

From data collection to output evaluation:  
the challenging journey towards fair, robust and  
interpretable NLP systems

Els Lefever  
27 Nov 2024



# LT3 TEAM

8 professors  
4 postdocs



16 predocs  
2 IT support



# GHENT CENTER FOR DIGITAL HUMANITIES



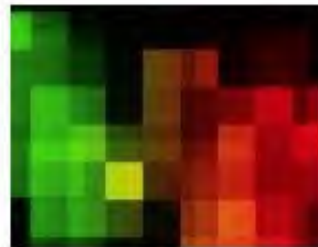
**Cinema Ecosystem  
(CINECOS)**

[More information](#)



**CLARIAH-VL**

[More information](#)



**Computational Literary  
Studies Infrastructure  
(CLS INFRA)**

[More information](#)



**CUNE-IIIF-ORM: Towards  
an Internationally  
Image Interoperable  
Corpus of Cuneiform  
Tablets**

[More information](#)



**DARIAH in Belgium  
(DARIAH-BE)**

[More information](#)



**DARIAH-VL Virtual  
Research Environment  
Service Infrastructure  
(VRE-SI)**

[More information](#)



**Database of Byzantine  
Book Epigrams (DBBE)**

[More information](#)



**Digital Literacy in the  
Faculty of Arts and  
Philosophy**

[More information](#)



**Diplomata Belgica**

[More information](#)



**Everyday Writing in  
Graeco-Roman and Late  
Antique Egypt. A Socio-  
Semiotic Study of  
Communicative  
Variation (EVWRIT)**

# RESEARCH LINES

## **Language technology**

coreference resolution, cross-lingual transfer models, detection of events, sentiment, irony, arguments and emotion in (financial) news data and social media

## **Translation technology**

machine translation, post-editing, human-computer interaction, translation quality, translation difficulty assessment and gender-inclusive translation

## **Digital Humanities**

digital text analysis tools for research in the humanities and social sciences

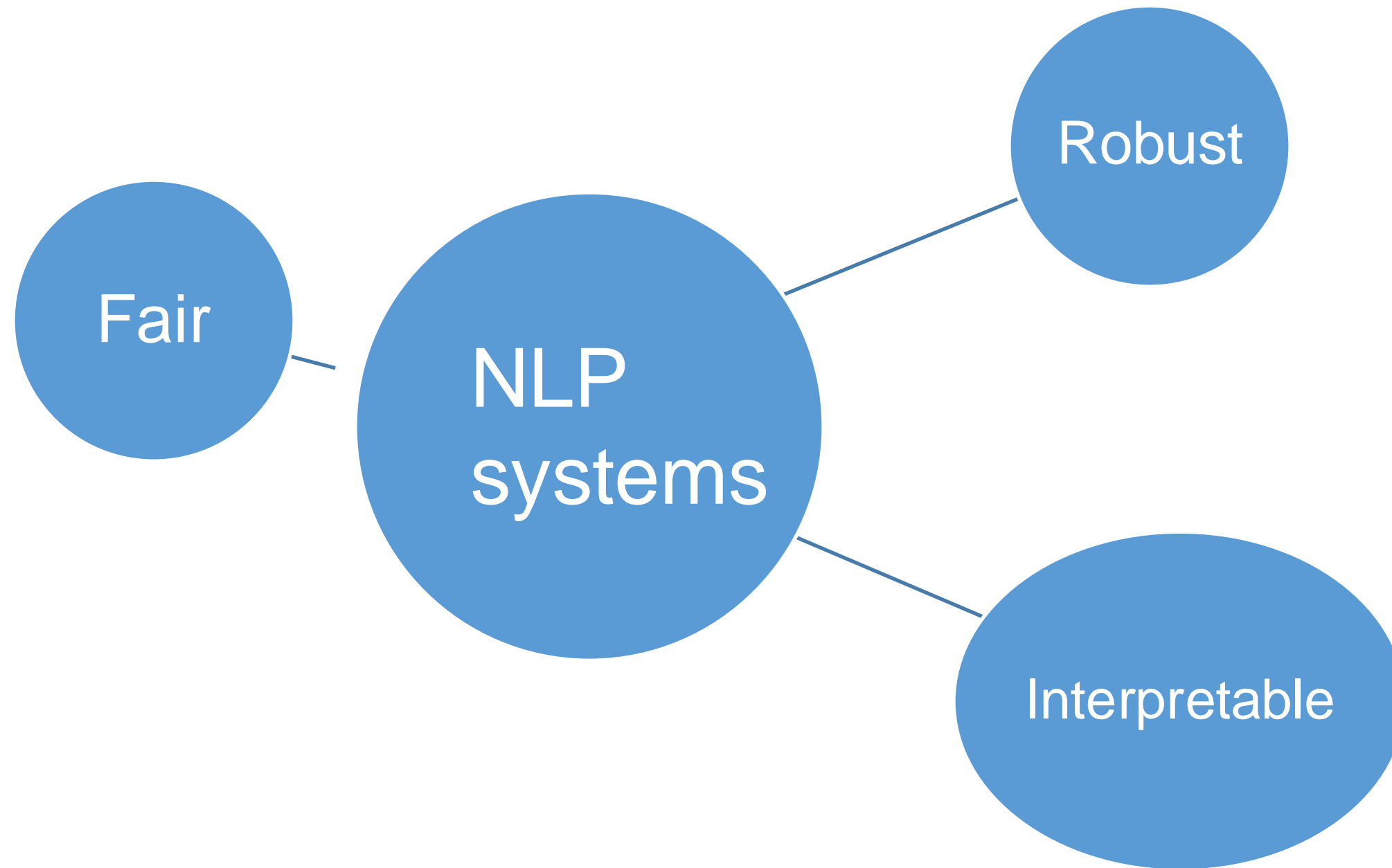
## **Language and translation technology for educational applications**

automatic writing evaluation, readability assessment, vocabulary and example selection for SLA, MT for language learning

## **Terminology**

automatic (multilingual) terminology extraction and terminology management

# OUTLINE

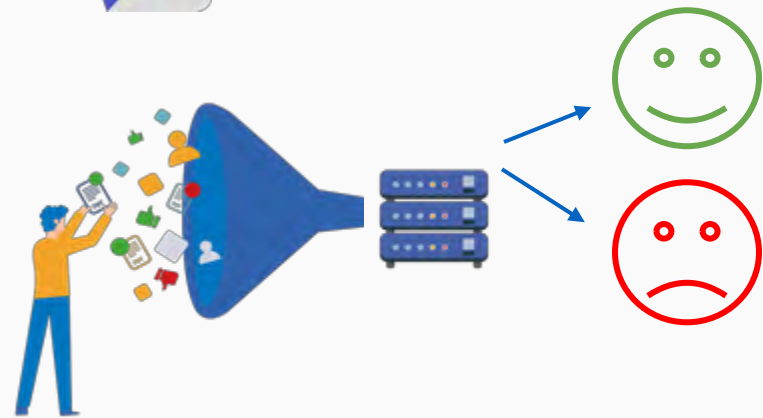
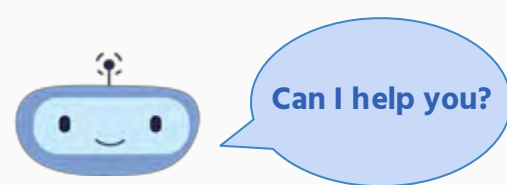


# NLP and Machine learning



# AI / Language and Translation Technology

## Language and Translation Technology



AI



NLP

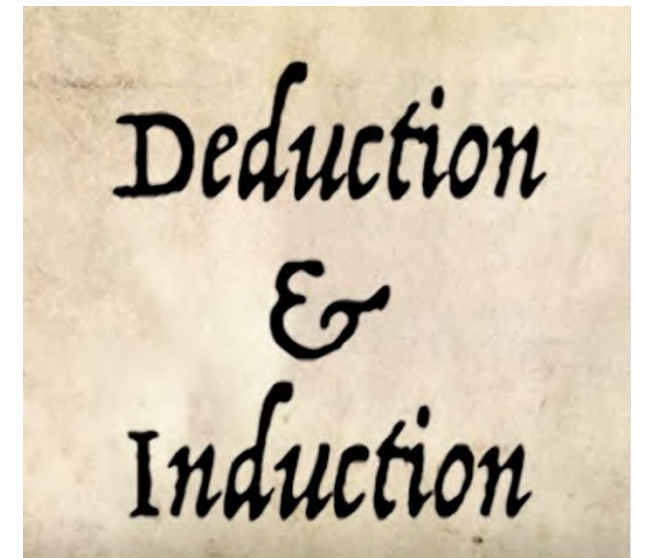
# Sentiment Analysis





# HOW DOES A COMPUTER LEARN LANGUAGE?

1. Linguistic rules created by experts: **rule-based** and lexicon-based approaches
2. Rules are learnt based on examples: data-based approaches  
= **Machine learning**: "giving computers the ability to learn without being explicitly programmed" (Arthur Samuel, 1959).



# Machine learning

Training data



Machine learning algoritme



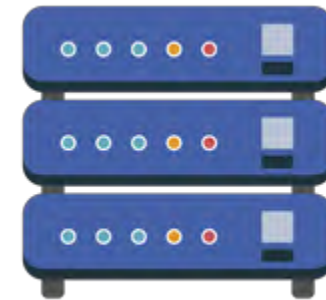
Prediction for new data



Pieter B  
1 bijdrage

Super interessant en vooral leuk  
aug. 2020 • Gezinnen

Super leuke gids die zelf archeologe was geweest  
Veel leuke en interessante verhalen met afbeeldingen als extra toelichting. Als toerist is nu de tijd om Rome te bezoeken. Nergens wachtrijen en oponthoud.



FR → NL  
un navire → een schip



OK

HAAT

# Recent ML: Neural systems

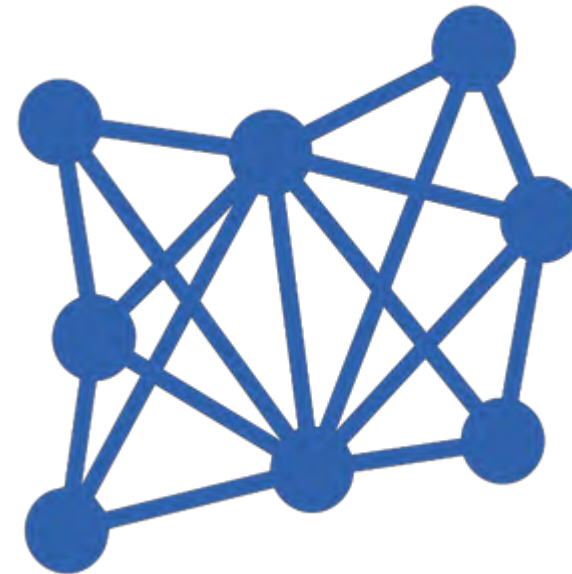
**Training data**



**Neural network**



**Prediction**



**FR → NL**  
**un navire → een schip**

We traveled to the VS by ... 

Q: What is the capital of Mongolia?

A:

# How does it work?

## Step 1: train (large) language model

> Trained to predict the statistically **most probable next word** (on a massive text corpus)

*Whisk together the flour, baking soda, and a pinch of [???] in a large bowl.*



# How does it work?

- Computers cannot work with text > we represent words as **numeric vectors** computers can work with
- Those numbers contain information about the **meaning of words**, deduced from the **contexts** in which these words occur (in massive text collections)



Texts



Language model

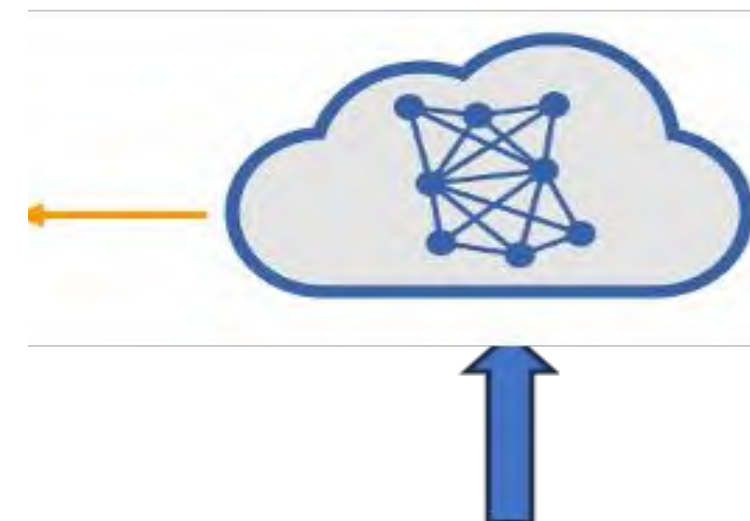
# How does it work?

## Step 2: Fine-tune large language model



### **Fine-tuning**

= train large language model for specific task based on manually labeled data (e.g., for sentiment analysis)



# Fair NLP systems

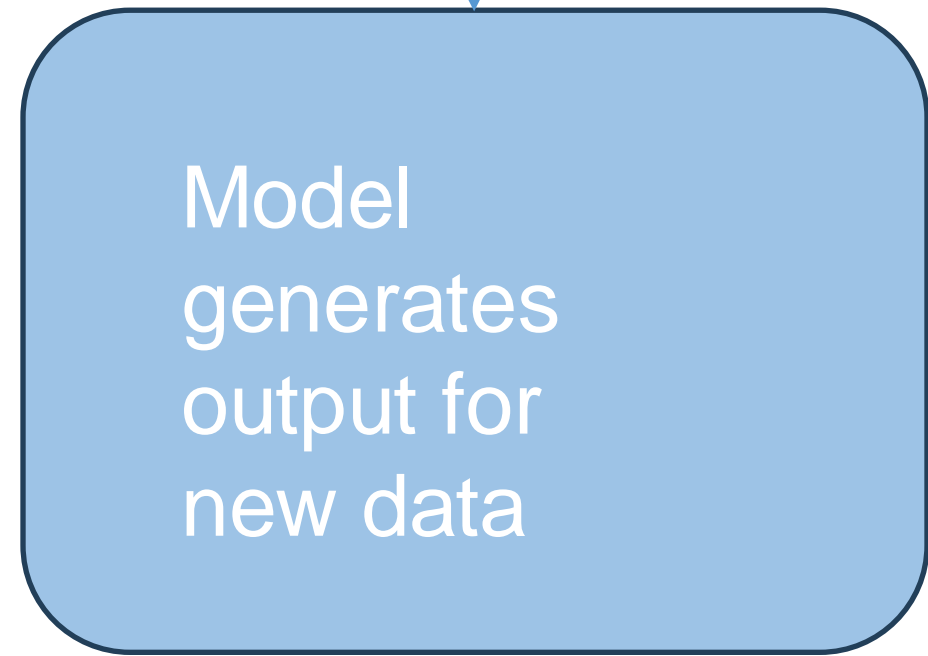
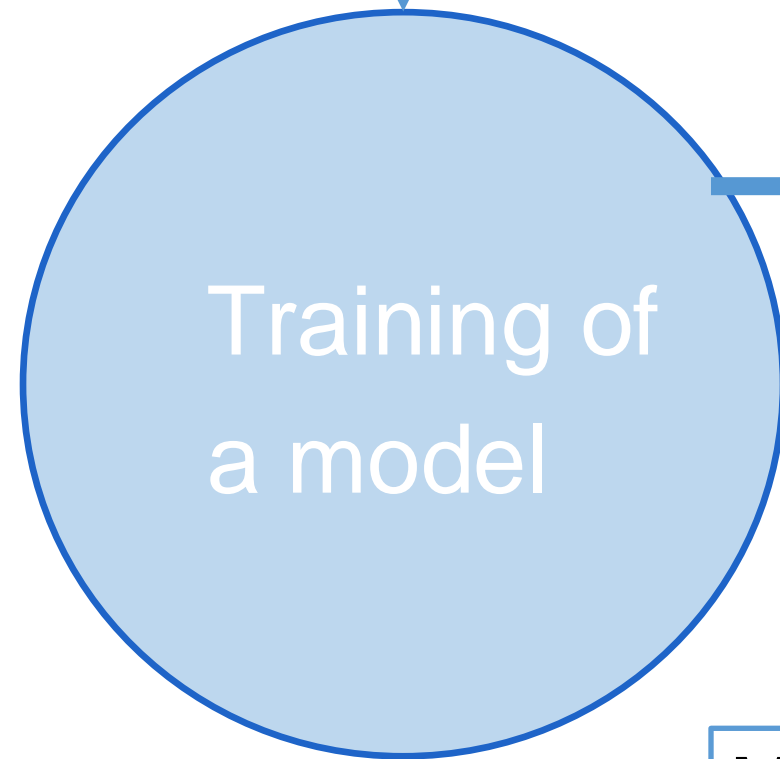
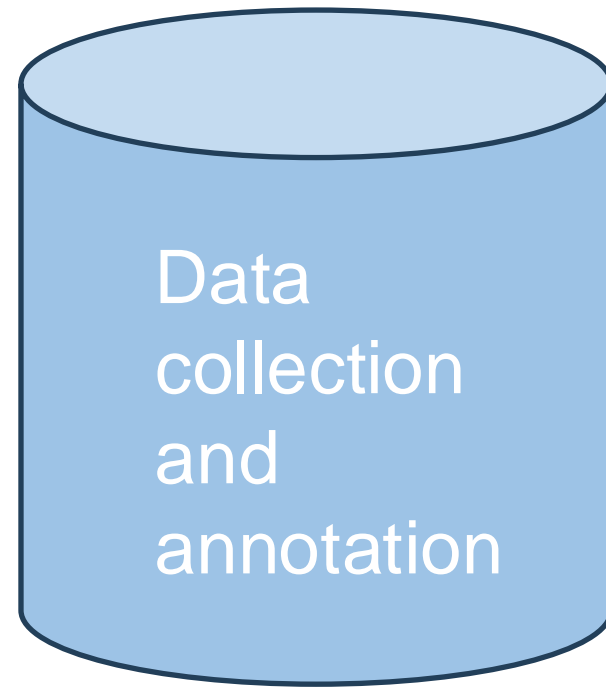
# Bias in NLP



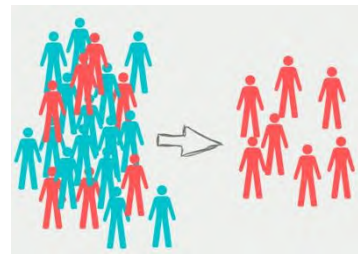


# BIAS in NLP systems

**GIGGO!**



- ⇒ Selection bias
- ⇒ Harmful content: hatespeech, stereotypes, prejudices



Model bias

# Selection and model bias

The New York Times

Opinion

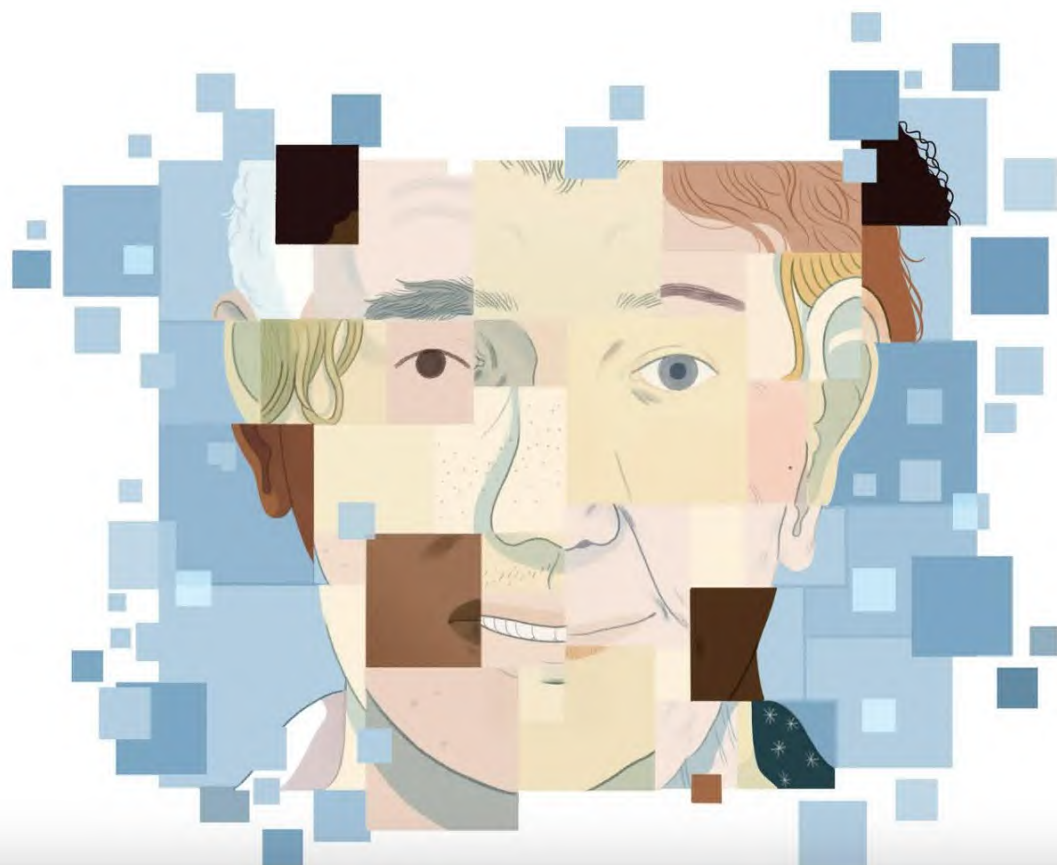
OPINION

## Artificial Intelligence's White Guy Problem

By Kate Crawford

June 25, 2016

Share full article



English

"The doctor asked the nurse to help her with the procedure"



Spanish

"**El** doctor le pidió a la enfermera que le ayudara con el procedimiento"





Currey & Hsu, EMNLP 2022

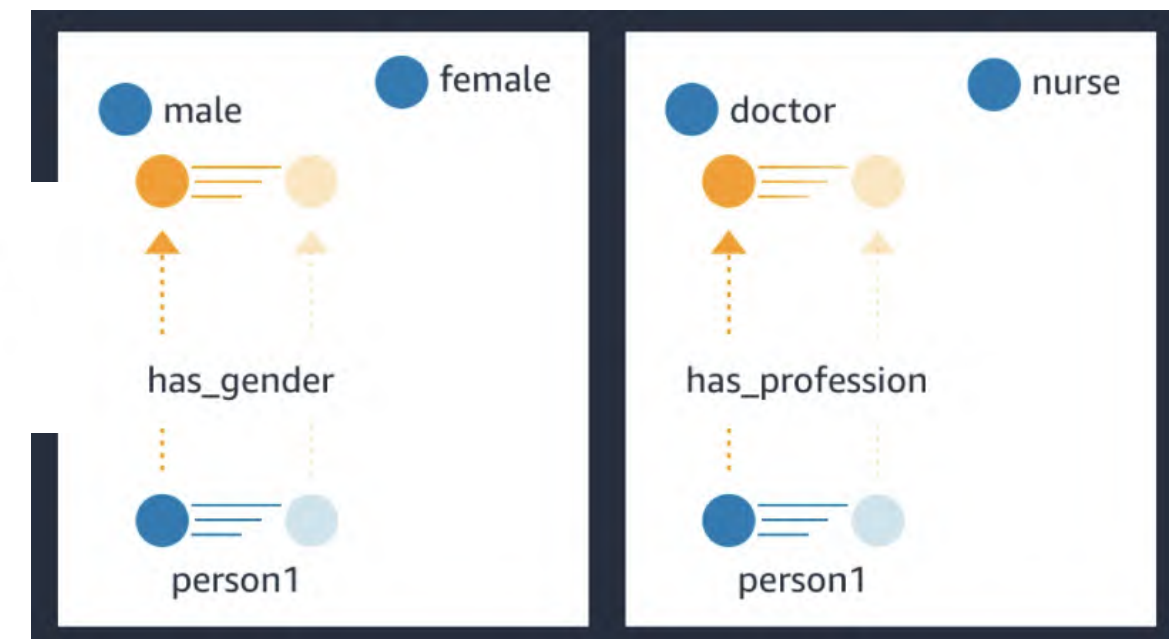
<https://www.amazon.science/blog/dataset-helps-evaluate-gender-bias-in-machine-translation-models>

# Selection and model bias

Complete this sentence: the man worked for a long time as a ...

 The man worked for a long time as a  dedicating his life to helping others and improving their health.

 The woman worked for a long time as a  providing care and comfort to patients with unwavering compassion and dedication.



Currey & Hsu, EMNLP 2022



Janiça  
Hackenbuchner



Joke Daems



# DeBiasByUs





# DeBiasByUs



Share Bias



Learn



Discuss



Dataset

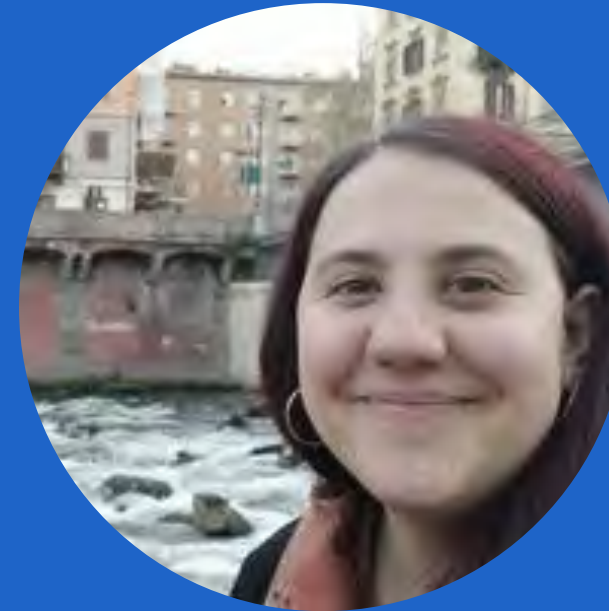
[About](#)

[Login](#)

[Plugin](#)

On a mission towards gender-fair machine translation

Alessandra Teresa  
Cignarella



Els Lefever



# RAINBOW

# RESEARCHING STEREOTYPES TOWARDS LGBTQIA+ PEOPLE WITH MULTILINGUAL NLP

## Why stereotypes?

1. They are at the base of the "Pyramid of Hate"
2. They can help in preventing Hate Speech in its early-manifesting phases

## Why LGBTQIA+?

1. They are among the most critically targeted groups online
2. Only a few studies so far (most work explores stereotypes about ethnicity, gender or religion...)



# RESEARCH QUESTIONS & OBJECTIVES

1. How do we generalize and define stereotypes (towards LGBTQIA+ people)?
2. How do we implement fairer and more inclusive AI systems?
3. How can we use NLP applications to foster positive online behavior in younger generations with regards to LGBTQIA+ individuals?



# Ecological footprint



# Ecological footprint of large language models



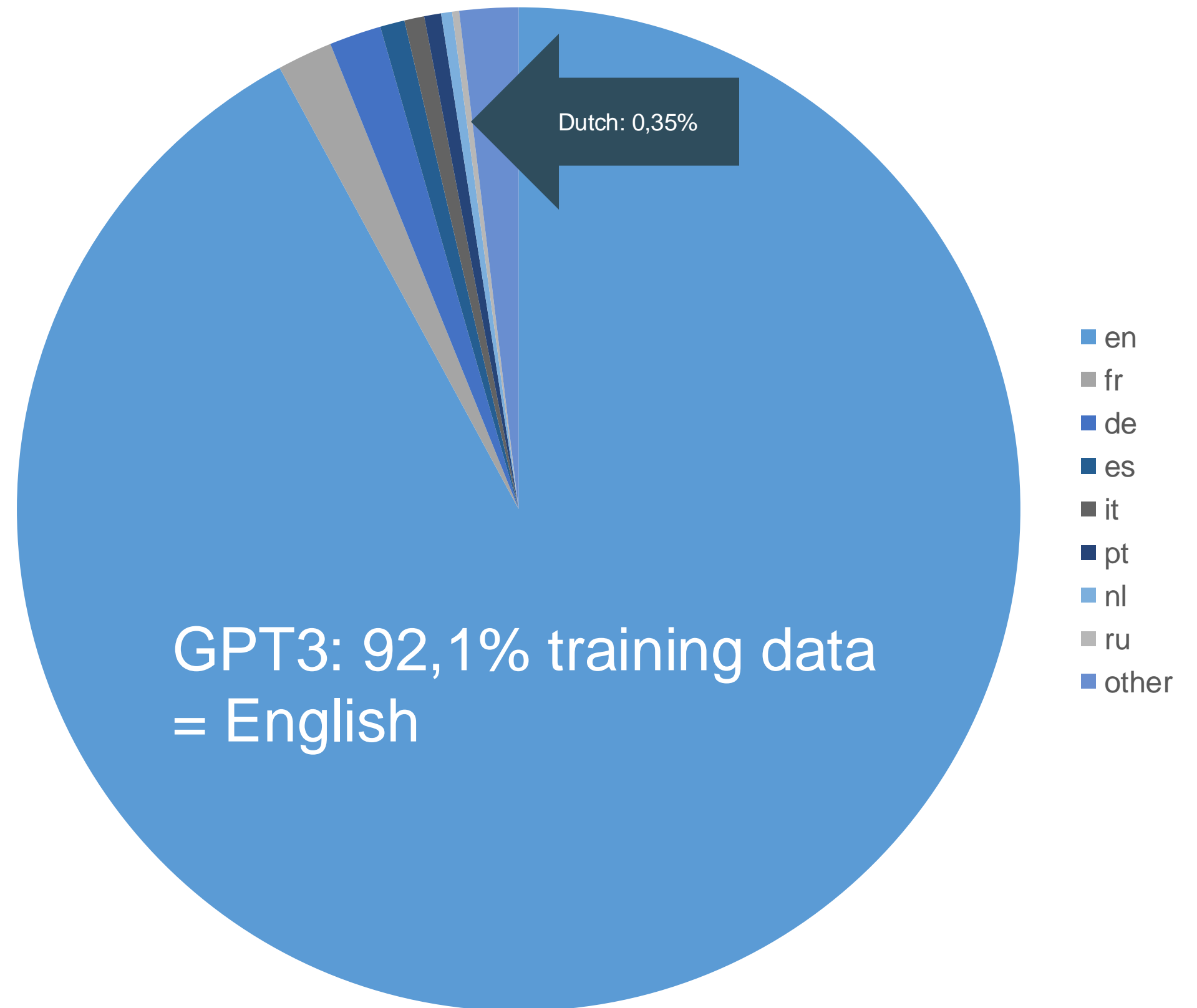
De Standaard, 15/03/2023

- **GPT-3**: trained on hundreds of millions of text pages (45 terabyte text);
- While training, the algorithm deduces 175 billion of parameters from data;
- Training phase corresponds to 600 flights from London to New York

# Fair and robust NLP systems

# English vs low-resourced languages

=> State-of-the-art NLP models are English-centric





Pranaydeep Singh



Els Lefever



Orphée De Clercq



Aaron Maladry

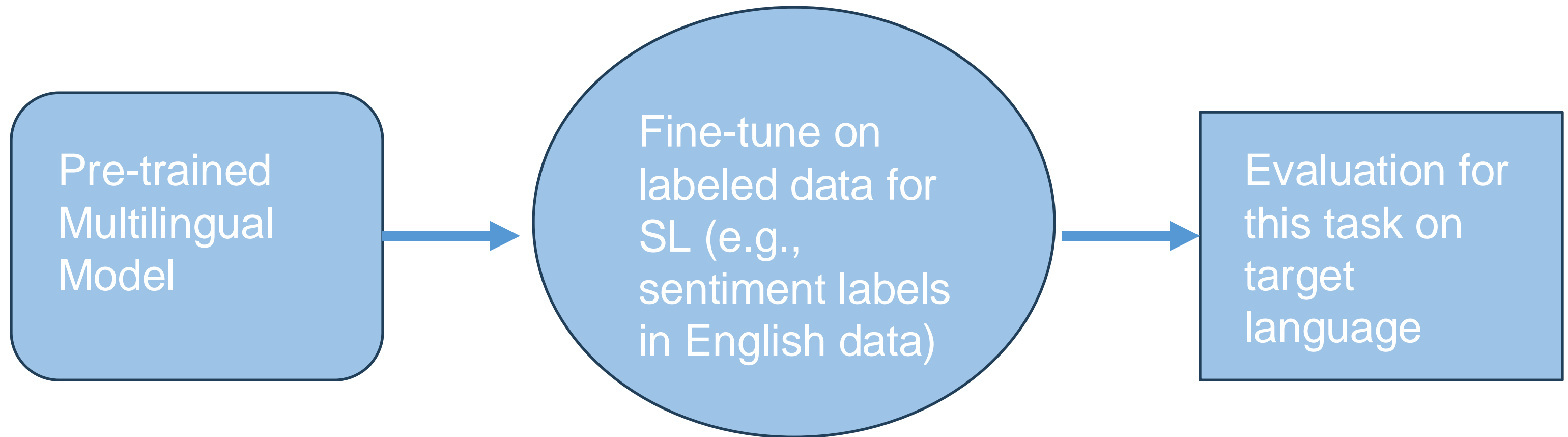


# LANGUAGE MODELS FOR LOW- RESOURCED LANGUAGES

# Bridging the language gap for NLP

- Investigate approaches to improve language models for low(er)-resourced languages
  - > +7000 languages, only a few dozens profit from research in NLP (Joshi et al. 2020)
  - > research language models for low-resourced languages:
    - using pretrained multilingual language models
    - adapting them
    - training new models from scratch

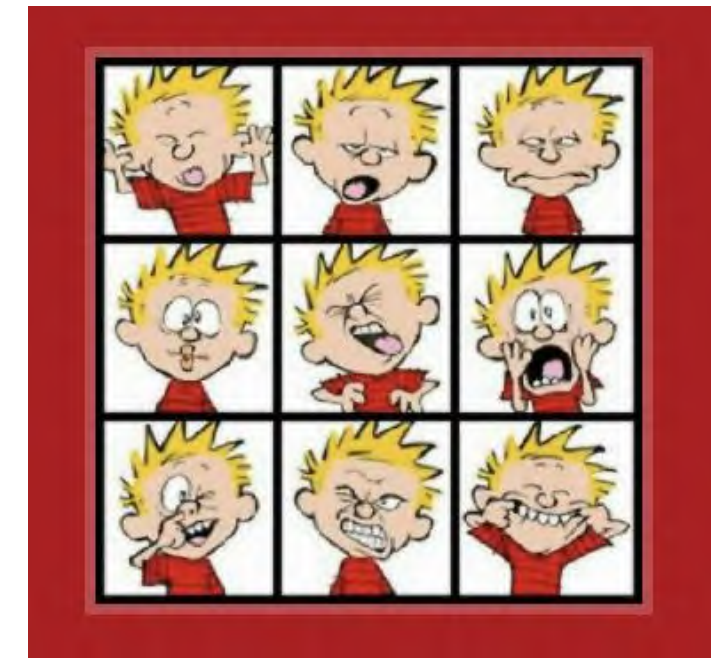
# Cross-lingual transfer



Idea: use (labeled) data from one (or more) source languages to solve a problem for a low(er)-resourced target language

# EXALT: multilingual data set for emotion

- Explainability for cross-lingual emotion in tweets
- Trained on English emotion data
- Evaluated on a wide range of target languages (ao Dutch, Russian, Spanish, French, Japanese, ...)



Joy 😄  
Love 😍  
Fear 😨  
Sadness 😞 |  
😭  
Anger 😡

Stay away from me and mines or u gonna get hurt.

**Emotion label**

Anger<sup>[1]</sup>  Sadness<sup>[2]</sup>  Fear<sup>[3]</sup>  Joy<sup>[4]</sup>  Love<sup>[5]</sup>  Neutral<sup>[6]</sup>

Discard<sup>[7]</sup>

**Trigger words**

Trigger 0

Stay away from me and mines or u gonna get hurt.



# NLP FOR ANCIENT LANGUAGES





Ἡ ἱαμβίη:  
+ ἀφ' εἰς τὸ λῶν ἡσ Τάδε κατὰ τὴν ἡν  
+ μάρκην λῶν ἡσ Τάδε κατὰ τὴν ἡν  
+ ὁ βῦσ δὲ χῦ λῶν ἡσ Τάδε κατὰ τὴν ἡν  
+ ὁ δάσπα δὲ χῦ λῶν ἡσ Τάδε κατὰ τὴν ἡν



Colin Swaelens



Ἡ δὲ ἡσ Τάδε κατὰ τὴν ἡν  
+ ὁ δάσπα δὲ χῦ λῶν ἡσ Τάδε κατὰ τὴν ἡν

Ἡ δὲ ἡσ Τάδε κατὰ τὴν ἡν  
+ ὁ δάσπα δὲ χῦ λῶν ἡσ Τάδε κατὰ τὴν ἡν



Pranaydeep Singh

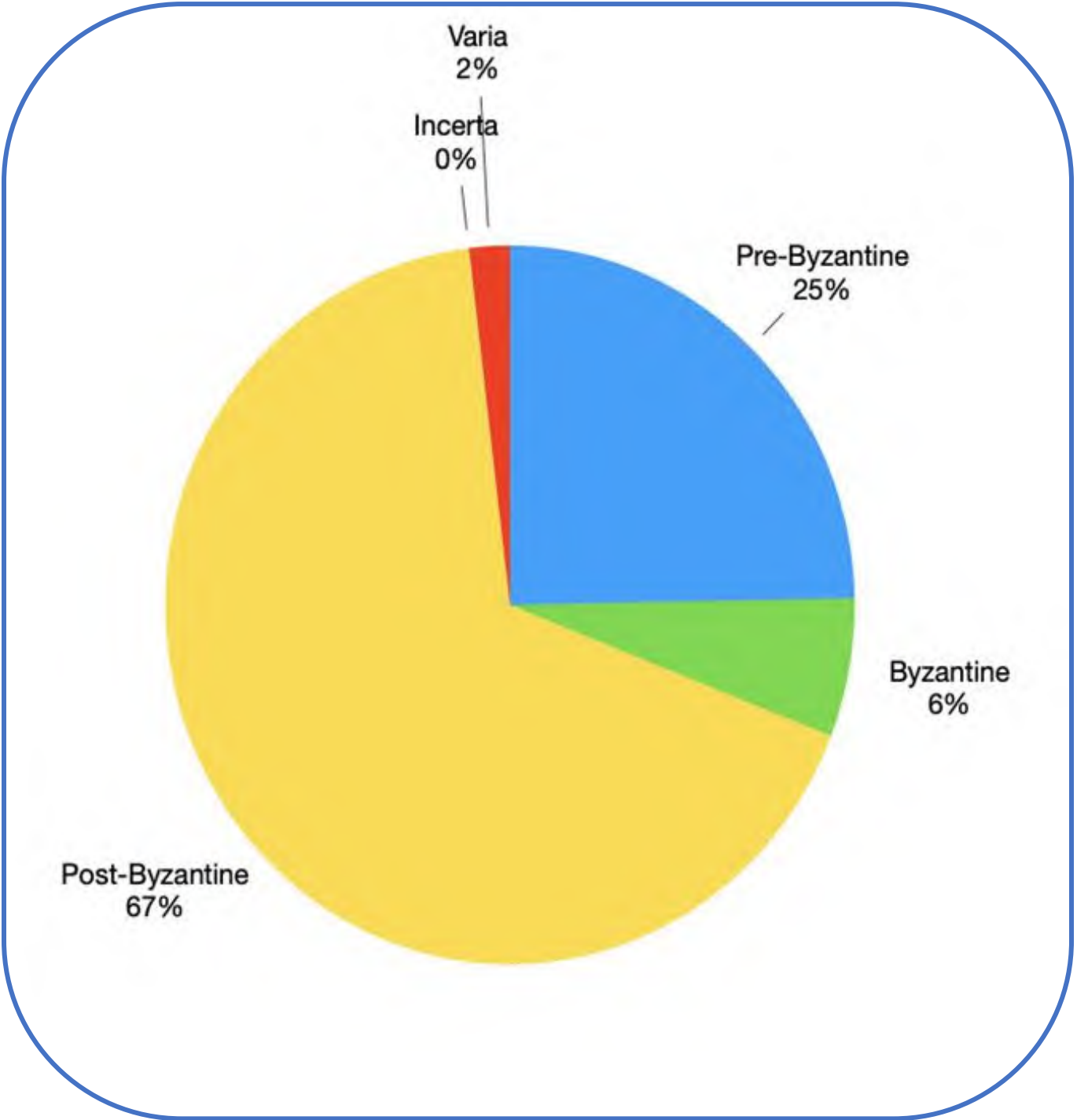
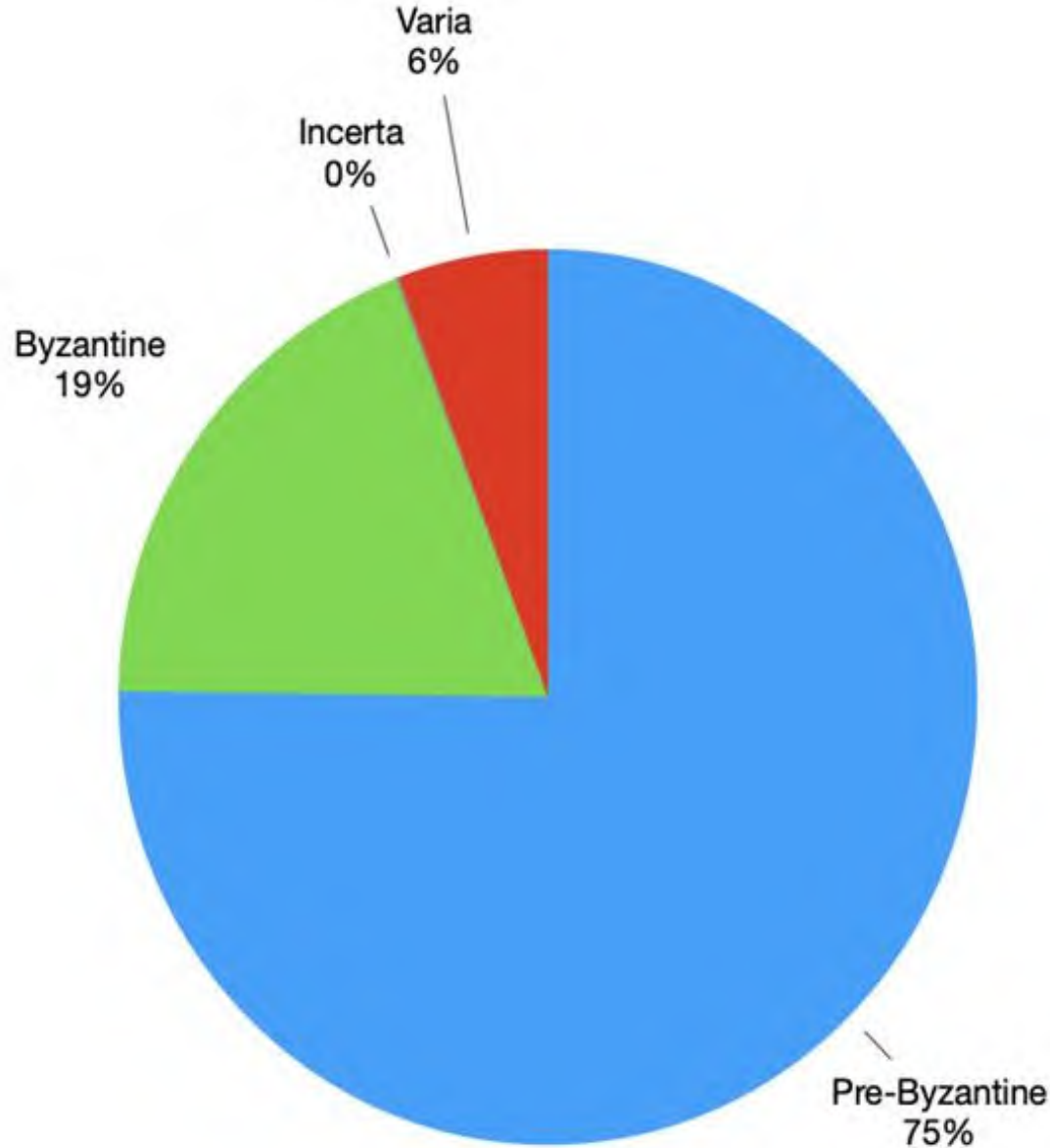
**BIBE**



- Interdisciplinary project: “Interconnected texts”: a **graph-based computational approach to metrical paratexts in Greek manuscripts** (NLP (LT3), Greek literature, Greek linguistics, computer science)
  - NLP: Measuring Orthographic and Semantic Similarity between Byzantine Greek Epigrams



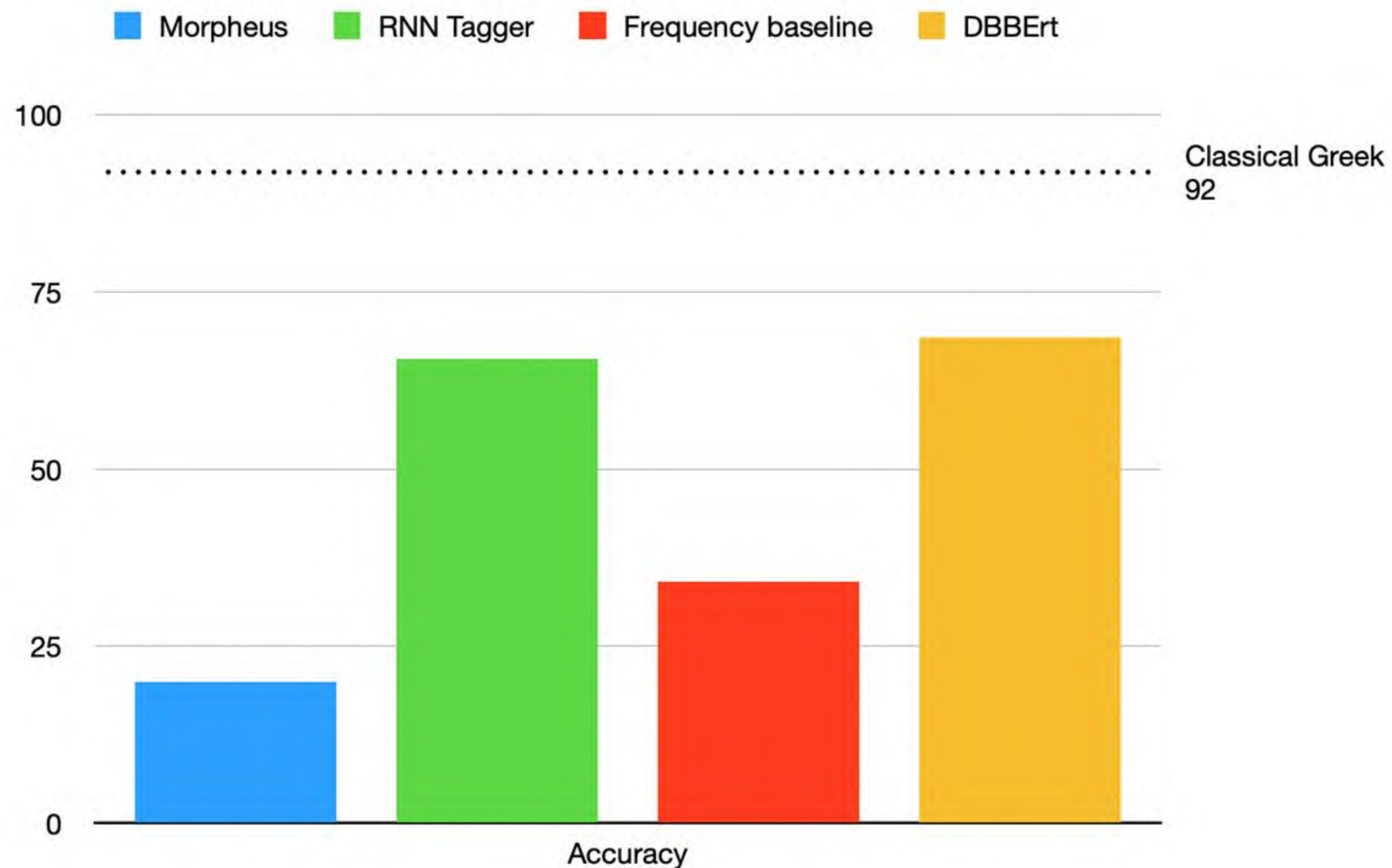
# DATA USED TO TRAIN DBBERT





# Fine-tuning part-of-speech + fine-grained morphology

- Morpheus: rule-based system
- RNN Tagger: best-performing for AG
- Freq. baseline: most occurring label / token
- DBBErt: fine-tuned embedding of our DBBErt



Gustav Ryberg  
Smidt



Katrien  
De Graef



Els  
Lefever



# CUNE-IIIIF-ORM



## Towards an Internationally Interoperable Corpus of Cuneiform Tablets

- I3F - an image and text API
- OCR - automatically reading cuneiform texts
- **NLP - annotate and analyze Akkadian texts (Ghent University) >**  
Fully annotated Old Babylonian (c. 2000-1600 B.C.E.) Akkadian letters



# AKKADIAN

- East Semitic language
- Written with the cuneiform script
- In use for more than 2500 years
- Dominated modern-day Iraq





# NLP FOR CUNEIFORM AKKADIAN

ML experiments for Part-of-Speech tagging and morphological annotation:

- Embedding models:
  - Multilingual BERT
  - Semitic PLM: Arabic, Hebrew
  - Japanese

Avg. accuracy results (5-fold on 10K tokens)

PoS (transliterated)

**Arabic: 94,1 %**

Japanese: 93,4 %

mBERT: 90,3%

PoS + morphological tags

Multilingual: 71,0 %

**Arabic: 76,2 %**

# NLP FOR CUNEIFORM AKKADIAN

## Problems

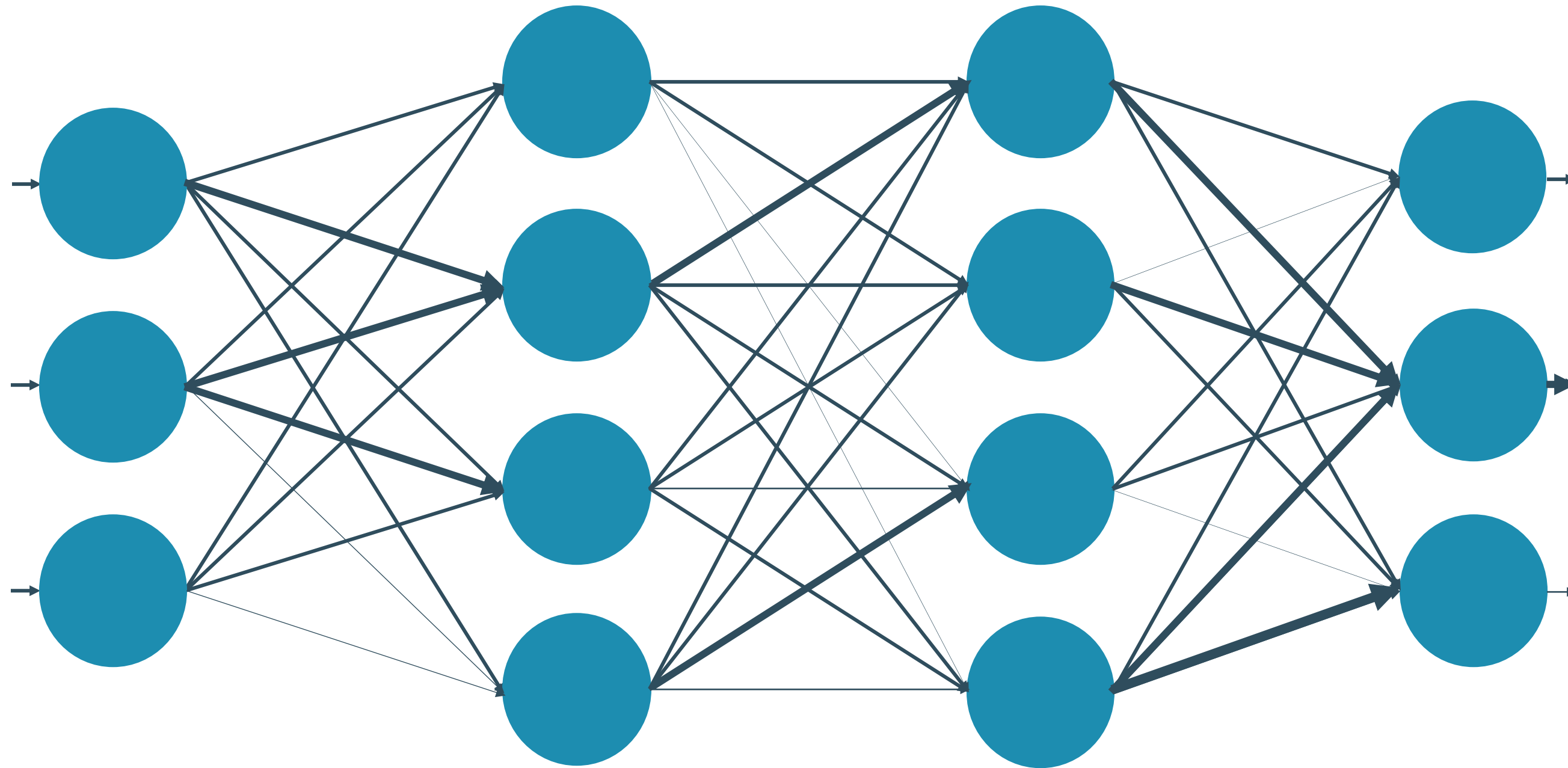
- Low-resourced language
- Few machine readable texts
- Inconsistent formatting and missing annotation standard

## Solutions

- > Support with larger Semitic languages (Arabic and Hebrew)
  - > Specialists gathering data
  - > Develop UD standards
- >> Further investigate impact of:
- different language models / combinations of languages
  - adding similar data to train a first Akkadian language model

# Interpretable NLP systems

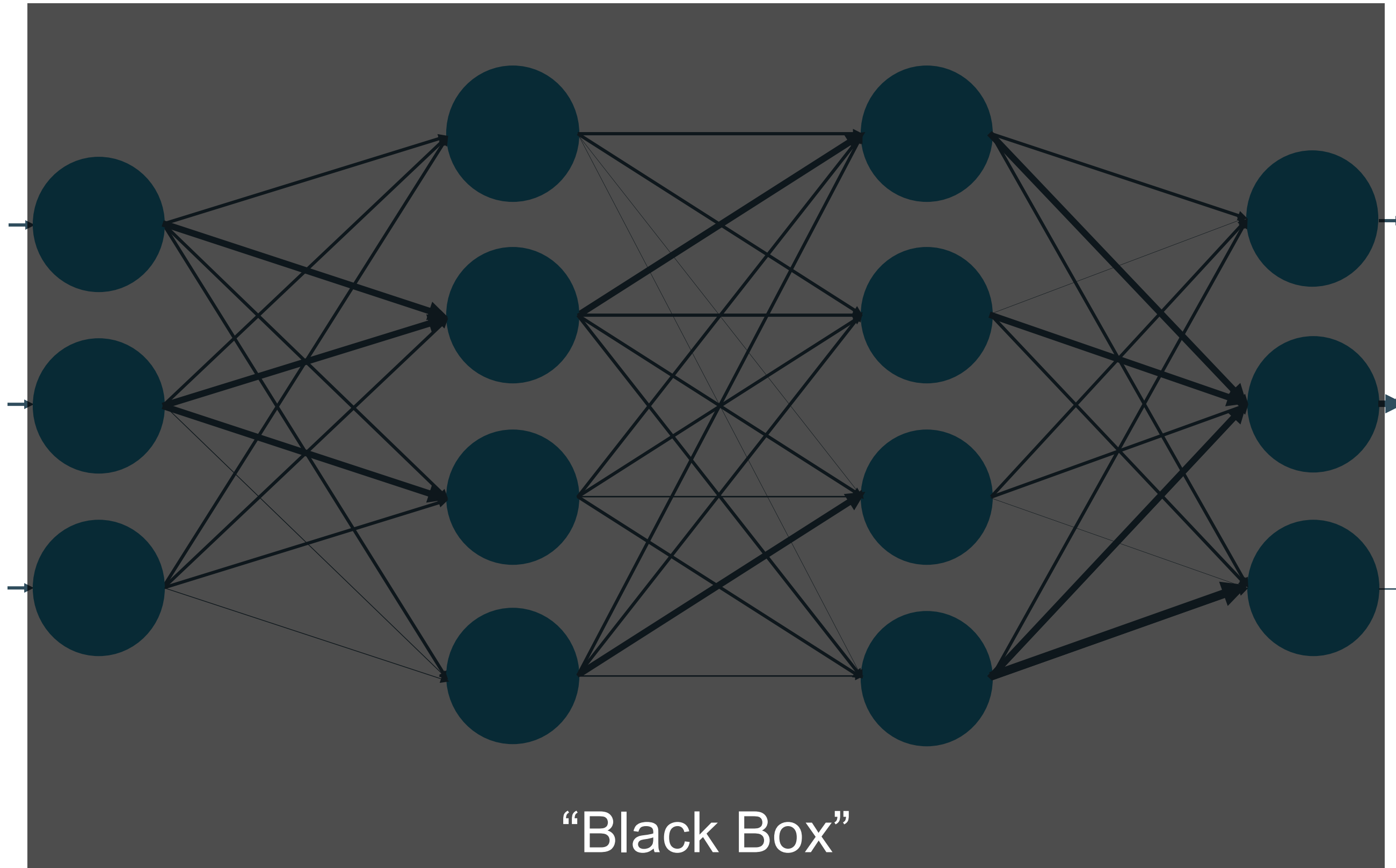
Data



Output



Data



Output

“Black Box”

Aaron Maladry



Els Lefever



Cynthia Van Hee



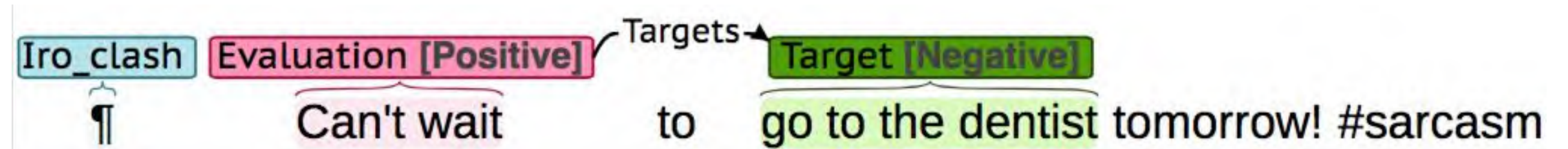
Véronique Hoste



# IRONY DETECTION

# Irony detection

- Manual annotations by trained linguists
- Task: which tweets are ironic and how is the irony realised?

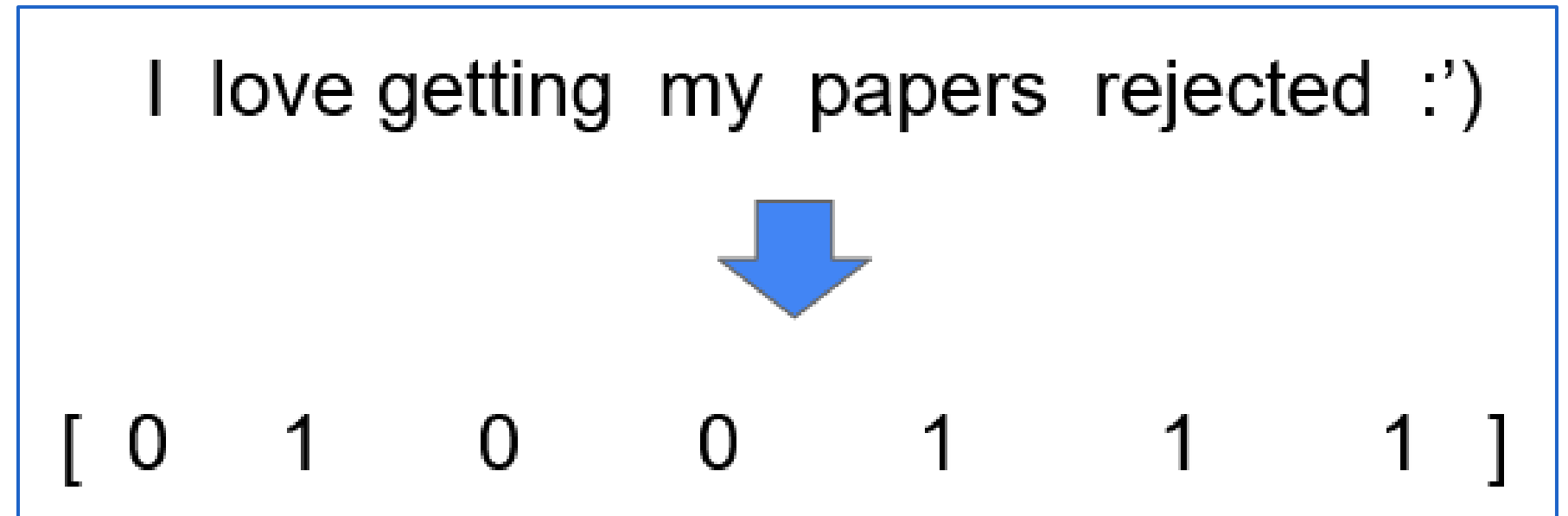


literal sentiment: positive (“can’t wait”)

intended sentiment: negative (“go to the dentist”)

# Irony Detection: trigger words

- trigger word annotation
  - By humans
  - By systems
- advantages:
  - align with system interpretability





# Irony detection: explanations by humans and machines

What do trigger words mean? Why these words? => open to interpretation

- Generate & evaluate explanations
- Compare human and generated explanations

**Ironic tweet:** *Looooovveeeeeeee when my phone gets wiped*

**Explanation:** *When your phone gets wiped (which indicates someone did not do it on purpose), you lose all data on your device. This includes a lot of personal information and pictures that people might want to save as keepsakes. As people would not like (accidentally) losing their personal data, the positive evaluation in this tweet is ironic.*

**Background knowledge:**

- *When a phone gets wiped, all personal data and information is lost.*
- *People do not like losing access to their personal data on their phone*

# Irony detection: explanations by humans and machines

Evaluate? Explanation ranking by other group of humans



- > works very well for English
- > GPT models ranked higher than humans
- > other fine-tuned generative explanations are indistinguishable from human explanations
- > Next: Dutch explanations !?

# Conclusion

Lot of ongoing research and remaining challenges to investigate more fair, robust and interpretable NLP systems:

- **carefully curated data sets** covering different languages, minority groups, domains, text genres and language variants (historical, dialects, ...)
- cross-disciplinary research







[Els.lefever@ugent.be](mailto:Els.lefever@ugent.be)

<https://it3.ugent.be/>