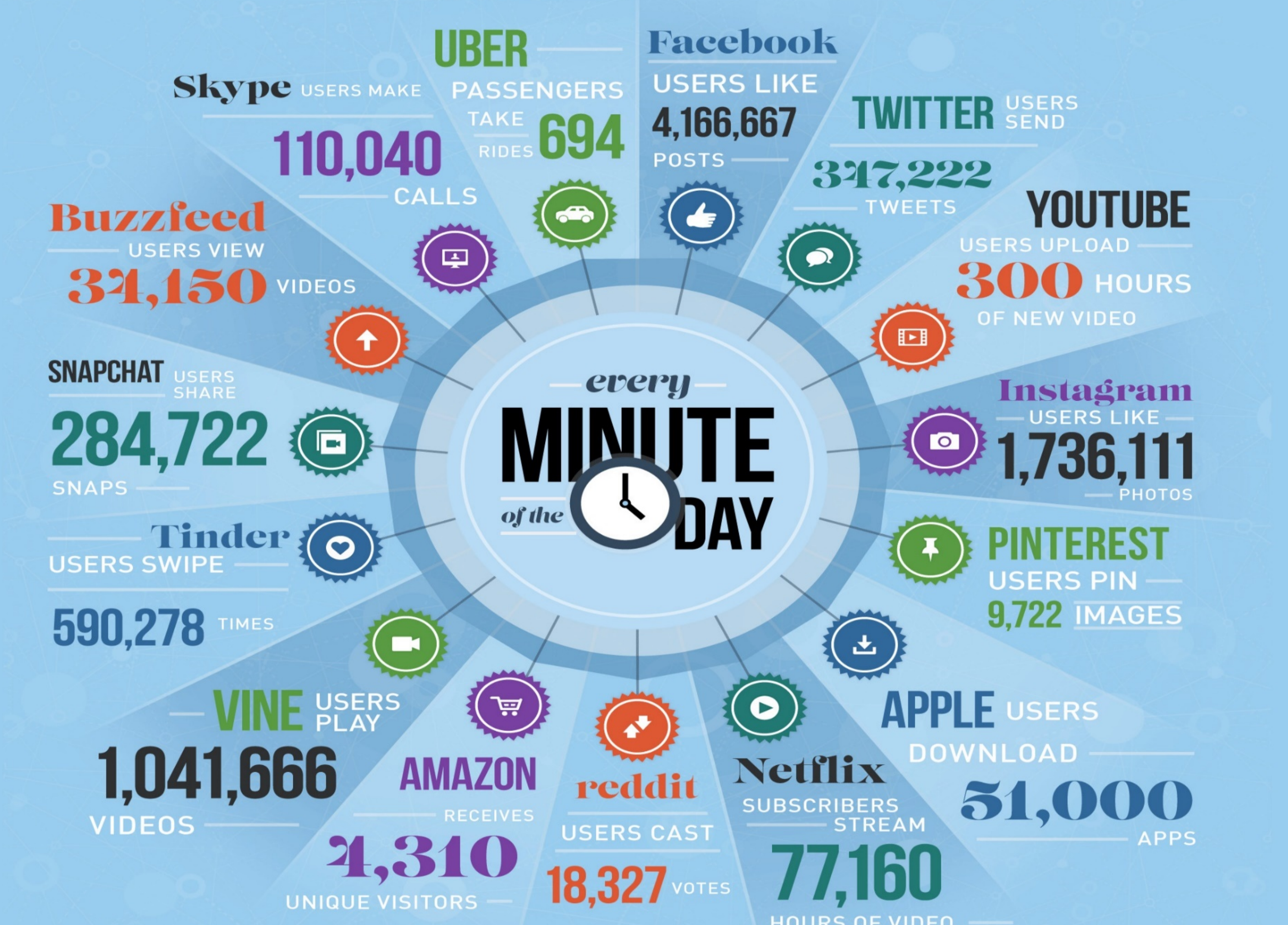
Analysis and Modeling of User Behavior over Social Media Sites

An Application of Point Processes

Introduction



Source:https://www.domo.com/blog/2015/08/data-never-sleeps-3-0

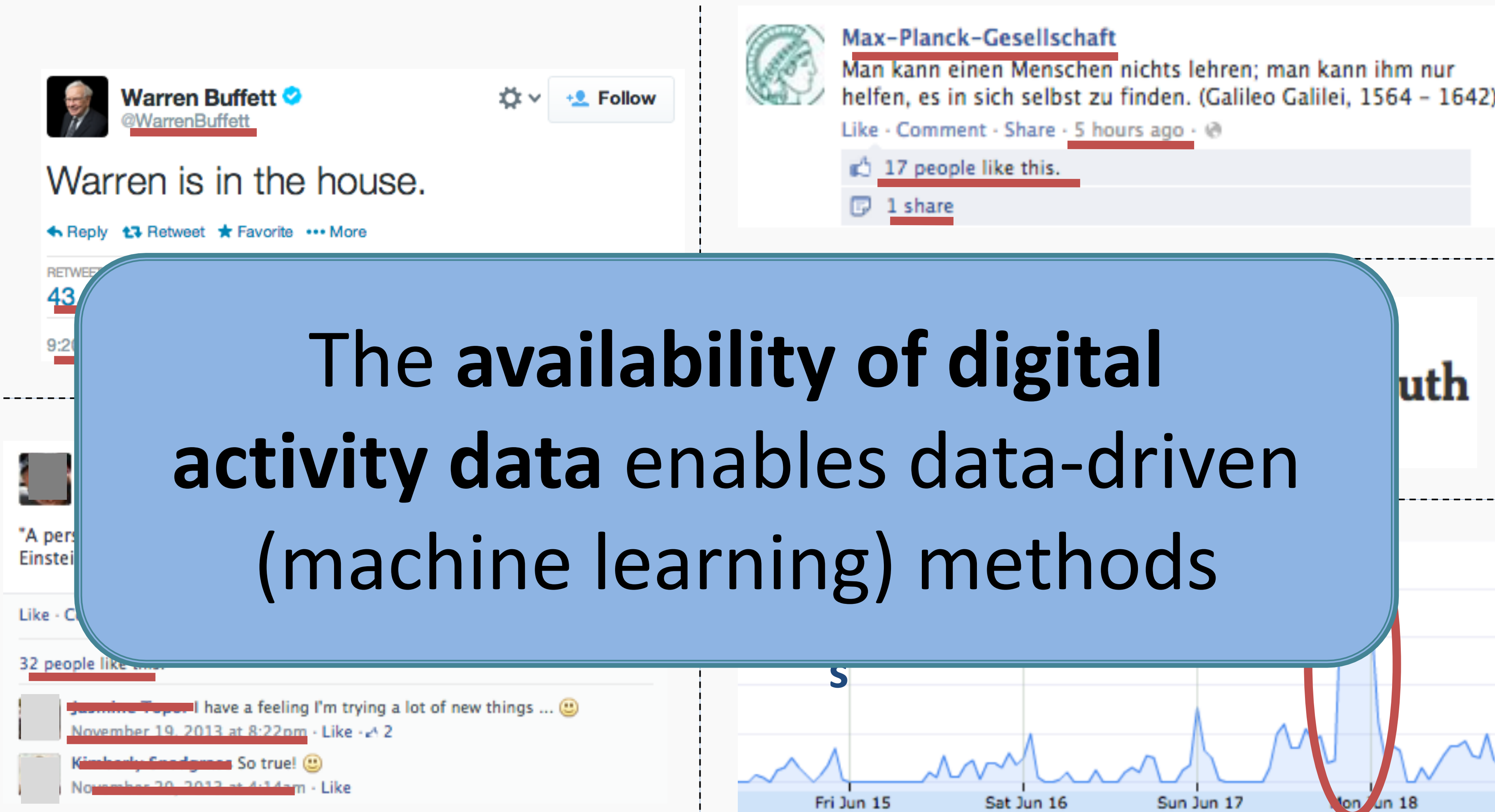
Motivation

- Without user activity …

- It is important for site owners to acquire and engage users
  - **User understanding**
    - **User behavior modeling**
  - **User engagement**

Motivation

DETAILED TRACES OF ACTIVITY

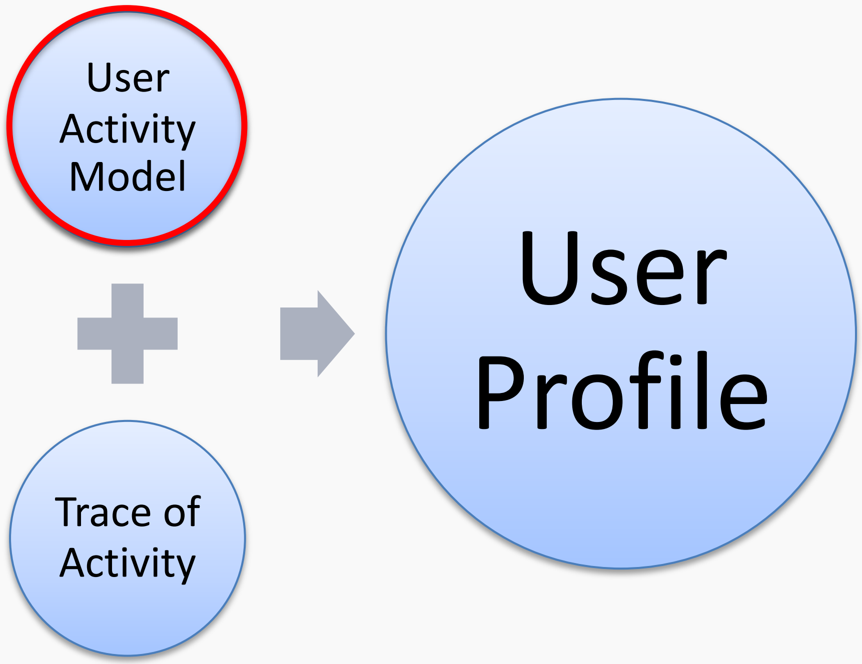


The **availability of digital activity data** enables data-driven (machine learning) methods

❑ User Behavior Modeling

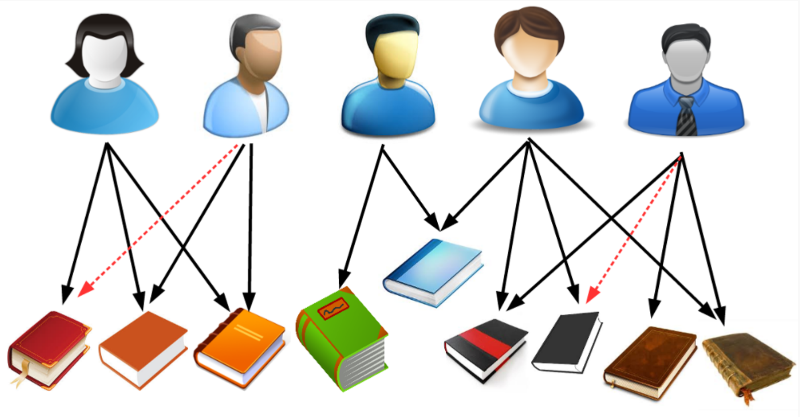
- **Activity model**
  - ➢ Point process
  - ➢ Differential Eq.
  - ➢ HMM

- **Activity Data**
  - ➢ Social Network
  - ➢ Event times
  - ➢ Consumed Items

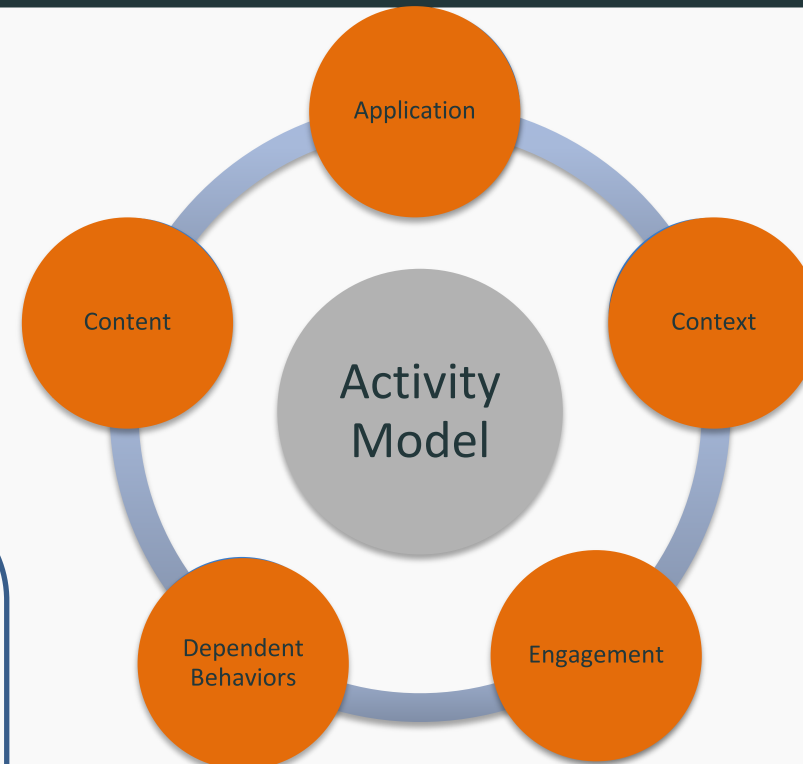


Applications

- ❑ Understanding user behavior
- ❑ Recommendation systems
- ❑ Information filtering
- ❑ Behavioral targeting
- ❑ Information diffusion



Challenges

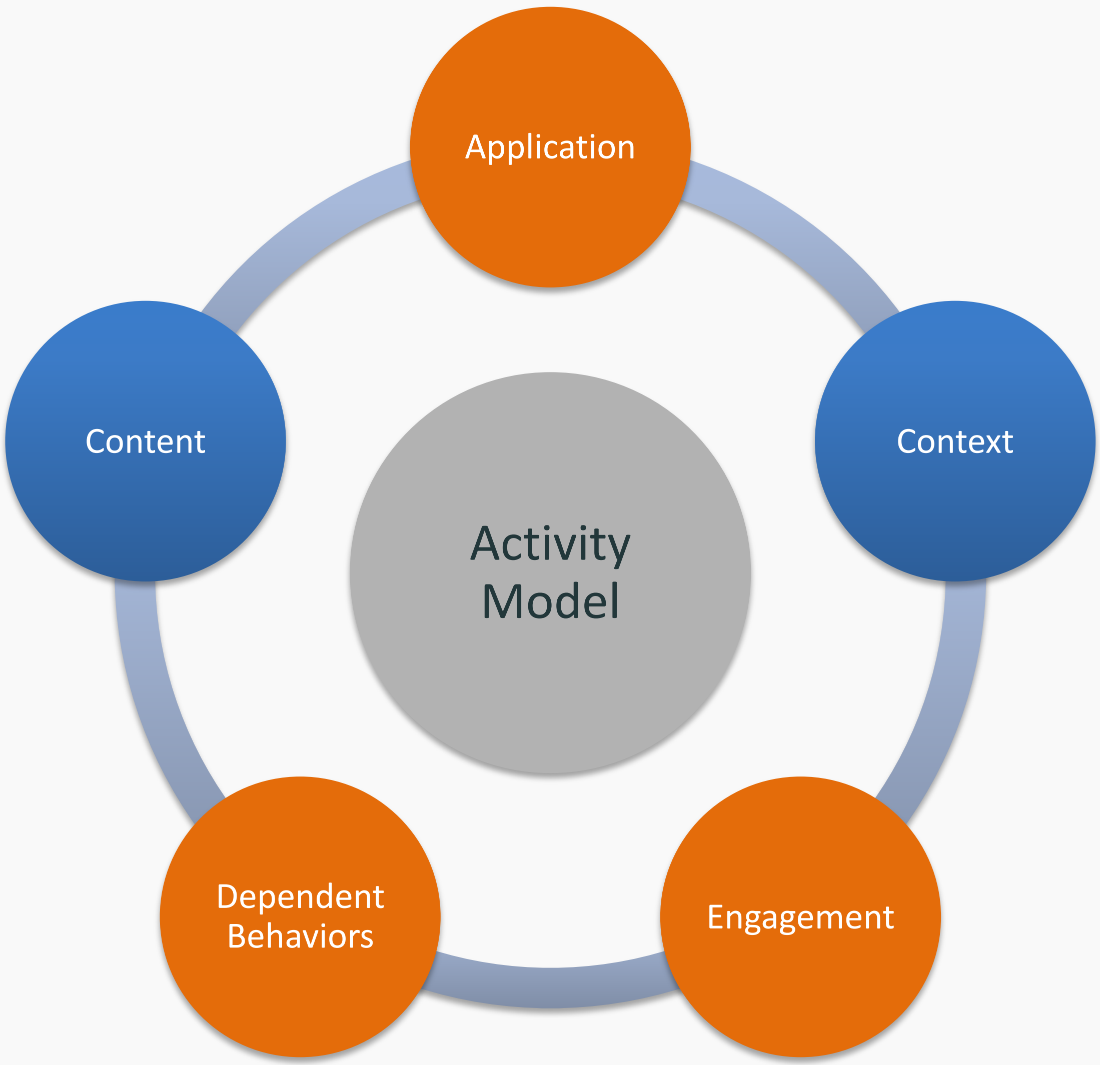

Application
Content
Context
Activity Model
Dependent Behaviors
Engagement


Dror Berman
November 19, 2013 near Palo Alto, CA, United States
"A person who never made a mistake never tried anything new." – Albert Einstein
Like · Comment · Share
32
2
32 people like this.
Jasmine Topor I have a feeling I'm trying a lot of new things ...
November 19, 2013 at 8:22pm · Like · 2
Kimberly Snodgrass So true!
November 20, 2013 at 4:14am · Like

Prior Works

	Approach	Pros.	Cons.
Temporal	Discrete time	Simple, run time	Not able to model activity times, bin lengths
	Continuous time	Simple, considering the time	**Independent behaviors, mostly for diffusion**
Engagement	Friends	Simple, considering the time	Missing other engagement parameters
	Gamification elements	More realistic	**Discrete time, not able to model the time**

Prior Works



Application
Content
Context
Activity Model
Dependent Behaviors
Engagement

Contributions

- Proposing continues-time user models using Temporal Point Processes concentrating on the weaknesses of previous works
  - **Modeling** the time and content of user events
  - **Inferring** latent patterns underlying events
  - **Predicting** future events using event history and learnt patterns

		Application	Modeling	Inference
Engagement	UMUB	CQA	Intertwined Point Processes	Variational EM
	ChOracle	Churn Prediction	Neural Temporal Point Process	Variational Back Propagation Through Time
Content	C4	Diffusion	Dependent Marked Temporal Point Processes	Convex Optimization
	RPF	Time Sensitive Recommendation	Factorized Point Processes	Variational Bayesian Approximation

Temporal Point Process

- Temporal point process is a stochastic process for modeling random times of events.

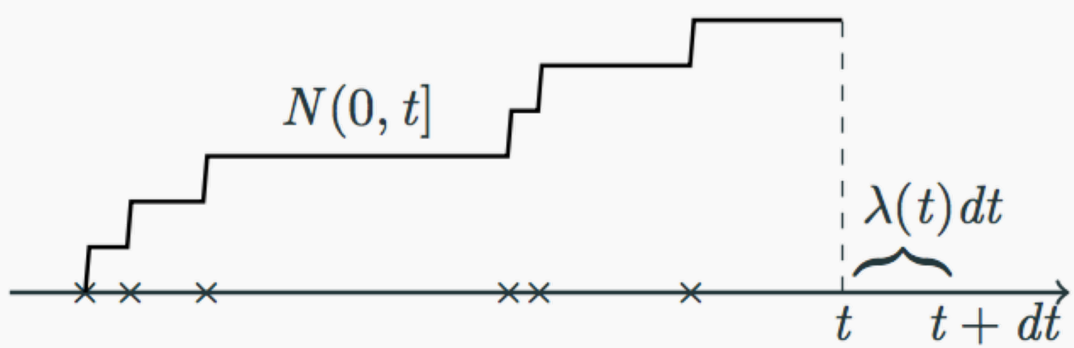
- To specify a point process its suffice to model its marginals

$$f(\mathrm{t}_1, \mathrm{t}_2, \dots) = \prod_i f(t_i | \dots, t_{i-2}, t_{i-1}) = \prod_i f(t_i | \mathcal{H}_t) = \prod_i f^*(t_i)$$

History of events until time t

- So we need only to define $f^*(t)$ or alternatively $\lambda^*(t)$

$$\lambda^*(t) = \frac{f^*(t)}{1 - F^*(t)} = \lim_{\mathrm{dt} \to 0} \mathbf{E}\left(\frac{d\boldsymbol{N}(t)}{dt} | \mathcal{H}_t\right)$$



Proposed Methods

Overview

- We have concentrated on the weaknesses of previous works in two domains:

Modeling User Engagement:

- Modeling User Behaviors in presence of Badges
- Modeling User Churn

Modeling Content:

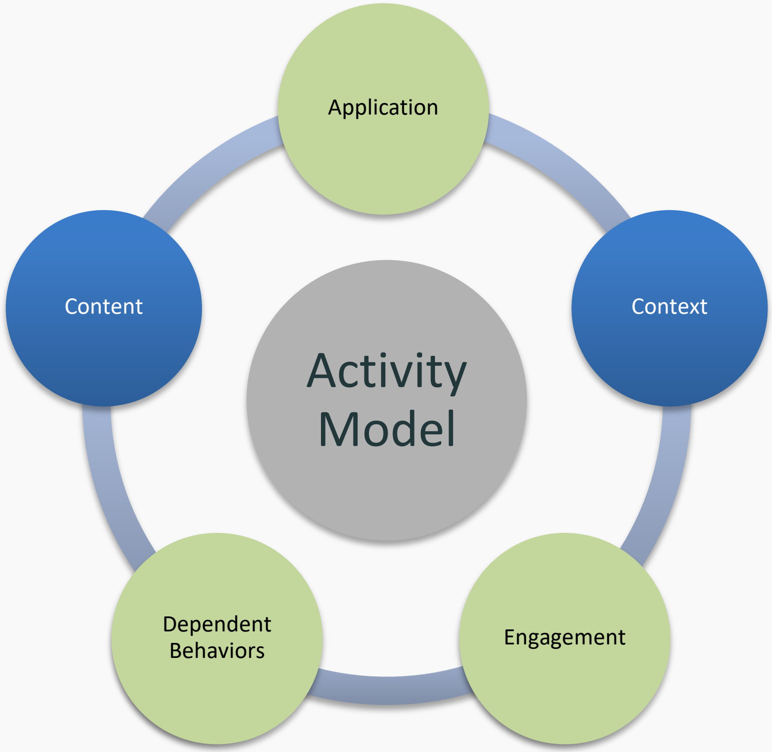
- Modeling the Spread of Multiple correlated cascades
- Time Sensitive Recommendations

User Engagement

UMUB Model

Modeling user activities in presence of gamification elements especially Badges.

- Extending the previous models by considering the impact of Badges on the intensity function
- Proposing temporal point processes for user actions in presence of badges
- Customizing the proposed process for user behavior over CQA sites using interdependent point processes.
- Modeling the dependency between time and content and also the processes.
- Proposing an inference algorithm based on Variational-EM.



- We import the badges into the intensity function of each user for doing each behavior.

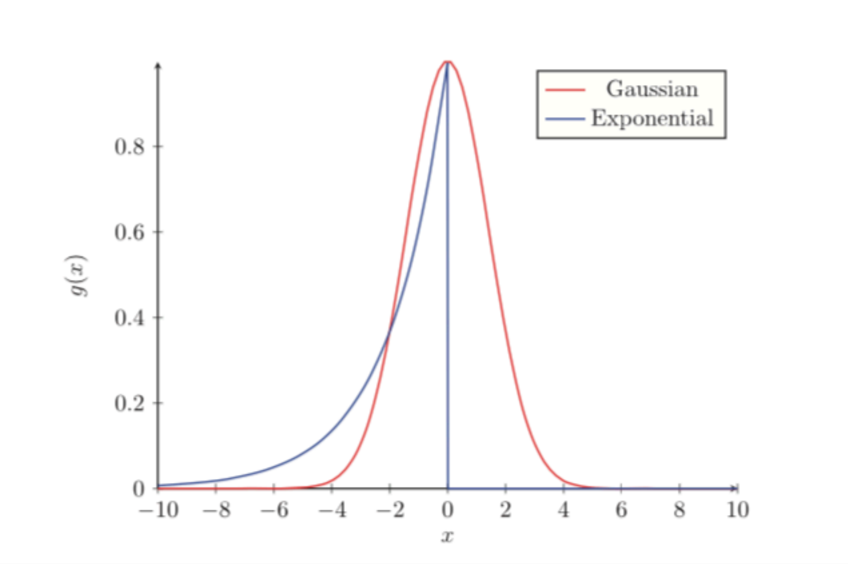
Non-negative
Kernel

$$\lambda_u^i(t) = \mu_u^i + \boxed{\rho_u^i} \sum_{b \in B^i} \boxed{g_w\left(h_b(D_u^i(t)), \boxed{\tau_b}\right)}$$

Impact of badges
on user

Threshold of
badge b

- $g_w(.)$
  - Non-negative
  - Exponential Increase



- We try to model user activities using interdependent processes

$(\boxed{t_i}, u_i, \boxed{z_i})$

$$\lambda_u^q(t) = \underbrace{\mu_u^q}_{\text{Exogenous Intensity}} \underbrace{+ \rho_u^q \sum_{b \in \mathcal{B}^q} g_w^q(h_b(\mathbf{D}_u^q(t)), \tau_b)}_{\text{Endogenous Intensity}}$$

$$\mathbf{P}(z_i = k | u_i) = \frac{\alpha_{u_i k}}{\sum_{s=1}^{K} \alpha_{u_i s}}$$

$(\boxed{t_i}, u_i, \boxed{p_i})$

$$\lambda_u^a(t) = \underbrace{\mu_u^a}_{\text{Exogenous Intensity}} \underbrace{+ \rho_u^a \sum_{b \in \mathcal{B}^a} g_w^a(h_b(\mathbf{D}_u^a(t)), \tau_b) + \sum_{e_i \in \mathbf{D}_\cdot^q(t)} \eta_{u z_i} f_w(t, t_i)}_{\text{Endogenous Intensity}}$$

$$\mathbf{P}(p_j = i | t_j, u_j) = \frac{\eta_{u_j z_i} f_\omega^a(t_i, t_j)}{\sum_{e_r \in \mathbf{D}_\cdot^q(t_j)} \eta_{u_j z_r} f_\omega^a(t_r, t_j)}$$

UMUB-Inference

- We want to infer the set of parameters:

$$\Theta = \{\mu_u^q, \mu_u^a, \rho_u^q, \rho_u^a, \eta_u, \alpha_u\}_{u \in U}$$

- **Likelihood**:
  - Direct maximization of log likelihood is infeasible
  - We define auxiliary random variables

$$\lambda_u^q(t_i, s_i) = \begin{cases} \mu_u^q & s_i = 1 \\ \rho_u^q \sum_{b \in \mathcal{B}^q} g_w^q\left(h_b(\mathbf{D}_u^q(t_i)), \tau_b\right) & s_i = 0 \end{cases}$$

$$\lambda_u^a(t_j, s_j) = \begin{cases} \mu_u^a & s_j = -1 \\ \rho_u^a \sum_{b \in \mathcal{B}^a} g_w^a(h_a(\mathbf{D}_u^a(t_j)), \tau_b) & s_j = 0 \\ \eta_{u z_{s_j}} f_w^a(t_j - t_{s_j}) & s_j \in \{1, 2, \ldots, |\mathbf{D}^q(t_j)|\} \end{cases}$$

- **Complete log-likelihood:**

$$\log p(\mathbf{D},\mathbf{S}|\Theta) = \sum_{e_i\in\mathbf{D}^q} \log(\lambda^q_{u_i}(t_i,s_i)) + \sum_{e_i\in\mathbf{D}^q} \log(f^q_{u_i}(z_i|t_i)) - \sum_u \int_0^T \lambda^q_u(\tau)d\tau$$
$$+ \sum_{e_j\in\mathbf{D}^a} \log(\lambda^a_{u_j}(t_j,s_j)) + \sum_{e_j\in\mathbf{D}^a} \log(f^a_{u_j}(p_j|t_j)) - \sum_u \int_0^T \lambda^a_u(\tau)d\tau$$

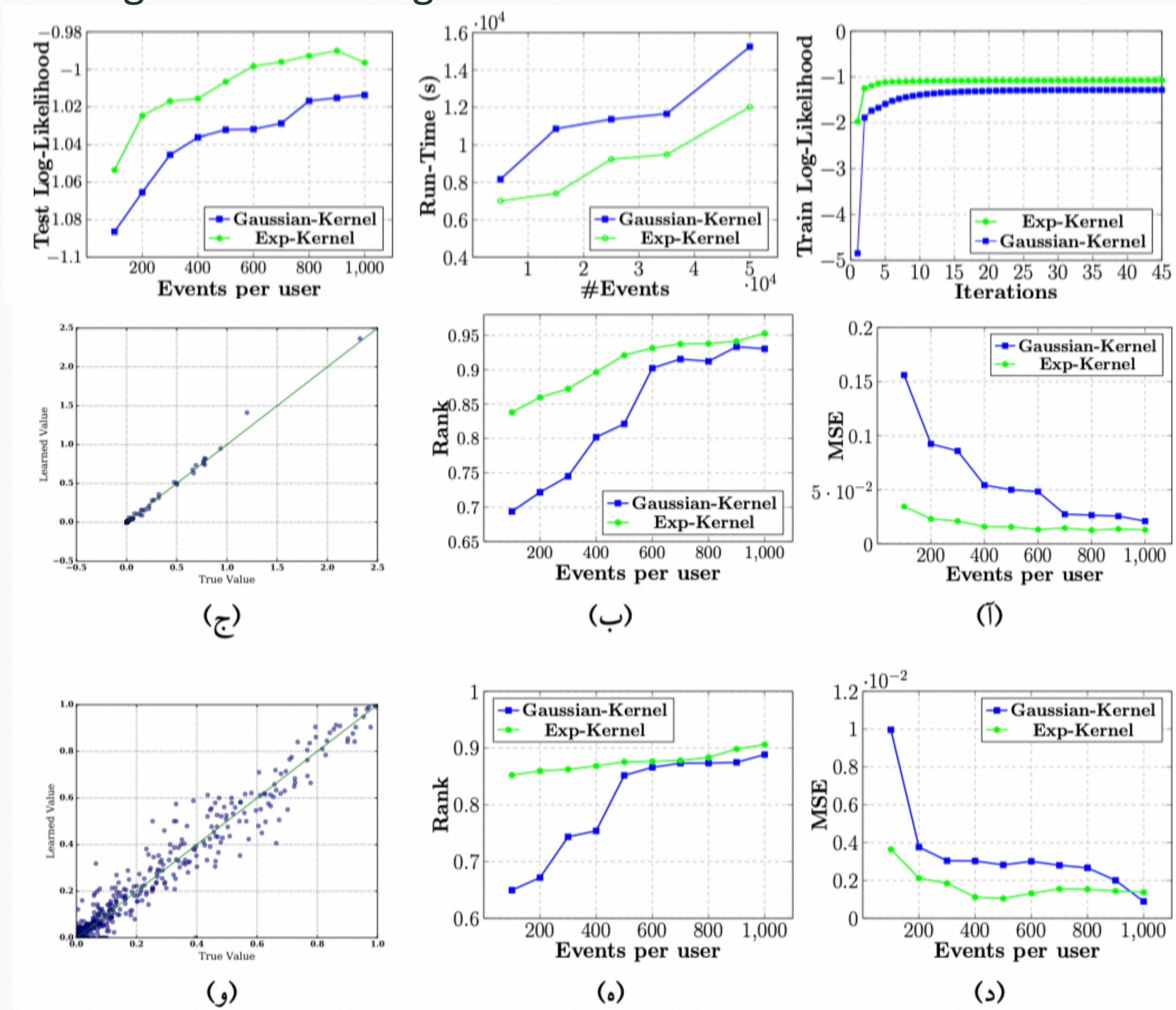
- **We use variational-EM to find parameters:**

$$q(\mathbf{S}) = \prod_{e_i\in\mathbf{D}^q} q(s_i|\phi^q_i) \prod_{e_j\in\mathbf{D}^a} q(s_j|\phi^a_j)$$

- **We maximize the ELBO**

UMUB-Experiments-Synthetic

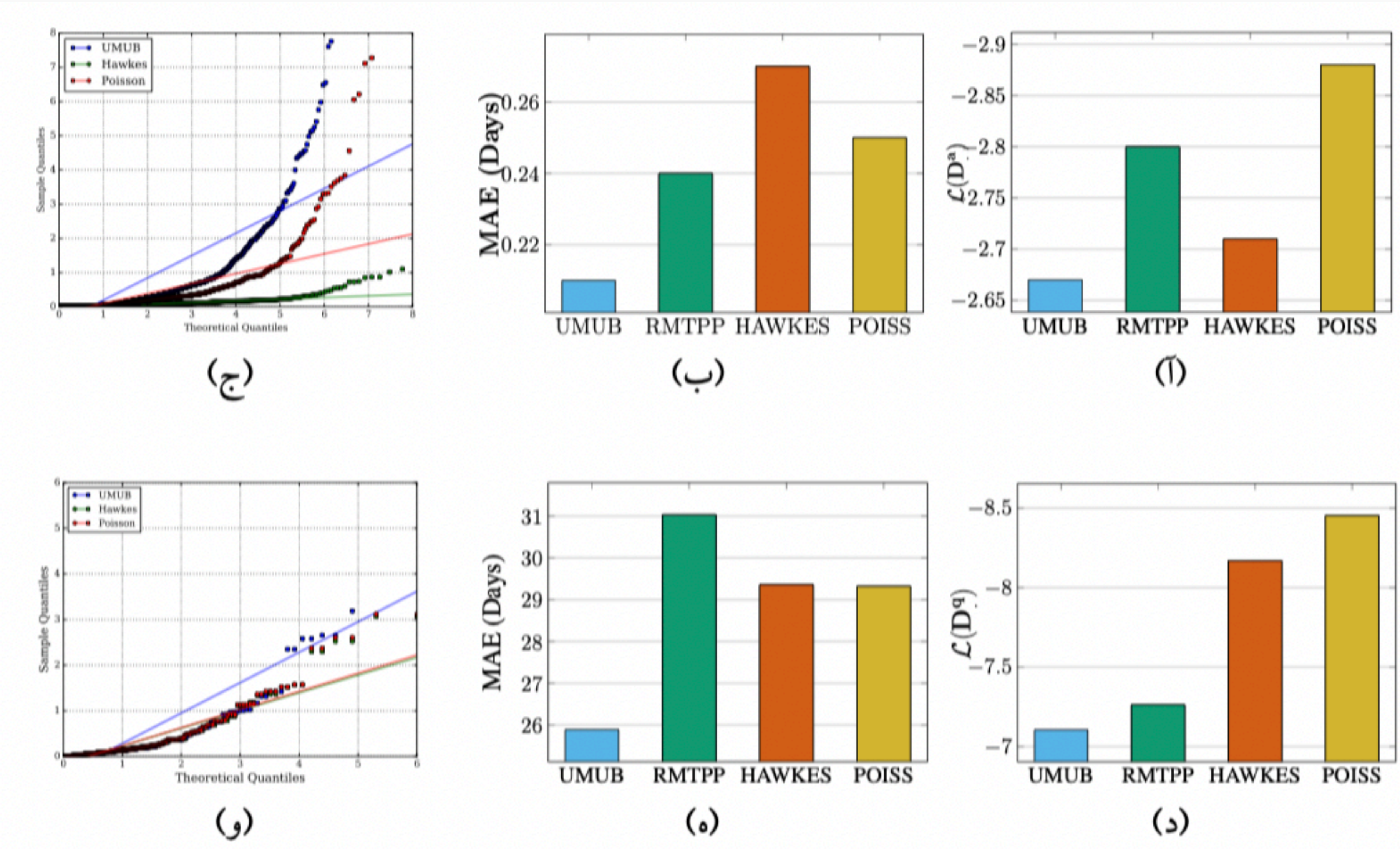
- Inference algorithm convergence? Parameters estimation? Predictions?



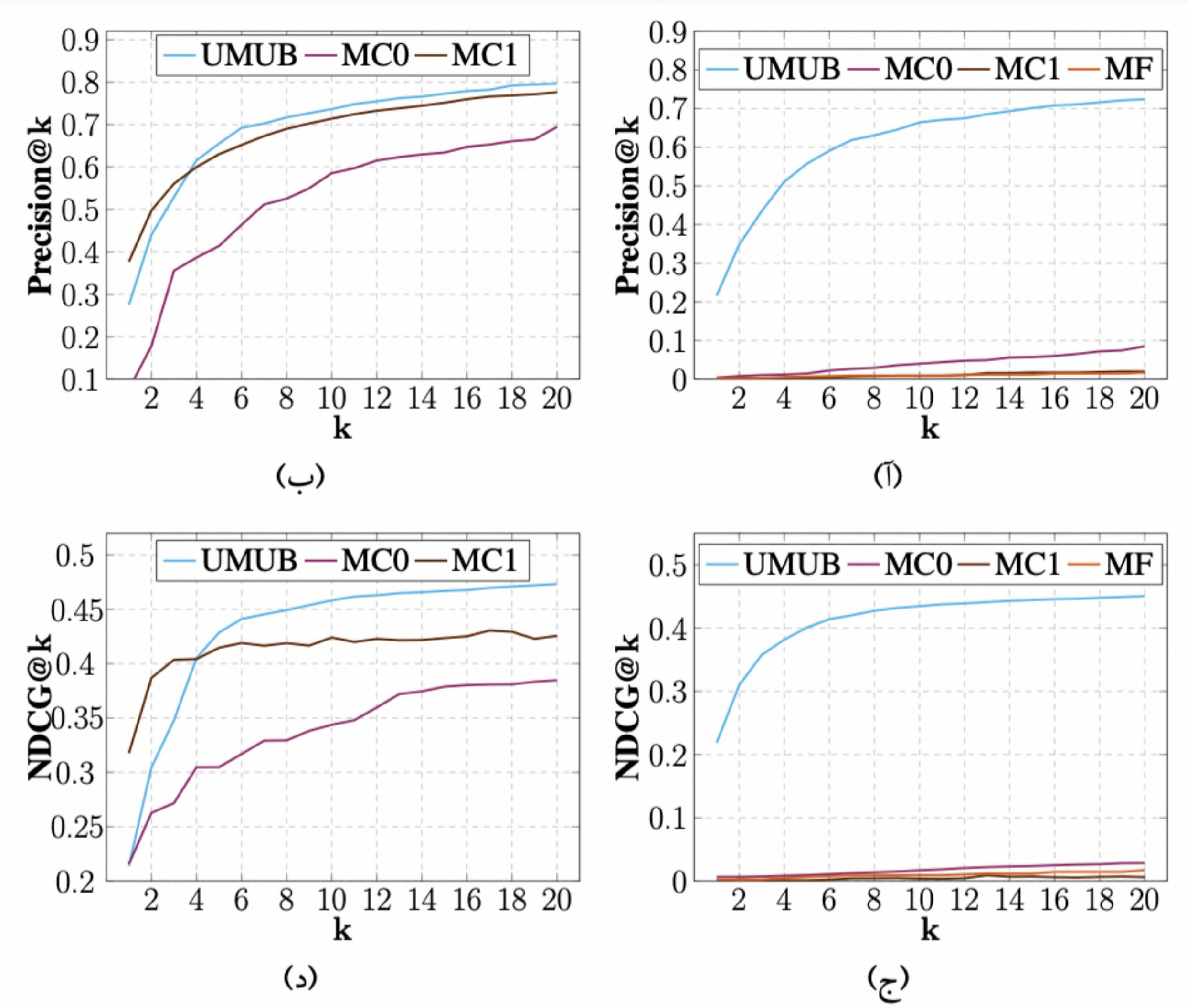
UMUB-Experiments-Real Data

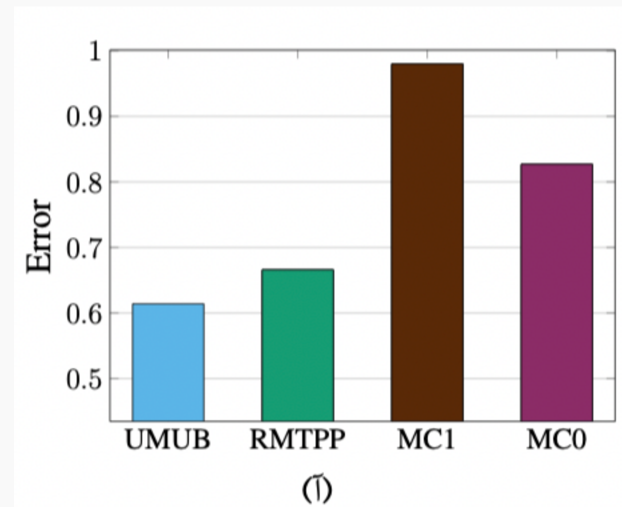
- **Dataset**:
  - Top **2000** users of stack-overflow
  - **3** question badges and **3** answer badges
  - **20** tags
- **Train data selection**:
  - Sort events based on time and select first **80%** for training and leave the rest for test
- **Baselines**:
  - **Time**: RMTPP, Hawkes, Poisson
  - **Content**: MC0, MC1
- **Quantitative Tasks**:
  - Event time prediction
  - Content prediction
- **Qualitative Tasks**

UMUB-Experiments Return Time Prediction

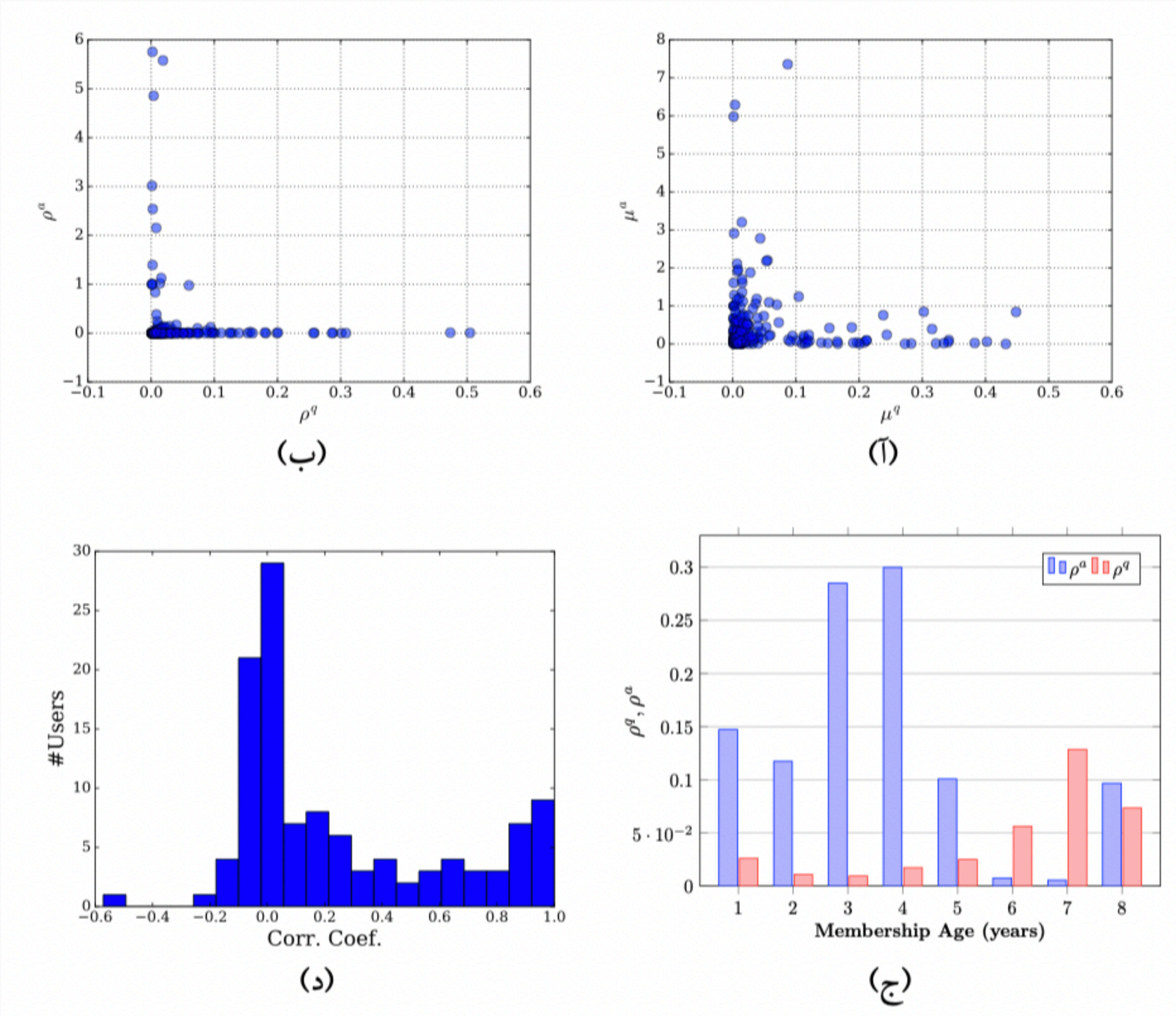


UMUB-Experiments Content Prediction





UMUB-Experiments Qualitative



Summary

- Modeling user engagement is of utmost importance for service owners.

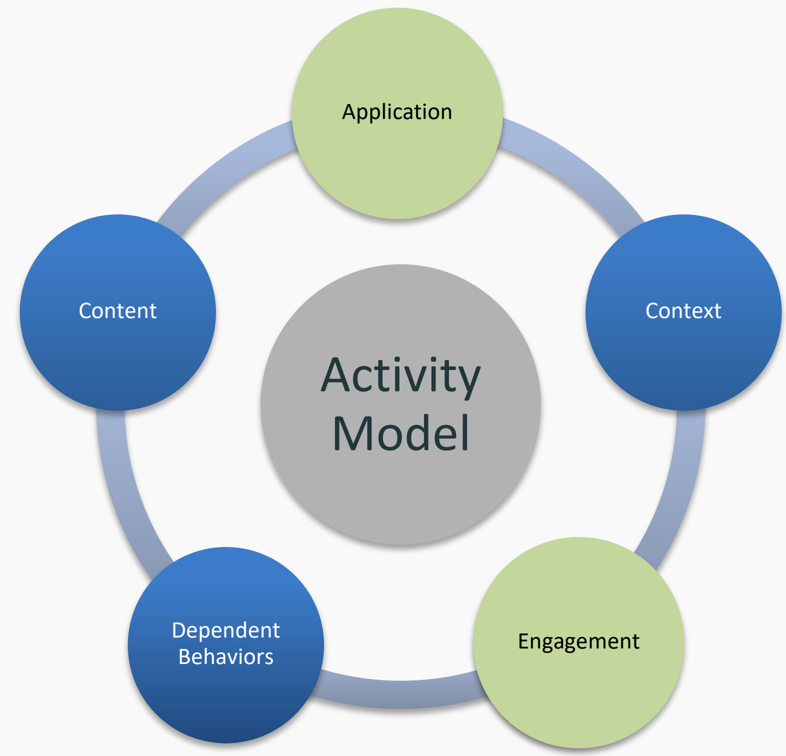
- UMUB is a continues time model that considers gamification elements in modeling user events.

- Contributions:
  - Incorporating the impact of badges in user intensity
  - Utilizing intertwined point processes for modeling two type of activities
  - Dependence of time and content to each others
  - An Inference approach based on Variational-EM

ChOracle Model

Modeling user churn in online services.

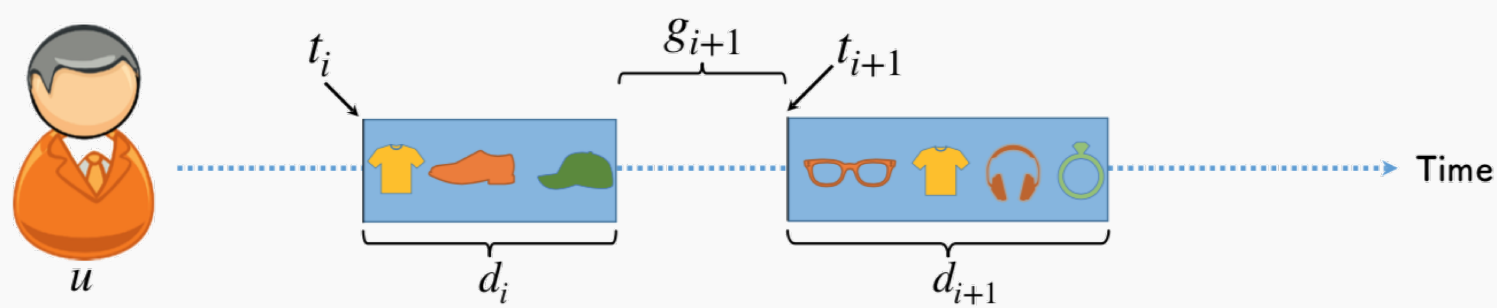
- Convert the churn prediction to return time prediction
- Proposing a temporal point process for inter session gaps and session durations.
- Incorporating **VRNNs** to model the intensity function.
- Utilizing latent random variables to increase the expressive power of model
- Proposing an inference algorithm based on BPTT on ELBO.



Churn Prediction

- **Goal**
  - Predicting user churn

- **Approach**
  - Groping users' events into sessions
  - Treat inter-session gaps and session duration as the interaction data
  - Inferring inter-event dependencies using a neural temporal point process
  - Predicting user churn by predicting her returning time to the system



ChOracle

- Instead of defining the form of intensity function we let a RNN to define it.
- Encoding events history and their corresponding patterns in a vector using RNN

$$\mathbf{h}_i = f_\theta(g_i, d_i, z_i, \mathbf{h}_{i-1})$$

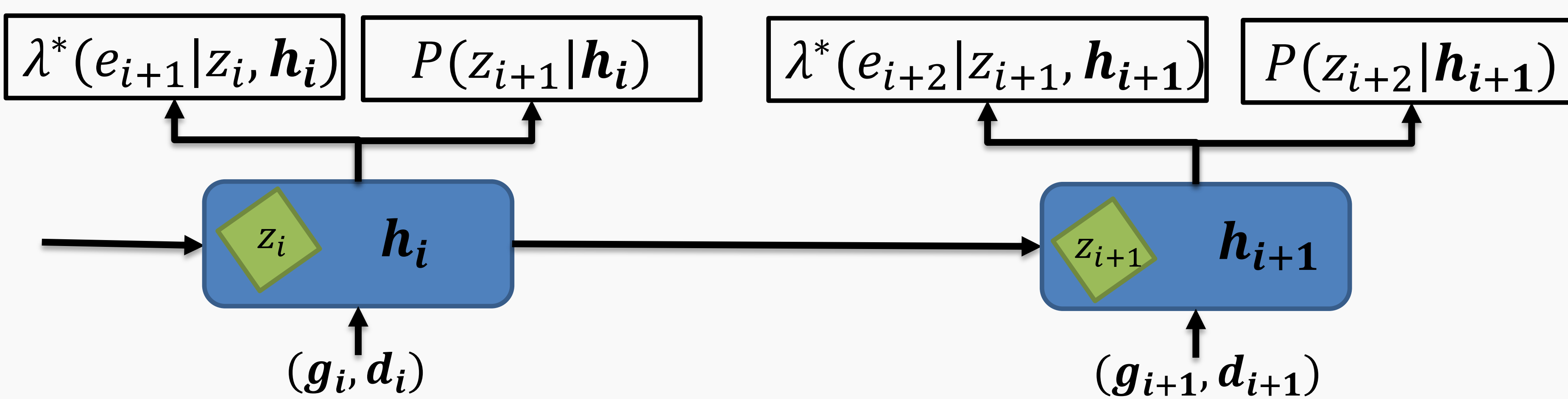
- Modeling latent pattern of events a logit-normal pdf

$$p(z_i|\mathbf{h}_{i-1}) = p_{\theta_p}(z_i|\mathbf{h}_{i-1}) = P(\mathcal{N}(\mu_0, \sigma_0^2)), \qquad \text{where,} \quad \theta_p = \{\mu_0, \sigma_0^2\}$$

- Modeling events by a temporal point process based on history vector and latent factor

$$\lambda^*(g|z_i, \mathbf{h}_i) = \exp\left(w^z z_i + w^h \mathbf{h}_i + w^t g + b^t\right)$$

$$p(d_{i+1} = k|z_i, \mathbf{h}_i) = \frac{\gamma_i^k e^{-\gamma_i}}{k!} \qquad \gamma_i = \exp(w^{z,\gamma} z_i + w^{h,\gamma} \mathbf{h}_i + b^\gamma)$$



Inference

- Approach
  - Maximizing ELBO using back propagation through time
- Complete Log Likelihood:

$$\mathcal{L}\Big(\Big\{\mathcal{S}^u(T),\mathcal{Z}^u(T)\Big\}_{u=1}^{U}\Big) = \sum_u \log P\Big(\mathcal{S}^u(T),\mathcal{Z}^u(T)\Big) = \sum_u\sum_i \log P\big(g_i^u, d_i^u, z_i^u | g_{<i}^u, d_{<i}^u, z_{<i}^u\big) = \sum_u\sum_i \Big(\log P(g_i^u|z_{i-1}^u, \mathbf{h}_{i-1})+ \log P(d_i^u|z_{i-1}^u, \mathbf{h}_{i-1}) + \log P(z_i^u|\mathbf{h}_{i-1})\Big)$$

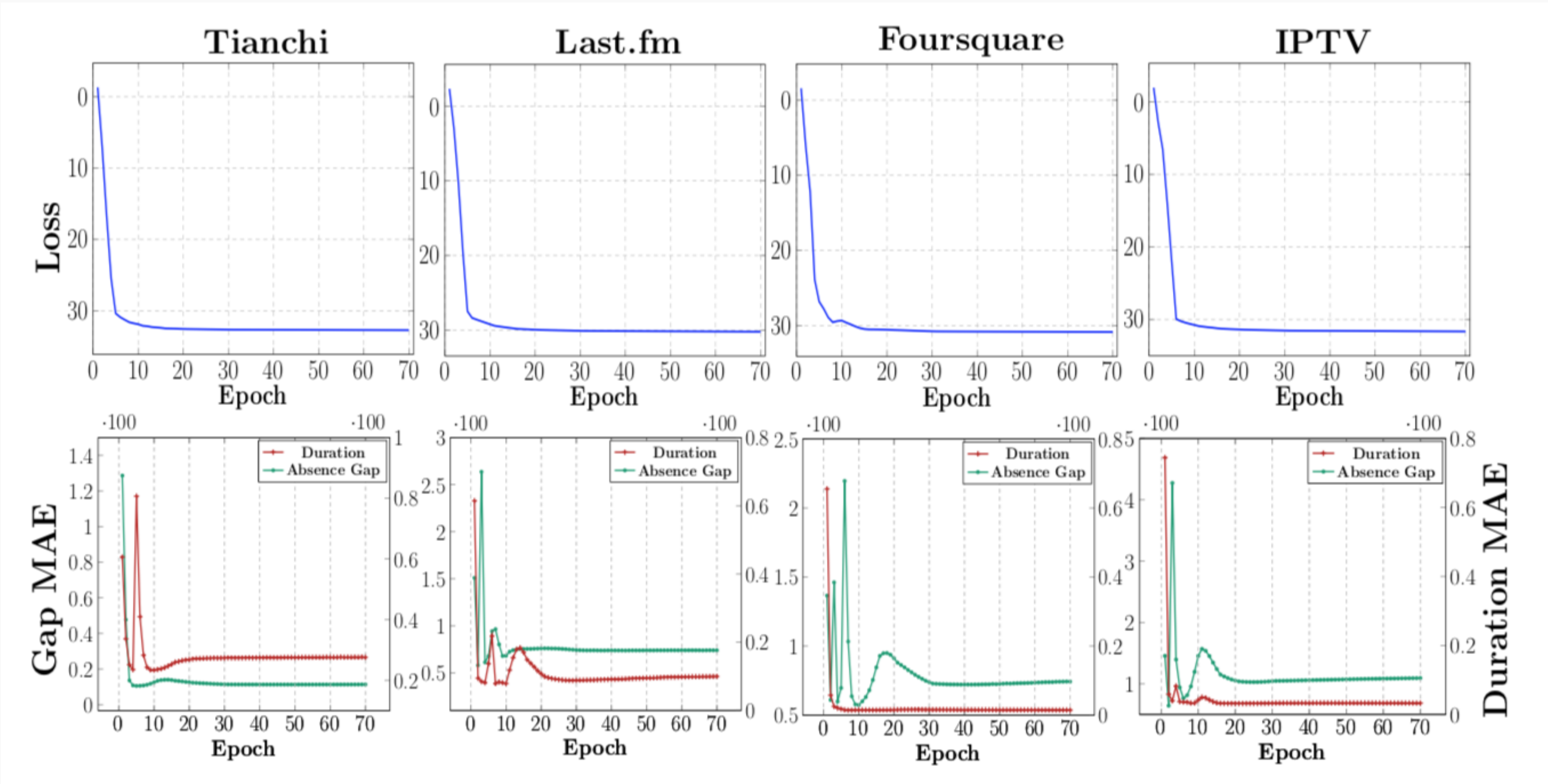
- Objective Function:

$$\sum_u \Bigg[\mathbf{E}_{q(z_{1:T}^u|g_{1:T}^u, d_{1:T}^u)}\Bigg[\sum_{i=1}^{T}\Big(\log P(g_i^u|z_{i-1}^u, \mathbf{h}_{i-1})+ \log P(d_i^u|z_{i-1}^u, \mathbf{h}_{i-1}) - \mathbf{KL}\Big(q(z_i^u|g_i^u, d_i^u, \mathbf{h}_{i-1}) \parallel p(z_i^u|\mathbf{h}_{i-1})\Big)\Big)\Bigg]\Bigg]$$

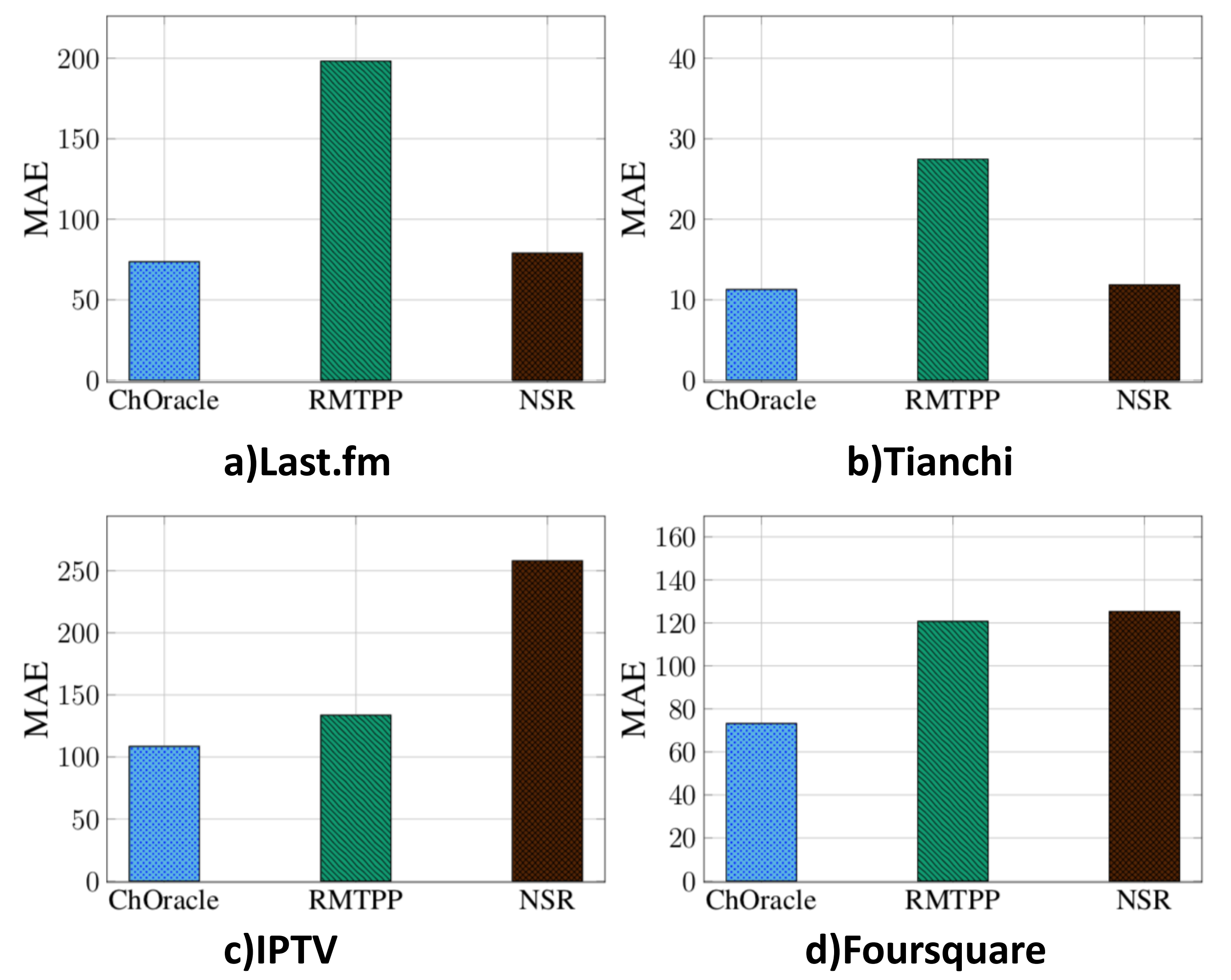
ChOracle-Experiments-Real Data

- **Dataset**:
  - **Last.fm: 418K** music listening logs of **1200** users and **1000** artists
  - **Tianchi: 1.2M** click logs of **1000** users on **2100** items in Alibaba platform
  - **Foursquare: 67K** check-ins of **890** users in **1158** venues with category and location
  - **IPTV: 2.4M** event log of **7100** users watching **436** TV programs with 1420 features
- We extracted user sessions from events
- **Train data selection**:
  - Sort events based on time and select first **80%** for training and leave the rest for test
- **Prediction tasks**:
  - Return time (absence gap) prediction

Experimental Results: Convergence Analysis

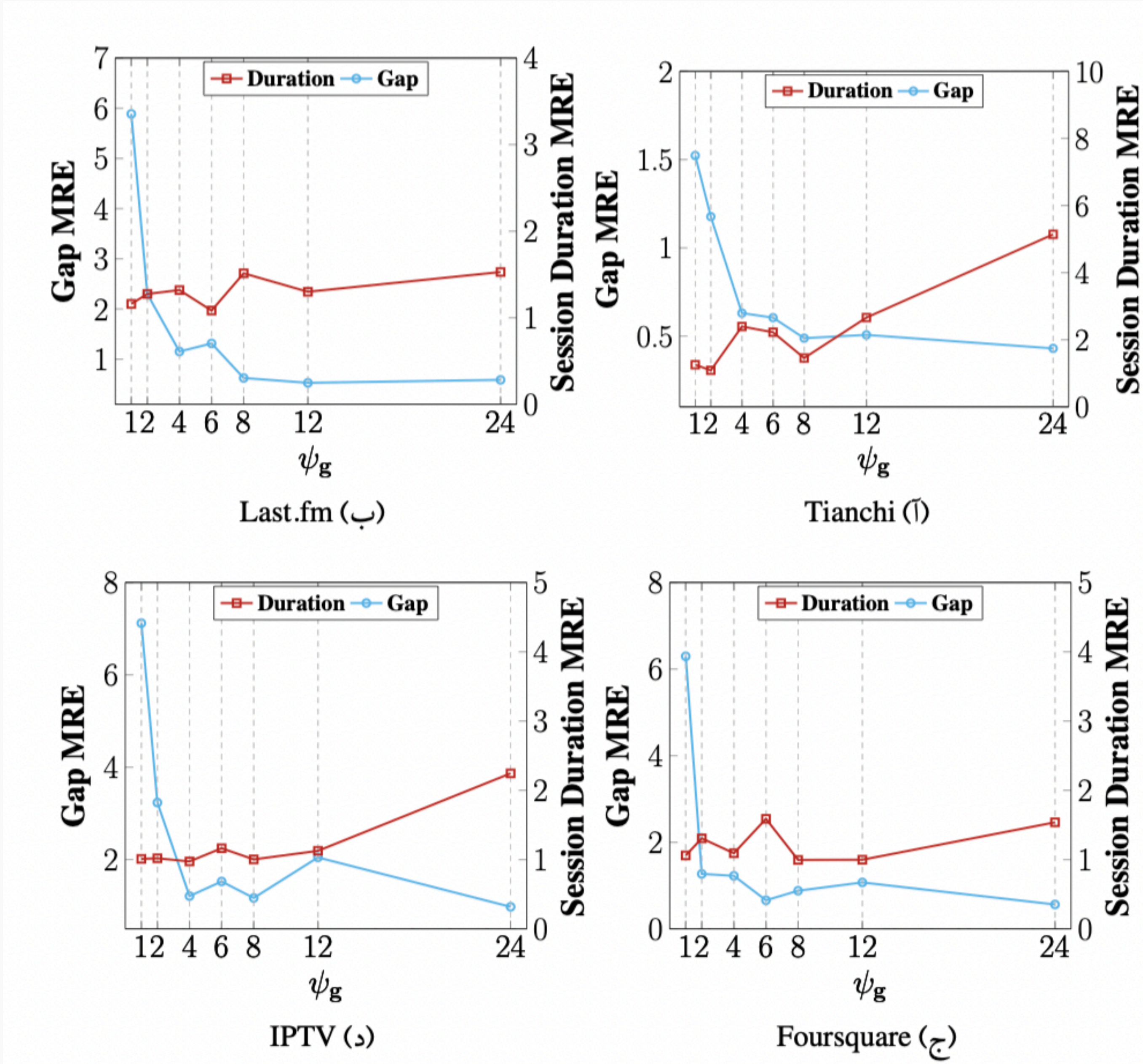


Experimental Results: Returning Time Prediction



a)Last.fm b)Tianchi c)IPTV d)Foursquare

Experimental Results: Returning Time Prediction



Last.fm (ب) Tianchi (آ)

IPTV (د) Foursquare (ج)

Summary

- ❑ Neural point processes provide a framework to learn dependency among events from data
- ❑ ChOracle is a neural point process which is able to model the user return times to the service

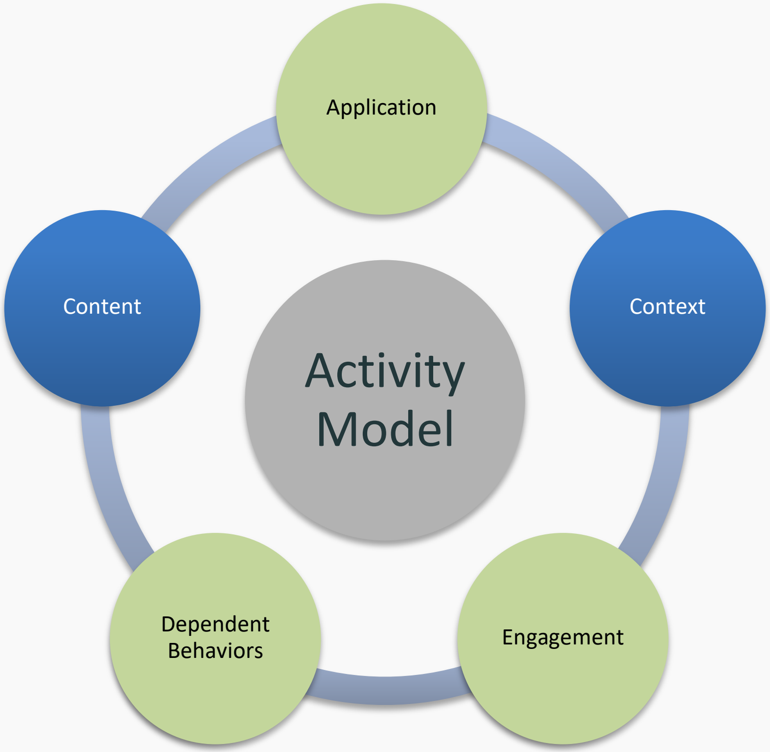
- ❑ Contributions:
  - Modeling the user churn in a continuous time manner
  - Using VRNNs to model the intensity function of point process
  - Incorporating the latent variables to improve the expressive power of RNN

Content

C4 Model

Modeling the spread of multiple correlated behaviors.

- Proposing a convex optimization formulation to learn the latent diffusion network and predict future events.
- Crawling a compelling dataset on a music streaming service.



C4-Generative Model

1. Draw time of events from a mutually-exciting Hawkes process:

$$t \sim PP\left(\lambda_u(t) = \sum_p h_{up}(t)\right)$$

$$h_{up}(t) = \mu_{up} + \sum_{e \in \mathbf{D}^p(t)} \alpha_{u_e u} e^{-(t-t_e)}$$

2. Draw type of behavior from a soft-max probability function:

$$p|t \sim \frac{\exp\left(\beta h_{up}(t)\right)}{\sum_q \exp\left(\beta h_{uq}(t)\right)}$$

- The likelihood is as the following:

$$\log \mathcal{L}(\theta|\mathcal{D}) = \sum_{i=1}^{|\mathcal{D}|} \log \lambda_{u_i}(t_i) - \sum_{u=1}^{N} \int_0^T \lambda_u(s)ds + \sum_{i=1}^{|\mathcal{D}|} \beta h_{u_i p_i}(t_i) - \sum_{i=1}^{|\mathcal{D}|} \log \left(\sum_{q=1}^{M} \exp\left(\beta h_{u_i q}(t_i)\right) \right)$$

- It can be decomposed:

$$\log \mathcal{L}(\theta|\mathcal{D}) = \sum_{u=1}^{N} \log \mathcal{L}(\theta_u|\mathcal{D}_u)$$

- Parameters can be learned in a distributed manner

$$\min_{\theta_u} \; -\log \mathcal{L}(\theta_u|\mathcal{D}_u) \quad s.t. \quad \theta_u \geq 0$$

Experiments

Data Sets

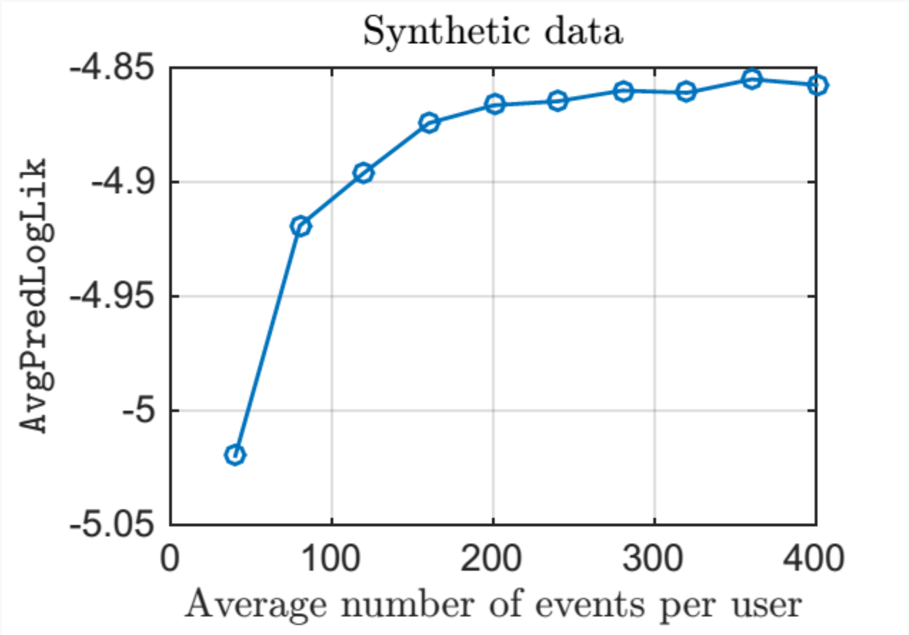
Statistics of Datasets for Evaluating Temporal Activity Model

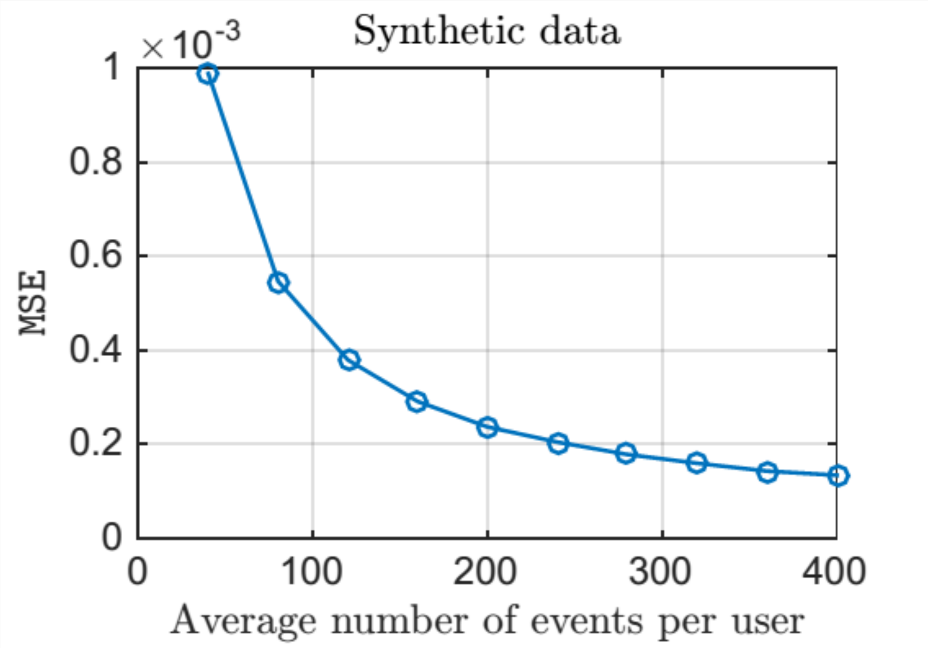
Characteristics	Synthetic	Real	
		URL Shortening	Music Streaming
Nodes	50	1000	1000
Activity Types	5	3	2
Events per node	400	100	50

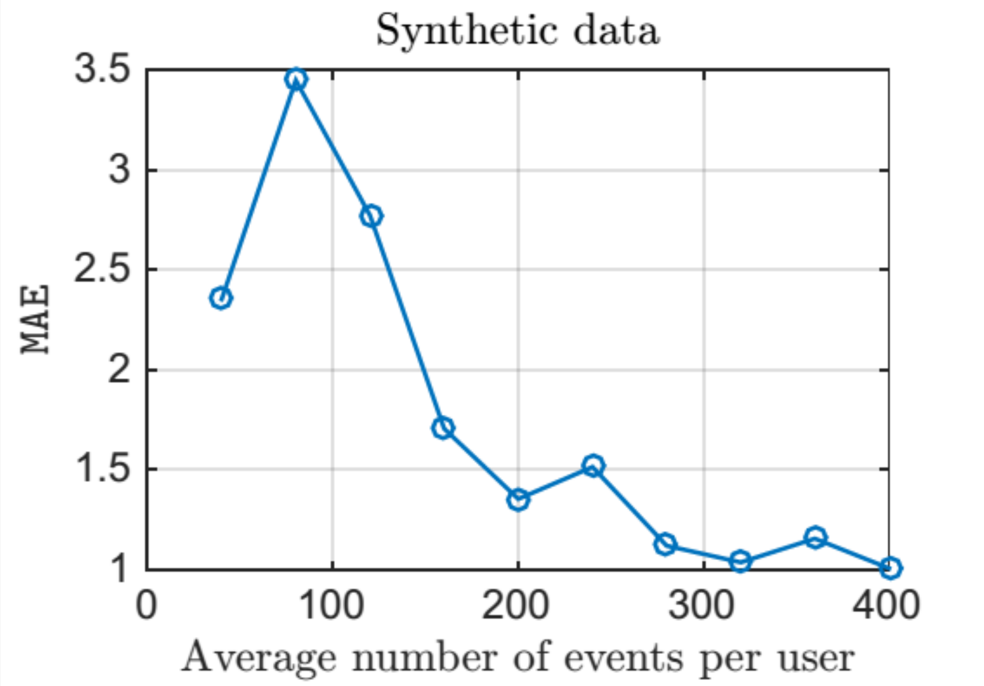
Algorithms for evaluation of temporal model

- Correlated Cascades (CC), proposed method
- Independent Cascades (IC)
- Competing Products (CP)

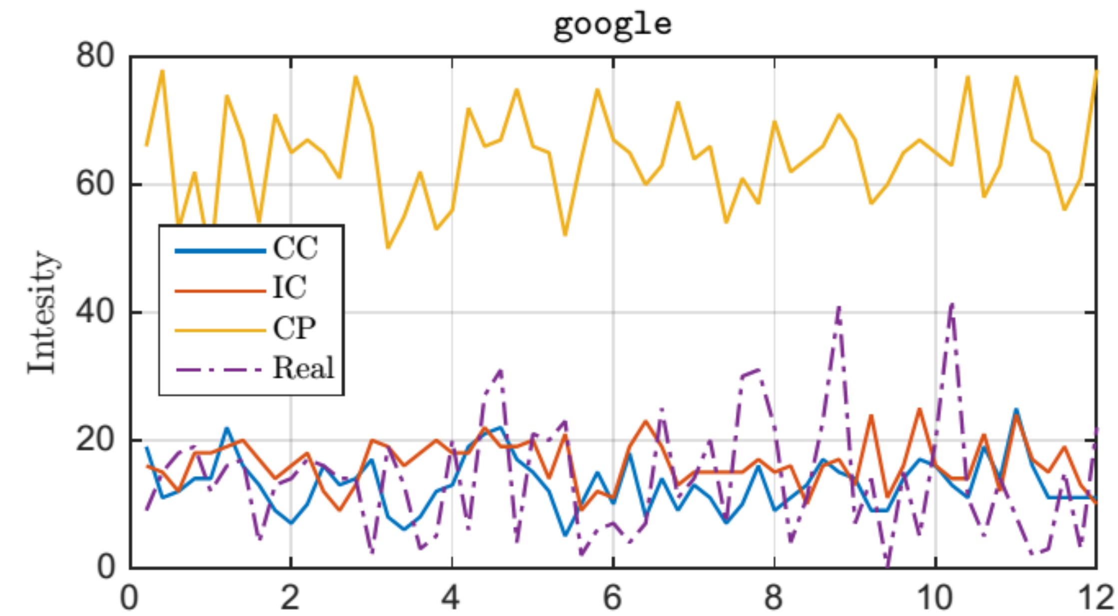
Synthetic Data Experiments

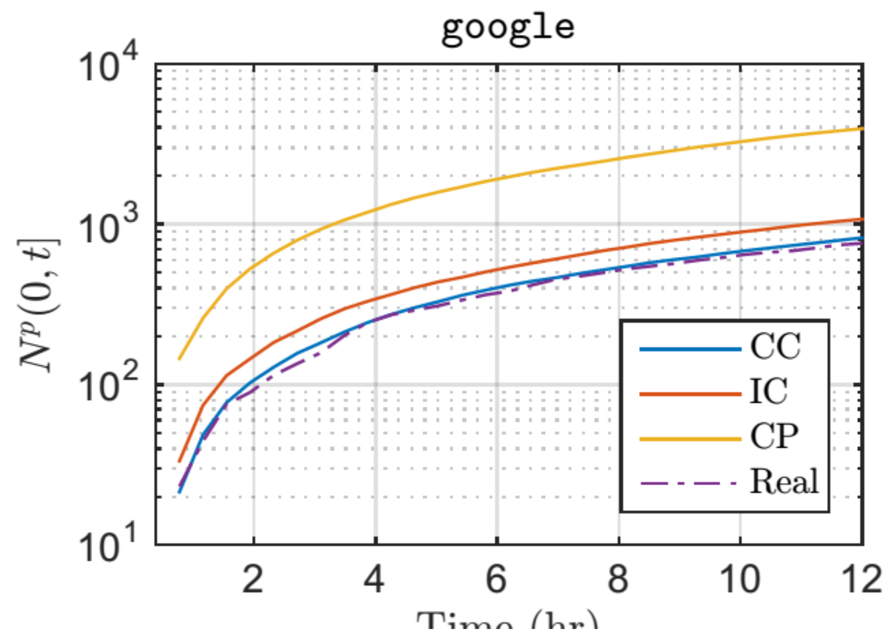


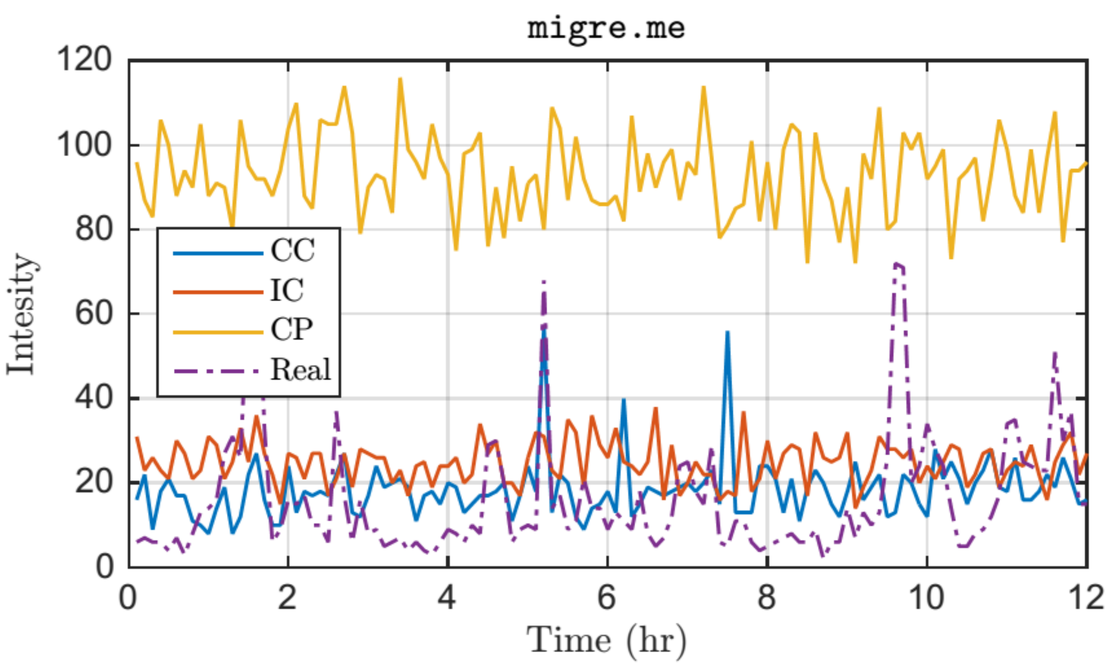


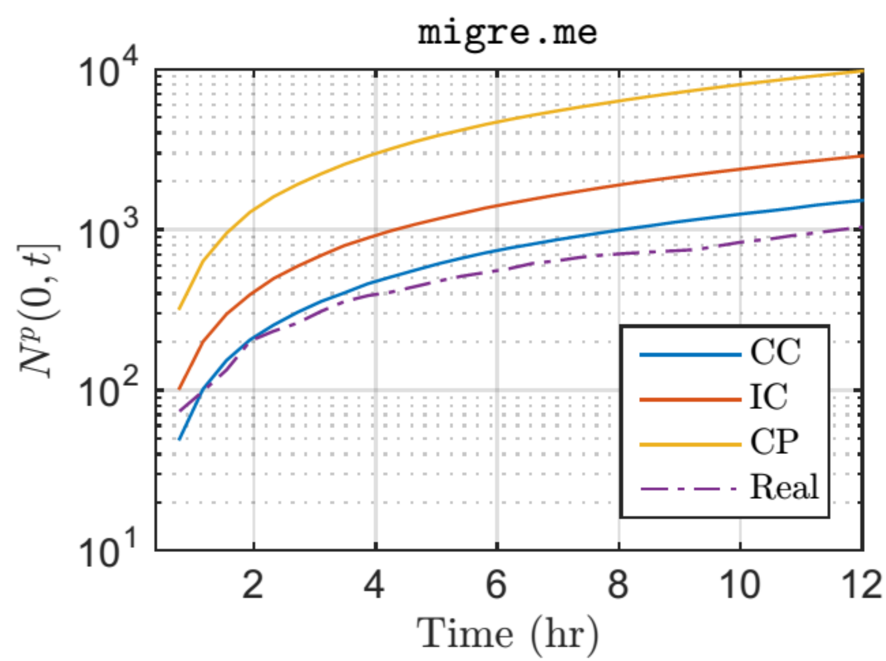


Real Data Experiments

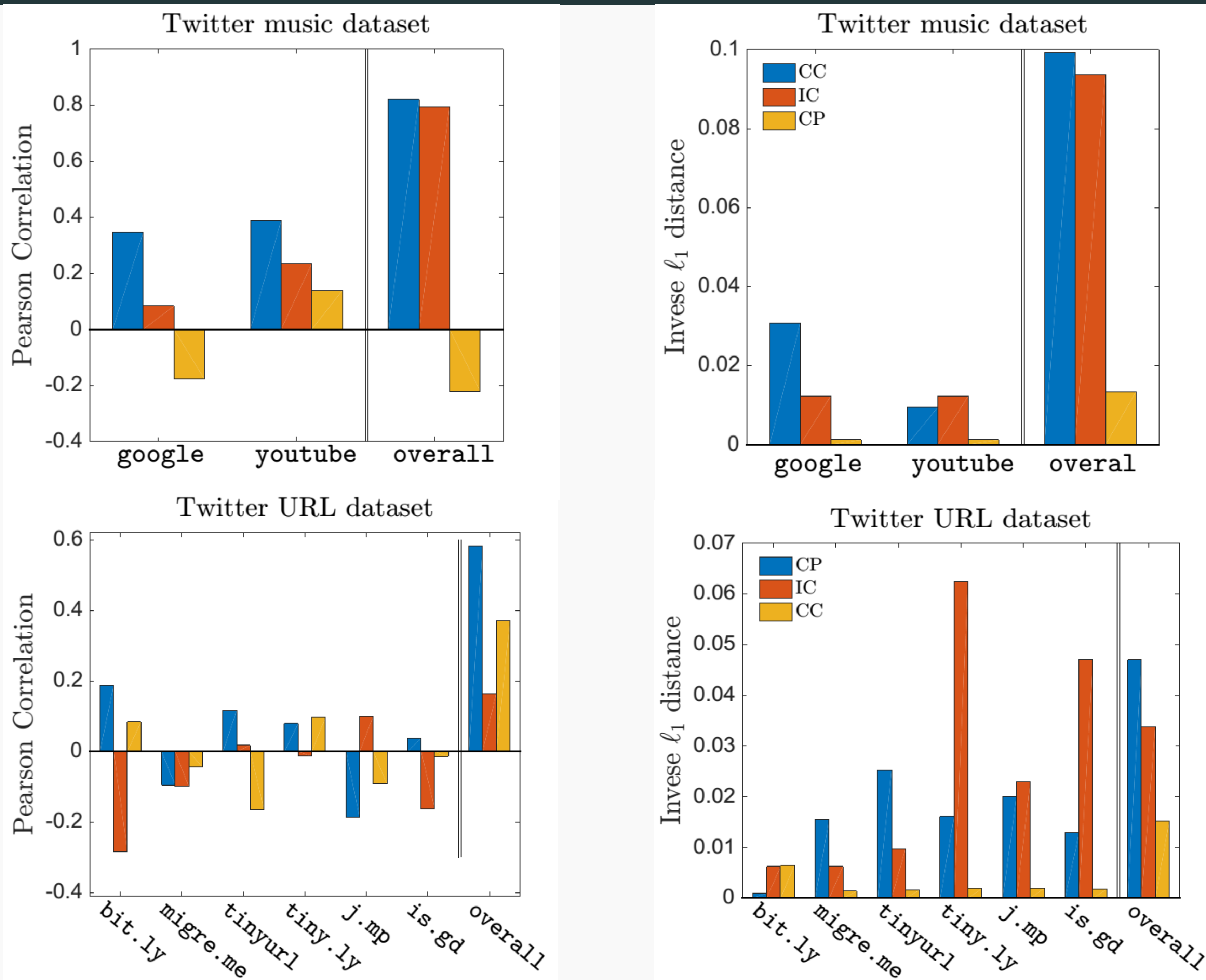








Real Data Experiments



Summary

- C4 provides a new approach for modeling the diffusion of multiple dependent products.

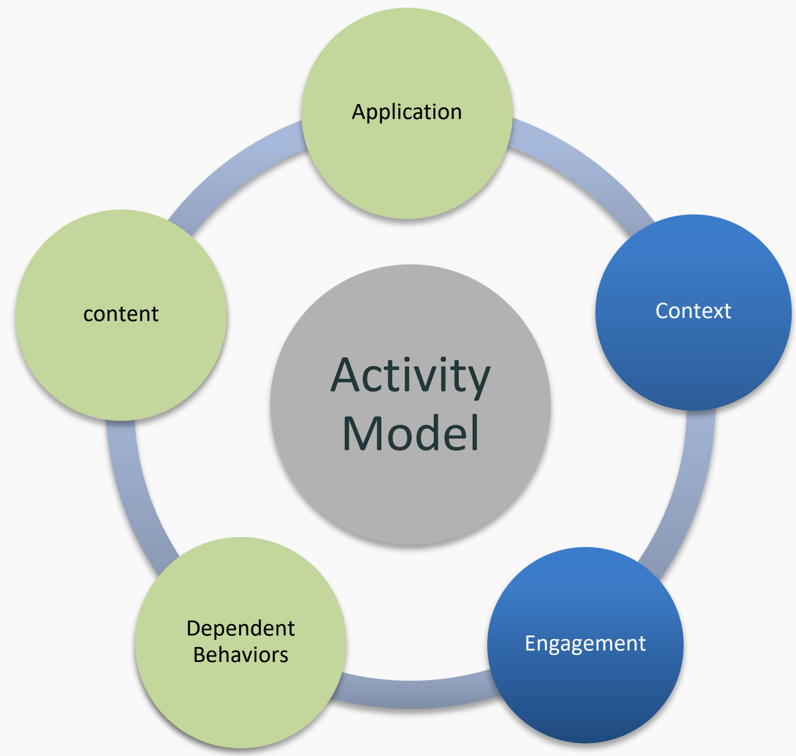
- Contributions:
  - Modeling competitive and cooperative diffusions.
  - Proving the convexity of objective function.
  - Crawling data sets.

RPF Model

Temporal Recommender Systems

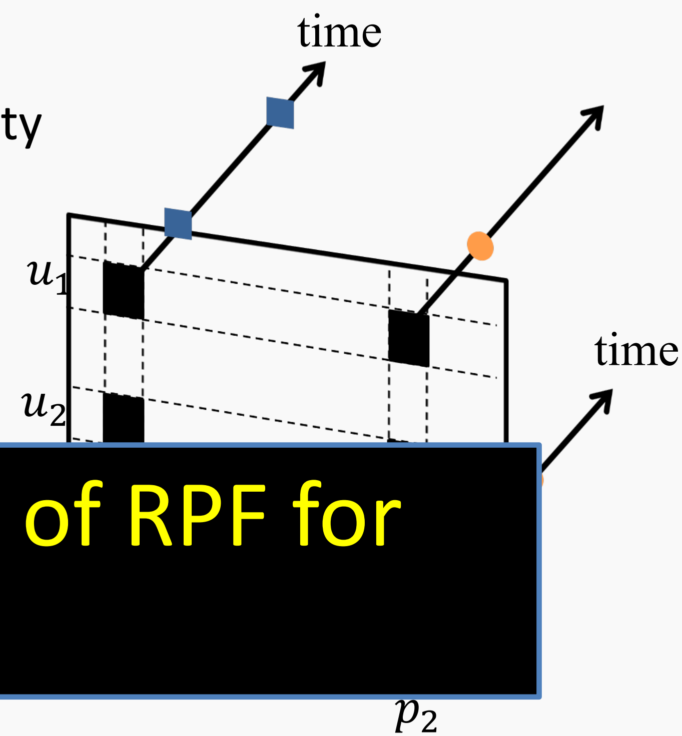
- Extending the PF framework to a continues time version
- Proposing different variants of model

- Proposing inference algorithm based on variational inference.

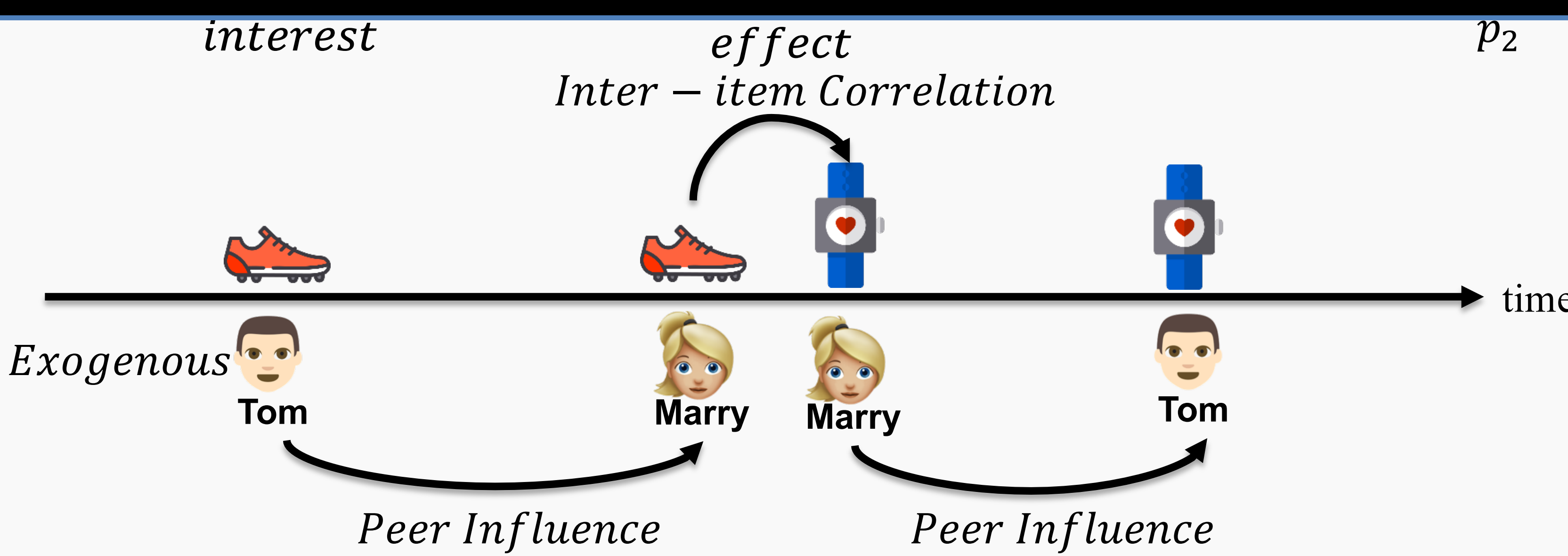


Recurrent Poisson Factorization

- ❑ Learning Common latent patterns among users interests
- ❑ Modeling Diversity of user's interests and item's popularity
- ❑ Dynamic users' interest and items' popularity over time
- ❑ Peer influence among users
- ❑ Inter-item correlations



We introduce different variants of RPF for different scenarios



Variants of RPF

$$\lambda_{up}(t) = \theta_u^\top \beta_p + \sum_{e \in H_{up}(t)} g_\omega(t, t_e)$$

$$\theta_{uk} \sim gamma(a_\theta^{shp}, \eta_u)$$
$$\beta_{pk} \sim gamma(a_\eta^{shp}, \xi_p)$$

$$\eta_u \sim gamma\left(a_\eta^{shp}, a_\eta^{rte}\right)$$
$$\xi_p \sim gamma\left(a_\xi^{shp}, a_\xi^{rte}\right)$$

HRPF

$$\lambda_{up}(t) = \theta_u^\top \beta_p + \sum_{v \in N_u} \sum_{e \in H_{vp}(t)} \tau_{vu}\, g_\omega(t, t_e)$$

$$\tau_{uv} \sim gamma(a_\eta^{shp}, \mu_u)$$

$$\mu_u \sim gamma\left(a_\mu^{shp}, a_\mu^{rte}\right)$$

SRPF

$$\lambda_{up}(t) = \theta_u^\top(t) \beta_p(t) + \tau_{uu} \sum_{e \in H_{up}(t)} g_\omega(t, t_e)$$

$$\theta_u(t) = \sum_{i=1}^{I} \theta_u^i h_i(t)$$

$$\beta_p(t) = \sum_{j=1}^{J} \beta_p^j l_j(t)$$

DRPF

$$\lambda_{up}(t) = \theta_u^\top \beta_p + \phi_u \sum_{e \in H_u(t)} \alpha_{p_e p} g_\omega(t, t_e)$$

$$\alpha_{pq} = \beta_p^\top \beta_q \qquad p \neq q$$

IIRPF

Inference

- In order to make the model conditionally conjugate, we introduce an auxiliary variable

$$\lambda^*_{up}(t,s) = \begin{cases} \theta^{i_s}_{uk_s}\beta^{j_s}_{pk_s} h_i(t) l_j(t) & -K \times I \times J < s \leq 0 \\ \tau_{u_s u} g_\omega(t - t_s) & 0 < s < N, p_s = p \\ \phi_u \alpha_{p_s p} g_\omega(t - t_s) & 0 < s < N, u_s = u, p_s \neq p. \end{cases}$$

- Since finding the exact posterior is computationally infeasible, we approximate it with a fully factorized function using variational Bayesian method:

$$\begin{aligned} & q(S, \beta, \theta, \tau, \pi, \phi, \xi, \eta, \mu, \psi, \rho) \\ & = \prod_{e \in E} q(s_e|\gamma^s_e) \prod_{p,k,j} q(\beta^j_{pk} \mid \gamma^{\beta,j}_{pk}) \prod_{u,k,i} q(\theta^i_{uk} \mid \gamma^{\theta,i}_{uk}) \\ & \prod_u q(\xi_u \mid \gamma^\xi_u) \prod_p q(\eta_p \mid \gamma^\eta_{pk}) \prod_{u,v} q(\tau_{uv} \mid \gamma^\tau_{uv}) \prod_u q(\mu_u \mid \gamma^\mu_u) \\ & \prod_{b,b'} q(\pi_{bb'} \mid \gamma^\pi_{bb'}) \prod_b q(\rho_b \mid \gamma^\rho_b) \prod_u q(\phi_u \mid \gamma^\phi_u) \prod_u q(\psi_u \mid \gamma^\psi_u). \end{aligned}$$

- The optimal q functions based on KL divergence can be found by:

$$\ln q^*_j(\cdot) = \mathbb{E}_{i \neq j}[\ln p(E, S, \beta, \theta, \tau, \pi, \phi, \xi, \eta, \mu, \psi, \rho)] + \text{const}$$

- The complexity of each iteration of algorithm is O(N+UK+PK)

Prediction

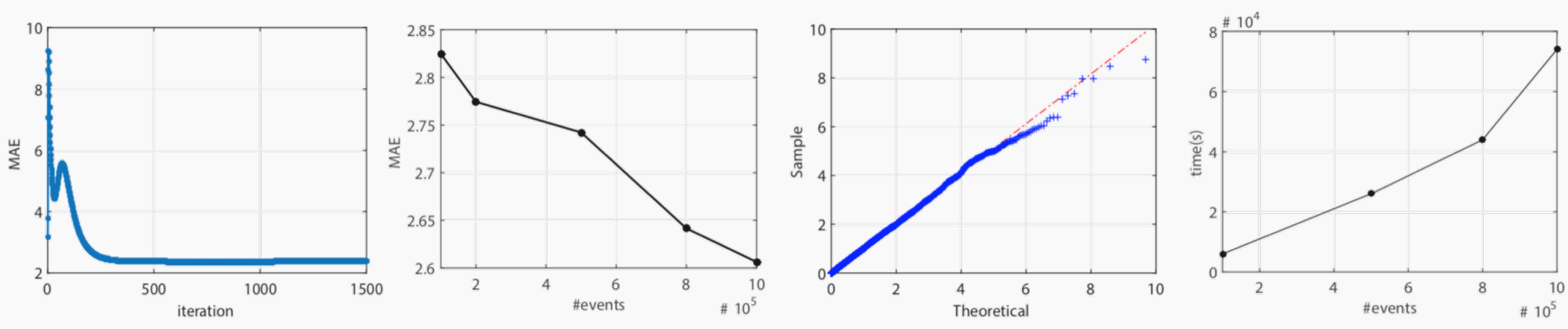
- Item Recommendation:
  - Sort items for a user based on the expected intensity of the user to engage with the item

$$E\left[\lambda_{up}(t)\right] = E[\theta^{\top}]E\left[\beta_p\right] + \sum_{v\in N_u}\sum_{e\in H_{vp}(t)} E[\tau_{vu}]g_{\omega(t_e,t)} + E[\phi_u]\sum_{e\in H_{u\overline{p}}} E\left[\alpha_{p_e p}\right]g_{\omega}(t_e,t)$$

- Returning Time Prediction
  - Sample from Poisson Process with intensity $E[\lambda_u(t)]$ using Ogata's algorithm
  - Report sample mean as the returning time of the user

Experimental Results - Synthetic

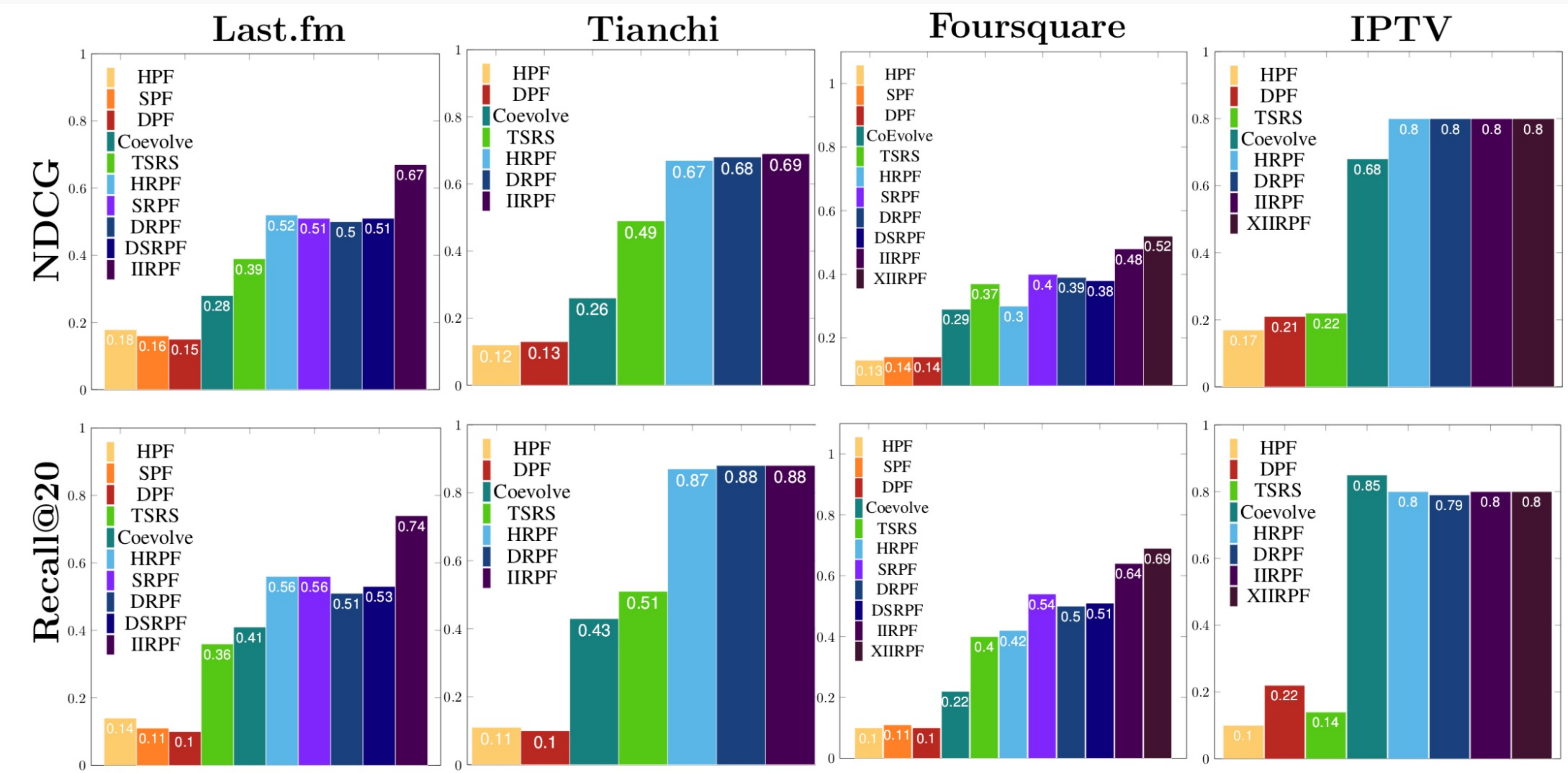
- Dataset Generation:
  - 1M interaction among 1000 users and 1000 products generated using SRPF model
  - The experiments are repeated 10 times and average over runs are reported
- Results:
  - Algorithm converges fast
  - Algorithm estimates become more accurate with more number of events
  - The learnt model captures the temporal dynamics very well
  - Algorithm runtime is almost linearly scalable.



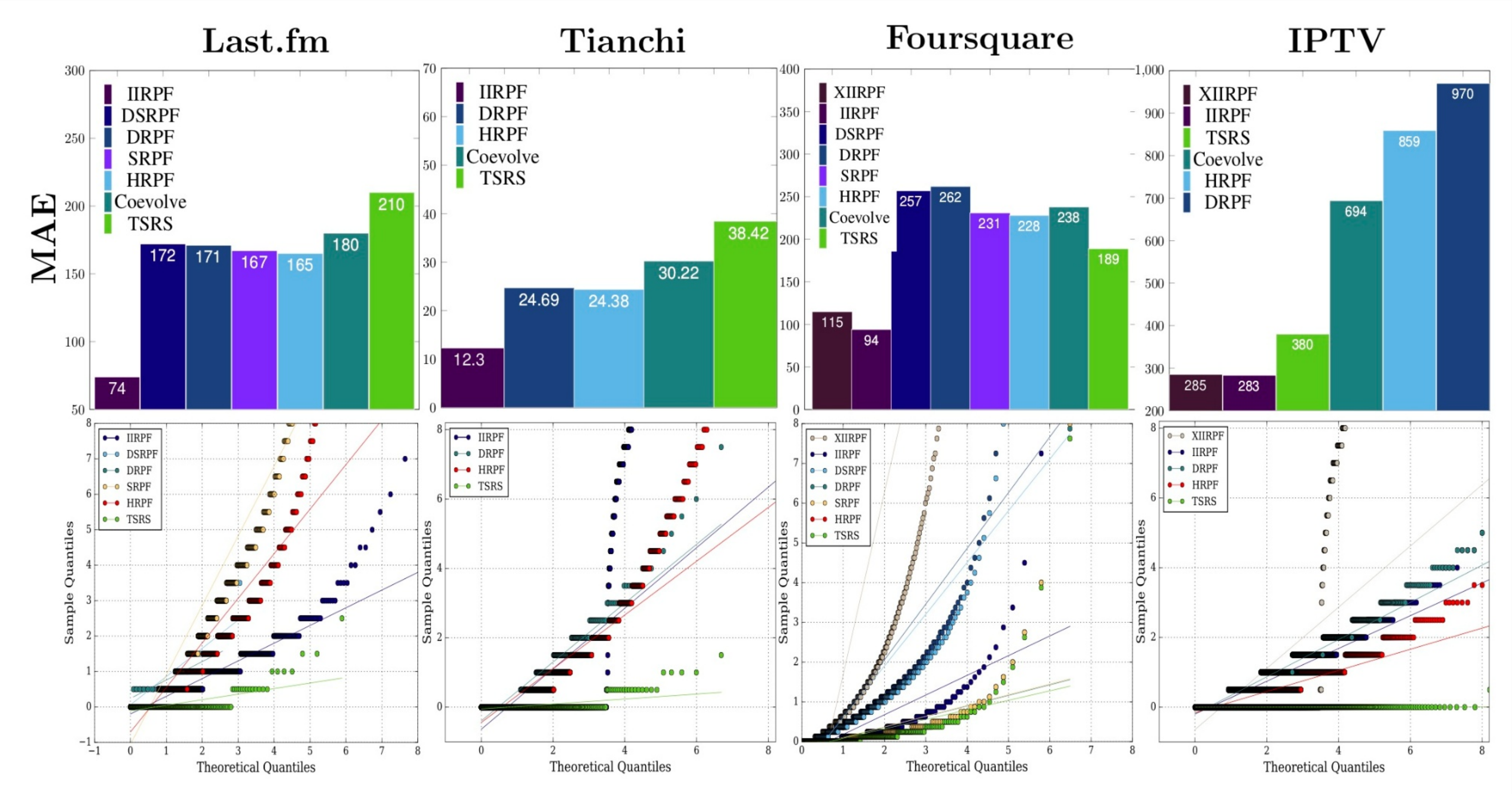
Experimental Results – Real Data

- **Dataset:**
  - **Last.fm:** **418K** music listening logs of **1200** users and **1000** artists in **6 months**
  - **Tianchi:** **1.2M** click logs of **1000** users on **2100** items in Alibaba platform
  - **Foursquare:** **67K** check-ins of **890** users in **1158** venues with category and exact location
  - **IPTV:** **2.4M** event log of **7100** users watching **436** TV programs with 1420 features
- **Train data selection:**
  - Sort events based on time and select first 80% for training and leave the rest for test
- **Quantitative tasks:**
  - Item prediction
  - Returning time prediction

Quantitative Results: Item Recommendation



Quantitative Results: Returning Time Prediction



Summary

- General framework for modeling marked events
    - Providing a low-dimensional framework to infer users’ interests over time
    - Provides different methods to model inter-event effects

- Contributions:
    - Extending the application of TPP to recommender systems
    - Extending the PF framework to continuous time version
    - Proposing different variants for different scenarios
    - Proposing an inference algorithm based on variational inference

Conclusion and Final Remarks

- **Modeling user behavior:** An emerging topic with huge impact in different application areas
- **Temporal Point Process**: A rich theoretical framework for modeling asynchronous event data
- **Our work**: Modeling user behavior paying more attention to engagement and content
  - **User Engagement Modeling:**
    - UMUB
    - ChOracle
  - **Content Modeling:**
    - C4
    - RPF

RPF

$$\theta_u^\top(t) r(t) \quad \sum \quad \sum \quad \tau_w g_w(t_e, t) \quad \phi_u \quad \sum \quad \alpha_{p_e} g_w(t_e, t)$$

ChOracle

$$\lambda_u(t) = f(H_u(t))$$

$$\mu_u + \sum_{s \in B} g(h_s(\mathbf{D}(t)), \tau_s)$$

UMUB

$$\mu_u + \sum_{e \in \mathbf{D}(t)} \alpha_{u_e u} \, e^{-(t - t_i)}$$

C4

Future Works

- ❑ Incorporating other gamification elements in the user activity model
  - Reputation system, …
- ❑ The badge placement and control of user behaviors
  - When to post problem
- ❑ Incorporating the other types of neural networks in defining intensity function of point process
  - GAN
- ❑ Incorporating the social impact on the intensity of neural point processes
- ❑ Combining stochastic neural point processes with Bayesian nonparametric models to model non-stationary event data
- ❑ Online learning of model parameters

Publications

1. "*Continuous-Time User Modeling in Presence of Badges: A Probabilistic Approach*", **Khodadadi**, Hosseini, Tavakoli, Rabiee, **ACM Transactions on Knowledge Discovery from Data (TKDD),** 2018.
2. "*ChOracle: A Unified Statistical Framework for Churn Prediction*", **Khodadadi**, Hosseini, Pajooheshgar, Mansouri, Rabiee. **Submitted to IEEE Transactions on Knowledge and Data Engineering** (**TKDE),** 2018**.**
3. "*Recurrent Poisson Factorization for Temporal Recommendation*", Hosseini, **Khodadadi**, Alizadeh, Arabzadeh, Farajtabar, Zha, Rabiee, **ACM SIGKDD International Conference on Knowledge Discovery and Data Mining** (**KDD**), 2017.
4. "*Recurrent Poisson Factorization for Temporal Recommendation*", Hosseini, **Khodadadi**, Alizadeh, Arabzadeh, Farajtabar, Zha, Rabiee**, IEEE Transactions on Knowledge and Data Engineering** (**TKDE**), 2018.
5. "*Correlated Cascades: Compete or Cooperate*", Zarezade, **Khodadadi**, Farajtabar, Rabiee, Zha. In **Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence (AAAI-17)**, 2017.

Publications

6. "*HNP3: A Hierarchical Nonparametric Point Process for Modeling Content Diffusion over Social Media*", Hosseini, **Khodadadi**, Arabzadeh, Rabiee, **IEEE 16th International Conference on Data Mining (ICDM)**, 2016.
7. "*Hierarchical Nonparametric Point Processes*", Hosseini, **Khodadadi**, Arabzadeh, Rabiee. **Submitted to Journal of Machine Learning Research (JMLR),** 2018**.**
8. "*Community Detection Using Diffusion Information*", Ramezani, **Khodadadi**, Rabiee. **ACM Transactions on Knowledge Discovery from Data (TKDD),** 2018.
9. "*Predicting anchor links between heterogeneous social networks*", Sajjadmanesh, Rabiee, **Khodadadi**. **Proceedings of the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM),** 2016.

Thank You!

Any Questions?