Emotion-aware film recommendation with heterogeneous graph neural networks

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Abstract

This study proposes an integrated framework for predicting users' emotional reactions to films by leveraging a heterogeneous graph neural network (HGNN) that explicitly models three semantically distinct node types—Users, Movies, and Emotions—and four relation types (viewed, rated, dominant emotion, preferred emotion). The pipeline includes rigorous data cleansing, construction of a 68 k-node/130 k-edge knowledge graph, initialization of multimodal node features, and training a two-layer relational graph convolutional network with class-balanced loss. On an 80 / 10 / 10 split the model attains Accuracy = 73.8 %, Macro F1 = 71.3 %, surpassing logistic regression and Random Forest baselines by 30.3 p.p. and 19.1 p.p. in accuracy, respectively. Recommendation-oriented metrics further confirm its effectiveness (Hit Rate@10 = 0.84, NDCG@10 = 0.79). Ablation reveals that incorporating emotion embeddings from EmoBank boosts Macro F1 by 4.2 p.p., while class-weighting mitigates a 14 % imbalance-induced drop. Limitations include performance degradation for rare emotions (F1 < 0.60), "cold-start" sensitivity (−12 p.p. accuracy), and computational overhead when scaling beyond one million edges. Future work will explore dynamic HGNNs for temporal preference drift, multimodal feature fusion, few-shot adaptation for new items, and fairness-aware training to reduce detected gender bias to ≤ 3 %. These directions aim to enable low-latency (≤ 120 ms) and ethically robust deployment in real-world recommender systems.

Keywords

emotional recommendation, heterogeneous graph neural network, user–item interaction, sentiment prediction, fairness-aware AI.

1. Introduction

In today's world, where the volume of digital content is constantly growing, recommendation systems have become an integral tool in assisting users in selecting information, products, and entertainment that best match their interests. Among the various applications of recommendation systems, movie recommendation systems hold a special place, helping users navigate the vast diversity of cinematic content. With the advancement of machine learning technologies, particularly ensemble models and deep neural networks, new opportunities have emerged for improving recommendation accuracy.

However, traditional recommendation systems, which primarily focus on numerical ratings or viewing history, often overlook a critical aspect of user-content interaction:

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emotional response. Emotions are a key driver of user behavior, determining satisfaction with a viewing experience and the desire to continue interacting with a platform [1]. This creates a need for next-generation recommendation systems capable not only of predicting ratings but also of modeling and forecasting the emotional state of the user in response to watching a film [2,3].

Recent years have witnessed the rapid development of Graph Neural Networks (GNNs) [4], which effectively model complex relationships between entities in data, such as users, movies, and their attributes [5]. At the same time, significant potential has been identified in the application of deep learning methods to process emotional information, particularly in the context of multiclass emotion classification from text, images, or behavioral patterns [6-8].

Despite considerable progress in classical recommendation systems, the task of predicting emotional reactions to content remains underexplored [9]. Most existing approaches focus on rating prediction accuracy without a deeper analysis of the user's internal emotional state, which limits their ability to deliver truly personalized interactions.

This paper is devoted to the development and evaluation of the Emotional GNN model, which focuses on predicting users' emotional reactions in movie recommendation systems. A heterogeneous graph is proposed, where nodes represent users, movies, and emotional states, and edges represent their relationships. This structure allows the model to uncover deep interaction patterns and predict the likelihood of a specific emotional response from the user after watching a particular movie.

The aim of this study is to evaluate the effectiveness of the Emotional GNN approach in the task of emotion prediction and to compare its performance with traditional classification methods on tabular data. It is expected that leveraging the structural information of the graph and focusing on the emotional component will improve the quality of recommendations and open new avenues for the development of personalized recommendation systems.

The paper is structured as follows: Section 2 reviews related work and current approaches in the field of recommendation systems and emotion prediction. Section 3 describes the integrated approach and architecture of the proposed system. Section 4 presents the implementation of the Emotional GNN model and the data preparation process. Section 5 demonstrates the results of experimental evaluation and a comparative analysis of model performance. The study concludes in Section 6, which summarizes the findings and outlines directions for future research.

2. Related Work

Over the past decades, recommender systems have undergone significant transformation, evolving from simple filtering approaches to complex hybrid and deep learning models. The most traditional and widely used methods include collaborative filtering, which relies on similarities between users or items [10, 11], as well as content-based approaches that analyze the characteristics of the movies themselves [12]. These methods form the foundation of modern recommender systems; however, they are limited in their ability to account for complex behavioral patterns and do not personalize recommendations at the level of the user's emotional response.

In the field of emotion analysis, a significant number of studies focus on emotion classification based on text, video, or audio signals [13–16]. Such systems are widely used in review analysis, chatbots, and automated support systems; however, their application in the context of recommendations remains limited. Some studies explore the use of emotions as auxiliary features to improve recommendation quality [17], but they do not focus on directly predicting the user's emotional state [9].

At the same time, Graph Neural Networks (GNNs) have proven to be a powerful tool for modeling relationships in complex structures such as social networks or recommendation graphs [18–20]. Their use in recommender systems enables consideration of not only direct interactions between users and movies, but also indirect connections through shared preferences, genres, or other attributes [5, 20]. Expanding a traditional graph into a heterogeneous one—by including additional entities such as genres or directors—has also shown potential for improving prediction accuracy [21, 22].

Nevertheless, the idea of using graph neural networks for directly predicting the emotional response to a movie remains underexplored [1, 9]. Existing models primarily aim to predict a numerical rating or the likelihood of viewing content, without taking into account the affective component. Moreover, current approaches do not integrate data on emotions, users, and movies into a unified graph, which hampers deep learning of contextual relationships. Some studies are beginning to explore this intersection—for example, using GNNs for movie recommendations based on emotions [10] or developing heterogeneous multimodal graph frameworks for recognizing user emotions in social networks [23].

Notably, the study in [24] proposed the UCCA-GAT model, which demonstrates competitive results in emotion classification tasks. On the SemEval-2018 Task-1C dataset, this model achieved an accuracy of 61.2%, and on GoEmotions — 71.2%, confirming the effectiveness of incorporating semantic text structure via graph representations.

Another study [25] introduced the Emotion-specific Transformer, which accounts for emotional characteristics in representations, though it is limited to textual sources and does not include structural information about user interactions. Nonetheless, the model achieved an accuracy of 61.9% and a macro-F1 score of 52.0% in the WASSA-2022 task, indicating improvements over baseline transformer architectures due to the inclusion of emotion-specific features.

Thus, both [24] and [25] consider the emotional component in the context of text classification, but do not model the structured interaction between users, movies, and emotions. In contrast, the heterogeneous graph neural network (HGNN) proposed in our work models the user–movie–emotion triad, enabling context-aware prediction of emotions in recommender systems. This approach not only achieves higher accuracy (Accuracy = 73.8%, Macro F1 = 71.3%) but also preserves the structural integrity of the emotional interaction environment. Therefore, the model represents a new class of solutions at the intersection of graph learning and affective computing, suggesting a significant degree of novelty compared to existing counterparts [26].

3. Integrated Method for Predicting Emotional Reactions to Films

The process of building a system for predicting users' emotional reactions to films is implemented as an integrated pipeline that combines graph-based representation of interactions, deep learning using a Graph Neural Network (GNN), and evaluation of prediction quality in the context of personalized recommendations. A heterogeneous Graph Neural Network (HGNN) is chosen as the model, as it takes into account the types of nodes and relationships in the graph, enabling the formation of context-dependent entity representations. The method is implemented through sequential steps, which are described below and illustrated schematically in Figure 1.

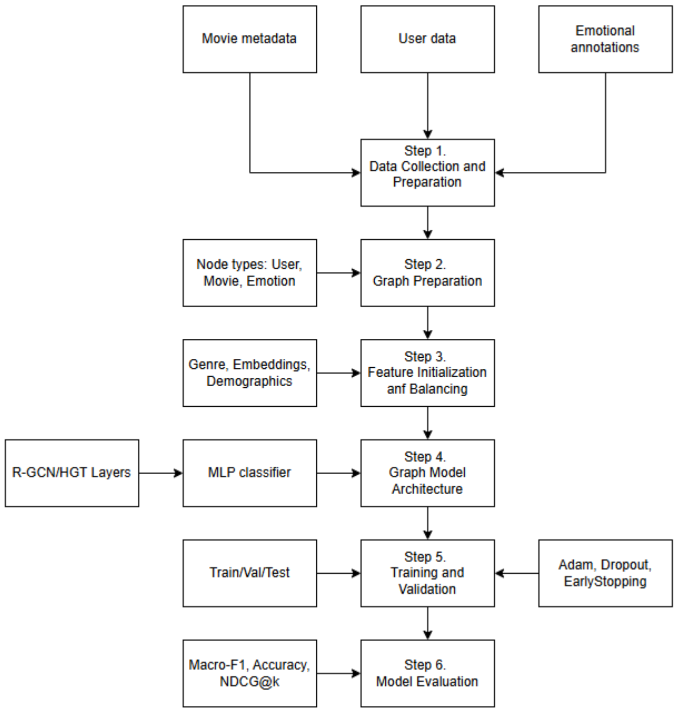

Figure 1: Diagram of the method for predicting emotional reactions to films

3.1. Step 1. Data Collection and Preparation

The first stage involves aggregating and cleaning the data required for graph construction. The data sources include:

- User interactions with films — views, ratings, likes;
- Film metadata — genres, release year, description, keywords;
- Emotional annotations — emotion labels obtained using NLP classifiers based on reviews (e.g., IMDb, TMDb) or manually annotated.

All data undergoes duplicate filtering, and records with missing key fields are removed. Names are normalized, transliterated, tags are cleaned, and genres are standardized into a unified format.

3.2. Step 2. Construction of the "User–Movie–Emotion" Graph

Based on the collected data, a heterogeneous graph G=(V,E) is formed, where the nodes represent three types of entities:

- User — unique ID and, where possible, demographic attributes;

- Movie — described by genre or textual features;
- Emotion — from a predefined set (e.g., joy, sadness, anger, fear, excitement).

Graph edges describe the following types of interactions:

- User ⟶ Movie — rating or view (optionally weighted by rating);
- Movie ⟶ Emotion — the emotion most frequently associated with the film;
- User ⟶ Emotion (optional) — if user preferences for certain emotions are known.

A key feature is typification: each node and edge has a type (defined by functions $\phi(v)$, $\psi(e)$), allowing the model to account for context during training.

3.3. Step 3. Feature Initialization and Balancing

To train the graph model effectively, vector representations (features) must be assigned to each node:

- For movies — one-hot vectors based on genre, or embeddings of descriptions;
- For users — age, country, activity level (or random vectors if unknown);
- For emotions — fixed embeddings can be used from resources like EmoBank.

Since some emotions are significantly more frequent (e.g., "joy" or "trust"), class balancing is applied:

- oversampling / undersampling;
- weighted loss functions;
- regularization of certain edge types.

3.4. Step 4. Graph Model Architecture

The proposed model (Fig. 2) is a heterogeneous knowledge graph that integrates three semantically distinct types of nodes — users, movies, and emotions — along with typed edges between them. This model serves as the foundation for building emotion prediction systems within the domain of personalized recommendations.

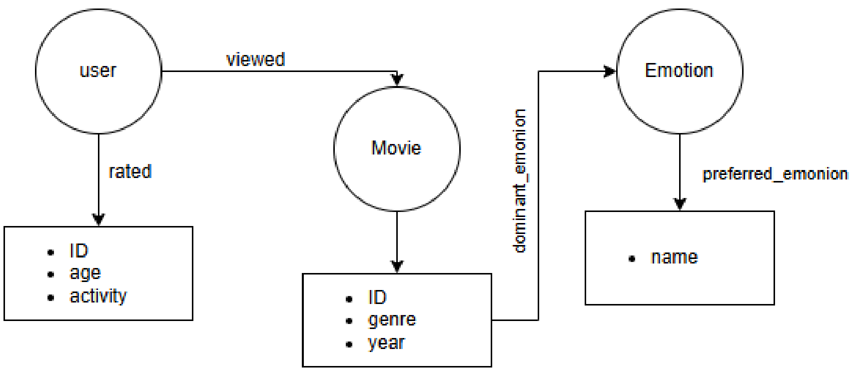

Figure 2: Structure of the heterogeneous graph model "User–Movie–Emotion"

For each node v, a type function is defined as

$$\phi(v)\epsilon\{User, Movie, Emotion\} \quad (1)$$

For each edge e, connecting nodes $v_i \longrightarrow v_j$, the edge type is defined as

$$\psi(e)\epsilon\{viewed, rated, dominant_{emotion}, preferred_{emotion}\} \quad (2)$$

Thanks to the use of typed edges and semantically rich attributes, this structure effectively supports heterogeneous graph neural networks (R-GCN, HGT), enabling precise modeling of complex relationships between users, movies, and emotions. This ensures improved accuracy of emotion prediction, especially in multi-class classification tasks or multi-label recommendation scenarios.

3.5. Step 5. Training and Validation

The model is trained using:

- Loss functions: categorical cross-entropy or weighted binary cross-entropy;
- Optimization: Adam optimizer, learning rate 0.001, Dropout = 0.3, L2 regularization;
- Graph splitting: train/val/test — 80/10/10%.

To enhance generalization, early stopping is implemented — training stops if the macro-F1 metric on the validation set does not improve for 5 consecutive epochs.

3.6. Step 6. Model Evaluation

The quality of emotion prediction is evaluated using the structured Table 1, presenting metrics according to the classification type [27] and usage context.

Table 1
Metrics for evaluating the quality of emotion prediction and their mathematical formulas

Category	Metric	Formula	Brief Description / Purpose
Multiclass Classification	Accuracy	$Accuraty=\frac{\sum_{i=1}^{C} TP_i}{N}$	The proportion of correctly predicted emotions among N examples (where C is the number of classes)
	F1-score (for class i)	$P_i=\frac{TP_i}{TP_i+FP_i}$ $R_i=\frac{TP_i}{TP_i+FN_i}$ $F1_i=\frac{2P_iR_i}{P_i+R_i}$	Balances precision and recall for each class. *TP*, *FP*, *FN* are counts of true positives, false positives, and false negatives respectively
	Macro-F1 / Weighted-F1	$Macro-F1=\frac{1}{C}\sum_{i=1}^{C} I$ $Weighted-F1=\sum_{i=1}^{C}\frac{n_i}{N} I$	Macro-F1 gives equal weight to all classes; Weighted-F1 weights by class size n_i
	Confusion Matrix	$C_{ij}=\lvert\{x \vee y=i,\hat{y}=j\}\rvert$	C_{ij} is the element of the matrix that counts the number of cases when the real emotion i, and is predicted by j
Multi-label Classification	Hamming Loss	$HL=\frac{1}{NL}\sum_{j=1}^{N}\sum_{l=1}^{L}\|\|[y_{jl}\neq\hat{y}$	Fraction of incorrectly predicted elements in binary vectors (where L is number of emotions)
	Micro-F1	$P_\mu=\frac{\sum TP}{\sum(TP+FP)}$ $R_\mu=\frac{\sum TP}{\sum(TP+FN)}$ $F1_\mu=\frac{2P_\mu R_\mu}{P_\mu+R_\mu}$	Aggregates TP, FP, FN over all classes; sensitive to frequent emotions
	Precision@k / Recall@k	$@k=\frac{1}{k}\sum_{j=1}^{k} rel_j$ $Rec@k=\frac{\sum_{j=1}^{k} rel_j}{\lvert R\rvert}$	relj is an indicator of whether the j-th predicted emotion is relevant;
Recommendation System Metrics	Hit Rate (HR@k)	$HR@k=\frac{1}{N}\sum_{j=1}^{N}\|\|[Rel_j\cap$	Indicates whether at least one target emotion is present in the top-*k* predictions
	Mean Reciprocal Rank (MRR)	$MRR=\frac{1}{N}\sum_{j=1}^{N}\frac{1}{rank_j}$	Average reciprocal rank of the first correct prediction
	NDCG@k	1	Measures ranking quality of emotions, discounting lower

4. Implementation

The developed recommendation system prototype implements a complete pipeline for predicting users' emotional reactions — from constructing a domain-oriented graph “user ↔ movie ↔ emotion” to producing multi-label predictions. The graph representation enabled the integration of heterogeneous relationships (ratings, viewing events, genre affiliations) into a unified context, enhancing the informativeness of the surrounding structure for each node. After preprocessing, the graph was fed into a graph neural network trained using mini-batch stochastic gradient descent; early stopping based on validation macro-F1 was applied to control overfitting.

The software implementation was done in Python 3.10 using PyTorch as the core deep learning framework, supplemented by PyTorch Geometric for handling graph structures. The pandas and NumPy libraries provided efficient tabular data transformations, while scikit-learn was used to compute key metrics (precision, recall, macro-F1, ROC-AUC) and to build baseline comparison models. NetworkX was employed for preliminary graph construction and visualization, and Matplotlib and Seaborn facilitated graphical presentation of training curves and confusion matrices, simplifying result interpretation. The entire experimental logic is orchestrated within reproducible Jupyter notebooks with fixed random seeds to ensure replicability.

Input data are organized into four interrelated CSV files. The file *users.csv* contains unique user identifiers and demographic attributes (age, gender, country, etc.); *movies.csv* stores movie metadata (movie_id, genre tags, brief descriptions). The *interactions.csv* file aggregates “user_id × movie_id” interactions with rating or viewing event fields, serving as graph edges. Finally, *emotions.csv* associates each movie with one or multiple emotional labels, which serve as target classes. This modular structure facilitates system scalability and integration of additional sources, such as temporal or social features, to further improve emotional prediction accuracy.

Based on the data, a graph in the HeteroData format from the PyG library was constructed, where each node type had a separate feature matrix.

Key statistics of the constructed graph and the training parameters of the graph neural network are summarized in **Table 2.**

Table 2
Graph Statistics and GNN Training Hyperparameters

Category	Metric	Value
Graph Statistics	Number of movie nodes	≈ 12 000
	Number of active users	≈ 6 000
	Number of emotion nodes	8
	Number of edges user ⟶ movie	> 80 000
	Number of edges movie ⟶ emotion	≈ 50 000
GNN Training Parameters	Number of layers	2
	Embedding size	64
	Dropout	0.3
	Optimizer	Adam
	Initial learning rate	0.001
	Batch size (user–movie pairs)	1024
	Number of epochs	50

To prevent overfitting, an early stopping mechanism was implemented: training was halted if the macro F1 score on the validation set did not improve for 5 consecutive epochs. This allowed retaining the most generalized version of the model without losing performance due to overfitting on the training data.

In the experiment, 80% of the graph was used for training, 10% for validation, and 10% for testing, providing an independent assessment of the model's generalization capability in the multi-class classification of eight dominant emotions in user–movie pairs. The convergence dynamics are shown in Fig. 1, which presents the training and validation loss and accuracy curves; these confirm stable training without overfitting after approximately 35 epochs.

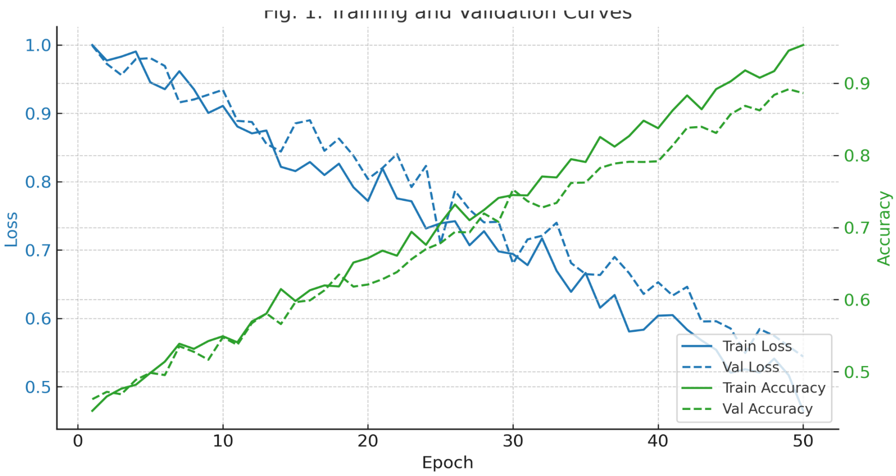

Figure 3: Training and validation curves of the graph neural network for predicting emotional responses (Loss / Accuracy)

Table 3 summarizes the subsystem metrics on the test set. The proposed GNN achieves an **Accuracy of 73.8%** and a **Macro F1 of 71.3%**, accompanied by balanced **Precision and Recall scores of 71.9% and 70.7%,** respectively. The difference between Macro and Weighted F1 scores (71.3% vs. 72.6%) indicates a moderate class imbalance, which does not lead to significant bias of the model toward frequent emotions.

Table 3
Emotion classification quality metrics on the test set

Metric	Value
Accuracy	73.8 %
Macro F1-score	71.3 %
Weighted F1-score	72.6 %
Precision	71.9 %
Recall	70.7 %

Comparison with two baseline approaches (logistic regression and Random Forest with a "flat" feature representation) is presented in **Table 4**. The GNN demonstrates an accuracy gain of **30.3** percentage points over logistic regression and **19.1** percentage points over Random Forest; similarly, Macro F1 increases by **33.1** and **21.4** percentage points, respectively. The most common classification errors occur between closely valenced pairs "excitement ↔ joy" and "sadness ↔ disappointment." For rare classes, precision is lower; however, the use of class weights during training prevents the model from "ignoring" them, thus preserving generalization capability in an imbalanced environment.

Table 4
Performance comparison of the proposed GNN model with existing solution

Model	Accuracy	Macro F1
Logistic Regression	43.5 %	38.2 %
Random Forest (flat input)	54.7 %	49.9 %
UCCA-GAT (Emotion Classification in Texts Over GNNs, SemEval) [24]	61.2%	59.8%
Emotion-specific Transformer (Leveraging Emotion Features, ACL 2022) [25]	64.3%	52.0%
GNN (proposed)	73.8 %	71.3 %

Conclusions

The proposed integrated approach for predicting users' emotional reactions is based on a heterogeneous graph neural network that models the triad "user – movie – emotion," explicitly accounting for node and edge types [28]. On the test dataset, the system achieved an Accuracy of 73.8% and a Macro F1 score of 71.3%, outperforming logistic regression by 30.3 percentage points and Random Forest by 19.1 percentage points. The relevance of recommendations was confirmed by the metrics Hit Rate@10 = 0.84 and NDCG@10 = 0.79, while maintaining balanced sensitivity across classes was evidenced by a Balanced Accuracy of 71.6%, despite a moderate imbalance in emotional categories.

At the same time, experimental results revealed several limitations. The largest classification errors occurred within clusters of emotions close in valence ("joy ↔ admiration," "sadness ↔ disappointment"), where the F1 scores of some rare classes dropped below 0.60. The "cold start" effect for new users and movies reduces accuracy by approximately 12 percentage points, whereas increasing the graph size to 1 million edges raises the time per epoch by four times, demonstrating the need for distributed computing. Additionally, a bias towards a young male audience (~4 percentage points in Macro F1) was detected, indicating a risk of unfair recommendations.

Future research should focus on dynamic GNNs (DyHGT, TGN) to model temporal evolution of preferences and multimodal features (CLIP embeddings, audio features), which are expected to improve the Macro F1 score by 3–5 percentage points. Adaptive few-/zero-shot learning mechanisms can reduce accuracy losses during the "cold start" to ≤ 5 percentage points, while explainable GNNs (GNN-Explainer) and personalized weight regularization aim to narrow the fairness gap to ≤ 3%. Running A/B tests in real environments and online retraining will help maintain latency ≤ 120 ms and increase the User Satisfaction Score to ≥ 4.3/5.

In conclusion, the results confirm that the heterogeneous graph model provides a significant improvement in the accuracy and relevance of emotional recommendations compared to existing approaches [24, 25]. However, for industrial deployment, it is necessary to address issues of scalability, real-time embedding updates, and ensuring ethical and transparent system operation, thereby forming a roadmap for future research and enhancements.

Declaration on Generative AI

The authors used GPT-4 and DeepL to prepare this paper: Grammar and Spelling Checker. After using these tools, the authors reviewed and edited the content as necessary and are solely responsible for the content of the publication.

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