Filozofski fakultet
Sveučilišta u Zagrebu

CLEOPATRA

Optimization of Portuguese Named Entity Recognition and Classification

Combination of Local Grammars and Conditional Random Fields Trained with Parsed Corpora

Diego Alves
Božo Bekavac
Marko Tadić

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Agenda

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- Data
- Methodology
- Results
- Conclusion and Perspectives
- References

Objective

- Associate NooJ syntactic local grammars with Conditional Random Fields (CRF) probabilistic method to improve Name-Entity Recognition and Classification (NERC) for Portuguese

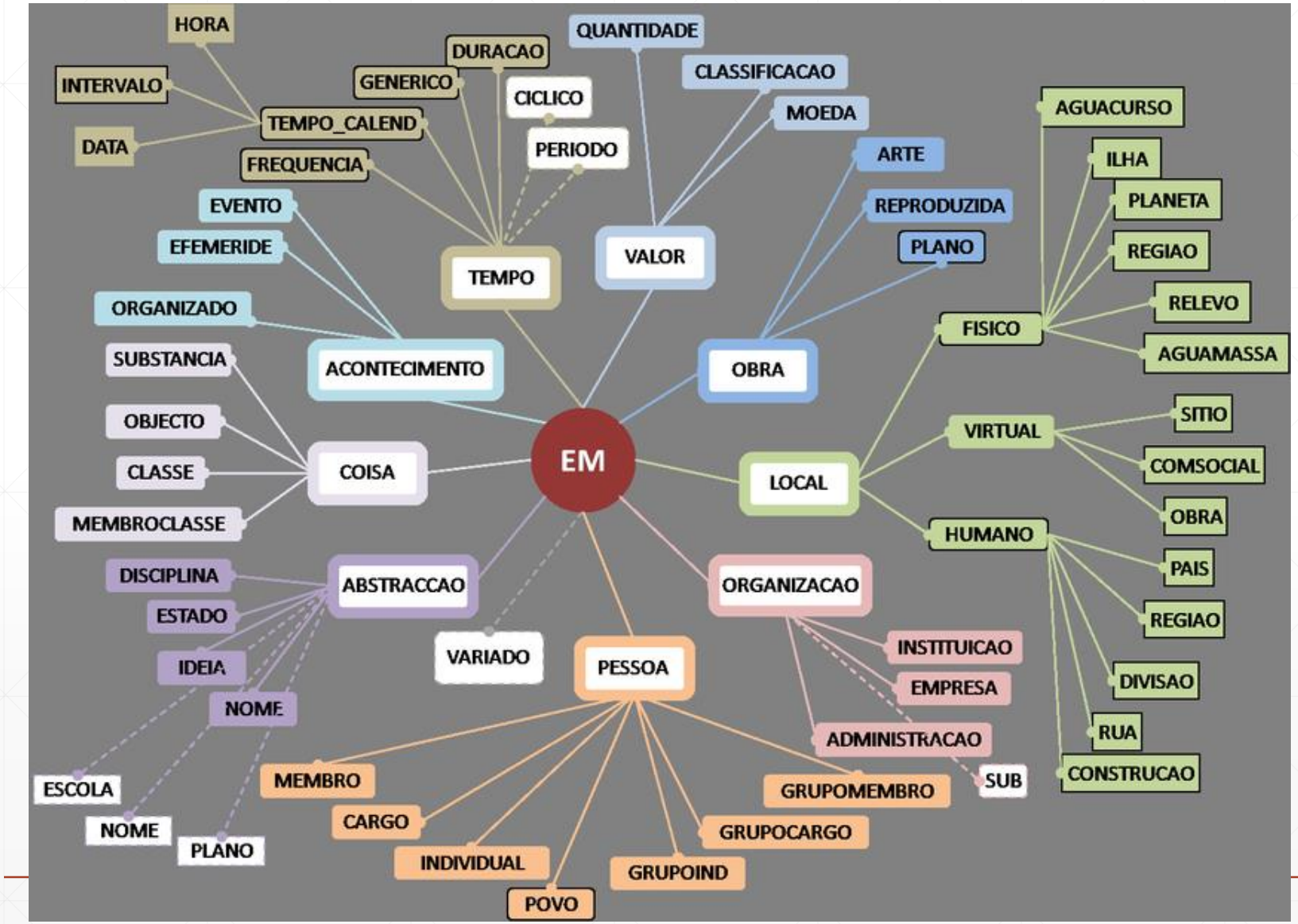
- Understand the synergy in training CRF models between information coming from parsed corpus and local grammars

- Focus on „TIME” category and its subcategories

Data

- Portuguese Second Harem:
  - Dataset provided for the second edition of an evaluation campaign for Portuguese, addressing named entity recognition (NER)
  - Golden set (GS):
    - 129 documents manually annotated according to HAREM guidelines for NER
    - Domains: news, didactic, opinion, blog, questions, interview, legal, literary, promotional, private manuscript
    - 4053 sentences
    - 89634 tokens

Second Harem NER Hierarchy



Second Harem structure

3-level hierarchy:

- First level: 10 categories
- Second level: 36 types
- Third level: 21 subtypes

Second Harem GS:

- 7846 entities

Second Harem: „TIME” category

- 1189 occurrences in HAREM Golden Set divided in:

Type	Subtype	Number of occurrences in HAREM GS
TIME_CALENDAR	DATE	873
	HOUR	37
	INTERVAL	63
DURATION	-	56
FREQUENCY	-	71
GENERIC	-	89

- Our study: BIO format

```xml
<DOC DOCID="H2-dftre765">
  <P>Fatores Demográficos e Econômicos Subjacentes</P>
  <P>
    A revolta histórica produz normalmente uma nova forma de pensamento quanto à forma de organização da sociedade. Assim foi com a
    <EM ID="H2-dftre765-1" CATEG="ABSTRACCAO|ACONTECIMENTO" TIPO="IDEIA|EFEMERIDE">Reforma Protestante</EM>
    . No seguimento do colapso de instituições monásticas e do escolasticismo
    nos finais da <EM ID="H2-dftre765-102" CATEG="OUTRO" COMENT="DUVIDA_DIRECTIVASTEMPO">Idade Média</EM>
    na
    <EM ID="H2-dftre765-37" CATEG="LOCAL" TIPO="HUMANO" SUBTIPO="DIVISAO">Europa</EM>
```

Second Harem xml file

```
Anos    B-DURACAO
e   I-DURACAO
anos    I-DURACAO
de  O
destruição  O
compulsiva  O
de  O
interlocutores  O
,   O
alguns  O
moderados   O
,   O
e   O
de  O
opressão    O
,   O
fizeram O
do  O
povo    O
palestiniano    O
uma O
nação   O
de  O
pedintes    O
.   O
```

Second Harem BIO file

Second Harem – Train and Test

- From Second Harem GS:
  - Random selection of sentences to compose train and test sets (70/30):

    - Train:
      - 2842 sentences
      - 63032 tokens
      - 808 entities

    - Test:
      - 1211 sentences
      - 26602 tokens
      - 352 entities

Methodology

- STEP 1: CRF trained with Parsed Harem Corpus.
  - Harem Corpus automatically annotated with UDPipe tool
    - UDpipe-bosque model
  - CRF:
    - Python library: sklearn_crfsuite
    - Basic Features for all tests (token, token -1 and token +1) - Baseline:
      - Lower case
      - Upper case
      - Token starts with upper case
    - Other Features studied:
      - Part Of Speech tag
      - Morphosyntactic tag
      - Dependency parsing tag
- STEP 2: NooJ local grammars.
  - Identification of „TIME” category (BIO)
- STEP 3: CRF trained with Parsed and NooJ Features

```
1   Assim   assim   ADV _   _   2   advmod   _   _
2   foi foi ADV _   _   0   root    _   _
3   com com ADP _   _   5   case    _   _
4   a   o   DET _   Definite=Def|Gender=Fem|Number=Sing|PronType=Art    5   det _   _
5   Reforma reforma PROPN   _   Gender=Fem|Number=Sing  2   obl _   _
6   Protestante Protestante PROPN   _   Number=Sing 5   flat:name   _   _
7   .   .   PUNCT   _   _   2   punct   _   _
```

Parsed Second Harem example

Step 1 – CRF - Results

- CRF trained with train corpus with basic features and linguistic data:
  - „Time” category, types and subtypes
  - BIO

Added Feature	Precision	Recall	F1-measure
Baseline	0.809	0.636	0.700
Part of Speech info	**0.838**	**0.671**	**0.735**
Morphosyntactic info	0.805	0.664	0.723
Parsing info	0.823	0.634	0.708
Part of Speech + Morphosyntactic info	0.807	0.670	0.727
Part of Speech + Dependency Parsing info	0.830	0.658	0.727
Part of Speech + Morphosyntactic + Dependency Parsing info	0.823	0.655	0.721

Results from CRF training using Linguistic Features from Parsed Harem file

Step 2 – NooJ local grammar - Results

- NooJ resources:
  - Portuguese general dictionary (PT-Dict.nod) available in NooJ website
  - Local grammar:
    - 22 graphs
    - Identification of Time expressions corresponding to „Time” category in Second HAREM (BIO).
      - B-TEMPO, I-TEMPO, O tags

	Precision	Recall	F1-measure
Train set	0.870	0.661	0.751
Test set	0.847	0.660	0.741

Evaluation of NooJ annotations

Step 3 – CRF + NooJ - Results

- NooJ tags combined with POS information:

Added Feature	Precision	Recall	F1-measure
Baseline	0.809	0.636	0.700
Part of Speech info	0.838	0.671	0.735
NooJ tags	**0.867**	**0.725**	**0.757**
Part of Speech + NooJ tags	0.797	0.675	0.700

Step 3 – CRF + NooJ – Detailed Results

- Results for each tag for the best CRF Model (with NooJ tags as feature):

Tag	Precision	Recall	F1-measure
B-DURACAO	0.333	0.059	0.100
I-DURACAO	0.333	0.089	0.140
B-FREQUENCIA	1.000	0.545	0.706
I-FREQUENCIA	1.000	0.516	0.681
B-GENERICO	0.500	0.138	0.216
I-GENERICO	0.800	0.082	0.148
B-TEMPO_CALEND-DATA	0.841	0.821	0.831
I-TEMPO_CALEND-DATA	0.828	0.857	0.842
B-TEMPO_CALEND-HORA	1.000	0.167	0.286
I-TEMPO_CALEND-HORA	0.750	0.194	0.308
B-TEMPO_CALEND-INTERVALO	0.778	0.438	0.560
I-TEMPO_CALEND-INTERVALO	0.778	0.404	0.532

Conclusions and Perspectives

- Part of Speech is the most relevant linguistic information when training CRF for NER
- NooJ pre-annotation can replace POS feature with better results
- Part of Speech and NooJ pre-annotation → Negative synergy (inferior to baseline)

- Disambiguation local grammars may increase NooJ precision and therefore enhance final results
- Use NooJ to pre-annotate following „Time” detailed structure may enhance problematic cases:
  - DURATION
  - GENERIC

References

- Freitas, C., Mota, C., Santos, D., Oliveira, H.G., Carvalho, P., Second HAREM: Advancing the State of the Art of Named Entity Recognition in Portuguese, LREC, 2010.
- Mota, C., Carvalho, P., Barreiro, A., Port4NooJ v3.0: Integrated Linguistic Resources for Portuguese NLP, LREC, 2016.
- Pirovani, J., Oliveira, E., Portuguese Named Entity Recognition using Conditional Random Fields and Local Grammars, LREC, 2018.
- Sklearn-crfsuite website: https://sklearn-crfsuite.readthedocs.io/en/latest/index.html (Last visited on: 29/05/2020).
- Sutton, C., McCallum, A., An Introduction to Conditional Random Fields, Foundations and Trends in Machine Learning, vol. 4, n.4, p.267-373, 2012.

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Questions?