Word Translation Prediction for Morphologically Rich Languages with Bilingual Neural Networks

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Summary

Choosing the correct surface form requires linguistic features of source and target context:

- in phrase-based SMT, access to source context depends on phrase segmentation
- linguistic features depend on available annotation tools and manual feature engineering

Our approach enables:

- accurate prediction of target translation stem and suffix given fixed amount of context
- automatic learning of relevant features with neural network architecture

This results in:

- significantly higher accuracies than maximum-likelihood baseline
- better ranking of translation options, small but significant BLEU gains in English-to-Russian

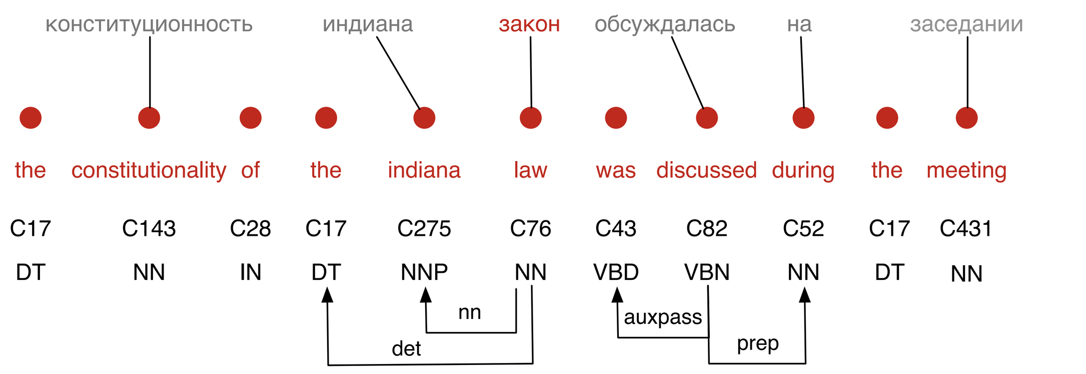
Motivation

[конституционность] [индиана закон] [обсуждалась] [на заседании]

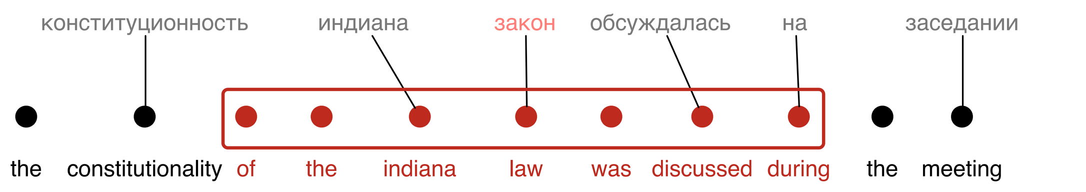
[the constitutionality of the] [indiana law] [was discussed] [during the meeting]

Wrong case translation of "law" due to the rare word "Indiana". The language model does not help in this case → Need a model to improve morphological prediction

Task: Predict target word translation given the source sentence and alignment link



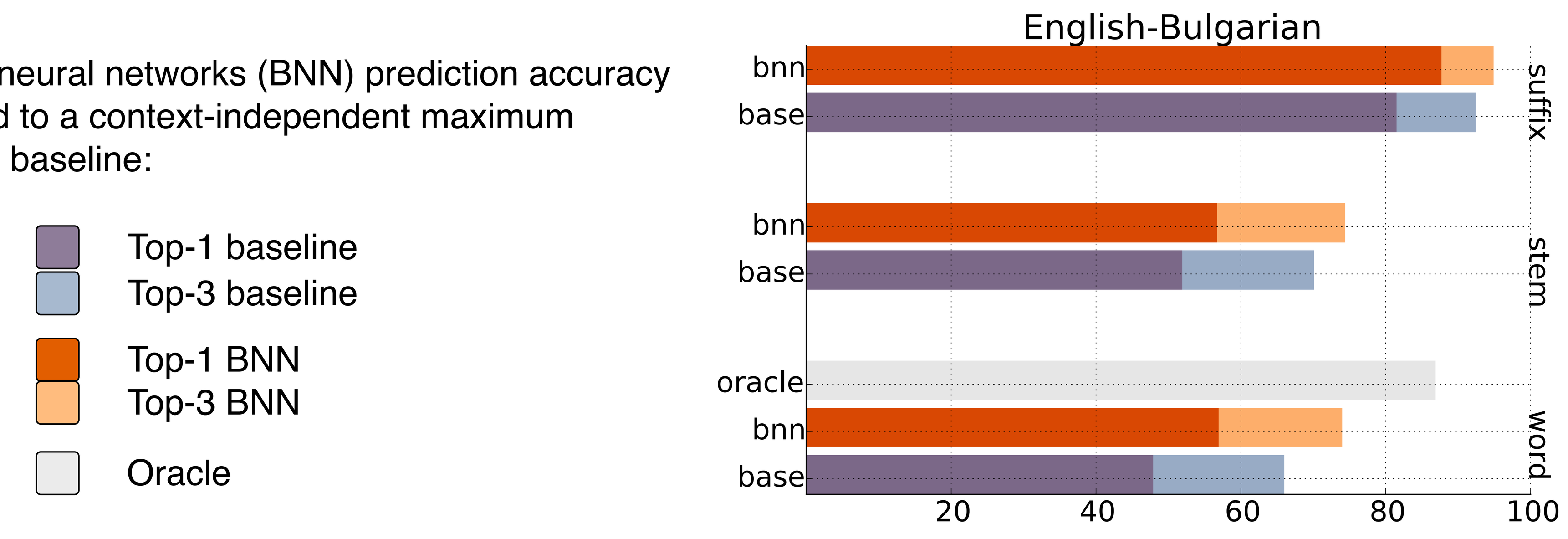
Previous approaches rely on linguistic annotations such as POS, dependency relations,...

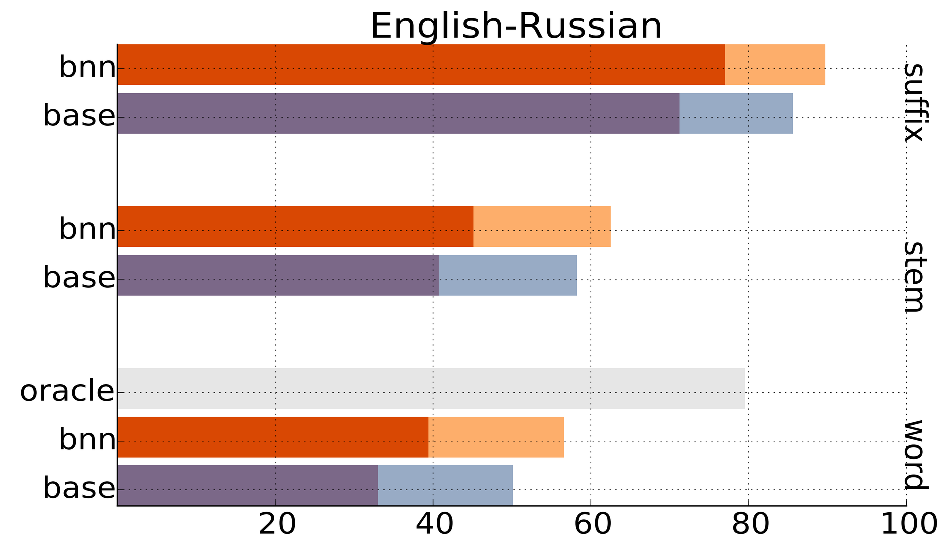


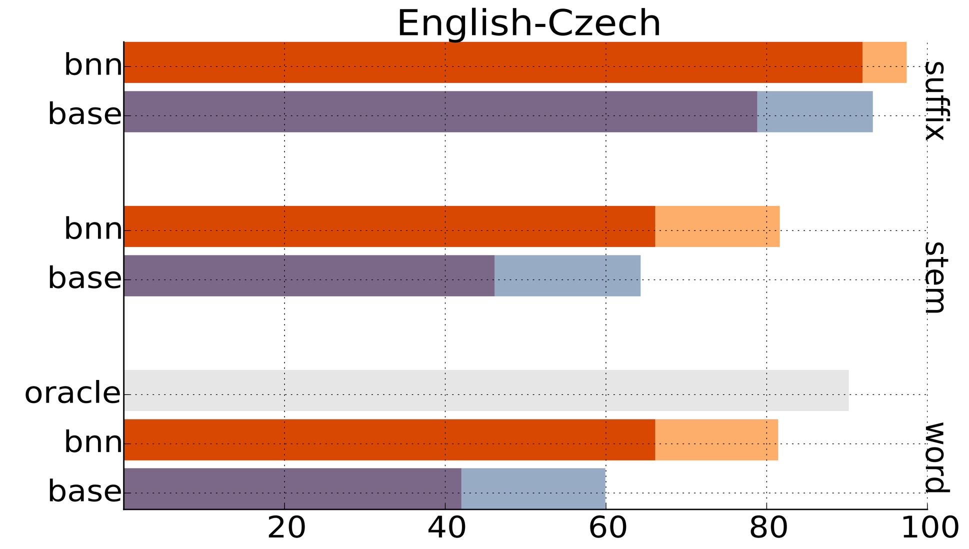
This work: use local context and learn relevant features automatically.

Translation prediction results

Bilingual neural networks (BNN) prediction accuracy compared to a context-independent maximum likelihood baseline:







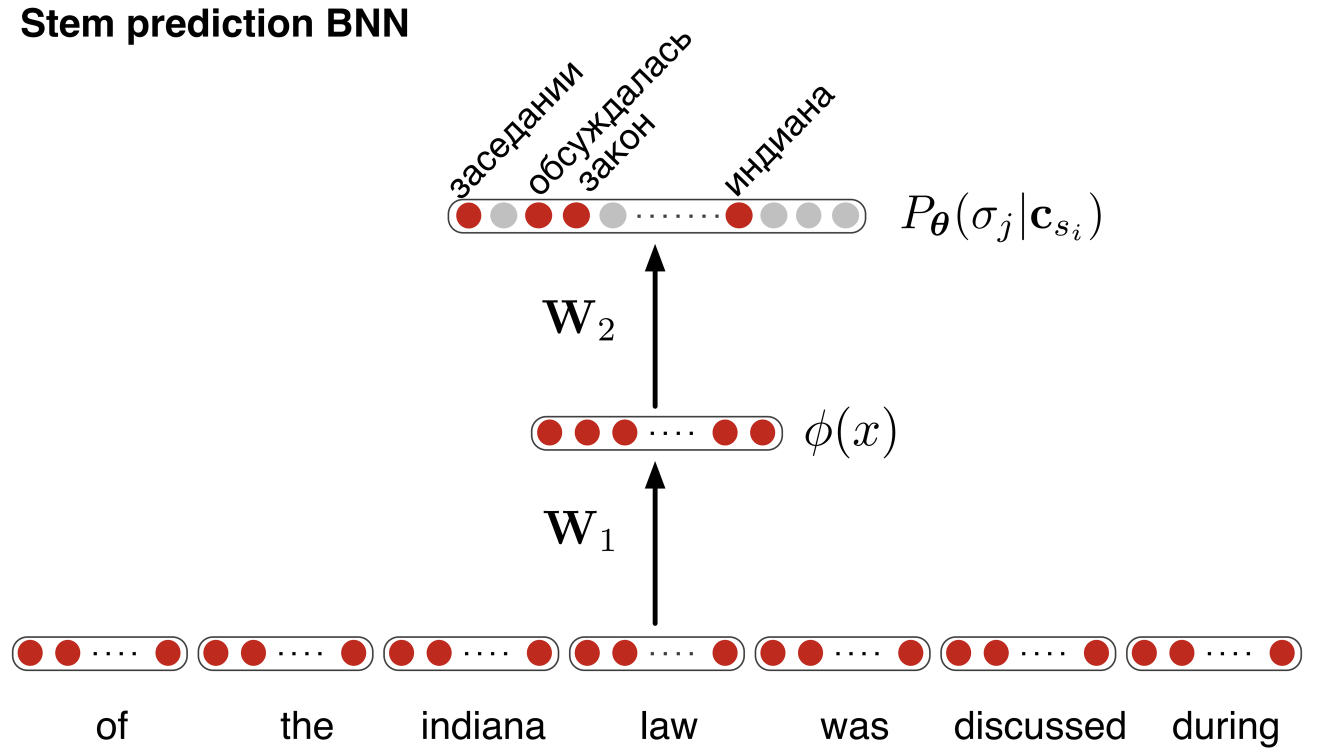
Approach: Bilingual Neural Network (BNN)

Factorize word translation probability into stem and suffix probabilities: $p(t_j|\mathbf{c}_{s_i}) = p(\sigma_j|\mathbf{c}_{s_i})p(\mu_j|\mathbf{c}_{s_i},\sigma_j)$

Conditional probability normalized over the set of translation candidates instead of the whole output vocabulary:

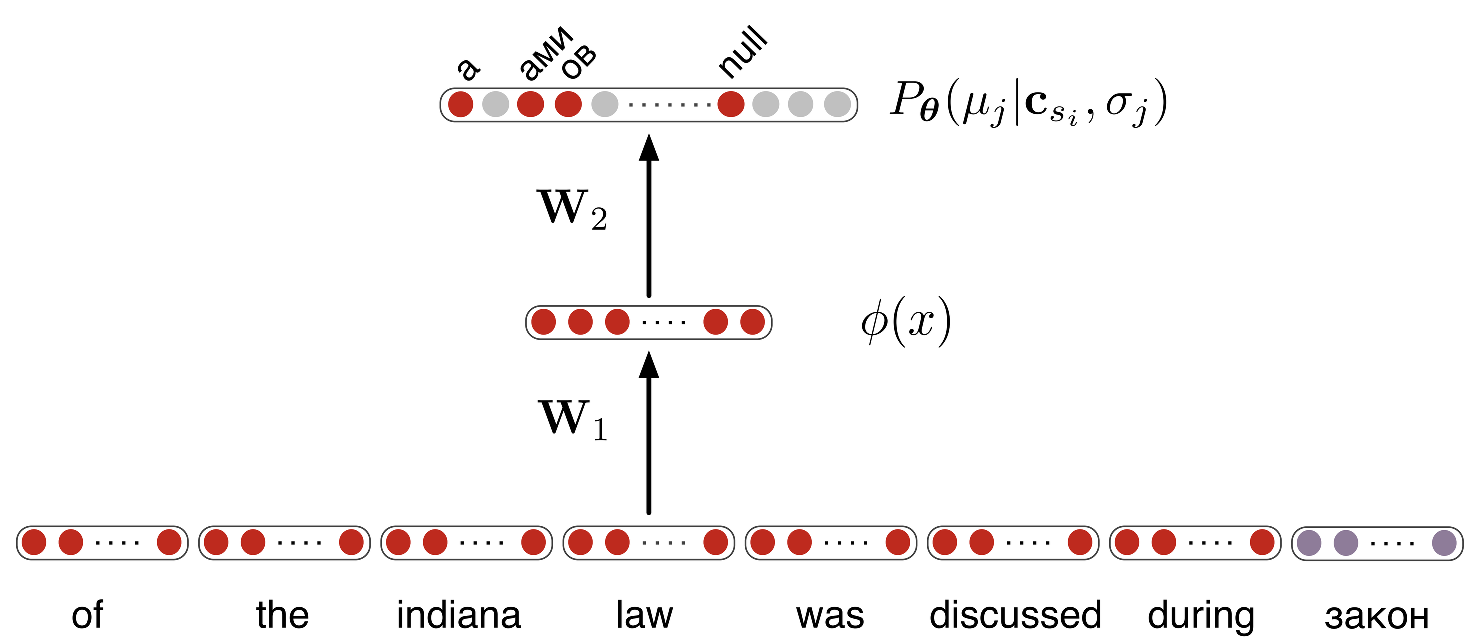
$$p(t_j|\mathbf{c}_{s_i}) = \frac{\exp(\mathbf{W}_2^{[t_j]}\phi(\mathbf{W}_1\mathbf{r}(\mathbf{c}_{s_i})))}{\sum_{t_k\in\mathrm{GEN}(s_i)}\exp(\mathbf{W}_2^{[t_k]}\phi(\mathbf{W}_1\mathbf{r}(\mathbf{c}_{s_i})))}$$

Stem prediction BNN



Input: fixed-size source context window

Suffix prediction BNN



Input: fixed-size source context window + target stem

SMT results

Compute BNN score for each phrase pair, similarly to lexical weighting:

$$P_{\text{BNN-p}}(\tilde{s},\tilde{t},a) = \prod_{i=1}^{|\tilde{s}|}\begin{cases}\frac{1}{|\{a_i\}|}\sum_{j\in\{a_i\}} P_{\text{BNN}}(t_j|\mathbf{c}_{s_i}) & \text{if } |\{a_i\}|>0\\ P_{\text{mle}}(\text{NULL}|s_i) & \text{otherwise}\end{cases}$$

	MLE	BNN	
	p(elf)	stem	suffix
indiana law / индиана закон	0.6	0.6	0.1
indiana law / индиана закона	0.1	0.6	**0.7**
indiana law / индиана законов	0.1	0.6	0.1

Effect of our BNN models on English-to-Russian translation quality (BLEU%) :

SMT system	wmt12 (dev)	wmt13 (test)
Baseline	24.7	18.9
+ stem/suff. BNN	25.1	**19.3***
Base+suff.LM	24.5	19.2
+ word. BNN	24.5	19.2
+ stem/suff. BNN	24.7	**19.6***

Target word coverage analysis of the English-to-Russian SMT system before and after adding the morphological BNN models:

	Base	+BNN
reference/MT-search-space [top-1]	57.6%	59.0%
reference/MT-search-space [top-3]	70.7%	70.9%
reference/MT-search-space [top-30]	86.0%	85.0%
reference/MT-output	50.0%	50.7%

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