# Collaborative Metric Learning

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# Collaborative Metric Learning

- A different perspective on collaborative filtering
- Better accuracy
- Extremely efficient Top-K recommendations
- Easy to interpret and extend

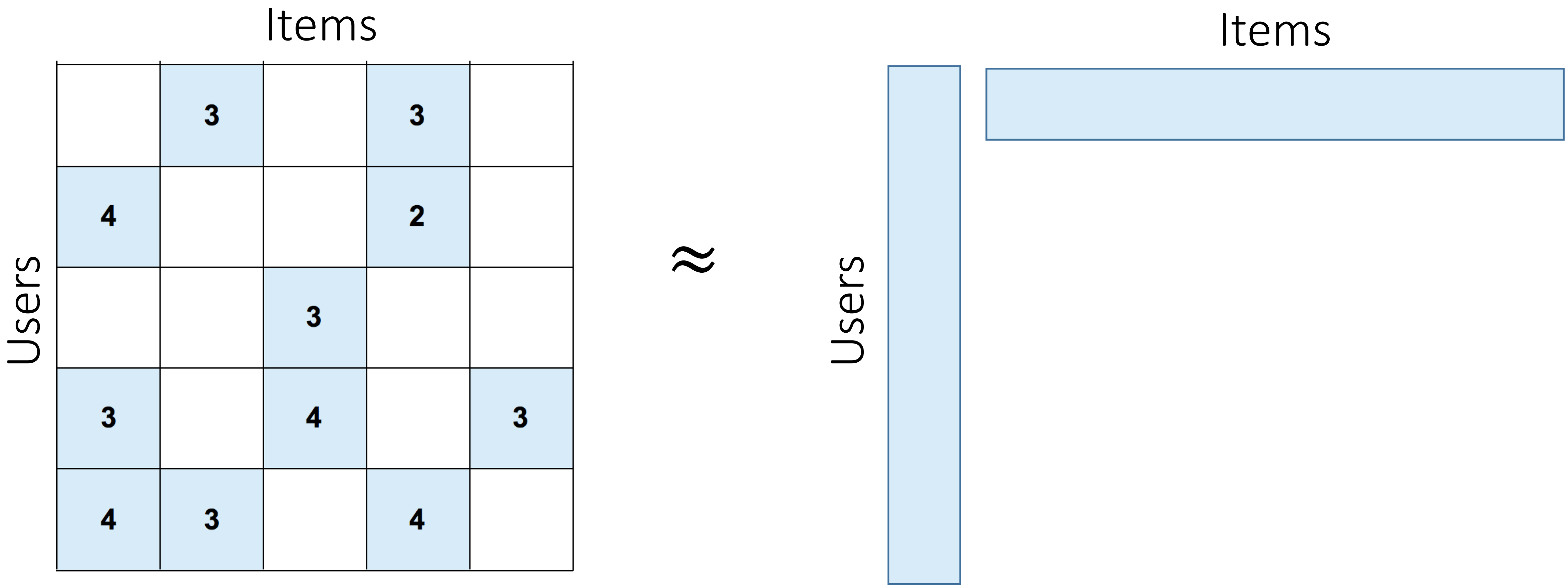
# User-Item Matrix

Items

Users

| | | | | |
|---|---|---|---|---|
| | 3 | | 3 | |
| 4 | | | 2 | |
| | | 3 | | |
| 3 | | 4 | | 3 |
| 4 | 3 | | 4 | |

# Matrix Factorization (MF)



# Implicit Feedback

- Ubiquitous in today's online services
- Only positive feedback is available
- Traditional MF does not work

Click Thumbs up Like

| | | | | |
|---|---|---|---|---|
| | ? | | ? | |
| ? | | | ? | |
| | | ? | | |
| ? | | ? | | ? |
| ? | ? | | ? | |

# Matrix Factorization for Implicit Feedback

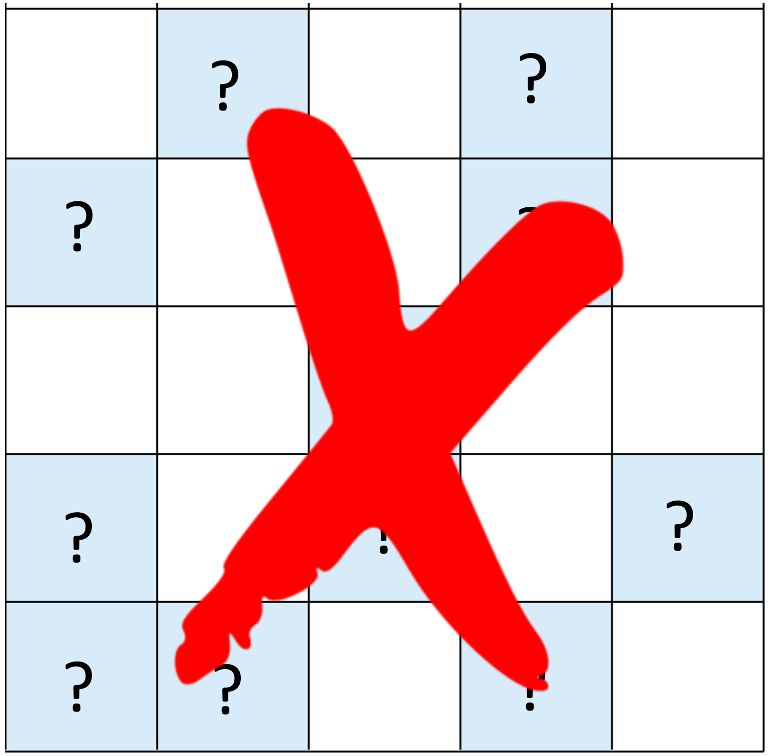
- Weighted Regularized Matrix Factorization (**WRMF**)  [Hu08]
- Probabilistic Matrix Factorization (**PMF**) [Salakhutdinov08]
- Bayesian Personalized Ranking (**BPR**) [Rendle09]

and many more …

# Think Beyond Matrix

Explicit ⟶ Implicit

- No longer about estimating ratings
- But about modeling the relationships between different user/item pairs



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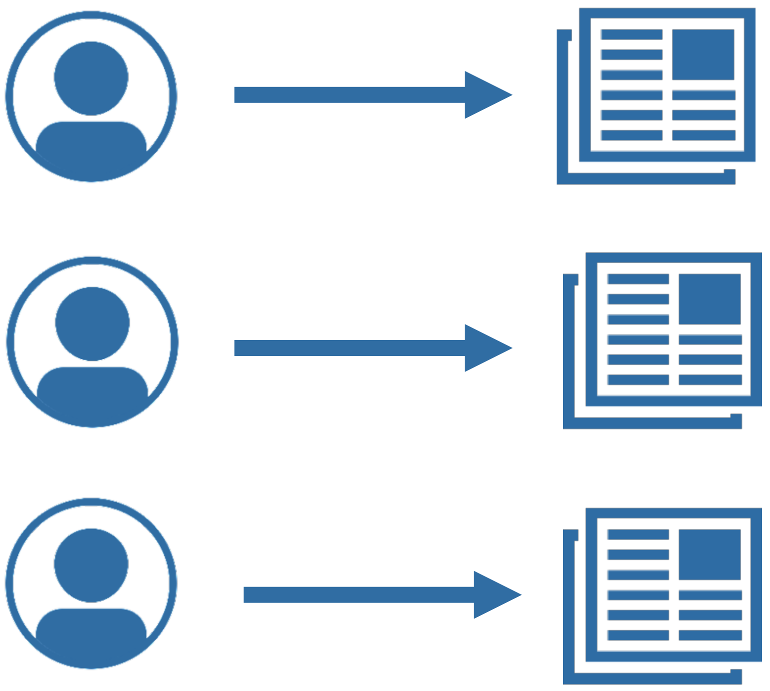
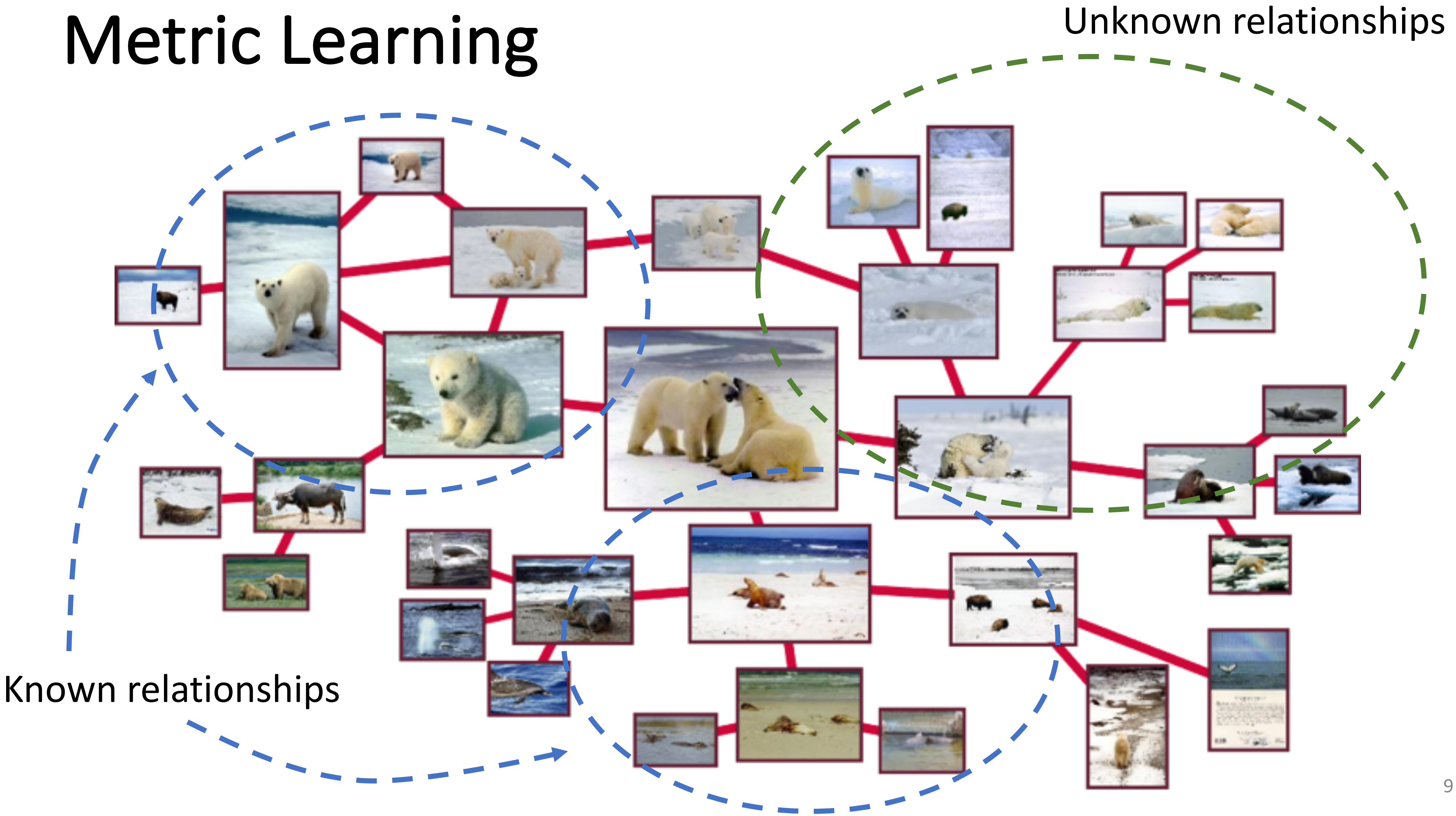
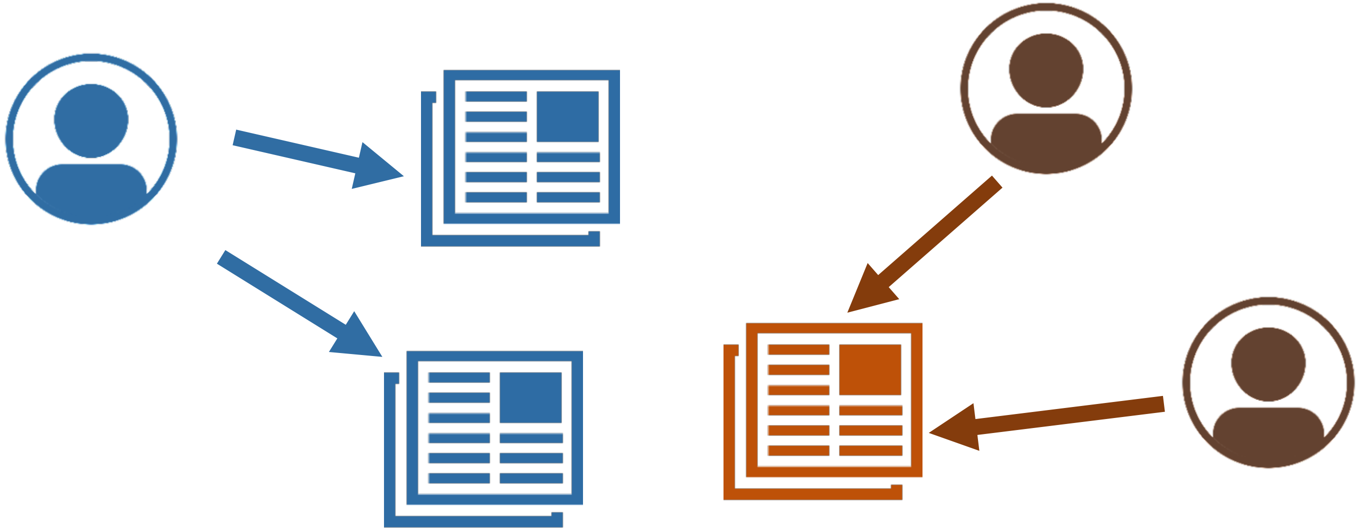


# Metric Learning



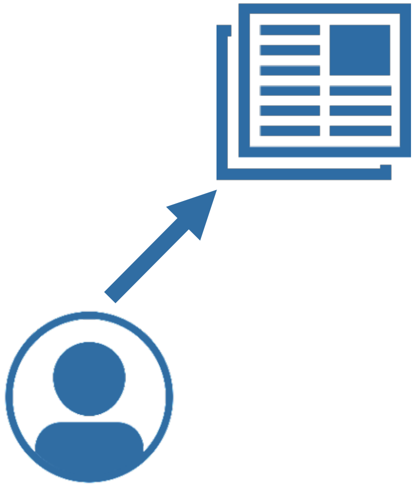
# Collaborative Metric Learning

- Learn a joint user-item distance metric.
- The Euclidean distances reflect the relationships between users/items.



# Based on the inherent Triangular Inequality of Metric Learning – If A is close to B, and B is close to C, then A is close to C.

- Fit the model with implicit feedback
    1. An user is pulled closer to the items she liked
    2. Other similar users are pulled closer.
    3. The items users liked are also pulled closer.



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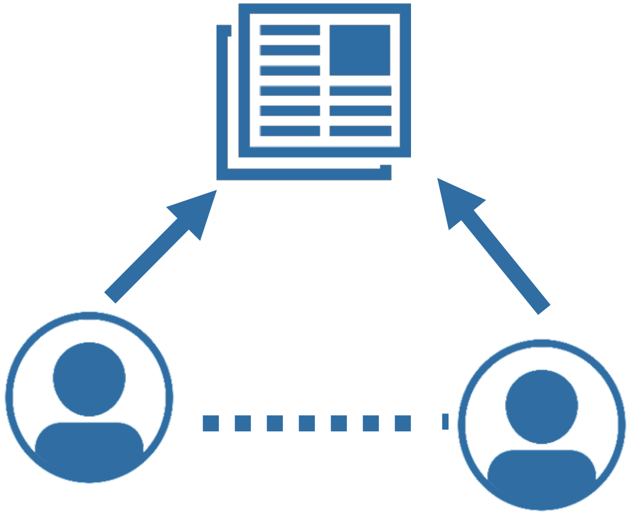

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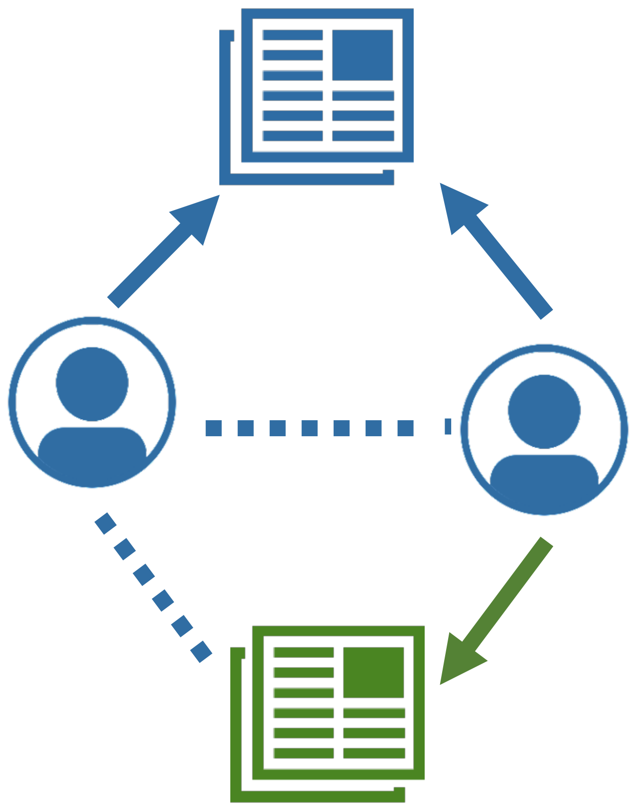

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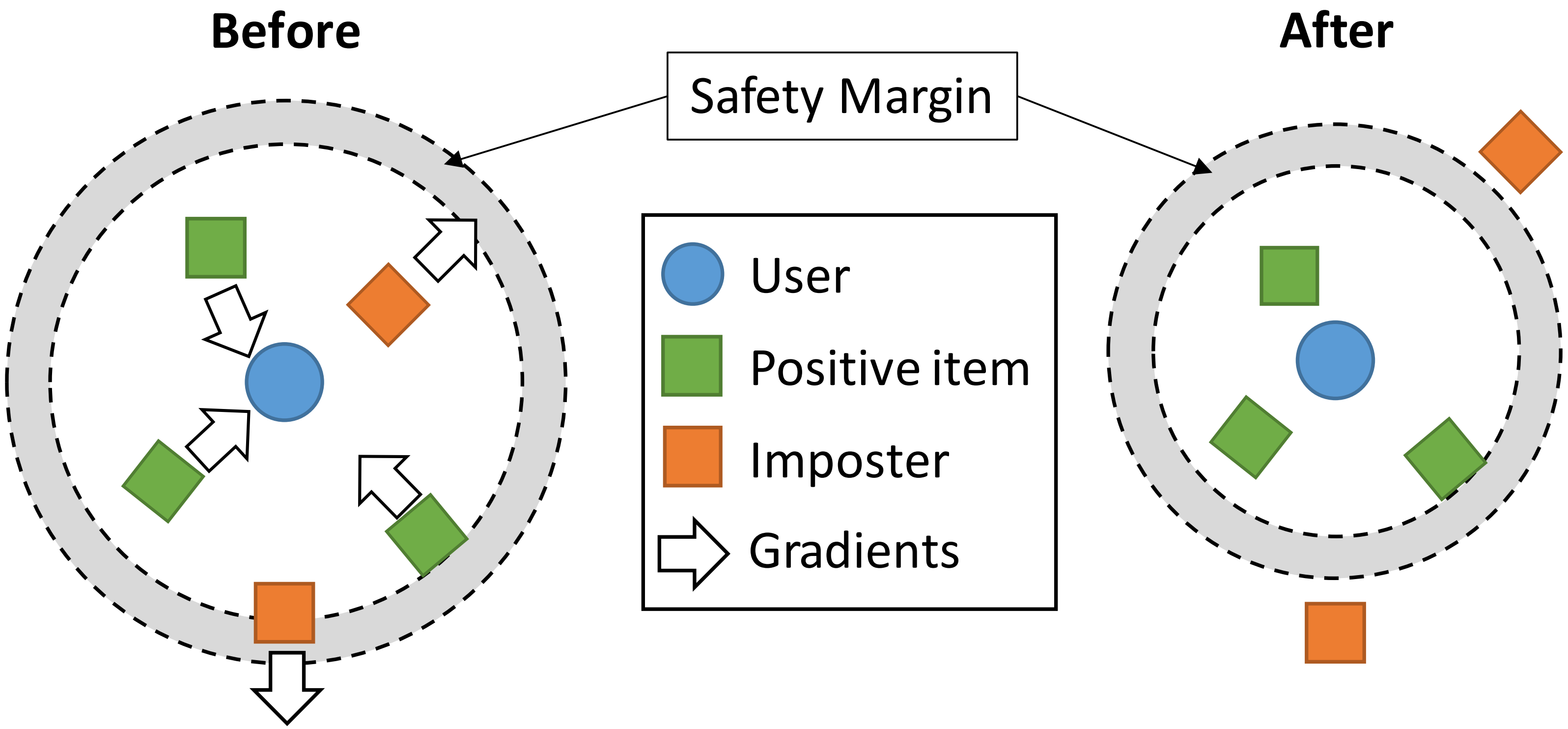
# Collaborative Large Margin Nearest Neighbor




* The outline of figure is inspired by Weinberger, Kilian Q., John Blitzer, and Lawrence Saul. "Distance metric learning for large margin nearest neighbor classification." *Advances in neural information processing systems* 18 (2006): 1473.

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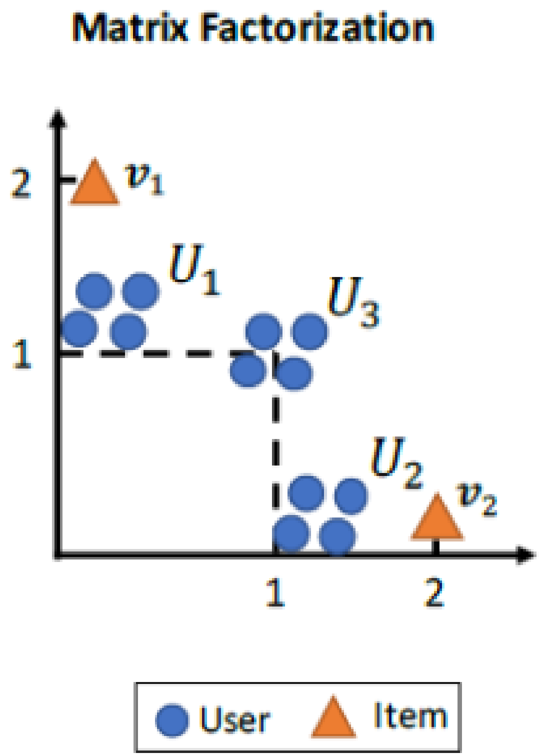


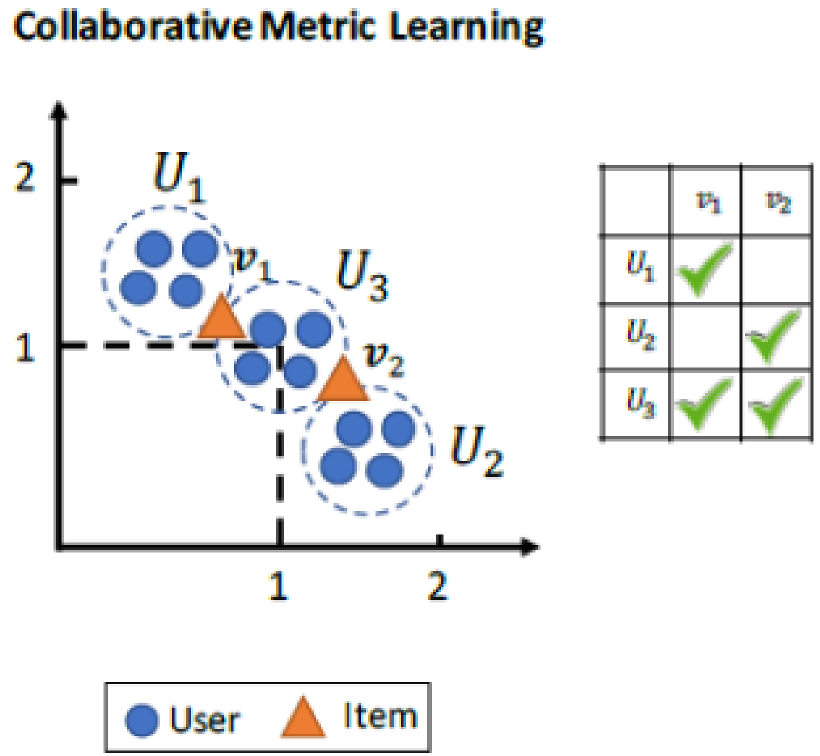

| | $v_1$ | $v_2$ |
|---|---|---|
| $U_1$ | ✓ | |
| $U_2$ | | ✓ |
| $U_3$ | ✓ | ✓ |

$V_1^T V_2 = 0$: does not reflect that they are both liked by $U_3$

$U_1^T U_2 = 0$: does not reflect that they both share the same interest as $U_3$

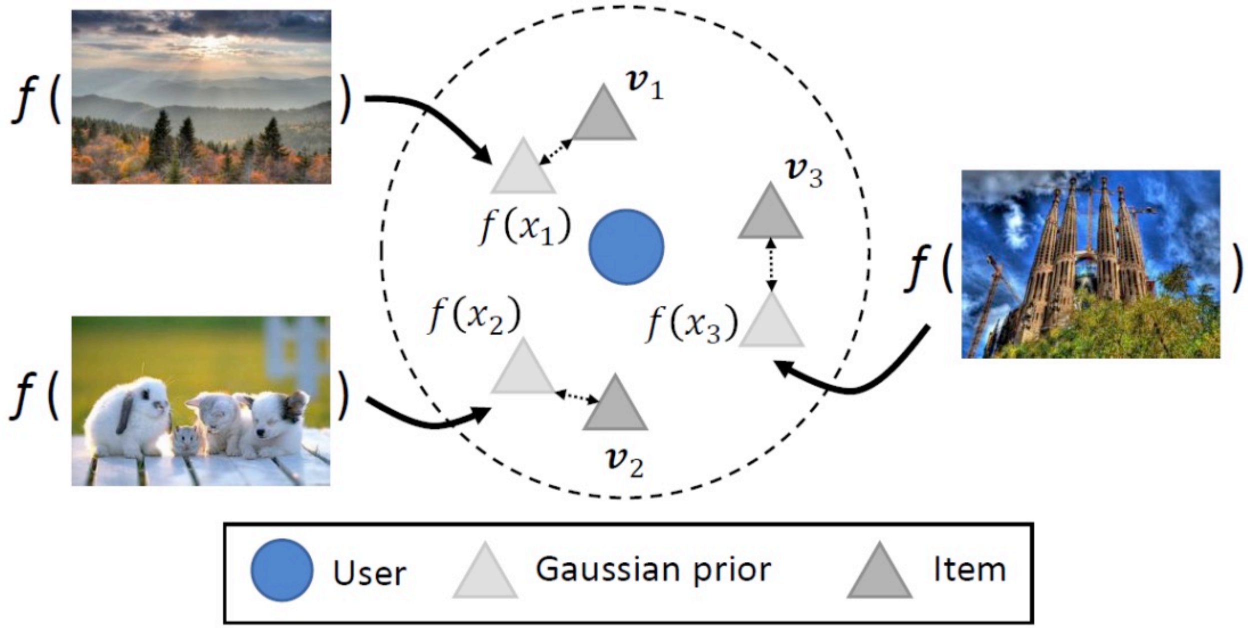
# Collaborative Metric Learning Embedding

- Euclidian distance faithfully reflects the relative relationships.



# Integrating Item Features

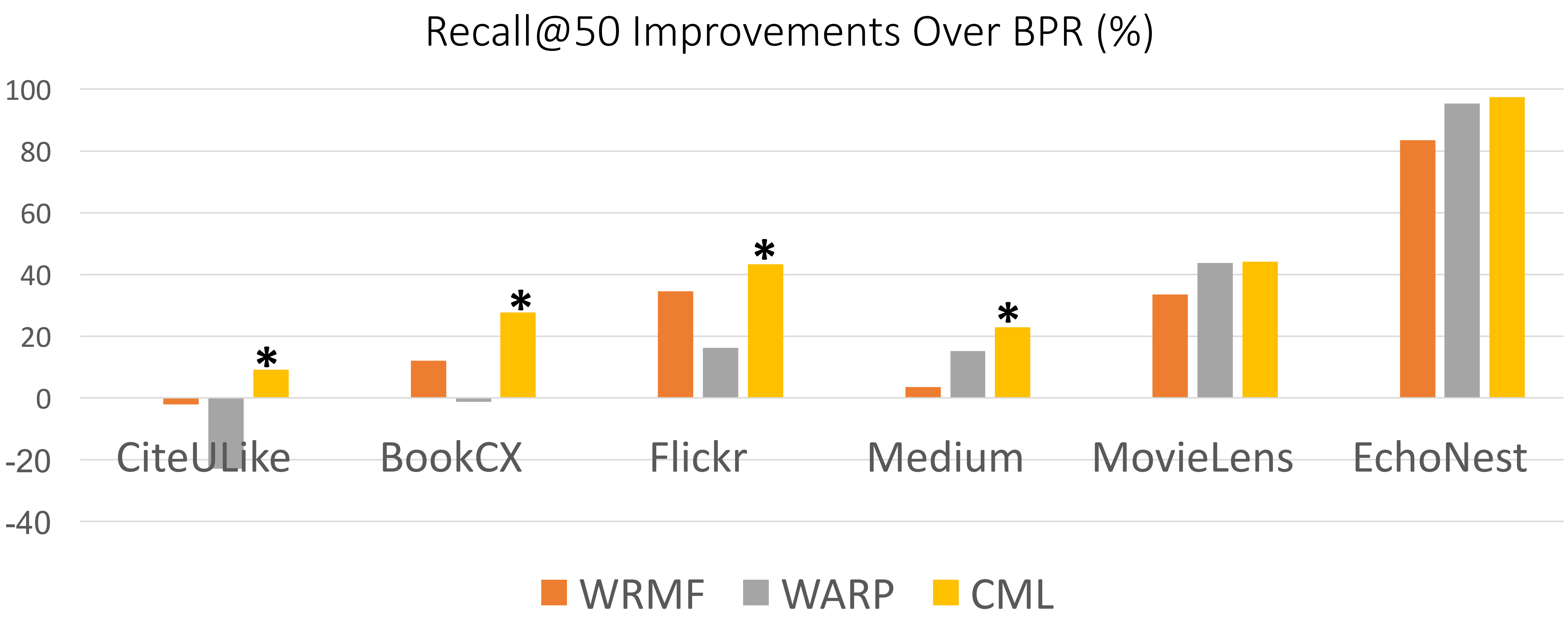
- Use a learnable function (e.g. Multi-Layer Perceptron) to project features into user-item embedding.
- Treat the projections as a prior for items' locations.



# Evaluation

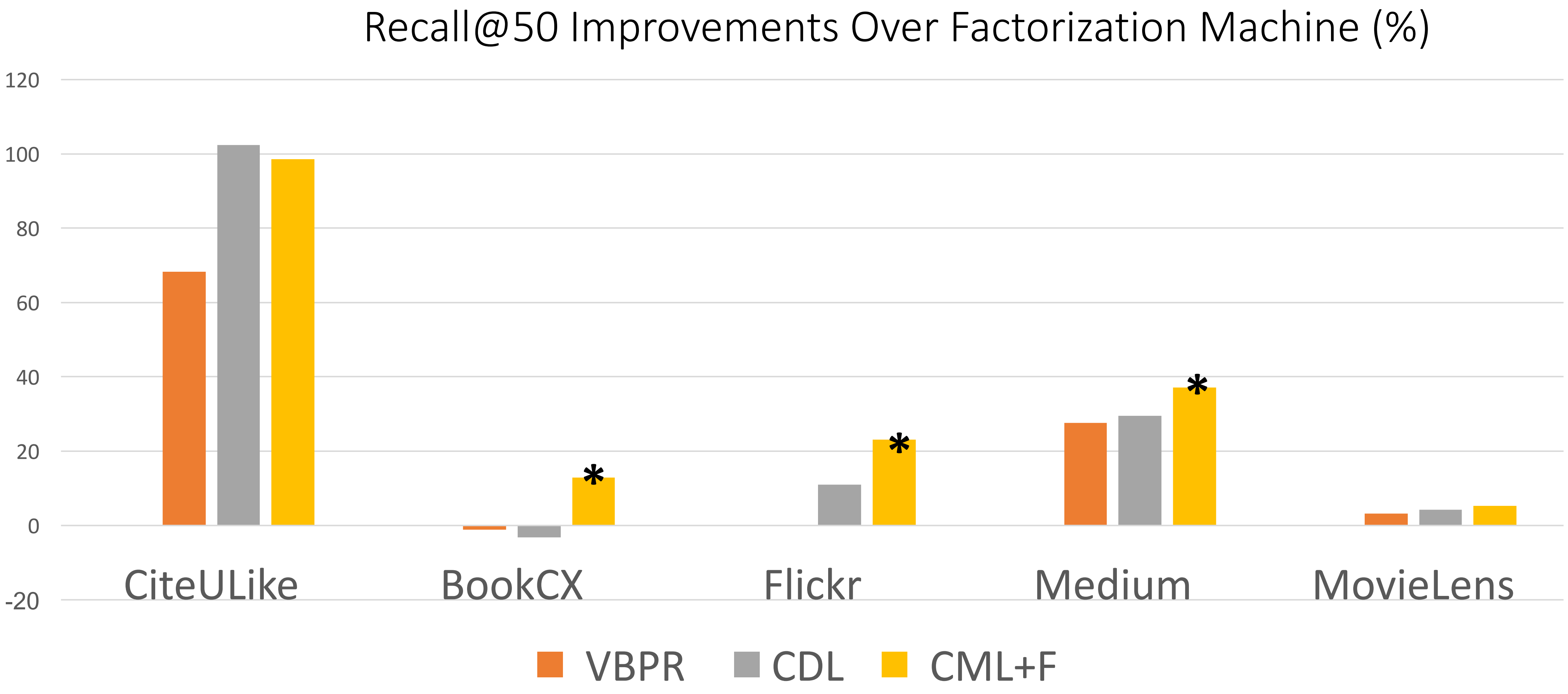
- 6 Datasets from Different Domains
  - **Papers** - CiteULike
  - **Books** - BookCrossing
  - **Photography** - Flickr
  - **Articles** - Medium
  - **Movies** - MovieLens
  - **Music** - EchoNest

# Accuracy (Recall@50)




* Indicate that CML > the second best algorithm is statistically significant according to Wilcoxon signed rank test

# Accuracy (with Item Features)

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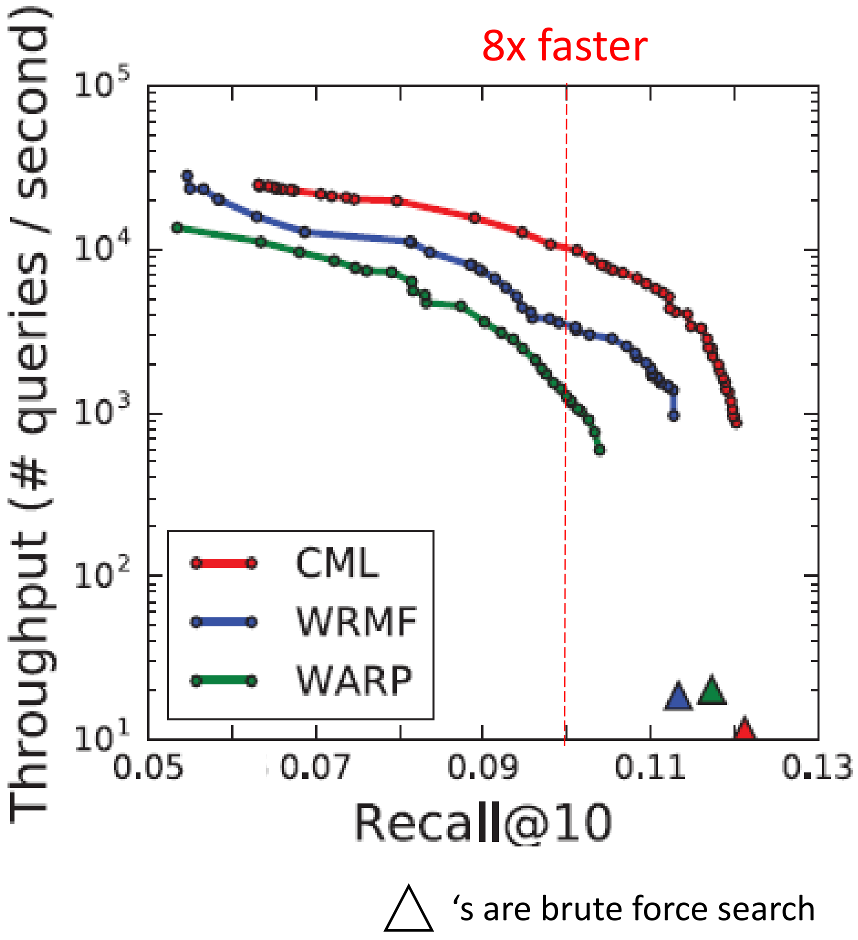
# Efficiency

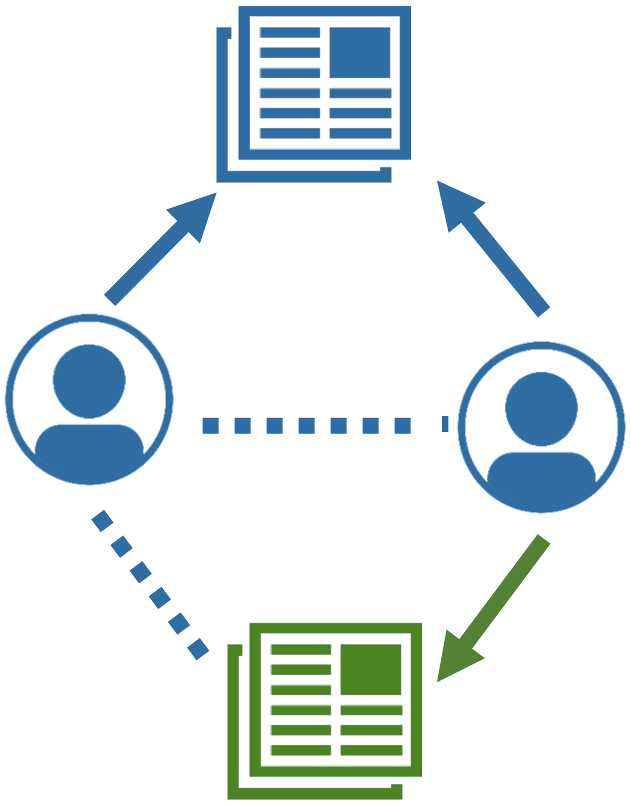
- All optimized with LSHs
- CML's throughput is improved by 106x with only 2% reduction in accuracy
- Over 8x faster than (optimized) MF models given the same accuracy



# Embedding Interpretability

# Conclusions

- The notion of user-item matrix and matrix factorization becomes less applicable with implicit feedback.
- CML is a metric learning model that has
  - better accuracy, efficiency, interpretability, and extensibility.
- Applying metric-based algorithms, such as K-means, and SVMs, to other recommendation problems.



# Thank you!

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