“Sarcasm is the lowest form of wit,
but the highest form of intelligence.”

Oscar Wilde (1854 - 1900)

Tutorial | *Computational Sarcasm* | Pushpak Bhattacharyya & Aditya Joshi |
7th September 2017 | EMNLP 2017 | Copenhagen

Computational Sarcasm

Pushpak BHATTACHARYYA
IIT Bombay & IIT Patna
pb@cse.iitb.ac.in
director@iitp.ac.in

Aditya JOSHI
IITB-Monash Research Academy
adityaj@cse.iitb.ac.in
ajos17@student.monash.edu

IITB-Monash Research Academy
Indian Institute of Technology Bombay
MONASH University
An Indian-Australian research partnership

Tutorial at Conference on Empirical Methods in Natural Language Processing (EMNLP) 2017, September 7, Copenhagen, Denmark

NLP-ML Synergy

Module 0

Objective: To place computational sarcasm in the larger context of ML-facilitated NLP


www.cfilt.iitb.ac.in

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CFILT, IIT Bombay

Center for Indian Language Technology (CFILT) was set up with a generous grant from the Department of Information Technology (DIT), Ministry of Communication and Information Technology, Government of India in 2000 at the Department of Computer Science and Engineering, IIT Bombay. Prior to this the Natural Language Processing (NLP) activity of the CSE Department, IIT Bombay took off in 1996 with a grant from the United Nations University, Tokyo to create a multilingual information exchange system for the web. The project called Universal Networking Language (UNL; www.undl.org) was participated in by 15 research groups across continents.

At any point of time about 30 research members work in CFILT, which includes PhD , masters and bachelor students, faculty members, linguists and lexicographers.

Deep semantics and multilinguality has throughout played a pivotal role in the activities of CFILT. The stress on semantics has led to research in the following fronts:

- **Lexical Resources:** Multilingual wordnets and ontologies and their linking
- **Lexical and Structural Disambiguation:** Resolve word and attachment ambiguities
- **Shallow Parsing:** Identifying correct parts of speech, named entities and non-recursive noun phrases for Marathi and Hindi
- **Cross Lingual Information Retrieval:** Indian language query to English and Hindi Retrieval
- **Machine Translation:** Automatic translation involving Marathi, Hindi and English
- **Text Entailment:** Testing if a piece text (hypothesis) is inferable from another (text)


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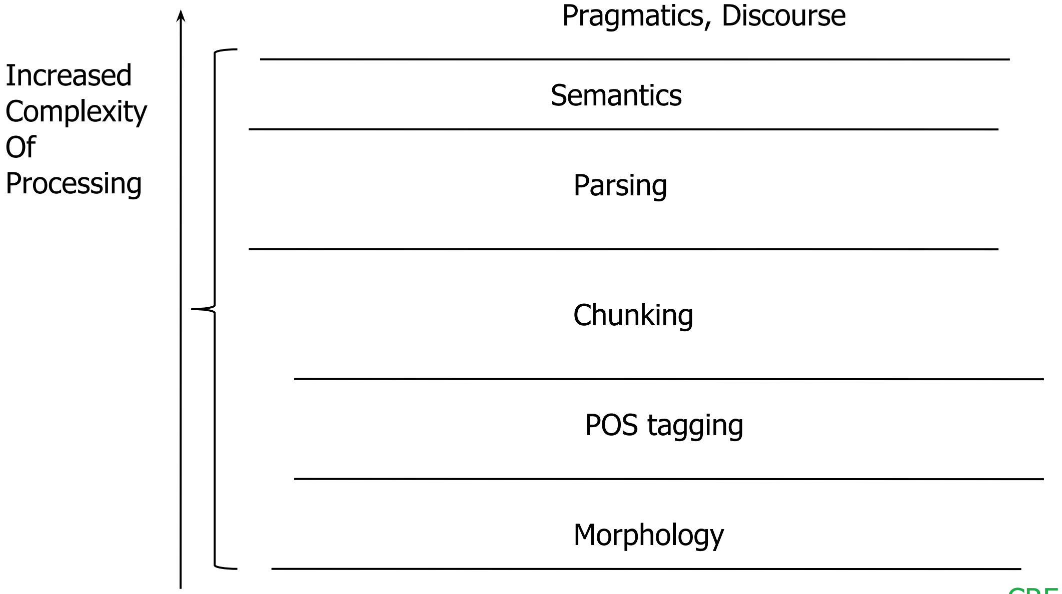
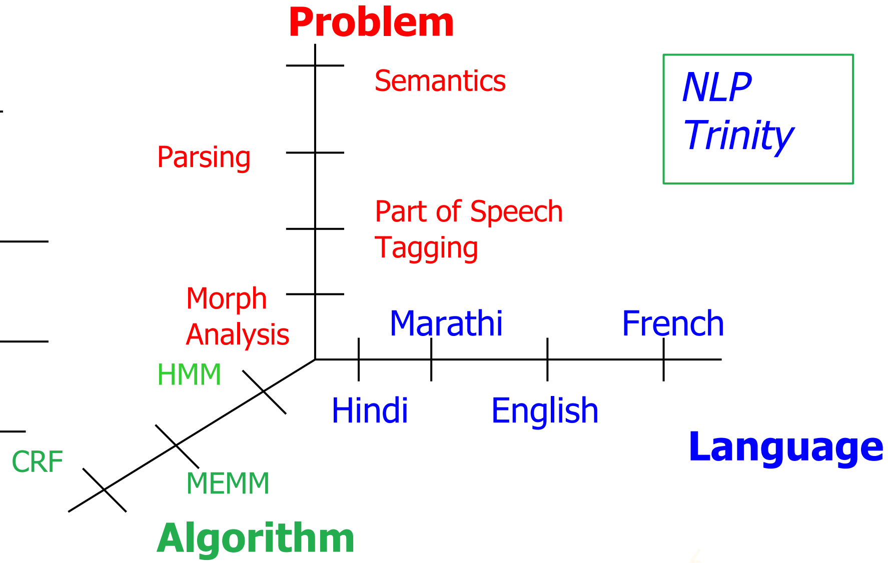
One paper has been accepted in Knowledge-Based Systems, Elsevier,
Three papers have been accepted in NLDB-2017.
One paper has been accepted in CICLING-2017.
Shweta Yadav, Research
AI-NLP-ML Group
Department of CSE, IIT Patna
The Artificial Intelligence-Natural Language Processing-Machine Learning (AI-NLP-ML) group at Department of Computer Science and Engineering, IIT Patna has started its official journey in June, 2015. The group is dedicated to explore the frontiers of Artificial Intelligence, Machine Learning and Natural Language Processing under the able guidance of Prof. Pushpak Bhattacharyya. The group also consists of other two faculty members, Dr. Asif Ekbal and Dr. Sriparna Saha, and around 30 members including research scholars, research engineers, lexicographers, B.Tech & M.Tech students. Several industry sponsored projects are currently being undertaken.
Elsevier, the renowned scientific literature publishing company has set up the Elsevier Centre of Excellence for Natural Language Processing to

NLP: Multi-layered, multi-dimensional





Need for NLP

- Humongous amount of language data in electronic form
- Unstructured data (like free flowing text) will grow to 40 zetabytes (1 zettabyte= 10^{21} bytes) by 2020.
- How to make sense of this huge data?
- Example-1: e-commerce companies need to know **sentiment** of online users, sifting through 1 lakh e-opinions per week: needs NLP
- Example-2: **Translation** industry to grow to $37 billion business by 2020

Machine Learning

Automatically learning rules and concepts from data

Learning the concept of table.

What is “tableness”

Rule: a flat surface with 4 legs (approx.: to be refined gradually)

Images of chairs taken from the web

NLP-ML marriage

Image of couple taken from the web

NLP = Ambiguity Processing

- Lexical Ambiguity
  - *Present (Noun/Verb/Adjective; time/gift)*
- Structural Ambiguity
  - *1 and 2 bed room flats live in ready*
- Semantic Ambiguity
  - *Flying planes can be dangerous*
- Pragmatic Ambiguity
  - *I love being ignored* (after a party, while taking leave of the host)

Another challenge of NLP: Multilinguality

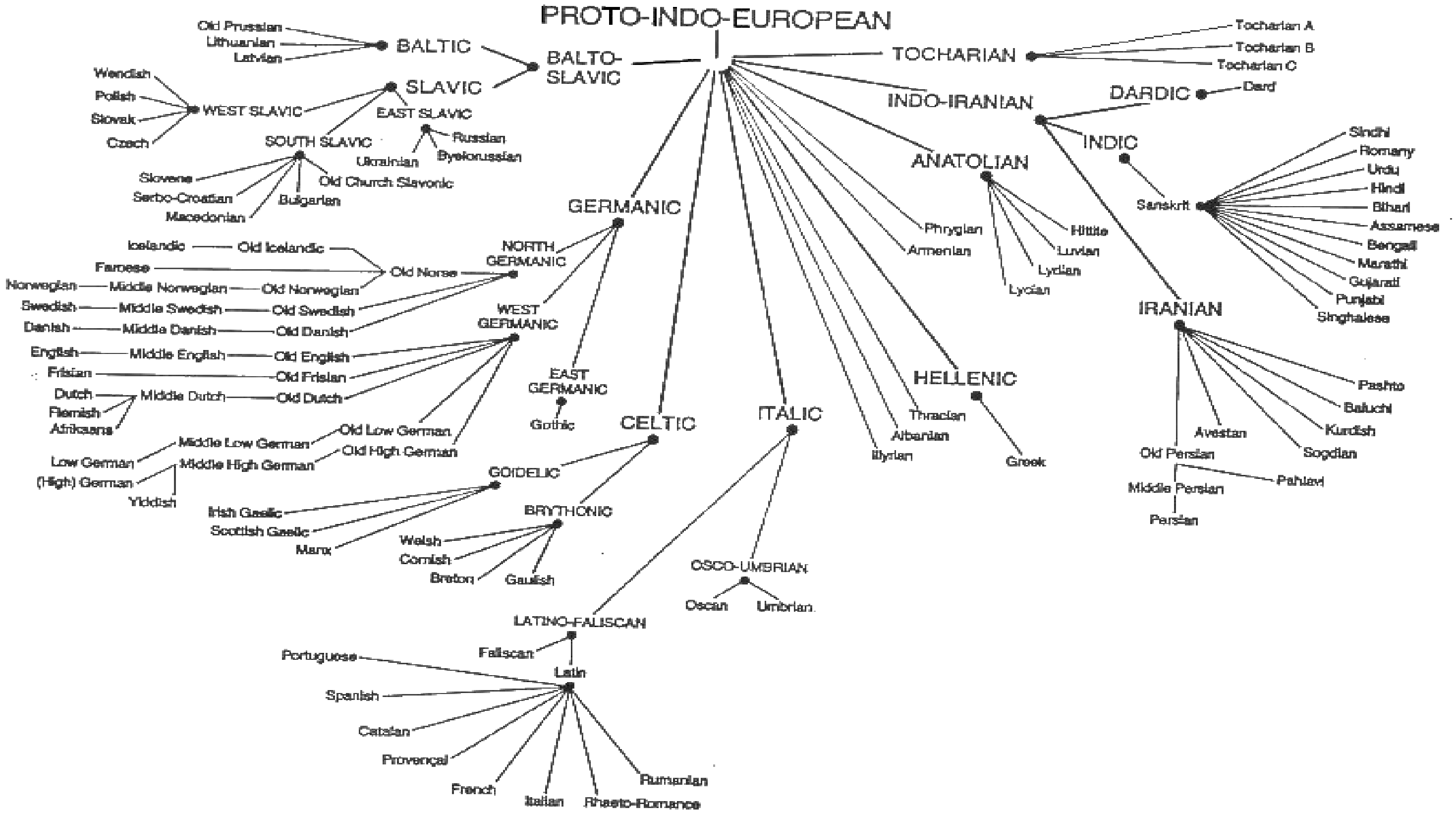


Image of tree taken from the web

Rules: when and when not

- When the phenomenon is understood AND expressed, rules are the way to go
- “Do not learn when you know!!”
- When the phenomenon “seems arbitrary” at the current state of knowledge, DATA is the only handle!
  - *Why do we say “Many Thanks” and not “Several Thanks”!*
  - *Impossible to give a rule*
- Rely on machine learning to tease truth out of data; Expectation not always met with☹

Impact of probability: Language modeling

Probabilities computed in the context of corpora

1. P("The sun rises in the east")
2. P("The sun rise in the east")
    - Less probable because of grammatical mistake.
3. P(The svn rises in the east)
    - Less probable because of lexical mistake.
4. P(The sun rises in the west)
    - Less probable because of semantic mistake.

Power of Data- Automatic image labeling

Automatically captioned: "Two pizzas sitting on top of a stove top oven"

(Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan, 2014)

Images of pizzas taken from the web

Automatic image labeling (cntd)

Images from the paper.

Main methodology

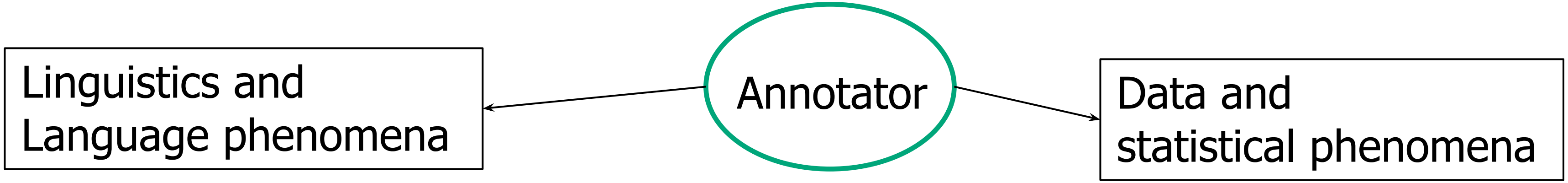
- Object A: extract parts and features

- Object B which is in correspondence with A: extract parts and features

- LEARN mappings of these features and parts
- Use in NEW situations: called DECODING

Linguistics-Computation Interaction

- Need to understand BOTH language phenomena and the data
- An annotation designer has to understand BOTH linguistics and statistics!



With that perspective in view,
let us begin.

Computational Sarcasm

Like ‘Computational Linguistics’,

We refer to *computational sarcasm* as the set of computational techniques to process sarcasm

To ‘process’ sarcasm:

To detect sarcasm,
To understand aspects of sarcasm,
To generate sarcasm, etc.

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Primary Reference:
Aditya Joshi, Pushpak Bhattacharyya, Mark J Carman,
'Automatic Sarcasm Detection: A Survey',
ACM Computing Surveys, Vol 50, No. 5, Article 73, 2017.

An older version at: arXiv:1602.03426

Scope of today's tutorial

Scope of today's tutorial

Introduction

Sarcasm in Linguistics

Datasets

Scope of today's tutorial

Introduction

Sarcasm in Linguistics

Datasets

Algorithms

Scope of today's tutorial

Introduction	Algorithms	Incorporating context

Introduction

Sarcasm in Linguistics

Datasets

Algorithms

Incorporating context

Beyond sarcasm detection

Conclusion

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Introduction

Challenges, Motivation, etc.

Sarcasm in Linguistics

Definitions, Theories, etc.
Notion of 'incongruity'

Datasets

Datasets, annotation strategies, challenges, etc.

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Context of the author, the conversation, etc.

Beyond sarcasm detection

Sarcasm generation, sarcasm v/s irony classification, etc.

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Summary, pointers to future work

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Algorithms

Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

Algorithms - 2

Traditional classifier techniques (contd), Deep learning-based techniques, etc.

Incorporating context

Context of the author, the conversation, etc.

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Image of coffee from wikimedia commons.

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Introduction

Module 1 of 7

Objective: To discuss the prevalence, importance and challenges of computational sarcasm

What is sarcasm?

Where is sarcasm seen?

Why would computational sarcasm be useful?

Why is computational sarcasm challenging?

Introduction

Module 1 of 7

What is sarcasm?

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What is Sarcasm?: Level 0

Sarcasm is the use of irony to mock or convey contempt (Source: Oxford Dictionary)

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This perfume is so awesome that I suggest you wear it with your windows shut.

(Pang and Lee, 2008)

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Amazing performance by Kohli. His score is just 185 short of his first double-century!*

* Kohli is an Indian cricket player.

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Sarcasm is a peculiar form of sentiment expression where words of a positive or neutral polarity may be used to imply a negative polarity

* Kohli is an Indian cricket player.

What is Sarcasm?: Level 1 (1/2)

Sarcasm may or may not have positive or negative words.
But the implied sentiment is negative.

What is Sarcasm?: Level 1 (1/2)

Visiting dentists is so much fun!: Positive surface sentiment

Sarcasm may or may not have positive or negative words.
But the implied sentiment is negative.

What is Sarcasm?: Level 1 (1/2)

Visiting dentists is so much fun!: Positive surface sentiment

His performance in Olympics has been terrible anyway (in response to the criticism of an Olympic medalist): Negative surface sentiment

Sarcasm may or may not have positive or negative words.
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What is Sarcasm?: Level 1 (1/2)

Visiting dentists is so much fun!: Positive surface sentiment

His performance in Olympics has been terrible anyway (in response to the criticism of an Olympic medalist): Negative surface sentiment

...and I am the Queen of England!: No surface sentiment

Sarcasm may or may not have positive or negative words.
But the implied sentiment is negative.

What is Sarcasm?: Level 1 (2/2)

Irony:

Sarcasm is a form of irony. Irony may not always be hurtful.

What is Sarcasm?: Level 1 (2/2)

Irony:

The fire station burnt down to ashes due to a fire last night.

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What is Sarcasm?: Level 1 (2/2)

Irony:

The fire station burnt down to ashes due to a fire last night.

Humble-bragging:

Signed three hundred autographs since morning. I am so tired - I hate my life!

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What is Sarcasm?: Level 1 (2/2)

Irony:

The fire station burnt down to ashes due to a fire last night.

Humble-bragging:

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Sarcasm is a form of irony. Irony may not always be hurtful. Humble-bragging is when the speaker pretends to ridicule themselves while they are actually not.

Introduction

Module 1 of 7

What is sarcasm?

<u>Where is sarcasm seen?</u>

Why would computational sarcasm be useful?

Why is computational sarcasm challenging?

Sarcasm in popular culture: Movies & TV (1/3)

Sarcasm in popular culture: Movies & TV (1/3)

Sarcasm to evoke humor

Friends
https://en.wikipedia.org/wiki/Friends

Sarabhai vs Sarabhai
https://en.wikipedia.org/wiki/Sarabhai_vs_Sarabhai

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Sarcasm in popular culture: Movies & TV (1/3)

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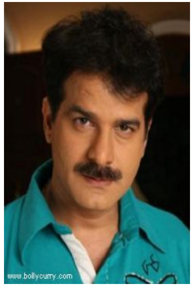
Inability to understand
Sarcasm to evoke humor

The Big Bang Theory
https://en.wikipedia.org/wiki/The_Big_Bang_Theory



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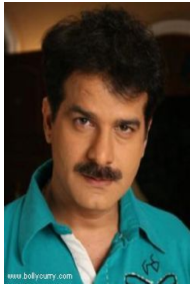

Khichdi
https://en.wikipedia.org/wiki/Khichdi

Sarcasm in science-fiction

Star Wars
https://en.wikipedia.org/wiki/R2-D2

The Simpsons
https://en.wikipedia.org/wiki/The_Simpsons

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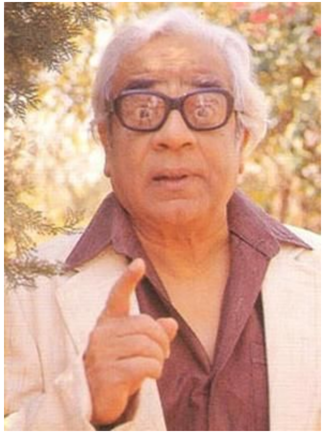
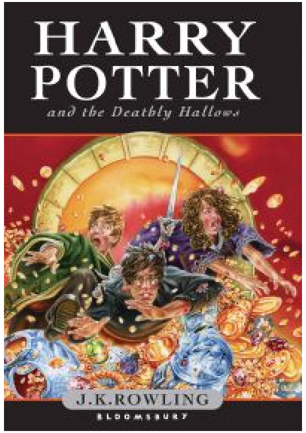
Sarcasm in popular culture: Literature (2/3)





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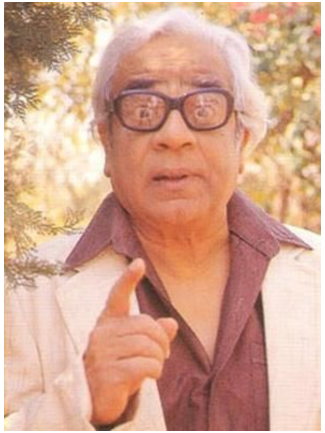
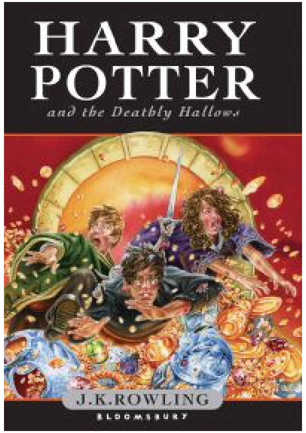
Sarcasm in popular culture: Literature (2/3)

"Aata tumhala punekar vhayche aahe ka? Jaroor vha. Aamche kaahi mhanne nahi. Pan mukhya salla haa, mhanje punha vichaar kara!"

"So you want to settle in the city of Pune? Great, you should, without a doubt. My only advice is, think again."





P L Deshpande's 'Mumbaikar Punekar Nagpurkar' (~1960-70)

https://en.wikipedia.org/wiki/Purushottam_Laxman_Deshpande

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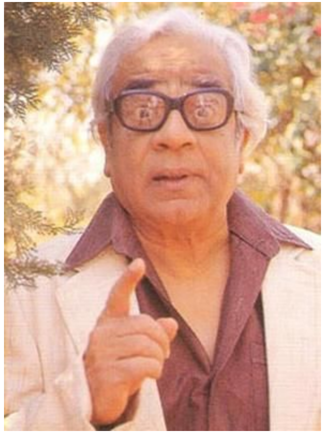
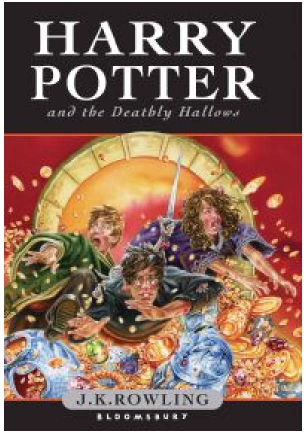




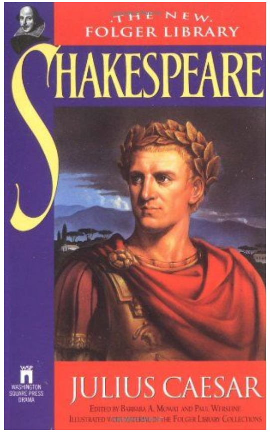
“Death's got an Invisibility Cloak?" Harry interrupted again.
"So he can sneak up on people," said Ron, "Sometimes he gets bored of running at them, flapping his arms and shrieking...”

J K Rowling’s ‘Harry Potter and the Deathly Hallows’ (2007)

https://en.wikipedia.org/wiki/Harry_Potter_and_the_Deathly_Hallows

Images taken from the web. No copyright claim.

Sarcasm in popular culture: Theater (3/3)



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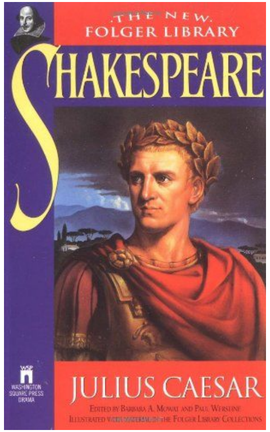
Sarcasm in popular culture: Theater (3/3)

Mhatara ituka na avaghe paaun-she vayman,
Lagna ajuni lahaan, avaghe paaun-she vayman

“He isn’t old -
25 less than 100, after all!
He is too young for marriage -
25 less than 100, after all!”



Govind Ballal Deval’s
‘Sangeet Sharda’ (1899)
https://en.wikipedia.org/wiki/Sangeet_Sharada

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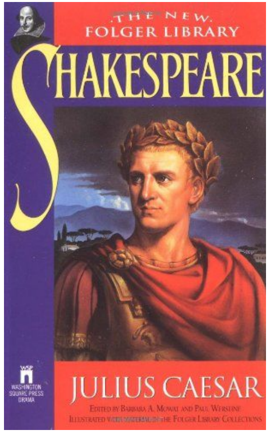


“Friends, Romans, countrymen,
lend me your ears;
…
For Brutus is an honourable man;
So are they all, all honourable men–
..
But Brutus says he was ambitious;
And Brutus is an honourable man”

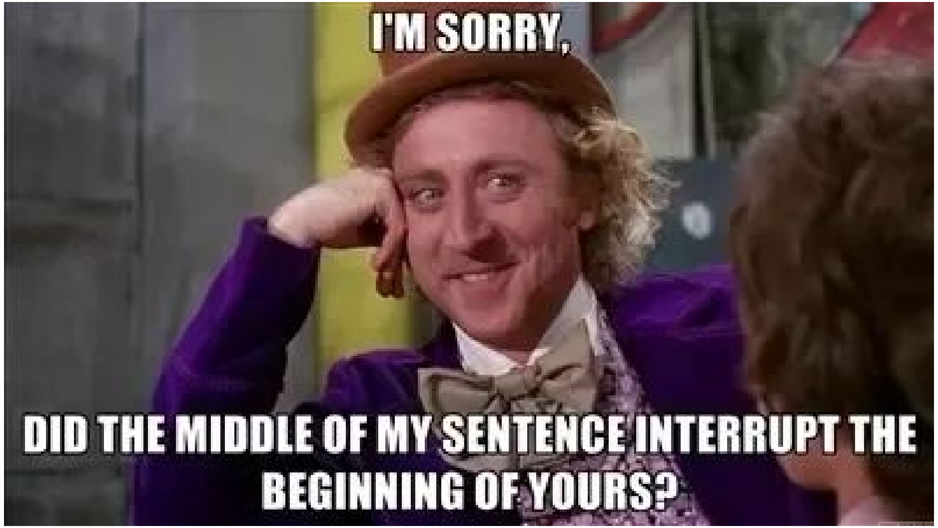
William Shakespeare’s ‘The Tragedy of Julius Caesar’ (1599)

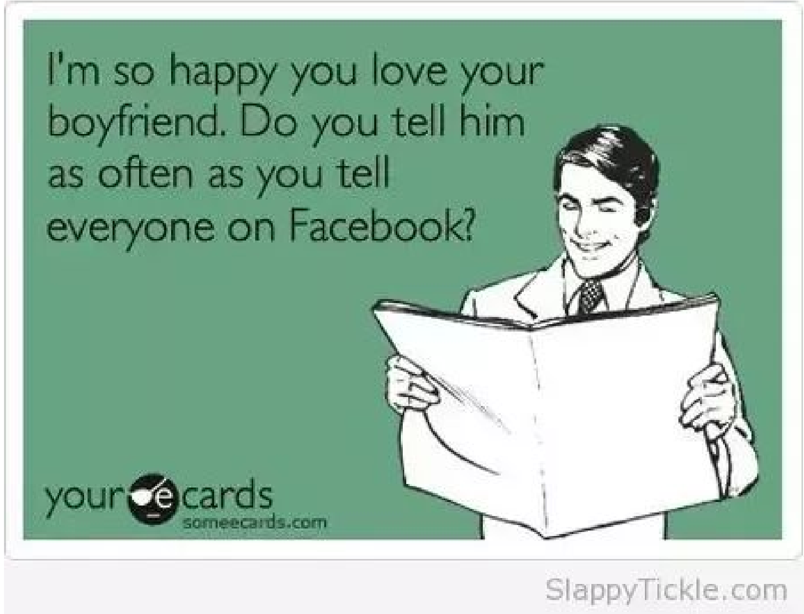
https://en.wikipedia.org/wiki/Julius_Caesar_(play)

Images taken from the web. No copyright claim.

Sarcasm on the web

Sarcasm on the web (memes, to be specific)





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Module 1 of 7

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Motivation

Oft-quoted challenge in sentiment analysis books (Pang and Lee, 2008)

Earliest known work: Tepperman et al. [2006] which deals with sarcasm detection in speech

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In the media

French company, Spotter reports 80% accuracy in sarcasm detection, BBC, 2013
(http://www.bbc.co.uk/news/technology-23160583)

US Secret Service seeks Twitter Sarcasm Detector, BBC, 2014

(http://www.bbc.com/news/technology-27711109)

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Two perspectives: (a) Relationship with Turing Test, (b) Impact on sentiment analysis

Turing Test-Completeness (1/2)

Turing [1950] gave a test for an ideal artificial agent: ‘An agent must be able to accurately imitate humans’

Sarcasm understanding is essential for a chat system to be able to imitate humans

Let’s try two chatbots: ALICE[1] and Assistant.ai[2]

1 The free version available on the ALICE website.
2 Default installation in Android phones.

Turing Test-Completeness (2/2)

Both chatbots do not respond appropriately to sarcasm

Two other popular chatbots throw up web search results.

Turing Test-Completeness (2/2)

Both chatbots do not respond appropriately to sarcasm

Human: You are slow like a snail

ALICE: There is a lot of network traffic right now.
Assistant.ai: A good assistant is whatever their boss needs them to be.

Two other popular chatbots throw up web search results.

Turing Test-Completeness (2/2)

Both chatbots do not respond appropriately to sarcasm

Human: You are slow like a snail

ALICE: There is a lot of network traffic right now.
Assistant.ai: A good assistant is whatever their boss needs them to be.

Human: You are fast like a snail

ALICE: Thank you for telling me I am fast like a snail.
Assistant.ai: A good assistant is whatever their boss needs them to be

Two other popular chatbots throw up web search results.

Impact on Sentiment Analysis (SA) (1/2)

We compare two SA systems:

MeaningCloud: https://www.meaningcloud.com/

NLTK (Bird, 2006)

Two datasets:

Sarcastic tweets by Riloff et al (2013)

Sarcastic utterances from our dataset of TV transcripts (Joshi et al, 2016b)

Impact on Sentiment Analysis (SA) (2/2)

	Precision (Sarc)	Precision (Non-sarc)
Conversation Transcripts		
MeaningCloud[1]	20.14	49.41
NLTK (Bird, 2006)	38.86	81
Tweets		
MeaningCloud[1]	17.58	50.13
NLTK (Bird, 2006)	35.17	69

[1] www.meaningcloud.com

Impact on Sentiment Analysis (SA) (2/2)

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NLTK (Bird, 2006)	35.17	69

The two sentiment analysis systems perform poorly for sarcastic text as compared to non-sarcastic text.

Maynard et al (2014) study the impact of sarcasm detection on sentiment analysis in detail.

[1] www.meaningcloud.com

Introduction

Module 1 of 7

What is sarcasm?

Where is sarcasm seen?

Why would computational sarcasm be useful?

Why is computational sarcasm challenging?

Challenges (1/2)

Challenges (1/2)

Resemblance to objective sentences

And I am the Queen of England.

Dependent on shared knowledge between speaker and listener

*Using this cell phone is as easy as doing a one-hand tree**

Non-verbal cues

(rolls eyes) Yeah right!

* An advanced Yoga pose.

Challenges (1/2)

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(rolls eyes) Yeah right!

Ridicule sans polarity flip

It's not that I wanted breakfast anyway #sarcasm Maynard et al (2014)

Presence of multiple targets

He has turned out to be such a great diplomat that no one takes him seriously.

* An advanced Yoga pose.

Challenges (1/2)

Dependent on speaker

I love solving math problems all weekend!

Cultural Background

Yay, it's raining outside and I am at work.

Resemblance to objective sentences

And I am the Queen of England.

Dependent on shared knowledge between speaker and listener

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Challenges (2/2)

The next challenge will blow your mind, just like most click-bait articles.

Image of bulb from wikimedia commons.

Challenges (2/2)

Every statement has at least one sarcastic interpretation

i.e.,

For **every** statement, there is at least one context where the statement will be sarcastic

Is this the true challenge of computational sarcasm?

The next challenge will blow your mind, just like most click-bait articles.

Image of bulb from wikimedia commons.

Scope of today's tutorial

Introduction

Challenges, Motivation, etc.

Sarcasm in Linguistics

Definitions, Theories, etc.
Notion of 'incongruity'

Datasets

Datasets, annotation strategies, challenges, etc.

Algorithms

Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

Algorithms - 2

Traditional classifier techniques (contd), Deep learning-based techniques, etc.

Incorporating context

Context of the author, the conversation, etc.

Beyond sarcasm detection

Sarcasm generation, sarcasm v/s irony classification, etc.

Conclusion

Summary, pointers to future work

Image of coffee from wikimedia commons.

Sarcasm in Linguistics

Module 2 of 7

Objective: To learn about sarcasm from research in linguistics

Definitions of sarcasm

Types of sarcasm

Sarcasm Theories

The notion of Incongruity

Sarcasm in Linguistics

Module 2 of 7

<u>Definitions of sarcasm</u>
Types of sarcasm
Sarcasm Theories
The notion of Incongruity

Etymology

- Greek: *‘sarkasmós’*: ‘to tear flesh with teeth’
- Sanskrit: *‘vakrokti’*: ‘a twisted (vakra) speech act (ukti)’

What is it called in your language?

皮肉
سخرية
ፌዝ
sarcasmo
Сарказм
gúny
sarcasmo
বিদ্রূপ
sarkasme
iğneleme
ismijavati
სარკაზმი
പരിഹസിക്കുന്ന
कटाक्ष
การเยาะเย้ย
諷刺
sarkasmus

Translations of ‘sarcasm’ as given by Google Translate at the time of creating the slide.

Definitions (1/2)

"A form of irony that is intended to express contempt or ridicule."

The Free Dictionary

"The use of irony to mock or convey contempt."

Oxford Dictionary

Definitions (1/2)

"A form of irony that is intended to express contempt or ridicule."

The Free Dictionary

"Verbal irony that expresses negative and critical attitudes toward persons or events."

(Kreuz and Glucksberg, 1989)

"The use of irony to mock or convey contempt."

Oxford Dictionary

"Irony that is especially bitter and caustic"

(Gibbs, 1994)

Definitions (2/2)

‘Deliberate attempt to point out, question or ridicule attitudes and beliefs by the use of words and gestures in ways that run counter to their normal meanings.’

(Deshpande, 2002)

Definitions (2/2)

'Deliberate attempt to point out, question or ridicule attitudes and beliefs by the use of words and gestures in ways that run counter to their normal meanings.'

(Deshpande, 2002)

- 'Deliberate attempt': **Intentional**
- 'To point out, question or ridicule…': **Ridiculing**
- 'User of words and gestures': **Verbal or non-verbal**
- 'In ways that run counter to their normal meanings': **Ironic**

Sarcasm in Linguistics

Module 2 of 7

Definitions of sarcasm

Types of sarcasm

Sarcasm Theories

The notion of Incongruity

Types of irony

Irony (Gibbs, 1975)

Verbal Irony	Situational Irony	Dramatic Irony
Real interpretation of words is different from the meaning. *‘I love being ignored.’*	Situations/statements contrasting with one another. *‘The scientist who discovered the cure to this disease died of it himself.’*	When the audience of a performance knows more than the characters. *A is cheating on spouse B. But B says, “You are the most loyal partner I could have ever asked for!”*

Relationship between sarcasm and irony

An “utterance” is sarcastic (possibly with respect to a situation)

A situation is not sarcastic

A situation can be ironic

Relationship between sarcasm and irony

An "utterance" is sarcastic (possibly with respect to a situation)
A situation is not sarcastic
A situation can be ironic

Irony: "Virodhaabaas" (*Virodh*: Contradictory, *Aabhaas*: Experience)
v/s
Sarcasm: "Vakrokti" (*Vakra*: Twisted, *Ukti*: Speech act)

Sarcasm is a form of **verbal irony** that is intended to express contempt or ridicule.
(Source: The Free Dictionary)

Types of Sarcasm

Sarcasm (Camp, 2012)

Propositional	Embedded	Like-prefixed	Illocutionary
A proposition that is intended to be sarcastic. *‘This looks like a perfect plan!’*	Sarcasm is embedded in the meaning of words being used. *‘I love being ignored’*	‘Like/As if’ are common prefixes to ask rhetorical questions. *‘Like you care’*	Non-speech acts (body language, gestures) contributing to the sarcasm *‘(shrugs shoulders) Very helpful indeed!’*

Sarcasm in Linguistics

Module 2 of 7

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Theories of Sarcasm

Theories of Sarcasm

Dropped Negation (Giora 1995)	Irony/sarcasm is a form of negation in which an explicit negation marker is lacking.	'*I love being ignored'* implies the sentence '*I do not love being ignored'* but the negation is dropped.

Theories of Sarcasm

Dropped Negation (Giora 1995)	Irony/sarcasm is a form of negation in which an explicit negation marker is lacking.	‘*I love being ignored’* implies the sentence ‘*I do not love being ignored’* but the negation is dropped.
Situational Disparity (Wilson 2006)	Sarcasm arises when there is situational disparity between text and contextual information.	‘*I love being ignored’* has a disparity between the word `*love’* and the sentiment associated with ‘*being ignored*’.

Theories of Sarcasm

Dropped Negation (Giora 1995)	Irony/sarcasm is a form of negation in which an explicit negation marker is lacking.	‘*I love being ignored’* implies the sentence ‘*I do not love being ignored’* but the negation is dropped.
Situational Disparity (Wilson 2006)	Sarcasm arises when there is situational disparity between text and contextual information.	‘*I love being ignored’* has a disparity between the word `*love’* and the sentiment associated with ‘*being ignored*’.
Echoic Mention (Sperber 1984)	A mention in the sarcastic sentence ‘echoes’ with the background knowledge of the listener. An implied proposition may not always be intended. The intention could be pure ridicule!	‘*I love being ignored’* reminds the listener of situations where people did not like being ignored.

Tuple Representation for Sarcasm Ivanko and Pexman (2003)

<S, H, C, U, p, p’>

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S	Speaker
H	Hearer
C	Context
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"I love being ignored!"

S	The person referred to by 'I'
H	The listener (say, host of a party)
C	General Background Context
U	'I love being ignored'
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“Good Job!”

S	A Professor
H	A student
C	The student copied an assignment
U	‘Good job’
p	‘I am happy with you’
p’	‘I am not happy with you’

How humans understand sarcasm (1/2)

- Campbell and Katz (2012) state that sarcasm can be understood by a human along four dimensions:
    a. Failed expectation,
    b. Pragmatic insincerity,
    c. Negative tension, and
    d. Presence of a victim

How humans understand sarcasm (1/2)

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    b. Pragmatic insincerity,
    c. Negative tension, and
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- *"Good Job!"*:
    - **Failed expectation:** 'Good job' is a positive appraisal of a negative situation 'copying an assignment'
    - **Pragmatic insincerity:** Knowing that the student has copied the assignment, it seems unlikely from the tone of the professor that (s)he is sincere
    - **Negative tension:** Copying an assignment is likely to evoke negative tension between the two
    - **Presence of a victim:** The student is the victim of sarcasm. Power relationship exists.

How humans understand sarcasm (2/2)

- Gibbs and O'Brien (1991): Sarcasm is understood because of violation of truthfulness maxims

How humans understand sarcasm (2/2)

- Gibbs and O’Brien (1991): Sarcasm is understood because of violation of truthfulness maxims

- “*Good Job!*”:
  - Copying an assignment will not evoke a praise
  - ‘Good job’ is a praise
  - Violation

How humans react to sarcasm

- Eisterhold et al. (2016) state that sarcasm has peculiar responses:
  - Laughter,
  - No response,
  - Smile,
  - Sarcasm (in retort),
  - A change of topic,
  - Literal reply,
  - Non-verbal reactions

How humans react to sarcasm

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  - Non-verbal reactions

- “*Good job!*” will likely have no response

Relationship between sarcasm, literality, deception, metaphor, humour (1/2)

- All (except literality) are forms of figurative speech
- (Gibbs 1994) (Lee and Katz 1998) (Long and Graesser 1988)
- A takes a spoonful of a soup made by B and says to B, “*Ah, this soup is great!*”
- Cases:
  - A liked the soup: Literality
  - A did not like the soup and A is lying: Deception
  - There is a fly floating on the top. A and B see it. A then says the soup is great: Sarcasm
- Literality versus sarcasm: Literal and implied sentiment are opposites
- Deception versus sarcasm: Shared knowledge between speaker and listener is absent versus present

Relationship between sarcasm, literality, deception, metaphor, humour (2/2)

- (Stieger 2011) calls sarcasm ‘a form of aggressive humor’
- (Gibbs 1994)
  - A to B: ’You are an elephant’: Metaphor for ‘you have a good memory’
- Metaphor: Comparison between two entities
- Metaphor can be used as a device for sarcasm
  - To a person who gets scared often: ‘You are a brave lion!’

Sarcasm in Linguistics

Module 2 of 7

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Incongruity

A situation where components of a text are incompatible either with each other or with some background knowledge.

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A situation where components of a text are incompatible either with each other or with some background knowledge.

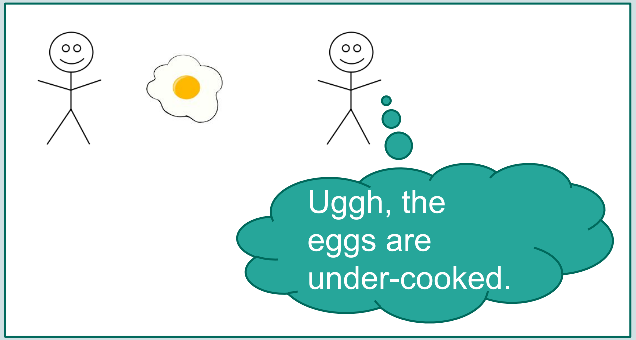
Incongruity

Gibbs (1994) : ‘verbal irony is recognized by literary scholars as a technique of using **incongruity** to suggest a distinction between reality and expectation’

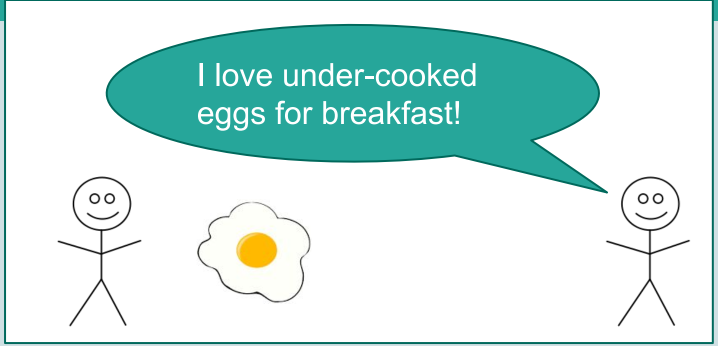
Ivanko and Pexman (2003) state that sarcasm/irony is understood because of **incongruity**.

Sarcasm through the lens of Incongruity

Incongruity provides a useful framework to understand and fit different forms of sarcasm



Sarcasm through the lens of Incongruity



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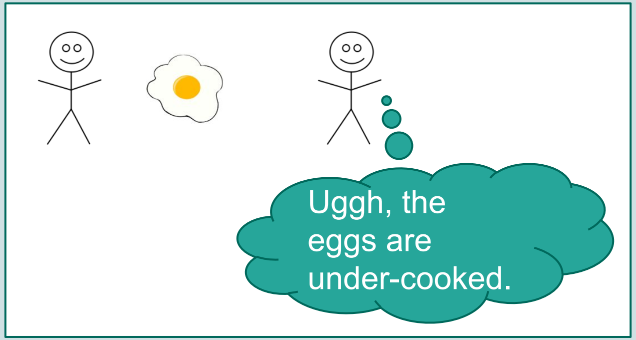

Image of egg from wikimedia commons.

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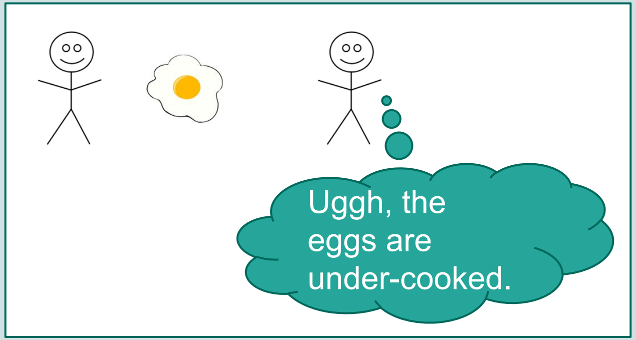

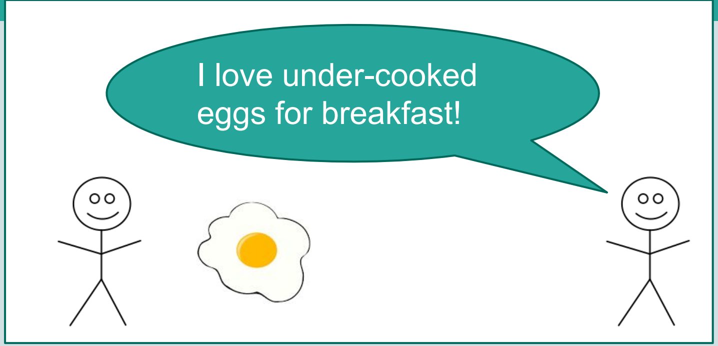

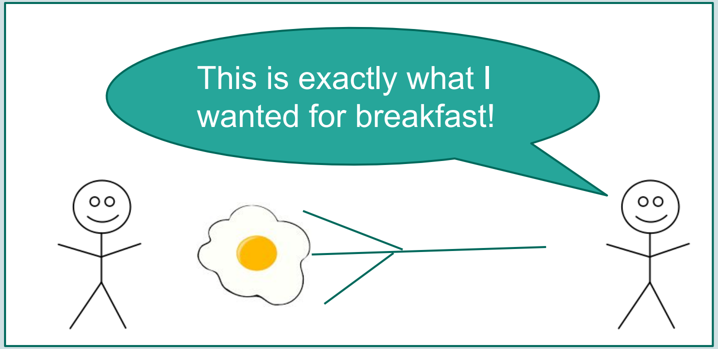

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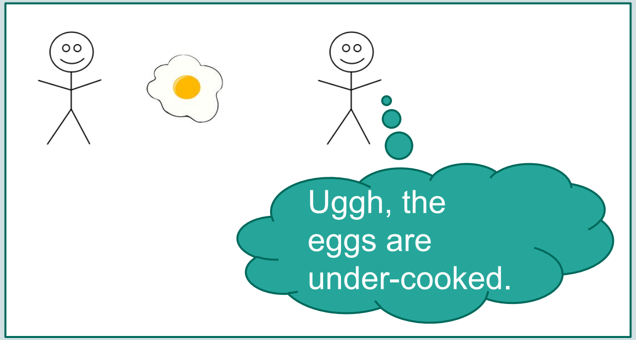

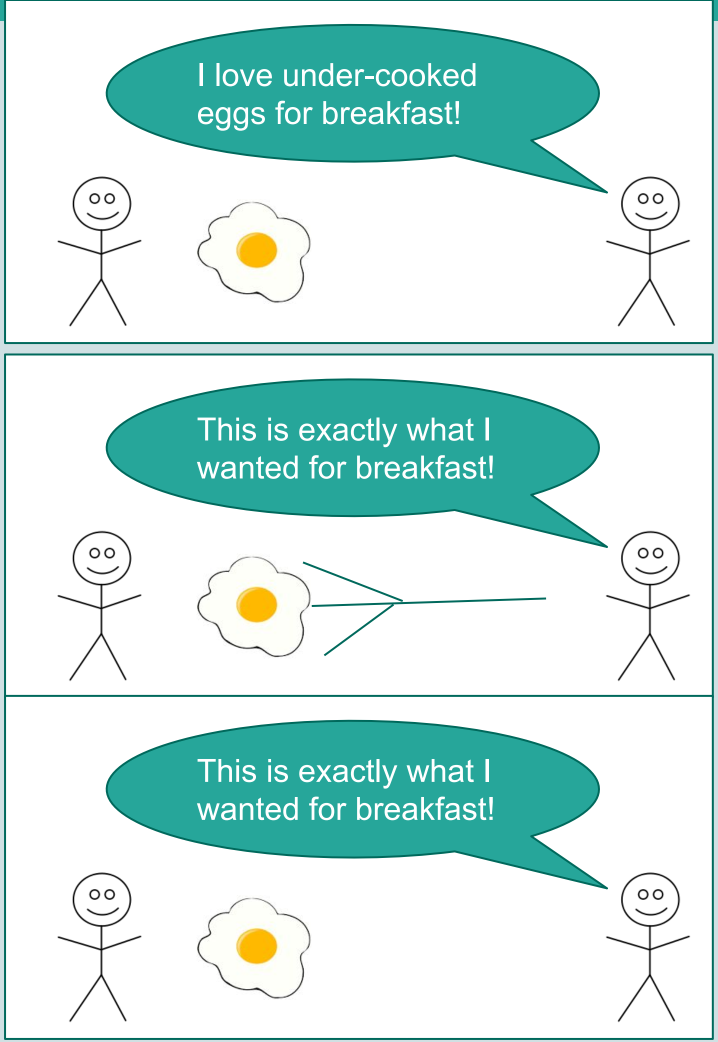

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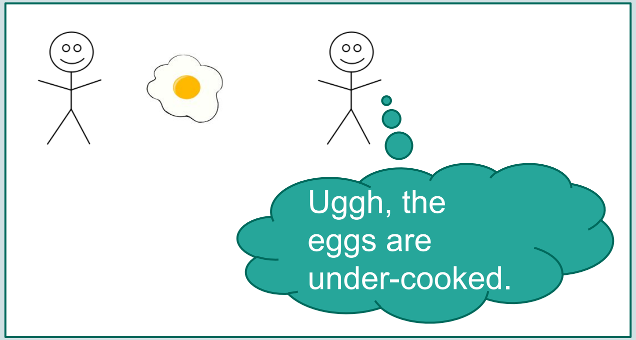

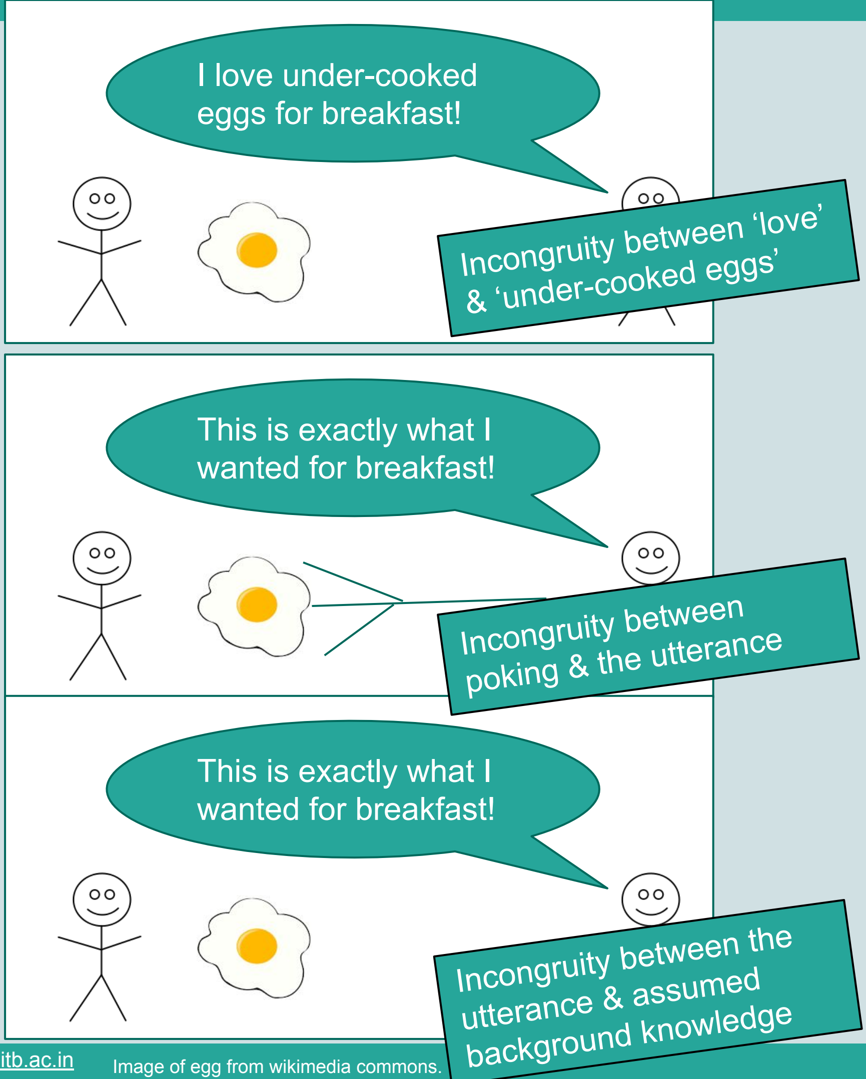

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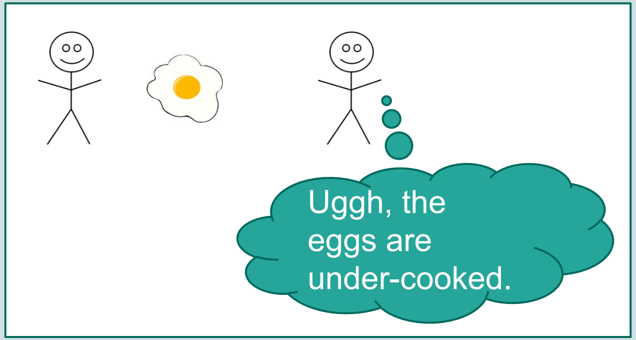

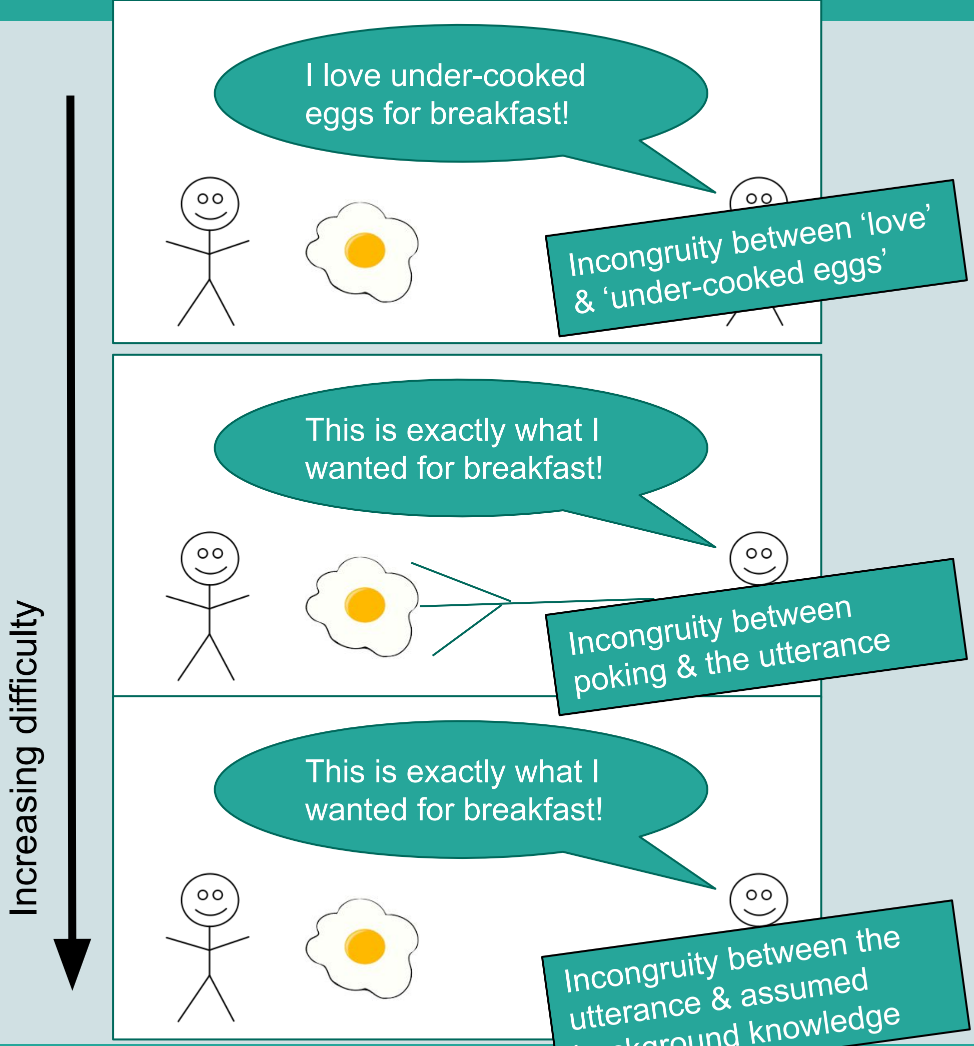

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Image of coffee from wikimedia commons.

Datasets for computational sarcasm

Module 3 of 7

Objective: To survey existing datasets, annotation techniques and challenges

Sarcasm-labeled datasets
Manual Annotation
Distant Supervision
Some unique datasets

Datasets for computational sarcasm

Module 3 of 7

Sarcasm-labeled datasets

Manual Annotation

Distant Supervision

Some unique datasets

Sarcasm-labeled datasets

- Labeled datasets form a basis for learners
- Each textual unit is marked as sarcastic or non-sarcastic

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Sarcasm-labeled datasets

- Labeled datasets form a basis for learners
- Each textual unit is marked as sarcastic or non-sarcastic

- To the best of our knowledge, no dataset exists for:
  - Sarcasm magnitude: *"I love being ignored"* vs *"I love being ignored and left to brood alone in a corner at my own birthday party"*
  - *Sarcasm types: ".. Yeah right" (Illocutionary) vs "I love being ignored" (Propositional)*

Overview of sarcasm-labeled datasets

Text form	Related Work
Short Text	**Tweets** **Manual**: [Riloff et al. 2013; Maynard and Greenwood 2014; Ptácek et al. 2014; Mishra et al. 2016; Abercrombie and Hovy 2016] **Hashtag-based**: [Davidov et al. 2010; González-Ibánez et al. 2011; Reyes et al. 2012; Reyes et al. 2013; Barbieri et al. 2014a; Joshi et al. 2015; Ghosh et al. 2015b; Bharti et al. 2015; Liebrecht et al. 2013; Bouazizi and Ohtsuki 2015a; Wang et al. 2015; Barbieri et al. 2014b; Bamman and Smith 2015; Fersini et al. 2015; Khattri et al. 2015; Rajadesingan et al. 2015; Abercrombie and Hovy 2016]
	Reddits [Wallace et al. 2014; Wallace and Charniak 2015; Khodak et al. 2017]
Long text	[Lukin and Walker 2013; Reyes and Rosso 2014; 2012; Buschmeier et al. 2014; Liu et al. 2014; Filatova 2012]
Transcripts & Dialogue	[Tepperman et al. 2006; Rakov and Rosenberg 2013; Joshi et al. 2016a]
Miscellaneous	[Kreuz and Caucci 2007; Veale and Hao 2010; Ghosh et al. 2015a; Mishra et al. 2016; Joshi et al. 2016b]

Image from the primary reference paper.

Datasets for computational sarcasm

Module 3 of 7

Sarcasm-labeled datasets

Manual Annotation

Distant Supervision

Some unique datasets

Manual Annotation

Employing human annotators to create sarcasm-labeled datasets

What are the annotators guidelines?

Basic: ‘*Is the writer of the text using sarcasm?*’ (Walker et al 2012)

More questions: (Kreuz and Caucci [2007]) Annotators answer three questions: *(i) How likely is this excerpt sarcastic, (ii) How sure are you, (iii) Why do you think it is sarcastic.*

Our experiences from manual annotation

Definition of the task and nature of text

Definition of labels with examples

Clarifications on labels

Our experiences from manual annotation

Definition of the task and nature of text

This task is sarcasm annotation. The text you will read are short snippets from books.

Definition of labels with examples

The task is to label each book snippet with one out of three labels: (a) sarcasm, (b) irony, (c) Philosophy. Sarcasm is defined as verbal irony that is intended to express contempt or ridicule. ….

Clarifications on labels

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Clarifications on labels

Sarcasm is not necessarily humorous. Sarcasm can be hyperbolic and caustic too.

Read a snippet only until you think you understand it. At that time, if you think it is sarcastic, label it as sarcastic. Do not over-analyze.

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True challenge of computational sarcasm?!

Read a snippet only until you think you understand it. At that time, if you think it is sarcastic, label it as sarcastic. Do not over-analyze.

Quality of Sarcasm Annotation

- Low inter-annotator agreement is characteristic to sarcasm-labeled datasets
- Tsur et al. [2010] indicate a Kappa score of 0.34.
- Joshi et al. [2016b]: 0.44.
- The value in the case of Fersini et al. [2015] is 0.79 while for Riloff et al. [2013], it is 0.81

Why?

Challenges of Manual Annotation

- Sarcasm annotation is different from ‘expertise-based tasks’ like POS tagging
    - ‘John eats rice’ -> ‘John_NNP eats_VBZ rice_NN’
    - Disagreement between language experts is likely to be low
- However, sarcasm annotation is more difficult

Possibly insufficient data: “*Yeah right*”	Possibly insufficient expertise: “*... Terri Schiavo….*”	Inability to understand the speaker: “*I love solving math problems all weekend.*”
Possible work-around: Show additional snippets of the conversation, if available. A complete conversation is useful to understand context.	We studied the impact of non-native annotators on sarcasm annotation. It may result in degradation in sarcasm classification. (Joshi et al, 2016b)	Who can say something is sarcastic more accurately than the one who said it?!

Datasets for computational sarcasm

Module 3 of 7

Sarcasm-labeled datasets

Manual Annotation

Distant Supervision

Some unique datasets

Motivation

- Rapid creation of datasets
- Only the author of a tweet can determine sarcasm with certainty if it is sarcastic
    - *‘I love solving math problems all weekend’*

Approach

- Availability of the Twitter API made tweets a popular data domain for sarcasm-labeled datasets
- Positive labels are determined based on presence of hashtags

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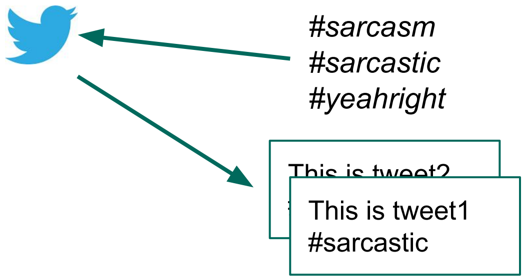

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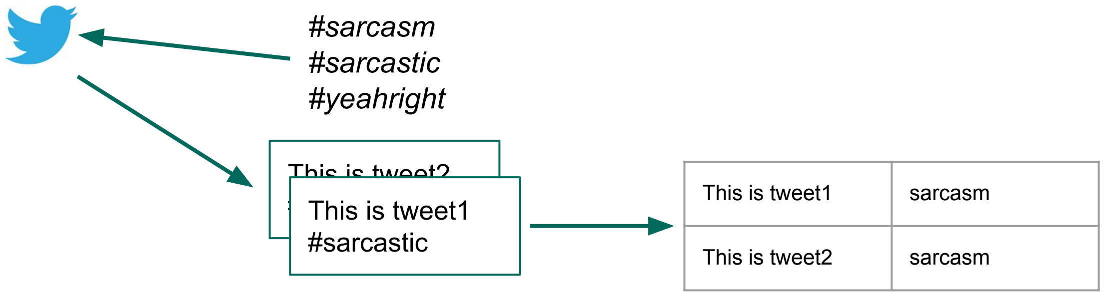

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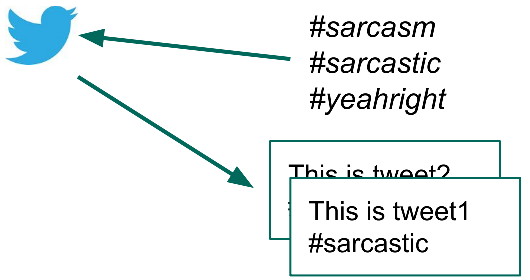

This is tweet1	sarcasm
This is tweet2	sarcasm

Positive instances

Negative instances

Image from wikimedia commons.

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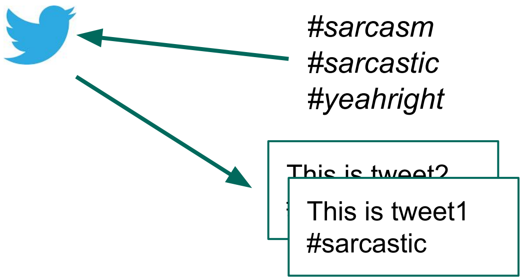

This is tweet1	sarcasm
This is tweet2	sarcasm

Positive instances

1) *#notsarcasm*
2) *Tweets by 'sarcasm' authors without the sarcasm hashtag*
3) *Tweets with an objective hashtag such as #politics (Reyes et al, 2012)*

Negative instances

Image from wikimedia commons.

Approach

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- Positive labels are determined based on presence of hashtags

#sarcasm
#sarcastic
#yeahright

This is tweet2

This is tweet1
#sarcastic

1) *#notsarcasm*
2) *Tweets by 'sarcasm' authors without the sarcasm hashtag*
3) *Tweets with an objective hashtag such as #politics*

This is tweet4

This is tweet3
#notsarcastic

This is tweet1	sarcasm
This is tweet2	sarcasm
This is tweet3	non-sarcastic
This is tweet4	non-sarcastic

Positive instances

Negative instances

Image from wikimedia commons.

Challenges & Workarounds

- Hashtag is dropped when assigning labels. That may eliminate the sarcasm in the tweet
  - *'I love college #not'* —> *'I love college'* labeled as sarcastic.
- Hashtag-based supervision is at best a technique to obtain large labeled datasets with 'near-gold' labels

Challenges & Workarounds

- Hashtag is dropped when assigning labels. That may eliminate the sarcasm in the tweet
  - *'I love college #not'* —> *'I love college'* labeled as sarcastic.
- Hashtag-based supervision is at best a technique to obtain large labeled datasets with 'near-gold' labels
- Workarounds:
  - Fersini et al (2015): Manual correction of labels assigned using hashtags
  - [Joshi et al. 2015; Ghosh and Veale 2016; Bouazizi and Ohtsuki 2015b]: Experimentation with multiple datasets: a large hashtag-annotated dataset and a smaller manually annotated dataset

Datasets for computational sarcasm

Module 3 of 7

Objective: To survey existing datasets, annotation techniques and challenges

Sarcasm-labeled datasets
Manual Annotation
Distant Supervision
Some unique datasets

Datasets with supplementary information

- Mishra et al (2016): Each textual unit has (a) sarcasm label, (b) eye-movement information of users when reading the text

- Khattri et al (2015)/Rajadesignan et al (2015): Each textual unit has (a) sarcasm label, (b) User, (c) Past tweets by the user

Other datasets

Similes marked as sarcastic or not
'*as interesting as watching wet paint dry*'
Veale et al (2010)

Transcripts of TV series 'Friends' with every utterance marked as sarcastic or not
``'*Chandler: Yeah right*' -- sarcastic
Joshi et al (2016a)

Parallel sentences: sarcastic and its non-sarcastic variant
'*I love being ignored*' -- '*I do not love being ignored'*
Peled and Reichad (2017)

Sarcastic sentence with word marked with sarcastic word sense
'*I am amazed to see the bad condition*' -- *'amazed'*
Ghosh et al (2015a)

A note on languages

Most research in English. Datasets in other languages that have been reported are:

Indonesian
Lunango et al (2013)

Dutch
Liebrecht et al (2013)

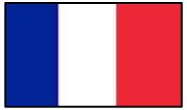
Chinese
Liu et al (2014)

Czech
Pt ˇ acek et al (2014)

Italian
Barbieri et al (2014)
Karoui et al (2017)

Hindi
Desai et al (2016)

Greek
Charalampakis et al (2016)



French
Karoui et al (2017)

All flags from Wikimedia commons, as returned by Google search.

Scope of today's tutorial

Introduction

Challenges, Motivation, etc.

Sarcasm in Linguistics

Definitions, Theories, etc.
Notion of 'incongruity'

Datasets

Datasets, annotation strategies, challenges, etc.

Algorithms

Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

Algorithms - 2

Traditional classifier techniques (contd), Deep learning-based techniques, etc.

Incorporating context

Context of the author, the conversation, etc.

Beyond sarcasm detection

Sarcasm generation, sarcasm v/s irony classification, etc.

Conclusion

Summary, pointers to future work

Image of coffee from wikimedia commons.

Algorithms for sarcasm detection

Module 4 of 7 (Part I)

Objective: To describe the philosophy, methodology, trends, etc. in algorithms used for sarcasm detection

Rule-based algorithms

Statistical algorithms

Algorithms for sarcasm detection

Module 4 of 7 (Part I)

Rule-based algorithms
Statistical algorithms

Algorithms for sarcasm detection

Module 4 of 7 (Part I)

Rule-based algorithms

Statistical algorithms

Rule-based algorithms

- Based on evidences of incongruity and ridicule
- Detect sarcasm through a set of rules
- Like any rule-based system, may suffer from limited coverage: high precision, low recall

Rule-based algorithms: Example (1/4)

Maynard and Greenwood (2014)

Incongruity occurs when: Sentiment of text in a tweet is opposite to that of hashtags

Salient components: (a) Hashtag tokenization (GATE), (b) Leverages on the fact that some hashtags are peculiar hashtags to indicate sarcasm (e.g. '#yeahright')

Rule-based algorithms: Example (1/4)

Maynard and Greenwood (2014)

Incongruity occurs when: Sentiment of text in a tweet is opposite to that of hashtags

Love my homework! #lifesucks

Salient components: (a) Hashtag tokenization (GATE), (b) Leverages on the fact that some hashtags are peculiar hashtags to indicate sarcasm (e.g. '#yeahright')

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Incongruity occurs when: Sentiment of text in a tweet is opposite to that of hashtags

Love my homework! #lifesucks

Love my homework! #life sucks

Salient components: (a) Hashtag tokenization (GATE), (b) Leverages on the fact that some hashtags are peculiar hashtags to indicate sarcasm (e.g. ‘#yeahright’)

Rule-based algorithms: Example (1/4)

Maynard and Greenwood (2014)

Incongruity occurs when: Sentiment of text in a tweet is opposite to that of hashtags

Love my homework! #lifesucks

Love my homework! #life sucks

Sentiment(Love my homework!) != sentiment(life sucks)

Prediction: Sarcastic

Salient components: (a) Hashtag tokenization (GATE), (b) Leverages on the fact that some hashtags are peculiar hashtags to indicate sarcasm (e.g. ‘#yeahright’)

Rule-based algorithms: Example (2/4)

Riloff et al (2013)

Incongruity occurs when positive verb followed by negative situations

Salient components: (a) Extraction of verb and situations through an iterative algorithm (see right above), (b) These phrases are also used as features for statistical classifiers

Rule-based algorithms: Example (2/4)

Riloff et al (2013)

Incongruity occurs when positive verb followed by negative situations

I love being ignored

‘Love’ <-> ‘being ignored’

Prediction: Sarcastic

Salient components: (a) Extraction of verb and situations through an iterative algorithm (see right above), (b) These phrases are also used as features for statistical classifiers

Rule-based algorithms: Example (2/4)

Riloff et al (2013)

Incongruity occurs when positive verb followed by negative situations

I love being ignored

‘Love’ <-> ‘being ignored’

Prediction: Sarcastic

1. Seed set of positive verbs
2. Repeat until convergence:
   a. For verbs in the set, Locate discriminative noun phrases in sarcastic text
   b. Add them to the set of negative situations
   c.

Salient components: (a) Extraction of verb and situations through an iterative algorithm (see right above), (b) These phrases are also used as features for statistical classifiers

Rule-based algorithms: Example (2/4)

Riloff et al (2013)

Incongruity occurs when positive verb followed by negative situations

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1. Seed set of positive verbs
2. Repeat until convergence:
   a. For verbs in the set, Locate discriminative noun phrases in sarcastic text
   b. Add them to the set of negative situations
   c. For situations in the set, Locate discriminative verbs in sarcastic text
   d. Add them to the set of positive verbs

Salient components: (a) Extraction of verb and situations through an iterative algorithm (see right above), (b) These phrases are also used as features for statistical classifiers

Rule-based algorithms: Example (3/4)

Bharti et al (2015)

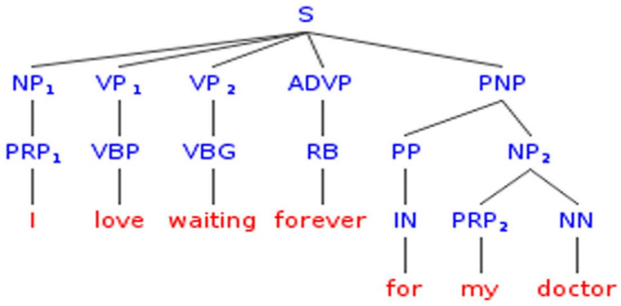
Incongruity occurs when a contrast between positive verb and negative situations, as seen in a parse tree

Salient components: (a) An extension of Riloff et al (2013), (b) They generate parses of sentences, and predict sarcasm if a positive verb and negative situation occur in certain relationships with each other in the parse

Rule-based algorithms: Example (3/4)

Bharti et al (2015)

Incongruity occurs when a contrast between positive verb and negative situations, as seen in a parse tree



Salient components: (a) An extension of Riloff et al (2013), (b) They generate parses of sentences, and predict sarcasm if a positive verb and negative situation occur in certain relationships with each other in the parse

Image from the original paper.

Rule-based algorithms: Example (4/4)

Veale and Hao (2010)

A simile needs to be detected as sarcastic or not. **Incongruity is detected using 9-rules**

Salient components: A set of 9-rules based on evidences such as web search results, lexical similarity between components, etc.

Rule-based algorithms: Example (4/4)

Veale and Hao (2010)

A simile needs to be detected as sarcastic or not. **Incongruity is detected using 9-rules**

As useful as a chocolate teapot

Salient components: A set of 9-rules based on evidences such as web search results, lexical similarity between components, etc.

Rule-based algorithms: Example (4/4)

Veale and Hao (2010)

A simile needs to be detected as sarcastic or not. **Incongruity is detected using 9-rules**

As useful as a chocolate teapot

Lexical similarity between ‘useful’ and ‘chocolate teapot’,
Difference in number of search results for ‘as useful as a chocolate teapot’ versus ‘about as useful as a chocolate teapot’

Prediction: Sarcastic

Salient components: A set of 9-rules based on evidences such as web search results, lexical similarity between components, etc.

Our rule-based algorithm

Joshi et al (2017)

Incongruity in sarcastic sentences goes against the expected language model.

Our rule-based algorithm

Joshi et al (2017)

Incongruity in sarcastic sentences goes against the expected language model.

I love being ______

Top words predicted by sentence completion

Rank	Word
0	star-struck
1	honest
5	overprotective
8	super-fit
12	open-minded
22	assertive
1102	ignored

Aditya Joshi, Samarth Agrawal, Pushpak Bhattacharyya, Mark J Carman, 'Expect the unexpected: Harnessing Sentence Completion for Sarcasm Detection', PACLING 2017, Yangon, Myanmar, August 2017.

Outline of our Approach

Input: Sentence

Parameter: Threshold

For every content word *cw* at position i:

  Get the most likely word *lw* for position i, given rest of the sentence

  Calculate similarity between *cw* and *lw*

If minimum similarity over all content words < threshold:

  Return sarcastic

Else:

  Return non-sarcastic

Outline of our Approach

Input: *'I love being ignored'*

Parameter: Threshold '0.3'

For every content word *cw* at position i: *{love, ignored}*

    Get the most likely word *lw* for position i, given rest of the sentence

    Calculate similarity between *cw* and *lw*

If minimum similarity over all content words < threshold:

    Return sarcastic

Else:

    Return non-sarcastic

Outline of our Approach: Example

Input: *'I love being ignored'*

Parameter: Threshold '0.3'

For every content word *cw* at position i: *{love, ignored}*

  Get the most likely word *lw* for position i, given rest of the sentence

  Calculate similarity between *cw* and *lw*

If minimum similarity over all content words < threshold:

  Return sarcastic

Else:

  Return non-sarcastic

I [] being ignored. → Expected word: hate
I love being [] → Expected word: happy

Outline of our Approach: Example

Input: *'I love being ignored'*

Parameter: Threshold '0.3'

For every content word *cw* at position i: *{love, ignored}*

    Get the most likely word *lw* for position i, given rest of the sentence

    Calculate similarity between *cw* and *lw*

If minimum similarity over all content words < threshold:

    Return sarcastic

Else:

    Return non-sarcastic

I [] being ignored. → Expected word: hate
I love being [] → Expected word: happy

similarity(love, hate) = 0
similarity(ignored, happy) = 0.0204

Outline of our Approach: Example

Input: *'I love being ignored'*

Parameter: Threshold '0.3'

For every content word *cw* at position i: *{love, ignored}*

    Get the most likely word *lw* for position i, given rest of the sentence

    Calculate similarity between *cw* and *lw*

If minimum similarity over all content words < threshold:

    Return <u>sarcastic</u>

Else:

    Return non-sarcastic

I [] being ignored. → Expected word: hate
I love being [] → Expected word: happy

similarity(love, hate) = 0
similarity(ignored, happy) = 0.0204

Two variants of the approach

Approach:

(1) Approach 1: Iterate over all words
(2) Approach 2: Iterate over top 50% most incongruous words (based on pair-wise word2vec similarity)

Results

Maynard et al (2014)

Tweets: Precision: 0.91

Veale and Hao (2010)

Similes: Accuracy: 0.88

Riloff et al (2013)

Tweets: F-score: 0.51

Bharti et al (2015)

Tweets: F-score: 0.82

Joshi et al (2017)

Discussion forum posts: F-score: 0.541

Tweets: F-score: 0.802

The values may not be directly comparable.

Algorithms for sarcasm detection

Module 4 of 7 (Part I)

Rule-based algorithms

Statistical algorithms

Statistical Algorithms

- Unigrams are often the common features
  - Liebrecht et al (2013)
- Semi-supervised extraction of patterns
- Other features to capture incongruity
- Classifiers

An early approach

Tsur et al (2010)

Extract phrases from a sarcastic corpus

Phrases that are ‘indicative’ of sarcasm become features

The feature vector representation is interesting (See right)

An early approach

Tsur et al (2010)

Extract phrases from a sarcastic corpus

Phrases that are ‘indicative’ of sarcasm become features

The feature vector representation is interesting (See right)

‘Staying awake at 4 am’
‘Visiting a dentist thrice a week’
‘Being ignored’

Semi-supervised extraction (1/2)

Tsur et al (2010)

Extract phrases from a sarcastic corpus

Phrases that are ‘indicative’ of sarcasm become features

The feature vector representation is interesting (See right)

‘Staying awake at 4 am’
‘Visiting a dentist thrice a week’
‘Being ignored’

$$\begin{cases} 1: & \text{Exact match – all the pattern components appear in the sentence in correct order without any additional words.} \\ \alpha: & \text{Sparse match – same as exact match but additional non-matching words can be inserted between pattern components.} \\ \gamma * n/N: & \text{Incomplete match – only } n > 1 \text{ of } N \text{ patte components appear in the sentence, while some non-matching words can be inserted in-between. At least one of the appearing components should be a HFW.} \\ 0: & \text{No match – nothing or only a single pattern component appears in the sentence.} \end{cases}$$

Semi-supervised extraction (1/2)

'I love being ignored'
love: 1, 'Being ignored': 1, 'Staying awake at 4 am': 0, 'Visiting … ': 0

Phrases that are 'indicative' of sarcasm become features

The feature vector representation is interesting (See right)

'Staying awake at 4 am'
'Visiting a dentist thrice a week'
'Being ignored'

$1:$	Exact match – all the pattern components appear in the sentence in correct order without any additional words.
$\alpha:$	Sparse match – same as exact match but additional non-matching words can be inserted between pattern components.
$\gamma * n/N:$	Incomplete match – only $n > 1$ of N patte components appear in the sentence, while some non-matching words can be inserted in-between. At least one of the appearing components should be a HFW.
$0:$	No match – nothing or only a single pattern component appears in the sentence.

Semi-supervised extraction (1/2)

'I love being ignored'
love: 1, 'Being ignored': 1, 'Staying awake at 4 am': 0, 'Visiting … ': 0

'I love being totally ignored '
love: 1, 'Being ignored': α, 'Staying awake at 4 am': 0, 'Visiting … ': 0

The feature vector representation is interesting (See right)

'Staying awake at 4 am'
'Visiting a dentist thrice a week'
'Being ignored'

1 :	Exact match – all the pattern components appear in the sentence in correct order without any additional words.
α :	Sparse match – same as exact match but additional non-matching words can be inserted between pattern components.
$\gamma * n/N$:	Incomplete match – only $n > 1$ of N patte components appear in the sentence, while some non-matching words can be inserted in-between. At least one of the appearing components should be a HFW.
0 :	No match – nothing or only a single pattern component appears in the sentence.

Semi-supervised extraction (1/2)

'I love being ignored'
love: 1, 'Being ignored': 1, 'Staying awake at 4 am': 0, 'Visiting … ': 0

'I love being totally ignored '
love: 1, 'Being ignored': α, 'Staying awake at 4 am': 0, 'Visiting … ': 0

'I love visiting a dentist often'
*love: 1, 'Being ignored': 0, 'Staying awake at 4 am': 0, 'Visiting … ': γ * 3/6*

'Staying awake at 4 am'
'Visiting a dentist thrice a week'
'Being ignored'

- 1 : Exact match – all the pattern components appear in the sentence in correct order without any additional words.
- α : Sparse match – same as exact match but additional non-matching words can be inserted between pattern components.
- $\gamma * n/N$: Incomplete match – only $n > 1$ of N patte components appear in the sentence, while some non-matching words can be inserted in-between. At least one of the appearing components should be a HFW.
- 0 : No match – nothing or only a single pattern component appears in the sentence.

Semi-supervised extraction (2/2)

The idea of semi-supervised extraction of patterns has been used in several other past work

Either sarcastic patterns or patterns with implicit sentiment

Patterns are used as features or knowledge bases

Features: Summary

	Salient Features
Tsur et al. [2010]	Sarcastic patterns, Punctuations
González-Ibánez et al. [2011]	User mentions, emoticons, unigrams, sentiment-lexicon-based features
Reyes et al. [2012]	Ambiguity-based, semantic relatedness
Reyes and Rosso [2012]	N-grams, POS N-grams
Liebrecht et al. [2013]	N-grams, emotion marks, intensifiers
Riloff et al. [2013]	Sarcastic patterns (Positive verbs, negative phrases)
Reyes et al. [2013]	Skip-grams, Polarity skip-grams
Barbieri et al. [2014a]	Freq. of rarest words, max/min/avg # synsets, max/min/avg # synonyms
Barbieri et al. [2014b]	Synonyms, Ambiguity, Written-spoken gap
Buschmeier et al. [2014]	Interjection, ellipsis, hyperbole, imbalance-based
Liu et al. [2014]	POS sequences, Semantic imbalance. Chinese-specific features such as homophones, use of honorifics
Ptácek et al. [2014]	Word shape, Pointedness, etc.
Hernández-Farías et al. [2015]	Length, capitalization, semantic similarity
Joshi et al. [2015]	Unigrams, Implicit incongruity-based, Explicit incongruity-based
Rajadesingan et al. [2015]	Readability, sentiment flips, etc.
Bouazizi and Ohtsuki [2015b]	Pattern-based features along with word-based, syntactic, punctuation-based and sentiment-related features
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@FRIEND1 Don't you totally love being ignored!

...
! : 1
…
...

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@FRIEND1 Don't you totally love being ignored!

...
Usermentions: 1
! : 1
Positive word: 1
Negative word: 1
…
...

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@FRIEND1 Don't you totally love being ignored!

...
Perplexity: 0.23111
Positive word: 1
Negative word: 1
…
...

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@FRIEND1 Don't you totally love being ignored!

...
VBP_VBG: 1
VBG_VBN: 1
Love_being: 1
Being_ignored: 1
….
......

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@FRIEND1 Don't you totally love being ignored!

...
Totally: 1
! : 1
…
...

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...
love_ignored: 1
Positive_negative: 1
…
...

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...
Max_synsets: 11
Min_synsets: 6
Avg_synsets: 9.5
…
...

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...
#written_corpus(love)-
#spoken_corpus(love)
#written_corpus(ignored) -
#spoken_corpus(ignored)
…
...

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...
Ellipsis: 0
Interjection: 1
…
...

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...
Honorific: 1
...
...

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...
Capitalized?: 1
Numeric?: 0
...

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...
Capitalized?: 1
Length?: 10
...

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...
#positive: 2
#negative: 1
#flips: 1
#longest_subseq: 2
...

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...

Readability score

...

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...
word2vec('love','ignored')
etc.
...

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...
Average duration per word
Average saccadic distance, etc.
...

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Classifiers

SVM [13 , 32 , 38 , 56 , 67 , 68]

Logistic Regression [2]

Balanced winnow algorithm to rank features [41]

Naive Bayes and Decision trees [59]

SVM-HMM [75, 43]

Fuzzy clustering [49]

Our statistical approach

Sentiment Incongruity is incongruity expressed through the use of sentiment words (Joshi et al, 2015)

Two types of sentiment incongruity:

- **Explicit Incongruity**: Words of both polarity are present
  - *Being stranded in traffic is the best way to start a week!*
- **Implicit Incongruity:** Words of one polarity are present, with a phrase of implied polarity
  - *I love this paper so much that I made a doggy bag out of it.*

Hypothesis: Augmenting features capturing sentiment incongruity can be useful for sarcasm detection

Aditya Joshi, Vinita Sharma, Pushpak Bhattacharyya, Harnessing context incongruity for sarcasm detection, ACL-IJCNLP 2015, Beijing, China, July 2015.

Sentiment Incongruity Features

Lexical	
Unigrams	Unigrams in the training corpus
Pragmatic	
Capitalization	Numeric feature indicating presence of capital letters
Emoticons & laughter expressions	Numeric feature indicating presence of emoticons and 'lol's
Punctuation marks	Numeric feature indicating presence of punctuation marks
Implicit Incongruity *	
Implicit Sentiment Phrases	Boolean feature indicating phrases extracted from the implicit phrase extraction step
Explicit Incongruity +	
#Explicit incongruity	Number of times a word is followed by a word of opposite polarity
Largest positive /negative subsequence	Length of largest series of words with polarity unchanged
#Positive words	Number of positive words
#Negative words	Number of negative words
Lexical Polarity	Polarity of a tweet based on words present

* Based on a Bootstrapping algorithm by Riloff et al (2013)
+ Based on features by Ramteke et al (2013)

Experiment Setup

Three datasets:

- Tweet-A (5208 total, 4172 sarcastic)
- Tweet-B (2278 total, 506 sarcastic) From Riloff et al. (2013)
- Discussion-A (1502 total, 752 sarcastic) from Walker et al. (2012)

LibSVM[1], five-fold cross-validation

1 https://www.csie.ntu.edu.tw/ cjlin/libsvm/

Chang, Chih-Chung, and Chih-Jen Lin. "LIBSVM: a library for sup[illegible] Systems and Technology (TIST) 2.3 (2011): 27.

Results

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**

Tweet-A

Approach	P	R	F
Riloff et al. (2013) (**best reported**)	0.62	0.44	0.51
Maynard and Greenwood (2014)	0.46	0.38	0.41
Our system (all features)	**0.77**	**0.51**	**0.61**

Tweet-B

Features	P	R	F
Lexical (**Baseline**)	0.645	0.508	0.568
Lexical+Explicit	0.698	0.391	0.488
Lexical+Implicit	0.513	0.762	0.581
All features	0.489	0.924	**0.640**

Discussion-A

Error Analysis

Subjective polarity: *'Yay for extra hours of Chemistry labs'*

No incongruity due to sentiment-bearing words: About 10% misclassified examples that we analyzed, contained no sentiment incongruity within the text.

Error Analysis

Subjective polarity: *'Yay for extra hours of Chemistry labs'*

No incongruity due to sentiment-bearing words: About 10% misclassified examples that we analyzed, contained no sentiment incongruity within the text.

Incongruity due to numbers: *'Going in to work for 2 hours was totally worth the 35 minute drive.'*

Annotation granularity: *'How special, now all you have to do is prove that a glob of cells has rights. I happen to believe that a person's life and the right to life begins at conception'.*

Politeness: *'Post all your inside jokes on facebook, I really want to hear about them'.*

Scope of today's tutorial

Introduction

Challenges, Motivation, etc.

Sarcasm in Linguistics

Definitions, Theories, etc.
Notion of 'incongruity'

Datasets

Datasets, annotation strategies, challenges, etc.

Algorithms

Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

Algorithms - 2

Traditional classifier techniques (contd), Deep learning-based techniques, etc.

Incorporating context

Context of the author, the conversation, etc.

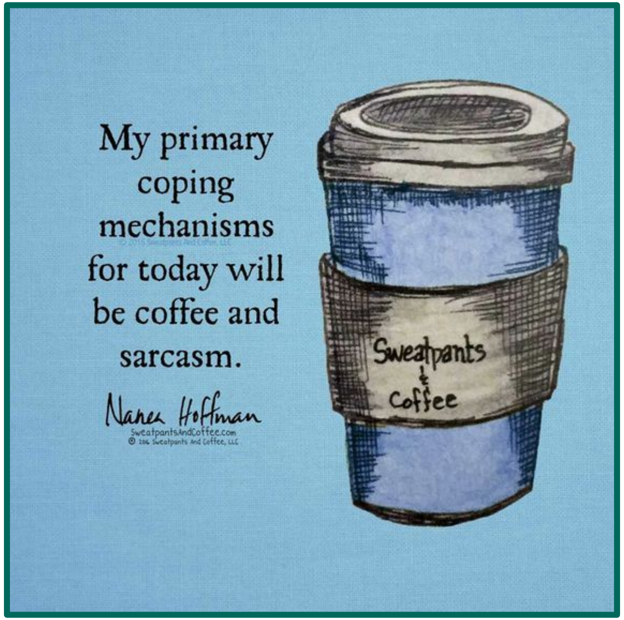
Beyond sarcasm detection

Sarcasm generation, sarcasm v/s irony classification, etc.

Conclusion

Summary, pointers to future work

Image of coffee from wikimedia commons.



Source: @sweatpantsandcoffee, pinterest

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Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

Algorithms - 2

Traditional classifier techniques (contd), Deep learning-based techniques, etc.

Incorporating context

Context of the author, the conversation, etc.

Beyond sarcasm detection

Sarcasm generation, sarcasm v/s irony classification, etc.

Conclusion

Summary, pointers to future work

Image of coffee from wikimedia commons.

Scope of today's tutorial

Introduction

Challenges, Motivation, etc.

Sarcasm in Linguistics

Definitions, Theories, etc.
Notion of 'incongruity'

Datasets

Datasets, annotation strategies, challenges, etc.

Algorithms

Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

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Traditional classifier techniques (contd), Deep learning-based techniques, etc.

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Image of coffee from wikimedia commons.

Algorithms for sarcasm detection

Module 4 of 7 (Part II)

Objective: To describe the philosophy, methodology, trends, etc. in algorithms used for sarcasm detection

Deep learning-based algorithms
Topic model for sarcasm
Comparison of results
Two focus works

Algorithms for sarcasm detection

Module 4 of 7 (Part II)

<u>Deep learning-based algorithms</u>

Topic model for sarcasm

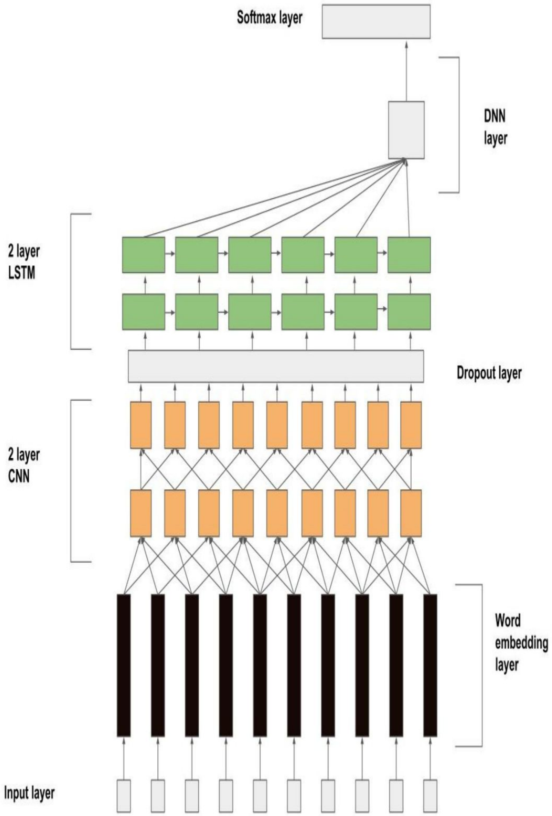
Comparison of results

Two focus works

Deep learning-based algorithms for sarcasm detection

1. LSTM/CNN-based architecture
2. Word embedding-based features for traditional classifiers

LSTM/CNN-based architectures



Fracking Sarcasm using Neural Network, Ghosh and Veale (2016)

Image from the original paper.

Results

Model	Feature/Hyper parameter	Precision	Recall	F-score
recursive SVM	BOW + POS	.719	.613	.663
recursive SVM	BOW + POS + Sentiment	.722	.661	.691
recursive SVM	BOW + POS + Sentiment + HT-splitter	.743	.721	.732
CNN + CNN	filter size = 64 + filter width = 2	.838	.857	.847
	filter size = 128 + filter width = 2	.842	.86	.854
	filter size = 256 + filter width = 2	.855	.879	.868
	filter size = 64 + filter width = 3	.839	.854	.847
	filter size = 128 + filter width = 3	.856	.879	.868
	filter size = 256 + filter width = 3	.861	.882	.872
LSTM + LSTM	hidden memory unit = 64	.849	.816	.832
	hidden memory unit = 128	.854	.871	.862
	hidden memory unit = 256	.868	.89	.879
CNN + LSTM + DNN (with dropout)	filter size = 256 + filter width = 2 + HMU = 256	.899	.91	.904
CNN + LSTM + DNN (without dropout)	filter size = 256 + filter width = 2 + HMU = 256	.912	.911	.912
CNN + LSTM + DNN (without dropout)	filter size = 256 + filter width = 3 + HMU = 256	.919	.923	.921

Our work

Some incongruity may occur without the presence of sentiment words

Hypothesis: Incongruity can be captured using word embedding-based features, **in addition to other features**

“A woman needs a man like a fish needs a bicycle.”

Word2Vec similarity(man,woman) = 0.766
Word2Vec similarity(fish, bicycle) = 0.130

	man	woman	fish	needs	bicycle
man	-	**0.766**	**0.151**	**0.078**	**0.229**
woman	0.766	-	0.084	0.060	0.229
fish	0.151	0.084	-	0.022	0.130
needs	0.078	0.060	0.022	-	0.060
bicycle	0.229	0.229	0.130	0.060	-

Aditya Joshi, Vaibhav Tripathi, Kevin Patel, Pushpak Bhattacharyya and Mark J Carman, 'Are Word Embedding-based Features Useful for Sarcasm Detection?'. EMNLP 2016, Austin, Texas, November 2016.

Also covered in MIT Technology Review as ‘How Vector Space Mathematics Helps Machines Spot Sarcasm’

https://www.technologyreview.com/s/602639/how-vector-space-mathematics-helps-machines-spot-sarcasm/

Word embedding-based features

Unweighted similarity features (S):

For every word and word pair,

1) Maximum score of most similar word pair
2) Minimum score of most similar word pair
3) Maximum score of most dissimilar word pair
4) Minimum score of most dissimilar word pair

	man	woman	fish	needs	bicycle
man	-	**0.766**	**0.151**	**0.078**	**0.229**
woman	0.766	-	0.084	0.060	0.229
fish	0.151	0.084	-	0.022	0.130
needs	0.078	0.060	0.022	-	0.060
bicycle	0.229	0.229	0.130	0.060	-

Distance-weighted similarity features (WS): 4 S features divided by square of linear distance between the two words

Both (S+WS): 8 features

Experiment Setup

- Dataset: 3629 Book snippets (759 sarcastic) downloaded from GoodReads website, labeled by users with tags. We download the ones with 'sarcasm' as sarcastic, ones with 'philosophy' as non-sarcastic
- Five-fold cross-validation
- Classifier: SVM-Perf (Joachims, 2006a) optimised for F-score
- Configurations:
  - Four prior works (augmented with our sets of features)
  - Four kinds of pre-trained word embeddings (Word2Vec[1], LSA[2], GloVe[3], Dependency weights-based[4])

1 https://code.google.com/archive/p/word2vec/
2 http://www.lingexp.uni-tuebingen.de/z2/LSAspaces/
3 http://nlp.stanford.edu/projects/glove/
4 https://levyomer.wordpress.com/2014/04/25/dependency-based-word-embeddings/

Results

Features	P	R	F
	Baseline		
Unigrams	67.2	78.8	72.53
S	64.6	75.2	69.49
WS	67.6	51.2	58.26
Both	67	52.8	59.05

Performance of our features on their own

	LSA			GloVe			Dependency Weights			Word2Vec		
	P	R	F	P	R	F	P	R	F	P	R	F
L	73	79	75.8	73	79	75.8	73	79	75.8	73	79	75.8
+S	81.8	78.2	**79.95**	81.8	79.2	**80.47**	81.8	78.8	80.27	80.4	80	**80.2**
+WS	76.2	79.8	77.9	76.2	79.6	77.86	81.4	80.8	81.09	80.8	78.6	79.68
+S+WS	77.6	79.8	78.68	74	79.4	76.60	82	80.4	**81.19**	81.6	78.2	79.86
G	84.8	73.8	78.91	84.8	73.8	78.91	84.8	73.8	**78.91**	84.8	73.8	**78.91**
+S	84.2	74.4	**79**	84	72.6	77.8	84.4	72	77.7	84	72.8	78
+WS	84.4	73.6	78.63	84	75.2	**79.35**	84.4	72.6	78.05	83.8	70.2	76.4
+S+WS	84.2	73.6	78.54	84	74	78.68	84.2	72.2	77.73	84	72.8	78
B	81.6	72.2	76.61	81.6	72.2	76.61	81.6	72.2	76.61	81.6	72.2	76.61
+S	78.2	75.6	**76.87**	80.4	76.2	**78.24**	81.2	74.6	**77.76**	81.4	72.6	76.74
+WS	75.8	77.2	76.49	76.6	77	76.79	76.2	76.4	76.29	81.6	73.4	77.28
+S+WS	74.8	77.4	76.07	76.2	78.2	77.18	75.6	78.8	77.16	81	75.4	**78.09**
J	85.2	74.4	79.43	85.2	74.4	79.43	85.2	74.4	79.43	85.2	74.4	79.43
+S	84.8	73.8	78.91	85.6	74.8	79.83	85.4	74.4	79.52	85.4	74.6	**79.63**
+WS	85.6	75.2	**80.06**	85.4	72.6	78.48	85.4	73.4	78.94	85.6	73.4	79.03
+S+WS	84.8	73.6	78.8	85.8	75.4	**80.26**	85.6	74.4	**79.6**	85.2	73.2	78.74

Table 3: Performance obtained on augmenting word embedding features to features from four prior works, for four word embeddings; L: Liebrecht et al. (2013), G: González-Ibánez et al. (2011a), B: Buschmeier et al. (2014) , J: Joshi et al. (2015)

Error Analysis

Embedding issues due to incorrect senses: 'Great. Relationship advice from one of America's most <u>wanted</u>.'

Contextual sarcasm: 'Oh, and I suppose the apple ate the cheese'.

Metaphors in non-sarcastic text: 'Oh my love, I like to vanish in you like a ripple vanishes in an ocean - slowly, silently and endlessly'.

Dataset Sizes for Deep learning-based systems

	Size	Labeling	Additional
Ghosh and Veale (2016)	39K total, 18k sarcastic	Hashtag-labeled	Also evaluated on manually labeled datasets
Joshi et al (2016b)	3629 total, 759 sarcastic	User tag-labeled	
Poria et al (2016)	120,000 tweets, 20,000 sarastic	Tagged using thesarcasmdetector	Two other datasets, one hashtag-supervised

Algorithms for sarcasm detection

Module 4 of 7 (Part II)

Deep learning-based algorithms
Topic model for sarcasm
Comparison of results
Two focus works

Topic Models for Sarcasm: Motivation

Sarcastic tweets are likely to have a mixture of words of both sentiments as against tweets with literal sentiment (either positive or negative)

Hypothesis: Our topic model discovers sarcasm-prevalent topics, in order to aid the task of sarcasm detection

1. A document-level topic variable that models sarcasm prevalence
2. A word-level sentiment variable that models sentiment mixture

Aditya Joshi, Prayas Jain, Pushpak Bhattacharyya, Mark J Carman, "'Who would have thought of that!': A Novel Hierarchical Topic Model for Extraction of Sarcasm-prevalent Topics and Sarcasm Detection', ExPROM-COLING 2016, Osaka, Japan, December 2016.

Input/Output

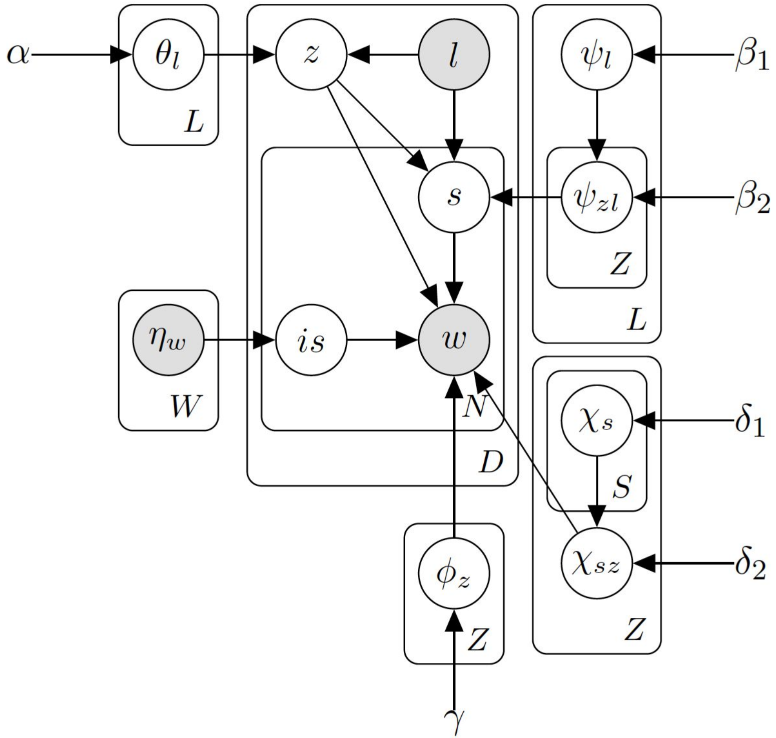
Input:

- Hashtag-based supervised dataset of tweets
  - Three labels: Literal positive, literal negative and sarcastic
- Word-sentiment distribution

Output:

- Sarcasm-prevalent topics
- Sentiment-label distributions
- Sentiment clusters corresponding to topics

Plate Diagram



Observed Variables and Distributions	
w	Word in a tweet
l	Label of a tweet; takes values: positive, negative, sarcastic)
Distributions	
η_w	Distribution over switch values given a word w
Latent Variables and Distributions	
z	Topic of a tweet
s	Sentiment of a word in a tweet; takes values: positive, negative
is	Switch variable indicating whether a word is a topic word or a sentiment word; takes values: 0, 1
Distributions	
θ_l	Distribution over topics given a label l, with prior α
ϕ_z	Distribution over words given a topic z and switch =0 (topic word), with prior γ
χ_s	Distribution over words given sentiment s and switch=1 (sentiment word), with prior δ_1
χ_{sz}	Distribution over words given a sentiment s and topic z and switch=1 (sentiment word), with prior δ_2
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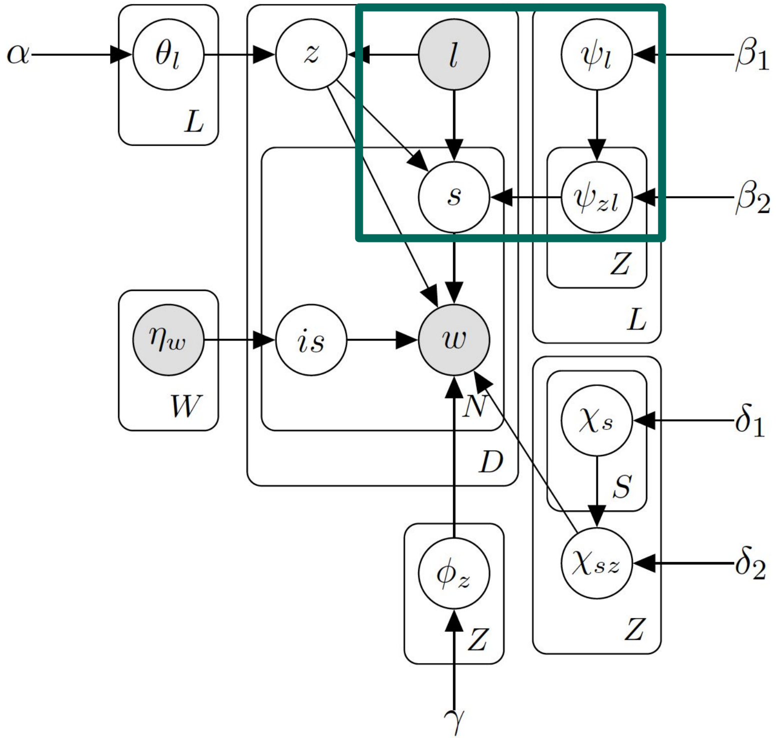

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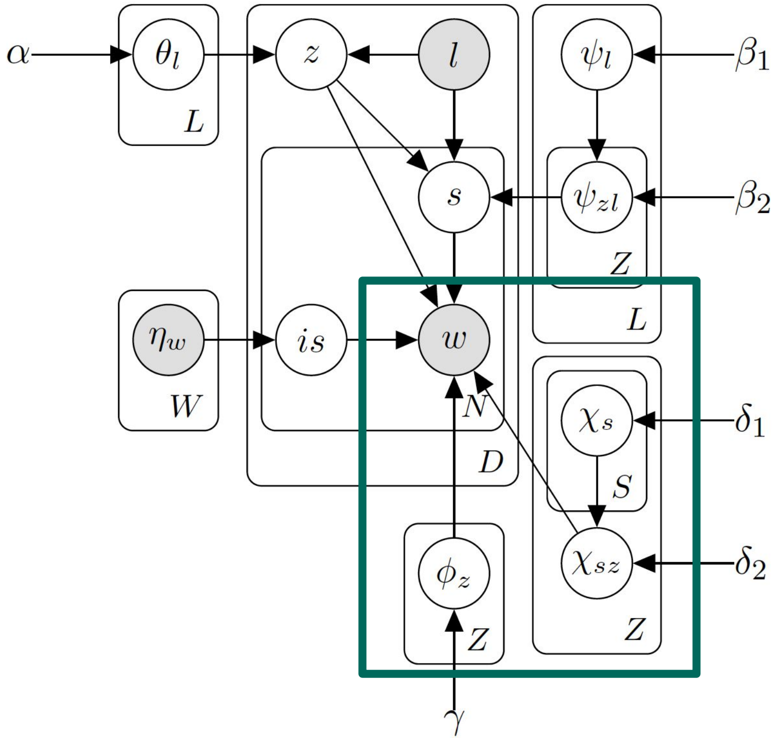

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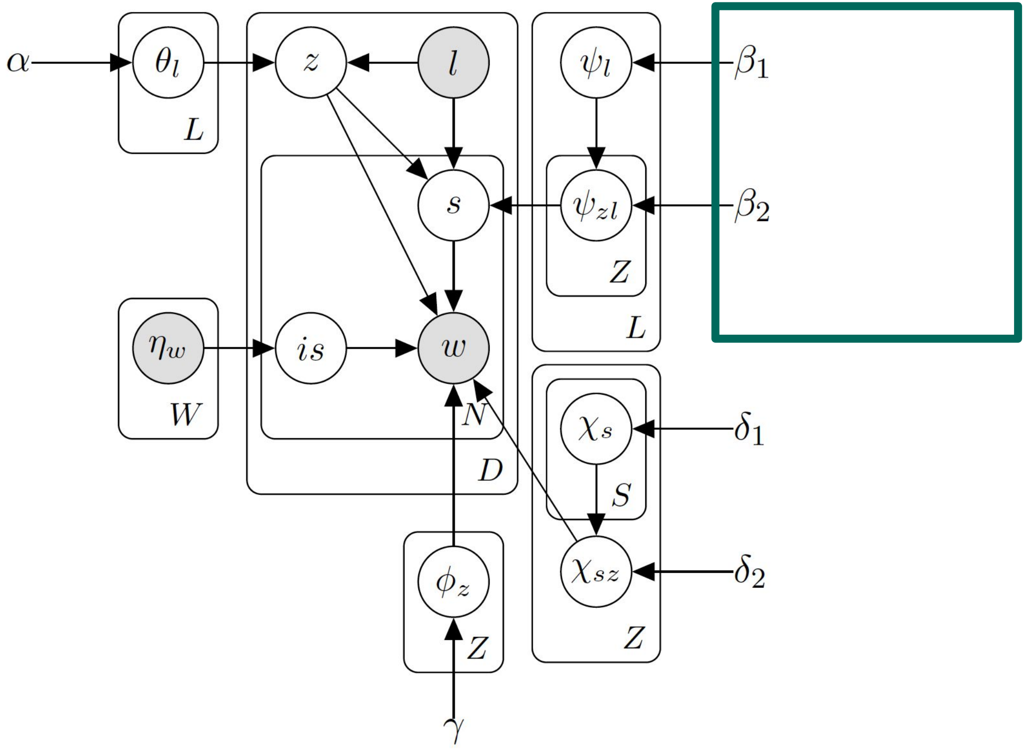

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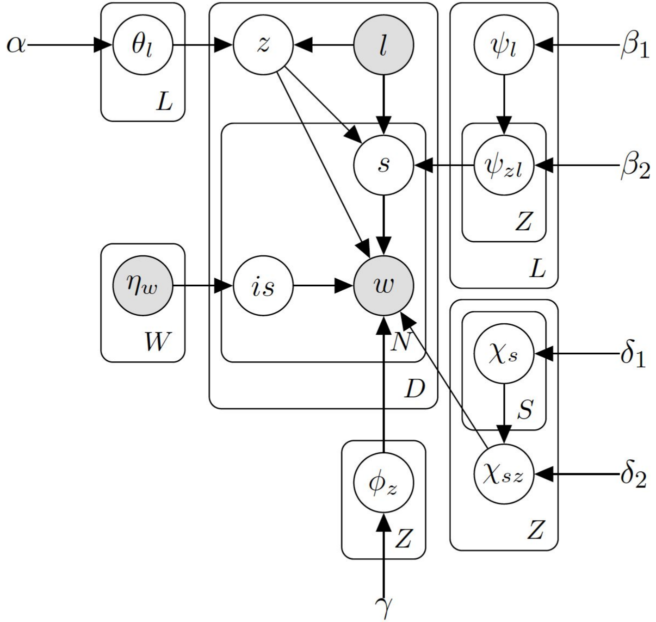
Experiment Setup

166,955 tweets, out of which nearly 75000 are sarcastic. Created using hashtag-based supervision



L=3

S=2

Z=50

Block-based Gibbs sampling

Results (1/4)

Music	work/school	Orlando Incident	Holiday	Quotes	Food
pop	work	orlando	summer	quote(s)	food
country	sleep	shooting	wekend	morning	lunch
rock	night	prayers	holiday	inspiration	vegan
bluegrass	morning	families	friends	motivation	breakfast
beatles	school	victims	sun,beach	mind	cake

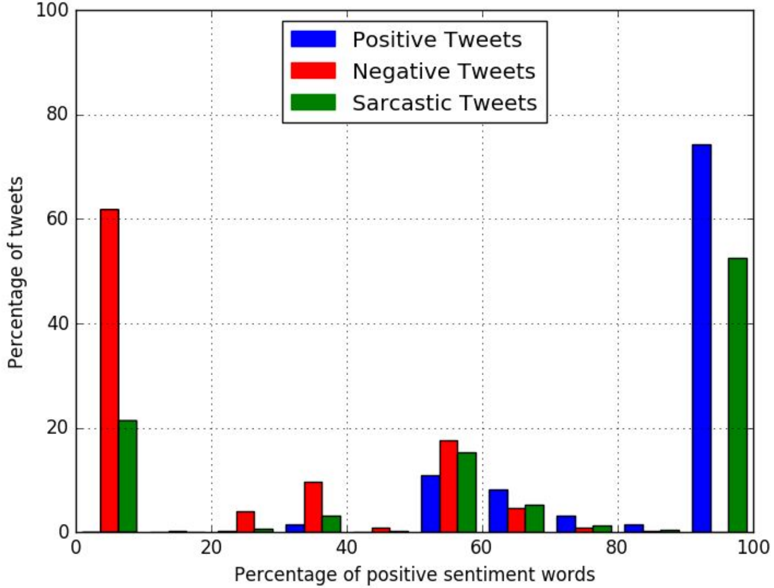
Stock(s)/ Commodities	Father	Gun	Pets	Health
silver	father(s)	gun(s)	dog	fitness
gold	dad	orlando	cat	gym
index	daddy	trump	baby	run
price	family	shooting	puppy	morning
consumer	work	muslim	pets	health

Top topic words for a set of topics

	Literal	Literal	
Topics P(l/z)	**Positive**	**Negative**	**Sarcastic**
Holiday	**0.9538**	0.0140	0.0317
Father	**0.9224**	0.0188	0.0584
Quote	**0.8782**	0.0363	0.0852
Food	**0.8100**	0.0331	0.1566
Music	**0.7895**	0.0743	0.1363
Fitness	**0.7622**	0.0431	0.1948
Orlando Incident	0.0130	**0.9500**	0.0379
Gun	0.1688	0.3074	**0.5230**
Work	0.1089	0.0354	**0.8554**
Humor	0.0753	0.1397	**0.7841**

Label distribution of topics

Results (2/4)



Distribution of tweets for different sentiment mixtures

Image from the original paper.

Application to sarcasm detection

1. Log-likelihood-based, for each label
2. Sampling-based

Compared with two prior works

Test set: 35398 total, 26210 positive, 5535 negative, **3653 sarcastic**

Results

Approach	P (%)	R (%)	F (%)
(Buschmeier et al., 2014)	10.41	100.00	18.85
(Liebrecht et al., 2013)	11.03	99.88	19.86
Topic Model: Log Likelihood	46.40	46.56	46.48
Topic Model: Sampling	45.94	47.70	**46.80**

Comparison of topic model-based sarcasm detection with past work;
For positive class

Algorithms for sarcasm detection

Module 4 of 7 (Part II)

Deep learning-based algorithms

Topic model for sarcasm

<u>Comparison of results</u>

Two focus works

	Details	Reported Performance
[67]	Conversation transcripts	F: 70, Acc: 87
[13]	Tweets	F: 54.5 Acc: 89.6
[68]	Reviews	F: 78.8
[69]	Similes	F: 88
[26]	Tweets	A: 75.89
[58]	Irony vs general	A: 70.12, F: 65
[56]	Reviews	F: 89.1, P: 88.3, R: 89.9
[41]	Tweets	AUC: 0.76
[45]	Discussion forum posts	F: 69, P: 75, R: 62
[55]	Speech data	Acc: 81.57
[59]	Irony vs humor	F: 76
[60]	Tweets	F: 51, P: 44, R: 62
[5]	Tweets	F: 62
[9]	Reviews	F: 71.3
[47]	Tweets	F: 91.03
[2]	Tweets	Acc: 85.1
[18]	Tweets	F: 83.59, Acc: 94.17
[20]	Tweets	Cosine: 0.758, MSE: 2.117
[22]	Tweets	F: 97.5
[28]	Irony vs politics	F: 81
[32]	Tweets/Disc. Posts	F: 88.76/64
[36]	Tweets	F: 88.2
[54]	Tweets	Acc: 83.46, AUC: 0.83
[73]	Reddits	P: 0.141, F: 0.377
[75]	Tweets	Macro-F: 69.13
[1]	Tweets	AUC: 0.6
[17]	Tweets	F: 82
[33]	TV transcripts	F: 84.4
[34]	Book snippets	F: 80.47
[48]	Tweets, Quotes and Reviews	F: 75.7
[50]	Reviews	F: 75.7
[63]	Tweets	Acc: 87.2

What is the state-of-art in sarcasm detection?

Algorithms for sarcasm detection

Module 4 of 7 (Part II)

Deep learning-based algorithms
Topic model for sarcasm
Comparison of results
Two focus works

Two works in focus

Sarcasm detection in numeric text

Sarcasm detection and understandability using eye-tracking

Two works in focus

Sarcasm detection in numeric text

Sarcasm detection and understandability using eye-tracking

Available on arXiv, September 2017.

About 17% of sarcastic tweets have origin in number

- This phone has an awesome battery back-up of 38 hours
- This phone has an awesome battery back-up of 2 hours
- This phone has a terrible battery back-up of 2 hours

About 17% of sarcastic tweets have origin in number

- This phone has an awesome battery back-up of 38 hours (Non-sarcastic)
- This phone has an awesome battery back-up of 2 hours (Sarcastic)
- This phone has a terrible battery back-up of 2 hours (Non-sarcastic)

Other examples

- waiting 45 min for the subway in the freezing cold is so much fun.
- well, 3 hrs of sleep this is awesome.
- gotta read 50 pages and do my math before tomorrow i'm so excited.
- -28 c with the windchill - fantastic 2 weeks.
- Woooo… when you're up to 12:30 finishing you're english paper.

Creating the dataset

Dataset-1	100000 (Sarcastic)	250000 (Non-Sarcastic)
Dataset-2	8681 (Numeric Sarcastic)	8681 (Numeric Non-Sarcastic)
Dataset-3	8681 (Numeric Sarcastic)	42107 (Numeric Non-Sarcastic)
Test Data	1843 (Numeric Sarcastic)	8317 (Numeric Non-Sarcastic)

Created using hashtag-based supervision

Three systems for numerical sarcasm detection

Rule-based

Statistical

Deep learning-based

Three systems for numerical sarcasm detection

Rule-based

Statistical

Deep learning-based

- Two repositories:
- Sarcastic and non-sarcastic, created using a training dataset
- Each entry in the repository is of the format:
    - *(Tweet No., Noun Phrase list, Number, Number Unit)*

"This phone has an awesome battery back-up of 2 hours",

```
(S
  This/DT
  (NP (NBAR phone/NN))
  has/VBZ
  an/DT
  (NP (NBAR awesome/JJ battery/NN backup/NN))
  of/IN
  2/CD
  (NP (NBAR hours/NNS)))
```

Noun phrases: ['phone', 'awesome', 'battery', 'backup', 'hours']

(Tweet No., ['phone', 'awesome', 'battery', 'backup', 'hours'], 2, 'hours')

Three systems for numerical sarcasm detection

Rule-based

Statistical

Deep learning-based

- Two repositories:
- Sarcastic and non-sarcastic, created using a training dataset
- Each entry in the repository is of the format:
  - *(Tweet No., Noun Phrase list, Number, Number Unit)*

Test sentence

- Consult the sarcastic tweet repository
- Match words in the noun phrase list between the test tweet and entries in the repository
- Select the most similar entry from the sarcastic repository
- If numbers are close, *sarcastic* else *non-sarcastic*
- *Repeat for non-sarcastic repository*
- *If numbers are far, sarcastic else non-sarcastic*

Three systems for numerical sarcasm detection

Rule-based

Statistical

Deep learning-based

- Two repositories:
- Sarcastic and non-sarcastic, created using a training dataset
- Each entry in the repository is of the format:
  - *(Tweet No., Noun Phrase list, Number, Number Unit)*

Test sentence

'I love writing this paper at 9 am'

- Consult the sarcastic tweet repository
- Match words in the noun phrase list between the test tweet and entries in the repository
- Select the most similar entry from the sarcastic repository
- If numbers are close, *sarcastic* else *non-sarcastic*
- *Repeat for non-sarcastic repository*
- *If numbers are far, sarcastic else non-sarcastic*

Closest sarcastic tweet: *'I love writing a paper at 3 am'*

*3 and 9 are **not close***

*Therefore, **non-sarcastic***

Three systems for numerical sarcasm detection

Rule-based

Statistical

Deep learning-based

- Two repositories:
- Sarcastic and non-sarcastic, created using a training dataset
- Each entry in the repository is of the format:
    - *(Tweet No., Noun Phrase list, Number, Number Unit)*

Test sentence

'I am so productive when my room is at 81 degrees'

- Consult the sarcastic tweet repository
- Match words in the noun phrase list between the test tweet and entries in the repository
- Select the most similar entry from the sarcastic repository
- If numbers are close, *sarcastic* else *non-sarcastic*
- *Repeat for non-sarcastic repository*
- *If numbers are far, sarcastic else non-sarcastic*

Closest non-sarcastic tweet: *'Very productive in my room when the temperature is 21 degrees'*

*81 and 21 are **not close***

*Therefore, **sarcastic***

Three systems for numerical sarcasm detection

Rule-based

Statistical

Deep learning-based

Three systems for numerical sarcasm detection

Rule-based

Statistical

Deep learning-based

Classifiers: SVM, KNN, Random Forest

Features:

Sentiment-based (#positive words, #negative words, #high emotional positive words, #high emotional negative words*, #both polarity words)

Emoticons (Positive emoticon, Negative emoticon, Both polarity emoticon),

Stylistic features (#exclamation, #dots, #question mark, #capitalization, #single quotes)

Numerical value

Unit of the numerical value

* Words with only these tags: 'JJ', 'JJR', 'JJS', 'RB', 'RBR', 'RBS', 'VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ'.

Three systems for numerical sarcasm detection

Rule-based

Statistical

Deep learning-based

Classifiers: SVM, KNN, Random Forest

Features:

Sentiment-based (#positive words, #negative words, #high emotional positive words, #high emotional negative words*, #both polarity words)

Emoticons (Positive emoticon, Negative emoticon, Both polarity emoticon),

Stylistic features (#exclamation, #dots, #question mark, #capitalization, #single quotes)

Numerical value

Unit of the numerical value

"This phone has an awesome battery back-up of 2 hours :) "

#positive: 1, #negative: 0, #high emotional: 0,.....

":)": 1 …. #capitalization: 1……

Numerical value: 2 Unit: hours

* Words with only these tags: 'JJ', 'JJR', 'JJS', 'RB', 'RBR', 'RBS', 'VB', 'VBD', 'VBG', 'VBN', 'VBP', 'VBZ'.

Three systems for numerical sarcasm detection

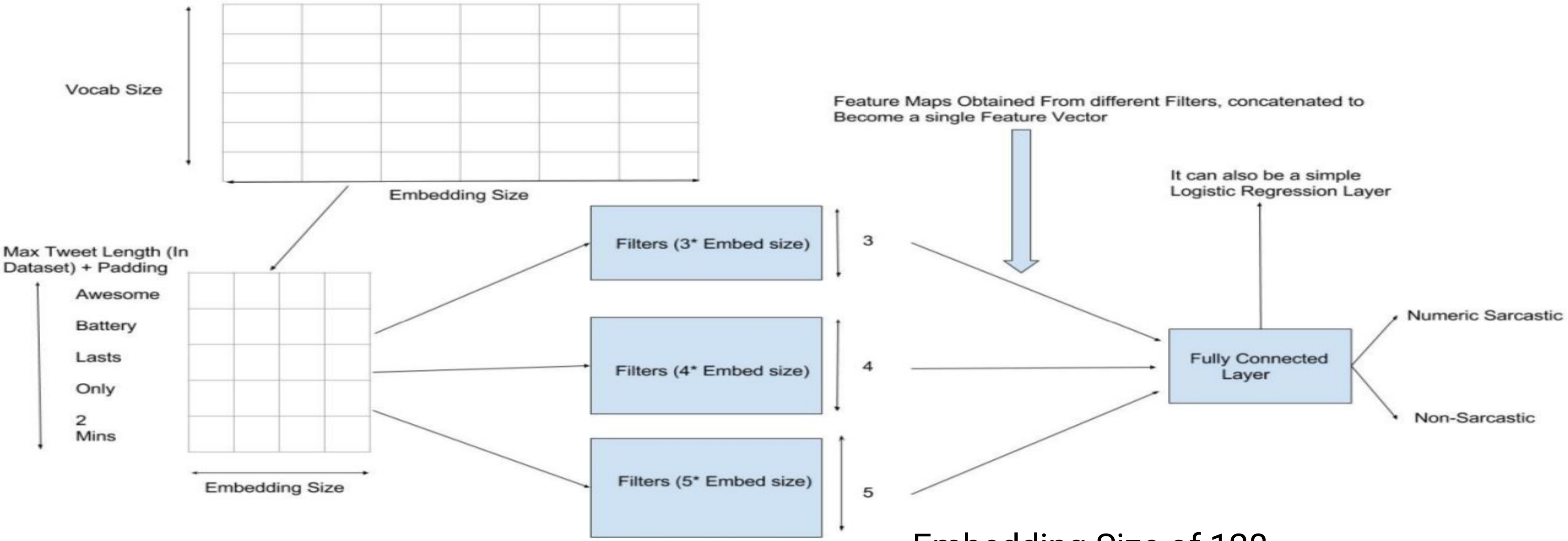
Rule-based

Statistical

Deep learning-based

Image from the original paper.

CNN-FF Model



Embedding Size of 128

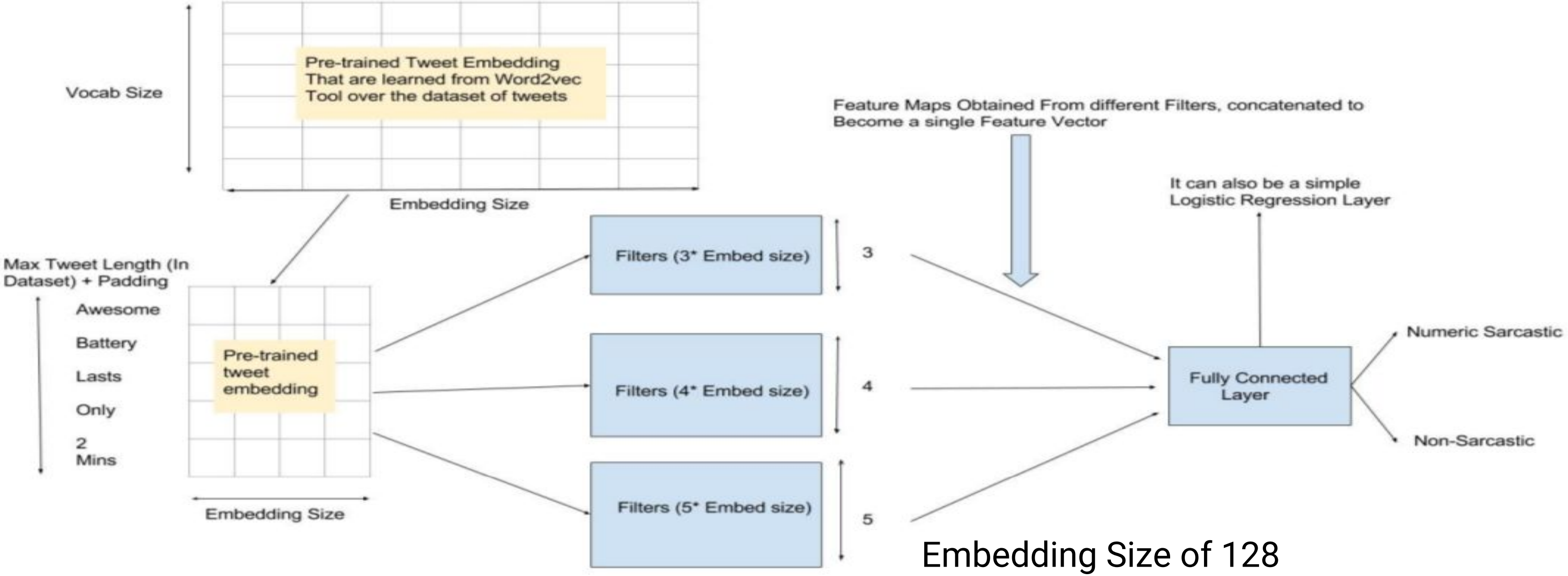
Maximum tweet length 36 words

Padding used

Filters of size 3, 4, 5 used to extract features

Image from the original paper.

CNN-FF Model



Embedding Size of 128

Maximum tweet length 36 words

Padding used

Filters of size 3, 4, 5 used to extract features

Results

Approaches	Precision			Recall			F-score		
	P(1)	P(0)	P(avg)	R(1)	R(0)	R(avg)	F(1)	F(0)	F(avg)
Past Approaches									
Buschmeier et.al.	0.19	0.98	0.84	0.99	0.07	0.24	0.32	0.13	0.16
Liebrecht et.al.	0.19	1.00	0.85	1.00	0.07	0.24	0.32	0.13	0.17
Gonzalez et.al.	0.19	0.96	0.83	0.99	0.06	0.23	0.32	0.12	0.15
Joshi et.al.	0.20	1.00	0.86	1.00	0.13	0.29	0.33	0.23	**0.25**
Rule-Based Approaches									
Approach-1	0.53	0.87	0.81	0.39	0.92	0.83	0.45	0.90	**0.82**
Approach-2	0.44	0.85	0.78	0.28	0.92	0.81	0.34	0.89	0.79
Machine-Learning Based Approaches									
SVM	0.50	0.95	0.87	0.80	0.82	0.82	0.61	0.88	**0.83**
KNN	0.36	0.94	0.84	0.81	0.68	0.70	0.50	0.79	0.74
Random Forest	0.47	0.93	0.85	0.74	0.81	0.80	0.57	0.87	0.82
Deep-Learning Based Approaches									
CNN-FF	**0.88**	**0.94**	**0.93**	**0.71**	**0.98**	**0.93**	**0.79**	**0.96**	**0.93**
CNN-LSTM-FF	0.82	0.94	0.92	0.72	0.96	0.92	0.77	0.95	0.92
LSTM-FF	0.76	0.93	0.90	0.68	0.95	0.90	0.72	0.94	0.90

1: Sarcastic, 0: Non-sarcastic

Analysis: Successes

- *“waiting 45 min for the subway in the freezing cold is so much fun iswinteroveryet”*
  - Classified as Numeric Sarcastic only by Deep learning based classifier
- *“unspeakably excited to take a four hour practice act for the 4th time.”*
  - Classified as Numeric Sarcastic by both the CNN architectures only.
- *"yeah wasted $3 to go two stops thanks for the service ttc crapservice.”*
  - Classified as Numeric Sarcastic only by Deep learning based classifier.

Analysis: Failures

- *“my mother has the talent of turning a 10 minute drive into a 25 minute drive needforspeed”.*
- *“arrived at school 6:30 this morning yeah we have an easy life we work 8-3 @ john h”.*
- *“woke up to hrs ago and i can barely keep my eyes open best part of my day i don't get home til 7 pm”.*
- *“hey airlines i really appreciate you canceling my direct flight home and sending me 1000 miles out of the way to connect”.*

Two works in focus

Sarcasm detection in numeric text

Sarcasm detection and understandability using eye-tracking

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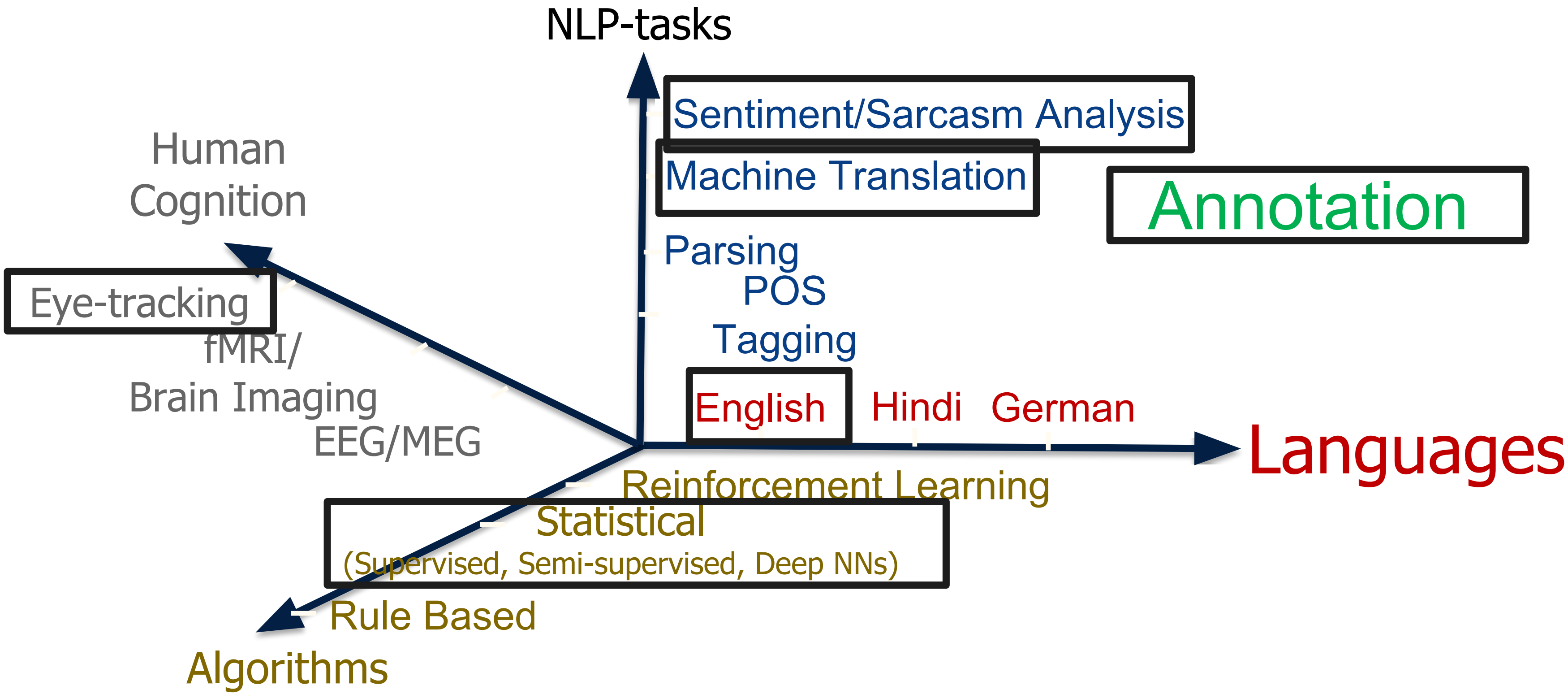
Let’s go back to the NLP Trinity



Eye-tracking Technology

Invasive and non-invasive eye-trackers

For linguistic studies, non-invasive eye-trackers are used

- **Data delivered by eye-trackers**
  - Gaze co-ordinates of both eyes (binocular setting) or single eye (monocular setting)
  - Pupil size
- **Derivable data**
  - Fixations, Saccades, Scanpaths, Specific patterns like progression and regression.

Images from www.tobii.com

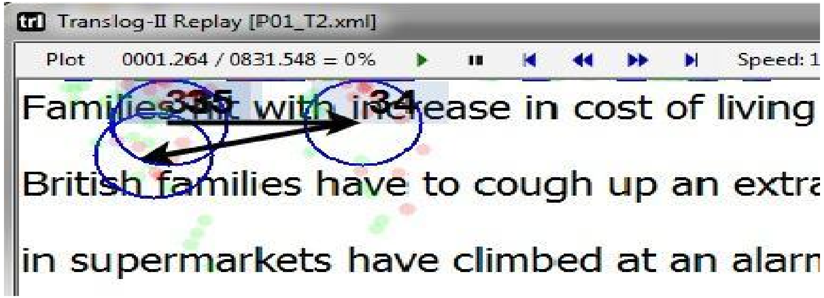
Nature of Gaze Data

- **Gaze Point:** Position (co-ordinate) of gaze on the screen

- **Fixations :** A long stay of the gaze on a particular object on the screen

- **Saccade:** A very rapid movement of eye between the positions of rest.
  - Progressive Saccade / Forward Saccade / Progression
  - Regressive Saccade / Backward Saccade / Regression

- **Scanpath:** A path connecting a series of fixations.



Images from www.tobii.com

Eye Movement and Cognition

Eye-Mind Hypothesis (Just and Carpenter, 1980)

When a subject is views a word/object, he or she also processes it cognitively, for approximately the same amount of time he or she fixates on it.

Considered useful in explaining theories associated with reading (Rayner and Duffy,1986; Irwin, 2004; von der Malsburg and Vasishth, 2011)

Linear and uniform-speed gaze movement is observed over texts having simple concepts, and often non-linear movement with non-uniform speed over more complex concepts (Rayner, 1998)

Images from www.tobii.com

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Harnessing Cognitive Features for Sarcasm Detection (Mishra, Bhattacharyya et al, ACL 2016)

Augmenting cognitive features

Textual	Simple gaze	Complex gaze
(1) Unigrams (2) Punctuations (3) Implicit incongruity (4) Explicit Incongruity (5) Largest +ve/-ve subsequences (6) +ve/-ve word count (7) Lexical Polarity (8) Flesch Readability Ease, (9) Word count	(1) Average Fixation Duration, (2) Average Fixation Count, (3) Average Saccade Length, (4) Regression Count, (5) Number of words skipped, (6) Regressions from second half to first half, (7) Position of the word from which the largest regression starts	(1) Edge density, (2) Highest weighted degree (3) Second Highest weighted degree (With different edge-weights)

Experiment Setup

- **Dataset**:
    - 994 text snippets : 383 positive and 611 negative, 350 are sarcastic/ironic
    - Mixture of Movie reviews, Tweets and sarcastic/ironic quotes
    - Annotated by 7 human annotators
    - Annotation accuracy: **70%-90%** with Fleiss kappa IAA of **0.62**

- **Classifiers**:
    - Naïve Bayes, SVM, Multi Layered Perceptron
    - Feature combinations:
        - Unigram Only
        - Gaze Only (Simple + Complex)
        - Textual Sarcasm Features (Joshi et., al, 2015) (Includes unigrams)
        - Gaze+ Sarcasm

- **Compared with** : **Riloff, 2013 and Joshi, 2015**

Results

Features	P(1)	P(-1)	P(avg)	R(1)	R(-1)	R(avg)	F(1)	F(-1)	F(avg)
Multi Layered Neural Network									
Unigram	53.1	74.1	66.9	51.7	75.2	66.6	52.4	74.6	66.8
Sarcasm (Joshi et. al.)	59.2	75.4	69.7	51.7	80.6	70.4	55.2	77.9	69.9
Gaze	62.4	76.7	71.7	54	82.3	72.3	57.9	79.4	71.8
Gaze+Sarcasm	63.4	75	70.9	48	84.9	71.9	54.6	79.7	70.9
Näive Bayes									
Unigram	45.6	82.4	69.4	81.4	47.2	59.3	58.5	60	59.5
Sarcasm (Joshi et. al.)	46.1	81.6	69.1	79.4	49.5	60.1	58.3	61.6	60.5
Gaze	57.3	82.7	73.8	72.9	70.5	71.3	64.2	76.1	71.9
Gaze+Sarcasm	46.7	82.1	69.6	79.7	50.5	60.8	58.9	62.5	61.2
Original system by Riloff et.al. : Rule Based with implicit incongruity									
Ordered	60	30	49	50	39	46	54	34	47
Unordered	56	28	46	40	42	41	46	33	42
Original system by Joshi et.al. : SVM with RBF Kernel									
Sarcasm (Joshi et. al.)	73.1	69.4	70.7	22.6	95.5	69.8	34.5	80.4	64.2
SVM Linear: with default parameters									
Unigram	56.5	77	69.8	58.6	75.5	69.5	57.5	76.2	69.6
Sarcasm (Joshi et. al.)	*59.9*	*78.7*	*72.1*	*61.4*	*77.6*	*71.9*	*60.6*	*78.2*	*72*
Gaze	**65.9**	75.9	72.4	49.7	86	73.2	56.7	80.6	72.2
Gaze+Sarcasm	63.7	79.5	74	61.7	80.9	74.1	62.7	80.2	74
Multi Instance Logistic Regression: Best Performing Classifier									
Gaze	65.3	77.2	73	53	**84.9**	73.8	58.5	**80.8**	73.1
Gaze+Sarcasm	62.5	**84**	**76.5**	**72.6**	76.7	**75.3**	**67.2**	80.2	**75.7**

Results

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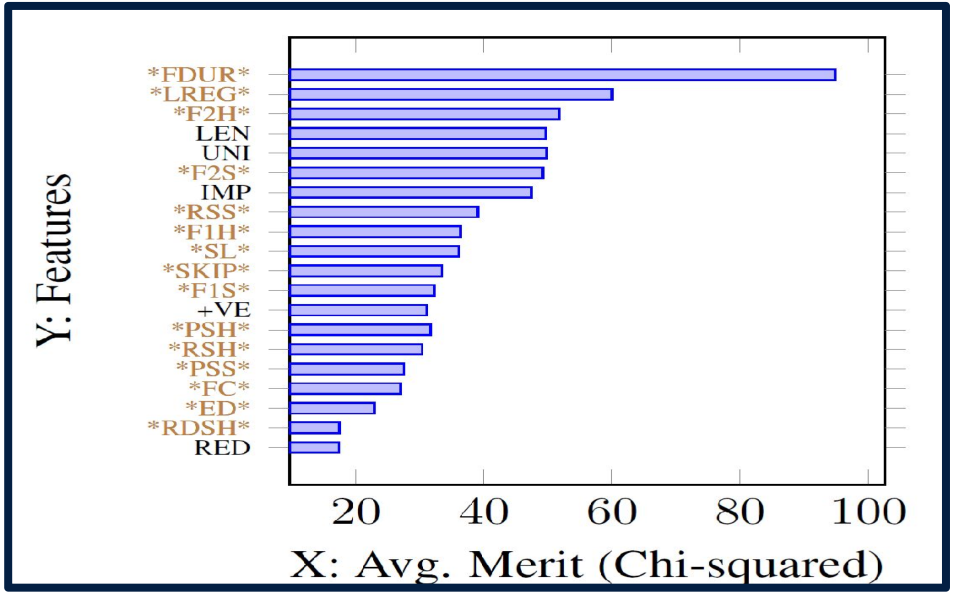
p=0.01

p=0.03

Feature Significance



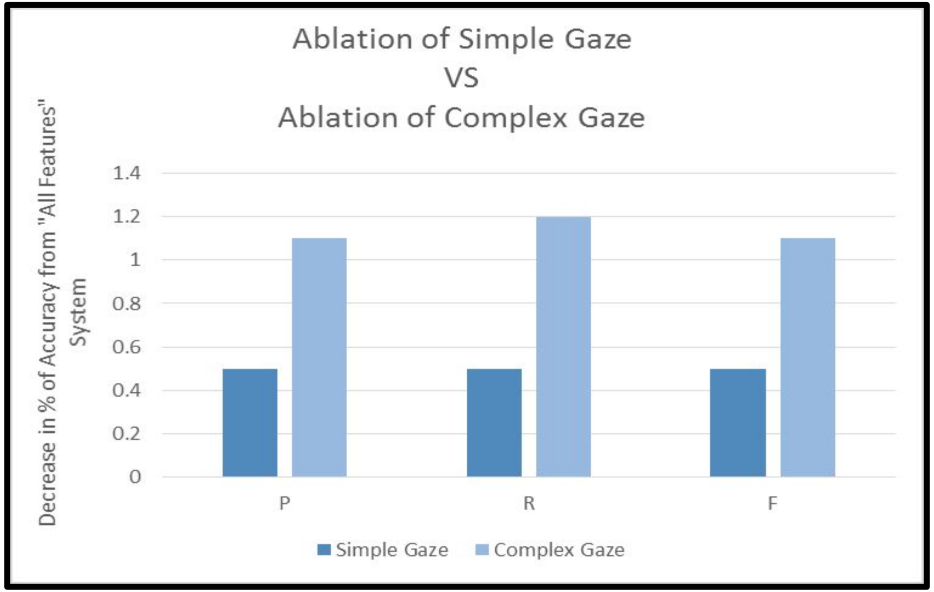


Image from the original paper.

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Sarcasm detection in numeric text

Sarcasm detection and understandability using eye-tracking

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Predicting Readers' Sarcasm Understandability By Modeling Gaze Behavior (Mishra, Bhattacharyya et al, AAAI 2016)

Sarcasm, cognition and eye movement

- Sarcasm often emanates from **context incongruity** (Campbell and Katz 2012), which, possibly, surprises the reader and enforces a re-analysis of the text.
- In the absence of any information, human brain would start processing the text in a sequential manner, with the aim of comprehending the literal meaning.
- When incongruity is perceived, the brain initiates a re-analysis to reason out such disparity (Kutas et al.,1980).

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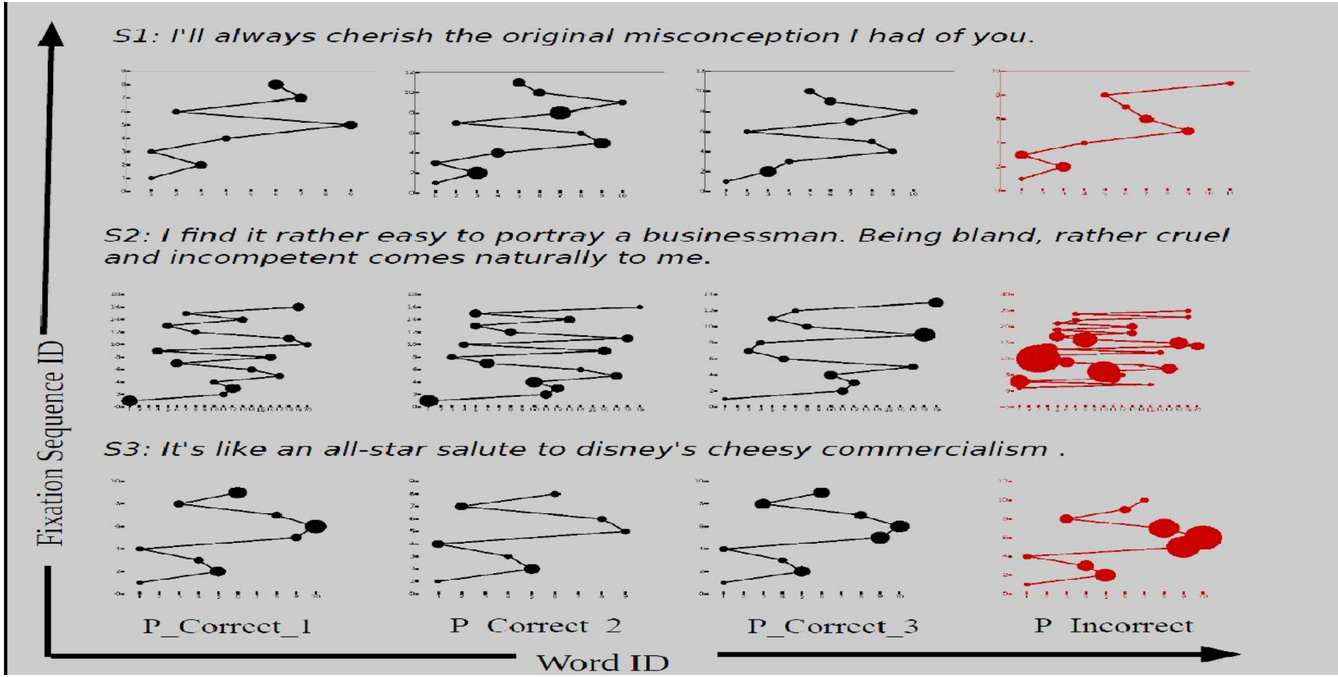
Hypothesis: Incongruity may affect the way eye-gaze moves through the text. Hence, distinctive eye-movement patterns may be observed when sarcasm is understood in contrast to an unsuccessful attempt.

Sarcasm understandability - Scanpath Representation



Dataset

- **Document Description:**1000 short texts – Movie reviews, tweets and quotes, 350 sarcastic 650 non-sarcastic
- Ground truth verified by linguists. Grammatical mistakes corrected to avoid reading difficulties.
- **Participant Description:** 7 graduates from Engineering and Science background.
- **Task Description:** Texts annotated with sentiment polarity labels. Gaze data collected using Eye-link 1000 plus tracker following standard norms (Holmqvist et al. 2011)
- **Annotation Accuracy (IAA):** Highest- **90.29%,** Lowest- **72.57%,** Average- **84.64**% (Domain wise: Movie: **83.27%**, Quote: **83.6%**, Twitter: **84.88%)**

Analysis of eye movement data

- **Variation in Basic Gaze attributes:** Average Fixation Duration and Number of Regressive Saccades significantly higher ($p<0.0001$ and $p<0.01$) when sarcasm is not understood than when it is.

- **Variation in Scanpaths:** For two incongruous phrases A and B, Regressive Saccades often seen from B to A when sarcasm is successfully realized. Moreover, Fixation duration is more on B than A.

- **Qualitative observations from Scanpaths:** Sarcasm not understood due to: (i) Lack of attention (ii) Lack of realization of context incongruity

Sarcasm understandability features

Textual	Gaze-based
(1) # of interjections (2) # of punctuations (3) # of discourse connectors (4) # of flips in word polarity (5) Length of the Largest Pos/Neg Subsequence (6) # of Positive words (7) # of Negative words (8) Flecsh's reading ease score (9) Number of Words	(1) Avg. Fixation Duration (AFD) (2) Avg. Fixation Count (3) Avg. Saccade Length (4) # of Regressions (5) # of words skipped (6) AFD on the 1^{st} half of the text (7) AFD on the 2^{nd} half of the text (8) # of regressions from the 2^{nd} half to the 1^{st} half (9) Position of the word from which the longest regression happens. (10) Scanpath Complexity

Results

Classifier: Multi-instance Logistic Regression (Xu and Frank 2004). Each training example corresponds to one sentence. Each example “bags” a maximum of 7 instances, one for each participant. Each instance is a combination of Gaze and Textual Features.

Class	sarcasm_miss			sarcasm_hit			Weighted Avg.			Kappa
	P	R	F	P	R	F	P	R	F	Avg.
	Baseline1: Classification based on class frequency									
All	16.1	15.5	15.7	86.5	87	86.7	85.9	86.71	86.3	0.014
	Baseline2: MILR Classifier considering time taken to read + textual features									
All	23.6	86.9	78.2	11.5	94.1	82.7	15.4	90.4	80	0.0707
	Our approach: MILR Classifier considering only gaze features									
All	82.6	36	50	89.9	98.7	94.1	88.8	89.4	87.5	0.4517
	Our approach: MILR Classifier considering gaze + textual features									
Quote	68.1	47.5	56.0	91.8	96.3	94.0	88.4	89.4	88.6	0.5016
Movie	42.9	36.6	39.5	88.6	91.0	89.8	81.4	82.5	81.9	0.293
Twitter	63.0	61.7	62.4	94.4	94.7	94.6	90.4	90.5	90.5	0.5695
All	**87.8**	**61**	**72**	**94.1**	**98.6**	**96.3**	**93.2**	**93.5**	**93**	**0.6845**

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3. **Learning cognitive features for sarcasm detection (ACL 2017)**

Abhijit Mishra, Kuntal Dey and Pushpak Bhattacharyya, *Learning Cognitive Features from Gaze Data for Sentiment and Sarcasm Classification Using Convolutional Neural Network*, ACL 2017, Vancouver, Canada, July 30-August 4, 2017.

CNN-FF combination

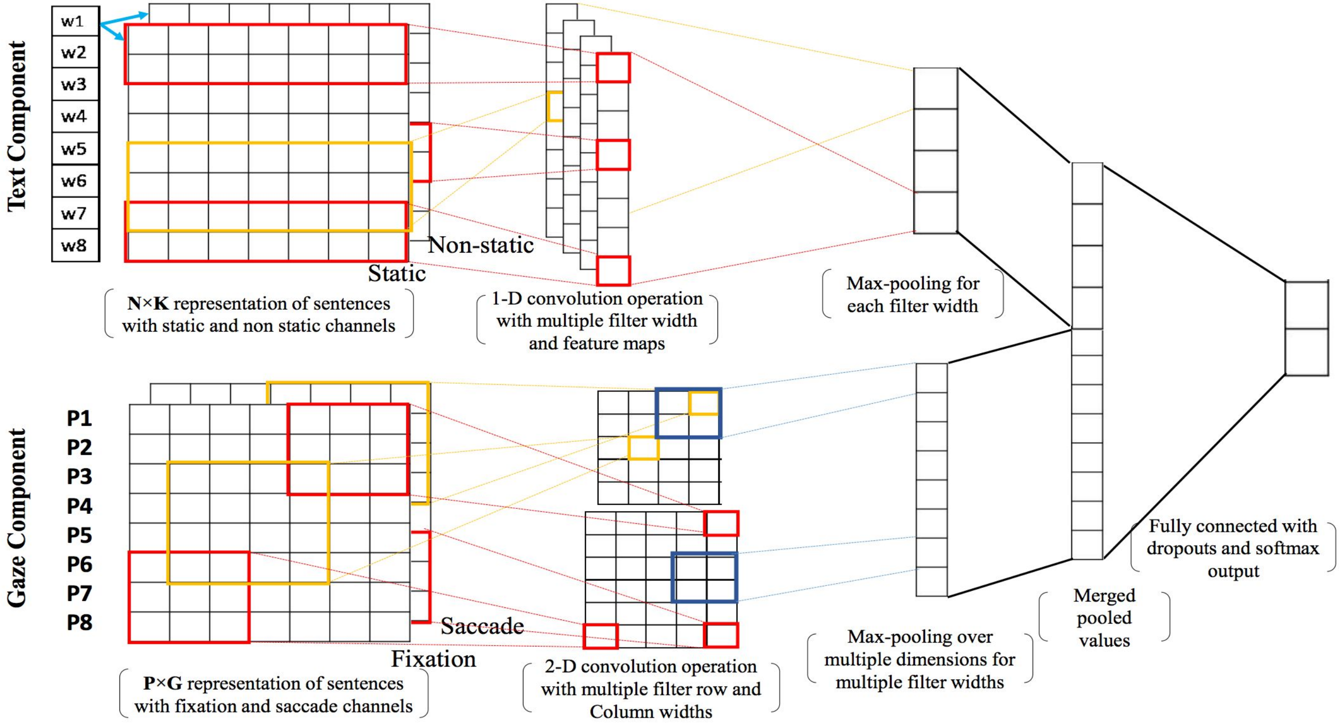


Image from the original paper.

Results

	Configuration	Precision	Recall	F_Score
Gaze	Gaze-Fixation	74.39	69.62	**71.93**
	Gaze-Saccade	68.58	68.23	68.40
	Gaze-Multi-channel	67.93	67.72	67.82
Text	Text-static	67.17	66.38	66.77
	Text-non-static	84.19	87.03	**85.59**
	Text-Multi-channel	84.28	87.03	**85.63**
Gaze & Text	Text-static_Gaze-Fixation	72.38	71.93	72.15
	Text-static_Gaze-Saccade	73.12	72.14	72.63
	Text-static_Gaze-Multi-channel	71.41	71.03	71.22
	Text-non-static_Gaze-Fixation	87.42	85.2	**86.30**
	Text-non-static_Gaze-Saccade	84.84	82.68	83.75
	Text-non-static_Gaze-Multi-channel	84.98	82.79	83.87
	Text-Multi-channel_Gaze-Fixation	87.03	86.92	**86.97**
	Text-Multi-channel_Gaze-Saccade	81.98	81.08	81.53
	Text-Multi-channel_Gaze-Multi-channel	83.11	81.69	82.39

(a) Results with Deep CNNs

Configuration	Precision	Recall	F_Score
Gaze_NB	73.8	71.3	71.9
Gaze_SVM	**72.4**	**73.2**	**72.2**
Gaze_MLP	71.7	72.3	71.8

(b) CoNLL systems with Gaze Features

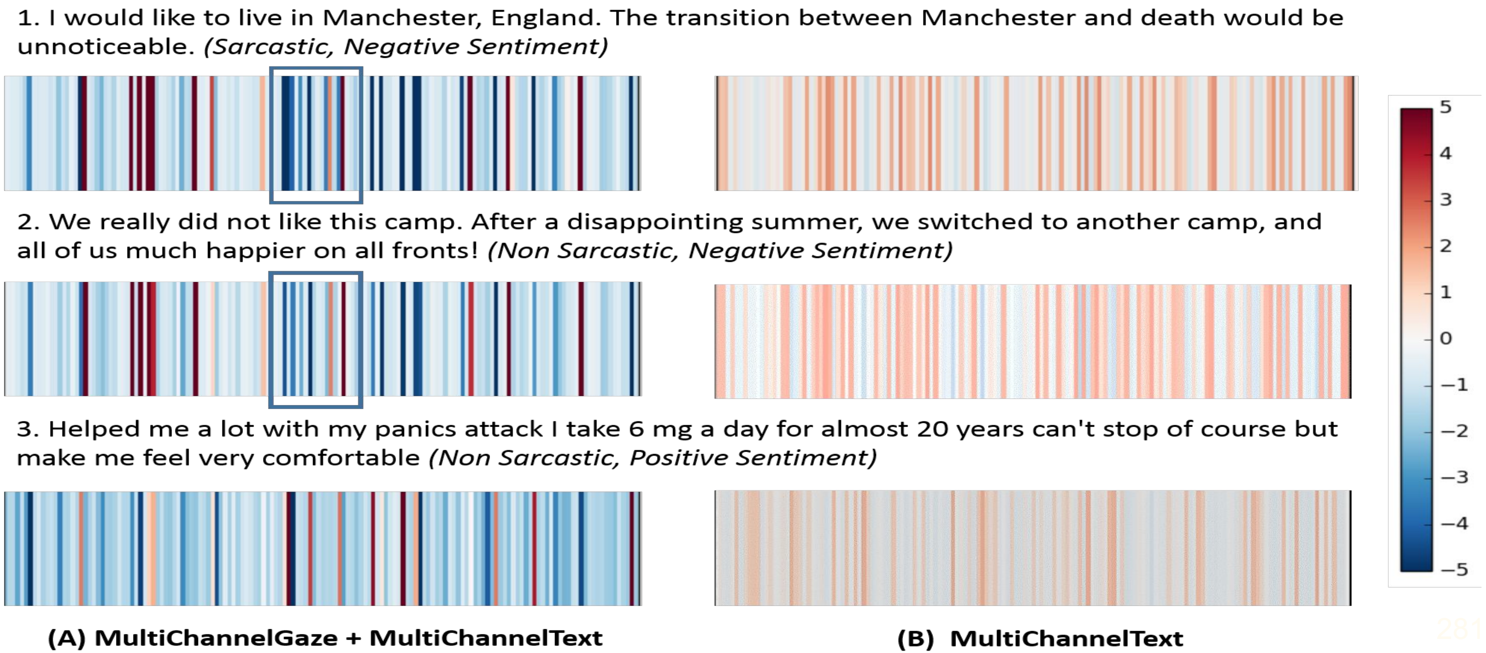
Configuration	Precision	Recall	F_Score
Gaze_Text_NB	**70.9**	71.9	71.2
Gaze_Text_SVM	**74**	**74.1**	**74**
Gaze_Text_MLP	70.9	71.9	70.9

(c) CoNLL systems with Gaze+Text Features

Observations

- **Higher classification accuracy**
  - Clear differences between vocabulary of sarcasm and no-sarcasm classes in our dataset, Captured well by non-static embeddings.
- **Effect of dimension variation**
  - Reducing embedding dimension improves accuracy by a little margin.
- **Effect of fixation / saccade channels:**
  - Fixation and saccade channels perform with similar accuracy when employed separately.
  - Accuracy reduces with gaze multichannel (may be because the higher variation of both fixations and saccades across sarcastic and non-sarcastic classes, unlike sentiment classes).

Analysis of Features



Visualization of representations learned by two variants of the network. The output of the Merge layer (of dimension 150) are plotted in the form of colour-bars following Li et al. (2016)

Scope of today’s tutorial

Introduction

Challenges, Motivation, etc.

Sarcasm in Linguistics

Definitions, Theories, etc.
Notion of ‘incongruity’

Datasets

Datasets, annotation strategies, challenges, etc.

Algorithms

Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

Algorithms - 2

Traditional classifier techniques (contd), Deep learning-based techniques, etc.

Incorporating context

Context of the author, the conversation, etc.

Beyond sarcasm detection

Sarcasm generation, sarcasm v/s irony classification, etc.

Conclusion

Summary, pointers to future work

Image of coffee from wikimedia commons.

Incorporating Context for Sarcasm Detection

Module 5 of 7

Objective: To discuss ways in which contextual information can be captured for sarcasm detection

Motivation
Background
Incongruity with Author's historical context
Incongruity with Conversational context

Incorporating Context for Sarcasm Detection

Module 5 of 7

Motivation

Background

Incongruity with Author’s historical context

Incongruity with Conversational context

A comic strip in reverse

Images of gift, watch, human and TV from the web.

A comic strip in reverse

An old, broken watch

Images of gift, watch, human and TV from the web.

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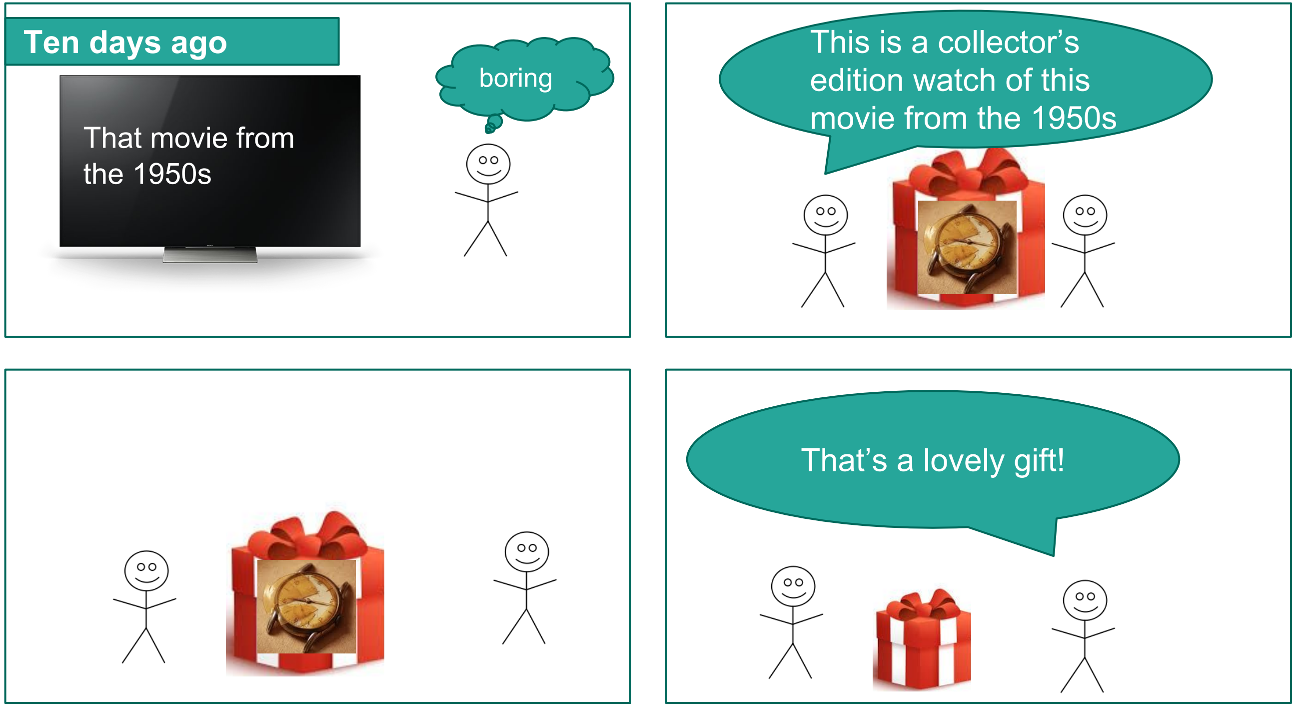

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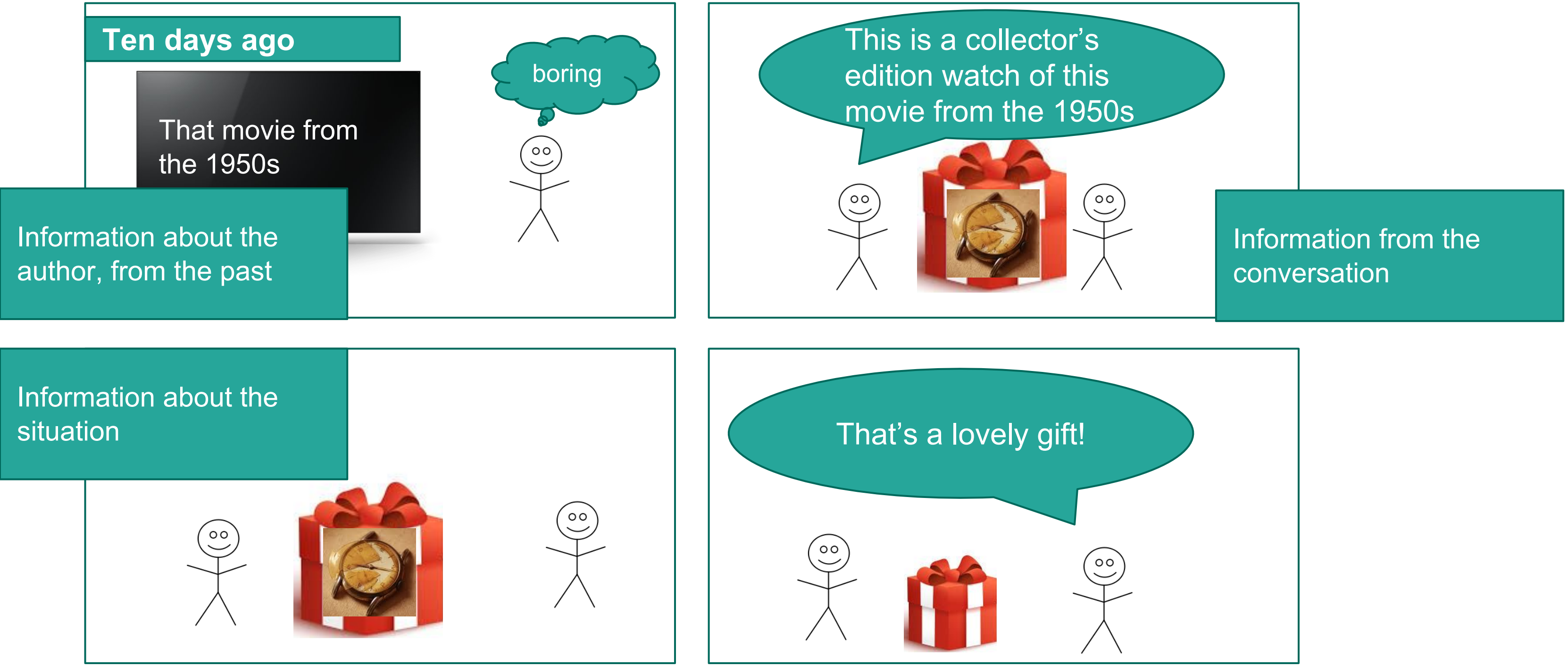

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Module 5 of 7

Objective: To discuss ways in which contextual information can be captured for sarcasm detection

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Incongruity with Author’s historical context
Incongruity with Conversational context

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- Contextual information becomes imperative for several forms of sarcasm
- Context: ‘*with*’-text
- Target text: The text to be classified as sarcastic or not
- Incongruity with some context

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Target text: ‘*Yeah right!*’

Potential context incongruity: Other statements in the conversation

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Target text: ‘*Yeah right!*’

Potential context incongruity: Other statements in the conversation

Target text: ‘*These are the best school holidays ever*”

Potential context incongruity: Other statements in the conversation, information about the situation

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- Context: ‘*with*’-text
- Target text: The text to be classified as sarcastic or not
- Incongruity with some context

Target text: ‘*Yeah right!*’

Potential context incongruity: Other statements in the conversation

Target text: ‘*These are the best school holidays ever*”

Potential context incongruity: Other statements in the conversation, information about the situation

Target text: *‘Students generally submit their assignments on time!’*

Potential context incongruity: Other statements in the conversation, information about the situation

Context

- Contextual information becomes imperative for several forms of sarcasm
- Context: ‘*with*’-text
- Target text: The text to be classified as sarcastic or not
- Incongruity with some context

Target text: ‘*Yeah right!*’

Potential context incongruity: Other statements in the conversation

Target text: ‘*These are the best school holidays ever*”

Potential context incongruity: Other statements in the conversation, information about the situation

Target text: *‘Students generally submit their assignments on time!’*

Potential context incongruity: Other statements in the conversation, information about the situation

Target text: ‘Yes, this looks good to me!’

Potential context incongruity: Other statements in the conversation, information about the situation

Context

- Contextual information becomes imperative for several forms of sarcasm
- Context: ‘*with*’-text
- Target text: The text to be classified as sarcastic or not
- Incongruity with some context
- ***Wallace et al (2014) presented a first study to highlight the need of context***

Target text: ‘*Yeah right!*’

Potential context incongruity: Other statements in the conversation

Target text: ‘*These are the best school holidays ever*”

Potential context incongruity: Other statements in the conversation, information about the situation

Target text: *‘Students generally submit their assignments on time!’*

Potential context incongruity: Other statements in the conversation, information about the situation

Target text: ‘Yes, this looks good to me!’

Potential context incongruity: Other statements in the conversation, information about the situation

Types of contextual information

Information about the author
- Background information
- Text generated in the past

Information about the conversation
- Non-verbal cues
- Previous utterances in the conversation

Information about the topic
- Historical context about the topic

Types of contextual information

Information about the author

- Background information
- Text generated in the past

} Information about the speaker from the speaker's historical interactions

Information about the conversation

- Non-verbal cues
- Previous utterances in the conversation

} Information about the conversation from utterances preceding (or following) the target text

Information about the topic

- Historical context about the topic

} Information about propensity of the topic to be sarcastic

Incorporating Context for Sarcasm Detection

Module 5 of 7

Motivation

Background

Incongruity with Author's historical context

Incongruity with Conversational context

Incongruity with historical context

Additional information about the speaker that may help determine sarcasm in the target text

Caveats:

Availability of data on the platform

Sparse data

Closed-world assumption

Incongruity with historical context

Additional information about the speaker that may help determine sarcasm in the target text

Caveats:

Availability of data on the platform: *Historical data needs to be accessible*

Sparse data

Closed-world assumption

Incongruity with historical context

Additional information about the speaker that may help determine sarcasm in the target text

Caveats:

Availability of data on the platform

Sparse data: *Historical data needs to be present (the classic ‘cold-start’)*

Closed-world assumption

Incongruity with historical context

Additional information about the speaker that may help determine sarcasm in the target text

Caveats:

Availability of data on the platform

Sparse data

Closed-world assumption: *What is present is true. Unless it can be determined otherwise, historical data is true and historical text is non-sarcastic.*

Incorporation of historical context

User's historical context has been incorporated for sarcasm classification in three ways:

1. As features in a statistical classifier
2. As rules in a rule-based systems
3. In the form of user embeddings

Historical Context Features: Categories

Demographic Properties

Demographic information of the user

Behavioral Properties

What kind of topics, sentiment, etc. has this user manifested in the past?

Familiarity-based Properties

How familiar is this user to express sarcasm on the given social medium?

Historical Context Features

	Rajadesingan et al (2015)	Bamman and Smith (2015)
Demographic Properties		User profile information: Gender, Age, etc.
Behavioral Properties	Positive/negative n-grams, number of sentiment changes, affective scores, etc.	Author historical salient terms: High TF-IDF terms by this author Author historical topics: Topic distribution of this author's tweets Profile unigrams: Unigrams in all tweets by this author Author historical sentiment: Probability of positive/negative
Familiarity-based Properties	Familiarity of language: Vocabulary skills, (usage of words), Grammar skills, Familiarity with sarcasm, Familiarity with Twitter:Frequency of tweeting, frequency of using hashtags, social network graph, etc.	Historical communication between author and addressee: Number of interactions, etc. Author/addressee interactional topics

Incorporating Historical Context as rules

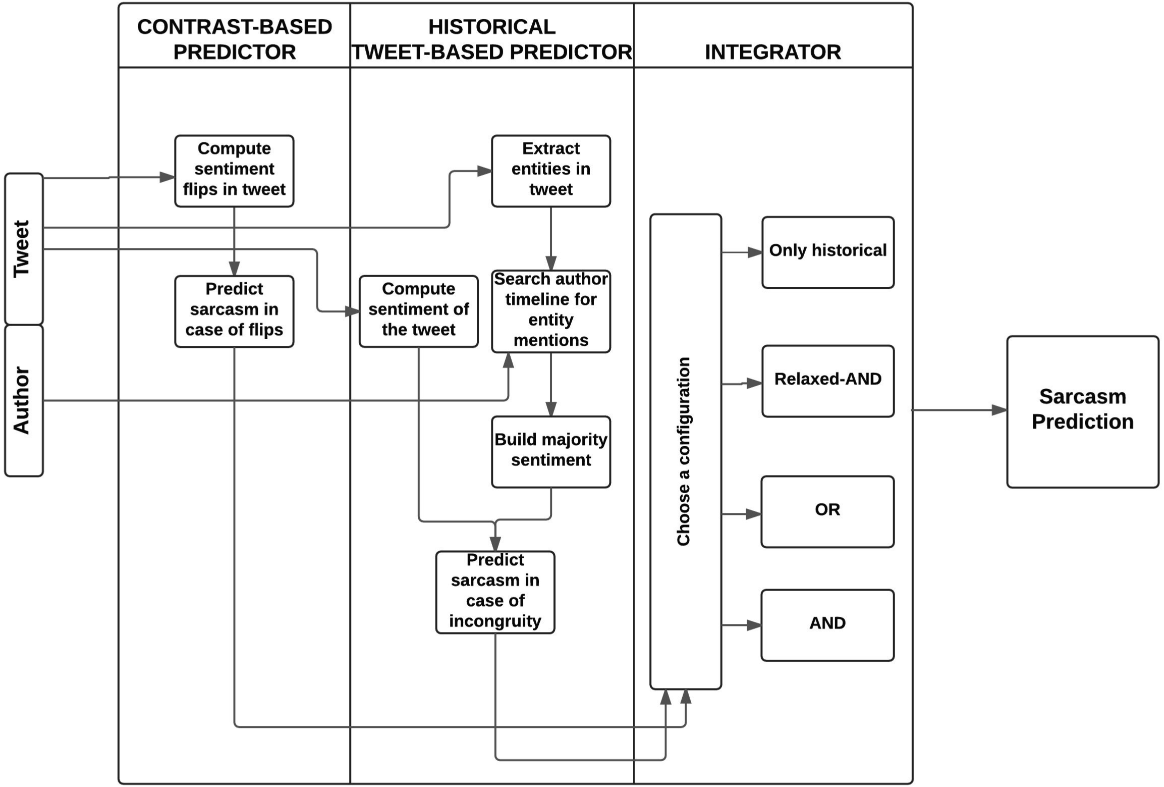
A rule-based system that combines simple sentiment incongruity with historical sentiment incongruity

Input: (Tweet, Twitter User/Author)
Output: Sarcastic/Non-sarcastic

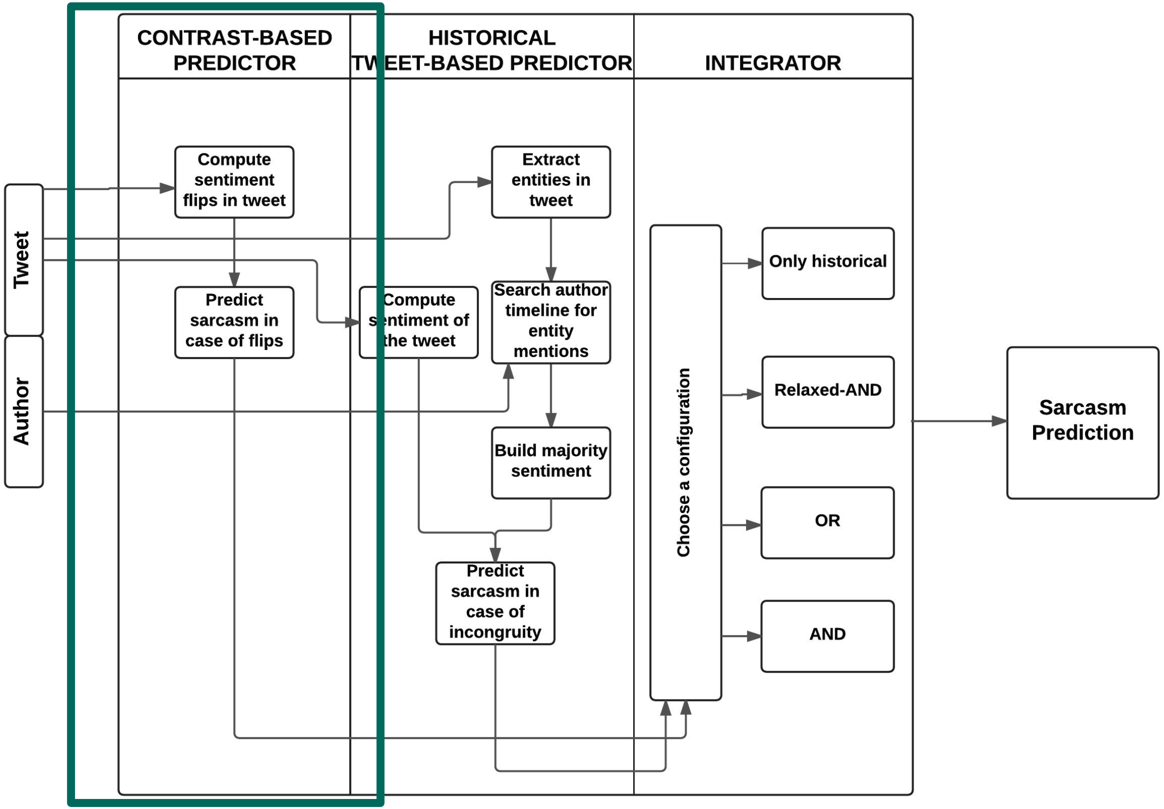
Assumption: The author has past tweets in order to capture her/his historical sentiment

Anupam Khattri, Aditya Joshi, Pushpak Bhattacharyya, Mark J Carman, Your sentiment precedes you: Using an author's historical tweets to predict sarcasm, WASSA at EMNLP 2015, Lisbon, Portugal, September 2015.

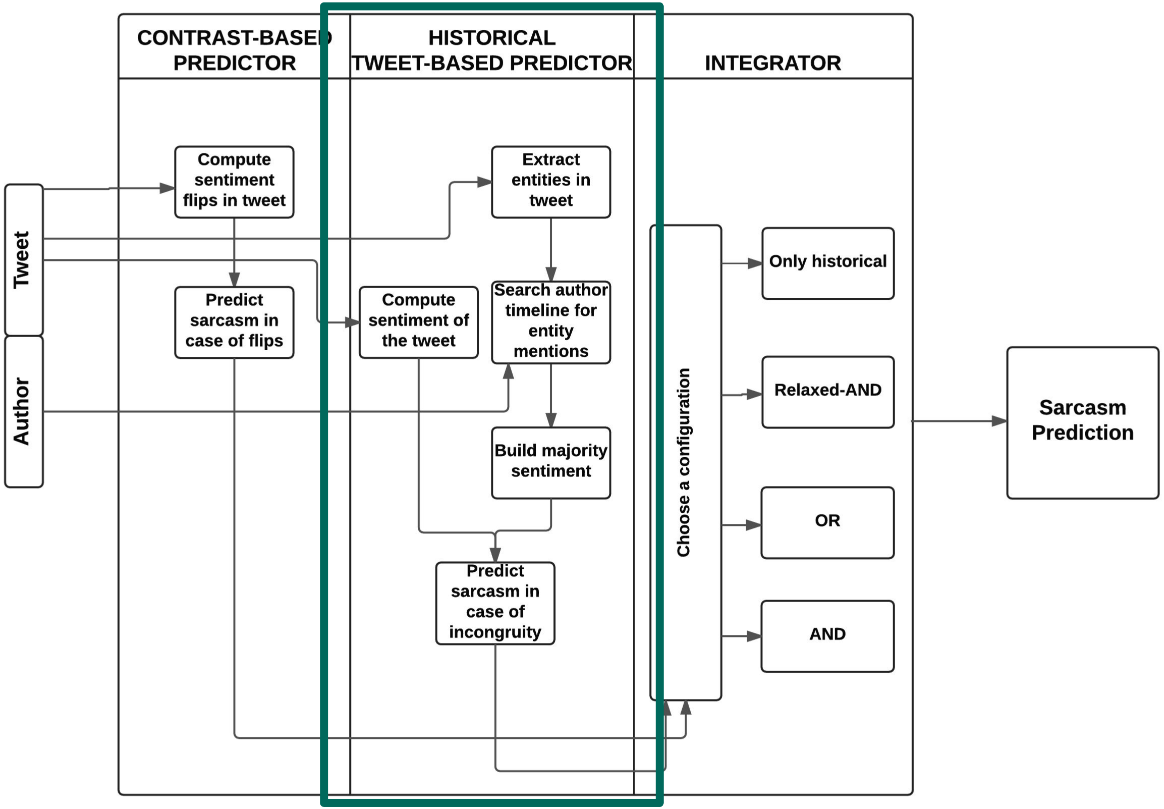
Architecture



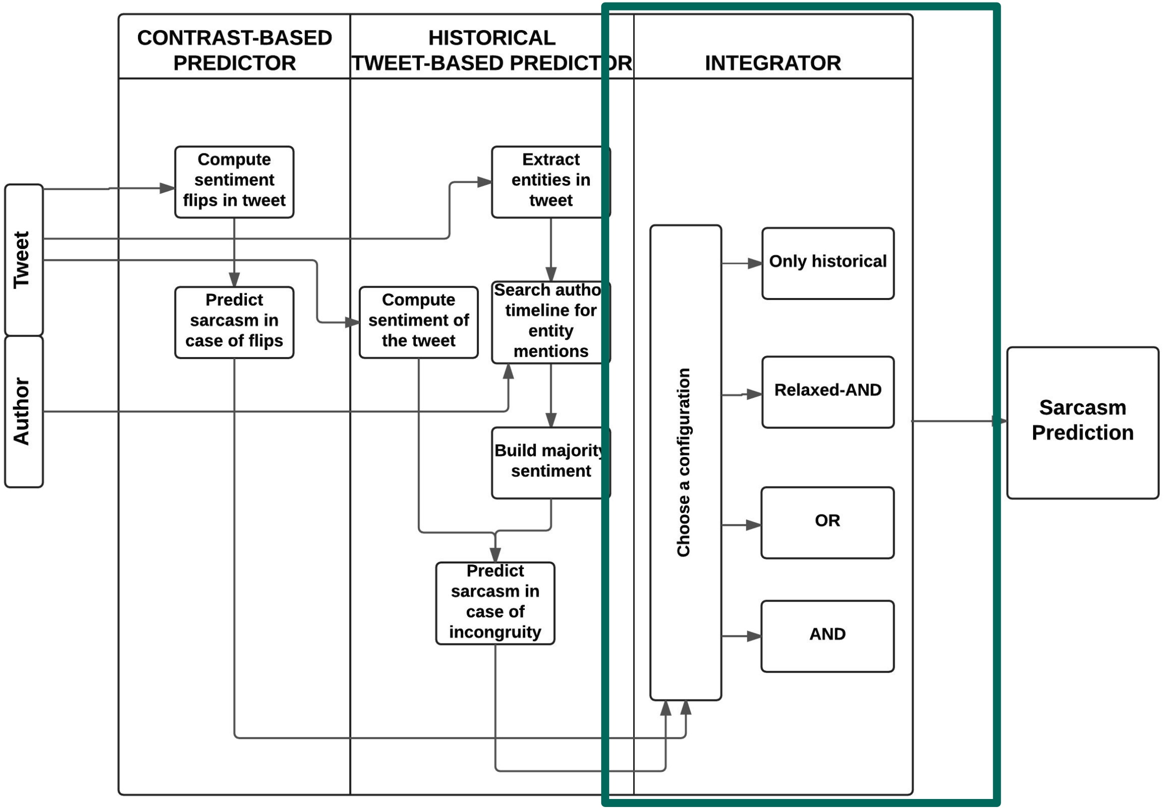
Architecture



Architecture



Architecture



Historical Context as Embeddings

Amir et al (2016)

Jointly learns and employs textual and author embeddings for sarcasm detection

An author's embeddings hope to capture the author sentiment maps as in previous cases

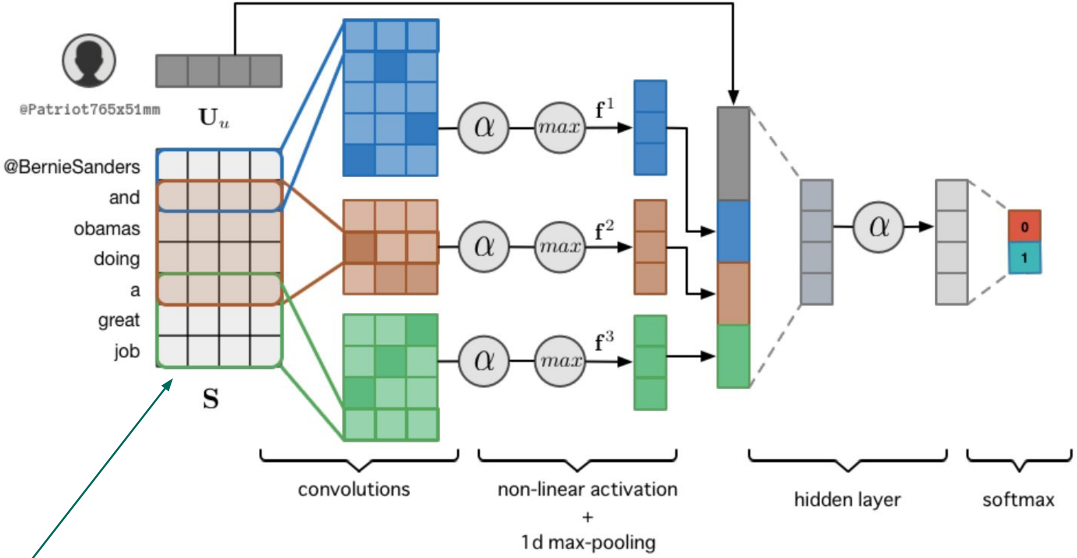
Generate an author embedding

The objective is to maximize the probability of a sentence:

$$P(S|\text{user}_j) = \sum_{w_i \in S} \log P(w_i|\mathbf{u}_j) + \sum_{w_i \in S} \sum_{w_k \in C(w_i)} \log P(w_i|\mathbf{e}_k)$$

To compute P(w|u), they create pseudo-negative examples based on words that the given user has not used but are common otherwise.

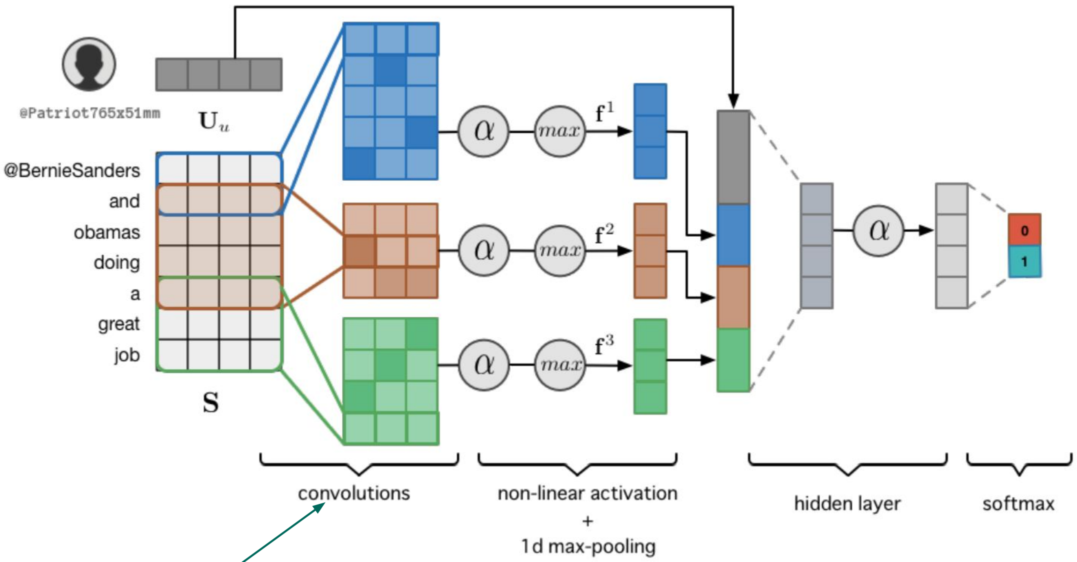
Architecture



Pre-trained word embeddings concatenated to form a sentence matrix

Image from original paper.

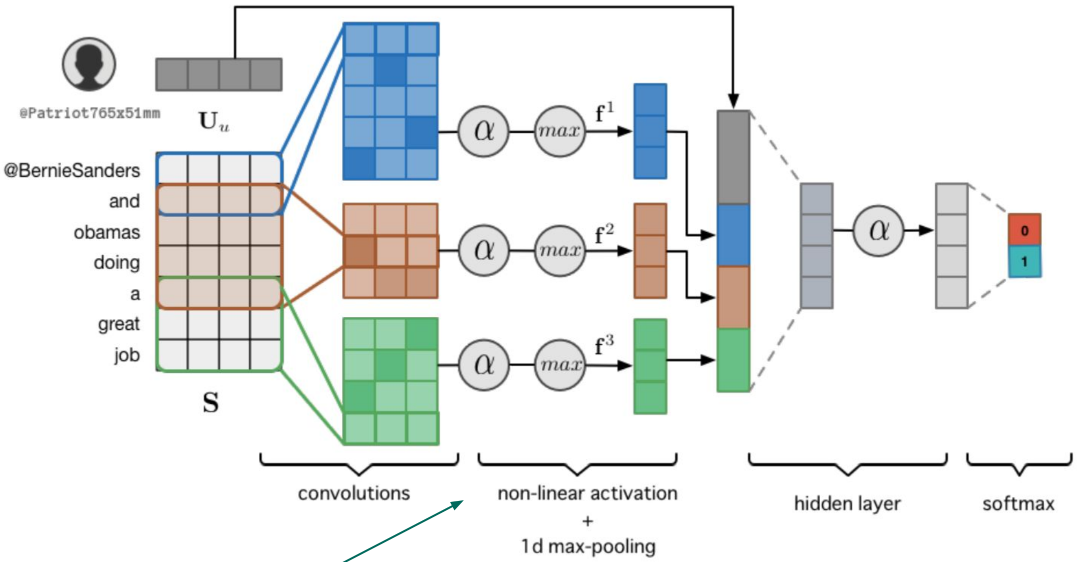
Architecture



Filters slide across the input

Image from original paper.

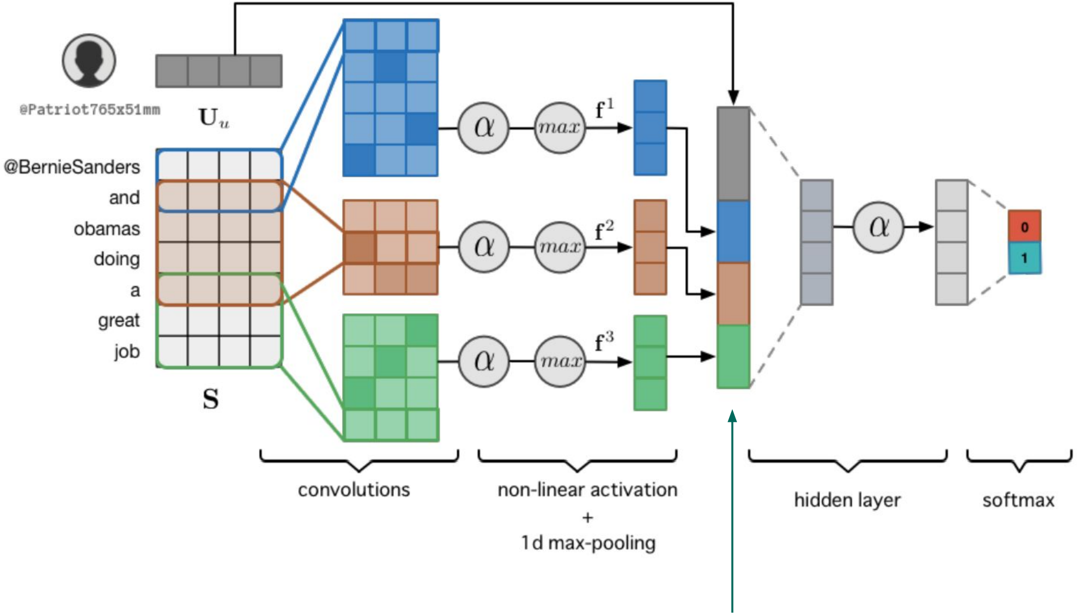
Architecture



Feature mapping with alpha weight, followed by 1-d max-pooling

Image from original paper.

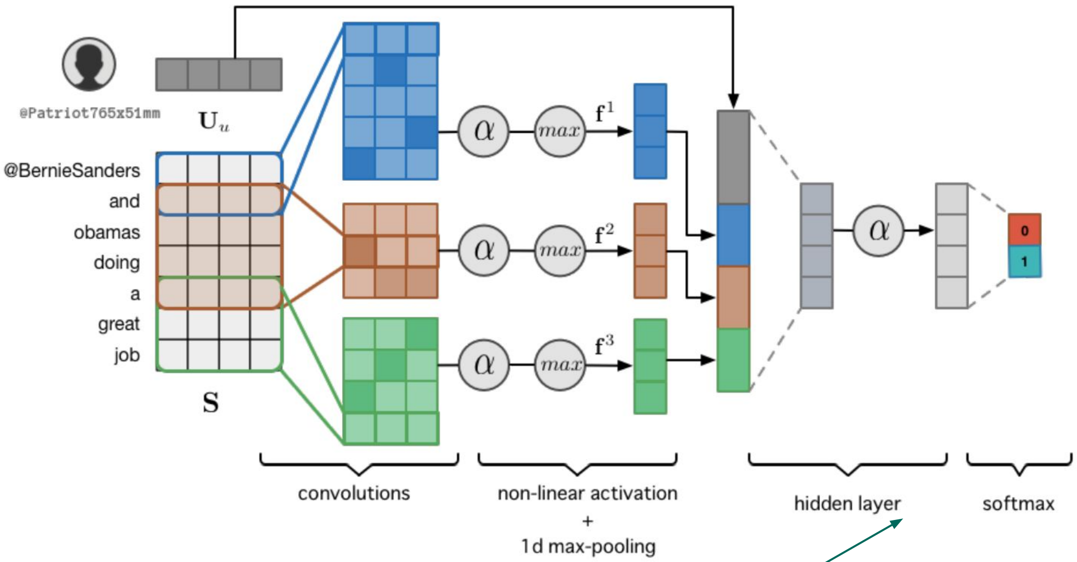
Architecture



The user embeddings concatenated to the remaining vector

Image from original paper.

Architecture



The model is learned from this vector.

Image from original paper.

Reported Results

Rajadesingan et al (2015)

Tweets: Accuracy 92.94%

Khattri et al (2015)

Tweets: F-score 0.826

Amir et al (2016)

Tweets: F-score 0.872

Incorporating Context for Sarcasm Detection

Module 5 of 7

Motivation
Background
Incongruity with Author’s historical context
Incongruity with Conversational context

Incongruity with conversational context

Additional information about the conversation that may help determine sarcasm in the target text

Caveats:

Degree of look-back

Non-verbal cues

Situational understanding

Incongruity with conversational context

Additional information about the conversation that may help determine sarcasm in the target text

Caveats:

Degree of look-back: *A seemingly non-sarcastic statement could be understood as sarcastic in the light of reference to a past statement*

Non-verbal cues

Situational understanding

Incongruity with conversational context

Additional information about the conversation that may help determine sarcasm in the target text

Caveats:

Degree of look-back

Non-verbal cues: : *A seemingly non-sarcastic statement could be understood as sarcastic due to non-verbal cues transcribed in a conversation*

Situational understanding

Incongruity with conversational context

Additional information about the conversation that may help determine sarcasm in the target text

Caveats:

Degree of look-back

Non-verbal cues

Situational understanding: *A seemingly non-sarcastic utterance may be understood as sarcastic due to information about participants*

Incorporation of conversational context

User’s historical context has been incorporated for sarcasm classification in two ways:

1. As features in a statistical classifier
2. Using a sequence labeling formulation as opposed to statistical classifier

Conversational context as features

	Features
Bamman and Smith (2015)	Pair-wise Brown similarity features between current and previous tweet Unigrams in previous tweet
Joshi et al (2015)	Sentiment flip features across target and previous tweet Unigrams in previous tweet
Wallace et al (2015)	Subreddit name Noun phrases in posts in the thread of the target post

Conversational context as alternative formulations

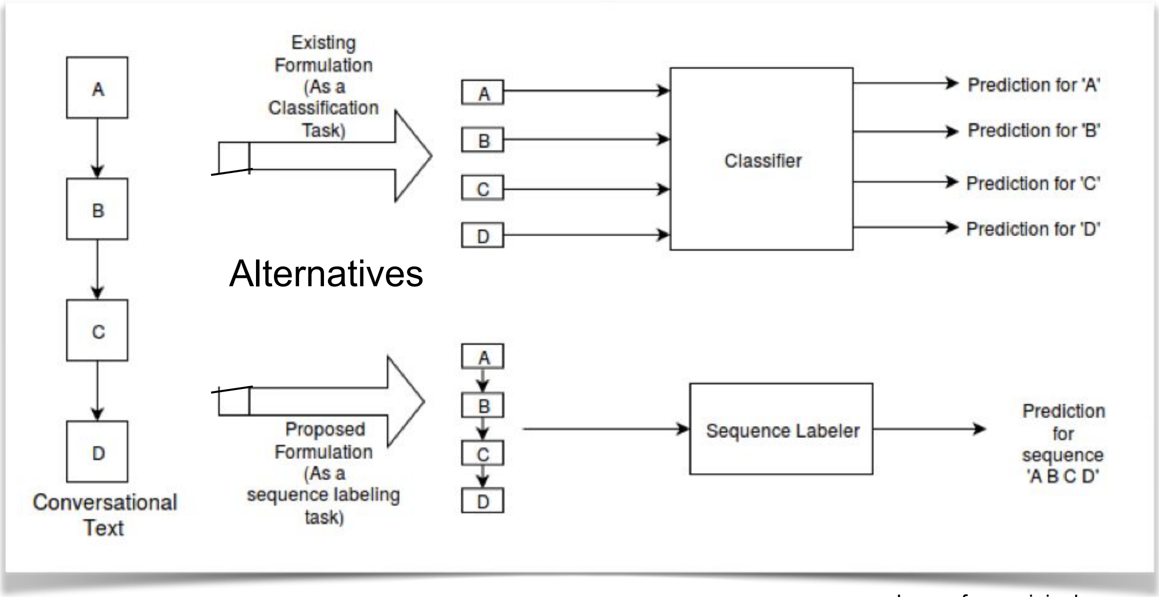


Image from original paper.

Conversational context as alternative formulations

Joshi et al (2016a): Using sequence labeling algorithms as opposed to classification algorithms for sarcasm detection from dialogue

Wang et al (2015):

Sequence labeling to detect sarcasm in the last element of a sequence. Other values are automatically determined

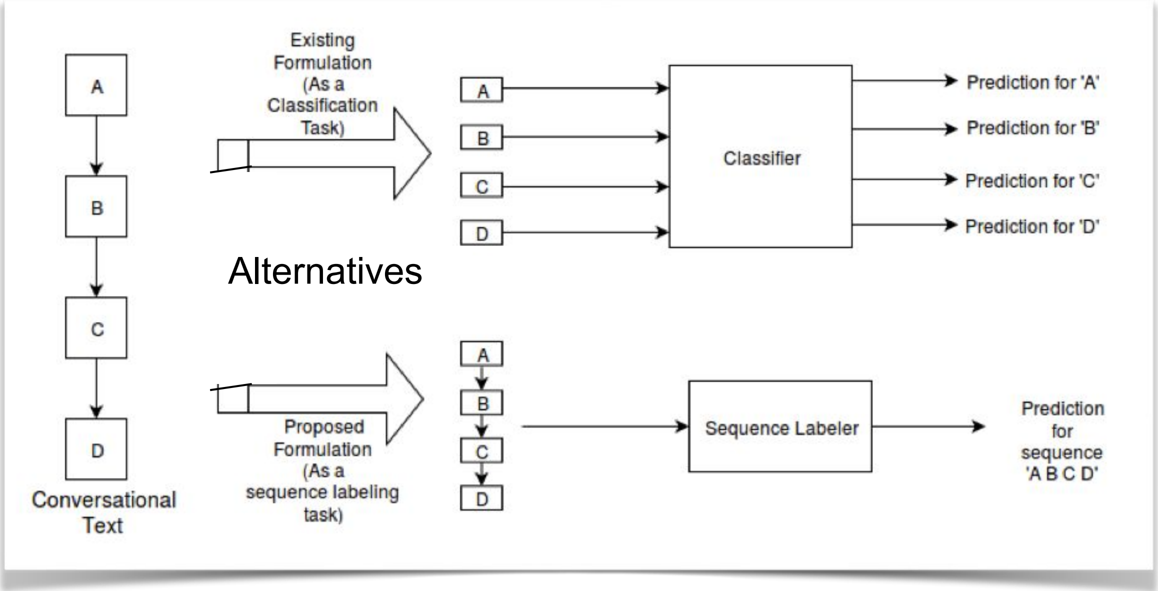


Image from original paper.

Reported Results

Bamman and Smith (2015)

Tweets: Binary Logistic Regression: Accuracy 85.1%

Joshi et al (2016a)

Friends Transcript: SVM-HMM: 84.4%

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.

Scope of today's tutorial

Introduction

Challenges, Motivation, etc.

Sarcasm in Linguistics

Definitions, Theories, etc.
Notion of 'incongruity'

Datasets

Datasets, annotation strategies, challenges, etc.

Algorithms

Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

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Traditional classifier techniques (contd), Deep learning-based techniques, etc.

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Context of the author, the conversation, etc.

Beyond sarcasm detection

Sarcasm generation, sarcasm v/s irony classification, etc.

Conclusion

Summary, pointers to future work

Image of coffee from wikimedia commons.

Beyond Sarcasm Detection

Module 6 of 7

Objective: To investigate computational sarcasm research other than sarcasm detection

Sarcasm versus irony classification

Sarcasm generation

Beyond Sarcasm Detection

Very little work apart from 'sarcasm detection': '*predicting whether a given piece of text is sarcastic or non-sarcastic*'

However,

Few other additional problem statements have gained attention

Beyond Sarcasm Detection

Module 6 of 7

Sarcasm versus irony classification

Sarcasm generation

Sarcasm versus irony classification

Sarcasm and irony differ in the degree of aggression (Wang, 2013)

Goal: Predicting if a given piece of text is sarcastic or ironic

Why is this distinction important?

Sarcasm, since it is contemptuous or ridiculing, may contribute to negative sentiment towards an entity

Irony may not.

Sarcasm versus irony

Sarcasm

This is the kind of movie that you watch because the theater has air conditioning.

Irony

You can put anything into words, except your own life.

The Human Perspective

Three annotators separately label book snippets as sarcasm, irony and philosophy

	All Three	versus Sarcasm-Irony	versus Sarcasm-Philosophy
A1	0.532	0.624	0.654
A2	0.479	0.537	0.615
A3	0.323	0.451	0.578

Inter-annotator agreement (IAA) statistics for annotator along with label

Aditya Joshi, Vaibhav Tripathi, Pushpak Bhattacharyya, Mark Carman, Meghna Singh, Jaya Saraswati and Rajita Shukla, 'How Challenging is Sarcasm versus Irony Classification?: A Study With a Dataset from English Literature', Australasian Language Technology Association (ALTA) 2016,Melbourne, Australia, December 2016.

The Computational Perspective

(Ling et al 2016)

On tweets

Feature Set	Irony vs. Sarcasm	Irony vs. Regular	Sarcasm vs. Regular	Figurative vs. Regular
Baseline	0.50	0.50	0.50	0.50
All−BoW	0.64	0.81	0.83	0.82
BoW Unigram	0.76	0.87	0.89	0.87
BoW Uni+Bigram	0.78	0.88	0.90	0.88
All	0.79	0.89	0.90	0.88

Features such as unigrams, emoticons,

Sentiment-based features, etc.

(Joshi et al 2016c)

On book snippets

	Precision (%)	Recall (%)	F-Score (%)
Sarcasm versus irony			
Average	65.4	65.4	65.4
Weighted Average	65.2	65.3	65.2
(b) Sarcasm versus philosophy			
Average	85	84.8	84.6
Weighted Average	76.5	77.7	77
(c) Sarcasm versus philosophy (class-balanced)			
Average	80.2	80	80
Weighted Average	80.2	80.1	80.1

Beyond Sarcasm Detection

Module 6 of 7

Sarcasm versus irony classification

Sarcasm generation

Sarcasm generation

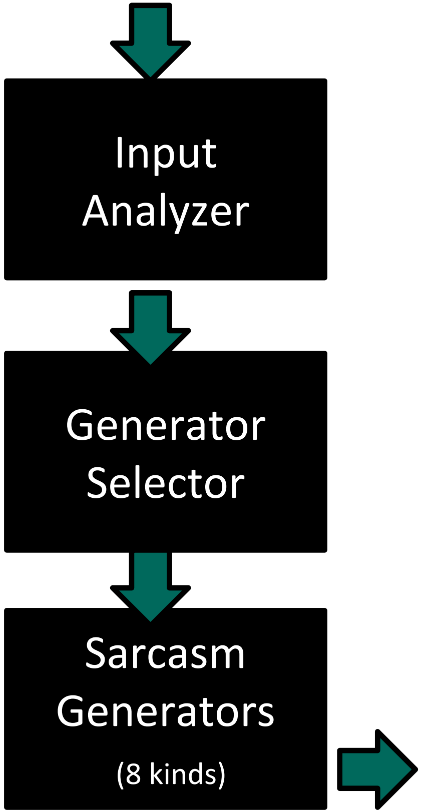
- Generate sarcastic text in response to a user input
- Can text-based chatbots respond sarcastically to user input?
- Do they need to?

Sarcasm generation

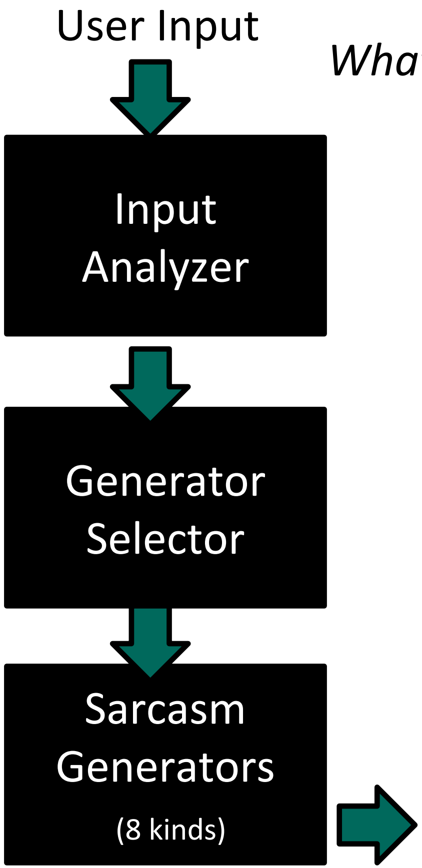
- Generate sarcastic text in response to a user input
- Can text-based chatbots respond sarcastically to user input?
- Do they need to?
- Currently, the application is only entertainment
- But can chatbots playing the role of a 'friend' want to be sarcastic in their responses?
- We presented an open-source sarcasm generation module for a chatbot: 'SarcasmBot' (Joshi et al, 2015)
- Template-based

Aditya Joshi, Anoop Kunchukuttan, Pushpak Bhattacharyya, Mark J Carman, SarcasmBot: An open-source sarcasm-generation module for chatbots, WISDOM at KDD 2015, Sydney, Australia, August 2015.

SarcasmBot: Architecture

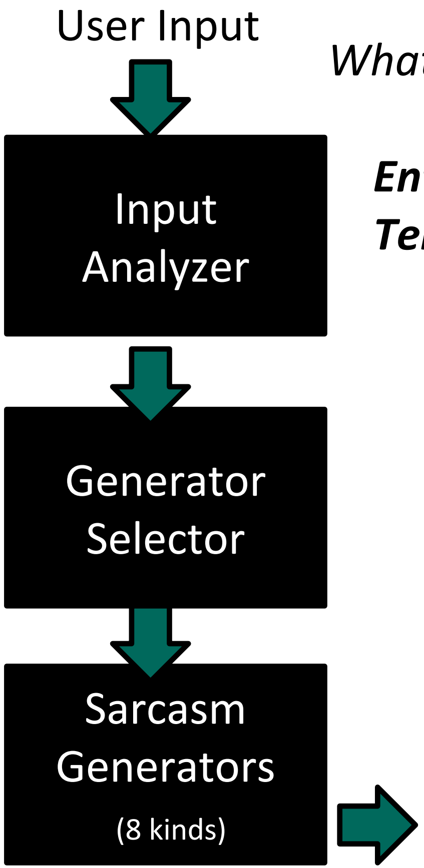


SarcasmBot: Architecture



What do you think of Greg?

SarcasmBot: Architecture

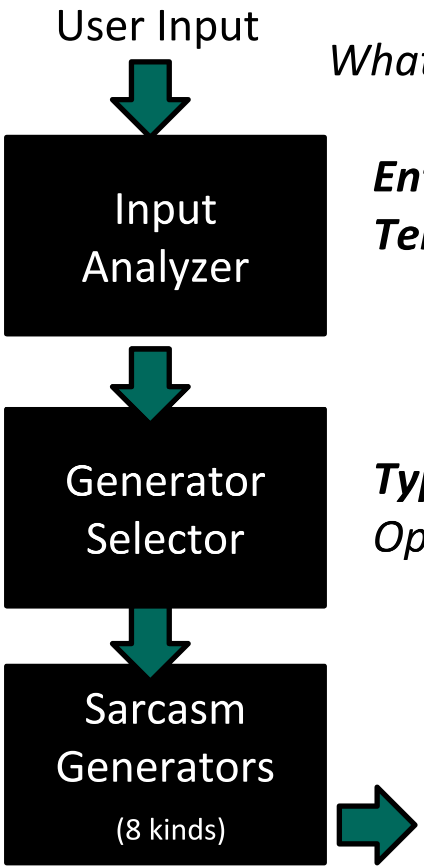


What do you think of Greg?

Entities: *"Greg: Name"*

Tense: *Present*

SarcasmBot: Architecture



What do you think of Greg?

Entities: *"Greg: Name"*
Tense: *Present*

Type of question:
Opinion question

SarcasmBot: Architecture

User Input

What do you think of Greg?

Input Analyzer

Entities: *"Greg: Name"*
Tense: *Present*

Generator Selector

Type of question:
Opinion question

Sarcasm Generators

(8 kinds)

I <sentiment-word> <entity>.
<Expression-of-opposite-sentiment>

SarcasmBot: Architecture

User Input

What do you think of Greg?

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Entities: *"Greg: Name"*
Tense: *Present*

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Type of question:
Opinion question

Sarcasm Generators
(8 kinds)

I <sentiment-word> <entity>.
<Expression-of-opposite-sentiment>

I like Greg. The way I love zero-accountability people.

Sarcasm Generators

Sarcasm Generator	Description
(a) Offensive Word Response Generator	In case an offensive word is used in user input, select a placeholder from a set of responses.
(b) Opposite Polarity Verb-Situation Generator	Randomly select a verb. Compute its sentiment. Discover a situation which is opposite in sentiment.
(c) Opposite Polarity Person-Attribute Generator	Randomly select a named entity. Select incongruent pairs of famous people.
(d) Irrealis Sarcasm Generator	Create a hypothetical situation that is impossible by selecting from a set of undesirable situations.
(e) Hyperbole Generator	Select a noun phrase in the user input. Generate a hyperbole with a 'best ever' style regular expression.
(f) Incongruent Reason Generator	Select an unrelated reason as a response for a user input.
(g) Sentiment-based Sarcasm Generator	Compute sentiment of user input. Generate a response opposite in sentiment.
(h) Random Response Generator	Select one positive exclamation and one negative exclamation randomly from a set of exclamations. Place them together.

Evaluation

Expt 1: Average Scores on three parameters

Evaluation Parameter	Average
Coherence	0.698
Grammatical correctness	0.903
Sarcastic nature	0.806

Expt 2: Identifying between ALICE and SarcasmBot

Strategy	Accuracy (%)
At least one evaluator is correct	87.09
Majority evaluators are correct	70.97
All evaluators are correct	61.29

Evaluation Parameter	Fleiss' Kappa
Identification of *SarcasmBot* output	0.476
Difficulty	0.164

https://github.com/adityajo/sarcasmbot

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Image of coffee from wikimedia commons.

Conclusion

Module 7 of 7

Objective: To summarize the tutorial and identify potential points of future work

Summary

Conclusion

Future Work

Conclusion

Module 7 of 7

Summary
Conclusion
Future Work

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Summary

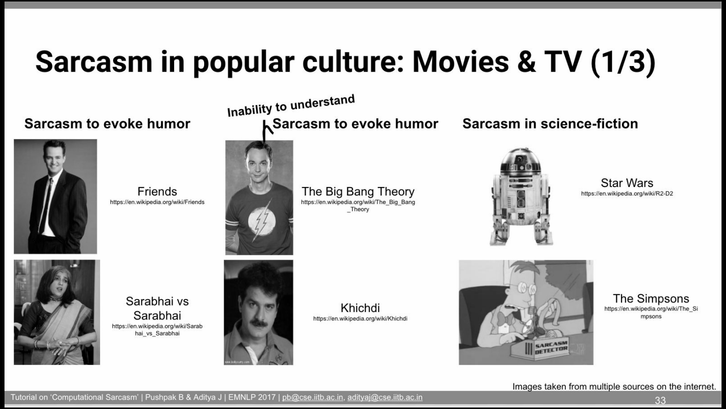
Module 1 of 7

Introduction

Sarcasm is a form of verbal irony which is intended to express contempt or ridicule

Sarcasm is a peculiar form of human sentiment expression

Computational Sarcasm impacts sentiment analysis



Impact on Sentiment Analysis (SA) (2/2)

	Precision (Sarc)	Precision (Non-sarc)
Conversation Transcripts		
MeaningCloud[1]	20.14	49.41
NLTK (Bird, 2006)	38.86	81
Tweets		
MeaningCloud[1]	17.58	50.13
NLTK (Bird, 2006)	35.17	69

The two sentiment analysis systems perform poorly for sarcastic text as compared to non-sarcastic text.

Maynard et al (2014) study the impact of sarcasm detection on sentiment analysis in detail.

[1] www.meaningcloud.com

Tutorial on 'Computational Sarcasm' | Pushpak B & Aditya J | EMNLP 2017 | pb@cse.iitb.ac.in, adityaj@cse.iitb.ac.in 53

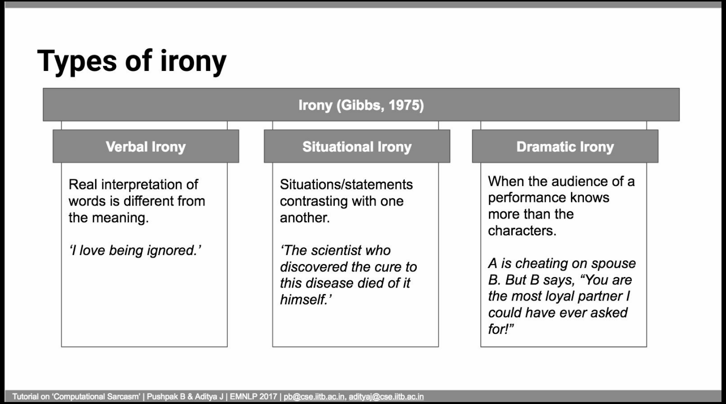
Summary

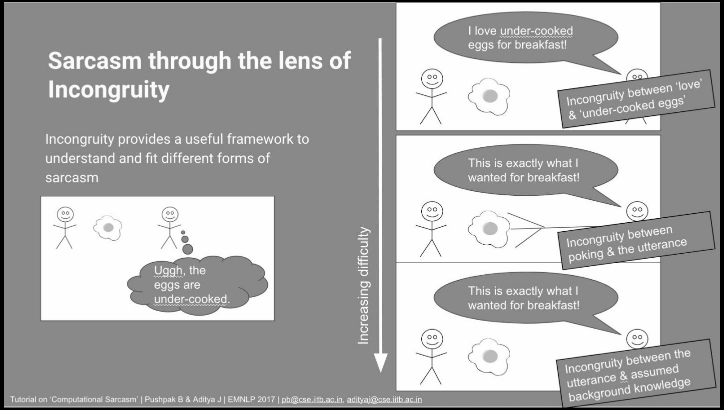
Module 2 of 7
Sarcasm in Linguistics

Sarcasm and irony are separated by the intent to ridicule

Sarcasm is of four types: propositional, embedded, like-prefixed and illocutionary

The notion of incongruity is central to sarcasm





Summary

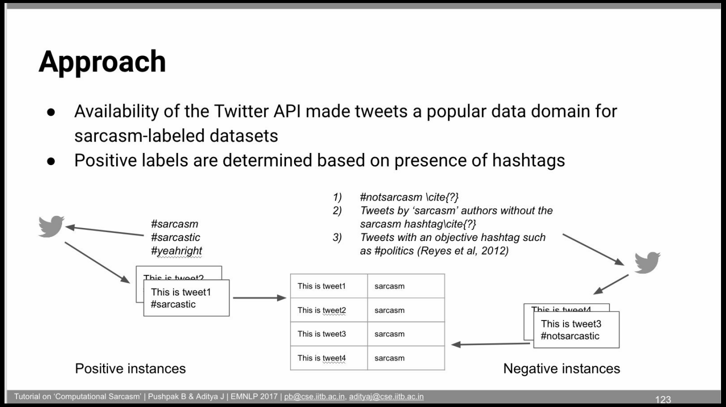
Module 3 of 7

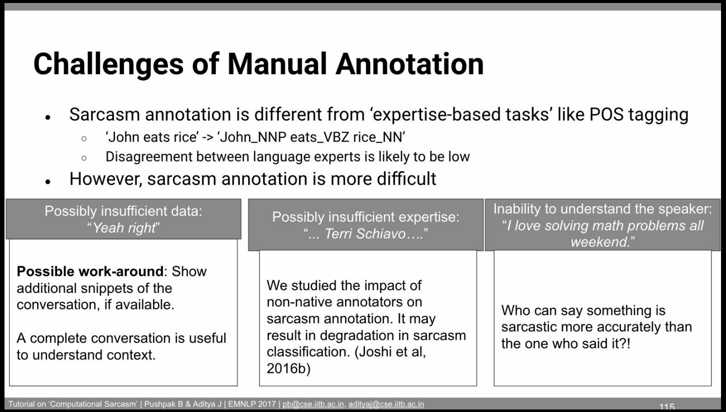
Datasets for computational sarcasm

A wide variety of sarcasm-labeled datasets have been reported.

Manually labeled sarcasm datasets often exhibit moderate inter-annotator agreement.

Distant supervision based on hashtags has been used in case of many sarcasm-labeled datasets.





Summary

Module 4 of 7

Algorithms for sarcasm detection (Part I)

Rule-based algorithms use heuristic-based rules to capture incongruity

Statistical algorithms use intuitive features to detect incongruity and hence sarcasm

Rule-based algorithms: Example (2/4)

Riloff et al (2013)

Incongruity occurs when positive verb followed by negative situations

I love being ignored

'Love' <-> 'being ignored'

Prediction: Sarcastic

1. Seed set of positive verbs
2. Repeat until convergence:
   a. For verbs in the set, Locate discriminative noun phrases in sarcastic text
   b. Add them to the set of negative situations
   c. For situations in the set, Locate discriminative verbs in sarcastic text
   d. Add them to the set of positive verbs

Salient components: (a) Extraction of verb and situations through an iterative algorithm (see right above), (b) These phrases are also used as features for statistical classifiers

Features: Summary

	Salient Features
Tsur et al. [2010]	Sarcastic patterns, Punctuations
González-Ibánez et al. [2011]	User mentions, emoticons, unigrams, sentiment-lexicon-based features
Reyes et al. [2012]	Ambiguity-based, semantic relatedness
Reyes and Rosso [2012]	N-grams, POS N-grams
Liebrecht et al. [2013]	N-grams, emotion marks, intensifiers
Riloff et al. [2013]	Sarcastic patterns (Positive verbs, negative phrases)
Reyes et al. [2013]	Skip-grams, Polarity skip-grams
Barbieri et al. [2014a]	Freq. of rarest words, max/min/avg # synsets, max/min/avg # synonyms
Barbieri et al. [2014b]	Synonyms, Ambiguity, Written-spoken gap
Buschmeier et al. [2014]	Interjection, ellipsis, hyperbole, imbalance-based
Liu et al. [2014]	POS sequences, Semantic imbalance. Chinese-specific features such as homophones, use of honorifics
Ptácek et al. [2014]	Word shape, Pointedness, etc.
Hernández-Farías et al. [2015]	Length, capitalization, semantic similarity
Joshi et al. [2015]	Unigrams, Implicit incongruity-based, Explicit incongruity-based
Rajadesingan et al. [2015]	Readability, sentiment flips, etc.
Bouazizi and Ohtsuki [2015b]	Pattern-based features along with word-based, syntactic, punctuation-based and sentiment-related features
Farías et al. [2016]	Affect-based features derived from multiple emotion lexicons
Joshi et al. [2016b]	Features based on word embedding similarity
Mishra et al. [2016]	Cognitive features derived from eye-tracking experiments

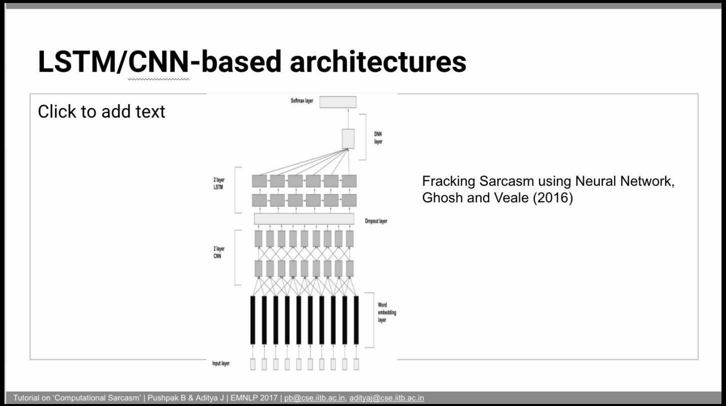
Summary

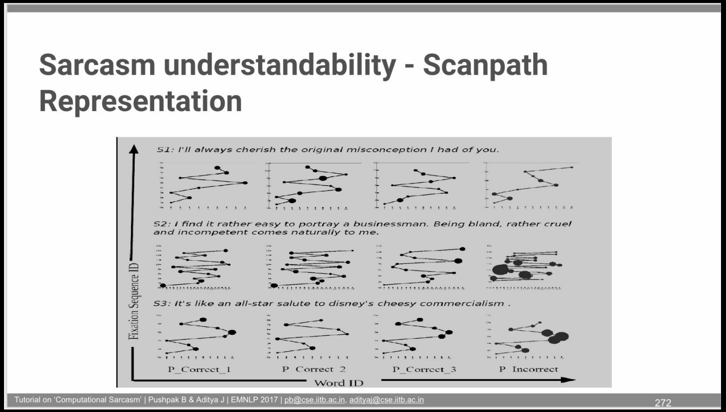
Module 4 of 7

Algorithms for sarcasm detection (Part II)

Deep learning-based algorithms use architectures that capture semantics of words

We also discussed two peculiar past works: (a) sarcasm in numeric text, (b) computational sarcasm using eye-tracking





Summary

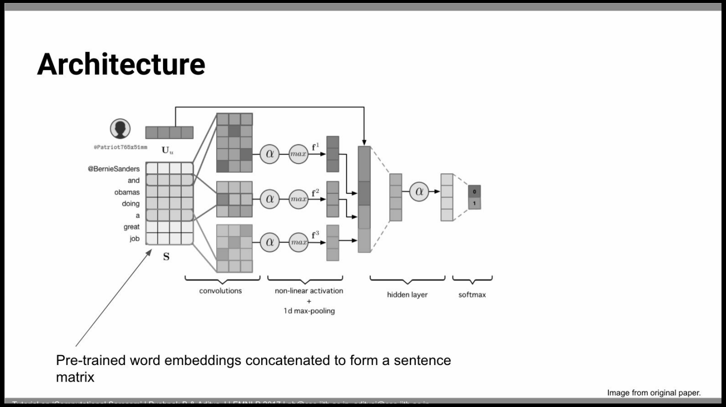
Module 5 of 7

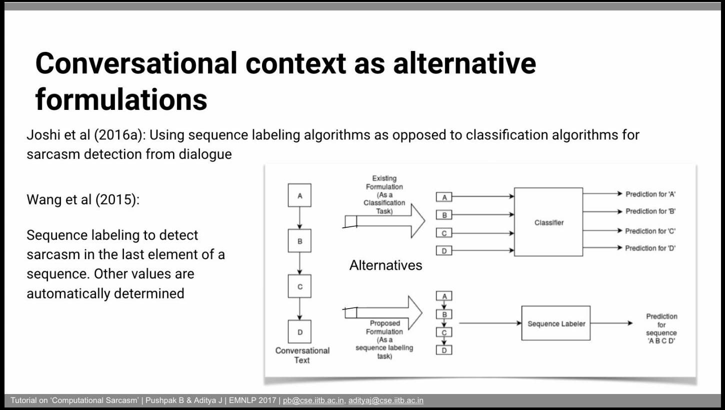
Incorporating context for sarcasm detection

Context is often necessary to detect sarcasm

Incongruity in author's historical context may be captured in terms of rules or user embeddings

Incongruity in conversational context may be captured using features or sequence labelers





Summary

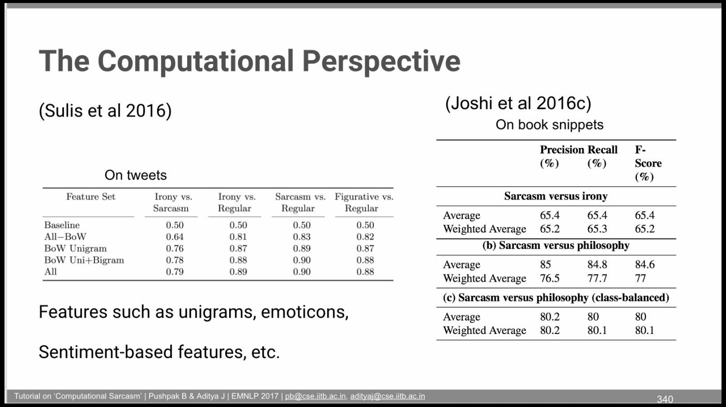
Module 6 of 7

Beyond sarcasm detection

We looked at two research problems apart from sarcasm detection

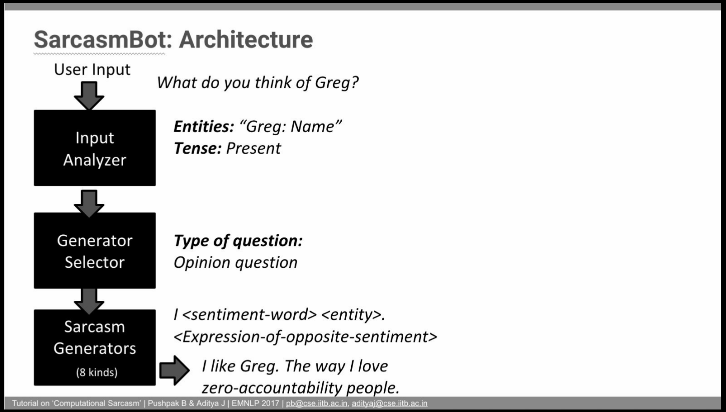
Past work in sarcasm versus irony classification highlight its difficulty.

Sarcasm may be generated in response to a textual input based on a template-based approach



Feature Set	Irony vs. Sarcasm	Irony vs. Regular	Sarcasm vs. Regular	Figurative vs. Regular
Baseline	0.50	0.50	0.50	0.50
All−BoW	0.64	0.81	0.83	0.82
BoW Unigram	0.76	0.87	0.89	0.87
BoW Uni+Bigram	0.78	0.88	0.90	0.88
All	0.79	0.89	0.90	0.88

	Precision (%)	Recall (%)	F-Score (%)
Sarcasm versus irony			
Average	65.4	65.4	65.4
Weighted Average	65.2	65.3	65.2
(b) Sarcasm versus philosophy			
Average	85	84.8	84.6
Weighted Average	76.5	77.7	77
(c) Sarcasm versus philosophy (class-balanced)			
Average	80.2	80	80
Weighted Average	80.2	80.1	80.1



Conclusion

Module 7 of 7

Summary
Conclusion
Future Work

Snapshot of past work

	Datasets			Approach			Annotatn.			Features					Context		
	Short Text	Long Text	Other	Rule-based	Semi-superv.	Superv	Manual	Distant	Other	Unigram	Sentiment	Pragmatic	Patterns	Other	Author	Conversation	Other
[Kreuz and Caucci 2007]			✓				✓			✓							
[Tsur et al. 2010]		✓			✓		✓			✓			✓				
[Davidov et al. 2010]		✓			✓		✓			✓			✓				
[Veale and Hao 2010]			✓	✓					✓	✓							
[González-Ibánez et al. 2011]	✓					✓		✓		✓	✓	✓					
[Reyes et al. 2012]	✓					✓		✓		✓	✓	✓		✓			
[Reyes and Rosso 2012]		✓				✓	✓			✓	✓			✓			
[Filatova 2012]		✓					✓										
[Riloff et al. 2013]	✓				✓		✓			✓		✓	✓				
[Lukin and Walker 2013]		✓			✓		✓			✓			✓				
[Liebrecht et al. 2013]	✓					✓		✓			✓		✓		✓		
[Reyes et al. 2013]	✓					✓		✓		✓	✓	✓		✓			
[Reyes and Rosso 2014]	✓	✓				✓		✓		✓	✓	✓		✓			
[Rakov and Rosenberg 2013]			✓			✓	✓			✓				✓			
[Barbieri et al. 2014b]	✓					✓		✓			✓			✓			
[Maynard and Greenwood 2014]	✓			✓			✓			✓	✓			✓			
[Wallace et al. 2014]		✓					✓										
[Buschmeier et al. 2014]		✓				✓			✓	✓	✓	✓			✓		
[Barbieri et al. 2014a]	✓					✓			✓	✓			✓				
[Joshi et al. 2015]	✓	✓				✓	✓	✓		✓	✓	✓	✓				
[Khattri et al. 2015]	✓			✓			✓			✓	✓				✓		
[Rajadesingan et al. 2015]	✓					✓		✓		✓	✓			✓	✓	✓	
[Bamman and Smith 2015]	✓					✓		✓		✓	✓	✓		✓	✓	✓	✓
[Wallace 2015]		✓				✓	✓			✓	✓			✓		✓	✓
[Ghosh et al. 2015b]	✓			✓	✓	✓		✓		✓		✓					
[Hernández-Farías et al. 2015]	✓					✓		✓		✓	✓	✓		✓			
[Wang et al. 2015]	✓					✓			✓	✓						✓	
[Ghosh et al. 2015a]			✓				✓			✓				✓			
[Liu et al. 2014]	✓	✓				✓		✓		✓	✓	✓		✓			
[Bharti et al. 2015]	✓				✓			✓		✓	✓		✓				
[Fersini et al. 2015]	✓					✓		✓		✓		✓		✓			
[Bouazizi and Ohtsuki 2015a]	✓					✓	✓			✓		✓		✓			
[Muresan et al. 2016]	✓					✓		✓		✓	✓	✓					
[Abhijit Mishra and Bhattacharyya 2016]	✓	✓	✓	✓			✓			✓	✓	✓		✓			
[Joshi et al. 2016a]			✓			✓	✓			✓	✓				✓	✓	
[Abercrombie and Hovy 2016]	✓					✓	✓			✓					✓	✓	✓
[Silvio Amir et al. 2016]	✓					✓		✓							✓		
[Ghosh and Veale 2016]	✓					✓	✓										
[Bouazizi and Ohtsuki 2015b]	✓				✓			✓		✓		✓	✓				
[Joshi et al. 2016b]			✓			✓		✓		✓				✓			

Recent version of the illustration in the ACM CSUR paper.

Snapshot of past work

	Datasets			Approach			Annotat.			Features					Context		
	Short Text	Long Text	Other	Rule-based	Semi-superv.	Superv	Manual	Distant	Other	Unigram	Sentiment	Pragmatic	Patterns	Other	Author	Conversation	Other
[Kreuz and Caucci 2007]			✓				✓			✓							
[Tsur et al. 2010]		✓			✓		✓			✓			✓				
[Davidov et al. 2010]		✓			✓		✓			✓			✓				
[Veale and Hao 2010]			✓	✓					✓	✓							
[González-Ibánez et al. 2011]	✓					✓		✓		✓	✓	✓					
[Reyes et al. 2012]	✓					✓		✓		✓	✓	✓		✓			
[Reyes and Rosso 2012]		✓				✓	✓			✓	✓			✓			
[Filatova 2012]		✓					✓										
[Riloff et al. 2013]	✓				✓		✓			✓		✓	✓				
[Lukin and Walker 2013]		✓			✓		✓			✓			✓				
[Liebrecht et al. 2013]	✓					✓		✓			✓		✓		✓		
[Reyes et al. 2013]	✓					✓		✓		✓	✓	✓		✓			
[Reyes and Rosso 2014]	✓	✓				✓		✓		✓	✓	✓		✓			
[Rakov and Rosenberg 2013]			✓			✓	✓			✓				✓			
[Barbieri et al. 2014b]	✓					✓		✓			✓			✓			
[Maynard and Greenwood 2014]	✓			✓			✓			✓	✓			✓			
[Wallace et al. 2014]		✓					✓										
[Buschmeier et al. 2014]		✓				✓			✓	✓	✓	✓			✓		
[Barbieri et al. 2014a]	✓					✓			✓	✓			✓				
[Joshi et al. 2015]	✓	✓				✓	✓	✓		✓	✓	✓	✓				
[Khattri et al. 2015]	✓			✓			✓			✓	✓				✓		
[Rajadesingan et al. 2015]	✓					✓		✓		✓	✓			✓	✓	✓	
[Bamman and Smith 2015]	✓					✓		✓		✓	✓	✓		✓	✓	✓	✓
[Wallace 2015]		✓				✓	✓			✓	✓			✓		✓	✓
[Ghosh et al. 2015b]	✓			✓	✓	✓		✓		✓		✓					
[Hernández-Farías et al. 2015]	✓					✓		✓		✓	✓	✓		✓			
[Wang et al. 2015]	✓					✓			✓	✓						✓	
[Ghosh et al. 2015a]			✓				✓			✓				✓			
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[Bharti et al. 2015]	✓				✓			✓		✓	✓		✓				
[Fersini et al. 2015]	✓					✓		✓		✓		✓		✓			
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[Muresan et al. 2016]	✓					✓		✓		✓	✓	✓					
[Abhijit Mishra and Bhattacharyya 2016]	✓	✓	✓	✓			✓			✓	✓	✓		✓			
[Joshi et al. 2016a]			✓			✓	✓			✓	✓				✓	✓	
[Abercrombie and Hovy 2016]	✓					✓	✓			✓					✓	✓	✓
[Silvio Amir et al. 2016]	✓					✓		✓							✓		
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[Bouazizi and Ohtsuki 2015b]	✓				✓			✓		✓		✓	✓				
[Joshi et al. 2016b]			✓			✓		✓		✓				✓			

Three key trends:

1. Sarcastic pattern discovery
2. Hashtag-based supervision for large-scale datasets
3. Use of contextual information

Recent version of the illustration in the ACM CSUR paper.

Conclusion

Computational sarcasm has been widely researched in terms of detection

Datasets based on manual or distant supervision have been reported

Several rule-based, statistical and deep learning-based architectures have been proposed. The notion of **incongruity** is useful to view the common thread between these approaches

Some novel directions in terms of sarcasm generation, sarcasm versus irony classification have also been studied

However, the problem is far from solved.

Conclusion

Module 7 of 7

Summary

Conclusion

Future Work

The road ahead (1/2)

Implicit sentiment of phrases

‘Who doesn’t hate riding a roller-coaster?!’: Sarcastic

Focus on types of sarcasm

Datasets

Error Analyses

The road ahead (1/2)

Implicit sentiment of phrases

‘Who doesn’t hate riding a roller-coaster?!’: Sarcastic

Understanding that ‘*riding a roller-coaster*’ is a positive phrase

Focus on types of sarcasm

Datasets: Labeling textual units into types of sarcasm

Error Analyses: Analysing which forms of sarcasm a proposed approach covers

The road ahead (2/2)

Discovering context

Use of distributed representations to discover three-level semantics:

1. General semantics
2. Speaker-specific semantics

New forms of context

1. Additional information from source platforms
2. Understanding of Speaker - Listener pair

Specific forms of sarcasm

1. Hyperbolic sarcasm
2. Numeric sarcasm, etc.

Typical off-shoots from sentiment analysis

Cross-lingual sarcasm detection
Cross-domain sarcasm detection

The road ahead (2/2)

Discovering context

Use of distributed representations to discover three-level semantics:

1. General semantics
2. Speaker-specific semantics

New forms of context

1. Additional information from source platforms
2. Understanding of Speaker - Listener pair: *Focusing on conversations*

Specific forms of sarcasm

1. Hyperbolic sarcasm: *This was the best movie ever!*
2. Numeric sarcasm, etc.

Typical off-shoots from sentiment analysis

Cross-lingual sarcasm detection: *Mi piace essere ignorato*
Cross-domain sarcasm detection: *I love how it is slow-paced. (movie versus an online course)*

Scope of today's tutorial

Introduction

Challenges, Motivation, etc.

Sarcasm in Linguistics

Definitions, Theories, etc.
Notion of 'incongruity'

Datasets

Datasets, annotation strategies, challenges, etc.

Algorithms

Algorithms - 1

Rule-based techniques, Traditional classifier techniques, etc.

Algorithms - 2

Traditional classifier techniques (contd), Deep learning-based techniques, etc.

Incorporating context

Context of the author, the conversation, etc.

Beyond sarcasm detection

Sarcasm generation, sarcasm v/s irony classification, etc.

Conclusion

Summary, pointers to future work

Image of coffee from wikimedia commons.

Last Word

Last Word

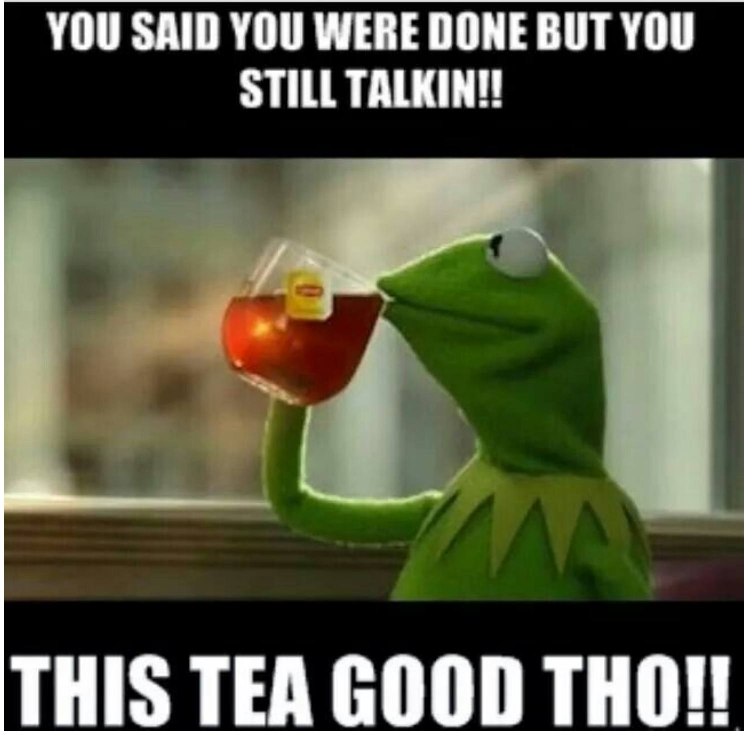

Image taken from Pinterest

Thank you.
You have been an amazing audience.
#NoSarcasm

皮肉
سخر
sarcasmo
gúny
Сарказм
sarcasmo
বিদ্রূপ
ismijavati
sarkasme
iğneleme
სარკაზმი
പരിഹസിക്കുന്ന
कटाक्ष
การเยาะ
เย้ย
sarkasmus
諷刺

Please send us your feedback at:
adityaj@cse.iitb.ac.in
pb@cse.iitb.ac.in

Aditya Joshi, Pushpak Bhattacharyya, Mark J Carman, '*Automatic Sarcasm Detection: A Survey*', ACM Computing Surveys, 2017.
A stale copy on arXiv at: https://arxiv.org/abs/1602.03426

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Extra Slides.

Motivation

Sarcasm may not be understood based on the sentence alone

Short, casual expressions: *‘Yeah right!’, ‘Absolutely right!’*

Hyperbolic statements: *‘These are the best school holidays ever!’*

Factual/Pretentious statements: *‘Students generally submit their assignments on time’*

Sentiment-bearing statements: *‘Yes, this looks very good to me’*

Motivation

Sarcasm may not be understood based on the sentence alone

Short, casual expressions: *'Yeah right!', 'Absolutely right!'*

In response to: *"One can't really pass exams without cheating!"*

Hyperbolic statements: *'These are the best school holidays ever!'*

Factual/Pretentious statements: *'Students generally submit their assignments on time'*

Sentiment-bearing statements: *'Yes, this looks very good to me'*

Motivation

Sarcasm may not be understood based on the sentence alone

Short, casual expressions: *'Yeah right!', 'Absolutely right!'*

Hyperbolic statements: *'These are the best school holidays ever!'*

In response to: *"They have asked us to write six essays and solve 50 math puzzles in the summer holidays."*

Factual/Pretentious statements: *'Students generally submit their assignments on time'*

Sentiment-bearing statements: *'Yes, this looks very good to me'*

Motivation

Sarcasm may not be understood based on the sentence alone

Short, casual expressions: *'Yeah right!', 'Absolutely right!'*

Hyperbolic statements: *'These are the best school holidays ever!'*

Factual/Pretentious statements: *'Students generally submit their assignments on time'*

In response to: *"Professor, I thought it was okay to submit my assignment late"*

Sentiment-bearing statements: *'Yes, this looks very good to me'*

Motivation

Sarcasm may not be understood based on the sentence alone

Short, casual expressions: *‘Yeah right!’, ‘Absolutely right!’*

Hyperbolic statements: *‘These are the best school holidays ever!’*

Factual/Pretentious statements: *‘Students generally submit their assignments on time’*

Sentiment-bearing statements: *‘Yes, this looks very good to me’*

In response to a student presenting an incompletely, badly done assignment to a professor