Personalized POI Recommendation Using CAGRU and Implicit Semantic Feature Extraction in LBSN

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ABSTRACT

With the intention of addressing the concern that existing point of interest recommendation methods fail to fully utilize the auxiliary information of the point of interest, from which it is challenging to extricate a substantial quantity of deeper feature information, a personalized point of interest (POI) recommendation model using Context-Aware Gated Recurrent Unit (CAGRU) and implicit semantic feature extraction was proposed. First, the check-in data is divided into five tags, and the continuous geographical location check-in data and time data are discretized. Then, the CAGRU was used to obtain the POI check-in features. Finally, the time sequence location information, user information and target location information are transformed through the nonlinear activation function to obtain the score of each location in the data set as the next POI location, and the Top-N recommendation is generated through the score. Experiments indicated that the results of the suggested method were better than the comparative methods.

KEYWORDS

Attention mechanism, Context-Aware Gated Recurrent Unit, Context information, Points of interest recommendation

INTRODUCTION

With the rapid development of artificial intelligence (Guebli & Belkhir, 2021; Jiao et al., 2022; Tan et al., 2022), the Internet of Things (Chamra & Harmanani, 2020; Madhu et al., 2022), big data (Thirumalaisamy et al., 2022), cloud-fog computing (Thoumi & Haraty, 2022; Vijayakumar et al., 2022), smart communication (Almomani et al., 2022; Dwivedi, 2022; Ling & Hao, 2022; Samir et al., 2020), and other fields, intelligent mobile devices have become a necessity for people's public lives, and the demand for location-based services is showing explosive growth. Location-based social networks (LBSNs) have attracted a large number of users (Werneck et al., 2021). Users share their travel photos or check-in data through social networks to record access history and share life experiences, thus accumulating a large number of access footprints or check-in record data with

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geographical markers (Lai & Zeng, 2023; Liu, 2018; Xing et al., 2019). The historical access data of these users provide an opportunity to get insights into people's behavior and can be effectively utilized for personalized point-of-interest suggestion via social networks (Chakraborty et al., 2020; Mishra et al., 2020; Xing et al., 2018; Yang et al., 2019).

In recent years, deep-learning techniques have effectively improved the performance of POI recommendations. The widely used neural networks in POI recommendation include convolutional neural networks (CNNs) and recurrent neural networks (RNNs) (Wang et al., 2022). Among them, RNNs can model short-term check-in behavior of users, but there are problems with gradient vanishing and exploding. Therefore, gated recurrent units (GRUs) are used to better capture the long-term dependencies of user check-in behavior (Jia, 2023). Transformer is used to better extract semantic features from user check-in data (Halder et al., 2023; Wang et al., 2022; Yang et al., 2022). However, many existing methods often struggle to balance time series features, contextual semantic information, and spatial features.

To overcome the above issues, a personalized POI-recommendation method (TFCAGRU) utilizing the Transformer encoder and CAGRU is suggested. The innovations of the suggested method are as follows:

(1) The embedding layer and Transformer encoder are combined to capture POI semantic and spatial features.
(2) With the context information of time and space, the different intentions of user behavior can be better discovered by slicing the time interval and space interval in different dimensions; multilayer attention is introduced to enhance the recommendation model's performance.
(3) When the context information is integrated into the gating structure, CAGRU can efficiently extract the spatiotemporal features of POI, which can better mine users' personalized interests.

RELATED WORK

Deep Learning–Based POI Recommendation

Personalized point-of-interest recommendation developed out of traditional recommendation methods. Then the classical recommendation algorithm was enhanced by considering the sparse data and strong correlation with geographical location. A recommendation model has been constructed based on the characteristics of point-of-interest recommendation data (Lim et al., 2019; Liu et al., 2021). The deep-learning method relies on a substantial volume of data to train the model and extract valuable insights (Abbasi-Moud et al., 2021; Liu, 2023). Hence, deep learning possesses the capability to more effectively extract information and comprehend the complex relationships among various aspects. Deep learning offers significant benefits in feature selection and high-level semantic feature learning when dealing with the challenge of constructing feature engineering on unstructured datasets (Baral et al., 2018).

Xia et al. (2017) employed RNN to make personalized POI recommendations to users according to the users' check-in order. However, this method is designed and implemented for specific scenarios and is modeled according to the temporal and sequential context for POI recommendation. According to Liu et al. (2016), utilizing temporal and spatial context information can be beneficial in predicting users' access preference at a specific location. This approach can significantly enhance the accuracy of predicting the next point of interest. A recommendation model called spatiotemporal recurrent neural network (ST-RNN) was suggested by building upon the recurrent neural network. Wang et al. (2017) utilized RNN and CNN to acquire the features of users and points of interest. The deep context-aware POI recommendation model comprises three primary components: a CNN layer for mining the features of user access points of interest, a RNN layer for modeling sequential dependency in user-preference information, and a matrix decomposition interaction layer that combines a CNN layer and a RNN layer. Chang et al. (2018) introduced a content-aware hierarchical POI embedding model for POI recommendation by utilizing the characteristics of POIs or the relationship between POIs. However, the above methods have weak capabilities in extracting time series information, and they are prone to ignoring the key features in POI check-in data.

Attention Mechanism–Based POI Recommendation

Gupta & Bedathur (2022) constructed a dual graph attention neural network model and utilized cross-domain knowledge transfer learning to improve POI-recommendation precision. Deep transfer learning enables the acquisition of the intricate user–project interaction dynamics, leading to more precise capture of users' overall preferences for transfer learning. Hossain et al. (2022) suggested a context-aware recency-based attention network (CARAN) to solve the issue of mining users' actual preferences in POI recommendation. This framework consists of a potential representation method and an attention-based deep convolutional neural network. It incorporates geographical influence and POI categories to effectively acquire the correlation between different POIs. Lai and Zeng (2023) utilized attention-mechanism modules and long short-term memory (LSTM) to capture sequence features and short-term preferences of historical data. Liu (2023) utilized multi-head attention to obtain user-preference information and modeled the nonlinear interaction between multidimensional features. Jia (2023) combined time-series features with distance-context features, effectively alleviating the sparsity of data. However, the above methods overlook the importance of semantic features.

Transformer-Based POI Recommendation

Halder et al. (2021) proposed a POI-recommendation model (TLR-M) that integrates multitask learning, multi-head attention, and Transformer, effectively integrating long-range dependencies between any two POI accesses. Wang et al. (2022a) improved Transformer and proposed the Long- and Short-Term Preference Learning with Enhanced Spatial Transformer (LSEST) model, which can model both long-term and short-term preferences simultaneously and deeply interact with the two to comprehensively extract user preferences. Yang et al. (2022) proposed a user-agnostic global trajectory flow graph and a new graph enhanced Transformer model (GETNext) to better utilize a wide range of collaborative signals, improve POI-recommendation performance, and effectively alleviate user cold-start problems. In order to improve user satisfaction, Halder et al. (2023) proposed a capacity-aware fair POI-recommendation model that integrates Transformer, attention mechanism, and LSTM. It can effectively capture spatiotemporal features and user interests from POI-access information and balance user satisfaction and POI-based exposure at the same time. These methods indicate that introducing Transformer into POI-recommendation tasks can effectively improve recommendation performance and thus enhance user satisfaction.

However, the Transformer-based POI-recommendation models mentioned above often struggle to simultaneously consider semantic information, time series features, and spatial characteristics of POIs. Taking inspiration from existing Transformer-based POI-recommendation models, the proposed model integrates Transformer, content-aware GRU, and attention mechanism, which can simultaneously consider semantic information, time series features, and spatial features, thereby further improving POI-recommendation performance.

PROBLEM DEFINITION

In order to better state the proposed POI-recommendation model, this section will explain some key concepts and then give the definition of the POI-recommendation issue.

(1) POI. According to the research content of this paper, a POI is described by four main attributes: location identification p, geographic latitude lat_p, geographic longitude $long_p$ and category C_p. The symbol P represents all POI sets.
(2) Check-in. A check-in contains a triplet (u, t, p), which represents that the user u has checked in POI_p at time t.
(3) POI check-in sequence. POI check-in sequence is the execution sequence of a check-in operation of the same user, which can be expressed as $L = \{p_1, p_2, \ldots, p_n\}$. The POI check-in sequences can be expressed as $\boldsymbol{L} = \{L_1, L_2, \ldots, L_n\}$. Assuming that the user's POI check-in sequence set contains a total of m sequences, it can be expressed as $\boldsymbol{L}^u = \{L_1, L_2, \ldots, L_m\}$.
(4) Context information. Context information refers to the scenario in which the user checks in. In POI recommendation, general context information includes geographic context, time context, the user's social situation, mood, current weather conditions, and so on.

The objective of the POI-recommendation task is to forecast the next POI most probable to appear in the given sequence according to the POI check-in sequence of a given user and the corresponding context information, generating a recommendation list for the user of the sequence according to the POI score predicted by the algorithm.

THE PROPOSED TFCAGRU-BASED POI-RECOMMENDATION METHOD

Overall Structure of the TFCAGRU Model

In the proposed TFCAGRU model, the Transformer encoder was used to extract semantic features from POI check-in data and the CAGRU was used to extract spatiotemporal features from POI check-in data. The attention layer then obtained the weight information of the user's time sequence location for the subsequent POI recommended location, with the intention of reducing or disregarding those irrelevant location details. Finally, the time sequence location information, user information, and target-location information were transformed through the nonlinear activation function to obtain the score of each location in the dataset as the next POI location, and the top-N recommendation was generated through the score. Fig. 1 indicates the overall structure of the proposed TFCAGRU model.

Embedded Learning Layer

In location-based social networks, the dataset contains the information of users' check-in locations at different times, including the uniquely identifiable tags user ID and POI-ID. POI position indicates the longitude and latitude information of the check-in POI. POI type is a specific category to which each POI belongs. In order to reflect the personalized preference of POI recommendation, the effects of time, space, and sequence correlation are represented by vectors.

The check-in data are divided into five tags: user, POI, time, POI semantics, and context for sequence input, and different types of data are one-hot encoded into vectors. For the above heterogeneous data, preprocessing is required, and the categories expressed by the user's ID, POI-ID, and POI semantics are uniformly recoded and sorted. Because the data need to be input in a structured way, continuous values (such as geographical location check-in data and time data) are discretized to represent the numerical information of the attribute. Fig. 2 shows the process of analyzing and processing the data affected by multiple factors and inputting it into the network structure.

User activities have two implicit characteristics: continuity and periodicity. To effectively measure the impact of time characteristics on user behavior, these two characteristics are divided more finely. Time stamps are divided into hours and weeks. A natural day is divided into $h \in \{0, 1, \ldots, 23\}$ time periods to represent different spatial intentions of different users in 24 hours. Similarly, for a week,

Figure 1. Structure of the proposed TFCAGRU model

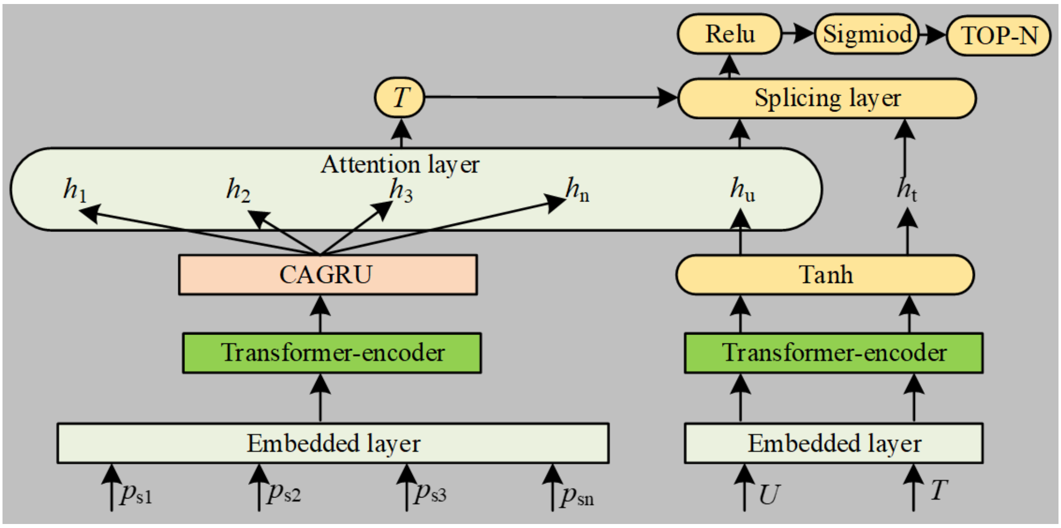
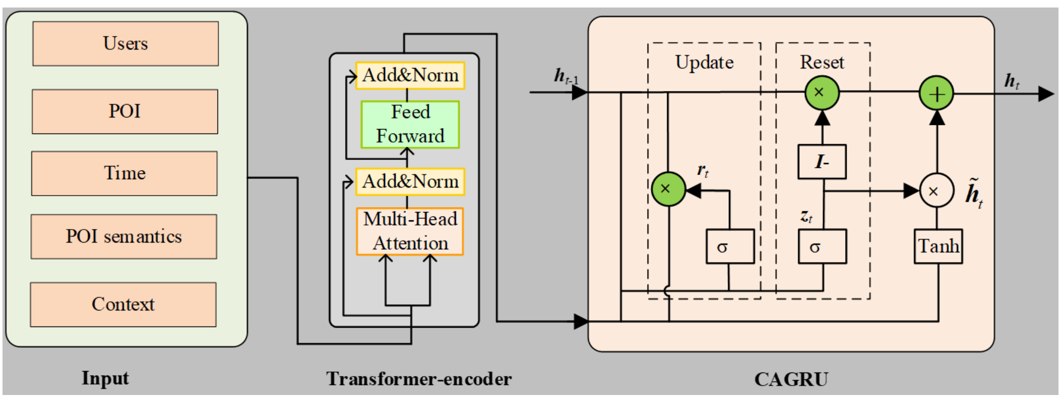


Figure 2. Model input with context information



use $week = 0$ or 1 to represent working days and rest days, respectively, and finally get its potential vector through one-hot coding. User behavior has high mobility and continuity, and the acceptance and influence between two different points of interest are asymmetric. Therefore, the contextual information in time and space is very important for the selection of the next place. The choice of different intervals will produce different spatial intentions. Therefore, three potential vectors, t_l, t_m, and t_m, are introduced to represent the transformation of long, medium, and short time intervals:

$$\lambda_t = 1 - \frac{\Delta_t}{\theta_t} \Delta_t \leq \theta_t \tag{1}$$

$$x_{ct} = \begin{cases} \lambda_t t_s + (1-\lambda_t) t_m & \lambda_t \geq 0 \\ t_l & \lambda_t < 0 \end{cases} \tag{2}$$

The next POI recommendation uses the time context factor to find the different intentions from user mobile behavior by slicing different dimensions of continuous time intervals. Specifically, as shown in (1) and (2), the time is represented by the interval vector x_{ct} . θ_t represents the threshold of the time interval Δ_t , θ_t is as a window, and the dominant time dependence x_{ct} is calculated through the linear interpolation between t_m and t_s . When $\Delta_t \leq \theta_t$, if the time interval Δ_t is close to the threshold θ_t , $\lambda_t \geq 0$ and smaller, t_s is dominant, $\lambda_t \geq 0$ and greater, t_m is dominant. Only when $\lambda_t < 0$, that is, when the time interval is greater than the threshold, t_l is only used as the conversion vector.

In addition to the continuous time representation of context information, it is also the same for the accessed spatial information. Similarly, in (3) and (4), the distance interval is also divided into d_l , d_m , d_s to represent the long, medium, and short distance vectors. Given a distance threshold θ_d , different geographical distances can segment the intention of users' mobile behavior. In the case of $\lambda_d \geq 0$, the smaller the distance, the easier it is to utilize a shorter distance vector d_s to indicate the distance label. On the contrary, the larger the distance, the more it is considered to be transferred by d_m . If the above conditions are not met, the distance is replaced by a longer vector d_l .

$$\lambda_d = 1 - \frac{\Delta_d}{\theta_d} \quad \Delta_d \leq \theta_d \tag{3}$$

$$x_{cd} = \begin{cases} \lambda_d d_s + (1 - \lambda_d) d_m & \lambda_d \geq 0 \\ d_l & \lambda_d < 0 \end{cases} \tag{4}$$

The spatial distance interval is calculated by spherical formula according to the geographical longitude and latitude (lon, lat) of the two points of interest y_a, y_b checked in in history. For longitude and latitude, a unified standard is adopted, with the primary meridian as the 0-degree benchmark. The east longitude is represented by + and the west longitude is represented by –. For the latitude, the north latitude is 90º minus the location latitude and the south latitude is 90º plus the location. The spherical distance between two points of interest can be obtained as follows:

$$\begin{aligned} C(y_a, y_b) = {} & \cos(lon_a - lon_b) \cdot \sin(lat_a) \cdot \sin(lat_b) \\ & + \cos(lat_a) \cdot \cos(lat_b) \end{aligned} \tag{5}$$

$$\Delta_d = R \cdot Arc\cos(C(y_a, y_b)) \cdot \frac{\pi}{180} \tag{6}$$

In the embedding layer, through the context information related to time, space, and sequence discussed above, the heterogeneous data such as user ID, POI-ID, category ID, time, and time-space interval are uniformly represented by one-hot vector x_t , which is mapped to the low-dimensional real value vector space to become uncorrelated sparse vectors so as to capture the implicit semantics in the sequence data. By retrieving the implicit embedded representation of each factor, the average vector is calculated and spliced into the coding layer.

Through the fusion and embedding of POI check-in data, the limitation of sequence length is broken so that users' mobile behavior preferences can be better mined and analyzed. Many existing methods typically input sequence data directly into the GRU module to extract spatiotemporal features, which can easily overlook the implicit semantic information in the check-in data. Therefore, in the proposed TFCAGRU model, the Transformer encoder layer is used to extract the implicit semantic features of POI check-in data.

CAGRU for Spatiotemporal Feature Extraction

By employing the GRU structure to represent the POI check-in sequence, the spatiotemporal features can be efficiently extracted. The integration of context information into the gating structure results in the proposal of CAGRU. By incorporating the category information of POI, the natural geographical location attribute, and the time point attribute of check-in behavior, this expansion has the potential to enhance the suitability of the GRU structure for tasks involving POI recommendation.

The context information in the suggested method incorporates geographic-distance context, time context, and POI-category information. The geographic-distance context refers to the geographic-distance value between the current check-in POI and the previous check-in POI, which is indicated by the symbol $dist$. For the convenience of modeling, $dist$ rounds down during calculation. For the first input of the sequence, set its corresponding geographic distance context to 0. Time context indicates the position of the check-in time in a time period, which is expressed as the symbol $\hat{t}$. Mainly considering the day of the week and the hour of the day, 168 (7*24) different time identifiers are defined as different time contexts. POI-category information refers to the category identification of the location, such as restaurants, shops, stations, parks, etc., which is represented by the symbol cat.

The context information at the current time obtained through the above processing first passes through the embedding layer to obtain their respective vectors expressed as $\boldsymbol{dist}_t$, $\hat{\boldsymbol{t}}_t$, and $\boldsymbol{cat}_t$, and then the embedded vectors are spliced to obtain the comprehensive context vector $\boldsymbol{c}_t$ at the current time.

$$\hat{y}_t = GRU_{dec}([h_t, y_{t-1}], \hat{y}_{t-1}) \tag{7}$$

The values of reset gate and update gate of CAGRU are not only determined by the input of the current time and the hidden state of the previous time, but also determined by the context information of the current time. The calculation process of resetting door $\boldsymbol{r}_t$ and updating door $\boldsymbol{z}_t$ of CAGRU is shown in (8) and (9).

$$\boldsymbol{r}_t = \partial(\boldsymbol{W}_r \boldsymbol{h}_{t-1} + \boldsymbol{U}_r \boldsymbol{p}_t + \boldsymbol{V}_r \boldsymbol{c}_t + \boldsymbol{b}_r) \tag{8}$$
$$\boldsymbol{z}_t = \partial(\boldsymbol{W}_z \boldsymbol{h}_{t-1} + \boldsymbol{U}_z \boldsymbol{p}_t + \boldsymbol{V}_z \boldsymbol{c}_t + \boldsymbol{b}_z), \tag{9}$$

where $\boldsymbol{h}_{t-1}$ indicates the hidden state of the previous time, $\boldsymbol{p}_t$ represents the representation vector of POI at the current time, and $\boldsymbol{c}_t$ represents the context vector at the current time. $\boldsymbol{W}$, $\boldsymbol{U}$, and $\boldsymbol{V}$ represent different weight matrices, $\boldsymbol{b}$ represents deviation vectors, and $\partial()$ represents sigmoid nonlinear activation functions.

After calculating the output of the reset gate and update gate, CAGRU will use the reset gate to control the inflow of the hidden state at the previous time and then calculate the candidate hidden state $\hat{\boldsymbol{h}}_t$ according to the inflow information, the input at the current time, and the context information. The computation process is the following:

$$\hat{\boldsymbol{h}}_t = \tanh(\boldsymbol{W}_h (\boldsymbol{r}_t \bullet \boldsymbol{h}_{t-1}) + \boldsymbol{U}_h \boldsymbol{p}_t + \boldsymbol{V}_h \boldsymbol{c}_t + \boldsymbol{b}_h), \tag{10}$$

where $\bullet$ represents that the matrix is multiplied by elements.

Finally, CAGRU uses the hidden state of the previous time and the candidate hidden state of the current time to obtain the hidden state of the current time through the combination of update gates. The calculation process is as follows:

$$\boldsymbol{h}_t = \boldsymbol{z}_t \bullet \boldsymbol{h}_{t-1} + (1 - \boldsymbol{z}_t) \bullet \hat{\boldsymbol{h}}_t \tag{11}$$

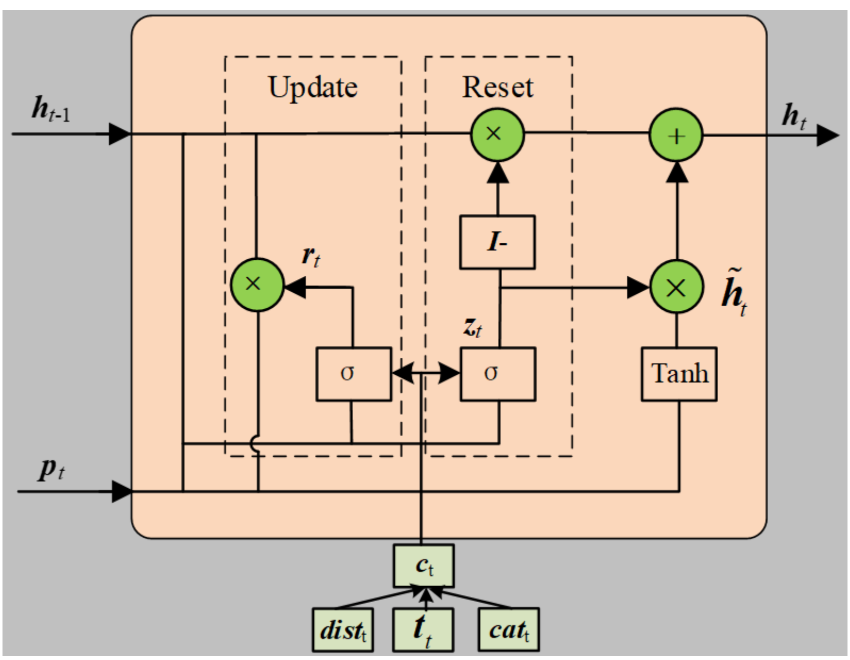
In general, the CAGRU structure integrates the context information in the POI check-in sequence and breaks the limitation of the limited amount of information in the shorter sequence in the sequence recommendation so it can better mine the implicit user preferences in the POI check-in sequence on the basis of the GRU structure. Fig. 3 shows the schematic diagram of the CAGRU structure.

Attention Layer for Key Feature Enhancement

The principle of the attention model is to simulate the cognitive function in biology, judging the importance of things by focusing on important factors and ignoring unimportant factors. This process enables the model to select from a vast quantity of data only those that are essential for the given task. In the coding–decoding framework, because semantic coding compresses the input information, it cannot fully represent all the information. The more the sequence length increases, the more serious the loss of information is. To solve this issue, the attention mechanism is implemented to mine users' long-term preferences from various influencing factors.

Fig. 4 shows the internal structure of the attention mechanism. $h_1, h_2, \ldots, h_t$ represents the hidden vector in the encoder for encoding the input, and S_j represents the $j\text{-}th$ step of decoding. The score of similarity between $h_1, h_2, \ldots, h_t$ and S_j is given by the Softmax function; that is, the context information most suitable for the output value at the current time is automatically selected for the

Figure 3. Schematic diagram of the CAGRU structure



decoding stage. Finally, the input context information of the $j\text{-}th$ stage in the decoder comes from the weighted sum of all h_j and b_t^j.

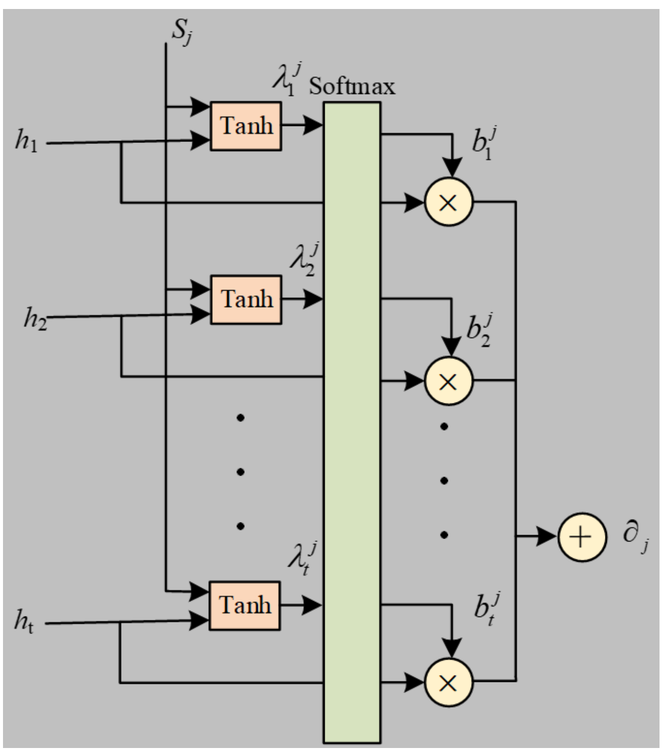
The attention mechanism can be classified into various types according to various classification methods. Attention can be separated into soft attention, hard attention, and local attention through the calculation area. For the structural level, it can be categorized as single-layer, multilayer, and multi-head attention. Soft attention is a common type of attention. It refers to all key contents and is weighted based on the global calculation method. Hard attention locates important factors according to the analysis and considers only the weights of key factors. Local attention is a compromise between the above two methods. It takes a positioning point as the center and selects the influenced area through the movement of a window. The calculation method of soft attention is adopted in this area. Single-layer attention is the most widely used method, and multilayer attention is based on multiple single layers to reflect the hierarchical relationship model. Multilayer attention uses multiple queries to make multiple attention choices for a paragraph of the original text, and each query pays attention to different parts of the original text. The suggested method mainly uses multilayer attention to enhance the performance of the recommendation model.

Loss Function and Optimization Algorithm

The binary cross-entropy loss function was used for the training of the proposed TFCAGRU model. It should be noted that using this loss function requires adding sigmoid function to the last layer of forward propagation of the model. The loss function is:

$$Loss = Y_n \cdot \log X_n + (1 - Y_n) \cdot \log(1 - X_n)\,, \tag{12}$$

Figure 4. Internal structure of the attention mechanism



where Y_n represents the category, which is 0 or 1 in this model, because there are only two categories, interest or no interest. X_n represents the probability predicted after model training.

Adam, an adaptive moment estimation algorithm, is utilized as the optimization algorithm in the proposed method. Assigning and dynamically adjusting the rate of learning of each parameter, the algorithm employs the first-order and second-order matrices of the gradient. One benefit is that, following adjustment, the learning rate of each iteration falls within a specific range, while the parameters remain relatively constant. If the network parameters θ_d are obtained after the $d\text{-}th$ iteration, the gradient $g_d = \nabla J(\theta_d)$ is calculated and the first-order moment estimation m_{d+1} and second-order moment estimation v_{d+1} of the gradient are updated as follows:

$$\begin{cases} m_{d+1} = \lambda_1 m_d + (1 - \lambda_1) g_d \\ v_{d+1} = \lambda_2 v_d + (1 - \lambda_2) g_d^2 \end{cases} \tag{13}$$

Measure the first-order moment deviation $\hat{m}_{d+1}$ and the second-order moment deviation $\hat{v}_{d+1}$:

$$\begin{cases} \hat{m}_{d+1} = \dfrac{m_{d+1}}{1 - \lambda_1^{d+1}} \\ \hat{v}_{d+1} = \dfrac{v_{d+1}}{1 - \lambda_2^{d+1}} \end{cases} \tag{14}$$

The updated model network parameters are:

$$\theta_{d+1} = \theta_d - \alpha \hat{m}_{d+1} \Big/ (\tau + \sqrt{\hat{v}_{d+1}}), \tag{15}$$

where α represents the step length, τ represents the stability constant, and α is generally small enough constant and is taken 0.001 here. In order to prevent the denominator of (15) from being 0, let $\tau = 10^{-9}$. In addition, let $\lambda_1 = 0.99$ and $\lambda_2 = 0.999$ be constants close to 1. Adam effectively utilizes the first-order moment mean and second-order moment mean to dynamically modify the learning rate of parameters. This allows the method to achieve higher output accuracy by mitigating the issues of saddle point residence and local suboptimal convergence.

EXAMPLE VERIFICATION AND RESULTS DISCUSSION

Experimental Environment and Evaluation Index

The system used in the experiment is Ubuntu Server 18.04, the key framework of POI personalized recommendation is TensorFlow, and the programming language used is Python. In the output layer of the proposed X model, the user-feature representation is multiplied with the POI-feature representation and the sigmoid function is used to obtain the user's prediction score for POI. Top-K POIs are selected to recommend to the user. The following metrics are utilized: recall (Recall@K), mean reciprocal rank (MRR@K), and precision (Precision@K), with K denoting the recommendation list's length. To ensure a precise assessment of the influence of varying list lengths on the outcomes of recommendations, choose the corresponding values for each evaluation index for report lists of 5, 10, and 15 in length. Recall is a critical metric utilized in recommendation systems to assess the extent to which items that ought to have been recommended have been recommended. For each user u, the POI that the user has not visited is recommended in the dataset and the recall of POI recommendation Recall@K is:

$$\mathrm{Recall@K} = \frac{|\, P(r) \cap P(u) \,|}{P(u)}, \tag{16}$$

where *P(r)* indicates the POI set recommended by the algorithm and *P(u)* indicates the POI set visited by the user.

MRR@K is a frequently employed metric for assessing the quality of recommendation list rankings. If the target POI in the recommendation list is at the $i\text{-}th$ position, MRR@K can be defined as:

$$\mathrm{MRR@K} = \begin{cases} 1 / i, i \le K \\ 0, i > K \end{cases} \tag{17}$$

For each user u, the POI that the user has not visited is recommended in the dataset, and the precision of POI recommendation Precision@K is:

$$\mathrm{Precision\,@}K = \frac{|\, P(r) \cap P(u) \,|}{k}, \tag{18}$$

where k indicates the number of POIs in the recommended POI sets.

Dataset

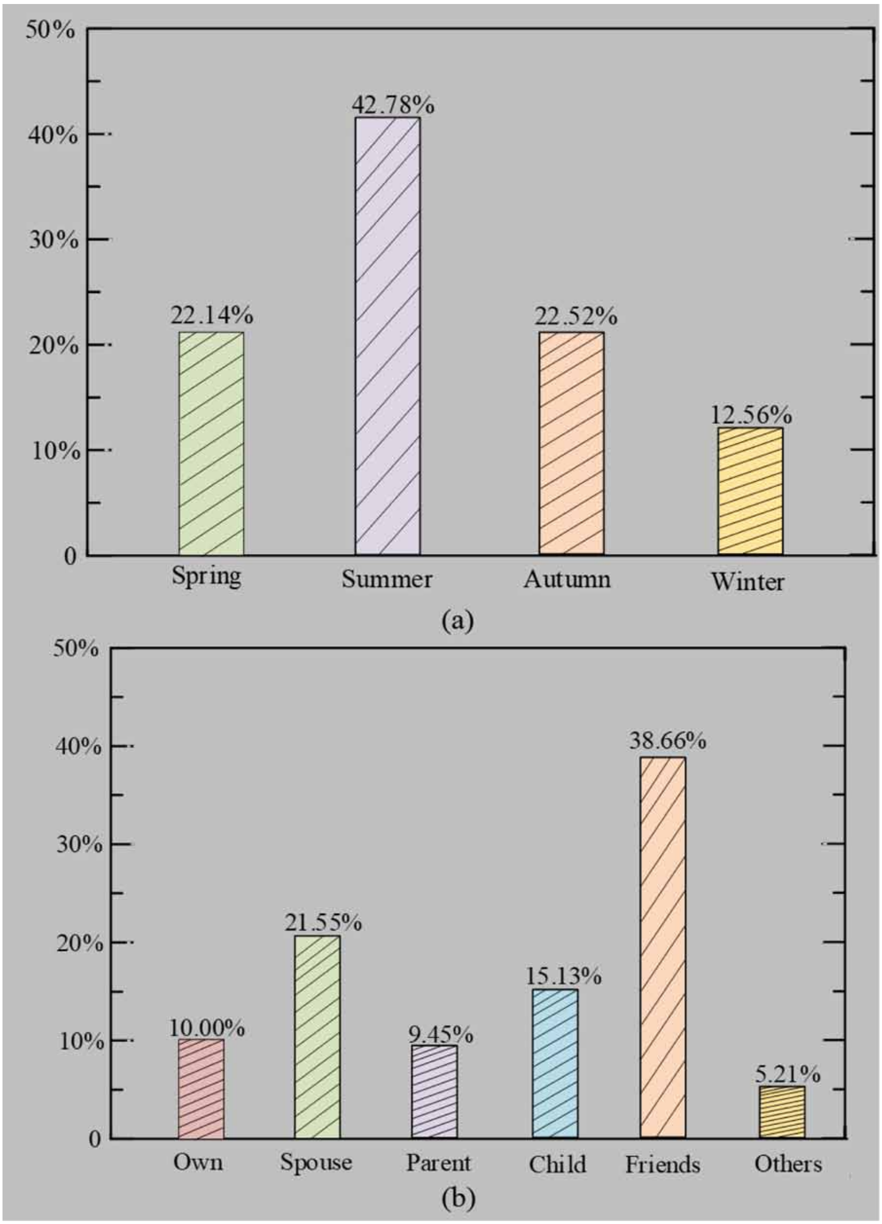
To validate the viability of the suggested system and method, a real tourism dataset was constructed with Henan Province as the example. The knowledge base includes 432 scenic spots in Henan Province. Travel notes were captured through the Ctrip platform, and after serialization processing, a total of 13,562 POI data points were obtained from 1,527 users, with a total of 125,895 check-ins. The evaluation length of a structured scenic-spot visit sequence is 9.5 scenic spots, and the average total travel time is 3.2 days. Fig. 5 shows the distribution of travel-season and companion-type travel tags of a scenic-spot visit sequence.

Super-Parameter Selection

To optimize the performance of the model on the given dataset, the super-parameters are determined using the training and validation sets. To ascertain the optimal hidden-state dimension for the CAGRU structure in the model, the hidden state dimension parameters are chosen from the training set and validation set, assuming all other parameters remain constant. The findings are illustrated in Fig. 6.

It is evident that the model's performance improves gradually as the number of hidden-state dimensions rises; however, as the number of dimensions rises each time, the rate of improvement steadily decelerates or ceases entirely. Increasing the dimension of the hidden state not only will result in increased computational complexity and training expenses but also will result in a highly complex model structure that is susceptible to overfitting issues when the available data are inadequate. With the intention of striking a balance between training overhead and model performance, the aforementioned analysis suggests that the concealed-state dimension of the proposed model be established at 250 dimensions.

Figure 5. Category distribution of scenic spot access sequence set: (a) Travel season, (b) Companion type

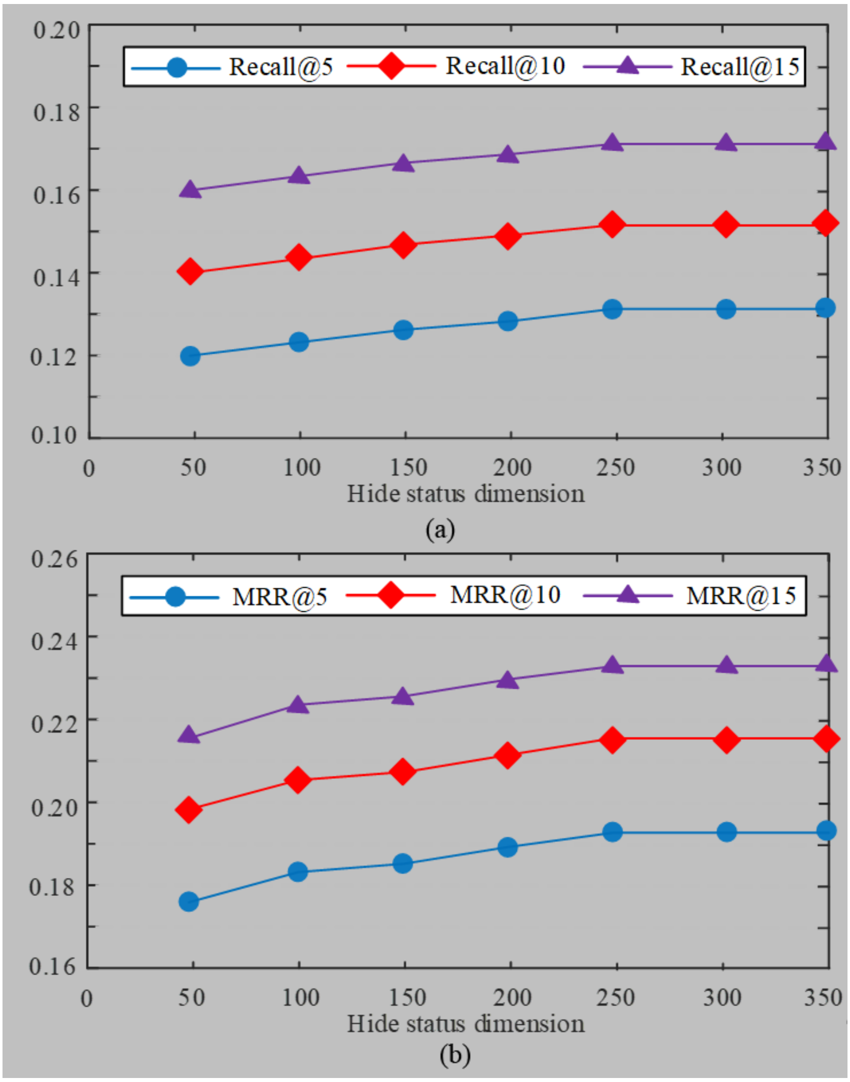


The loss function curve of the proposed TFCAGRU model is shown in Fig. 7.

In Fig. 7, as the epoch increased, the loss value of the model gradually decreased. After 25 epochs, the proposed TFCAGRU model reached a convergence state.

In addition, to avoid overfitting issues, the dropout mechanism was introduced into the proposed CAGRU model. Through parameter sensitivity analysis experiments, it was found that when its value was set to 0.4, the proposed CAGRU model achieved the best performance. While the Adam algorithm is capable of dynamically adjusting the learning rate of various parameters during training using first-order and second-order moment estimation of gradients, the manual-specified initial learning

Figure 6. Experimental results of hidden state dimension parameter selection of the proposed model on the dataset: (a) Recall@K Index, (b) MRR@K Index

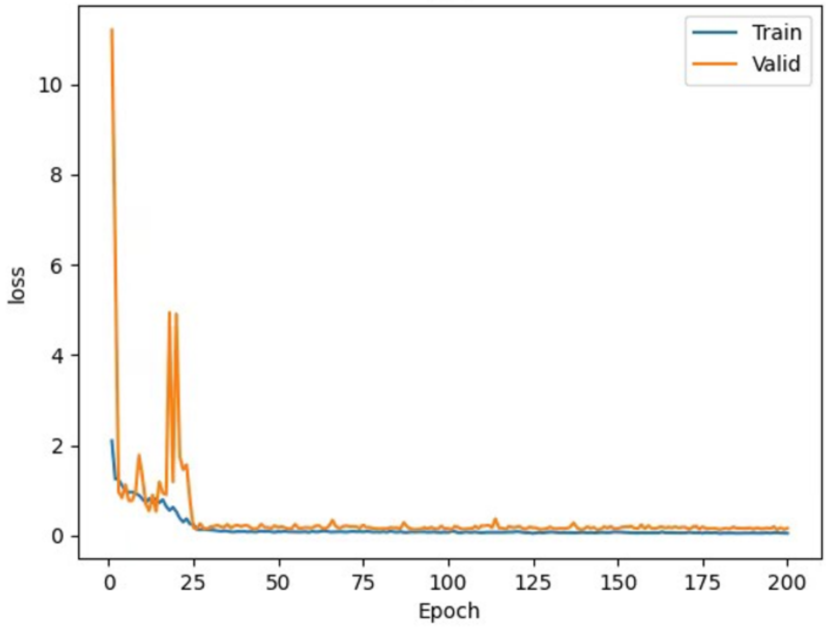


rate will continue to restrict the approximate range of the learning rate. When the learning rate of the optimization algorithm is excessively high, the initial decrease in model loss is rapid, followed by significant fluctuations. Consequently, convergence will not occur. As the learning rate of the optimization algorithm is reduced, there is a gradual decrease in the model's loss. The optimal outcome can be attained only through a significant number of iterations. Configure the Adam algorithm's initial learning rate to 0.001.

Comparison With the State-of-the-Art Methods

To show the merits of the suggested personalized point-of-interest recommendation method, the transfer learning–based POI-recommendation method (Gupta & Bedathur, 2022), the CARAN method (Hossain et al., 2022), and GETNext (Yang et al., 2022) were compared with the proposed method under identical experimental conditions. The efficacy of each model's recommendations was assessed

Figure 7. Loss function curve of the proposed TFCAGRU model



using Precision@K and Recall@K. To eliminate experimental result contingency, the recommended POI K numbers are 5, 10, and 15. The results of the investigation are illustrated in Fig. 8.

In Fig. 8, the performance of both Transformer-based POI-recommendation models is superior to that of the other models, and using Transformer can extract semantic features from POI check-in data. It can be seen that semantic features are very important for improving POI-recommendation performance. The proposed TFCAGRU model improved GRU by introducing content-aware attributes, which can effectively enhance the model's ability in spatiotemporal feature extraction. In addition, the introduction of attention mechanisms helped to reinforce important features. Therefore, the proposed TFCAGRU model achieved slightly better performance than the GETNet model.

Ablation Experiment

In order to verify the roles of various components in the proposed TFCAGRU model, ablation experiments were designed, the results of which are shown in Table 1. Among them, each ablation model is represented as follows:

M1 (without Transformer encoder): remove the Transformer encoder and input the encoding result of the embedded layer directly into the CAGRU layer.
M2 (without CAGRU): remove the CAGRU layer and directly enhance the attention of the data output by the Transformer encoder layer.
M2 (without CAGRU, with GRU): remove the CAGRU layer and replace it with the original GRU.
M3 (without attention): remove the attention mechanism and directly perform fully connected and linear operations on the features output by the CAGRU layer.

As shown in Table 1, regardless of which component is removed, the performance of the proposed TFCAGRU model is reduced. Among them, when the Transformer module is removed, the performance of the proposed TFCAGRU model decreases the most significantly, indicating that

Figure 8. Comparison of different methods in Precision@K and Recall@K Indices: (a) Precision@K Index (b) Recall@K Index

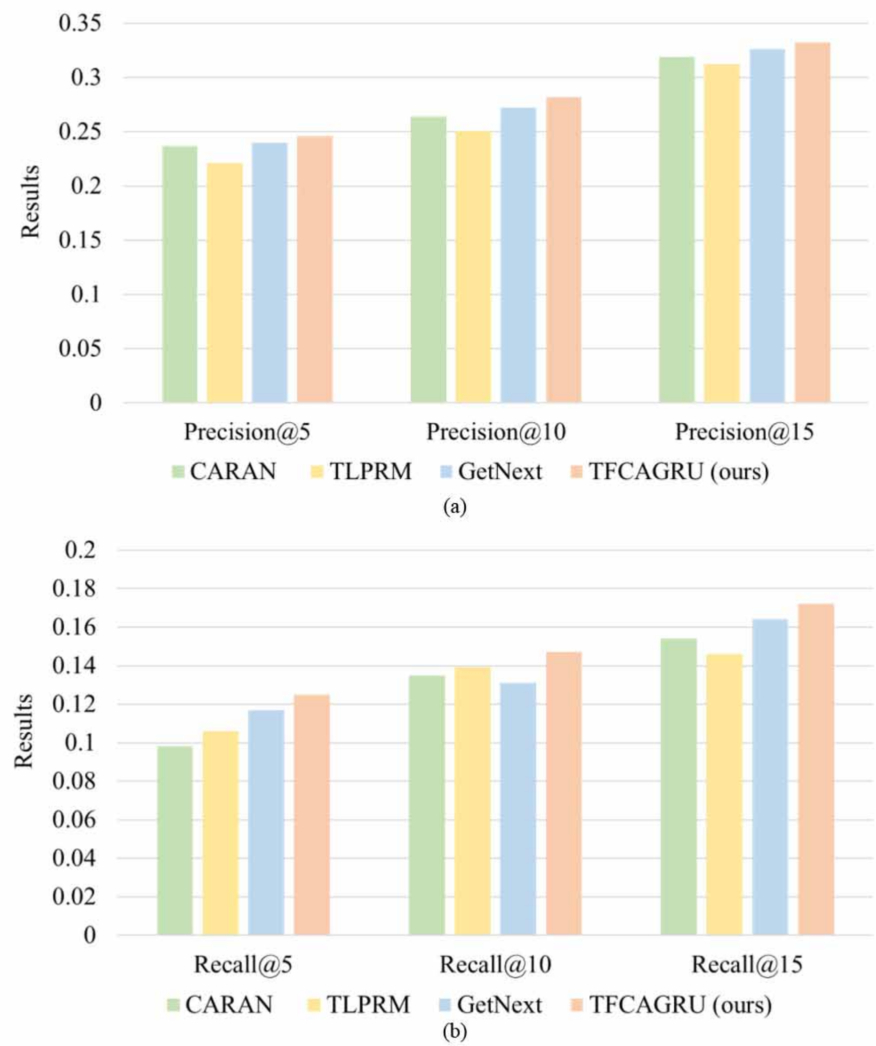


Table 1. The ablation results of the proposed TFCAGRU model

Ablation Model	Precision@15	Recall@15	Test Time for Single Sample(s)
M1	0.313	0.158	0.016
M2	0.318	0.160	0.017
M3	0.328	0.169	0.021
M4	0.324	0.166	0.019
TFCAGRU	0.332	0.172	0.022

semantic features are of great help in improving the overall performance of POI. In addition, in terms of testing time for a single sample, the proposed TFCAGRU has the most significant reduction in testing time after removing the Transformer module, mainly because the Transformer module contains diverse attention mechanisms, which to some extent increase computational overhead. However, overall, compared to the removed smile model, the testing time of the proposed TFCAGRU did not show a significant increase, and even if applied in real-world applications, it is still acceptable.

CONCLUSION

Existing POI-recommendation methods often struggle to balance semantic features and spatiotemporal features in POI check-in data. Therefore, a personalized POI-recommendation model using CAGRU and Transformer was proposed. The TFCAGRU model can effectively extract semantic features from POI check-in data, and CAGRU is used to effectively extract spatiotemporal features. The introduction of the attention mechanism effectively strengthens important features, thereby improving the overall POI-recommendation performance. The proposed TFCAGRU-based POI-recommendation method has potential application value for tourist-attraction recommendation, hotel recommendation, shopping-venue recommendation, merchant promotion, etc. In addition, the proposed TFCAGRU model can significantly enhance user experience in terms of POI-recommendation precision, recall rate, and test time.

However, the proposed TFCAGRU model failed to take into account the impact of some additional information on the effectiveness of POI recommendations, such as weather, holidays, cultural environment, etc., which will to some extent affect user satisfaction. In future work, additional auxiliary information will be introduced into the proposed TFCAGRU model to enhance its practicality and user satisfaction. In addition, some new technologies will be introduced into the proposed TFCAGRU model, such as pre-trained language models (Mei et al., 2023) and graph convolutional networks (Zhu et al., 2023), to further improve the recommendation performance of the TFCAGRU model.

AUTHORS' NOTE

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APPENDIX

Table A1. Acronyms

Abbreviation	Full Name
POI	Point of interest
CAGRU	Context-aware gated recurrent unit
LBSN	Location-based social network
CNN	Convolutional neural network
RNN	Recurrent neural network
GRU	Gated recurrent unit
TFCAGRU	Transformer encoder and context-aware gated recurrent unit
ST-RNN	Spatiotemporal recurrent neural network
MF	Matrix factorization
LSTM	Long short-term memory
CARAN	Context-aware recency-based attention network

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