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Hybrid Temporal Dynamics Feature Extraction in Recommendation Systems for Improved Ranking of Items

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Abstract— In today's retail landscape, shopping malls and e-commerce platforms employ various psychological tactics to influence customer behavior and increase profits. In line with these strategies, this paper introduces an innovative method for recognizing sentiment patterns, with a specific emphasis on the evolving temporal aspects of user interests within Recommendation Systems (RS). The projected method, called Temporal Dynamic Features based User Sentiment Pattern for Recommendation System (TDF-USPRS), aims to enhance the performance of RS by leveraging sentiment trends derived from a user's past preferences. TDF-USPRS utilizes a hybrid model combining Short Time Fourier Transform (STFT) and a layered architecture based on Bidirectional Long Short-Term Memory (BiLSTM) to retrieve temporal dynamics and discern a user's sentiment trend. Through an examination of a user's sequential history of item preferences, TDF-USPRS produces sentiment patterns to offer exceptionally pertinent recommendations, even in cases of sparse datasets. A variety of popular datasets, including as MovieLens, Amazon Rating Beauty, YOOCHOOSE, and CiaoDVD are utilised to assess the suggested technique. The TDF-USPRS model outperforms existing approaches, according to experimental data, resulting in recommendations with greater accuracy and relevance. Comparing the projected model to existing approaches, the projected model displays a 6.5% reduction in RMSE and a 4.5% gain in precision. Specifically, the model achieves an RMSE of 0.7623 and 0.996 on the MovieLens and CiaoDVD datasets, while attaining a precision score of 0.5963 and 0.165 on the YOOCHOOSE and Amazon datasets, respectively.

Keywords- Collaborative Filtering, Hybrid Recommendation System, Temporal dynamics, User interests, Feature extraction, Item ranking.

I. INTRODUCTION

In today's retail landscape, shopping malls strategically employ psychological tactics to influence customer behavior and optimize their shopping experience. Similarly, the E-commerce industry follows such psychological approach that aims to maximize profits by providing personalized recommendations to customers. This research paper introduces an innovative approach to sentiment pattern recognition within Recommendation Systems (RS) that effectively captures the temporal dynamics of user interests over time.

The internet contains an immense and continuously expanding wealth of information, giving rise to the issue of information inundation [1]. Recommendation Systems (RS) have emerged as a valuable solution to this issue by providing personalized recommendations based on user interests. The incorporation of sentiment patterns in RS can further enhance customer satisfaction in business settings. Trust [2] [3] and contextual information [4] [5] [6] play crucial roles in improving the quality of recommendations. The impact of RS is significant, affecting billions of online users and driving further research in the field.

The arrangement of items in shopping malls based on psychological order has been proven to attract customers, highlighting the importance of effective recommendation options for both customers and online sellers. RS helps establish trust and loyalty between vendors and customers by providing relevant and accurate recommendations. E-commerce companies benefit from the ability to offer customers timely and tailored suggestions, facilitating efficient product discovery.

However, existing RS encounter challenges like data sparsity [7-8] and the cold start problems [9-10]. Data sparsity occurs when a large number of users express preferences for a limited number of items, making it problematic to generate recommendations. The cold start problem arises due to insufficient data pertaining to new users, hindering the recommendation process. These issues negatively affect the

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performance of Collaborative Filtering (CF) [11] techniques commonly used in RS.

User behavior and interests evolve over time [12-13] and in different contexts, making it challenging to establish correlations. This study aims to enhance RS performance by leveraging users' historical sentiment patterns. A novel model called TDF-USPRS is proposed here. This hybrid model combines collaborative filtering and temporal dynamics to analyze users' sequential histories of item interests and generate sentiment patterns. The TDF-USPRS model addresses cold start and data sparsity issues, leading to highly relevant recommendations.

Experiments were conducted using various datasets, including MovieLens, Amazon Rating Beauty, YOOCHOOSE, and CiaoDVD, to assess the effectiveness of the projected TDF-USPRS model. The outcomes demonstrate that the TDF-USPRS approach consistently superior to the latest technologies in terms of recommendation accuracy and relevance.

The contributions of this work can be summed up as,

1. Innovative Approach for Recognizing Sentiment Patterns: The paper presents a unique approach to sentiment pattern recognition in Recommendation Systems (RS). By identifying and capturing the temporal dynamics of user interests over time, the proposed method offers valuable insights into users' sentiment patterns, enabling more accurate and personalized recommendations.
2. Incorporation of Historical Sentiment Patterns: The research focuses on leveraging users' historical sentiment patterns to improve the performance of RS. By considering users' sequential histories of item interests, the proposed model, TDF-USPRS, effectively generates sentiment patterns that contribute to providing highly relevant recommendations, even in scenarios with sparse datasets.
3. Hybrid Model with Collaborative Filtering and Temporal Dynamics: The TDF-USPRS model introduces a hybrid architecture that combines collaborative filtering with temporal dynamics. This combination allows for a comprehensive understanding of users' preferences and interests, enabling the model to generate more precise and personalized recommendations.
4. Evaluation on Natural and Public Datasets: The proposed method is rigorously evaluated on various natural and public datasets, including popular ones like MovieLens, Amazon Rating Beauty, YOOCHOOSE, and CiaoDVD. This evaluation ensures the effectiveness and generalizability of the TDF-USPRS model across different domains and datasets.
5. Improved Performance over cutting-edge techniques: The experimental findings show that the TDF-USPRS model overtakes present approaches in terms of recommendation accuracy and relevance. The proposed model achieves a significant improvement of 6.5% in RMSE and 4.5% in precision compared to modern approaches, showcasing its superiority in generating accurate and meaningful recommendations.

To sum up, this paper introduces a novel strategy that addresses the challenge of accurate item ranking in recommendation systems. By combining temporal dynamics and feature extraction, the proposed approach aims to deliver more relevant and individualized recommendations to users. The subsequent sections will delve into literature review, the details of the hybrid approach and its methodology, and results and analysis, then a description of the outcomes follows and the conclusion.

II. LITERATURE REVIEW

In recent times, researchers have extensively explored various techniques to enhance the efficiency of RS. This paper's approach is centered on uncovering user sentiment patterns. To establish the foundation for this strategy, a comprehensive literature review of RS is conducted, with a specific emphasis on the integration of sentiment analysis to enhance generated recommendations.

The authors in [14] conducted an extensive review of RS techniques. The work encompassed a comprehensive analysis of the challenges encountered within RS. In the contemporary landscape, these systems grapple with issues such as temporal sensitivity, data sparsity, user sentiment analysis, the cold start problem, generating Top-N recommendations, and diversifying recommendations. The authors underscored the significance of user sentiment analysis in predicting precise and pertinent recommendations. User preference changes over time, which makes it essential to discover user concept drifts with time to produce the most accurate predictions. Temporal RS have been developed to capture the patterns of user choice and build personalized user profiles. Several studies have focused on understanding the user liking temporal patterns and items' features. To increase the accuracy of recommendations, Liu et al. [15] suggested a temporal rating model using user-item ratings and reviews. For capturing the continuous user-item communications over time, Rafailidis et al. [16] proposed a tensor-based approach. A temporal matrix factorization (TMF) method has been described by Lo et al. [13] for monitoring conceptual change over time in each user latent vector. Chen et al. [17] developed a recommendation technique based on dynamic clustering using temporal data.

Temporal dynamics extraction is proposed by Zhang et al. [18]. The Multi-Trans MF approach with a time factor is developed. Liao et al. [19] presented the Ant CF scheme to discover the users-item relationship and capture user liking changes over time. Li et al. [20] investigated the correlation between time and the location of social networks when it comes to cold-start recommendations. Wen et al. [21] proposed an

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extended factorization machine approach for sequential recommendations that considers temporal information and patterns to understand user behavior.

Choe et al. [22] used a RNN to analyze long-term time series, a thorough examination of RSs for building energy effectiveness was presented by Himeur et al. [23]. Using time based knowledge graphs to characterize the time-dependent user-service interactions, Mezni et al. [24] suggested an approach for recommendation.

Sritrakool et al. [25] designed a personalized model to track the drift of user likings, while Jiang et al. [26] proposed a dynamic sequential recommendation using time context and matrix factorization.

A time-series model was presented by Z. Wang et al. [27] to represent temporal patterns of user interest. W. Jia et al. [28] captured temporal activity prediction of each user. W. Ali et al. [29] proposed item-context similarity (ICS) model using time context to produce relevant recommendations. T. Tuna et al. [30] introduced DL techniques for time-series examination.

The consideration of time sequence for the selection of items is a novel approach these days, as the difficulty lies in the analysis related to interests of the user, which gradually changes over time. Thus, there has been a gradual shift in CF designs from researchers to address the time sequence and changes in interests of the user. The researchers in recommender frameworks also concentrate on algorithmic item selection and ranking methodologies. A top-N target-oriented method has been designed that uses sequence learning to capture user choice using the time domain, which also handles the cold start problem [31]. Anelli et al. [32] presented improving ranking accuracy of recommendations using Neural MF.

The consideration of time sequence for item selection is a novel approach, as user interests gradually change over time. Research in RS has shifted towards addressing time sequence and changes in user preferences which has many challenges. Algorithmic item selection and ranking methodologies remain a focus of research in the domain of recommender frameworks.

III. METHODOLOGY

Addressing the scalability issue in collaborative filtering RS is crucial since many contemporary RS grapple with the complexities of the cold start problem and data sparsity, making it difficult to provide accurate recommendations. To enhance the RS's correctness, incorporating contextual and trust information, and user temporal patterns is essential in accurately modelling user preferences. However, leveraging temporal contextual information for improving recommendation accuracy remains a significant challenge in RS and requires further research efforts in user modeling structure. We posit that considering a user's emotional tone could lead to more precise recommendations, and utilizing time series ratings dataset is vital for achieving this.

A key objective of RS is identifying user sentiment towards items to aid in their purchase decisions. The prevalent CF approach primarily focuses on item ratings given by users, categorizing them to gauge user interest in similar items. However, many RS systems rely solely on ratings for this categorization, leading to gaps in the rating dataset. Filling these gaps is a critical task, and various approaches, including user-to-user relation factors, have proven successful in existing methodologies. CF and MF have shown promising results in identifying missing entries and imputing them with new rating values.

For effective item recommendation, clustering users based on similar interests is a valid strategy. However, when considering a large number of items and historical interests of all users, item recommendation becomes sparse due to significant dissimilarities among user interests. Addressing sparseness problems effectively requires the application of machine learning techniques. While K-means clustering has been used, it tends to be insensitive to sparseness, leading to performance degradation in RS. Hence, selecting the appropriate clustering technique is of paramount importance to improve the recommendation system's overall performance.

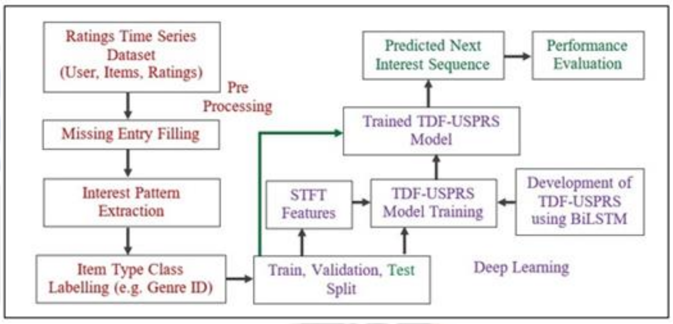

Figure 1. TDF-USPRS approach flowchart

Another crucial factor to consider is the change in user interests and behavior. For instance, even though similar users may be grouped based on their interests in certain items, their preferences for subsequent items in the list could differ. This sentiment-based analysis and recommendation approach focus on recognizing the interest patterns of items based on user sentiments derived from historical rating data. The proposed TDF-USPRS method, depicted in figure 1, embodies this approach.

The processing of the input dataset for performance evaluation involves several stepwise methods, which are elaborated in the following sub-sections. The initial step in this work is to address missing entries in the ratings dataset, as these gaps disrupt the user interest patterns. To accomplish this, a user-user trust-centric approach, as proposed by Awati et al. in [33] and J. Bobadila et al. [34], is used for filling the missing entries. Once the missing entry-filled dataset is pre-processed, it undergoes vectorization for further processing.

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A. Vectorization of Sentiment Pattern

The sentiment pattern recognition offers a viable alternative to the conventional regression strategy in recommendation systems. In this approach, the rating value associated with an item number is represented as a decimal number, reflecting the user interest level or preference for that particular item. By analyzing the sequence of item numbers associated with a user, we can discern a sentiment pattern that characterizes the user's historical interests. Leveraging this sentiment pattern from the user's historical data allows us to predict their potential future interests. The intricate numeric patterns are captured within the item sequences, a deep learning technique is employed, specifically a BiLSTM based model. The BiLSTM model is well-suited for sequential data analysis, as it can effectively learn and capture the dependencies and patterns present in the item sequences. By training the BiLSTM on the historical item sequences of users, the model gains a deep understanding of the numeric patterns, enhancing the accuracy of future interest predictions. For a clearer illustration, let's consider a sample portrayed in figure 2. The horizontally displayed list contains item IDs, representing the historical interests of a user, denoted as "U." Each entry in the list corresponds to an item number, and the sequence of these item numbers forms the user's sentiment pattern, reflecting their past preferences.

44	12	54	78	32	89	61	58	31	26

Figure 2. User's Interest Pattern

The process begins with obtaining an input pattern from which the subsequent target values are predicted. To facilitate the training process, the list of historical item sequences is divided into two parts, as depicted in figure 3. The first part of the list, referred to as the "input pattern," serves as the training input for the model. It contains an order of item IDs representing the user's past interests and preferences. This input pattern is fed into the model to learn and capture the underlying numeric patterns and dependencies present in the user's historical data.

X(n):	44	12	54	78	32	89	61	58	31	26
Y(n):	12	54	78	32	89	61	58	31	26	71

Figure 3. Input and output vector formation

In the proposed model, the input is represented by the variable "X," and the corresponding target values are represented by the variable "Y." The architecture is designed such that each interest in the item sequence, denoted as "n^{th}" item interest in X, serves as the input, and the subsequent interest, denoted as "$(n+1)^{th}$" item in the sequence, acts as the target in Y. This relationship is illustrated in figure 3.

B. Item list to class type conversion

In order to address the item number problem and convert it into a more manageable scaled region, the item list pattern is transformed into a class-type pattern based on movie genres. Each movie is associated with a specific genre, and since the number of genres is limited, genre-based sentiment analysis proves to be a robust approach for simplifying the problem. For instance, when dealing with a large number of movie items, such as 100,000, it can be challenging for all users to watch and rate every single movie. This situation leads to the need for clustering users based on genre preferences. Segmenting movie items into ten distinct genres streamlines the identification of shared interests among users., making the clustering process more efficient. In this context, figure 4 illustrates the sequence of sentiment patterns based on genres, a modification of the previous figures, 2 and 3. This genre-based pattern sequence is crafted by utilizing the genre data within the dataset and applying the label encoder technique. This method assigns uniform genre labels ranging from 1 to 10, and it provides an output of the labelled sequence based on these genres. By converting the item list pattern into a genre-based class-type pattern, the sentiment analysis becomes more interpretable and manageable. Users' preferences are now associated with specific genres, enabling the recommendation system to understand and predict genre-based interests more effectively. This methodology dramatically decreases the intricacy of the recommendation process and allows for better user clustering and personalized recommendations based on genre preferences.

X(n):	4	2	1	6	3	4	7	8	7	3
Y(n):	2	1	6	3	4	7	8	7	3	6

Figure 4. Item ID to Genre ID Converted Interest Pattern (e.g. Movie Genre)

Figure 4 showcases the genre (class type) sequence, where each genre is considered as an "nth" input X, and the subsequent genre in the sequence becomes the "$(n+1)^{th}$" target Y during training the proposed TDF-USPRS. The training process involves using the "$(n+1)^{th}$" genre as input for predicting the "$(n+2)^{th}$" genre, and so on, maintaining a sequential flow of genre interests.

C. Temporal Dynamics Feature Extraction

Temporal dynamic feature extraction from a 1D data vector of interest patterns is a crucial step in understanding and modeling the progressing nature of user likings over time. By capturing the temporal changes and dynamics inherent in the sequence of interests, this process enables the identification of patterns, trends, or shifts that reflect the shifting needs, evolving tastes, or changing sentiments of users. This extraction of temporal features holds significant value for recommendation systems,

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personalized marketing strategies, user behavior analysis, and other time-dependent analyses.

When extracting temporal dynamic features, the goal is to go beyond static representations of user preferences and delve into the dynamic nature of their interests. By considering the sequential order of interests and their corresponding timestamps, it becomes possible to derive valuable insights into the temporal patterns that shape user behavior. These insights can subsequently enhance the accuracy, relevance, and personalization of recommendation systems.

The extracted features serve as a representation of the temporal dynamics present within the interest patterns. They encapsulate information about the frequency, intensity, duration, or temporal distribution of interests over time. This information can be leveraged to identify patterns, such as recurring interests, seasonal trends, sudden shifts in preferences, or gradual changes in user sentiment. By analyzing these temporal features, it becomes possible to gain a deeper understanding of user behavior and make more informed predictions about future interests.

Temporal Dynamic features are extracted using two parallel methods to make a hybrid model. First method uses STFT and second technique uses BiLSTM based network which analyzes the time series data for temporal dynamics.

1) STFT for Temporal Dynamic Features

The temporal dynamics features are extracted with the STFT method that involves stepwise processing on input data vector as shown in figure 5.

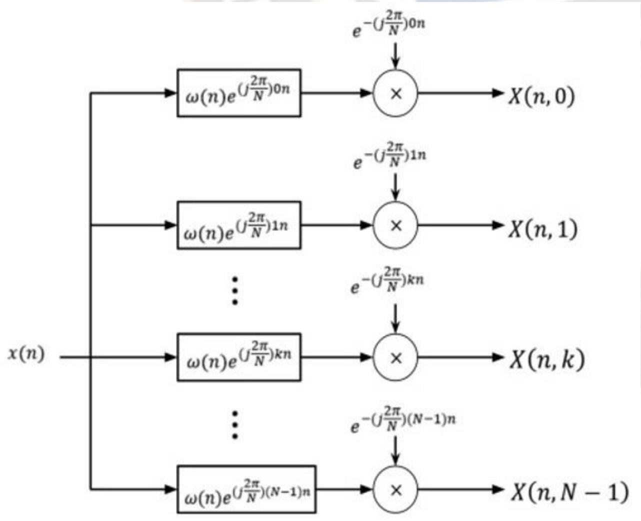

Figure 5. STFT based temporal dynamic feature extraction of x (n)

(a) Define the parameters:

(1) Window size: W (number of samples in each window)

(2) Hop size: H (number of samples between consecutive windows)

(3) Sampling rate: fs (number of samples per second)

(b) *Prepare the input signal:*

(1) Let x (n) be the 1D data vector of interests pattern of length N representing the input.

(c) *Prepare the input signal:*

(1) Divide the input into overlapping windows with a length of W and a hop size of H. This can be represented by the following equation for the k-th window:

(2)Apply a windowing function, such as the Hamming window, to each windowed segment to reduce spectral leakage:

$$x\_w\_win(k,n) = x\_w(k,n) * w(n)\ for\ n = 0,1,\ldots,W-1 \qquad (1)$$

Where w (n) is the window function.

(3)Compute the Discrete Fourier Transform (DFT) of each windowed segment to obtain the frequency domain representation:

$$x\,X(k,m) = \sum_{n=0}^{W-1} x\_w\_win(k,n) * exp(-j * 2\pi * m * n / W) \quad for\ m = 0,1,\ldots,W-1 \qquad (2)$$

(4) Obtain the magnitude spectrogram by taking the absolute value of the complex DFT coefficients:

$$S(k,m) = |X(k,m)| for\ k = 0,1,\ldots,K-1\ and\ m = 0,1,\ldots,W-1 \qquad (3)$$

Where K is the number of windows.

(d) *Extract temporal features:*

(1) Temporal features can be computed based on the magnitude spectrogram S(k, m). Some common features include:

Mean:

$$\mu(k) = (1/W) * \sum_{m=0}^{W-1} S(k,m) \qquad (4)$$

Standard deviation

$$\sigma(k) = \sqrt{[(1/W) * \sum_{m=0}^{W-1}(S(k,m)-\mu(k))^2]} \qquad (5)$$

Energy:

$$E(k) = (1/W) * \sum_{m=0}^{W-1}(S(k,m))^2 \qquad (6)$$

These features can be calculated for each window (k) to capture the temporal dynamics of the signal.

(e) *Post-process and utilize the features:*

(1) Further processing or normalization steps can be applied to the extracted temporal features, depending on the specific requirements of your application.

(2) The resulting features can then be used as input for various tasks such as classification, regression, or recommendation systems.

These equations provide a general framework for extracting temporal features using STFT from a 1D data vector. There are variations and extensions of the STFT algorithm, and need to adapt the equations based on specific implementation details or domain-specific considerations.

A model consists of an input layer, three BiLSTM layers, a ReLU activated dense layer, and a softmax activated

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classification dense layer and also an attention mechanism is incorporated within the model:

D. Attention based BiLSTM model for Temporal Dynamics Features

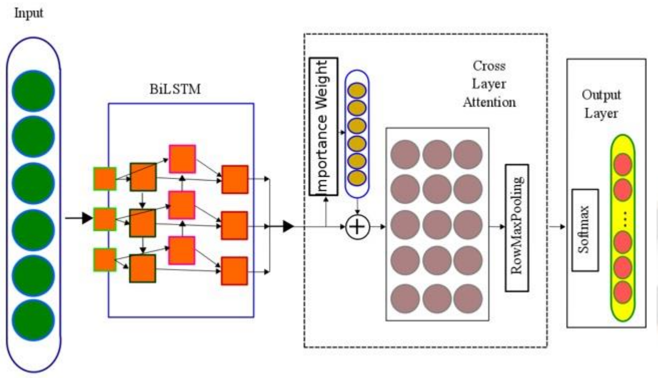

Figure 6. Proposed BiLSTM based Model Architecture

BiLSTM based analysis is important for finding the dynamic shifts in user interests as temporal features. The longer analysis of short term data is important aspect while providing the recommendation of items where seasonal, festival based impacts are seen in E-commerce businesses. Such a dynamic shifts are required to be captured on the other hand multiple attributes that show impact may increase the sparseness in analysis. For example, at a time either seasonal shifts are important or festival based shifts are important. Considering both at a time increase the confusion in system to degrade the overall system performance. This effect further can be understood with effective outcomes from the experimentation where specific data points window is fixed for getting maximum performance of the model. The details of BiLSTM based model processing steps as shown in figure 6 are follows.

1) Input Layer:

Let's assume the input to the model is an order of embeddings or features denoted as X. The shape of X is (batch_size, sequence_length, embedding_dimension).

2) BiLSTM Layers:

(a) First BiLSTM layer:

Forward LSTM:

Compute the forward hidden state:

$$h\_f^{1(t)} = LSTM\_f^{1(X[:,t,:])} \quad (7)$$

Backward LSTM:

Compute the backward hidden state:

$$h\_b^{1(t)} = LSTM\_b^{1(X[:,t,:])} \quad (8)$$

Concatenate the forward and backward hidden states:

$$h^{1(t)} = h\_f^{1(t)}, h\_b^{1(t)} \quad (9)$$

(b) Second BiLSTM layer:

Forward LSTM:

Compute the forward hidden state:

$$h\_f^{2(t)} = LSTM\_f^{2(h^{1[:,t,:]})}) \quad (10)$$

Backward LSTM:

Compute the backward hidden state:

$$h\_b^{2(t)} = LSTM\_b^{2(h^{1[:,t,:]})}) \quad (11)$$

Concatenate the backward and forward hidden states:

$$h^{2(t)} = h\_f^{2(t)}, h\_b^{2(t)} \quad (12)$$

(c) Third BiLSTM layer:

Forward LSTM:

Compute the forward hidden state:

$$h\_f^{3(t)} = LSTM\_f^{3(h^{2[:,t,:]})}) \quad (13)$$

Backward LSTM:

Compute the backward hidden state:

$$h\_b^{3(t)} = LSTM\_b^{3(h^{2[:,t,:]})}) \quad (14)$$

Concatenate the backward and forward hidden states:

$$h^{3(t)} = h\_f^{3(t)}, h\_b^{3(t)} \quad (15)$$

3) Attention Mechanism:

(a) Compute the attention weights for each time step using a trainable weight matrix W_a and a bias term b_a:

Attention weights:

$$alpha(t) = softmax(W\_a * h^{3(t)} + b\_a) \quad (16)$$

(b) Apply the attention weights to the hidden states $h^{3(t)}$ using element-wise multiplication:

Weighted hidden states:

$$h^{3\_att(t)} = alpha(t) * h^{3(t)} \quad (17)$$

(c) Sum the weighted hidden states along the time axis to obtain the context vector c:

$$c = sum\,(h^{3\_att}, axis = 1) \quad (18)$$

4) ReLU Activated Dense Layer:

Compute the intermediate features by applying a fully connected layer with ReLU activation:

Intermediate features:

$$h\_relu = ReLU(W\_r * c + b\_r) \quad (19)$$

5) Classification Dense Layer (Softmax):

Compute the logits for each class using a fully connected layer:

$$logits = W\_c * h\_relu + b\_c \quad (20)$$

Apply softmax activation to obtain the predicted probabilities for each class:

Predicted probabilities:

$$y\_pred = softmax(logits) \quad (21)$$

At each BiLSTM layer, you can use self-attention mechanisms. The model's attention process enables it to concentrate on different elements within the same sequence representation, capturing relevant dependencies between elements. Self-attention is applied separately within the forward and backward BiLSTMs in each layer. After applying self-attention within each BiLSTM layer, you can introduce cross-layer attention connections. This means that the hidden states of

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one BiLSTM layer will be used to attend to the hidden states of another BiLSTM layer, either from the same direction (forward or backward) or from both directions. The attention mechanism introduced in step 3 allows the model to pay attention to various elements of the input sequence during computation. By assigning attention weights to each time step, the model learns to weigh the importance of different hidden states at different time steps. This can be particularly useful when dealing with long sequences, as it enables the model to selectively attend to the most relevant information. Here most relevant information is shifts in the interests of particular user.

IV. RESULTS AND DISCUSSION

This segment provides insights into the datasets employed in the experiments, which were used for assessing performance across various hyperparameters and conducting comparative examination.

A. Datasets

The research work utilized the TDF-USPRS system and conducted evaluations on four publicly available time series datasets to assess its performance. Table I shows the dataset statistics. These datasets included MovieLens, a widely used resource in recommendation system research, containing 100,000 ratings from 943 users on 1,682 movies with genre and timestamp information [35]. The Amazon rating beauty dataset captured user ratings for beauty products, featuring details on users, items, categories, and timestamps [36]. The YOOCHOOSE dataset comprised user sessions from a merchant, recording buy events on various items and providing information on sessions, items, timestamps, and categories [37]. Lastly, the CiaoDVD dataset offered user ratings for movies, along with genre and timestamp data [38]. These representative datasets allowed for a comprehensive evaluation of the TDF-USPRS model's performance, enabling insights into its effectiveness and suitability for different real-world scenarios.

TABLE I. DATASET STATISTICS

Dataset	#Rating	#Users	#Items	Publication Year and Orgnization Name	Class Type Used
Movie Lens [35]	1,00,000	943	1,682	1998, GroupLens	Movie Genre
Amazon rating beauty [36]	20,23,070	12,10,271	2,49,274	Amazon, (May 1996 - July 2014)	Item category
YOO-CHOOSE [37]	11,50,753	5,09,696	19,949	2014, RecSys Challenge	Item category
CiaoDVD [38]	2,78,483	7,375	99,746	CiaoDVD, 2013	Movie Genre

B. Performance Measures

In our experimental setup, we partitioned the dataset into training data (80%) and testing data (20%) to evaluate the effectiveness of the projected TDF-USPRS method.

We assess the performance of the proposed TDF-USPRS technique using various performance metrics, including RMSE, accuracy, precision, sensitivity and specificity.

Accuracy, sensitivity and specificity formulae:

$$Accuracy = TP + TN/(TP + TN + FP + FN) \tag{22}$$

$$Sensitivity = TP/(TP + FN) \tag{23}$$

$$Specificity = TN/(TN + FP) \tag{24}$$

The precision formula:

$$Precision\ @\ k = \frac{Number\ of\ items\ recommended\ @\ k\ that\ are\ relevant}{Number\ of\ items\ recommended\ @\ k} \tag{25}$$

RMSE formula:

$$RMSE = \frac{\sqrt{\sum_{i=1}^{N}(x_i - y_i)^2}}{N} \tag{26}$$

x_i = real rating, y_i = forecasted rating

Table 2 illustrates exemplar results acquired for three distinct users. In this context, the model takes the n^{th} input interest category and predicts the subsequent $(n+1)^{th}$ interest. A comparison between the actual ground truth and the forecasted output is provided in Table II for reference.

TABLE II. EXEMPLAR RESULTS FOR VARIOUS USERS

User	Current preference	Next preference (Ground Truth)	Predicted next preference	Category number
14	8	4	4.05	4
	4	6	5.98	6
	6	3	2.96	3
	3	5	5.02	5
	5	4	4.03	4
	4	2	1.97	2
131	2	3	2.94	3
	3	5	5.03	5
	5	3	3.03	3
	3	7	7.98	8
	7	8	7.85	8
	8	10	10.3	10
157	10	3	2.94	3
	3	5	4.96	5
	5	6	6.08	6
	6	7	6.95	7
	7	4	3.95	4
	4	9	8.98	9

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C. Window Based Peak Performance

In temporal dynamics based work, the window of selected length of fata points under consideration is important factor that defines the sensitivity of the model to the changes in the pattern. The input interest pattern vector x is thus divided in different sized windows that constitute length of items in input sequence at a time. If there are N number of total items in ratings dataset, total K segments are obtained by dividing the N by J number of items in each segment. The x is a set defined as,

$$x = \{x_1, x_2, \dots, x_k\} \tag{27}$$

Where, $x_1, x_2, \dots, x_k$ are the segments of data points having dimension 1×J.
Thus, the number of inputs are K for which there are K output segments represented as,

$$y = \{y_1, y_2, \dots, y_k\} \tag{28}$$

Where $y_1, y_2, \dots, y_k$ the outputs in output are set y for one user at a time.
The window size of temporal dynamic selection is thus defined by value of J which will impact on the sensitivity of changes in patterns of each segment.
The performance for different widow sizes is observed. The peak performance if the model is seen for the window size of 10 for input and 10 for output as shown in figure 7.

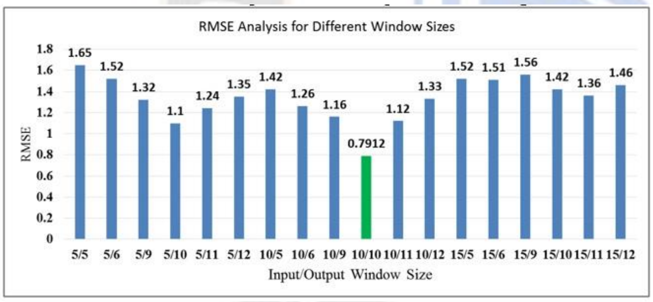

Figure 7. Peak Performance with Respect to Window Size Variations

As per the performance of the model, for all the remaining experiments, input window size is set to 10 for input vector and output to 10 during training and evaluation.

D. Optimizing the hyperparameters of the suggested TDF-USPRS approach

The TDF-USPRS model, as put forth, undergoes evaluation across a range of datasets. Specifically, in the MovieLens dataset, which encompasses 10 genres, it is transformed into 10 distinct classes, reliant on user preferences and ratings. The evaluation procedure adopts a genre-centric strategy. Correspondingly, for the Amazon Rating Beauty and YOOCHOOSE datasets, they are restructured into labeled datasets by taking individual categories into account. The CiaoDVD dataset follows a similar genre-based transformation akin to the MovieLens dataset. The fine-tuning of hyperparameters is performed on diverse datasets, with a specific analysis presented herein for the MovieLens dataset. Figure 8 illustrates the assessment of RMSE across varying neuron quantities within the range of 16 to 1024. The results show that the RMSE is minimized when utilizing 3 layers of BiLSTM and 256 hidden neurons in a dense layer. Table III shows the hyper-parameter configurations.

TABLE III. HYPER PARAMETER CONFIGURATIONS

Hyper Parameter	Configuration Values
Quantity of neurons in penultimate layer	16, 32, 64, 128, 256, 512, 1024
Training Epochs	200,300,400, 500,600,700,800

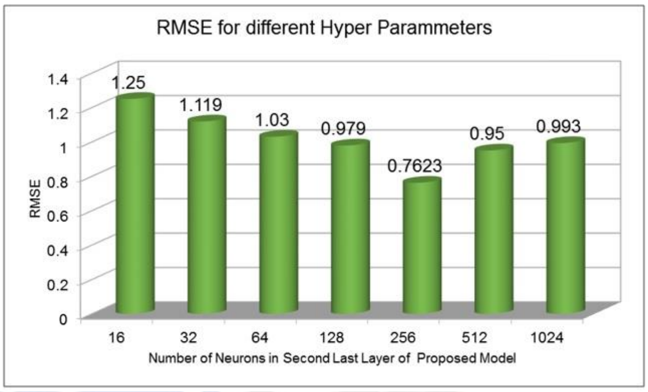

Figure 8. Assessment of RMSE across varying neuron quantities.

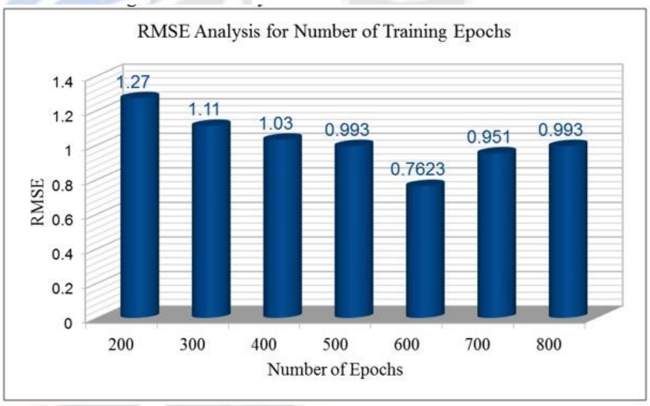

Figure 9. RMSE examination for various Epochs

In figure 9, the hyperparameter analysis of the TDF-USPRS model is presented, investigating the impact of varying the quantity of neurons in its penultimate layer. Among the tested configurations, the TDF-USPRS model with 256 neurons in the second last layer yielded the best performance and is hence referred to as the TDF-USPRS configuration. To assess the effectiveness of the TDF-USPRS model, Specificity, accuracy, and sensitivity metrics were measured for each dataset. Figure 10 displays the Performance assessment of projected TDF-USPRS approach using different datasets.

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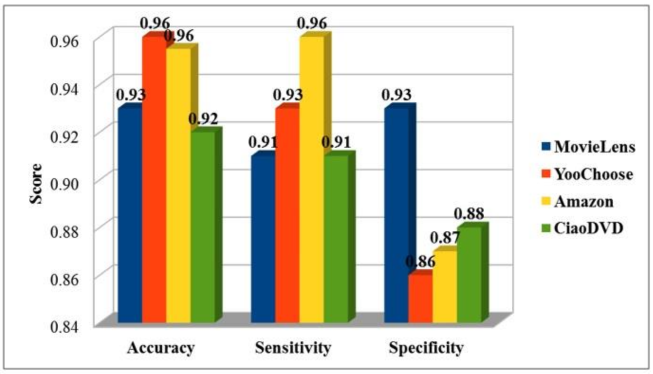

Figure 10. Performance assessment of projected TDF-USPRS technique utilizing various datasets

E. Assessing the effectiveness the projected TDF-USPRS approach against cutting-edge methods

1) Relative examination of cutting-edge techniques alongside the TDF-USPRS approach using the MovieLens dataset

In figure 11, a relative examination of TDF-USPRS with TMF [13], PCC [39], HCRDa [40], WSOVU [41], NCF [42], and DGCF [43] methods is presented on the MovieLens dataset.

TMF: MF is implemented using temporal dynamics of user. [13].

PCC: PCC aims to enhance the performance of Collaborative Filtering (CF) techniques [39].

HCRDa: HCRDa simultaneously learns users' and items' feature representations to generate personalized recommendations [40].

WSOVU: This method represents an innovative CF approach for delivering personalized movie recommendations. [41].

NCF: NCF combines neural networks with CF techniques to learn from user and item interactions and produce valuable recommendations [42].

DGCF: DGCF employs a graph neural network and community profiling to generate recommendations [43].

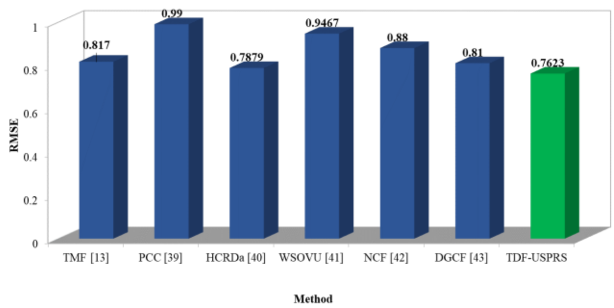

Figure 11. Relative examination of cutting-edge techniques alongside the TDF-USPRS approach using the MovieLens dataset

2) Relative examination of cutting-edge techniques alongside the TDF-USPRS approach using the CiaoDVD dataset

The projected TDF-USPRS technique is related with three cutting-edge techniques, namely DTI-CF [17], ITR [39], and TMJ similarity and CPCC [44], on the CiaoDVD dataset. Figure 12 illustrates the relative examination of these cutting-edge techniques with TDF-USPRS.

Now, let's delve into the descriptions of the cutting-edge approaches:

DTI-CF: DTI-CF is designed to improve collaborative filtering recommendations by leveraging the combined effects of time and user interest [17].

ITR (Improved Triangle similarity measure): ITR aims to enhance recommendation performance by taking into account user preferences, offering a comprehensive approach [39].

TMJ (Triangle Multiplying Jaccard similarity): TMJ provides more detailed information about co-rated and non-co-rated users, enabling the generation of precise recommendations for users [44].

CPCC (Constrained Pearson Correlation Coefficient): CPCC considers the significance of ratings in its calculations, contributing to improved performance of Recommendation Systems [44].

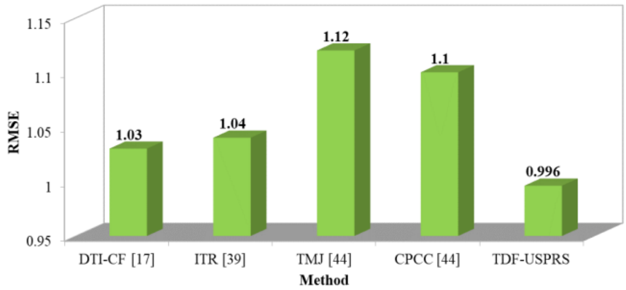

Figure 12. Relative examination of cutting-edge techniques alongside the TDF-USPRS technique using the CiaoDVD dataset

3) Assessing the effectiveness of the TDF-USPRS technique using the YOOCHOOSE dataset

The proposed TDF-USPRS approach is contrasted with two cutting-edge techniques, namely AOS4Rec [45] and GRASER model [46], on the YOOCHOOSE dataset. Figure 13 presents the comparative analysis of these methods with TDF-USPRS.

Here are the descriptions of the cutting-edge approaches:

AOS4Rec: This method enhances Recommendation Systems (RS) performance by incorporating time-varying interactions and sequential learning [45].

GRASER: GRASER enhances the efficiency of session-based RS [46].

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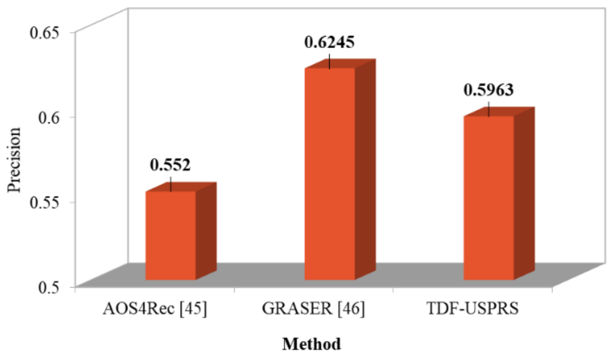

Figure 13. Relative examination of cutting-edge techniques alongside the TDF-USPRS approach using the YOOCHOOSE dataset

4) Assessing the effectiveness of the TDF-USPRS technique using the Amazon dataset.

Figure 14 presents a relative examination of cutting-edge techniques alongside the TDF-USPRS approach using the Amazon dataset. In this evaluation, the projected TDF-USPRS technique is contrasted with two other advanced techniques, namely MP4Rec [47] and NeuACF [48].

Here's a concise summary of the cutting-edge techniques:

MP4Rec [47]: MP4Rec aims to generate top-N recommendations that are clear and interpretable. To achieve this, it employs afresh developed pair-wise objective function, combined with matrices for user-user and item-item similarity.

NeuACF [48]: NeuACF employs DNN to effectively learn and combine these aspects in its recommendation process.

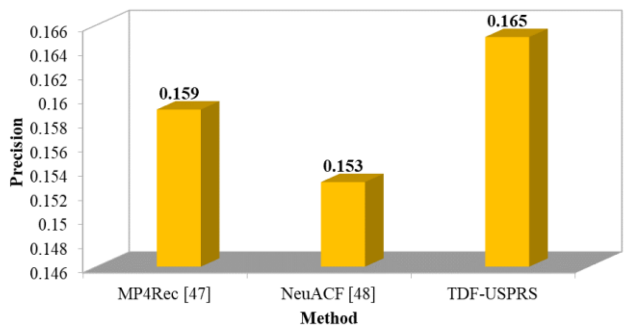

Figure 14. Relative examination of cutting-edge techniques alongside the TDF-USPRS approach using the Amazon dataset

F. Discussion

The projected TDF-USPRS technique is subjected to evaluation and in contrast with cutting-edge techniques using various performance measures. The findings reveal that as the sparsity of the dataset grows, the efficacy of numerous existing methods tends to degrade, whereas the TDF-USPRS method exhibits improved performance even under such conditions. The study plays crucial roles in enhancing the system's overall performance.

Unlike many other approaches that focus on maximum rating filling for missing entries, the TDF-USPRS method prioritizes emotional interest patterns and discovers that improved rating value filling might not always be the optimal choice. Instead, it adopts a cluster-based user-user trust factor estimation, ensuring that filled entries obtain maximum values within the cluster while preserving the extraction of emotional pattern features. This approach justifies the formation of communities and promotes accurate recommendations within them.

Moreover, the TDF-USPRS model effectively addresses data sparsity and cold start issues commonly encountered in RS. The predictions of next interests using TDF-USPRS demonstrate remarkable efficiency when compared to cutting-edge techniques, particularly regarding precision and RMSE. The model's performance is also analyzed for various window sizes, and the optimal peak performance is observed for a window size of 10 for input and 10 for output.

The integration of sentiment patterns and the utilization of user-user trust factor estimation contribute significantly to the enhanced performance of the TDF-USPRS model. Overall, the study showcases the productiveness of the projected technique in improving the recommendation system's accuracy and alleviating the challenges posed by data sparsity and cold start challenges.

V. CONCLUSION

The primary challenge in RS is transient user interest, where user preferences change over time. This paper focuses on addressing this challenge by introducing a novel approach to temporal dynamics in sentiment pattern recognition within RS. The main objective is to identify user interests and provide accurate recommendations that align with their changing preferences. The proposed approach, Temporal Dynamic Features based User Sentiment Pattern for Recommendation System (TDF-USPRS), leverages historical sentiment patterns of users to enhance RS performance. It utilizes a hybrid model that combines STFT and BiLSTM in collaborative filtering, effectively capturing the temporal patterns of user interests. By analyzing the user's chronological history of item preferences, the TDF-USPRS model generates sentiment patterns, enabling it to offer highly relevant recommendations even in scenarios with sparse datasets. The suggested approach's efficiency is tested on natural and public datasets, including MovieLens, Amazon Rating Beauty, YOOCHOOSE, and CiaoDVD.

The outcomes of experiments show the superiority of the TDF-USPRS model compared to cutting-edge techniques, achieving significant improvements in both RMSE and precision. Specifically, the proposed model achieves a 6.5% reduction in RMSE and a 4.5% increase in precision over existing methods. For instance, the RMSE values for MovieLens and CiaoDVD datasets are 0.7623 and 0.996, respectively, while the precision values for YOOCHOOSE and Amazon datasets are 0.5963 and 0.165, respectively.

Overall, the proposed TDF-USPRS approach offers a valuable solution to the challenge of transient user interest in RS. Taking into account the temporal patterns of user likings, it ensures that recommendations align with users' changing interests over time, leading to improved accuracy and relevance. The findings from this research contribute to the advancement of RS techniques and open up new possibilities for designing more effective recommendation systems in the future.

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