Toronto Metropolitan University

Data Science & Analytics Graduate Studies

2023-2024 M.Sc. in Data Science and Analytics

Assessing Recommender System Architectures: A Comparative Study of Collaborative Filtering, Graph-Based, and Hypergraph-Based Models

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Objective: The aim of this study is to determine which recommender system architecture, collaborative filtering, graph-based, or hypergraph-based systems delivers the most accurate and relevant movie recommendations by evaluating their performance. Additionally, this project aims to investigate how effectively each model addresses the cold-start problem, and to assess which model delivers the most reliable recommendations when faced with sparse data environments.

Background: In recent years, recommender systems have become essential for enhancing user experiences on digital platforms, particularly in the entertainment industry. As the demand for more accurate and personalized recommendations has grown, the field has rapidly evolved, introducing innovative approaches to meet these needs.

Collaborative filtering (CF) has been a foundational method in this evolution, known for its simplicity and effectiveness in using user-item interaction data to generate personalized recommendations. However, as the complexity of user interactions has increased, CF has shown limitations, especially in sparse data environments or when dealing the cold-start problem.

To address these challenges, **graph neural networks (GNNs)** have emerged as a significant advancement, offering enhanced capabilities for modeling complex user-item interactions through graph structures. This approach allows for more detailed and accurate recommendations, effectively overpowering some of the shortcomings of traditional CF methods.

Building on the strengths of GNNs, **hypergraph-based systems** take the modeling of user-item relationships even further by capturing high-order interactions between users, items, and additional attributes. This richer context enables these systems to provide even more nuanced and relevant recommendations.

Given these advancements, the objective of this research is to implement and compare various algorithms to understand the strengths and limitations of each approach.

Results:

Scenario	Algorithm	MSE	RMSE	MAE	P@10	Re@10	Time
Normal	SVD	0.779164	0.882703	0.676092	0.746351	0.518142	1.232592
Sparse	SVD	0.895253	0.946178	0.735762	0.718301	0.509393	0.324698
New User	SVD	0.778264	0.882193	0.674224	0.745780	0.525009	1.197195

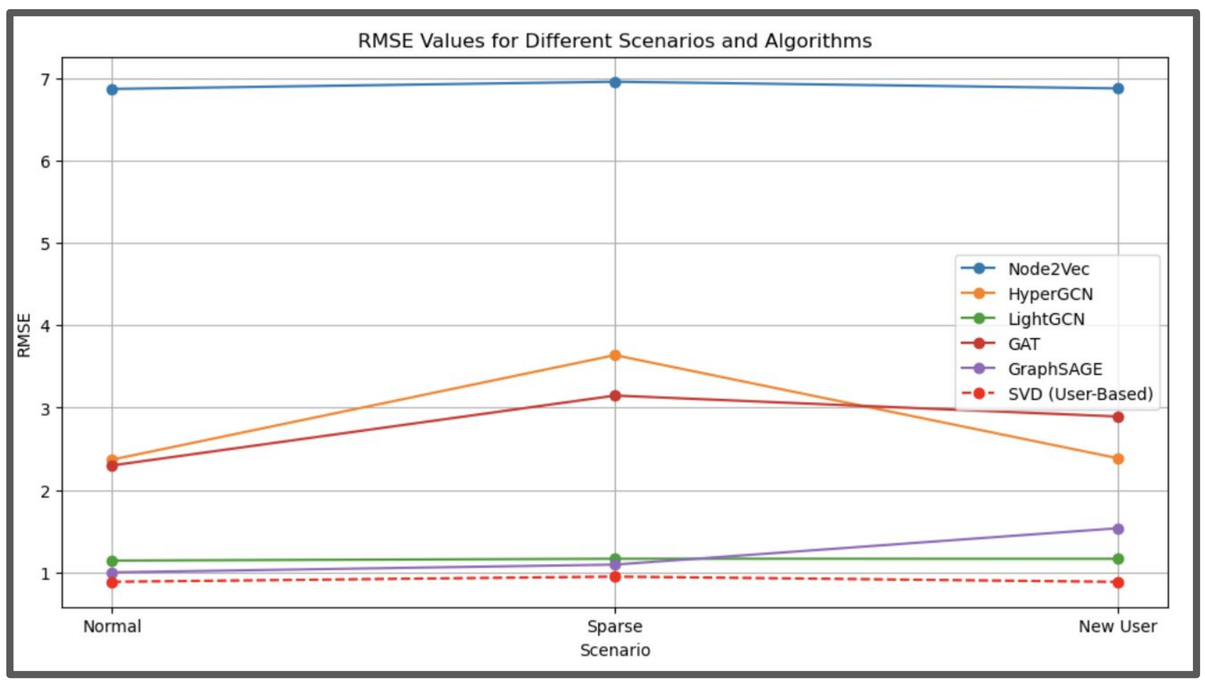
Scenario	Algorithm	MSE	RMSE	MAE	P@10	R@10	Time
Normal	LightGCN	1.300472	1.140382	0.814420	0.749278	0.503184	16.588426
Sparse	LightGCN	1.353399	1.163357	0.837602	0.750687	0.504528	2.137099
New User	LightGCN	1.352309	1.162888	0.837188	0.751206	0.504964	0.539947

Scenario	Algorithm	MSE	RMSE	MAE	P@10	R@10	Time
Normal	GAT	5.279527	2.297722	1.813445	0.640868	0.339237	76.762282
Sparse	GAT	9.903407	3.146968	2.508598	0.665226	0.375002	9.373171
New User	GAT	8.366129	2.892426	2.294709	0.656693	0.358051	2.174327

Scenario	Algorithm	MSE	RMSE	MAE	P@10	R@10	Time
Normal	GraphSAGE	0.995274	0.997634	0.765923	0.737043	0.525224	71.149196
Sparse	GraphSAGE	1.191938	1.091759	0.853637	0.729891	0.473050	8.101512
New User	GraphSAGE	2.352740	1.533864	1.183540	0.732416	0.497194	1.240817

Scenario	Algorithm	MSE	RMSE	MAE	P@10	R@10	Time
Normal	HyperGCN	5.608074	2.368137	2.050150	0.116924	0.009341	86.924503
Sparse	HyperGCN	13.239963	3.638676	3.480585	0.000000	0.000000	11.528216
New User	HyperGCN	5.691181	2.385620	2.063831	0.105558	0.008382	88.792880

Scenario	Algorithm	MSE	RMSE	MAE	P@10	R@10	Time
Normal	Node2Vec	47.267650	6.875147	5.017519	0.473556	0.104442	57.877078
Sparse	Node2Vec	48.482455	6.962934	5.095941	0.407286	0.099925	38.807848
New User	Node2Vec	47.357681	6.881692	4.988233	0.442582	0.097093	59.448123



Methodology:

1. Extract data from the MovieLens group (100k ratings dataset).
2. Split the dataset into 80% train set and 20% test set.
3. From the train set, extract 10% to simulate a training set for the cold-start problem when new user are introduced and the data sparsity problem.
4. Implement various algorithms including:
   a. KNN, SVD, Coclustering — CF
   b. LightGCN, GAT, GraphSAGE — Graph based models
   c. HyperGCN, Node2vec — Hypergraph based models
5. Evaluate the models using MSE, RMSE, MAE, Precision@10 and recall@10.
6. Focus on RMSE as key evaluation metrics because it offers a balanced compromise MAE and MSE.

Conclusions: Our analysis found that **SVD** was the most reliable algorithm for our movie recommendation, balancing accuracy and efficiency across all the scenarios. While **GraphSAGE** and **LightGCN** also performed well, especially in specific scenarios, **Node2Vec** and **HyperGCN** consistently underperformed. Our expectation that hypergraph models would outperform other algorithms was not met. This is likely be explained by the fact that hypergraphs have theoretical advantages in capturing higher-order relationships in complex data, but the dataset we have worked on may have not been enough complex to fully leverage these strengths.