Prompt Consistency for Zero-Shot Task Generalization

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Abstract

One of the most impressive results of recent NLP history is the ability of pre-trained language models to solve new tasks in a *zero-shot* setting. To achieve this, NLP tasks are framed as natural language prompts, generating a response indicating the predicted output. Nonetheless, the performance in such settings often lags far behind its supervised counterpart, suggesting a large space for potential improvement. In this paper, we explore methods to utilize unlabeled data to improve zero-shot performance. Specifically, we take advantage of the fact that multiple prompts can be used to specify a single task, and propose to regularize *prompt consistency*, encouraging consistent predictions over this diverse set of prompts. Our method makes it possible to fine-tune the model either with extra unlabeled training data, or directly on test input at inference time in an unsupervised manner. In experiments, our approach outperforms the state-of-the-art zero-shot learner, T0 (Sanh et al., 2021), on 9 out of 11 datasets across 4 NLP tasks by up to 10.6 absolute points in terms of accuracy. The gains are often attained with a small number of unlabeled examples.[1]

1 Introduction

While the past decade has demonstrated that pre-trained language models (PLMs) are powerful tools for improving generalization from training datasets to test datasets (Devlin et al., 2019; Liu et al., 2019; Raffel et al., 2020), more recent work has shown that they can even perform *zero-shot generalization to new tasks* without any annotated examples (Brown et al., 2020; Wei et al., 2021; Sanh et al., 2021). These systems leverage natural language prompts that specify the task for the model and represent different tasks in a unified format (Liu et al., 2021). Zero-shot task generalization suggests a path towards generic systems that perform a wide variety of NLP tasks with no annotated examples. However, while enticing conceptually, zero-shot performance often remains relatively low compared to systems trained using even a small amount of task-specific labeled data.

In this paper, we examine methods to make PLMs better zero-shot learners using unlabeled text. Our work is motivated by consistency training methods that regularize model predictions to be invariant to perturbation (e.g. noise or paraphrasing) of the input examples. Consistency training is widely used in semi-supervised learning literature as an effective technique to utilize unannotated examples (Bachman et al., 2014; Sajjadi et al., 2016; Beyer et al., 2019; Xie et al., 2020a). It is often understood as a type of smoothness regularization or data augmentation (Xie et al., 2020a) and attains strong performance in semi-supervised learning. Instead of example-level consistency, we propose to regularize *prompt consistency*, where a model is regularized to make the same prediction across a diverse set of synonymous task prompts. Prompt consistency regularization makes sense intuitively since PLMs should be robust across synonymous prompts, whereas it is known that model predictions are empirically very sensitive to the wording of the task prompts (Jiang et al., 2020).

Specifically, we design a pairwise distillation loss that encourages consistency between every pair of prompts (Figure 1). We refer to our method as *swarm distillation*, and it has the advantage of being fully unsupervised, only requiring unannotated inputs. Notably, unannotated examples are often abundant and relatively easy to collect. Drafting several prompts for a task is also far cheaper than annotating labels for each example – in fact, there are already well-designed prompts available for a wide range of NLP tasks (Sanh et al., 2021).

Previous work on example-level consistency regularization typically minimizes a consistency loss along with a supervised loss in a semi-supervised

[1] Code is provided in the supplementary material.

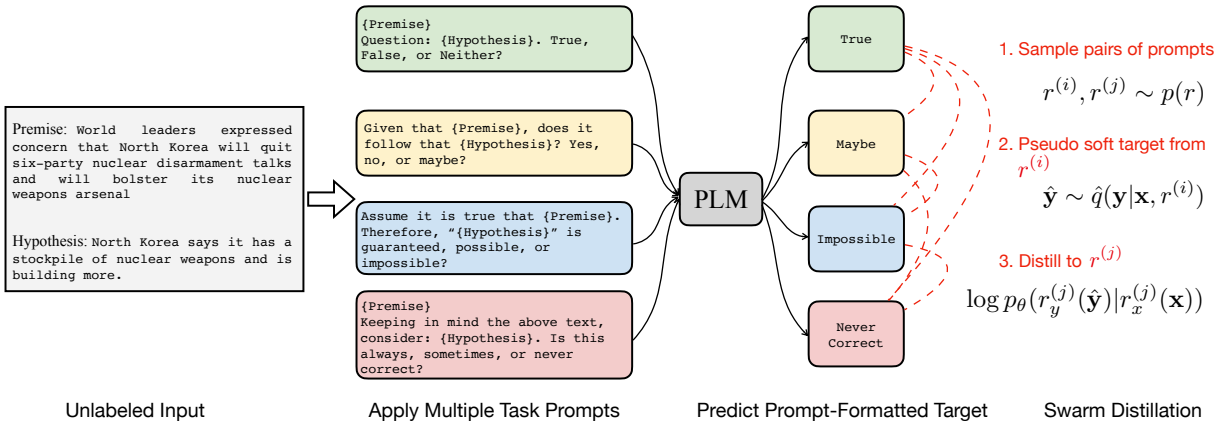


Figure 1: An example of the proposed approach in an NLI task. We apply multiple synonymous prompt templates to the unlabeled example, then we regularize the consistency of the predictions from different prompts, through our swarm distillation loss. Note that we are not regularizing the predicted text form $r_y^{(i)}(\mathbf{y})$ to be the same since different prompts have different target templates as shown above – we are actually regularizing the discrete labels $\mathbf{y}$ underneath to be consistent, as detailed in Eq. 2.

setting (Miyato et al., 2018; Xie et al., 2020a). Recently, Elazar et al. (2021) performed experiments optimizing a prompt consistency loss in the context of a relation prediction task, also incorporating a supervised version of the masked language model pretraining objective. In contrast, we (1) optimize a novel prompt consistency loss alone, making our approach completely unsupervised and agnostic to the model's pretraining objective, and (2) experiment on and demonstrate the practicality of such an approach for a broad variety of NLP tasks. Notably, this unsupervised setting poses additional learning challenges: without explicit supervision, the model may suffer from catastrophic forgetting and even exhibit a form of collapse where the model always makes the same predictions for any input. To address this issue, we adopt two simple strategies: (1) we utilize parameter-efficient tuning techniques (Houlsby et al., 2019; He et al., 2021) to only update a small number of extra parameters, naturally mitigating catastrophic forgetting by fixing the original PLM parameters; (2) we propose an unsupervised criterion to select the model checkpoint before it falls into a collapsed local optimum.

In experiments, we build our method on top of a state-of-the-art zero-shot task learner, T0 (Sanh et al., 2021), and validate its performance on 11 datasets from 4 NLP tasks: natural language inference, coreference resolution, word sense disambiguation, and sentence completion. We show that our swarm distillation method improves the accuracy of the 3B-parameter T0 model on 9 out of 11 datasets by up to 10.6 absolute points. We further scale model size up to 11B parameters, and demonstrate that our approach outperforms the 11B-parameter T0 model on 4 out of 4 datasets. Notably, analysis implies that these gains are sometimes possible with only tens of unannotated examples, suggesting a small computation overhead.

2 Prompt-based Zero-Shot Task Generalization

Given a task where the input is denoted as $\mathbf{x} \in \mathcal{X}$ and the goal is to predict $\mathbf{y} \in \mathcal{Y}$, we focus on the zero-shot task generalization setting: we aim to feed a PLM with $\mathbf{x}$ to predict $\mathbf{y}$, where the PLM is never trained on the specific task to be performed. Zero-shot task generalization goes beyond traditional dataset generalization, as the model must generalize to new functions $f : \mathcal{X} \rightarrow \mathcal{Y}$ as opposed to new input examples, $\mathbf{x}$. Recently, the development of prompting methods has advanced zero-shot task generalization by representing different tasks in a unified format (Liu et al., 2021), and several prompt-based approaches have attained reasonable zero-shot performance (Brown et al., 2020; Sanh et al., 2021; Wei et al., 2021).

A prompt r consists of an input template r_x, an output template r_y, and metadata to re-format the original $\mathbf{x}$ and $\mathbf{y}$ into new prompt-formatted input and target, $r_x(\mathbf{x})$ and $r_y(\mathbf{y})$. For example, as shown in Figure 1, in a natural language inference task to predict "entailment", "neutral", or "contradiction" between two texts, the input includes the field `Premise` and `Hypothesis` and the target consists of the field `Label`. An input template could be `Given that {Premise}, does it follow that {Hypothesis}? Yes, no, or maybe?`, and the target tem-

plate is `Choices[{label}]`. Here `Choices` is the metadata that is a list containing [`Yes`, `Maybe`, `No`] to correspond to the digit labels. We note that such metadata is prompt-specific and can differ with different prompts for the same task – for instance, in Figure 1 each prompt actually has a different `Choices` list from others; the `Choices` list of the first prompt on the top is [`True`, `False`, `Neither`]]. In prompt-based approaches the PLM models the conditional probability $q(\mathbf{y}|\mathbf{x}, r)$ through $p_\theta(r_y(\mathbf{y})|r_x(\mathbf{x}))$ where θ denotes the model parameters. In classification tasks where $\mathcal{Y}$ is a finite label set, $q(\mathbf{y}|\mathbf{x}, r)$ is normalized over the possible labels at inference time to predict $\mathbf{y}$:

$$q(\mathbf{y}|\mathbf{x}, r) = \frac{p_\theta(r_y(\mathbf{y})|r_x(\mathbf{x}))}{\sum_{\mathbf{y}' \in \mathcal{Y}} p_\theta(r_y(\mathbf{y}')|r_x(\mathbf{x}))}. \quad (1)$$

In generation tasks where $\mathcal{Y}$ is an infinite sequence space, the target template is typically instantiated as the target itself, i.e. $p_\theta(r_y(\mathbf{y})|r_x(\mathbf{x})) = p_\theta(\mathbf{y}|r_x(\mathbf{x}))$, then the output can be directly decoded through sequence decoding approaches. Through designing such prompts for each task, all NLP tasks share the same data format, and models trained on one task may generalize to others.

3 Prompt Consistency Training

3.1 Problem Definition

In this paper, we aim to explore unannotated examples to improve prompt-based zero-shot task generalization. Formally, we are given an unlabeled dataset in the task of interest $\{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_N\}$, and we assume the dataset has K different prompts, $\{(r_x^{(1)}, r_y^{(1)}), \cdots, (r_x^{(K)}, r_y^{(K)})\}$. Our goal is to utilize these resources and adapt a PLM to predict $r_y(\mathbf{y})$ conditioned on $r_x(\mathbf{x})$. We note that unlabeled input and a diverse set of prompts are not difficult to collect practically – the inputs to most NLP tasks are plain text such as reviews, documents, or questions, and empirically our method is effective even with tens to hundreds of unlabeled examples as we will show in §4.4; drafting prompts for each task is much easier than annotating labels for each example, in fact, the community efforts have pushed out a Public Pool of Prompts (P3)[2] that contains thousands of prompts for hundreds of NLP datasets already (Sanh et al., 2021). In this paper, we are going to focus our experiments on a subset of datasets supported by P3.

[2]https://github.com/bigscience-workshop/promptsource

3.2 The Prompt Consistency Loss

Consistency regularization is a method that creates different views (e.g. paraphrases of text) of the input and regularizes the outputs to be close to each other, and has achieved significant success in semi-supervised learning (Clark et al., 2018; Xie et al., 2020a,b). While previous methods use an additional module to perturb each example and then optimize example-level consistency, we propose to optimize prompt-level consistency which (1) is conceptually simple, and (2) can mitigate the fact that the predictions of PLMs are typically inconsistent with different prompts for the same task (Jiang et al., 2020; Elazar et al., 2021). Intuitively, we propose to regularize the predictions of different prompts for a given input to be close to each other, using a pairwise distillation loss to draw the predictions from one prompt closer to those from the other. Concretely, we randomly sample a few pairs of prompts and distill the pseudo target $\hat{\mathbf{y}}$ from one prompt $r^{(i)}$ to the other prompt $r^{(j)}$, as illustrated in Figure 1. The loss function is defined as:

$$\mathcal{L} = -\mathbb{E}_{\mathbf{x}\sim p_d(\mathbf{x})} \mathbb{E}_{r^{(i)}, r^{(j)} \sim p(r)} \mathbb{E}_{\hat{\mathbf{y}}\sim \hat{q}(\mathbf{y}|\mathbf{x}, r^{(i)})} \log p_\theta(r_y^{(j)}(\hat{\mathbf{y}})|r_x^{(j)}(\mathbf{x})), \quad (2)$$

where $p_d(\mathbf{x})$ is the empirical data distribution, $p(r)$ is a uniform distribution over possible prompts in the prompt set, and $\hat{q}(\mathbf{y}|\mathbf{x}, r)$ is the conditional target distribution defined as in Eq. 1 but with a stopping gradient operator. We do not propagate gradients to $\hat{q}(\mathbf{y}|\mathbf{x}, r^{(i)})$ following Miyato et al. (2018) and Xie et al. (2020a).[3] Stopping the gradient of one side in a pairwise consistency loss is also shown to help mitigate the collapse issue where all inputs lead to the same predictions (Chen and He, 2021). Different from traditional distillation that distills from a teacher model to a student model (Hinton et al., 2015), or previous consistency training that a single teacher distills to several students (Clark et al., 2018; Xie et al., 2020a), we perform distillation among a swarm of prompts where each prompt is a teacher and student at the same time, thus we term our method as *swarm distillation*. In our implementation, we approximate the expectation over the paired prompts $(r^{(i)}, r^{(j)})$ with k randomly sampled pairs instead of enumerating all pairs for training efficiency.

Prompt consistency is related to example-level consistency when viewing different prompt-

[3]Note that $\hat{q}(\mathbf{y}|\mathbf{x}, r)$ still changes as we train the model.

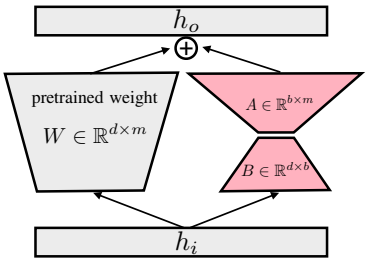


Figure 2: A diagram of LoRA in the FFN sublayer. Only the LoRA parameters, A and B, are updated during training while other parameters are fixed.

formatted inputs $r_x^{(i)}(\mathbf{x})$ as separated views of the same example, thus our swarm distillation approach shares spirit with previous work on example-level consistency training and can be understood similarly from the perspective of unsupervised data augmentation, smoothness regularization, or label propagation (Xie et al., 2020a). In this paper, we focus on classification tasks where $\mathcal{Y}$ is a finite label set, while Eq. 2 can be directly applied to sequence generation tasks as well with sequence distillation (Kim and Rush, 2016).

Our approach differs from previous consistency training methods which often combine an unsupervised consistency loss with a supervised loss in a semi-supervised setting (Miyato et al., 2018; Clark et al., 2018; Xie et al., 2020a). Elazar et al. (2021) try to improve prompt consistency for a relation filling task with a pairwise two-sided KL divergence loss, while they also optimize a supervised version of the original PLM objective that turns out to be important. In contrast, our approach minimizes the swarm distillation loss in Eq. 2 alone, and therefore is completely unsupervised and agnostic to the pretraining objective. However, this setting also poses challenges in learning, which we discuss next.

3.3 Training

Being trained without explicit supervision, the PLM may forget what it learns during pretraining since the unsupervised consistency loss is different from the pretraining objective. Also, we note that prompt consistency may be achieved with a trivial solution – if the predictions from each example and each prompt collapse to the same label then maximal consistency among prompts can be reached. To mitigate such catastrophic forgetting and collapse issues, we propose two techniques:

Parameter-efficient tuning: It has recently been observed that updating a small number of added parameters in a PLM is able to achieve comparable performance to tuning all the parameters (Houlsby et al., 2019; Li and Liang, 2021; Hu et al., 2021; He et al., 2021). Parameter-efficient tuning methods naturally mitigate catastrophic forgetting and collapse through fixing the original PLM parameters. Specifically, we use LoRA (Hu et al., 2021), a low-rank adaptation method for PLMs. As shown in Figure 2, LoRA learns a low-rank approximation of the pretrained matrix updates: given a pretrained weight matrix $W \in \mathbb{R}^{d\times m}$, LoRA learns to update it as $W \leftarrow W + \alpha BA$, where $B \in \mathbb{R}^{d\times b}$, $A \in \mathbb{R}^{b\times m}$ are low-rank matrices and α is a hyperparameter, and only B and A are updated during training. $b \ll d$ is referred to as the *bottleneck dimension*. Following He et al. (2021), we apply LoRA to the feed-forward weight matrices of every layer in the pretrained transformer (Vaswani et al., 2017) model. We emphasize that B (or A) needs to be initialized as a zero matrix to ensure the output distribution after adding LoRA layers is the same as the original PLM before training, otherwise, the zero-shot ability of PLMs would be broken upon initialization and there is no supervision to learn it back. In our preliminary experiments, we found that LoRA is less likely to suffer from collapse, while we still observe collapse sometimes. This motivates us to develop a criterion to select the model checkpoint before the model falls into a collapsed local optimum, which we describe next.

Unsupervised model selection criterion: In supervised learning, model selection is typically performed on a held-out validation set using supervised metrics. However, our zero-shot setting requires to develop an unsupervised selection criterion. Intuitively, it is straightforward to use a consistency metric as the criterion since we are optimizing towards prompt consistency, but a naive consistency metric would reach its maximum when the model is collapsed. Therefore, we would like to have a metric that encourages consistency but simultaneously penalizes collapse. With that in mind, we focus on Fleiss' kappa (Fleiss, 1971), a commonly used metric to assess the reliability of agreement between a fixed number of raters. In our setting, Fleiss' kappa expresses the extent to which the amount of agreement among prompts exceeds what would be expected if all prompts made their predictions according to the marginalized distribution of labels. This design naturally penalizes collapse and is computing a notion of "relative consistency". Formally, let n_{ij} be the number of

prompts that predict the j-th label for the i-th example. There are a total of NK predictions where N is the number of examples and K is the number of prompts. Given an example $\mathbf{x}_i$, the agreement probability p_i is to compute how many prompt pairs are in agreement, divided by the number of all possible pairs:

$$p_i = \frac{1}{K(K-1)} \sum_j n_{ij}(n_{ij}-1), \quad (3)$$

then p_i is averaged across examples to obtain the "absolute consistency":

$$\bar{P} = \frac{1}{N} \sum_{i=1}^{N} p_i. \quad (4)$$

It can be seen that $\bar{P}$ is maximized in the case of collapse. However, Fleiss' kappa considers the marginalized distribution of labels: how likely are two prompts consistent if they make predictions randomly according to the marginalized label distribution? This chance probability $\bar{P}_e$ is:

$$\bar{P}_e = \sum_j p_j^2, \qquad p_j = \frac{1}{NK} \sum_{i=1}^{N} n_{ij}, \quad (5)$$

where p_j represents the marginalized distribution of labels, i.e. $p(\mathbf{y} = j)$. $\bar{P}_e$ is large when collapse happens and one label dominates in the entire corpus. Finally, Fleiss' kappa is computed as:

$$\kappa = \frac{\bar{P} - \bar{P}_e}{1 - \bar{P}_e}, \quad (6)$$

where $1 - \bar{P}_e$ gives the degree of consistency that is attainable above chance, $\bar{P} - \bar{P}_e$ gives the degree of consistency actually achieved above chance. κ ranges from -1 to 1. Eq. 6 naturally penalizes collapse, and in our experiments, we always observe a monotonic decrease of κ when collapse happens. Therefore, we select the model checkpoint after which κ monotonically decreases.[4] We emphasize that we perform validation on the data that the model is trained on and do not require an additional development dataset.

4 Experiments

Our experiments below are designed to (1) measure whether swarm distillation is able to improve zero-shot task generalization; and (2) analyze how much resource (number of prompts and unlabeled examples) our method demands.

[4] In most of the settings, this criterion is equivalent to using maximal κ as the criterion, except for few cases where the beginning of training exhibits large fluctuations in κ.

4.1 General Setup

Datasets: Following Sanh et al. (2021), we evaluate our method on 11 NLP datasets across 4 unseen tasks. They are (1) natural language inference: ANLI (Nie et al., 2020) (there are three versions of ANLI with different levels of difficulty, which we denote as ANLI R1/R2/R3), CB (De Marneffe et al., 2019), RTE (Wang et al., 2019); (2) sentence completion: COPA (Roemmele et al., 2011), HellaSwag (Zellers et al., 2019), Story Cloze (Mostafazadeh et al., 2016); (3) coreference resolution: WSC, Winogrande (Levesque et al., 2012); and (4) word sense disambiguation: WIC (Pilehvar and Camacho-Collados, 2019). We access them using Hugging Face Datasets (Lhoest et al., 2021) and most of them are from the SuperGLUE benchmark (Wang et al., 2019). All of these datasets are classification-based, predicting a discrete label from a finite set. Each of these datasets has a diverse set of prompts provided by the Public Pool of Prompts (Sanh et al., 2021) The number of prompts ranges from 4 to 15. Please refer to Appendix A for detailed statistics of these datasets.

Setup: We build our method on top of the PLM T0 (Sanh et al., 2021). T0 is an adapted version of the pretrained T5 model (Raffel et al., 2020) that is continually trained on multiple tasks with supervised, prompt-formatted examples. T0 outperforms GPT3 (Brown et al., 2020) and demonstrates state-of-the-art performance in zero-shot task generalization. All the tasks that we are studying are not included in T0's training data. We focus our major study on the T0 model version with 3 billion parameters (T0-3B), while we also include results using the largest T0 model with 11 billion parameters (T0-11B) on some datasets, due to the high computational cost of training T0-11B. T0 is the main baseline that we compare our approach against. We tune the hyperparameters (e.g. the optimization hyperparameters) on the RTE dataset with its validation set and fix them for all other datasets. During optimization of Eq. 2, we randomly sample a batch of k pairs of prompts where k is the largest number that our GPU memory can fit and accumulate gradients for one update. We use a bottleneck dimension of 1 for LoRA. Complete setup details can be found in Appendix B.

4.2 Evaluation

Metrics: We use accuracy as the metric for all datasets. We report two different types of accuracy

Task	Dataset	T0-3B Ens.	T0-3B Med.	Swarm Distillation (train) Ens.	Swarm Distillation (train) Med.	Swarm Distillation (test) Ens.	Swarm Distillation (test) Med.
NLI	RTE	64.6	64.1	75.2±0.8 ↑10.6	73.9±0.8 ↑9.8	75.2±0.2 ↑10.6	73.5±0.1 ↑9.4
	CB	46.4	50.0	47.6±1.0 ↑1.2	48.2±0.0 ↓1.8	46.4±0.0 ↑0.0	48.8±1.0 ↓1.2
	ANLI R1	34.6	33.7	37.4±0.5 ↑2.8	35.5±0.7 ↑1.8	38.5±0.3 ↑3.9	35.7±0.5 ↑2.0
	ANLI R2	33.7	33.4	37.9±0.8 ↑4.2	36.6±0.5 ↑3.2	37.7±0.2 ↑4.0	35.4±0.4 ↑2.0
	ANLI R3	34.7	33.3	34.0±0.3 ↓0.7	34.6±0.1 ↑1.3	34.1±0.2 ↓0.6	33.5±0.0 ↑0.2
Compl.	COPA	78.0	79.0	82.3±0.6 ↑4.3	79.0±0.5 ↑0.0	83.0±1.0 ↑5.0	79.7±0.6 ↑0.7
	HellaSwag	27.8	27.5	34.2±0.2 ↑6.4	33.4±0.2 ↑5.9	33.7±0.6 ↑5.9	33.2±0.3 ↑5.7
	Story Cloze	86.5	85.1	–	–	87.3±0.1 ↑0.8	86.9±0.2 ↑1.8
Coref.	Wino.	50.9	50.5	52.0±0.3 ↑1.1	51.4±0.0 ↑0.9	52.1±0.3 ↑1.2	51.2±0.2 ↑0.7
	WSC	69.2	64.4	58.3±1.1 ↓10.9	59.3±2.0 ↓5.1	57.7±0.0 ↓11.5	58.8±0.6 ↓5.6
WSD	WIC	50.3	50.4	55.4±1.1 ↑5.1	54.4±0.7 ↑4.0	55.5±0.8 ↑5.2	54.8±0.5 ↑4.4

Table 1: Accuracy results on the validation set of 11 NLP datasets based on the T0-3B model. Swarm Distillation (train) and Swarm Distillation (test) use the unlabeled training split and validation split of datasets to train the model respectively, corresponding to training-time and test-time tuning. The Story Cloze dataset does not have a training split. We report the mean and std across 3 random runs, and also denote the absolute accuracy change compared to the T0-3B baseline.

given that we have multiple prompts. The *ensemble accuracy* (Ens.) averages the output distributions of multiple prompts and makes predictions according to it. Ensembling multiple prompts has been explored before and found superior to using a single prompt (Jiang et al., 2020; Qin and Eisner, 2021). The *median accuracy* (Med.) within the set of prompts serves as a proxy for the expected performance when users specify a single prompt and input a prompt-formatted example. As our approach assumes availability of a set of prompts for the downstream task, and it is relatively cheap to craft several prompts for a task, ensemble prediction is the better option given input $\mathbf{x}$, and it does empirically yield higher accuracy overall than the median for both the baseline and our method. Therefore, we will report both numbers but mainly discuss ensemble accuracy. We compute these metrics on the validation split of each dataset. We run the experiments with 3 random seeds and report the mean and standard deviation.

Evaluation scenarios: We provide our methods with different unlabeled sources which lead to two practical scenarios during evaluation: (1) *training-time tuning*: we use the unlabeled training split from the corresponding dataset to train the model. This is similar to traditional settings where training and test data are different; and (2) *test-time tuning* (Sun et al., 2020; Wang et al., 2021): we directly adapt the PLM on the test data. This setting is reasonable, as we will always have access to the test inputs at test time. Intuitively, the unlabeled test sample $\mathbf{x}$ often provides hints about the distribution it was drawn, suggesting that we may update the model before making the prediction. This scenario is attractive since it alleviates the common distribution mismatch issue when there is a distribution shift between the training and test data. Compared to training-time tuning, test-time tuning typically uses less unlabeled data in our experiments since it uses the validation split itself. In the major experiments, we focus on the offline test-time tuning where we assume access to the entire test data[5] and train our approach on all test examples, while in §4.4 we will discuss the potential for online adaptation where data arrives in a stream.

Dataset	T0-11B Ens.	T0-11B Med.	Swarm Dist. Ens.	Swarm Dist. Med.
WSC	63.5	62.5	65.4 ↑1.9	62.0 ↓0.5
RTE	83.8	82.0	86.6 ↑2.8	85.0 ↑3.0
HellaSwag	34.4	33.6	45.0 ↑10.6	43.0 ↑9.4
WIC	57.2	56.8	62.1 ↑4.9	60.7 ↑3.9

Table 2: Accuracy on the validation set based on T0-11B.

4.3 Results

How well does swarm distillation work? We compare swarm distillation against the T0-3B baseline. We run our own evaluation using the released T0 weights to obtain the T0 baseline accuracy.[6]

[5] To clarify, test data is not the test split of the dataset, but the data that we evaluate on, i.e. the validation split.

[6] We are able to reproduce the numbers reported in Sanh et al. (2021), except for COPA where our T0 median number is higher than the originally reported one.

	RTE	CB	ANLI R1	ANLI R2	ANLI R3	COPA	HS	Story.	Wino.	WSC	WIC	Avg.
T0-3B	0.644	0.440	0.221	0.189	0.170	0.586	0.164	0.765	0.396	0.255	0.398	0.384
Swarm Dist.	0.662	0.254	0.145	0.156	0.177	0.699	0.402	0.862	0.509	0.462	0.517	**0.440**

Table 3: Fleiss' kappa on 11 datasets based on T0-3B. Swarm distillation is trained on training split of the respective dataset.

The results are shown in Table 1. The ensemble accuracy of swarm distillation exceeds the T0-3B baseline on 9 out of 11 datasets in both training- and test-time tuning settings. Particularly, our approach improves the zero-shot performance on RTE by around 10 absolute points in all cases. Our approach slightly hurts ensemble accuracy of ANLI R3 and median accuracy of CB, but is overall comparable on these two datasets. We note that swarm distillation severely fails on WSC with a 10-point accuracy decrease, this is because Fleiss' kappa selects a bad model checkpoint, while our approach actually improves the performance on WSC in the middle of training as we will discuss more in §4.4. Although it may be argued that swarm distillation only works when the base PLM can attain reasonable performance in the first place, notably, our approach improves T0-3B greatly on several datasets where T0-3B only shows nearly chance accuracy, such as ANLI R1/R2/R3 (3 labels), HellaSwag (4 labels), Winogrande (2 labels), and WIC (2 labels). In addition, we observe that swarm distillation in the test-time tuning setting performs comparably well to the training-time one despite using much less training data, as shown in Appendix A. It is worth noting that prompt-based zero-shot task generalization is challenging, for example, T0 with even 11 billion parameters reports a median accuracy of only $\sim$ 40 on ANLI R1/R2/R3, 33.7 on HellaSwag, and 57.2 on WIC (Sanh et al., 2021). These numbers are surely still far from satisfactory, yet we hope to inspire future research to explore prompt-formatted, unlabeled data to build better zero-shot learners.

Scaling to 11B parameters: We now evaluate our method based on the largest version of T0 model, T0-11B. T0-11B is a very powerful zero-shot baseline that greatly outperforms GPT3 with 175 billion parameters. Due to the expensive computation to train T0-11B, we use one dataset per task, a total of 4 datasets as our benchmark, and only run with one random seed in the test-time tuning setting. Results are shown in Table 2. Swarm distillation outperforms T0-11B on all 4 datasets in terms of ensemble accuracy, and notably, improves the ensemble accuracy on HellaSwag from 34.4 to 45.0 without any annotation. Table 1 and Table 2 demonstrate the effectiveness of swarm distillation across different model sizes.

4.4 Analysis

Are predictions more consistent across different prompts after swarm distillation? We are interested to know whether the gains of swarm distillation are attained together with more consistent predictions across different prompts. To this end, we report Fleiss' kappa, a commonly used metric for group agreement as detailed in §3.3. Results are shown in Table 3. Fleiss' kappa on 8 out of 11 datasets increases after swarm distillation, which boosts the averaged Fleiss' kappa of T0-3B by 14.6% relatively. This implies that swarm distillation facilitates prompt consistency, and potentially improves the robustness of PLMs to different wording of prompts.

Does the unsupervised criterion select the best model checkpoint? In §3.3, we discussed using Fleiss' kappa to select the best model checkpoint for evaluation, here we report the oracle accuracy numbers obtained by selecting the model checkpoint with the best validation accuracy, and compare it to the one selected by Fleiss' kappa. We compare the ensemble accuracy using T0-3B in the training-time tuning setting, with results in Figure 3. On most of the datasets, Fleiss' kappa is able to achieve numbers close to the best ones. On all 11 datasets, our oracle number outperforms the T0-3B baseline. In Table 1 we show that swarm distillation hurts the performance on WSC a lot, while in Figure 3 swarm distillation (oracle) in fact outperforms T0-3B, implying that the issue lies on model selection. Therefore, swarm distillation could potentially work better if an annotated dev set is available or when it is combined with other techniques in few-shot learning settings, where good checkpoints may be selected out more easily.

How many prompts do we need? Our approach requires a diverse set of prompts to regularize prompt consistency. Here we perform ablation experiments to understand the effect of the number

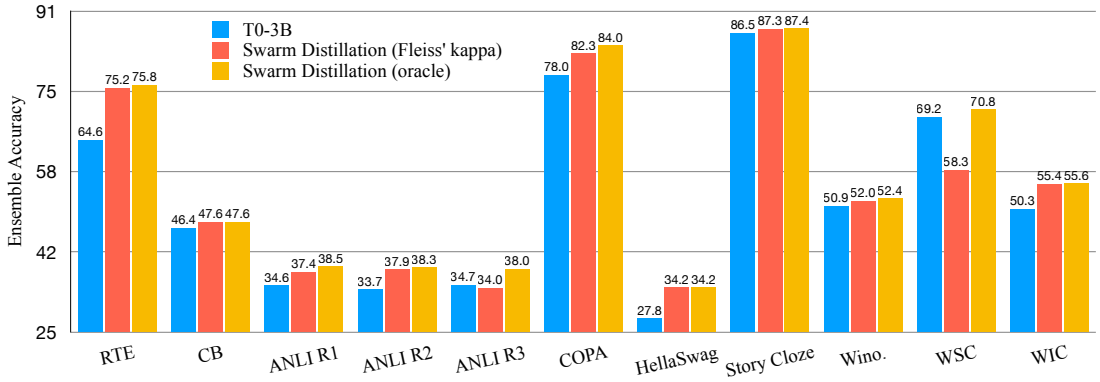
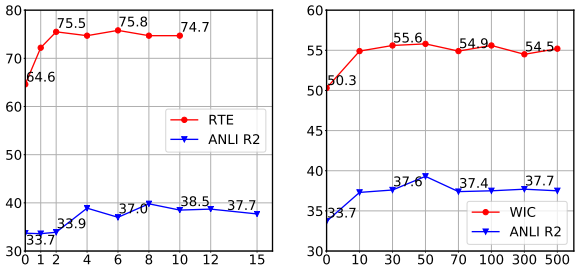


Figure 3: Analysis results to compare the model checkpoints selected by the unsupervised criterion Fleiss' kappa with the oracle model checkpoints selected by validation accuracy.



(a) Accuracy v.s. #prompts (b) Accuracy v.s. #examples

Figure 4: Ensemble accuracy of swarm distillation on three example datasets, demonstrating the effect of prompt size and unlabeled data size. The PLM is T0-3B.

of prompts on the performance. We take RTE and ANLI R2 as example datasets which have 10 and 15 prompts, respectively. We then vary the number of available prompts by randomly sampling a subset of prompts. We report the ensemble accuracy of swarm distillation (train) in Figure 4a. On both RTE and ANLI R2, we observe gains as we increase the number of prompts from 0 (0 means the baseline), yet the performance saturates very quickly and relatively stabilizes when we provide 2 and 4 prompts for RTE and ANLI R2 respectively. This implies that swarm distillation is not prompt-hungry and could work well with a small number of prompts. Interestingly, on RTE swarm distillation shows substantial improvement even with one prompt – this is not very surprising because our swarm distillation loss in Eq. 2 degenerates to self-distillation or self-training (Scudder, 1965), which has proven to effectively utilize unlabeled data and achieved success in various applications (He et al., 2020; Xie et al., 2020b; Zhang et al., 2020).

How many unlabeled examples do we need? We measure the effect of unlabeled data size. Specifically, we randomly sample a subset of examples from the train split for training and report results on the entire validation dataset. Results on WIC and ANLI R2 are shown in Figure 4b. Notably, swarm distillation is able to outperform the baselines (#examples=0) by a large margin on both datasets with only 10 unlabeled examples, and the performance starts to saturate quickly afterward. These results suggest that swarm distillation is not data-hungry and works reasonably well with few *unlabeled* examples, allowing swarm distillation to remain as a relatively light approach while typical unsupervised training (e.g. pretraining) often requires a large amount of data and computation. Also, we argue that the phenomenon demonstrated in the results implies that swarm distillation may be applied to the online setting of test-time tuning, where the batches of test data arrive in a stream. Online test-time tuning is a practical setting in real life, and we leave the study of swarm distillation in this setting as future work.

5 Discussion

In this paper, we explore prompt consistency regularization to make PLMs better zero-shot learners. Our approach utilizes unlabeled examples to attain zero-shot gains. While we use it in a post-adaptation way to adapt PLMs with the proposed swarm distillation loss alone, our regularization loss could be potentially combined with the pre-training objectives in the pretraining stage, with the multi-prompt training loss (Sanh et al., 2021; Wei et al., 2021), or even with annotated data in few-shot learning settings. Combining the swarm distillation loss with these other losses may easily bypass the model collapse issue since the other loss typically discourages the collapsed local optimum. The potential applications of unsupervised swarm distillation on sequence generation tasks are also worth studying in the future.

Ethics Statement

Our work adapts a PLM to be better zero-shot learners, thus the resulted system admits similar risks and ethics concerns that large PLMs generally have, such as concerns about biased generation (Bordia and Bowman, 2019) or private information leakage (Carlini et al., 2021). Besides, prompt-based zero-shot task generalization is often an open-ended generation setting, thus toxic content may be unexpectedly produced with certain prompts due to lack of control in the process. This is a common issue for prompting methods generally (Radford et al., 2019; Brown et al., 2020; Sanh et al., 2021; Wei et al., 2021) and there is a recent study to teach machines to behave ethically (Jiang et al., 2021). However, our approach does not add additional risks beyond the existing systems as far as we can tell.

With respect to the environmental impact (Strubell et al., 2019) from adapting the PLM with swarm distillation, our approach is not data-hungry and works well with a small number of unlabeled examples as discussed in §4.4, thus it does not require huge computation. For example, the training time of all the experiments based on the T0-3B model is less than 3 hours with only one A40 GPU; the training time of T0-11 model is 2-6 hours with 4 A40 GPUs. These numbers are benchmarked from our main experiments that train with the entire training or validation dataset, yet our analysis in §4.4 implies that we may train with only tens of examples to greatly save computation, we leave this as future work to explore.

References

Philip Bachman, Ouais Alsharif, and Doina Precup. 2014. Learning with pseudo-ensembles. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 3365–3373.

Lucas Beyer, Xiaohua Zhai, Avital Oliver, and Alexander Kolesnikov. 2019. S4L: self-supervised semi-supervised learning. In *2019 IEEE/CVF International Conference on Computer Vision, ICCV 2019, Seoul, Korea (South), October 27 - November 2, 2019*, pages 1476–1485. IEEE.

Shikha Bordia and Samuel R. Bowman. 2019. Identifying and reducing gender bias in word-level language models. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Student Research Workshop*, pages 7–15, Minneapolis, Minnesota. Association for Computational Linguistics.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Nicholas Carlini, Florian Tramer, Eric Wallace, Matthew Jagielski, Ariel Herbert-Voss, Katherine Lee, Adam Roberts, Tom Brown, Dawn Song, Ulfar Erlingsson, et al. 2021. Extracting training data from large language models. In *30th USENIX Security Symposium (USENIX Security 21)*, pages 2633–2650.

Xinlei Chen and Kaiming He. 2021. Exploring simple siamese representation learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 15750–15758.

Kevin Clark, Minh-Thang Luong, Christopher D. Manning, and Quoc Le. 2018. Semi-supervised sequence modeling with cross-view training. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing*, pages 1914–1925, Brussels, Belgium. Association for Computational Linguistics.

Marie-Catherine De Marneffe, Mandy Simons, and Judith Tonhauser. 2019. The commitmentbank: Investigating projection in naturally occurring discourse. In *proceedings of Sinn und Bedeutung*, volume 23, pages 107–124.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Yanai Elazar, Nora Kassner, Shauli Ravfogel, Abhilasha Ravichander, Eduard Hovy, Hinrich Schütze, and Yoav Goldberg. 2021. Measuring and improving consistency in pretrained language models. *Transactions of the Association for Computational Linguistics*, 9:1012–1031.

Joseph L Fleiss. 1971. Measuring nominal scale agreement among many raters. *Psychological bulletin*, 76(5):378.

Junxian He, Jiatao Gu, Jiajun Shen, and Marc'Aurelio Ranzato. 2020. Revisiting self-training for neural sequence generation. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net.

Junxian He, Chunting Zhou, Xuezhe Ma, Taylor Berg-Kirkpatrick, and Graham Neubig. 2021. Towards a unified view of parameter-efficient transfer learning. *ArXiv preprint*, abs/2110.04366.

Geoffrey Hinton, Oriol Vinyals, and Jeff Dean. 2015. Distilling the knowledge in a neural network. *ArXiv preprint*, abs/1503.02531.

Neil Houlsby, Andrei Giurgiu, Stanislaw Jastrzebski, Bruna Morrone, Quentin de Laroussilhe, Andrea Gesmundo, Mona Attariyan, and Sylvain Gelly. 2019. Parameter-efficient transfer learning for NLP. In *Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA*, volume 97 of *Proceedings of Machine Learning Research*, pages 2790–2799. PMLR.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. 2021. Lora: Low-rank adaptation of large language models. *ArXiv preprint*, abs/2106.09685.

Liwei Jiang, Jena D Hwang, Chandra Bhagavatula, Ronan Le Bras, Maxwell Forbes, Jon Borchardt, Jenny Liang, Oren Etzioni, Maarten Sap, and Yejin Choi. 2021. Delphi: Towards machine ethics and norms. *arXiv preprint arXiv:2110.07574*.

Zhengbao Jiang, Frank F. Xu, Jun Araki, and Graham Neubig. 2020. How can we know what language models know? *Transactions of the Association for Computational Linguistics*, 8:423–438.

Yoon Kim and Alexander M. Rush. 2016. Sequence-level knowledge distillation. In *Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing*, pages 1317–1327, Austin, Texas. Association for Computational Linguistics.

Diederik P Kingma and Jimmy Ba. 2015. Adam: A method for stochastic optimization. In *International Conference on Learning Representations*.

Hector Levesque, Ernest Davis, and Leora Morgenstern. 2012. The winograd schema challenge. In *Thirteenth International Conference on the Principles of Knowledge Representation and Reasoning*.

Quentin Lhoest, Albert Villanova del Moral, Yacine Jernite, Abhishek Thakur, Patrick von Platen, Suraj Patil, Julien Chaumond, Mariama Drame, Julien Plu, Lewis Tunstall, Joe Davison, Mario Šaško, Gunjan Chhablani, Bhavitvya Malik, Simon Brandeis, Teven Le Scao, Victor Sanh, Canwen Xu, Nicolas Patry, Angelina McMillan-Major, Philipp Schmid, Sylvain Gugger, Clément Delangue, Théo Matussière, Lysandre Debut, Stas Bekman, Pierric Cistac, Thibault Goehringer, Victor Mustar, François Lagunas, Alexander Rush, and Thomas Wolf. 2021. Datasets: A community library for natural language processing. In *Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 175–184, Online and Punta Cana, Dominican Republic. Association for Computational Linguistics.

Xiang Lisa Li and Percy Liang. 2021. Prefix-tuning: Optimizing continuous prompts for generation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 4582–4597, Online. Association for Computational Linguistics.

Pengfei Liu, Weizhe Yuan, Jinlan Fu, Zhengbao Jiang, Hiroaki Hayashi, and Graham Neubig. 2021. Pre-train, prompt, and predict: A systematic survey of prompting methods in natural language processing. *ArXiv preprint*, abs/2107.13586.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *ArXiv preprint*, abs/1907.11692.

Takeru Miyato, Shin-ichi Maeda, Masanori Koyama, and Shin Ishii. 2018. Virtual adversarial training: a regularization method for supervised and semi-supervised learning. *IEEE transactions on pattern analysis and machine intelligence*, 41(8):1979–1993.

Nasrin Mostafazadeh, Nathanael Chambers, Xiaodong He, Devi Parikh, Dhruv Batra, Lucy Vanderwende, Pushmeet Kohli, and James Allen. 2016. A corpus and cloze evaluation for deeper understanding of commonsense stories. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 839–849, San Diego, California. Association for Computational Linguistics.

Yixin Nie, Adina Williams, Emily Dinan, Mohit Bansal, Jason Weston, and Douwe Kiela. 2020. Adversarial NLI: A new benchmark for natural language understanding. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4885–4901, Online. Association for Computational Linguistics.

Mohammad Taher Pilehvar and Jose Camacho-Collados. 2019. WiC: the word-in-context dataset for evaluating context-sensitive meaning representations. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 1267–1273, Minneapolis, Minnesota. Association for Computational Linguistics.

Guanghui Qin and Jason Eisner. 2021. Learning how to ask: Querying LMs with mixtures of soft prompts. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5203–5212, Online. Association for Computational Linguistics.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67.

Jie Ren, Samyam Rajbhandari, Reza Yazdani Aminabadi, Olatunji Ruwase, Shuangyan Yang, Minjia Zhang, Dong Li, and Yuxiong He. 2021. Zero-offload: Democratizing billion-scale model training. *arXiv preprint arXiv:2101.06840*.

Melissa Roemmele, Cosmin Adrian Bejan, and Andrew S Gordon. 2011. Choice of plausible alternatives: An evaluation of commonsense causal reasoning. In *2011 AAAI Spring Symposium Series*.

Mehdi Sajjadi, Mehran Javanmardi, and Tolga Tasdizen. 2016. Regularization with stochastic transformations and perturbations for deep semi-supervised learning. In *Advances in Neural Information Processing Systems 29: Annual Conference on Neural Information Processing Systems 2016, December 5-10, 2016, Barcelona, Spain*, pages 1163–1171.

Victor Sanh, Albert Webson, Colin Raffel, Stephen H Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Teven Le Scao, Arun Raja, et al. 2021. Multitask prompted training enables zero-shot task generalization. *ArXiv preprint*, abs/2110.08207.

Henry Scudder. 1965. Probability of error of some adaptive pattern-recognition machines. *IEEE Transactions on Information Theory*, 11(3):363–371.

Emma Strubell, Ananya Ganesh, and Andrew McCallum. 2019. Energy and policy considerations for deep learning in NLP. In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 3645–3650, Florence, Italy. Association for Computational Linguistics.

Yu Sun, Xiaolong Wang, Zhuang Liu, John Miller, Alexei A. Efros, and Moritz Hardt. 2020. Test-time training with self-supervision for generalization under distribution shifts. In *Proceedings of the 37th International Conference on Machine Learning, ICML 2020, 13-18 July 2020, Virtual Event*, volume 119 of *Proceedings of Machine Learning Research*, pages 9229–9248. PMLR.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. In *Advances in Neural Information Processing Systems 30: Annual Conference on Neural Information Processing Systems 2017, December 4-9, 2017, Long Beach, CA, USA*, pages 5998–6008.

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2019. Superglue: A stickier benchmark for general-purpose language understanding systems. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 3261–3275.

Dequan Wang, Evan Shelhamer, Shaoteng Liu, Bruno A. Olshausen, and Trevor Darrell. 2021. Tent: Fully test-time adaptation by entropy minimization. In *9th International Conference on Learning Representations, ICLR 2021, Virtual Event, Austria, May 3-7, 2021*. OpenReview.net.

Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. 2021. Finetuned language models are zero-shot learners. *ArXiv preprint*, abs/2109.01652.

Qizhe Xie, Zihang Dai, Eduard H. Hovy, Thang Luong, and Quoc Le. 2020a. Unsupervised data augmentation for consistency training. In *Advances in Neural Information Processing Systems 33: Annual Conference on Neural Information Processing Systems 2020, NeurIPS 2020, December 6-12, 2020, virtual*.

Qizhe Xie, Minh-Thang Luong, Eduard H. Hovy, and Quoc V. Le. 2020b. Self-training with noisy student improves imagenet classification. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition, CVPR 2020, Seattle, WA, USA, June 13-19, 2020*, pages 10684–10695. IEEE.

Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. 2019. HellaSwag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, pages 4791–4800, Florence, Italy. Association for Computational Linguistics.

Yu Zhang, James Qin, Daniel S Park, Wei Han, Chung-Cheng Chiu, Ruoming Pang, Quoc V Le, and Yonghui Wu. 2020. Pushing the limits of semi-supervised learning for automatic speech recognition. *ArXiv preprint*, abs/2010.10504.

A Datasets

		#train set	#validation set	#labels	#prompts
NLI	RTE	2,490	277	2	10
	CB	250	57	3	15
	ANLI R1	16,946	1000	3	15
	ANLI R2	45,460	1000	3	15
	ANLI R3	100,459	1200	3	15
Compl.	COPA	400	100	2	8
	HellaSwag	39,905	10,042	4	4
	Story Cloze	-	1,871	2	5
Coref.	Winogrande	40,398	1,267	2	5
	WSC	554	104	2	10
WSD	WIC	5,428	637	2	10

Table 4: Statistics of the datasets

We present the statistics of the 11 datasets in Table 4. For the training-time tuning scenario, we use up to 10,000 data points from the training set for training if the train set contains more than 10,000 data points.

B Training Details

We use LoRA (Hu et al., 2021) as our parameter-efficient tuning model and set the bottleneck dimension of LoRA weight matrices to be 1 for both 3B and 11B models. For both models, we set the dropout probability for the the LoRA intermediate representations to be 0.3. Let α denote the scaling factor of LoRA that is used to scale the output of the LoRA layer before adding to the hidden states of the pre-trained model. We set α to be 4 and 2 respectively for the 3B and 11B model. The peak learning rates of the 3B and 11B models are set to be 3e-5 and 5e-5 respectively with a warm-up stage of 100 steps and polynomial learning rate scheduler. We train for a maximum of 1,500 steps. Note that the hyperparameters for the 3B model is tuned on the RTE dataset and used for other datasets. We did not tune the hyperparameters of the 11B model.

With respect to implementation details, at each update we first sample one input example $\mathbf{x}$ and apply multiple prompts to reformat it as $r_x^1(\mathbf{x}), \cdots, r_x^K(\mathbf{x})$, then we perform inference for them and randomly shuffle the predictions. Next we iterate over them with a batch size of 5/10 (3B/11B)[7] and use the shuffled predictions to supervise them to compute the distillation loss, this implements the swarm distillation mechanism in Eq. 2 and in fact approximates the expectation over paired prompts with K random pairs. We accumulate the gradients for 16 steps for one update so that each gradient descent is computed from 16 data examples. And we use 1 A40 GPU (45GB memory) to train the 3B model and 4 A40 GPUs with DeepSpeed Zero-2 (Ren et al., 2021) to train the 11B model. In general, training converges pretty fast and takes around 1 - 3 GPU hours for the 3B model and 2 - 6 hours for the 11B model depending on early stop points of different datasets. We use Adam (Kingma and Ba, 2015) as the optimizer with $\beta_1 = 0.9$, $\beta_2 = 0.98$ and $\epsilon = 1e-6$.

For the Transformer (Vaswani et al., 2017) models with model dimension d, the feed-forward intermediate dimension m and number of layers l, the additional parameters used in LoRA with bottleneck dimension b is calculated as $b*(m+d)*2*l*2$. As we set b to be 1 for both the 3B and 11B models, the additional number of LoRA parameters is 1,671,168 for the T0-3B model ($d = 1024, m = 16384, l = 24$) and 6,389,760 for the T0-11b model ($d = 1024, m = 65536, l = 24$).

[7] Because the GPU memory sometimes cannot handle all the prompts within one batch.

C Limitations of Our Work

We propose an unsupervised method for better zero-shot learner. There are two limitations of our work: (1) Because our method is operated in a fully unsupervised manner, there is no supervised development data for us to either select the best model or tune hyperparameters. Thus, we propose to use Fleiss' Kappa as our unsupervised development metric for model selection, which attains decent performance in most cases. However, we also see on very few datasets that the proposed metric fails to select the best checkpoints and hurt the model's performance. As discussed in §4.4, our method can be combined with few-shot learning where a few labeled data are provided and we believe this can largely alleviate the issues of model selection in the unsupervised setting. (2) The other limitation and at the same time an advantage of our method is that the proposed method can work well even with 10 unlabeled data points. This certainly makes our method a good candidate for the online setting where batches of test data come in a stream. However, as we discussed in §4.4, the performance of our model saturates quickly as we increase the number of unlabeled data, which means the performance of our method cannot scale well with tons of unlabeled data like self-supervised pretraining. As discussed in §5, we expect combining our

method with few-shot learning setting / pre-training can lead to further improvements as the supervised signals may guide the model to a better local optimum.