Discovering Topical Interactions in Text-based Cascades using Hidden Markov Hawkes Process (HMHP)

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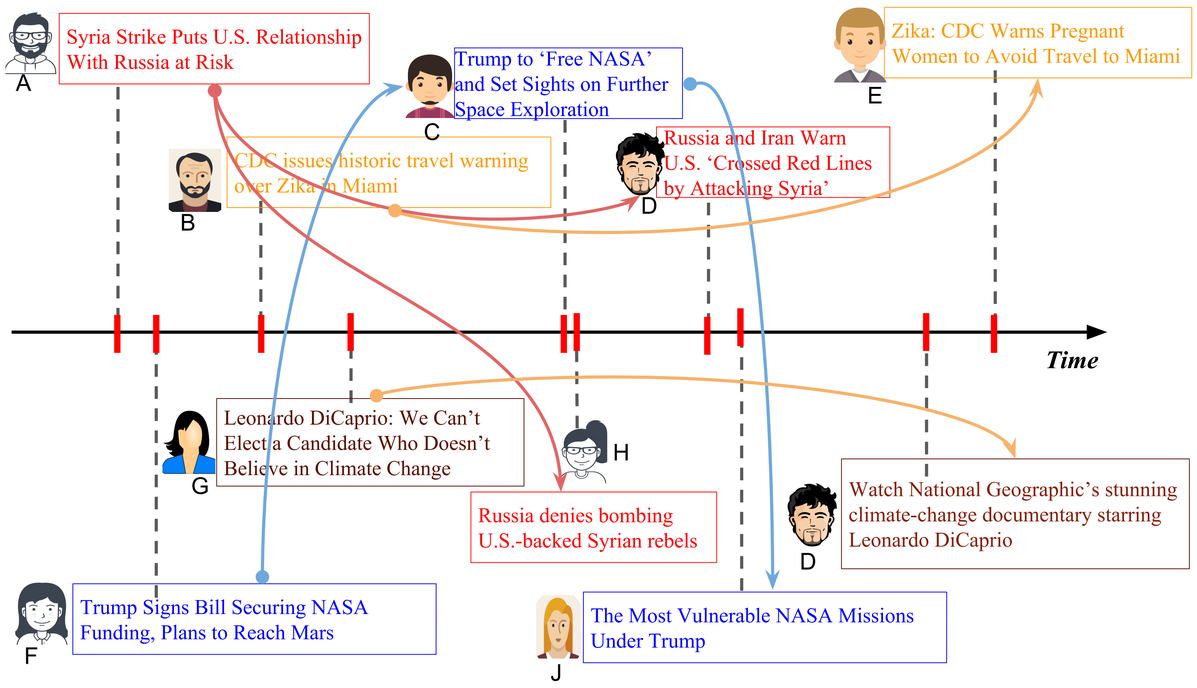
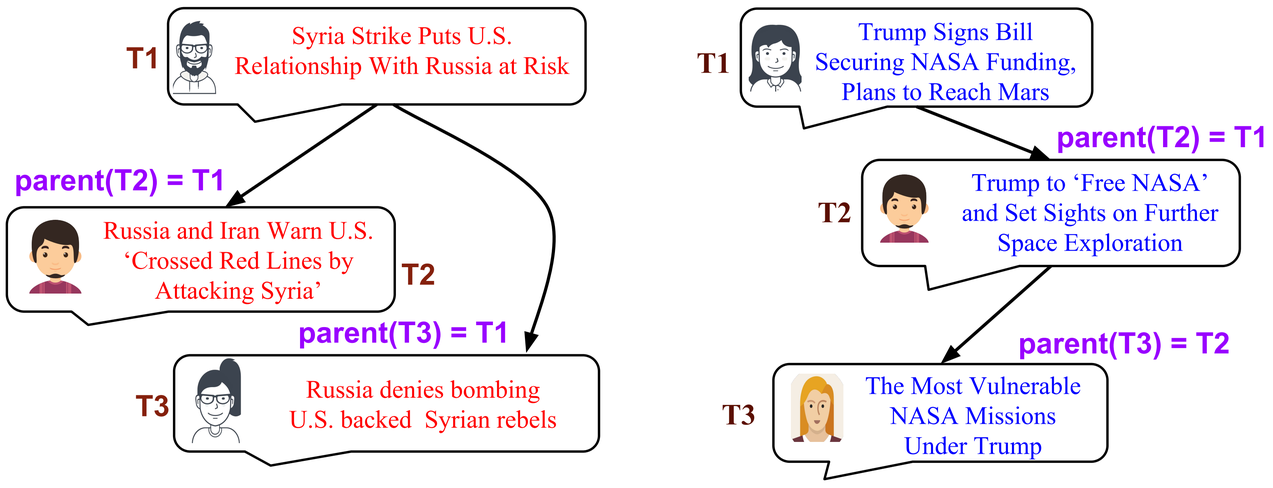
Motivation



User Network + Time-series of Tweets (Mixture of conversations)

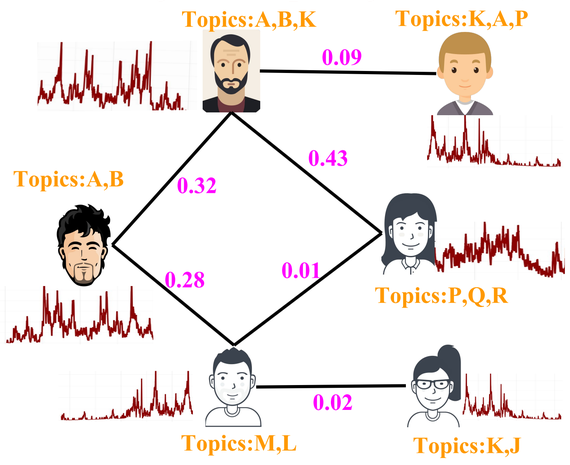
Questions



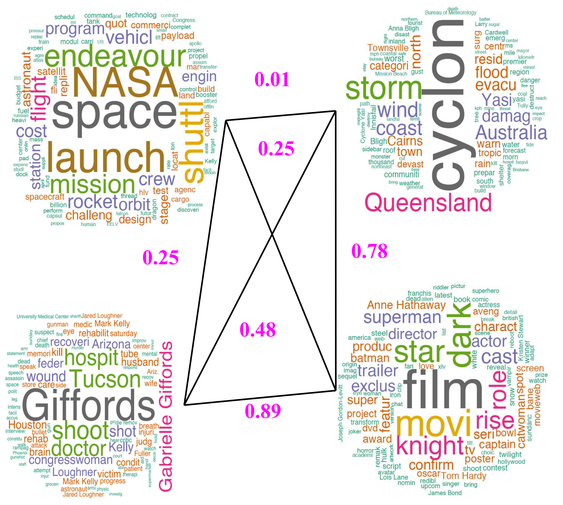
Separate these conversations out…!!!

1) What are the different conversations i.e. Parent-Child Structure among Tweets? ***(Cascade Reconstruction)***

2) When and how frequently do users generate content and on what topic? ***(Temporal Dynamics and Preferred Topics of each user)***



3) Who responds to whom and how quicky? ***(User-User Influence)***



4) What are the various Topics in the data and how do topics interact? ***(Topics and Topical Interactions)***

Why Topical Interactions?

Parent-Child tweet pair

Gellman:My definition of whistleblowing:are you shedding light on crucial decision that society should be making for itself. #snowden

Gellman we are living inside a one way mirror,they & big corporations know more and more about us and we know less about them #sxsw

- ***Parent-child from different topics***
- ***Topic pair occurs frequently***
- ***HMHP assigns to different topics with high transition probability***

Random walk over topics to detect topic drifts - from TV shows to Entertainment

Hashtags from top-3 transitioned topics

agentsofshield, arrow, tvtag, supernatural, chicagoland

Topic-1: *idol, bbcan2, havesandhavenots, thegamebet*
Topic-2: *tvtag, houseofcards, agentsofshield, arrow,*
Topic-3: *soundcloud, hiphop, mastermind, nowplaying*

Frequent topical transitions from football related hashtags to baseball related hashtags

Parent-child topics Hashtags

steelers,browns,seahawks, fantasyfootball, nfl

mlb, orioles, rays, usmnt, redsox

HMHP Generative Model

- **Coupled Multivariate Hawkes Processes and (Hidden) Markov Chains**
- **Coupled inference: Collapsed Gibbs sampling**

1) Generate (t_e, c_e, z_e) for all events according Multivariate Hawkes Process.
2) For each topic k: sample $\boldsymbol{\zeta}_k \sim Dir_{\mathcal{W}}(\boldsymbol{\alpha})$
3) For each topic k: sample $\boldsymbol{\mathcal{T}}_k \sim Dir_K(\boldsymbol{\beta})$
4) For each node v: sample $\boldsymbol{\phi}_v \sim Dir_K(\boldsymbol{\gamma})$
5) For each event e at node $c_e = v$:
   a) i) **if** $z_e = 0$ (level 0 event): draw a topic $\eta_e \sim Discrete_K(\boldsymbol{\phi}_v)$
      ii) **else**: draw a topic $\eta_e \sim Discrete_K(\boldsymbol{\mathcal{T}}_{\eta_{z_e}})$
   b) Sample document length $N_e \sim Poisson(\lambda)$
   c) For $w = 1 \ldots N_e$: draw word $x_{e,w} \sim Discrete_{\mathcal{W}}(\boldsymbol{\zeta}_{\eta_e})$

Events are generated according to ***Multivariate Hawkes Process.***

Topic of event is sampled as one which is more related to or interacts with parents topic. **(Markov Chain over Topics)**

HTM [1] v/s HMHP

Repeating patterns in the topics of the parent and child events

[#MASalert] Statement By Our Group CEO, Ahmad Jauhari Yahya on MH370 Incident. Released at 9.05am/8 Mar 2014

Missing #MalaysiaAirlines flight carrying 227 passengers (including 2 infants) of 13 nationalities and 12 crew members.

Generation of Topic of child event in HTM [1]

If event $\boldsymbol{e}$ *is not spontaneous, then*

$\boldsymbol{Topic(e) \sim Normal(Topic(parent(e)), \sigma^2 I)}$

v/s

Generation of Topic of child event in HMHP

If event $\boldsymbol{e}$ *is not spontaneous, then*

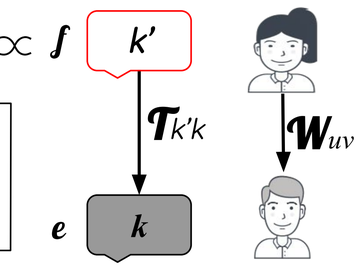
$\boldsymbol{Topic(e) \sim \mathcal{T}(Topic(parent(e)))}$

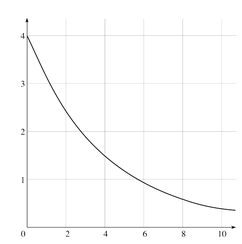
where, $\boldsymbol{\mathcal{T}}$ *is Topical Interaction Distribution*

Inference

$$\mathcal{P}\left(parent(e) = f \mid Topics, W, \mu, timeStamps\right) \propto f$$

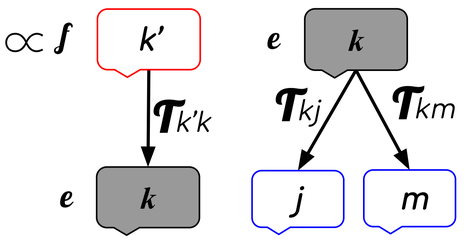
Probability of event f being a parent of event e is proportional to ***topical interaction*** between topic of event f and topic of event e.





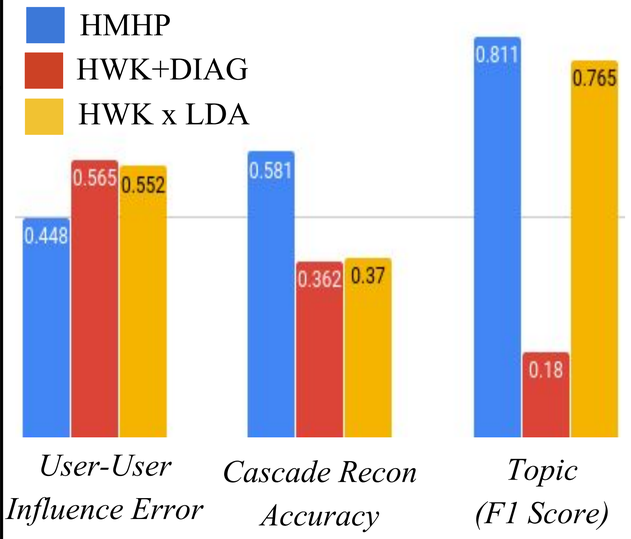
$$\mathcal{P}\left(Topic(e) = k \mid parents, tweet, \{Topic(f) \mid f \mathrel{!}= e\}\right) \propto f$$

Probability of event e having topic k is proportional to ***topical interaction*** between the parents topic and topic k ***topical interaction*** between k topics of child events.



Results

- **HWK + DIAG:** HMHP + diagonal Topic Interactions
- **HWK x LDA:** Networks Hawkes [2] + LDA Mixture Model (for content)



Reconstruction Accuracy (Semi-Synthetic Data)

Heldout Log-Likelihood

#Topics	HMHP	HWK+Diag	HWKxLDA
25	***-34736237***	-37399849	-34832568
50	***-34429519***	-37937426	-34433305
75	***-34146202***	-37944457	-34234787

Generalization Performance (Twitter Data)

Significant improvement over HTM [1] on scaled down datasets.
HTM [1] does not scale for our dataset.

References

1) ***He, X., Rekatsinas, T., Foulds, J., Getoor, L., & Liu, Y. (2015, June). Hawkestopic: A joint model for network inference and topic modeling from text-based cascades. In ICML***
2) ***Linderman, S., & Adams, R. (2014, January). Discovering latent network structure in point process data. In International Conference on Machine Learning (pp. 1413-1421).***