Meta Learning

Meta Learning

- Learning to Learn

사람의 경우 새로운 개념이나 기술을 학습할 때, 머신러닝에 비해 효율적이고 빠르게 학습한다.

이는 이전의 학습 경험(previous experience) 을 토대로, 적은 예제와 시도만으로도 쉽게 학습한다.

Meta Learning은 이러한 이전의 학습 경험을 통해 다음 학습을 빠르게 하는 것을 머신러닝에 적용하고자 한다.

Can we explicitly learn priors from previous experience that lead to efficient downstream learning?

Meta learning

- Prior tasks: $t_j \in T$
- Learning algorithms(configurations): $\theta_j \in \emptyset$
- Prior scalar evaluations: $P_{i,j} = P(\theta_i, t_j)$

We want to train a meta-learner(L) that predicts recommended configurations θ_{new}^{*} for new task t_{new}

- Hyperparameter optimization : $\theta = hyperparameters$
- AutoML : $\theta = architecture$
- Multi-task learning
- Transfer Learning
- etc

Meta learning landscape

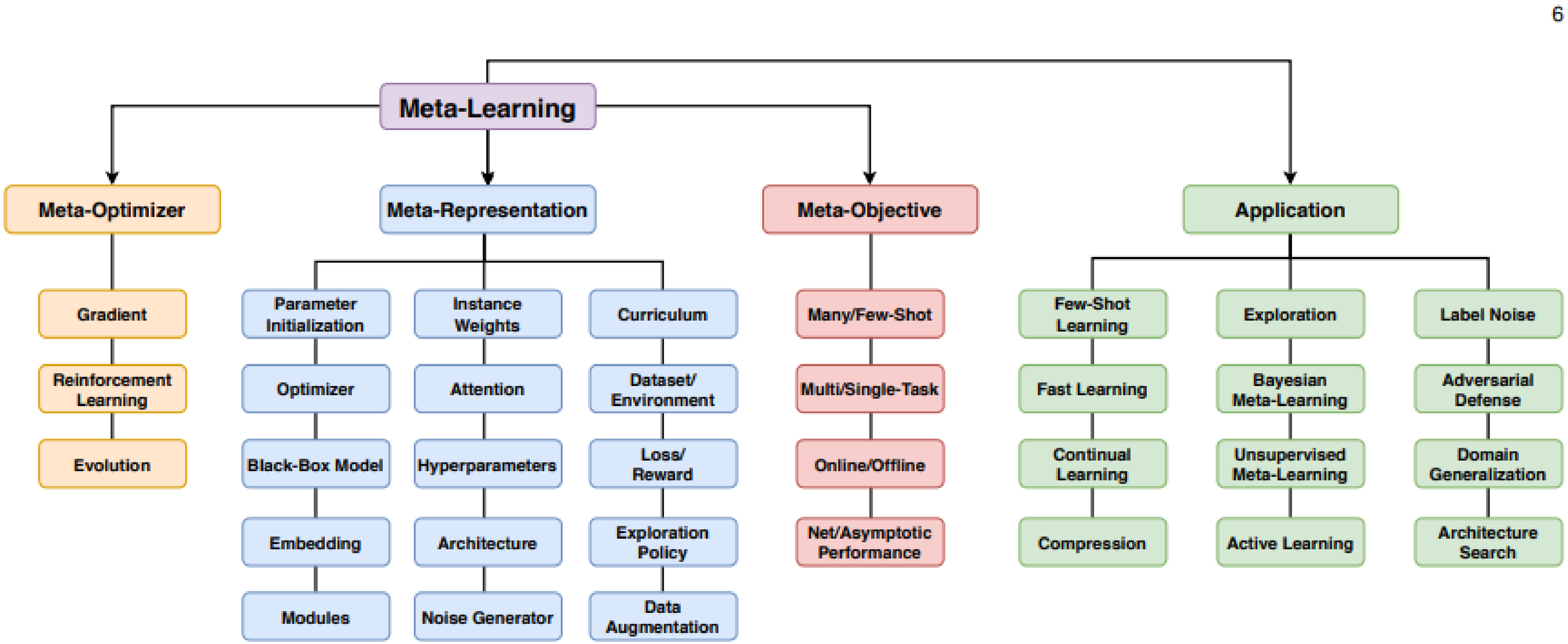


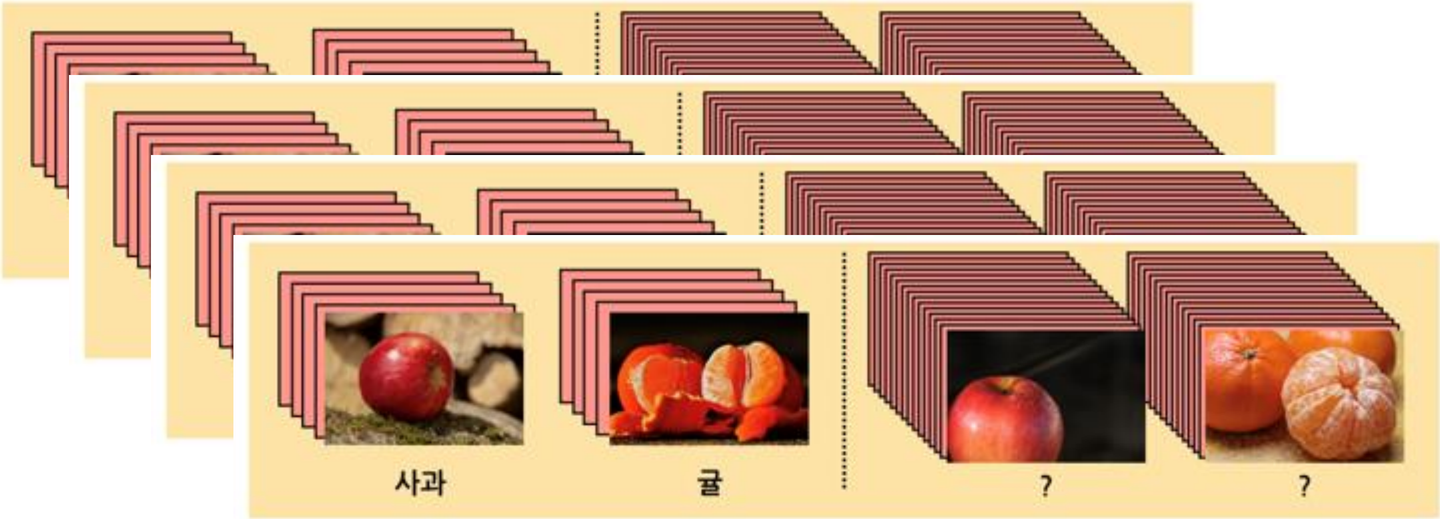
Fig. 1. Overview of the meta-learning landscape including algorithm design (meta-optimizer, meta-representation, meta-objective), and applications.

Hospedales, Timothy, et al. "Meta-learning in neural networks: A survey." *arXiv preprint arXiv:2004.05439* (2020)

Ex) Few shot learning

- N-way K-shot problem

How to solve? => Meta Learning

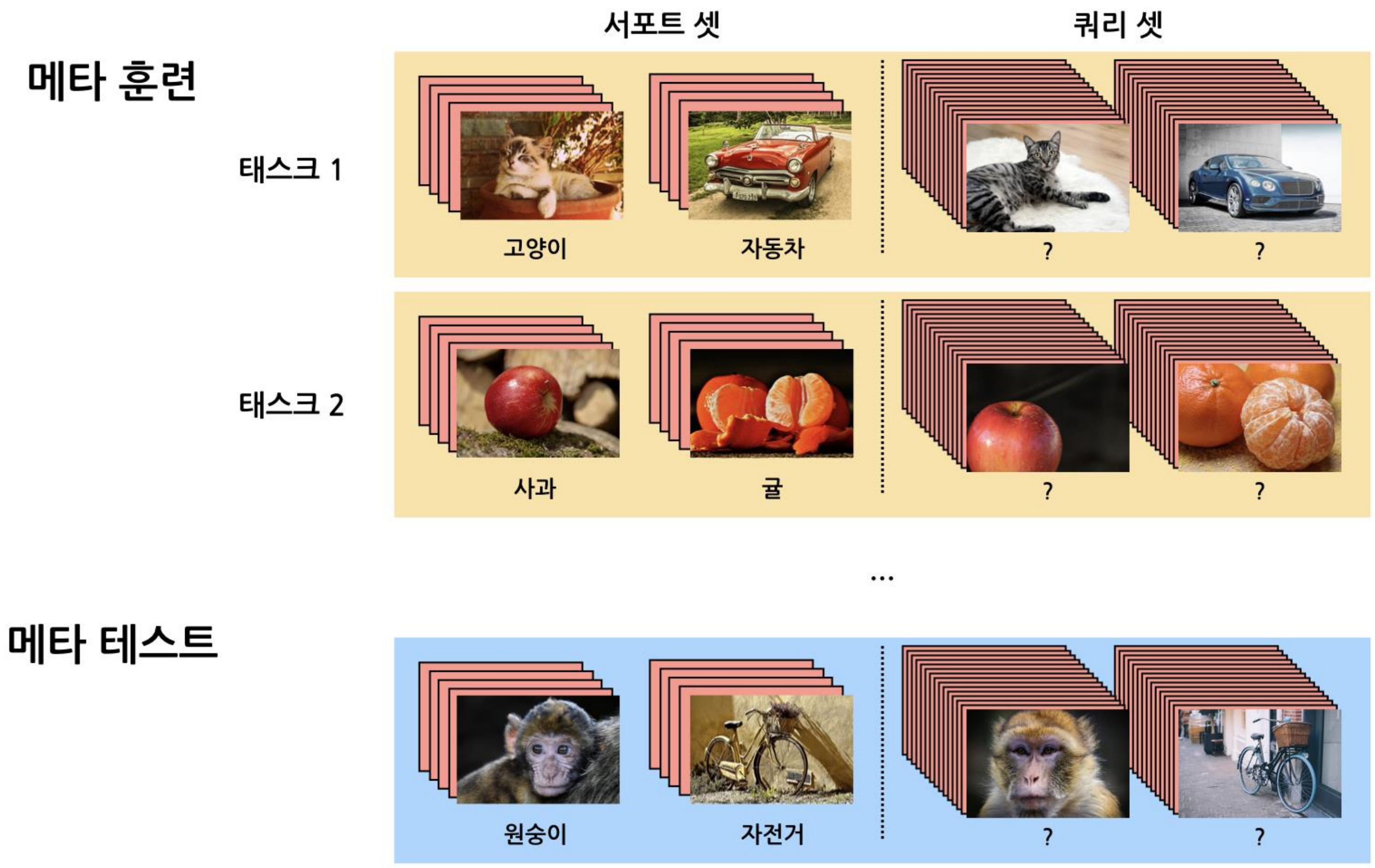


Ref : https://www.kakaobrain.com/blog/106

Ex) Few shot learning

- N-way K-shot problem with meta learning

$$\theta^* = \arg\min_{\theta} E_{D\sim p(D)}[L_\theta(D)]$$



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Meta learning common approaches

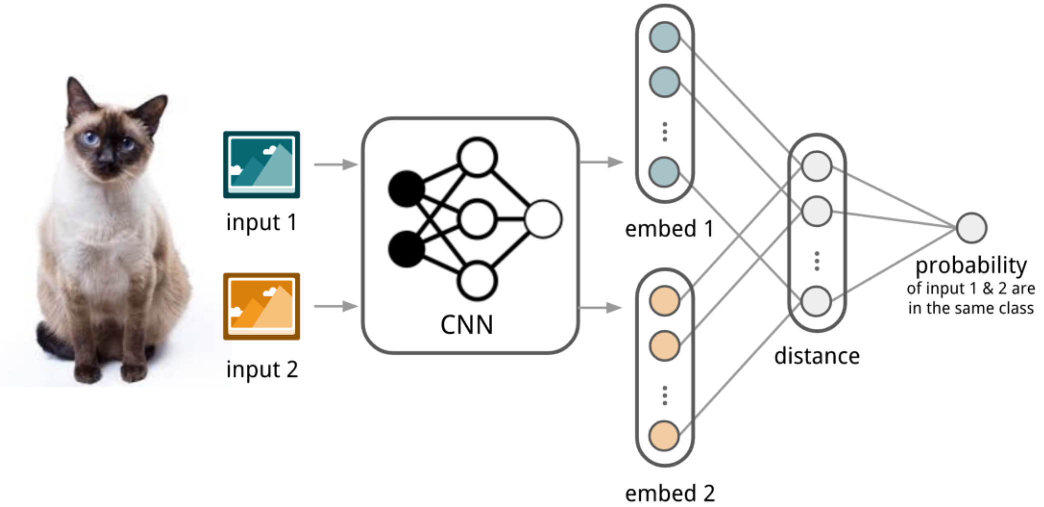
Model based

Metric based

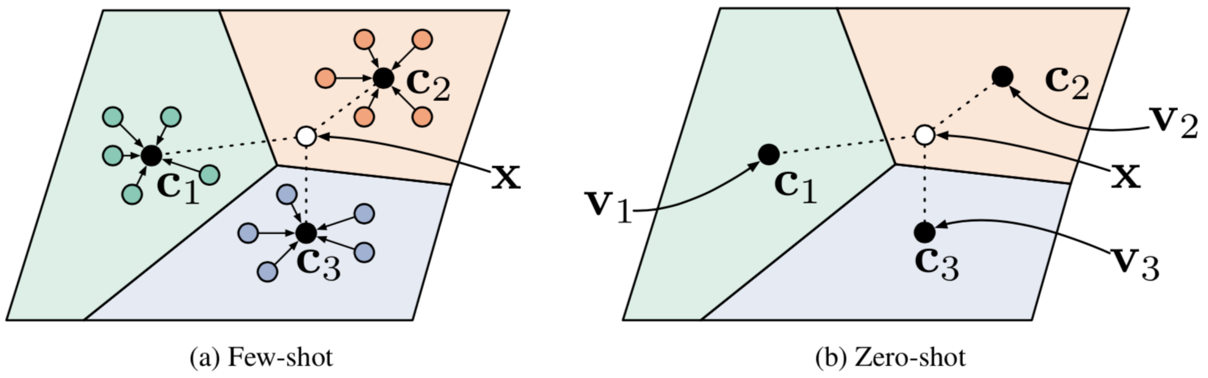
Optimization based

Metric based approach

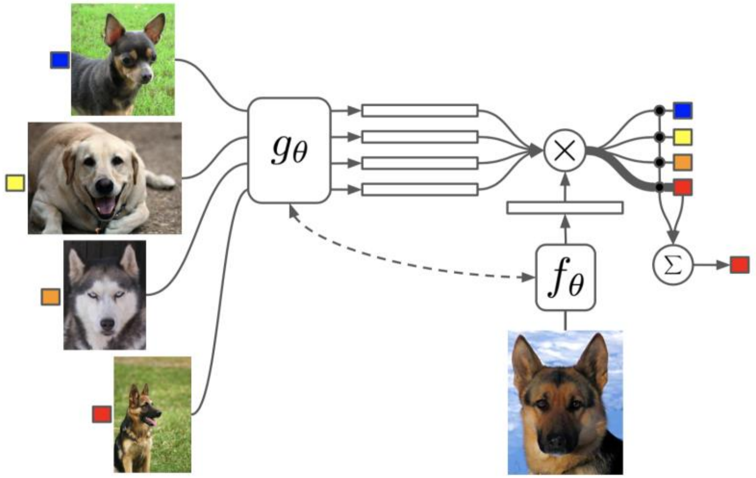
Siamese Neural Network



Prototypical Networks



Matching Network



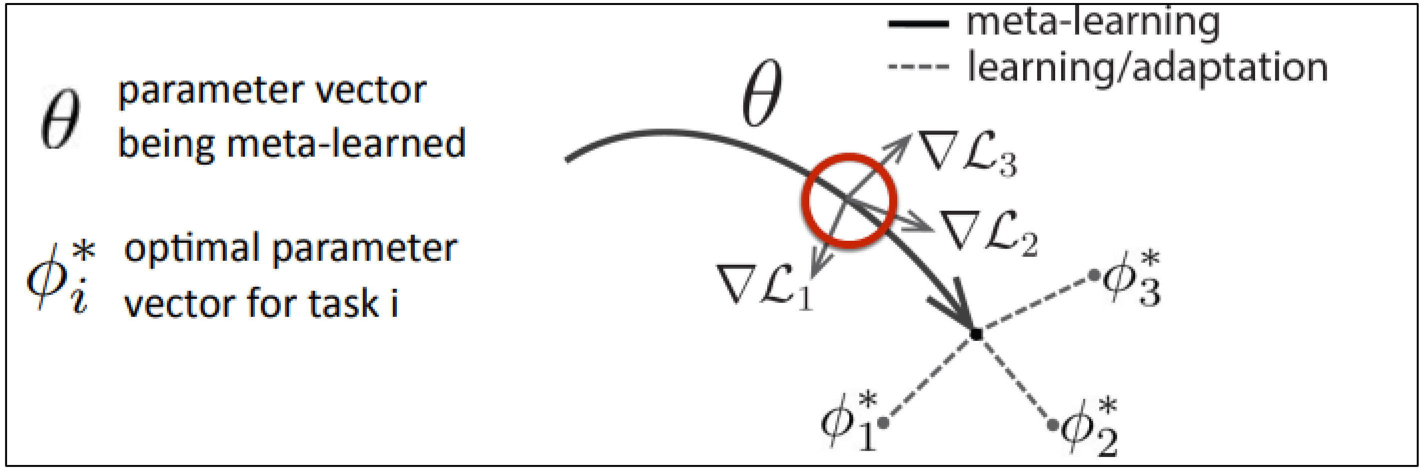
Optimization based approach

MAML(Model Agnostic Meta Learning)

Key idea: Acquire θ through optimization, served as initialize parameters for fine-tuning

Fine-tuning(test-time) : $\emptyset \leftarrow \theta - \alpha \nabla_\theta L(\theta, D^{train})$

Meta-learning: $$\min_\theta \sum_{task\ i} L\left(\theta - \alpha \nabla_\theta L\left(\theta, D_i^{tr}\right), D_i^{ts}\right)$$



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