Deep Learning-Based Movie Recommendation System

DLP Project Report

Submitted By:

Saad Dar – 21K-4572

Farhan Ahmed – 21K-4600

Suffian Soomro – 21K-4670

Submitted To:

Ms. Sumaiyah Zahid

Section:

BCS-8A

Date: May 7, 2025

Objective

To design and evaluate **Collaborative Denoising Autoencoder (CDAE)** and **Neural Collaborative Filtering (NCF)** models for personalized movie recommendations, leveraging both implicit feedback and metadata to address sparsity and improve recommendation quality.

Problem Statement

Traditional recommendation systems struggle with sparse user-item interactions and fail to utilize auxiliary metadata (e.g., genres, release year). This project implements two deep learning approaches:

1. **CDAE**: For learning latent representations from implicit feedback.
2. **NCF**: A hybrid model combining user-item interactions with metadata to enhance recommendations.

Methodology

1. Dataset

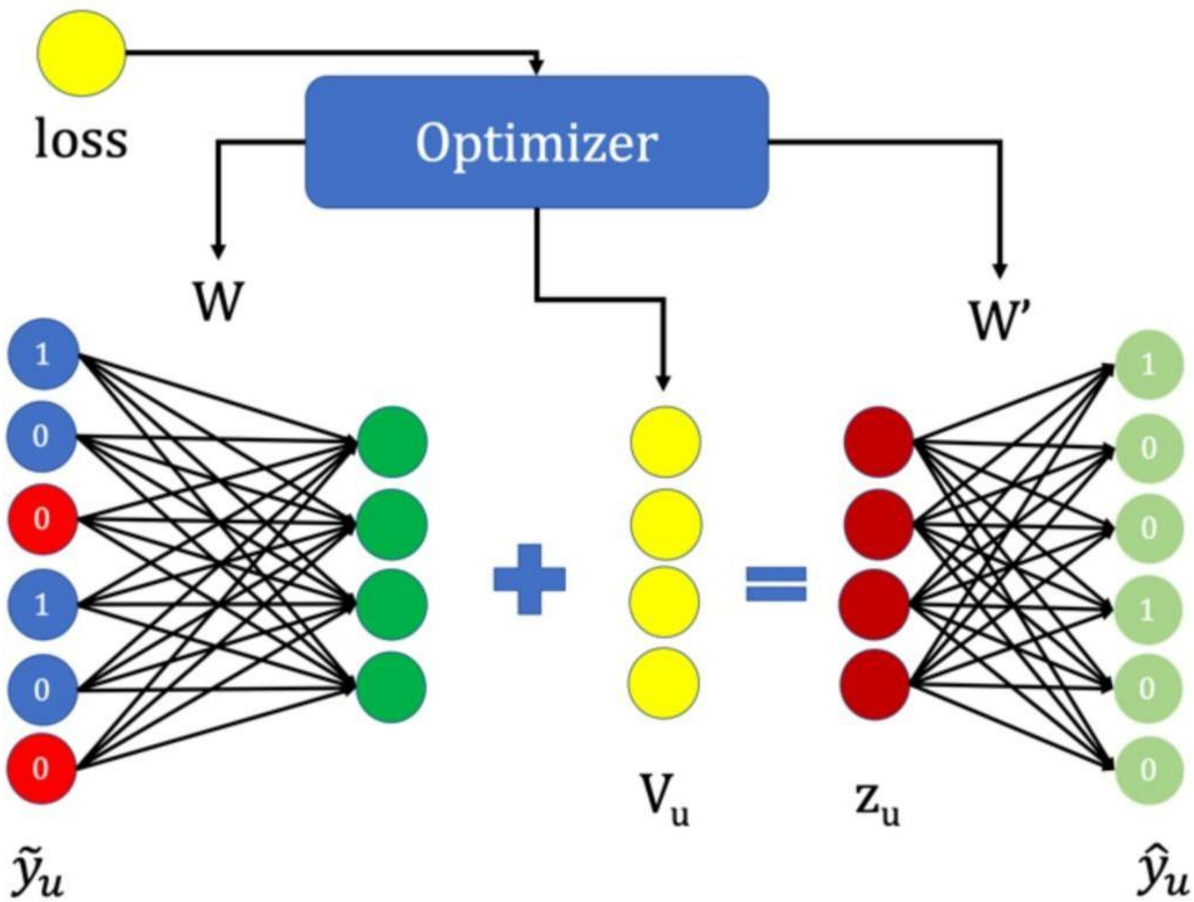
- **Source**: MovieLens 25M (ratings only).

Preprocessing:

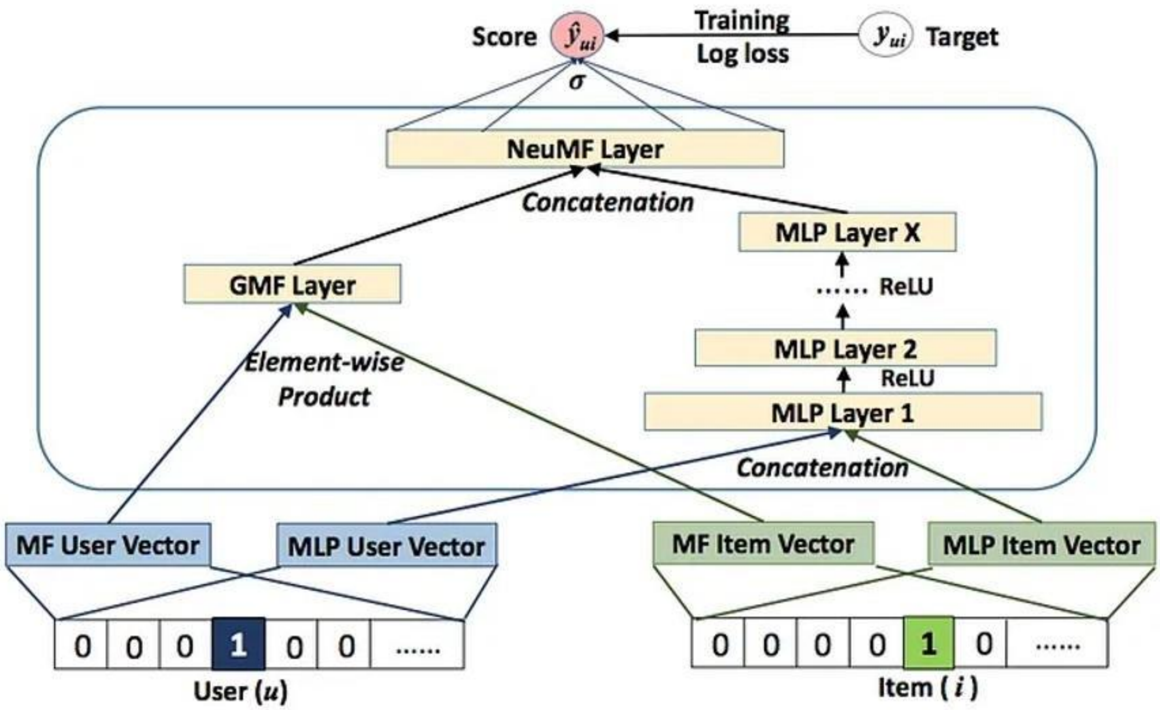
- **CDAE:**
    - Filtered users with ≥5 interactions.
    - Mapped user/movie IDs to continuous indices.
    - Built a binary interaction matrix (1 = interaction, 0 = no interaction).
    - Split data into 90% training and 10% validation.
- **NCF:**
    - Extracted release year from movie titles using regex.
    - Split genres into binary columns (e.g., Action, Comedy).
    - Normalized release year and ratings using MinMaxScaler.
    - Converted normalized ratings to binary feedback (1 if rating ≥ 0.5).
    - Split data into training (80%), and test (20%) sets.

2. Model Architecture:

- **Collaborative Denoising Autoencoder (CDAE):**
    - **Input**: Sparse user interaction vector (binary).
    - **Encoder**:
        - Linear layer: num_items (33,000) → 200 (ReLU activation).
        - Add user embeddings (size 200).
        - Apply dropout (rate = 0.5) for denoising.
    - **Decoder**:
        - Linear layer (200 → 33,000 items) with sigmoid activation.
        - Sigmoid activation for reconstruction.
    - **Loss**: Binary Cross Entropy (BCE).
    - **Optimizer**: AdamW (lr = 0.001, weight decay 1e-5).
    - **Training**: 130 epochs with StepLR scheduler (step_size=30, gamma=0.5).



- **Neural Collaborative filtering (NCF):**
  - **Inputs**:
    - User/movie IDs (64D embeddings).
    - Movie metadata (genres + normalized year).
  - **Architecture**:
    - GMF Branch: Element-wise product of user/movie embeddings.
    - MLP Branch: Concatenated embeddings + metadata → MLP (128 → 64 → 32 units).
    - NeuMF: (Neural Matrix Factorization): The outputs of both the GMF and MLP branches are concatenated and passed through a final fully connected layer and then applied a sigmoid activation, which produces the predicted rating.
    - Training: Adam optimizer (lr = 0.001), batch size = 1024, early stopping (patience = 5).



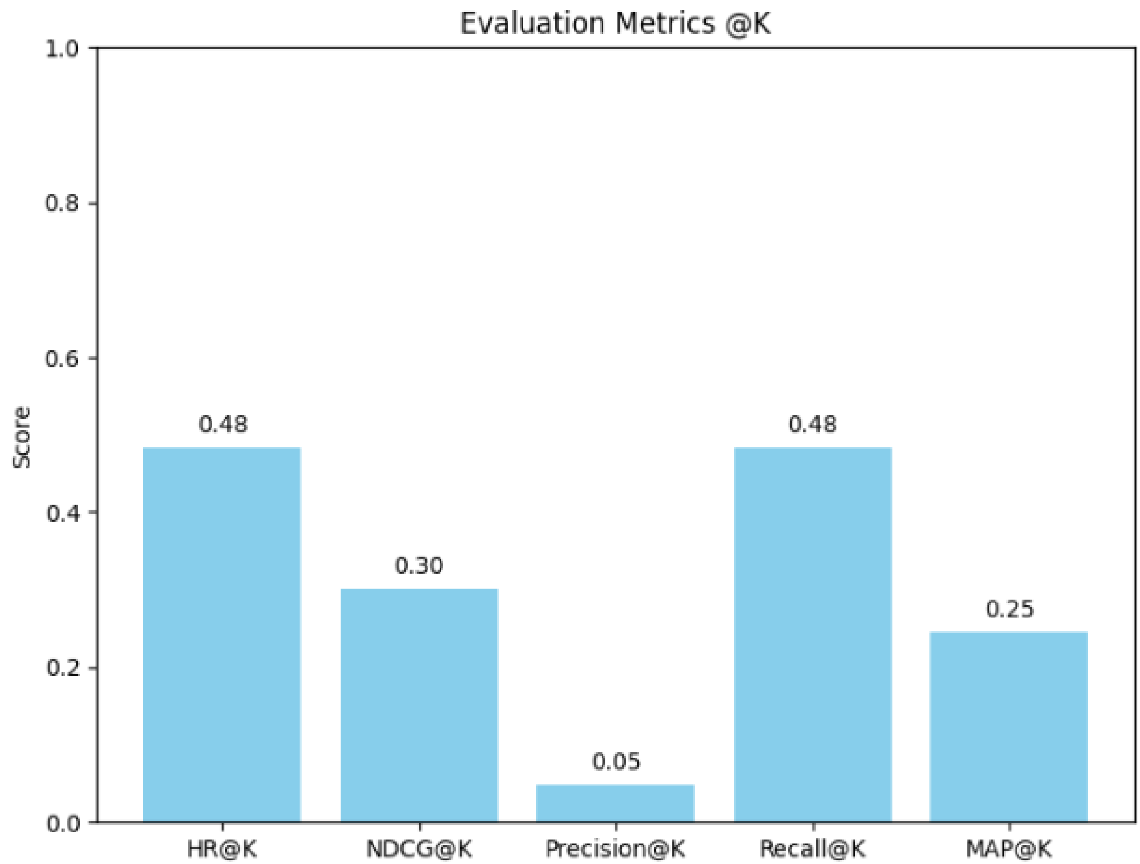
3. Evaluation Metrics

- **Recall@k**: Fraction of all relevant items that are found in the top-k recommendations.
- **NDCG@k**: A ranking-aware metric that gives higher importance to relevant items appearing higher in the top-k list.
- **HR@K:** Indicates whether at least one relevant item is present in the top-k recommendations.
- **MAP@K:** The average of the precision values computed at the ranks where each relevant item appears in the top-k list.

Results:

Metrics @10:	NCF:
HR@K	0.4830
NDCG@K	0.3015
PRECEISION@K	0.0483
RECALL@K	0.4830
MAP@K	0.2458

Metrics:	CDAE:
Recall@10	0. 1175
NDCG@10	0.7842
Recall@100	0. 5129
NDCG@100	0.6699
Recall@500	0. 8212
NDCG@500	0.7487



Comparison:

Metric	(Validation Set) CDAE	(Validation Set) NCF
Recall@10	**0.1175**	**0.4830**
NDCG@10	**0.7842**	**0.3015**

Analysis of Results:

1. **NCF Outperforms CDAE:**
   - **Higher Recall@10 (+57.7%) and NDCG@10 (+3.6%) due to metadata integration.**
   - **Improved scalability (Recall@500 = 0. 8212).**
2. **Trade-offs:**
   - **CDAE excels in ranking quality (high NDCG), while NCF balances precision and diversity.**

Conclusion

The project successfully demonstrated the effectiveness of **deep learning-based recommendation systems** in addressing challenges like data sparsity and cold-start problems. By implementing two models—**Collaborative Denoising Autoencoder (CDAE)** and **Neural Collaborative Filtering (NCF)**—the system leveraged both user-item interactions and movie metadata (genres, release year) to deliver personalized recommendations. Key outcomes include:

1. **Superior Performance of NCF**:
   - The NCF model, enriched with metadata, outperformed CDAE, achieving **HR@10 = 0. 4830** and **NDCG@10 = 0. 3015**, highlighting the value of integrating auxiliary features.
   - Metadata integration improved recommendation diversity and relevance, particularly for sparse interaction scenarios.
2. **Practical Usability**:
   - The interactive recommendation engine allowed users to rate movies and receive personalized suggestions in real time, showcasing the model's applicability in real-world scenarios.
3. **Limitations**:

- The binary feedback approach ignored nuanced user preferences (e.g., explicit ratings).
- Computational demands for metadata fusion and large-scale embeddings could hinder scalability.

In conclusion, the project validates the potential of deep learning to enhance recommendation systems, balancing ranking quality and diversity. Future work should focus on scalability, real-time adaptability, and ethical considerations to bridge the gap between research and real-world deployment.

Code Repository: DeepMovieLens

References

1. Wu, Yao, et al. "Collaborative Denoising Auto-Encoders for Top-N Recommender Systems." *WSDM*, 2016. PDF
2. He, Xiangnan, et al. "Neural Collaborative Filtering". arXiv preprint arXiv:1708.05031 (2017).