Worst-Case-Aware Curriculum Learning for Zero and Few Shot Transfer

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Abstract
Multi-task transfer learning based on pre-trained language encoders achieves state-of-the-art performance across a range of tasks. Standard approaches implicitly assume the tasks, for which we have training data, are equally representative of the tasks we are interested in, an assumption which is often hard to justify. This paper presents a more agnostic approach to multi-task transfer learning, which uses automated curriculum learning to minimize a new family of worst-case-aware losses across tasks. Not only do these losses lead to better performance on outlier tasks; they also lead to better performance in zero-shot and few-shot transfer settings.

Introduction
Multi-task learning is the problem of minimizing the average error across \( n \) tasks, as measured on held-out samples, and motivated by the observation that sometimes learning a single model with partially shared parameters performs better than \( n \) single-task models. In the learning-to-learn setting, we worry about our error on a task \( n+1 \). Both of these settings apply to randomly initialized base learners, as well as architectures pre-trained on yet another task(s). In learning-to-learn, the new task \( n+1 \) is assumed to come from an ambiguity set defined by the \( n \) tasks.

Unsurprisingly, most approaches to multi-task learning minimize the average loss across the training samples available for these tasks. This does not always lead to the best solution, however, since the relations between loss and error may differ across tasks. Several off- and online methods for normalizing these relations have been proposed (Chen et al. 2018, Bronskill et al. 2020), but even with this, minimizing average loss across tasks has two disadvantages: (a) Performance on outlier tasks may be very poor (Zhang, Yeung, and Xu 2010, Hernandez-Lobato, Hernandez-Lobato, and Ghahramani 2015), and (b) in the learning-to-learn setting, minimizing average loss is optimal if the task selection is unbiased (Wolpert 1996, Oren et al. 2019, Zhou et al. 2020).

Minimizing the worst-case loss across tasks instead of the average loss, in theory solves these two problems, which is why this approach is popular in algorithmic fairness (Hashimoto et al. 2018) and domain adaptation under covariate shift assumptions (Duchi, Hashimoto, and Namkoong 2020). In some multi-task settings, it is possible to directly modify the loss that is minimized in multi-task learning (Mehta, Lee, and Gray 2012), but this is for example not possible in the common approach to multi-task learning where each batch is sampled from one of \( n \) tasks at random (Caruana 1997, Baxter 2000). We present a more general approach to multi-task learning with worst-case-aware loss minimization, instead relying on automated curriculum learning (Graves et al. 2017).

Contributions
We present an automated curriculum learning approach to robust multi-task transfer learning. Our approach is general and parameterizes a family of worst-case-aware objectives, with minimax and loss-proportional minimization at the two extremes. In a series of experiments on the GLUE multi-task benchmark (Wang et al. 2018), we show that several of these objectives lead to better performance on the benchmark itself, but more importantly, also lead to much better (zero-shot and few-shot) generalization to other out-of-domain data sets.

Worst-Case-Aware Multi-Task Curriculum Learning
In multi-task learning, we minimize a loss over a set of \( n \) related tasks:

\[
\min_{\theta} \ell(\theta) = \min_{\theta} \sum_{i \leq n} \ell_i(\theta)
\]

(1)

where \( \ell_i(\theta) \) is the loss of the \( i \)-th task, and \( f \) is some function combining the task-specific losses. Most multi-task learning algorithms simply use \( \sum(\cdot) \) for \( f(\cdot) \), but often task losses are weighted to compensate for differences in data set sizes and complexities (Stickland and Murray 2019). Mehta, Lee, and Gray (2012), in contrast, explore the \( \| \ell_i(\theta) \|_{\ell_p} \) family of losses for multi-task learning, i.e., of minimizing the \( \ell_{\ell_p} \)-norm of the loss vector, with \( \ell_1 \) equivalent to the standard average loss, and \( \ell_{\infty} \) corresponding to worst-case minimization over the \( n \) tasks.

If the tasks and datasets are sampled \( i.i.d. \), minimizing \( \sum_{i \leq n} \ell_i(\theta) \) or \( \| \ell_i(\theta) \|_{\ell_1} \) makes sense, but if not, minimizing average error is unlikely to generalize well. In practice, moreover, some tasks may be easier to learn than others, and their loss may decrease quickly, whereas the loss for other tasks will decline more gradually. Common sampling

\[
\min_{\theta} \ell(\theta) = \min_{\theta} \sum_{i \leq n} \ell_i(\theta)
\]
techniques will likely result in overfitting on some tasks and under-fitting on others. Finally, optimizing for one task may impair performance of another task. Minimizing the average loss over \( n \) tasks leads to better average performance (if data is \( i.i.d \), but provides no guarantees for worst-case performance. All of this motivates more dynamic training strategies that pay attention to tasks on which our joint model performs poorly. We refer to such training strategies as worst-case-aware strategies.

We argue it makes more sense to minimize a worst-case loss when the task selections or the datasets are biased, and all we can assume is that the tasks at hand are members of an ambiguity set from which future tasks will also be sampled: Assume, for example, that tasks are sampled from an unknown \( \alpha \)-ball of distributions with uniform probability (Kuhn et al., 2019; Yue, Kuhn, and Wiesemann, 2020). We can assume that each observed task is within the \( \alpha \)-ball. In other words, our best estimate of the center of the \( \alpha \)-ball is not, for example, the Gaussian mean over tasks, but simply their centroid. Worst-case minimization minimizes the expected worst-case loss within this \( \alpha \)-ball.

The approach in Mehta, Lee, and Gray (2012) is based on computing norms over batches composed of data from multiple tasks. Such an approach would interact heavily with batch size and batch normalization, which are key hyper-parameters in deep learning. We instead propose a much simpler wrapper method, in which the departure from the standard multi-task objective is delegated to a multi-armed bandit used for sampling data batches during training. The multi-armed bandit is trained to optimize a worst-case aware loss. We call this worst-case-aware multi-task curriculum learning.

**Architecture**

In the remainder of this section, we describe our approach in detail. Our family of loss functions will be different from Mehta, Lee, and Gray (2012). Instead of introducing a continuum from \( \ell_1 \)-loss to \( \ell_\infty \)-loss, we introduce a continuum from (minimax) \( \ell_\infty \)-loss to loss-proportional loss, i.e., a stochastic, adaptive form of worst-case optimization. The entire continuum is worst-case-aware and, from an optimization perspective, represents degrees of stochastic exploration. Our overall architecture is presented in Figure 1.

Our architecture consists of four parts: the sampler, the buffer, the trainer, and the model itself. The sampler, i.e., a multi-armed bandit, selects data batches from the \( n \) tasks by revising an automated curriculum learning policy, and the losses associated with these batches are then evaluated by the multi-task learning model. The buffer maintains \( n \) fixed-length queues to cache the sampled data and their loss values according to the current model. The trainer chooses a task that is worth optimizing for the multi-task learning model to update the parameters of the model and sends rewards to the sampler. We describe our approach to curriculum learning in detail in the next section. Since most state-of-the-art architectures in natural language processing rely on pre-trained language encoders, we will assume the multi-task learning model is, in part, initialized by pre-training with a masked language modeling objective (Devlin et al., 2019). Specifically, we adopt MT-DNN (Liu et al., 2019) as our multi-task learning architecture; see paper for details. We will evaluate our \( n \)-task fine-tuned model on the \( n \) tasks, as well as new tasks \( (n+1) \), with and without additional data for fine-tuning. We refer to the latter scenarios as few-shot and zero-shot transfer learning. We will not explore the impact of pre-training on the learned curricula in this paper, but preliminary experiments suggest that effects of worst-case aware learning on generalization are even stronger in randomly initialized networks.
Our algorithm is presented in Algorithm 1 and consists of three steps:

Step 1: Populating the Buffer  This is the step in lines 2–6 of Algorithm 1. The sampler selects a sequence of $k$ arms (out of a total of $n$ arms, and over $R$ rounds) leading to a total of $kR$ steps with $1 \leq a_{\tau} \leq n$: $a_1, \ldots, a_k, \ldots, a_{kR}$. In the $i$th step, if the $i$th arm is selected, a batch of data $B_i^{(\tau)}$ – or simply $b_\tau$ – is sampled from task $i$ (line 2). Selecting the $i$th arm in the $r$th action yields a pay-off $r_i^{(r)}$ by evaluating the loss $\hat{\ell}_i^{(r)}$ of the multi-task model on the data batch (line 3). The batch $b_i$ and its loss $\hat{\ell}_i^{(r)}$ are stored in the buffer, i.e., $n$ queues of maximum length $m$. Specifically, $(b_\tau, \hat{\ell}_i^{(r)})$ is pushed to the queue $Q_i$ (line 5). The buffer thus contains data instances across $n$ queues that are deemed good under $\phi$, from which the multi-task trainer selects its training data by either sampling a task $i$ with likelihood proportional to the average loss in $Q_i$, or simply the task with the highest loss. See Step 2 for details. The arms are selected stochastically according to a policy $\pi$.

This procedure is repeated $k$ times at each round, and the sampler updates its policy after receiving rewards from the trainer.

Step 2: Worst-Case-Aware Training  In multi-task learning with $n$ tasks, it is common practice to minimize the sum of losses across the $n$ tasks; i.e., $\min_{\theta} \sum_{i \leq n} \ell_i(\theta) = \min_{\theta} \sum_{i \leq n} \ell_i(\theta)$. This is typically implemented by uniformly sampling data across tasks during training. Another approach is to sample size-proportionally (Glover and Hokamp [2019] Stickland and Murray [2019]), i.e., to rely on a weighted sum, $\sum_{i \leq n} N_i \ell_i(\theta)$, where $N_i$ is the size of the training set for task $i$. We instead present a general class of worst-case-aware minimization strategies parameterized by the parameter $\phi \in [0, 1]$. Our worst-case-aware minimization strategy can be defined as:

$$
\min \ell(\theta) = \begin{cases} 
\min_{\theta} \sum_{i \leq n} \ell_i(\theta), & p < \phi \\
\min_{\theta} \ell_i(\theta), & p \geq \phi, \tilde{i} \sim P_{\tilde{i}}
\end{cases}
$$

(2)

where $p$ is a randomly generated real number in $[0, 1]$; $P_{\tilde{i}}$ is the probability distribution of the current, normalized task losses, i.e., $P_{\tilde{i}} = \frac{\ell_i}{\sum_{j \leq n} \ell_j}$; and $\tilde{i}$ is the index of the task that is chosen by our strategies, either because it is the task with the highest loss (when $p < \phi$), or when it is stochastically sampled with the probability of its normalized task loss (when $p \geq \phi$). If $\phi$ equals 1, our trainer just optimizes for the worst-case task. If $\phi$ equals 0, the strategy samples loss-proportionally. In practice, the loss of task $i$ is approximated by the average loss of the batches for that task in the buffer.

where $v_i$ is the hyper-parameter representing the weight of the task, which can be simply all set to 1 if tasks are treated equally.

Step 3: Updating $\pi$  Since rewards will change dynamically throughout learning, we adopt the fixed share method (Herbster and Warmuth [1998]) to mix in weights additively.

The sampling policy $\pi$ in $\tau$-th round is:

$$
\pi_i^{(\tau)} = (1 - \gamma) \cdot \frac{w_i^{(\tau)}}{\sum_{j \leq n} w_j^{(\tau)}} + \frac{\gamma}{n}
$$

(4)

where $\gamma$ is an egalitarianism factor which balances the explore-exploit trade-off.

If the arm $i$ is selected in a round with $k$ actions,

$$
r_i^{(\tau)} = \begin{cases} 
\frac{|Q_i^{(\tau)}| - |Q_i^{(\tau-1)}|}{\max_{j \neq i}(|Q_j^{(\tau)}| - |Q_j^{(\tau-1)}|)}, & i = \tilde{i} \\
\frac{|Q_i^{(\tau)}| - |Q_i^{(\tau-1)}|}{\max_{j \neq i}(|Q_j^{(\tau)}| - |Q_j^{(\tau-1)}|)}, & i \neq \tilde{i}
\end{cases}
$$

(5)

where $| \cdot |$ means the count of the queue, and $\tilde{i}$ is the index of the task that is chosen by the trainer. Note the reward $r_i^{(\tau)}$.

The batches in the buffer are not re-evaluated once they are in, in order to speed up training. The loss of new batches is always computed using the current model, and old batches that are not selected are eventually replaced with batches with loss values based on recent models.
Table 1: Dataset Characteristics. STS-B and SICK-R are regression tasks, while the rest are classification tasks. We use SciTail’s development set for evaluation, since the test set labels are not public available. IMDB: (Maas et al. 2011); Yelp-2: https://www.kaggle.com/yelp-dataset/yelp-dataset; SICK-R/E: (Marelli et al. 2014); SNLI: (Bowman et al. 2015); SciTail: (Khot, Sabharwal, and Clark 2018); WikiQA: (Yang, Yih, and Meek 2015).

Table 2: Comparison of Sampling Strategies using GLUE development sets. †From Glover and Hokamp (2019). ‡From Stickland and Murray (2019). The results of the four different approaches to worst-case-aware multi-task learning are not significantly different after Bonferroni correction.
Baselines

The baselines used for comparison in this paper all use BERT\textsubscript{BASE} as the encoder. The main differences are the sampling and training strategies used: MT-DNN \cite{Liu2019} uses a size-proportional sampling strategy; \cite{Glover2019} propose learning a sampling policy using counterfactual estimation (denoted as π\textsubscript{C}), and compare it to uniformly random sampling (π\textsubscript{RANDOM}), size-proportional sampling (π\textsubscript{TASK SIZE}) and automated curriculum learning (π\textsubscript{EXP3.S}) \cite{Graves2017, Stickland2019} present PALS, using an annealed sampling strategy, which changes from size-proportional sampling to uniformly random sampling during the training procedure. They also compare the method to the square-root-size-proportionally sampling strategy. In Table 2, we compare the different sampling strategies. Since our worst-case-aware sampling strategies are not significantly different, we hedge our bets and rely on \(\phi = 0.5\) and \(\phi = 0 \rightarrow 1\) in our remaining experiments; we refer to these as \(\phi = 0.5\) and ANNEAL-\(\phi\).

Experimental Setups

Our implementation is based on the open-source implementation of MT-DNN\cite{https://github.com/namisan/mt-dnn}. The original MT-DNN code adopts a size-proportional sampling strategy, but we replace this with our automated curriculum learning strategy. We also use BERT\textsubscript{BASE} as our pre-trained encoder for comparability. Our hyper-parameters were optimized on the GLUE development sets: We initialize the task-specific weights \(w_t\) to 1 at the beginning of each epoch. The weight \(v_i\) of loss is set to 1. The batch size is set to 8, and the gradient accumulation step is set to 4. The γ value in automated curriculum learning is set to 0.001. The number \(k\) of actions in a round is set to twice the number of tasks, which is 16. At the beginning of each round, we push one data batch per task to the queue, in case the queue of a task is empty when the trainer selects, this is excluded in the calculation of rewards. The capacity of the queue in the buffer is set to 50. We report results with \(\phi\) set to 0, 0.5 and 1 respectively, as well as with increasing \(\phi\) from 0 to 1 by 0.15 per epoch. All other hyper-parameter values were adopted from \cite{Liu2019} without further optimization. Our code will be publicly available\cite{https://github.com/anonymous}.

Note, again, that our method is designed for zero-shot and few-shot transfer learning, and we are therefore mainly interested in out-of-domain performance. In our domain transfer experiments, we either evaluate our models directly on unseen domains or randomly select 1% and 10% of the target domain training set. We refer to the unsupervised domain adaptation scenario as zero-shot, and the scenarios with limited supervision as few-shot. Note our models are trained with worst-case-aware multi-task learning, but not fine-tuned for the target task. For few-shot learning, we repeat our experiments five (5) times and report average scores to reduce the variance that results from randomly subsampling the training data.

In-Domain Results

To sanity check our system, we submitted our result files to GLUE online evaluation system\cite{https://gluebenchmark.com/} the results are shown in Table 3. The first row shows the result of fine-tuning the BERT\textsubscript{BASE} model on each single task separately, followed by the result of MT-DNN\textsubscript{BASE} model trained on all tasks. We can see that compared with single-task learning, the MTL model is comparable in terms of four tasks with large data volume (SST-2, QQP, MNLI and QNLI), and shows substantial improvement on RTE task, due to its shared encoder that contains the information from similar MNLI and QNLI tasks. However, the performance on the outlier task, such as CoLA, has been significantly undermined. This shows that MTL models with size-proportionally random sampling strategy pay more attention to dominant tasks (e.g. tasks with large amount of data) than the out-of-domain tasks, which is consistent with the findings by \cite{Liu2019, Glover2019}.

The lower part of Table 3 shows the results of our models using the worst-case-aware minimization strategies. It can be seen that our models are comparable with the MT-DNN model and achieve better performance on some small datasets, such as CoLA, MRPC and STS-B, which demonstrates that our sampling and training strategies have the...
ability to balance the training between the dominant task and the outlier task.

**Domain Transfer Results**

Table 4 presents our transfer learning results after fine-tuning on 0% of the training data for the new task (zero shot), or 1% or 10% of it (few shot). In the zero-shot setting, our models are considerably better than the MT-DNN models, across different $\phi$ values, especially for SICK-R/E and SciTail tasks. In the few-shot setting, we see the same trend. Compared to the MT-DNN model, our models still perform much better on small tasks (SICK-R/E, SciTail and WikiQA) and slightly better on average. The gap between our models and the original MT-DNN models narrows as more training data is available.

### Analysis

#### Figure 2: Sampling Probability of Tasks per Epoch

(a) Sampling Probability (by Trainer), $\phi = 0.5$

(b) Number of Iterations, $\phi = 0.5$

Figure 2 shows statistics of each task selected by the trainer during the training process. In Figure 2a, the sampling probability of each task is initially proportional to the size of the training data (except for the STS-B, which uses numerically larger mean squared error loss; see Figure 3). When we inspect the number of times a task was selected (iterations) across epochs, curves cluster in two groups of four (4) tasks; see Figure 3b. Tasks in the lower cluster have relatively large amounts of data, and the curves gradually converge to around 1. On the contrary, tasks in the upper cluster have small amounts of data, and their datasets are queried several times per epoch. Note that our approach does not explicitly take dataset size into account.

#### Figure 3: Loss Curves

(a) $\phi = 0$

(b) $\phi = 1$

Figure 3 shows the trend of training loss of each task when $\phi$ is set to two extremes 0 and 1. If $\phi$ equals 0, the task is sampled loss-proportionally. The loss for some tasks drops quickly, but they can still be selected by the trainer, therefore curves are apart from each other. On the contrary, the trainer selects the worst-case task when $\phi$ equals 1. Once the loss of a task is not the maximum, it will not be selected by the trainer, as a result, the curves are close to each other.

### Related Work

**Sampling strategies for multi-task learning** While most previous work in multi-task learning relies on uniform or proportional sampling, more sophisticated sampling techniques have been proposed. Stickland and Murray (2019) presents square root sampling, which balances uniform and proportional sampling, as well as annealed sampling, which gradually moves from one to the other across training epochs. Xu et al. (2019) use language models to assign weights to data before sampling. None of this work evaluates the robustness of sampling strategies in domain transfer scenarios.

**Multi-task curricula** Guo, Pasunuru, and Bansal (2019) use Bayesian optimization to learn a fixed curriculum for
multi-task learning problems derived from the GLUE benchmark. Glover and Hokamp (2019) evaluate fixed curricula, as well as the automated curriculum learning approach in Graves et al. (2017), on the GLUE benchmark and show how this approach can be improved by counterfactual policy estimation. Zaremoodi and Haffari (2020), in contrast, formulate the curricular as a Markov decision process and adopt oracle policy to adaptively and dynamically select different tasks.

Robust curricula We are not the first to use automated curriculum learning to minimize a worst-case loss. Cai, Liu, and Song (2018) learn curricula of adversarial examples generated by attacks. Sharma et al. (2018) also present three worst-case-aware algorithms for learning multi-task curricula, which they evaluate on stochastic computer games, quite different from the GLUE benchmark: Two of them use multi-armed bandits to update the sampling distribution by the end of each episode. The reward used to train the multi-armed bandit is the normalized task performance of the three (currently) worst tasks. Apart from the fact that the learning problem considered here is very different from theirs, our approach also differs from theirs in that we use a more general loss function instead of relying on the top-3 heuristic.

Conclusion In this work, we introduce a worst-case-aware approach to automated curriculum learning for zero-shot and few-shot applications of multi-task learning architectures. Our models achieve competitive or slightly better average performance on the GLUE benchmark and, more importantly, improves generalization to out-of-domain tasks in zero-shot and few-shot settings. Our approach also generally leads to better performance on small tasks. We analyze the learning dynamics of automated curriculum learning in this context and show how it learns a very different sampling strategy from commonly used baseline heuristics.

Table 4: Main Results (Domain Transfer). Our models have great advantages in zero-shot and few-shot learning settings, although the gap narrows as the data volume increases. Few shot results are averages over five (5) repeated experiments to reduce the variance from random subsampling.

| Setting   | Model   | IMDB  | Yelp-2 | SICK-R | SICK-E | SNLI  | SciTail | WikiQA | Avg.  |
|-----------|---------|-------|--------|--------|--------|-------|---------|--------|-------|
| Zero Shot (0%) | MT-DNN$_{\text{BASE}}$ | 85.1  | 86.2  | 80.7/79.3 | 50.4  | 78.8  | 77.4  | 78.8/79.6 | 76.7  |
|           | $\phi = 0.5$ | **86.2** | **88.2** | **83.0/79.4** | **57.1** | 79.7  | 80.6  | 78.5/79.3 | 78.8  |
|           | ANNEAL-$\phi$ | 86.1  | 87.7  | 82.1/78.7 | 56.1  | **79.9** | **82.3** | **81.9/82.5** | **79.3** |
| Few Shot (1%) | MT-DNN$_{\text{BASE}}$ | **87.0** | 91.9  | 82.9/79.1 | 82.0  | 85.2  | 87.5  | 79.7/80.8 | 85.0±0.49 |
|           | $\phi = 0.5$ | 86.8  | **92.1** | **85.6/80.0** | 85.0  | 85.0  | 87.4  | 79.9/80.8 | 85.6±0.32 |
|           | ANNEAL-$\phi$ | 86.7  | 92.0  | 85.0/79.4 | **85.7** | 84.9  | **88.1** | **82.1/82.9** | **86.0±0.17** |
| Few Shot (10%) | MT-DNN$_{\text{BASE}}$ | 88.7  | **94.3** | 86.8/81.9 | 87.2  | **88.1** | 91.6  | 83.1/84.4 | 88.3±0.09 |
|           | $\phi = 0.5$ | **89.0** | 94.2  | **87.8/82.6** | 87.4  | 87.8  | **92.4** | **83.1/84.0** | **88.5±0.10** |
|           | ANNEAL-$\phi$ | 88.7  | 94.2  | 87.3/82.1 | **87.4** | 87.7  | 92.0  | **84.5/85.5** | **88.5±0.14** |

References

Baxter, J. 2000. A model of inductive bias learning. Journal of Artificial Intelligence Research 12.

Bowman, S. R.; Angeli, G.; Potts, C.; and Manning, C. D. 2015. A large annotated corpus for learning natural language inference. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, 632–642. Lisbon, Portugal: Association for Computational Linguistics. doi:10.18653/v1/D15-1075. URL https://www.aclweb.org/anthology/D15-1075

Bronskill, J.; Gordon, J.; Requeima, J.; Nowozin, S.; and Turner, R. E. 2020. TaskNorm: Rethinking Batch Normalization for Meta-Learning. arXiv preprint arXiv:2003.03284

Bubeck, S.; Munos, R.; and Stoltz, G. 2008. Pure Exploration for Multi-Armed Bandit Problems. arXiv preprint arXiv:2004.07162

Cai, Q.-Z.; Liu, C.; and Song, D. 2018. Curriculum adversarial training. In Proceedings of the 27th International Joint Conference on Artificial Intelligence, 3740–3747.

Caruana, R. 1997. Multitask Learning. Mach. Learn. 28(1):4175. ISSN 0885-6125. doi:10.1023/A:1007379606734. URL https://doi.org/10.1023/A:1007379606734

Chen, Z.; Badrinarayanan, V.; Lee, C.-Y.; and Rabinovich, A. 2018. GradNorm: Gradient Normalization for Adaptive Loss Balancing in Deep Multitask Networks. In International Conference on Machine Learning, 794–803.

Clark, K.; Luong, M.-T.; Khandelwal, U.; Manning, C. D.; and Le, Q. V. 2019. BAM! Born-Again Multi-Task Networks for Natural Language Understanding. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 5931–5937. Florence, Italy: Association
and Potts, C. 2011. Learning word vectors for sentiment 
for Computational Linguistics. doi:10.18653/v1/P19-1595. 
URL https://www.aclweb.org/anthology/P19-1595

Devlin, J.; Chang, M.-W.; Lee, K.; and Toutanova, K. 2019. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 4171–4186. Minneapolis, Minnesota: Association for Computational Linguistics. doi:10.18653/v1/N19-1423. URL https://www.aclweb.org/anthology/N19-1423

Duchi, J. C.; Hashimoto, T.; and Namkoong, H. 2020. Distributionally Robust Losses Against Mixture Covariate Shifts. In Unpublished manuscript.

Glover, J.; and Hokamp, C. 2019. Task Selection Policies in Multitask Learning. arXiv preprint arXiv:1907.06214.

Graves, A.; Bellemare, M. G.; Menick, J.; Munos, R.; and Kavukcuoglu, K. 2017. Automated curriculum learning for neural networks. In Proceedings of the 34th International Conference on Machine Learning-Volume 70, 1311–1320. JMLR. org.

Guo, H.; Pasunuru, R.; and Bansal, M. 2019. AutoSeM: Automatic Task Selection and Mixing in Multi-Task Learning. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 3520–3531.

Hashimoto, T.; Srivastava, M.; Namkoong, H.; and Liang, P. 2018. Fairness Without Dedicmographics in Repeated Loss Minimization. In International Conference on Machine Learning, 1929–1938.

Herbster, M.; and Warmuth, M. K. 1998. Tracking the Best Expert. Mach. Learn. 32(2): 151–178. URL http://dblp.uni-trier.de/db/journals/ml/ml32.html#HerbsterW98

Hernandez-Lobato, D.; Hernandez-Lobato, J. M.; and Ghahramani, Z. 2015. A Probabilistic Model for Dirty Multi-task Feature Selection. In Bach, F.; and Blei, D., eds., Proceedings of the 32nd International Conference on Machine Learning, volume 37 of Proceedings of Machine Learning Research, 1073–1082. Lille, France: PMLR. URL http://proceedings.mlr.press/v37/hernandez-lobato15.html

Khot, T.; Saharwal, A.; and Clark, P. 2018. Scitail: A textual entailment dataset from science question answering. In Thirty-Second AAAI Conference on Artificial Intelligence.

Kuhn, D.; Esfahani, P. M.; Nguyen, V. A.; and Shafieezadeh-Abadeh, S. 2019. Wasserstein Distributionally Robust Optimization: Theory and Applications in Machine Learning. CoRR abs/1908.08729. URL http://arxiv.org/abs/1908.08729

Liu, X.; He, P.; Chen, W.; and Gao, J. 2019. Multi-Task Deep Neural Networks for Natural Language Understanding. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, 4487–4496.

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-volume 1, 142–150. Association for Computational Linguistics.

Marelli, M.; Menini, S.; Baroni, M.; Bentivogli, L.; Bernardi, R.; Zamparelli, R.; et al. 2014. A SICK cure for the evaluation of compositional distributional semantic models. In LREC, 216–223.

Mehta, N.; Lee, D.; and Gray, A. G. 2012. Minimax multitask learning and a generalized loss-compositional paradigm for MTL. In Advances in Neural Information Processing Systems, 2150–2158.

Oren, Y.; Sagawa, S.; Hashimoto, T.; and Liang, P. 2019. Distributionally Robust Language Modeling. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 4227–4237. Hong Kong, China: Association for Computational Linguistics. doi:10.18653/v1/D19-1432. URL https://www.aclweb.org/anthology/D19-1432

Sharma, S.; Jha, A. K.; Hegde, P. S.; and Ravindran, B. 2018. Learning to Multi-Task by Active Sampling. In International Conference on Learning Representations. URL https://openreview.net/forum?id=B1nZ1weCZ

Stickland, A. C.; and Murray, I. 2019. BERT and PALs: Projected Attention Layers for Efficient Adaptation in Multi-Task Learning. In ICML.

Wang, A.; Singh, A.; Michael, J.; Hill, F.; Levy, O.; and Bowman, S. 2018. GLUE: A Multi-Task Benchmark and Analysis Platform for Natural Language Understanding. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, 353–355. Brussels, Belgium: Association for Computational Linguistics. doi:10.18653/v1/W18-5446. URL https://www.aclweb.org/anthology/W18-5446

Wolpert, D. H. 1996. The Lack of A Priori Distinctions Between Learning Algorithms. Neural Computation 8(7): 1341–1390. doi:10.1162/neco.1996.8.7.1341. URL https://doi.org/10.1162/neco.1996.8.7.1341

Xu, Y.; Liu, X.; Shen, Y.; Liu, J.; and Gao, J. 2019. Multi-task Learning with Sample Re-weighting for Machine Reading Comprehension. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), 2644–2655. Minneapolis, Minnesota: Association for Computational Linguistics. doi:10.18653/v1/N19-1271. URL https://www.aclweb.org/anthology/N19-1271

Yang, Y.; Yih, W.-t.; and Meek, C. 2015. WikiQA: A Challenge Dataset for Open-Domain Question Answering. In Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing, 2013–2018. Lisbon, Portugal: Association for Computational Linguistics. doi:10.18653/v1/D15-1237. URL https://www.aclweb.org/anthology/D15-1237
Yue, M.-C.; Kuhn, D.; and Wiesemann, W. 2020. On Linear Optimization over Wasserstein Balls. *arXiv preprint arXiv:2004.07162*.

Zaremoodi, P.; and Haffari, G. 2020. Learning to Multi-Task Learn for Better Neural Machine Translation. *arXiv preprint arXiv:2001.03294*.

Zhang, Y.; Yeung, D.-Y.; and Xu, Q. 2010. Probabilistic Multi-Task Feature Selection. In Lafferty, J. D.; Williams, C. K. I.; Shawe-Taylor, J.; Zemel, R. S.; and Culotta, A., eds., *Advances in Neural Information Processing Systems 23*, 2559–2567. Curran Associates, Inc. URL [http://papers.nips.cc/paper/4150-probabilistic-multi-task-feature-selection.pdf](http://papers.nips.cc/paper/4150-probabilistic-multi-task-feature-selection.pdf).

Zhou, K.; Yang, Y.; Hospedales, T. M.; and Xiang, T. 2020. Deep Domain-Adversarial Image Generation for Domain Generalisation. *CoRR* abs/2003.06054. URL [https://arxiv.org/abs/2003.06054](https://arxiv.org/abs/2003.06054).