

# Word Meaning Representation and Negotiation

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# Introduction: Personal background

Bachelor in Linguistics



UNIVERSITAT DE  
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+ Research assistant



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*Barcelona*



# Introduction: Personal background

Bachelor in Linguistics



UNIVERSITAT DE  
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St Petersburg  
University



# Introduction: Personal background

Erasmus Mundus  
Master in NLP



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Erasmus Mundus  
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L-Università  
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# Introduction: Personal background

PhD



université  
PARIS-SACLAY

Postdoc 1

Postdoc 2



*Inria*



# Introduction: Research interests

## Computational Lexical Semantics

How can **word meaning** be represented computationally?

out-of-context

compositional  
meaning

in-context

semantic  
relationships

connotative  
meaning

figurative  
meaning

# Introduction: Research interests

## Computational Lexical Semantics



But what even is (word) meaning??

**Distributional semantics:** A tangible, empirical solution!

(Imperfect, but it has taken us very far, in NLP and Computational Linguistics)

# Introduction: Research directions

## 1. **Word Meaning Representation (in Neural Language Models)**

How can word meaning be represented computationally?

## 2. **Word Meaning in Interaction**

(How) do we manage to understand each other?



# Word Meaning Representation

in Neural Language Models

# The An NLP Revolution

November 2017



**BERT** on arXiv (Devlin et al, 2018)

October 2018

June 2018, NAACL

Peters et al., (2018)

**ELMo**

**Interpretability**



# The An NLP Revolution

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**BERT** on arXiv (Devlin et al, 2018)  
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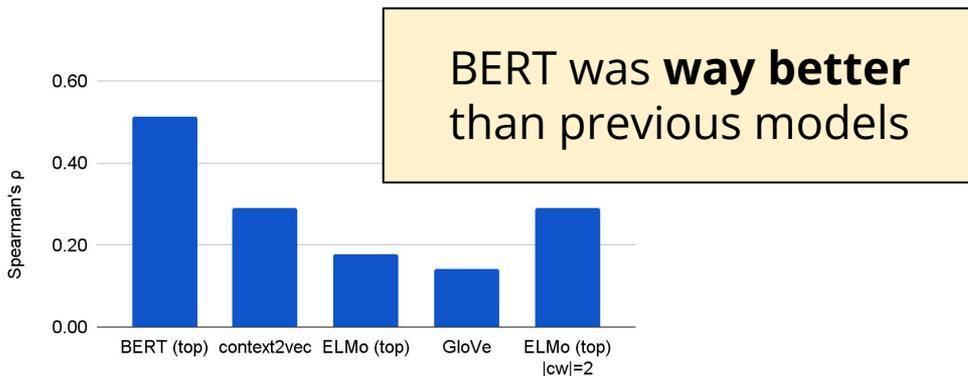
June 2018, NAACL  
Peters et al., (2018)

**ELMo**



# How well do these models represent word meaning in context?

- Lexical substitution
- Word usage similarity



This is also at the very essence or heart of being a **coach**.



1.3 / 10

We hopped back onto the **coach**.



bus  
carriage  
trainer

# Does the semantic space built by contextual models reflect words' degree of polysemy?

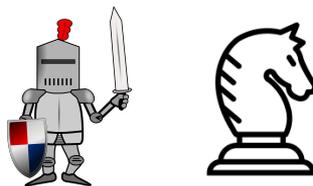
**Monosemous:** one sense

**Polysemous:** multiple senses

sofa



knight



shot



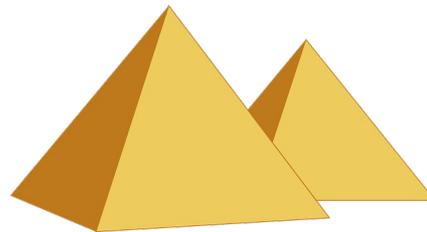
...

A word's degree of polysemy is reflected in BERT representations, regardless of the context it is found in

# Semantic Relationships



**old** vs **ancient**



~~healthy~~ apple

**healthy** dessert



# The Impact of Word Splitting on the Semantic Content of Contextualized Word Representations

# Subword tokenization

Let's **tokenize** this sentence into **subwords**



let ' s **token** **##ize** this sentence into **sub** **##words**

- Rare / out-of-domain words

conjunctivitis [con ##jun ##ct ##iv ##itis]

- Morphologically complex words

multiprocessor [multi ##pro ##ces ##sor]

- Misspelled words

tabel, aaaaaand [tab ##el], ['aaa', '##aa', '##and']

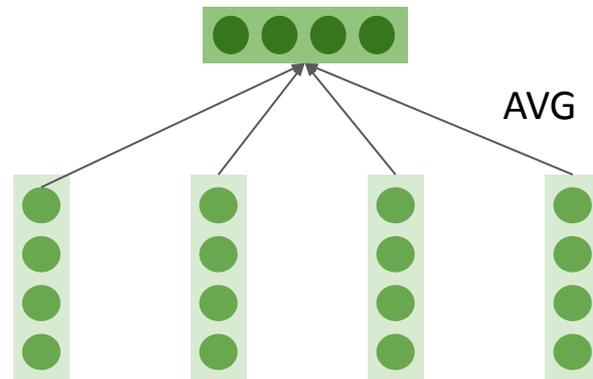
# Contextualized Word Representations

... But we often work at the word level!



[window]

**full-word**



[multi ##pro ##ces ##sor]

**split-word**

# Our questions

1. What is the best strategy to create a representation for split-words?
2. (Given a good strategy) how does the quality of the semantic content in split-word representations compare to that in full-word representations?

# Our questions

The task

word similarity estimation

1. What is the best strategy to create a representation for split-words?
2. (Given a good strategy) how does the quality of the semantic content in split-word representations compare to that in full-word representations?

# Our questions



1. What is the best strategy to create a representation for split-words?
2. (Given a good strategy) how does the quality of the semantic content in split-word representations compare to that in full-word representations?



Expectation: it's worse

# Similarity and split-words

$\text{sim}(w_1, w_2)$

**full**-word vs **full**-word

{accordion} vs {guitar}

0-SPLIT

**full**-word vs **split**-word

{ash, ##tray} vs {weather}

1-SPLIT

**split**-word vs **split**-word

{tom, ##fo, ##ole, ##ry} vs {loaf, ##ing}

2-SPLIT

# Inter-word similarity

## → Inter-word

*... as an adult **adoptee**, this...*

*... she was a **descendant** of...*



**In-context**



**Out-of-context**

Datasets: CoSimLex (Armendariz et al., 2020), SWCS (Huang et al, 2012)

# Inter-word similarity

→ **Inter-word**

*descendant*

*adoptee*



In-context



**Out-of-context**

Datasets: SimLex-999 (Hill et al., 2015), WS535 (Agirre et al., 2009), CARD-660 (Pilehvar et al., 2018)...

# Inter-word similarity

→ **Inter-word**

*descendant*

*adoptee*



In-context



Out-of-context

Existing datasets have a weak representation of 1- and 2-SPLIT pairs



# Inter-word similarity data: words and sentences

- 1. Select all noun and verb lemmas in WordNet (Fellbaum, 1998)

*accordion, guitar, tomfoolery...*

- 2. Extract at least 10 sentences per lemma in the c4 corpus (Raffel et al., 2020) (that contain the same lemma form & correct POS)

..... accordion .....

accordion .....

..... accordion

..... accordion .....

..... guitar .....

guitar .....

..... guitar

..... guitar .....

..... tomfoolery .....

tomfoolery .....

..... tomfoolery

..... tomfoolery .....

# Inter-word similarity data: word pairs and similarities

3. Exhaustively pair all lemmas and calculate their **WUP similarity** (Wu and Palmer, 1994)

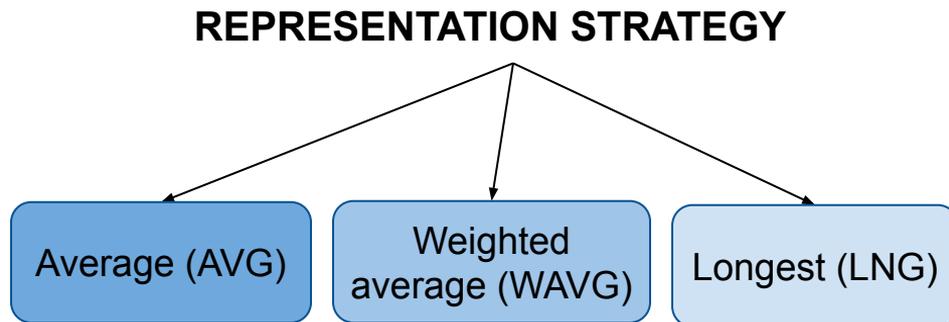
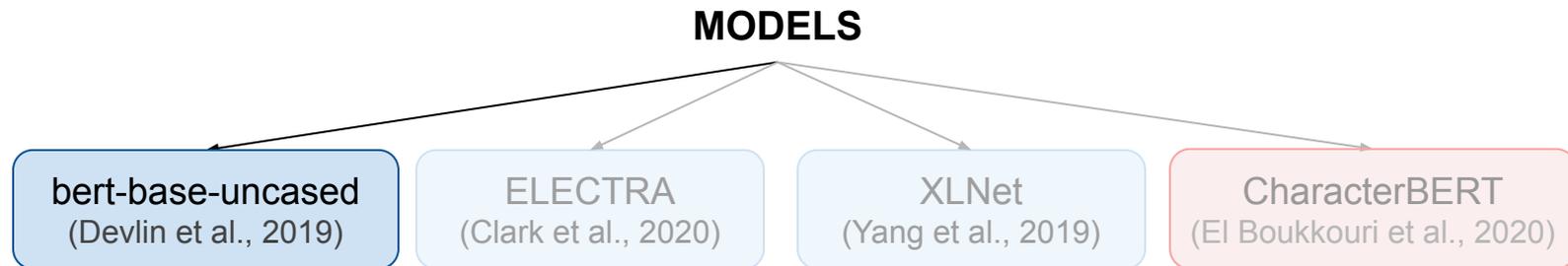
*(accordion, guitar)*  
*(accordion, tomfoolery)*  
*(guitar, tomfoolery)*

...

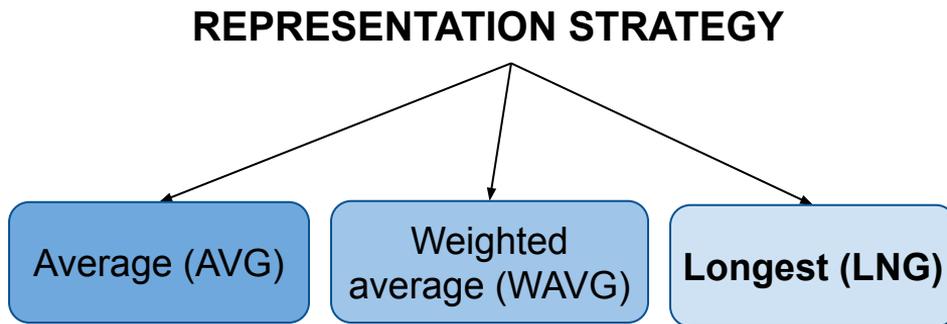
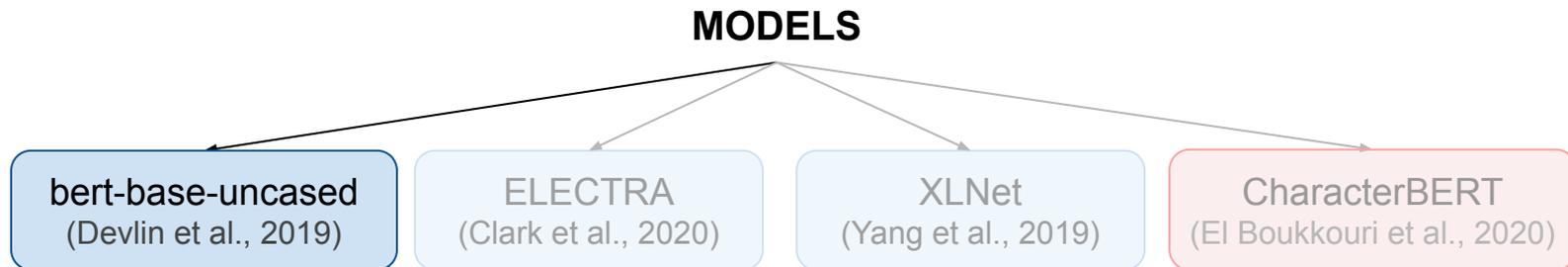
4. Select a subset ensuring a balanced representation of split-types and similarity ranges

<b>SPLIT-SIM subset</b>	<b># pairs</b>
monosemous nouns (M-N)	67,500
monosemous verbs (M-V)	2,550
polysemous nouns (P-N)	15,000
polysemous verbs (P-V)	15,000

# Experimental Setup



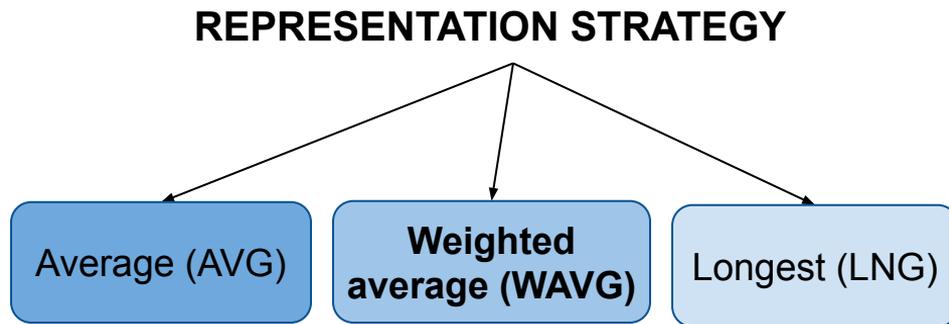
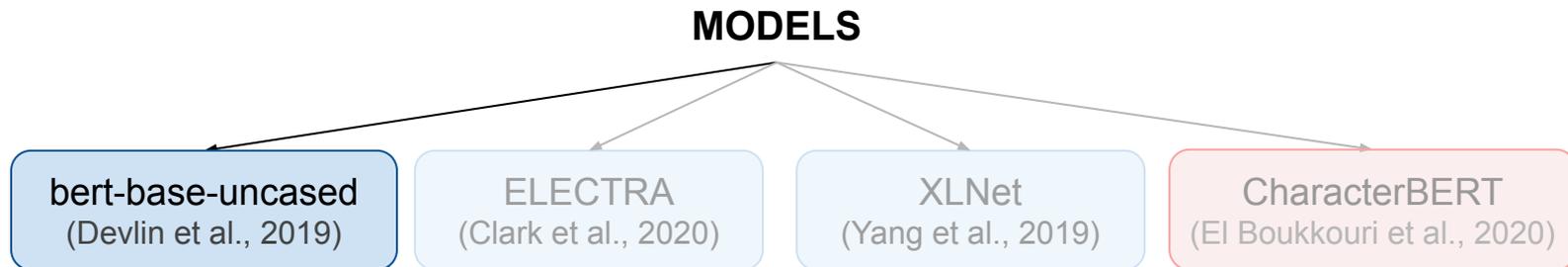
# Experimental Setup



ash

##tray

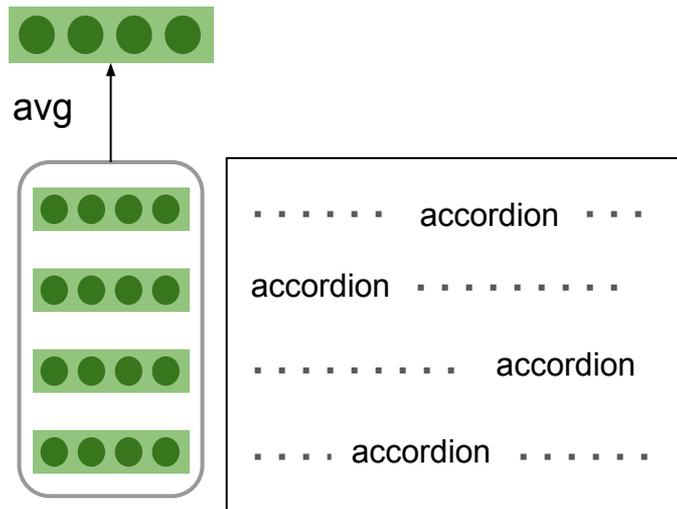
# Experimental Setup



$$3/7 * \text{ash} + 4/7 * \text{##tray}$$

# Experimental Setup

**CONTEXTS: 10 sentences**

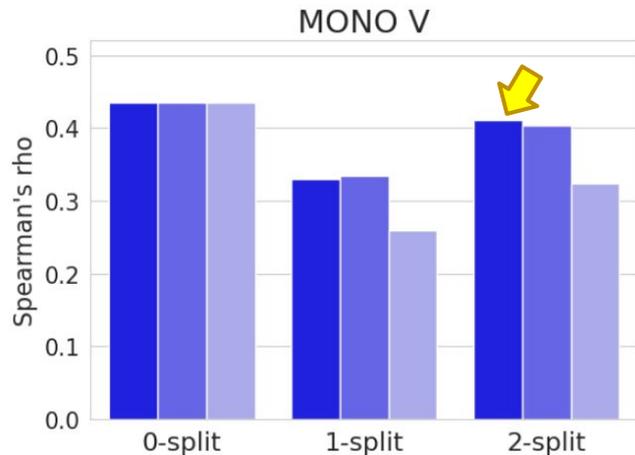
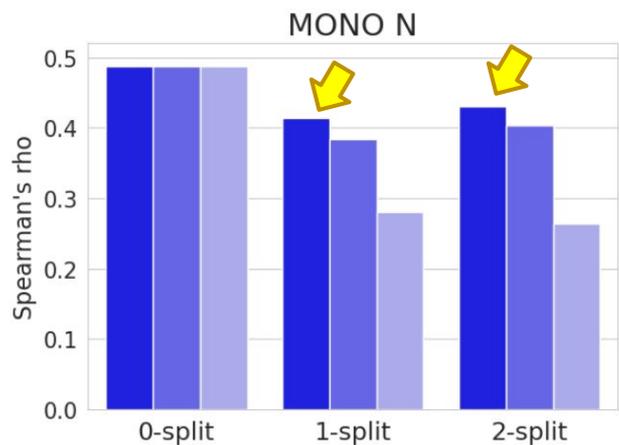


**EVALUATION**

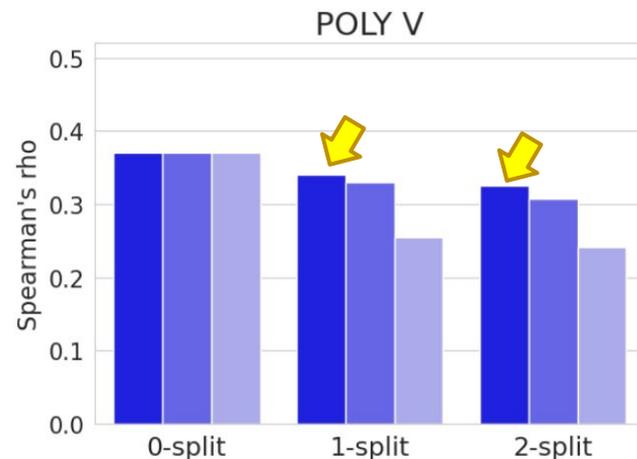
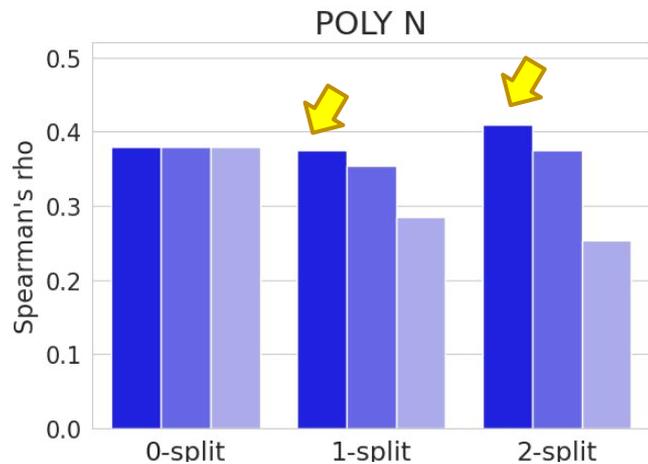
Spearman's  $\rho$  between WUP similarity and cosine similarity

# Results

# What is the best representation strategy?

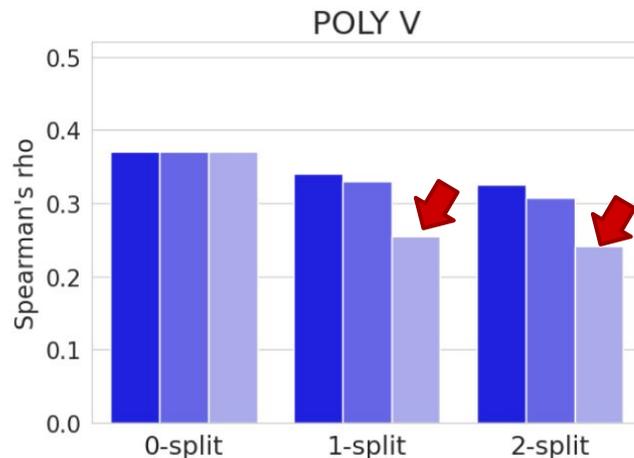
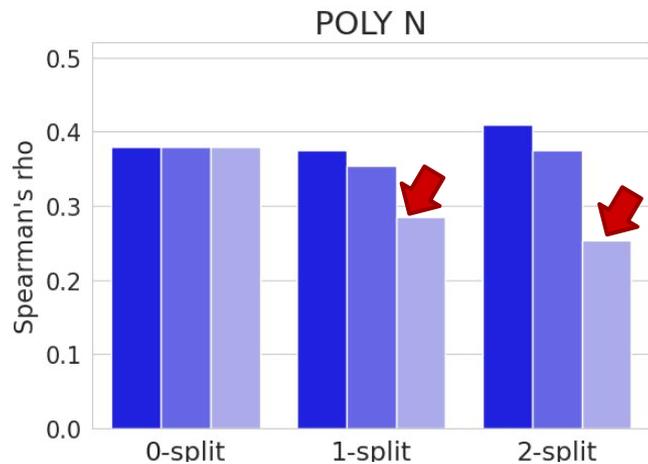
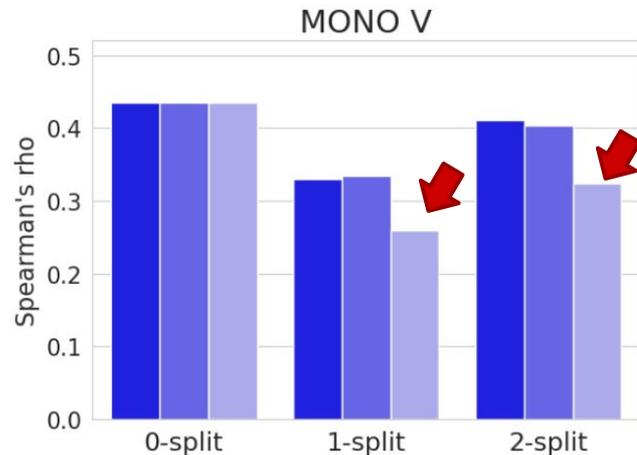
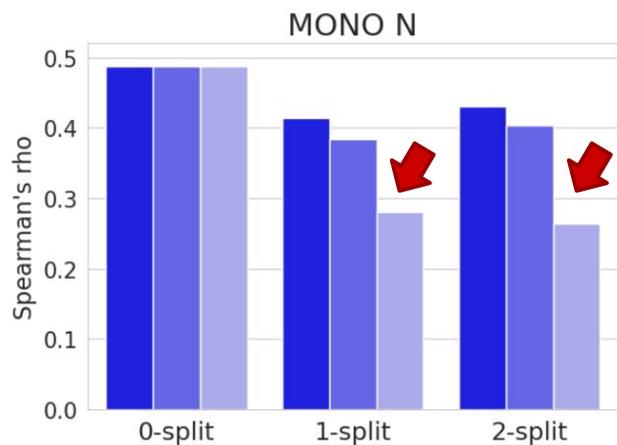


■ BERT (AVG)  
■ BERT (WAVG)  
■ BERT (LNG)



➤ The simple average

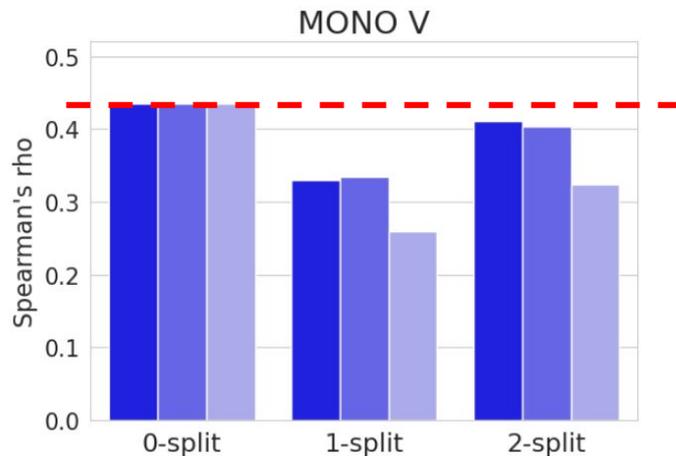
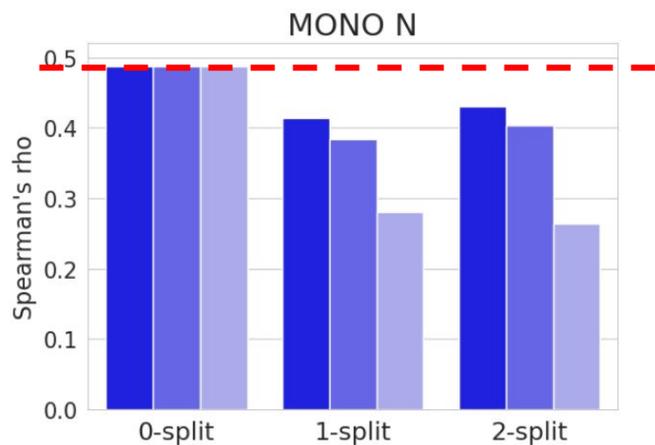
# What is the best representation strategy?



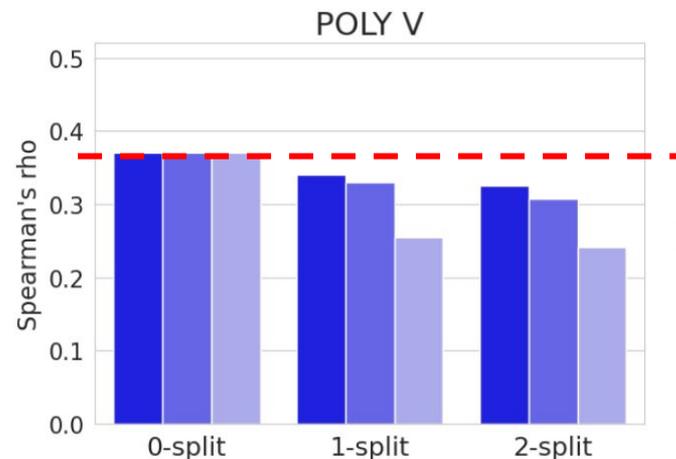
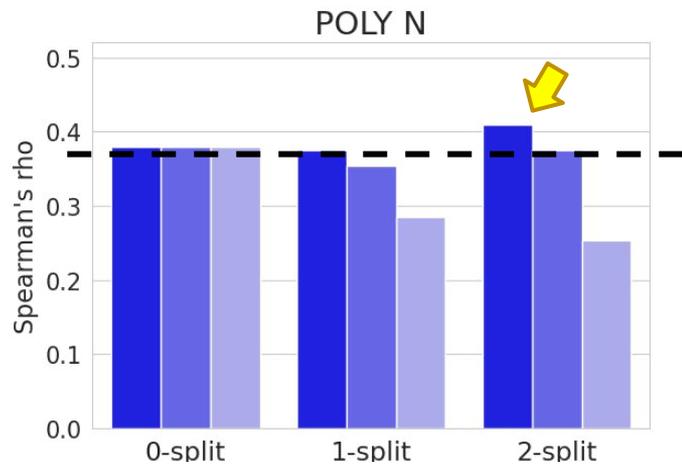
■ BERT (AVG)  
■ BERT (WAVG)  
■ BERT (LNG)

➤ LNG is really not a good strategy

# Is performance on pairs involving split-words worse than on 0-SPLIT pairs?

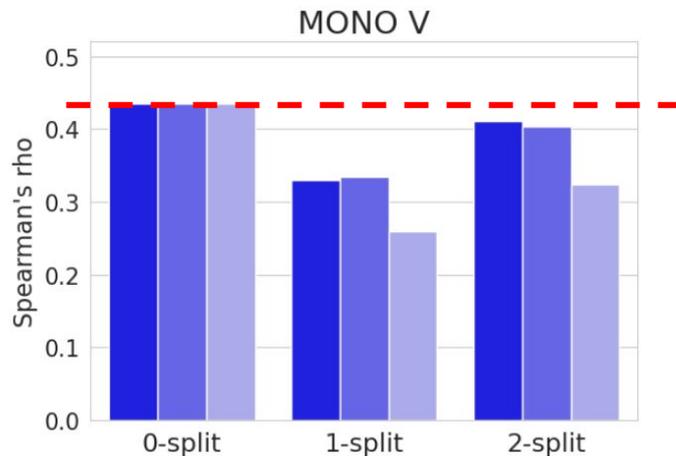
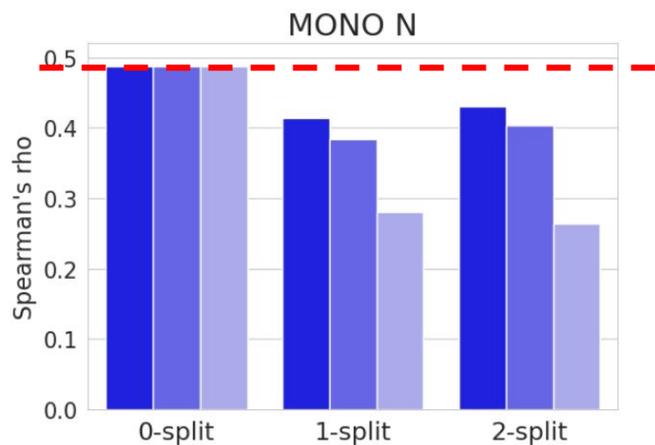


■ BERT (AVG)  
■ BERT (WAVG)  
■ BERT (LNG)

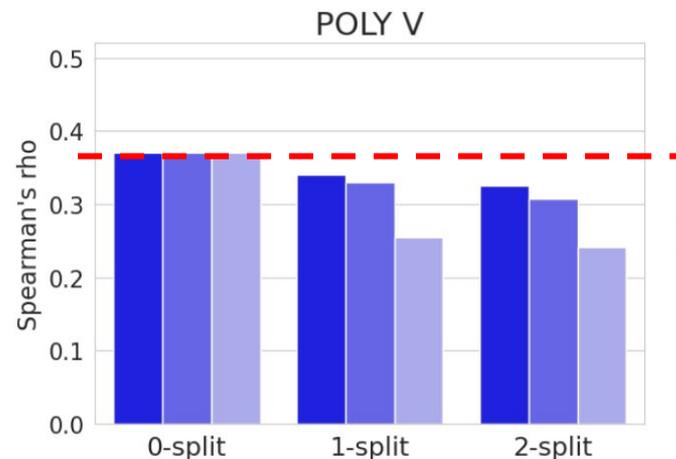
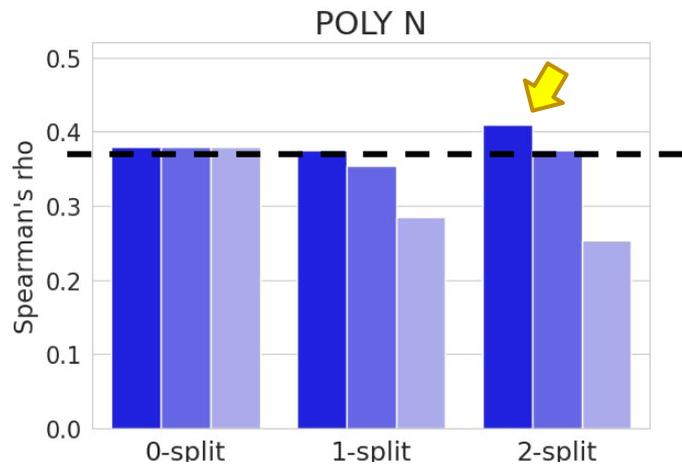


➤ Mostly yes, except for polysemous nouns

# Is performance on pairs involving split-words worse than on 0-SPLIT pairs?



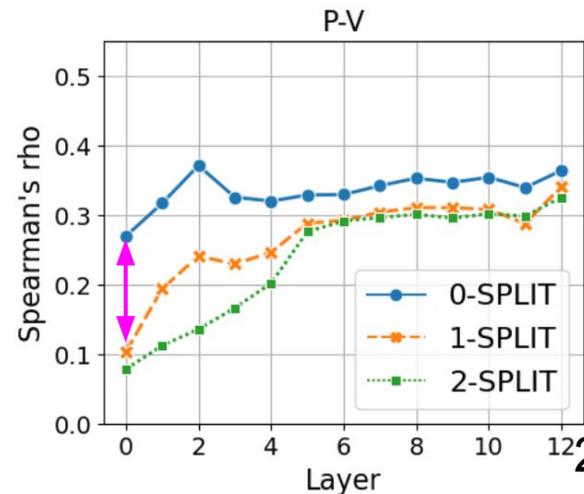
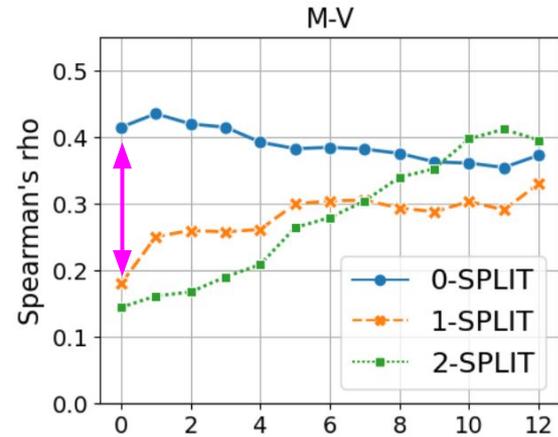
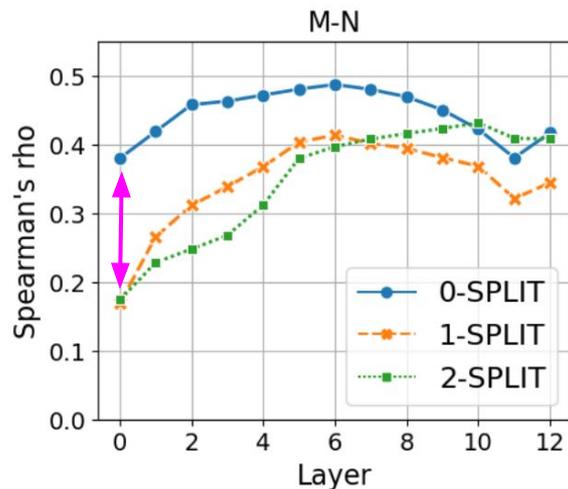
■ BERT (AVG)  
■ BERT (WAVG)  
■ BERT (LNG)



➤ The observed pattern holds when controlling for frequency 24

# How do results change across layers for every split-type?

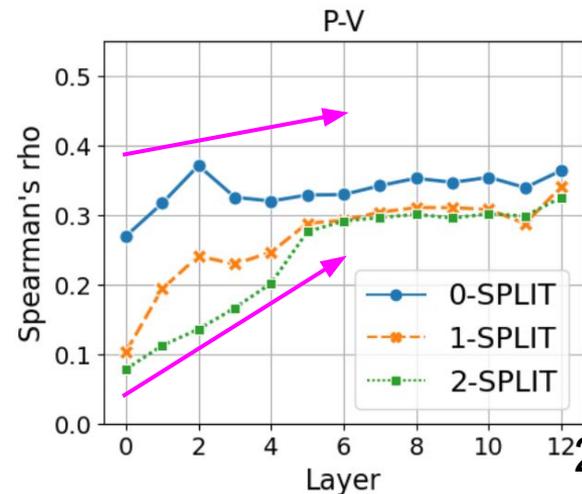
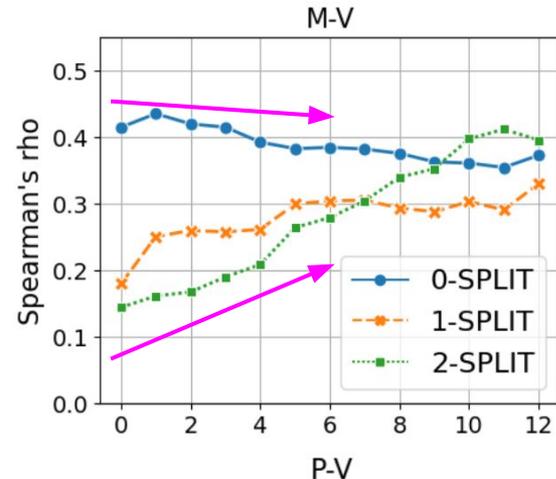
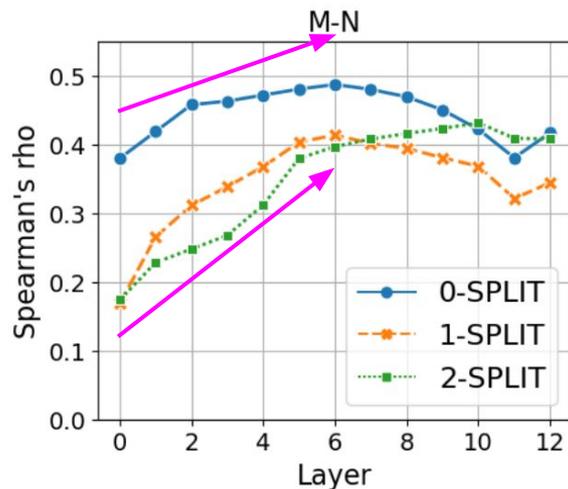
➤ At earlier layers the quality of 1- and 2-split similarity estimations is much lower than that of 0- SPLIT pairs.



# How do results change across layers for every split-type?

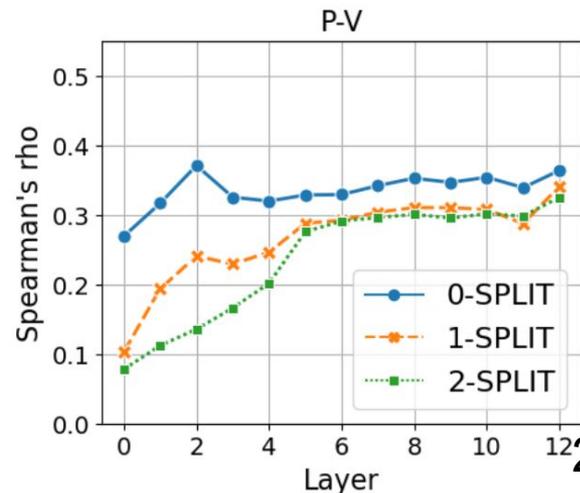
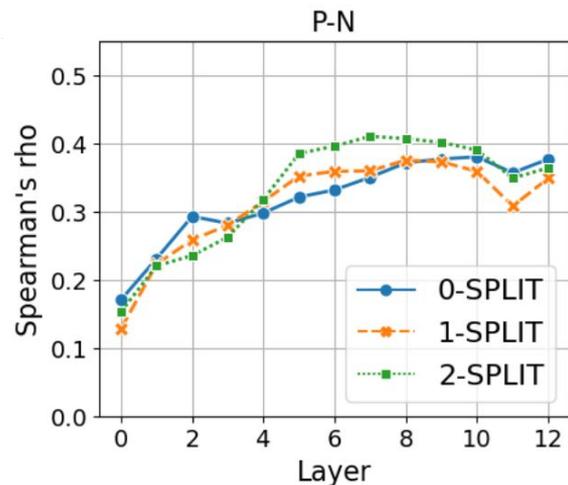
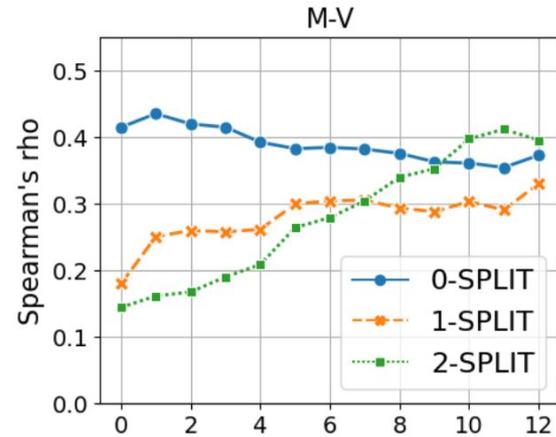
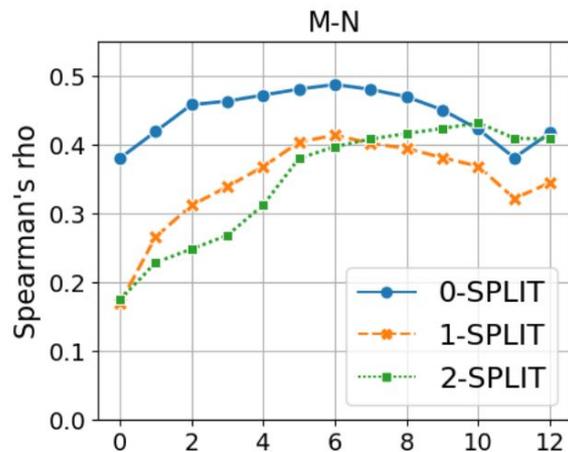
➤ At earlier layers the quality of 1- and 2-split similarity estimations is much lower than that of 0- SPLIT pairs.

➤ However, their quality improves at a higher rate than that of 0- SPLIT, which remains more stable.



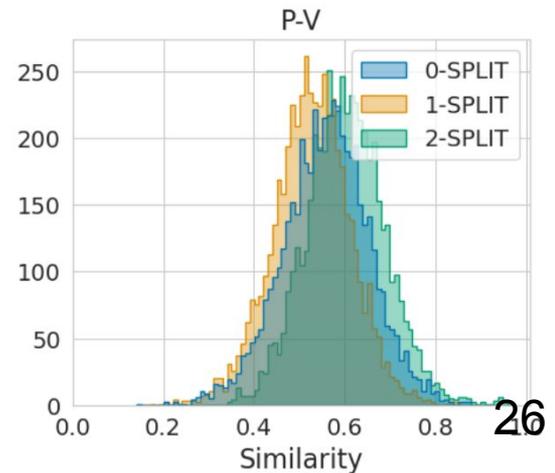
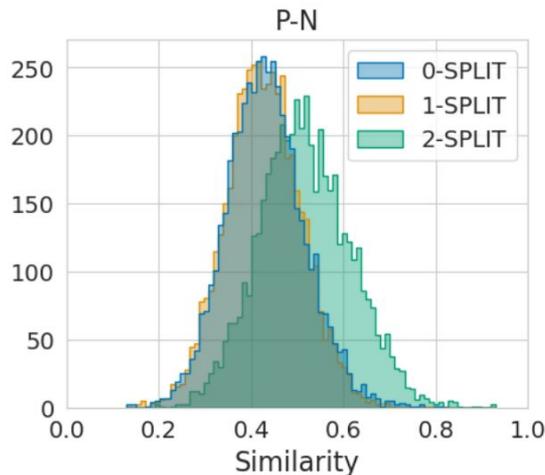
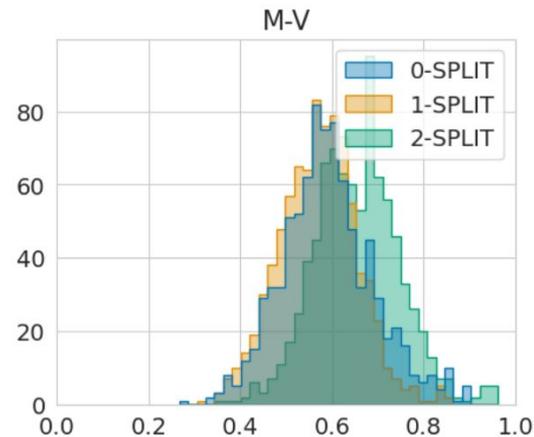
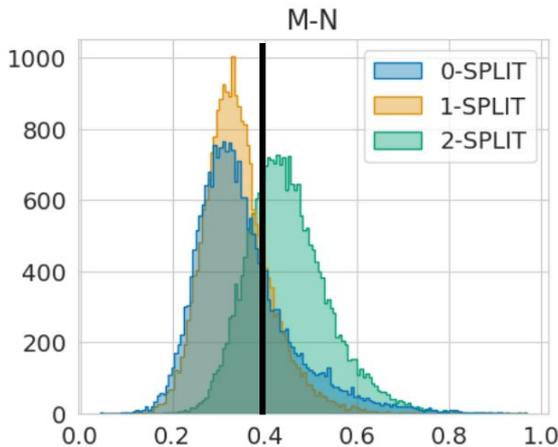
# How do results change across layers for every split-type?

➤ For polysemous nouns, instead, 0- SPLIT pairs behave in a similar way as 1- and 2- SPLIT pairs from the very first layers.



# Do similarity predictions vary across split-types?

- Similarities in 2-SPLIT pairs are in a different range: comparison of similarity values across split-types can be misleading



# Does the number of subwords have an impact on the representations' semantic content?

{ash, ##tray}

{weather}



3 (2+1)

{tom, ##fo, ##ole, ##ry}

{loaf, ##ing}

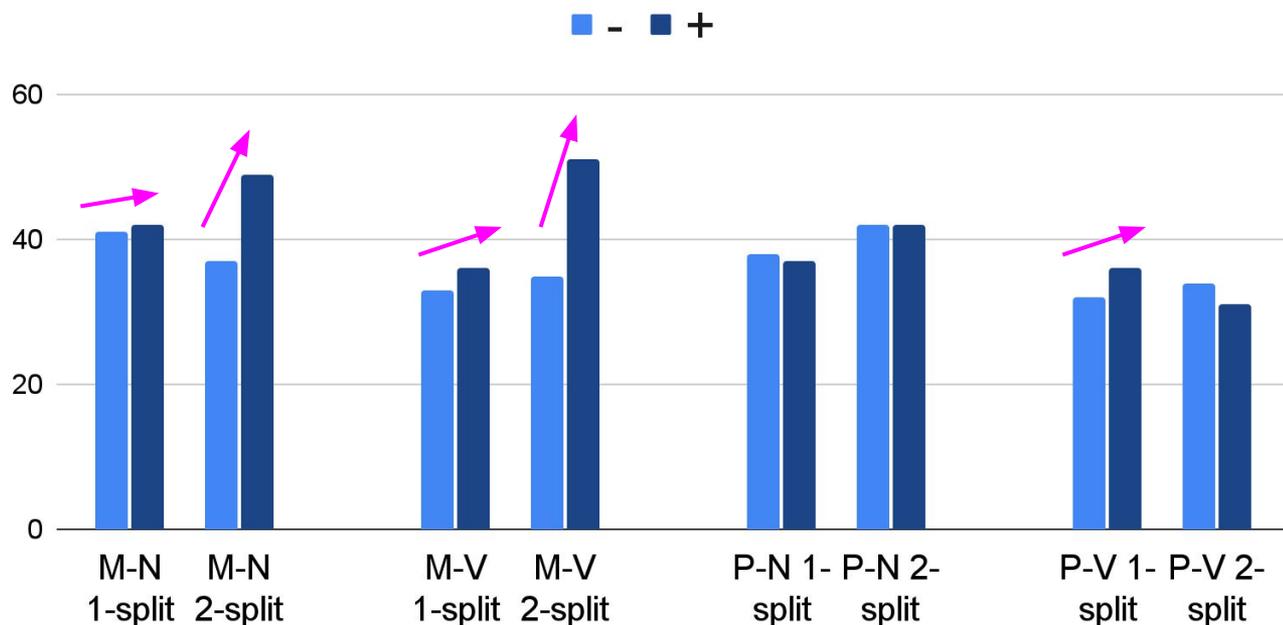


6 (4+2)

	-	+
1-split	3	>3
2-split	≥5	>5

**Expectation:** more subwords  worse quality

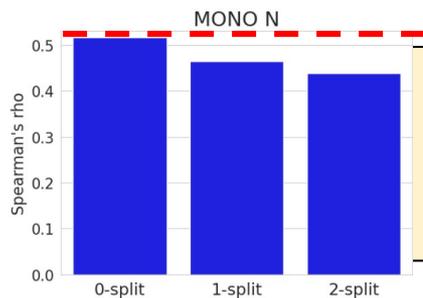
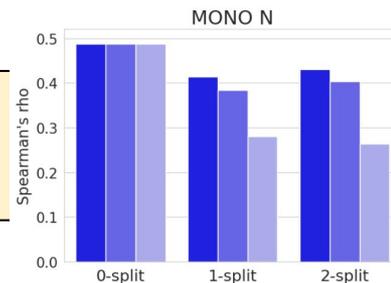
# Does the number of subwords have an impact on the representations' semantic content?



➤ Most of the time, more tokens was better!

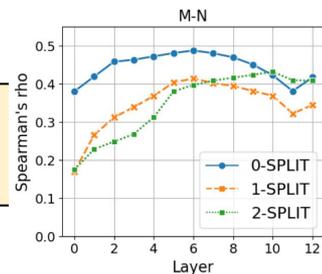
# Conclusion

**Averaging representations of all tokens is the best strategy to represent split-words**



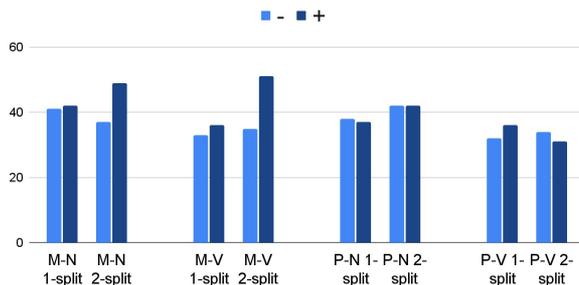
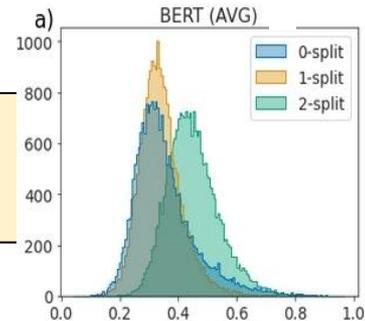
The **quality of split-word representations is worse than that of full-words**, but it depends on the kind of words considered

**The best layers to use differ across split-types**



# Conclusion

**Similarity values** obtained **between two split-words** are generally **higher** than similarities involving full-words



**A higher number of tokens does not decrease representation quality.**

# Word Meaning in Interaction

# Conversational alignment

**Alignment (or entrainment):** phenomenon by which people mimic each other in conversations.

It can happen at different levels: lexical, syntactic, prosodic, postural...

# Conceptual alignment

**Conceptual alignment:** The extent to which two dialog participants “mean the same things when using the same words” (Schober et al., 2005)

Knowing the meaning of a word does not guarantee conceptual alignment:

- Different mental representations of words (connotation, associations, detail)
- Ambiguity
- Novel usages

*Do language models understand?*

*Is she tall?*

# Lexico-semantic alignment

We can't access people's mental representations of words...



We propose a more restricted notion of conceptual alignment:

## **Lexico-semantic alignment**

“The convergence of word meaning inferrable from textual information alone”

# Are dialogs more “polysemous” than monologs?

(Are words used in more different senses in dialogs than in monologs?)

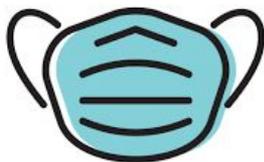
- Inter-personal differences in dialogs (backgrounds, world knowledge, idiolect, language level, opinion...) can lead to misunderstandings and disagreements
- **One Sense per Discourse** hypothesis: only tested on monolog-like data

It's even less true of dialog

# Do contextualized word representations reflect stance?

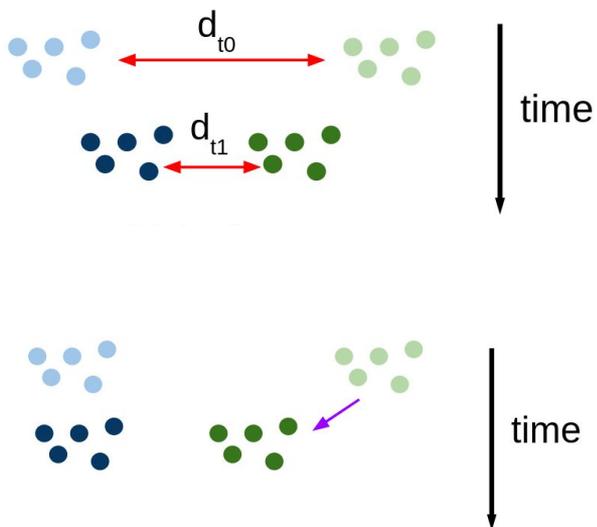
Differences in opinion are a likely source of misalignment

Yes.



# Can we measure lexico-semantic alignment?

We propose measures capturing different aspects of lexico-semantic alignment and relying on contextualized word representations



# Lexico-semantic alignment

Our measures reflected multiple semantic phenomena that characterize the way each side of a debate uses specific words...

...But we can't evaluate them!

Let's find examples of cases where speakers signal misalignment explicitly

# Word Meaning Negotiation: The NeWMe Corpus

# Word Meaning Negotiation (WMN)

3 components:

J3VPSUNK

Okay good . Erm a few **hard facts** just to confirm first of all

Trigger

PS3PB

Hard , what 's a hard fact ?

Indicator

J3VPSUNK

Your name and your address .

Negotiation

PS3PB

Oh right . So why are they called hard facts ?

# Word Meaning Negotiation (WMN)

2 main WMN types:

- NONs (originating from non-understanding)
- **DINs** (originating from disagreement)

Mavericgamer\_##\_t1\_cnf02s\_##\_rt-t1\_cnfcl4z

In reply to the edit: Yes, I could do the same. I could also do a "football/soccer flop" and fake **pain** when I'm not in it. I could even make the robot do that for important things like when it was detecting structural damage, because if you can invoke empathy, it is an important survival trait. But at that point, philosophically, isn't it just that we have created a being that can feel **pain**?

FarkCookies\_##\_t1\_cnf9en\_##\_rt-t1\_cnf02s

Not by any meaningful definition of **pain**. You equate **pain** and response to negative stimulus.

Mavericgamer\_##\_t1\_cnfdeva\_##\_rt-t1\_cnf9en

What else is **pain** than a response to a negative stimulus? I believe that is the *\*only\** meaningful definition of **pain**.

FarkCookies\_##\_t1\_cnfdkj\_##\_rt-t1\_cnfdeva

Ah it is cool then. Your rules, your game.

# The NeWMe (**N**egotiating **W**ord **M**eaning) corpus

Annotation of WMN in existing conversational corpora:

- **Switchboard Dialog Act Corpus** (Stolcke et al., 2000)  
Oral - dyadic phone conversations
- **British National Corpus** (BNC Consortium, 2007)  
Oral - lectures, meetings, interviews...
- **Winning Arguments (ChangeMyView) Corpus** (Tan et al., 2016)  
Written (Reddit) - debate-like

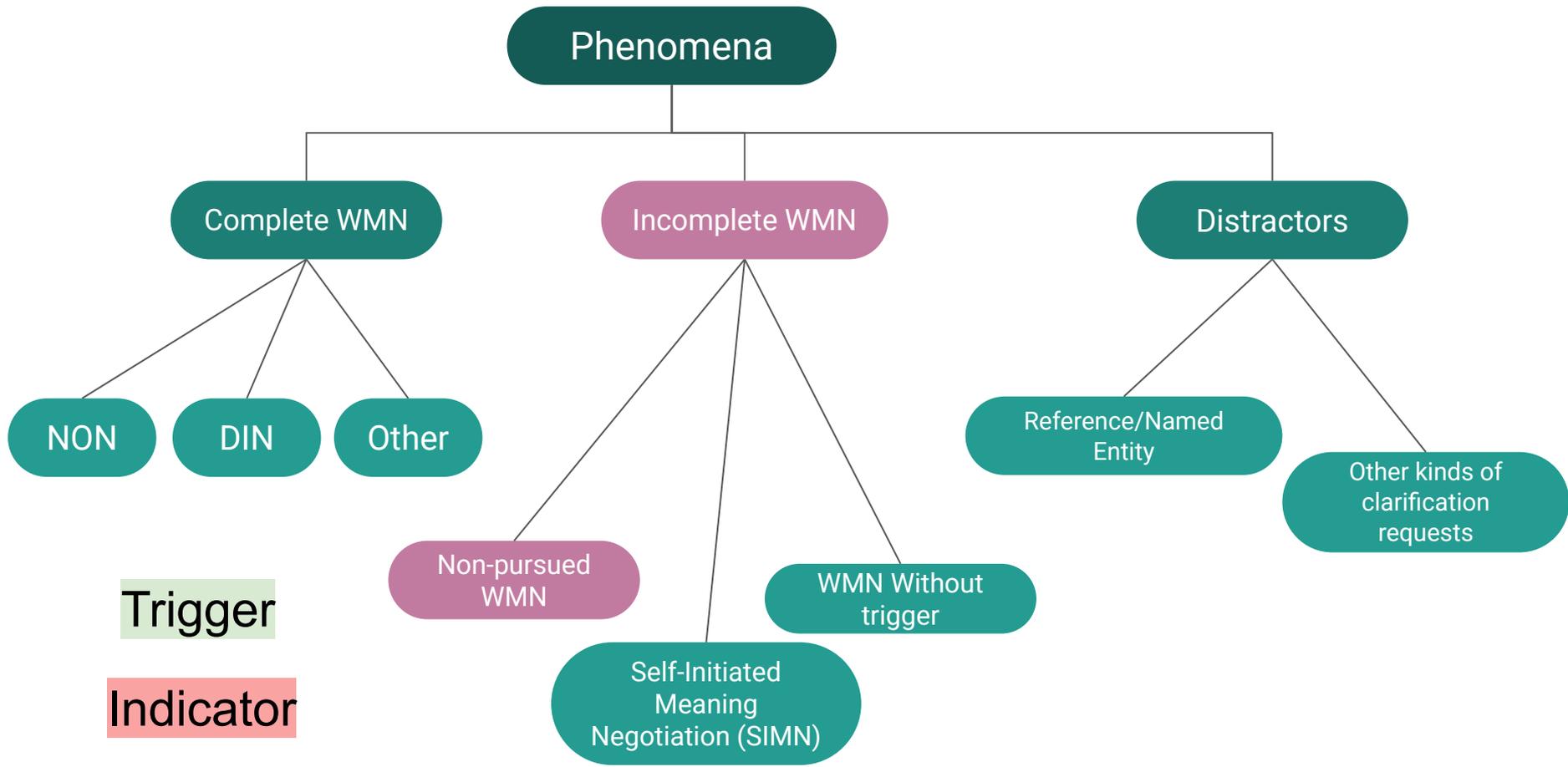
# Data collection

- Focus on **indicators**: the part of a WMN with least variability
- Regular expression matching

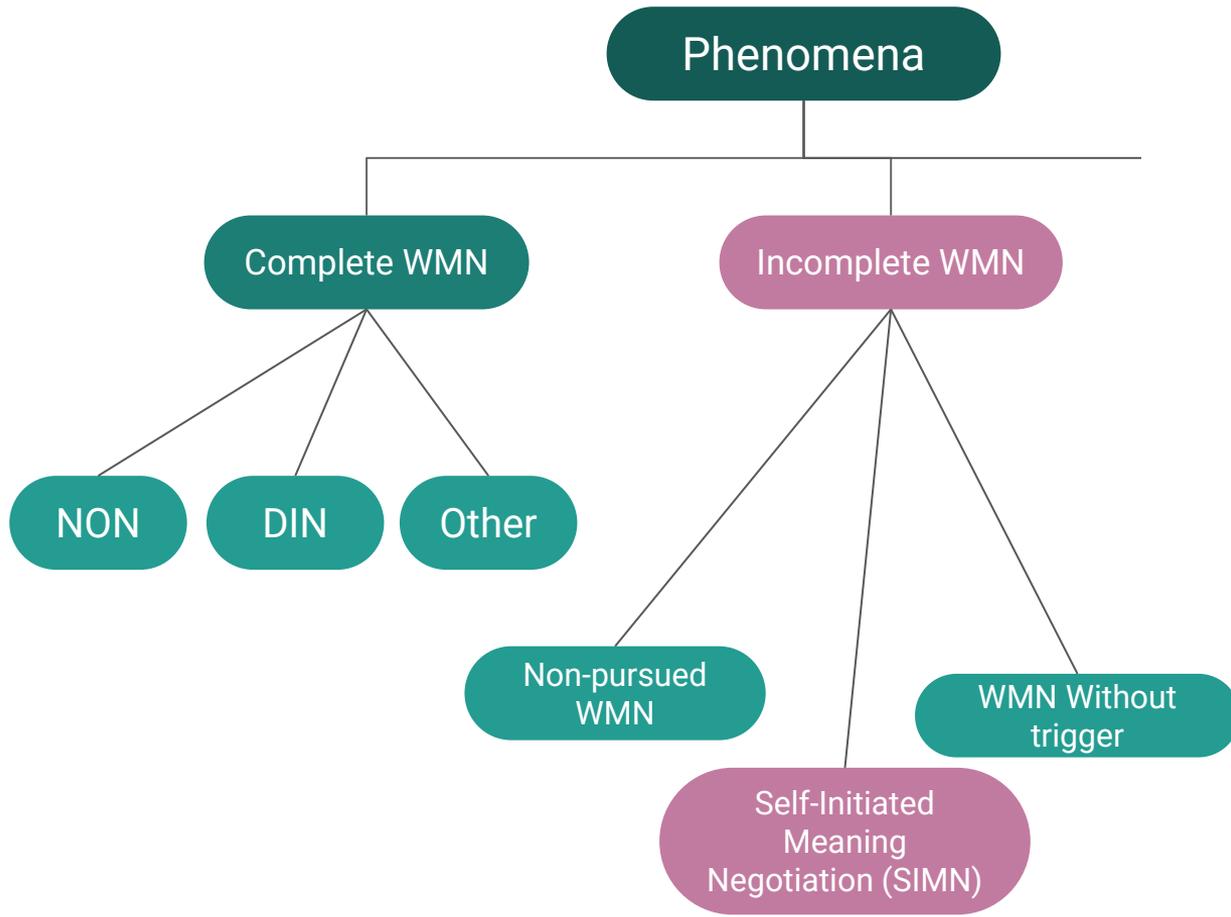
- ❑ `(what|wtf) do you (actually) mean by`
- ❑ `this is not X`
- ❑ `meaning of`
- ❑ `definition of`
- ❑ `what is the difference between`
- ❑ `S1: ...hard facts.. S2: hard facts?`
- ❑ `...`

Result: 8313 potential indicators

# Annotation schema

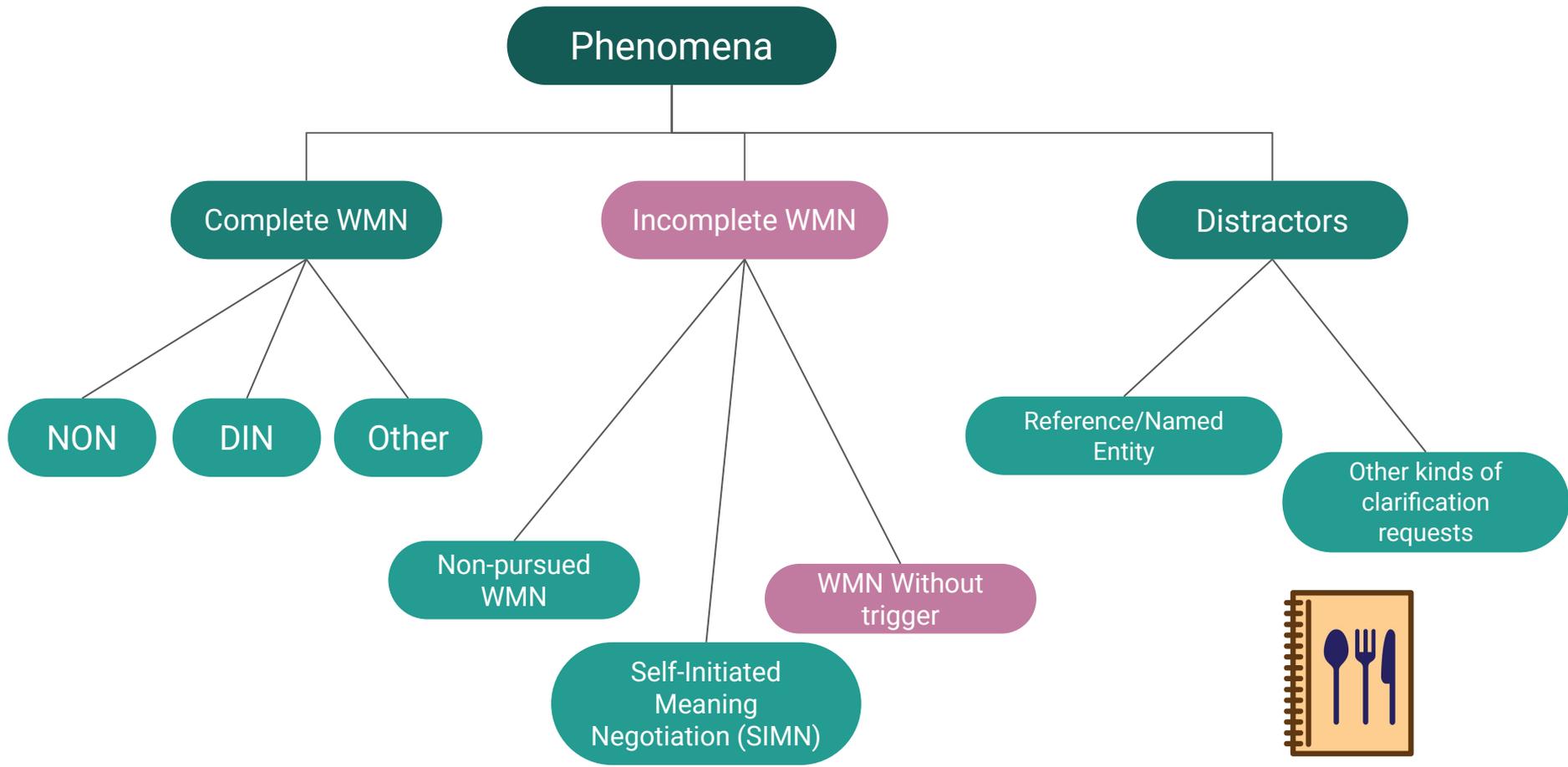


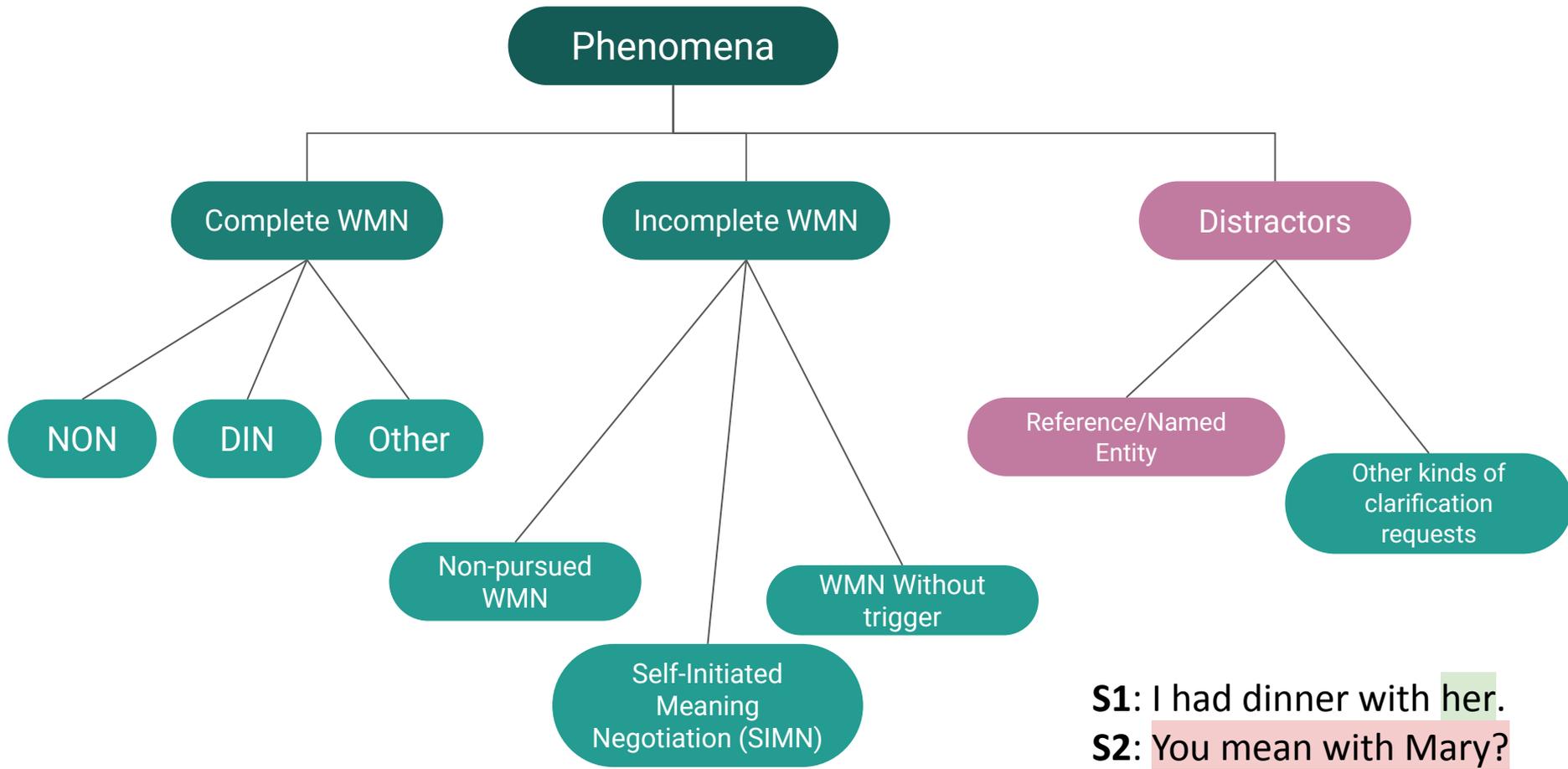
...



**S1:** We need to calibrate the machine before we start using it.  
Do you understand what calibrate means?

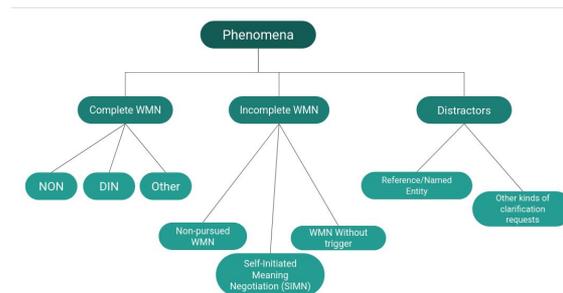
**S2:** It means to adjust it properly.  
...





# Annotation schema

- Phenomenon label



- Spans

trigger, indicator, negotiation

# Annotation procedure

2 expert annotators

## 1st round

Regular meetings to discuss difficult cases and refine the annotation schema

Annotation guidelines write-up

## 2nd round

Double-checking all phenomena for consistency

## 3rd round

Inter-annotator agreement

# Statistics

	<b>BNC</b>	<b>Reddit</b>	<b>Switchboard</b>	<b>Total</b>
<b>NONs</b>	116	66	33	215
<b>DINs</b>	11	158	0	169
<b>WMN: Other</b>	14	3	3	20
<b>Non-pursued</b>	4	197	2	203
<b>SIMN</b>	37	2	3	42
<b>Without trigger</b>	10	0	2	12
<b>Reference/NE</b>	7	3	18	28
<b>Other kinds of clarification requests</b>	15	109	49	173
<b>Nothing</b>	3746	2353	1188	7287
<b>Total</b>	3984	2892	1298	8174
<b>Total phenomena</b>	214	538	110	721

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404  
WMNs

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# Inter-annotator agreement

## Expert annotation

256 instances

**86-90%** total agreement → 94-96% after discussion

Can we obtain reliable results by training annotators with our annotation guidelines?

# Inter-annotator agreement

3 Master's students in Computational Linguistics with an advanced level of English

## LEARNING

- Annotation guidelines
- 2 training videos
- Common meeting for Q&A

## TRAINING

- Two 15-instance annotation samples
- Individual meetings with feedback

Guidelines  
revision

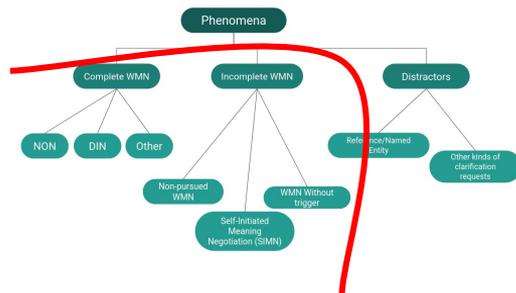
## ANNOTATION

Annotation of the  
same sample  
without feedback  
(704 instances)

# Inter-annotator agreement

Lessons learned:

- Moderate\* agreement on a higher-level distinction is reachable (by some annotators, on some corpora)
  - Reddit data was harder to annotate
  - Subjectivity, recurrent mistakes...
- We need more training, examples and feedback, with an emphasis on Reddit



# NeWMe: Next steps

- First corpus of its kind
- But it could be bigger: working on its semi-automatic extension



It will enable

- Characterizing and detecting problematic word usages
- Studying signaling behavior and negotiation strategies
- Determining the success of a negotiation

Later...

- Writing assistants
- Human-machine interaction

# Concluding thoughts

## Word Meaning Representation

- Complex
- (Still) relevant
  - NLP: less mainstream tasks, domains and languages
  - (Computational) Linguistics, Lexicography
  - Social sciences
  - Often more light-weight and computationally cheaper

# Concluding thoughts

## Word Meaning Negotiation

- Every speaker has their own “semantic network” - word-related misunderstandings are a window into inter-personal differences and language variation
- We only collected cases of **detected and signaled** conceptual misalignment
- To learn about how communication works, we need to study how and why it fails
- A model that succeeds at communicating needs to be able to avoid, detect and/or navigate word-related misunderstandings and disagreements

Thank you!