Extracting Fast and Slow: User-Action Embedding with Inter-temporal Information

Akira Matsui,1,* Emilio Ferrara2,3,4

1 College of Business, Yokohama National University, Yokohama, Kanagawa, Japan
2 Annenberg School of Communication, University of Southern California, Los Angeles, CA, US
3 Information Sciences Institute, University of Southern California, Marina Del Rey, CA, US
4 Department of Computer Science, Viterbi School of Engineering, University of Southern California, Los Angeles, CA, US

Abstract

With the recent development of technology, data on detailed human temporal behaviors has become available. Many methods have been proposed to mine those human dynamic behavior data and revealed valuable insights for research and businesses. However, most methods analyze only sequence of actions and do not study the inter-temporal information such as the time intervals between actions in a holistic manner. While actions and action time intervals are interdependent, it is challenging to integrate them because they have different natures: time and action. To overcome this challenge, we propose a unified method that analyzes user actions with inter-temporal information (time interval). We simultaneously embed the user’s action sequence and its time intervals to obtain a low-dimensional representation of the action along with intertemporal information. The paper demonstrates that the proposed method enables us to characterize user actions in terms of temporal context, using three real-world data sets. This paper demonstrates that explicit modeling of action sequences and inter-temporal user behavior information enable successful interpretable analysis.

Introduction

Human temporal behaviors contain a wide range of valuable information. Mining human physical, social, or economic dynamic behavior has contributed greatly to our understanding of human mobility, social phenomena, or consumption behavior. However, most human dynamic behaviors models focus only on the sequence of users’ actions. For example, statistical time-series models study the variation of values in the data over the course of time. While this analysis is very natural in many contexts, those analysis does not explicitly model or integrate inter-time information such as time intervals between actions. Despite the importance of the information about time intervals for human behavior analysis, the existing user models in computer science mainly focus on sequences of actions and do not integrate time-interval information into action.

Time intervals between actions provide crucial information about the context of those actions. There is much literature that shows that time intervals between actions can tell the human cognitive states. Wickens and Carswell (1997) and Graesser, Millis, and Zwaan (1997) proposed a model that incorporates the information of time intervals into action. A model that incorporates the information of time intervals into action is needed. An obstruction that prevents us from modeling user actions and their time intervals in a holistic way is the fact that actions and time intervals are incompatible. Action is categorical data, and time interval is numerical data. One natural solution is to discretize time intervals using several time bins. However, making time bins requires hyperparameters, and validating those predetermined parameters is a cumbersome process. In addition, even if we successfully discretize time intervals, it is not trivial how to incorporate time interval information into actions.

To take into account the context when mining and interpreting actions, a model that incorporates the information of time intervals into action is needed. A model that incorporates the information of time intervals into action is needed. An obstruction that prevents us from modeling user actions and their time intervals in a holistic way is the fact that actions and time intervals are incompatible. Action is categorical data, and time interval is numerical data. One natural solution is to discretize time intervals using several time bins. However, making time bins requires hyperparameters, and validating those predetermined parameters is a cumbersome process. In addition, even if we successfully discretize time intervals, it is not trivial how to incorporate time interval information into actions.

To overcome the aforementioned challenges, this paper proposes a model that embeds inter-temporal information to obtain the low-dimensional representations of users actions. Firstly, to discretize time intervals, we leverage the statistical properties of time intervals that have been well exploited. Our model estimates as a mixture exponential distribution and use those estimated parameters to group the time intervals. Leveraging that statistical procedure can ensure the objectivity of the analysis avoiding the hyper-parameters selection for time bins. Also, this procedure ensures that discretized time intervals capture the nature of observed time intervals. We then construct the action sequences where action and its time intervals show up one after the other and make n-grams from them. Then our framework calculates a low-dimensional representation of user actions with time interval information using a word embedding technique. Lastly, we study the inter-temporal context for each action using the obtained action embedding vectors. To do so, we propose an interpretable measurement of action timing context (ATC), which represents whether a given action belongs to a long-term (fast pace) context or a short-term (slow pace) context. We illustrate the schematic of our study in Figure 1.
and summarize the terminologies in Table 1 to make our paper easy to follow.

With the proposed model, we conduct the three empirical studies to reveal the inter-temporal context of users’ actions using ATC. We firstly show the inter-temporal context of actions corresponds to apps’ categories. Second, we demonstrate that ATC can compare the behavior differences of different types of students in terms of their temporal behavior. The second analysis investigates the behavior differences between the drop-out and non drop-out students in a Massive Open Online Courses (MOOC) platform. In the third study, we study the dynamics of the context of actions. With a student behavior dataset over an academic term, we demonstrate that the inter-temporal context of actions changes according to the event on the campus, such as the mid-term weeks. Those three empirical studies show that our framework and proposed measurement (ATC) captures the inter-temporal context of actions in an interpretable way.

| Terminology | Description |
|-------------|-------------|
| Action      | Single unit of the observed behavior (e.g., user smartphone application, physical contact, ...) |
| Time interval | A gap between two consecutive actions |
| ATC         | Action Timing Context defined at Eq 7 in Section . |

Finally, we summarize the contributions of this paper as:

- Constructing a framework to extract the inter-temporal context of actions
- Proposing an interpretable measurement that represents the inter-temporal context of action
- Conducting several empirical studies to demonstrate our framework reveal inter-temporal human behaviors

**METHOD**

This paper aims to study human behavior considering inter-temporal information. For this aim, our method will try to obtain a low-dimensional representation of the action sequence. We construct action sequences of each user with the actions and their time interval and then utilize a word embedding method on the constructed action sequences.

**Capturing inter-temporal information with time bins**

This subsection will discuss how we estimate the time intervals between actions and convert them into the action sequence using time bins. While calculating time intervals between consecutive actions is straightforward, it is not trivial to discretize this continuous-time value to put them in the action sequence. A natural solution for this discretization problem is to let some time bins be as hyperparameters. For example, (Wang et al. 2016) use predefined bins such as \((0 - 1\text{min}), [1\text{min} - 10\text{min}], [10\text{min} - 60\text{min}], [60\text{min} - \text{<}])\) and then classify calculated time intervals into those time bins. However, since there are numerous patterns of the time bins, it isn’t easy to make an appropriate pattern of time bins without any prior information. Such a combination of time bins without considering the features of the time intervals in the data, such combination of the time bins might miss the inter-temporal information between actions, which is the primary interest of this study.

Therefore, this study will estimate the statistical property of the time intervals of data to construct the time bins based on the estimated parameters rather than using hyperparameter time bins. The goal of this time bins construction is to capture the behavior states of the users from their time intervals and represent the behavior states by the time bins. For this aim, we study the behavior states estimating the mixture distributions.

**Time interval bins estimation by a mixture of exponential distributions**

This paper estimates the time interval distribution between actions and constructs the time bins based on the estimated distribution. We assume that the observed time intervals follow the mixture of exponential distributions. To estimate the mixture of exponential distributions, we utilize the EM algorithm and the model selection criterion.

Recent development in the literature reveals that the mixture of the exponential distribution with a few components can well fit the time intervals of various empirical data (Okada, Yamanishi, and Masuda 2020). Following (Okada, Yamanishi, and Masuda 2020), we estimate the mixture of the exponential distribution using the EM algorithm and selecting the number of components by the model selection criteria.

**EM algorithm:** To study the mixture of exponential distribution from the observed time interval between actions \(x = \{x_1, \ldots, x_n\}\), we estimate the parameters in the following equation,

\[
f(x) = \sum_{k=1}^{K} \pi_k f_k(x; \lambda_k) \tag{1}
\]

where of the time \(\pi_k\) is the mixture parameters (mixing weights), \(\pi_k \geq 0\) and \(\sum_{k=1}^{K} \pi_j = 1\); \(f\) is the probability density function (PDF) of an exponential distribution and \(\lambda_k\) is the parameter of the exponential distribution of \(k\) component (rate parameter).

To estimate the parameters \(\pi_k\) and \(\lambda_k (k = 1, \ldots, K)\), the EM algorithm takes E (Expectation) step and M (Maximization) step. At E step during the iteration \(t\), the algorithm calculates so-called membership probability (weight) \(r_{ik}^t\) by,

\[
\gamma_{ik}^t = \frac{\pi_k f(x_i; \lambda_k^t)}{\sum_{j=1}^{K} \pi_j f(x_i; \lambda_j^t)}. \tag{2}
\]

Intuitively, the membership weight \(r_{ik}^t\) describes the probability of a given data (time interval, \(x_i\)) is generated from

\(\text{Okada, Yamanishi, and Masuda} 2020\) uses a slightly different wordings than this paper. They describe actions in this paper as “events”, and time intervals as “inter-event times”. To keep our wordings consistent, we use our terminology in Table 1.
We first construct the action sequence of each user and calculate time intervals between two consecutive actions. Then, we estimate the mixture distribution of time intervals to discretize the time intervals. With the discretized time-intervals and action, we construct the sequences of action + time interval. Also, we construct trigrams from those sequences. Using the data constructed at (c), we learn the embedding vector of actions and trigrams. (e) We study the inter-temporal context of action extracting Action Timing Context (ATC) from obtained embedding vectors.

Action sequence and N-gram

To represent the context of the actions by users, we first construct the sequence of actions and their time intervals where they are in chronological order. Then we construct N-grams from those actions sequences.

Action sequence: With the actions and time intervals between them, we construct action sequences for each user. Let User $i$ have the actions $\{A_{i,j}\}_{j=0}^M$ where $M$ is the number of unique actions, and its time interval is $T_{ij}$ that is the time interval between $A_{i,j}$ and $A_{i,j+1}$. By using the time bin constructed in (b), we attribute time interval $T_{ij}$ to a time bin $T_{ij}$, which is one of $\{T_0, \ldots, T_K\}$. With User i’s actions $\{A_{i,j}\}_{j=0}^M$ and their time intervals $\{T_{ij}\}_{j=0}^M$, we construct User i’s action sequence as

$$A_{i,1}T_{i,1}A_{i,2}T_{i,2}A_{i,3} \ldots T_{i,1}A_{i,J−1}T_{i,J−1}A_{i,J}$$

We construct this action sequence for each user and we will make N-grams from those actions sequences.

Action N-gram: Our action n-gram captures the context of users’ actions, representing the order of actions and their time interval. For an action sequence $\{A_1T_1 \ldots T_{J−1}A_J\}$, we make n-gram separating action $A_j$ and $T_j$. In this study, we use trigram $(n=3)$ of the action sequence, and it will be

$\{A_1T_1A_2, T_1A_2T_2, \ldots T_{J−2}A_{J−1}T_{J−1}, A_{J−1}T_{J−1}A_J\}$

While the others may prefer to use the set of action and its time interval as one unit to make n-gram such as $A_jT_j$ making n-gram with separating those two will benefit from studying the time interval context of the action (to be discussed in Section ).

We use $A_j$ and $T_j$ for $A_{i,j}$ and $T_{i,j}$ respectively, abbreviating the notation $i$ for user.
Embedding

We use the Skip-gram with negative sampling (SGNS) algorithm to obtain low-dimensional representation of actions and n-grams (Mikolov et al. 2013a,b). This section will discuss the prediction problem that SGNS solves in this paper to understand the embedding vectors to be obtained from the action sequence. The SGNS model the distribution, \( p(d \mid w, c) \), where \( d \) takes 1 when a pair of word \( c \) and context \( w \) is observed in the data otherwise 0. The SGNS maximize the following conditional log-likelihood \( \mathcal{L} \) (Dyer 2014),

\[
\mathcal{L} = \sum_{(w,c) \in \mathcal{D}} \{ \log p(d = 1 \mid c, w) \\
+ kE_{\bar{w} \sim q} \log p(d = 0 \mid c, \bar{w}) \},
\]

where \( q \) is the noise distribution in negative sampling, and \( k \) is the sample size from the noise. The SGNS especially calculates the conditional probability \( p(d = 1 \mid c, w) \) by \( \sigma(v_c \cdot v_w) \), where \( \sigma(x) \) is sigmoid function and \( v_w, v_c \in \mathbb{R}^d \). In other words, the SGNS seeks the parameter \( v_w, v_c \) that maximizes the above conditional probability, and \( v_w, v_c \) is the embedding vectors of interests.

“Word” and “Context” in this paper: This paper treats actions and n-grams of action sequences as either contexts or words. Note that we treat actions as both words and contexts, and we treat n-grams of action sequences as well. We calculate the conditional probability of actions/n-gram given actions/n-gram to obtain the low-dimensional representation. For implementation, we use the ngram2vec (Zhao et al. 2017), which is the modified version of word2vec (Levy and Goldberg 2014).

Extracting action timing context (ATC) using n-gram actions

In order to contextualize the actions with the inter-temporal information, we use the embedding vectors of the n-grams. As discussed in Section , n-grams contain elements that have an action between time intervals, such as \( TAT \). We leverage the embedding vector of this type of n-gram as the references that represent the inter-temporal context.

Constraining the reference vectors: To do so, we firstly make the two types of reference n-grams: the long and short time interval context. Let \( T_{long} \) and \( T_{short} \) be the longest and the shortest time interval bin, respectively. Note that those bins are defined in Section . Then, we calculate the reference vector for the long and the short interval context as

\[
v_{long} = \frac{1}{|V_{long}|} \sum_{v \in V_{long}} v \tag{5}
\]

where \( V_{long} \) is the set of the embedding of the n-gram where actions are between the longest time intervals. That is,

\[
V_{long} = \{ T_{long}AT_{long} \} A \in \mathcal{A}
\]

, and \( \mathcal{A} \) is the set of all actions. Similarly, we make \( V_{short} \) using \( T_{short} \).

Definition of the “long term context” and “short term context”: The reference vectors, \( V_{long} \) and \( V_{short} \) represent an action taken between the long term intervals or the short term intervals. For example, when an action \( A \) is similar to \( V_{long} \), it means that the user takes a long time break (interval) before/after that action. We can interpret such action as the action that the users spend a long time execution time. On the other hand, when an action \( A \) is similar to \( V_{short} \), it means the users tend to execute with a short-term execution time.

Aligning actions into long vs. short term context: To study the time interval context of a given action \( A \), we calculate the relative distance \( r(A) \) between the two reference vectors for each action of interest,

\[
r(A) = \cos(v_{long}, a) - \cos(v_{short}, a) \tag{7}
\]

where \( a \) is the embedding vector of action \( A \), and \( \cos \) is the cosine similarity. When \( r(A) \) is large, action \( A \) is in the long term context; the other means \( A \) is in the short term context. We provide a schematic illustration of this relative distance in Figure 2.

Data & Experiment Settings

In this dataset, we will discuss the dataset and experiment setting for the embedding model. We employ the three datasets to investigate the wide range of human behavior in terms of inter-temporal context using ATC discussed in Section.
Table 2: Basic dataset statistics

| Dataset Statistics | App Usage | MoocData | StudentLife |
|--------------------|-----------|----------|-------------|
| Observation period | 1 week    | 2 years 11 days | 11 weeks   |
| Observation date   | Jun ’16   | Jun ’15-Jun ’17 | Mar ’13 - May ’13 |
| Observation field  | Smartphone | MOOC platform | University campus |
| Environment        | Digital device | Digital platform | Digital device and Real place |
| # unique actions   | 1,696     | 22       | 800         |
| # total users      | 871       | 225,642  | 49          |
| # total actions    | 4,171,950 | 42,110,402 | 219,360    |
| Avg. # actions per user | 4789.83 | 186.62   | 4476.73    |
| Avg. # unique actions per user | 1.94 | 9.74    | 16.326     |
| # components of the mixture of exp distributions | 3 | 3 | 3 |

Note: The basic statistics of the three datasets used for our analysis. This table reports the basic statistics of the data sets after preprocessed described in Sec. # components is determined by DNML as discussed in Sec.

Datasets

We apply our method to the three data sets. We firstly use the app usage history dataset (Feng et al. 2019) to study the correspondences between the inter-temporal context differences (ATC) and the category of the apps. Then, we use ATC to study the behavior difference between different individuals to demonstrate that our method captures human behavior in terms of inter-temporal context. For this analysis, we use the clickstream data from the MOOC platform (Yu et al. 2018). Lastly, we turn to the dynamics of ATC, studying the student behavior sensing data (Wang et al. 2014).

App Usage Dataset (Feng et al. 2019) We use the smartphone app usage history data published by Feng et al. (2019). The dataset provides the user history of smartphone app usage, including the timestamp and the category of the app. We consider the usage of the app as actions and labeled with its categories.

MoocData (Yu et al. 2018) MoocData is the clickstream data on the users in the XuetangX platform (the MOOC platform in China). The dataset contains the users’ learning activities logs, including what functions of the platform they use during their learning. While the dataset provides a massive amount of logs, it also serves as the dataset for the dropout prediction. We utilize this subset of the dataset to compare the behavior differences between two distinct types of users in terms of academic performance: Dropout VS Non-Dropout.

StudentLife (Wang et al. 2014) StudentLife dataset provides a wide range of behavior data from automatic sensing using participants’ smartphone. Wang et al. (2014) recruit the students for the study and track their behavior on the campus during one academic term. The dataset contains the smartphone usage history and eating behavior (e.g., lunch), physical activities (e.g., walking), etc. In addition to the action data, this dataset provides the survey data based on Ecological Momentary Assessment (EMA). The EMA data contains the self-report of the physiological state of the students throughout the data period. We use the three questionnaires to study the correlation between the ATC of students’ activity and the students’ psychological state.

We utilize the above three datasets to demonstrate that ATC can capture human behavior from the inter-temporal point of view.

Experiment Settings

As discussed in Sec , we estimate the mixture of time intervals between actions to construct the time bins. We use the implementation by Okada, Yamanishi, and Masuda (2020). For each dataset, we randomly sample 10k time intervals and estimate the distributions.

For embedding, we use the ngram2vec implemented by Zhao et al. (2017) based on word2vec (Levy and Goldberg 2014). We use SGNS to learn embedding vectors (300 dim). We use a flexible window size: two windows for bi-gram and one window for actions as illustrated in Fig 1(d) to ensure that our embedding model captures the dependency among actions and time intervals. We remove the users who have less than 10 action.

Empirical analysis with action timing context (ATC)

This section reports the empirical analysis of extraction of action timing contexts with real-world datasets. Our empirical analysis to demonstrate the action timing context extracts the informative insights of human behavior from the action sequence. To this aim, we utilize the three different datasets: the student behavior data observed in a field study,

Table 3: EMA Questions

| Question                           | Option (scale)                        |
|------------------------------------|---------------------------------------|
| how happy do you feel?             | 1. little bit, 2. somewhat, 3. very much, 4. extremely |
| how sad do you feel?               | 1. little bit, 2. somewhat, 3. very much, 4. extremely |
| How are you right now?             | 1. happy, 2. stressed, 3. tired       |
| How many hours did you sleep last night? | 18 scales (0.5-hour grid from less than 3 hours to more than 12 hours) |

Note: The EMA questions used in this paper. The participants who only answer “yes” to “Do you feel AT ALL happy (sad) right now?” answer the first two questions (“how happy(sad) do you feel?”).
the smartphone app usage data, and the students’ behavior in a Massive Open Online Courses (MOOC).

Our empirical analysis compares the differences in action timing contexts between different types of entities. First, we show that the ATC of app usage depends on its category. Since each application has a different purpose, it is evident that these differences can reflect on its ATC. Next, we utilize our method to find behavior differences between successful students and those not in the academic environment. We compare the differences in the ATC of the dropout student and non-dropout student in the MOOC platform. Lastly, we study the transition of the ATC of the student behavior in a real academic environment. We use the datasets covering physical and digital behavior (smartphone usage) over an academic term.

**ATC differences among smartphone apps usage**

Smartphone apps are an essential tool for our modern daily life, providing a wide range of functions such as games or health. Those apps are supposed to have different ATCs depending on their purpose. To study this point, we calculate the mean ATC for each app category. Figure 3 demonstrates that different category apps have different ATC means.

In the figure, the Reference category app has the smallest ATC (-0.27), meaning that the apps in the reference, such as the dictionary, are used in a short span. On the other hand, Infant & Mom has the largest ATC (1.1). The users of the apps for infant care and monitoring use those apps for the long-term context. Our analysis also reveals that the apps that do not belong to a definitive context. Finance category apps, for example, are around the median ATC (0.27). Therefore, the finance category apps usage spans from the long term to the short term context.

**ATC differences between dropout and non-dropout students**

Our method can reveal the behavior differences in an interpretable way. To demonstrate this, we use the student clickstream data from the MOOC platform. Along with the clickstream, the datasets provide labels of dropout or not for each student. We split the dataset into the data of dropout students and non-dropout and then learn embedding from each to calculate ATC. By doing this, we can compare ATCs of the same action but different types of students (dropout/non-dropout).

Figure 4 plots the differences in ATC of the same action between the dropout and non-dropout students. The figure calculates the differences by subtracting the ATC of dropout students from one of the non-dropout. Therefore, a positive difference in ATC of action implies that the dropout students use that action in the long term, but the non-dropout students do in the short term.

The most evident distinction in the figure is in “Pause Video” (0.45). This positive difference suggests that the dropout students do not often pause the course video, but the non-dropout students pause a video in a short span in their learning. Contrastingly, we find the negative differences in commenting (ATC of “Delete Comment”: −0.61; “Create Comment”: −0.51), revealing that the non-drop out students take their time for their commenting compared to dropout students in their learning. Although we find the differences in ATC between the two distinct types of students, they are similar in their ATC of “Close Courseware” (-0.01). Combining these three differences will shed light on the behavior differences between dropout and non-drop students. Compared to non-dropout students, dropout students are less likely to “pause” the video when it plays and less likely to spend a lot of time commenting on it.

**Capturing behavior dynamics by ATC**

Lastly, we use our method to study a dynamic behavior from the action sequence. We utilize the StudentLife dataset to analyze how ATC transit over an academic term (11 weeks). StudentLife dataset provides a wide range of students’ behavior trace from their smartphones such as physical activity, eating behavior, or apps usage. We first construct action sequences of the students and split them into weeks (i.e., 11 weeks). Then we obtain the embedding vectors from each week and calculate the ATC of each action.
Figure 4: Action timing context differences: Drop-out students VS Non-dropout students

Note: Action timing context difference between the different types of users (standardized on each student type). We calculate the action timing context of the students in the MOOC platform. We calculate the action timing context for the students who dropped out of their course and the students. A positive difference of action represents the dropout users take that action in the long-term context, but the non-dropout students use that action in the short-term context. For example, the dropout students use “Pause Video” in the long-term context, but the non-dropout students use it in the short-term (difference 0.45). This difference implies that the dropout students do not often pause the course video, but the non-dropout students do so.

Figure 5a plots the transition of ATCs over the course of the academic term. The figure shows that the ATCs of physical behavior settles over the term but the ATCs of eating behavior swings around Week 45 where the students had the midterm. This suggests that the students compress the time interval between their eating actions during the mid-term to save their time for their study. After the mid-term, their eating behavior gets stable in terms of ATC. The ATC of the eating behavior remains a plateau after Week 6. For reference, we picked up the popular smartphone apps among the participants (Gmail and Youtube), which are between physical and eating behaviors.

The result above shows that the ATC can reveal the action that can be affected by external circumstances. Figure 5a tells that eating behaviors can change according to an educational event (the mid-term), but the physical behaviors do not. The box plot in Figure 5b demonstrates this difference in the vulnerability of ATC, where the ATCs of the physical behaviors have shorter bars and ones of the eating behavior have more extended bars.

Finally, we study the correlation between ATCs and students’ physiological states. Figure 6 plots the correlation between the answer of EMA by students and the ATCs of the eating actions (Breakfast, Lunch, Supper, Snack). Figure 6 shows that the eating ATCs are correlate with the mental state (happy or sad). ATC of eating action is positively correlated with the happy mood, and it is negatively correlated with the sad mood. On the other hand, they are not correlate with the question about sleep or question about moods in general (“How are you right now?”) . Those correlations suggest that eating in the short term (low ATC) is associated with a sad mood and vice versa. We also study the correlation between the EMA and the ATCs of the physical actions (Walking, Running, Other Activity), and we do not find any clear correlation. We acknowledge that they are just correlations found by a simple linear regression model. However, this result suggests a promising result that our model with the inter-temporal context between actions may capture the user’s psychological state.

Related Research

This section discusses the related work to our study. We firstly discuss the research on user modelings with embedding methods and human temporal behavior using embedding techniques. Then, we study the research on the interaction times of human behavior.

User modeling with embedding

Word embedding models have been mainly used to obtain the low dimensional representation of word semantics (Mikolov et al. 2013a,b). It is also known that word embedding can capture the biases hidden in the text data (Gonen and Goldberg 2019; Bolukbasi et al. 2016; Garg et al. 2018; Caliskan, Bryson, and Narayanan 2017) or semantic dynamics (Hamilton, Leskovec, and Jurafsky 2016; Di Carlo, Bianchi, and Palmonari 2019).

The applications of such embedding techniques are not only in natural language processing but also in user modeling. The most popular application is the models that take embedding vectors of user consumption as feature vectors for recommendations (Grbovic et al. 2015; Chen et al. 2018) or online advertisement (Ren et al. 2018; Djuric et al. 2014; Attenberg, Pandey, and Suel 2009; Zhang, Chen, and Wang 2016). In addition, there is a line of literature that employs the temporal points process to model the dynamics of user behaviors (Du et al. 2016; Sharma et al. 2021).

For modeling user dynamic behavior, (Han et al. 2020) propose an embedding model that obtains the vector-reorientation of user dynamic from the user actions sequence. Also, it (Liu et al. 2020) predicts the students’ academic performances by embedding the students’ daily behavior sequences.

Recently, it has been found that the embedding model can construct the axis to study the hidden structure of the platform. (Waller and Anderson 2021) Propose the method and
application to study the social phenomena in the online community (Reedit) in a data-driven way. They characterize the online community (sub-reedit) by the users’ posts and study the political polarization dynamics.

The major difference between our study and the studies discussed above is that our study explicitly embeds temporal structure into actions. Existing studies use action sequences to represent the dynamics of user behavior and abstract the time intervals between actions, even though, as mentioned in the introduction, temporal information is necessary to understand human behavior. Certainly, using point processes and other methods can improve prediction accuracy, but such models complicate understanding human behavior. In this study, we explicitly model the temporal structure in the embedding of behavior by estimating the time interval. This makes the model structure very simple and enables a unified analysis of user behavior using indicators such as ATC as proposed in this study.

### Inter-action times of human behavior

Studying interactions between human actions and their time intervals reveals a deep mechanism of human behaviors such as the human cognitive states (Stanovich and West 2000; Graesser, Millis, and Zwaan 1997; Wickens and Carswell 2021; Kahneman 2011). Many researchers have devoted themselves to model human cognition based on this temporal information. The most popular theory in this literature is “Dual-process theory” introduced by (Graesser, Millis, and Zwaan 1997) and (Kahneman 2011) developed. We propose our framework, ATC, to study the temporal structure of users’ actions based on this simple yet solid foundation.

In addition to the cognitive process that generates action time intervals, the statistical properties of the time interval distributions have attracted the attention of researchers, especially in network science (Holme and Saramäki 2012; Masuda and Lambiotte 2016; Vazquez et al. 2006; Barabási 2005; Oliveira and Barabási 2005). Especially, (Okada, Yamanishi, and Masuda 2020) summarize the literature that the two classes of models generate the distribution of the time intervals as priority queue models (Barabási 2005) and modulated Markov processes (Holme and Saramäki 2012; Masuda and Lambiotte 2016).

### Conclusion & Discussion

In this study, we proposed a method to analyze users’ actions while considering the inter-temporal context. Our framework is based on the idea that the time interval between actions corresponds to users’ cognitive state. To examine the cognitive state from the distribution of time intervals, we discretized the time intervals based on mixture distribution estimation. Then, we learned embedding vectors of actions based on the discretized time intervals and action sequences and proposed ATC, an inter-temporal context index for each action, using the obtained low-dimensional representation of actions.

Our proposed framework conducted empirical studies on user behavior with the three different datasets. As a result of the analysis, we found that ATC captures actions and differences in behavior among users and how the inter-temporal context changes depending on the situation. We also showed that ATC is a unified and interpretable measure of inter-temporal context.
This paper has shown that incorporating the vital information, “time-interval”, into the human behavior analysis can lead to a unified understanding of human dynamic behavior. However, our new framework opens up several exciting directions for future work. First, we need to analyze the extent to which our framework captures human cognitive changes. While a simple analysis with EMA data showed a promising result, we need to conduct more rigorous analysis on this point. It needs to build a dataset that combines behavioral data with subjects’ diachronic psychological changes for such an analysis. Such an interdisciplinary study may open a new academic research topic. For example, the dual-process theory assumes binary human cognitive behavior. An analysis with large-scale and high-dimensional data, however, might make it possible to analyze these cognitive states in detail, such as how people switch cognitive states capturing the transition between states not as a binary transition but the continuous change of cognitive state.

Lastly, there is a need to analyze the user’s behavior with the embedding vectors of actions. This paper focused on the inter-temporal context of actions. It is natural to calculate the user-behavior vector that represents the user behavior from the obtained embedding vector of actions. Just as existing research obtains the vector of text by averaging the word embeddings of each word in the text, we can calculate the feature vector of the user by averaging the vectors of the actions in the user’s action sequence. However, the dependency between the time points of the user’s actions is lost in this case. Therefore we need a method that preserves the order of the vectors to calculate the user’s feature vector.

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