Disability annotation on documents from the biomedical domain

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Abstract

This paper describes the UPC 2 system participation in DIANN (*Disability annotation on documents from the biomedical domain*) shared task, framed in the IBEREVAL 2018 evaluation workshop[a]. The system tackles the detection of disabilities using a CRF to perform IOB Named Entity Recognition (NER). Regarding the detection of negated disabilities, the out-of-the-box NegEx rule-based system is used.

[a]http://nlp.uned.es/diann

1. Introduction: Task

- **Annotate disabilities** and their textbfnegation on documents from the biomedical domain.
- Input documents: **short texts** with the disabilities and negations **tagged with XML**.
- Simple disability annotation:

```
... reliability of the MCA in Spanish to identify <dis>mild cognitive
 impairment</dis> (<dis>MCI</dis>)...
```

- Negated disability annotation:

```
... <scp> <neg>without</neg> <dis>dementia</dis> </scp>, significant
 differences were obtained in terms ...
```

2. Approach

- The approach to the problem was to solve it in two steps:
- **Disabilities:**
  - Convert all words into tuples: *(word, POS, IOB-tag)*
  - Use Conditional Random Fields (CRF) to predict the disability IOB-tags.
  - Convert IOB-tags to sentences/disabilities.
- **Negation:**
  - Feed each tuple sentence/disability to a negation software
  - Filter out the probable false positives
  - Convert input back again into XML tagged files.

3. Creating the training data

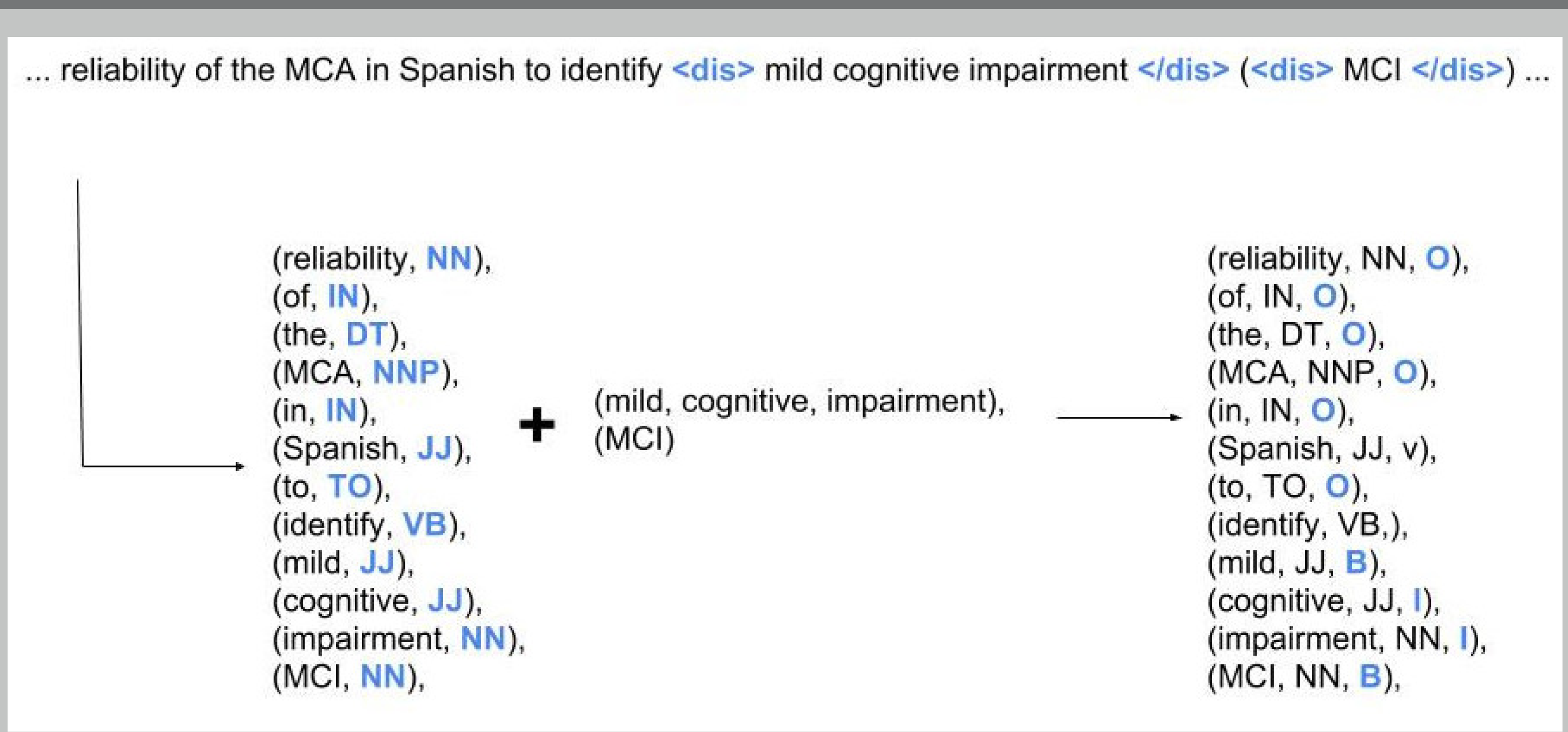
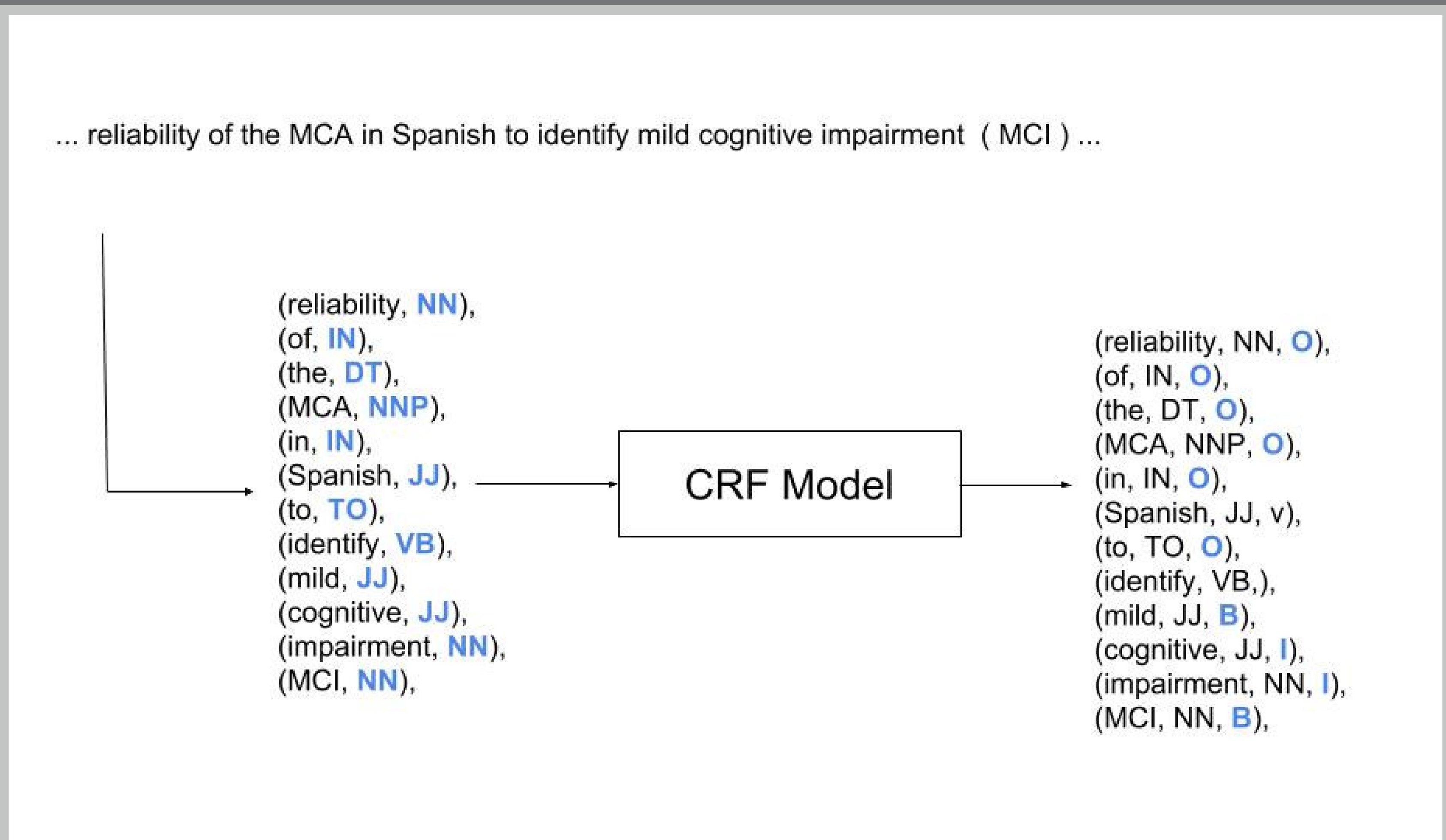


Figure: Pipeline followed to create training data for the CRF model.

4. CRF Model & Features



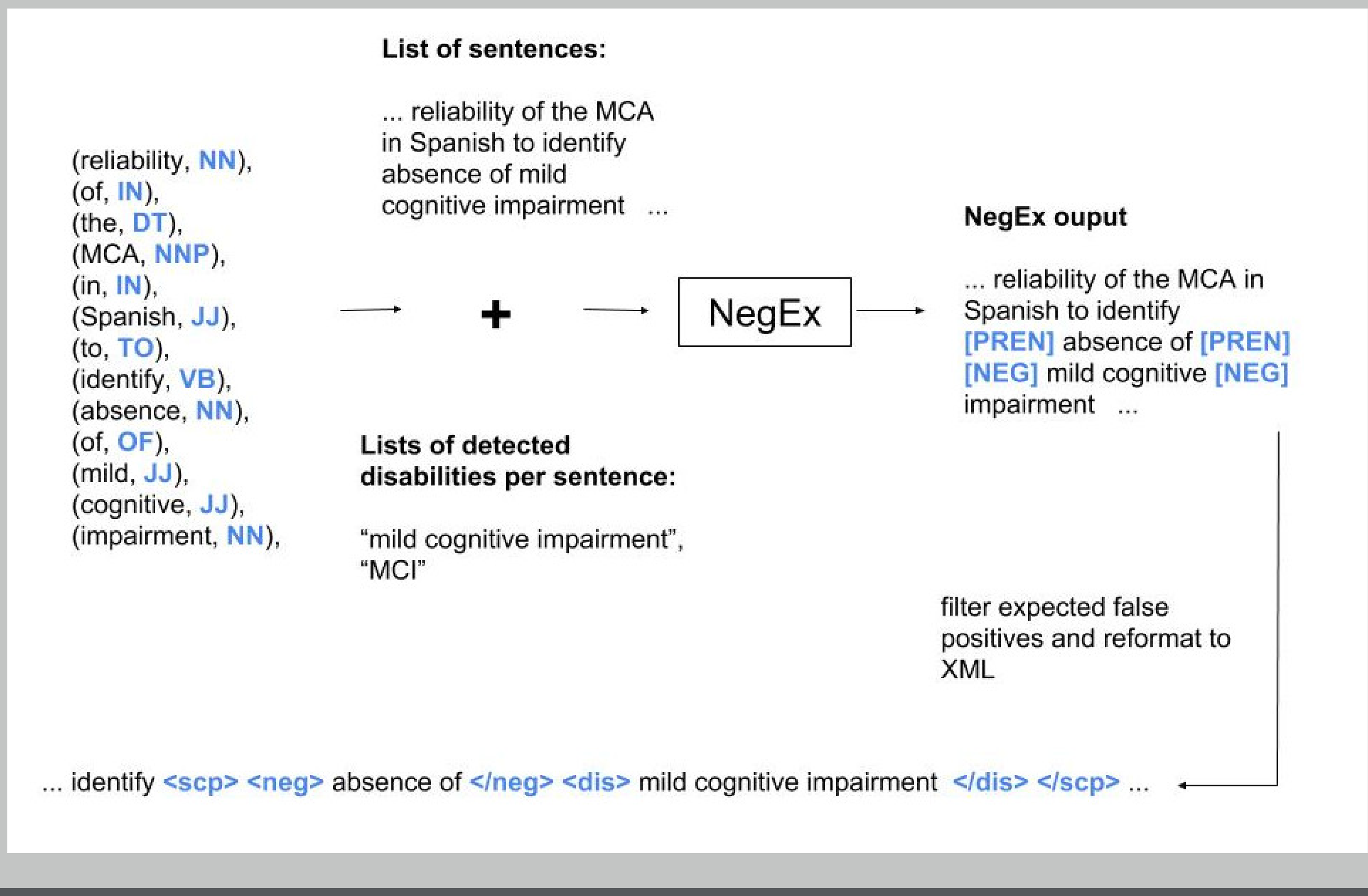
Groups of features:

- 1. Derived from the **curent word** like word, POS, lemma or all-caps.
- 2. Build from **entitites/acronyms lists** such as is-acronym.
- 3. Derived from the **previous/next words** like word, POS, or lemma.
- 4. **Concatenation of a feature of the current word and one of the next/previous** one
- 5.**Concatenation of a feature of the two previous/next** words

5. CRF Model: Training

- Feature Selection[a]:
  - Start with all groups activated and with all features per group
  - Deactivate a group and check if precision increases/decrease
  - If precision increases:
    - Reactivate the group
    - Deactivate each feature of the group and reactivate it only if precision decreases
  - If precision decreases just remove the group from the feature's set.
- Lists' Creation:
  - During model evaluation, entities/acronyms lists are created out of the training fold
  - Once the model is chosen, built the lists with all the training data.

6. Negation Detection



7. Experiments and Results

	Spanish			English		
	Precision	Recall	F1 score	Precision	Recall	F1 score
Group disabled: 2						
Negation	0.50	0.55	0.52	0.46	0.35	0.40
Disability	0.72	0.63	**0.68**	0.72	0.58	0.64
Group disabled: 3						
Negation	0.50	0.50	0.50	**0.48**	0.35	0.41
Disability	0.73	0.51	0.60	**0.75**	0.56	0.64
Group disabled: 4						
Negation	0.51	**0.58**	**0.54**	**0.48**	0.40	**0.44**
Disability	**0.74**	0.59	0.65	0.74	0.65	0.70
Group disabled: 5						
Negation	0.51	0.55	0.53	**0.48**	0.38	0.42
Disability	0.71	0.59	0.64	**0.75**	0.65	0.69
Group disabled: None						
Negation	**0.52**	0.55	0.53	0.47	**0.41**	0.43
Disability	**0.74**	0.62	**0.68**	**0.75**	**0.67**	**0.71**

Table: Results of cross-validation experiments deactivating one feature group at a time

	Exact Match			Partial Match		
	Precision	Recall	F1 score	Precision	Recall	F1 score
English						
Disability	0.756	0.560	0.643	0.822	0.588	0.686
Negated Disability	0.647	0.478	0.550	0.941	0.696	0.800
Non-negated + Negated Disability	0.724	0.519	0.604	0.822	0.588	0.686
Spanish						
Disability	0.732	0.502	0.596	0.828	0.568	0.674
Negated Disability	0.737	0.636	0.683	0.895	0.773	0.829
Non-negated + Negated Disability	0.710	0.480	0.573	0.819	0.555	0.661

Table: Final testing results with the full-featured model.

[a]All validation results use 10-fold cross-validation