Slovenian Language Assistance Bot (SLAB)

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Abstract

Slavko je car!

Keywords

Large Language Models, Machine Translation, Conversational AI, Slovene, Question Answering

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Introduction

Natural Language Processing (NLP) is an exciting field of Artificial Intelligence that focuses on teaching machines how to understand and respond to human language. In this report, we will discuss our project for the Natural Language Processing course 2022/23, where we aim to develop a Slovenian Language Assistance Bot (SLAB) using NLP techniques. We will provide an overview of our preliminary research, discuss our idea to use a GPT-based model, and explore various data sources that we plan to use to train our model. Finally, we will discuss the importance of estimating the amount of data required to train a model effectively.

Related Work

Transformers & Large Language Models

Attention [1] is a key component of transformer models, which are widely used in natural language processing tasks such as language translation and text summarization. It is also a part of many modern large language models (LLM) that we will use during this project. In transformer models, attention mechanisms allow the model to focus on the most relevant parts of the input sequence at each step of processing. This is achieved by assigning weights to each element in the input sequence based on its relevance to the current step. By doing so, the transformer can capture long-range dependencies between different parts of the input sequence, which is particularly important for language processing.

SloBERTa [2] is a Slovene large language model. It is a large pre-trained masked language model based on the BERT architecture. The authors trained the model on a large corpus of Slovene text and evaluated it on various downstream tasks such as text classification, named entity recognition, and part-of-speech tagging. The results show that SloBERTa outperforms existing Slovene language models and achieves competitive performance with state-of-the-art multilingual language models.

We examine the alignment of language model paradigm using reinforcement learning such as InstructGPT [3]. However due to the lack of resources we instead focus our attention to using already compiled high quality datasets for a one-time training of our model. However their work points out the total number of collective prompts used in training their model, which was $77k$. This gives us an approximate estimate of how much data to use in the fine-tuning process. Additionally they discuss deduplication, however in future works such as [4] have pointed out that repeating prompts is not a big issue.

Datasets

The P3 dataset is a collection of prompted English datasets covering a diverse set of NLP tasks. The use of prompts allows for the creation of consistent and standardized data examples across different datasets, which can facilitate the development of new models and the comparison of results across different tasks [5].

A corpus of automatically annotated TV series subtitles for dialogue construction was developed in [6]. The authors used a combination of rule-based and machine-learning techniques to identify speaker turns and assign speaker identities. They evaluated their method on a corpus of subtitled TV series episodes and achieved high accuracy in speaker identification and turn-taking recognition. The resulting corpus was used for various downstream tasks such as emotion recognition and dialogue act classification.

GOS [7] is a reference corpus of spoken Slovene language. The methodology used to collect the corpus involved recording conversations of native Slovene speakers in various domains such as business, education, and social interactions.

The transcription process involved annotating the recordings with orthographic, phonetic, and prosodic information. The resulting corpus was used for various research tasks such as acoustic modeling, speaker recognition, and speech synthesis.

Alpaca [4] by Standford University is a set consisting of a data generation procedure, dataset, and training recipe. It is a fine tuned model from 7B LLaMA [8] on 52K instruction-following data generated by the techniques in the Self-Instruct [9] paper, with some modifications. In a preliminary human evaluation, it was found that the Alpaca 7B model behaves similarly to the GPT-3 model on the Self-Instruct instruction-following evaluation suite.

BLOOM [10] a multilingual LLM was trained on the ROOTS corpus [11], amounting to 1.61 terabytes of text that span 46 natural languages and 13 programming languages. Unfortunately Slovenian is not one of the available languages. However, due to vast collections of datasets available such as Hugging Face datasets [12], we focus on developing tools for robust translation in order to translate the large amounts of available data to Slovenian in order to facilitate the development of a conversational LLM.

SuperGLUE [13] is a benchmark for evaluating the performance of natural language understanding models. It consists of eight challenging natural language understanding tasks, including both textual entailment and commonsense reasoning tasks. The benchmark is designed to test the ability of models to handle more complex linguistic phenomena and to generalize to new examples. The authors compare the performance of several state-of-the-art models on SuperGLUE and find that there is still a significant gap between the best models and human performance.

The paper [14] discusses the challenges of question answering for less-resourced languages and presents an adaptation of the English UnifiedQA approach to the Slovene language. The adaptation uses encoder-decoder transformer models (SloT5 and mT5) to handle different question-answering formats, and existing Slovene adaptations of four datasets, as well as machine translation of the MCTest dataset. The study shows that a general model can perform at least as well as specialized models for answering questions in different formats. However, the performance of the Slovene model still lags behind that of English, and cross-lingual transfer from English is used to improve the results.

The paper "OpenAssistant: Aligning Large Language Models with Human Preferences using Open-Source Conversations" [15] presents a new corpus of human-generated, human-annotated assistant-style conversations called OpenAssistant Conversations. The corpus consists of 161,443 messages distributed across 66,497 conversation trees, in 35 different languages, annotated with 461,292 quality ratings, and was created through a worldwide crowd-sourcing effort involving over 13,500 volunteers. The authors also release their code and data under fully permissive licenses, making their work easily accessible to the wider research community.

Initial Plan

Due to large amounts of conversational datasets being available in other languages. We focus on translating the most widely used and well-composed datasets into Slovenian. For this reason, one of our main tasks is developing a framework for robust translation from English to Slovene.

Our initial idea for doing this is to use multiple methods of translation and aggregate the results in a meaningful way. To this aim we consider the Slovene NMT [16], NLLB-200 [17], DeeplTranslator [18], GoogleTranslate [19], or other open-source translator supported by the deep translator python library [20]. The initial idea is to produce a metric of agreement on the individual translations and in this way filter the translated data. This should reduce the individual mistakes of each of the used methods and yield at least some usable data for further use.

For evaluating the quality of translations and generating new data examples we look at adapting the Self-Instruct [9] pipeline for self supervised data filtering.

An interesting remark in the recent GPT-4 report by Openai claims that pre-training had much more of an effect on the performance of the model as opposed to fine-tuning. However, we disclaim that this is a statement we are not able to verify as thier results are not reporoducible. Still, they have been in the foreground of the recent LLM developments so, we also put an emphasis on using and looking into additional resources for unsupervised pre-training for the Slovenian language.

To this purpose we examine the following resources; the NLP projects of other groups and large Slovenian language corpuses such as Gigafida [21] and ccKRES [22] , we also consider the Šolar corpus [23], with considerations that the written language of primary and high school students could potentially have an impact on the models performance, and GOS [7] with similar considerations about spoken language.

Methods

Recently the OpenAssistant Conversations Dataset (OASST1) has been released. We focus on translating the dataset in the conversation tree form where multiple replies can be nested to form conversations. We select a subset of trees that are "ready for export" as they have deleted spam messages and do not contain low quality messages and trees with only one prompt. Since OASST1 contains messages in various languages we translated the messages only from the 4 most common langauges in the dataset: namely english, spanish, russian and german. Some of the messages also contain code which was replaced with a predefined substring at the time of translation. The reason for this is that the tested translators translate literally which does not preserve keywords and other integral parts of code. With the use of the deep translator library and google translate we translate 8654 trees which totals to 78474 messages. We observe that the translations obtained using google translate are of good quality. Some of the other translators also provide fairly good translations but overall google

translate performs best.

We're currently in the process of setting up Slovene NMT to get another source for translations. After this we will use this data (possibly only a subset) to train a smaller model such as T5 to see how well it can converse in Slovene.

Results

Discussion

Acknowledgments

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