SAIL

SustAInable Life-cycle
of Intelligent Socio-Technical Systems

Subproject as part of SAIL:
Longitudinal Analysis of Change and Variety of Natural Language Data

Computational linguistic methods for modeling lexical-semantic dynamics of hate speech

by Sanne Hoeken

Supervised by dr. Özge Alaçam and prof. dr. Sina Zarrieß

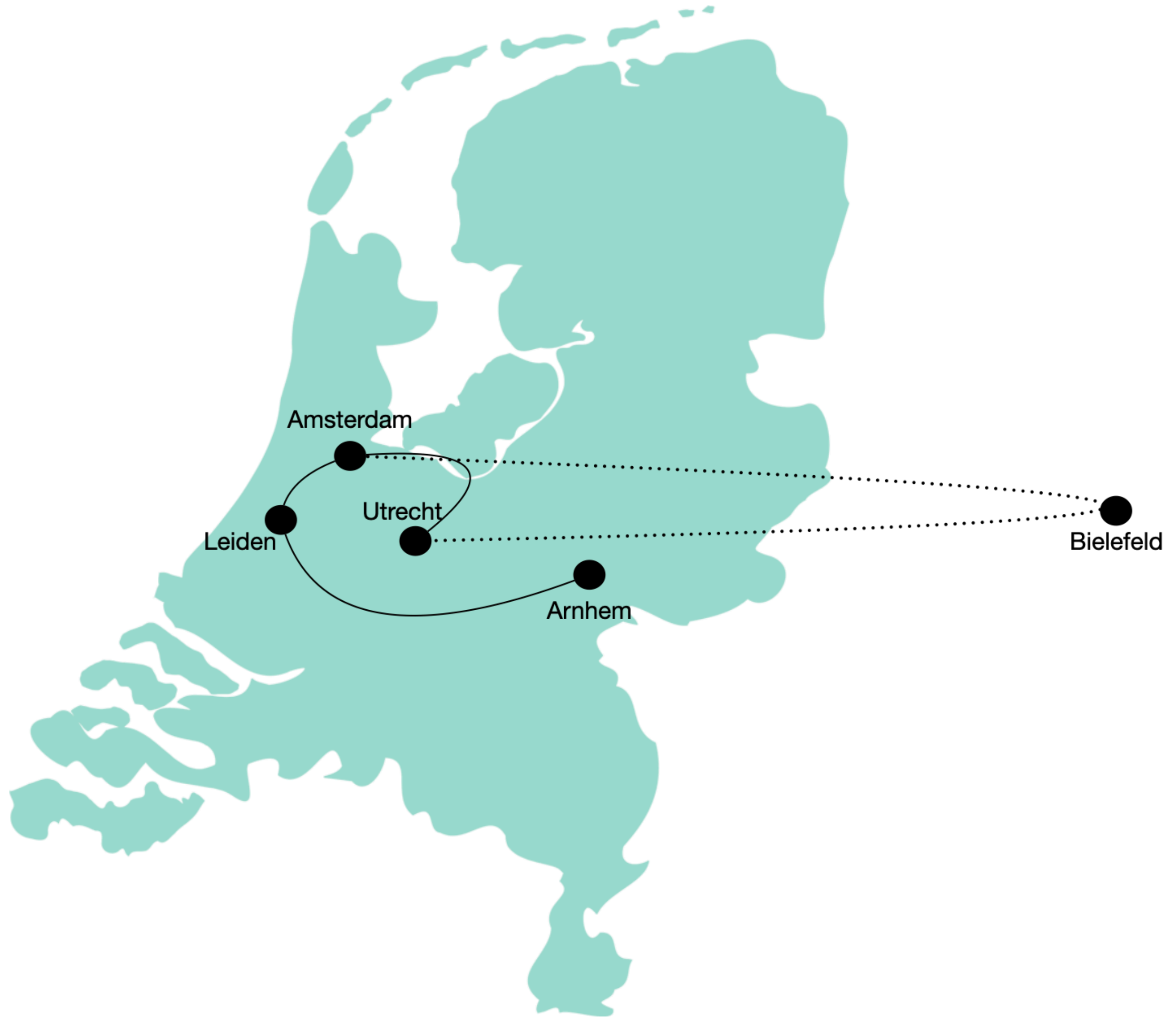
But first…

Who am I?

- (3rd year) PhD in Computational Linguistics - Bielefeld University
- MA Human Language Technology - Vrije Universiteit Amsterdam
- BA Linguistics - Leiden University

Besides spiralling my way into NLP,

I also love sports (gym, running, cycling, skiing, …) and cooking (others with a named sourdough starter?)



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Change and Variety

dynamics

Change **over time**

dynamics

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Change over time

dynamics

→ the evolution of
hateful word meanings

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Variety **across different contexts**

dynamics

individual *Variety* across different contexts

dynamics

individual *Variety* across different contexts

Computational linguistic methods for modeling lexical-semantic dynamics of hate speech

Hateful Word in Context Classification

Sanne Hoeken[1], **Sina Zarrieß**[1] **and Özge Alaçam**[1,2]

[1]Computational Linguistics, Department of Linguistics, Bielefeld University, Germany
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The 2024 Conference on Empirical Methods in Natural Language Processing (EMNLP)

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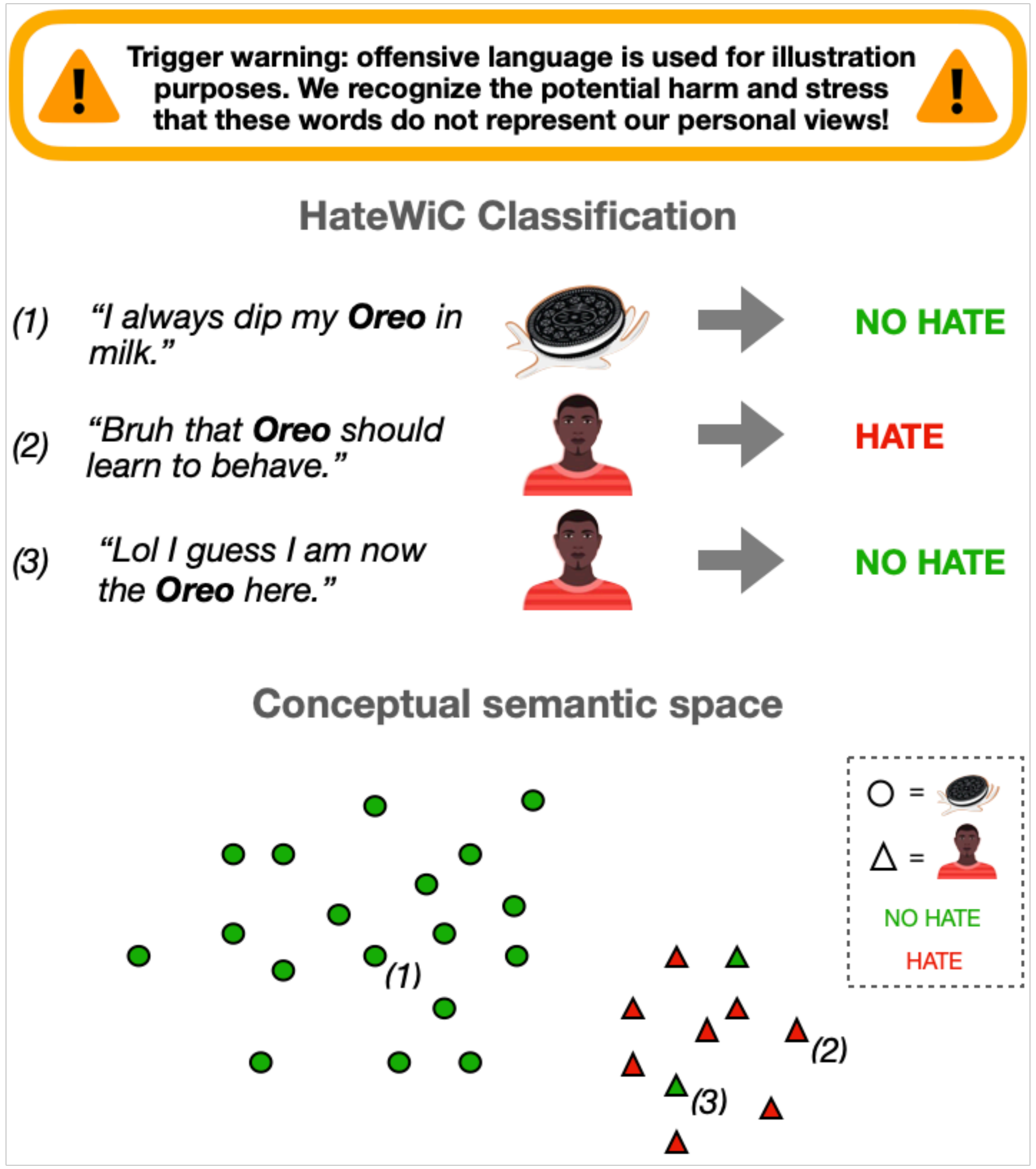
HateWiC classification

because hateful senses are <u>not</u>…

- … enough in focus within HSD research
  - Predominant focus on entire utterances
    (e.g. Waseem & Hovy, 2016; Davidson et al., 2017)
- … descriptive only, but highly subjective
  - Hateful connotation depends on contextual factors
    (Frigerio & Tenchini, 2019)
  - Current HSD data typically reflect single perspectives
    (e.g. Zampieri et al., 2020; Mathew et al., 2020)



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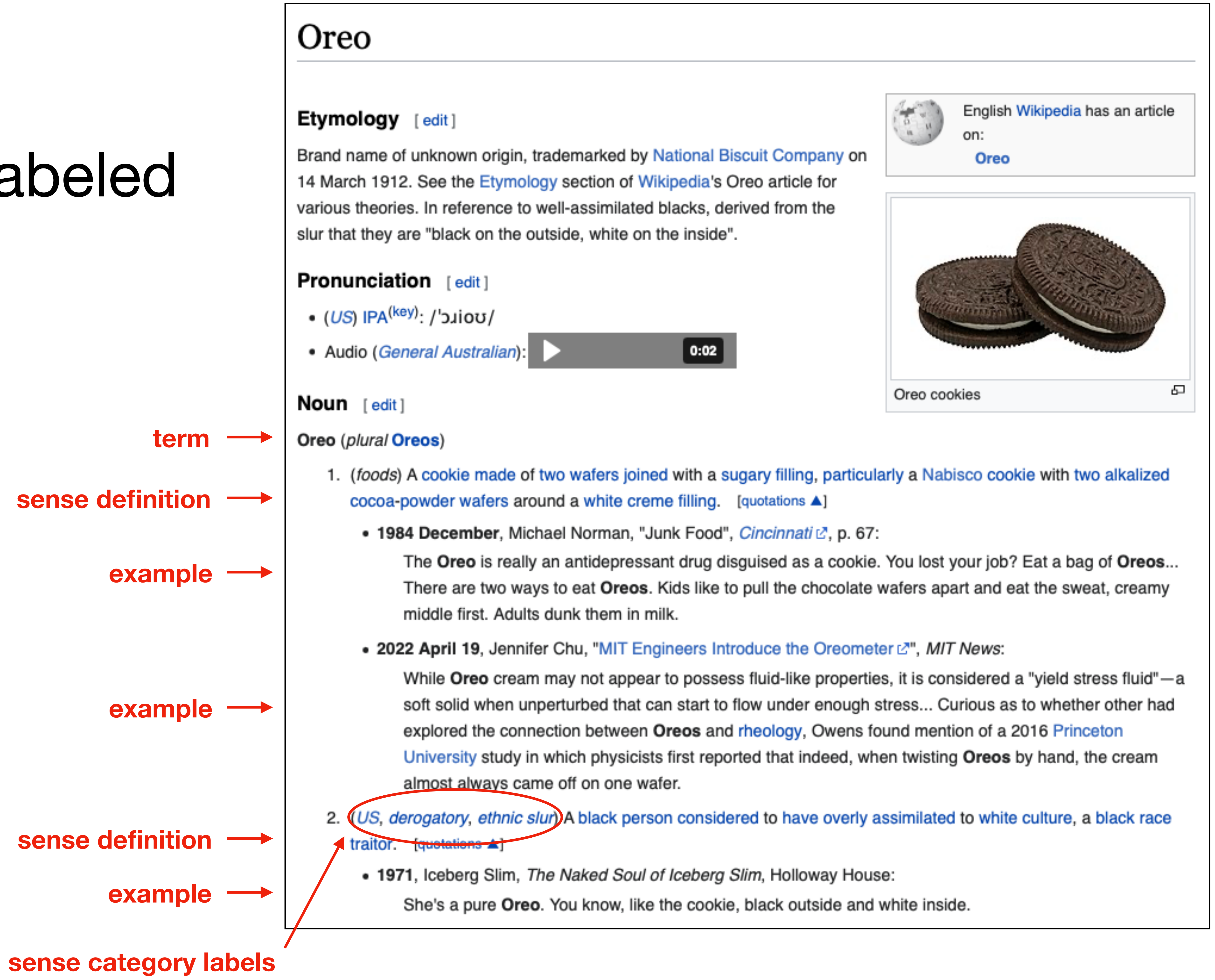
The HateWiC dataset

Starting with Wiktionary…

- 1087 entries with at least one sense labeled with category *offensive* or *derogatory*

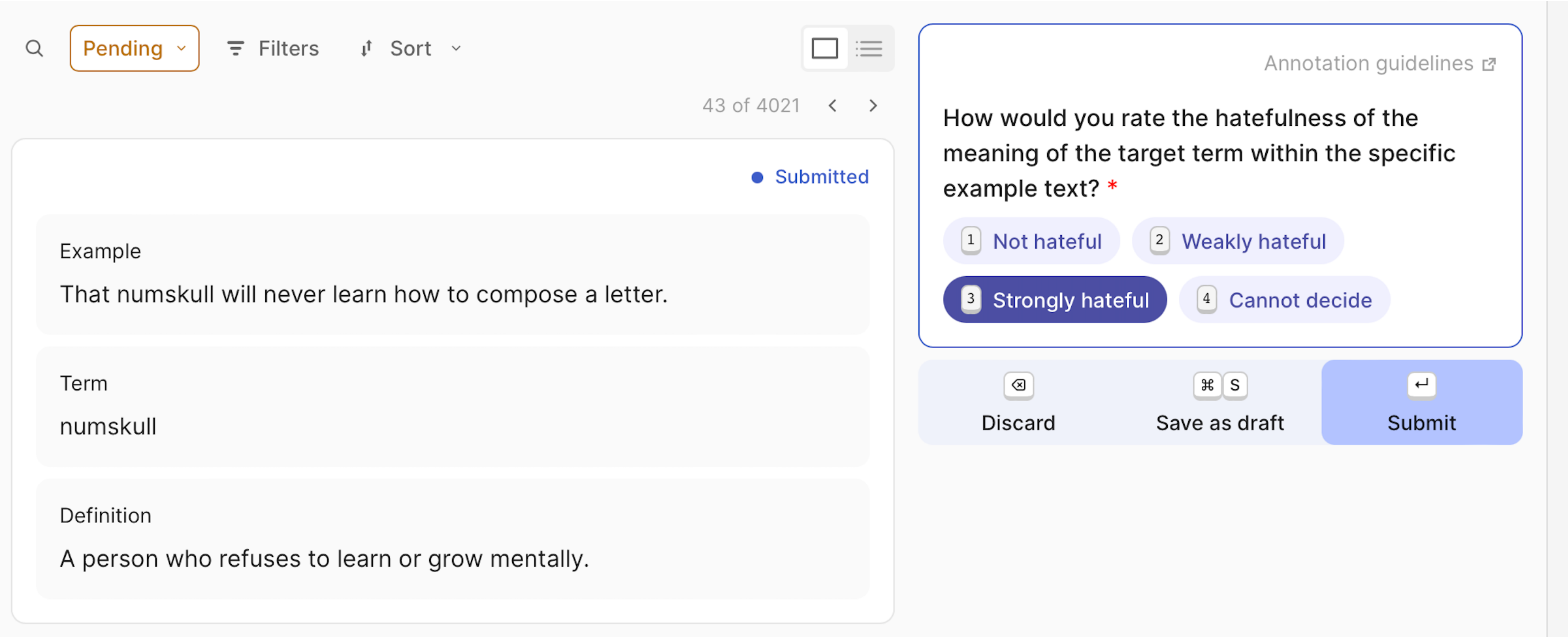
After cleaning:

- 826 terms
- 1888 sense definitions
- 4029 examples



The HateWiC dataset

Annotation



The HateWiC dataset

Annotation

- Crowd-sourced annotations using Prolific
- Three annotations per instance; 250 instances per annotator
  → 48 annotators (with diverse backgrounds)
  → 12442 individual annotations (48% hate and 52% non-hate ratings)
- Inter-annotator agreement of 0.33 (three-class) and 0.45 (binary)
  → inherent subjectivity of the task!

The HateWiC dataset

Annotation

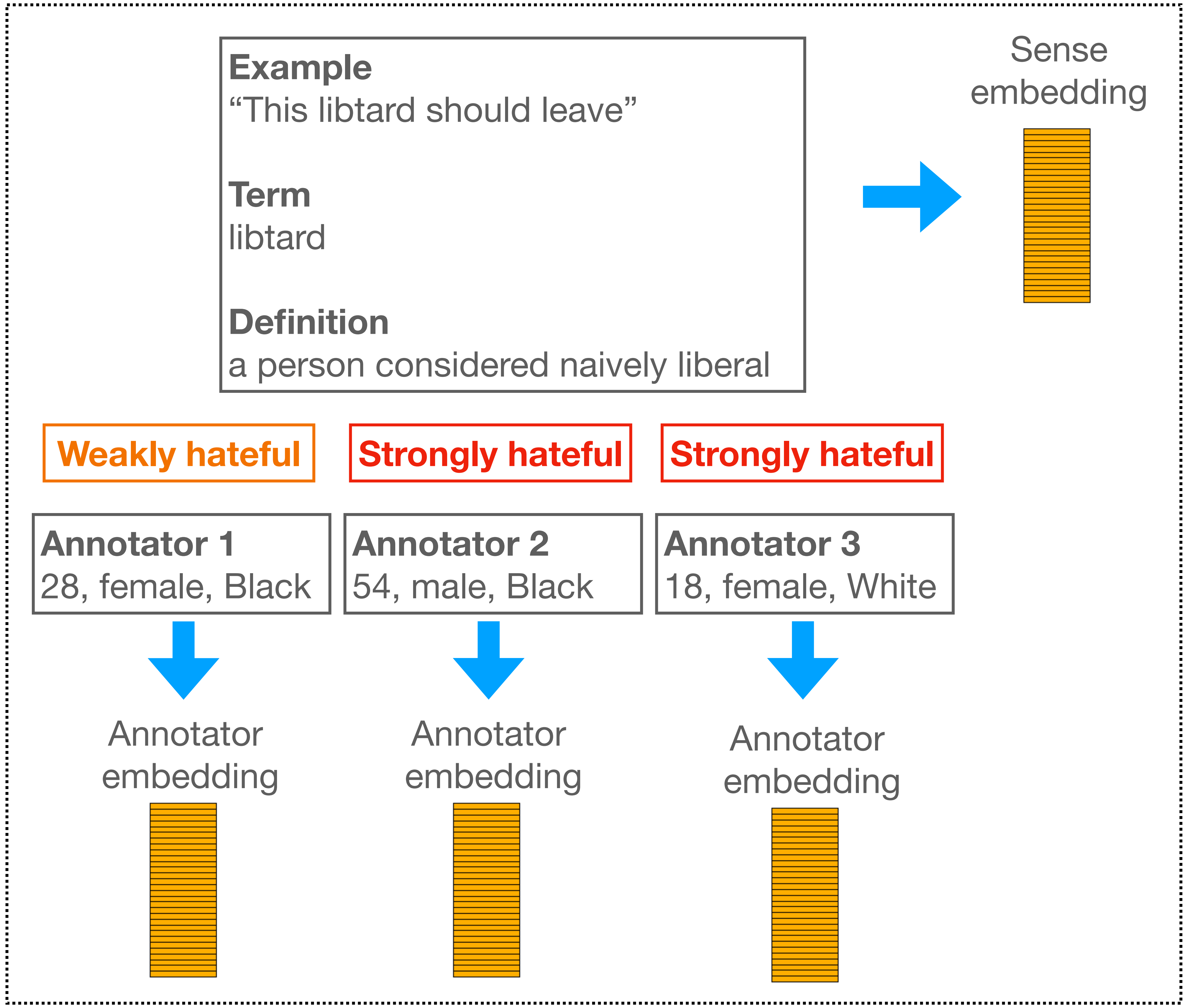
Example	Term	Definition	Annotations	Binary labels	Majority label	Hate-hetero-geneous sense	Agreement on binary
(1) “Me having an up to date style even though I’ve turned into a carrot cruncher.”	carrot cruncher	Someone from a rural background.	Nh, Nh, Nh	0, 0, 0	0	True	True
(2) “you’re a friggn’ carrot cruncher and you support the bloody scally’s.”	carrot cruncher	Someone from a rural background.	Sh, Sh, Sh	1, 1, 1	1	True	True
(3) “The bugger’s given me the wrong change.”	bugger	A foolish person or thing.	Wh, Sh, Sh	1, 1, 1	1	False	True
(4) “He’s a silly bugger for losing his keys.”	bugger	A foolish person or thing.	Nh, Wh, Sh	0, 1, 1	1	False	False

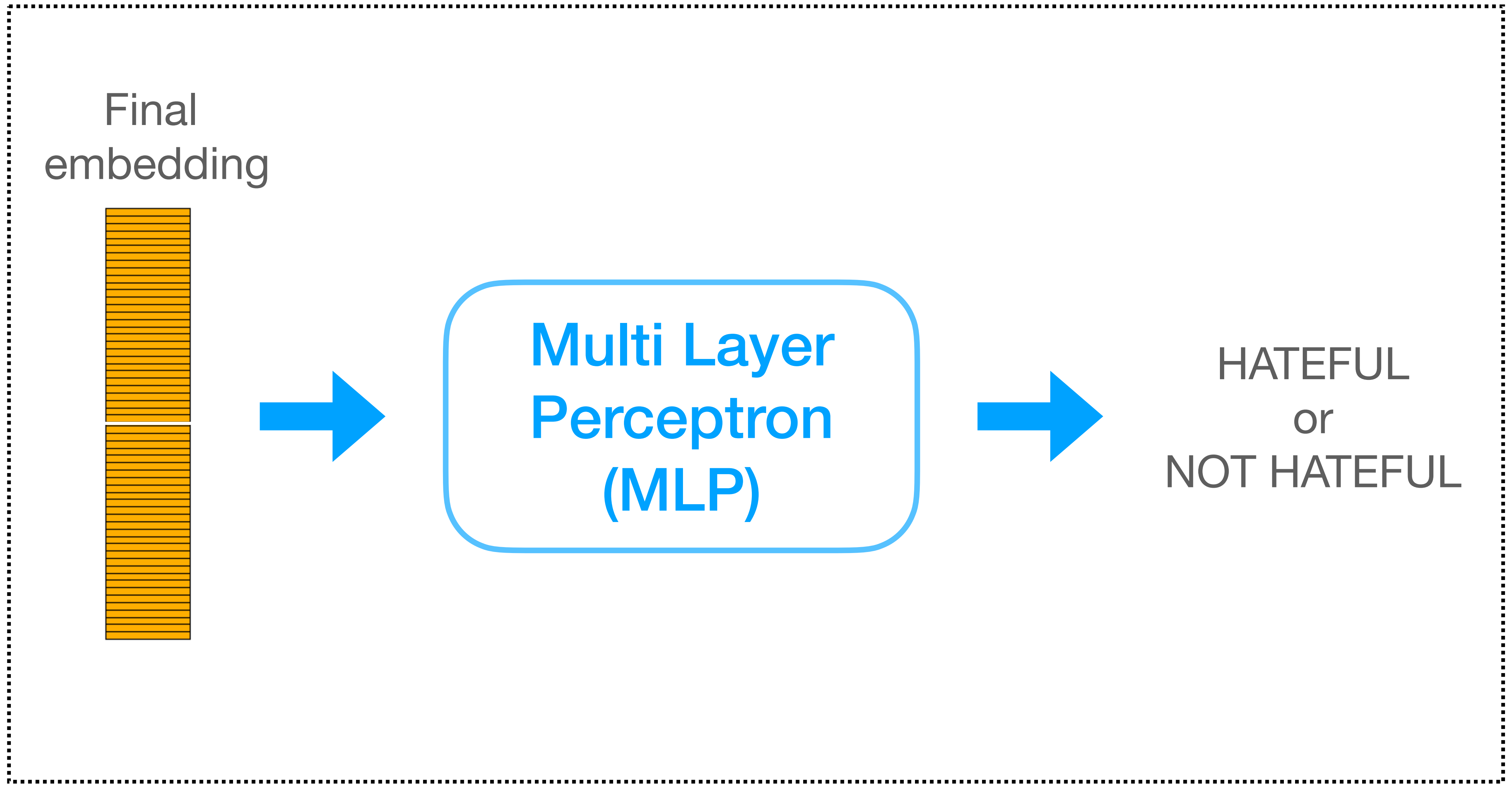
Table 1: HateWiC examples with their annotations, illustrating the phenomena of annotator disagreement and hate-heterogeneous word senses (Nh = Not hateful, Wh = Weakly hateful, Sh = Strongly hateful)

- 319 hate-heterogeneous definitions (wrt majority ratings!)
  → hateful connotation of a word sense is not exclusively determined by its descriptive definition!

HateWiC Classification

Overview

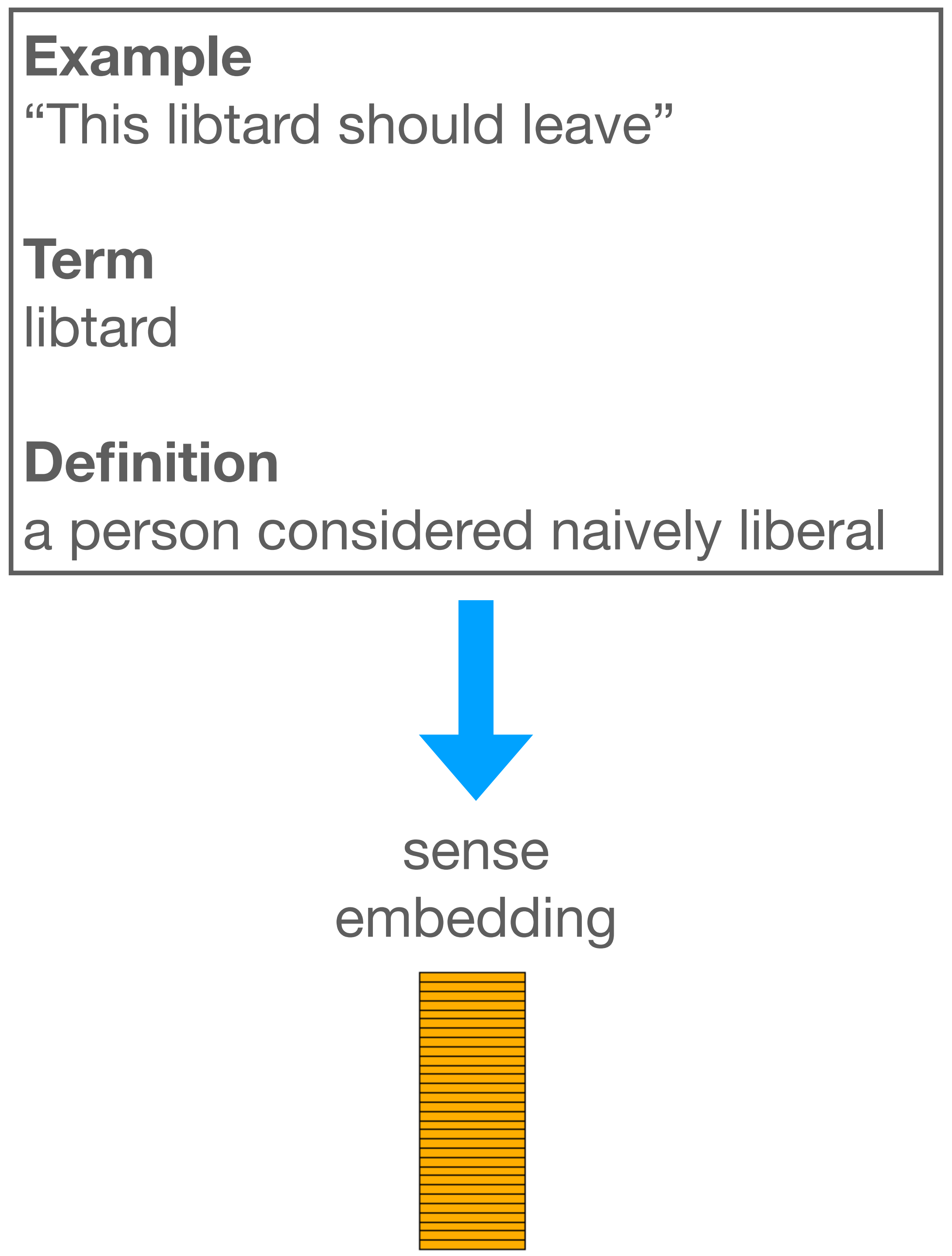




HateWiC Classification

Sense representations

- Encoder models
  - BERT *(Devlin et al., 2019)*
  - HateBERT *(Caselli et al., 2021)*
  - WSD Biencoder *(Blevins and Zettlemoyer, 2020)*
- Embeddings
  - Word in Context (WiC)
  - Definition (Def)
  - T5-generated definition (T5Def)



HateWiC Classification

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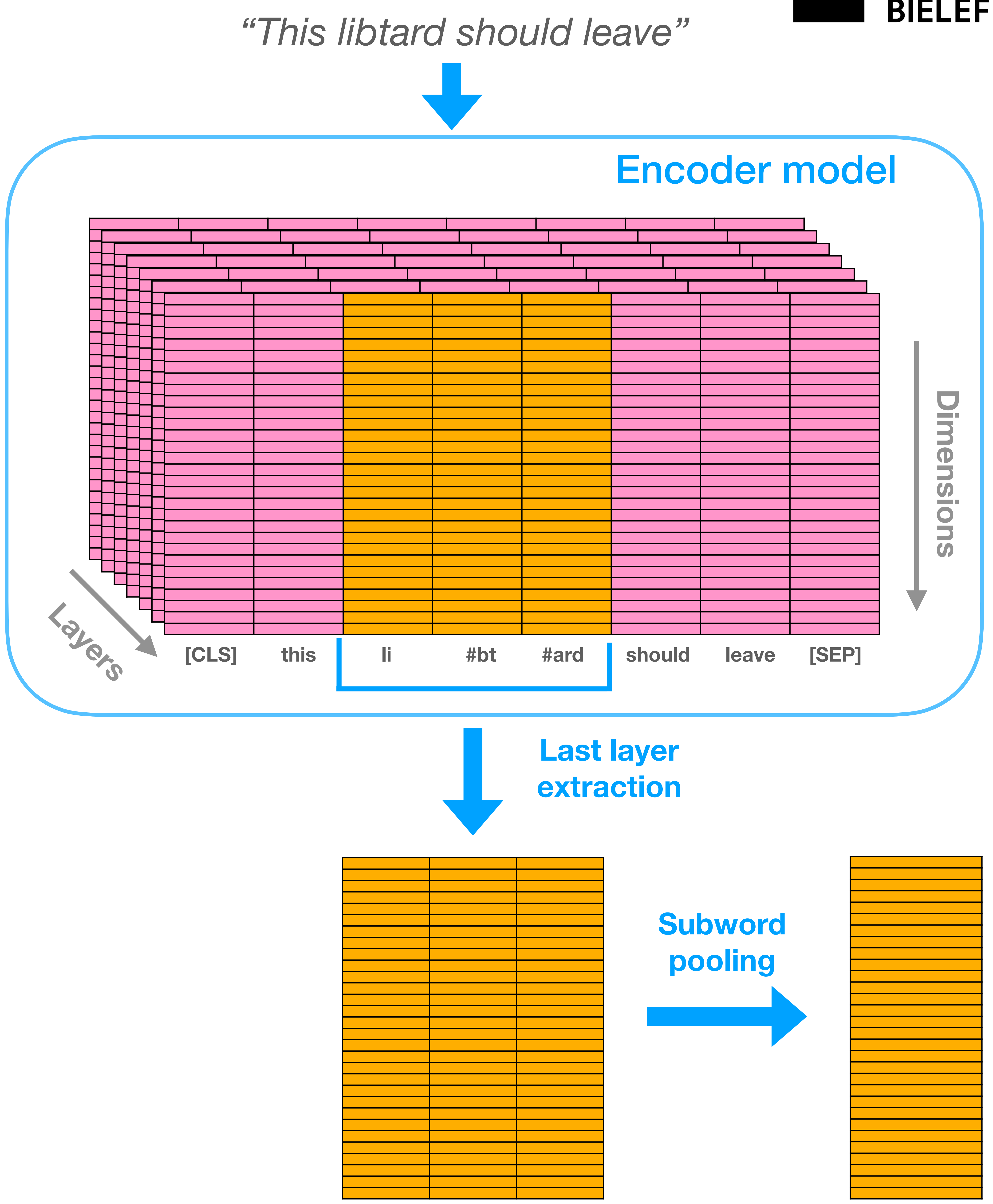
  - WSD Biencoder *(Blevins and Zettlemoyer, 2020)*
- Embeddings
  - **Word in Context (WiC)**
  - Definition (Def)
  - T5-generated definition (T5Def)



HateWiC Classification

Sense representations

- Encoder models
  - BERT *(Devlin et al., 2019)*
  - HateBERT *(Caselli et al., 2021)*
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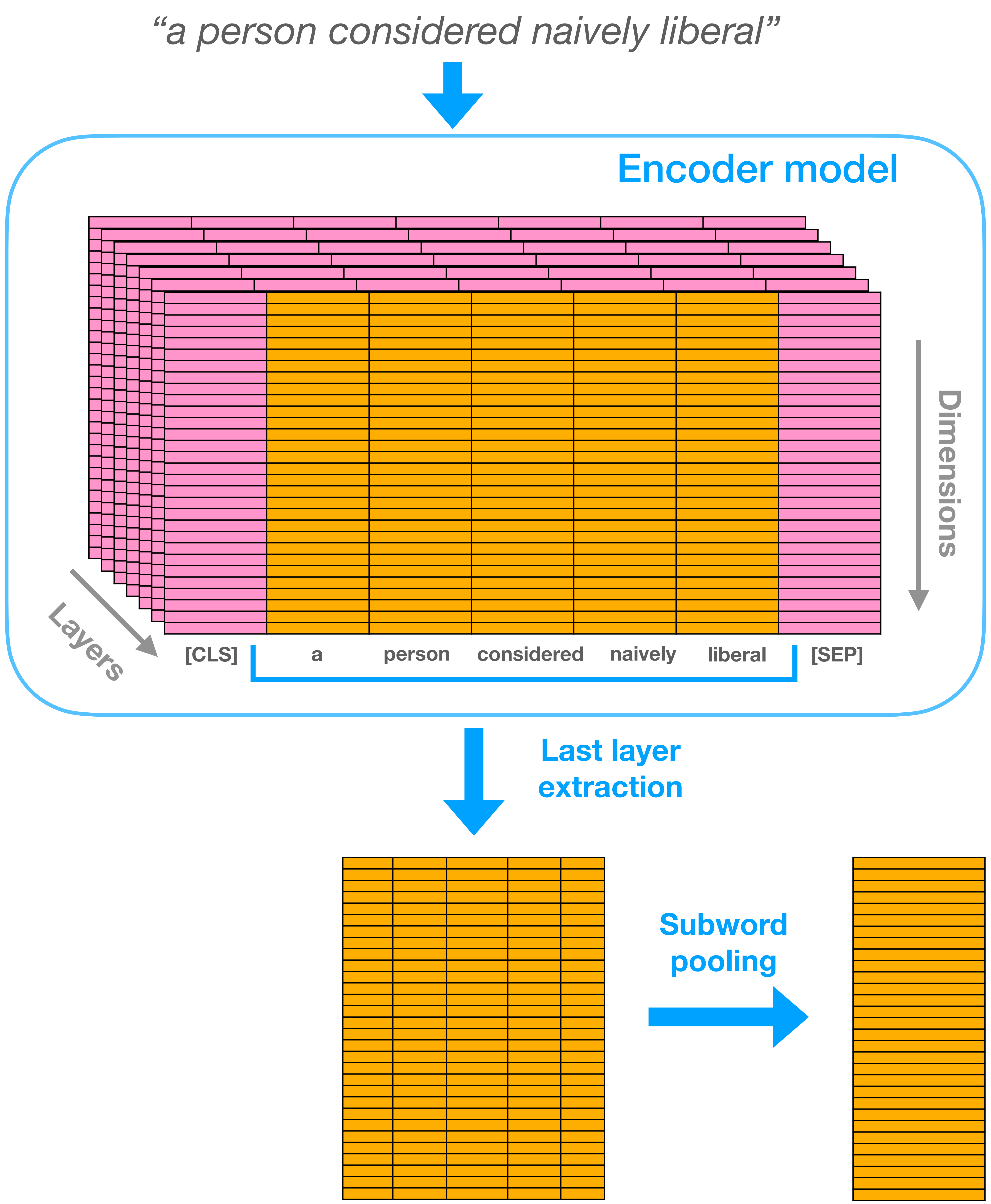
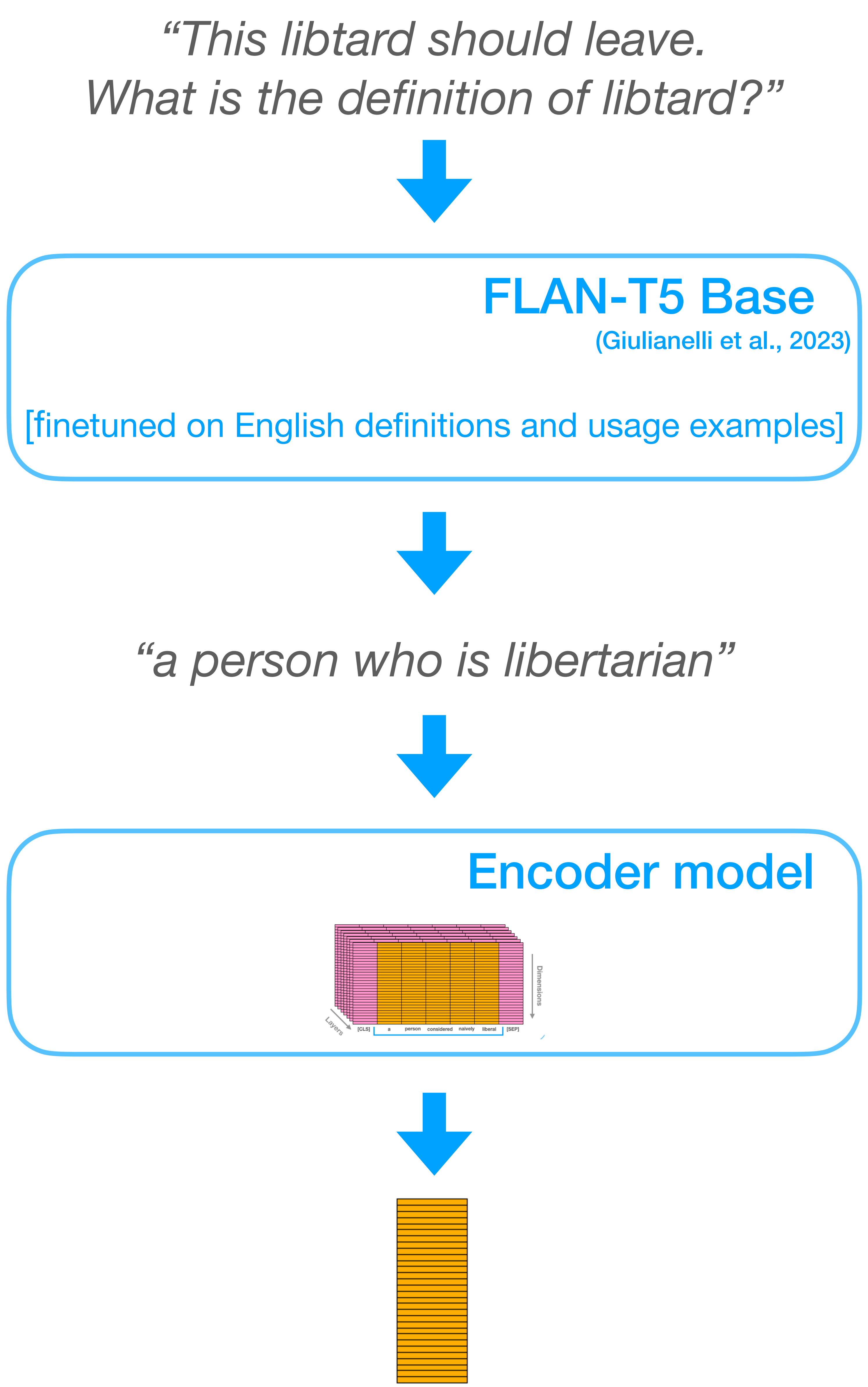
- Embeddings
  - Word in Context (WiC)
  - **Definition (Def)**
  - T5-generated definition (T5Def)



HateWiC Classification

Sense representations

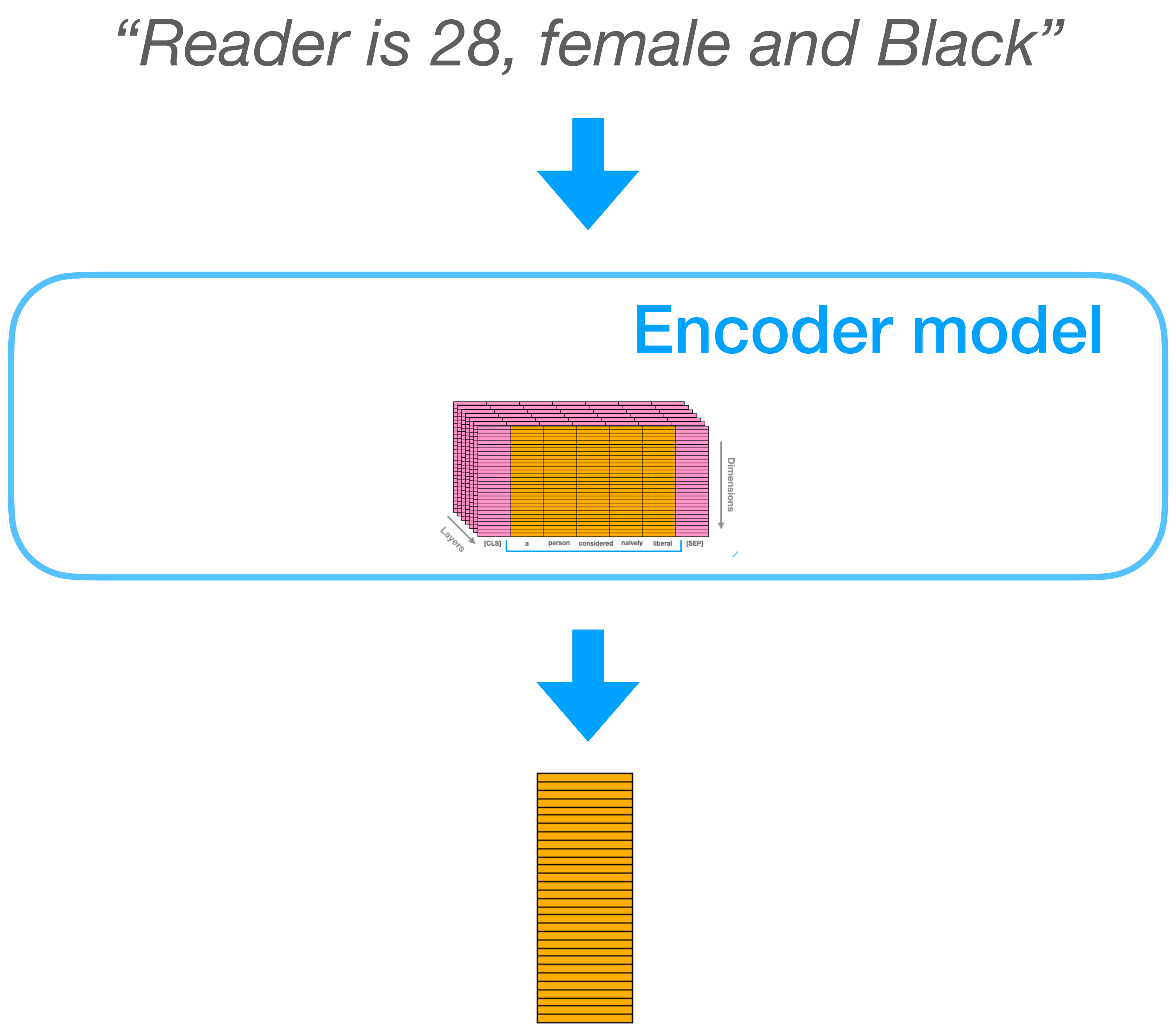
- Encoder models
  - BERT *(Devlin et al., 2019)*
  - HateBERT *(Caselli et al., 2021)*
  - WSD Biencoder *(Blevins and Zettlemoyer, 2020)*
- Embeddings
  - Word in Context (WiC)
  - Definition (Def)
  - **T5-generated definition (T5Def)**



HateWiC Classification

Annotator information

- Annotator description embeddings (Ann)



HateWiC Classification

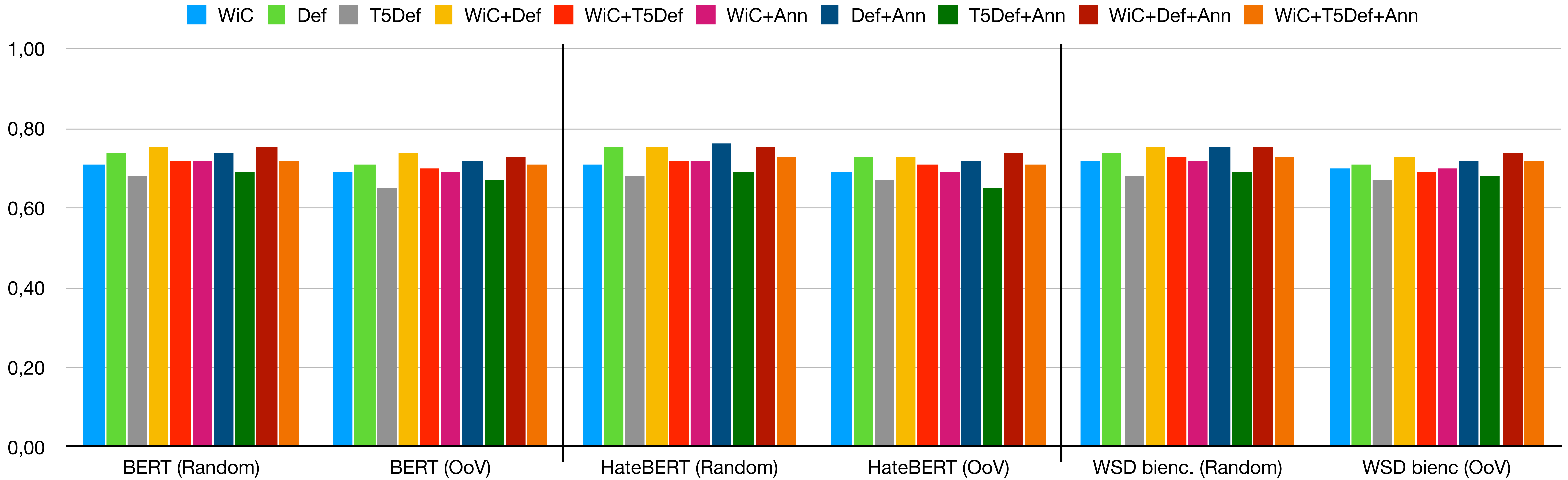
Evaluation

- Evaluating individual label prediction (i.e. 12442 instances)
- Ten-fold cross-validation with two variants of data split for each fold:
    1. **Random**: based on example sentences
    2. **Out-of-Vocabulary (OoV)**: based on terms
       → testing zero-shot capabilities

Results

Overall

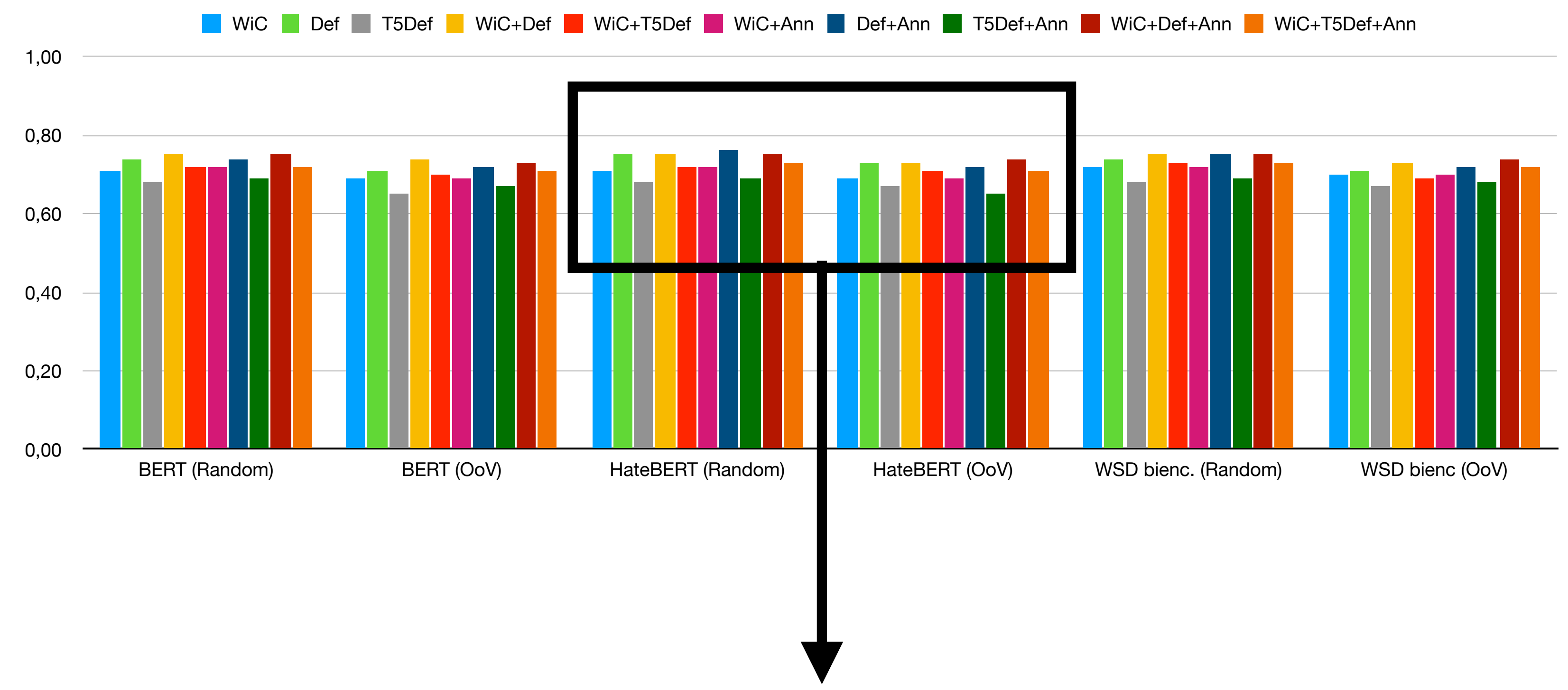
- Effectiveness of all methods
- Only slight drop for OoV-terms
- Negligible differences between encoders

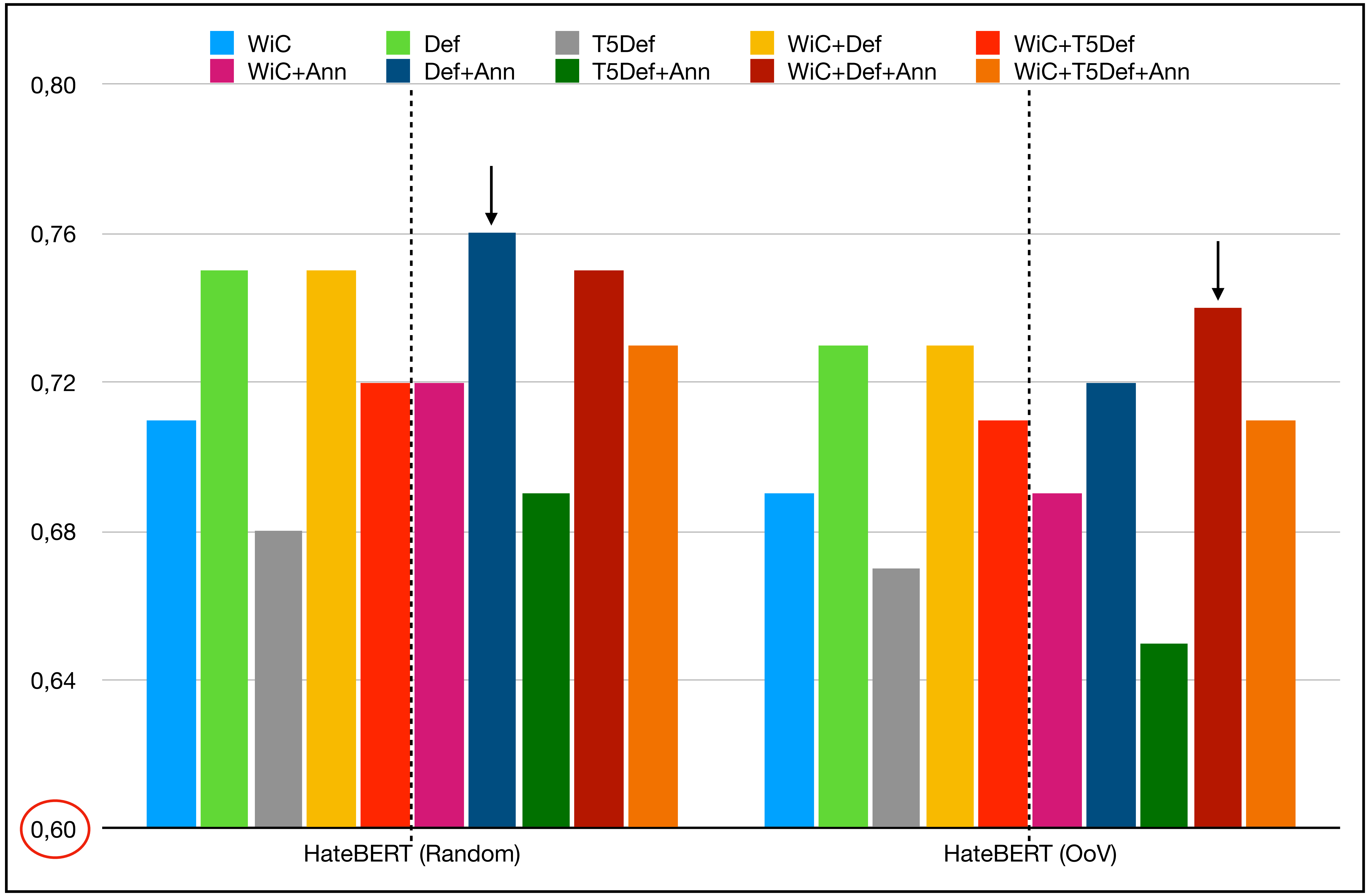


Results

Embeddings

- Def and WiC+Def > WiC
- T5Def performs worst
- +Ann: minimal improving effect
- Def+Ann best for Random
- WiC+Def+Ann best for OoV terms



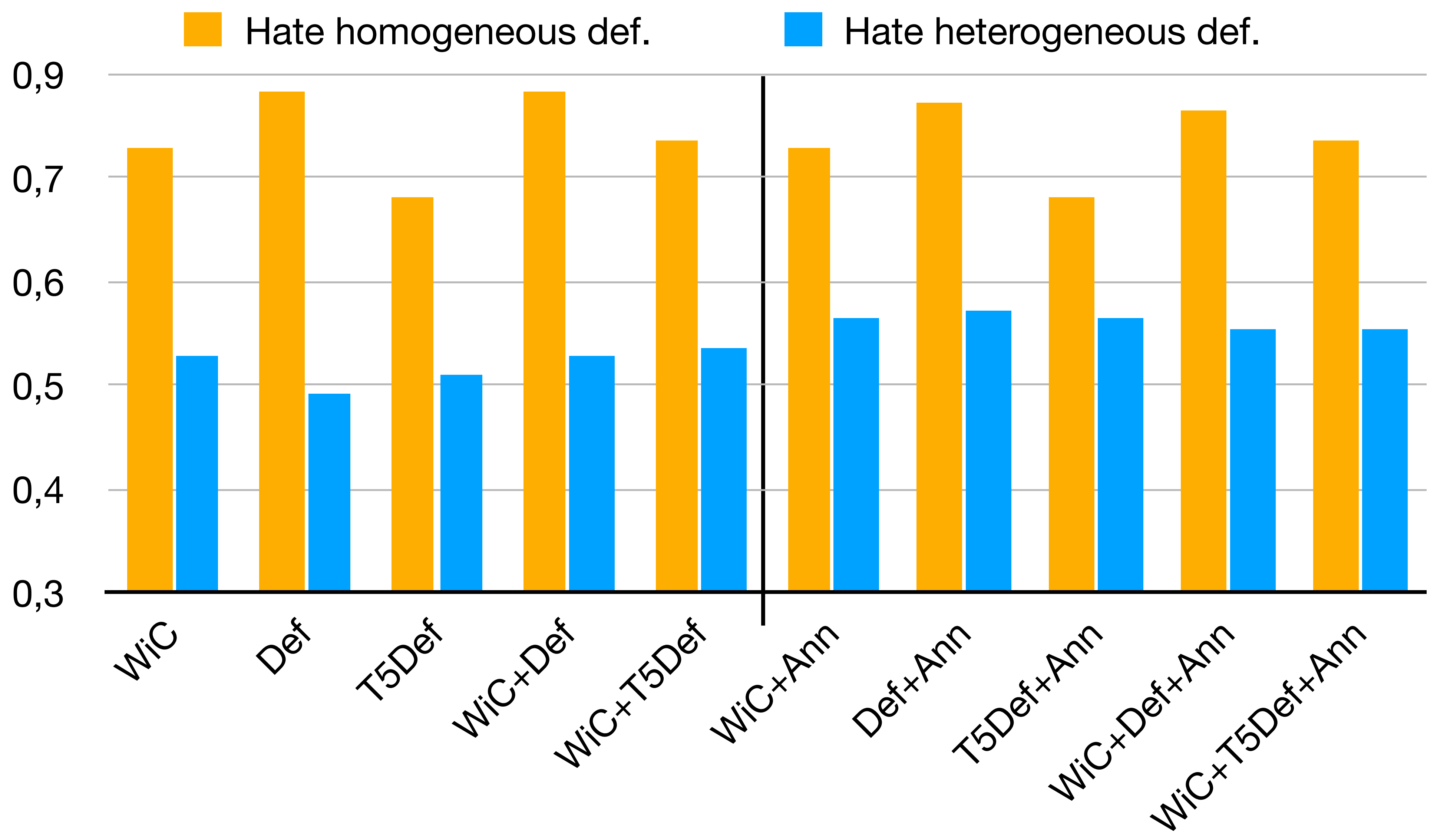


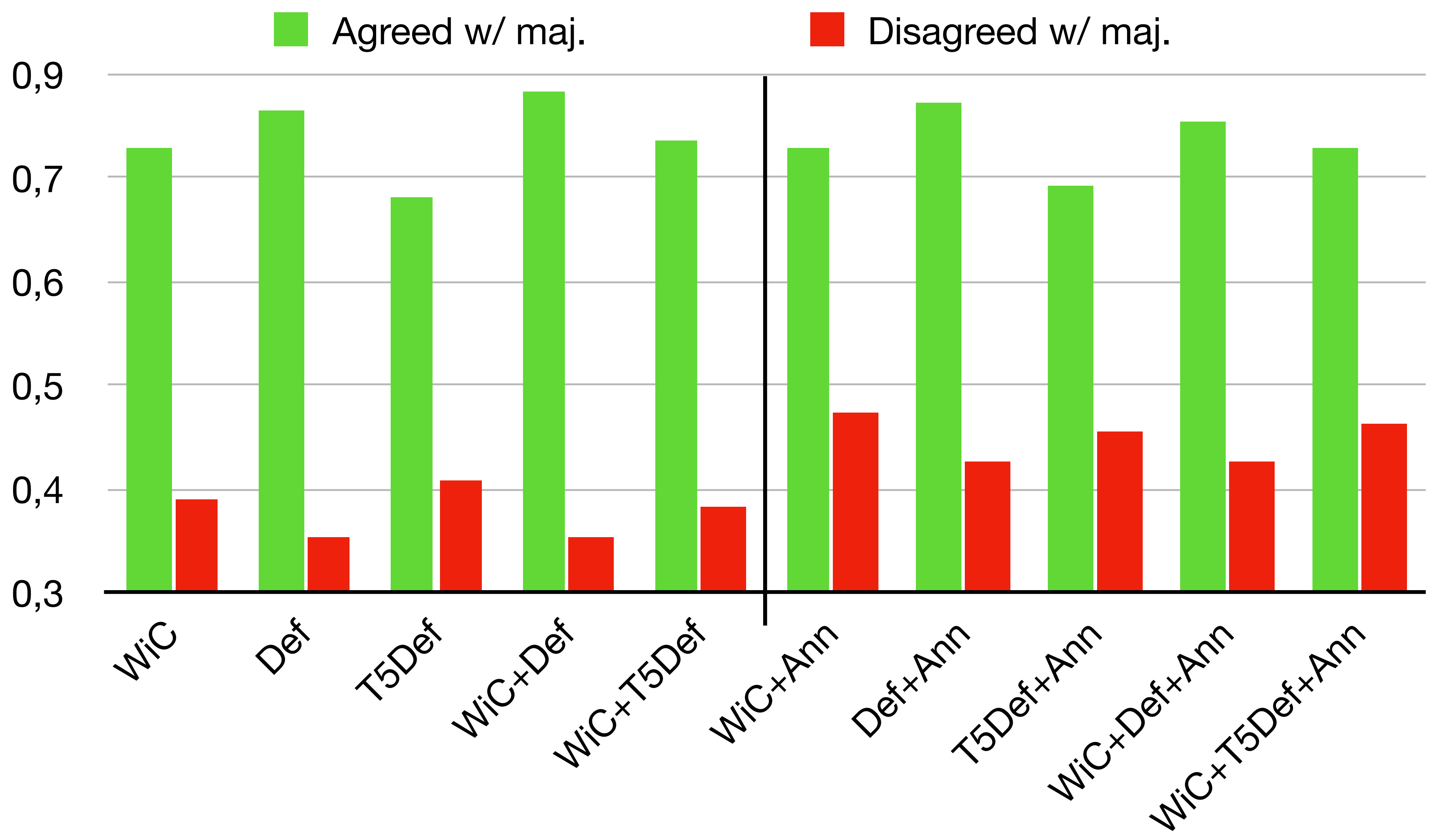
Results

in highly subjective scenarios

- Scenario 1: Hate-heterogeneous sense definition
- Scenario 2: Annotator disagrees with majority label
- In both, performance of all embeddings drops significantly!

(results for HateBERT with Random test split)



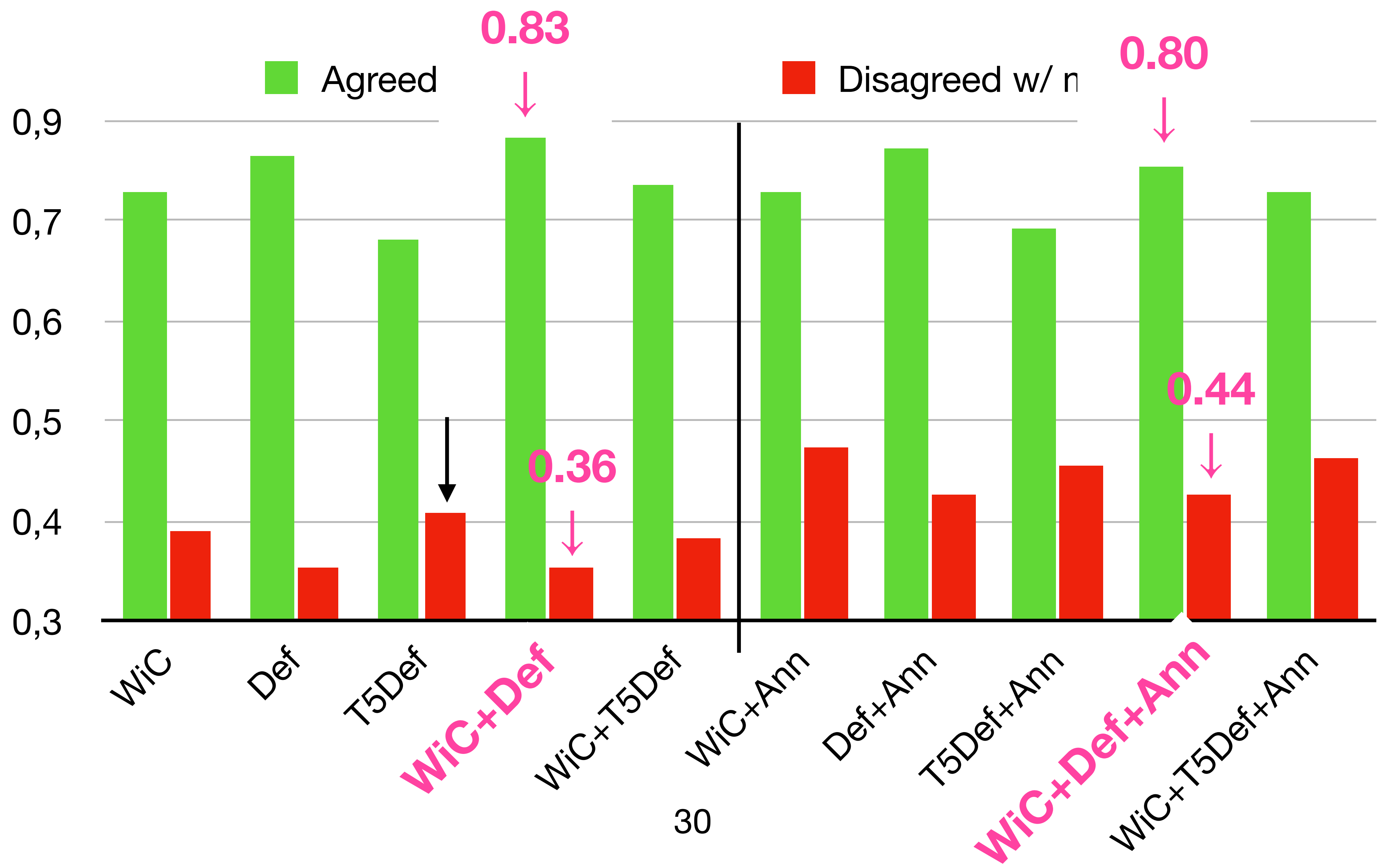


Results

in highly subjective scenarios

- Highest drop for Def embeddings (up to 47%), less so for T5-generated
  → aligning with more context-specific nature of T5Def-embeddings

- Incorporating annotator information mitigates drop up to 11%
  → thus, contributes to cases with high-subjectivity



Final remarks

Insights into hate speech detection through the lens of lexical semantics!

- To define or not define?
  → potential usefulness of generating context-specific definitions for subjective lexical semantic tasks.

- To individualize anyway?
  → yes, value of personalizing models to account for subjectivity in annotations.

Final remarks & next steps

Insights into hate speech detection through the lens of lexical semantics!

- To define or not define?
  → potential usefulness of generating context-specific definitions for subjective lexical semantic tasks.
- **Next steps:** more advanced and task-tailored definition generation methods?
- To individualize anyway?
  → yes, value of personalizing models to account for subjectivity in annotations.
- **Next steps:** exploring the effectivity of different annotator embeddings?

  → *going beyond annotator demographics?*

Next steps

My questions…

Utrecht University

Dealing with Meaning Variation in NLP

- Can we systematically identify dimensions to **profile** hateful word meanings in order to explain their variation?

  i) Lexical semantic dimensions: what semantic features (e.g. referential transparency), relations (e.g. metaphor) and literal domains (e.g. animals, food, diseases) can we observe?

  ii) Pragmatic dimensions: what contextual features can we observe (e.g. speaker intention and identity, time, place)?

- Can we **model** meaning variation of hateful words better, incorporating this structured information?

Next steps

Some more concrete (but preliminary) example thoughts…

- Can we systematically identify dimensions to **profile** hateful word meanings in order to explain their variation?

i) Lexical semantic dimensions: what semantic features (e.g. **referential transparency**), relations (e.g. metaphor) and literal domains (e.g. animals, food, diseases) can we observe?

  - **Referential transparency**: a *bastard* versus *cheesehead* issue?
  - E.g., do word meanings with more descriptive content carry a higher degree of derogatory autonomy?

Next steps

Some more concrete (but preliminary) example thoughts…

- Can we systematically identify dimensions to **profile** hateful word meanings in order to explain their variation?

  i) Lexical semantic dimensions: what semantic features (e.g. referential transparency), relations (e.g. metaphor) and **literal domains** (e.g. animals, food, diseases) can we observe?

     - **Literal domain**: a *pig* versus *potato* issue?
     - E.g., are metaphorical mappings (onto a target group) from animals more sensitive to reinforce a subjective hateful meaning than from food?

Next steps

My questions…

Utrecht University

Dealing with Meaning Variation in NLP

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Next steps

Your questions?

Utrecht University

Dealing with Meaning Variation in NLP

Thank you for listening!

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