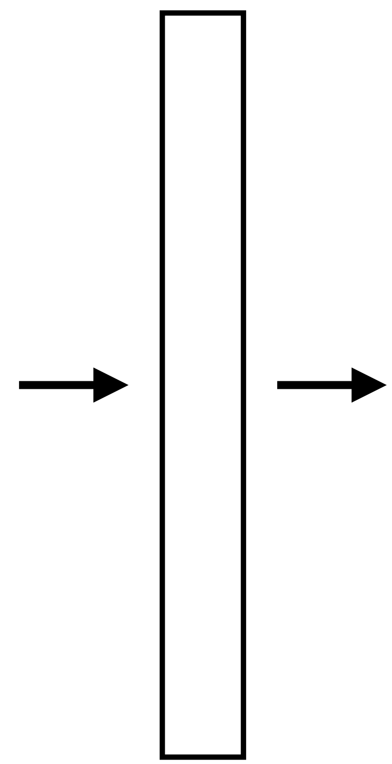
Carnegie Mellon University
Heinz College

95-865 Pittsburgh Lecture 11: Time Series Analysis With Recurrent Neural Nets

George Chen

RNNs

What we've seen so far are "feedforward" NNs



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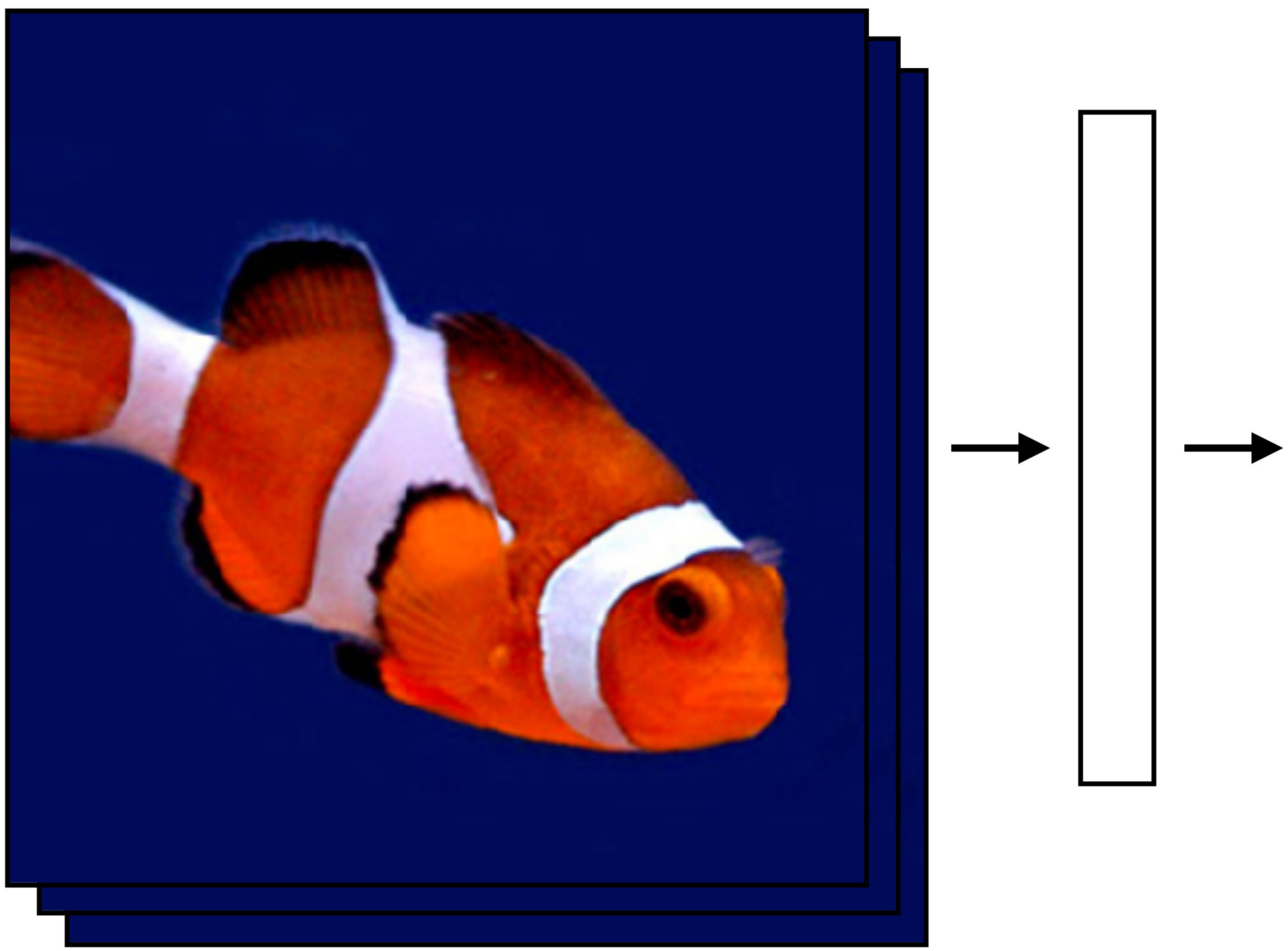
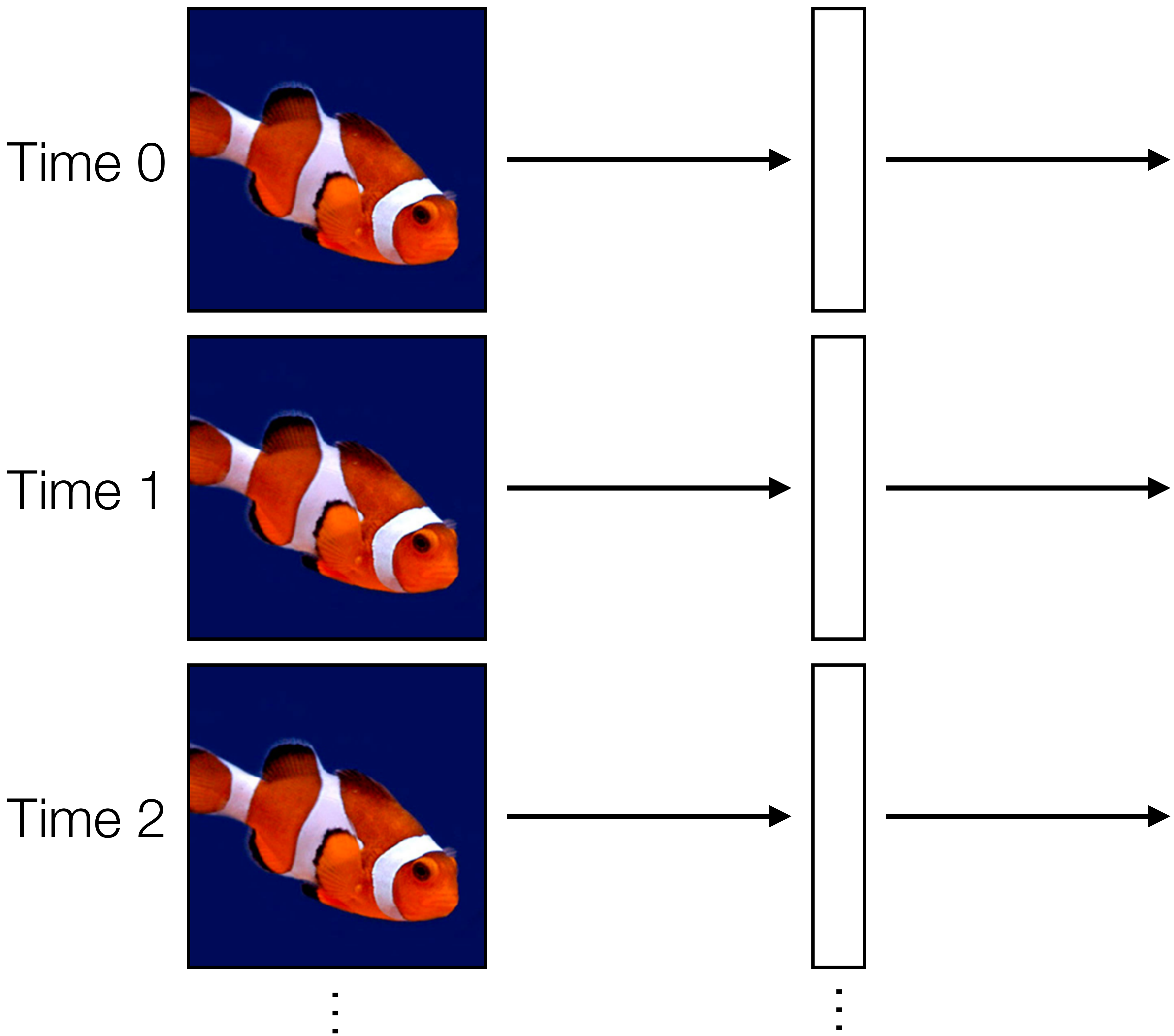


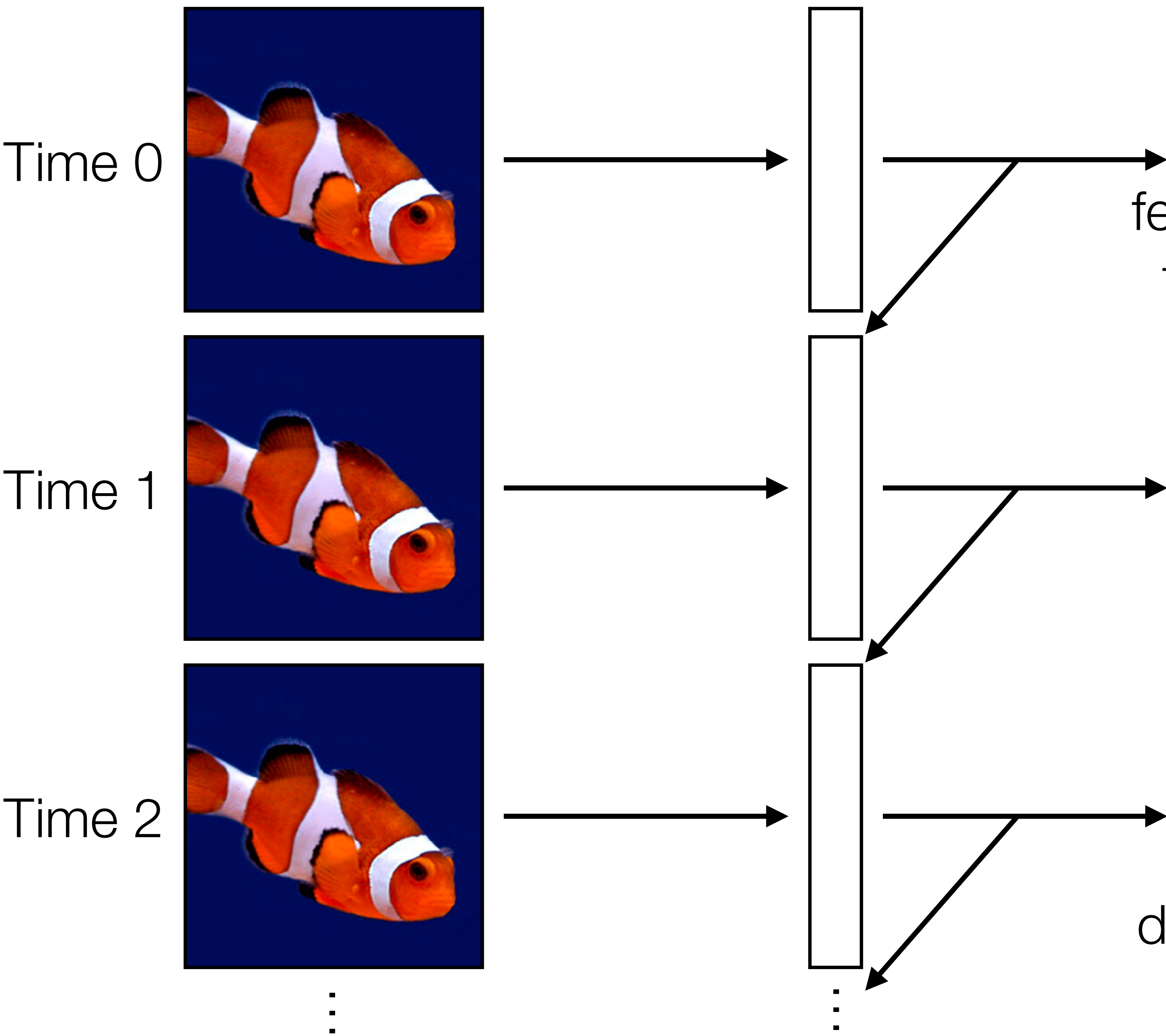
What if we had a video?

RNNs

Feedforward NN's:
treat each video frame separately



RNNs



Feedforward NN's: treat each video frame separately

RNN's: feed output at previous time step as input to RNN layer at current time step

In `keras`, different RNN options: `SimpleRNN`, `LSTM`, `GRU`

Recommendation: don't use `SimpleRNN`

RNNs

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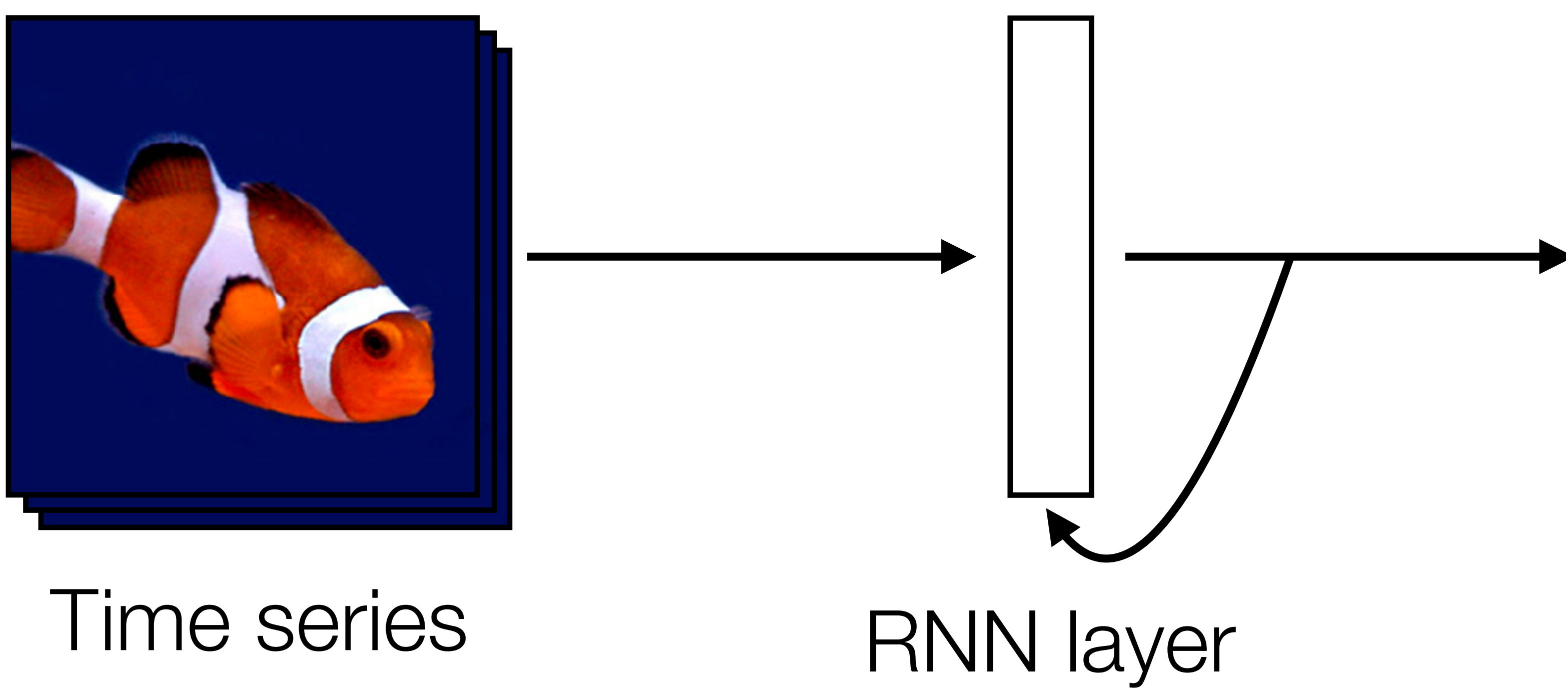


Under the Hood

```
current_state = 0

for input in input_sequence:

  output = g(input, current_state)

  current_state = output
```

Different functions g correspond to different RNNs

Example: SimpleRNN

memory stored in `current_state` variable!

```
current_state = 0

for input in input_sequence:

  output = activation(np.dot(W, input)
                      + np.dot(U, current_state)
                      + b)

  current_state = output
```

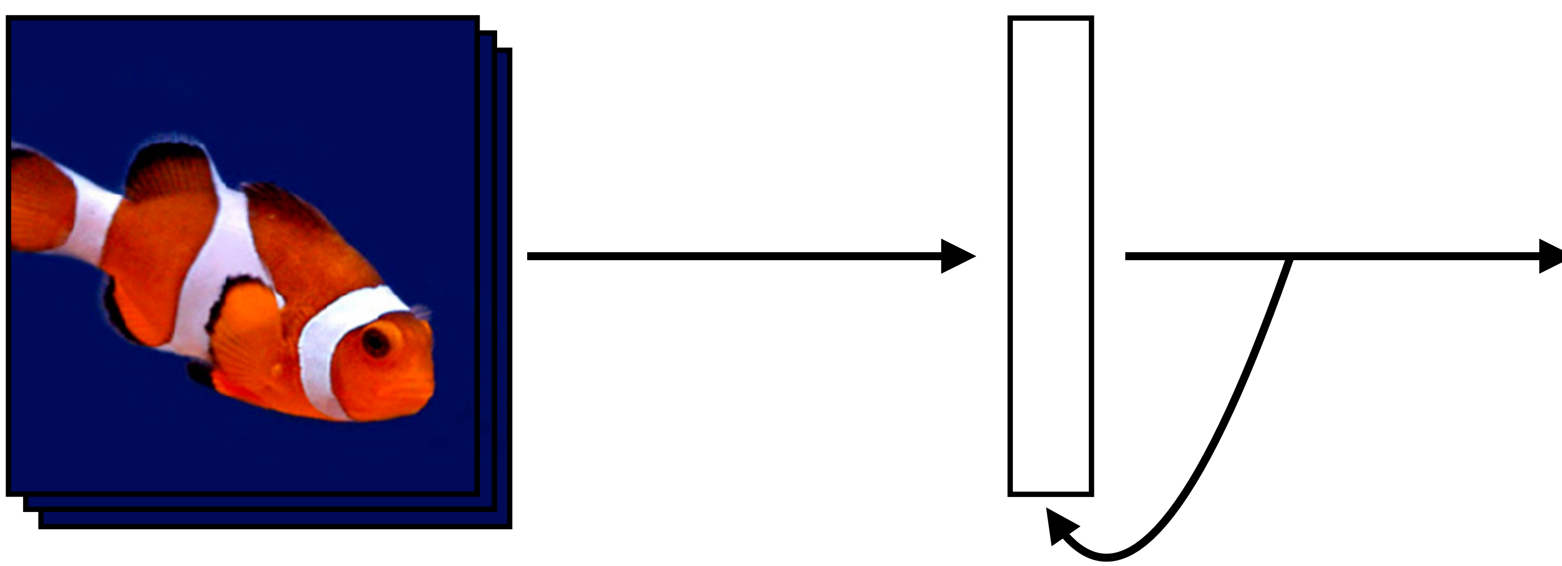
Activation function could, for instance, be ReLU

Parameters: weight matrices `W` & `U`, and bias vector `b`

Key idea: **it's like a dense layer in a `for` loop with some memory!**

RNNs

readily chains together with other neural net layers



Time series

RNN layer

like a dense layer that has memory

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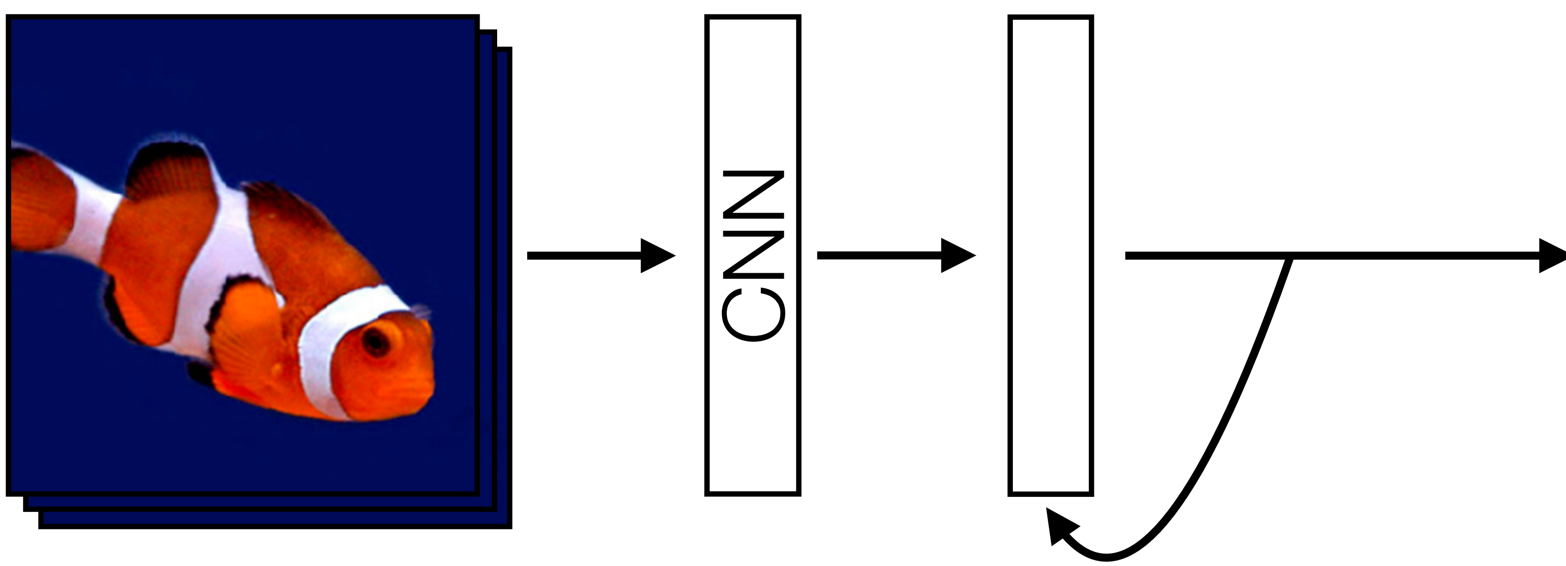

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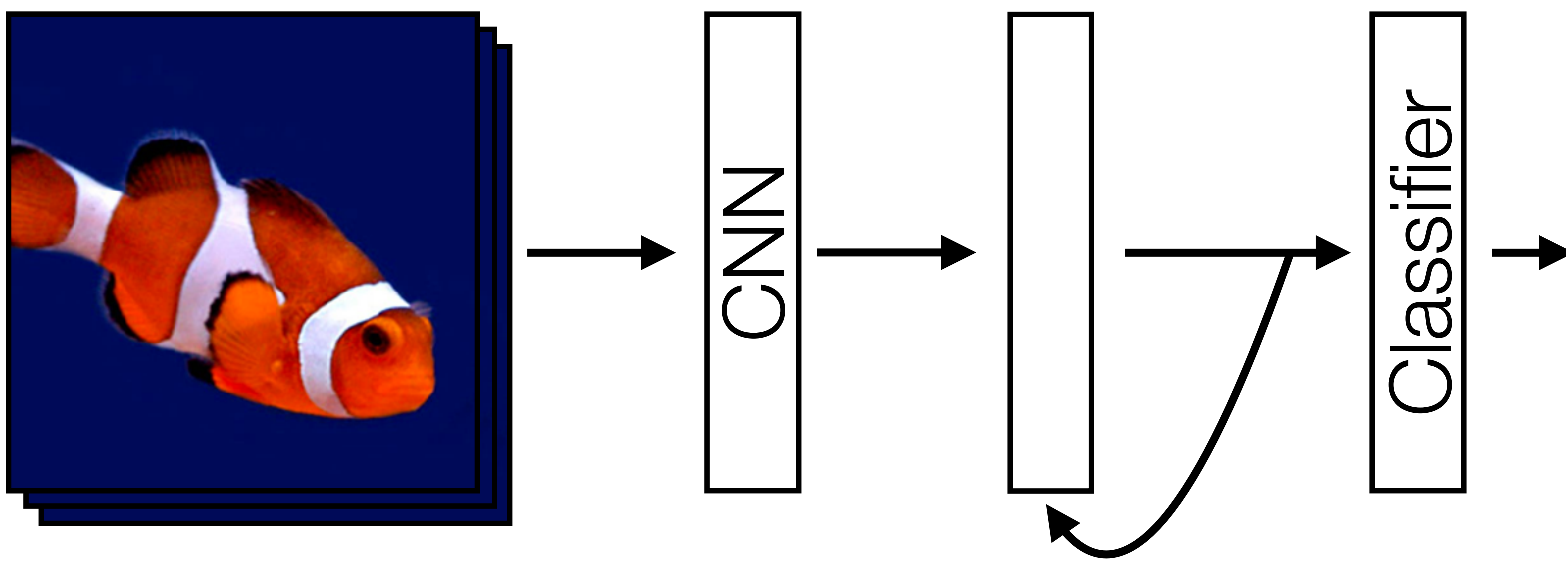

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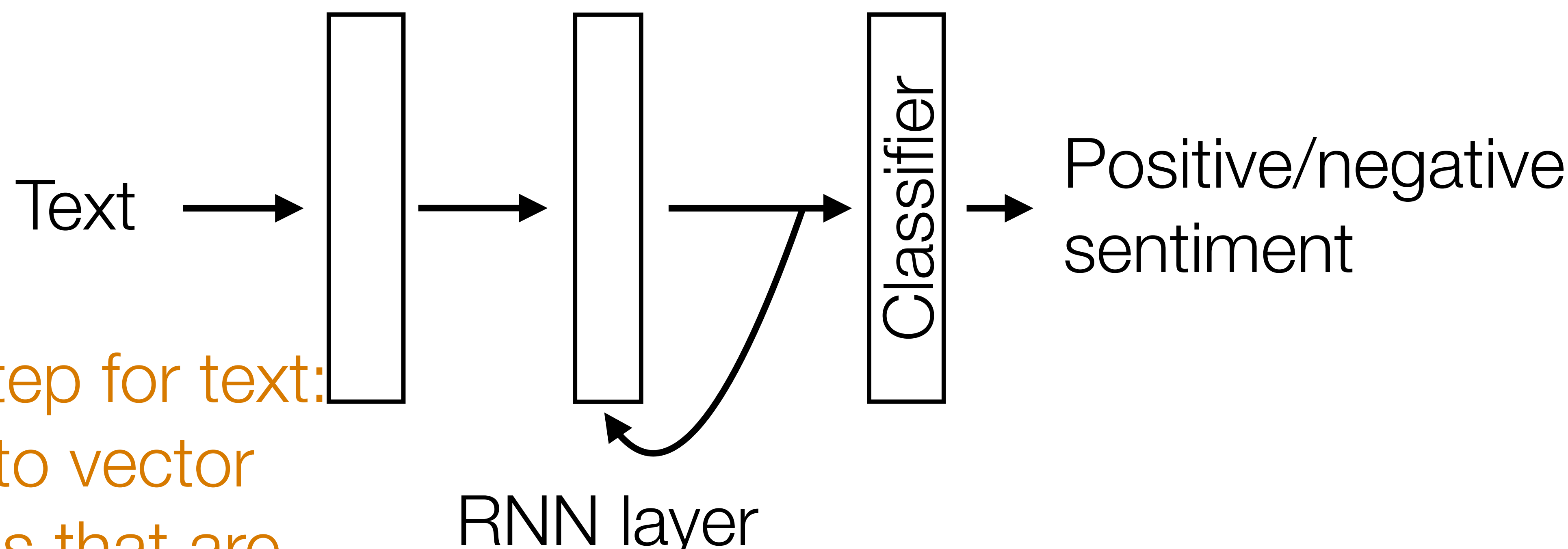
RNNs

Example: Given text (e.g., movie review, Tweet), figure out whether it has positive or negative sentiment (binary classification)



Common first step for text: turn words into vector representations that are semantically meaningful

(Flashback) Example Application of PMI: Word Embeddings

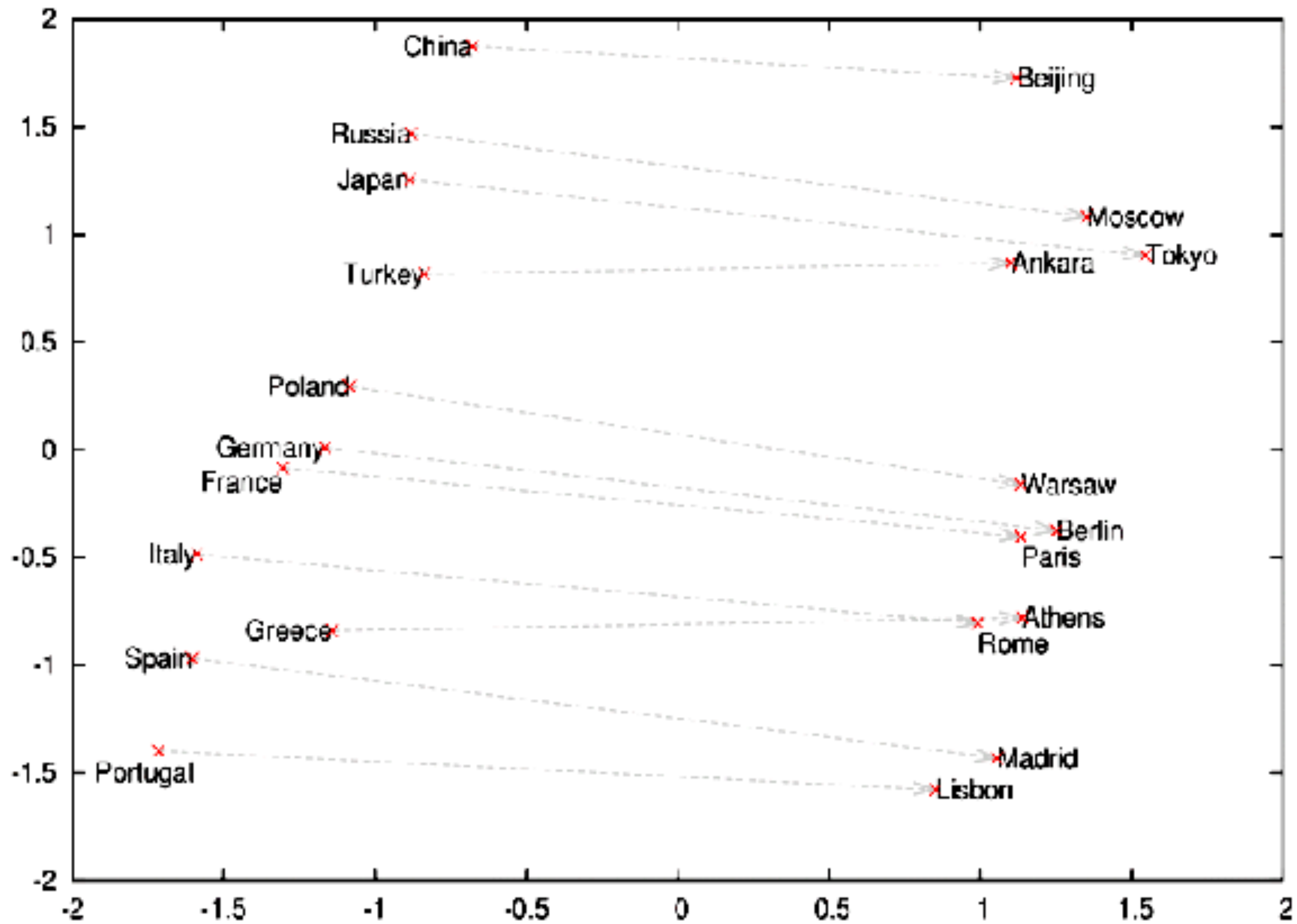


Image source: https://deeplearning4j.org/img/countries_capitals.png

Omer Levy and Yoav Goldberg. Neural word embeddings as implicit matrix factorization. NIPS 2014.

(Flashback) Do Data Actually Live on Manifolds?

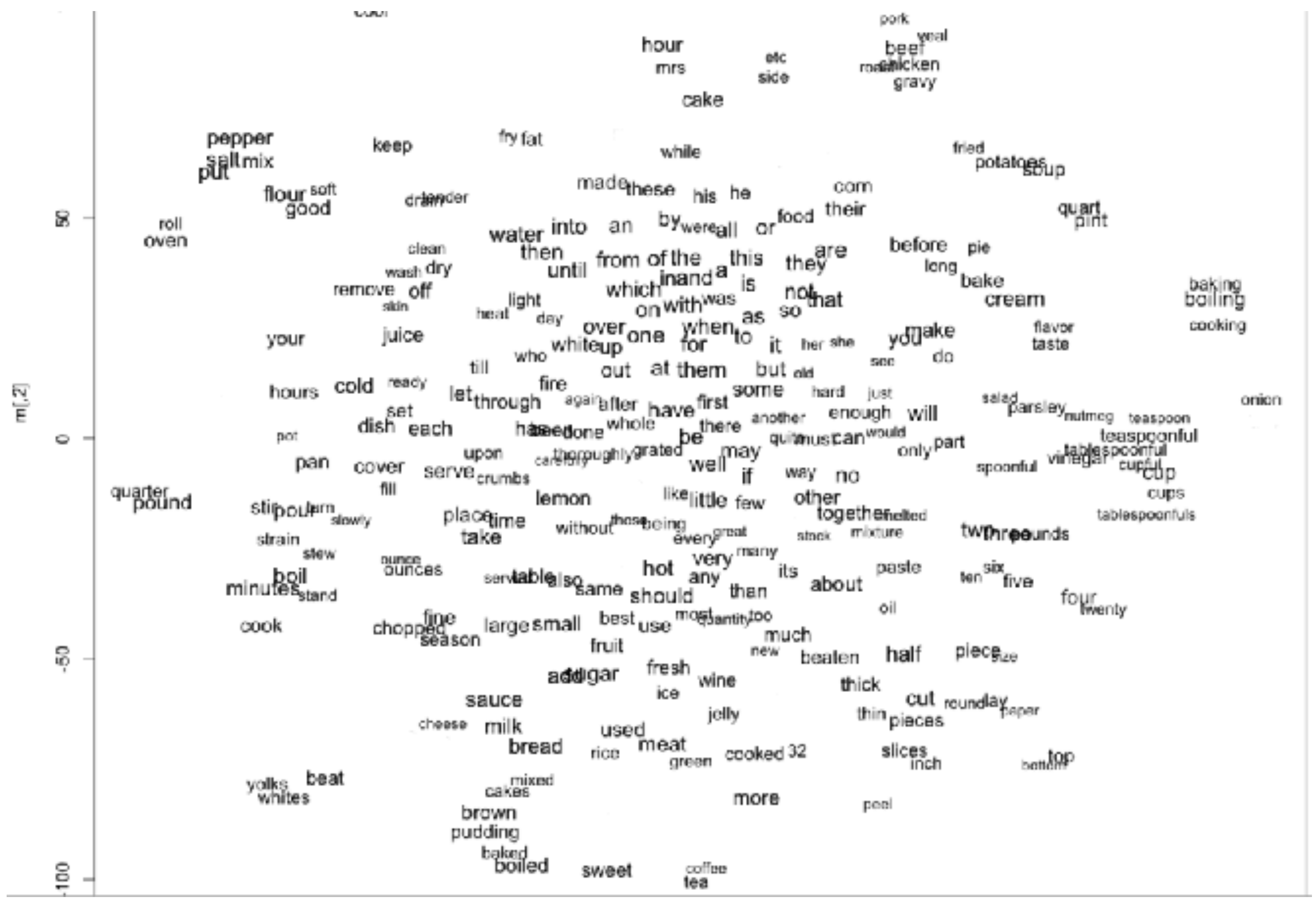
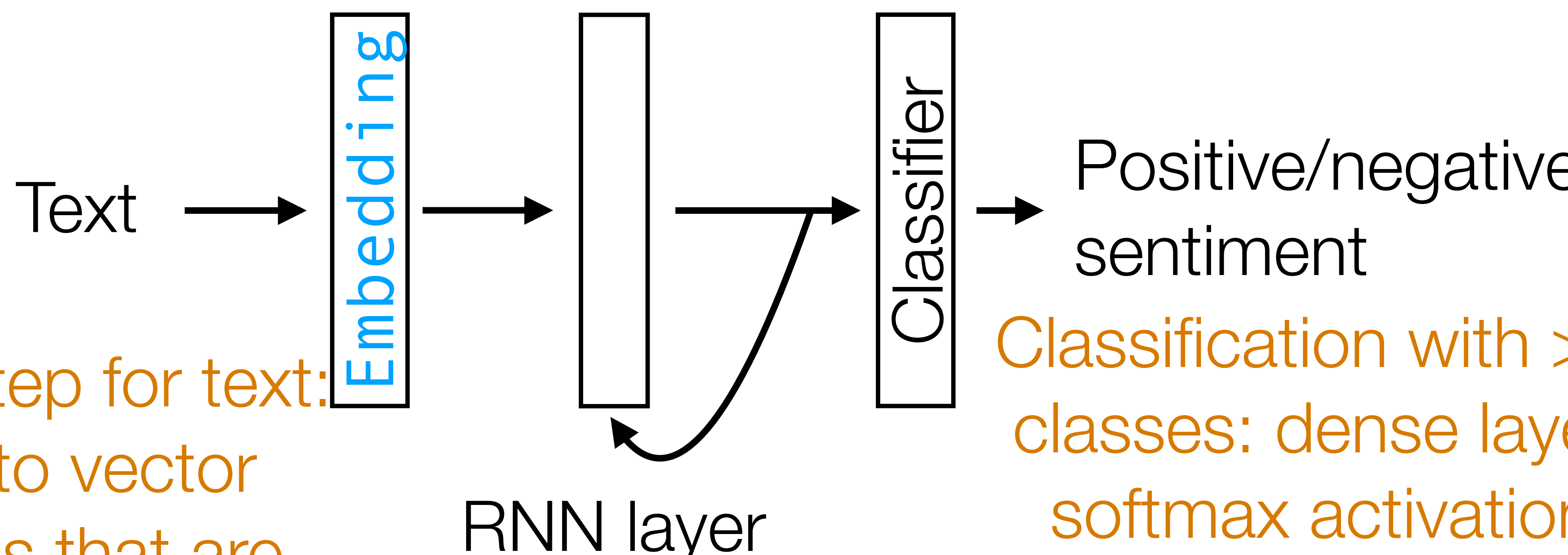


Image source: http://www.adityathakker.com/wp-content/uploads/2017/06/word-embeddings-994x675.png

RNNs

for loss function, replace *category cross entropy* with *binary cross entropy*

Example: Given text (e.g., movie review, Tweet), figure out whether it has positive or negative sentiment (binary classification)



Common first step for text: turn words into vector representations that are semantically meaningful

In `keras`, use the `Embedding` layer

Classification with > 2 classes: dense layer, softmax activation

Classification with 2 classes: dense layer with 2 neurons & softmax equivalent to dense layer with 1 neuron & sigmoid activation (called **logistic regression**)

Word Embeddings

Example of **self-supervised learning**

Even without labels, we can set up a prediction task!

Hide part of training data and try to predict what you've hid!

Word embeddings will be covered in your next recitation
(it's a clever application of predictive data analytics concepts)

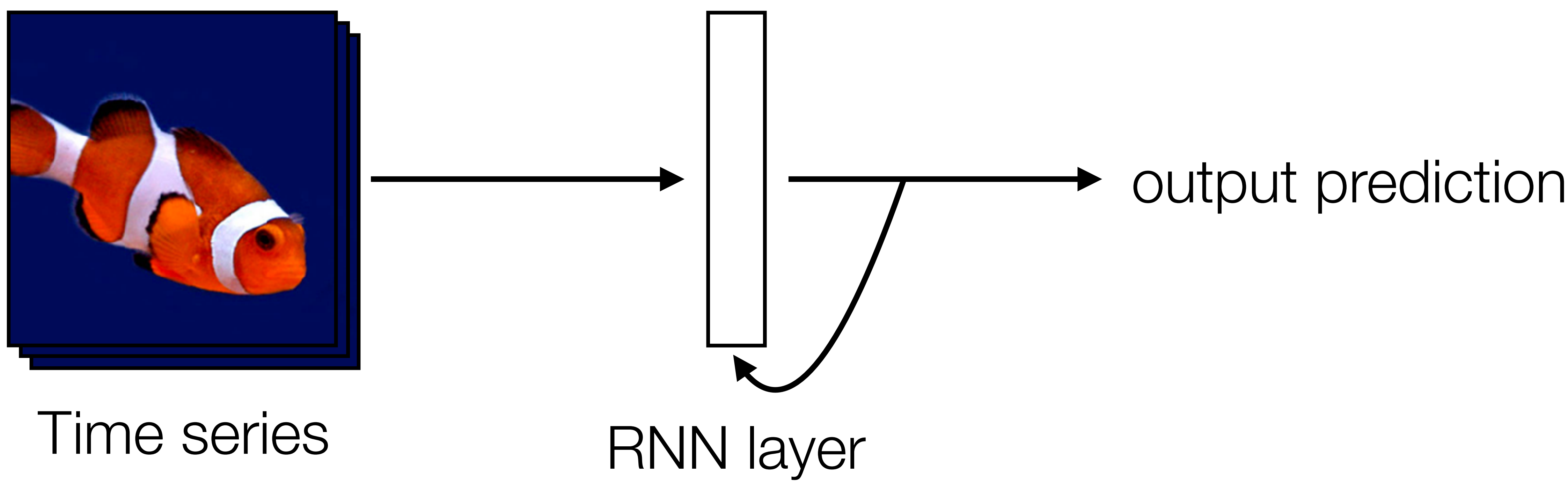
RNNs

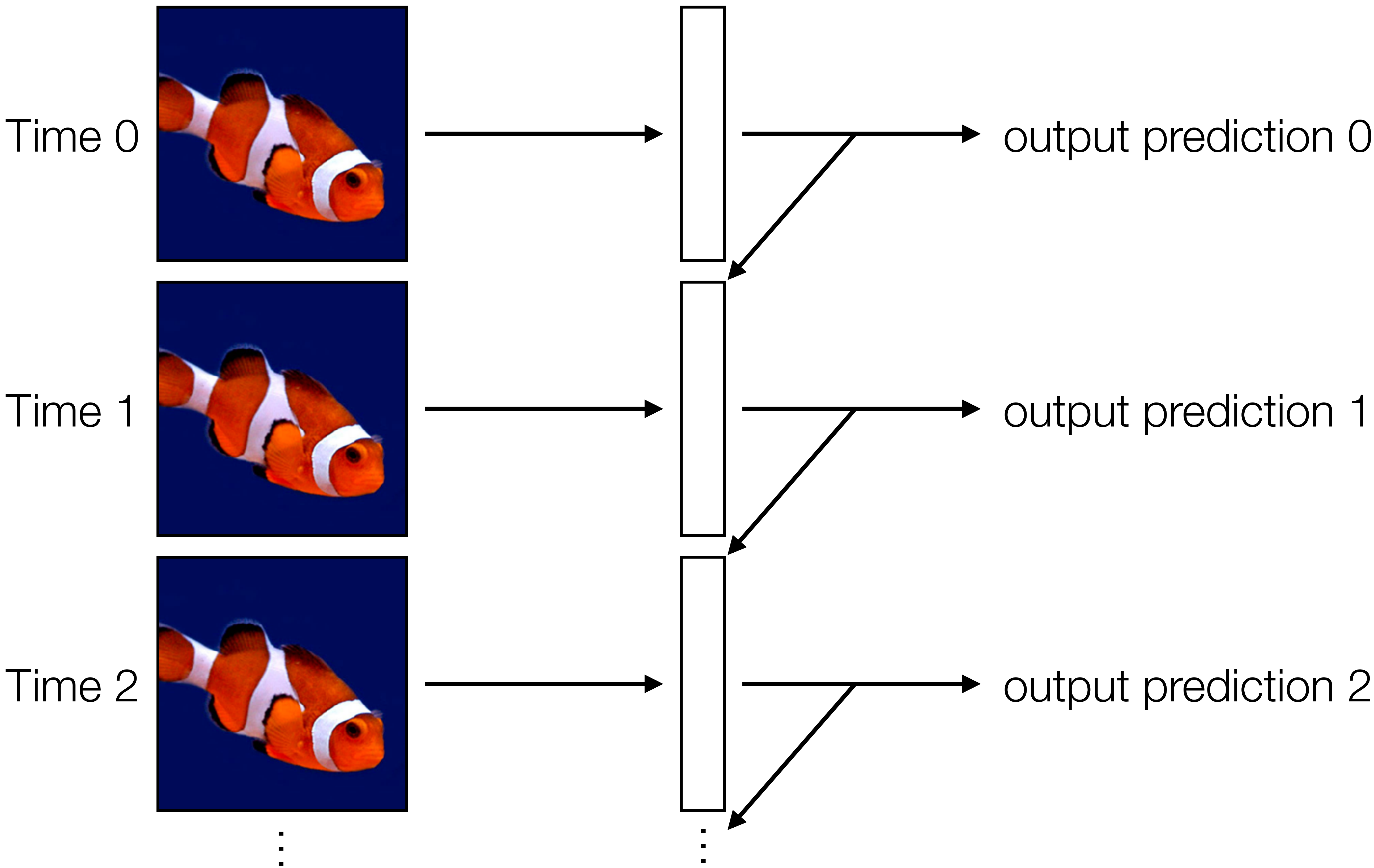
Demo

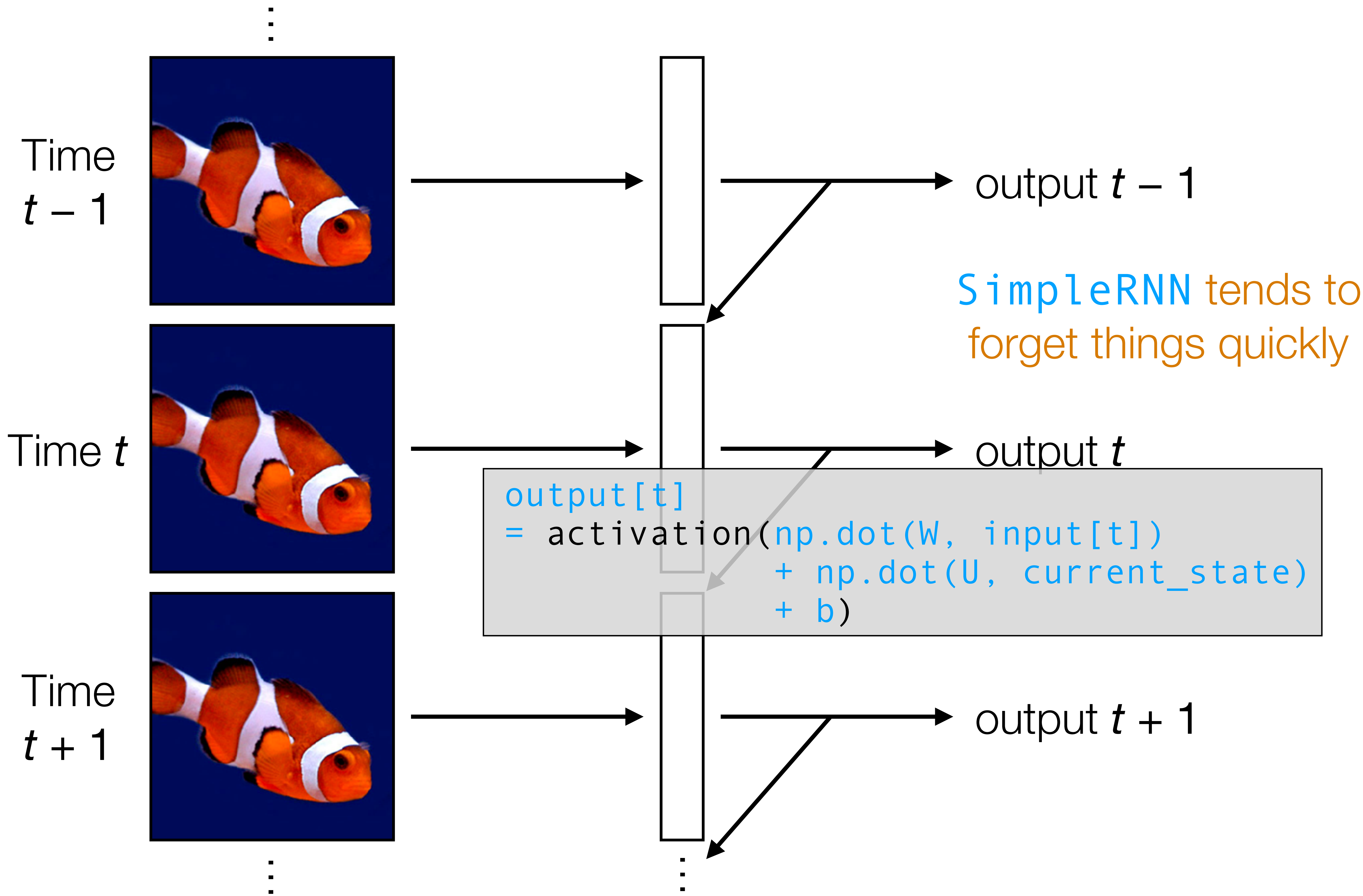
RNNs

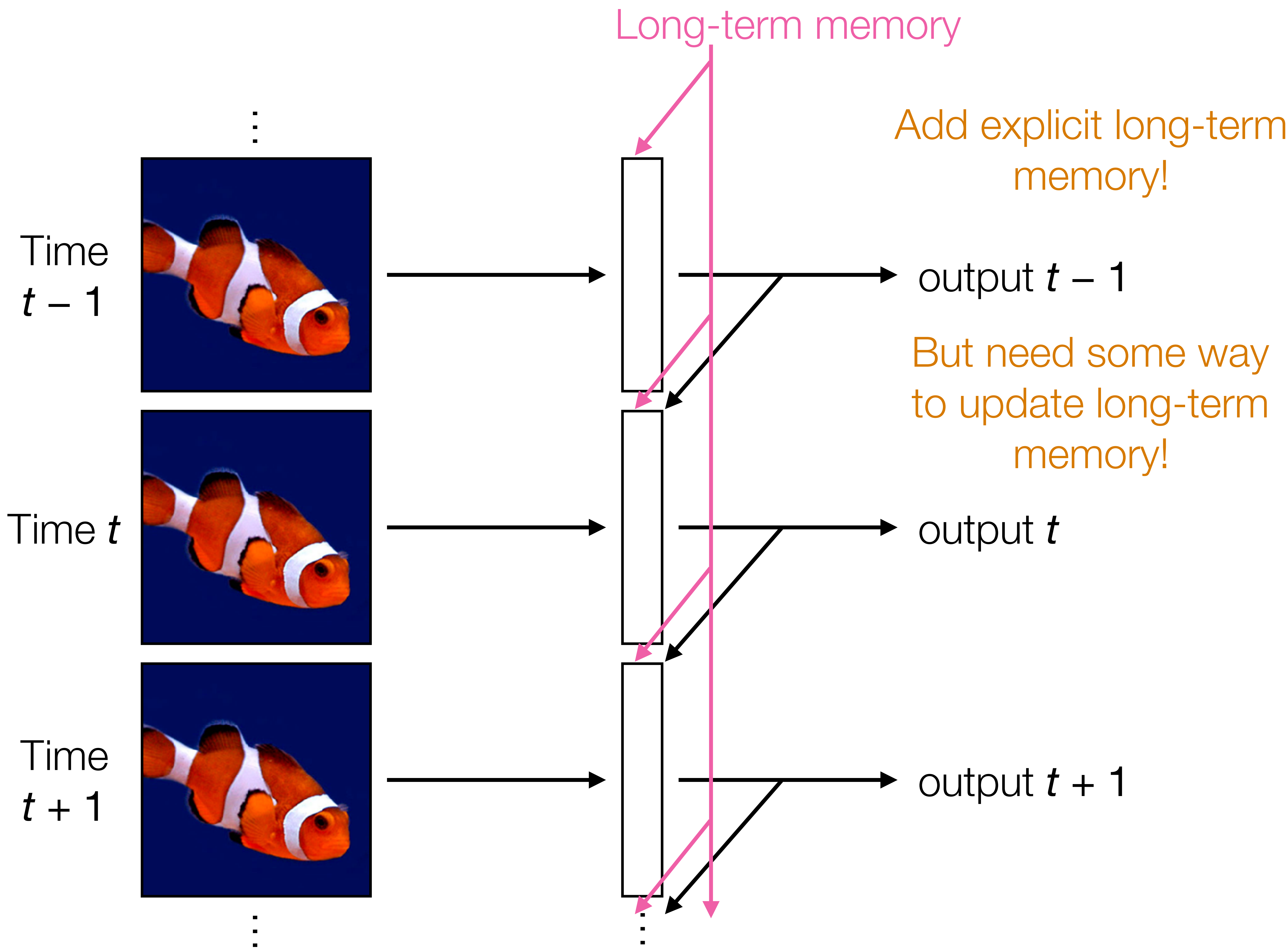
- Neatly handles time series in which there is some sort of global structure, so memory helps
  - If time series doesn't have global structure, RNN performance might not be much better than 1D CNN
- An RNN layer by itself doesn't take advantage of image/text structure!
  - For images: combine with convolution layer(s)
  - For text: combine with embedding layer

A Little Bit More Detail

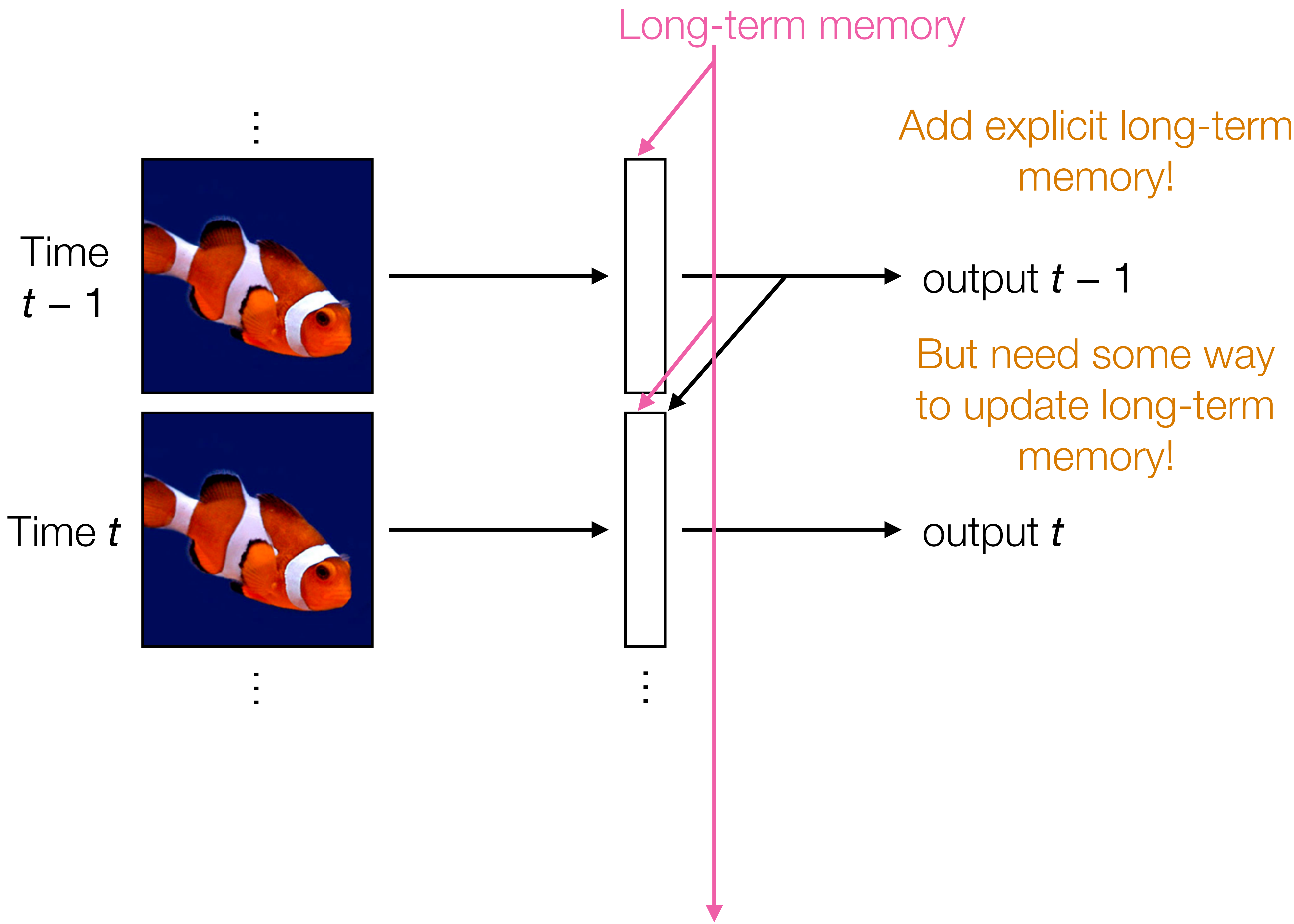



Time 0
Time 1
Time 2
output prediction 0
output prediction 1
output prediction 2


Time
t – 1
Time t
Time
t + 1
output t – 1
output t
output t + 1
SimpleRNN tends to
forget things quickly
output[t]
= activation(np.dot(W, input[t])
+ np.dot(U, current_state)
+ b)



Long-term memory
Add explicit long-term memory!
But need some way to update long-term memory!
Time $t-1$
Time t
Time $t+1$
output $t-1$
output t
output $t+1$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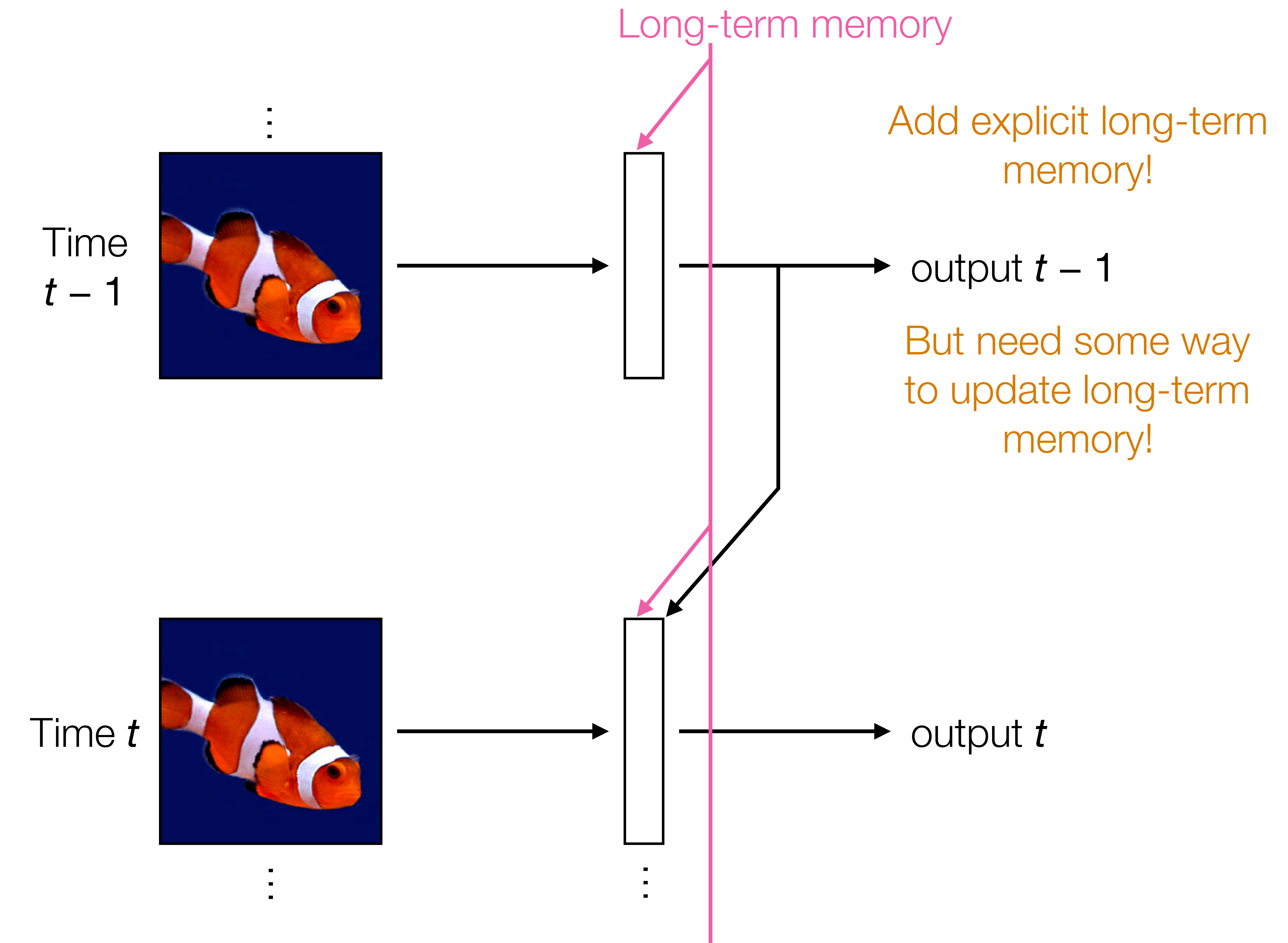
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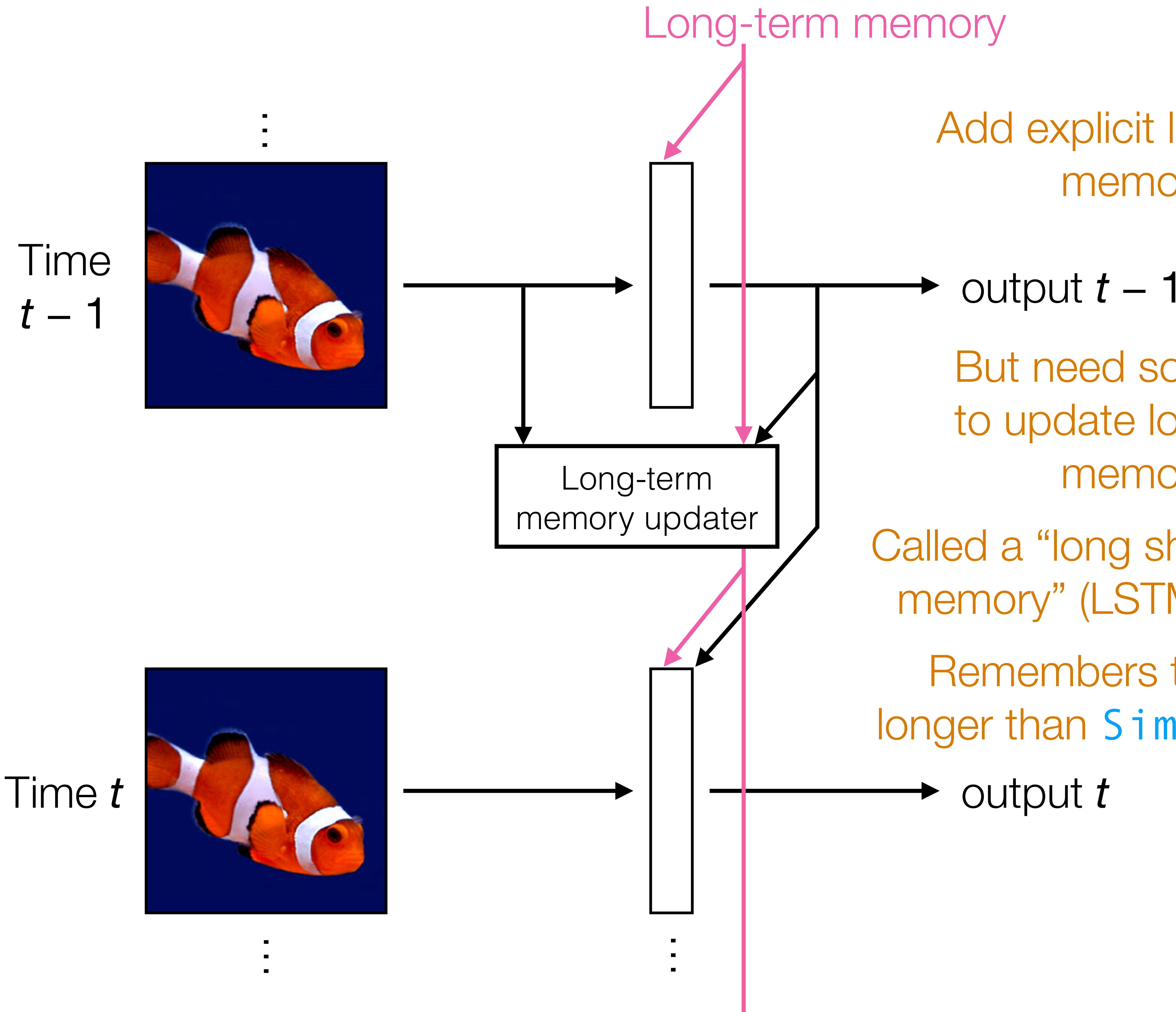


Add explicit long-term memory!

But need some way to update long-term memory!

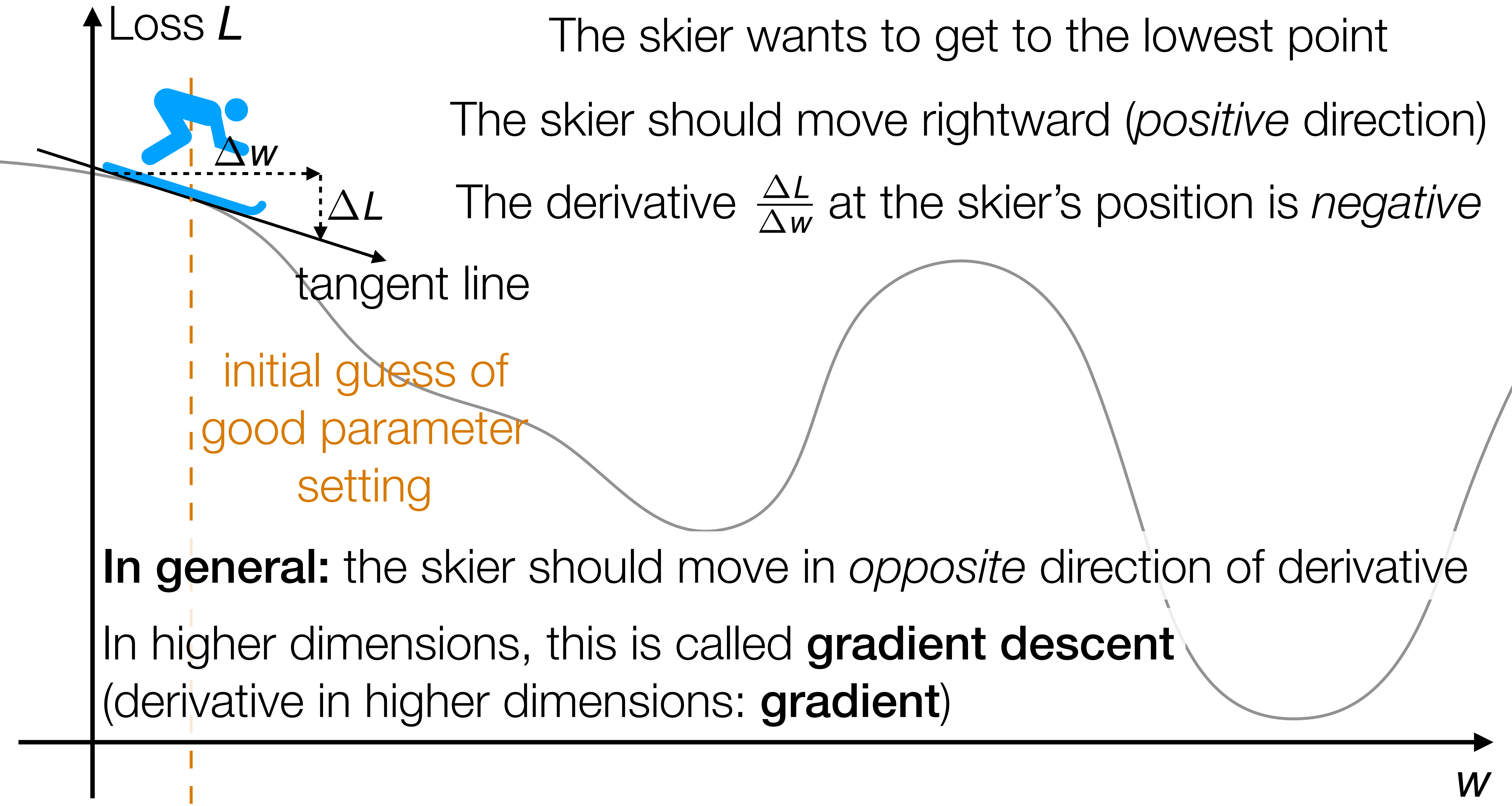
Called a "long short-term memory" (LSTM) RNN

Remembers things longer than `SimpleRNN`

Learning a Deep Net

Gradient Descent

Suppose the neural network has a single real number parameter ***w***



The skier wants to get to the lowest point

The skier should move rightward (*positive* direction)

The derivative $\frac{\Delta L}{\Delta w}$ at the skier's position is *negative*

In general: the skier should move in *opposite* direction of derivative

In higher dimensions, this is called **gradient descent**
(derivative in higher dimensions: **gradient**)

Gradient Descent

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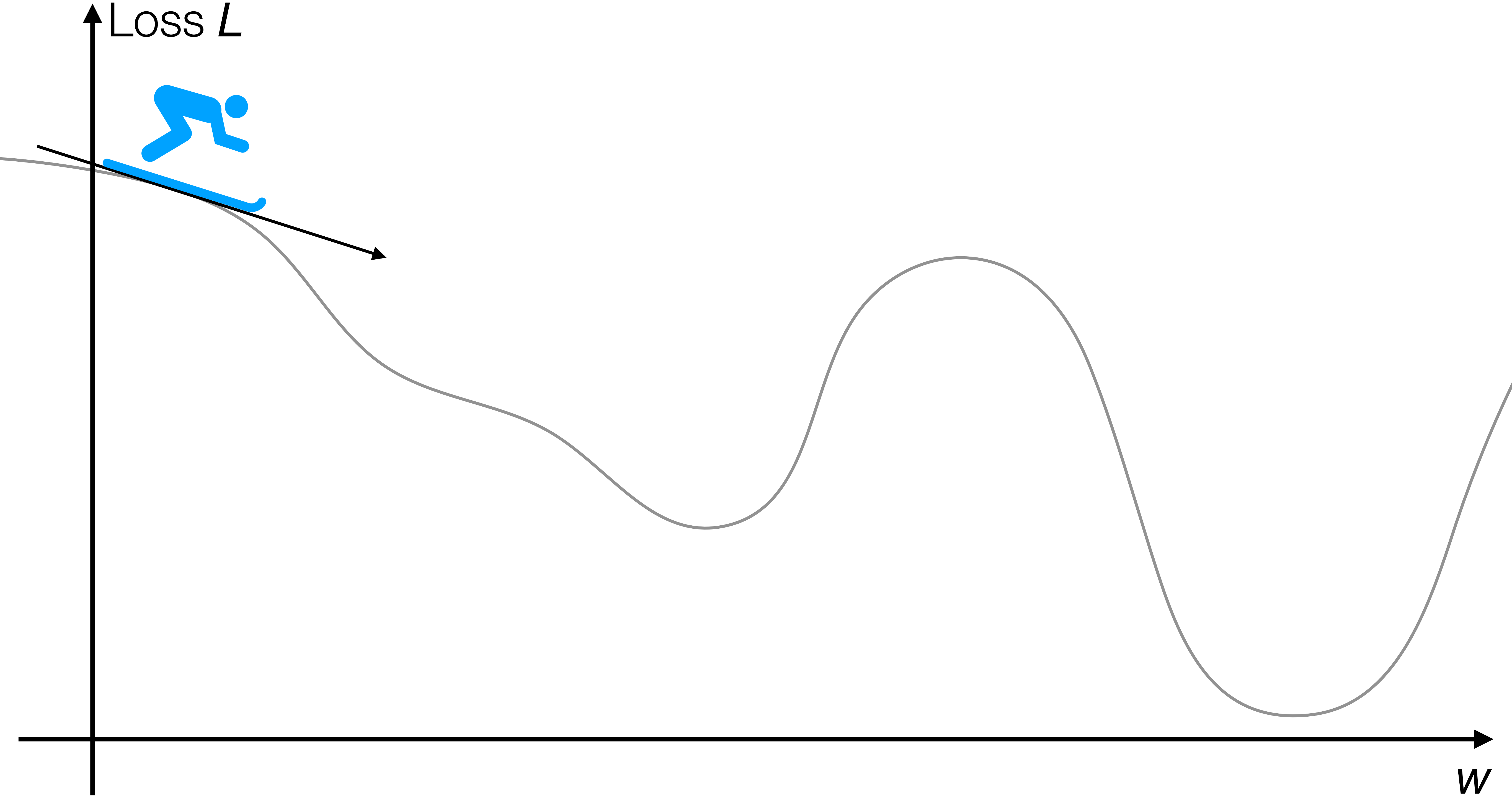

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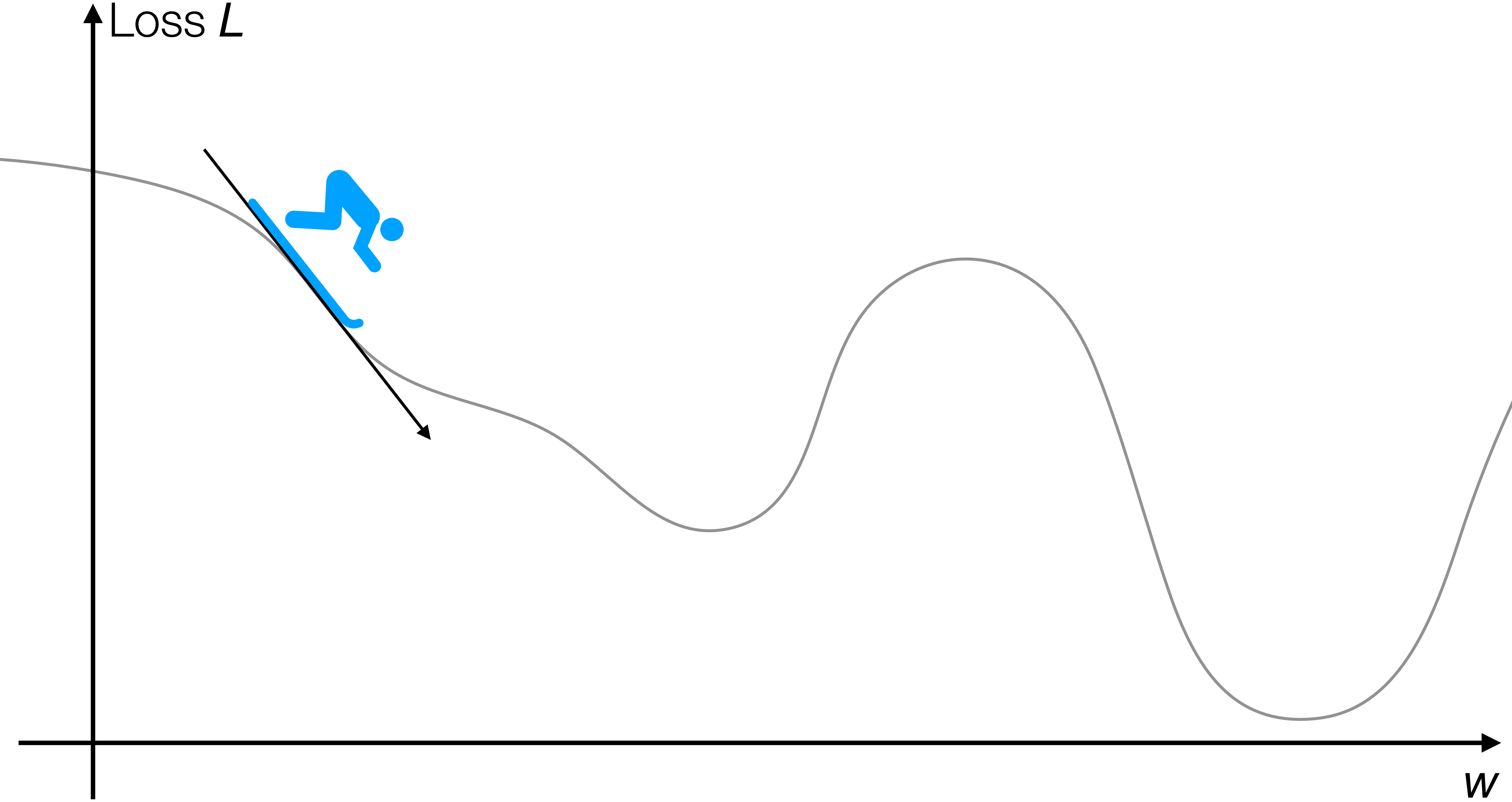

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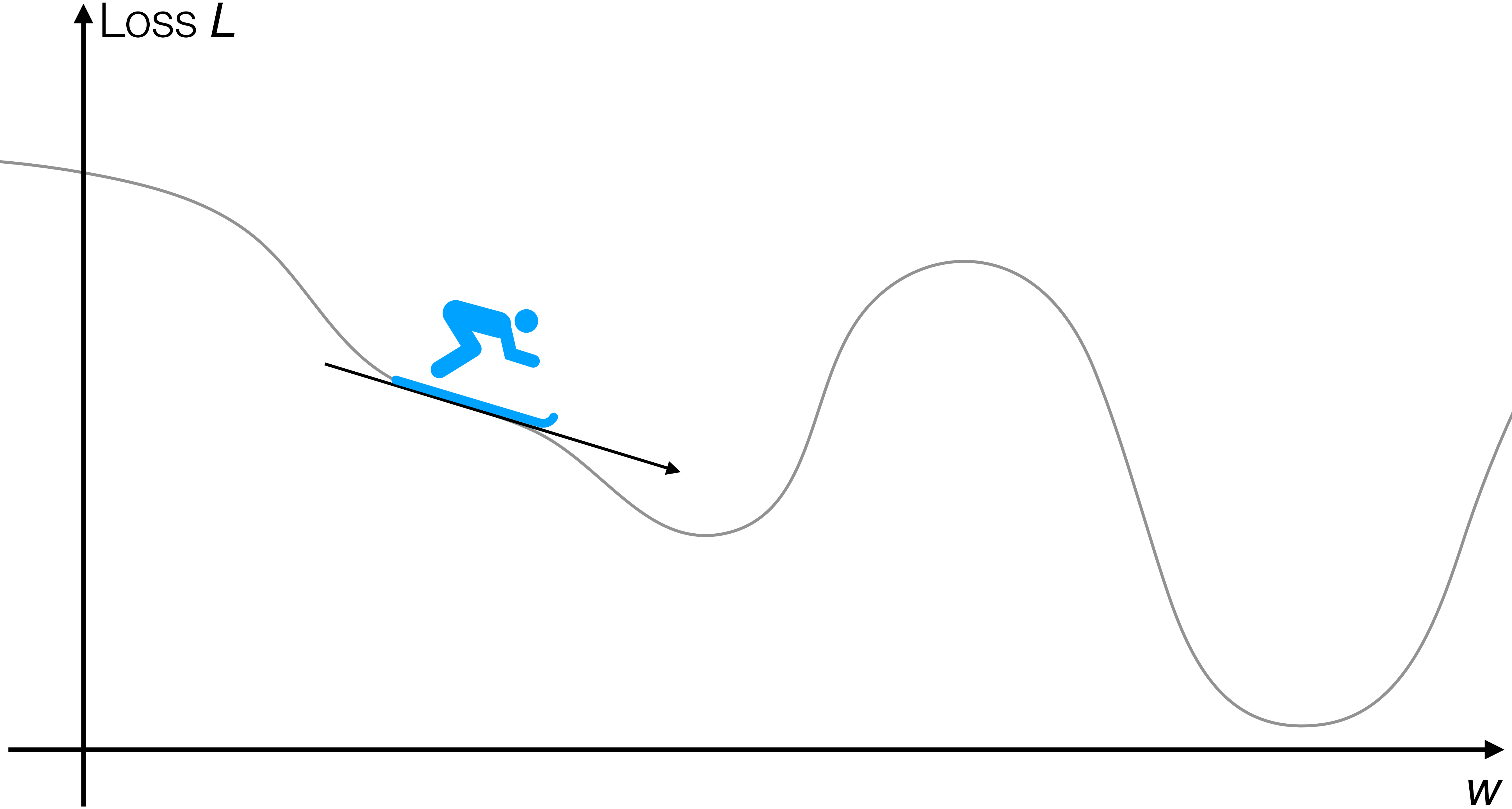

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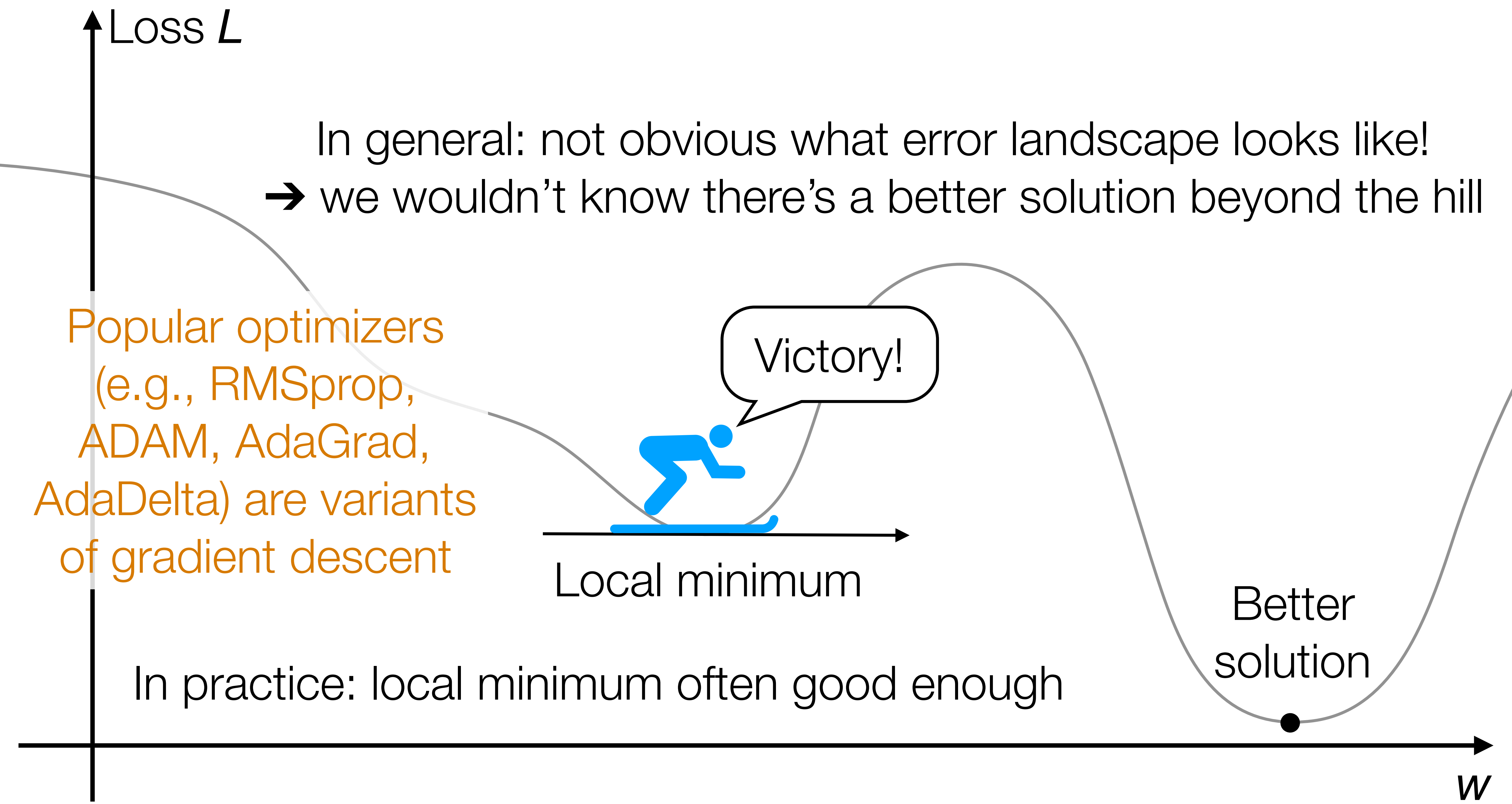


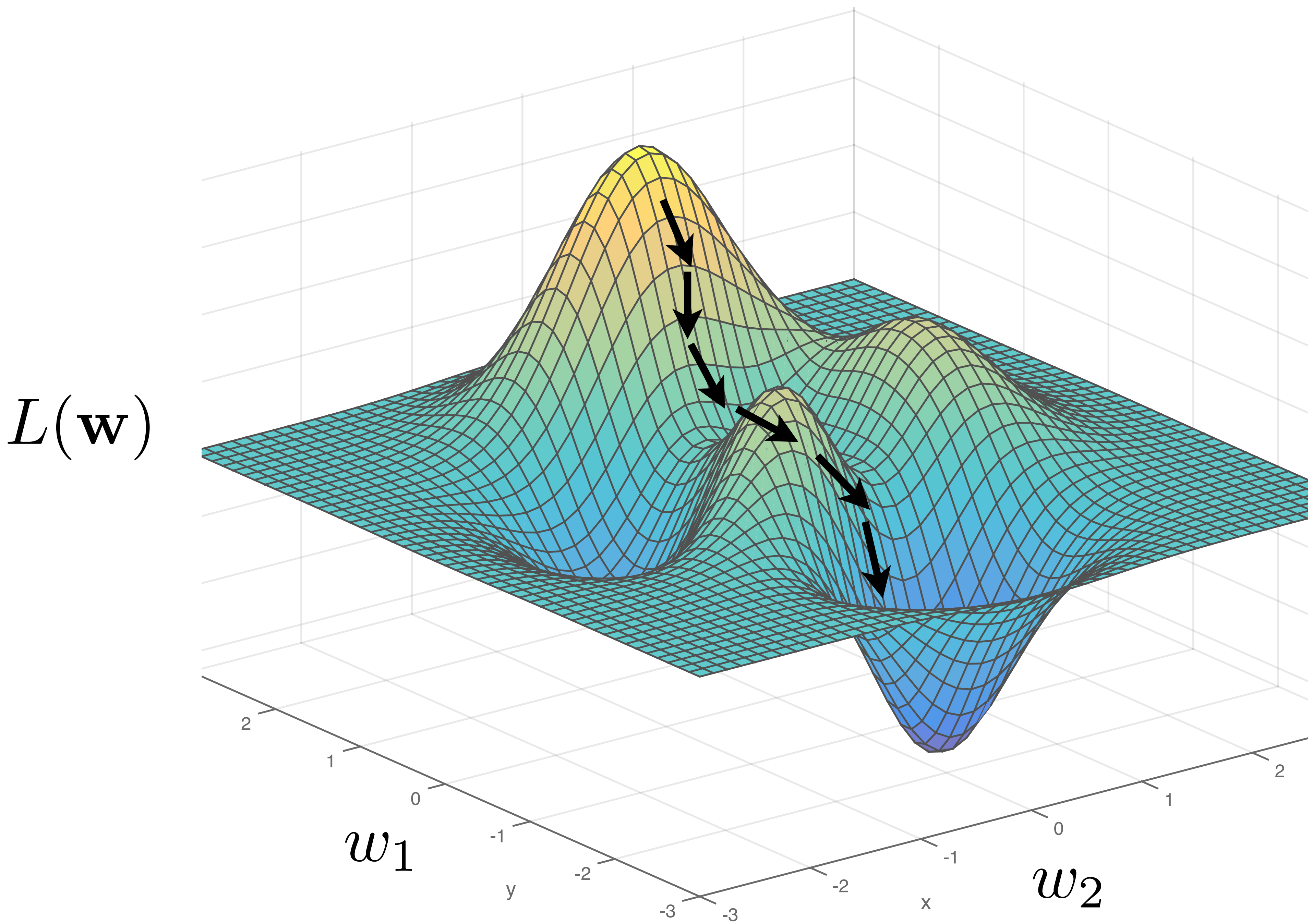
In general: not obvious what error landscape looks like!
➔ we wouldn't know there's a better solution beyond the hill

Popular optimizers (e.g., RMSprop, ADAM, AdaGrad, AdaDelta) are variants of gradient descent

In practice: local minimum often good enough

Gradient Descent

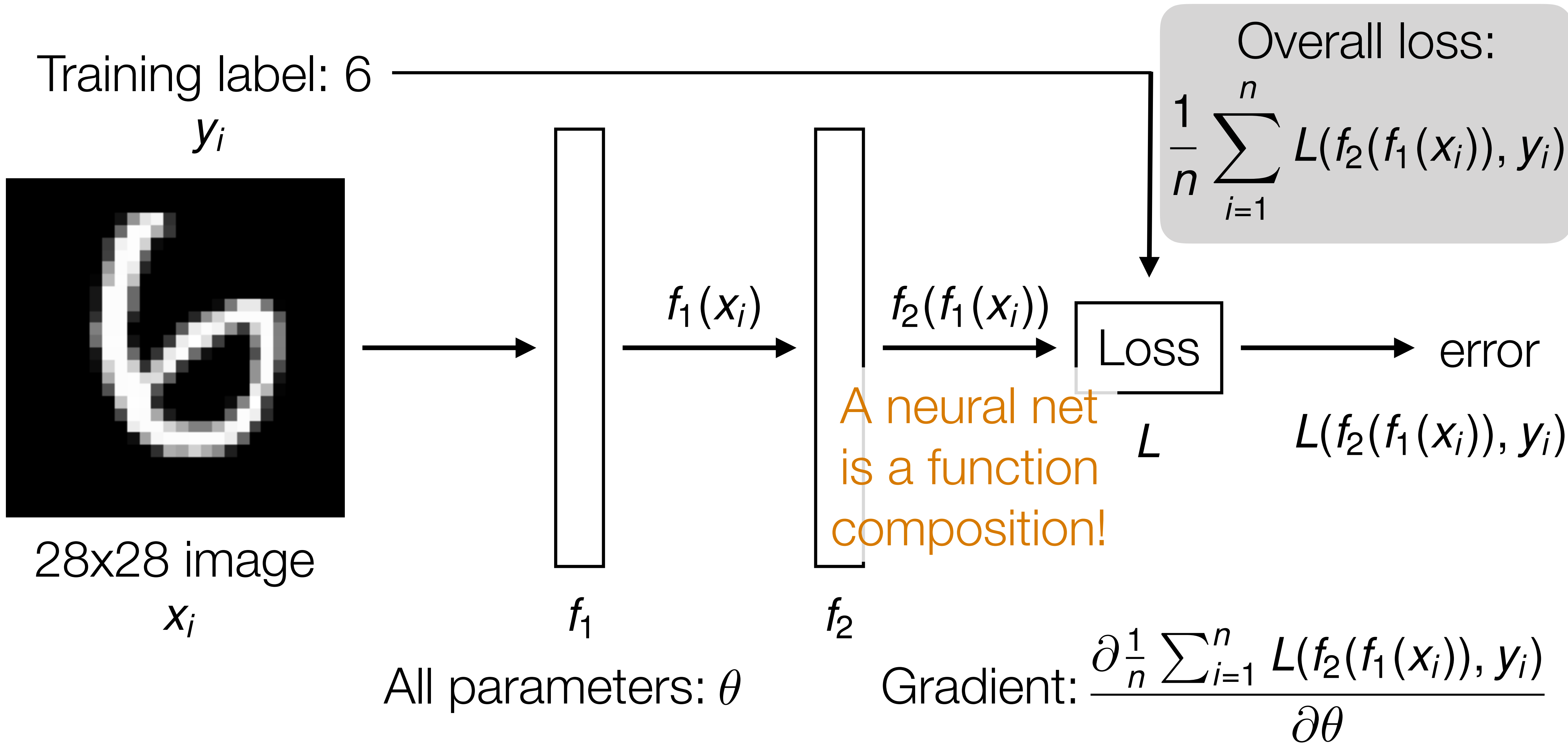
2D example



Slide by Phillip Isola

Remark: In practice, deep nets often have > *millions* of parameters, so *very* high-dimensional gradient descent

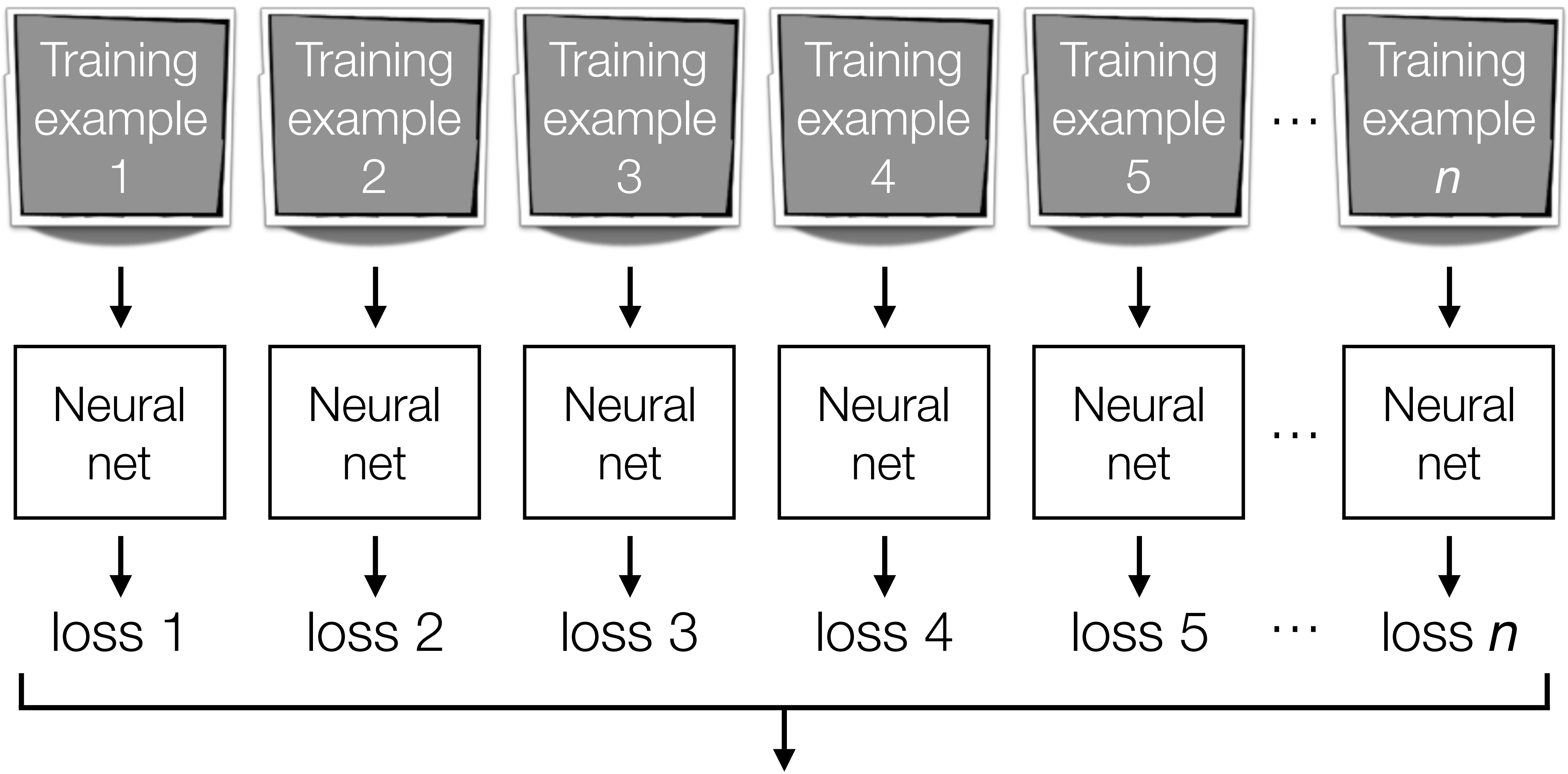
Handwritten Digit Recognition



Automatic differentiation is crucial in learning deep nets!

Careful derivative chain rule calculation: **back-propagation**

Gradient Descent



We have to compute lots of gradients to help the skier know where to go!

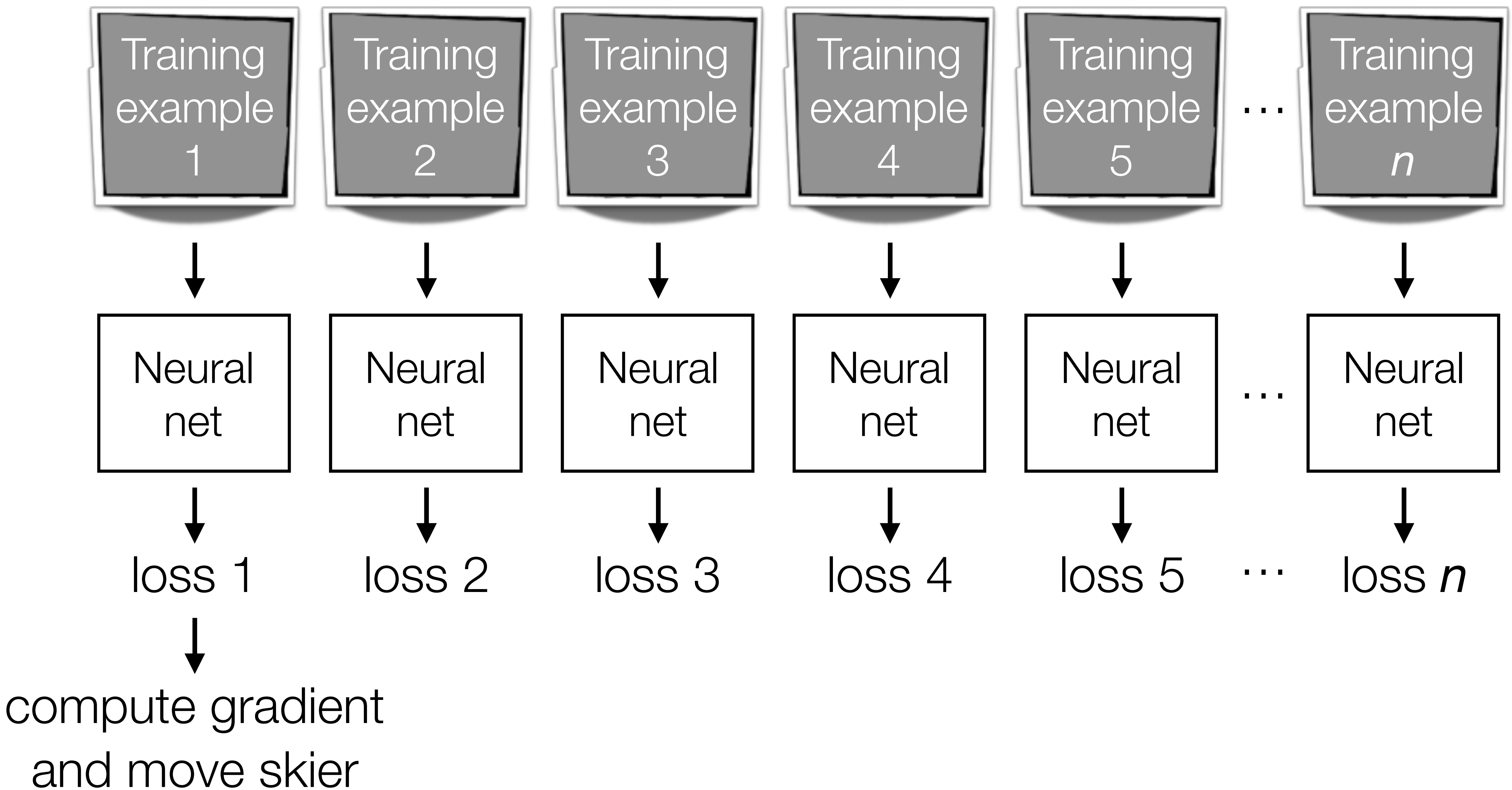
average loss

↓

compute gradient and move skier

Computing gradients using all the training data seems really expensive!

Stochastic Gradient Descent (SGD)



SGD: compute gradient using only 1 training example at a time
(can think of this gradient as a noisy approximation of the “full” gradient)

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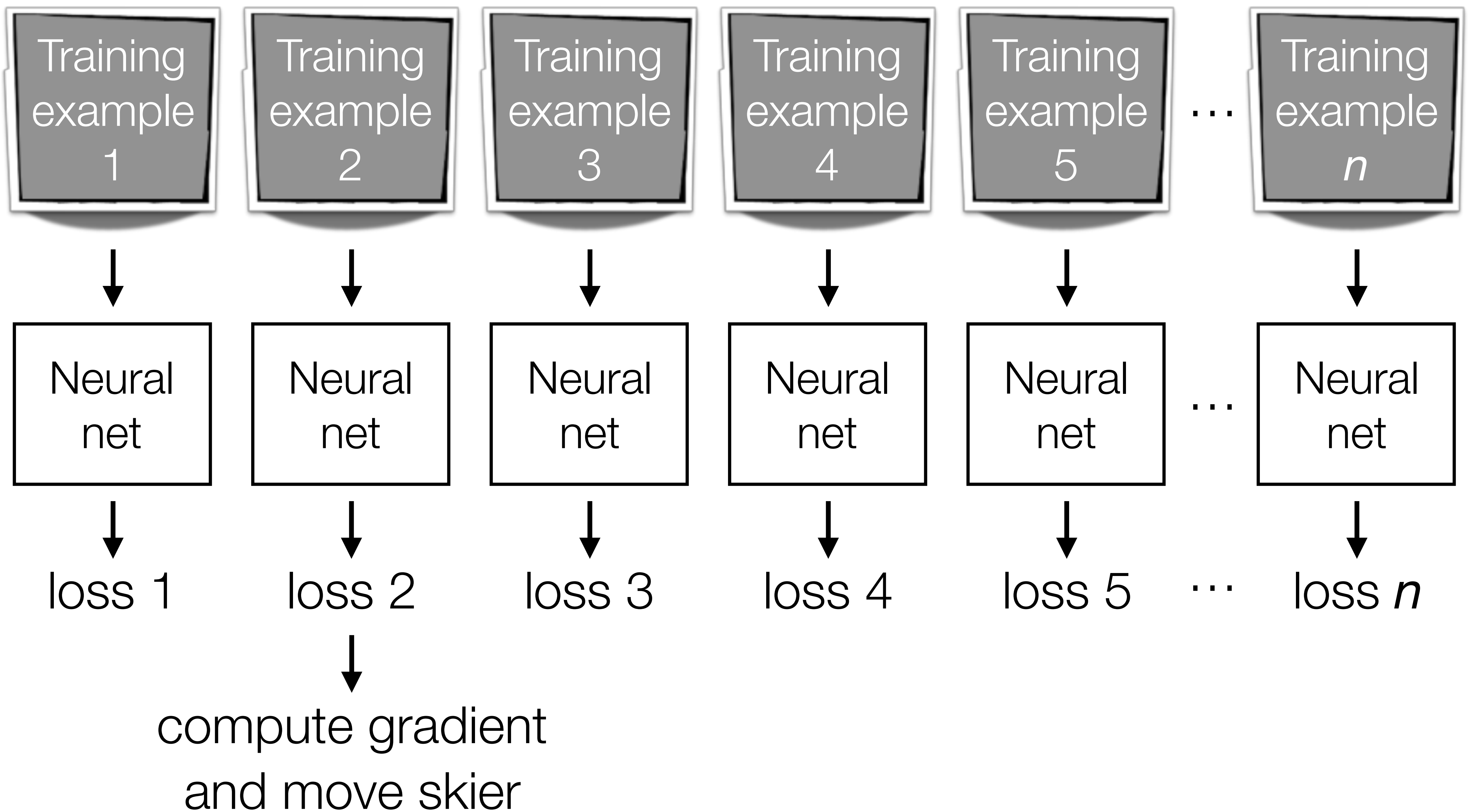

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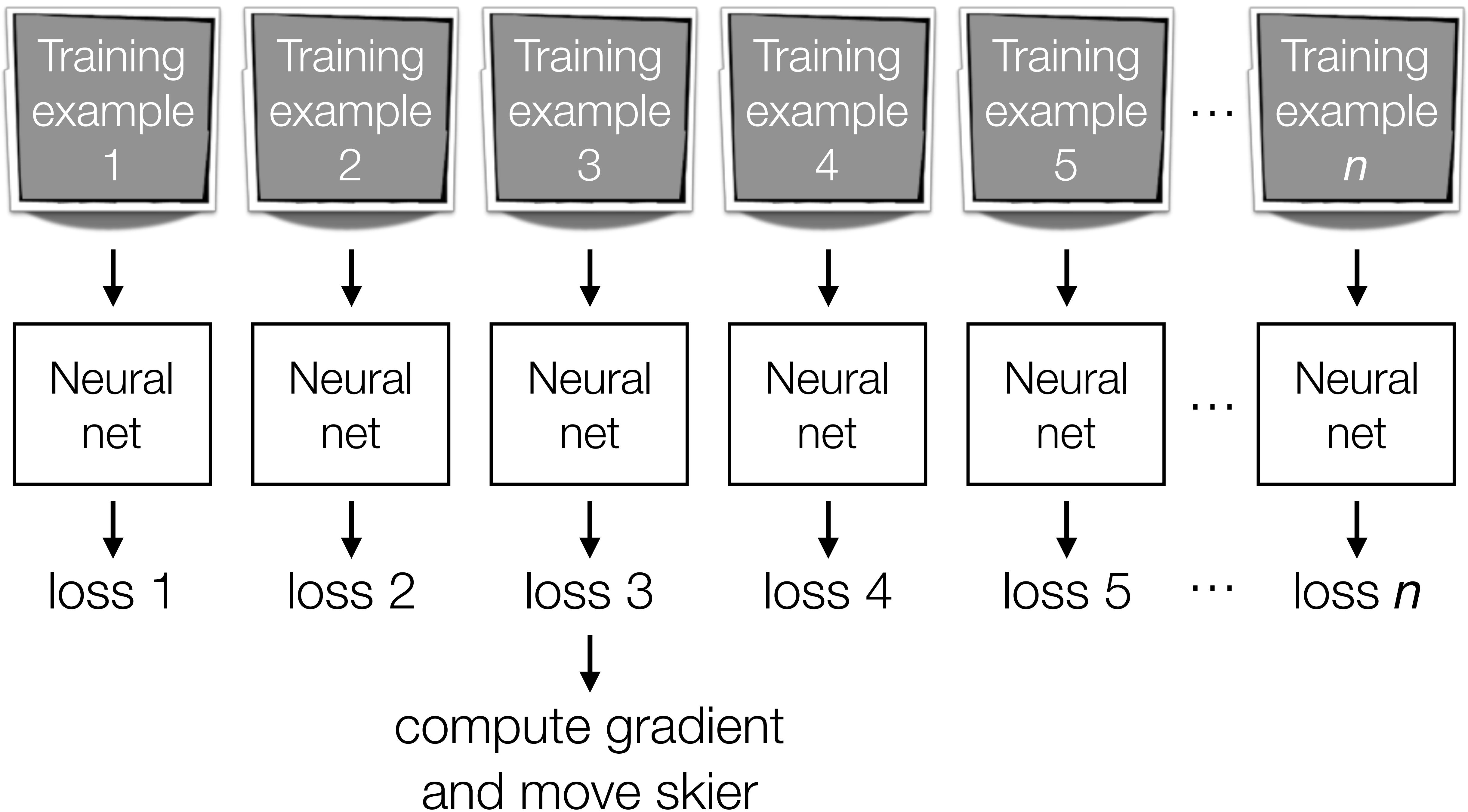

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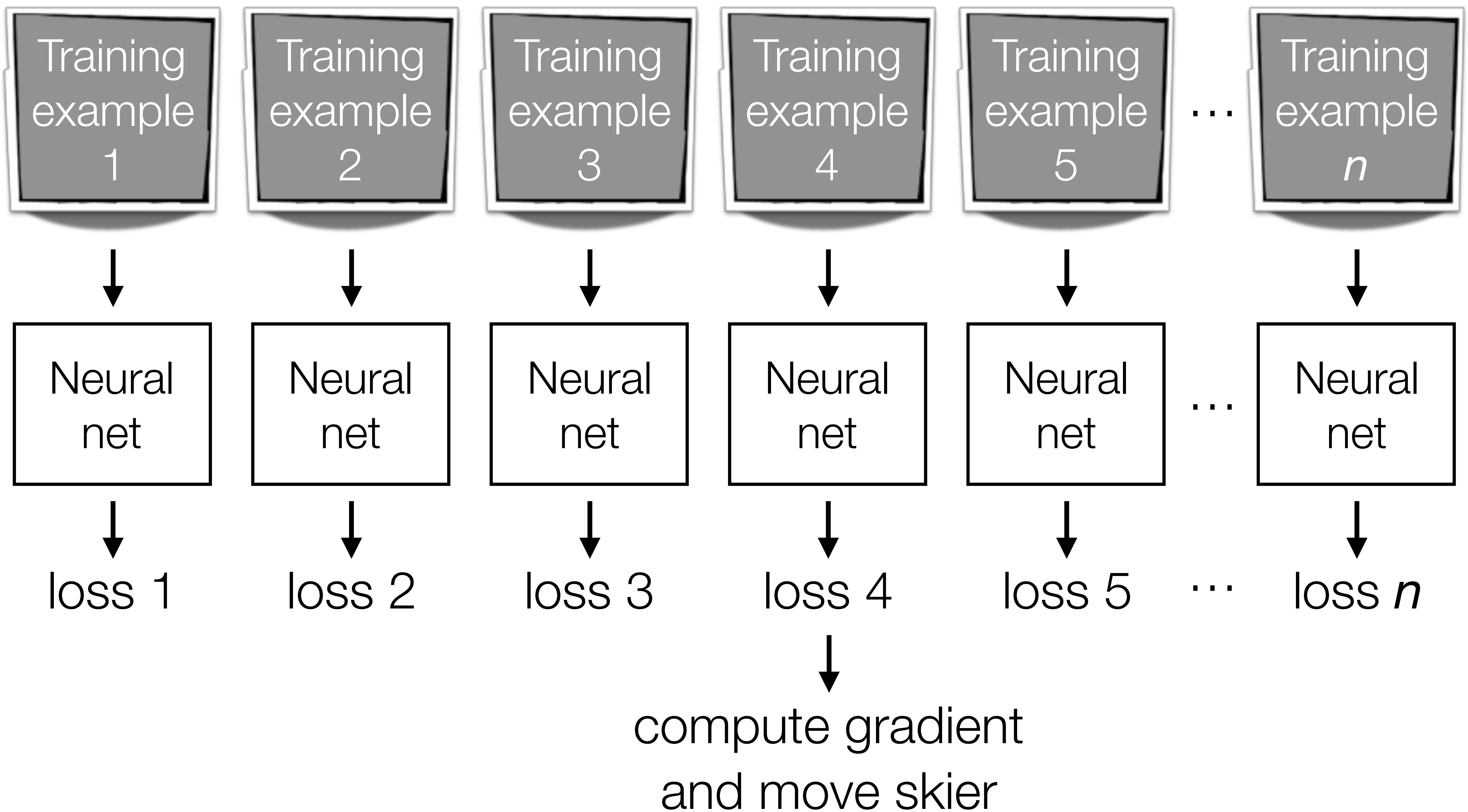

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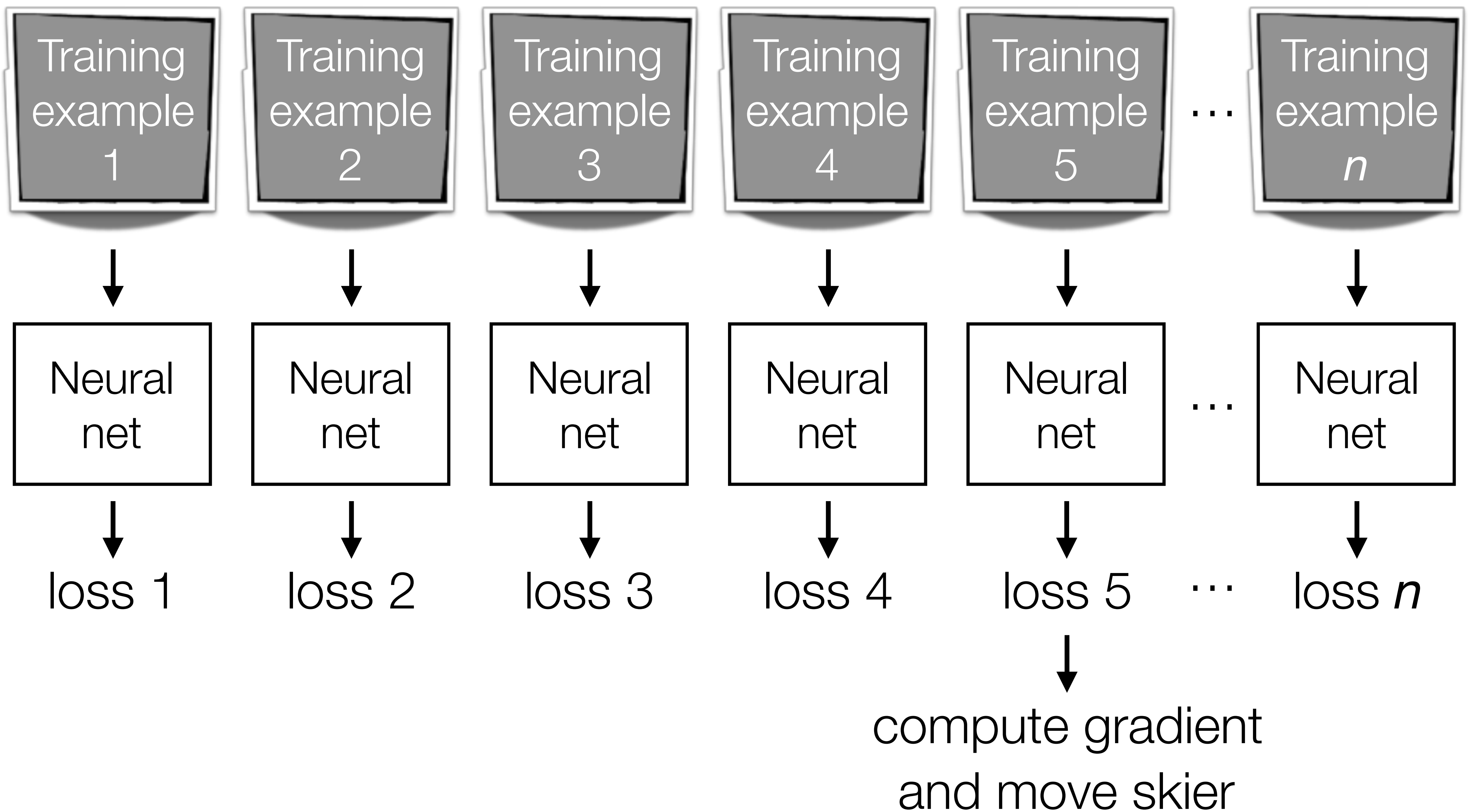

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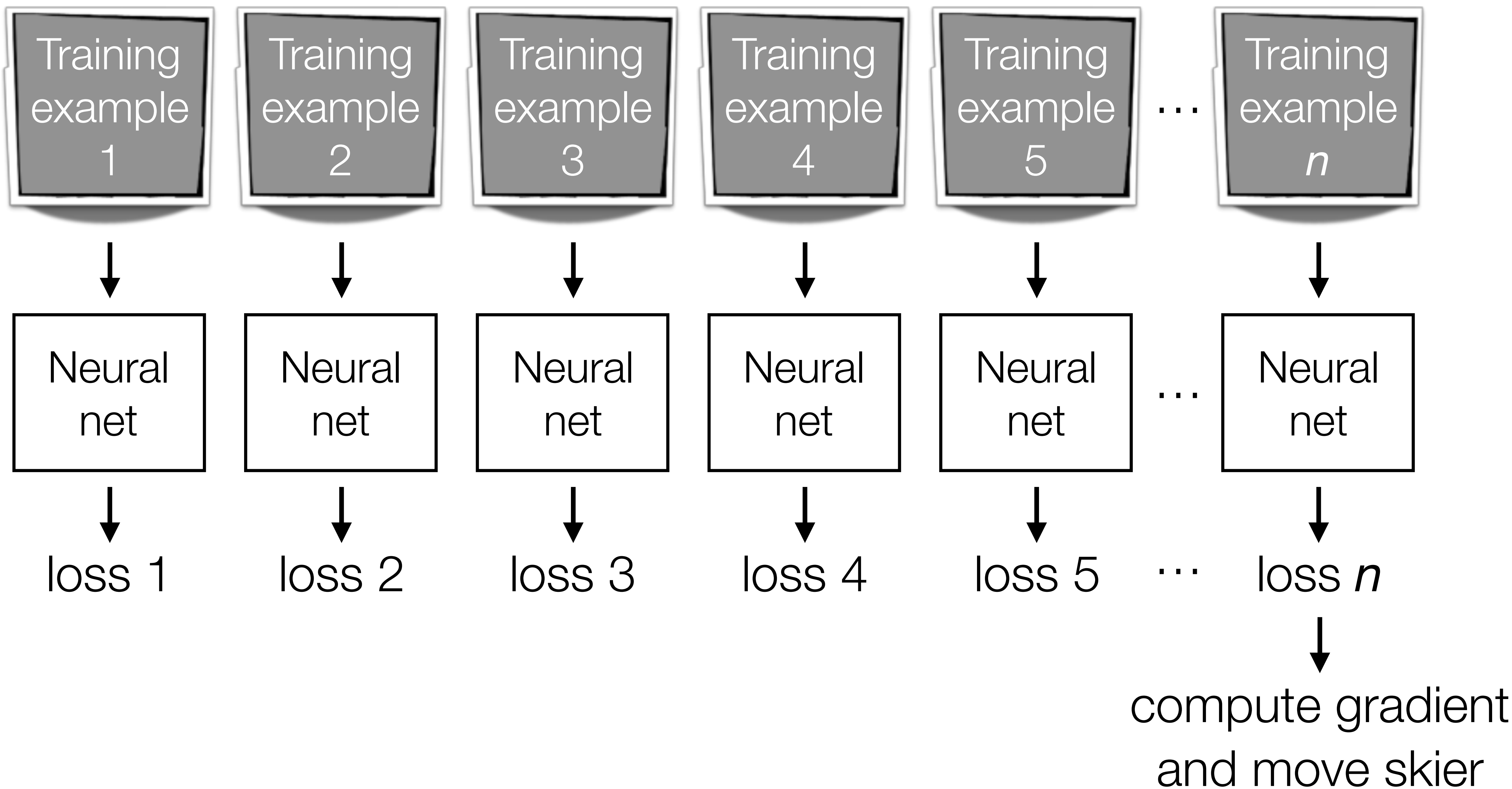

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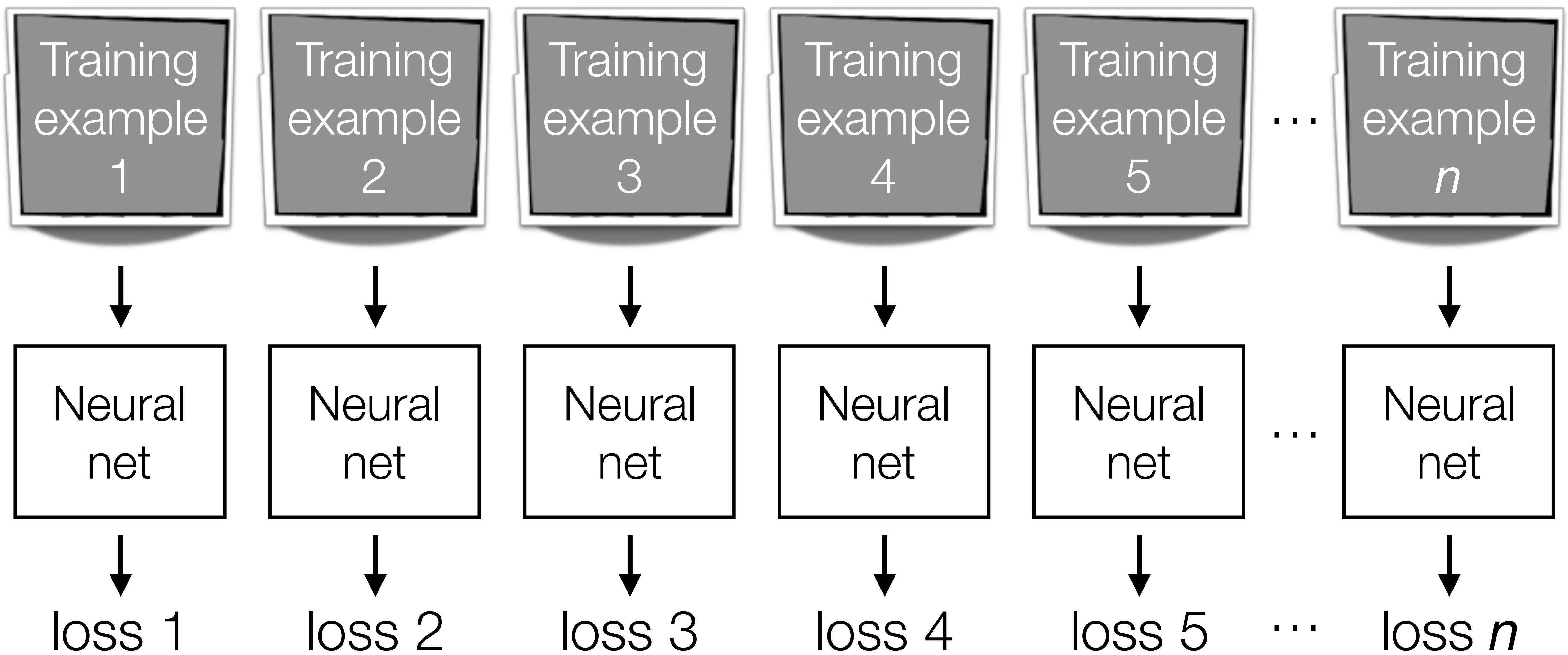

compute gradient
and move skier

An epoch refers to 1 full pass
through all the training data

SGD: compute gradient using only 1 training example at a time
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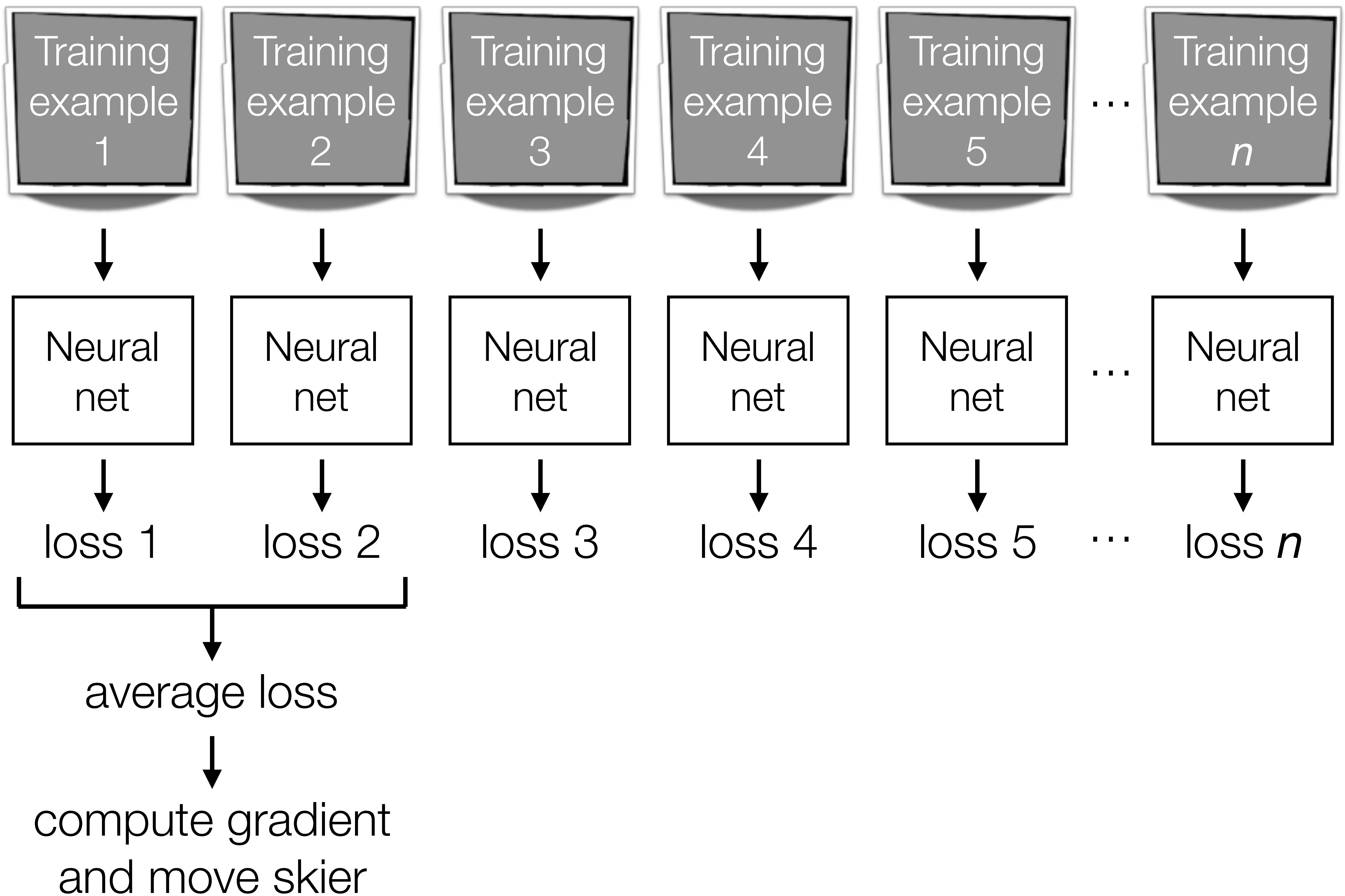
Mini-Batch Gradient Descent



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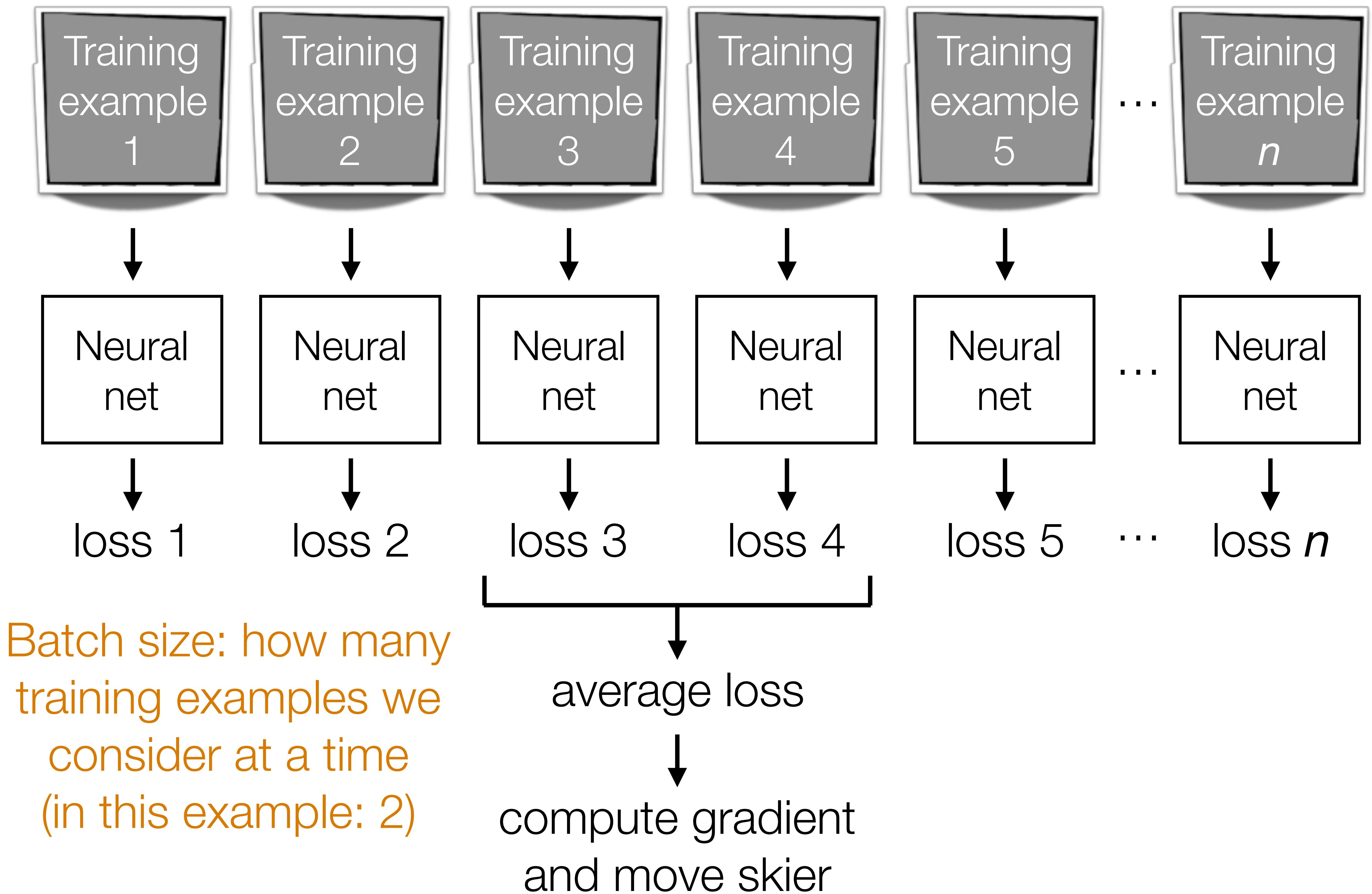

Best variant of SGD to use?
Best # of epochs? Best batch size?

Active area of research

Depends on problem, data, hardware, etc

Example: even with a GPU, you can get slow learning (slower than CPU!) if you choose # epochs/batch size poorly!!!