Coreference Resolution for Russian: The Impact of Semantic Features

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- An important task for many high-level NLP tasks:
  - Machine translation
  - Discourse parsing
  - Summarization
  - ...

(1) Но дача была так расположена, что откуда бы я ни заходил, я мог видеть только небольшой угол двора. Он был так же пуст и невозделан, как и окружающая местность.

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    - No open coreference resolution system trained for Russian available for research

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RuCor annotation guidelines

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- No singleton annotation — NP is annotated only if it is a part of a coreference chain

Experiments design

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- Two coreference scores: MUC and B^3

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- As it is often the case, some of the decisions about data modeling and annotation could be done differently:
  - What to annotate
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$\Rightarrow$ The task is not to resolve coreference *in general*... but to predict coreference relations according to the RuCor annotation guidelines

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Mention-pair model

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- For each NP there is a set of NPs — possible antecedents
- For each such pair we can predict if they are coreferent
- After all the decisions are made, positive pairs are grouped together

Rule-based baselines

A few simple rule-based baselines:

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Rule-based baselines

	MUC			B^3		
	P	R	F_1	P	R	F_1
StrMatch	94.29	37.36	53.52	97.09	38.19	54.82
StrMatchPro	84.90	52.42	64.82	89.34	43.35	58.37
HeadMatch	87.78	47.06	61.27	92.11	43.64	59.22
HeadMatchPro	84.89	52.50	64.87	89.29	43.38	58.40

Table 1: Rule-based coreference systems, gold mentions

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	MUC			B^3		
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StrMatch	94.29	37.36	53.52	97.09	38.19	54.82
StrMatchPro	84.90	52.42	64.82	89.34	43.35	58.37
HeadMatch	87.78	47.06	61.27	92.11	43.64	59.22
HeadMatchPro	84.89	52.50	64.87	89.29	43.38	58.40

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	MUC			B^3		
	P	R	F_1	P	R	F_1
StrMatch	52.86	32.29	40.09	33.54	34.04	33.79
StrMatchPro	34.40	45.46	39.16	26.89	39.58	32.02
HeadMatch	35.26	41.38	38.07	29.57	38.88	33.59
HeadMatchPro	34.40	45.49	39.18	26.89	39.58	32.02

Table 2: Gold boundaries, mention detection f-score 51.38

Baseline ML models

Two ML models:

- Basic set of features

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Two ML models:

- Basic set of features
- Extended feature set:
  - Distance features
  - Morphological features
  - Lexical features
  - Syntactical features

Basic feature set

- The distance between an anaphoric NP and a candidate antecedent is 1 sentence.
- Both NPs are not pronouns and after removing any demonstratives they match.
- NPs agree in animacy and if they are not pronouns their syntactic heads match.
- Anaphoric NP is a pronoun.
- Candidate antecedent is a pronoun.
- Both NPs are pronouns.
- NPs agree in gender.
- NPs agree in number.
- Both NPs are proper.
- An anaphoric NP is a demonstrative.
- NPs are in the appositive relation.

Extended features

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    - NPs are subjects
    - NPs are objects
    - Syntactic parallelism: both NPs are in the beginning of sentences and they are both subjects

Extended features: examples

- Modifiers:

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- Acronyms:

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Baseline ML models: results

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	P	R	F_1	P	R	F_1
HEADMATCHPRO	84.89	52.50	64.87	89.29	43.38	58.40
MLMENTIONPAIR	73.98	62.24	67.61	71.40	49.34	58.36
MLUPDATED	79.29	63.01	70.22	79.42	48.39	60.14

Table 3: ML-based coreference systems, gold mentions

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Named entities

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- But: should help for the non-standard vocabulary

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- Thesaurus RuThes-Lite
- Used to look up two NPs or their heads:
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Results

	MUC			B^3		
	P	R	F_1	P	R	F_1
MLMentionPair	73.98	62.24	67.61	71.40	49.34	58.36
MLUpdated	79.35	63.44	70.51	79.37	48.60	60.29
NamedEntities	79.43	63.72	70.71	79.37	48.86	60.48
word2vec	79.29	63.49	70.52	79.25	48.64	60.28
RuThes	79.19	63.79	70.66	78.92	48.78	60.29
All	79.19	63.97	70.77	78.85	48.94	60.39

Table 5: The impact of semantic information, gold mentions

Results: gold boundaries

	MUC			B^3		
	P	R	F_1	P	R	F_1
MLMentionPair	37.91	55.85	45.16	21.88	43.98	29.22
MLUpdated	37.94	53.87	44.52	25.00	42.61	31.51
NamedEntities	38.01	54.10	44.65	24.99	42.83	31.56
word2vec	37.69	53.92	44.37	24.95	42.68	31.49
RuThes	36.27	54.20	43.46	24.63	42.83	31.28
All	36.08	54.32	43.36	24.60	42.94	31.28

Table 6: Gold boundaries, mention detection f-score 51.21

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  RusVectores output for *профессор*:

  - доцент 0.68
  - проф 0.66
  - преподаватель 0.66
  - ректор 0.66
  - ученый 0.63
  - академик 0.62
  - доктор 0.59
  - декан 0.58
  - преподавать 0.57
  - адъюнкт-профессор 0.57

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- But some cases are problematic:

  (8) дача — таинственное жилище

  Ruthes output:
  - дача < загородный дом < жидое здание < здание < недвижимое имущество
  - жилище < место в пространстве

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- Even though there are some limitations, these approaches improves the quality
- Further elaboration of each of them could improve the overall quality further:
    - Using a NER system
    - Using distributional models in a more complex way
    - Handling ontologies more carefully to minimize the amount of generated homonymy

Thank you!

Any questions?

RuCor corpus: `http://rucoref.maimbava.net`

Jupyter notebooks: `https://github.com/max-ionov/rucoref/tree/master/notebooks/coreference-dialog-2017`