Item Cold-start Recommendations: Learning Local Collective Embeddings

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Cold-Start

When new user/item enters the system

No past information $\longrightarrow$ No effective recommendations

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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

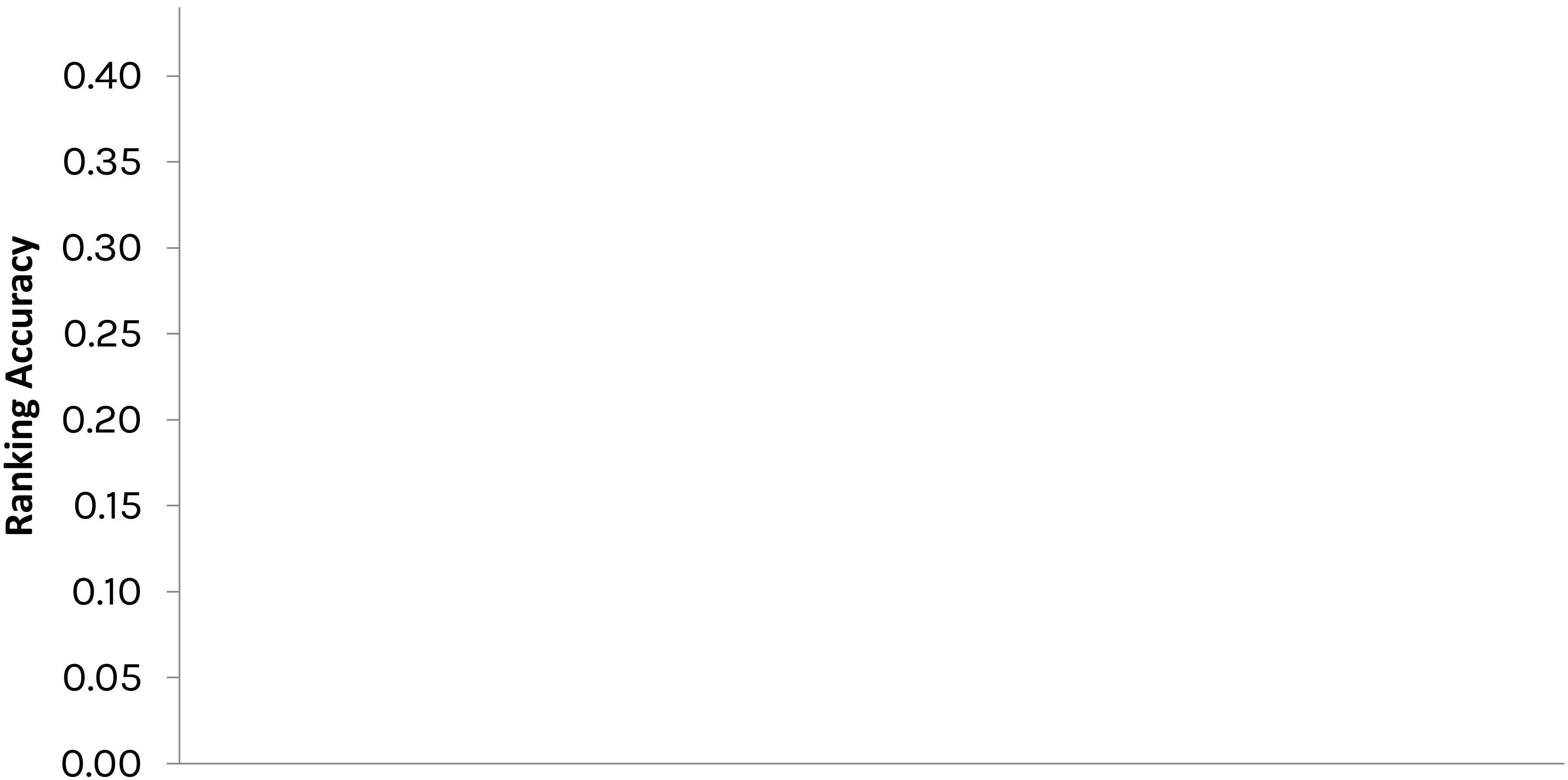
- Yahoo News: ~100 new articles / day
- eBay or Amazon: >1000 items / day ???

Jump-start collaborative filtering systems

- Make new items “popular”
- Enough feedback to achieve the expected performance

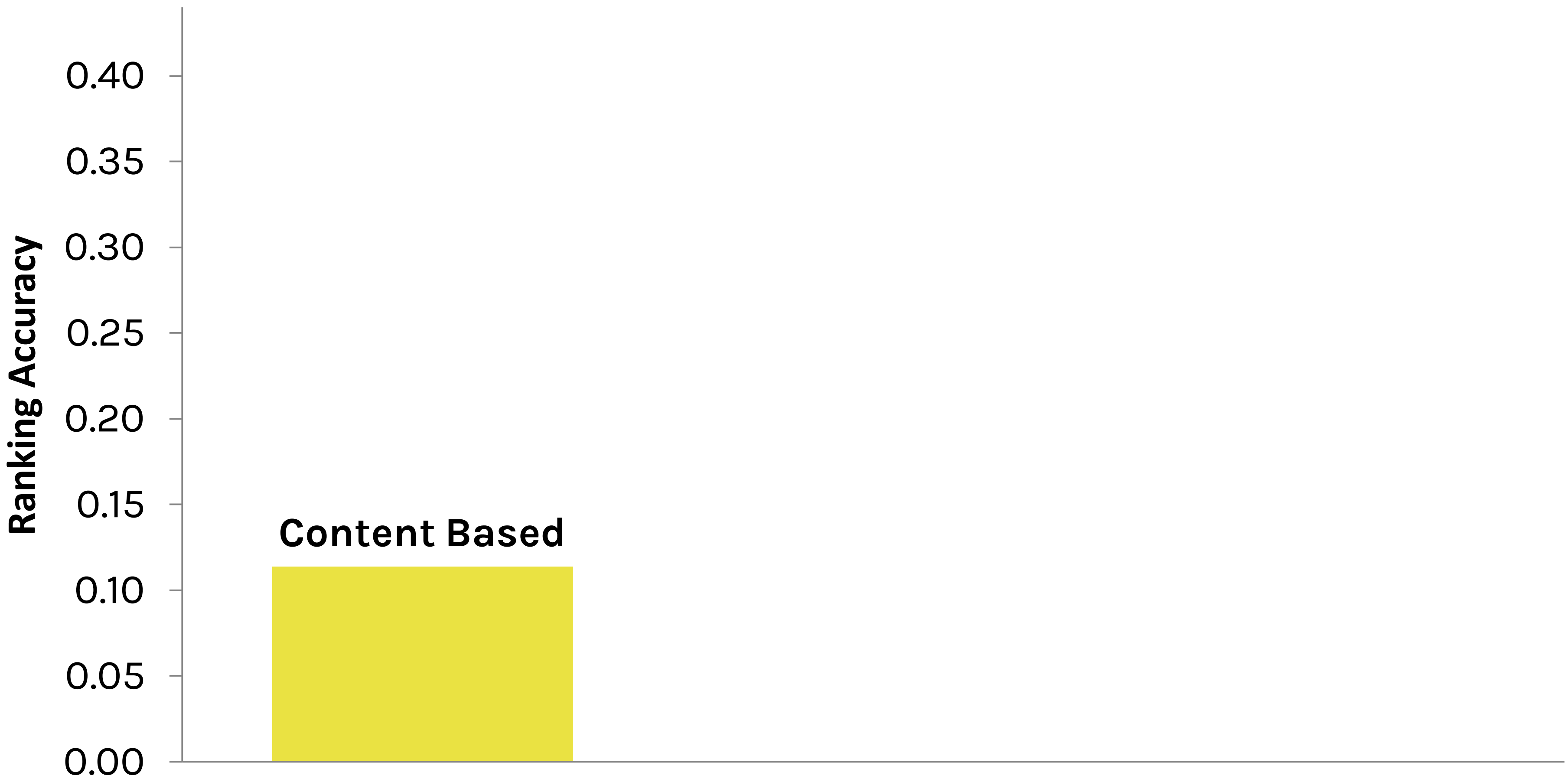
News Recommendation

Yahoo News



News Recommendation

Yahoo News



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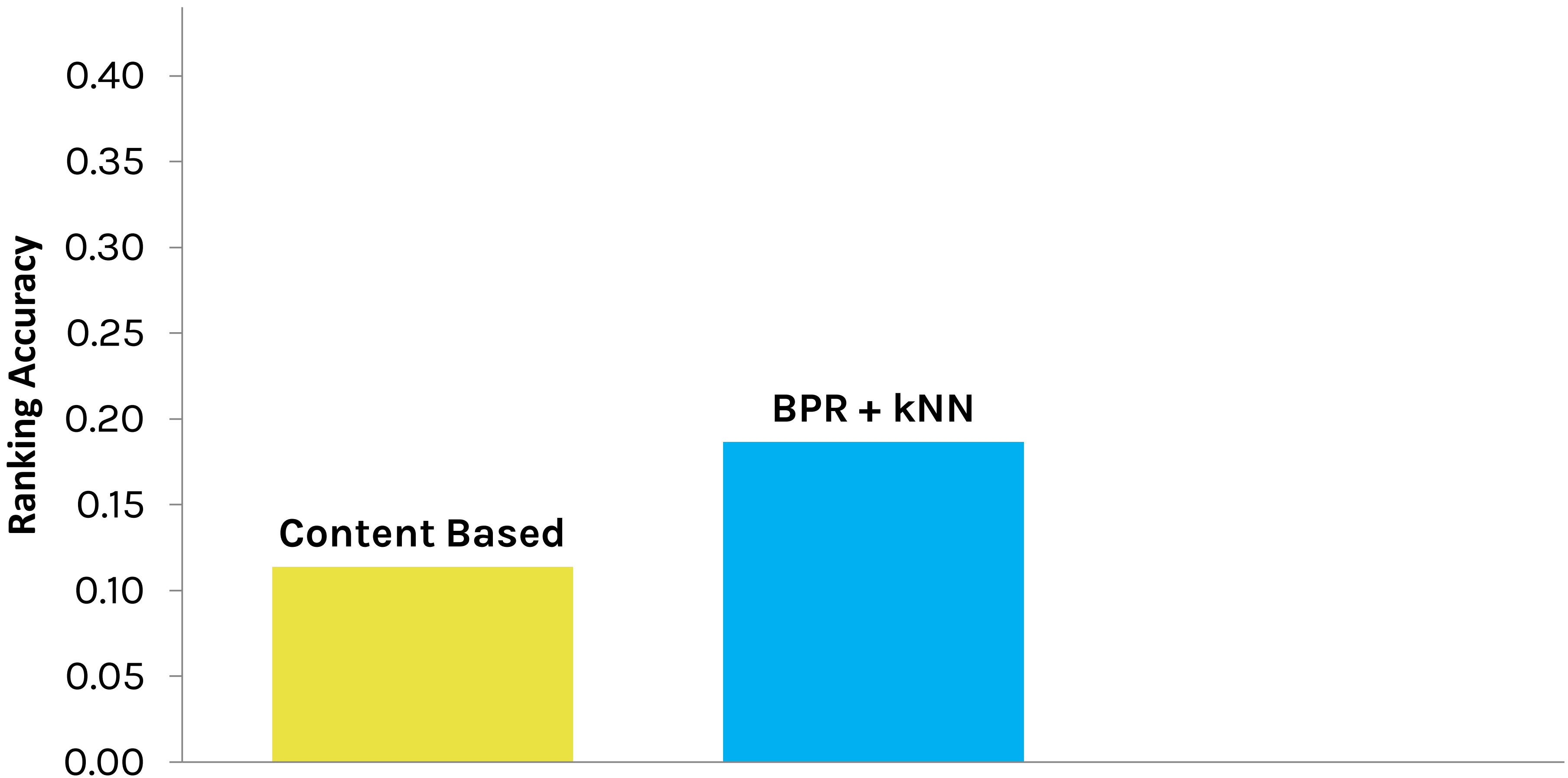

News Recommendation

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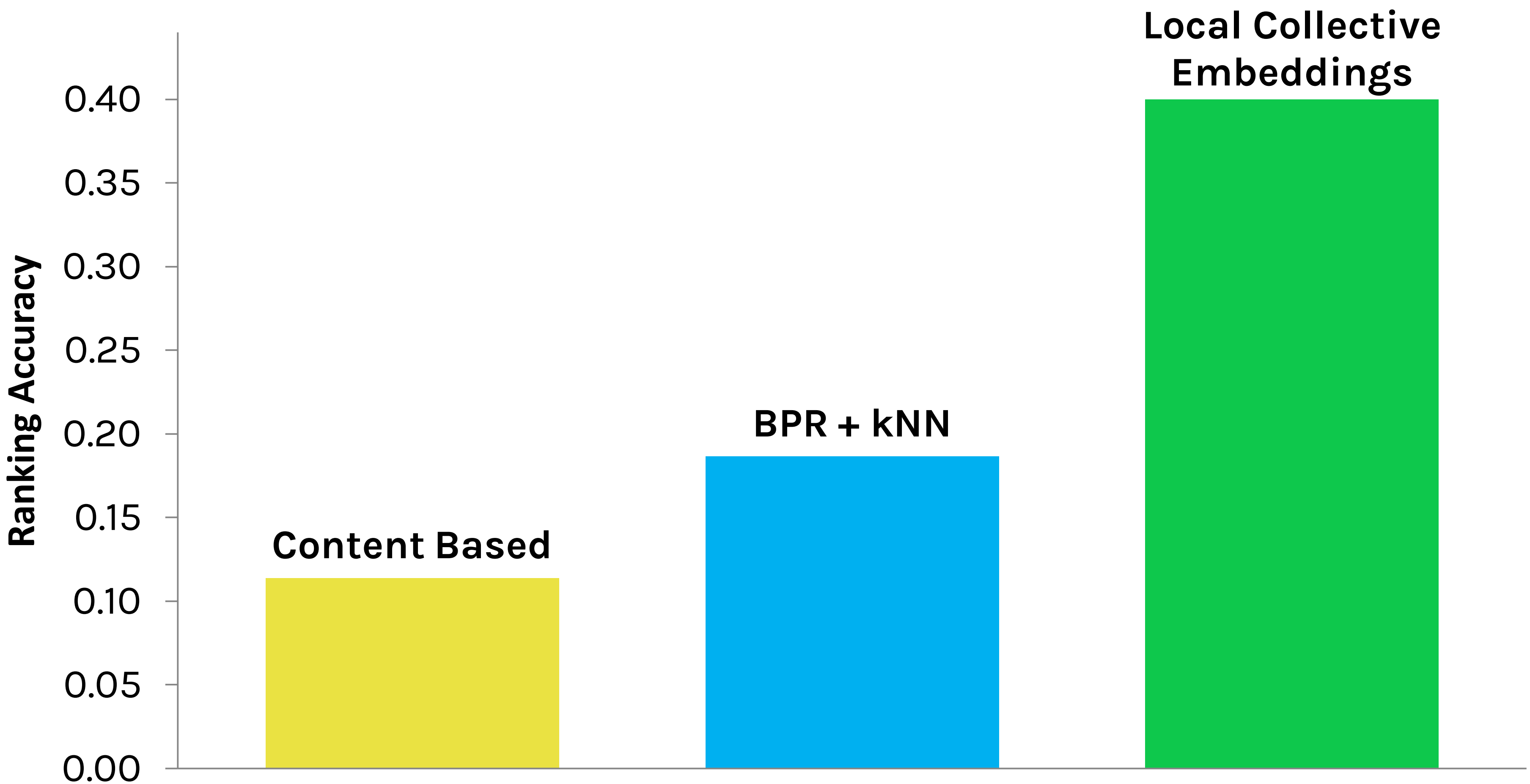


Local Collective Embeddings

2 Main Ideas

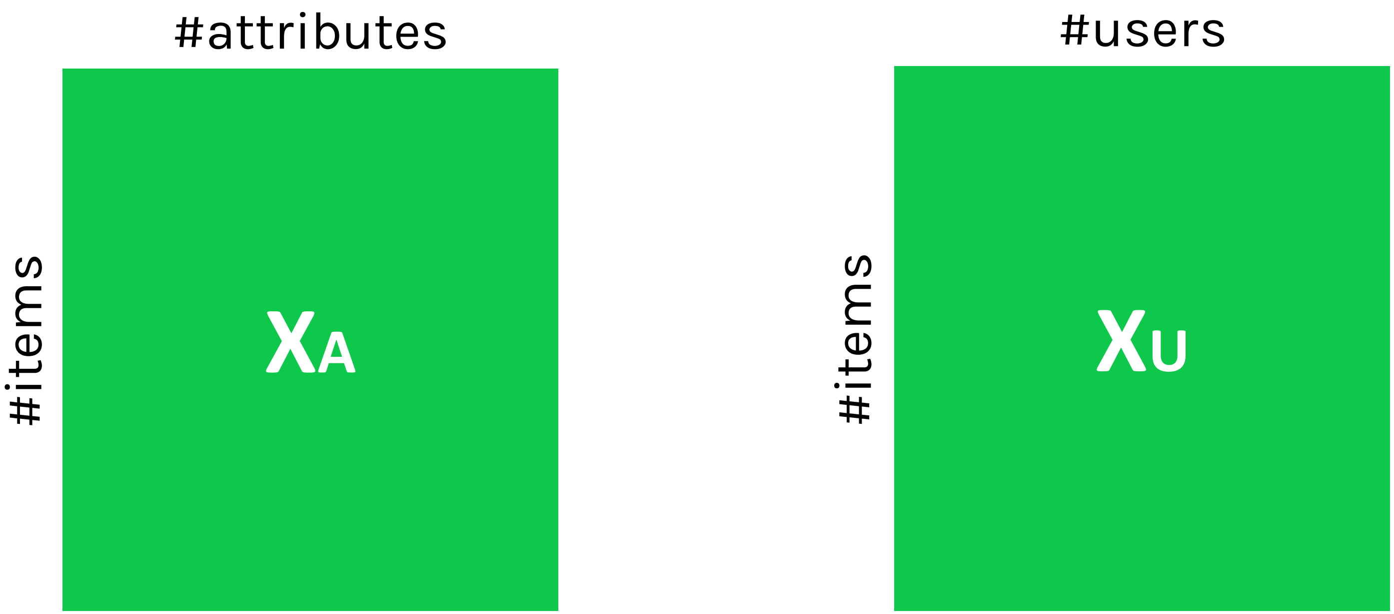
1) Combine content and past collaborative data

- Link item properties and users
- Topics and Communities

2) Exploit data locality

- Data may lie in a manifold
- Graph regularization

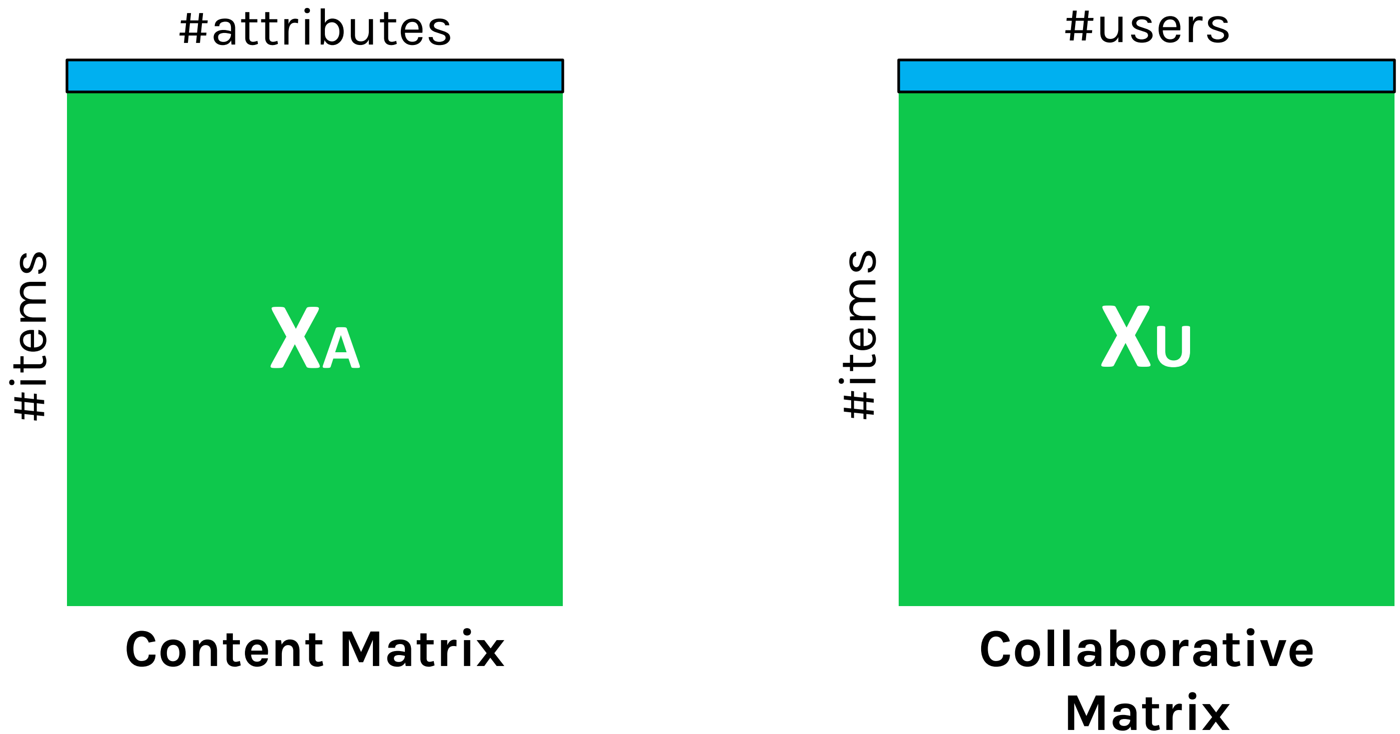
Data in Matrix Form



Content Matrix

Collaborative Matrix

Data in Matrix Form



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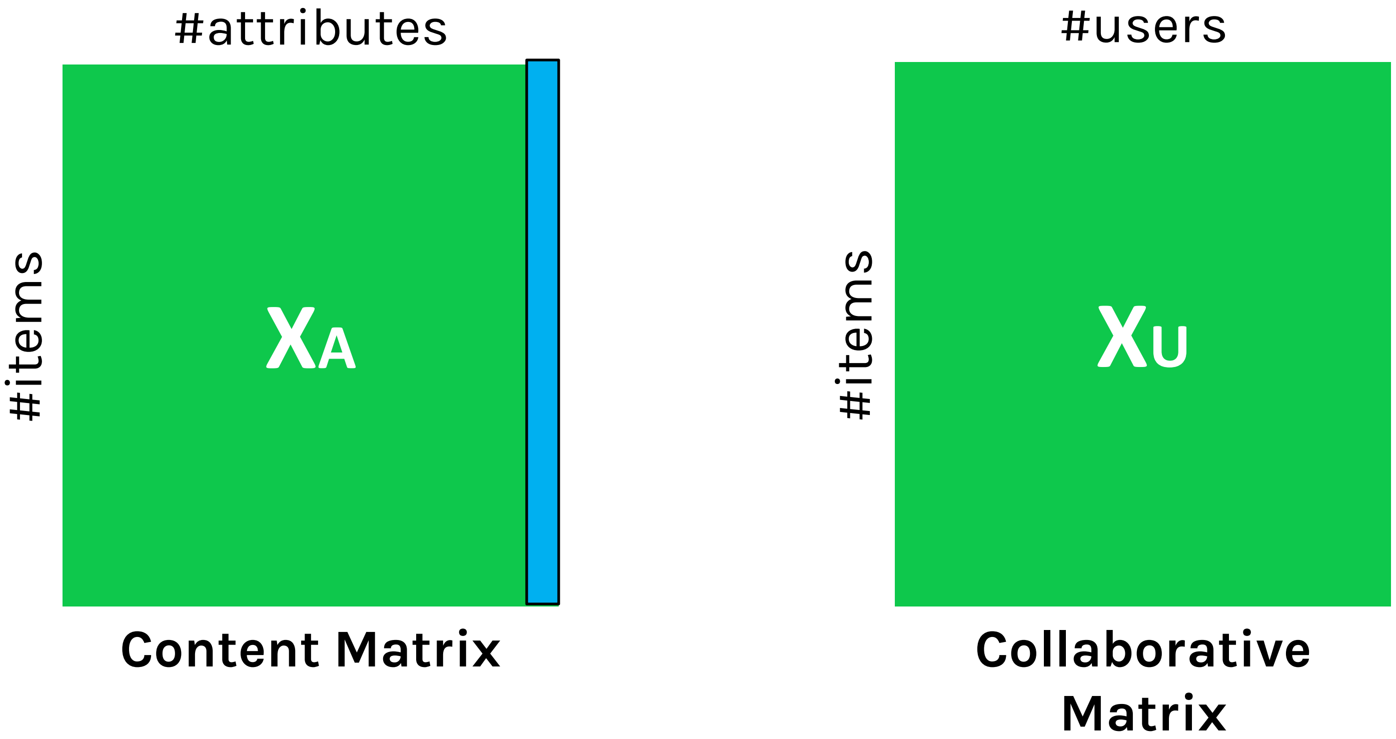

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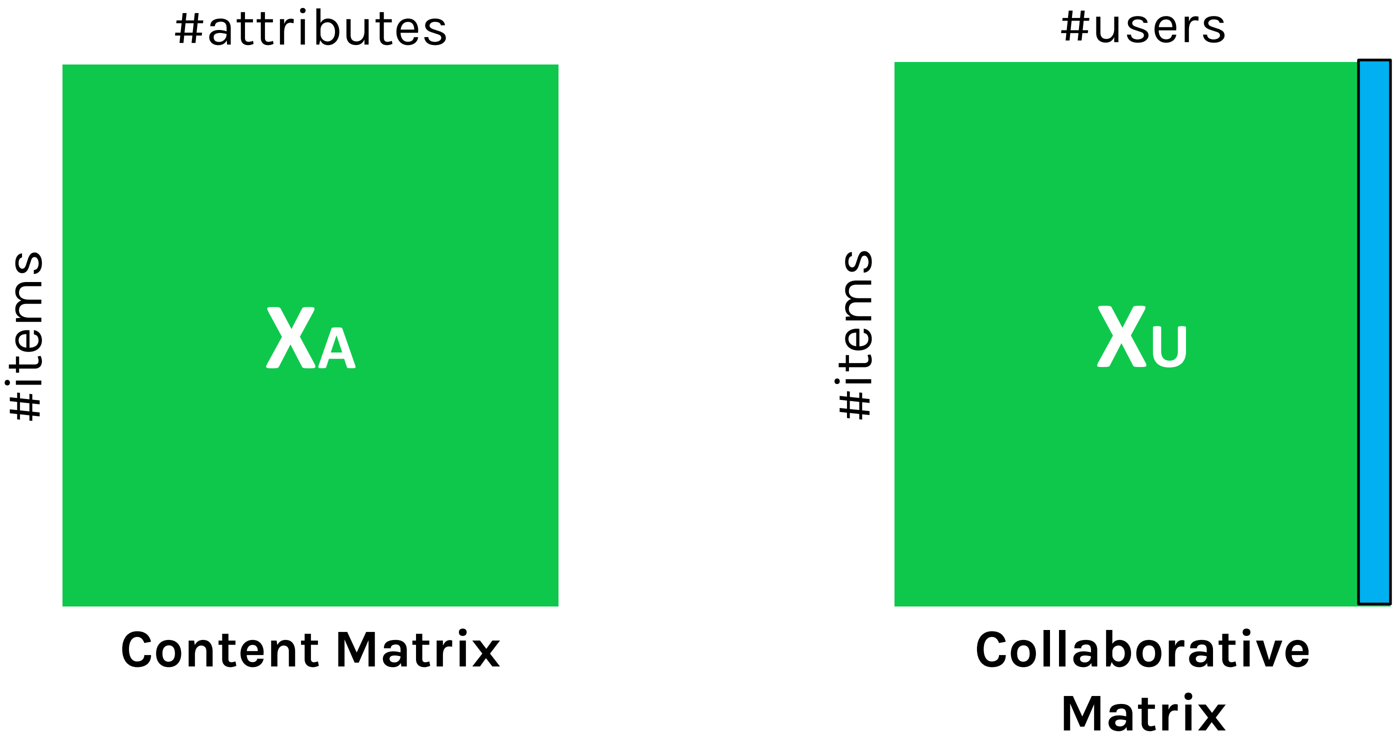
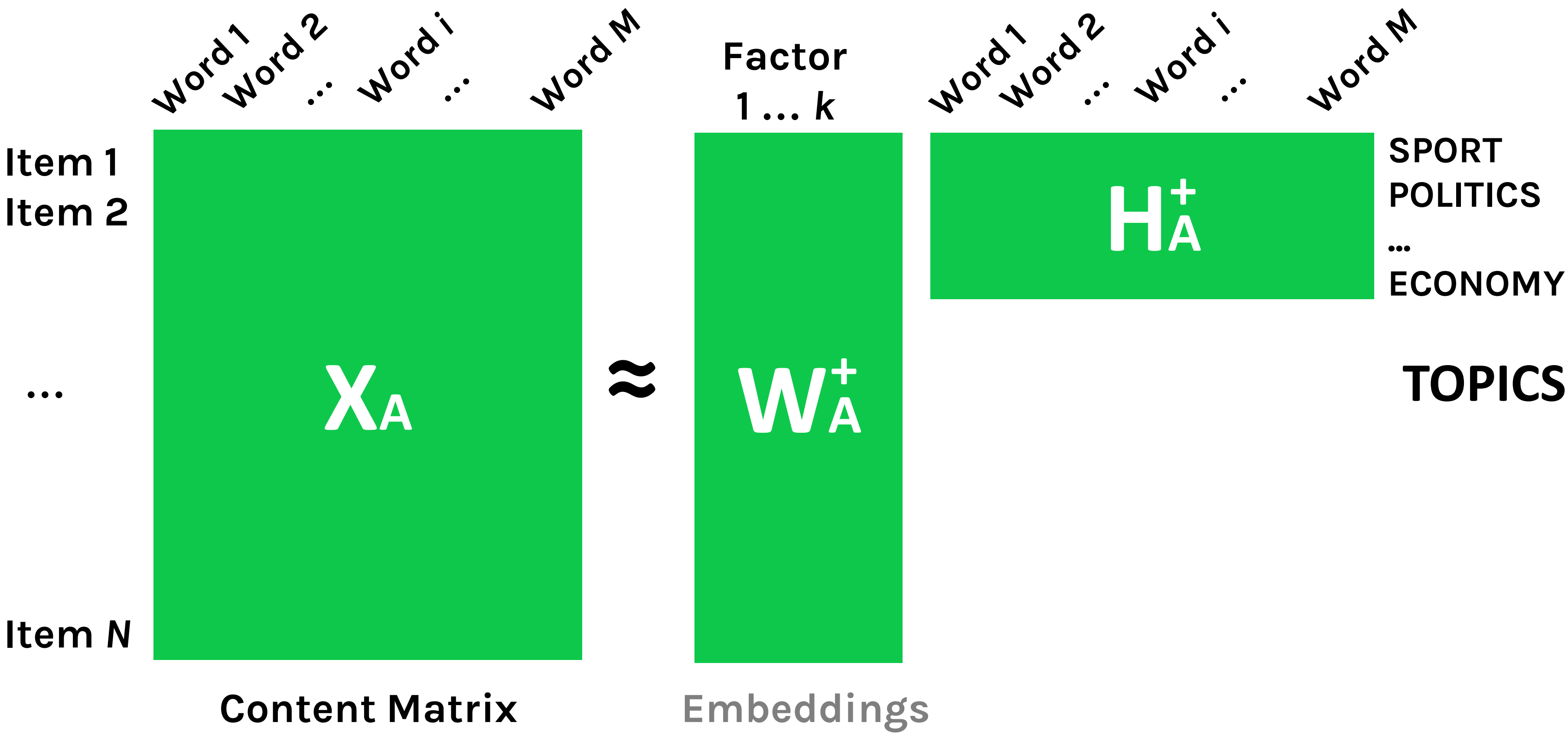


Content Embeddings



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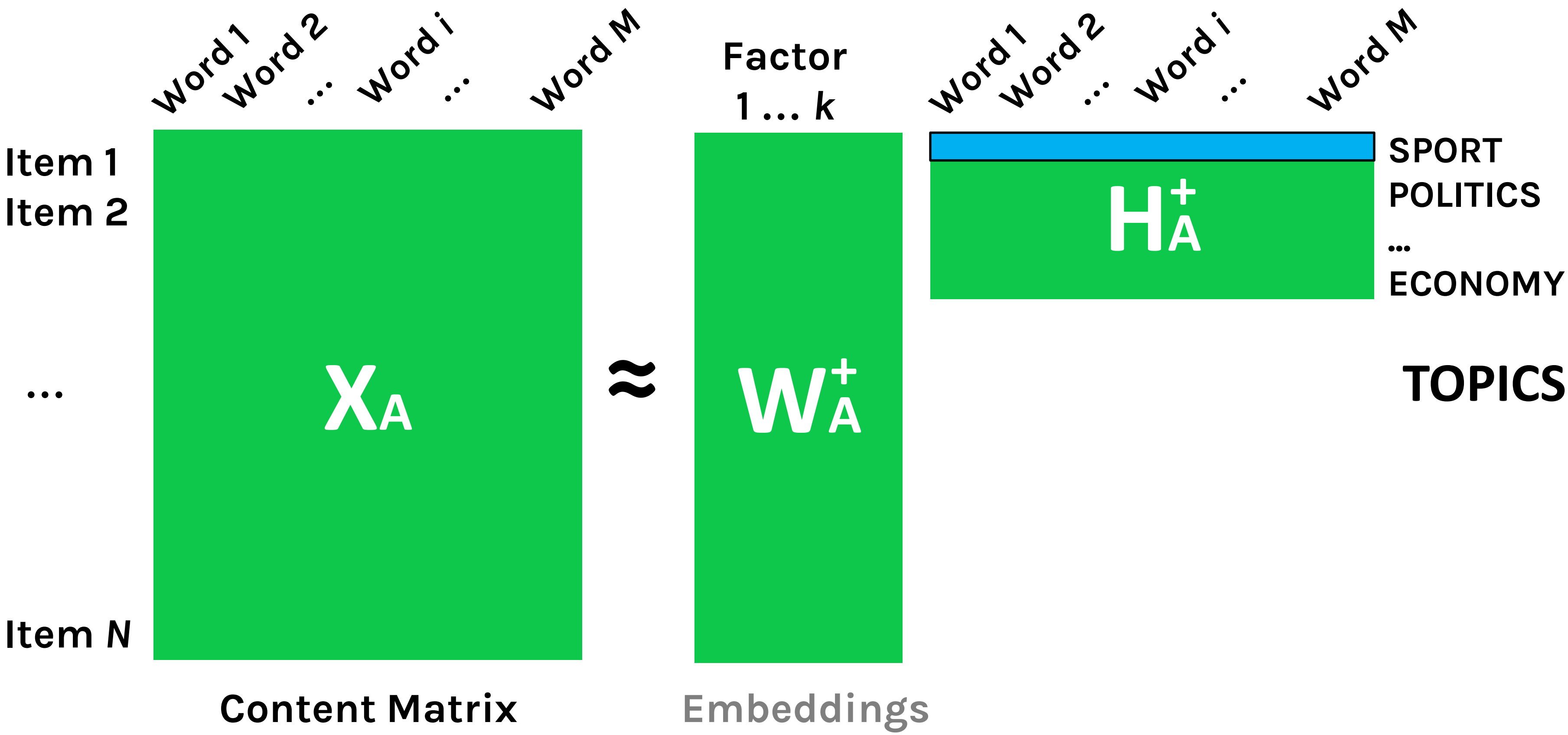

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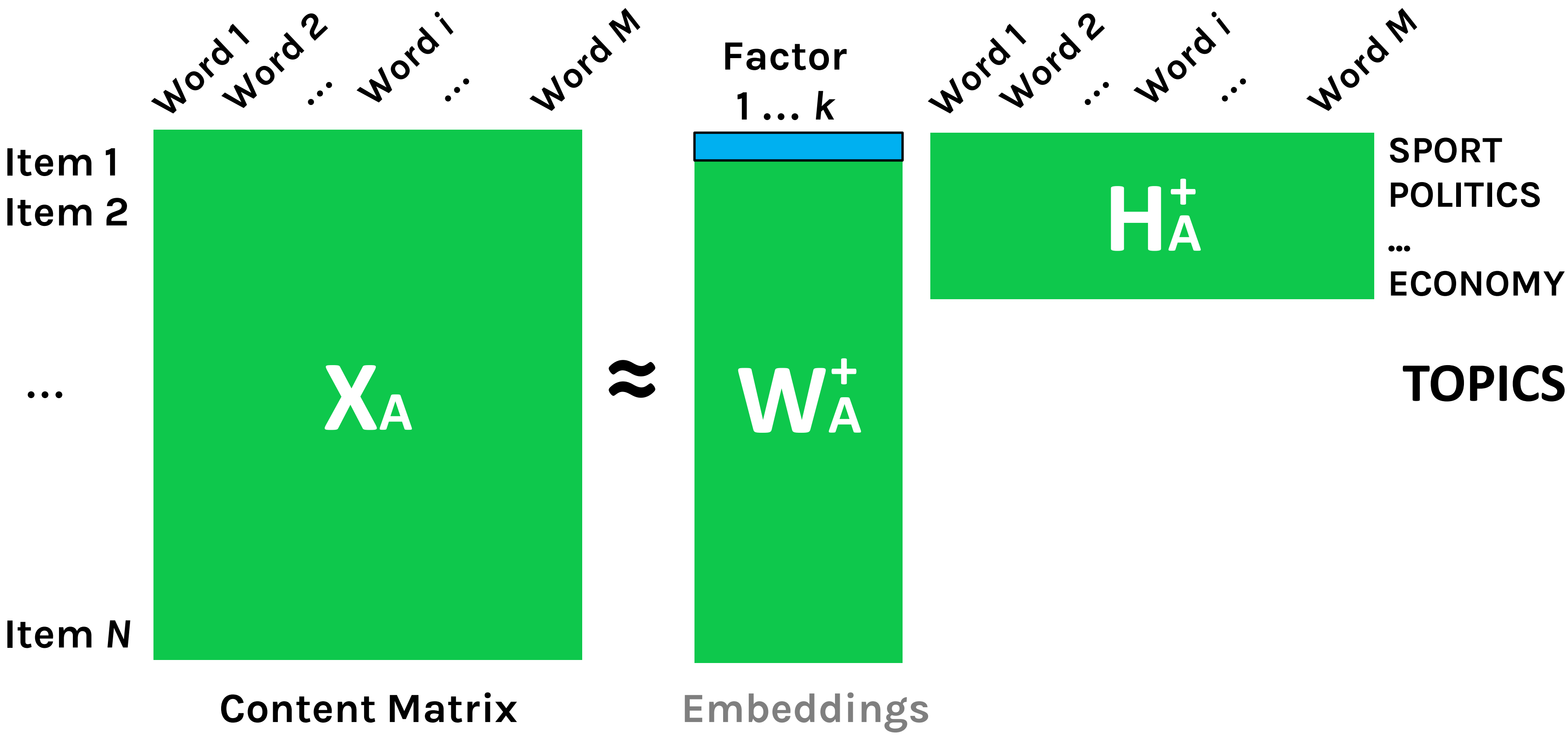
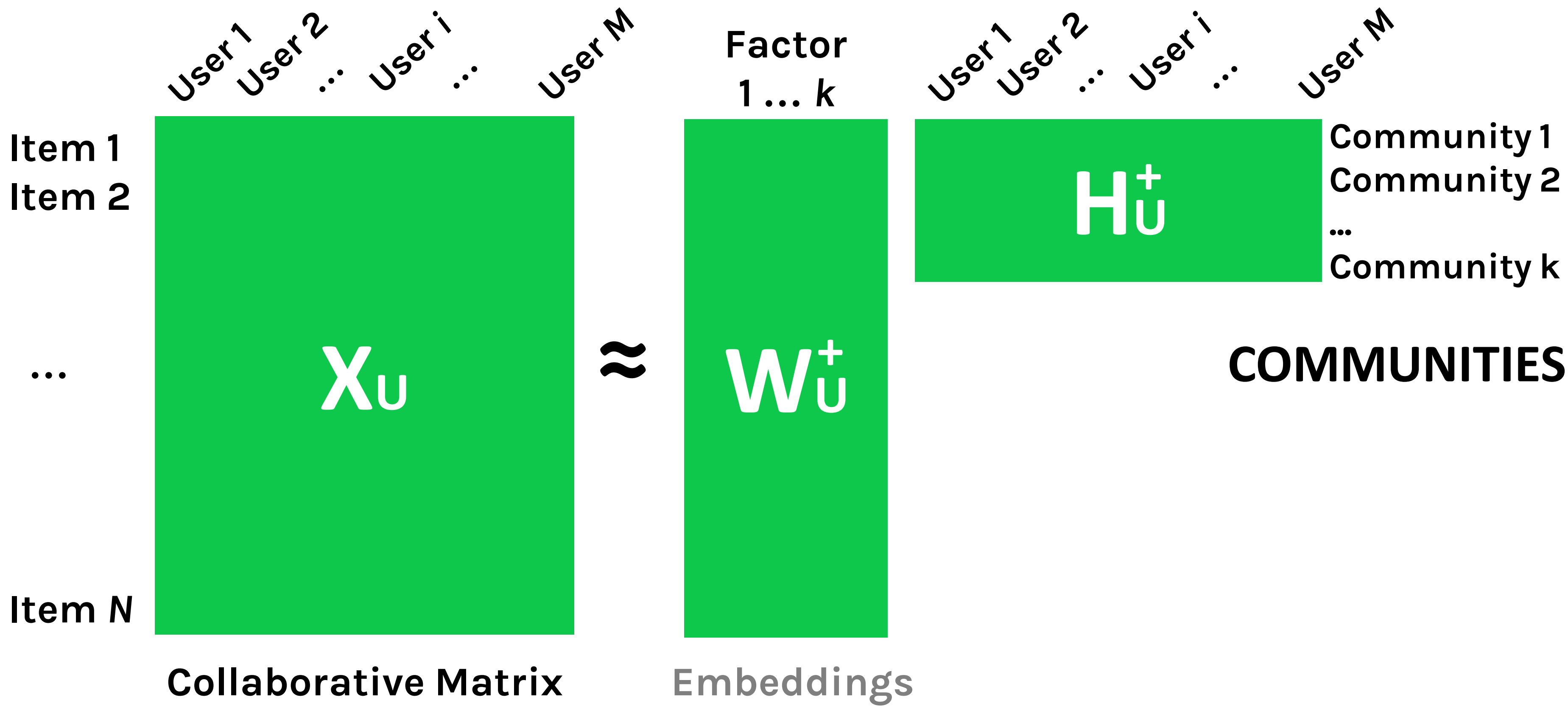
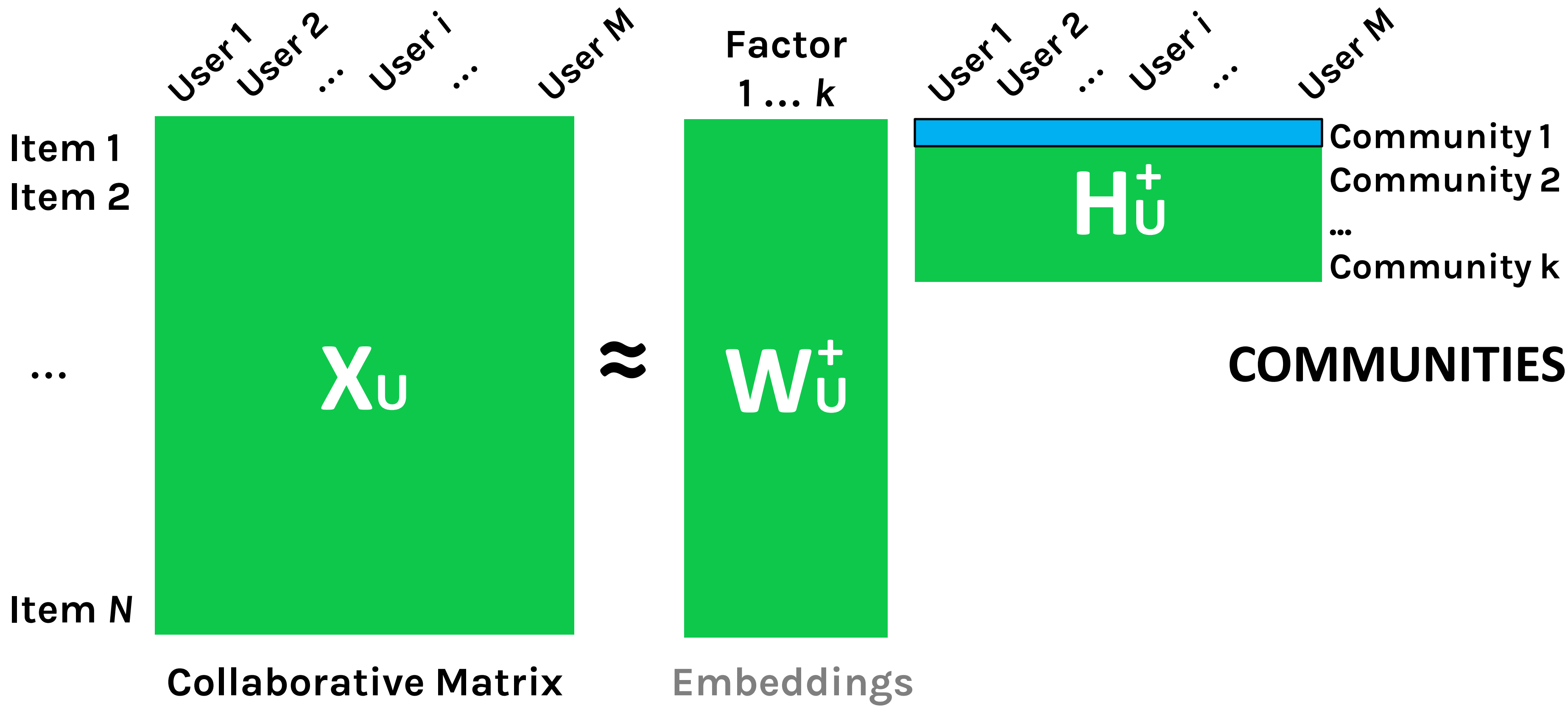


Collaborative Embeddings



Collaborative Embeddings



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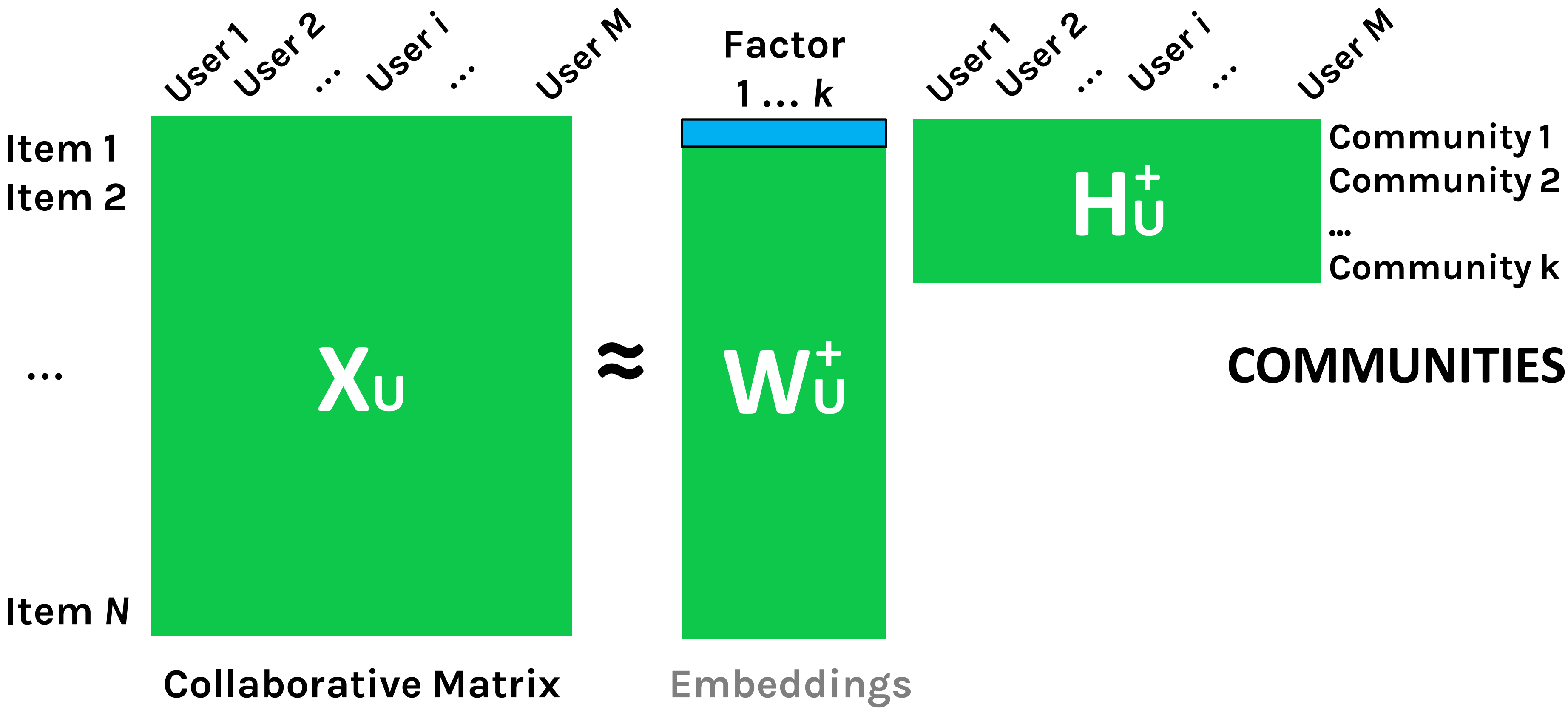
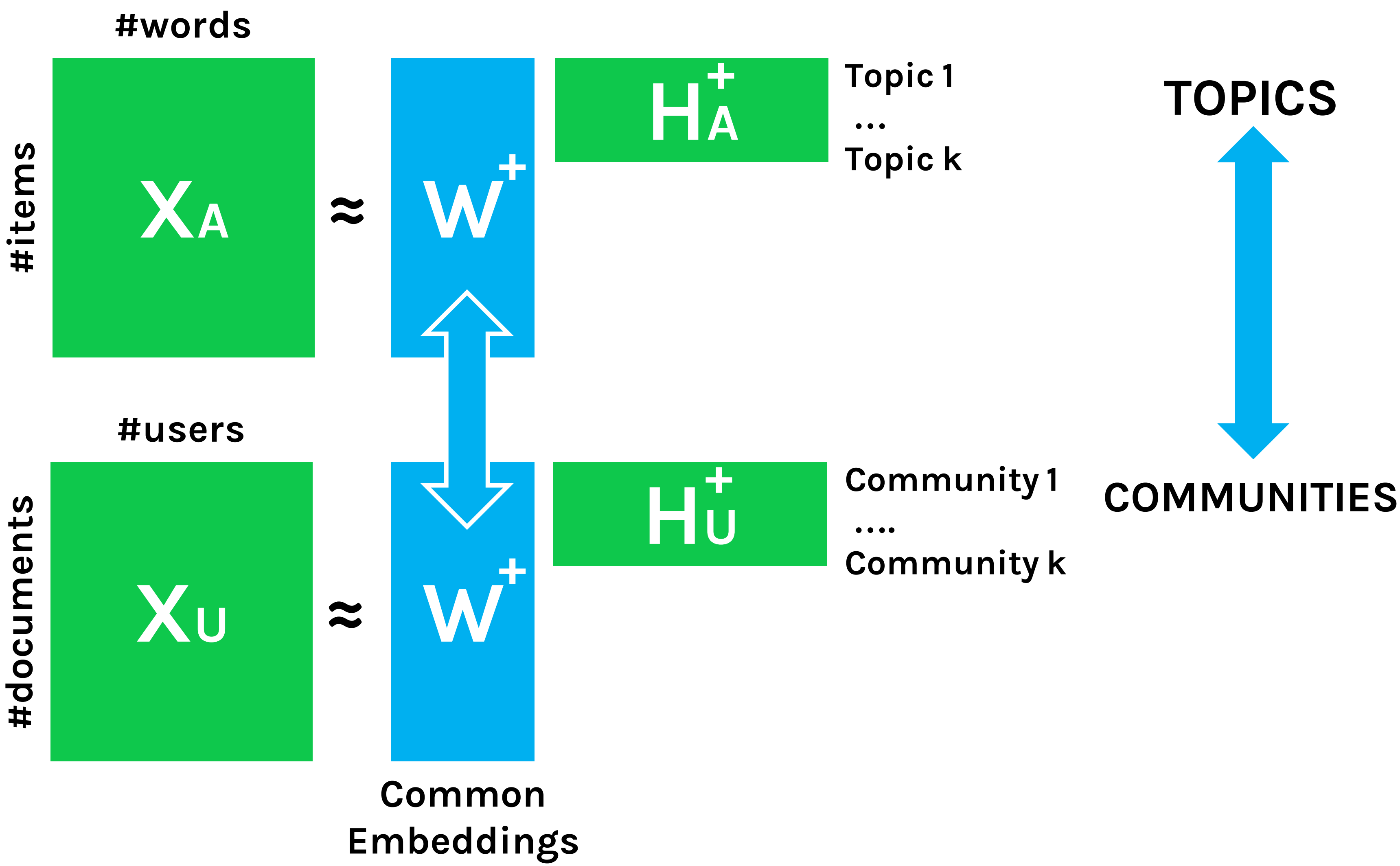


Collective Embeddings



Collective Embeddings

Inference

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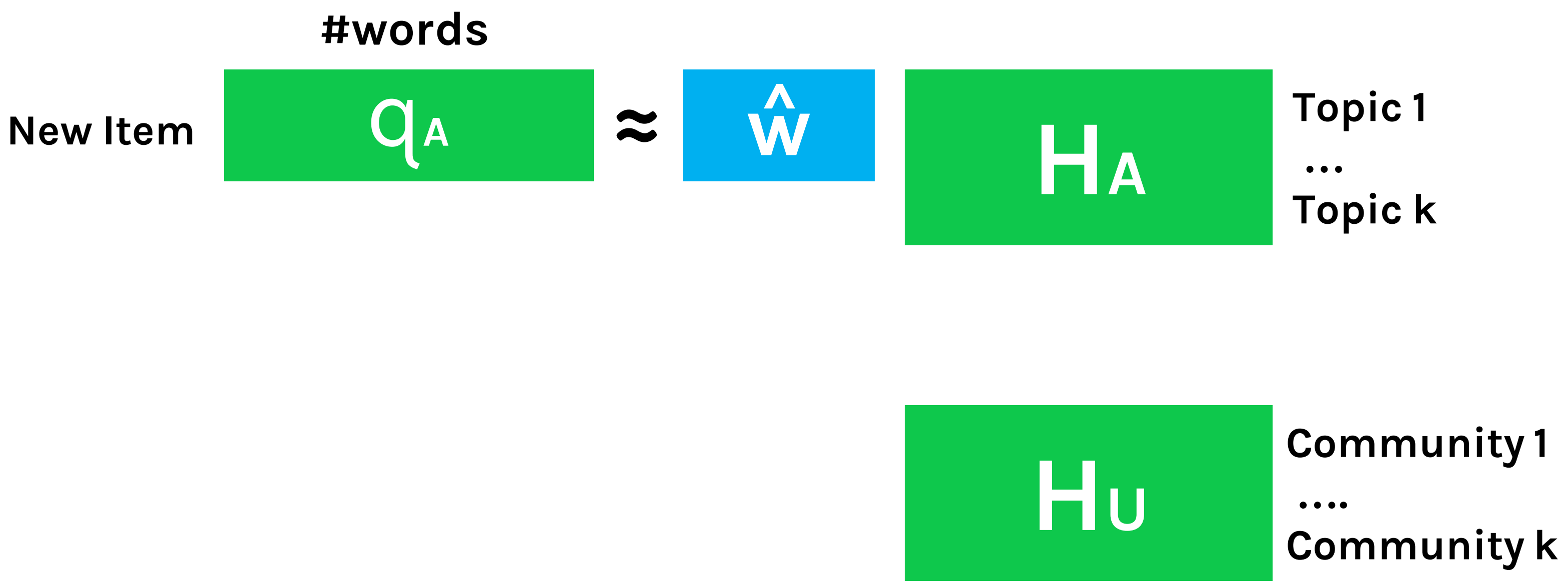
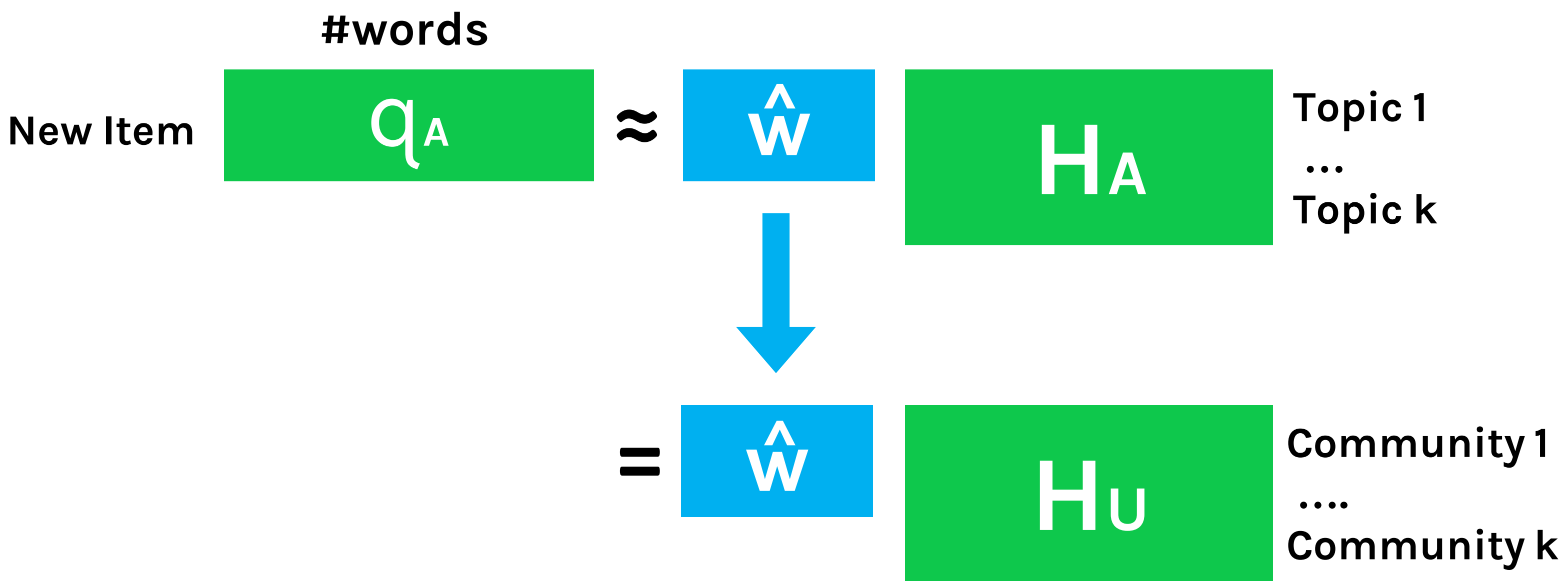


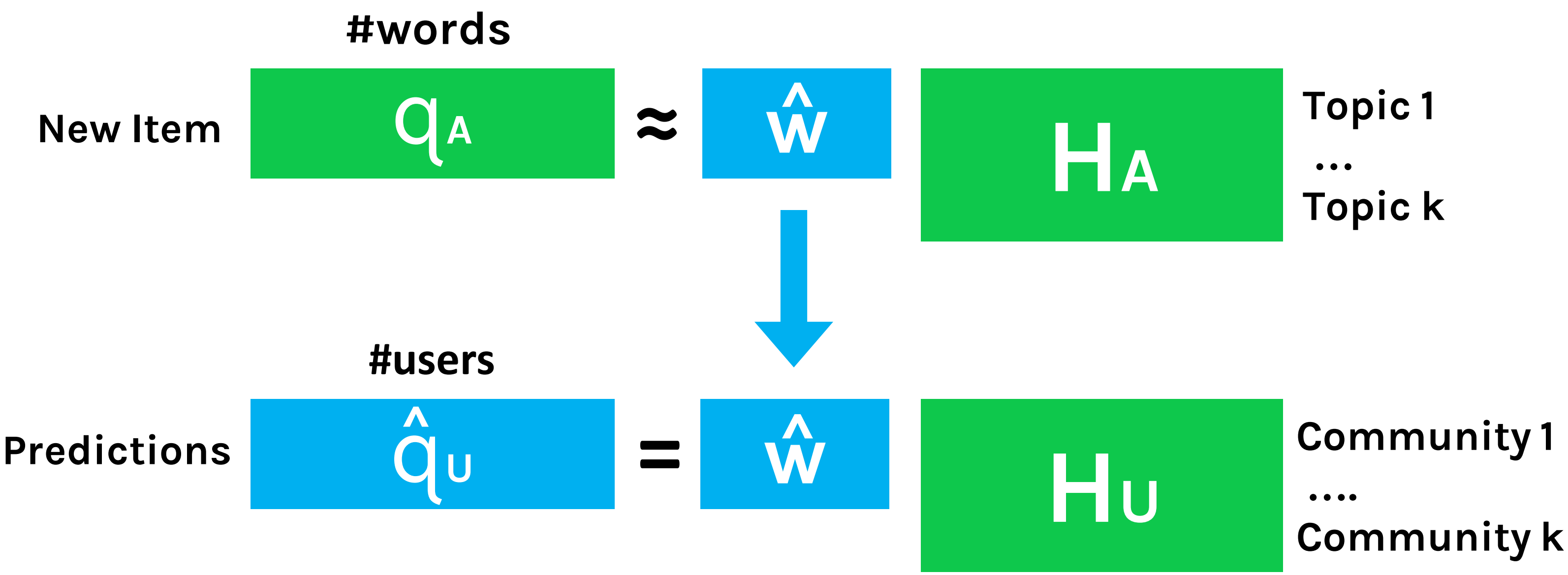
Collective Embeddings

Inference



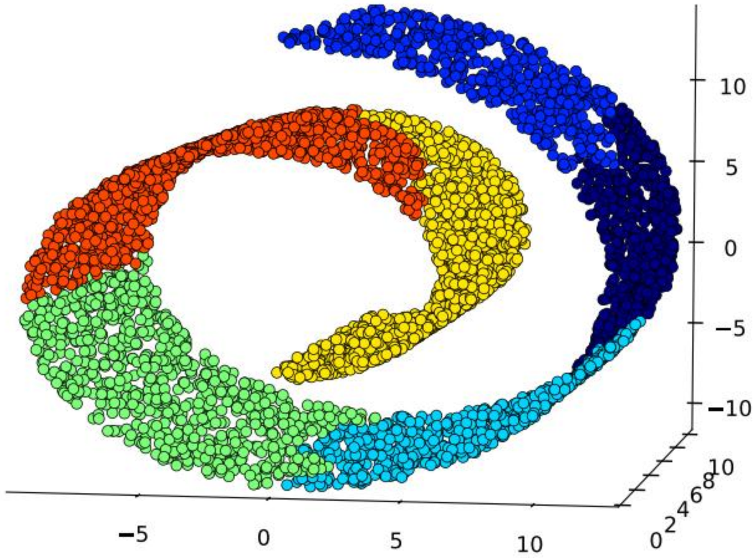
Collective Embeddings

Inference



Exploiting Locality

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

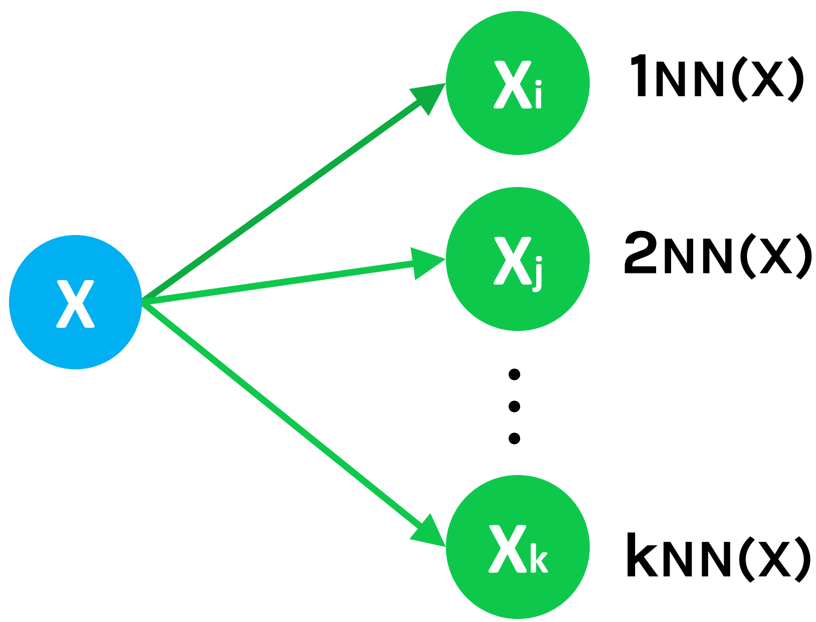


Swiss Roll

Graph Regularization

Nearest Neighbors → Similar embeddings

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



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 Ranking + kNN (BRP-kNN) [Gantner'10]
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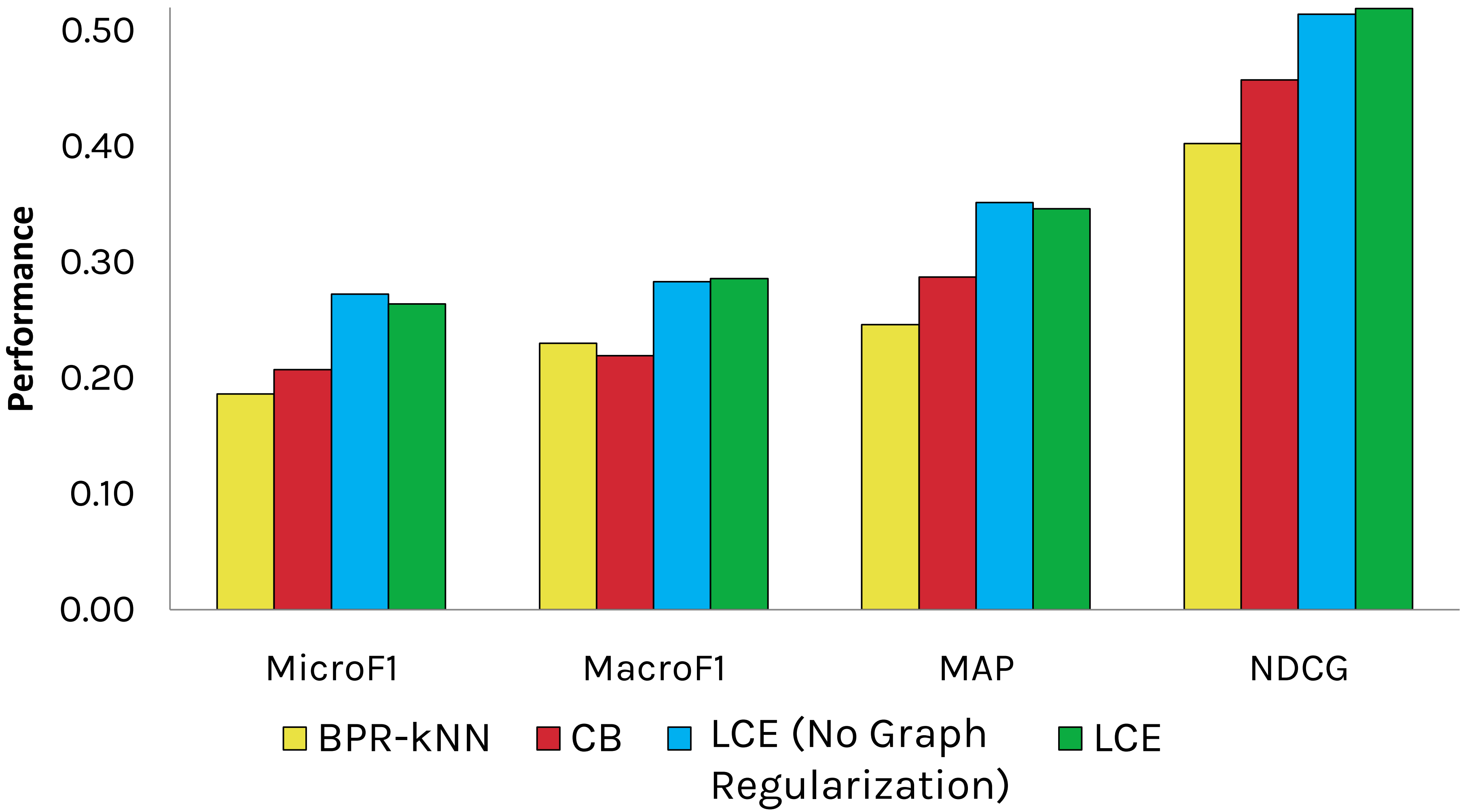
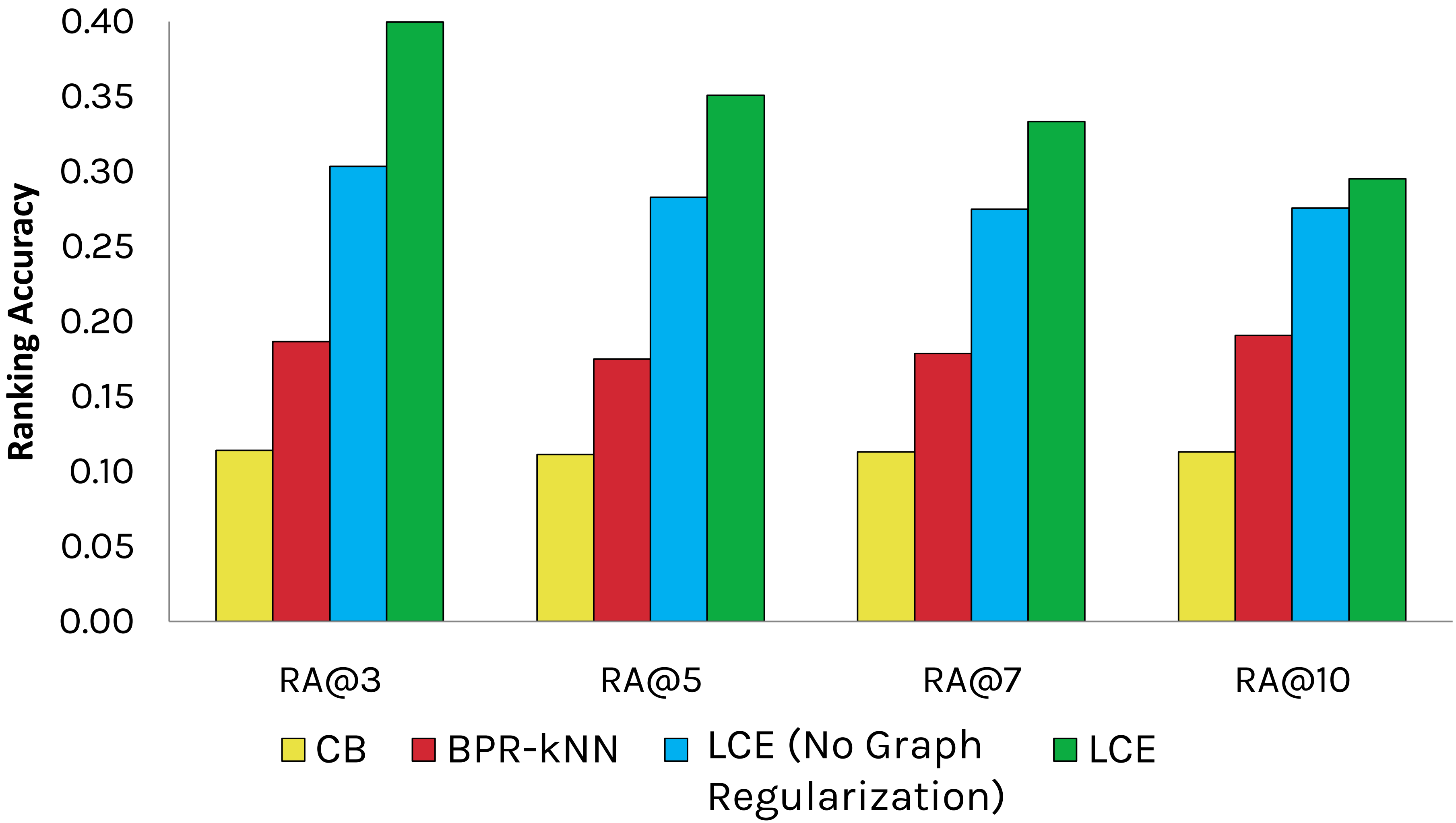
Experimental Results



News Recommendation

Experimental Results



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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