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NLP Methods for Automated Fact-Checking

Dissertation Minimum Study of
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Chapter **1**
Introduction

My dissertation, as well my long-term research, centers around the field of *automated fact checking* through the means of Natural Language Processing (NLP) and its modern methods. The work consists of the analysis of the whole fact-checking process, its subdivision and simplification into tasks that can be efficiently addressed using the current state-of-the-art NLP methods, collection of data appropriate to benchmark such tasks, delivery of example solutions and their validation against similar research in other languages and related tasks.

The main focus of mine and of our research group are the fact-checking-related tasks in the West Slavic languages (Czech, Slovak and Polish) and secondarily in English. My contribution has so far been the collection and publication of novel datasets for the fact-checking task and its subroutines, models trained for the tasks and their debate, including the ongoing establishment of metrics that would explainably rate the model success and error rates in terms close to the human notion of *facticity* (which proves to be a challenge on its own, requiring another round of novel research [Koto et al., 2020, Wright et al., 2022]).

My doctoral aim is to cover every step on the path from gathering a factual claim – for example, extracting it from a political debate – to predicting its veracity verdict and justifying it rigorously with hard data. With the recent boom in NLP beginning with the advent of transformer networks and later the Large Language Models (LLMs) [Zhao et al., 2023], few-shot learning [Brown et al., 2020] and prompting [Liu et al., 2023a] a significant part of the research is and has to be an appropriate and timely adoption of new ever-evolvingstate-of-the-art NLP solutions, based on well-designed studies in our specific context.

Overall, my agenda is to follow up on my published research on fact checking in Czech with methods that reiterate on our results in other languages and evolving our previous methodology based on transformer *pre-training & fine-tuning* paradigm to a computationally feasible design based on LLMs, which are already exhibiting superiority tasks similar to ours [Chen et al., 2023] in English.

My recent focus within the whole grand fact-checking scheme is the step of *claim generation*, which I aim to establish among the other commonly benchmarked NLP tasks within the scientific community, adjacent to that of *abstractive summarization*. To benchmark the task, one would need a set of metrics that properly reflect phenomena such as *model hallucinations* – a common problem of modern day LLMs [Ji et al., 2023]. As the exact word-level metrics for NLP generative tasks do not correlate well with human judgement [Zhang* et al., 2020] and model-based metrics are hard to explain, my research also focuses on a delivery of a set of human-understandable model-based metrics.

The goal of this study is to show the directions I am taking to address these challenges, reasoning behind them, my research questions and current results that motivated them.

Figure 1.1: A real world example of fact checking done by `https://politifact.org`

1.1 Motivation

The spread of misinformation in the online space has a growing influence on the Czech public [STEM, 2021]. It has been shown to influence people's behaviour on the social networks [Lazer et al., 2018] as well as their decisions in elections [Allcott and Gentzkow, 2017], and real-world reasoning, which has shown increasingly harmful during the COVID-19 pandemic [Barua et al., 2020] and the Russo-Ukrainian war [Stănescu, 2022].

The recent advances in artificial intelligence have unintentedly contributed to the spread of misinformation on social media [Buchanan and Benson, 2019], as well as they hold a large potential for the false content generation [Sebastian, 2023].

Recent research has shown promising results [Thorne et al., 2019] in false claim detection for data in English, using a trusted knowledge base of true claims (for research purposes typically fixed to the corpus of Wikipedia articles), mimicking the *fact-checking* efforts in journalism.

Fact-checking (Figure 1.1) is a process of matching every information within a *factual claim* to its *evidence* (or *disproof*) in trusted data sources to infer the claim veracity and verifiability. In exchange, if the trusted *knowledge base* contains a set of "ground truths" sufficient to fully infer the original claim or its negation, the claim is labelled as **supported** or **refuted**, respectively. If no such *evidence set* can be found, the claim is marked as **unverifiable**[1].

1.2 Automated Fact Checking

Despite the existence of end-to-end fact-checking services, such as `politifact.org` or `demagog.cz`, the human-powered approach shows weaknesses in its scalability. By design, the process of finding an exhaustive set of evidence that decides the claim veracity is much

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[1]Hereinafter labelled as NOT ENOUGH INFO, in accordance to related research.

Figure 1.2: Automated fact-checking pipeline, reprinted from [Guo et al., 2022]

slower than that of generating false or misguiding claims. Therefore, efforts have been made to move part of the load to a computer program that can run without supervision.

The common research goal is a fact verification tool that would, given a claim, semantically search provided knowledge base (stored for example as a *corpus* of some natural language), propose a set of evidence (e. g. k semantically nearest paragraphs of the corpus) and suggest the final verdict (Figure 1.2) [Guo et al., 2022]. This would reduce the fact-checker's workload to mere adjustments of the proposed result and correction of mistakes on the computer side.

The goals of the ongoing efforts of FactCheck team at AIC CTU, are to explore and adapt the state-of-the-art methods used for fact verification or similar tasks in other languages, currate appropriate datasets for it and propose strong systems for such a task in Czech.

1.3 A word on the Transformers

For the past six years, the state-of-the-art solution for nearly every Natural Language Processing task is based on the concept of *transformer networks* or, simply, *Transformers*. This has been a major breakthrough in the field by [Vaswani et al., 2017], giving birth to the famous models such as Google's BERT encoder [Devlin et al., 2019] and its descendants, or the OpenAI's GPT-3 decoder [Brown et al., 2020] and GPT-4 [OpenAI, 2023] that are used in the booming online AI service ChatGPT[2].

In our proposed methods, we use Transformers in every step of the fact verification pipeline. Therefore, we would like to introduce this concept to our reader to begin with.

Transformer is a neural model for *sequence-to-sequence* tasks, which, similarly e.g. to the *LSTM-Networks* [Cheng et al., 2016], uses the Encoder–Decoder architecture. Its main point is that of using solely the *self-attention* mechanism to represent its input and output, instead of any sequence-aligned recurrence [Vaswani et al., 2017].

In essence, the *self-attention* (also known as the *intra-attention*) transforms every input vector to a weighted sum of the vectors in its neighbourhood, weighted by their *relatedness* to the input. One could illustrate this on the *euphony* in music, where every tone of a song relates to all of the precedent and successive ones, to some more than to the others.

The full Transformer architecture is depicted in Figure 1.3.

1.4 Dissertation minimum study outline

■ **Chapter 1** introduces the dissertation topic, motivates the research sets up our chal-

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[2]https://chat.openai.com

Figure 1.3: Transformer model architecture, reprinted from [Vaswani et al., 2017]

lenges for the future research

- **Chapter 2** examines the most relevant research in the field and tries to highlight the recent paradigm shift from models trained for a single task to a single large models that perform well in everything

- **Chapter 3** explains our current contributions to the field of automated fact-checking and NLP in Czech

- **Chapter 4** describes our plan for the dissertation and justifies the directions we are taking

- Finally, **Chapter 5** concludes the study with a wrapup of its findings

Chapter 2
State of the Art

This chapter will first describe the originally popular models for general NLP such as BERT and the recent paradigm shift from *pretrain + finetune* transfer learning framework popular since the original [Devlin et al., 2019] paper to the currently booming LLMs which often outperform the smaller models even without the fine-tuning step [OpenAI, 2023, Touvron et al., 2023a, Vicuna, 2023]. We will then take a look at the performance optimization methods that enable training multi-billion parameter pre-trained models on a set of task-specific data on a single GPU and their potential for our research.

To show how it relates to our main topics, we are gonna introduce currently published approaches for the automated fact-checking task, efforts related to claim generation and evaluation of NLP model outputs.

2.1 Pretrain + Finetune

For the last decade, the *pretrain-finetune* paradigm has been a cornerstone in the field of Natural Language Processing (NLP) and has significantly shaped the development of modern NLP models. Its history in NLP can be traced back to the advent of neural networks and deep learning in the early 2010s. Initially, researchers pre-trained word embeddings using methods like Word2Vec [Mikolov et al., 2013] and GloVe [Pennington et al., 2014] which captured semantic relationships among words and then tweaked the general-task models for various related tasks.

2.1.1 BERT and derivatives

The *pretrain-finetune* paradigm truly rose to fame with the introduction of transformer-based models, particularly the revolutionary BERT (Bidirectional Encoder Representations from Transformers) in 2018. BERT [Devlin et al., 2019] demonstrated the power of pretraining large-scale language models on massive text corpora using an easy-to-automate general task such as *Masked Language Modeling*, or *Next Sentence Prediction*, followed by fine-tuning on specific downstream tasks using smaller, harder to obtain data. This approach achieved state-of-the-art results across various NLP benchmarks. Subsequently, numerous variations of pre-trained models like GPT (Generative Pre-trained Transformer) and RoBERTa emerged, each refining the pretrain-finetune paradigm to improve language understanding, generation, and transfer learning capabilities.

Importantly, BERT's success inspired a number of publications in training similar transformer models, varying in the definition of the general pre-training task, model size, architecture training corpus

- In Czech language, monolingual models CZERT [Sido et al., 2021], FERNET [Lehečka and Švec, 2021], RobeCzech [Straka et al., 2021], and small-e-czech [Kocián et al., 2021] are available for further finetuning

- In Polish, HerBERT [Mroczkowski et al., 2021] achieved state of the art in multiple tasks in 2021

- In Slovak, SlovakBERT [Pikuliak et al., 2021] was released by KInIT and Gerulata

- A multitude of multilingual models, such as M-BERT or XLM-RoBERTa [Conneau et al., 2019] were pretrained on data in all three of these languages (and many others), proving that the large transformers can capture a notion of semantics and relations between pieces of text even *without* the convenient constriction of a single language

2.2 Few-shot and Zero-shot learning

The ever-growing (sometimes, billions of parameters in size) transformer models have not only demonstrated superior performance on benchmark datasets but have also shown remarkable zero-shot and few-shot learning abilities, where they can perform tasks with minimal or no task-specific training data [Brown et al., 2020].

Few-shot learning refers to the capability of a model to perform a task when provided with only a limited amount of labeled examples. Zero-shot learning takes this concept a step further by enabling models to tackle tasks they have never seen during training. The integration of these learning paradigms into large language models like GPT-3 and subsequent iterations has spread the NLP hype even further. By utilizing a prompt or a few examples, these models can quickly adapt to new tasks, making them highly versatile, adaptable and usable to the general public.

2.2.1 OpenAI LLMs: GPT-3 and GPT-4

In 2020, the few-shot learning was exhibited on GPT3 – a 175B-parameter autoregressive model trained by [Brown et al., 2020]. The model was trained on the task of generating text based on user's and its own previous outputs. The training procedure and data[1] is throughly described in the publication, however, is prohibitively costly for most labs to reproduce, or even fine-tune at such scale.

In the fall of 2022, GPT-3 became widely popular thanks to its ChatGPT[2] fine-tune and demonstration app, which puts the user in the role of *prompter*, texting back and forth with an LLM that predicts the most fitting reply to each conversation.

With the arrival of GPT-4, the ChatGPT was already massively famous, and the new model already shipped with a paid-service business scheme no longer publishing the training data, tasks or even model size [OpenAI, 2023].

2.3 Open source LLMs

This puts the research community in an awkward position, as the GPT-4 achieves the state of the art in numerous NLP benchmarks [OpenAI, 2023, Liu et al., 2023b], but is

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[1]A mixture of crawled websites, books and Wikipedia.
[2]https://chat.openai.com

designed not to be used in any way other than as a black box, making the derived research rigorosity and reproducibility disputable.

From the prediction times, OpenAI claims and general trends in NLP, there are also reasons to believe that GPT-4 is orders of magnitude larger than already wasteful GPT-3. This motivates an uptick in research of other LLMs that would be able to operate on smaller scale with similar results, using a peer-reviewed architecture, training scheme and data that is available in open source.

2.3.1 LLaMA-2 and derivatives

A popular foundational LLM to compete with the GPT family has become the LLaMA [Touvron et al., 2023a] from Meta research. LLaMA was trained on about 5TB of publicly available textual data[3] mostly in English.

It comes in various sizes between 7B and 65B parameters, achieving a SOTA among open-source solvers in various tasks, and an unmatched performance in the field of single-GPU (7B and 13B) model sizes. LLaMA proceeds to be used as a goto base model for a number of successful open-source chatbots such as Alpaca [Taori et al., 2023], Vicuna [Vicuna, 2023], and OpenAssistant [Köpf et al., 2023].

The pretrained LLaMA weights are, however, published under a restrictive license that prohibits republishing the model weights even after tuning its parameters, which limits its fine-tuners to publishing delta- or xor-weights that can not be properly used without Meta's permission.

LLaMA-2 [Touvron et al., 2023b] addresses this inconvenience (as well as delivers its own take on the *chatbot* task), yielding an ideal strong base model for experimentation with any NLP task in 7B, 13B and 70B sizes. The only obstacle left in the way is the computational cost of fine-tuning across so many parameters.

2.3.2 LoRA and other optimization

To be able to fine-tune multi-billion-parameter models such as LLaMA-2 [Touvron et al., 2023b] on a single TPU, successful approaches have been published to dramatically cutdown the training expenses. Parameter-efficient fine-tuning (PEFT) [Liu et al., 2022] proposes approaches to only fine-tune *a few* weights as opposed to the whole neural network, reducing the number of trainable parameters by orders of magnitude. Low-Rank Adaptation of Large Language Models (LoRA) [Hu et al., 2021] does so by freezing the pre-trained model weights and injecting trainable rank decomposition matrices into each layer of Transformer architecture.

Quantization, which cuts the costs of working with 32- or 16-bit float parameters and opting for data types of bitsize as small as 4, also proves to be a powerful tool for LLM finetuning performance optimization [Dettmers et al., 2023]. Quantized QLoRA takes LLaMA and finetunes it into a Guanaco model family which outperforms all previous openly released LLMs on Vicuna benchmark [Dettmers et al., 2023] and achieves 99.3% of the ChatGPT's performance on it while only requiring 24 hours on a single GPU.

As per an alleged leaked Google's memo [Patel and Ahmad, 2023], this could put the future state of the art in NLP disciplines back into the hands of open source and public research, not giving any of the big tech companies a "moat" advantage.

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[3]To be specific, LLaMA was trained using an autoregressive language modelling task on a mixture of English CommonCrawl Corpus, C4 [Raffel et al., 2020], Github, Wikipedia, project Gutenberg, Books3 corpus, ArXiv and Stack Exchange

Either way, it goes to show that the open-source LLMs have a promising future in NLP and will be indismissible as an approach for the NLP task of *Automated fact checking.*

2.4 Fact checking approaches

Back in the late 2010s, the misinformation and its spread in the era of internet and social media became a discussed topic in the Western world, multiple institutions such as European Council marking it a severe threat to democracy and national safety [Wardle and Derakhshan, 2017]. The public attention and maturation of appropriate technologies motivated numerous efforts in business and academia to tackle the challenge. Among other events, a Fake News Challenge occured in 2017 [Pomerlau and Rao, 2017] exploring the uses of technologies in the field and applying, for example, the LSTMs to detect stances among textual data [Hanselowski et al., 2018].

2.4.1 FEVER and followups

Soon, standard tasks started being formulated and data collected. The FEVER (Fact Extraction and VERification) [Thorne et al., 2018a] dataset and shared task rose to prominence in natural language processing research. Relatively early on, it formalized the task as a two-step problem of:

1. Retrieving information within a structured corpus to fact-check a given claim (this resembles a standard NLP problem called *information retrieval* – IR)

2. Classifying the inference relation between retrieved information and claim as one of:

    a. **supports** – information semantically implies the claim
    b. **refutes** – information semantically implies the negation of the claim
    c. **not enough info** otherwise

    This classification task became known as *natural language inference* and mostly replaced the previous binary classification NLP task of *recognizing textual entailment* (RTE)

The FEVER dataset was a collection of 185K human-annotated claims, their veracity labels, and sets of evidence from a structured corpus that sufficed to justify the labels. The corpus of choice was a 2017 English Wikipedia structured into articles, due to its reasonable size, informational richness and open license.[4]

FEVER yields interesting benchmark with statistically quantifiable model success, motivated multiple interesting public solutions [Thorne et al., 2018b, Thorne et al., 2019], gives insights into the complexities of automated fact-checking task and strong baselines for research in the field. The data was later enriched by contrastive evidence in VitaminC [Schuster et al., 2021] and by reasoning over tabular data in FEVEROUS [Aly et al., 2021].

To date, it keeps being a reference point in the automated fact checking research despite its limitations, such as its requirement for a fixed knowledge base and "atomicity"[5] of claims.

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[4]Is Wikipedia a trustworthy informatial canon though? No, it is not supposed to – FEVER states that it is crucial to always maintain that the fact-checking classifiers only classify *with respect to* data and their reliability goes only as far as that of the underlying knowledge corpus. Therefore, *supports* does not directly translate to *true*, nor *refutes* to *false*

[5]See section 4.1.2.3

◖◗ 🇨🇿 Open-Domain Fact Checking (Bing API & GPT-3.5)

This is a prototype CEDMO application to fact-check a real-world text.

Text to extract

Stříž se jednoznačně vyjádřil, že ministr spravedlnosti Pavel Blažek není prověřován.

Speaker

Eva Decroix

Affiliation

ODS

Date

20.08.2023

[Clear] [Submit]

👍 **Částečně souhlasí**

Je Pavel Blažek ministr spravedlnosti?

Pavel Blažek – Wikipedie

Pavel Blažek (* 8. dubna 1969 Brno) je český právník, v letech 2012 až 2013 **ministr spravedlnosti ČR** ve vládě Petra Nečase a znovu od prosince 2021 **ministr spravedlnosti ČR** ve vládě Petra Fialy, v letech 2010 až 2014 místopředseda ODS, od října 2013 poslanec Poslanecké sněmovny PČR, v letech 2002 až 2014 zastupitel města …
👏 **Souhlasí**

Pavel Blažek | Vláda ČR - vlada.cz

Pavel Blažek. ministr spravedlnosti. Pavel Blažek se narodil v Brně, kde vystudoval Právnickou fakultu Masarykovy univerzity. V letech 1992–2002 působil jako interní učitel na Právnické fakultě MU v Brně, **obor správní právo** a **správní věda.**
‼️ Úplný výmysl

Je Pavel Blažek prověřován?

Pavel Blažek - Wikipedie

Prezident republiky jej členem Nečasovy vlády jmenoval 3.

července 2012 v 10 hodin. Obvinění z trestného činu Dne 31. července 2012 publicista Jan Urban a obecně prospěšná organizace Kverulant.org zveřejnili prohlášení, ve kterém obvinili Pavla Blažka ze spáchání trestného činu podle **§ 209 trestního zákoníku** – podvodu.
👍 **Částečně souhlasí**

Figure 2.1: Proof-of-concept Czech fact-checking based on live-internet search (Bing API) and LLM prompting, based on the proposals of [Chen et al., 2023] in Czech, using a real-world claim that was fact-checked by `demagog.cz` in June 2023

2.4.2 Open-domain fact-checking

Due to these limitations, some researchers consider the scheme from FEVER an oversimplification – the real politics' claims to be fact-checked by journalists often consist of long syntactical structures, combine information together in a non-trivial manner and often require the most up-to-date evidence.

"Complex Claim Verification with Evidence Retrieved in the Wild" [Chen et al., 2023] proposes a different scheme that overcomes these shortcomings:

1. Arbitrarily complex claim is decomposed into a set of yes/no questions

2. An open-domain search (bing is proposed in the paper) fetches several evidence documents for each question

3. A claim-focused summary is extraced from each document

4. A veracity classifier goes through each pair of evidence and question, ranging from "faithful" to "completely wrong"

5. The scores are combined (all need to be "faithful" for a faithful claim, otherwise, a severity of inaccuracies can be approximated using some averaging

GPT-3 is used in steps 1, 3 and 4 of the scheme in the prototype delivered in [Chen et al., 2023] in a few- and zero-shot fashion, few-shot unsurprisingly coming out a little better. The scheme is transducible to Czech and Figure 2.1 shows my early experiments

with my interactive reproduction of it, predictors based on Bing and GPT-3.5 (a polished version of GPT-3).

While the shift from an established FEVER framework to complex real-world claims and evidence retrieval "in the wild" feels exciting and practical, an obvious pitfall arises – anyone can publish anything on internet, having it appear in Bing search and other crawlers alike. I argue that this might lead into a sort of a circular dependency of needing to reliably fact-check the evidence we have retrieved from the web, in order to be able to build a reliable fact-checker in the first place.

Anyhow, the open-domain fact-checking idea opens a whole new range of approaches and shows the power of LLMs in fact-checking at its every step.

2.5 Claim generation

Another step of the fact-checking pipeline, covered by very few research publications, is the generation of the claim to be checked in the first place [Guo et al., 2022].

The current state of things is that journalists that fact-check statements within, say, a Facebook status, need to read through the whole document multiple times, formulate its factual claims from the stances and facts expressed in text themselves and then fact-check each of them separately.

What has been examined so far were for example:

- Using Question Generation (QG) solver and converting them into a declarative sentences to emulate more claims and more data for fact checking [Pan et al., 2021]

- Numerous CLEF CheckThat! challenges explored the task of estimating *checkworthiness* of different parts of a long texts, such as lines in a political debate [Elsayed et al., 2021, Nakov et al., 2021]

- The task of extreme summarization (XSum) consists of summarizing a long body of text into a single sentence, focusing on its most relevant aspects and facts. Large datasets XSum [Narayan et al., 2018] in English and XL-Sum [Hasan et al., 2021] in 44 languages both present expertly annotated data from BBC news for it, as their article standard features a single-sentence summary at the beginning of each text.

2.5.1 NLP summarization benchmarking

An important caveat to note with the NLP tasks reducing longer text to shorter text – such as summarization or claim extraction – is that the standard automatic metrics such as ROUGE [Lin, 2004] and METEOR [Banerjee and Lavie, 2005] only focus on the *content selection* aspect of tasks, based on a word-by-word overlap and were designed to use on multiple gold summaries per input, which are not often provided with modern large-scale datasets. [NLP-Progress, 2023, Zhang* et al., 2020, Zha et al., 2023]

These serious limitations make it questionable for anyone to claim state of the art on these tasks and motivate research for new metrics to cover all the important aspects of claim generation and do so in correlation with expert human judgment.

This will be the topic of section 4.1.2, which also introduces the state-of-the-art research we are working with to arrive to a valid set of benchmarks.

Chapter 3

Current Contribution

We have collected novel data for the fact-checking task in our application context, emulated and scraped inavailable datasets making them public or readying them for doing so, we have established numerous state-of-the-art models and we are currently working on establishing the topic of claim generation as a summarization-related NLP task.

3.1 Datasets

Having the automated fact-checking scheme established in chapter 2, every machine-learning solution must start with the choice or collection of appropriate training data. Due to the novelty of the task in Czech and other West Slavic languages, I explored a multitude of ways to acquire such data, many of them resulting in a publicly available dataset in our Huggingface repository [1], beginning to be reused by others.

3.1.1 CsFEVER

An early "temporary benchmark" for our endeavours in adapting the FEVER [Thorne et al., 2018a] task for the Czech context was the CsFEVER [Ullrich et al., 2023] dataset.

In [Ullrich, 2021], I have proposed a simple FEVER data transduction scheme that can be simplified as follows:

1. Each FEVER claim is translated using the (at the time maturing) Machine Translator

2. Evidence from English Wikipedia is not translated using MT, but mapped onto its Czech-Wikipedia counterpart using the publicly available Wikidata[2]

3. Data with any loss in evidence due to the step 2. is discarded

This design was relatively cheap to compute (as translating the whole 2017 Wikipedia corpus would have been a long and wasteful computation), delivering an open-license dataset of 127K claims, their labels and evidence justifications. My hope was, as both the 2017 EnWiki and our 2020 CsWiki corpus only featured the first paragraph (abstract) of each article, a document-level alignment could be assumed – both the Czech and English text always summarize the basic facts about the same entity.

This showed to be only partly true as a later human annotation on a 1% sample of CsFEVER data showed that about a third of data exhibits some levels of noise, mostly introduced during dataset translation [Ullrich et al., 2023].

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[1] `https://huggingface.co/ctu-aic`

[2] Used, for example, for showing the "see this article in other languages" suggestions in Wikipedia sidebar

While noisy, the CsFEVER data still got its use in training of the information retrieval schemes of [Rýpar, 2021, Gažo, 2021, Ullrich et al., 2023] used to this day and is openly available[3] under a CC license.

My research on it also motivated a creation of a inference-only version of the dataset, which does not support the Information Retrieval task and therefore, does not require the mapping of evidence into a live version of Wikipedia. Therefore, only the EnWiki *excerpts* needed to build evidence can be translated, bringing down the computational difficulty and enabling me to deliver a dataset without the transduction noise called CsFEVER-NLI[4].

Another round of research CsFEVER motivated and I supervised was the successful thesis of [Mlynář, 2023], modernizing the data and machine-translation methods into the 2023 state of the art. [Mlynář, 2023] further experimented with methods of automated noise detection and removal, which has not shown to be an efficient way to tackle the issue of high noise in CsFEVER.

However, it delivers a partly cleaned versions of it[5] and motivates a future research of generating such data differently, using a claim generation scheme like that from [Pan et al., 2021].

3.1.2 FCheck Annotations Platform

The imperfections in translated CsFEVER data, as well as the ongoing colaboration with ČTK and the Faculty of Social Sciences brought me to also look for ways how to hand-annotate a whole new natively Czech dataset, which would both lack the noise of translated data and take the task of automated fact checking to next level, replacing a rigid, simple Wikipedic data with a more "real world" news report corpus of ČTK.

Figure 3.1 shows an open-source platform FCheck[6] I developed to collaborate with 316 FSV CUNI students of on a collection of novel dataset in Czech using ČTK data as a ground truth corpus.

Figure 3.1: FCheck – platform for fact-checking data collection developed for TAČR project; collects data for claim generation, information retrieval and natural language inference tasks

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[3]https://huggingface.co/datasets/ctu-aic/csfever
[4]https://huggingface.co/datasets/ctu-aic/csfever_nli
[5]https://huggingface.co/datasets/ctu-aic/csfever_v2
[6]https://fcheck.fel.cvut.cz (testuser), source at: github.com/aic-factcheck/fcheck-annotations-platform

We have established a 4-step annotation procedure inspired by the time-proven methodology of [Thorne et al., 2018a] where chech-worthy paragraphs are first hand-picked among samples from the whole archive of ČTK's 3.3 M news reports published between 1 January 2000 and 6 March 2019. Then, the annotator is sampled such a paragraph and asked to *extract claims* from it, i.e., formulate single-sentence summaries of some facts that appear in paragraph. This claim is always *supported* by the data, so the next phase is to perturb the claim by annotator's world knowledge and form the claim *mutations* – substitutions of entities, generalizations, specifications, paraphrases or negations of the original claim. The mutated claim is then fact-checked by (typically) another annotator, using the ČTK data narrowed down to a reasonable number of relevant articles (in an IR sense) as *supportable*, *refutable* or *not enough info*, providing a set of evidence as a verdict justification.

The whole application is running on multiple levels – a yii-framework-powered PHP app is running the annotation interface, while a flask server in python is running our models based on TF-IDF [Chen et al., 2017] and mBERT (section 2.1.1) for information retrieval trained among other data on the CsFEVER dataset (section 3.1.1). The models are solving the Information Retrieval task on-demand (with cache) on the proprietary ČTK corpus, whenever the annotation app needs it to provide a context to the fact-checker.

The scheme and its implementations are exhaustively described in [Ullrich, 2021], chapter 4 and in [Ullrich et al., 2023], also chapter 4. Multiple "cross-annotations" were collected for each claim, to measure agreement and give insights into task complexity.

■ 3.1.3 CTKFacts

After completing the first year of annotation experiments, we have extracted a total of 3,116 multi-annotated claims. 47% were SUPPORTed by the majority of their annotations, REFUTES and NEI labels were approximately even, the full distribution of labels is listed in Table 3.1.

	CTKFacts uncleaned, balanced			**CTKFacts (launch)** cleaned, stratified		
	SUPPORTS	REFUTES	NEI	SUPPORTS	REFUTES	NEI
train	1,164	549	503	1,104	556	723
dev	100	100	100	142	85	105
test	200	200	200	176	79	127

Table 3.1: Label distribution in CTKFacts splits before and after cleaning. Reprinted from [Ullrich et al., 2023]

Of all the annotated claims, 1,776, that is 57%, had at least two independent labels assigned by different annotators. I used this multiplicity to asses the quality of our data and ambiguity of the task, as well as to propose annotation cleaning methods used to arrive to our final cleaned CTKFacts dataset.

■ Inter-Annotator Agreement

Due to our cross-annotation design, I had generously sized sample of independently annotated labels in our hands. As the total number of annotators was greater than 2, and as missing observations were allowed, I have used the Krippendorff's alpha measure [Krippendorff, 1970] which is the standard for this case [Hayes and Krippendorff, 2007]. For the comparison with [Thorne et al., 2018a] and [Nørregaard and Derczynski, 2021], I also list a 4-way Fleiss' κ-agreement [Fleiss, 1971] calculated on a sample of 7.5% claims.

I have calculated the resulting Krippendorff's alpha agreement to be 56.42% and Fleiss' κ to be 63% and interpreted this as an adequate result that testifies to the complexity of the task of news-based fact verification within a fixed knowledge scope. It also encourages a round of annotation cleaning experiments that would exploit the number of cross-annotated claims to remove common types of noise.

■ CTKFᴀᴄᴛs publication

CTKFᴀᴄᴛs dataset was then subject to a thorough human-in-the-loop data cleaning until a 100% agreement among the data was reached, in order to remove data that contains obvious noise and reveal phenomena that lead to erroneous annotations. The full process as well as it results are described in [Ullrich et al., 2023].

Ultimately, a dataset of 3.1K thoroughly cleaned data points in a form of a factual claim, its veracity label and justifications consisting of ČTK paragraphs was published in a version for Information Retrieval[7] for those who have access to the ČTK knowledge base to retrieve from, as well as in a special version for the task of Natural Language Inference[8] containing all the required ČTK excerpts we have negotiated to publish under open license for everyone to use.

The datasets have become our standard benchmark within the AIC NLP group [Semin, 2023, Mlynář, 2023] and are starting to be referred and used in others' research in the field [Štefánik et al., 2023].

■ 3.1.4 Other NLP datasets in West Slavic languages

Over the time, we have accumulated numerous sets of data in Czech and other Slavic languages that have previously been poorly covered or not available at all, some of which are to be referred in our future publications. For the convenience of others, most of them are already listed in our public repositories. Let us mention some significant examples:

1. We have machine-translated the most popular NLI training and benchmark datasets such as Stanford NLI [Bowman et al., 2015], Adversarial NLI [Nie et al., 2019b] and MultiNLI [Williams et al., 2018] picking a machine translator empirically for each dataset between DeepL [DeepL, 2021], Google Translate [Google, 2021] and CUB-BITT [Popel et al., 2020].

    The resulting datasets can are maintained at our public repositories:

    a. `https://huggingface.co/datasets/ctu-aic/snli_cs`
    b. `https://huggingface.co/datasets/ctu-aic/anli_cs`
    c. `https://huggingface.co/datasets/ctu-aic/multinli_cs`

2. For the task of claim generation we are establishing and performing in Czech, we have adapted the existing related datasets and are working with:

    a. CTKSum – `https://huggingface.co/datasets/ctu-aic/ctksum` based on source articles and extracted claims within the original CTKFᴀᴄᴛs set
    b. FEVERSum (based on FEVER Wikipedia abstract and extracted claims) – `https://huggingface.co/datasets/ctu-aic/fever-sum`

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[7]`https://huggingface.co/datasets/ctu-aic/ctkfacts`
[8]`https://huggingface.co/datasets/ctu-aic/ctkfacts_nli`

c. Its DeepL translation CsFEVERSum – `https://huggingface.co/datasets/ctu-aic/csfever-sum`

d. Our reproduction of a crawled Slovak summarization dataset described by [Šuppa and Adamec, 2020] SMESum based on articles from `https://sme.sk` – `https://huggingface.co/datasets/ctu-aic/smesum`

Up until now, some of the data was restricted to private repositories, but with this study, I am publishing most of them, as I have now found the licensing to be rather relaxed. If some of the repositories reader might be interested in would not be reachable, please request access to the `https://huggingface.co/datasets/ctu-aic` organization to be able to see into the private part of our dataset library.

3.2 Models

The most significant pretrained models I have made public address two tasks – the Natural Language Inference and Claim Generation viewed as a form of Abstractive Summarization task.

3.2.1 Natural Language Inference

My previous work [Ullrich, 2021, Ullrich et al., 2023] also focused on establishing a strong starting state of the art on our own datasets in the tasks of NLI. In my publications, I have tried and compared a multitude of neural networks for the tasks, ultimately arriving to:

- **XLM-RoBERTA-Large@XNLI@CsFEVER-NLI**, a model with 561M parameters trained on 100-language CommonCrawl corpus finetuned on multilingual XNLI [Conneau et al., 2018] inference datased and then finetuned *again* on the CsFEVER-NLI task yields an unmatched 73.7% F1 macro score on the denoised CsFEVER-NLI inference task: `https://huggingface.co/ctu-aic/xlm-roberta-large-xnli-csfever_nli`

- **XLM-RoBERTA-Large@SQuAD2**, a model version finetuned on a Question answering SquAD2 [Rajpurkar et al., 2016] task has shown remarkable practicality in my NLI applications and after task specific finetuning, it was able to tackle:

  1. CTKFActsNLI[9] task with 76.9% macro-F1
  2. CsFEVER[10] (noisy) task with 83.2% macro-F1
  3. The original English FEVER NLI task[11] [Thorne et al., 2018a, Nie et al., 2019a], achieving 75.9% macro-F1 and a significant superiority over previous shared task winner [Nie et al., 2019a] (which had 69.5 macro-F1 with NSMNs)

3.2.2 Claim generation

In my current research, I am finding appropriate configurations and data to train models for the task of claim generation – generating a factual claim (or more) into a single sentence that contains a fluent, atomic, decontextualized and faithful claim. In section 4.1.1,

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[9] `https://huggingface.co/ctu-aic/xlm-roberta-large-squad2-ctkfacts_nli`

[10] `https://huggingface.co/ctu-aic/xlm-roberta-large-squad2-csfever_nearestp`

[11] `https://huggingface.co/ctu-aic/xlm-roberta-large-squad2-enfever_nli`

I propose the claim generation as an abstractive summarization setting, and therefore, the models already have their practical use in the general task of summing up longer texts into shorter ones.

As has been shown in section 2.5.1, NLP summarization task does not have a reliable standard benchmark that would capture all its required output qualities. Therefore, it remains questionable to claim the state of the art on any summarization task and I proceed to present models that excel in our empirical tests and demonstrations for project stakeholders:

1. **mBART** [Liu et al., 2020] multilingual Transformer model has been finetuned by our team's [Krotil, 2022] on SumeCzech and proprietary CNC News summarization dataset on the "full text to headline" task, obtaining encouraging scores across numerous summarization metrics in Czech.
   I have taken this model a step further for the claim generation task, finetuning it on the CsFEVERSum and CTKFactsSum datasets, yielding a working model for the task.[12]

   Another experiments are being carried out with the same model finetuned on Slovak[13] and Polish[14] data.

2. **LLaMA-2** shows promising result when it comes to claim generation. I have finetuned[15] it using the QLoRA (section 2.3.2) approach, XL-Sum [Hasan et al., 2021] dataset and a concatenation-based prompting strategy [Touvron et al., 2023b], to facilitate training across the entire length of input.

All prototype models are currently being iterated with our CEDMO project partners (fact-checkers from European organizations), tweaked, and future tests are being designed for them based on empirical results and questionnaires.

3.3 Applications

Numerous applications demonstrating our contributions with screenshots throughout this study are currently deployed and available online due to the CEDMO project and their testing with future users, let us therefore present the main applications I and my supervisor Jan Drchal have developed for the tasks:

1. Claim extractor at `https://fcheck.fel.cvut.cz:1830` (figure 3.2) demonstrates the single or multiple claim generation task with our LLaMA-2 or mBART models for English and Czech texts, respectively, using a GRADIO interactive application and an API

2. `https://fcheck.fel.cvut.cz:1831` runs a FactSearch platform by Jan Drchal, demonstrating our best performing models for the whole fact-checking tasks, integrating the XLM-RoBERTas trained on CsFEVER-NLI data

3. `https://fcheck.fel.cvut.cz:1832` runs the same scheme with our best performing English models and data

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[12]`https://huggingface.co/ctu-aic/mbart25-large-eos`

[13]`https://huggingface.co/ctu-aic/mbart-at2h-cs-smesum-2`

[14]`https://huggingface.co/ctu-aic/mbart-at2h-cs-polish-news3`

[15]`https://huggingface.co/ctu-aic/Llama-2-7b-xlsum-en`

Figure 3.2: Factual claim extraction application done for the CEDMO project

Here we will show off the demonstration tools, as well as our open-source platform `https://fcheck.fel.cvut.cz` and currently running claim extraction tools.

Chapter 4

Dissertation plan

4.1 Current research agenda

4.1.1 Automated claim generation

TODO:

4.1.2 Claim generation metrics

The common problem with generative tasks in NLP is that of explaining model reasoning in human-understandable manner and troubleshooting the prediction faults, such as the *model hallucination.*

For the task of claim generation, where we also face the challenge of the *relevance* of the information extracted by the model, we postulate the following metrics:

1. **Fluency** – *is the claim grammatically correct and intelligible?*

   Currently, we are working with two emulations of claim fluency, challenge that is similar to a standard NLP task of Gramatical Error Detection (GED): LM-Critic (Figure 4.1) [Yasunaga et al., 2021] perturbs the claim words and characters to find local optima in output probability of its tokens, using a language model such as GPT-2 as its reference. GPTScore [Fu et al., 2023] uses prompting a LLM (such as GPT-3) to obtain a model-inferred score using few- or zero-shot learning.

   Both can be adapted for Czech and the latter is demonstrated in Figure 4.2.

2. **Decontextualization** – *can the claim be correctly interpreted without any additional context from the source document or elsewhere?*

   A common problem with machine-extracted factual claims is reusing excerpts from source document along with inexplicable contextual pronouns ("President won't sue *them*") and relative referencing ("*Last year*, CTU had 23K students").

   [Choi et al., 2021] proposes decontextualization as a sequence to sequence task with two texts on input (s, c) – sentence and context. T5 model [Raffel et al., 2019] is then trained on machine-generated gold data from Wikipedia to output sentence s' such that the truth-conditional meaning of s' in an empty context is the same as that of s in c.

   [Mohri et al., 2023] improves upon this, altering the problem formulation to minimizing surrogate loss, rejecting with a fixed predictor and claiming to get as close as $\sim 3\%$ away from the theoretical limit for the task.
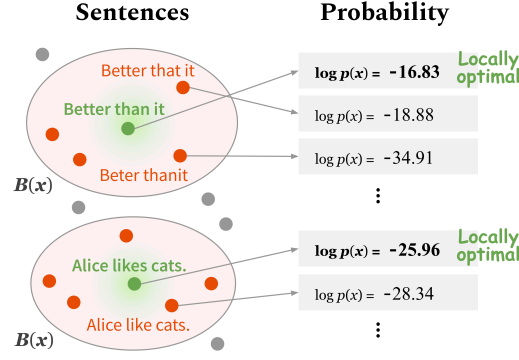
Figure 4.1: LM-Critic – deciding text fluency viewed as finding local optima of Language Model output probability, reprinted from [Yasunaga et al., 2021]

The approaches are reproducible using Czech Wikipedia corpus and appropriate for further examination.

3. **Atomicity** – *does the claim describe a single entity, relation or process?*

   can be checked using the Relationship Extraction methods such as LUKE [Yamada et al., 2020]. To put it simply, the RE task is to identify the entities of a text (persons, institutions,…) and the relations between them (such as (*"study at"*, *Herbert*, *CTU*)). The atomicity evaluation can be converted to a RE task by attempting to extract such fact triples and mark the claim as atomic if there is at most one such triple found (after removing symmetries)

4. **Faithfulness** – *does the claim only contain information that is consistent with the source document?*

   This metric is crucial to pinpoint *model hallucinations* – parts of claim where the model outputs stray from the information present in source text and begin to just "make stuff up". We proceed to use two alternative metrics – a score proposed within the FFCI evaluation framework [Koto et al., 2020] as:

   $$\text{AvgTop-}n_{s_j \in X, t_i \in Y'}(\text{BERTSCORE}(t_i, s_j))$$

   Where the AvgTop-n simply averages across the top n (say, 5) highest scores, X, Y' are the sets of sentences in source document and model output, respectively (so, in the claim generation scenario $|Y'| = 1$) and BERTSCORE [Zhang* et al., 2020] is a recently popular similarity score between two sentences that doesn't compare the texts on a verbatim level (like e.g., ROUGE [Lin, 2004] which correlates poorly with human judgement) but expresses the sentence similarity as a sum of cosine similarities between their tokens' embeddings – this should capture semantical relations rather than the word-for-word similarity, which could be benefitial in highly inflected languages such as Czech.

   Similar metric called ALIGNSCORE was proposed in [Zha et al., 2023], looking for optimum alignment of output and input parts, in terms of a RoBERTa model [Liu et al., 2019] trained to detect inconsistencies on 4.7M training examples adapted from various tasks (inference, question answering, paraphrasing,…) and while it is relatively small (355M parameters), it outperforms metrics based on GPT-4 that is orders of magnitude larger.

Figure 4.2: A self-evaluating claim generation model based on GPT-4 [OpenAI, 2023] using the `OpenAI API` and a few-shot approach

Empirically, the models work encouragingly well on spotting hallucinations and inconsistencies in English, and while the transduction of BERTSCORE is trivial, using a Czech embedding model such as CZERT [Sido et al., 2021] or FERNET [Lehečka and Švec, 2021], reproducing the success of ALIGNSCORE will require more research and data.

5. **Focus**@k – *if we generate k claims using this model, what will be the proportion of gold (relevant) information among all the information listed in the generated claims?*

The metric is analogous to the concept of *precision* in the common machine learning applications, however, its deciding gets more ambiguous in the natural language settings, where we are dealing with synonyms and endless number of possible wordings for every piece of information.

An ellegant and functional perspective on the problem has been brought around in QAGS[1] evaluation protocol [Wang et al., 2020], where the idea is to use a Question Generation model (QG) to formulate questions in natural language based on all k predicted claims. The questions are then twice answered using a Question Answering (QA) model, giving it knowledge from (i.) the predicted claims (ii.) the gold claims written by a human. The focus is then defined as the proportion of questions with the same answers extracted from the gold and predicted claims, among all questions model can generate from the predicted claims.

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[1]Pronounced "kags", stands for "Question Answering and Generation for Summarization"

6. **Coverage**@k – *if we generate k claims using this model, what proportion of gold (relevant) information from the source text will be covered?*

   Anologous to *recall@k* in general machine learning, QAGS proposes to generate questions using gold claims and try to answer them using the predicted claims, much like in the *focus* scenario, but vice versa.

4.2 Data Collection

4.2.1 Human-in-the-loop grading of claim generators

4.2.2 Validation of the model outputs with human fact-checkers

4.2.3 Polish dataset scraping

Will be first of its kind for NLP purposes

4.2.4 Crowd-sourced fact checking platform

TODO: Cite boys [Bútora, 2023]

4.3 The grand scope

1. **Claim extraction metrics proposal based on factuality of summarization**

2. **Claim extraction paradigm that benchmarks best in the newly given metrics**

3. Systems for NLI built on top of LoRA paradigm to score best in the task, as showed promising by Daniil

Chapter 5
Conclusion

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Appendix A
Acronyms

BERT Bidirectional Encoder Representations from Transformers

GPT Generative Pre-trained Transformer

FEVER Fact Extraction and Verification – series of Shared tasks focused on fact-checking

CLI Command-Line Interface

NLI Natural Language Inference

ČTK Czech Press Agency