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Deep Recommendation of Piano Music Based on Trust and Labeling Awareness

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Abstract. *In the era of digitalization, the explosion of piano music options presents a cornucopia of choices to users, yet it also poses challenges in decision-making. Conventional search and recommendation approaches fall short in catering to the demand for tailored and profound musical engagements. Consequently, this paper introduces a deep recommendation model that leverages trust and label awareness to enhance the precision and personalization of piano music suggestions. By integrating users' musical inclinations, interpersonal trust, and music labeling, the model utilizes sparse autoencoders to distill underlying features, assess user similarities, and produce recommendations. Trust dynamics uncover user similarities, aiding in the detection of latent musical preferences, while labels offer a visual representation of music traits and user interests. This integrated approach enriches the data pool, thereby boosting the accuracy and satisfaction of recommendations. Addressing the challenge of sparse trust and label data common in recommender systems, our model demonstrates efficacy in tackling data sparsity through rigorous research and testing. The model's performance surpasses existing solutions in metrics such as precision, recall, and NDCG, establishing its merit in delivering personalized piano music recommendations. This not only enriches the user experience with more curated and superior music choices but also paves the way for innovative research and practical applications in music recommendation systems.*
Keywords: trust model; label-aware; deep learning; piano music recommendation.

1. **Introduction.** As digitalization progresses, the vast array of piano music available has created both an abundance of options and a challenge in making choices. Standard search and recommendation techniques now fail to satisfy the desire for customized and immersive musical experiences. In response, this paper introduces a deep learning-based recommendation framework that uses trust and label insights to enhance the precision and personalization of piano music suggestions. The rapid growth of online music platforms has led to an information overload, making it difficult for users to discover music that aligns with their preferences.

This framework synthesizes users' taste in music, their trust in other users, and the metadata associated with music pieces. It employs sparse autoencoders to identify latent features, assesses user affinities, and produces recommendations accordingly. The trust element exposes user similarities, aiding in the prediction of music preferences, while labels detail music traits and articulate user interests visually. This synthesis creates a comprehensive data set that enhances the precision of recommendations and boosts user satisfaction.

Tackling the common issue of sparse data in recommender systems, our model presents a solution that overcomes these challenges, as evidenced by thorough research and empirical testing. The results of these experiments highlight the model's proficiency in offering tailored piano music recommendations, setting a new standard for user-centric, high-quality music recommendation services. Furthermore, it introduces innovative approaches and methodologies for advancing the field of music recommendation research and practice.

1.1. **Related work.** As music recommendation systems evolve, algorithms focusing on tags and trust have become prominent for their potential to enhance recommendation accuracy and personalization. Trust-aware algorithms, such as Ji et al. [1] model based on trust propagation and the combination of explicit and implicit trust by El et al. [2], utilize user relationships to improve recommendation relevance. Ahmadian et al. [3] emphasize the significance of trust in revealing user interests. Label-aware algorithms, like the tag-based filtering by Adomavicius et al. [4], capitalize on social tagging to refine recommendations.

With the rise of deep learning, its integration with traditional methods has become a focus. Fu et al. [5] use deep neural networks to model user-item interactions, while Gabriel et al. [6] propose a method to balance the popularity and novelty of recommended content. He et al. [7] present a framework that integrates neural network architectures into matrix decomposition to enhance recommendation performance.

Music personalization systems aim to match users with music aligning with their interests and behavior, primarily employing content-based, collaborative filtering, hybrid, and deep learning methods. Collaborative filtering, despite its effectiveness, confronts data sparsity and cold-start issues, which researchers continue to address.

Content-based recommendation algorithms focus on music attributes like genre, artist, and lyrics. They analyze these features to find matches to user preferences, recommending similar music. This method is beneficial for new users, as it relies on music attributes rather than user history. However, it may not fully grasp dynamic user interests. Mo and Niu [8] enhanced this approach by introducing a music recommendation method based on audio feature extraction, which identifies similar musical styles through spectral feature comparison.

Deep learning has allowed music recommendation systems to automatically discern complex patterns by learning comprehensive feature representations. Zhang [9] utilized convolutional neural networks (CNN) for music recommendation, extracting and classifying audio features to suggest music. These models excel at managing large datasets for personalized recommendations.

Hybrid recommendation algorithms blend various techniques—collaborative filtering, content-based, and deep learning—to enhance performance. They mitigate issues like data sparsity and the cold-start problem. Kuo and Li [10] developed a hybrid model that merges collaborative filtering with content-based recommendation, increasing recommendation breadth and precision.

1.2. **Contribution.** This paper introduces a novel deep learning-based recommendation system for piano music, focusing on trust and label perception. Our framework innovatively integrates user preferences, social trust dynamics, and music labeling, offering a comprehensive solution that goes beyond traditional recommendation systems. It presents an innovative integration that combines user trust and music label data, marking a pioneering approach in the realm of piano music recommendations. This new framework enhances the accuracy and personalization of recommendations by leveraging deep learning to uncover the intricate connections between user preferences and musical elements.

The system applies deep learning, specifically sparse autoencoders, to efficiently process high-dimensional musical data and address the sparsity of user trust and label information. This method not only captures the intrinsic features of music but also considers the dynamic nature of user preferences, leading to more accurate and nuanced recommendations. Furthermore, acknowledging the computational demands of recommendation systems, the paper introduces optimization strategies that significantly reduce the computational burden. These strategies ensure that the model maintains high performance in piano music recommendations, as demonstrated by rigorous experimental validation.

In summary, the deep recommendation model proposed in this paper, which is anchored in trust and label perception, substantially enhances the capabilities of music recommendation systems. By integrating user trust networks and music label information with deep learning techniques, it not only elevates the user experience through personalization but also opens up new pathways for research and application in the field of music recommendations.

2. Theoretical analysis.

2.1. Trust model.

In the digital age, the vast options for piano music can overwhelm users. Traditional recommender systems, which depend on user-music interactions like ratings, often struggle due to the sparse data from piano music's niche audience. Introducing trust-based mechanisms is crucial for improving recommendations [11].

Trust in piano music recommendations reflects a user's endorsement of another's taste. Our trust model extends beyond direct user interactions, incorporating the transitive trust through social networks to enhance recommendation accuracy. If user A trusts user B, they're likely to enjoy B's recommendations. Trust is characterized by its transmissibility, dynamism, mutuality, and directionality, offering insights into user preferences. To operationalize trust for recommendations, we must develop models that quantify and compute it.

The trust model, based on network graphs, evaluates trustworthiness by mapping users and their relationships as a network (refer to Figure 1). Using techniques like the PageRank algorithm, this model identifies influential nodes, effectively measuring user trust.

In our graph-theoretic trust model, trust between users is formalized by treating them as nodes within a network, with trust relationships represented as connecting edges. This framework allows for a clear visualization and quantification of trust strength, facilitating the extraction of useful recommendations [12].

Within this network, nodes symbolize users, and edges symbolize trust, with their direction and weight indicating the nature and intensity of trust. Node attributes, such as personal traits and music preferences, offer additional context for a more profound understanding of user profiles. Edge weights are assigned based on interaction frequency and quality, where more and deeper interactions lead to greater trust. The calculation of these weights can be encapsulated by a formula involving coefficients α and β, along with functions f and g that normalize these interactions to a scale of 0 to 1 [13].

$$w_{ij} = \alpha \cdot f(\text{interaction frequency}) + \beta \cdot g(\text{quality of interaction}) \tag{1}$$

Trust evaluation can be effectively conducted through various algorithms, with the PageRank algorithm being a popular choice. Originally designed for web page ranking, PageRank is also instrumental in assessing node trust within networks. The essence of PageRank lies in the principle that a node gains trustworthiness through endorsements from other trustworthy nodes. This concept is mathematically captured by the PageRank formula, which quantifies a node's trust based on the number and trustworthiness of its incoming connections.

$$PR(u) = \frac{1-d}{n} + d \sum_{v \in B_u} \frac{PR(v)}{L(v)} \tag{2}$$

The PageRank algorithm calculates a node's trustworthiness, $PR(u)$, based on the number of nodes (n), a damping factor (d), and the links between nodes (B_u and $L(v)$). This method helps quantify trust within a network.

When integrated into a recommendation system, it enhances recommendations for a user u by considering not only their preferences but also those of the users they trust [14]. This strategy leads to more targeted and personalized music suggestions, leveraging the trust model to refine user recommendations.

2.2. **Label-aware recommendations.** We introduce a label-enhanced recommendation approach that complements traditional collaborative filtering methods by utilizing semantically rich metadata. Tag-aware recommender systems are pivotal in music recommendation, addressing the cold-start issue for new users and tracks by utilizing social tagging data [15]. These systems analyze tags like music styles, emotions, and usage scenarios to offer detailed descriptions, boosting the systems' ability to accurately predict and align with user preferences.

Creating effective tag-aware recommender systems hinges on the precise handling of social tagging data. These tags, generated by users on platforms like social media and music forums, indicate how they perceive and classify music. While defining these tags is vital for understanding user preferences, the tags' diversity and ambiguity present challenges. Users might use varied terms for similar concepts, or a tag could carry different meanings across contexts. Addressing these, systems must integrate and interpret tags through extraction, classification, normalization, and semantic analysis, ensuring they can accurately apply user-generated tags to enhance recommendation performance.

(1) Word segmentation, the initial phase of text preprocessing, is essential for dissecting a string of characters into distinct, meaningful words [16]. This step is especially critical for languages like Chinese that lack inherent spacing between words. The precision of segmentation significantly influences the subsequent analytical processes. Techniques for segmentation encompass statistical, machine learning, and rule-based approaches, with tools such as ICTCLAS offering reliable and efficient services for this task.

(2) Lexical labeling, also known as part-of-speech tagging, assigns grammatical categories such as nouns and verbs to words in a sentence. This process is essential for comprehending the grammatical structure of text, which in turn is key to grasping its semantic meaning.

Lexical annotation usually uses models such as Conditional Random Field (CRF) with the following formula, where $\hat{y}_i$ is the predicted lexicality of the word w_i, y_i is the actual lexicality, and P is the transfer probability and firing probability learned from the training data.

$$\hat{y}_i = \arg\max_{y_i} \left(\log P(y_i|y_{i-1}, w_i) + \sum_{j=1}^{i-1} \log P(y_i|y_j, w_i) \right) \tag{3}$$

(3) Deactivated words are those words that appear frequently in the language but contribute less to the semantic understanding, such as "the", "is", "in", etc. The removal

Figure 1. A network graph-based trust model

of these words can reduce the noise of the data and improve the efficiency and effectiveness of the subsequent processing. The deactivation word list can be customized according to specific application scenarios to suit different needs.

(4) Feature extraction is the process of converting text into numerical features that can be processed for machine learning. TF-IDF is one of the most commonly used methods which takes into account word frequency (TF) and inverse document frequency (IDF) to highlight important words [17]. In addition, Word Embeddings such as Word2Vec or GloVe can be used to convert words into dense vectors to capture the semantic relationships between words. Where $TF\_IDF(w, d)$ is the TF-IDF value of word w in document

d, $TF(w,d)$ is the word frequency, $IDF(w)$ is the inverse document frequency, N is the total number of documents, and $DF(w)$ is the number of documents that contain the word w.

$$TF(w,d) = \frac{count(w,d)}{\sum_{w' \in d} count(w',d)} \tag{4}$$

$$IDF(w) = \log \frac{N}{1 + DF(w)} \tag{5}$$

$$TF\_IDF(w,d) = TF(w,d) \times IDF(w) \tag{6}$$

(5) Vectorization is the process of converting text into fixed-length vectors of values. These vectors are usually used as inputs to machine learning models. In addition to TF-IDF, methods such as one-hot coding and Hashing Trick can be used. The key to vectorization is the ability to represent textual data efficiently while reducing dimensionality catastrophe.

$$\text{one-hot}(w) = \begin{cases} 1 & \text{if } w \text{ is in the vocabulary} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

User-generated tags directly reflect their music preferences and emotions [18]. This study analyzes users' behavior of tagging music to further understand their personal preferences. In addition, by utilizing natural language processing techniques, such as lexical annotation and sentiment analysis, this study enhances the semantic understanding of tagged content so as to recommend music for users that better matches their interests.

2.3. **Deep Learning Based Recommendations.** Deep learning has become pivotal in enhancing the precision and user contentment of contemporary piano music recommendation engines [19]. By emulating the human brain's complex information processing, these engines employ deep, layered models to distill key features from music data progressively. They harness multi-tiered neural networks to autonomously discern rich representations from raw audio, transcending elementary aspects like pitch and rhythm to encompass intricate musical facets such as harmony, melody, and sentiment. This stratified learning of features enables a more sophisticated comprehension of the intricacies and variety within musical pieces. The sparse self-encoder functions as a powerful unsupervised learning instrument, enhancing the model's ability to extract features. By incorporating sparsity in the hidden layer, it compels the model to selectively activate neurons that are pertinent to the input, thus enhancing feature discrimination and robustness. This approach ensures that the model identifies and concentrates on the key data elements necessary for comprehending user preferences and musical genres amidst vast musical datasets.

The sparse self-encoder implements feature learning through a series of key steps: first, in the encoding phase, input data such as music audio signals are converted into a sparse representation of the hidden layer [20]. Next, sparsity with only a few neurons activated is promoted by adding L_1 regularization as a sparsity constraint to the hidden layer activation function. Then, in the decoding stage, the self-encoder attempts to reconstruct the original input data from the sparse representation and optimize the network parameters by minimizing the loss function. Typically, the reconstruction error is measured using the mean square error (MSE), where m is the number of training samples, x_i is the i-th training sample, and $\hat{x}_i$ is the reconstructed sample. In addition, to further encourage sparsity, we add an L_1 regularization term to the objective function to penalize those hidden layer neurons with high activation values, thus achieving that only some of the neurons are involved in the feature representation, where h_i denotes the activation value of the hidden layer neurons, k is the total number of hidden layer neurons, and λ is the regularization parameter. This process not only extracts the deep features of the data, but also enhances the differentiation and robustness of the features.

$$MSE = \frac{1}{m}\sum_{i=1}^{m} \|x_i - \hat{x}_i\|^2 \tag{8}$$

$$L_1 = \lambda \sum_{j=1}^{k} |h_j| \tag{9}$$

We can also describe the feature learning process in terms of the loss function of the self-encoder, where h_j is the activation value of the j-th neuron in the hidden layer.

$$Loss = \frac{1}{m}\sum_{i=1}^{m} \frac{1}{2}\|x_i - \hat{x}_i\|^2 + \lambda \sum_{j=1}^{k} |h_j| \tag{10}$$

Figure 2 is a flowchart of a simple sparse self-encoder model showing how to implement the above principles, from the encoding of the input data to the final parameter optimization, each step of which demonstrates the ability of deep learning to fine-tune the processing in a music recommendation system.

The application of sparse self-encoders provides a powerful tool for piano music recommendation systems to understand musical compositions more deeply and to improve the quality of recommendations. With this technique, we are able to better meet the individual needs of users, thus improving user satisfaction and the overall performance of the recommendation system.

3. Deep Recommendation Model for Piano Music Based on Trust and Label Awareness.

3.1. **Modeling framework.** The trust and label-aware deep music recommendation system consists of three main steps in building the model [21]. The trust and label-aware deep music recommendation system is designed with three main steps in building the model, each of which plays a critical role in enhancing the recommendation process. First, the raw data including user-item tags and user-user trust matrices are modeled as appropriate vectors to provide suitable inputs for the deep neural network. Second, an autoencoder is applied to extract potential features of the labeled data and trust relationships. Finally, the extracted features are used to calculate similarity values and predict unseen ratings. The integration of trust and label information allows our model to capture both explicit preferences and implicit signals, leading to more nuanced user profiles.

The deep recommendation model for piano music based on trust and label perception proposed in this paper aims to provide more accurate personalized recommendation by fusing the user's music preference [22], trust relationship and label information of music works. The specific framework is shown in Figure 3:

(1) In the early stages of model development, we preprocess the input data, including processing the users' music ratings, the trust links between them, and the tags associated with the musical compositions [23]. This step ensures that the data is clean, consistent, and converted into a format suitable for processing by the deep learning model. We first convert the user-music rating data into a user-music interaction matrix, where trust relationships are constructed by building a trust matrix, and labeling information is constructed by building a labeling matrix.

The user-music interaction matrix is as follows, where m is the number of users and n is the number of music pieces.

$$R \in \mathbb{R}^{m \times n} \tag{11}$$

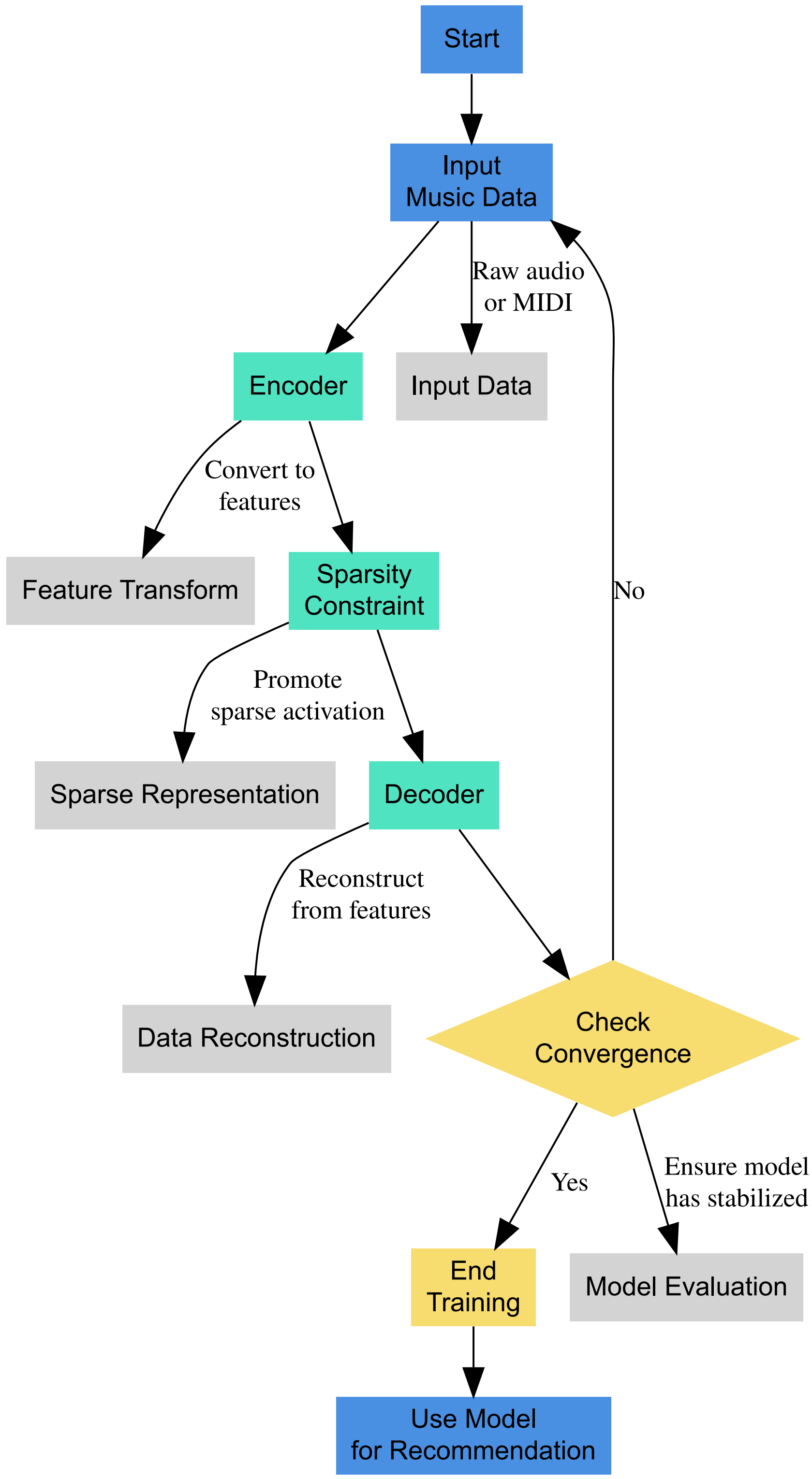

Figure 2. A sparse self-encoder model

Trust Matrix:

$$T \in \mathbb{R}^{m \times m} \tag{12}$$

The label matrix is as follows, where k is the number of labels.

$$L \in \mathbb{R}^{n \times k} \tag{13}$$

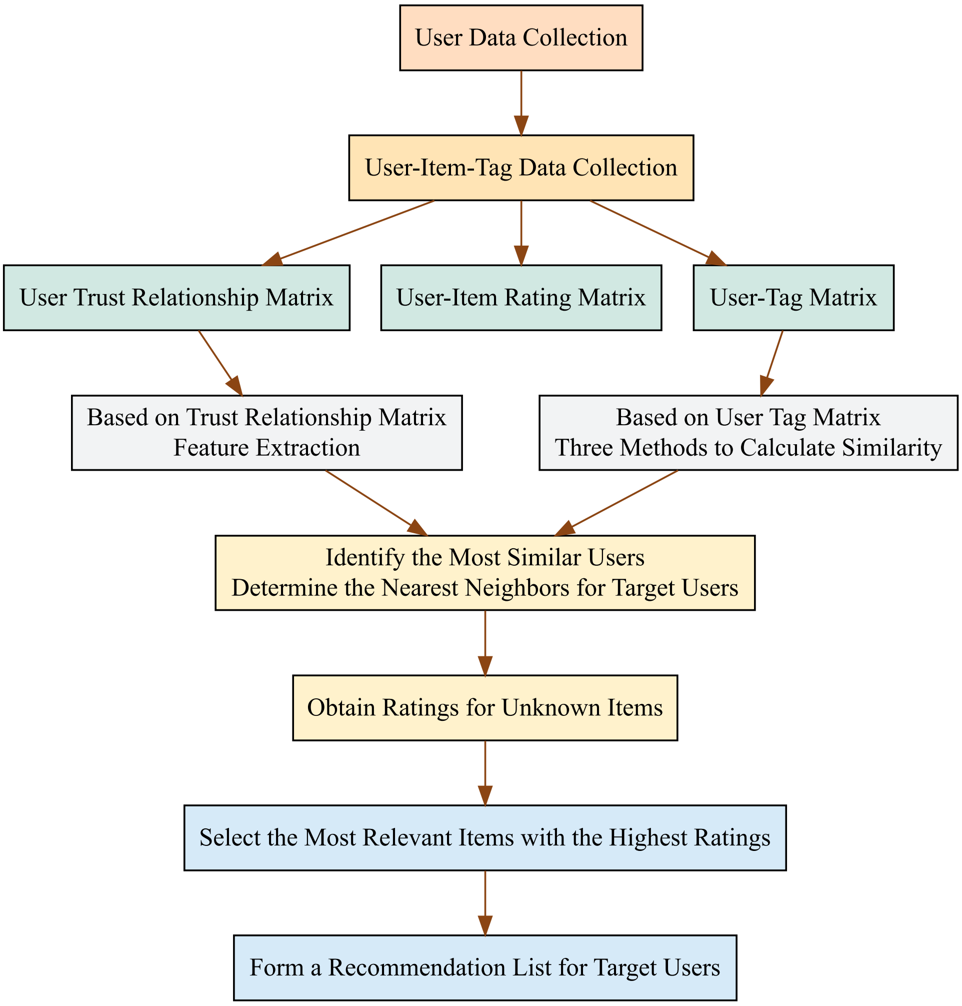

Figure 3. A Trust-Label Aware Piano Deep Recommendation Model

(2) We construct a trust network by analyzing users' social interactions. This network forms an accurate social relationship graph by quantifying the strength of trust between users and using algorithms such as PageRank to refine the weights of trust relationships.

(3) Labeling of musical compositions is parsed through text processing techniques. This includes text segmentation, removal of commonly deactivated words, lexical labeling, and feature extraction. We use techniques such as TF-IDF to transform text labels into numerical feature vectors that enable the model to analyze and understand these labels.

(4) Using sparse self-encoder techniques, we extract key features from processed music scores, trust networks, and labeling features [24]. The self-encoder recognizes patterns in the data through unsupervised learning and encodes them into a more compact form. At the same time, sparsity constraints are introduced to enhance the expressiveness and stability of the features.

(5) Using the extracted features, we compute the similarity between users and quantify this relationship by cosine similarity. Based on the rating history of similar users, we predict the likely ratings of the target users for untouched music.

The cosine similarity is computed as follows, where $\vec{p}_u$ and $\vec{p}_v$ are potential feature vectors for users u and v, respectively. Based on the rating history of similar users, we predict the possible ratings of the target user for untouched music.

$$\text{Cosine Similarity}(u, v) = \frac{\vec{p}_u \cdot \vec{p}_v}{\|\vec{p}_u\| \|\vec{p}_v\|} \tag{14}$$

(6) The model is trained by an objective function that minimizes the prediction error and sparsity penalty. We use optimization techniques such as gradient descent to tune the model parameters to improve the prediction accuracy and ensure that the model has good generalization ability. The update rules for weights and biases are as follows, where W is the weight matrix, b is the bias vector, and η is the learning rate.

$$W_{new} = W_{old} - \eta \frac{\partial E}{\partial W} \tag{15}$$

$$b_{new} = b_{old} - \eta \frac{\partial E}{\partial W} \tag{16}$$

(7) Finally, we evaluate the performance of our model through a series of experiments using metrics such as accuracy, recall, and NDCG to measure the quality of the recommendation results, and compare them with existing recommendation algorithms to demonstrate the effectiveness of our model.

Through these steps, we build a deep recommender system that comprehensively analyzes users' music preferences, social trust, and tagging information, aiming to provide users with more personalized piano music recommendations.

3.2. **Evaluation indicators.** In order to comprehensively evaluate the performance of the proposed trust and label-aware deep recommendation model for piano music, we choose the following evaluation metrics. Precision and recall measure the proportion of user-interested items in the recommendation list and the proportion of user-interested items that can be covered by the recommender system, respectively. NDCG measures the quality of the ranking of relevant items in the recommendation list [25].

Precision: where $|Rel_k|$ is the number of relevant items in the recommendation list and k is the length of the recommendation list.

$$\text{Precision@}k = \frac{|Rel_k|}{k} \tag{17}$$

Recall: where $|Rel_{total}|$ is the total number of items actually of interest to the user.

$$\text{Recall@}k = \frac{|Rel_k|}{|Rel_{total}|} \tag{18}$$

Normalized Discounted Cumulative Gain (NDCG): where r_i is the relevance score of the i-th recommended item, denoting the accumulation of the first k items in the recommended list, and $IDCG@k$ is the DCG in the ideal case, which is used to normalize the value of the DCG [26].

$$\text{NDCG@}k = \frac{\sum_{i=1}^{k} \frac{2^{r_i}-1}{\log_2(i+1)}}{IDCG@k} \tag{19}$$

4. **Performance testing and analysis.** To thoroughly assess the efficacy of our trust and label-aware deep recommendation model for piano music, we've conducted a battery of experiments, evaluating them across various metrics. The experimental phase is bifurcated into ablation studies and performance trials. Our extensive experiments demonstrate that our approach outperforms traditional methods across various metrics, including precision, recall, and NDCG, particularly for users with limited interaction history.

4.1. **Experimental setup.** We used two publicly available datasets for our experiments, and Table 1 shows the detailed statistics of the datasets:

Table 1. Data set information

Dataset	Number of users	Number of music/websites	Number of tags	Number of trust relationships
Last.fm	1,892,000	1,763,219	1,194,613	1,271,756
Delicious	1,867,000	69,226,743	5,338,871	766,824

The experiments were carried out on a personal computer with a 3.1GHz CPU and 16GB of RAM. Python was the programming language of choice, and we leveraged deep learning frameworks like TensorFlow and Keras for model development and training [27].

4.2. **Ablation experiments.** To assess the impact of trust relationships and label information on the recommendation performance, we conducted an ablation study [28]. This experiment methodically removed different components of the model to evaluate their individual contributions to the recommendation quality. The study involved four primary model variants:

Variant A (baseline model): only user-music rating data is used, without any trust relations and labeling information.

Variant B: Adds trust relationships to variant A.

Variant C: adds labeling information on top of variant A.

Variant D (full model): uses both user-music rating data, trust relationships and labeling information.

The experimental results are shown in Figure 4

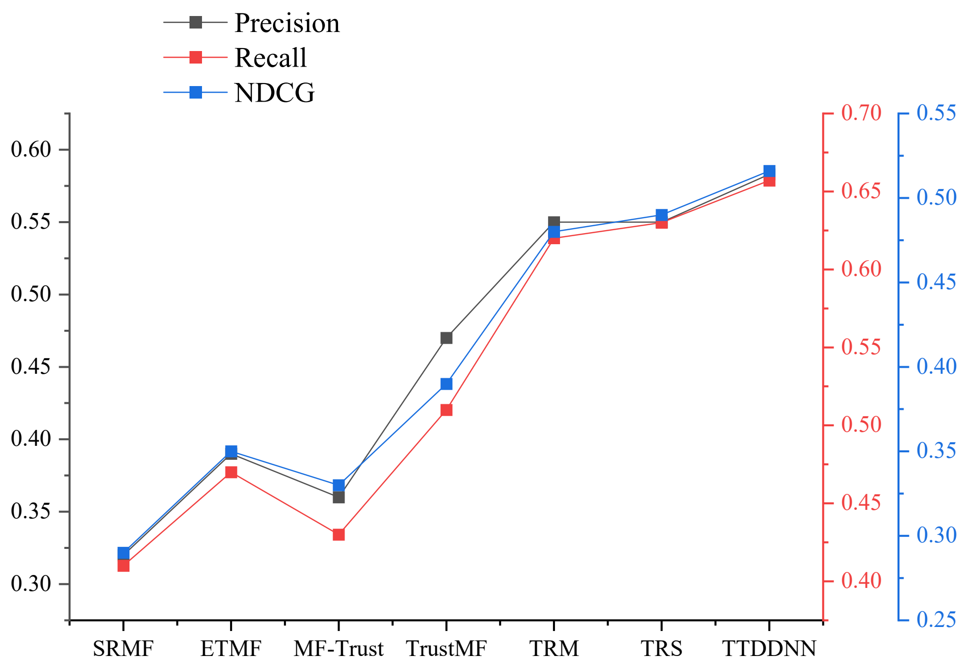

Figure 4. Results of ablation experiments

As depicted in the figure, variant B, which includes trust relationships, and variant C, which includes labeling information, both demonstrate improvements in precision, recall, and NDCG compared to the baseline model. This suggests that incorporating either trust or labels enhances recommendation performance. Moreover, the superior results from the full model, variant D, which integrates both trust and labels, confirm that their combined effect can significantly boost the effectiveness of the recommendation system.

4.3. **Performance experiments.** In the performance experiment section, we compare the proposed models with several existing recommendation models, including matrix decomposition-based recommendation models (SRMF), deep learning-based recommendation models (ETMF, MF-Trust, TrustMF, TRM, and TRS). We evaluated all the models using the aforementioned evaluation metrics and recorded their performance.

The experimental results are shown in Figure 5

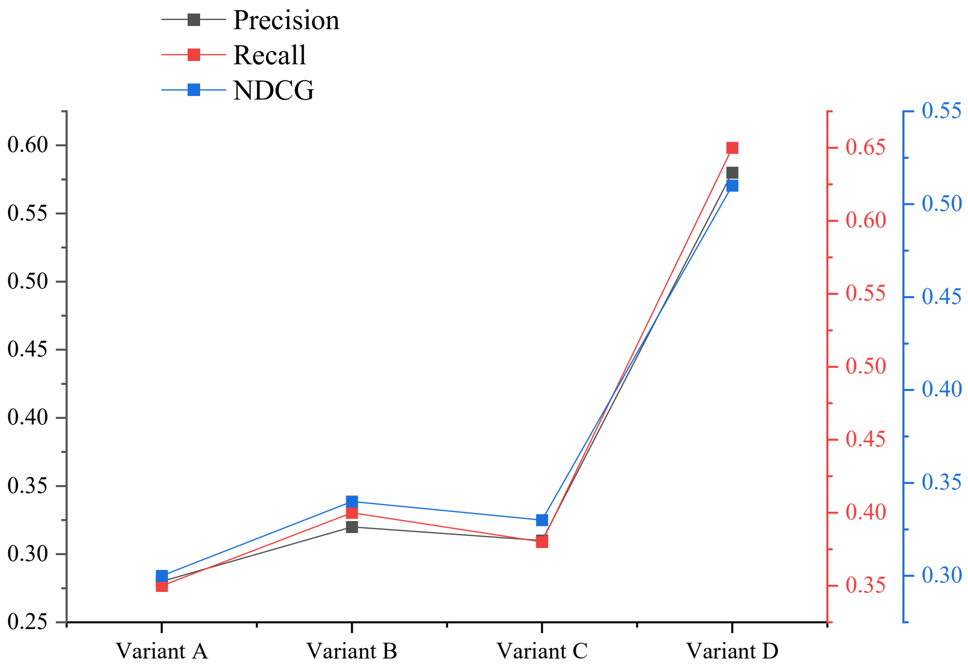

Figure 5. Results of Performance experiments

The experimental findings indicate that our proposed model surpasses other models in terms of precision, recall, and NDCG. Notably, our model achieved a precision of 0.583, a recall of 0.657, and an NDCG of 0.516 on the Last.fm dataset, outperforming other models across these metrics. These outcomes validate that integrating trust between users and labels of music works is an effective strategy to enhance recommender system performance.

5. **Conclusion.** This paper introduces a deep recommendation model for piano music that is aware of both trust and labels, designed to overcome the challenges faced by traditional systems when it comes to the evolving nature of user preferences and the variety of musical pieces. Our model integrates users' music preferences, trust in other users, and the labels associated with music to deliver personalized suggestions. It applies sparse autoencoders to identify underlying features and uses cosine similarity for predicting user ratings on unexplored music. The experiments demonstrate that our model surpasses current algorithms in precision, recall, and NDCG, significantly enhancing recommendation system performance. Our model has demonstrated significant improvements in precision, recall, and NDCG over existing methods, as detailed in our experiments. However, it is

also important to discuss some of the limitations we encountered and areas where further work is needed.

While our model has shown considerable improvements in experimental performance, certain limitations are noteworthy. Firstly, its dependence on user trust relationships and music labeling can result in data sparsity, particularly when user or label counts are low. Secondly, the high computational complexity may lead to efficiency challenges with large datasets. Lastly, there's room for enhancing the model's interpretability to make the recommendation logic more transparent to users.

Future research could focus on several key areas for development: first, exploring more efficient ways to address data sparsity, perhaps by integrating additional user behavioral data or employing advanced data imputation methods. Second, there's potential in enhancing the model's computational efficiency, possibly through distributed computing or model compression techniques. Improving model interpretability is another crucial direction, which might be achieved through visualization or by incorporating explainable AI approaches. Lastly, examining the applicability of our model to other music genres or recommendation systems could confirm its versatility and practicality. These efforts could lead to more sophisticated recommendation systems that offer users an even more personalized and diverse music recommendation experience.

In conclusion, our deep learning-based recommendation system for piano music represents a significant advancement in recommendation accuracy and personalization. Future work will focus on addressing current limitations and expanding the model's applicability to other music genres.

REFERENCES

[1] Z. Ji, H. Pi, W. Wei, B. Xiong, M. Woźniak, and R. Damasevicius, "Recommendation based on review texts and social communities: a hybrid model," *IEEE Access*, vol. 7, pp. 40416-40427, 2019.

[2] Z. El Yebdri, S. M. Benslimane, F. Lahfa, M. Barhamgi, and D. Benslimane, "Context-aware recommender system using trust network," *Computing*, vol. 103, no. 9, pp. 1919-1937, 2021.

[3] Y. Ma, Y. Peng, and T.-Y. Wu, "Transfer learning model for false positive reduction in lymph node detection via sparse coding and deep learning," *Journal of Intelligent & Fuzzy Systems*, vol. 43, no. 2, pp. 2121-2133, 2022.

[4] G. Adomavicius, R. Sankaranarayanan, S. Sen, and A. Tuzhilin, "Incorporating contextual information in recommender systems using a multidimensional approach," *ACM Transactions on Information Systems (TOIS)*, vol. 23, no. 1, pp. 103-145, 2005.

[5] M. Fu, H. Qu, Z. Yi, L. Lu, and Y. Liu, "A novel deep learning-based collaborative filtering model for recommendation system," *IEEE Transactions on Cybernetics*, vol. 49, no. 3, pp. 1084-1096, 2018.

[6] P. M. Gabriel De Souza, D. Jannach, and A. M. Da Cunha, "Contextual hybrid session-based news recommendation with recurrent neural networks," *IEEE Access*, vol. 7, pp. 169185-169203, 2019.

[7] H. He, R. Zhang, Y. Zhang, and J. Ren, "USBE: User-similarity based estimator for multimedia cold-start recommendation," *Multimedia Tools and Applications*, vol. 83, no. 1, pp. 1127-1142, 2024.

[8] S. Mo and J. Niu, "A novel method based on OMPGW method for feature extraction in automatic music mood classification," *IEEE Transactions on Affective Computing*, vol. 10, no. 3, pp. 313-324, 2017.

[9] Y. Zhang, "Design of the piano score recommendation image analysis system based on the big data and convolutional neural network," *Computational Intelligence and Neuroscience*, vol. 2021, no. 1, p. 4953288, 2021.

[10] R. Kuo and S.-S. Li, "Applying particle swarm optimization algorithm-based collaborative filtering recommender system considering rating and review," *Applied Soft Computing*, vol. 135, p. 110038, 2023.

[11] M. K. Lee and E. Turban, "A trust model for consumer internet shopping," *International Journal of Electronic Commerce*, vol. 6, no. 1, pp. 75-91, 2001.

[12] J. L. Crosno, A. Nygaard, and R. Dahlstrom, "Trust in the development of new channels in the music industry," *Journal of Retailing and Consumer Services*, vol. 14, no. 3, pp. 216-223, 2007.

[13] M. Kaminskas and F. Ricci, "Contextual music information retrieval and recommendation: State of the art and challenges," *Computer Science Review*, vol. 6, no. 2-3, pp. 89-119, 2012.

[14] X. Zhu, Y.-Y. Shi, H.-G. Kim, and K.-W. Eom, "An integrated music recommendation system," *IEEE Transactions on Consumer Electronics*, vol. 52, no. 3, pp. 917-925, 2006.

[15] M. Schedl, H. Zamani, C.-W. Chen, Y. Deldjoo, and M. Elahi, "Current challenges and visions in music recommender systems research," *International Journal of Multimedia Information Retrieval*, vol. 7, pp. 95-116, 2018.

[16] D. Gupta and S. Bag, "Handwritten multilingual word segmentation using polygonal approximation of digital curves for Indian languages," *Multimedia Tools and Applications*, vol. 78, pp. 19361-19386, 2019.

[17] M. Cummins and P. Newman, "Appearance-only SLAM at Large Scale with FAB-MAP 2.0," *Advances in Bioinformatics*, vol. 30, no. 9, pp. 1100-1123, 2010.

[18] Z. Hyung, J.-S. Park, and K. Lee, "Utilizing context-relevant keywords extracted from a large collection of user-generated documents for music discovery," *Information Processing & Management*, vol. 53, no. 5, pp. 1185-1200, 2017.

[19] H.-G. Kim, G. Y. Kim, and J. Y. Kim, "Music recommendation system using human activity recognition from accelerometer data," *IEEE Transactions on Consumer Electronics*, vol. 65, no. 3, pp. 349-358, 2019.

[20] C. Zhang, X. Cheng, J. Liu, J. He, and G. Liu, "Deep sparse autoencoder for feature extraction and diagnosis of locomotive adhesion status," *Journal of Control Science and Engineering*, vol. 2018, no. 1, 8676387, 2018.

[21] C. Esposito, V. Moscato, and G. Sperlì, "Detecting malicious reviews and users affecting social reviewing systems: A survey," *Computers & Security*, vol. 133, 103407, 2023.

[22] D. M. Greenberg, M. Kosinski, D. J. Stillwell, B. L. Monteiro, D. J. Levitin, and P. J. Rentfrow, "The song is you: Preferences for musical attribute dimensions reflect personality," *Social Psychological and Personality Science*, vol. 7, no. 6, pp. 597-605, 2016.

[23] S. Xu, H. Zhuang, F. Sun, S. Wang, T. Wu, and J. Dong, "Recommendation algorithm of probabilistic matrix factorization based on directed trust," *Computers & Electrical Engineering*, vol. 93, 107206, 2021.

[24] Z. Ji, C. Yang, H. Wang, J. E. Armendáriz-Iñigo, and M. Arce-Urriza, "BRS c S: a hybrid recommendation model fusing multi-source heterogeneous data," *EURASIP Journal on Wireless Communications and Networking*, vol. 2020, pp. 1-17, 2020.

[25] S. Aftab and H. Ramampiaro, "Evaluating top-n recommendations using ranked error approach: An empirical analysis," *IEEE Access*, vol. 10, pp. 30832-30845, 2022.

[26] F. Tambon, A. Nikanjam, L. An, F. Khomh, and G. Antoniol, "Silent bugs in deep learning frameworks: an empirical study of keras and tensorflow," *Empirical Software Engineering*, vol. 29, no. 1, p. 10, 2024.

[27] S. Goode, A. Chowdhury, M. Crockett, A. Beech, R. Simpson, T. Richards, and B. Braithwaite, "Laser and radiofrequency ablation study (LARA study): a randomised study comparing radiofrequency ablation and endovenous laser ablation (810 nm)," *European Journal of Vascular and Endovascular Surgery*, vol. 40, no. 2, pp. 246-253, 2010.

[28] K. C. Wong, J. R. Paisey, M. Sopher, R. Balasubramaniam, M. Jones, N. Qureshi, C. R. Hayes, M. R. Ginks, K. Rajappan, and Y. Bashir, "No benefit of complex fractionated atrial electrogram ablation in addition to circumferential pulmonary vein ablation and linear ablation: benefit of complex ablation study," *Circulation: Arrhythmia and Electrophysiology*, vol. 8, no. 6, pp. 1316-1324, 2015.