Part-of-speech Tagging with Rich Language Description

Daniil Anastasyev, Andrew Andrianov, Eugene Indenbom

ABBYY, Moscow

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   - Target classes
   - Neural network
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   - Train data
   - Evaluation results
   - Example of work
   - Errors analysis
4. Summary

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- Accurate morphological analyser can highly increase speed of the syntactic parsing by reducing the number of obtained hypotheses.

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2. LSTM neural network.
   - Aims to construct the best grammatical values.

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Possible grammatical values of the word «мыла»

1. *мыть* **Par1** VERB Tense=Past Number=Sing Gender=Fem Voice=Act VerbForm=Fin Mood=Ind (freq=$2.03 \cdot 10^{-7}$)
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- The description's tagset is taken from ABBYY Compreno.
  - It differs considerably from Universal Dependencies.

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     - E.g., «ддосить» and «гундосить».
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- The found score is treated in the same way as probability of known word.

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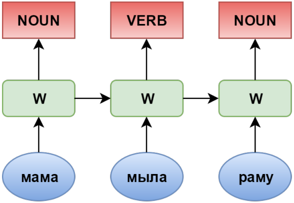

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   - Words are fed one by one.
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   - Usually LSTM or GRU are used.
   - Can handle longer dependencies.

Used features

- Grammatical value.

Feature description

- Probabilities of each possible grammeme by dictionary.
- Мыла:
  - Freq of Genitive form – $7.57 \cdot 10^{-7}$.
  - Freq of Nominative form – $3.81 \cdot 10^{-7}$.
  - Freq of Accusative form – $3.48 \cdot 10^{-7}$.
- $\mathbf{P}(\text{Case}=\text{Acc}) = \frac{3.48 \cdot 10^{-7}}{(7.57+3.81+3.48) \cdot 10^{-7}} \approx 0.234$.

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- Probabilities of each possible grammatical values.

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Feature description

- Presence of particular punctuation mark at the left or right.
- Binary feature.

Used features

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- Word's case type.

Feature description

- Proper, lower, UPPER or FiXed capitalisation.
- Binary feature.

Used features

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- Ambiguity classes' probabilities.
- Punctuation.
- Word's case type.
- Suffixes.

Feature description

- Last 1-3 letters of the word:
  - -ыла, -ла, -а.
- Used separate embedding layer for each suffix length.

Used features

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- Ambiguity classes' probabilities.
- Punctuation.
- Word's case type.
- Suffixes.
- Word embeddings.

Feature description

Can be initialised:

- Uniformly, for the first ≤ 20000 most frequent words.
- By pretrained embeddings.
  - Led to larger model and did not give any significant improvement.

Target classes

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   - E.g., classification between three possible values of category «Number»: Singular, Plural, Not defined.
   - Leads to fewer number of classes.
   - Did not enhance quality of the model.

Proposed neural network architecture

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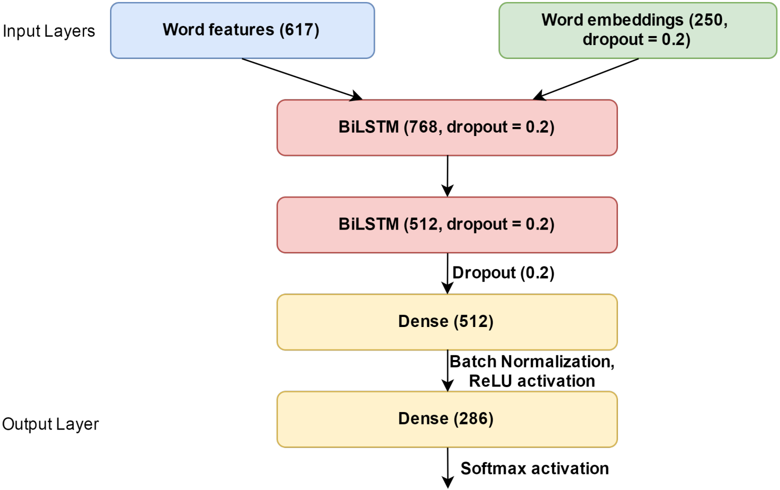
- Dense layer with Dropout and ReLU activation.
- Dense output layer with Softmax activation.

Structure of the neural network



Train data

- GICR subcorpus.
  - Contains about 1 million words.
  - Uses Universal Dependencies tagset and conventions that correspond to test set.
- Wikipedia subcorpus.
  - Contains more than 3 million words.
  - Uses Compreno tagset.
- Corpus of novels.
  - Contains about 30 million words.
  - Uses Compreno tagset.

Tagsets conversion

- The annotation format of Wikipedia and Novels corpora was automatically converted.
- The achieved annotation had number of differences from the competition format.
- This differences were smoothed out by proper training of the neural network.

Fine tuning of the model

- Model gains from usage of large corpus on pretrain stage.
- Model requires training on corpus with more appropriate annotation.

Performance of the model on validation set

Train corpus	**Accuracy on validation set**
GICR	96.41%
Novels	95.36%
Pretrained on Novels, Trained on GICR	97.78%

Evaluation results

- Model achieved following results on the test set.
- The last model was pretrained on Novels corpus, others were trained on GICR subcorpus only.

Results with different parameters

Model	Fiction	News	Social media
1BiLSTM(768) + 0.2 Dropout	94.95% / 69.54%	97.01% / 75.70%	94.30% / 71.30%
1BiLSTM(768) + Dense(768) + 0.2 Dropout	95.35% / 71.83%	97.20% / 76.82%	94.66% / 73.94%
1BiLSTM(768) + 2BiLSTM(512) + Dense(768) + 0.2 Dropout	95.57% / 73.10%	97.37% / 78.77%	95.13% / 74.47%
1BiLSTM(768) + 2BiLSTM(512) + Dense(768) + 0.5 Dropout	95.30% / 73.35%	97.54% / 79.89%	95.15% / 75.00%
Third model pretrained on large corpus (final results)	97.45% / 81.98%	97.37% / 87.71%	96.52% / 81.34%

Example of work on out-of-vocabulary words

- Analysis of sentence that fully consists of unknown words.

Глокая *глокий* ADJ Case=Nom Gender=Fem Number=Sing Degree=Pos		**куздра** *куздра* NOUN Case=Nom Gender=Fem Number=Sing	**штеко** *штеко* ADV Degree=Pos	**будланула** *будлануть* VERB Gender=Fem Number=Sing Tense=Past Voice=Act	**бокра** *бокра* NOUN Case=Nom Gender=Fem Number=Sing
Глокая *глокать* VERB Voice=Act Tense=Notpast VerbForm=Conv	,	**куздра** *куздра* NOUN Case=Nom Gender=Fem Number=Sing	**штеко** *штеко* ADV Degree=Pos	**будланула** *будлануть* VERB Gender=Fem Number=Sing Tense=Past Voice=Act	**бокра** *бокра* NOUN Case=Nom Gender=Fem Number=Sing

Errors summary

- Ambiguity between nominative and accusative cases – $\sim 30\%$ of all mistakes.
- Ambiguity in the numbers of nouns – $\sim 11\%$ of all mistakes.

The most common mistakes

Correct tag	**Number of occurrences**	**Predicted tag**	**Number of errors**
Nominative	2650	Accusative	60
Accusative	1644	Nominative	37
Plural	2777	Singular	28
Nominative	2650	Genitive	19
DET	656	PRON	14
PRON	1133	DER	11

Examples of errors

- Some errors in identification of nominative and accusative cases and numbers of noun.

Минуту спустя	**кровать** *кровать* NOUN Case=Acc Gender=Fem Number=Sing	его принималась скрипеть...
	Минуты *минута* NOUN Case=Gen Gender=Fem Number=Sing	, проведенные дедом...

Examples of errors

- Some errors in test data annotation.

…эти слова в ласку и	**нежность** *нежность* NOUN Animacy=Inan Case=Nom Gender=Fem Number=Sing	, их жестокости не скроешь…
при некоторых видах	**плетения** *плетение* NOUN Animacy=Inan Case=Nom Gender=Neut Number=Plur	когда вращение купола…

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  4. Pretraining on large corpus.