Czech
Technical University
in Prague

F3

Faculty of Electrical Engineering
Department of Computer Science

NLP Methods for Automated Fact-Checking

Dissertation Thesis of

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FCHECK.FEL.CVUT.CZ

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Field of study: **Informatics**
Subfield: **Natural Language Processing**
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Chapter 1
Introduction

My dissertation, as well as my long-term research, centers on *automated fact-checking* using modern Natural Language Processing (NLP) 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.

Our group focuses primarily on fact-checking tasks in West Slavic languages (Czech, Slovak, Polish), and secondarily in English. So far, I have collected and published datasets for fact-checking and its subroutines, trained and analyzed models, and begun work on explainable metrics that capture *facticity*—a challenge in itself [?, ?].

My doctoral aim is to cover the full path from obtaining a factual claim—for example, extracting it from a political debate—to predicting its veracity and justifying it rigorously with evidence. With the recent NLP boom—sparked by transformers and later by Large Language Models (LLMs) [?], few-shot learning [?], and prompting [?]—a significant part of the work is the timely adoption and evaluation of fast-evolving SOTA methods in our context.

Overall, I build on prior Czech fact-checking research, extend it to other languages, and evolve the transformer *pre-training & fine-tuning* paradigm toward an LLM-centric design, which already shows strong performance on related tasks in English [?].

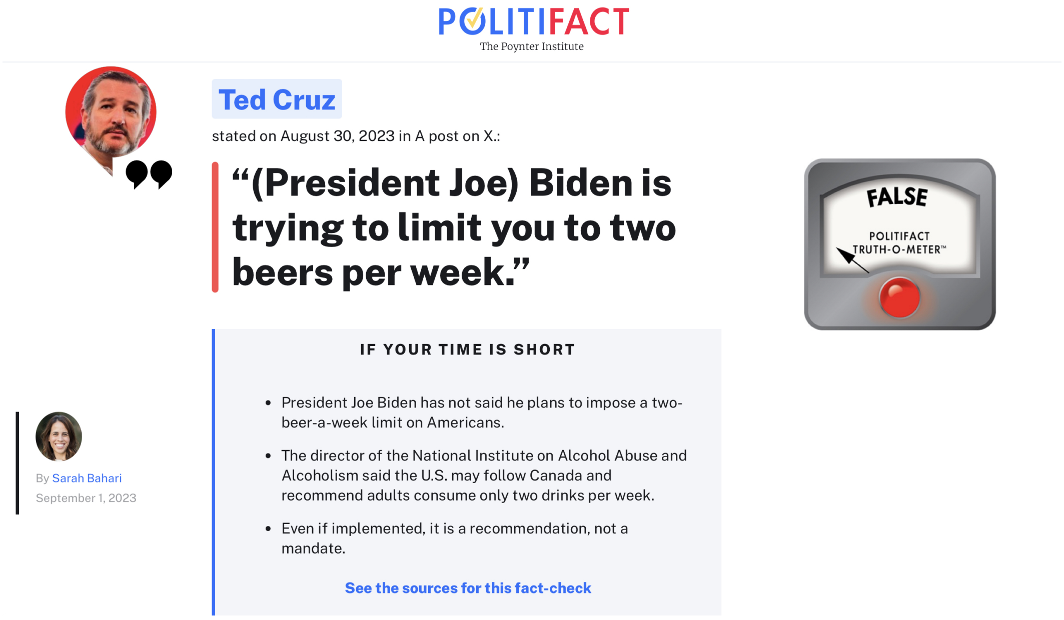
My recent focus within the broader fact-checking pipeline is *claim generation*, which I aim to establish as a benchmarked NLP task adjacent to *abstractive summarization*. To benchmark the task, we need metrics that capture phenomena such as *model hallucinations*—a common issue in modern LLMs [?]. Because word-overlap metrics for generation correlate poorly with human judgment [?] and model-based metrics can be opaque, I also focus on human-understandable model-based metrics.

This study aims to show the directions I am taking to address these challenges, the reasoning behind them, my research questions, and the current results that motivated them.

1.1 Motivation

The spread of misinformation in the online space has a growing influence on the Czech public [?]. It has been shown to influence people's behaviour on the social networks [?] as well as their decisions in elections [?], and real-world reasoning, which has shown increasingly harmful during the COVID-19 pandemic [?] and the Russo-Ukrainian war [?].

The recent advances in artificial intelligence have unintendedly contributed to the spread of misinformation on social media [?], as well as they hold a large potential for the false



POLITIFACT
The Poynter Institute

Ted Cruz

stated on August 30, 2023 in A post on X.:

"(President Joe) Biden is trying to limit you to two beers per week."

FALSE
POLITIFACT TRUTH-O-METER™

By Sarah Bahari
September 1, 2023

IF YOUR TIME IS SHORT

- President Joe Biden has not said he plans to impose a two-beer-a-week limit on Americans.
- The director of the National Institute on Alcohol Abuse and Alcoholism said the U.S. may follow Canada and recommend adults consume only two drinks per week.
- Even if implemented, it is a recommendation, not a mandate.

See the sources for this fact-check

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

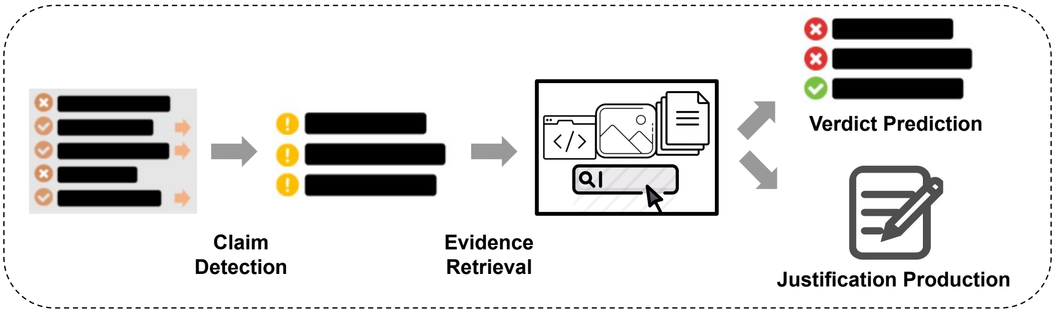


Figure 1.2: Automated fact-checking pipeline, reprinted from [?]

content generation [?].

Recent research has shown promising results [?] 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 ??) 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 labeled 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

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

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 the 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 **??**) [**?**]. 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, curate 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 [**?**], giving birth to the famous models such as Google's BERT encoder [**?**] and its descendants, or the OpenAI's GPT-3 decoder [**?**] and GPT-4 [**?**] 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 readers to begin with.

Transformer is a neural model for *sequence-to-sequence* tasks, which, similarly, e.g., to the *LSTM-Networks* [**?**], 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 [**?**].

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 others.

The full Transformer architecture is depicted in Figure **??**.

1.4 Dissertation outline

- **Chapter ??** introduces the dissertation topic, motivates the research, sets up our challenges for future research
- **Chapter ??** examines the most relevant research in the field and tries to highlight the recent paradigm shift from models trained for a single task to single large models that perform well in everything
- **Chapter ??** explains our current contributions to the field of automated fact-checking and NLP in Czech
- **Chapter ??** describes our plan for the dissertation and justifies the directions we are taking
- Finally, **Chapter ??** concludes the study with a wrapup of its findings

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

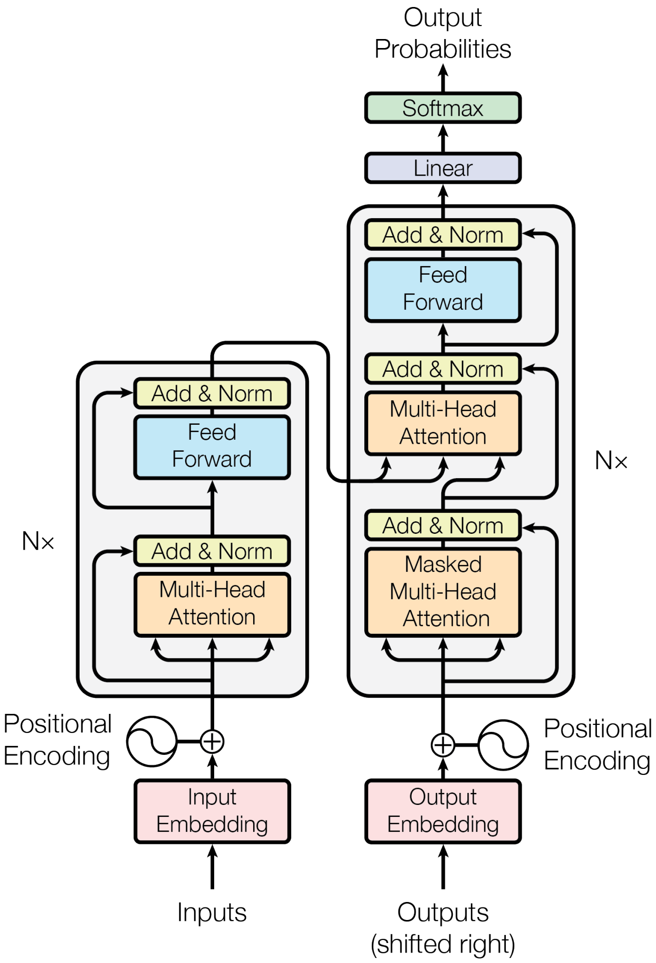


Figure 1.3: Transformer model architecture, reprinted from [?]

Chapter 2 State of the Art

This chapter surveys the evolution from BERT-style transfer learning to instruction-following LLMs that often outperform smaller fine-tuned models even without additional training [?, ?, ?, ?]. We then review efficiency methods that make fine-tuning multi-billion-parameter models on a single GPU practical and discuss their relevance to our work.

To show how it relates to our main topics, we will 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 Natural Language Processing (NLP). It has significantly shaped the development of modern NLP models. Its use 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 [?] and GloVe [?], 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 [?] 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 many 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 [?], FERNET [?], RobeCzech [?], and small-e-czech [?] are available for further finetuning
- In Polish, HerBERT [?] achieved state-of-the-art in multiple tasks in 2021

- In Slovak, SlovakBERT [?] was released by KInIT and Gerulata
- A multitude of multilingual models, such as M-Bert or XLM-RoBERTa [?] were pre-trained 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 [?].

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 [?]. 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 thoroughly described in the publication. However, it is prohibitively costly for most labs to reproduce or even fine-tune at such a 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 [?].

2.3 Open source LLMs

This puts the research community in an awkward position, as the GPT-4 achieves state-of-the-art in numerous NLP benchmarks [?, ?], but is 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 a smaller scale with similar results, using a peer-reviewed architecture, training scheme, and data that is available in open source.

[1] A mixture of crawled websites, books, and Wikipedia.

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

2.3.1 LLaMA-2 and derivatives

A popular foundational LLM to compete with the GPT family has become the LLaMA [?] from Meta research. LLaMA was trained on about 5TB of publicly available textual data[3] mainly 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 [?], Vicuna [?], and OpenAssistant [?].

The pre-trained 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 [?] 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 [?] on a single TPU, successful approaches have been published to dramatically cut down the training expenses. Parameter-efficient fine-tuning (PEFT) [?] 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) [?] 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 [?]. Quantized QLoRA takes LLaMA and finetunes it into a Guanaco model family, which outperforms all previous openly released LLMs on Vicuna benchmark [?] 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 memo [?], 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.

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 the internet and social media became a discussed topic in the Western world, with multiple institutions such as the European Council marking it a severe threat to democracy and national safety [?]. The public attention and maturation of appropriate technologies motivated

[3] To be specific, LLaMA was trained using an autoregressive language modeling task on a mixture of English CommonCrawl Corpus, C4 [?], Github, Wikipedia, Gutenberg Project, Books3 corpus, ArXiv and Stack Exchange

numerous efforts in business and academia to tackle the challenge. Among other events, a Fake News Challenge occurred in 2017 [?] exploring the uses of technologies in the field and applying, for example, the LSTMs to detect stances among textual data [?].

2.4.1 FEVER and followups

Soon, standard tasks began to be formulated and data collected. The FEVER (Fact Extraction and VERification) [?] dataset and shared task became prominent in natural language processing research. Relatively early on, it formalized the task as a two-step problem:

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 an interesting benchmark with statistically quantifiable model success, motivated multiple well-performing public solutions [?, ?], 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 [?] and by reasoning over tabular data in FEVEROUS [?].

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

2.4.2 Open-domain fact-checking

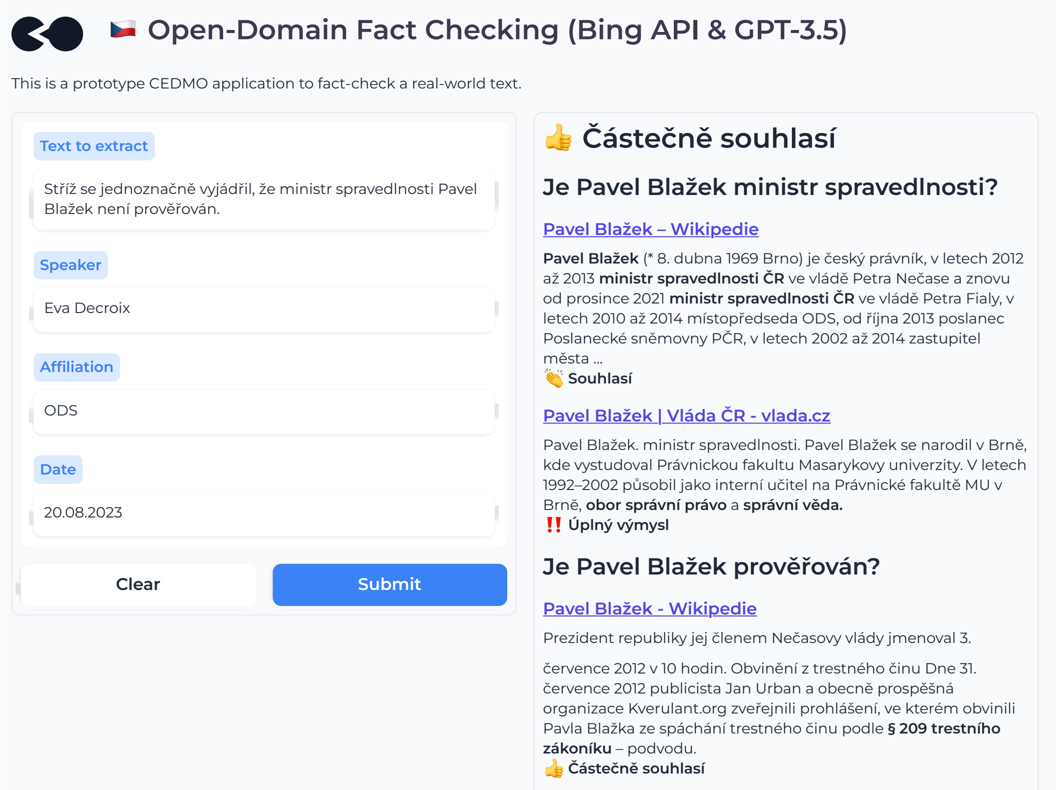
Due to these limitations, some researchers consider the scheme from FEVER an oversimplification – the real politics' claims to be fact-checked by journalists often consist of long syntactical structures, combine information together in a non-trivial manner and often require the most up-to-date evidence.

"Complex Claim Verification with Evidence Retrieved in the Wild" [?] proposes a different scheme that overcomes these shortcomings:

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

[4] Is Wikipedia a trustworthy informational 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.??



🇨🇿 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

👍 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 [?] in Czech, using a real-world claim that was fact-checked by `demagog.cz` in June 2023

2. An open-domain search (Bing is proposed in the paper) fetches several evidence documents for each question
3. A claim-focused summary is extracted 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, the 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 [?] in a few- and zero-shot fashion, with few-shot unsurprisingly coming out a little better. The scheme is transducible to Czech, and Figure **??** 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 the internet, having it appear in Bing search and other crawlers alike. I argue that this might lead into a sort of 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 [?].

The current state of things is that journalists who 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 the text themselves, and then fact-check each separately.

What has been examined so far were, for example:

- Using Question Generation (QG) solver and converting the questions into declarative sentences to emulate more claims and more data for fact checking [?]
- Numerous CLEF CheckThat! challenges explored the task of estimating *checkworthiness* of different parts of a long text, such as lines in a political debate [?, ?]
- 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 [?] in English and XL-Sum [?] 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 [?] and METEOR [?] 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. [?, ?, ?]

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 ??, 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

extitWe collected novel data for fact-checking in our application context, emulated or scraped unavailable datasets (publishing or preparing them for release), established strong baseline models, and are working to position claim generation as a summarization-adjacent NLP task.

3.1 Datasets

With the automated fact-checking scheme established in Chapter **??**, any ML solution begins with choosing or collecting 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 endeavors in adapting the FEVER [**?**] task for the Czech context was the CsFEVER [**?**] dataset.

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

1. Each FEVER claim is translated using a 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 step 2. is discarded

This design was relatively cheap (translating the entire 2017 Wikipedia would be costly and wasteful), yielding a CC-licensed dataset of 127K claims, labels, and evidence. Since both 2017 EnWiki and our 2020 CsWiki corpora contained only the first paragraph (abstract) per article, we hoped document-level alignment would hold: both languages summarize 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 [**?**].

[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, CsFEVER has been used to train IR components [?,?,?] still in use today and is openly available[3] under a CC license.

My research on it also motivated the creation of an 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].

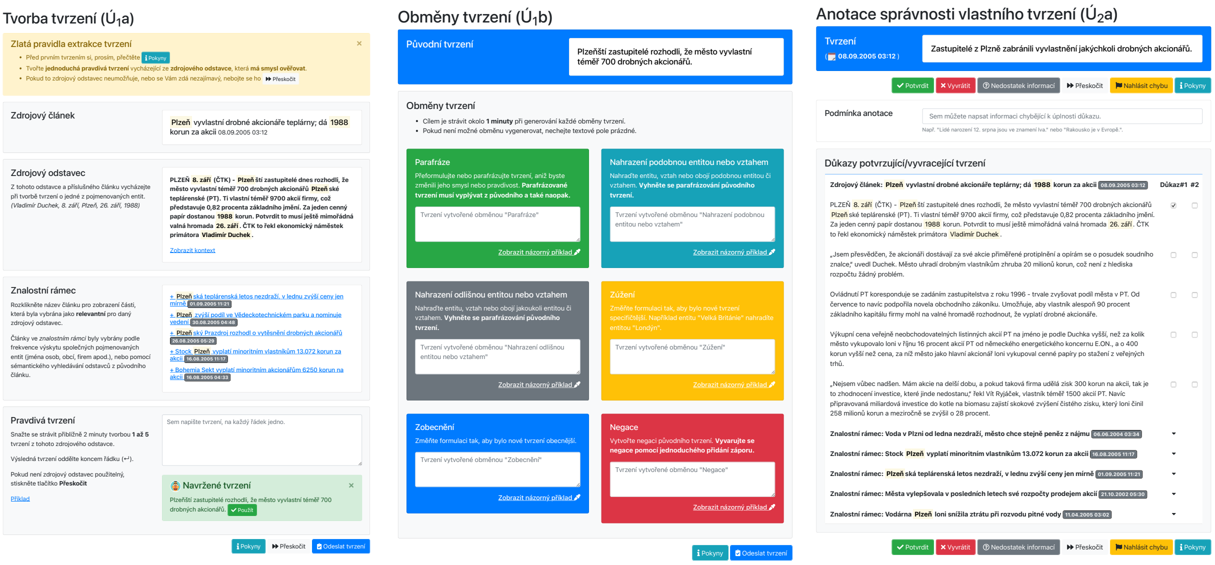
Another round of research CsFEVER motivated, and I supervised, was the successful thesis of [?], modernizing the data and machine-translation methods into the 2023 state of the art. [?] further experimented with methods of automated noise detection and removal, which has not shown to be an efficient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

Anyhow, it delivers a partly cleaned version of it[5] and motivates future research to generate such data differently, using a claim generation scheme like that from [?].

3.1.2 FCheck annotations platform

The imperfections in translated CsFEVER data, as well as the ongoing collaboration 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 introduced in translation and also take the task of automated fact-checking to the next level, replacing a rigid, simple Wikipedic data with a more “real world” news report corpus of ČTK.

Figure **??** 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.



Tvorba tvrzení (Ú$_1$a)

Zlatá pravidla extrakce tvrzení

- Před prvním tvrzením si, prosím, přečtěte Pokyny
- Tvořte **jednoduchá pravdivá tvrzení** vycházející ze **zdrojového odstavce**, která **má smysl ověřovat**.
- Pokud to zdrojový odstavec neumožňuje, nebo se Vám zdá nezajímavý, nebojte se ho Přeskočit

Zdrojový článek

Plzeň vyvlastní drobné akcionáře teplárny; dá 1988 korun za akcii 08.09.2005 03:12

Zdrojový odstavec

Z tohoto odstavce a příslušného článku vycházejte při tvorbě tvrzení o jedné z pojmenovaných entit. *(Vladimír Duchek, 8. září, Plzeň, 26. září, 1988)*

PLZEŇ 8. září (ČTK) - Plzeňští zastupitelé dnes rozhodli, že město vyvlastní téměř 700 drobných akcionářů Plzeňské teplárenské (PT). Ti vlastní téměř 9700 akcií firmy, což představuje 0,82 procenta základního jmění. Za jeden cenný papír dostanou 1988 korun. Potvrdit to musí ještě mimořádná valná hromada 26. září . ČTK to řekl ekonomický náměstek primátora Vladimír Duchek .

Zobrazit kontext

Znalostní rámec

Rozklikněte název článku pro zobrazení části, která byla vybrána jako **relevantní** pro daný zdrojový odstavec.

Články ve *znalostním rámci* byly vybrány podle frekvence výskytu společných pojmenovaných entit (jména osob, obcí, firem apod.), nebo pomocí sémantického vyhledávání odstavců z původního článku.

+ Plzeňská teplárenská letos nezdraží, v lednu zvýší ceny jen mírně 01.09.2005 11:21
+ Plzeň zvýší podíl ve Vědeckotechnickém parku a nominuje vedení 30.08.2005 04:48
+ Plzeňský Prazdroj rozhodl o vytěsnění drobných akcionářů 26.08.2005 05:29
+ Stock Plzeň vyplatí minoritním vlastníkům 13.072 korun za akcii 16.08.2005 11:17
+ Bohemia Sekt vyplatí minoritním akcionářům 6250 korun na akcii 16.08.2005 04:33

Pravdivá tvrzení

Snažte se strávit přibližně 2 minuty tvorbou **1 až 5** tvrzení z tohoto zdrojového odstavce.

Výsledná tvrzení oddělte koncem řádku (↵).

Pokud není zdrojový odstavec použitelný, stiskněte tlačítko **Přeskočit**

Příklad

Sem napište tvrzení, na každý řádek jedno.

Navržené tvrzení

Plzeňští zastupitelé rozhodli, že město vyvlastní téměř 700 drobných akcionářů. ✓ Použít

Obměny tvrzení (Ú$_1$b)

Původní tvrzení

Plzeňští zastupitelé rozhodli, že město vyvlastní téměř 700 drobných akcionářů.

Obměny tvrzení

- Cílem je strávit okolo **1 minuty** při generování každé obměny tvrzení.
- Pokud není možné obměnu vygenerovat, nechejte textové pole prázdné.

Parafráze

Přeformulujte nebo parafrázujte tvrzení, aniž byste změnili jeho smysl nebo pravdivost. **Parafrázované tvrzení musí vyplývat z původního a také naopak.**

Tvrzení vytvořené obměnou "Parafráze"

Zobrazit názorný příklad

Nahrazení podobnou entitou nebo vztahem

Nahraďte entitu, vztah nebo obojí podobnou entitou či vztahem. **Vyhněte se parafrázování původního tvrzení.**

Tvrzení vytvořené obměnou "Nahrazení podobnou entitou nebo vztahem"

Zobrazit názorný příklad

Nahrazení odlišnou entitou nebo vztahem

Nahraďte entitu, vztah nebo obojí jakoukoli entitou či vztahem. **Vyhněte se parafrázování původního tvrzení.**

Tvrzení vytvořené obměnou "Nahrazení odlišnou entitou nebo vztahem"

Zobrazit názorný příklad

Zúžení

Změňte formulaci tak, aby bylo nové tvrzení specifičtější. Například entitu "Velká Británie" nahradíte entitou "Londýn".

Tvrzení vytvořené obměnou "Zúžení"

Zobrazit názorný příklad

Zobecnění

Změňte formulaci tak, aby bylo nové tvrzení obecnější.

Tvrzení vytvořené obměnou "Zobecnění"

Zobrazit názorný příklad

Negace

Vytvořte negaci původního tvrzení. **Vyvarujte se negace pomocí jednoduchého přidání záporu.**

Tvrzení vytvořené obměnou "Negace"

Zobrazit názorný příklad

Anotace správnosti vlastního tvrzení (Ú$_2$a)

Tvrzení (08.09.2005 03:12)

Zastupitelé z Plzně zabránili vyvlastnění jakýchkoli drobných akcionářů.

Podmínka anotace

Sem můžete napsat informaci chybějící k úplnosti důkazu.

Např. "Lidé narození 12. srpna jsou ve znamení lva." nebo "Rakousko je v Evropě.".

Důkazy potvrzující/vyvracející tvrzení

Zdrojový článek: Plzeň vyvlastní drobné akcionáře teplárny; dá 1988 korun za akcii 08.09.2005 03:12 **Důkaz#1 #2**

PLZEŇ 8. září (ČTK) - Plzeňští zastupitelé dnes rozhodli, že město vyvlastní téměř 700 drobných akcionářů Plzeňské teplárenské (PT). Ti vlastní téměř 9700 akcií firmy, což představuje 0,82 procenta základního jmění. Za jeden cenný papír dostanou 1988 korun. Potvrdit to musí ještě mimořádná valná hromada 26. září. ČTK to řekl ekonomický náměstek primátora Vladimír Duchek . ☑ ☐

„Jsem přesvědčen, že akcionáři dostávají za své akcie přiměřené protiplnění a opírám se o posudek soudního znalce,“ uvedl Duchek. Město uhradí drobným vlastníkům zhruba 20 milionů korun, což není z hlediska rozpočtu žádný problém. ☐ ☐

Ovládnutí PT koresponduje se zadáním zastupitelstva z roku 1996 - trvale zvyšovat podíl města v PT. Od července to navíc podpořila novela obchodního zákoníku. Umožňuje, aby vlastník alespoň 90 procent základního kapitálu firmy mohl na valné hromadě rozhodnout, že vyplatí drobné akcionáře. ☐ ☐

Výkupní cena veřejně neobchodovatelných listinných akcií PT na jméno je podle Duchka vyšší, než za kolik město vykupovalo loni v říjnu 16 procent akcií PT od německého energetického koncernu E.ON., a o 400 korun vyšší než cena, za níž město jako hlavní akcionář loni vykupoval cenné papíry po stažení z veřejných trhů. ☐ ☐

„Nejsem vůbec nadšen. Mám akcie na delší dobu, a pokud taková firma udělá zisk 300 korun na akcii, tak je to zhodnocení investice, které jinde nedostanu,“ řekl Vít Ryjáček, vlastník téměř 1500 akcií PT. Navíc připravovaná miliardová investice do kotle na biomasu zajistí skokové zvýšení čistého zisku, který loni činil 258 milionů korun a meziročně se zvýšil o 28 procent. ☐ ☐

Znalostní rámec: Voda v Plzni od ledna nezdraží, město chce stejně peněz z nájmu 06.06.2004 03:34 ▾

Znalostní rámec: Stock Plzeň vyplatí minoritním vlastníkům 13.072 korun za akcii 16.08.2005 11:17 ▾

Znalostní rámec: Plzeňská teplárenská letos nezdraží, v lednu zvýší ceny jen mírně 01.09.2005 11:21 ▾

Znalostní rámec: Města vylepšovala v posledních letech své rozpočty prodejem akcií 21.10.2002 05:30 ▾

Znalostní rámec: Vodárna Plzeň loni snížila ztrátu při rozvodu pitné vody 11.04.2005 03:02 ▾

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

We have established a 4-step annotation procedure inspired by the time-proven methodology of [?] where check-worthy paragraphs are first hand-picked among samples from

[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`

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 the paragraph. This claim is always *supported* by the data, so the next phase is to perturb the claim by the 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 application has two layers: a Yii-based PHP interface for annotation and a Python Flask service hosting our IR models based on TF-IDF [?] and mBERT (Section ??), trained (among other data) on CsFEVER (Section ??). 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 context to the fact-checker.

The scheme and its implementations are exhaustively described in [?], chapter 4, and in [?], 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 `SUPPORT`ed by the majority of their annotations, `REFUTES` and `NEI` labels were approximately even, the full distribution of labels is listed in Table ??.

	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 [?]

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 assess data quality and task ambiguity, and to propose cleaning methods for the final cleaned CTKFacts dataset.

Inter-annotator agreement

Due to our cross-annotation design, I had a 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 [?] which is the standard for this case [?]. For the comparison with [?] and [?], I also list a 4-way Fleiss' κ-agreement [?] calculated on a sample of 7.5% claims.

Krippendorff's alpha was 56.42% and Fleiss' κ 63%, an adequate result reflecting the complexity of news-based 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.

CTKFacts publication

The CTKFacts dataset then underwent thorough human-in-the-loop cleaning to reach 100% agreement on the retained items, removing obvious noise and revealing sources of annotation error. The full process, as well as its results, are described in [?].

Ultimately, a dataset of 3.1K thoroughly cleaned data points in the 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.

These datasets are now standard benchmarks within the AIC NLP group [?, ?] and are beginning to appear in external research [?].

3.1.4 Other NLP datasets in West Slavic languages

Over 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 [?], Adversarial NLI [?] and MultiNLI [?] picking a machine translator empirically for each dataset between DeepL [?], Google Translate [?] and CUBBITT [?].

   The resulting datasets 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 CTKFacts set
   b. FEVERSum (based on FEVER Wikipedia abstract and extracted claims) – `https://huggingface.co/datasets/ctu-aic/fever-sum`
   c. Its DeepL translation CsFEVERSum – `https://huggingface.co/datasets/ctu-aic/csfever-sum`
   d. Our reproduction of a crawled Slovak summarization dataset described by [?] 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 the 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.

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

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

3.2 Models

The most significant released models address two tasks: Natural Language Inference and Claim Generation (as Abstractive Summarization).

3.2.1 Natural Language Inference

My previous work [?, ?] 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 at the following:

- **XLM-RoBERTA-Large@XNLI@CsFEVER-NLI**, a model with 561M parameters trained on 100-language CommonCrawl corpus finetuned on multilingual XNLI [?] inference dataset 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 [?] 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] [?, ?], achieving 75.9% macro-F1 and surpassing the prior shared-task winner [?] (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 claim generation – generating a factual claim (or more) into a single sentence containing a fluent, atomic, decontextualized, and faithful claim. In section ??, 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 ??, the 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:

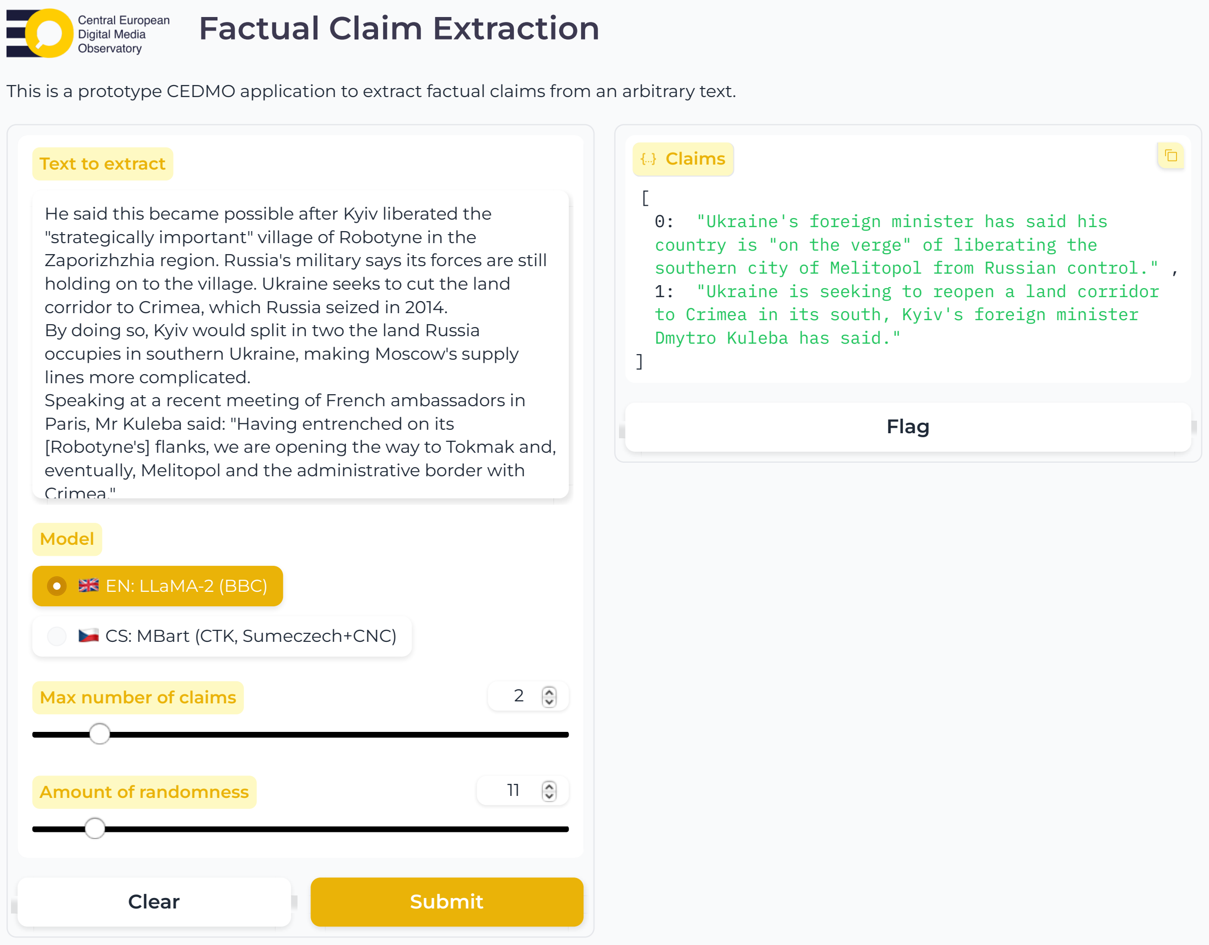
1. **mBART** [?] multilingual Transformer model has been finetuned by our team's [?] on SumeCzech and proprietary CNC News summarization dataset on the "full text to headline" task, obtaining encouraging scores across numerous summarization metrics in Czech.
   I have taken this model a step further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

[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`

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



Factual Claim Extraction

This is a prototype CEDMO application to extract factual claims from an arbitrary text.

Text to extract

He said this became possible after Kyiv liberated the "strategically important" village of Robotyne in the Zaporizhzhia region. Russia's military says its forces are still holding on to the village. Ukraine seeks to cut the land corridor to Crimea, which Russia seized in 2014.
By doing so, Kyiv would split in two the land Russia occupies in southern Ukraine, making Moscow's supply lines more complicated.
Speaking at a recent meeting of French ambassadors in Paris, Mr Kuleba said: "Having entrenched on its [Robotyne's] flanks, we are opening the way to Tokmak and, eventually, Melitopol and the administrative border with Crimea."

Model

● 🇬🇧 EN: LLaMA-2 (BBC)

○ 🇨🇿 CS: MBart (CTK, Sumeczech+CNC)

Max number of claims 2

Amount of randomness 11

Claims

```
[
  0:  "Ukraine's foreign minister has said his
  country is "on the verge" of liberating the
  southern city of Melitopol from Russian control." ,
  1:  "Ukraine is seeking to reopen a land corridor
  to Crimea in its south, Kyiv's foreign minister
  Dmytro Kuleba has said."
]
```

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

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

2. **LLaMA-2** shows promising results when it comes to claim generation. I have finetuned[15] it using the QLoRA (section **??**) approach, XL-Sum [**?**] dataset and a concatenation-based prompting strategy [**?**], to facilitate training across the entire length of input.

All prototype models are currently being iterated with our CEDMO[16] project partners (fact-checkers from European organizations), tweaked, and future tests are being designed for them based on empirical results and questionnaires.

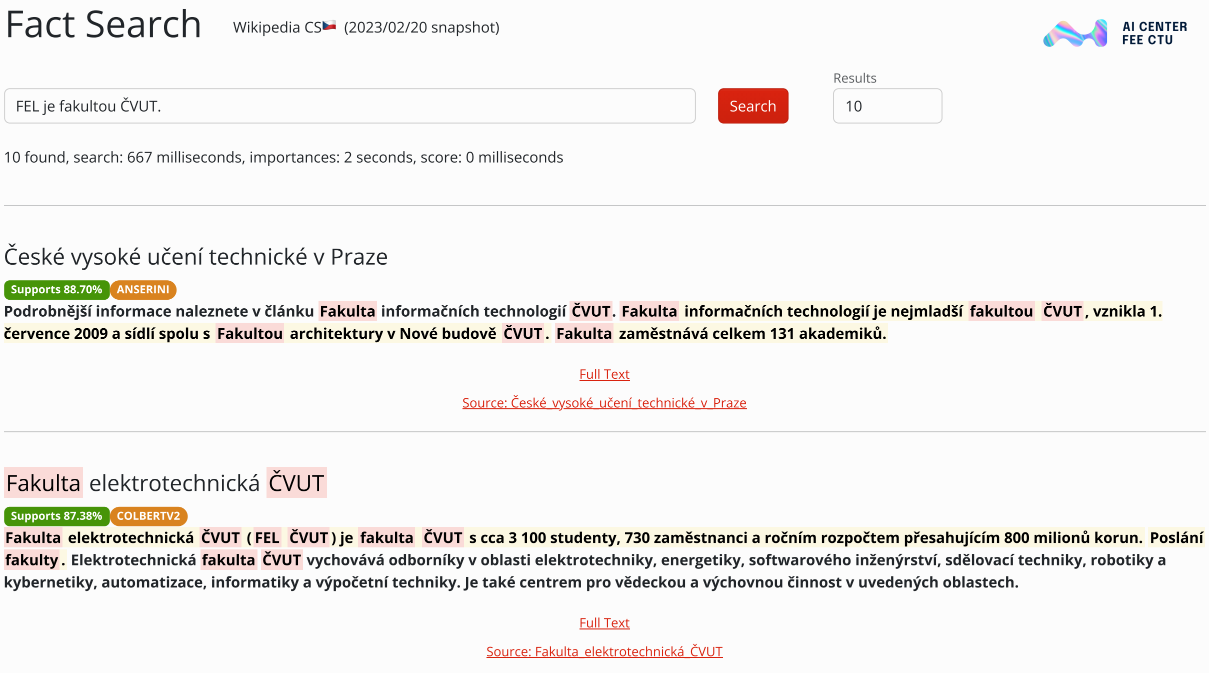
An application in the figure **??** demonstrates the single or multiple claim generation task with our LLaMA-2 or mBART models for English and Czech texts, respectively – I put it together as a GRADIO interactive application and an API. Another interactive application (Figure **??**), developed by Jan Drchal [**?**], demonstrates our best-performing end-to-end fact-checking models, integrating XLM-RoBERTa trained on CsFEVER-NLI.

[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

[16] https://cedmohub.eu



FEL je fakultou ČVUT.

10

10 found, search: 667 milliseconds, importances: 2 seconds, score: 0 milliseconds

České vysoké učení technické v Praze

Podrobnější informace naleznete v článku Fakulta informačních technologií ČVUT. Fakulta informačních technologií je nejmladší fakultou ČVUT, vznikla 1. července 2009 a sídlí spolu s Fakultou architektury v Nové budově ČVUT. Fakulta zaměstnává celkem 131 akademiků.

Source: České_vysoké_učení_technické_v_Praze

Fakulta elektrotechnická ČVUT

Fakulta elektrotechnická ČVUT (FEL ČVUT) je fakulta ČVUT s cca 3 100 studenty, 730 zaměstnanci a ročním rozpočtem přesahujícím 800 milionů korun. Poslání fakulty. Elektrotechnická fakulta ČVUT vychovává odborníky v oblasti elektrotechniky, energetiky, softwarového inženýrství, sdělovací techniky, robotiky a kybernetiky, automatizace, informatiky a výpočetní techniky. Je také centrem pro vědeckou a výchovnou činnost v uvedených oblastech.

Source: Fakulta_elektrotechnická_ČVUT

Figure 3.3: Automated fact-checking application “fact-search” verifying claims against Czech Wikipedia using our SOTA models

Chapter 4
Dissertation plan

extitThis chapter describes my current research agenda for automated fact-checking with NLP methods; the final section outlines the dissertation.

4.1 Automated claim generation

An article in preparation proposes *automated claim generation* as extracting factual claims from a document. This can assist fact-checkers and emulate data for related tasks (fact-checking, NLI).

Extracting fluent, atomic claims from naturally written text raises challenges—what information best characterizes the text? How does one resolve the pronouns and coreferences in source text? How does one adapt the extraction scheme for different speakers and stylistic forms?

These problems overlap with *abstractive summarization*, which recently made progress via Transformer models [?, ?].

The summarization setup needs minor tweaks: enforce single-sentence outputs and encourage diverse factual foci via sampling (top-k[1] and top-p[2] [?]).

Initial training data comes from XL-Sum [?], EnFEVER, and CTKFacts. We train mBART, Pegasus, T5 [?], and LLaMA-2 (QLoRA) models, with additional experiments via chat APIs.

Going forward, we will iterate on data and models in tandem and, crucially, develop reliable, explainable metrics that correlate with human judgment. As shown in section ??, the standard automated summarization metrics are not appropriate as a benchmark for the task.

4.2 Claim generation metrics

Generative tasks pose two issues: explaining model behavior in human-understandable terms and diagnosing failures such as *hallucinations*.

For the task of claim generation, where we also face the challenge of the *relevance* of the information extracted by the model, we suggest the use of the following metrics rooted in the current research on similar topics:

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

[1] Each output token is sampled from the k most probable words.

[2] Each token is sampled from the smallest prefix of tokens whose total probability mass is at most p.

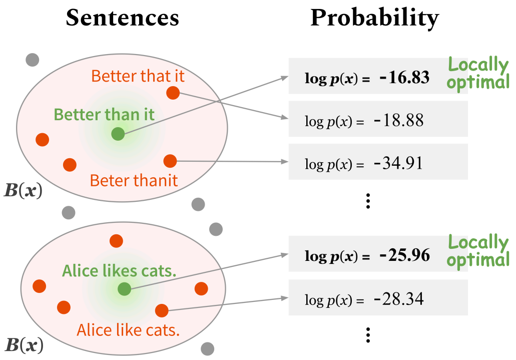


Figure 4.1: LM-Critic – deciding text fluency viewed as finding local optima of Language Model output probability, reprinted from [?]

We explore two proxies for claim fluency—akin to Grammatical Error Detection (GED): LM-Critic (Figure ??) [?] perturbs tokens to probe local optima of LM probabilities (e.g., GPT-2 as reference), and GPTScore [?] prompts an LLM (e.g., GPT-3) for a direct fluency score in few-/zero-shot settings.

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

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 documents along with inexplicable contextual pronouns ("President won't sue *them*") and relative referencing ("*Last year*, CTU had 23K students").

   [?] proposes decontextualization as a sequence-to-sequence task with two texts on input (s, c) – sentence and context. T5 model [?] 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.

   [?] improves upon this, altering the problem formulation to minimization of surrogate loss, rejecting with a fixed predictor, and claiming to get as close as $\sim 3\%$ away from the theoretical limit for the task.

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

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

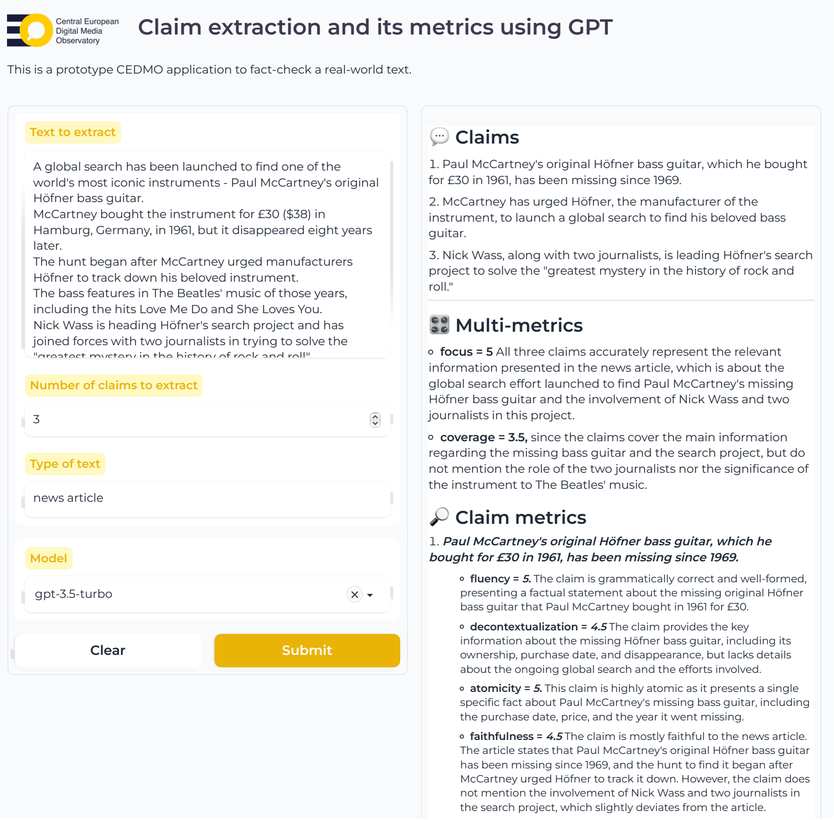
   Claim atomicity can be proxied via Relation Extraction (RE), e.g., LUKE [?]. Identify entities and relations (e.g., (*study at*, *Herbert*, *CTU*)); mark a claim as atomic if at most one such triple is found (after symmetry normalization).

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

   This metric is crucial to pinpoint *hallucinations*—parts of the claim unsupported by the source. We use two alternatives: a score within the FFCI framework [?]:

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

   Here AvgTop-n averages the top n (e.g., n=5) scores; X and Y' are sentence sets from the source and the model output (for claim generation, $|Y'|$=1). BERTScore [?]



Central European Digital Media Observatory

Claim extraction and its metrics using GPT

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

Text to extract

A global search has been launched to find one of the world's most iconic instruments - Paul McCartney's original Höfner bass guitar.
McCartney bought the instrument for £30 ($38) in Hamburg, Germany, in 1961, but it disappeared eight years later.
The hunt began after McCartney urged manufacturers Höfner to track down his beloved instrument.
The bass features in The Beatles' music of those years, including the hits Love Me Do and She Loves You.
Nick Wass is heading Höfner's search project and has joined forces with two journalists in trying to solve the "greatest mystery in the history of rock and roll"

Number of claims to extract

3

Type of text

news article

Model

gpt-3.5-turbo

💬 Claims

1. Paul McCartney's original Höfner bass guitar, which he bought for £30 in 1961, has been missing since 1969.

2. McCartney has urged Höfner, the manufacturer of the instrument, to launch a global search to find his beloved bass guitar.

3. Nick Wass, along with two journalists, is leading Höfner's search project to solve the "greatest mystery in the history of rock and roll."

🎛️ Multi-metrics

- **focus = 5** All three claims accurately represent the relevant information presented in the news article, which is about the global search effort launched to find Paul McCartney's missing Höfner bass guitar and the involvement of Nick Wass and two journalists in this project.
- **coverage = 3.5,** since the claims cover the main information regarding the missing bass guitar and the search project, but do not mention the role of the two journalists nor the significance of the instrument to The Beatles' music.

🔎 Claim metrics

1. ***Paul McCartney's original Höfner bass guitar, which he bought for £30 in 1961, has been missing since 1969.***
    - **fluency = *5.*** The claim is grammatically correct and well-formed, presenting a factual statement about the missing original Höfner bass guitar that Paul McCartney bought in 1961 for £30.
    - **decontextualization = *4.5*** The claim provides the key information about the missing Höfner bass guitar, including its ownership, purchase date, and disappearance, but lacks details about the ongoing global search and the efforts involved.
    - **atomicity = *5.*** This claim is highly atomic as it presents a single specific fact about Paul McCartney's missing bass guitar, including the purchase date, price, and the year it went missing.
    - **faithfulness = *4.5*** The claim is mostly faithful to the news article. The article states that Paul McCartney's original Höfner bass guitar has been missing since 1969, and the hunt to find it began after McCartney urged Höfner to track it down. However, the claim does not mention the involvement of Nick Wass and two journalists in the search project, which slightly deviates from the article.

Figure 4.2: A self-evaluating claim generation model based on GPT-3.5-turbo and GPT-4 [?] using the OpenAI API and a single-shot (one gold example given) approach

compares sentence embeddings rather than surface word overlap (e.g., ROUGE [?]), which helps in morphologically rich languages like Czech.

A related metric, AlignScore [?], optimizes alignment between input and output spans via a RoBERTa [?] model trained for inconsistency detection on 4.7M examples spanning NLI, QA, paraphrase, etc. Despite being relatively small (355M parameters), it outperforms some GPT-4-based metrics.

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 [?] or FERNET [?], 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 *precision*, but decisions are ambiguous in natural language due to synonyms and many valid phrasings.

An elegant and functional perspective on the problem has been brought around in QAGS[3] evaluation protocol [?], 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

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

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 the model can generate from the predicted claims.

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

   Analogous 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.

The metrics are proposed in accordance with other research on model-based evaluation of similar NLP tasks [?, ?] and are to be refined upon experiments with annotators.

4.3 Data collection

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

To validate and progress the metrics referred to in section **??**, one needs human-annotated data for the task. I aim to use an experiment similar to that of [?], presenting annotators with ordinal scales for the claim qualities and appropriate grading for each metric conditioned by objective rules.

My research will attempt to design the experiment in a way that yields the best data, checking its validity using inter-annotator agreement and other forms of feedback and publishing the data and scheme alongside the other solutions. Collected data will be used to validate the prototype metrics from section **??** and propose their variations based on the findings.

4.3.2 Polish dataset scraping

While Czech has its SumeCzech [?] and in Slovak, we can still reproduce the SMESum [?] research, a large-scale single-sentence summarization dataset in Polish has yet to be established. The closest data I have found is the online news corpus [?] collected for the purposes of studying political polarization (and nowhere published, despite my e-mail urgences).

A scraping experiment in the Polish media, such as TVP, Rzeczpospolita, Gazeta Wyborcza, Fakt, etc., is therefore being prepared to obtain an appropriate single-sentence dataset for publication – it is also going to be another incremental step toward the dissertation on the overall topic of NLP fact-checking and its stages, focusing on English and West Slavic languages.

4.3.3 Crowd-sourced fact-checking platform

In 2023, other members of our team [?] with funding from Avast developed a crowd-sourced fact-checking platform[4], where users gather reputations like on Wikipedia, by sharing check-worthy pieces of information found across the internet, and by their checking with sources.

While I am not directly involved in the implementation of the project apart from early consulting, experiments with FSV CUNI are to be launched, populating this platform with

[4] `https://factcheck.fel.cvut.cz`

data and users. After the experiments, other data and applications will be delivered, and their processing will be another part of my dissertation project.

4.3.4 CTKFacts expansion

In 2021/2022, another round of the CTKFacts annotation experiment (see section **??**) was carried out with the FSV CUNI students, yielding about 5K new data points, including, for example, claims extracted from the Czech Twitter.

The data is being cleaned and examined and will be attached to one of the other upcoming publications and presented in the dissertation thesis.

4.4 Pipeline modernization

As mentioned throughout the chapter **??**, the state of the art in NLP has shifted dramatically over the last year, and another of the tasks I am currently working on is the modernization of our pipeline – Claim Generation, Information Retrieval, Natural Language Inference models – and appropriate use of LLMs in the tasks.

So far, I have successfully finetuned LLaMA-2 [**?**] for the claim generation task, and we have a LoRA finetuning experimental setup ready for the NLI models. The use of LLaMA-2 and its successors for our tasks will be a topic on its own, as most publicly available LLMs filter out the other languages and focus solely on English.

4.5 The grand scope

Overall, in brief points, the main topics of my dissertation are expected to be:

1. Introduction of the fact-checking task and its data, strong model baselines, and specific properties in the **West Slavic** context.

2. An integration of the step of **Claim generation** step into it, based on methods of abstractive summarization.

3. A delivery of reliable **metrics** for the tasks and their validation with expert-level humans.

4. Modernization of the automated fact-checking framework and solutions in English and Czech into the age of **Large Language Models**. Solutions were proposed already – based on proprietary black-box LLMs such as GPT-3.5 [**?**] – our next goal is to deploy open-source LLMs in-house, experiment with different architectures, fine-tuning tasks and data, improving the SOTA on our benchmark data.

   Due to our aim to produce transparent and reproducible research, using open-source LLMs is preferred over popular proprietary ones like GPT-4.

5. As the current instruction-tuned Large Language Models exhibit an **ability to explain their reasoning** [**?**], the methods of eXplainable AI (XAI) may also be integrated into our automated fact-checking framework, giving the fact-checker further insights what is behind the model classification.

6. Multiple **validation experiments** are planned with real-world fact-checkers[5] to testify to the usability of our solutions in the real world.

[5] Partners from CEDMO and other projects

Chapter 5
AVeriTeC Paper

5.1 Introduction

We release a pipeline for fact-checking claims using evidence retrieved from the web consisting of two modules – a *retriever*, which picks the most relevant sources among the available knowledge store[1] and an *evidence & label generator* which generates evidence for the claim using these sources, as well as its veracity label.

Our pipeline is a variant of the popular Retrieval-augmented Generation (RAG) scheme [?], making it easy to re-implement using established frameworks such as Langchain, Haystack, or our attached Python codebase for future research or to use as a baseline.

This paper describes our pipeline and the decisions taken at each module, achieving a simple yet efficient RAG scheme that improves dramatically across the board over the baseline system from [?], and scores third in the AVeriTeC leaderboard as of August 2024, with an AVeriTeC test set score of 50.4%.

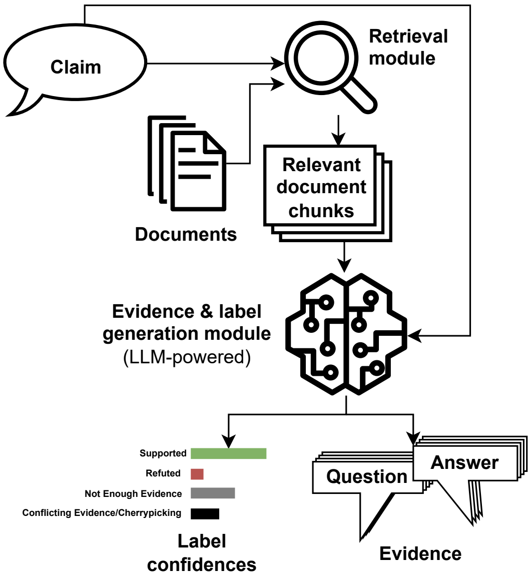


Figure 5.1: Our pipeline

[1] Due to the pre-retrieval step that was used to generate knowledge stores, our retriever module could more conventionally be referred to as a reranker, which we refrain from, to avoid confusion with reranking steps it uses as a subroutine.

5.2 Related work

1. **AVeriTeC shared task** [?] releases the datase of real-world fact-checked claims, annotated with evidence available at the date the claim was made.

   It proposes the **AVeriTeC Score** – a method of unsupervised scoring of fact-checking pipeline against this gold data using Hungarian METEOR score, matching the evidence questions (Q) or the whole evidence (Q+A). The score is then calculated as the proportion of claims with accurate label and sound evidence (using a threshold for Hu-METEOR such as 0.25) among all claims in the dataset, giving an estimate on how often the whole fact-checking pipeline succeeds end to end.

   The provided **baseline** is a pipeline of search query generation, API search (producing a knowledge store), sentence retrieval, Question-and-answer (QA) generation, QA reranking, QA-wise claim classification and label aggregation, achieving an overall AVeriTeC test set score of 11%.

2. **FEVER Shared Task** [?], a predecessor to the AVeriTeC, worked with a similar dataset engineered on top of the enclosed domain Wikipedic data rather than real-world fact-checks. Its top-ranking solutions used a simpler pipeline of Document Retrieval, Sentence Reranking and Natural Language Inference, improving its modules in a decoupled manner and scoring well above 60% in a similarly computed FEVER score [?] on this data.

3. **Our previous research** on fact-checking pipelines [?,?] using data similar to FEVER and AVeriTeC shows significant superiority of fact-checking pipelines that **retrieve the whole documents** for the inference step, rather than retrieving out-of-context sentences.

4. **Retrieval-Augmented Generation (RAG) for Knowledge-Intensive Tasks** [?] takes this a step further, leveraging Large Language Model (LLM) for the task, providing it the whole text of retrieved documents (each a chunk of Wikipedia) and simply instructing it to predict the evidence and label on top of it, achieving results within 4.3% from the FEVER state of the art by the time of its publication (December 2020) *without* engineering a custom pipeline for the task.

5.3 System description

Our system design prioritizes simplicity, and its core idea is using a straightforward RAG pipeline without engineering extra steps, customizing only the retrieval step and LLM prompting (Listing **??** in Appendix **??**). Despite that, this section describes and justifies our decisions taken at each step, our additions to the naive version of RAG modules to tune them for the specific task of fact-checking, and their impact on the system performance.

5.3.1 Retrieval module

To ease comparison with the baseline and other systems designed for the task, our system does not use direct internet/search-engine access for its retrieval, but an AVeriTeC *knowledge store* provided alongside each claim.

To use our pipeline in the wild, our retrieval module is decoupled from the rest of the pipeline and can be swapped out in favour of an internet search module such as SerpApi[2] as a whole, or it can be used on top of a knowledge store emulated using large crawled corpora such as CommonCrawl[3] and a pre-retrieval module.

Knowledge stores

Each claim's knowledge store contains pre-scraped results for various search queries that can be derived from the claim using human annotation or generative models. The knowledge stores used with ours as well as the baseline system can be downloaded from the AVeriTeC dataset page[4], containing about 1000 pre-scraped *documents*[5], each consisting of 28 sentences at mediandevsetnote, albeit varying wildly between documents. The methods used for generating the knowledge stores are explained in more detail by averitec2024.

Our retrieval module then focuses on picking a set of k ($k = 10$ in the examples below, as well as in our submitted system) most appropriate document chunks to fact-check the provided claim within this knowledge store.

Angle-optimized embedding search

Despite each article in any knowledge store only needing to be compared *once* with its *one specific* claim, which should be the use-case for CrossEncoder reranking [**?**], our empirical preliminary experiments made us favour a *cosine-similarity* search based on vector embeddings instead. It takes less time to embed the whole knowledge store into vectors than to match each document against a claim using crossencoder, and the produced embeddings can be re-used across experiments.

For our proof of concept, we explore the MTEB [**?**] benchmark leaderboard, looking for a reasonably-sized open-source embedding model, ultimately picking Mixedbread's mxbai-large-v1 [**?**, **?**] optimized for the cosine objective fitting our inteded use.

To reduce querying time at a reasonable exactness tradeoff, we use Faiss index [**?**, **?**] to store our vectors, allowing us to only precompute semantical representation once, making the retriever respond rapidly in empirical experiments, allowing a very agile prototyping of novel methods to be used.

Chunking with added context

Our initial experiments with the whole AVeriTeC documents for the Document Retrieval step have revealed a significant weakness – while most documents fit within the input size of the embedding model, outliers are common, often with *hundreds of thousands* characters, exceeding the 512 input tokens with little to no coverage of their content.

Upon further examination, these are typically PDF documents of legislature, documentation and communication transcription – highly relevant sources real fact-checker would scroll through to find the relevant part to refer.

This workflow inspires the use of *document chunk retrieval* as used in [**?**], commonly paired with RAG. We partition each document into sets of its sentences of combined length of N characters at most. To take advantage of the full input size of the vector embedding

[2] `https://serpapi.com/`

[3] `https://commoncrawl.org/`

[4] `https://fever.ai/dataset/averitec.html`

[5] The numbers are orientational and were computed on knowledge stores provided for the AVeriTeC dev set.

model we use for semantical search, we arbitrarily set our bound $N = 512 * 4 = 2048$, where 512 is the input dimension of common embedding models, 4 often being used as a rule-of-thumb number of characters per token for US English in modern tokenizers [**?**].

Importantly, each chunk is assigned metadata – the source URL, as well as the full text of the next and previous chunk within the same document. This way, chunks can be presented to the LLM along with their original context in the generation module, where the length constraint is much less of an issue than in vector embedding. As shown in [**?**], fact-checking models benefit from being exposed to larger pieces of text such as paragraphs or entire documents rather than out-of-context sentences. Splitting our data into the maximum chunks that fit our retrieval model and providing them with additional context may help down the line, preventing the RAG sources from being semantically incomplete.

Pruning the chunks

While the chunking of long articles prevents their information from getting lost to retriever, it makes its search domain too large to embed on demand. As each of the thousands of claims has its own knowledge store, each of possibly tens of thousands of chunks, we seek to omit the chunks having little to no common tokens with our claim using an efficient BM25 [**?**] search for the nearest ω chunks, setting the ω to 6000 for dev and 2000 for test claims. This yields a reasonably-sized document store for embedding each chunk into a vector, taking an average of 40 s to compute and store using the method described in Section **??** for each dev-claim using our Tesla V100 GPU.

This allows a quick and agile production of vectorstores for further querying and experimentation, motivated by the AVeriTeC test data being published just several days before the announced submission deadline. The pruning also keeps the resource intensity moderate for real-world applications. However, if time is not of the essence, the step can be omitted.

Diversifying sources: MMR

Our choice of embedding search based on the entire claim rather than generating search queries introduces less noise and captures the semantics of the whole claim. It is, however, prone to redundancy among search results, which we address using a reranking by the results' Maximal Marginal Relevance (MMR) [**?**], a metric popular for the RAG task, which maximizes the search results' score computed as (for $D_i \in P$)

$$\lambda \cdot \mathrm{Sim}(D_i, Q) - (1 - \lambda) \cdot \max_{D_j \in S} \mathrm{Sim}(D_i, D_j)$$

Sim denoting the cosine-similarity between embeddings, Q being the search query, and P the pre-fetched set of documents (by a search which simply maximizes their Sim to Q), forming S as the final search result, by adding each D_i as MMR-argmax one by one, until reaching its desired size.

In our system, we set $\lambda = 0.75$ to favour relevancy rather than diversity, $|S| = 10$ and $|P| = 40$, obtaining a set of diverse sources relevant to each claim at a fraction of cost and complexity of a query-generation driven retrieval, such as that used in [**?**].

5.3.2 Evidence & label generator

The second and the last module on our proposed pipeline for automated fact checking is the Evidence & Label Generator, which receives a claim and k sources (document chunks), and returns l (in our case, $l = 10$) question-answer pairs of evidence abstracted from the sources, along with the veracity verdict – in AVeriTeC dataset, a claim may be classified as *Supported*, *Refuted*, *Not Enough Evidence*, or *Conflicting Evidence/Cherrypicking* with respect to its evidence.

Our approach leverages a Large Language Model (LLM), instructing it to output both evidence and the label in a single step, as a chain of thought. We rely on JSON-structured output generation with source referencing using a numeric identifier, we estimate the label confidences using Likert-scale ratings. The full system prompt can be examined in Listing **??** in Appendix **??**, and this section further explains the choices behind it.

JSON generation

To be able to collect LLM's results programmatically, we exploit their capability to produce structured outputs, which is on the rise, with datasets available for tuning [**?**] and by the time of writing of this paper (August 2024), systems for strictly structured prediction are beginning to be launched by major providers [**?**].

Despite not having access to such structured-prediction API by the time of AVeriTeC shared task, the current generation of models examined for the task (section **??**) rarely strays from the desired format if properly explained within a system prompt – we instruct our models to output a JSON of pre-defined properties (see prompt Listing **??** in Appendix **??**) featuring both evidence and the veracity verdict for a given claims.

Although we implement fallbacks, less than 0.5% of our predictions threw a parsing exception throughout experimentation, and could be easily recovered using the same prompting again, exploiting the intrinsic randomness of LLM predictions.

Chain-of-thought prompting

While JSON dictionary should be order-invariant, we can actually exploit the order of outputs in our output structure to make LLMS like GPT-4o output better results [**?**]. This is commonly referred to as the chain-of-thought prompting – if we instruct the autoregressive LLM to first output the evidence (question, then answer), then a set of all labels with their confidence ratings (see section **??**) and only then the final verdict, its prediction is both cheaper as opposed to implementing an extra module, as well as more reliable, as it must attend to all of the intermediate steps as well.

Source referring

To be able to backtrack the generated evidence to the urls of the used sources, we simply augment each question-answer pair with a source field. We assign a 1-based index[6] to each of the sources to facilitate tokenization and prompt the LLM to refer it as the source ID with each evidence it generates. While hallucination can not be fully prevented, it is less common than it may appear – with RAG gaining popularity, the models are being trained to cite their sources using special citation tokens [**?**], not dissimilarly to our proposal.

[6] We chose the 1-based source indexing to exploit the source-referring data in LLM train set such as Wikipedia, where source numbers start with 1. The improvement in quality over 0-based indexing was not experimentally tested.

Dynamic few-shot learning

To utilise the few-shot learning framework [?] shown to increase quality of model output, we provide our LLMs with examples of what we expect the model to do. To obtain such examples, our evidence generator looks up the AVeriTeC train set using BM25 to get the 10 most similar claims, providing them as the few-shot examples, along their gold evidence and veracity verdicts. Experimentally, we also few-shot our models to output an *answer type* (*Extractive*, *Abstractive*, *Boolean,...*) as the *answer type* is listed with each sample anyways, and we have observed its integration into the generation task to slightly boost our model performance.

Likert-scale label confidences

Despite modern LLMs being well capable of predicting the label in a pick one fashion, research applications such as ours may prefer them to output a probability distribution over all labels for two reasons.

Firstly, it measures the confidence in each label, pinpointing the edge-cases, secondly, it allows ensembling the LLM classification with any other model, such as Encoders with classification head finetuned on the task of Natural Language Inference (NLI) (see section **??**).

As the LLMs and other token prediction schemes struggle with the prediction of continuous numbers which are notoriously hard to tokenize appropriately [?], we come up with a simple alternative: instructing the model to print each of the 4 possible labels, along with their Likert-scale rating: 1 for strongly disagree, 2 for disagree, 3 for neutral, 4 for agree and 5 for strongly agree [?].

On top of the ease of tokenization, Likert scale's popularity in psychology and other fields such as software testing [?] adds another benefit – both the scale itself and its appropriate usage were likely demonstrated many times to LLMs during their unsupervised training phase.

To convert the ratings such as `{Supported:2, Refuted:5, Cherrypicking:4, NEE:2}` to a probability distribution, we simply use softmax [?]. While the label probabilities are only emulated (and may only take a limited, discrete set of values) and the system may produce ties, it gets the job done until further research is carried out.

Choosing LLM

In our experiments, we have tested the full set of techniques introduced in this section, computing the text completion requests with:

1. GPT-4o (version `2024-05-13`)
2. Claude-3.5-Sonnet (`2024-06-20`), using the Google's Vertex API
3. LLaMA 3.1 70B, in the final experimets to see if the pipeline can be re-produced using open-source models

Their comparison can be seen in tables **??** and **??**; for our submission in the AVeriTeC shared task, GPT-4o was used.

5.4 Other examined approaches

In this section, we also describe a third, optional module we call the *veracity classifier*, which takes the claim and its evidence generated by our evidence & label generator (section **??**) and predicts the veracity label independently, based on the suggested evidence, using a fine-tuned NLI model. We also describe the options of its ensembling with veracity labels predicted in the generative step (section **??**).

The absence of a dedicated veracity classifier has not been shown to decrease the performance of our pipeline significantly (as shown, e.g., in tables **??** and **??**) so we suggest to omit this step altogether and we proceed to participate in the AVeriTeC shared task without it, proposing a clean and simple RAG pipeline without the extra step (Figure **??**) for the fact-checking task.

5.4.1 Single-evidence classification with label aggregation

In the earliest stages of experimenting, we utilized the baseline classifier provided by AVeriTeC authors[7] [**?**]. It is based on the BERT [**?**] and was further fine-tuned on the AVeriTeC dataset [**?**]. It takes one claim and one question-answer evidence as input – each claim therefore has multiple classifications, one for each evidence. The classifications are then aggregated using a heuristic of several if-clauses to determine the final label.

We experiment with altering this heuristic (e.g. by making *not enough evidence* the final label only when no other labels are present at any evidence), and training NLI models that could work better with it, such as 3-way DeBERTaV3 [**?**] without a breakthrough result, motivating a radically different approach.

5.4.2 Multi-evidence classification

The multi-evidence approach is to fine-tune a 4-way Natural Language Inference (NLI) classifier, using the full scope of evidence directly at once, without heuristics. For that, we concatenate all of the evidence together using a separator `[SEP]` token. This allows the model to know exact question-answer borders, albeit using a space has turned out to be just as accurate as the experiments went on. As the veracity verdict should be independent of the evidence ordering, we also experiment with sampling different permutations in the fine-tuning step to increase the size of our data.

We carry out the fine-tuning using the AVeriTeC train split with gold evidence and labels on DeBERTaV3 [**?**] in two variants: the original large one[8] and one pre-finetuned on NLI tasks[9], and also Mistral-7B-v0.3 model[10] with a classification head (MistralForSequenceClassification) provided by the Huggingface Transformers library [**?**] that utilizes the last token. In the preliminary testing phase, the original DeBERTaV3 Large performed the best and was used in all other experimental settings.

From the approaches described above, we achieved the best results for the development split with gold evidence and labels with a model without permuting the evidence, achieving 0.71 macro F_1 score using a space-separation. The `[SEP]` model achieved a comparable 0.70 macro F_1 score, and the random order model performed worse with a 0.67 macro F_1 score, all improving significantly upon baseline, yet falling behind the capabilities of

[7] `https://huggingface.co/chenxwh/AVeriTeC`

[8] `https://huggingface.co/microsoft/deberta-v3-large`

[9] `https://huggingface.co/cross-encoder/nli-deberta-v3-large`

[10] `https://huggingface.co/mistralai/Mistral-7B-v0.3`

generating the labels alongside evidence in a single chain-of-thought. We provide our best DeBERTaV3 finetuned model publicly in a Huggingface repository[11].

5.4.3 Ensembling classifiers

Encouraged by the promising results of our multi-evidence classifiers, we go on to try to ensemble the models with LLM predictions from section **??**, using a weighted average of the class probabilities of our models. We have experimented with multiple weight settings: 0.5:0.5 for even votes, 0.3:0.7 in favour of the LLM to exploit its accuracy while tipping its scales in cases of a more spread-out label probability distribution, as well as 0.1:0.9 to use the fine-tuned classifier only for tie-breaking, listing the results in Table **??**.

We also tried tuning our ensemble weights based on a subset of the dev split, without a breakthrough in accuracy on the rest of dev samples.

The last method we tried was stacking using logistic regression. However, this setup classified no labels from *Not Enough Evidence* and *Conflicting Evidence/Cherrypicking*, and we could not achieve reasonable results. For logistic regression, we used the scikit-learn library [**?**].

We conclude that the augmentation of the pipeline from Figure **??** with a classification module using a single NLI model or an ensemble with LLM is unneccessary, as it adds complexity and computational cost without paying off on the full pipeline performance (Table **??**).

5.4.4 Conflicting Evidence/Cherrypicking detection

During the experiments, we discovered that classifying the *Conflicting Evidence/Cherrypicking* class is the most challenging task, achieving a near-zero F_1-score across our various prototype pipelines. To overcome this problem, we tried to build a binary classifier with cherrypicking as positive class. We tried to use the DeBERTaV3 Large model with both basic and weighted cross-entropy loss (other experimental settings were the same as in section **??**), but it could not pick up the training task due to the *Conflicting Evidence/Cherrypicking* underrepresentation in train set – less than 7% of the samples carry the label.

Even after exploring various other methods, we did not get a reliable detection scheme for this task, perhaps motivating a future collection of data that represents the class better. While writing this system description paper, we found an interesting research by jaradat2024contextawaredetectioncherrypickingnews that uses a radically different approach to detect cherrypicking in newspaper articles.

5.5 Results and analysis

We examine our pipeline results using two sets of metrics – firstly, we measure the prediction accuracy and F_1 over predict labels without any ablation, that is obtaining predicted labels using the predicted evidence generated on top the predicted retrieval results. While the retrieval module is fixed throughout the experiment (a full scheme described in section **??**), various Evidence & Label generators and classifiers are compared in Table **??**, showcasing their performance on the same sources. The results show that if we disregard the quality of evidence, models are more or less interchangeable, without a clear winner

[11] `https://huggingface.co/ctu-aic/deberta-v3-large-AVeriTeC-nli`

Classifier	Acc	F_1	Prec.	Recall
GPT4o	0.72	0.46	0.48	0.47
Claude 3.5 Sonnet	0.64	0.49	0.50	0.52
DeBERTa	0.63	0.39	0.40	0.41
DeBERTa - random@10	0.65	0.41	0.41	0.44
$0.5 \cdot$ DeBERTa $+ 0.5 \cdot$ GPT4o	0.70	0.43	0.41	0.45
$0.5 \cdot$ DeBERTa $+ 0.5 \cdot$ Claude	0.68	0.47	0.50	0.49
$0.3 \cdot$ DeBERTa $+ 0.7 \cdot$ GPT4o	0.72	0.45	0.45	0.46
$0.3 \cdot$ DeBERTa $+ 0.7 \cdot$ Claude	0.66	**0.50**	**0.51**	**0.53**
$0.1 \cdot$ DeBERTa $+ 0.9 \cdot$ GPT4o	0.72	0.39	0.46	0.43
$0.1 \cdot$ DeBERTa $+ 0.9 \cdot$ Claude	0.64	0.49	0.50	0.54
Llama 3.1	**0.73**	0.44	0.43	0.46

Table 5.1: Evalution of the label generators, classifier models and their ensembles on the AVeriTeCdevelopment set. F_1, Precision and Recall are computed as macro-averages. The random@10 suffix indicates that the classifier used average of 10 different random orders of QA pairs for each claim. GPT4o stands for the Likert classifier based on GPT-4o, Claude 3.5 Sonnet is the Likert classifier based on Claude 3.5 Sonnet, and DeBERTa is classifier based on DeBERTaV3 Large fine-tuned on AVeriTeC gold evidence and labels.

across the board – an ensemble of DeBERTA and Claude-3.5-Sonnet gives the best F_1 score, while GPT-4o scores 72% accuracy.

In real world, however, the evidence quality is critical for the fact-checking task. We therefore proceed to estimate it using the hu-METEOR evidence question score, QA score and AVeriTeC score benchmarks briefly explained in Section **??** and in greater detail in [?]. We use the provided AVeriTeC scoring script to calculate the values for Table **??**, using its EvalAI blackbox to obtain the test scores without seeing the gold test data.

The latter experiments shown in Table **??** suggests the superiority of GPT-4o to predict the results for our pipeline with a margin. Even if we simplify the evidence & label generation step by omitting the dynamic few-shot learning (section **??**), answer-type tuning and Likert-scale confidence emulation, it still scores above others, also showing that our pipeline can be further simplified when needed. Regardless of the LLM in use, the results of our pipeline improve upon the AVeriTeC baseline dramatically.

Posterior to the original experiments and to the AVeriTeC submission deadline, we also compute the pipeline results using an open-source model – the Llama 3.1 70B[12] [?] obtaining encouraging scores, signifying our pipeline being adaptable to work well without the need to use a blackboxed proprietary LLM.

[12] `https://huggingface.co/hugging-quants/Meta-Llama-3.1-70B-Instruct-AWQ-INT4`

Pipeline Name	Dev Set Scores			Test Set Scores		
	Q only	Q+A	AVeriTeC	Q only	Q+A	AVeriTeC
GPT-4o (full-featured pipeline)	**0.46**	**0.29**	**0.42**	0.46	**0.32**	**0.50**
GPT-4o (simplified pipeline)	0.45	0.28	0.38	0.45	0.30	0.47
Claude-3.5-Sonnet (full-featured)	0.43	0.28	0.35	0.42	0.30	0.46
GPT-4o (with DeBERTa classification)	0.45	0.28	0.36	–	–	–
AVeriTeC baseline	0.24	0.19	0.09	0.24	0.20	0.11
Llama 3.1 70B (full-featured)	**0.46**	0.27	0.36	**0.47**	0.29	0.42

Table 5.2: Comparison of Pipeline Scores on Dev and Test Sets. Q, Q+A are Hu-METEOR scores against gold data, AVeriTeC scores are calculated as referred in section **??** thresholded at 0.25. Full-featured pipelines use the all the improvement techniques introduced in section **??**, while the simplified pipeline omits the dynamic few-shot learning, answer-type-tuning and Likert-scale confidence emulation described in section **??**

5.5.1 API costs

During our experimentation July 2024, we have made around 9000 requests to OpenAI's `gpt-4o-2024-05-13` batch API, at a total cost of $363. This gives a mean cost estimate of $0.04 per a single fact-check (or $0.08 using the API without the batch discount) that can be further reduced using cheaper models, such as `gpt-4o-2024-08-06`.

We argue that such costs make our model suitable for further experiments alongside human fact-checkers, whose time spent reading through each source and proposing each evidence by themselves would certainly come at a higher price.

Our successive experiments with Llama 3.1 [**?**] show promising results as well, nearly achieving parity with GPT. The use of open-source models such as LLaMa or Mistral allows running our pipeline on premise, without leaking data to a third party and billing anything else than the computational resources. For further experiments, we are looking to integrate them into the attached Python library using VLLM [**?**].

5.5.2 Error analysis

In this section, we provide the results of an explorative analysis of 20 randomly selected samples from the development set. We divide our description of the analysis into the pipeline and dataset errors.

Pipeline errors

Our pipeline tends to rely on unofficial (often newspaper) sources rather than official government sources, e.g., with a domain ending or containing `gov`. On the other hand, it seems that the annotators prefer those sources. This could be remedied by implementing a different source selection strategy, preferring those official sources. For an example, see Listing **??** in Appendix **??**.

Another thing that could be recognised as an error is that our pipeline usually generates all ten allowed questions (upper bound given by the task [**?**]). The analysis of the samples shows that the last questions are often unrelated or redundant to the claim and do not contribute directly to better veracity evaluation. However, since the classification step of our pipeline is not dependent on the number of question-answer pairs, this is not a critical error. Listing **??** in Appendix **??** shows an example of a data point with some unrelated questions.

When the pipeline generates extractive answers, it sometimes happens that the answer is not precisely extracted from the source text but slightly modified. An example of this error can be seen in Listing **??** in Appendix **??**. This error is not critical, but it could be improved in future works, e.g. using post-processing via string matching.

Individual errors were also caused by the fact that we do not use the claim date in our pipeline and because our pipeline cannot analyse PDFs with tables properly. The last erroneous behaviour we have noticed is that the majority of questions and answers are often generated from a single source. This should not be viewed as an error, but by introducing diversity into the sources, the pipeline would be more reliable when deployed in real-world scenarios.

Dataset errors

During the error analysis of our pipeline, we also found some errors in the AVeriTeC dataset that we would like to mention. In some cases, there is a leakage of PolitiFact or Factcheck.org fact-checking articles where the claim is already fact-checked. This leads to a situation where our pipeline gives a correct verdict using the leaked evidence. However, annotators gave a different label (often Not Enough Evidence). An example of this error is shown in Listing **??** in Appendix **??**.

Another issue we have noticed is the inconsistency in the questions and answers given by annotators. Sometimes, they tend to be longer, including non-relevant information, while some are much shorter, as seen in Listing **??** in Appendix **??**. The questions are often too general, or the annotators seem to use outside knowledge. This inconsistency in the dataset leads to a decreased performance of any models evaluated on this dataset.

Summary

Despite the abovementioned errors, the explorative analysis revealed that our pipeline consistently gives reasonable questions and answers for the claims. Most misclassified samples in those 20 data points were due to dataset errors.

5.6 Conclusion

In this paper, we describe the use and development of a RAG pipeline over real world claims and data scraped from the web for the AVeriTeC shared task. Its main advantage are its simplicity, consisting of just two decoupled modules – Retriever and an Evidence & Label Generator – and leveraging the trainable parameters of a LLM rather than on complex pipeline engineering. The LLMs capabilities may further improve in future, making the upgrades of our system trivial.

In section **??**, we describe the process of adding features to both modules well in an iterative fashion, describing real problems we have encountered and the justifications of their solution, hoping to share our experience on how to make such systems robust and well-performing. We publish our failed approaches in section **??** and the metrics we observed to benchmark our systems in section **??**. We release our Python codebase to facilitate further research and applications of our system, either as a baseline for future research, or for experimenting alongside human fact-checkers.

5.6.1 Future works

1. Integrating a search API for use in real-world applications
2. Re-examine the Likert-scale rating (section **??**) to establish a more appropriate and fine-grained means of tokenizing the label probabilities
3. Generating evidence in the form of declarative sentences rather than Question-Answer pairs should be explored to see if it leads for better or worse fact-checking performance
4. RAG-tuned LLMs such as those introduced in [**?**] could be explored to see if they offer a more reliable source citing

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Chapter 7
Conclusion

This study outlined current challenges and motivations—building automated support for fact-checking. Most solutions rely on transformers, the SOTA for almost every NLP task. The paradigm is shifting from *fine-tuning* pre-trained encoders/decoders to *prompting* and few-shotting instruction-tuned LLMs, which impacts this dissertation and requires modernizing prior work.

So far, we have collected several datasets—most notably CsFEVER and CTKFacts —deployed a working fact-checking pipeline, and released trained models for reuse.

Next, we aim to establish claim generation and its model-based metrics, conclude ongoing model training and data collection (Czech, English, Polish, Slovak), and propose updated end-to-end solutions leveraging modern LLMs.

The preceding chapters summarized what has been done, why it matters, the surrounding context, and the likely next steps.

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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

IR Information Retrieval

SOTA State of the Art

XSum Extreme Summarization – summarizing article into one sentence

NLI Natural Language Inference

ČTK Czech Press Agency

Appendix B
LLM configuration used in FEVER 8

~~~
You are a professional fact checker, formulate up to 10 questions that cover all the facts needed to validate whether the factual statement (in User message) is true, false, uncertain or a matter of opinion. Each question has one of four answer types: Boolean, Extractive, Abstractive and Unanswerable using the provided sources.
After formulating Your questions and their answers using the provided sources, You evaluate the possible veracity verdicts (Supported claim, Refuted claim, Not enough evidence, or Conflicting evidence/Cherrypicking) given your claim and evidence on a Likert scale (1 - Strongly disagree, 2 - Disagree, 3 - Neutral, 4 - Agree, 5 - Strongly agree). Ultimately, you note the single likeliest veracity verdict according to your best knowledge.
The facts must be coming from these sources, please refer them using assigned IDs:
---
## Source ID: 1 [url]
[context before]
[page content]
[context after]
...

---
## Output formatting
Please, you MUST only print the output in the following output format:
```json
{
 "questions":
     [
         {"question": "<Your first question>", "answer": "<The answer to the Your first question>", "source": "<Single numeric source ID backing the answer for Your first question>", "answer_type":"<The type of first answer>"},
         {"question": "<Your second question>", "answer": "<The answer to the Your second question>", "source": "<Single numeric Source ID backing the answer for Your second question>", "answer_type":"<The type of second answer>"}
     ],
 "claim_veracity": {
     "Supported": "<Likert-scale rating of how much You agree with the 'Supported' veracity classification>",
     "Refuted": "<Likert-scale rating of how much You agree with the 'Refuted' veracity classification>",
     "Not Enough Evidence": "<Likert-scale rating of how much You agree with the 'Not Enough Evidence' veracity classification>",
     "Conflicting Evidence/Cherrypicking": "<Likert-scale rating of how much You agree with the 'Conflicting Evidence/Cherrypicking' veracity classification>"
 },
 "veracity_verdict": "<The suggested veracity classification for the claim>"
}
```
---
## Few-shot learning
You have access to the following few-shot learning examples for questions and answers.:

### Question examples for claim "{example["claim"]}" (verdict {example["gold_label"]})
"question": "{question}", "answer": "{answer}", "answer_type": "{answer_type}"
...
~~~

Listing B.1: System prompt for the LLMs, AVeriTeC claim is to be entered into the user prompt. Three dots represent omitted repeating parts of the prompt. Reused and reprinted from ullrich-etal-2024-aic.

Appendix C

Thinking tokens example

~~~~
<think>
Okay, let's tackle this query. The user is claiming that due to Imran Khan's criticism
  ↪ of Macron's comments on Islam, French authorities cancelled the visas of 183
  ↪ Pakistani citizens and deported 118 from the country. I need to verify this using
  ↪ the provided sources.

First, I'll look through the sources to see if there's any mention of visa
  ↪ cancellations or deportations related to Imran Khan's criticism.

Looking at Source ID 1, it talks about Imran Khan responding to Macron's remarks and
  ↪ the condemnation of Islamophobic policies, but there's no mention of visa
  ↪ cancellations or deportations.

Source ID 2 discusses a diplomatic row where Pakistan refused to accept a deportee,
  ↪ Muhammad Mansha, until his credentials were verified. This seems related to a
  ↪ specific case but not the large numbers mentioned in the claim.

Source ID 3 mentions protests in Pakistan against France's republishing of cartoons,
  ↪ but again, no visa or deportation numbers here.

Source ID 4 and 5 discuss diplomatic tensions, but not specific numbers of
  ↪ deportations. Source 5 and 6 from Newscomworld.com talk about fears of
  ↪ deportations of Pakistanis in France but don't mention specific numbers like 183
  ↪ or 118.
...

None of the sources mention 183 visas cancelled or 118 deported. The closest is Source
  ↪ 2, which mentions one individual, Muhammad Mansha, but that's a single case. The
  ↪ other sources discuss diplomatic tensions, protests, and possible fears of
  ↪ deportations but no actual numbers provided.

Therefore, the claim about 183 and 118 seems to be unsupported. The answer would be
  ↪ that there's no evidence of such numbers in the sources provided. The veracity
  ↪ verdict would be Refuted, as the sources don't support the specific numbers given.
</think>

```json
{
    "questions": [
        {"question": "Did French authorities cancel visas or deport Pakistani citizens
  ↪ in response to Imran Khan's criticism of Macron's comments on Islam?", "answer":
  ↪ "No specific information about visa cancellations or deportations of 183 Pakistani
  ↪ citizens or 118 deportees is mentioned in the provided sources.", "source": "10",
  ↪ "answer_type": "Boolean"},
        ...
    ],
    "claim_veracity": {
        "Supported": "1",
        "Refuted": "5",
        "Not Enough Evidence": "1",
        "Conflicting Evidence/Cherrypicking": "1"
    },
    "veracity_verdict": "Refuted"
}
```
~~~~

Listing C.1: Qwen3 thinking tokens example.