What do Language Models know about word senses?

Zero-Shot WSD with Language Models and Domain Inventories

Oscar Sainz, Oier Lopez de Lacalle, Eneko Agirre and German Rigau

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Previous works on WSD using LMs

- SOTA is achieved by fine-tuning LMs on SemCor (Vial et al., GWC 2019).
- Zero-Shot methods are evaluated on lemmas unseen during training, but rely on WSD data to learn the task itself (Lacerra et al., AAAI 2020).
- Present unsupervised and knowledge-based methods do not rely on LMs.

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- What about removing supervised data from LMs?

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- What about removing supervised data from LMs?

	WiC Accuracy
Fine-tuned SOTA	**76.1**
Fine-tuned BERT-Large	69.6
GPT-3 Few-Shot	49.4

(Brown et al., 2020) Language Models are Few-Shot Learners

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- What about removing supervised data from LMs?

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Random baseline	50.0

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Recent Advances in DeepLearning for NLP

- 2013 Word Embeddings
- 2018 Transformers & Pretrained Language Models
- 2020 Zero- and Few-Shot prompting
- 2021 Instruction fine-tuning

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__Prompting__ is the practice of adding natural language text, often short phrases, to the input or output to encourage pre-trained models to perform specific tasks.

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Prompting strategies

EXAMPLE BASED

Translate English to French:

sea otter => loutre de mer

peppermint => menthe poivrée

plush girafe => girafe peluche

cheese => ……………………………………

TEMPLATE BASED

Best pizza ever! It was ………………

great | bad

………… News: OpenAI presents a new model!

World | Sports | Tech

It's snowing. ……………, it's cold.

Yes | Maybe | No

PROXY TASK BASED

premise: I am feeling grouchy.
hypotheses:
It expresses love.
It expresses anger.
It expresses sadness.

C: China has purchased two nuclear submarines from Russia last month.

Q: Who bought something?
A: China
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Proxy Task Based

(Emotion classification as Textual Entailment)

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(Argument extraction as Question Answering)

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Textual Entailment as a proxy

PREMISE

Two men on bicycles competing in a race.

(Bowman et al, 2015) A large annotated corpus for learning natural language inference.

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Men are riding bicycles on the street.

CONTRADICTION HYPOTHESIS

Few people are catching fish.

Entailment: the hipothesis is entailed by the premise.

Neutral: the hipothesis can not be entailed by the premise.

Contradiction: the hipothesis contradicts the premise.

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Domain Labelling with Textual Entailment

hospital: a health facility where patients receive threatment.

BIOLOGY	BUSINESS	CULTURE	ECONOMY	LEGAL	MEDICINE	POLITICS

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HYPOTHESIS TEMPLATE

The domain of the sentence is about {label}.

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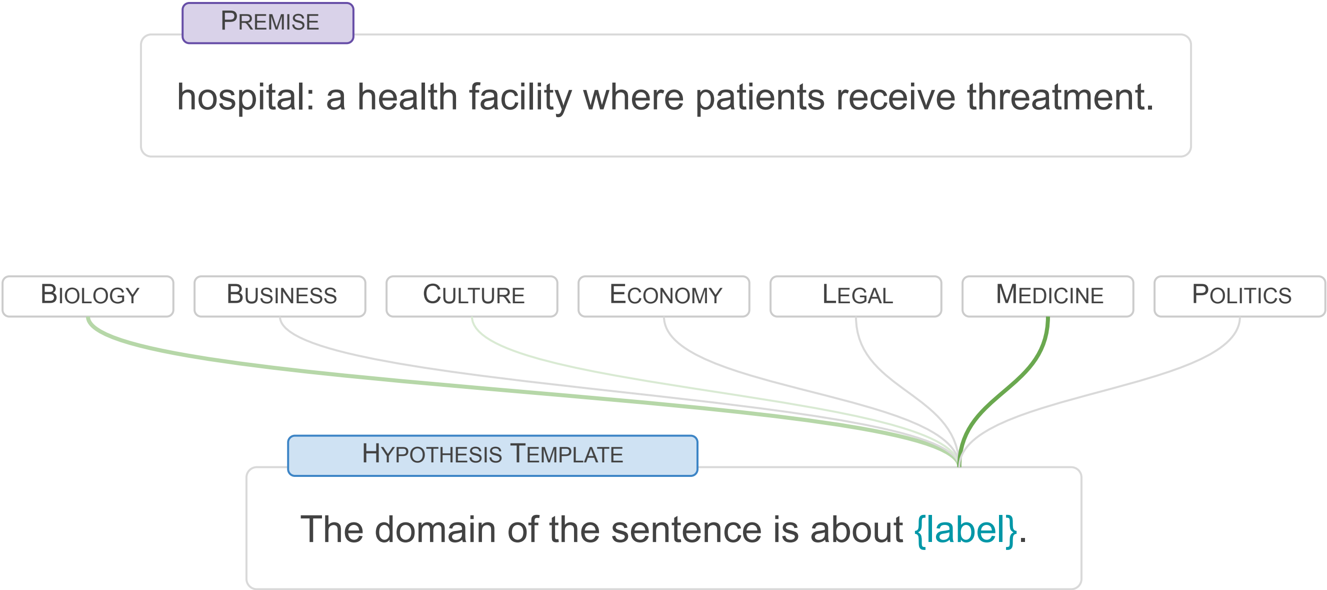

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The task of Word Sense Disambiguation

The medicine can only be obtained with a prescription.

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6788565-n

6788565-n: directions prescribed beforehand; the action of prescribing authoritative rules or directions.

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3999280-n: a drug that is available only with written instructions from a doctor or dentist to a pharmacy.

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6366002-n: written instructions for an optician on the lenses for a given person.

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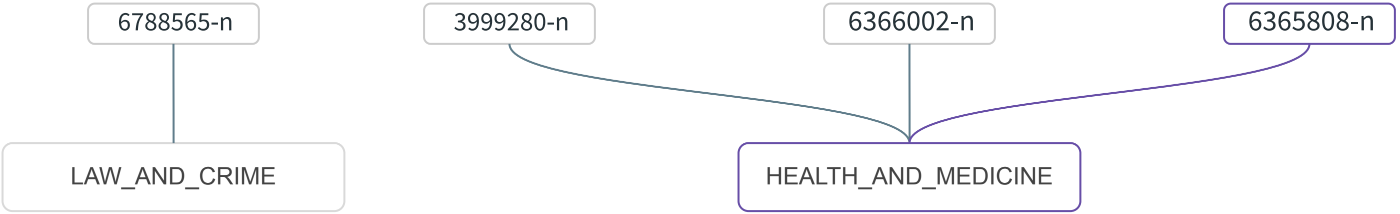

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Domain Inventories

BabelDomains

- Unified domain information for Wikipedia, WordNet and BabelNet.
- Inherits from Wikipedia domains.
- 34 **coarse** domain labels.
- Semi-automatically annotated.

Coarse Sense Inventory

- Created to reduce the granularity of WordNet synsets.
- High agreement among annotators.
- 45 domain labels.
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WordNet Domains

- Hierarchical domain definition.
- Domain information for WordNet synsets.
- 160 **fine-grained** domain labels.
- Due to the high granularity and hierarchical nature we kept only 60 labels.

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Target word   Ambiguous words

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Correct answer

Target word

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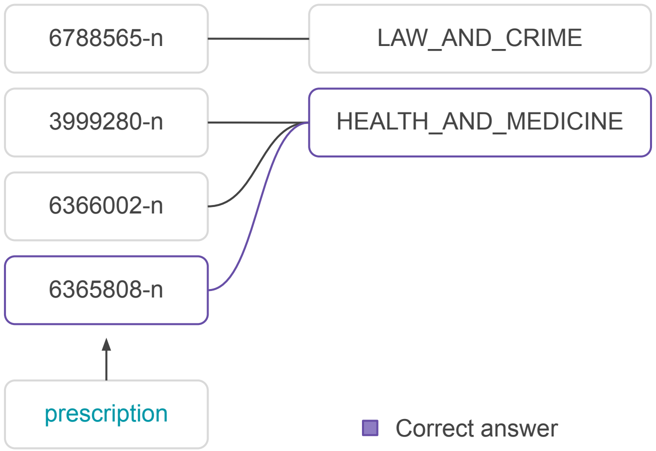
Word Sense Disambiguation with Textual Entailment

Label simplification using Domain Inventories:



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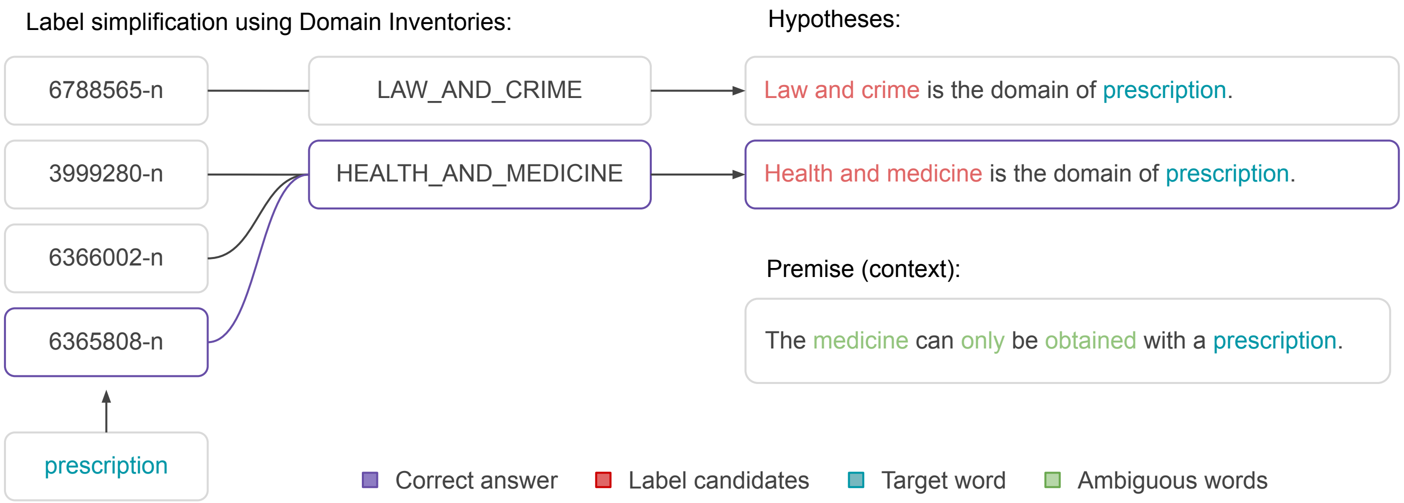

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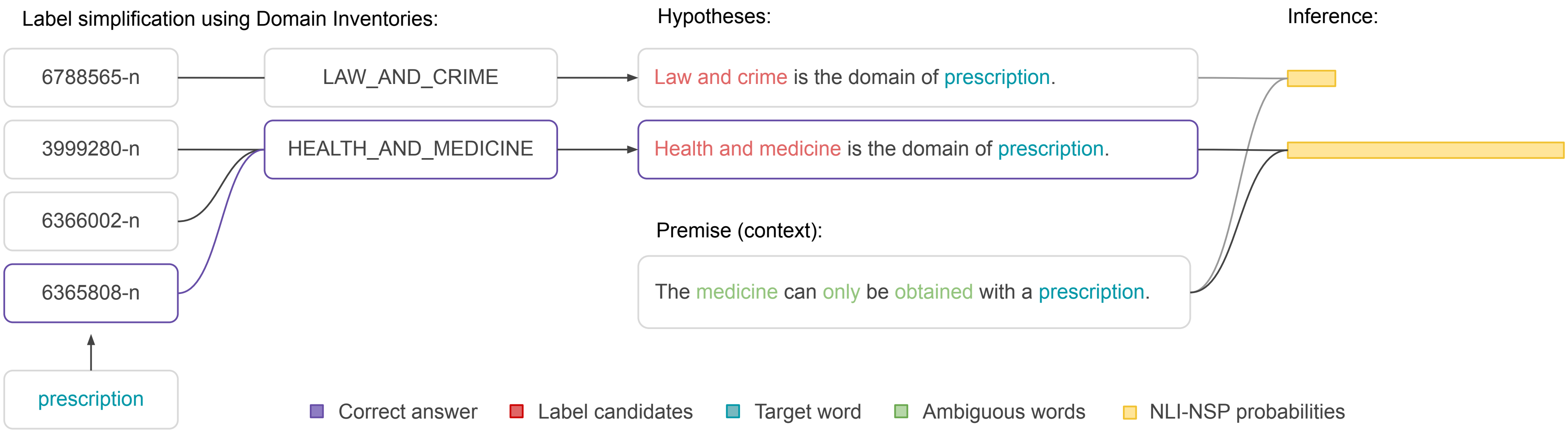

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  - RoBERTa: a pretrained Masked Language Model (similar to BERT) but for larger number of steps.

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  - NSP: Next Sentence Prediction is the task of predicting whether a sentence follows another or not.

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- 2 different fine-tuning tasks:
  - NSP: Next Sentence Prediction is the task of predicting whether a sentence follows another or not.
  - Textual Entailment: the task of predicting the entailment relation between premises and hypotheses, also known as NLI.

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- 2 different training objectives:
    - Next Sentence Prediction (NSP) and Textual Entailment (NLI)
- Different pre-training data regimes for Textual Entailment:

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  - Using several Textual Entailment datasets: SNLI, MNLI, Fever-NLI and aNLI.

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  - NLI: just MNLI
  - NLI*: MNLI, SNLI, Fever-NLI and ANLI

Are language models able to discriminate domains in sense glosses?

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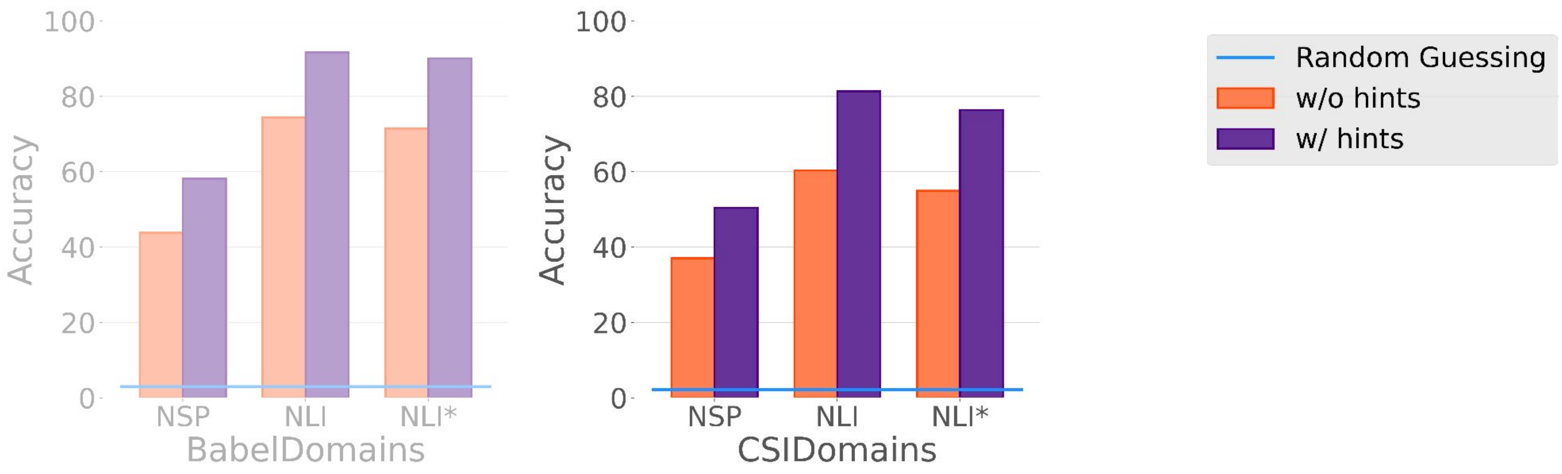

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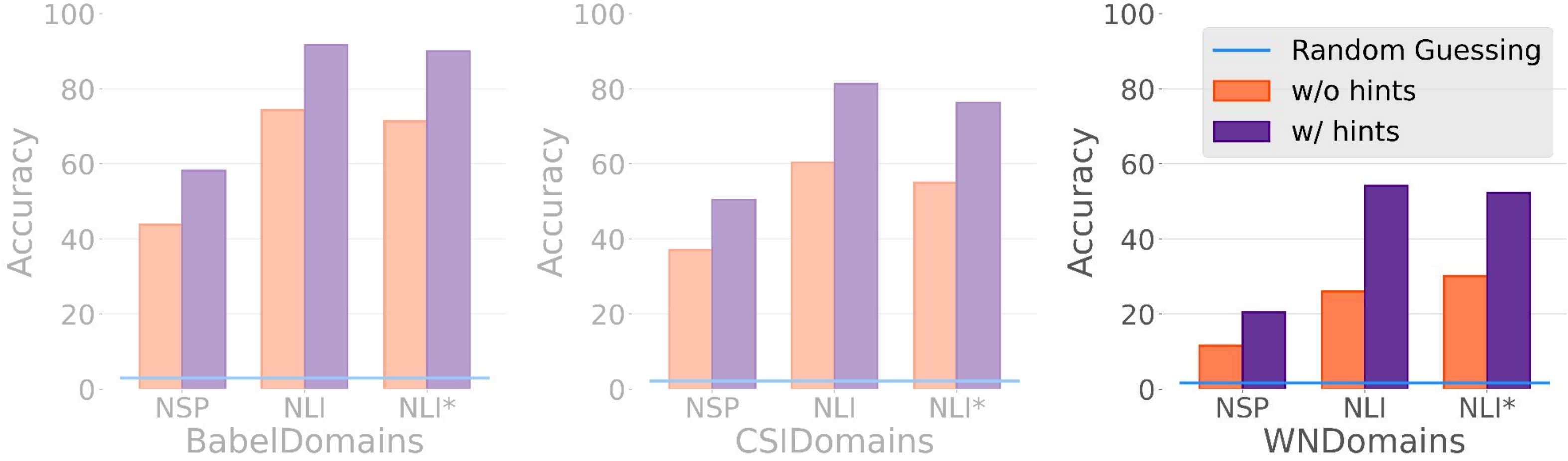

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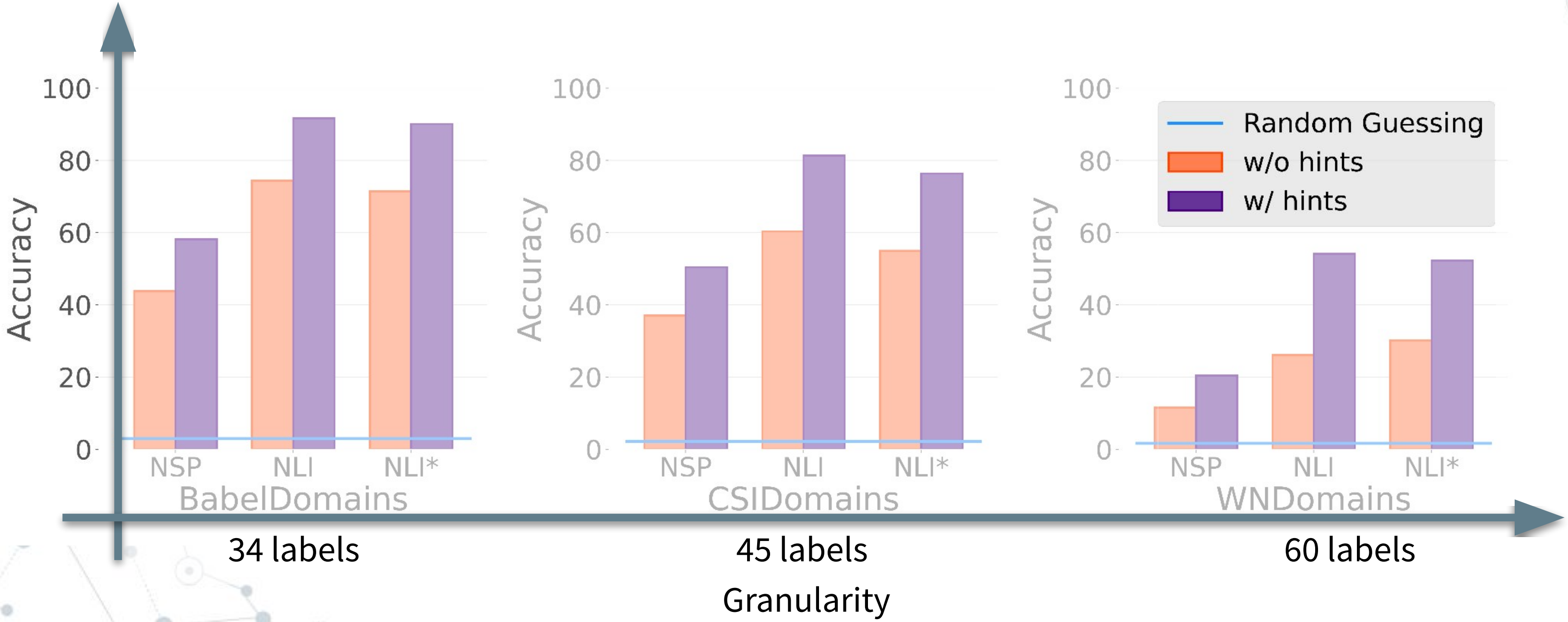

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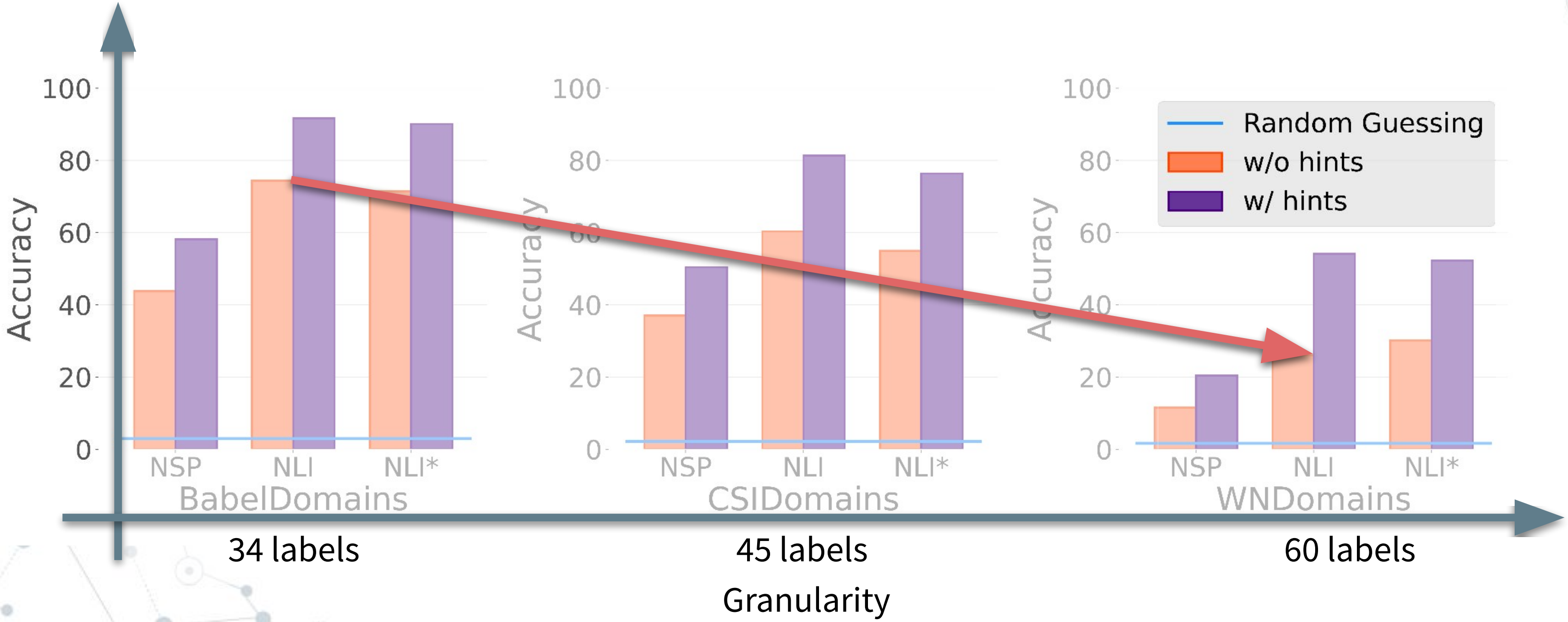

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Supervised — Random Guessing — sent prompt — word prompt

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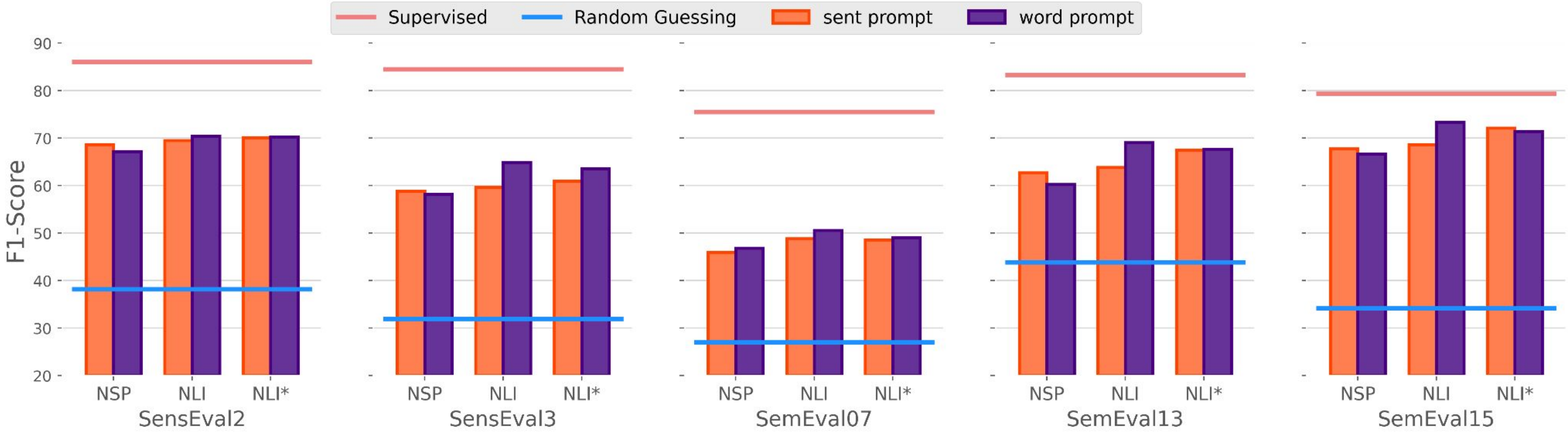

Do Language Models perform differently depending on the word category?

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NSP	60.3	84.9	50.4	86.6	62.6
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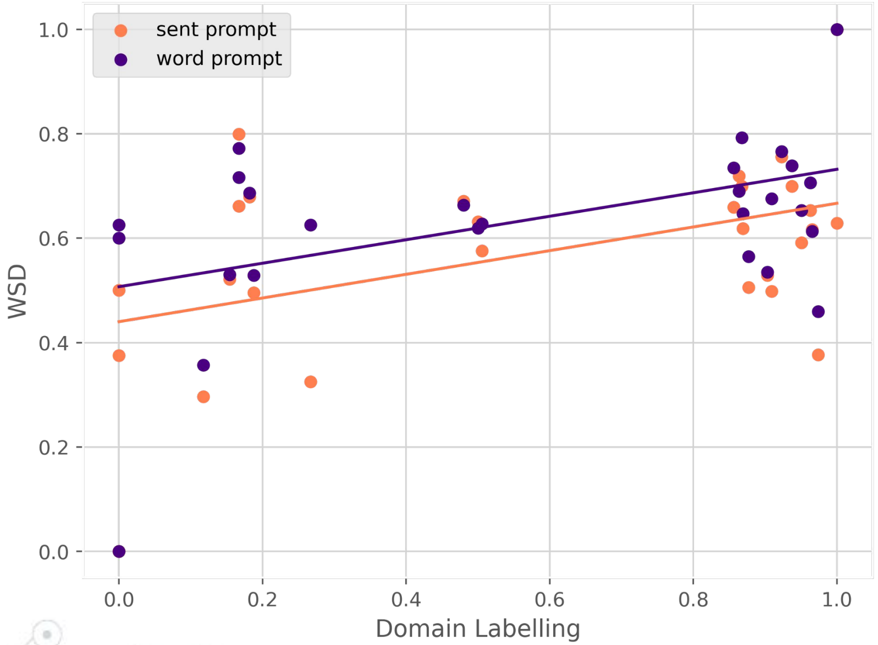
To what extent does the performance on Domain Labelling affects WSD?



	Dom Lab.	WSD_{sent}	WSD_{word}
Dom Lab.	1.00	0.32	0.41
WSD_{sent}	0.32	1.00	0.81
WSD_{word}	0.41	0.81	1.00

Table 4: Spearman's correlation of F1-Scores between tasks using shared labels. The scores correspond to the NLI model.

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