Exploring Universal Intrinsic Task Subspace via Prompt Tuning

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Abstract

Why can pre-trained language models (PLMs) learn universal representations and effectively adapt to broad NLP tasks differing a lot superficially? In this work, we empirically find evidence indicating that the adaptations of PLMs to various few-shot tasks can be reparameterized as optimizing only a few free parameters in a unified low-dimensional intrinsic task subspace, which may help us understand why PLMs could easily adapt to various NLP tasks with small-scale data. To find such a subspace and examine its universality, we propose an analysis pipeline called intrinsic prompt tuning (IPT). Specifically, we resort to the recent success of prompt tuning and decompose the soft prompts of multiple NLP tasks into the same low-dimensional nonlinear subspace, then we learn to adapt the PLM to unseen data or tasks by only tuning parameters in this subspace. In the experiments, we study diverse few-shot NLP tasks and surprisingly find that in a 250-dimensional subspace found with 100 tasks, by only tuning 250 free parameters, we can recover 97\% and 83\% of the full prompt tuning performance for 100 seen tasks (using different training data) and 20 unseen tasks, respectively, showing great generalization ability of the found intrinsic task subspace. Besides being an analysis tool, IPT could further help us improve the prompt tuning stability. The codes are publicly available at https://github.com/thunlp/Intrinsic-Prompt-Tuning.

1 Introduction

Pre-trained language models (PLMs) have shown dominant performances on various natural language processing (NLP) tasks (Han et al., 2021; Min et al., 2021). After pre-training huge parameters on massive data, a PLM can effectively adapt to diverse downstream NLP tasks with small-scale data through full-parameter fine-tuning or parameter-efficient tuning methods (Lester et al., 2021; Houlsby et al., 2019a). Nevertheless, the mechanisms behind such adaptations remain unclear. Why can PLMs learn universal representations through task-irrelevant pre-training objectives and easily adapt to diverse NLP tasks differing a lot? Towards answering this question, in this paper, we hypothesize that the adaptations of PLMs to various downstream tasks can be reparameterized as optimizing only a few free parameters in a unified low-dimensional parameter subspace, which we call intrinsic task subspace (Figure 1).

Specifically, during adaptation to a certain downstream task, PLMs optimize the tunable adaptive parameters. This is typically a high-dimensional optimization problem. For instance, in conventional fine-tuning, the adaptive parameters are all the PLM parameters, which may exceed hundreds of millions. However, Aghajanyan et al. (2021) show that the adaptation to a single task of a PLM can be reparameterized into only optimizing hundreds of free parameters in a low-dimensional subspace and then randomly projecting the tuned parameters back into the full parameter space. This motivates our hypothesis that adaptations to multiple tasks can be reparameterized into optimizations in a unified low-dimensional intrinsic task subspace. If this hypothesis holds, then (1) the existence of a common task reparameterization sub-
space explains the universality of PLMs and (2) the low dimensionality explains why the adaptations can be done with relatively small-scale data. From this perspective, the PLMs serve as general compression frameworks, which compress the learning complexity of various tasks from very high dimensionalities to low dimensionalities.

To find evidence for the hypothesis, we need to develop methods for finding the common intrinsic task subspaces of PLMs. Naturally, the subspace should contain adaptation solutions (i.e., tuned adaptive parameters) for various tasks, hence we can approximate the subspace by training a low-dimensional decomposition of the adaptive parameters using multiple tasks and then examine whether we can learn unseen tasks in the found subspace. However, training a decomposition for all the PLM parameters (the case of fine-tuning) is computationally unaffordable since the required parameters of the decomposition would be hundreds of times of PLMs. Fortunately, prompt tuning (PT) provides a parameter-efficient alternative, whose number of adaptive parameters (soft prompts), are only tens of thousands. PT can also achieve close performance to fine-tuning on both understanding (Lester et al., 2021) and generation (Li and Liang, 2021) tasks.

In experiments, we explore the common intrinsic subspace through PT under the few-shot learning setting, which ensures the data scales of various tasks are balanced. We name the analysis pipeline used in this paper as Intrinsic Prompt Tuning (IPT), which consists of two phases: multi-task subspace finding (MSF) and intrinsic subspace tuning (IST). During MSF, we first obtain trained soft prompts for multiple tasks and then learn an auto-encoder by first projecting them into the desired low-dimensional subspace and then reconstructing them with a back-projection. During IST, to adapt the PLM to unseen data and tasks, we only train the few free parameters in the low-dimensional subspace found by MSF through a fixed back-projection.

Surprisingly, we find that the intrinsic task subspace may not only exist but also is extremely low-dimensional. We study diverse few-shot NLP tasks and find that in a 250-dimensional subspace found by 100 tasks with MSF, we can recover 97% and 83% of the full PT performance with IST for 100 seen tasks (using different training data) and 20 unseen tasks, respectively. Furthermore, we analyze the effect of training task types, the number of training tasks, and training data scales for IPT. We also show that IPT and the intrinsic task subspace could help us analyze task differences and improve training stability. We encourage future work to explore how to better find the intrinsic task subspace and develop techniques taking inspiration from universal reparameterizations of PLM adaptations.

2 Related Work

PLM, Fine-tuning and Prompt tuning. Since the success of BERT (Devlin et al., 2019), pre-trained language models bring a new paradigm to NLP, that is to pre-train a massive model as the universal backbone and then adapt the PLMs to specific downstream tasks. The mainstream way of downstream adaptation is fine-tuning, which adds task-specific classification heads and tunes all the PLM parameters with supervised data.

Recently, researchers found that promising results can be achieved by casting downstream tasks into the form of pre-training tasks and adding some prompt tokens into the input, including human-designed explainable prompts (Brown et al., 2020; Schick and Schütze, 2021a,b) and automatically searched prompts (Jiang et al., 2020; Shin et al., 2020; Gao et al., 2021). Following this line of study, the prompts are extended from real tokens to trainable embeddings, i.e., soft prompts (Hambardzumyan et al., 2021; Zhong et al., 2021; Qin and Eisner, 2021). Furthermore, some works (Lester et al., 2021; Li and Liang, 2021) demonstrate that only tuning soft prompts and keeping PLMs frozen can achieve excellent performance in various tasks, especially for large-scale PLMs. In this work, we try to understand these phenomena, i.e., why can PLMs learn universal abilities to adapt to various tasks with few data points and tunable parameters.

Intrinsic Dimensionality. Intrinsic dimension (ID) is the minimal number of variables needed to represent some data or approximate a function. Li et al. (2018) propose to measure the IDs of objective functions optimized by neural networks through randomly projecting all the trainable parameters into linear subspaces and finding the minimal dimensions that satisfactory solutions appear. Following this, Aghajanyan et al. (2021) show that the IDs of PLM adaptations (via fine-tuning) to a single task can be smaller than thousands and pre-training implicitly lowers the IDs of downstream tasks, which motivates this work. Considering the
existence of individual subspace for each task has been proved, here we aim to study whether the subspace is universal. However, the random linear projections of previous methods inevitably introduce redundant task-irrelevant information and make the investigated subspace not compact for reparameterizing task adaptations. Therefore, we resort to stronger subspace-finding methods and use supervision from diverse tasks to train a nonlinear low-dimensional decomposition for the adaptive parameters.

**Unifying Different NLP Tasks.** Although various NLP tasks differ a lot on the surface, there have been long-standing attempts to unify different NLP tasks into the same form (Sun et al., 2021) and thus handle them with similar techniques, especially after the success of the prompting methods (Liu et al., 2021) to cast various tasks into the form of pre-training tasks of PLMs. The analyses in this paper may help us understand why this can be possible and explore how to better unify different tasks from the perspective of intrinsic task subspace.

### 3 Methodology

We first introduce essential preliminaries for both fine-tuning and prompt tuning in § 3.1, and then introduce our proposed analysis pipeline Intrinsic Prompt Tuning (IPT) in § 3.2, which consists of two stages: (1) Multi-task Subspace Finding (MSF) and (2) Intrinsic Subspace Tuning (IST). In Figure 2, we visualize the paradigms of fine-tuning, prompt tuning and our IPT.

#### 3.1 Preliminaries

Assume we are given a series of NLP tasks $\{T_1, \ldots, T_T\}$ partitioned into training tasks $T_{\text{train}}$ and test tasks $T_{\text{test}}$. Following Raffel et al. (2019), without loss of generality, we cast each task $T_i$ into the unified conditional generation format. Given a training instance $(X, Y)$ of $T_i$, where both the input $X$ and the target $Y$ consist of a sequence of tokens, i.e., $X = \{w_1, \ldots, w_{|X|}\}$ and $Y = \{y_1, \ldots, y_{|Y|}\}$. Our goal is to learn a mapping function $F_i : \mathcal{X} \rightarrow \mathcal{Y}$, and the de-facto way is to model $F_i$ with a PLM $M$, which first converts the input $X$ into embeddings $E = \{w_1, \ldots, w_{|X|}\} \in \mathbb{R}^{d \times |X|}$, where $d$ denotes the input embedding dimension, then encodes $E$ into hidden representations $H = \{h_1, \ldots, h_{|X|}\} \in \mathbb{R}^{d \times d}$ and finally decodes $Y$ conditioning on $H$. The goal is to optimize the following objective:

$$
\mathcal{L}_{\text{LM}} = -\frac{1}{|Y|} \prod_{j=1}^{|Y|} p(y_j | w_1, \ldots, w_{|X|}, y_1, \ldots, y_{j-1}).
$$

In traditional fine-tuning, all parameters of $M (\theta_M)$ are tuned during the optimization. Rather, prompt tuning (PT) prepends some task-specific embeddings (i.e., *soft prompts*) $P_i = \{p_1, \ldots, p_n\}$ parameterized by $\theta_P$ before $E$, and thus modify the input embeddings into $E^* = \{p_1, \ldots, p_n; w_1, \ldots, w_{|X|}\} \in \mathbb{R}^{(n+|X|) \times d}$. Then we keep $\theta_M$ frozen and only tune $\theta_P$ to adapt $M$ to $T_i$ during PT. The training objective of PT is essentially the same as $\mathcal{L}_{\text{LM}}$ and denoted as $\mathcal{L}_{\text{LM}}(P_i)$.

#### 3.2 Intrinsic Prompt Tuning

To verify our hypothesis that the adaptations of PLMs to various downstream tasks can be reparameterized as optimization within a unified low-dimensional intrinsic task subspace, we propose a two-phase analysis pipeline IPT. The first phase MSF aims to find the intrinsic task subspace with multiple tasks’ prompts, which are defined by an auto-encoder consisting of a projection function...
and a back-projection function. The second phase IST tunes a low-dimensional vector in the subspace and then recovers the vector to soft prompts through the back-projection function.

**Multi-task Subspace Finding.** We first conduct prompt tuning for each downstream task $T_i$ and obtain the trained soft prompts $P_i \in \mathbb{R}^{n \times d}$. During MSF, we try to find a satisfactory intrinsic task subspace of a low dimension $d_i$ by learning a decomposition for the matrix $P_i$. Inspired by text autoencoders (Bowman et al., 2016), the decomposition consists of a projection function $\text{Proj}_i(\cdot)$ to project $P_i$ into the $d_i$-dimensional subspace and a back-projection function $\text{Proj}_i^b(\cdot)$ to project the $d_i$-dimensional vectors back into soft prompts of $T_i$, and we optimize the reconstruction loss $L_{\text{AE}}^i$:

$$P_i^* = \text{Proj}_i(\text{Proj}_i^b(P_i)),
L_{\text{AE}}^i = \|P_i^* - P_i\|_2^2,$$

where $\text{Proj}_i(\cdot)$ is implemented with a one-layer feed-forward network and $\text{Proj}_i^b(\cdot)$ is parameterized by a two-layer nonlinear perceptron.

Moreover, finding the decomposition of a certain task’s prompt $P_i$, which is essentially a matrix, is somewhat trivial. Since the desired intrinsic task subspace should work for broad tasks, we introduce multi-task training and also take the task-oriented language modeling (using the reconstructed soft prompts) losses as objective functions. By jointly optimizing the reconstruction losses and the task-oriented losses, the subspace could gain the ability to reparameterize various task adaptations. The overall training objective of MSF is as follows:

$$L_{\text{MSF}}^{\theta_{\text{proj}}} = \frac{1}{|T_{\text{train}}|} \sum_{i=1}^{|T_{\text{train}}|} \left( L_{\text{LM}}(P_i^*) + \alpha L_{\text{AE}}^i \right),$$

where $\alpha$ denotes the hyper-parameter controlling the ratio between the two losses, and $\theta_{\text{proj}}$ denotes the parameters of both $\text{Proj}$ and $\text{Proj}_i^b$. During MSF, we only optimize $\theta_{\text{proj}}$ while keeping other parameters fixed. By introducing downstream task supervision and nonlinearity, we could find more redundant and effective subspaces than the random linear subspaces (Aghajanyan et al., 2021).

**Intrinsic Subspace Tuning.** In this stage, we want to evaluate if the subspace found by MSF is generalizable to previously (1) unseen training data of $T_{\text{train}}$ and (2) unseen tasks $T_{\text{test}}$. If the answer is yes, we can say that we successfully find the intrinsic task subspace reparameterizing the adaptations of PLMs to various tasks to some extent. Specifically, we only retain $\text{Proj}_i$ learned during MSF and keep both $\text{Proj}_i$ and $\mathcal{M}$ fixed. Then for each task $T_i$, instead of conducting vanilla prompt tuning, we tune only $d_i$ (bottleneck dimension) free parameters ($\theta_{\text{proj}}$) in the found subspace, which form a randomly initialized intrinsic vector $V_i \in \mathbb{R}^{d_i}$, and project them into soft prompts with the fixed $\text{Proj}_i$. The objective function for training a specific task $T_i$ could be formulated as:

$$L_{\theta_{\text{proj}}}^{\text{IST}} = L_{\text{LM}}(\text{Proj}_i^b(V_i)).$$

### 4 Experiment and Analysis

In this section, we first describe the experimental settings in § 4.1, including the tasks and corresponding datasets, evaluation pipeline, evaluation metrics and training details. Then we introduce the experimental results and analyses in § 4.2 and § 4.3. We provide notation descriptions in appendix C.

#### 4.1 Experimental Settings

**Tasks and Datasets.** To cover broad NLP tasks, we randomly choose 120 few-shot NLP tasks ($\mathcal{T}_{\text{all}}$, see appendix F for details) from CrossFit Gym (Ye et al., 2021), including text classification, question answering, conditional generation, etc. To evaluate the generalization ability of IPT, we randomly split the overall task set $\mathcal{T}_{\text{all}}$ into training tasks $T_{\text{train}}$ and test tasks $T_{\text{test}}$. We adopt three task splits as listed in Table 1 to investigate the influence of task types. Each task $T_i \in \mathcal{T}_{\text{all}}$ consists of a tuple of $(D_i^{\text{train}}, D_i^{\text{dev}}, D_i^{\text{test}})$, and the sizes of $D_i^{\text{train}}$ and $D_i^{\text{dev}}$ are both set to $K$ for the few-shot setting. For classification and regression tasks, $K = 16$; while for other categories, $K = 32$. The few-shot setting ensures the data scales of tasks are balanced so that the subspace found by MSF will not be easily biased towards data-rich tasks.

**Evaluation Pipeline: MSF.** During MSF, we first conduct prompt tuning for each task and obtain the soft prompts. Then we train an auto-encoder on $T_{\text{train}}$, and (1) evaluate the reconstructed prompts on $T_{\text{train}}$ (denoted as $T_{\text{train}}$ (MSF)) to see how much performance we could retain after reconstruction from a $d_i$-dimensional subspace. This performance provides an empirical upper bound for the generalization to unseen data and tasks in our setting. (2) We also directly reconstruct the soft prompts...
which will provide evidence for our hypothesis that Table 1, for the investigate whether adaptations to various tasks can Since different tasks have Evaluation Metrics. 

| Shorthand | $T_{\text{train}}$ | $T_{\text{test}}$ |
|-----------|--------------------|------------------|
| random    | 100 random         | 20 random        |
| non-cls.  | 35 non-cls. / 42 non-cls. ($T_{\text{train}}$) / 43 cls. ($T_{\text{test}}$) | |
| cls.      | 35 cls. / 8 cls. ($T_{\text{train}}$) / 77 non-cls. ($T_{\text{test}}$) | |

Table 1: The overall 120 tasks $T$ all consist of 43 classification tasks (cls.) and 77 non-classification tasks (non-cls.). Three task splits are evaluated, including random, non-cls and cls., with details listed above, e.g., for non-cls partition, 35 non-cls. are chosen as $T_{\text{train}}$ and 42 non-cls. / 43 cls. are chosen as $T_{\text{train}}^{\text{non-cls}} / T_{\text{test}}^{\text{non-cls}}$, respectively.

of $T_{\text{test}}$ with the learned auto-encoder and test their performance ($T_{\text{test}}$ (MSF)) to see the auto-encoder’s reconstruction ability for unseen soft prompts.

**Evaluation Pipeline: IST.** During IST, we investigate whether adaptations to various tasks can be reparameterized into the found subspace.

We first carry out experiments on $T_{\text{train}}$ using exactly the same $D_{\text{train}}^i / D_{\text{dev}}^i$ utilized in MSF training, and get the result $T_{\text{train}}^{\text{same}}$ (IST). Then we evaluate the generalization ability of IPT with two challenges: (1) unseen-data challenge and (2) unseen-task challenge.

- For the unseen-data challenge, we sample different $D_{\text{train}}^i / D_{\text{dev}}^i$ for $T_{\text{train}}$ while keeping test data the same. Then we conduct IST with the new data and test its performance on $T_{\text{train}}$, which is denoted as $T_{\text{test}}^{\text{diff}}$ (IST). This challenge evaluates whether the learned subspace can also reparameterize optimization on unseen data, which leads to different optimization trajectories than the seen data.

- For the unseen-task challenge, we evaluate the soft prompts obtained by IST on $T_{\text{test}}$, which are tasks unseen during MSF. We aim to investigate how well can optimization in the found subspace recover PLM adaptations of unseen tasks, which will provide evidence for our hypothesis that the reparameterization subspaces for different task adaptations are not orthogonal. In the task splits in Table 1, for the random split, the results of this challenge are denoted as $T_{\text{test}}$ (IST); for the non-cls and cls. splits, we have two test sets with different task types and the corresponding results are denoted as $T_{\text{test}}^{\text{in}}$ (IST) and $T_{\text{test}}^{\text{diff}}$ (IST), respectively.

**Evaluation Metrics.** Since different tasks have distinct evaluation protocols (e.g., F1 score for discriminative tasks and BLEU for generative tasks typically), following Ye et al. (2021), we mainly choose average relative performance ($E_{\text{rel}}$) as the evaluation metric, instead of absolute performance (also reported in appendix A.1 for reference). Specifically, let $T = \{T_1, ..., T_{|T|}\}$ be the evaluated tasks and $E_T$ denotes the test score of $T_i$ for IPT (either in MSF or IST), $E_{\text{rel}}^* = 1/|T| \sum_{T_i \in T} E_T / E_{T_i}^{\text{baseline}}$, where $E_{T_i}^{\text{baseline}}$ denotes the performance of $T_i$ using either prompt tuning ($E_T^{\text{PT}}$) or fine-tuning ($E_T^{\text{FT}}$). $E_{\text{rel}}^{\text{PT}} / E_{\text{rel}}^{\text{FT}}$ denotes our IPT’s relative performance to prompt tuning / fine-tuning.

**Training Details.** We use BART$_{\text{BASE}}$ (Lewis et al., 2020) for the experiments in the main paper, and unify all tasks into the same sentence-to-sequence format. We also test BART$_{\text{LARGE}}$ in appendix A.3. For the prompt tuning / fine-tuning baseline, we perform grid search on the combination of a series of learning rates and batch sizes and choose the best checkpoint using $D_{\text{dev}}$. We set the number of soft prompts to be 100 for all tasks and randomly initialize them. For IPT, we examine the dimension $d_I \in \{5, 10, 50, 100, 250\}$. Note that for fine-tuning / prompt tuning, 139M / 76, 800 parameters are tuned, while IPT only tunes $d_I$ free parameters. More details are left in appendix D.

4.2 Main Results

Based on the experimental results shown in Figure 3, we study the following questions:

Q1. Do PLMs really reparameterize various task adaptations into a universal task subspace? From the results in Figure 3 (a), we observe that: (1) for the unseen-data challenge ($T_{\text{train}}^{\text{diff}}$ (IST)), IST on unseen i.i.d. data could recover more than 90% of the full prompt tuning performance of the 100 training tasks; (2) for the unseen-task challenge ($T_{\text{test}}$ (IST)), we can also achieve 83% performance by only tuning 250 parameters. From these results, we can say that the low-dimensional reparameterizations in the subspaces found by MSF successfully recover the PLM adaptations of $T_{\text{train}}$ and can also generalize to unseen tasks. Thus non-trivial performance can be achieved by only tuning a few free parameters in these subspaces. This strongly supports our hypothesis that PLMs reparameterize various task adaptations into the same low-dimensional subspace, or at least the low-dimensional reparameterization subspaces for various task adaptations (Aghajanyan et al., 2021) should have a substantial intersection, otherwise the subspace found with $T_{\text{train}}$ in MSF would be almost impossible to also work for $T_{\text{test}}$. 
Q2. **What limits IPT?** Although strong evidence is observed, the effectiveness of IPT could still be improved, especially at low dimensions. From the results in Figure 3 (a) and (b), we discuss what factors may limit the effectiveness and provide insights for improving the analysis pipeline.

1. **Reconstruction ability of the auto-encoder.** The performance on $\mathcal{T}_{\text{train}}$ when we directly reconstruct soft prompts using the auto-encoder of MSF ($\mathcal{T}_{\text{train}}(\text{MSF})$) can be even better than vanilla prompt tuning (PT). This is because MSF explicitly enforces multi-task knowledge sharing within a unified subspace. Such knowledge sharing equips the subspace with better representational capabilities, making the subspace more universal. Thus the performance of MSF could even exceed conducting vanilla PT for each individual task. However, from the comparisons between $\mathcal{T}_{\text{train}}(\text{MSF})$ and $\mathcal{T}_{\text{test}}(\text{MSF})$, we can see that directly reconstructing soft prompts of unseen tasks performs poorly. It indicates that the reconstruction ability of the auto-encoders trained in MSF cannot generalize well to unseen soft prompts, which will limit IPT to some extent. This may come from the limited representation ability of the networks used to parameterize $\text{Proj}_T(\cdot)$ and $\text{Proj}_B(\cdot)$. Nevertheless, IST could find better solutions ($\mathcal{T}_{\text{test}}(\text{IST})$) than MSF reconstructed prompts ($\mathcal{T}_{\text{test}}(\text{MSF})$) with task-specific supervisions on $\mathcal{T}_{\text{test}}$.

2. **Optimization in IST.** The performance of $\mathcal{T}_{\text{train}}(\text{MSF})$ is always near 100%, which demonstrates that there exists good enough solutions for $\mathcal{T}_{\text{train}}$ in the found subspace. However, even using exactly the same training data, IST cannot find these good solutions (the gap between $\mathcal{T}_{\text{train}}(\text{MSF})$ and $\mathcal{T}_{\text{same}}(\text{IST})$), which shows that the adopted optimization algorithm may limit IST performance. We also observe that with $d_I$ increasing, the recovering performance of IST generally becomes better, which is because a higher dimension brings larger representational capacities.

3. **Adaptive parameters.** Comparing the results in Figure 3 (a) and (b), we observe that the relative performance of fine-tuning ($E_{\text{rel}}^{\text{FT}}$) is always poorer than that of PT ($E_{\text{rel}}^{\text{PT}}$). Since both of them have the same numerator, the above phenomenon is because PT is slightly inferior to fine-tuning under the few-shot setting. Since the performance of IPT is bounded by PT, ideally, $E_{\text{rel}}^{\text{IST}}$ could be improved by designing better PT algorithms or selecting more appropriate adaptive parameters.

Q3. **What is the influence of task types?** We first divide the studied tasks into cls (classification), which are discriminative tasks and non-cls (non-classification), which tend to be generative tasks. From the results in Figure 3 (c)-(d), we find that there exists a huge generalization gap between the two coarse-grained task types. When using only one kind of tasks during MSF, the found subspaces work well for the same kind of tasks ($\mathcal{T}_{\text{test}}^{\text{in}}(\text{IST})$) but generalize poorly to the other kind of tasks ($\mathcal{T}_{\text{test}}^{\text{out}}(\text{IST})$). This shows that the found subspace is severely biased by the training task types. We
further conduct more fine-grained analyses on task types to fathom their influence in appendix E.

4.3 Analyses and Properties

Comparison of Subspace-finding Methods. In Figure 4, we compare the relative fine-tuning performance ($E_{rel}^{FT}$) of subspaces found by IPT with various subspace-finding methods on the unseen-task challenge under random split\(^1\). (1) First, we investigate the randomly generated subspaces of Aghajanyan et al. (2021): the first trial Random\(_{prompt}\) conducts IST within random subspaces of soft prompts. The subspaces are defined by randomly initialized auto-encoders of the same architecture as MSF; the second trial Random\(_{all\ param.}\) conducts IST within random subspaces of all PLM parameters, which are generated by the efficient Fastfood transform (Le et al., 2013). We can see that the random subspace-finding methods can also find effective unified reparameterization subspaces at large dimensionality, which supports our universal reparameterization subspace hypothesis. In addition, IPT performs much better using much fewer dimensions, which indicates the effectiveness of MSF to exclude redundant task-irrelevant information and find compact subspaces. (2) Then we explore another parameter-efficient tuning method, Adapter (Houlsby et al., 2019b), as the backbone of our method, i.e., we conduct IPT pipeline using the adapter parameters\(^2\) instead of soft prompts. We observe that this method (IPT (Adapter)) performs consistently better than the original IPT using soft prompts (IPT (Prompt)) and can even outperform fine-tuning at 2000 dimensionality, which may be due to the better performance of adapter than prompt tuning (Hu et al., 2021). This further shows that IPT is agnostic to the specific tuning method and provides stronger empirical evidence for our research hypothesis.

\(^1\)Results on $T_{train}$ are shown in appendix A.4
\(^2\)The implementation details are shown in appendix D.2.

Impacts of the Data Scale. Although we adopt the few-shot setup to control the influence of data amount in this paper, it is also interesting to investigate IPT’s ability given more training data. Here we take an initial trial using the task split $cls$ by doubling / quadrupling the number of data shots $K$ of both seen and unseen tasks (from 16 to 32 / 64), and investigate the performance of IPT under the unseen-data ($T_{train}^{diff}$ (IST)) and unseen-task ($T_{test}^{diff}$ (IST)) challenges. Note that with different number of data points, the PT performance (denominator of $E_{rel}^{PT}$) is also different. The results are shown in Figure 5, from which we observe that when the data scale grows, the performance of IPT generally becomes better, especially at low dimensions. This shows that the subspace approximated with more data is more universal. Hence we encourage future work to explore how strong the performance of IPT on data-rich scenarios will be.

Impacts of the Number of Training Tasks. During MSF, the auto-encoder is optimized to reparameterize the adaptive parameters of various training tasks. Ideally, the coverage of $T_{train}$ would significantly impact the generalization ability of IPT on unseen tasks $T_{test}$. To demonstrate this, we randomly sample $\{20\%, 40\%, 60\%, 80\%\}$ tasks from $T_{train}$ of the random task split to train the auto-encoder, then evaluate IPT ($d_{l} = \{10, 100\}$) on original $T_{test}$ with the unseen-task challenge. From the results visualized in Figure 6, we observe that with the number of training tasks growing, the generalization ability of the found intrinsic task subspace generally improves. This reflects that increasing the coverage and diversity of seen tasks could help IPT find more universal subspaces.

Visualization of the Found Intrinsic Subspace. We visualize the intrinsic vectors $V_{j}$ (the free parameters learned during IST in the found subspace) using PCA in Figure 7, from which we observe that: (1) there exists a clear dividing line between the clusters of classification tasks and
Without loss of generality, we choose the task split of \( \frac{d_I}{100} \) runs comparing IPT (\( d_I = 10 \)) of test scores over multiple runs. \( d_I \) of IPT is chosen to be 10.

Specifically, we conduct vanilla PT of split random on \( T_{\text{test}} \) choosing \( d_I = 10 \) and initialize the soft prompts by back-projecting the IST solutions in the subspace. Other details are kept the same as the PT baseline. We observe that the std achieved in this way is significantly lower than the vanilla PT (1.65 v.s. 4.19) and we can achieve 103.4\% of \( E_{\text{rel}}^{\text{PT}} \), i.e., the performance could also be improved. This indicates that IPT and vanilla PT can be combined in a two-stage manner to improve the training stability and achieve satisfying performance.

| Method   | \( T_{\text{train}} \) | \( T_{\text{test}} \) | \( T_{\text{all}} \) |
|----------|------------------------|-----------------------|----------------------|
| Fine-tuning | 2.16 | 2.40 | 2.20 |
| Prompt Tuning | 3.06 | 4.19 | 3.25 |
| IPT       | 1.12 | 0.73 | 1.06 |

Table 2: Standard deviations (std) of test scores over various tasks can be reparameterized as optimizations within a unified low-dimensional intrinsic task subspace. We develop an analysis tool IPT. It first finds a subspace by jointly decomposing the adaptive parameters of multiple tasks and then tunes parameters within the subspace for unseen data and tasks. Experiments show the found subspaces contain good solutions for PLM adaptations, which is strong evidence for our hypothesis.

**Relation to the scaling law.** Recently, researchers have found that larger PLMs tend to be more sample-efficient (Kaplan et al., 2020), parameter-efficient (Lester et al., 2021) and cross-task generalizable (Wei et al., 2021). Our hypothesis may help us understand this phenomenon: the adaptations of larger PLMs can be better reparameterized into a unified subspace so that the cross-task generalization will be easier, and Aghajanyan et al. (2021) show larger PLMs have lower reparameterization dimensions, hence they should need fewer data and tunable parameters. This also implies that the characteristics of intrinsic task subspaces could be used to examine how well a PLM is trained.

**Utilize and manipulate intrinsic vectors.** The intrinsic vectors obtained during IST depict the adaptations to different tasks and it is worthwhile to explore whether we can (1) utilize them to find the relations among different tasks, and (2) manipulate these vectors to achieve cross-task gen-

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**Improving Prompt Tuning Stability with IPT.**

In Table 2, we show the mean standard deviations (std) of test scores for 120 few-shot tasks over 10 runs comparing IPT (\( d_I = 10 \)), fine-tuning and prompt tuning (PT). We observe that PT is the most unstable strategy with the highest std, while fine-tuning is far more stable. The instability of PT may influence its practical uses. Intuitively, IPT only tunes a few free parameters, which will conduce to improving the stability, and IPT surely becomes the most stable method in Table 2.

Furthermore, we propose to use the solutions found by IPT as the initialization for the vanilla PT.
eralization. We also encourage future works to explore more methods to tune PLMs within low-dimensional intrinsic task subspaces, which may have some practical benefits such as avoiding over-parameterization and being more environmentally friendly with fewer tunable parameters.

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whether the conclusions will also hold for larger PLMs or PLMs with extremely large sizes. All the experiments in § 4 are conducted with this paper, we do not experiment on other kinds of space and advance further research explorations, in the existence of the universal intrinsic task sub-

mensions. Since our main focus is to demonstrate for PLMs with larger sizes at small intrinsic di-

dimensions, we encourage future work to investi-

gering that Aghajanyan et al. (2021) indicate that intr-

sinsic task subspaces for larger PLMs. Consid-

ering that non-trivial performance can be recovered in the found subspaces. However, when \( d_I \) is extremely low (5 ∼ 10), the performance is obviously worse than the cases of BART\textsc{Base}, especially on the \textsc{cls} split. This phe-

omenon may come from the difficulty of finding intrinsic task subspaces for larger PLMs. Consid-

ering that Aghajanyan et al. (2021) indicate that larger PLMs generally have smaller intrinsic di-

mensions, we encourage future work to investi-

gate how to better find the intrinsic task subspace for PLMs with larger sizes at small intrinsic di-

mensions. Since our main focus is to demonstrate the existence of the universal intrinsic task subspace and advance further research explorations, in this paper, we do not experiment on other kinds of PLMs or PLMs with extremely large sizes.

### Appendices

#### A Additional Experiments

##### A.1 Absolute Performance

In the experiments, we mainly report the relative performance (\( E_{\text{rel}} \)). For reference, we also report the average absolute performance (\( E_{\text{abs}} \)) in this section. Let \( E_{d_I} \) denote the test score of \( T \) for IPT, \( E_{\text{abs}} = \frac{1}{|T|} \sum_{T \in T} E_{d_I} \). The \( E_{\text{abs}} \) of BART\textsc{Base} for prompt tuning and fine-tuning are shown in Table 3, and the \( E_{\text{abs}} \) of IPT on three task splits are shown in Table 4, Table 5 and Table 6, respectively.

##### A.2 Relative Performance to Fine-tuning

In the experiments, we report the relative performance to prompt tuning as the main evaluation metric except in Figure 3 (b), which reports the relative performance to fine-tuning on the \textsc{random} split for analyses. In this section, we additionally report \( E_{\text{rel}} \) on \textsc{non-cls} and \textsc{cls} splits in Figure 8 for reference, where we can see the general conclusions are consistent with our analyses in § 4.2.

##### A.3 BART\textsc{Large} Performance

All the experiments in § 4 are conducted with BART\textsc{Base} model (Lewis et al., 2020), which is also the main evaluated model of our adopted evaluation platform CrossFit (Ye et al., 2021). To see whether the conclusions will also hold for larger models, we take a prior trial by conducting experiments on BART\textsc{Large}. As the results in Figure 9 suggest, the overall conclusions are consistent with those of BART\textsc{Base} that non-trivial performance can be recovered in the found subspaces. However, when \( d_I \) is extremely low (5 ∼ 10), the performance is obviously worse than the cases of BART\textsc{Base}, especially on the \textsc{cls} split. This phe-

nomenon may come from the difficulty of finding intrinsic task subspaces for larger PLMs. Consid-

ering that Aghajanyan et al. (2021) indicate that larger PLMs generally have smaller intrinsic di-

mensions, we encourage future work to investi-

gate how to better find the intrinsic task subspace for PLMs with larger sizes at small intrinsic di-

mensions. Since our main focus is to demonstrate the existence of the universal intrinsic task subspace and advance further research explorations, in this paper, we do not experiment on other kinds of PLMs or PLMs with extremely large sizes.

### Table 3: Average absolute performance for prompt tuning / fine-tuning on the three task splits we adopted.

| Split   | Prompt Tuning | Fine-tuning |
|---------|---------------|-------------|
|         | \( T_{\text{train}} \) | \( T_{\text{test}} \) | \( T_{\text{train}} \) | \( T_{\text{test}} \) |
| random  | 32.6          | 40.1 (\( T_{\text{non-cls}} \)) | 35.2          | 40.7 (\( T_{\text{test}} \)) |
| non-cls | 23.0          | 28.0 / 49.0 | 24.4          | 29.6 / 52.2 |
| \textsc{cls} | 48.6          | 50.9 / 25.7 | 52.5          | 51.1 / 27.2 |

### Table 4: Average absolute performance on the \textsc{random} task split.

| Split   | Prompt Tuning | Fine-tuning |
|---------|---------------|-------------|
|         | \( T_{\text{train}} \) | \( T_{\text{test}} \) | \( T_{\text{train}} \) | \( T_{\text{test}} \) |
| \textsc{train} | 23.1          | 21.9        | 22.7          | 22.2         |
| \textsc{test}  | 27.4          | 23.4        | 27.2          | 26.2         |
| \textsc{diff}  | 25.8          | 22.8        | 25.4          | 25.8         |
| \textsc{intrinsic} | 17.4          | 17.7        | 18.6          | 21.5         |
| \textsc{out}   | 1.0           | 0.8         | 1.4           | 3.9          |

### Table 5: Average absolute performance on the \textsc{non-cls} task split.

| Split   | Prompt Tuning | Fine-tuning |
|---------|---------------|-------------|
|         | \( T_{\text{train}} \) | \( T_{\text{test}} \) | \( T_{\text{train}} \) | \( T_{\text{test}} \) |
| \textsc{train} | 50.0          | 48.0        | 49.5          | 48.7         |
| \textsc{test}  | 35.2          | 31.9        | 51.0          | 49.1         |
| \textsc{diff}  | 34.3          | 31.9        | 49.7          | 46.2         |
| \textsc{intrinsic} | 21.0          | 24.5        | 32.7          | 38.1         |
| \textsc{out}   | 0.7           | 1.0         | 2.3           | 4.6          |

### Table 6: Average absolute performance on the \textsc{cls} task split.

| Split   | Prompt Tuning | Fine-tuning |
|---------|---------------|-------------|
|         | \( T_{\text{train}} \) | \( T_{\text{test}} \) | \( T_{\text{train}} \) | \( T_{\text{test}} \) |
| \textsc{intrinsic} | 35.2          | 31.9        | 51.0          | 49.1         |
| \textsc{out}   | 34.3          | 31.9        | 49.7          | 46.2         |
| \textsc{intrinsic} | 21.0          | 24.5        | 32.7          | 38.1         |
| \textsc{out}   | 0.7           | 1.0         | 2.3           | 4.6          |

### A.4 Comparison of Subspace-Finding Methods on \( T_{\text{train}} \)

In § 4.3, we compare IPT and other subspace-finding methods on \( T_{\text{test}} \) of \textsc{random} split, i.e., the \textsc{unseen task} challenge. Here we additionally compare them on the \textsc{unseen data} challenge, i.e., \( T_{\text{train}} \). The results are shown in Figure 10, from which we can see that: (1) the methods relying on a random subspace (Random\textsc{prompt} and Random\textsc{all param.}) do not involve training and thus their performance
is poorer than our IPT, especially at low dimensions; (2) for IPT(Prompt) and IPT(Adapter), their performance is consistently high at each dimension, which suggests that our pipeline works well in memorizing (fitting) the reparameterization of training tasks.

B Additional Visualization

We visualize the intrinsic vectors of fine-grained categories of QA and text classification tasks using PCA in Figure 11. We observe that points belonging to the same category exhibit a compact cluster. This further shows that the learned intrinsic vectors could serve as task representations and help us analyze the similarity and differences of diverse NLP tasks.

C Descriptions of Notations

We explain some of the notations used in this paper in Table 7, so that readers could more easily navigate through the whole paper.

D Implementation Details

As mentioned in § 3.1, all tasks are processed into a unified sequence-to-sequence format following Raffel et al. (2019) and Khashabi et al. (2020) for ease of handling them with unified text-to-text PLMs.
\[
\begin{array}{l}
\text{Notation} & \text{Description} \\
\text{IPT} & \text{The analysis pipeline proposed in this paper (Intrinsic Prompt Tuning).} \\
\text{MSF} & \text{The first stage of IPT (Multi-task Subspace Finding).} \\
\text{IST} & \text{The second stage of IPT (Intrinsic Subspace Tuning).} \\
\end{array}
\]

\[
\begin{array}{l}
\mathcal{T}_{\text{train}}(\text{MSF}) & \text{Reconstructing the trained soft prompts of training tasks by training an auto-encoder.} \\
\mathcal{T}_{\text{test}}(\text{MSF}) & \text{Testing the generalization of the trained auto-encoder on test tasks.} \\
\mathcal{T}_{\text{train}}(\text{IST}) & \text{Conducting IST for each training task with the same training data used in MSF.} \\
\mathcal{T}_{\text{test}}(\text{IST}) & \text{Conducting IST for each test task with the different training data used in MSF (unseen-data challenge).} \\
\mathcal{T}_{\text{train}}(\text{IST}) & \text{Conducting IST for each test task (unseen-task challenge).} \\
\mathcal{T}_{\text{test}}(\text{IST}) & \text{Conducting IST for each test task belonging to the same categories of training tasks (unseen-task challenge).} \\
\end{array}
\]

\[
\begin{array}{l}
\mathcal{D}_{\text{train}} & \text{The training set of the task } \mathcal{T}_i. \\
\mathcal{D}_{\text{dev}} & \text{The development set of the task } \mathcal{T}_i. \\
\mathcal{D}_{\text{test}} & \text{The test set of the task } \mathcal{T}_i. \\

E_{\text{rel}}^\text{FT} & \text{Average relative performance compared with fine-tuning (FT).} \\
E_{\text{rel}}^\text{PT} & \text{Average relative performance compared with prompt tuning (PT).} \\
\text{random} & \text{Randomly split tasks } \mathcal{T}_{\text{train}} \text{ into training tasks } \mathcal{T}_{\text{train}} \text{ and test tasks } \mathcal{T}_{\text{test}}. \\
\text{non-cls} & \text{Choose a subset of non-classification tasks as the training tasks } \mathcal{T}_{\text{train}}. \\
\text{cls} & \text{Choose a subset of classification tasks as the training tasks } \mathcal{T}_{\text{train}}. \\
\end{array}
\]

Table 7: Descriptions about the notations used in this paper.

Figure 11: PCA plots of the intrinsic vectors learned during IST. We label points with different colors to represent their corresponding categories. Specifically, we show the clusters of fine-grained categories of QA (left) and text classification tasks (right). Without loss of generality, we choose the task split of random and \(d_I = 100\).

The experiments of MSF could be finished within 24 hours using 8 GPUs, and each experiment in IST could be finished within 6 hours on average using 1 GPU.

For detailed model implementation, as mentioned in §3.2, the projection function \(\text{Proj}(\cdot)\) is implemented with a one-layer feed-forward network and \(\text{Proj}_b(\cdot)\) is parameterized by a two-layer perceptron as follows:

\[
\text{Proj}_b(d_I) = W_2(\tanh(W_1 d_I + b_1)) + b_2,
\]

where \(W_1 \in \mathbb{R}^{d_I \times d_I'}, b_1 \in \mathbb{R}^{d_I'}, W_2 \in \mathbb{R}^{n \times d_I \times d_I'}\) and \(b_2 \in \mathbb{R}^{n \times d}\) are trainable parameters. \(d_I\) denotes the intrinsic dimension investigated in this paper. We set the inner hidden size \(d_I'\) of \(\text{Proj}_b\) to 768 for both BART\textsubscript{BASE} and BART\textsubscript{LARGE}.

D.2 Subspace-Finding with Adapter

The proposed IPT is agnostic to the specific parameter-efficient tuning method. To demonstrate this, we apply the techniques of IPT to Adapter (Houlsby et al., 2019b), which is a representative parameter-efficient tuning algorithm.

Adapter plugs in lightweight feed-forward networks between Transformer layers (both after the MHA module and the FFN module). Every adapter module consists of a down-projection matrix \(W_{\text{down}} \in \mathbb{R}^{r_A \times d}\), a non-linear activation function \(f(\cdot)\), and a up-projection matrix \(W_{\text{up}} \in \mathbb{R}^{d \times r_A}\), where \(r_A\) denotes the bottleneck dimension, and \(d\) denotes the hidden size of the PLM. Given an input \(h\), the adapter applies a residual connection as follows:

\[
h \leftarrow h + W_{\text{up}} f(W_{\text{down}} h).
\]

The essence of IPT is to define a projector from the intrinsic task subspace to the original parameter space. For Adapter, the parameter space is decided by the newly introduced matrices \(W_{\text{down}}\) and \(W_{\text{up}}\) in each layer. During the first stage MSF, we parameterize both \(W_{\text{down}}\) and \(W_{\text{up}}\) as the product of a low-dimensional intrinsic vector \(V \in \mathbb{R}^{d_I}\), lying in the intrinsic task subspace, and the corresponding projection matrices as follows:

\[
(W_{\text{up}}, W_{\text{down}}) = \text{Proj}(V),
\]

where the projection \(\text{Proj}\) is implemented by a two-layer perceptron. During the second stage of IST,
only a $d_I$-dimensional (randomly initialized) intrinsic vector $V$ is optimized. Other implementation details are kept the same as IPT(Prompt).

E Fine-grained Analyses on Task Types

In §4, we evaluate the performance of IPT on 120 tasks and also divide them into cls. (classification) and non-cls. (non-classification) tasks to see the difference between these two types. Here we take a step further to investigate IPT at a more fine-grained level based on the task ontology of Ye et al. (2021). Specifically, we choose 6 cls. task types (cls/topic, cls/fact checking, cls/NLI, cls/emotion, cls/paraphrase, cls/sentiment analysis) and 6 non-cls. task types (qa/multiple-choice qa, qa/long-form qa, cg/summarization, other/linguistic phenomenon, cg/dialogue, qa/MRC). We report the relative performance of IPT compared with prompt tuning ($E_{\text{rel}}^{\text{PT}}$) on these fine-grained task types, including two settings:

- included means that MSF is conducted on the training tasks of the random split (100 tasks in total, including all the task types), and IST is conducted on the tasks of the investigated type;
- excluded means that MSF is conducted on the training tasks excluding the tasks of the investigated type. In other words, we exclude the investigated type of tasks from the training tasks, to form the new training task set. The experiments of IST are conducted using the tasks of the investigated type. The test tasks of both settings (included and excluded) are the same.

Intuitively, if we exclude a specific task type from the training tasks, the approximated intrinsic task subspace may fail to include the language skills required by this task type, and would thus result in poor recovering performance during IST on the investigated task type. However, if other tasks in the training set share similar language skills of the investigated task type, the above issue could be mitigated to some extent. In this sense, the performance gap between excluded and included of a task type reflects the relation (common language skills) of the investigated type to other task types.

From the results shown in Figure 12, we can observe that: (1) some task types have a significant distinction from other types (reflected in the huge gap between excluded and included performance), such as cls/topic, cls/fact checking, and cls/NLI, which may come from the unique skills required to solve these tasks; (2) instead, some tasks tend to require similar language skills than other task types (reflected in the close performance between excluded and included), such as other/linguistic phenomenon, cg/dialogue, and qa/MRC. The above results demonstrate the potential of IPT to analyze task differences and we encourage future works to explore it systematically; (3) IPT achieves obvious improvements compared to vanilla prompt tuning (i.e., $E_{\text{rel}}^{\text{PT}} > 100\%$) on some task types such as cls/topic and qa/MRC, which indicates that tuning PLMs within the intrinsic task subspace is promising to obtain performance benefits.

Taking a step further, the above results also raise...
interesting research questions: (1) first of all, can we break the task barrier and decompose each task into a series of “atom tasks”? (2) Does there exist a limited number of atom task set, building on which all NLP tasks can be composed? Intuitively, solving each atom task requires a specific skill of neural models. By splitting each task into corresponding atom tasks and correctly defining the required skills of each atom task, we can better understand the characteristics of each task and fathom the relation among different tasks. Our analyses in this paper could provide supporting facts for the above questions. For instance, one can view each dimension of our intrinsic subspace as one kind of skill PLMs own, and solving each task can be seen as stimulating and composing the latent skills stored in PLMs. We encourage future works to investigate these interesting research questions.

F Task Details

We list details for all the evaluated tasks in this paper in Table 8.
Table 8: The tasks evaluated in our experiments. We refer to Ye et al. (2021) for task ontology.

| Ontology                        | Task Name                  | Reference                        |
|---------------------------------|----------------------------|----------------------------------|
| cls/sentiment analysis          | glue-sst2                  | Socher et al. 2013               |
|                                 | imdb                       | Maas et al. 2011                 |
|                                 | rotten_tomatoes            | Pang and Lee 2005                |
|                                 | emo                        | Chatterjee et al. 2019           |
|                                 | tweet_eval-emoji           | Barbieri et al. 2020             |
|                                 | tweet_eval-hate            | Barbieri et al. 2020             |
|                                 | tweet_eval-irony           | Barbieri et al. 2020             |
|                                 | tweet_eval-offensive       | Barbieri et al. 2020             |
|                                 | tweet_eval-sentiment       | Barbieri et al. 2020             |
|                                 | tweet_eval-stance_abortion | Barbieri et al. 2020             |
|                                 | tweet_eval-stance_atheism   | Barbieri et al. 2020             |
|                                 | tweet_eval-stance_climate  | Barbieri et al. 2020             |
|                                 | tweet_eval-stance_feminist | Barbieri et al. 2020             |
|                                 | tweet_eval-stance_hillary  | Barbieri et al. 2020             |
| cls/emotion                     | ethos-disability           | Mollas et al. 2020               |
|                                 | ethos-gender               | Mollas et al. 2020               |
|                                 | ethos-national_origin      | Mollas et al. 2020               |
|                                 | ethos-religion             | Mollas et al. 2020               |
|                                 | ethos-sexual_orientation   | Mollas et al. 2020               |
|                                 | hate_speech18              | Davidson et al. 2017             |
|                                 | hatexplain                 | Mathew et al. 2020               |
| cls/NLI                         | anli                       | Nie et al. 2020                   |
|                                 | glue-nnli                  | Williams et al. 2018             |
|                                 | glue-qnli                  | Raipurkar et al. 2016            |
|                                 | glue-rt                    | Dagan et al. 2005; Bar-Haim et al. 2006 |
|                                 | glue-wnli                  | Faruqui and Das 2018             |
|                                 | scitail                    | Khot et al. 2018                  |
|                                 | superglue-rtc              | Dagan et al. 2005; Bar-Haim et al. 2006 |
| cls/fact checking               | climate_fever              | Diggelmann et al. 2020           |
|                                 | kilt_fever                 | Thorne et al. 2018               |
|                                 | liar                       | Wang 2017                        |
| cls/paraphrase                  | glue-qqp                   | (link)                           |
|                                 | medical_questions_pairs    | McCreery et al. 2020             |
|                                 | paws                       | Zhang et al. 2019                |
| cls/topic                       | ag_news                    | Gulli (link)                     |
|                                 | dbpedia_14                 | Lehmann et al. 2015              |
| cls/other                       | ade_corpus_v2-classification| Gurulingappa et al. 2012         |
|                                 | discovery                  | Sileo et al. 2019                |
|                                 | glue-cola                  | Warstadt et al. 2019             |
|                                 | google_wellformed_query     | Faruqui and Das 2018             |
|                                 | smx_spam                   | Almeida et al. 2011              |
|                                 | superglue-wic              | Pilehvar and Camacho-Collados 2019 |
|                                 | superglue-wsc              | Levesque et al. 2012             |
|                                 | wiki_qa                    | Yang et al. 2015                  |
| qa/closed-book qa              | freebase_qa                | Jiang et al. 2019                |
|                                 | jeopardy                   | (link)                           |
|                                 | kilt_hotpotqa              | Yang et al. 2018                  |
|                                 | kilt_nq                    | Kwiatkowski et al. 2019          |
|                                 | kilt_trex                  | Elsahar et al. 2018              |
|                                 | kilt_zsre                  | Levy et al. 2017                  |
|                                 | lama-conceptnet            | Petroni et al. 2019, 2020         |
|                                 | lama-google_re             | Petroni et al. 2019, 2020         |
|                                 | lama-squad                 | Petroni et al. 2019, 2020         |
|                                 | lama-trex                  | Petroni et al. 2019, 2020         |
|                                 | numer_sense                | Lin et al. 2020a                  |
|                                 | search_qa                  | Dunn et al. 2017                  |
|                                 | squad-no_context           | Rajpurkar et al. 2016            |
|                                 | web_questions              | Berant et al. 2013                |
| qa/binary                      | boolq                      | Clark et al. 2019                |
|                                 | mc_taco                    | Zhou et al. 2019                 |
| Ontology                  | Task Name                          | Reference                        |
|--------------------------|------------------------------------|----------------------------------|
| qa/multiple-choice qa    | ai2_arc                            | Clark et al. 2018                |
|                          | aqua_rat                           | Ling et al. 2017                 |
|                          | codah                              | Chen et al. 2019                 |
|                          | commonsense_qa                     | Talmor et al. 2019               |
|                          | cosmos_qa                          | Huang et al. 2019                |
|                          | dream                              | Saha et al. 2018                 |
|                          | hellaswag                          | Zellers et al. 2019              |
|                          | math_qa                            | Amini et al. 2019                |
|                          | openbookqa                         | Mihaylov et al. 2018             |
|                          | qasc                               | Khot et al. 2020                 |
|                          | quail                              | Rogers et al. 2020               |
|                          | quarrel                            | Tafjord et al. 2019a             |
|                          | quartz-no_knowledge                | Tafjord et al. 2019b             |
|                          | quartz-with_knowledge              | Tafjord et al. 2019b             |
|                          | race-high                          | Lai et al. 2017                  |
|                          | race-middle                        | Lai et al. 2017                  |
|                          | social_1_qa                        | Sap et al. 2019                  |
|                          | superglue-copa                     | Gordon et al. 2012               |
|                          | superglue-mtirc                    | Khashabi et al. 2018             |
|                          | swag                               | Zellers et al. 2018              |
|                          | wino_grande                        | Sakaguchi et al. 2020            |
| qa/long-form qa          | eli5-askh                          | Fan et al. 2019                   |
|                          | eli5-asks                          | Fan et al. 2019                   |
|                          | eli5-eli5                          | Fan et al. 2019                   |
| qa/MRC                   | adversarialqa                      | Bartolo et al. 2020              |
|                          | biomrc                             | Pappas et al. 2020               |
|                          | quoref                             | Dasigi et al. 2019               |
|                          | ropes                              | Lin et al. 2019                   |
|                          | superglue-record                   | Zhang et al. 2018                 |
| cg/summarization         | gigaword                           | Napoles et al. 2012              |
|                          | multi_news                         | Fabbri et al. 2019               |
|                          | samsun                             | Gliwa et al. 2019                |
|                          | xsum                               | Narayanan et al. 2018            |
| cg/dialogue              | empathetic_dialogues               | Rashkin et al. 2019              |
|                          | kilt_wow                           | Dinan et al. 2019                |
| cg/other                | spider                             | Yu et al. 2018                    |
|                          | wiki_bio                           | Lebret et al. 2016               |
|                          | wiki_split                         | Botha et al. 2018                 |
|                          | wikisql                            | an 2017                           |
| other/linguistic         | blimp-anaphor_gender_agreement     | Warstadt et al. 2020             |
| phenomenon              | blimp-ellipsis_n_bar_1             | Warstadt et al. 2020             |
|                          | blimp-sentential_negation_npi_scope| Warstadt et al. 2020             |
| other/generate          | cos_e                              | Rajani et al. 2019               |
| explanation             |                                    |                                  |
| other/slot_filling      | ade_corpus_v2-dosage               | Gurulingappa et al. 2012          |
|                          | ade_corpus_v2-effect               | Gurulingappa et al. 2012          |
| other/entity linking    | kilt_ay2                           | Hoffart et al. 2011              |
| other/other             | acronym_identification              | Pouran Ben Veyseh et al. 2020    |
|                          | art                                | Bhagavatula et al. 2020           |
|                          | aslg_pc12                           | Othman and Jenni 2012            |
|                          | break-QDMR                          | Wolfson et al. 2020              |
|                          | break-QDMR-high-level               | Wolfson et al. 2020              |
|                          | common_gen                         | Lin et al. 2020b                 |
|                          | crawl_domain                        | Zhang et al. 2020                |
|                          | crows_pairs                         | Nangia et al. 2020               |
|                          | definite_pronoun_resolution         | Rahman and Ng 2012                |
|                          | e2e_nlg_cleaned                     | Dušek et al. 2020, 2019           |
|                          | limit                              | Manotas et al. 2020              |
|                          | piqa                               | Bisk et al. 2020                 |
|                          | proto qa                           | Boratko et al. 2020              |
|                          | qa_srl                             | He et al. 2015                    |