

# Topics, Administration

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Heidelberg SS2019

- Background
- Motivation
- Topics
- Administration

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- 4 Topics: Metaphor Recognition

*“Les Tropes sont des figures par lesquelles ont fait prendre à un mot une signification qui n’est pas précisément la signification propre de ce mot”*

*DuMarsais, Cesar Chesneau and Douay-Soublin, Françoise  
(1730): Des Tropes où des Différents Sens*

**“Trope:** [. . .] jede Form der Rede, die das Gemeinte nicht direkt und sachlich durch das eigentl. Wort ausspricht, sondern [. . .] durch e. Anderes, Naheliegendes, e. “”ubertragenen” Ausdruck wiedergibt.”

*Gero von Wilpert (1989): Sachwörterbuch der Literatur*

- **Metaphor:** Transferral via Similarity. Establishing a comparison. *sweet child*
- **Metonymy:** Transferral via world knowledge relations. *traumatised by Vietnam*
- **Idioms:** fixed, conventionalised and non-compositional multiword phrases. *break the ice*
- **Irony/Sarcasm:** Say opposite of what you mean but mark it for the hearer to recognise. *I love being woken up at 5am by drilling*
- **Hyperbole:** *He told me that a million times.*

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# Conventionality

Figurative Language can be very innovative or pretty conventionalised.

Conventionalised:

*“I didn’t know it at the time, but behind the scenes Evan had to pull strings in order to hire me. ”*

*Stone (2014): Things a little bird told me*

or is it ?

*“I didn’t know it at the time, but behind the scenes Evan had to pull strings in order to hire me. Actually they were more like ropes. Or cables — the kind that hold up suspension bridges. ”*

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# Vehicle/Tenor or Source/Target

**Vehicle/Source:** Domain from which the transferral takes place. *sweet* or the domain of taste in *sweet child*.

**Tenor/Target:** Domain to which you transfer. *child* or the domain of character/personality in *sweet child*.

Mostly applicable to metaphor (and metonymy)

Up to now: **linguistic metaphors**

But categorisation is essential for metaphors (and metonymies)

*“Our ordinary conceptual system, in terms of which we both think and act, is fundamentally metaphoric in nature.”*

*Lakoff und Johnson (1980): Metaphors we live by*

Relate two cognitive domains systematically

ARGUMENT IS WAR is a conceptual metaphor between source domain WAR and target domain ARGUMENT. Instantiated via linguistic metaphors such as

- *He attacked my position.*
- *They bombarded me with counter-arguments*
- *Ich habe aber gleich zurückgeschossen.*

More in the Berkeley Master Metaphor List: <http://araw.mede.uic.edu/~alansz/metaphor/METAPHORLIST.pdf>

# Conceptual Metaphor

Leads to structural analogies such as

- argumentative positions = positions in a war
- people who argue = soldiers
- counter-arguments = weapons
- making up = peace

- Metaphor recognition (focus of most work)
  - Approaches on short phrases (abstractiveness, multilingual, multimodal ...)
  - Neural approaches on metaphors in full context
- Metaphor interpretation. Can we just paraphrase? *sweet child* → *kind child/friendly child*
- Applications: MT, educational applications, sentiment mining
- Recognition and interpretation of metonymies
- Recognition of irony: social networks, world knowledge, context



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# Why do we care about figurative language: Inference

Inferences and *entailment* vary between literal and metaphorical meanings

- *They attacked our houses* → probably property and/or person damage
- *They attacked my arguments* → no physical damage

Most extreme for irony!

# Why are we interested in figurative language: Cognition

Thibeadeau und Boroditzky (2013, 2011):

## Beispiel

Crime is **a beast/virus** ravaging the city of Addison. Five years ago Addison was in good shape, with no obvious vulnerabilities. Unfortunately, in the past five years the city's defense systems have weakened, and the city has succumbed to crime. Today, there are more than 55,000 criminal incidents a year - up by more than 10,000 per year. There is a worry that if the city does not regain its strength soon, even more serious problems may start to develop.

- Increase street patrols that look for criminals.
- Increase prison sentences for convicted offenders.
- Reform education practices and create after school programs.
- Expand economic welfare programs and create jobs.
- Develop neighborhood watch programs and do more community outreach.



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- More background on definition
- Background on metaphor and inference as well as metaphor and cognition

Thibodeau und Boroditsky (2013): *Natural Language Metaphors covertly influence reasoning*. In PloS ONE.

## **TSV - Tsvetkov et al (2014)**

Around 2000 adjective noun-pairs  
with train-test split

Metaphor	Literal
deep thought	cold weather
green energy	empty can
empty promise	dry skin

## **MOH - Mohammad et al. (2016)**

647 Verb/subject/object pairs  
(10-fold CV)

metaphor	literal
absorb cost	attack village
breathe life	breathe air

# Annotation and Datasets. Metaphor in Context

Main dataset VU Amsterdam Metaphor Corpus. Ca 238K tokens of which 25K are metaphoric. Most conventional.

<http://www.vismet.org/metcor/search/showPage.php?page=start> and <http://metaphorlab.org/>.

## Example

he has become involved **in** a row **over** his **attack on** the **Pharisees** of British society

- Annotation Methodology: binary, best/worst . . . . Emphasis on methodology you can use for other seminars/theses as well.
- Innovative vs. Conventional (?)
- Can we annotate metaphors with high agreement?



Start 29th of May!

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# T.I.1: Abstractness for metaphor recognition (Basis)

Potential Papers: Turney et al (2011), Koeper and Schulte im Walde (2016), Koeper and Schulte im Walde (2017)

## Main ideas

- Lakoff/Johnson (1980): concrete domain to abstract domain: ARGUMENT IS WAR, BADNESS IS DARKNESS
- Calculate abstractness of a word
- Metaphoricity results from tension between, for example, an abstract noun and a concrete adjective

Word	Abstr. rating
dark	0.43356
bad	0.63326
mood	0.61858

*bad mood* literal, *dark mood* metaphoric

- Koeper and Schulte im Walde (2016): German particle verbs
- Koeper and Schulte im Walde (2017): extension to phrases and senses. Better learning of abstractiveness ratings.

## T.I.2: Metaphor recognition on short phrases (Basis)

Tsvetkov et al (ACL 2014) *Metaphor detection with cross-lingual model transfer*.

### Main Idea

- Supervised Learning in source language on SVO and AN tuples
- Use conceptual features
- Transfer via bilingual lexicon: *schmutzig*  $\rightarrow$  *dirty, filthy, grimy* ...
- Average feature vectors of the translation. No retraining in new language

	SVO	AN
EN	0.79	0.85
RU	0.84	0.77
ES	0.76	0.72
FA	0.75	0.74

Shutova et al. (NAACL 2016) *Black holes and white rabbits: Metaphor identification with visual features*

## Main Idea

- $\cos(w_1, w_2)$  with linguistic as well as visual embeddings (*bitter man*)
- Other models based on phrase similarities . . .

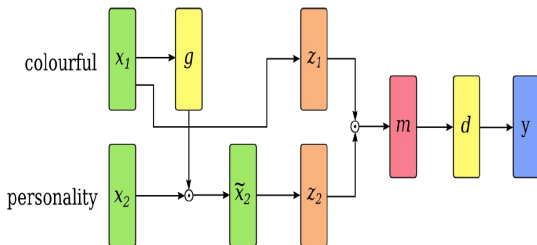


1. Under creative commons license, originator Tabish\_q. 2. Under creative commons licence, originator Ananian

# T.I.2: Metaphor recognition on short phrases, deep learning (Advanced)

Rei et al (EMNLP 2017) *Grasping the Finer Point: A Supervised Similarity Network for Metaphor Detection*

Builds on Shutova et al's core idea of cosine similarities. Expands this into a deep learning approach.



## T.1.3: Metaphor detection in running text

- Leong et al (2018): *A report on the 2018 VUA metaphor detection shared task*

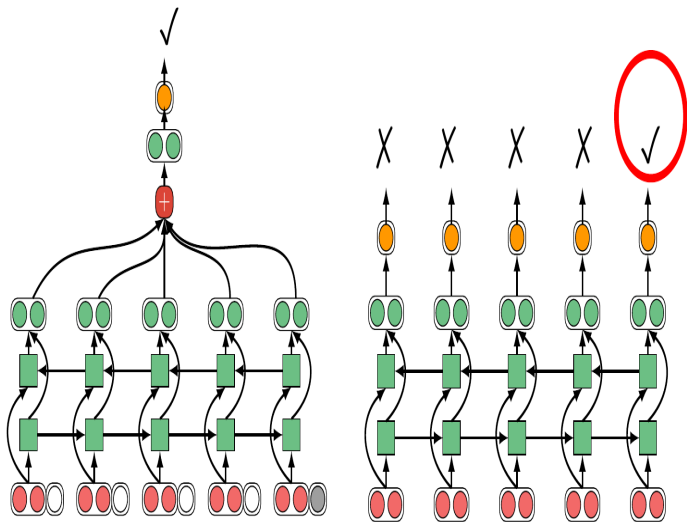
### Example

he has become involved in a row over his **attack** on the **Pharisees** of British society

- A feature-based logistic regression baseline building on Klebanov et al (2016) still performs well
- All participants used some form of neural network. Not that many beat the baseline for all POS.
- Best performing system is a CNN/LSTM hybrid by Wu et al (2018)

## T.1.3: Metaphor detection in running text (Advanced)

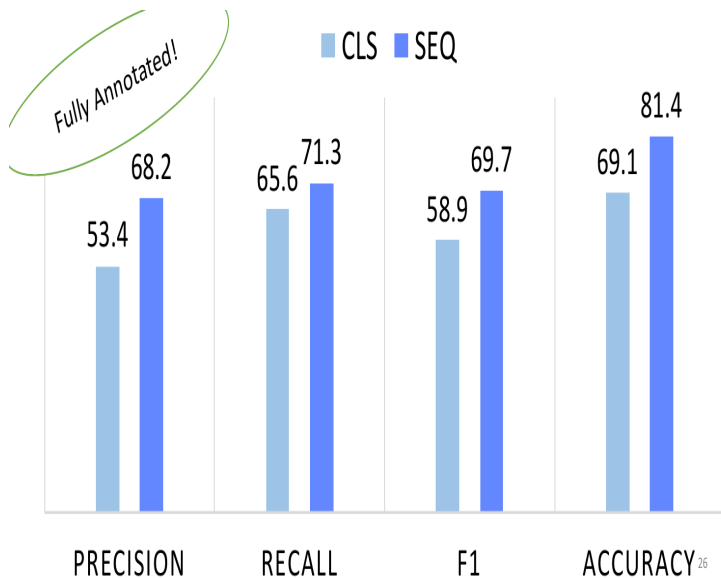
Current state of the art is the sequence to sequence labeling model in Gao et al (EMNLP 2018): *Neural Metaphor Detection in Context*





## T.1.3: Metaphor detection in running text (advanced)

Current state of the art Gao et al (EMNLP 2018): *Neural Metaphor Detection in Context*

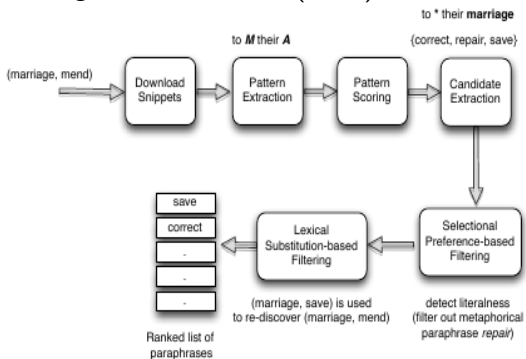


# T.II: Metaphor interpretation as paraphrasing

Bollegala and Shutova (PLOS One 2013): Metaphor interpretation using paraphrases extracted from the web and

Bizzoni and Lappin (2018) Predicting human metaphor paraphrase judgments with deep neural networks.

From Bollegala and Shutova (2013):



Several Options (see literature list):

- schizophrenia detection (Basis)
- metaphor and MT
- metaphor and sentiment (Basis)

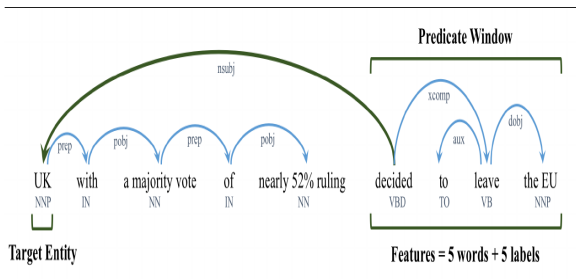
# T.IV: Metonymies

Gritta et al (ACL 2017): Vancouver welcomes you! Minimalist Location Metonymy Resolution

Location metonymies relevant for geo-parsing as they are false positives:

- *traumatized by **Vietnam***
- *All **London** is going to the parade*

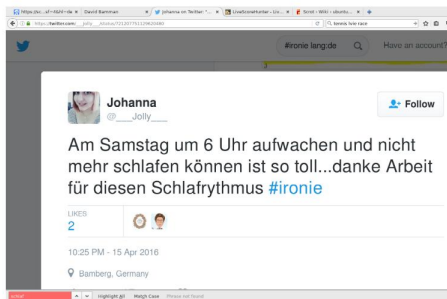
Gritta et al combine an LSTM with syntactic knowledge for metonymy identification:



# T.V.1: Irony recognition in social networks (Basis)

Ghosh et al (EMNLP 2015): *Sarcastic or not: word embeddings to predict the literal or sarcastic meaning of words* and

Gonzales-Ibanez et al (ACL 2011): *Identifying sarcasm in twitter: a closer look*



## Methods

- **Distant supervision**: Tweets marked with #sarcasm, #irony or similar: positive Instances
- Other Tweets: negative
- Mostly supervised learning with features such as: emotion, lexical, emojis, embeddings . . .
- Is distant supervision adequate for the task?

## T.V.2 Irony Recognition: The inclusion of context (Advanced)

Ghosh et al (EMNLP 2017): *Magnets for Sarcasm: Making Sarcasm Detection Timely, Contextual and Very Personal*

**Speaker Utterance:** @MSNBC of course all of those jobs  
will be in China

**In reply to @realDonaldTrump:** I will be the greatest jobs-  
producing president that God ever created.

- Use tweet you reply to
- Use writers personality and mood as evinced by previous tweets

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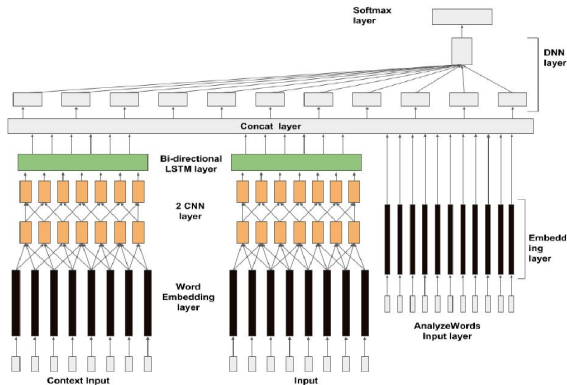


Figure 1: A Neural Architecture for Detecting Sarcasm in Contextualized Utterances



# T.V.2: World knowledge for irony recognition

Riloff et al. (EMNLP 2013) *Sarcasm as Contrast between a Positive Sentiment and Negative Situation.* or Van Hee et al (CL 2018): *We usually dont like going to the dentist: Using common sense to detect irony on twitter*

## Example

Thank you 2018 for the worst migraine ever. This is what I call a perfect beginning.

Collect negative situations:

- Riloff et al: bootstrapping
- Van Hee et al: Twitter crawls and knowledge bases

