WikiNER:

Brute-force Named Entity Recognition leveraging *Wikipedia* dataset

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What is **Named Entity Recognition**?

Text

Iowa State University of Science and

Technology is a public land-grant

research university in Ames, Iowa.

Tags

- [Organization] Iowa State University of Science and Technology
- [Location] Ames
- [Location] Iowa

What is **Named Entity Recognition**?

Text

[Iowa State University of Science and
B I I I I I
Technology]ORG is a public land-grant
I
research university in [Ames]LOC,
B
[Iowa]LOC.
B

Tagging

Tags

- [Organization] Iowa State University of Science and Technology
- [Location] Ames
- [Location] Iowa

What is **Named Entity Recognition**?

Text

[Iowa State University of Science and

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Technology]ORG is a public land-grant

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research university in [Ames]LOC,

B

[Iowa]LOC.

B

Tagging

Tags

- [Organization] Entity 1 on *Wikipedia*
- [Location] Entity 2 on *Wikipedia*
- [Location] Entity 2 on *Wikipedia*
- ……

WikiNER uses *Wikipedia* entities as Named Entities tags!

Why WikiNER?

The entities in *Wikipedia* are a good source of tags to recognize WHO, WHERE, and WHAT in a sentence

- **Massive** in the number of entities of each type (i.e., organization, locations, persons)
- Being **evolving** and expanding
- Applicable to **different domains**

Use the **top ranked *Wikipedia* Named Entities** to label a sentence with a **brute-force approach**

How did we build **WikiNER?**

1. Retrieve ***Wikipedia* top ranked NEs** from *Wikidata* API

2. Build a **brute-force model** to perform NER tagging

3. **Evaluate** the model using a tagged *corpus* as a benchmark

Retrieve ***Wikipedia* top ranked NEs** from ***Wikidata* API**

1. download ***.csv* file** from *Wikidata QRank project* with **ordered** *Wikipedia* entities

Entity	QRank
Q178995	219893853
Q635	113674399
Q866	93345399
…	…

2. call ***Wikidata* API** for each entity to retrieve its **English label**

*https://www.wikidata.org/w/api.php?action=wbgetentities&ids=**Q178995**&languages=**en**&format=json&props=**labels***

3. create an output ***.csv* file** with the **top k Named Entities labels**

Entity	QRank	Label
Q178995	219893853	**HTTP cookie**
Q635	113674399	**Cleopatra**
Q866	93345399	**YouTube**
…	…	**…**

Retrieve *Wikipedia* **top ranked NEs** - with **aliases**

```
def top_N_NEs(
    input_csv_ranking_file_path: str,
    output_csv_file_path: str,
    top_N=1000,
    aliases=False
):
```

The function we implemented to extract the labels

- It is also possible to retrieve all the **aliases** of a Named Entity with the same API, **increasing** the **performances**!

*https://www.wikidata.org/w/api.php?action=wbgetentities&ids=Q178995&languages=en&format=json&props=labels|**aliases***

Entity	QRank	Label
Q178995	219893853	**HTTP cookie**
Q178995	219893853	**cookie**
Q178995	219893853	**web cookie**
Q178995	219893853	**browser cookie**
Q178995	219893853	**internet cookie**
Q178995	219893853	**cookies**
Q635	113674399	**Cleopatra**
Q635	113674399	**Cleopatra VII Philopator**
Q635	113674399	**Cleopatra VII**
Q866	93345399	**YouTube**
Q866	93345399	**YT**
…	…	**…**

Build a **brute-force model** to perform **NER tagging**

```
def brutal_force_NER(
    sentence_tokens: list[str],
    NE_list: list[str],
    tokenizer,
    scheme="BIO"
):
```

The function we implemented to tag a sentence using the Wikipedia NEs with brute-force approach

1. Find all the **not-overlapping *Matches*** * in the sentence using all the NEs (brute-force)

2. Represent this matches according to the specified **tagging scheme** (i.e., *BIO*, *BILOU*)

*A *Match* is an **occurrence** of a Named Entity in the sentence, represented as a tuple of **indexes** *(a,b)*: *a* is the **start** index, *b* is the (exclusive) **ending** index

Example of **brute-force tagging**

sentence_tokens = [‘I’, ‘went', ‘to’, ‘school’, ‘at’, ‘Iowa’, ‘State’, ‘University’, ‘in’, ‘Fall’, ‘2022’]

NE_list = ['Microsoft', 'Iowa State', 'Fall 2022', 'Deep Learning', 'Iowa State University', '2022', 'school']

(3,4), (5,8), (9,11)

Matches

I	went	to	school	at	Iowa	State	University	in	Fall	2022
O	O	O	B	O	B	I	I	O	B	I
O	O	O	U	O	B	I	L	O	B	I

BIO and BILOU representations

Challenge #1: **Overlapping NEs**

- We solved the problem of **overlapping** Named Entities prioritizing always the **longest Named Entity**

sentence_tokens = [‘I’, ‘went', ‘to’, ‘school’, ‘at’, ‘Iowa’, ‘State’, ‘University’, ‘in’, ‘Fall’, ‘2022’]
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overlapping *Matches*		**not-overlapping** *Matches*		BIO representation
(3,4), (5,7), (5,8) (9,11), (10,11)	→	(3,4), (5,8), (9,11)	→	I went to school at Iowa State University in Fall 2022 O O O O O B I I O B I

Supported **tagging schemes**

- Our ***WikiNER*** model supports 2 different tagging schemes:

BIO:

B – Beginning
I – Inside
O – Outside

BILOU:

B – Beginning
I – Inside
L – Last
O – Outside
U – Unit

Challenge #2: **Entity type (LOC, PER, ORG, MISC, etc.)**

- NER problem also expects to find the **type** of each Named Entity (LOCation, PERson, ORGanization, etc.)

- But this is **impossible** using just a the *Wikidata* API, since it does **not** provide the type of an entity

- **Solution**: using another model (like **BERT**) to also find the type of NEs (*to be continued*)

Evaluate the model using a tagged *corpus* as **benchmark**

- Use **CoNLL2003 dataset** as benchmark
  - It contains a *corpus* of sentences whose Named Entities have been tagged in their respective **types** using the **BIO scheme**
- Use the ***WikiNER*** model to tag its sentences
- Evaluate the **performances** comparing the **predicted tags** with the **real tags** in the *corpus* (ignoring the NE type)

token	POS tag	chunk tag	NER tag
EU	NNP	B-NP	**B-ORG**
rejects	VBZ	B-VP	**O**
German	JJ	B-NP	**B-MISC**
call	NN	I-NP	**O**
to	TO	B-VP	**O**
boycott	VB	I-VP	**O**
British	JJ	B-NP	**B-MISC**
lamb	NN	I-NP	**O**
.	.	O	**O**
Peter	NNP	B-NP	**B-PER**
…	…	…	**…**

Evaluation metrics

- **Precision**

$$\frac{True\ Positives}{True\ Positives + False\ Positives}$$

Among all the predicted NEs, how many of them were **true NEs**

- **Recall**

$$\frac{True\ Positives}{True\ Positives + False\ Negatives}$$

Among all the real NEs, how many of them we were able to **predict**

- **F1-score**

$$2 * \frac{Precision\ * Recall}{Precision + Recall}$$

Harmonic mean between *precision* and *recall*

WikiNER performances on *CoNLL2003* dataset

- We used ***seqeval*** library to compute *precision*, *recall* and *F1-score*
- **Compare** the results using **different numbers** of Wikipedia top NEs

#NEs	Precision	Recall	F1-score
100	0.94	0.05	0.09
1,000	0.89	0.14	0.24
10,000	0.26	0.22	0.24

*with **no** aliases*

#NEs	Precision	Recall	F1-score
100	0.82	0.06	0.11
1,000	0.44	0.17	**0.25**
10,000	0.15	**0.29**	0.20

***with** aliases*

Timing problems

- *WikiNER* is a very **time-consuming** approach!
  - **extracting** *Wikipedia* NEs
  - **executing** the brute-force model

#NEs	time
100	~20s
1,000	~3min
10,000	~30min

*estimated times to **extract** NEs*

#NEs	no aliases	with aliases
100	~5min	~20min
1,000	~30min	~2h
10,000	~3h	~12h

*estimated times to execute **WikiNER** on **CoNLL2003***

Conclusions

- *WikiNER* brutal force model is **ineffective** to perform a NER task
  - **Low performances** (max recall: 29% - 10,000 NEs and aliases)
  - **Time-consuming** (it takes hours)
  - **No NEs types**

- Two issues in *Wikipedia* entities:
  - The presence of **more NEs** naturally **decreases precision** (although **increases recall**)
  - The *Wikipedia* entities are **not universal** enough to capture benchmark entities

- Better to resort to more sophisticated models such as **BERT** (next step)

Questions?

Thank You!