Efficient Hierarchical Domain Adaptation for Pretrained Language Models

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Abstract

Generative language models are trained on diverse, general domain corpora. However, this limits their applicability to narrower domains, and prior work has shown that continued in-domain training can provide further gains. In this paper, we introduce a method to scale domain adaptation to many diverse domains using a computationally efficient adapter approach. Our method is based on the observation that textual domains are partially overlapping, and we represent domains as a hierarchical tree structure where each node in the tree is associated with a set of adapter weights. When combined with a frozen pretrained language model, this approach enables parameter sharing among related domains, while avoiding negative interference between unrelated ones. It is efficient and computational cost scales as $O(\log(D))$ for $D$ domains. Experimental results with GPT-2 and a large fraction of the 100 most represented websites in C4 show across-the-board improvements in-domain. We additionally provide an inference time algorithm for a held-out domain and show that averaging over multiple paths through the tree enables further gains in generalization, while adding only a marginal cost to inference.

1 Introduction

Pretrained language models (Peters et al., 2018; Devlin et al., 2019; Liu et al., 2019; Radford et al., 2019), trained on massive general-domain corpora, have enabled great progress in many natural language processing (NLP) benchmarks (Wang et al., 2018). Nonetheless, continuing pretraining a language model on a narrower domain (Han and Eisenstein, 2019; Lee et al., 2019; Gururangan et al., 2021) is beneficial, although computationally expensive (Maronikolakis and Schütze, 2021), which indicates that domain-relevant data is important for downstream tasks.

Prior work typically makes the assumption that individual domains are distinct, and models them accordingly. For example, Domain-Adaptive Pretraining (DAPT; Gururangan et al., 2020), fine-tunes one model for each textual domain. This is related to data selection (Moore and Lewis, 2010; Axelrod et al., 2011; Plank and van Noord, 2011), which aims to select the best matching data for a new domain. This process is computationally expensive and does not scale to a large number of domains. Moreover, this approach does not allow parameter sharing among related domains, as each textual domain is modeled with a separate set of parameters. At the other extreme, training one model on all domains as is common during unsupervised pre-training does not account for their similarities and differences and might hinder the model’s generalization ability due to negative interference.

As an alternative, we start with the observation that the term “domain” is often vaguely defined, but it typically denotes a distribution over language characterizing a given topic or genre, and that domains are partially overlapping. For example, a sentiment model processing hotel reviews could be expected to benefit by also including data from restaurant reviews, which might in turn benefit from cooking recipes, but combing hotel reviews and recipes may be detrimental.

To overcome this problem, we propose a data-driven approach to modeling domains that automatically clusters domains into a hierarchical tree using language model representations (Aharoni and Goldberg, 2020). We then introduce an ef-
cient adapter based method that allows parameter sharing among related domains, while avoiding negative interference among unrelated ones. Adapters (Rebuffi et al., 2017; Houlsby et al., 2019) are lightweight layers, usually added after each transformer (Vaswani et al., 2017) layer that are trained on each domain, while the pre-trained language model remains unchanged. In our case, each node in the tree is associated with a separate set of adapter weights that are only activated for a particular domain. For example, in Figure 1 training data from BOOKING.COM will activate parameters in nodes 3, 6, and 7, and enable parameter sharing with the highly related YELP.COM through nodes 6 and 7. In this way, the parameters at the leaves can specialize to each individual domain, while allowing nodes higher up in the tree to learn more general information across several related domains.

We verify the efficacy of our approach in two settings. We begin by manually defining a tree structure, using websites\(^1\) as the leaves. In this small setting, we empirically verify that our method outperforms prior work including DAPT (Gururangan et al., 2020) and multi-domain pre-training when using adapters with GPT-2 (Radford et al., 2019) when tested in-domain. We further show that our method generalizes better to held-out websites then the baselines.

We then scale our model to a larger setting across almost 100 websites. We induce the hierarchical structure in an unsupervised way using representations from GPT-2 with a Gaussian Mixture Model (GMM) and hierarchical clustering, similar to Das Gupta et al. (2015). In this way, the clusters model textual domains using a soft assignment, and the GMM provides a mechanism to automatically find the closest training websites to any held-out domain. Our empirical results show across-the-board improvements over strong baselines when using websites in the training corpus. We also show that an efficient inference time algorithm that averages over multiple paths through the tree improves generalization when tested on held-out websites.

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\(^1\)To avoid ambiguity, we refer to text originating from a single internet domain such as GITHUB.COM as a website, to distinguish from a domain of related text.

## 2 A Hierarchical Representation of Domains

In this section, we first present the intuition for a hierarchical ordering of domains. We then describe how we add a hierarchical structure to an already trained language model and present the training process. Additionally, we show how a path in the tree is selected to evaluate the in-domain and out-of-domain sets. We finally discuss the computational cost of our approach compared to the baselines and our experimental setup.

### 2.1 Domain

While there is no commonly-accepted definition of a domain in text (Plank, 2016), we use the provenance of a textual corpus as a reasonable proxy. For the scope of this paper we treat the data that appears in a single website as coming from the same textual domain. Although this is a noisy approximation, it allows us to obtain a very large number of domains using C4 (Raffel et al., 2020), an available web-scale corpus.

### 2.2 Hierarchical Structure

Domains generally overlap with each other and have different degrees of granularity. A model that encodes them should capture domain-specific but also general-domain information. To this end, we propose representing domains as a tree. An example of a tree structure is shown in Figure 1. Specific domains are encoded in the leaf nodes (such as FRONTIERSIN.ORG, JOURNALS.PLOS.ORG), while more general-domain knowledge is encoded in the upper nodes (the domain of SCIENTIFIC ARTICLES). If a domain (leaf node) is low-resource, but is similar to a high-resource domain, it could benefit from the representation of a related node. In the example of Figure 1, if FRONTIERSIN.ORG is low-resource, it can leverage information from node 5, that has been trained on related data (from both JOURNALS.PLOS.ORG and FRONTIERSIN.ORG). This way, the representation of the model for this specific domain would improve.

### 2.3 Model Architecture

**Adapter layer.** Adapters are typically added to a pretrained model in each transformer layer. An adapter module uses as input the output of the previous layer.

Formally: Let \( h_i \) be the output of the \( i \)-th layer, of dimension \( m \). We first apply a layer-
normalization (Ba et al., 2016), followed by a down-projection $W^D \in \mathbb{R}^{n \times d}$, a ReLU activation and an up-projection $W^U \in \mathbb{R}^{d \times m}$, where $d$ is the bottleneck dimension of the adapter module and the only tunable parameter. The up-projection is finally combined with a residual connection (He et al., 2016) with $z_i$:

$$\text{Adapter}_i(h_i) = W^U \text{ReLU}(W^D \text{LN}(h_i)) + h_i$$  

(1)

**Hierarchical Adapters.** Assuming a training corpus with data from $n$ domains, we consider the setting where we have a pretrained model $M$. We want to use $M$ to adapt to $n$ new domains. To adapt efficiently, we use adapter modules, as they combine the benefits of fine-tuning with the modularity of feature-based transfer. The nodes of the tree are the trainable parameters added to the pretrained model. We represent each node with an adapter layer. The pretrained model $M$ is not updated.

We note that while Houlsby et al. (2019) insert adapters but re-train the layer normalization parameters of the pretrained model and Bapna and Firat (2019) introduce new layer normalization parameters for every adapter, we introduce just one set of layer normalization parameters in each transformer layer and these parameters are shared between all the adapters of a transformer layer.

**2.4 Training & Computational Cost**

When our input consists of data from a particular domain, we only update the adapter layers of the path that leads to this domain.

As a concrete example, let us consider again the setup of Figure 1, where we have data from four domains, namely FRONTIERSIN.ORG, JOURNALS.PLOS.ORG, BOOKING.COM, and YELP.COM. During training, at the forward pass, suppose that a mini-batch from FRONTIERSIN.ORG is fed to the model. Nodes 1, 5 and 7 will be activated, as these nodes lead to the domain of interest.

The output $h_i$ of the $i$-th transformer layer is given as input to $\text{adapter}_i^1$ ($\text{adapter}_i^1$ denotes the set of adapters -one for each transformer layer-corresponding to node 1). It is also the input of $\text{adapter}_i^5$ (parent) and $\text{adapter}_i^7$ (root). Their outputs $y_i^1, y_i^5, y_i^7$ are then averaged. The final representation $y_i$ is passed as input to the next transformer layer.

Using this simple training process, we allow sharing between related domains. Upper nodes in the tree are updated more often (e.g., node 5, which corresponds to the domain of SCIENTIFIC ARTICLES, is updated on mini-batches from domains 1 and 2). Parent nodes are thus better trained and encode more domain-general knowledge. More precisely, the root node of the hierarchical model in Figure 1 gets 22K updates. Each leaf node of the same model only gets 5.5K updates. Details are shown in Table 1.

In terms of computational cost, although our model adds a large number of trainable parameters (total parameters), only a small fraction of them is used for each forward pass (active parameters).

At inference time, to evaluate performance on a domain using the tree of Figure 1, our approach with a single path uses 126M parameters (GPT-2 has 112M and the adapters of each path account for 14M additional parameters). When we average two paths, 23M parameters are added to GPT-2.

Kaplan et al. (2020) provided a detailed breakdown of compute cost for transformer language models. For a model with $N$ non-embedding parameters, the approximate cost of a forward pass is $2N$ flops per token. Extending their calculations to our setting, for a model with $L$ layers, model dimension $d_{model}$, and adapter bottleneck size $d$, a single adapter adds $4Ld_{model}d$ flops per forward pass over the cost of running the GPT-2 model. Our hierarchical method requires running $T$ adapters per layer per forward pass, where $T$ is the average tree depth. For the large scale setting in § 4 with $L = 12$, $d_{model} = 768$, $d = 64$, $N = 84M$, $T = 8$, this gives an increase of approximately 11% flops over the unadapted GPT-2 model.

When running inference for two paths through the tree (§ 4.5), a naive implementation requires twice the computational cost for the adapters. The cost of running the fixed GPT-2 model is unchanged, and the total additional cost of our method is approximately 22%.

**2.5 In-domain/Out-of-domain Evaluation**

At inference time, we need to define which path should be activated for a specific domain. When we perform in-domain evaluation, this is straightforward. We always activate the path through the tree that leads to the node that is assigned to this specific domain.

When we perform out-of-domain evaluation, we need to find the path that is a better fit to the held-out domain. We can also use multiple paths, as
Table 1: Parameters used by our approach (hierarchical) and the multi-domain adapters baseline. The small setup is explained in Section 3, while the large setup is explained in Section 4.

|                     | Small Setup | Large Setup |
|---------------------|-------------|-------------|
| Adapter Size        | 256         | 64          |
| # Adapters          | 7           | 49          |
| Average path length | 3           | 8           |
| Total parameters    | 33M         | 58M         |
| Active parameters   | 14M         | 9.5M        |
| Number of updates - root | 22K   | 11K         |
| Number of updates - leaf | 5.5K  | 400         |

3.2 Approach

We use the hierarchical structure shown in Figure 1, with the two leaf nodes representing scientific articles sharing a parent, the two leaf nodes representing reviews sharing a parent, and a single grandparent shared by the two parents. This tree structure was manually chosen using domain knowledge. We use a pretrained GPT-2 model as our base model, and add one set of adapters per node in the tree. We freeze the weights in the GPT-2 model and train the adapter weights on language modeling of the domains of interest. The training process is explained in detail in Subsection 2.4.

3.3 Experimental Setup

We add 7 adapters to GPT-2, one for each node in the tree. Each adapter has a bottleneck dimension $d$ of 256. For a single training step, a single path through the tree is active, depending on which domain of text is represented in the current batch; when the text is from FRONTIERS.ORG, for example, the leaf node representing that domain is active, as are its parent and grandparent. Here, active nodes in the tree are used when computing the forward pass and updated when computing the backward pass (during training), while those that are not active are not used in the computation.

We evaluate two baselines: a multi-domain adapter which is trained on all the in-domain data, and a set of single adapters. Each of the single adapters is trained only on a single domain. The multi-domain adapter has a bottleneck dimension $d$ of 768, and the single-domain adapters have a bottleneck dimension $d$ of 256. These dimensions were chosen so that each configuration uses the same amount of compute for a forward pass. For this setup, we also ensure that the model is exposed to an equal amount of data from each domain. Results are shown after 20 epochs or training (22K training steps).

3 Hierarchical Domain Adaptation with a Manually Created Tree

In this section, we implement the model described in the prior section for a very limited number of domains, to comprehensively examine design choices and verify the performance in a restricted setting, before moving to a large scale setting in § 4.

3.1 Data

We manually select four websites to be represented by leaf nodes in our tree: two that contain scientific articles (FRONTIERS.ORG, JOURNALS.PLOS.ORG) and two that contain reviews (BOOKING.COM and YELP.COM). We use text from the C4 corpus (Raffel et al., 2020), a web-scale corpus of English data; these four internet domains are four of the largest sources of text in the dataset. We use the publicly available version\(^2\) of the corpus (Dodge et al., 2021). The sizes of the corpora used are presented in Appendix A.1.
### 3.4 In-Domain Results

In-domain evaluation scores are presented in Table 2. Our model clearly surpasses the multi-domain adapters baseline in all four domains we examine. On average, hierarchical adapters lower the perplexity by 0.7 compared to multi-domain adapters. Compared to just evaluating GPT-2 (without additional training), our model yields a large improvement (+12.5 on average), confirming prior work that suggests that further training a pretrained language model in-domain is highly effective. Single adapters (also referred to as task adapters in literature) marginally outperform multi-domain adapters in this scenario.

### 3.5 Out-of-Domain Results

We have 7 out-of-domain evaluations, some of which represent similar textual domains to our in-domain data, some of which are significantly different. For example, NCBI, LINKSPRINGER, and SCHOLARS.DUKE contain text from scientific documents, similar to two of our in-domain sources of text, but TECHCRUNCH and MEDIUM are quite dissimilar to the in-domain text the models are trained on.

All models out perform the baseline of just evaluating GPT-2 (see Table 3). We hypothesize that the pretraining data from GPT-2, which has not been publicly released, had a somewhat different distribution or format to C4, and thus further training on any data from C4 seems to improve performance. However, as shown in the table, the best results are obtained with hierarchical adapters.

However, which set of single adapters we should use to evaluate a held-out domain is not obvious. For example, to evaluate on LONELYPLANET, it intuitively makes sense to use single adapters trained on a reviews/travelling domain, such as BOOKING or YELP, but to evaluate on LINKSPRINGER, we might want to use single adapters trained on a scientific domain, such as FRONTIERSIN or JOURNALS.PLOS. We have no a priori criterion to choose the model that will provide better adaptation for a held-out domain. This is also true for our proposed model, hierarchical adapters, as there exist multiple paths in the tree and choosing the most suitable one is not straightforward. To fully explore different options for the hierarchical model, we perform an ablation study shown in Table 4.

Comparing our hierarchical adapters to multi-domain adapters, we see that when evaluating a single path through the tree, multi-domain adapters slightly outperform hierarchical adapters (compare column 3 of Table 3 with columns 1-4 of Table 4), but with a second path through the tree active the hierarchical adapters outperform all other approaches (columns 3 and 4 of Table 3). This highlights an advantage of the hierarchical adapters: they are extensible even after training, allowing for flexible performance-efficiency trade-offs that other approaches (like training a single multi-domain adapter) do not.
Figure 2: Dendrogram obtained using KL divergences of the Gaussian distributions of the GMMs. The leaf nodes correspond to the cluster centers. Each cluster center assigns highest probability to a specific training domain.

| Ind | Domain                  | Ind | Domain                  |
|-----|-------------------------|-----|-------------------------|
| 0   | city-data.com           | 12  | forums.macrumors.com    |
| 0   | baltimoresun.com        | 13  | instructables.com       |
| 0   | chicagotribune.com      | 14  | aljazeera.com           |
| 2   | answers.sap.com         | 15  | npr.org                 |
| 3   | express.co.uk           | 16  | deviantart.com          |
| 4   | lonelyplanet.com        | 17  | androidheadlines.com    |
| 5   | insiderpages.com        | 18  | wired.com               |
| 6   | eventbrite.com          | 19  | frontiersin.org         |
| 7   | si.com                  | 20  | gsmarena.com            |
| 7   | oreilly.com             | 21  | medium.com              |
| 8   | librarything.com        | 22  | link.springer.com       |
| 9   | dailymail.co.uk         | 23  | pcworld.com             |
| 10  | csmonitor.com           | 24  | ign.com                 |
| 11  | prweb.com               |     | glassdoor.com           |

Table 5: Each of the clusters of GMM assigns the highest probability to one or multiple internet domains, as shown in the Table. Ind refers to the cluster index.

4 Hierarchical Domain Adaptation with an Automatically Created Tree

In this section, we scale our approach to a much larger set of domains, and thus a much larger hierarchy, adding more adapters in our model. In the previous section, we manually selected a tree structure based on our domain knowledge, but in this section we automatically create a tree using unsupervised methods. We leverage domain clusters obtained using Gaussian Mixture Models and hierarchical clustering and provide an algorithm for out-of-domain evaluation, leveraging the flexibility of hierarchical adapters, that can be combined to improve performance with a minimal cost.

4.1 Data

As a training and evaluation corpus, we use data from C4. Specifically, we use text from 30 websites as our training corpus and we perform out-of-domain evaluation of our model and the baselines on 38 other websites. All websites used belong to the top 100 sites in C4. More details can be found in Appendix A.1.

4.2 Approach

We want to create a hierarchical structure that represents the relations between domains. To this end, we fit a Gaussian Mixture Model (GMM) and then use an agglomerative clustering algorithm on the GMM. A GMM assumes that all data points are generated from a mixture of a $k$ Gaussian distributions and defines the probability for data points to belong to any of these distributions. We consider a GMM to be a suitable approach for representing domains because, as it is a probabilistic model, it can account for the uncertainty of cluster assignment and allow soft assignments. This correlates well with our notion of domain, as a sentence can belong to more than one domain.

Similar to Aharoni and Goldberg (2020), we generate contextual representations of 1,000 sequences (uniformly sampled) from each of our 30 training websites using GPT-2. We then use PCA for dimensionality reduction on the representations, as it has shown to improve the quality of clustering.
in terms of purity (Manning et al., 2008). We then fit a GMM with 30 components to our data (so, 30 clusters). After fitting the GMM, we find the Gaussian which assigns highest probability to text from each website, and remove any Gaussian which does not assign the highest probability to any website (note, it can be the case that text from more than one website are assigned the highest probability by the same Gaussian). The websites and the index of the Gaussian which assigns the highest probability to data from a given website are shown in Table 5.

To perform hierarchical clustering, we use the symmetrized Kullback-Leibler (KL) divergence as a distance metric. Suppose we have two multivariate normal distributions, with means $\mu_0, \mu_1$ and covariance matrices $\Sigma_0, \Sigma_1$, obtained by the GMM. To measure the difference between the two distributions, assuming that they have the same dimension $N$, we can compute the KL divergence. Because it is asymmetric, we cannot directly use it to measure the distance between distributions, so we compute the symmetrized version as follows:

\[
D_{KL}(N_0||N_1) = \frac{1}{2} \text{tr} \left( \Sigma_1^{-1} \Sigma_0 + \ln \left( \frac{\det \Sigma_1}{\det \Sigma_0} \right) \right) + \frac{1}{2} \left( (\mu_1 - \mu_0)^T \Sigma_1^{-1} (\mu_1 - \mu_0) - N \right) \tag{2}
\]

\[
D_{KLsym}(N_0, N_1) = \frac{1}{2} \left( D_{KL}(N_0||N_1) + D_{KL}(N_1||N_0) \right) \tag{3}
\]

Using Equation 3 as a distance metric, we leverage agglomerative (bottom-up) hierarchical clustering to infer the structure of our data. We start from 25 clusters, computed by the GMM. We ignore the clusters that do not assign a high probability to data samples from any website, see Appendix A.2 for the full confusion matrix. The clustering algorithm leads to a tree, depicted in Figure 2. Nodes 0-24 correspond to the clusters (normal distributions) of the GMM. Each website is assigned to a specific cluster and the alignment can be seen in Table 5.

### 4.3 Experimental Setup

We use 1000 sequences from each domain (of 800 tokens) and encode them with GPT-2 (hidden dimension 768). We project them to 100 dimensions using PCA. We cluster them with a GMM with 30 clusters. Each mixture component has its own covariance matrix. For the hierarchical clustering, we use a distance matrix computed using the symmetrical KL divergence. The clustering algorithm provides a tree of 49 nodes. Therefore, we add 49 adapters to GPT-2, one for each node in the tree. Each adapter has a bottleneck dimension $d$ of 64. For a single training step, just one path in the tree is active. This follows the training process of the previous section.

In this set of large experiments we used our computational budget to compare against our strongest baseline, multi-domain adapters, as that provided the most competitive results both in- and out-of-domain in §3. Comparing against single adapters could be relevant but we chose to allocate our budget on our primary model and strongest baseline since single adapters have shown to be less able to generalize to held-out domains. We train both our hierarchical model and the multi-domain adapter baseline for 4 epochs (11k training steps), using 1 GPU per model and stopping training after 51 hours. For this setup, we oversample the low-resource domains in order to avoid overfitting.

| In-domain scores | GPT-2 | multi adapters | hierarchical adapters |
|-----------------|------|----------------|------------------------|
| ign.com         | 30.0 | 25.5           | 23.8                   |
| insiderpages.com| 30.0 | 19.7           | 18.4                   |
| eventbrite.com  | 34.5 | 27.4           | 25.5                   |
| androidheadlines.com | 21.8 | 17.6           | 16.9                   |
| link.springer.com| 27.9 | 22.6           | 21.5                   |
| librarything.com| 29.4 | 25.8           | 24.8                   |
| csmonitor.com   | 29.4 | 25.8           | 24.8                   |
| city-data.com   | 36.2 | 31.2           | 30.3                   |
| forums.macrumors.com | 37.0 | 27.7           | 26.0                   |
| Glassdoor.com   | 20.7 | 7.9            | 7.5                    |
| oreilly.com     | 27.4 | 21.5           | 20.5                   |
| pcworld.com     | 24.3 | 19.7           | 18.9                   |
| express.co.uk   | 22.2 | 15.0           | 14.0                   |
| answers.sap.com | 60.3 | 34.5           | 30.3                   |
| prweb.com       | 25.8 | 20.1           | 18.9                   |
| instructables.com| 32.8 | 28.2           | 26.6                   |
| deviantart.com  | 42.5 | 33.1           | 31.2                   |
| entrepreneur.com| 26.3 | 22.0           | 20.9                   |
| si.com          | 22.2 | 17.3           | 16.4                   |
| gsnowarena.com  | 56.3 | 34.5           | 30.3                   |
| wired.com       | 30.0 | 24.3           | 23.8                   |
| medium.com      | 29.1 | 23.1           | 22.6                   |
| baltimoresun.com| 27.1 | 20.9           | 20.1                   |
| npr.org         | 22.2 | 18.0           | 17.5                   |
| frontiersin.org | 22.0 | 18.4           | 17.2                   |
| chicagotribune.com | 27.1 | 21.1           | 20.7                   |
| foxnews.com     | 27.2 | 15.3           | 14.9                   |
| aljazeera.com   | 22.2 | 17.8           | 17.1                   |
| dailymail.co.uk | 27.1 | 21.1           | 20.7                   |
| lonelyplanet.com| 35.5 | 19.5           | 17.1                   |

**Table 6**: In-domain evaluation perplexity.
4.4 In-Domain Results

Our in-domain results are shown in Table 6. To evaluate the performance of our model in-domain, we use the path through the tree that leads to the cluster that assigns the highest probability to the domain of interest (so, the same as during training). For example, to evaluate the performance of the model on PCWORLD.COM, we use the path that leads to cluster 22. The average path length in the tree is 8.3, so we “activate” 8 adapters on average at every training step. We also “activate” 8 adapters on average at inference time, to perform in-domain evaluation. Our approach consistently outperforms multi-domain adapters, yielding +1.3 on average in terms of perplexity.

We do not experiment with combining multiple paths during training or inference time for in-domain evaluation, leaving this for future work.

4.5 Out-of-Domain Results

We perform out-of-domain evaluation on 38 held-out websites, shown in Appendix A.1. We want to automatically find the best path in the tree for a held-out website. To this end, we use the fitted GMM to assign probabilities to data from the held-out website. We intuitively want to place a held-out website close to websites that are similar to it, so that it can benefit from positive transfer.

To do that, we assume that we have a set of $N$ sequences from a given out-of-domain website that we can use to find the best path through the tree for all data from that website.

For a given out-of-domain website $i$, we assume we have a held-out set of $N$ sequences (where in our experiments $N = 1000$) that we can use to find the best path through the tree; this path will then be used to evaluate the rest of the data from this website (e.g., for computing perplexity). Following a similar procedure to our training regime, we use GPT-2 to encode the $N$ sequences, then use the fitted GMM to find the probability assigned to each of the $N$ vectors by each cluster (i.e., each leaf node in the tree). The single best path through the tree leads to the leaf node that corresponds to the cluster $m$, where $m$ assigns the highest probability to the largest fraction of the $N$ sequences from website $i$. The second best path through the tree leads to the cluster $n$ that assigns highest probability to the second-most number of the $N$ sequences from website $i$. Thus, using the GMM clusters and the hierarchical structure we have inferred, without needing to train more parameters, we are able to evaluate out-of-domain data using the adapters that were trained on the most similar data. This approach is similar to the “cached” setting in Gururangan et al. (2021), and we note that it does require a held-out set of $N$ sequences that are only used for finding the best path through the tree (and not used for computing perplexity). This is realistic setting when one has a significant amount of data from a single source, and we leave other approaches (e.g., finding the the best path through the tree for every input sequence individually) to future work.

We show in Table 7 results of the out-of-domain evaluations. Our hierarchical adapter model largely outperforms the baseline of just evaluating GPT-2. We notice that using a single path, our approach provides worse results compared to multi-domain adapters. In this evaluation, the multi-domain adapters and the hierarchical model have the same number of active parameters, but the adapters in the hierarchical model are trained on less data (except the adapter associated with the root of the tree, which has the same number of updates as the multi-domain adapter while being significantly smaller). However, we can leverage the flexibility of the hierarchical model by having more than one path through the tree active. On average, the hierarchical model with the best two paths through the tree active at evaluation time surpasses multi-domain adapters. This yields an average improvement of +0.6 in terms of perplexity. We note that at inference time, our approach with a single active path uses 122M parameters (112M of GPT-2 and 10M parameters for a path of average length). When two paths are active, at most 132M parameters are used. The computational overhead is thus quite small; if the two paths have some overlap, this computation is potentially significantly less. We also note that on average, the active parameters in our hierarchical model are trained on significantly less data than the multi-domain adapters (for example, the leaf nodes only see on average 400 updates, as shown in Table 1).

5 Related work

Our approach draws on prior work in domain adaptation and efficient language model fine-tuning.

5.1 Domain Adaptation

Domain adaptation has been widely explored in Natural Language Processing (Jiang and Zhai,
Table 7: Out-of-domain evaluation perplexity.

| Domain          | GPT-2 | multi adapters | hierarchical 1 path | hierarchical 2 paths |
|-----------------|-------|----------------|---------------------|---------------------|
| reuters.com     | 20.9  | 16.0           | 16.4                | 16.3                |
| ibtimes.co.uk   | 24.3  | 19.5           | 19.7                | 19.5                |
| bbc.com         | 23.6  | 19.1           | 18.9                | 18.7                |
| tripadvisor.com | 40.4  | 34.8           | 35.9                | 33.8                |
| cnet.com        | 26.8  | 23.3           | 22.2                | 22.9                |
| telegraph.co.uk | 30.9  | 23.6           | 24.5                | 22.2                |
| theatlantic.com | 28.5  | 23.6           | 23.8                | 23.6                |
| foxbusiness.com | 22.9  | 17.5           | 19.9                | 18.2                |
| thesun.co.uk    | 26.8  | 19.9           | 19.9                | 18.2                |
| nydailynews.com | 24.5  | 19.3           | 19.5                | 18.2                |
| dailystar.co.uk | 20.7  | 13.9           | 12.2                | 12.2                |
| fastcompany.com | 27.9  | 21.3           | 21.4                | 20.9                |
| nypost.com      | 26.3  | 18.9           | 18.9                | 18.7                |
| businessinsider.com | 24.3 | 20.5       | 20.7                | 20.9                |
| deadline.com    | 33.1  | 26.3           | 33.1                | 26.8                |
| breitbart.com   | 22.9  | 16.9           | 17.8                | 17.1                |
| techcrunch.com  | 27.7  | 21.5           | 21.8                | 20.1                |
| nme.com         | 28.2  | 20.1           | 23.8                | 20.5                |
| fool.com        | 23.8  | 22.2           | 22.4                | 22.2                |
| finance.yahoo.com | 22.6 | 20.1        | 20.3                | 20.1                |
| youtube.com     | 15.3  | 14.2           | 14.4                | 13.5                |
| ncbi.nlm.nih.gov | 20.7 | 18.5       | 18.4                | 18.2                |
| scholars.duke.edu | 22.6 | 20.7       | 20.3                | 20.3                |
| inquiriesite.com | 22.4 | 17.5        | 16.4                | 16.4                |
| simple.wikipedia.org | 22.2 | 19.5       | 20.5                | 19.5                |
| kickstarter.com | 26.6  | 24.0           | 24.6                | 22.2                |
| mashable.com    | 27.1  | 22.0           | 22.0                | 21.8                |
| booking.com     | 29.7  | 22.9           | 24.8                | 22.0                |
|etsy.com         | 28.8  | 26.3           | 26.8                | 24.5                |
| Fineartamerica.com | 25.5 | 26.6       | 26.6                | 24.5                |
| githut.com      | 32.8  | 30.3           | 30.6                | 30.6                |
| Journals.plos.org | 23.3 | 20.1        | 20.1                | 18.2                |
| itunes.apple.com | 34.8 | 28.8        | 33.1                | 30.0                |
| agraretown.com  | 44.7  | 40.0           | 39.6                | 35.9                |
| premium.wpmudev.org | 31.5 | 27.7       | 30.0                | 27.7                |
| homestars.com   | 34.1  | 29.4           | 28.2                | 28.2                |
| reference.com   | 28.5  | 24.5           | 25.3                | 24.5                |
| cnbc.com        | 21.1  | 17.6           | 18.4                | 17.6                |

Average: 26.8 22.3 23.0 21.7

More recently, fine-tuning a pretrained language model in using data from the target task (Howard and Ruder, 2018) or data from the target domain (Rietzler et al., 2020; Han and Eisenstein, 2019) has shown to be helpful to mitigate the domain shift between train and test data distributions of the same task. Gururangan et al. (2020) showed that a pretrained language model can further improve by fine-tuning on data from a domain that is related to the domain of the task (this approach is named DAPT). While this work suggests fine-tuning a different model to the domain of each task and requires parameters that grow linearly with the number of tasks, our approach trains a single model to adapt to all domains. Another key difference is that DAPT does not permit parameter sharing between domains. Nonetheless, our hierarchical adapter model leverages similarities between pertinent domains and improves adaptation even in low-resource settings.

Recent work has developed domain expert mixture (DEMix) layers (Gururangan et al., 2021) to enable conditioning a language model on the domain of input text. DEMix layers replace feed-forward layers in a transformer and each of them is updated only based on data from a specific domain. Then, a modular LM is trained from scratch. On the contrary, our approach leverages a pretrained language model and only trains adapter layers on the target domains. Since each feed-forward layer is essentially replaced with a mixture of experts, the parameters added grow linearly with the number of domains. In our approach, however, the number of parameters grows logarithmically, due to the hierarchical structure used.

5.2 Adapters

Adapters (Rebuffi et al., 2017; Houlsby et al., 2019) have been largely used as an efficient fine-tuning approach in many NLP tasks, such as neural machine translation (Bapna and Firat, 2019), cross-lingual transfer (Pfeiffer et al., 2020) and dependency parsing (Üstün et al., 2020). Adapters can be trained on a single task or language (Pfeiffer et al., 2020), but also in a language-agnostic way (Üstün et al., 2021). To the best of our knowledge, we are the first to use them in a hierarchical structure for domain adaptation.

6 Conclusion & Future Work

In this paper, we present a novel approach for efficient domain adaptation on multiple domains using hierarchical adapters. Our approach creates a hierarchical structure that encodes the similarities and differences of domains, allowing parameter sharing between them but avoiding negative transfer. We first evaluate our approach with a manually defined tree and then scale to a large tree, created in an unsupervised way. We also provide an evaluation-time algorithm that allows combining multiple paths to best adapt to an unseen domain.

In the future, we would like to investigate a more efficient evaluation-time approach, using only a few tokens of an unseen domain. We would also potentially like to train a model in even more domains, to account for all the 100 most represented internet domains of C4. It would also be interesting to extend our model to a multi-lingual setup, as it is currently only used for domain adaptation in English text.
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A Appendix

A.1 Corpus description

In Table 8, we present the sizes of the training and evaluation corpora used for the large setup. Only one corpus is used for the small but not the large setup, namely YELP.COM. This corpus has 684M training tokens and 20M evaluation tokens. We randomly subsample 53M training tokens of this corpus for our first, small setup, as we want to train a balanced model.

A.2 Confusion Matrix

Figure 3 depicts the confusion matrix of the GMM. We can observe visually that some clusters assign a high probability to multiple internet domains, while others remain empty. This shows that the intuition have for what a domain is does not correspond exactly to the cluster obtained by an unsupervised, data-driven approach. Our visualization is based on publicly available code 3.

3https://github.com/roeeaharoni/unsupervised-domain-clusters
| Domain                         | Train (Eval.) Tokens | Eval. Tokens | Domain                         | Train (Eval.) Tokens | Eval. Tokens |
|-------------------------------|-----------------------|--------------|-------------------------------|-----------------------|--------------|
| frontiersin                  | 38M (6M)              |              | Journals.plos.org             | 53M (6M)              |              |
| chicagotribune.com           | 31M (4M)              |              | food.com                      | 34M (4M)              |              |
| link.springer.com            | 28M (4M)              |              | businessinsider.com           | 32M (4M)              |              |
| aljazeera.com                | 26M (3M)              |              | theatlantic.com               | 30M (4M)              |              |
| instructables.com            | 25M (3M)              |              | booking.com                   | 30M (4M)              |              |
| npr.org                      | 25M (3M)              |              | kickstarter.com               | 26M (3M)              |              |
| dailymail.co.uk              | 25M (3M)              |              | telegraph.co.uk               | 25M (3M)              |              |
| csmonitor.com                | 23M (3M)              |              | cnet.com                      | 24M (3M)              |              |
| baltimoresun.com             | 23M (3M)              |              | ncbi.nlm.nih.gov              | 23M (3M)              |              |
| city-data.com                | 22M (3M)              |              | foxbusiness.com               | 23M (3M)              |              |
| forums.macrumors.com         | 22M (3M)              |              | cnbc.com                      | 20M (2M)              |              |
| medium.com                   | 22M (3M)              |              | ibtimes.co.uk                 | 18M (2M)              |              |
| foxnews.com                  | 22M (3M)              |              | reuters.com                   | 17M (2M)              |              |
| si.com                       | 18M (2M)              |              | bbc.com                       | 17M (2M)              |              |
| wired.com                    | 18M (2M)              |              | nytimes.com                   | 15M (2M)              |              |
| prweb.com                    | 17M (2M)              |              | nydailynews.com               | 14M (2M)              |              |
| express.co.uk                | 16M (2M)              |              | fastcompany.com               | 14M (2M)              |              |
| entrepreneur.com             | 16M (2M)              |              | mashable.com                  | 14M (2M)              |              |
| androidheadlines.com         | 14M (2M)              |              | thesun.co.uk                  | 13M (2M)              |              |
| pcworld.com                  | 14M (2M)              |              | techcrunch.com                | 13M (2M)              |              |
| gsmarena.com                 | 12M (2M)              |              | inquisitr.com                 | 13M (2M)              |              |
| eventbrite.com               | 11M (1M)              |              | youtube.com                   | 11M (1M)              |              |
| ign.com                      | 10M (1M)              |              | itunes.apple.com              | 11M (1M)              |              |
| oreilly.com                  | 9M (1M)               |              | breitbart.com                 | 10M (1M)              |              |
| deviantart.com               | 9M (1M)               |              | etsy.com                      | 10M (1M)              |              |
| insiderpages.com             | 8M (1M)               |              | github.com                    | 10M (1M)              |              |
| lonelyplanet.com             | 6M (1M)               |              | agreatertown.com              | 9M (1M)               |              |
| answers.sap.com              | 6M (1M)               |              | premium.wpmudev.org           | 9M (1M)               |              |
| glassdoor.com                | 4M (300K)             |              | deadline.com                  | 9M (1M)               |              |
| librarything.com             | 3M (500K)             |              | dailystar.co.uk               | 9M (1M)               |              |
|                             |                       |              | reference.com                 | 7M (1M)               |              |
|                             |                       |              | scholars.duke.edu             | 7M (1M)               |              |
|                             |                       |              | tripadvisor.com               | 7M (1M)               |              |
|                             |                       |              | simple.wikipedia.org          | 6M (1M)               |              |
|                             |                       |              | nme.com                       | 5M (1M)               |              |
|                             |                       |              | Homestars.com                 | 3M (500K)             |              |
|                             |                       |              | Fineartamerica.com            | 2M (500K)             |              |

Table 8: Domains that make up our in-domain (training) and out of-domain (evaluation) corpus for the large setup, including the size of our training and evaluation data. All data is extracted from C4 (Raffel et al., 2020).
Figure 3: Confusion Matrix. The x-axis depicts the clusters that the internet domains are assigned to. If no data samples are added to a cluster (for example, cluster 2), the corresponding Gaussian distribution is not used for the hierarchical clustering. The y-axis depicts the internet domains used for training and in-domain evaluation. The cluster numbers shown here are not the exact ones shown in the final dendrogram, but one can easily observe that, for example, the same cluster assigns the highest probability to CITY-DATA.COM, BALTIMORESUN.COM and CHICAGOTRIBUNE.COM. This is mirrored in Table 5 of the main paper.
Figure 4: In-domain performance comparison of our approach to the multi-domain adapter model.