SpellRuEval: the First Competition on Automatic Spelling Correction for Russian

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- We need a benchmark algorithm for spellchecking.
- And a benchmark dataset...

Spellchecking contests

- HOO Shared Task (Dale et al., 2010, 2011; assisting authors in writing)
- Microsoft Spelling Alteration Workshop (Wang, 2011; search query correction)
- CoNLL 2013 Shared Task (Ng, 2013; grammar error correction)

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Text normalization:

- Twitter lexical normalization (ACL-IJCNLP Shared Task; Baldwin et al., 2015)

Goals of SpellRuEval Shared Task

- Few works address Russian spellchecking.
- But spellchecking is a *language-dependent* task.

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  - typos (мнея $\mapsto$ меня),
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  - intentional incorrect writing (хоцца $\mapsto$ хочется, ваще v вообще),
  - grammatical errors (agreement etc.) (он видят $\mapsto$ он видит),
  - errors in hyphen and space positioning (както $\mapsto$ как-то),
  - mixed usage of digits and letters in numerals (2-ух $\mapsto$ двух),
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- Other errors (not corrected):
  - foreign words including cyrillic (e.g Ukrainian or Belorussian),
  - informal abbreviations (прога $\mapsto$ программа)
  - punctuation errors (all punctuation is omitted)
  - capitalization errors
  - non-distinction of *e* and *ë* letters

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- Finally, more than 5000 sentences given to annotators.

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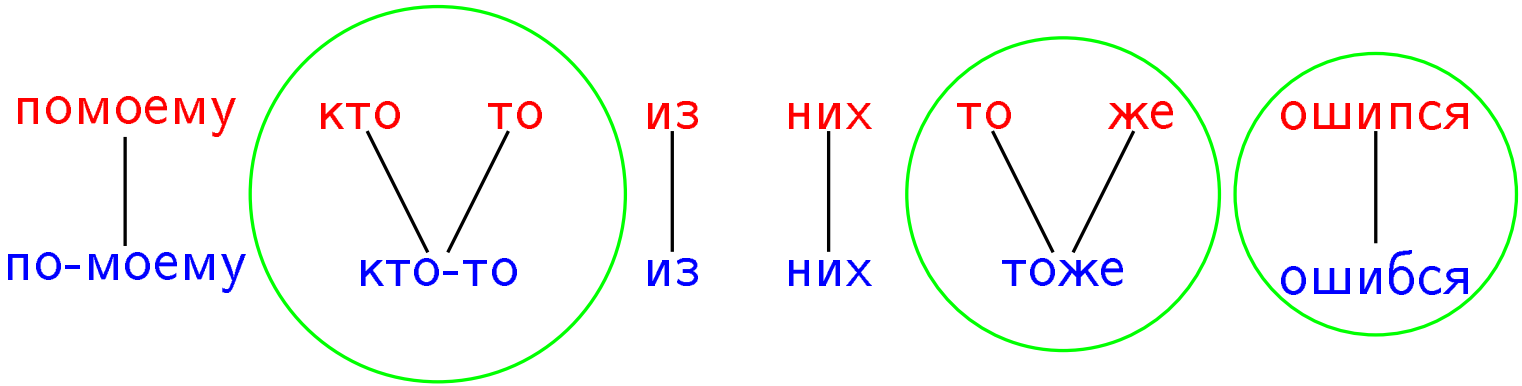
- During testing procedure, these 2000 sentences were uniformly spread among 100000 taken from the same sample.

Measuring performance

- First, we aligned the source sentence with its correction:



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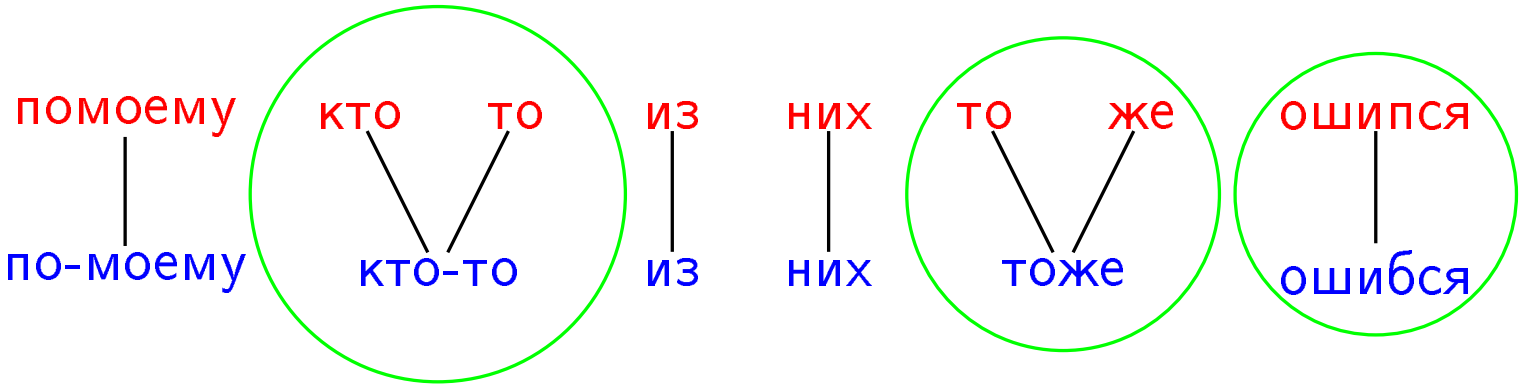

- We obtain a list of non-identical pairs (tokens):

кто то	кто-то
то же	тоже
ошипся	ошибся

- They are called *nontrivial tokens*.

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- The number of properly corrected sentences was also measured.

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- We expect some kind of language model for candidate selection.

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- Proper names, often colloquial

  Ну и конечно Мак покатился с ним, чтобы оценить ситуацию со стороны.

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- The winner system also uses:
  - Phonetic similarity,
  - Weighted edit model.

Results

Place	Team	Prec.	Recall	F-Measure	Corr. sent.
1	GICR, MSU	81,98	69,25	75,07	70,32
2	Orfogrammatika	67,54	62,31	64,82	61,35
3	MIPT	71,99	52,31	60,59	58,42
4	ISP RAS	60,77	50,75	55,31	55,93
	BASELINE	55,91	46,41	50,72	48,06
5	HSE	74,87	27,99	40,75	50,45
6	InfoCubes	23,50	30,00	26,36	24,95
7	NLP@CLOUD	17,50	9,65	12,44	33,96

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All materials available at:
https://drive.google.com/drive/u/0/folders/0B8XxHuDfyogmMnM5RFdKdWdzZmM

Спасибо за внимание!

Thank you for attention!

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