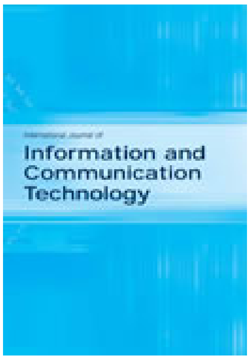

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Application of intelligent personalised information recommendation technology in the operation of new media platform

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Abstract: The diversity and complexity of new media information bring great pressure to personalised information recommendation, so intelligent terminals need to be improved with the support of reliable recommendation algorithms. This paper proposes a time-aware (TA) multi-hop path recommendation inference model TACKG-TDPRec to improve the intelligent push effect of personalised information on new media platforms, and introduces the TA path diversity reasoning method, uses time information to improve the accuracy of recommendation results, and enhances personalised diversity rewards on the basis of personalised diversity rewards designed according to user needs. It can be seen that the AUC of the recommended model is as high as 97.94, which is much higher than other models of the same type. From the diversity comparison, it can be seen that TACKG-TDPRec model can adapt to various types of information recommendation needs, and the similarity of items is low, so it has strong practicability.

Keywords: new media; personalisation; information; intelligent push.

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Biographical notes: Cheng Shaoxiao is mainly engaged in research on the internet and new media, etc. In recent years, he published over ten papers in domestic core Chinese journals and provincial journals, participated in and presided over four provincial and ministerial-level projects, and presided over two municipal (departmental) level projects. He also obtained multiple invention patents and software copyrights. He guided students to win over 20 awards in professional competitions at or above the provincial level.

1 Introduction

The application of artificial intelligence technology in personalised information push services can promote the innovation and diversified development of new media content. Through artificial intelligence can comprehensively analyse user behaviour data and content consumption patterns to identify users' diversified news information needs. This technology enables new media platforms to push richer and more diversified content for

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different user groups, and stimulates content creators to create content that is more in line with users' preferences, thus enriching the platform content ecology (Wu et al., 2023). In addition, personalised information push services based on artificial intelligence technology can also find potential audiences for marginalised topics or niche content, so that relevant news information content can be exposed and recognised. This content innovation and push mechanism centred on user needs has promoted the continuous activity and development of new media content ecology, and realised a virtuous circle of content innovation and diversity (Hayes et al., 2021).

Through refined analysis of user behaviour data and preferences, personalised push can provide users with highly relevant content that fits their interests, and improve user satisfaction and platform experience. When users find that the platform can continuously provide news information content that meets their interests, they will be more inclined to stay on the platform for a long time and are willing to explore more content, thus forming a very high user stickiness. Meanwhile, through continuous learning and optimisation, personalised push can adapt to changes in users' interests and continuously meet users' needs, which will gradually enhance users' dependence and trust on the platform and then transform it into loyalty to the platform. Loyal user groups will not only visit the platform frequently, but also attract new users to join through word-of-mouth communication, forming a positive cycle and further enhancing the market competitiveness of the platform (Cheng et al., 2022).

Information filtering bubble and island of views are the main problems faced by personalised information push services of new media platforms based on artificial intelligence technology. Its essence lies in the fact that personalised push algorithms tend to recommend information consistent with their expressed preferences to users, resulting in users being confined to a narrow range of information for a long time, thus losing many opportunities to get in touch with different opinions and news information (Hermann, 2022).

Although artificial intelligence technology enables new media platforms to provide customised content recommendations based on users' historical behaviours and preferences, it is sometimes difficult for push mechanisms to achieve a balance between satisfying users' interests and ensuring content diversity. With the popularisation of new media platforms, the speed of information generation and dissemination has been greatly accelerated, including a lot of false or misleading information. The existence of this information seriously affects the ecological health of information and users' information consumption experience. Moreover, false information is beautifully packaged and has strong emotional appeals, which is easy to attract users' attention and cause widespread dissemination. However, in the absence of a sufficiently effective content verification mechanism, artificial intelligence push algorithm will inadvertently promote these false contents and expand the spread and influence of false information.

This paper proposes a TA multi-hop path recommendation inference model TACKG-TDPRec to improve the intelligent push effect of personalised information on new media platforms. Moreover, this paper introduces the TA path diversity reasoning method into the recommendation system, uses time information to improve the accuracy of recommendation results, and enhances personalised diversity rewards on the basis of personalised diversity rewards designed according to user needs.

This article aims to study and propose a time aware diversity multi hop path recommendation inference model TACKG-TDPRec to enhance the personalised information intelligent push effect of new media platforms. The research objective is to address the shortcomings of traditional recommendation systems in terms of timeliness and diversity by introducing a time aware path diversity inference method and designing personalised diversity rewards based on user needs. The main contribution of this article is to propose an innovative recommendation model TACKG-TDPRec, which significantly improves the accuracy and diversity of recommendation results by integrating time information and personalised diversity rewards; The effectiveness of each structural function of the model was verified through ablation experiments, demonstrating the strong generalisation ability and practical application ability of the model; This provides new ideas for personalised information push on new media platforms and also serves as a reference for improving other similar models.

2 Related works

1 ID-based recommendation algorithm

The traditional ID feature-driven recommendation system is mainly composed of collaborative filtering and content-based information filtering methods. Among them, the earliest proposed and widely used technology is content-based recommendation technology. Its core concept is to capture and express product attributes by using vector space patterns (such as TF-IDF method), construct user models and product models, and then use the nearest neighbour strategy (KNN) to understand consumer preferences. Then the recommendation list is generated according to the similarity between the two (Cho et al., 2024). Collaborative filtering technology is a way to realise intelligent selection of product preferences based on personal past behaviour records. This strategy makes use of the consistency among consumers to discover their common hobbies and push specific product information to them accordingly, so as to meet personal needs and expectations. This can be classified into two types: one is the neighbour-centred method (that is, relying on customer relationship), and the other is relying on product characteristics. The first is mainly to find those consumer groups who have similar hobbies with the current target customers as the promotion targets of new products. At the same time, it will consider the liking degree of each person in these groups in order to give an appropriate reference value, and it usually uses reference indicators such as Pearson correlation index or Cosine distance. The second is to find what is most likely to attract the attention of a specific individual based on knowing what everyone likes. For example, tools such as Cosine distance or Jaccard index are used to measure the relationship strength of different objects and then combine them to form a detailed list for an individual to choose (Pavlik, 2023). Finally, with the help of linear algebra techniques, some hidden information is extracted from the original data and then someone's attitude towards the goods without scoring is predicted. This process is simple and easy to understand and can maintain a certain degree of fault tolerance. Freiling et al. (2023) established a unified viewpoint for the existing latent factor models from the perspective of probability, and proposed a new model SinkhornCF based on Sinkhorn divergence by establishing a unified framework to identify the potential connections of different latent factor models, which solved the geometric structure problem caused by the loss function ignoring the similarity of items in the existing models. Livingstone et al. (2023) studied the new problem of geometric disentangled collaborative filtering (GDCF), so as to reveal and unravel the underlying intent factors across multiple spaces, and proposed a new generative GDCF model to learn geometric representations by inferring advanced concepts related to user intent and various geometries, which compensates for the defects of similarity trees. Shehata and Strömbäck (2021) proposed a content-based recommendation method, PMSC-UGR, which is specifically used for evaluation in the field of expert discovery and document filtering. Shehata and Strömbäck (2021) proposed a recommendation system based on geographical location and content, which uses the minimum boundary rectangle of the region to construct an R-tree-based query algorithm and can quickly locate the centre of geographical location.

For the classical recommendation system that depends on ID, the main problem is that with the increase of time and space complexity, the cost of maintaining the similarity matrix of users' interests shows a nonlinear growth trend. At the same time, because the similarity between users fluctuates greatly and is difficult to understand, the recommendation results lack clarity and accuracy.

2 Recommendation algorithm based on traditional deep learning

With the development and growth of natural language processing technology, recommendation system has gradually become an important application scenario of deep learning in recent years, which has not only attracted the attention of the academic community, but also the attention of the industry. The key to deep learning is to obtain higher-level representations through in-depth understanding of multi-dimensional data. Whether based on supervision or unsupervised methods, stochastic gradient descent or its improved version can be used to adjust the differentiable objective function to achieve any structure with neural differentiable characteristics. With the help of deep learning, Meese and Hurcombe (2021) used neural network architecture to mine advanced attributes of users and projects, and then captured their characteristics and made recommendations based on them. Ronzhyn et al. (2023) adopted embedding technology and multi-layer neural network architecture to build the system framework, which enables the system to effectively combine and optimise the ability to understand continuous variables and complex relationships to surpass the previous traditional methods such as collaborative filtering or logistic regression for search result ranking and product screening in search engines. By adding high-order terms, new hybrid machine learning algorithms like DeepFM can further improve efficiency and reduce the need for manual operations; At the same time, it also brings short-term performance improvement, which is better than other methods that rely on a single factor, such as MF-based matrix factorisation model (Dan et al., 2021).

In the recommendation strategy that relies on deep learning, improving the time sensitivity of news recommendation by introducing time factors will help promote the diffusion of newly released information. However, this may also have a certain negative effect on the dominant role of users' personal preferences, so it is necessary to find a balance between news timeliness and users' preferences. In addition, the news recommendation method customised according to geographical location can help users discover the new events around them and capture the changes of the current environment. However, this method is more inclined to optimise the positioning accuracy, but often ignores the user preference problem under location awareness.

3 Recommendation algorithm based on attention mechanism

At present, the research focuses on the recommendation system based on attention mechanism, and its core idea is to use this method to give weight to product characteristics, so as to better understand the product characteristics that consumers are concerned about. In this field, many experts have conducted in-depth discussions. Farkas and Bene (2021) developed a graph attention-based recommendation model (GAMP), which can learn the embedded vector expression between users and products, and then use the attention mechanism to calculate the weight of products, so as to determine the product attributes that consumers are most concerned about. Lee and Eastin (2021) advocated the use of multiple head attention mechanisms as recommendation strategies, and tried to create multiple semantic subspaces to simulate user dialogue behaviour, all of which aim to improve the efficiency of recommendation systems and customer satisfaction. Van Dijck (2021) designed a recommendation scheme based on Self Attention mechanism, which can use this mechanism to mine the relationship between commodities, so as to obtain more accurate commodity similarity evaluation results. Van Dijck (2021) tried to apply multi-head attention mechanism to deal with the weighting problem of users and their product attributes, all of which help to further optimise the performance of recommendation system and customer experience.

Recommendation system based on attention mechanism is becoming the frontier topic of today's research, and has made remarkable achievements in many fields at home and abroad. In recent years, the technical model based on pre-training and fine-tuning has triggered major changes in the technical field, such as NPA, DKN, DFM, NRMS, LSTUR, etc. These recommended strategies all have significant advantages. First, through the learning of a large number of unlabeled text materials, a universal expression can be obtained, thus improving the efficiency of follow-up work. Secondly, when using large-scale data sets, it can reduce the possibility of over-adaptation to small samples, which is actually a regularised processing method.

3 Diverse multi-hop path recommendation based on time series knowledge graph

3.1 Problem description and basic definition

This paper considers the diversity needs of different users, proposes a targeted supervised pathfinding strategy to evaluate the probability of users' diversity needs, designs a personalised diversity reward function to improve the diversity of recommendations, and adds temporal information to the knowledge graph to improve the interpretability of recommendations. TA interaction is integrated into KG as a heterogeneous information graph (time aware interactive collaborative knowledge graph, TACKG) to provide users with accurate and diversified projects at the right time, and recommend accurate and diversified projects at the right time. Diversified project goals.

Considering TA interactions, a time aware collaborative knowledge graph (TACKG) is constructed. Specifically, the interaction timestamps are divided into L groups by time series clustering, and the interaction relationship h is extended to $\{H^1, H^2, \cdots, H^L\}$. Therefore, TACKG is denoted as $G_N = \{(h, r, t) \mid h, t \in T, r \in R_L\}$, where $R_L = R \cup \{H^1, H^2, \cdots, H^L\}$.

Moreover, this paper proposes a TA diversity multi-hop recommended path reasoning task, and the input TACKG G_N is given a user and timestamp (T). The recommendation model yields a set of items $(\hat{V} \subseteq V)$ with a corresponding explainable inference path, and for each item $(\tilde{v} \in \hat{V})$, there is a corresponding interpretable inference path $\theta_{u,\tilde{v}} = [u \xrightarrow{r_1} e_1 \xrightarrow{r_2} \cdots \xrightarrow{r_{k-1}} e_{k-1} \xrightarrow{r_k} \tilde{v}]$, where $e_{i-1} \xrightarrow{r_i} e_i$ represents $(e_{i-1}, r_i, e_i) \in G_N$, $i \in [k]$.

3.2 TACKG-TDPRec model

The overall framework of TACKG-TDPRec is shown in Figure 1. Figure 1 clearly illustrates the training process of the TACKG-TDPRec model, including user project interaction, path exploration of time aware agents, introduction of reward mechanisms, path inference and selection, and construction of TACKG. These components work together to enable the model to provide accurate and personalised information push services while considering time factors and diversity requirements. The model aims to improve the accuracy and diversity of personalised information push through time aware and diversity enhanced path inference. Specifically, as follows:

1 User project interaction

   Starting point: The recommendation process for each user starts from the user entity (User). Interaction path: Users interact with projects (ltems) through a series of relationships. These relationships can be different types of behaviours such as clicking, browsing, purchasing, etc.

2 Time aware agent

   At time step k, the agent selects the next hop path based on time constraints. This means that the agent will consider the time factor when selecting the next interaction node to ensure the timeliness of the recommendation. Agents explore paths in the knowledge graph until they reach a project node or meet stopping conditions.

3 Reward mechanism

   Time aware path reward: When the agent stops at a project node, it will receive a time aware path reward based on the time information in the path. This encourages the model to recommend projects at the appropriate time. Agents will also receive personalised diversity rewards based on users' diverse needs. This helps the model recommend not only accurate but also diverse items.

4 Path reasoning and selection

   Multi hop path inference: The model uses path inference techniques to determine a set of recommended items and their corresponding solvable inference paths. This increases the transparency and credibility of the recommendation. Optimal path selection: By considering both time aware path rewards and personalised diversity rewards, the model selects the optimal recommendation path and items.

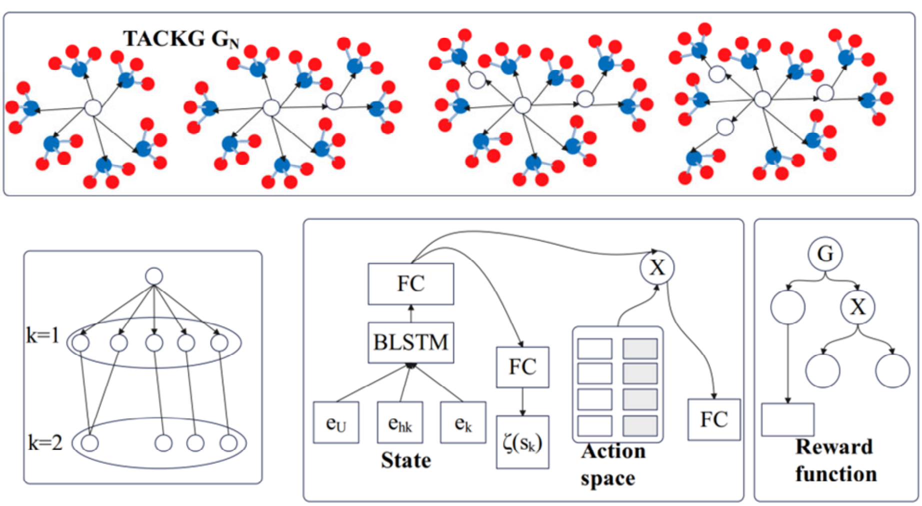
5 TACKG

Construction process: TACKG is built by integrating user project diagrams and relatively static knowledge graphs, and incorporating time aware interaction relationships. This enables the graph to capture the temporal dynamics of user behaviour and semantic information of projects. TACKG provides rich information and structural support for the model, making the recommendation process more accurate and efficient.

The model continuously optimises its parameters and strategies through iterative training to improve the accuracy and diversity of recommendations. The ultimate goal is to generate a set of recommendation items and their interpretable reasoning paths that meet both user needs and diversity.

For user *u*, as shown by the purple shade of TACKG. It will receive a TA path reward and a personalised diversity reward *G* according to the user's diversity needs. The shaded path of purple starts at user *u* and ends at item $\tilde{v}$, which shows why the TACKG-TDPRec model would recommend items to user *u*. TACKG-TDPRec can ensure the diversity of recommendations according to user needs, and use the RL framework to make recommendations. The interaction timestamp $T = \{t_1, t_2, \cdots, t_n\}$ is divided into *L* classes. By extending a single interaction type to $H^T = \{H^1, H^2, \cdots, H^L\}$, we can integrate the user project graph and the relatively static knowledge graph, and finally get TACKG.

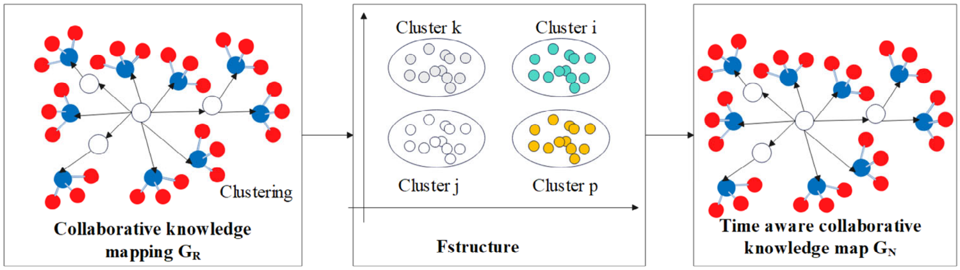
Figure 1 Training process of TACKG-TDPRec model (see online version for colours)



Time characteristics are divided into two characteristics, namely, time statistical characteristics and time structure characteristics. Time statistical characteristics represent some changes in time sequence, and have the characteristics of regularity and periodicity.

The TA interaction relationship extraction process is shown in Figure 2.Figure 2 illustrates the process of time aware interaction extraction, which is a critical step used to extract time aware interaction relationships when constructing the TACKG. The following is a detailed explanation of Figure 2.

Figure 2 TA interaction extraction process (see online version for colours)



Time aware interaction extraction process

1 Timestamp mapping

Each interaction relationship is accompanied by a timestamp that records the time point at which the interaction occurred. In the process of time aware interaction extraction, these timestamps are first mapped to the temporal feature space. This means that each timestamp is converted into a set of feature values that capture the statistical and structural characteristics of the timestamp.

2 Time statistical feature extraction

Annual, seasonal, monthly, and weekly statistical features: For each timestamp, extract its annual, seasonal, monthly, and weekly level statistical features. For example, a certain interaction occurs in the spring, March, and 12th week of 2023. Feature encoding and concatenation: Encode these statistical features and concatenate them to form a unified temporal statistical feature vector.

3 Time structure feature extraction

First order structural feature: measures the trend of changes in the number of interactions during the current period relative to the past period. This helps to capture short-term changes in user behaviour. Second order structural feature: represents the momentum of the interaction trend, that is, the rate of change of the trend. This helps to understand the long-term trends in user behaviour. Feature connection: Connect the first-order and second-order structural features to form a temporal structural feature vector.

4 Time feature space merging

Merge time statistical features and time structural features to form a complete spatial representation of time features. This representation contains rich information about timestamps, taking into account both statistical patterns and structural changes.

5 Construction of time aware interaction relationship

Use Gaussian mixture model (GMM) to cluster time in the temporal feature space. This can classify similar timestamps into the same category, where each category represents a time aware interaction relationship. By assigning clustering values and replacing the original interaction relationships, the traditional collaborative knowledge graph (CKG) is ultimately transformed into a TACKG.

Its statistical characteristics can be expressed as (Trepte, 2021):

$$F_{statistic} = y(t) \odot s(t) \odot m(t) \odot w(t) \tag{1}$$

In the formula, $y(t)$, $s(t)$, $m(t)$ and $w(t)$ represent annual, seasonal, monthly and weekly statistical characteristics, respectively. $F_{statistic}$ encodes these statistical features and are concatenated by $\odot$, where $\odot$ is the concatenation operator.

- Temporal structural features: In addition to statistical features, structural features are utilised to characterise user behaviour, which measure the propensity to buy at timestamp t. The structural feature is defined as:

  $$F_{structure} = q'_g(t) \odot q''_g(t) \tag{2}$$

  A and B denote big head and small head respectively

  In the formula, $q'_g(t)$ and $q''_g(t)$ denote the first-order and second-order structural feature, as shown in formula (3) and formula (4) respectively, g represents the window period length. And represents the momentum of the interaction trend (Schreurs and Vandenbosch, 2021).

  $$q'_g(t) = \frac{\sum_{i=t-g}^{t} q(i) - \sum_{i=t-2g}^{t-g} q(i)}{g} \tag{3}$$

  $$q''_g(t) = \frac{\sum_{i=t-g}^{t} q'(i) - \sum_{i=t-2g}^{t-g} q'(i)}{g} \tag{4}$$

  In the formula, $q(i)$ represents the number of interactions that occurred at timestamp i. For historical interactions with timestamp t less than $2g$, their historical information is not sufficient to calculate $q'_g(t)$. In this case, the time structure features of the most recent timestamp are used to fill in their corresponding features, and $q''_g(t)$ is also applicable. The gap g is set to 90 (season), 30 (month), 7 (week), and 1 (day), and they are simply connected as time structure features $\beta \in R^m$ and merged into the time feature space of timestamp t:

  $$\beta = F_{statistic} \odot F_{structure} \tag{5}$$

- Building TACKG: The TA interaction relationship is constructed. L GMMs are used. For a timestamp t with time features, the probability generated by the l^{th} Gaussian model can be obtained. From this, the interaction relationship r_t at timestamp t can be obtained as shown in the following formula:

  $$r_t = I_{\max(s_t)} H^T \tag{6}$$

Among them, $s_t = [s_t^1, s_t^2, \cdots, s_t^L]$ represents the t-specific probability distribution derived by the Gaussian model. $H^T = \{H^1, H^2, \cdots, H^L\}$ is the TA interaction set, H^l is the l^{th} cluster relationship, and in the formula r_t is replaced by the most likely relationship in H^T.

3.3 TA representation learning

In a given TACKG triplet (h, r, t), d-dimensional embeddings represent the head entity, relation, and tail entity, e_h, r, $e_t \in R^d$,as shown in the following formula (Chadwick et al., 2025).

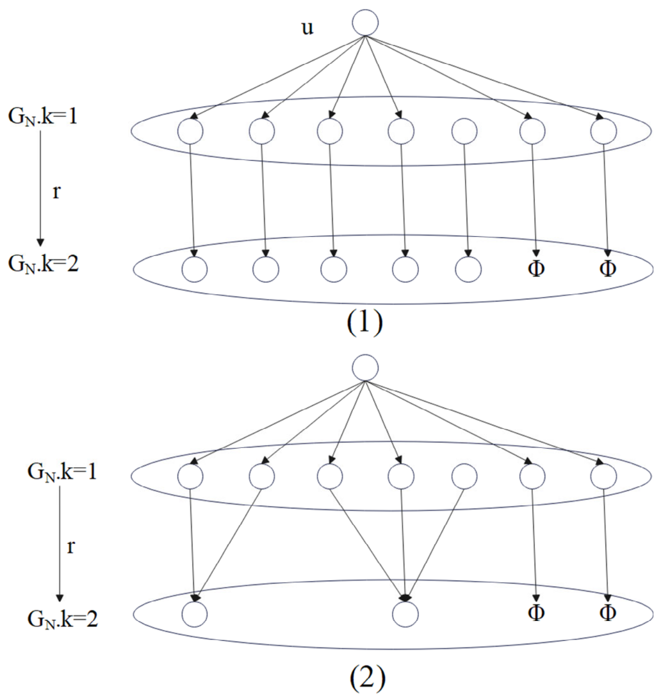
$$d_r = \left\| e_h + r - e_t \right\|_2^2 \tag{7}$$

In the formula, the smaller the score of d_r, the more likely fact (h, r, t) is to be true. The TACKG embedding is trained using a pairwise loss function, as shown in the following formula:

$$L_{tdckg} = \sum_{(h,r,t,t') \in S} - \ln \sigma \left(d_r \left(h,r,t' \right) \right) - d_r \left(h,r,t \right) \tag{8}$$

Among them, $S = \{ \left(h,r,t,t' \right) \| \left(h,r,t' \right) \in G_N, (h,r,t) \notin G_N \}$, and $\sigma(\cdot)$ is a sigmoid function.

Figure 3 Schematic diagram of user diversity needs



To accurately capture the diverse needs of users, the TACKG-TDPRec model adopts a supervised pathfinding strategy in the knowledge graph. The model takes the target user as the starting node, randomly selects a path that the user has interacted with, and then stores the entity nodes that this path passes through into a specific set, and walks until a certain entity node stops. This innovative method not only improves the diversity of recommendations, but also provides users with more personalised recommendation results that meet their actual needs.

As shown in Figure 3, when the model makes recommendations for user u, it first walks around the one-hop item in the item set in G_N. In the process of walking, the model will randomly choose a relationship to walk and save the entities it passes through.

In order to analyse users' diversity needs, this paper judges the dispersion degree of user-item interaction with the help of structured and semantic information of KG. The user's diversity needs score $y_d(v \mid u)$ is defined as (Chadwick and Azab, 2021):

$$y_d(v \mid u) = \frac{\sum_{v_i, v_j \in \overline{v_u}, i \neq j} dis\left(v_i, v_j\right)}{M(M-1)} \tag{9}$$

Among them, $\overline{v_u}$ represents the set of items that the user has recently interacted with, $|\overline{v_u}| = M$. In KG, each item v_i in $\overline{v_u}$ is associated with an entity through a corresponding relationship. The entities corresponding to the same relationship are used to classify v_i. $dis(v_i, v_j)$ is defined as:

$$dis\left(v_i, v_j\right) = \frac{\sum_{r_q} \delta\left(E_{v_i}^{r_q}, E_{v_j}^{r_q}\right)}{|R|} \tag{10}$$

In the formula, $r_q \in R$ represents a relationship in G_N, $E_{v_i}^{r_q}$ represents the entity set connected to item $\tilde{v}_i$ through relationship r_q, and $\delta(\cdot)$ represents whether there is an intersection between $E_{v_i}^{r_q}$ and $E_{v_j}^{r_q}$. If $E_{v_i}^{r_q} \cap E_{v_j}^{r_q} = \varnothing, \delta(\,) = 1$ otherwise $\delta(\,) = 0$. $dis(\,)$ uses the semantic relationship between G_N entities to explicitly analyse the diverse needs of users, and normalises $dis(\,) \in [0, 1]$. When $dis(\,)$ is larger, it means that the user's diverse needs are greater.

3.4 Diversity and multi-hop path reasoning based on TA

After the embeddings of entities and relationships are established. Existing path inference models do not consider temporal information, which may lead to inaccurate interpretations. In order to solve these problems, TA reward and personalised diversity reward are set in the process of path reasoning to introduce time information and diversity requirements.

- Bonus: There are no target items in the recommendation that the user knows beforehand, especially in time-sensitive interpretable recommendations. In the process of path search , TACKG-TDPRec only considers the final reward. TACKG-TDPRec carefully designs a reward function that can softly reward e_k when the node's final state is $s_k = \left(u, h_k, e_k\right)$, which is expressed as:

$$R_k = \frac{G\left(e_k \middle| u\right)}{\max_{v \in V} G(v \mid u)} \tag{13}$$

Among them, $e_k \in V$ and the value of R_k is limited to the range of [0, 1]. In this section, the final reward function G_k is defined as the sum of the TA path reward $g_r(\tilde{v} \mid u)$ and the personalised diversity reward $g_d(\tilde{v} \mid u)$ obtained based on the user's diversity demand score $y_d(\tilde{v} \mid u)$.

The reward function is $g_R(\tilde{v} \mid u)$:

$$g(\tilde{v} \mid u) = \left(e_u + r_{interact}\right) \cdot e_{\tilde{v}} + b_{e_{\tilde{v}}} \tag{14}$$

Among them, $u \in U$, $\tilde{v} \in \tilde{V}, \theta_{u,\tilde{v}}$, and $b_{e_{\tilde{v}}}$ is the embedding bias. The reason is that it is not directly possible to determine which TA interaction relationship $r_{interact} \in H^T = \{H^1, H^2, \cdots, H^L\}$ is used for user u.

For each user u, a personalised interaction relationship is designed based on its history h_u, which can be expressed as:

$$r_{\tilde{v}_u^T} \leftarrow W_{h_u} H^T \tag{15}$$

Among them, $W_{h_u} = \{w_{h_u}^1, w_{h_u}^2, \cdots, w_{h_u}^L\}$ is the temporal clustering weight derived from the interaction history $h_u = \{v_u^1, v_u^2, \cdots, v_u^q\}$ of user U, and q is the length of h_u. The weight of the l^{th} interaction relationship is $w_{h_u}^l$, where $l \in [1, 2, \cdots, L]$ is the formula as follows:

$$w_{h_u}^l = \frac{\sum_{i=1}^{q} \partial\left(v_u^i = H^l\right)}{q} \tag{16}$$

Among them, $\partial(\cdot)$ is the indicator function. The TA reward scoring:

$$g_r\left(\tilde{v} \middle| u\right) = \left(e_u + r_{\tilde{v}_u^T}\right) \cdot e_{\tilde{v}} + b_{e_{\tilde{v}}} \tag{17}$$

4 System construction and test

4.1 System construction and test methods

In the personalised information intelligent push system for new media platforms, time is integrated into multi-point path inference, mainly through the construction of TACKG. TACKG clusters and extends interaction timestamps into time-dependent interaction relationships, and combines GMMs to form graph structures containing temporal information. In addition, introducing time aware rewards, rewards are given based on the time aware interaction relationships along the path, taking into account the changes in user interests over time. This approach not only enhances the diversity of recommendations, avoids content homogenisation, but also improves the accuracy of recommendations, ensuring that the pushed content is more in line with users' current interests and preferences, while capturing the timeliness of the content.

In the personalised information intelligent push system for new media platforms, the time factor is integrated into multi-point path inference by constructing a TACKG and designing a time aware reward mechanism. TACKG groups user interaction timestamps through time series clustering and extends them to time aware interaction relationships, enabling recommendation systems to capture the dynamic changes in user interests over time. In the process of path inference, the time aware reward mechanism adjusts the recommendation weights based on the degree of matching between the interaction time and the current time, while combining personalised diversity rewards to ensure the richness of the recommendation results. This integration significantly improves the quality of recommendations: time perception makes recommendations more in line with users' current interests, improving accuracy. The diversity reward mechanism avoids excessive focus on recent content and enhances recommendation diversity.

In this paper, the personalised information recommendation system is developed by separating the front and back ends, as shown in Figure 4.

Figure 4 Recommendation system architecture diagram

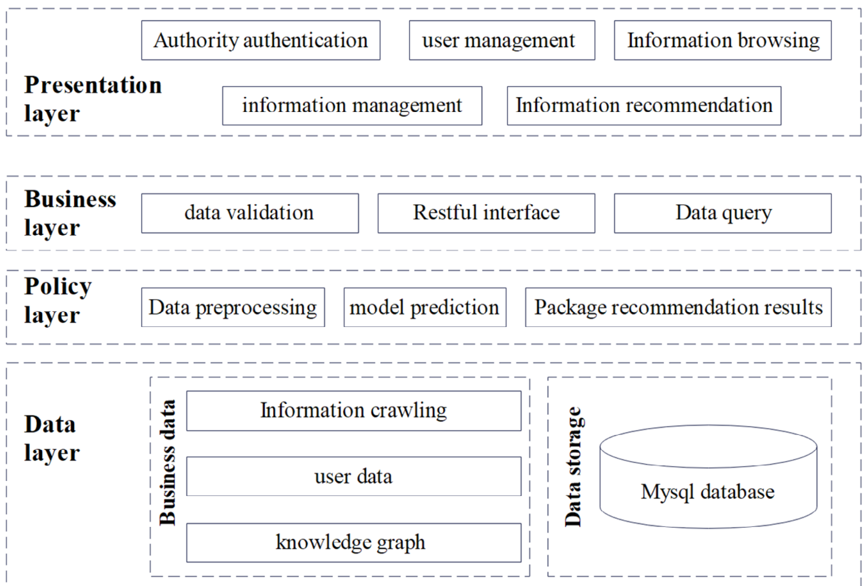
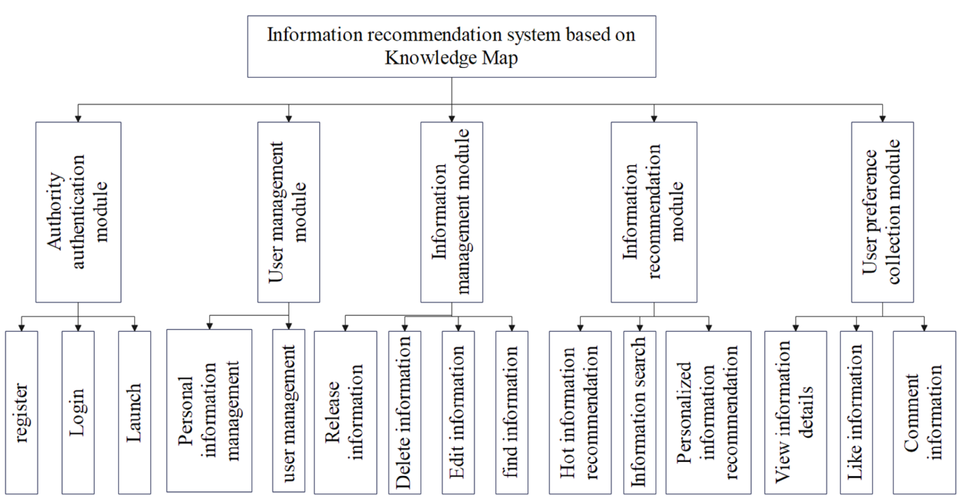


Figure 5 Functional module diagram of recommendation system



The presentation level provides interactive services to users, and users can click and browse media information on the visual graphical interface, so that they have a good reading experience. The business layer processes the user's operation requests at the presentation layer, including permission authentication when the user registers and logs in, as well as other functional interfaces, queries the database to obtain data, and processes and calls the recommendation model of the strategy layer to obtain the recommendation results and return the results to the presentation layer. The policy layer is the core part of the recommendation system, which encapsulates the logic of the recommendation algorithm and provides the recommendation results. The data layer includes media information data crawling, media information data and user data storage, etc. necessary for the media information recommendation system.

According to the functional nature, the modules of the system are mainly divided into five parts, namely, authority authentication module, user management module, media information management module, media information recommendation module and user preference collection module, as shown in Figure 5.

1 Authority authentication module

   The authentication module mainly includes two functions: registration and login. New users of the system must register in the system first, and after completing the registration, they can log in to the system for a series of operations such as browsing media information.

2 User management module

   This system has two user roles: general user and administrator. Users can modify their basic personal information in the personal information management module.

3 Media information management module

   Media information is the main data of this system, which comes from web crawler data and published by system administrators. Administrators can add, delete, modify and check all media information data in the system.

4 Media information recommendation module

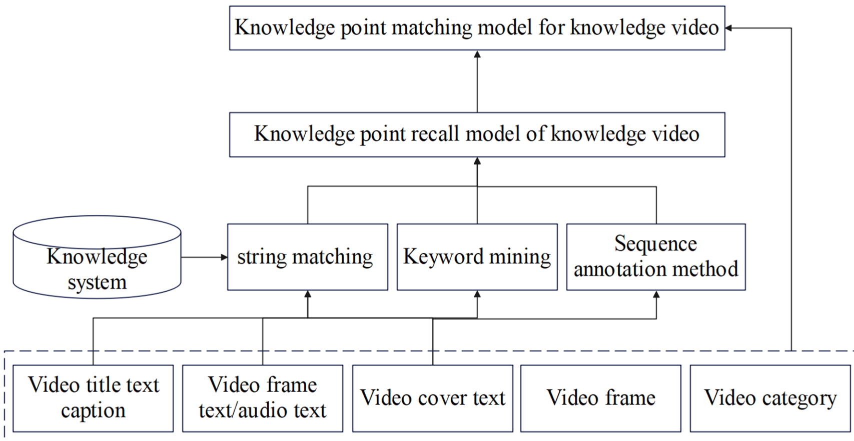
   This module is the core module of the media information recommendation system. The recommendation results are presented to users in the form of a list. When a user logs in to the system, the system obtains the user's preference representation from the database, and after preprocessing, it is input into the recommendation model to obtain the recommendation results.

5 User preference collection module

   The user preference collection module is responsible for collecting the clicking behaviour of each user in the system, including clicking to view media information, commenting and liking media information, and so on.

Because it involves judging entities or concepts in knowledge short videos, it is difficult to directly extract information through traditional information extraction methods such as sequence annotation. Inspired by the pattern of retrieval and recall + fine sorting commonly used in recommendation systems, this paper proposes to split the knowledge point extraction task into two steps. Firstly, some candidate knowledge points are recalled from the knowledge system, then these candidate knowledge points are matched, and the matching score is greater than a certain threshold as the knowledge points of this knowledge short video. The overall process is shown in Figure 6.

Figure 6 Flowchart of short video knowledge point extraction scheme based on recall + matching



The model is used to match candidate knowledge points, and the figure shows multiple candidate knowledge points. Each candidate knowledge point is matched with different texts and elements in the video. These texts and elements include video title text (caption), video frame text/Audio text, video cover text, etc. The recall model uses three main methods to recall: string matching, keyword mining and sequence labelling.

This paper evaluates the performance of TACKG-TDPRec through experiments. The databases used in this paper are Factiva, LexisNexis, and Xinhua Multimedia Database (XH-Multimedia). For normal test comparisons, the same training set and test set are used. That is, 70% of user purchases are randomly selected for model training, and the remaining 30% are tested. The comparison methods in this paper are UserCF, GRU, Wide&Deep, YoutubeDNN, DeepFM, DSSM, Deep&CrossNet, LibFM, DFM, NRMS, NPA, and LSTUR. The experiments in this paper are completed on the pytorch deep learning platform.

4.2 Results

The comparison of model recommendation performance under the Factiva database is presented in Tables 1 and 2. These data are evaluated using multiple recommendation metrics, such as ACC, AUC, F1-score, HR, MRR, NDCG, etc.

To further verify the generalisation ability of the proposed model, the NRMS and LSTUR models with better performance in Table 1 are selected for comparison with TACKG-TDPRec. In addition, Factiva, LexisNexis, and XH-multimedia datasets are selected as experimental data, and the results are shown in Table 3.

Recommendation diversity is a measure of the degree of difference between items in a single recommendation list. It is measured by calculating the average value of similarity between items in the same recommendation candidate list. This paper uses the cosine similarity of feature vectors to calculate. After the items are expressed as feature vectors, the smaller the angle between the two feature vectors, the more similar the two vectors are. Then, military, economy, life, and culture are used as comparison items. The diversity comparison experiment is shown in Table 4.

Table 1 Comparison of model recommendation performance under Factiva dataset

	ACC	*AUC*	*F1*	*HR*	*MRR*	*NDCG*
UserCF	49.27	74.09	61.14	34.05	25.04	26.12
GRU	64.33	81.04	72.40	40.43	32.88	35.12
Wide&Deep	62.96	80.13	75.53	41.66	29.52	30.83
Youtube DNN	59.04	83.81	77.40	39.62	28.59	29.75
DeepFM	60.42	84.29	79.31	41.19	30.25	31.68
DSSM	65.52	85.15	83.56	43.22	31.63	33.11
Deep&CrossNet	62.75	80.16	76.01	47.20	30.34	34.08
LibFM	60.63	84.08	78.02	39.98	28.17	30.13
DFM	63.84	82.49	80.85	45.08	28.53	32.26
NRMS	69.57	85.09	82.70	49.32	34.10	34.98
NPA	66.63	83.40	80.03	40.57	33.00	34.07
LSTUR	69.16	85.64	83.67	45.72	31.04	36.30
TACKG-TDPRec	77.66	97.94	91.21	53.09	35.85	40.79

Table 2 Comparison data table of ablation experiment effects of each module under Factiva data set

	ACC	*AUC*	*F1*	*HR*	*MRR*	*NDCG*
Knowledge graph	58.04	65.85	61.02	38.25	29.43	32.33
FC	55.18	56.94	60.35	36.68	30.53	30.32
BLSTM	59.82	61.12	64.20	42.42	29.45	34.39
Information fusion	63.77	67.05	67.36	44.41	27.58	31.54
Time perception	67.96	69.87	79.82	46.46	31.37	35.70

Table 3 Comparison of model generalisation capabilities under Factiva, LexisNexis, XH-Multi media datasets

Data set	*Model*	*ACC*	*AUC*	*F1*	*HR*	*MRR*	*NDCG*
Factiva	NRMS	69.57	85.09	82.7	49.32	34.1	34.98
	LSTUR	69.16	85.64	83.67	45.72	31.04	36.3
	TACKG-TDPRec	77.66	97.94	91.21	53.09	35.85	40.79
LexisNexis	NRMS	69.75	85.50	84.49	50.01	34.59	35.30
	LSTUR	72.10	85.89	86.06	46.58	31.87	36.36
	TACKG-TDPRec	79.81	99.61	93.05	53.59	36.95	42.02
XH-multi media	NRMS	73.41	85.80	84.32	49.39	34.92	35.96
	LSTUR	74.39	87.08	85.59	47.70	32.28	39.17
	TACKG-TDPRec	77.76	102.66	98.92	55.98	38.70	44.78

Table 4 Diversity comparison experiments

Model	*Military affairs*	*Economic*	*Life*	*Culture*
NRMS	0.025	0.018	0.021	0.018
LSTUR	0.012	0.006	0.0091	.0.01
TACKG-TDPRec	0.009	0.0035	0.0064	0.0082

4.3 Analysis and discussion

The first of the three groups is the recommendation algorithms based on the ID paradigm, such as UserCF, ItemCF, CB, GRU, etc. The second is the recommendation algorithms when early deep learning technology was involved, such as Wide&Deep, YoutubeDNN, DeepFM, DSSM, Deep&CrossNet, and LibFM. The last group is the recommendation algorithms that use pre-trained ones, represented by DFM, NRMS, NPA, and LSTUR. Observing the data in Table 5, we can see that the indicators of the third type of recommendation algorithm are significantly higher than those of the first two types, which proves the pre-training + fine-tuning method. The reason is that the model has the ability to adapt to the scene and has a significant advantage. Among the three strategies in this article, TACKG-TDPREC ranks second in the ACC index and ranks first in the AUC index, exceeding the average by 2.5%. Moreover, its performance in the F1 index is also quite good, leading all other data points. In addition, it ranks second and third in the HR index and MRR index, respectively, exceeding the average by 2%. Finally, this paper finds that the NDCG index is its best result, far exceeding the average by 1.5%. In summary, the comprehensive ranking of the TACKG-TDPREC model in this paper ranks first in the third category of recommendation algorithms and is completely higher than the first two categories, which verifies the feasibility of the overall construction idea of the model.

The TACKG TDDPRec model introduces a time aware path diversity inference method into recommendation systems, significantly improving the accuracy of recommendations by utilising temporal information. The model groups interaction timestamps through time series clustering and adds time information to the knowledge graph, thereby improving the interpretability and timeliness of recommendation results.

The TACKG TDDPRec model has designed a personalised diversity reward function to improve recommendations based on users' diverse needs Diversity. This method not only considers the user's interest preferences, but also takes into account the diversity of recommended content, avoiding the problem of information filtering foam and island of views. The TACKG TDDPRec model combines the advantages of knowledge graphs and deep learning, capturing the degree of dispersion in user item interactions through the structured and semantic information of knowledge graphs, thereby more accurately analysing users' diverse needs. The model adopts a supervised pathfinding strategy to find suitable recommendation paths for users in the knowledge graph. This method not only enhances the diversity of recommendations, but also provides interpretable reasoning paths, enhancing users' trust and satisfaction.

The TACKG TDDPRec model integrates information from multiple data sources, including user behaviour data, content data, and time information. By integrating multiple sources of information, the model can gain a more comprehensive understanding of user needs, thereby improving the accuracy and diversity of recommendations. The model constructed a TACKG, which integrates user project graphs and relatively static knowledge graphs to form a heterogeneous information graph. This graph structure can better represent complex relationships and semantic information, providing richer context for recommendations.

From the ablation test, the overall performance of the model has been improved by gradually adding and fusing different components. The TA model has the best performance, which shows that considering the time factor and multi-source information fusion can significantly improve the model effect. FC layer doesn't seem to bring significant benefits in this setting, and the promotion effect is slight.

The NRMS model performs well on the Factiva dataset (ACC: 69.57%, AUC: 85.09, etc.), but its performance on the LexisNexis and XH-MultiMedia datasets has declined, especially in terms of ACC and AUC. The LSTUR model performs moderately on the Factiva dataset (ACC: 69.16%, AUC: 85.64, etc.), but improves on the other two datasets, especially in terms of the higher F1 score on the LexisNexis dataset (86.06). Moreover, the ACKG-TDPRec model performs well on all datasets. In particular, on the XH-MultiMedia dataset, the ACC reaches 77.76% and the AUC is as high as 97.66%. The model performs well in F1, HR, MRR, and NDCG indicators on all datasets, showing strong generalisation ability.

Overall, the TACKG-TDPRec model has the most stable and excellent performance on all data sets, showing strong generalisation ability. The second is the NRMS model, although its performance on different data sets fluctuates, but its overall performance is acceptable. However, although the LSTUR model performs well in some indicators, its overall generalisation ability is relatively weak. The reason for this is that the NRMS model and the LSTUR model have relatively single functionality. Although they have improved to a certain extent compared with traditional models, they still do not have strong generalisation ability. TACKG-TDPRec model belongs to the fusion model, which solves the problem of timeliness of interpretation and diversity of recommendation. Enhances the personalised diversity reward on the basis of the personalised diversity reward designed according to the user's needs.

Judging from the diversity comparison experiment, TACKG-TDPRec has the lowest item similarity in military, economic, life, and cultural comparison items, which verifies that the TACKG-TDPRec model has a strong ability to improve recommendation diversity.

The TACKG TDDPRec model effectively reduces the risk of reinforcing existing biases and ensures the diversity of recommendations through personalised diversity reward mechanisms, time aware interaction relationship extraction, multi-source information fusion, and knowledge graph construction strategies, thereby alleviating information filtering bias or 'filtering bubbles' problems.

The TACKG TDDPRec model effectively reduces bias risks in recommendation systems and ensures content diversity through various innovative mechanisms. Firstly, it adopts personalised diversity reward functions and time aware path reasoning to dynamically balance user interests and content diversity; Secondly, by utilising the semantic association and cross domain connectivity capabilities of knowledge graphs, we can break through the limitations of a single interest dimension; Furthermore, by exploring and utilising balance mechanisms and group diversity protection strategies, systematic bias accumulation can be prevented; Finally, establish a multidimensional evaluation system and continuous optimisation mechanism to ensure the long-term healthy development of the recommendation system. These technical measures work together to effectively alleviate the filtering bubble effect while maintaining recommendation accuracy in the model.

In the TACKG TDDPRec framework, time information is modelled by a dynamic temporal graph neural network (Dy TGNN) to model user interest drift, transforming interaction sequences into heterogeneous graph structures with timestamps. At the same time, a counterfactual causal reasoning module is introduced to separate confounding factors and construct a user item causal graph through do calculus. The causal effect weights of time decay are added to the recommendation path decision. The synergistic effect of the two is manifested as: the temporal module captures the periodic characteristics of ‘when to recommend’, the causal module solves the interpretability problem of ‘why to recommend’, and finally achieves dynamic bias correction through the temporal causal joint attention mechanism.

On the whole, the TACKG-TDPRec model has good recommendation effect, and the algorithm has certain reliability and scalability. The effectiveness of each structural function of the model is verified by ablation experiments, which also provides a reference for subsequent related model construction. From the comparison of generalisation ability, it can be seen that the TACKG-TDPRec model has strong generalisation ability and strong practical application ability, and can meet various information recommendation needs. From the comparison of diversity, it can be seen that the TACKG-TDPRec model can adapt to various types of information recommendation needs, and the project similarity is low, which is very practical.

To improve the practicality of the TACKG-TDPRec model, optimisation needs to be carried out from three dimensions: engineering efficiency, business adaptation, and effectiveness assurance. In terms of engineering efficiency, a dynamic incremental update mechanism can be used to only process recent interactive data, combined with knowledge distillation technology to compress model size, and an adaptive caching strategy can be adopted to reduce real-time computing load, thereby increasing inference speed by 3-5 times. At the business adaptation level, design pluggable feature adapters to achieve cross scenario migration, integrate social relationship graphs to supplement sparse data for cold start problems, and establish a multi-objective adjustment mechanism to dynamically balance indicators such as click through rate and duration. In terms of effectiveness assurance, the focus is on building counterfactual data generators to enhance causal robustness, and deploying time sensitive indicators (such as...) NDCG@T). Develop a closed-loop evaluation system and develop visualisation tools to analyse critical causal paths.

5 Conclusions

This paper proposes a TA diversity multi-hop path recommendation reasoning model TACKG-TDPRec, which solves the timeliness problem of explanation and the diversity problem of recommendation. Enhances personalised diversity rewards based on personalised diversity rewards designed according to user needs. In future work, TACKG-TDPRec can be extended to automatically form rewards by utilising an adversarial learning model for more accurate recommendation results. In addition, time information can be combined with diversity recommendations to find more regularities and improve the diversity of recommendations. Furthermore, causal reasoning can also be combined with TACKG-TDPRec to obtain better interpretability.

Declarations

All authors declare that they have no conflicts of interest.

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