Improving Cross-domain, Cross-lingual and Multi-modal Deception Detection

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Abstract

With the increase of deception and misinformation especially in social media, it has become crucial to be able to develop machine learning methods to automatically identify deceptive language. In this proposal, we identify key challenges underlying deception detection in cross-domain, cross-lingual and multi-modal settings. To improve cross-domain deception classification, we propose to use inter-domain distance to identify a suitable source domain for a given target domain. We propose to study the efficacy of multilingual classification models vs translation for cross-lingual deception classification. Finally, we propose to better understand multi-modal deception detection and explore methods to weight and combine information from multiple modalities to improve multi-modal deception classification.

1 Introduction

Deception detection is a deliberate choice to mislead to gain some advantage or avoid some penalty (DePaulo et al., 2003). Deception detection is an important goal of law enforcement, military and intelligence agencies, as well as commercial organizations. In recent years, automatic deception detection in text has gained popularity in the Natural Language Processing (NLP) community, and researchers have studied cues to deception in a diverse set of domains. These include detecting deception in news (Wang, 2017), online reviews (Ott et al., 2011), interview dialogues (Levitan et al., 2018), trial testimonies (Fornaciari and Poesio, 2013), and in games (Soldner et al., 2019). These studies have been useful for identifying linguistic characteristics of deception, and for developing machine learning techniques to automatically detect deceptive language. However, we are still a long way from applying these state-of-the-art deception detection models in real-world deception scenarios. We currently lack information about how deception detection models perform across domains, languages, and in multiple modalities. In this proposal we outline current limitations in these three areas of deception detection: across domains, across languages and in multiple modalities. We propose work to address these limitations, with the goal of developing robust deception detection models that can generalize from lab-based datasets to real-world deception.

For each of the three topics of deception detection, we discuss current limitations, formulate research questions, and state proposed work to address the research questions. For some of our research questions, we present completed or ongoing work to answer the questions. For cross-domain deception classification, we first establish baseline performance at within and cross-domain deception classification using the well-established NLP model BERT. We identify major performance gaps between within and cross-domain deception classification. To understand the cross-domain performances, we formulate distance metrics and propose a cross-domain classification model that does not require target domain labeled training data and outperforms several baseline models. We also discuss ongoing and future research to further our understanding of and further improve cross-domain deception detection.

For cross-lingual deception classification, we formulate the task for deception detection in two non-English languages: Bulgarian and Arabic. We discuss the effectiveness of using a wide range of classifiers including multilingual BERT (Devlin et al., 2019), and propose additional experiments to further understand and improve cross-lingual deception detection.

Finally, we present proposed work in deception detection in a multi-modal setting from text and image features. Learning to identify deception is a challenging task, especially when there is one modality, and we propose to dynamically fuse in-
formation from multiple modalities. The thorough experiments in the proposed work will contribute substantially to our understanding of cross-domain, cross-lingual, and multi-modal deception detection, and to the development of robust deception detection technologies.

2 Current limitations

2.1 Cross-domain deception classification

Although deception detection is a popular task in the NLP research community, and there is a strong interest in commercial applications of this work, there exists a large gap between deception models trained under laboratory conditions, and the performance level that is needed in real-world deception. Although researchers have in some cases obtained very strong performance at deception detection, these studies have focused on single domains, often using small datasets. We currently lack information about how small-scale, single-domain models of deception may or may not generalize to real-world data and new domains. We directly address this gap by first benchmarking the within- and cross-domain deception classification performance using five popular deceptive text datasets. We then attempt to understand performance gaps by analyzing the features of the datasets and the learned embeddings representations by the models. Finally, we propose a novel approach to leverage distance between domains to improve cross-domain deception classification.

Studying cross-domain deception detection is critical for understanding and contextualizing the successes of deception detection models thus far and gaining insights about the unique challenges of deception detection. The insights gained will motivate and inform the development of more robust models of deception.

2.2 Cross-lingual deception classification

There has been recent work in the NLP community aimed at identifying general misinformation on social media (Shu et al., 2017; Mitra et al., 2017) and particularly COVID-19 misinformation (Hossain et al., 2020).

However, most of this prior work has focused on data in English. There is a severe data shortage of high quality datasets that are labeled for misinformation in multiple languages. Because of this, we need to develop models of deception and misinformation that can utilize smaller datasets in non-English languages or leverage large amounts of training data in a source language, such as English, and generalize to new target languages.

2.3 Multi-modal deception classification

To build classifiers that can detect deception at a high accuracy, it is necessary to have high quality training data. Although a lot of prior work has focused on predicting deception from text (Potthast et al., 2017; Ott et al., 2011; Fornaciari and Poesio, 2014; Levitan et al., 2018), it is generally harder to identify deception from just one modality.

Nakamura et al. (2020) propose models to combine the image and text modalities by simple concatenation, addition, subtraction or taking dimension-wise maximum of image and text feature vectors. However, it still seems unclear how much importance should be attributed to each modality. Whether there are better ways to combine modalities is still unknown.

3 Proposed work and preliminary exploration

To address the limitations discussed above, we formulate concrete research questions that would help study deception classification across domains, languages and modalities. We now discuss proposed work and findings from initial experiments for each research question.

3.1 Cross-domain deception classification

RQ1. How do current models of deception perform within domain and across domain?

To address this research question, we select five deception datasets from different domains for our analysis. They were selected because they are all publicly available, and have been widely used for training and evaluating within-domain deception detection performance. This collection of datasets includes (1) Fake news containing fake and legitimate news compiled via a combination of crowdsourcing and webscraping (Pérez-Rosas et al., 2018), (2) Open-domain deception consisting of short, open-domain truths and lies obtained via crowdsourcing (Pérez-Rosas and Mihalcea, 2015), (3) Cross-cultural deception consisting of a set of deceptive and truthful essays about three topics: opinions on abortion, opinions on death penalty, and feelings about a best friend (Pérez-Rosas and Mihalcea, 2014), (4) Deceptive opinion spam containing truthful and deceptive hotel reviews of 20
Chicago hotels (Ott et al., 2011), and (5) Liar liar pants on fire containing a set of short statements, mostly by politicians, in various contexts spanning across a decade (Wang, 2017). Since each dataset was collected under different experimental settings and have different topics and styles, we consider each dataset to represent a different domain without loss of generality. The summary statistics of the datasets in each domain are shown in Table 1. 4 of the 5 datasets have perfectly balanced classes, while Liar has approximately 35% truthful samples and 65% deceptive samples. It is important to note that the method of obtaining deception labels can vary for different datasets. Broadly, each dataset can be categorized into self reported deception or observed reported deception, based on whether they were reported by the speakers/writers or by human labelers respectively. We show the deception type for various datasets in Table 1. We perform a stratified splitting of the dataset of each domain into training and test splits with 80% of the data used for training and 20% used for testing, sizes of which are shown in Table 1. These train/test splits are used consistently across all experiments in this work to ensure a fair comparison of results across experiments.

We applied a state-of-the-art NLP model BERT (Devlin et al., 2019) to establish a strong baseline for cross-domain deception detection. We used a 10% random split of the source domain training data as the development data. For deception classification, we fine-tuned a BERT-based sequence classification model.\footnote{bert-base-uncased model in Transformers library (Wolf et al., 2020).} For training the BERT-based model the Adam optimizer (Kingma and Ba, 2014) was used with a learning rate of 1e-5. The training was stopped when the development accuracy did not improve for 5 consecutive epochs.

We observe in Table 2 that for any given target domain, the in-domain accuracies are generally higher than the cross-domain accuracies. This finding is consistent with observations made by Glen-ski et al. (2020). In some cases, the gap between within and across domain performance is egregious. For example, BERT classifier fine-tuned on DeceptiveOpinion has a within domain accuracy of 0.909, while the cross-domain performance of a model trained on DeceptiveOpinion ranges from 0.453-0.550 for the four other target domains. Further, the cross-domain performance of models trained on other domains and tested on DeceptiveOpinion ranges from 0.456-0.572. Although the DeceptiveOpinion model has very strong within domain performance and is a useful model of deceptive hotel reviews, it is clearly not a robust model of deception and cannot generalize to other deception domains.

**RQ2. When there is a performance gap between within and across domain deception detection, can we explain why that occurs?**

![Deception UMAP embeddings](image1.png)

To gain a deeper understanding of the classification results, we take BERT [CLS] token’s representation to extract sentence level embedding of each sentence. To visualize the deception sentence embeddings, we project the sentence embeddings into a 2D space using UMAP (McInnes et al.,...
We first formulate the general notion of distance.

$$SD_D = \frac{1 - \cos(SD_S, SD_T)}{2}$$

where $SD_S$ is the mean of all the sentence embeddings in $D_S$ and $SD_T$ is the mean of all the sentence embeddings in $D_T$. Upon computing the Pearson correlation between cross-domain distances and accuracies, the correlation coefficient is found out to be -0.519, asserting that $distance(D_S, D_T)$ is negatively correlated with the cross-domain accuracy as expected.

We propose to understand the cross-domain deception performance by analyzing linguistic features of text in different domains. The list of linguistic features include politeness (Danescu-Niculescu-Mizil et al., 2013), concreteness (Kleinberg et al., 2019), complexity (Lu and Ai, 2015), readability (Dubay, 2004), sentiment and lexical features such as sentence length. Our analysis will include finding out the linguistic features correlated to deception for each domain and comparison of these features across domains.

**RQ3. Can we leverage our understanding of these performance gaps to improve cross-domain deception detection?**

We aim to develop a classification approach that leverages the notion of domain distance to improve cross-domain deception detection. The main idea is as follows: given a target domain, find the optimal source domain to use for training a deception detection model. We compute the domain distance between the target domain and all possible source domains. Then, we recommend the source domain which has the smallest distance from the target domain.

We compare the performance of this recommender system with 2 baselines: (1) A random recommendation system which chooses a source domain uniformly at random for a given target domain. To get a reliable cross-domain accuracy, we consider 100,000 trials of random recommendation and calculate the average cross-domain accuracy across all trials. (2) Multi-source leave-one-out training, which combines all source domains, excluding the target domain, for classification. The recommendation results are shown in Table 3. The table shows the accuracy upon using the recommended source domain for a given target domain. We observe that the recommendation using sentence embeddings based distance metrics is better than both random recommendation and leave one out multisource recommendation. This is an important use case of distance metrics, showing that they can reliably be used for improving cross-domain performance.

We find in Table 3 that while recommending a source domain is a relatively easier task for some target domains, recommendation is difficult in some other domains. For example, for the target domains FakeNews and OpenDomain, the recommendation using average sentence embeddings is right in a majority of cases. However, this is more challenging for Liar as the target domain, since no model achieves an accuracy that is substantially above 50%. To improve recommendation for such cases, we propose to compute the distance between a sample and all the potential source domains using sentence embeddings. By doing the recommendation at a sample level, we hope to improve the overall prediction on the target domain.

Table 2: In-domain and cross-domain accuracies of deception detection. For each target domain, the in-domain accuracy is underlined and the best cross-domain accuracy is bold-faced.

| Target domain | FakeNews | OpenDomain | CrossCultural | DeceptiveOpinion | Liar |
|---------------|----------|------------|---------------|------------------|------|
| FakeNews      | 0.786    | 0.518      | 0.5           | 0.572            | 0.62 |
| OpenDomain    | 0.474    | 0.642      | 0.4           | 0.478            | 0.581|
| CrossCultural | 0.566    | 0.504      | 0.613         | 0.456            | 0.501|
| DeceptiveOpinion | 0.52      | 0.5        | 0.55          | 0.909            | 0.453|
| Liar          | 0.5      | 0.504      | 0.5           | 0.506            | 0.674|
### 3.2 Cross-lingual deception classification

**RQ4. How effective are state of the art multilingual NLP models at cross linguistic deception classification?**

To answer this question, we use the findings from Panda and Levitan (2021) who used the tweet data provided for the Fighting the COVID-19 Infodemic shared task (Shaar et al., 2021) for analysis. The data was created by answering 7 questions about COVID-19 for each tweet about the following aspects: verifiable factual claim, false information, interest to general public, harmfulness, need of verification, harmful to society, and require attention. Each question has a Yes/No (binary) annotation. The data includes tweets in three languages: English, Bulgarian and Arabic. The data falls in the observed reported deception category (see the data discussion in Section 3.1). The training, development and test data sizes for each of the three languages are shown in Table 4. An example of an English tweet from the dataset is

> Anyone else notice that COVID-19 seemed to pop up almost immediately after impeachment failed?

The 7 corresponding labels are Q1 Yes, Q2 Yes, Q3 Yes, Q4 Yes, Q5 No, Q6 Yes, Q7 No.

When the features from multilingual BERT (Devlin et al., 2019) are used for training on the source language and then testing is done on the target language, the scores as reported in Panda and Levitan (2021) are shown in Table 5. This is the Zero shot setup. The source language is set to English and the target languages are Bulgarian and Arabic. The scores for training using the target language (Target setup) are also shown for comparison. We observe that the cross-lingual F1 scores in the Zero shot setup are lower than the scores in the Target setup. Without the target language training data, the model as expected finds it harder to predict accurately when tested on the target language.

**RQ5. What is the impact of amount of target language training data on prediction quality?**

To answer this question, all the source language training data combined with $n$ training samples from the target language is used for training. $n$ is set to 50, 100 and 150. This is called the Few shot setup. A special case of this setup is the Full shot setup, where $n$ is set to the total size of the target language training data. We observe in Table 5 that as we increase the target language training samples in the few shot setup, the performance increases in general, as one would expect. Notably, even with just 50 samples from the target language training data, there is a noticeable increase in the cross-lingual performance in comparison to the Zero shot setup.

**RQ6. How effective is using machine translation for cross lingual deception classification?**

We propose to study the effectiveness of translation with multilingual COVID-19 misinformation classification models. In most cases, training data is available in English. The main idea is to translate either the training or the test non-English data to English using a pre-trained machine translation system. We plan to use the state-of-the-art machine translation systems by Tiedemann and Thottingal (2020) to

1. Translate the non-English test set to English and use an English model for prediction.

| Recommendation                        | FakeNews | OpenDomain | CrossCultural | DeceptiveOpinion | Liar |
|---------------------------------------|----------|------------|---------------|-----------------|------|
| Random recommendation                 | 0.553    | 0.484      | 0.507         | 0.506           | 0.508|
| Multisource leave one out             | 0.541    | 0.500      | 0.550         | 0.447           | 0.521|
| Avg. sentence embed.                  | **0.620**| **0.581**  | 0.501         | **0.550**       | 0.500|
| Best possible recommendation          | 0.620    | 0.581      | 0.566         | 0.550           | 0.506|

Table 3: Cross-domain accuracies upon recommending for various target domains.

| Language → | English | Bulgarian | Arabic |
|------------|---------|-----------|--------|
| Train      | 869     | 3000      | 2336   |
| Dev        | 53      | 350       | 520    |
| Test       | 418     | 357       | 1000   |
| Total      | 1340    | 3707      | 4056   |

Table 4: Data sizes of English, Bulgarian and Arabic datasets for COVID-19 misinformation detection.

| Setup      | Eng. → Bulgarian | Eng. → Arabic |
|------------|------------------|---------------|
| Zero shot  | 0.810            | 0.672         |
| Few-50     | 0.819            | 0.775         |
| Few-100    | 0.823            | 0.824         |
| Few-150    | 0.821            | 0.791         |
| Full shot  | 0.834            | 0.787         |
| Target     | 0.843            | 0.738         |

Table 5: Cross-lingual (source language → target language) F1 scores when tested on the target language. Few-n setup denotes that only $n$ samples in the target language are used for training.
Table 6: Data sizes for different categories for multi-modal deception classification.

| 2-way classification | Category | Train | Dev | Test |
|----------------------|----------|-------|-----|------|
| True                 | 215490   | 22585 | 22798 |
| Fake                 | 337449   | 35567 | 35309 |
| — Total —            | 552939   | 58152 | 58107 |

| 3-way classification | Category                  | Train | Dev | Test |
|----------------------|---------------------------|-------|-----|------|
| Completely True      | 215490                    | 22585 | 22798 |
| Fake with False text | 323721                    | 34217 | 33835 |
| Fake with True text  | 13728                     | 1350  | 1474 |
| — Total —            | 552939                    | 58152 | 58107 |

| 6-way classification | Category                  | Train | Dev | Test |
|----------------------|---------------------------|-------|-----|------|
| True                 | 215490                    | 22585 | 22798 |
| Misleading content   | 104136                    | 10970 | 10959 |
| False connection     | 167471                    | 17766 | 17429 |
| Manipulated content  | 21437                     | 2161  | 2286 |
| Satire/parody        | 32718                     | 3438  | 3419 |
| Imposter content     | 11687                     | 1232  | 1216 |
| — Total —            | 552939                    | 58152 | 58107 |

2. Translate English training data to a target language and train the m-BERT classification model using this translated data.

Results from the above experiments will help quantify the effectiveness of using translation for deception detection.

3.3 Multi-modal deception classification

RQ7. Are there better ways to fuse text and image features in comparison to static fusion?

Recent work such as Nakamura et al. (2020) have created multimodal deception datasets and also provided baselines of fusing multiple modalities. The dataset by Nakamura et al. (2020), called Fakeddit, is the largest publicly available multi-modal deception dataset. It contains two modalities: text and image. There are three labels for each data sample, varying on granularity. The fine-grained labels are true content, misleading content, false connection, manipulated content, satire/parody and imposter content. These labels come from subreddits in from which the content is taken from (see details in Nakamura et al. (2020)). This dataset can be used to train a classifier to predict deception on a desired fine-grained level, the choices of which are 2-way, 3-way and 6-way. The Fakeddit dataset falls under the self reported deception category (see the data discussion in Section 3.1). The sizes of the Fakeddit dataset are shown in Table 6.

We propose to use an attention module (Luong et al., 2015) that dynamically fuses the text and image feature vectors as shown in Figure 2. The text feature vector comes from the [CLS] token’s representation of BERT. The image feature vector comes from ResNet. The attention module decides how much weight to assign for each modality. Specifically it uses the input features for each modality and computes as many attention scores as the number of modalities. These attention scores are positive and sum to 1 when added together. The feature vector from each modality is scaled using the corresponding attention score. Then the scaled feature vectors are added together to obtain a single vector, which can be passed through a final linear layer to produce logits. We plan to answer the following questions by analyzing the results of attention-based fusion.

1. For each category of samples, what is the average attention on each modality?
2. Are there samples for which the attention to one modality is negligible? Are there patterns among these samples?
3. Does dynamic fusion of the text and image feature vectors lead to better overall prediction than static fusion?

4 Ethical considerations

Although automatic deception detection has the potential to benefit society, there are several ethical concerns within this line of research. Automatic
deception detection has varying degrees of severity depending on the application area. The impact of a false positive is substantially lower when detecting deceit in informal activities such as gaming. However, when detecting dishonesty in a criminal investigation, a false positive can have serious implications. In general, automatic deception detection should be employed with caution, especially when there is no manual human verification involved.

For the case of cross-domain deception detection applications, it is important to test the model on the target domain before deploying it, as mentioned in Section 1. To understand the differences between deception domains, a linguistic feature analysis should be performed, as we mention in Section 3.1. Finally, to increase transparency in multi-modal deception detection, it is critical to compute importance scores for each modality as mentioned in Section 3.3. As automatic deception detection across domains, languages and modalities becomes a more widely studied subject, it is important to be aware of the ethical considerations and also take the necessary precautions to avoid harm to society.

5 Conclusion

We identify key challenges in deception detection in cross-domain, cross-lingual and multi-modal scenarios. For cross-domain deception classification, we quantified the gap between in-domain and cross-domain accuracies. Our proposed recommender based on distance measures improves cross-domain performance over two baselines. We plan to extend the completed work by improving the recommendation process by recommending at the sample level instead of the domain level. We also plan to analyze the cross-domain results using linguistic features. For cross-lingual deception classification, we discuss the challenges in predicting deception in a target language with no or little training data. We propose to study the effectiveness of using translation text for training and testing. For multi-modal deception classification, we discuss the merits and limitations of the current state-of-the-art models. We propose to dynamically fuse the text and image feature vectors using an attention module to better understand the importance of each modality.

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