

Reading Comprehension in Czech via Machine Translation and Cross-lingual Transfer

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Abstract. Reading comprehension is a well studied task, with huge training datasets in English. This work focuses on building reading comprehension systems for Czech, without requiring any manually annotated Czech training data. First of all, we automatically translated SQuAD 1.1 and SQuAD 2.0 datasets to Czech to create training and development data, which we release at <http://hdl.handle.net/11234/1-3249>. We then trained and evaluated several BERT and XLM-RoBERTa baseline models. However, our main focus lies in cross-lingual transfer models. We report that a XLM-RoBERTa model trained on English data and evaluated on Czech achieves very competitive performance, only approximately 2 percent points worse than a model trained on the translated Czech data. This result is extremely good, considering the fact that the model has not seen any Czech data during training. The cross-lingual transfer approach is very flexible and provides a reading comprehension in any language, for which we have enough monolingual raw texts.

Keywords: Reading Comprehension · Czech · SQuAD · BERT · Cross-lingual Transfer.

1 Introduction

The goal of a reading comprehension system is to understand given text and return answers in response to questions about the text. In English, there exist many datasets for this task, some of them very large. In this work, we consider the frequently used SQuAD 1.1 dataset [12], an English reading comprehension dataset with around 100,000 question-answer pairs, which is widely used to train many different models with relatively good accuracy. We also utilize SQuAD 2.0 dataset [11], which combines SQuAD 1.1 dataset with 50,000 unanswerable questions linked to already existing paragraphs, making this dataset more challenging for reading comprehension systems.

In this paper, we pursue construction of a reading comprehension system for Czech without having any manually annotated Czech training data, by reusing English models and English datasets. Our contributions are:

- We translated both SQuAD 1.1 and SQuAD 2.0 to Czech by state-of-the-art machine translation system [10] and located the answers in the translated text using MorphoDiTa [13] and DeriNet [14], and released the dataset.

- We trained several baseline systems using BERT and XLM-RoBERTa architectures, notably a system trained on the translated Czech data, and a system which first translates a text and a question to English, uses an English model, and translates the answer back to Czech.
- We train and evaluate cross-lingual systems based on BERT and XLM-RoBERTa, which are trained on English and then evaluated directly on Czech. We report that such systems have very strong performance despite not using any Czech data nor Czech translation systems.

2 Related Work

There exist many English datasets for reading comprehension and question answering, the readers are referred for example to [12] for a nice overview.

Currently, the best models for solving reading comprehension are based on BERT architecture [4] (which is a method of unsupervised pre-training of contextualized word embeddings from raw texts), or on some follow-up models like ALBERT [7] or RoBERTa [9].

Most BERT-like models are trained on English, with two notable exceptions. Multilingual BERT (mBERT), released by [4], is a single language model pre-trained on monolingual corpora in 104 languages including Czech; XLM-RoBERTa (XLM-R) [2] is a similar model pre-trained on 100 languages, and is available in both *base* and *large* sizes, while only *base* mBERT is available.

Cross-lingual transfer capability of mBERT has been mentioned in 2019 by many authors, for example by Kondratyuk et al. [6] for morphosyntactic analysis or by Hsu et al. [5] for reading comprehension.

Very similar to our paper is the parallel independent work of Lewis et al. [8], who perform cross-lingual transfer evaluation of reading comprehension models on six non-English languages (neither of them being Czech).

3 Constructing Czech Reading Comprehension Dataset

The SQuAD 1.1 dataset consists of 23,215 paragraphs belonging to 536 articles. Attached to every paragraph is a set of questions, each with several possible answers, resulting in more than 100,000 questions. While the train and the development datasets are public, the test set is hidden. We refer the readers to [12] for details about the dataset construction, types of answers and reasoning required to answer the questions.

The SQuAD 2.0 dataset [11] extends SQuAD 1.1 with more than 50,000 unanswerable questions linked to the existing paragraphs.

3.1 Translating the Data and Locating the Answers

We employed the English-Czech state-of-the-art machine translation system [10] to translate the SQuAD data.¹ Translation of all texts, questions and answers of SQuAD 2.0 took 3 days.

¹ Available on-line at <https://lindat.mff.cuni.cz/services/translation/>.

Because the answers are subsequences of the given text in SQuAD, we also needed to locate the translated answers in the text. We considered several alternatives:

- Estimate the alignment of the source and target tokens using attention of the machine translation system, and choose the words aligned to the source answer. Unfortunately, we could not reliably extract alignment from the attention heads of a Transformer-based machine translation system.
- Mark the answer in the text before the translation, using for example quotation marks, similarly to [8]. Such an approach would however result in a dataset with every question linked to a custom text, which would deviate from the SQuAD structure.
- Locate the answer in the given text after the translation, without relying on the assistance from the machine translation system.

We chose the third alternative and located the translated answers in the texts as follows:

1. We lemmatized the translated text and answer using MorphoDiTa [13].
2. We replaced the lemmas by roots of their word-formation relation trees according to the DeriNet 2.0 lexicon [14].
3. Then we found all continuous subsequences of the text with the same DeriNet roots as the answer, but with any word order.
4. Finally, if several occurrences were located, we chose the one with the relative position in the text being the most similar to the relative position of the original answer in the original text.

We believe the proposed algorithm has substantially high precision (after manually verifying many of the located answers), and we also find its recall satisfactory. Notably, in the SQuAD 2.0 training dataset, we have preserved 107,088 questions (which is 82.2% of the English ones) and in the development dataset we kept 10,845 questions, 91.3% of the original dataset. The detailed sizes of the created Czech datasets are presented in Table 1. Note that the ratio of the kept data in SQuAD 1.1 is lower, because unanswerable questions of SQuAD 2.0 are always preserved.

The dataset is available for download at <http://hdl.handle.net/11234/1-3249>.

Table 1. Size of the translated Czech variant of SQuAD 1.1 and SQuAD 2.0.

Dataset		English Questions	Czech Questions	Percentage Kept
SQuAD 1.1	Train	87,599	64,164	73.2%
	Test	10,570	8,739	82.7%
SQuAD 2.0	Train	130,319	107,088	82.2%
	Test	11,873	10,845	91.3%

3.2 Evaluation Metrics

The SQuAD dataset is usually evaluated using two metrics: **exact match**, which is the accuracy of exactly predicted answers, and **F1-score** computed over individual words of the answers.

Given that Czech is a morphologically rich language, we performed lemmatization and then replaced lemmas by DeriNet roots (as in Section 3.1) prior to evaluation with the official evaluation script.

4 Model Training and Evaluation

Considering that the current best SQuAD models are all BERT based, we also employ a BERT-like architecture. We refer readers to [4] for detailed description of the model and the fine-tuning phase.

Because our main goal is Czech reading comprehension, we consider such BERT models which included Czech in their pre-training, notably Multilingual BERT (mBERT), released by [4], both cased and uncased, and also XLM-RoBERTa (XLM-R) [2], both *base* and *large*. As a reference, we also include English BERT *base*, both cased and uncased.

We finetuned all models using the 🤖 `transformers` library [15]. For all *base* models, we used two training epochs, learning rate $2e-5$ with linear warm-up of 256 steps and batch size 16; for XLM-RoBERTa we increased batch size to 32 and for XLM-RoBERTa *large* we decreased learning rate to $1.5e-5$ and increased warm-up to 500.

All our results are presented in Table 2 and also graphically in Figure 1.

English For reference, we trained and evaluated all above models on English SQuAD 1.1 and SQuAD 2.0. The results are consistent with the published results. It is worth noting that the only *large* model reaches considerably better performance, and that mBERT achieves better results than English BERT.

Czech Training, Czech Evaluation Our first baseline model is trained directly on the Czech training data and then evaluated on the development set. The relative performance of the BERT variants is very similar to English, but the absolute performance is considerably lower. Several facts could contribute to the performance decrease – a smaller training set, noise introduced by the translation system and morphological richness of the Czech language.

English Models, Czech Evaluation via Machine Translation Our second baseline system (denoted CS-EN-CS in the results) reuses English models to perform Czech reading comprehension – the Czech development set is first translated to English, the answers are then generated using English models, and finally translated back to Czech.

The translation-based approach has slightly higher performance for *base* models, which may be caused by the smaller size of the Czech training data. However, for the *large* model, the direct approach seems more beneficial.

Table 2. Development performance of English and Czech models on SQuAD 1.1, 2.0.

Model	Train	Dev	SQuAD 1.1		SQuAD 2.0	
			EM	F1	EM	F1
BERT cased	EN	EN	81.43%	88.88%	72.85%	76.03%
BERT uncased	EN	EN	80.92%	88.59%	73.35%	76.59%
mBERT cased	EN	EN	81.99%	89.10%	75.79%	78.76%
mBERT uncased	EN	EN	81.98%	89.27%	74.88%	77.98%
XLM-R base	EN	EN	80.91%	88.11%	74.07%	76.97%
XLM-R large	EN	EN	87.27%	93.24%	83.21%	86.23%
BERT cased	EN	CZ	9.53%	21.62%	53.48%	53.84%
BERT uncased	EN	CZ	6.16%	21.75%	54.78%	54.83%
mBERT cased	EN	CZ	59.49%	70.62%	58.28%	62.76%
mBERT uncased	EN	CZ	62.09%	73.89%	59.59%	63.89%
XLM-R base	EN	CZ	64.63%	75.85%	62.09%	65.93%
XLM-R large	EN	CZ	73.64%	84.07%	73.50%	77.58%
BERT cased	EN	CZ-EN-CZ	64.06%	76.78%	64.35%	69.11%
BERT uncased	EN	CZ-EN-CZ	63.57%	76.61%	65.26%	69.86%
mBERT cased	EN	CZ-EN-CZ	65.09%	77.47%	67.40%	71.96%
mBERT uncased	EN	CZ-EN-CZ	65.00%	77.38%	66.20%	70.72%
XLM-R base	EN	CZ-EN-CZ	64.52%	76.91%	65.62%	70.00%
XLM-R large	EN	CZ-EN-CZ	69.04%	81.33%	72.82%	78.04%
mBERT cased	CZ	CZ	59.49%	70.62%	66.60%	69.61%
mBERT uncased	CZ	CZ	62.11%	73.94%	64.96%	68.14%
XLM-R base	CZ	CZ	69.18%	78.71%	64.98%	68.15%
XLM-R large	CZ	CZ	76.39%	85.62%	75.57%	79.19%

Cross-lingual Transfer Models The most interesting experiment is the cross-lingual transfer of the English models, evaluated directly on Czech (without using any Czech data for training). Astonishingly, the results are very competitive with the other models evaluated on Czech, especially for XLM-R *large*, where there are within 1.6 percent points in F1 score and 2.75 percent points in exact match of the best Czech model.

4.1 Main Findings

Why Does Cross-lingual Transfer Work The performance of the cross-lingual transfer model is striking. Even if the model never saw any Czech reading comprehension data and it never saw any parallel Czech-English data, it reaches nearly the best results among all evaluated models.

This strong performance is an indication that mBERT and XLM-R represent different languages in the same shared space, without getting an explicit training signal in form of parallel data. Instead, we hypothesise that if there is a large-enough similarity among languages, the model exploits it by reusing the same part of the network to handle this phenomenon across multiple languages. This in turn saves capacity of the model and allows reaching higher likelihood, improving

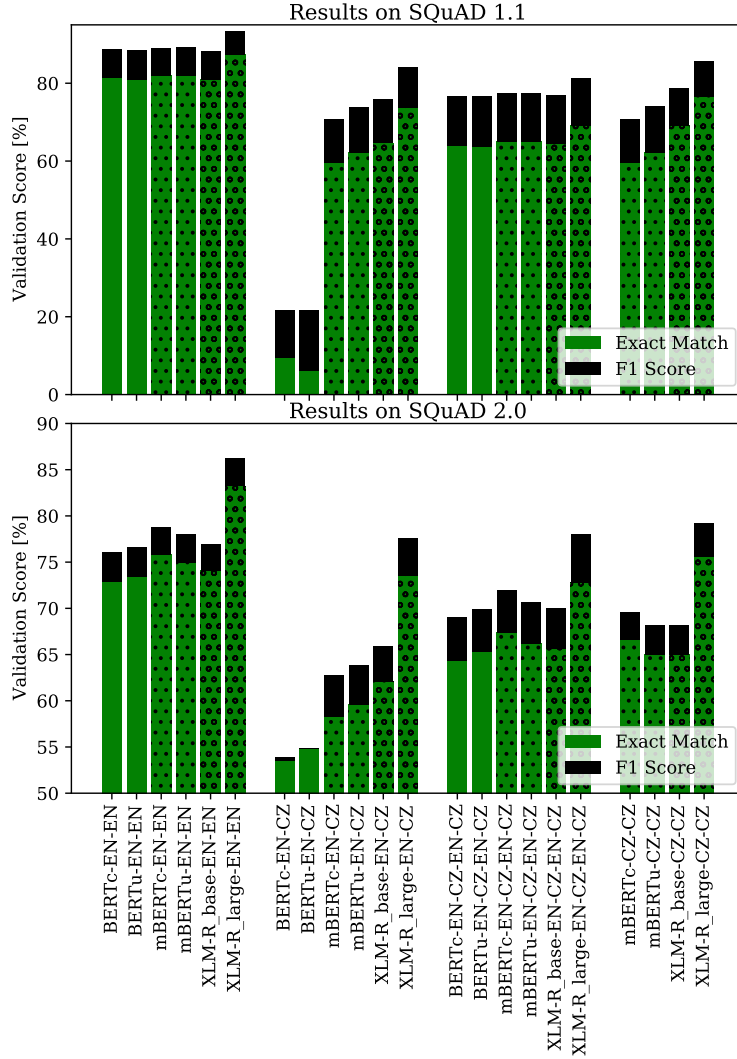


Fig. 1. Development set performance of all models for English and Czech SQuAD 1.1 and SQuAD 2.0 datasets.

the quality of the model. In other words, greedy decrease of a loss function performed by SGD is good enough motivation for representing similarities in a shared way across languages.

Furthermore, word embeddings for different languages demonstrate a remarkable amount of similarity even after a simple linear transformation, as demonstrated for example by [1] or [3]. Such similarities are definitely exploitable (and as indicated by the results also exploited) by BERT-like models to achieve shared representation of multiple languages.

Pre-training on Czech is Required The strong performance of cross-lingual models does not necessarily mean the models can “understand” Czech – the named entities could be similar enough in Czech and English, and the model could be capable of answering without understanding the question.

Therefore, we also considered an English reading comprehension model based on English BERT, which did not encounter any other language but English during pre-training. Evaluating such a model directly on Czech delivers surprisingly good performance on SQuAD 2.0 – the model is unexpectedly good in recognizing unanswerable questions. However, the performance of such model on SQuAD 1.1 is rudimentary – 9.53% exact match and 21.62% F1-score, compared to 62.90% exact match and 73.89% F1-score of an mBERT uncased model.

Cased versus Uncased Consistently with intuition, cased models seem to perform generally better than uncased. However, in the context of cross-lingual transfer, we repeatedly observed uncased models surpassing the cased ones. We hypothesise that this result could be caused by larger intersection of Czech and English subwords of the uncased models (which discard not only casing information, but also diacritical marks), because larger shared vocabulary could make the cross-lingual transfer easier.

5 Conclusion

In this paper, we have explored Czech reading comprehension without any manually annotated Czech training data. We trained several baseline BERT-like models using translated data, but most importantly we evaluated a cross-lingual transfer model trained on English and then evaluated directly on Czech. The performance of this model is exceptionally good, despite the fact that no Czech training data nor Czech translation system was needed to train it.

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