MAPer: A **M**ulti-scale **A**daptive **Per**sonalized Model for Temporal Human Behavior Prediction

Sarah Masud Preum

John A. Stankovic

Yanjun Qi

University of Virginia

Modeling Temporal Human Behavior

- Generation of human behavior data
  - Online behavior:
    - social media, search log
    - Targeted advertising/ content sharing
    - Personalized IR
  - Offline behavior:
    - Sensors, smart devices
    - **Predicting** occupancy and energy usage
    - Anomaly detection in assisted living facilities

Factors Affecting Regular Temporal Behavior

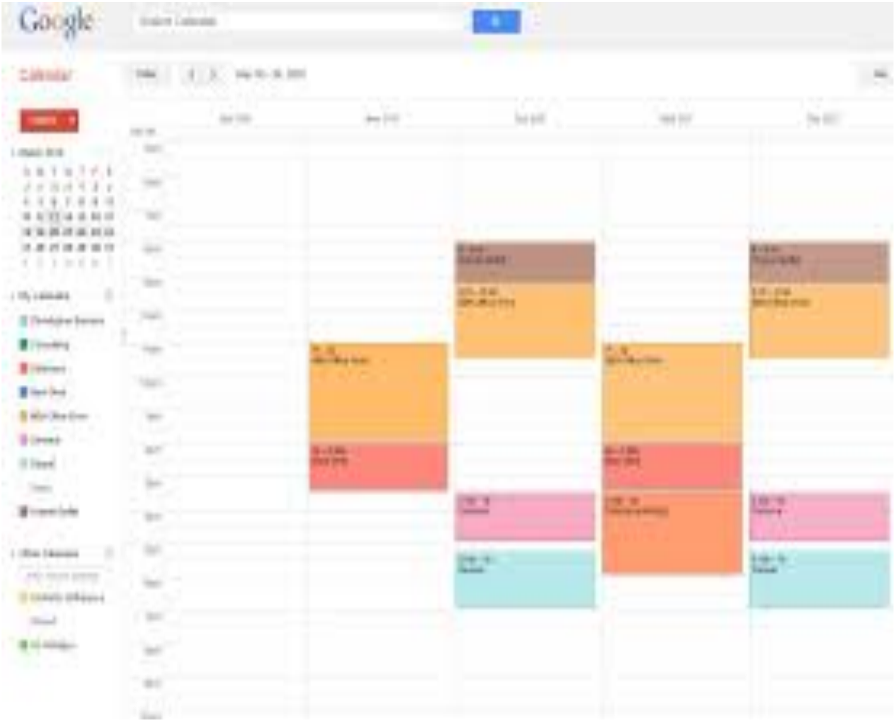
- Temporal smoothness (lag)
  - Working from 3 pm to 4pm (and then continue after 4pm)
- Behavior rhythm (cycle)
  - Watching TV at every Saturday night
- Interaction among multiple activities
  - Working till late night delays sleep time

Fa
inc

Pe
m

Dynamic Nature Of Behavior

– Factors vary over multi-scale temporal contexts
  - Hour of the day
  - Day of the week



Adaptive modeling

Contribution: **M**ulti-scale **A**daptive **Per**sonalized Model (**MAPer**)

- Extracts features from major temporal factors
- Encodes multi-scale temporal contexts to ensure adaptive learning
- A linear predictive model with explanatory power

Solution Overview

Behavior time series

↓

Behavior Matrix

↓

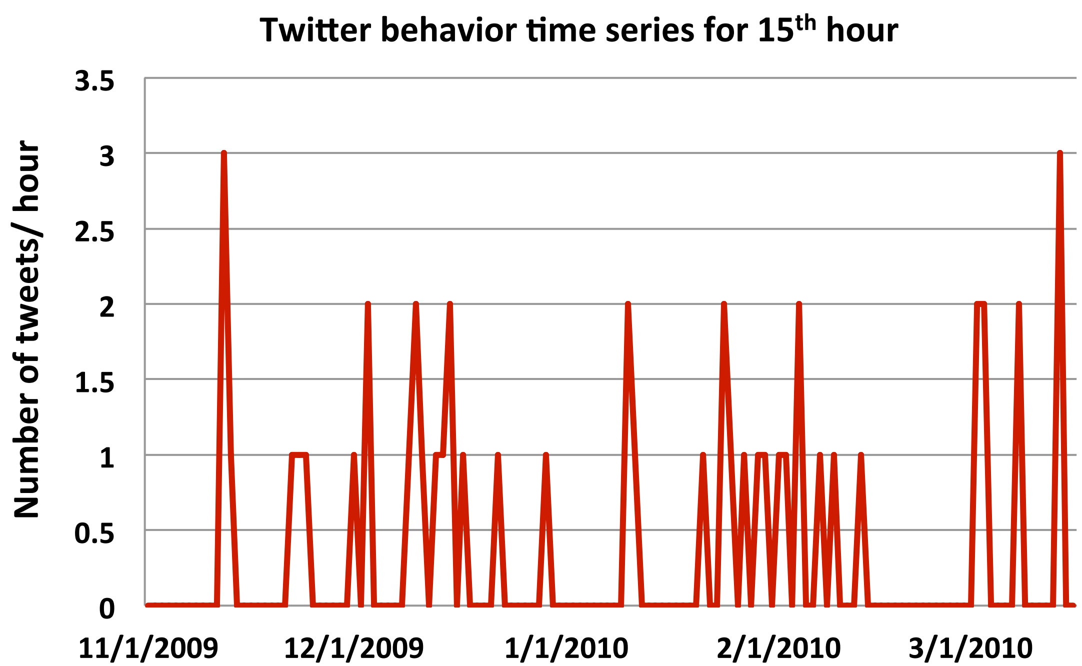
Extract features: **lag, cycle, interaction, temporal context**

↓

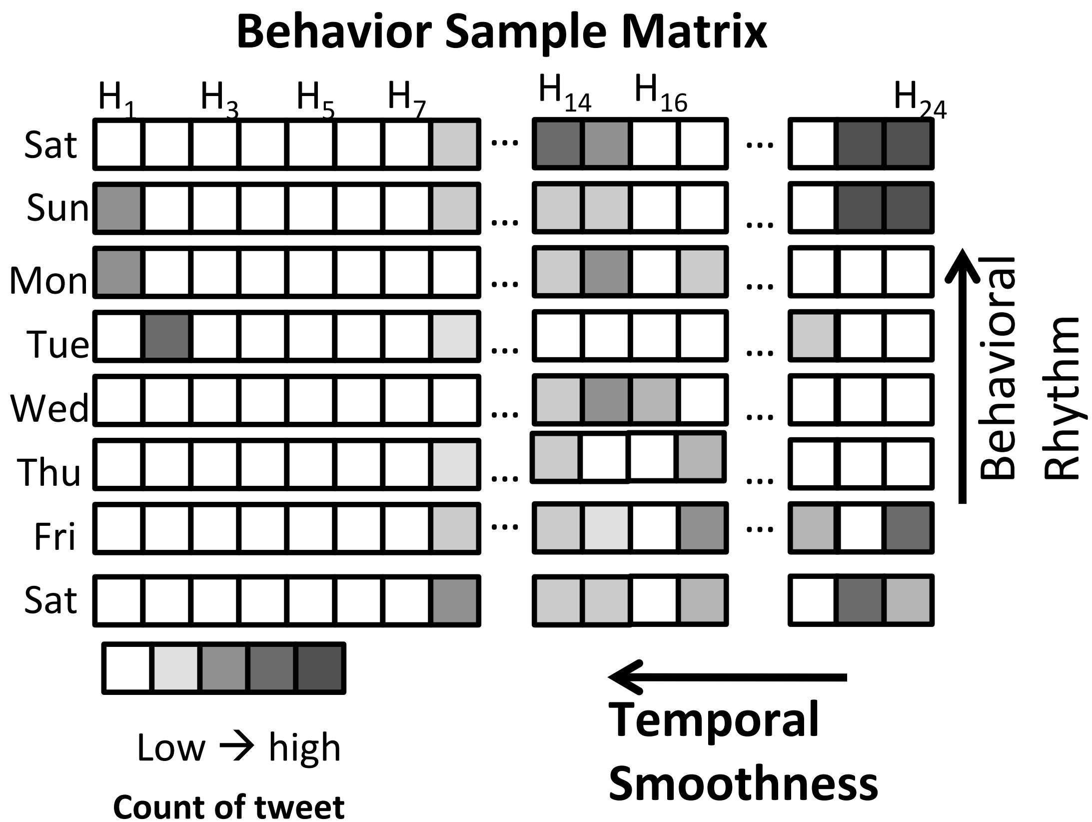
Use features for prediction

Creating Behavior Time Series

- Quantify behavior in the temporal domain as discrete behavior sample



Creating Behavior Sample Matrix



Lag and Cycle Features

- Lag of order i at time y_t : y_{t-i}

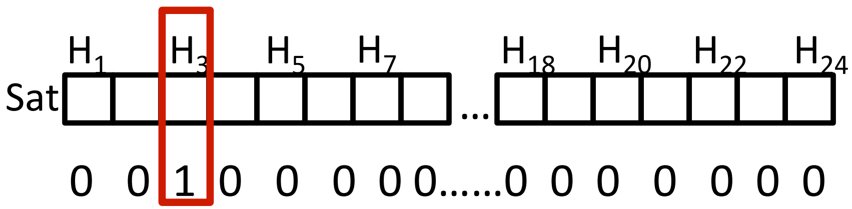
$$\hat{y}_t \approx \sum_{i=1}^{l} \alpha_i \cdot y_{(t-i)}$$

- Cycle of behavior time series

$$\hat{y}_t \approx \sum_{i=1}^{l} \alpha_i \cdot y_{(t-i)} + \boxed{\sum_{j=1}^{c} \beta_j \cdot y_{(t-cj)}}$$

Temporal Context Features

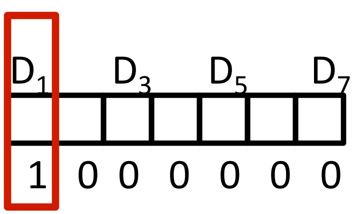
- Daily basis vector: $\vec{B}_d$



Example: Basis vector for hour 3

- Weekly basis vector: $\vec{B}_w$

Quantify the effect of temporal context on behavior



Example: Basis vector for Saturday

Features for a Single Activity

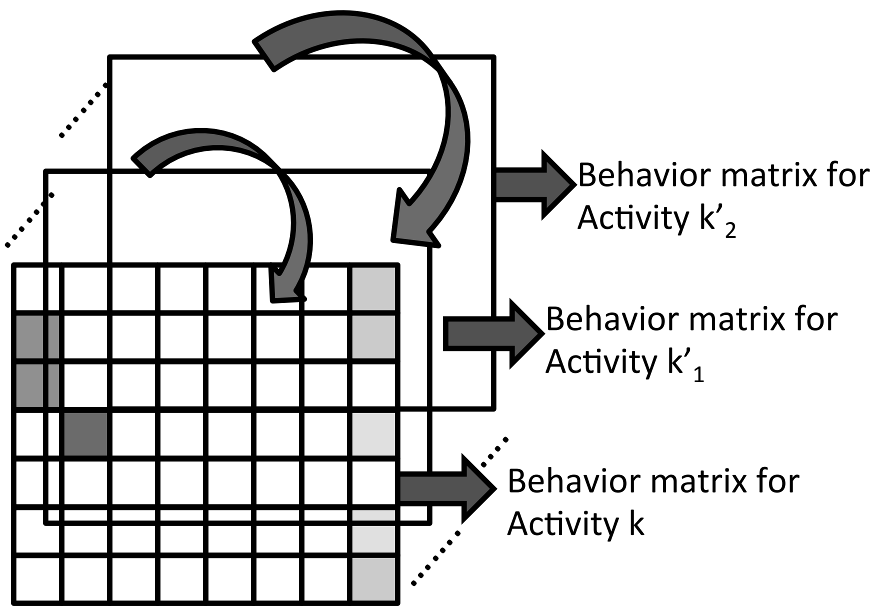
$$\underbrace{\hat{y}_t^k \approx \sum_{i=1}^{L_k} \alpha_i^k \cdot \hat{y}_{t-i}^k}_{\text{Lag}} + \underbrace{\sum_{j=1}^{C_k} \beta_j^k \cdot \hat{y}_{t-c_j}^k}_{\text{Cycle}} + \underbrace{\gamma^k \cdot (\vec{\mathrm{B}}_d, \vec{\mathrm{B}}_w)}_{\text{Temporal Context}}$$

Only daily basis vector: $\vec{B}_d$
Daily scale Adaptive Personalized model (**DAP**er)

Only weekly basis vector: $\vec{B}_w$
Weekly scale Adaptive Personalized model (**WAP**er)

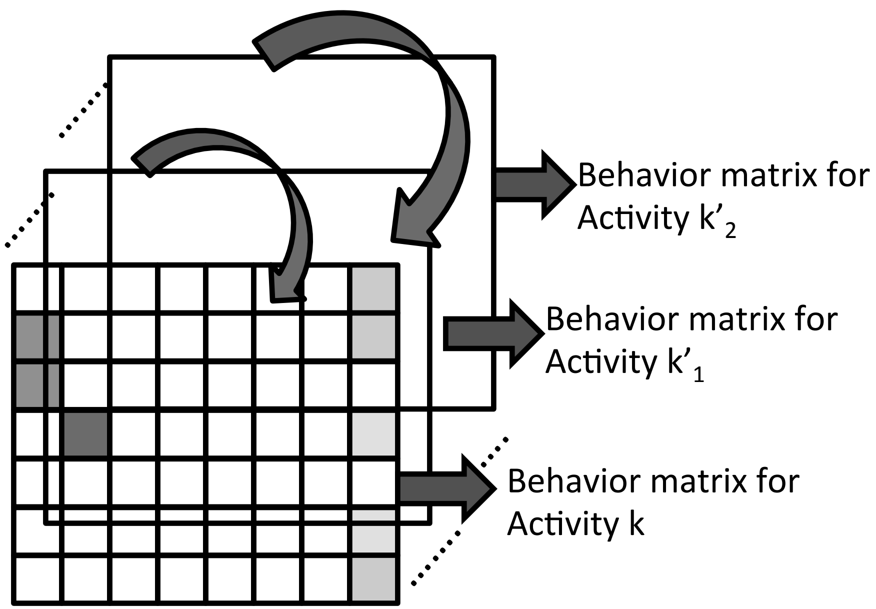
Both $\vec{B}_d$ and $\vec{B}_w$:
Multi-scale Adaptive Personalized model (**MAP**er)

Interaction Features for Multiple Activities



$$\hat{y}_t^k \approx \sum_{i=1}^{L_k} \alpha_i^k \cdot y_{t-i}^k + \sum_{j=1}^{C_k} \beta_j^k \cdot y_{t-c_j}^k + \gamma^k \cdot (\vec{\mathrm{B}}_d, \vec{\mathrm{B}}_w) + \underbrace{\sum_{k' \in S} \sum_{l'=1}^{L_{k'}} W_{l'}^{(k,k')} \cdot y_{t-l'}^{k'}}_{\textbf{interaction}}$$

Interaction Features for Multiple Activities



activity	Interactions
R1 sleep	Brushing teeth Using internet Watching TV
R2 sleep	Brushing teeth Watching TV Washing dishes
R1 snack	Watching TV Using internet Talking on phone
…	…

interaction

Related Works

- Time series prediction
  - Seasonal ARIMA (SARIMA) model
  - Does not consider temporal context of behavior
- Modeling online user behavior
  - Search query [K. Radnisky et al, WWW 2012; J. Yang et al, WSDM 2011]
  - Social media posts [F. Abel et al, UMAP 2011]
  - Focus on temporal pattern of user generated contents rather than actual user behavior
- Modeling offline user behavior
  - Computer vision and WSN: Sensing and recognizing different activities of daily living
  - Don’t focus on predicting

Overview of Evaluation

- Predicting behavior intensity at a time interval as a regression problem
  - Performance metric: MSE, Pearson Correlation
- 4 real datasets
- Comparison with
  - Parametric and non parametric baselines
  - state-of-art SARIMA model
- Sensitivity analysis

Datasets

Online Behavior Data

Dataset	Span	# of users	Behavior sample
Twitter	5 months	**1274**	# of tweets /hour
Search log	3 months	**1307**	# of unique search queries /hour

Offline Behavior Data

Dataset	Span	# of resident	Behavior sample
ARAS	1 month	**2**	Duration of activity/half hour
HOLMES	3 months	**1**	

Baselines

- Moving average over both lag and cycle terms (**MA**)

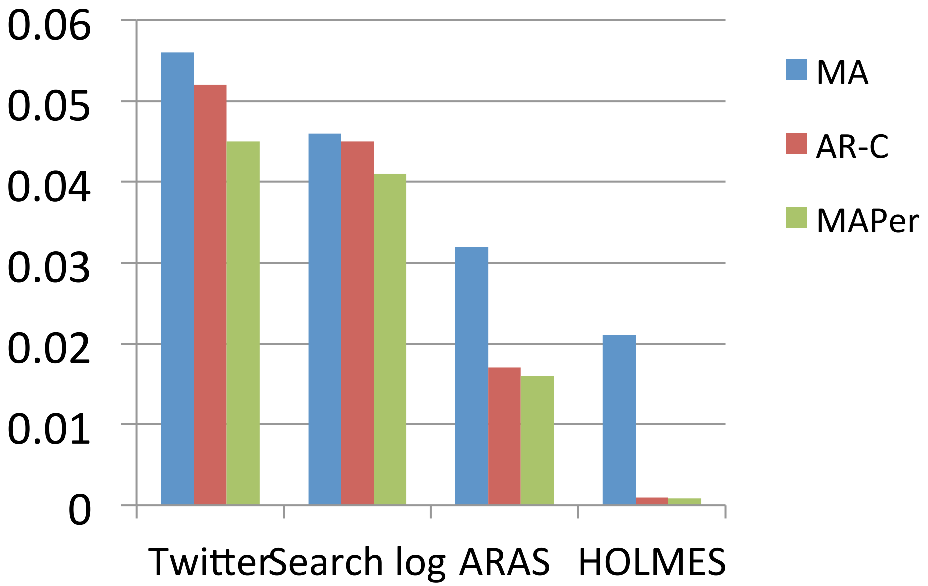
$$\hat{y}_t = \frac{1}{2}\left(\frac{\sum_{i=1}^{l} y_{t-i}}{l} + \frac{\sum_{j=1}^{c} y_{(t-j*24)}}{c} \right)$$

- Auto-regressive method with cycle feature (**AR-C**)

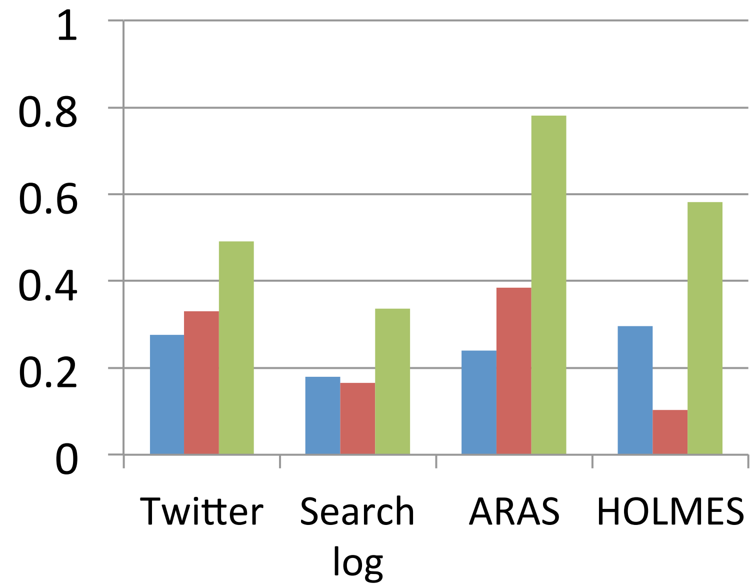
$$\hat{y}_t \approx \sum_{i=1}^{l} \alpha_i \cdot y_{(t-i)} + \sum_{j=1}^{c} \beta_j \cdot y_{(t-cj)}$$

Comparing with Baselines

- On average, MAPer reduces MSE by 10% and increases Pearson correlation by 83%



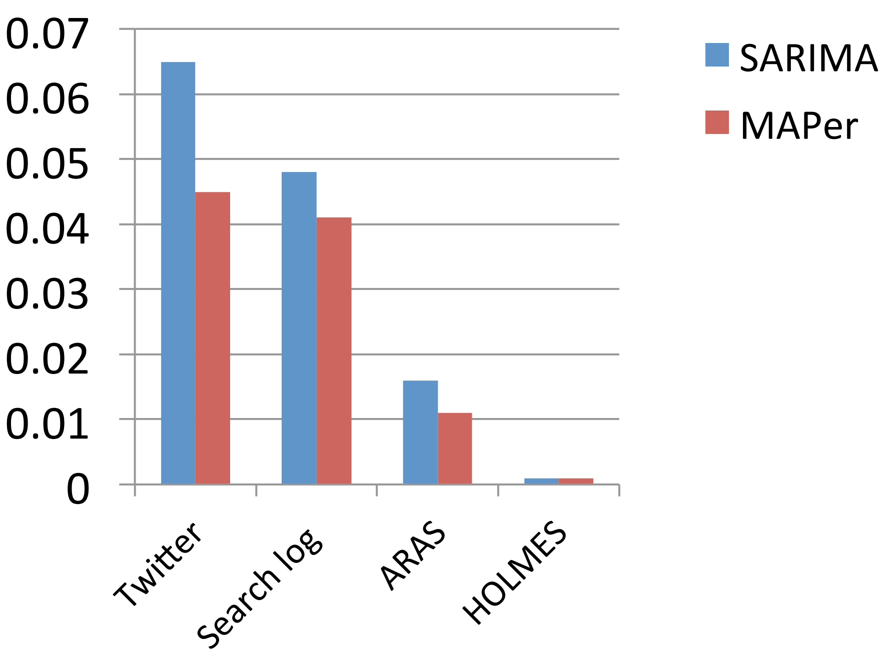
Mean Square Error



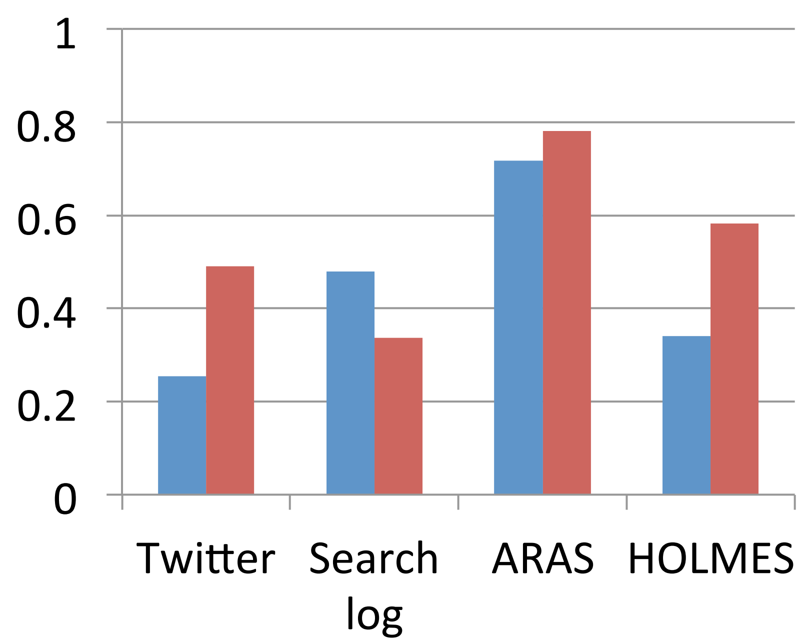
Pearson Correlation

Comparing with State of Art

- On average, MAPer reduces MSE by 14% and increases Pearson Correlation by 44% than SARIMA



Mean Square Error



Pearson Correlation

Effect of Temporal Context Features

- Daily context is more useful than weekly context

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

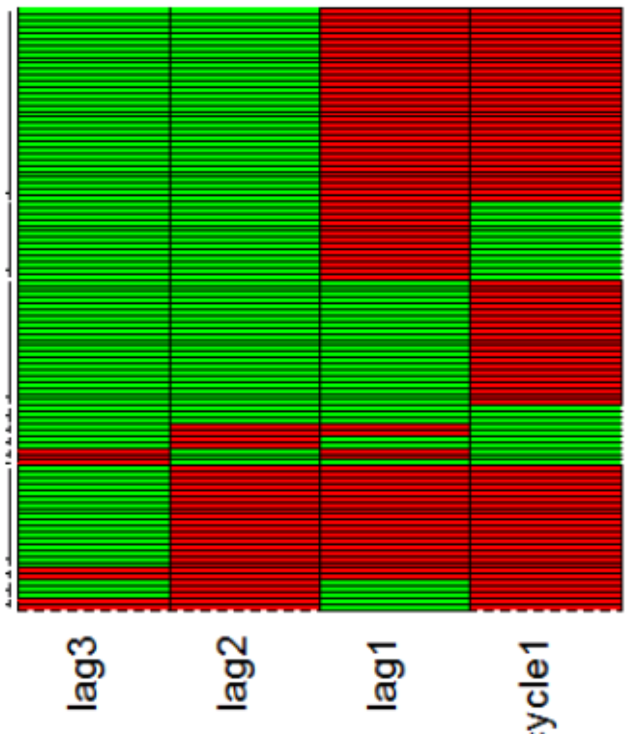
Effect of Interaction Features

- Interaction features improves the performance

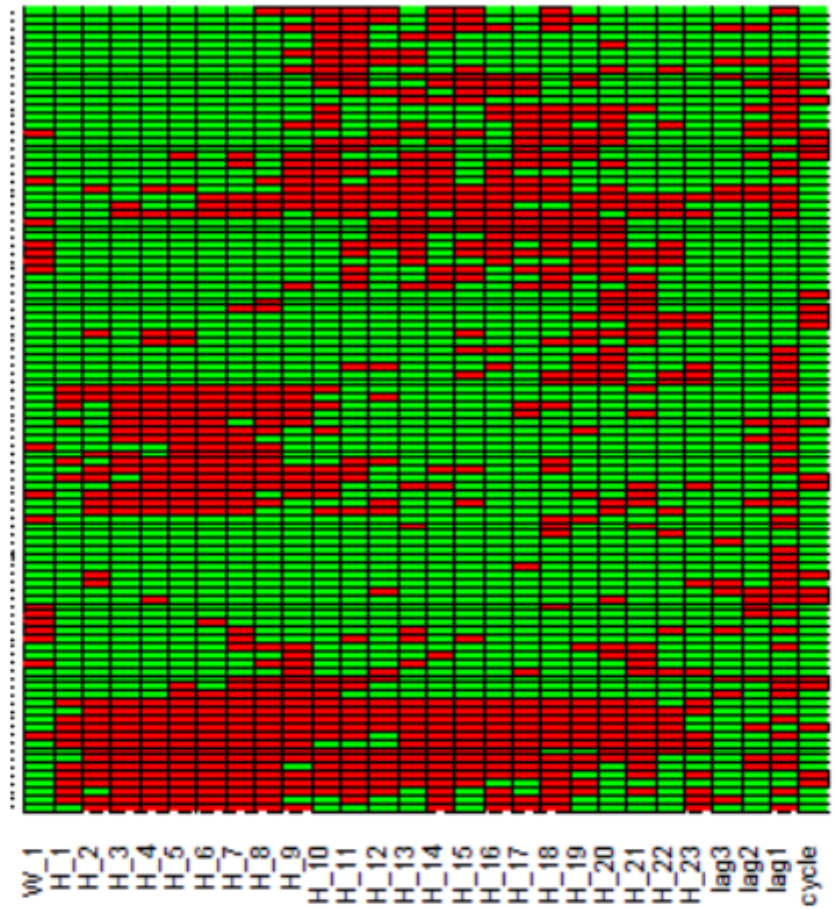
	Pearson Correlation		Mean Square Error	
	ARAS	HOLMES	ARAS	HOLMES
MAPer w/o Interaction	0.7169	0.385	0.0184	0.0009
MAPer	0.782	0.583	0.016	0.0009
%Improvement	9	51	15	-

Results: Explanatory Power of MAPer

- Quantify effect of different features
- Detecting user similarity more precisely



(a) AR-C model



(b) MAPer model

Insights from results

Experiment	Online Behavior	Offline Behavior
Prediction	MAPer	MAPer with interation
Personalization	✓	NA
Adaptive Learning	✓	✓
Variation of temporal window length	Higher better	Varies for each activity: *having snack vs sleep*
Variation of training set size	Lower better	
Variation of lag	No significant effect	

Concluding Remarks

- A personalized interpretable model for temporal behavior prediction
- Virtual and physical behavior
- Some regularity in behavior that conforms with hours of the day, day of the week

Thanks!