Deep Graph Embeddings in Recommender Systems

Thesis Defense

Data-Driven Decision-Making Lab

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2019, August 26

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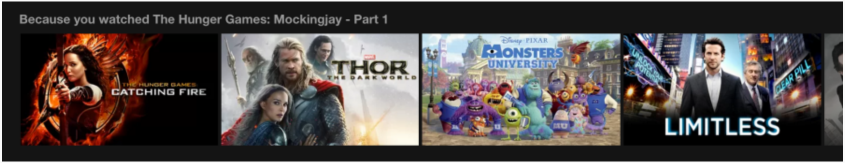
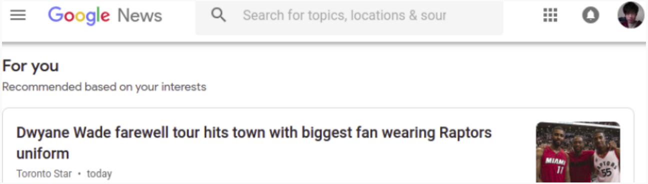
Recommender Systems for the World



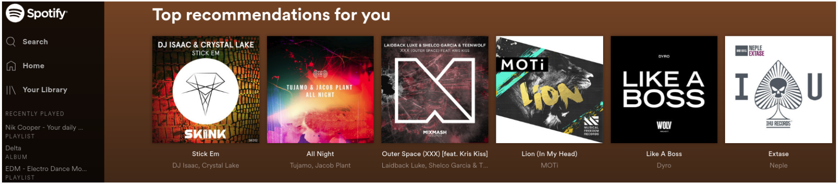
Netflix Movie Recommender worth [about $1 billion](#).

Amazon Shopping Recommender accounts for [35% of sales](#).

Recommender Systems in Industry



Google News Recommender generates 38% more clicks.

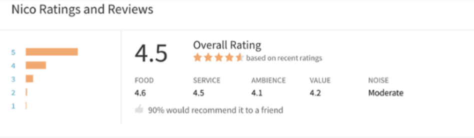


Spotify Music Recommender streams 5 billion tracks in a year.

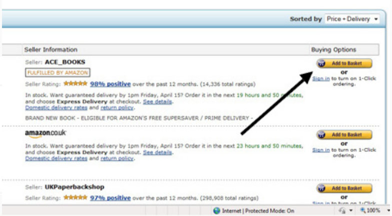
Recommendation Datasets and Challenges

Recommendation Datasets and Challenges

What type of data does recommender systems receive?



Ratings



Purchases

- Explicit Data: ratings, right swipes, likes
- Implicit Data: clicks, views, purchases

Challenge: **One-class feedback** for implicit data.

- 1 represents positive feedback
- 0 represents negative or unaware feedback

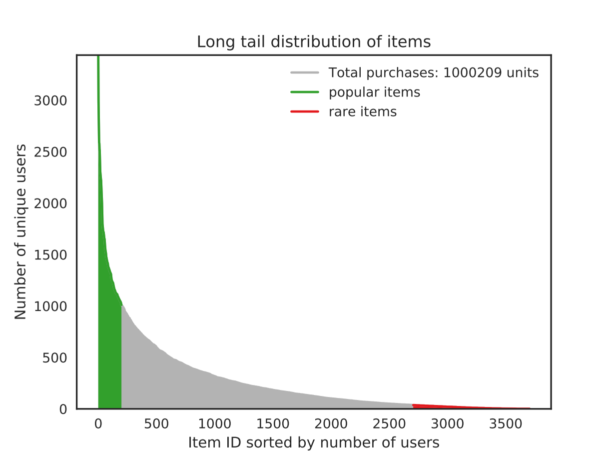
Recommendation Datasets and Challenges

Dataset	$\|U\|$	$\|I\|$	$\|R\|$	$\frac{\|R\|}{\|U\|*\|I\|}$
MovieLens-100k	943	1682	100000	6.30×10^{-2}
MovieLens-1m	6040	3706	1000209	4.46×10^{-3}
BookCrossing	7721	5000	253967	6.58×10^{-3}
Amazon Video Games	7926	5000	107359	2.71×10^{-3}

Each user interacts with only a few items.

Challenge: **Scalability** due to huge number of users and items.
Challenge: **Sparsity** due to relatively low number of interactions.

Recommendation Datasets and Challenges



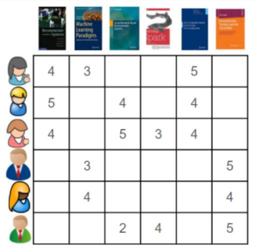
A niche set of popular items dominate the dataset

Challenge: **Imbalanced** item distribution.

Recommendation Problem

Recommendation Problem Formulation

R = (sparse) Rating Matrix
U = Set of users
I = Set of items
R_{train} = Train Rating Matrix
R_{test} = Test Rating Matrix
$R = R_{train} \cup R_{test}$, $R_{train} \cap R_{test} = \emptyset$
$\hat{R} = f(R_{train})$ = Predicted Matrix
$\hat{R}$ is dense.
f = Recommender System

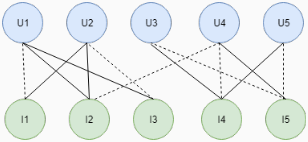


User-Item Rating Matrix

Predict scores for missing entries of the Rating Matrix, $R_{missing} \approx \hat{R}$.
Then, recommend the Top-K missing entries for each user.

Recommendation Problem Formulation

$G =$ Bipartite Graph
$V^U =$ Set of users nodes
$V^I =$ Set of items nodes
$E =$ (sparse) interaction edges
$E = E_{train} \cup E_{test}$, $E_{train} \cap E_{test} = \emptyset$
$\hat{E_{test}} = f(E_{train}) =$ Link Prediction
$\hat{E_{test}}$ is dense.
$f =$ Recommender System



User-Item Bipartite Graph

Predict scores for missing edges in the bipartite graph.
Then, recommend the Top-K missing edges for each user nodes.

Deep Graph Embeddings

Success of Deep Embeddings

A dog is standing on a hardwood floor.

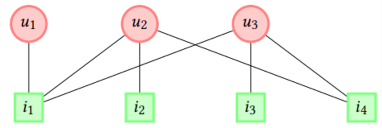
A group of people sitting on a boat

CNN Embeddings

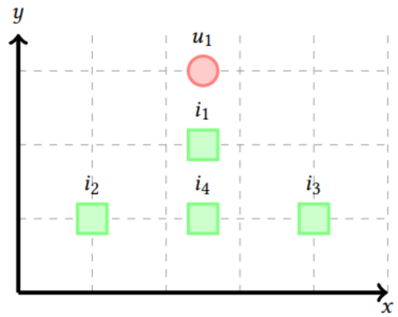
SGNS embeddings

Generalize Deep Embeddings to Deep Graph Embeddings

Spectral Graph Convolution



Bipartite Graph

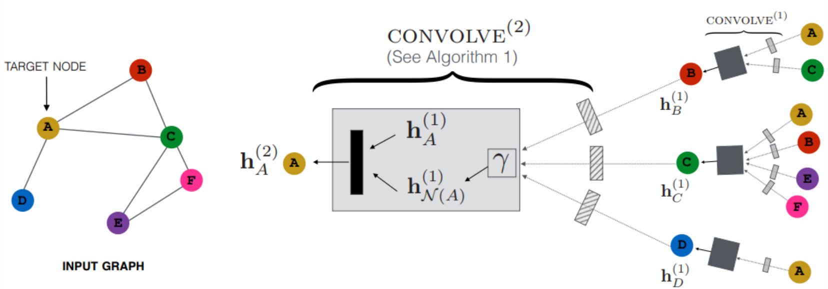


Spectral Convolution Embeddings

Spectral domain carries connectivity information.

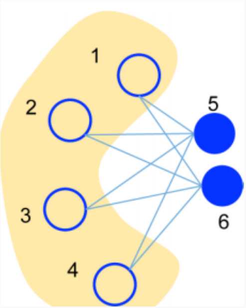
u_1 is more connected to i_4 compared to i_2 or i_3.

Spatial Graph Convolution

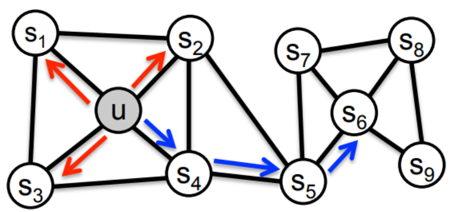


Node's embedding is a convolution of its neighbours convolved embeddings.

DeepWalk



Random Walk on nodes



Breadth-First vs Depth-First Walks

Nodes on random walk are pulled closer in embedding space.

Research Questions

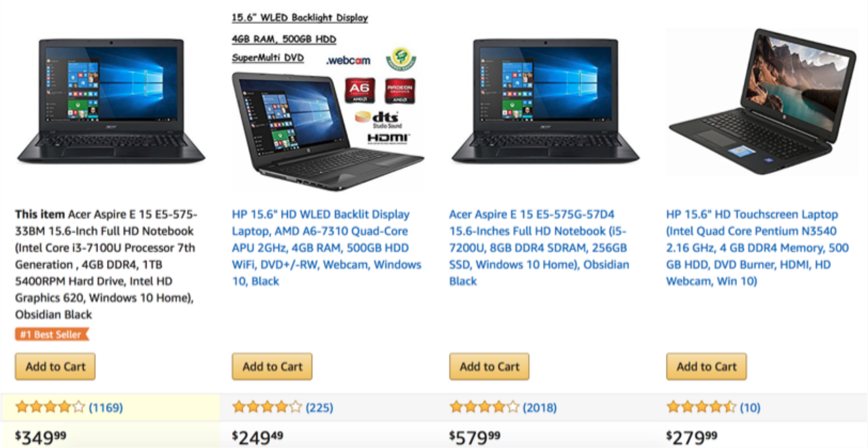
Research Questions

- What are the properties of graph embeddings?
- How do graph embeddings compare to state-of-the-art algorithms?
- How to extend graph embeddings for personalized recommendations?

Analyzing Embeddings of Recommender Systems

Debugging: Embeddings within a category should be clustered.

Applications of Embeddings

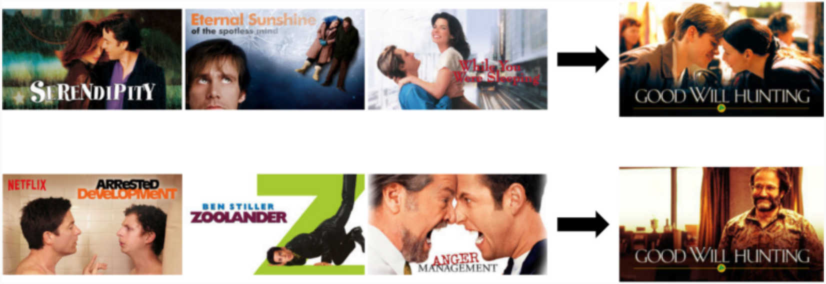


Item Retrieval: Retrieving item substitutes for comparison before purchase.

Applications of Embeddings

Interpretability: Explain recommendations based on similarity to item.

Applications of Embeddings



Personalization: Similar to average a user's past interactions.

Item Similarity Matrix

Item Similarity, S^I

1.00	0.27	0.79	0.32	0.98	0.00
0.27	1.00	0.00	0.00	0.34	0.65
0.79	0.00	1.00	0.69	0.71	0.18
0.32	0.00	0.69	1.00	0.32	0.49
0.98	0.34	0.71	0.32	1.00	0.00
0.00	0.65	0.18	0.49	0.00	1.00

$$S^I = W^I \cdot (W^I)^T$$

$$W^I \in R^{|I| \times d}$$

S^I must respect metric spaces.

- Identity Similarity
- Clustering Coherency
- Similarity Propagation
- Average Similarity

Unsupervised Similarity Analysis

Table 5.1: Identity Similarity Analysis

Model	IdentitySimilarity
DeepWalk	**0.9969493593654668**
ProfitWalk	0.9920683343502136
KNN	0.9286150091519219
WRMF	0.8425869432580841
BPR	0.7809640024405126
GC-MC	0.7559487492373398
PMF	0.6168395363026236
PureSVD	0.5247101891397193
DeepRec	0.07931665649786455
SpectralCF	0.0018303843807199512
Popular	0.0006101281269066504

Table 5.2: MovieLens-100k Identity Similarity

Model	IdentitySimilarity
KNN	**0.9771677086164718**
DeepWalk	0.9747213916825225
ProfitWalk	0.9567817341668932
WRMF	0.9141070943191084
PMF	0.8486001630877956
GC-MC	0.39657515629247075
PureSVD	0.2304974177765697
BPR	0.0008154389779831476
DeepRec	0.0005436259853220984
SpectralCF	0.0005436259853220984
Popular	0.0002718129926610492

Table 5.3: MovieLens-1m Identity Similarity

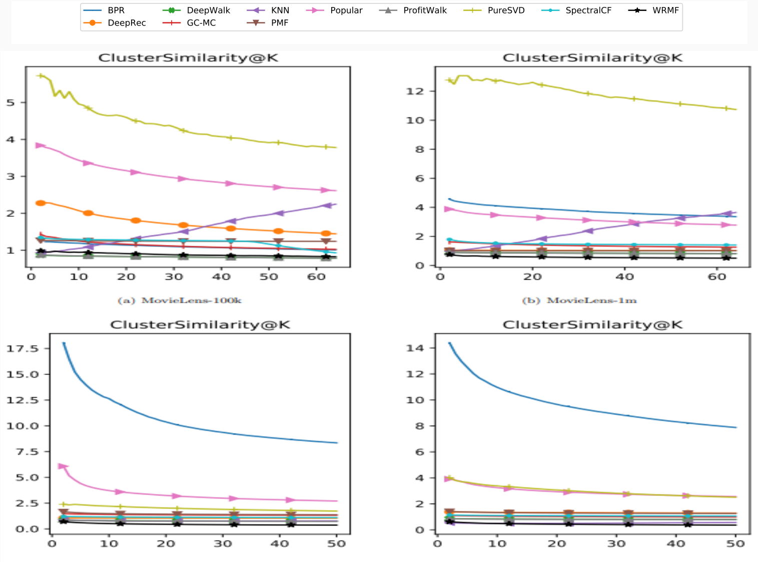
Model	IdentitySimilarity
DeepWalk	**0.9936**
KNN	0.984
ProfitWalk	0.9338
WRMF	0.8808
PMF	0.8258
GC-MC	0.7444
PureSVD	0.181
DeepRec	0.0502
BPR	0.0008
SpectralCF	0.0002
Popular	0.0002

Table 5.4: BookCrossing Identity Similarity

Model	IdentitySimilarity
DeepWalk	**0.9959895728895127**
KNN	0.9921796671345499
ProfitWalk	0.9797473430920393
WRMF	0.9422498496089834
GC-MC	0.9049528774814518
PMF	0.5660717866452777
DeepRec	0.23180268698616402
PureSVD	0.09123721676358532
BPR	0.0010026067776218166
SpectralCF	0.00020052135552436334
Popular	0.00020052135552436334

Table 5.5: Amazon Video Games Identity Sim.

Unsupervised Similarity Analysis



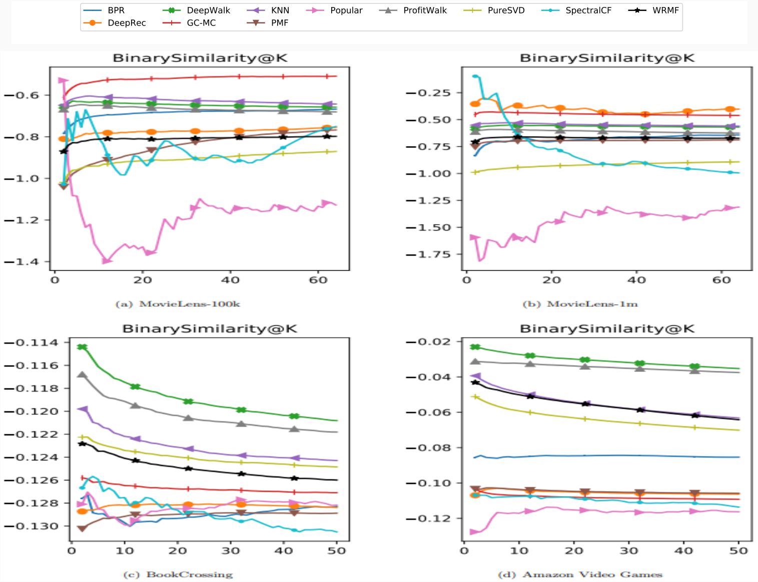
(a) MovieLens-100k

(b) MovieLens-1m

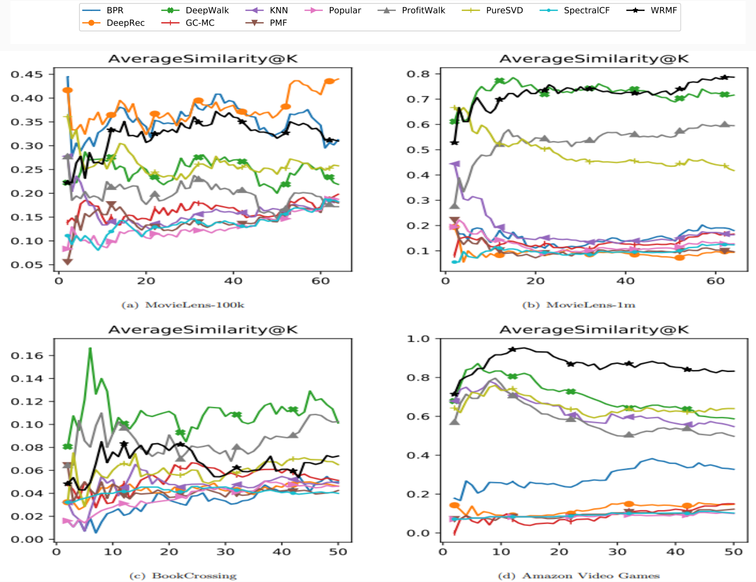
(c) BookCrossing

(d) Amazon Video Games

Supervised Similarity Analysis



Supervised Similarity Analysis



Top-K Ranking Recommendation

Top-K Ranking Recommendation

Model	R-Precision
BPR	**0.22579149237442533**
WRMF	0.1841242282690616
DeepRec	0.17368522306349038
ProfitWalk	0.14920530109228317
PureSVD	0.134121742616618
DeepWalk	0.13407648848231915
Popular	0.12942480308774157
PMF	0.08037262846870519
SpectralCF	0.04243381758161209
GC-MC	0.04206175310215691
KNN	0.028821922164207498

Table 6.3: MovieLens-100k R-Precision

Model	R-Precision
PureSVD	**0.16712794423094776**
ProfitWalk	0.14874195923762576
DeepWalk	0.1376663334186439
WRMF	0.13525588818481504
BPR	0.125815116748618
Popular	0.10634943136289311
DeepRec	0.07818605888941238
SpectralCF	0.07615882526088245
KNN	0.053240445295168304
PMF	0.04351476384548103
GC-MC	0.016550159020925787

Table 6.4: MovieLens-1m R-Precision

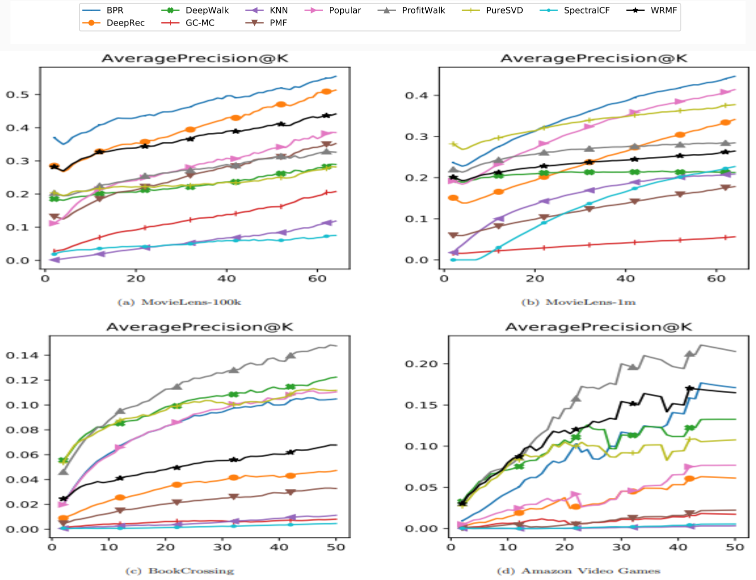
Model	R-Precision
DeepWalk	**0.03537717620367315**
ProfitWalk	0.028105778250450776
PureSVD	0.027979193552098422
BPR	0.013798620384167482
Popular	0.013788971609372492
WRMF	0.01528680219247615
DeepRec	0.004230860304362016
PMF	0.0029544114180469483
SpectralCF	0.0013064369976799556
GC-MC	0.0011663642887627282
KNN	0.0007282023657656779

Table 6.5: BookCrossing R-Precision

Model	R-Precision
DeepWalk	**0.027476066515407804**
ProfitWalk	0.024723589142794496
WRMF	0.02267812923406185
PureSVD	0.01942766456071679
BPR	0.006751490554507684
DeepRec	0.0030388102916909794
Popular	0.00293726167961445
SpectralCF	0.001033168189966927
GC-MC	0.0007350850942178361
PMF	0.0005112025682056364
KNN	0.0001622652973791078

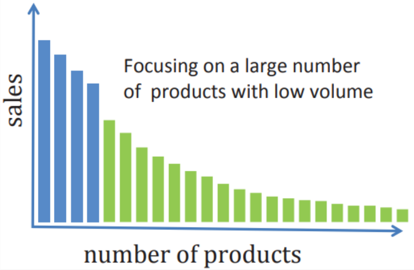
Table 6.6: Amazon Video Games R-Precision

Top-K Ranking Recommendation



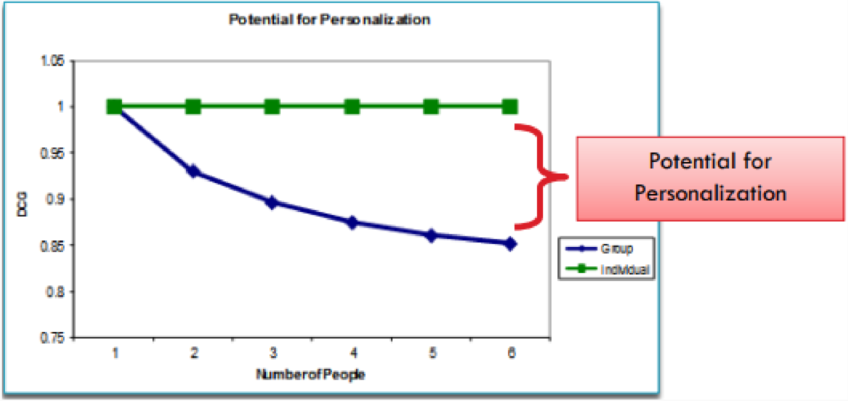
Profitability in Long-Tail Recommendations

Profitability in Long-Tail Recommendations



Long Tail [1]

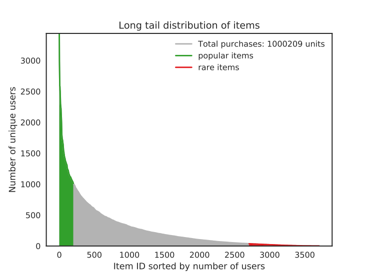
Personalization



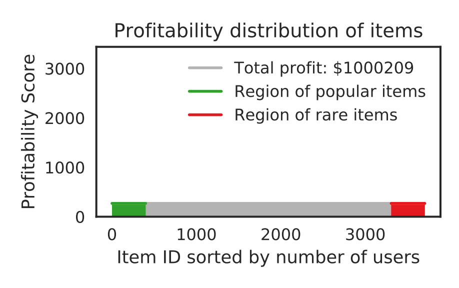
A single universal ranking is suboptimal.

Popularity is the optimal non-personalization algorithm.

Profitability Score Metric

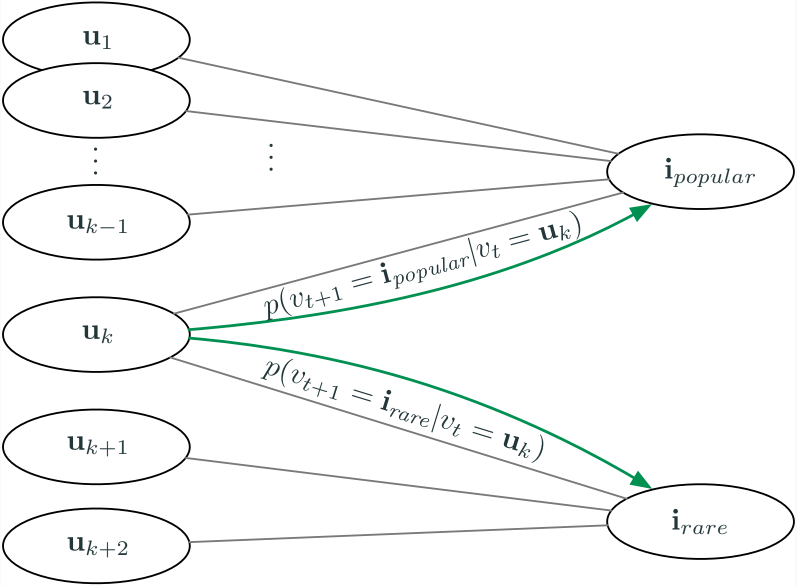


Precision Score Distribution



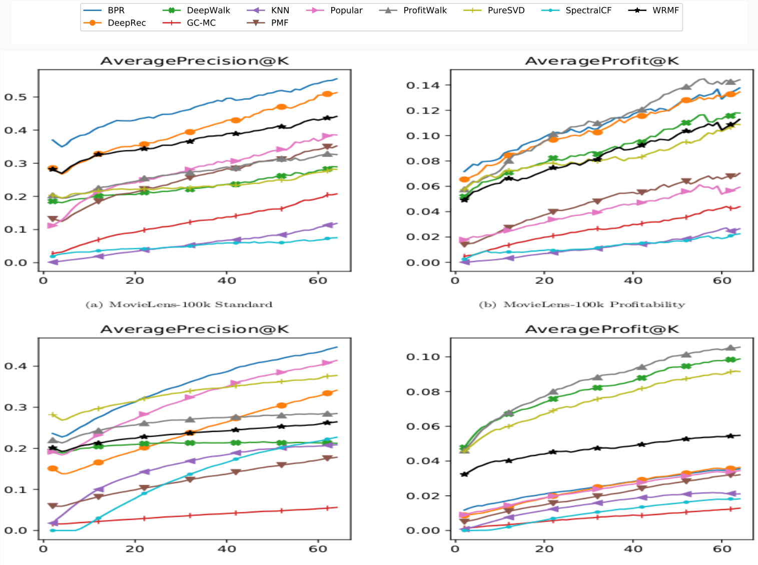
Profit Score Distribution

ProfitWalk



$\mathbf{u}_1$
$\mathbf{u}_2$
$\mathbf{u}_{k-1}$
$\mathbf{u}_k$
$\mathbf{u}_{k+1}$
$\mathbf{u}_{k+2}$
$\mathbf{i}_{popular}$
$\mathbf{i}_{rare}$
$p(v_{t+1} = \mathbf{i}_{popular} | v_t = \mathbf{u}_k)$
$p(v_{t+1} = \mathbf{i}_{rare} | v_t = \mathbf{u}_k)$

Results



(a) MovieLens-100k Standard

(b) MovieLens-100k Profitability

(c) MovieLens-1m Standard

(d) MovieLens-1m Profitability

Results

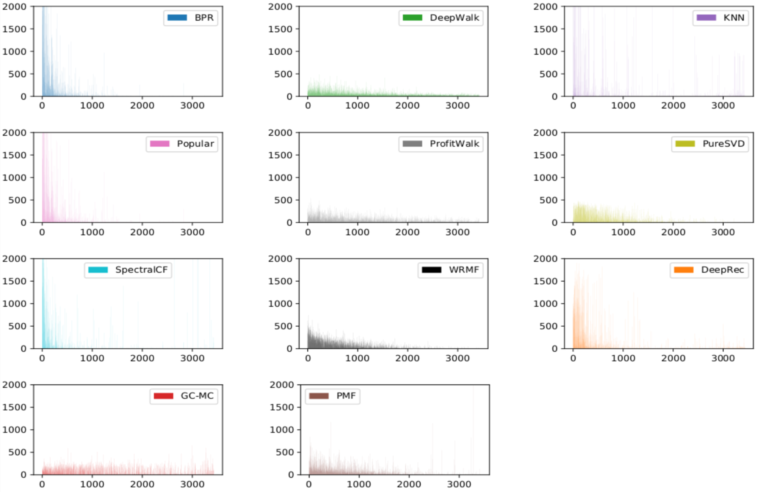
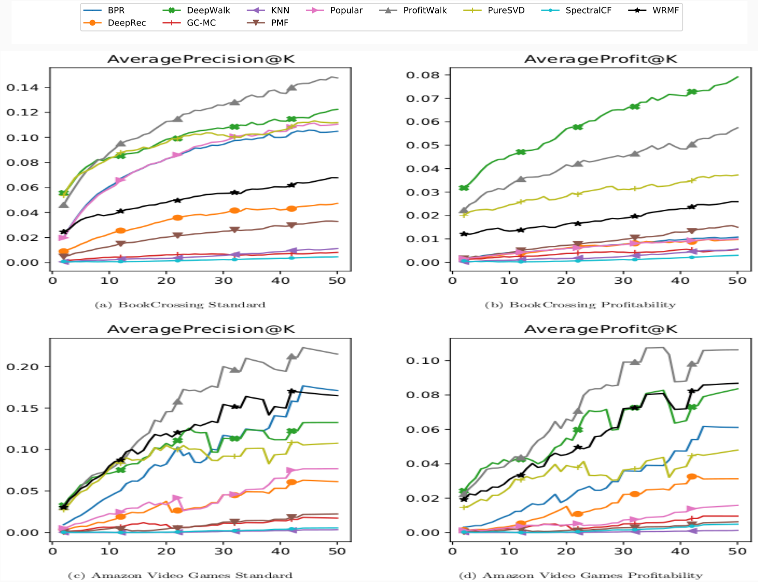


Figure 7.6: Recommendation Popularity of Algorithms on MovieLens-1m

Results



(a) BookCrossing Standard

(b) BookCrossing Profitability

(c) Amazon Video Games Standard

(d) Amazon Video Games Profitability

Results

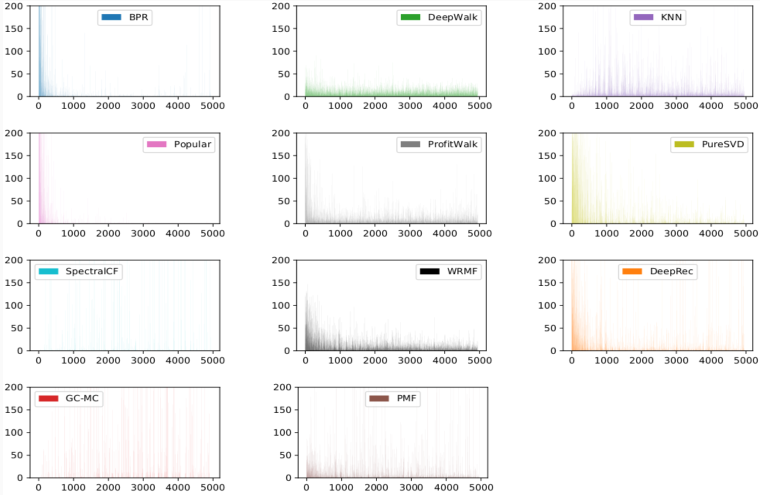


Figure 7.7: Recommendation Popularity of Algorithms on BookCrossing

Conclusion

Conclusion

Convolution-based Deep Graph Embeddings:

- under-performs under recommender system's analysis.

SGNS-based Deep Graph Embeddings:

- has great embeddings, respects metric spaces and is able to predict categorical information.
- outperforms on sparse datasets, especially on the long-tail.
- can be extended to optimize for the long-tail
- has better popularity distribution.

Bias training of existing models towards profitability.
New metric that encourages profitable recommendations.

Questions

Appendix

Identity Similarity: An item should be most similar to itself.

$$Identity\ Similarity = \frac{1}{|I|}\sum_{i=1}^{|I|} 1[\operatorname*{argmax}_j(W_i^I \cdot W_j^I) == i] \tag{1}$$

Cluster Similarity: Average of similarity within a cluster centered at an item should be similar relative to that item's similarity against its K nearest neighbours similarity score.

$$\begin{aligned}
Cluster\ Similarity@K &= \frac{1}{|I|}\sum_{i=1}^{|I|}\frac{within_i@K}{center_i@K} \\
within_i@K &= \frac{2}{K(K-1)}\sum_{j=1}^{K-1}\sum_{l=j+1}^{K} W_j^I \cdot W_l^I \\
center_i@K &= \frac{1}{K}\sum_{j=1}^{K} W_i^I \cdot W_j^I \\
I_j, I_k &\in I_i^{KNN}
\end{aligned} \tag{1}$$

Appendix

Binary Similarity: K-Nearest neighbour predicts the correct label using Binary Cross Entropy.

$$
\begin{aligned}
Binary\ Similarity@K &= \frac{1}{|I|}\sum_{i=1}^{|I|}\sum_{c=1}^{|C_i|} P_i(class(i)=c)\ log_2(P_{I_i^{KNN}}(class(i)=c)) \\
P_i(class(i)=c) &= \frac{1+\alpha}{|C_i|(1+\alpha)} \\
P_{I_i^{KNN}}(class(i)=c) &= \frac{1}{K}\sum_{j\in I_i^{KNN}} \frac{1[c\in C_j]+\alpha}{|C_j|(1+\alpha)}
\end{aligned} \tag{1}
$$

$\alpha = 10$ is a positive constant for numerical stability if there exist a class $c \in C_i$ where none of the neighbours of item i intersects.

Average Similarity: Average of items in the same label should result in being closest to another item in the same label.

$$
\begin{aligned}
Average\ Similarity@K &= \frac{1}{|C|}\sum_{c \in C} ClassPrecision@K_c(I_c^{KNN}) \\
W_c^l &= \frac{1}{K}\sum_{k=1, i_k \in I_c}^{K} W_{i_k}^l
\end{aligned} \tag{1}
$$

Appendix

$$
\begin{aligned}
\text{HitItemSet@}K_u &= \hat{r}_{u,:K} \cap r^{test}_{u,:} \\
\text{HitScore@}K_u &= \sum_{i \in \text{HitItemSet@}K_u} s_i \\
\text{OptimalScore@}K_u &= \sum_{i \in r^{test}_{u,:K}} s_i \\
\text{Precision@}K_u &= \frac{\text{HitScore@}K_u}{\text{OptimalScore@}K_u} \\
\text{AP@}K_u = \text{AveragePrecision@}K_u &= \frac{1}{K} \sum_{k=1}^{K} \text{Precision@}k_u \\
\text{mAP@}K = \text{AveragePrecision@}K &= \frac{1}{|U^{test}|} \sum_{u \in U^{test}} \text{AP@}K_u \\
\text{HitScore}_i = \sum_{u \in r^{test}_{:,i}} s_i &= |r^{test}_{:,i}| \times s_i, \text{TotalScore} = \sum_{i \in I^{test}} \text{HitScore}_i
\end{aligned}
\tag{1}
$$

Comparison between Standard and Profitability

Properties	Standard	Profitability
$\textbf{score}_i = s_i$	1.0	$\frac{1}{\lvert r^{test}_{:,i}\rvert} * (\frac{\lvert R^{test}\rvert}{\lvert I^{test}\rvert})$
$\textbf{HitScore@}K_u$	$\lvert\textbf{HitItemSet@}K_u\rvert$	as defined above
$\textbf{OptimalScore@}K_u$	K	as defined above
$\textbf{HitScore}_i$	$\lvert r^{test}_{:,i}\rvert$	$\frac{\lvert R^{test}\rvert}{\lvert I^{test}\rvert} = constant$
$\textbf{TotalScore}$	$\lvert R^{test}\rvert$	$\lvert R^{test}\rvert$
$range(\textbf{mAP@}K)$	[0.0, 1.0]	[0.0, 1.0]

Future Work

Future Work

- Develop embeddings that explicitly respect metric spaces.
- Develop embeddings that are robust towards adversarial attacks.
- Remove bias towards sensitive attributes from embeddings.

References i

[1] H. Yin, B. Cui, J. Li, J. Yao, and C. Chen.
Challenging the long tail recommendation.
Proceedings of the VLDB Endowment, 5(9):896–907, 2012.