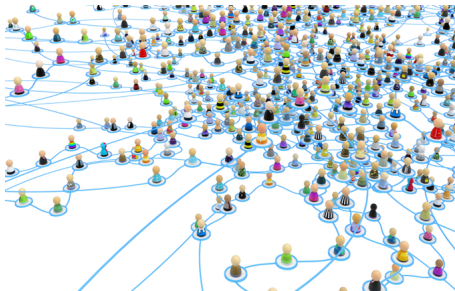


# Stance classification and Diffusion Modelling

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# Outline

## 1 Stance Classification

- Hawkes Process
- Deep Learning

## 2 Information Diffusion

- Hawkes Process
- Deep Learning

# Stance Classification in Twitter

## Rumour Stance Classification

- Classify tweets as supporting, denying, questioning, or commenting an event.
- Useful for rumour truthfulness classification.

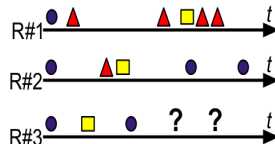
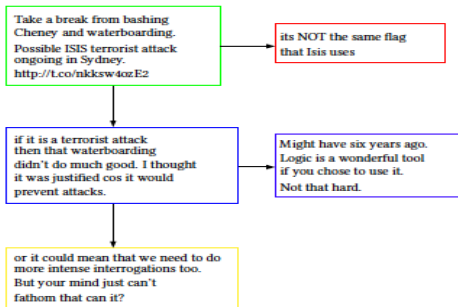


text	position
Birmingham Children's hospital has been attacked!	supporting
Really?	questioning
no sign of any trouble	denying

## Stance Classification in Twitter

## Time Sensitive Sequence Classification

- Tweets form a conversation structure with reply tweets.
- Tweet classification as **sequence labelling** problem.
- Each tweet is associated with the time of occurrence.

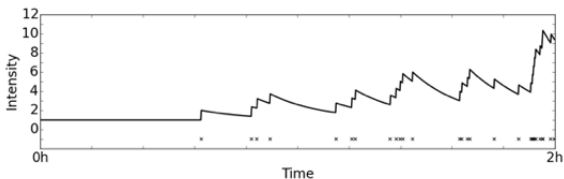


# Point Processes in Twitter

- Twitter data containing information tweet time, text, meme category and user  $\{d_n = (t_n, \mathbf{W}_n, m_n, i_n)\}_{n=1}^N$ .

## Hawkes Process

- Models the spiky behaviour typically observed in social networks
- Self exciting point process with intensity for user  $\lambda_i(t) = \mu_i + \sum_{t_\ell < t} \mathbb{I}(i_\ell == i) \alpha_i \kappa(t - t_\ell)$   
Base intensity influence of past tweets
- Past tweets influence future tweets but decays exponentially over time  $\kappa(t - t_\ell) = \omega \exp(-\omega(t - t_\ell))$



# Point Processes in Twitter

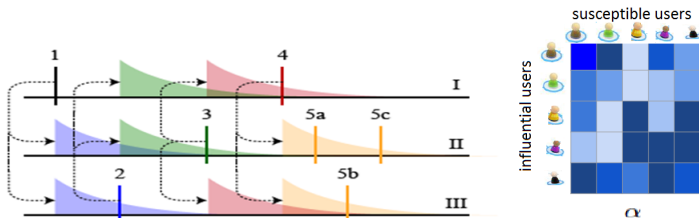
- Twitter data containing information tweet time, text, meme category and user  $\{d_n = (t_n, \mathbf{W}_n, m_n, i_n)\}_{n=1}^N$ .

## Hawkes Process

- Multivariate Hawkes models the influence of other users.  

$$\lambda_i(t) = \mu_i + \sum_{t_\ell < t} \alpha_{i_\ell, i} \kappa(t - t_\ell)$$
- Joint modelling of users and memes with multivariate Hawkes.

$$\lambda_{i,m}(t) = \mu_i \gamma_m + \sum_{t_\ell < t} \mathbb{I}(m_\ell == m) \alpha_{i_\ell, i} \kappa(t - t_\ell)$$



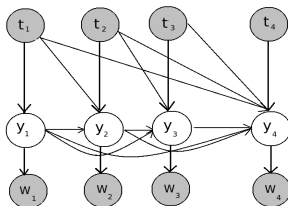
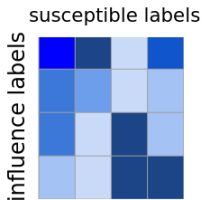
## Time Sensitive Sequence Classification [Lukasik et al., 2016]

- Twitter data containing tweet time, text and label  $\{d_n = (t_n, \mathbf{W}_n, m_n, y_n)\}_{n=1}^N$ .

## Multivariate Hawkes Process for stance classification

- Intensity modelled over labels  $\lambda_{y,m}(t) = \mu y + \sum_{t_\ell < t} \mathbb{I}(m_\ell == m) \alpha_{y_\ell, y} \kappa(t - t_\ell)$
- Classification of tweet depends on the textual Content  $p(\mathbf{W}_n | y_n) = \prod_{v=1}^V \beta_{y_n}^{W_{nv}}$ .
- Likelihood of a tweet belonging to a class is proportional to  

$$p(\mathbf{W}_n | y_n) \times \lambda_{y_n, m_n}(t_n)$$
 emission likelihood  $\times$  transition likelihood
- Generative non-Markovian model** : Past tweet labels influence future tweet labels
- Generalizes Multinomial, Naive Bayes, hidden markov models.



# Time Sensitive Sequence Classification

## Learning and Prediction

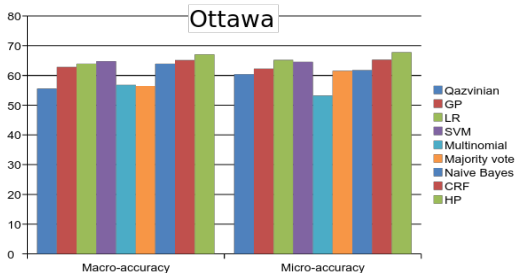
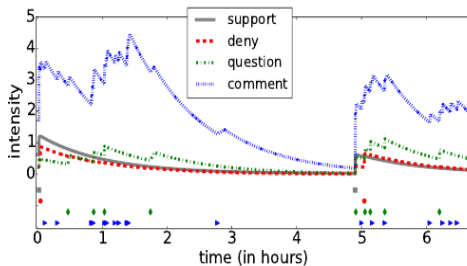
- Likelihood  $\prod_{n=1}^N p(\mathbf{W}_n | y_n) \times \left[ \prod_{n=1}^N \lambda_{y_n, m_n}(t_n) \right] \times p(E_T)$
- Learning by **maximum likelihood** approach.  

$$\sum_{y=1}^{|Y|} \sum_{m=1}^M \int_0^T \lambda_{y,m}(s) ds + \sum_{n=1}^N \log \lambda_{y_n, m_n}(t_n) + \sum_{n=1}^N \sum_{v=1}^V W_{nv} \log \beta_{y_n v}$$
- Prediction of labels uses a greedy approach

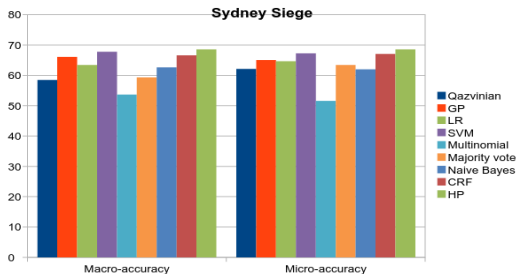
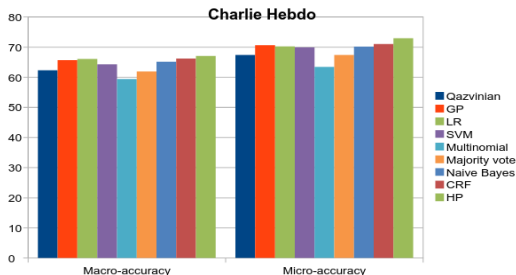
## Datasets

Dataset	Tweets	Supporting	Denying	Questioning	Commenting
Ottawa shooting	782	161	76	64	481
Ferguson riots	1017	161	82	94	680
Charlie Hebdo	1053	236	56	51	710
Sydney siege	1124	89	223	99	713

## Time Sensitive Sequence Classification (experimental results)



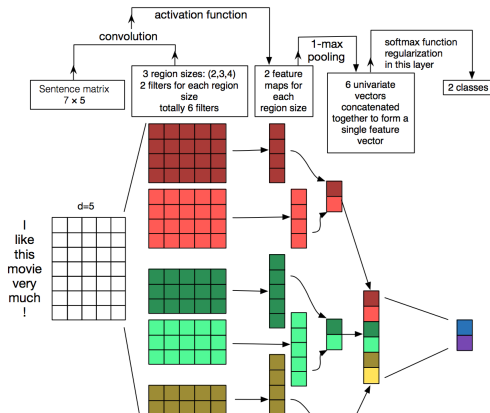
## Time Sensitive Sequence Classification (experimental results)



# Deep learning for stance classification

## Convolutional Neural Network for Text

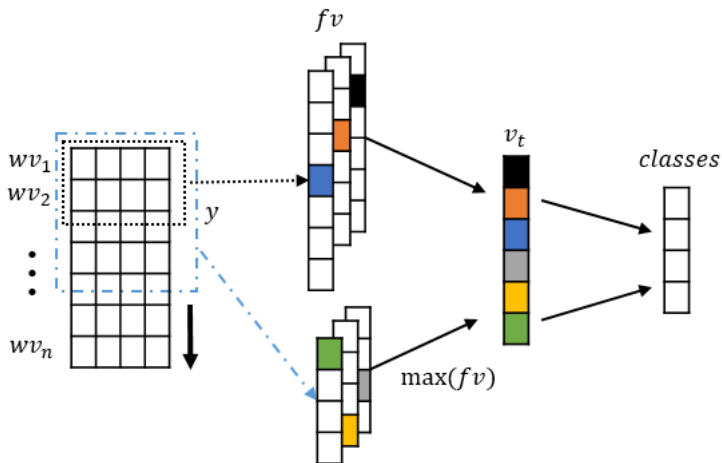
- Documents/sentence represented as a matrix.
  - Row corresponds to vector representation of a word (word embeddings (word2vec/Glove))
  - Filters slide over full rows of the matrix, width of filter same as embedding dimension.



# Deep learning for stance classification

## Convolutional Neural Network for stance classification [chen et al., 2017]

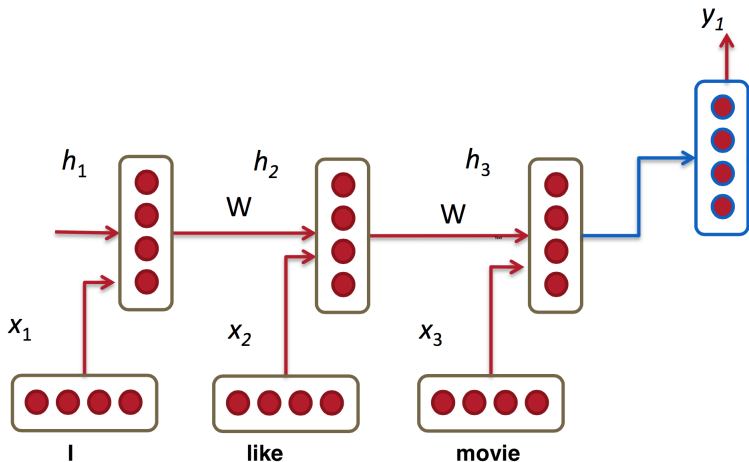
- Learn word embedding as well as Glove representation.
- Uses different sized filters with number of filters of same size being 128.



# Deep learning for stance classification

## Recurrent Neural Network for stance classification

- Use word embedding from Glove representation.
- Unroll over words in a tweet and predict the label.



## Deep learning for stance classification

## Neural Network for stance classification

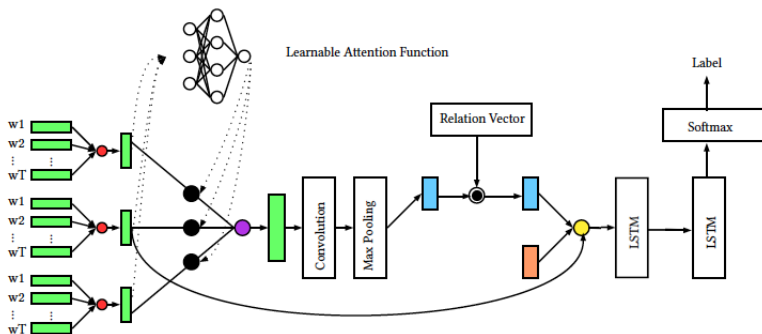
- deep learning model is the best method in terms of F1 score.

Event	Ottawa		Ferguson	
	Acc	F <sub>1</sub>	Acc	F <sub>1</sub>
GP	62.28	42.41	64.31	32.9
Lang. model	53.2	42.66	49.56	34.35
NB	61.76	40.64	62.05	31.29
HP Approx.	67.77	32.29	68.44	25.99
HP Grad.	63.43	42.4	63.23	33.14
<b>CNN</b>	61.74	<b>44.9</b>	62.31	36.49
<b>CNN(GloVe)</b>	59.61	38.87	63.03	<b>39.48</b>
<b>RNN(GloVe)</b>	52.49	38.66	51.49	32.52

# Deep learning for stance classification

## CNN and LSTM combination [amir et al., 2017]

- deep learning model is the best method in terms of F1 score.

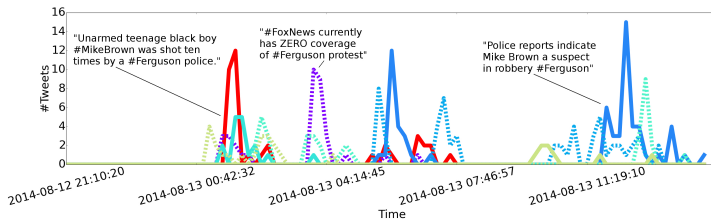


Model	Sydney Siege		Charlie Hebdo		Ferguson		Ottawa	
	Accuracy	$F_1$ Macro	Accuracy	$F_1$ Macro	Accuracy	$F_1$ Macro	Accuracy	$F_1$ Macro
HP [5]	68.59	32.49	72.93	32.56	68.44	25.99	67.77	32.29
Ours	<b>73.15</b>	<b>40.98</b>	<b>77.09</b>	<b>40.81</b>	<b>72.14</b>	<b>36.17</b>	<b>74.93</b>	<b>43.08</b>

# Information Diffusion

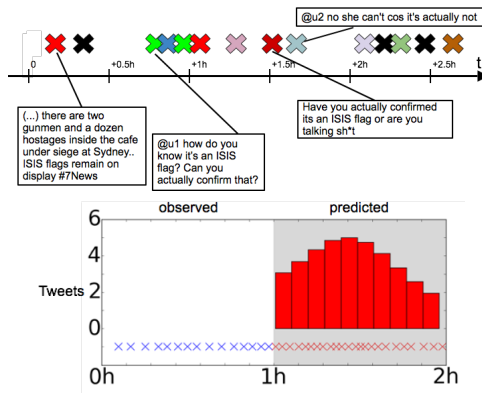
## Information Diffusion

- Model evolution of memes over time.
- Model the behaviours of users, how they influence each other.
- Predict their popularity of memes



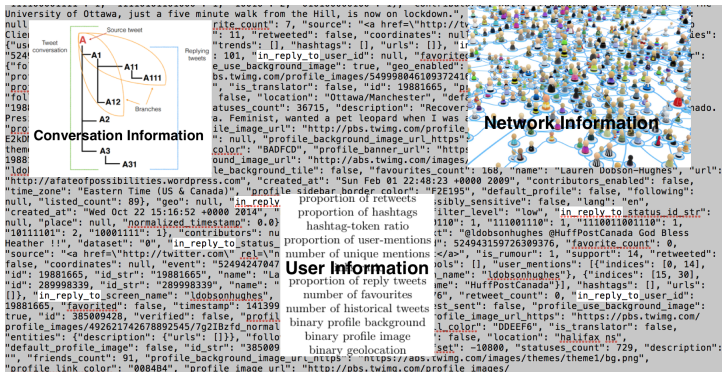
# Predicting Rumour Popularity

- Predict rumour popularity measured as number of tweets in future time intervals
- Motivation: Assist officials and journalists with debunking rumours.



## Hawkes Process for Twitter [Srijith et al., 2017]

- Twitter contain information on conversation structure, users, and network.
- Model Hawkes process to consider Twitter Information.



# Hawkes Process for Twitter

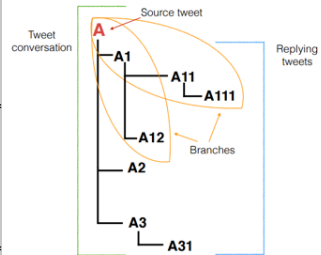
## HPconversion

- Hawkes Process model considering conversational structure
- **HPconversion** : Models conversational structure (spontaneous/replyto tweet)

$$\lambda_{i_n, m_n}(t) = \mu_{i_n} \gamma_{m_n} Z_{nn} + \sum_{\ell=1}^n \mathbb{I}(m_\ell == m_n) Z_{\ell n} \alpha_{i_\ell, i_n} \kappa(t - t_\ell)$$

- Avoids performing summation over all previous terms

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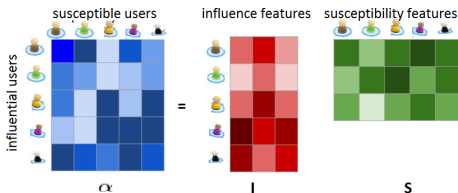


## Hawkes Process for Twitter

## HPdecomposition

- **HPdecomposition** : Decompose matrix to lower rank non-negative components.  

$$\lambda_{i_n, m_n}(t) = \mu_{i_n} \gamma_{m_n} Z_{nn} + \sum_{\ell=1}^n \mathbb{I}(m_\ell == m_n) Z_{\ell n} [I \cdot S^T]_{i_\ell, i_n} \kappa(t - t_\ell)$$
- Prevents overfitting by learning a reduced number of parameters.



## Hawkes Process for Twitter

## HPUserfeatures

- Hawkes Process model considering user features
- **HPUserfeatures** : Consider user features by parameterizing influence and susceptibility matrices
 
$$\lambda_{i_n, m_n}(t) = \mu_{i_n} \gamma_{m_n} Z_{nn} + \sum_{\ell=1}^n \mathbb{I}(m_\ell == m_n) Z_{\ell n} \sigma([\mathbf{x}_{i_\ell} \mathbf{I}] \cdot [\mathbf{x}_{i_n} \mathbf{S}]^T) \kappa(t - t_\ell).$$
- Learns the features determining influence and susceptibility
- Links ratio depends on number of followers and followees.  $\log\left(\frac{(\phi_{lis}+1)(\phi_{in}+1)^2}{\phi_{out}+1}\right)$ .

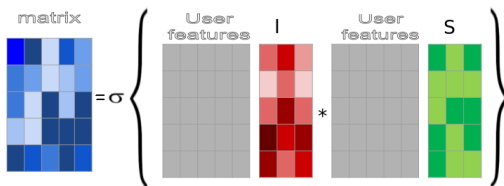


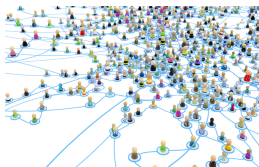
Table 1: User features used for learning influences.

Feature id	Feature name
1	proportion of retweets
2	proportion of hashtags
3	hashtag-token ratio
4	proportion of user-mentions
5	number of unique mentions
6	links ratio
7	proportion of reply tweets
8	number of favourites
9	number of historical tweets
10	binary profile background
11	binary profile image
12	binary geolocation

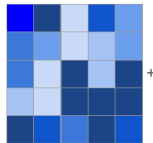
# Hawkes Process for Twitter

## HPconnection

- Hawkes Process model considering connection information
- **HPconnection** : Consider network information by selectively regularizing matrix.
- Users which are not connected are less influential.
- **HPregularization** : Regularize matrix entries using  $l_2$  norm.

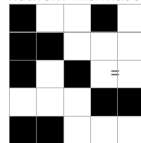


user influence matrix



+

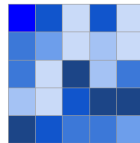
network information



=

=

regularized influence matrix



## Hawkes Process for Twitter

## Learning

- Complete Likelihood is given by

$$\prod_{n=1}^N \lambda_{i_n, m_n}(t_n) \times \exp(-\sum_{i=1}^R \sum_{m=1}^M \int_0^T \lambda_{i,m}(s) ds)$$

inst. probabilities over all tweets  $\times$  survival probability

- Parameters are learnt by maximizing regularized **log-likelihood**.

$$\ell(\mu, \gamma, \alpha, \omega) = \sum_{n=1}^N \log \lambda_{i_n, m_n}(t_n) - \sum_{i=1}^R \sum_{m=1}^M \int_0^T \lambda_{i,m}(s) ds.$$

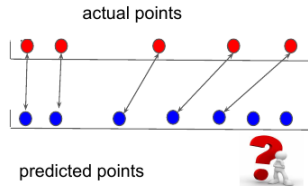
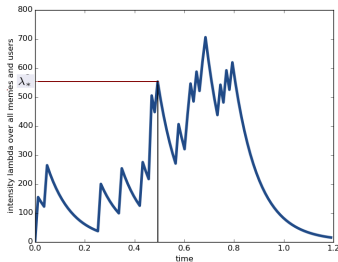
$$\begin{aligned} \ell(\mu, \gamma, \alpha, \omega) = & \sum_{n=1}^N Z_{n,n} \log(\mu_{i_n} \gamma_{m_n}) + \sum_{n=1}^N \sum_{\ell=1}^{n-1} \mathbb{I}(m_\ell = m_n) Z_{\ell,n} \log \alpha_{i_\ell, i_n} \kappa(t_n - t_\ell) \\ & - T \sum_{i=1}^R \sum_{m=1}^M \mu_i \gamma_m - \sum_{i=1}^R \sum_{\ell=1}^N \alpha_{i_\ell, i} K(T - t_\ell) \end{aligned}$$



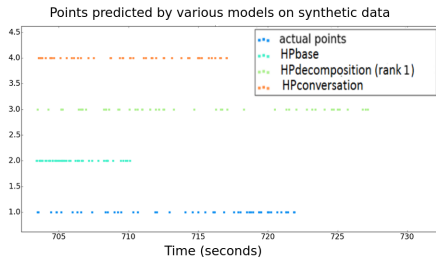
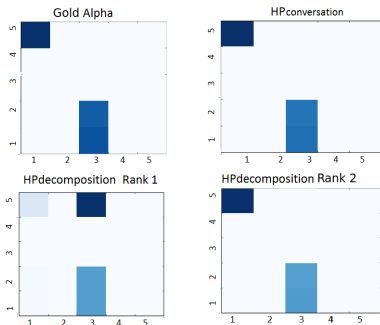
# Hawkes Process for Twitter

## Prediction and Evaluation

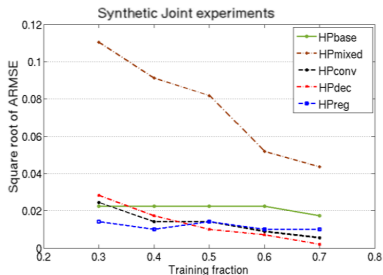
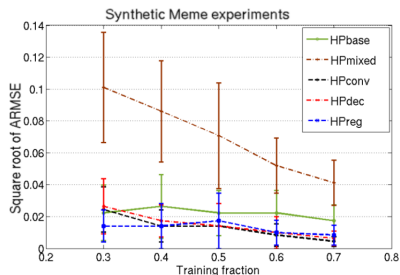
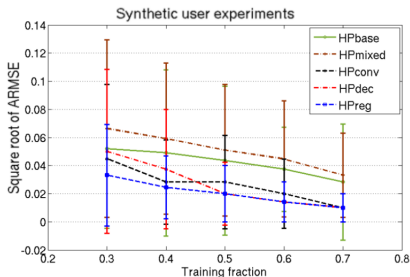
- Prediction by modified **thinning algorithm**.
  - Similar to rejection sampling
  - Consider an upper bound  $\lambda_* \geq \lambda(t)$  in  $[s, u]$
  - Generate a sample from homogenous Poisson process with rate  $\lambda_*$
  - Accept based on the ratio  $\frac{\lambda(t)}{\lambda_*}$
  - Upper bound  $\lambda_*$  easy to obtain for Hawkes Process !
- Evaluation using aligned mean squared error and number of predictions



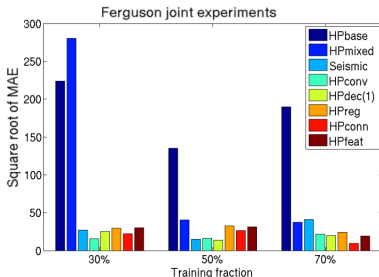
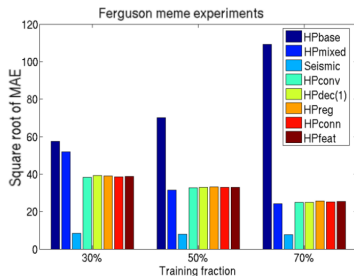
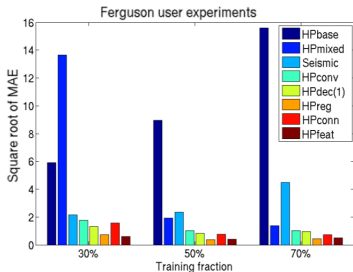
## Hawkes Process for Twitter : Experimental Results (Synthetic)



# Hawkes Process for Twitter : Experimental Results (Synthetic)



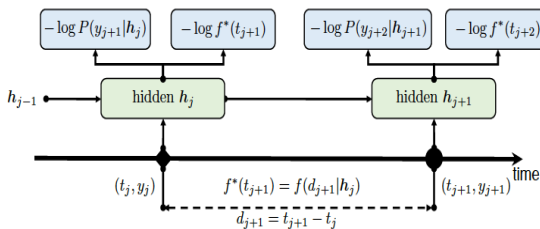
# Hawkes Process for Twitter : Experimental Results (Ferguson)



## Recurrent point process [du et al., 2017]

## Recurrent point process

- Hawkes process assumes that the influences from past events are linearly additive
- True relationship is not known
- Recurrent neural networks helps to learn the non-linear relationships

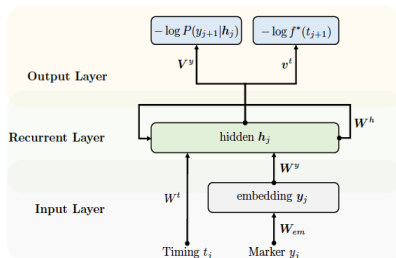


## Recurrent point process [du et al., 2017]

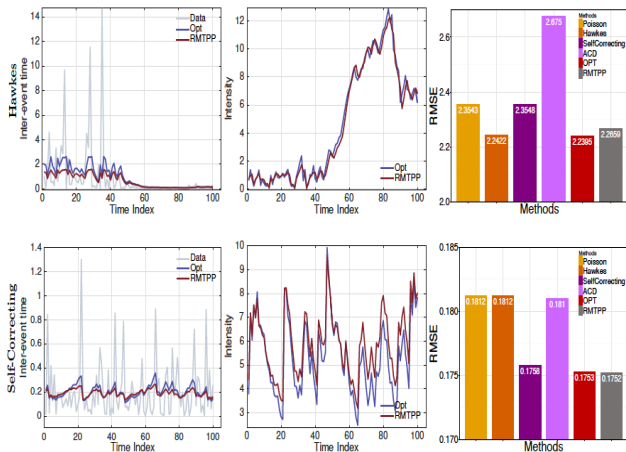
$$h_j = \max \left\{ \mathbf{W}^y y_j + \mathbf{W}^t t_j + \mathbf{W}^h h_{j-1} + b_h, 0 \right\}.$$

$$P(y_{j+1} = k | h_j) = \frac{\exp \left( \mathbf{V}_{k,:}^y \cdot h_j + b_k^y \right)}{\sum_{k=1}^K \exp \left( \mathbf{V}_{k,:}^y \cdot h_j + b_k^y \right)},$$






$$\lambda^*(t) = \exp \left( \underbrace{v^{t^\top} \cdot h_j}_{\text{past influence}} + \underbrace{w^t (t - t_j)}_{\text{current influence}} + \underbrace{b^t}_{\text{base intensity}} \right),$$



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Thank you

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