RMIT UNIVERSITY

School of Science, Engineering and Technology

Assignment 3: Recommender System

COSC2670 – Practical Data Science with Python

Student: Nguyen Ngoc Hai (s3978281)
Lecturer: Professor Feng Xia

Task 1: KNN-based Collaborative Filtering (CF)

1. Methodology

- User-based collaborative filtering using **KNN** algorithm.
- **Parameters tested:**
  - similarity metrics: **Cosine Similarity** and **Pearson Correlation** [1]
  - k values: [5, 10, 20, 50, 100]

2. Testing approach

- Randomly selected user for testing
- Predicted ratings for all movies in test set
- Evaluate using **RMSE** [2]

3. Analysis

- Both metrics showed **significant improvement** as **k increases**.
- Largest improvement occurs between **k=5** and **k=20**
- Cosine similarity slightly **outperformed** Pearson correlation for most k values
- Optimal performance for both metrics was achieved at **k=100**
- Diminishing returns observed as k increased beyond 50

16 rows ⌄ 16 rows × 3 columns

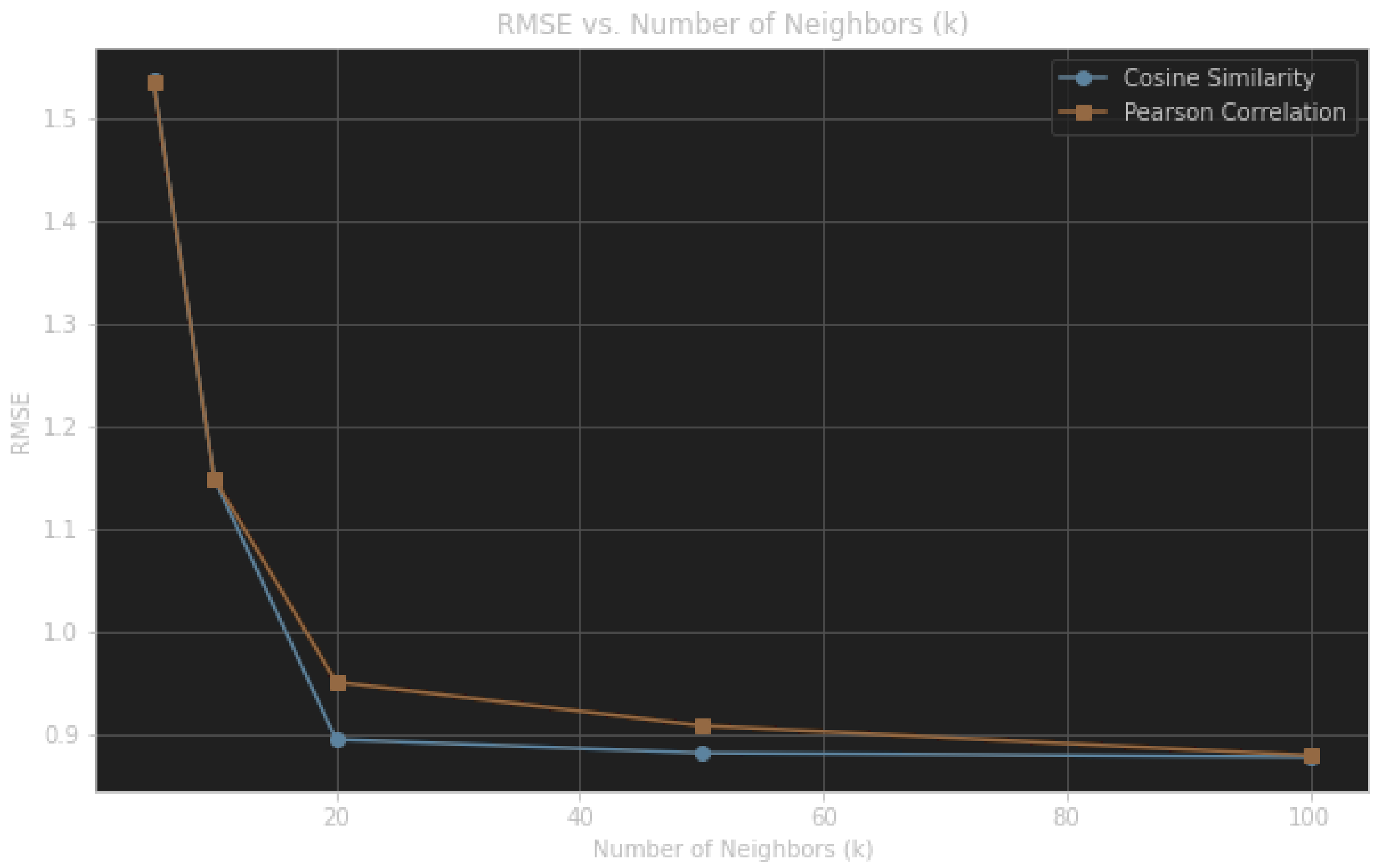
	MovieID	Predicted Rating	Actual Rating
0	21	3.669552	4.0
1	449	4.000000	5.0
2	1257	4.006865	5.0
3	1270	4.228521	5.0
4	1663	4.107669	5.0
5	2003	3.307900	4.0

k value	Cosine Similarity	Pearson Correlation
5	1.5365	1.5360
10	1.1486	1.1488
20	0.8944	0.9505
50	0.8812	0.9079
100	0.8771 (Optimal)	0.8788 (Optimal)

Task 1: KNN-based Collaborative Filtering (CF)

4. Conclusions

- **Good performance:** RMSE < 0.9 for higher k values
- Cosine similarity is **marginally better** than Pearson correlation
- **Higher k value** generally led to **better predictions**
- **Optimal k=100:** considering a large number of similar users improves prediction accuracy
- **Small difference between k=50 and k=100:** indicated potential for computational optimization without significant loss in accuracy.

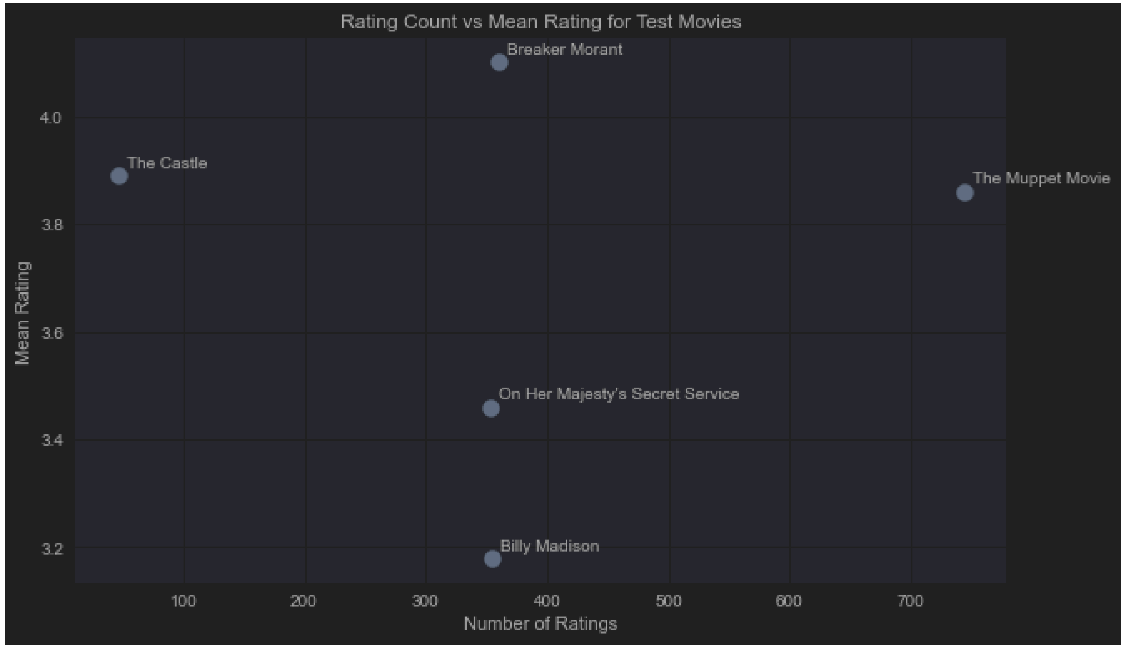


Task 2: Matrix Factorization-based Recommendation

1. Matrix Factorization Approach

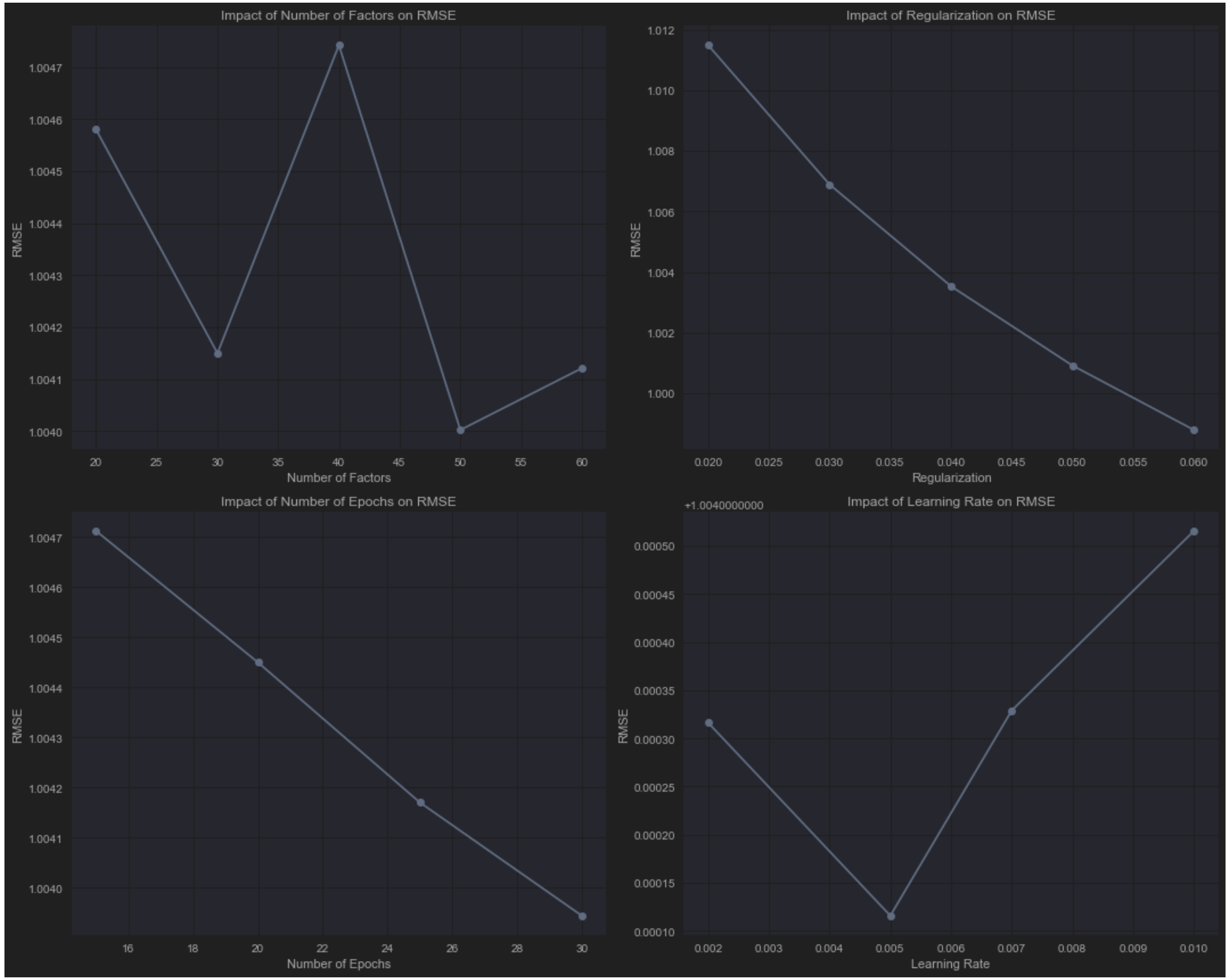
- Implement **Singular Value Decomposition (SVD)** [3] technique
- Decomposes user-item rating into latent factors
- **Randomly** selected 5 movies as test set:
  - Range from 46 to 744 ratings per movie
  - Diverse genres and years (1969 – 1997)

Movie	Genre	Ratings	Mean Rating
The Muppet Movie (1979)	Children’s | Comedy	744	3.86
Breaker Morant (1980)	Drama | War	360	4.10
Billy Madison (1995)	Comedy	355	3.18
On Her Majesty's Secret Service (1969)	Action	353	3.46
The Castle (1997)	Comedy	46	3.89



Task 2: Matrix Factorization-based Recommendation

2. Improvement Analysis and Results



Systematic Tuning

Model Simplifications:

- Reduce **factors (30)** for better generalization
- Increased **regularization (0.06)** to prevent overfitting

Training Optimization:

- Extend training **epochs (30)**
- Maintained optimal **learning rate (0.005)**

Results:

- Initial RMSE: **1.0123**
- Final RMSE: **0.9971**
- Improvement: **1.50%**

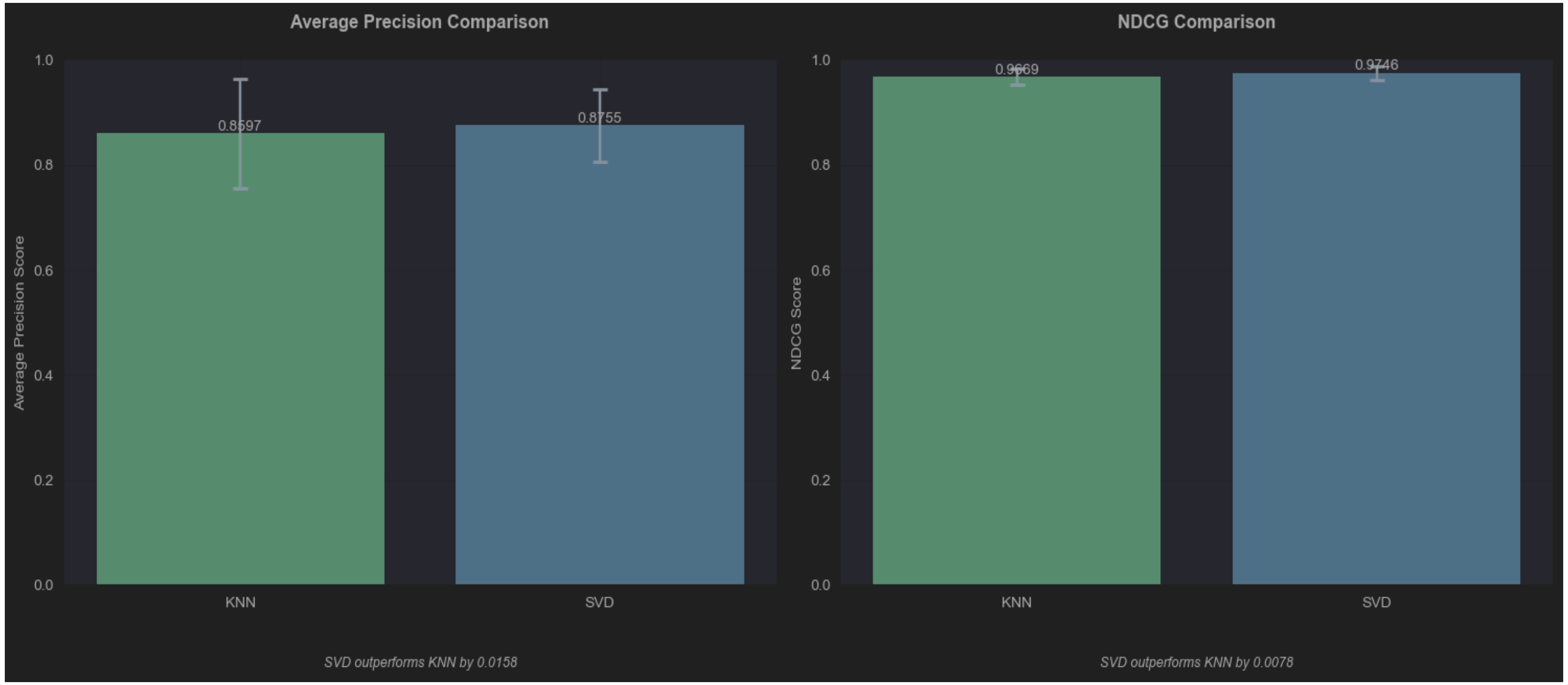
Task 3: Ranking-based Evaluation and Comparison

1. Evaluation Process

- **Train-Test** Split: 80% - 20%
- Users with sufficient ratings in both sets for reliable evaluation
- Generated **top-20** recommendations for each test user
- Compared predictions against **actual ratings** in test set

2. Results Overview

- **Models used:** KNN Collaborative Filtering (KNNCF) and SVD
- **Evaluation Metrics:** AP [3] and NDCG Score [4]
- **Key observations:**
  - Both models performed well overall.
  - SVD consistently outperformed KNNCF in both AP and NDCG
  - Both models performed well in recommending high-rated movies, but SVD was more consistent across different users.



	KNNCF	IMFR (SVD)
AP	0.8597	0.8755
NDCG	0.9669	0.9746

Task 3: Ranking-based Evaluation and Comparison

2. Limitations of KNN

Scalability [5]
- Must compute similarities with all users
- Computationally expensive for large datasets

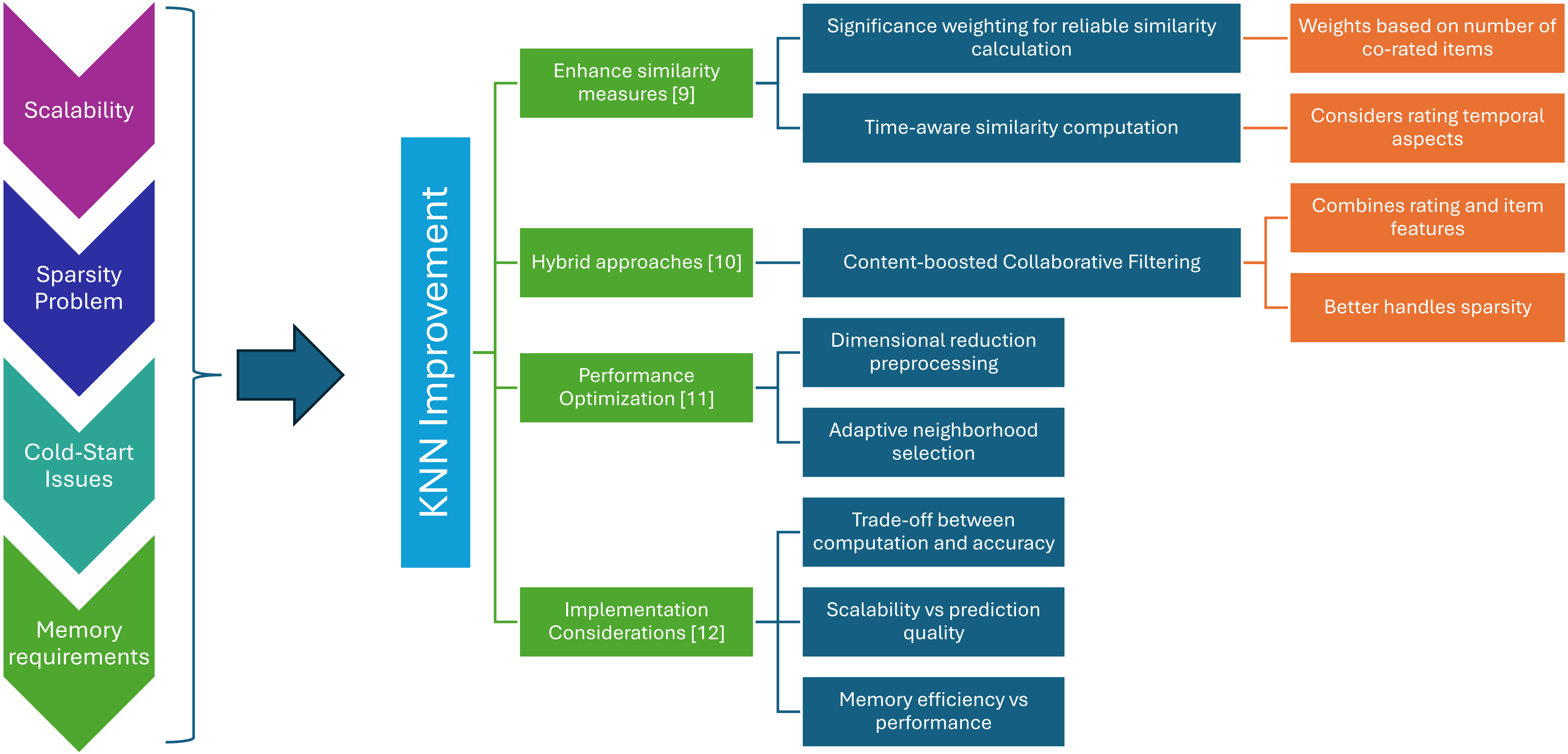
Sparsity Problem [6]
- Requires sufficient common ratings for reliable similarity
- Performance degrades with sparse rating matrices

Cold-Start Issues [7]
- Struggles with new users/items
- Needs enough ratings to make good predictions

Memory requirements [8]
- Need to store entire user-item matrix
- Memory usage grows with user base

Task 3: Ranking-based Evaluation and Comparison

3. How to improve KNN performance



Task 3: Ranking-based Evaluation and Comparison

4. Why IMFR (SVD) Performs Better?

SVD Advantages

Dimensionality Reduction [13]	• Captures latent factors in user-item interactions • Reduces noise in rating data
Data Sparsity Handling [14]	• Better generalization through latent factors • Less sensitive to missing ratings • Efficient learning from available data
Computational Benefits [11]	• Faster recommendation generation • Lower memory requirements after training • More scalable with growing datasets
Prediction Stability [15]	• Consistent performance across user profiles • Better cold-start handling than KNN • More reliable rating predictions

References

[1] Dharaneeshwaran, S. Nithya, A. Srinivasan and M. Senthilkumar, "Calculating the user-item similarity using Pearson's and cosine correlation," 2017 International Conference on Trends in Electronics and Informatics (ICEI), Tirunelveli, India, 2017, pp. 1000-1004, doi: 10.1109/ICOEI.2017.8300858.

[2] T. Chai and R. R. Draxler, "Root mean square error (RMSE) or mean absolute error (MAE)? – Arguments against avoiding RMSE in the literature," Geoscientific Model Development, vol. 7, pp. 1247–1250, 2014. doi: 10.5194/gmd-7-1247-2014.

[3] A. Garrod, S. Parr, M. O'Neil, and R. Guarasci, "A digital elevation model (DEM) for hydrological analysis," CiteSeerX, Accessed: Oct. 24, 2024. [Online]. Available: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=18d3b02c75d6e350b497fb8b3a06a9033bbb5c07

[4] Y. Wang and G. Mori, "A Discriminative Latent Model of Object Classes and Attributes," in Proceedings of the 30th International Conference on Machine Learning, Atlanta, GA, USA, 2013. [Online]. Available: https://proceedings.mlr.press/v30/Wang13.html

[5] C. C. Aggarwal, Recommender Systems: The Textbook. Cham, Switzerland: Springer, 2016, pp. 139-157. doi: 10.1007/978-3-319-29659-3.

[76] F. Ricci, L. Rokach, and B. Shapira, Eds., Recommender Systems Handbook. New York: Springer, 2015. doi: 10.1007/978-1-4899-7637-6.

[7] A. I. Schein, A. Popescul, L. H. Ungar, and D. M. Pennock, "Methods and metrics for cold-start recommendations," in Proceedings of the 25th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval, Tampere, Finland, 2002, pp. 253-260. doi: 10.1145/564376.564421.

[8] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," Computer, vol. 42, no. 8, pp. 30-37, Aug. 2009. doi: 10.1109/MC.2009.263.

[9] S. Kabbur, X. Ning, and G. Karypis, "FISM: Factored Item Similarity Models for Top-N Recommender Systems," in Proceedings of the 19th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, Chicago, IL, USA, 2013, pp. 659-667. doi: 10.1145/2487575.2487589.

[10] R. Burke, "Hybrid Recommender Systems: Survey and Experiments," User Modeling and User-Adapted Interaction, vol. 12, no. 4, pp. 331-370, Nov. 2002. doi: 10.1023/A:1021240730564.

[11] G. Linden, B. Smith, and J. York, "Amazon.com recommendations: Item-to-item collaborative filtering," *IEEE Internet Computing*, vol. 7, no. 1, pp. 76-80, Jan.-Feb. 2003. doi: 10.1109/MIC.2003.1167344.

[12] L. Candillier, F. Meyer, and M. Boullé, "Comparing state-of-the-art collaborative filtering systems," in Proceedings of the 5th International Conference on Machine Learning and Data Mining in Pattern Recognition, Leipzig, Germany, 2007, pp. 548-562. doi: 10.1007/978-3-540-73499-4_42.

[13] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," Computer, vol. 42, no. 8, pp. 30-37, Aug. 2009. doi: 10.1109/MC.2009.263.

[14] A. Paterek, "Improving regularized singular value decomposition for collaborative filtering," in Proceedings of KDD Cup and Workshop, 2007, pp. 39-42.

[15] A. Gunawardana and C. Meek, "A unified approach to building hybrid recommender systems," in *Proceedings of the Third ACM Conference on Recommender Systems*, New York, NY, USA, 2009, pp. 117-124. doi: 10.1145/1639714.1639734.