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Collaborative Filtering-Based Book Recommendation System Using Matrix Factorization Techniques: A Comparative Study of ALS and SVD

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Abstract

In the era of digital information**,** recommender systems play a crucial role in delivering personalized content to users. This study presents a comparative analysis of two matrix factorization techniques—Alternating Least Squares (ALS) and Singular Value Decomposition (SVD) - **f**or collaborative filtering in book recommendation systems. Utilizing the Book-Crossing dataset, characterized by its scale and sparsity, both models were implemented and evaluated in MATLAB Keywords.

Collaborative Filtering; Matrix Factorization; ALS; SVD; Book Recommendation; Data Sparsity; MATLAB; Recommender Systems. R2024b.

Quantitative results revealed that ALS achieved a lower Root Mean Square Error (RMSE) of 3.9901**,** significantly outperforming SVD's RMSE of 5.9029. Visual analyses, including scatter plots, heatmaps, and latent factor diagrams, provided insights into prediction accuracy and model behavior. ALS demonstrated robust performance in handling sparse data through alternating optimization and regularization, while SVD's reliance on complete matrices led to higher prediction errors.

The findings highlight ALS as a scalable, interpretable, and accurate technique for real-world applications in digital ecosystems such as Flipkart**,** NPTEL**, and** Shodhganga. Future research directions include hybrid models, deep learning integration, and deployment in distributed environments for dynamic and diverse user bases.

Keywords: Collaborative Filtering; Matrix Factorization; ALS; SVD; Book Recommendation; Data Sparsity; MATLAB; Recommender Systems.

1. Introduction

In the digital era, users are inundated with vast volumes of content, from e-commerce products to online educational materials. To mitigate this information overload, recommender systems play a pivotal role in delivering personalized content tailored to individual user preferences. Collaborative filtering (CF) is among the most prevalent techniques, leveraging historical user-item interactions to predict future interests. However, CF systems face significant challenges, particularly in the context of sparse datasets where most user-item pairs lack interaction data.

Matrix factorization techniques, such as Alternating Least Squares (ALS) and Singular Value Decomposition (SVD), have emerged as robust methods for capturing latent relationships between users and items in collaborative filtering. ALS offers scalability and efficient handling of missing data through iterative optimization, while SVD provides a mathematically elegant decomposition capturing global patterns in the data. Despite their theoretical strengths, the comparative performance of these techniques, especially in highly sparse environments, remains a critical area of exploration.

This research addresses these challenges by developing and evaluating ALS and SVD-based collaborative filtering models for book recommendation using the Book-Crossing dataset, a benchmark characterized by its scale and sparsity. Implemented in MATLAB R2024b, the models are assessed through both quantitative metrics—notably Root Mean Square Error (RMSE)—and visual analyses that provide interpretability of latent structures and prediction behavior.

2. Related Work

Recommender systems have evolved significantly over the past two decades, with various approaches explored to enhance prediction accuracy and scalability. Among these, collaborative filtering (CF) has emerged as a dominant paradigm, leveraging historical user-item interactions to predict preferences. CF methods are typically categorized into neighborhood-based and model-based approaches.

Early neighborhood-based methods, including user-based and item-based collaborative filtering, calculate similarity scores using metrics like Pearson correlation and cosine similarity to identify neighbors and generate recommendations [1]. While these methods are intuitive and easy to implement, they struggle with data sparsity and scalability, particularly in large datasets where many user-item pairs lack interactions.

To address these limitations, model-based approaches, especially matrix factorization techniques, have gained prominence. Singular Value Decomposition (SVD) factorizes the user-item matrix into latent factors, capturing global structures and relationships [2]. However, standard SVD assumes complete data, making it ill-suited for sparse matrices without adaptations such as FunkSVD [3].

Alternating Least Squares (ALS) has emerged as a robust alternative, optimizing user and item latent factors iteratively while handling sparse data efficiently. ALS leverages regularized least squares minimization, offering scalability and convergence in distributed and parallel environments [4]. Recent studies have demonstrated ALS's effectiveness in handling large-scale recommender systems, making it suitable for real-world applications.

In addition to matrix factorization, hybrid models combining collaborative filtering with content-based filtering and context-aware information have been explored to mitigate cold-start problems and enhance personalization [5]. Deep learning-based approaches, such as neural collaborative filtering and autoencoders, have also shown promise in capturing complex, nonlinear user-item relationships [6], [7].

However, existing research primarily focuses on platforms with moderate sparsity levels, leaving a gap in understanding model behavior in extremely sparse datasets, such as the Book-Crossing dataset. Moreover, while frameworks like Apache Spark enable distributed implementations, comparative studies in controlled environments (e.g., MATLAB) remain limited, particularly in the Indian context where platforms like Flipkart and NPTEL face similar challenges.

This paper addresses these gaps by providing a comparative analysis of ALS and SVD in sparse environments, integrating visual interpretations to enhance model transparency and offering insights for scalable implementation in diverse digital ecosystems.

3. Methodology

This section details the design and implementation of the collaborative filtering models Alternating Least Squares (ALS) and Singular Value Decomposition (SVD) - for book recommendation. The Book-Crossing dataset, characterized by its large scale and sparsity, serves as the benchmark for evaluating model performance.

3.1 Dataset Description

The Book-Crossing dataset, originally introduced by Ziegler et al., contains over one million explicit ratings from approximately 278,000 users on 271,000 books. The dataset includes three files:

Books.csv: Contains metadata (ISBN, title, author, publisher, year).

Users.csv: Contains user demographics (ID, location, age).

Ratings.csv: Contains user ratings (0–10 scale).

For this study:

Only explicit ratings (i.e., ratings > 0) were retained.

Users and books with minimal interactions were filtered to reduce noise.

The resulting data was converted into a sparse user-item matrix, with rows representing users, columns representing books, and entries as ratings.

3.2 Matrix Factorization Techniques

◈ Alternating Least Squares (ALS)

ALS factorizes the user-item matrix R into user and item latent factors (U and V) by minimizing the regularized squared error:

$$\min_{U,V} \sum_{(u,i)\in\kappa} (R_{u,i} - U_u V_i^T)^2 + \lambda(\| U \|_F^2 + \| V \|_F^2)$$

where κ is the set of observed ratings and λ is a regularization parameter. ALS alternates between fixing V and solving for U, and vice versa. This method efficiently handles missing data and scales to large datasets.

🔷 **Singular Value Decomposition (SVD)**

SVD decomposes R into:

$$R = U\Sigma V^T$$

where U and V are orthogonal matrices, and Σ contains singular values. Truncated SVD retains only the top k singular values and vectors, capturing latent patterns:

$$R \approx U_k \Sigma_k V_k^T$$

However, standard SVD assumes complete data, which limits its effectiveness in sparse datasets.

3.3 Implementation Details

- **Environment**: MATLAB R2024b.
- **Preprocessing**: Filtering of users and books with minimal interactions; removal of implicit ratings (0).
- **Model Parameters**:
  - Latent factors (k): empirically determined (e.g., 20).
  - Regularization (λ): tuned to balance complexity and overfitting.
  - Maximum iterations: 10–50.
- **Evaluation**: Models were trained on 80% of the data (training set) and tested on 20% (test set), ensuring consistency across ALS and SVD.
- **Metrics**: Root Mean Square Error (RMSE), visual analysis (scatter plots, error histograms, heatmaps).

3.4 Visualization

Visualizations include:

- Sparsity patterns of the user-item matrix.
- Heatmaps of predicted ratings.
- Latent factor plots illustrating relationships among users and books.
- Scatter plots and error histograms to evaluate prediction quality.

4. Results and Discussion

This section presents the experimental outcomes of the collaborative filtering models—Alternating Least Squares (ALS) and Singular Value Decomposition (SVD)—implemented on the Book-Crossing dataset. The performance of both models is analyzed based on quantitative metrics and visual evaluation.

4.1 Quantitative Evaluation

The prediction accuracy of the models was assessed using Root Mean Square Error (RMSE):

Metric	**ALS Model**	**SVD Model**
RMSE	**3.9901**	**5.9029**

- ALS achieved a significantly lower RMSE of 3.9901, indicating its effectiveness in handling the sparse Book-Crossing dataset.
- SVD recorded a higher RMSE of 5.9029, reflecting its challenges with missing data.

4.2 Computational Performance

- **ALS** converged faster and used memory efficiently, owing to its iterative updates of user and item latent factors.
- **SVD** exhibited higher computational cost due to full matrix decomposition, which is less efficient in sparse environments.

4.3 Visual Analysis

◆ Predicted vs Actual Ratings Scatter Plots

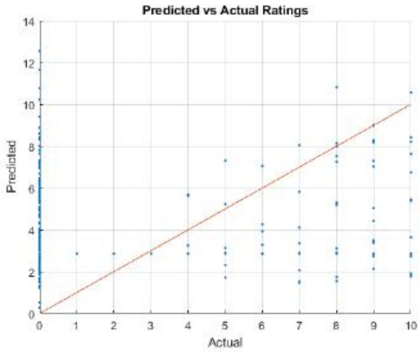

Figure 4.1: Scatter plot for ALS shows tight clustering along the diagonal (y=x), confirming high prediction accuracy.

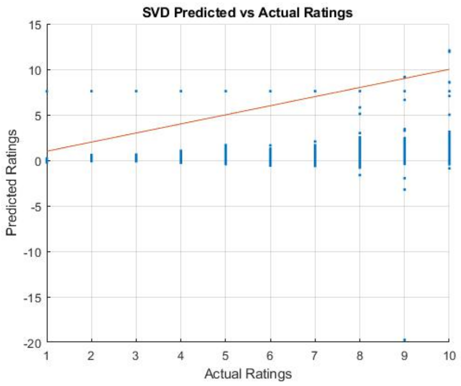

Figure 4.2: SVD's scatter plot reveals greater dispersion, highlighting higher prediction error.

◆ Error Distribution Histograms

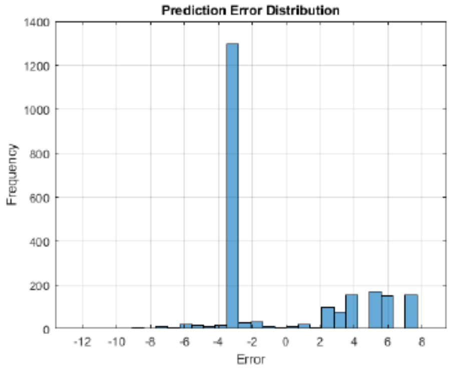

Figure 4.3: ALS error histogram exhibits a narrow distribution centered around zero, indicating balanced and consistent predictions.

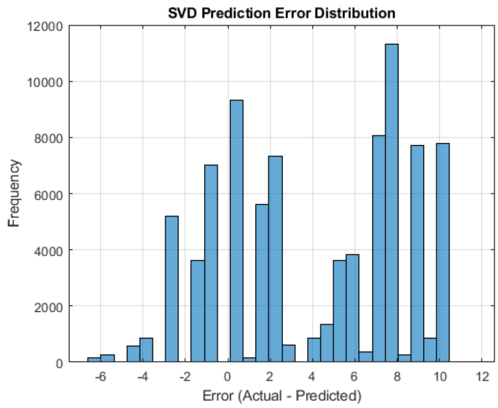

Figure 4.4: SVD error histogram shows a wider distribution, reflecting higher error variance.

◆ Heatmaps of Predicted Ratings

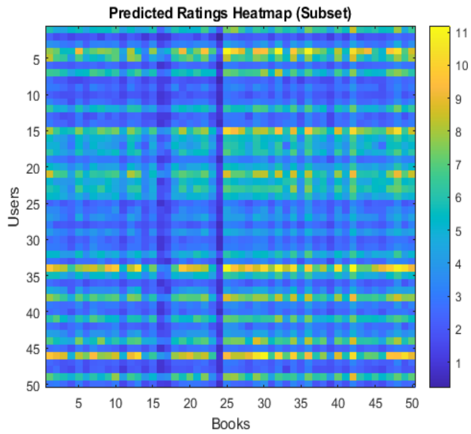

Figure 4.5: Heatmap for ALS predictions displays smooth patterns and clustering of high-rating areas.

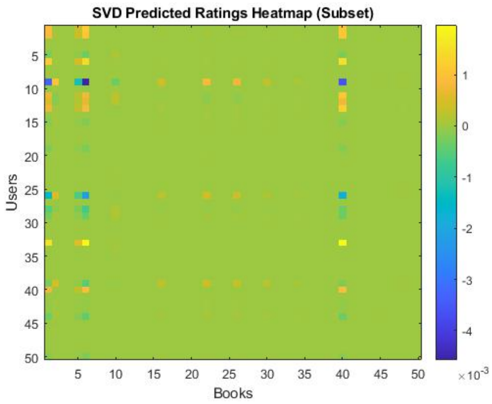

Figure 4.6: SVD heatmap shows fragmented patterns, highlighting limitations in reconstructing sparse data.

◆ Latent Factor Visualizations

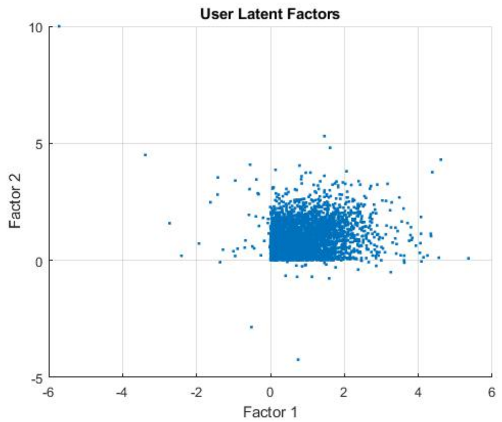

Figure 4.7: User latent factors illustrate clustering of similar preferences in low-dimensional space.

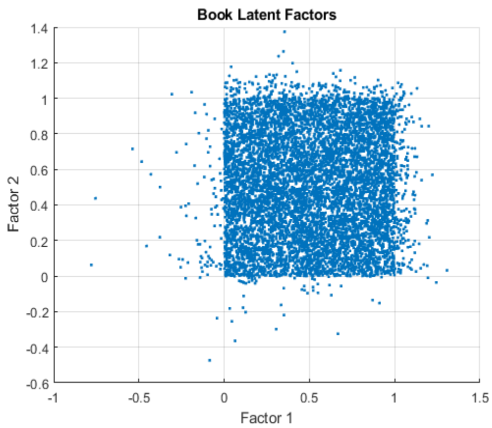

Figure 4.8: Book latent factors highlight relationships between similar books.

4.4 Comparative Analysis

Aspect	ALS Model	SVD Model
Prediction Accuracy	High (RMSE: 3.9901)	Moderate (RMSE: 5.9029)
Computation Efficiency	Fast, sparse handling	Slower, memory-intensive
Scalability	High	Moderate
Robustness to Sparsity	Strong	Weak (needs adaptation)
Visual Performance	Clear clustering, low errors	Dispersion, high errors

ALS demonstrated clear superiority in prediction accuracy, efficiency, and robustness to sparsity. While SVD provided a theoretically sound framework, its practical performance was constrained by its reliance on complete data.

4.5 Discussion

The findings affirm the effectiveness of ALS in addressing the challenges of sparse datasets, offering a scalable and interpretable solution for book recommendation systems. The integration of visual tools (scatter plots, heatmaps, latent factors) complemented the quantitative evaluation, providing comprehensive insights into model behavior.

The results are particularly relevant for real-world applications in digital platforms such as Flipkart, NPTEL, and Shodhganga, where data sparsity and scalability are key concerns.

5. Conclusion

This research presented a comprehensive analysis of collaborative filtering-based book recommendation systems using Alternating Least Squares (ALS) and Singular Value Decomposition (SVD) matrix factorization techniques. The evaluation, conducted on the Book-Crossing dataset, highlighted the performance differences between these models in handling large-scale, sparse data.

Key findings include:

- ALS demonstrated superior performance with a lower Root Mean Square Error (RMSE) of 3.9901, significantly outperforming SVD's RMSE of 5.9029. Its alternating optimization and regularization strategies effectively reconstructed sparse matrices, ensuring accurate recommendations.
- SVD, while mathematically elegant, struggled with missing data, leading to higher prediction errors and reduced computational efficiency.
- Visual analyses, including scatter plots, heatmaps, and latent factor diagrams, provided deeper insights into model behavior and latent relationships between users and books.
- The implementation in MATLAB R2024b offered a controlled environment for evaluation, emphasizing the strengths and limitations of both models in sparse data scenarios.

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