# Meta Learning: Learn to learn

Hung-yi Lee

What does “meta” mean? meta-X = X about X

Source of iamge: https://medium.com/intuitionmachine/the-brute-force-method-of-deep-learning-innovation-58b497323ae5 (Denny Britz’s graphic)

# 這門課的作業在做甚麼？

感謝 沈昇勳 同學提供圖檔

## Industry

Using 1000 GPUs to try 1000 sets of hyperparameters

## Academia

“Telepathize” (通靈) a set of good hyperparameters

**Can machine automatically determine the hyperparameters?**

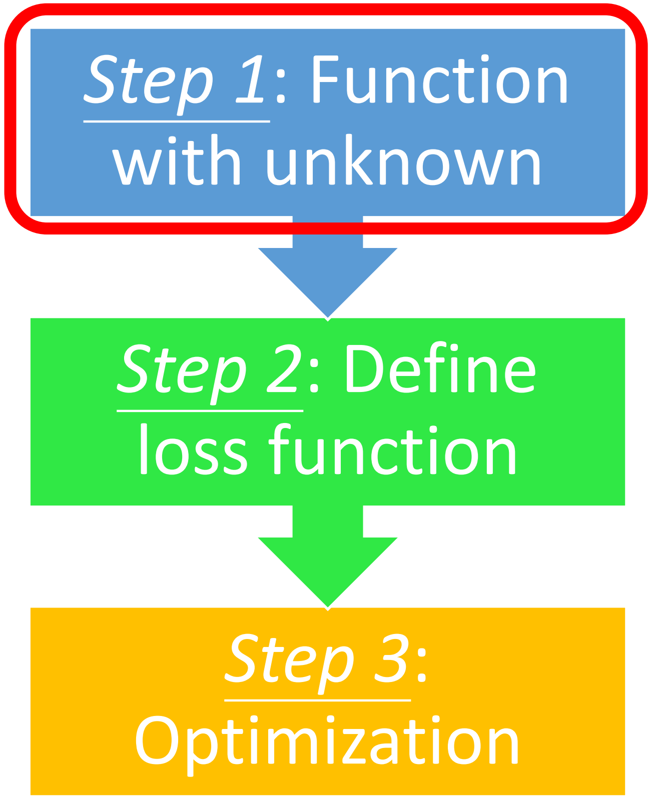
# Machine Learning 101

# Machine Learning

**= Looking for a function**

Dog-Cat Classification

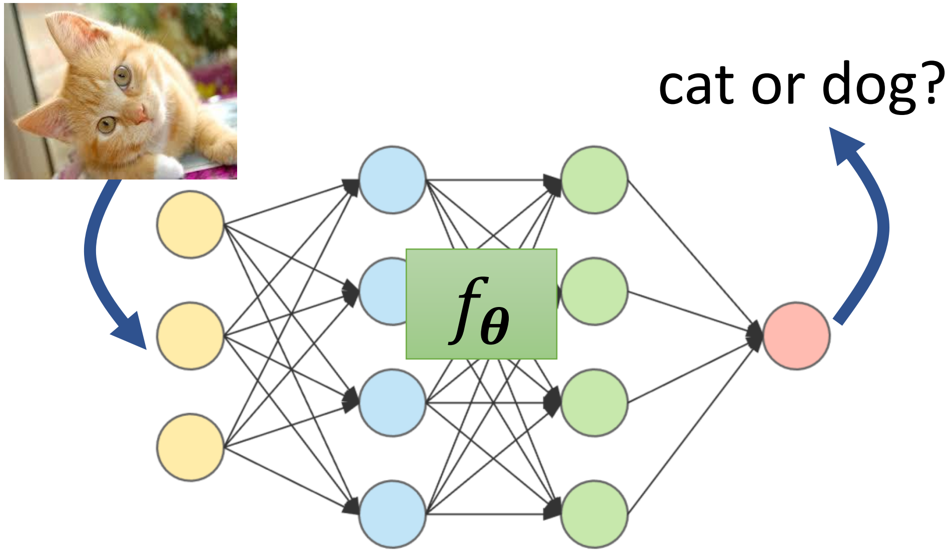
$f($ $)$ = "cat"



*Step 1*: Function with unknown

*Step 2*: Define loss function

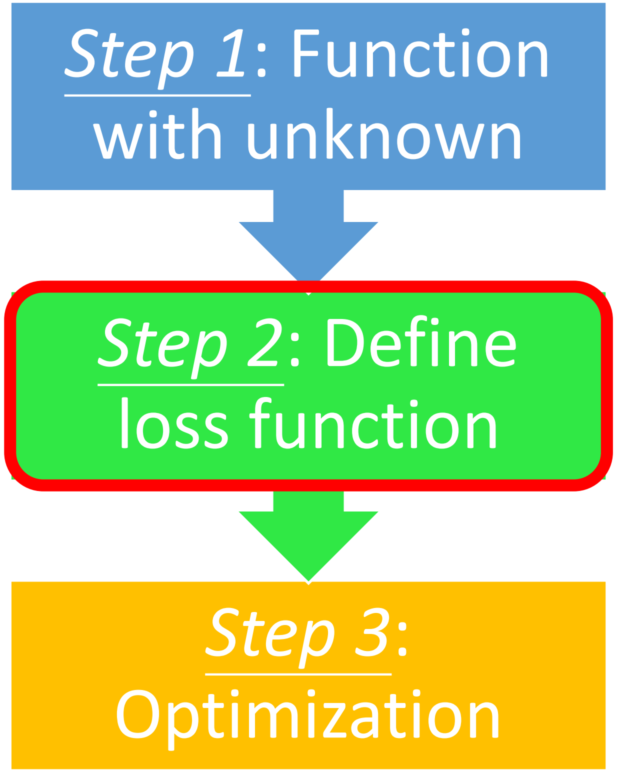
*Step 3*: Optimization



Weights and biases of neurons are unknown parameters (*learnable*).

Using $\boldsymbol{\theta}$ to represent the unknown parameters.

# Machine Learning

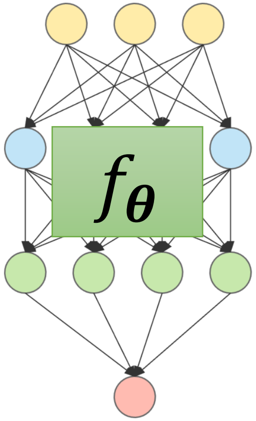


*Step 1*: Function with unknown

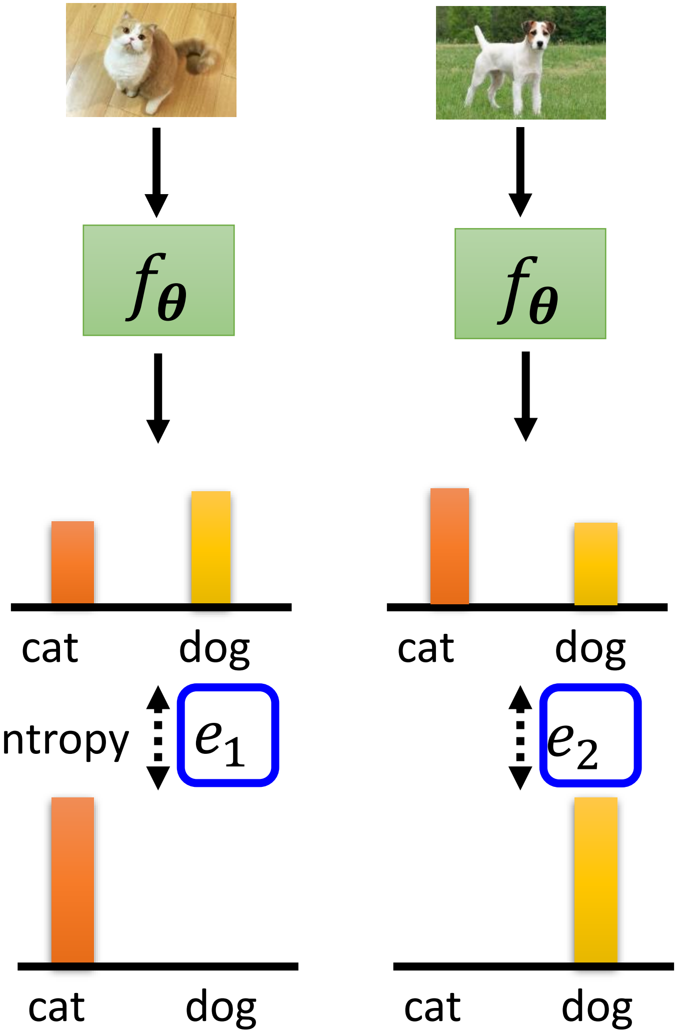
*Step 2*: Define loss function

*Step 3*: Optimization

$\boxed{L(\boldsymbol{\theta})}$



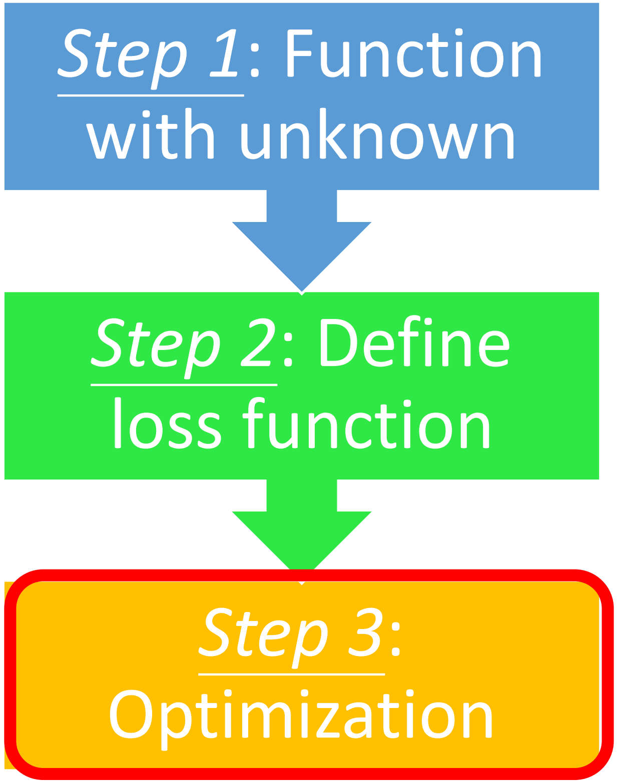
*Training Examples*



$$\boxed{L(\boldsymbol{\theta})} = \boxed{\sum_{k=1}^{K} e_k}$$

*Ground Truth*

# Machine Learning 101



*Step 1*: Function with unknown

*Step 2*: Define loss function

*Step 3*: Optimization

loss: $L(\boldsymbol{\theta}) = \sum_{k=1}^{K} e_k$ sum over training examples

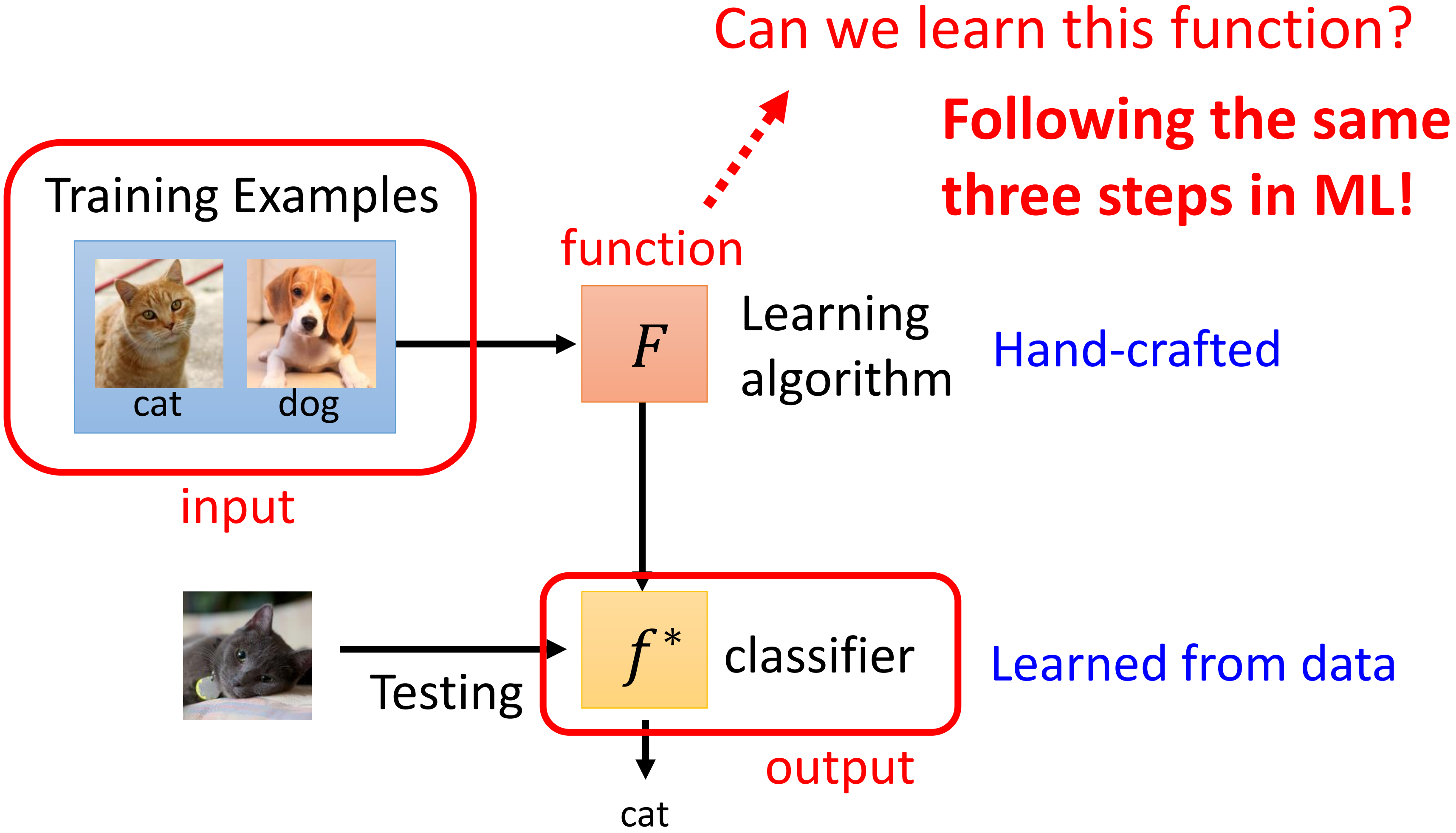
$$\boldsymbol{\theta}^* = arg \min_{\boldsymbol{\theta}} L(\boldsymbol{\theta})$$

done by gradient descent

$f_{\boldsymbol{\theta}^*}$ is the function learned by learning algorithm from data

# Introduction of Meta Learning

# What is Meta Learning?



Can we learn this function?

**Following the same three steps in ML!**

Training Examples

cat

dog

input

function

$F$

Learning algorithm

Hand-crafted

Testing

$f^*$

classifier

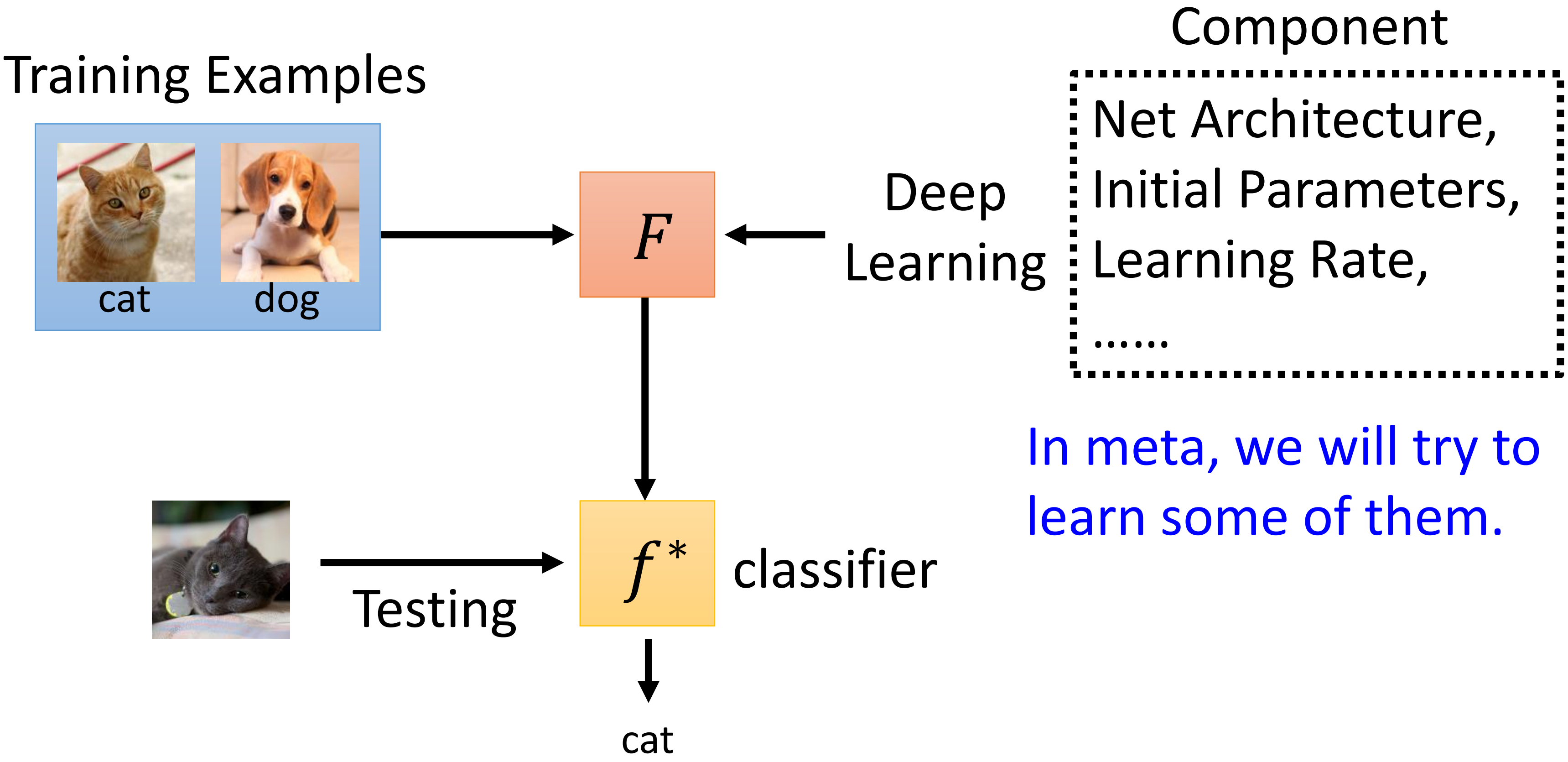
Learned from data

output

cat

# Meta Learning – Step 1

- What is ***learnable*** in a learning algorithm?



Training Examples

cat

dog

$F$

Deep Learning

Component

Net Architecture,
Initial Parameters,
Learning Rate,
……

Testing

$f^*$

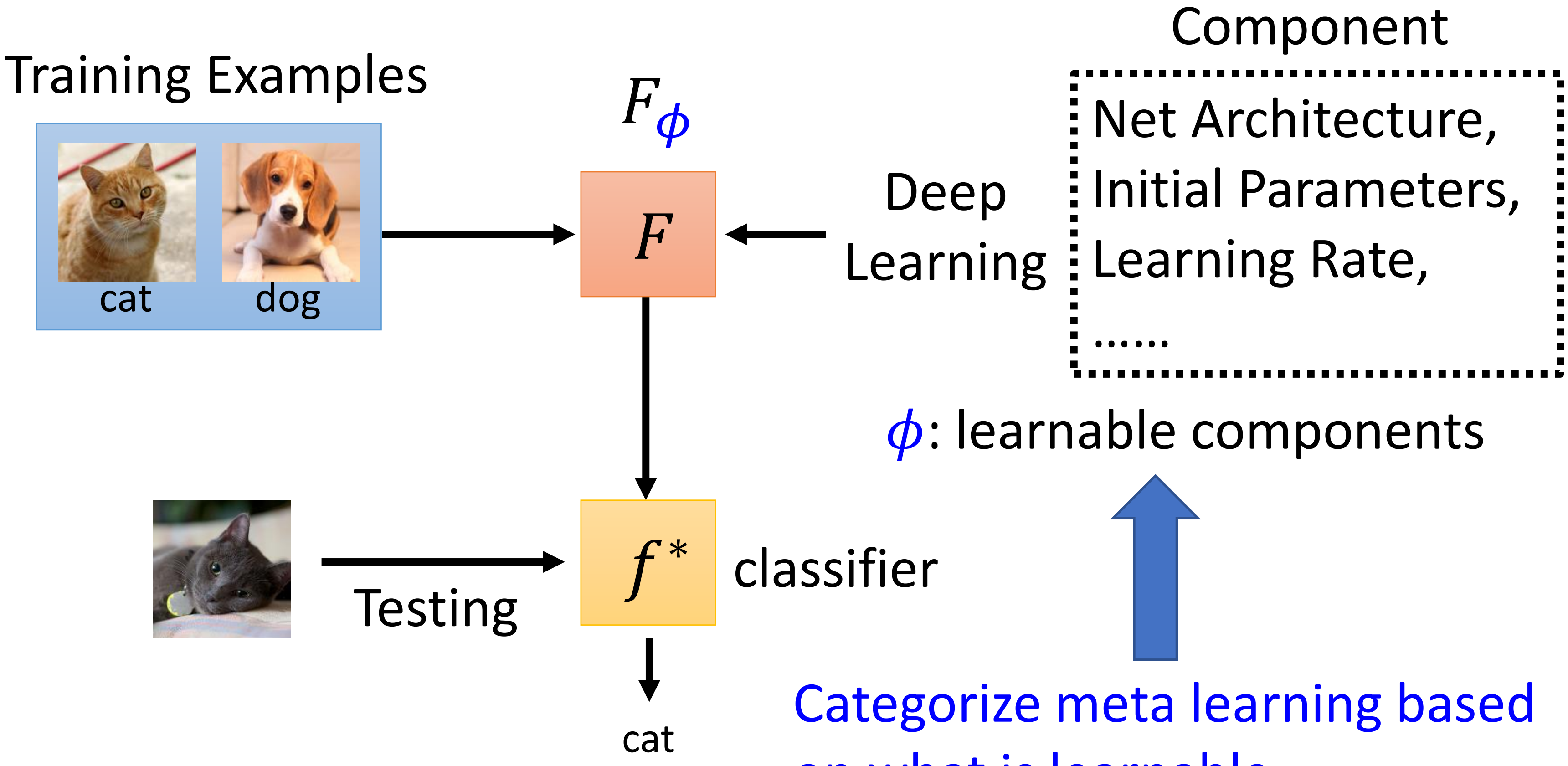
classifier

cat

In meta, we will try to learn some of them.

# Meta Learning – Step 1

- What is ***learnable*** in a learning algorithm?



Training Examples

cat dog

$F_{\phi}$

$F$

Deep Learning

Component

Net Architecture,
Initial Parameters,
Learning Rate,
……

$\phi$: learnable components

$f^*$ classifier

Testing

cat

Categorize meta learning based on what is learnable

# Meta Learning – Step 2

- Define ***loss function*** for ***learning algorithm*** $F_{\phi}$

$$L(\phi)$$

$L(\phi)\downarrow$ 👍 $L(\phi)\uparrow$ 👎

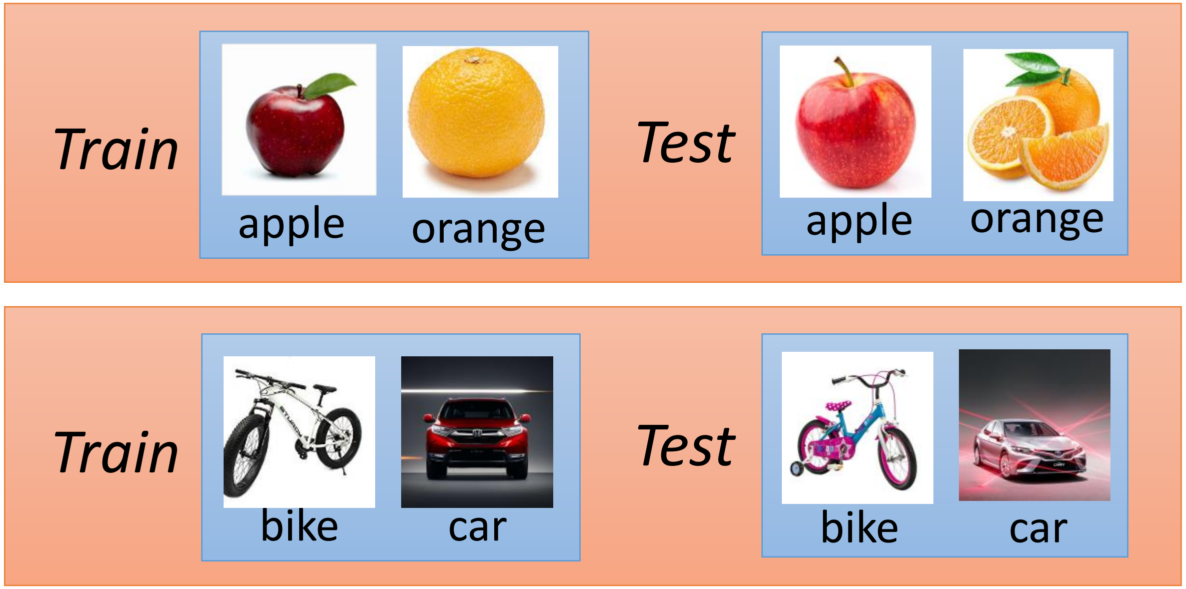
**Training Tasks**

*Task 1*

Apple & Orange

*Task 2*

Car & Bike



*Train*

apple orange

*Test*

apple orange

*Train*

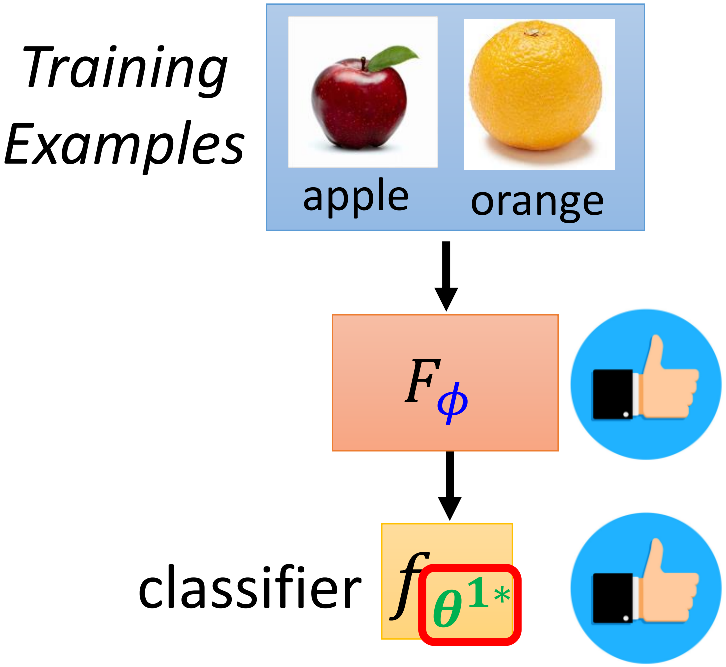
bike car

*Test*

bike car

# *Meta Learning – Step 2*

**Task 1**



*Training Examples*

apple

orange

$F_{\phi}$

classifier $f_{\theta^{1*}}$

How to define $L(\phi)$

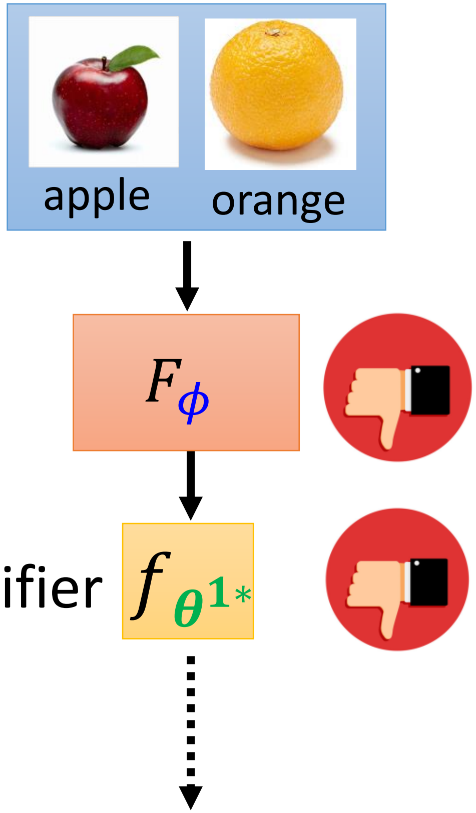
$L(\phi)$ ↓

$\boxed{\theta^{1*}}$: parameters of the classifier learned by $F_{\phi}$ using the training examples of task 1

# ***Meta Learning – Step 2***

**Task 1**

*Training Examples*



classifier

How to define $L(\phi)$

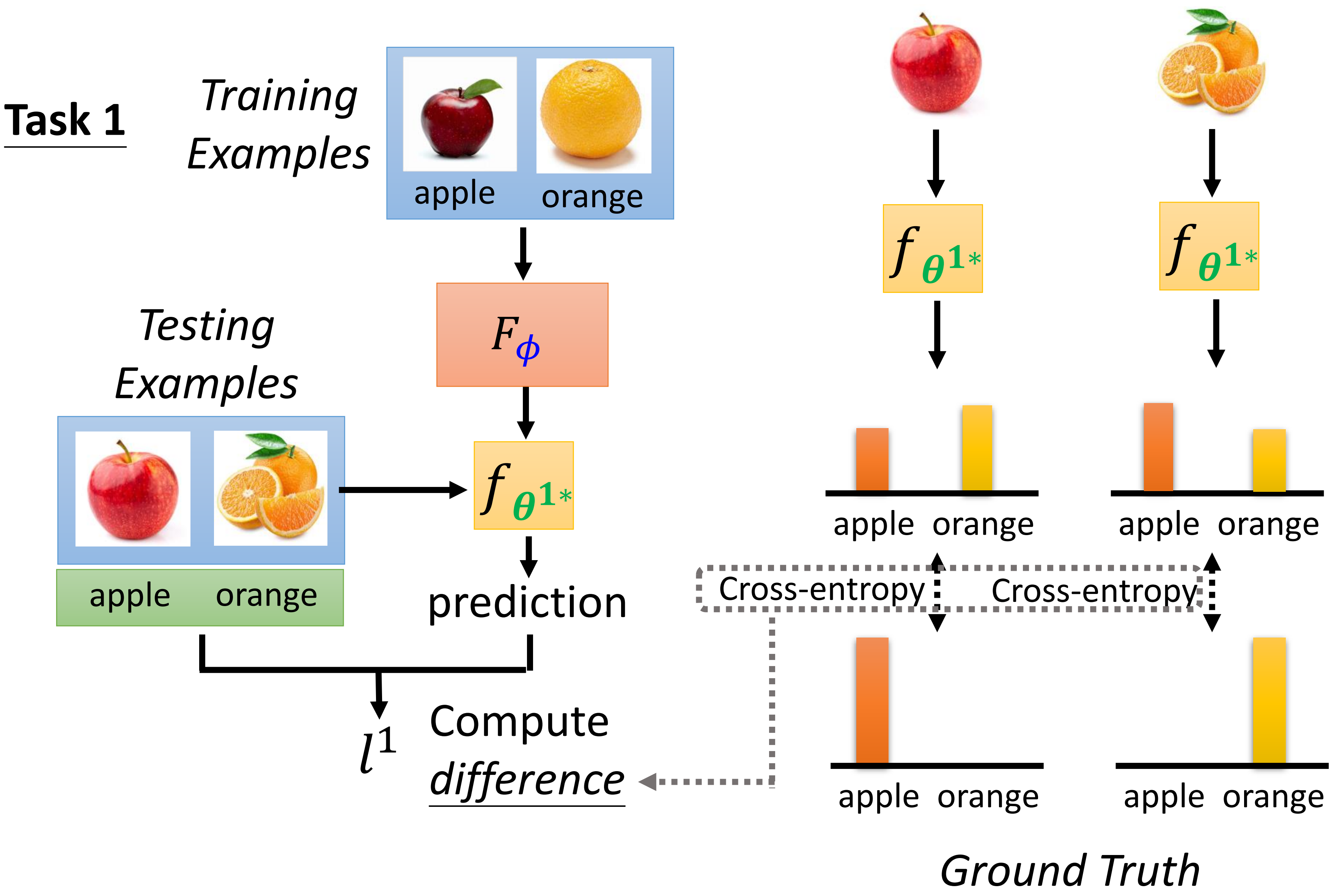
$L(\phi)$ ↑

How can we know a classifier is good or bad?

Evaluate the classifier on testing set

# Meta Learning – Step 2

Testing Examples



Task 1

Training Examples

apple orange

$F_{\phi}$

$f_{\theta^{1*}}$

Testing Examples

apple orange

prediction

$l^1$

Compute *difference*

Cross-entropy

Cross-entropy

apple orange

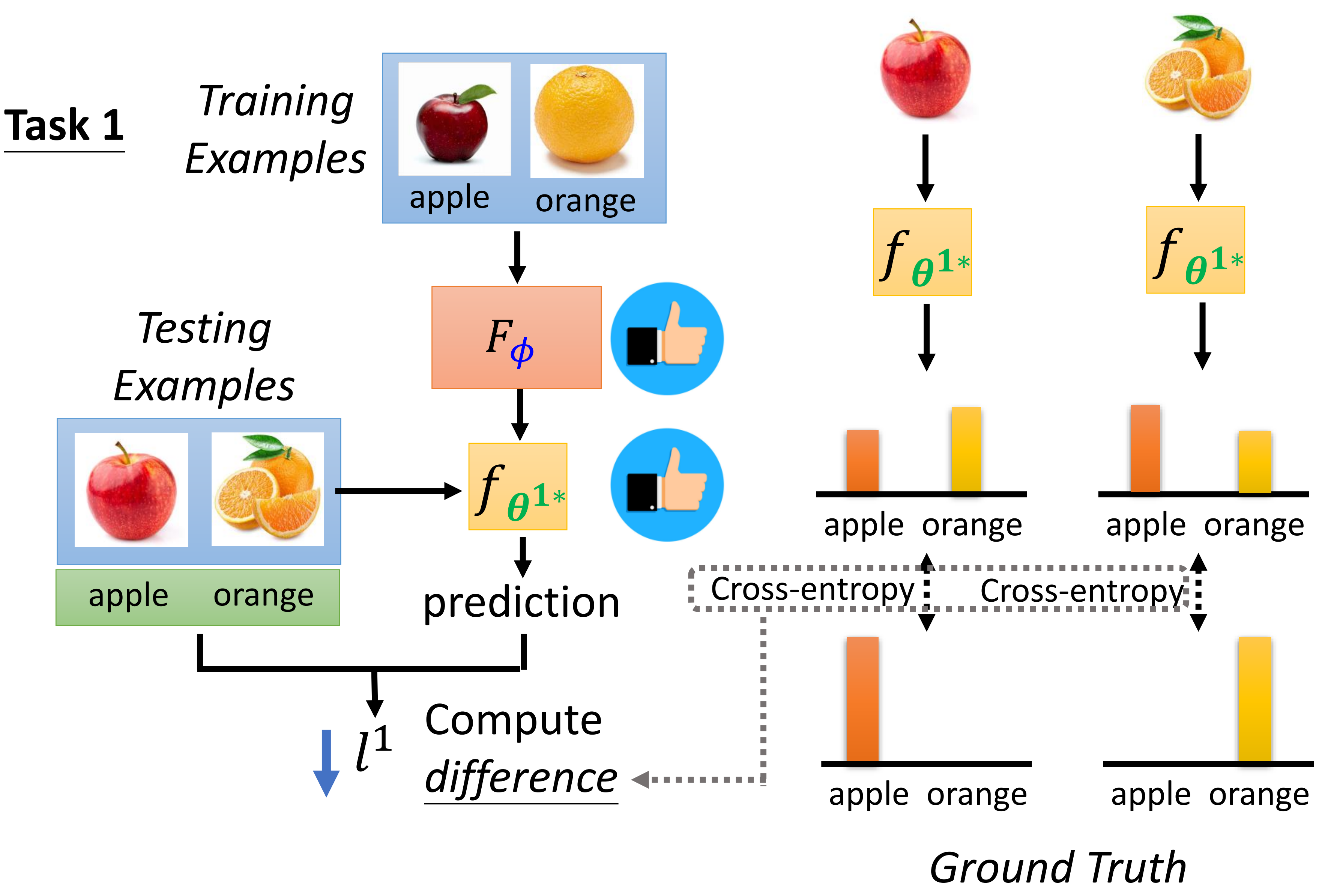
apple orange

apple orange

apple orange

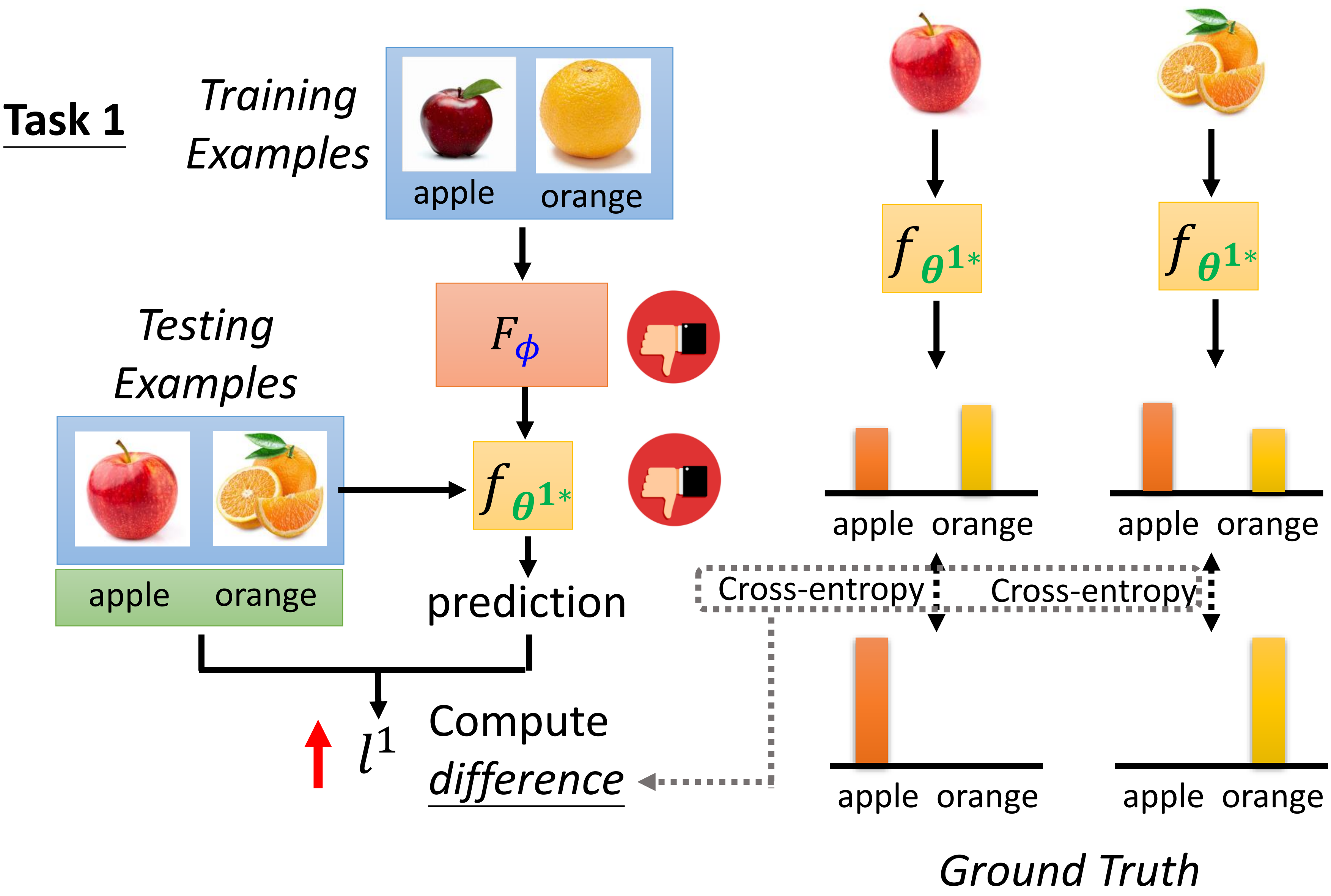
Ground Truth

# Meta Learning – Step 2



# Meta Learning – Step 2

Testing Examples



Task 1

Training Examples

apple orange

$F_\phi$

Testing Examples

apple orange

$f_{\theta^{1*}}$

prediction

$l^1$

Compute *difference*

$f_{\theta^{1*}}$ $f_{\theta^{1*}}$

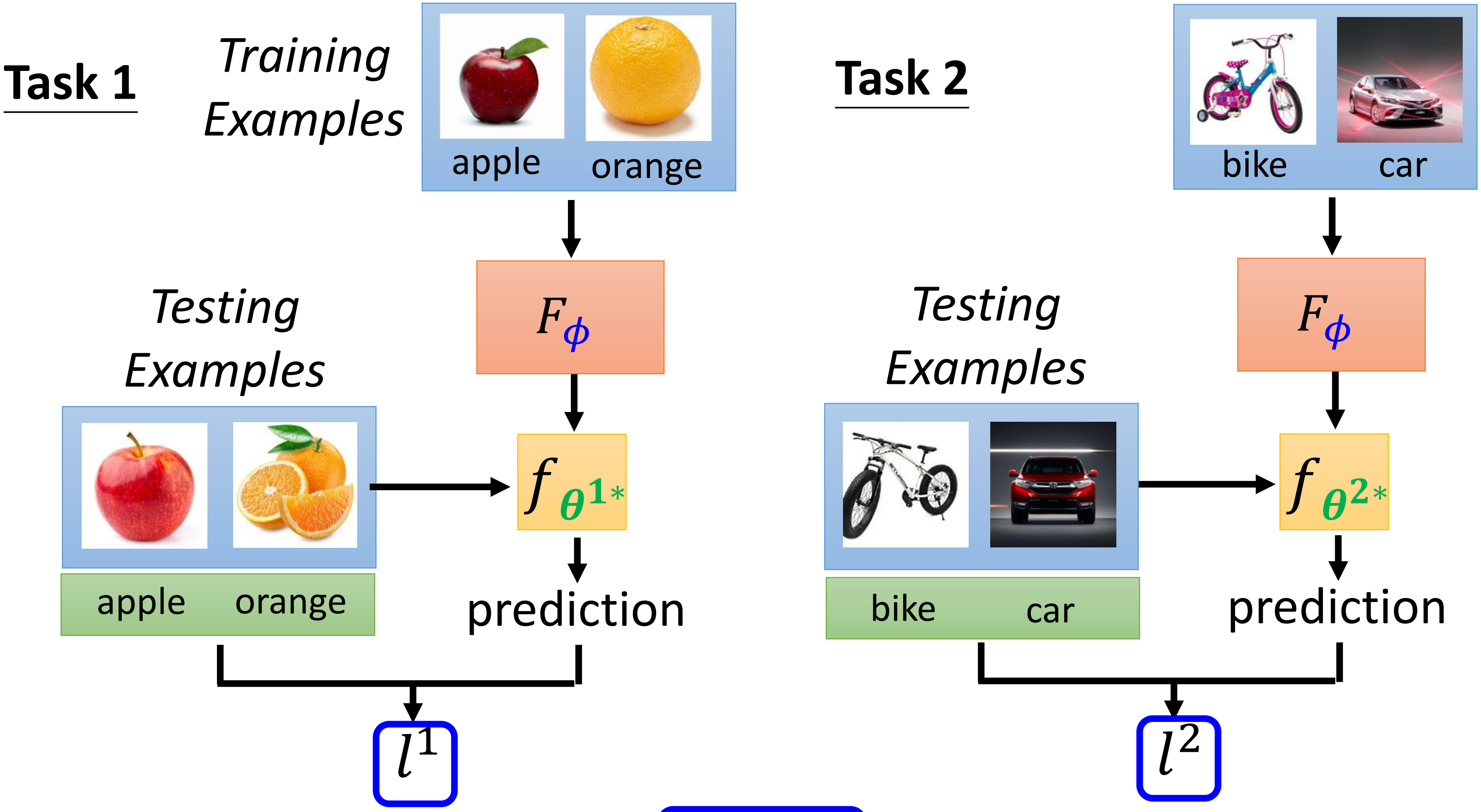
apple orange apple orange

Cross-entropy Cross-entropy

apple orange apple orange

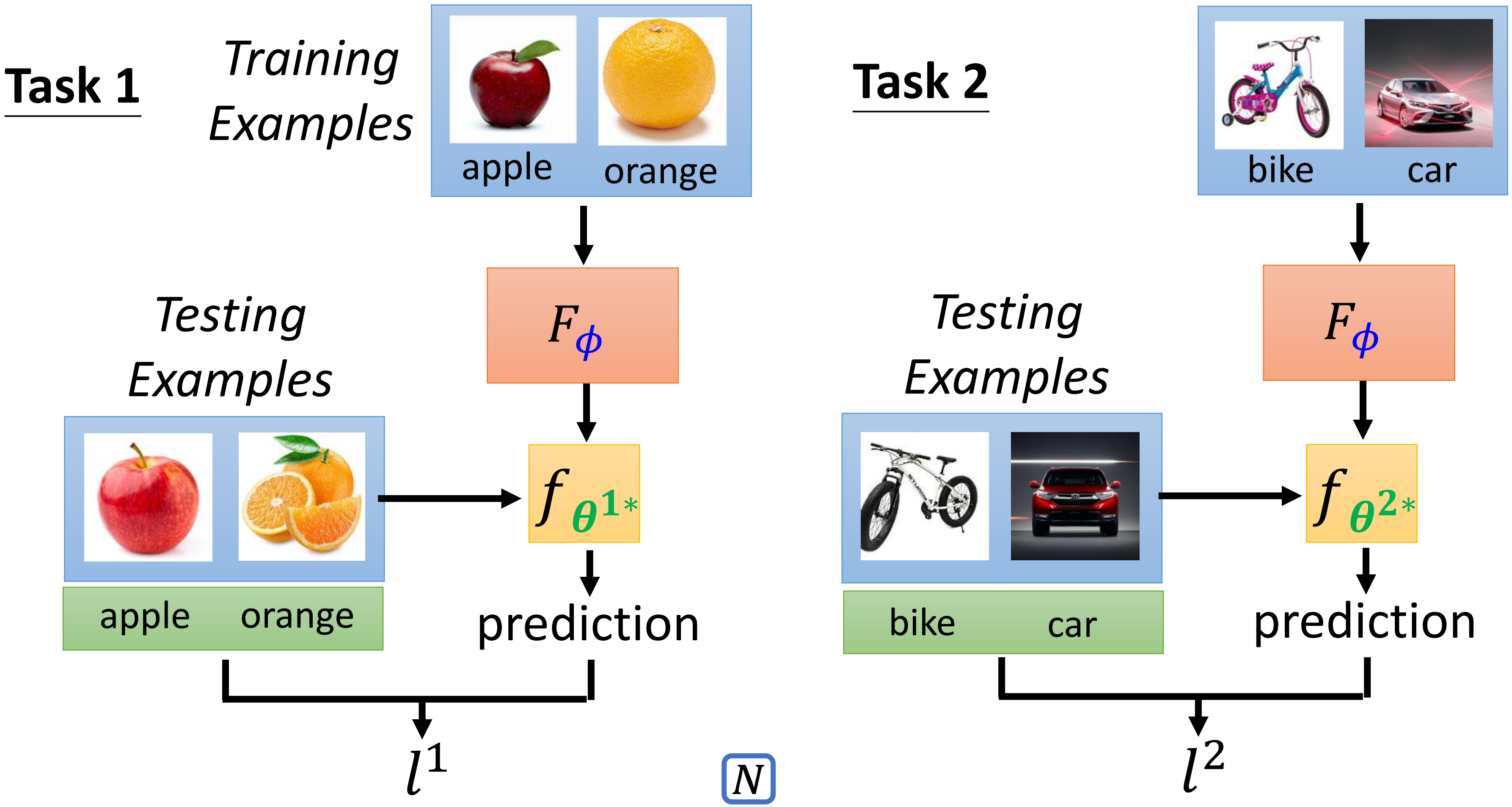
Ground Truth

# *Meta Learning – Step 2*



Total loss: $L(\phi) = \boxed{l^1 + l^2}$ (sum over all the training tasks)

# *Meta Learning – Step 2*



Total loss: $L(\phi) = \sum_{n=1}^{\boxed{N}} l^n$ ($N$ is the number of the training tasks)

# *Meta Learning – Step 2*

**Task 1**

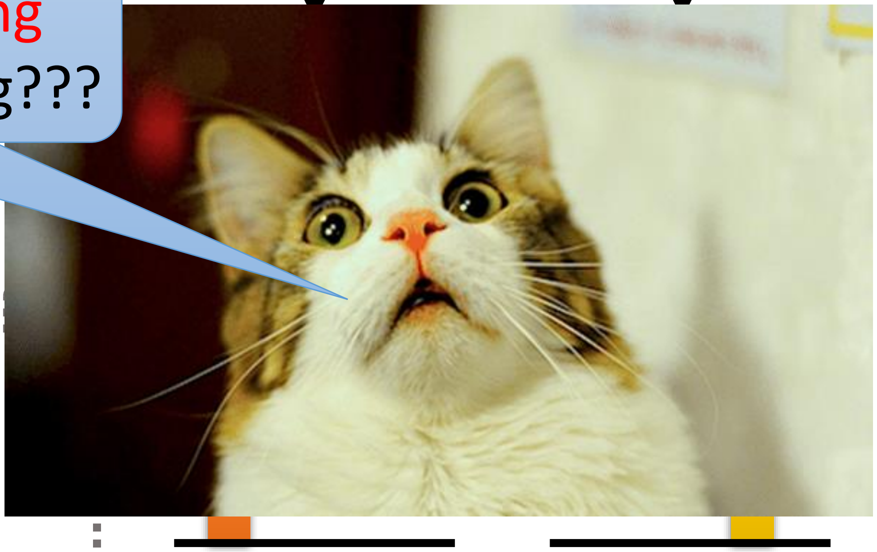
In typical ML, you compute the loss based on training examples

In meta, you compute the loss based on testing examples

*Testing Examples*

$f_{\theta^{1*}}$ $f_{\theta^{1*}}$

Hold on! You use testing examples during training???



apple orange

prediction

$l^1$ Compute *difference*

apple orange apple orange

*Ground Truth*

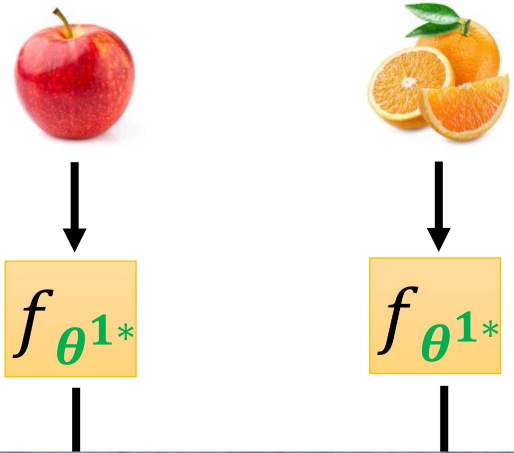
# *Meta Learning – Step 2*

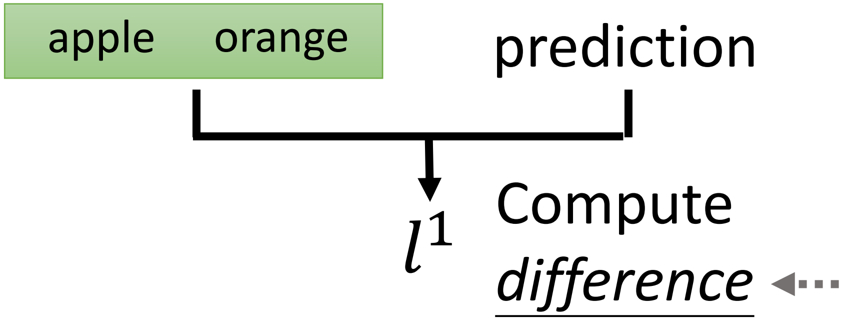
**Task 1**

In typical ML, you compute the loss based on training examples

In meta, you compute the loss based on testing examples of training tasks.

*Testing Examples*





# Meta Learning – Step 3

- Loss function for learning algorithm $L(\phi)=\sum_{n=1}^{N}l^n$
- Find $\phi$ that can minimize $L(\phi)$ $\quad \phi^*=arg\min_{\phi}L(\phi)$
- Using the optimization approach you know

If you know how to compute $\partial L(\phi)/\partial\phi$

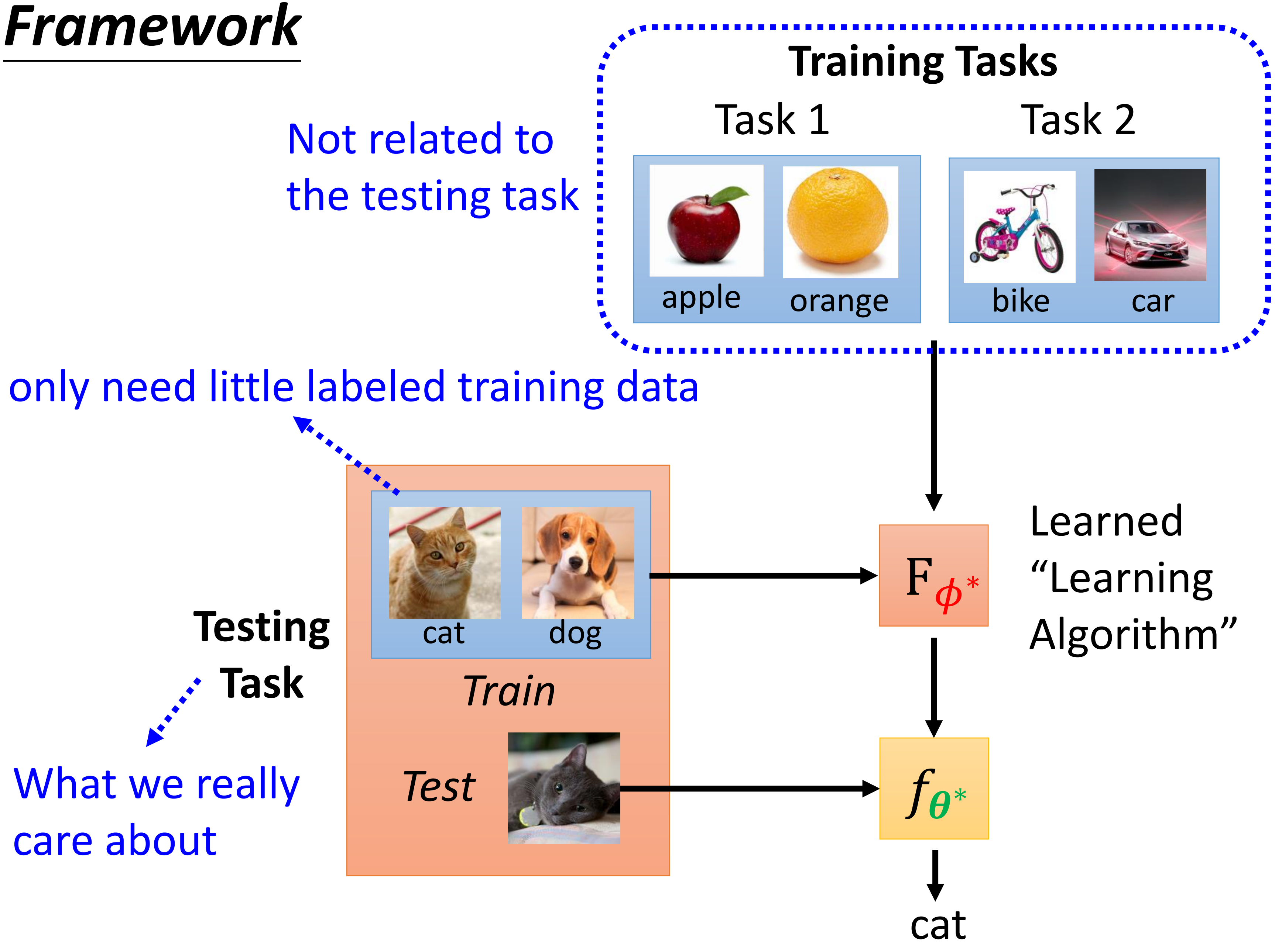
Gradient descent is your friend.

What if $L(\phi)$ is not differentiable?

Reinforcement Learning / Evolutionary Algorithm

Now we have a learned “learning algorithm” $\mathrm{F}_{\phi^*}$

# *Framework*



Training Tasks

Task 1

apple

orange

Task 2

bike

car

Not related to the testing task

only need little labeled training data

cat

dog

*Train*

*Test*

Testing Task

What we really care about

$F_{\phi^*}$

Learned "Learning Algorithm"

$f_{\theta^*}$

cat

# ML v.s. Meta

# Goal

**Machine Learning** ≈ find a function f

Dog-Cat Classification

$f($ $) =$ "cat"

**Meta Learning**

≈ find a function F that finds a function f

Learning Algorithm

$F($ $) = f$

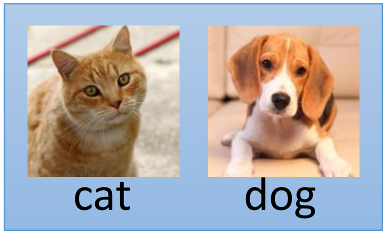
cat dog cat dog

Training Examples

# Training Data

## Machine Learning

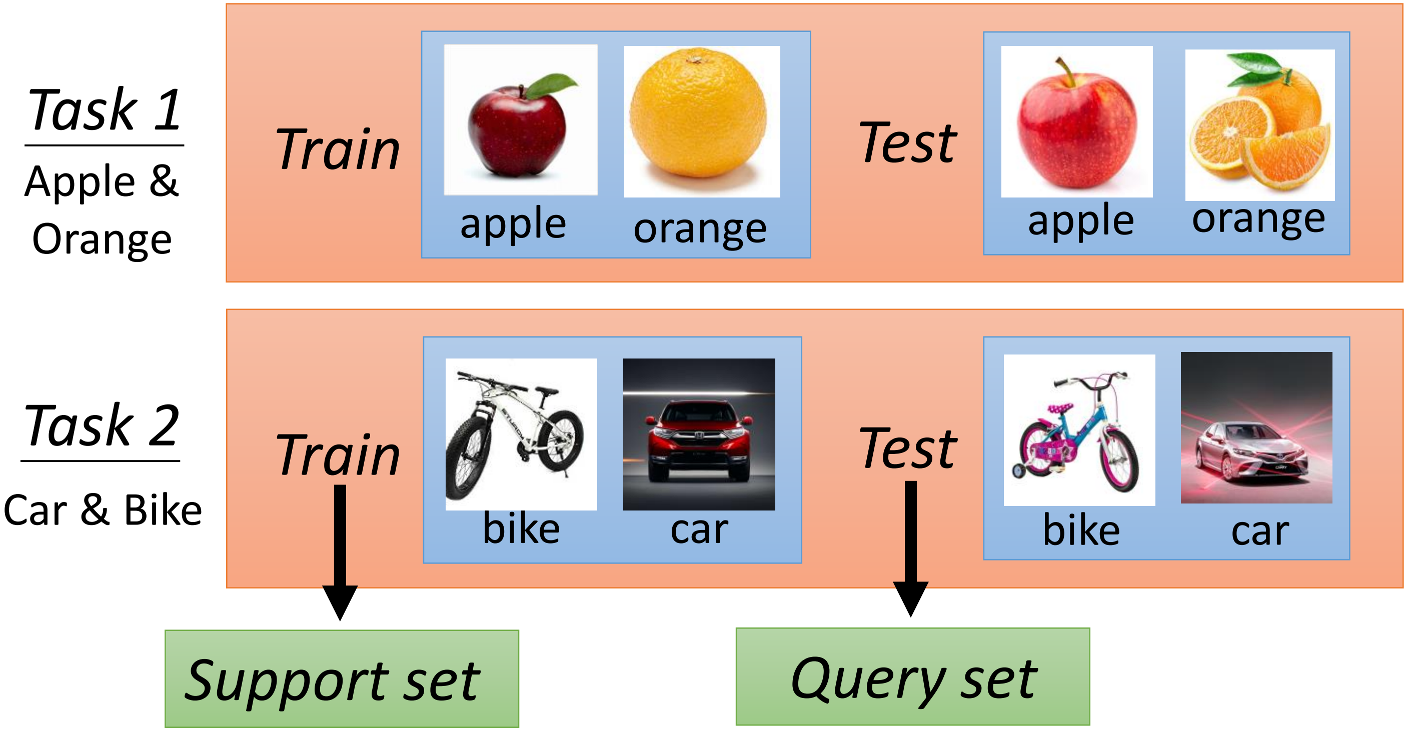
**One task**



*Train*

## Meta Learning

**Training tasks**



*Task 1*

Apple & Orange

*Train*

*Test*

*Task 2*

Car & Bike

*Train*

*Test*

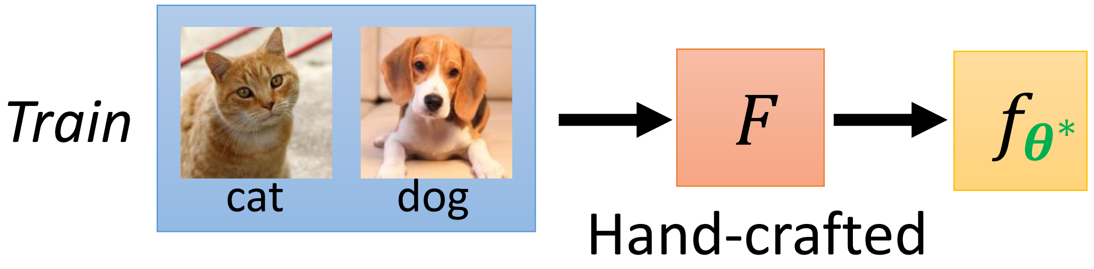
*Support set*

*Query set*

(in the literature of "*learning to compare*")

## Machine Learning

## *Within-task Training*



*Train*

cat

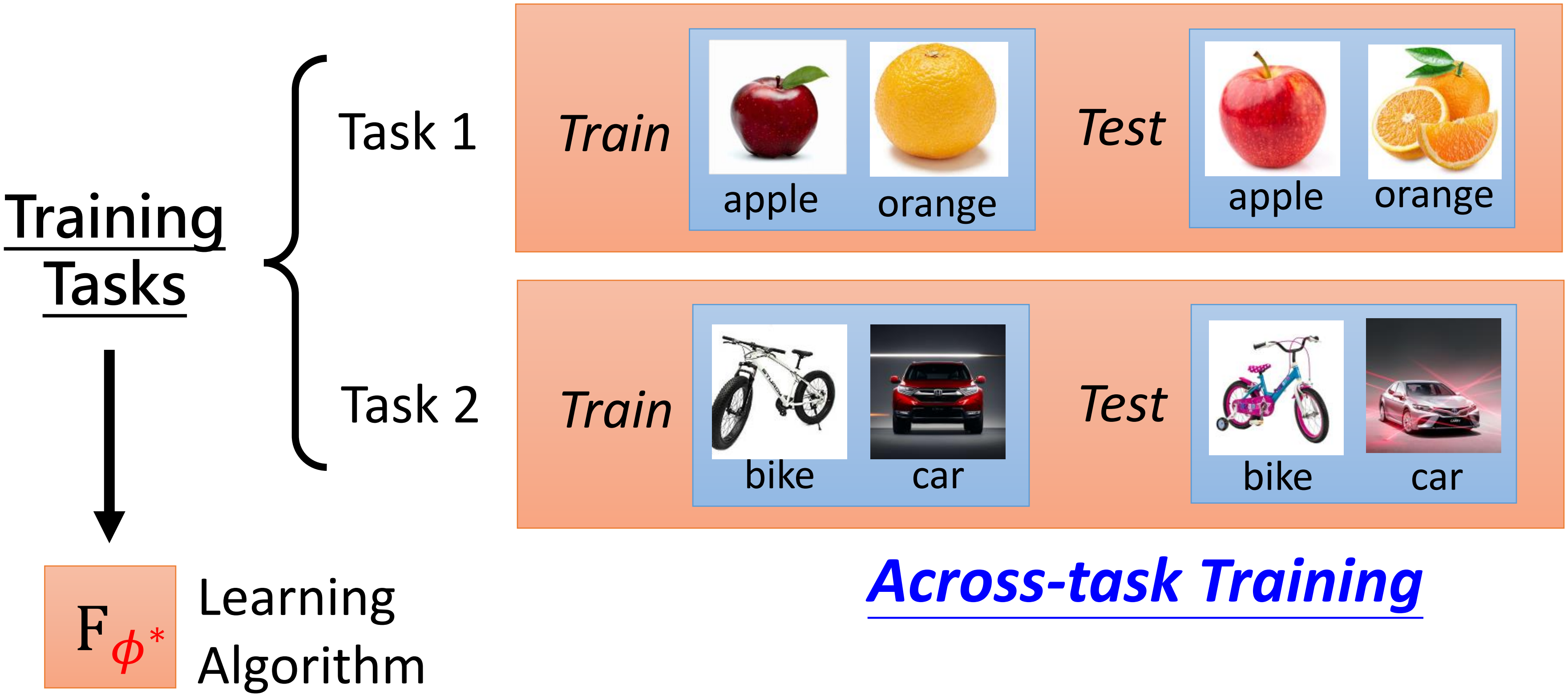
dog

$F$

$f_{\theta^*}$

Hand-crafted

## Meta Learning



Training Tasks

Task 1

*Train*

apple

orange

*Test*

apple

orange

Task 2

*Train*

bike

car

*Test*

bike

car

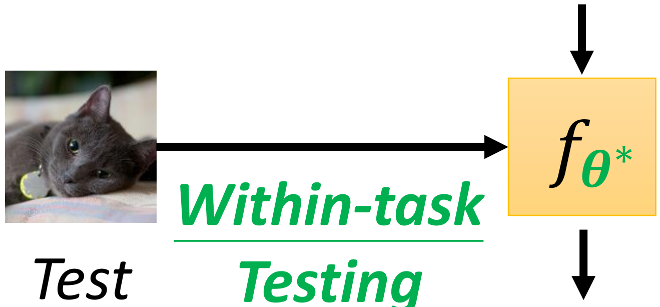
$F_{\phi^*}$

Learning Algorithm

## *Across-task Training*

# Machine Learning

Training Examples



*Test*

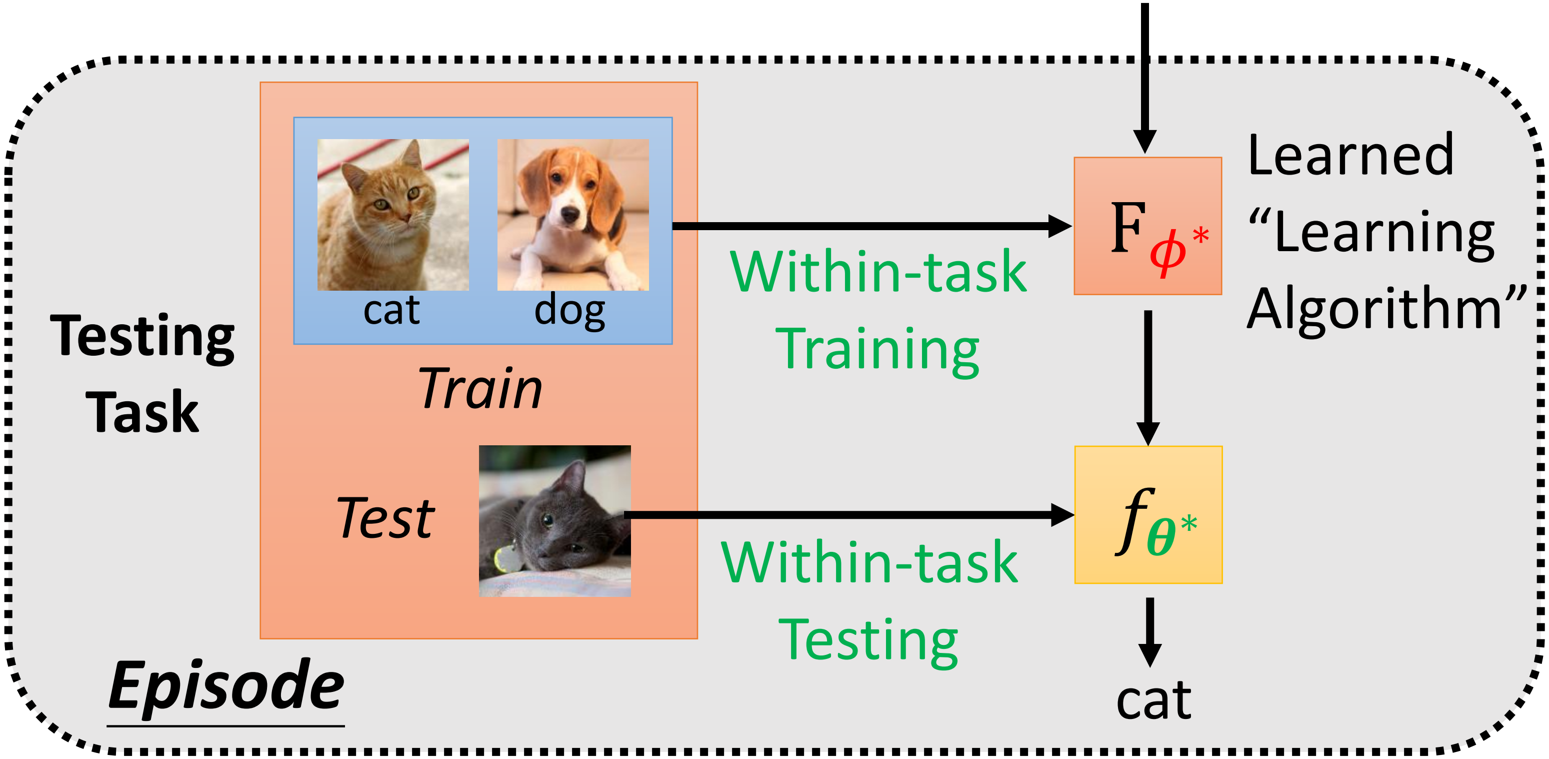
***Within-task Testing***

$f_{\theta^*}$

cat

# Meta Learning

Training Tasks



cat

dog

*Train*

*Test*

**Testing Task**

Within-task Training

$F_{\phi^*}$

Learned “Learning Algorithm”

Within-task Testing

$f_{\theta^*}$

cat

***Episode***

***Across-task Testing***

# Loss

## Machine Learning

$$L(\boldsymbol{\theta}) = \boxed{\sum_{k=1}^{K} e_k}$$

Sum over training examples in one task

## Meta Learning

$$L(\phi) = \boxed{\sum_{n=1}^{N} \boxed{l^n}}$$

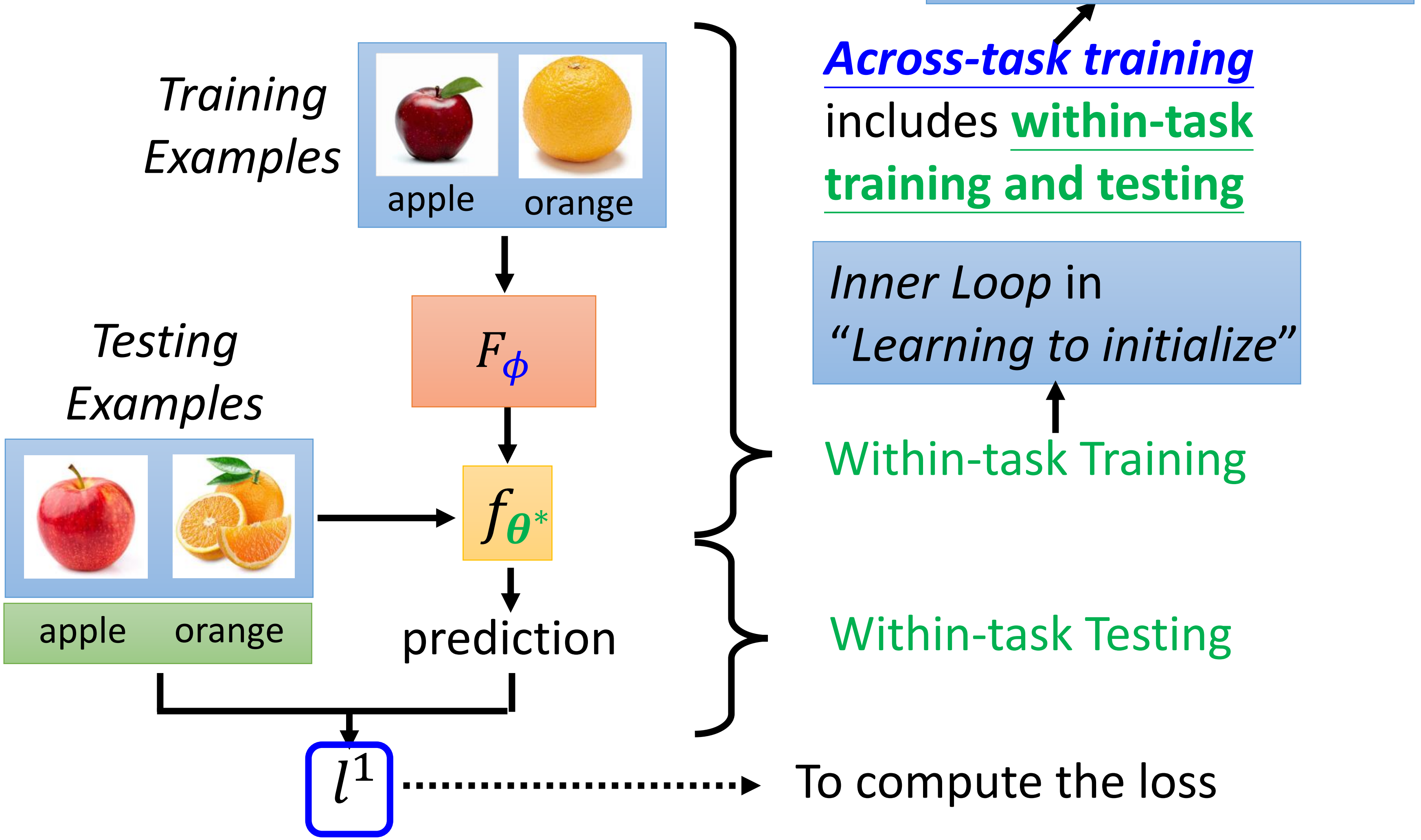
Sum over testing examples in one task

Sum over training tasks

$$L(\phi) = \sum_{n=1}^{N} \boxed{l^n}$$

If your optimization method needs to compute $L(\phi)$

*Outer Loop* in *"Learning to initialize"*



***Across-task training*** includes **within-task training and testing**

*Inner Loop* in *"Learning to initialize"*

Within-task Training

Within-task Testing

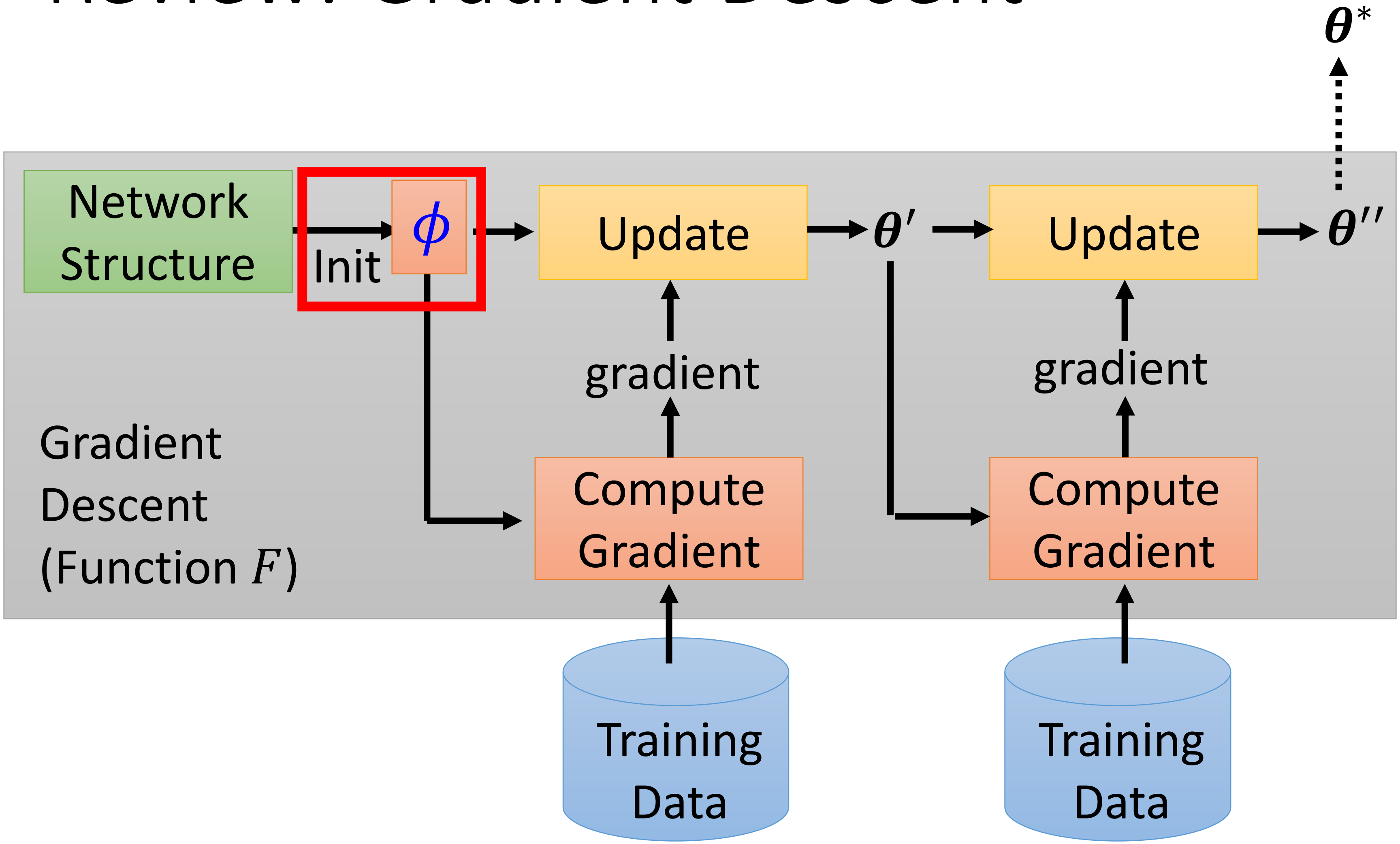
To compute the loss

# Meta Learning v.s ML

- What you know about ML can usually apply to meta learning
    - Overfitting on training tasks
    - Get more training tasks to improve performance
    - Task augmentation
    - There are also hyperparameters when learning a learning algorithm ……
    - Development task ☺

# What is learnable in a learning algorithm?

# Review: Gradient Descent



# Learning to initialize

- Model-Agnostic Meta-Learning (MAML)

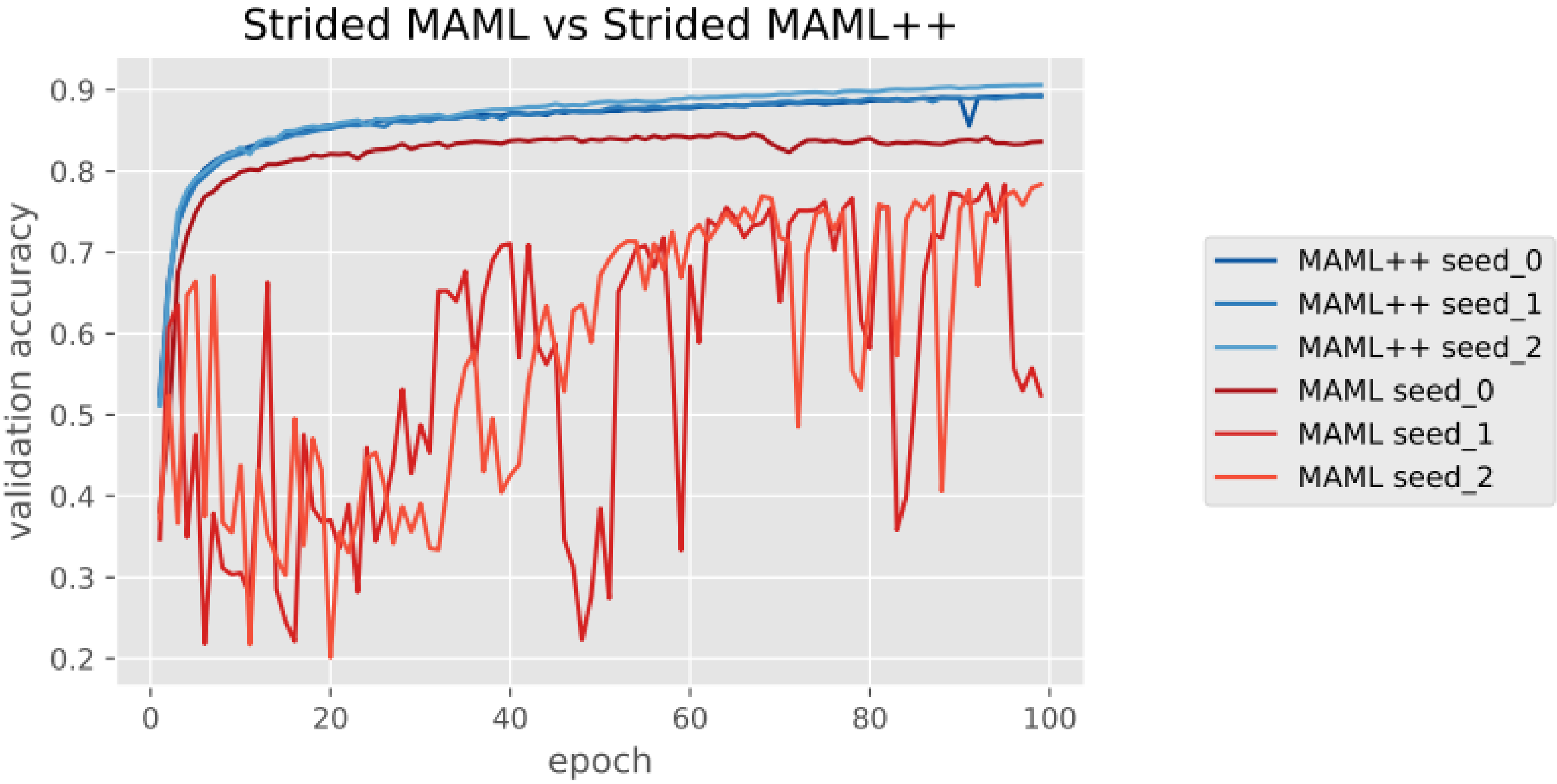
Mammals

Chelsea Finn, Pieter Abbeel, and Sergey Levine, “Model-Agnostic Meta-Learning for Fast Adaptation of Deep Networks”, ICML, 2017

- Reptile

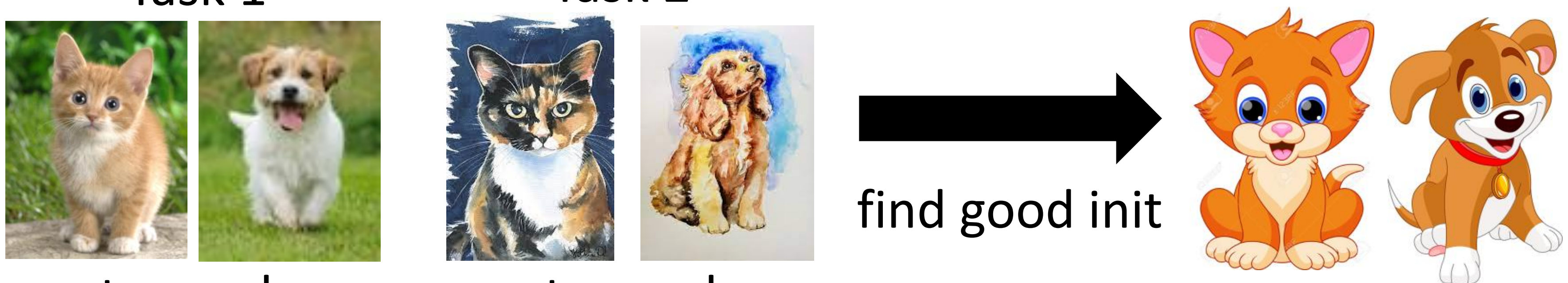
https://arxiv.org/abs/1803.02999

# How to train your ~~Dragon~~ MAML



Antreas Antoniou, Harrison Edwards, Amos Storkey, How to train your MAML, ICLR, 2019

***MAML***



Task 1

cat dog

Task 2

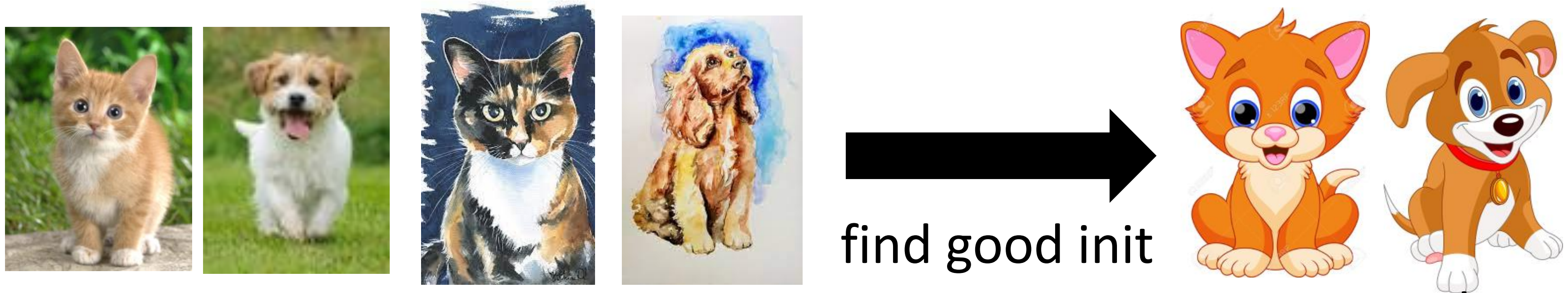
cat dog

find good init

Testing Task

cat dog

***Pre-training*** (Self-supervised Learning)



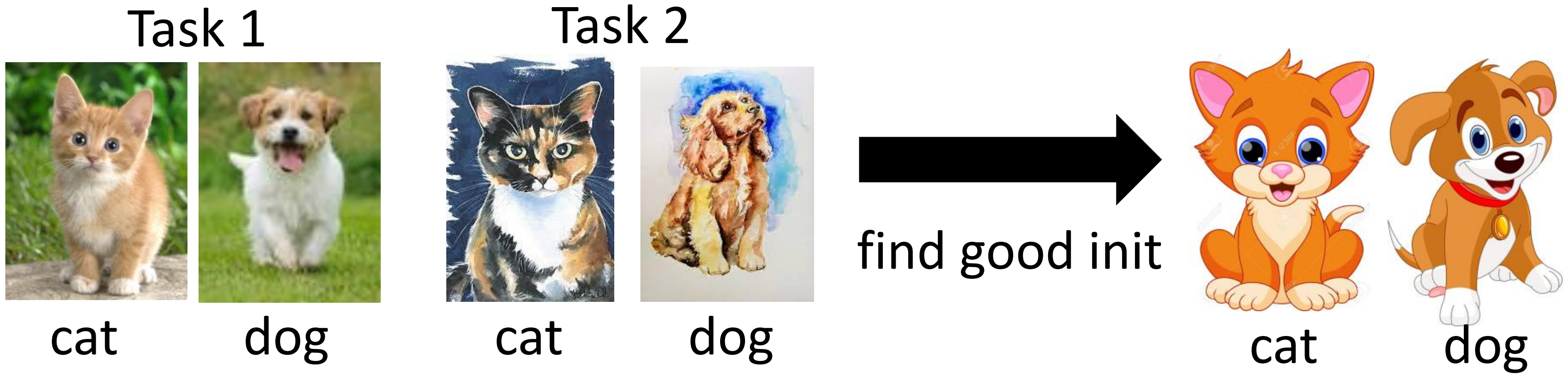
find good init

cat dog

Trained by proxy tasks
(fill-in the blanks, etc.)

# *MAML*

Isn’t it domain adaptation / transfer learning?



Task 1

cat dog

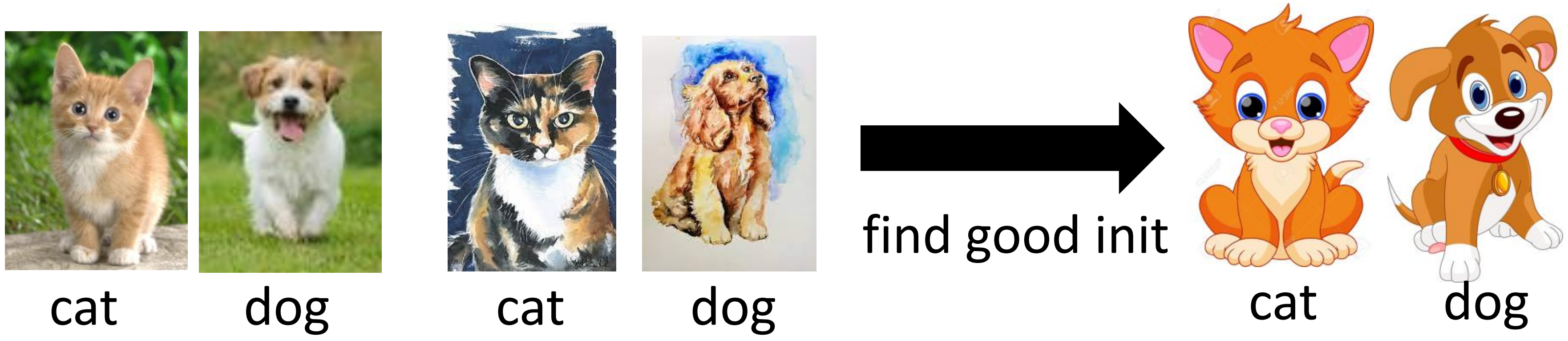
Task 2

cat dog

find good init

cat dog

## *Pre-training* (more typical ways)



cat dog cat dog

find good init

cat dog

Use data from different tasks
to train a model

Also known as multi-task
learning (baseline of meta)

# MAML v.s. Pre-training

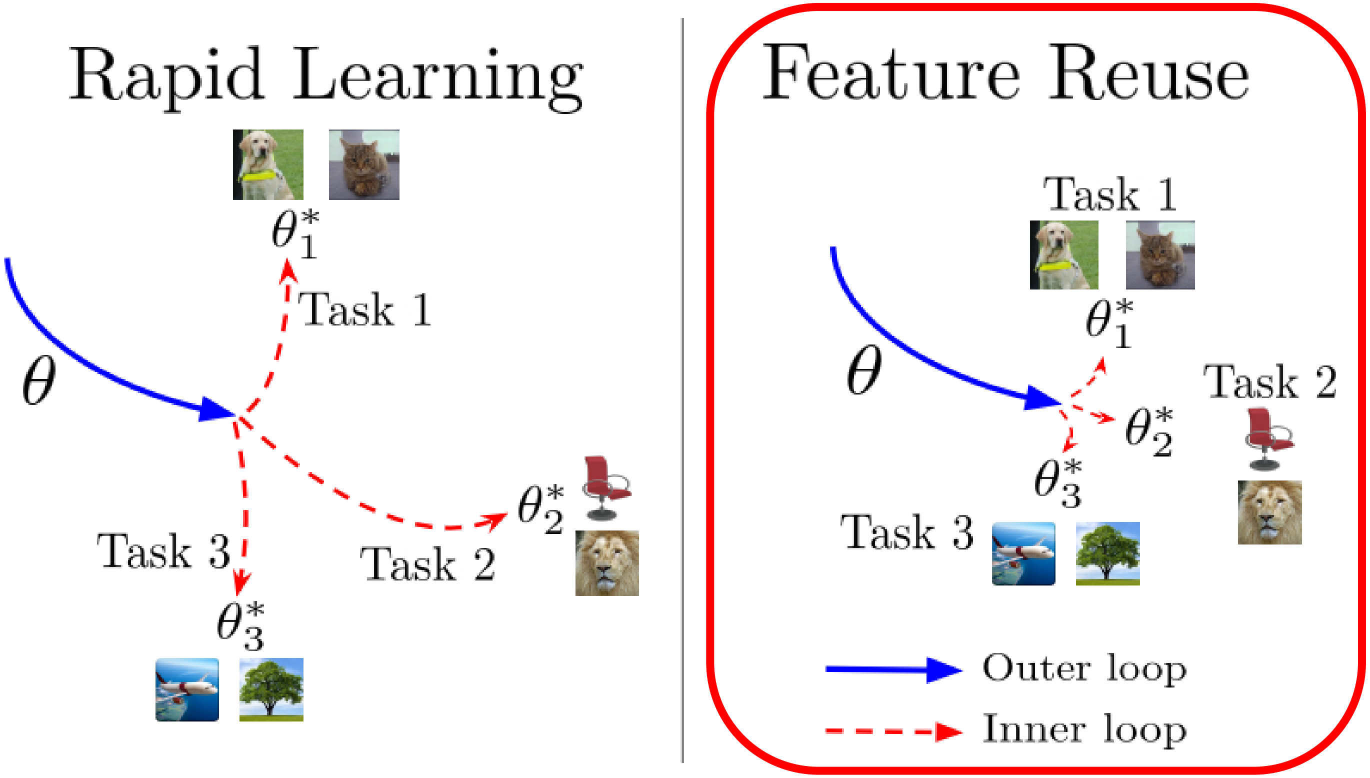
- https://youtu.be/vUwOA3SNb_E

影片中有防不勝防
的業配

這就是 “meta 業配”

# MAML is good because ……

- ANIL (Almost No Inner Loop)

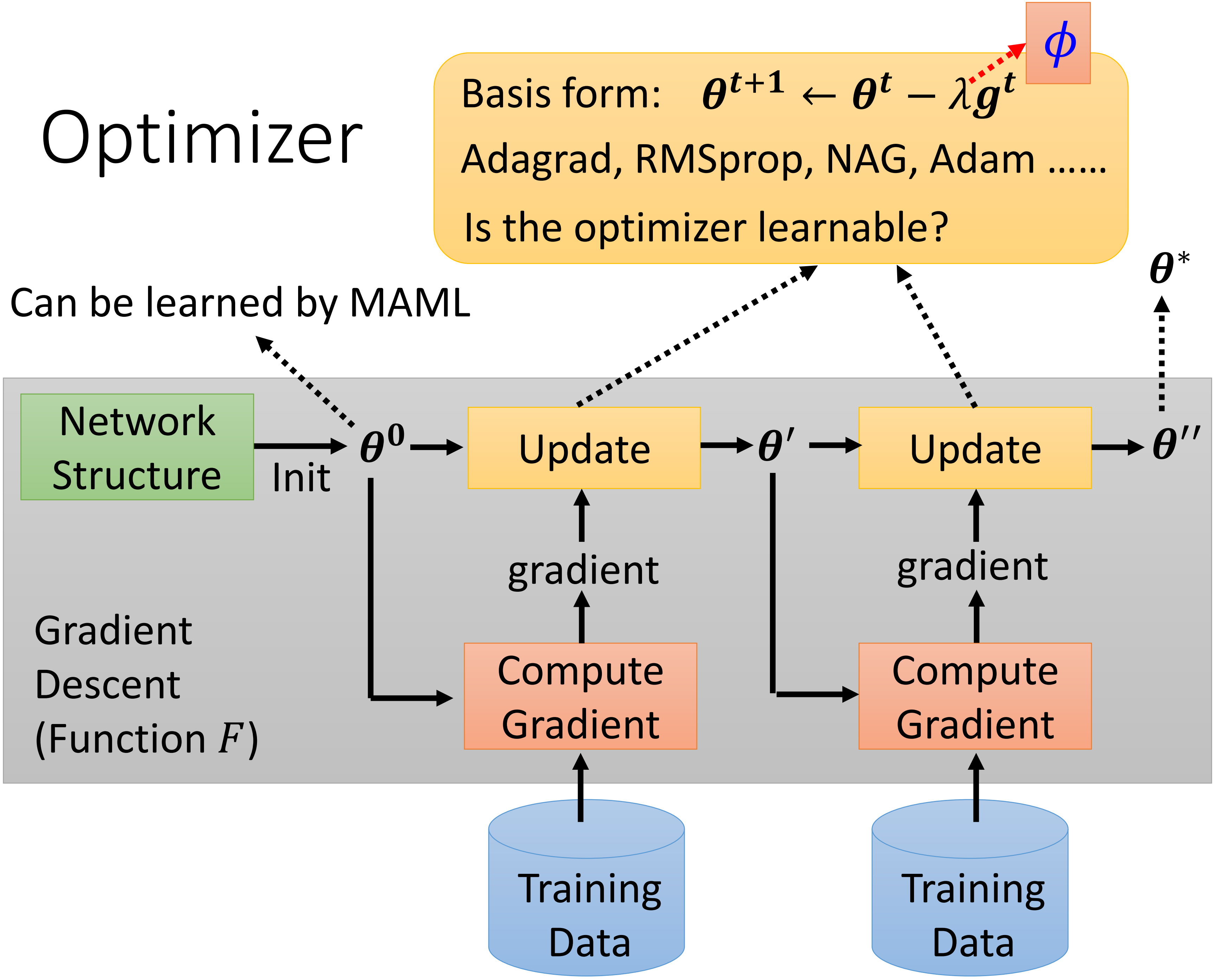


Aniruddh Raghu, Maithra Raghu, Samy Bengio, Oriol Vinyals, Rapid Learning or Feature Reuse? Towards Understanding the Effectiveness of MAML, ICLR, 2020

# More about MAML

- More mathematical details behind MAML
  - https://youtu.be/mxqzGwP_Qys
- First order MAML (FOMAML)
  - https://youtu.be/3z997JhL9Oo
- Reptile
  - https://youtu.be/9jJe2AD35P8

# Optimizer



Basis form: $\boldsymbol{\theta}^{t+1} \leftarrow \boldsymbol{\theta}^{t} - \lambda \boldsymbol{g}^{t}$

$\phi$

Adagrad, RMSprop, NAG, Adam ……

Is the optimizer learnable?

Can be learned by MAML

$\boldsymbol{\theta}^{*}$

Network Structure

Init

$\boldsymbol{\theta}^{0}$

Update

$\boldsymbol{\theta}'$

Update

$\boldsymbol{\theta}''$

gradient

gradient

Compute Gradient

Compute Gradient

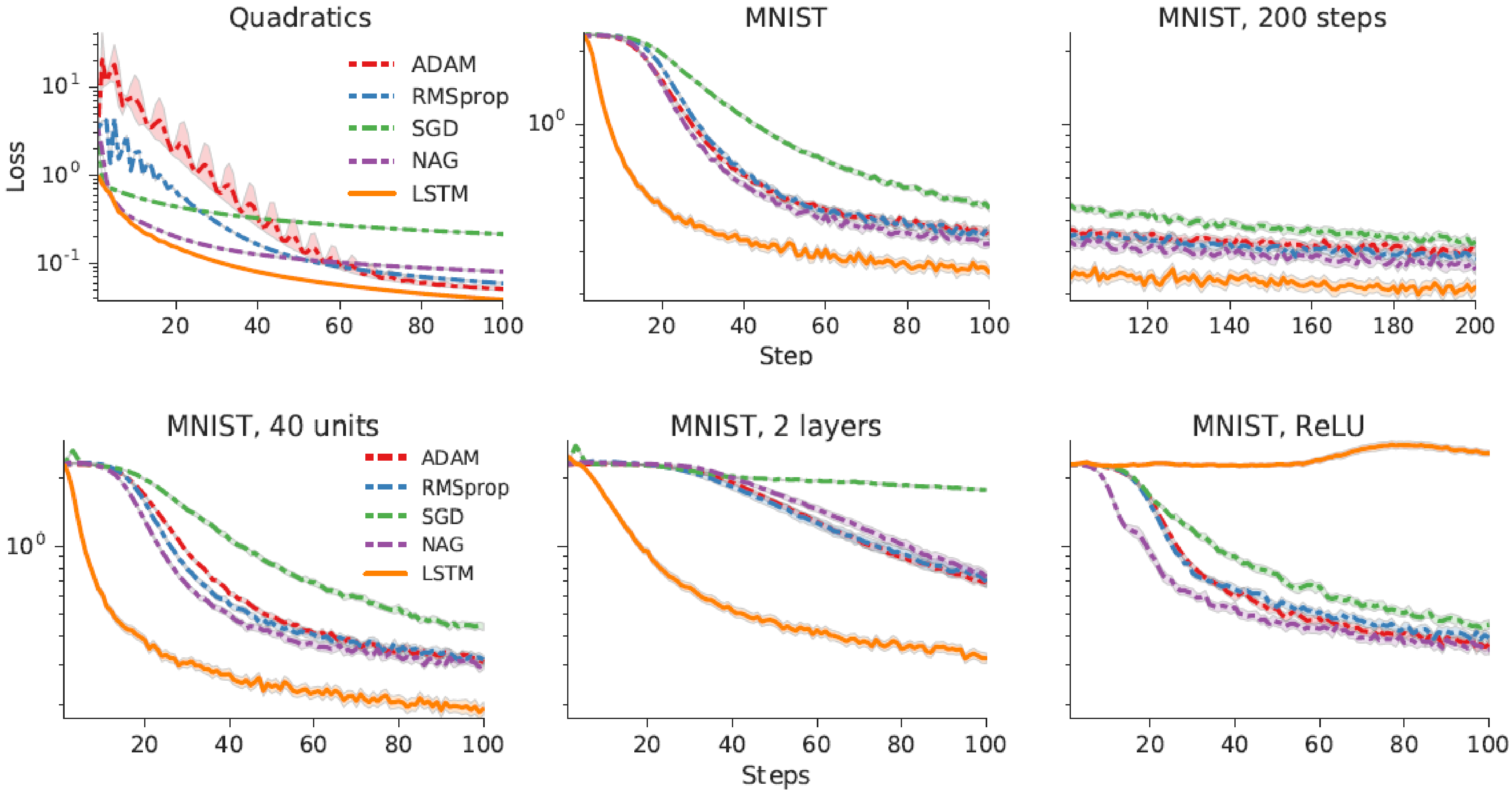
Gradient Descent (Function $F$)

Training Data

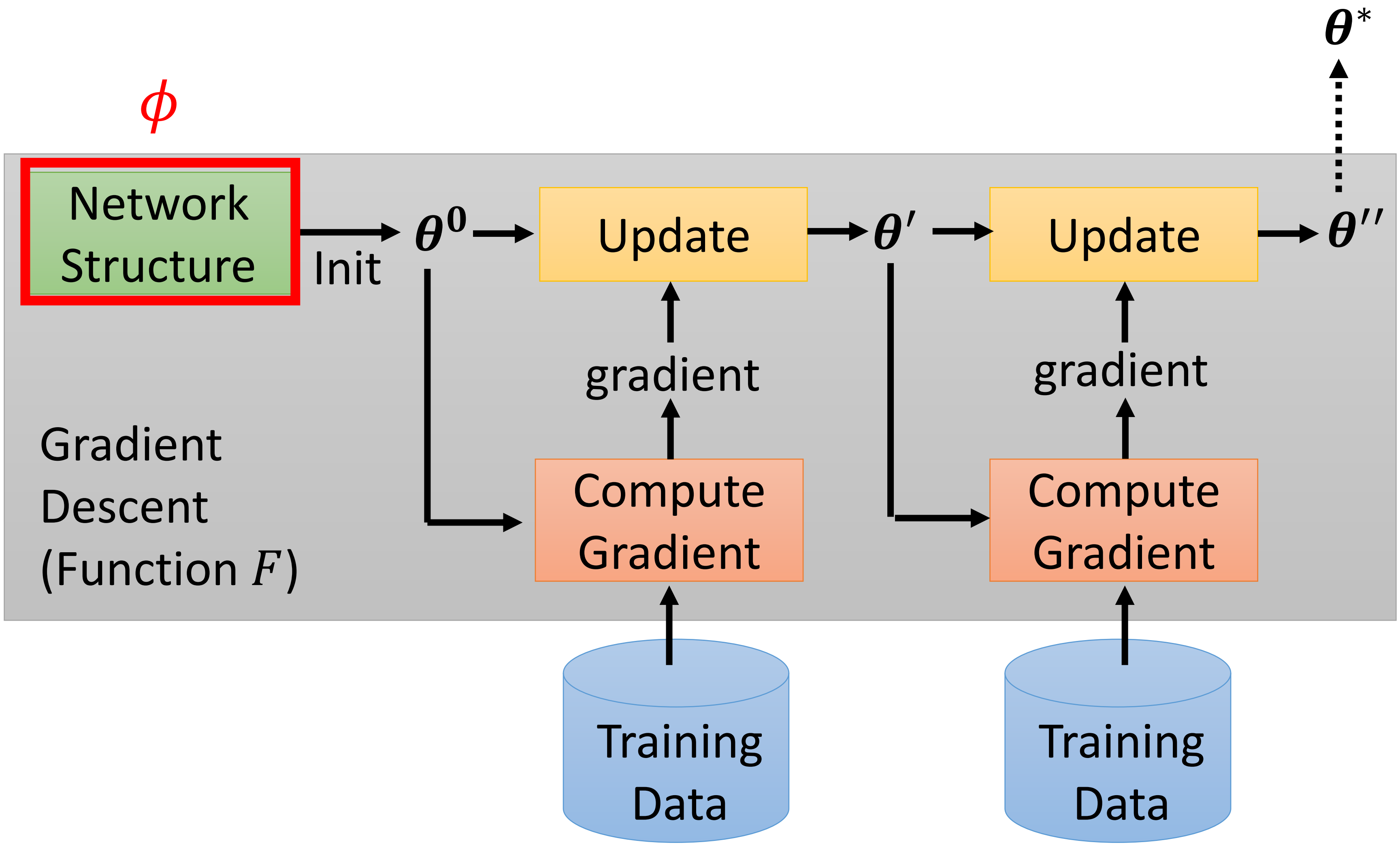
Training Data

# Optimizer

Marcin Andrychowicz, et al., Learning to learn by gradient descent by gradient descent, NIPS, 2016



# Network Architecture Search (NAS)



# *Network Architecture Search (NAS)*

$$\hat{\phi} = arg\min_{\phi} L(\phi) \qquad \nabla_{\phi} L(\phi) = ?$$

Network Architecture

- Reinforcement Learning
  - Barret Zoph, et al., Neural Architecture Search with Reinforcement Learning, ICLR 2017
  - Barret Zoph, et al., Learning Transferable Architectures for Scalable Image Recognition, CVPR, 2018
  - Hieu Pham, et al., Efficient Neural Architecture Search via Parameter Sharing, ICML, 2018

An agent uses a set of actions to determine the network architecture.

$\phi$: the agent's parameters

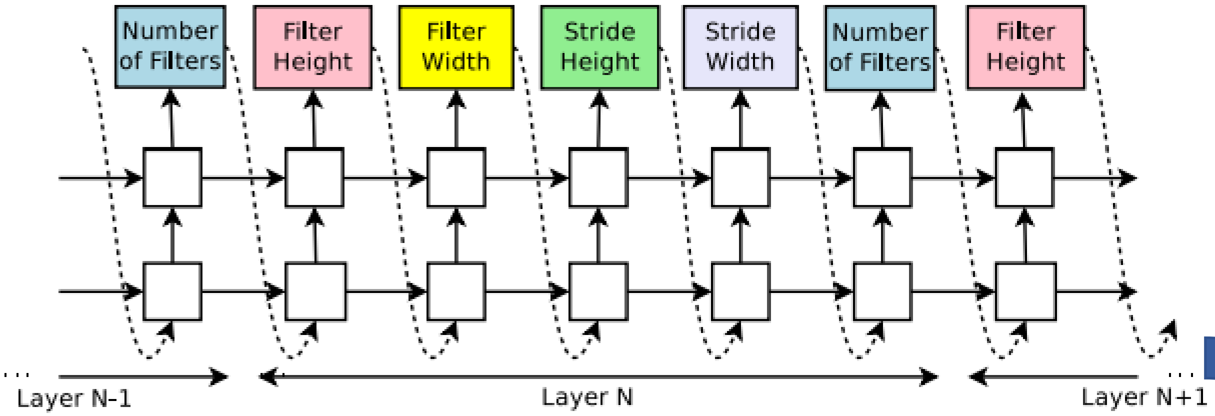
$-L(\phi)$

Reward to be maximized

# *Network Architecture Search (NAS)*

Across-task Training

Update $\phi$ to maximize reward $-L(\phi)$

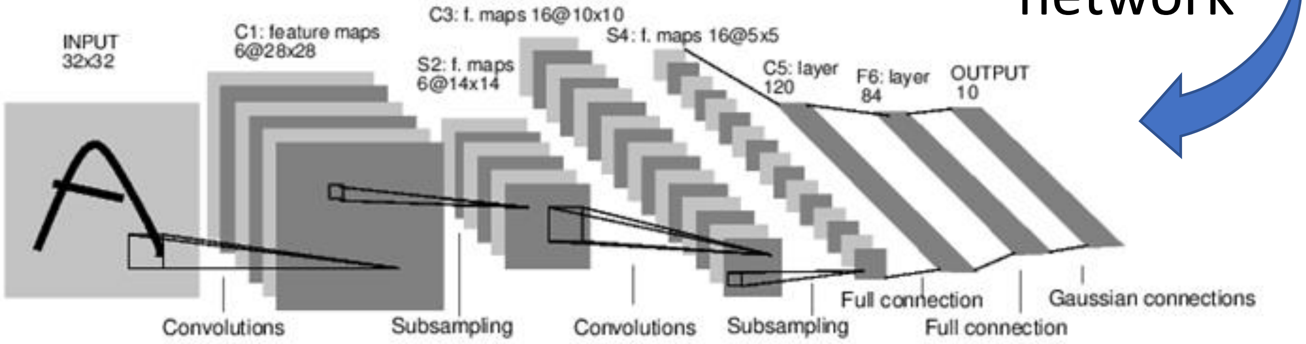


agent $\phi$ (RNN)

form a network

$-L(\phi)$

Accuracy of the network



A Full Convolutional Neural Network (LeNet)

Train the network

Within-task Training

# Network Architecture Search (NAS)

$$\hat{\phi} = arg \min_{\phi} L(\phi) \qquad \nabla_{\phi} L(\phi) = ?$$

Network Architecture

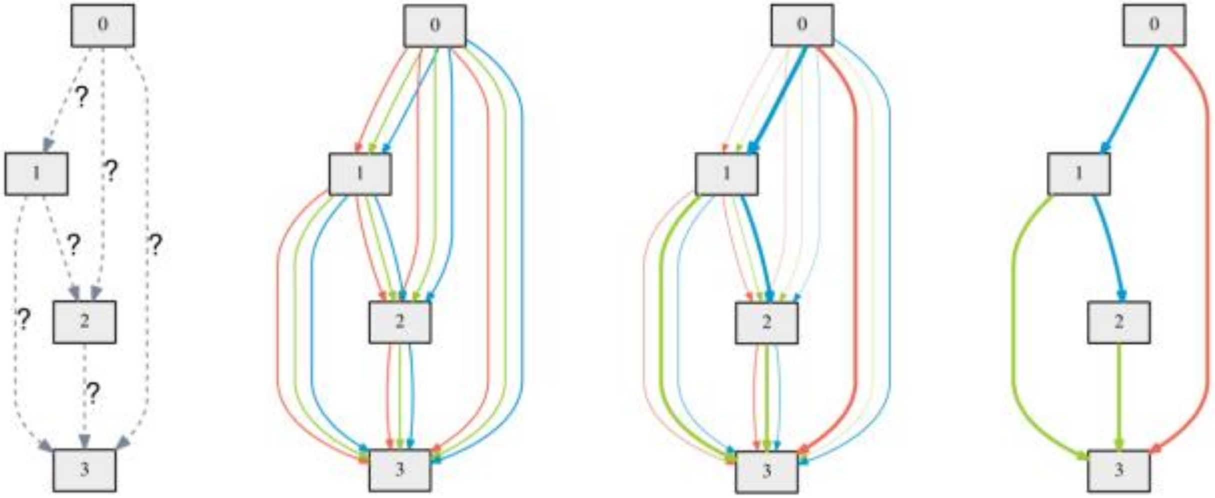
- Reinforcement Learning
  - Barret Zoph, et al., Neural Architecture Search with Reinforcement Learning, ICLR 2017
  - Barret Zoph, et al., Learning Transferable Architectures for Scalable Image Recognition, CVPR, 2018
  - Hieu Pham, et al., Efficient Neural Architecture Search via Parameter Sharing, ICML, 2018
- Evolution Algorithm
  - Esteban Real, et al., Large-Scale Evolution of Image Classifiers, ICML 2017
  - Esteban Real, et al., Regularized Evolution for Image Classifier Architecture Search, AAAI, 2019
  - Hanxiao Liu, et al., Hierarchical Representations for Efficient Architecture Search, ICLR, 2018

# *Network Architecture Search (NAS)*

$$\hat{\phi} = arg \min_{\phi} L(\phi) \qquad \nabla_{\phi} L(\phi) = ?$$

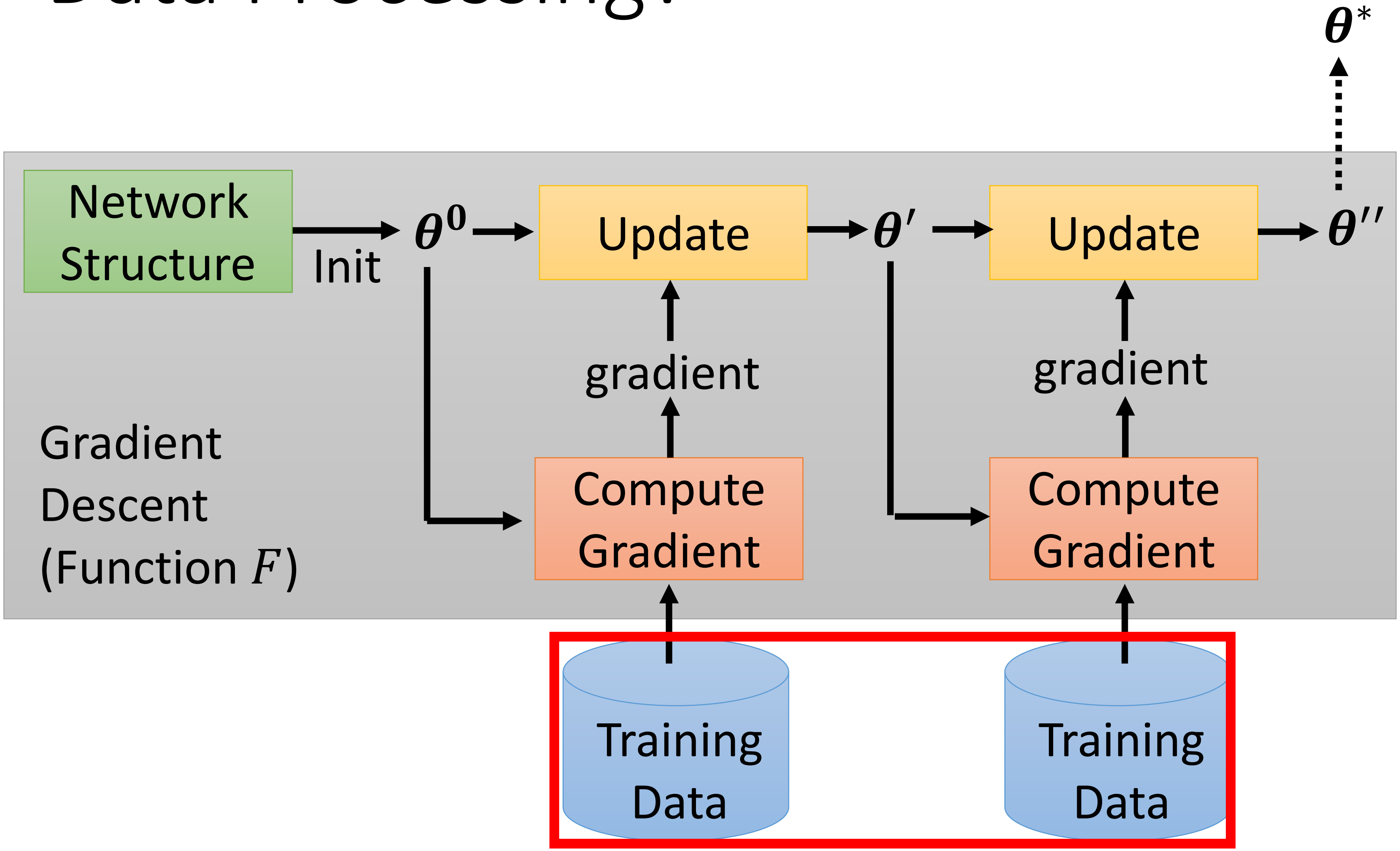
Network Architecture

- DARTS Hanxiao Liu, et al., DARTS: Differentiable Architecture Search, ICLR, 2019

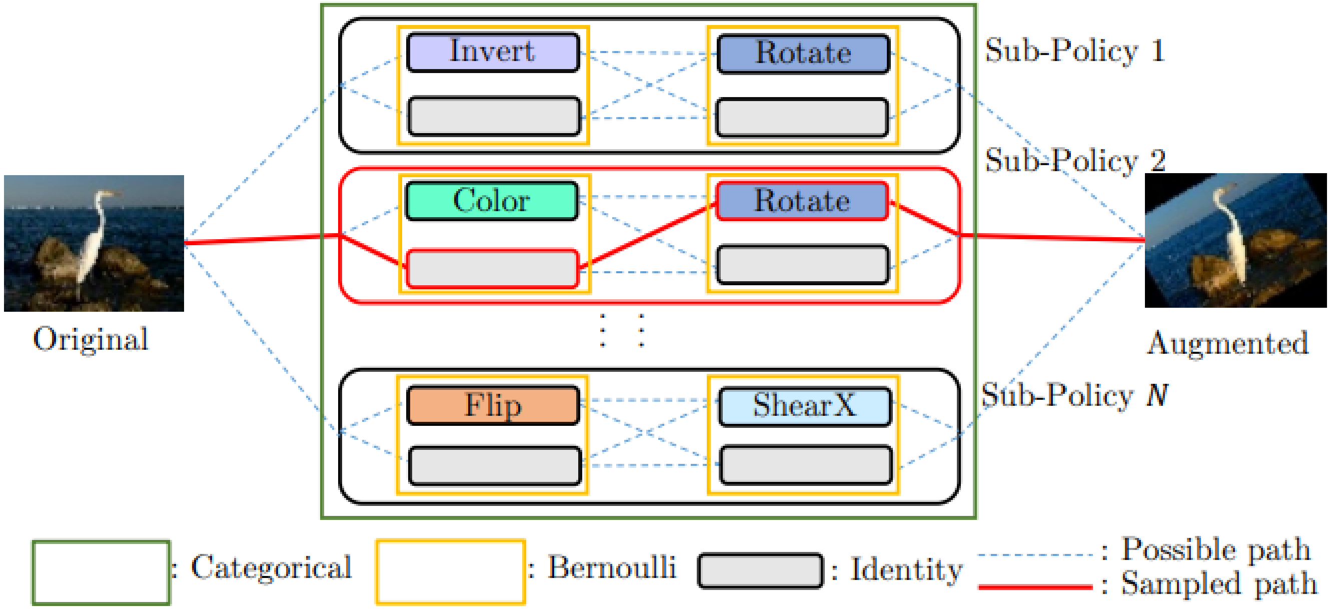


(a) (b) (c) (d)

# Data Processing?



# Data Augmentation



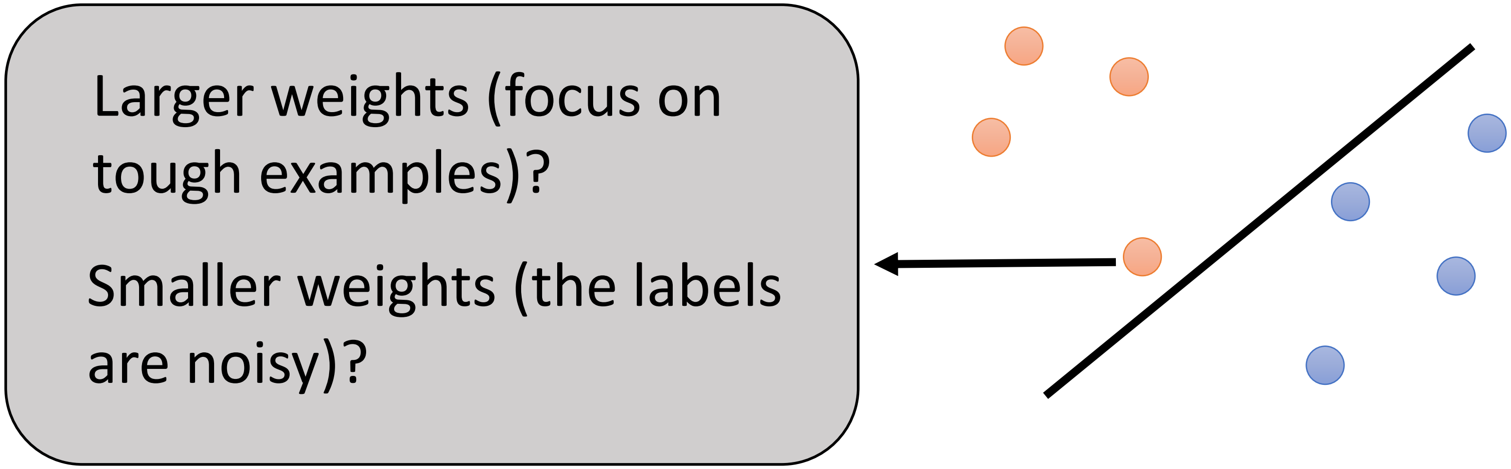
Yonggang Li, Guosheng Hu, Yongtao Wang, Timothy Hospedales, Neil M. Robertson, Yongxin Yang, DADA: Differentiable Automatic Data Augmentation, ECCV, 2020

Daniel Ho, Eric Liang, Ion Stoica, Pieter Abbeel, Xi Chen, Population Based Augmentation: Efficient Learning of Augmentation Policy Schedules, ICML, 2019

Ekin D. Cubuk, Barret Zoph, Dandelion Mane, Vijay Vasudevan, Quoc V. Le, AutoAugment: Learning Augmentation Policies from Data, CVPR, 2019

# Sample Reweighting

- Give different samples different weights



Larger weights (focus on tough examples)?

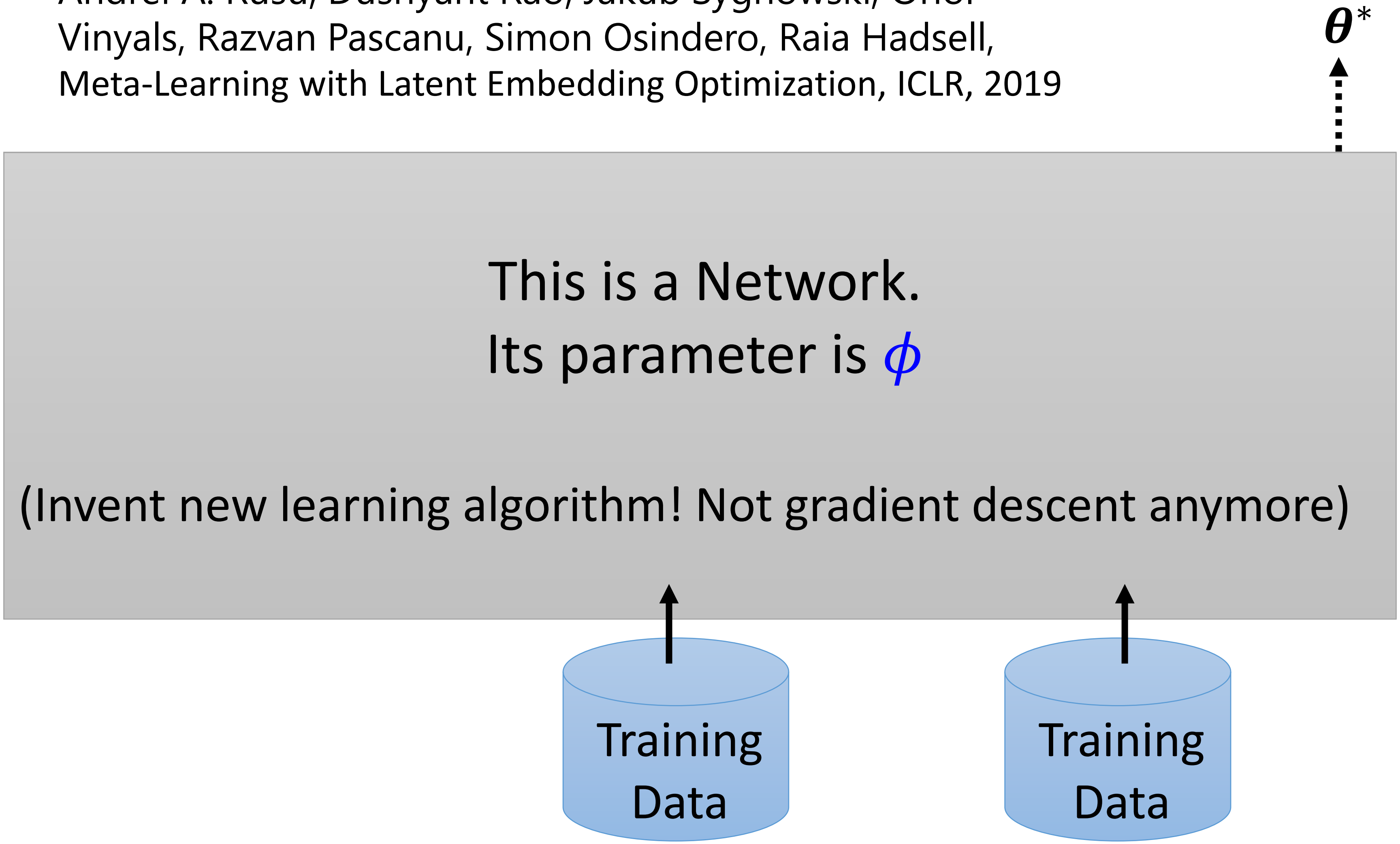
Smaller weights (the labels are noisy)?

***Sample Weighting Strategies*** → Learnable $\phi$

Jun Shu, Qi Xie, Lixuan Yi, Qian Zhao, Sanping Zhou, Zongben Xu, Deyu Meng, Meta-Weight-Net: Learning an Explicit Mapping For Sample Weighting, NeurIPS, 2019
Mengye Ren, Wenyuan Zeng, Bin Yang, Raquel Urtasun, Learning to Reweight Examples for Robust Deep Learning, ICML, 2018

# Data Processing?

Andrei A. Rusu, Dushyant Rao, Jakub Sygnowski, Oriol Vinyals, Razvan Pascanu, Simon Osindero, Raia Hadsell, Meta-Learning with Latent Embedding Optimization, ICLR, 2019

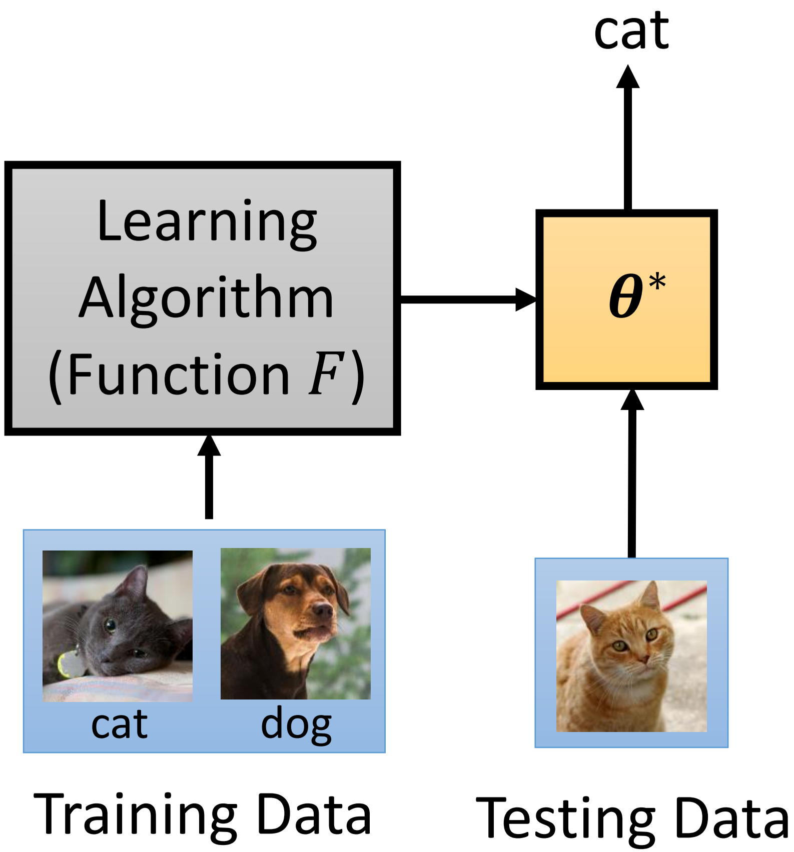


This is a Network.

Its parameter is $\phi$

(Invent new learning algorithm! Not gradient descent anymore)

Until now ......


cat

Learning Algorithm (Function $F$)

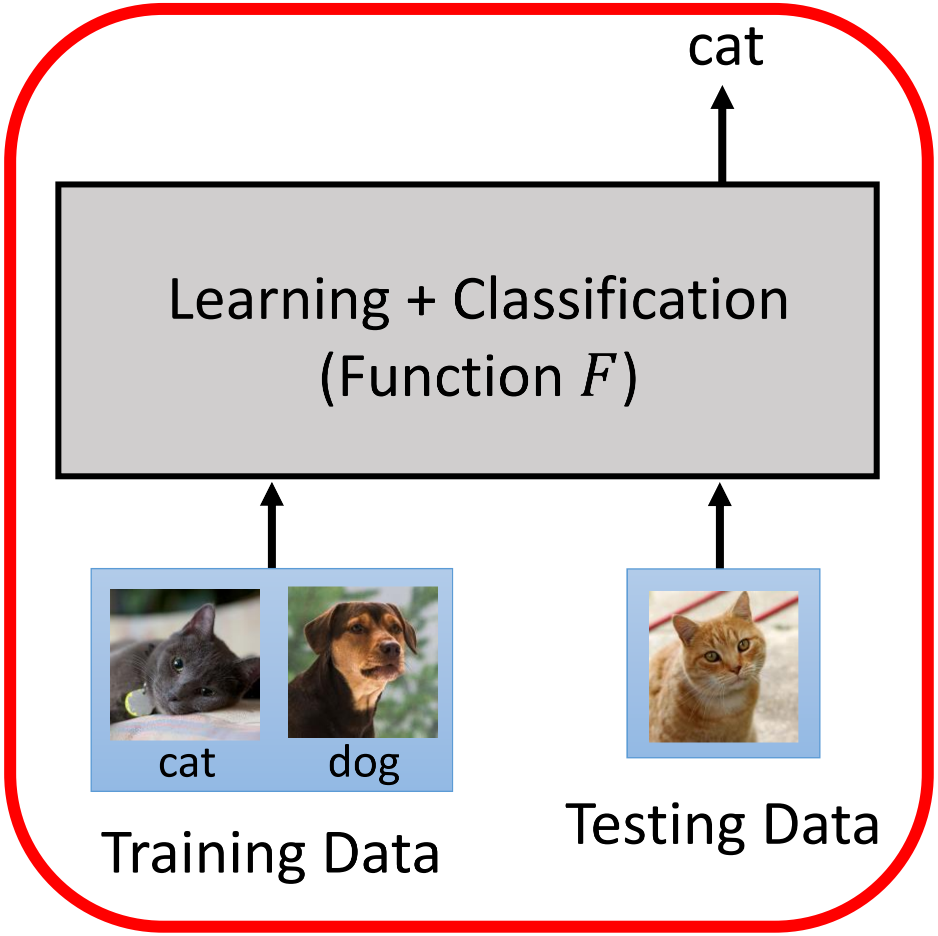
$\boldsymbol{\theta}^*$

cat dog

Training Data

Testing Data

How about?


cat

Learning + Classification (Function $F$)

cat dog

Training Data

Testing Data

***<u>Learning to compare</u>***

(metric-based approach)

https://youtu.be/yyKaACh_j3M

https://youtu.be/scK2EIT7klw

https://youtu.be/semSxPP2Yzg

https://youtu.be/ePimv_k-H24

# Applications

# Few-shot Image Classification

- Each class only has a few images.

Class 1

Class 1

Class 2

Class 2

Class 3

Class 3

Which class?

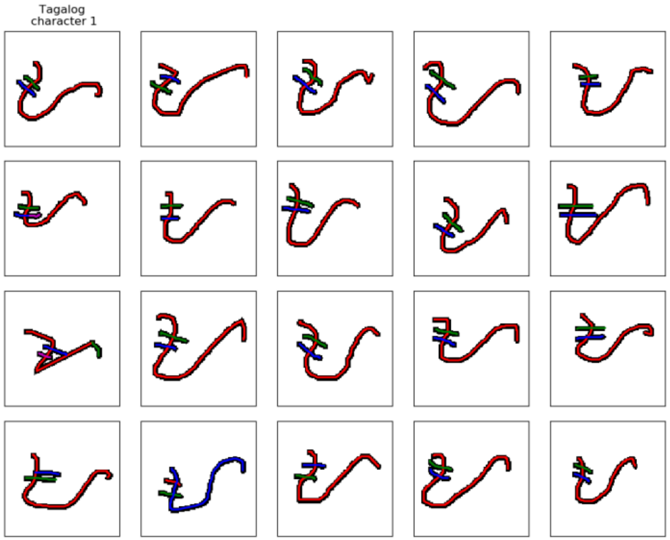
3-ways 2-shot

- N-ways K-shot classification: In each task, there are N classes, each has K examples.
- In meta learning, you need to prepare many N-ways K-shot tasks as training and testing tasks.

# Omniglot

https://github.com/brendenlake/omniglot

- 1623 characters
- Each has 20 examples



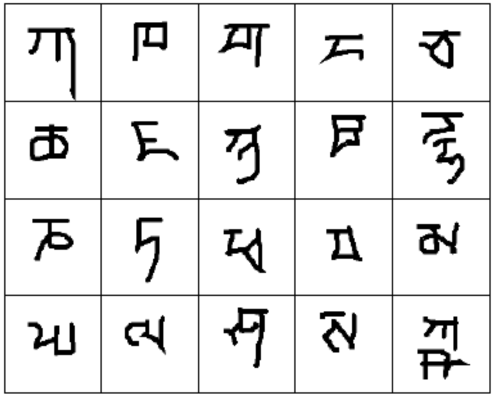
# Omniglot

Demo:
https://openai.com/blog/reptile/

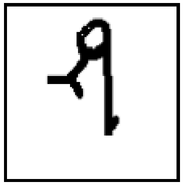
***20 ways***

***1 shot***

Each character represents a class

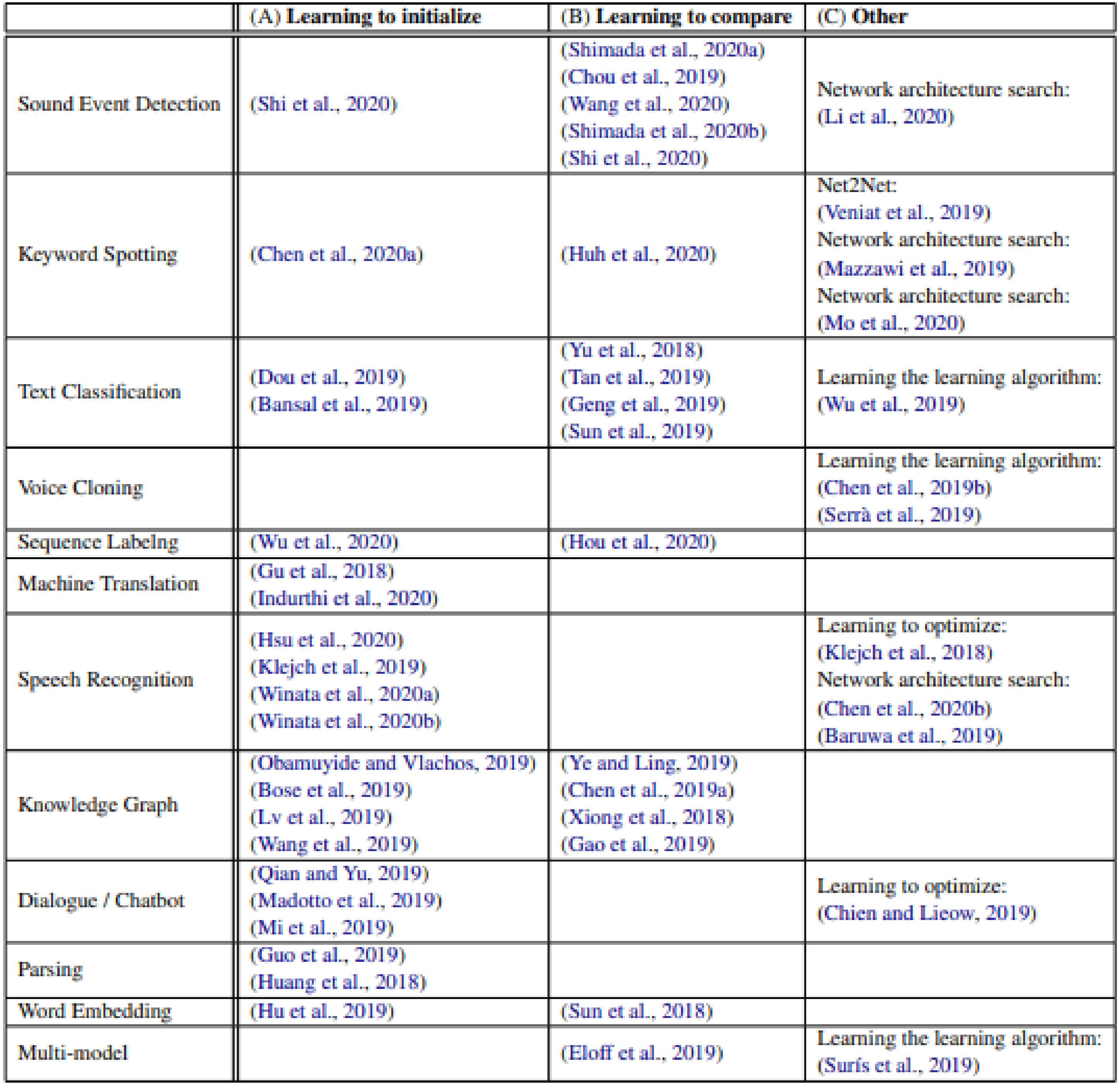


Training set (Support set)



Testing set (Query set)

- Split your characters into training and testing characters
  - Sample N training characters, sample K examples from each sampled characters → one training task
  - Sample N testing characters, sample K examples from each sampled characters → one testing task



| | (A) **Learning to initialize** | (B) **Learning to compare** | (C) **Other** |
|---|---|---|---|
| Sound Event Detection | (Shi et al., 2020) | (Shimada et al., 2020a)<br>(Chou et al., 2019)<br>(Wang et al., 2020)<br>(Shimada et al., 2020b)<br>(Shi et al., 2020) | Network architecture search:<br>(Li et al., 2020) |
| Keyword Spotting | (Chen et al., 2020a) | (Huh et al., 2020) | Net2Net:<br>(Veniat et al., 2019)<br>Network architecture search:<br>(Mazzawi et al., 2019)<br>Network architecture search:<br>(Mo et al., 2020) |
| Text Classification | (Dou et al., 2019)<br>(Bansal et al., 2019) | (Yu et al., 2018)<br>(Tan et al., 2019)<br>(Geng et al., 2019)<br>(Sun et al., 2019) | Learning the learning algorithm:<br>(Wu et al., 2019) |
| Voice Cloning | | | Learning the learning algorithm:<br>(Chen et al., 2019b)<br>(Serrà et al., 2019) |
| Sequence Labelng | (Wu et al., 2020) | (Hou et al., 2020) | |
| Machine Translation | (Gu et al., 2018)<br>(Indurthi et al., 2020) | | |
| Speech Recognition | (Hsu et al., 2020)<br>(Klejch et al., 2019)<br>(Winata et al., 2020a)<br>(Winata et al., 2020b) | | Learning to optimize:<br>(Klejch et al., 2018)<br>Network architecture search:<br>(Chen et al., 2020b)<br>(Baruwa et al., 2019) |
| Knowledge Graph | (Obamuyide and Vlachos, 2019)<br>(Bose et al., 2019)<br>(Lv et al., 2019)<br>(Wang et al., 2019) | (Ye and Ling, 2019)<br>(Chen et al., 2019a)<br>(Xiong et al., 2018)<br>(Gao et al., 2019) | |
| Dialogue / Chatbot | (Qian and Yu, 2019)<br>(Madotto et al., 2019)<br>(Mi et al., 2019) | | Learning to optimize:<br>(Chien and Lieow, 2019) |
| Parsing | (Guo et al., 2019)<br>(Huang et al., 2018) | | |
| Word Embedding | (Hu et al., 2019) | (Sun et al., 2018) | |
| Multi-model | | (Eloff et al., 2019) | Learning the learning algorithm:<br>(Surís et al., 2019) |

http://speech.ee.ntu.edu.tw/~tlkagk/meta_learning_table.pdf