TweeTime:

A Minimally Supervised Method for Recognizing and Normalizing Time Expressions in Twitter

Jeniya Tabassum

Alan Ritter Wei Xu

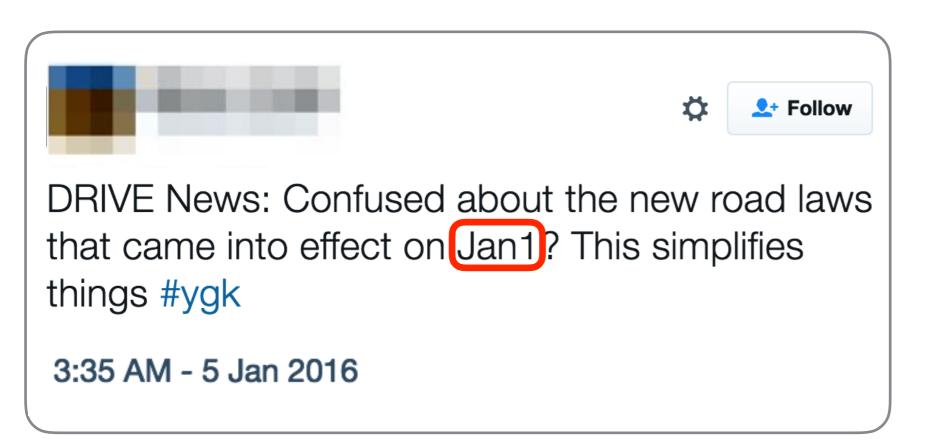


A Minimally Supervised Method for Recognizing and Normalizing Time Expressions in Twitter

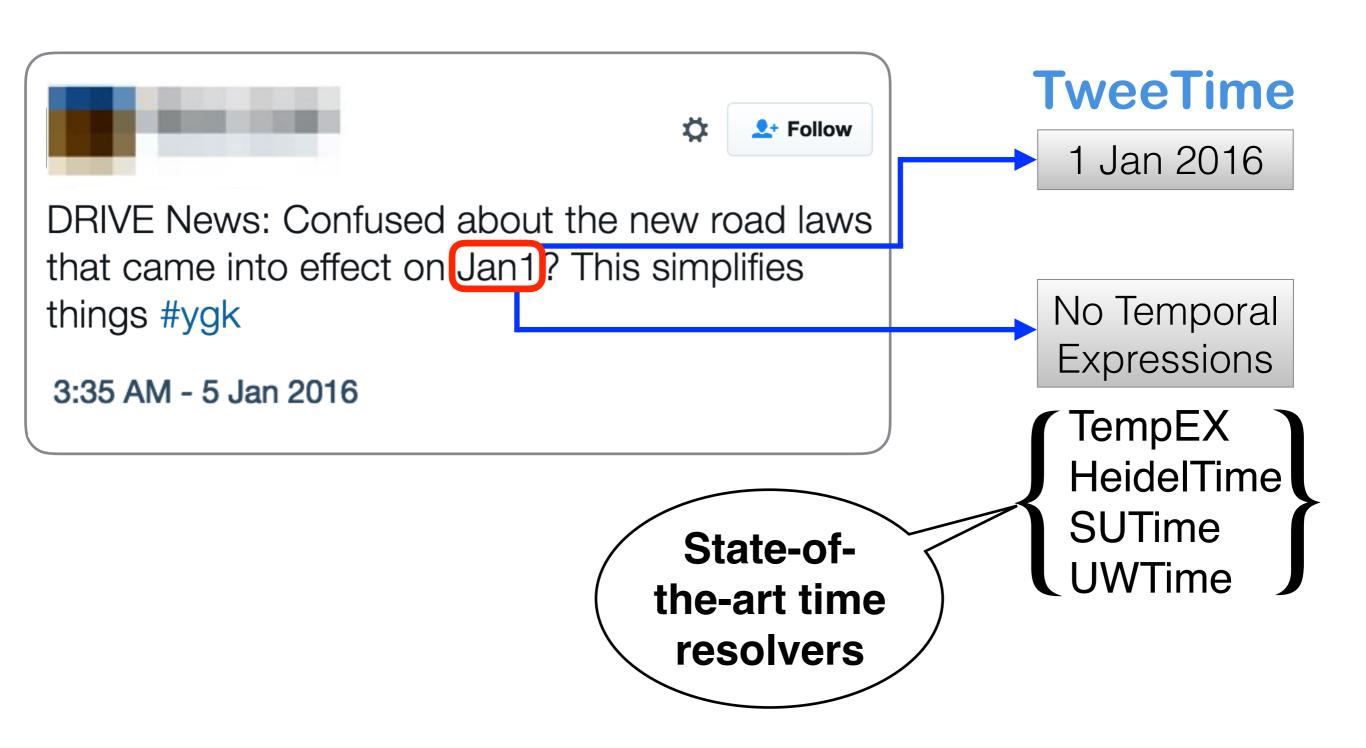
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Time Resolution from Tweets



Time Resolution from Tweets



Challenge: Diversity

Tomorrow

2m 2ma 2mar 2mara 2maro 2marrow 2mor 2mora 2moro 2morow 2morr 2morro 2morrow 2moz 2mr 2mro 2mrrw 2mrw 2mw tmmrw tmo tmoro tmorrow tmoz tmr tmro tmrow tmrrow tmrrw tmrw tmrww tmw tomaro tomarow tomarro tomarrow tomm tommarow tommarrow tommoro tommorow tommorrow tommorw tommrow tomo tomolo tomoro tomorow tomorro tomorrw tomoz tomrw tomz

Rule-Based SuTime [Strötgen & Gertz, 2013]
SuTime [Chang & Manning, 2012]
TempEX [Mani & Wilson, 2000]

Previous **rule based systems** do not handle noisy text.

Previous **supervised systems** perform poorly due to domain mismatch.

Supervised — UWTime [Lee et al., 2014]

Requires

— ParsingTime [Angeli et al., 2012/2013]

Human Labels

Social Media is Hard





Social Media is Hard





Date Resolution in Social Media

Event Extraction

Disease Outbreaks

Cyber Security



[Kanhabua et al., 2012]

Victim	Date
spamhaus	2013/03/18
soca	2011/06/20
etrade	2012/01/05
interpol	2012/02/29
ustream	2012/05/09

[Ritter et al., 2015]

[Chang et al., 2016]

Date Resolution in Social Media

Event Extraction

Disease Outbreaks

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[Kanhabua et al., 2012]

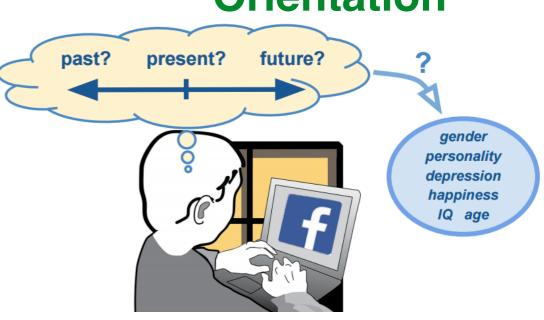
Victim	Date
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[Ritter et al., 2015]

[Chang et al., 2016]

Social Science

Temporal Orientation



[Schwartz et al., 2015]

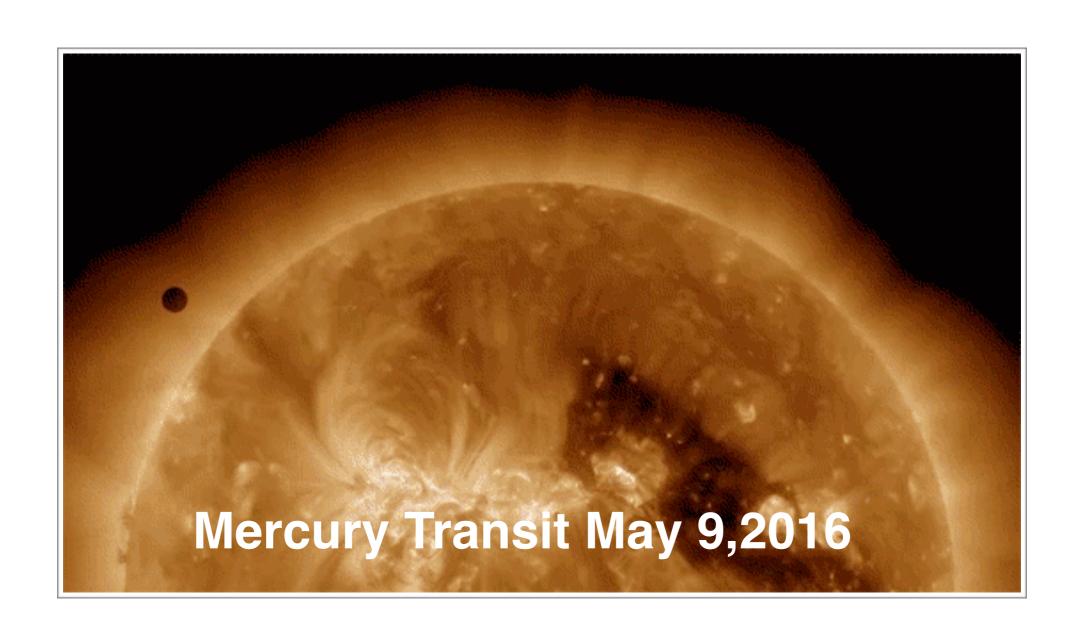
No existing temporal resolver for social media

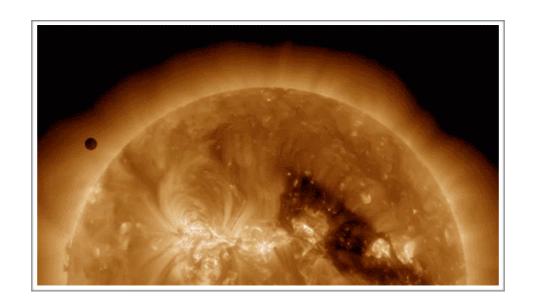
TweeTime

can handle noisy Twitter Text

Distant Supervision

(no human labels needed!)





8 May

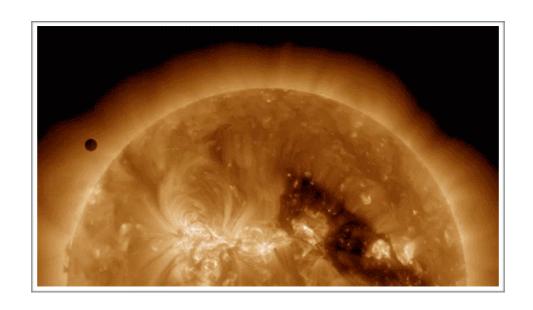
9 May

10 May









8 May

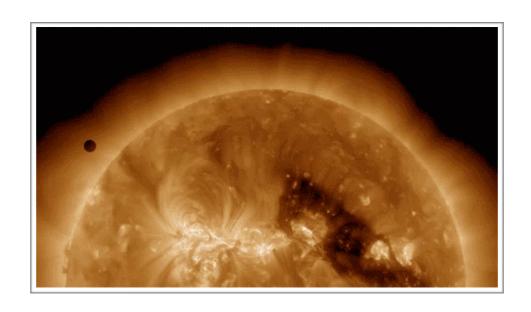
9 May

10 May









8 May

9 May

10 May





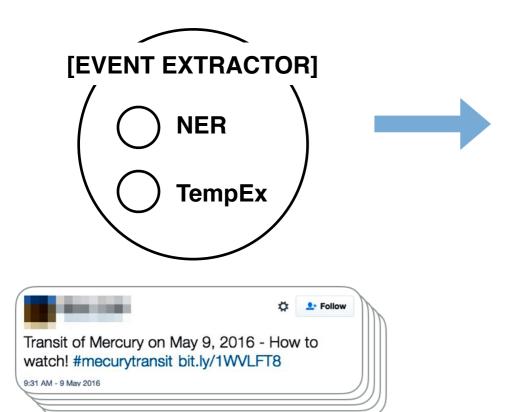


Tweets posted near an event that mention a key entity are likely to contain time expressions referring to the event's date.

Contribution

- First distant Supervision approach for date resolution
 - Most prior work on relation extraction [Mintz et al., 2009b; Riedel et al., 2010; Hoffmann et al., 2011]
- Novel multiple-instance-learning tagging model
 - Learns word-level tags using only sentence labels
- State of the art results on social media domain
 - 17% increase in F-score over SUTime

System Overview



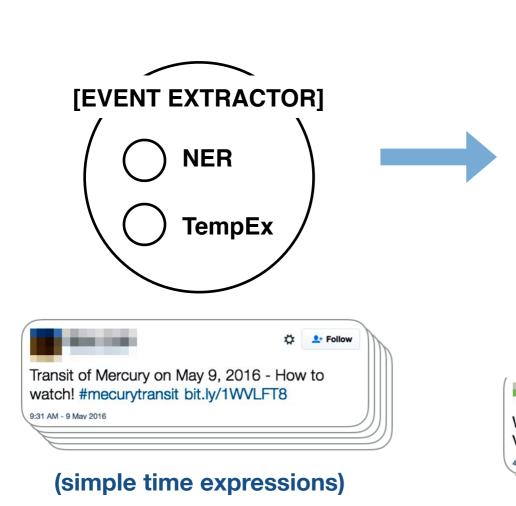
[10,000 events] [EVENT DATABASE]

ENTITY	DATE		
Mercury	5/9/2016		

(simple time expressions)

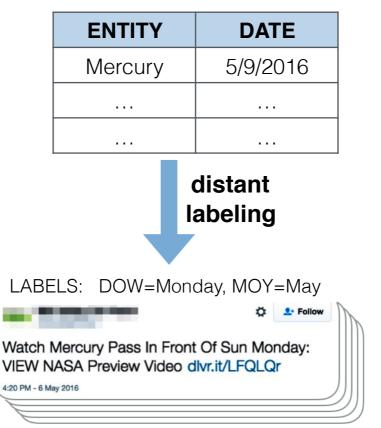
[120 Million Tweets]

System Overview



[120 Million Tweets]

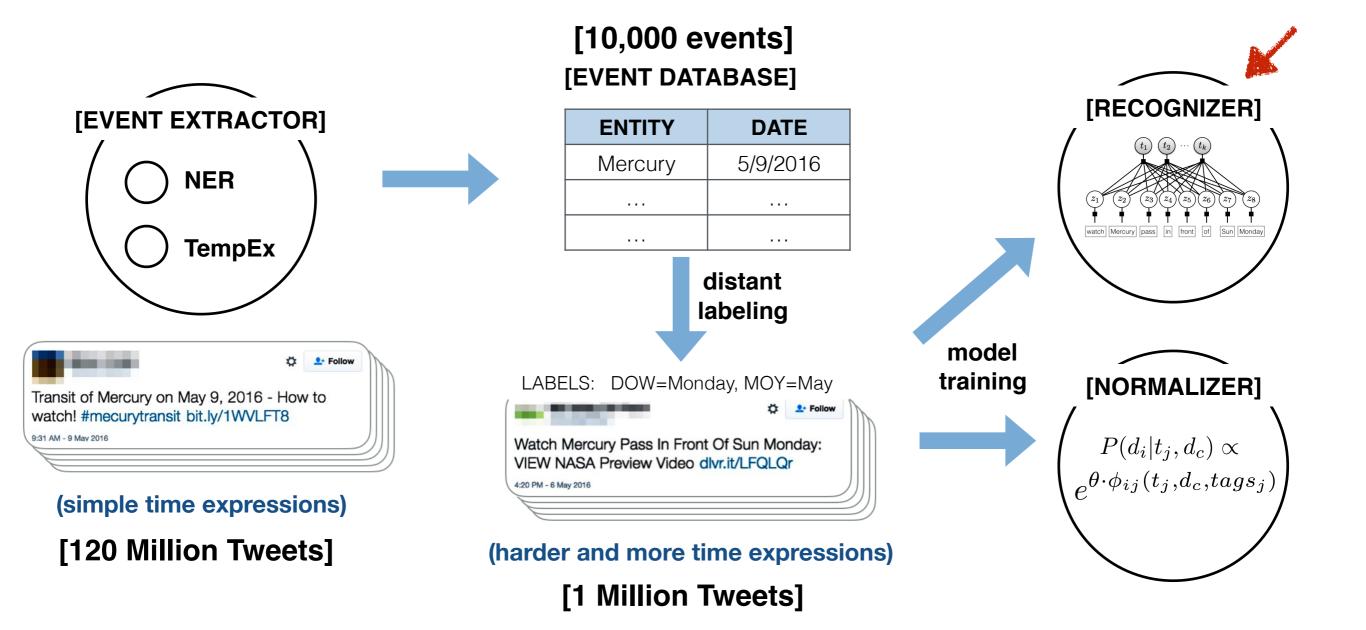
[10,000 events] [EVENT DATABASE]



(harder and more time expressions)

[1 Million Tweets]

System Overview



Temporal Recognizer





LABELS: Day of Week, Day of Month, Month, Timeline

< Monday, 9, May, Future >

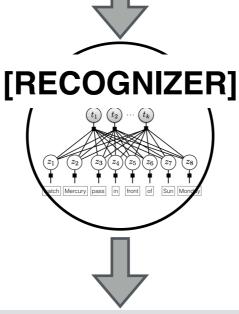
[Event Database]

ENTITY	DATE		
Mercury	5/9/2016		



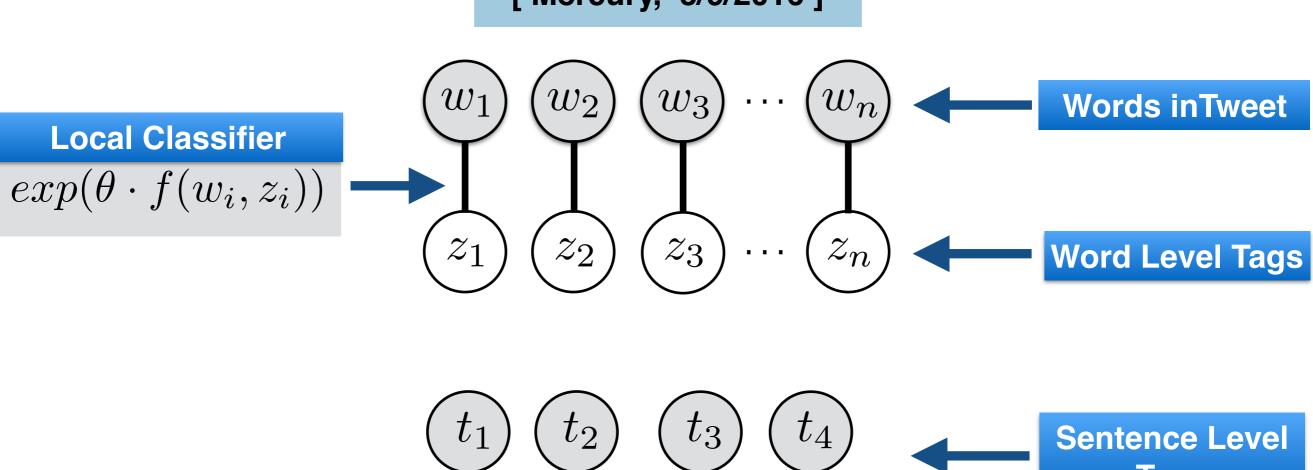
[1 Million Tweets]

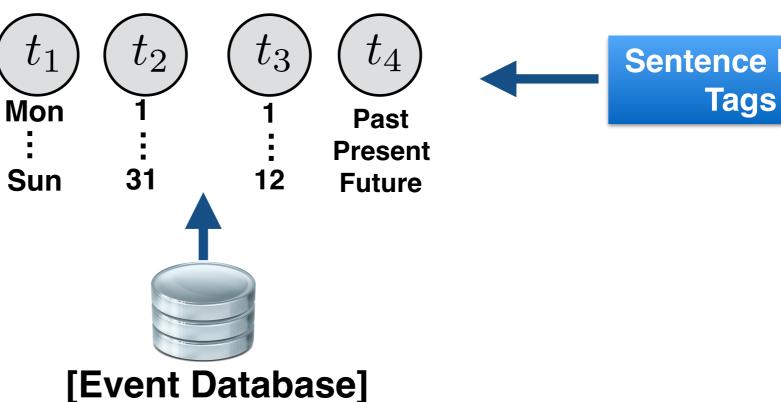
automatically labeled

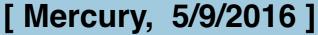


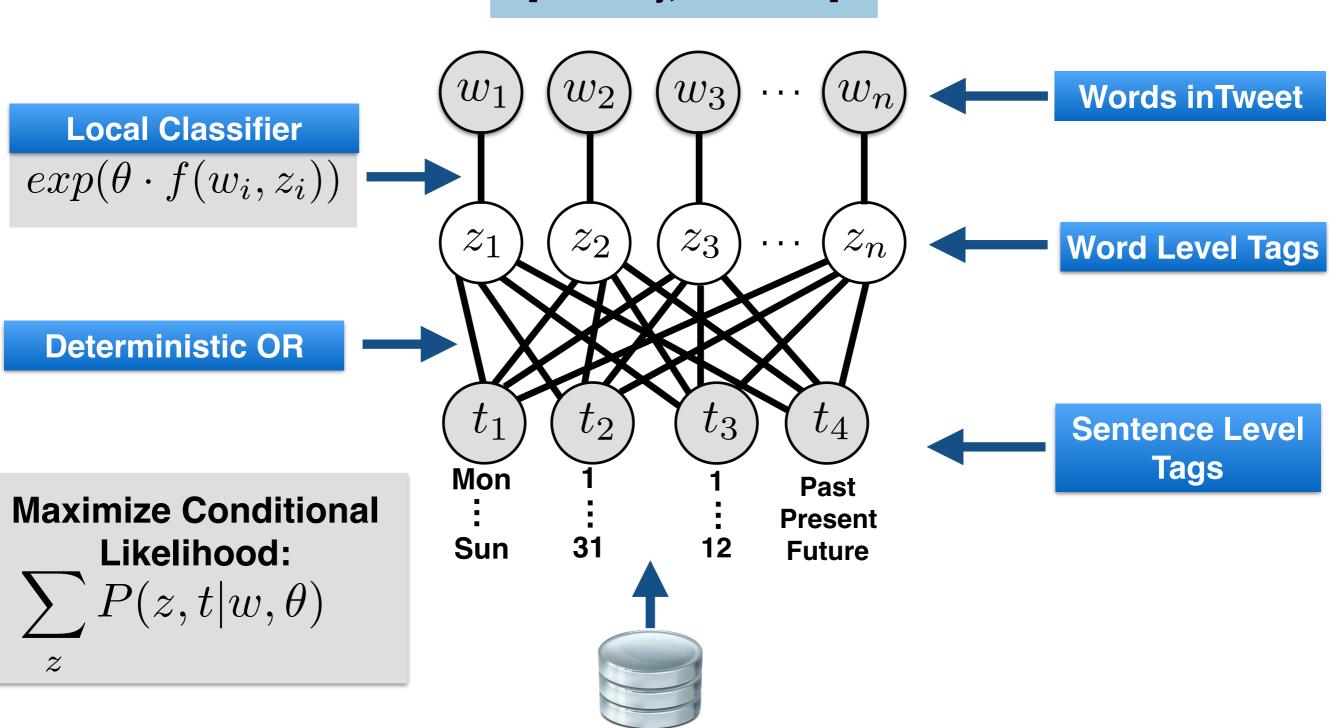
Word	Нарру	Friday!	#Fri	yey	#TGIF
Tag	NA	FRI	FRI	NA	FRI



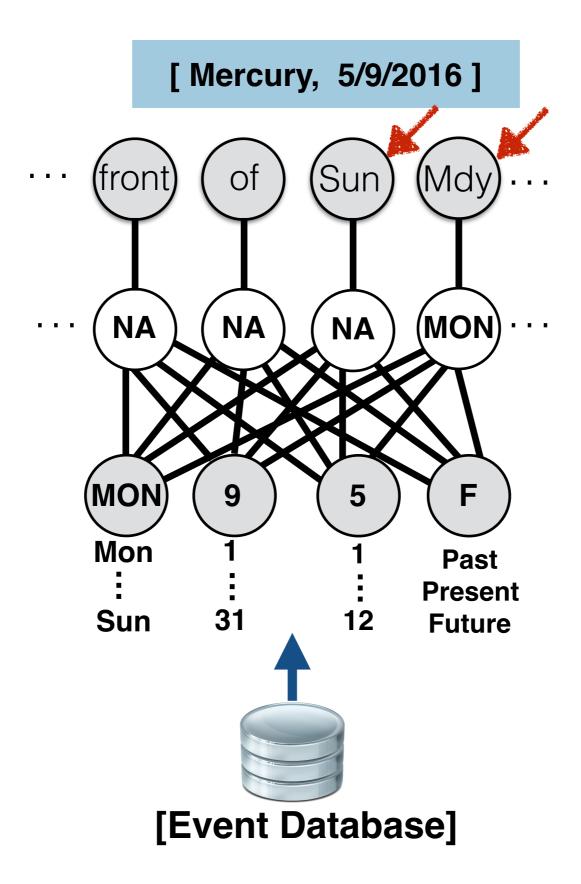






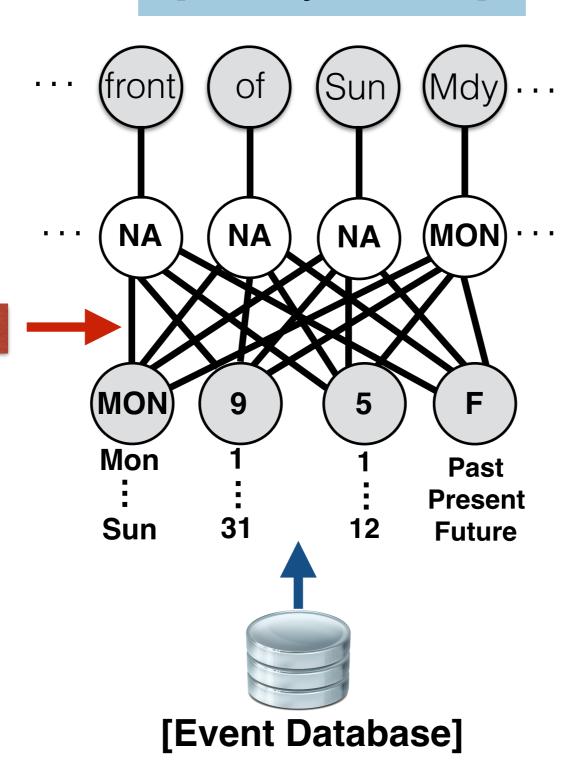


[Event Database]

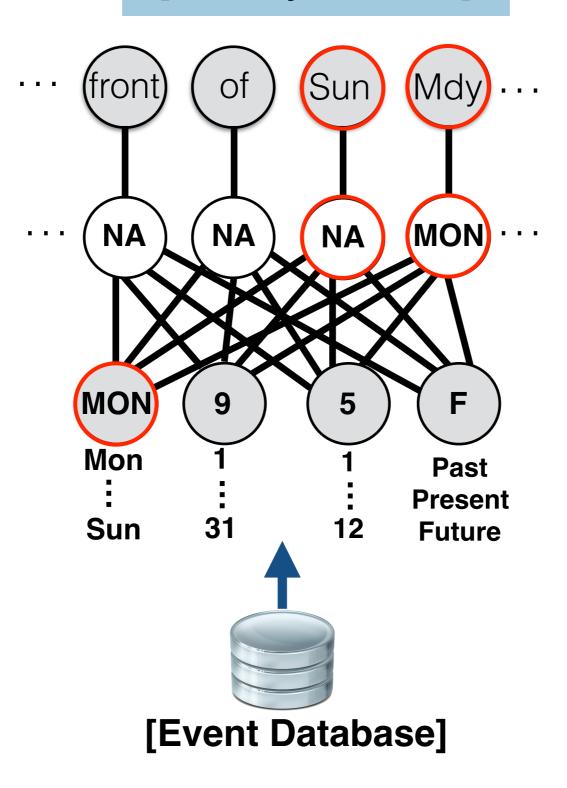


Deterministic OR

[Mercury, 5/9/2016]



[Mercury, 5/9/2016]



MultiT: Learning

Latent-Variable Perceptron (MAP-based learning)

Gradient of Conditional Log-Likelihood:

$$\nabla P(t|w) = \sum_{z} P(z|w, t; \theta) \cdot f(z, w) - \sum_{t, z} P(t, z|w; \theta) \cdot f(z, w)$$

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$$\nabla P(t|w) = \max_{P(z|w, t; \theta)} f(z, w) - \max_{P(t, z|w; \theta)} f(z, w)$$

Weighted Edge Cover Problem

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Assumptions: MultiT Tagger

Sentence Level $Tags \in Word \ Level \ Tags$

Assumptions: MultiT Tagger



Sentence Level Tags:

TL = Future
MOY= May
DOM=9
DOW= Mon

Sentence Level $Tags \in Word \ Level \ Tags$

Assumptions: MultiT Tagger

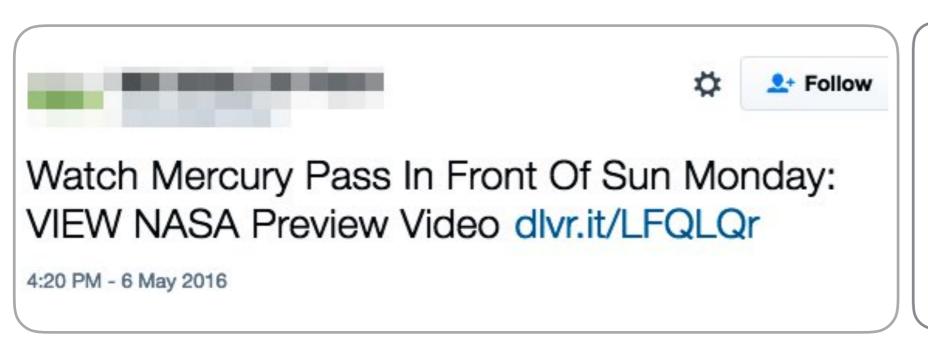


Sentence Level Tags:

TL = Future
MOY= May
DOM=9
DOW= Mon

Sentence Level $Tags \in Word$ Level Tags Word Level $Tags \in Sentence$ Level Tags

Missing Data Problem



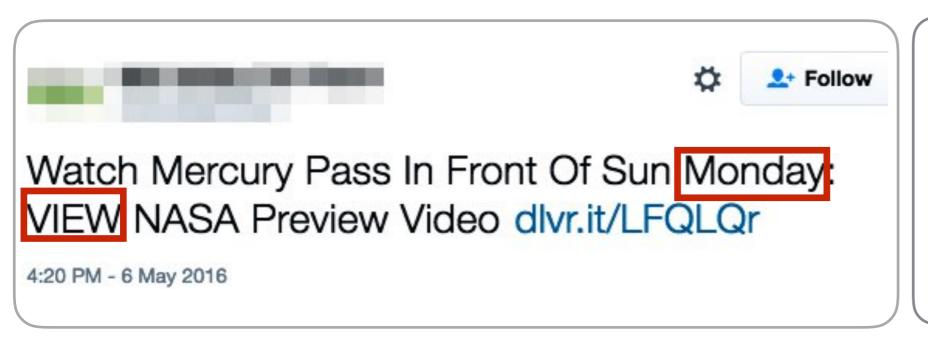
Sentence Level Tags:

TL = Future MOY= May

DOM=9

DOW= Mon

Missing Data Problem



Sentence Level Tags:

- ✓ TL = Future
- X MOY= May
- X DOM=9
- ✓ DOW= Mon

Missing Data Problem



Sentence Level Tags:

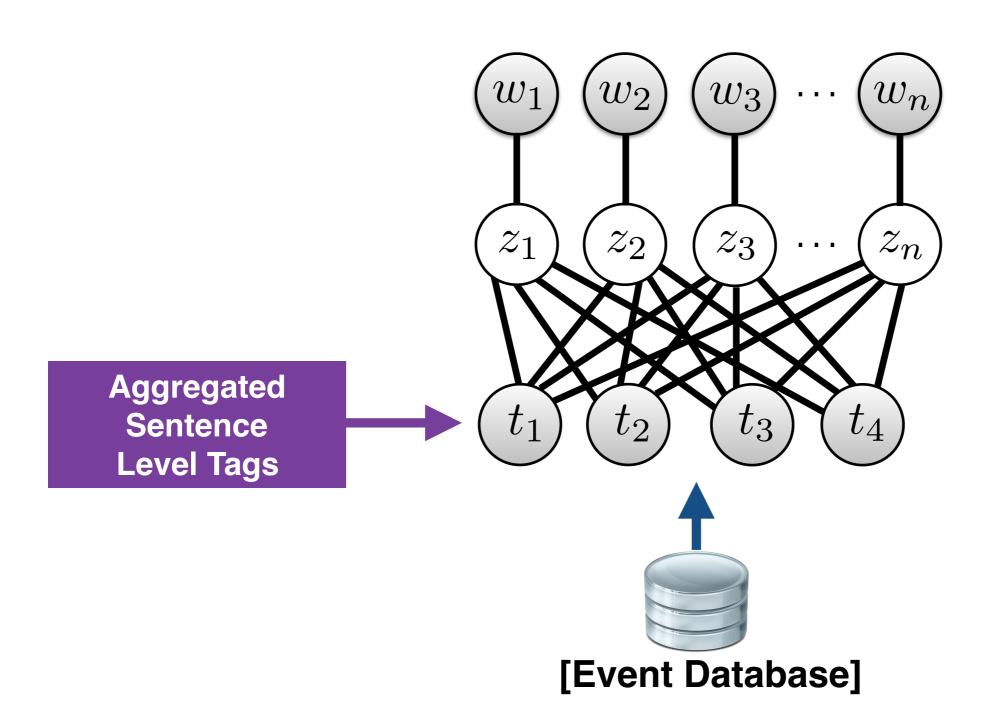
- ✓ TL = Future
- X MOY= May
- X DOM=9
- **✓** DOW= Mon

Sentence Level $Tag \notin Word Level Tag$ $Word Level Tag \notin Sentence Level Tag$

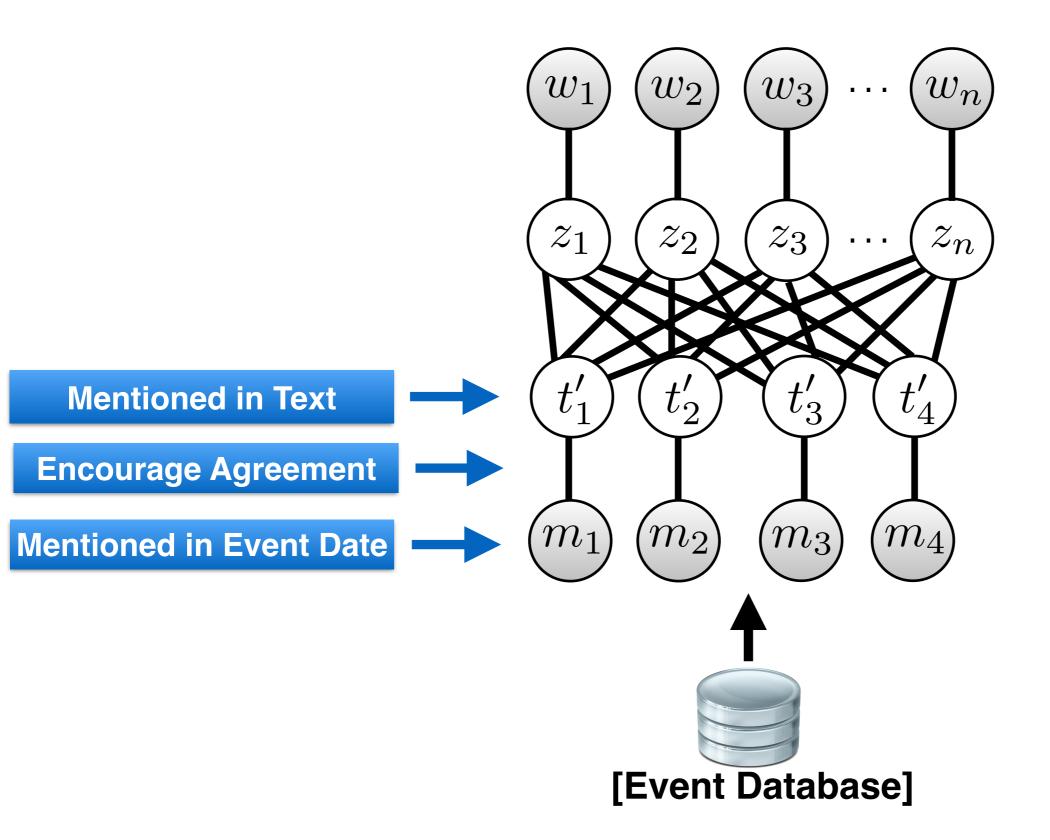
Solution:

Multiple Instance Learning Missing Data Model

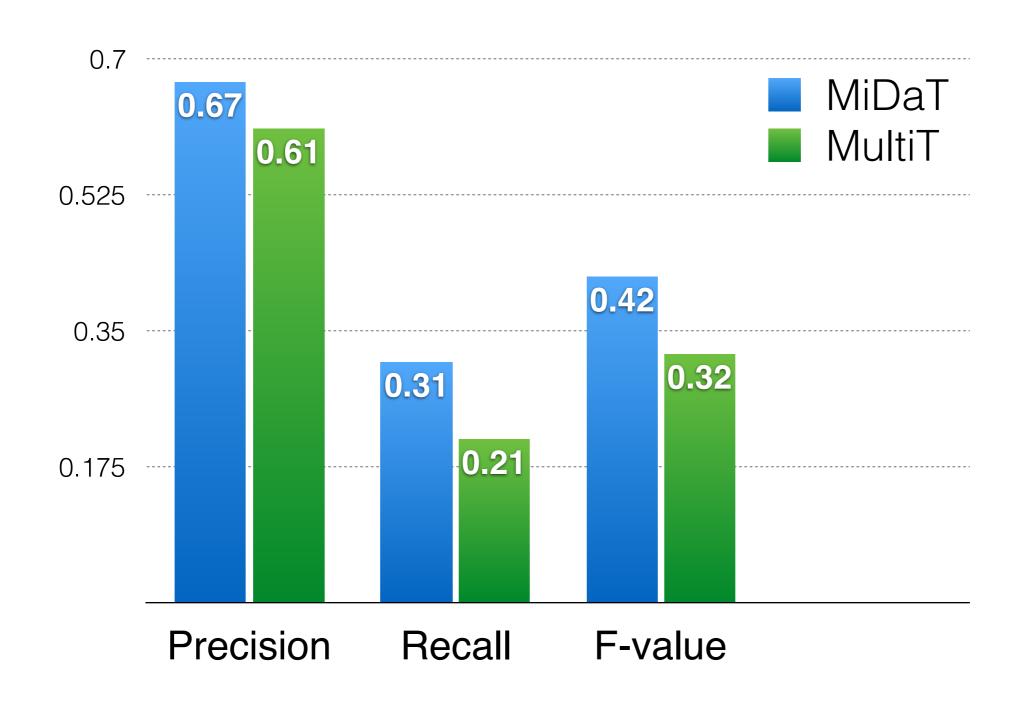
Missing Data Extension



MiDaT Tagger [Extension of MultiT]



MultiT Vs MiDaT [Intrinsic evaluation]



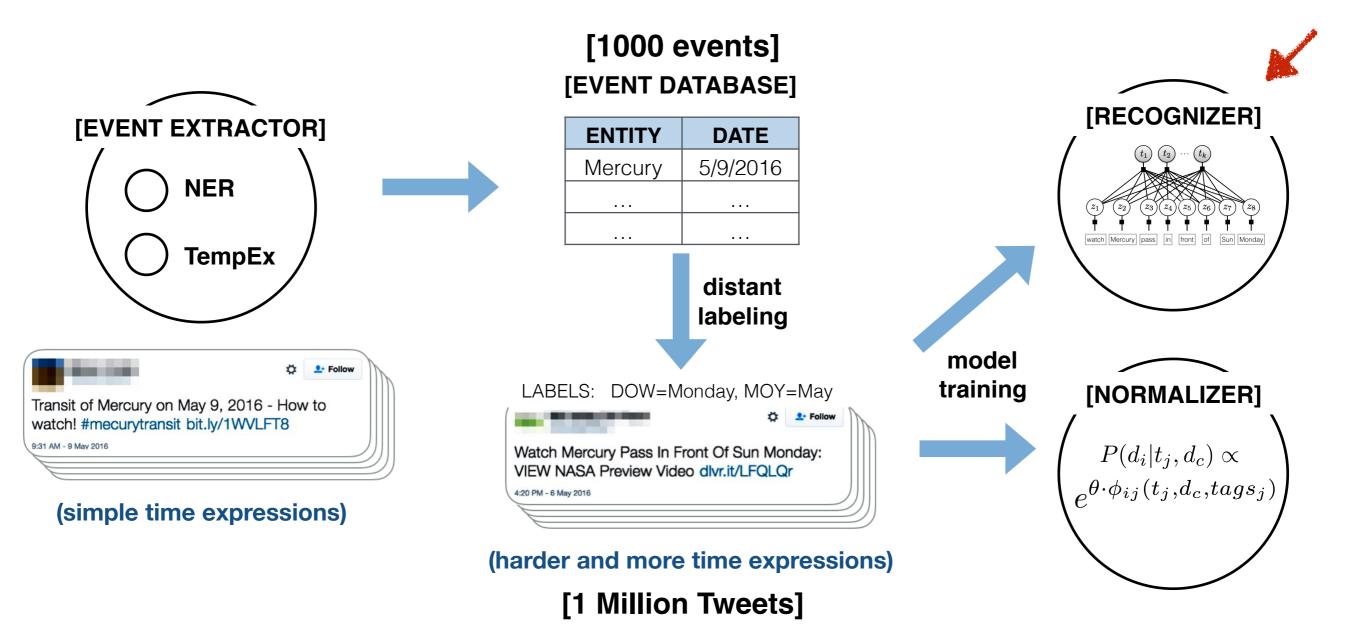
Example Tags

Word	Im	Hella	excited	for	tomorrow
Tag	NA	NA	Future	NA	Future

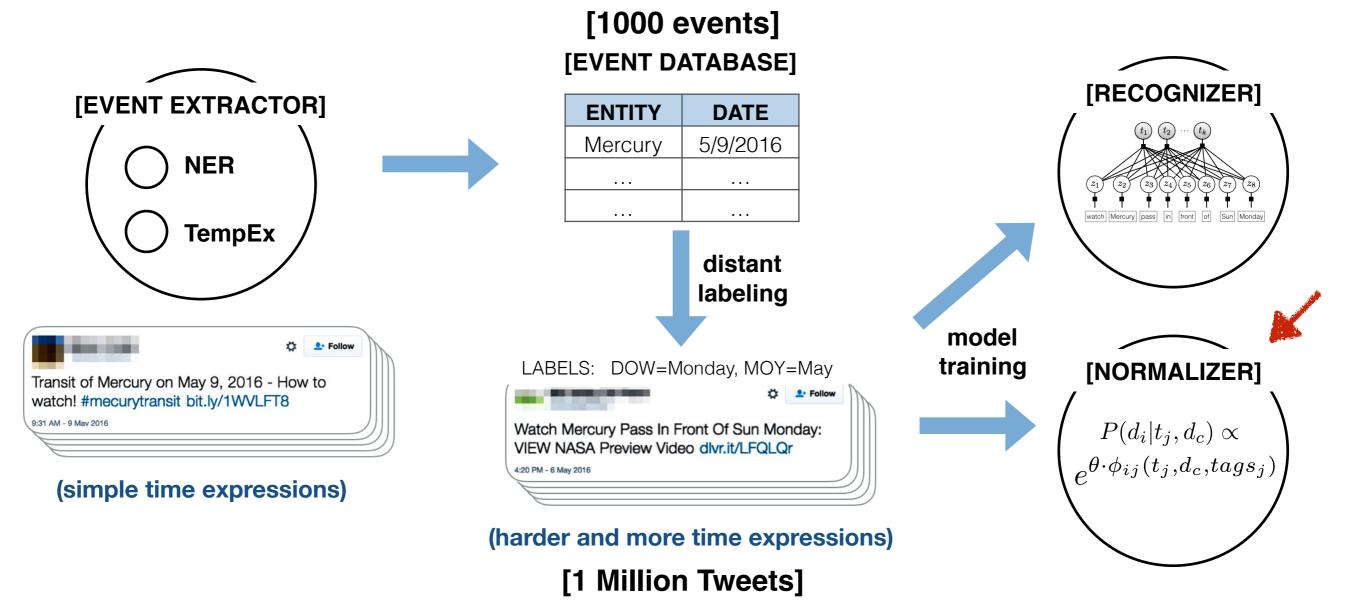
Word	Thnks	for	a	Christmas	party	on	fri
Tag	NA	NA	NA	Dec	NA	NA	FRI

Not always matches human intuition

System Overview



System Overview



Temporal Normalizer



LABEL: May 9 2016

[Event Database]



[$\frac{1}{2}$ Million Tweets]



[NORMALIZER]

$$\left(e^{\theta \cdot \phi_{ij}(t_j, d_c, tags_j)}\right)$$

Temporal Normalizer



LABEL: May 9 2016

[Event Database]



[$\frac{1}{2}$ Million Tweets]



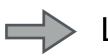
[NORMALIZER]

$$\left(e^{\theta \cdot \phi_{ij}(t_j, d_c, tags_j)}\right)^{P(d_i|t_j, d_c, tags_j)}$$

$$P(d_i|t_j,d_c) \propto e^{\theta \cdot \phi_{ij}(t_j,d_c,tags_j)}$$

Temporal Normalizer





LABEL: May 9 2016



 $[\frac{1}{2}$ Million Tweets]

Creation Date: 11/1

EMNLP starts 4m tmrw!

[NORMALIZER]

 $e^{\theta \cdot \phi_{ij}(t_j, d_c, tags_j)}$

 $P(d_i|t_j, d_c) \propto e^{\theta \cdot \phi_{ij}(t_j, d_c, tags_j)}$



$$\begin{array}{c} D_{-10} \\ \hline 10/22 \end{array}$$

$$D_{-1}$$
 10/31

$$D_0$$
11/1

$$D_{+1}$$

$$11/2$$

$$\underbrace{D_{+10}}_{11/11}$$

 $P(extstyle{ t Candidate Date: 5/9/2016 | \cdots }) \propto f$

Lexical Features

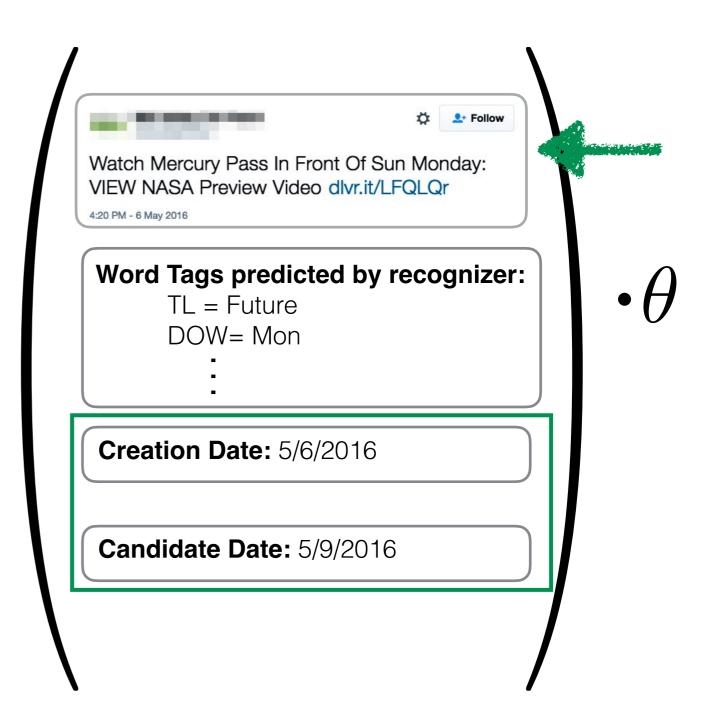
Tag Features

Time Difference Features



 $P(extstyle{ t Candidate Date: 5/9/2016 | \cdots extstyle)} \propto f$

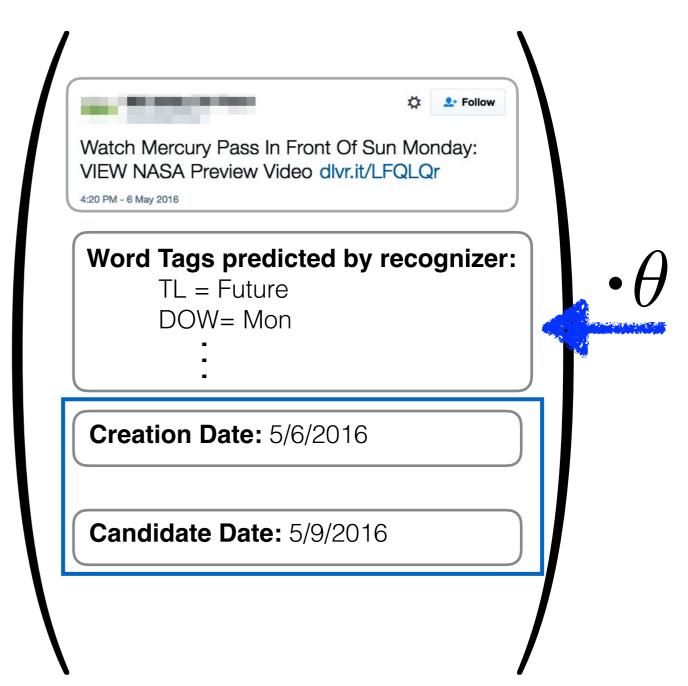
Lexical Features



w = "Monday" \land candidate date \in Monday

 $P(extstyle{igcap} ext{Candidate Date: 5/9/2016} \mid \cdots igcap}) \propto f$

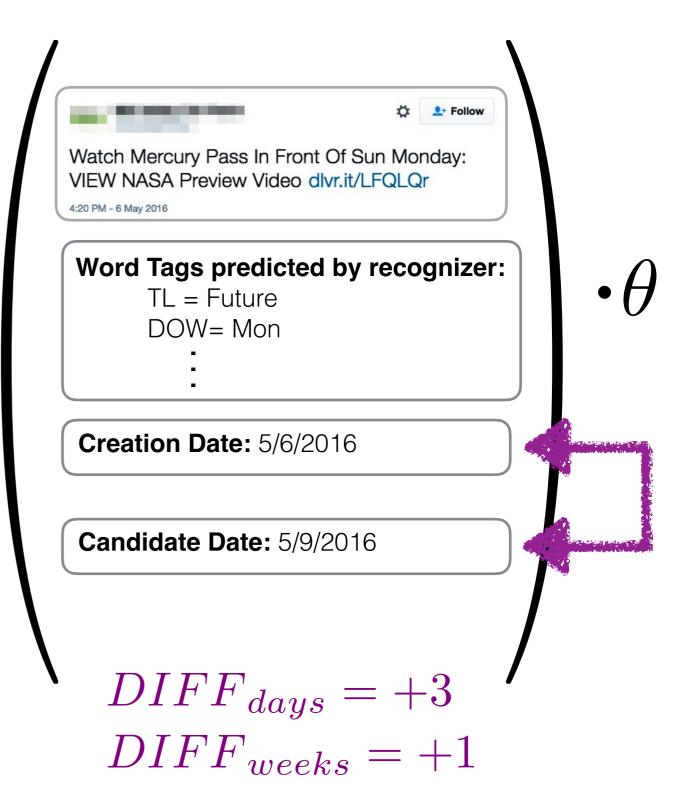
Tag Features



 $t = \text{Future} \land \text{candidate date} \in future$

P(extstyle e

Time Difference Features



Evaluation

250 Tweet [2014-2015]

dev : 50

test: 200

Manually

Annotaated

Temporal Resolver

[TweeTime, HeidelTime, UWTime, SUTime, TempEX]

Evaluation

250 Tweet [2014-2015]

dev : 50

test: 200

Manually

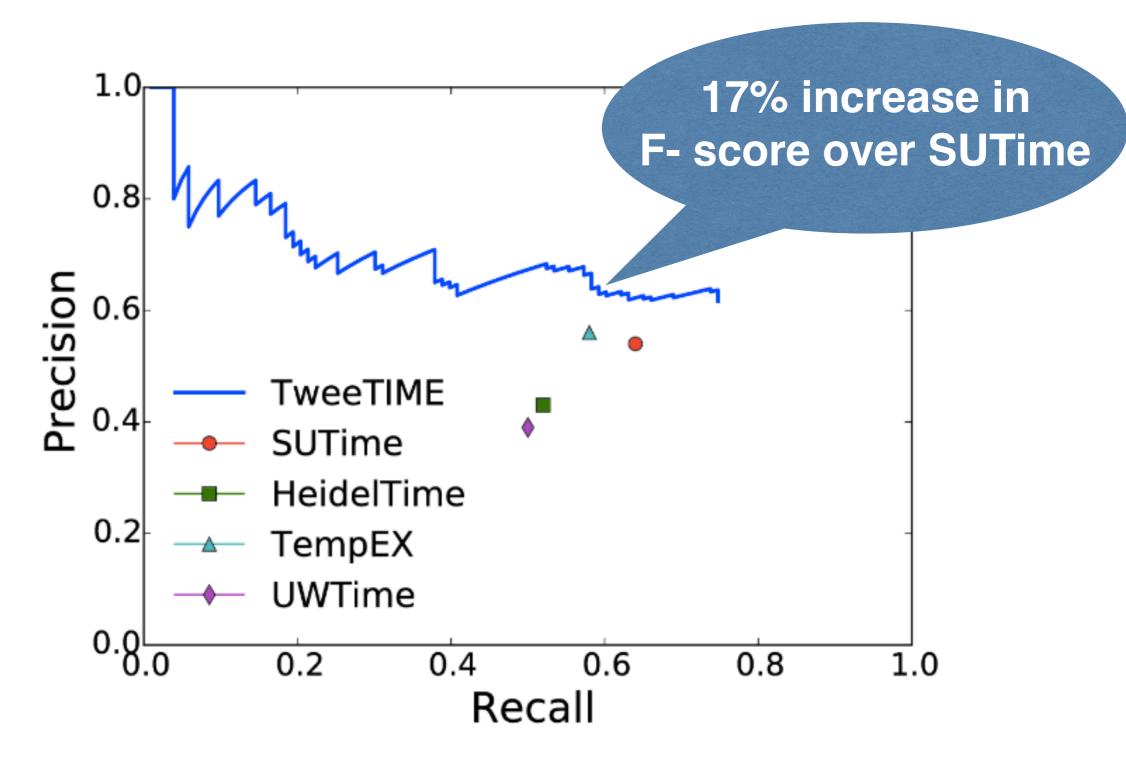
Annotated

Temporal Resolver

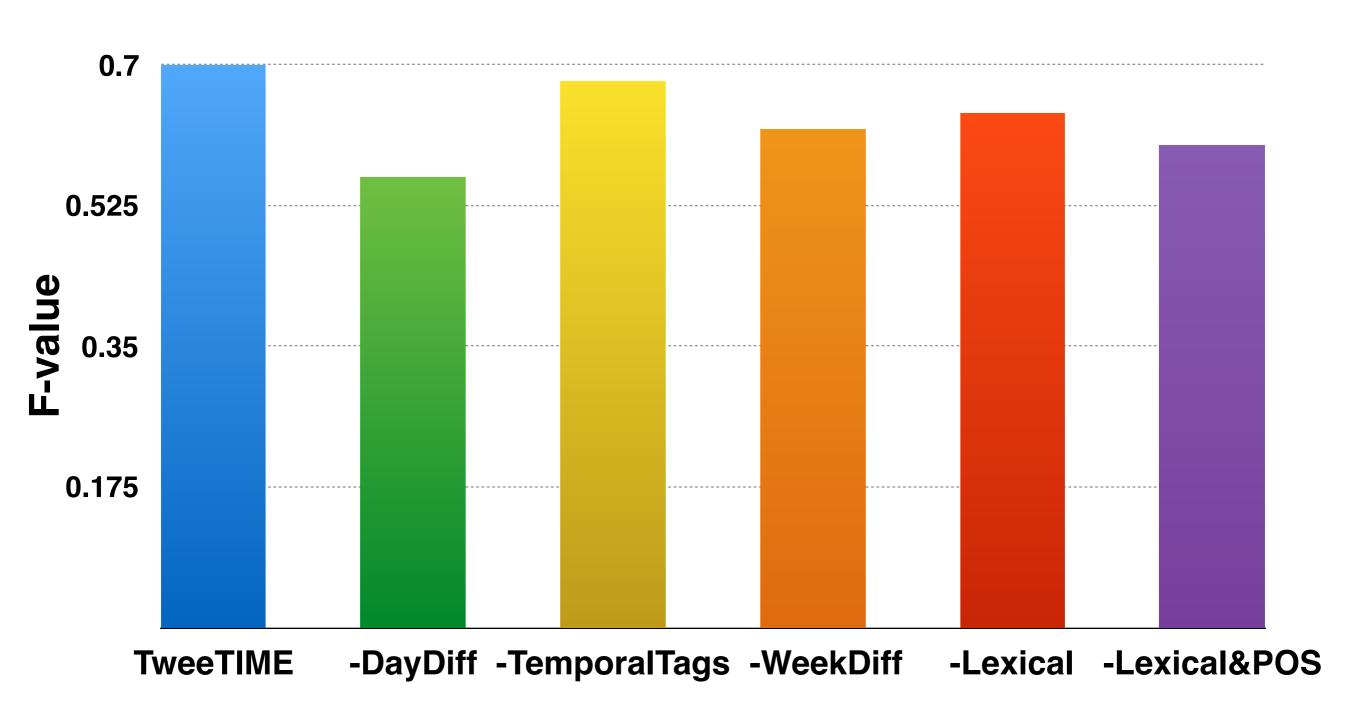
[TweeTime, HeidelTime, UWTime, SUTime, TempEX]

Train Set [2011-2012]

System Performance



Feature Ablation



Takeaways

- 1st and best date resolver for Twitter
- 1st use of distant supervision for time expressions (no human labels needed)
- Code will be available: <u>https://github.com/jeniyat/TweeTime</u>

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