Characterization of effects of transfer learning across domains and languages

Sovesh Mohapatraa,b
aUniversity of Massachusetts Amherst
bAudioShelf
soveshmohapa@umass.edu

Abstract

With ever-expanding datasets of domains, tasks and languages, transfer learning (TL) from pre-trained neural language models has emerged as a powerful technique over the years. Many pieces of research have shown the effectiveness of transfer learning across different domains and tasks. However, there remains uncertainty around when a transfer will lead to positive or negative impacts on performance of the model. To understand the uncertainty, we investigate how TL affects the performance of popular pre-trained models like BERT, RoBERTa and XLNet over three natural language processing (NLP) tasks. We believe this work will inform about specifics on when and what to transfer related to domain, multi-lingual dataset and various NLP tasks.

1 Introduction

TL is when a model is pre-trained on a rich dataset before fine-tuning or using feature-based transfer for a domain-specific task [1–3]. The role of TL in carrying out NLP tasks has increased significantly due to the need for understanding task interests in target domains where there is a lack of large enough datasets. In such cases, the transfer of knowledge from other domains is known to mitigate the problems of overfitting and yield strong model performance while carrying out the predictions [4, 5].

Earlier studies using the traditional kernel-based and feature-based models have shared various methods for domain adaptation, examples including structure correspondence learning, instance weighting, and many such [6, 7].

In recent years, we have seen a significant increase in the use of TL for deep neural networks because of their higher ability to learn non-linear features over traditional methods [8, 9]. This ability brings a risk of being prone to overfitting, due to which TL becomes important as it can be used to train the neural networks because of the incremental learning nature.

Along with all the positives that TL brings, many works have shown negative impacts when TL is being used over solely supervised training on in-target data. The negative impact caused by the TL is widely termed as negative transfer. Generally, it is observed when a transfer is shown with two less closely related datasets, like the transfer of knowledge of an English Part-of-Speech (POS) tagger [10, 11] and applying it to a Hindi corpus. However, it is still uncertain when and how the TL will be used with different in-target data to get the best model performance.

In this study, we aim to investigate how TL affects the performance of popular pre-trained models like BERT, RoBERTa, and XLNet when the knowledge is being transferred over different domains and languages on three NLP tasks: text classification, sentimental analysis, and sentence similarity.

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2 Related Work

Several works have shown the effectiveness of TL across various domains starting from image segmentation to several tasks in NLP [12–14]. Felbo et al. represented the understanding of emotions, sentiment and sarcasm across the text from various domains using the knowledge from a huge data source and transferring it to the model when the prediction was performed on the target domains [15]. There is an improvement in the prediction against the model performance when trained only using the target dataset.

TL has shown great improvement on the traditional feature-based models while performing cross-lingual tasks. Chen et al. have shown that when language-invariant and language-specific features are coupled at the instance level, the cross-lingual TL approach has shown great potential in creating cross-lingual NLP models [16]. The inclusion of unsupervised multilingual embeddings has approached even to work when there is no resource for the model to train, like target language data or cross-lingual information.

With all the effectiveness that TL has brought for the NLP research, it has given rise to the uncertainties of its uses. Several works have effectively reported the negative transfer of knowledge from the source to the target for various aspects. Meftah et al. have shown that knowledge transfer between related domains like news and tweets can even negatively affect the model’s performance which is further proved using quantitative and qualitative analysis [17].

Many researchers have reported methods and approaches to avoid or detect the happening of negative transfer. Chen et al. have reported a novel approach for suppressing negative transfer, called Batch Spectral Shrinkage, which uses a penalizing technique where the smaller singular values are penalized for suppressing the untransferable spectral components [18].

3 Methodology

In this study, we conducted a series of analyses using state-of-art pre-trained models like BERT, XLNet, and ROBERTa on three different NLP tasks. In each of the tasks, we are going to analyze the TL from two different perspectives. One is how knowledge transfer affects the model’s performance when the prediction is made in a somewhat different domain. The second is to see how knowledge transfer affects when the prediction is made cross-lingual tasks with somewhat related languages (French, German and Spanish).

3.1 Details about analyses

In this section, we will understand the datasets used in each analysis, along with the pre-trained models deployed for the tasks.

3.1.1 Analysis - 1: text classification

The datasets to be used:

- IMDB Movie Reviews Dataset: A large dataset classifying the movie reviews into two classes: positive and negative [19].
- Small SMS Spam Collection: A section of a large dataset classifying the messages to be spam or not.
- French and Spanish Reviews Dataset: A small dataset of reviews in French and Spanish classified into positive and negative.

3.1.2 Analysis - 2: sentimental analysis

The datasets to be used:

- IMDB Genre Classification Dataset: A large dataset classifying the movie into 27 different genres using the descriptions.
- Small Section of GoEmotions Dataset: A fine grained annotated dataset with sentences being classified into 28 emotions including neutral.
Table 1: Statistics and examples of the datasets of the analysis - 1

| Data Type       | IMDB Movie Reviews | SMS Spam Collection | French and Spanish Reviews |
|-----------------|--------------------|---------------------|---------------------------|
| Statistics      |                    |                     |                           |
| Train           | 35,000             | 3,900               | 140                       |
| Test            | 15,000             | 1,370               | 60                        |

Snippets of the datasets

| Data Requirement | Dataset                  | Text                                                                 | Classification |
|------------------|--------------------------|----------------------------------------------------------------------|----------------|
| Fine-Tuning       | IMDB Movie Reviews       | Probably my all-time favorite dedication ... “up” for this movie.    | positive       |
| Fine-Tuning       | IMDB Movie Reviews       | An awful film! It must have been up against ... with same brevity.    | negative       |
| Target Dataset    | SMS Spam Collection      | Ok lar... Joking wif u oni...                                        | not spam       |
| Target Dataset    | SMS Spam Collection      | Free entry in 2 a wkly comp to win FA Cup final tkt ... 08452810075over18's | spam           |
| Cross Lingual     | French and Spanish Reviews | Je pensais que c'était une ... intéressante que "Superman" une super comédie à aller voir entre amis. | positive       |
| Cross Lingual     | French and Spanish Reviews | En gros, il y a une famille où un petit ... Jake : ignorez-les.       | negative       |

- French - German Emotions Dataset: A small dataset with machine translation sentences classified into 13 different emotions.

3.1.3 Analysis - 3: sentence similarity

The datasets to be used:

- Paraphrase Adversaries from Word Scrambling (PAWS): A large dataset containing human-labeled sentence similarity [20][21].
- Financial Domain Dataset: A small dataset consisting of related ticker names used in the stock exchange.
- Section of PAWS-X Dataset: A small dataset containing cross-lingual sentence similarity data.

In these analyses, we will use the pre-trained models. Each model will be fine-tuned with the first dataset given in each analysis. Then, using the knowledge, we will perform the prediction on a somewhat different domain where it would predict different aspects of a smaller dataset. Then, using the initially acquired knowledge, we will see how the model’s prediction work on the cross-lingual dataset. Upon which, the fine-tuned models’ performance will be compared with how each model performed when they were only trained on the target sets to understand the effects of TL on how it performs the NLP tasks in both the above-discussed perspectives.

4 Results

We have divided our analyses into two experiments based on the parameters to check model performance. In the first experiment, the models have trained on the target dataset for the tasks: text classification, sentimental analysis, and sentence similarity. Similarly, in the second experiment, the
### Table 2: Statistics and examples of the datasets of the analysis - 2

| Data Type | IMDB Genre Classification | Section of GoEmotion | French - German Emotions |
|-----------|---------------------------|----------------------|--------------------------|
| Train     | 33,657                    | 3,800                | 1232                     |
| Test      | 14,425                    | 1,400                | 538                      |

#### Snippets of the datasets

| Data Requirement | Dataset | Text                                                                                                                                 | Classification |
|------------------|---------|---------------------------------------------------------------------------------------------------------------------------------------|----------------|
| Fine-Tuning      | IMDB Genre Classification | Listening in to a conversation between his doctor and parents ... sweetheart Peggy Blue. | drama          |
| Fine-Tuning      | IMDB Genre Classification | A brother and sister with a past incestuous ... who get too close to him.                                                        | thriller       |
| Target Dataset   | Section of GoEmotion      | I'm really sorry about your situation :(...                                                                                  | sadness        |
| Target Dataset   | Section of GoEmotion      | It's wonderful because it's awful. At not with                                                                                   | admiration     |
| Cross Lingual    | French - German Emotions  | Moi moi gros triste..                                                                                                             | sadness        |
| Cross Lingual    | French - German Emotions  | Gleiche Kleidung und die Tür ist auf der anderen Seite schwarz - sieht so echt aus !!                                              | approval       |

### Table 3: Statistics and examples of the datasets of the analysis - 3

| Data Type | PAWS | Financial Domain | Section of PAWS-X |
|-----------|------|------------------|-------------------|
| Train     | 34,580 | 1,500           | 2800              |
| Test      | 14,820 | 612             | 1200              |

#### Snippets of the datasets

| Data Requirement | Dataset   | Text-1                                                                                                                                 | Text-2                                                                 |
|------------------|-----------|----------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------|
| Fine-Tuning      | PAWS      | In Paris, in October 1560, ... England through Scotland.                                                                               | In October 1560, he secretly met with ... England.                     |
| Fine-Tuning      | PAWS      | The NBA season of 1975 – 76 was the ... Basketball Association.                                                                        | The 1975 – 76 season of the National ... of the NBA                    |
| Target Dataset   | Financial Domain | vanguard small cap index adm                                                  | vanguard small-cap index fund inst                                    |
| Target Dataset   | Financial Domain | schwab intl large company index etf                                           | schwab strategic tr fundamental intl large co index etf               |
| Cross Lingual    | Section of PAWS-X | El Prudential Building (HMB) anteriormente Houston ...                                                                             | fue un rascacielos en el Centro...                                   |
| Cross Lingual    | Section of PAWS-X | L'exception tait entre fin 2005 et 2009 lorsqu'il ...                                                                               | La rivi re Tabaci est un affluent de la rivi                           |
models were fine-tuned with the first dataset of each analysis. Then, the models were made to make predictions on the target dataset using the acquired knowledge from the source.

4.1 Evaluation of models’ performance in experiment - 1

We have trained the pre-trained neural language models on the second and third datasets to see the model performance without the knowledge transfer on the target dataset.

4.1.1 Models’ performance on text classification

Figure - 1(a,b) shows how the accuracy has changed across the ten epochs for each model while training on small SMS spam collection and French and Spanish reviews datasets. Here, the accuracy is based on the training set designed for the model. This clearly explains where the models go away from the expected prediction the most.

In this case, we see that the model ROBERTa is performing the best with an average accuracy of 0.732 for the spam collection dataset. However, when the prediction happened in the cross-lingual dataset (French-Spanish reviews dataset), the BERT performed accurately on an average of 0.63.

4.1.2 Models’ performance on sentimental analysis

Figure - 1(c,d) shows the accuracy changed over the ten epochs for the models training on a small section of GoEmotions and the French and German emotion datasets. The accuracy is based on the training set, which is 70% of the full dataset.

In this case, we found that the BERT performs the best across all the three models with an average accuracy of 0.832 when predicted upon the small section of GoEmotions; whereas, in the case of the French and German emotion dataset, the ROBERTa performs the best with an accuracy of 0.716.

4.1.3 Models’ performance on sentence similarity

Figure - 1(e,f) shows the accuracy changed across the ten epochs for each model trained over the second and third datasets from the analysis - 3. Similar to the above, the accuracy is based on the training set.
Table 4: Comparing the Average Accuracy of Models’ with and without knowledge transfer from the source dataset

| Task Kind       | Task Name                              | BERT  | BERT (fine-tuned) | ROBERTa | ROBERTa (fine-tuned) | XLNet | XLNet (fine-tuned) |
|-----------------|----------------------------------------|-------|-------------------|---------|---------------------|-------|-------------------|
| Text Classification | Small SMS Spam Collection             | 0.71  | 0.621             | 0.732   | 0.548               | 0.576 | 0.48              |
| Text Classification | French and Spanish Reviews Dataset    | 0.63  | 0.672             | 0.58    | 0.51                | 0.44  | 0.46              |
| Sentimental Analysis | Small Section of GoEmotions Dataset | 0.832 | 0.89              | 0.71    | 0.76                | 0.59  | 0.62              |
| Sentimental Analysis | French - German Emotions Dataset      | 0.68  | 0.61              | 0.716   | 0.66                | 0.57  | 0.53              |
| Sentence Similarity | Financial Domain Dataset             | 0.67  | 0.52              | 0.72    | 0.67                | 0.55  | 0.47              |
| Sentence Similarity | Section of PAWS-X Dataset            | 0.67  | 0.61              | 0.736   | 0.711               | 0.58  | 0.62              |

In the case of the sentence similarity task, we found that the ROBERTa performs the best with an accuracy of 0.72 when trained the model on a financial domain-specific dataset. While in the case of the cross-lingual dataset, the ROBERTa performs the best with the accuracy of 0.736.

4.2 Evaluation of models’ performance in experiment - 2

In this experiment, we have fine-tuned models using a larger dataset. For each analysis, we used the first dataset to fine-tune the models and then transferred the knowledge into a task that is from a somewhat related domain and into a cross-lingual task.

4.2.1 Knowledge transferred models’ performance in text classification

Table - 4 represents how the accuracy was performed using the knowledge from the other domain concerning the accuracy produced when the model was trained on the target dataset. In the case of SMS spam collection, due to a significant representation of what is spam and not spam, the model trained directly on the target dataset performed better than the model which used the transferred knowledge, making it a negative transfer.

Although the case of the cross-lingual task showed us that the transferred knowledge model is better than the model trained directly on the dataset. The reasons could be the small size of the representations and the syntactic understanding of the language transferred from the larger domain, making it a positive transfer.

4.2.2 Knowledge transferred models’ performance in sentiment analysis

Table - 4 compares the accuracy between the models’ performance when knowledge was being transferred from a different domain for the prediction of the target dataset with the models’ performance when trained directly on the training dataset. In the case of prediction on the small section of the GoEmotions dataset, we observed that the model with knowledge transferred performed better than the model trained directly. The reason could be the understanding of the plot description matched with the genre upon which the model was fine-tuned. The relationship between the genres and emotions could have helped the model to predict better. Hence, this became a positive transfer.

Although with the cross-lingual task, we found that the model performed better when it was trained directly on the target set than the one with acquired knowledge from a different source. This shows that the syntactic knowledge of the language might not be the only factor in understanding the emotion behind the text. Hence, this became a negative transfer.
4.2.3 Knowledge transferred models’ performance in sentence similarity

Table - 4 shows the prediction accuracy on the target dataset of the models when performed with knowledge transferred from a somewhat related domain with the models trained directly with no fine-tuning. In the case of prediction on the financial domain-specific dataset, we observed the model trained directly performed better. The reason could be because of the kind of data where the full names of tickers could not be understood with any pattern or linguistic knowledge which could be acquired from another domain. Hence, this makes the transfer to be a negative one.

A similar case was observed with the cross-lingual task where the model with knowledge transferred performed worse than that of the model trained directly. The reason could be the confusing nature of the syntax in any particular language used when paraphrasing. This resulted in the transfer being a negative one.

5 Limitations and Future Works

The small lexicons considering closely related languages to English resulted in detecting a relatively narrow understanding of how the effects of TL would appear when used in cross-lingual tasks. Furthermore, the performance behind the model on the cross-lingual tasks is vastly dependent on the task and the diversity in the source data. This was observed when we saw a positive transfer in the case of text classification.

In our study, we nevertheless saw some interesting knowledge transfer results, like in Section 4.2.2 where the positive transfer of genre knowledge helped predict better sentiments over the small section of GoEmotions. In Section 4.2.1 where the models with binary sentiment knowledge didn’t help in predicting the spam.

Future works, including understanding the impact of various methods of TL affecting the prediction, can share which particular way would be ideal for a specific task. Considering some unrelated languages like Chinese, Korean, Hindi and more would shed light on how the TL should be fine-tuned to provide better predictions on cross-lingual tasks. Additionally, adding more specific domains to see where the models could use the acquired knowledge from the source would help to identify the related domains better.

6 Conclusion

We collected and created specific datasets to analyze how TL affects the prediction of specific NLP tasks. Our analysis showed some transfers that could help better understand when and what to transfer specific to the domains and tasks while performing the prediction. We also demonstrated how in some cases, the knowledge transferred could also help in the cross-lingual tasks without prior understanding of the target language.

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