Item Cold-start Recommendations: Learning Local Collective Embeddings

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Cold-Start

When new user/item enters the system
No past information $\rightarrow$ No effective recommendations
Cold-Start

When new user/item enters the system
No past information → No effective recommendations

User Cold-start
• Visits from users who are not logged in
• Content-based/Collaborative-filtering not applicable

Item cold-start
• No previous feedback available
• Collaborative filtering is not an option
Motivation
Cold-start

Hundreds/thousands of new items every day
• Yahoo News: ~100 new articles / day
• eBay or Amazon: >1000 items / day ???

Jump-start collaborative filtering systems
• Make new items “popular”
• Enough feedback to achieve the expected performance
News Recommendation
Yahoo News
News Recommendation

Yahoo News

Ranking Accuracy

- Content Based
- BPR + kNN
News Recommendation

Yahoo News

![Bar chart showing ranking accuracy for different methods: Content Based, BPR + kNN, and Local Collective Embeddings. Local Collective Embeddings have the highest ranking accuracy.](image-url)
Local Collective Embeddings

2 Main Ideas

1) Combine content and past collaborative data
   • Link item properties and users
   • Topics and Communities

2) Exploit data locality
   • Data may lie in a manifold
   • Graph regularization
Data in Matrix Form

Content Matrix

\( X_A \)

Collaborative Matrix

\( X_U \)
Data in Matrix Form

Content Matrix

$X_A$

Collaborative Matrix

$X_U$
Data in Matrix Form

Content Matrix

\[ X_A \]

Collaborative Matrix

\[ X_U \]
Data in Matrix Form

- Content Matrix: $X_A$
  - #attributes
  - #items
- Collaborative Matrix: $X_U$
  - #users
  - #items
Content Embeddings

Content Matrix

Embeddings

$X_A$ ≈ $W_A^+$

$H_A^+$

Item 1

Item 2

...

Item N

Word 1

Word 2

...

Word i

...

Word M

Factor 1...k

Topic Matrix

Sports

Politics

Economy

Topics
Content Embeddings

\[ X_A \approx W_A^+ \]

Content Matrix

Embeddings

\[ H_A^+ \]

Topics

Sports

Politics

Economy
Content Embeddings

\[ X_A \approx W_A^+ H_A^+ \]

- Content Matrix
- Embeddings

Topics: Sport, Politics, Economy
Collaborative Embeddings

Collaborative Matrix \( X_U \) ≈ Embeddings \( W_U^+ \)

Factor 1 \( \cdots \) k

User 1 \( \cdots \) User i \( \cdots \) User M

Community 1 \( \cdots \) Community k

COMMUNITIES
Collaborative Embeddings

Collaborative Matrix \( X_U \) ≈ Embeddings \( W_U^+ \)

Factor 1 \( \ldots \) k

\[ \mathbf{H}_U^+ \]

User 1 User 2 User i \( \ldots \) User M

Item 1 Item 2 Item \( \ldots \) Item N

Community 1 Community 2 Community \( \ldots \) Community k

COMMUNITIES
Collaborative Embeddings

$X_U \approx W_U^+$

Collaborative Matrix

Embeddings

$H_U$

COMMUNITIES

Community 1
Community 2
...
Community k
Collective Embeddings

#items
#users
#documents

\[ X_A \approx W^+ H_A^+ \]

\[ X_U \approx W^+ H_U^+ \]

Topic 1
... 
Topic k

Community 1
... 
Community k

TOPICS
COMMUNITIES

Common Embeddings
Collective Embeddings

Inference

New Item

\[ Q_A \]

\#words

\[ H_A \]

Topic 1
... Topic k

\[ H_U \]

Community 1
.... Community k
Collective Embeddings

Inference

New Item $q_A$ \approx \hat{w} \rightarrow H_A

# words

Topic 1 ... Topic k

Community 1 .... Community k

HU
Collective Embeddings

Inference

New Item

$Q_A$

#words

$\hat{W}$

$H_A$

Topic 1

... Topic k

$\hat{W}$

$H_U$

Community 1

.... Community k
Collective Embeddings

Inference

\[ Q_A \approx \hat{\mathbf{W}} H_A \]

\[ Q_U = \hat{\mathbf{W}} H_U \]

\#words

New Item

Topic 1
... Topic k

\#users

Predictions

Community 1
.... Community k
Exploiting Locality

- So far: linear approximation of the data
- Data may lie in small subspace
Graph Regularization

- Manifold approximation using kNN Graph
- Weighting by the Laplacian Matrix: $L = D - A$

Nearest Neighbors $\rightarrow$ Similar embeddings
Local Collective Embeddings Learning

Non-convex Optimization Problem
• Hard to find the global minimum
• Convex when all but one variable are fixed

Multiplicative Update Rules
• Simple and easy to implement
• Non-increasing w.r.t. objective function
Experimental Evaluation

News recommendation
• Yahoo News: 40 days
• 41k articles, 650k users (random sample)
• Implicit feedback

Email Recipient Recommendation
• Enron: 10 mailboxes
• 36k emails, 5k users
• Explicit feedback
Baselines

Experimental Evaluation

1. Content Based Recommender (CB)
2. Content Topic Based Recommender
3. Latent Semantic Indexing on user profiles [Soboroff’99]
4. Author Topic Model [M. Rosen-Zvi’04]
5. Bayesian Personalized Ranked Ranking + kNN (BRP-kNN) [Gantner’10]
6. fLDA [Agarwal’10]
Baselines
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Email Recipient Recommendation

Experimental Results

Performance

MicroF1 | MacroF1 | MAP | NDCG

- BPR-kNN
- CB
- LCE (No Graph Regularization)
- LCE

Graph showing performance metrics for different recommendation methods.
News Recommendation

Experimental Results

Ranking Accuracy

RA@3  RA@5  RA@7  RA@10

- CB
- BPR-kNN
- LCE (No Graph Regularization)
- LCE

Graph showing the ranking accuracy for RA@3, RA@5, RA@7, and RA@10 with different recommendation techniques.
Conclusion

- New hybrid recommender for item cold-start
- Linking content and collaborative information helps
- Graph regularization is useful in some cases
Thank you!
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