

# Scaling Expert Language Models with Unsupervised Domain Discovery

Suchin Gururangan<sup>\*1†</sup> Margaret Li<sup>\*12</sup> Mike Lewis<sup>2</sup> Weijia Shi<sup>12</sup> Tim Althoff<sup>1</sup>  
Noah A. Smith<sup>13</sup> Luke Zettlemoyer<sup>12</sup>

## Abstract

Large language models are typically trained densely: all parameters are updated with respect to all inputs. This requires synchronization of billions of parameters across thousands of GPUs. We introduce a simple but effective method to *asynchronously* train large, sparse language models on arbitrary text corpora. Our method clusters a corpus into sets of related documents, trains a separate expert language model on each cluster, and combines them in a sparse ensemble for inference. This approach generalizes embarrassingly parallel training by automatically discovering the domains for each expert, and eliminates nearly all the communication overhead of existing sparse language models. Our technique outperforms dense baselines on multiple corpora and few-shot tasks, and our analysis shows that specializing experts to meaningful clusters is key to these gains. Performance also improves with the number of experts and size of training data, suggesting this is a highly efficient and accessible approach to training large language models.

## 1. Introduction

Language models (LMs) are trained on up to trillions of tokens of text (Hoffmann et al., 2022; Touvron et al., 2023). This improves performance on many tasks, but also incurs an extreme cost: thousands of GPUs need to be active simultaneously to update all parameters at each step (Zhang et al., 2022; Chowdhery et al., 2022). Branch-Train-Merge (BTM; Li et al. 2022) alleviates this cost by dividing the total compute among a collection of smaller expert language models (ELMs), each independently trained on a distinct subset (or *domain*) of the training corpus and ensembled

<sup>\*</sup>Equal contribution <sup>†</sup>Work done while at Meta AI.  
<sup>1</sup>University of Washington <sup>2</sup>Meta AI <sup>3</sup>Allen Institute for Artificial Intelligence. Correspondence to: Suchin Gururangan <sg01@cs.washington.edu>, Margaret Li <margsl@cs.washington.edu>.

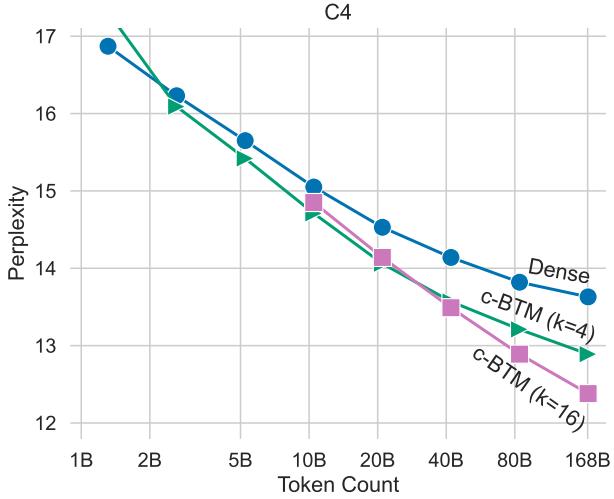
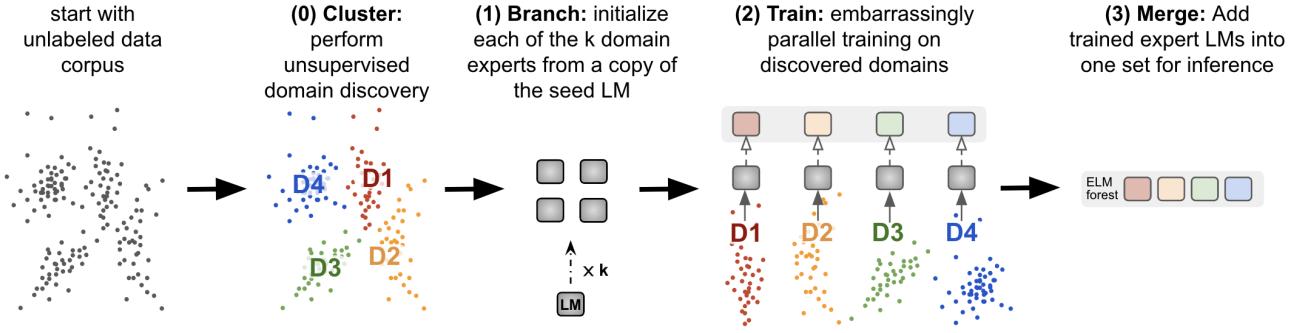


Figure 1. We present c-BTM, a new technique to asynchronously scale expert LMs (§2). c-BTM splits a corpus into  $k$  clusters, trains an expert LM on each cluster, and creates a sparse ensemble during inference. Above, LMs trained with c-BTM (with 4 or 16 clusters) achieve lower validation perplexity than compute-matched dense LMs. These LMs begin with OPT-1.3B (Zhang et al., 2022), and are further trained on C4 (Raffel et al., 2019). The optimal cluster count for c-BTM, and its performance gains, increase with the size of training data (shown in log-scale).

during inference. However, BTM relies on document metadata to identify domains, and such supervision is not always available (e.g., in large Internet crawls; Raffel et al., 2019; Rae et al., 2021; Gao et al., 2021). Moreover, the optimal number of metadata-based domains for a fixed budget is unknown, since metadata cannot be easily merged or divided.

In this work, we introduce Cluster-Branch-Train-Merge (C-BTM; Figure 1), a metadata-free algorithm to scale LMs without massive multi-node synchronization. We use unsupervised clustering to discover domains in a corpus, and train an ELM on each cluster independently (§2.1). At inference time, we *sparingly* activate a subset of the trained ELMs (§2.2). We ensemble ELMs by weighting their outputs with the distances between an embedding of the current context and each expert’s cluster center. This enables simple and efficient sparse computation (Fedus et al., 2022) by retrieving only the top- $k$  experts when predicting each new token.

## Scaling Expert Language Models with Unsupervised Domain Discovery



**Figure 2. c-BTM training process (§2.1).** c-BTM begins with unsupervised domain discovery using  $k$ -means clustering. We then initialize expert language models (ELMs) with a seed language model (e.g., OPT; Zhang et al. 2022) and train an ELM on each cluster. The resulting experts are added to a larger collection for sparse inference.

c-BTM generalizes BTM by allowing for fine-grained control over the number and size of data clusters, since they are automatically learned without being constrained by available metadata. We use this new capability to investigate the scaling properties of c-BTM as a function of the number of experts trained, controlling for a variety of factors (§3). Extensive experiments show that training more clusters always results in better validation perplexity than single cluster (i.e., dense) models, and the optimal cluster count increases with the overall compute (§4.1). These results are consistent for both 1.3B and 6.7B parameter experts.

With more clusters, we can aggressively parallelize expert training: for example, we train 128 ELMs (168B parameters in total) on 168B tokens of text in aggregate with only 8 GPUs at a time. This enables us to avoid many practical difficulties associated with training large LMs across many nodes simultaneously (§4.2). Moreover, the number of parameters at inference time can be kept constant even as the number of experts grows (§4.3): using just the top-2 or top-4 experts is comparable to using all experts, while using just the top-1 expert still outperforms the dense model. Training with more clusters is also more effective than training larger dense models: in §4.4, we demonstrate that training many 1.3B expert LMs, and sparsifying them to a 5.2B parameter LM, achieves the same perplexity as a 6.7B dense model, but with only 29% as many training FLOPs. These gains are also reflected in few-shot text classification experiments (§5), which show that c-BTM models outperform dense baselines even with heavily sparsified inference.

c-BTM provides a radically simplified sparse modeling approach that eliminates nearly all communication overhead from existing sparse LM schemes. Existing sparse LMs typically route different tokens to specialist parameters (Lepikhin et al., 2021; Fedus et al., 2021; Clark et al., 2022). However, they have yet to be widely adopted, perhaps due in part to the communication costs of routing each token in each sparse layer (Artetxe et al., 2021), challenges in learning to specialize experts to tokens (Zhou et al., 2022),

and the necessity of additional mechanisms to balance expert utilization (Lewis et al., 2021). c-BTM improves over sparse LMs by routing sequences (instead of tokens) using offline balanced clustering (instead of online load balancing) with no shared parameters between experts. We compare directly to a mixture-of-experts model with top-2 routing (Lepikhin et al., 2021) in §6.

Our final analysis (§7) shows that balanced clustering is key to c-BTM performance; it works as well as expert assignment with gold metadata, and strongly outperforms random and unbalanced clustering baselines. Overall, our findings suggest that c-BTM is an efficient and accessible method to scale large language models into massive datasets. We release our code and models publicly.<sup>1</sup>

## 2. c-BTM

We introduce c-BTM, a method for embarrassingly parallel training that specializes expert language models to domains discovered through clustering instead of metadata. c-BTM enables scaling to arbitrary numbers of domains and compute budgets on any corpus. In this section, we outline c-BTM training (Figure 2) and inference (Figure 3).

### 2.1. Training

**Step 0: Cluster** To segment our corpus, we employ  $k$ -means clustering, enforcing balanced clusters. ELMs trained without this constraint perform worse (§7.2).<sup>2</sup>

Consider the iterative, hard expectation-maximization view of  $k$ -means clustering. In the expectation step, each document embedding is assigned to a cluster center based on its Euclidean distance to each center. In the maximization step, each cluster center is updated to be the mean embedding of the current set of documents assigned to it. To balance the

<sup>1</sup><https://github.com/kernelmachine/cbtm>

<sup>2</sup>Other techniques to improve clusters, e.g.  $k$ -means++ (Arthur & Vassilvitskii, 2007), can be used to improve performance.

clusters, we formulate the expectation step as a balanced linear assignment problem (Malinen & Fränti, 2014). Given  $D$  document embeddings with representations  $\{w_1, \dots, w_D\}$  and  $K$  cluster centers with representations  $\{h_1, \dots, h_K\}$ , we assign each document  $d$  to a cluster with the assignment index  $a_d \in \{0, \dots, K\}$ :

$$\max_{a_1, \dots, a_D} \sum_{d=1}^D -\text{dist}(h_{a_d}, w_d) \text{ s.t. } \forall k, \sum_{d=1}^D \mathbb{1}_{a_d=k} = \frac{D}{K} \quad (1)$$

where  $\text{dist}$  is the Euclidean distance. Many algorithms exist to solve this problem; we follow Lewis et al. (2021) and use the auction algorithm (Bertsekas, 1992). We only use balancing when estimating the cluster centers; we use greedy inference when predicting clusters, as balancing at inference time is cumbersome for massive corpora.

In our experiments, we use a simple tf-idf embedding function, which is highly efficient at scale and leads to interpretable clusters.<sup>3</sup> We only use a single shard of each corpus to train our clustering model. Any new document, once embedded, can be efficiently mapped to its nearest cluster(s) without additional training. Any embedding function can be used, though the choice of embedder may apply different assumptions of what constitutes a textual domain and come with efficiency trade-offs.<sup>4</sup> Comparing to other embedding or clustering methods is an interesting area for future work, and could likely improve performance.

**Step 1: Branch (from seed LM)** To begin training experts on each of the  $k$  clusters from Step 0, we first *branch* from (i.e., make  $k$  copies of) a *seed* LM. Seed LMs are critical for the overall functionality of ELMs, and ELMs perform best when the seed LM has been trained with a diverse corpus (Li et al., 2022). In our experiments, we use an OPT LM (Zhang et al., 2022) as our seed.<sup>5</sup>

**Step 2: Train** We assign each ELM to a single cluster, and train on each cluster with the log likelihood objective.

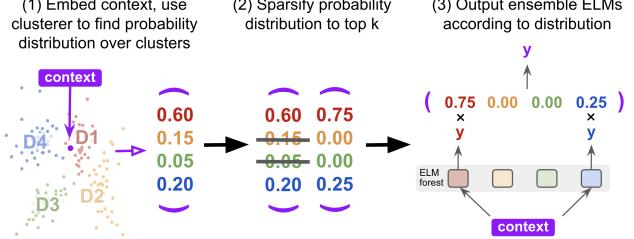
**Step 3: Merge** After training on the assigned domain, we add the new ELM into a larger collection for inference.

In this work, we focus on a single iteration of C-BTM for simplicity. Future work may explore branching from already trained experts in multiple iterations.

<sup>3</sup>In initial experiments, tf-idf outperformed other scalable text embeddings, like hash embeddings (Svenstrup et al., 2017).

<sup>4</sup>tf-idf assumes that domains are lexically-driven, which may not correspond with other notions of domain.

<sup>5</sup>Li et al. 2022 find that dedicating more compute to branching (rather than seed training) leads to better in-domain performance, and the choice of seed LM has a strong effect on the modularity of the resulting ELMs. Future work may explore the effect of different seed LMs on C-BTM performance.



**Figure 3. C-BTM inference process (§2.2).** At inference time, we embed each incoming context and estimate a probability distribution over clusters, by calculating the distance between the embedded context and each cluster center. We use this probability distribution, optionally sparsified to use only the top- $k$  experts, to weight an output ensemble of the ELMs.

## 2.2. Inference

At inference time, we use a sparse ensemble of the outputs of ELMs for incoming test contexts (Figure 3). Formally, consider that the language model provides, at each timestep,  $p(X_t | \mathbf{x}_{<t})$ . We introduce a domain variable  $D$ , alongside each sequence. Then the next-step conditional distribution on the history  $\mathbf{x}_{<t}$  is:

$$p(X_t | \mathbf{x}_{<t}) = \sum_{j=1}^k p(X_t | \mathbf{x}_{<t}, D = j) \cdot \underbrace{p(D = j | \mathbf{x}_{<t})}_{\text{ensemble weights}} \quad (2)$$

With the pretrained embedder and clustering model from Step 0 (§2.1), we embed the context  $h_{x_{<t}}$  and use the  $k$  cluster centers  $\{h_{c_0} \dots h_{c_k}\}$ . We set ensemble weights as:

$$p(D = j | \mathbf{x}_{<t}) \propto \text{topk}[\exp(-\text{dist}(h_{x_{<t}}, h_{c_j})^2 / T)] \quad (3)$$

Where  $\text{dist}$  is the Euclidean distance,  $T$  is a temperature parameter which sharpens or smoothes the probability distribution over cluster centers, and the top- $k$  function filters for the top- $k$  probabilities and renormalizes the distribution to sum to 1. This formulation is reminiscent of nearest-neighbor retrieval mechanisms for language models (Khandelwal et al., 2019; Shi et al., 2022).

These ensemble weights are updated for every incoming token, although in separate experiments we observe that we find that cluster assignments (and in effect, ensemble weights) can be fixed for the second half of a document with no drop in performance; this can further speedup inference.

We find that, in practice, the performance of our models is robust to even top-2 or top-4 experts, meaning that the inference costs of the language model are equivalent to a much smaller LM. We perform an empirical study of inference variations in §4.3.

### 2.3. Comparing to Dense Training

Dense LMs are typically trained using hundreds or thousands of concurrent GPUs, all of which synchronize gradients each update. For example, OPT-175B (Zhang et al., 2022) was trained on 992 80GB A100 GPUs, and PaLM-540B (Chowdhery et al., 2022) was trained on 6144 TPU v4 chips. C-BTM improves training efficiency by reducing communication overhead, as only GPUs training the same ELM must communicate. Furthermore, the chance of a GPU failure can grow considerably with the number of GPUs. C-BTM improves the resiliency of distributed training, since a single GPU failure only delays training for a single ELM, whereas in dense training, a single GPU failure afflicts training on all other GPUs. C-BTM also makes training large LMs more feasible on shared GPU clusters, since it effectively decomposes training into smaller jobs which can run asynchronously. This makes job scheduling more efficient by reducing the number of GPUs that need to be allocated simultaneously.

### 2.4. Comparing to BTM (Li et al., 2022)

Our method addresses several limitations of the training and inference techniques proposed by Li et al. (2022).

First, BTM is limited to training data with metadata which can be used to determine its domains. Typical LM corpora, including C4 (Raffel et al., 2019) and the Pile (Gao et al., 2021), are sourced from the Internet without retaining document provenance at collection time, and are infeasible to label manually. Also, the optimal number of experts for a fixed corpus size, model architecture, and budget remains unknown, and is difficult to explore with metadata-based domains, since they cannot be easily merged or divided. C-BTM broadens the applicability of BTM to arbitrary datasets.

Moreover, BTM inference follows the *cached prior* method introduced by Gururangan et al. (2022), where the ensemble weights are estimated using Bayes’ rule on additional held out data, and the prior  $P(D = j)$  is estimated with an exponential moving average over sequences of posterior estimates that require forward passes on experts. This estimate is then fixed during test data evaluation.

With C-BTM, we route based only on the current context. Thus, no additional data or forward passes through the experts are needed to estimate ensemble weights, nor do we need to assume that adjacent documents in the test set come from the same distribution. This also implies that the parameter averaging technique of Li et al. (2022) is not well suited to our setting, as it requires fixing the weights assigned to each expert for a set of evaluation documents. Future work may explore merging expert parameters for each context during inference.

### 2.5. Comparing to Mixture-of-Experts (MoE)

Like MoE models (e.g., Fedus et al., 2022), C-BTM allows for efficient scaling of large LMs while keeping inference costs manageable. However, C-BTM routes sequences (instead of tokens) using offline balanced clustering (instead of online load balancing) with no shared parameters between experts. This eliminates effectively all complexities associated with balancing expert utilization (Lewis et al., 2021), avoids expensive all-to-all operations between experts (Artetxe et al., 2021), and naturally leads to interpretable expert specialization to domains of the training corpus. In §6, we compare directly to MoE baselines trained with sparse upcycling (Komatsuzaki et al., 2022), which initializes the MoE with a dense checkpoint, mirroring how C-BTM initializes ELMs.

## 3. Experimental Setup

We design a set of experiments to study C-BTM on two large corpora (Figure 4) selected to be distinct from the corpus used to train our seed OPT model, and report perplexity on held out data from each corpus.

### 3.1. Data

**C4 (Raffel et al., 2019)** C4 is a publicly available distribution of a Common Crawl snapshot on Huggingface datasets.<sup>6</sup> We use the *no blocklist* version (`en.noblocklist`) to train on a dataset that is out of distribution to our seed (OPT) pretraining corpus. C4 consists of 393M documents totaling 220B BPE tokens. We train on up to 168B tokens.

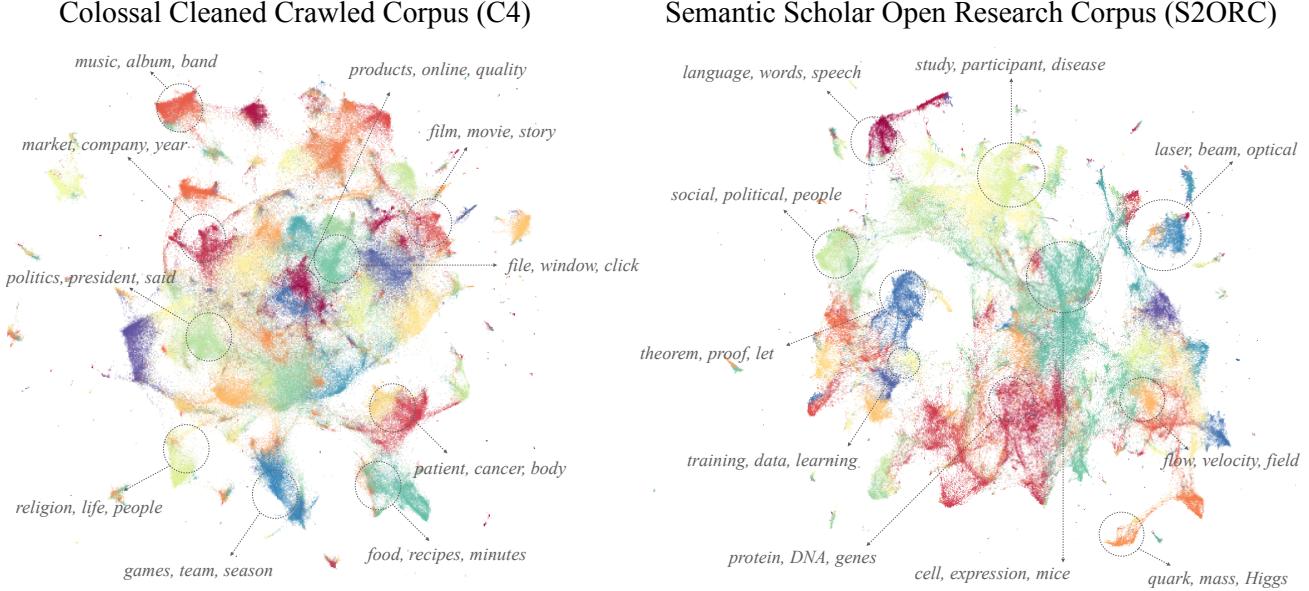
**S2ORC (Lo et al., 2019)** The Semantic Scholar Research Open Corpus (S2ORC) is a publicly available corpus of full-text academic papers from the Semantic Scholar.<sup>7</sup> The corpus spans 20 fields of study (e.g., Biology, Computer Science, Art), and contains 16M documents, totaling 87B BPE tokens. We train on up to 168B tokens over multiple epochs.<sup>8</sup>

**Evaluation data** For all experiments, we report language modeling perplexity on 200 randomly-sampled held out documents. Because S2ORC does not come with pre-defined validation data, we create a validation corpus by sampling an equal number of documents from each field of study.

<sup>6</sup><https://huggingface.co/datasets/c4>

<sup>7</sup><https://allenai.org/data/s2orc>

<sup>8</sup>While it is not common to train large LMs for multiple epochs, we do not observe overfitting in any of our experiments, consistent with other studies that train LMs on academic literature for multiple epochs (Taylor et al., 2022).



**Figure 4. We train and evaluate on two large text corpora (§3.1).** C4 (left; Raffel et al. 2019) and S2ORC (right; Lo et al. 2019) are diverse and contain many different clusters of text, indicated by these UMAP visualizations of 400K random documents in each corpus, colored with 32 automatically discovered and annotated clusters. See §7.3 for the description of our clustering and annotation procedure, and Figure A in the appendix for annotations of all clusters in these plots.

### 3.2. Experimental Setup

**Clustering the data** We segment each corpus using balanced  $k$ -means clustering for  $k \in \{2, 4, 8, 16, 32, 64, 128\}$  (§2.1). To train the clustering models, we first embed all data with a tf-idf vectorizer using scikit-learn,<sup>9</sup> with minimal assumptions: we only remove stop-words from a fixed lexicon and replace numbers with a dummy token. We then reduce the dimensionality of the resulting embeddings; we perform truncated SVD with 100 dimensions, then normalize the vector by removing its mean and scaling to unit variance, which we observed in initial experiments improved the clustering quality. Finally, these representations are clustered using a custom Pytorch implementation.<sup>10</sup> We present learned clusters and visualizations in Figure 4 and Figure A (in the appendix). We use a single shard of each training corpus (384K documents for C4, 155K documents for S2ORC) to train the clustering model and its embedder. No evaluation data is used in this process.

**Seed LM** As LMs trained on diverse corpora make for better seeds (Li et al., 2022), we use pretrained OPT language models (Zhang et al., 2022) as our seed for all experiments.

**Model hyperparameters** We use the OPT architecture implemented in Metaseq (Zhang et al., 2022). We use OPT-

1.3B for the initial set of experiments, and replicate our experiments with OPT-6.7B. Following Zhang et al. 2022, we use the GPT-2 vocabulary of 50,257 BPE types (Radford et al., 2019), and train with 2,048-token sequences, across document boundaries. We prepend a beginning-of-document token to each document. We set dropout to 0.1 for all parameters except those of the embedding layer.

**Training hyperparameters** For all models, we fix the learning rate to that used during OPT pretraining (2e-4 for 1.3B parameter models; 1.2e-4 for 6.7B parameter models; Zhang et al. 2022) using a linear decay learning rate schedule to zero (with no warmup), which we found to work well for most settings after a grid search of fastest learning rates that avoided divergence. We use a batch size of 8 for each GPU, and train with fp16 and fully-sharded data-parallel (Artetxe et al., 2021). We train on NVIDIA V100 32GB GPUs. All models are trained with Metaseq (Zhang et al., 2022). For a given number of clusters  $k$  and total GPU budget  $n$ , each ELM is allocated  $n/k$  GPUs, keeping the total effective number of FLOPs fixed across models exposed to the same number of tokens. See §A.2 for more details.

**Scaling** We train for a total of 10K steps in each run; to expose the model to more tokens, we increase the total GPU budget proportionally, up to 64 GPUs. We simulate larger budgets, up to 1024 GPUs, by increasing gradient accumulation steps with 64 GPUs. This method of scaling increases the model’s effective batch size for the same number of

<sup>9</sup><https://scikit-learn.org/>

<sup>10</sup><https://github.com/kernelmachine/balanced-kmeans>

steps, and maintains near constant run-times across our many experiments. This experimental setup also means that as the number of clusters increases, the overall set of ELMs is exposed to more data with less simultaneous computation among GPUs.

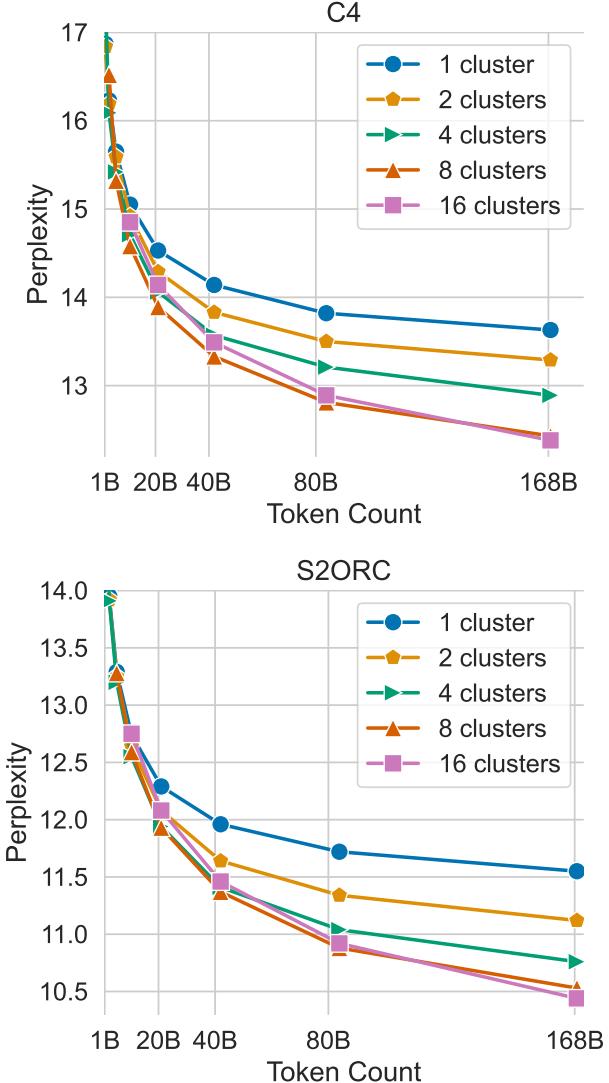
Other ways of training on more data (e.g., by keeping total batch size fixed and increasing step count) may yield different results. The best batch size and learning rate combinations for training language models are likely specific to a variety factors, including the model size, dataset, and total compute available (Shallue et al., 2018; McCandlish et al., 2018; Yang et al., 2021). In preliminary experiments, we found that expert models benefit from faster learning rates and larger batch sizes. Given a sufficiently large batch size, experts are robust to a variety of learning rates. Our larger budget experiments might benefit from higher learning rates, but we leave further tuning for future work.

**Inference** One of the key hyperparameters for inference is the temperature  $T$  (Equation 3), which governs the sharpness of the probability distribution over experts for a given context. We find that setting  $T=0.1$  works well for most settings (see §A.6 for more details). We also compute the nearest cluster centers for every incoming context, regardless of how stable the cluster assignments already are for a document. However, we find that these assignments can be fixed for the second half of a document with no drop in perplexity; this can further speedup inference. The other important hyperparameter is the top-k value, which sparsifies the probability distribution over experts. For our core experiments in §4.1, we set top-k to the total number of experts we have trained for each model. We explore the effect of enforcing sparsity with lower top-k values in §4.3.

**Baselines** In our primary experiments (§4), we compare with a strong dense baseline (i.e., our 1-cluster model) following OPT pretraining. We also progressively increase the number of clusters we train with for a fixed number of tokens. In subsequent experiments (§6), we compare to MoE language models initialized from a dense checkpoint.

### 3.3. Making Fair Model Comparisons

We follow the recommendations of Dehghani et al. (2021) and report results with multiple cost metrics, and detail our choices here. When comparing model training budgets, we are primarily concerned with the true monetary cost of model training, which is typically billed in direct proportion to GPU-time. Model inference comparisons have two main considerations: monetary cost incurred by the model deployer, again measured in GPU-time, and latency for end-users, or wall-clock time (i.e., how slow a model inference is for an end-user).



**Figure 5. Increasing cluster count in C-BTM improves language modeling performance for a fixed compute budget (§4.1).** Performance of ELMs trained with C-BTM as a function of the total number of tokens trained on, which, in our experiments, equals FLOP count. Training with more than one cluster always outperforms the compute-matched, single cluster dense model, and we observe improving performance (and in §4.2, faster updates) as we increase the number of clusters.

We explicitly do *not* compare or match the number of model parameters during training, which has minimal bearing on the cost of model training separately from its influence on GPU-time. The number of training parameters is a particularly misleading cost measure that is unsuitable for sparse models, since they can maintain the FLOPs and inference speed of dense models despite training many more parameters (Dehghani et al., 2021).

**Training GPU-time** Assuming fixed hardware, GPU-time during model training is determined mostly by FLOPs and inter-machine communications. However, prior work typically only FLOP-matches, ignoring the additional inter-GPU communications incurred by some models (e.g., MoE) that increase training costs. Ideally, our comparisons could directly fix GPU-time. This is challenging in practice, as even identical computations on the same GPU node at different times can vary wildly in speed due factors like temperature, other activity on the node, or the quality of GPU interconnect. To maintain consistency and fairness despite these confounds, our results compare FLOP-matched models with the same training data budget over the same number of updates (§4.1), but also report the speed of training for each FLOP-matched model (§4.2). This allows us to disentangle and accurately reflect multiple cost metrics of training. Since, in our experiments, models exposed to the same number of tokens incur the same number of FLOPs, we use training data size as a more interpretable measurement of the overall training budget (see §A.2 for more details).

**Inference GPU-time** Inference GPU-time is also primarily the result of FLOPs and communication costs. Since communication during inference is minimal, we compare FLOPs via inference parameters (§4.3). We do not account for the FLOPs of the C-BTM router, which varies based on the clustering approach, and is relatively negligible.

**Inference latency** FLOPs is not an ideal metric for inference latency of our models, because C-BTM allows for parallel inference across ELMs. This means that if ELMs share the same architecture (e.g., OPT-1.3B), inference latency is always equivalent to that of a single ELM, regardless of the number of experts active. However, inference latency may be quite different between model architectures (e.g., OPT-1.3B and OPT-6.7B); we discuss this further in §4.4. As with inference GPU-time, we do not consider the latency of the C-BTM router.

## 4. Language Modeling Results

We begin with a set of experiments in which we train LMs with C-BTM on datasets from §3.1. We are interested in measuring how performance changes as we increase overall compute. We first compare models against training costs: *total training tokens* (§4.1) and *training time* (§4.2). Then, in §4.3, we compare model performance along an axis of inference costs: the *total parameter count at inference time*. Finally, in §4.4 we compare model performance by fixing both training and inference costs. Across all computational budgets, C-BTM provides substantial benefits over dense training, and performance improvements increase as the total compute grows.

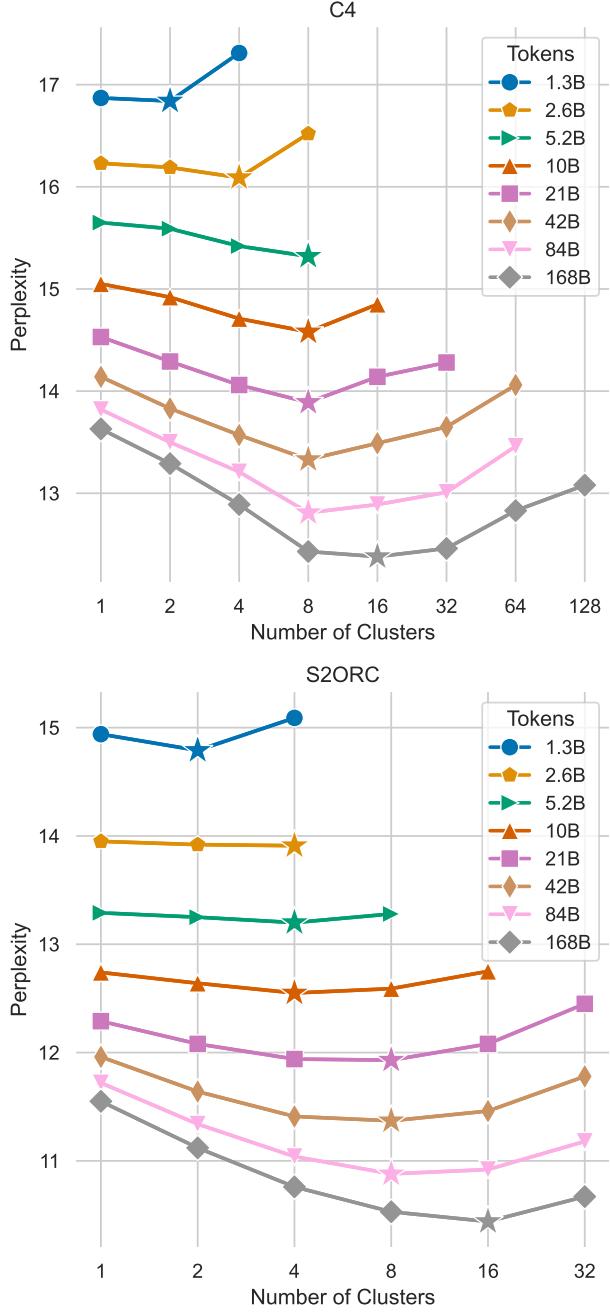


Figure 6. There exists an optimal cluster count for each compute budget (§4.1). The optimal cluster count increases as one increases the compute budget, but using too many clusters without sufficiently increasing compute can degrade performance. For both C4 and S2ORC, 16 clusters gets the best performance at the highest budget (168B tokens), although higher cluster counts still outperform the 1-cluster (dense) model ( $x = 1$  in this graph).

### 4.1. Controlling for Total Training Tokens

First, we compare model performance controlling for overall training data size (or equivalently, training FLOPs; §3.3).

Figure 5 shows evaluation perplexity on C4 and S2ORC with up to 16 clusters. Training on more than one cluster always outperforms training with a single cluster (i.e., a dense model). As the amount of training data grows, the gap between our models and the dense one widens, indicating that experts make better use of larger training datasets, possibly due to their increased specialization. These results suggest that as we increase the amount of data available, C-BTM benefits from more clusters.

However, Figure 6 shows that there exists an optimal cluster count for each token budget that we consider. Each number of clusters has a budget range in which they are optimal, and the optimum smoothly progresses from smaller to larger cluster counts as we increase the training data size. If we increase the cluster count past the optimum, each expert has an insufficient share of the data, resulting in worse performance.

Nevertheless, we observe that using more clusters than optimal for the highest token budget settings still outperforms the dense model. Since it is cheaper to train with more clusters for a fixed training data size due to parallelism, it may be preferable in some settings to train with a large number of clusters despite their less-than-optimal performance. Based on the trends we observe at this scale, we expect that higher cluster counts would become optimal as we scale the training data size even further.

The consistency of our results on C4 and S2ORC suggests that these general trends may be widely applicable to many datasets. However, the optimal number of clusters for a given computational budget is likely dataset specific. Future work may explore relationships between dataset features and the optimal cluster count.

These trends are consistent as we increase the size of our experts to 6.7B parameters (Figure 7), although the gaps between our baselines reduce, likely due to the substantial increase in pretraining FLOPs for OPT-6.7B.<sup>11</sup>

#### 4.2. Comparing Training Time

Now, we turn to comparing our models based on training times. We measure the speed of training each model with the maximum seconds-per-update for each training run.<sup>12</sup> For C-BTM models with more than one cluster, we use the maximum seconds-per-update across all experts. To make our comparisons fair, we only compare the training times of models that have the same effective batch size (§3.3). Our results are displayed in Figure 8. As we increase the number

<sup>11</sup>OPT-6.7B was pretrained for 1.83 ZFLOPs, while the OPT-1.3B was trained for 0.34 ZFLOPS.

<sup>12</sup>Other measures of seconds-per-update (e.g., average, median) tend to be noisy, due to factors such as dataloading and bursty GPU activity.

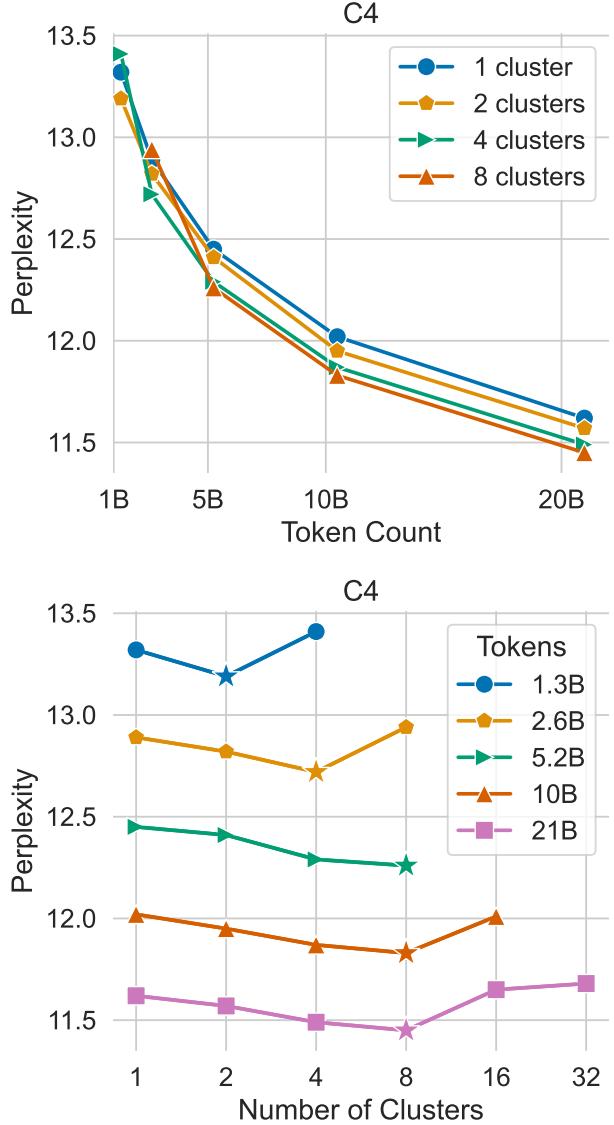
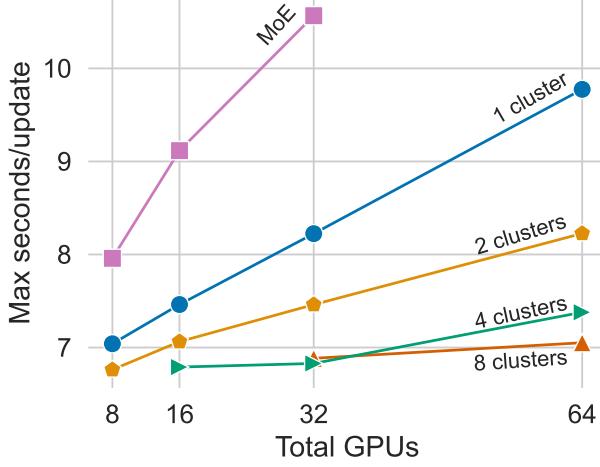


Figure 7. Our results are consistent even as we increase expert size to 6.7B parameters (§4.1). 8 clusters is optimal at 21B tokens, as it is for the 1.3B parameter ELMs. However, the gaps between these models are smaller, due to the substantial increase in pretraining FLOPs for the OPT-6.7B checkpoint.

of clusters and training data size, the update speed for C-BTM *increases*, since models with higher cluster counts use fewer GPUs per expert under a fixed budget, and there is no communication between experts. This suggests that C-BTM models with more clusters can be exposed to more data for the same amount time as dense models.

As discussed in §2.3, c-BTM also provides important practical speedups when training large LMs at scale. C-BTM divides large compute budgets among many models, such that we can train on 168B tokens with only 8 GPUs per expert in the 128-cluster setting. On shared multi-node clus-



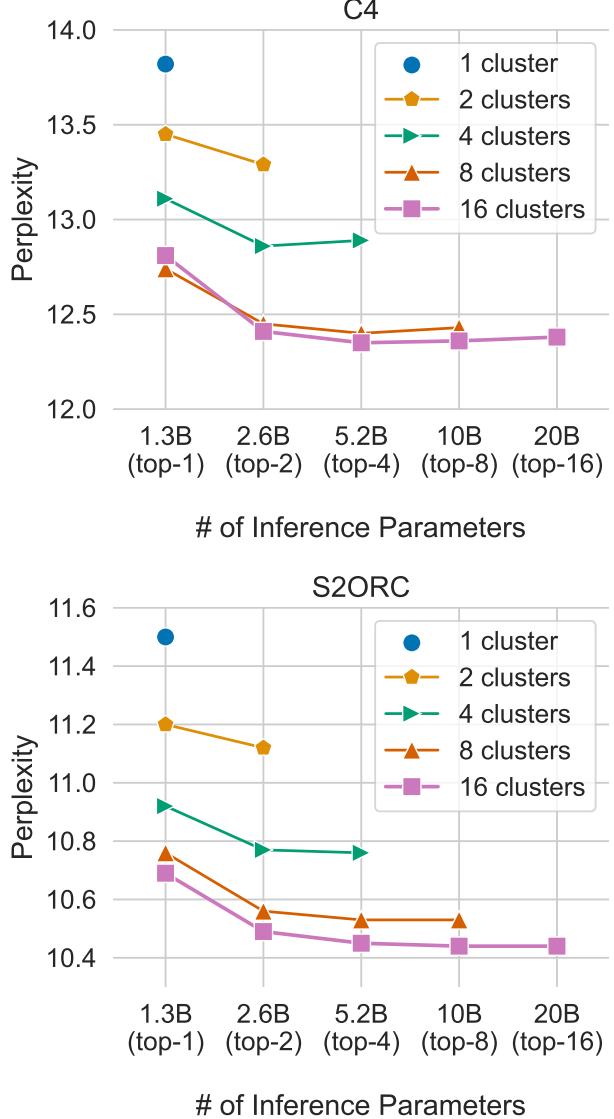
**Figure 8. Models trained with more clusters have faster updates as we increase the total compute (§4.2).** We display the maximum seconds-per-update for c-BTM and MoE models with varying GPU counts (across all experts). Under fixed compute, training with more clusters uses fewer GPUs per expert, and c-BTM avoids communication between experts, resulting in faster updates. On the other hand, MoE models are much slower to train, due to extensive communication between experts (§6.3), as well as additional FLOPs from top-2 routing (Artetxe et al., 2021).

ters, allocating many smaller jobs incurs shorter cumulative wait times than a single, large synchronous job, since they can make more efficient use of shared resources, and run on short-lived, idle nodes (Wortsman et al., 2022). Furthermore, large LM training is prone to node failures, gradient spikes, and other unexpected behaviors (Zhang et al., 2022). With dense models, when one node fails, all nodes must restart due to synchronization. With c-BTM, experts are trained independently; if a node fails, only the corresponding expert needs to be restarted, and all other experts are unaffected.

### 4.3. Controlling for Inference Costs via Parameter Count

Comparing models with just training budgets ignores the fact that c-BTM inference GPU-time costs grow as we increase the number of clusters, since we train more parameters. To mitigate these costs, we can use the top-k function (Equation 3) to dynamically use a subset of experts for each incoming context during evaluation (§2.2). Next, we study the effect of inference parameter count on model performance. We focus on the largest training budget (i.e., 16B tokens) for these experiments.

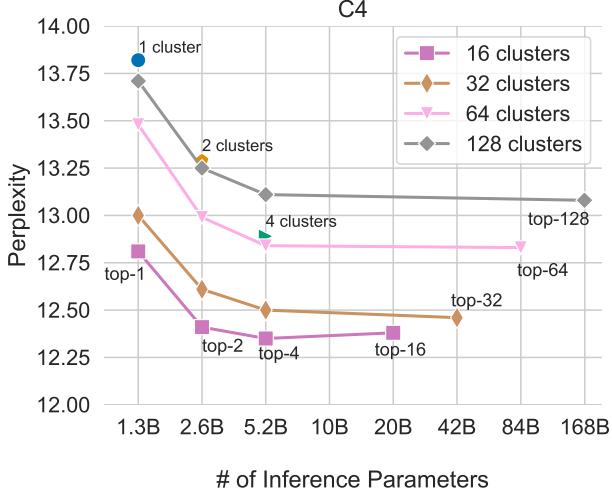
Results (Figure 9) show that despite training many more parameters, training c-BTM with many clusters and then using only the top-1 expert still outperforms the dense model. Further, using the top-2 or top-4 experts yields comparable



**Figure 9. Sparse top-k inference performance at 168B token budget (§4.3).** ELMs perform well even with heavily sparsified inference. Top-1 inference substantially outperforms the densely trained baseline at no additional inference cost, and top-2 and top-4 inference performs comparably to (and is sometimes slightly better than) activating all experts. In our setup, inference parameters are proportional to inference FLOP count (§3.3).

performance to activating all experts. Sometimes we observe that sparsifying can even slightly *improve* performance over using all experts (for example, see the 16 cluster model for C4 in Figure 9). We speculate that having all experts active may introduce interference effects from experts that are specialized to clusters unrelated to test-time contexts.

Our results in Figure 10 suggest that sparsifying even larger expert models (i.e., those with more clusters than the optimal



**Figure 10. Train large, then sparsify (§4.3).** Despite using more than the optimal cluster count for the 168B token budget, sparsifying the 32, 64, and 128-cluster models with top-1, top-2, or top-4 experts is usually better than training 1-, 2-, or 4-cluster models.

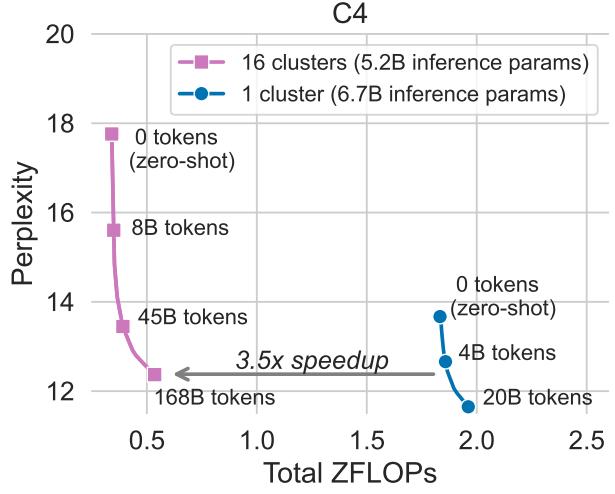
for a given token budget) is still highly effective. At the most extreme setting, using the top-1 expert for the 128 cluster model (using 0.7% of total parameters at inference time for each context) still outperforms the dense model, and the top-4 expert model (3.1% of total parameters) performs comparably to using all experts.

These results suggest that C-BTM results in a highly sparse LM, and that inference costs can be kept constant even as the number of experts grows, though additional experts can be added to further boost performance.

#### 4.4. Comparing to a Larger Dense Model

In our final comparison of this section, we consider both training and inference costs together. We compare a 6.7B 1-cluster (dense) model and C-BTM model with 1.3B parameter experts, which uses 16 clusters (optimal in our experiments from §4.1) and top-4 inference, resulting in 5.2B inference parameters. This C-BTM model has lower inference cost than the larger 6.7B parameter dense model (§3.3). The former uses fewer inference parameters, incurring a smaller inference GPU-time cost, and has lower latency, comparable to that of a single 1.3B-parameter ELM.

We compare the FLOPs used to train each model. Following Artetxe et al. (2021), we build continuous efficiency curves by interpolating between our empirical observations. Specifically, we calculate the speedup between our cluster expert models and dense model by interpolating between the discrete observations of perplexity values for a given empirical number of FLOPs.<sup>13</sup> Our goal is to identify the FLOP



**Figure 11. Training with C-BTM is substantially more efficient than training a larger dense LM (§4.4).** We train a 16-cluster C-BTM model and use top-4 inference, resulting in a 5.2B parameter LM, and compare its performance with a 6.7B parameter dense LM. The C-BTM model at 168B tokens achieves the same perplexity on C4 as a 6.7B dense model with 3.5x fewer ZFLOPs. The total ZFLOPs includes the cost of pretraining the seed OPT checkpoints.

count necessary to achieve a particular perplexity value. If ELMs trained with C-BTM achieve the same perplexity as the dense model with half the FLOPs, we conclude that C-BTM achieves a 2× speedup.

Our results are presented in Figure 11. A smaller C-BTM model, exposed to 168B tokens of text, can achieve the same perplexity as the larger 6.7B dense model with 3.5× speedup. These speedup estimates are dependent on the amount of pretraining performed on each model. Future work may perform these experiments with larger models and many more ELMs.

#### 4.5. Summary

Our results demonstrate that controlling for a variety of different types of computational budget, C-BTM outperforms dense training in language modeling. Furthermore, we demonstrate that C-BTM results in an effective *sparse* language model, where the top-1, top-2 and top-4 experts from models with at least 8 clusters significantly outperform 1-cluster, 2-cluster and 4-cluster models. These results suggest the possibility of outperforming dense models by increasing margins, while keeping both training and inference costs fixed, as compute and the number of experts grow.

<sup>13</sup>See §A.3 for details on this interpolation.

↓ Model (inference parameters)	Few-shot Text Classification Accuracy (%)						
	AGNews Topic	DBPedia Topic	SST-2 Sentiment	Amazon Sentiment	Phrasebank Sentiment	Twitter Hatespeech	Average
Random chance	25.0	7.10	50.0	50.0	33.3	50.0	35.9
OPT (1.3B)	42.9	57.2	72.8	81.3	72.5	<b>65.1</b>	65.3
OPT (6.7B)	51.9	58.9	77.0	83.8	76.4	39.6	64.6
1-cluster (1.3B)	47.4	61.1	80.2	80.7	66.6	60.9	66.2
1-cluster (6.7B)	<b>68.1</b>	62.4	80.7	<b>84.9</b>	<b>80.6</b>	37.4	69.0
C4 16-cluster; top-1 (1.3B)	47.1	<b>62.9</b>	74.3	79.1	72.9	56.4	65.4
16-cluster; top-4 (5.2B)	49.3	62.3	80.0	81.3	78.7	61.3	68.8
16-cluster; top-16 (20.8B)	50.6	62.0	<b>84.0</b>	83.2	78.6	61.7	<b>69.9</b>

**Table 1. C-BTM models outperform dense counterparts on downstream text classification tasks (§5.2).** We display accuracy of models from §4 on six text classification tasks, using eight demonstrations for each example and no additional fine-tuning. We report accuracy averaged over five random seeds. The 1- and 16-cluster models are trained on 168B tokens of C4 (i.e., our highest budget). The 16-cluster model, with top-4 or top-16 inference, always outperforms the 1-cluster model, and top-1 inference usually outperforms the 1-cluster model at no additional inference cost. We include average performance of models across tasks for readability.

## 5. Downstream Task Results

Do the trends from §4 extend to downstream settings? To begin to answer this question, we perform few-shot evaluation on six downstream text classification tasks. We indeed find that models trained with C-BTM outperform their dense counterparts in these settings.

### 5.1. Experimental Setup

**Tasks** We experiment with six text classification tasks, spanning topic, sentiment, and hatespeech classification. Details of the datasets are in Appendix A.7.

**Few-shot inference** We perform 8-shot evaluations. For each task, we randomly sample 8 examples with their labels from the train set, and prepend them as demonstrations for each test example. For C-BTM models, we estimate ensemble weights for each example by passing both the example and the demonstrations through our pretrained clusterer (§2.2). We calculate the probability of each label for the task under the model, and report accuracy by counting the proportion of test examples where the gold label has the highest probability. We report average accuracy over 5 random seeds. We leave careful analysis of C-BTM with varying numbers of demonstrations and few-shot inference techniques to future work.

**Baselines** We compare the performance of 1- and 16-cluster C-BTM models trained on 168B tokens of C4 (i.e., our highest budget from §4). For the 16-cluster model, we also perform top-1 and top-4 inference (§4.3). We additionally compare against a random baseline, the original OPT-1.3B and 6.7B models (without any additional training), and the 6.7B parameter 1-cluster model trained on 20B tokens of C4.

### 5.2. Results

Our results in Table 1 show that the 16-cluster C-BTM model always outperforms the 1-cluster, 1.3B parameter baseline, sometimes dramatically. This aligns with our language modeling results (§4.1). The 1-cluster model achieves lower accuracy than OPT-1.3B on some tasks despite additional training, suggesting that our models may suffer from catastrophic forgetting, since the C4 corpus is out-of-domain to OPT.

Nevertheless, the 16-cluster model outperforms OPT-1.3B on all tasks other than Twitter. Also, top-1 and top-4 inference matches or exceeds using all experts in some settings, consistent with our language modeling results in §4.3. We examine the clusters associated with the most likely experts for each task, and find that their top-terms are relevant to the task’s domain (Table 10 in the appendix). This supports our hypothesis that C-BTM is able to leverage any part of the corpus which is in-domain to the test task, even if the training corpus as a whole might be sufficiently out-of-domain as to have a negative effect on performance.

We then mirror the analysis in §4.4, by comparing our 16-cluster models to 6.7B parameter dense models. First, we observe that our 1-cluster 6.7B model outperforms OPT-6.7B on all tasks except Twitter, possibly because this model has had less exposure to C4, and suffers from less catastrophic forgetting. Our 16-cluster model performs comparably to both 6.7B models, and on multiple tasks, our 16-cluster model *outperforms* both 6.7B models, which have been trained with at least  $3.5 \times$  more compute (§4.4). With top-4 inference, C-BTM models activate even fewer parameters than the 6.7B parameter models, yet perform comparably. These results corroborate our findings in §4.4 that compared to larger dense models, models trained with C-BTM have more training efficiency and lower inference latency, and result in comparable or better performance.

In separate experiments, we observe that routing examples to experts based on their performance on few shot examples, rather than their clusters, results in even better downstream task performance with c-BTM models. This is likely because few-shot performance depends on factors such as example order, label distributions, and the quality of the demonstrations, which are not necessarily tied to the domain of the task (Min et al., 2022; Lu et al., 2022). We analyze this finding further in §A.7, and leave more careful development of routing protocols for downstream tasks to future work.

### 5.3. Summary

We demonstrate that, consistent with the language modeling results in §4.1, C-BTM improves downstream performance on a variety of few-shot text classification tasks. C-BTM models consistently outperform dense 1-cluster baselines, and usually outperform the original OPT models, despite being trained on an out-of-domain corpus. We also find that top- $k$  activation reduces inference costs with negligible effects on downstream task performance. C-BTM models perform comparably to larger, 6.7B OPT and 1-cluster dense baseline models, despite being trained with 3.5x less compute, and even when activating fewer inference parameters.

## 6. Comparing to Mixture-of-Experts

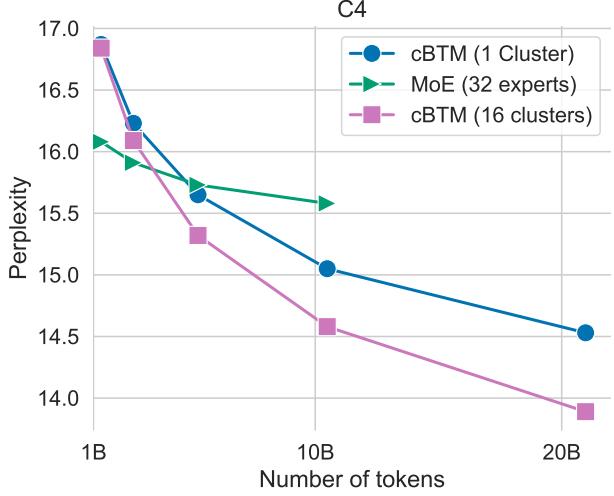
Finally, we compare C-BTM against an alternative sparse LM, a mixture-of-experts (MoE) which learns a routing between tokens and feedforward experts in the transformer (Lepikhin et al., 2021; Fedus et al., 2021). As discussed in §2.5, C-BTM is substantially simpler than MoE.

### 6.1. Sparse Upcycling

To mirror C-BTM seed initialization, we initialize our MoE with a dense checkpoint. We use the *sparse upcycling* technique from Komatsuzaki et al. (2022). Upcycling a dense model into an MoE with  $k$  experts entails initializing shared parameters (e.g., attention and embedding layers) and  $k$  expert parameters (e.g., every other feedforward layer) from a dense checkpoint, and initializing new parameters for the router. Then the model is simply trained as an MoE. Here, we use top-2, token-level routing (Lepikhin et al., 2021).

### 6.2. Experimental Setup

**Hyperparameters** We train an MoE with sparse upcycling on C4, starting from OPT-1.3B and using the same general experimental setup detailed in §3.2. We follow the settings from Komatsuzaki et al. (2022) as closely as possible. We conducted experiments with 8, 16, 32, 64, and 128 experts for each compute budget. 8 and 16 experts are similar to, but slightly worse than, 32 experts; 64 experts and 128 experts consistently have exploding losses, and the



**Figure 12. MoE underperforms c-BTM (§6.3).** We compare a 32-expert MoE with top-2 routing (Lepikhin et al., 2021) trained with sparse-upcycling (Komatsuzaki et al., 2022). While the MoE outperforms C-BTM models with 16 experts at small budgets, it fails at larger budgets, even under-performing the dense model. We speculate this could be due to distribution shifts after pretraining, which might increase the instability of upcycling.

few which successfully train are also similar to but slightly worse than 32 experts. In general, we find that both large expert count (and higher compute budgets) result in sparse upcycling training instability.

We use 32 experts in our MoE, a capacity factor of 2, and continue training without resetting the optimizer from that used during OPT pretraining. We set all hyperparameters to be the same as our c-BTM models (§3.2), except that we use a peak learning rate of 2e-5, which we found to be the highest learning rate that did not result in divergence after a sweep. We release our code for sparse upcycling, implemented in Fairseq (Ott et al., 2019), publicly.<sup>14</sup>

**Baselines** We compare the 32-expert MoE LM to 1-cluster (i.e., dense) and 16-cluster C-BTM models.

## 6.3. Results

The MoE expends more FLOPs than the other models due to the additional feedforward layer at every other transformer block for top-2 routing, as well as the routing projection (Artetxe et al., 2021). For clarity and consistency, we update-match and separately report GPU-time cost of updates, as in §4.1.

We display results in Figure 12. MoE substantially underperforms C-BTM with 16 clusters as the compute budget

<sup>14</sup><https://github.com/kernelmachine/moe-fairseq>

grows. Surprisingly, we observe that with enough compute, MoE underperforms even the dense LM, and that when compute budgets are further increased, losses consistently explode. This suggests that sparse upcycling is highly unstable, possibly due to distribution shifts from pretraining.

In Figure 8, we compare the maximum seconds-per-update of the MoE model with that of the C-BTM models. MoE becomes substantially slower as more GPUs are used during training. This is largely due to expensive all-to-all communication that occurs between experts during MoE training, which is necessary to route tokens to experts (Artetxe et al., 2021). On the other hand, our method does not have any shared parameters between experts. Also, MoE expends more FLOPs during training than the C-BTM models. Finally, MoE still requires synchronous compute to train experts due to shared parameters, so they are also afflicted by the practical difficulties of training dense language models at scale §4.2.

#### 6.4. Summary

Our results suggest that language models trained with C-BTM substantially outperform MoEs trained to the same budget. The performance gains of our technique likely are a result of the simplicity of our deterministic routing (based on empirically derived clusters), instabilities associated with sparse upcycling, and other factors.

### 7. Analysis

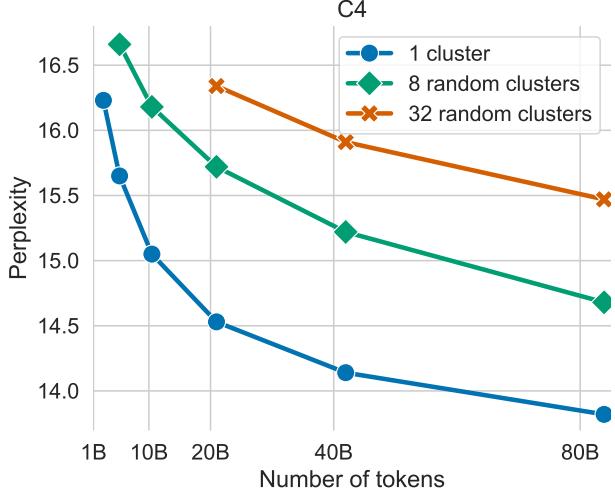
In §4, §5, and §6, we demonstrate that C-BTM outperforms compute-matched densely trained and MoE baselines. We now study our clustering approach in more detail and describe its effect on overall performance of C-BTM.

#### 7.1. Is clustering important?

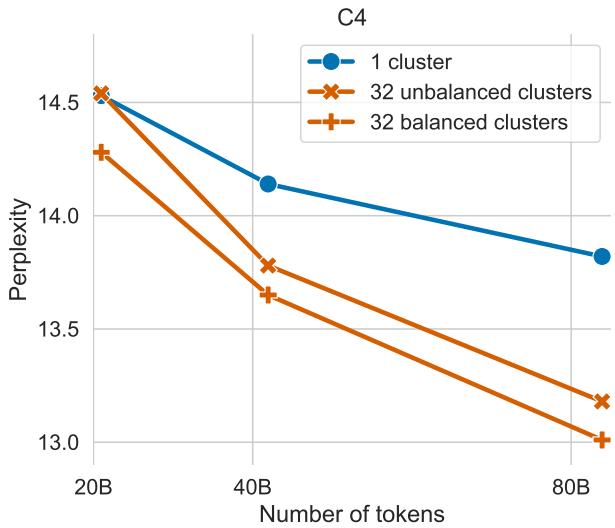
To assess the importance of the clustering algorithm, we perform C-BTM as above, except that we assign each document to a random cluster, rather than a learned one. This is equivalent to the random ensemble baseline from Li et al. (2022). Results in Figure 13 demonstrate that using random clusters dramatically underperforms both our method and the dense baseline. Therefore, cluster specialization is vital for C-BTM. This confirms results from Li et al. (2022), who found that domain specialization of ELMs is critical for performance the ensemble, as well as those from Jang et al. (2023), who show that instruction-specialized ELMs transfer to other tasks with similar instructions.

#### 7.2. Is it important to balance the clusters?

Applying a balancing constraint in  $k$ -means avoids the degenerate outcome of a long tail in cluster sizes (Chang et al.



**Figure 13. Random clusters underperform (§7.1).** Training experts on random clusters underperforms even the dense, single cluster model, showing the importance of cluster specialization. Random clusters become more harmful as the cluster count grows.



**Figure 14. Cluster balancing improves performance (§7.2).** When training on C4 with 32 clusters, balancing consistently improves over the unbalanced version, suggesting that cluster size is an important aspect to C-BTM.

2014). Indeed, with 10K documents of held out validation data in C4, we observe that balanced clustering significantly increases the median cluster size, and narrows its range, relative to an unbalanced baseline (§A.4). To assess the effect of balancing cluster size on the performance of C-BTM, we perform C-BTM with a  $k$ -means clustering model but remove the balancing constraint. For the 8-cluster model, we observe that balancing has little effect. However, for the 32-cluster model (Figure 14), unbalanced clustering consistently leads to worse performance. These results suggest

that balancing becomes more important as one scales the number of clusters. This is consistent with separate experiments that show that the long tail in cluster sizes becomes a more consistent problem with higher cluster counts.

### 7.3. Are clusters well defined? Do experts specialize?

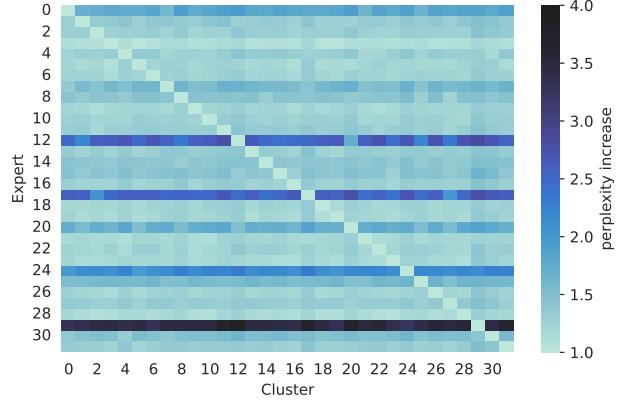
Since we use tf-idf as our document embedder in C-BTM, we can perform an inverse transform from the cluster centers into the vocabulary space to identify terms that most likely would have been embedded as the cluster center. We display the top five terms per cluster in §A.1. We observe that as the number of clusters increases, the top terms across clusters become more specific and varied.

Next, we study whether ELMs trained on these clusters specialize. Using the 32-cluster model trained on 84B tokens of C4, we compute perplexity of all experts across 200 held out documents in each cluster. For each cluster, we then measure the ratio of the perplexity of each expert to the perplexity of the expert trained on that cluster. We display those ratios in Figure 15. We see that all experts perform best on their own cluster. Some experts do not transfer well at all to other clusters, while others do reasonably well. Cross referencing with the cluster term tables in §A.1, we see that cluster experts 3 and 5 tend to generalize well and the top terms in these clusters are more generic (with words such as *"just, like, love"*). The experts specialized to content such as *"site, page, website"* (cluster 0) and *"app, phone, video"* (cluster 29), tend to do poorly on all other clusters.<sup>15</sup> These results suggest that experts specialize to their cluster. We infer that the success of sparse C-BTM inference is a result of expert specialization, and that C-BTM performance gains may be partially due to the sample efficiency of specialized training.

### 7.4. How do clusters and metadata domains compare?

The key motivation for C-BTM is to remove the reliance on metadata to delineate the domains to which ELMs specialize. How well do clusters reflect the dataset segmentation produced by metadata? We use S2ORC to study this question. First, we align the learned clusters from a 32-cluster model with the fields-of-study metadata available from S2ORC (Lo et al., 2019). Then we visualize the overlap between the metadata and clusters (Figure 16). We observe only a partial alignment between metadata and clusters in S2ORC. Documents with some metadata labels (e.g., Environmental Science, Political Science) are mostly assigned to their own clusters, while documents with other labels (e.g., Computer Science, Physics) are distributed across multiple clusters.

<sup>15</sup>This result imply that cluster experts can be removed to filter out unwanted generations after training, without significantly impacting performance on other content. We leave such exploration to future work.

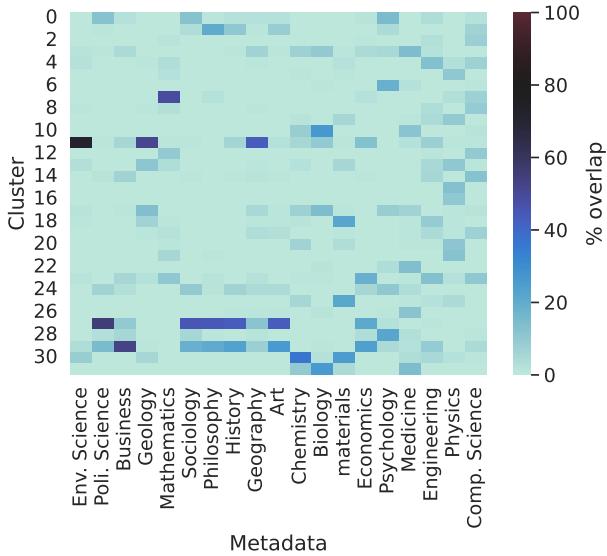


**Figure 15. Experts specialize to their cluster (§7.3).** Here, we use the 32-cluster model trained on 84B tokens of C4. Each cell is a ratio between one expert’s test perplexity on a cluster to that of the expert trained on that cluster. The diagonal indicates that experts perform best on the cluster they were trained on. Many experts transfer well across clusters, but some do not.

The partial alignment between metadata and clusters suggests that C-BTM models may not have the same performance as those trained with metadata labels to delineate domains. To investigate this hypothesis further, we perform experiments using a subset of the Pile (Gao et al., 2021) to compare the performance of experts trained with metadata and experts trained with clusters. See §A.5 for more details on this corpus. We observe that experts trained with learned clusters perform slightly better than those with metadata labels on a held out validation data (Table 8 in the appendix). Both techniques perform better than training with just a single cluster on the Pile, confirming our results from §4.1. These results imply that metadata may not correspond with the most optimal segmentation of the corpus. However, using metadata has the advantage of interpretability and simplicity, and metadata can identify domains that are not just lexically driven (e.g., Lucy & Bamman, 2021; Gururangan et al., 2022). Future work may explore combining metadata- and cluster-specialized ELMs.

### 7.5. Summary

Our analysis demonstrates that the improvements from C-BTM are not the result of ensembling alone. Various components of our training method, particularly the nature of the learned clusters, play a critical role in C-BTM performance. Improving the representation of domains in a corpus, perhaps using other pretrained representations (Aharoni & Goldberg, 2020) or more sophisticated clustering algorithms (Ester et al., 1996; Chronopoulou et al., 2022), are likely to improve C-BTM performance.



**Figure 16. Clusters and metadata do not perfectly align (§7.4).** Each cell in the heatmap is the % overlap between a cluster and a metadata label identifying the field-of-study of a document in S2ORC; high overlap indicates that most documents with the corresponding label get assigned to the corresponding cluster. While documents with certain labels (e.g., Environmental Science, Political Science, Business) get primarily assigned to a single cluster, documents with other labels (e.g., Engineering, Physics, Computer Science) are distributed across multiple clusters.

## 8. Related Work

**Sparse Models** c-BTM is closely related to sparse models which activate only a subset of parameters (Evcı et al., 2020; Mostafa & Wang, 2019; Dettmers & Zettlemoyer, 2019). c-BTM is inspired by MoE, but is much simpler and more efficient to train. Most MoE methods rely on training token-based routing mechanisms (Lepikhin et al., 2021; Fedus et al., 2021; Lewis et al., 2021; Roller et al., 2021), but others rely on task (Kudugunta et al., 2021) or domain (Gururangan et al., 2022) routing.

**Expert Language Models** As we note throughout the study, this work is most directly related to BTM (Li et al., 2022). BTM is in turn partially inspired by prior work on variations of MoE models (Jacobs et al., 1991), but especially DEMix layers (Gururangan et al., 2022), which replace transformer feedforward layers with metadata-defined domain experts. Jang et al. (2023) train expert language models on instruction-based tasks, while Pfeiffer et al. (2022) train expert language models on different languages.

**Cluster Routing** Chronopoulou et al. (2022) and Chronopoulou et al. (2023) use hierarchical clustering to identify domains to specialize adapter experts to, and use the adapters in an ensemble or parameter average at inference

time. Duan et al. (2021) build ensembles of task-specific models by clustering the training data of supervised tasks. Gross et al. (2017) employ a cluster-based router similar to ours in an image classification setting using ResNets. However, they use a hard routing (or only activate a single expert) in both training and inference, while we use hard routing during training but ensemble experts during inference. Our inference technique is inspired by nearest neighbor retrieval mechanisms in language models (Khandelwal et al., 2019; Shi et al., 2022).

**Communication-efficient training** Our study contributes to a line of research into communication-efficient algorithms for training large models. Some previous work proposes ways to train large dense models collaboratively over distributed networks of servers (Borzunov et al., 2022; Yuan et al., 2022). Other works focus on new forms of data (Gan et al., 2021), model (Ryabinin et al., 2023), and pipeline (Wang et al., 2022) parallelism to allow for model training on heterogeneous devices that can recover from node failures. Wortsman et al. (2022) propose a communication-efficient method of fine-tuning by training a collection of models with different hyperparameters on individual GPU nodes, and then averaging their parameters after training. Our work uses expert specialization for communication efficient training, and c-BTM can be combined with any of these other techniques to improve training efficiency.

## 9. Conclusion

We introduce c-BTM, a new technique to efficiently train sparse LMs. c-BTM splits a corpus into  $k$  clusters, trains an expert LM on each cluster, and creates a sparse ensemble during inference. We observe that the optimal number of clusters for c-BTM increases with the amount of data, and using more clusters also allows us to aggressively parallelize training to efficiently scale into massive datasets. Future work could investigate c-BTM in multitask or multilingual settings, the usefulness of multiple iterations of c-BTM on a corpus (perhaps with hierarchical clustering), or the possibility of combining metadata- and cluster-based routing to scale into many heterogeneous datasets in parallel.

## Acknowledgements

This paper benefited from thoughtful feedback from a number of people: Armen Aghajanyan, Tim Dettmers, Sneha Kudugunta, Stephen Roller, Swabha Swayamdipta, and Mitchell Wortsman.

## References

- Aharoni, R. and Goldberg, Y. Unsupervised domain clusters in pretrained language models. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pp. 7747–7763, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.692. URL <https://aclanthology.org/2020.acl-main.692>.
- Artetxe, M., Bhosale, S., Goyal, N., Mihaylov, T., Ott, M., Shleifer, S., Lin, X. V., Du, J., Iyer, S., Pasunuru, R., Anantharaman, G., Li, X., Chen, S., Akin, H., Baines, M., Martin, L., Zhou, X., Koura, P. S., O’Horo, B., Wang, J., Zettlemoyer, L., Diab, M., Kozareva, Z., and Stoyanov, V. Efficient large scale language modeling with mixtures of experts, 2021. URL <https://arxiv.org/abs/2112.10684>.
- Arthur, D. and Vassilvitskii, S. K-means++: The advantages of careful seeding. In *Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms*, SODA ’07, pp. 1027–1035, USA, 2007. Society for Industrial and Applied Mathematics. ISBN 9780898716245.
- Barbieri, F., Camacho-Collados, J., Espinosa Anke, L., and Neves, L. TweetEval: Unified benchmark and comparative evaluation for tweet classification. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pp. 1644–1650, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.findings-emnlp.148. URL <https://aclanthology.org/2020.findings-emnlp.148>.
- Bertsekas, D. P. Auction algorithms for network flow problems: A tutorial introduction. *Computational Optimization and Applications*, 1:7–66, 1992.
- Borzunov, A., Baranchuk, D., Dettmers, T., Ryabinin, M., Belkada, Y., Chumachenko, A., Samygin, P., and Rafel, C. Petals: Collaborative inference and fine-tuning of large models, 2022. URL <https://arxiv.org/abs/2209.01188>.
- Chang, X., Nie, F., Ma, Z., and Yang, Y. Balanced k-means and min-cut clustering, 2014. URL <https://arxiv.org/abs/1411.6235>.
- Chowdhery, A., Narang, S., Devlin, J., Bosma, M., Mishra, G., Roberts, A., Barham, P., Chung, H. W., Sutton, C., Gehrmann, S., Schuh, P., Shi, K., Tsvyashchenko, S., Maynez, J., Rao, A., Barnes, P., Tay, Y., Shazeer, N., Prabhakaran, V., Reif, E., Du, N., Hutchinson, B., Pope, R., Bradbury, J., Austin, J., Isard, M., Gur-Ari, G., Yin, P., Duke, T., Levskaya, A., Ghemawat, S., Dev, S., Michalewski, H., Garcia, X., Misra, V., Robinson, K., Fedus, L., Zhou, D., Ippolito, D., Luan, D., Lim, H., Zoph, B., Spiridonov, A., Sepassi, R., Dohan, D., Agrawal, S., Omernick, M., Dai, A. M., Pillai, T. S., Pellat, M., Lewkowycz, A., Moreira, E., Child, R., Polozov, O., Lee, K., Zhou, Z., Wang, X., Saeta, B., Diaz, M., Firat, O., Catasta, M., Wei, J., Meier-Hellstern, K., Eck, D., Dean, J., Petrov, S., and Fiedel, N. Palm: Scaling language modeling with pathways, 2022. URL <https://arxiv.org/abs/2204.02311>.
- Chronopoulou, A., Peters, M., and Dodge, J. Efficient hierarchical domain adaptation for pretrained language models. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 1336–1351, Seattle, United States, July 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.naacl-main.96. URL <https://aclanthology.org/2022.naacl-main.96>.
- Chronopoulou, A., Peters, M. E., Fraser, A. M., and Dodge, J. Adaptersoup: Weight averaging to improve generalization of pretrained language models. *ArXiv*, abs/2302.07027, 2023.
- Clark, A., Casas, D. d. l., Guy, A., Mensch, A., Paganini, M., Hoffmann, J., Damoc, B., Hechtman, B., Cai, T., Borgeaud, S., Driessche, G. v. d., Rutherford, E., Hennigan, T., Johnson, M., Millican, K., Cassirer, A., Jones, C., Buchatskaya, E., Budden, D., Sifre, L., Osindero, S., Vinyals, O., Rae, J., Elsen, E., Kavukcuoglu, K., and Simonyan, K. Unified scaling laws for routed language models, 2022. URL <https://arxiv.org/abs/2202.01169>.
- Dehghani, M., Arnab, A., Beyer, L., Vaswani, A., and Tay, Y. The efficiency misnomer, 2021. URL <https://arxiv.org/abs/2110.12894>.
- Dettmers, T. and Zettlemoyer, L. Sparse networks from scratch: Faster training without losing performance. *CoRR*, abs/1907.04840, 2019. URL <http://arxiv.org/abs/1907.04840>.
- Duan, Z., Zhang, H., Wang, C., Wang, Z., Chen, B., and Zhou, M. Enslm: Ensemble language model for data diversity by semantic clustering. In *Annual Meeting of the Association for Computational Linguistics*, 2021.
- Ester, M., Kriegel, H.-P., Sander, J., and Xu, X. A density-based algorithm for discovering clusters in large spatial databases with noise. In *Proceedings of the Second International Conference on Knowledge Discovery and Data Mining*, KDD’96, pp. 226–231. AAAI Press, 1996.
- Evci, U., Gale, T., Menick, J., Castro, P. S., and Elsen, E. Rigging the lottery: Making all tickets

- winners. In III, H. D. and Singh, A. (eds.), *Proceedings of the 37th International Conference on Machine Learning*, volume 119 of *Proceedings of Machine Learning Research*, pp. 2943–2952. PMLR, 13–18 Jul 2020. URL <https://proceedings.mlr.press/v119/evci20a.html>.
- Fedus, W., Zoph, B., and Shazeer, N. Switch transformers: Scaling to trillion parameter models with simple and efficient sparsity. *J. Mach. Learn. Res.*, 23:1–40, 2021.
- Fedus, W., Dean, J., and Zoph, B. A review of sparse expert models in deep learning, 2022. URL <https://arxiv.org/abs/2209.01667>.
- Gan, S., Lian, X., Wang, R., Chang, J., Liu, C., Shi, H., Zhang, S., Li, X., Sun, T., Jiang, J., Yuan, B., Yang, S., Liu, J., and Zhang, C. Bagua: Scaling up distributed learning with system relaxations, 2021. URL <https://arxiv.org/abs/2107.01499>.
- Gao, L., Biderman, S., Black, S., Golding, L., Hoppe, T., Foster, C., Phang, J., He, H., Thite, A., Nabeshima, N., Presser, S., and Leahy, C. The pile: An 800gb dataset of diverse text for language modeling, 2021. URL <https://arxiv.org/abs/2101.00027>.
- Gross, S., Ranzato, M., and Szlam, A. Hard mixtures of experts for large scale weakly supervised vision. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pp. 6865–6873, 2017.
- Gururangan, S., Lewis, M., Holtzman, A., Smith, N. A., and Zettlemoyer, L. DEMix layers: Disentangling domains for modular language modeling. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 5557–5576, Seattle, United States, July 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.nacl-main.407. URL <https://aclanthology.org/2022.nacl-main.407>.
- Hoffmann, J., Borgeaud, S., Mensch, A., Buchatskaya, E., Cai, T., Rutherford, E., de Las Casas, D., Hendricks, L. A., Welbl, J., Clark, A., et al. Training compute-optimal large language models. 2022.
- Jacobs, R. A., Jordan, M. I., Nowlan, S. J., and Hinton, G. E. Adaptive mixtures of local experts. *Neural computation*, 3(1):79–87, 1991.
- Jang, J., Kim, S., Ye, S., Kim, D., Logeswaran, L., Lee, M., Lee, K., and Seo, M. Exploring the benefits of training expert language models over instruction tuning, 2023. URL <https://arxiv.org/abs/2302.03202>.
- Khandelwal, U., Levy, O., Jurafsky, D., Zettlemoyer, L., and Lewis, M. Generalization through memorization: Nearest neighbor language models, 2019. URL <https://arxiv.org/abs/1911.00172>.
- Komatsuzaki, A., Puigcerver, J., Lee-Thorp, J., Ruiz, C. R., Mustafa, B., Ainslie, J., Tay, Y., Dehghani, M., and Houlsby, N. Sparse upcycling: Training mixture-of-experts from dense checkpoints, 2022. URL <https://arxiv.org/abs/2212.05055>.
- Kudugunta, S., Huang, Y., Bapna, A., Krikun, M., Lepikhin, D., Luong, M.-T., and Firat, O. Beyond distillation: Task-level mixture-of-experts for efficient inference, 2021. URL <https://arxiv.org/abs/2110.03742>.
- Lehmann, J., Isele, R., Jakob, M., Jentzsch, A., Kontokostas, D., Mendes, P., Hellmann, S., Morsey, M., Van Kleef, P., Auer, S., and Bizer, C. Dbpedia - a large-scale, multilingual knowledge base extracted from wikipedia. *Semantic Web Journal*, 6, 01 2014. doi: 10.3233/SW-140134.
- Lepikhin, D., Lee, H., Xu, Y., Chen, D., Firat, O., Huang, Y., Krikun, M., Shazeer, N., and Chen, Z. {GS}hard: Scaling giant models with conditional computation and automatic sharding. In *International Conference on Learning Representations*, 2021. URL <https://openreview.net/forum?id=qrwe7XHTmYb>.
- Lewis, M., Bhosale, S., Dettmers, T., Goyal, N., and Zettlemoyer, L. Base layers: Simplifying training of large, sparse models, 2021. URL <https://arxiv.org/abs/2103.16716>.
- Li, M., Gururangan, S., Dettmers, T., Lewis, M., Althoff, T., Smith, N. A., and Zettlemoyer, L. Branch-train-merge: Embarrassingly parallel training of expert language models, 2022. URL <https://arxiv.org/abs/2208.03306>.
- Lo, K., Wang, L. L., Neumann, M., Kinney, R., and Weld, D. S. S2orc: The semantic scholar open research corpus, 2019. URL <https://arxiv.org/abs/1911.02782>.
- Lu, Y., Bartolo, M., Moore, A., Riedel, S., and Stenetorp, P. Fantastically ordered prompts and where to find them: Overcoming few-shot prompt order sensitivity. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 8086–8098, Dublin, Ireland, May 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.acl-long.556. URL <https://aclanthology.org/2022.acl-long.556>.
- Lucy, L. and Bamman, D. Characterizing English variation across social media communities with BERT.

- Transactions of the Association for Computational Linguistics*, 9:538–556, 2021. doi: 10.1162/tacl\_a\_00383. URL <https://aclanthology.org/2021.tacl-1.33>.
- Maas, A. L., Daly, R. E., Pham, P. T., Huang, D., Ng, A. Y., and Potts, C. Learning word vectors for sentiment analysis. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pp. 142–150, Portland, Oregon, USA, June 2011. Association for Computational Linguistics. URL <https://aclanthology.org/P11-1015>.
- Malinen, M. I. and Fräntti, P. Balanced k-means for clustering. In *International Workshop on Structural and Syntactic Pattern Recognition*, 2014.
- Malo, P., Sinha, A., Korhonen, P., Wallenius, J., and Takala, P. Good debt or bad debt: Detecting semantic orientations in economic texts. *Journal of the Association for Information Science and Technology*, 65, 2014.
- McCandlish, S., Kaplan, J., Amodei, D., and Team, O. D. An empirical model of large-batch training, 2018. URL <https://arxiv.org/abs/1812.06162>.
- Min, S., Lyu, X., Holtzman, A., Artetxe, M., Lewis, M., Hajishirzi, H., and Zettlemoyer, L. Rethinking the role of demonstrations: What makes in-context learning work? In *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pp. 11048–11064, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. URL <https://aclanthology.org/2022.emnlp-main.759>.
- Mostafa, H. and Wang, X. Parameter efficient training of deep convolutional neural networks by dynamic sparse reparameterization. In Chaudhuri, K. and Salakhutdinov, R. (eds.), *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pp. 4646–4655. PMLR, 09–15 Jun 2019. URL <https://proceedings.mlr.press/v97/mostafa19a.html>.
- Ott, M., Edunov, S., Baevski, A., Fan, A., Gross, S., Ng, N., Grangier, D., and Auli, M. fairseq: A fast, extensible toolkit for sequence modeling, 2019. URL <https://arxiv.org/abs/1904.01038>.
- Pfeiffer, J., Goyal, N., Lin, X., Li, X., Cross, J., Riedel, S., and Artetxe, M. Lifting the curse of multilinguality by pre-training modular transformers. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pp. 3479–3495, Seattle, United States, July 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.naacl-main.255. URL <https://aclanthology.org/2022.naacl-main.255>.
- Radford, A., Wu, J., Child, R., Luan, D., Amodei, D., and Sutskever, I. Language models are unsupervised multitask learners. 2019.
- Rae, J. W., Borgeaud, S., Cai, T., Millican, K., Hoffmann, J., Song, F., Aslanides, J., Henderson, S., Ring, R., Young, S., Rutherford, E., Hennigan, T., Menick, J., Cassirer, A., Powell, R., Driessche, G. v. d., Hendricks, L. A., Rauh, M., Huang, P.-S., Glaese, A., Welbl, J., Dathathri, S., Huang, S., Uesato, J., Mellor, J., Higgins, I., Creswell, A., McAleese, N., Wu, A., Elsen, E., Jayakumar, S., Buchatskaya, E., Budden, D., Sutherland, E., Simonyan, K., Paganini, M., Sifre, L., Martens, L., Li, X. L., Kuncoro, A., Nematzadeh, A., Gribovskaya, E., Donato, D., Lazaridou, A., Mensch, A., Lespiau, J.-B., Tsimpoukelli, M., Grigorev, N., Fritz, D., Sottiaux, T., Pajarskas, M., Pohlen, T., Gong, Z., Toyama, D., d’Autume, C. d. M., Li, Y., Terzi, T., Mikulik, V., Babuschkin, I., Clark, A., Casas, D. d. L., Guy, A., Jones, C., Bradbury, J., Johnson, M., Hechtman, B., Weidinger, L., Gabriel, I., Isaac, W., Lockhart, E., Osindero, S., Rimell, L., Dyer, C., Vinyals, O., Ayoub, K., Stanway, J., Bennett, L., Hassabis, D., Kavukcuoglu, K., and Irving, G. Scaling language models: Methods, analysis & insights from training gopher, 2021. URL <https://arxiv.org/abs/2112.11446>.
- Raffel, C., Shazeer, N., Roberts, A., Lee, K., Narang, S., Matena, M., Zhou, Y., Li, W., and Liu, P. J. Exploring the limits of transfer learning with a unified text-to-text transformer, 2019. URL <https://arxiv.org/abs/1910.10683>.
- Roller, S., Sukhbaatar, S., Szlam, A., and Weston, J. E. Hash layers for large sparse models. In Beygelzimer, A., Dauphin, Y., Liang, P., and Vaughan, J. W. (eds.), *Advances in Neural Information Processing Systems*, 2021. URL <https://openreview.net/forum?id=1MgDDWb1ULW>.
- Ryabinin, M., Dettmers, T., Diskin, M., and Borzunov, A. Swarm parallelism: Training large models can be surprisingly communication-efficient, 2023. URL <https://arxiv.org/abs/2301.11913>.
- Shallue, C. J., Lee, J., Antognini, J., Sohl-Dickstein, J., Frostig, R., and Dahl, G. E. Measuring the effects of data parallelism on neural network training. 2018. doi: 10.48550/ARXIV.1811.03600. URL <https://arxiv.org/abs/1811.03600>.

- Shi, W., Michael, J., Gururangan, S., and Zettlemoyer, L. knn-prompt: Nearest neighbor zero-shot inference, 2022. URL <https://arxiv.org/abs/2205.13792>.
- Svenstrup, D., Hansen, J. M., and Winther, O. Hash embeddings for efficient word representations, 2017. URL <https://arxiv.org/abs/1709.03933>.
- Taylor, R., Kardas, M., Cucurull, G., Scialom, T., Hartshorn, A., Saravia, E., Poulton, A., Kerkez, V., and Stojnic, R. Galactica: A large language model for science, 2022. URL <https://arxiv.org/abs/2211.09085>.
- Touvron, H., Lavril, T., Izacard, G., Martinet, X., Lachaux, M.-A., Lacroix, T., Rozière, B., Goyal, N., Hambro, E., Azhar, F., Rodriguez, A., Joulin, A., Grave, E., and Lample, G. Llama: Open and efficient foundation language models, 2023. URL <https://arxiv.org/abs/2302.13971>.
- Wang, J., Yuan, B., Rimanic, L., He, Y., Dao, T., Chen, B., Re, C., and Zhang, C. Fine-tuning language models over slow networks using activation compression with guarantees, 2022. URL <https://arxiv.org/abs/2206.01299>.
- Wortsman, M., Gururangan, S., Li, S., Farhadi, A., Schmidt, L., Rabbat, M., and Morcos, A. S. lo-fi: distributed fine-tuning without communication, 2022. URL <https://arxiv.org/abs/2210.11948>.
- Yang, G., Hu, E., Babuschkin, I., Sidor, S., Liu, X., Farhi, D., Ryder, N., Pachocki, J., Chen, W., and Gao, J. Tuning large neural networks via zero-shot hyperparameter transfer. In Ranzato, M., Beygelzimer, A., Dauphin, Y., Liang, P., and Vaughan, J. W. (eds.), *Advances in Neural Information Processing Systems*, volume 34, pp. 17084–17097. Curran Associates, Inc., 2021. URL <https://proceedings.neurips.cc/paper/2021/file/8df7c2e3c3c3be098ef7b382bd2c37ba-Paper.pdf>.
- Yuan, B., He, Y., Davis, J. Q., Zhang, T., Dao, T., Chen, B., Liang, P., Re, C., and Zhang, C. Decentralized training of foundation models in heterogeneous environments, 2022. URL <https://arxiv.org/abs/2206.01288>.
- Zhang, S., Roller, S., Goyal, N., Artetxe, M., Chen, M., Chen, S., Dewan, C., Diab, M., Li, X., Lin, X. V., Mihaylov, T., Ott, M., Shleifer, S., Shuster, K., Simig, D., Koura, P. S., Sridhar, A., Wang, T., and Zettlemoyer, L. Opt: Open pre-trained transformer language models, 2022. URL <https://arxiv.org/abs/2205.01068>.
- Zhang, X., Zhao, J., and LeCun, Y. Character-level convolutional networks for text classification, 2016.
- Zhou, Y., Lei, T., Liu, H., Du, N., Huang, Y., Zhao, V., Dai, A., Chen, Z., Le, Q., and Laudon, J. Mixture-of-experts with expert choice routing, 2022. URL <https://arxiv.org/abs/2202.09368>.

## A. Appendix

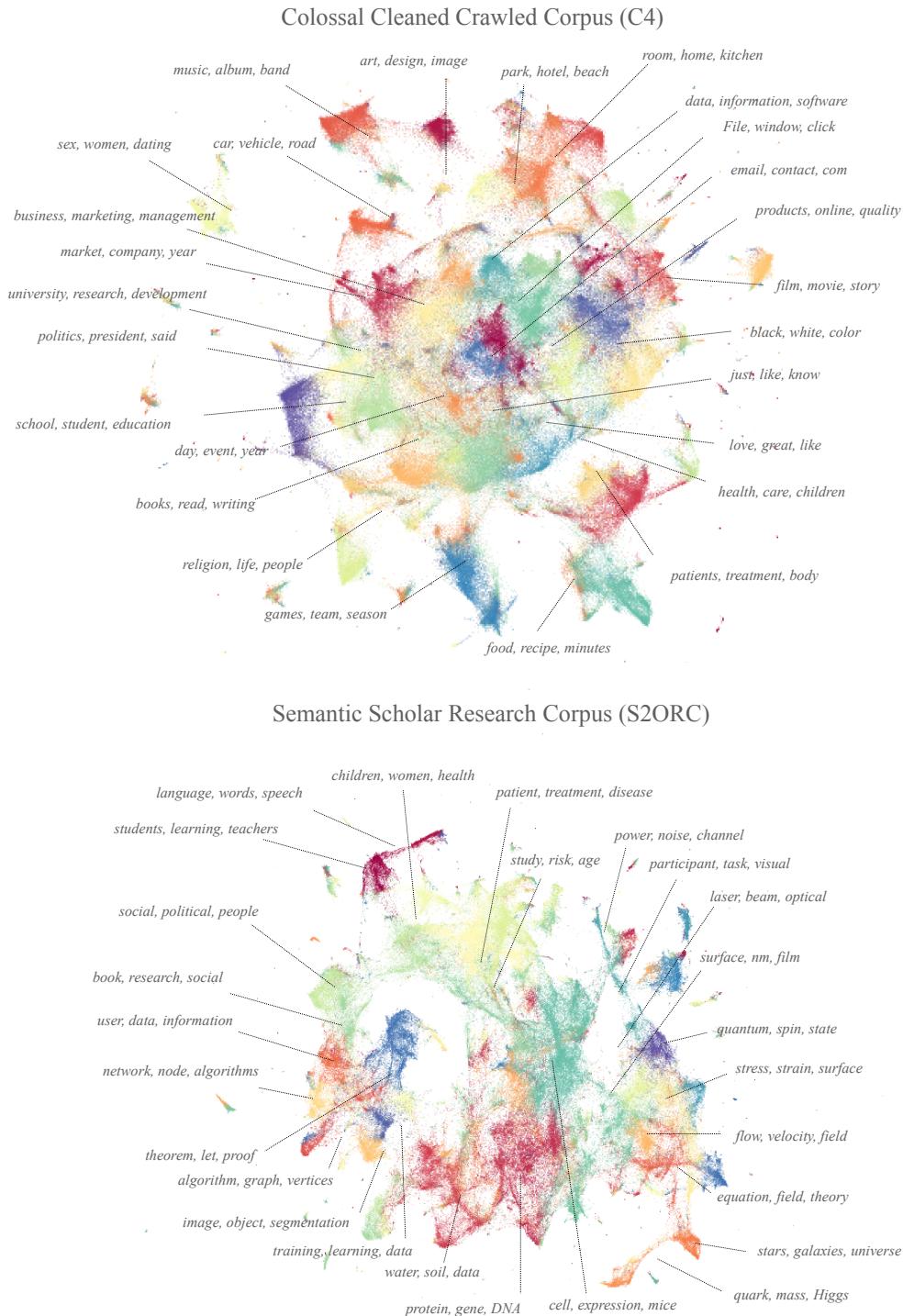


Figure 17. Fully annotated UMAP visualization of 32 clusters in C4 and S2ORC. We annotate the clusters using an inverse transformation from our cluster centers back into the tf-idf vocabulary space, identifying the most likely words to generate the cluster center. We display the top 3 terms associated with each cluster center here.

**A.1. Clusters**

Cluster	Term 0	Term 1	Term 2	Term 3	Term 4
0	fig	energy	al	et	field
1	data	patients	social	time	al

Table 2. Top terms associated with each cluster in S2ORC (2 clusters)

Cluster	Term 0	Term 1	Term 2	Term 3	Term 4
0	eq	energy	quantum	equation	field
1	algorithm	image	model	data	noise
2	cells	cell	fig	al	protein
3	students	social	people	research	education
4	patients	patient	study	participants	children
5	fig	temperature	energy	surface	beam
6	user	data	node	network	nodes
7	et	al	stars	galaxies	velocity

Table 3. Top terms associated with each cluster in S2ORC (8 clusters)

Cluster	Term 0	Term 1	Term 2	Term 3	Term 4
0	students	learning	teachers	teaching	education
1	language	word	words	speech	english
2	network	node	nodes	networks	algorithm
3	study	risk	age	data	group
4	power	noise	channel	signal	frequency
5	quantum	spin	state	magnetic	states
6	participants	task	visual	stimulus	et
7	theorem	let	proof	lemma	set
8	training	learning	data	network	model
9	laser	beam	optical	fig	pulse
10	protein	genes	gene	dna	proteins
11	water	soil	data	et	al
12	algorithm	graph	vertices	problem	vertex
13	flow	velocity	field	magnetic	wave
14	user	data	users	information	service
15	stars	galaxies	et	al	star
16	quark	mass	gev	higgs	energy
17	et	al	brain	neurons	fig
18	stress	strain	surface	shear	fig
19	image	images	algorithm	object	segmentation
20	energy	electron	fig	eq	state
21	equation	field	eq	equations	theory
22	patients	patient	treatment	study	disease
23	model	time	robot	state	control
24	children	child	women	health	social
25	surface	nm	film	layer	graphene
26	patient	patients	pain	surgery	treatment
27	social	political	people	policy	public
28	social	participants	health	self	people
29	book	research	social	information	data
30	temperature	water	heat	phase	thermal
31	cells	cell	expression	mice	fig

Table 4. Top terms associated with each cluster in S2ORC (32 Clusters).

Cluster	Term 0	Term 1	Term 2	Term 3	Term 4
0	like	just	time	new	great
1	new	information	use	business	services

Table 5. Top terms associated with each cluster in C4 (2 clusters)

Cluster	Term 0	Term 1	Term 2	Term 3	Term 4
0	students	health	research	school	university
1	music	new	love	film	art
2	said	year	state	team	new
3	business	company	services	service	market
4	like	just	time	don	really
5	use	information	data	page	click
6	design	black	white	color	high
7	home	water	food	park	area

Table 6. Top terms associated with each cluster in C4 (8 clusters)

Cluster	Term 0	Term 1	Term 2	Term 3	Term 4
0	site	page	website	web	search
1	art	design	image	images	gallery
2	health	care	children	child	medical
3	just	like	don	know	ve
4	data	information	software	use	management
5	love	great	like	just	really
6	game	team	games	season	play
7	information	email	contact	com	address
8	power	high	use	light	steel
9	students	school	student	education	learning
10	market	company	year	financial	tax
11	patients	treatment	body	cancer	pain
12	room	home	kitchen	bedroom	living
13	music	album	band	song	songs
14	car	vehicle	cars	new	road
15	park	hotel	beach	area	travel
16	day	event	year	time	wedding
17	service	services	quality	customer	best
18	book	books	read	writing	story
19	film	movie	story	new	like
20	black	white	color	dress	look
21	business	company	marketing	management	customers
22	university	research	development	education	science
23	city	community	county	said	police
24	sex	women	porn	dating	girls
25	products	product	online	quality	order
26	religion	life	people	jesus	time
27	water	skin	use	oil	like
28	said	politics	president	government	state
29	app	phone	video	mobile	casino
30	file	windows	use	click	software
31	food	add	recipe	minutes	wine

Table 7. Top terms associated with each cluster in C4 (32 Clusters).

## A.2. Comparing FLOP counts via training data size

To make fair comparisons across models with different numbers of ELMs, for a given number of clusters  $k$  and total GPU budget  $n$ , each ELM is allocated  $n/k$  GPUs. This keeps the total effective number of FLOPs fixed across models exposed to

the same number of tokens. We can show this analytically; following Artetxe et al. 2021, we calculate the number of FLOPs to train a single ELM in our experiments:

$$F_{\text{ELM}(T,k)} = \frac{96lh^2T}{k} \left( 1 + \frac{s}{6h} + \frac{V}{16lh} \right)$$

where  $T$  is the total training tokens (i.e., sequence length  $\times$  batch size per GPU  $\times$  number of GPUs),  $k$  is the number of clusters,  $l$  is the number of layers,  $h$  is the hidden dimension,  $s$  is the sequence length, and  $V$  is the vocabulary.

Therefore, the total cost in FLOPs to train  $k$  ELMs with a particular model architecture (e.g., OPT-1.3B) on  $T$  tokens in aggregate is equivalent to that of a single dense LM of the same architecture trained on  $T$  tokens:

$$k \cdot F_{\text{ELM}(T,k)} = F_{\text{ELM}(T,1)}$$

This means that even though C-BTM trains  $k$  times more parameters than an equivalent dense model, it does so *at the same overall cost in FLOPs*. So, our comparisons of models with various numbers of ELMs are fair, as long as they have been exposed to the same number of training tokens and have the same underlying architecture for each ELM. Therefore, throughout the paper, we use training data size as a more interpretable metric of the overall compute budget.

### A.3. Interpolating between empirical observations when comparing training costs and performance

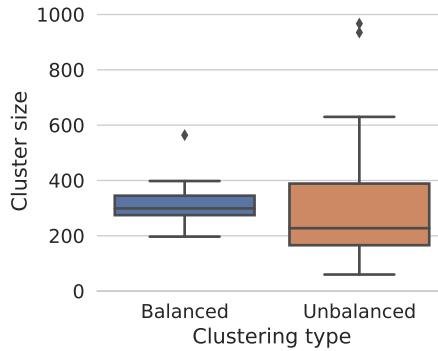
We interpolate between our empirical observations using the following function, proposed in Artetxe et al. 2021:

$$c(t) = \exp(\log c_{lo}(t) + r(\log c_{hi}(t) - \log c_{lo}(t)))$$

where  $r = \frac{t - t_{lo}}{t_{hi} - t_{lo}}$ ,  $t_{hi}$  and  $t_{lo}$  are the closest empirical performances to  $t$  and  $c_{lo}(t)$  and  $c_{hi}(t)$  are their corresponding training cost in FLOPs. We use this interpolation to compute the speedup factor  $c_{dense}(t)/c_{cbtm}(t)$ .

### A.4. Effect of cluster balancing on cluster sizes

Using a held out set of 10K documents from C4, we ablate our balancing procedure from §2.1, and display a boxplot showing cluster sizes in Figure 18.



**Figure 18. Cluster balancing narrows the range, and increases the median size, of clusters (§7.2).** Here, we ablate our balancing procedure from §2.1 on a 10K held-out documents in C4.

### A.5. The Pile experiments

For the experiment in §7.4, we additionally train on The Pile, which is a publicly available corpus of diverse language modeling datasets. We use the filtered version from the OPT pretraining data (Zhang et al., 2022), and subselect 8 datasets of the 13 used for OPT pretraining, which enabled easier experimentation §7.4. These 8 datasets include: Common

Crawl, HackerNews comments, Reddit comments<sup>16</sup>, the Gutenberg corpus, STORIES corpus, OpenWebText2, Deepmind-Mathematics, and English Wikipedia. In aggregate, these datasets consist of 420M documents, totaling 116B BPE tokens. For evaluation, we sample an equal number of documents from each constituent dataset. We also train a  $k=8$  clustering model on this dataset with one shard, or 1.5M documents.

5.2B Tokens		
8 Metadata	8 Clusters	1 Cluster
8.4	8.3	8.5

**Table 8. Experts trained with clusters perform slightly better than experts trained with metadata (§7.4).** Here, we train each model for 5.2B tokens on 8 corpora of the Pile, and evaluate perplexity on a held out random sample of the constituent datasets. See §A.5 for more details on the dataset.

## A.6. Sparsity

	Dense	2-cluster		8-cluster				32-cluster					
		top-1	top-2	top-1	top-2	top-4	top-8	top-1	top-2	top-4	top-8	top-16	top-32
TEMPERATURE	0.01	<b>13.82</b>	<b>13.64</b>	13.60	<b>13.64</b>	13.50	13.49	13.49	<b>13.55</b>	13.45	13.45	13.45	13.45
	0.05	-	-	13.51	-	13.32	13.25	13.25	-	13.25	13.19	13.17	13.17
	0.1	-	-	<b>13.50</b>	-	<b>13.27</b>	<b>13.22</b>	<b>13.24</b>	-	13.16	<b>13.05</b>	<b>13.00</b>	<b>13.01</b>
	0.2	-	-	13.54	-	13.29	13.34	13.50	-	<b>13.14</b>	13.06	13.07	13.28
	0.3	-	-	13.59	-	13.33	13.45	13.72	-	13.17	13.15	13.27	13.54
	0.5	-	-	13.64	-	13.38	13.59	13.97	-	13.22	13.30	13.57	14.02
	1	-	-	13.69	-	13.43	13.73	14.19	-	13.30	13.49	13.89	14.46

**Table 9.** Results with the dense (1-cluster), 2-cluster, 8-cluster, and 32-cluster C4 models trained on 84B tokens when varying the temperature ( $T$ ) and  $topk$  hyperparameters. Optimal performance for almost every model and  $topk$  value is achieved at  $T = 0.1$ .

## A.7. Downstream tasks

**Tasks** We experiment with six text classification tasks which span topic classification (AGNews; Zhang et al. 2016 and DBpedia; Lehmann et al. 2014); sentiment analysis (SST-2; Maas et al. 2011, Amazon; Zhang et al. 2016, and Phrasebank Malo et al. 2014); and hatespeech detection (Twitter; Barbieri et al. 2020).

**Performance Routing** We introduce additional routing procedures for few-shot text classification, as the clustering method described in §2.2 ignores the significance of labels and does not take into account the context’s word order, which may be crucial when the context contains demonstrations for a downstream task. Further, the specific ordering of in-context demonstrations is known to affect model performance (Lu et al., 2022). There is not sufficient evidence to suggest that the relative rank of different models on a task stays constant through these performance variances; thus it may be important to route to experts differently depending on demonstration example order. To take into account the order of tokens in the context, we introduce 3 variations on routing, based on expert performance on the end task, which take inspiration from the mixture probability estimation methods of Gururangan et al. (2022); Li et al. (2022).

To perform *Fixed Performance Routing with demonstrations and validation set examples*, we select 8 examples randomly from the validation set, such that there is no overlap with the 8 demonstration examples used in the context at test time. We concatenate the 8 demonstrations with one validation set context and evaluate the accuracy of each ELM on the sequence, repeating for each of the 8 examples from the validation set. The final routing probability distribution over experts for this task is determined by a softmax over the average accuracy of the model over the 8 examples. We use this fixed probability distribution for all test examples.

To perform *Fixed Performance Routing with only demonstrations*, we adapt the procedure above such that no validation examples are necessary. Instead, we take a random permutation of the 8 demonstration examples. We remove the label of the last, such that we effectively use the first 7 as demonstrations, and rely on the last example to estimate performance.

<sup>16</sup>Reddit comments, like the rest of these datasets, are not collected by us but were part of the Pile (Gao et al., 2021), a publicly available third-party dataset.

Task	1st	2nd	3rd
AGNews	<i>game, team, season</i>	<i>said, government, president</i>	<i>business, company, market</i>
DBPedia	<i>students, school, university</i>	<i>said, government, president</i>	<i>city, park, hotel</i>
SST-2	<i>book, film, life</i>	<i>love, family, great</i>	<i>music, art, band</i>
Amazon	<i>book, film, life</i>	<i>just, like, know</i>	<i>game, team, season</i>
Phrasebank	<i>business, company, market</i>	<i>service, customer, products</i>	<i>said, government, president</i>
Twitter	<i>data, software, download</i>	<i>click, website, page</i>	<i>just, like, know</i>

Table 10. Top-terms of clusters associated with top-3 experts for each classification task (§5.2) By inspection, the highest probability experts are usually quite relevant to task’s domain.

We repeat this 8 times, generating a new random permutation each time, and once again take the softmax over the average accuracy of the model for each permutation, fixing this distribution for all test examples.

Finally, we have *Updating Performance Routing*, in which no estimations are done before test-time. At test time, we begin with a uniform probability over all experts, which we update with an exponential moving average with each test example: after each example (prepended with the 8 demonstrations), we update the expert probabilities with the softmax over the accuracy of each expert on that example. Once again, this distribution is fixed for all test examples.

**Results** Full results, in Table 11, show that *Fixed Performance Routing with demonstrations and validation set examples* achieves the best performance overall, with optimal performance occurring at top-4 expert activation, which we also found in the language modeling results of §4.1. Both *Fixed Performance Routing* methods perform best with top-4 expert activation, and only suffer small performance degradations when reduced to top-1 expert activation. This aligns well with the patterns observed in §4.1, which further supports the incorporation of end task performance in routing when adapting to new tasks, even when we base this evaluation only on the demonstration examples – that is, without any additional data. We leave for future work further tuning of the optimal settings for Performance Routing.

↓ Model (inference parameters)	Few-shot Text Classification Accuracy (%)						
	AGNews Topic	DBPedia Topic	SST-2 Sentiment	Amazon Sentiment	Phrasebank Sentiment	Twitter Hatespeech	Average
Random chance	25.0	7.10	50.0	50.0	33.3	50.0	35.9
OPT (1.3B)	42.9	57.2	72.8	81.3	72.5	65.1	65.3
OPT (6.7B)	51.9	58.9	77.0	83.8	76.4	39.6	64.6
1-cluster (1.3B)	47.4	61.1	80.2	80.7	66.6	60.9	66.2
1-cluster (6.7B)	<b>68.1</b>	62.4	80.7	<b>84.9</b>	80.6	37.4	69.0
<i>Cluster Routing</i>							
16-cluster; top-1 (1.3B)	47.1	62.9	74.3	79.1	72.9	56.4	65.4
16-cluster; top-4 (5.2B)	49.3	62.3	80.0	81.3	78.7	61.3	68.8
16-cluster; top-16 (20.8B)	50.6	62.0	84.0	83.2	78.6	61.7	69.9
<i>Updating Performance Routing</i>							
16-cluster; top-1 (1.3B)	54.5	<b>63.4</b>	83.4	83.6	74.7	64.8	63.3
16-cluster; top-4 (5.2B)	51.6	61.5	88.6	83.7	<b>80.7</b>	<b>65.3</b>	68.8
16-cluster; top-16 (20.8B)	51.1	60.4	86.0	83.5	79.8	62.9	69.1
<i>Fixed Performance Routing (8 demonstrations)</i>							
16-cluster; top-1 (1.3B)	45.3	61.9	81.2	83.6	76.4	60.1	68.1
16-cluster; top-4 (5.2B)	51.2	60.9	81.4	83.0	80.5	60.9	69.6
16-cluster; top-16 (20.8B)	50.6	60.2	84.1	83.5	79.1	60.5	69.6
<i>Fixed Performance Routing (8 demonstrations + 8 validation examples)</i>							
16-cluster; top-1 (1.3B)	54.5	<b>63.4</b>	83.4	83.6	74.7	64.8	70.7
16-cluster; top-4 (5.2B)	51.6	61.5	<b>88.6</b>	83.7	<b>80.7</b>	<b>65.3</b>	<b>71.9</b>
16-cluster; top-16 (20.8B)	51.1	60.4	86.0	83.5	79.8	62.9	70.6

**Table 11. c-BTM models with performance routing achieve even better performance on downstream tasks (§A.7).** We display performance of models on six text classification tasks, using eight demonstrations for each example and no additional fine-tuning. We compare our cluster routing method (described in §5) to variants of performance routing (described in §A.7). Fixed performance routing with 8 demonstrations and 8 validation examples usually gets the best performance on downstream tasks, consistently outperforming even the 6.7B parameter baselines. Fixed performance routing with top-4 inference always improves performance over using all experts, and top-1 inference does substantially better than the dense baselines at no additional inference costs. We include average performance across tasks for readability.