

# few shot learning method

🔗 <https://www.youtube.com/playlist?list...>

- Bayesian learning

One typical type of FSL methods is Bayesian learning [35, 76]. It combines the provided training set  $D_{train}$  with some prior probability distribution which is available before  $D_{train}$  is given

- ▼ transfer learning

- Multi-Content GAN for Few Shot Font Style Transfer

- [🔗 https://arxiv.org/pdf/1712.00516.pdf](https://arxiv.org/pdf/1712.00516.pdf)

- Feature Space Transfer for Data Augmentation

- [🔗 https://arxiv.org/pdf/1801.04356.pdf](https://arxiv.org/pdf/1801.04356.pdf)

- Label efficient learning of transferable representations across domains and tasks

- [🔗 \[1712.00123\] Label Efficient Learning o...](#)

- ▼ Data

- ▼ Data augmentation

数据增强没有什么神秘感，可以是手动在数据上修改（例如图片的旋转、句子中的同义词替换等），也可以是复杂的生成模型（生成和真实数据相近的数据）。数据增强的方式有很多种，大量合适的增强一定程度上可以缓解FSL问题，但其能力还是有限的。

- DAGAN

- [🔗 \[1711.04340\] Data Augmentation Gen...](#)

- learn from imaginary data

- [🔗 CVPR 2018 Open Access Repository](#)

- ▼ Model

从模型的角度是定义了假设的解空间，model下面的这四种学习策略可以定义不同的假设空间

- ▼ multitask learning

When there exist similar tasks or auxiliary tasks, multitask learning can be used to constrain the  $H$  of the few-shot task. **However, note that joint training of all the tasks together is required. Thus, when a new few-shot task arrives, the whole multitask model has to be trained again, which can be costly and slow.** Moreover, the sizes of  $D$  and  $D_c$  should not be comparable, otherwise, **the few-shot task may be overwhelmed by tasks with many samples.**

- parameter sharing

- 固定前几层来提取通用特征，后面几层随着不同task自己去学习，这些task需要一定的要求

- parameter tying

- ▼ embedding learning

投影train set和test set图片到特征空间，计算相似度

- Task-Specific

Task-specific embedding methods **learn an embedding function tailored for each task**, by using only information from that task

- ▼ Task-Invariant

Task-invariant embedding methods **learn a general embedding function from a large-scale data set containing sufficient samples with various outputs**, and then **directly use this on the new few-shot Dtrain without retraining**

- Relation network

- 🔗 <https://arxiv.org/pdf/1711.06025v2.pdf>

- Prototypical network

- 🔗 <https://arxiv.org/pdf/1703.05175v2.pdf>

- Matching network

- 🔗 <https://arxiv.org/pdf/1606.04080.pdf>

- hybrid

Although task-invariant embedding methods can be applied to new tasks with a low computation cost, they do not leverage specific knowledge of the current task

- learning with external memory

**Learning with external memory extracts knowledge from Dtrain**, and stores it in an external memory. Each new sample  $x_{test}$  is then represented by a weighted average of contents extracted from the memory. **This limits  $x_{test}$  to be represented by contents in the memory, and thus essentially reduces the size of  $H$**

The weakness of this strategy is that it incurs additional space and computational costs, which increase with memory size.

- generative modeling

- ▼ Algorithm

- ▼ meta learning

- MAML

- 🔗 [\[1703.03400\] Model-Agnostic Meta-Le...](#)

- MAML++

- 🔗 [\[1810.09502\] How to train your MAML](#)

- Meta-SGD

- 🔗 [\[1707.09835\] Meta-SGD: Learning to L...](#)

- REPTEL

- ▼ 与few-shot learning相关的一些技术

**weakly supervised learning** with incomplete supervision **mainly uses unlabeled data as additional information** in  $E$ , while **FSL leverages various kinds of prior knowledge such as pre-trained models, supervised data from other domains or modalities** and does not restrict to using unlabeled data. Therefore, FSL becomes weakly supervised learning problem only when prior knowledge is unlabeled data and the task is classification or regression

## ▼ Weakly supervised learning

🔗 [https://cs.nju.edu.cn/\\_upload/tpl/01/0...](https://cs.nju.edu.cn/_upload/tpl/01/0...)

learns from experience  $E$  containing only weak supervision (such as incomplete, inexact, inaccurate or noisy supervised information).

### ▪ Semi-supervised learning

🔗 <http://pages.cs.wisc.edu/~jerryzhu/pu...>

from a small number of labeled samples and (usually a large number of) unlabeled samples in  $E$

### ▪ Active learning(主动学习)

🔗 [Active Learning Literature Survey | Se...](#)

主动学习通过机器学习的方法获得难例，让人工确认和审核，将人工标注得到的数据再次使用有监督学习模型或者半监督学习模型进行训练，逐步提升模型效果，将人工经验融入机器学习的模型中

### ▪ Imbalanced learning

🔗 <http://www.ele.uri.edu/faculty/he/PDFf...>

Imbalanced learning learns from experience  $E$  with a skewed distribution for  $y$ . **This happens when some values of  $y$  are rarely taken**, as in fraud detection and catastrophe anticipation applications. It trains and tests to choose among all possible  $y$ 's. **In contrast, FSL trains and tests for  $y$  with a few examples, while possibly taking the other  $y$ 's as prior knowledge for learning.** 由于类别之间不平衡可能让模型觉得数量较多的类别属于一种先验知识

### ▪ Transfer learning

the prior knowledge is transferred from the source task to the few-shot task.

**迁移学习主要有以下三个研究问题：1) 迁移什么，2) 如何迁移，3) 何时迁移。**

- “迁移什么”提出了迁移哪部分知识的问题。一些知识对单独的域或任务有用，一些知识对不同的领域是通用的，可以用来提高目标域或目标任务的性能。
- “何时迁移”提出了哪种情况下运用迁移学习。当源域和目标域无关时，强行迁移可能并不会提高目标域上算法的性能，甚至会损害性能。这种情况称为负迁移。
- 当前大部分关于迁移学习的工作关注于“迁移什么”和“如何迁移”，隐含着一个假设：源域和目标域彼此相关。然而，**如何避免负迁移是一个很重要的问题。**

### ▪ Meta-learning

the meta-learner gradually **learns generic information (meta knowledge) across tasks**, and the learner **generalizes the meta-learner for a new task  $T$  using task-specific information.**

the meta-learner is taken as prior knowledge to guide each specific FSL task