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

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<th>Items</th>
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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
Think Beyond Matrix

Explicit → Implicit

• No longer about estimating ratings
• But about modeling the relationships between different user/item pairs
Metric Learning

Known relationships

Unknown relationships
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.

• Top-K recommendations are simply KNN search (a well-optimized task)
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Collaborative Large Margin Nearest Neighbor

Pitfalls of Matrix Factorization (Dot-Product)

• Dot-Product violates triangle inequality $\rightarrow$ misleading embedding.
Pitfalls of Matrix Factorization (Dot-Product)

- Dot-Product violates triangle inequality → misleading embedding.

\[ V_1^T V_2 = 0 \]: 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)

Recall@50 Improvements Over BPR (%)

* Indicate that CML > the second best algorithm is statistically significant according to Wilcoxon signed rank test.
Accuracy (with Item Features)

Recall@50 Improvements Over Factorization Machine (%)

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