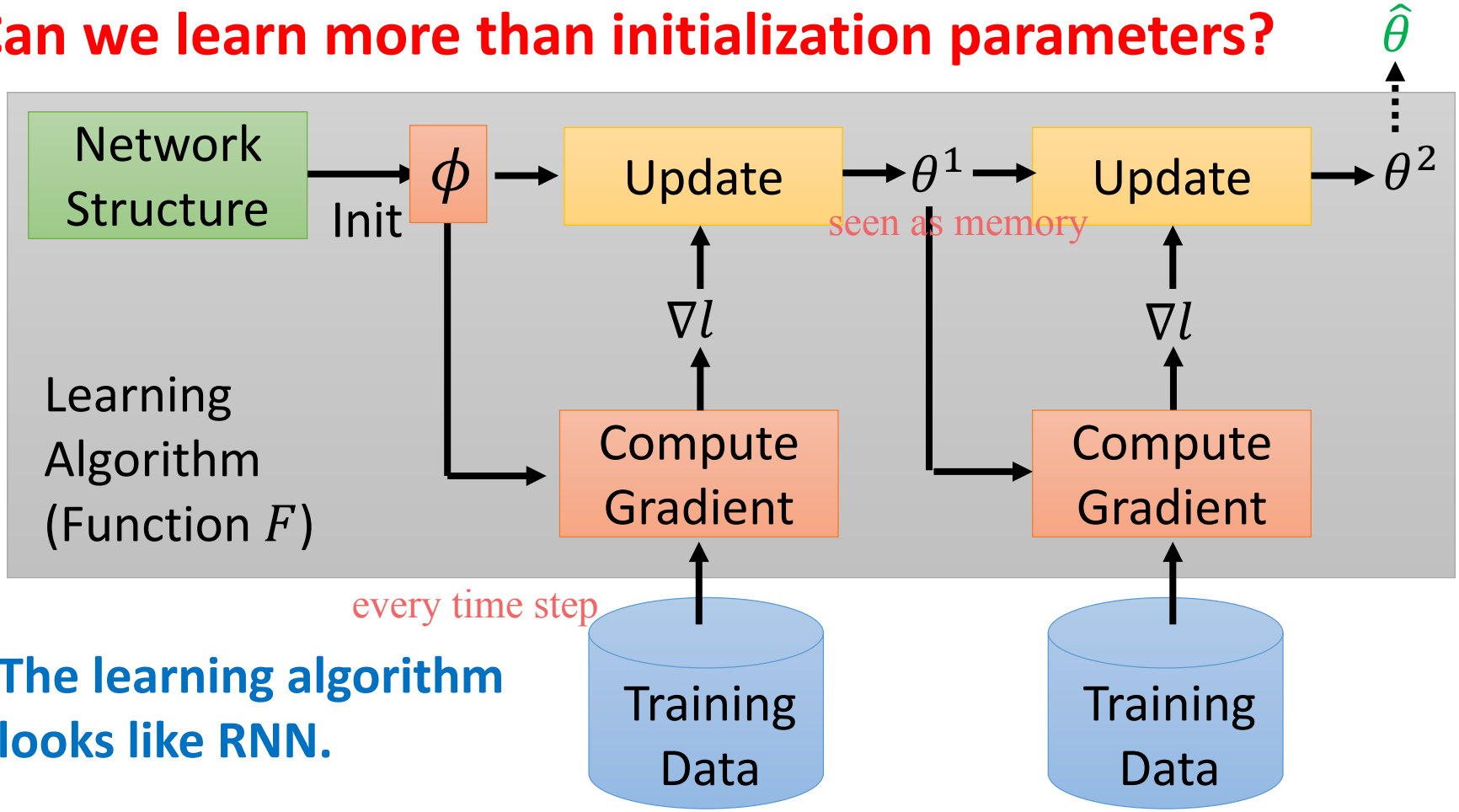
# Meta Learning (Part 2):
# Gradient Descent as LSTM

Hung-yi Lee

# Can we learn more than initialization parameters?




**The learning algorithm looks like RNN.**

## Optimization as a Model for Few-Shot Learning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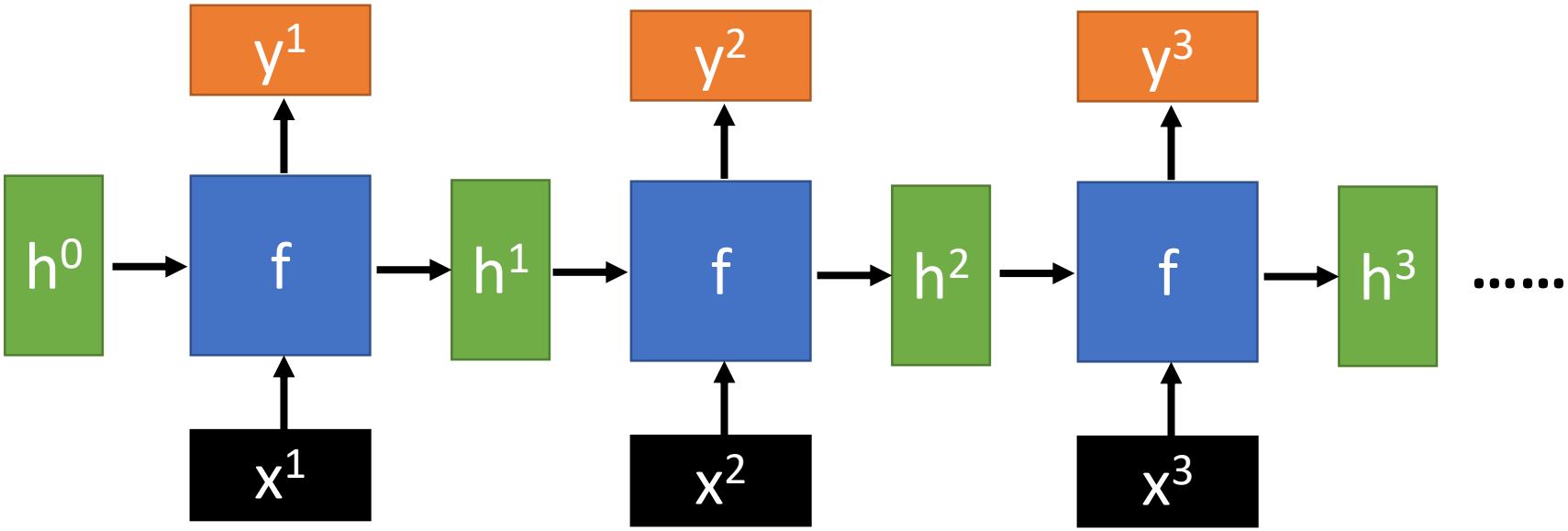
## Learning to learn by gradient descent by gradient descent


**Marcin Andrychowicz[1], Misha Denil[1], Sergio Gómez Colmenarejo[1], Matthew W. Hoffman[1], David Pfau[1], Tom Schaul[1], Brendan Shillingford[1,2], Nando de Freitas[1,2,3]**
[1]Google DeepMind [2]University of Oxford [3]Canadian Institute for Advanced Research

# Recurrent Neural Network

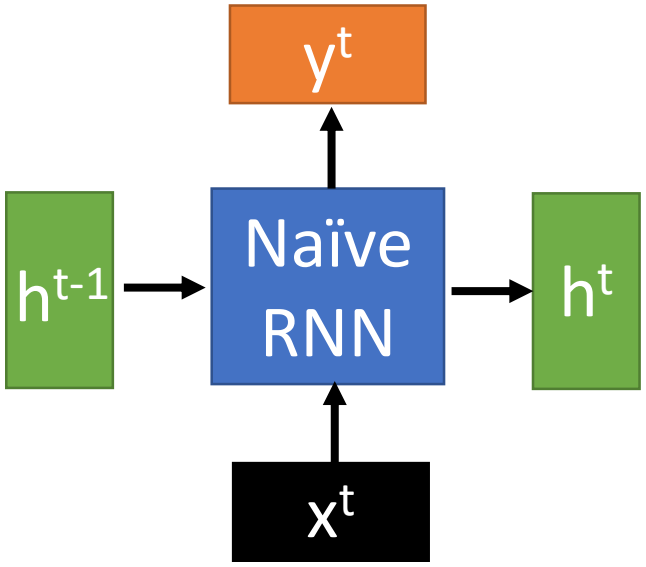
- Given function f: $h', y = f(h, x)$

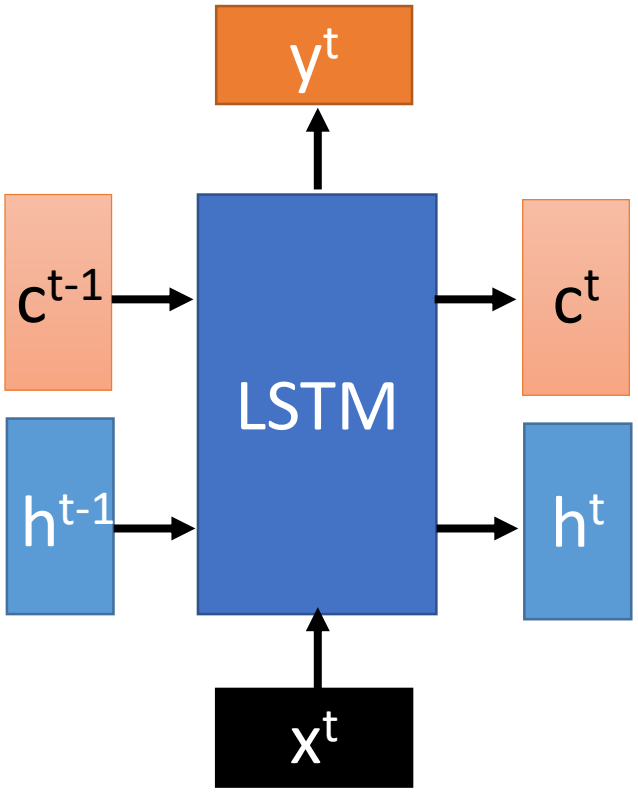
h and h' are vectors with the same dimension




No matter how long the input/output sequence is, we only need one function f

# LSTM



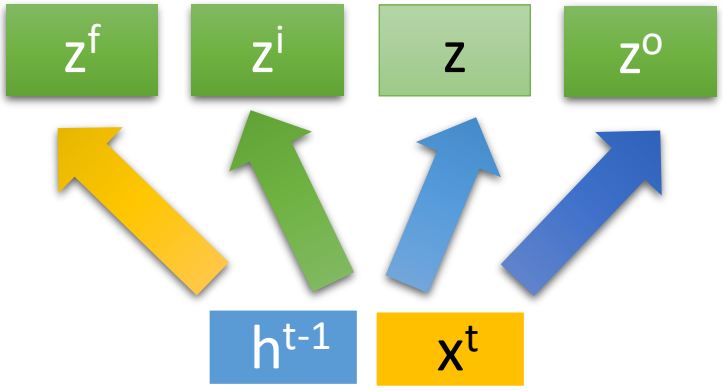




c change slowly ➡ $c^t$ is $c^{t-1}$ added by something

h change faster ➡ $h^t$ and $h^{t-1}$ can be very different

# Review: LSTM

$c^{t-1}$




$$z = tanh\left(W \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix}\right)$$

$$z^i = \sigma\left(W^i \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix}\right)$$

input

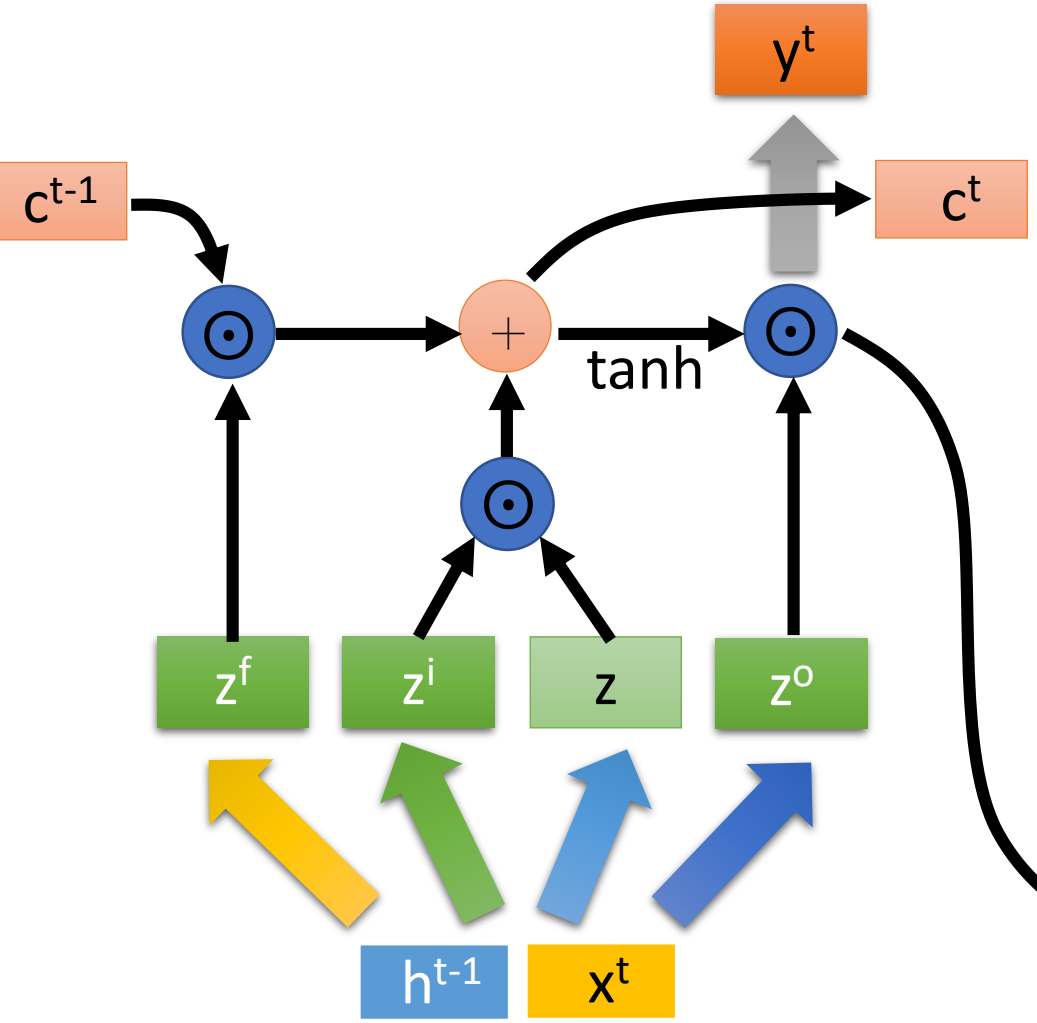
$$z^f = \sigma\left(W^f \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix}\right)$$

forget

$$z^o = \sigma\left(W^o \begin{bmatrix} x^t \\ h^{t-1} \end{bmatrix}\right)$$

output

# Review: LSTM

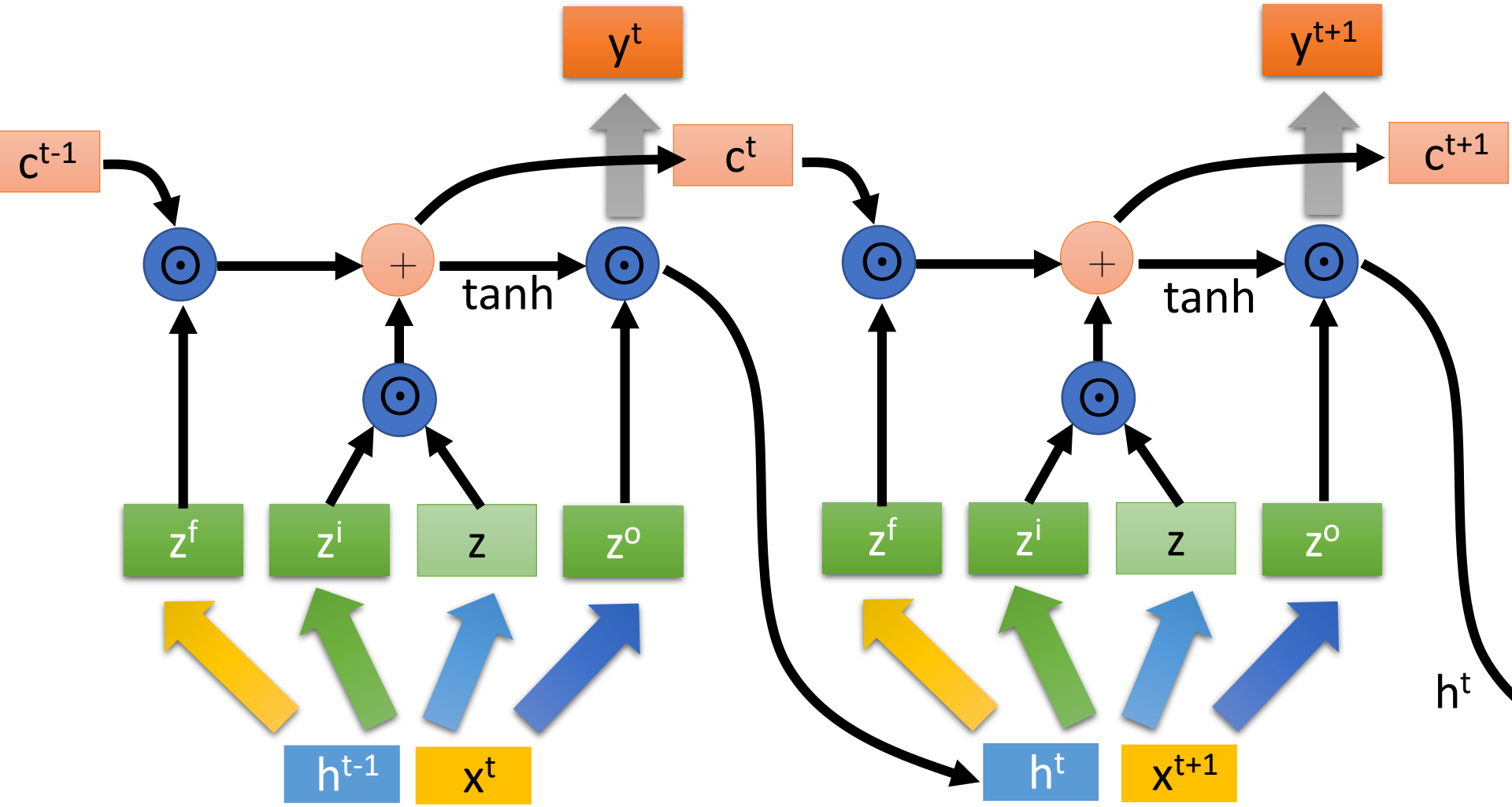



$$c^t = z^f \odot c^{t-1} + z^i \odot z$$

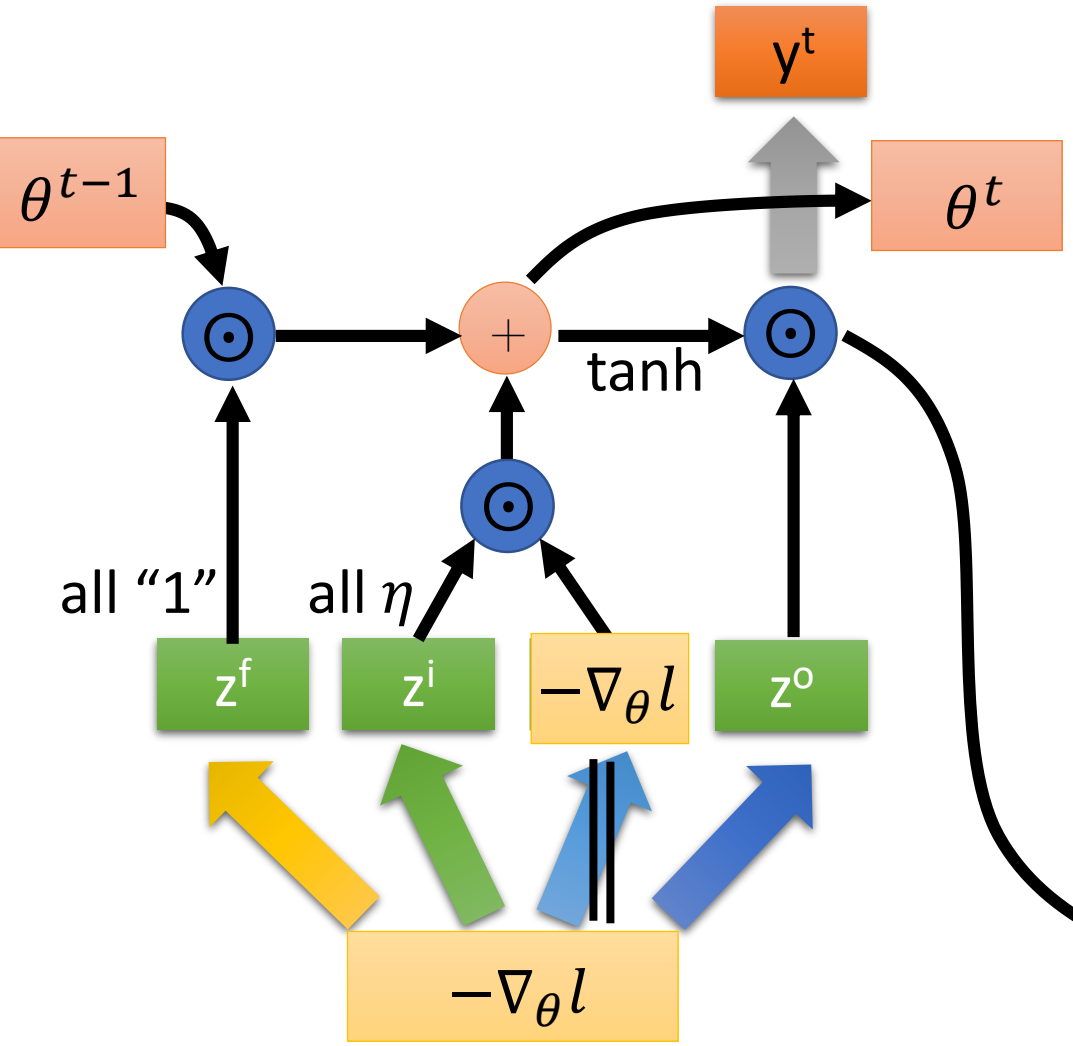
$$h^t = z^o \odot tanh(c^t)$$

$$y^t = \sigma(W' h^t)$$

# Review: LSTM



# *Similar to gradient descent based algorithm*




$$\theta^t = \theta^{t-1} - \eta \nabla_\theta l$$

assume $\begin{bmatrix} 1 \\ 1 \\ \vdots \end{bmatrix}$ assume $\begin{bmatrix} \eta \\ \eta \\ \vdots \end{bmatrix}$

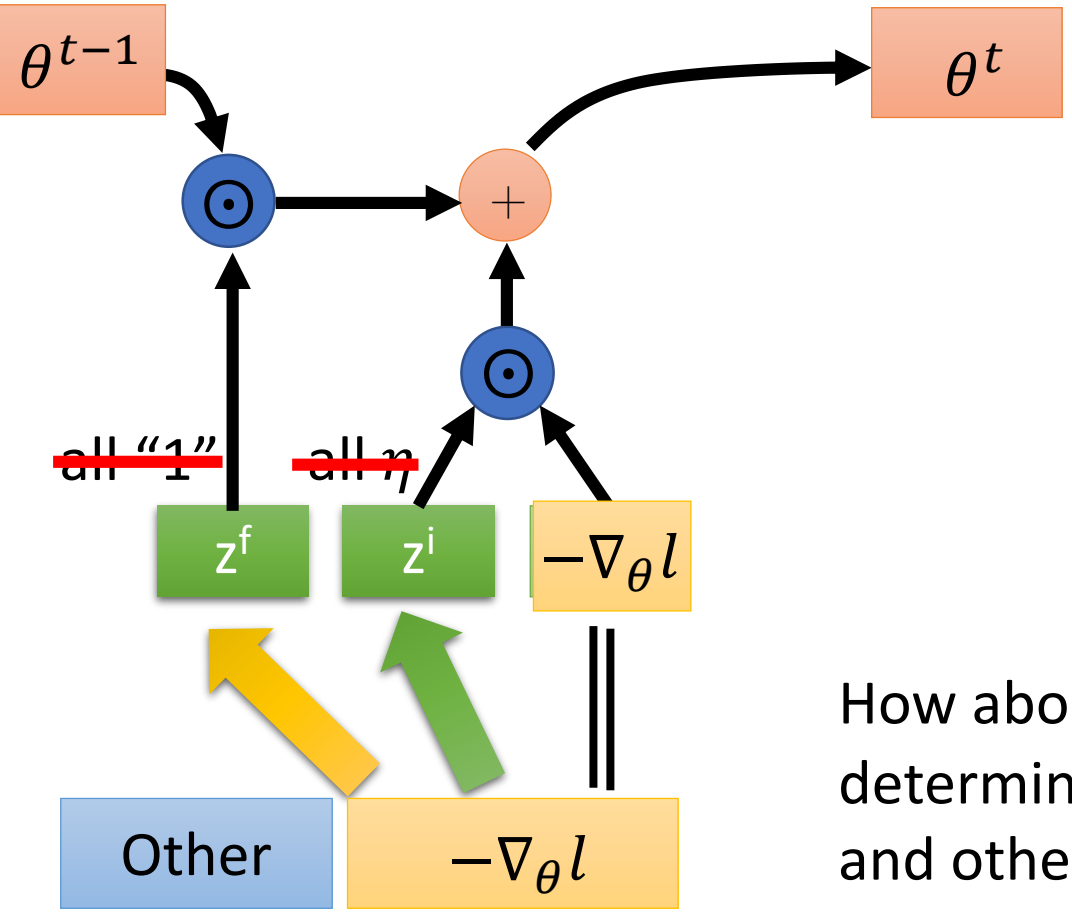
$$\theta^t = z^f \odot \theta^{t-1} + z^i \odot -\nabla_\theta l$$

$$h^t = z^o \odot tanh(c^t)$$

$$y^t = \sigma(W' h^t)$$

# *Similar to gradient descent based algorithm*

$$\theta^t = \theta^{t-1} - \eta \nabla_\theta l$$




Something like regularization

$c^t = z^f \odot c^{t-1} + z^i \odot z$

$\theta^t = z^f \odot \theta^{t-1} + z^i \odot -\nabla_\theta l$

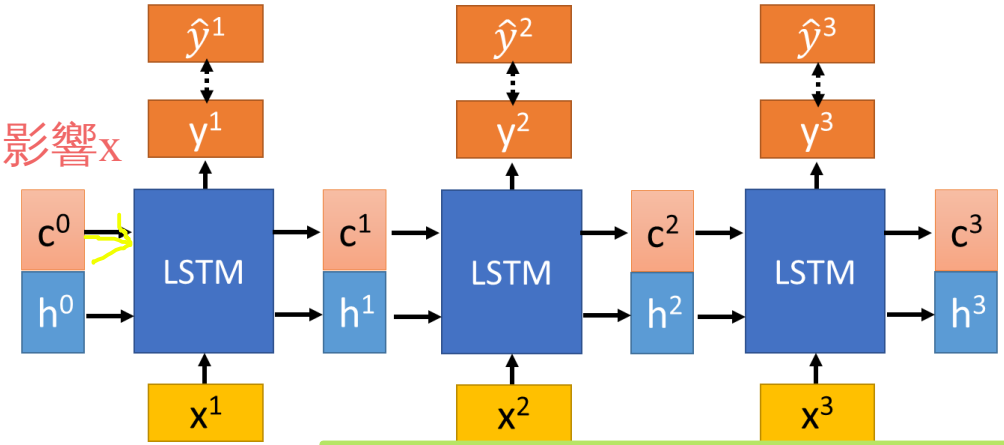
train

gradient

Dynamic learning rate

How about machine learn to determine $z^f$ and $z^i$ from $-\nabla_\theta l$ and other information?

## Typical LSTM




## LSTM for Gradient Descent

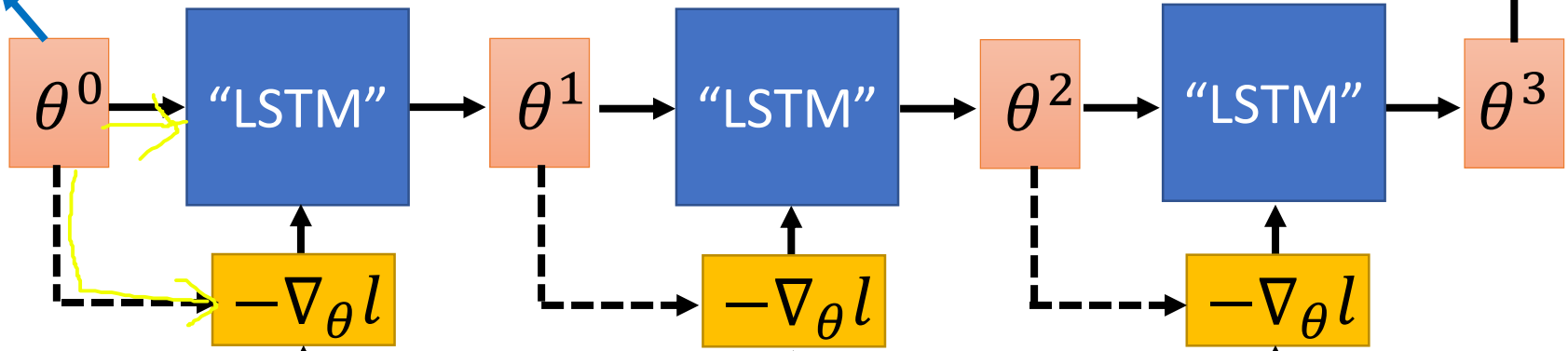
$$\theta^t = z^f \odot \theta^{t-1} + z^i \odot -\nabla_\theta l$$

Learn to minimize

Testing Data → $l(\theta^3)$

3 training steps

Learnable




Independence assumption

theta會影響輸入

Batch from train

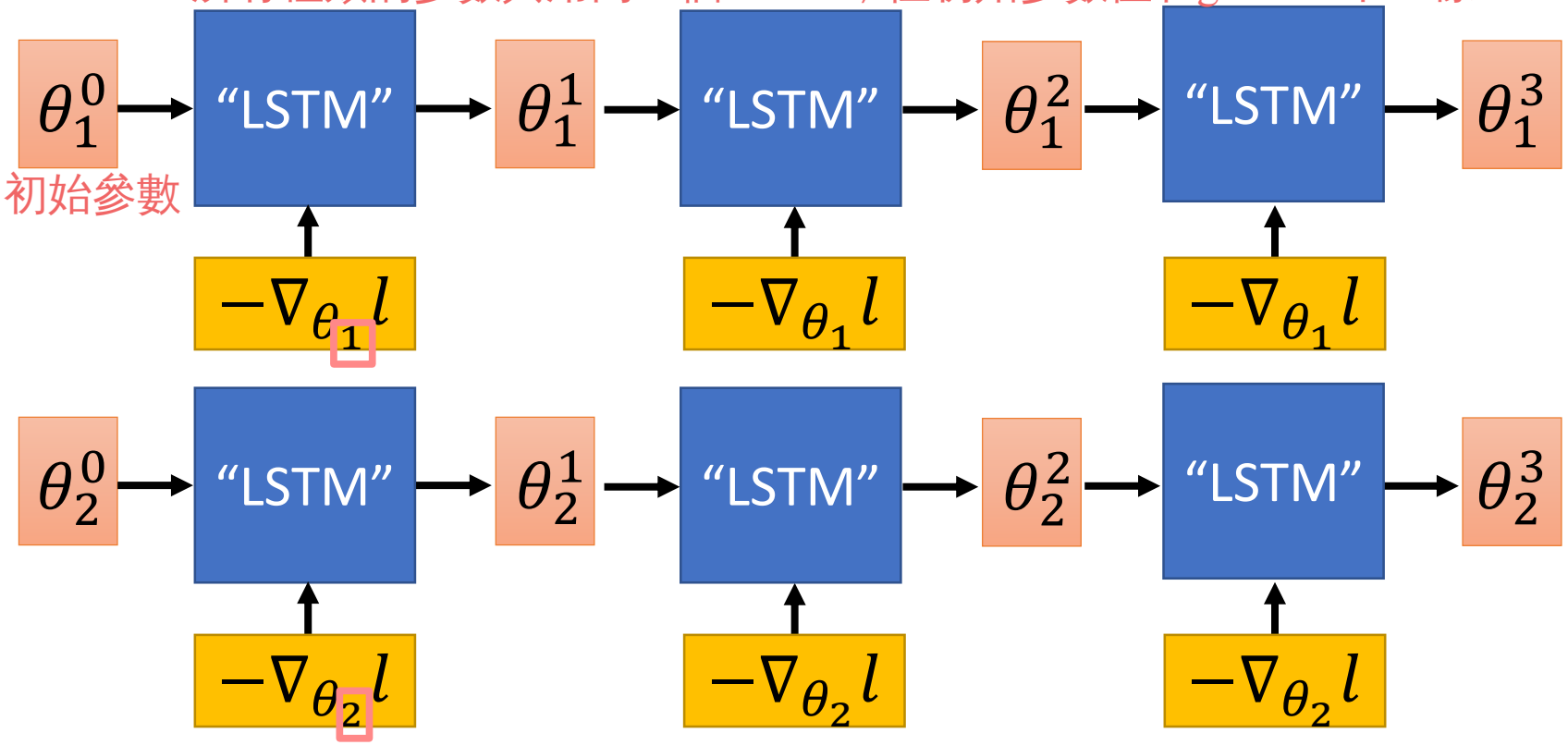
Batch from train

Batch from train

# Real Implementation

The LSTM used only has one cell. Share across all parameters

所有種類的參數共用同一個LSTM，但初始參數值和gradient不一樣...




- Reasonable model size
- In typical gradient descent, all the parameters use the same update rule
- Training and testing model architectures can be different.

https://openreview.net/forum?id=rJY0-Kcll&noteId=ryq49XyLg

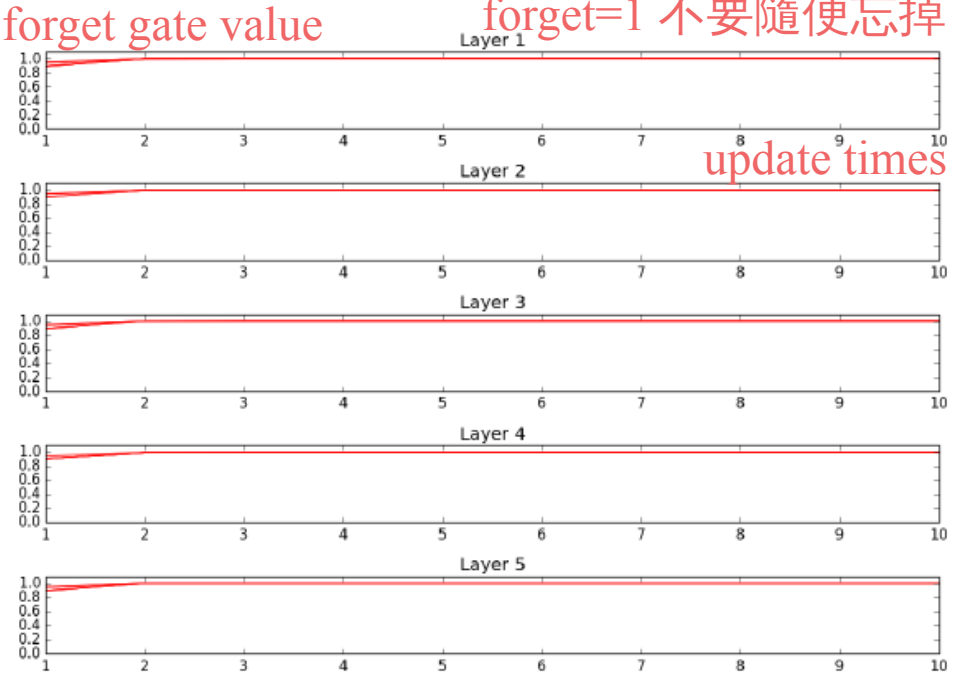
# Experimental Results

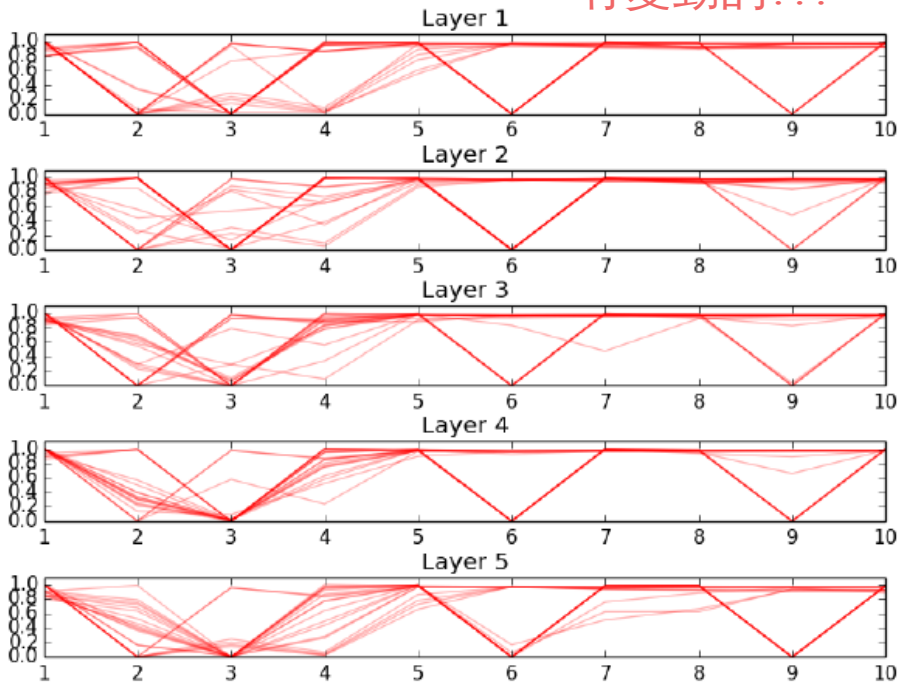
$$\theta^t = z^f \odot \theta^{t-1} + z^i \odot -\nabla_\theta l$$

forget gate value

forget=1 不要隨便忘掉

learning rate是有變動的???




(a) Forget gate values for 1-shot meta-learner

(b) Input gate values for 1-shot meta-learner

Parameter update depends on not only current gradient, but ***previous gradients***.

## RMSProp

$$w^1 \leftarrow w^0 - \frac{\eta}{\sigma^0} g^0 \qquad \sigma^0$$

$$w^2 \leftarrow w^1 - \frac{\eta}{\sigma^1} g^1 \qquad \sigma^1$$

$$w^3 \leftarrow w^2 - \frac{\eta}{\sigma^2} g^2 \qquad \sigma^2$$

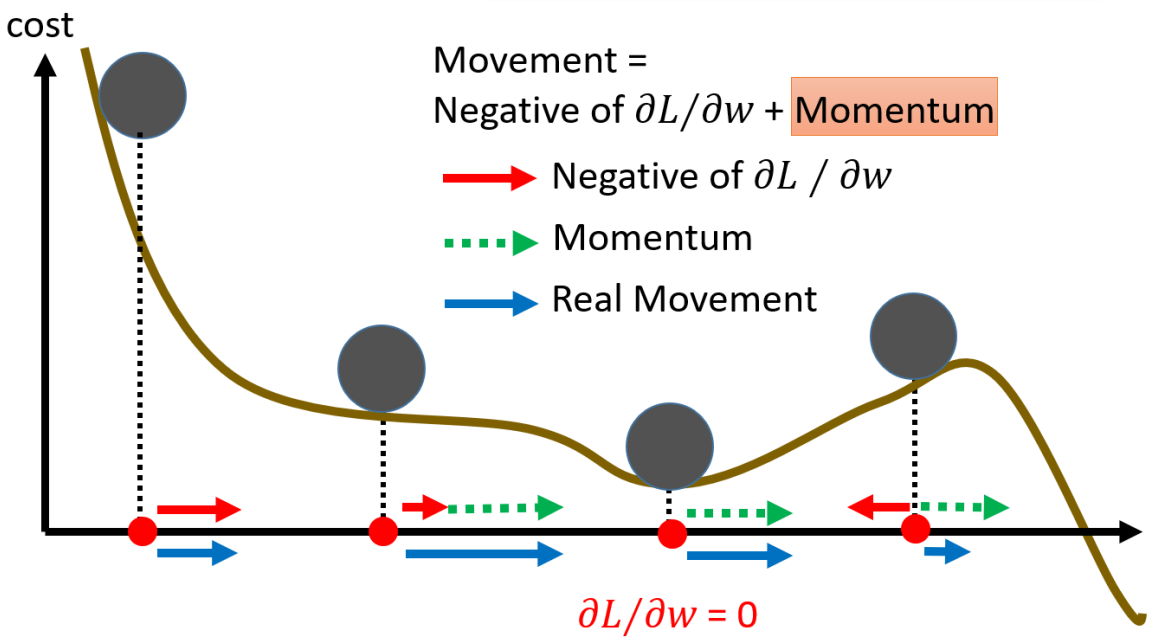
$$\vdots$$

$$w^{t+1} \leftarrow w^t - \frac{\eta}{\sigma^t} g^t \qquad \sigma^t$$

Rc
with

## Momentum

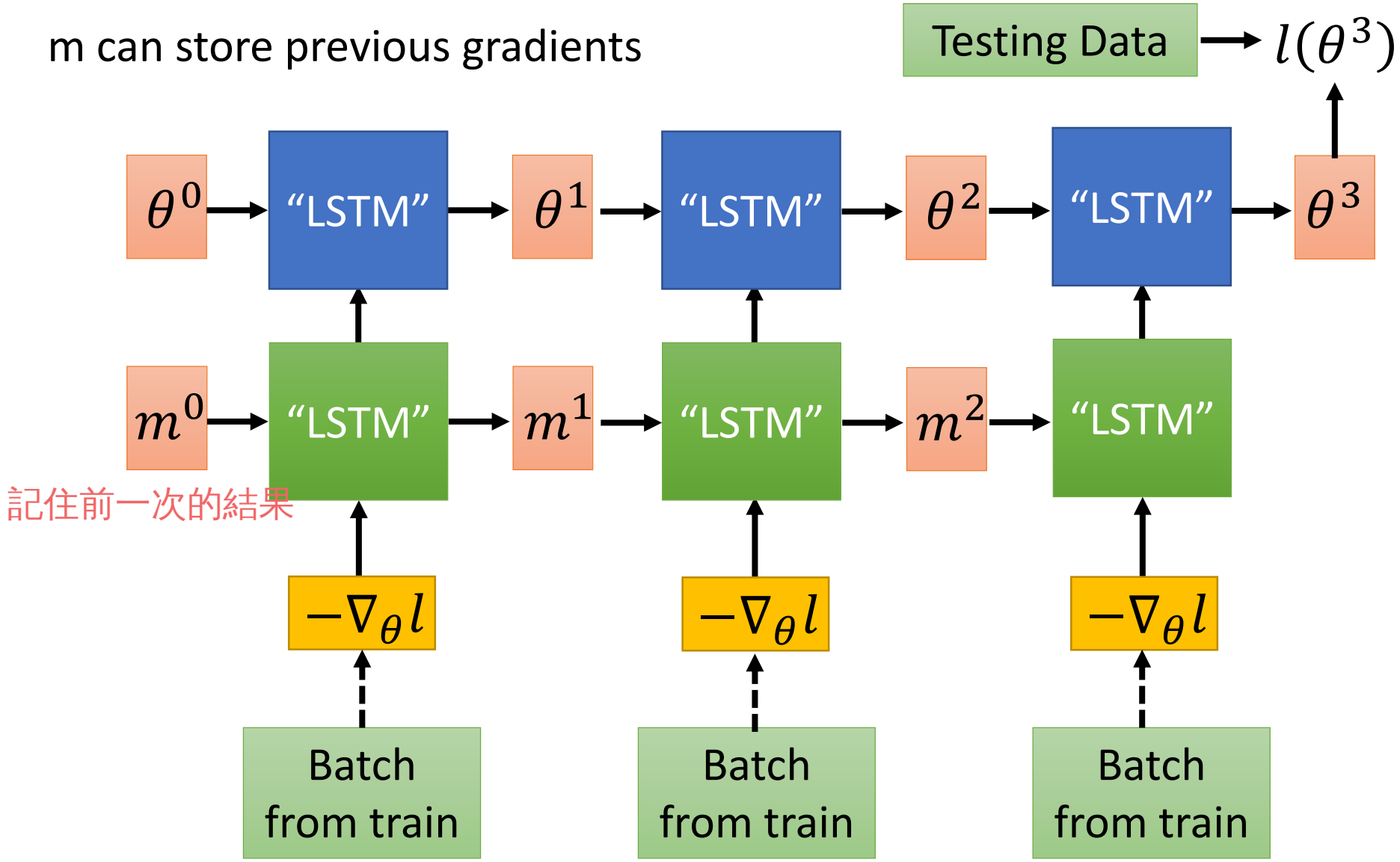
Still not guarantee reaching global minima, but give some hope ……



# *LSTM for Gradient Descent (v2)*

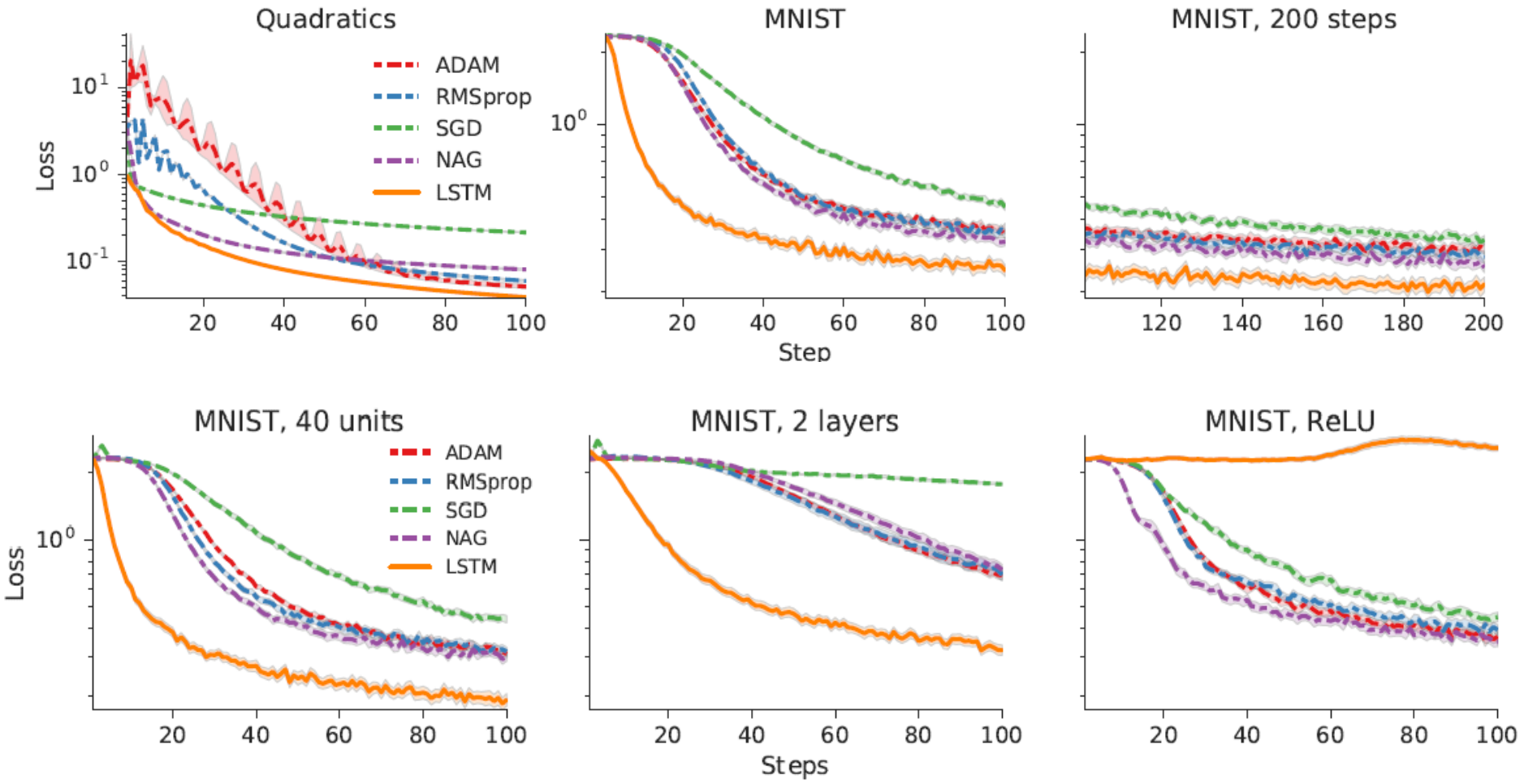
3 training steps

m can store previous gradients



https://arxiv.org/abs/1606.04474

# Experimental Results

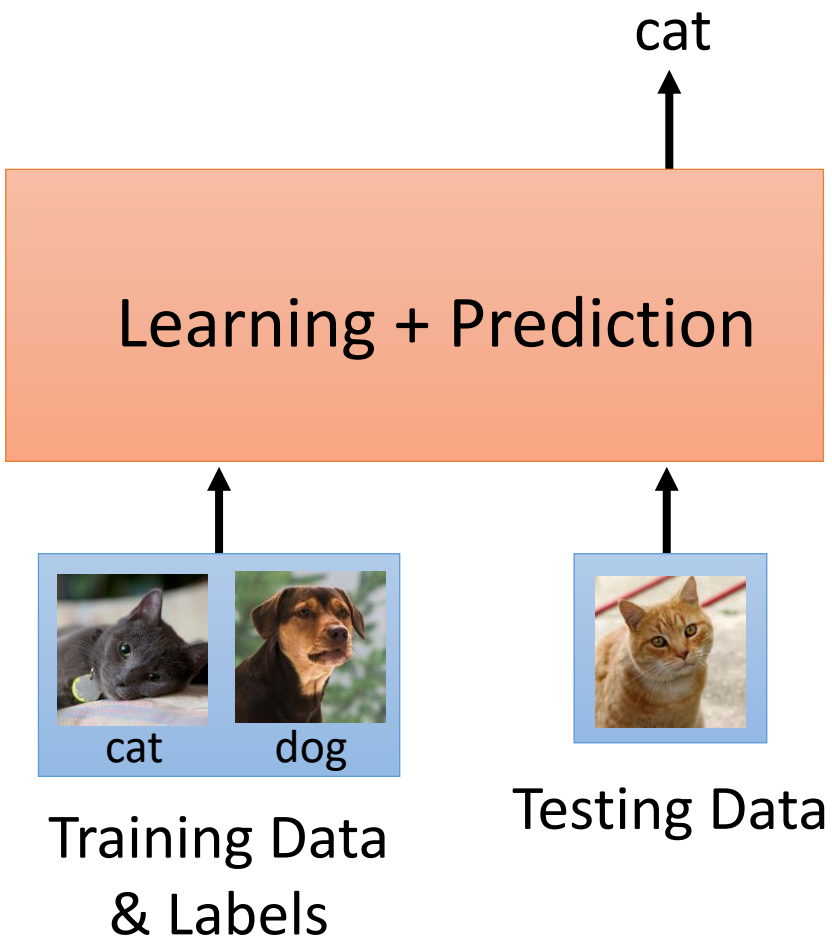


# Meta Learning (Part 3)

Hung-yi Lee

# Even more crazy idea …

- Input:
  - Training data and their labels
  - Testing data
- Output:
  - Predicted label of testing data



identification:是那組人臉的哪一個人

# Face Verification

verification:判斷是否是某個人(驗證)

In each task:

註冊的臉就是訓練資料

Training

Few-shot Learning

Registration (Collecting Training data)

Testing

Unlock your phone by Face


https://support.apple.com/zh-tw/HT208109

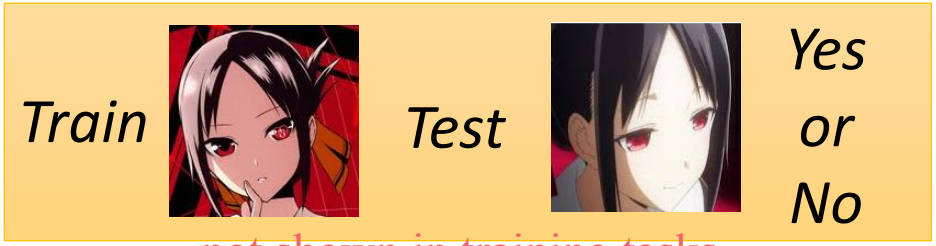
# Meta Learning

Same approach for Speaker Verification

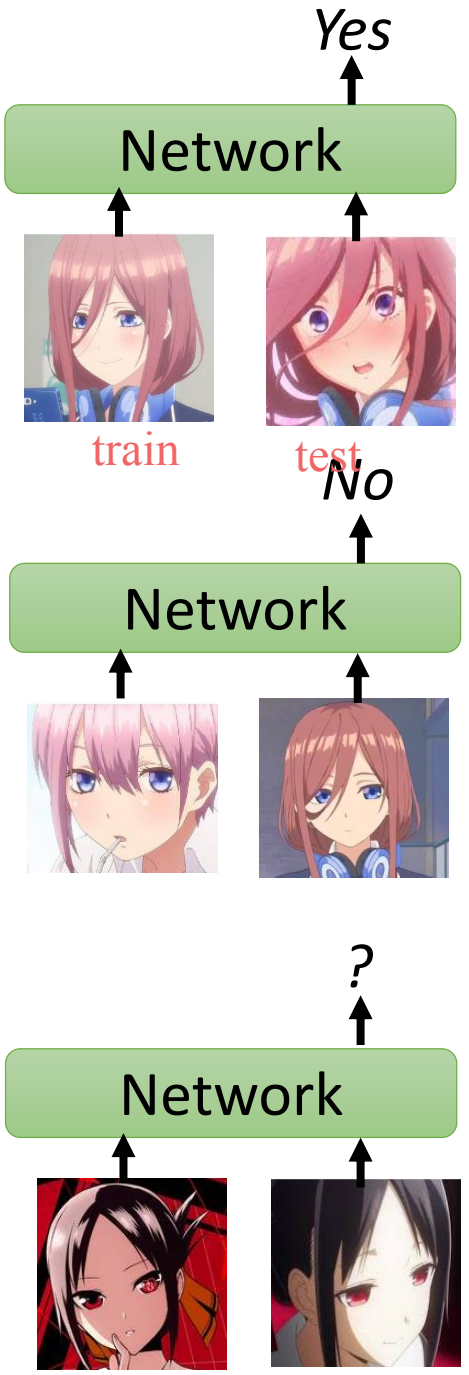
Training Tasks



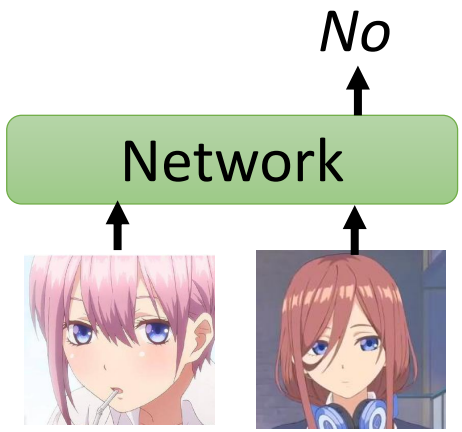

Testing Tasks




not shown in training tasks



# Siamese Network




Train

***Same***

Test

CNN

share

sharing parameters

CNN

embedding

embedding

Similarity

if same, score 高

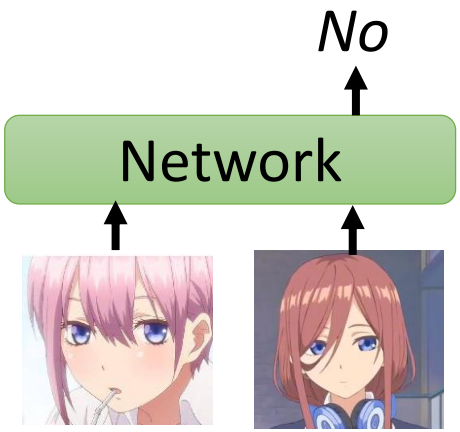
score

Large score ➡ *Yes*

Small score ➡ *No*

# Siamese Network

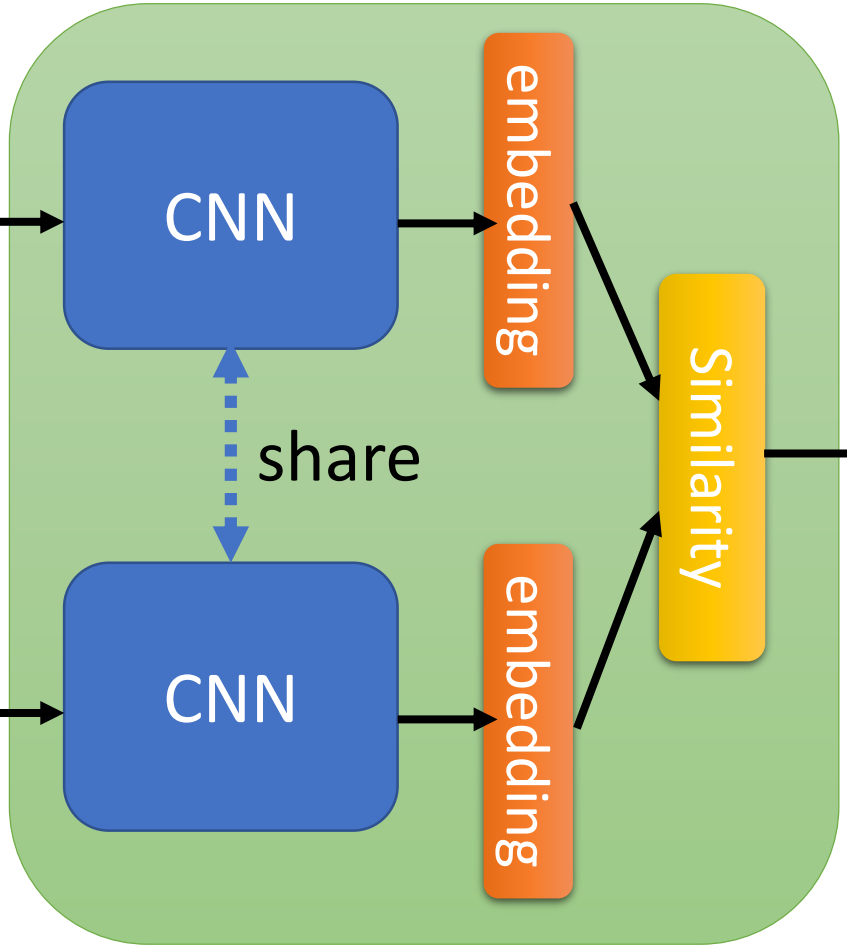
孿生




Train

***Different***

Test




score

Large score → *Yes*

Small score → *No*

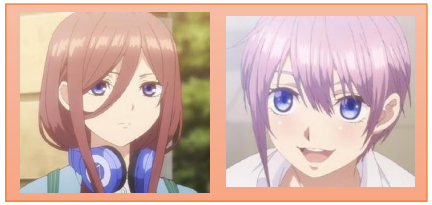
# Siamese Network
# - Intuitive Explanation

- Binary classification problem: “Are they the same?”

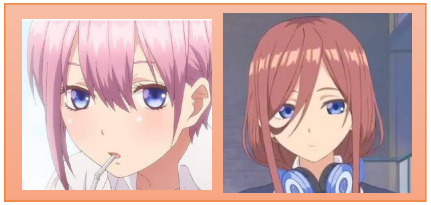
每一筆資料裡面有兩張圖片
output:same or different?

same

**Training Set**



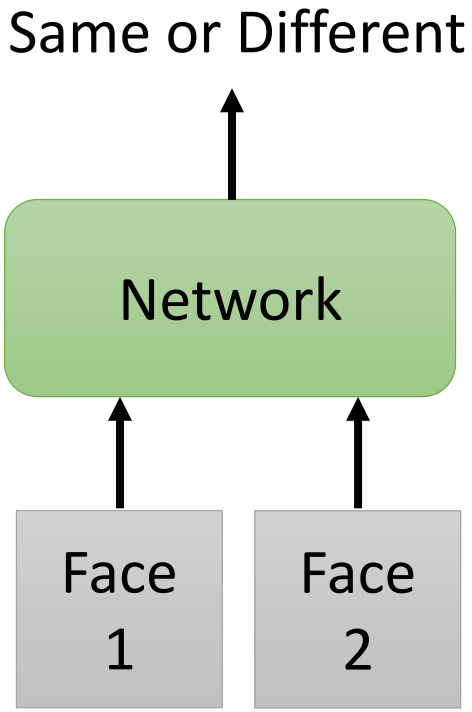
different



different

**Testing Set**

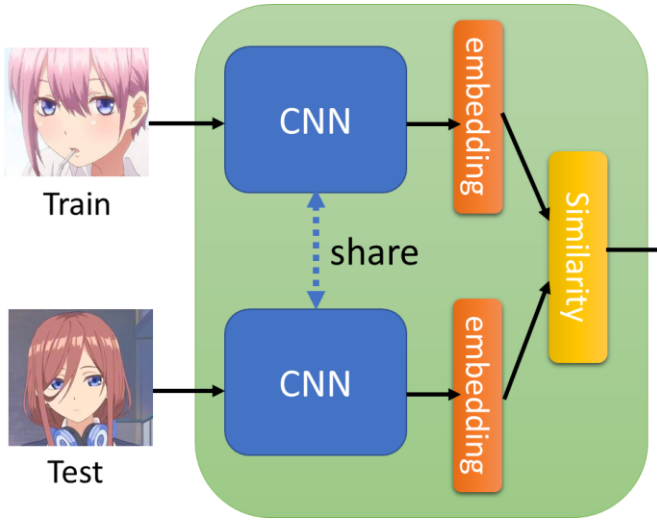
?

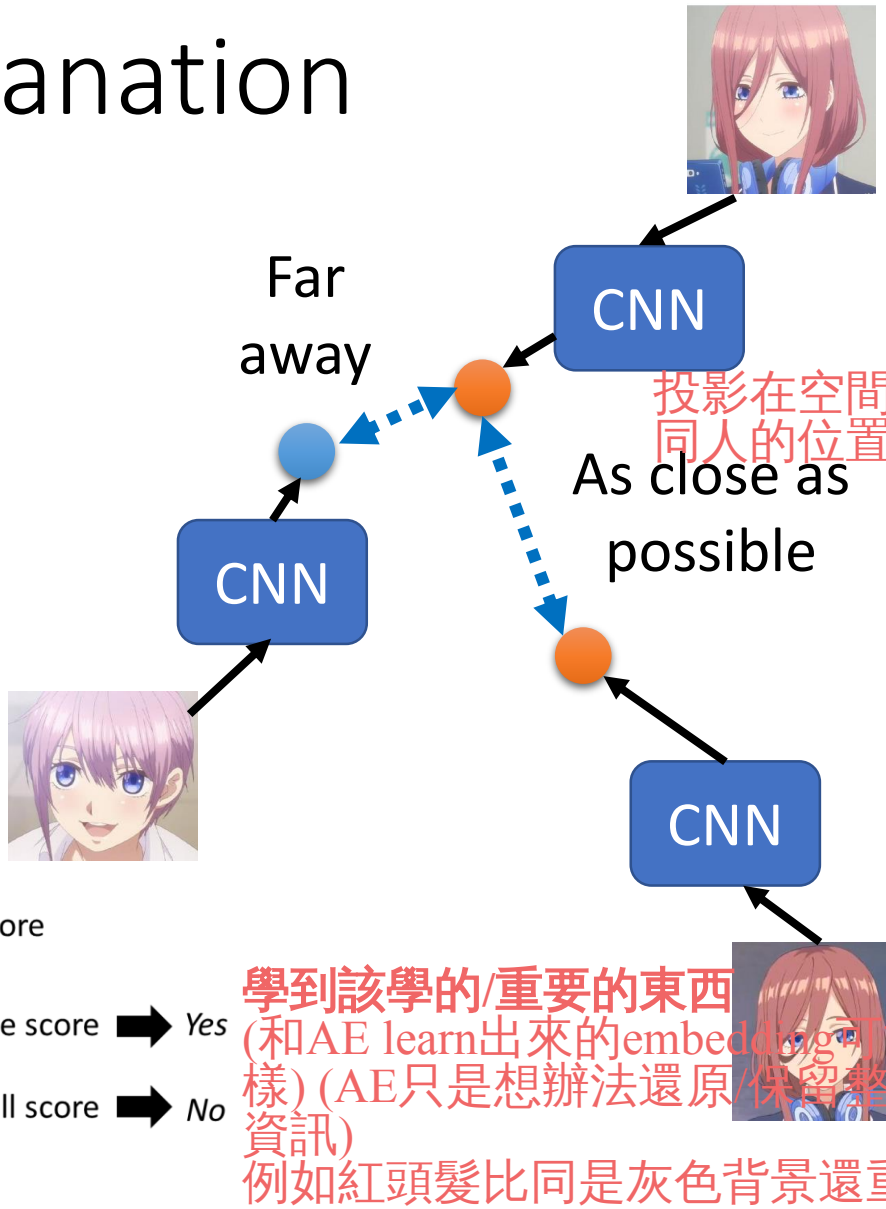


# Siamese Network - Intuitive Explanation

Learning embedding for faces

e.g. learn to ignore the background



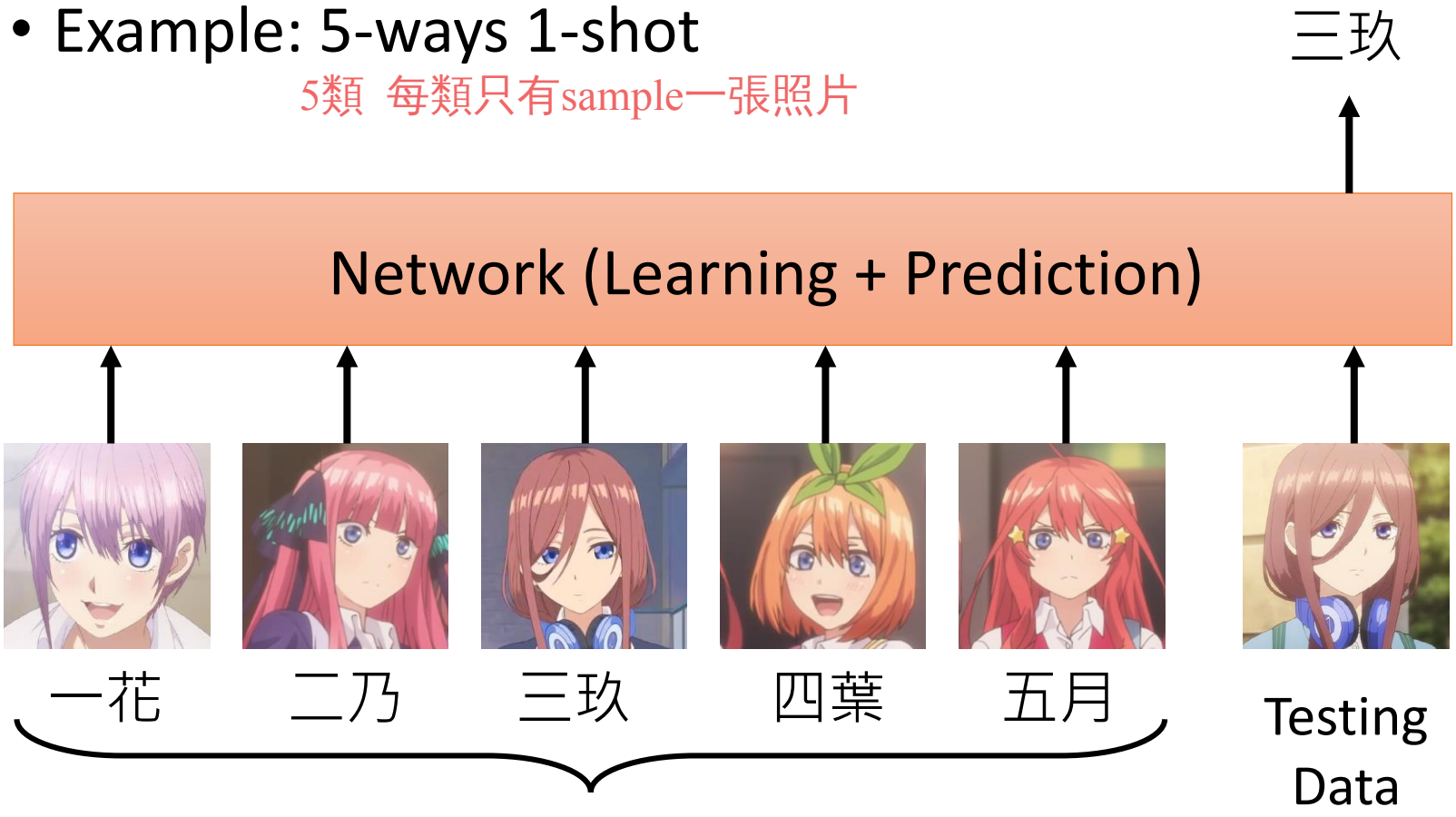
# To learn more …

- What kind of distance should we use?
  - SphereFace: Deep Hypersphere Embedding for Face Recognition
  - Additive Margin Softmax for Face Verification
  - ArcFace: Additive Angular Margin Loss for Deep Face Recognition
- Triplet loss
  - Deep Metric Learning using Triplet Network
  - FaceNet: A Unified Embedding for Face Recognition and Clustering

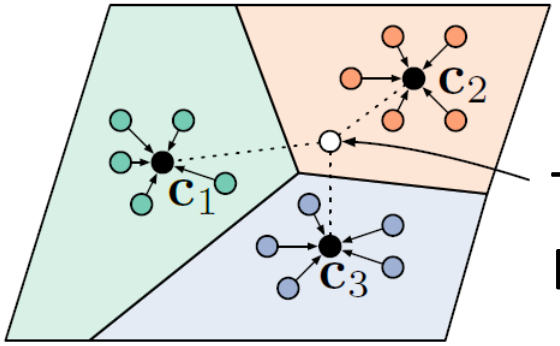
# N-way Few/One-shot Learning

- Example: 5-ways 1-shot

5類 每類只有sample一張照片



# Prototypical Network




Testing Data

-> softmax -> minimize cross entropy

得到五個相似度

$s_1$ $s_2$ $s_3$ $s_4$ $s_5$

CNN CNN CNN CNN CNN

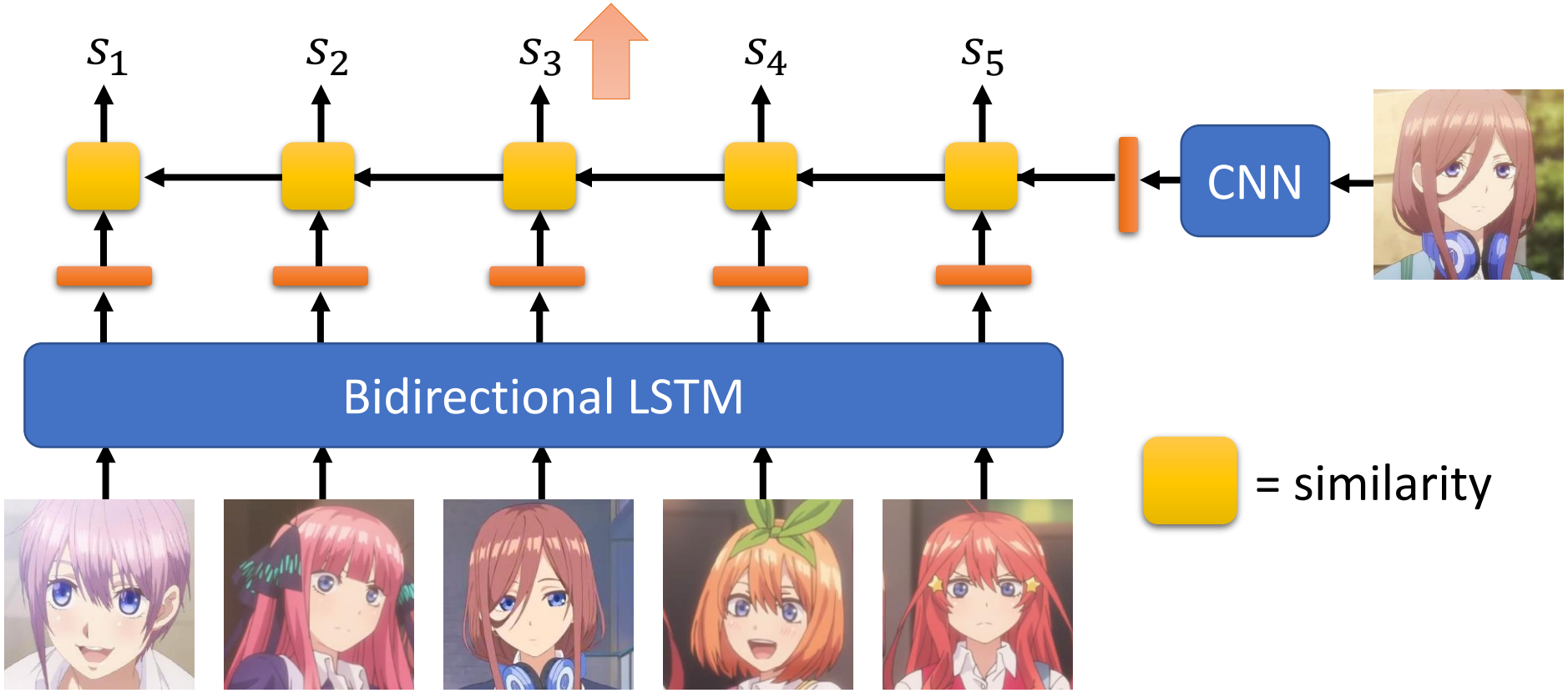
CNN

= similarity

https://arxiv.org/abs/1703.05175

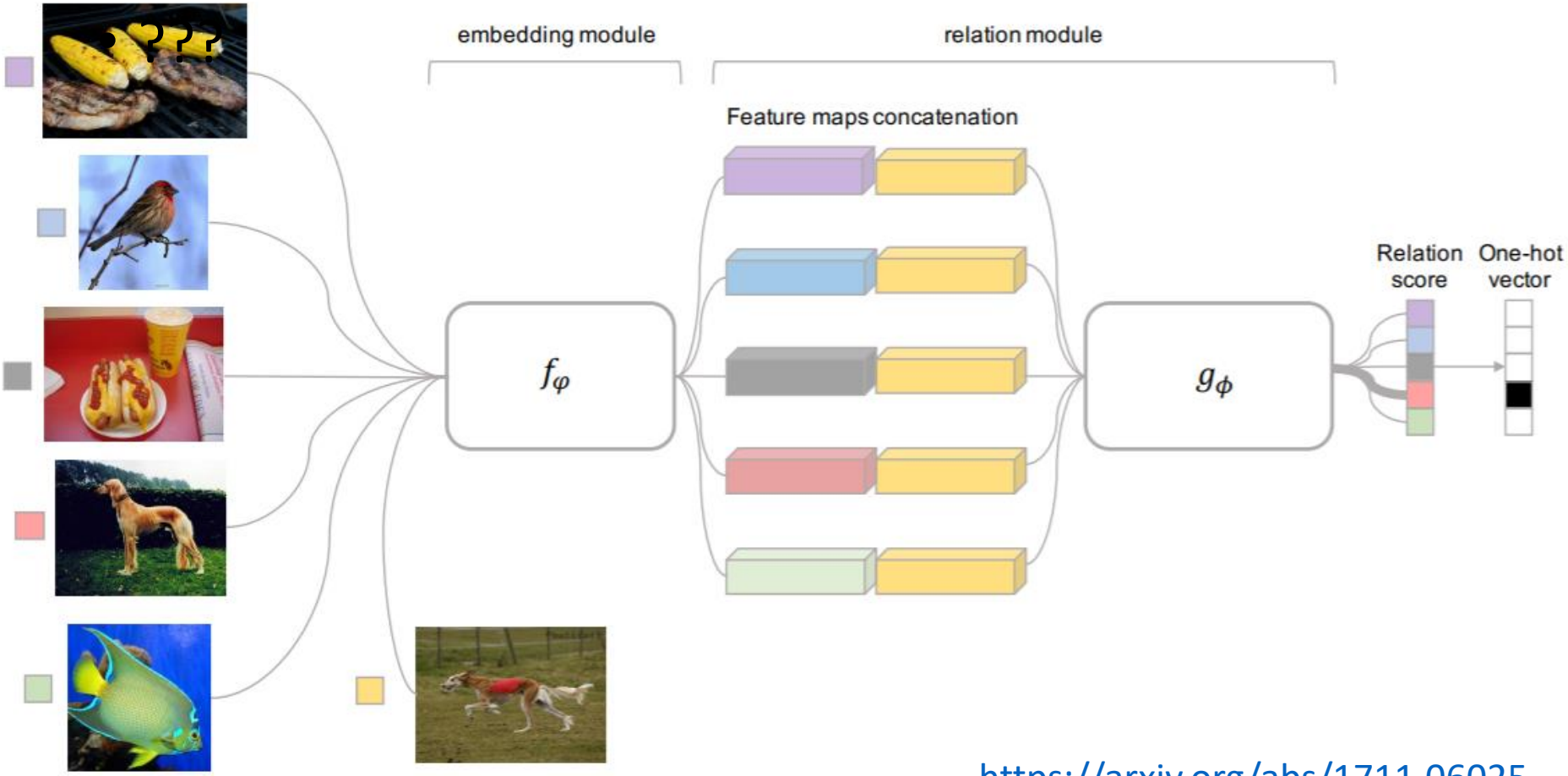
# Matching Network

Considering the relationship among the training examples



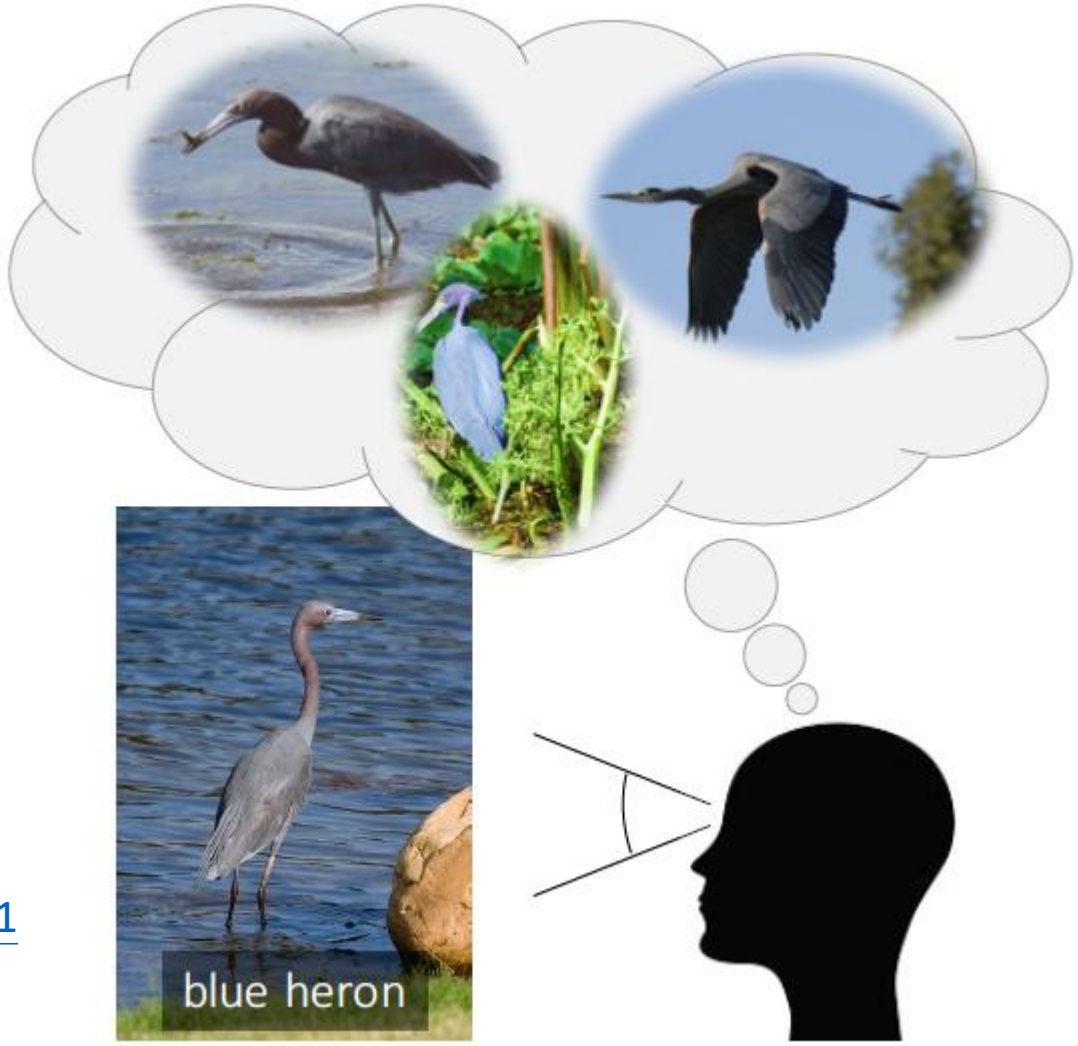

https://arxiv.org/abs/1606.04080

# Relation Network



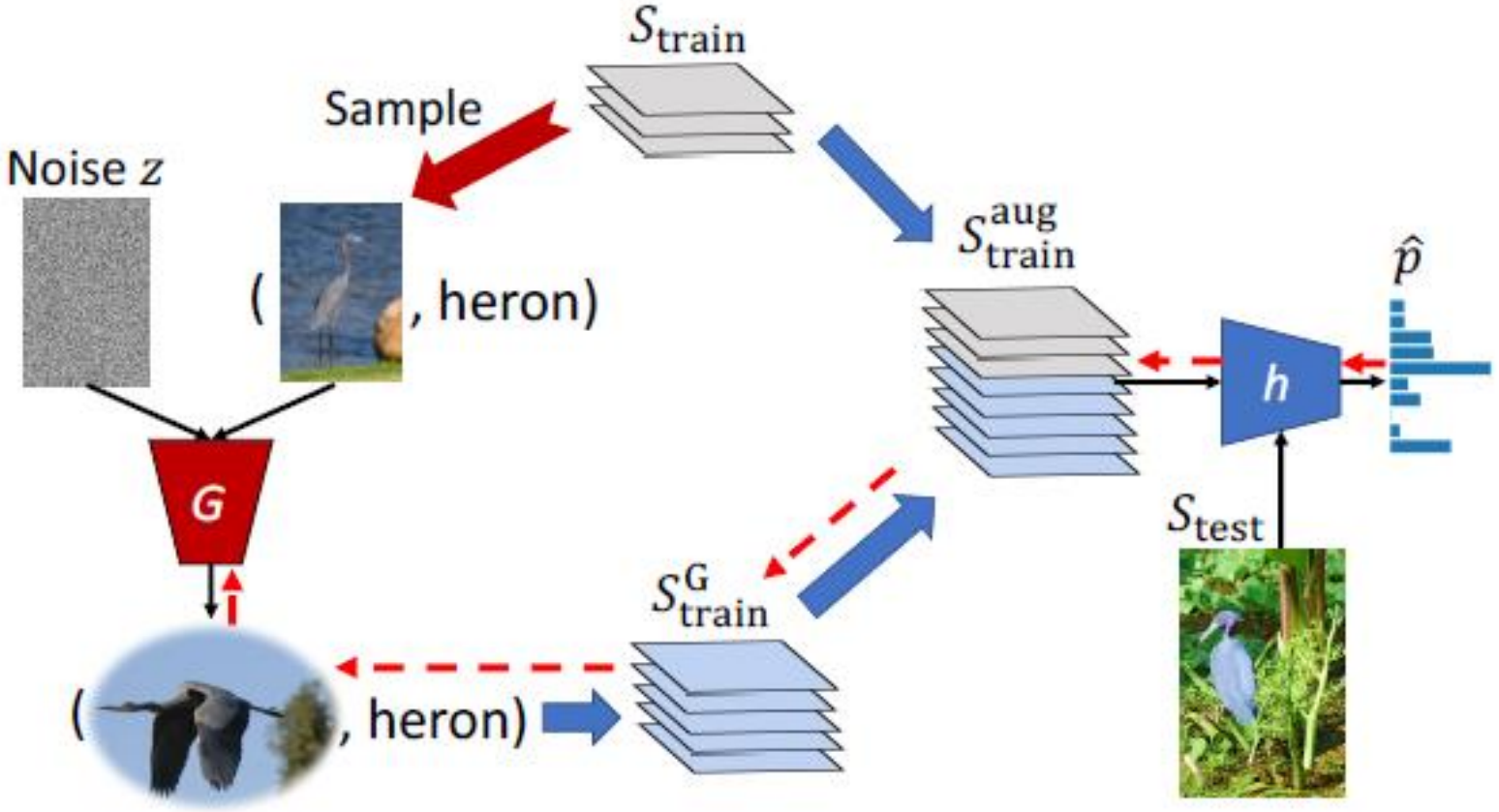

https://arxiv.org/abs/1711.06025

# Few-shot learning for imaginary data




https://arxiv.org/abs/1801.05401

# Few-shot learning for imaginary data




https://arxiv.org/abs/1801.05401