Cross-lingual Transfer Learning for Check-worthy Claim Identification over Twitter

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ABSTRACT
Misinformation spread over social media has become an undeniable infodemic. However, not all spreading claims are made equal. If propagated, some claims can be destructive, not only on the individual level, but to organizations and even countries. Detecting claims that should be prioritized for fact-checking is considered the first step to fight against spread of fake news. With training data limited to a handful of languages, developing supervised models to tackle the problem over lower-resource languages is currently infeasible. Therefore, our work aims to investigate whether we can use existing datasets to train models for predicting worthiness of verification of claims in tweets in other languages. We present a systematic comparative study of six approaches for cross-lingual check-worthiness estimation across pairs of five diverse languages with the help of Multilingual BERT (mBERT) model. We run our experiments using a state-of-the-art multilingual Twitter dataset. Our results show that for some language pairs, zero-shot cross-lingual transfer is possible and can perform as good as monolingual models that are trained on the target language. We also show that in some languages, this approach outperforms (or at least is comparable to) state-of-the-art models.

CCS CONCEPTS
• Information systems → Clustering and classification.

KEYWORDS
multilingual, cross-lingual transfer, claim identification

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1 INTRODUCTION
One of the major issues faced by typical users of social media is misinformation infecting their timelines. Manual and automated efforts to detect and verify claims are indispensable to protect and inform users, especially in critical times like the current COVID-19 pandemic [14, 28]. While scanning a timeline, a user or a fact-checker is faced by many posts that are potentially false. Verifying all these claims can become cumbersome. Thus, the first step in the process of fact checking is identifying which posts contain claims that are worth verifying [28]. Not all claims are as important; some can have catastrophic impact on a large population, such as the popular claims discouraging COVID-19 vaccination [36]. Other claims might not cause any lasting impact or invoking any action. Figure 1 shows examples of tweets containing claims borrowed from Task 1 of the CheckThat! 2021 evaluation lab [39]. Tweet in Figure 1a was labelled as containing a check-worthy claim since the news might cause an international political crisis if propagated, making verification of the claim essential before its spread.

A claim check-worthiness is usually defined by its importance to the public and fact-checkers [9, 22, 39]. However, for this work, we adopt a more concrete definition from the check-worthiness estimation task at the CheckThat! lab at CLEF2021 [29, 39]. In the task, a check-worthy sentence is one that: 1) contains a factual claim, 2) is of interest to the public, 3) can potentially cause emotional or physical harm to a person or an organization, 4) a journalist might be interested in covering, and 5) a fact-checker should verify.
Social media enables and contains highly multilingual streams with many users following content in multiple languages. Moreover, specific groups of users such as journalists or news agencies usually track multilingual content for news reporting and even fact-checking [8]. The same claim might propagate in multiple languages (e.g., after translation) which might result in repeated verification efforts across languages [8, 28]. This poses a need for multilingual systems for check-worthy claim detection. Most existing systems are monolingual, such as those participating in the CheckThat! challenge [39]. Recently, few exceptions emerged, usually considering multilingual transformer models to handle multilingual input (e.g., [12, 41]). Such preliminary studies focused on multilingual support, i.e., training a system using multilingual data including the targeted language and testing it on a set of sentences in a target language. This setup assumes that some training data is available for the target language. However, for low resource languages and for an emerging problem, such as the check-worthiness detection, this might not be feasible.

In this work, we ask the following question: *can we build an effective supervised model for check-worthiness detection without the need for training data in the target language?* We address this question by testing six setups to perform cross- and multilingual check-worthiness detection over tweets. Our work mainly focuses on a well-known setup in related problems, called zero-shot transfer learning, where no labeled examples in the target language are used during model training or fine-tuning. We start from the highly effective classification architecture based on multilingual BERT (mBERT) [18]. Architectures based on mBERT demonstrated effectiveness in cross-lingual transfer learning in several text classification tasks [45]. Up to our knowledge, this is the first study of this kind and scale for the problem of check-worthiness detection. We mainly address the following research questions:

**[RQ1]** Given labeled data in a source language, how effective is zero-shot cross-lingual check-worthiness prediction on a different target language?

**[RQ2]** Does translation between source and target languages improve the performance?

**[RQ3]** How much improvement can we achieve by adding few labeled examples in the target language to labeled examples in source language (i.e., few-shot transfer learning)?

**[RQ4]** Will adversarial training with unlabeled examples in target language improve over the zero-shot cross-lingual setup?

**[RQ5]** Can we improve the performance if we transfer from multiple source languages to a single target language?

**[RQ6]** How effective is cross-lingual transfer compared to the state of the art models?

Our contribution in this work is four-fold:

- We extensively explore and benchmark diverse methods to train cross-lingual check-worthiness prediction models including zero-shot, few-shot, and translation-based approaches. Existing studies for the task have not provided such a large-scale comparative study with different variants.
- We demonstrate that for some language pairs, cross-lingual transfer learning (e.g., from Arabic to Turkish) is at least comparable or even significantly better than monolingual models exclusively trained on target language. While for other languages (Bulgarian and Spanish), cross-lingual transfer is not effective regardless of the setup or source language.
- Our results show that for some target languages, cross-lingual transfer models are as good as state-of-the-art models developed for check-worthiness estimation on the same dataset.
- This study is the first to experiment with adversarial training for cross-lingual check-worthiness prediction.

The remainder of this paper is presented as follows. We summarize existing studies in Section 2. Section 3 presents the approach and design of experiments we follow in this study. We present and discuss the experimental setup and results in Sections 4 and 5. Section 6 summarizes the work and presents concluding remarks.

## 2 RELATED WORK

The problems of claim detection and verification has attracted enormous attention in the past few years. Due to the volume of proposed systems, several literature surveys already exist (e.g., [20, 28]). Thus, we only focus here on two aspects: check-worthiness detection over tweets in general and multilingual approaches to the problem.

ClaimBuster is one of the pioneering approaches to check-worthiness detection [22]. The system computes features for each input sentence such as its sentiment score, and part-of-speech tags and trains a supervised model with typical classifiers (e.g., SVM). More recent systems usually use neural models and specifically, classification architectures based on transformer models (e.g., [5, 13, 24, 37, 42, 44]). A more recent version of ClaimBuster [27] combines BERT [18] and gradient-based adversarial training to build a more effective model. In this system, perturbations are added to the embeddings generated by BERT for an input sentence, and the final model is fine-tuned minimizing both classification and adversarial losses. Both ClaimBuster models were tested on political debates or tweets but limited to English, while we target multilingual streams.

In a very recent study [3], a dataset of English and Arabic tweets about COVID-19 was annotated on several aspects including check-worthiness. The authors fine-tune several transformer models for the task, but train a model for each of Arabic and English independently. In a further study [4], the dataset was augmented with Bulgarian and Dutch tweets, and initial experiments on multilingual classification were conducted. In the proposed system, mBERT model [18] is fine-tuned using all of the four languages and then tested on each. Uyangodage et al. [41] follow the same approach but considering two datasets: NLP4IF [38] and the CheckThat! 2021 Task 1 dataset [39]. Differently and more comprehensively, we examine multiple alternatives for cross-lingual transfer where minimal or no training data in the target language is required. Moreover, we do not limit our work to tweets on one topic (i.e., COVID-19).

Among the most prominent efforts to approach the problem of check-worthiness detection are those part of the CLEF CheckThat! lab for the past four years [29]. In the initial two editions of the lab, the problem targeted claims within political debates [10, 11]. In the next editions, the lab focused on the social media domain and specifically, check-worthiness estimation for tweets [21, 39, 40]. The problem was defined as follows: given a stream of tweets on a topic, the participating systems were asked to rank the tweets by check-worthiness for the topic. Our work focuses on a more comprehensive approach that includes multilingual streams.
general definition of the problem, modeling it as a classification task without a limitation to any topic. That is to say, we aim to develop a system to detect check-worthy claims in a general stream of tweets. This definition is inline with some of the existing studies [9, 22, 27].

The last lab edition (CheckThat! 2021) offered a first-of-its-kind multilingual dataset (CT–CWT–21) for the problem. The dataset contained labelled tweets in five languages: Arabic, Bulgarian, English, Spanish and Turkish. This is the evaluation dataset we use in this work (further details in Section 4.1). Only few systems participating in the lab attempted to benefit from the unique nature of this dataset. Schlicht et al. (team UPV) [12] proposed a transformer-based model jointly trained for two tasks: check-worthiness detection and language identification. The team fine-tunes a multilingual transformer model called sentence-BERT [32] optimizing for both classification tasks. The language identification task aims at mitigating bias to any of the training languages. Again, in their study, authors train the model over all five languages in CT–CWT–21, however, we focus on cross-lingual transfer. The work of Zengin et al. [48] is the closest to ours. The authors attempted a cross-lingual approach where mBERT is fine-tuned on each pair of the five languages in CT–CWT–21, then tested per language. Differently, we examine a wider set of variants for cross-lingual check-worthiness estimation and show how they compare to several existing baselines. In a more recent work by the same authors [25], mBERT is tested in cross-lingual transfer for three languages only (Arabic, English and Turkish). We also observe a potential source of issues in their evaluation setup since the datasets came from different domains (political debates and tweets) and follow different annotation strategies across the languages, while in our setup we maintain consistency as much as possible using tweets only.

3 APPROACH

Our study tackles the problem of check-worthiness detection over multilingual streams. We formally define the problem as follows: Given a stream of tweets in any language, detect tweets containing check-worthy claims. This section describes the main architecture we use throughout our experiments. We then present the design of experiments answering our research questions.

3.1 System Architecture

Our work is motivated by the strong line of research showing the effectiveness of transformer models, such as BERT, for text classification. In the area of fact-checking, architectures based on transformer models are among the best performing for different tasks including check-worthiness prediction [24, 39, 43, 48], claim verification [47] and evidence retrieval [33].

For all our experiments, we start from the same BERT-based classification architecture depicted in Figure 2. This architecture is constructed based on previous literature using BERT for text classification. Specifically, following BERT layers, we add a feed-forward network with one hidden linear layer (of 256 nodes) with ReLu activation. Softmax activation function is finally applied to the output layer, resulting in two predicted probabilities (one for each of the two classes). As an input, we pass a single sequence which is the sentence $S$ that we would like to predict its check-worthiness. The input to our model is formatted as follows: [[CLS], $S$, [SEP]]. Typically, after training the full architecture (including fine-tuning of the pre-trained model), the hidden state $h$ produced by the transformer model for the [CLS] token is used as representation of the input to the remainder of the classification architecture. However, during our preliminary experiments on development subsets, we found that using mean pooling over all tokens yields better classification results, thus we adopt this pooled representation. At inference time, the probability of the positive class determines the predicted label for the input sentence with a 0.5 threshold. We train the model minimizing cross entropy loss.

3.2 Cross-lingual Check-worthiness Transfer

The main aim of our work is to investigate whether check-worthiness learning can be transferred across languages, and then identify potentially effective systems with none or minimal labeled data originally written in a target language. To that end, we study different strategies for transfer learning from source language $A$ to target language $B$, starting from the zero-shot transfer learning setup, going through methods that employ minimal labelled (or unlabelled) data from the target language and domain, and finally, approaches that enrich zero-shot transfer learning with translation. We next describe each of the approaches investigated in this work.

3.2.1 Zero-shot Cross-lingual Transfer Learning (ZS).

Given the strong ability of pre-trained models, such as mBERT in zero-shot cross-lingual transfer over multiple NLP tasks [45], we fine-tune the system described in Section 3.1 on a source language and apply it directly at inference time to a test set in the target language. This approach represents the basic ZS model we test in this work; it is a commonly-adopted approach in related cross-lingual transfer learning studies [49].

3.2.2 Zero-shot with Translation (ZS-Tr).

In the second research question, we aim to find an improved setup over ZS by translation. Instead of depending on transfer ability of mBERT, we unify the language of both train and test sets using two strategies:

- **ZS-TrSrc**: In this setup, we translate the training set of source language $A$ to the target language $B$, then fine-tune our model on the translated data. The model is then directly applied to the test set of the target language $B$.
- **ZS-TrTrg**: This setup shows the second possible translation approach. We first fine-tune our model using the original training set of the source language $A$. We then translate the

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Figure 2: Classification architecture. BERT layer represents all BERT-based transformer models used in this work.

We used Google Translation API at https://cloud.google.com/translate.
test set of the target language $B$ into language $A$, and apply our model on it.

3.2.3 Transfer Learning with Few Shots (FS). In this setup, we experiment with transfer learning extended with the addition of few labelled training examples from the training set of the target language. This is different from the translation-based approaches, since the labeled examples where originally written in the target language, rather than being translated. Few-shot cross-lingual transfer with two-stage fine-tuning has gained importance recently, since it generally improves performance with small annotation cost for target language examples (e.g., [23]). In this setup, we fine-tune our model in two stages; first it is fine-tuned over the source language $A$, then further fine-tuned using few examples from the target language $B$. We use random sampling with balanced classes to select few shots for the second stage (details in Section 5.3).

3.2.4 ZS with Adversarial Training (ZS-Adv). Adversarial learning is one the approaches that was shown to be successful in zero-shot cross-lingual transfer learning for text classification [19, 26]. Existing methods generally used adversarial networks and training techniques to extract features that are invariant to the change of language when performing cross-lingual transfer [16]. We test the effect of using adversarial training to improve ZS for our problem. To that end, we test an existing model [26] proposed for other text classification tasks, and test it only using English as the source language. This model extends typical mBERT classification architecture with the addition of an adversarial classification task trained in parallel to the actual classification task (check-worthiness in our case). This additional task includes two components: a discriminator that uses mBERT embeddings representing an input sentence to predict whether it is in the source language, and a generator that tries to generate embeddings that are difficult for the discriminator to detect. Eventually, this adversarial task aims to train mBERT to generate embeddings less fitted to the source training language while being fine-tuned for the text classification task.

To train such architecture, we need two components: training set in the source language and unlabeled sentences from the target language. In our experiments (Section 5.4), we use unlabeled examples sampled from the target training set which results in more consistency between training and test sets in terms of domain and topics. However, we note that this is not an optimal scenario as this might not be easy to achieve in the case of some target languages where a training set in that language is not available. We leave investigating the use of other approaches to acquire sentences in the target language to future work.

4 EXPERIMENTAL SETUP

This section presents the experimental evaluation setup, designed to answer our research questions, including the datasets used in experiments, evaluation approach, and implementation details for the classification architecture.

4.1 Datasets

Before running this study, we needed to identify a dataset that allows us to examine check-worthiness estimation in a multilingual setup. Since this problem is very recent, we only found two datasets that satisfy this condition. The first covers 4 languages (Arabic, Bulgarian, Dutch, and English) and limited only to tweets about COVID-19 [3]. We opt to use the second one (denoted as CT–CWT–21) that was part of the CheckThat! lab of CLEF 2021 conference [29]. The dataset was created to evaluate systems for the task of check-worthiness estimation over tweets in five languages, namely Arabic, Bulgarian, English, Spanish, and Turkish. In addition to having five languages as opposed to four in [3], CT–CWT–21 is not limited to COVID-19 only. Generally, tweets in CT–CWT–21 cover two general topics, politics and COVID-19. In CT–CWT–21, the per language subsets were created independently following a similar definition of check-worthiness. A tweet in each subset has two potential labels: check-worthy claim or non-check-worthy sentence. We consider the former label to be the positive label in this work.

Before proceeding with CT–CWT–21, we first combine the training and development sets per language to acquire a larger training set. We observed a great difference in the training set size across languages, ranging from 962 to 4.1k tweets. More importantly, the class distribution varies significantly with the percentage of positive labels falling between 8% and 38% across languages. Although such class distribution prior might be observed in real-world cases, this can shift the focus of this work from understanding check-worthiness estimation differences across languages to how to best handle this imbalance. Moreover, this imbalance can mask or exaggerate system performance across languages. Such observations were made in previous research concerning systems for cross-lingual transfer [34].

We alleviate the problem of varied dataset sizes across languages by down-sampling the training subset per language using a stratified random sampling approach. This ensures that we have the same dataset size and class distribution across languages. We chose the sample size per class based on the minimum number of labels per class across languages. Eventually, for each language except English, we end-up with 300 positive and 1,400 negative examples. As for the English dataset, number of negative examples available was smaller than 1,400. Thus, we have 300 positive and only 612 negative English examples. As for the test subsets, we keep them as released in the lab to allow for comparison with existing systems tested on the same subsets. Moreover, our aim in this work is not to compare the system performance on the test subsets across languages, and thus, variation in distributions of labels across test subsets does not affect the conclusions we make in this study. Table 1 summarizes datasets per language.

| Dataset | Topics | Total | # CW | Total | # CW |
|---------|--------|-------|------|-------|------|
| Arabic | Politics & COVID-19 | 1700 | 300 | 600 | 242 |
| Bulgarian | COVID-19 | 1700 | 300 | 357 | 76 |
| English | COVID-19 | 912 | 300 | 350 | 19 |
| Spanish | Politics | 1700 | 300 | 1248 | 120 |
| Turkish | Politics & COVID-19 | 1700 | 300 | 1013 | 183 |
4.2 Implementation Details

Due to the extent of the experiments we run and the limited dataset sizes, we unify the model parameters across experiments without hyperparameter tuning (unless otherwise stated). We set the parameters following optimal values identified in the original BERT paper (Appendix A.3 in [18]) and a recent paper that examined mBERT performance for multilingual text classification [31]. We set the training batch size to 32, learning rate to 3e-5, and a maximum sequence length of 128. We fine-tuned the model for three epochs (in line with related work on the same dataset [41]) and repeated model training five times with different random seeds to account for any randomness in model initialization and training. In this work, we report the average performance over those five re-runs.

We evaluate the models using the $F_1$ score of predicting the positive class. We chose this measure since our aim is to understand the model effectiveness in identifying check-worthy claims. The statistical significance of difference between systems is tested with two-sided paired t-test over the five re-runs with $\alpha < 0.05$.

For all experiments, we use pre-trained BERT models from the HuggingFace (HF) library (Table 2). Base version of the models with 12 layers was used. These models are among the most effective and commonly-used for the target languages. For all languages but Bulgarian, we found a model solely pre-trained on the target language. For Bulgarian, we only found a model pre-trained on four Slavic languages including Bulgarian.

5 RESULTS AND DISCUSSION

In this section, we present and discuss the results of the experiments we designed to answer each of the research questions.

As a baseline for all of our experiments (unless otherwise stated), we report the performance of mBERT when fine-tuned on the training set of the target language.

5.1 Zero-shot Cross-lingual Transfer Learning

We start by understanding the model effectiveness in zero-shot cross-lingual transfer learning (RQ1). For this purpose, we train an independent model for each of the five languages, then report the models’ performance on the test set of each target language. Table 3 shows the results, and the baseline per language on the diagonal.

This experiment shows promising results that answer RQ1. We notice that for Arabic, English, and Turkish, the best ZS performance is at least as good as the baseline where mBERT was fine-tuned on the target language. We even observe that for English and Turkish, we identified a source language that results in a significant improvement over the baseline. One of the most notable observations in Table 3 is the great performance improvement due to ZS from Arabic to Turkish. We anticipate this is the case for at least the following reason. All language subsets, except Spanish (es), had similar annotation strategy. However, we observe that en and bg datasets only focused on tweets about COVID-19, while ar and tr covered other additional topics, making generalization from ar to tr more probable. One might stop here and notice that the transfer in the opposite direction from tr to ar is ineffective compared to the monolingual baseline. We believe this is due to the pre-training of mBERT, as Turkish is a lower resource language that was underrepresented compared to Arabic. Such issue has been shown to negatively affect language representation learnt by mBERT and thus affect performance of the model after fine-tuning [46].

5.2 Effect of Translation on ZS

In RQ2, we aim to find an improved setup over ZS by translation. In this experiment, we show check-worthiness estimation performance when translating from each of the two directions: translate from the source language or from the target language.

5.2.1 ZS with Source Translation (ZS-TrSrc). Table 4 shows results with translation applied to the training set of the source language, with the baseline per language on the diagonal. We find that, on average, translation of the source language resulted in improved performance over original ZS in 8 out of 20 pairs, with an average improvement of 5.7 points in $F_1$. As for the cases when performance degradation is observed, the average of the absolute differences between baseline and translation setups is 3.1 points in $F_1$. Overall, that indicates slight improvement with translation. Translation did not seem to help Turkish specifically as the performance degraded to negatively affect language representation learnt by mBERT and thus affect performance of the model after fine-tuning [46].

5.2.2 ZS with Target Translation (ZS-TrTrg). We continue to answer RQ2 by translation of the test set of the target language to match the source language. Table 5 shows results under this setup. We find that, on average, translation of the target language resulted in improved performance over original ZS in 10 out of 20 pairs, with

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Table 2: Pre-trained models used in experiments.

| Model        | Language     | HF Model Name                                      |
|--------------|--------------|----------------------------------------------------|
| mBERT [18]   | Multilingual | bert-base-multilingual-cased                      |
| AraBERTv1 [6]| Arabic       | aubmindlab/bert-base-arabert                      |
| BERT [18]    | English      | bert-base-uncased                                  |
| SlavicBERT [7]| Slavic      | DeepPavlov/bert-base-bg-cs-pl-ru-cased            |
| BETO [15]    | Spanish      | dccuchile/bert-base-spanish-wwm-cased             |
| BERTurk [35] | Turkish      | dbmdz/bert-base-turkish-cased                     |

Table 3: ZS results. Bold and underlined values represent best and second best per test set, respectively. * indicates significant difference from baseline on same test set.

| source | target | ar      | bg      | es      | en      | tr      |
|--------|--------|---------|---------|---------|---------|---------|
|        |        | 49.5    | 35.2    | 12.1    | 26.6    | 50.3    |
| bg     |        | 04.6    | 58.2    | 16.6    | 07.4    | 27.4    |
| en     |        | 47.7    | 41.0    | 13.3    | 27.6    | 46.1    |
| es     |        | 00.3    | 06.7    | 11.1    | 54.0    | 24.8    |
| tr     |        | 12.3    | 20.5    | 16.8    | 15.6    | 28.4    |
Table 4: Effect of translating the source language on transfer learning. Values in () represent the percentage of difference between the performance in this setup and corresponding ZS cell from Table 3. * indicates significant difference from baseline on same target language.

| source | ar  | bg  | en  | es  | tr  |
|--------|-----|-----|-----|-----|-----|
| ar     | 49.5| 31.2 (-1) | 10.3 (-15) | 25.9 (-3) | 47.0 (-7) |
| bg     | 09.7* (111)| 58.2| 17.9* (8) | 19.2* (159) | 21.8 (-20) |
| en     | 45.7 (-4) | 36.3* (-11) | 13.3 | 30.0* (9) | 38.0 (-18) |
| es     | 00.0* (-100) | 17.3* (158) | 16.0* (44) | 54.0* | 24.6 (-1) |
| tr     | 18.9* (54) | 14.0* (-32) | 16.3 (-3) | 18.4* (18) | 28.4 |

Table 5: Effect of translating the target language on transfer learning. Values in () represent the percentage of difference between the results for this setup and corresponding ZS cell from Table 3. * indicates significant difference from baseline on same target language.

| source | ar  | bg  | en  | es  | tr  |
|--------|-----|-----|-----|-----|-----|
| ar     | 49.5| 35.9* (2) | 11.4* (-6) | 27.2* (2) | 44.1* (-12) |
| bg     | 53.1 (1.1K) | 58.2| 13.1 (-21) | 27.8* (276) | 36.5 (33) |
| en     | 48.4 (1) | 40.9* (0) | 13.3 | 30.5* (11) | 38.1* (-17) |
| es     | 38.7 (12.8K) | 28.8* (330) | 14.5 (31) | 54.0* | 31.5 (27) |
| tr     | 51.2 (316) | 37.1* (81) | 13.8 (-18) | 25.6* (64) | 28.4 |

5.3 Transfer Learning with Few Shots (FS)

We now turn to answer RQ3 concerning the effect of adding few shots from the target language. Table 6 shows the results when we continue fine-tuning each of the models from Section 5.1 using 1% of the target language training set. For all target languages except English, this means we continue training using randomly sampled 17 examples from the target language, among which 8 are positive. As for English, we sample 9 examples, with 4 of them being positive. For sampling those additional examples, we fix the random seed across all languages. In additional (not shown) experiments with other seeds, we observe some variance in performance per model, which is consistent with a recent work on few shot learning [49]. However, we find that the overall observations are not affected by the different samples, thus we report results using a single sample seed. The baseline per language is on the diagonal of Table 6.

Compared to ZS, we observe better overall improvements. For the 20 language pairs, we find that few-shots learning improved over ZS in 14 cases with an average improvement of 15.8 points in F1. This indicates that this setup is better than the case when we apply translation (maximum observed was 5.7 points).

The experiments further showed that adding as few as 17 Arabic examples to models, fine-tuned on each of the other languages except Spanish, resulted in comparable performance to the baseline, in which we train on the whole Arabic training set. We also observe extreme improvements compared to pure ZS, except when English is the source language; for English, we observe that the performance is comparable. We anticipate this happened because Arabic is written in very different script (as opposed to remaining languages) making the addition of few target examples useful for mBERT to learn necessary structural and lexical information, which is consistent with observations made in a recent study [49] regarding the effect of writing scripts on FS. These results highlight that with very small annotation effort, we can achieve as good performance as the case where much more annotations in the target language were collected. This is inline with recent studies on other text classification tasks [23].

What happens when we change the number of the few shots? Figure 3 shows the effect of continuing the fine-tuning of ZS models with k randomly sampled examples of the target language. We experiment with $k \in \{2, 4, 8, 10, 50, 100, 200\}$. The figure indicates several observations. First, for most target languages, an optimal setting of parameter $k$ is needed to get most benefit of few shots.
learning transfer, but we need to consider the corresponding annotation cost. Second, Arabic is generally the language that benefited the most from this setup, showing increasing performance gain with the increase of $k$, regardless of the source language. Third, for all target languages, except Bulgarian, we observe an interesting pattern, where at the addition of 200 shots from the target language, the achieved performance is very similar regardless of the source language. This indicates that the added 200 shots were enough to almost suppress the effect of the source language. Fourth, for Spanish and Turkish, we observe a consistent pattern in performance across all source languages as we change the number of the few shots. Finally, there are clear source language winners in most cases, regardless of the number of few shots. English as a source language was almost always better for Arabic, Bulgarian, and Spanish, while Arabic as a source language was almost always better for Turkish. However, there was no clear winner for English as a target language, with $F_1$ limited between 10-15. This is somewhat expected, given that only 5% of English test set is positive, making it very sensitive to mistakes in prediction.

In response to RQ3, FS with the addition of as little as 1% of the target language training set, has resulted in notable improvements over ZS for most language pairs. We also observe that effectiveness of FS depends on finding an optimal setting for number of few shots for different language pairs, as adding more shots did not always result in improved performance.

5.4 ZS with Adversarial Training (ZS-Adv)

In this experiment, we address RQ4. We randomly sample unlabelled examples from the target language training set and add them to the the training set of the source language to train the adversarial model explained in Section 3.2.4. Figure 4 shows the performance of this model in comparison to the ZS model. Note here that due to the size of the adversarial model and limited memory, we decrease the batch size to be 8 per model (including re-training the ZS model with this new batch size). We omit results for Spanish and Turkish source languages due to the results being close to zero.

The figures show conflicting observations. On one hand, ZS-Adv was helpful when transferring from Arabic to other languages. On the other hand, we generally observe degradation in performance when transferring from Bulgarian or English to other languages. Moreover, none of the target languages except English consistently benefited from ZS-Adv. We note here that this preliminary experiment was conducted using a single adversarial training approach for cross-lingual transfer. There might be more effective approaches for the classification task at hand, which we leave for future work.

### Table 7: Performance of multilingual ZS model on the target language test set. * indicates significant difference from baseline mBERT target on same test set.

| Model          | ar | bg | en | es | tr |
|----------------|----|----|----|----|----|
| mBERT target   | 49.5* | 38.2 | 13.3 | 54.0 | 28.4 |
| ZSbest         | 47.7 | 41.0* | 16.8* | 27.6* | 50.3* |
| ZS_all-target  | 24.4* | 26.8* | 13.5 | 25.6* | 34.0 |

5.5 Multilingual ZS

We finally address RQ5: will ZS benefit from multilingual training? Differently from vanilla ZS (Section 5.1) and typically used in literature, we fine-tune our check-worthiness prediction model over multilingual examples excluding the target language. For each language but the target language, we randomly sample examples with the same fixed class priors, ending up with 1,700 total examples across all four languages, with 300 positive examples and each language is equally represented in the training set. This is
The models we test are those shown in Table 2. Such setup, is negatively affected.

We further support our claim by running an experiment in which we incrementally increase the number of source languages (excluding the target language) during fine-tuning, and report the transfer performance on a low resource (bg) and a high resource (en) target languages. As with ZS_{all-target}, we fix the total training examples to 1.7k and keep each source language equally represented in the training sample. For the case of 1, 2, or 3 source languages, we try all combinations; thus, for those cases, we end up with multiple performance values depending on the combination of source language(s) used during fine-tuning; we report the maximum observed scores for (bg) and (en) in Figure 5a. The figure shows the transfer performance degrades for both languages as we increase the number of languages on which mBERT is fine-tuned. This is consistent with the phenomenon observed by Conneau et al. [17] for transformer models during pre-training.

A question arises on whether this effect can be mitigated by increasing the training set size as we increase the number of languages. We repeated the previous experiment, but increased training set size to be 1,700 per source language. Figure 5b shows, again, degradation in performance but not as severe. Overall, experiments indicate that increasing the number of source languages (i.e., introducing multilinguality in training set) is not as effective for our task.

### 5.6 Comparison to State of the Art Models

Answering RQ6, we would like now to see how the previous setups compare to baselines that we hypothesize are the state of the art on the given test set. We experiment with the following baselines:

1. **mBERT** target, as described earlier.
2. **monoBERT** target, in which we fine-tune a monolingual pre-trained BERT model per target language (e.g., AraBERTv1 for Arabic) using the training set of the target language.

The models we test are those shown in Table 2. Such setup compared to the vanilla ZS. We argue that this is due to the curse of multilinguality that was observed on multilingual transformer models due to limited model capacity dedicated to each language during pre-training, causing degraded transfer ability [17]. We believe a similar issue is emerging during fine-tuning using multiple languages; with each language being represented by small number of examples, the transfer ability of the model, compared to pure ZS setup, is negatively affected.

Table 7 compares results of this model, denoted as ZS_{all-target}, with two baselines: (1) mBERT_{target}, in which we fine-tune the mBERT model over the training set of the target language, and (2) ZS_{best}, which is the best per-target-language performing ZS model in Table 3, which is fine-tuned with one source language. We observe that for 3 out of the 5 languages, unified language in training and test sets (i.e., mBERT_{target}) yields the best performance. Surprisingly, this experiment shows that multilinguality in training did not actually help the model achieve better performance equal in total size and distribution to the training sets of the target languages, to ensure fair comparisons.

![Figure 4: Effect of adversarial training on check-worthiness prediction.](image)

![Figure 5: Effect of number of source languages used during fine-tuning on transfer performance to two target languages.](image)
Table 8: Comparison of performance of best ZS setup for each target language and state-of-the-art models.

| Model        | ar | bg | en | es  | tr |
|--------------|----|----|----|----|----|
| CT!2021_best | 60.0 | 63.9 | 15.3 | 27.0 | 53.9 |
| mBERT_target | 49.5 | 58.2 | 13.3 | 54.0 | 28.4 |
| monobERT_target | 56.3 | 57.8 | 14.2 | 49.0 | 37.2 |
| ZS_best      | 47.7 | 41.0 | 16.8 | 27.6 | 50.3 |
| ZS-TrSrC_best | 45.7 | 36.3 | 17.9 | 30.0 | 47.0 |
| ZS-TrTrg_best | 52.0 | 40.9 | 14.1 | 27.9 | 51.9 |
| FS_best      | 55.1 | 40.9 | 14.5 | 30.5 | 44.1 |

is expected to be effective, since the monolingual model is pre-trained on a large corpora in the target language.

(3) CT!2021_best, which is the model with best reported performance per target language in CheckThat! 2021 lab [39].

Table 8 compares the performance of the above baselines with the best performing models per setup from those presented above, where none or minimal labeled examples in the target language were considered in fine-tuning. The comparison yields a clear observation; for three languages, ar, en, and tr, at least one of the ZS setups had comparable or insignificantly-different performance to both of the BERT-based baselines trained on the training set of the target language. More notably, for two languages, en and tr, translation yields performances gains that are significantly different from those two baselines. Moreover, our best ZS-TrSrC model outperforms all baselines on en. Overall, the comparisons indicate that it is possible to train an effective cross-lingual check-worthiness model for at least three languages without the need for any training examples in the target language.

However, we note that for bg and es, the proposed models consistently under-perform compared to BERT-based baselines. We believe that for Bulgarian compared to mBERT_target, this is due to the initial pre-training of mBERT, where Bulgarian (among other low-resource languages) was greatly under-represented compared to English and other higher-resource languages. We are aware that these results on Bulgarian are not consistent with those in a relevant recent study [30]. In that study, a multitask learning approach was adopted using mBERT for cross-lingual or few-shot transfer learning on seven joint tasks including check-worthiness. Due to the evaluation being done as a weighted score over all tasks, that study did not show clearly how the cross-lingual mBERT model performed for check-worthiness task specifically, and even showed that, overall, the proposed model is as is a good as monolingual models trained on the full training set. This further demonstrates the importance of our work for check-worthiness estimation, where we managed to identify that for Bulgarian, cross-lingual transfer learning is not effective.

As for Spanish, we note that the annotation strategy for this language is slightly different, which might have caused a difference in the criteria of check-worthiness compared to the other languages. That is, the problem is no longer transfer between languages, but also between slightly different classification tasks. In Section 5.2.2 we also observed potential generalization limitation of the models between topics from the training and test sets. This raises a "yet to be answered" question on the accuracy of the currently available claim check-worthiness definitions in terms of how well they match true user needs. For example, should the topic be considered as part of estimating check-worthiness or not? We leave answering this question and studying sensitivity of cross-lingual transfer across datasets with different definitions of check-worthiness or different topics to future work.

The table also shows that systems from CheckThat! 2021 achieved the best performance for ar, bg, and tr. We note that this is a bit unfair comparison, since those systems were trained on much larger training sets (recall that we under-sample the training sets from CT!2021 in all our experiments (Table 1)). Even with that disadvantage to our models, the models show comparable performance to those from CT!2021 on three languages (en, es, and tr). This demonstrates the strong cross-lingual transfer ability of mBERT for our problem, especially when translation is employed to unify the source and target languages. A more important observation here is that with as few as 1.7k labelled examples, which, in our experience, are not very difficult to acquire for the check-worthiness prediction task, the cross-lingual models achieve comparable performance to state-of-the-art models from the CheckThat! lab on this dataset for those languages.

6 CONCLUSIONS AND FUTURE WORK

In this study, we aimed to investigate and identify optimal setups to facilitate check-worthiness estimation over multilingual streams. Our work is motivated by the current dire need to provide multilingual support for the problem given the scale of propagating misinformation and the parallel efforts being put to verify the same claims across languages. Our in-depth experiments showed that cross-lingual transfer models result in comparable performance to the monolingual models trained on examples in the target language for at least three languages, Arabic, English and Turkish. Moreover, multilinguality during fine-tuning negatively affected the model transfer performance. We also showed that our proposed models are as effective as the state of the art models on English, Spanish and Turkish. Our experiments did not show much benefit from employing adversarial training to decrease model over-fitting to source language. Finally, the addition of few shots showed to be generally helpful for three target languages (Arabic, Bulgarian and Spanish) compared to zero shot learning transfer setups.

For future work, we plan to investigate more advanced adversarial training setups. We are also interested in investigating the performance of other multilingual transformer models (e.g., XLM-R). Another natural extension to the work is to experiment with more languages and even out-of-domain datasets.
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