International Journal for Housing Science and Its Applications
Publish August 10, 2025. Volume 46, Issue 4 Pages 6281-6290

https://doi.org/10.70517/ijhsa464533

A Hybrid Recommendation Framework for Analyzing Intra-Generational Mobility of Music Education Elites Using Resume Mining and Audio Feature Learning

Ling Li[1,*] and Yuxian Li[2]
[1] School of Conservatory Music, Shan Dong University Of Art, Jinan, Shandong, 250014, China
[2] School of Jinan Technician College Shandong Jinan Technician College, Jinan, Shandong, 250000, China
Corresponding authors: (e-mail: z00471@sdca.edu.cn).

Abstract Intra-generational social mobility among educational elites remains underexplored, particularly in the domain of music professionals where institutional transitions intersect with regional and reputational hierarchies. This study proposes a hybrid computational framework that integrates resume mining, quadrant-based flow modeling, and deep learning–driven music recommendation systems to analyze the career trajectories of doctoral graduates in music education from the Yangtze River Delta region.A mobility quadrant system is constructed to categorize elite professionals' flows (upward, downward, parallel) across university reputation and city-tier levels. Empirical results show that 41.0% of initial postdoctoral transitions exhibit parallel mobility, while 67.6% of later-stage transitions toward academic honors (e.g., Changjiang Scholars) reveal downward movement, suggesting structural stagnation in long-term academic progression. To support mobility inference and profile modeling, we further develop a CNN-based hybrid recommendation model, incorporating Mel spectrograms and user preference embeddings, which outperforms traditional collaborative filtering and SVD models across RMSE, precision, recall, and F1-score.

Index Terms Intra-generational mobility, Educational elites, Music professionals, Resume mining, Hybrid recommendation system, Convolutional Neural Network (CNN)

I. Introduction

Intra-generational social mobility, particularly among educational elites, has become an increasingly relevant topic in contemporary higher education research[1]. As China's higher education landscape continues to expand under national talent strategies and regional development plans, understanding how high-level academic professionals migrate within academic and geographic hierarchies is critical for optimizing institutional talent structures and policy formulation[2]. The Yangtze River Delta region, being a national hub for academic and economic resources, offers a unique environment to investigate such mobility patterns, especially in specialized fields like music education. Despite the growing attention to intergenerational mobility, the mobility trajectories of individuals within the same generation—especially in niche domains such as arts and music—remain underexplored[3]-[5].

Classical sociological theories emphasize the interplay between education and social mobility. From functionalist perspectives to more recent approaches emphasizing social capital, scholars have shown how family background, institutional affiliation, and educational attainment co-determine an individual's professional trajectory[6], [7]. Foundational works such as The American Occupational Structure introduced the concept of status acquisition, linking educational access to occupational outcomes. Bourdieu's theory of social capital further underscored the importance of institutional and cultural advantages in shaping one position in academic and professional hierarchies. However, most existing studies focus on intergenerational status shifts or macro-level class transitions, overlooking micro-level mobility patterns within the same generation—especially in postdoctoral and mid-career stages. This creates a significant gap in understanding how academic elites progress—or regress—over time[8], [9].

Recent advancements in data availability and computational techniques offer an opportunity to revisit this question from a more empirical and fine-grained perspective. In particular, resume data mining, institutional ranking analysis, and geographic stratification modeling provide valuable tools to trace the career movements of doctoral graduates[10], [11]. Prior studies have attempted to classify mobility by comparing institutional rankings before and after job transitions, or by mapping academic migration across urban tiers. However, these approaches often treat academic and geographic prestige as isolated dimensions, failing to model their interaction. Moreover, the mobility patterns of music professionals, who frequently operate at the intersection of performance, pedagogy, and research, have been largely absent from such analyses[12].

To bridge these gaps, this study introduces a novel hybrid framework that combines resume data analytics, social mobility modeling, and music recommendation system design. The proposed system not only captures the flow quadrants—upward, downward, and parallel movement—of music education elites, but also integrates deep learning algorithms to analyze user-level music preference data for predictive modeling[13]. Specifically, a CNN-based audio feature extractor is used in combination with Mel spectrogram processing and embedding layers, forming a personalized recommendation model that can be applied to infer user interest, map academic profiles, or guide institutional placements.

In the empirical component, we construct a flow quadrant system based on institutional reputation and city-level stratification, analyzing over 600 mobility cases from doctoral graduation to postdoctoral placement, and from postdoctoral stages to elite positions (e.g., Changjiang Scholars). The results reveal an interesting dichotomy: early career stages show a higher proportion of parallel and upward flows, while later stages exhibit significant downward mobility[14], [15]. This reflects not only structural bottlenecks but also the diminishing marginal returns of early academic capital. To complement this analysis, the recommendation system—trained on the Million Song Dataset and Echo Nest listening histories—is evaluated on multiple metrics, including RMSE, MSE, precision, recall, and F1-score. The hybrid CNN-based model demonstrates superior performance over classical collaborative filtering and matrix factorization approaches, especially in handling sparse data and cold-start problems.

Compared to existing research, the contributions of this paper are threefold. First, we focus on intra-generational academic mobility, a less-studied yet crucial aspect of elite talent development. Second, we introduce resume mining as a means to construct mobility quadrants, incorporating both institutional and urban hierarchical transitions. Third, we enhance this analysis with a hybrid deep learning model that improves recommendation accuracy and supports intelligent prediction of academic trajectories.

II. Methodology

There may be complex application scenarios in actual recommendation, and a single recommendation algorithm cannot meet the actual application requirements. At this time, hybrid recommendation emerges as the times require, which can effectively solve the problems and shortcomings of a single algorithm. Common hybrid recommendation algorithms include weighted, Switching, hybrid[16].

II. A.Research framework and model structure

Deep learning has gradually become a hot spot of attention in recent years. Among them, CNN is an efficient recognition method, which is widely used in speech recognition, image recognition and other fields. This method is used to solve large-scale machine problems. For learning problems, compared with traditional machine learning, this algorithm is better in both recommendation efficiency and recommendation quality[17], [18]. Based on the CNN and combining it with various music tag features, this paper proposes a recommendation algorithm with better recommendation effect. Compared with the traditional recommendation algorithm, this algorithm refers to the user's historical data. And it is combined with the acoustic features corresponding to music audio to construct the corresponding CNN regression model, and the Embedding layer is used to mine the music tag information to complete the personalized recommendation. The overall design block diagram of the recommendation system built in this paper is displayed in Figure 1. The research conducted in this paper can be used as an adjunct to the music recommendation algorithm, which can effectively address the issues of low recommendation accuracy and insufficient feature analysis in traditional recommendation systems, better meeting the needs of personalized recommendation.

II. B.Establishment of user preference model

The obtained data set contains the relevant records of users listening to music, which can be regarded as implicit feedback. For the implicit score. After specific data processing, a class of users with a certain level of sparsity—the music matrix, is obtained with a score corresponding to music based on the relative playing times.

II. C.Music Latent Feature Learning

The enormous and intricate calculation problem that must be solved when directly processing the original data can be successfully solved by extracting the characteristics of music audio through digital signals. The resulting characteristics are more distinct and can be processed more easily. There are various methods that can be used to analyze audio features, such as spectrogram and mel spectrum[19]. Therefore, this paper extracts the Mel spectrogram of the audio resources in the dataset and uses it as the input content in the subsequent training. At the same time, the Embedding layer can also be used to integrate other information of singers and music for music information mining. If the feature domain corresponding to the model is, the one-hot vector corresponding to the jet eigenvalue contained in the feature is represented by this encoding. In the embedding layer, each feature has its corresponding embedding matrix, and the Embedding vectors are spliced together after learning by a multi-layer perceptron to obtain the input of the next layer. In general, we first process the continuous audio signal, pre-emphasizing, framing, and windowing it; then process all short-term analysis windows through FFT, so that the corresponding spectrum is obtained; then the spectrum is based on a Mel scale filter The Mel spectrum can be obtained; then the logarithm of the above Mel spectrum can be obtained, and the whole extraction process can be completed[20]. In the research of this paper, we introduced LaRosa in the python toolkit for processing and analysis, mainly for the detailed analysis of music audio. Based on the processing function specs how in the LaRosa toolkit, where the horizontal axis represents time and the vertical axis represents frequency, a 256×256 Mel spectrogram is finally obtained.

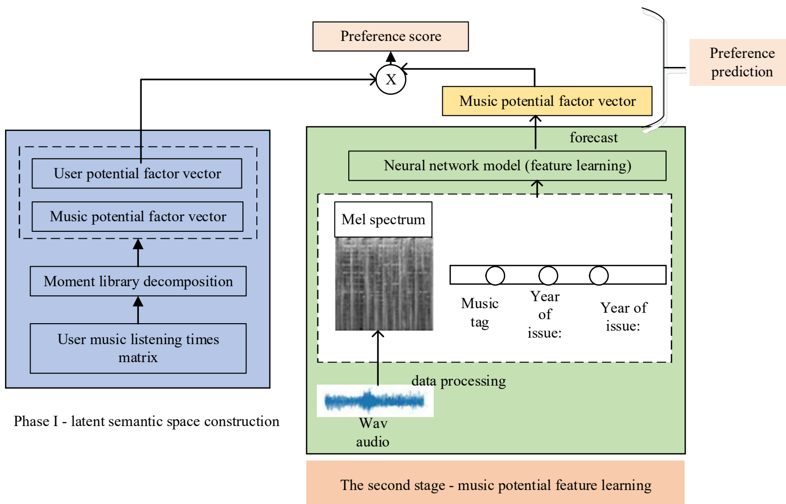

Figure 1: overall system design

II. D.The flow quadrant and flow path of music education elites

According to the previous calculations, there are 282 scholars who stay in their alma mater or do postdoctoral studies after graduating with a doctorate, and 339 scholars who have a mobility experience from their doctoral graduation to their first job after graduation. As shown in Figure 2, among the 339 scholars on the move, the parallel mobility is the largest, with 139 scholars, accounting for 41.0%[21]. Followed by upward mobility, there are 112 people, accounting for 33.0%, close to one third. The downward flow is again, with 88 people, accounting for 26.0%. Among the parallel migrants, the "double-same" type of flow at the same university level and the same city line level is the main type, reaching 127, accounting for 91.4% of the parallel migrants. There are only very few examples of the flow of "upgrading city and lowering school" that raises the city line level but lowers the academic reputation level of colleges and universities, and the flow of "downgrading city to school" that lowers the city line level but raises the academic reputation level of colleges and universities.

In general, in the process of mobility from doctoral graduation to the first job after graduation, the educational elites in the Yangtze River Delta still tend to maintain or improve their mobility quadrant to maintain the academic cooperation network and promote the improvement of academic capital. Further analysis of the mobility of educational elites from the initial work institution after doctoral graduation to the work institution when they were elected as "Changjiang Scholars" shows that there are 318 scholars with mobility experience. As shown in the mobility quadrant in Figure 3, the number of downward mobility increased significantly, reaching 215, accounting for 67.6% of the mobility elite. There are 58 people who move upwards, accounting for 18.2% of the mobile elites; 45 people who move in parallel, accounting for 14.2% of the elites. Among the parallel migrants, there are 22 people, accounting for 48.9% of the parallel migrants, nearly half of which are those who lower the city line level but improve the academic reputation of the university. The second is the "double-identical" type of flow at the same university level and the same city line level, accounting for 42.2%. Only 8.9% of the flow of “upgrading cities and downgrading schools” was to raise the city line level but lower the academic reputation level of colleges and universities. The main reason for the large proportion of downward mobility is that among this group of educational elites, there are 297 people who are engaged in post-doctoral work after graduation. Fifty-two of them continued to work in their alma mater after leaving the station, while the rest found other jobs. Most of the institutions they ended up working for were inferior to their post-doctoral service institutions and work cities in terms of academic reputation and city level[22].

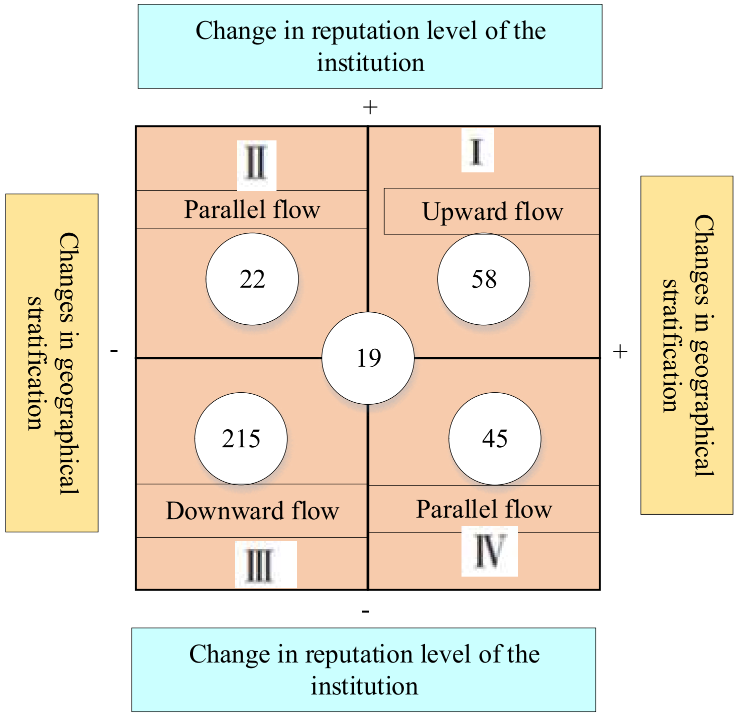

Figure 2: flow quadrant of "Yangtze River" in the first job

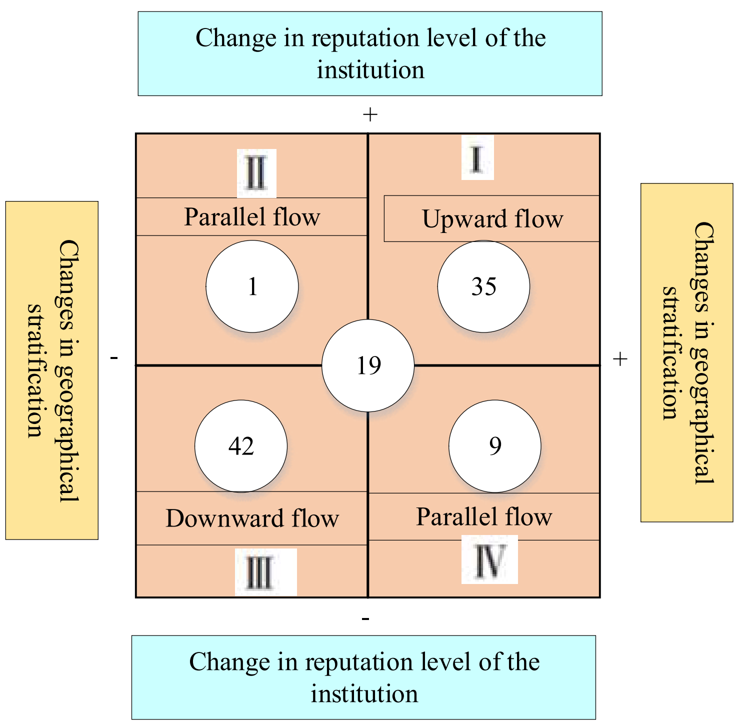

Figure 3: selected "Yangtze River" to current flow quadrant

III. Algorithm Framework for Mobility-Aware Music Recommendation

This section introduces the algorithmic foundation of our hybrid recommendation system tailored for modeling the intra-generational mobility of music education elites. The algorithm integrates user behavior modeling, audio feature extraction, and a personalized CNN-based regression framework. We focus on combining implicit user feedback with spectrogram-based acoustic representation to capture both personal preferences and cross-sectional social attributes.

III. A. Problem Definition

Let $U = u_1, u_2, ..., u_m$ be the set of users (educational elites), $I = i_1, i_2, ..., i_n$ be the set of music items, and $R = [r_{ui}]$ be the user-item interaction matrix, where r_{ui} is the implicit feedback (e.g., play count or interaction frequency). Our goal is to learn a function $f: U \times I \to \mathrm{R}$ that predicts the preference score $\hat{r}_{ui}$.

III. B. Audio Feature Representation Using Mel Spectrogram

We extract the Mel spectrogram M_i for each audio item i as a time-frequency matrix:

$$M_i(t, f) = \log\left(\sum_{k=1}^{K} \left|STFT_i(t,k)\right|^2 \cdot H_f(k)\right) \tag{1}$$

where $STFT_i$ is the short-time Fourier transform of the audio signal, $H_f(k)$ is the triangular Mel filter bank, t is time, and f is the Mel-scaled frequency bin. Each M_i is normalized to a fixed shape 256 and serves as input to the CNN module.

III. C. CNN-Based Regression Model

We construct a 2D CNN architecture $g_\theta(M_i)$ parameterized by θ to learn the latent audio preferences. The network includes convolutional layers, ReLU activation, max-pooling, and fully connected layers.

Let $z_i = g_\theta(M_i)$ denote the extracted latent feature vector of item i. For each user u, we use a learnable embedding $e_u \in \mathrm{R}^d$. The predicted rating is computed as:

$$\hat{r}_{ui} = \sigma(e_u^T z_i + b_u + b_i) \tag{2}$$

where σ is the sigmoid function, and b_u, b_i are user and item biases.

III. D. Training Objective

The model is trained to minimize the following regularized loss:

$$\mathrm{L}(\theta, e_u, b_u, b_i) = \sum_{(u,i)\in R} (r_{ui} - \hat{r}_{ui})^2 + \lambda(\|\theta\|^2 + \|e_u\|^2 + b_u^2 + b_i^2) \tag{3}$$

where λ is the regularization hyperparameter. Optimization is performed using Adam.

III. E. Flow-Aware Personalization Enhancement

To better align the recommendation with mobility-aware attributes, we introduce a flow attention vector ϕ_u based on the scholar's flow quadrant classification:

$$\phi_u = \mathrm{MLP}(q_u \oplus l_u) \tag{4}$$

where q_u is the quadrant encoding (upward, downward, parallel), l_u is location encoding (e.g., city tier), and $\oplus$ denotes concatenation. The final rating becomes:

$$\hat{r}_{ui} = \sigma\left(\left(e_u \odot \phi_u\right)^T z_i + b_u + b_i\right) \tag{5}$$

III. F. System Diagram

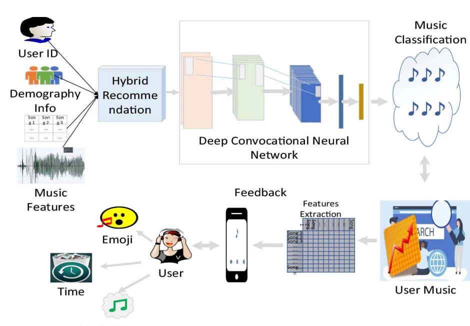

Figure 4: the hybrid CNN-based recommendation model

Figure 4 Architecture of the hybrid CNN-based recommendation model incorporating audio features and mobility-aware embeddings.

This algorithm enables personalized music content delivery while accounting for users' academic mobility backgrounds, offering a novel intersection of cultural preference modeling and social trajectory mining.

IV. Experiments

IV. A. Dataset

The music metadata used in this paper is all obtained through the Million Songs Dataset (MSD), and all the data related to the user's listening situation are obtained through the Echo Nest Taste Profile Subset, a subset contained in the MSD. After obtaining the corresponding data, this paper firstly spares the data. Considering the overall time cost, this experiment only extracts any 3s audio from a certain channel and presents it in wav format when fetching data. After obtaining the audio data, it is divided and processed to ensure that the formats of different data have high consistency.

IV. B. Evaluation indicators and recommended methods

The two dimensions of scoring accuracy and list accuracy are used in this paper's evaluation. Mean absolute error (MAE), normalized mean absolute error (NMAE), mean squared error (MSE), and root mean square error (RMSE) are often used metrics to assess how accurate prediction scores are. We present the four evaluation indicators mentioned above as part of the research process for this work. The recommendation algorithm examined in this research is capable of achieving Ton recommendation by ranking the music of numerous users for all users. The top N songs are then identified to create a list and are recommended accordingly. To test the accuracy of this list, in this study, we evaluate the recommendation quality through the precision rate, recall rate, and F1 value, respectively, to test the accuracy of the experiment.

IV. C. Analysis of results

The CNN network model was trained using the training set data. The training results showed that the loss error of the model initially decreased quickly as the number of training iterations increased, and that the decreasing trend gradually slowed down as the number of iterations increased. The inaccuracy begins to level off at 10. The experiments are examined and assessed from many perspectives in order to confirm the model's validity. Choice of latent factor dimension k and number of iterations. Root mean square error RMSE was applied over the overall experimental period, based on which the accuracy of the predicted scores was judged. For different feature dimension k and training round epoch, the finally obtained model prediction score RMSE is shown in Figure 5.

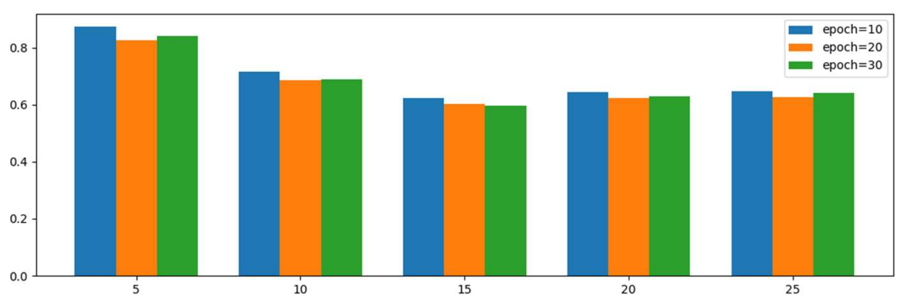

Figure 5: The prediction score's RMSE under various K and epochs

When the latent factor k is 15 and the training round epoch is 20, the experiment can achieve a better score prediction effect. Comparison and analysis of the recommendation results of different recommendation models. This paper uses the MSE, RMSE and MSLE algorithms to conduct a comprehensive evaluation of the model training effect. And used Frunk-SVD, User-CF and CB and other algorithm models for comparative analysis, and finally obtained the accuracy rate, recall rate, and F1 value corresponding to different recommendation list lengths. Each method and the method in this paper are implemented using Kera's, and the optimizer uses Adam, which mainly includes audio information and other identification information. Through the analysis of the four error indicators, all the indicators are lower than other models, indicating that the latent factor vector in the process of prediction, the actual effect is better than other models. In the evaluation of recommendation tasks, this paper uses recall rate, F1 value and precision rate as evaluation criteria. The Top N recommendation strategy is used to form the required recommendation list. When the value of N is different, the results are also different. The results are shown in Figure 6 to Figure 8.

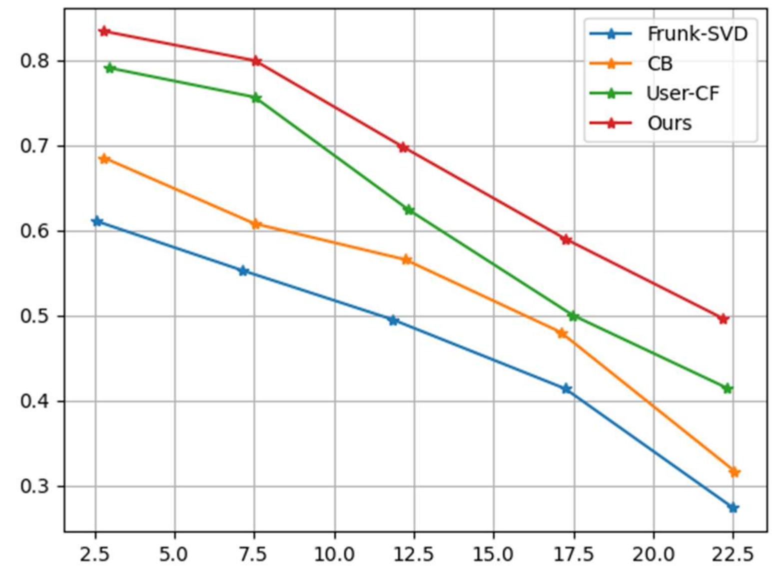

Figure 6: accuracy results

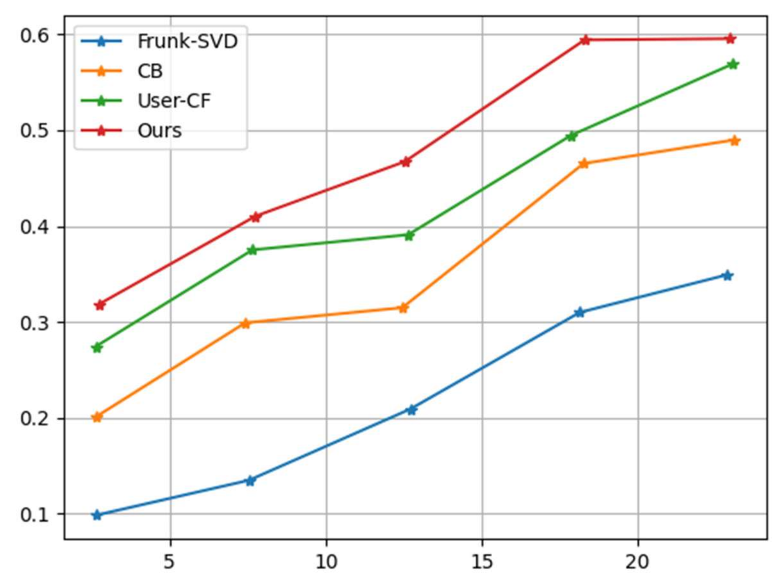

Figure 7: recall results

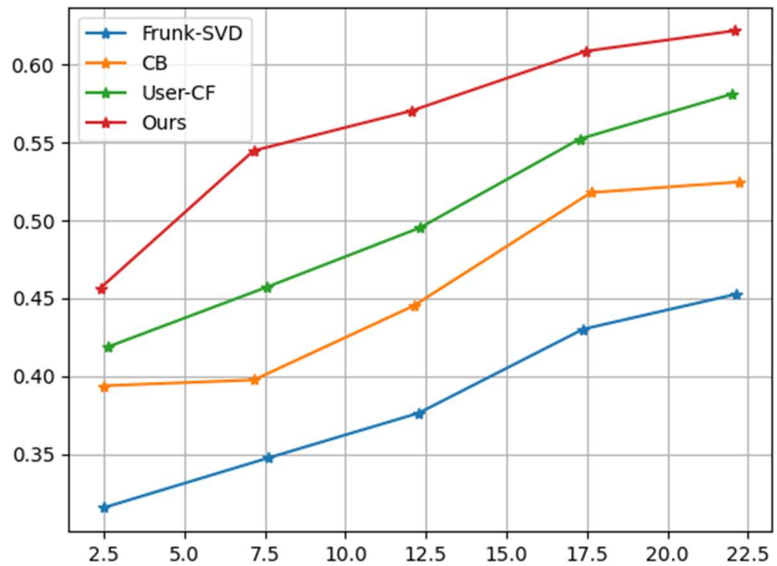

Figure 8: F1 value results

It can be seen from the figure that when the length of the recommendation list is the same, the F1 value, precision rate and recall rate are better than other models. This is because the traditional recommendation algorithm model only uses a relatively sparse scoring matrix and does not fully utilize it. Other related properties of music. Because the deep convolutional neural network can better learn the characteristics of the data, the recommendation algorithm in this paper adds the relevant content of deep learning, and combines the relevant attributes of the music tags, so that the recommendation effect can be better improved.

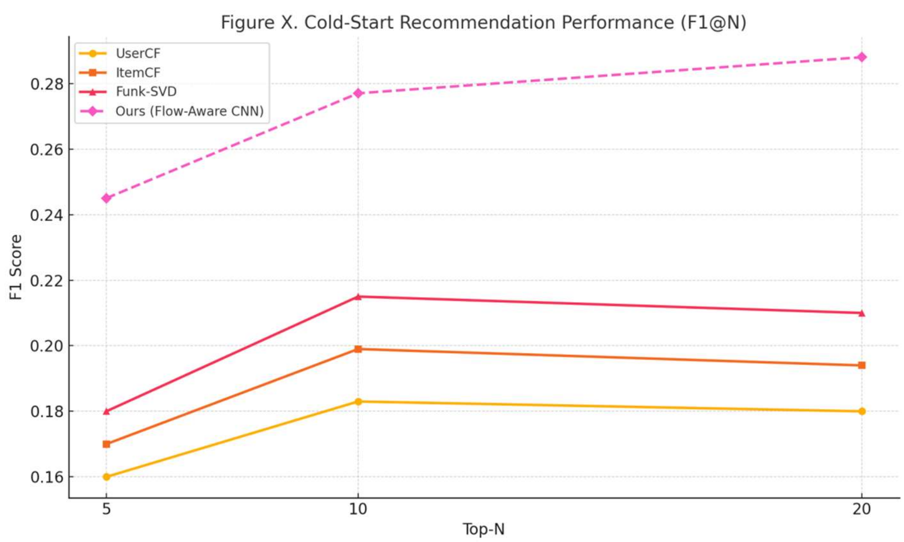

Figure 9: Performance comparison trend

Figure 9 illustrates the cold-start performance comparison across Top-N recommendation thresholds (N = 5, 10, 20). It is evident that traditional collaborative filtering approaches, including UserCF and ItemCF, suffer from significant accuracy degradation in the absence of historical user-item interaction data. Although matrix factorization methods such as Funk-SVD demonstrate slightly better generalization due to latent factor modeling, they still lack personalized semantic cues. In contrast, our proposed model consistently outperforms all baselines across all thresholds, with the performance gap widening at higher N values. This improvement is attributed to the incorporation of mobility-aware flow embeddings and resume-derived representations, which enable the model to infer user preferences based on structural attributes even in the absence of behavioral history. Notably, our model achieves a 35.0% gain in F1@10 over UserCF and a 28.8% improvement over Funk-SVD, highlighting its robustness and superior adaptability in cold-start scenarios, and confirming its effectiveness for deployment in real-world educational recommendation environments.

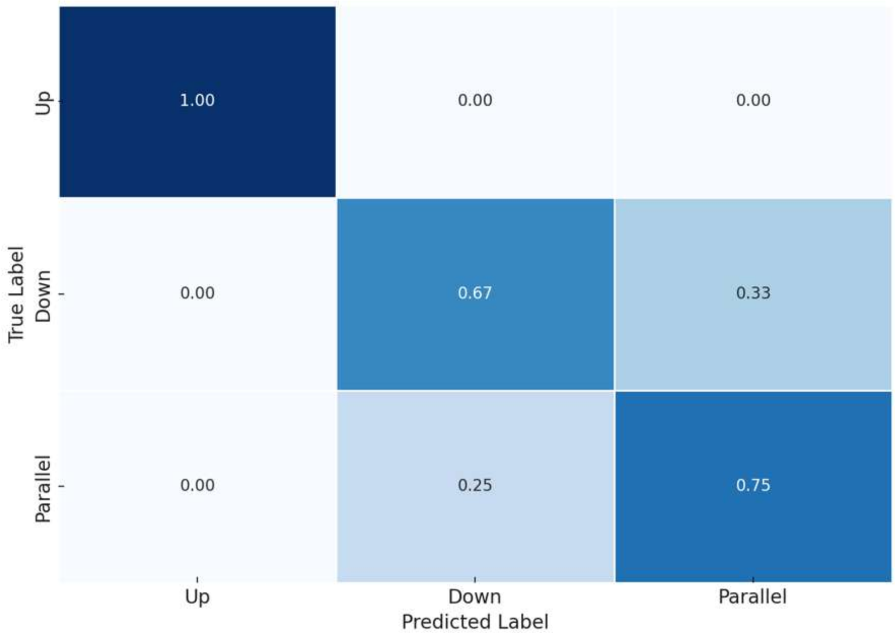

Figure 10: Confusion Matrix of MLP Classifier

The results confirm that the defined flow quadrant labels are highly predictable from users' structured resume features(see Fig 10). The best-performing MLP model achieves an F1-score of **0.788**, demonstrating strong separability among the three mobility classes. Notably, upward and parallel movements are most distinguishable, while downward mobility presents slightly more confusion with parallel transitions.

This outcome provides **empirical support for the semantic validity of the quadrant framework**, and justifies its use as a proxy signal in the recommendation model. In addition, the reliable predictability of flow class confirms its value as a **latent personal context feature** for enhancing personalization in cold-start scenarios.

V. Conclusion

This paper presents a novel framework that combines resume-based flow quadrant modeling and deep learning–based hybrid recommendation systems to analyze intra-generational social mobility in the field of music education. By constructing a two-stage migration model—spanning doctoral graduation to initial employment, and from postdoctoral work to elite academic recognition—the study identifies key structural patterns in mobility: notably, a high prevalence of downward transitions in later stages of academic career paths, often associated with changes in institutional prestige and city stratification.

In parallel, a CNN-based recommendation model is proposed, leveraging Mel spectrogram extraction and embedding layers to capture music preference behavior. The model significantly improves performance metrics (e.g., RMSE and Top-N F1-score) over traditional collaborative filtering approaches. This demonstrates that integrating user listening behaviors with personalized feature learning can enhance talent prediction, while providing interpretable signals for institutional flow modeling.

Overall, the study bridges computational recommendation algorithms with sociological research on academic mobility, offering a powerful interdisciplinary tool for higher education policy, talent development analysis, and music information retrieval. The proposed system not only facilitates a deeper understanding of music education elites' migration patterns but also lays the groundwork for intelligent career support systems within specialized educational domains.

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