The (In)Effectiveness of Intermediate Task Training
For Domain Adaptation and Cross-Lingual Transfer Learning

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Abstract
Transfer learning from large language models (LLMs) has emerged as a powerful technique to enable knowledge-based fine-tuning for a number of tasks, adaptation of models for different domains and even languages. However, it remains an open question, if and when transfer learning will work, i.e. leading to positive or negative transfer. In this paper, we analyze the knowledge transfer across three natural language processing (NLP) tasks - text classification, sentimental analysis, and sentence similarity, using three LLMs - BERT, RoBERTa, and XLNet - and analyzing their performance, by fine-tuning on target datasets for domain and cross-lingual adaptation tasks, with and without an intermediate task training on a larger dataset. Our experiments showed that fine-tuning without an intermediate task training can lead to a better performance for most tasks, while more generalized tasks might necessitate a preceding intermediate task training step. We hope that this work will act as a guide on transfer learning to NLP practitioners.

Introduction
Knowledge-based transfer learning leverages zero or few-shot learning from a pre-trained model to predict for a range of similar tasks (You et al. 2020; Raffel et al. 2020; Houlsby et al. 2019). The ability to use a pre-trained model, as-is or with very limited training, has proposed a very lucrative opportunity, as compared to training from scratch for every single task (Pan 2020; Day and Khoshgoftaar 2017). The applications of transfer learning have ranged from NLP to image, and even video tasks (Kim et al. 2020; Salza et al. 2022; Bengio 2012).

In recent works, people have applied transfer learning to a range of NLP tasks, observing mixed results, both positive and negative transfer (Zhang et al. 2022; Pruksachatkun et al. 2020). Pruksachatkun et al. (2020) showed how transfer learning with intermediate task training could affect a number of target and probing English-language NLP tasks. In most cases, positive transfer from LLMs, such as BERT, has been noted for similar language NLP tasks, like hate speech classification (Mozafari, Farahbaksh, and Crespi 2019), propaganda detection (Vlad et al. 2019), and biomedical NLP tasks (Peng, Yan, and Lu 2019). Negative transfer has been shown in attempts to transfer an English Part-of-Speech (POS) tagger to a Hindi corpus (Dell’Orletta 2009; Rayson et al. 2007), and other NLP tasks (Wang et al. 2019).

Transfer learning for domain adaptation has been widely studied and applied across language and medical fields (Xu, He, and Shu 2020; Ghafoorian et al. 2017; Kouw and Loog 2018). Savini and Caragea (2022) showed how intermediate task training on sarcasm helped in transfer learning, similar to Felbo et al. (2017) and Baroiu and Trausan-Matu (2022). However, in another domain adaptation task, Meftah et al. (2021) showed that knowledge transfer between related seemingly similar domains like news and tweets resulted in negative transfer, probing the results using both quantitative and qualitative methods.

Cross-lingual tasks are another area where transfer learning strategies have shown a lot of potential (Ahmad et al. 2020; Luo et al. 2021; Chen et al. 2022). Chen et al. (2018) have shown that when language-invariant and language-specific features are coupled at the instance level.

In this work, we analyze the effect of intermediate task training on a larger dataset for three different NLP tasks - text classification, sentiment analysis, and sentence similarity - and evaluate three language models - BERT, RoBERTa, and XLNet. For each NLP task, we have one domain adaptation and another cross-lingual task. In total, we have eighteen experiments on a range of NLP tasks.

Methodology
Here, we present an overview of our methodology, including information on transfer learning for intermediate task training, and domain adaptation, and cross-lingual fine-tuning and evaluation for the NLP tasks, and the datasets.

In each of the following tasks, both intermediate task training and fine-tuning were performed by training over 70% of the dataset, and evaluated on the remaining 30%. For the intermediate task training, each pre-trained LLM was trained for 100 epochs using the large dataset. For fine-tuning after and without intermediate task training, transfer learning to the target dataset was performed by training for 10 epochs. In both cases of transfer learning, all the model weights were updated, or none of the layers were frozen.

Model instances for LLMs, BERT, RoBERTa, and XLNet, were obtained from the respective GitHub repositories.
In each of the NLP tasks, the dataset used for the intermediate task training from the LLM is at least an order of magnitude larger than the dataset used for fine-tuning the model to the target task. The target task for domain adaptation, and the respective datasets, have been chosen to be in a similar field, as of the intermediate task dataset. For cross-lingual target tasks, we have tried to ensure that the task is in the same domain, and the language has semantic and syntactic similarity.

Text classification
For text classification, we performed intermediate task training using the IMDB movie reviews dataset (Maas et al. 2011). The IMDB movie reviews dataset has 50,000 examples classifying the movie reviews into two classes: positive and negative.

To evaluate domain adaptation, we used a randomly sampled subset of SMS spam collection dataset, with 5,600 examples (Delany, Buckley, and Greene 2012), annotated as spam or not. For cross-lingual task evaluation, we created a dataset of French and Spanish movie reviews, with 100 examples of each language, obtained by web scraping. Each example was translated into English using Google Translate and annotated as positive or negative.

Sentiment analysis
IMDB genre classification dataset was used for intermediate task training for the sentiment analysis task (Kumar et al. 2022). This dataset consisted of 49,000 examples, classified into 27 different movie genres.

We sampled the GoEmotions dataset for 5,200 examples across all 28 different emotions, including neutral (Demszky et al. 2020) for the domain adaptation task. Similar to text classification, we manually created a dataset of French and German sentences with 1,700 examples, and used Google Translate to translate them into English, and then manually annotate them into 13 different emotions.

Sentence similarity
We used the Paraphrase Adversaries from Word Scrambling (PAWS) dataset, containing human-labeled sentence similarity for more than 49,000 pair-wise examples, for the intermediate task training (Zhang, Baldridge, and He 2019).

For domain adaptation, we collected about 2,100 stock names, listed on the New York Stock Exchange and NASDAQ-traded stocks. We sampled 4,000 exampled from the PAWS-X dataset to evaluate cross-lingual sentence similarity (Yang et al. 2019).

Results and Discussion
To understand the effects of fine-tuning with and without intermediate task training, we analyzed the accuracy of the three NLP tasks for both domain adaptation and cross-lingual predictions.

RoBERTa and BERT with intermediate task training are the best models, depending on the task
In our observations, we observed that fine-tuning a post-intermediate task training learnt LLMs has been noted for different tasks. The rows represent the NLP tasks, and the columns represent the transfer learning tasks. Specific datasets used for the intermediate task training have been mentioned to the right of the NLP task, and the transfer learning datasets used for training and testing have been noted on the graphs.
Table 1: Accuracy of the target-task fine-tuned large language models with and without intermediate task training has been noted for the different NLP tasks. The specific LLMs are BERT, RoBERTa, and XLNet, with the appended note mentioning if the specific model had an intermediate task training or not. Models with intermediate task training (I) on the larger dataset followed by fine-tuning (F) to the target task have been noted as ‘ModelName-IF’, such as BERT-IF, and if the model has only been fine-tuned, then it has been noted as ‘ModelName-F’, such as BERT-F. In target tasks per NLP task, the first task is for domain adaptation, and the next one is for cross-lingual adaptation. The best performing model accuracy for each NLP target-task has been noted in bold.

| NLP Task            | Target Task                     | BERT-IF | BERT-F | RoBERTa-IF | RoBERTa-F | XLNet-IF | XLNet-F |
|---------------------|--------------------------------|---------|--------|------------|-----------|----------|---------|
| Text Classification | SMS Spam                       | 0.62    | 0.71   | 0.55       | 0.73      | 0.48     | 0.58    |
|                     | French/Spanish Movie Reviews    | 0.67    | 0.63   | 0.51       | 0.58      | 0.46     | 0.44    |
| Sentimental Analysis| GoEmotions                     | 0.89    | 0.83   | 0.76       | 0.71      | 0.62     | 0.59    |
|                     | French/German Emotions         | 0.61    | 0.68   | 0.66       | 0.72      | 0.53     | 0.57    |
| Sentence Similarity | Stock Ticker                   | 0.52    | 0.67   | 0.67       | 0.72      | 0.47     | 0.55    |
|                     | PAWS-X                         | 0.61    | 0.67   | 0.71       | 0.74      | 0.62     | 0.58    |

Irrespective of the tasks, we noted that the change in accuracy against the fine-tuning epochs for the LLMs the followed a similar trend. RoBERTa and XLNet improved on the accuracy metric for about 5 to 7 epochs, and then the accuracy started to go down. BERT had almost similar accuracy with minor improvements, or even worsening, as the fine-tuning epochs increased. We attribute such behavior to an observation of the linguistic information storage noted by pruning of layers in BERT, RoBERTa, and XLNet in a recent work (Durrani, Sajjad, and Dalvi 2021), stating that BERT stored the information deep in the network, while RoBERTa and XLNet localized it in the lower layers. Their observations qualitatively indicate higher rates of fine-tuning in the early epochs for RoBERTa and XLNet, aligning with our observations. In the later epochs, such behavior aligns with the bias-variance trade-off that comes with fine-tuning a generalized model to the target task, where too much training erodes the generalizability of the intermediate task training and starts overfitting to the target dataset.

Fine-tuned RoBERTa, without intermediate task training, outperforms other transfer learnt LLMs in most tasks

Across all models, both with and without intermediate task training, RoBERTa, only fine-tuned on the target dataset, has the highest accuracy in four out of six tasks, while BERT with intermediate task training followed by fine-tuning leads in the other two - text classification - cross-lingual prediction and sentiment analysis - domain adaptation (Table 1). Comparison of accuracy with and without intermediate task training for the LLMs provides us the opportunity to discuss the effects of positive and negative transfer, and thus the (in)effectiveness of transfer learning for domain adaptation and cross-lingual predictions.

The negative transfer noted across most of the tasks indicated that intermediate task training led to an unnecessary and ineffective generalization for the domain adaptation and cross-lingual tasks. For instance, in the case of text classification - domain adaptation, the intermediate task training on IMDB movie reviews, followed by fine-tuning, led to the best model as BERT with an accuracy of 0.62, whereas direct fine-tuning led to an accuracy of 0.71, 0.73, and 0.58 for BERT, RoBERTa, and XLNet, respectively. The similar performance of BERT and RoBERTa, in this specific task, show how fine-tuning is effective. The performance of XLNet, with an accuracy of 0.58, which is closer to the best intermediate task trained - fine-tuned model’s accuracy of 0.62, further provides convincing argument for the case. We observed similar trends for the negative transfer for other tasks, except in the cases where BERT with both intermediate task training and fine-tuning on the target dataset outperformed the only fine-tuned models. We further do a case-by-case analysis and try to provide a qualitative argument for the positive and negative transfer.

For text classification, we noted that the SMS spam collection, though seemingly similar to the movie reviews, is fundamentally different with distinct spamming patterns, thereby leading to better performance on direct fine-tuning. However, cross-lingual predictions for French/Spanish movie reviews follow a linguistically, specifically the semantics and syntax, similar notation to the English reviews, thereby leading to a positive transfer with the intermediate task training.

In the context of sentiment analysis, sentiments in GoEmotions dataset are similar to the movie genres, for instance, the emotion love corresponding to the genre romance, which might be leading to an internal covariate shift with the fine-tuning, preceded by the intermediate task training, thus being aided by a positive transfer. However, the French-German emotions classification have only thirteen emotions, instead of the twenty-seven genres and twenty-eight emotions in the GoEmotions domain adaptation task, which might lead to a harder covariate shift in the confusion matrix for classification. Additionally, it shows that the syntactic knowledge of the English language might not be the only factor in understanding the emotion behind the French/German text.

Ultimately, for sentence similarity, we attribute the directly fine-tuned model performing better on the financial domain adaptation to the lack of inherent pattern for the full names of tickers, which have been adapted from a very specialized domain. In this case, the linguistic knowledge from the general PAWS dataset does not transfer any finance-specific knowledge to the model. We believe that a similar
argument can be made for the confusing nature of syntax in any particular language used when paraphrasing, thereby leading to a negative transfer for a cross-lingual sentence similarity task.

**Limitations and Future Work**

In the case of domain adaptation, the focus on SMS spam similarity to movie reviews, genre to emotions, is a limited field of view. We would like to expand on these tasks and extend the study to multiple cases to see if there are design principles based on similarity of the domain that could predict positive or negative transfer. We believe that future work including multiple domains, with a quantitative similarity on the domains themselves, would be helpful in arriving at conclusions about the effectiveness of transfer learning in domain adaptation.

For transfer learning for cross-lingual tasks, we are limited by the small lexicons considering closely related languages to English. Furthermore, the model performance on the cross-lingual tasks is dependent on the task and the diversity in the source data. Considering unrelated languages, such as Chinese, Korean, Hindi and more would shed light on how transfer learning strategies could be developed to provide better predictions, without the necessity of training models from scratch.

**Conclusion**

In this work, we analyzed the effectiveness of transfer learning by fine-tuning to a target task, with and without an intermediate task training step. We observed that in almost all cases, the intermediate task training leads to a negative transfer for both domain adaptation and cross-lingual NLP tasks. On the performance of different LLMs, we noted that BERT and RoBERTa performed similarly, and outperformed XLNet on the tasks when an intermediate task training step was involved. However, when we compared all models both with and without the intermediate task training step, only fine-tuned RoBERTa emerged as a clear winner. We hope that these results, and those that arise as part of this work in the near future, inform the community on the positive and negative effects of transfer learning with an intermediate task training step.

**References**

Ahmad, Z.; Jindal, R.; Ekbal, A.; and Bhattacharyya, P. 2020. Borrow from rich cousin: transfer learning for emotion detection using cross lingual embedding. *Expert Systems with Applications*, 139: 112851.

Ameer, I.; Arif, M.; Sidorov, G.; Gomez-Adorno, H.; and Gelbukh, A. 2022. Mental illness classification on social media texts using deep learning and transfer learning. *arXiv preprint arXiv:2207.01012*.

Barouli, A.-C.; and Trausan-Matu, S. 2022. Automatic Sarcasm Detection: Systematic Literature Review. *Information*, 13(8): 399.

Bengio, Y. 2012. Deep learning of representations for unsupervised and transfer learning. In *Proceedings of ICML workshop on unsupervised and transfer learning*, 17–36. JMLR Workshop and Conference Proceedings.

Chen, X.; Awadallah, A. H.; Hassan, H.; Wang, W.; and Cardie, C. 2018. Multi-source cross-lingual model transfer: Learning what to share. *arXiv preprint arXiv:1810.03552*.

Day, O.; and Khoshgoftaar, T. M. 2017. A survey on heterogeneous transfer learning. *Journal of Big Data*, 4(1): 1–42.

Delany, S. J.; Buckley, M.; and Greene, D. 2012. SMS spam filtering: Methods and data. *Expert Systems with Applications*, 39(10): 9899–9908.

Dell’Orletta, F. 2009. Ensemble system for Part-of-Speech tagging. *Proceedings of EVALITA*, 9: 1–8.

Demszky, D.; Movshovitz-Attias, D.; Ko, J.; Cowen, A.; Nemade, G.; and Ravi, S. 2020. GoEmotions: A dataset of fine-grained emotions. *arXiv preprint arXiv:2005.00547*.

Durrani, N.; Sajjad, H.; and Dalvi, F. 2021. How transfer learning impacts linguistic knowledge in deep NLP models? *arXiv preprint arXiv:2105.15179*.

Felbo, B.; Mislove, A.; Søgaard, A.; Rahwan, I.; and Lehmann, S. 2017. Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm. *arXiv preprint arXiv:1708.00524*.

Ghafoorian, M.; Mehrtash, A.; Kapur, T.; Karssemeijer, N.; Marchiori, E.; Pesteie, M.; Guttmann, C. R.; Leeu, F.-E. d.; Tempary, C. M.; Ginneken, B. v.; et al. 2017. Transfer learning for domain adaptation in MRI: Application in brain lesion segmentation. In *International conference on medical image computing and computer-assisted intervention*, 516–524. Springer.

Gupta, P.; Gandhi, S.; and Chakravarthi, B. R. 2021. Leveraging transfer learning techniques—bert, roberta, albert and distilbert for fake review detection. In *Forum for Information Retrieval Evaluation*, 75–82.

Houlsby, N.; Giurgiu, A.; Jastrzebski, S.; Morrone, B.; De Laroussilhe, Q.; Gesmundo, A.; Attariyan, M.; and Gelly, S. 2019. Parameter-efficient transfer learning for NLP. In *International Conference on Machine Learning*, 2790–2799. PMLR.

Kim, Y.-G.; Kim, S.; Cho, C. E.; Song, I. H.; Lee, H. J.; Ahn, S.; Park, S. Y.; Gong, G.; and Kim, N. 2020. Effectiveness of transfer learning for enhancing tumor classification with a convolutional neural network on frozen sections. *Scientific Reports*, 10(1): 1–9.

Kouw, W. M.; and Loog, M. 2018. An introduction to domain adaptation and transfer learning. *arXiv preprint arXiv:1812.11806*.

Kumar, S.; Kumar, N.; Dev, A.; and Naorem, S. 2022. Movie genre classification using binary relevance, label powerset, and machine learning classifiers. *Multimedia Tools and Applications*, 1–24.

Luo, J.; Wang, J.; Cheng, N.; Xiao, E.; Xiao, J.; Kucsko, G.; O’Neill, P.; Balam, J.; Deng, S.; Flores, A.; et al. 2021. Cross-language transfer learning and domain adaptation for end-to-end automatic speech recognition. In *2021 IEEE International Conference on Multimedia and Expo (ICME)*, 1–6. IEEE.
Maas, A. L.; Daly, R. E.; Pham, P. T.; Huang, D.; Ng, A. Y.; and Potts, C. 2011. Learning Word Vectors for Sentiment Analysis. In Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies, 142–150. Portland, Oregon, USA: Association for Computational Linguistics.

Meftah, S.; Semmar, N.; Tamaazousti, Y.; Essafi, H.; and Sadat, F. 2021. On the hidden negative transfer in sequential transfer learning for domain adaptation from news to tweets. In Proceedings of the Second Workshop on Domain Adaptation for NLP, 140–145.

Mozafari, M.; Farahbakhsh, R.; and Crespi, N. 2019. A BERT-based transfer learning approach for hate speech detection in online social media. In International Conference on Complex Networks and Their Applications, 928–940. Springer.

Pan, S. J. 2020. Transfer learning. Learning, 21: 1–2.

Peng, Y.; Yan, S.; and Lu, Z. 2019. Transfer learning in biomedical natural language processing: an evaluation of BERT and ELMo on ten benchmarking datasets. arXiv preprint arXiv:1906.05474.

Pruksachatkun, Y.; Phang, J.; Liu, H.; Htut, P. M.; Zhang, X.; Pang, R. Y.; Vania, C.; Kann, K.; and Bowman, S. R. 2020. Intermediate-task transfer learning with pretrained models for natural language understanding: When and why does it work? arXiv preprint arXiv:2005.00628.

Qiu, X.; Sun, T.; Xu, Y.; Shao, Y.; Dai, N.; and Huang, X. 2020. Pre-trained models for natural language processing: A survey. Science China Technological Sciences, 63(10): 1872–1897.

Raffel, C.; Shazeer, N.; Roberts, A.; Lee, K.; Narang, S.; Matena, M.; Zhou, Y.; Li, W.; Liu, P. J.; et al. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. J. Mach. Learn. Res., 21(140): 1–67.

Rajapaksha, P.; Farahbakhsh, R.; and Crespi, N. 2021. BERT, XLNet or RoBERTa: The Best Transfer Learning Model to Detect Clickbaits. IEEE Access, 9: 154704–154716.

Rayson, P.; Archer, D. E.; Baron, A.; Culpeper, J.; and Smith, N. 2007. Tagging the Bard: Evaluating the accuracy of a modern POS tagger on Early Modern English corpora. In Proceedings of the Corpus Linguistics conference: CL2007.

Salza, P.; Schwizer, C.; Gu, J.; and Gall, H. C. 2022. On the effectiveness of transfer learning for code search. IEEE Transactions on Software Engineering.

Savini, E.; and Caragea, C. 2022. Intermediate-task transfer learning with BERT for sarcasm detection. Mathematics, 10(5): 844.

Vlad, G.-A.; Tanase, M.-A.; Onose, C.; and Cercel, D.-C. 2019. Sentence-level propaganda detection in news articles with transfer learning and BERT-BiLSTM-capsule model. In Proceedings of the second workshop on natural language processing for internet freedom: Censorship, Disinformation, and Propaganda, 148–154.