

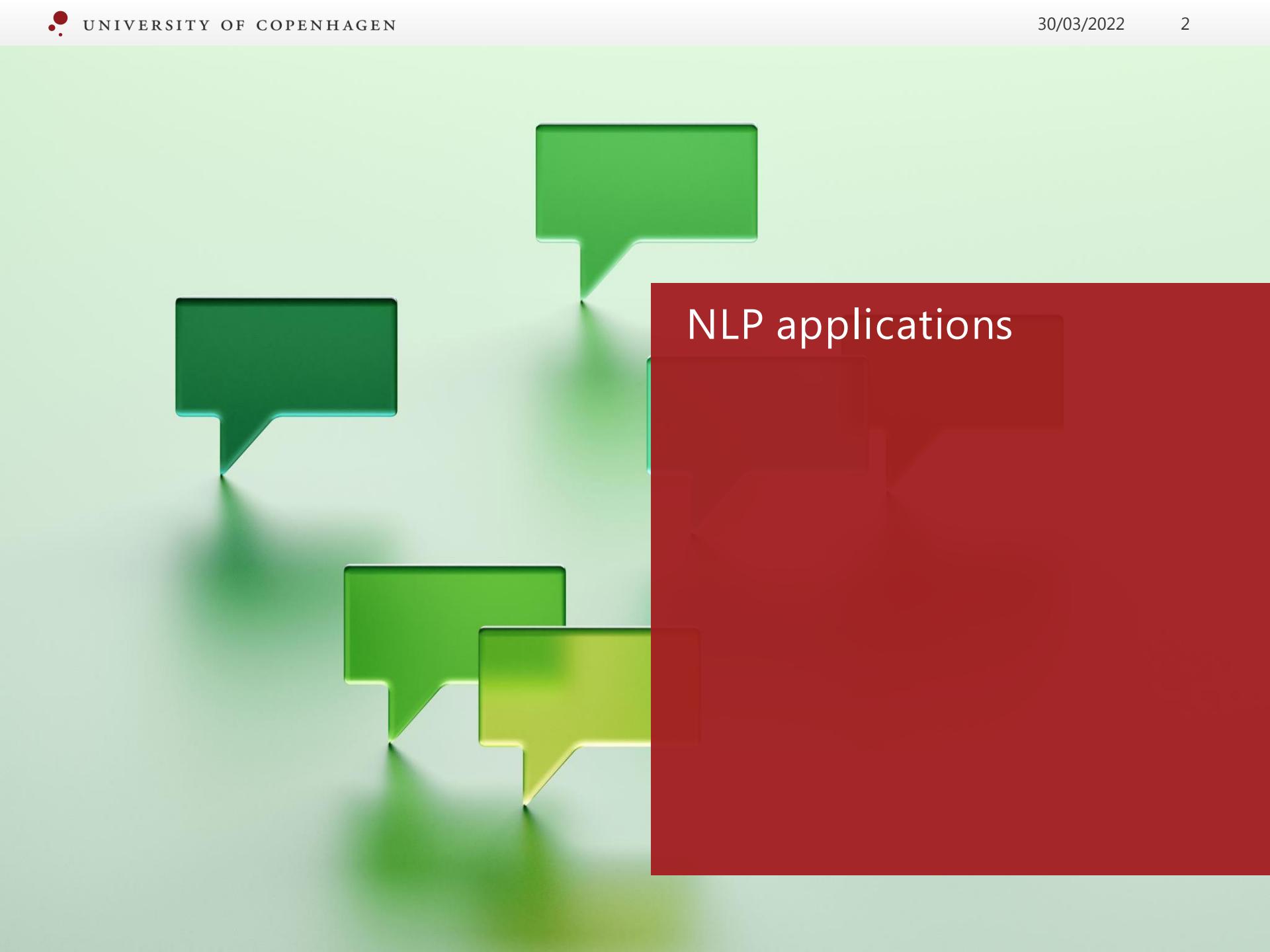
Cultural and Environmental Considerations in Natural Language Processing

University of Haifa
Information Systems Seminar
30 March 2022

Daniel Hershcovich

UNIVERSITY OF COPENHAGEN





NLP applications

Debating

Opening speeches

Pre-debate: both sides receive the motion and prepare 15 min

Moderator introduces the motion to the audience

Second speeches

Project Debater delivers the 'government' opening speech 4 min

Human debater delivers the 'opposition' opening speech and replies 4 min

Summary speeches

Project Debater offers rebuttal and additional points 4 min

Human debater offers rebuttal and additional points 4 min

Project Debater provides final rebuttal and closing statements 2 min

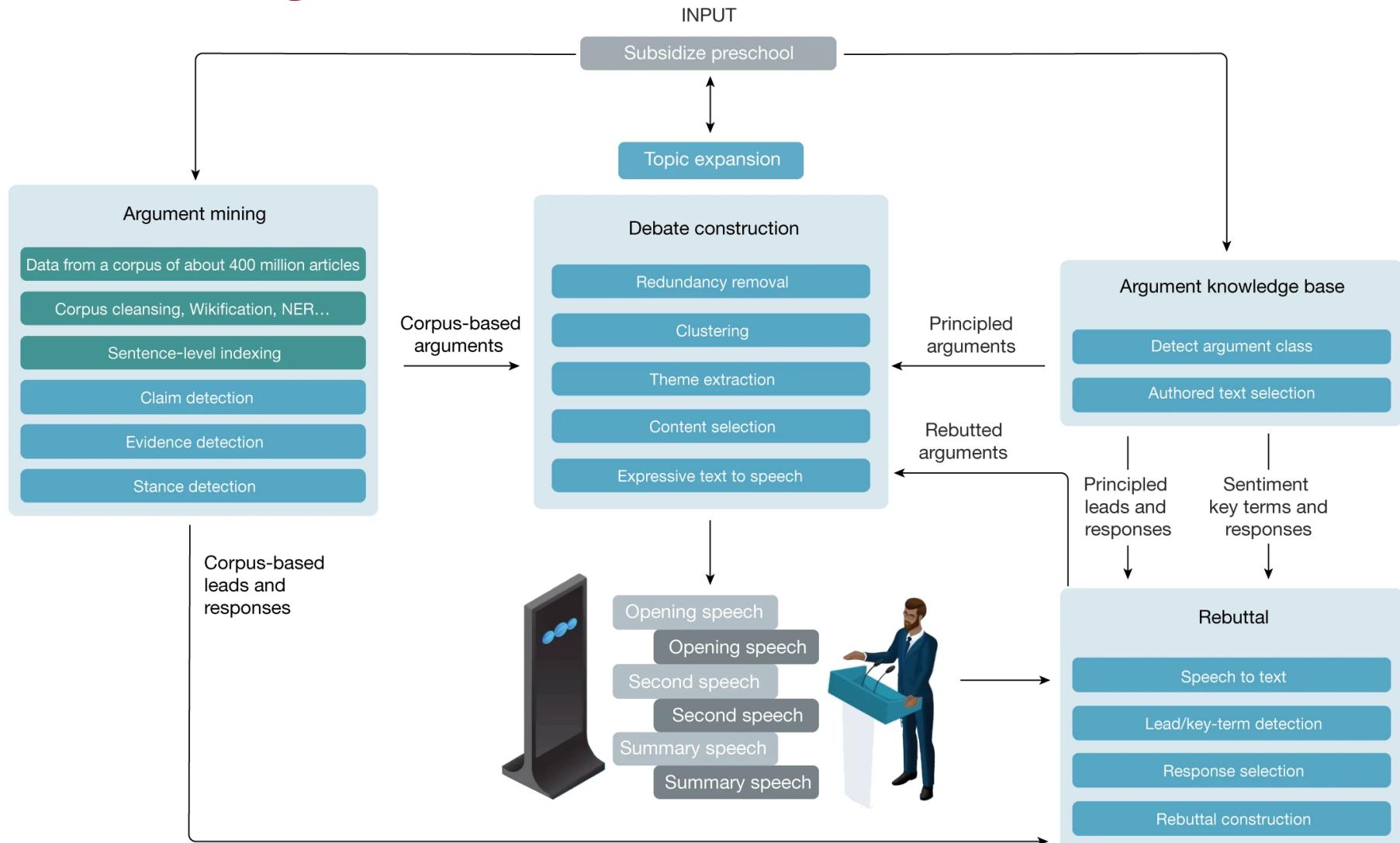
Human debater provides final rebuttal and closing statements 2 min



An autonomous debating system

Slonim et al. (Nature 2021)

Debating



An autonomous debating system
Slonim et al. (Nature 2021)

Fact checking

Examples of disinformation



False claims such as 'drinking bleach or pure alcohol can cure the coronavirus infections': on the contrary, drinking bleach or pure alcohol can be very harmful. **Belgium's Poison Control Centre has recorded an increase of 15% in the number of bleach-related incidents.**

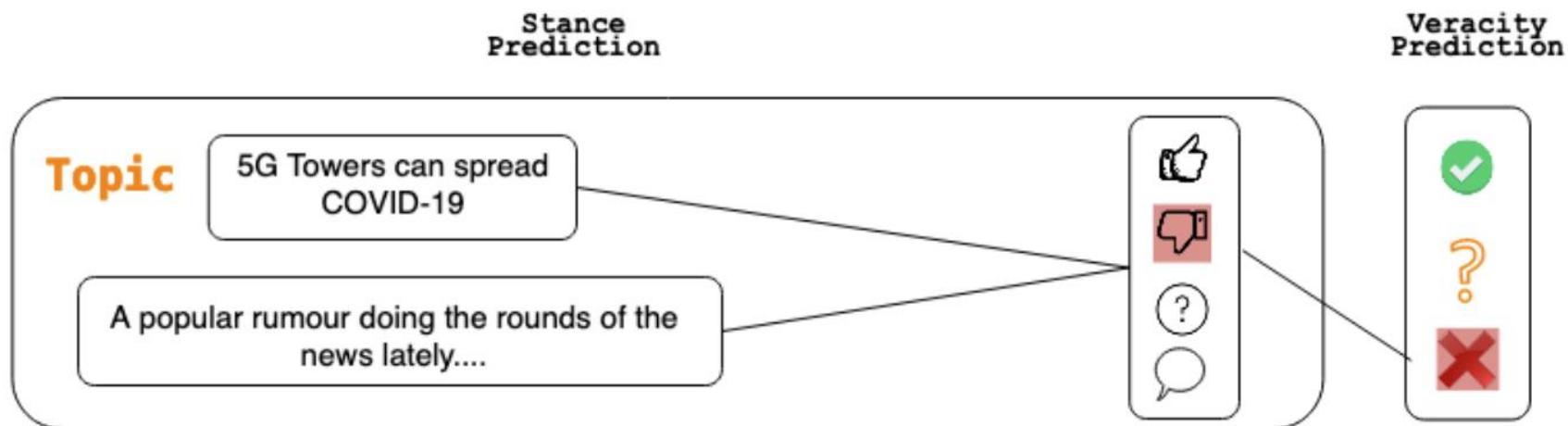


Conspiracy theories, such as the claim that coronavirus is 'an infection caused by the world's elites for reducing population growth'. The scientific evidence is clear: the virus comes from a family of viruses originating in animals that include other viruses such as SARS and MERS.



Claims that '5G installations would be spreading the virus'. These theories had no specific substantiation and led to attacks on masts.

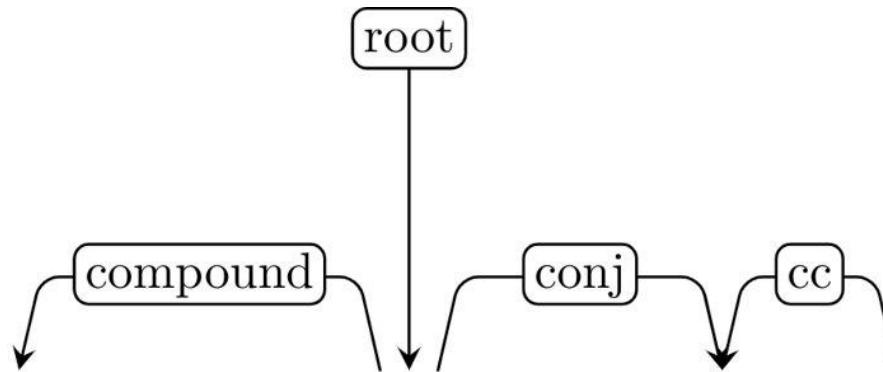
Fact checking



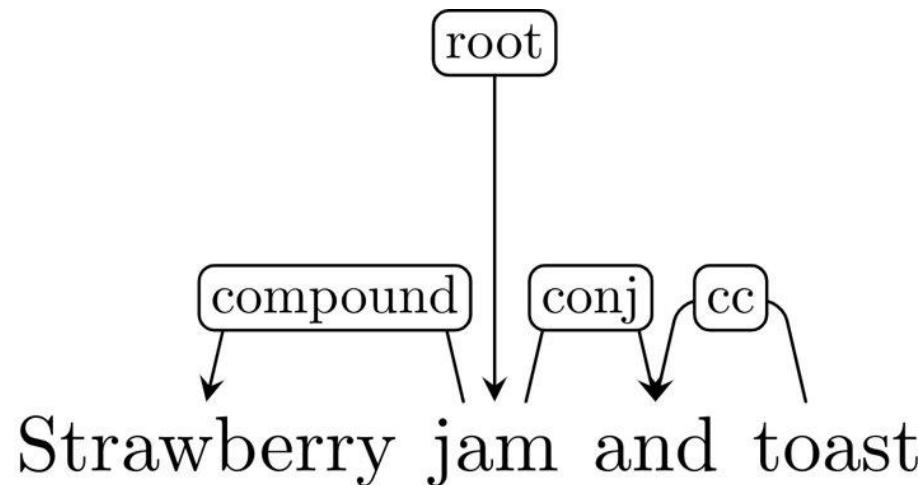


NLP methods

Syntactic dependency representation



Meaning representation and parsing



Strawberry jam and toast

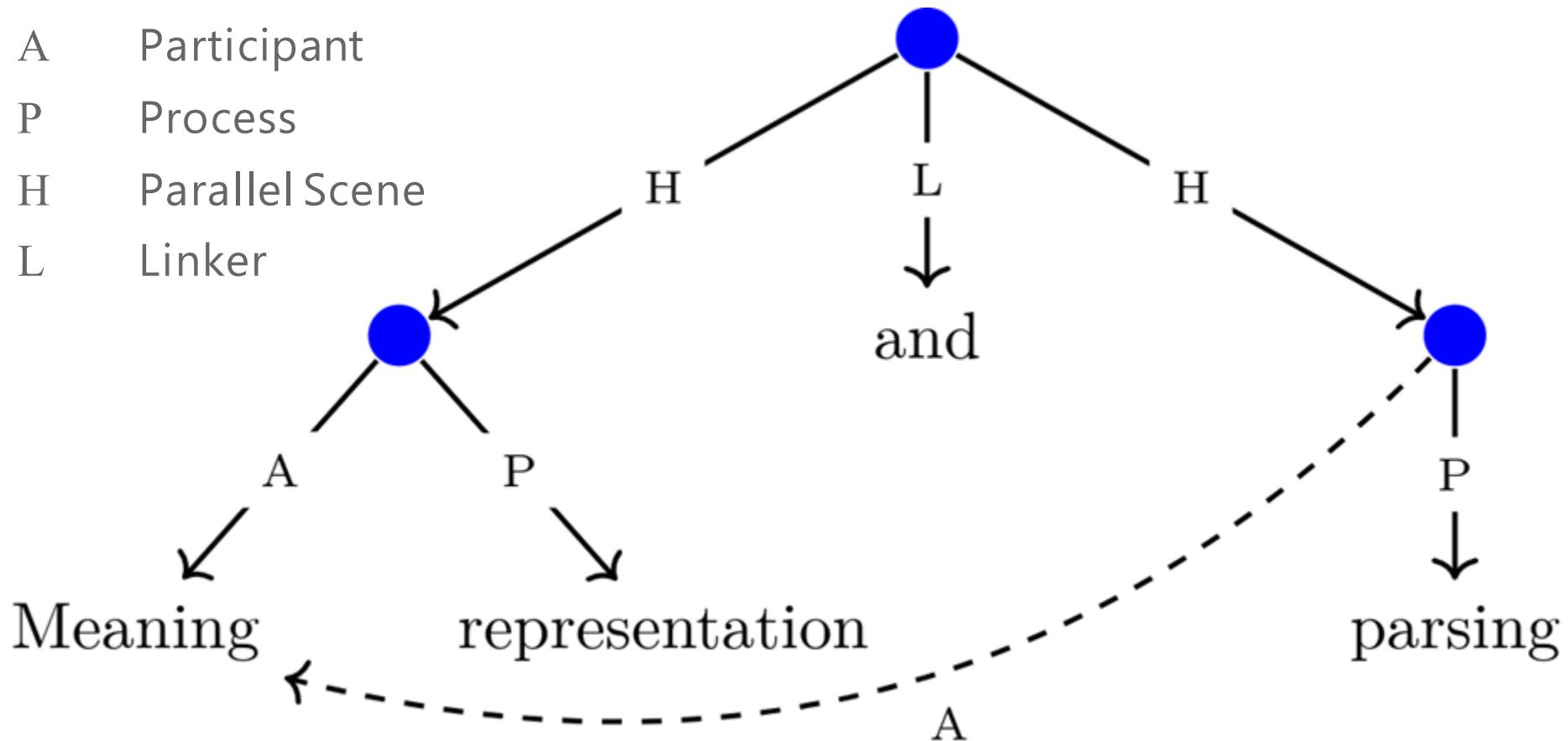


Meaning representation

Example: UCCA



A	Participant
P	Process
H	Parallel Scene
L	Linker



Implicit meaning

Example: UCCA

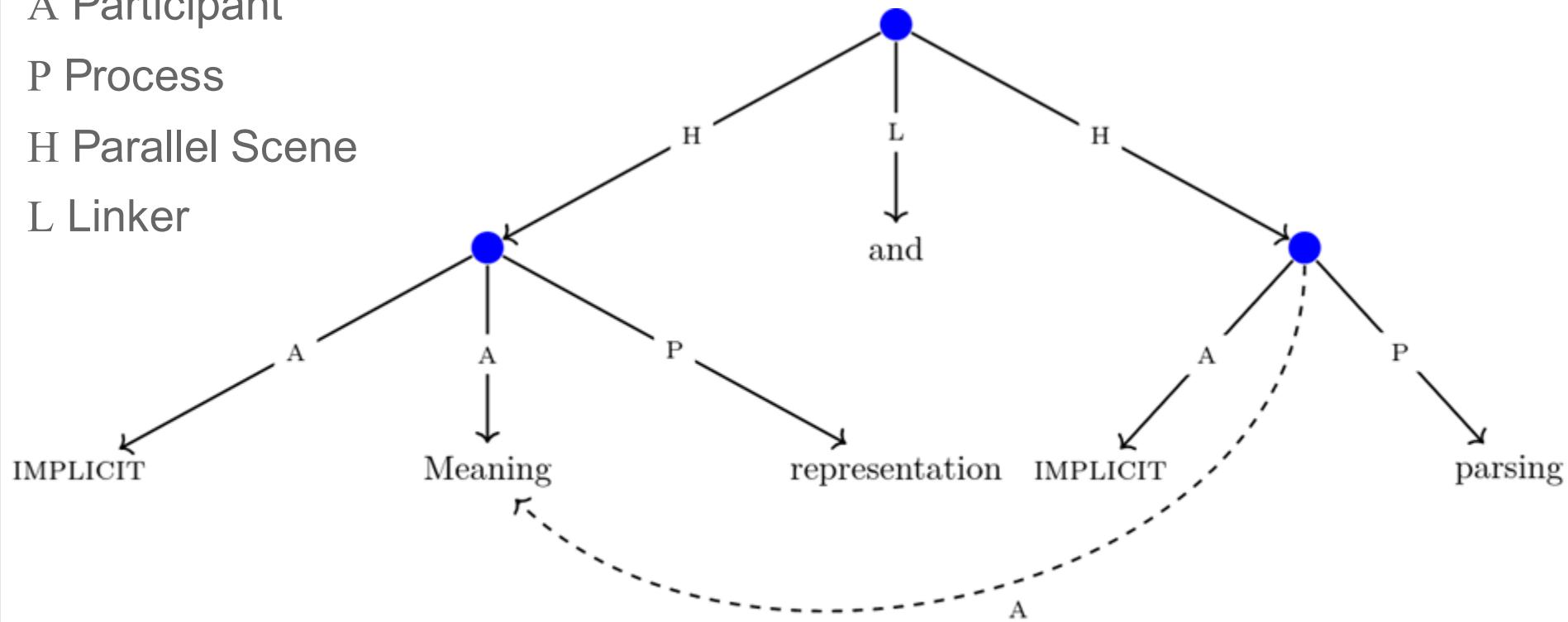


A Participant

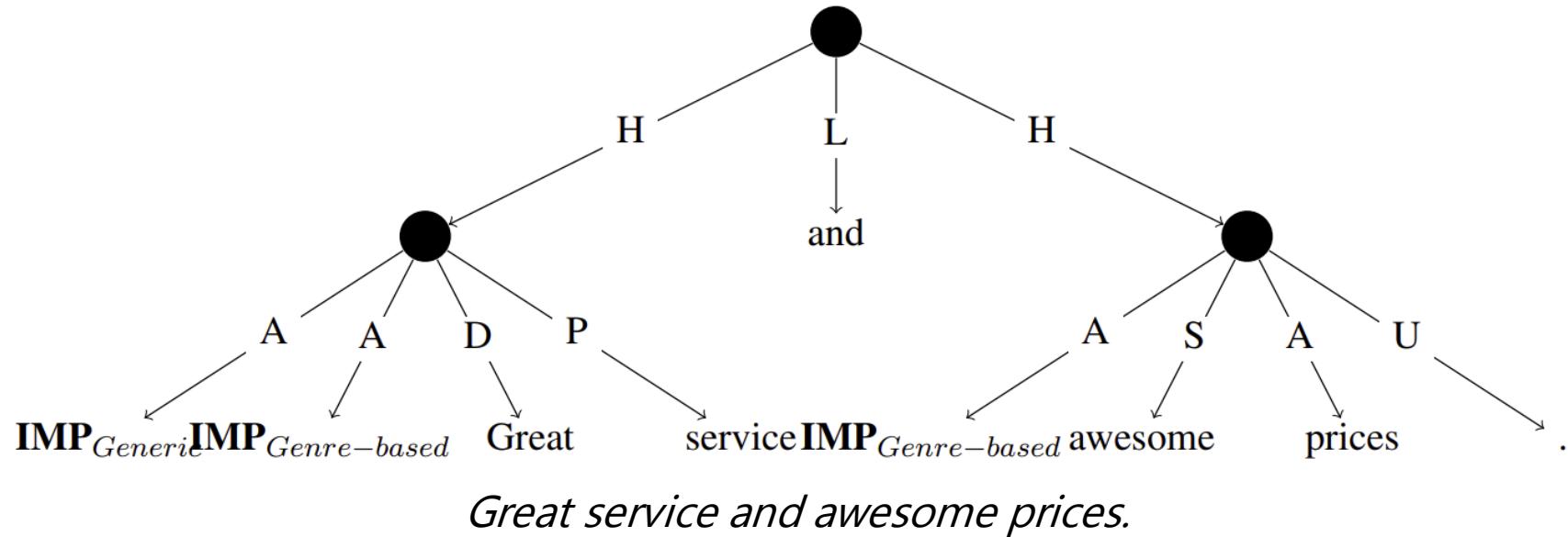
P Process

H Parallel Scene

L Linker



Implicit arguments



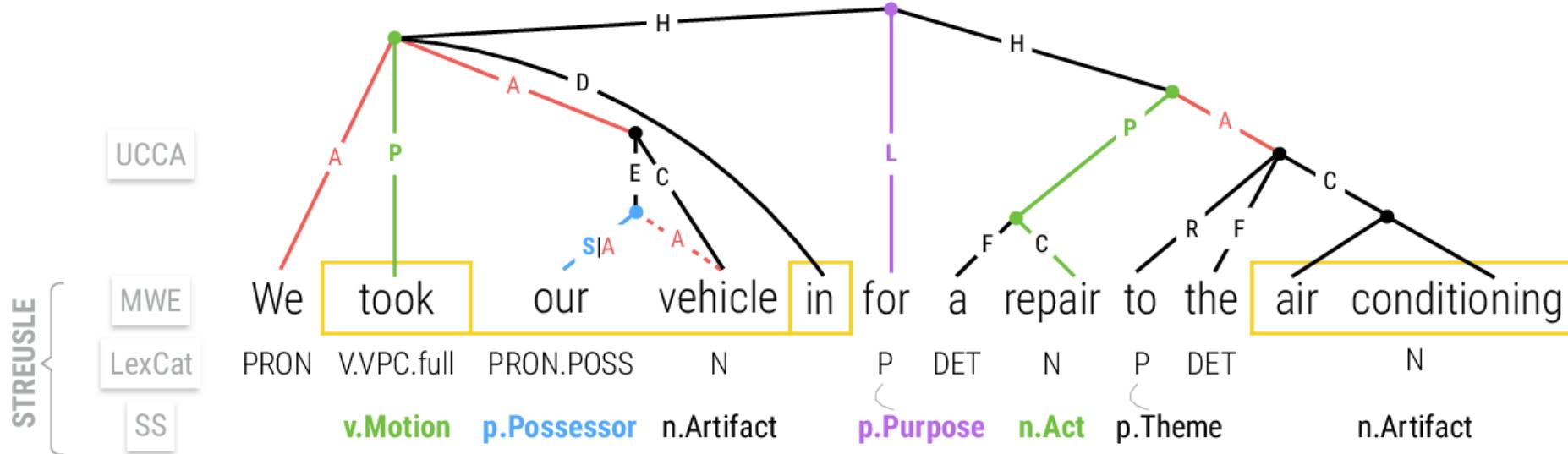
Refining Implicit Argument Annotation for UCCA

(Cui & Hershcovitch, DMR 2020)

Great Service! Fine-grained Parsing of Implicit Arguments

(Cui & Hershcovitch, IWPT 2021)

Lexical and compositional meaning



Comparison by Conversion: Reverse-Engineering UCCA from Syntax and Lexical Semantics

(Hershcovitch et al., COLING 2020)

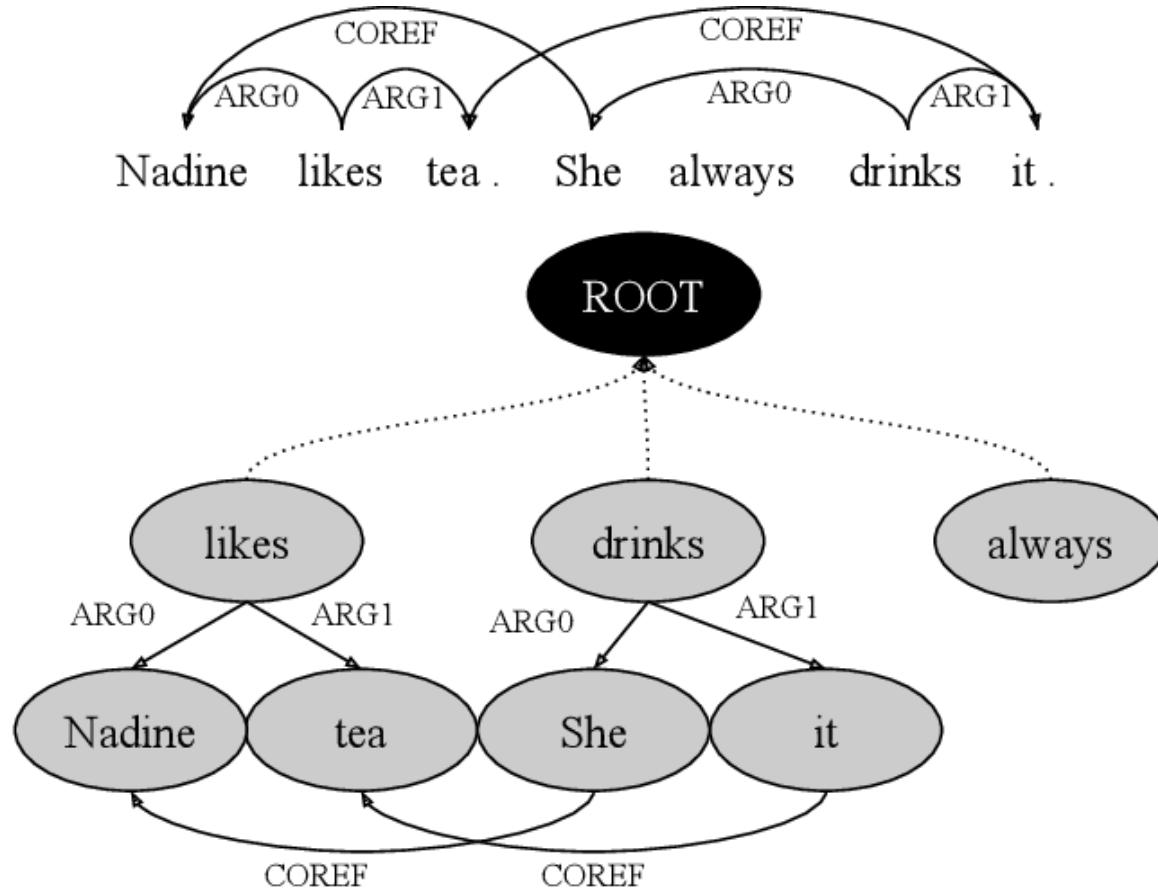
Coreference

[Lynyrd Skynyrd]₁ was formed in Florida₂. Other bands from [the Sunshine State]₂ include Fireflight and Marilyn Manson.

On March 19, Obama continued his outreach to the Muslim world, releasing a New Year's video message to the people and government of Iran. This attempt was rebuffed by the Iranian leadership.

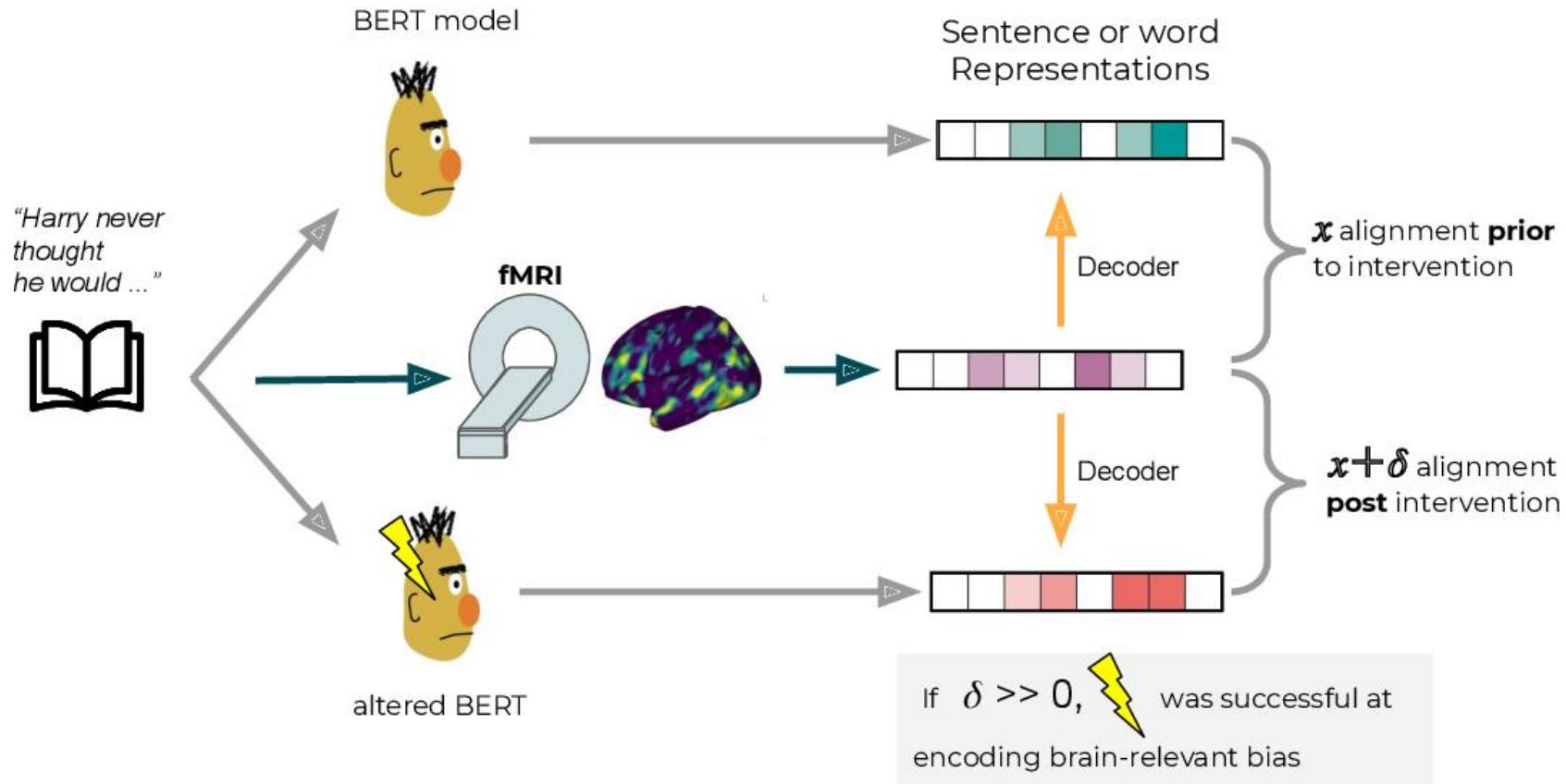
Rewarding Coreference Resolvers for Being Consistent with World Knowledge (Aralikatte et al., EMNLP 2019)

Semantic roles



Joint Semantic Analysis with Document-Level Cross-Task Coherence Rewards
(Aralikatte et al., AAAI 2021)

Investigating human language processing



Does injecting linguistic structure into language models lead to better alignment with brain recordings?
(Abdou et al., 2021)

Question answering from knowledge bases

Lang. Question

En Did Lohengrin's male actor marry Margarete Joswig

He האם רשחקן הגברי של לוהנגרין התחתן עם מרגרט יוסוויג

Kn លោកស្រីអង់គ្លេសណាត់ខ្លែងនៅវិវាទវត្ថុរម្យភាពីជាអង់គ្លេស

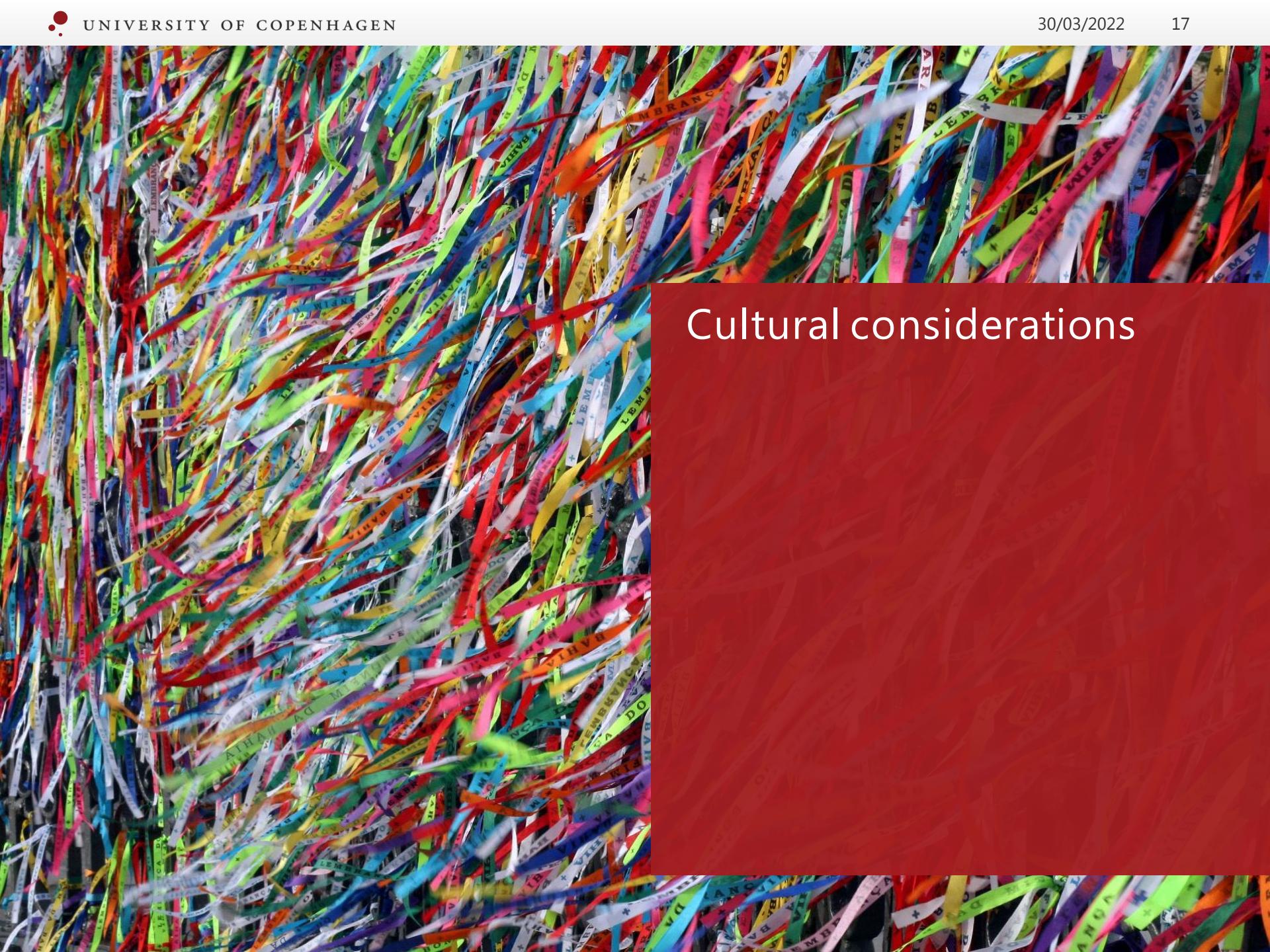
Zh Lohengrin的男演员嫁给了Margarete Joswig吗

SPARQL Query:

```
ASK WHERE { ?x0 wdt:P453 wd:Q50807639 . ?x0 wdt:P21
wd:Q6581097 . ?x0 wdt:P26 wd:Q1560129 . FILTER (
?x0 != wd:Q1560129 )}
```

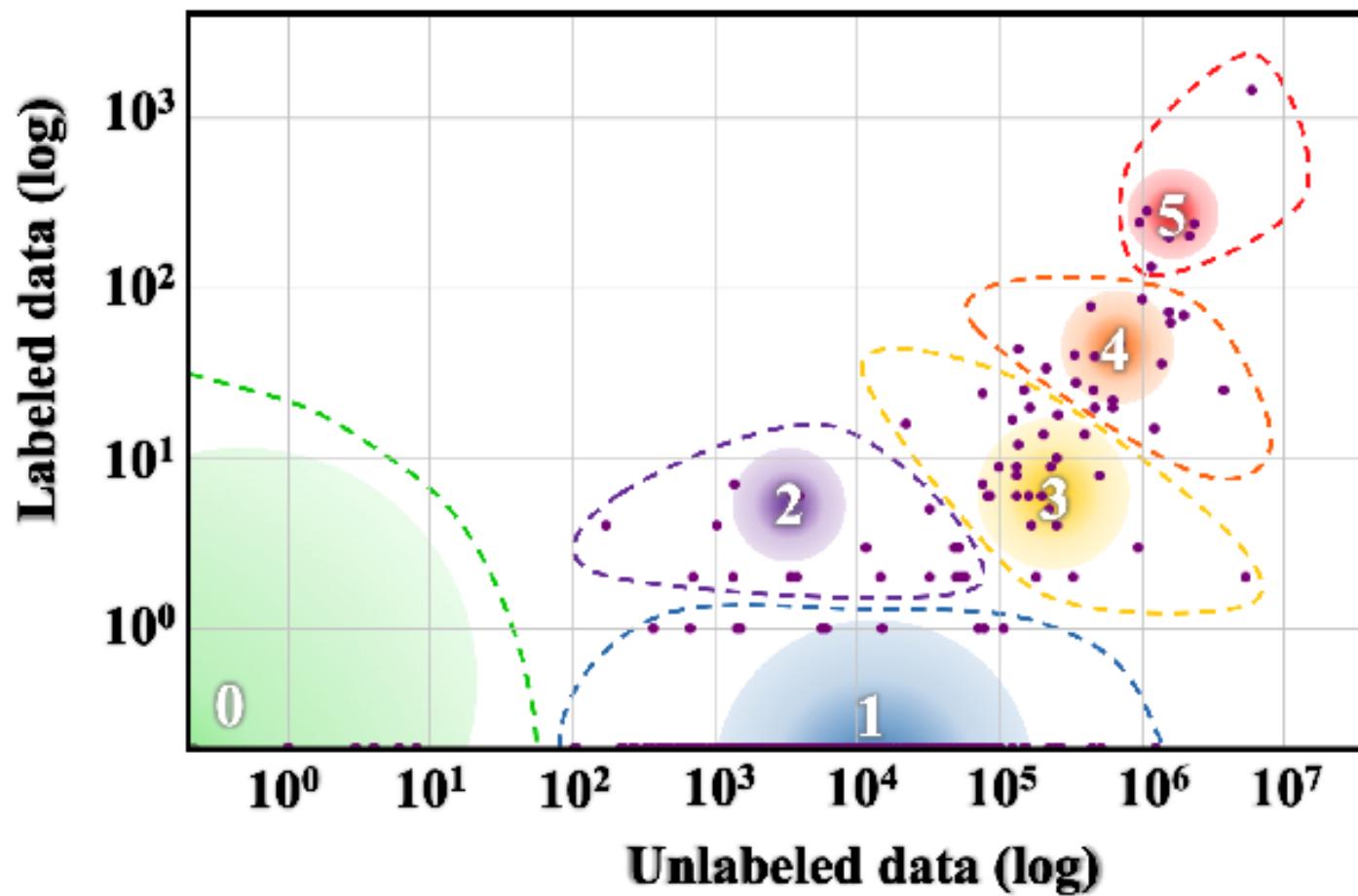
Multilingual Compositional Wikidata Questions
(Cui et al., 2021)



A close-up photograph of a large number of colorful ribbons tied together, creating a dense, textured mass. Many of the ribbons are white with the words "LEMBRANÇA" and "DIA DA MÃE" printed on them in black ink. The ribbons are in various colors including red, blue, green, yellow, and pink.

Cultural considerations

Resource disparity for languages



The State and Fate of Linguistic Diversity and Inclusion in the NLP World
(Joshi et al., ACL 2020)

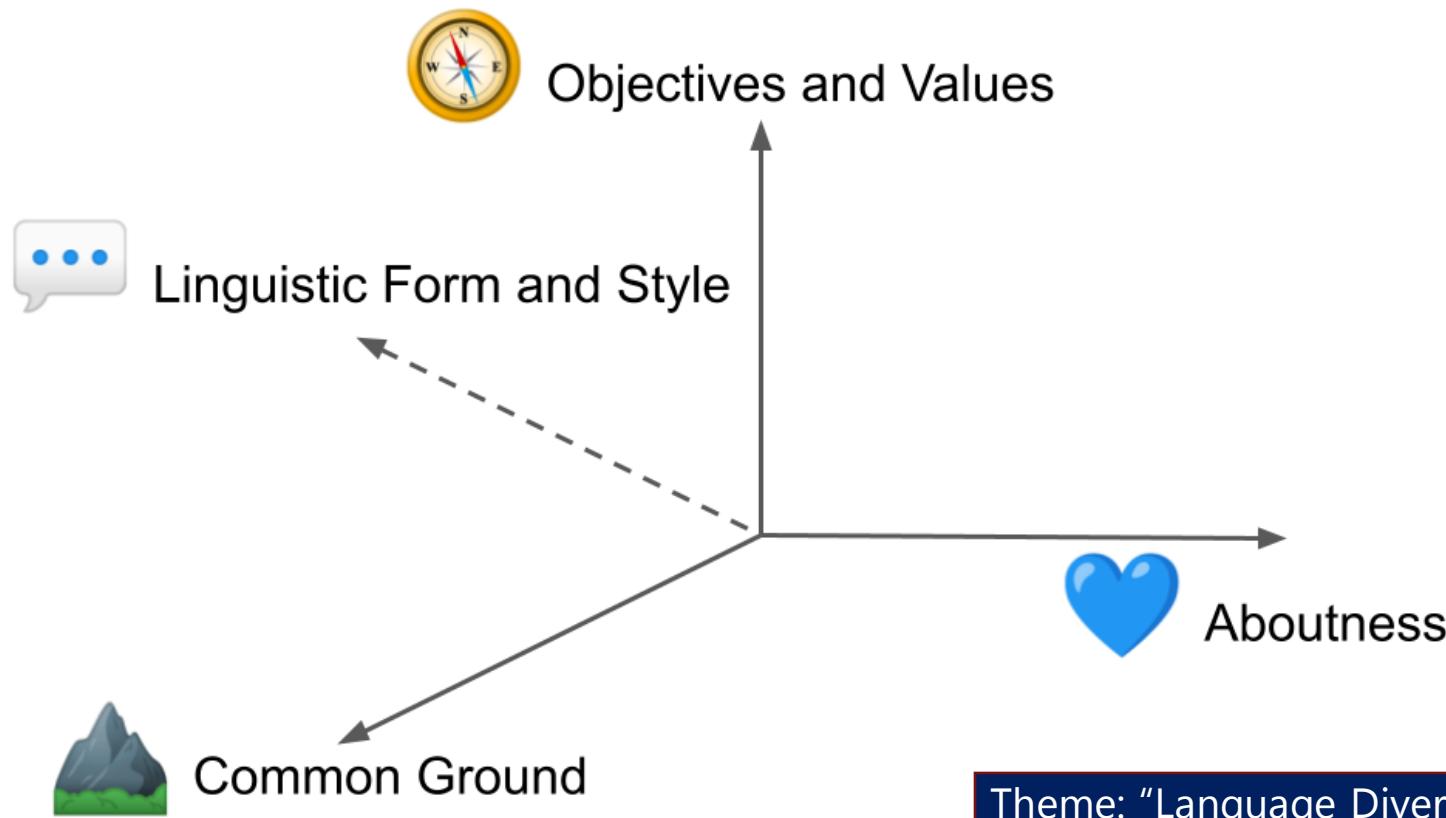
Social factors

NLP is for people (not just languages)



The Importance of Modeling Social Factors of Language: Theory and Practice
(Hovy & Yang, NAACL 2021)

Dimensions of culture



Theme: "Language Diversity: from Low-Resource to Endangered Languages"



Form

- *How we express ourselves in language*
- Morphosyntax, word choice...
- Stylistic aspects of linguistic form:

Directness

Formality

Politeness

Emotional expression

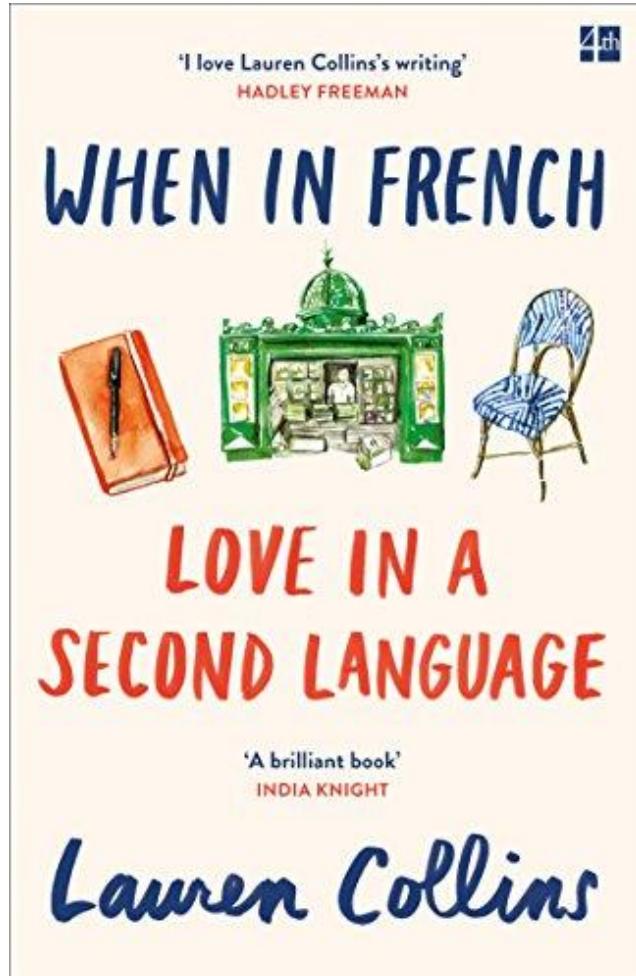
Common ground

Shared knowledge based
on which people reason
and communicate

Conceptualisation

Commonsense

Common ground 🏘️



- └ Conceptualisation
- └ Commonsense
- └ Stories
- └ Metaphors
- └ Clichés
- └ ...

Conceptualisation



Tamil
ஜல்லிக்கட்டு
jallikattu

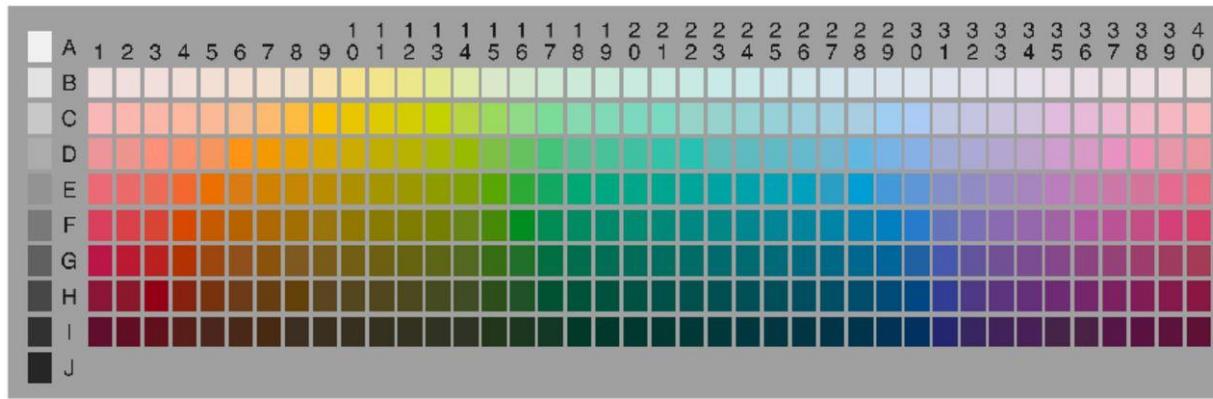
Swahili
leso



Visually Grounded Reasoning across Languages and Cultures
(Liu et al., EMNLP 2021)

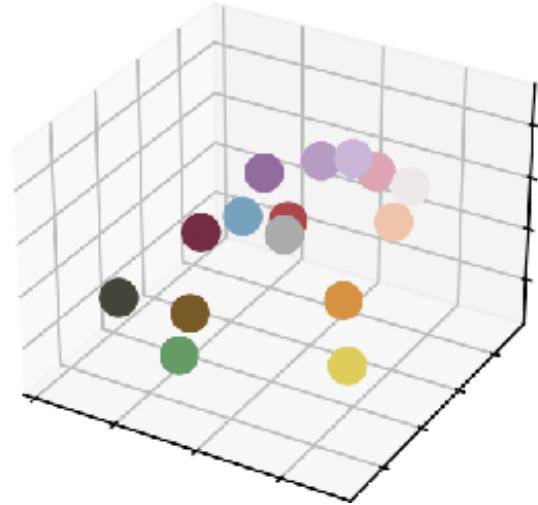
Colour

World Colour Survey

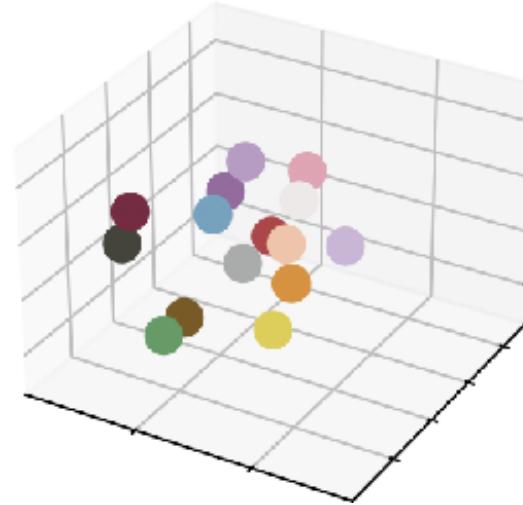


Probing colour

CIELAB



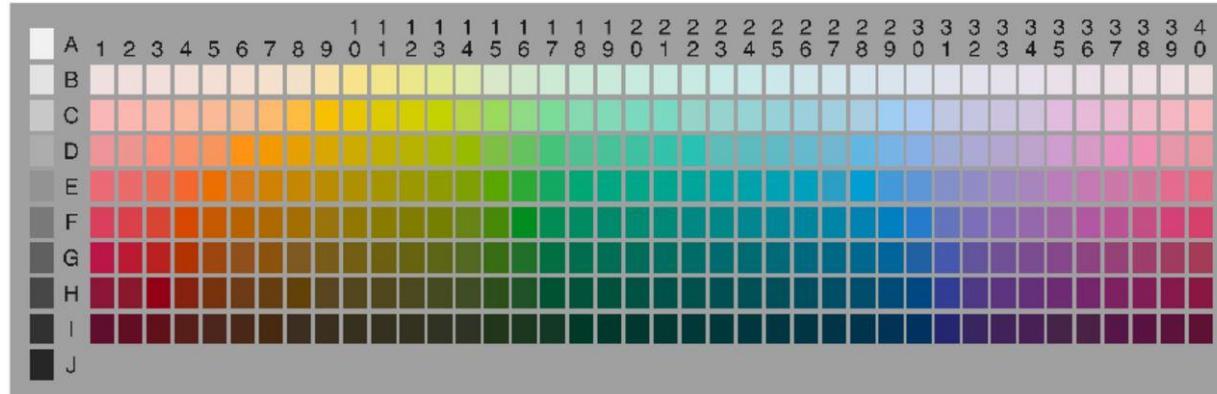
BERT, controlled context



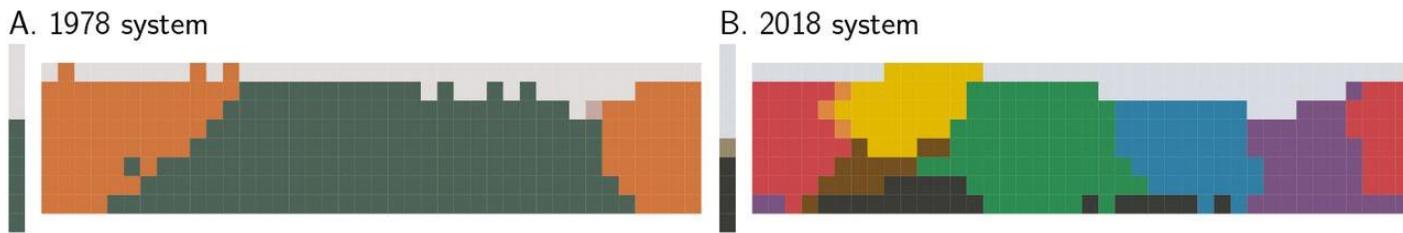
English BERT aligns with English-speaking Americans.
(What about others?)

[Can Language Models Encode Perceptual Structure Without Grounding? A Case Study in Color](#)
(Abdou et al., CoNLL 2021)

Differences in colour grounding



Nafaanra, a language of Ghana and Côte d'Ivoire



The evolution of color naming reflects pressure for efficiency: Evidence from the recent past

(Zaslavsky et al., Journal of Language Evolution 2022)

Commonsense

"Commonsense is the basic level of practical knowledge and reasoning concerning everyday situations and events that are commonly shared **among most people.**"

Commonsense Reasoning for Natural Language Processing

(Sap et al., ACL 2020 Tutorial)



Bola basket (Indonesian)

Mpira wa kikapu (Swahili)

篮球 (Chinese)

Basketbol (Turkish)

கூடைப்பந்தாட்டம் (Tamil)

Visually Grounded Reasoning across Languages and Cultures
(Liu et al., EMNLP 2021)

Commonsense

Before a wedding,
the bride...



... plans the wedding



... gets to know groom's family



... buys a dress

A funeral usually
takes place...



... in church or a funeral home



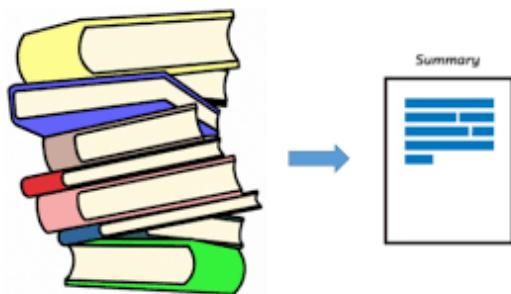
... at cremation / funeral grounds



... at home

Aboutness ❤️

- What content do people *care about*?
- Related to topic/domain



Visual
concepts



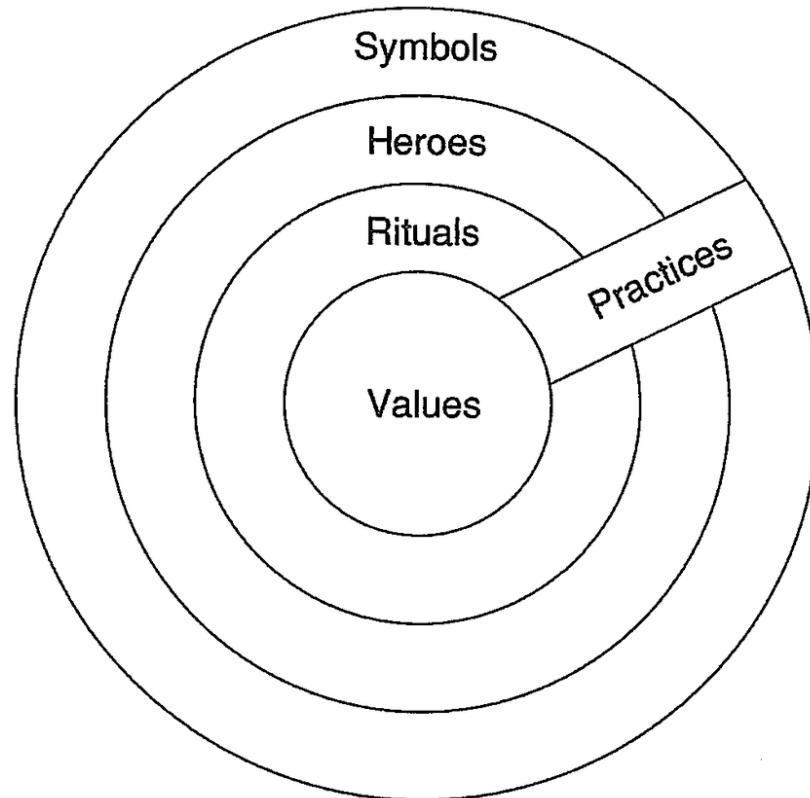
Beer
reviews



News
generation

Values

- Objectives and goals people strive for
- What is considered desired or desirable



Cultures and Organizations: Software of the Mind
(Hofstede, 1991)

(Meta) values

- *Why* are we doing NLP?
- Users may have different goals, often implicit
- Common meta-objectives in *NLP research culture*

Accuracy

Fairness

Robustness

Interpretability

Conflicting objectives?



Researchers



Practitioners



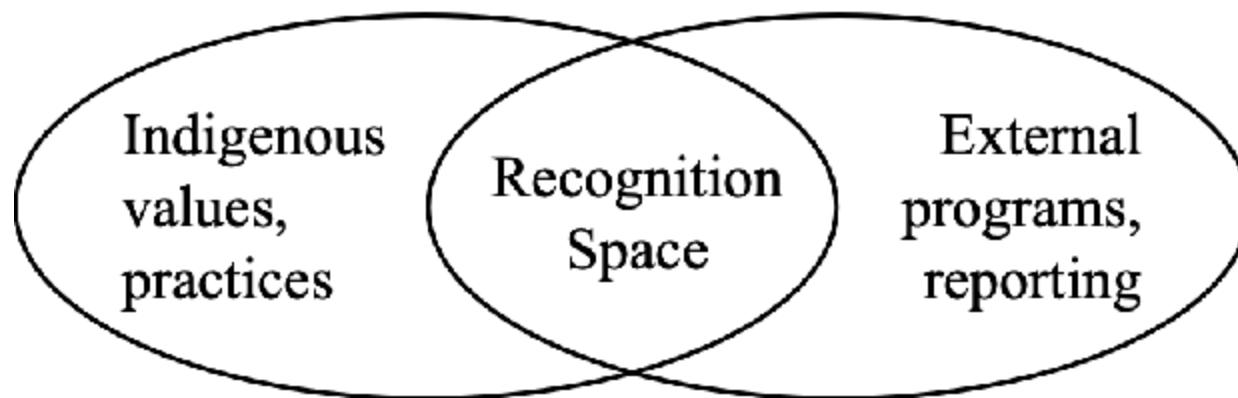
End-users



Regulators



Language technology for all (potential) users



Decolonising Speech and Language Technology
(Bird, COLING 2020)

Strategies



DATA



MODELS



TASKS

Data



Selection



Annotation

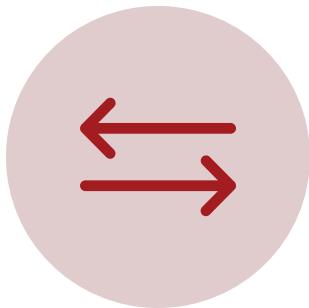


Projection

Models



TRAINING

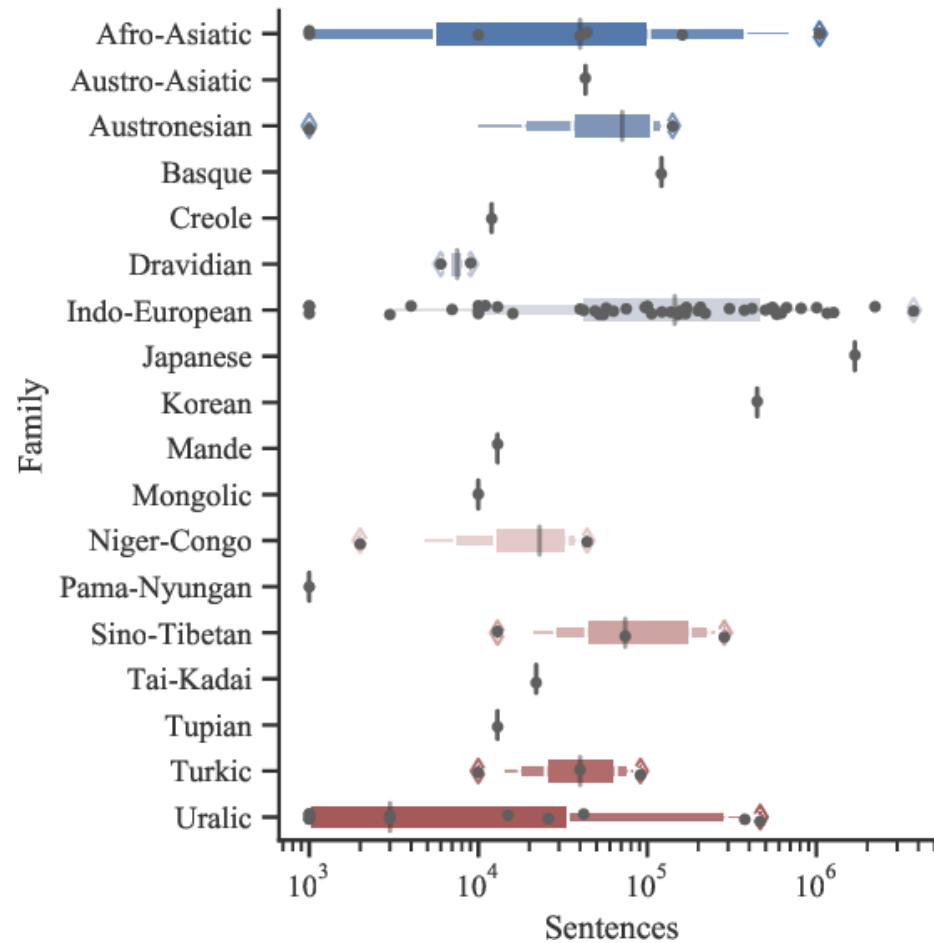


TRANSFER



PRE-TRAINED
LANGUAGE MODELS

Robust optimisation



Minimax and Neyman–Pearson Meta-Learning for Outlier Languages
(Ponti et al., Findings 2021)

Robust optimisation does not always work

Tamil	Mandarin(我们)	Cantonese(拍拖)	English	Malay	Eng	Malay	Hokkien/ Hakka(店)	X
Dey Hey	wǒ men ,	paktor we	always date	makan always	at eat	at kopitiam	coffee shop	<INTJ>

Standard English: “Hey, when we date we always eat at the coffee shop”

On Language Models for Creoles
(Lent et al., CoNLL 2021)

Social bias in language models

Models	Demographics Alignment															
bert-base-cased																
bert-base-uncased																
bert-base-multilingual-cased																
bert-large-cased																
bert-large-uncased																
distilbert-base-uncased																
albert-base-v2																
albert-large-v2																
albert-xxlarge-v2																
roberta-base																
roberta-large																
google/electra-large-generator																
google/electra-small-generator																
gpt2																
gpt2-medium																
gpt2-large																
gpt2-xl																
Group																
Mean Rank	3.1	3.4	4.0	6.1	6.1	8.1	8.1	9.2	9.8	9.9	10.3	10.3	10.8	11.1	12.0	13.8

Sociolectal Analysis of Pretrained Language Models
(Zhang et al., EMNLP 2021)

Knowledge bias in language models

Query

en X was created in MASK.
de X wurde in MASK erstellt.
it X è stato creato in MASK.
nl X is gemaakt in MASK.

Two most frequent predictions

[Japan (170), Italy (56), ...]
[Deutschland (217), Japan (70), ...]
[Italia (167), Giappone (92), ...]
[Nederland (172), Italië (50), ...]

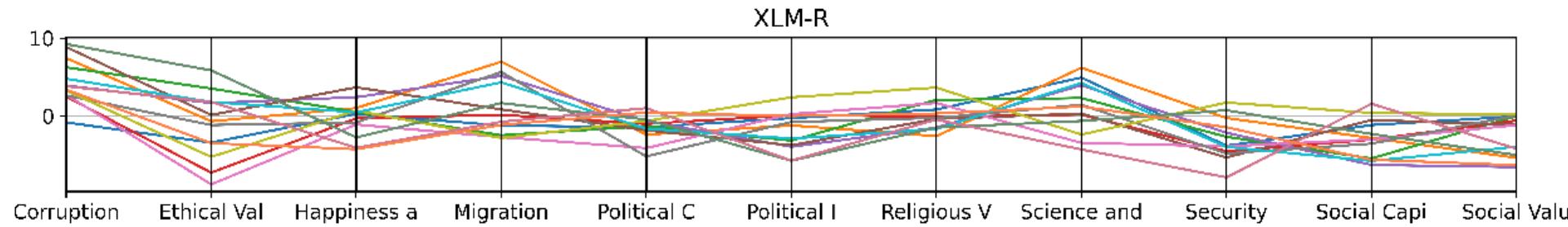
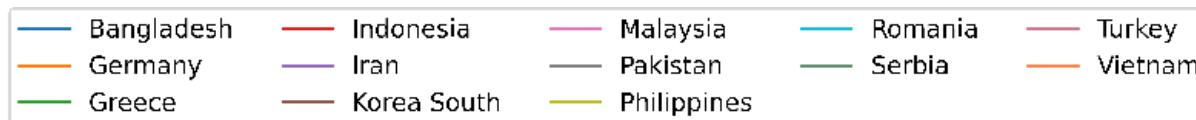


Multilingual LAMA: Investigating Knowledge in Multilingual Pretrained Language Models (Kassner et al., EACL 2021)

Value bias in language models

For each of the following, indicate how important it is in your life. Would you say it is (read out and code one answer for each):

		Very important	Rather important	Not very important	Not at all important
Q1	Family	1	2	3	4
Q2	Friends	1	2	3	4
Q3	Leisure time	1	2	3	4
Q4	Politics	1	2	3	4
Q5	Work	1	2	3	4
Q6	Religion	1	2	3	4

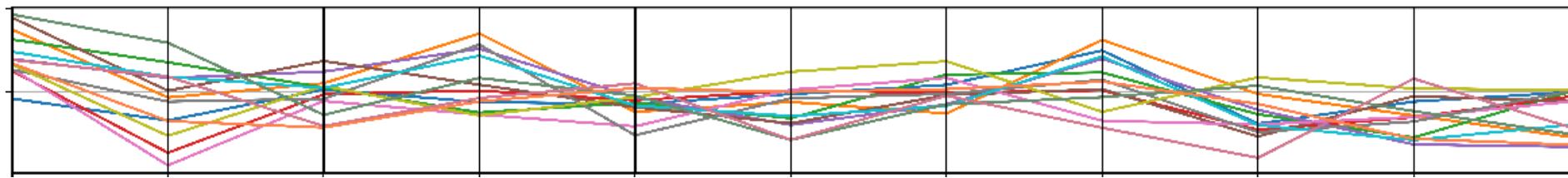


Probing Pre-Trained Language Models for Cross-Cultural Differences in Values
 (Arora et al., 2022)

Implicit context

For each of the following, indicate how important it is in your life.

XLM-R



Open question: who is the implied speaker?

Cross-cultural translation

Bridging between cultures
as a task



"I saw Merkel eating a Berliner from Dietsch on the ICE"



I saw Biden eating a Boston Cream from Dunkin' Donuts on the Acela

Adapting Entities across Languages and Cultures

(Peskov et al., Findings 2021)

Style transfer

Entity adaptation

Explanation by analogy

Levels of granularity

- Linguistic variation within a "language"
- Also applies to cultures



Idiolect	Sociolect, dialect	Standardised language	Language, language family
Individual	Social group or region	Country	

Multi-granularity adaptation

A Juror Selection

JUROR SHEET A
RACE Hispanic ✓
GENDER Female ✓
SEATS 4
Add characteristic

JUROR SHEET B
RACE Black ✓
AGE RANGE 25-34 ✓
SEATS 8
Add characteristic

+ Add juror sheet

Your jury composition: A₁, A₂, B₁, B₂, B₃, B₄, A₃, A₄, B₅, B₆, B₇, B₈

Your input example: This is an example comment entry.
View jury outcome →

B Jury Learning Results

Outcome summary: JURY VERDICT Slightly toxic (1.21 / 4.00)
95% of juries are between 0.21 - 1.83
Based on the median outcome of 100 juries sampled from your provided jury composition

DISTRIBUTION OF JURY OUTCOMES: Select a jury to view Jury Trends

Jury outcome (Yellow dots), Selected jury outcome (Red dot)

C Jury Trends (Jury 43)

GROUP BY Juror sheet ▾

Juror sheet A — 4 of 12 jurors (Race: Hispanic, Gender: Female)
Average label: Slightly to Moderately toxic (1.65 / 4.00)
Label distribution: Histogram showing predicted labels for Juror sheet A jurors.

Juror sheet B — 8 of 12 jurors (Race: Black, Age Range: 25-34)
Average label: Not at all toxic (0.43 / 4.00)
Label distribution: Histogram showing predicted labels for Juror sheet B jurors.

D Juror Details

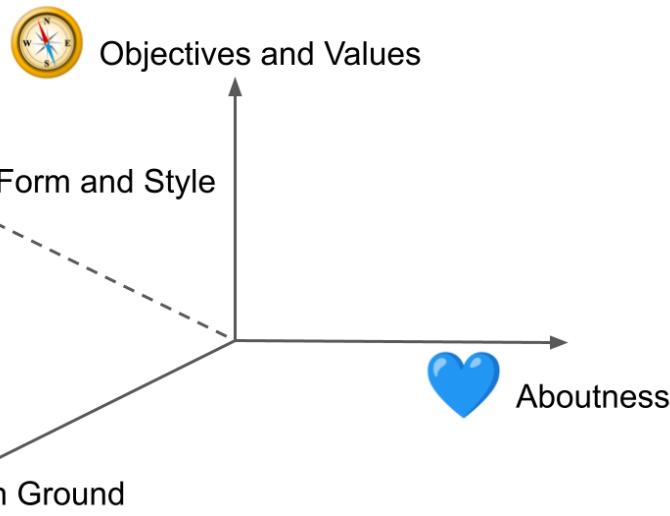
Jury 43, Juror B₅
Predicted label: Slightly toxic (1.12 / 4.00)
Juror background: RACE Black, GENDER Female, POLITICAL AFFIL. Independent, AGE RANGE 25-34
Comment: this is an example comment (2.3), this is another example comment (2.1), this is yet another example comment (3.4)

E Counterfactual juries

New jury composition	Jury verdict	Jury edits
	(0.87 / 4.00)	C ₁ — Race: White, Political Affiliation: Conservative
	(0.79 / 4.00)	D ₁ — Race: Black, Importance of religion: Not important
	(0.63 / 4.00)	E ₁ , E ₂ — Age range: 45-54, Importance of religion: Very important

Jury Learning: Integrating Dissenting Voices into Machine Learning Models
(Gordon et al., CHI 2022)

Interim summary



NLP is for people (not just languages)

Culture is multidimensional

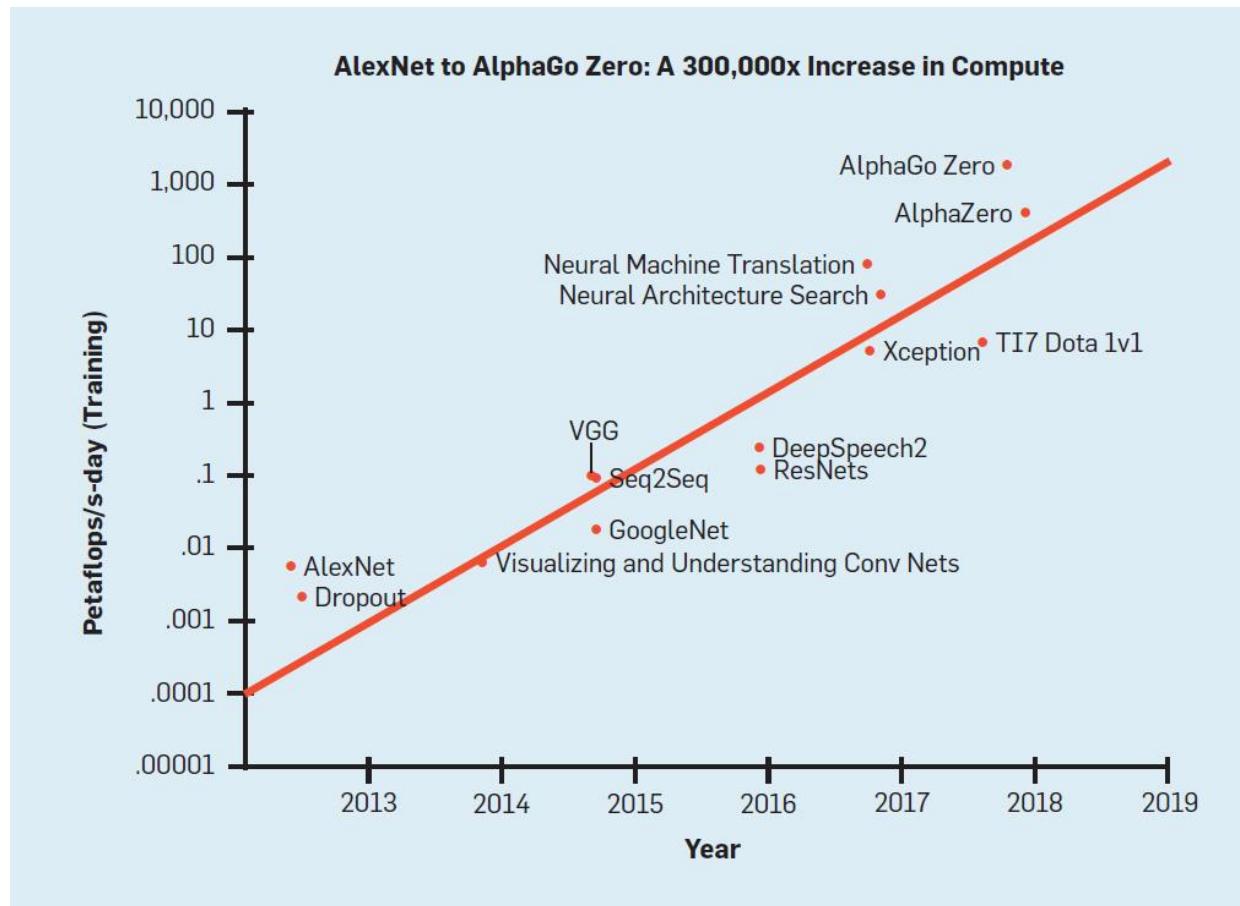
Objectives are conflicting

Generalisation-representation trade-off

Environmental considerations



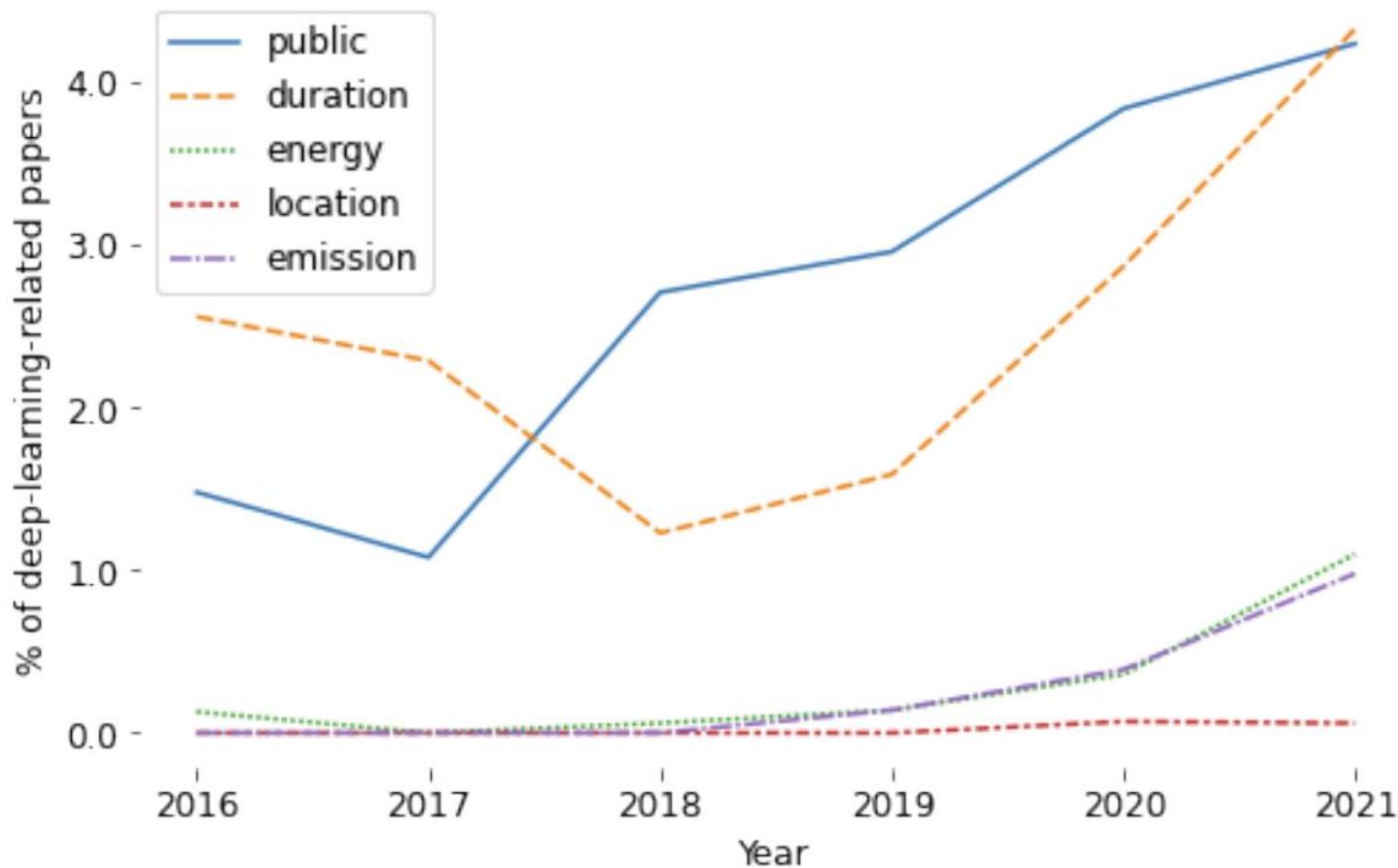
Green NLP



Green AI

(Schwartz et al., Communications of the ACM 2020)

Climate awareness



Towards Climate Awareness in NLP Research
(under review)

Climate awareness

climatebert/distilroberta-base-climate-f

Fill-Mask PyTorch Transformers en arxiv:2110.12010

Model card Files and versions Settings

Climate performance model card

Minimum card

1. Is the resulting model publicly available?	Yes
2. How much time does the training of the final model take?	8 hours
3. How much time did all experiments take (incl. hyperparameter search)?	288 hours
4. What was the energy consumption (GPU/CPU)?	0.7 kW
5. At which geo location were the computations performed?	Germany

Extended card

6. What was the energy mix at the geo location?	470 gCO2eq/kWh
7. How much CO2eq was emitted to train the final model?	2.63 kg
8. How much CO2eq was emitted for all experiments?	94.75 kg
9. What is the average CO2eq emission for the inference of one sample?	0.62 mg

Towards Climate Awareness in NLP Research
(under review)

Climate awareness

Principles:

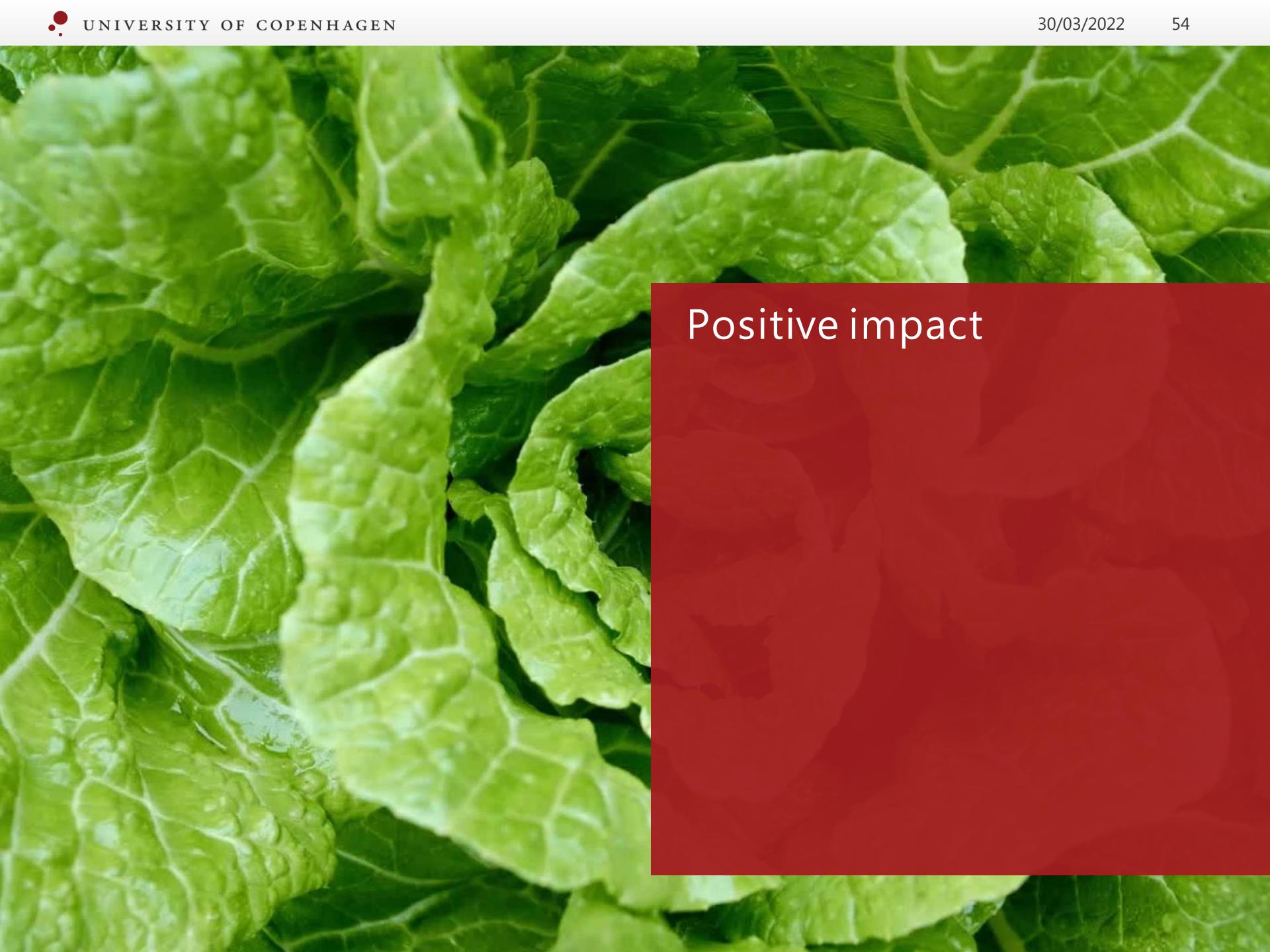
- Relevance
 - Completeness
 - Consistency
 - Transparency
 - Accuracy
- + Positive impact

Towards Climate Awareness in NLP Research
(under review)

The collective action paradox

- Individual action cannot save the planet
- How can we make a difference?





Positive impact

Greenwashing detection

- Financial reporting increasingly discuss climate
- Claims are false or not specific

Claim:	97% consensus on human-caused global warming has been disproven.
Evidence: REFUTE	In a 2019 CBS poll, 64% of the US population said that climate change is a ""crisis"" or a ""serious problem"", with 44% saying human activity was a significant contributor.
Claim:	The melting Greenland ice sheet is already a major contributor to rising sea level and if it was eventually lost entirely, the oceans would rise by six metres around the world, flooding many of the world's largest cities.
Evidence : SUPPORT	The Greenland ice sheet occupies about 82% of the surface of Greenland, and if melted would cause sea levels to rise by 7.2 metres.

ClimateBert: A Pretrained Language Model for Climate-Related Text

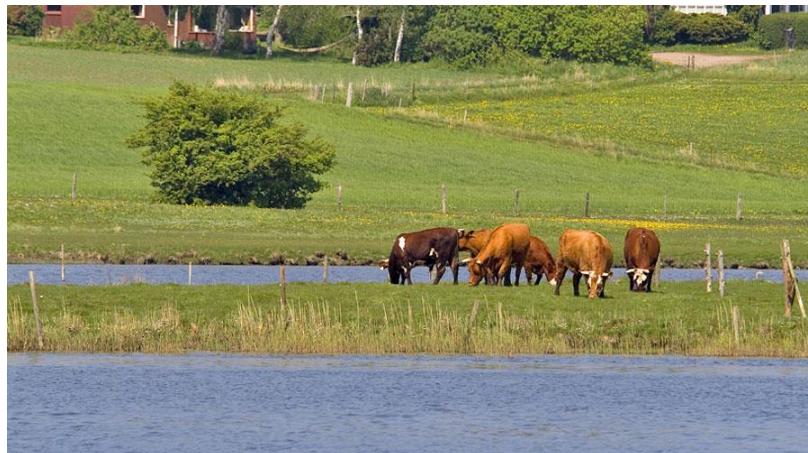
(Webersinke et al., 2021)

Cheap talk and cherry-picking: What ClimateBert has to say on corporate climate risk disclosures

(Bingler et al., Finance Research Letters 2022)

Government funding for plant-based foods

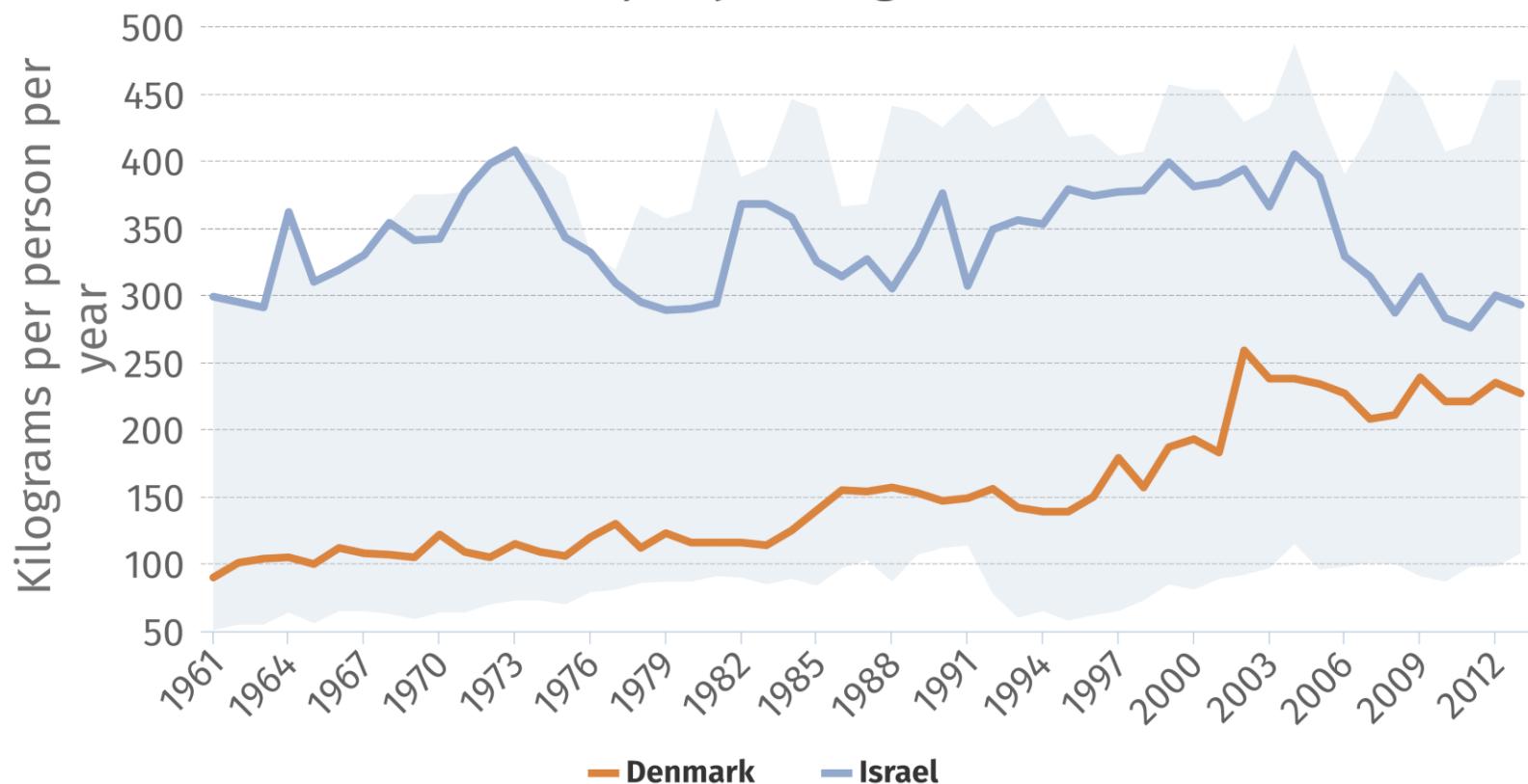
- Denmark: climate agreement for food and agriculture
- "Central element in the green transition"
- Consumer demand is an essential component



<https://fm.dk/media/25215/aftale-om-groen-omstilling-af-dansk-landbrug.pdf>

Historical Developments

Average amount of fruits and vegetables available per person per year (kg)



Historical precedence



Argument mining for green nutrition

- Dietary preferences are hard to change:
 - Perceptions of taste
 - Knowledge and skills
- Existing interventions:
 - Guidelines and policies
 - Everyday habits and convenience
- Work in progress: dataset and models for mining arguments on Twitter



- Potential applications:
 - Surveying public attitudes and exposing misinformation
 - Generation of convincing arguments and nudging

Opportunity for integration

- Cultural differences in consumer preferences



Summary



Climate awareness will make efficient NLP mainstream



Efficient is not enough – net impact should be positive



Compliance and consumer

Thank you

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