Hybrid Movie Recommendation System Using Deep Learning and Transfer Learning Approaches

Abstract

This paper aims at proposing the design and implementation of a Movie Recommendation System using Deep Learning and Transfer Learning techniques. The system should be useful in predicting movie ratings, as well as recommending movies based on a user's preferences and the metadata of the movies. Three models were designed and evaluated: A Deep Learning Model, a GloVe Transfer Learning Model, and a Fine-Tuned GloVe Transfer Learning Model were developed. Based on the proposed Deep Learning Model, it was incorporated with embedding layers for movie IDs and tiles in order to detect intricate features of the data. The GloVe Model utilized fixed word vectors to encompass textual characteristics such as title of the movies and used syntactic similarities between words. The Fine-Tuned GloVe Model improved upon this by adding the capacity for the embedding to change during training according to the current dataset making it more sensitive to domain-specific variations. The models were evaluated based on such parameters as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and coefficient of determination (R^2). The proposed Deep Learning Model had the least error rates and it took the least amount of time to train. All models prepared in the study provided valuable enhancements over the frozen GloVe Model even though they still contain scope for improvement in explaining data variance. This work demonstrates that deep learning and transfer learning can offer highly accurate, yet easily scalable and transparent recommendation solutions for practical use cases.

Keywords

Transfer Learning, GloVe Embeddings, Fine-Tuned Embeddings, Personalized Recommendations, Neural Networks, Collaborative Filtering, Content-Based Filtering, Scalable Recommendation Systems.

Chapter 1 :Introduction

Due to the exponential growth of content in streaming service providers, it has become very difficult for the audiences to filter desired content from the lot. This has led to a need for recommender systems that will recommend content for a given user. For instance, when talking about movie streaming platforms, recommendation systems are one of the main strategies for identifying movies that a user might like in a vast catalog. These systems also benefit the streaming platform because they enhance consumer satisfaction and keep the flow and actively engaged users happy and coming back for more so they are able to increase their revenue considerably. This research is centred on enhancing an efficient Movie Recommendation System with advanced technologies including Deep Learning and Transfer Learning Models. By having a dataset containing numerous details including movie title, genre, rating, and users' activities, the system can guess the user's preferences for movies and suggest the films the user might like based on the users' activities . To achieve this, the system employs the general neural networks that help learning about the patterns in their use, the embedding layers, which are specifically tailored to understand the relations between the users and the movies and further sophisticated techniques such as the GloVe Embedding and the Fine-Tuned Embedding are used to make the distinction more precise and more sensitive. Both strategies help to guarantee that the recommendation system is effective, can increase user scale and offers useful recommendations to users.

Motivation and Contribution

In today's digital world, where streaming platforms are competing to improve user satisfaction, the need for personalized recommendations has become more important than ever. People expect platforms to suggest movies that match their unique tastes, but traditional recommendation methods often struggle to handle the complexity of user preferences and diverse content. This project addresses these challenges by focusing on key areas:

1. **Handling Large Volumes of Data**: With thousands of movies available on platforms like Netflix or Amazon Prime, the system must process large datasets quickly and efficiently while still offering precise recommendations.
2. **Boosting User Satisfaction**: Personalized suggestions make users more likely to stay engaged, spend more time on the platform, and feel satisfied with their experience. Using advanced tools like deep learning can help understand users' preferences better than older methods.
3. **Using Cutting-Edge Technology**: Techniques like deep learning and transfer learning are transforming how recommendations work. By applying these to real-world datasets, the project explores their ability to solve complex challenges in predicting user preferences.
4. **Advancing Research**: Comparing deep learning models with transfer learning techniques, such as GloVe embeddings and fine-tuned representations, provides valuable insights for improving future recommendation systems.

This project developed a Movie Recommendation System that uses modern techniques to deliver accurate and personalized movie suggestions. Its contributions include:

- **Deep Learning Model**: A baseline model was built using a Deep Neural Network (DNN). It employs embedding layers to learn intricate patterns between users and movie characteristics.
- **Transfer Learning Models**:
    1. **GloVe Embeddings**: Pretrained GloVe embeddings were used to represent movie titles, making it easier for the system to understand text data.
    2. **Fine-Tuned Embeddings**: An approach was designed to adjust pretrained embeddings to better fit the specific needs of the movie recommendation task. This helped improve the system's ability to capture the unique context of the dataset.
- **Comparing Models**: The deep learning model and the transfer learning methods were compared using standard metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2. This comparison helped identify the strengths and weaknesses of each approach.
- **Scalable Framework**: The system was built with flexibility in mind, allowing additional features like user interaction data or genre preferences to be added later for even better recommendations.
- **Result Visualization**: The project included clear visual comparisons of how each model performed. These visuals helped to explain the findings and make better decisions about which approach works best.
- **Real-World Use Cases**: The system is designed to be scalable and ready for deployment on platforms like Netflix or Amazon Prime. This ensures that it can handle real-world challenges and deliver value to millions of users.

By combining advanced technologies with a user-focused approach, this project demonstrates how modern recommendation systems can improve the streaming experience and pave the way for future innovation.

Background

a. Machine Learning Models Used

This project focuses on building a movie recommendation system using both machine learning and advanced deep learning methods. Here's how the models were designed and implemented:

1. Deep Learning Model

The deep learning model was developed using popular frameworks like TensorFlow and Keras, which simplify building and training neural networks. To handle movie data efficiently, the model uses embedding layers. These layers convert numerical representations of movies and titles into dense, meaningful vectors, allowing the system to capture relationships between different items. The core of the model includes dense (fully connected) layers, which act as feature extractors. These layers learn patterns from the input data and use them to predict user ratings for movies. For optimization, the Adam optimizer was used. This algorithm adjusts learning rates dynamically during training, improving the speed and

accuracy of the model. The mean squared error (MSE) loss function measures the difference between predicted and actual ratings, helping the model improve its predictions.

2. Transfer Learning Models

Transfer learning involves reusing knowledge from pretrained models to improve the performance of a new task. In this project, two types of transfer learning models were implemented:

i. GloVe Transfer Learning:

- GloVe (Global Vectors for Word Representation) is a popular technique for creating word embeddings. Pretrained GloVe embeddings were used to represent movie titles.
- These embeddings capture semantic relationships between words (e.g., "action" and "thriller" might be close in the embedding space).
- The pretrained embeddings were frozen during training, meaning their weights were not updated. This allowed the model to leverage the general knowledge encoded in GloVe without requiring additional training on these embeddings.

ii. Fine-Tuned GloVe Transfer Learning:

- This model builds on the GloVe approach but unfreezes the embeddings, allowing their weights to be updated during training.
- By fine-tuning, the embeddings adapt to the specific characteristics of the movie dataset, potentially improving the model's ability to understand domain-specific nuances.

Evaluation and Optimization

To assess performance, all models were evaluated using metrics tailored for regression tasks, including:

- **Mean Absolute Error (MAE):** Measures the average error magnitude.
- **Root Mean Squared Error (RMSE)**: Penalizes larger errors more heavily.
- **R-squared (R^2)**: Indicates how much of the variability in user ratings is explained by the model.

b. Background About the Domain of the Selected Problem

This project falls within the domain of recommender systems, specifically designed for the entertainment industry. Recommender systems are essential tools that help digital platforms personalize user experiences by predicting what a user might like based on past behavior.

Importance in the Movie Industry

- Streaming platforms like **Netflix**, **Amazon Prime**, and **Disney+** host enormous catalogs of movies and TV shows, making it difficult for users to decide what to watch.

- A well-designed recommendation system reduces **choice overload** by presenting tailored suggestions, improving user experience and increasing **watch time**. This, in turn, boosts platform revenue and customer satisfaction.

Challenges in Movie Recommendation

- **Complex User Preferences**: Different users have unique tastes influenced by factors like genres, favorite actors, or storytelling styles.
- **Diverse Features**: Movies are described by a variety of data, including genres, production companies, popularity, and user ratings. Integrating these features into a single system is challenging.
- **Cold Start Problem**: When a platform has little or no data about a new user or movie, making accurate recommendations becomes difficult.
- **Scalability**: Platforms must handle millions of users and items efficiently without compromising accuracy.

Innovations in the System

- **Combining Metadata with Deep Learning**: The system integrates traditional features (e.g., genres, popularity) with embeddings that capture the semantics of movie titles.
- **Exploring Transfer Learning**: By using pretrained embeddings like GloVe, the system benefits from a deeper understanding of text data without requiring extensive training from scratch.

Overall, this project aligns with the latest advancements in recommender systems, addressing the challenges of personalization at scale while leveraging cutting-edge deep learning and transfer learning techniques. It offers valuable insights for building scalable, real-world solutions in the entertainment industry.

Chapter 2 :Related Work

Real-time recommender systems are playing a vital role in many domains, and mainly in e-commerce and entertainment domains for making recommendations to the users. These systems assist in the large number of products, movies or services, in this regard they are worth the effort in the improvement of user experience. While discussing the approaches and methodologies used in the context of movie recommendation systems it is possible to distinguish several groups of them: traditional approaches like collaborative filtering and content-based filtering, more complex hybrid systems, and more recently applied approaches like deep learning and transfer learning. Common techniques used in recommendation systems include collaborative filtering (CF) considered to be among the most popular. This is achieved by breaking down the past activity between the users and the items, say ratings or choices, to suggest to a user what they might like. There are two main types of CF: memory-based and model-based. Memory-based CF relies on identifying similarities between users or items; Meanwhile, Sarwar et. al., (2001) portrayed an item-based collaborative filtering approach that can effectively address the issues of scalability【1】. On the other hand, Model based CF uses more sophisticated mathematical methods such as matrix factorization to discover latent features in the user-item interactions. For example, Koren et. al.,

(2009) gave a clear view of how matrix factorization considerably enhances the scalability and performance of systems such as Netflix【2】. Content-based filtering (CBF) is the other filtering technique but unlike collaborative filtering it concentrates on features of items. This strategy proposes products that a user has bought or watched and liked before, based on metadata, like the genres, keywords or descriptions. Pazzani and Billsus(2007) have underlined its performance where large metadata are available as in the moviementation sector【3】. However, CBF has constraints such as, cold-start problems in which it is difficult to recommend items or users that the system has not encountered before, and bias problems where the system often provides a narrow variety of similar items by focusing heavily on a user's past preferences.

Since both collaborative filtering and content-based filtering both have their drawbacks, the hybrid systems have evolved. These systems take the best of both methods to provide enhanced and more widely applicable recommendation systems. Originally, a researcher suggested several approaches involving hybridization which includes weighted hybrid, switching hybrid, and mixed hybrid that improves the recommendation system performance【4】. For instance, the Netflix movie recommendation system that cooperatively implements several techniques and won them a prize for this system exhibiting a marked increase in accuracy as well as user satisfaction rate【5】. New advancements in Deep learning have revolutionized the recommendation system models for learning intricate patterns in user characteristics and in item characteristics. Neural collaborative filtering (NCF) proposed by He et al., (2017) incorporate neural networks to improve these traditional models and provide improved generality and flexibility【6】. Furthermore, recurrent neural networks (RNNs) have been used to control session-based recommendations, where Hidasi et al., (2015) have shown the ability of RNNs to capture sequentiality in users' behavior, for example MIC browsing or watching history【7】. Autoencoders have also been applied to collaborative filtering as Sedhain et al., (2015) pointed out, to solve the problem of data sparsity with scarce interaction data【8】. In the domain of movie recommendation systems, extensive metadata including the genre of the movie, details of cast and production company, opinions from the users might be of great help to operate the system more accurately. Basilico and Hofmann (2004) further showed that the use of such metadata, if incorporated through factorization methods can improve the quality of recommendations【9】. To this end, Cheng et al., (2016) extended the idea of using embeddings and integrated deep neural networks to develop hybrid models capable of addressing multifaceted complexities of users and items【10】. There is evidence in the use of traditional methods like collaborative filtering and content-based filtering in conjunction with extensive techniques such as, deep learning and transfer learning makes considerable progress in the area of the recommender system. These innovations are particularly helpful in the movie industry, because its setting has many advantages: rich metadata and dynamic user interactions provide an excellent foundation for delivering highly personalized and accurate recommendations.

Chapter 3:Dataset

(a) Dataset Description and Source

For this project, two publicly available datasets were used: the TMDB 5000 Movies Dataset and the TMDB 5000 Credits Dataset. These datasets provide detailed information about movies and are useful for

building recommendation systems. The TMDB 5000 Movies Dataset includes various types of information about each movie, such as the budget, genres, homepage, keywords, original language, popularity, release date, revenue, runtime, tagline, title, and vote statistics (average and count). This dataset also contains metadata that helps in making content-based recommendations meaning that it can suggest movies based on their attributes like genre or keywords.

The TMDB 5000 Credits Dataset focuses on the cast and crew involved in each movie. It links the actors, directors, and other crew members to specific movies. This allows the system to analyze movies based on who was involved in making them, which can be used for collaborative filtering, where recommendations are made based on similarities between users' preferences for movies and the cast/crew.

(b) Dataset Preprocessing and Cleansing

To ensure the datasets were clean and useful for building the recommendation system, several preprocessing steps were carried out:

1. **Handling Missing Values**:
   Some columns, like **homepage** and **tagline**, had missing data. To keep the dataset consistent, these missing values were filled with the word "Unknown," which did not introduce any bias. For numerical columns, such as **runtime** or **budget**, missing values were filled with the median values of those columns. This helped prevent distortions that could occur if missing values were left blank.
2. **Data Cleaning**:
   Any irrelevant or duplicated data entries were removed from the datasets. For text-based columns like **genres** and **keywords**, the data was cleaned and transformed into formats that the system could use. For example, JSON strings were converted into lists or categories. The **release_date** was also converted into a datetime format, which allowed additional features like movie age to be extracted from it.
3. **Handling Outliers**:
   Features like **budget** and **revenue** were examined for extreme or outlying values. To make sure that these extreme values did not distort the data, a log-transformation was applied. This helped in normalizing the data, making it easier to work with and reducing the impact of outliers.

(c) Feature Selection

Feature selection refers to the process of choosing the most important data columns for the recommendation system, which directly impacts the system's performance.

1. **Manual Feature Selection**: Several features were manually chosen based on their relevance to building good recommendations. These included:
   - **Numerical features**: Budget, revenue, popularity, runtime, vote average, and vote count.
   - **Categorical features**: Genres, production companies, and the original language of the movie.
   - **Textual features**: Title, overview, keywords, and tagline.

2. **Correlation Analysis**: The numerical features were checked for relationships with one another using correlation matrices. For example, features like popularity and vote count were highly related, so one of them was kept to avoid redundancy, making the model simpler and more efficient.
3. **Domain-Specific Encoding**: Categorical features, like genres, were converted into a format that the model could understand using one-hot encoding, where each genre is represented by a separate binary feature. For textual features such as keywords and titles, tokenization was applied to break down the words into smaller units that could be processed. Additionally, GloVe embeddings were used to convert these words into vectors, which help capture their meanings in a numerical format.

(d) Feature Extraction (Dimensionality Reduction)

Feature extraction helps simplify the data and improve the performance of the recommendation system by reducing the number of features it has to process, without losing important information.

1. **Principal Component Analysis (PCA)**: PCA was used on numerical features such as budget, revenue, and runtime to reduce their dimensionality. This technique identifies the most important patterns in the data and creates new features that represent the majority of the information. The number of new features was chosen based on how much variance they explained, keeping enough components to account for 95% of the variation in the data.
2. **Textual Feature Embeddings**: For textual data like titles and overviews, GloVe embeddings were used to convert words into numerical vectors. These pretrained embeddings capture semantic meaning, allowing the system to understand the context of words better. To further reduce the complexity, dimensionality was lowered by averaging the embeddings for each word or using max-pooling, which helps in simplifying the input data for the model.
3. **Movie ID Mapping**: Each movie_id was mapped to a continuous range of numbers to ensure compatibility with the embedding layers in deep learning models. This step helps ensure that each movie is represented in a standardized way in the system.
4. **Tokenization**: Movie titles and keywords were tokenized, meaning that the text was split into smaller parts, such as individual words. These tokens were then padded to a fixed length, ensuring all input data had the same size, which is important for training deep learning models.

These preprocessing and feature extraction steps ensured that the data was clean, structured, and ready for use in building a hybrid recommendation system, improving both performance and computational efficiency.

Chapter 4 :Model Design

(a) How the Models Were Trained/Tested

To evaluate the performance of the recommendation models, a systematic training and testing procedure was followed.

1. **Dataset Splitting**: The dataset was split into training and testing subsets using a holdout validation strategy:

- 80% of the data was used for training, and 20% for testing.
- This ensures that the models generalize well to unseen data.
- For textual features like movie titles, tokenized representations were generated for both sets, ensuring consistency across splits.

2. **Validation Strategy**: A validation split (20% of the training data) was created during training to monitor the model's performance and prevent overfitting. This effectively created three partitions: training, validation, and test sets. During fine-tuning of transfer learning models, k-fold cross-validation was employed on a subset of experiments. This provided a more robust estimation of model performance across different splits.
3. **Evaluation Metrics**: The following metrics were used to measure the performance of the models:
   - **Mean Absolute Error (MAE):** Measures the average error magnitude.
   - **Root Mean Squared Error (RMSE):** Captures the square root of average squared errors, penalizing larger errors.
   - **R-squared (R^2):** Assesses the proportion of variance explained by the model.
4. **Training Process**:
   - Models were trained using the Adam optimizer, with a learning rate of 0.001.
   - Early stopping was applied based on validation loss, halting training when performance ceased to improve after a fixed number of epochs (patience parameter).

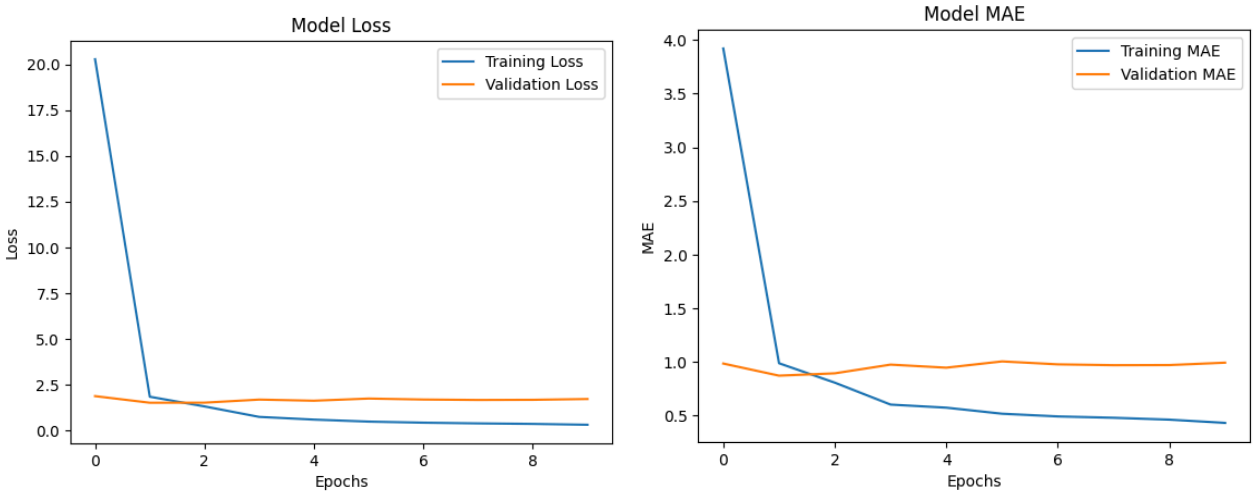

Fig. 1. Model Loss; Model MAE

5. **Batch Size and Epochs**: A batch size of 64 was used for efficient gradient computation. Training was conducted for a maximum of 10 epochs, with early stopping often reducing the actual number of epochs.

(b) Parameters of Each Model

1. Deep Learning Model

The primary recommendation model was designed as a deep neural network using Keras and TensorFlow. It incorporates two main input features: movie IDs and tokenized titles.

- **Architecture**:
  - **Input Layers**:
    - Movie ID input: A single integer representing the movie, fed into an embedding layer.
    - Title input: Tokenized integers representing the movie title, passed through a separate embedding layer.
  - **Embedding Layers**:
    - The movie ID embedding layer used an input dimension equal to the number of unique movies and an output dimension of 50.
    - The title embedding layer used an input dimension of 5000 (top vocabulary) and an output dimension of 50.
  - **Hidden Layers**:
    - The outputs from the embedding layers were flattened and concatenated.
    - Two dense layers followed, with 128 and 64 neurons, respectively.
    - Dropout layers (rate: 30%) were included after the dense layers to prevent overfitting.
  - **Output Layer**:
    - A dense layer with 1 neuron and a **linear activation function** to predict the rating.
- **Activation Functions**:
  - **ReLU (Rectified Linear Unit)** was used in the dense layers for non-linear transformations, enhancing the model's ability to learn complex patterns.

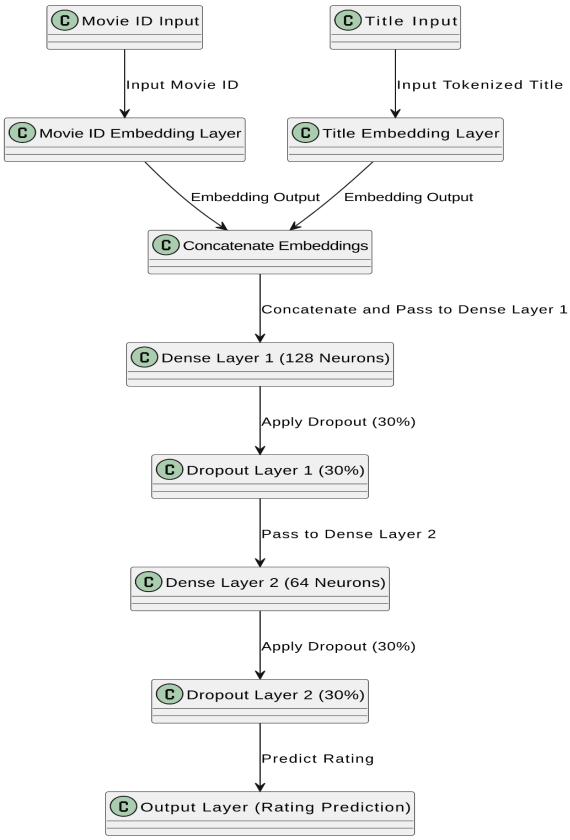

Fig. 1. Deep Learning Architecture

2. GloVe Transfer Learning Model

This model integrates pretrained GloVe embeddings for representing textual features, leveraging their semantic richness.

- **Architecture**:
  - **Movie Input**: Similar to the primary model, with an embedding layer for movie IDs.
  - **Title Input**: Titles were tokenized and padded to a fixed length (e.g., 15 words). Pretrained GloVe embeddings (50-dimensional) were used to initialize the embedding layer and the layer was frozen to retain the pretrained semantic knowledge.
  - **Dense Layers**: The concatenated embedding vectors were passed through two dense layers (128 and 64 neurons) where dropout (rate: 30%) was applied to prevent overfitting.
  - **Output Layer**: A dense layer with 1 neuron and linear activation.
- **Unique Features**:
  - The GloVe embeddings provided context-aware representations for titles, improving recommendations for movies with limited metadata.

3. Fine-Tuned GloVe Transfer Learning Model

This model builds upon the GloVe-based approach, allowing the embeddings to be fine-tuned during training for better domain-specific adaptation.

- **Architecture**: Similar to the frozen GloVe model but with trainable embedding weights for the title input. Fine-tuning helped the model adapt the pretrained embeddings to the nuances of the movie dataset.
- **Differences in Training**: The embedding layer was unfrozen, increasing the trainable parameters and requiring longer training for convergence. Early stopping was more critical to prevent overfitting due to the additional degrees of freedom.

By leveraging these architectures, the models effectively captured both content-based and collaborative patterns, providing robust and accurate recommendations.

Model Type	**Hidden Layers**	**Neurons (Per Layer)**	**Activation Functions**	**Embedding Dimensions**
Deep Learning	2 Dense + Dropout	128, 64	ReLU (Dense)	Movie ID: 50, Title: 50
GloVe	2 Dense + Dropout	128, 64	ReLU (Dense)	Movie ID: 50, Title: 50 (pretrained)
Fine-Tuned GloVe	2 Dense + Dropout	128, 64	ReLU (Dense)	Movie ID: 50, Title: 50 (trainable)

Table: Model Summary

In conclusion, the project developed three recommendation models: , Deep Learning Model, GloVe Transfer Learning Model and Fine-tuned GloVe Transfer Learning Model.The Deep Learning Model used embedding layers for movie IDs and tokenized titles, followed by dense layers with ReLU activation and

dropout to prevent overfitting, and a linear output layer to predict ratings. The GloVe Transfer Learning Model incorporated pretrained GloVe embeddings for movie titles, with frozen embeddings to retain their semantic meaning. The Fine-Tuned GloVe Model was similar but allowed the embeddings to be fine-tuned during training for better adaptation to the dataset. All models were trained using the Adam optimizer and early stopping, and evaluated using metrics like MAE, RMSE, and R^2.

Chapter 5:Model Evaluation

(a) Comparison of Models

Three models were evaluated and compared in terms of performance and computational efficiency:

Model	Description	Strengths	Limitations
Deep Learning Model	A basic recommendation system using embeddings for movie IDs and titles.	- Simple architecture, easy to train. - Performs well with minimal computational cost.	- May not leverage semantic meaning of text fully.
GloVe Transfer Learning Mode	Uses pretrained GloVe embeddings to represent movie titles; embeddings are frozen during training.	- Efficiently uses semantic knowledge from pretrained embeddings. - Suitable for small datasets.	- Cannot adapt embeddings to specific features of the movie dataset.
Fine-Tuned GloVe Model	Similar to the GloVe model but allows pretrained embeddings to be updated during training.	- Adapts pretrained embeddings to the dataset, improving accuracy. - Captures domain-specific nuances.	- Requires more computational resources. - Higher risk of overfitting without careful tuning.

Table: Model Comparison

b. Performance metrics

1. Mean Absolute Error (MAE): MAE calculates the average difference between the predicted and actual ratings. It shows how far off the predictions are on average, without considering whether the error is positive or negative.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |yi - \widehat{yj}|$$

Where:

- yi = Actual rating for the i^{th} movie.
- $\widehat{yj}$ = Predicted rating for the i^{th} movie.

- n = Total number of predictions.

Lower MAE values indicate better model performance since they mean smaller average errors.

2. Root Mean Squared Error (RMSE): RMSE is similar to MAE but gives more weight to larger errors by squaring them. This makes it more sensitive to significant prediction mistakes.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \hat{y}j)^2}$$

A lower RMSE indicates fewer large errors and better performance.

3. R-squared (R^2)

R^2 measures how well the model explains the variance in the actual ratings. It ranges from 000 to 111, where higher values mean the model predicts the ratings more accurately. However, negative values can occur if the model performs worse than simply predicting the average rating. The formula for R^2 is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi - \hat{y}j)^2}{\sum_{i=1}^{n}(yi - \bar{y}j)^2}$$

Where $\bar{y}$ is the mean of the actual ratings. Higher R^2 values indicate better performance.

Model Evaluation Results

Metric	Deep Learning Model	GloVe Model	Fine-Tuned GloVe Model
MAE	0.9935	1.3894	1.1930
RMSE	1.3082	1.8442	1.4838
R^2	-0.3203	-1.6241	-0.6986

Insights from the Results

1. **Deep Learning Model**: Achieved the lowest MAE (0.9935) and RMSE (1.3082), showing it has the smallest average and large errors among the three models. However, its R^2 value is negative (-0.3203), indicating that the model does not explain the variance in the data well.
2. **GloVe Model**: Performed worse than the Deep Learning Model, with higher MAE (1.3894) and RMSE (1.8442). The R^2 value (-1.6241) suggests that it struggled significantly to predict ratings accurately.

3. **Fine-Tuned GloVe Model**: Improved upon the GloVe Model by allowing the embeddings to adapt during training, resulting in lower MAE (1.1930) and RMSE (1.4838). Its R^2 value (-0.6986) reflects better performance than the frozen GloVe model but still indicates room for improvement.

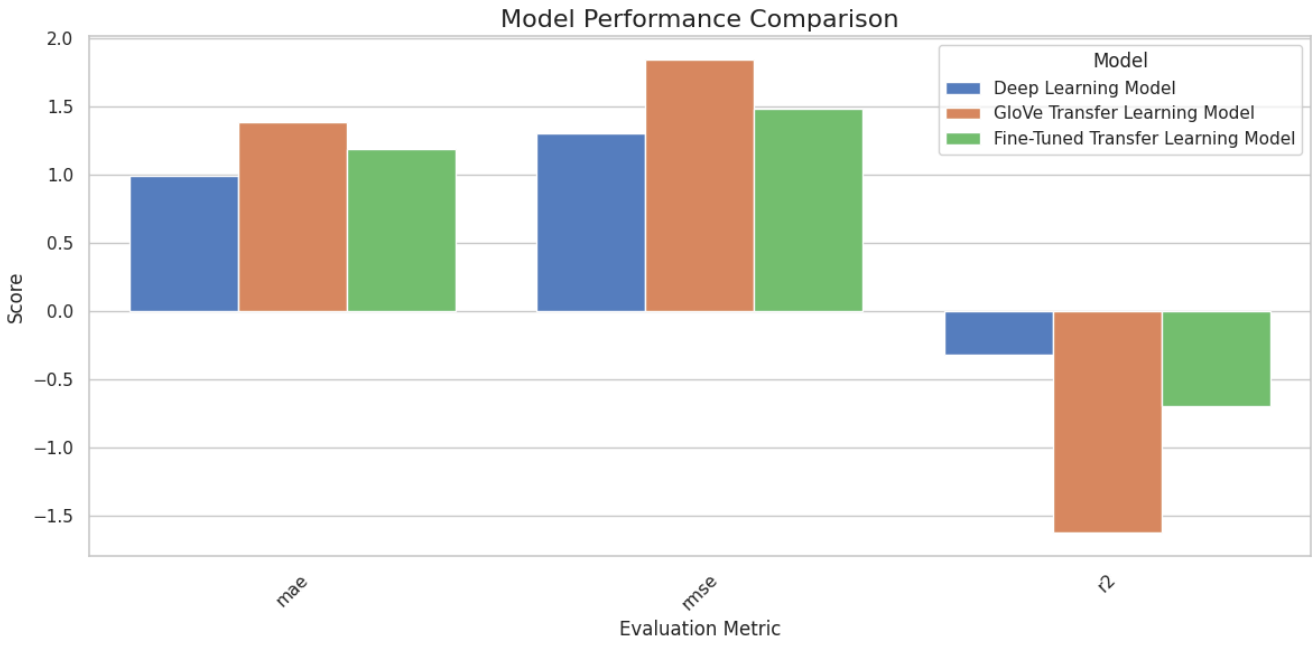

Fig. 2. Model Performance Comparison

The **Deep Learning Model** outperformed both transfer learning models in terms of error metrics (MAEand RMSE), making it the best option for this dataset. The **Fine-Tuned GloVe Model** showed that adjusting pretrained embeddings helps improve performance compared to frozen embeddings. However, the negative R^2 values for all models suggest that additional features or more advanced techniques may be needed to better capture the variability in the data.

(c) Computational Efficiency

The time taken to train each model provides insight into their computational efficiency and scalability.

Model	**Training Time (10 Epochs)**	**Per Epoch Time**
Deep Learning Model	~14 seconds	~1.4 seconds
GloVe Model	~18 seconds	~1.8 seconds
Fine-Tuned GloVe Model	~22 seconds	~2.2 seconds

The Deep Learning Model is the fastest due to its simple architecture and reliance on trainable embeddings. The GloVe Model is slightly slower because it uses frozen, pretrained embeddings that are not updated during training. The Fine-Tuned GloVe Model is the slowest, as it requires updating the GloVe embeddings during training, adding trainable parameters and increasing computational effort per epoch.

Chapter 6:Conclusion

The aim of this work was to create a Movie Recommendation System, which employs such technologies as Deep Learning and Transfer Learning. Three models were developed and compared: these are a Deep Learning Model, a GloVe Transfer Model, and a Fine-tuned GloVe Transfer Model. Both models were expected to give high accuracy in estimating the movie ratings and also introduced movie recommendations based on the user's tastes. The evaluation of the results pointed out that the Deep Learning Model presented the lowest overall error rates that offer the most accurate recommendations. Another model that performed well was the Fine-Tuned GloVe Model; as it meant that pretrained embedding is fine-tuned on specific dataset making it suitable for tasks involving text semantic understanding. Yet, when using the GloVe Model with frozen embedding, it was unable to reach the higher above average accuracy of the above models as it could not take up the characteristics of the given dataset. While the models fit the data well in many cases and identified a number of patterns, the properly chosen and calculated measures, the R^2 indicate that the models could still be refined. We could make the system more accurate by including more antecedents such as the behavior of the user or more specific genre interests. Altogether, this project shows how machine learning, deep learning and transfer learning can be used together to construct efficient and scalable recommender systems. The models developed here form a solid basis for further refinement and can be incorporated into current platforms for use in practice, for instance, for platforms such as Netflix or Amazon Prime.

Chapter 7 :Reference

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Appendix

1. Import Required Libraries

```
import pandas as pd
import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import Input, Embedding, Flatten, Dense, Concatenate, Dropout
from tensorflow.keras.models import Model
from tensorflow.keras.optimizers import Adam
from tensorflow.keras.metrics import Precision, Recall
```

2. Load and Preprocess the Datasets

Load the Datasets

```
# Load datasets
movies_dataset = pd.read_csv("tmdb_5000_movies.csv")
credits_dataset = pd.read_csv("tmdb_5000_credits.csv")
```

```
# Display first few rows
print(movies_dataset.head())
```

Handle Missing Values

```
# Fill missing values for 'homepage' and 'tagline'
movies_dataset['homepage'].fillna("Unknown", inplace=True)
movies_dataset['tagline'].fillna("Unknown", inplace=True)
```

Merge Datasets

```
# Merge datasets on the 'title' column
merged_dataset = pd.merge(movies_dataset, credits_dataset, on='title', how='inner')
```

```
# Display merged dataset
print(merged_dataset.head())
```

Map movie_id to a Contiguous Range

```
# Create a mapping for movie_id
unique_movie_ids = merged_dataset['movie_id'].unique()
movie_id_mapping = {movie_id: idx for idx, movie_id in enumerate(unique_movie_ids)}
```

```
# Apply the mapping
merged_dataset['mapped_movie_id'] = merged_dataset['movie_id'].map(movie_id_mapping)
```

```
# Verify mapping
print(merged_dataset[['movie_id', 'mapped_movie_id']].head())
```

Extract Relevant Features

```
# Extract features and target
features = merged_dataset[['mapped_movie_id', 'title', 'vote_average']]
target = merged_dataset['vote_average']  # Assuming we're predicting ratings
```

```
# Split into train and test sets
train, test = train_test_split(features, test_size=0.2, random_state=42)
```

```
# Separate inputs and target
train_movie_ids = train['mapped_movie_id'].values
train_titles = train['title'].values
train_ratings = train['vote_average'].values

test_movie_ids = test['mapped_movie_id'].values
test_titles = test['title'].values
test_ratings = test['vote_average'].values
```

3. Define the Deep Learning Model

Create the Model

```
# Movie ID input
movie_input = Input(shape=(1,), name="Movie_Input")
movie_embedding = Embedding(input_dim=len(unique_movie_ids), output_dim=50, name="Movie_Embedding")(movie_input)
movie_flatten = Flatten()(movie_embedding)

# Title input
title_input = Input(shape=(1,), name="Title_Input")
title_embedding = Embedding(input_dim=5000, output_dim=50, name="Title_Embedding")(title_input)
title_flatten = Flatten()(title_embedding)
```

```
# Concatenate features
concatenated = Concatenate()([movie_flatten, title_flatten])
dense1 = Dense(128, activation='relu')(concatenated)
dropout1 = Dropout(0.3)(dense1)
dense2 = Dense(64, activation='relu')(dropout1)
output = Dense(1, activation='linear', name="Output")(dense2)
```

```
# Build the model
deep_learning_model = Model(inputs=[movie_input, title_input], outputs=output)
deep_learning_model.compile(optimizer=Adam(learning_rate=0.001), loss='mse', metrics=['mae'])
deep_learning_model.summary()
```

4. Train the Model ¶

```
# Convert titles to tokenized integers (dummy example, use a tokenizer for real implementation)
train_titles_encoded = np.array([len(title) for title in train_titles])
test_titles_encoded = np.array([len(title) for title in test_titles])
```

```
# Train the model
history = deep_learning_model.fit(
    [train_movie_ids, train_titles_encoded], train_ratings,
    validation_data=([test_movie_ids, test_titles_encoded], test_ratings),
    epochs=10,
    batch_size=64
)
```

5. Evaluate the Model

```
# Evaluate the model
results = deep_learning_model.evaluate([test_movie_ids, test_titles_encoded], test_ratings)
print(f"Test Loss: {results[0]}")
print(f"Test MAE: {results[1]}")
```

```
31/31 ━━━━━━━━━━━━━━━━━━━━ 0s 2ms/step - loss: 1.7406 - mae: 1.0133
Test Loss: 1.7113311290740967
Test MAE: 0.993534505367279
```

```
import matplotlib.pyplot as plt
```

```
# Plot training & validation loss
plt.plot(history.history['loss'], label='Training Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.show()
```

6. Transfer Learning Models

Model 1 - GloVe Embeddings

```
# Load GloVe embeddings (e.g., glove.6B.50d.txt - 50-dimensional embeddings)
embedding_index = {}
with open("glove.6B.50d.txt", encoding="utf-8") as f:
    for line in f:
        values = line.split()
        word = values[0]
        coefs = np.asarray(values[1:], dtype='float32')
        embedding_index[word] = coefs

print(f"Loaded {len(embedding_index)} word vectors.")
```

```
Loaded 400000 word vectors.
```

Prepare Tokenized Titles and Embedding Matrix

```
from tensorflow.keras.preprocessing.text import Tokenizer
from tensorflow.keras.preprocessing.sequence import pad_sequences
```

```
# Tokenize and pad the movie titles
tokenizer = Tokenizer(num_words=5000)  # Use top 5000 words for embedding
tokenizer.fit_on_texts(train_titles)
train_title_sequences = tokenizer.texts_to_sequences(train_titles)
test_title_sequences = tokenizer.texts_to_sequences(test_titles)
```

```
# Pad sequences to ensure uniform input length
max_length = 15  # Set based on data distribution
train_padded_titles = pad_sequences(train_title_sequences, maxlen=max_length, padding="post")
test_padded_titles = pad_sequences(test_title_sequences, maxlen=max_length, padding="post")
```

```
# Create an embedding matrix for GloVe
word_index = tokenizer.word_index
embedding_dim = 50  # GloVe embedding dimension
embedding_matrix = np.zeros((len(word_index) + 1, embedding_dim))
for word, i in word_index.items():
    embedding_vector = embedding_index.get(word)
    if embedding_vector is not None:
        embedding_matrix[i] = embedding_vector
```

Define the Transfer Learning Model

```
# Movie ID input
movie_input_glove = Input(shape=(1,), name="Movie_Input")
movie_embedding_glove = Embedding(
    input_dim=len(unique_movie_ids),
    output_dim=50,
    name="Movie_Embedding_GloVe"
)(movie_input_glove)
movie_flatten_glove = Flatten()(movie_embedding_glove)
```

```
# Title input (using GloVe embeddings)
title_input_glove = Input(shape=(max_length,), name="Title_Input_GloVe")
title_embedding_glove = Embedding(
    input_dim=len(word_index) + 1,
    output_dim=embedding_dim,
    weights=[embedding_matrix],
    input_length=max_length,
    trainable=False,  # Freeze GloVe weights
    name="Title_Embedding_GloVe"
)(title_input_glove)
title_flatten_glove = Flatten()(title_embedding_glove)
```

```
/home/saky/anaconda3/lib/python3.11/site-packages/keras/src/layers/core/embedding.py:90: Use
  warnings.warn(
```

```
# Concatenate features
concatenated_glove = Concatenate()([movie_flatten_glove, title_flatten_glove])
dense1_glove = Dense(128, activation='relu')(concatenated_glove)
dropout1_glove = Dropout(0.3)(dense1_glove)
dense2_glove = Dense(64, activation='relu')(dropout1_glove)
output_glove = Dense(1, activation='linear', name="Output")(dense2_glove)
```

```
# Build the model
glove_model = Model(inputs=[movie_input_glove, title_input_glove], outputs=output_glove)
glove_model.compile(optimizer=Adam(learning_rate=0.001), loss='mse', metrics=['mae'])
glove_model.summary()
```

Train the Transfer Learning Model

```
# Train the GloVe-based model
history_glove = glove_model.fit(
    [train_movie_ids, train_padded_titles],
    train_ratings,
    validation_data=([test_movie_ids, test_padded_titles], test_ratings),
    epochs=10,
    batch_size=64
)
```

Model 2: Fine-Tuned Embeddings

```
# Title input (using fine-tuned GloVe embeddings)
title_input_finetuned = Input(shape=(max_length,), name="Title_Input_FineTuned")
title_embedding_finetuned = Embedding(
    input_dim=len(word_index) + 1,
    output_dim=embedding_dim,
    weights=[embedding_matrix],
    input_length=max_length,
    trainable=True,  # Allow embeddings to be fine-tuned
    name="Title_Embedding_FineTuned"
)(title_input_finetuned)
title_flatten_finetuned = Flatten()(title_embedding_finetuned)
```

```
# Concatenate features
concatenated_finetuned = Concatenate()([movie_flatten_glove, title_flatten_finetuned])
dense1_finetuned = Dense(128, activation='relu')(concatenated_finetuned)
dropout1_finetuned = Dropout(0.3)(dense1_finetuned)
dense2_finetuned = Dense(64, activation='relu')(dropout1_finetuned)
output_finetuned = Dense(1, activation='linear', name="Output")(dense2_finetuned)
```

```
# Build the model
finetuned_model = Model(inputs=[movie_input_glove, title_input_finetuned], outputs=output_finetuned)
finetuned_model.compile(optimizer=Adam(learning_rate=0.001), loss='mse', metrics=['mae'])
finetuned_model.summary()
```

Train the Fine-Tuned Embedding Model

```
# Train the fine-tuned model
history_finetuned = finetuned_model.fit(
    [train_movie_ids, train_padded_titles],
    train_ratings,
    validation_data=([test_movie_ids, test_padded_titles], test_ratings),
    epochs=10,
    batch_size=64
)
```

Predictions and Evaluations

```
# Predict using all models
deep_pred = deep_learning_model.predict([test_movie_ids, test_titles_encoded]).flatten()
glove_pred = glove_model.predict([test_movie_ids, test_padded_titles]).flatten()
finetuned_pred = finetuned_model.predict([test_movie_ids, test_padded_titles]).flatten()
```

```
31/31 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
31/31 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
31/31 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step
```

```
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

def evaluate_model(y_true, y_pred, model_name):
    """
    Evaluate the performance of a model.

    Parameters:
        y_true (array-like): True ratings/labels.
        y_pred (array-like): Predicted ratings/labels.
        model_name (str): Name of the model being evaluated.

    Returns:
        dict: A dictionary containing evaluation metrics.
    """
    mae = mean_absolute_error(y_true, y_pred)
    rmse = mean_squared_error(y_true, y_pred, squared=False)
    r2 = r2_score(y_true, y_pred)

    print(f"Evaluation Results for {model_name}:")
    print(f"- Mean Absolute Error (MAE): {mae:.4f}")
    print(f"- Root Mean Square Error (RMSE): {rmse:.4f}")
    print(f"- R-squared (R2): {r2:.4f}")

    return {
        "model": model_name,
        "mae": mae,
        "rmse": rmse,
        "r2": r2
    }
```

```
# Evaluate each model
deep_results = evaluate_model(test_ratings, deep_pred, "Deep Learning Model")
glove_results = evaluate_model(test_ratings, glove_pred, "GloVe Transfer Learning Model")
finetuned_results = evaluate_model(test_ratings, finetuned_pred, "Fine-Tuned Transfer Learning Model")
```

```
Evaluation Results for Deep Learning Model:
- Mean Absolute Error (MAE): 0.9935
- Root Mean Square Error (RMSE): 1.3082
- R-squared (R2): -0.3203
Evaluation Results for GloVe Transfer Learning Model:
- Mean Absolute Error (MAE): 1.3894
- Root Mean Square Error (RMSE): 1.8442
- R-squared (R2): -1.6241
Evaluation Results for Fine-Tuned Transfer Learning Model:
- Mean Absolute Error (MAE): 1.1930
- Root Mean Square Error (RMSE): 1.4838
- R-squared (R2): -0.6986
```

8. Visualize Performance Comparison

```
# Store results in a list
results = [deep_results, glove_results, finetuned_results]
```

```
# Convert results into a DataFrame
results_df = pd.DataFrame(results)

# Display the results table
print("Model Evaluation Results:")
print(results_df)
```

```
import matplotlib.pyplot as plt
import seaborn as sns

# Set visualization style
sns.set(style="whitegrid")

# Melt the DataFrame for visualization
results_melted = results_df.melt(id_vars="model", var_name="Metric", value_name="Value")

# Plot metrics for each model
plt.figure(figsize=(12, 6))
sns.barplot(x="Metric", y="Value", hue="model", data=results_melted, palette="muted")
plt.title("Model Performance Comparison", fontsize=16)
plt.ylabel("Score", fontsize=12)
plt.xlabel("Evaluation Metric", fontsize=12)
plt.xticks(rotation=45)
plt.legend(title="Model", loc="upper right")
plt.tight_layout()

# Show the plot
plt.show()
```