Eliciting Transferability in Multi-task Learning with Task-level Mixture-of-Experts

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Abstract

Recent work suggests that transformer models are capable of multi-task learning on diverse NLP tasks. However, the potential of these models may be limited as they use the same set of parameters for all tasks. In contrast, humans tackle tasks in a more flexible way, by making proper presumptions on what skills and knowledge are relevant and executing only the necessary computations. Inspired by this, we propose to use task-level mixture-of-expert models, which has a collection of transformer layers (i.e., experts) and a router component to choose among these experts dynamically and flexibly. We show that the learned routing decisions and experts partially rediscover human categorization of NLP tasks – certain experts are strongly associated with extractive tasks, some with classification tasks, and some with tasks requiring world knowledge.

1 Introduction

Pre-trained transformer models (Devlin et al., 2019; Liu et al., 2019b) have demonstrated remarkable capabilities in natural language processing (NLP) in recent years. Moreover, generative transformers can be viewed as a universal model that can be optimized for any language task primed into text-to-text format (Raffel et al., 2020). Recently, researchers found that training these transformer models to multi-task on a diverse collection of NLP tasks is beneficial – not only are they better at handling seen tasks (Aghajanyan et al., 2021; Aribandi et al., 2022), but also at generalizing and adapting to unseen tasks (Wei et al., 2021; Sanh et al., 2022).

However, little is known about how multi-tasking capabilities and cross-task generalization is achieved, especially that the exact same set of weights is applied, and the same computation is executed, for very different tasks. Humans, on the other hand, do not exhaust their brain capacity for every task at hand. Humans develop skill sets and accumulate knowledge during learning, and can readily reuse and recompose them when facing a task. Inspired by this, we explore whether we can enable this process more explicitly with a new model that can emulate this behavior.

A natural fit for this goal would be task-level mixture-of-expert models (Jacobs et al., 1991; Kudugunta et al., 2021), where the model computation is conditioned on the task at hand. More specifically, the model contains a collection of experts and a router that chooses from the experts and composes the final model (Fig. 1). We empirically compare several key design choices (§5) and analyze the learned routes by aligning them with manually-labeled task features (§6).

Figure 1: In this work, we train a dynamic task-level mixture-of-expert model (§4) on diverse NLP tasks in a multi-task learning setting, aiming to elicit knowledge and skill sharing more explicitly. We empirically compare several key design choices (§5) and analyze the learned routes by aligning them with manually-labeled task features (§6).
acteristics, such as the task being a classification task, the task being extractive, or the task requiring world knowledge. However, despite different model variants we tried (selection function, router architecture, task representation initialization), the routing models struggle to outperform simple multi-tasking baselines, which calls for further investigation and development of algorithms that can stably optimize the dynamic model.

2 Related Work

Massive Multi-task Learning. Multi-task learning (Caruana, 1997) has been continuously explored in NLP and is shown to be beneficial (McCann et al., 2018; Liu et al., 2019a). Recently, multi-task learning is brought to a new scale by using a significantly larger collection of tasks and examples (Aghajanyan et al., 2021; Aribandi et al., 2022; Khashabi et al., 2020). These work demonstrate that multi-task learning improves the learning of text representation and thus boost the performance of seen tasks. Moreover, it is shown that models trained in this way exhibit strong adaptability to unseen tasks, in both few-shot (Ye et al., 2021) and zero-shot settings (Wei et al., 2021; Sanh et al., 2022; Mishra et al., 2021). Despite their effectiveness on performance, how a multi-task model learns and develop language skills from these tasks is a relatively under-explored topic. In our work, we try to address these questions and aim at better understanding multi-task models. Very recent works (Ponti et al., 2022; Gupta et al., 2022) share a similar motivation with our work.

Mixture-of-Experts in NLP. Mixture-of-experts models (Jacobs et al., 1991) divide the problem space into several sub-spaces and allow experts to be specialized in each subspace. Recently this concept is successfully applied to NLP (Shazeer et al., 2017), enabling models of billion or even trillion parameter scale (Fedus et al., 2021; Du et al., 2021; Artetxe et al., 2021). However these applications mainly focus on the scaling aspects. Besides, most of them select experts on a per-example basis. In this work we are interested in multi-task learning with per-task gating decisions (Rosenbaum et al., 2018; Kudugunta et al., 2021), and mainly focus on understanding and interpreting task disentanglement and transferability in multi-task learning by investigating the learned gating decisions.

Task Transferability. Phang et al. (2018) explored supplementary training on intermediate tasks (STILT), i.e., training on a data-rich intermediate task before fine-tuning on the target task. STILT improves performance on the target task and stabilizes the fine-tuning process. Pruksachatkun et al. (2020) further investigated when and why intermediate task transfer works, and Vu et al. (2020a) proposed to select the best transfer task based on text embeddings and task embeddings (computed with fisher information). These studies mainly focus on transferability between specific source-target pairs, while we consider a more realistic yet sophisticated setting of transferring between and beyond a collection of diverse tasks. Padmakumar et al. (2022) find that selecting an appropriate set of intermediate tasks helps achieve performance comparable with massive multi-task models, but with reduced computation costs.

3 Problem Setting

Our goal is to better understand multi-task learning with an explicit routing mechanism. With the hypothesis that each part (expert) of the model should play different role during the learning stage, we examine whether models can learn by summarizing and combining basic skills during multi-task learning, and explore the potential benefits of such dynamic models. In the following, we introduce the problem setting, including data usage (§3.1), training procedure (§3.2), and evaluation protocol (§3.3).

3.1 Data Usage

Assume that we have a collection of diverse NLP tasks \( T \), partitioned into three non-overlapping sets (\( T_{\text{train}}, T_{\text{dev}}, T_{\text{test}} \)). \( T_{\text{train}} \) is mainly used for multi-task learning, while \( T_{\text{dev}} \) and \( T_{\text{test}} \) are used to quantify the model’s adaptability to new tasks. Each task \( T \in T \) has three subsets, i.e., \( T = \{D_{\text{train}}, D_{\text{dev}}, D_{\text{test}}\} \). Additionally, we assume that all tasks are cast to a unified text-to-text format, i.e., \( D = \{(x, y)\} \), where \( x \) is the input text sequence, and \( y \) is the output text sequence.

3.2 Training Procedure

The training procedure has two stages: (1) an upstream learning stage for multi-task learning, to study the underlying skills that needed to solve different tasks; and (2) a downstream fine-tuning stage for evaluating the model’s ability to adapt to
new tasks. During the upstream learning stage, the model is expected to be trained for multi-task learning with the $D_{\text{train}}$ from tasks in $T_{\text{train}}$. $D_{\text{dev}}$ for tasks in $T_{\text{train}}$ will be used for hyperparameter tuning and model selection. During the downstream fine-tuning stage, the model will be fine-tuned on each task in $T_{\text{test}}$ respectively. $D_{\text{train}}$ will be used for fine-tuning, $D_{\text{dev}}$ for model validation.

### 3.3 Evaluation Protocol

Each task in $T$ has a pre-defined evaluation metric. During the upstream learning stage, for simplicity, the model is validated on the average dev performance on all tasks in $T_{\text{train}}$, and we report average dev performance and test performance. During the downstream fine-tuning stage, we compare the model’s performance to fine-tuning a vanilla transformer baseline, and compute the average performance gain (ARG) as our evaluation metric of model effectiveness. More details about the baselines and ARG are deferred in §7.

### 4 Task-level MoE Transformers

Recall that our goal is to better understand how transformer models develop language skills during multi-task learning, and how those skills contribute to the model performance. We focus on experimenting with a mixture-of-experts variant of transformer models, which we also denote as routing transformer. The model contains two major components: (1) a router that selects and decides which experts to use for each task in each layer, based on their task representation; (2) a collection of experts that are dynamically composed into a final model based on the router selection. See Fig. 2 for an illustration of the model architecture.

In this work, we make some additional assumptions to narrow down the scope of the study: (1) We consider each transformer layer as an expert, so that the whole model is “route-able”; (2) The model has $n$ layers. In each layer, there are $m$ experts to choose from. The collection of experts in the $i$-th layer and the collection in the $j$-th layer are independent from each other.

In the following, we introduce the router and the transformer layers with more details. Note that we adopt a general formulation in this section, and leave more specific design choices in §5.1 for empirical comparison.

**Collection of Experts.** In an original implementation of transformer models, there are $n$ transformer layers stacked and executed sequentially. For encoder-decoder models, the first half consists of encoder layers and the second half consists of decoder layers. In our variant of transformer models, we forked the layer for $m$ times at each layer, resulting in $m \times n$ experts in total. We refer to the $j$-th expert in the $i$-th layer as $E^{(i,j)}$.

**Router.** For a given task $T_k \in T$, with $k$ as its task index, the router first takes the task embedding ($T_k$) from a look-up embedding table ($T$). The router network outputs a matrix $L \in \mathbb{R}^{m \times n}$, where $L_{i,j}$ represents the logits of using Expert $E^{(i,j)}$ in layer $i$. Then $L$ goes through a selection function $f$ to normalize or discretize the routing decisions, resulting in a final decision matrix $D \in \mathbb{R}^{m \times n}$.

**Task-level MoE Transformers.** We use the decision matrix $D$ from the router to control the computation conducted by the experts. More specifically, in layer $i$, given input hidden states $h^{(i)}_m$, the output $h^{(i)}_{\text{out}}$ would be the weighted sum of all experts in the layer, and the weights are specified in $D_{i,:}$, i.e.,

$$h^{(i)}_{\text{out}} = \sum_{j=1}^{m} D_{i,j} E^{(i,j)}(h^{(i)}_m)$$  \hspace{1cm} (1)

### 5 Multi-task Learning Experiments

#### 5.1 Investigation on Design Choices

**Baselines.** We first apply standard multi-task learning to vanilla BART-Base and BART-Large model, and consider them as baselines. To separate out the influence brought by the MoE architecture, we use an additional baseline of
Expert Selection. The selection function is responsible for normalizing and discretizing (if necessary) the logit output of router network into final decisions. We consider three variants: (a) Softmax, the default design in most MoE models. (b) Gumbel-Softmax (Jang et al., 2016), which add gumbel-distributed noise to the logits and promote discrete decisions. (c) Gumbel-Softmax ST, where ST stands for straight-through estimator. This rounds up the top-1 selection score to 1, and still allows back-propagation. For (c) and (d), we additionally apply the temperature annealing mechanism to encourage exploration in the beginning of training stage.

Router Architecture. Router is a key component for our MoE model which computes the logits of selecting experts based on input task representations (see §4). We consider three router architecture with different complexities: (e) MLP, which contains two dense layers separated by a GELU activation. (f) Bi-LSTM, which takes the sum of the task representation and the positional embedding as input at each time step. (g) Transformer (Vaswani et al., 2017), which takes the same input as Bi-LSTM and applies one single transformer encoder layer (i.e., self-attention and two dense layers).

Task Representations. Vu et al. (2020b) suggest that pre-computed task representations contain rich information for predicting task transferability. Here we consider incorporating these task representations as the initialization for the look-up embedding table $T$ in our model (§4). In particular, we consider: (h) Random, which initialized every task representation with a randomly initialized 768d vector. (i) TextEmb, which is produced by encoding the input text with a pre-trained BART-Base model and taking the hidden representations of the last encoder layer. We tried both the average pooling of all tokens embedding (AVG) in the sequence and the special token embedding for the begin of sequence (BOS). (j) FT-TextEmb, which is mostly identical to (i), despite that the BART-Base model is first fine-tuned on the $D_{train}$ of the current task. (k) Fisher, which is the diagonal of fisher information of the trainable parameters in a model. We use adapter-based (Houlsby et al., 2019) fine-tuning on $D_{train}$ and compute the fisher information on these adapter parameters to avoid expensive computations over the full model.

Freezing Task Representations. Since adaptability to unseen task is considered in this study, we further consider between (l) not freezing and (m) freezing the task representations during multi-task learning. We conjecture that the structure of seen task representations may be changed after multi-task learning, while the unseen task representations may not reflect the change; hence the freezing variant.

5.2 Experiment Details

Data. We previously discussed that a collection of diverse NLP tasks is required for the purpose of our analysis (§3.1). In our experiments, we use the task collection in Ye et al. (2021), which contains 160 different NLP tasks, covering a wide range of task formats (classification, multiple choice, generation, etc.), goals (question answering, fact checking, etc.) and domains (biomedical, social media, etc.). This setting is ideal for us to explore how transformers learn skills from diverse tasks and reuse skills and knowledge for new ones. Additionally, we adopt the Random partition in Ye et al. (2021), which randomly separate the 160 tasks into 120/20/20 for $T_{train}/T_{dev}/T_{test}$. All tasks are converted to a unified text-to-text format.

Model and Its Initialization. All of our routing transformer experiments are based on the pre-trained BART-Base model (Lewis et al., 2020), a 12-layer encoder-decoder transformer model ($n = 12$). All experts in layer $i$ are initialized from the $i$-th layer of the pre-trained BART-Base model. Additionally we add a Gaussian noise with variance of $1e-8$ to the weights of each expert to avoid symmetry. We manually set the number of experts per layer $m = 3$ to allow sufficient flexibility while maintain a manageable model size.

Training Details. We concatenate the $D_{train}$ of the 120 tasks in $T_{train}$ into a large dataset and use it for multi-task learning. We adopt heterogeneous batching (Aghajanyan et al., 2021), i.e., each batch contains examples from different tasks. For the vanilla BART-Base baseline, we train the model for 30,000 steps, with the batch size equals to 32 and the learning rate equals to $3e-5$. For BART-Large we use the same setting, except that the learning
rate is set to 1e-5. For the routing transformer variants, models are trained with a basic learning rate of 1e-5, while we set the router with bigger learning rate of 1e-3 based on our pilot experiments. For the task embedding, we use 1e-2 as learning rate for random initialization, and 1e-3 for pre-computed initializations. We train the model for 60000 steps because it needs more exploration time before routes getting stable. Both the vanilla model and routing model are optimized by the Adam algorithm (Kingma and Ba, 2014).

5.3 Results

We visualized the learned routing decisions in Fig. 3. We present the performance of variants mentioned above in Table 1. For selected models, we run three times with different random seeds to reduce variance in performance (Table 2).

We have the following observations. Firstly, according to test performance in Table 2, we found that the average routing baseline is slightly better than vanilla bart-base. This suggest that the routing transformer architecture is in general helpful for multi-task learning. Secondly, by comparing different design choices in Table 1, we found that the routing model is very sensitive to the selection of selection function – gumbel-softmax with straight-through achieves the best performance among the three choices. Thirdly, we did not observe significant difference with choices in router architecture or task representation initialization. Supposedly, LSTMs and transformers are able to capturing relations more complicated than MLPs, and pre-computed task representations carry richer information about the task than random initialization. This unexpected observation suggests that the router still struggle to leverage task-level information with the current supervision signals. Lastly, the best routing-models we trained still cannot beat the multi-task baseline. This motivates our analysis on learned routes in §6 and also calls for more investigation and research on improving the learning algorithm.

6 Interpreting the Routes and Experts

6.1 Correlation with Hand Features

To better understand the routing decisions learned by the router, we investigate the relation between the routing decisions and a series of manually defined features. In the following, we first describe the methodology of computing correlation, then describe the hand features used, and finally the findings.
Method. For each task in $\mathcal{T}_{\text{train}}$, we first compute the routing decisions $\mathbf{D} \in \mathbb{R}^{m \times n}$ using the learned model. For each expert $E^{(i,j)}$, we consider the routing decision $D_{i,j}$ of all tasks as a learned feature. Altogether, we have $m \times n$ features of dimension $|\mathcal{T}_{\text{train}}|$ (the number of tasks). Additionally, we have $t$ hand features on all train tasks, giving $t$ features of dimension $|\mathcal{T}_{\text{train}}|$. We then compute Pearson correlation coefficient between each pair of learned feature and hand feature, resulting in a $(m + n) \times t$ matrix quantifying the correlation between learned routing decisions and hand features.

Hand Features. We consider the following hand features and quantify their correlation with the learned routes. We admit that several categorization criteria are subjective and such categorization is by no means exhaustive for fully describing a language task. We use these features mainly to quantify the relation between human perception of tasks and the learned routes.

- **Task Ontology.** We use the task ontology provided in Ye et al. (2021). The top-level labels include Classification, Question Answering, Conditional Generation, and Others. Tasks in each category are divided into sub-categories. For example, QA tasks are further categorized into machine reading comprehension (MRC), multiple-choice QA, closed-book QA, etc.

- **Input/Output Length.** For input length, we first rank average input length of each task; then we label the shortest 25% tasks with `hasShortInput`, the longest 25% with `hasLongInput`, and the remaining as `hasMediumInput`. For output length, the distribution is more skewed. We define tasks with average output shorter than 3 tokens as `hasShortOutput`, longer than 10 tokens as `hasLongOutput`, and the remaining as `hasMediumOutput`.

| Model          | Dev       | Test      |
|----------------|-----------|-----------|
| Vanilla Transformers |          |           |
| BART-Base      | 54.47%±0.05% | 48.93%±0.23% |
| BART-Large     | 58.10%±0.20% | 54.06%±0.22% |

| Mixture-of-Experts | (a) 54.61%±0.11% | 50.02%±0.19% |
|                   | (d) + (e) + (k) + (l) 53.07%±0.45% | 48.16%±0.34% |
|                   | (d) + (e) + (k) + (m) 53.06%±0.19% | 47.64%±0.79% |

Table 2: Three-run Performance on Selected Models.

Figure 4: Pearson Correlation Between Learned Routes and Selected Hand Features. Correlation with $p<0.01$ are visualized. “LOE1” stands for expert 1 in layer 0. The correlation is based on a $(d) + (e) + (h) + (l)$ model, where (h) means the task embedding table $T$ is randomly initialized. This suggests that without prior knowledge of the tasks, the router can partially rediscover human categorization of tasks during multi-task learning. Results on more features are deferred in Fig. 6.

- **Text Domain.** Domain knowledge can largely influence downstream performance; and the routing model may be able to disentangle domain-specific signals during multi-task learning. We categorize tasks with into domains such as Science & Technology, Social Network, News, Web, Bio-Medical, Review, Dialog, and Books.

- **Granularity.** We categorize tasks into Span-
level (e.g., acronym identification); Sentence-level (e.g., tweet classification); Paragraph-level (e.g., news summarization) based on the main focus of the task. Note that this is different from input length.

- **Task Format and High-level Skills.** We additionally describe several characteristics that tasks can share in common in Table 4. These include whether a task is Extractive, requires Sentence Completion, or requires high-level skills such as Commonsense, Co-reference, etc.

**Findings.** Results on selected hand features are visualized in Fig. 4. We have the following observations: (1) There exists strong correlation between several pairs of routing decisions and hand features. For example, L1E2, L3E1, L6E1 are positively correlated with the feature of Classification, suggesting that these experts are likely to be selected for classification tasks. (2) The correlations are strongest with the top-level ontology features (i.e., Classification, QA, Conditional Generation), suggesting that the router may understand and categorize tasks in a way similar to ours. (3) However, correlation does not imply causation. The correlation patterns of Classification and hasShortOutput are similar, the same applies to Conditional Generation and hasLongOutput. It is still unclear to conclude whether the router is making router decisions on output length, task format, or other hidden aspects.

### 6.2 Expert Disabling Experiments

We further verify the observed correlations by disabling these experts during evaluation. We select three hand features: Classification, Conditional Generation, Closed-book QA, and select three tasks per feature. We find the top 3 experts that positively correlate with these features, and disable them during evaluation. By “disabling”, we simply set the pre-softmax logit to be -inf, so that the second-best expert in that layer will be selected instead. Results are listed in Table 3. As expected, these correlated experts are indispensable for the task performance. Performance gradually drops as more experts are disabled (All $\rightarrow$ Top1 $\rightarrow$ Top3).

### 7 Few-shot Adaptation to Novel Tasks

In this section we further study whether the routing-based multi-task learning induces better few-shot learning performance on unseen tasks.

| Hand Feature | Top3 Exp | Task | All | Top1 | Top3 |
|--------------|----------|------|-----|------|------|
| Classification | L1E2 | IMDB | 92.49 | 91.87 | 88.70 |
|               | L6E1 | SMS Spam | 63.54 | 63.54 | 62.88 |
|               | L3E1 | Emo | 82.06 | 65.46 | 16.22 |
| Conditional Generation | L9E2 | gigaword | 30.00 | 26.51 | 17.91 |
|               | L5E3 | aestc | 14.52 | 15.31 | 14.76 |
|               | L7E2 | kilt_wow | 6.39 | 6.01 | 4.73 |
| Closed-book QA | L3E2 | kilt_trex | 31.85 | 25.63 | 28.13 |
|               | L4E2 | kilt_zsre | 13.13 | 11.25 | 9.38 |
|               | L6E3 | numer_sense | 34.38 | 33.75 | 20.00 |

Table 3: Expert Disabling Experiments. Top1 means the top 1 expert is disabled. By gradually disabling the positively correlated experts, performance drops, suggesting that the correlated experts contribute to the performance of a specific types of tasks.

### 7.1 Compared Methods

**Vanilla BART.** For each unseen task, we fine-tune the off-the-shelf BART-Base model with its $D_{train}$.

**Multi-task BART.** We take the multi-task BART-Base baseline from §5 as initialization and fine-tune the model on $D_{train}$.

**Routing BART.** We first take the $(d) + (e) + (k) + (m)$ model and the $(d) + (f) + (k) + (m)$ model from §5. Both models uses fisher information as the task representation and the representations for seen tasks are frozen during multi-task learning. For the unseen task, we first compute its fisher information and feed it to the learned router to select experts. Then fine-tune the selected experts on $D_{train}$.

### 7.2 Experiment Details

For few-shot fine-tuning we mainly follow the experiment setting in Ye et al. (2021). Each task has five different few-shot samples of $(D_{train}, D_{dev})$. We train on $D_{train}$ for 1000 steps, and validate on $D_{dev}$ every 100 steps. We run a grid search for learning rate (1e-5, 2e-5, 5e-5) and batch size (2,4,8) for each few-shot sample. Finally, the model with best $D_{dev}$ performance is evaluated on $D_{test}$.

We compute and report the average performance gain (ARG) over vanilla BART for the multi-task BART and routing BART methods. For example, if fine-tuning vanilla BART achieves 50% accuracy on task A and 80% F1 on task B, and fine-tuning multi-task BART achieves 80% accuracy on task A and 60% F1 on task B, the ARG would be the average of $(80\% - 50\%)/50\%$ and $(60\% - 80\%)/80\%$, which equals to 17.5%.
| Feature Name | Example | Description |
|--------------|---------|-------------|
| Task Format  | Extractive: SQuAD, Race
Sentence Completion: HellaSwag, LAMA-Probes | Output is always a substring of the input
Requires the model to fill in a blank in the input or continue to generate based on the input |

| Required Skills and Knowledge | Linguistic: Blimp, GLUE-CoLA | Tasks focusing on grammatical correctness, semantic equivalence and linguistic phenomenon |
| Commonsense: CommonsenseQA | Tasks testing commonsense knowledge and reasoning capabilities |
| Co-reference | Tasks requiring co-reference resolution |
| Implicit Knowledge: Closed-book TriviaQA | Tasks requiring world knowledge (acquired during pre-training) |
| Synthesize: Break, XSum | Combining ideas and allowing an evolving understanding of text |

Table 4: High-level Hand Features Used in the Correlation Study.

Figure 5: Few-shot Performance on Unseen Tasks. Bar heights represent relative performance gain over fine-tuning a pre-trained BART-Base model. The right-most green bars are the average performance gain for each model.

7.3 Results

Results are presented in Fig. 5. Multi-task BART remains a strong baseline. The multi-task model achieves an ARG of 12.95%, and the two routing BART models achieves 10.03% and 10.15% respectively. The gap is mainly brought by the task yelp_polarity, whose performance is extremely unstable in few-shot settings. All four methods achieve similar validation performance (96% accuracy), while direct fine-tuning and fine-tuning the routing models have more degenerated runs among the five few-shot samples. In these degenerated runs, models achieves accuracy below 70% on $D_{test}$, despite high accuracy on $D_{dev}$. Multi-task BART is more stable for this task. We hypothesize that the routing architecture introduces more risks and instability to the model, and will develop methods to mitigate this issue in future work.

8 Conclusions

In this paper, based on the observation that transformer models trained by massive tasks have better ability to generalize to unseen tasks, we hope to provide a new sight on exploring how this cross-task generalization ability is achieved and reused. Inspired by the way that humans sparsely recall learned skills to solve new tasks, we explicitly model this process by resorting to a task-level mixture-of-expert model, where each expert represents different skills and tasks are routed by a router network based on the task property. We empirically investigate several importance design choices, i.e., routing models, expert selection strategies, task representations to exploring their influence on final model. Secondly, by conducting a detailed analysis on the final routing decisions, we find it has a strongly correlation with human-defined task ontology (e.g., classification) and task characteristics (e.g., extractive, linguistic) even without any prior knowledge. We believe the result is valuable and promising in understanding the skills learned behind the black-box transformer models.

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A Appendix

A.1 Details on Computing Task Representations

TASKEMB Inspired by the methodology of TASK2VEC(Achille et al., 2019), which generate visual classification tasks embedding based on the fisher information matrix(FIM). We take the gradient information defined by the FIM of probe
model’s parameters as the task embedding. the FIM provides a measure of the information a particular parameter learns about the loss corresponding to the probe model, so it is disable to represent task (Wang et al., 2021, Vu et al., 2020b).

Given probe model $M_\theta$, for example bart-base, we first calculate the loglikelihood with respect to the model parameters($\theta$) as: $P_\theta = \log M_\theta(y \mid x)$, then FIM is calculated as the covariance of gradients of the loglikelihood:

$$F_\theta = \mathbb{E}_{x,y \sim M_\theta(x,y)} \nabla \theta P_\theta \nabla \theta P_\theta^T$$ (2)

Here we compute FIM by using the empirical distribution defined by the training set of task instead of ideal distribution. Besides, we only use the diagonal entries following(Achille et al., 2019), since the full parameter size of probe model is undesirably large(millions of dimensions)) and our limited training data of each task is insufficient to train whole probe model. We resort to use the parameter-efficient adapter network, which add only a few trainable parameters to well pre-trained model while keep original network parameters fixed(Houlsby et al., 2019). Following the architecture of the adapter module in (Houlsby et al., 2019), we integrate adapter after the projection following multiheaded attention and after the two feed-forward layers of each transformer layer, which we indicate as Adapter-Bart with parameters: $\Theta = \{\theta, \alpha\}$. In a word, for each task we finetune a task-specific Adapter-Bart with the entire training dataset, then calculate the loglikelihood using whole parameters as: $P_\Theta = \log M_\Theta(y \mid x)$, while only calculate FIM values corresponding to the adapter parameters($\alpha$):

$$F_\alpha = \frac{1}{n} \sum_{i=1}^{n} \left[ \nabla \alpha P_\Theta(y^i \mid x^i) \nabla \alpha P_\Theta(y^i \mid x^i)^T \right]$$ (3)

Where $n$ is the number of training pairs, and the diagonal $F_\alpha$ is averaged over the input tokens and over the entire training set. However the resulting FIM is still too large (hundreds of thousands) and too sparse to represent task in data-constrained scenarios. As a result we use PCA to perform dimensionality reduction.

**Fine-tuned TEXTEMB** For fair comparison with TASKEMB, we also represent each task by their fine-tuned version of TEXTEMB in Vu et al., 2020b. To be specific, we use the averaged Bart token-level representations of the encoder inputs(FT-TextEmb-AVG) and the [BOS] embedding of the encode inputs(FT-TextEmb-AVG). Given a task $T$, we fine-tune Bart-base with the training set of $T$, then forward each encoder input sample $x_i$ to the fine-tuned Bart-base model. Then compute the averaged token-level embedding of final encoder layer(h_i,α) or simply retrieve the [BOS] embedding(h_i,b). Finally, the fine-tuned TEXTEMB of $T$ is calculated by the average pooling of entire training set by FT-TextEmb-AVG = $\frac{1}{n} \sum_{i=1}^{n} h_{ia}$ and FT-TextEmb-BOS = $\frac{1}{n} \sum_{i=1}^{n} h_{ib}$.

In this way we encode both the linguistic and label space information into final task embeddings.

**B Extended Hand Feature Correlation Results**

We show the detailed results of Pearson Correlation between our learned routes (based on a (d) + (e) + (h) + (l) model or (d) + (e) + (k) + (l) model) and selected Hand features in Figure 6 and Figure 7.

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1Vu et al., 2020b indicates TaskEmb computed from a fine-tuned task-specific BERT has better results on task transferability in data-constrained scenarios.
Figure 6: **Pearson Correlation Between Learned Routes and Hand Features.** Correlation with $p<0.01$ are visualized. The correlation is based on a (d) + (e) + (h) + (l) model.

Figure 7: **Pearson Correlation Between Learned Routes and Hand Features.** Correlation with $p<0.01$ are visualized. The correlation is based on a (d) + (e) + (k) + (l) model.
C Tasks Used and References

We list all the tasks used in this paper in Table 5.
Table 5: Tasks used in this work.

| Task Name | Ontology | Reference |
|-----------|----------|-----------|
| acronym_identification | other | Pouran Ben Veyseh et al. 2020 |
| ade_corpus_v2-classification | cls/other | Gurulingappa et al. 2012 |
| ade_corpus_v2-dosage | other/slot filling | Gurulingappa et al. 2012 |
| ade_corpus_v2-effect | other/slot filling | Gurulingappa et al. 2012 |
| adversarialqa | qa/machine reading comprehension | Bartolo et al. 2020 |
| aesi | cg/summarization | Zhang and Tetreault 2019 |
| ai2_arc | cls/topic | Clark et al. 2018 |
| amazon_polarity | qa/multiple-choice qa | McAuley and Leskovec 2013 |
| anli | cls/sentiment analysis | Nie et al. 2020 |
| app_reviews | other/regression | Missing |
| aqua_rat | qa/multiple-choice qa | Ling et al. 2017 |
| art (abductive nli) | other | Bhagavatula et al. 2020 |
| biosmr | machine reading comprehension | Pappas et al. 2020 |
| blimp-anaphor_gender_agreement | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-anaphor_number_agreement | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-determiner_noun_agreement_with_adj_irregular_1 | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-ellipsis_n_bar_1 | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-ellipsis_n_bar_2 | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-existential_there_quantifiers_1 | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-irregular_past_participle_adjectives | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-sentential_negation_npi_licensor_present | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-sentential_negation_npi_scope | other/linguistic phenomenon | Warstadt et al. 2020 |
| blimp-wh_questions_object_gap | qa/binary | Clark et al. 2019 |
| boolq | qa/multiple-choice qa | Wolfson et al. 2020 |
| break-QDMR_high-level | qa/multiple-choice qa | Wolfson et al. 2020 |
| circa | cls/sentiment checking | Digglemann et al. 2020 |
| codah | qa/multiple-choice qa | Chen et al. 2019 |
| commonsense_qa | qa/multiple-choice qa | Lin et al. 2020b |
| commonsense_qa | other/generate explanation | Talmer et al. 2019 |
| cosmos_qa | qa/multiple-choice qa | Rajani et al. 2019 |
| crawl_domain | other/summary | Huang et al. 2019 |
| crowds_pairs | other/summary | Zhang et al. 2020 |
| dbpedia_14 | cls/topic | Ng et al. 2020 |
| definite_pronoun_resolution | other/summary | Lehmann et al. 2015 |
| dream | other/summary | Rahman and Ng 2012 |
| emo | other/summary | Sileo et al. 2019 |
| emotion | qa/multiple-choice qa | Sun et al. 2019 |
| empathetic_dialogues | qa/machine reading comprehension | Saha et al. 2018 |
| ethos-directed_vs_generalized | other/summary | Dukel et al. 2020, 2019 |
| ethos-disability | qa/long-form qa | Fan et al. 2019 |
| ethos-gender | qa/long-form qa | Fan et al. 2019 |
| ethos-national_origin | qa/long-form qa | Fan et al. 2019 |
| ethos-race | qa/long-form qa | Fan et al. 2019 |
| ethos-religion | qa/long-form qa | Fan et al. 2019 |
| ethos-sexual_orientation | qa/long-form qa | Fan et al. 2019 |
| financial_phrasebank | qa/long-form qa | Fan et al. 2019 |
| freebase_qa | qa/long-form qa | Fan et al. 2019 |
| gigaword | qa/long-form qa | Fan et al. 2019 |
| glue-colab | qa/long-form qa | Fan et al. 2019 |
| glue-mmli | qa/long-form qa | Fan et al. 2019 |
| glue-mrpc | qa/long-form qa | Fan et al. 2019 |
| glue-squad | qa/long-form qa | Fan et al. 2019 |
| glue-sts2 | qa/long-form qa | Fan et al. 2019 |
| glue-wnli | qa/long-form qa | Fan et al. 2019 |
| google_wellformed_query | qa/long-form qa | Fan et al. 2019 |
| hate_speech18 | qa/long-form qa | Fan et al. 2019 |
| hate_speech_offensive | qa/long-form qa | Fan et al. 2019 |
| hatexplain | qa/long-form qa | Fan et al. 2019 |
| health_fact | qa/long-form qa | Fan et al. 2019 |
| hellaswag | qa/long-form qa | Fan et al. 2019 |
| hotpot_qa | qa/long-form qa | Fan et al. 2019 |
| imdb | qa/long-form qa | Fan et al. 2019 |
| jeopardy | qa/long-form qa | Fan et al. 2019 |
| kilt_ay2 | qa/long-form qa | Fan et al. 2019 |
| kilt_fever | qa/long-form qa | Fan et al. 2019 |
| kilt_hotpotqa | qa/long-form qa | Fan et al. 2019 |
| kilt_nq | qa/long-form qa | Fan et al. 2019 |
| kilt_trex | qa/long-form qa | Fan et al. 2019 |

Continued on next page
| Task Name                      | Ontology                        | Reference                                      |
|-------------------------------|---------------------------------|------------------------------------------------|
| kilt_wow                      | cg/dialogue                    | Dinan et al. 2019                             |
| kilt_zsre                     | qa/closed-book qa               | Levy et al. 2017                               |
| lama_conceptnet               | qa/closed-book qa               | Petroni et al. 2019, 2020                      |
| lama_google_re                 | qa/closed-book qa               | Petroni et al. 2019, 2020                      |
| lama_squad                    | qa/closed-book qa               | Petroni et al. 2019, 2020                      |
| lama-trex                     | qa/closed-book qa               | Petroni et al. 2019, 2020                      |
| liar                          | clo/fact checking               | Wang 2017                                      |
| limit                         | other                           | Munião et al. 2020                             |
| math_qa                       | qa/multiple-choice qa           | Amini et al. 2019                              |
| mc_taco                       | qa/binary                       | Zhou et al. 2019                               |
| medical_questions_pairs       | clo/paraphrase                  | McCrinky et al. 2020                           |
| mocha                         | other/ regression               | Chen et al. 2020a                              |
| multi_news                    | cg/summarization                | Fabbri et al. 2019                             |
| numerator                     | qa/closed-book qa               | Lin et al. 2020a                               |
| onesetop_english              | qa/closed-book qa               | Vajjala and Lučić 2018                         |
| openbookqa                    | qa/multiple-choice qa           | Mihaylov et al. 2018                           |
| paws                          | clo/other                       | Zhang et al. 2019                              |
| psqa                          | clo/other                       | Bisk et al. 2020                               |
| proto qa                      | clo/other                       | Sheng and Uthus 2020                           |
| qa_qrl                        | qa/multiple-choice qa           | Khot et al. 2020                               |
| quail                         | qa/multiple-choice qa           | Rogers et al. 2020                             |
| quarel                        | qa/multiple-choice qa           | Tafjord et al. 2019a                           |
| quartz-no_knowledge           | qa/multiple-choice qa           | Tafjord et al. 2019b                           |
| quartz-with_knowledge         | qa/machine reading comprehension | Lai et al. 2017                                |
| quoref                        | qa/machine reading comprehension | Lai et al. 2017                                |
| race-high                     | qa/multiple-choice qa           | Dusghi et al. 2019                             |
| race-middle                   | qa/multiple-choice qa           | Kim et al. 2019                                |
| redditi_tifu-title            | qa/machine reading comprehension | Lai et al. 2017                                |
| redditi_tifu-tridt            | qa/machine reading comprehension | Kim et al. 2019                                |
| ropes                         | qa/machine reading comprehension | Lin et al. 2019                                |
| rotten_tomatoes               | qa/machine reading comprehension | Pang and Lee 2005                              |
| samsum                        | qa/other                        | Gilwa et al. 2019                              |
| sentic                        | qa/machine reading comprehension | Cohan et al. 2019                             |
| scicite                       | qa/other                        | Welbl et al. 2017                              |
| sciq                          | qa/other                        | Khot et al. 2018                               |
| scitail                       | qa/other                        | Dunn et al. 2017                               |
| search_qa                     | qa/other                        | Marelli et al. 2014                            |
| sick                          | qa/other                        | Almeida et al. 2011                            |
| smsspam                       | qa/other                        | Sup et al. 2019                                |
| social_i_qa                   | qa/other                        | Yu et al. 2018                                 |
| spider                        | qa/other                        | Rajpurkar et al. 2016                          |
| squad-no-context              | qa/other                        | Rajpurkar et al. 2016                          |
| squad-with-context            | qa/other                        | de Marneffe et al. 2019                        |
| superglue-ch                  | qa/other                        | Gordon et al. 2012                             |
| superglue-copa                | qa/other                        | Khoshabi et al. 2018                           |
| superglue-multirc             | qa/other                        | Dagan et al. 2005; Bar-Haim et al. 2006         |
| superglue-record              | qa/other                        | Giampiccolo et al. 2007; Bentivogli et al. 2009 |
| superglue-re                  | qa/other                        | Piłchvar and Camacho-Collados et al. 2019       |
| superglue-wic                 | qa/other                        | Levesque et al. 2012                           |
| superglue-wisc                | qa/other                        | Zellers et al. 2018                            |
| swag                          | qa/other                        | Chen et al. 2020b                              |
| tab_fact                      | qa/other                        | Li and Roth 2002; Hovy et al. 2001              |
| trec                          | qa/other                        | Li and Roth 2002; Hovy et al. 2001              |
| trec-finegrained              | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-emoji              | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-emotion            | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-hate               | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-irony              | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-offensive          | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-stance-abortion    | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-stance-atheism     | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-stance_climate     | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-stance_feminist    | qa/other                        | Barbieri et al. 2020                           |
| tweet_eval-stance_hillary     | qa/other                        | Barbieri et al. 2020                           |
| tweet_qa                      | qa/other                        | Xiong et al. 2019                              |
| web_questions                 | qa/other                        | Berant et al. 2013                             |
| wiki_auto                     | qa/other                        | Jiung et al. 2020                              |
| wiki_bio                      | qa/other                        | Lebret et al. 2016                             |
| wiki qa                       | qa/other                        | Yang et al. 2015                               |
| wiki_split                    | qa/other                        | Botha et al. 2018                              |
| wikisql                       | qa/other                        | an 2017                                        |
| wino_grande                   | qa/other                        | Sakaguchi et al. 2020                          |
| wiki                         | qa/other                        | Tandon et al. 2019                             |
| xsum                          | qa/other                        | Narayan et al. 2018                            |
| yaho_answers_topics           | qa/other                        | (link)                                         |
| yelp_polarity                 | qa/other                        | Zhang et al. 2015; (link)                      |
| yelp_review_full              | qa/other                        | Zhang et al. 2015; (link)                      |