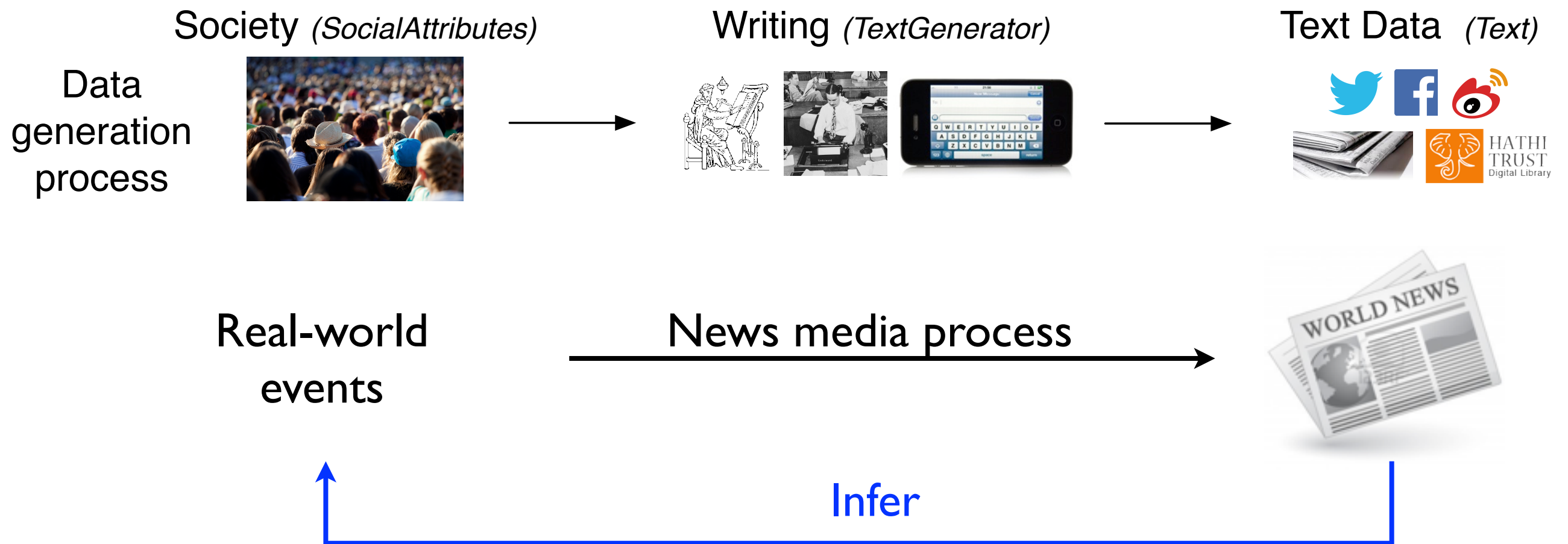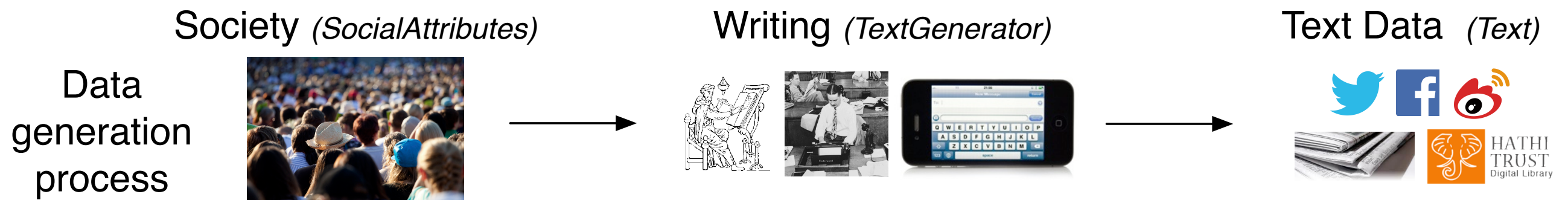# Identifying police killings from news text with distant supervision

Brendan O'Connor
College of Information and Computer Sciences
University of Massachusetts Amherst
http://brenocon.com

Joint work with: Katherine Keith, Abram Handler,
Michael Pinkham, Cara Magliozzi, Joshua McDuffie

http://slanglab.cs.umass.edu/PoliceKillingsExtraction/

1

Data generation process

Society *(SocialAttributes)* → Writing *(TextGenerator)* → Text Data *(Text)*

Real-world events → News media process → WORLD NEWS

Infer

2

Data generation process

Society *(SocialAttributes)* → Writing *(TextGenerator)* → Text Data *(Text)*

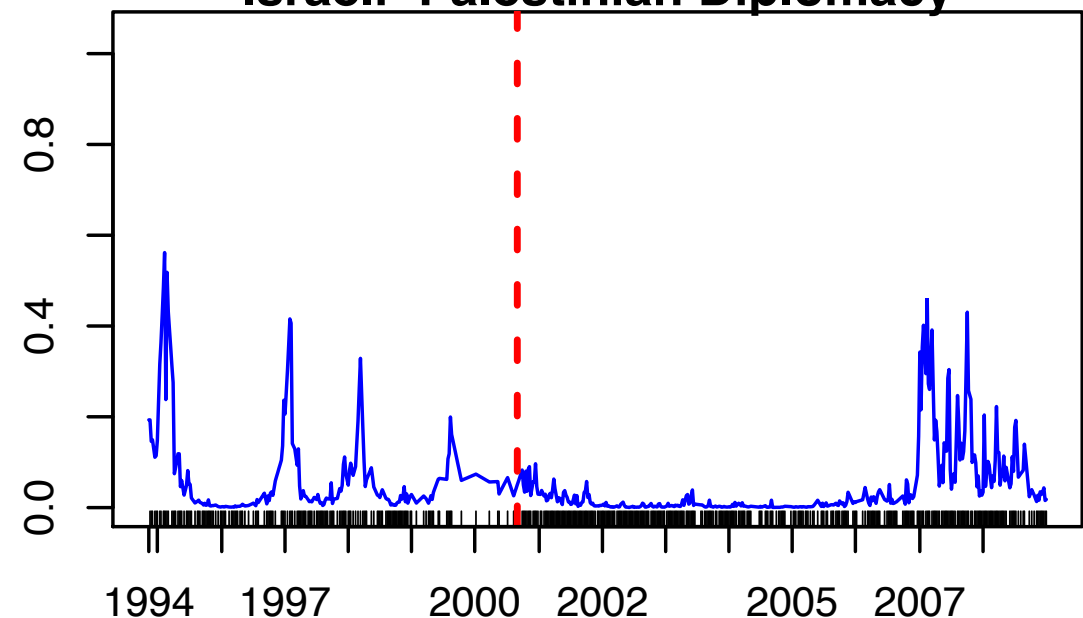Real-world events ← **News media process** → WORLD NEWS

Infer

[meet with, sign with, praise, say with, arrive in, host, tell, welcome, join, thank, meet, travel to, criticize, leave, take to, begin to, begin with, summon, reach with, hold with...]

Israeli–Palestinian Diplomacy

[O'Connor, Stewart, Smith ACL 2013]

3

Police killings

4

Police killings
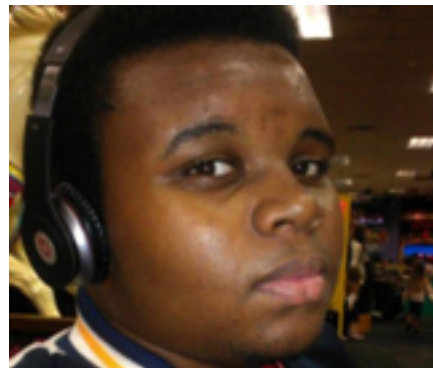

July 17, 2014
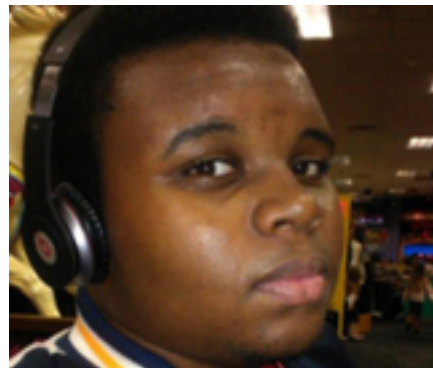
Police killings

July 17, 2014

Aug 9, 2014

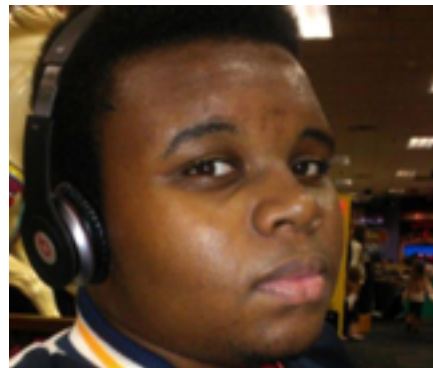# Police killings

July 17, 2014

Aug 9, 2014

July 5, 2016

Police killings

July 17, 2014

Aug 9, 2014

July 5, 2016

July 6, 2016

4

Police killings

Data?

July 17, 2014			Eric Garner	New York, NY
Aug 9, 2014			Michael Brown	Ferguson, MO
July 5, 2016			Alton Sterling	Baton Rouge, LA
July 6, 2016			Philando Castile	Falcon Heights, MN

4

Police killings

Data?

Eric Garner	New York, NY
Michael Brown	Ferguson, MO
Alton Sterling	Baton Rouge, LA
Philando Castile	Falcon Heights, MN

5

Police killings

Data?

- Are there more or fewer fatalities than last year?

Eric Garner	New York, NY
Michael Brown	Ferguson, MO
Alton Sterling	Baton Rouge, LA
Philando Castile	Falcon Heights, MN

5

Police killings

- Are there more or fewer fatalities than last year?
- Is there racial disparity/ discrimination?

Data?

Eric Garner	New York, NY
Michael Brown	Ferguson, MO
Alton Sterling	Baton Rouge, LA
Philando Castile	Falcon Heights, MN

5

Police killings

- Are there more or fewer fatalities than last year?
- Is there racial disparity/discrimination?
- Which police departments are better or worse? What policing strategies are most effective or safe?

Data?

Eric Garner	New York, NY
Michael Brown	Ferguson, MO
Alton Sterling	Baton Rouge, LA
Philando Castile	Falcon Heights, MN

5

Police killings

Data?

- Are there more or fewer fatalities than last year?
- Is there racial disparity/discrimination?
- Which police departments are better or worse? What policing strategies are most effective or safe?

- **Need good data for the public interest and social science / policy making**

Eric Garner	New York, NY
Michael Brown	Ferguson, MO
Alton Sterling	Baton Rouge, LA
Philando Castile	Falcon Heights, MN

5

Issues in government data

Monday, August 14, 17

Issues in government data

- Washington Post, Oct. 16, 2016:
  "Americans actually have no idea" about how often police use force because nobody has collected enough data.

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Issues in government data

- Washington Post, Oct. 16, 2016:
  "Americans actually have no idea" about how often police use force because nobody has collected enough data.

FBI director: 'Americans have no idea' if police target black people unfairly
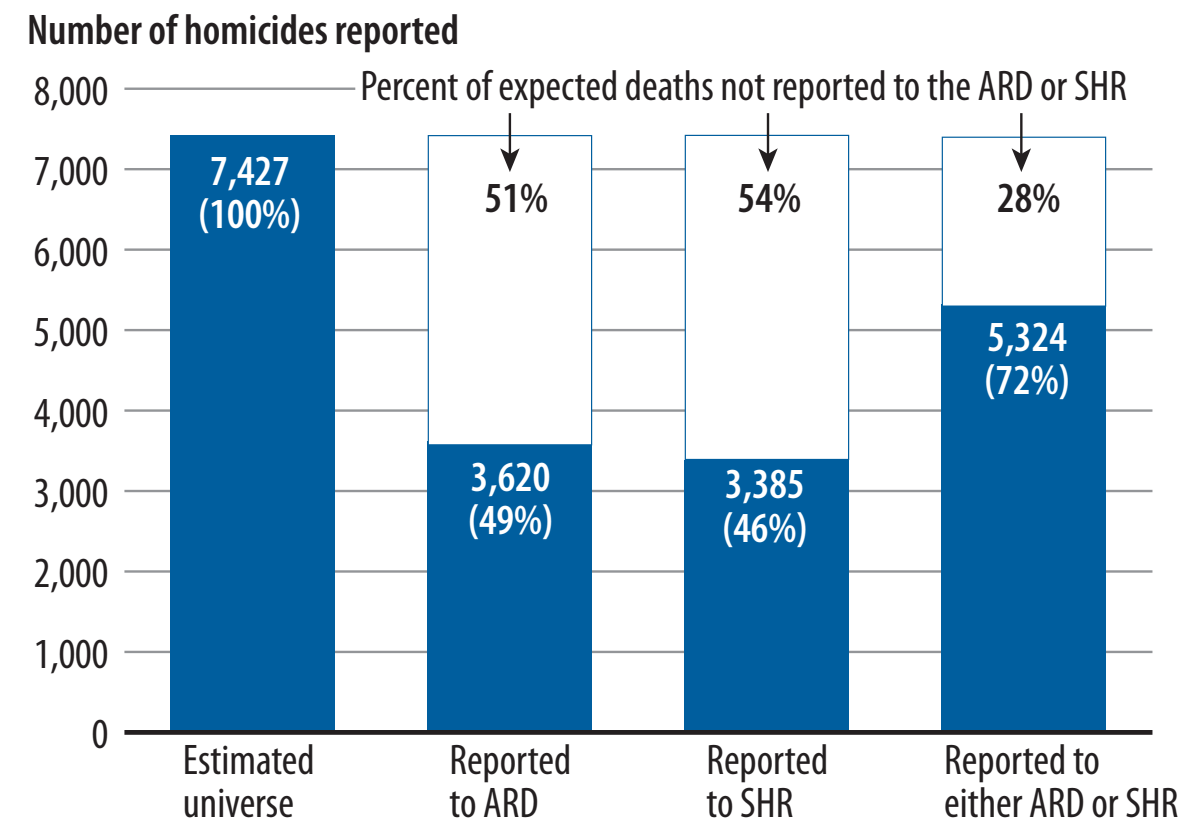
▶ Play Video 1:28

In a speech to police chiefs on Oct. 16, FBI Director James Comey said videos of police shootings have given the public an inaccurate impression that there's an epidemic of police violence against black people. (Editor's note: This video contains breaks and a facial-recognition square from the source.) (Youtube/fbi)

Issues in government data

- Unreliable partial compliance between local agencies and federal government
  - Massively undercounts deaths *[Banks et al. 2015 (BJS/DOJ), Lum and Ball 2015 (HRDAG, external)]*
- Uncertain future for DOJ programs?

- [Compare: National Justice Database's voluntary participation approach; Center for Policing Equity, John Jay College]

Estimated number of law enforcement homicides and percent not reported, by data source, 2003–2009 and 2011

Number of homicides reported

Percent of expected deaths not reported to the ARD or SHR

7,427 (100%)	51%	54%	28%
	3,620 (49%)	3,385 (46%)	5,324 (72%)

8,000
7,000
6,000
5,000
4,000
3,000
2,000
1,000
0

Estimated universe | Reported to ARD | Reported to SHR | Reported to either ARD or SHR

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Alternative: news media reports

- Populate a database by manually reading news articles (filtered by keyword search)
  - FatalEncounters.org, KilledByPolice.net, The Guardian, Washington Post...
    - FE: volunteers have read 2M articles or ledes (!)
    - Augment with open records requests
  - BJS, Dec. 2016: media reports double the count compared to previous government collection efforts
- Secondary vs primary sources

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Computational approach

- Goal: extract fatality records from a news corpus
  - Off-the-shelf event extractors work poorly (ACE, FrameNet training/ontologies)
  - Instead, train models for this problem (distant supervision+EM)
- NLP and social analysis
  - Concrete, real-world tasks useful testbed for NLP research
  - Can NLP offer something useful for important tasks?
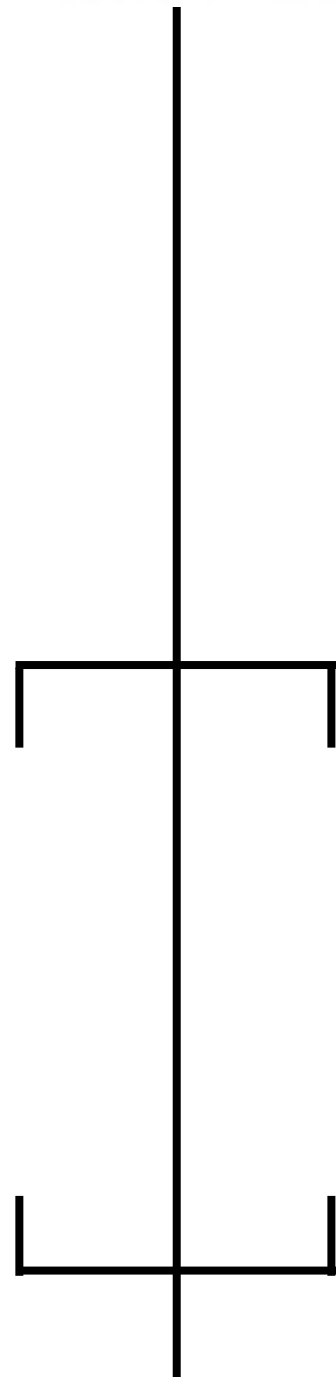- Public data and government accountability

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Computational approach

- ● July 17, 2014
- ● Aug 9, 2014
- ● July 5, 2016
- ● July 6, 2016

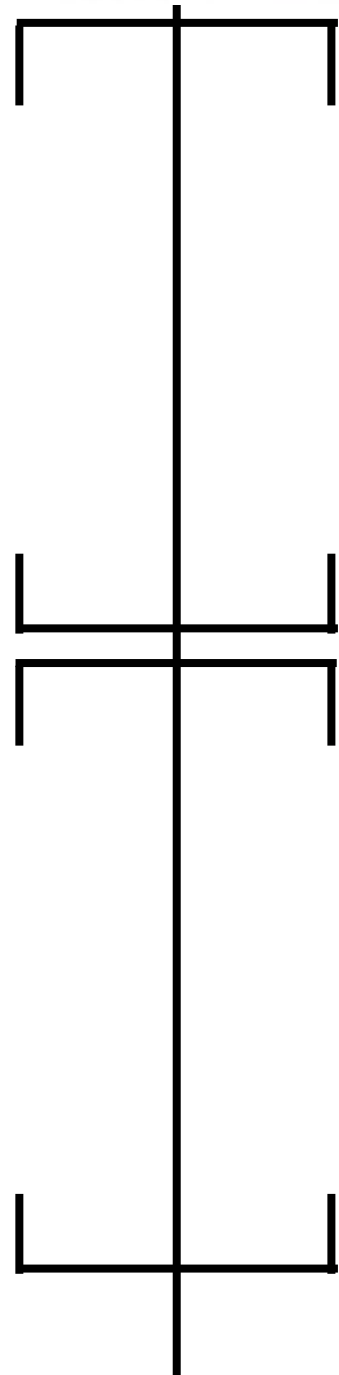| Eric Garner	New York, NY
Michael Brown	Ferguson, MO
Alton Sterling	Baton Rouge, LA
Philando Castile	Falcon Heights, MN

Task: Database Population

Time-delimited corpus

Infer names of persons killed by police during that timeframe

Alton Sterling	Baton Rouge, LA
Philando Castile	Falcon Heights, MN

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Task: Database Update

Eric Garner	New York, NY
Michael Brown	Ferguson, MO
Alton Sterling	Baton Rouge, LA
Philando Castile	Falcon Heights, MN

Historical data
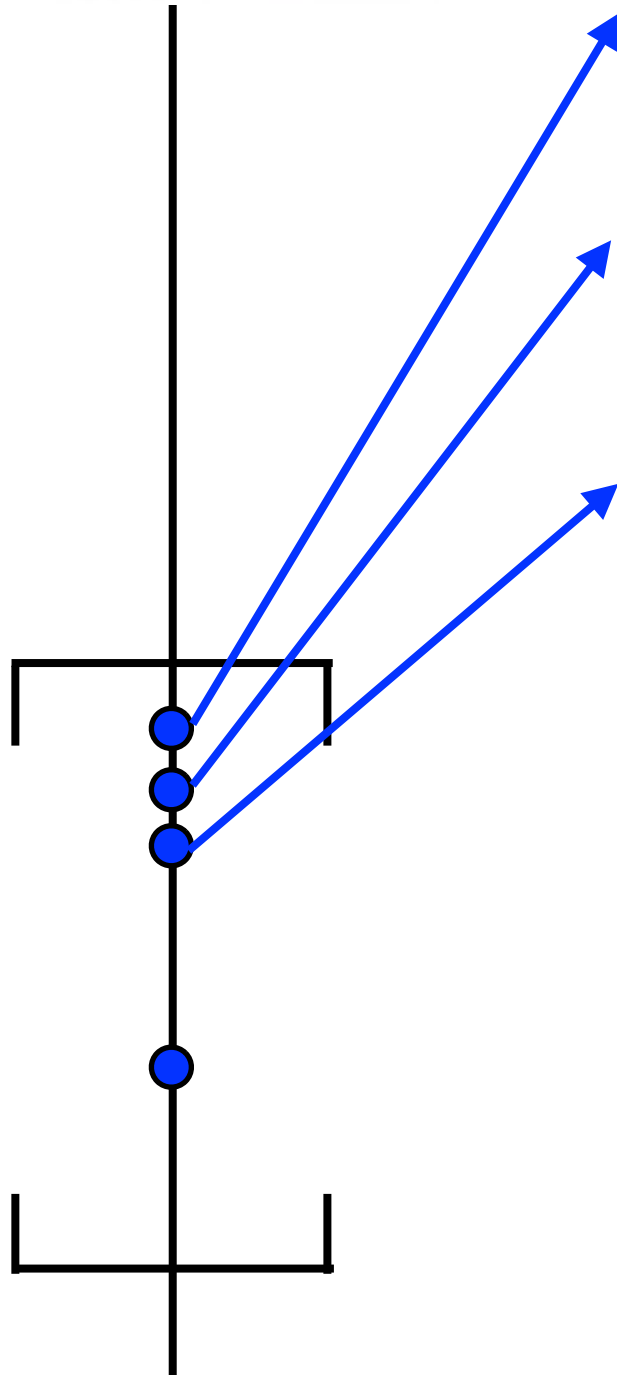(Distant supervision)

Testing/Runtime

Mentions

The Baton Rouge Police Department confirms that confirms **Alton Sterling** , 37 , died during a shooting at the Triple S Food Mart

... the two officers involved in Tuesday 's shooting of **Alton Sterling** ...

... **Alton Sterling** was a resident of Baton Rouge...

Mentions

The Baton Rouge Police Department confirms that confirms **Alton Sterling** , 37 , died during a shooting at the Triple S Food Mart
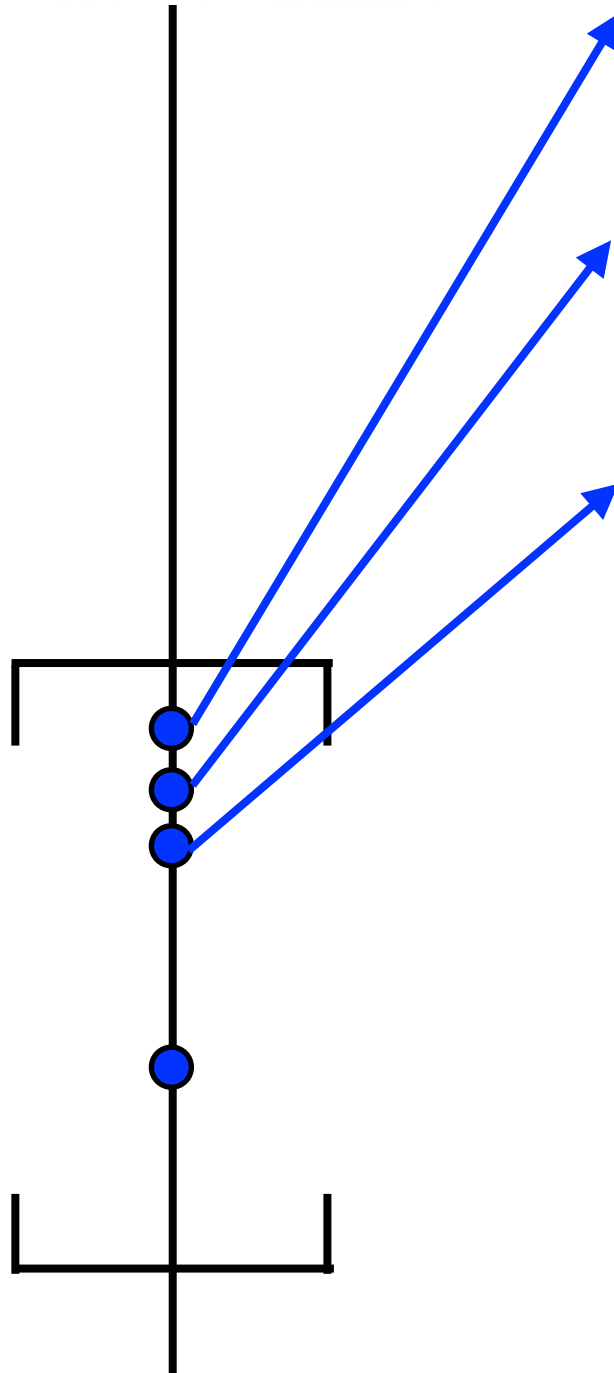
0.4

... the two officers involved in Tuesday 's shooting of **Alton Sterling** ...

0.8

... **Alton Sterling** was a resident of Baton Rouge...

0.01

13

Mentions

The Baton Rouge Police Department confirms that confirms **Alton Sterling** , 37 , died during a shooting at the Triple S Food Mart

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aggregate: add to database?

13

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The Baton Rouge Police Department confirms that confirms **Alton Sterling** , 37 , died during a shooting at the Triple S Food Mart

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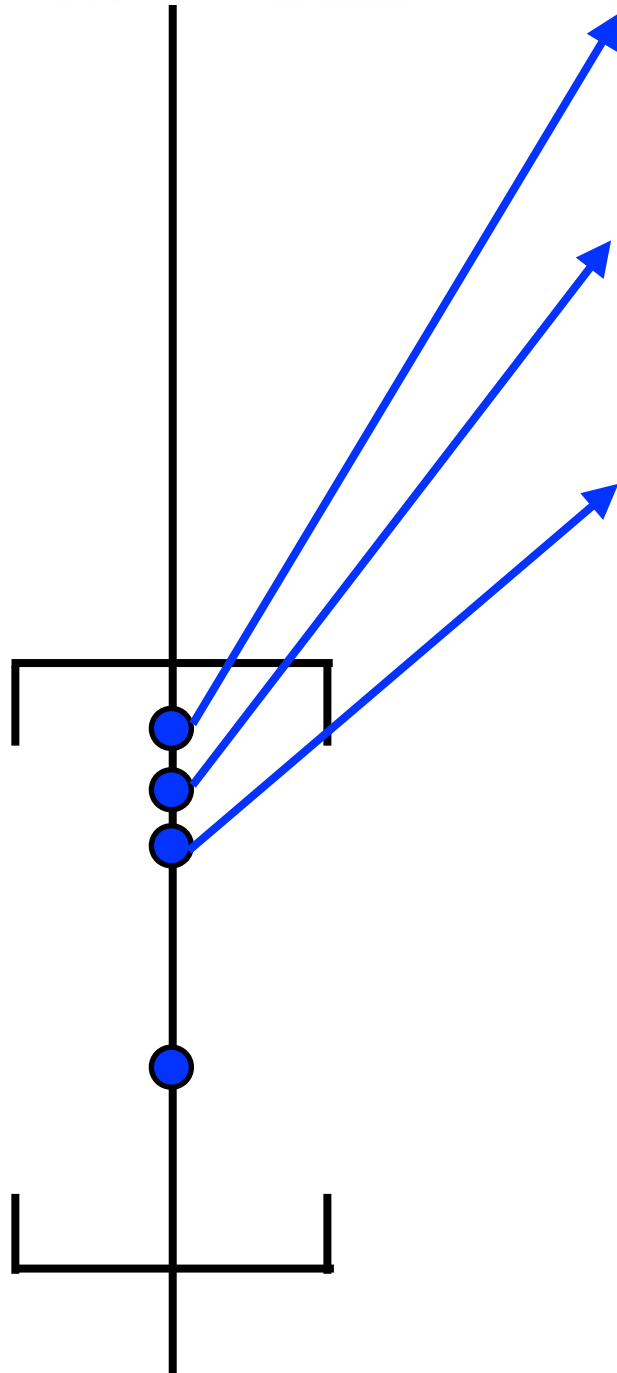... **Alton Sterling** was a resident of Baton Rouge...

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0.01

aggregate: add to database?

Alton Sterling

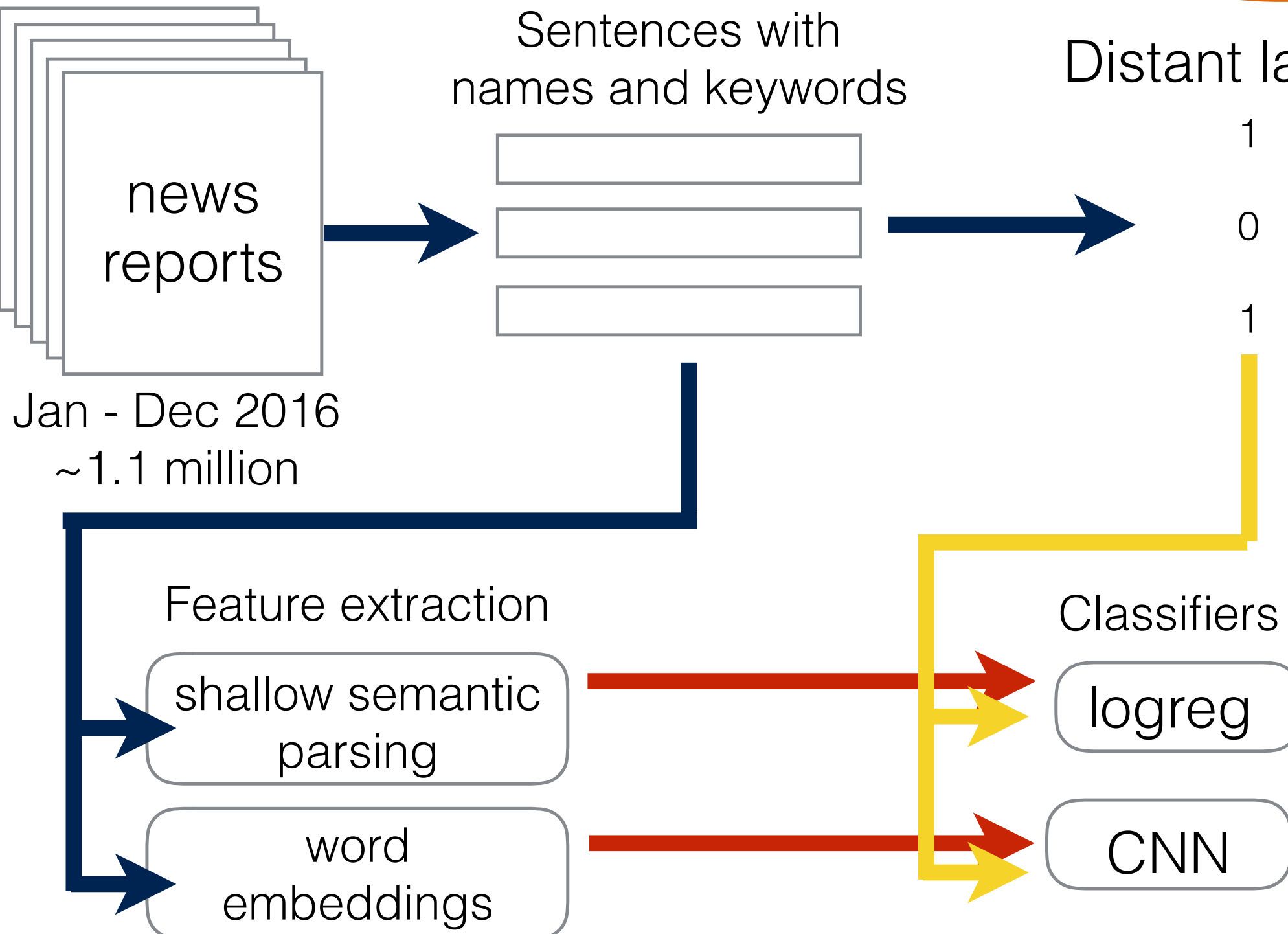Entity-level fatality record (name)

13

Pipeline (incl. training)

Data

Knowledge base	Historical	Test
FE incident dates	Jan 2000 – Aug 2016	Sep 2016 – Dec 2016
FE gold entities ($\mathcal{G}$)	17,219	452

News dataset	Train	Test
doc. dates	Jan 2016 – Aug 2016	Sep 2016 – Dec 2016
total docs. ($\mathcal{D}$)	793,010	317,345
total ments. ($\mathcal{M}$)	132,833	68,925
pos. ments. ($\mathcal{M}^+$)	11,274	6,132
total entities ($\mathcal{E}$)	49,203	24,550
pos. entities ($\mathcal{E}^+$)	916	258

- Keyword-querying web scraper running throughout 2016
- Preprocessing: text extraction, deduplication (shingling/union find), spaCy NER+parsing, name cleanups

15

Can NLP help?

- Rule-based event extraction: labor-intensive
- Supervised learning: we tried off-the-shelf event extractors
  - SEMAFOR: trained for FrameNet *[Das et al. 2014]*
  - RPI Joint Info. Extraction: trained for ACE *[Li and Ji 2014]*
    - Found useful for gun violence extraction *[Pavlick and Callison-Burch 2016]*

	Rule	Prec.	Recall	F1
SEMAFOR	R1	0.011	0.436	0.022
	R2	0.031	0.162	0.051
	R3	0.098	0.009	0.016
RPI-JIE	R1	0.016	0.447	0.030
	R2	0.044	0.327	0.078
	R3	0.172	0.168	**0.170**
Data upper bound		1.0	0.57	0.73

16

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	R3	0.172	0.168	**0.170**
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- Hard problem!
- Domain adaptation? Text cleanliness? Training data weirdness?

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Model

- (1) Identify sentence-level fatality assertions

- (2) Aggregate to entity (person)-level predictions

17

Model

- (1) Identify sentence-level fatality assertions

$$P(z_i = 1 \mid x_i) = \sigma(\beta^{\mathsf{T}} f_\gamma(x_i))$$

describes police killing event?

sentence

e.g. logistic regression, convolutional neural network

Text	Person killed by police?
Alton Sterling was killed by police.	True
Officers shot and killed **Philando Castile**.	True
Officer **Andrew Hanson** was shot.	False
Police report **Megan Short** was fatally shot in apparent murder-suicide.	False

- (2) Aggregate to entity (person)-level predictions

17

Model

- (1) Identify sentence-level fatality assertions

$$P(z_i = 1 \mid x_i) = \sigma(\beta^{\mathsf{T}} f_\gamma(x_i))$$

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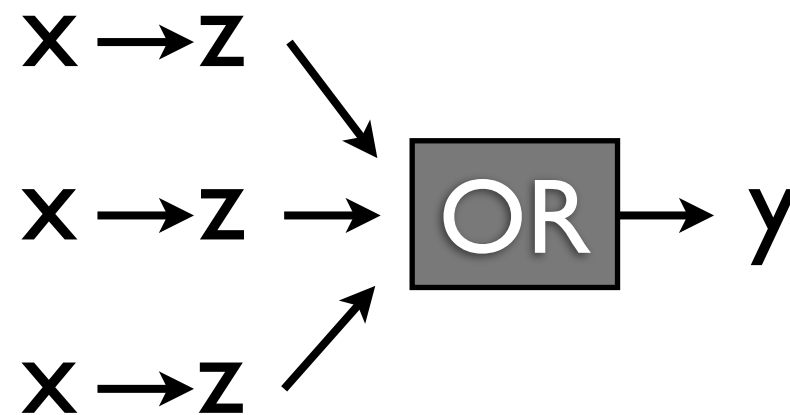| Text	Person killed by police?
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Police report **Megan Short** was fatally shot in apparent murder-suicide.	False

- (2) Aggregate to entity (person)-level predictions

$$P(y_e = 1 | x_{\mathcal{M}(e)})$$

was person **e** killed by police?

all sentences mentioning person **e**

17

Model

- Prediction through disjunction:
  - Decide an entity was killed by police,
    if at least one of their sentences asserts they were
    killed by police

- Integrate over x→z uncertainty: *noisyor*
  [e.g. Craven and Kumlien 1999]

$$P(y_e = 1 | x_{\mathcal{M}(e)}) = 1 - \prod_{i \in \mathcal{M}(e)} (1 - P(z_i = 1 \mid x_i))$$

was person **e**
killed by police?
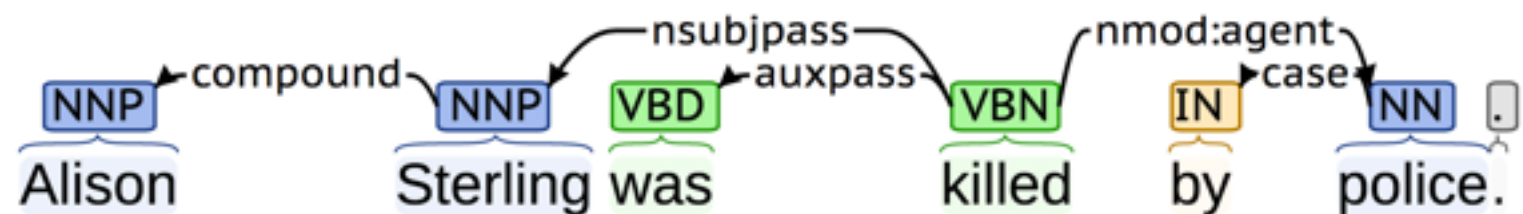
all sentences mentioning person **e**

18

Mention-level models

$$P(z_i = 1 \mid x_i) = \sigma(\beta^{\mathsf{T}} f_\gamma(x_i))$$
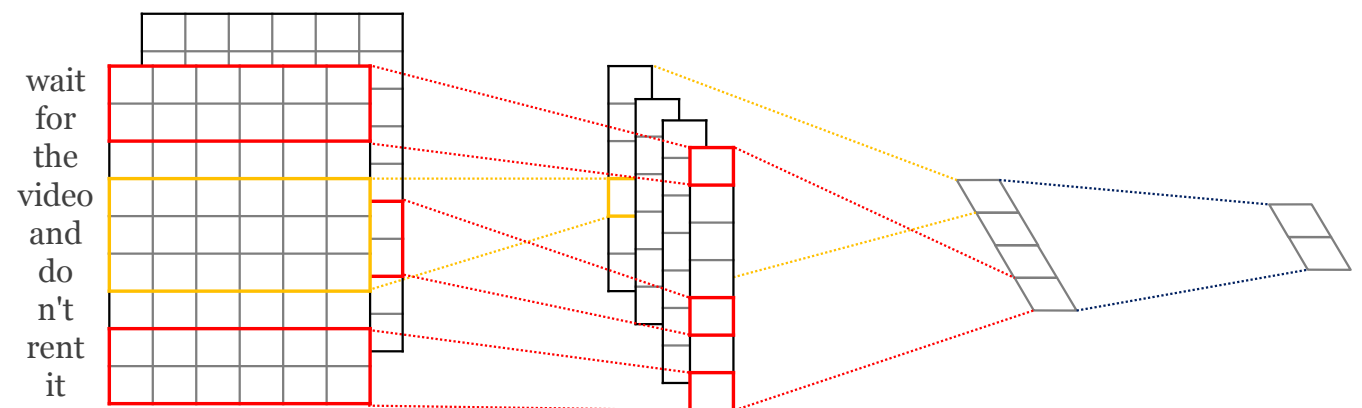
describes police killing event?

sentence

1. Feature-engineered logistic regression
   - Syntactic dependency paths
   - N-grams

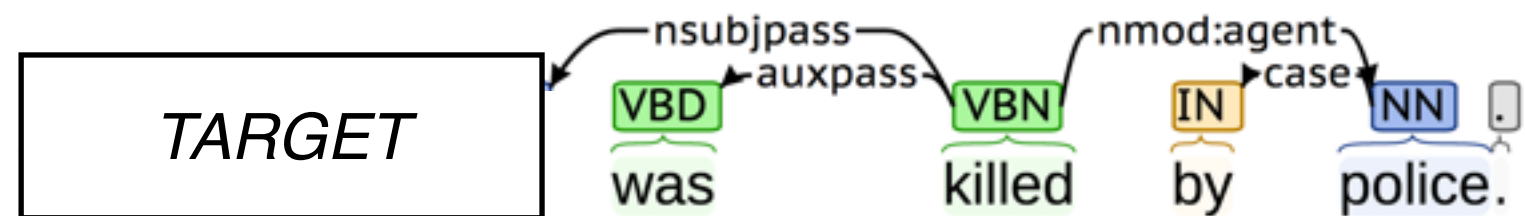2. Convolutional neural network *[e.g. Nguyen and Grishman 2015]*

Mention-level models

$$P(z_i = 1 \mid x_i) = \sigma(\beta^\mathsf{T} f_\gamma(x_i))$$
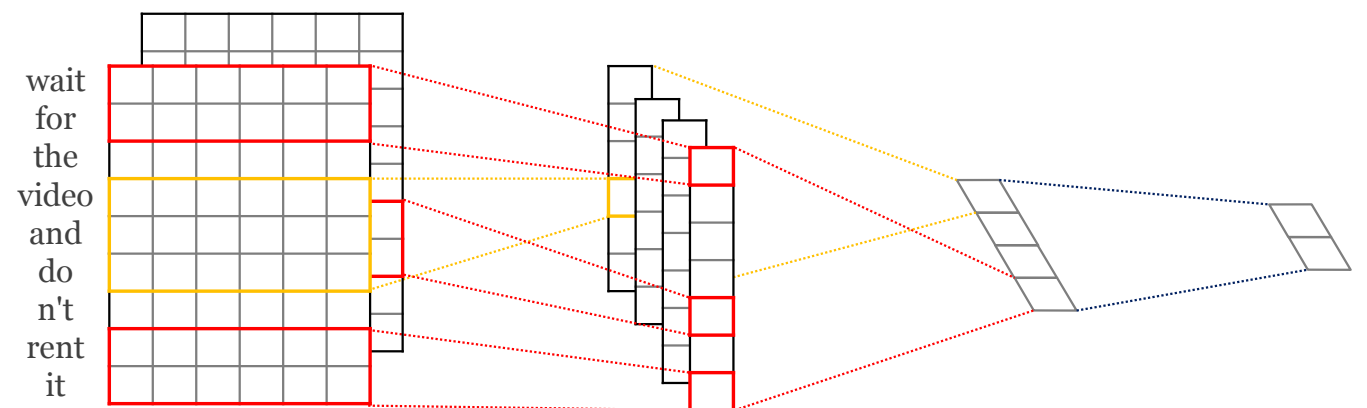
describes police killing event?

sentence

1. Feature-engineered logistic regression
   - Syntactic dependency paths
   - N-grams

2. Convolutional neural network *[e.g. Nguyen and Grishman 2015]*

19

Distant supervision

entities $(e \in \mathcal{E})$	entity label (y_e)	sentences (x_i)	sent. label (z_i)
Katy Perry	0	"Katy Perry reacts to police killings."	0
Alton Sterling	1	"Alton Sterling was killed by police."	?
		"Alton Sterling was a resident of Baton Rouge.	?

e not in database:
enforce hard **0** label

e in database:
assume _at least one_ is positive
(latent variable!)

- Multiple instance learning *[Bunescu and Mooney 2007]*
  - Much more accurate than assuming every sentence asserts the event!
- Probabilistic joint training: account for this uncertainty by maximizing marginal likelihood

$$P(y \mid x) = \sum_z P(y \mid z) P_\theta(z \mid x)$$

20

EM Training *[Dempster et al. 1977]*

E-step: posterior inference given at-least-one disjunction

$$q(z_i) := P(z_i \mid x_{\mathcal{M}(e_i)}, y_{e_i})$$

M-step: use soft labels

$$\max_{\theta} \sum_i \sum_{z \in \{0,1\}} q(z_i = z) \log P_{\theta}(z_i = z \mid x_i)$$

- Logistic regression: full M-step (convex opt., L-BFGS)
- Neural network: several epochs of stochastic gradient descent (Adagrad)
  - Similar to: Expected Conjugate Gradient *[Salakhutdinov et al. 2003]*
- Staged initialization (log.reg. training is nonrandom :))

Results

Model	AUPRC	F1
hard-LR, dep. feats.	0.117	0.229
hard-LR, n-gram feats.	0.134	0.257
hard-LR, all feats.	0.142	0.266
hard-CNN	0.130	0.252
soft-CNN (EM)	0.164	0.267
soft-LR (EM)	**0.193**	**0.316**
Data upper bound (§4.6)	0.57	0.73
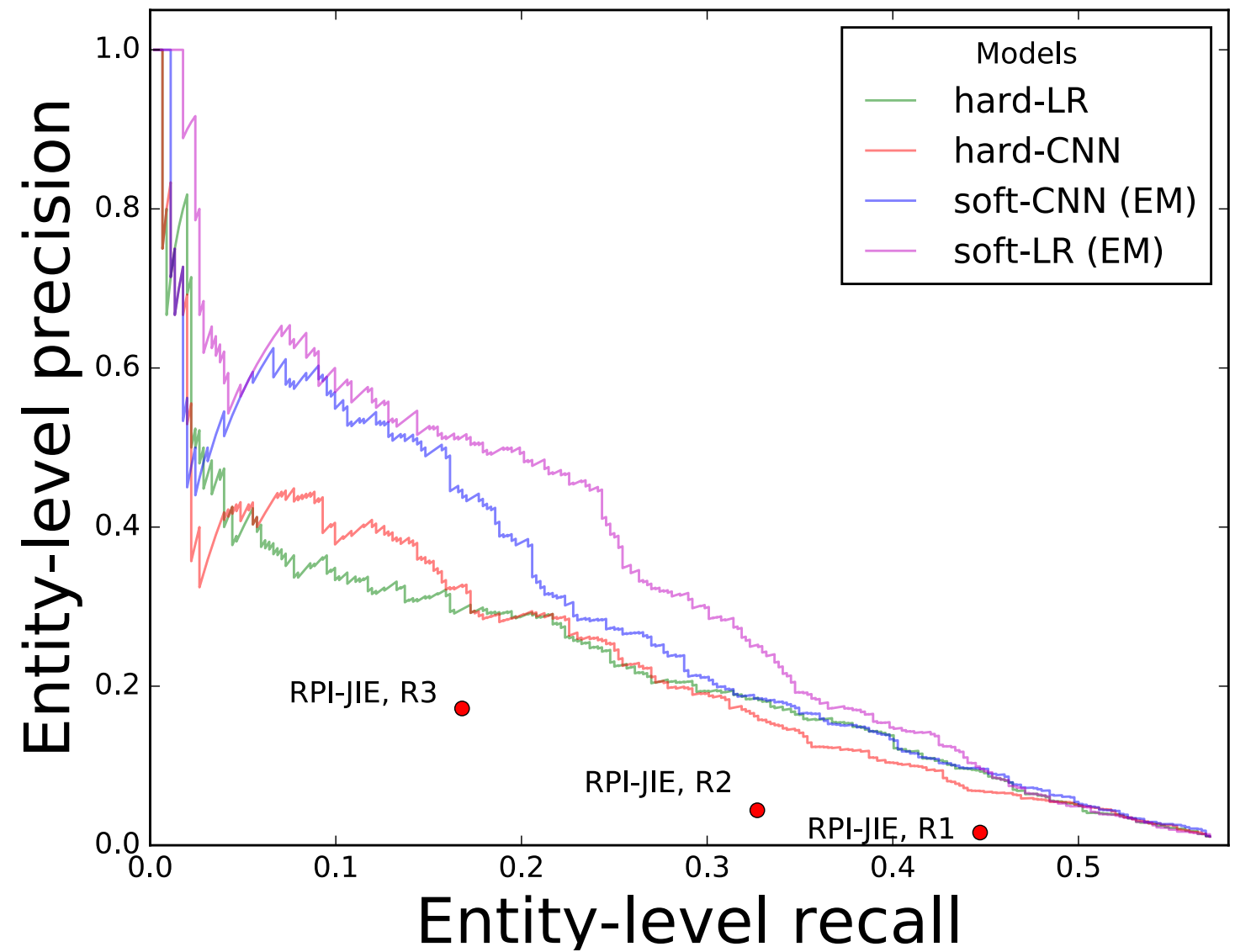
EM Training Logistic regression
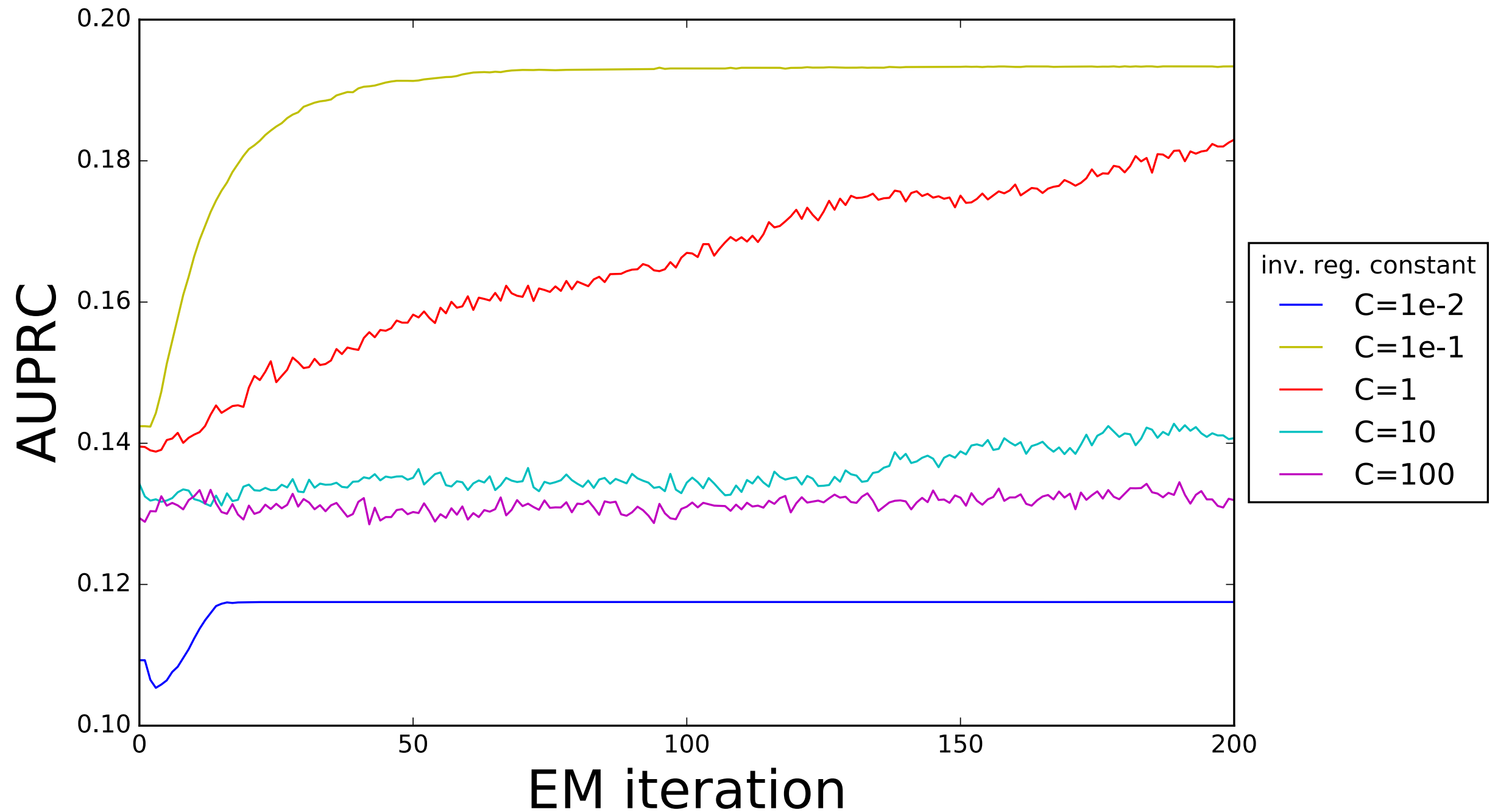
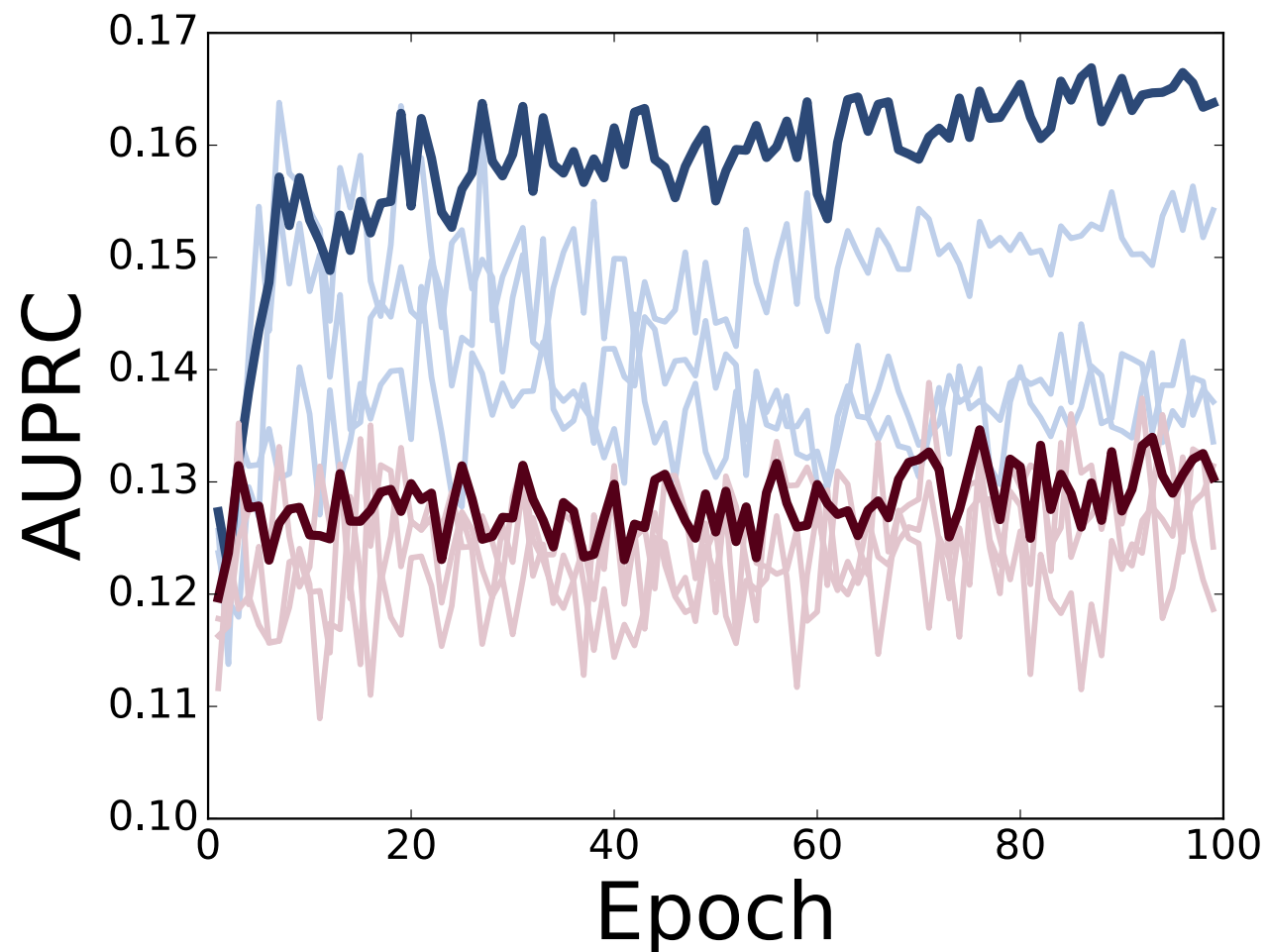# EM Training Neural network

Figure 3: Test set AUPRC for three runs of soft-CNN (EM) (**blue**, higher in graph), and hard-CNN (**red**, lower in graph). Darker lines show performance of averaged predictions.

Predictions

entity (e)	ment.(i) prob.	ment. text (x_i)
Keith Scott (true pos)	0.98	Charlotte protests Charlotte's Mayor Jennifer Roberts speaks to reporters the morning after protests against the police shooting of **Keith Scott**, in Charlotte, North Carolina .
Terence Crutcher (true pos)	0.96	Tulsa Police Department released video footage Monday, Sept. 19, 2016, showing white Tulsa police officer Betty Shelby fatally shooting **Terence Crutcher,** 40, a black man police later determined was unarmed.
Mark Duggan (false pos)	0.97	The fatal shooting of **Mark Duggan** by police led to some of the worst riots in England's recent history.
Logan Clarke (false pos)	0.92	**Logan Clarke** was shot by a campus police officer after waving kitchen knives at fellow students outside the cafeteria at Hug High School in Reno, Nevada, on December 7.

Table 7: Example of highly ranked entities, with selected mention predictions and text.

Predictions: top-ranked

rank	name	positive	analysis
1	**Keith Scott**	**true**	
2	**Terence Crutcher**	**true**	
3	Alfred Olango	true	
4	Deborah Danner	true	
5	Carnell Snell	true	
6	Kajuan Raye	true	
7	Terrence Sterling	true	
8	Francisco Serna	true	
9	Sam DuBose	false	name mismatch
10	Michael Vance	true	
11	Tyre King	true	
12	Joshua Beal	true	
13	Trayvon Martin	false	killed, not by police
14	**Mark Duggan**	**false**	**non-US**
15	Kirk Figueroa	true	
16	Anis Amri	false	non-US
17	**Logan Clarke**	**false**	**shot not killed**
18	Craig McDougall	false	non-US
19	Frank Clark	true	
20	Benjamin Marconi	false	name of officer

Conclusions

- Natural language processing can help *acquire more behavioral data* from news
    - International relations *[Schrodt and Gerner, 1994; Schrodt, 2012; Boschee et al., 2013; O'Connor et al., 2013; Gerrish, 2013]*
    - Protests *[Hanna 2017]*
    - Gun violence *[Pavlick et al. 2016]*
    - Europe Media Monitor *[Piskorski et al. 2011]*
- For police fatalities: Need to perform better at high-recall settings, to support semi-automated work
    - Interactive approaches? e.g. DeepDive, SEER, InstaRead, IKE...
- Assumes media production reflects reality
    - Alternative: analyze e.g. media bias/attention, as in political science or literature analysis
- NLP and social analysis
    - Concrete, real-world tasks useful testbed for NLP research
    - NLP could offer something useful for important tasks!