

Item Cold-start Recommendations: Learning Local Collective Embeddings

Martin Saveski
MIT Media Lab

Amin Mantrach
Yahoo Labs Barcelona

Cold-Start

When new user/item enters the system

No past information → No effective recommendations

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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

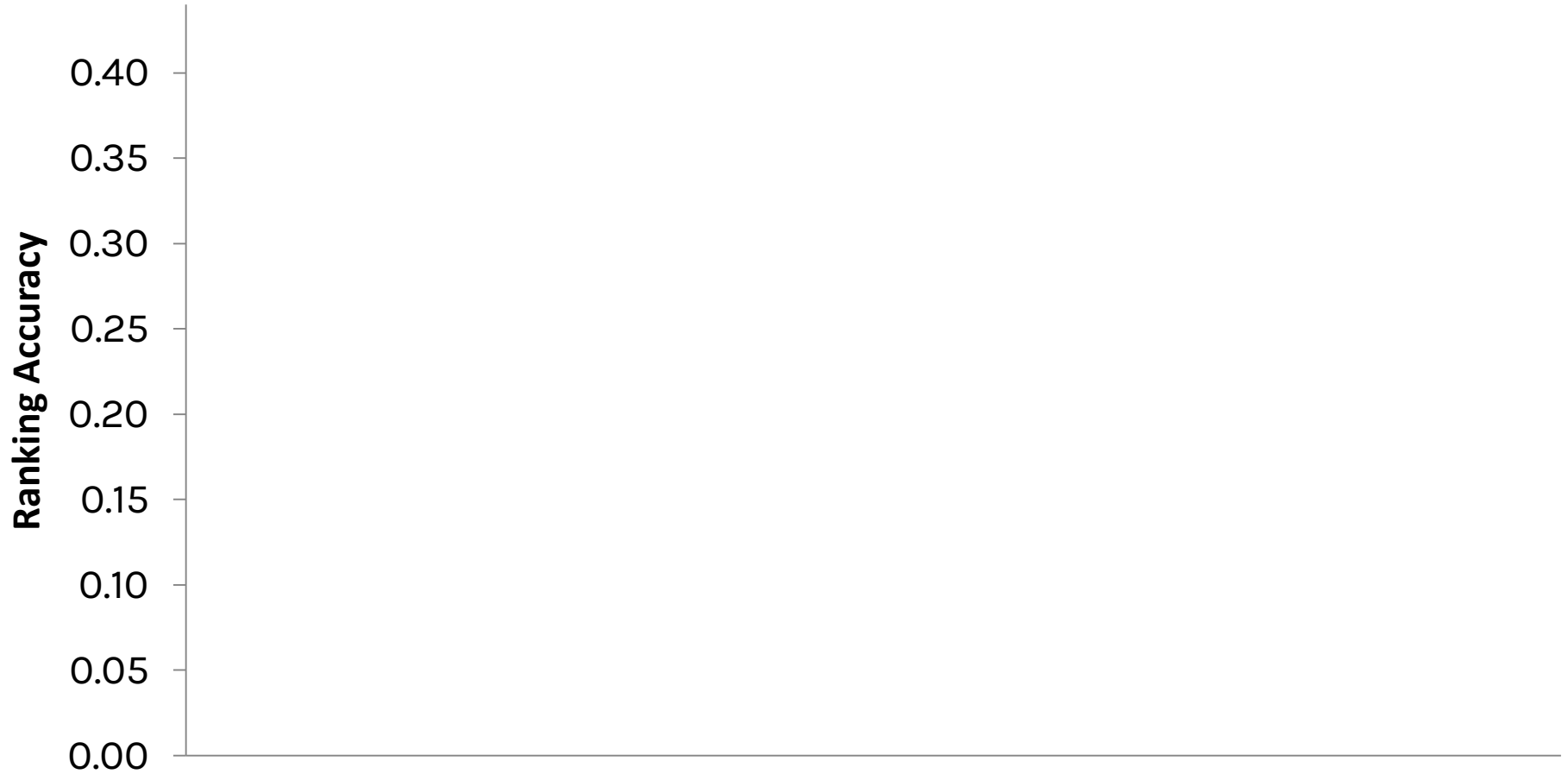
- Yahoo News: ~100 new articles / day
- eBay or Amazon: >1000 items / day ???

Jump-start collaborative filtering systems

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

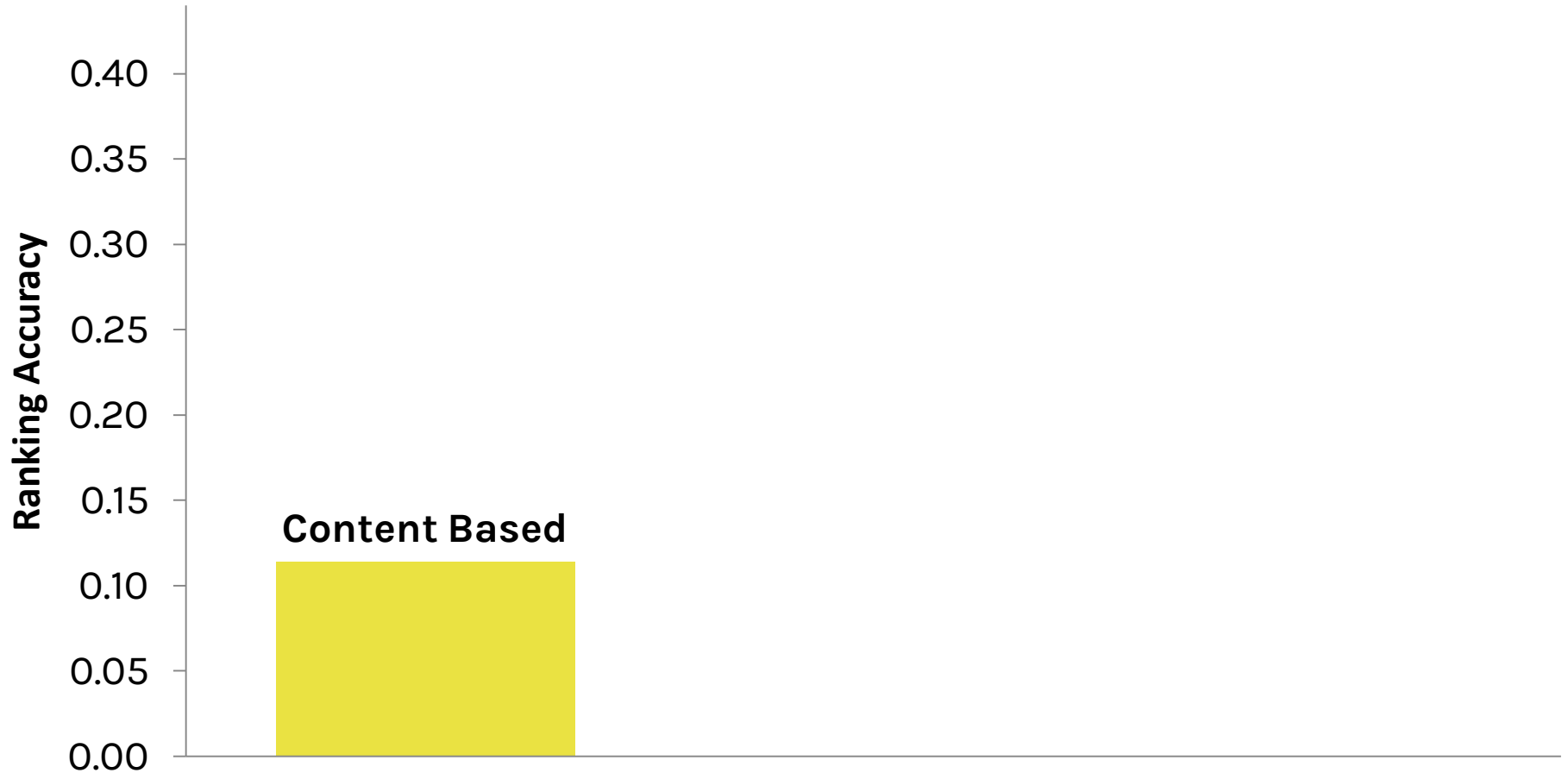
News Recommendation

Yahoo News



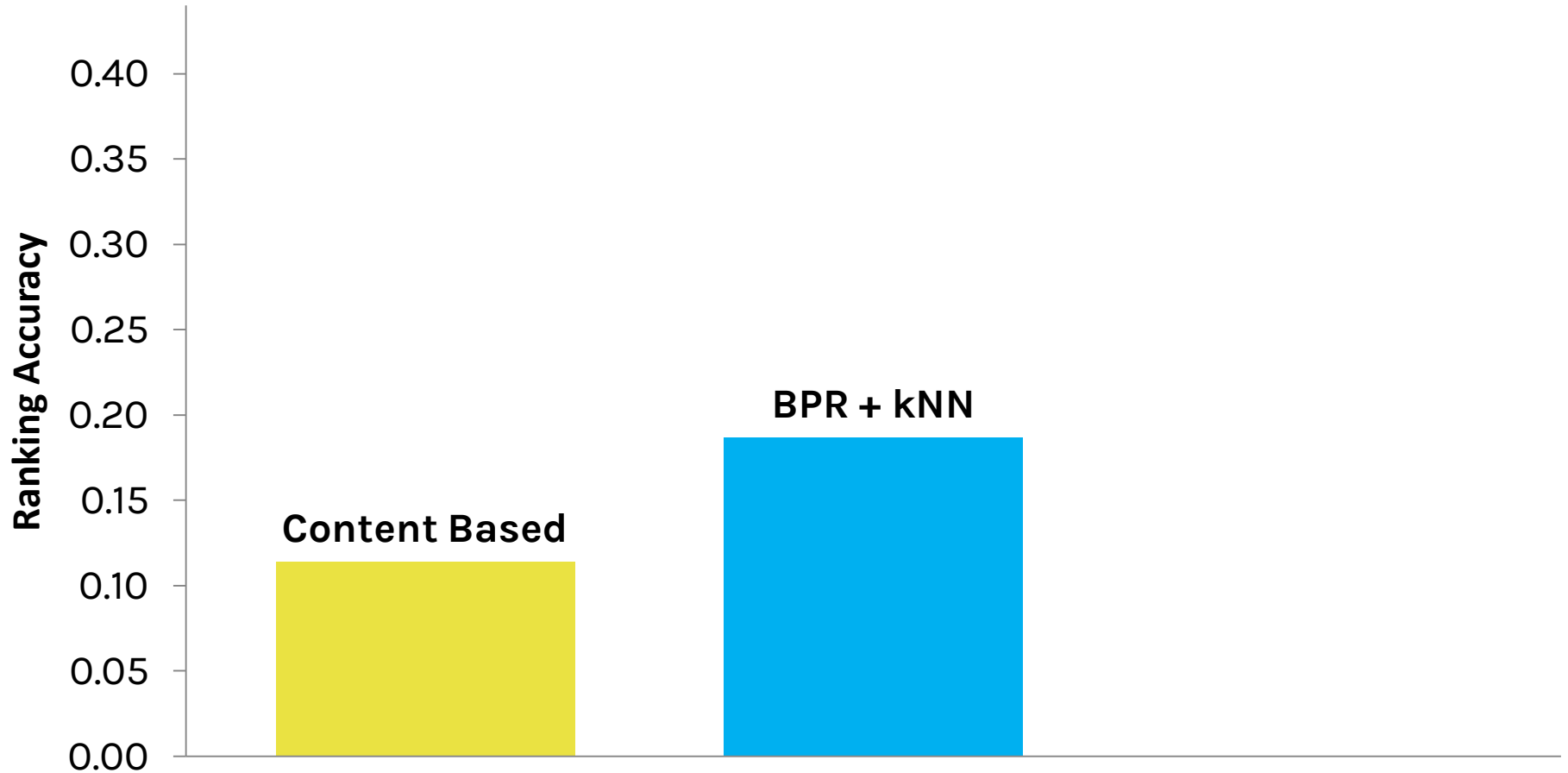
News Recommendation

Yahoo News



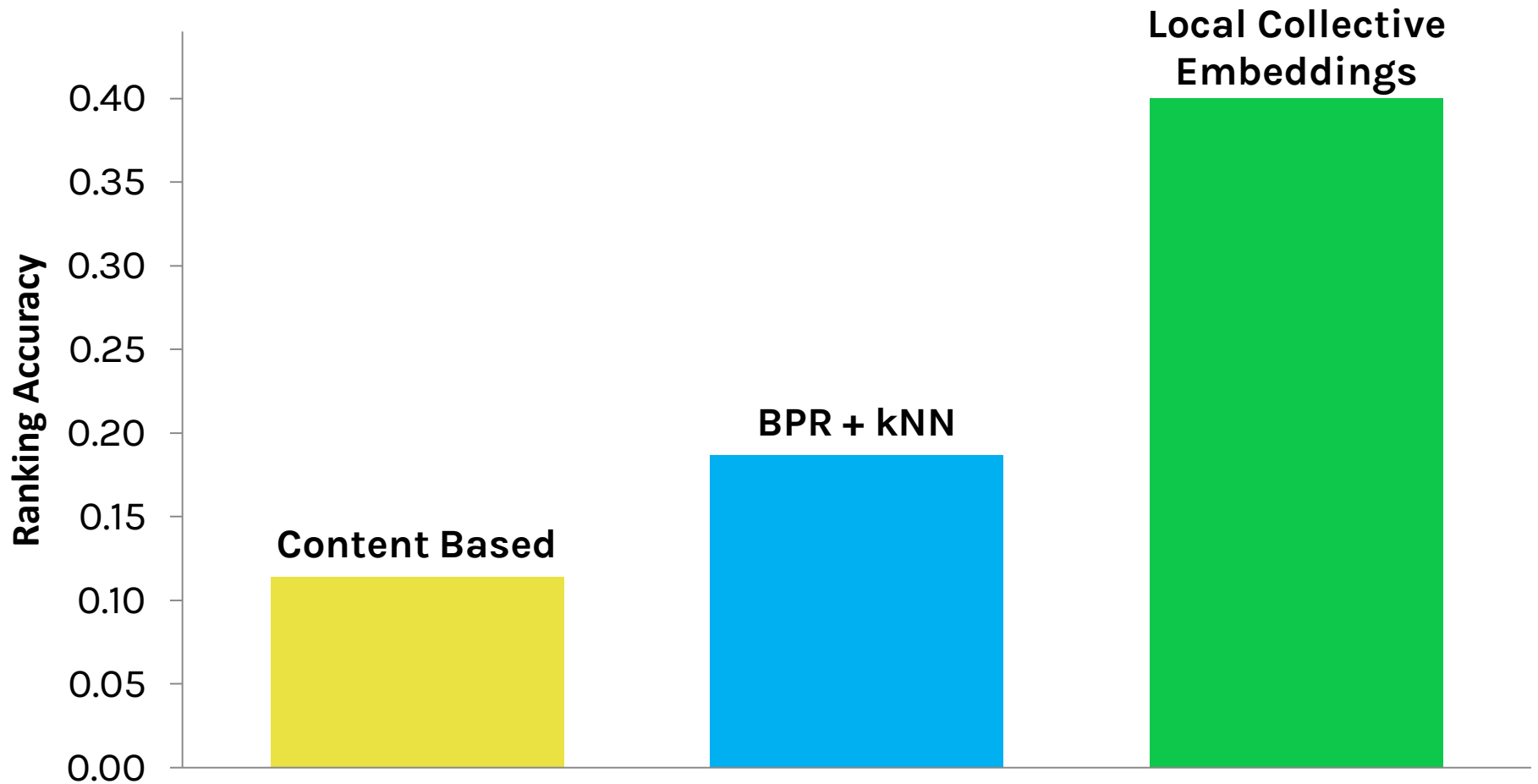
News Recommendation

Yahoo News



News Recommendation

Yahoo News



Local Collective Embeddings

2 Main Ideas

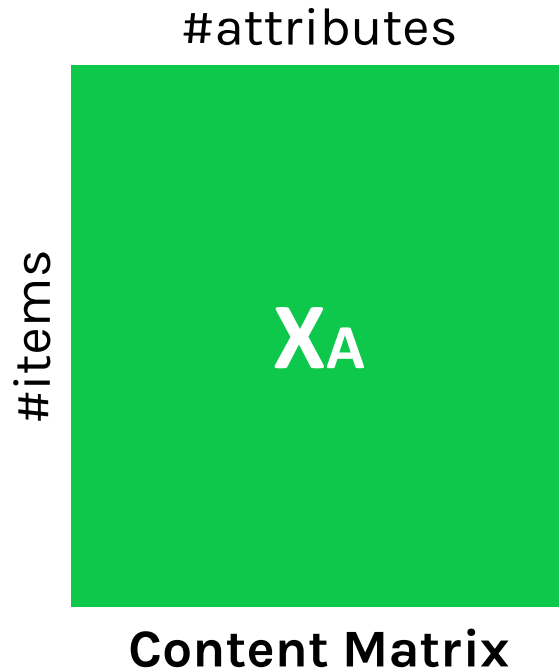
1) Combine content and past collaborative data

- Link item properties and users
- Topics and Communities

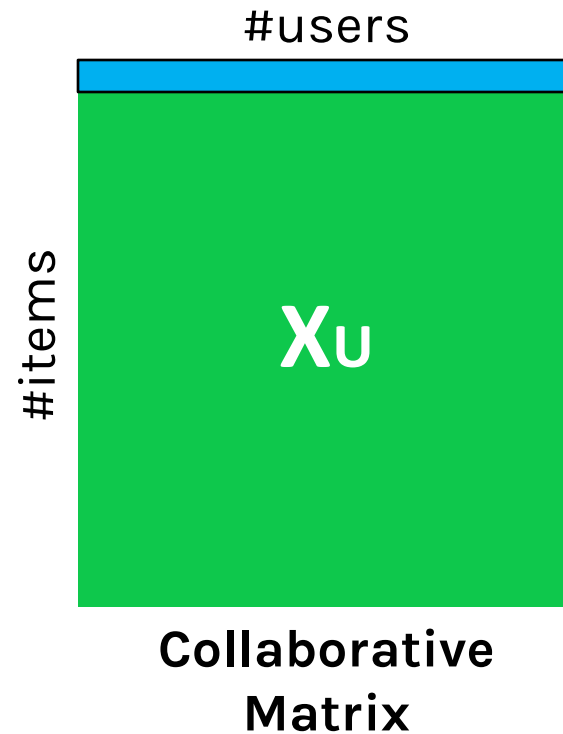
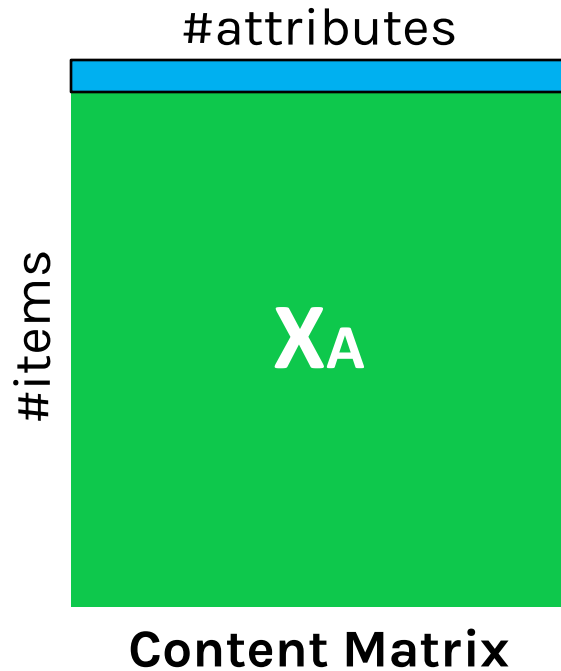
2) Exploit data locality

- Data may lie in a manifold
- Graph regularization

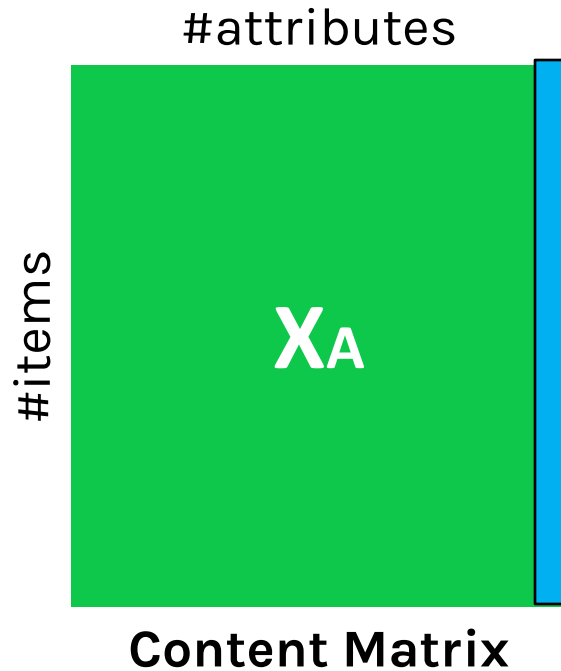
Data in Matrix Form



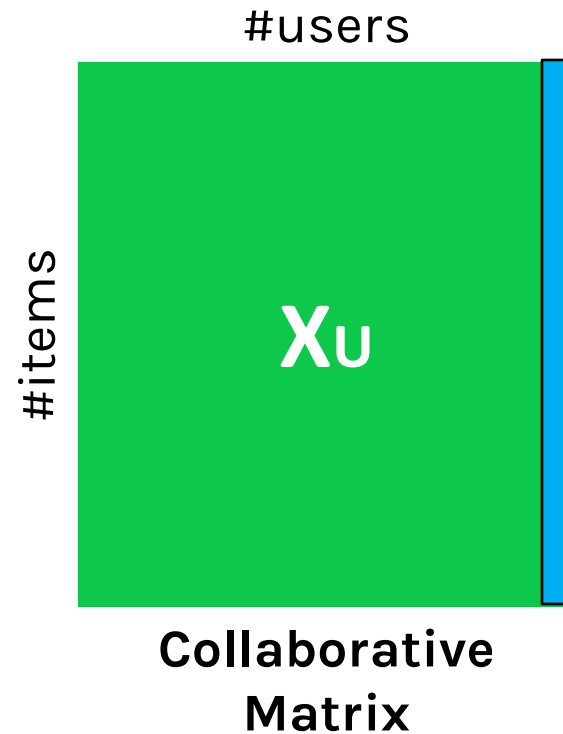
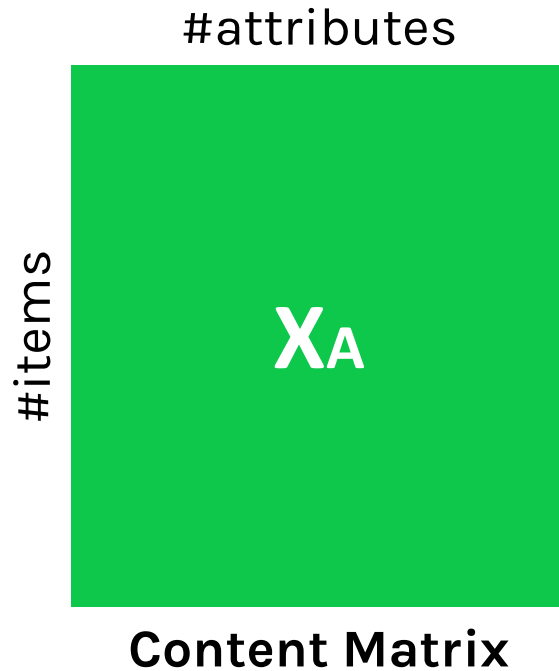
Data in Matrix Form



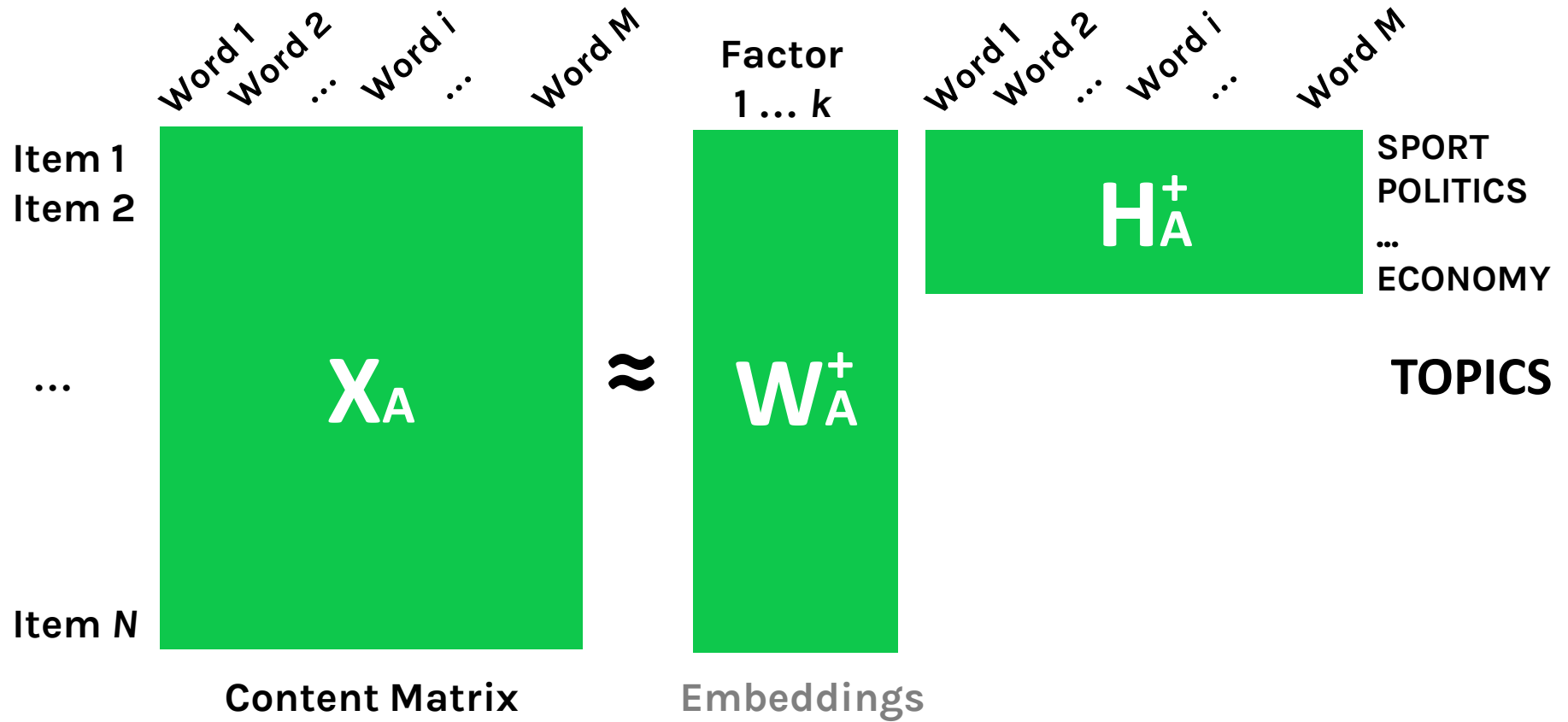
Data in Matrix Form



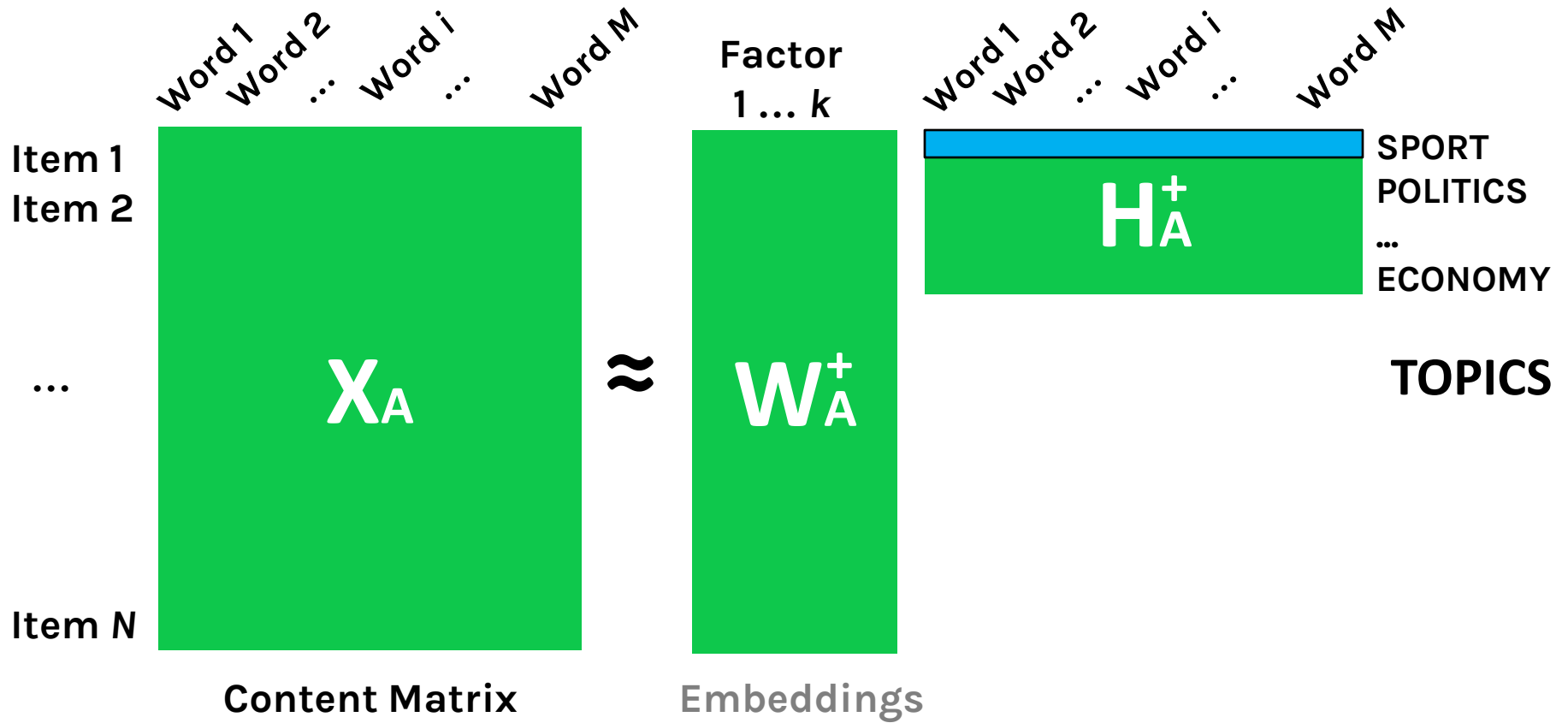
Data in Matrix Form



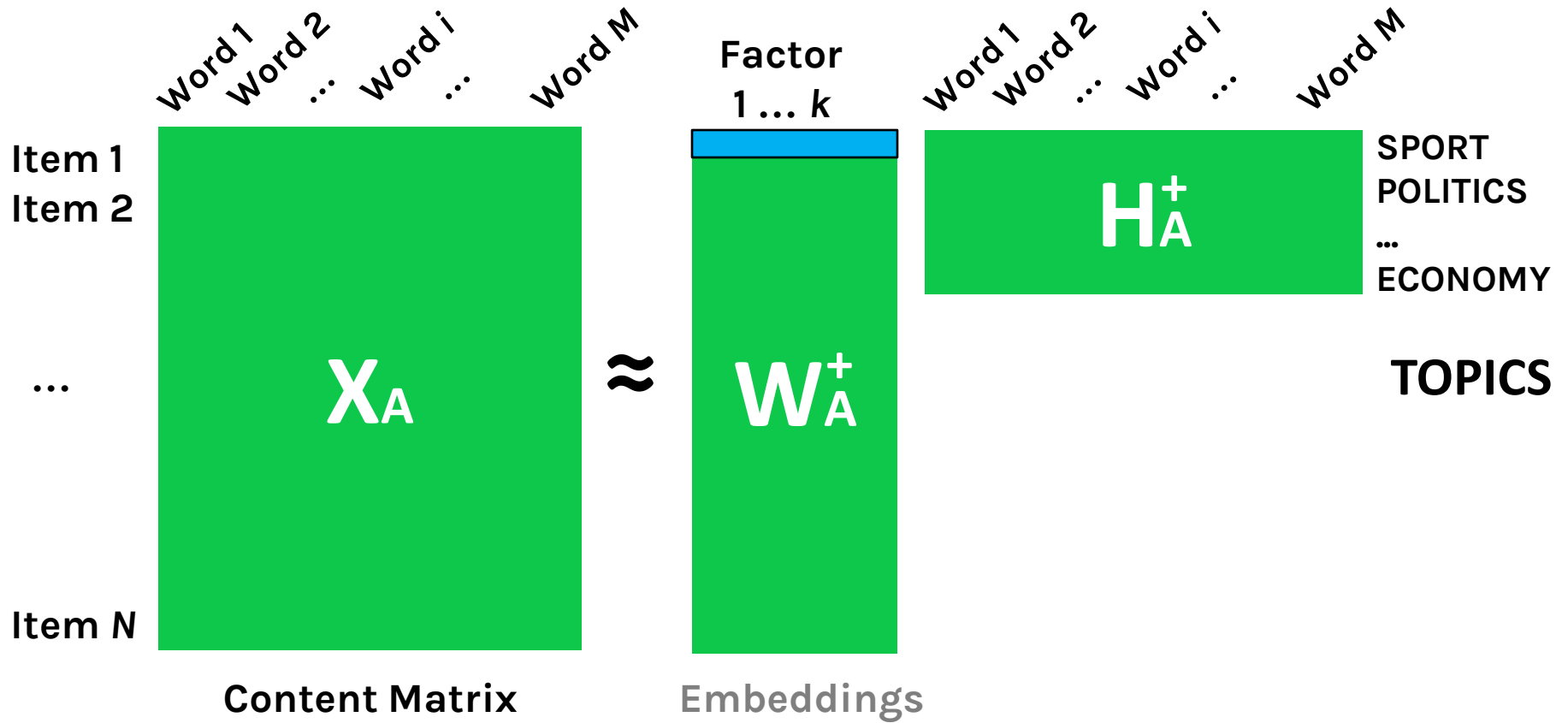
Content Embeddings



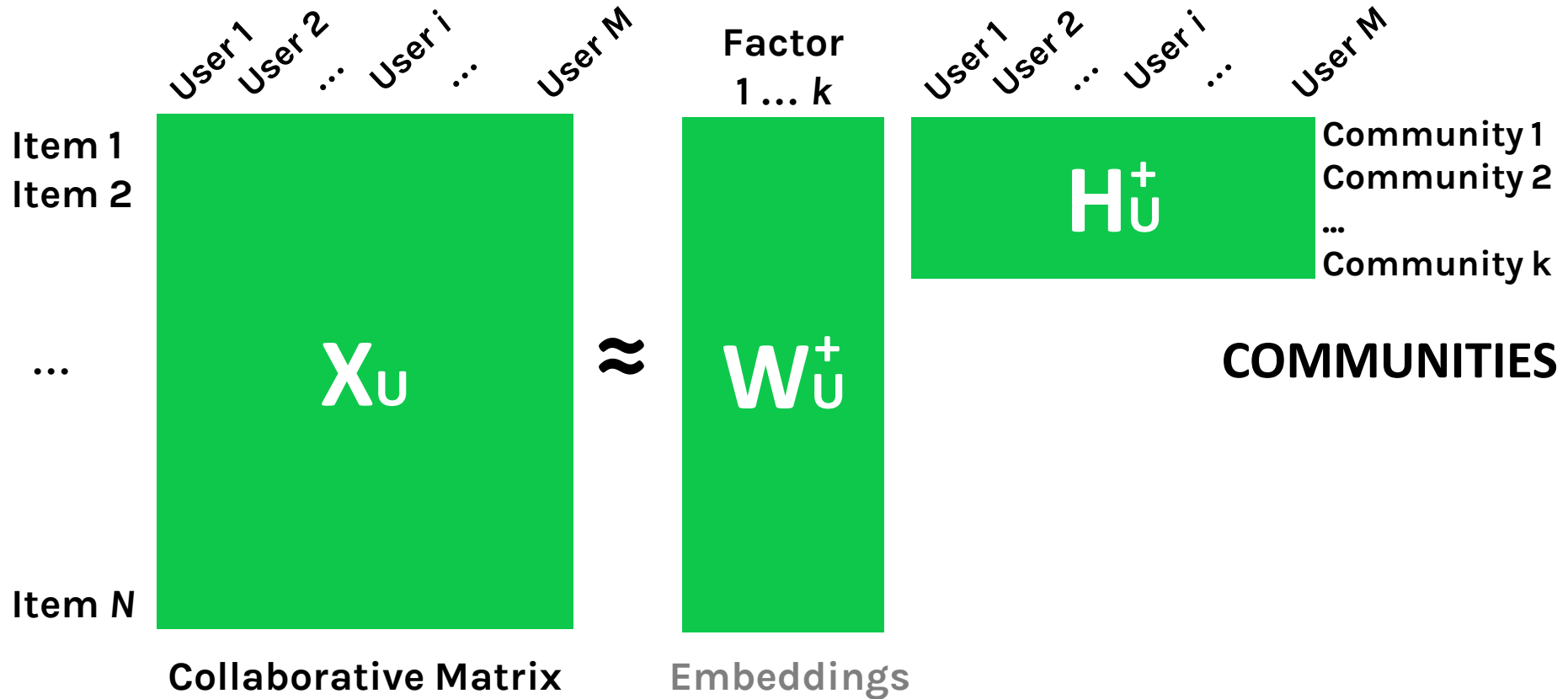
Content Embeddings



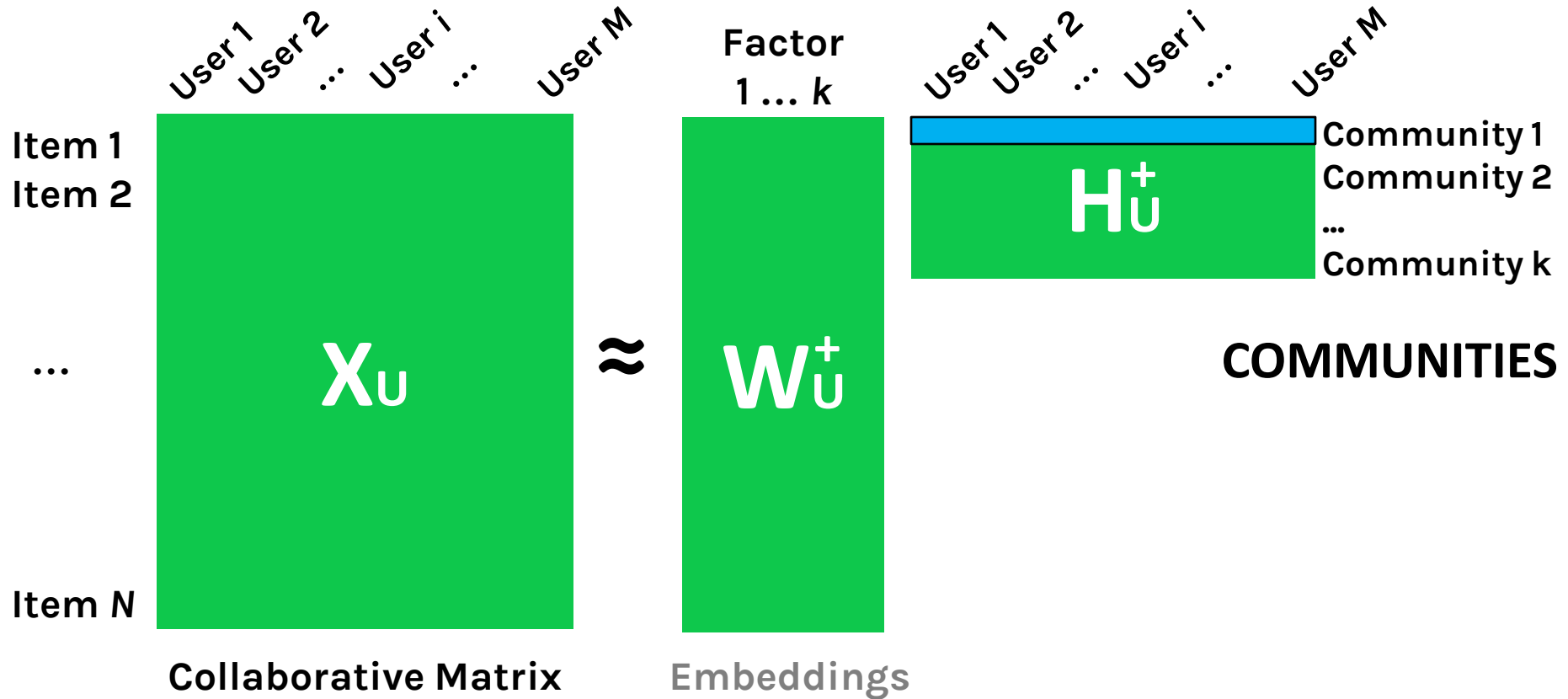
Content Embeddings



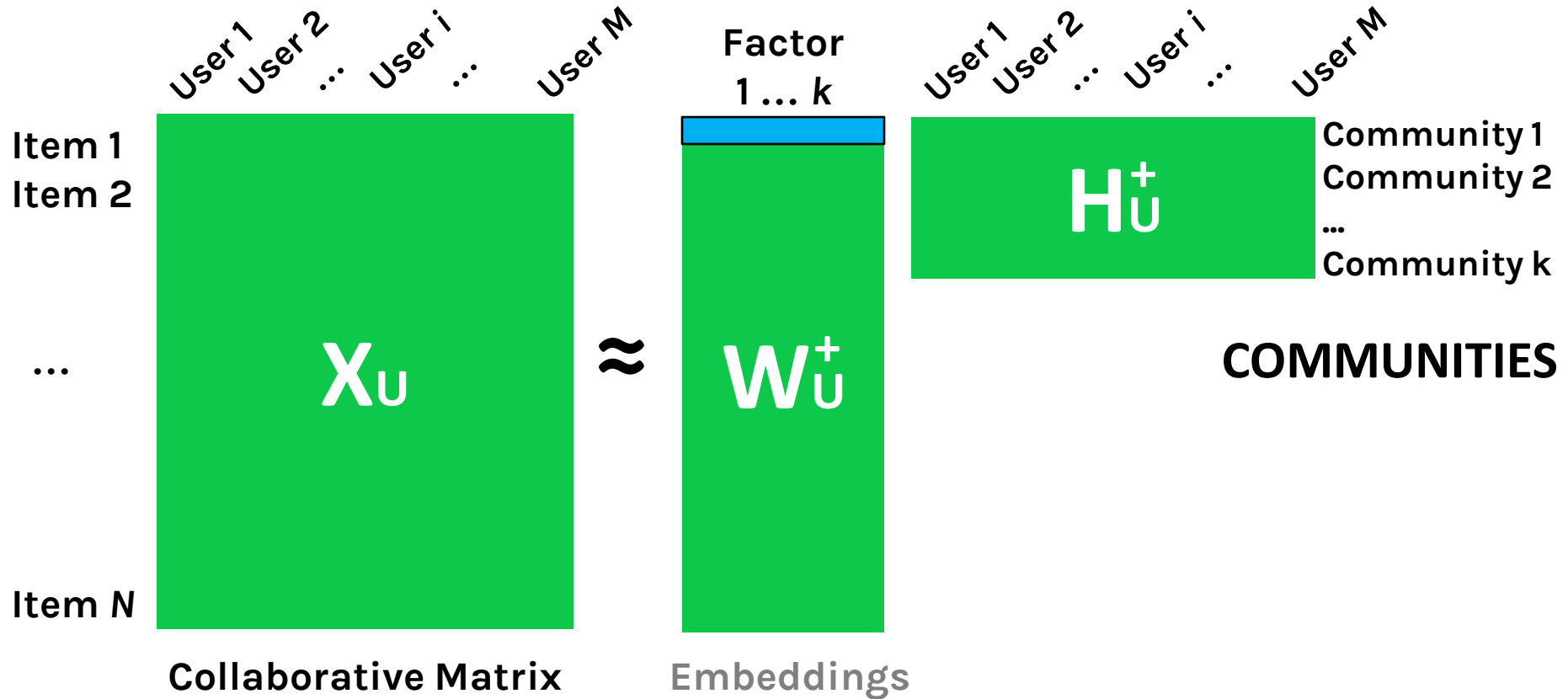
Collaborative Embeddings



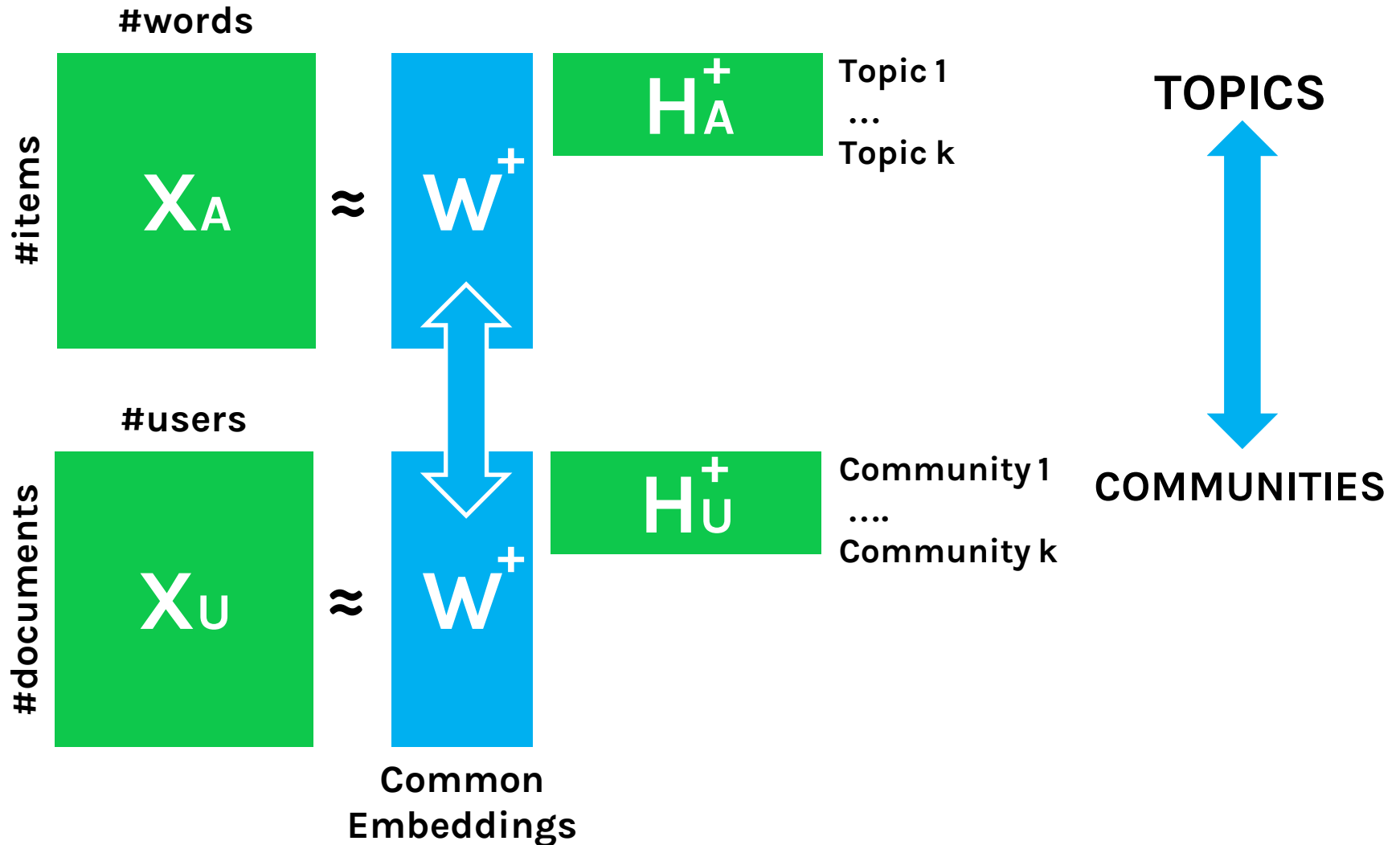
Collaborative Embeddings



Collaborative Embeddings



Collective Embeddings



Collective Embeddings

Inference

New Item

#words

q_A

H_A

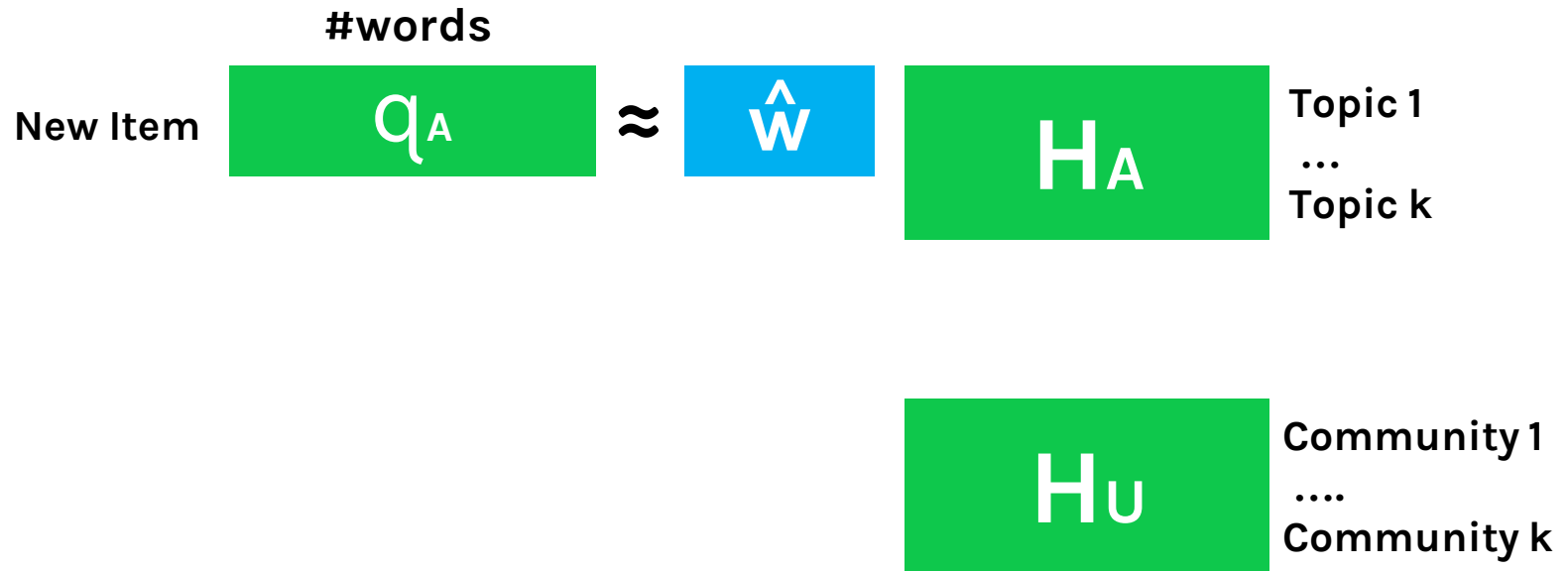
Topic 1
...
Topic k

H_U

Community 1
...
Community k

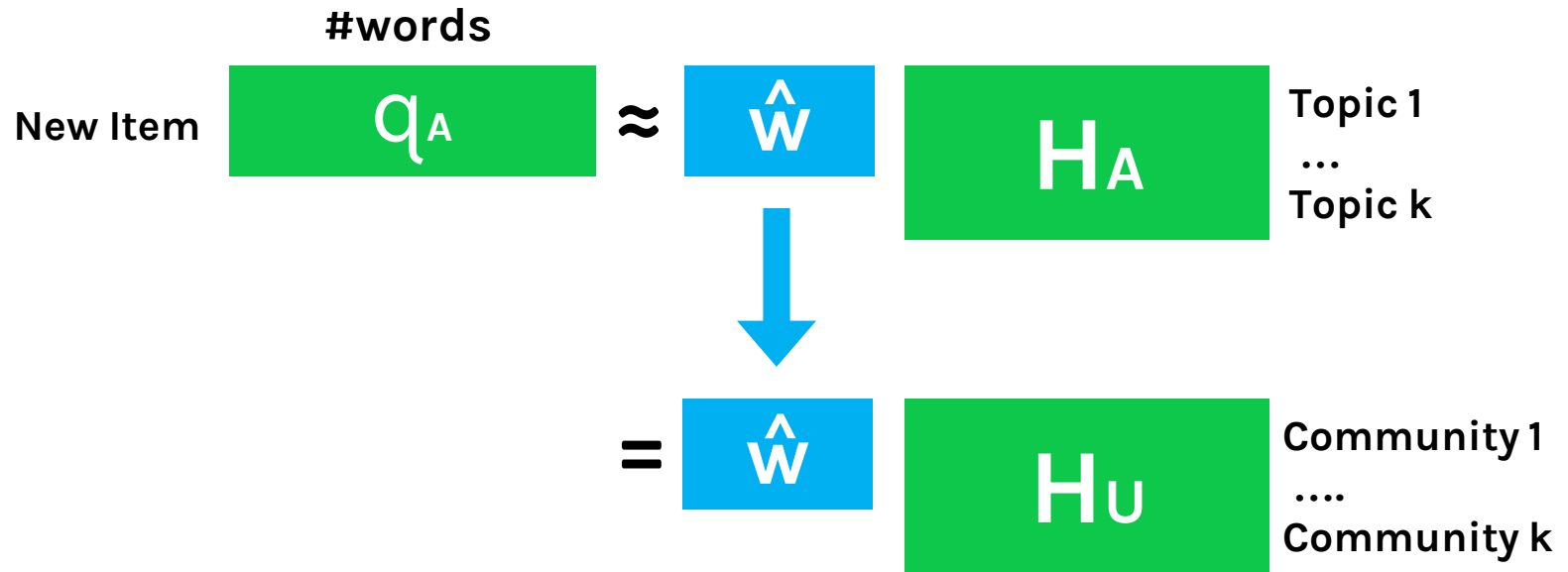
Collective Embeddings

Inference



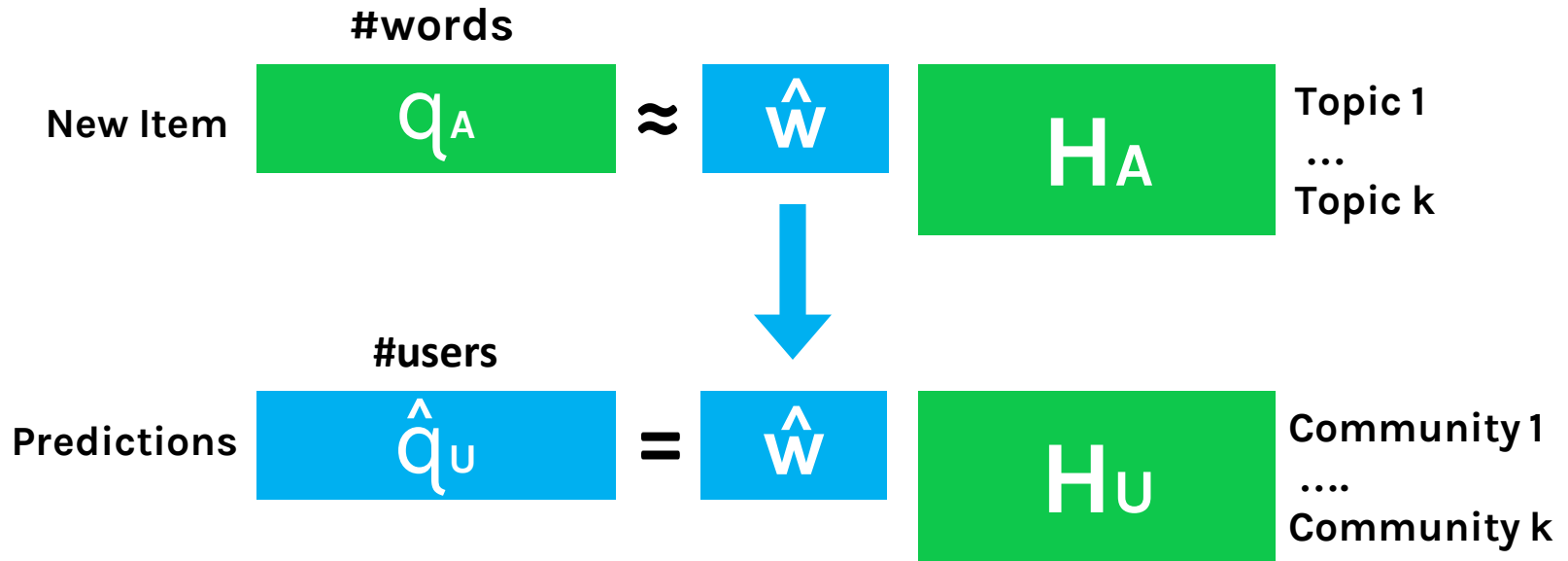
Collective Embeddings

Inference



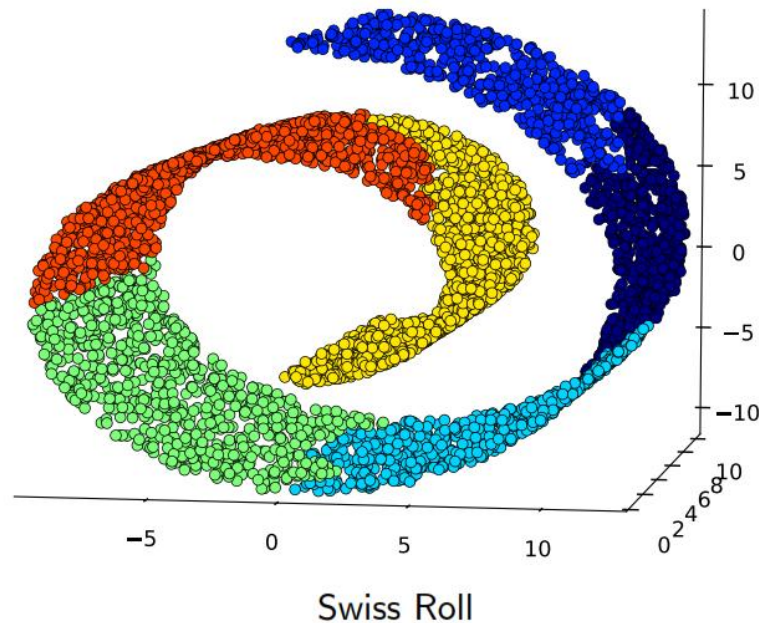
Collective Embeddings

Inference



Exploiting Locality

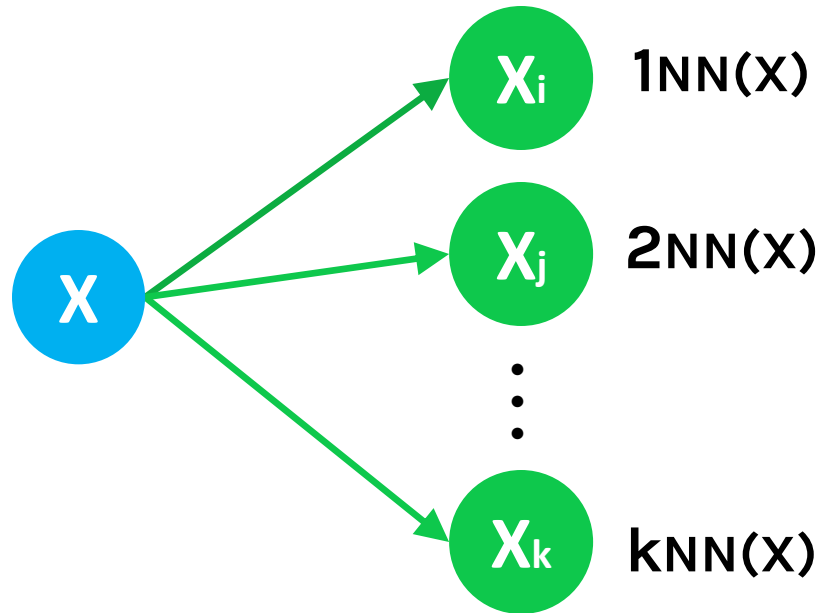
- So far: linear approximation of the data
- Data may lie in small subspace



Graph Regularization

Nearest Neighbors \rightarrow Similar embeddings

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



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]
6. fLDA [Agarwal'10]

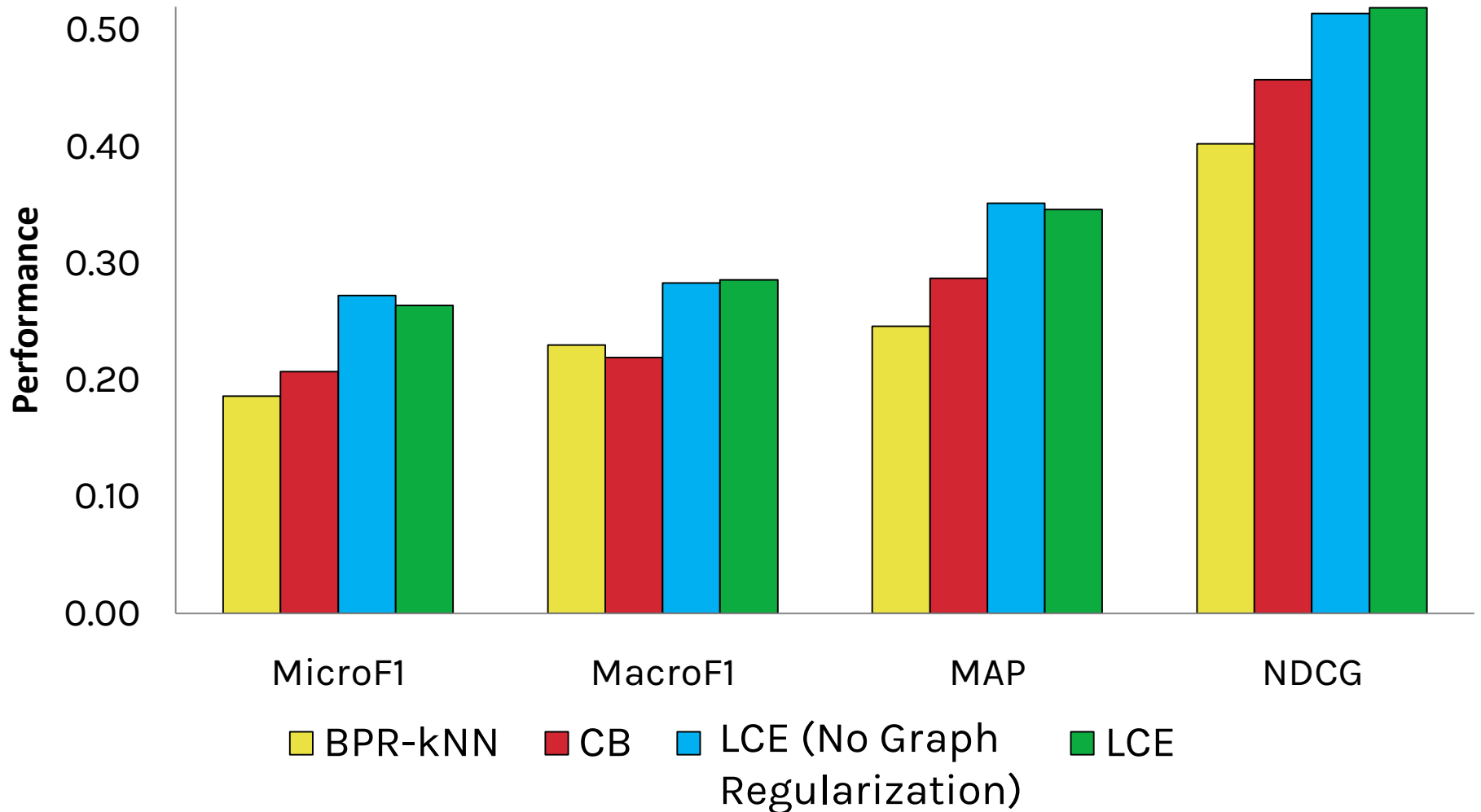
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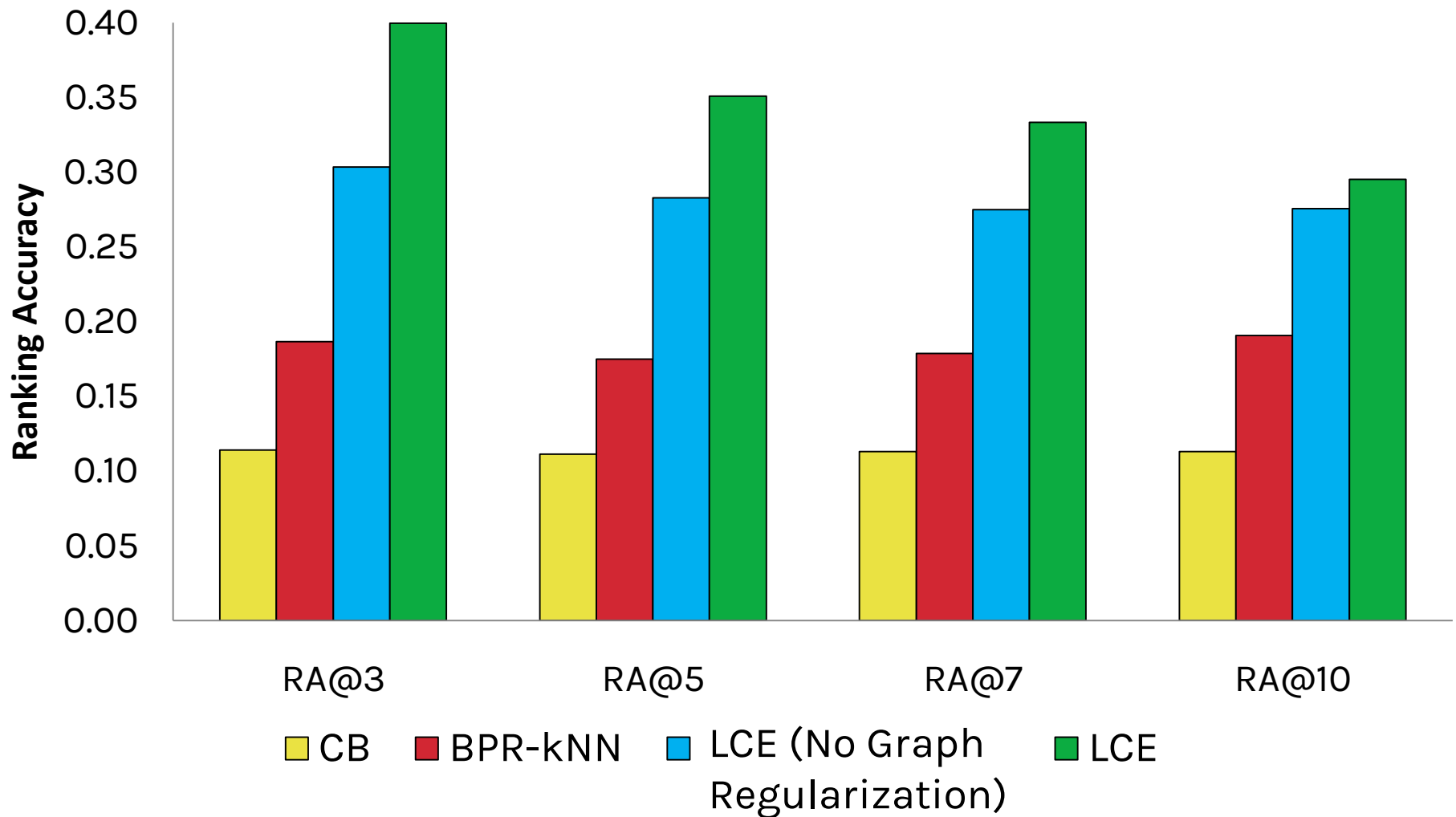
Email Recipient Recommendation

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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