MetaXT: Meta Cross-Task Transfer between Disparate Label Spaces

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Abstract

Albeit the universal representational power of pre-trained language models, adapting them onto a specific NLP task still requires a considerably large amount of labeled data. Effective task fine-tuning meets challenges when only a few labeled examples are present for the task. In this paper, we aim to address the problem of few shot task learning by exploiting and transferring from a different task which admits a related but disparate label space. Specifically, we devise a label transfer network (LTN) to transform the labels from source task to the target task of interest for training. Both the LTN and the model for task prediction are learned via a bi-level optimization framework, which we term as MetaXT. MetaXT offers a principled solution to best adapt a pre-trained language model to the target task by transferring knowledge from the source task. Empirical evaluations on cross-task transfer settings for four NLP tasks, from two different types of label space disparities, demonstrate the effectiveness of MetaXT, especially when the labeled data in the target task is limited.

1 Introduction

Recent advances in large-scale self-supervised pre-training have greatly impacted and shaped transfer learning for natural language processing. Namely, a two-stage process including pre-training with self-supervision loss and fine-tune on task data (Devlin et al., 2018; Radford et al.; Conneau et al., 2019; Yang et al., 2019; Raffel et al., 2019) has become a standard. Increasingly larger pre-trained language models provide richer and more powerful representations for text reducing the need for large amounts of task labeled data (Brown et al., 2020). However to attain the best task performance, adequate amount of task labeled data is still required. For example, the largest pre-trained language model to date, GPT-3 (Brown et al., 2020), achieves an average score of 70.3 on SuperGLUE (Wang et al., 2019) on few-shot setting, while the best supervised model, as the time of writing, scored 90.3, demonstrating the importance of task labeled examples even with large pre-trained models.

Many NLP tasks may have limited amounts of training data, making it challenging to train performant models. However, it is often possible that a reasonably large dataset from a related task can be found - such related tasks are often referred to as auxiliary tasks. To alleviate the scarcity of task labeled data in low-resource tasks, many NLP methods leverage multi-task learning or cross-task transfer learning, e.g. (Ruder, 2017; Balikas et al., 2017; Augenstein et al., 2018; Pfeiffer et al., 2020b), to incorporate additional data from one or more auxiliary tasks into the training process.

In this paper, we focus on studying cross-task transfer from an auxiliary source task, where large amount of labeled examples might be readily available or easier to acquire, to a low-resource target task, where limited labeled data is available. Note that unlike traditional Multi-task learning (Caruana, 1997), we do not attempt to learn multiple task jointly, rather we focus on improving perfor-
performance on the low-resource target task using data from a resource-rich source task. We focus on scenarios where the source task and the target task may be related, albeit having disparate label spaces (e.g., different label granularity, disjoint tag sets, etc.). Previous work has shown that similar tasks that have originated from similar probability distributions (Caruana, 1997) or have similar inductive biases (Baxter, 2000) tend to perform well in multi-task learning settings. While no universal measure for task similarity exists, there has been several attempts at quantifying task similarity and its effect on transfer learning performance (Ruder, 2017; Schröder and Biemann, 2020).

Learning models for multiple loosely related tasks have mostly been studied in a multi-task joint training (Augenstein et al., 2018) or splitting parameters into shared and private spaces (Liu et al., 2017). We hypothesize that directly optimizing for the target task would result in better performance. However, this may be challenging given the disparate label spaces between the source auxiliary task and the target task. To overcome this challenge, we propose a meta-learning based method, MetaXT, to bridge the gap between the disparate label spaces and allow for effective transfer to low-resource tasks. MetaXT learns to transfer the label space from the source task to the target task in a way that maximally facilitates transfer to the low-resource target task using a label transfer network (LTN). Directly training the LTN in a supervised fashion is not possible due to lack of parallel data between the source and target tasks; instead we adopt a data-driven approach to learn both the main model architecture and the LTN via a bi-level optimization formulation. Figure 1 shows an illustration for an actual task setting and the purpose of LTN.

MetaXT enjoys the following advantages:

- The LTN learns a direct mapping from source task labels to target task, allowing explicit transfer across types, even when they come from disparate label spaces;

- The data-driven approach of learning offers flexibility in the transfer between tasks, which makes the method generally applicable to a wide range of NLP task pairs.

We conduct empirical evaluations of MetaXT over different data sets and task pairs; comparisons with several multi-task training based methods verify the effectiveness of the proposed approach.

2 Background and Preliminaries

Given a few-shot transfer learning setting, the target task has a k-shot training set \( D_t := \{(x_1, y_1), ..., (x_k, y_k)\} \), \( x \in X_t \), \( y \in \mathcal{Y}_t \), which is also augmented with labeled examples from a source task \( D_s := \{(x_1, y_1), ..., (x_N, y_N)\} \), \( x \in X_s \), \( y \in \mathcal{Y}_s \) such that \( k < N \). Note that in general \( \mathcal{Y}_s \) is different from \( \mathcal{Y}_t \), meaning that the target task label space is disparate from that of the auxiliary task. The auxiliary task is also referred to as the source task, as we look to improve the target task by transferring knowledge from it. Existing works on multi-task learning often involves building on top of a text feature encoder \( f_\theta \), often a pre-trained language model, and adding task-specific layers to map the text representations onto the respective label spaces, parameterized by \( v \) and \( w \) for the source and target tasks, respectively. For simplicity, we denote the complete source task model and target task model as \( f_{\theta,v} \) and \( f_{\theta,w} \), respectively, where \( \theta \) denotes the weights of the pre-trained language model shared by both tasks.

The classic multi-task joint training then aims to minimize the combined loss over a set of tasks, hoping that the model could benefit from other tasks. A recent line of work on adaptors (Pfeiffer et al., 2020a,b) builds on top of multi-task joint training by training and leveraging task or language specific expert models, however these still lie in the category of multi-task joint training. One major difference between multi-task joint learning and cross-task transfer for a particular target task is that, multi-task joint learning aims to improve over all tasks while cross-task transfer only aims to improve the target task of interest where the other tasks are only used as auxiliary information to improve the target task performance. Recent work on measuring the similarities among NLP tasks and identifying the correct task to use as auxiliary task for a particular target task reveals the advantage of leveraging auxiliary tasks for transfer learning (Schröder and Biemann, 2020).

3 MetaXT: Meta Cross-task Transfer

In traditional multi-task learning settings, all tasks are jointly learned via minimizing the combined loss over them. However, this might be sub-optimal as severe data imbalance between the two tasks might render the learned model to either favor the source task for its larger training size or over-fit on the limited labels from the target task. Instead in
this paper, we propose to leverage the source task explicitly by transferring from its label space onto the target task, in a way such that the produced pseudo label can directly benefit the target task. Specifically, we devise a label transfer network (LTN) \( g_\alpha : \mathcal{X}_s, \mathcal{Y}_s \rightarrow \mathcal{Y}_t \), a component parameterized by \( \alpha \) which sources a source example as input and produces a transferred label in the target label space. Specifically, for a labeled example in the source task, the LTN attempts to estimate its soft label in the target task space by \( \hat{y}_t = g_\alpha(x_s, y_s) \).

Directly training such LTN in a supervised manner is typically infeasible as in general the parallel correspondence between labeled examples from the source task and target task is unknown. Instead, we follow a simple intuition to train the LTN that an effective LTN should produce accurate transferred labels in target task label space from examples in the source task, which further allows us to train a good target task model such that it incurs low evaluation loss on a separate set of target task examples. This can be formulated as the following bi-level optimization problem:

\[
\min_{\alpha} \mathcal{L}_{\text{meta}}(\theta^*_\alpha, w^*_\alpha) \\
\text{s.t. } \theta^*_\alpha, w^*_\alpha, v^*_\alpha = \arg \min_{\theta, w, v, \alpha} \mathcal{L}_{\text{train}}(\theta, w, v, \alpha)
\]

where

\[
\mathcal{L}_{\text{meta}} \triangleq \mathbb{E}_{(x, y) \in \mathcal{D}_s} \ell(f_{\theta^*_\alpha, w^*_\alpha}(x), y) \\
\mathcal{L}_{\text{train}} \triangleq \mathbb{E}_{(x, y) \in \mathcal{D}_s} \ell(f_{\theta, w, v}(x), y) + \gamma_1 \mathbb{E}_{(x, y) \in \mathcal{D}_s} \ell(f_{\theta, v}(x), y) + \gamma_2 \mathbb{E}_{(x, y) \in \mathcal{D}_s} \ell(f_{\theta, w}(x), g_\alpha(x, y))
\]

The upper component of the above problem aims to minimize the evaluation loss \( \mathcal{L}_{\text{meta}} \) of the trained target task model on the few-shot test examples for the target task, while the lower component specifies that the target task model \( f_\theta, w, v \) is trained by minimizing a summed loss of three terms, listed as follows respectively

- \( \ell(f_{\theta, w}(x_i), y_i) \) encodes the supervised loss over the source task;
- \( \ell(f_{\theta, v}(x_i), y_i) \) encodes the supervised loss over the source task;
- \( \ell(f_{\theta, w}(x_i), \hat{y}_i) \) encodes the supervised loss over the transferred labels produced by the LTN, where \( \hat{y}_i = g_\alpha(x_s, y_s) \).

Hyper-parameters \( \gamma_1 \) and \( \gamma_2 \) controls the balances among the three terms, and they are to be tuned by cross-validation.

Note that it is crucial for \( \hat{y}_i \) to be a soft label to allow gradient propagation back from \( \mathcal{L}_{\text{meta}} \) all the way back to the LTN parameters, which can be instantiated by using a softmax as the output layer for the LTN (We defer the detailed design for LTN used in this paper to Section 3.1). For sentence classification and sequence tagging problems, cross-entropy (CE) loss is used for \( \ell \) which can be easily extended to support soft labels as \(- \sum y_i \log p_i\) where \( y \) is a soft-label with \( \sum y_i = 1 \) and each \( y_i \geq 0 \), and \( p \) is a probability vector for a model’s output. Note that it boils down to classic cross-entropy loss for a hard label \( y \) if \( y \) is expressed in its one-hot form.
3.1 Label Transfer Network (LTN)

Recall that the LTN is a function taking a source example pair and producing a pseudo-label in the target label space. To ease the design complexity of LTN and to add minimal parameter overhead from the task model, we devise the LTN as 3-layer feed-forward network, whose input dimension is \( h_{\text{dim}} + z_{\text{dim}} \), where \( h_{\text{dim}} \) is the representation dimension of a data example and \( z_{\text{dim}} \) is the embedding dimension to encode the discrete source task label. The LTN outputs a vector with dimension equal to the number of classes in the target task.

With a pre-trained LM (PLM), like BERT, serving as the text representation encoder as typically used for various NLP tasks. In practice, we take the contextualized representation of a source task example \( x_s \) to feed into the LTN for sequence-level tasks (or the token representation for token-level tasks). This also relieves the LTN from the burden of encoding the raw text thus making the LTN lightweight. Refer to Figure 2(c) for an illustration of LTN used throughout this paper.

3.2 Model Learning for MetaXT

Similar to many bi-level optimization problems, analytically solving Eq. (1) is infeasible, as every change on the LTN parameters \( \alpha \) requires solving for the optimal solution to lower optimization problem. Instead, a widely used strategy to approximate the solution to the lower problem with a one-step SGD estimate (Finn et al., 2017; Liu et al., 2018; Shu et al., 2019; Zheng et al., 2021). To be concrete, we solve the following proxy problem

\[
\min_{\alpha} \mathcal{L}_{\text{meta}}(\Theta(\alpha))
\]

s.t. \( \Theta(\alpha) = \Theta - \eta \nabla_\Theta \mathcal{L}_{\text{train}}(\Theta, \alpha) \) \hspace{1cm} (4)

where \( \Theta \) is a shorthand for the group of main parameters \( \{\theta, w, v\} \) and \( \eta \) is the learning rate for them. Computing the meta-gradient \( \nabla_\alpha \mathcal{L}_{\text{meta}}(\Theta(\alpha)) \) is the essence of training MetaXT, which can be obtained as follows

\[
\nabla_\alpha \mathcal{L}_{\text{meta}}(\Theta(\alpha)) = \nabla_\alpha \mathcal{L}_{\text{meta}}(\Theta - \eta \nabla_\Theta \mathcal{L}_{\text{train}}(\Theta, \alpha)) \\
= -\eta \nabla^2_\alpha \mathcal{L}_{\text{meta}}(\Theta, \alpha) \nabla_\Theta \mathcal{L}_{\text{train}}(\Theta, \alpha) + \nabla_\Theta \mathcal{L}_{\text{train}}(\Theta, \alpha) \nabla_\Theta \mathcal{L}_{\text{meta}}(\Theta') \\
= -\eta \left( \nabla_\Theta \mathcal{L}_{\text{train}}(\Theta, \alpha) \nabla_\Theta \mathcal{L}_{\text{meta}}(\Theta') \right) \hspace{1cm} (5)
\]

where \( \Theta' = \Theta - \eta \nabla_\Theta \mathcal{L}_{\text{train}}(\alpha, \Theta) \). Detailed procedure to train MetaXT is in Algorithm 1.

while not finished do

| Sample source task batch \((x_s, y_s)\) and target task batch \((x_t, \hat{y}_t)\) |
| Split target task batch \((x_t, \hat{y}_t)\) into \((x_t', \hat{y}_t')\) and \((x_t'', \hat{y}_t'')\) |
| Update LTN parameters \(\alpha\) by descending Eq. (5) |
| Update model parameters \(\Theta\) by descending \(\nabla_\Theta \mathcal{L}_{\text{train}}(\Theta, \alpha)\) |
end

Algorithm 1: MetaXT Training procedure

Eq. (5) shows how to compute the gradient of the LTN parameters \(\alpha\) (or meta-parameters). Following Figure 2, for each round updating the meta-parameters \(\alpha\), the steps are as follows:

1. Data example pair from source task \((x_s, y_s)\) is fed to the LTN and an estimate of the corresponding target label \(\hat{y}_t = g_\alpha(x_s, y_s)\) is produced;
2. Now with three data and label pairs, i.e., \(\{(x_s, y_s), (x_t', \hat{y}_t'), (x_s, \hat{y}_t)\}\), the joint training loss \(\mathcal{L}_{\text{train}}\) is computed following Eq. (3);
3. Back-propagate \(\mathcal{L}_{\text{train}}\) onto and update the main model parameters \((\theta, v, w)\), which are functions of the LTN parameters;
4. With the updated model, compute the meta-evaluation loss \(\mathcal{L}_{\text{meta}}\) on a separate set of target task examples \((x_t'', \hat{y}_t'')\) following Eq. (2), which at its core is also function of LTN parameters \(\alpha\);
5. Back-propagate \(\mathcal{L}_{\text{meta}}\) onto the LTN parameters \(\alpha\) and update the LTN.

The updates of the main parameters \((\theta, v, w)\) are the same as standard multi-task training. At inference time, the LTN is not used and the trained main model with the target task predictor is used.

4 Experiments

We conduct experiments to evaluate MetaXT over a range of data sets consisting different NLP tasks, comparing with a set of relevant baselines (Code for MetaXT will be made publicly available).

4.1 Datasets

Our goal is to study cross-task transfer learning between disparate label spaces, therefore we select data sets according to the following two criterion:
Table 1: Data set and task overview. (PS: Polarity Sentiment, MS: Multi-scale Sentiment, POS: Part-of-Speech, MWE: Multi-Word Expr., NER: Named Entity Recognition)

| Source Target | Dataset Task(#labels) | Dataset Task(#labels) |
|---------------|-----------------------|-----------------------|
| Yelp Pol PS(2) | Yelp Full MS(5) | |
| Amazon Pol PS(2) | Amazon Full MS(5) | |
| UD English POS(17) | Streusle MWE(3) | |
| Conll03(Germ) NER(8) | GermEval14 NER(25) | |

• **Tasks with different label granularities.** This involves tasks of the same type but with different label granularities. For example, sentiment analysis with polarity (positive or negative) and that with multi-scale scores constitute one such pair of task. We pick two review data sets for this category, Yelp and Amazon. Note that for this setting we only evaluate transferring from polarity sentiment analysis to multi-scale sentiment analysis, as the reverse problem can be naively solved by thresh-holding the multi-scale scores to get the optimal polarity sentiment.

• **Tasks with different label types.** A more challenging setting than transferring between different label granularities is to learn to transfer from one type of task to a different type, for example, from part-of-speech (POS) tagging to Multi-Word Expressions(MWE) and between two related NER tag sets. For the first example, we transfer between POS tagging in UD English dataset to MWEs available in Streusle (Schneider and Smith, 2015) and for the second one we transfer from the Conll2003 (German) corpus to the GermEval2014 (Benikova et al., 2014) NER task.

Table 1 presents the statistics of all data sets used for evaluation. It is worth noting that, for a target task of interest it is possible to find better auxiliary task to transfer from as pointed out by (Schröder and Biemann, 2020). However this is orthogonal to this paper, where we aim to address better cross-task transfer from a methodological perspective, and thus finding the best source task is beyond the scope of this paper and thus left as future work.

4.2 Baselines

We aim to compare MetaXT with a comprehensive set of baseline methods that are relevant to the settings. Since the problem we study involves multiple tasks, we consider the following set of applicable baseline methods (for details of the experimental setup please refer to Appendix A):

- **Target Only**, which trains only on the few-shot target task examples. Note that a source only baseline is not applicable due to the different label spaces between source and target tasks;

- **Multi-task**, which jointly optimizes to learn both the source and target task with two task prediction heads put on top of the textual feature encoders;

- **AdapterFusion**, a recent work on building multi-task learners based on separately trained adapter modules for each task and then a fusion layer is trained to aggregate knowledge from all the task adapters (Pfeiffer et al., 2020a).

It’s worth noting that even though MAML (Finn et al., 2017) also addresses transfer learning between tasks with meta learning, it is not readily applicable for this setting as it aims to transfer and generalize from a set of source tasks onto new tasks unseen in training, i.e., the target task is unknown to the model in training, while in this paper we always assume that the target task is available for training. Additionally, MAML explicitly requires that all tasks at hand have the same dimensionality in their label spaces (even though they are different tasks).

4.3 Main Results

4.3.1 Task transfer with different label granularities

**Yelp Dataset:** The performance of the various models on the Yelp Datasets are shown in Figure 3 for 5 different number of labeled examples $k$ in the target task, i.e., $k \in \{20, 50, 100, 200, 500\}$.

Overall, while all methods benefit from a larger amount of target task data, they behave differently for a given $k$. The Target Only baseline performs only marginally better than random guess when $k$ is small ($k = 20$). The Multi-task and AdapterFusion baselines perform better by leveraging similarities with the source task. However, due to the limited number of labeled examples from the target task, multi-task joint training is unable to effectively counter the imbalance between source and
target tasks, as shown by $k = 20$ and $k = 100$. Instead, MetaXT is able to effectively leverage the estimated target labels generated by LTN from source task examples as additional supervision for training a target task model, particularly when the number of target task examples $k$ is small. Interestingly, the smaller $k$ is, the larger gain MetaXT achieves over the Target Only and Multi-task baselines, demonstrating the effectiveness of MetaXT for few-shot transfer learning settings. As more number of target task labeled examples are available, e.g. $k = 200$ or $500$, the gaps between all the methods shrink. This is expected, as transferring from the source task might no longer be required.

**Amazon Dataset:** The performance of MetaXT on product reviews in the Amazon dataset is similar to that on the Yelp dataset, as shown in Figure 4. In addition, we observe that MetaXT achieves significantly higher gains over all the baseline methods when $k$ is small, i.e., $k \leq 200$, which again validates that MetaXT is well suited for the few-shot learning setting for task transfer.

### 4.3.2 Task transfer with different label types

#### POS Tagging to MWE

We demonstrate transfer from Parts-of-Speech (POS) tagging from the Universal Dependencies (UD) English Tree Bank to MultiWord Expression (MWE) identification in Streusle (Streusle 4.0 Dataset, (Schneider and Smith, 2015). We use the "standard" POS tagging with 17 classes provided by the UD Dataset. For MWE, we use simplified BIO tagging of the Strong MWEs in Streusle, similar to (Changpinyo et al., 2018). The results are as shown in Figure 5.

In this example, to adapt to the different domains of the source and target, we used a representation transfer network (RTN) (Xia et al., 2021) at the sixth layer of the transformer encoder in addition to the label transfer network. The representation transfer network was a 3 layer feed-forward network used only to adapt the source representation to the target while optimizing for the label transfer. This results in a modification of the 3rd term in Equation (3) to $\gamma_2 \mathbb{E}_{(x,y) \in D_s} \ell_w(f_\theta,w,\phi(x),g_\alpha(x,y))$, where $\phi$ represents the parameters of the RTN.

For this particular transfer setting on token level classification tasks, we observe that joint-training based methods, including Multi-task and Adapter-Fusion, helps the target task by leveraging the source task. MetaXT is able to achieve the best results on 3 out of 5 settings, while being close to the best performing methods for other cases.
Additionally, MetaXT is able to handle the additional challenges brought by token-level classification tasks, as well as the data domain shift, i.e., from English Tree Bank to Streusle.

Transfer between related NER tag sets We also demonstrate transfer between two different but related NER tag sets - Conll 2003 German and GermEval2014(Benikova et al., 2014). GermEval2014 NER tag set is a superset of the NER tagsets provided in Conll2003 by adding derived, partitioned and other labels. Similar to the MWE task, we use an RTN at the sixth layer of the encoder to adapt the source domain to the target domain. The F1 scores for the transfer task are as shown in Figure 6.

It can be seen that the standard multitask model and the MetaXT models perform better than the Target Only model, where as the AdapterFusion models do not perform competitively in comparison to full fine-tuning for transfer between tag sets.

4.4 Analysis and Ablation Studies

4.4.1 What exactly does the LTN learn?

Besides evaluating the overall performance of MetaXT with relevant baselines, we analyze the learned LTN for the cross-task learning for sentiment analysis as follows:

For the sentiment analysis task transfer on Yelp and Amazon, as a-priori the target task (sentiment score is a scale of 1-5) is in strongly linear correlation with the input source target task (bi-polar sentiment), we seek to evaluate if the learned LTN is actually able to transfer from a polarity sentiment correctly to the multi-scale score. As such, we take the learned LTN and plot the pairs of (input bi-polar sentiment, produced multi-scale score) as shown in Figure 7 for Yelp and Amazon.

We can see that the learned LTN from MetaXT is able to figure out that a source label “thumbs-down” is mostly likely to correlate with a 1-star rating in the target label space. (Note that the model itself does not have access to such information when it’s trained). There is still some noise in the inferred target label distribution given a source label, which could be explained by optimization difficulty brought by the the bi-level optimization framework. For an analysis of LTN behavior with the NER tasks please refer to Appendix B.

4.4.2 Ablation studies

Effectively, there are two novel ingredients in MetaXT: a) The model architecture with a separate LTN besides a standard multi-task model; b) The bi-level optimization strategy to train both the main model and the LTN for best transferring the source task examples to help the target task. We seek to evaluate the effect the bi-level optimization strategy while keeping the LTN, i.e., using the LTN as a third source of multi-task training besides the source and target task data, by directly optimizing \( \min_{\alpha,\theta,v,w} \mathcal{L}_{\text{train}} \) where \( \mathcal{L}_{\text{train}} \) is training loss defined the same as Eq (3). Note that there is no meta-parameter in this formulation as \( \alpha \) is also part of the main parameters to optimize. We term this model variant as XT due to its nature of lacking the meta-learning formulation. At its core, XT is a multi-task training baseline with the additional model capacities from the LTN.

We evaluate XT against MetaXT on the Yelp and Amazon data sets on the setting of transferring from bi-polar sentiment to multi-scale ratings. Table 2 shows that without the bi-level optimization formulation, XT’s performance drops significantly from MetaXT. Note that XT is worse than the Multi-Task baseline, even with additional model parameters (from the LTN). This is however expected as the pseudo-labels from the LTN is trusted as a third source of information in training the main model, however without the bi-level optimization, there’s no way to ground the generated labels from the LTN such that the low quality labels from the LTN causes the model to dramatically decrease in performance. Similar trends are observed on the Amazon

| Table 2: MetaXT vs XT - Yelp Dataset (Acc. %) |
|-----|-------|-------|-------|-------|-------|
| k   | 5     | 10    | 50    | 100   | 500   |
| Multi-Task | 21.8 | 31.1 | 37.7 | 43.8 | 47.7 |
| MetaXT     | 31.4 | 38.0 | 42.0 | 43.9 | 48.1 |
| XT         | 20.6 | 20.1 | 22.5 | 22.9 | 38.5 |
Table 3: MetaXT vs XT - Amazon Dataset (Acc. %)

| k    | 20  | 50  | 100 | 200 | 500 |
|------|-----|-----|-----|-----|-----|
| Multi-Task | 23.8 | 33.6 | 34.4 | 45.3 | 49.9 |
| MetaXT     | 35.9 | 40.6 | 42.4 | 47.1 | 50.0 |
| XT         | 20.5 | 19.8 | 26.4 | 23.5 | 37.6 |

data set (Table 3).

5 Related Work

Transfer learning across tasks: Adapting a pre-trained language model to a specific NLP task is a form of transfer learning between the language modeling task (during pre-training) and the downstream task (during fine-tuning) that has become a de facto standard for many NLP tasks. However, it still leaves margin for improvement by transferring between related downstream NLP tasks, especially for the few-shot setting where limited labeled data is available for a given task. Many NLP methods leverage multi-task learning to improve performance across related NLP tasks, e.g. (Ruder et al., 2019; Balikas et al., 2017; Augenstein et al., 2018; Pfeiffer et al., 2020b) and loosely connected, such as transferring from POS tagging to NER or chunking (Ruder et al., 2019), transferring between POS tagging and neural machine translation (Niehues and Cho, 2017).

Multi-task learning methods typically use techniques like joint training (Augenstein et al., 2018) or splitting parameters into shared and private spaces (Liu et al., 2017). Most recently, task adapters (Pfeiffer et al., 2020a,b), small learnt bottleneck layers inserted within each layer of a pre-trained model, were successfully used for multi-task learning. We build on top of this line of work but we focus on cross-task transfer where limited labeled data is available for the target task. We show that our approach, using a bi-level optimization technique, can best leverage the data from an auxiliary task to optimize the performance on the target task.

Meta-learning for task adaptation: Another line of work related to this paper is on meta-learning for multi-task learning (Finn et al., 2017; Chen et al., 2018). MAML (Finn et al., 2017) aims to learn from a set of training tasks and to generate well onto unseen testing tasks by learning model initializations for faster adaptation. MANN (Santoro et al., 2016) builds on top of MAML by explicitly leveraging a memory network to improve task level generalization. Our setting is different in that first we assume that the target task in observed in training data and second, we focus on the few-shot aspect for the target task to explicitly highlight the potential values of transferring from an auxiliary source task.

Domain adaptation Another closely related line of work is on the domain adaptation and transfer, which looks to transfer and re-use knowledge obtained from one domain to another, or to address the intrinsic distribution shift underlying the data (Kouw and Loog, 2018; Teshima et al., 2020; Motiian et al., 2017; Hu et al., 2018; Chidlovskii et al., 2016). This line of work typically focuses on the transfer between different data spaces, whereas in this paper, we mainly focus on the transfer between the task spaces, specially for those with disparate label spaces. Though we don’t emphasize the potential differences of the underlying domains between the source and target task, our method is applicable to such settings, which is also validated by the experiments on the transfer from POS tagging to MWE and from NER between two different German NER sets. For a discussion on related work in the area of weak supervision please refer to Appendix C.

6 Conclusions and Future Work

In this paper, we study the problem of transfer learning across NLP tasks from disparate label spaces in the few shot setting. Directly fine-tuning a pre-trained language model on the target task or jointly training on both tasks tends to be sub-optimal due to limited labeled data. Instead, we devise a label transfer network (LTN) to explicitly transform the available source task labels into the target task label space such that the target task model trained with these amended “pseudo” labels can best perform on a separate portion of the target task labeled set via a bi-level optimization framework termed MetaXT. We conduct experiments on four different transfer settings across two different types of disparate label spaces and empirical evaluations verify that MetaXT outperforms the baselines or comparably to the best model, particularly on the few-shot settings. A potential direction is to extend MetaXT onto settings with multiple source tasks by building a universal LTN for all source tasks to transfer to the same target task space to leverage knowledge from multiple sources simultaneously.
Ethical Considerations
This work addresses cross task transfer between disparate label spaces. The proposed method is computationally intensive to some degree as it involves computation of second order gradients over pre-trained Language Models in order to compute the meta-gradients. This might impose a negative carbon footprint from training the described models. Future work on developing efficient meta-learning optimization methods and accelerating the meta-learning training procedures might help in alleviating this concern.

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A Details of experimental setup

For all methods, we use the same PLM as the textual feature encoder for all data sets, i.e., BERT (Devlin et al., 2018). For the NER transfer dataset, the pretrained German BERT models were used as the PLM. Hyper-parameters of all methods are selected based on the model performance on a separate validation data set. All models were trained with a batch size of 10. For the Adapter Fusion models, we use the single-task adapters to train on the source and target tasks, and then adapt the model to the target task. For the MetaXT Model, the batch was split into two mini-batches for training and meta-training. To evaluate the performance of the models in true low example target settings, the size of the validation set was sized to be similar to the small training set of the target task. For sequence classification tasks, the target training and the validation datasets were balanced to have equal representation from all classes. The sequence tagging dataset sizes were selected to have a minimum number of examples from all classes. The sequence lengths for the granularity datasets were capped at 128 tokens and the sequence lengths for the sequence tagging datasets was capped at 64 (due to smaller average sentence sizes in the overall dataset). We describe processing procedures specific to the data sets in the following section. We implement all baseline methods in PyTorch and code for MetaXT will be made publicly available.

B LTN Analysis - GermEval 2014

The average distribution of learned LTN labels for transfer between different NER tag sets is shown in Figure 8. The tag sets for the target task are higher fidelity, and some of the derived labels correspond to the generic NER label ’O’ of the source tag set. There are however, some tags that are common between the two (such as ’B-ORG’, ’I-PER’). For some of the direct correspondence labels, the LTN is able to identify and reinforce the target label with additional examples. With others, such as ’I-PER’, the LTN identifies a correspondence, but does not fully learn the direct correspondence. The LTN is able to identify that there are correlations between certain labels that are a consequence of annotation guidelines. For example, there is correlation between ’B-ORGpart’ and ’B-LOC’ due to the frequent specification of location details associated with organization text, and having location information commonly be part of organization names, such as “[Linke-Europaabgeordnete](ORGpart)”

C Related Work - Weak Supervision

Given the problem scope in this paper, one might also attempt to treat the source task as weak supervision signals for the target task and leverage existing work on learning with weak supervision to address transfer learning on tasks. However, one major hurdle that prevents applying such methods is that the existing work on weakly supervised learning is only applicable to the setting where the weak labels are from the same label space as the target task. Such work ranges from jointly learning with clean and weak labels (Sukhbaatar et al., 2014; Tanaka et al., 2018; Shu et al., 2020a), to learning to re-weight the weakly supervised labels (Ren et al., 2018; Shu et al., 2019, 2020b), to aim to correct the weak or noisy labels as in (Patrini et al., 2017; Hendrycks et al., 2018; Zheng et al., 2021). To transfer between disparate label spaces, the notion of weak supervision goes beyond existing work on weakly supervised learning, while the proposed MetaXT can also be viewed as an attempt to address this generalized notion of weak supervision defined from a source task.

\footnote{https://github.com/dbmdz/berts#german-bert}
Figure 8: Distribution of $\hat{Y}_t$ given $Y_s$ for German NER tag transfer dataset run with 100 examples. Even with 50 target examples, the LTN is able to learn and reinforce some correlations with the target data. For example, the connection between B-ORGpart and Location and Misc information (I-LOC, I-MISC), and identification that label ‘O’ in the source label maps could map to many derived labels in the target NER label space.