Word Embeddings, Cosine Similarity and Deep Learning for Identification of Professions & Occupations in Health-related SocialMedia

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Introduction

During situation of risk, detecting vulnerable occupations, be it due to their risk of direct exposure to the threat or due to mental health issues associated with work-related aspects, is critical to prepare preventive measures.

Figure 1: Tweet example.

ProfNER-ST focuses on the recognition of professions and occupations from Twitter using Spanish data. Our participation is based on a combination of word-level embeddings as well as cosine similarity computed over a subset of entities that serve as input for an encoder-decoder architecture with attention mechanism.

Dataset Description

10. 000 health-related tweets in spanish [1] annotated with proffessions and employment statuses by linguistic experts.

	Training	Validation	Training and Development
Words	32357	14836	39389
Characters	590	403	667

Table 1: Vocabulary statistics.

Next table describes the statistics of the dataset relevant for the proposed system.

	Training	Validation	Test
Tweets	6000	2000	2000

Table 2: Tweets compilation.

Method and System Description

Preprocessing

- Clear corpus
- Tokenization spaCy
- Annotations to BIOES schema

Tokenized sentece: Mary was born in Mississippi, and is currently living with daughter in Grand Island.

BIO representation: Mary/B-PATIENT was/O born/O in/O Mississipi/B-STATE ,/O and/O is/O currently/O living/O with/O daughter/O in/O Grand/B-CITY Island/I-CITY ./O

BIOES representation: Mary/S-PATIENT was/O born/O in/O Mississipi/S-STATE ,/O and/O is/O currently/O living/O with/O daughter/O in/O Grand/B-CITY Island/E-CITY ./O

Features

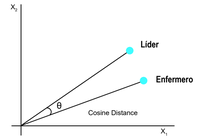
Words: Two different 300 dimensional representations based on pre-trained word embeddings [2] [3] and contextual embeddings generated with a fine-tuned BETO [4] .

Part-of-speech: An embedding representation of this feature is learned during training using the PoS-Tagging model provided by the Spacy.

Characters: Character-level embeddings of the words learned during training.

Syllables: Syllables-level embeddings of the words learned during training.

Cosine Similarity: Cosine similarity between BETO representation of the word to be analyzed and BETO embeddings of the entities found in the training and validation set



$$similarity(A,B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \times \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Architecture

Encoder-Decoder arquitecture with attention mechanism.

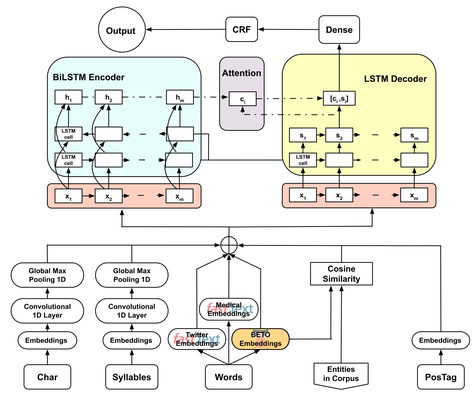


Figure 2: System Architecture.

Results

- Evaluation Metrics: Precision, Recall, F1-score.
- Training set was used for training the model while validation set was exploited to hyperparameter fine tuning.

Parameters	Tuned range	Opt
Train Batch size	[8, 32, 64]	32
Epoch number	[2, 3, 4, 5, 6]	4
Dropout	[0.4, 0.5]	0.4
Max Seq Length	[50, 75, 100]	75
Learning rate	[0.01, 0.001, 0.0001]	0.001
Optimizer	-	Adam

Table 3: Hyper-parameters details.

- Results with optimal parametric config.

	Precision	Recall	F1-Score
Validation	0.893	0.753	0.817
Test	0.883	0.77	0.823

Table 4: Final results obtained competition

Error Analisys

Three type of errors:

- Incorrect bondaries.
- Missing the entity mention (Missed).
- Incorrectly distinguishing the entity mention (Incorrectly distinguish).

Figure 3: Incorrect detections word cloud.

Figure 4: Missed word cloud.

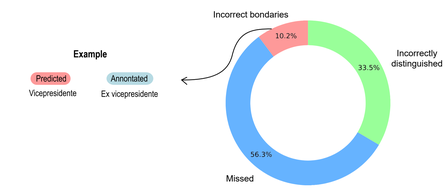


Figure 5: Error percentage.

Conclusion

Our encoder-decoder architecture with attention mechanism powered by word embeddings generates competitive results.

Future work:

- Data Augmentation techniques
- Other entities information as companies or organizations.

References

[1] Antonio Miranda-Escalada, Vicent Briva-Iglesias, Eu-làlia Farré, Salvador Lima López, Marvin Aguero,and Martin Krallinger. 2020.ProfNER corpus:gold standard annotations for profession detection inSpanish COVID-19 tweets. Funded by the Plan deImpulso de las Tecnologías del Lenguaje (Plan TL).

[2] Antonio Miranda-Escalada, Marvin Aguero, and Mar-tin Krallinger. 2021a. Spanish covid-19 twitter em-beddings in fasttext. Funded by the Plan de Impulsode las Tecnologías del Lenguaje (Plan TL).

[3] Felipe Soares, Marta Villegas, Aitor Gonzalez-Agirre,Jordi Armengol-Estapé, Siamak Barzegar, and Mar-tin Krallinger. 2020. Fasttext spanish medical em-beddings. Funded by the Plan de Impulso de lasTecnologías del Lenguaje (Plan TL).

[4] José Cañete, Gabriel Chaperon, Rodrigo Fuentes, Jou-Hui Ho, Hojin Kang, and Jorge Pérez. 2020. Span-ish pre-trained bert model and evaluation data. InPML4DC at ICLR 2020.