Bachelor Project

Czech
Technical
University
in Prague

F3

Faculty of Electrical Engineering
Department of Computer Science

Bias Detection in Czech News

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Supervisor: Ing. Jan Drchal, Ph.D
Field of study: Open Informatics
Subfield: Artificial Intelligence and Computer Science
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BACHELOR‘S THESIS ASSIGNMENT

I. Personal and study details

Student's name: **Horych Tomáš** Personal ID number: **484011**

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Study program: **Open Informatics**

Specialisation: **Artificial Intelligence and Computer Science**

II. Bachelor’s thesis details

Bachelor’s thesis title in English:

Bias Detection in Czech News

Bachelor’s thesis title in Czech:

Metody detekce vyváženosti zpravodajských textů

Guidelines:

1. Review the state-of-the-art methods of gender and media bias detection and mitigation related to machine learning algorithms for Natural Language Processing.
2. Construct Czech datasets using machine translation from available data (most likely English).
3. Analyze the qualities of the datasets.
4. Train NLP classifiers and compare the results to the original counterparts.
5. Evaluate the models on Czech news corpora supplied by the supervisor.

Bibliography / sources:

[1] Chen, Wei-Fan, et al. "Detecting media bias in news articles using gaussian bias distributions." arXiv preprint arXiv:2010.10649 (2020).
[2] Chen, Wei-Fan, et al. "Analyzing political bias and unfairness in news articles at different levels of granularity." arXiv preprint arXiv:2010.10652 (2020).
[3] Mehrabi, Ninareh, et al. "A survey on bias and fairness in machine learning." arXiv preprint arXiv:1908.09635 (2019).
[4] Blodgett, Su Lin, et al. "Language (technology) is power: A critical survey of" bias" in nlp." arXiv preprint arXiv:2005.14050 (2020).
[5] Jacob Devlin, Ming-Wei Chang, Kenton Lee, Kristina Toutanova: BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. NAACL-HLT (1) 2019: 4171-4186.

Name and workplace of bachelor’s thesis supervisor:

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Name and workplace of second bachelor’s thesis supervisor or consultant:

Date of bachelor’s thesis assignment: **27.01.2022** Deadline for bachelor thesis submission: __________

Assignment valid until: **30.09.2023**

Ing. Jan Drchal, Ph.D. Supervisor’s signature	prof. Ing. Tomáš Svoboda, Ph.D. Head of department’s signature	prof. Mgr. Petr Páta, Ph.D. Dean’s signature

III. Assignment receipt

The student acknowledges that the bachelor's thesis is an individual work. The student must produce his thesis without the assistance of others, with the exception of provided consultations. Within the bachelor's thesis, the author must state the names of consultants and include a list of references.

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Date of assignment receipt

Student's signature

Acknowledgements

We thank the CTU in Prague for being a very good *alma mater*.

Declaration

I declare that this work is all my own work and I have cited all sources I have used in the bibliography.

Prague, February 10, 2022

Prohlašuji, že jsem předloženou práci vypracoval samostatně, a že jsem uvedl veškerou použitou literaturu.

V Praze, 10. února 2022

Abstract

This manual shows how to use the ctuthesis LaTeX class, what are the requirements, etc.

Keywords: bias detection, transformers, text classification

Supervisor: Ing. Jan Drchal, Ph.D

?abstractname?

Tento mánuál představuje LaTeXovou třídu ctuthesis, její použití, požadavky na systém atd.

Keywords: bias detekce, transformers, text classification

Contents

Figures Tables

Chapter 1

Introduction

This is an introduction to my thesis, motivation. taky něco o nlp

1.1 Motivation

tady něco o nlp

1.2 My contribution

1.3 Outline

Before I turned my whole attention to media bias detection, I have researched the possibilities of gender bias detection. Hence, I dedicate a small section to my results, an examination of one gender-focused dataset, and potential future extensions.

Chapter 2

State of the art

2.1 Bias

Mitigatin vs Detection, importance, types of bias

2.2 Gender bias

Most of the work done regarding gender bias aims to study gender bias introduced in the models and methods to measure, clarify, and possibly mitigate it. There is clear evidence that current language models possess implicit bias. Whether it means in terms of learned embeddings (odkaz na nurse to woman like man to fighter) or simply underrepresentation of one sex in the training data.

Yet, my work aspires to classify news texts, therefore I examined the possibilities of gender classification on a sentence level.

I closely followed the approach of Dinan et al. [**?**]. Where they define three gender bias dimensions: bias when speaking *ABOUT* someone, *TO* someone or *AS* someone. The word bias here simply means an aspect of the statement that implies a gender of a particular person along mentioned dminesions.

Authors further propose that unbiased sentence would mean that machine learning model would not be able to classify a gender in a sentence because there would be basically no difference between the classes.

For measuring this kind of bias around all three dimensions, large-scale dataset (**MD_gender**) has been introduced. Authors train a multitask model to capture all three dimensions, however, only *ABOUT* dimension and very small fraction of *AS* dimension is publicly available, thus I only focused on the first one mentioned.

- **md_gender**[1] - is a collection of automatically labeled large-scale data gathered from various sources around the internet, where gender annotation of the particular dimension is provided (eg. gender information of a user in internet discussion). It also include one small gold-labeled dataset for evaluation.

[1] `https://huggingface.co/datasets/md_gender_bias`

To mimic the results of the paper mentioned above, I sampled 150k of sentences across all datasets with an *ABOUT* dimension label and translated them via DeepL (more on machine translation in section **??**). Then I managed to train a classifier that achieved a score 80% on small gold-standard evaluation dataset. Unfortunately, the results are not comparable because I took a bit different approach. I share this model on huggingface hub, where I also present a demo. Usage of the demo can be seen in appendix.

2.3 Media bias detection

2.3.1 Informational vs Lexical

Many do lexical, framing, něco o dalších, WCL.

2.3.2 Methodology (SOTA)

bla bla Article level vs sentence level. Neural nets vs classical machine learning. Multitask learning.

Chapter 3

Datasets

Due to the varying definitions of bias, different datasets try to capture different aspects of bias. In this section, I present a collection of all datasets related to biased writing and subjectivity detection available.

Because there are not many media bias datasets of sufficient quality, I included other relevant datasets which are at least on some level linked to media bias and eventually leveraged their bias information to augment smaller ground truth datasets. For details see experiment section **??**.

As discussed in **??** this work only focuses on sentence level classification, thus data that focus only on the article level were not considered.

3.0.1 SUBJ

As allsides.com[1] consider subjective adjectives as a form of media bias, it is reasonable to include datasets that focus on this particular feature. The Subjectivity dataset (SUBJ) [?] consists of 10000 sentences gathered from movie review sites. Sentences are labeled as subjective and objective with 1:1 ratio.

The data were collected in an automatic way. The authors made an assumption that all reviews from Rottentomatoes[2] are subjective and all plot summaries from IMBD[3] are objective. Thus, the labels can be assumed to be noisy. For each class, 5k sentences were sampled **randomly**.

3.0.2 MPQA

Multi-**P**erspective **Q**uestion **A**nswering (MPQA) Opinion corpus is another dataset that can be used for subjectivity detection. I used the MPQA Opinion corpus version 2.0, which consists of 692 articles from 187 different news sources summing up to 15802 sentences. All articles are from June 2001 to May 2002.

The corpus offers a rich annotation scheme [?] that focuses on sentiment and subjectivity annotations.

[1] `https://www.allsides.com`
[2] https://www.rottentomatoes.com/
[3] www.imdb.com

To extract the bias information, I focused on two types of annotations:

- Direct subjective
- Expressive subjective

Which were present if any form of subjectivity was suspected by the annotator. Each annotation consists of indices of span in the text and properties. For each sentence in corpus I extracted labels as follows:

If there was at least one annotation **direct_subjective** or **expressive_subjectivity** with span inside the sentence and the intensity tag was not *low*, the sentence was labelled as *subjective* $\sim$ *biased*. All other sentences were extracted as *objective* $\sim$ *unbiased*.

This approach has yielded 9484 subjective sentences and 6318 objective sentences.

3.0.3 BASIL

BASIL dataset [?] comprises 300 articles with 1727 sentence level bias annotations. The authors of the dataset distinguish between **lexical** and **informational** bias. Here, lexical bias is defined as a form of bias which does not depend on the context and usually introduces polarized words.

The annotations were performed by two experts and further resolution discussions have later led to 0.56 and 0.7 Inter-Annotator Agreement (IAA) score for lexical and informational bias, respectively.

Even though BASIL brings the sufficient annotation quality, most of the labelling resulted in informational bias annotations, leaving only 478 sentences for the lexical bias class. Informational bias requires a different approach to detection [?] and usually depends on context dramatically. Therefore, I extracted all sentences with *informational* label as a neutral class.

3.0.4 Ukraine Crisis Dataset

This dataset [?] offers 2057 sentences with binary media bias labels. All sentences are related to one topic - Ukraine-Russian crisis and data were gathered from 90 news sources.

The authors introduce rich annotations for each sentence. Each one of them looks at the bias from a different perspective, so called *bias dimensions*:

1. Hidden Assumptions and Premises
2. Subjectivity
3. Framing

In addition, the *overall bias* annotation is presented. Together, the data involve 44547 fine-grained annotations. For simplicity, I only included the overall bias annotation. Even though this dataset encompasses comprehensive bias information, it also suffers from low IAA score. Specifically Krippendorff's $\alpha = -0.05$. Therefore, its usability is limited.

3.0.5 NFNJ

The NFNJ[4] dataset provides 966 sentences from 46 articles with annotations on a fine-grained level.

Authors share the dataset for research purposes, however, the public version differs from the one described in the original paper. Therefore, while extracting the final dataset, I made a few assumptions:

In the raw data, contributions from multiple annotators on each sentence are provided. Therefore, I extracted the labels as a simple arithmetical mean of the labels. Furthermore, the original labels stand for

- 1: 'neutral'
- 2: 'slightly biased but acceptable'
- 3: 'biased'
- 4: 'very biased'

To obtain the final truth labels in a unbiased/biased format, I simply assumed sentences with mean-score ≤ 2 as neutral and > 2 as biased.

The Fleiss Kappa IAA score averaged at zero, which makes it practically unusable as a standalone dataset.

3.0.6 BABE

Bias **A**nnotations **B**y **E**xperts (BABE) is a key media bias dataset from Media Bias Group (MBG), which is to the best of my knowledge, the highest quality media bias dataset to this day. It builds on top of MBIC [**?**] which is a smaller crowdsourced dataset.

BABE contains 3700 sentences. 1700 sentences are from MBIC, which were extracted from 1000 news articles, and in addition extended by 2000 more sentences, altogether covering 12 topics, annotated with binary bias indications. In addition, the annotations were enriched with a list of biased words. However, the presence of biased words does not always result in an overall biased sentence label. See **??** for examples.

It has been annotated by 8 experts resulting in IAA Krippendorfs $\alpha = 0.39$, which exceeds other media bias datasets by a significant margin. It also provides detailed information about the annotator background, making it a **reliable** source of information. The pipeline of the collection of BABE can be seen in **??**.

This dataset plays a pivotal role in my approach to media bias detection and is selected as a target for tuning language models in chapter **??**. Examples of BABE data points can be seen in **??**

[4] [**?**] refer to this dataset as NFNJ, however in the original paper the name is not presented.

sentence	label
Americans know President Donald Trump is an outrageous, scandal-ridden character.	biased
Biden said he would seek Muslims to serve in his administration.	unbiased
Biden's shift radically leftward reflects that of his party.	biased
Anti-vaccine groups take dangerous online harassment into the real world.	unbiased

Table 3.1: Example of biased and unbiased sentences from **BABE**

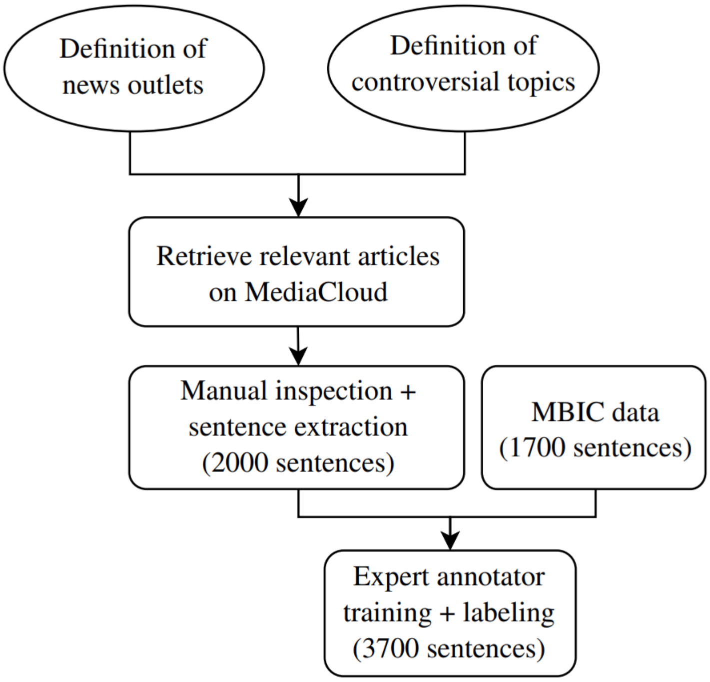

Figure 3.1: Data collection and annotation pipeline of **BABE**, reprinted from [?]

3.1 Wikipedia NPOV datasets

Due to annotation costs and the overall lack of large-scale datasets in the media bias setting, many researches [?, ?, ?] used Wikipedia's Neutral Point Of View (NPOV) policy[5] to construct large-scale corpora automatically.

Wikipedia's NPOV policy is a set of rules which aim to preserve neutrality in Wikipedia articles. Some examples of NPOV principles are:

- Avoid stating opinions as facts.
- Avoid stating facts as opinions.
- Prefer nonjudgmental language.

When neutrality is contested, Wikipedia article can be moved to NPOV dispute by tagging it with {{NPOV}} or {{POV}}[6] template. Debate on

[5] `https://en.wikipedia.org/wiki/Wikipedia:Neutral_point_of_view`
[6] Other POV related variations are ofthen used.

specific details of neutrality violations is then initialized among editors and eventually resolved, leading to removal of the tag.

This editorial information can be leveraged to extract parts of the text that violate NPOV and their unbiased counterparts. However, it has been shown [?, ?] that such automatic extraction can suffer from noisy labelling. In some cases [?] up to 60% of data positive points were actually neutral.

Even though these datasets introduce a large amount of samples that are highly related to media bias, they are all sampled from Wikipedia's environment, which can be very different from the news environment. Effect of this domain gap on a training of a model is studied in **??** section.

3.1.1 Wiki Neutrality Corpus

Wiki Neutrality Corpus (WNC) [?] is a parallel corpus of 180k pairs of biased and unbiased sentences. For the collection of the data, **??** approach was adopted. The authors crawled revisions from 2014 - 2019. Each revision has been processed to check if it contains any variation of POV related text in it. This approach yielded 180k pairs such that the sentence before edit is considered biased and the modified/added sentence after edit is considered neutral/unbiased.

In addition to WNC, 385k of sentences which have not been changed during the NPOV dispute were extracted as neutral and for word-level classification purposes, a subset of WNC corpus, where only one word is changed in the biased-unbiased pair, were added.

3.1.2 CW-HARD

Hube et. al [?] constructed a dataset based on NPOV, where only revisions with one sentence diff were filtered. However, because of the potentially noisy outcome, 5000 sentences were sampled and annotated using crouwdsourcing. Yet, the Krippendorffs Alpha agreement score measured only $\alpha = 0.124$ which is generally considered low.

After filtering out sentences which annotators labeled with "I dont know" option, the final dataset consists of 1843 statements labeled as biased and 3109 labeled as neutral, a total of 4953 sentences.

3.1.3 WikiBias

This is the latest dataset based on Wikipedia. The authors [?] closely follow the approach of WNC [?] and extract another parallel wiki corpus of 214k sentences. To achieve a higher quality corpus, 4099 sentence pairs were randomly sampled and labeled by trained annotators. As a result, introduced **WikiBias-Manual** dataset consists of 3400 biased and 4798 neutral sentences annotated with high IAA score of Cohen's $\kappa = 0.734$

Dataset	Size	Annotation	Agreement
SUBJ	10.000	automatic	-
MPQA	15.802	annotators	high
BASIL	1.727	annotators	medium
Ukraine Crisis Dataset	2.057	crowdsourcing	low
NFNJ	888	crowdsourcing	low
BABE	3673	annotators	medium
WNC	362.990	automatic	-
CW-hard	4953	crowdsourcing	low
WikiBias	8198	annotators	high

Table 3.2: Comparison of all bias related datasets collected

3.2 Unused datasets

Some datasets focus on a slightly different task, yet still carry potentially useful information. Such data can be useful in a Multi-Task setting **??**. To name a few, which are focused on a detection of ideology:

- **NewsB** - Consists of labels capturing authors political ideology (liberal, conservative)
- **IBC** - Also focuses on ideology detection, however, it is not publicly available.

3.3 Datasets summary

In the previous section, I introduced all resources that are potentially useful for media bias analysis and are publicly available. The overview of all datasets and its properties can be seen in figure **??**.

Chapter 4

Theoretical background

4.1 Text classification

4.2 Neural Networks

4.3 Attention and transformers

4.4 Transfer learning

Chapter 5

Czech datasets

Czech language is a so-called **low resource language**, which, in the machine learning community, means that, for a particular language, a limited number of datasets of sufficient quality and size, is available. Thus, the bias detection task in Czech environment is complicated. Despite the relatively sufficient number of datasets in English, there is essentially no Czech one suitable.

In essence, three options to solve this problem are feasible. The most promising way is to annotate a new gold-standard dataset. However, media bias is a nontrivial, complex, and subtle linguistic feature, hence a lot of effort must be put into annotator training and eventually filtering of implicitly biased annotations.

Another way is to use an automatic approach. **Allsides**[1] for example, provide annotations on source and article level with expert annotation quality. However, since I focus on a statement level only, using such data leads to oversimplification and results in a very noisy dataset. Regardless, it can still be used for domain-specific pretraining [**?**]. Unfortunately, there is no Czech site that would provide **useful** bias information on neither source or article level. Server Nadační fond nezávislé žurnalistiky (NFNZ) [2] provides scoring for different news sources. Yet, only a fraction of their scoring is related to the actual linguistic aspect of the writing. Most of the scoring is based on meta-information such as transparency, proper citation, advertisement, etc.

Nonetheless, automatic creation of a dataset can be done in a clever way like described in section **??**. Despite the limitation caused by the size of the particular Wikipedia, this approach is suitable for Czech environment, since Czech Wikipedia has a comparably large editor base[3] ranking #26 in a number of edits worldwide. I took this approach and I present a **new parallel corpus** for bias detection based on Czech Wikipedia **??**.

Finally, for low resource languages, it is reasonable to translate English datasets. As one of my contributions to bias detection in Czech news, I reviewed, collected, and translated most of the relevant datasets described in chapter **??** using **DeepL**, and finally processed them into a unified format **??**. .

[1] `https://www.allsides.com/unbiased-balanced-news`

[2] https://www.nfnz.cz/

[3] `https://en.wikipedia.org/wiki/List_of_Wikipedias`

5.1 Machine Translation

Since translation of large datasets by human translators would be too costly and from a time perspective practically impossible, automatic machine translation systems are used. In recent years, machine translation, as other fields of Natural Language Processing (NLP), has experienced a massive boost in performance, due to the rise of attention mechanism and complex transformer architectures **??**.

Modern machine translation models use the **encoder-decoder** architecture (usually more encoders and decoders stacked on top of each other **??**), where the encoder part distils (encodes) the information from the input sequence and the decoder part is responsible for decoding this distilled information and mapping it to a sequence in the target language.

For translation of datasets I chose **DeepL** translator, which is purely[4] NMT based system which outperforms other translation systems by a large margin.

5.2 Processing

For convenience, every dataset has been processed into "sentence,label" format, where $label \in \{0, 1\}$ stands for **unbiased** and **biased**, respectively. Using this simplified data format makes merging and combining several datasets convenient.

Moreover, all sentences, which were originally cased were not lower-cased, since I used transformer models that can deal with cased tokens.

[4]For example Google combines Neural Machine Translation (NMT) with statistical approaches, other systems incorporates hardcoded rules, etc.

5.3 Translated data

In the list below, I present all translated datasets in the unified format. I hope this collection will serve as a good starting point for future research of media bias in Czech News.

I will share all listed datasets on HugginFace[5] hub.

- BABE-CS
- Basil-CS
- WikiBias-CS
- CW-hard-CS
- MPQA-CS
- NFNJ-CS
- SUBJ-CS
- UA-crisis-CS
- WNC-large-CS[6]

Together, approximately 400k of bias labelled translated sentences were collected.

5.4 Czech Wiki Neutrality Corpus

Finally, I present two novel parallel corpora extracted directly from Czech Wikipedia. To the best of my knowledge, this is the only original Czech dataset related to media bias and subjectivity detection. The only partially relevant dataset is **SubLex**[?] which is a subjectivity lexicon mainly focused on sentiment. However, lexicon-based approaches are nowadays outperformed by neural models.

I followed two main existing approaches, both of them relying on the extraction of revisions that includes the {{NPOV}} tag or its variation. The NPOV tag has also its Czech version *Nezaujatý Úhel Pohledu* (NÚP). However, the Czech version is practically not used and so for the extraction, the English variations were used.

[5] `https://huggingface.co/`

[6] additional *large* is added for distinction between large translated WNC and czech version of WNC

Nizozemsko je známé svým **pokrokovým** liberálním postojem vůči psychoaktivním drogám.	
Nizozemsko je známé svým liberálním postojem vůči psychoaktivním drogám.	
Mezi jeho nejznámější a zvlášť populární je jeho hudba ke hrám a filmům, která téměř zlidověla.	
Mezi jeho nejznámější a zvlášť populární je jeho hudba k divadelním hrám a filmům, která v některých případech téměř zlidověla.	

Table 5.1: Example of pairs of biased sentences and their rewritten neutral form

5.4.1 CWNC-noisy

I closely followed the [**?**] approach and used their script. Firstly, a file with all pages and its complete edit history is downloaded from the wiki dump[7]. I used the **20220201** version. Then the edits containing one of the NPOV related tags are extracted and then the process of sentence extraction follows. All used tags can be seen in appendix.

This approach yields 15k sentences, however, it uses a rather trivial assumption that when NPOV tag is removed, **all** removed sentences are biased and all added are unbiased. This annotating strategy led to poor results **??**. For this reason, I excluded this dataset from further experiments entirely.

5.4.2 CWNC

This dataset was created following [**?**] approach. The process is the same as described in section **??**. I used **20220201** snapshot of Wikipedia dump, which was, at the time of dataset collection, the latest snapshot that included all necessary files. I used the script publicly available on Github[8],with a few slight modifications so the processing fits the Czech language properties:

1. Used Regex was extended to exclude czech words that contain "pov" inside eg. povstání, povlak etc.[9]

2. All cases has been preserved, since bert like models can handle cased language.

3. Czech Morphodita tokenizer was used[10]

The final dataset consists of:

- 3k of *before* and *after* sentence pairs
- 1.7k subset where only one word has been changed
- 7.5 sentences, where the change was rejected or reversed, implying neutrality of the original sentence

[7] `https://dumps.wikimedia.org/cswiki/`
[8] `https://github.com/rpryzant/neutralizing-bias`
[9] Regular expression used to match npov related comments:
[10] `https://ufal.mff.cuni.cz/morphodita/users-manual`

In total, 5838 sentences. The neutral corpus,which contains only neutral sentences, is saved for a potential need of oversampling. Two examples of CWNC sentence pairs can be seen in **??**

5.5 Not translated

Due to a big size of some data, I was not able to translate more than one large-scale dataset. For this reason NewsB dataset has not been translated, since it is one of the few datasets that doesn't focus on the very same task.

Chapter 6

Experiments

In this section I present experiments on text classification over colelcted datasets. Main target dataset for evaluations is BABE, because of its high quality and properties.

Because of novelty of CWNC I also perform evaluation on this dataset. I follow the current standard approaches and use pretrained transformers for further pretraining and fine-tuning. One possibility is to use multilingual models, which are trained on set of languages to capture general language properties. In recent years, there have also purely czech models emerged.

6.0.1 Czech models

- RobeCZECH
- Czert
- FERNET-C5
- FERNET-News

6.0.2 Multi-lingual models

- SlavicBert
- mBERT

15% of BABE data has been saved for final evaluation. Steps are as follows:

- BASELINE: 5-CV plain model finetuning on BABE (could be split to train validation but we dont have that many data)
- HYPERPARAM-TUNING: 5-CV model tuning parameters (grid search) on BABE
- DATA-COMBINATIONS: 5-CV model with tuned hyperparams with varying combinations of data on BABE

- EVALUATION: pick the best model, train it with params and early stopping, and run it on - BABE test set - CWNC test set early stopping only on final training! Because the authors essentially made early stopping on "testing set" + it is not recommended to use early stopping in cross validation

All training has been done on a single GPU on RCI cluster.

6.1 Baseline setup

As a baseline, I finetuned all Czech models listed above on BABE and evaluated them using 5-fold stratified cross validation. Hyperparameters were the same as used by authors [?]. However, the authors used 10 epochs and early stopping, together with cross validation and used the validation split inside CV to early stop, which is not ideal since the split should be used only for evalaution. That way the model can "see" the data before evaluation, hence I did not use early stopping with CV at all and fixed number of epochs on 3, as authors of BERT [?] suggest. All other hyperaparemeters remained unchanged. Adam optimizer is used with learning reate $5e-5$

6.2 Hyperparameter tuning

To get the most out of the language models, I decided to tune the hyperparameters via Bayesian Optimization framework. Because a complexity of searching for optimal hyperparameters grows exponentially with number of items, it is reasonable to not try every combination. Bayesian optimization limits this search space by using Bayes theorem.

6.3 Combining Datasets

Here i can combine datasets.

6.3.1 Pretraining on English WNC

6.3.2 Subjectivity pretraining

6.3.3 Media Bias Pretraining

6.3.4 Combining all datasets together Without WNC

6.4 Inference on Czech News Samples

- Analysis and statistics
- Few words Article level

6.5 Multi-Task learning approach

Chapter 7
Conclusion

7.1 Summary of work done

In this work I presented 8 parallel czech datasets for tackling the media bias detection. 6 of which are related to subjectivity detection and one is.

7.2 Future perspective

As discussed in the section [experimenty] reasearch [citace] suggests that multitask learning increases classification accuracy significantly ref. However, multitask model environment requires a lot of tasks [odkaz na exT5] to perform better than single task models.