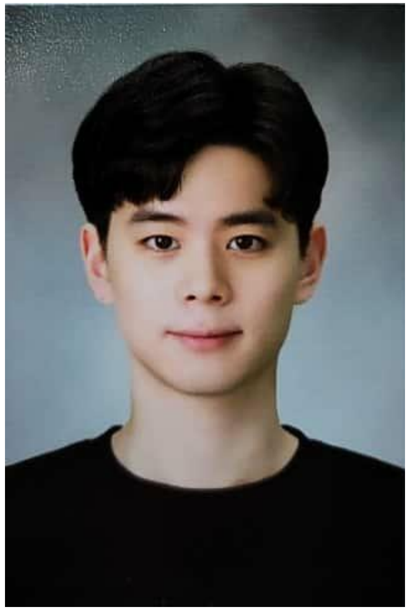
Metric-based approaches to meta-learning

목충협

2020.11.06

발표자



- 목충협(Chunghyup Mok)
  - ✓ 고려대학교 산업경영공학
  - ✓ Data Mining & Quality Analytics Lab.
  - ✓ 석박통합과정(2019.03 ~)

- 관심분야
  - ✓ Machine learning / Deep learning
  - ✓ Meta-learning / Multitask learning

- E-mail : mokch@korea.ac.kr

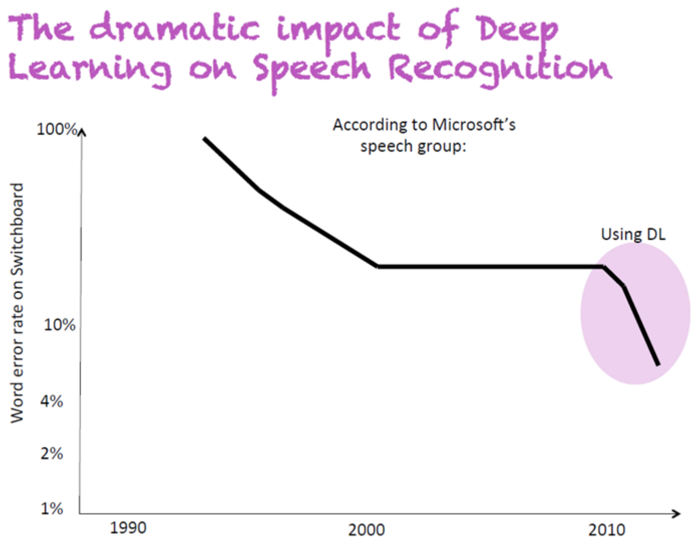
Contents

Introduction

Background

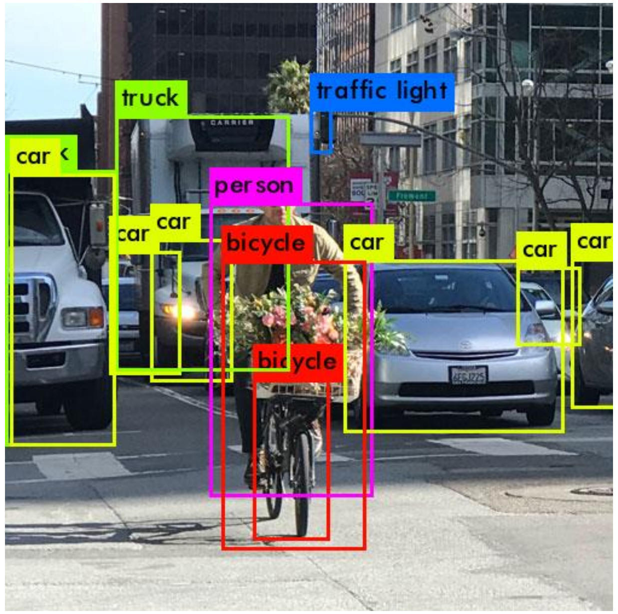
딥러닝 = 우수한 성능

음성인식

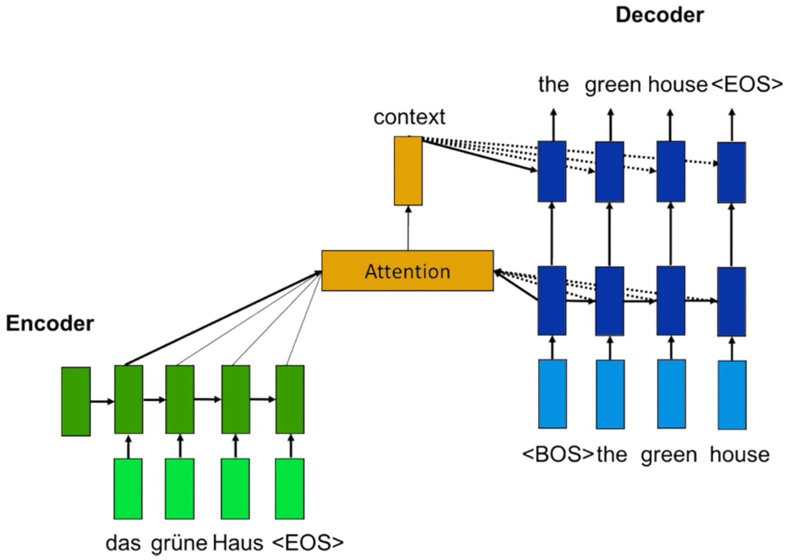


마이크로소프트의 음성인식 오류율 변화(참고2, Yoshua Bengio 발표자료)

이미지 처리



자연어 처리



Introduction

Background

딥러닝 모델의 성능을 위해서는

많은 양의 데이터가 필요!

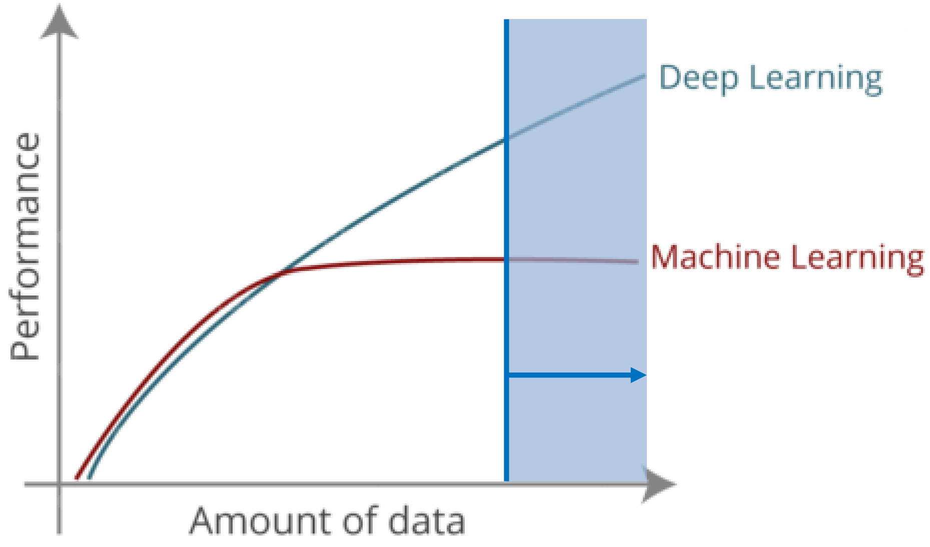


사진 : https://medium.com/@adityatiwari13/difference-between-ai-vs-ml-vs-dl-d6382f851dcb

Introduction

Background

현실 데이터는 계속 변화하며,

해야 하는 일도 변화하는 경우가 대부분

사진 : https://jjeongil.tistory.com/657

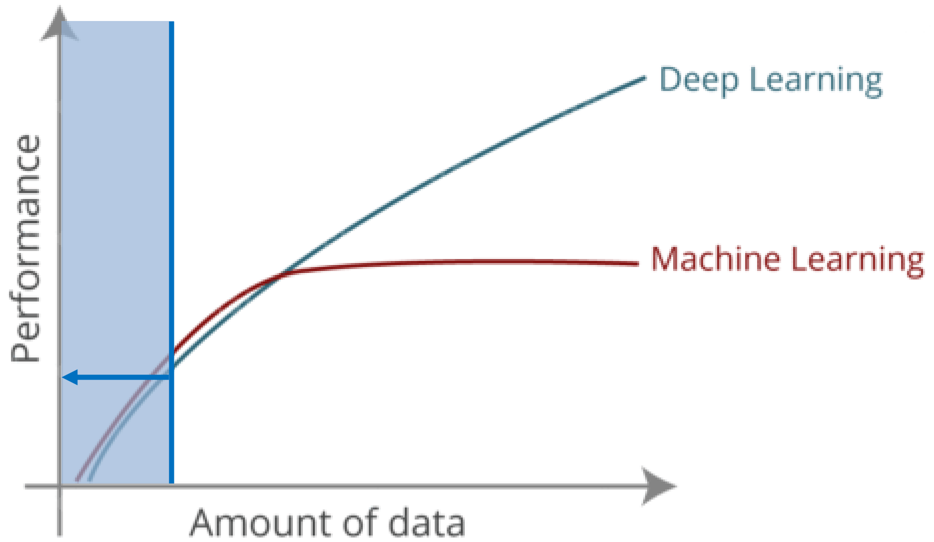
Introduction

Background

충분한 양의 데이터를 사용할 수 없는 경우

좋은 성능을 보장할 수 없음

(데이터 의존도 높음)



Introduction

Background

데이터 의존도를 낮추기 위한 방법들

Domain adaptation

Semi-supervised learning

Self-supervised learning

Meta-learning

⋮

데이터 의존도를 낮추기 위한 방법들

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⋮

Meta-learning?

학습을 위한 학습(Learning to learn)

학습 : 데이터를 이용한 일반화

학습을 잘 한다 : 적은 데이터로도 적절한 일반화가 가능하다

Meta-learning?

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Meta-learning

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Few-shot learning

Few-shot learning

Definition

❖ N-way, K-shot classification

- 학습 데이터의 양, N : class의 수, K : example 수

Few-shot learning

Definition

❖ N-way, K-shot classification

- 학습 데이터의 양, N : class의 수, K : example 수

N = 3, K = 2인 예시

Train dataset

	Novel Class 1	Novel Class 2	Novel Class 3
Example 1			
Example 2			

Test dataset

Class ? Class ?

사진 : https://medium.com/ai%C2%B3-theory-practice-business/what-is-few-shot-learning-4b2842646b47

Few-shot learning

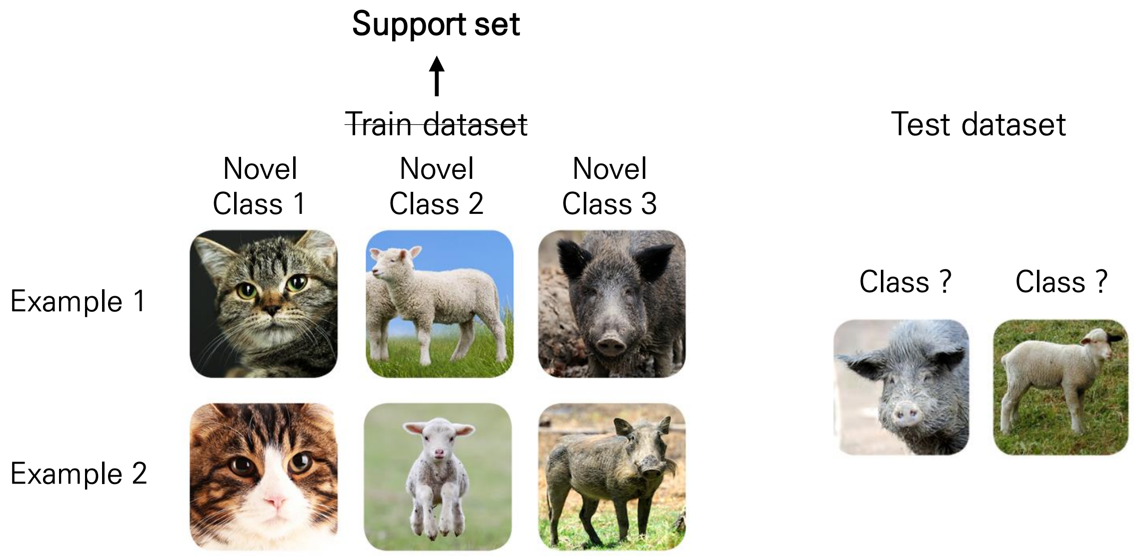
Definition

❖ N-way, K-shot classification

- 학습 데이터의 양, N : class의 수, K : example 수

❖ Support set

- 새로운 클래스에 대한 학습 데이터셋



Few-shot learning

Definition

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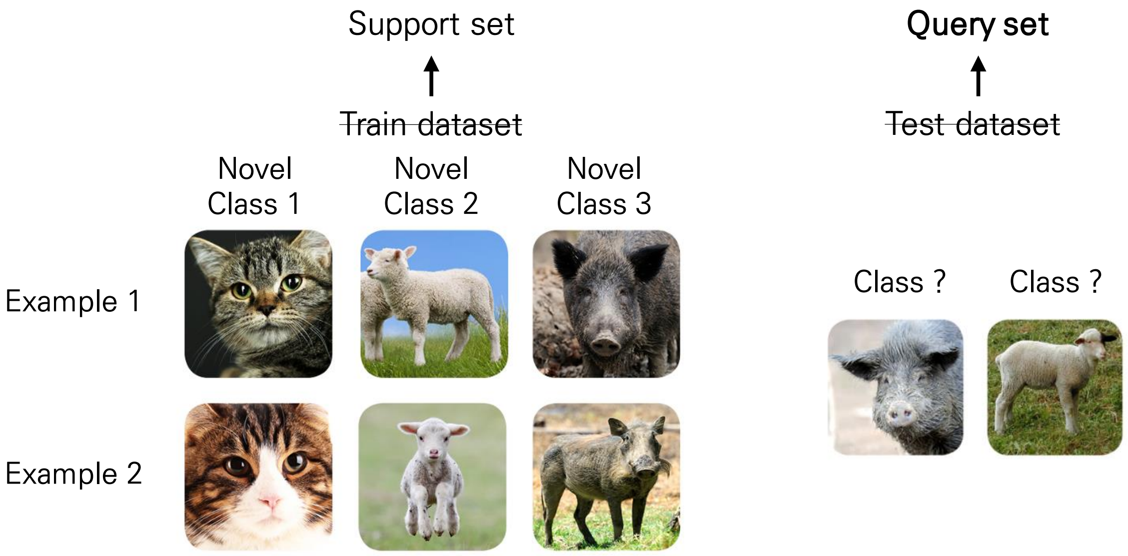
  - 학습 데이터의 양, N : class의 수, K : example 수
- Support set
  - 새로운 클래스에 대한 학습 데이터셋
- Query set
  - 새로운 클래스에 대한 테스트 데이터셋



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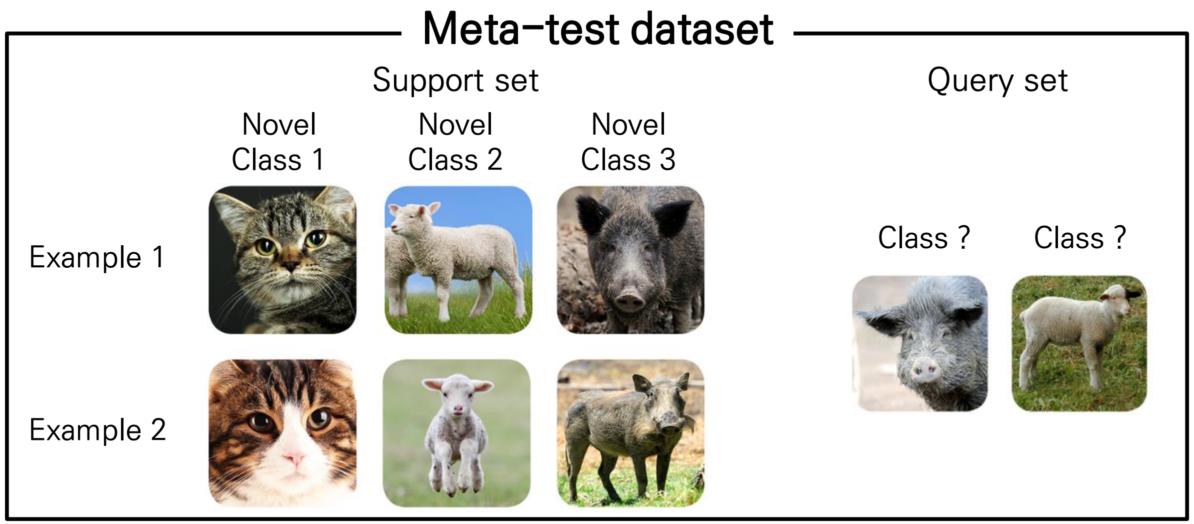
  - 새로운 클래스에 대한 테스트 데이터셋
- ❖ Meta-test dataset
  - 새로운 클래스에 대한 Support set + Query set



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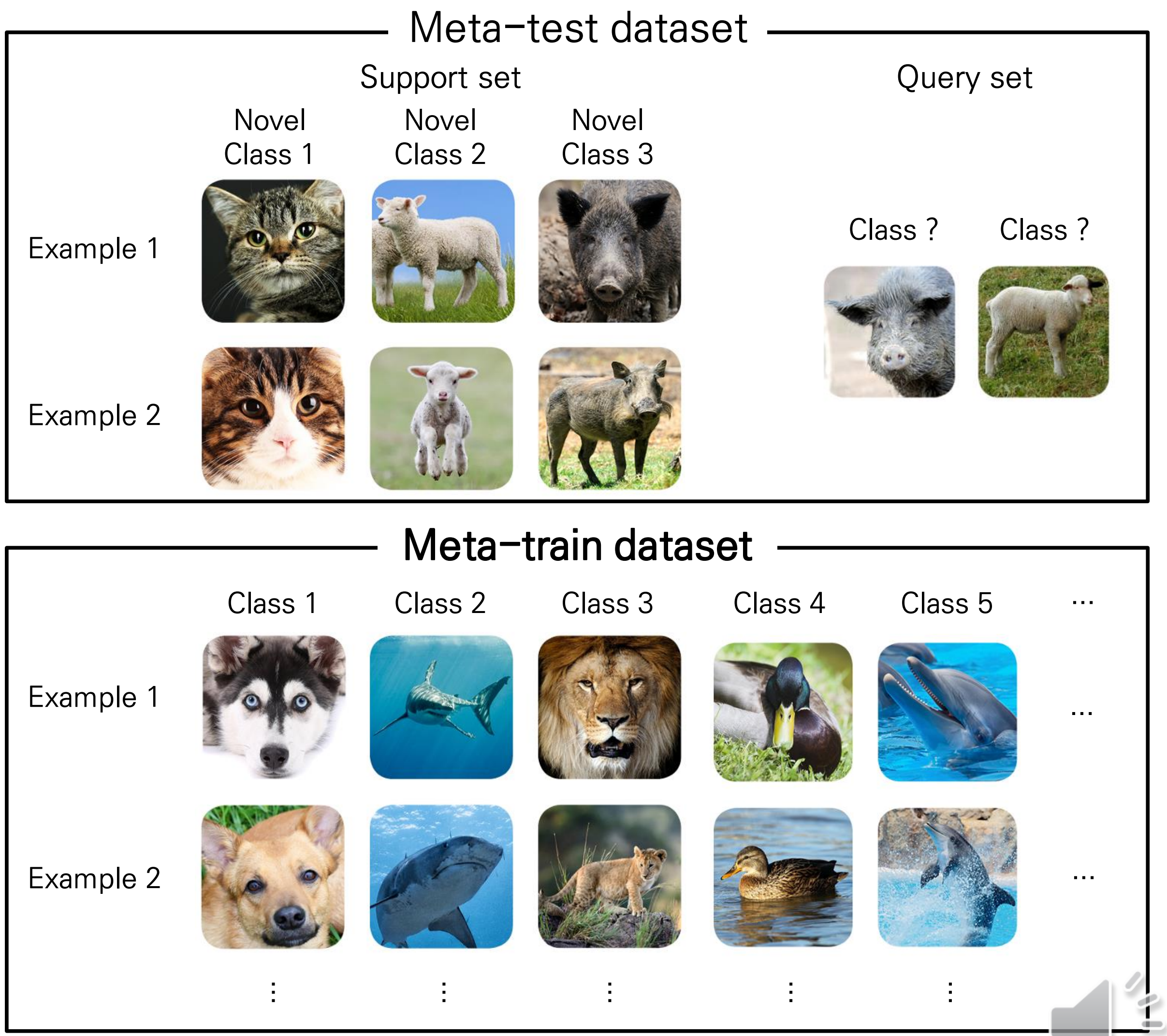
  - 새로운 클래스에 대한 테스트 데이터셋
- ❖ Meta-test dataset
  - 새로운 클래스에 대한 Support set + Query set
- ❖ Meta-train dataset
  - Meta-learning에 사용되는 데이터셋

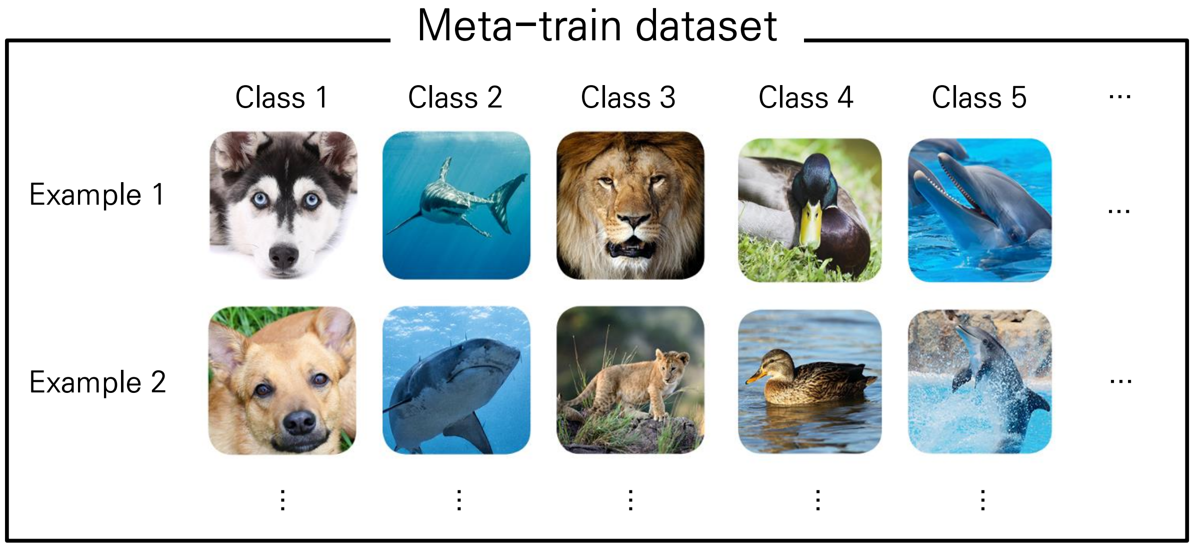


Few–shot learning

Training strategy

❖ Episode training

$$\theta = \underset{\theta}{\operatorname{argmax}}\ E_{L\sim T}\left[E_{S\sim L,B\sim L}\left[\sum_{(x,y)\in B} logP_\theta(y|x,S)\right]\right]$$



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- Task sampling($E_{L\sim T}$)
  - 모든 class 중 학습시킬 N개 class 샘플링

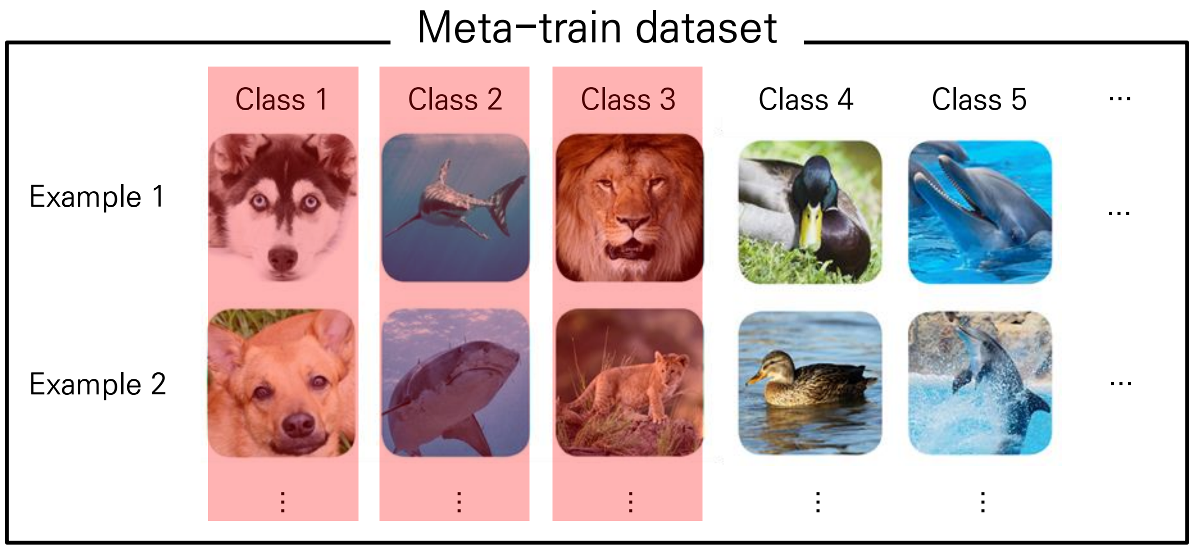

사진 : https://medium.com/ai%C2%B3-theory-practice-business/what-is-few-shot-learning-4b2842646b47
Episode training : https://proceedings.neurips.cc/paper/2016/hash/90e1357833654983612fb05e3ec9148c-Abstract.html

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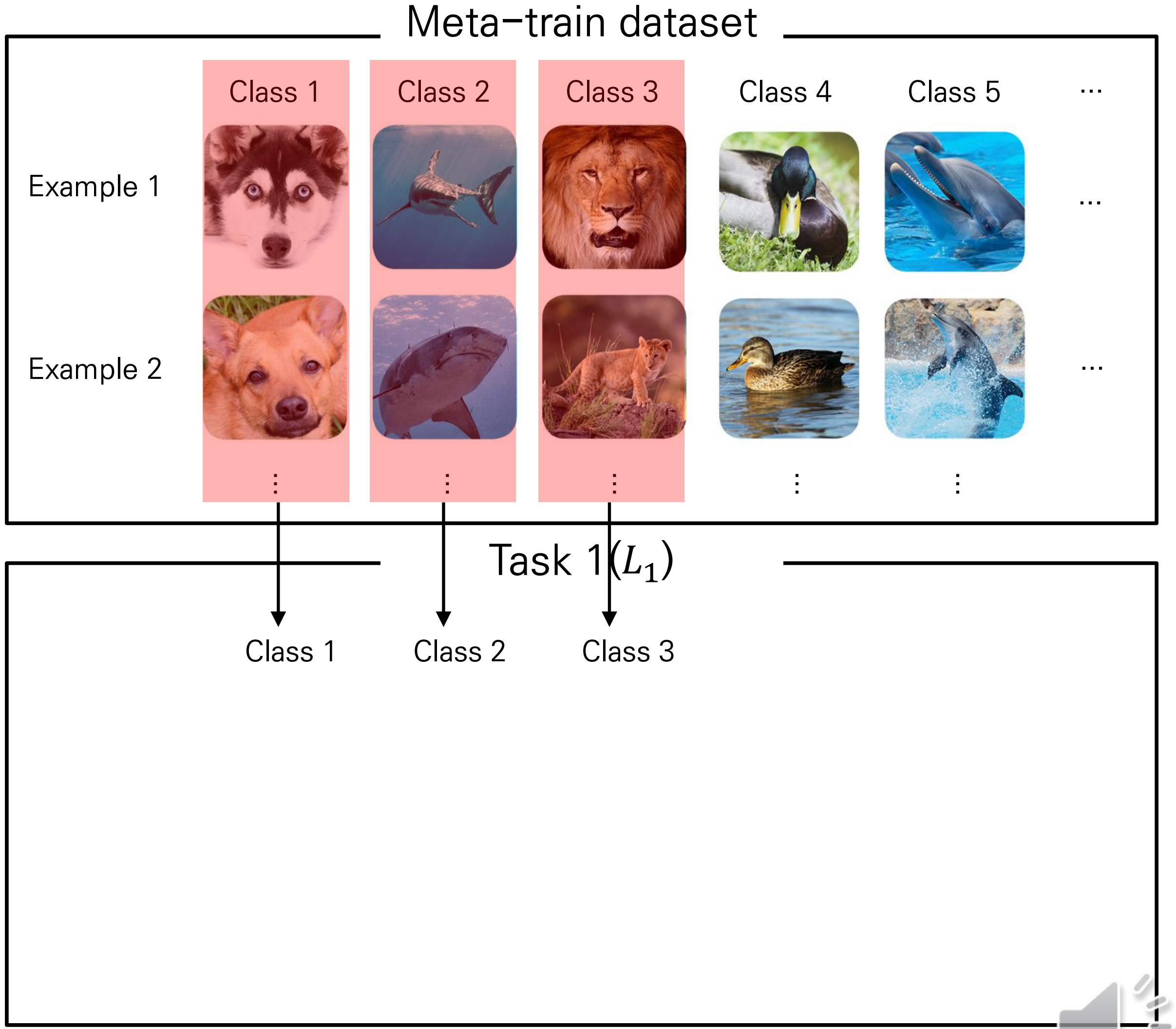

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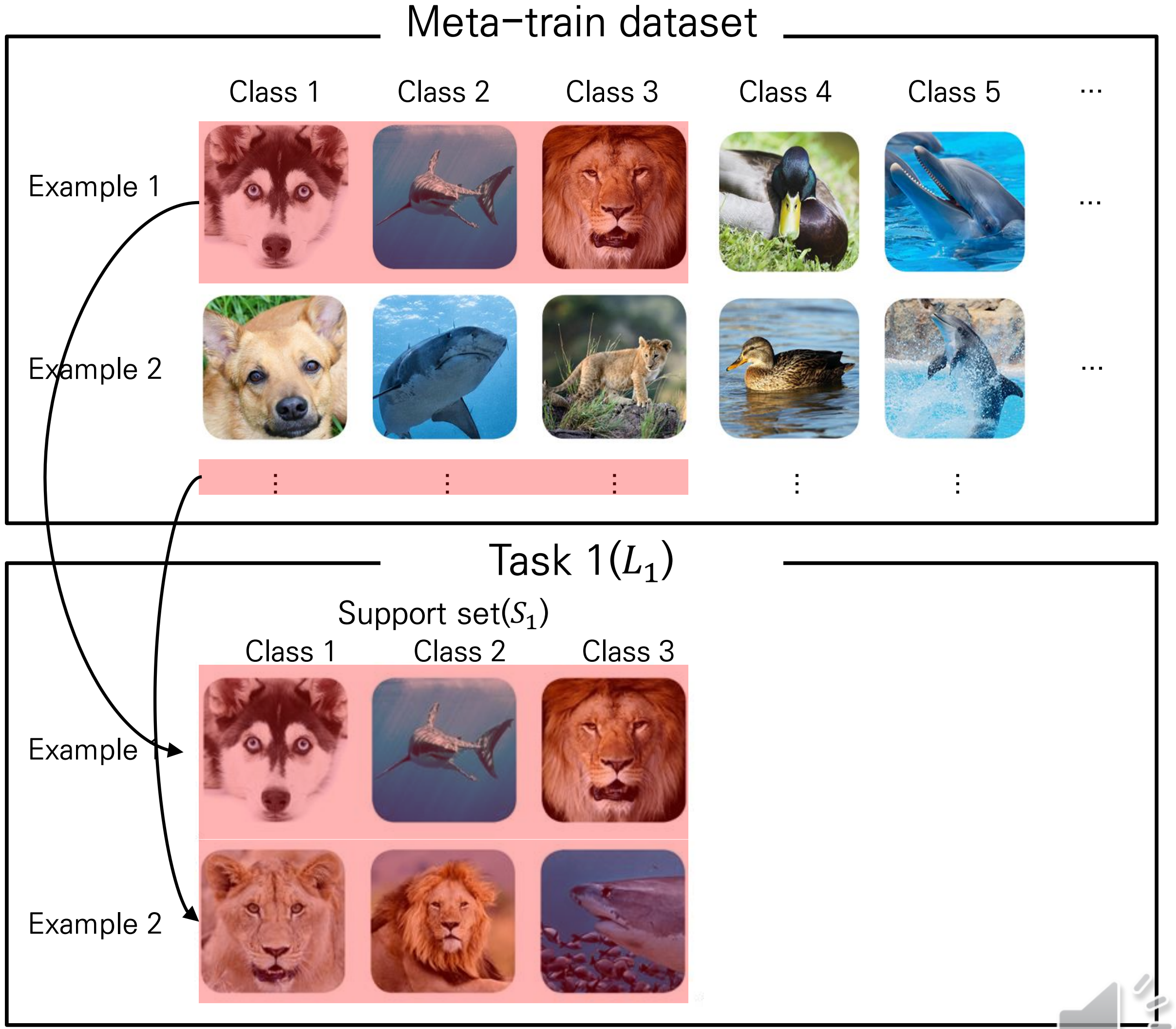

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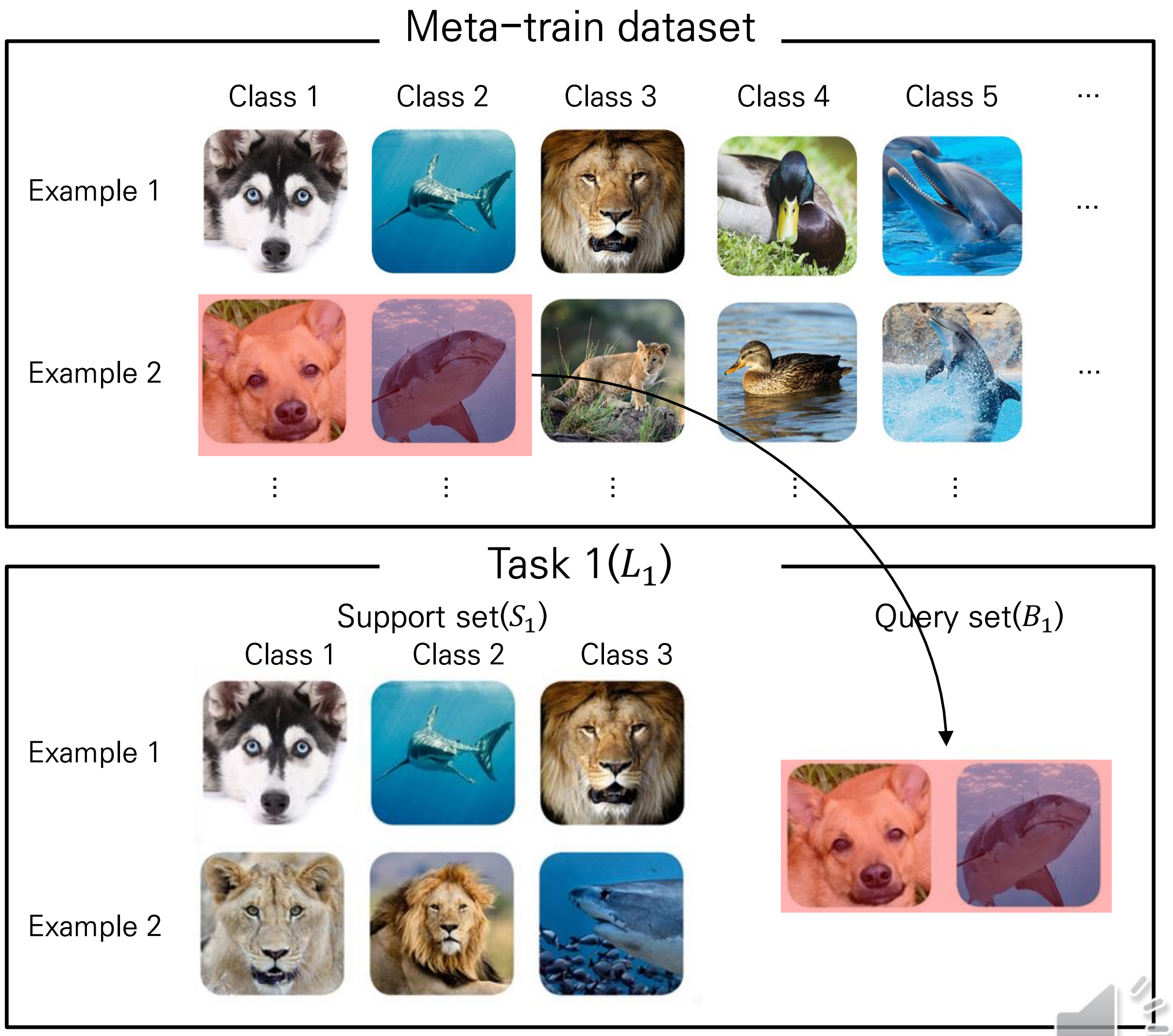

Few-shot learning

Training strategy

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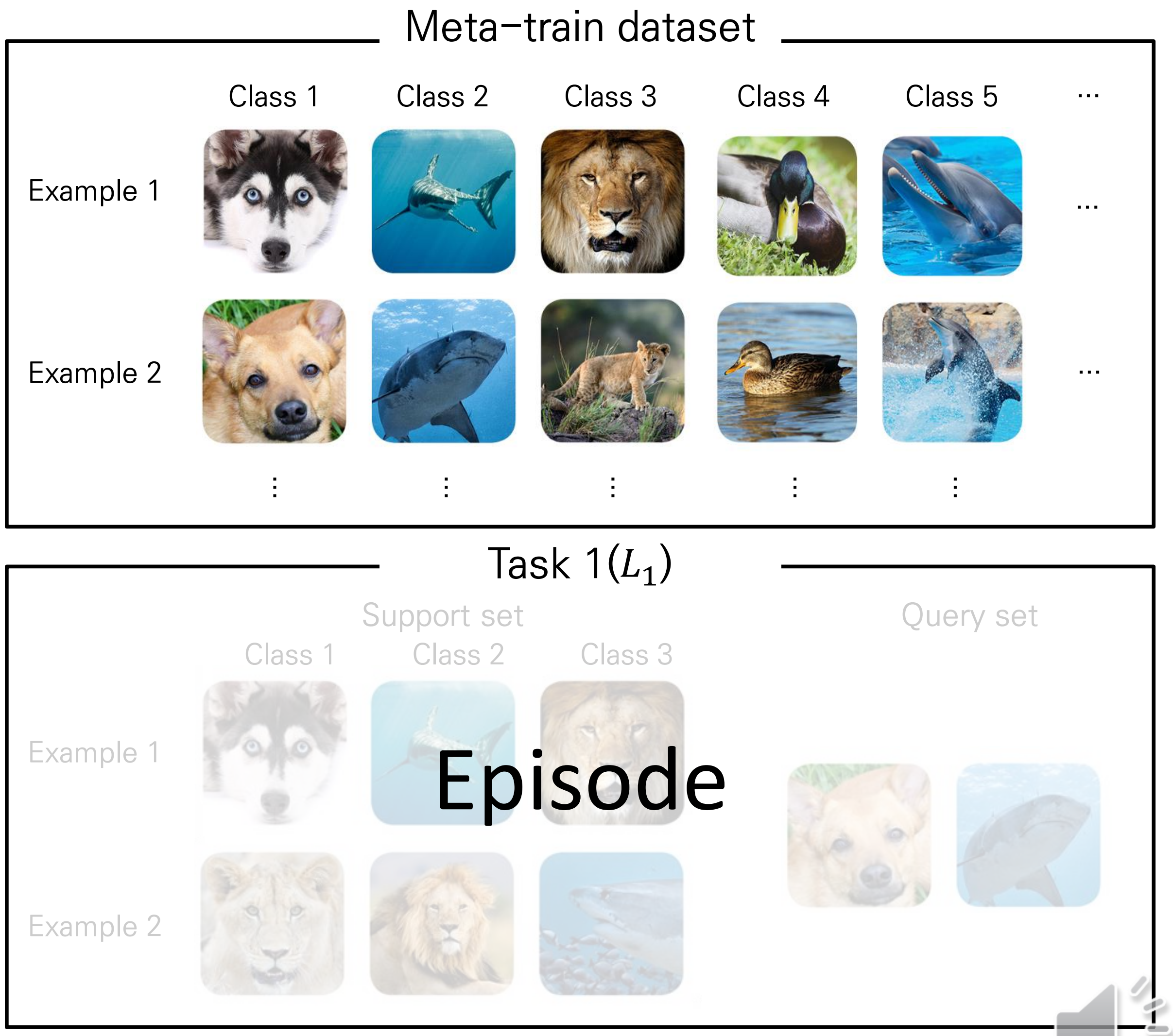

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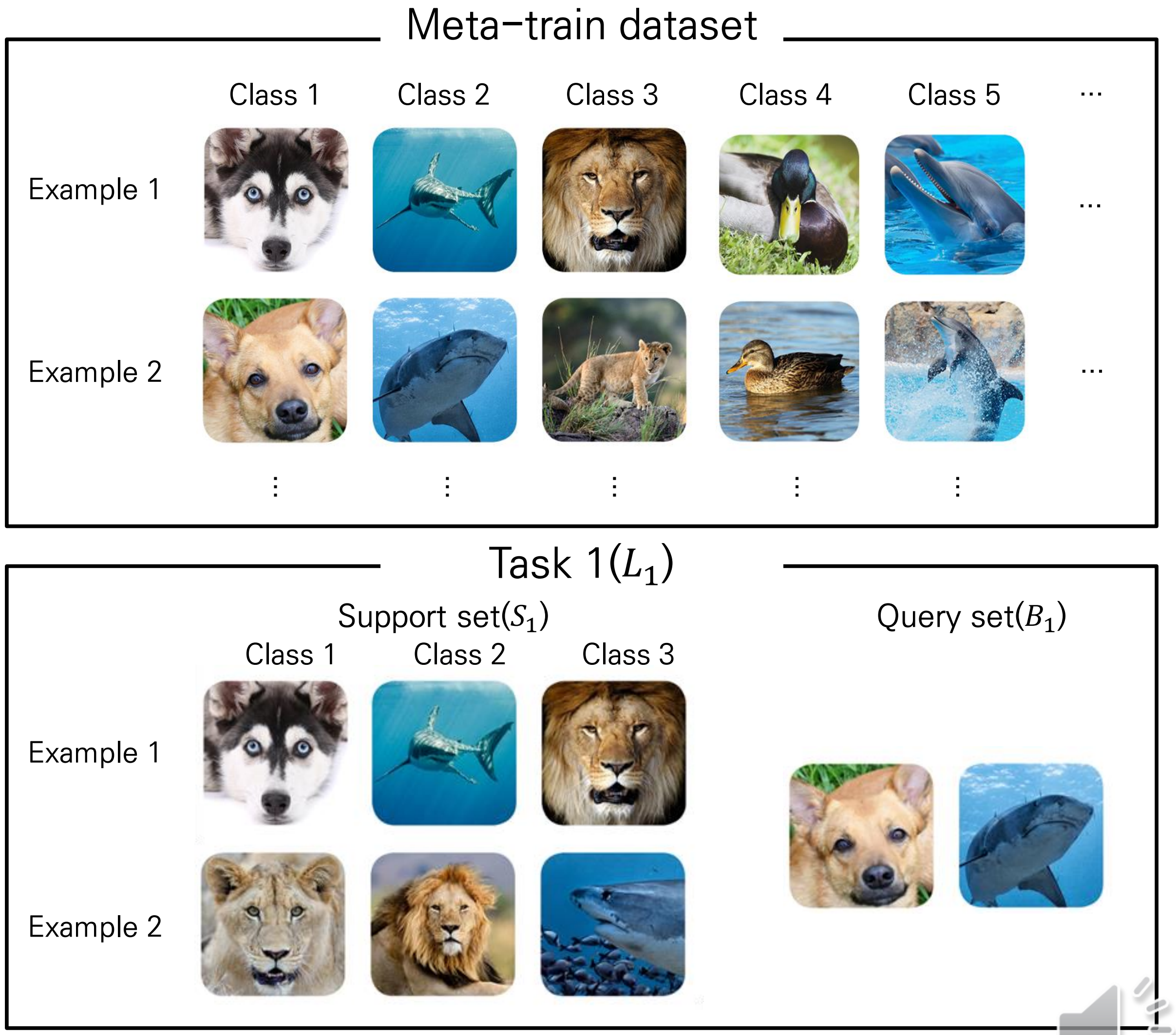
  - N개 class 별 각각 u개의 examples 샘플링
- Query set의 class를 가장 잘 맞추는 파라미터 θ 학습



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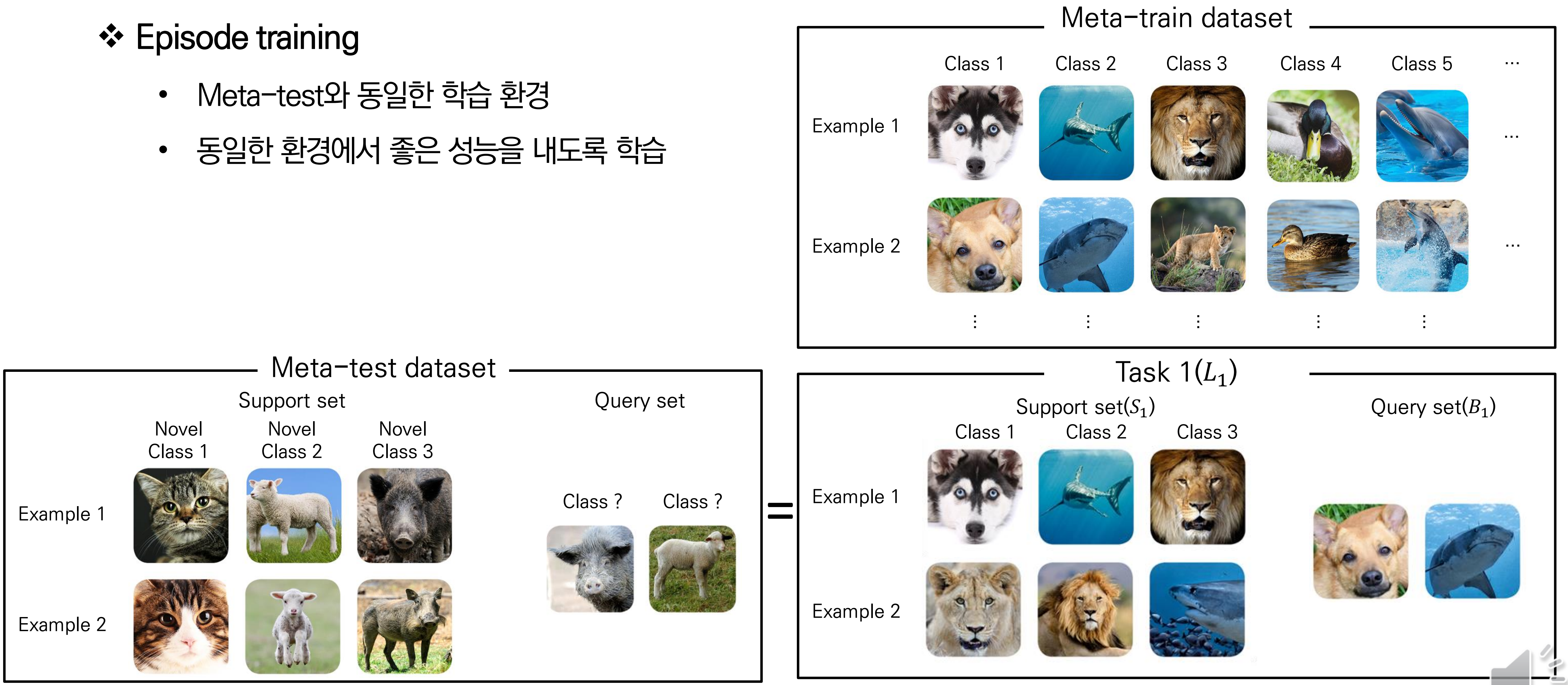
Few-shot learning

Training strategy

❖ Episode training

- Meta-test와 동일한 학습 환경
- 동일한 환경에서 좋은 성능을 내도록 학습



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Metric-based approaches to meta-learning

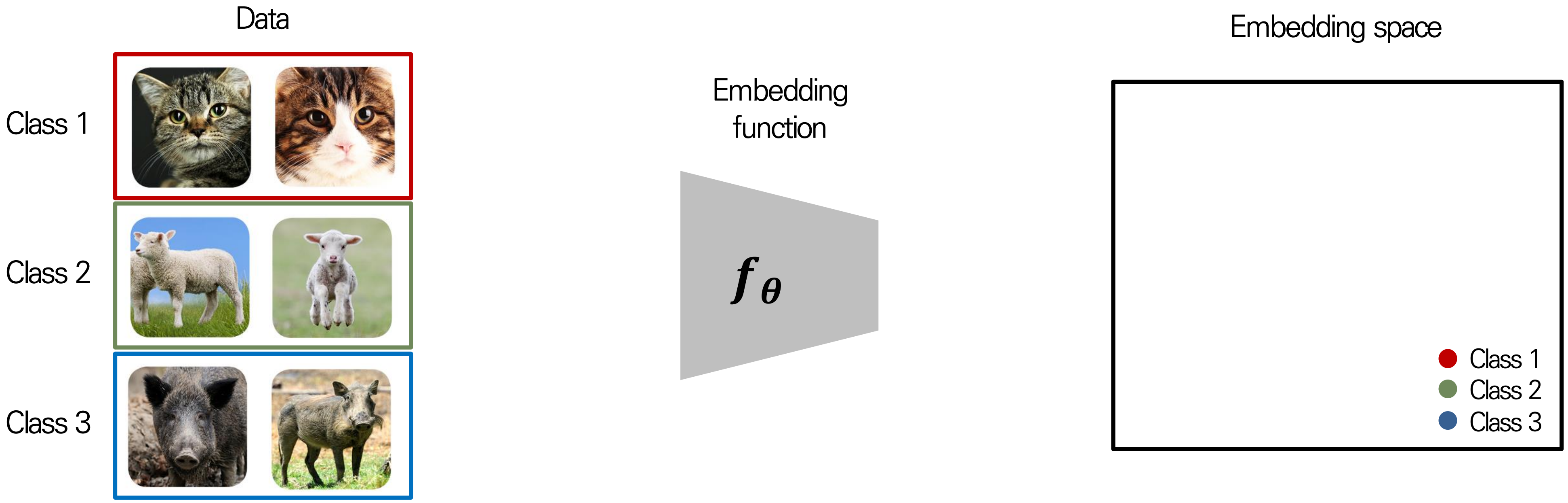
Metric learning

❖ Embedding function

- 데이터를 저차원으로 임베딩하는 함수

❖ Distance

- 임베딩 공간에서 데이터간 거리



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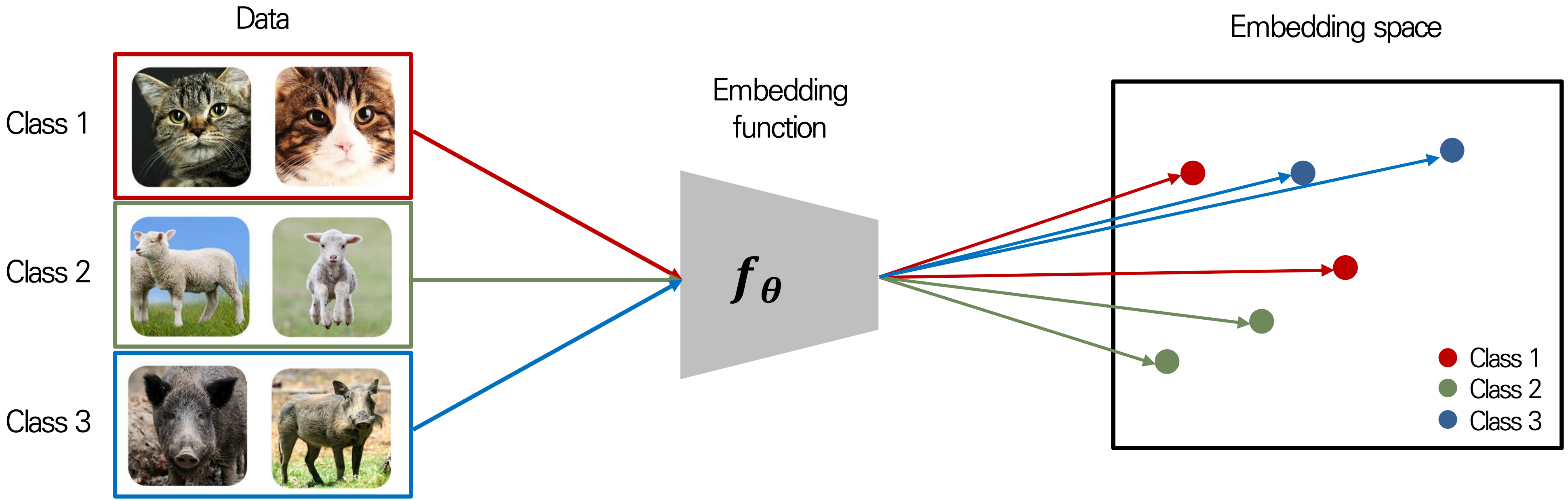

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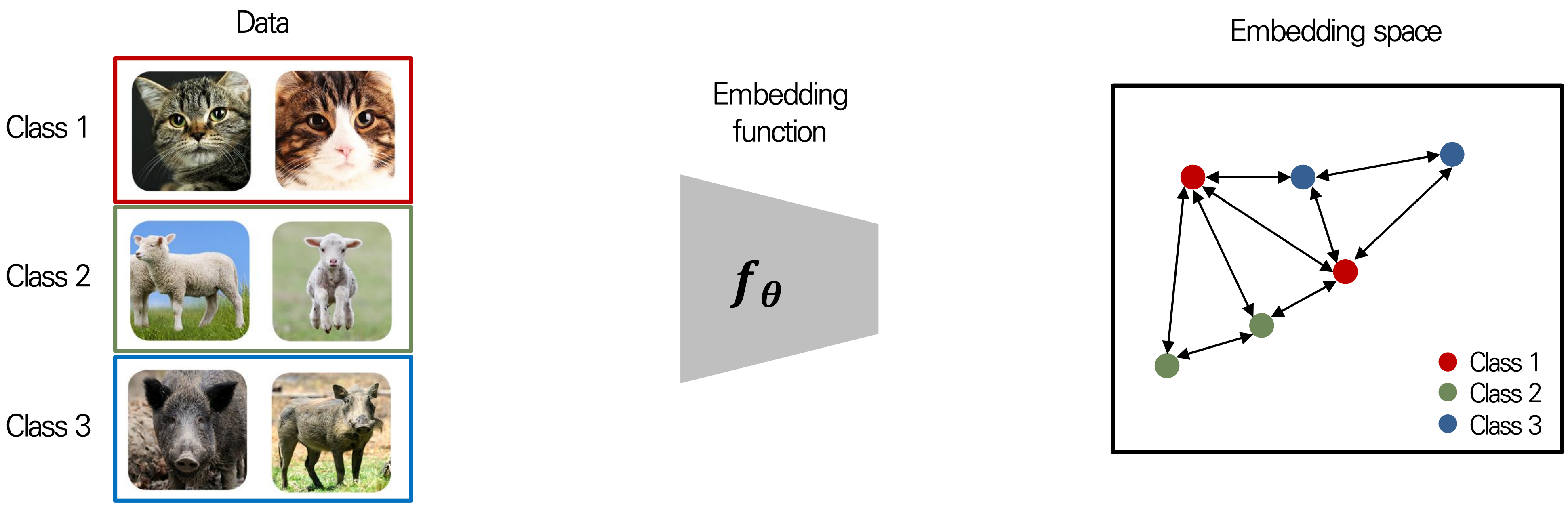

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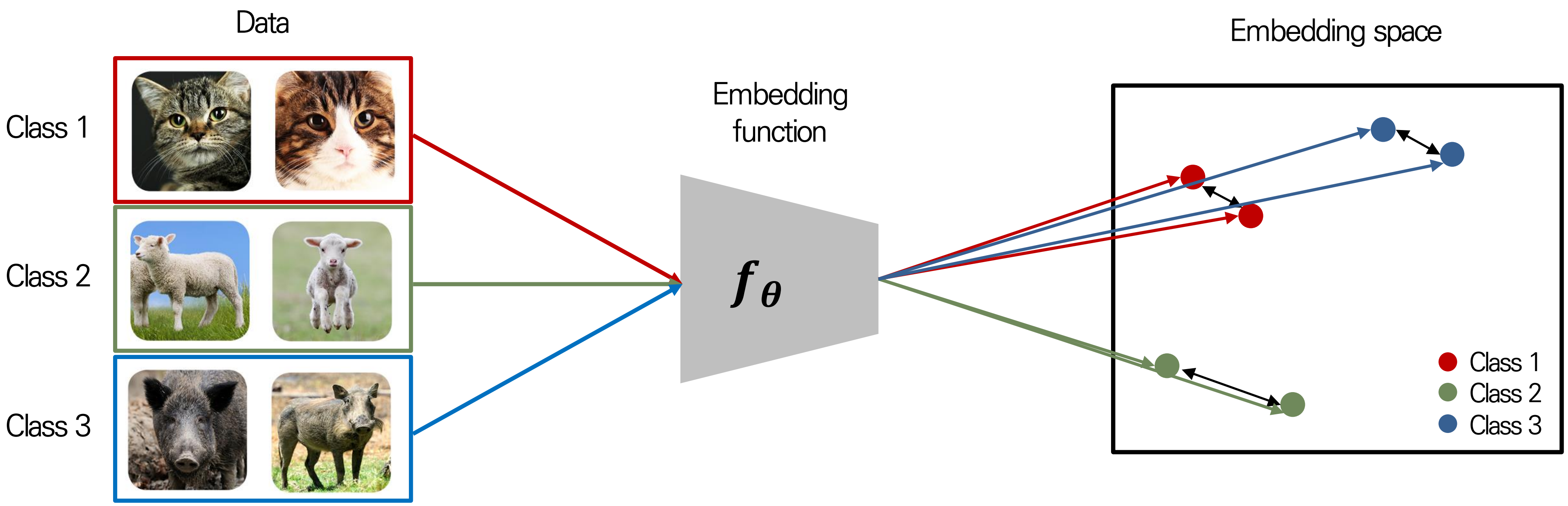

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Metric-based approaches to meta-learning

Matching networks

- Advances in Neural Information Processing Systems 29 (NIPS 2016)
- Google DeepMind
- 1967회 인용(2020.11.05 기준)

Matching Networks for One Shot Learning

Oriol Vinyals
Google DeepMind
vinyals@google.com

Charles Blundell
Google DeepMind
cblundell@google.com

Timothy Lillicrap
Google DeepMind
countzero@google.com

Koray Kavukcuoglu
Google DeepMind
korayk@google.com

Daan Wierstra
Google DeepMind
wierstra@google.com

Abstract

Learning from a few examples remains a key challenge in machine learning. Despite recent advances in important domains such as vision and language, the

Metric-based approaches to meta-learning

Matching networks

❖ Embedding function

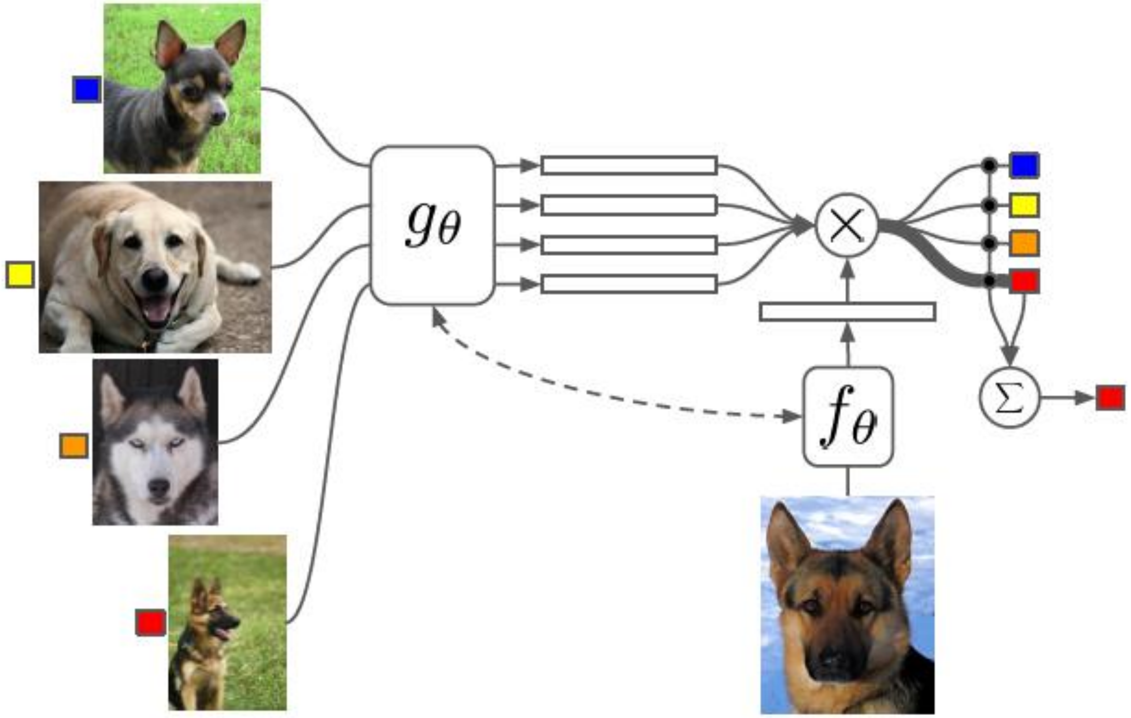


Figure 1: Matching Networks architecture

Metric-based approaches to meta-learning

Matching networks

❖ Embedding function

- g_θ : Support set의 임베딩 함수
- f_θ : Query set의 임베딩 함수

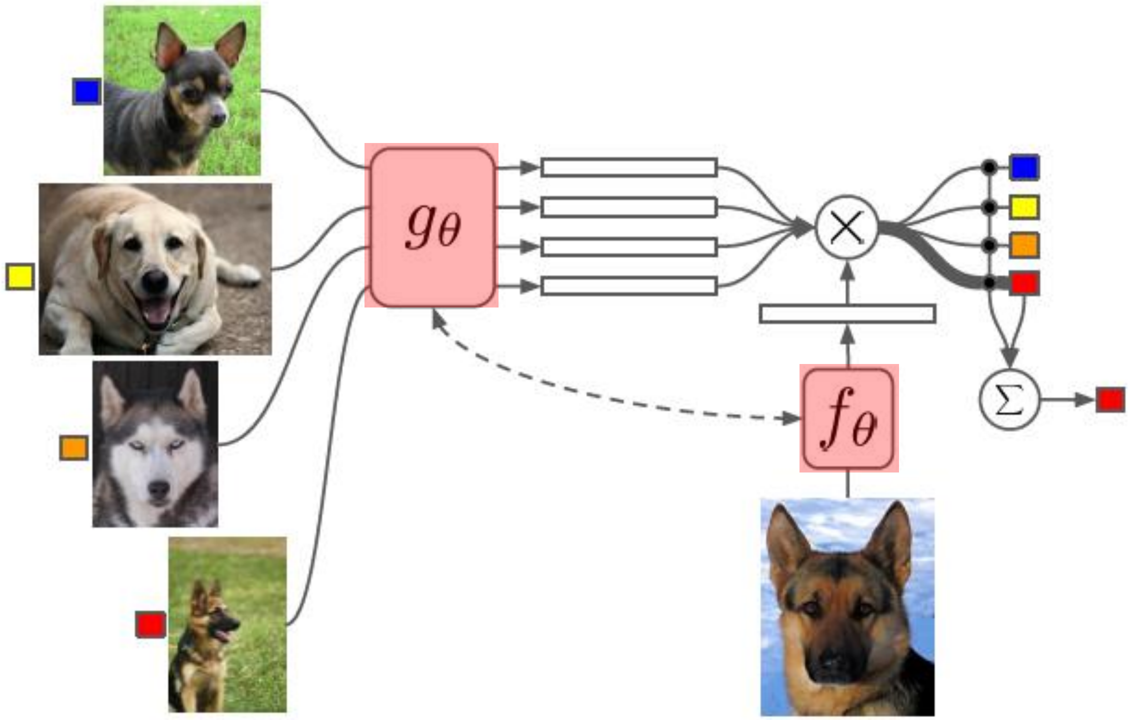
1. Simple embedding($g_\theta = f_\theta$)

   Conv-4

2. Full contextual embeddings($g_\theta \neq f_\theta$)

   g_θ : bi-LSTM

   f_θ : attLSTM



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Metric-based approaches to meta-learning

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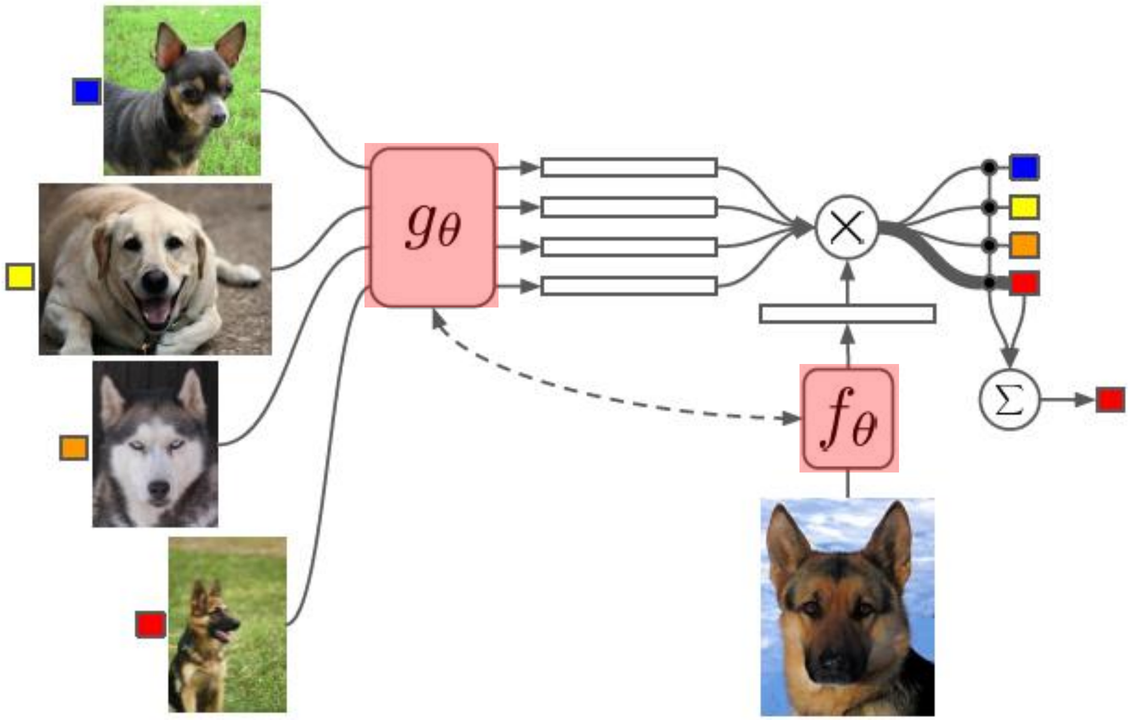


Figure 1: Matching Networks architecture

Metric-based approaches to meta-learning

Matching networks

❖ Distance

- Cosine similarity(attention)

$$a(x, x_i) = \frac{exp(cosine(f(x), g(x_i))}{\sum_{j=1}^{k}(cosine(f(x), g(x_j))}$$

❖ Training strategy

- Episode training

$$\theta = \underset{\theta}{\text{argmax}}\; E_{L\sim T}\left[E_{S\sim L, B\sim L}\left[\sum_{(x,y)\in B} logP_\theta(y|x, S)\right]\right]$$

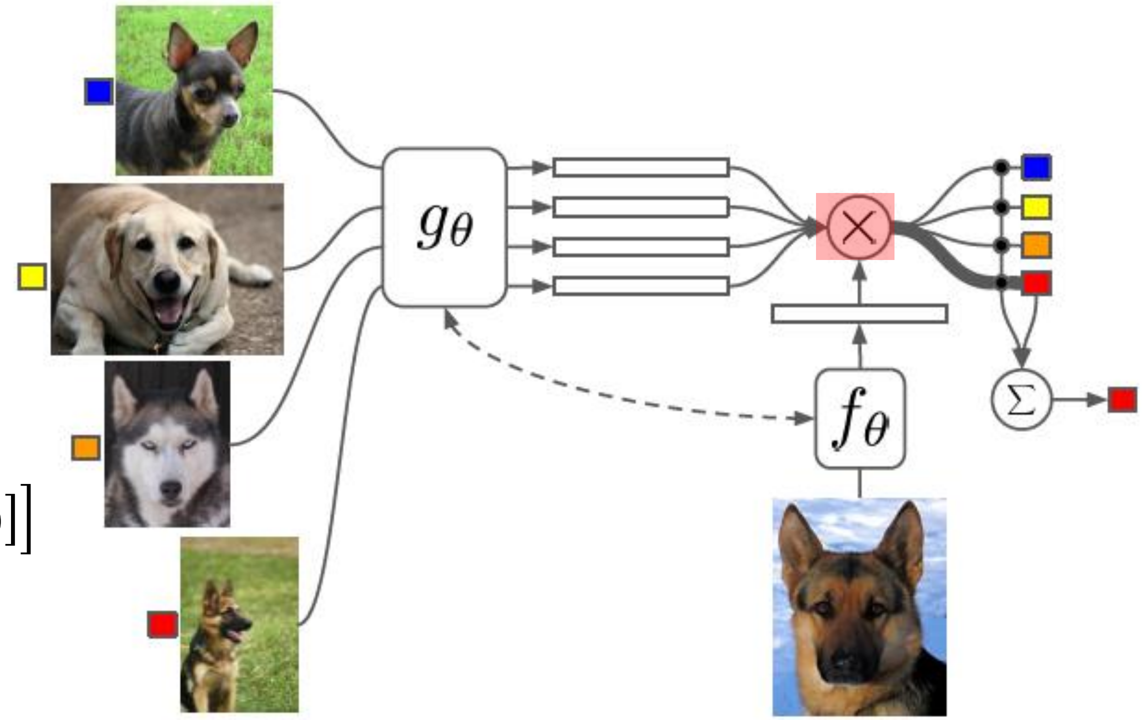


Figure 1: Matching Networks architecture

Metric-based approaches to meta-learning

Prototypical networks

- Advances in Neural Information Processing Systems 30 (NIPS 2017)
- 1632회 인용(2020.11.05 기준)

Prototypical Networks for Few-shot Learning

Jake Snell
University of Toronto*
Vector Institute

Kevin Swersky
Twitter

Richard Zemel
University of Toronto
Vector Institute
Canadian Institute for Advanced Research

Abstract

We propose *Prototypical Networks* for the problem of few-shot classification, where a classifier must generalize to new classes not seen in the training set, given only a small number of examples of each new class. Prototypical Networks learn a metric space in which classification can be performed by computing distances to prototype representations of each class. Compared to recent approaches for few-shot learning, they reflect a simpler inductive bias that is beneficial in this limited-data regime, and achieve excellent results. We provide an analysis showing that some simple design decisions can yield substantial improvements over recent

Metric-based approaches to meta-learning

Prototypical networks

❖ Embedding function

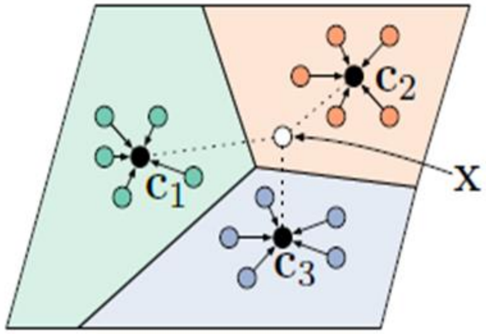
- $f_{\emptyset}$: support, query embedding function, Conv-4 사용

❖ Prototype

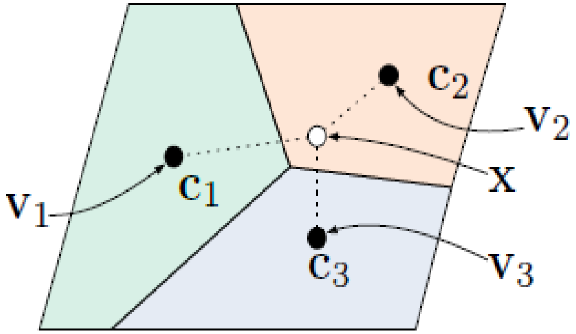
- $c_k = \frac{1}{|S_k|} \sum_{(x_i, y) \in S_k} f_{\emptyset}(x_i)$ → c_k는 class k의 prototype
- 모든 Support embedding vector와 거리계산하지 않아도 됨
- Zero-shot learning에도 사용할 수 있음

❖ Distance

- Euclidean distance 사용
- Cosine similarity 보다 Euclidean distance가 더 좋음
- 미분가능한 모든 distance 사용 가능



(a) Few-shot



(b) Zero-shot

Metric-based approaches to meta-learning

Relation Network

- Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition(CVPR 2018)
- 852회 인용(2020.11.05 기준)

Learning to Compare: Relation Network for Few-Shot Learning

Flood Sung Yongxin Yang[3] Li Zhang[2] Tao Xiang[1] Philip H.S. Torr[2] Timothy M. Hospedales[3]
[1]Queen Mary University of London [2]University of Oxford [3]The University of Edinburgh
floodsung@gmail.com t.xiang@qmul.ac.uk
{lz, phst}@robots.ox.ac.uk {yongxin.yang, t.hospedales}@ed.ac.uk

Abstract

We present a conceptually simple, flexible, and general framework for few-shot learning, where a classifier must learn to recognise new classes given only few examples from each. Our method, called the Relation Network (RN), is trained end-to-end from scratch. During meta-learning, it learns to learn a deep distance metric to compare a small number of images within episodes, each of which is designed to simulate the few-shot setting. Once trained, a RN is able to classify images of new classes by computing relation scores between query images and the few examples of each new class without further updating the network. Be-

zero-shot [11, 3, 24, 45, 25, 31] learning.

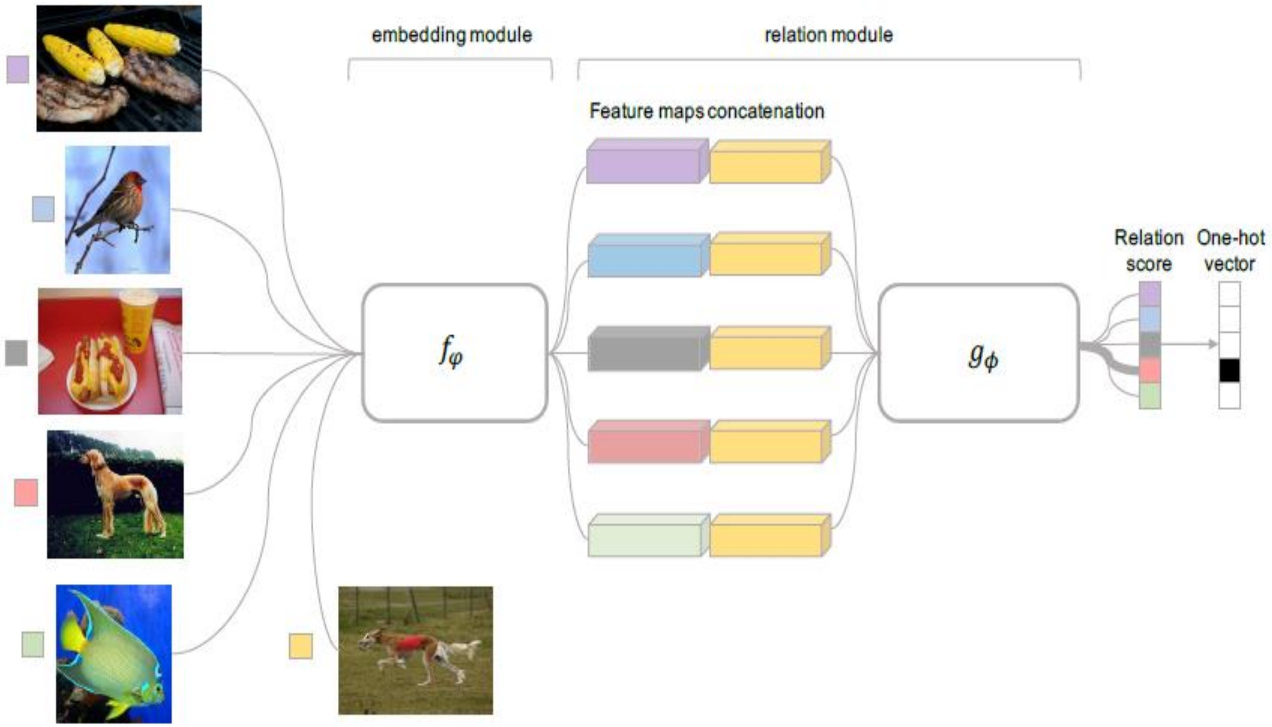
Few-shot learning aims to recognise novel visual categories from very few labelled examples. The availability of only one or very few examples challenges the standard 'fine-tuning' practice in deep learning [10]. Data augmentation and regularisation techniques can alleviate overfitting in such a limited-data regime, but they do not solve it. Therefore contemporary approaches to few-shot learning often decompose training into an auxiliary meta learning phase where transferrable knowledge is learned in the form of good initial conditions [10], embeddings [36, 39] or optimisation strategies [29]. The target few-shot learning problem is then learned by fine-tuning [10] with the learned op-

Metric-based approaches to meta-learning

Relation Network

❖ Embedding function

- f_φ : support, query embedding function
- Conv-4 사용



Metric-based approaches to meta-learning

Relation Network

❖ Embedding function

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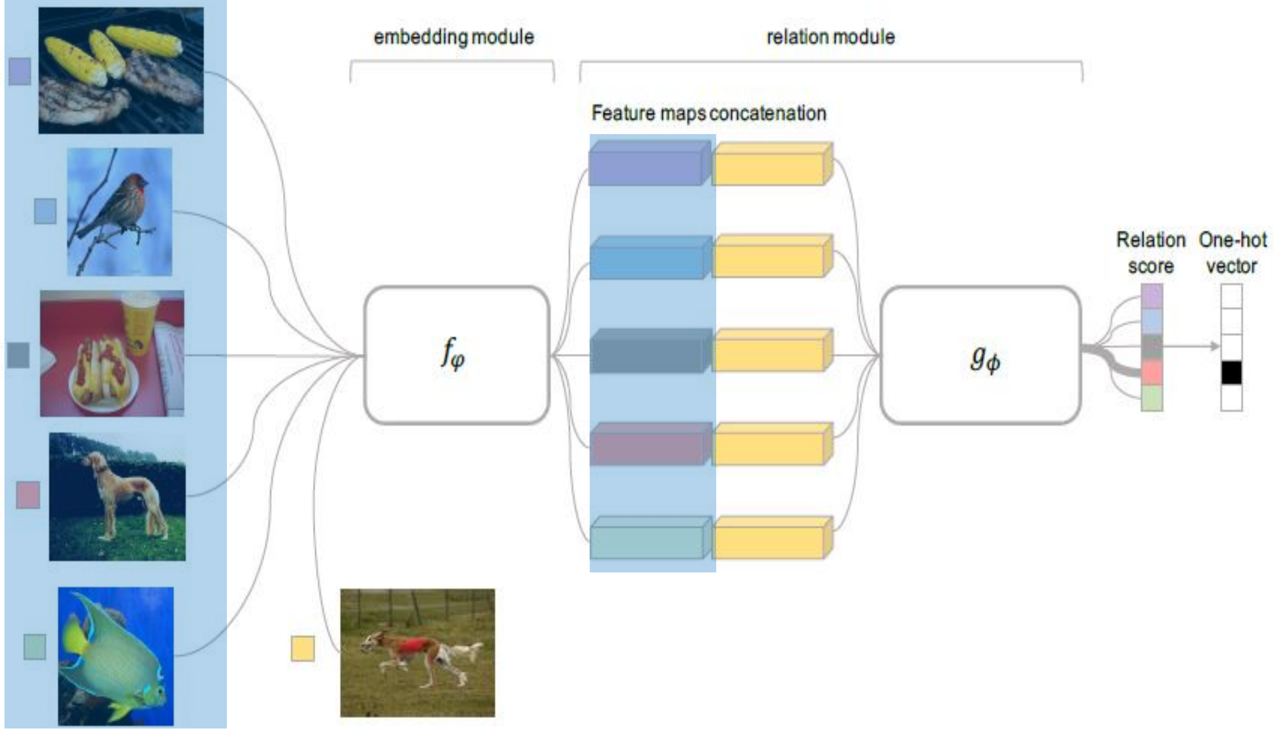
- Conv-4 사용

❖ Distance

- Relation module
  1. Support input의 feature map과 query input의 feature map을 붙임
  2. 합쳐진 featuremap으로 relation score(r_{ij})를 예측하는 모델 학습



$$\varphi, \emptyset = \underset{\varphi,\emptyset}{argmin} \sum_{i=1}^{m} \sum_{j=1}^{n} (r_{ij} - 1(y_i == y_j))^2$$

Metric-based approaches to meta-learning

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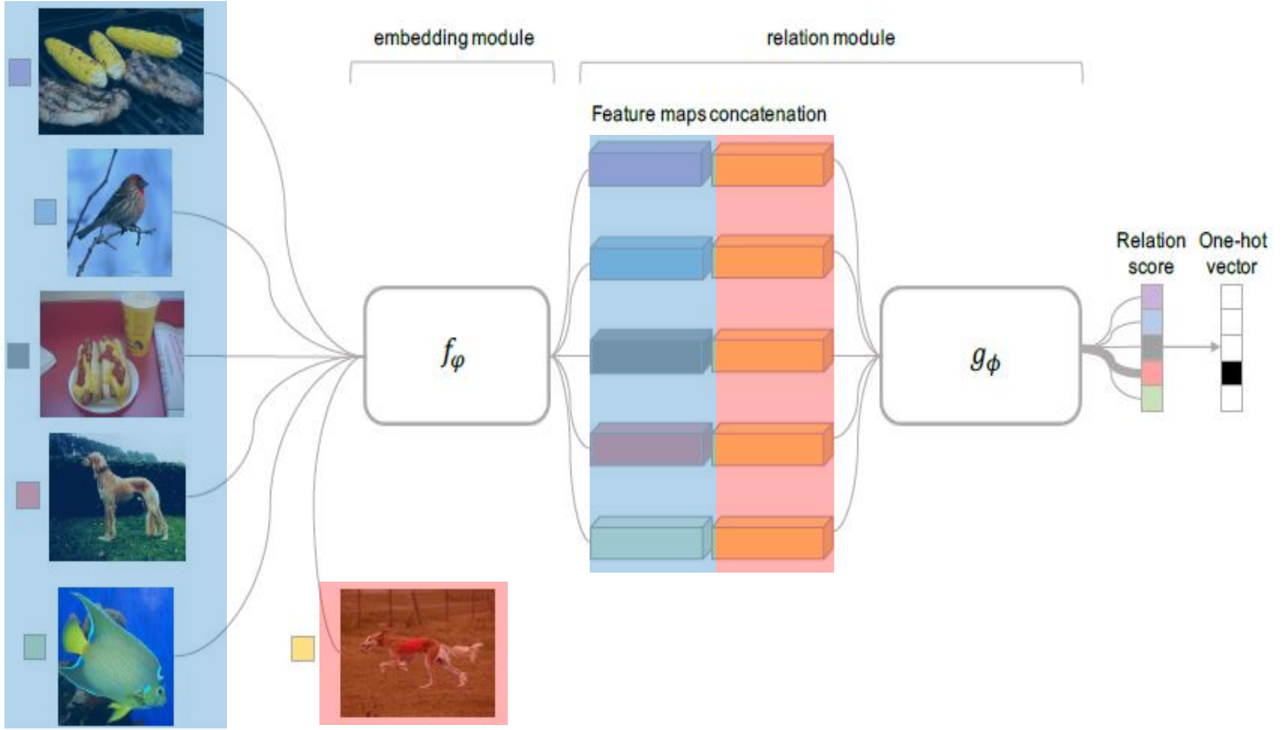

Evaluations

A closer look at few-shot classification

- 7th International Conference on Learning Representations(ICLR 2019)
- 852회 인용(2020.11.05 기준)

A Closer Look at Few-shot Classification

Wei-Yu Chen
Carnegie Mellon University
weiyuc@andrew.cmu.edu

Yen-Cheng Liu & Zsolt Kira
Georgia Tech
{ycliu,zkira}@gatech.edu

Yu-Chiang Frank Wang
National Taiwan University
ycwang@ntu.edu.tw

Jia-Bin Huang
Virginia Tech
jbhuang@vt.edu

Abstract

Few-shot classification aims to learn a classifier to recognize unseen classes during training with limited labeled examples. While significant progress has been made, the growing complexity of network designs, meta-learning algorithms, and differences in implementation details make a fair comparison difficult. In this paper, we present 1) a consistent comparative analysis of several representative few-shot classification algorithms, with results showing that deeper backbones significantly reduce the performance differences among methods on datasets with limited domain differences, 2) a modified baseline method that surprisingly achieves competitive performance when compared with the state-of-the-art on both the *mini-*

Evaluations

A closer look at few-shot classification

❖ Models

- Baseline
- Baseline++
- MatchingNet
- ProtoNet
- MAML
- RelationNet

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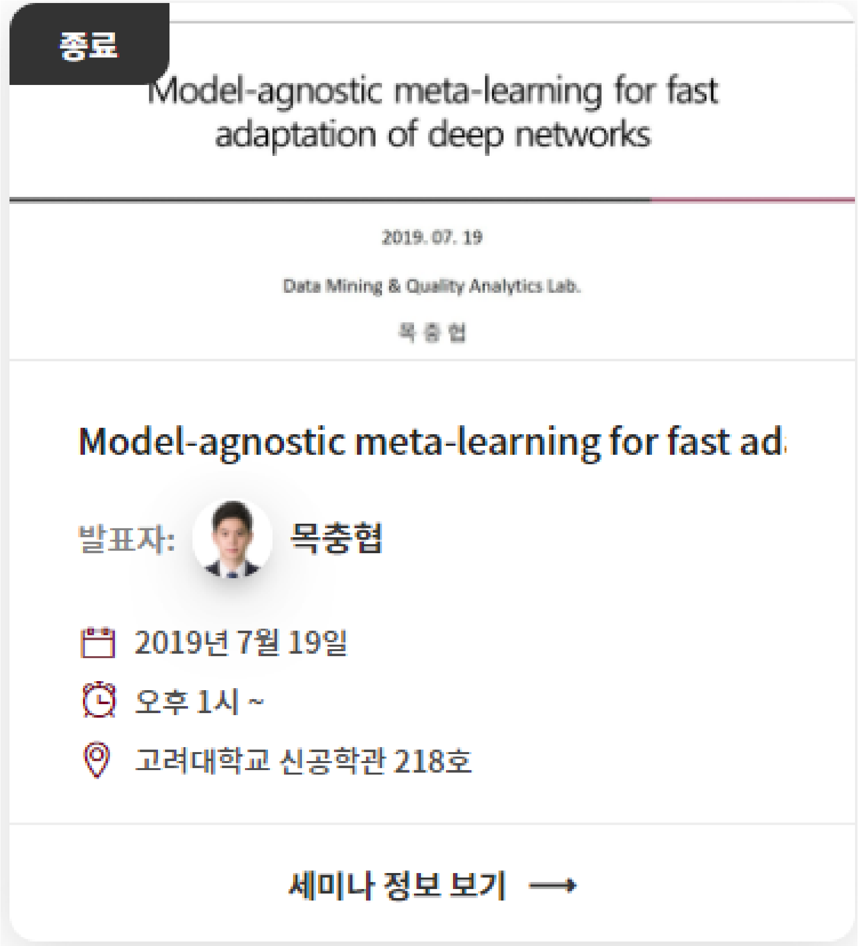


Evaluations

A closer look at few-shot classification

❖ Models

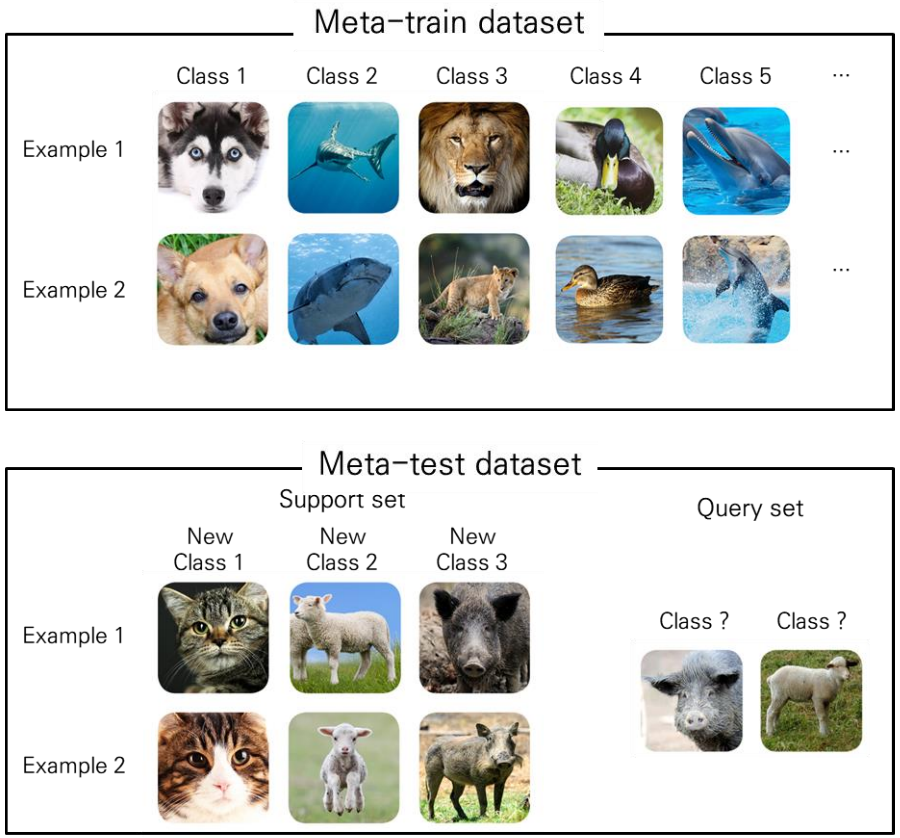
- Baseline
- Baseline++

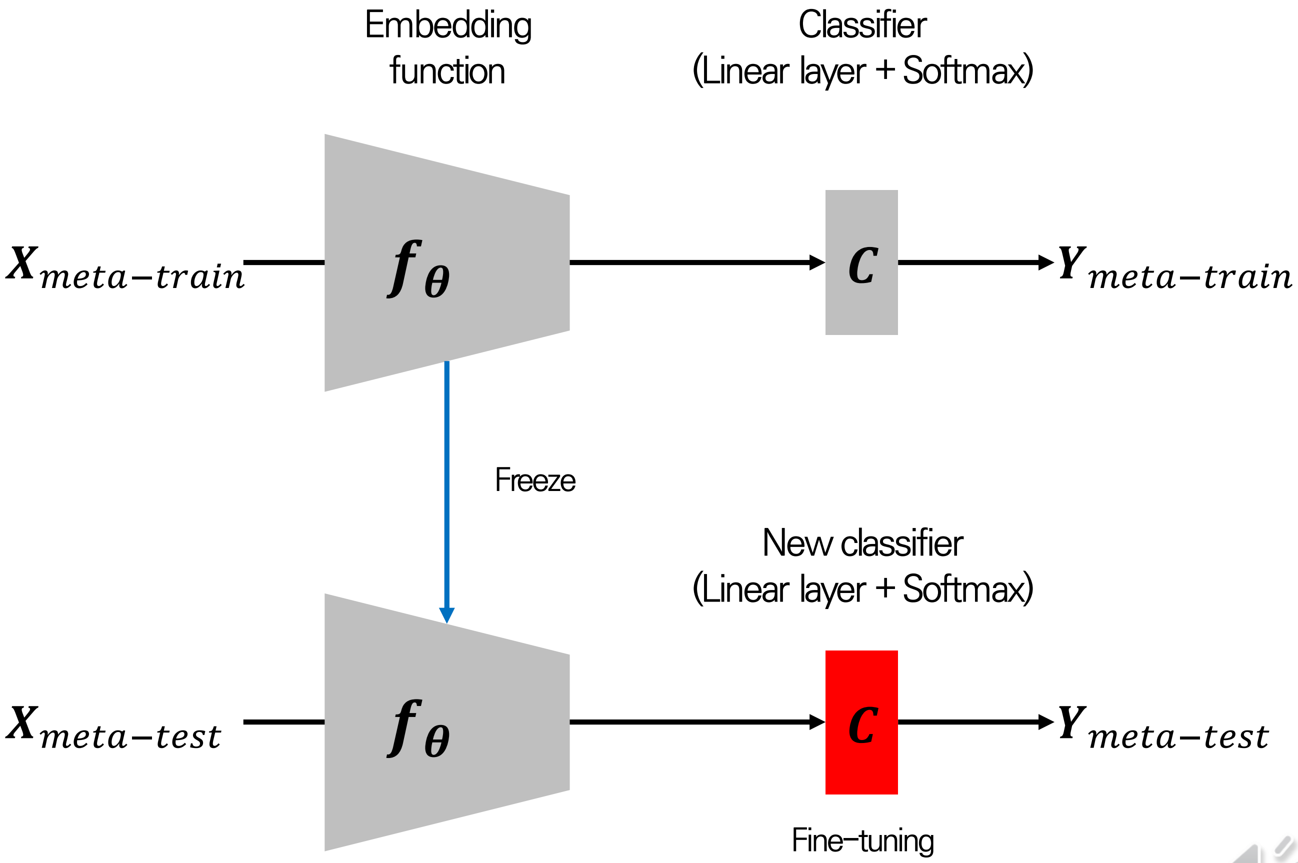
Evaluations

A closer look at few-shot classification

❖ Baseline

- Simple fine-tuning model



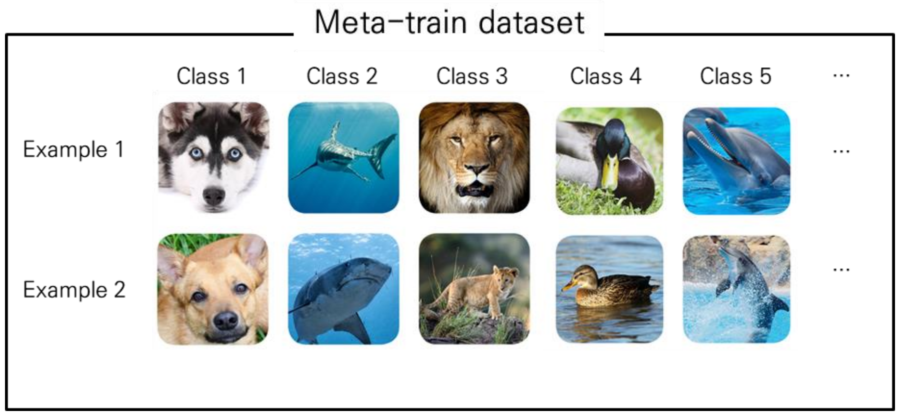


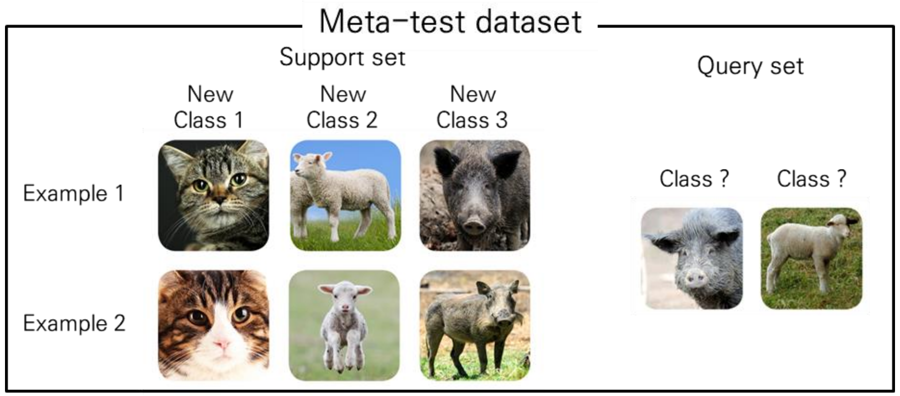
Evaluations

A closer look at few-shot classification

❖ Baseline++

- Simple fine-tuning model





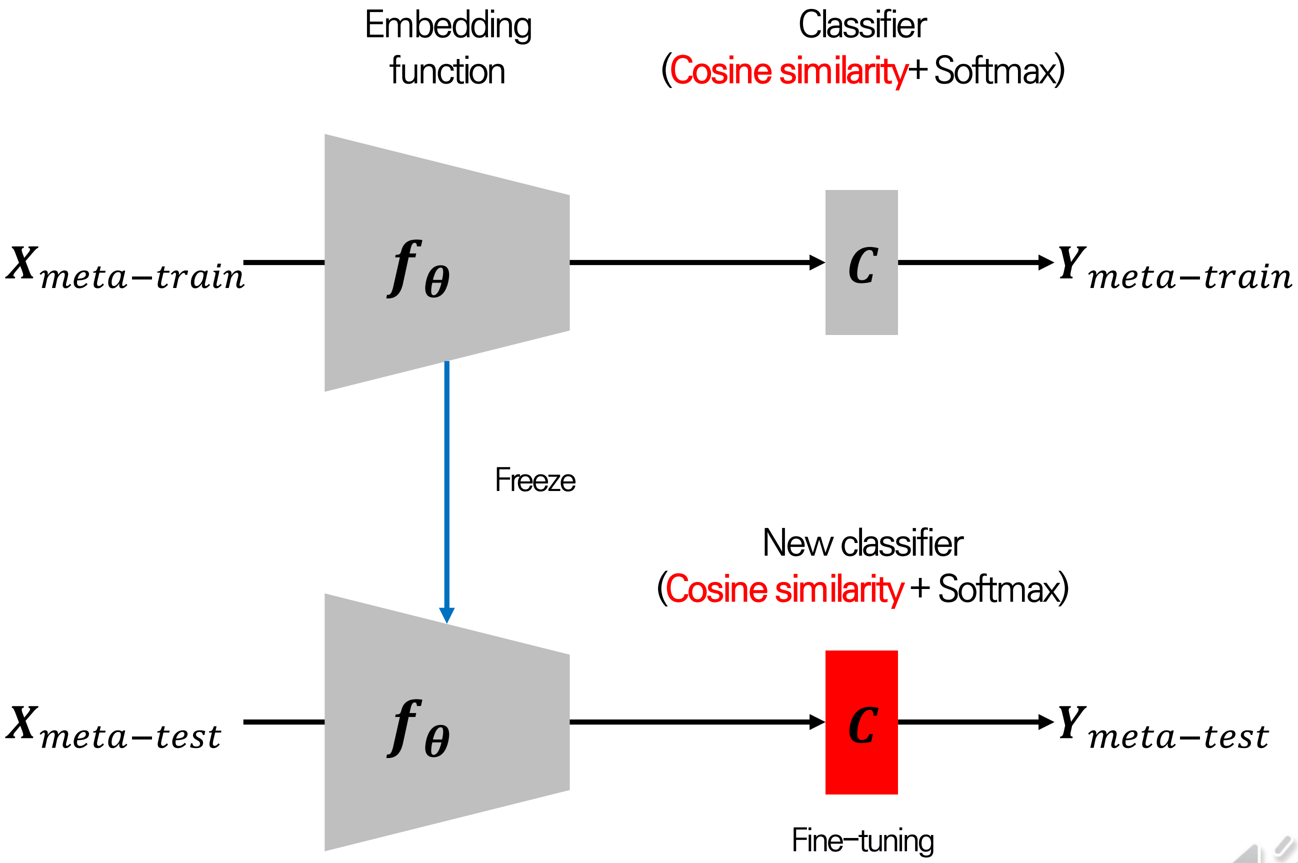


사진 : https://medium.com/ai%C2%B3-theory-practice-business/what-is-few-shot-learning-4b2842646b47
논문 : https://arxiv.org/abs/1904.04232

Evaluations

A closer look at few-shot classification

❖ Datasets

- mini-ImageNet
  - 100 Classes (64 base, 16 validation, 20 novel)
  - 각 클래스별 600장
  - 다양한 class로 이루어져 있음
- CUB
  - 200 Classes (100 base, 50 validation, 50 novel)
  - 각 클래스별 60장
  - 새(조류)에 관한 class로 이루어져 있음

Evaluations

A closer look at few-shot classification

❖ Re-implementation

- mini-ImageNet dataset, Conv-4 사용
- * → augmentation 미적용

Method	1-shot Reported	1-shot Ours	5-shot Reported	5-shot Ours
Baseline	-	42.11 ± 0.71	-	62.53 ±0.69
Baseline*[3]	41.08 ± 0.70	36.35 ± 0.64	51.04 ± 0.65	54.50 ±0.66
MatchingNet[3] Vinyals et al. (2016)	43.56 ± 0.84	48.14 ± 0.78	55.31 ±0.73	63.48 ±0.66
ProtoNet	-	44.42 ± 0.84	-	64.24 ±0.72
ProtoNet# Snell et al. (2017)	49.42 ± 0.78	47.74 ± 0.84	68.20 ±0.66	66.68 ±0.68
MAML Finn et al. (2017)	48.07 ± 1.75	46.47 ± 0.82	63.15 ±0.91	62.71 ±0.71
RelationNet Sung et al. (2018)	50.44 ± 0.82	49.31 ± 0.85	65.32 ±0.70	66.60 ±0.69

Evaluations

A closer look at few-shot classification

❖ Baseline++

- Baseline / Baseline++ 의 차이는 마지막 레이어가 linear layer / cosine similarity 인지의 차이
- Baseline++ 는 논문에서 제시한 방법이며, 성능이 좋은 이유는 Intra-class variation을 줄이기 때문

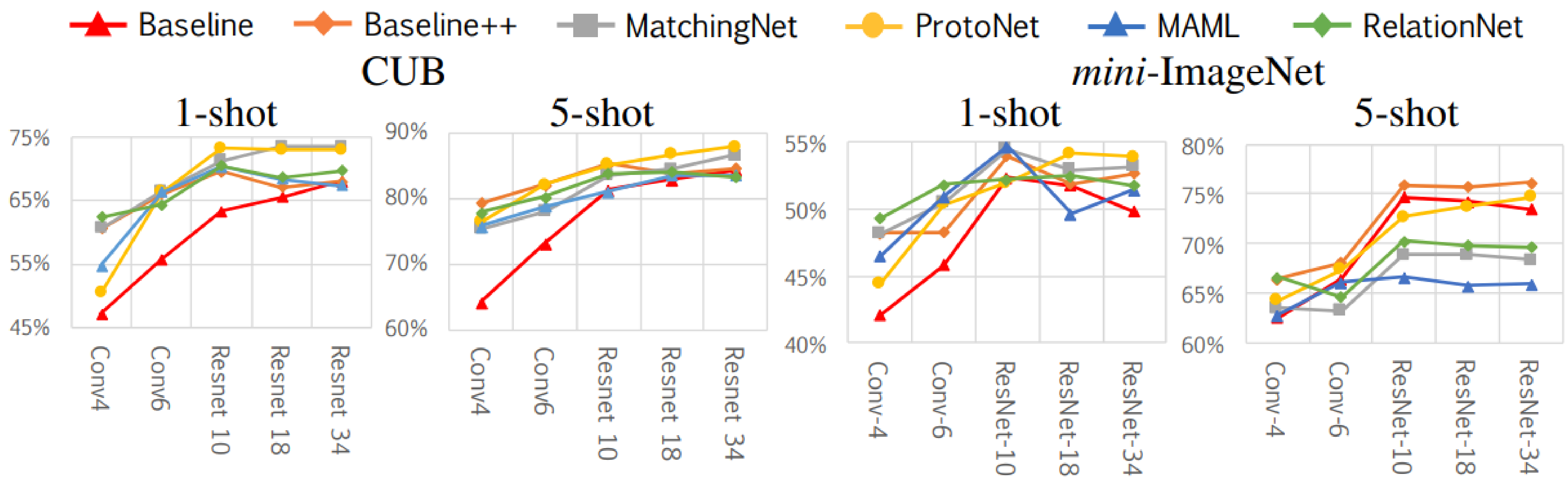
Method	**CUB** 1-shot	5-shot	***mini*-ImageNet** 1-shot	5-shot
Baseline	47.12 ± 0.74	64.16 ± 0.71	42.11 ± 0.71	62.53 ± 0.69
Baseline++	60.53 ± 0.83	79.34 ± 0.61	48.24 ± 0.75	66.43 ± 0.63
MatchingNet Vinyals et al. (2016)	60.52 ± 0.88	75.29 ± 0.75	48.14 ± 0.78	63.48 ± 0.66
ProtoNet Snell et al. (2017)	50.46 ± 0.88	76.39 ± 0.64	44.42 ± 0.84	64.24 ± 0.72
MAML Finn et al. (2017)	54.73 ± 0.97	75.75 ± 0.76	46.47 ± 0.82	62.71 ± 0.71
RelationNet Sung et al. (2018)	62.34 ± 0.94	77.84 ± 0.68	49.31 ± 0.85	66.60 ± 0.69

Evaluations

A closer look at few-shot classification

❖ Backbone depth

- Backbone의 깊이가 깊어질수록, 성능 차이가 줄어듬
- 데이터셋 (CUB/mini-ImageNet dataset)에 따라 메타 러닝의 효과가 차이남

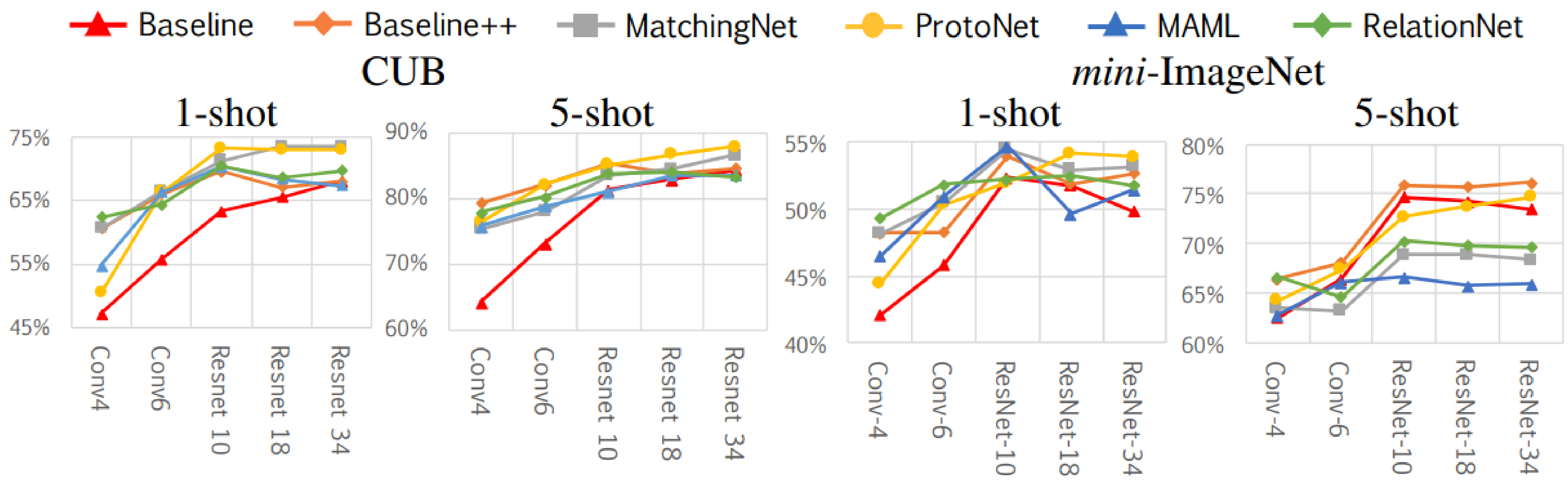


Evaluations

A closer look at few-shot classification

❖ Backbone depth

- Backbone의 깊이가 깊어질수록, 성능 차이가 줄어듬 → Intra-class variance
- 데이터셋 (CUB/mini-ImageNet dataset)에 따라 메타 러닝의 효과가 차이남 → Domain difference

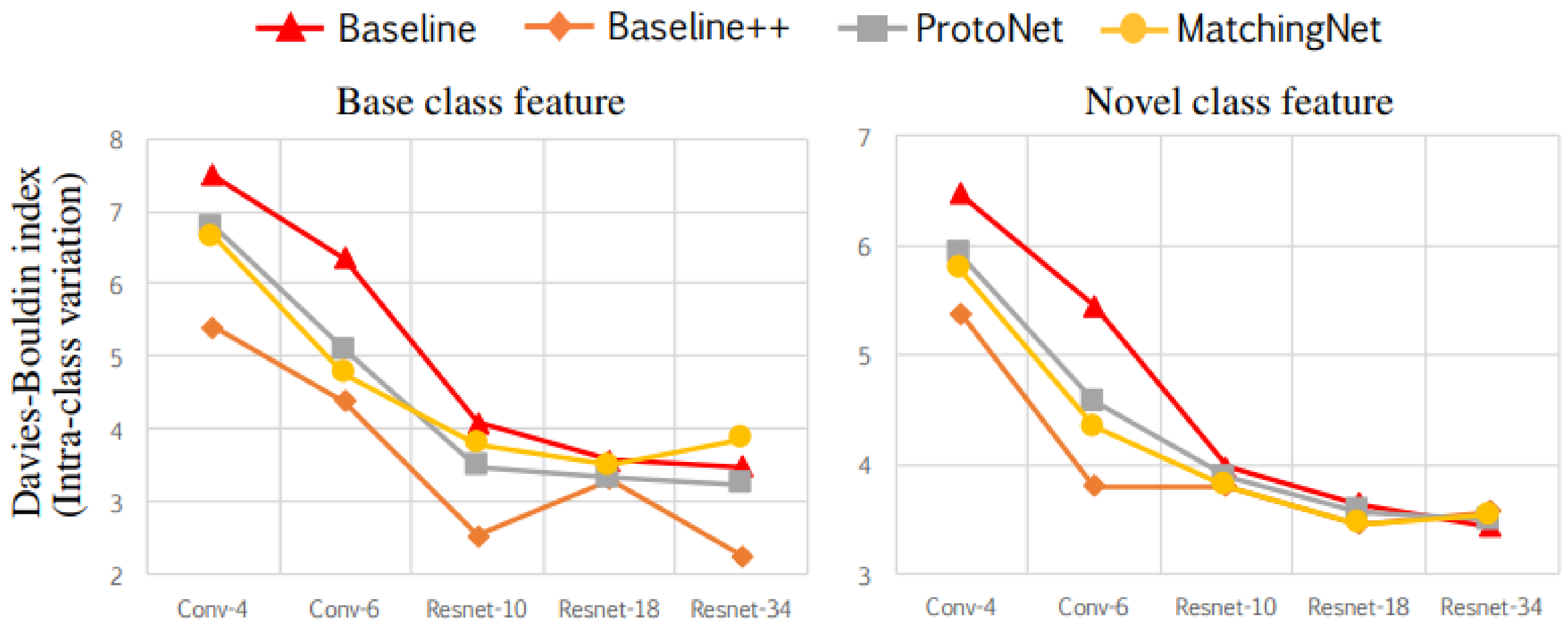


Evaluations

A closer look at few-shot classification

❖ Intra-class variance

- Backbone의 깊이가 깊어질수록, Intra-class variance가 줄어듦 → Class별로 잘 모여있음

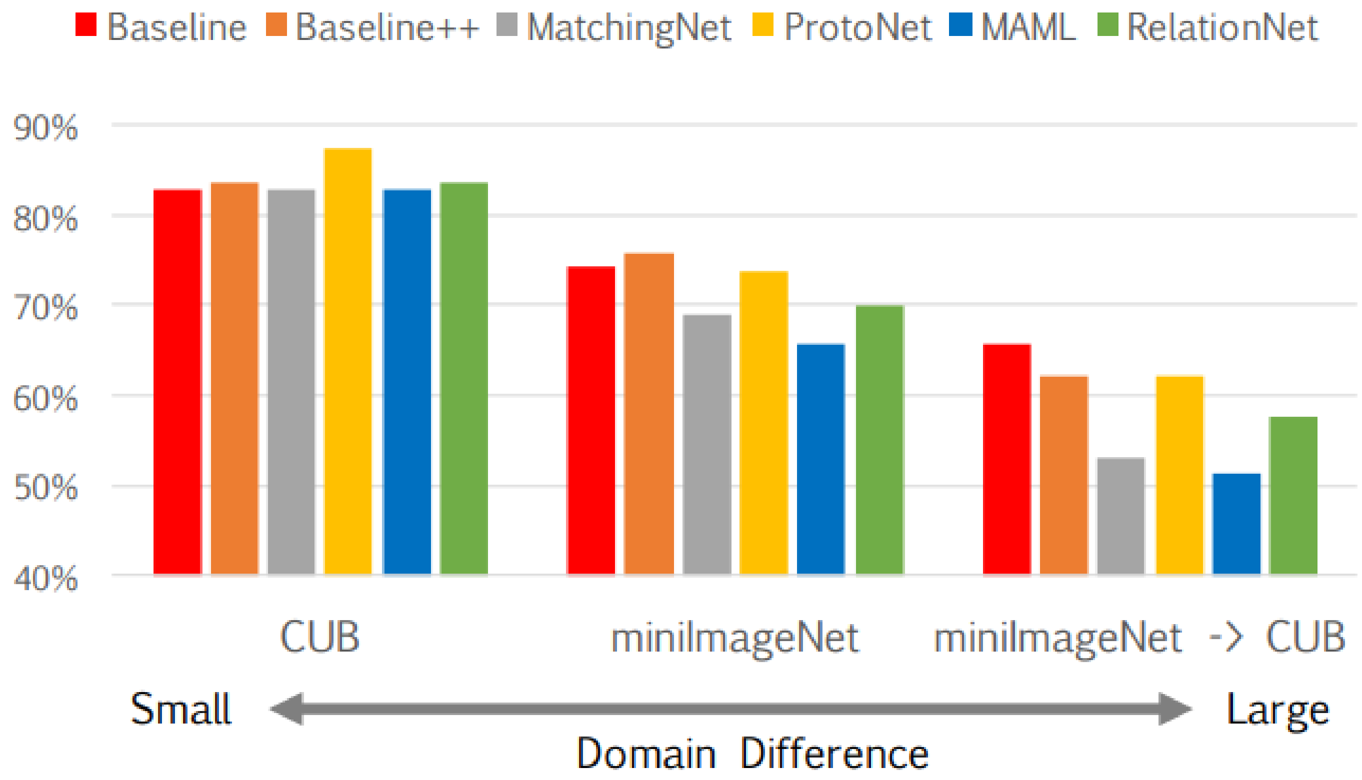


Evaluations

A closer look at few-shot classification

❖ Domain difference

- 도메인이 바뀌면, 기존의 데이터들은 학습에 큰 도움이 되지 않음

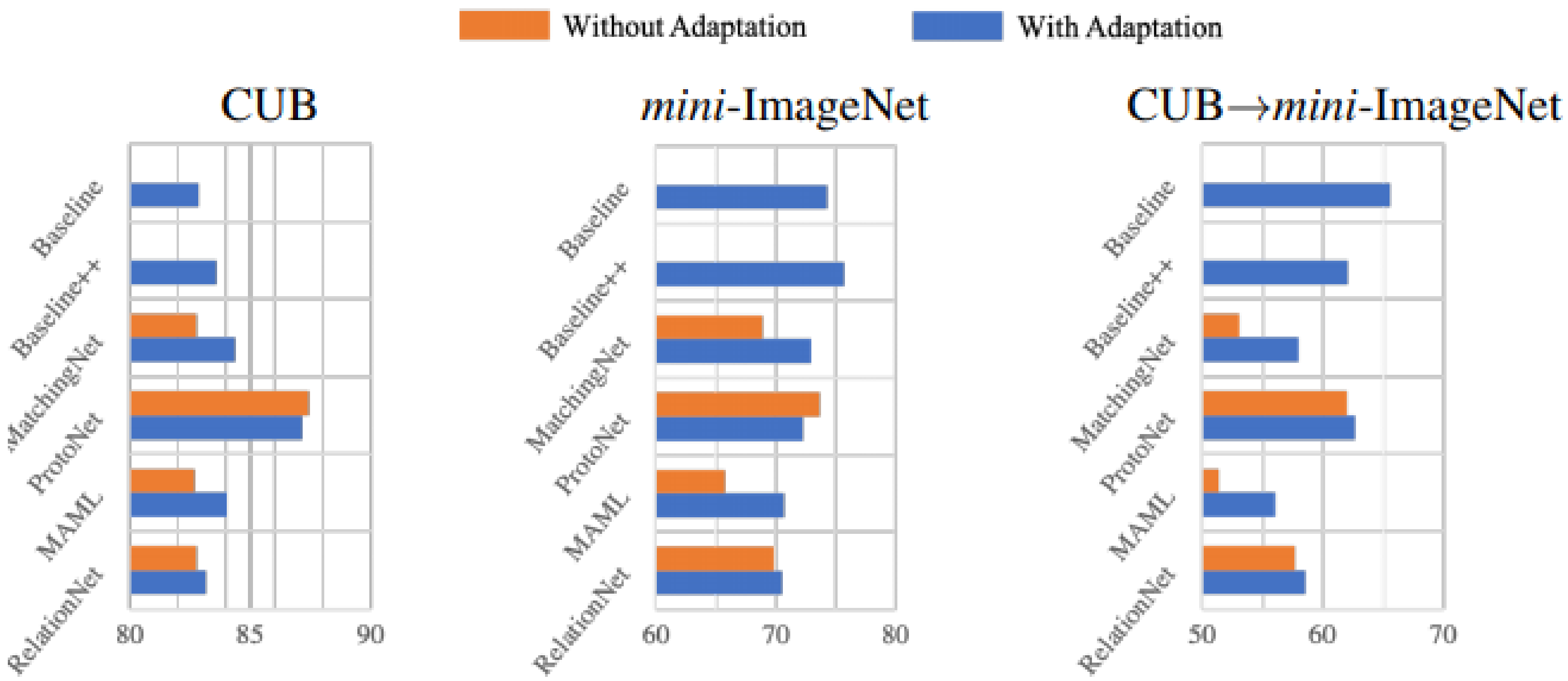


Evaluations

A closer look at few-shot classification

❖ Domain adaptation

- 마지막 layer만 fine-tuning 진행



Conclusion

❖ Metric-based approaches to meta-learning의 장점

- 단순하고 직관적이어서 이해하기 쉬움

- 임베딩을 이용하기 때문에 시각화하기 편하고, 어떤 일이 일어나는지 해석하기 쉬움

- Metric이나 Embedding space를 변경할 수 있기 때문에 도메인 지식이나 혹은 다른 정보들을 적용하기 쉬움

Conclusion

❖ Metric-based approaches to meta-learning의 단점

- Adaptation이 어렵기 때문에, Domain 변경에 취약
- Metric/Embedding이 성능에 많은 영향을 주는데, 결정하기가 쉽지 않음
- Distance를 계산하기 때문에, 데이터가 증가할수록 계산량이 많음
- Classification 외의 Task에는 적용하기 어려움

Conclusion

❖ Comments

- Few-shot learning을 넘어 Many-shot learning…
- 목적이 같은 Self-supervised / Semi-supervised 등 여러 방법론들과 공유하는 아이디어들이 많음
- 데이터의 양이 적기 때문에 Uncertainty를 잘 이용할 수 있어야함
- 딥러닝 아이디어들에 대한 해석이 매우 다양함

Thank you