MAPer: A Multi-scale Adaptive Personalized Model for Temporal Human Behavior Prediction

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ABSTRACT

The primary objective of this research is to develop a simple and interpretable predictive framework to perform temporal modeling of individual user's behavior traits based on each person's past observed traits/behavior. Individual-level human behavior patterns are possibly influenced by various temporal features (e.g., lag, cycle) and vary across temporal scales (e.g., hour of the day, day of the week). Most of the existing forecasting models do not capture such multi-scale adaptive regularity of human behavior or lack interpretability due to relying on hidden variables. Hence, we build a **multi-scale adaptive personalized** (**MAPer**) model that quantifies the effect of both lag and behavior cycle for predicting future behavior. MAper includes a novel basis vector to adaptively learn behavior patterns and capture the variation of lag and cycle across multi-scale temporal contexts. We also extend MAPer to capture the interaction among multiple behaviors to improve the prediction performance.

We demonstrate the effectiveness of MAPer on four real datasets representing different behavior domains, including, habitual behavior collected from Twitter, need based behavior collected from search logs, and activities of daily living collected from a single resident and a multi-resident home. Experimental results indicate that MAPer significantly improves upon the state-of-the-art and baseline methods and at the same time is able to explain the temporal dynamics of individual-level human behavior.

Keywords

Time series prediction; Temporal human behavior modeling

1. INTRODUCTION

Regular human behaviors are constantly being captured in virtual platforms (e.g., social media, search logs) as well as in physical platforms (e.g., smart phone, smart watch) [16]. The vast amount of individual user data generated by these platforms facilitates modeling the temporal footprint of different human behaviors. Accurate and explanatory temporal behavior models can serve as the building block of several useful applications.

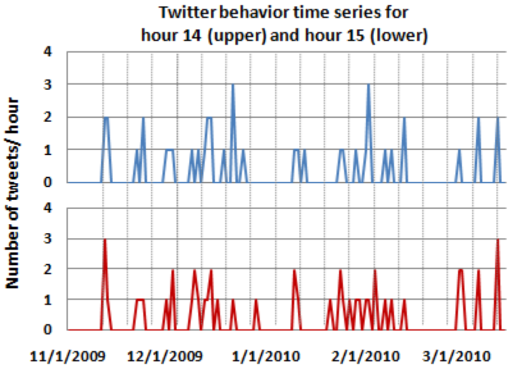

Figure 1: A Twitter user often tweets at hour 14 and hour 15 at the same day. This depiction from real data suggests an impact of lag on tweeting behavior, i.e., the behavior at hour 14 is followed by the behavior at hour 15.

For example, predicting when an online user is going to be active (e.g., searching a query, posting a tweet) can be useful for targeted advertising (e.g., finding peak *social* hours to maximize visibility of content among target audience) [6], churn prediction (i.e., predicting users who are likely to leave a service provider) [27], and temporal user profiling [1, 11]. Similarly, a predictive model that can model human behaviors in the context of daily activities (e.g., sleeping, cooking, or eating) is extremely useful for functional assessment of elderly people [9] and designing behavior intervention for rehabilitation [26]. Scott et al. demonstrated that dynamically predicting room occupancy and energy usage patterns of its residents enable efficient designing of smart thermostats and thus save energy costs significantly [23]. Explanatory predictive models can serve end users who use smart phones and smart watches for self monitoring: a sleep monitoring application that builds explanatory predictive models of sleep pattern can help the user to detect sleep anomaly and suggest sleep time.

This paper focuses on a data-driven modeling of temporal human behavior at a single individual level. Our goal is to build an accurate and interpretable temporal behavior model that can serve as a building block for the motivating examples presented above.

Individual-level temporal behavior is often influenced by three major temporal features: (1) temporal smoothness (i.e., lag), (2) behavior rhythms (i.e., cycle), and (3) interac-

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tion among multiple behaviors. Temporal smoothness refers to lag phenomenon: behavior at time t can be influenced by the behavior at time $(t-1)$ (Figure 1). Behavior rhythm refers to the repetitive habits of a human. For instance, some online users frequently post tweets on Friday night (i.e., cycle length is 7 days). Moreover, often the interaction among multiple behavior traits/activities needs to be captured to model a single behavior, e.g., watching TV until late night can delay sleep time. Quantifying the effects of these features on a specific behavior of an individual is challenging, because they vary with multi-scale temporal contexts (e.g., specific hour of the day or day of the week). Such as, working people may prefer watching TV for a longer duration during weekend nights rather than during weekday mornings. Here, the lag length is changing due to the change in temporal context from a weekday morning to a weekend night. To address such personalized temporal dynamics, we need a modeling approach that dynamically adapts with such variation of features over multiple time scales.

The existing time series prediction models are too general to be applicable in this context. With regard to the computational behavior modeling methods, the most relevant existing study is from Zhu et al. where they predict user activity level in social media [27]. But their modeling of temporal behavior dynamics is limited to reducing the impact of out-of-date training data. Another work uses Bayesian networks to predict future activity based on current activity in a home setting [20]. Neither of these works quantify the effect of variation of the temporal features across multi-scale temporal contexts (e.g., daily, weekly).

The main contributions of this paper are following. (i) We build a **multi-scale adaptive personalized** model, namely **MAPer**, that models regular temporal human behavior by capturing the effects of three temporal features: lag, cycle, and interaction among multiple behaviors. (ii) We introduce a novel approach to capture the variation of these behavior features across multi-scale temporal contexts and learn adaptively. (iii) Our performance analysis demonstrates the overall effectiveness of MAPer as compared to multiple baselines and a state-of-art time series prediction model (SARIMA). Using behavior data collected from Twitter [7], search logs [21], and two smart homes [3, 13], we show the effectiveness of the key parts of the model, demonstrate the value of personalization, and perform a sensitivity analysis along three dimensions: training set size, temporal scale, and order of lag. These experiments show MAPer reduces prediction error by about 15%, 31% and 10% over the state-of-art SARIMA model for Twitter, search log, and a single resident smart home data, respectively. (iv) Another key value of our solution is its explanatory capability. As MAPer uses a linear model for prediction based on only observed behavior, it has higher interpretability over other predictive models that are non-linear or rely on unobserved variables (e.g., state space model or hidden Markov model).

2. PROBLEM FORMULATION

2.1 Extracting Discrete Time Series from Temporal Behavior Data Stream

We use $H(t)$ to represent a given behavior data with corresponding time stamp spanning over a total stream length T. We divide T into a set of n equal length time intervals $t_1, t_2, \ldots, t_i, \ldots, t_n$. Then we summarize $H(t)$ over each interval to obtain behavior sample $Hs(s, t_i)$, such that Hs applies a summarizing process s over the behavior of interval t_i. The summarizing process s can be frequency/average/length of some countable behavior measure. With this process we get a discrete series of n behavior samples: $Hs(s,t_1)$, $Hs(s,t_2)$,...,$Hs(s,t_n)$ For example, consider a set of tweets from a Twitter user u, where each tweet has its corresponding time stamp. After sorting the tweets according to their increasing time stamp, we find the total window length T that spans from the starting time stamp to the ending time stamp. Assume there are n different days in T. Next, we divide T into hourly/daily/weekly intervals. If the chosen interval is *hour* and the chosen summarizing process is *total count of tweets* then the behavior sample will be *total count of tweets per hour.* In this case, the length of the behavior sample time series will be $n \times 24$, since we divide each day into 24 hours. The choices of interval and summarizing process depend on a specific application requirement.

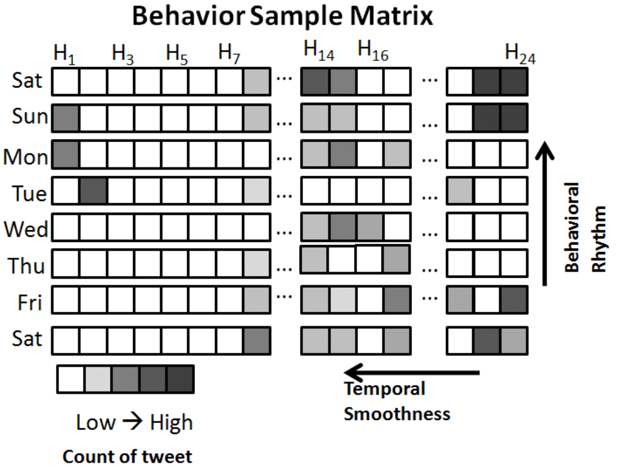


Figure 2: An example of behavior sample matrix representation: demonstrating lag and cycle for modeling an individual user's behavior in the context of Twitter usage. The cells are darkened in proportion to the number of tweets at the corresponding time interval.

We denote the time series $Hs(s, t_i)$ as y_i in the rest of the paper. In addition, we denote y_i for an activity[1] k of a user (e.g., an activity of daily living) as y_t^k. Our goal is to predict y_i^k based on it's previous values i.e., $y_1^k, y_2^k, \ldots, y_{i-1}^k$.

Essentially, a more accurate notation would be $y_t^{k,u}$ to indicate modeling specific activity k from an individual u. Instead, we use the simplified notation y_t^k since we do not consider interaction among multiple users for predicting future activity of a single user.

2.2 Behavior Sample Matrix Generation

After generating the discrete time series from historical longitudinal behavior data of a user (u^k), we create corresponding behavior-sample matrix (M) to extract features corresponding to lag, cycle, and interaction with other behaviors. This matrix representation encodes the temporal patterns of behavior concisely. Specifically, each row of M represents a day (d_i) and each column of M represents an hour (h_j). The content of a cell $M_{i,j}^k$ is the sample of a

[1] We use the terms activity and behavior interchangeably in this paper.

behavior k from a user u on day d_i and hour h_j. In other words, $M_{i,j}^k$ represents the intensity of overall activity level of the user at the j-th hour of the i-th day.

Figure 2 demonstrates a Twitter behavior sample matrix where the behavior sample is the count of tweets per hour. It appears this particular user is most active during weekend nights. Tweets generated at hour 14 might act as a lag feature to tweets generated at hour 15. The Twitter user usually tweets on hour 24 during weekends. So there is a possible cycle of this behavior that repeats on weekends. As shown in Figure 2, the contents of same columns contribute to behavior rhythm or cycle and the contents of same rows contribute to temporal smoothness or lag.

This matrix representation highlights the lag and cycle properties of regular human behavior and is easily generalizable to represent more coarse or granular time scales. After generating behavior sample matrix, we build a general temporal model for behavior prediction that extracts the temporal features from this matrix.

3. MULTI-SCALE ADAPTIVE PERSONALIZED MODEL

In this section we present incrementally the formation of the MAPer model. Since MAPer combines lag, cycle, and interaction among multiple behaviors across multiple temporal scales, we first describe extracting lag feature(s) and then incrementally add features culminating in the complete model in Section 3.1.4.

3.1 Extracting Features for Temporal Behavior Prediction

3.1.1 Temporal Smoothness/Lag Features

For the purpose of forecasting the lag features can be represented using auto regression (**AR**), a standard linear time series forecasting technique. An l-th order auto-regressive model for predicting the t-th item of a behavior time series time series is described as,

$$\hat{y_t} = \sum_{i=1}^{l} \alpha_i \cdot y_{t-i} + c + \epsilon \tag{1}$$

where $\alpha_1, \alpha_2, \ldots, \alpha_l$ are lag parameters to learn, c is a constant, and the random variable ϵ represents white noise [12]. The coefficient value of α_i quantifies the effect of the i-th lag component for the current time point. Referring to Figure 2, for a cell $M_{i,j}^k$ in a behavior time series matrix M^k, we consider $M_{i,j-1}^k$ as the lag of order 1, $M_{i,j-2}^k$ as the lag of order 2, and so on. We also wrap the matrix to extract lag features for early hours of a day. Such as, when predicting for hour 1 of a day and considering a lag of order 4, we extract lag features from hour 21 to hour 24 of the past day.

3.1.2 Behavioral Rhythm/Cycle Features

Human behaviors often demonstrate cyclic pattern, such as, cooking meal on every Friday night (i.e., the cycle is 7 days). To capture the behavior rhythm effect, we add a cycle component in Equation 1. The derived model for a single individual is presented below.

$$\hat{y_t} = \sum_{i=1}^{l} \alpha_i \cdot y_{t-i} + \sum_{j=1}^{c} \beta_j \cdot y_{t-c_j} + c' + \epsilon \tag{2}$$

Here, the value of the coefficient β_j quantifies the effect of j-th cyclic component on the current time point of interest. If the cycle of a behavior time series is found to be 7 days, we will use $M_{3,16}^k$ as a cycle feature to predict the value of $M_{10,16}^k$. We describe the method of selecting cycles of a behavior time series in Section 3.2.

In the rest of the paper, we refer to the model corresponding to Equation 2 as the auto regression with cycle component (**AR-C**) model.

3.1.3 Interaction Features

So far for predicting future values of time series of activity k (i.e., y_t^k), we have extracted features from only the time series y_t^k. But often time series of one activity can influence another from the same user as the corresponding activities interact with each other. We define such interaction of human behaviors/activities in terms of co-occurrence. We hypothesize that, if two activities are frequently observed consecutively, the former activities can influence the prediction of the later for which they *interact*. For instance, watching TV and using internet until late night often delay sleeping. In this case, *watching TV* and *using internet* are interacting with *sleeping*. Similarly, having a meal is usually followed by washing dishes. To consider such interactions among activity k and other activities, we update equation 2 as below.

$$\hat{y_t}^k \approx \sum_{i=1}^{L_k} \alpha_i^k \cdot y_{t-i}^k + \sum_{j=1}^{C_k} \beta_j^k \cdot y_{t-c_j}^k + \sum_{k' \in S} \sum_{l'=1}^{L_{k'}} W_{l'}^{(k,k')} \cdot y_{t-l'}^{k'} \tag{3}$$

Here, S is a set of activities of a user u and $k \neq k'$ such that activity k' precedes activity k and interacts with it. $L_{k'}$ refers to the length of lag that we are considering for the behavior time series $y_t^{k'}$. Note that we omit $c'' + \epsilon$ from Equation 5 and subsequent equations to simplify notations.

Unlike Equation 2, Equation 3 models an individual's single activity k using historical values of k and a set of other activities (i.e., k's) that influence k.

3.1.4 Multi-scale Adaptive Features

For regular daily human behavior the two most common temporal contexts of behavior are day of the week and hour of the day. Often behavior varies over such multi-scale temporal contexts. The lag length, cycle, and amount of interaction vary with the temporal contexts too. Such as, the order of lag of watching TV is likely to vary from morning to night for working class people, as they have to leave home early in the morning. Here the lag is varying with hour of the day. Similarly, it can vary with day of the week. Therefore, we need a feature representation to encode such multi-scale variation and adapt the prediction model dynamically.

Hence, we introduce a discrete binary vector representation describing multi-scale temporal contexts whose length is determined by the corresponding scale (e.g., hour of the day or day of the week) and whose value is determined by the current time stamp. Specifically, hour i can be represented as a 24-dimensional binary vector with a series of $(i-1)$ zeroes followed by an one and $(24-i)$ zeroes. Thus, hour 3 can be represented by a series of two zeroes followed by an one and 21 zeroes. The corresponding vector B_3 is $[00100\ldots0]$, where $|B_3| = 24$. Similarly, we obtain a basis vector representation describing different days of the week.

We denote the combination of daily basis vector and weekly basis vector as $\vec{B_d}, \vec{B_w}$. We add this basis vector representation in Equation 3 to represent the multi-scale temporal context.

$$\hat{y_t}^k \approx \sum_{i=1}^{L_k} \alpha_i^k \cdot y_{t-i}^k + \sum_{j=1}^{C_k} \beta_j^k \cdot y_{t-c_j}^k + \gamma^k \cdot (\vec{B_d}, \vec{B_w}) + \sum_{k' \in S} \sum_{l'=1}^{L_{k'}} W_{l'}^{(k,k')} \cdot y_{t-l'}^{k'} \qquad (4)$$

We use the model corresponding to Equation 4 when we consider interaction between multiple streams of behavior. Otherwise, we use the following model.

$$\hat{y_t}^k \approx \sum_{i=1}^{L_k} \alpha_i^k \cdot y_{t-i}^k + \sum_{j=1}^{C_k} \beta_j^k \cdot y_{t-c_j}^k + \gamma^k \cdot (\vec{B_d}, \vec{B_w}) \qquad (5)$$

It should be noted that unlike lag and cycle features, the value of $(\vec{B_d}, \vec{B_w})$ is not unique for all y_t where $t \in 1, 2, \ldots, n$. $(\vec{B_d}, \vec{B_w})$ is same for y_i and y_j if they represent same day of the week and same hour of the day. This is necessary to encode the temporal context of behavior: behavior samples from similar context share similar features. Equation 4 captures the effect of temporal smoothness, behavior rhythm, interaction, and multi-scale temporal contexts using parameters α_i, β_j, γ, and basis vectors $(\vec{B_d}, \vec{B_w})$, respectively. This model is personalized for each user and is customized for each activity of the user. In addition, the basis vector representation enables the model to learn adaptively across multi-scale temporal contexts. Hence we denote the model corresponding to Equation 4 as the **M**ulti-scale **A**daptive **Per**sonalized (**MAPer**) model.

With different combination of basis vectors, we have two variations of MAPer: (i) daily scale adaptive personalized (**DAPer**) model that uses only daily basis vector $(\vec{B_d})$ and (ii) weekly scale adaptive personalized (**WAPer**) model that uses only weekly basis vector $(\vec{B_w})$. MAPer uses both daily and weekly basis vectors. MAPer can be also generalized to add more coarse/granular temporal contexts.

3.2 Feature Selection

Cycle Features: The cycle of a behavior can vary across individual users and individual activities. We extract the cycle length of a behavior time series by applying discrete Fast Fourier Transform (FFT) analysis, a spectral decomposition technique where we treat the time series as an input signal. Although there are other time series decomposition techniques including piecewise polynomial, symbolic, wavelets, etc. [24], they are out of scope of this paper. We derive a set of frequencies from the FFT analysis and choose the highest C frequencies as the relevant cycle features, where the frequencies are sorted according to their amplitudes. We plug in these C frequencies as the cycle features in the models corresponding to Equation 2 to Equation 5.

Interaction Features: Considering all activities for modeling interaction can introduce noise rather than signal and increase the feature space prohibitively, since only a subset of behaviors interact with each other usually. To select a subset of activities that interact with our target activity k, we propose a frequent item-set mining approach. Specifically, for each day we sample every two hours and create an itemset of activities that took place during that window. We empirically set the window length to two hours. We do not use a strict window to create itemsets as (i) it results into large number of unique itemsets (i.e., occur only once), (ii) it can not capture fluctuation of routine: one may frequently have dinner at anytime between 7.30pm to 8.30pm. After all the itemsets are generated over the training set, we generate the closed itemsets[2] using ECLAT [5], a fast algorithm for frequent item set mining. For each activity of our interest, we sort other activities that appear in the closed itemsets based on how frequently they co-occur. Finally, for each activity k we use the top three activities derived from the closed item set such that they precede the k-th activity. The interaction features for activity k are extracted from these three activities according to Equation 4. Using frequent itemset mining for interaction features is scalable as the number of candidates (i.e., ADLs) for interaction is limited in our case.

4. CONNECTING TO PAST STUDIES

Although the exact problem we are trying to solve is unique in the literature, there are various relevant areas of existing research as presented below.

Time series forecasting: For the task of time series prediction, the existing algorithms can be broadly categorized as parametric and non-parametric approaches. Parametric approaches assume the underlying stationary process has a structure which can be estimated using a number of parameters. Hence, these methods normally fit a statistical model on the time series data and have better interpretability. The Autoregressive Integrated Moving Average (**ARIMA**) model [15] is used to forecast a stationary time series[3]. The ARIMA model predicts a stationary time series (y_t) using lags of the dependent variable (y_{t-l}) and lags of forecasting error $(e_t = y_t - \hat{y_t})$. A non seasonal ARIMA model is expressed as ARIMA(p,d,q) where p,d, and q are the model parameters corresponding to the number of auto-regressive terms, the number of nonseasonal differences needed for stationarity, and the number of lagged forecast errors used in the prediction equation. Suppose Y_t denotes the d-th difference of y_t, i.e., if $d = 0$ then Y_t=y_t, if $d = 1$ then Y_t=$y_t - y_{t-1}$, and so on. Then the general forecasting equation for the ARIMA model is

$$\hat{Y_t} \approx \mu + \sum_{i=1}^{l} \phi_i \cdot Y_{t-i} + \sum_{i=1}^{l} \theta_i \cdot e_{t-i} \qquad (6)$$

The ARIMA model is one of the most general time series forecasting models as many forecasting models are merely a special case of ARIMA model. For instance, ARIMA(l,0,0) is the l-th order auto-regressive model expressed as Equation 1. A seasonal ARIMA (SARIMA) model is a state-of-art parametric model of time series forecasting. It uses seasonal lag and differencing to fit the seasonal pattern. The SARIMA model can be expressed as ARIMA (p,d,q) × (P,D,Q), where P, D, and Q denote the number of seasonal autoregressive terms, the number of seasonal differencing, and the number of seasonal moving-average terms.

[2] An itemset is closed if none of its immediate supersets has the same support as the itemset.

[3] A time series is stationary if its statistical properties are constant over time. A non stationary time series can be made stationary by differencing and non-linear transformation (if required).

On the other hand, nonparametric approaches (e.g., neural network based local forecasting models) approximate the underlying structure of the stationary process that generates the time series without making any structural assumption. A comprehensive survey on time series forecasting can be found in [8]. There are also several variations of vector autoregressive methods that aim at multi-dimensional time series forecasting [18].

Activity Prediction: Although a lot of works from computer vision and sensing community focus on activity recognition, the problem of daily activity prediction is largely unexplored. A recent work [20] proposes an activity prediction approach using Bayesian network. Unlike us, they model the problem as a multi-label classification and predict activity label and relative start time using current activity label, location, and temporal context. Although they consider daily and weekly context of behavior, their approach does not quantify the effect of different temporal features and lacks explanatory power. Pentland et al. propose that some human behaviors (e.g., driving, running) can be described as a set of dynamic models (e.g., Kalman filters) sequenced together by a Markov chain. However, as their application domain involves more granular behavior, it does not require quantifying the effect of cycle on behavior or how lag/cycle varies with multi-scale temporal contexts.

Zhu et al. focus on predicting user activity level in social networks to facilitate churn prediction (i.e., identify users who are likely to leave a service) [27]. They build a personalized and socially regularized time decay model based on logistic regression to capture effects of user diversity, social influence on future activity level. A novel approach of activity prediction was proposed in [25]. They predict a set of future popular activities by analyzing textual content of Twitter posts using keyword matching. Unlike other works [20, 27], they focus on aggregated behavior rather than individual behavior. Although these research focus on behavior prediction, unlike us they do not explicitly quantify the effect of different temporal factors (e.g., lag, cycle) on regular human behavior.

Modeling Temporal Behavior: Recently, the temporal modeling of online user population has been extensively studied in order to improve query search performance [22, 4, 17], to understand and model content generation in social networking sites [1, 2], and to model mobile behavior of users [10, 19].

For example, aiming to improve the query auto-suggestion and the ranking results, Radinsky et al. recently developed a temporal modeling framework that predicts temporal patterns of aggregated web search behavior [22]. Specifically, they model temporal features, like, trend, periodicity, and sudden spikes of queries by using dynamic state space models. Although their work is similar to ours in terms of modeling behavior based on temporal features, they focus on temporal modeling of search queries, while our study focuses on directly modeling the temporal behavior of humans. Baskaya et al. analyzed the effects of a set of search-related human behaviors (e.g., formulate a query, scan, click a link) on retrieval performance [4]. In [17] the authors studied how search behaviors of users evolve over time, e.g., long term users demonstrate more complex behavior than newbies.

In addition to improving query based content-search, temporal modeling has also been explored to analyze user behavior in social media or on content sharing platforms. Abel et al. demonstrated how temporal profiling of Twitter users based on their shared contents facilitates personalized news article recommendation [1]. Although these previous studies mostly analyzed user generated textual contents for modeling the temporal dynamics, our proposed temporal modeling of individual-level human behavior could facilitate their goals as well.

Name	**Entities**	**Span**	**Domain**
Search log	1307 users	3 months	Need based behavior
Twitter	1274 users	5 months	Habitual behavior
ARAS	27 ADLs	1 month	Multi-resident home
HOLMES	14 ADLs	3 months	Single-resident home

Table 1: Summary of datasets used for evaluation.

5. EXPERIMENTAL SETUP

5.1 Data

To evaluate the effectiveness and generality of our model we use four benchmark datasets each representing different aspects of human behavior. The datasets are summarized in Table 1. The details are described below[4].

Search Log Data Representing Need Based Behavior

We use AOL search log data [21] for predicting temporal query search behavior. This dataset consists of around 20M web queries collected from 650k users. The data was collected for over three months starting from March 2006 to May 2006. The dataset includes anonymized user ID, search query, time stamp of query, and click information (whether a search result was clicked or not). The data is sorted by anonymous user ID and is sequentially arranged according to their time stamps. We have used a subset of this dataset containing 1307 unique users so that each user has a search log spanning 60 days. In our sampled dataset there are 449,423 unique queries in total. However, from our experiments we discover that our modeling approach is generalizable to other cases where the training phase is as small as 2 weeks (Section 6.3.1).

We consider number of unique queries per hour as the behavior sample and generate a normalized behavior sample matrix as described in Section 2.2. Other choices of behavior samples include number of queries, number of clicks, duration of a session. Also, the temporal resolution of the interval (i.e., hour) can be adjusted to different granularity (e.g., week, day).

Twitter Data Representing Habitual Behavior

We use a Twitter dataset [7] for predicting users' temporal social media behavior. It consists of 121,022 users and more than 9 million time-stamped tweets that were collected from September 2009 to January 2010. However, it does not include any re-tweet and follow relationships. We sample the dataset to obtain the users who have Twitter posts spanning over at least 120 days. In total we obtain 1,275,709 tweets from 1,274 Twitter users for evaluating our predictive model.

We consider number of tweets per hour as the behavior sample. Alternatively, one can use number of Twitter messages, number of re-tweets, duration of Twitter session, or a weighted combination of these as a behavior sample. The

[4] The datasets are available here: https://goo.gl/Za0YIs

generation of a Twitter behavior sample matrix is similar to the generation of a search log behavior sample matrix.

ARAS: ADL Data from a Multi Resident Setting

We consider Activities of Daily Living (ADL) data as the behavior captured from physical world where each activity corresponds to a behavior.

We use the ARAS smart home project [3] dataset as a multi-resident ADL dataset. It contains labelled sensor data from a system deployed in a smart home of 2 residents. This dataset has 27 annotated activities of daily living for each user. It contains start time and end time of each activity. With a preference to model and predict health related behaviors, we focus on 5 behaviors from each user. They are: sleeping, snacking, having breakfast, lunch, and dinner. However, for resident 2, the number of samples for having breakfast, lunch and dinner are too few. So we model 7 activities for 2 users in total: sleeping of both residents, snacking of both residents, and breakfast, lunch, and dinner of resident 1.

HOLMES: ADL Data from a Single Resident Setting

We use HOLMES dataset as a single resident ADL dataset [13]. We use three months data from this dataset. It contains 15 annotated activities from which we model the following health related activities: sleeping, breakfast, lunch, dinner, snack, shower, and cooking.

While in case of the Twitter data and the search log data we model each user separately, in case of the ADL data we perform forecasting of each activity of each user separately[5]. Unlike the Twitter or search log data, we use the duration of an activity as the behavior sample instead of count of activity since most of the ADL take place only once per interval. We sample each activity duration every half an hour for each day to form a time series of duration of each activity. Later, we vary the temporal resolution/scale to demonstrate the effect of temporal resolution on the prediction accuracy. We normalize the behavior sample matrix, M such that if activity k takes place over the whole span of interval j on day i, then $M_{i,j}^{k}$ contains 1; if activity a^k takes place over half of the span of interval j of day i, then $M_{i,j}^{k}$ contains 0.5 and so on.

5.2 Comparing with Baseline Methods

1. Moving Average (MA): As one of the simplest time series forecasting method, the moving average method predicts average of l lag values as the next value. We modify the original moving average model to include the effect of cycle. Specifically, the prediction at y_t is the average of all l lag components and all c cyclic components. Using our behavior sample matrix, the lag components are selected from l previous columns of the same row and the cycle components are selected from c previous rows of the same column. Mathematically,

$$\hat{y_t} \approx 0.5 \times \left(\frac{\sum_{i=1}^{l} y_{t-i}}{l} + \frac{\sum_{i=1}^{c} y_{(t-i*24)}}{c} \right).$$

In our experiments we set $l = 4$ hours and $c = 14$ days. To compare the performance of MAPer with a non-parametric baseline method that considers both lag and cycle, we use this method.

2. Auto regression with Cycle Component (AR-C): Equation 2 refers to this baseline method.

To compare the performance of MAPer with a parametric baseline method that considers both lag and cycle, we use this method. It is also used to highlight the effectiveness of adaptive learning.

5.3 Comparing with state-of-art

We compare MAPer with the SARIMA model, a parametric state-of-art forecasting model described in Section 4. We use an R implementation of SARIMA model provided in [14]. For parameter estimation of SARIMA model, we use a function that conducts a search over all possible models and return the best model according to AIC value. We use this model to explore the predictive power of MAPer across different behavior domains.

For the SARIMA model and MAPer, we perform two parameter estimation settings: global and local. In general, we divide a chronologically sorted behavior dataset into training and testing sets. For global parameter estimation, we estimate the parameters only once using the full training set. But for local parameter estimation, we take a sliding window approach to form a separate training set for each point of test set. Specifically, for predicting i-th point in the test set, we construct the training set from $(i - w)$ to $(i - 1)$ point where w is the length of the sliding window.

5.4 Response Variable and Metrics

We evaluate our model mainly in a regression setting to predict the future intensity of a behavior marker based on its historical samples. In this setting, the content of each cell of behavior sample matrix acts as a response variable (y_i) where $y_i \in [\ 0, 1]$. The features described in Section 3 act as the predictor variables. We measure the performance in terms of two standard evaluation metrics: mean square error (MSE) of prediction and Pearson correlation (PC) between the actual y and the predicted y.

We compare the baselines described in Section 5.2 with MAPer and show how effective the various features (described in Section 3) of MAPer are. We also evaluate the effectiveness of (i) multi-scale adaptive features, (ii) personalized modeling, and (iii) interaction among activities. While comparing different methods, we set the corresponding parameters to default values. Later, we perform sensitivity analysis by varying its hyper-parameters.

6. EXPERIMENTAL RESULTS

6.1 Effectiveness of MAPer

6.1.1 Comparing with Baseline Methods

In this section we compare the performance of MAPer with two baseline methods (Section 5.2). Referring to **Tables 2** and **3**, MAPer outperforms all baseline methods in terms of MSE for search log, Twitter, and HOLMES data. MAPer increases the Pearson Correlation at least 1.5 times when compared to the baseline methods for all of the datasets. This highlights the significance of using temporally adaptive learning method where the significance of lag and cycle features varies over time.

[5] Given a Twitter dataset that annotates different activities of a user (e.g., tweeting, re-tweeting, sending message), we can model each activity of a Twitter user separately too.

Dataset	Baseline Methods		state-of-art		Multi-scale Adaptive Methods		% Improvement
	MA	AR-C	Global SARIMA	Local SARIMA	Global MAPer	Local MAPer	over state-of-art
Search log	0.046	0.045	0.065	0.048	0.045	**0.041**	14.6
Twitter	0.056	0.052	0.073	0.065	0.049	**0.045**	30.7
ARAS	0.032	0.017	0.042	**0.011**	0.018	0.016	-
HOLMES	0.021	0.001	0.082	0.001	0.001	**0.0009**	10

Table 2: Comparing different methods in terms of mean **MSE**. The best performing (statistically significant) results are shown in bold. The right-most column shows the performance improvement of MAPer over the state-of-art (Local SARIMA). Local models outperforms global models and MAPer results into the lowest prediction error.

Dataset	Baseline Methods		state-of-art		Multi-scale Adaptive Methods		% Improvement
	MA	AR-C	Global SARIMA	Local SARIMA	Global MAPer	Local MAPer	over state-of-art
Search log	0.180	0.165	0.098	**0.479**	0.228	0.337	-
Twitter	0.277	0.330	0.079	0.254	0.410	**0.491**	93.3
ARAS	0.239	0.384	0.204	0.7166	0.446	**0.782**	9
HOLMES	0.296	0.104	0.136	0.340	0.277	**0.583**	71.5

Table 3: Comparing different methods in terms of mean **Pearson Correlation**. MAPer outperforms the SARIMA model for all datasets except the search log data.

6.1.2 Comparing with SARIMA

Tables 2 and **3** demonstrate that the local model outperforms the global model for all four datasets in case of both the SARIMA model and MAPer. This highlights the dynamic pattern of human behavior. In subsequent sections we use only the local estimation approach, i.e., MAPer refers to local MAPer.

In terms of MSE, MAPer with local parameter estimation outperforms SARIMA for both online behavior dataset and for HOLMES dataset. Specifically, it reduces MSE from the SARIMA model by 14.6%, 30.7%, and 10% for search log, Twitter, and HOLMES dataset, respectively. This performance improvement is statistically significant at 95% confidence interval as found in a pair wise t-test. In terms of Pearson correlation, MAPer increases the performance by about 93.3%, 9%, and 71.5% for Twitter, ARAS, and HOLMES data, respectively. The local SARIMA model performs better than MAPer in terms of Pearson correlation for search log data. Because, issuing search query is a need based behavior and MAPer performs better in case of predicting habitual behavior.

Overall, MAPer demonstrates better or at least equal predictive power to SARIMA model for all four datsets. In case of Twitter, MAPer significantly outperforms the SARIMA model as Twitter behavior is habitual and MAPer is designed to capture the dynamics of habitual behavior over multi-scale temporal contexts. Among the ADL datasets, MAPer performs at least as good as the SARIMA model. The ground truth suggests more regular activity pattern for the HOLMES dataset rather than the ARAS data. So MAPer outperforms the SARIMA in terms of both performance metrics for HOLMES dataset.

6.1.3 Effect of Multi-scale Temporal Adaptive Features

We measure the effectiveness of using multi-scale adaptive features. Specifically, we compare performances of daily scale adaptive (DAPer), weekly scale adaptive (WAPer), and multi-scale adptive (MAPer) models (Table 4). For search log and Twitter, MAPer shows better prediction performance as it has lower MSE and higher Pearson correlation. For the two activities of daily living (ADL) datasets, DAPer results in better performance. These results suggest for online behavior considering both hour of the day and day of the week as potential temporal contexts results in better performance and for ADL behavior considering only the hour of the day results in better performance in this case. It should be noted that for both of the ADL datasets, most of the activities have very low number of samples when compared to the number of samples of online behavior datasets. Hence it is more difficult to capture behavior variation across weekly scale for the ADL datasets.

Dataset	Pearson Correlation			Mean Square Error		
	DAPer	WAPer	MAPer	DAPer	WAPer	MAPer
Search log	0.33	0.21	**0.34**	0.041	0.044	**0.041**
Twitter	0.49	0.40	**0.49**	0.045	0.048	**0.045**
ARAS	**0.78**	0.68	0.78	0.016	0.019	0.016
HOLMES	**0.58**	0.33	0.58	0.0009	0.0009	0.0009

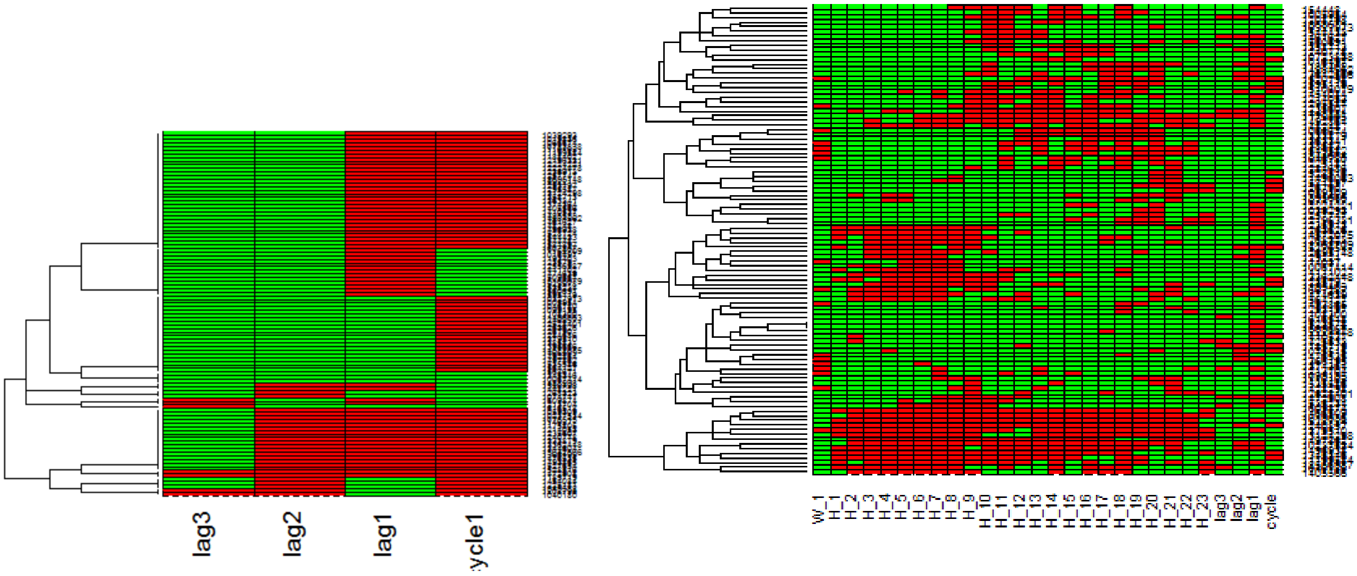
Table 4: Analyzing the effect of using multi-scale adaptive features: the best performing statistically significant results are shown in bold. For online behavior, considering both daily and weekly contexts results in better prediction result while for activities of daily living considering only daily context yields better results.

6.1.4 Effect of Personalization

So far we have assumed to predict individual level behavior we need to estimate the model parameters from corresponding individual user's data. In this section we compare personalized modeling approach with aggregated modeling approach. In case of aggregated approach we estimate model parameters using aggregated behavior data and then use those parameters for individual level prediction. Following Table 5, personalization drastically increases performance of prediction for both search log and Twitter behavior: Pearson correlation increases more than 2.5 times for both datasets and MSE decreases by as much as 64%. Improvement of search log data is higher than the improvement of Twitter data. We perform this experiment only for online behavior data as for the ADL datasets we have no more than two individuals.

6.1.5 Effect of Interaction

In this section we present the results of analysing interaction among activities and the effect of interaction on prediction. Table 6 presents the set of interactive activities for each activity that we want to model in case of the ARAS



(a) AR-C model

(b) MAPer model

Figure 3: Demonstrating how our modeling approach explains effect of different parameters using heatmap for randomly chosen 100 search log users. Each row represents a user and each column of a row represents the significance of a parameter for modeling the users behavior. Red (the darker shade) and green indicate significance and insignificance of corresponding parameters, respectively. Users who are similar in terms of their behavior model (i.e., set of learned parameters from training model), are clustered together.

	Pearson Correlation		Mean Square Error	
	Search log	Twitter	Search log	Twitter
Personalized	**0.337**	**0.491**	**0.041**	**0.045**
Aggregated	0.127	0.192	0.114	0.064
Improvement	2.65 times	2.56 times	64%	30%

Table 5: Personalized models for each user significantly improve the prediction performance for both Twitter and search log datasets.

dataset. We found these interactive activities by adopting a frequent itemset mining approach (as described in Section 3.2). It indicates both residents 1 and 2 watch TV before going to sleep. Both of the residents are found to watch TV while having snacks. Resident 1 is found to talk on the phone before having lunch or dinner. These are also confirmed in the actual dataset. Although resident 1 washes dishes often before / after breakfast and lunch, resident 2 washes dishes frequently after dinner and before going to bed. Hence, for resident 2 washing dishes influences sleep time. Due to space limitation, we are not showing the interactive activities found in HOLMES dataset.

When we consider interaction among activities as features of prediction we find an increase in prediction performance of MAPer. The percent improvement of performance due to adding interaction is presented in Table 7. For example, in case of HOLMES dataset, the Pearson correlation of MAPer without interaction (Equation 5) and MAPer with interaction (Equation 4) are 0.385 and 0.583, respectively. So adding interaction features increases Pearson Correlation by 51% for HOLMES dataset.

6.2 Explanatory Power of MAPer

MAPer is an explanatory model as it uses the features that are relevant and specific to desirable human behavior.

Activity	**Influential Activities**
R1:sleep	brushing teeth, using internet, watching TV
R2:sleep	brushing teeth, watching TV, washing dishes
R1:snack	watching TV, using internet, talking on the phone
R2:snack	watching TV, having shower, using internet
R1:breakfast	preparing breakfast, using internet, watching TV
R1:lunch	preparing lunch, talking on the phone, watching TV
R1:dinner	talking on the phone, watching TV, preparing dinner

Table 6: Interaction among different activities of ARAS dataset: the left column contains the activities we want to predict and the right column contains the activities that interact with them.

Therefore each of the model parameters quantifies the effect of corresponding feature on the behavior. This is demonstrated in Figure 3 (a-b) using heatmap representation. Here we present two heatmaps of model parameters corresponding to the AR-C model and MAPer model for a set of randomly chosen 100 search log users. Figure 3 (a) demonstrates the lag and cycle features that are significant in the AR-C model for the 100 users. Figure 3 (b) demonstrates the lag, cycle, and multi-scale adaptive features that are significant in the MAPer model for the same set of users. Each row of a heatmap represents a user and each column of a row represent significance of a parameter (in terms of p-value) in the behavior model of that user. Here the red cells correspond to the significant parameters. Users who are similar in terms of their behavior model (i.e., set of learned parameters

	Pearson Correlation		Mean Square Error	
	ARAS	HOLMES	ARAS	HOLMES
MAPer w/o Interaction	0.7169	0.385	0.0184	0.0009
MAPer	0.782	0.583	0.016	0.0009
%Improvement	9	51	15	-

Table 7: Increase in performance due to adding interaction features.

Parameter	Range	
	Online Behavior	Offline Behavior
Scale (hours)	**1**,2,4,6	**1/2**,1,2,4
Training set size (weeks)	2,**4**,6,8	NA[6]
Lag (hours)	2,3,**4**,6,8	1/2,1,**2**,3,4

Table 8: The range of different parameters used in experiments. The default values of parameters are shown in bold.

from training model), are clustered together using hierarchical agglomerative clustering algorithm. The explanatory power of MAPer is multi-fold.

Firstly, when comparing the two figures, we see that MAPer does not only capture the significance of lag and cycle, but also the significance of hour of the day and day of the week. This can serve as a useful behavior model for the end users. As MAPer not only predicts future behavior but also provide a set of temporal contexts when the prediction accuracy of behavior is higher.

Secondly, from Figures 3a and 3b, MAPer has much higher number of clusters. Here a cluster represents a set of users who have similar model parameter and thus presumably similar temporal behavior. So, MAPer essentially detects similar users in a more granular scale than the AR-C model. This is useful for detecting user community based on temporal behavior and finding an equivalent class of users.

Thirdly, unlike several existing methods MAPer directly quantifies the effect of a feature in behavior modeling. For instance, from Figure 3b, the feature corresponding to lag of order 3 is significant for only a handful of users. Thus we can infer which parameter is more important under different temporal contexts for the behavior modeling of an individual.

6.3 Sensitivity Analysis

Here we evaluate our model by varying its hyper-parameters: temporal scale, training set size, and lag length (l). The default value and range of each parameter are presented in Table 8.

6.3.1 Varying Training Set Size

Methods	Pearson Correlation		Mean Square Error	
	Search log	**Twitter**	**Search log**	**Twitter**
2 weeks	**0.4**	**0.52**	**0.039**	**0.044**
4 weeks	0.34	0.49	0.041	0.045
6 weeks	0.31	0.45	0.042	0.048
8 weeks	-	0.44	-	0.048
% Improvement	31	18	7	8

Table 9: Training set with more recent data results into better prediction.

In the previous sections we have used a dynamic training approach where for each data point in test set, we consider behavior data from the immediate previous 4 weeks as the training set. In this section we vary the training set size according to Table 9 and analyze its effect on prediction performance.

For search log data we vary training set size as 2, 4, and 6 weeks. For Twitter data, we vary training set size as 2, 4, 6, and 8 weeks. In both cases, smaller training set size results into smaller MSE and higher Pearson correlation. This indicates that human behavior changes over time and recent behavior is a better predictor of future behavior.

6.3.2 Varying Temporal Scale

Scale	Pearson Correlation		Mean Square Error	
	Search log	**Twitter**	**Search log**	**Twitter**
1 hour	0.337	0.49	0.041	0.045
2 hours	0.38	0.45	0.022	0.0261
4 hours	0.427	0.49	0.011	0.0138
6 hours	**0.431**	**0.50**	**0.008**	**0.0094**
Improvement	27%	11%	5 times	4.7 times

Table 10: Varying temporal scale: larger scale results into better prediction performance for online behavior data.

So far, we have analyzed performance of different baseline methods and MAPer by keeping the temporal scale 1 hour for search log and Twitter data and half hour for ADL data. In this experiment we vary the temporal scale according to Table 8 and investigate its effect on prediction performance. We fix the other parameters in their default values.

For search log and Twitter data, higher temporal scale results into lower MSE and higher Pearson correlation (PC) (Table 10). Specifically, as we move from 1 hour to 6 hours' scale, MSE decreases by about 5 times for both datasets. In terms of PC, with an increase in temporal scale there is 27% and 11% improvement in case of search log and Twitter data, respectively. This is because as we move to larger temporal scale the sparsity of data reduces and the task of parameter estimation gets less difficult.

On the other hand, in case of both of the ADL datasets the results vary with different scales without conforming to any particular trend. Because different temporal scales are suitable for modeling different activities. For example, while predicting *sleep*, half hourly scale results in better performance. But for predicting dinner, breakfast, and lunch, 2 hourly scale is more effective as the start time of these activities slightly vary across different days. On average, there is 45% and 42% performance improvement due to scale variation in terms of Pearson correlation and mean square error, respectively. Due to space limit we are not tabulating the results from the two ADL datasets.

6.3.3 Varying Order of Lag

In this experiment we vary the lag length as described in Table 8 while keeping the other parameters in their default values. The MSE values decrease very slightly with increase of lag for all four datasets. The Pearson correlation increases by 6.5%, 8.4%, 2% and 3% with increase of lag for search log, Twitter, ARAS, and HOLMES dataset, respectively. Over all the effect of changing lag is limited for all datasets. Due to space limitation, we are skipping the detailed results here.

7. DISCUSSION

Our extensive experiments with four real world behavior data suggest that by using a combination of lag, cy-

[6] As the sample size for most of the activities of both ADL dataset is too small to vary training period, this experiment was performed only on online behavior data

cle, and interaction of activities, MAPer improves prediction performance significantly. They also demonstrate the effectiveness of using an adaptive learning approach that adapts with multi-scale temporal contexts. These features enable MAPer to perform equally or better than the parametric state-of-art SARIMA model. From an extensive sensitivity analysis, we discover that (i) using only 2 weeks data can result in higher accuracy for most of the online users, (ii) using recent training data is more useful as human behavior changes over time, and (iii) the suitable temporal scale vary over activities. In addition, MAPer yields explanatory results which can be useful for several interesting applications. Such as, detecting user community or recommending friends based on similarity of temporal behavior as explained in Section 6.2. MAPer can be paired with text mining approaches to provide personalized information retrieval, i.e., retrieving entertainment related queries during weekends. Other potential application domains where our model is applicable include personalized human activity understanding, temporal user profiling, or social recommendations from an individual user's online behavior.

We also find that MAPer is not generalizable to all human behavior as it assumes regularity in behavior. Hence, it's performance is limited in case of predicting the need based behavior (e.g., issuing search query) or random behavior. In addition, using more granular temporal scales like minutes instead of hours can incur significant computational cost. Finally, evaluation using longer ADL datasets can yield more comprehensive results.

8. CONCLUSION

With the surge of easy online access and ubiquitous sensing, abundant data contents have been generated that capture the individual human behavior over time. In spite of having great potentials to provide real-time insights, personalized temporal modeling of human behavior patterns remains largely unexplored. In this work, we introduce a multi-scale adaptive personalized **MAPer** model, an easy-to-interpret and simple-to-build predictive method for modeling the temporal dynamics of human behavior. Through results obtained from four real datasets of multiple individuals' behavior records over time, our model yields statistically significantly better predictions than a parametric state-of-art method (SARIMA model). Specifically, MAPer reduces the mean square error of the SARIMA model by about 15%, 31%, and 10% for the Twitter, ARAS, and HOLMES datasets, respectively.

Currently we are using only temporal footprint of activities. In the future, we want to model behavior by extracting textual features from user generated contents. We also want to combine virtual and physical world behaviors of an individual using smart devices.

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