Social Media & Text Analysis

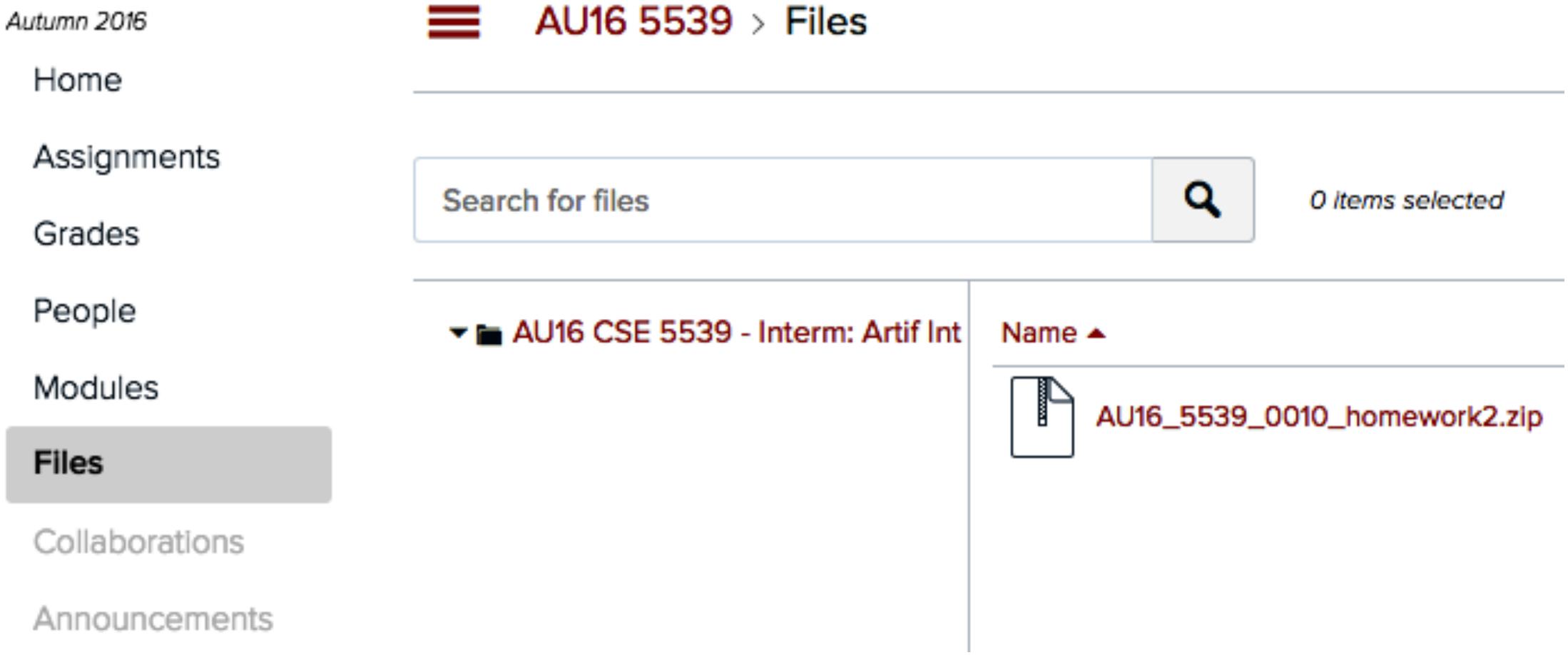
lecture 7 - Twitter Paraphrases and Latent Variable Models

CSE 5539-0010 Ohio State University

Instructor: Wei Xu

Website: socialmedia-class.org

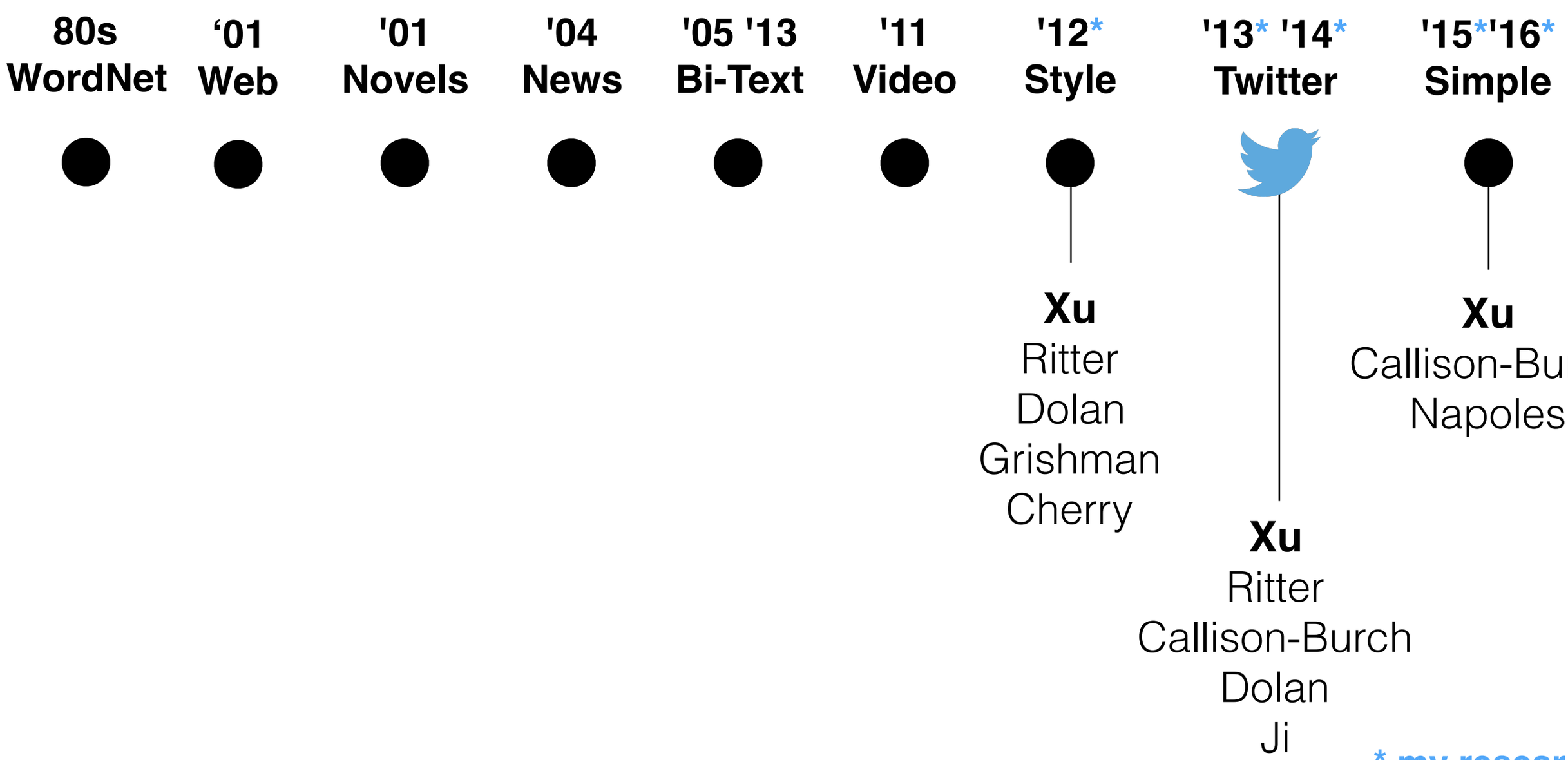
Homework #2 is out
Due in three weeks



Collaborators

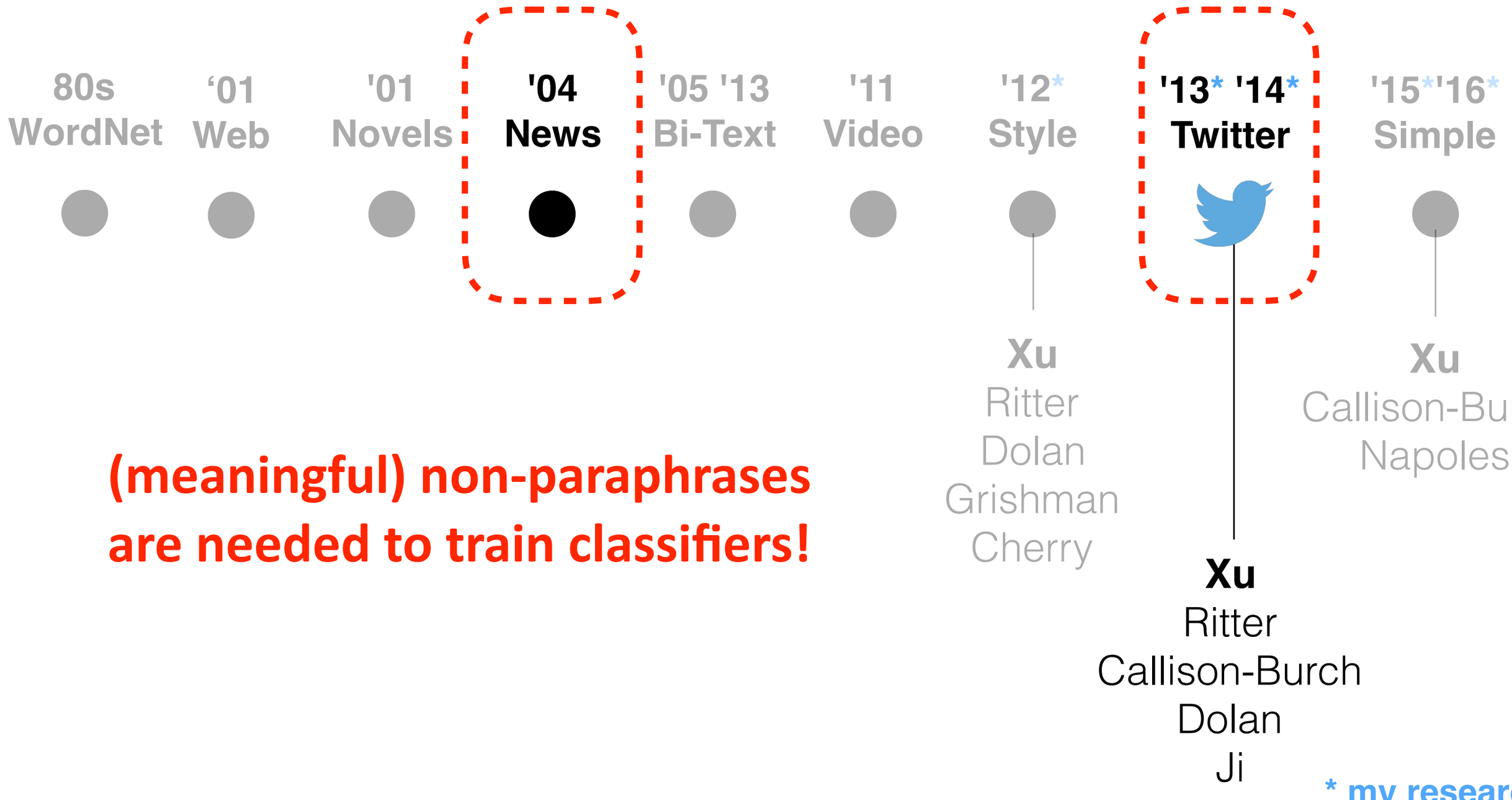
Chris Callison-Burch	UPenn
Alan Ritter	UW / OSU
Bill Dolan	MSR
Yangfeng Ji	GaTech
Jeniya Tabassum	OSU
Wuwei Lan	OSU
Ralph Grishman	NYU
Raphael Hoffmann	UW / AI2 Incubator
Joel Tetreault	ETS / Yahoo!
Le Zhao	CMU / Google
Maria Pershina	NYU
Colin Cherry	NRC
Courtney Napoles	JHU
Lyle Ungar	UPenn
Daniel Preoţiuc-Pietro	UPenn
Ellie Pavlick	UPenn
Mingkun Gao	UPenn / UIUC
Quanze Chen	UPenn / UW
Martin Chodorow	CUNY

Paraphrase Research



Wei Xu. "Data-driven Approaches for Paraphrasing Across Language Variations" PhD Thesis (2014)

Paraphrase Research



(meaningful) non-paraphrases are needed to train classifiers!

* my research

Wei Xu. "Data-driven Approaches for Paraphrasing Across Language Variations" PhD Thesis (2014)

News

only a few hundreds news agencies
only big events
only well-edited text
(the MSR Paraphrase Corpus)

(Dolan, Quirk and Brockett, 2004; Dolan and Brockett, 2005; Brockett and Dolan, 2005)

Twitter as a new resource

Rep. Stacey Newman @staceynewman · 5h
So sad to hear today of former WH Press Sec **James Brady**'s **passing**.
@bradybuzz & family will carry on his legacy of #gunsense.

Jim Sciutto @jimsciutto · 4h
Breaking: Fmr. WH Press **Sec. James Brady** has died at 73, crusader for gun control after wounded in '81 Reagan assassination attempt

NBC News @NBCNews · 2h
James Brady, President Reagan's press secretary shot in 1981 assassination attempt, dead at 73 nbcnews.to/WX1Btq pic.twitter.com/1ZtuEakRd9

average sentence length: news ≈18.6 words Twitter ≈11.9 words

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Twitter as a powerful resource

thousands of users
talk about both big/micro events daily

Very diverse!

a very broad range of paraphrases:
synonyms, misspellings, slang, acronyms and colloquialisms

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Paraphrase Model

obtain sentential paraphrases automatically

Mancini has been sacked by Manchester City

Mancini gets the boot from Man City

Yes!

WORLD OF JENKS IS ON AT 11

World of Jenks is my favorite show on tv

No!

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

(On news data - MSR Paraphrase Corpus)

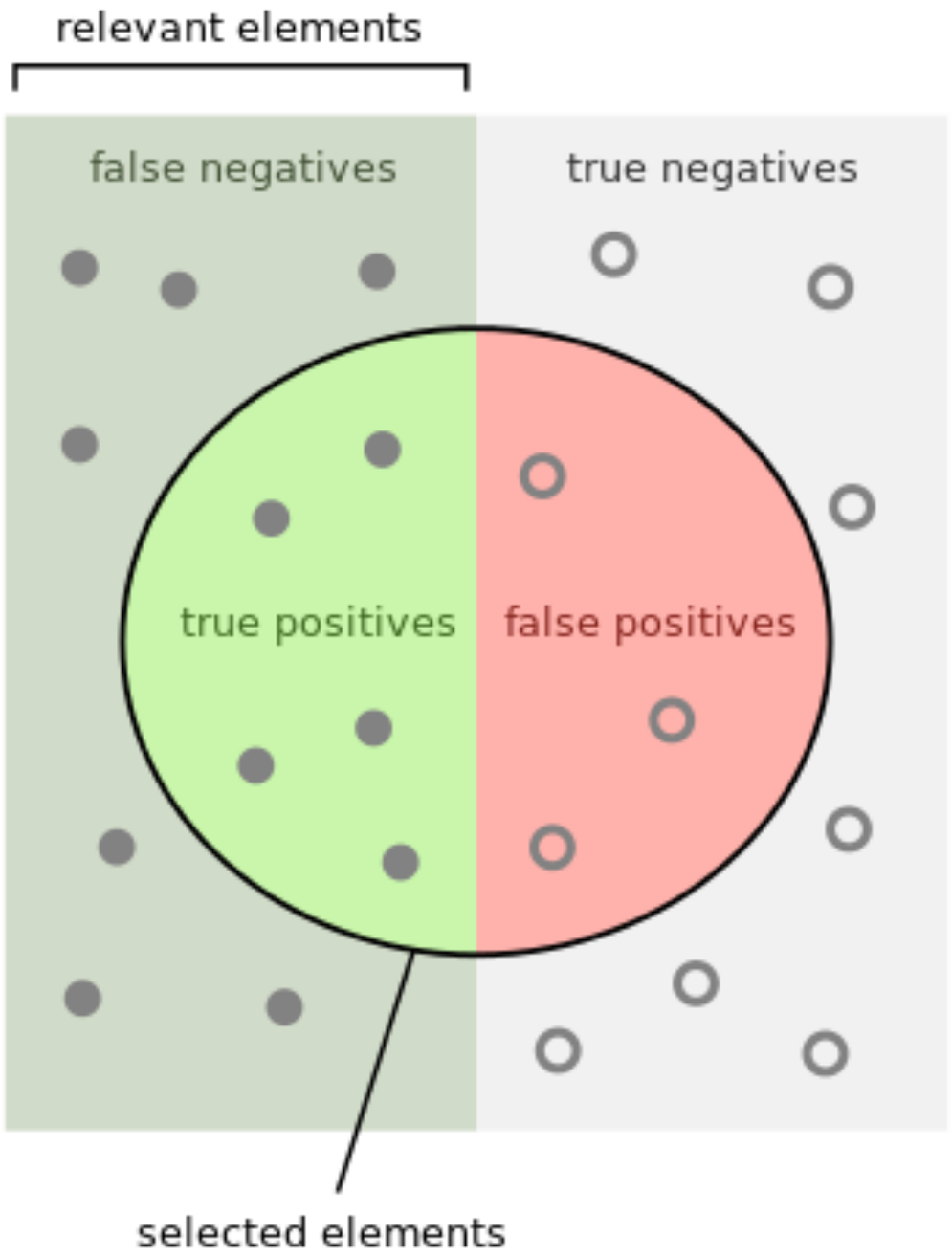
Paraphrase Identification

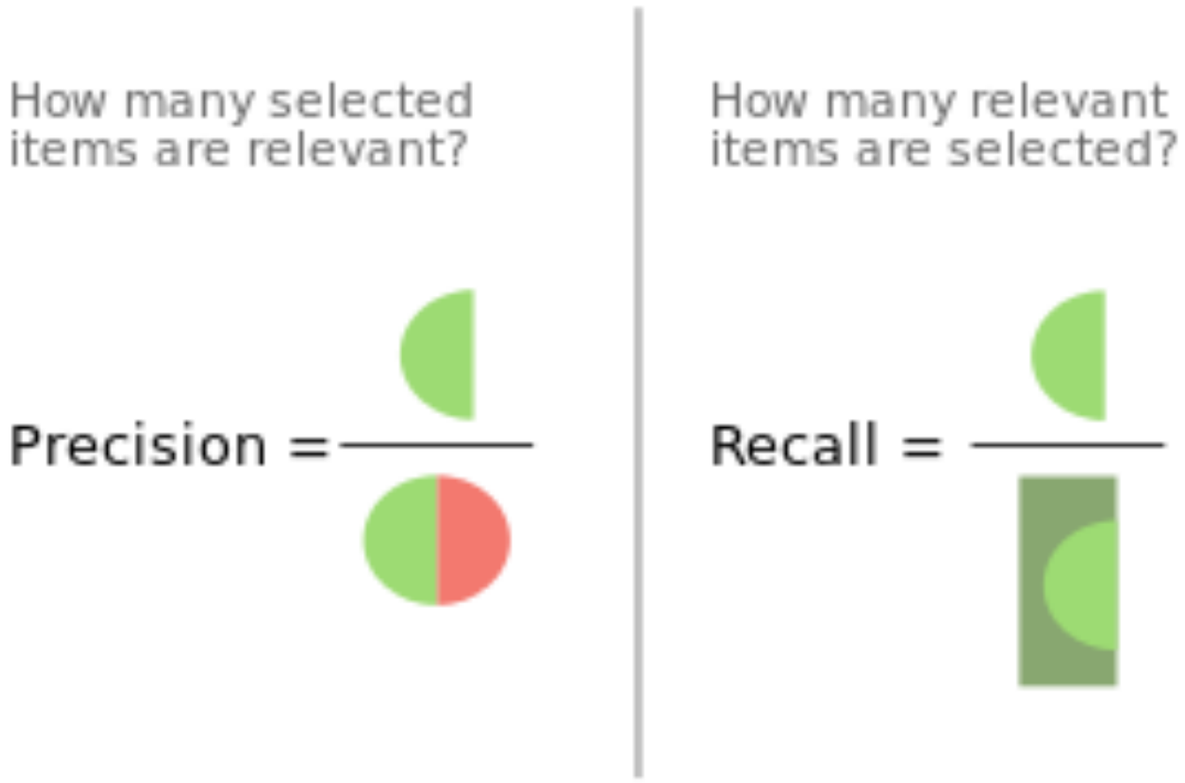
Algorithm	Reference	Description	Supervisi	Accurac	F1
Vector	Mihalcea et al. (2006)	cosine similarity with tf-idf weighting	unsupervised	65.40%	75.30%
ESA	Hassan (2011)	explicit semantic space	unsupervised	67.00%	79.30%
KM	Kozareva and Montoyo (2006)	combination of lexical and semantic features	supervised	76.60%	79.60%
LSA	Hassan (2011)	latent semantic space	unsupervised	68.80%	79.90%
RMLMG	Rus et al. (2008)	graph subsumption	unsupervised	70.60%	80.50%
MCS	Mihalcea et al. (2006)	combination of several word similarity measures	unsupervised	70.30%	81.30%
WTMF	Guo and Diab (2012)	latent space model for short text	unsupervised	71.51%	---
STS	Islam and Inkpen (2007)	combination of semantic and string similarity	unsupervised	72.60%	81.30%
SSA	Hassan (2011)	salient semantic space	unsupervised	72.50%	81.40%
QKC	Qiu et al. (2006)	sentence dissimilarity classification	supervised	72.00%	81.60%
ParaDetect	Zia and Wasif (2012)	PI using semantic heuristic features	supervised	74.70%	81.80%
SDS	Blacoe and Lapata (2012)	simple distributional semantic space	supervised	73.00%	82.30%
matrixJcn	Fernando and Stevenson (2008)	JCN WordNet similarity with matrix	unsupervised	74.10%	82.40%
FHS	Finch et al. (2005)	combination of MT evaluation measures as features	supervised	75.00%	82.70%
PE	Das and Smith (2009)	product of experts	supervised	76.10%	82.70%
WDDP	Wan et al. (2006)	dependency-based features	supervised	75.60%	83.00%
SHPNM	Socher et al. (2011)	recursive autoencoder with dynamic pooling	supervised	76.80%	83.60%
MTMETRICS	Madnani et al. (2012)	combination of eight machine translation metrics	supervised	77.40%	84.10%
Bi-CNN-MI	Yin and Schutze (2015)	convolutional neural network w/ multi-granular interaction	supervised	78.40%	84.60%
MP-CNN	He et al. (2015)	convolutional neural network w/ multiple perspectives	supervised	78.60%	84.73%
Recon	Cheng and Kartsaklis (2015)	Recursive NNs w/ syntax-aware multi-sense word embeddings	supervised	78.60%	85.30%
LEXDISCRIM	Ji and Eisenstein (2013)	combination of latent space and lexical features	supervised	80.41%	85.96%

https://www.aclweb.org/aclwiki/index.php?title=Paraphrase_Identification_(State_of_the_art)

Classification Evaluation:

Precision, Recall, F-measure





$$F_1 = \frac{2 \cdot precision \cdot recall}{precision + recall}$$

Source: Wikipedia

Classification Evaluation:

Accuracy

- In classification problems, the primary source for accuracy estimation is the confusion matrix

		True Class: Positive	True Class: Negative
Predicted Class	Positive	True Positive Count (TP)	False Positive Count (FP)
Predicted Class	Negative	False Negative Count (FN)	True Negative Count (TN)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

$$True\ Positive\ Rate = \frac{TP}{TP + FN}$$

$$True\ Negative\ Rate = \frac{TN}{TN + FP}$$

$$Precision = \frac{TP}{TP + FP} \qquad Recall = \frac{TP}{TP + FN}$$

Source: Turban et al. (2011), Decision Support and Business Intelligence Systems

Multi-instance Learning

Paraphrase Model

Challenges of Twitter Data

Mancini has been sacked by Manchester City

Mancini gets the boot from Man City

Yes!

very short, lexically divergent

Techniques

- Multiple Instance Learning
- **Probabilistic Graphical Models**
- Markov Networks with Latent Variables

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Assumption

Mancini has been sacked by Manchester ***City***

Mancini gets the boot from Man ***City***

Yes!

At-least-one Paraphrase Anchor

two sentences about the same topic are paraphrases
if and only if
they contain at least one word pair that is
a paraphrase **anchor** (in the context)

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Assumption

*The **new** Ciroc **flavor** has arrived*

*Ciroc got a **new flavor** coming out*

Yes!

At-least-one Paraphrase Anchor

two sentences about the same topic are paraphrases
if and only if
they contain at least one word pair that is
a paraphrase **anchor** (in the context)

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Assumption

*Manti bout to be the **next** Junior Seau*

*Teo is the little **new** Junior Seau*

Yes!

At-least-one Paraphrase Anchor

two sentences about the same topic are paraphrases
if and only if
they contain at least one word pair that is
a paraphrase **anchor** (in the context)

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Assumption

WORLD OF JENKS ***IS ON*** *AT 11*

World of Jenks ***is*** *my favorite show* ***on*** *tv*

No!

At-least-one Paraphrase Anchor

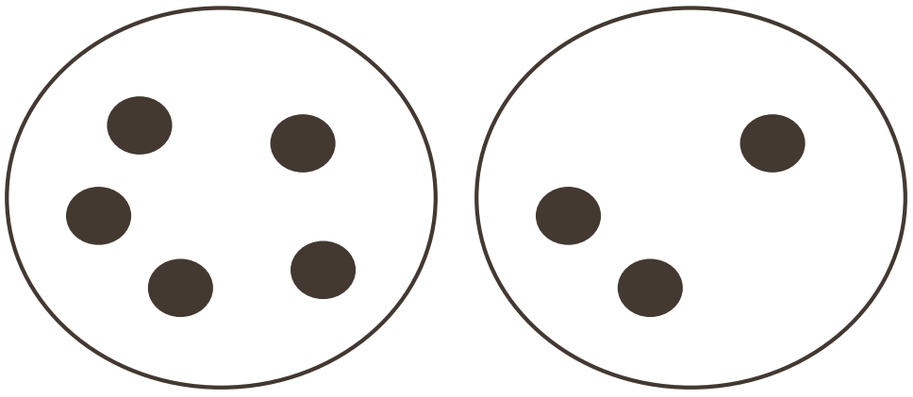
two sentences about the same topic are paraphrases
if and only if
they contain at least one word pair that is
a paraphrase **anchor** (in the context)

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Multi-instance Learning

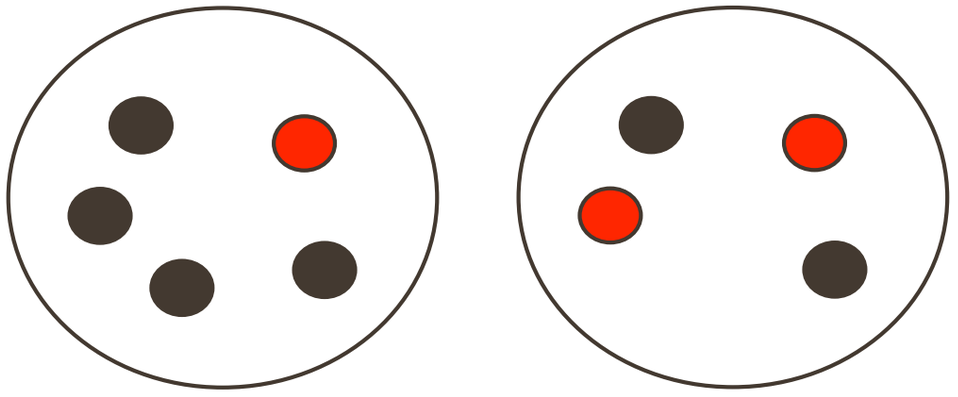
Instead of labels on each individual instance,
the learner only observes labels on bags of instances.

Negative Bags



A bag is labeled negative, if
all the examples in it are negative

Positive Bags



A bag is labeled positive, if
there is **at least one** positive example

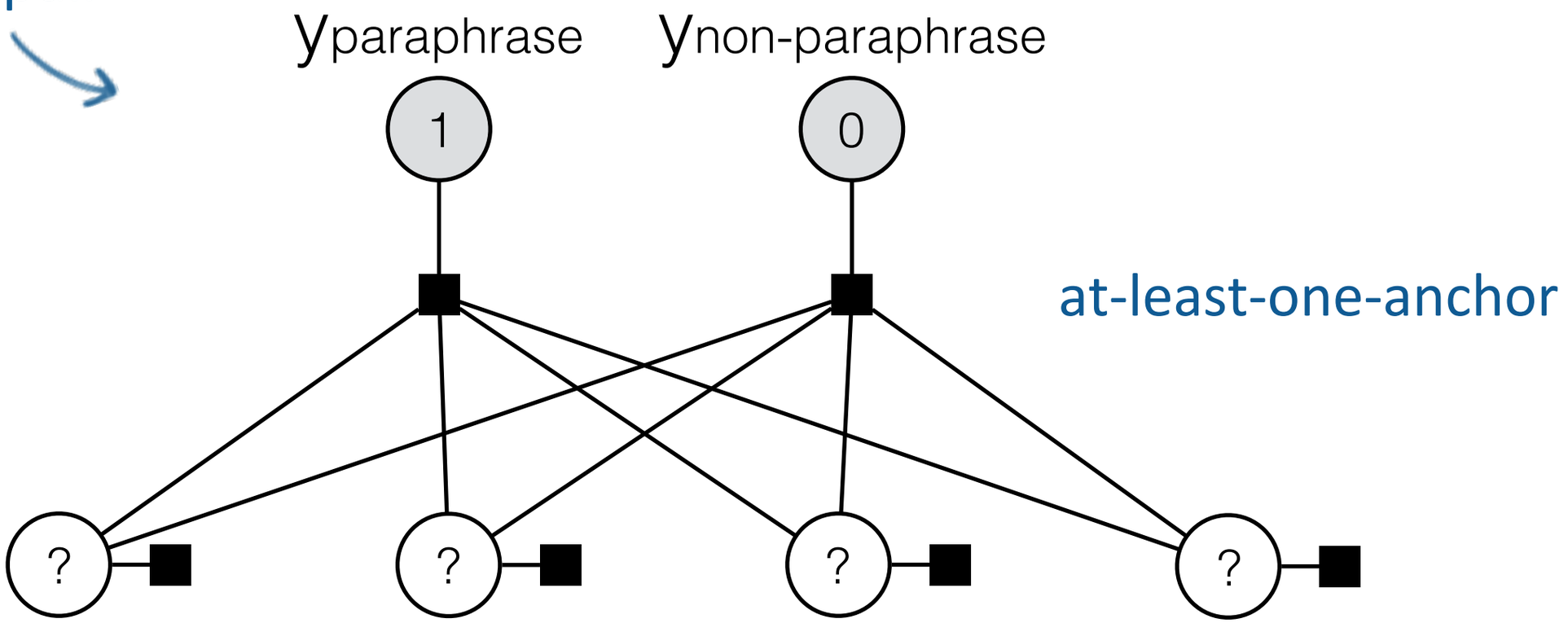
(Dietterich et al., 1997)

Multi-instance Learning Paraphrase Model

Mancini has been sacked by Manchester City

Mancini gets the boot from Man City

sentence pair



word pair

has | gets	has | boot	city | city	sacked | boot	. . .

features

diff_word	diff_word	same_word	diff_word
same_pos_verb	diff_pos_verb	same_pos_noun	diff_pos_verb
not_both_sig		both_sig	diff_pos_noun
…	not_both_sig	…	not_both_sig
	…		…

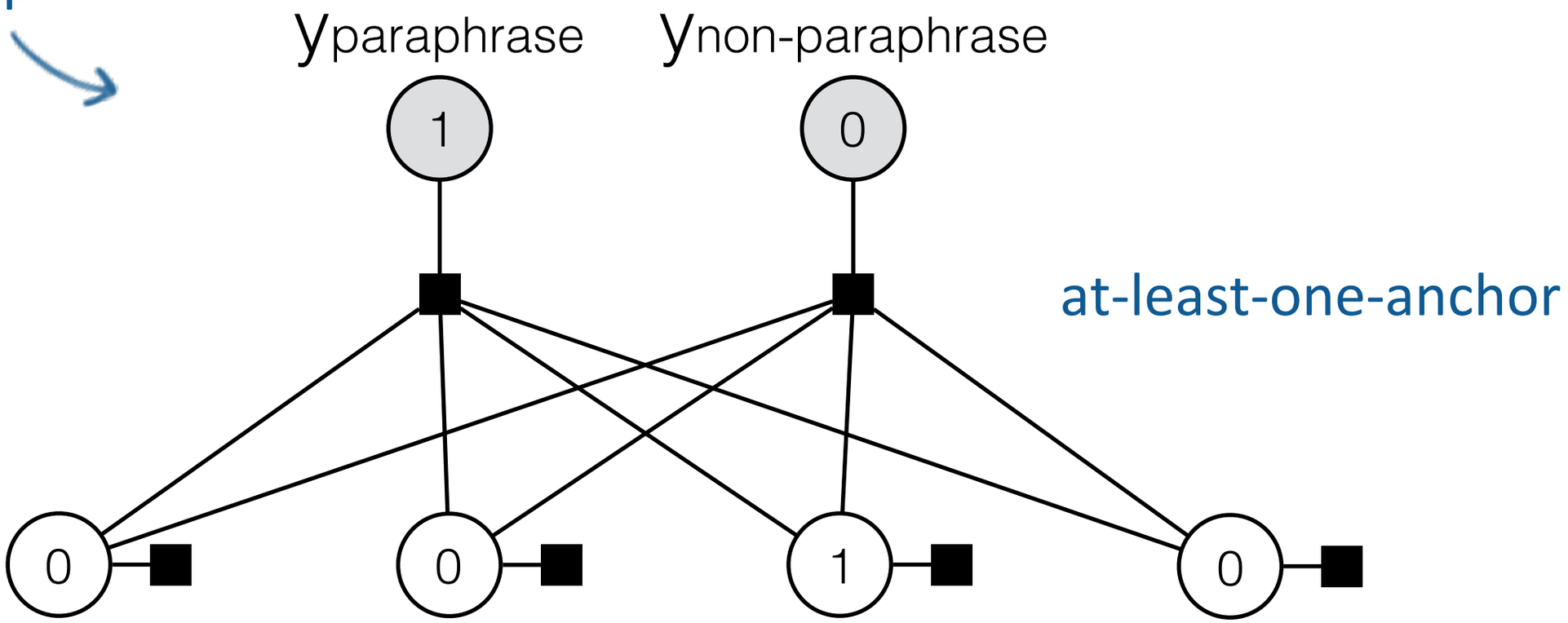
Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Multi-instance Learning Paraphrase Model

Mancini has been sacked by Manchester ***City***

Mancini gets the boot from Man ***City***

sentence pair



word pair

has | gets	has | boot	city | city	sacked | boot	. . .

features

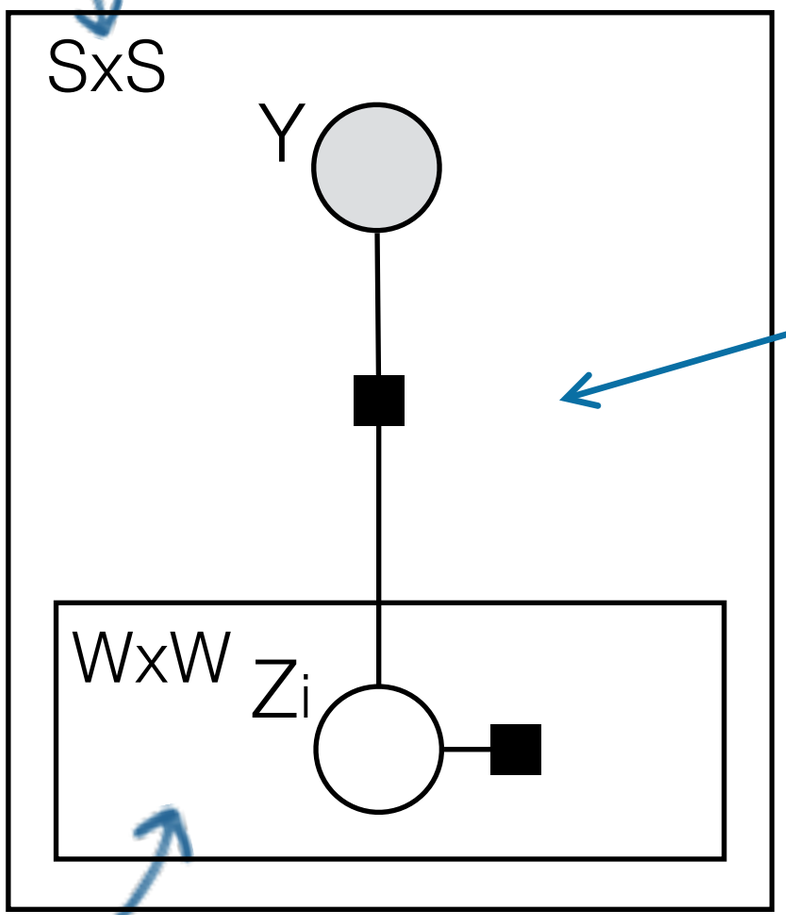
diff_word	diff_word	same_word	diff_word
same_pos_verb	diff_pos_verb	same_pos_noun	diff_pos_verb
not_both_sig		both_sig	diff_pos_noun
…	not_both_sig	…	not_both_sig
	…		…

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Multi-instance Learning

Model the assumption:
sentence-level paraphrase
is anchored by at-least-one word pair

sentence pair



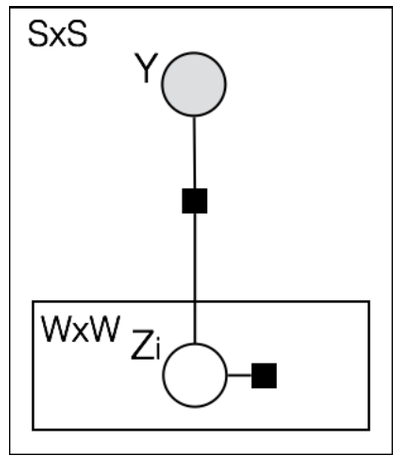
word pair

$$\sigma(\mathbf{z}, \mathbf{y}) = \begin{cases} 1 & \text{if } \mathbf{y} = true \wedge \exists i : z_i = 1 \\ 1 & \text{if } \mathbf{y} = false \wedge \forall i : z_i = 0 \\ 0 & \text{otherwise} \end{cases}$$

$$P(\mathbf{z}_i, y_i | \mathbf{w}_i; \theta) = \prod_{j=1}^{m} \exp(\theta \cdot f(z_j, w_j)) \times \sigma(\mathbf{z}_i, y_i)$$

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Learning Algorithm



Objective:

learn the parameters that maximize conditional likelihood over the training corpus

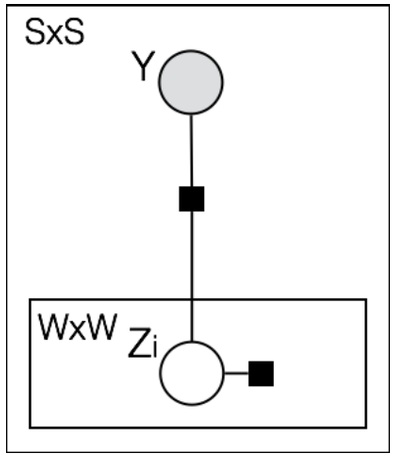
$$\theta^* = \arg\max_{\theta} P(\mathbf{y}|\mathbf{w};\theta) = \arg\max_{\theta} \prod_{i} \sum_{\mathbf{z}_i} P(\mathbf{z}_i, y_i|\mathbf{w}_i;\theta)$$

***i*th training sentence pair**

all possible values of the latent variables

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

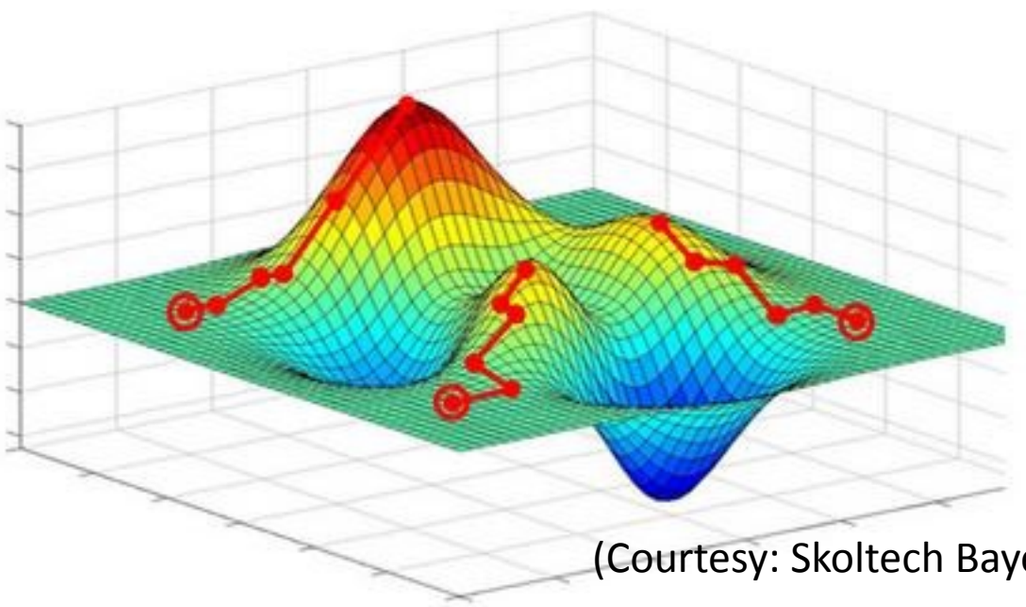
Learning Algorithm



Finding maximum likelihood estimate:

stochastic gradient ascent

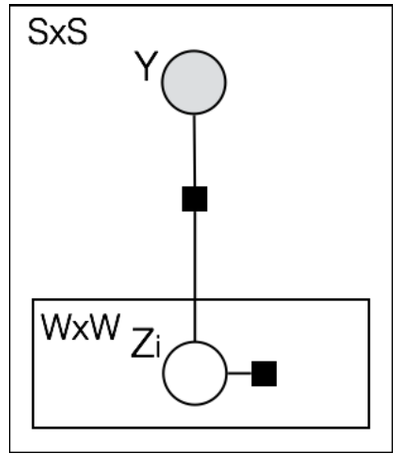
$$\frac{\partial \log P(\mathbf{y}|\mathbf{w};\theta)}{\partial \theta} = \mathbf{E}_{P(\mathbf{z}|\mathbf{w},\mathbf{y};\theta)}\Big(\sum_i f(\mathbf{z}_i, \mathbf{w}_i)\Big) - \mathbf{E}_{P(\mathbf{z},\mathbf{y}|\mathbf{w};\theta)}\Big(\sum_i f(\mathbf{z}_i, \mathbf{w}_i)\Big)$$



(Courtesy: Skoltech Bayesgroup)

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Learning Algorithm



Perceptron-style Update:

Viterbi approximation + online learning

O(# word pairs)

$$\frac{\partial \log P(\mathbf{y}|\mathbf{w};\theta)}{\partial \theta} = \mathbf{E}_{P(\mathbf{z}|\mathbf{w},\mathbf{y};\theta)}\Big(\sum_i f(\mathbf{z}_i, \mathbf{w}_i)\Big) - \mathbf{E}_{P(\mathbf{z},\mathbf{y}|\mathbf{w};\theta)}\Big(\sum_i f(\mathbf{z}_i, \mathbf{w}_i)\Big)$$

$$\approx \sum_i f(\mathbf{z}_i^*, \mathbf{w}_i) - \sum_i f(\mathbf{z}_i', \mathbf{w}_i)$$

reward correct (conditioned on labels)

penalize wrong (ignoring labels)

$$\mathbf{z}^* = \arg\max_{\mathbf{z}} P(\mathbf{z}|\mathbf{w},\mathbf{y};\theta) \qquad \mathbf{y}', \mathbf{z}' = \arg\max_{\mathbf{y},\mathbf{z}} P(\mathbf{z},\mathbf{y}|\mathbf{w};\theta)$$

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Twitter Paraphrase Dataset

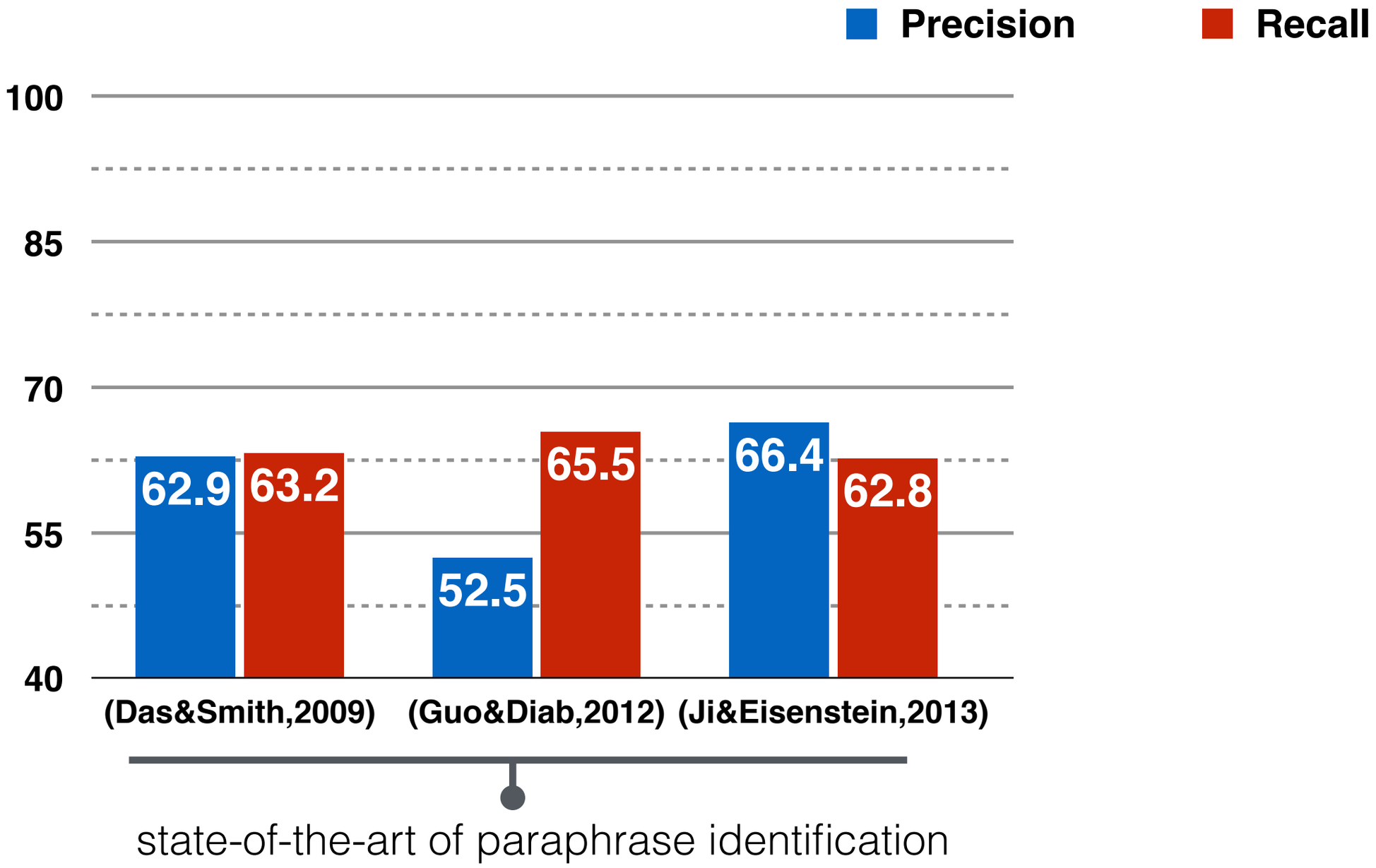
18,762 labeled sentence pairs
1/3 paraphrase, 2/3 non-paraphrase

Techniques

- **Crowdsourcing** (Human-Computer Interaction)
- SumBasic algorithm for sentence filtering
- Multi-armed bandits algorithm for topic selection

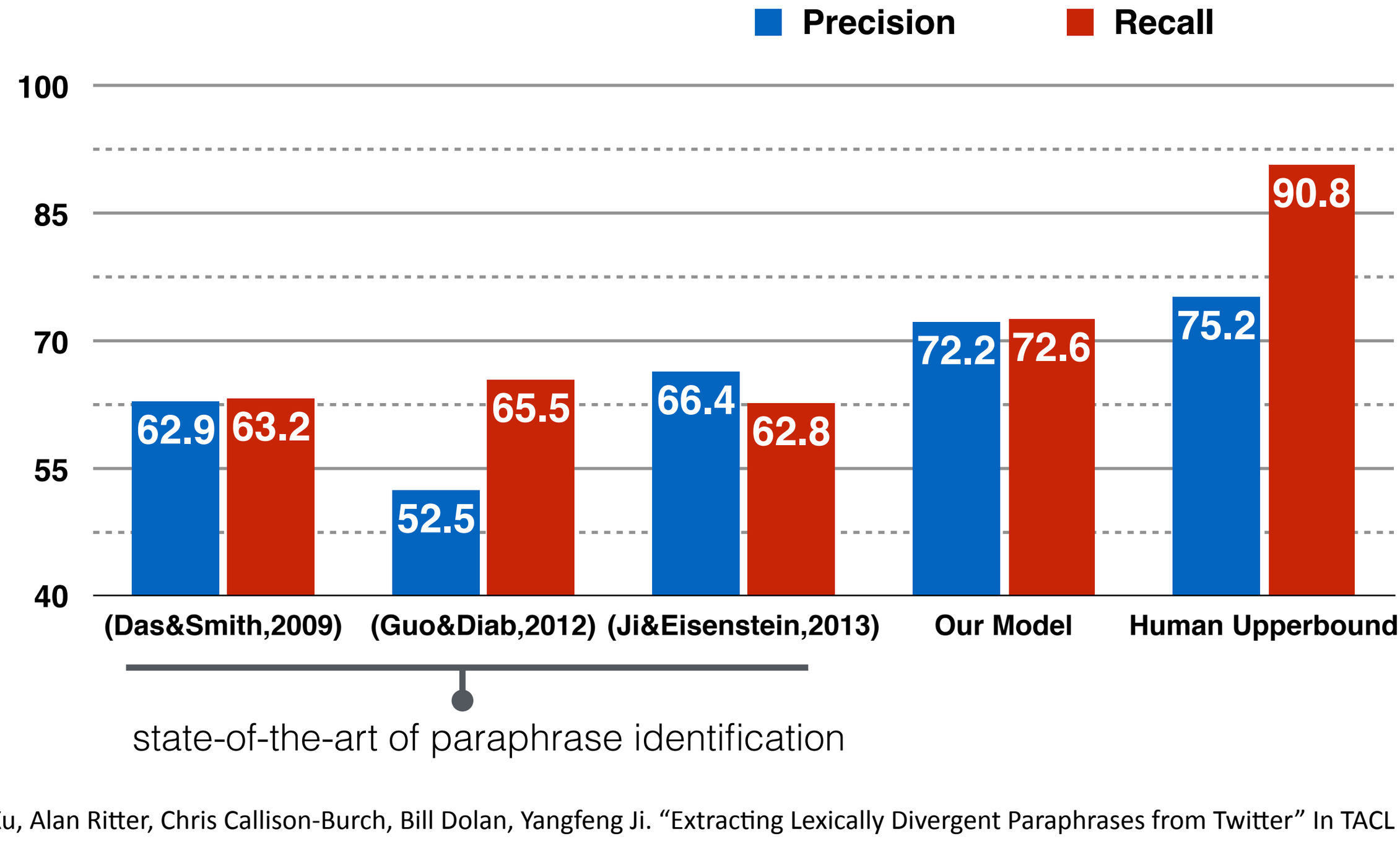
Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Performance



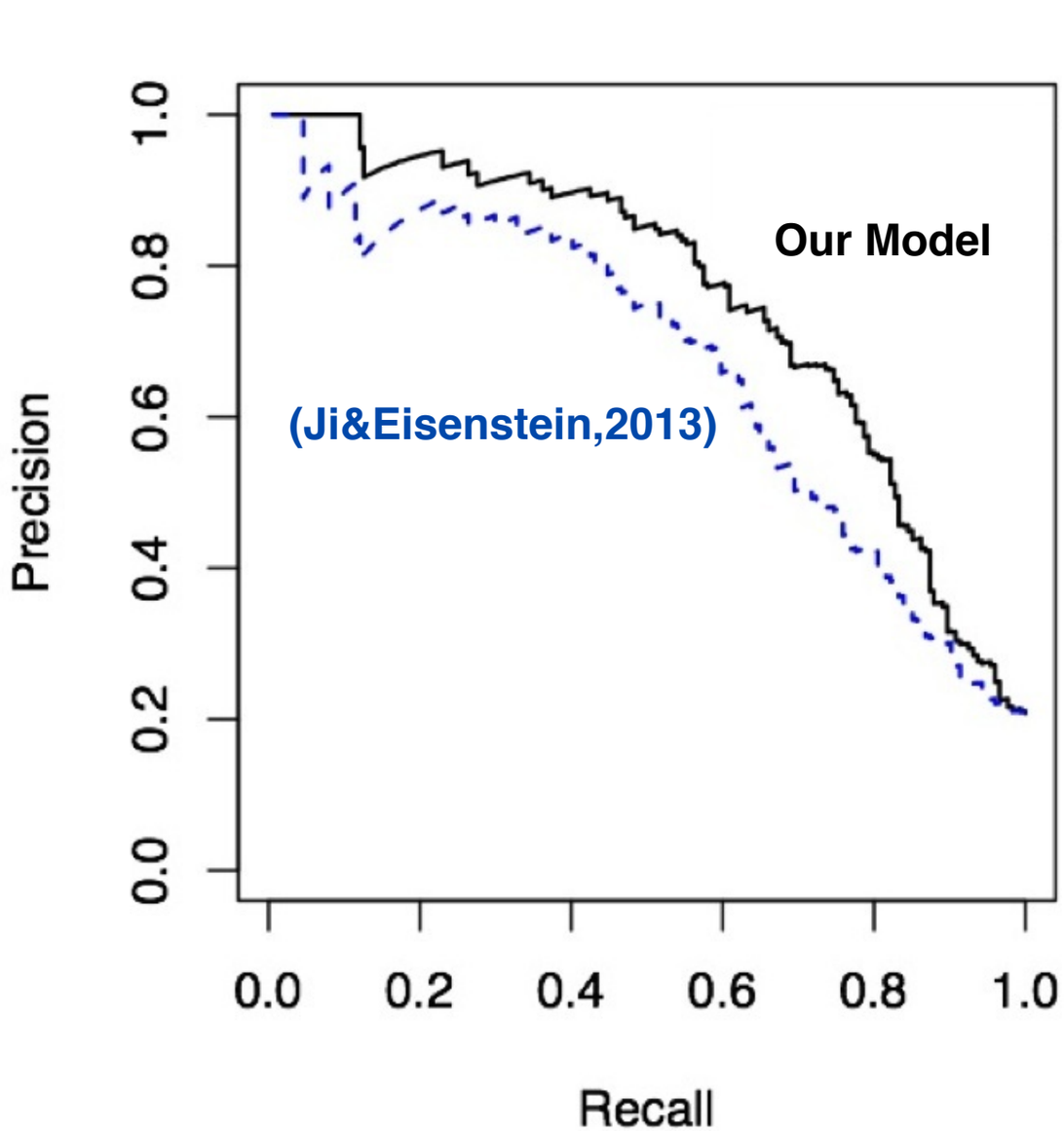
Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

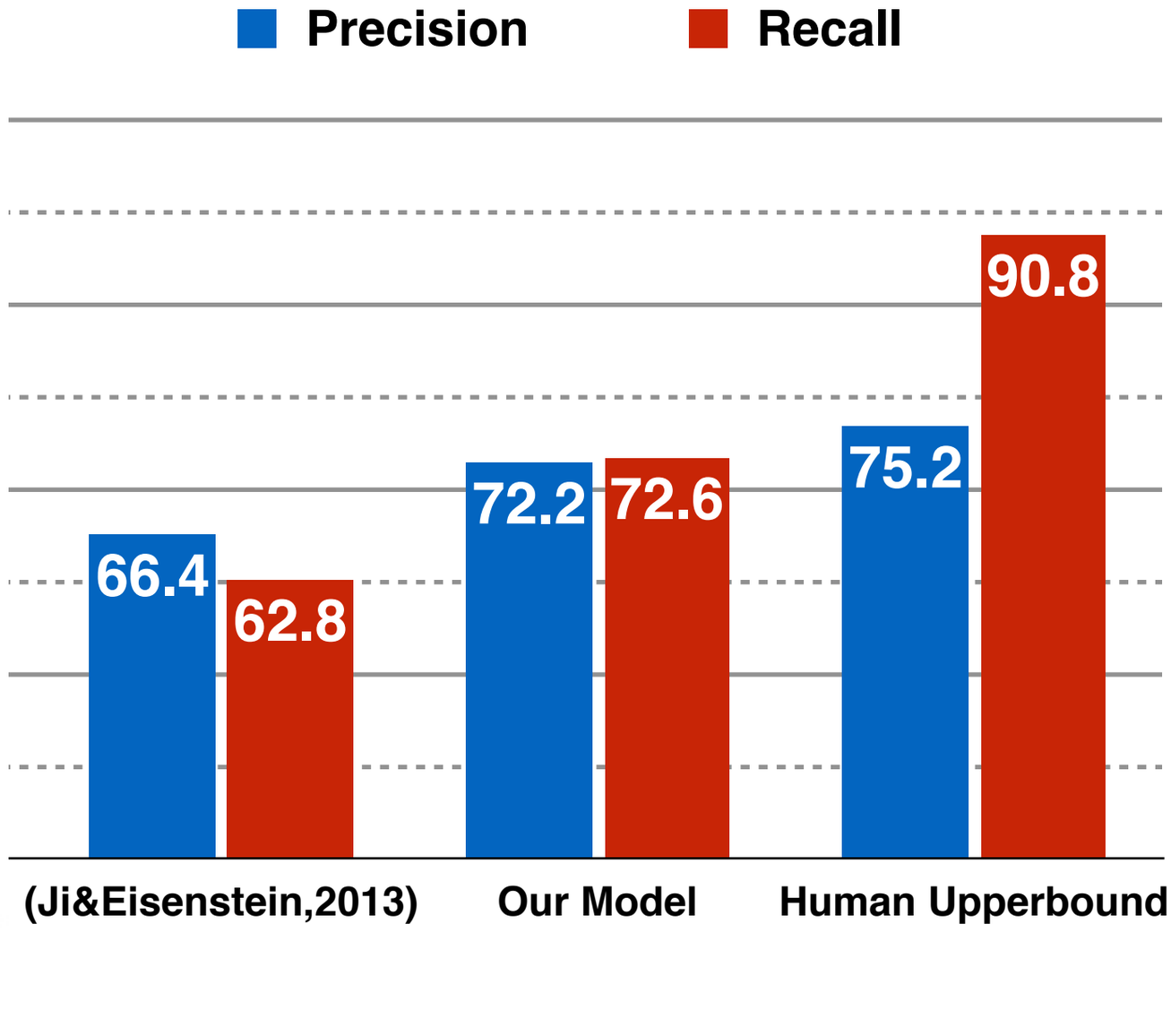
Performance



Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Performance





Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Multi-instance Learning

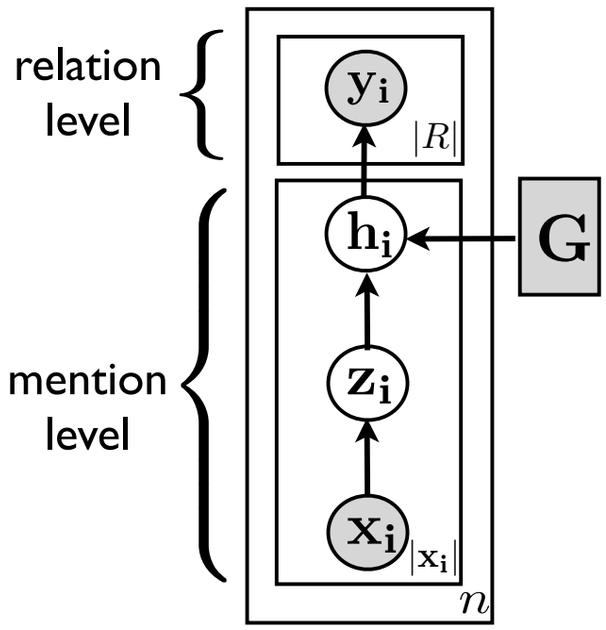
Other Application: Learning Knowledge Base

… the forced resignation of the CEO of Boeing, Harry Stonecipher, for …

Harry Stonecipher

CEO, Boeing

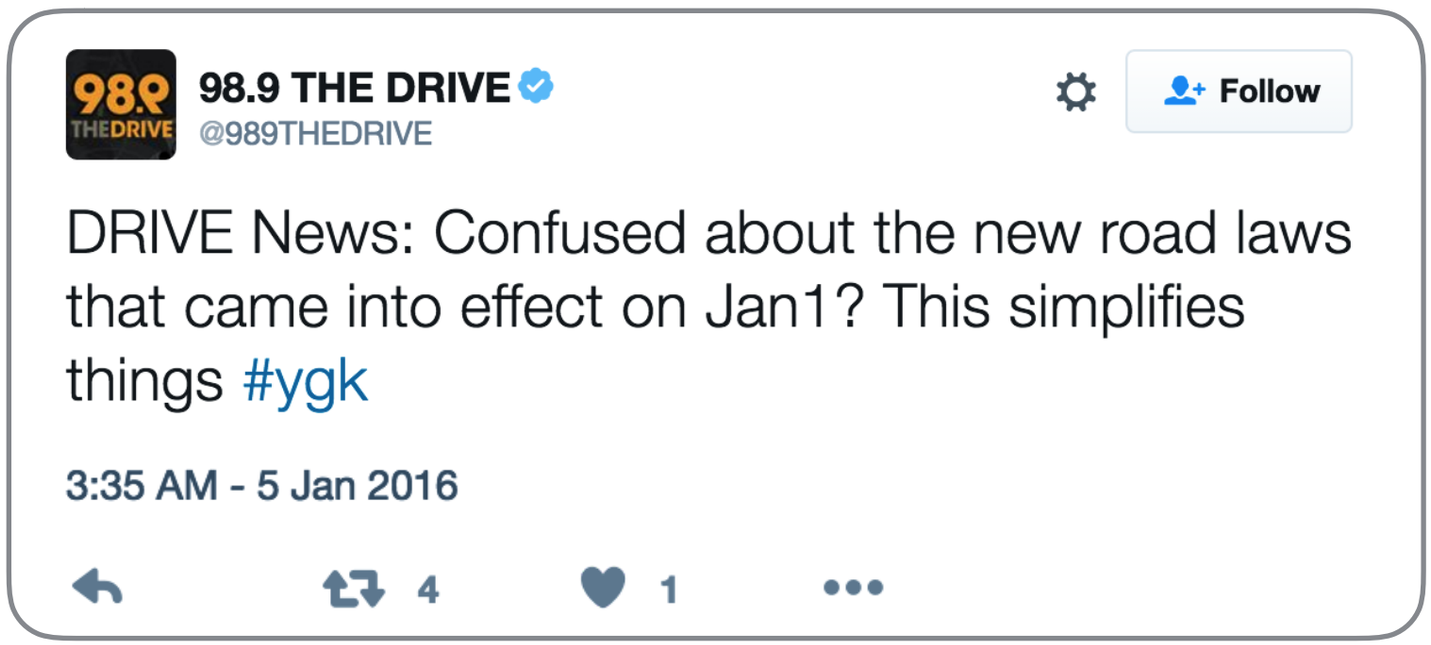
In office
2003-2005



Wei Xu, Ralph Grishman, Le Zhao. “Passage Retrieval for Information Extraction using Distant Supervision” In IJCNLP (2011)
Wei Xu, Raphael Hoffmann, Le Zhao, Ralph Grishman. “Filling Knowledge Base Gaps for Distant Supervision of Relation Extraction” In ACL (2013)
Maria Pershina, Bonan Min, Wei Xu, Ralph Grishman. “Infusion of Labeled Data into Distant Supervision for Relation Extraction” In ACL (2014)

Multi-instance Learning

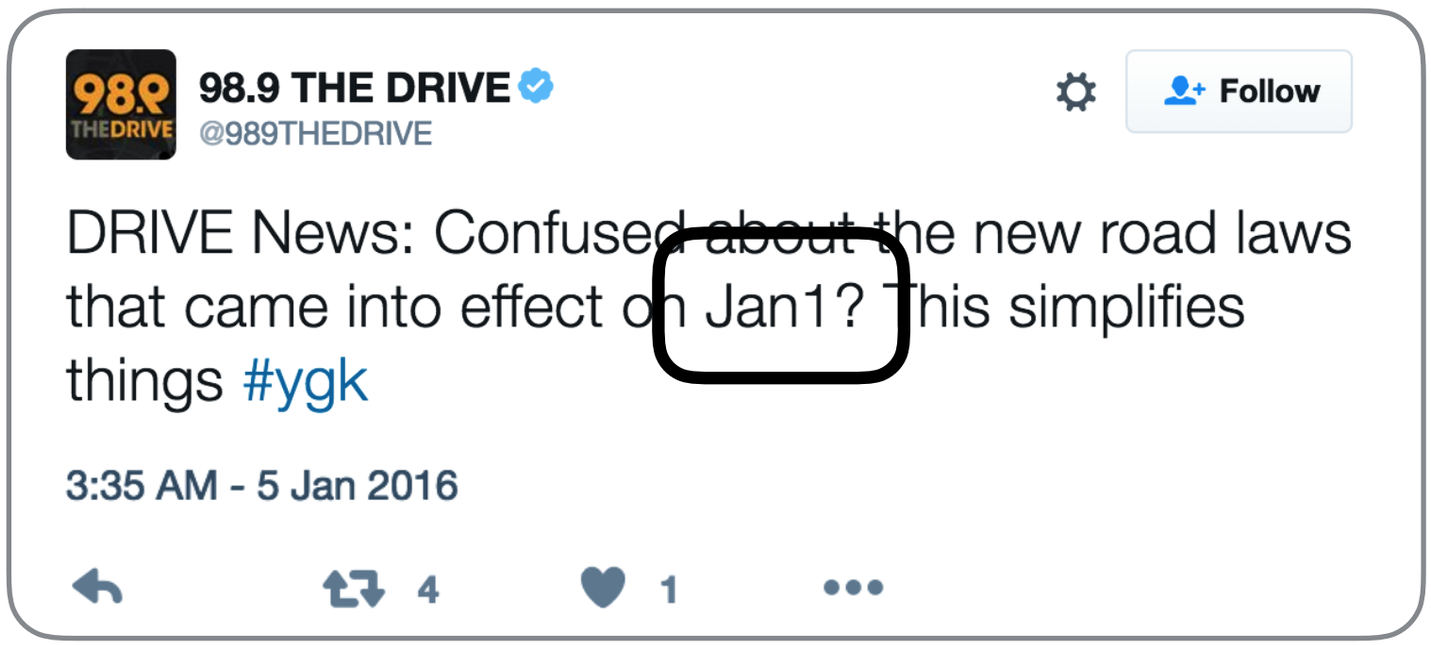
Other Application: Resolving Time Expressions



Jeniya Tabassum, Alan Ritter, Wei Xu. “A Minimally Supervised Method for Recognizing and Normalizing Time Expressions in Twitter” In EMNLP (2016)

Multi-instance Learning

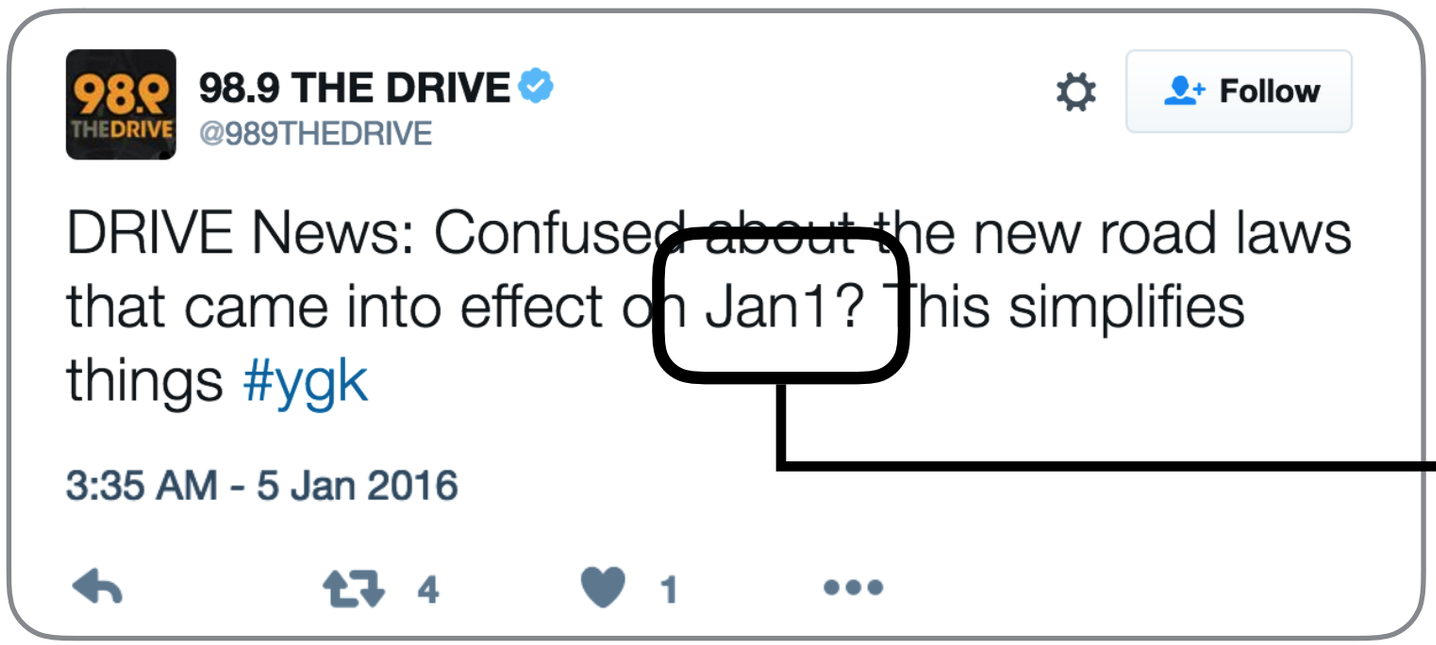
Other Application: Resolving Time Expressions



Jeniya Tabassum, Alan Ritter, Wei Xu. “A Minimally Supervised Method for Recognizing and Normalizing Time Expressions in Twitter” In EMNLP (2016)

Multi-instance Learning

Other Application: Resolving Time Expressions



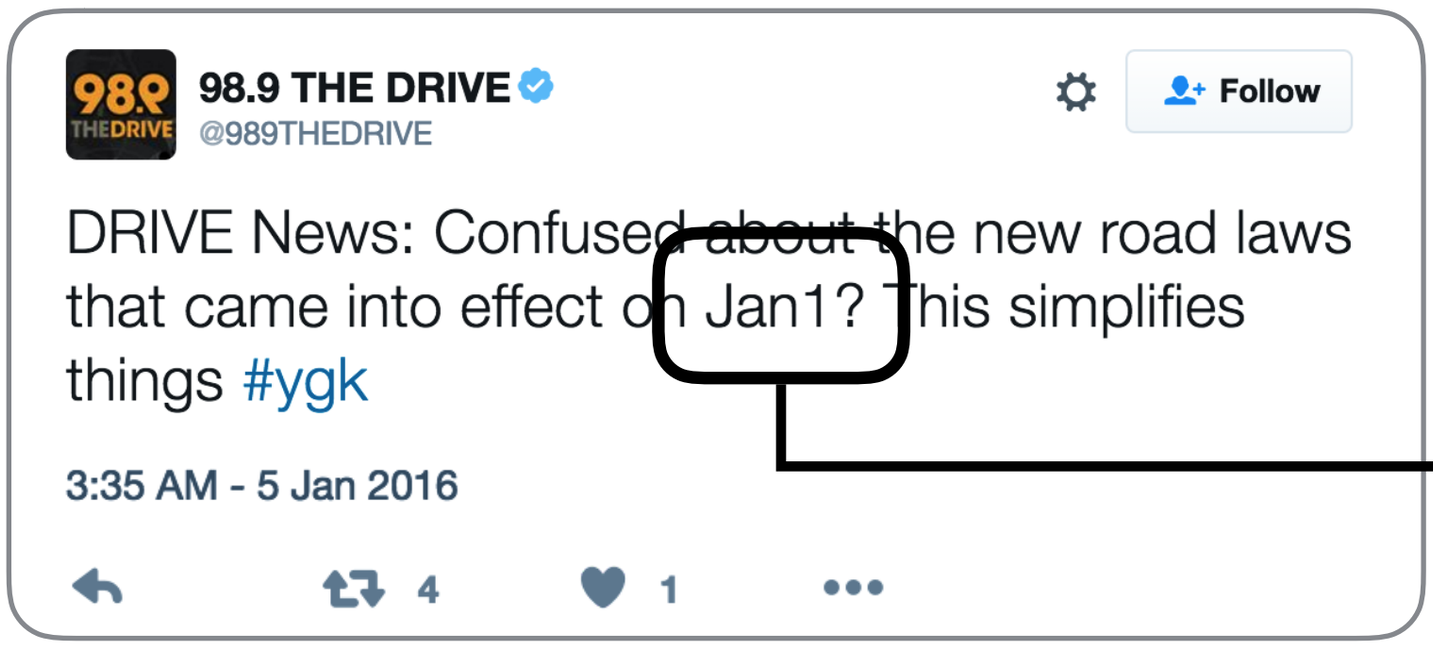
TweeTime

1 Jan 2016

Jeniya Tabassum, Alan Ritter, Wei Xu. “A Minimally Supervised Method for Recognizing and Normalizing Time Expressions in Twitter” In EMNLP (2016)

Multi-instance Learning

Other Application: Resolving Time Expressions



TweeTime

1 Jan 2016

All other state-of-the-art time resolvers { TempEX, HeidelTime, SUTime, UWTime } failed.

Jeniya Tabassum, Alan Ritter, Wei Xu. "A Minimally Supervised Method for Recognizing and Normalizing Time Expressions in Twitter" In EMNLP (2016)

Multi-instance Learning

Other Application: Resolving Time Expressions

[EVENT EXTRACTOR]

NER

TempEx

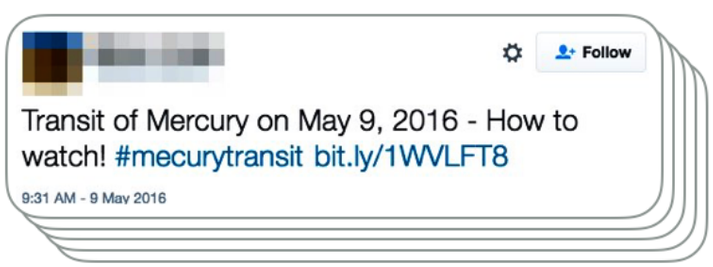
[10,000 events]

[EVENT DATABASE]

ENTITY	DATE
Mercury	5/9/2016
…	…
…	…

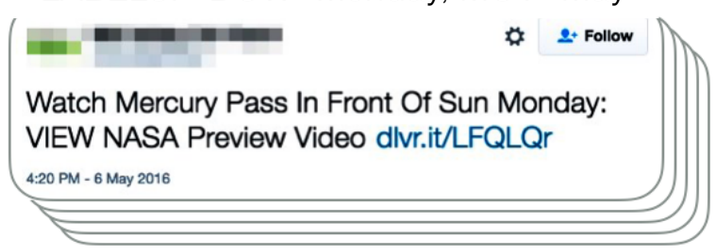
distant labeling

LABELS: DOW=Monday, MOY=May



(simple time expressions)

[120 Million Tweets]



(harder and more time expressions)

model training

[RECOGNIZER]

[NORMALIZER]

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

[1 Million Tweets — Automatically Labeled Training Data]

Jeniya Tabassum, Alan Ritter, Wei Xu. "A Minimally Supervised Method for Recognizing and Normalizing Time Expressions in Twitter" In EMNLP (2016)

More about TweeTime

- **Jeniya Tabassum (OSU)**
- **Tuesday**, Oct 25, 12:45 pm, McPherson 2019
- A Minimally Supervised Method for Recognizing and Normalizing Time Expressions in Twitter

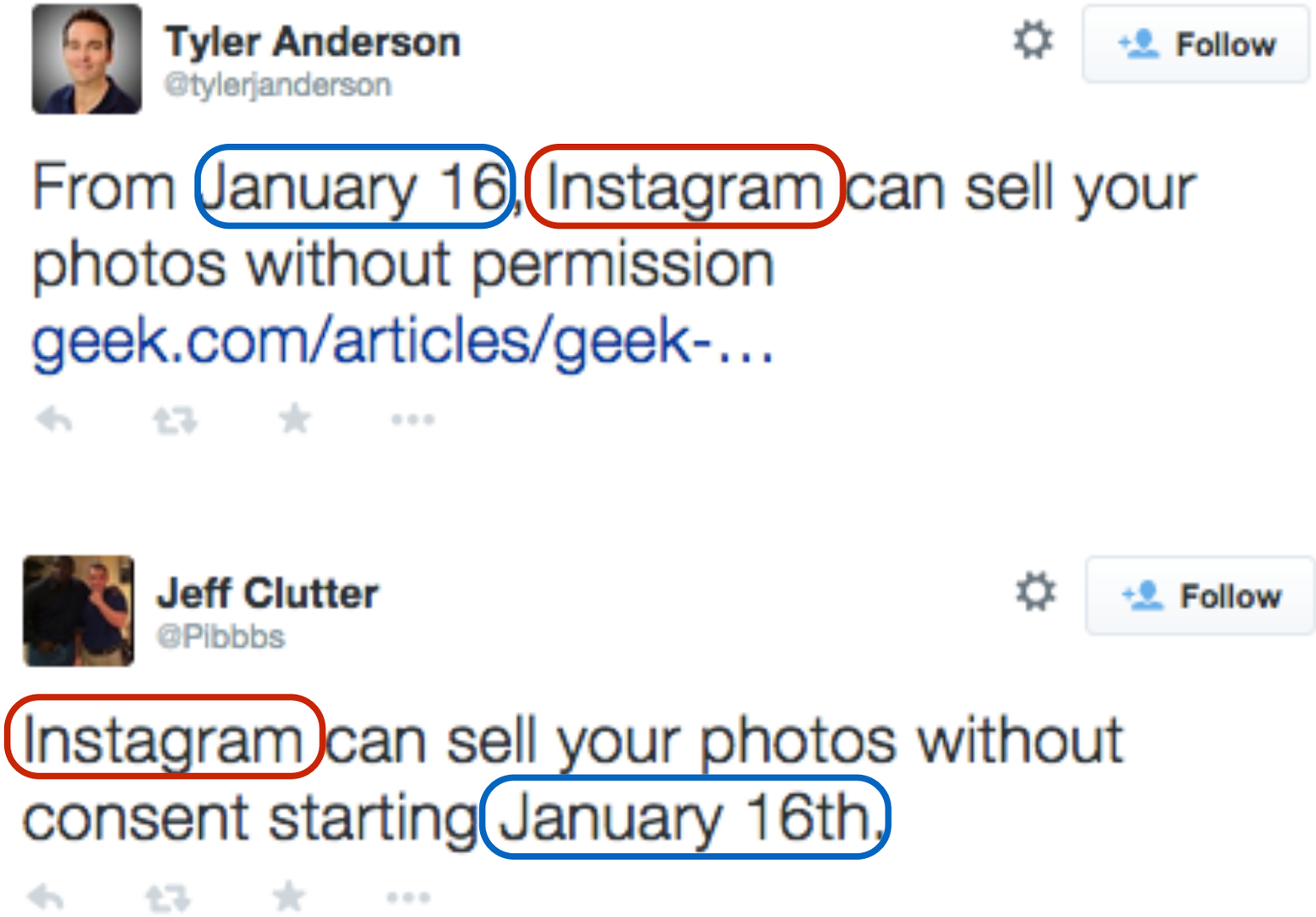
Crowdsourcing Training Data

Early Attempts on Twitter Paraphrase

- 1242 tweet pairs, tracking celebrity & hashtags
  (Zanzotto, Pennacchiotti, Tsioutsiouliklis, 2011)
- named entity + date
  (**Xu**, Ritter, Grishman, 2013)
- bilingual posts, only phrases
  (Ling, Dyer, Black, Trancoso, 2013)

Early Attempt:

Named Entity + Date



Wei Xu, Alan Ritter, Ralph Grishman. “Gathering and Generating Paraphrases from Twitter with Application to Normalization” In BUCC (2013)

Early Attempt:

Self-translation

(Ling, Dyer, Black and Trancoso, 2013)

Crowdsourcing

art

(Courtesy: The Sheep Market by Aaron Koblin)

Crowdsourcing

paraphrase

Here Is The Question To You:

Original Sentence: ***Borussia Dortmund advanced to the final***

Select ALL sentences that have similar meaning from below:

- [ ] Borussia Dortmund has clinched their Champions League final spot
- [ ] Real Madrid efforts are not enough as Cinderella Borussia Dortmund advances to the Champions League Final
- [ ] But it s Borussia Dortmund whose heading to Wembley Park
- [ ] Congratulations Borussia Dortmund s going to Wembley

amazon mechanical turk™
Artificial Artificial Intelligence

Mingkun Gao, Wei Xu, Chris Callison-Burch. “Cost Optimization for Crowdsourcing Translation” In TACL (2014)

Simple Quality Control

- Cohen's Kappa — used to remove bad workers

simple agreement between <u>two</u> raters

$$\kappa = \frac{p_0 - p_e}{1 - p_e}$$

likelihood that agreement is attributed to chance

		B	
		Yes	No
A	Yes	45	15
	No	25	15

$$\kappa = \frac{0.60 - 0.54}{1 - 0.54} = 0.1304$$

		B	
		Yes	No
A	Yes	25	35
	No	5	35

$$\kappa = \frac{0.60 - 0.46}{1 - 0.46} = 0.2593$$

A Problem

only **8%** sentence pairs
about the same Twitter's trending topic
have similar meaning

hurts both quantity and quality

non-experts lower their bars

amazon mechanical turk™
Artificial Artificial Intelligence

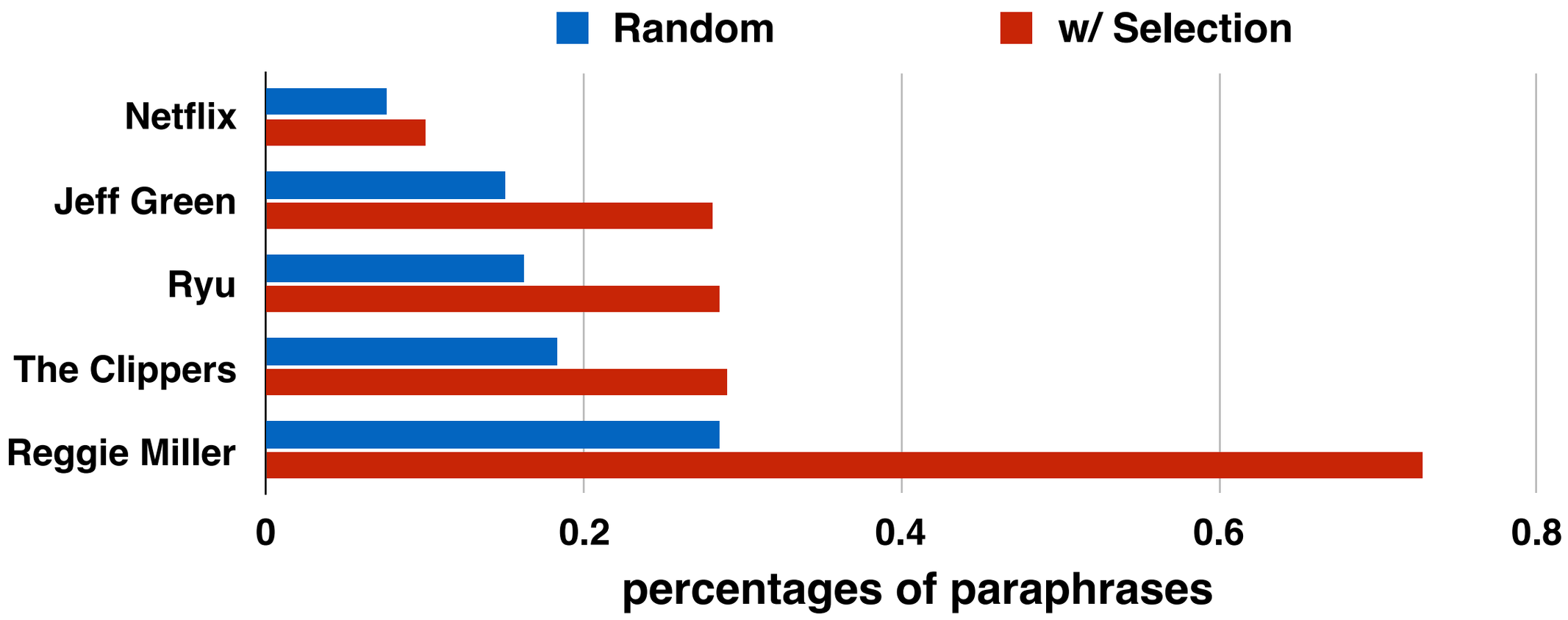
Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. "Extracting Lexically Divergent Paraphrases from Twitter" In TACL (2014)

Sentence Selection

SumBasic Algorithm

8% → 16%

$$Salience(s) = \sum_{w_i \in s} \frac{P(w_i)}{|w_i | w_i \in s|}$$

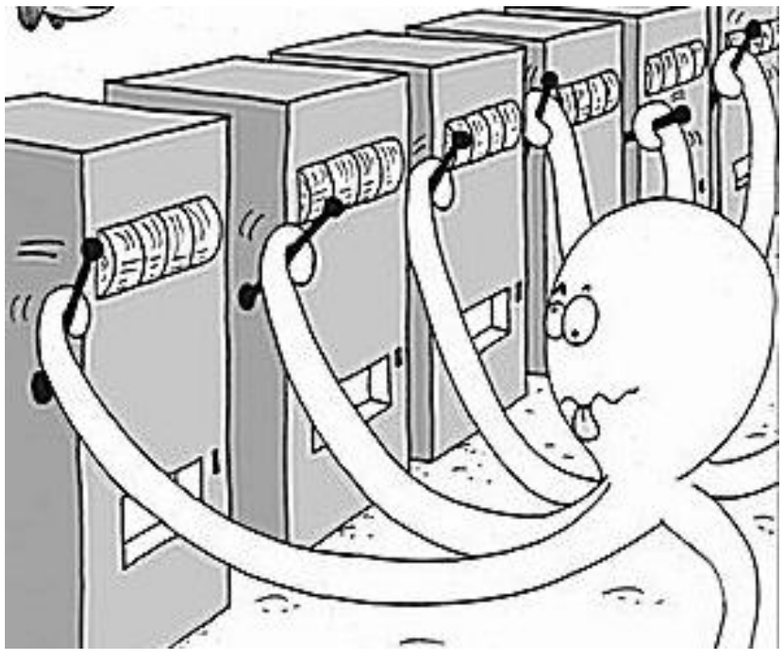


Wei Xu, Alan Ritter, Ralph Grishman. “A Preliminary Study of Tweet Summarization using Information Extraction” in LASM (2013)
Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

Topic Selection

Multi-Armed Bandits

16% → 34%



$$\max \sum_{i \in \{n | r_n(t_1) > 0\}} \hat{\mu}_i(t_0) r_i(t_1)$$

$$\text{s.t.} \sum_{i \in \{m | r_m(t_0) > 0\}} r_i(t_0) \leq (1 - \epsilon) B, \forall i : 0 \leq r_i(t_1) \leq l - r_i(t_0)$$

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. “Extracting Lexically Divergent Paraphrases from Twitter” In TACL (2014)

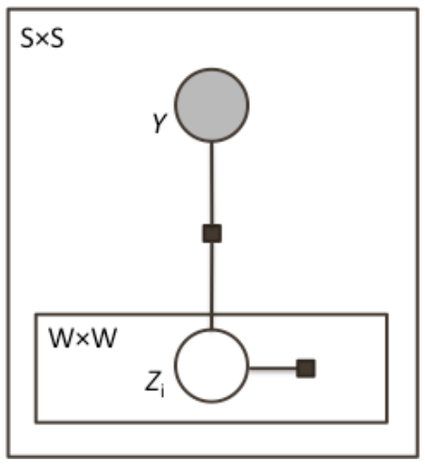
Innovations

Web-scale Paraphrase from Twitter

Mancini has been sacked by Manchester City
Mancini gets the boot from Man City

Yes!

Multi-instance Learning Paraphrase Model



- Twitter's big data stream
- joint sentence-word alignment
- no word-level annotation needed
- extensible latent variable model

Wei Xu, Alan Ritter, Chris Callison-Burch, Bill Dolan, Yangfeng Ji. "Extracting Lexically Divergent Paraphrases from Twitter" In TACL (2014)

Impact & Future Work

[SemEval 2015 Shared-Task 1]

Paraphrase and Semantic Similarity in Twitter

Wei Xu
(University of Pennsylvania)

Chris Callison-Burch
(University of Pennsylvania)

Bill Dolan
(Microsoft Research)

Participation

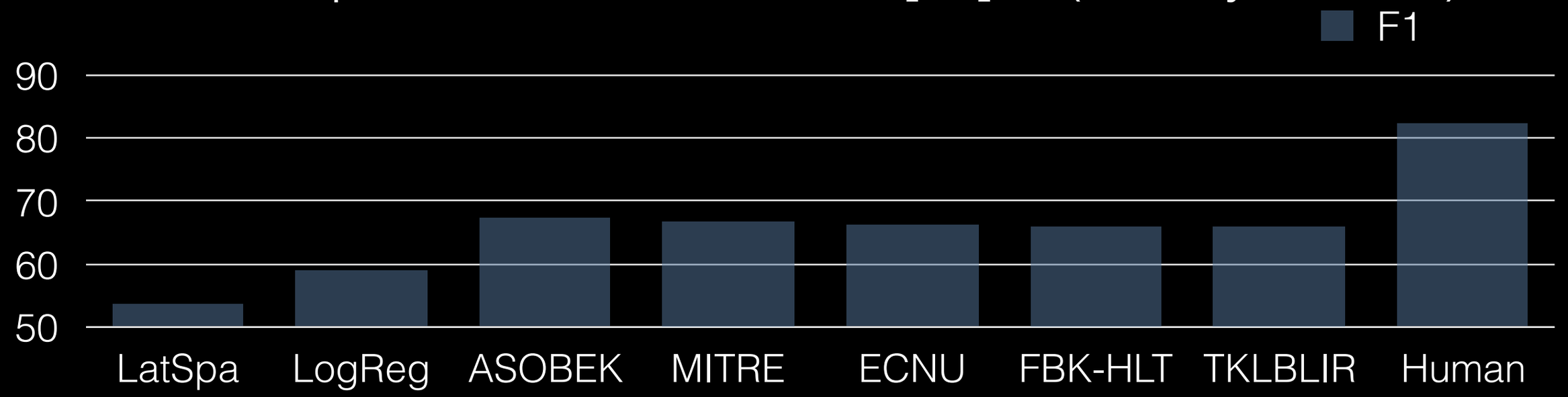
9 teams participated
150 + research groups requested data

Popular Techniques

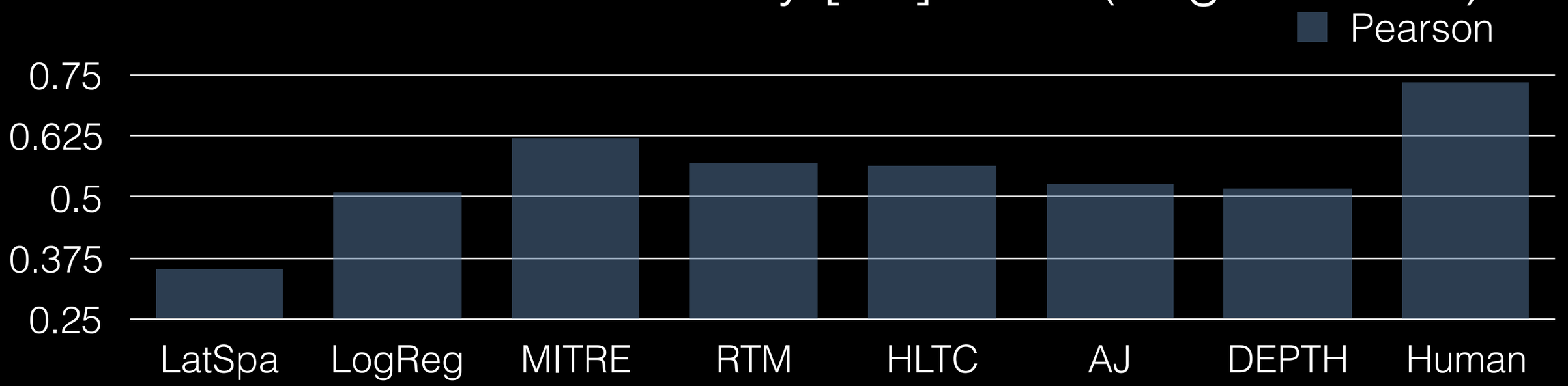
- Word Embeddings
- String Similarities
- Syntactic Similarities
- Semantics
  (LSA, CRM; WordNet; Entailment;
  different parsers: constituency, logical, Boxer …)
- MT metrics
- POS
- Named Entity
- various classifiers: SVM, MaxEnt, neural network
  …

Performance

#1 Paraphrase Identification [PI] (binary 0 or 1)



#2 Semantic Similarity [SS] (degreed 0~1)



Challenging Cases

(Mariano "Mo" Rivera is a baseball pitcher)

paraphrase

Classy gesture by the Mets for Mariano

real class shown by the Mets Mo Rivera is a legend

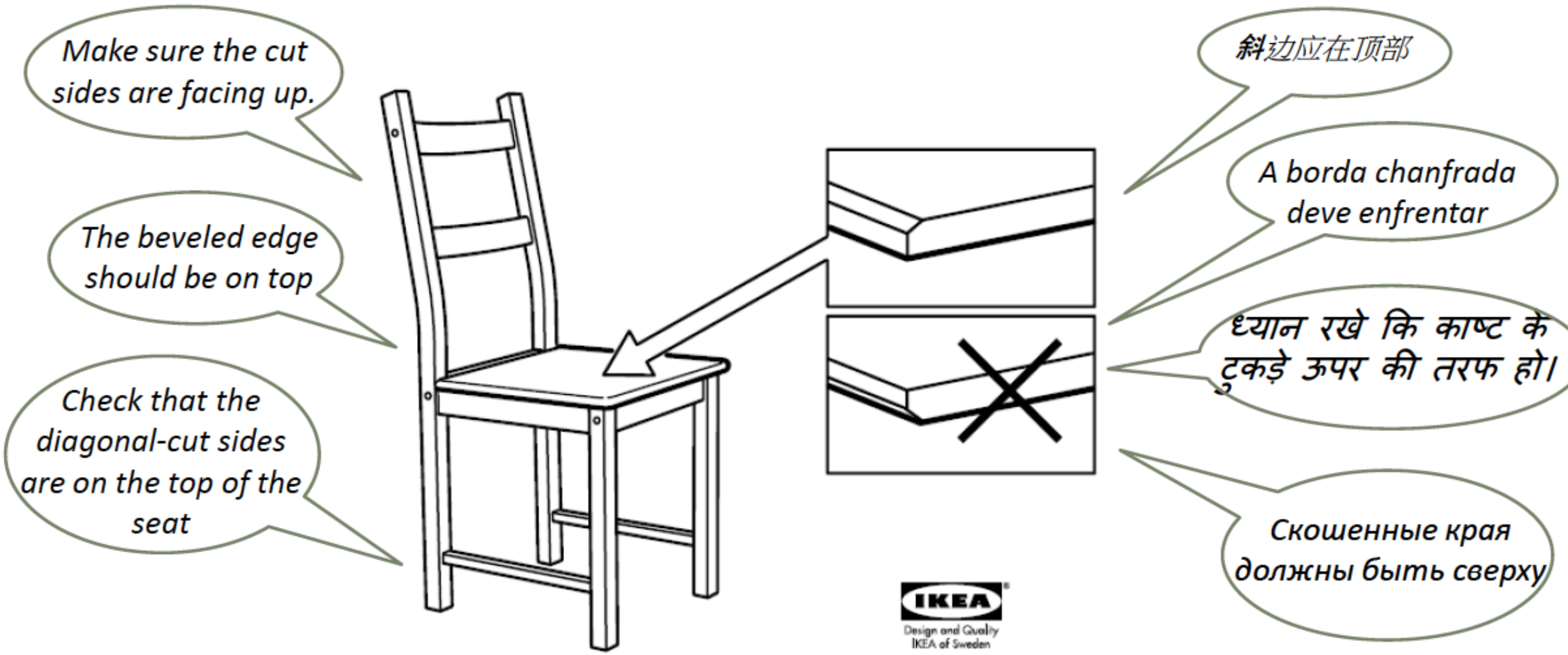
non-paraphrase

The world of jenks is such a real show

Jenks from the World of Jenks is such a good person

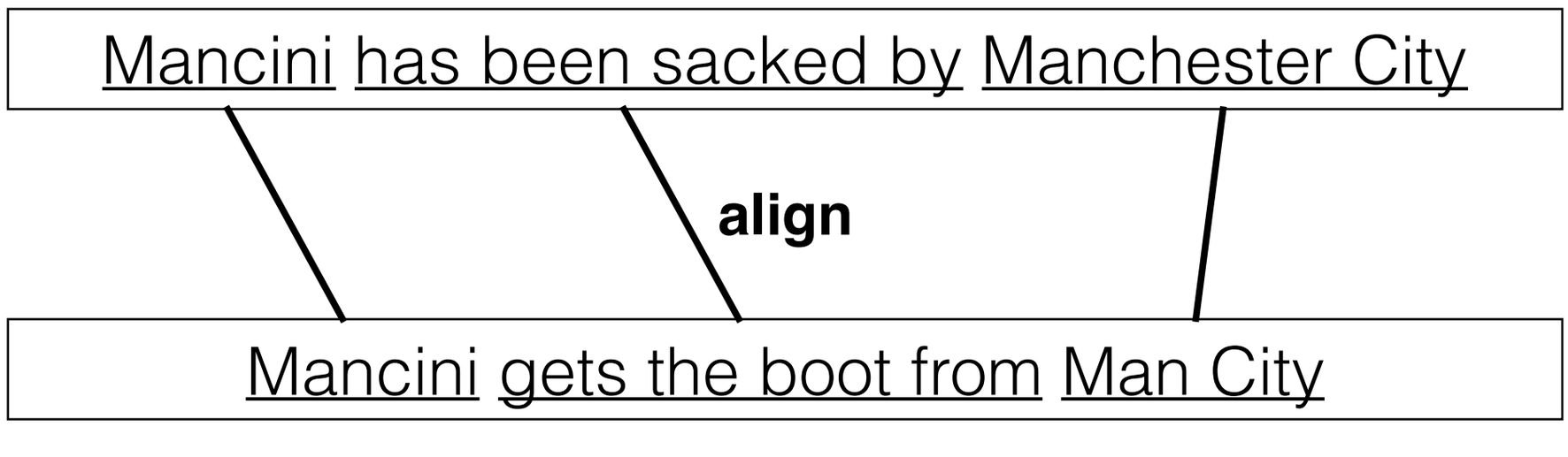
An Vo et al. “FBK-HLT: An Effective System for Paraphrase Identification and Semantic Similarity in Twitter” In SemEval (2015)

Multi-lingual Paraphrases



Wuwei Lan, Siyu Qiu, Wei Xu (Ongoing Work)

Extract Phrasal Paraphrases



Techniques

- Word/Phrase Alignment
- Probabilistic Graphical Models

Wei Xu, Joel Tetreault, Martin Chodorow, Ralph Grishman, Le Zhao. "Exploiting Syntactic and Distributional Information for Spelling Correction with Web-Scale N-gram Models" In EMNLP (2011)

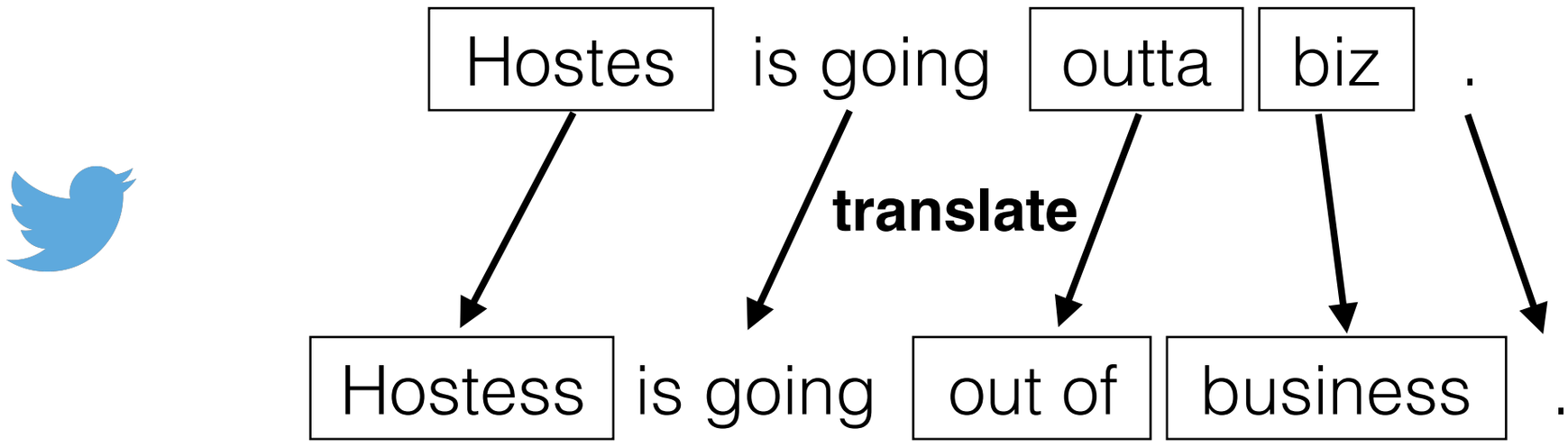
Wei Xu, Alan Ritter, Ralph Grishman. "Gathering and Generating Paraphrases from Twitter with Application to Normalization" In BUCC (2013)

Timothy Baldwin, Marie-Catherine de Marneffe, Bo Han, Young-Bum Kim, Alan Ritter, Wei Xu. "Shared Tasks of the 2015 ACL Workshop on Noisy User-generated Text: Twitter Lexical Normalization and Named Entity Recognition" In WNUT (2015)

Extract Phrasal Paraphrases

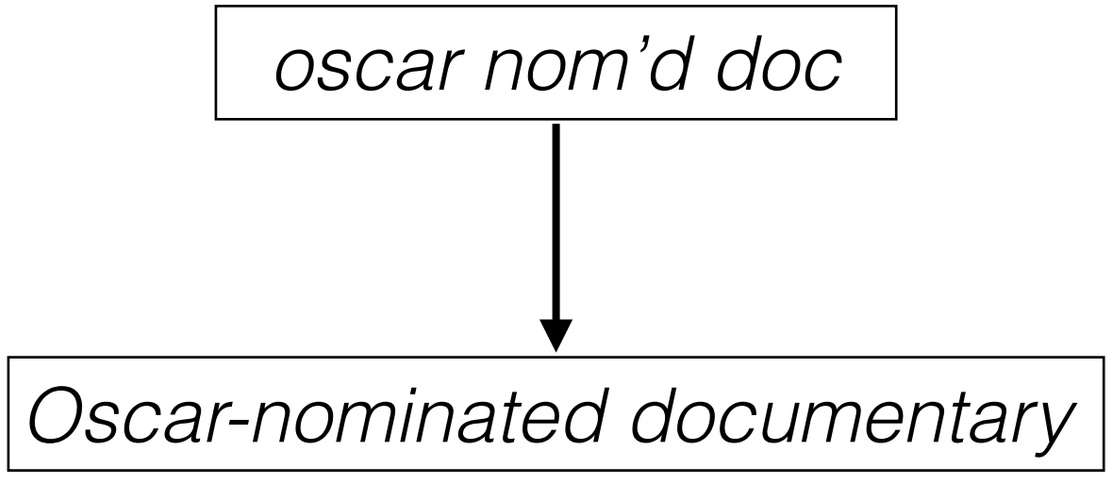
has been sacked by	gets the boot from
manchester city	man city
4	for
4	four
outta	out of
hostes	hostess

Noisy Text Normalization



Wei Xu, Joel Tetreault, Martin Chodorow, Ralph Grishman, Le Zhao.
“Exploiting Syntactic and Distributional Information for Spelling Correction with Web-Scale N-gram Models” In EMNLP (2011)
Wei Xu, Alan Ritter, Ralph Grishman. “Gathering and Generating Paraphrases from Twitter with Application to Normalization” In BUCC (2013)
Timothy Baldwin, Marie-Catherine de Marneffe, Bo Han, Young-Bum Kim, Alan Ritter, Wei Xu. “Shared Tasks of the 2015 Workshop on
Noisy User-generated Text: Twitter Lexical Normalization and Named Entity Recognition” In WNUT (2015)

Noisy Text Normalization



Wei Xu, Joel Tetreault, Martin Chodorow, Ralph Grishman, Le Zhao. "Exploiting Syntactic and Distributional Information for Spelling Correction with Web-Scale N-gram Models" In EMNLP (2011)

Wei Xu, Alan Ritter, Ralph Grishman. "Gathering and Generating Paraphrases from Twitter with Application to Normalization" In BUCC (2013)

Timothy Baldwin, Marie-Catherine de Marneffe, Bo Han, Young-Bum Kim, Alan Ritter, **Wei Xu**. "Shared Tasks of the 2015 Workshop on Noisy User-generated Text: Twitter Lexical Normalization and Named Entity Recognition" In WNUT (2015)

Natural Language Generation

noisy ⟶ standard **'13* '14***

stylistic ⟷ plain **'12* '14***

complex ⟶ simple **'15* '16***

erroneous ⟶ correct **'11* '13***

feminine ⟷ masculine **'16***

and more (future work) …

*** my research**

Wei Xu. “Data-driven Approaches for Paraphrasing Across Language Variations” PhD Thesis. (2014)

Voice Assistant

who wants to get a beer?

want to get a beer?

who else wants to get a beer?

who wants to go get a beer?

who wants to buy a beer?

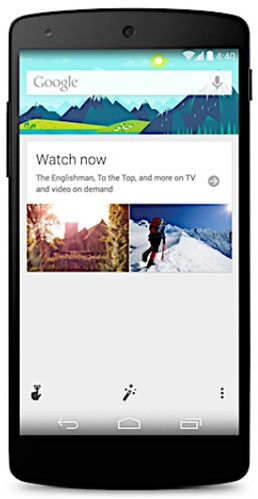
who else wants to get a beer?

trying to get a beer?

… (21 different ways)

Apple Siri

Google Now



Windows Cortana

Wei Xu, Alan Ritter, Ralph Grishman. “Gathering and Generating Paraphrases from Twitter with Application to Normalization” In BUCC (2013)

Unlimited Text in theory

“Almost any single (relatively complex) meaning can be implemented by an astonishingly high number of synonymous surface expressions.”

Meaning-Text Linguistic Theory (Žolkovskij & Mel’čuk, 1965; ~ now)

meaning = invariant of paraphrases

text = ‘virtual paraphrasing’

paraphrases = synonymous linguistic expressions

Unlimited Text in theory

“Almost any single (relatively complex) meaning can be implemented by an astonishingly high number of synonymous surface expressions.”

Meaning-Text Linguistic Theory (Žolkovskij & Mel’čuk, 1965; ~ now)

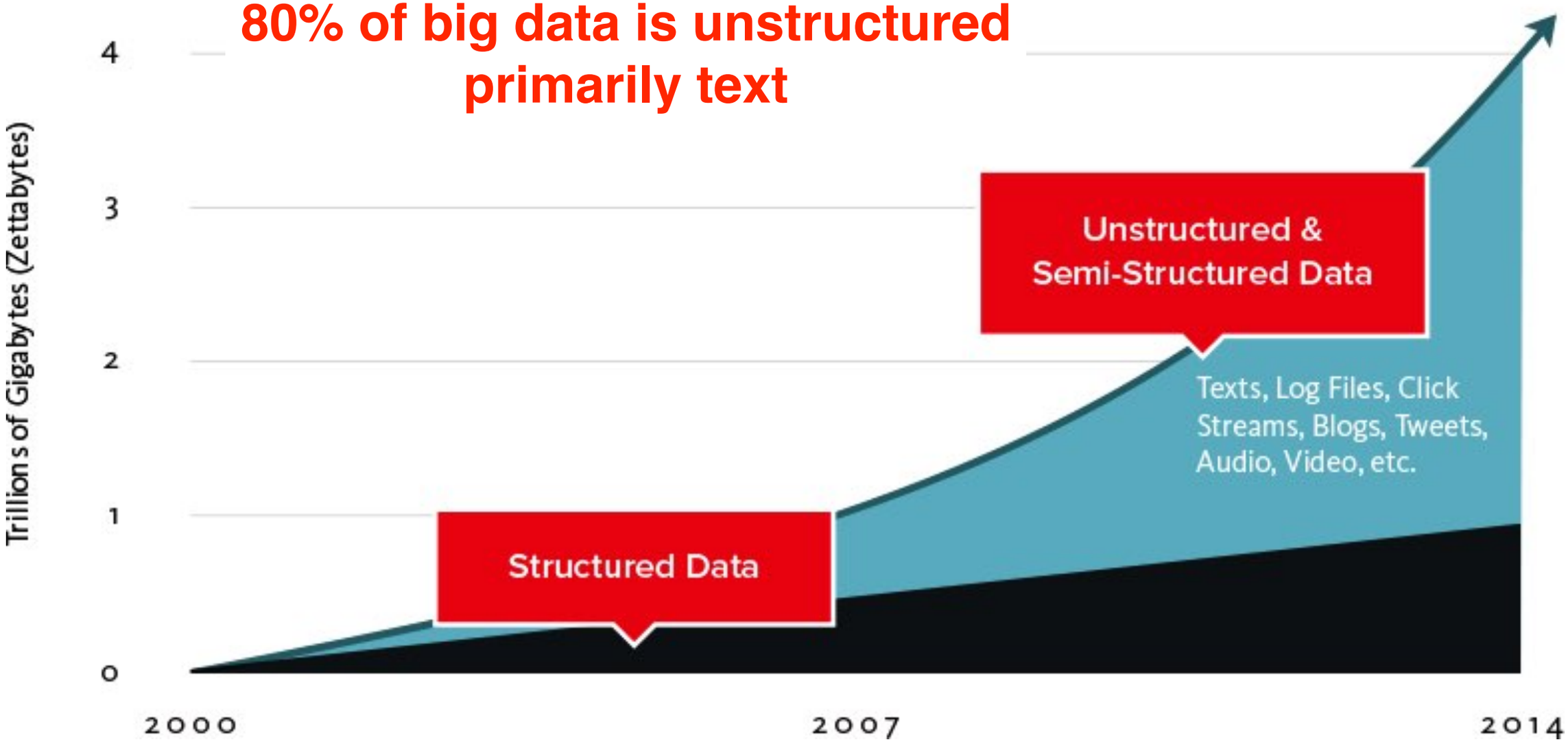
meaning = invariant of **paraphrases**

text = ‘virtual **paraphrasing**’

paraphrases = synonymous linguistic expressions

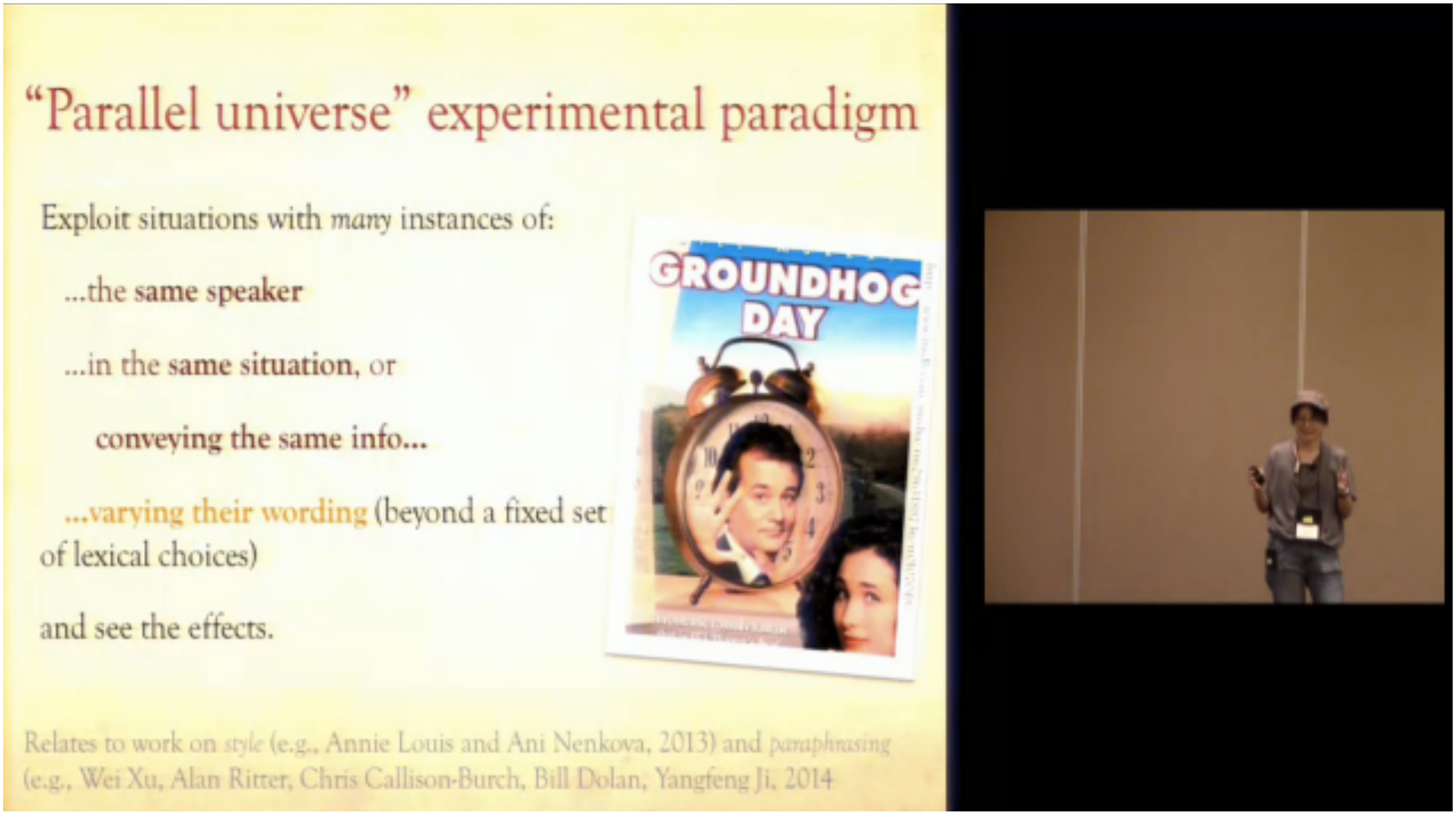
Unlimited Text in practice

80% of big data is unstructured primarily text



(Source: IDC Research & Couchbase)

Social Science



(Lillian Lee's Keynote Speech at NAACL 2015)

Social Science

wonderfully delightfully beautifully fine well good nicely superbly

she says

he says

(also age & income)

Daniel Preotiuc, Wei Xu, Lyle Ungar. “Discovering User Attribute Stylistic Differences via Paraphrasing” in AAAI (2016)

Sentiment Analysis

*This nets vs bulls game is **great***

*This Nets vs Bulls game is **nuts***

***Wowsers** to this nets bulls game*

*this Nets vs Bulls game is **too live***

*This Nets and Bulls game is a **good** game*

*This netsbulls game is **too good***

*This NetsBulls series is **intense***

Language Education

Aaaaaaaaand Stephen Curry ***is on fire***

What an incredible performance *from Stephen Curry*

Listen & Speak
Like a Native Speaker

Quanze Chen, Wei Xu (Ongoing Work)

Thank You

thank u 4 ur time

thanku

thanking you

appreciate it

gratitude

thx

3x

tyvm

thanks

say thanks

thank you very much

thnx

wawwww thankkkkkkkkkkk you alottttttttttt!

thanks a lot

I am grateful

socialmedia-class.org

Follow @cocoweixu

all software and data are available at: http://web.cse.ohio-state.edu/~weixu/