Advanced Machine Learning Project

Naive Zero-shot NER and Discussion of LUKE

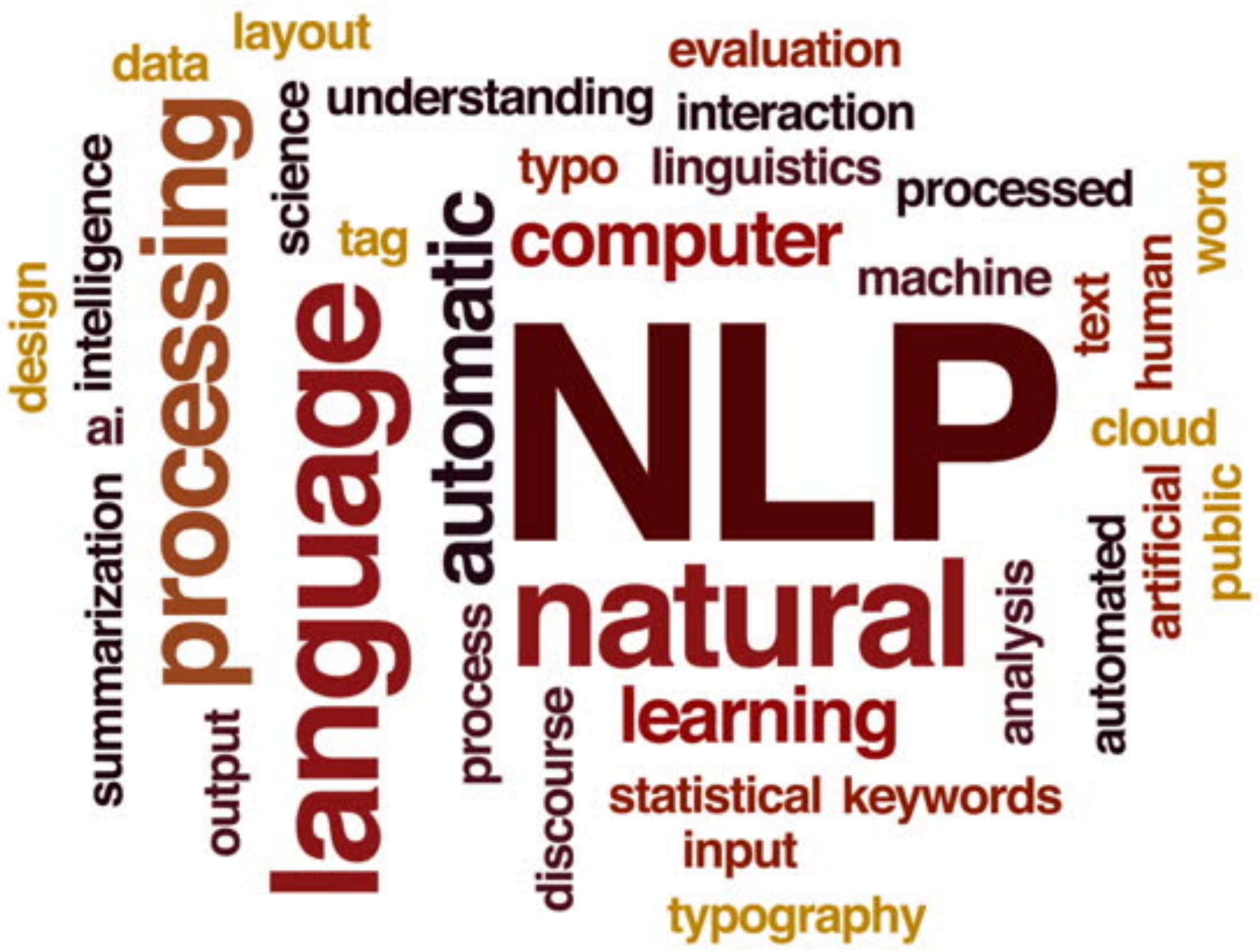
Ayan Gangopadhyay 24th February 2021

Introduction

What is NER?

Why NER is required for NLP.

- Information Retrieval.
- Question Answering systems.
- Modern Conversational Agents for slot filling.
- Feature Extraction.
- ASR systems.



Difficulties in NER tasks.

Why is NER hard?

- Free form text or unstructured text.
- Context - based entities.
- Nested Entities.
- Abbreviations and Acronyms.
- Homonyms.

CoNLL-2003.

Dataset and Task.

- One of the most popular dataset for NER benchmarking.
- Language Independence.
- Only English portion freely available.
- Drawbacks of IOB structure.

Word	POS	Syntactic Chunk	NE Tag
U.N.	NNP	I-NP	I-ORG
official	NN	I-NP	O
Ekeus	NNP	I-NP	I-PER
heads	VBZ	I-VP	O
for	IN	I-PP	O
Baghdad	NNP	I-NP	I-LOC
.	.	.	O

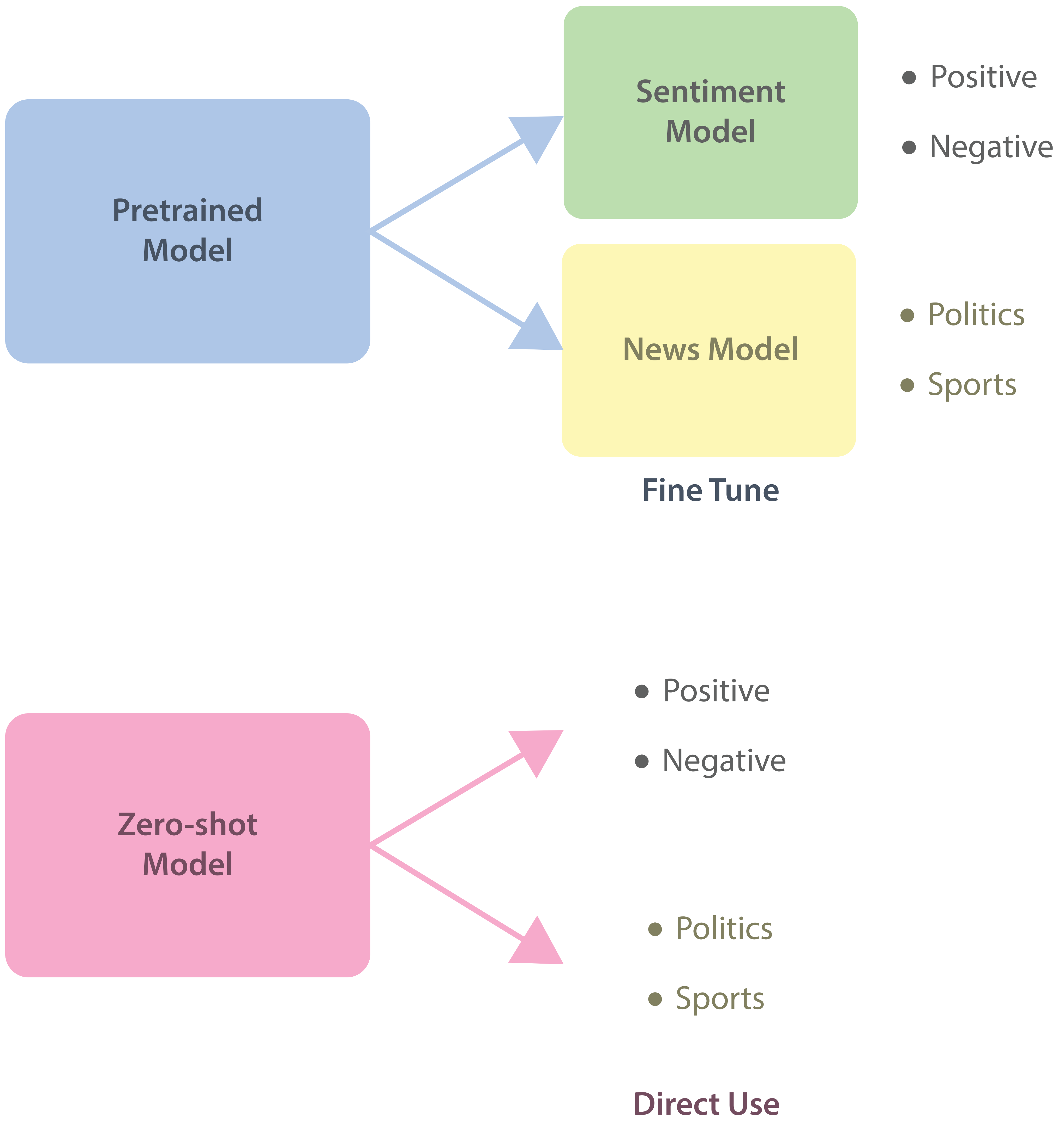
Prefix	Meaning
I	Start of a new entity.
B	Continuation of entity from previous line.

Naive Zero-shot approach

Zero-shot learning.

Setting and Use Cases.

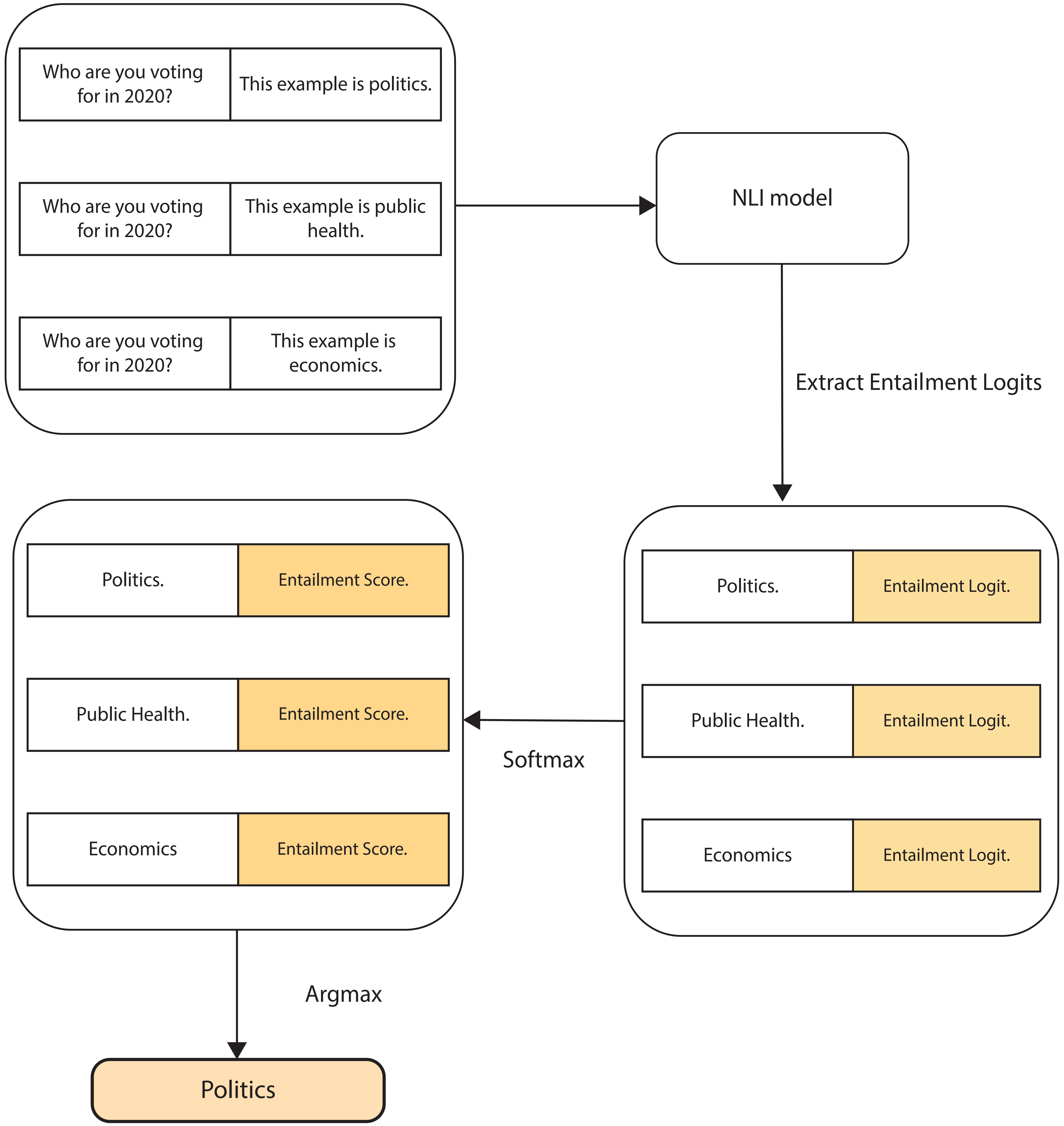
- **Pros :**
  - No fine tuning/training for downstream task.
  - Extremely useful in practical scenarios if done well.
- **Cons :**
  - Higher inference times in general.
  - Task is harder, and hence performance suffers.
  - Difficult to build effective zero-shot learners as model complexity is higher.



Zero-shot Classification.

Methodology.

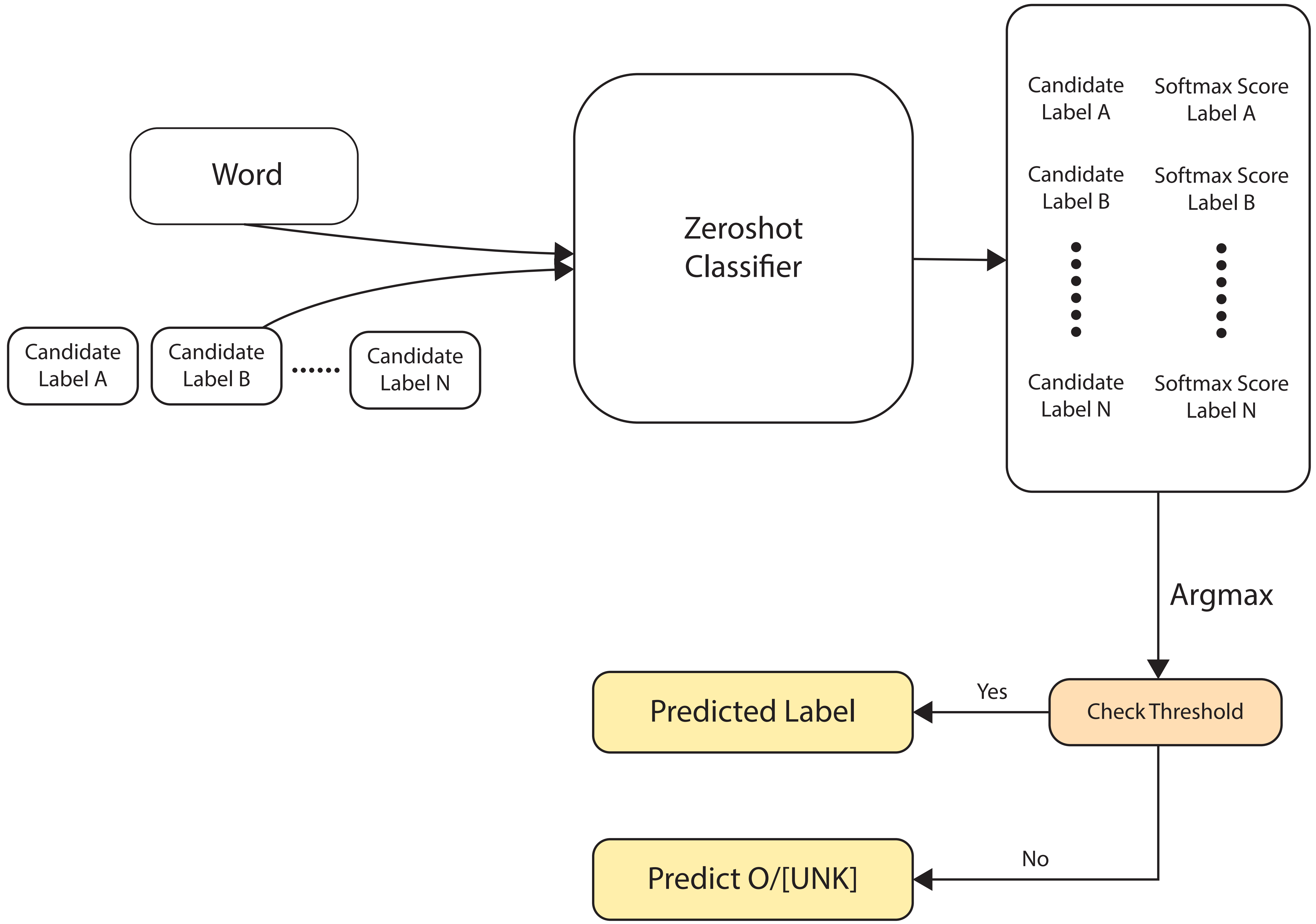
- Classification as Natural Language Inference.
- Proposed by Yin et. al. in 2019.
- Implemented using the BART model in Huggingface.



Naive Zero-shot NER.

Methodology.

- How can the zero-shot classification pipeline be used naively for NER?
- **Pros :**
  - Easy to implement.
  - Beats baseline for original task even without any kind of fine tuning.
- **Cons :**
  - Does not make use of contextual information.
  - Current methods beats this by a wide margin.



Naive Zero-shot NER.

Results and Discussions.

- Threshold of 0.7 seems good enough and passes the baseline.
  Increasing threshold causes call performance measures to drop.
- Using meaningful label names is important.
- Much better performance from modern Deep Learning NER approaches.
- Still this method shows promise and further work is necessary.
- Use the CoNLL-2003 processor to exhaustively enumerate all entity spans and try classification.

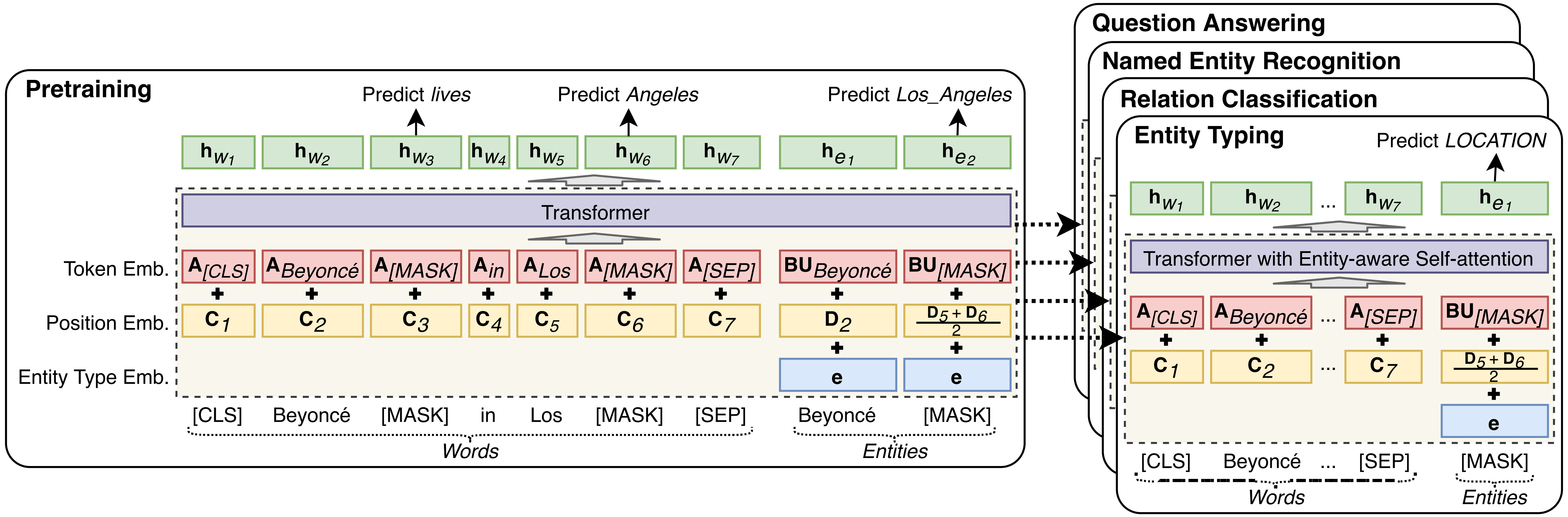
Label Type	Threshold	Precision	Recall	F1
Meaningful	0.5	57.56%	65%	59.72
	0.6	72.99%	67.52%	69.49
	0.7	75.83%	68.12%	70.27
Meaningless	0.5	1.72%	37.44%	3.21
	0.6	0.42%	38.01%	0.82
	0.7	0.07%	43.35%	0.15

LUKE

LUKE

What is new and different?

- Drawback of KB methods.
- Drawback of of old CWR methods.
- Differentiating entities and words.



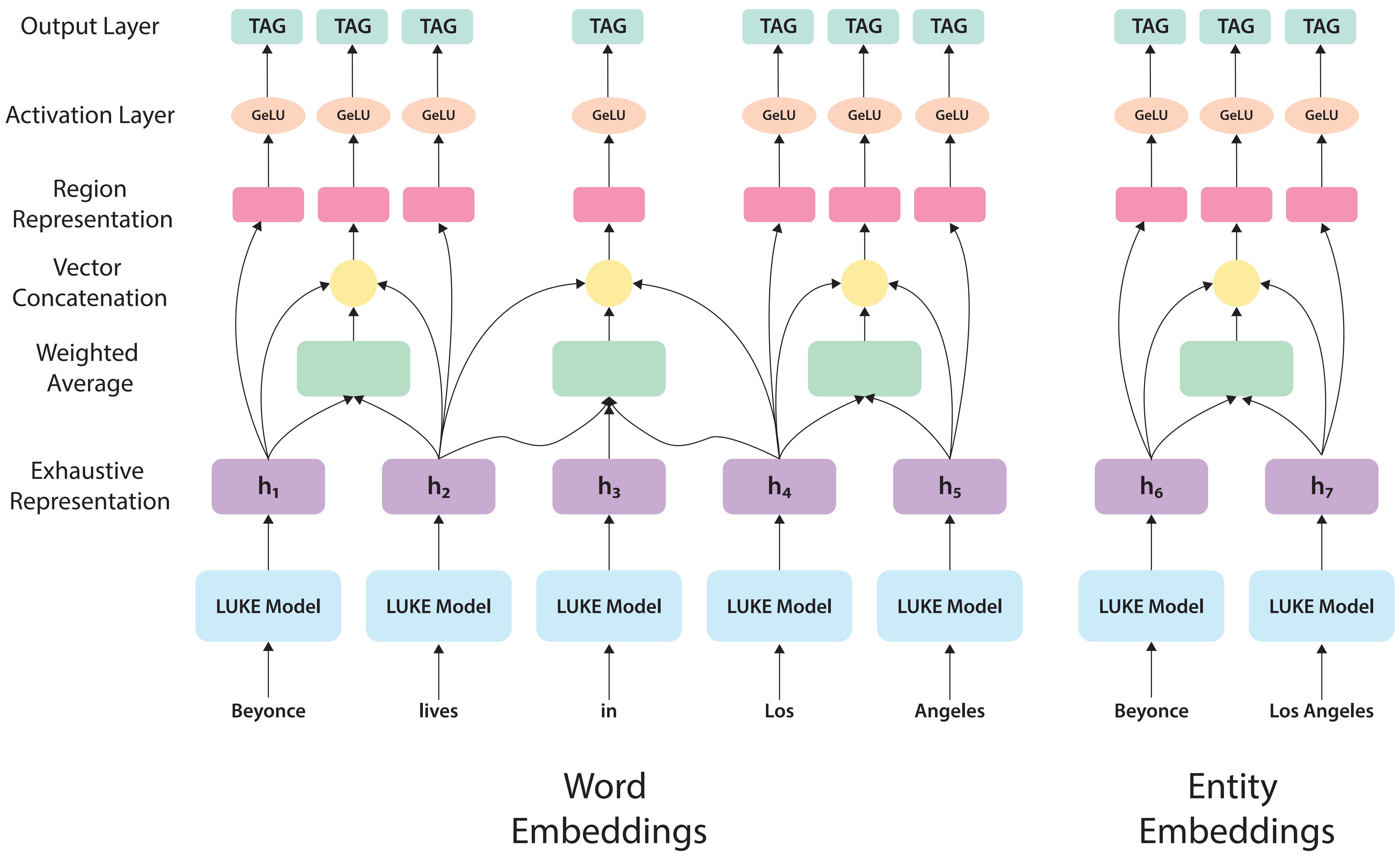
*Picture taken from the LUKE paper by Yamada *et. al.*

Exhaustive Enumeration for NER.

How we do NER using the entity aware LUKE model.

- The methodology for doing NER using the LUKE model was taken from the very effective entity representation scheme due to <u>Sohrab and Miwa.</u>

- Is able to detect both nested and flat entities.



*Picture adapted for LUKE from Sohrab and Miwa's paper.

LUKE.

Results.

- Achieves SOTA on 5 well known datasets.
    - Open Entity
    - TACRED
    - CoNLL-2003
    - ReCoRD
    - SQuAD
- Has an F1 score of 94.3 on the CoNLL-2003 dataset.
- Results reproduced.
- Fast and Effective.
- PyTorch implementation available on GitHub.

Conclusion

Conclusion and Future work

What was observed.

- Naive zero-shot NER promising but needs more work.
- Can try out the exhaustive enumeration scheme with this approach.
- Not much point in doing plain NER approaches because current methods are effective and tractable.
- Currently going through LUKE source code to understand how to incorporate exhaustive enumeration with zero-shot NER.

Acknowledgement and References

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