Meta-learning for Few-shot Natural Language Processing: A Survey

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Abstract

Few-shot natural language processing (NLP) refers to NLP tasks that are accompanied with merely a handful of labeled examples. This is a real-world challenge that an AI system must learn to handle. Usually we rely on collecting more auxiliary information or developing a more efficient learning algorithm. However, the general gradient-based optimization in high capacity models, if training from scratch, requires many parameter-updating steps over a large number of labeled examples to perform well (Snell et al., 2017).

If the target task itself cannot provide more information, how about collecting more tasks equipped with rich annotations to help the model learning? The goal of meta-learning is to train a model on a variety of tasks with rich annotations, such that it can solve a new task using only a few labeled samples. The key idea is to train the model’s initial parameters such that the model has maximal performance on a new task after the parameters have been updated through zero or a couple of gradient steps.

There are already some surveys for meta-learning, such as (Vilalta and Drissi, 2002; Vanschoren, 2018; Hospedales et al., 2020). Nevertheless, this paper focuses on NLP domain, especially few-shot applications. We try to provide clearer definitions, progress summary and some common datasets of applying meta-learning to few-shot NLP.

1 What is meta-learning?

To solve a new task which has only a few examples, meta-learning aims to build efficient algorithms (e.g., need a few or even no task-specific fine-tuning) that can learn the new task quickly.

Conventionally, we train a task-specific model by iterating on the task-specific labeled examples. For example, we treat an input sentence as a training example in text classification problems. In contrast, the meta-learning framework treats tasks as training examples—to solve a new task, we first collect lots of tasks, treating each as a training example and train a model to adapt to all those training tasks, finally this model is expected to work well for the new task.

In the regular text classification tasks, we usually assume that the training sentences and test sentences are in the same distribution. Similarly, meta-learning also assumes that the training tasks and the new task are from the same distribution of tasks $p(T)$. During meta-training, a task $T_i$ is sampled from $p(T)$, the model is trained with $K$ samples, and then tested on test set from $T_i$. The test error on the sampled task $T_i$ serves as the training error of the meta-learning process at the current $i$-th iteration\(^1\). After the meta-training, the new task, sampled from $p(T)$ as well, measures the models performance after learning from $K$ samples.

Since the new task only has $K$ labeled examples and a large set of unlabeled test instances, each training task also keeps merely $K$ labeled examples during the training. This is to make sure that the training examples (means those training tasks here) have the same distribution as the test example (means the new task here). Usually, the $K$ labeled examples are called “support set”.

To describe meta-learning at a higher level: meta-learning doesn’t learn how to solve a specific task. It successively learns to solve many tasks. Each time it learns a new task, it becomes better at learning new tasks: it learns to learn if “its performance at each task improves with experience and with the number of tasks” (Thrun and Pratt, 1998).

Meta-learning vs. Transfer learning. Conventionally, transfer learning uses past experience of a

\(^1\)Here the “test error” is the training loss, because what we really care is the test performance on the target task.
source task to improve learning on a target task — by pre-training a parameter prior plus optional fine-tuning. Transfer learning refers to a problem area (task A helps task B) while meta-learning refers to methodology which can be used to improve transfer learning as well as other problems (Hospedales et al., 2020).

Technically, the pretraining in transfer learning often does not take its ultimate application scenario (e.g., a few-shot task) into consideration; meta-learning, instead, is optimized particularly towards benefiting the target task (for example, the system configuration is optimized so that it only needs a few gradient updates in a target few-shot problem).

In effect, meta-learning assumes that the training tasks are in the same distribution with the target task; this often means that all the so called tasks (including training tasks and the target task) are essentially the same problem in different domains, such as from reviews of other product domains to the target cellphone’s review domain. Transfer learning, instead, does not have such a strict assumption; in theory, transfer learning can pretrained on any source tasks that can be potentially helpful to the target task (such as from a question answering task to a coreference resolution task).

**Meta-learning vs. Multi-task learning.** If we think the aforementioned transfer learning is often implemented as a sequential training flow from source tasks to the target task, multi-task learning is to train all the tasks together simultaneously.

Since meta-learning also relies on a set of training tasks, meta-learning is also a kind of multi-task learning. We summarize three differences here:

- The conventional goal of multi-task learning is to learn a well pretrained model that can generalize to the target task; meta-learning tries to learn an efficient learning algorithm that learns the target task quickly.
- In addition, multi-task learning may favor tasks with significantly larger amounts of data than others, as shown in Figure 1.
- Since meta-learning treats tasks as training examples, ideally, the more training tasks the better. However, multi-task learning may meet increasing challenges in training simultaneously over too many tasks.

## 2 Meta-learning milestones

Transferable knowledge in meta-learning is derived in the form of generalizable representation space or optimization strategies. The target few-shot task is then handled in a feed-forward distance function without updating network weights or learned by fine-tuning with the efficient optimization strategy.

### 2.1 Learning to embed: metric-based meta-learning

Metric-based meta-learning (or called “metric learning”) learns a distance function between data points so that it classifies test instances by comparing them to the $K$ labeled examples. The “distance function” often consists of two parts: one is an embedding function which encodes any instances into a representation space, the other is a similarity metric, such as cosine similarity or Euclidean distance, to calculate how close two instances are in the space. If the distance function is learnt well on the training tasks, it can work well on the target task without fine-tuning.

**Siamese Network.** Koch et al. (2015) proposed a Siamese network which takes two instances as input and outputs a scalar indicating they belong to the same class or not. The Siamese network, trained on training tasks, is essentially a distance function. However, it does not follow the principle of meta-learning: Siamese network was neither trained specifically to minimize the test losses on training tasks nor trained to learn an efficient gradient-based algorithm.

**Matching Network.** Vinyals et al. (2016) proposed “matching network”, the first metric-based meta-learning algorithm, to solve one-shot problem. Matching network is essentially a parametric nearest neighbors algorithm, defined as follows:

$$P(\hat{y} | \hat{x}, S) = \sum_{i=1}^{k} a(\hat{x}, x_i) y_i$$  \hspace{1cm} (1)
Table 1: Some representative metric-learning literature.

| name | embedding function | similarity metric | other notes |
|------|--------------------|-------------------|-------------|
| Siamese Network (Koch et al., 2015) | deep neural net | sigmoid over weighted $L_1$ distance |  |
| Matching Network (Vinyals et al., 2016) | deep neural net | cosine | the embedding function depends on the support set |
| Prototypical Network (Snell et al., 2017) | deep neural net | Euclidean distance | compare the test example with the classes rather than support examples |
| Relation Network (Sung et al., 2018) | deep neural net | deep net outputs one scalar |  |

where $S$ is a support set containing $k$ labeled examples $\{x_i, y_i\}, i = 1, \ldots, k$; $\hat{x}$ is a text example with its gold label $\hat{y}$. $a(\cdot)$ is a similarity function given the representations of $\hat{x}$ and $x_i$. One contribution is that each support/testing example learns its representation with the background $S$; it means the whole support set influences the representation learning of each example. In experiment, they tried one-shot problems with and without fine-tuning; but fine-tuning does not show improvements. Matching networks can be interpreted as a weighted nearest-neighbor classifier applied within an embedding space (Snell et al., 2017).

**Prototypical Network.** Snell et al. (2017) proposed “Prototypical Networks” with two novelties compared with “Matching Networks”: (i) Using class representations rather than example representations in the support set; (ii) They found the choice of similarity metric is vital—Euclidean distance outperforms cosine similarity. Prototypical Networks differ from Matching Networks in the few-shot case with equivalence in the one-shot scenario. In addition, This literature claimed that the support-set-aware representation learning is unnecessary.

**Relation Network.** Sung et al. (2018) proposed “Relation Network” that defines the metric as:

$$r_{i,j} = s(e(x_i), e(x_j))$$

where function $e(\cdot)$ is an embedding function which generates a representation vector for any input instance; function $s(\cdot)$ is a scoring function that produces a scalar $r_{i,j}$ between 0 and 1 representing the similarity between the two elements $x_i$ and $x_j$. Different with the “Prototypical Networks”, the scoring function $s(\cdot)$ is a deep neural network rather than the Euclidean distance.

Following the routine of metric-based meta learning, Yu et al. (2018) learned multiple metrics for few-shot text classification problems. Essentially, metric-learning is a pretrained nearest-neighbor algorithm.

2.2 Learning to fine-tune: optimization-based meta-learning

Optimization-based methods learn a good point of parameter initialization for a neural model from which a few steps of gradient descent, given a few examples, can reach the optimal point for a new task. For each training task (it has $train$ and $validation$), the rationale is “how to fine-tune the model on $train$ so that it can perform well on $validation$”. In order to get good performance on the $validation$ of each training task, the meta-learning uses the validation error on $validation$ as

\footnote{They correspond to the $support$ and $test$ of a target task.}
the optimization loss. This loss is implemented through a two-step procedure: first assume the model has fine-tuned on the train, obtaining the updated parameters (here are just some “assumed” updated parameters, the original model parameters has not been updated in reality), then applying these updated parameters to predict the validation, getting the error which is converted as a loss value; this loss is used to compute gradients, and the original parameters will be updated at this step.

**MAML.** Finn et al. (2017) proposed MAML (model-agnostic meta learning) which consists of the following steps in one episode:

- Create a copy of the model with its initial parameters $\theta$.
- Train the model on the training set $\mathcal{D}_i^{train}$ (only a few gradient descents):
  \[
  \hat{\theta} = \theta - \alpha \nabla_\theta L_i(\theta, \mathcal{D}_i^{train})
  \]  
- Apply the model with the updated parameters $\hat{\theta}$ on the validation set $\mathcal{D}_i^{val}$.
- Use the loss on the validation set to update the initial parameters $\theta$.
  \[
  \theta = \theta - \beta \nabla_\theta \sum_i L_i(\hat{\theta}, \mathcal{D}_i^{val})
  \]

Then, in the next episode, MAML runs the same process on a newly sampled training task. The process is depicted in Figure 2.

During meta-training, the MAML learns initialization parameters that allow the model to adapt quickly and efficiently to a new task with a few examples.

MAML is model agnostic; this means that it can virtually be applied to any neural networks. However, MAML is quite hard to train because there are two levels of training: the meta-backpropagation implies the computation of gradients of gradients.

**FOMAML—First-Order MAML (Finn et al., 2017).** The standard MAML has expensive computation. FOMAML is a simplified implementation as follows:

\[
\theta = \theta - \beta \nabla_\theta \sum_i L_i(\hat{\theta}, \mathcal{D}_i^{val})
\]

Comparing the Equations 4-5, FOMAML updates the original parameters $\theta$ by considering only the gradients on the last version of “fake” parameters $\hat{\theta}$, So, the gradients from $\hat{\theta}$ to the $\theta$ is omitted.

**Reptile (Nichol et al., 2018).** Reptile is another first-order optimization-based meta-learning, as shown in Figure 3. It also samples training tasks from $p(\mathcal{T})$: $\tau_1, \ldots, \tau_n$, Each training task does not have $\{\mathcal{D}_i^{train}, \mathcal{D}_i^{val}\}$ separations. For training task $\tau_i$, let’s assume the original parameters $\theta$ have went through $m$ steps of updating and become $\theta_i^m$ (i.e., $\theta_i^m = \text{SGD}(L_{\tau_i}, \theta, m)$), then Reptile updates $\theta$ as follows:

\[
\theta = \theta + \beta \frac{1}{n} \sum_{i=1}^{n} (\theta_i^m - \theta)
\]

The Reptile algorithm looks like the standard SGD in minibatch; if $m = 1$, they are the same; if $m > 1$, the expectation $\mathbb{E}_\tau[\text{SGD}(L_{\tau}, \theta, m)]$ differs from SGD($\mathbb{E}_\tau[L_{\tau}], \theta, m$)

MAML explicitly optimizes the efficiency of the algorithm on the support set, making sure the learnt algorithm can learn fast in the few-shot examples of the target task. In contrast, Reptile tries to optimize the system so that it can work well on all training tasks—it may work well if the target task is very close to the training tasks.

### 3 Progress specific to few-shot NLP

Usually, the progress of meta-learning is split by its techniques, such as metric-based or optimization-based. Whichever technique applies, the applications are often limited to simulated datasets where each classification label is treated as a task. To be specific to NLP problems, we separate the progress in the following two categories: (i) Meta-learning on different domains of the same problem. This category usually have access of different domains of datasets which essentially belong to the same problem, such as different domains of datasets for sentiment classification, different domains of datasets for intent classification; (ii) Meta-learning on diverse problems and then it is applied to solve a new problem.

#### 3.1 Meta-learning within a problem

Here, “the same problem” is often studied in two types: one is one dataset of multiple classes where each class is treated as a task; the other is related to exploring the same task, such as sentiment classification, on different domains.

**A class is a task.** Jiang et al. (2018) studied topic classification problem in which each topic is a task. Some topics are training tasks, some are testing
3.2 Meta-learning on distinct problems

To solve a target few-shot task, how to make use of other types of problems that have rich-annotation datasets is more challenging and practically useful.

Gu et al. (2018) framed low-resource translation as a meta-learning problem: eighteen high-resource language translation tasks as training tasks, five low-resource ones as testing tasks. Then, an extended MAML system is developed to handle this translation problem.

Bansal et al. (2019) used GLUE (Wang et al., 2019) tasks along with SNLI (Bowman et al., 2015) as the training tasks, and evaluated on distinct tasks: entity typing, relation classification, sentiment classification, text categorization and SciTail (an entailment dataset by (Khot et al., 2018)). Their approach LEOPARD showed better performance than some competitive baselines including BERT (Devlin et al., 2019) fine-tuning, multi-task learning and prototypical networks.

Dou et al. (2019) compared three typical optimization-based meta-learning, including MAML, First-order MAML and Reptile on GLUE benchmarks: treating the low-resource tasks CoLA, MRPC, STS-B and RTE as the testing tasks, and the four high-resource tasks SST-2, QQP, MNLI and QNLI as the training tasks. They also showed that meta-learning approaches surpass finetuned BERT and multi-task learning.

4 Datasets for few-shot NLP

4.1 Class as task

FewRel (Han et al., 2018), a relation classification dataset, has 100 relations, each with 700
labeled sentences. The official set uses 64, 16, and 20 relations as training/dev/test tasks. This dataset is constructed by manually annotating the distantly supervised results on Wikipedia corpus and Wikidata knowledge bases. Hence, all the training/dev/testing examples are from the same domain. A latest version, named FewRel-2.0 (Gao et al., 2019b), added a new domain of test set and “none-of-above” relation. FewRel is reported by Sun et al. (2019), Gao et al. (2019a) and so on, and there is a leaderboard\(^3\).

**SNIPS** (Coucke et al., 2018)\(^4\) is an intent classification dataset with only seven intent types. Both (Xia et al., 2018, 2020) used two intents as few-shot classes and other intents for training.

### 4.2 Domain as task

**CLINC150** (Larson et al., 2019)\(^5\) is an intent classification dataset. It has 23,700 instances in which 22,500 examples covers 150 intents, and 1,200 instances are out-of-scope. The 150 intents are distributed in 10 domains: “banking”, “work”, “meta”, “auto & commute”, “travel”, “home”, “utility”, “kitchen & dining”, “small talk” and “credit cards”; each domain has 15 intents.

**ARSC** (Blitzer et al., 2007) is a sentiment classification dataset. It is comprised of Amazon reviews for 23 types of products (each product corresponds to a domain). For each product domain, there are three different binary classification tasks with different thresholds on the review rating: the tasks consider a review as positive if its rating = 5 stars, >= 4 stars or >= 2 stars (Yu et al., 2018). Therefore, this dataset has totally 23 × 3 = 69 tasks. Both (Yu et al., 2018; Sui et al., 2020) used 12 tasks from 4 domains as target tasks, and the remaining domain tasks are training tasks.

Despite the existence of some few-shot NLP datasets, more challenging and realistic benchmarks are needed. As Triantafillou et al. (2020) claimed: (i) Real-life applications vary in the numbers of classes and examples per class, and are unbalanced. Existing datasets, such as FewRel and CLINC150 mainly consider homogeneous learning tasks; (ii) We are eventually hoping that the model can generalize to tasks of new distributions, as Bansal et al. (2019) did. Existing datasets often measure only within-dataset generalization. In terms of benchmark building, the computer vision community has made some progresses, such as the “META-DATASET” by (Triantafillou et al., 2020).

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\(^3\)https://thunlp.github.io/1/fewrel1.html

\(^4\)https://github.com/snipsco/nlu-benchmark/

\(^5\)https://github.com/clinc/oos-eval
