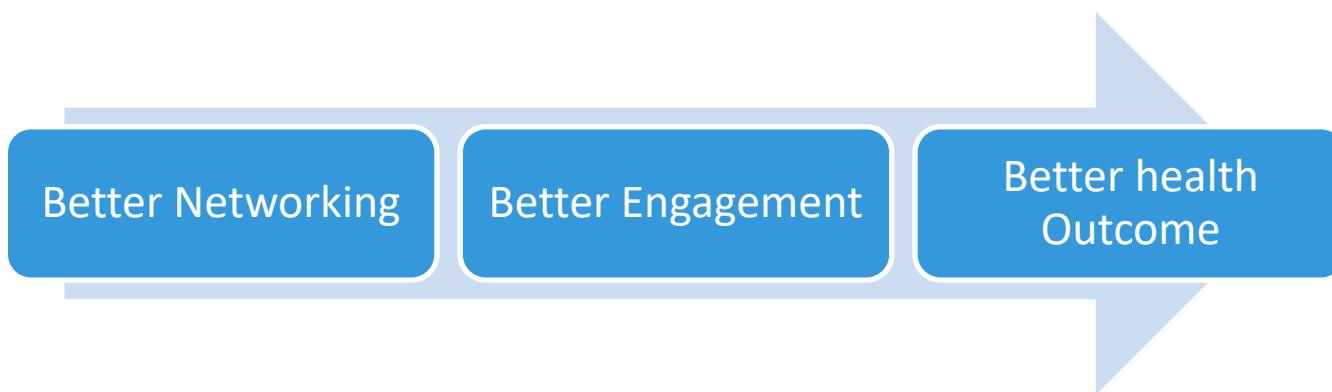
- OHC enables social networking
 - Similar health concerns
 - Share health info and emotionally support
- Emergence of the Internet results in high reliance on OHCs.
- Recommending users improves the OHC systems.



Motivation

Multi-Relational Link Prediction

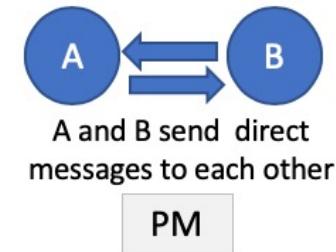
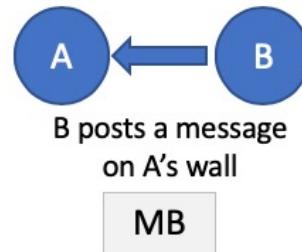
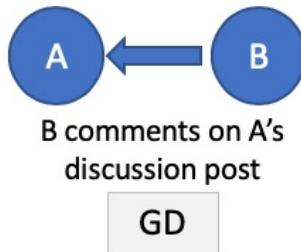
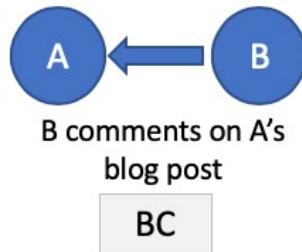
- **Networking** is a key to a better health outcome
- Can we utilize users' communication data for better networking?
 - Generate a network from each channel (**multi-relational network**)
 - Recommend friends to users that share similar interests utilizing information from network (**link prediction**)



Data & Setup

Data

- Source: **BecomeAnEx** - OHC for smoking cessation
- 6 years of users' interaction (2010 - 2015) in 4 channels
 - Blog posts & comment (BC)
 - Group discussion (GD)
 - Message board (MB)
 - Private messages (PM)



Data & Setup

Communication Network



- Four subnetworks: one undirected network for each channel
 - G_{BC} , G_{GD} , G_{MB} , G_{PM}
- One aggregated network (G_{AGG})
- Both seekers and providers can benefit from communications
- 32 consecutive weeks were considered

	G_{BC}	G_{GD}	G_{MB}	G_{PM}	G_{AGG}
Number of nodes	1516	899	2953	369	3694
Number of edges	22706	1418	8873	666	27837
Average degree	29.955	3.155	6.009	3.610	15.071
Maximum degree	1076	111	756	83	1303
Degree standard deviation	65.590	5.440	27.723	7.739	52.710
Clustering coefficient	0.575	0.016	0.185	0.133	0.312
Number of connected components	2	45	20	35	33
Assortativity	-0.281	-0.096	-0.342	-0.210	-0.283

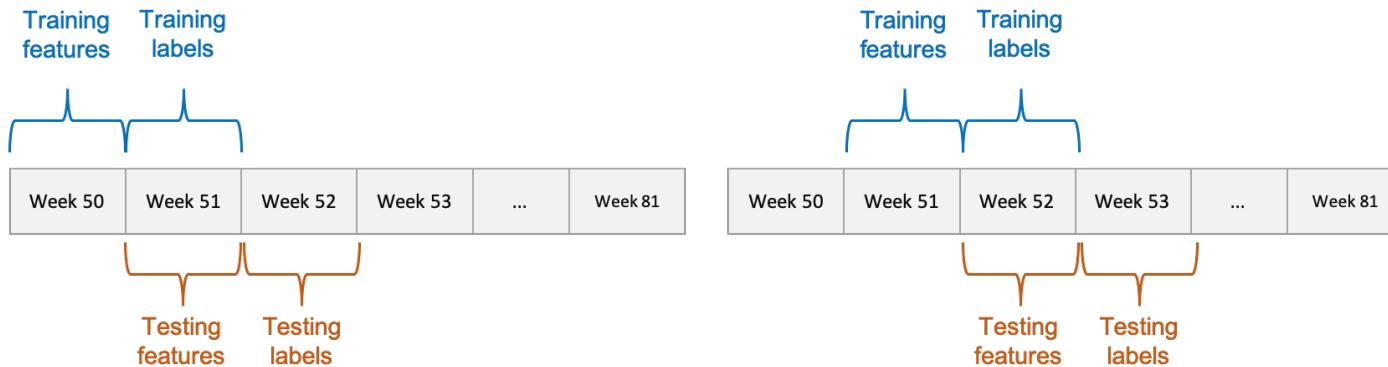
^aThe graphs are constructed with the user interactions that occurred anytime during the weeks from 50 to 81.



Data & Setup

Experiment Setup

- Task:
 - Predict the next week's newly formed network ties, no matter which channel
 - Leverage the current week's network structures
- A sliding window approach:



[Supervised Link Prediction]

- **Instances:** Pairs of users in the G_{Agg} for week t
- **Features:** Similarity scores computed for the pair of user for week t
- **Labels:** Binary **1**: if the pair is connected in the G_{Agg} for week $t+1$
0: otherwise

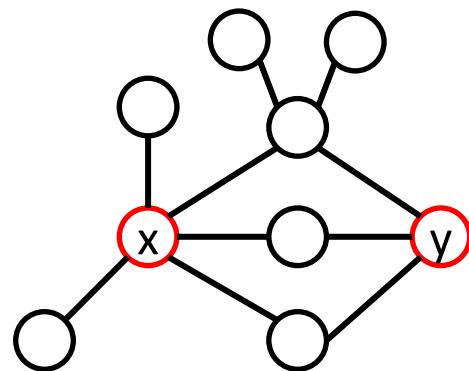
Features (Similarity Measures)

Neighbor-based

- Jaccard's coefficient $\frac{|\tau(x) \cap \tau(y)|}{|\tau(x) \cup \tau(y)|}$
 - Idea: penalizing nonshared neighbor



Symbol	Definition
$\tau(x)$	Neighbor of x



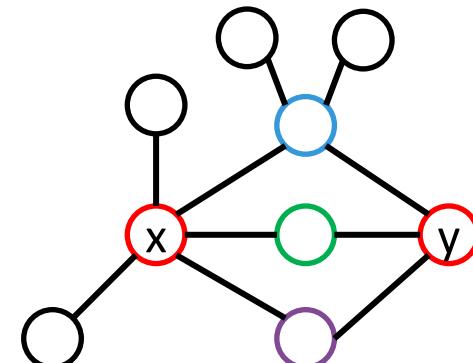
$$\text{score}_{\text{JC}}(x, y) = \frac{3}{5}$$

Features (Similarity Measures)

Neighbor-based

- Jaccard's coefficient $\frac{|\tau(x) \cap \tau(y)|}{|\tau(x) \cup \tau(y)|}$
 - Idea: penalizing nonshared neighbor
- Adamic Adar $\sum_{z \in \tau(x) \cap \tau(y)} \frac{1}{\log k(z)}$
 - Idea: penalizing 'shared neighbor' that has many neighbors

Symbol	Definition
$\tau(x)$	Neighbor of x
z	Common neighbor of x and y
$k(z)$	Degree of z



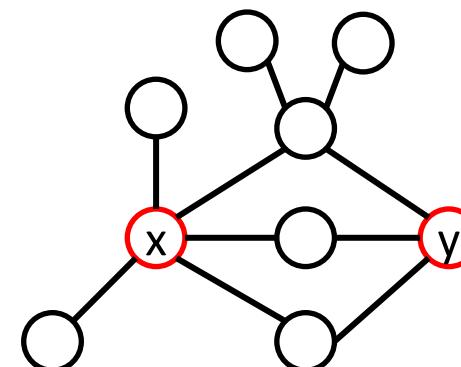
$$\text{score}_{\text{AA}}(x, y) = \frac{1}{\log 4} + \frac{1}{\log 2} + \frac{1}{\log 2}$$

Features (Similarity Measures)

Neighbor-based

- Jaccard's coefficient $\frac{|\tau(x) \cap \tau(y)|}{|\tau(x) \cup \tau(y)|}$
 - Idea: penalizing nonshared neighbor
- Adamic Adar $\sum_{z \in \tau(x) \cap \tau(y)} \frac{1}{\log k(z)}$
 - Idea: penalizing 'shared neighbor' that has many neighbors
- Preferential attachment $k(x) \times k(y)$
 - Idea: richer gets richer

Symbol	Definition
$\tau(x)$	Neighbor of x
z	Common neighbor of x and y
$k(z)$	Degree of z



$$\text{score}_{\text{PA}}(x, y) = 5 \times 3$$

P. Jaccard. "Etude comparative de la distribution florale dans une portion des alpes et des jura", Bulletin de la Societe Vaudoise des Sciences Naturelles 1901

L. A. Adamic, E. Adar, "Friends and neighbors on the Web," Social Networks 03

A. L. Barabasi, H Jeong, Z Neda et al, "Evolution of the social network of scientific collaborations", Physica A 02

M. Mitzenmacher, "A brief history of generative models for power law and lognormal distributions", Internet Mathematics 2004



Methods

Baseline vs. MRLP (Proposed Method)

- Baseline features extract 3 similarity measures (JC, AA, PA) for each of the 4 subnetworks and aggregated network
 - F_{BC} : 3 similarity measures from G_{BC}
 - F_{GD} : 3 similarity measures from G_{GD}
 - F_{MB} : 3 similarity measures from G_{MB}
 - F_{PM} : 3 similarity measures from G_{PM}
 - F_{Agg} : 3 similarity measures from G_{Agg}
- MRLP considers a social network as multi-relational by stacking F_{BC} , F_{GD} , F_{MB} , F_{PM} (12 features in total)
 - F_{ALL} : $F_{BC} + F_{GD} + F_{MB} + F_{PM}$



Methods

Preformance Measures

- Classifiers
 - Random Forest, Logistic Regression, AdaBoost, Neural Network
- Evaluation Measure
 - Precision, Precision@k
 - Goal is to recommend top future links with high accuracies
 - Normalized discounted cumulative gain (nDCG@k)
 - It's important to rank links that occurred higher than those that did not occur

Results

Baseline vs. MRLP



Metric	Classifier	Baseline Approach					MRLP
		F_{AGG}	F_{BC}	F_{GD}	F_{MB}	F_{PM}	
Precision	Random Forest	0.249	0.229	0.000	0.114	0.070	0.282
	Logistic Regression	0.466	0.418	0.000	0.315	0.084	0.445
	AdaBoost	0.439	0.426	0.000	0.207	0.115	0.388
	Neural Network	0.511	0.491	0.000	0.325	0.052	0.551
nDCG@10	Random Forest	0.400	0.300	0.008	0.157	0.038	0.370
	Logistic Regression	0.617	0.583	0.024	0.380	0.121	0.640

MRLP

Considering features
from each network



Baseline

Considering a single
network or
aggregated network

PREC@20	Logistic Regression	0.603	0.535	0.016	0.328	0.102	0.600
	AdaBoost	0.513	0.432	0.008	0.247	0.028	0.463
	Neural Network	0.597	0.533	0.008	0.318	0.057	0.610
nDCG@20	Random Forest	0.405	0.301	0.007	0.124	0.045	0.351
	Logistic Regression	0.619	0.567	0.019	0.351	0.117	0.622
	AdaBoost	0.507	0.432	0.012	0.248	0.039	0.470
	Neural Network	0.610	0.561	0.008	0.334	0.070	0.624

^aValues that are in bold denote the largest value for each evaluation metric.



Can we do better?

More Features

- F_{COM} : Community-based features
 - Modularity maximization (4 features, each from $G_{BC}, G_{GD}, G_{MB}, G_{PM}$)
 - Label propagation (4 features, each from $G_{BC}, G_{GD}, G_{MB}, G_{PM}$)
- F_{EMB} : Embedding-similarity features
 - DeepWalk (4 features, each from $G_{BC}, G_{GD}, G_{MB}, G_{PM}$)
- F_{TEX} : Text-similarity features
 - Latent Dirichlet allocation (LDA, 3 features, each from G_{BC}, G_{GD}, G_{MB})





More Features

Community-Based Feature (F_{COM})

- Idea: Two nodes are similar if they belong to the same community

- Modularity maximization

$$s_{xy} = \begin{cases} 1, & \text{if } x, y \in C_i, \quad (1 \leq i \leq k_{CM}) \\ 0, & \text{otherwise} \end{cases}$$

Nodes that are in same community

Number of communities detected
using modularity maximization

- Label propagation

$$s_{xy} = \begin{cases} 1, & \text{if } x, y \in C_i, \quad (1 \leq i \leq k_{CLP}) \\ 0, & \text{otherwise} \end{cases}$$

Number of communities detected
using label propagation

More Features

Embedding-Similarity Feature (F_{EMB})

- Idea: Two nodes with similar representations are close to each other
- How to learn representation of nodes in the graph?
 - DeepWalk



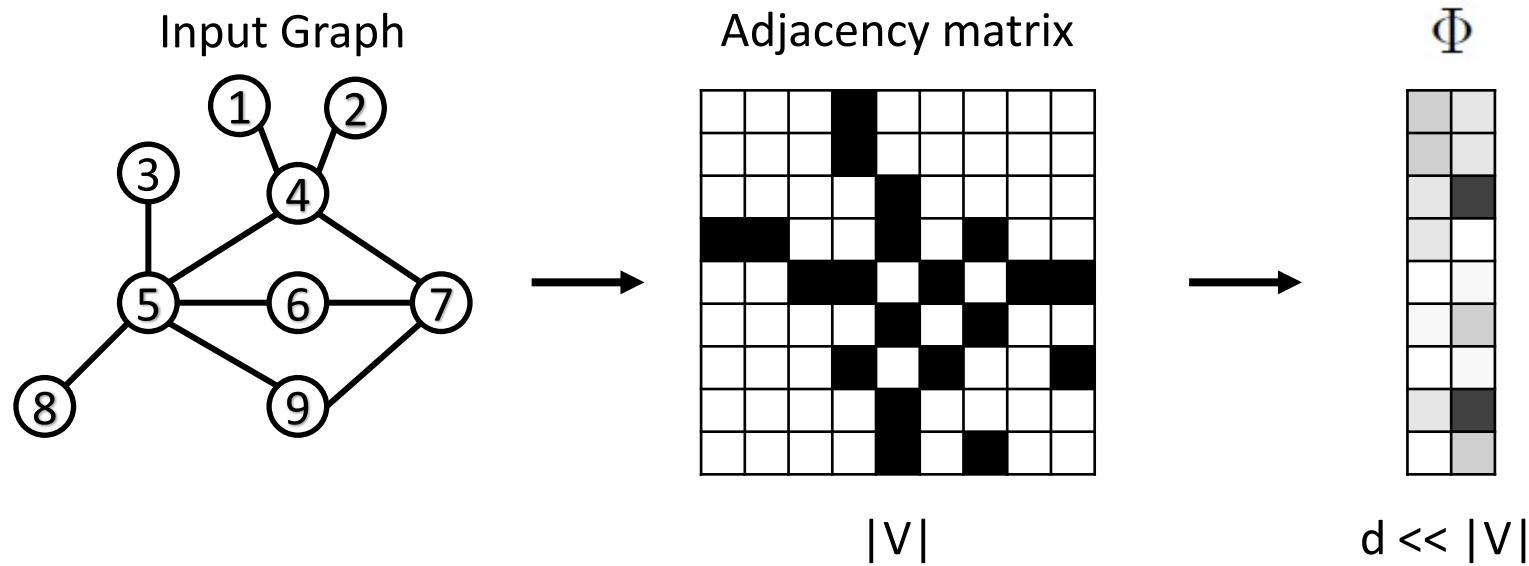


More Features

Embedding-Similarity Feature (F_{EMB})

- Idea: Skip-gram (word embedding) - Learn a vector representation of word such that nearby words would have similar representation
- Input: $G = (V, E)$
- Output: $\Phi : v \in V \rightarrow \mathbb{R}^{|V| \times d}$

DeepWalk



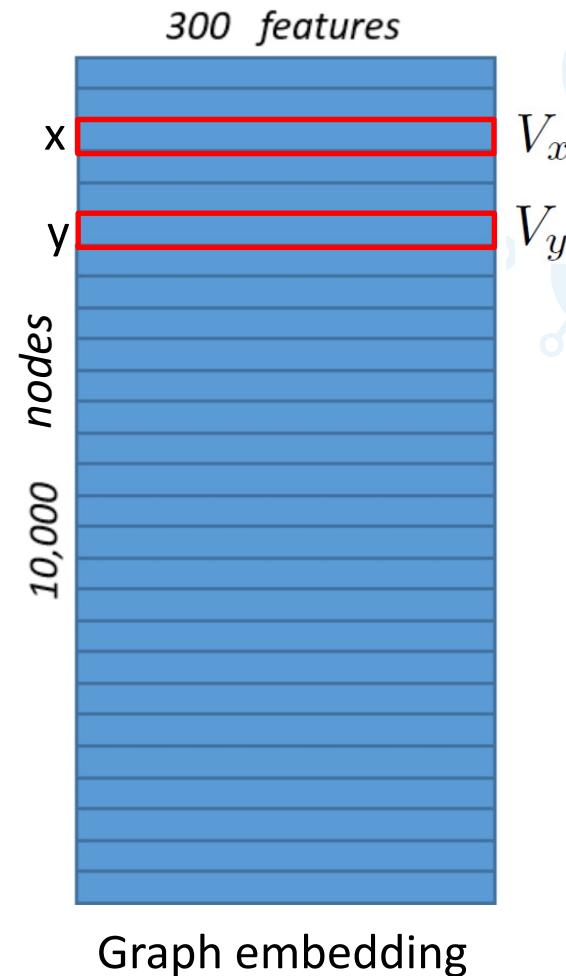
More Features

Embedding-Similarity Feature (F_{EMB})

- After the embedding is learned, compute cosine similarity of the two vectors

$$s_{xy} = \cos(V_x, V_y)$$

- Nodes that have similar embedding have higher score



More Features

Text-Similarity Feature (F_{TEX})

- Idea: Users who care about similar topics in an OHC may have a higher chance of interacting with each other
- Compute text similarity among users' posts as a measure of similarity





More Features

Text-Similarity Feature (F_{TEX})

- Combined posts across 30 weeks
- Applied latent Dirichlet allocation (LDA)
 - Each post has a topic distribution (30 dimensional vector)
 - If a user posted n posts in a channel for a week, then the topic distribution is averaged over n topic distributions
- Two users have similar topic distributions if they expressed interest in similar topics with each other

$$s_{xy} = \cos(A_x, A_y), \text{ where } A_i = \frac{\sum_{p=1}^n T_{ijtp}}{n}$$

Topic distribution for
- user i
- channel j
- week t
- number of posts n

Results

MRLP vs. MRLP + more features

$$F_{ALL} : F_{BC} + F_{GD} + F_{MB} + F_{PM}$$

F_{COM} : Community-based feature

F_{EMB} : Embedding-similarity feature

F_{TEX} : Text-similarity feature

Table 3: Performance of additional features on MRLP

Metric	Classifier	MRLP	MRLP+More Feature Sets			
		F_{ALL}	$F_{ALL} + F_{COM}$	$F_{ALL} + F_{EMB}$	$F_{ALL} + F_{TEX}$	$F_{ALL} + F_{COM} + F_{EMB}$
Precision	Random Forest	0.282	0.290	0.318	0.308	0.323
	Logistic Regression	0.445	0.463	0.446	0.448	0.462
	AdaBoost	0.388	0.387	0.389	0.386	0.385
	Neural Network	0.551	0.558	0.584	0.516	0.462
PREC@10	Random Forest	0.370	0.373	0.367	0.437	0.360
	Logistic Regression	0.640	0.637	0.650	0.623	0.640
	AdaBoost	0.440	0.480	0.410	0.487	0.463
	Neural Network	0.640	0.597	0.637	0.627	0.607
nDCG@10	Random Forest	0.366	0.380	0.385	0.467	0.349
	Logistic Regression	0.655	0.650	0.656	0.642	0.662
	AdaBoost	0.460	0.494	0.433	0.500	0.480
	Neural Network	0.648	0.620	0.663	0.629	0.623
PREC@20	Random Forest	0.347	0.358	0.367	0.382	0.378
	Logistic Regression	0.600	0.622	0.607	0.580	0.613
	AdaBoost	0.463	0.453	0.463	0.497	0.450
	Neural Network	0.610	0.573	0.607	0.577	0.572
nDCG@20	Random Forest	0.351	0.368	0.379	0.417	0.366
	Logistic Regression	0.622	0.635	0.623	0.604	0.635
	AdaBoost	0.470	0.471	0.463	0.503	0.465
	Neural Network	0.624	0.595	0.633	0.592	0.593

^aValues that are in bold denote the largest value for each evaluation metric.

Embedding effects in each channel

Effects of channels for MRLP+Embedding

- Drop the embedding feature generated by each channel to compare the embedding effects of each channel

BC : Blog posts & Comments
GD : Group Discussion
MB : Message Board
PM : Private Messages

Metric	Classifier	MRLP+Emb	MRLP+Emb for three channels			
		F_{ALL} + F_{EMB}	F_{ALL} + F_{EMB-BC}	F_{ALL} + F_{EMB-GD}	F_{ALL} + F_{EMB-MB}	F_{ALL} + F_{EMB-PM}
Precision	Neural Network	0.584	0.528	0.543	0.551	0.538
PREC@10	Logistic Regression	0.650	0.657	0.643	0.647	0.650
nDCG@10	Neural Network	0.663	0.636	0.618	0.626	0.659
PREC@20	Logistic Regression	0.607	0.607	0.603	0.607	0.615
nDCG@20	Neural Network	0.633	0.604	0.595	0.599	0.625

^aValues that are in bold denote the best performing value for $F_{ALL} + F_{EMB}$.

^bValues that are in red denote the highest value when the embedding feature for a channel is dropped.

^cValues that are in blue denote the lowest value when the embedding feature for a channel is dropped.

- The embedding similarity in group discussion channel provide more information that could not capture in F_{ALL} .

Discussions and Conclusion



- Our MRLP method of utilizing multi-relational information outperforms baseline methods
- Embedding-similarity feature further improved the performance as well as community-based features
- Text-similarity does not help the predictions → future work
- Implications for the design and management of OHCs
 - Recommend other users' blog posts and encourage to participate in group discussions
 - Recommend users to access other users' wall and send direct messages if belong to the same community
 - Allow users to communicate with others not in the same community but have the high similarity score in embedding



Thank you! Questions?

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