"Silence is the language of God,
all else is poor translation."

-Rumi, Sufi Poet & Philosopher (1207-1273)

Isn't NLP all about rules?! | Aditya Joshi | 24.06.2017

Isn't NLP* all about a bunch of rules?!

Aditya Joshi
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24.06.2017

* Natural Language Processing

Learning in Humans: The story of my nephew

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Source of 10-rupee note image: Wikimedia commons

Learning in Humans: The story of my nephew

When children learn languages,
is it rule-based or statistical?

Source of 10-rupee note image: Wikimedia commons

Natural Language Processing (NLP)

- Branch of Artificial Intelligence

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- Automatic approaches to solve problems pertaining to text

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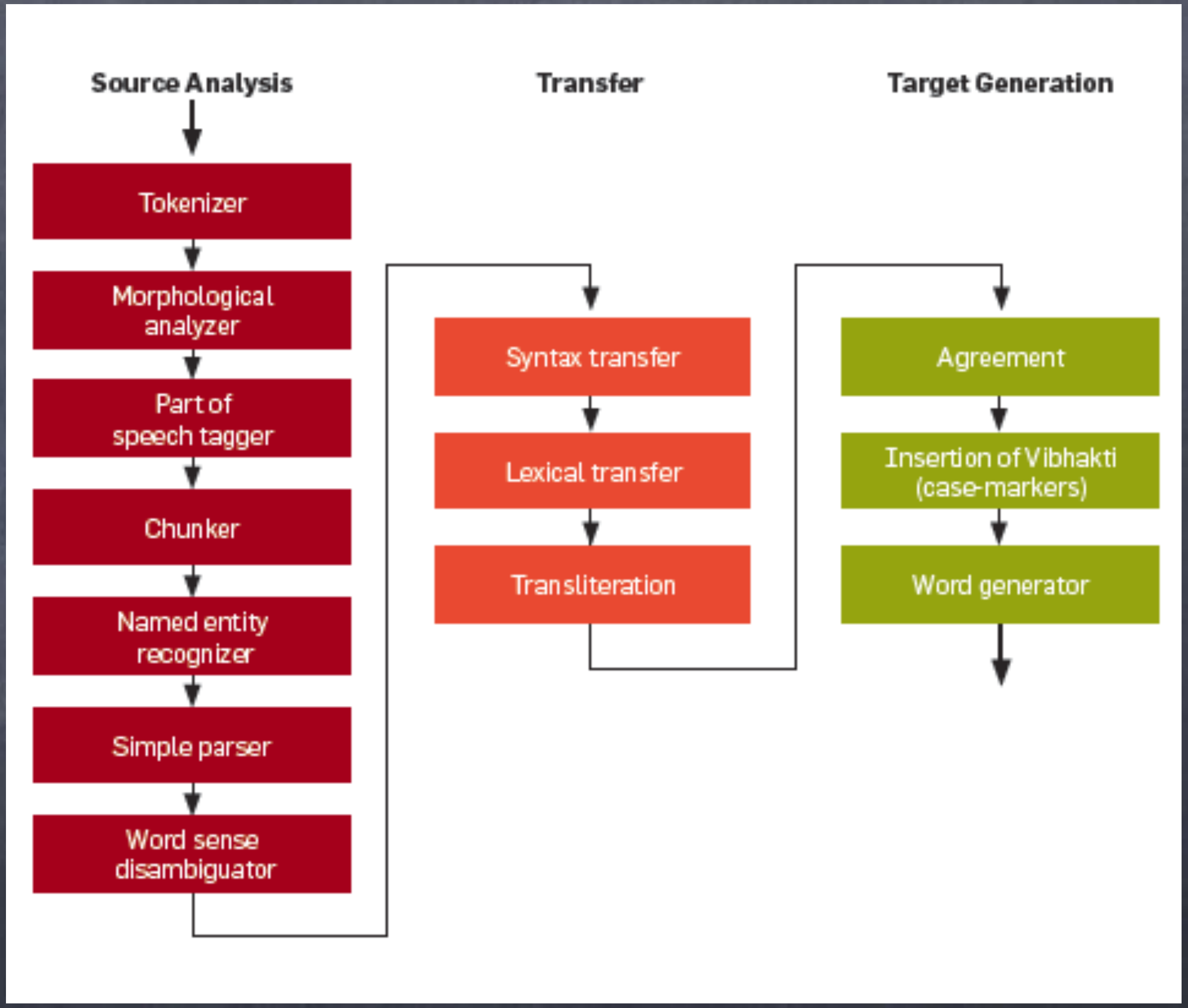
- Branch of Artificial Intelligence
- Automatic approaches to solve problems pertaining to text
- Evolving motivation, evolving use-cases
- Overlapping terms: Computational Linguistics, Text Analytics

Traditional view of NLP

- Layered approach
  - Words - Phrases - (Subject-Verb-Object) - Meaning - Implicatures
- Expert systems

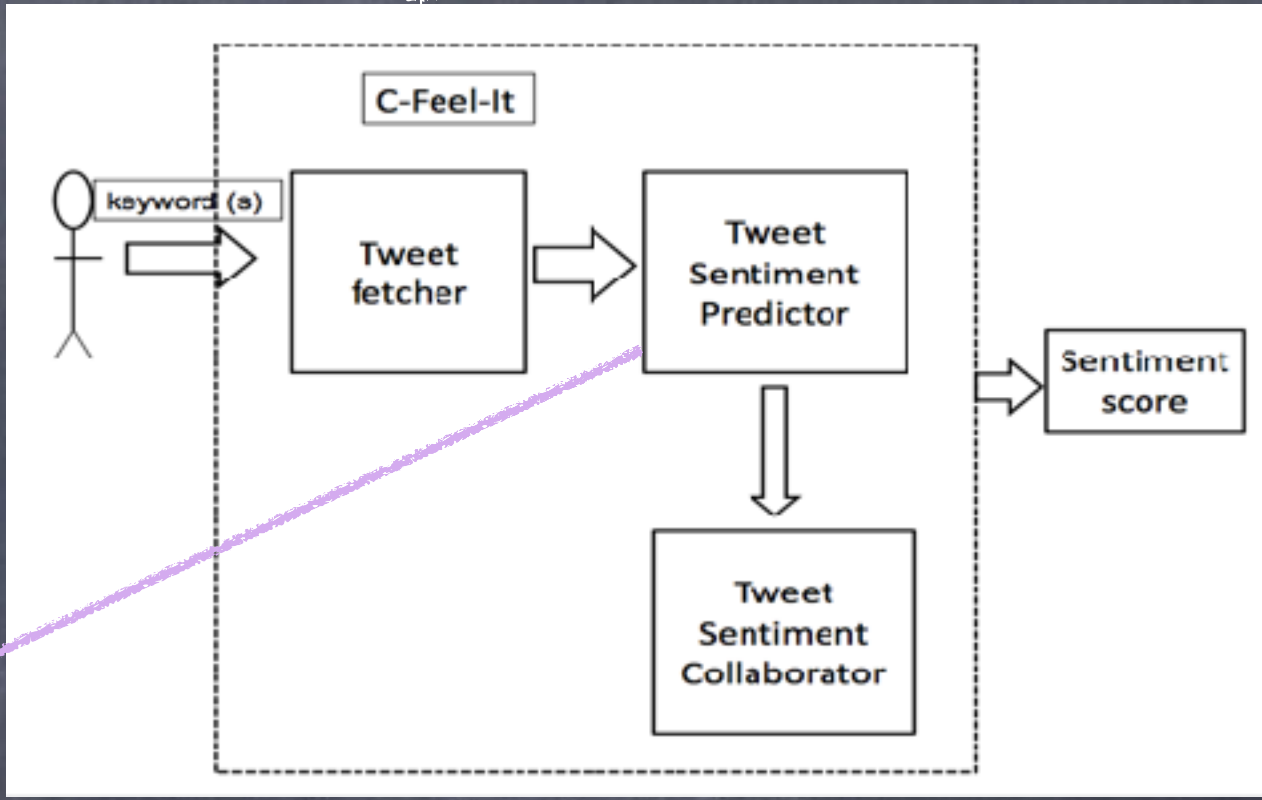
NLP via rules: Traditional automatic translation

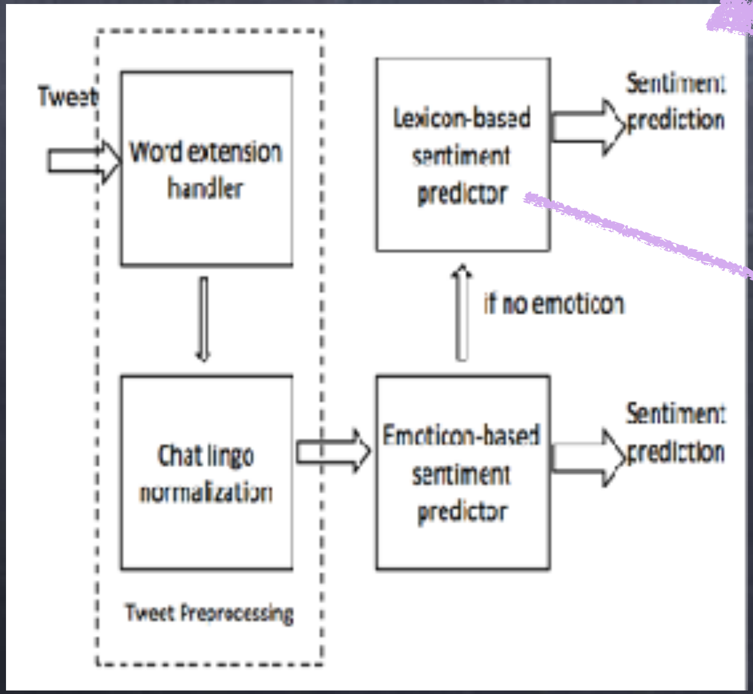
- Layers across source and target side
- Basis of SysTran (1979)

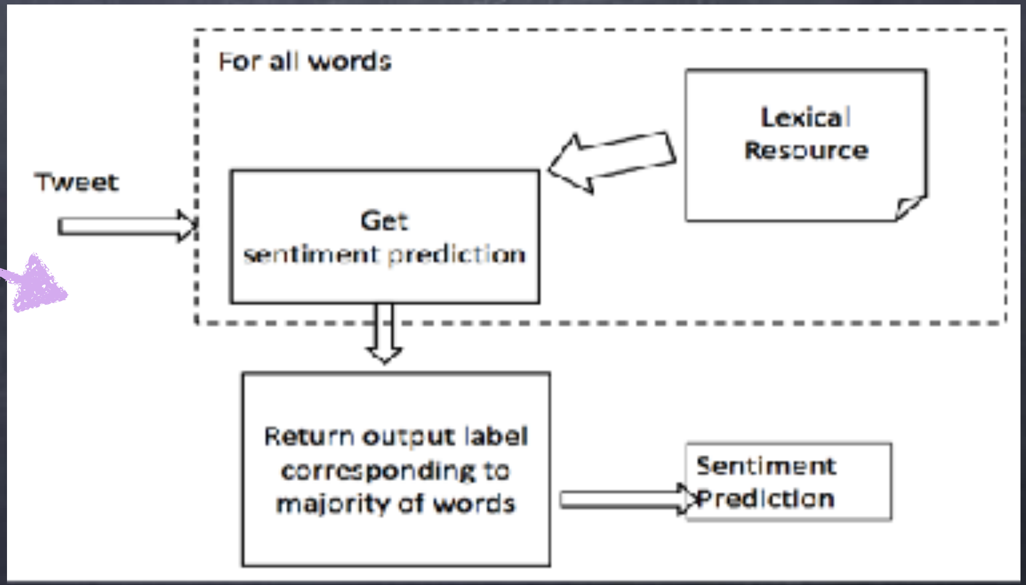


NLP via rules: Traditional sentiment analysis

- Lookup from a sentiment dictionary
- Rules for syntactic structures
- Joshi et al (2011)







Limitations of Rule-based NLP

- Rules are specific and do well in the ‘positive’ cases
- They may not always generalise
- A well-known problem in NLP

Limitation of Rule-based systems: High Precision-Low Recall

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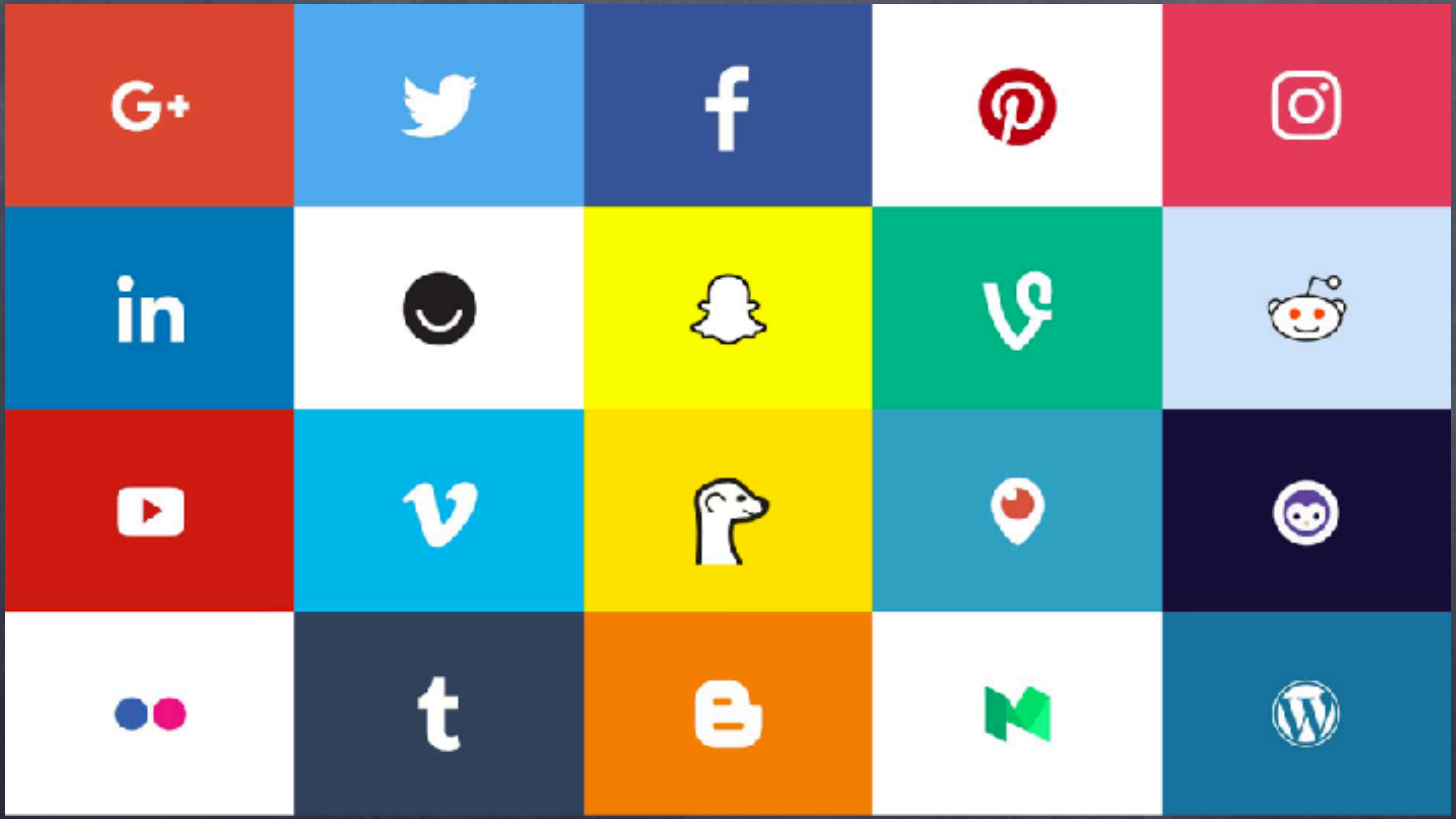
- They may not always generalise
- A well-known problem in NLP

Features	P	R	F
Original Algorithm by Riloff et al. (2013)			
Ordered	0.774	0.098	0.173
Unordered	0.799	0.337	0.474
Our system			
Lexical (**Baseline**)	0.820	0.867	0.842
Lexical+Implicit	0.822	0.887	0.853
Lexical+Explicit	0.807	0.985	0.8871
All features	0.814	0.976	**0.8876**

Rule-based

Statistical

Enter: Web-scale Textual Data



Source: dustntv

Statistical NLP

- Use of statistical/machine learning techniques for NLP
- The key idea is to model NLP problems as machine learning tasks:
  - Part-of-speech tagging: Sequence labelling
  - Sentiment analysis: Classification, etc.

Manning, Christopher D., and Hinrich Schütze.
Foundations of statistical natural language processing.
Cambridge: MIT press, 1999.

- In this talk, I share my experience with three statistical NLP projects

Outline

Research area of NLP	Specific Task	Statistical Algorithm
Machine Translation		
Opinion Mining		
Sarcasm detection		

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Part 1 of 3:

Machine Translation

Joint work with Pushpak Bhattacharyya, IIT-B

Algorithm, code and results appear in the textbook 'Machine Translation', CRC Press

Source: https://d1yi8yosmemxim.cloudfront.net/field/image/saying_hello_in_different_languages.jpg

Machine Translation (MT)

- Machine Translation deals with translating a text from a source language to a target language

  Input: I eat rice (EN)
  Output: Io mangio il riso (IT)

- Applications and use cases
- Training data: Parallel sentences

  I eat pasta : Io mangio la pasta
  You eat rice: Tu mangi il riso

- The notion of alignment

Image is a movie still taken from the web

Introducing: Alignment

- Can you guess the translation?

Introducing: Alignment

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the boy dances : pomesu pimo
the man dances: pomesu grollo
the man jumps: junesu grollo

the boy jumps : ?

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Source	Target
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the boy	pimo
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- Two components: (a) learning the mapping, (b) learning the order
- Alignment is the mapping between words and phrases across the languages
- Complex as the size of parallel text grows

Expectation-Maximization (EM) Algorithm

- Iterative method to find maximum likelihood estimates of parameters
- Iterates between E-step and M-step

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Initialize parameters

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E-Step

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E-Step

Expected log-likelihood given the current estimates of the parameters

M-Step

Update the parameters as the value to maximise the log-likelihood

EM for Alignment discovery in MT

- Source sentence: e_1, e_2... e_m
- Target sentence: f_1, f_2 .... f_n
- Goal: Learn Pr(f_j|e_i) for every pair of source and target language words
- Initialization: Uniform probabilities (or better?)

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$$C(e_i \leftrightarrow f_j; e \leftrightarrow f) = \frac{\Pr(f_j \mid e_i)}{\sum_x \Pr(X \mid e_i)}$$

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$$\Pr(f_j \mid e_i) = \frac{\sum_s C(e_i \leftrightarrow f_j; e^s \leftrightarrow f^s)}{\sum_s \sum_X C(e_i \leftrightarrow X; e^s \leftrightarrow f^s)}$$

EM for Alignment discovery in MT: Example 1

- three rabbits: trois lapins
- rabbits of grenoble: lapins de Grenoble

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<u>E-Step</u>

Expected log-likelihood given the current estimates of the parameters

<u>M-Step</u>

Update the parameters as the value to maximise the log-likelihood

I	trois	lapins	de	Grenoble
1	0.25	0.25	0.25	0.25
2	0.176471	0.588235	0.117647	0.117647
3	0.14391	0.697713	0.079189	0.079189
4	0.111096	0.788899	0.050002	0.050002
5	0.080374	0.85985	0.029888	0.029888
6	0.054612	0.911439	0.016975	0.016975
7	0.035049	0.946536	0.009207	0.009207
8	0.021411	0.968983	0.004803	0.004803
9	0.01256	0.982584	0.002428	0.002428
10	0.007137	0.990464	0.001199	0.001199
11	0.003962	0.994874	0.000582	0.000582
12	0.002163	0.997279	0.000279	0.000279
13	0.001167	0.998567	0.000133	0.000133

EM for Alignment discovery in MT: Example 2

- three white rabbits : trois lapins blancs
- three white swans : trois cygnes blancs

EM for Alignment discovery in MT: Example 2

- three white rabbits : trois lapins blancs
- three white swans : trois cygnes blancs

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EM for Alignment discovery in MT: Example 2

- three white rabbits : trois lapins blancs
- three white swans : trois cygnes blancs

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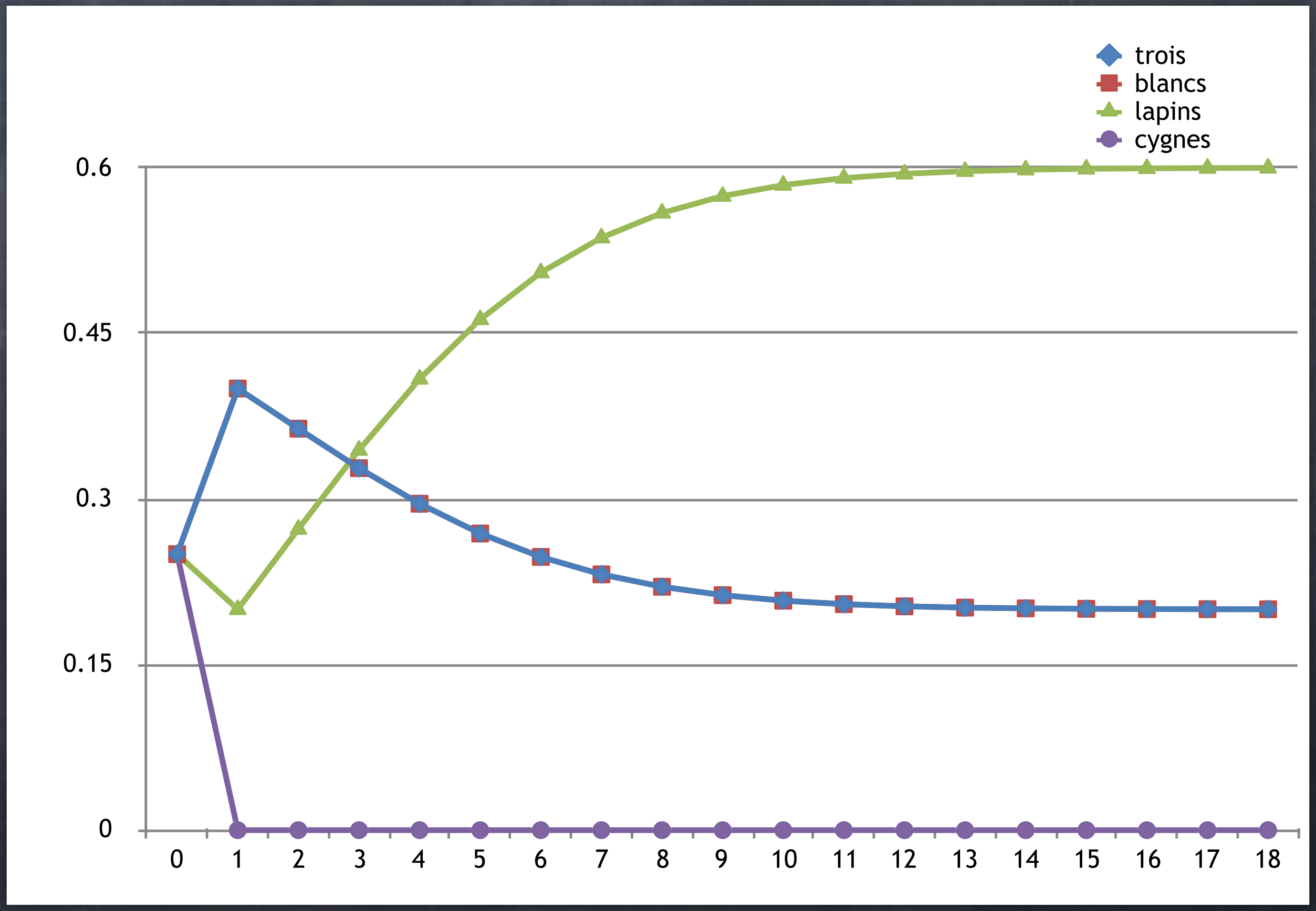

EM for Alignment discovery in MT: Limitations

- One word aligns to one word
- Not always true
  - He went to Paris -> È andato a Parigi
  - Ram went to Paris -> Ram andò a Parigi
- Advanced concept: Notion of 'fertility'

Example Credit: Soudip Roy Chowdhury, Cuddle.ai

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Part 2 of 3:

Opinion Mining

Joint work with Pushpak Bhattacharyya and Mark Carman

Aditya Joshi, Pushpak Bhattacharyya, Mark Carman, 'Political Issue Extraction Model: A Novel Hierarchical Topic Model That Uses Tweets By Political And Non-Political Authors', WASSA at NAACL 2016, San Diego, USA, June 2016.

Source: Wikimedia Commons

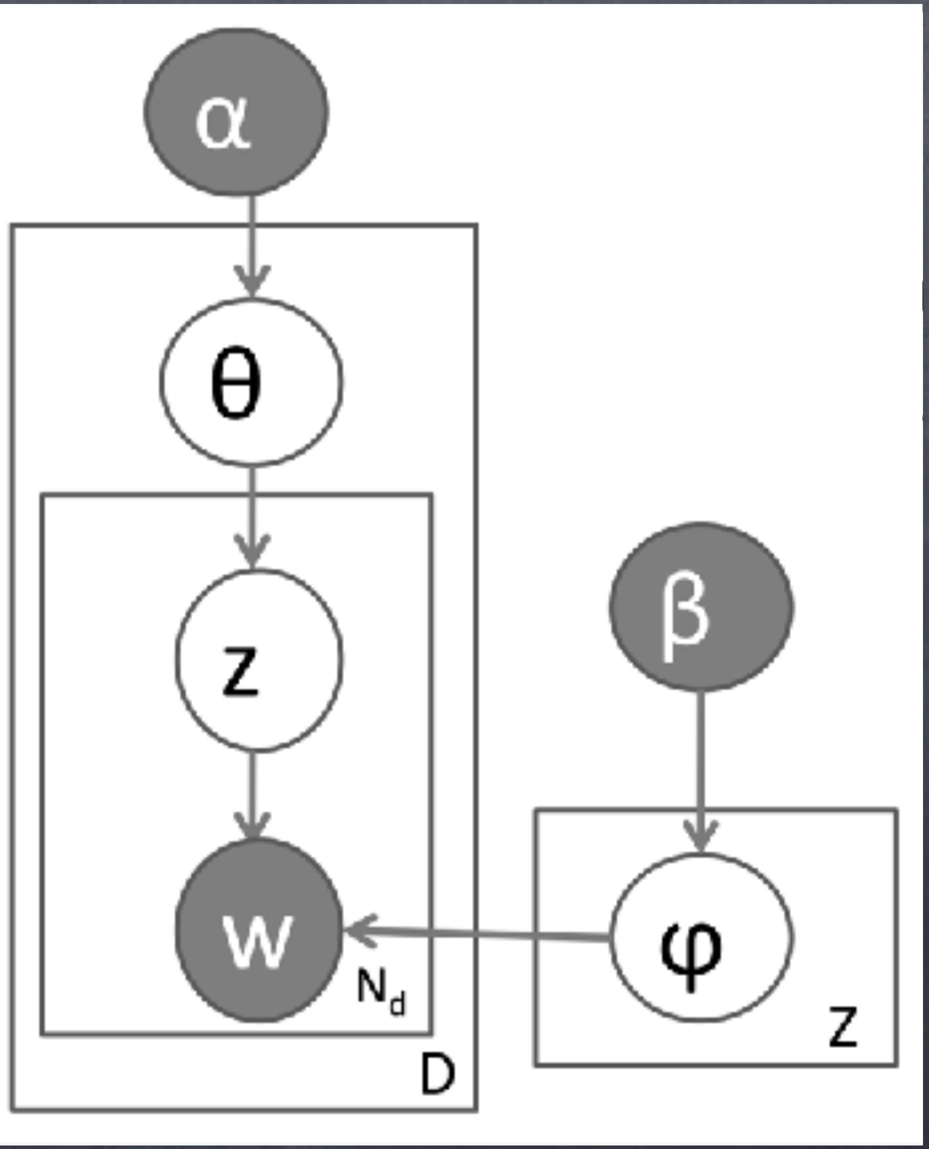
Opinion Mining

- Predicting opinion polarity in text
- Fine-grained opinion mining: Along aspects and issues
- Example: Political issue, opinion and orientation discovery

Source: Wikimedia Commons

Latent Dirichlet Allocation (LDA) Model

- Helps to discover themes underlying an unsupervised corpus
- Generate word clusters based on co-occurrence of words
- Several extensions for specific tasks have been reported

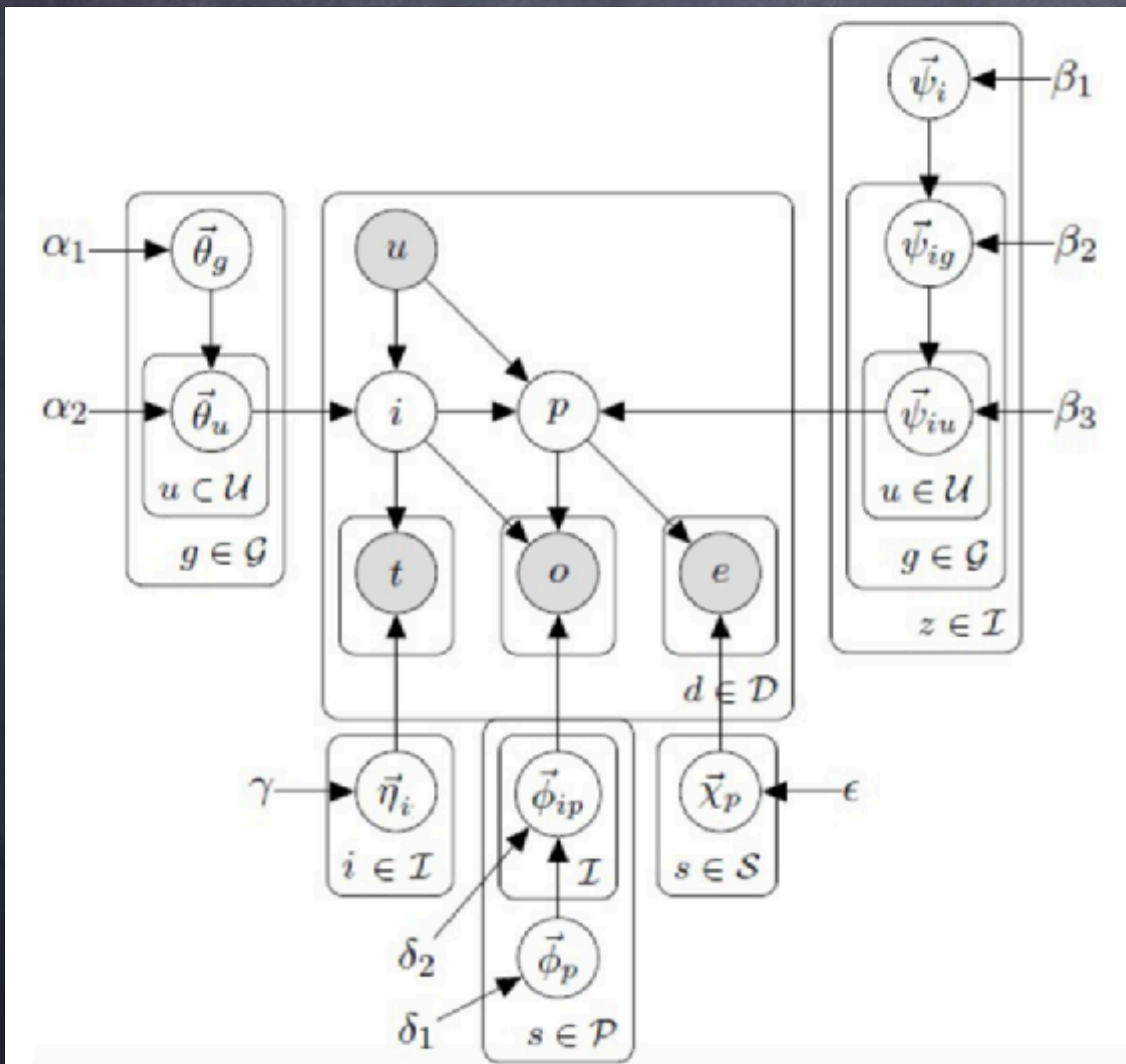


LDA Model

Political Issue & Orientation Mining

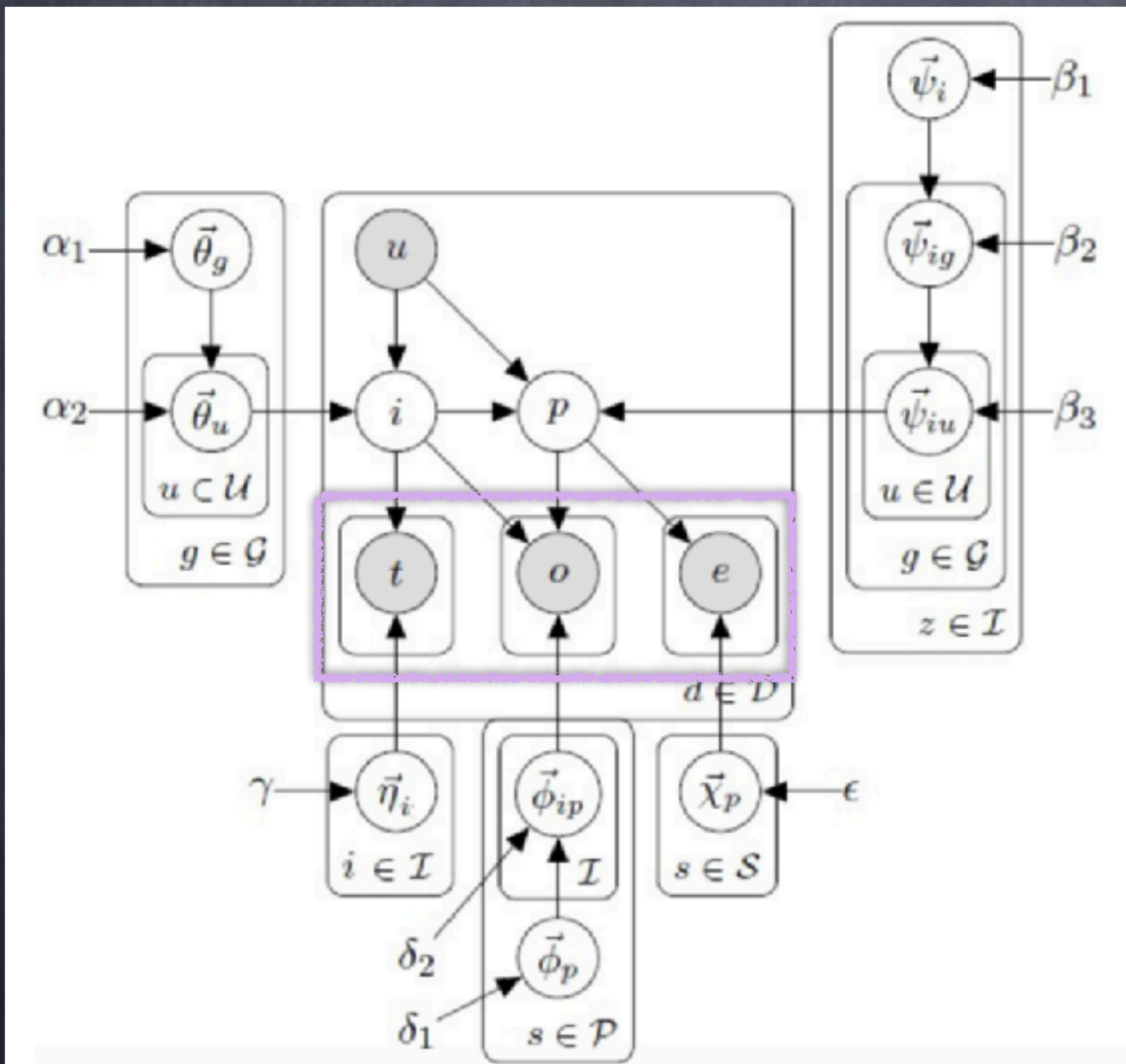
- Goal: An LDA-based model to discover political issues and positions from an unlabelled dataset of tweets
- Premise: Use twitter timelines of both political and nonpolitical authors
- Dataset: 2.4 million tweets from American users
- Input: (a) Twitter timelines of authors, and (b) political affiliation for a subset of authors (namely, Democrats, Republicans, Unknown)
- Output: (a) Clusters of words corresponding to political issues and positions, and (b) Group-wise distributions for political issues and positions

LDA-based Hierarchical Topic Model



Random Variables	
u, g	Author of a tweet and Group of the author
i, p	Issue and position of a tweet
t, o	Issue/Position-word in a tweet
e	Emoticon in a tweet
Distributions	
$\vec{\theta}_{u/g}$	Dist. over issues for author u / group g
$\vec{\psi}_{i,u/g}$	Dist. over positions for issue i and author/group
$\vec{\eta}_i$	Dist. over topic-words for issue i
$\vec{\phi}_{i,p}$	Dist. over opinion-words for issue-position pair
$\vec{\chi}_p$	Dist. over emoticons for position p
Hyper-parameters	
α, β	Concentration par. issue/position dist.
γ	Concentration par. for issue-word dist.
δ	Concentration par. for position-word dist.
ϵ	Concentration par. for emoticon dist.
Counts	
$N_{i,i}^{(t)}$	Frequency of topic-word t in tweets for topic i
$N_{i,u}^{(i)}$	Frequency of tweets on topic i by author u
$V^{(t)}$	Vocabulary size for topic words

LDA-based Hierarchical Topic Model



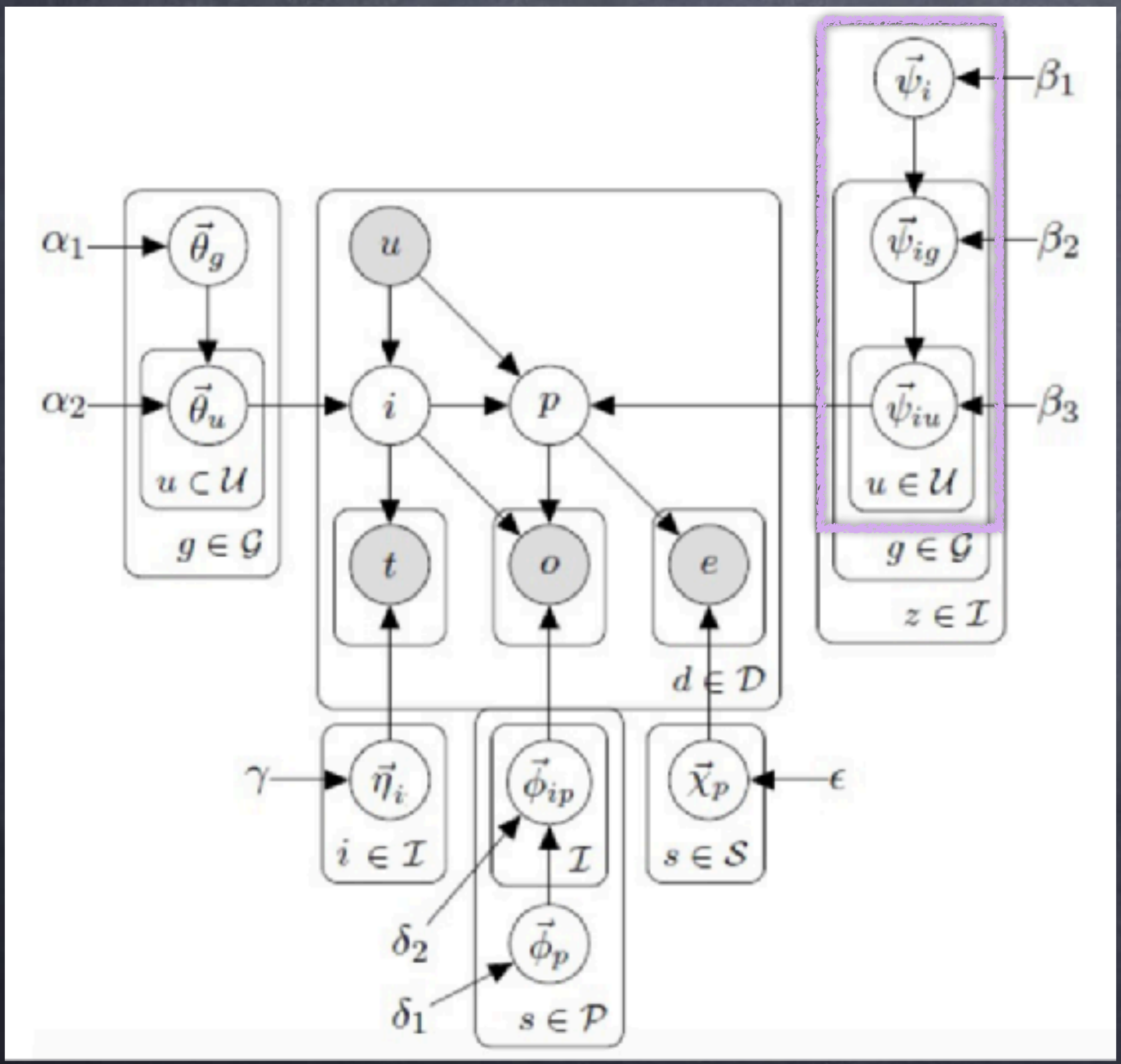
This country needs to seal its borders :)

Issue words: 'country', 'borders'

Position words: 'seal'

Emoticon: :)

LDA-based Hierarchical Topic Model



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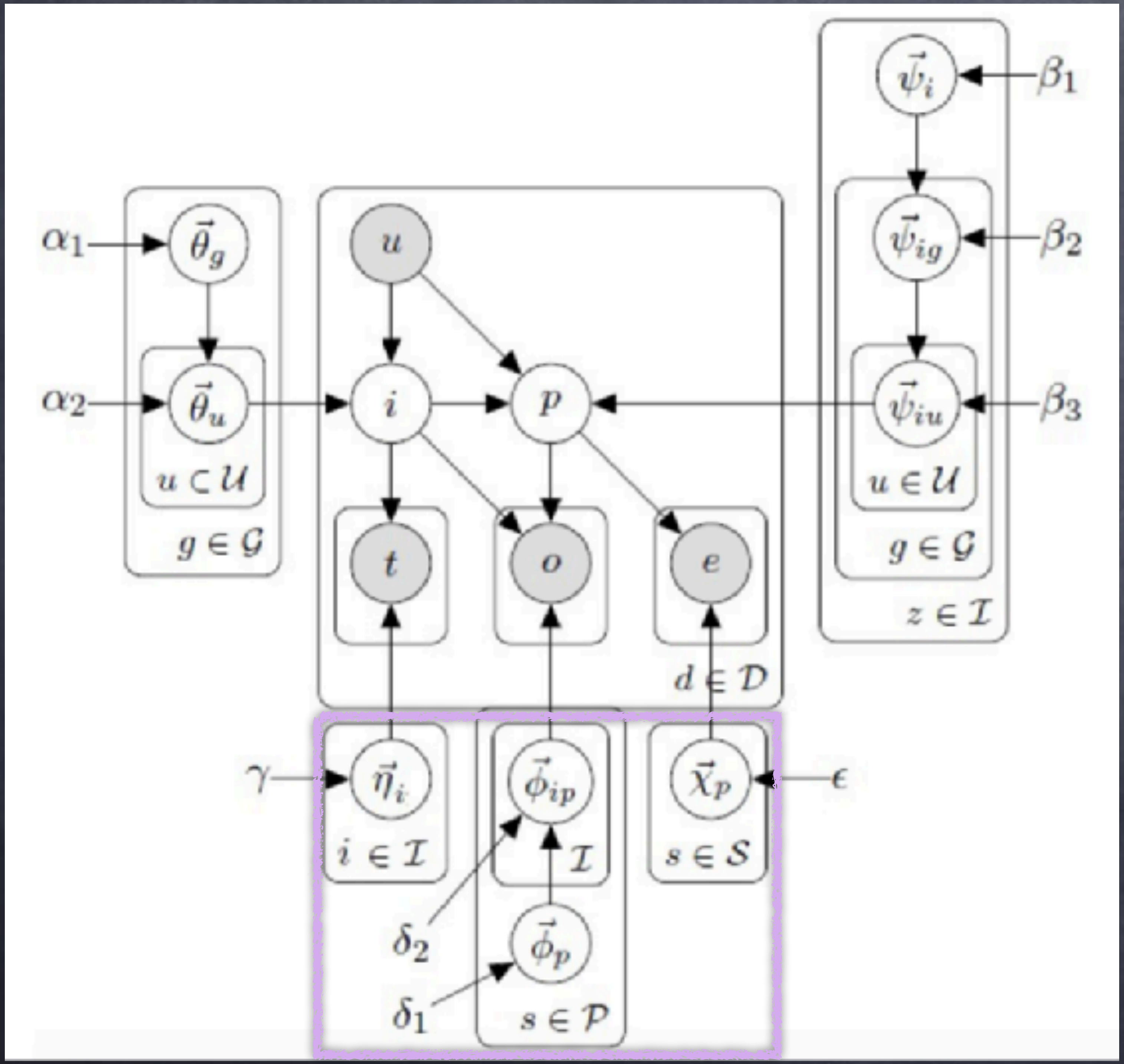
Emoticon: :)

User u takes position 'pro' towards issue 'abortion' in 90% of their tweets

LDA-based Hierarchical Topic Model



This country needs to seal its borders :)

Issue words: 'country', 'borders'

Position words: 'seal'

Emoticon: :)

User u takes position 'pro' towards issue 'abortion' in 90% of their tweets

'abortion' is most likely described using 'baby', 'life'; 'pro-abortion' using 'freedom', 'health'

Estimation

- Block-based Gibbs sampling
- I = 35, P = 2
- 32 Republicans, and 46 Democrats

What are the political issues and positions?

Insurance	Gun laws	Crime
health	people	scene
insurance	gun	police
people	laws	man
care	guns	fire
plan	control	suspect
Abortion	**Security/War**	**Employment**
abortion	attack	workers
baby	video	job
babies	security	wages
freedom	police	jobs
women	forces	people
Immigration	**Economy**	**Climate**
workers	tax	climate
immigration	jobs	people
stories	debt	change
patriot	taxes	warming
politics	spending	years
Marriage	**Election**	**Disasters**
people	bill	acres
freedom	vote	fire
marriage	campaign	weather
rights	state	snow
women	election	storm

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babies	security	wages
freedom	police	jobs
women	forces	people
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workers	tax	climate
immigration	jobs	people
stories	debt	change
patriot	taxes	warming
politics	spending	years
Marriage	**Election**	**Disasters**
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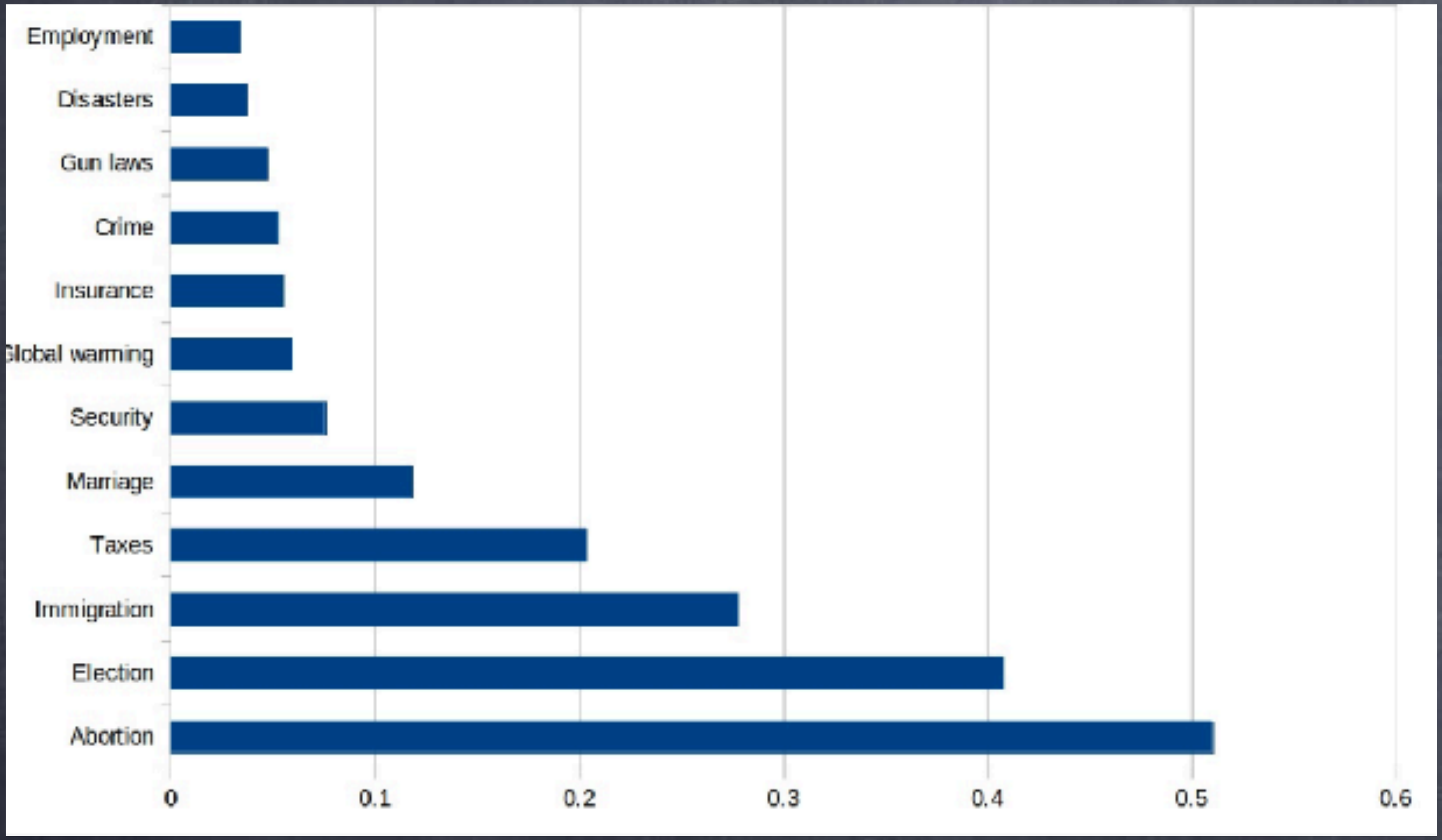
women	election	storm

Abortion		**Security/War**	
Join	Prolife	Killed	Military
Religious	Killed	Syrian	Illegal
Stand	Born	Military	Russian
Support	Unborn	Fast	Targeting
Conservative	Aborted	Furious	Back
Gun laws		**Immigration**	
Illegal	Dont	Join	Top
Free	Free	Support	Enter
Dont	Stop	Back	Check
Vote	Illegal	Stand	Stop
Stop	Give	Proud	Join
Insurance		**Marriage**	
Pay	Check	Back	Gay
Federal	Hear	Don	Religious
Signed	Here	Lost	Political
Paid	Call	Liberal	Free
Uninsured	Hope	Great	**

What are the most controversial issues? Can this be used to predict political affiliation?



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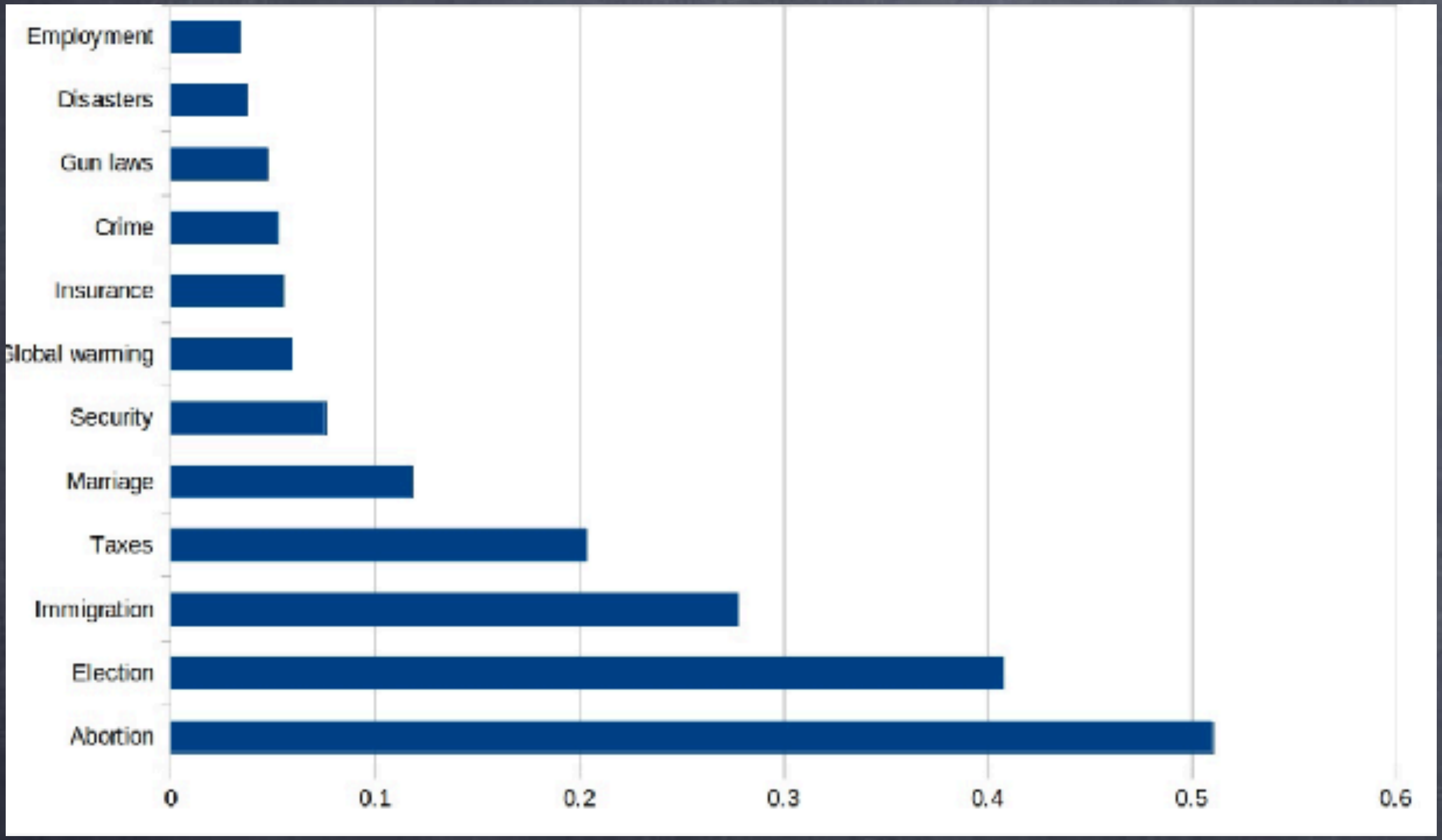

Approach	Accuracy (%)
Baseline: *Gottipati et al. (2013)*	60
Log likelihood-based	68

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Part 3 of 3:

Sarcasm Detection

Joint work with Vaibhav Tripathi, Pushpak Bhattacharyya and Mark Carman

Aditya Joshi, Vaibhav Tripathi, Pushpak Bhattacharyya and Mark J Carman, 'Harnessing Sequence Labeling for Sarcasm Detection in Dialogue from TV Series Friends', CONLL 2016, Berlin, Germany, August 2016.

Image: Maya Sarabhai, Sarabhai versus Sarabhai
Source: India Today

Sarcasm Detection

- Sarcasm is verbal irony that is intended to express contempt or ridicule
  - 'I love being ignored.'
- Past work in sarcasm detection: Features+Classifiers
- Applications?

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- Applications?

Sarcasm Detection of Dialogue: Motivation

Shubham: You are loving this talk!

Sarcasm Detection of Dialogue: Motivation

Shubham: You are loving this talk!

Shubham's neighbor: (takes notes, with a lot of interest)
Shubham: You are loving this talk!

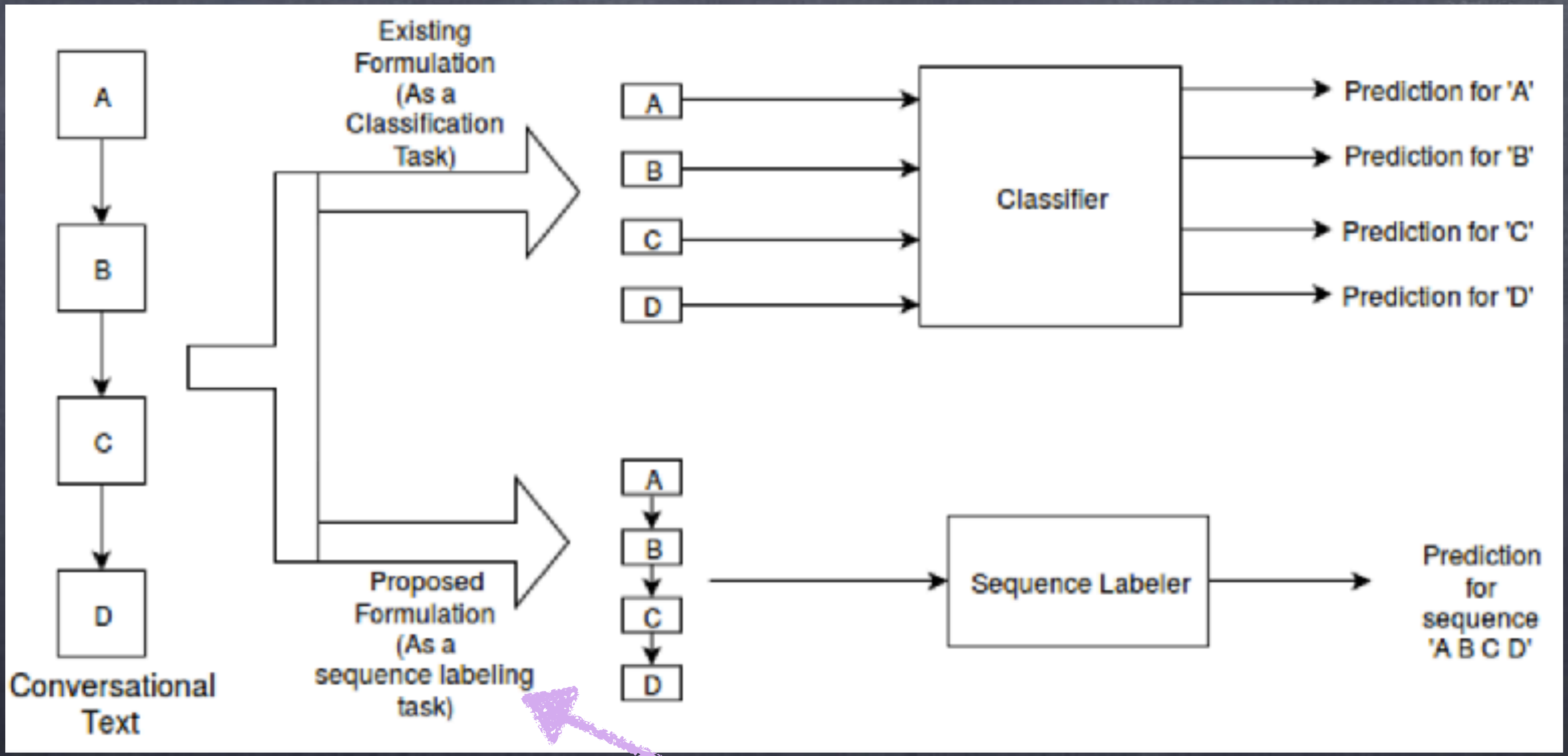
Sarcasm Detection of Dialogue: Motivation

Shubham: You are loving this talk!

Shubham's neighbor: (yawns) (yawns again)
Shubham: You are loving this talk!

Shubham's neighbor: (takes notes, with a lot of interest)
Shubham: You are loving this talk!

Sequence Labeling for Sarcasm Detection of Dialogue



SVM-HMM (a variant of HMM)

Dataset (1/2)

- Transcripts of TV Series 'Friends'
- 913 scenes, 17338 utterances, 1888 sarcastic utterances, average 18.6 utterances per scene

Dataset (2/2)

Character	% sarcastic
Phoebe	9.70
Joey	11.05
Rachel	9.74
Monica	8.87
Chandler	22.24
Ross	8.42

	Surface Positive Sentiment Score	Surface Negative Sentiment Score
Sarcastic	1.55	1.20
Non-sarcastic	0.97	0.75
All	1.03	0.79

	Actions (%)
Sarcastic	28.23
Non-sarcastic	23.95
All	24.43

Features & Results

Feature	Description
Lexical Features	
Spoken words	Unigrams of spoken words
Conversational Context Features	
Actions	Unigrams of action words
Sentiment Score	Positive & Negative score of utterance
Previous Sentiment Score	Positive & Negative score of previous utterance in the sequence
Speaker Context Features	
Speaker	Speaker of this utterance
Speaker-Listener	Pair of speaker of this utterance and speaker of the previous utterance

Algorithm	Precision (%)	Recall (%)	F-Score (%)
Formulation as Classification			
SVM (U)	83.6	48.6	57.2
SVM (O)	**84.4**	76.8	79.8
Naïve Bayes	77.2	33.8	42
Formulation as Sequence Labeling			
SVM-HMM	83.8	**88.2**	**84.2**
SEARN	82.6	83.4	82.8

Summary

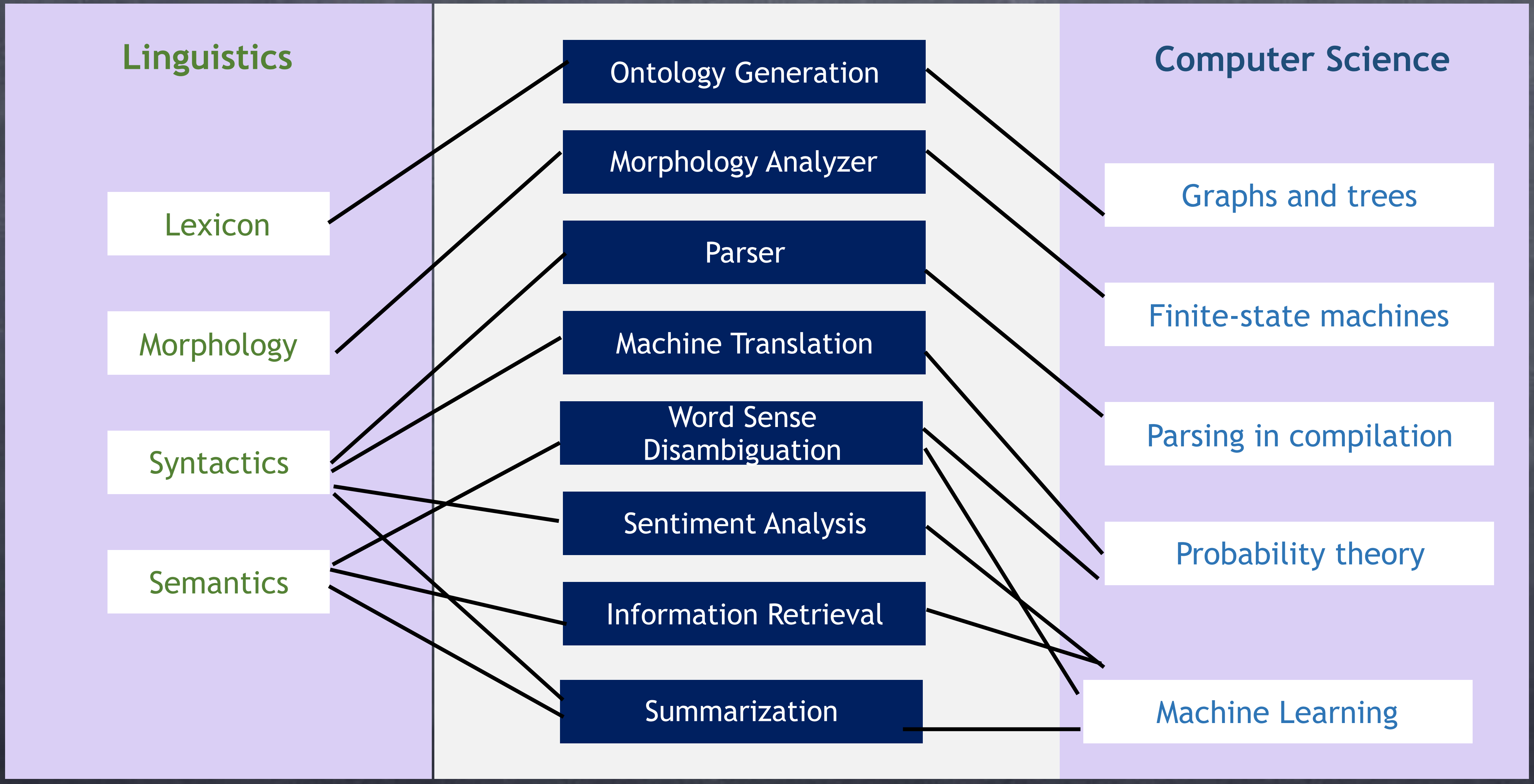
- We looked at three statistical NLP problems: machine translation, opinion mining and sarcasm detection
- Statistical NLP leverages on large scale data and machine learning to automate NLP tasks

NLP: At the confluence of linguistics and computer science

Linguistics		Computer Science
Lexicon		Graphs and trees
Morphology		Finite-state machines
Syntactics		Parsing in compilation
Semantics		Probability theory
		Machine Learning

Credit: Rupa Hadaye, Cuddle.ai, Fractal Analytics

NLP: At the confluence of linguistics and computer science



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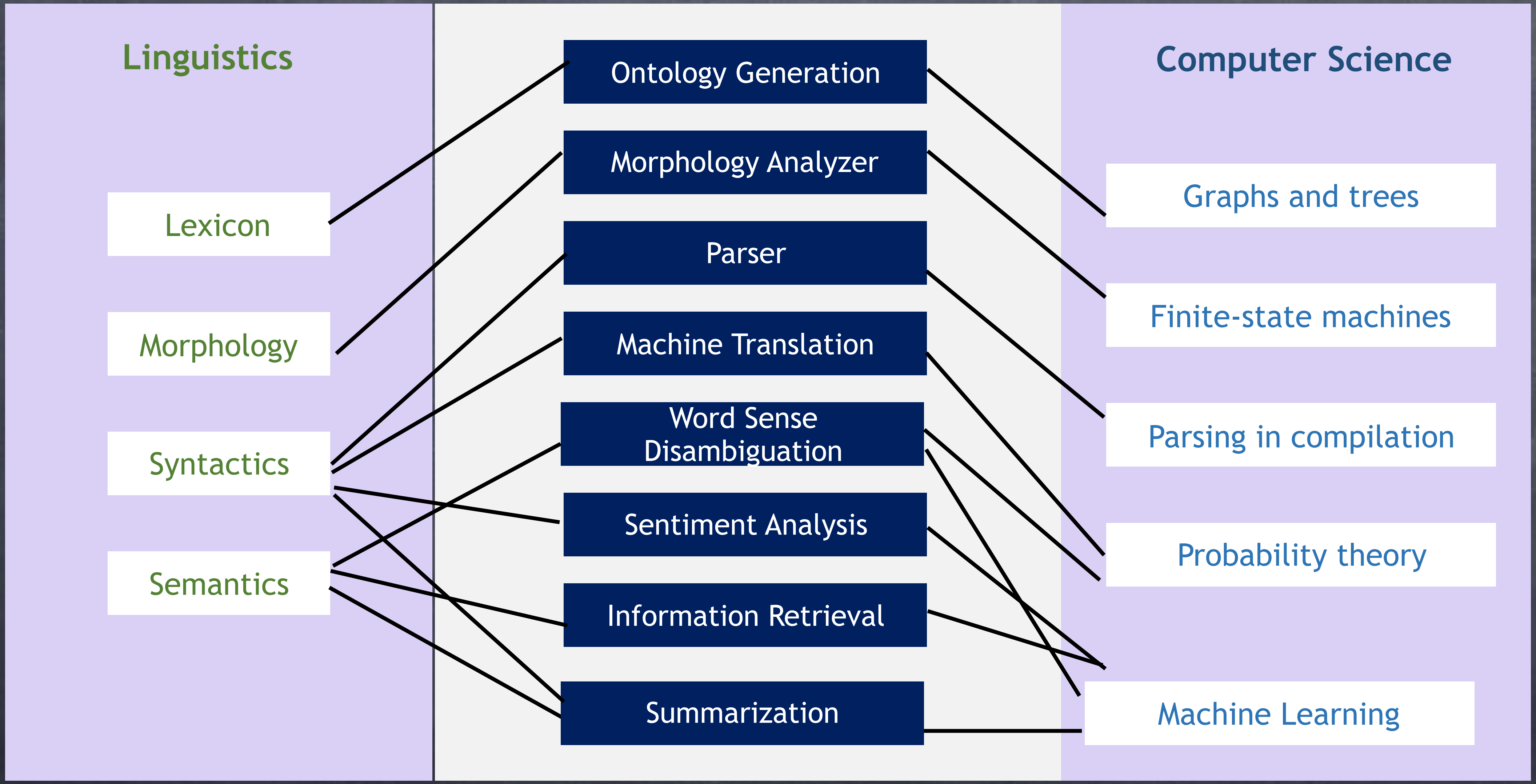

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Errm.. you didn't really answer the question...

Isn't NLP all about a bunch of rules?!

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Statistical NLP is an alternative.

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Errm.. you didn't really answer the question...

Isn't NLP all about a bunch of rules?!

Statistical NLP is an alternative.

How do I decide then?

Availability of data

Potential to formulate as a ML task

Credit: Rupa Hadaye, Cuddle.ai, Fractal Analytics

References

- Aditya Joshi, Vaibhav Tripathi, Pushpak Bhattacharyya and Mark J Carman, 'Harnessing Sequence Labeling for Sarcasm Detection in Dialogue from TV Series Friends', CONLL 2016, Berlin, Germany, August 2016.

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- Bhattacharyya, Pushpak. Machine translation. CRC Press, 2015.