Temporal point processes in practice

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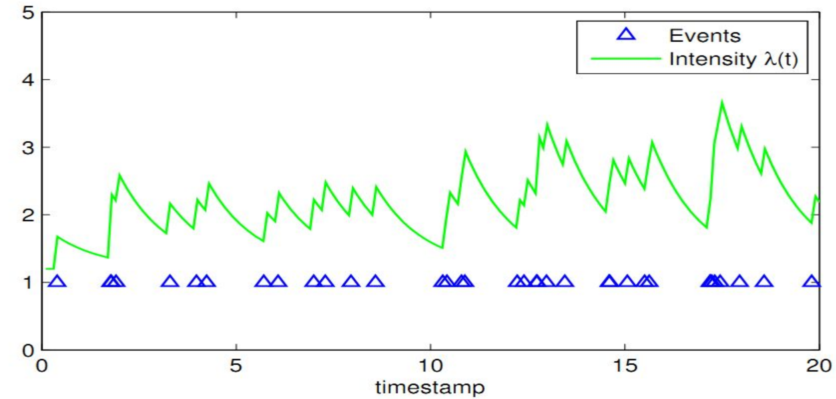
Outline

- Typical real-world applications via TPP
- Dyadic Event in temporal point process
- Marked Event in temporal point process
- Cross-domain Event in temporal point process
- Parametric influence in temporal point process

Temporal Point Process

- Describe data localized at a finite set of time points

$$\lambda(t|\mathcal{H}_t) = \lim_{\Delta t \to 0} \frac{\mathbb{E}[N(t+\Delta t)|\mathcal{H}_t]}{\Delta t}$$



Univariate Hawkes process:

Base Intensity

How likely an event will occur when no other event triggers it

$$\lambda^*(t) = \boxed{\mu(t)} + \boxed{\int_{-\infty}^{t} \kappa(t-s)dN(s)}$$

Self-exciting property: the occurrence of one event increases the probability of related events in the near future.

Influence between sequential events

Multi-dimensional Hawkes Process

Base Intensity

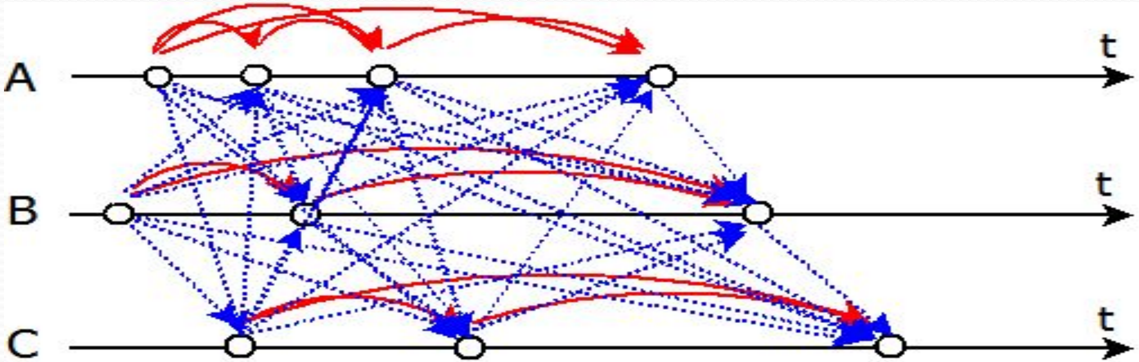
How likely an event happens on dimension m spontaneously

$$\lambda_m(t) = \boxed{\mu_m} + \boxed{\sum_{t_l < t} \alpha_{m_l,m}\kappa(t - t_l)}$$

Social Infectivity

Influence between sequential events

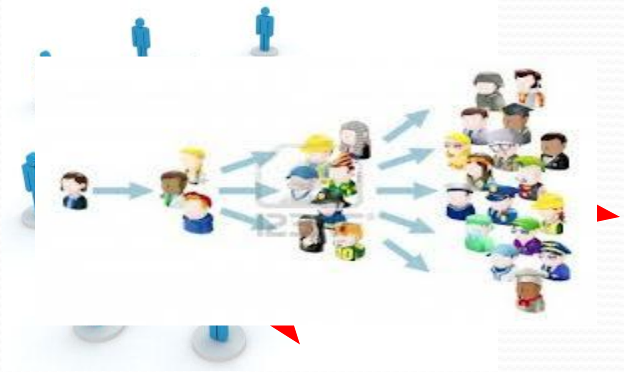
How likely a historical event will trigger an event on dimension m



MHP captures additional event influence than UHP.

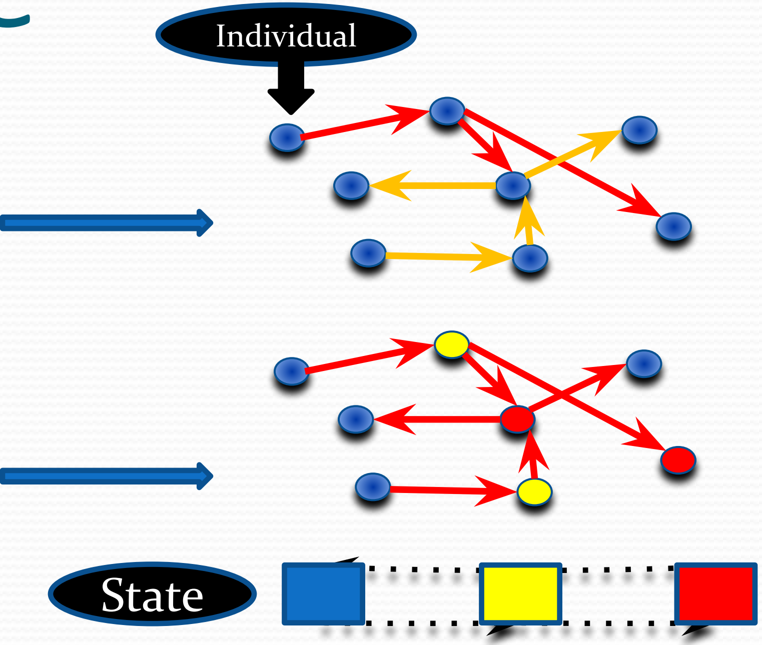
Influence

- What?
  - The effect that people have upon the beh
  - Behavior
    - Active: retweet
    - Passive: virus infection
- Why?
  - People interact & learn from the past
- Where?
  - Self-influence
  - Mutual-influence
    - Between individuals
- How?
  - Historical behaviors influence current beha



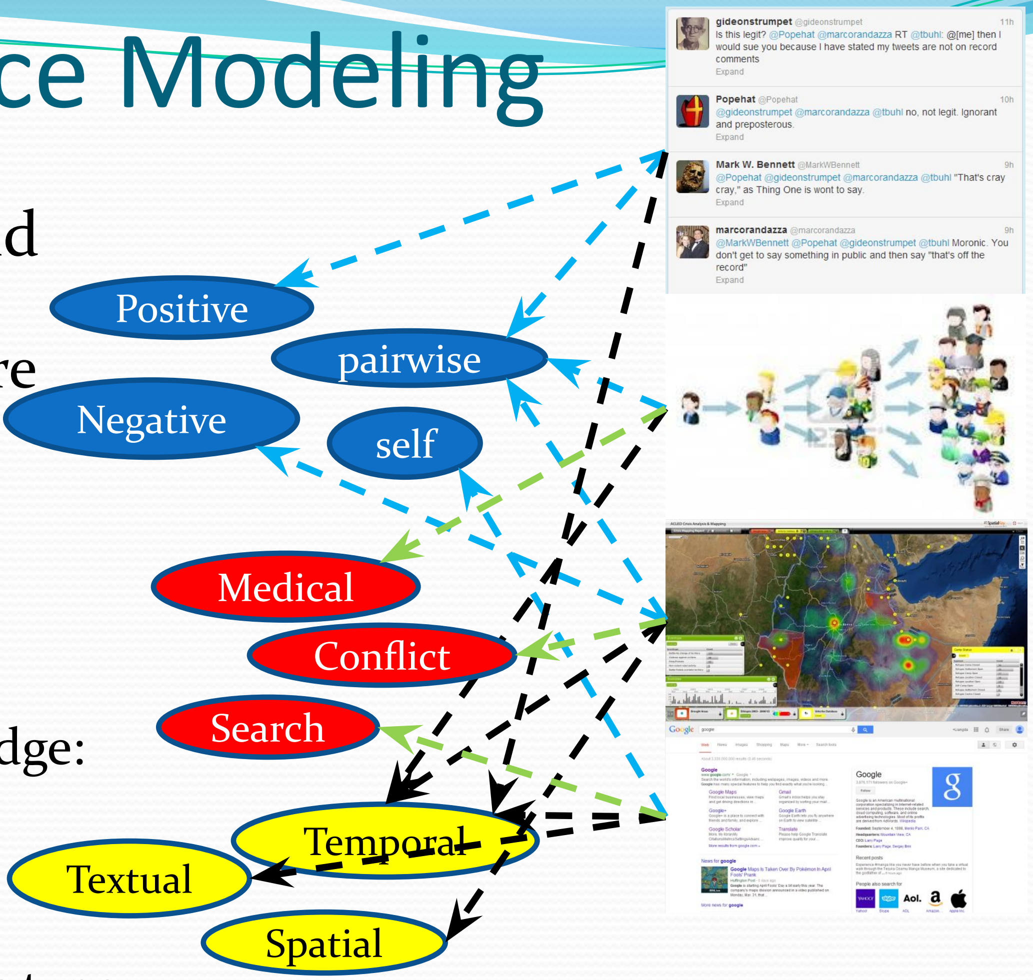
Effect & Importance

- Influenced individual
  - Carry on the same type of behavior
    - Retweet the same post;
    - Infected by the same virus.
  - Respond with some other type of behavior based on certain rules
    - The attack against one country may cause its revenge to the attacker's allies;
    - The results of current search task may trigger a related search task in the next.
- Tracking the diffusion of memes
- Study the chain reactions



Issues in Influence Modeling

- Under different real-world scenarios:
  - The specific influence are diverse:
  - Each demands unique solution using:
    - Domain-specific knowledge:
    - Observed data of specific type:



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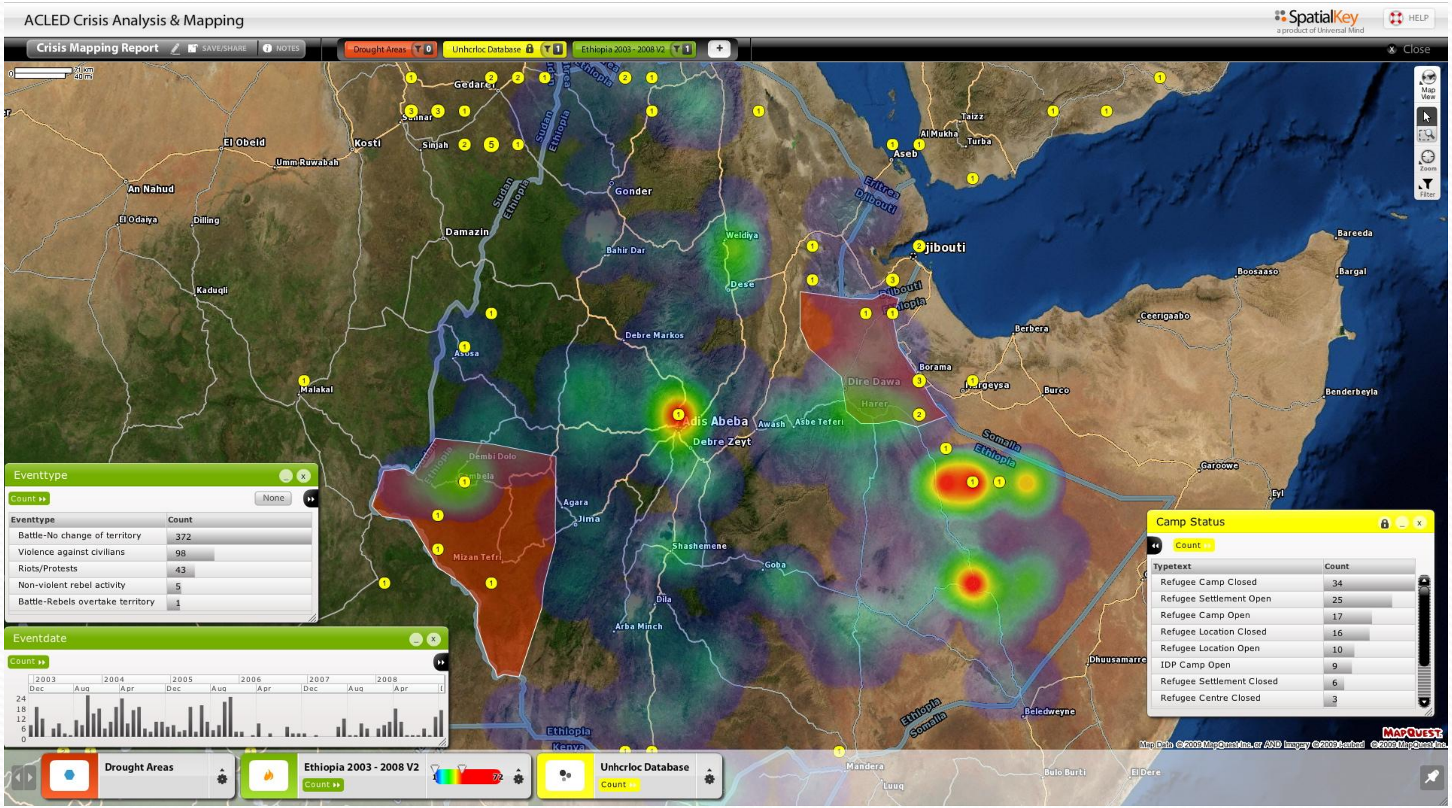
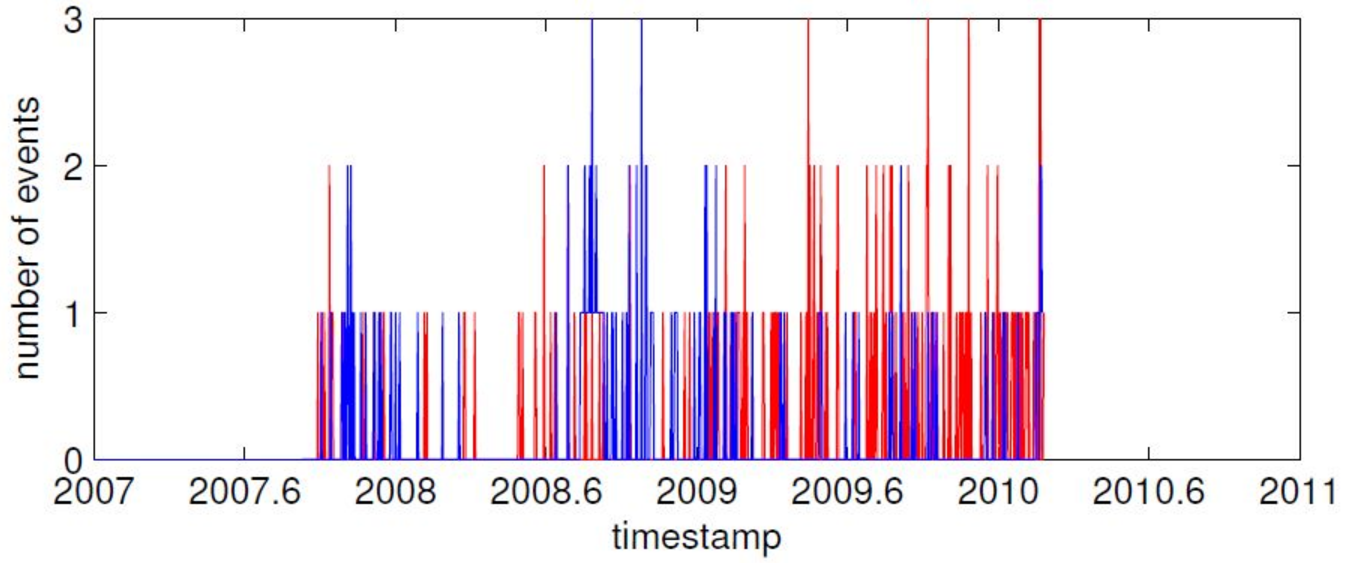
Dyadic Event

- Dyadic event: Timestamped interactions involving pairs of actors
  - Email communication, conflict between two forces
- More complicated than single actor events
- Actors of events can be unobserved – Dyadic Event Attribution Problem (DEAP)

Scenario - Conflict Data



Self- & mutual-excitation in Conflicts



- One conflict will trigger future conflicts happen between the same actor-pair;
- One conflict will trigger future conflicts that share at least one actor.

Mixture of Hawkes Process (MHP)

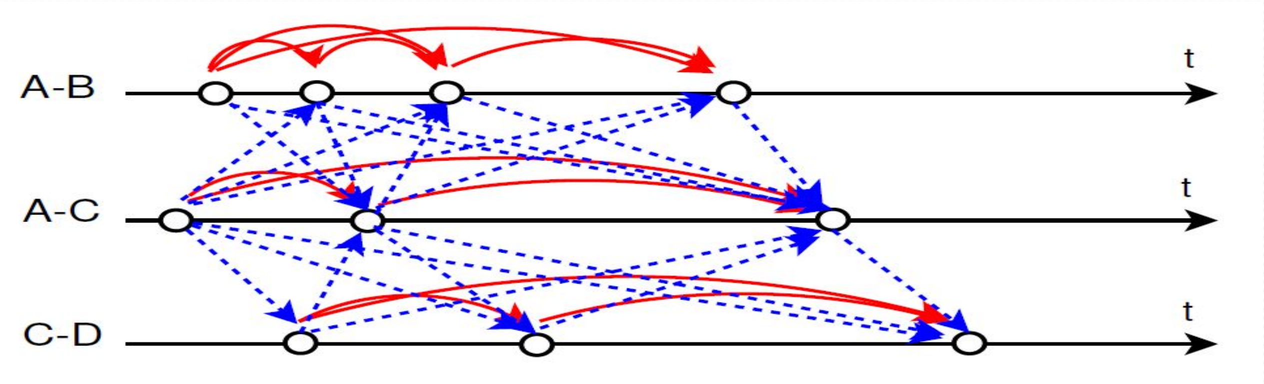
Base Intensity

How likely a conflict happens between actor-pair m spontaneously

$$\lambda_m^*(t) = \boxed{\mu_m} + \sum_{t_l<t} \boxed{\alpha_m \kappa(t-t_l) \sum_{m' \in S_m} Z_{l,m'}}$$

how likely a historical conflict will trigger a conflict between actor-pair m

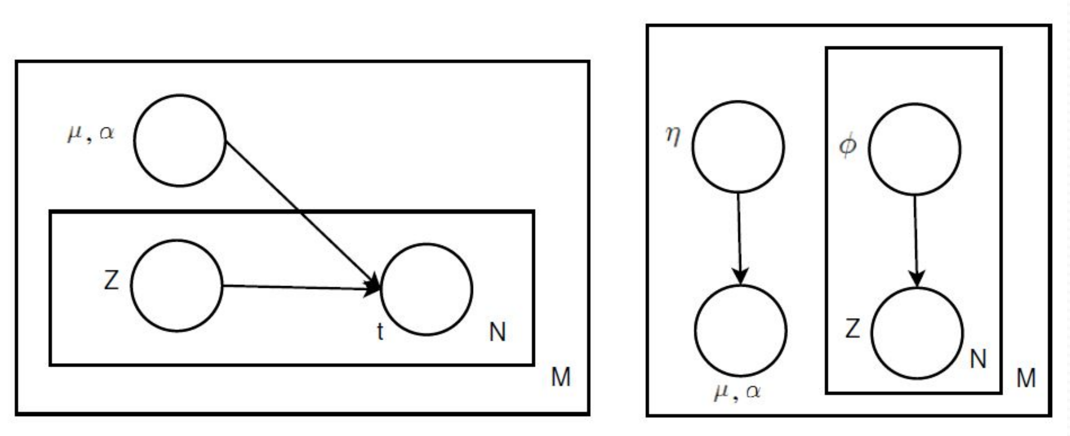
Influence between sequential conflicts



MHP captures additional event influence than existing models.

Model Inference and Additive Model

- Variational inference



$$\mu_m = \mu'_{m1} + \mu'_{m2}, \quad \alpha_m = \alpha'_{m1} + \alpha'_{m2},$$

- Additive model
  - parameterize each actor instead of each actor-pair

Accuracy of Event Attribution

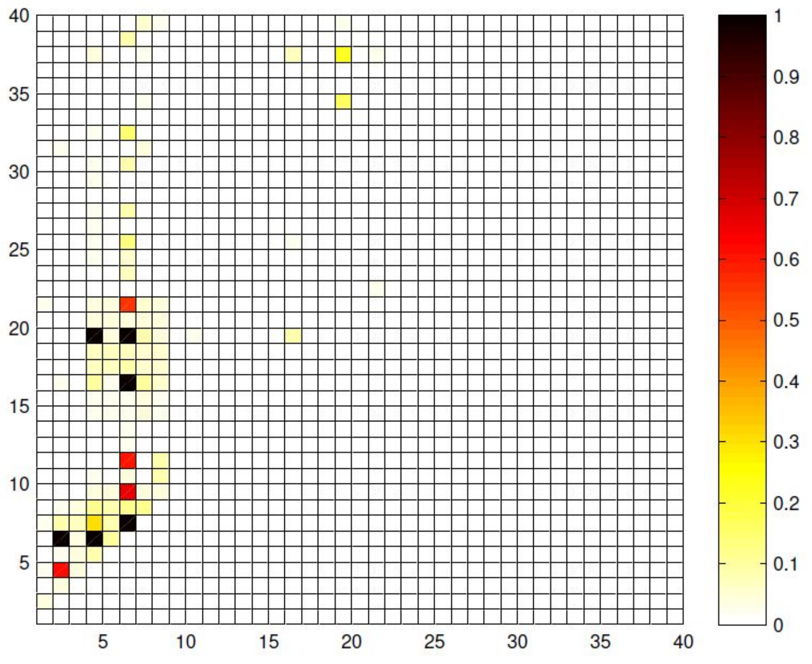
Data set	Method	Top 1	Top 2	Top 3	Top 4	Top 5
Afghanistan	PFHP	11.8%	17.0%	20.2%	21.8%	24.2%
	ESA	12.6%	18.1%	21.3%	23.0%	25.5%
	LPPM	13.4%	20.9%	23.8%	25.4%	26.5%
	MHP	14.6%	23.3%	26.8%	28.6%	30.1%
	AMHP	15.5%	24.0%	27.7%	29.3%	30.8%
Random Guess		0.1%	0.2%	0.3%	0.4%	0.5%
Africa	PFHP	9.0%	14.6%	18.2%	20.0%	22.3%
	ESA	9.9%	15.7%	19.5%	21.3%	23.7%
	LPPM	11.2%	18.7%	21.6%	23.2%	24.4%
	MHP	12.4%	20.9%	24.7%	26.1%	27.5%
	AMHP	13.1%	21.5%	25.4%	26.9%	28.1%
Random Guess		0.1%	0.2%	0.3%	0.4%	0.5%

Afghanistan:
3384 dyadic events
68 actors
1010 actor-pairs

Africa:
52605 dyadic
events
3537 actors
1007 actor-pairs

- The model not only fits timestamps of loan occurrence, but also accurately predicts loan types.

Relational Graph

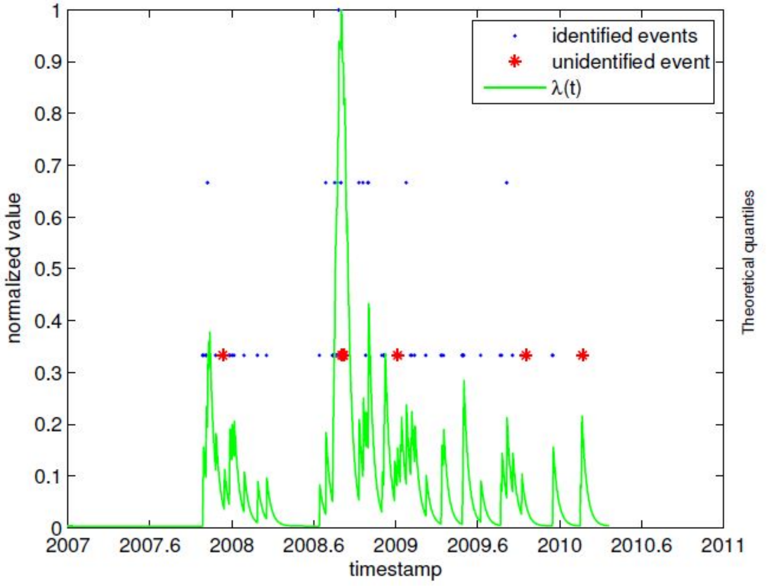


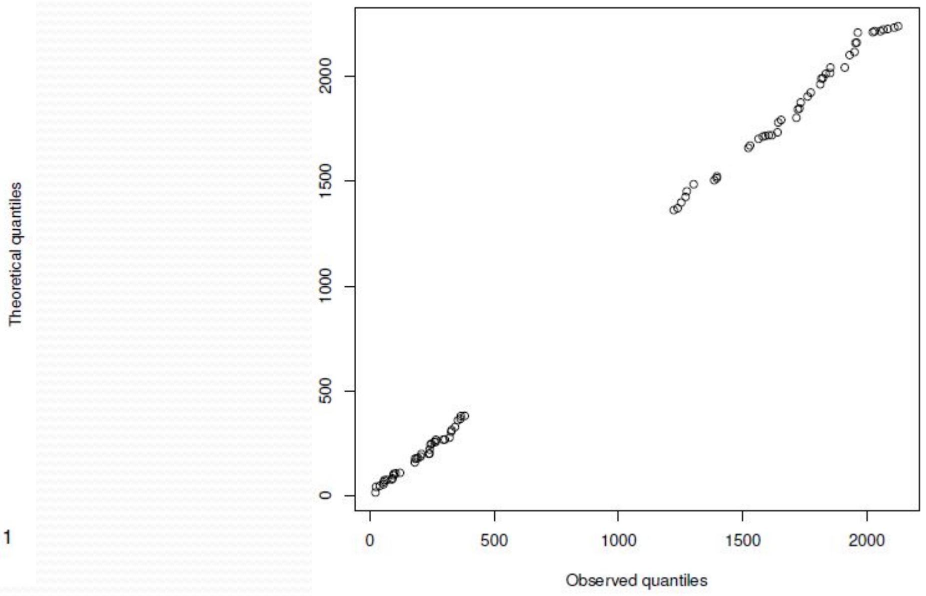
Indice of important actors:

4-Civilans
6-Taliban
7-Afghanistan Army
9-Britain Army
11-Afghan Government
16-Police Force
19-ISAF

- Relational graph among actors in Afghanistan Conflict data
- Most sequential conflicts in Afghanistan happened between limited actor-pairs.

How MHP Fits Conflict Data





- Although inferred with part of actor-pair unknown, MHP fits both identified conflicts and unidentified conflicts very well.

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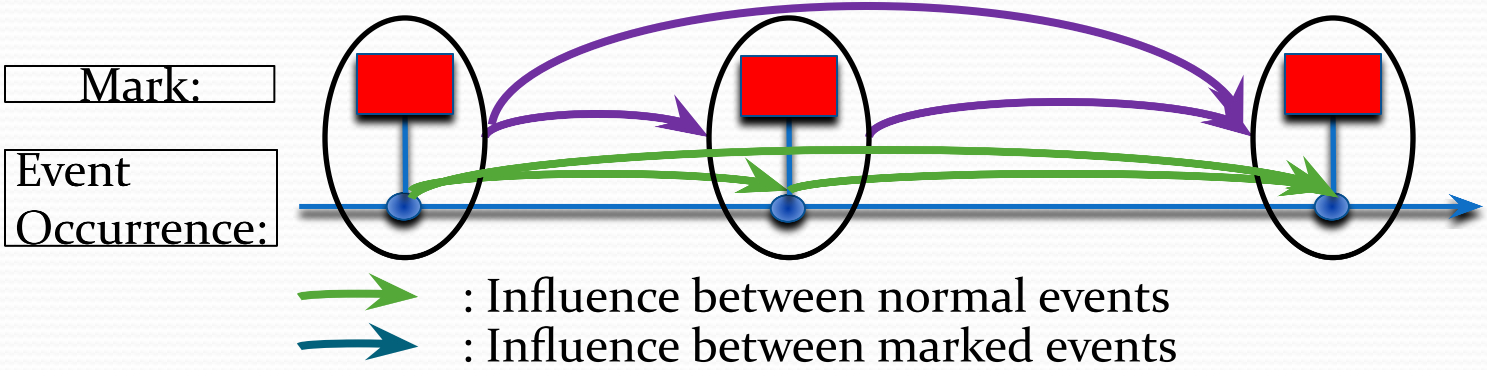
Marked Event

- Mark: detailed information of the corresponding event other than the temporal information.
- Marks can also affect the influence between events.

Event	Mark
Conflict	Casualty
Earthquake	Magnitude
Appliance usage	Consumed energy

Influence Between Marked Events



- How the occurrence and the mark of an event *together* influence the occurrence and the mark of subsequent events in the near future.

Marked Hawkes Processes

- Enables the modeling of the influence between marked events
- Directly modeling the relationship between marks and occurrences of different events is difficult
- Combine multivariate Hawkes processes and topic models

$$\lambda_m(t) = \mu_m + \sum_{t_l<t} \sum_{m'} Y_{m',l} \boxed{\sum_{k} Z_{m,n,k}} Z_{m',l,k'} \boxed{\beta_{m,m',k,k'}} \kappa(t - t_l)$$

The category membership

The number of infectivity parameters is $O(M^2K^2)$

- Enforce the sparsity of β by imposing lasso type of regularization.

Scenario - Energy Disaggregation

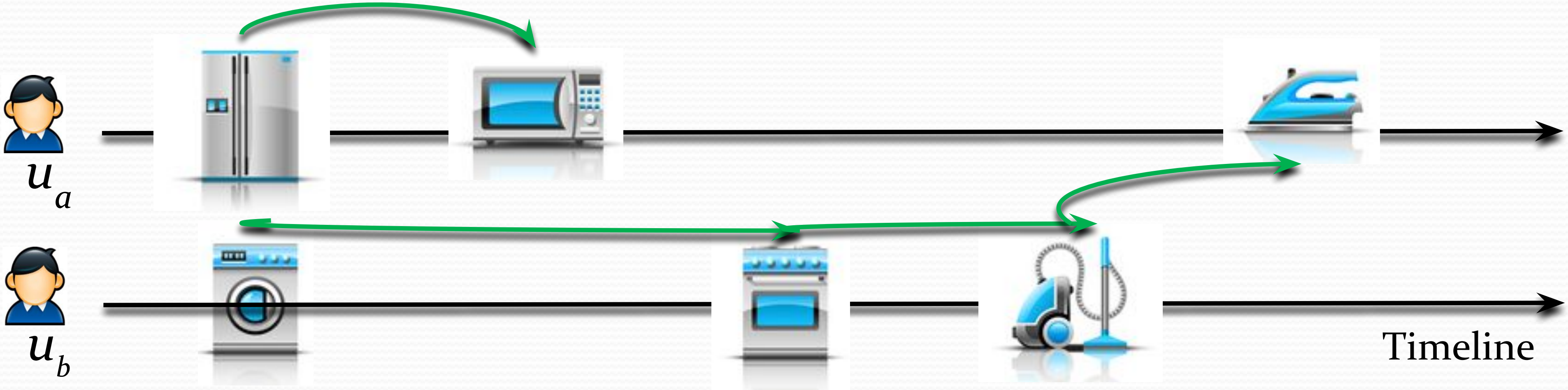
- Energy disaggregation
  - Take a whole home electricity signal and decompose it into its component appliances.
  - Essential for energy conservation
- Fine-grained energy consumption data is not readily available
  - Require numerous additional meters installed on individual appliances

User Energy Usage Behavior

- One powerful cue for breaking down the entire household's energy consumption.
  - how users perform their daily routines.
  - how they share the usage of appliances.
  - users' habits in using certain types of appliances.
- Influence between energy usage behaviors is the key to infer the usage amount

Influence in Energy Usage Behavior

- Why influence modeling is important?

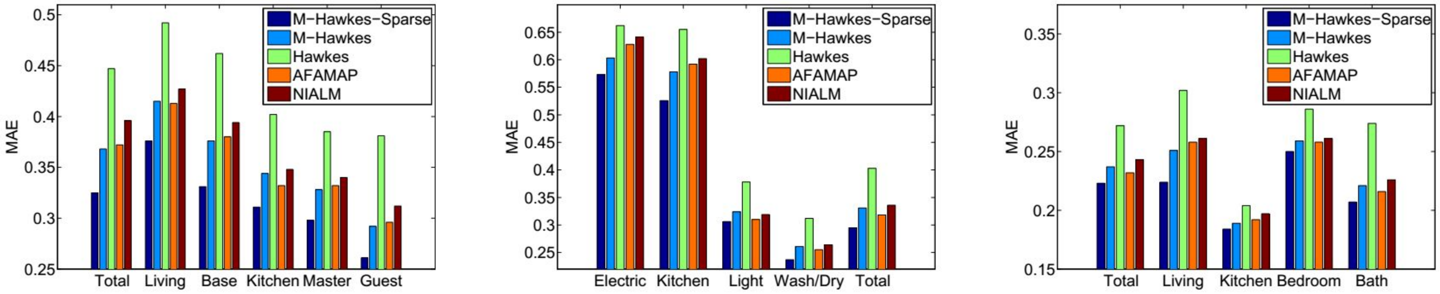


- Influence between energy usage behaviors is hard to model directly.
- Instead, model the influence among various appliances across different time slots.

Energy Disaggregation Data Set

- Smart*: 3 homes, 50 appliances
- REDD: 6 homes, 20 appliances
- Pecan: 450+ homes, 20 appliances

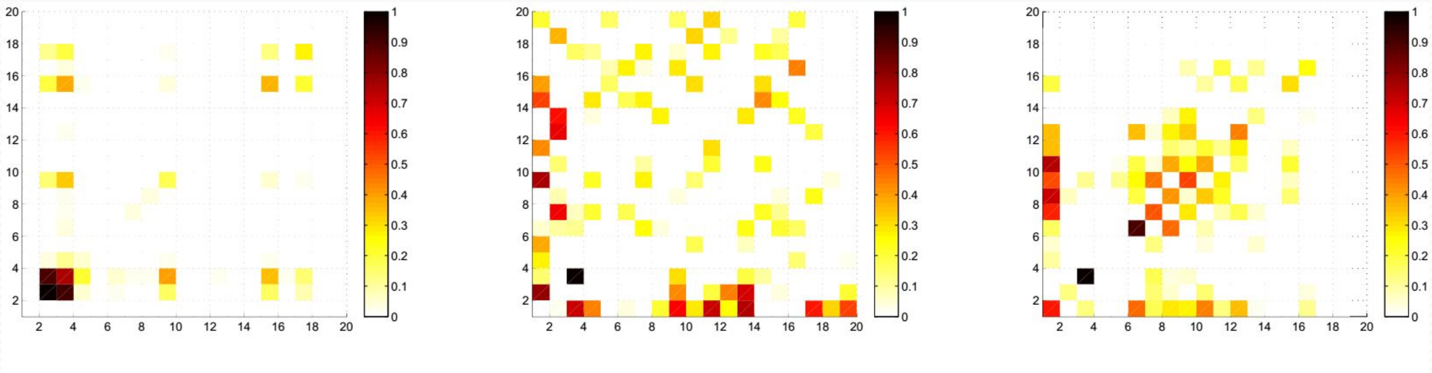
Experiments



(a) Smart* (b) REDD (c) Pecan

- M-Hawkes-Sparse > M-Hawkes > AFAMP, NIALM > Hawkes
- Only a limited number of dependencies exist between appliances in real world energy consumption.

Energy Usage Pattern

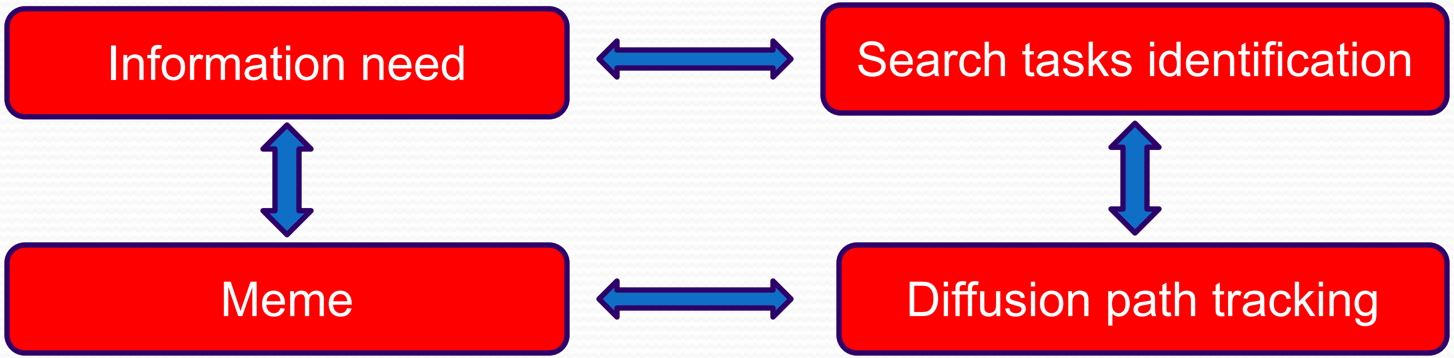


(a) Smart* (b) REDD (c) Pecan

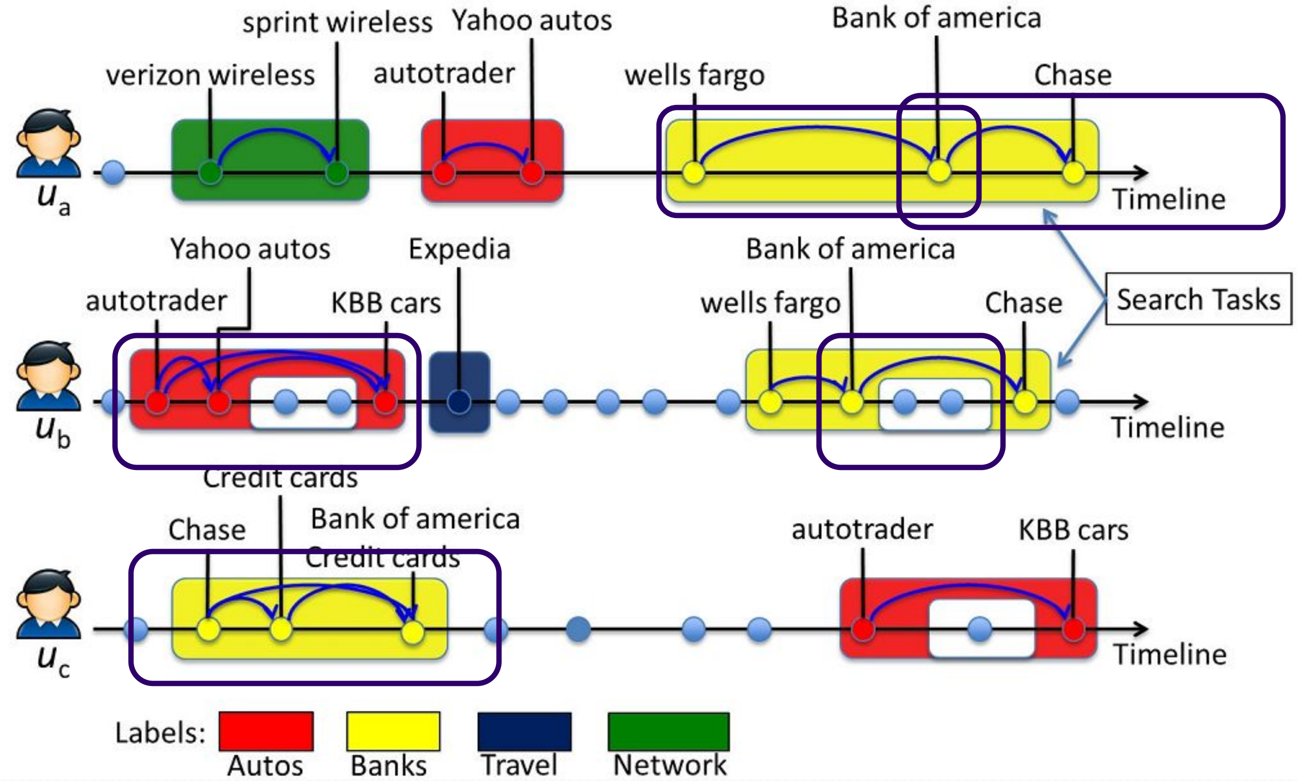
- Smart*: refrigerator-microwave > refrigerator-toaster
- REDD: washer-dryer
- Pecan: refrigerator->microwave > microwave->refrigerator

Scenario - Search Task Identification

- Search task
  - A set of queries serving for the same information need.
- Challenge
  - Intertwined multiple intents in a user's query sequence.
- Solution



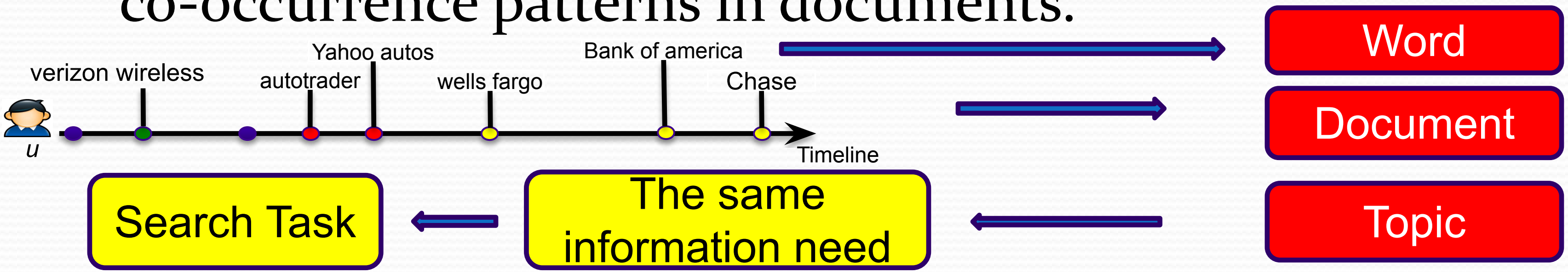
Consecutive Queries vs Search Tasks



- Consecutive or temporally-close queries issued many times are more likely semantically related, i.e., belong to one search task.

LDA and Query Co-occurrence

- LDA
  - One powerful graphical model that exploits word co-occurrence patterns in documents.



- Temporally weighted query co-occurrence
  - How a document in LDA model is defined?

Temporally weighted Co-occurrence

- Time window
  - Document: consecutive queries in a fixed time window.
  - Drawbacks:
    - No optimal solution for window choice.
    - Ignore personal information.
- Solution:
  - Weighing query co-occurrence by probability of influence existence.

Social influence in Search Task

- Influence
  - The occurrence of one query raises the probability that the other query will be issued in the near future.

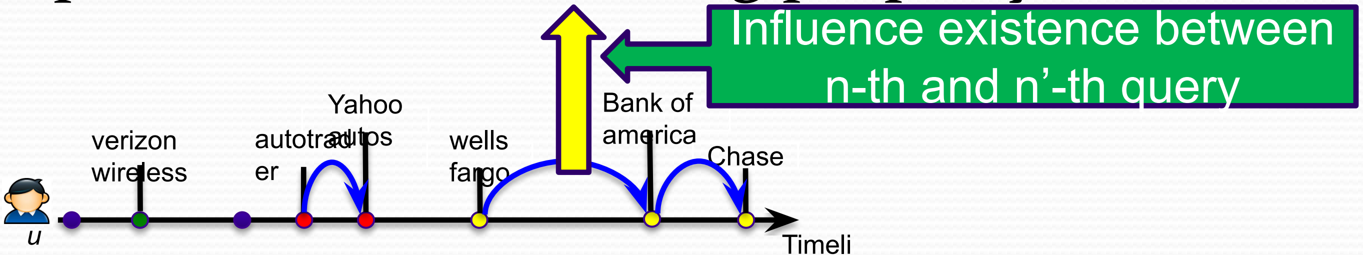
Temporally close query co-occurrence

User's unique query submission frequency

Temporally regular query co-occurrence

$$\lambda_m(t) = \mu_m + \sum_{t_{m,l}<t} R_{m,l,n}\beta_m\kappa(t - t_{m,l})$$

- Hawkes processes – self-exciting property



Issues in Influence Estimation

- Issues:
  - Not all temporally-close query-pairs have the actual influence in between.
  - Intractable to obtain an optimal solution of influence existence.
- Solution
  - Concentrate on the influence existence between semantically related queries.

Semantic Influence

- Search task ⟺ A sequence of semantically related queries linked by influence.
- Casting both influence existence and query-topic membership into latent variables.

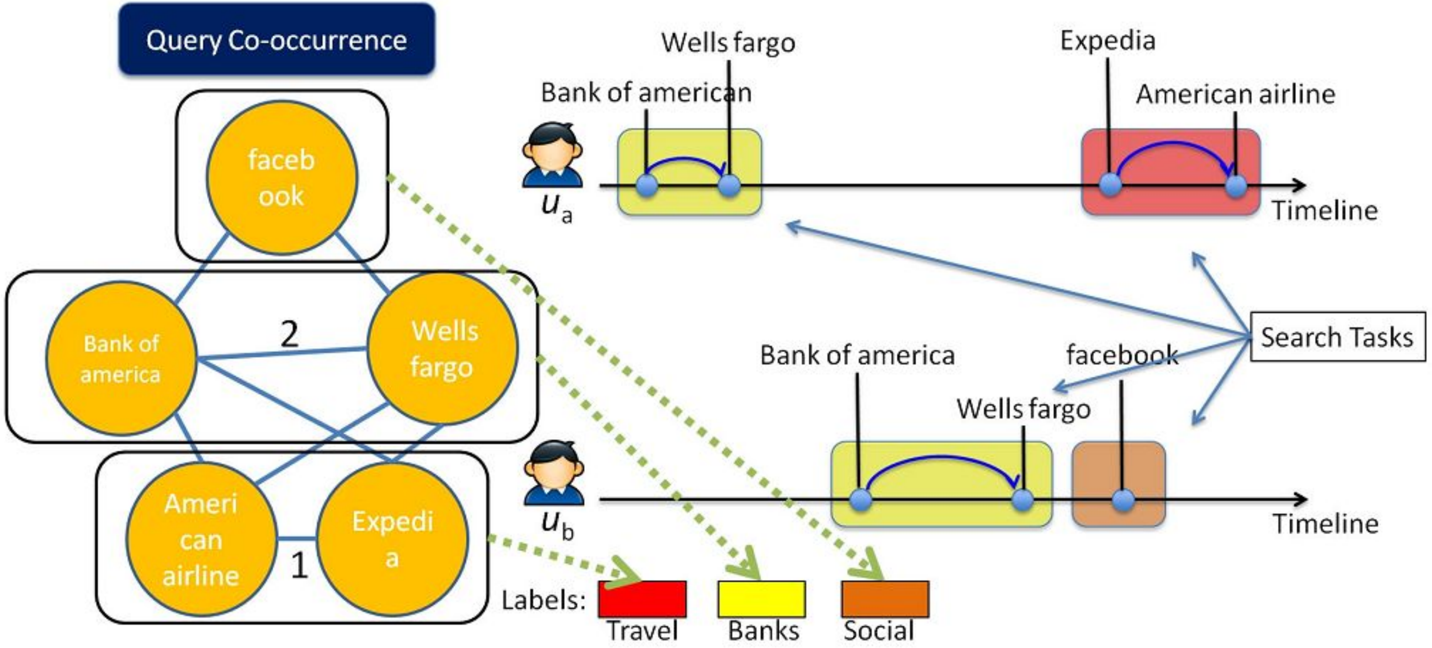
$$R_{m,n,n'} = Y_{m,n}^{T} * Y_{m,n'}$$

The existence probability of pairwise influence ⟺ The similarity of the memberships of two queries

Hawkes ⟺ LDA

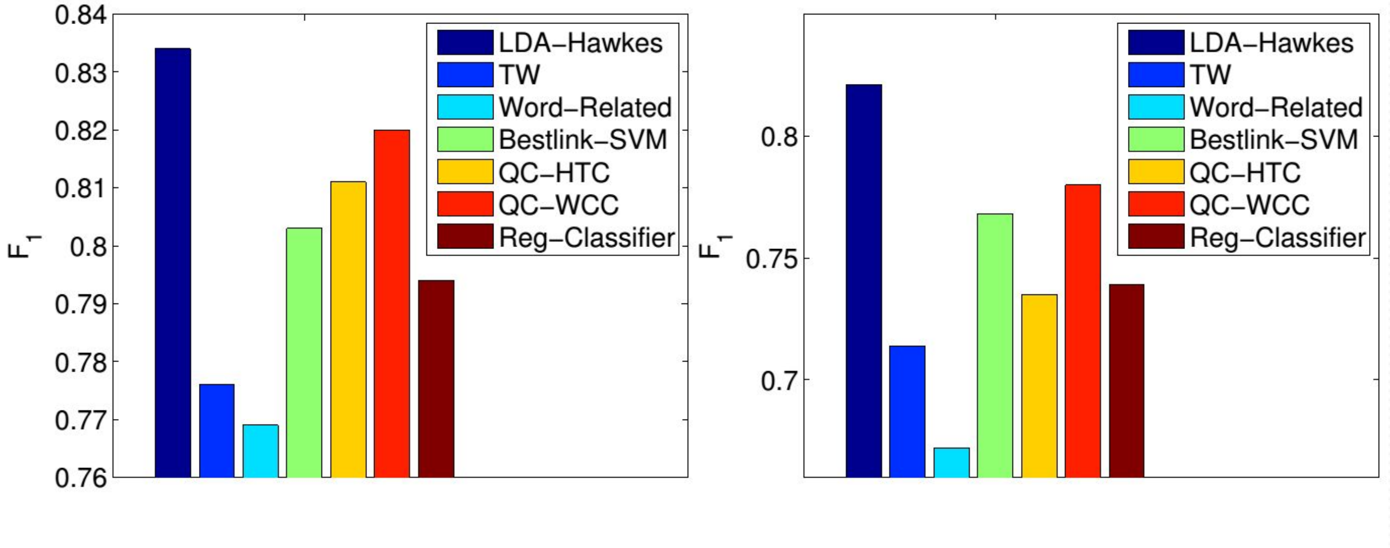
Temporal Information ⟺ Textual Information

A Toy Example



Weigh co-occurrence ⟺ Limit the solution space of Influence existence

Experiments



(a) AOL (b) Yahoo

- Annotated search tasks in AOL & Yahoo.
- LDA-Hawkes > QC > SVM,Reg-Classifier > TW, W-R

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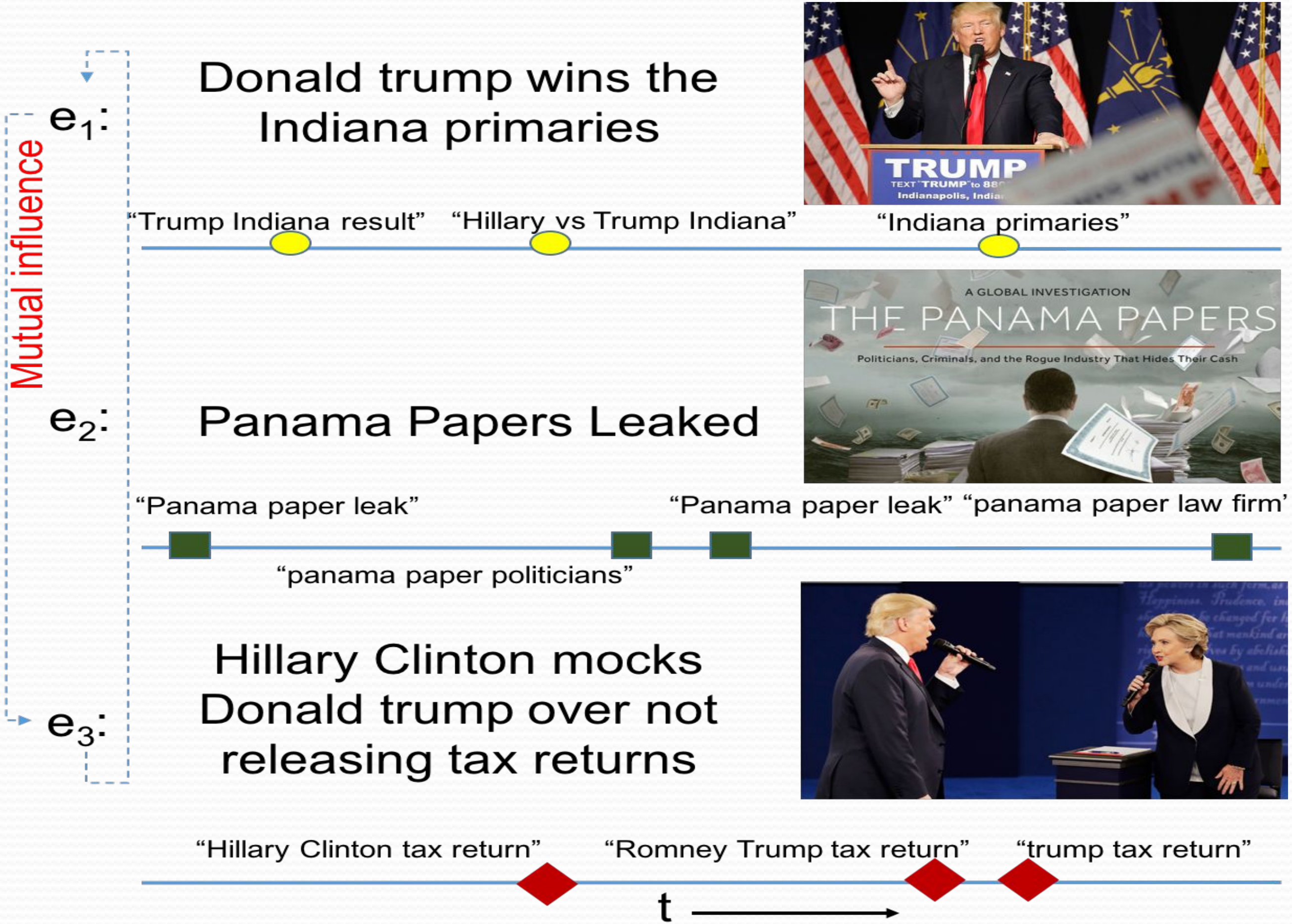
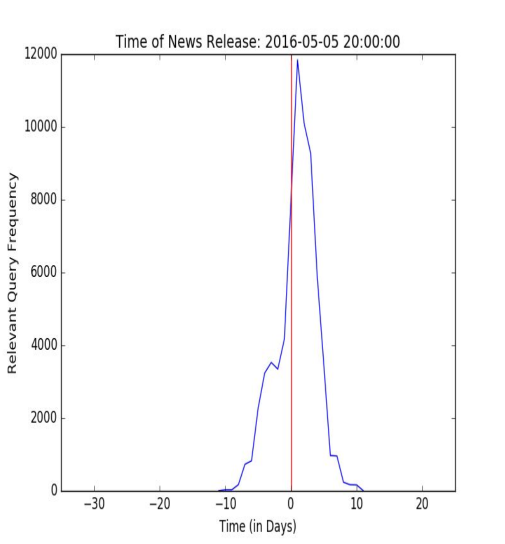
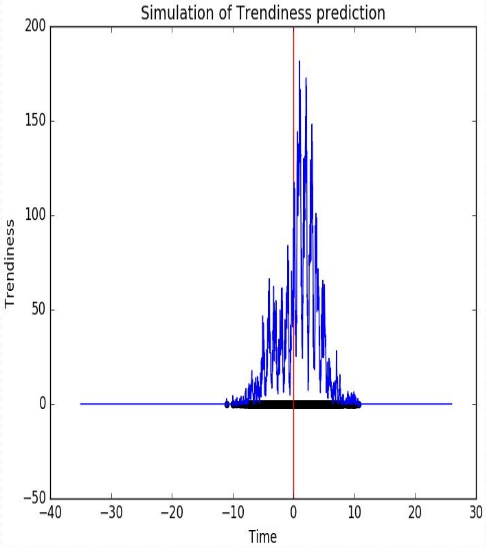
Influence between News and Web Search



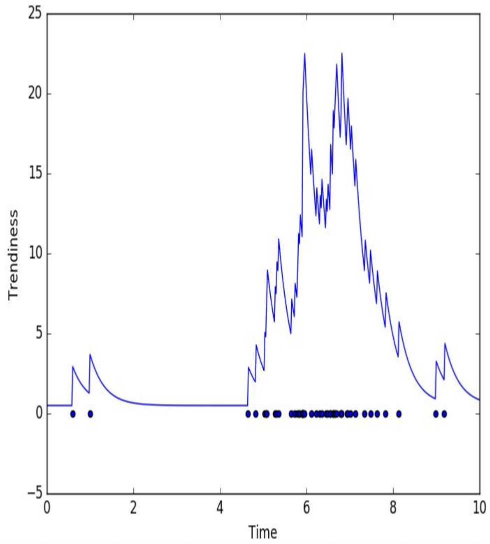
Influence between News and Web Search



Evidence of Influence

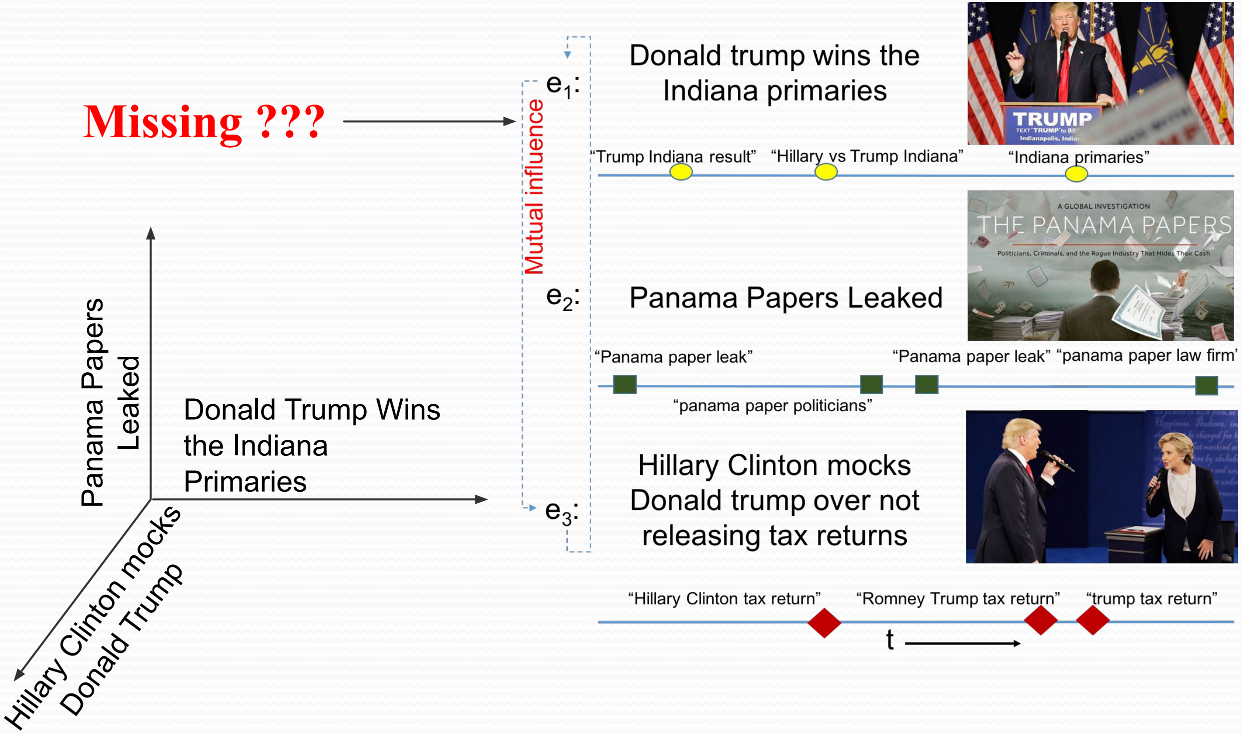


Simulation of Influence



Hawkes Process

Mutual Influence



Cross-domain Influence TPP Model

Base Influence

Mutual Influence

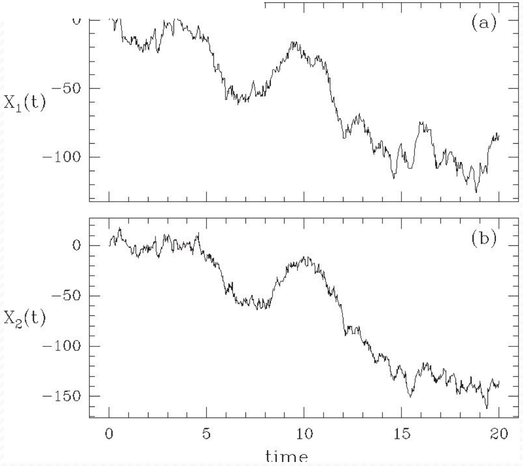
Decay Function

Impact Function

$$\lambda_j(t) = \eta_j + \sum_{j=1}^{k} v_{ji} \int_{(-\infty,t)\times R} w_j(t-s) g_j(x) e_j(ds \times dx)$$

Numerical Version

$$\hat{\lambda}_j(t_i) = \eta_j + \sum_{m=1}^{i-1} v_{j,d_m} w(t_i - t_m) g_{d_m}(x_m)$$



Estimation of Optimal Parameters

$$\Theta^* = \arg\max_{\Theta} \left(\log \hat{L}(\Theta) - ||\Theta|| \right)$$

Log-Likelihood Function

$$\log L = \sum_{j=1}^{d} \int_{[T_*, T^*]\times R} \log \lambda_j(t) e_j(dt \times dx) + \sum_{j=1}^{k} \int_{[T_*, T^*]\times R} \log f_j(x) e_j(dt \times dx) - \sum_{j=1}^{k} \Lambda_j(T^*)$$

$$\Lambda_j(t) = \eta_j(t - T_*) + \sum_{m=1}^{k} v_{jm} \int_{(-\infty, t)\times R} [\hat{w}_j(t-u) - \hat{w}_j(T_* - u)] g_m(x) e_m(du \times dx)$$

Numerical Version

$$\log \hat{L} = \sum_{i=1}^{n} \log \Big\{ \eta_j + [\lambda_j(t_{i-1} - \eta_j)] \exp[-\alpha_j(t_i - t_{i-1})] + v_{j,d_{i-1}} g_{d_{i-1}}(x_{i-1}) \alpha_j \exp[-\alpha_j(t_i - t_{i-1})] \Big\} + \sum_{i=1}^{n} \log \left(\frac{\rho_{d_i} \mu_{d_i}^{\rho_{d_i}}}{(x + \mu_{d_i})^{\rho_{d_i}+1}} \right) - \sum_{j=1}^{k} \left\{ \eta_j(T^* - T_*) + \sum_{i=1}^{n} v_{j,d_i} \bar{w}_j(t^* - t_i) g_{d_i}(x_i) \right\}$$

$$g_{d_i}(x) = \frac{(\rho_{d_i} - 1)(\rho_{d_i} - 2)}{\phi_j(\rho_{d_i} - 1)(\rho_{d_i} - 2) + \psi_{d_i} \mu_{d_i}(\rho_{d_i} - 2)} (\phi_{d_i} + \psi_{d_i} x)$$

Data set

Section	Total # of events	Avg. Title Length	Avg. Body Length	Total # of queries	Avg. Textual Sim.
Movies	25	18.88	458.08	193,282	2.49
Sports	15	19.53	508.4	616,449	2.48
US	18	20.38	487.77	204,926	1.99
World	11	18.18	438.81	22,197	1.96

Table 1: Description of Event-Query Joint Dataset

How to compare influences posed by different events?

Events	Sections			
	Movies	**Sports**	**US**	**World**
1	Movie: "Captain America: Civil War" (11.5514)	Horse-Racing: Kentucky Derby (13.5346)	Donald trump Vs Hillary Clinton (14.0117)	Panama Papers Released (0.8179)
2	Movie: "X-men: Apocalypse" (2.0532)	Basketball: Stephen Curry (6.6432)	Las Vegas Squatters Housing Collapse (9.6340)	Philippine Presidential Race (0.5821)

parameter	η	α	ρ	μ	ϕ	ψ
Movies	0.1961	0.8697	4.9706	3.0197	0.4542	0.1644
Sports	0.317	1.1999	6.2745	4.2272	1.1608	0.5304
US	0.2328	1.0999	6.3056	1.777	0.6962	0.508
World	0.074	0.677	3.9747	1.5226	0.2465	0.1685

Table 3: Parameters learnt for different categories of events

Movies (0.9319)	**Sports** (0.9649)	**US** (0.9192)	**World** (0.9213)

Table 4: Spectral Radius of MIC Mat. for different categories

max(eigenValues(MIC)) < 1

Experiments

Forecast the next most influenced query

Metric	Methods	Movies	Sports	US	World
Accuracy	NF	0.3281	0.4894[2]	0.5717[2]	0.3879
	AR	**0.3879**[1]	0.4794	0.5400	0.4504
	ARD	0.2424	0.1965	0.4410	0.0443
	VAR	0.0023	0.0007	0.0029	0.0001
	IIM	0.3413	0.3660	0.5408	**0.4710**[1]
	JIM	0.3642	0.4688	0.5563	0.3035
	JIM-G	0.3820[2]	**0.5134**[1]	**0.5843**[1]	0.4544[2]

Table 9: Predicting the most frequent query in future

Rank queries based on future influence

Metric	Method	Movies	Sports	US	World
NDCG	NF	0.5914	0.6693	0.8060	0.4465
	AR	0.6713[2]	0.7440[2]	0.7789	0.5200
	ARD	0.2642	0.2977	0.4717	0.0827
	VAR	0.0087	0.0052	0.0136	0.0015
	IIM	0.6355	0.6976	0.8121[2]	**0.6555**[1]
	JIM	0.6484	0.7204	0.8022	0.4809
	JIM-G	**0.6870**[1]	**0.7650**[1]	**0.8430**[1]	0.6062[2]
RBO	NF	0.4349	0.5707	0.6491	0.3665
	AR	0.4947[2]	0.5908[2]	0.6102	0.4130
	ARD	0.1803	0.2191	0.3237	0.0538
	VAR	0.0042	0.0019	0.0045	0.0001
	IIM	0.4562	0.5174	0.6509[2]	**0.4676**[1]
	JIM	0.4782	0.5724	0.6436	0.3048
	JIM-G	**0.5059**[1]	**0.6172**[1]	**0.6764**[1]	0.4332[2]

Table 10: Predicting future frequencies for multiple queries. (Wilcoxon's signed rank test at level 0.05)

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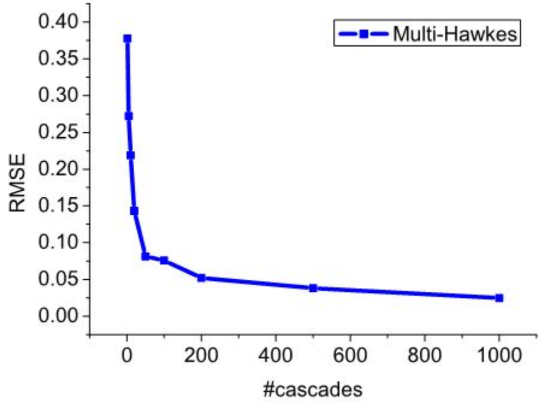
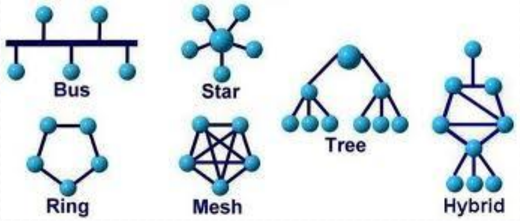
Why Parametric

10 * 10 network



- Problem Complexity
  - $O(M^2)$ α's to learn
    - Hundreds of millions of individuals
  - No sufficient historical events
    - Require multiple cascades
    - The successive event history needs to be segmented into a number of independent cascades in advance.

Why Parametric – cont.



- Dependency in Infectivity Matrix
  - α's are closely related.
  - A priori assumptions on the network topology limit the adaptive social networks of the approaches.
- Time-varying Infectivity
  - Learning separate α for each time interval or with time-dependent function, greatly increase problem complexity.

Parametric Model

- A compact model to parameterize the infectivity between individuals.
- Time-varying features
  - $O(M^2) \longrightarrow$ O(K)
  - Require only one cascades for learning
  - Features incorporate infectivity dependency
    - Simultaneously capture various network topologies
  - Time-varying infectivity

Definition

- For individual-pair (m, m')

$$\alpha_{m,m'} = \beta^T \mathbf{x}_{m,m'}(t)$$

- Optimization problem:

$$\min_{\mu \geq 0, \beta \geq 0} -\mathcal{L}(\mu, \beta) + \boxed{\lambda ||\beta||_1}$$

- Non-differentiable

Select effective features and avoid overfitting

Optimization

- Alternating direction method of multipliers (ADMM)

$$\min_{\mu\geq 0,\beta\geq 0,\mathbf{z}} -\mathcal{L}(\mu,\beta)+\lambda\|\mathbf{z}\|_1,$$
$$\text{subject to} \quad \beta=\mathbf{z}.$$

ℓ_1

$$\mu^{i+1},\beta^{i+1} = \text{argmin}_{\mu\geq 0,\beta\geq 0} -\mathcal{L}_\rho(\mu,\beta,\mathbf{z}^i,\mathbf{u}^i),$$
$$\mathbf{z}^{i+1} = S_{\lambda/\rho}(\beta^{i+1}+\mathbf{u}^i),$$
$$\mathbf{u}^{i+1} = \mathbf{u}^i+\beta^{i+1}-\mathbf{z}^{i+1}.$$

ℓ_2

$O(N * K + M)$ Para-Hawkes

- Complexity: $O(N^2 + M^2)$ Multi-dimensional Hawkes

Time-varying Features

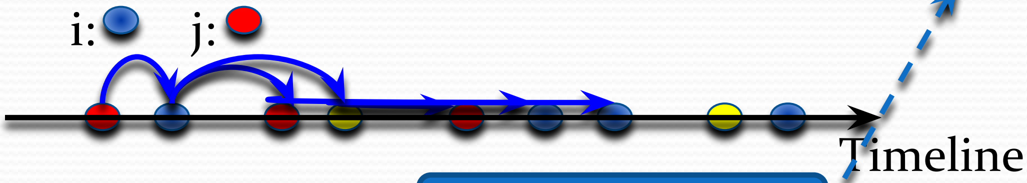
- Individual feature
  - Instant self-property of each individual.
- Dyadic feature
  - Instant relationship between each pair of individuals.

$in(i)$

$i \circlearrowleft^{(v)}$

$i \xrightarrow{(v)} j$

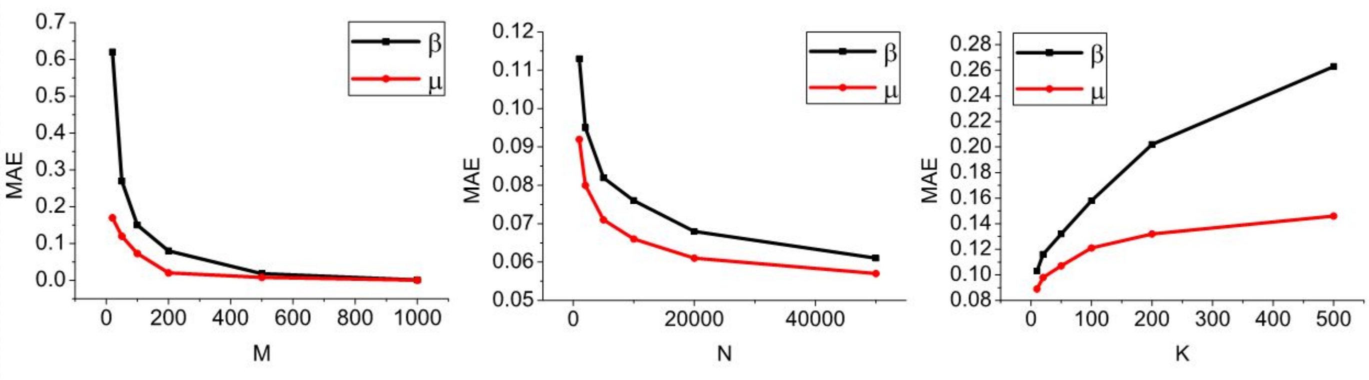
$i \xleftrightarrow{(v,v')} j$



Pattern counting

- Formation $\mathbf{x}_{m,m'}(t) = \boxed{\{x(p)(t, \Delta t) | p} \in \mathcal{P}_{m,m'}, \Delta t > 0\}$

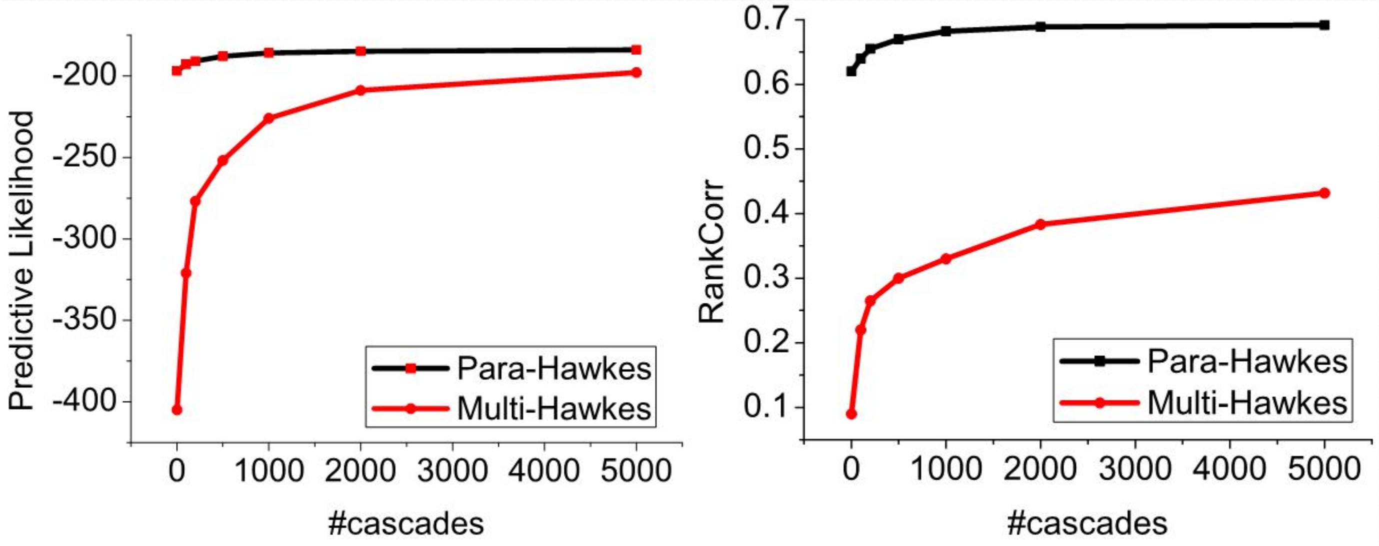
Model Dimension Variation



(a) M (b) N (c) K

- The impact of model dimension variation on μ is smaller than that on β .

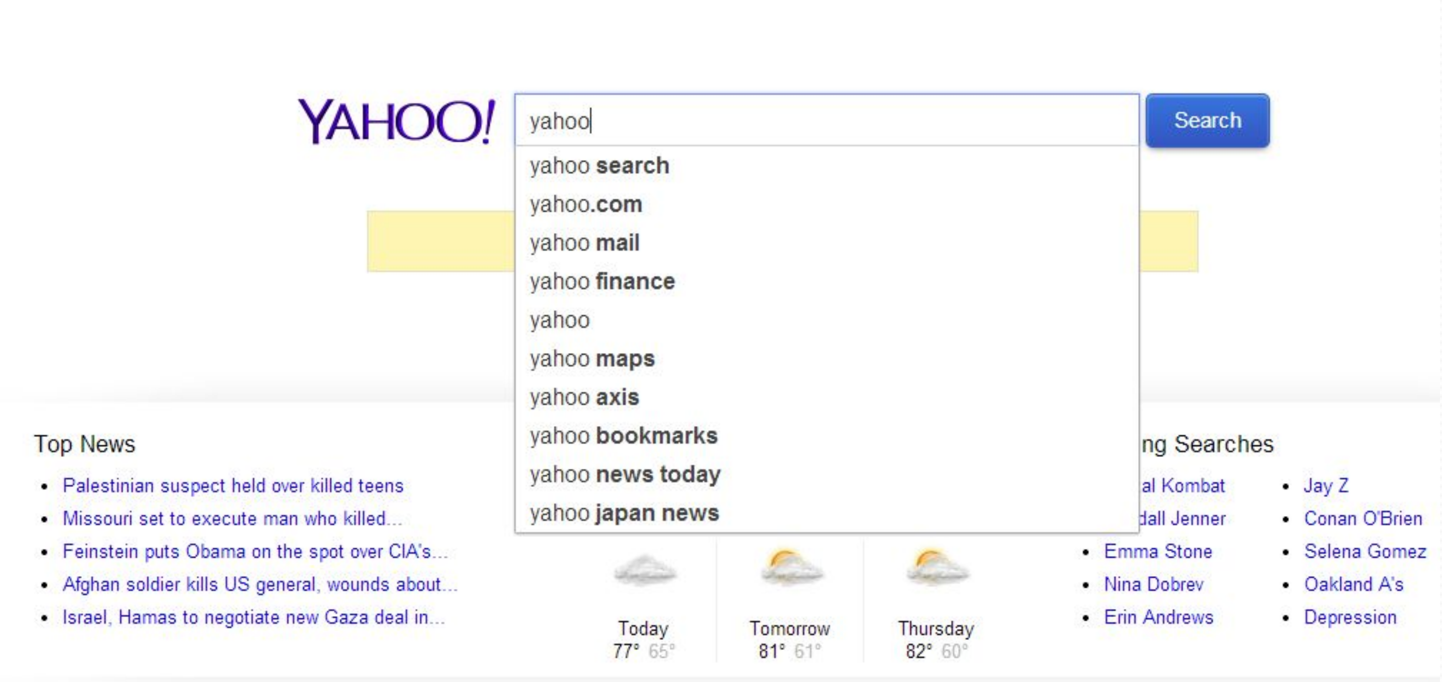
Performance vs #Cascade



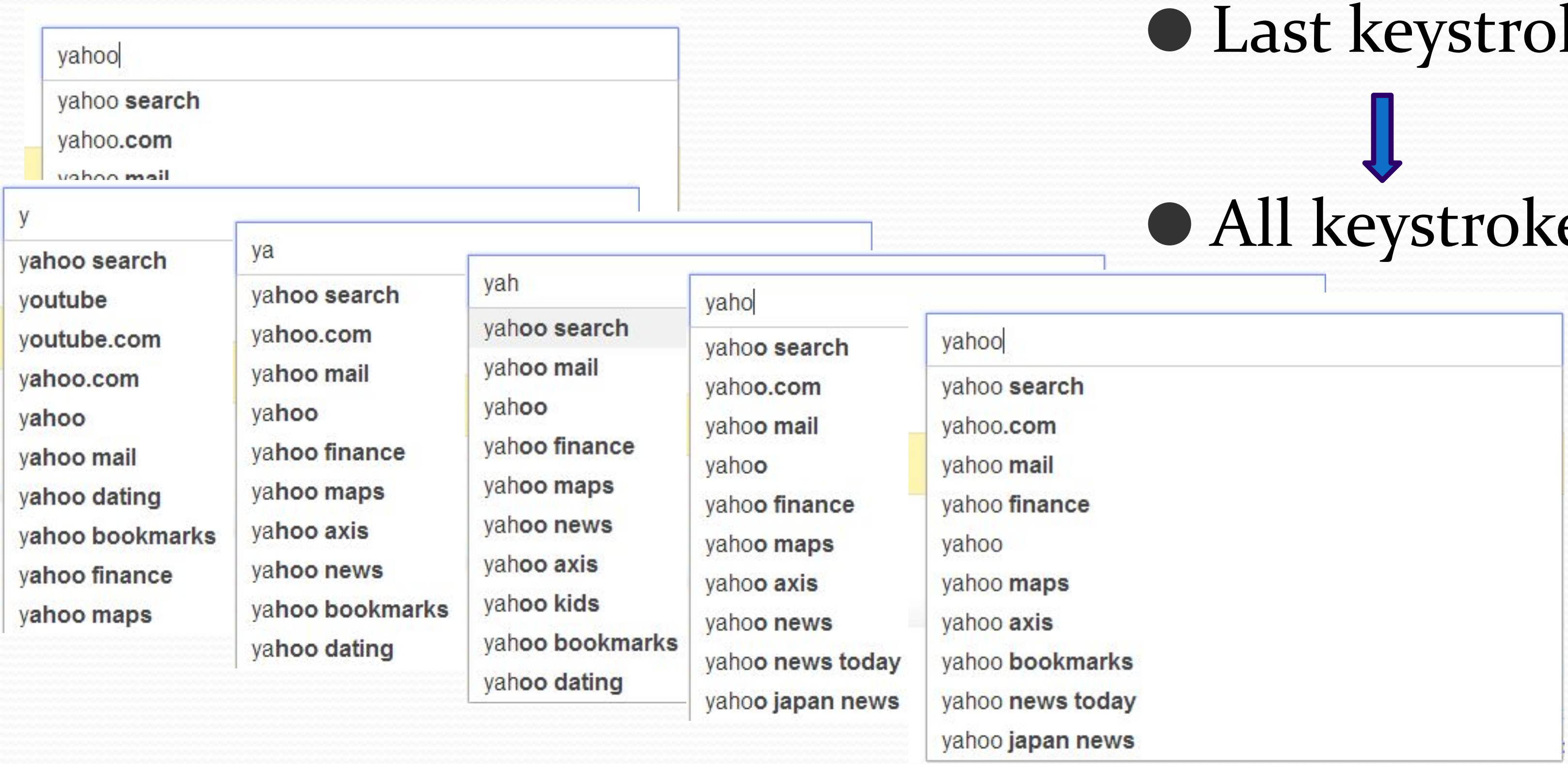
(a) Predictive Likelihood (b) RankCorr

- Works well without multiple cascades

Scenario - Query Auto-Completion



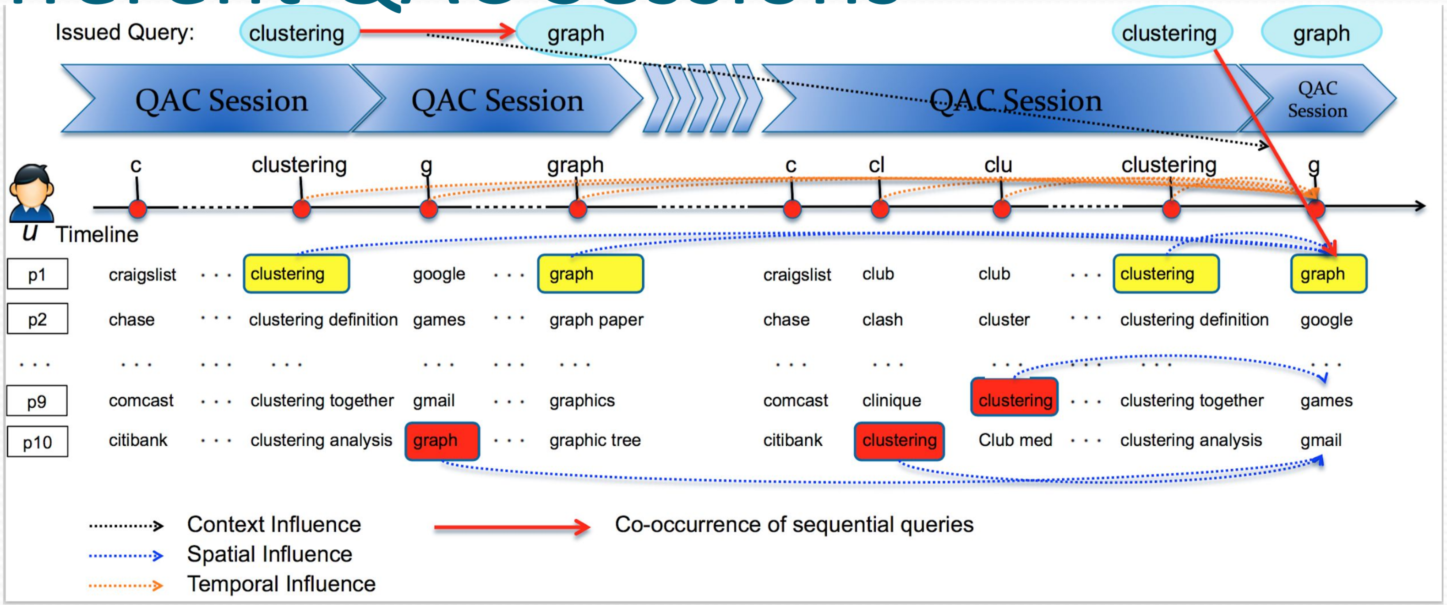
Query Auto-Completion Log



- Last keystroke

- All keystrokes

Influence between Click Events in different QAC Sessions



- Influence between users' click choices across different QAC sessions arise from three representative factors:
  - context, position, temporal information.

Factors that Influence User's Click Choices - Slot

- The spatial slot (Position) information
  - the displayed position of the suggested query

- Quantify the degree of the influence between the click events from the spatial slot aspect via the following formula: $\kappa(|\mathbf{p}_l - \mathbf{p}|)$

Factors that Influence User's Click Choices – Timestamp

- The timestamp (temporal) information
  - the temporal stamp whether the click event occurs

- Quantify the degree of the influence between click events from the temporal aspect via the following formula: $\kappa(t_l - t)$

Factors that Influence User's Click Choices - Context

- Rich contextual data carries value (context) information for the query suggestion prediction

- A set of contextual features is designed to describe the relationship between the content of a historical query q' and

$$\mathbf{x}_{q',q}(t) = \{\boxed{x(p)(t, \Delta t)} | p \in \mathcal{P}_{q',q}, \Delta t > 0\}$$

Pattern counting

- These features count the number of appearances of a certain pattern in a certain time range.

Factorial Hawkes

- A univariate Hawkes process on each user's issued query sequence.

$$\lambda(t, \mathbf{p}) = \mu + \sum_{t' < t} \beta \overbrace{\boxed{\mathbf{x}_{q',q}(t)}}^{\text{Contextual Factor}} \Big(\underbrace{\boxed{\kappa(t - t')}}_{\text{Temporal Factor}} + \alpha \overbrace{\boxed{\kappa(|\mathbf{p} - \mathbf{p}'|)}}^{\text{Spatial Factor}} \Big)$$

- Simultaneously leveraging these factors and using them to capture the actual influence exists between click events across QAC sessions

Query Auto-Completion

Data/Platform	Hawkes	TDCM	RBCM	MPC	UBM	BSS
Measured by MRR@Last						
OldQAC/PC	**0.694**	**0.592**	**0.608**	0.543	0.441	0.545
OldQAC/MB	**0.770**	**0.685**	**0.708**	0.649	0.431	0.650
NewQAC/PC	**0.732**	**0.602**	**0.642**	0.567	0.501	0.552
NewQAC/MB	**0.811**	**0.691**	**0.749**	0.631	0.482	0.654
Measured by MRR@All						
OldQAC/PC	**0.612**	**0.538**	**0.554**	0.464	0.467	**0.531**
OldQAC/MB	**0.671**	**0.611**	**0.629**	0.564	0.471	0.524
NewQAC/PC	**0.664**	**0.578**	**0.602**	0.522	0.508	**0.572**
NewQAC/MB	**0.754**	**0.628**	**0.676**	0.592	0.521	0.554

$$MRR = \frac{1}{|Q|} \sum_{q \in Q} \frac{1}{\text{rank}_q}$$

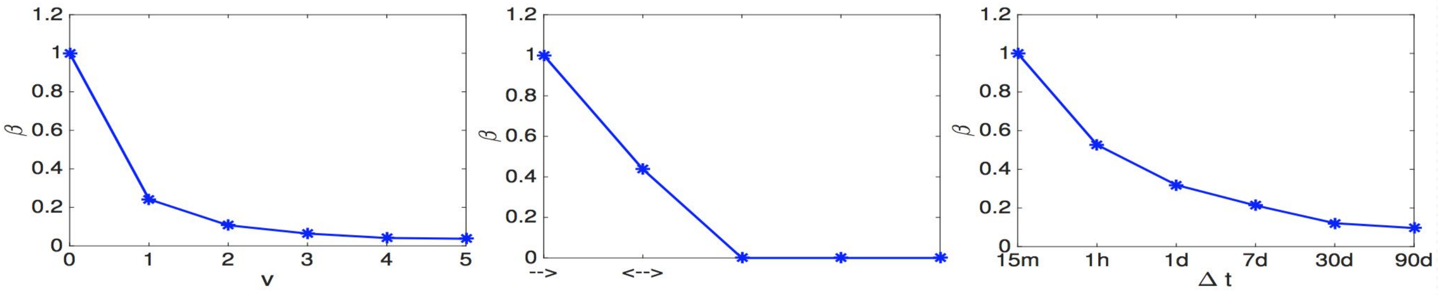
- RBCM > TDCM > RBCM > MPC, UBM, BBS

Strategy Selection

Data set	T & S & C	T & C	S & C	T & S
Measured by MRR@Last				
OldQAC/PC	0.694	0.658	0.632	0.611
OldQAC/MB	0.770	0.740	0.727	0.720
NewQAC/PC	0.732	0.711	0.691	0.652
NewQAC/MB	0.811	0.798	0.775	0.761
Measured by MRR@All				
OldQAC/PC	0.612	0.588	0.570	0.559
OldQAC/MB	0.671	0.649	0.638	0.634
NewQAC/PC	0.664	0.646	0.625	0.611
NewQAC/MB	0.754	0.719	0.698	0.682

- Factor importance: Context > Temporal > Spatial

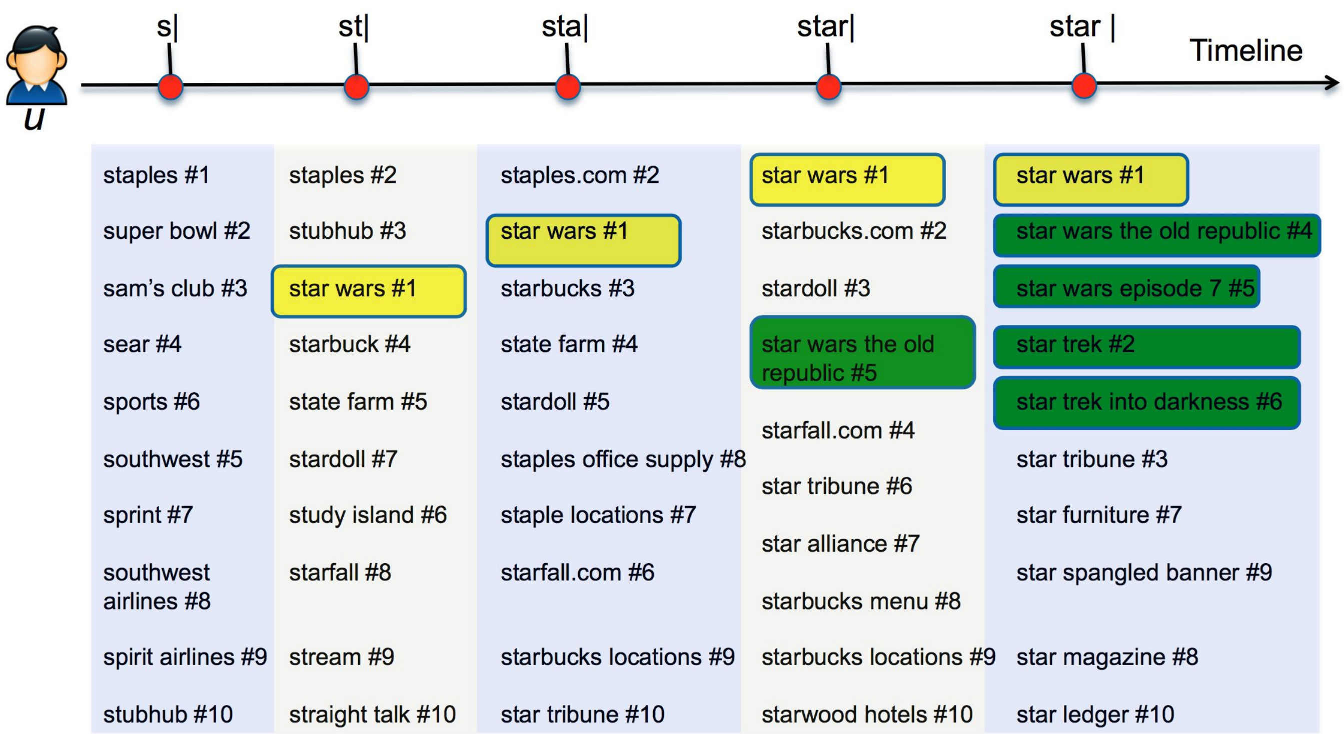
Coefficient Learning of Contextual Features



(a) Query Distance (b) Temporal Order (c) History Range

- The relationship between two queries becomes significantly weaker wrt. the increase of temporal distance in-between.
- Search engine users do have some preference on the temporal order of queries they submit.
- Users' click choices can vary with respect to different periods.

Case Study



- Appropriate modeling of influence between users’ click behaviors in different QAC sessions is critical for predicting users’ instant intent given short prefixes under the current QAC session.

Q & A

Thank you!

Appendix