Exploiting Cloze Questions for Few Shot Text Classification and Natural Language Inference

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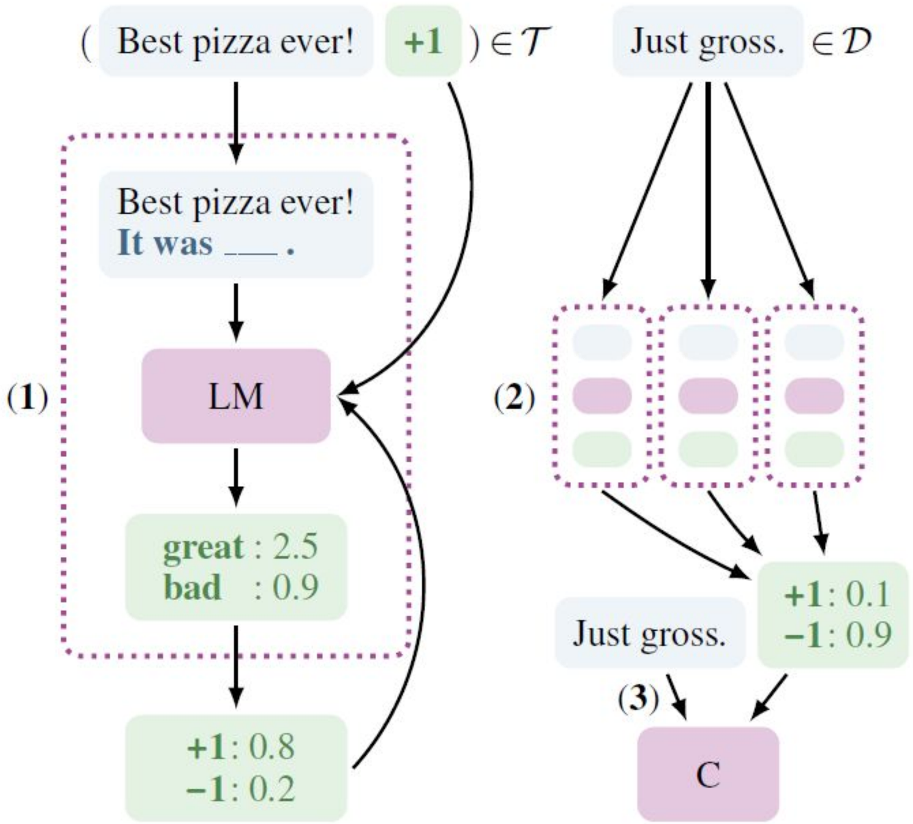
Motivation

Big LMs can perform some tasks with "task description". However, in some case, the performance is not comparable to supervised learning.

In this paper:

Employs patterns in small dataset to annotate soft-label

Train supervised model on that semi-supervised dataset.



Patterns exploiting training

Pattern Verbalize Pair (PVP): using masked LM to predict the labels of the pairs

$$P_1(a) = \text{It was } \_\_\_\_.\ a$$

$$P_2(a) = a.\ \text{All in all, it was } \_\_\_\_.$$

$$P_3(a) = \text{Just } \_\_\_\_!\ \|\ a$$

$$P_4(a) = a\ \|\ \text{In summary, the restaurant is } \_\_\_\_.$$

We define a single verbalizer v for all patterns as

$$v(1) = \text{terrible} \quad v(2) = \text{bad} \quad v(3) = \text{okay}$$
$$v(4) = \text{good} \quad v(5) = \text{great}$$

Yelp review

$$P_1(\mathbf{x}) = \text{“}\ a\ \text{”}\ ?\ \|\ \_\_\_\_\ ,\ \text{“}\ b\ \text{”}$$

$$P_2(\mathbf{x}) = a\ ?\ \|\ \_\_\_\_\ ,\ b$$

and consider two different verbalizers v_1 and v_2 that are defined as follows:

$$v_1(0) = \text{Wrong} \quad v_1(1) = \text{Right} \quad v_1(2) = \text{Maybe}$$
$$v_2(0) = \text{No} \quad v_2(1) = \text{Yes} \quad v_2(2) = \text{Maybe}$$

MNLI

Combining PVPs

PVPs varies that we don’t know which one is good. So

1. For each sample x in a labeled dataset, finetune a LM on x
2. On a unsupervised dataset, combine all finetuned LMs to get a soft label for all samples
3. Then use this scores as training signal to train a supervised model

This might propagate falsely labeled data into the model

Iterative PET (iPET)

Train multiple classifiers on increasing dataset sizes

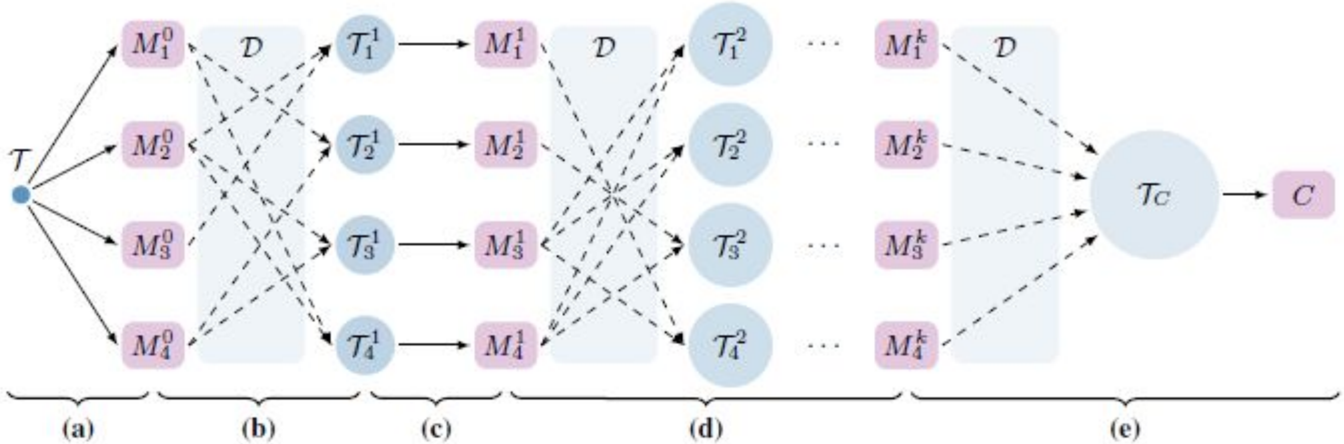


Figure 2: Schematic representation of iPET (a) The initial training set is used to train an ensemble of models as in regular PET. (b) For each model, a random subset of two other models ($\lambda = 2/3$) is used to generate a new training set by labeling examples from $\mathcal{D}$. (c) A new set of PET models is trained using the larger, model-specific datasets. (d) The previous two steps are repeated k times, each time increasing the size of the generated training sets by a factor of d. (e) The set of models at iteration k is used to create a soft-labeled dataset $\mathcal{T}_C$ as in regular PET; the final classifier C is trained on this dataset.

Result

Examples	Training Mode	Yelp	AG's News	Yahoo	MNLI (m)
$\lvert\mathcal{T}\rvert = 0$	unsupervised (avg)	33.8 ± 9.6	69.5 ± 7.2	44.0 ± 9.1	39.1 ± 4.3
	unsupervised (max)	40.8 ± 0.0	79.4 ± 0.0	56.4 ± 0.0	43.8 ± 0.0
	iPET	$\mathbf{56.7 \pm 0.2}$	$\mathbf{87.5 \pm 0.1}$	$\mathbf{70.7 \pm 0.1}$	$\mathbf{53.6 \pm 0.1}$
$\lvert\mathcal{T}\rvert = 10$	supervised	21.1 ± 1.6	25.0 ± 0.1	10.1 ± 0.1	34.2 ± 2.1
	PET	52.9 ± 0.1	87.5 ± 0.0	63.8 ± 0.2	41.8 ± 0.1
	iPET	$\mathbf{57.6 \pm 0.0}$	$\mathbf{89.3 \pm 0.1}$	$\mathbf{70.7 \pm 0.1}$	$\mathbf{43.2 \pm 0.0}$
$\lvert\mathcal{T}\rvert = 50$	supervised	44.8 ± 2.7	82.1 ± 2.5	52.5 ± 3.1	45.6 ± 1.8
	PET	60.0 ± 0.1	86.3 ± 0.0	66.2 ± 0.1	63.9 ± 0.0
	iPET	$\mathbf{60.7 \pm 0.1}$	$\mathbf{88.4 \pm 0.1}$	$\mathbf{69.7 \pm 0.0}$	$\mathbf{67.4 \pm 0.3}$
$\lvert\mathcal{T}\rvert = 100$	supervised	53.0 ± 3.1	86.0 ± 0.7	62.9 ± 0.9	47.9 ± 2.8
	PET	61.9 ± 0.0	88.3 ± 0.1	69.2 ± 0.0	74.7 ± 0.3
	iPET	$\mathbf{62.9 \pm 0.0}$	$\mathbf{89.6 \pm 0.1}$	$\mathbf{71.2 \pm 0.1}$	$\mathbf{78.4 \pm 0.7}$
$\lvert\mathcal{T}\rvert = 1000$	supervised	63.0 ± 0.5	$\mathbf{86.9 \pm 0.4}$	70.5 ± 0.3	73.1 ± 0.2
	PET	$\mathbf{64.8 \pm 0.1}$	$\mathbf{86.9 \pm 0.2}$	$\mathbf{72.7 \pm 0.0}$	$\mathbf{85.3 \pm 0.2}$

Table 1: Results for RoBERTa (large) on Yelp, AG's News, Yahoo and MNLI (matched) for various training set sizes. Scores for PET were obtained using the weighted variant with manually defined verbalizers.