Carnegie Mellon University
Heinz College

Time Series Analysis with Recurrent Neural Networks (RNNs), and Roughly How Learning a Deep Net Works

George Chen

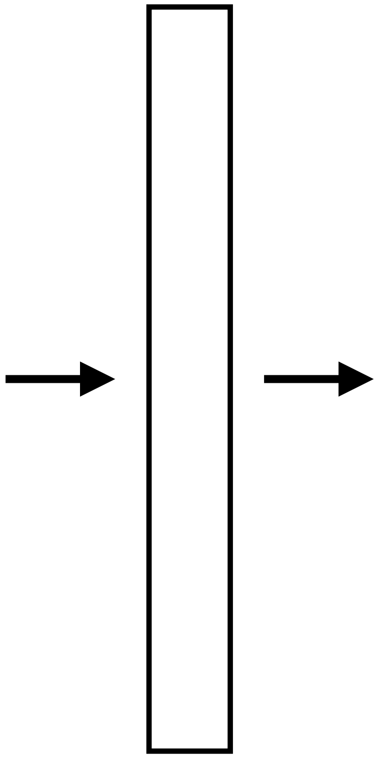
It’s Gauss’s birthday

One of the original “AI” researchers

Time series analysis with Recurrent Neural Networks (RNNs)

RNNs

What we’ve seen so far are “feedforward” NNs



RNNs

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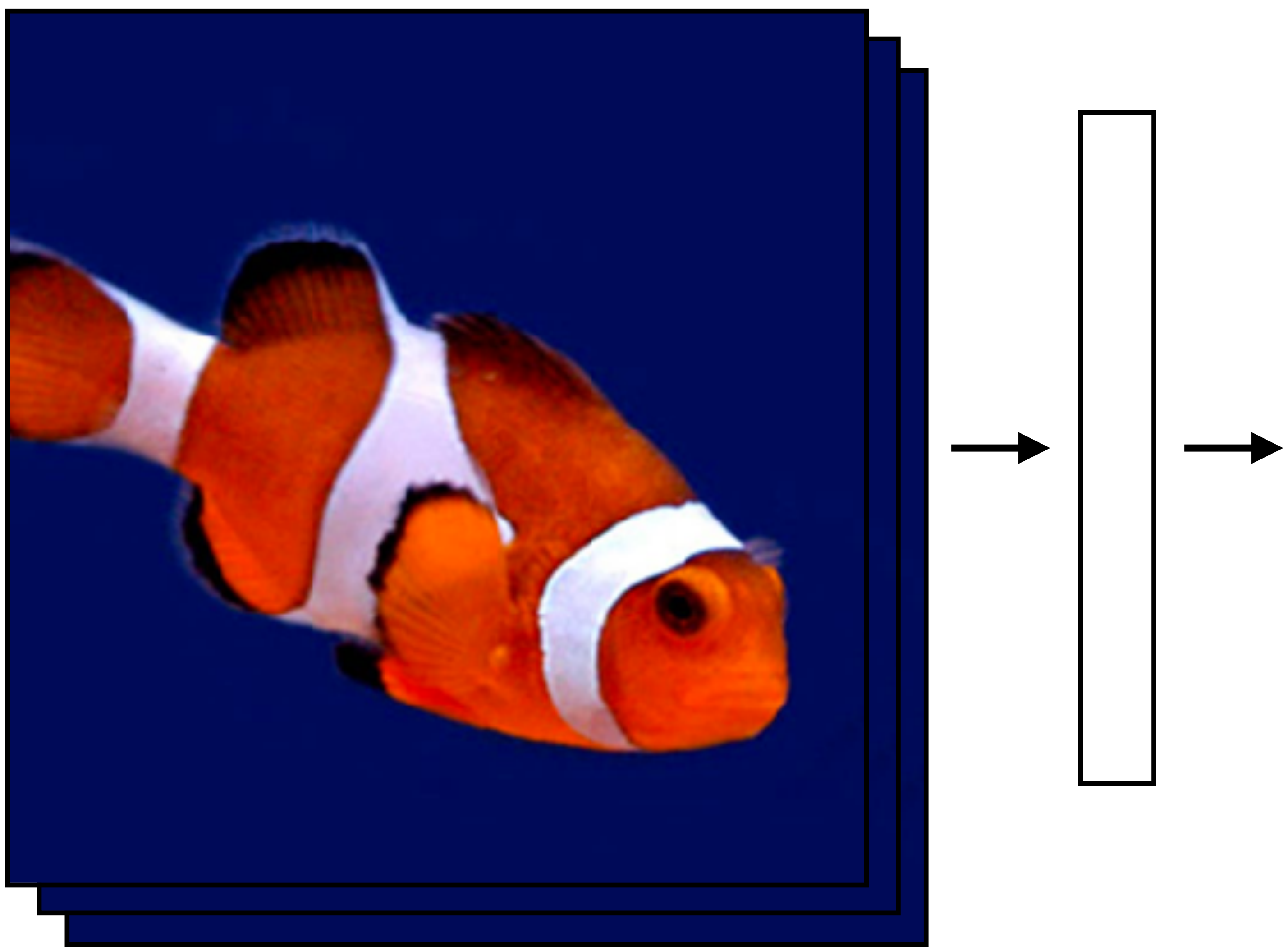
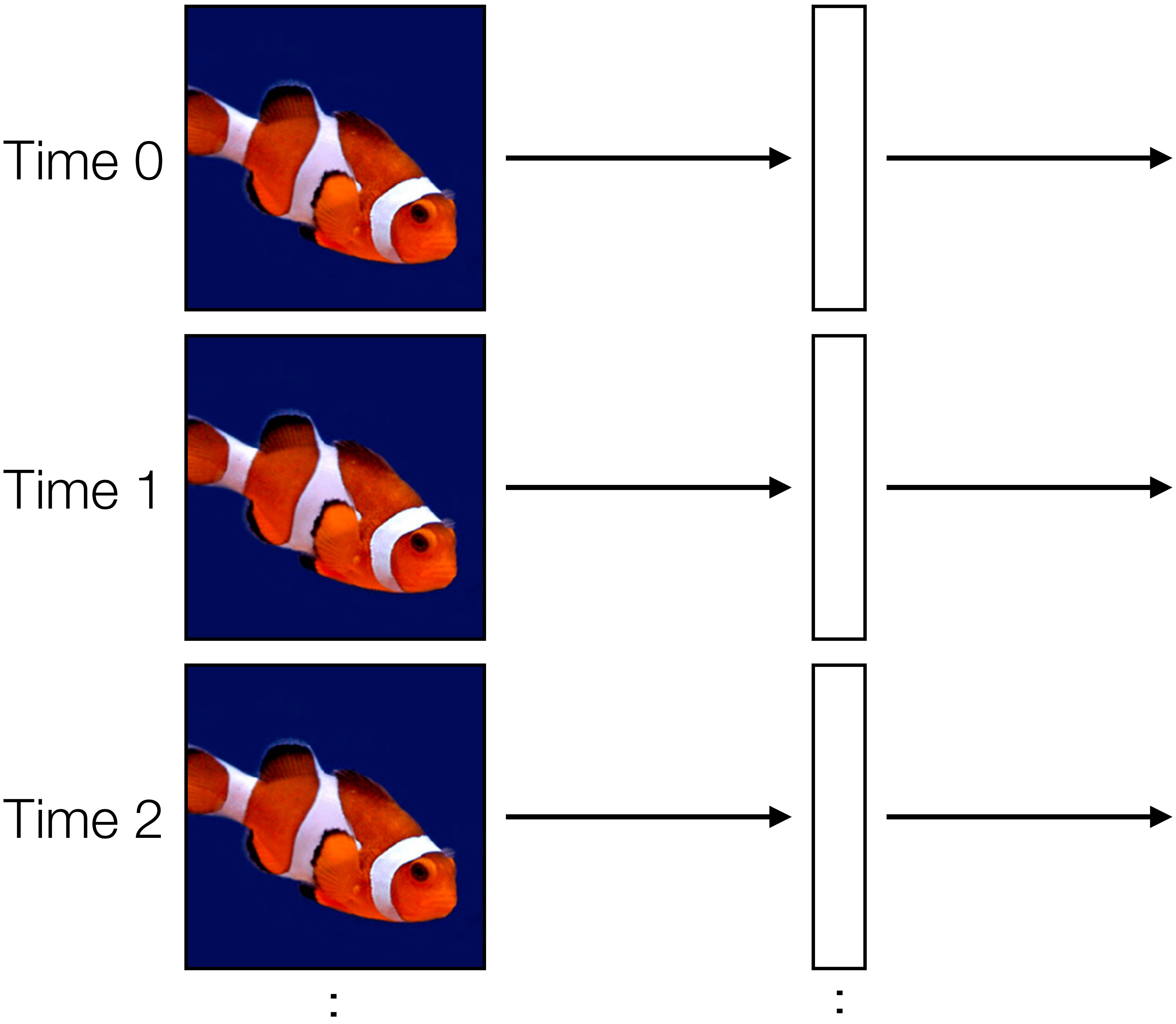


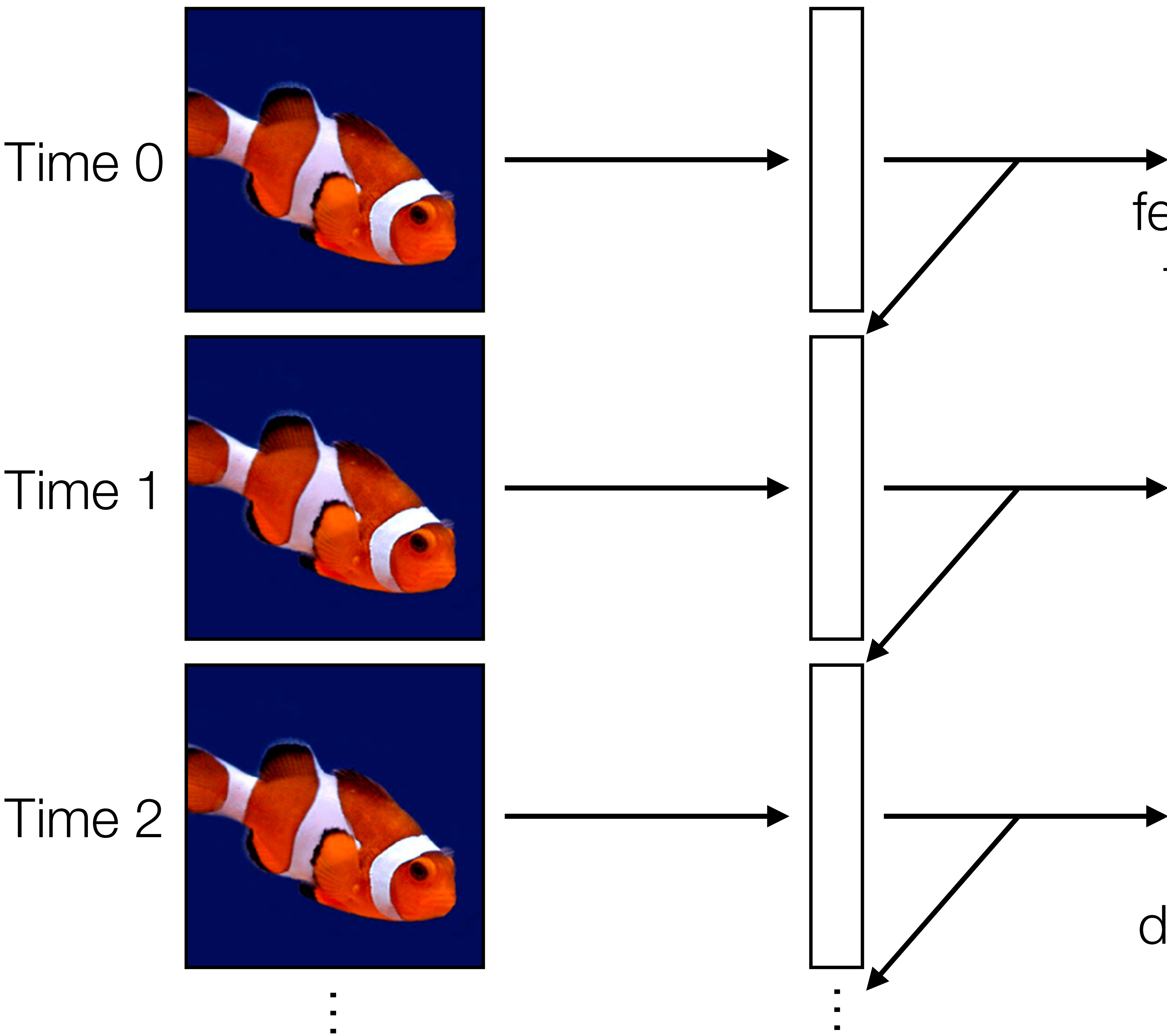
What if we had a video?

RNNs

Feedforward NN's:
treat each video frame
separately



RNNs



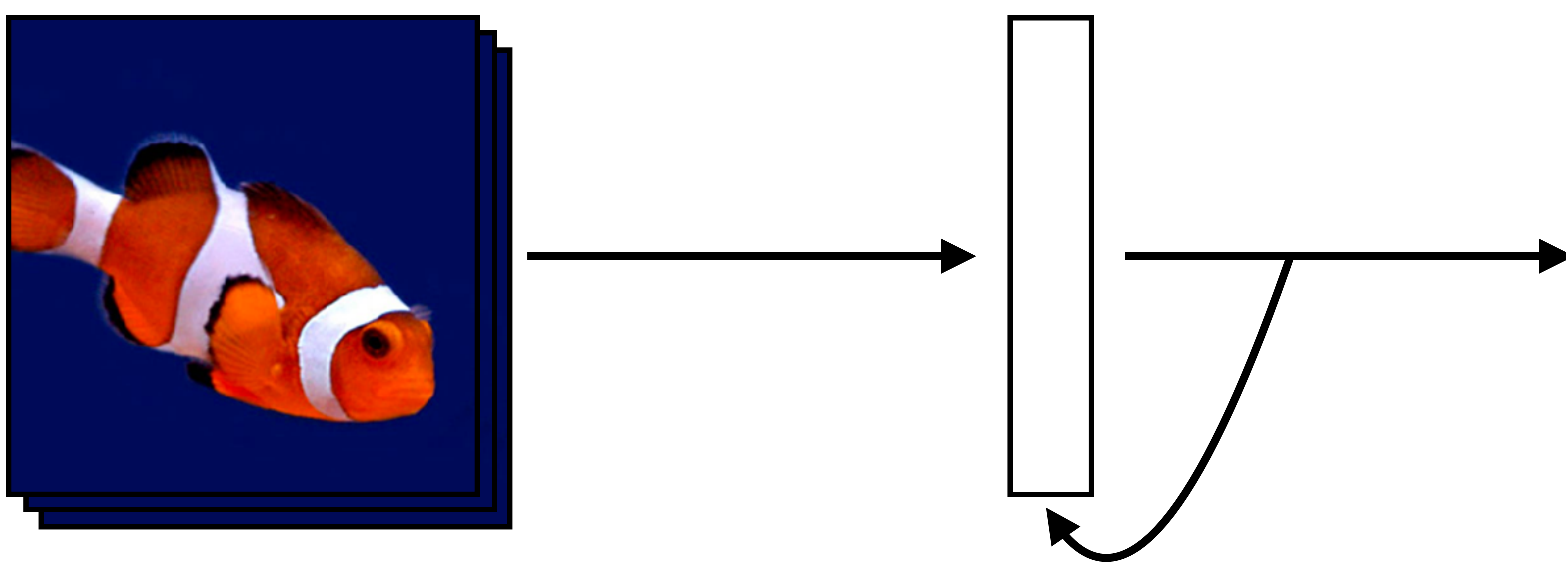
Feedforward NN's:
treat each video frame separately

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



Time series

RNN layer

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Under the Hood

```
current_state = 0

for input in input_sequence:

  output = f(input, current_state)

  current_state = output
```

Different functions f 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
```

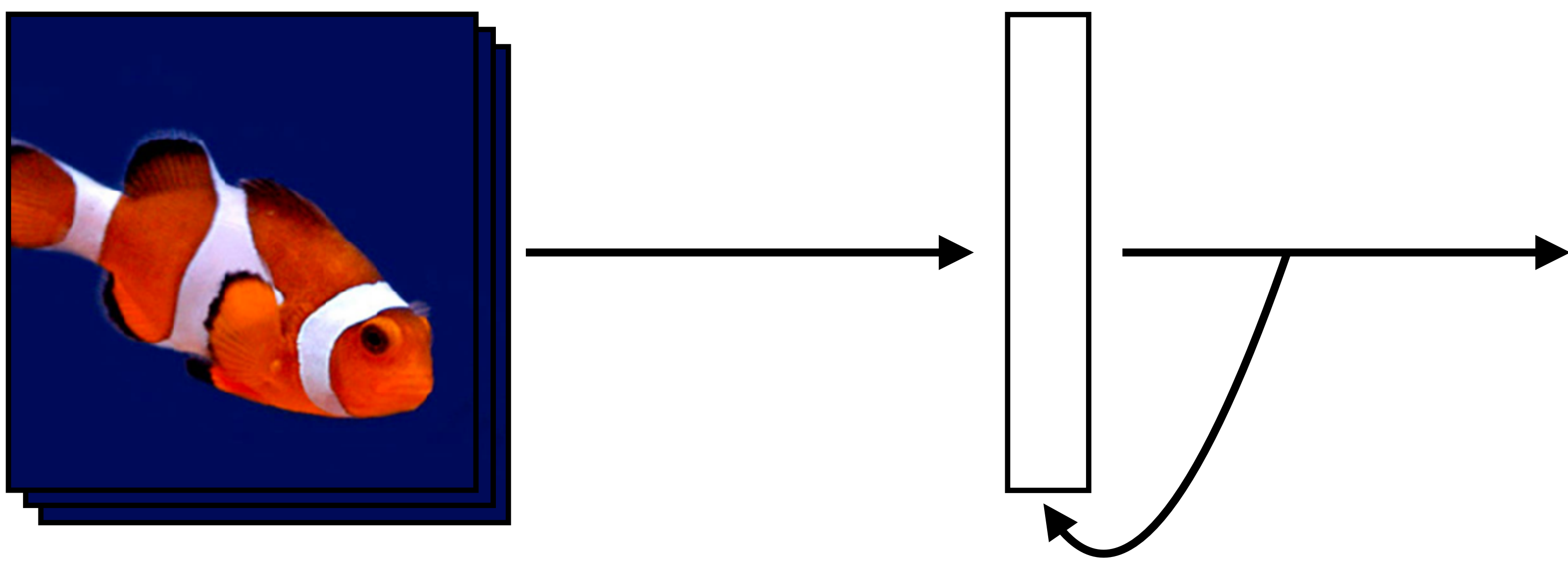
Activation function could, for instance, be ReLU

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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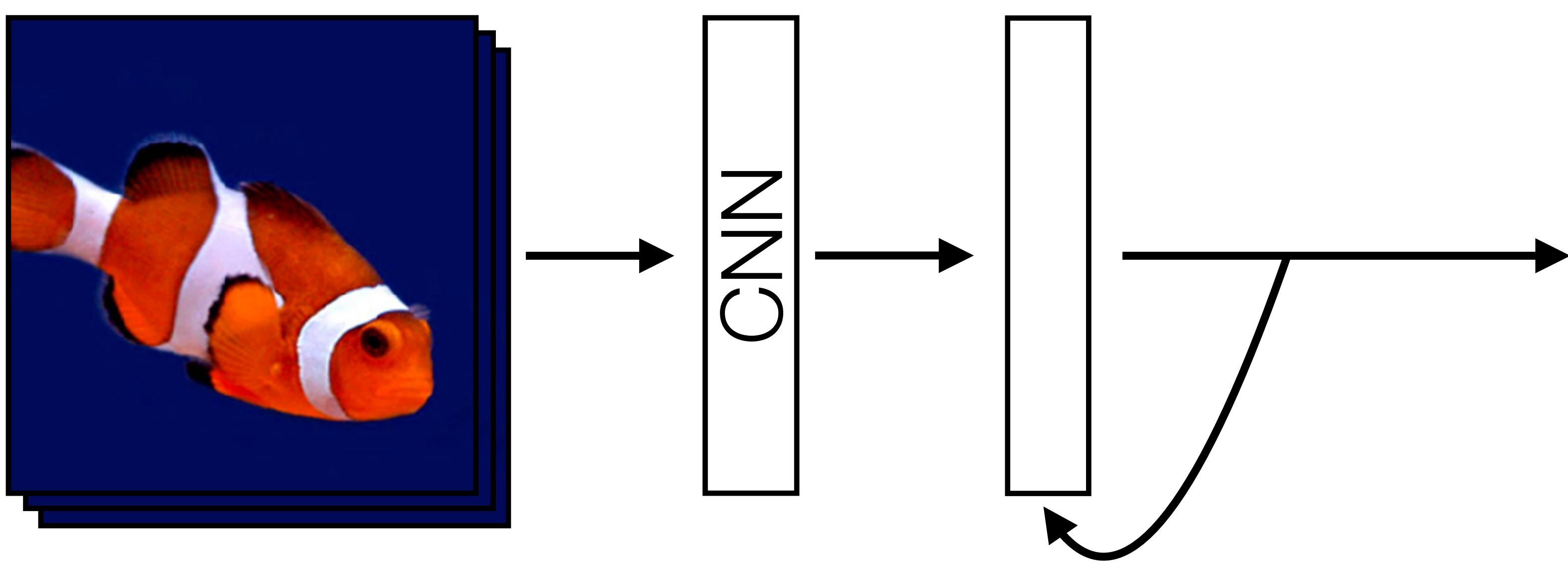

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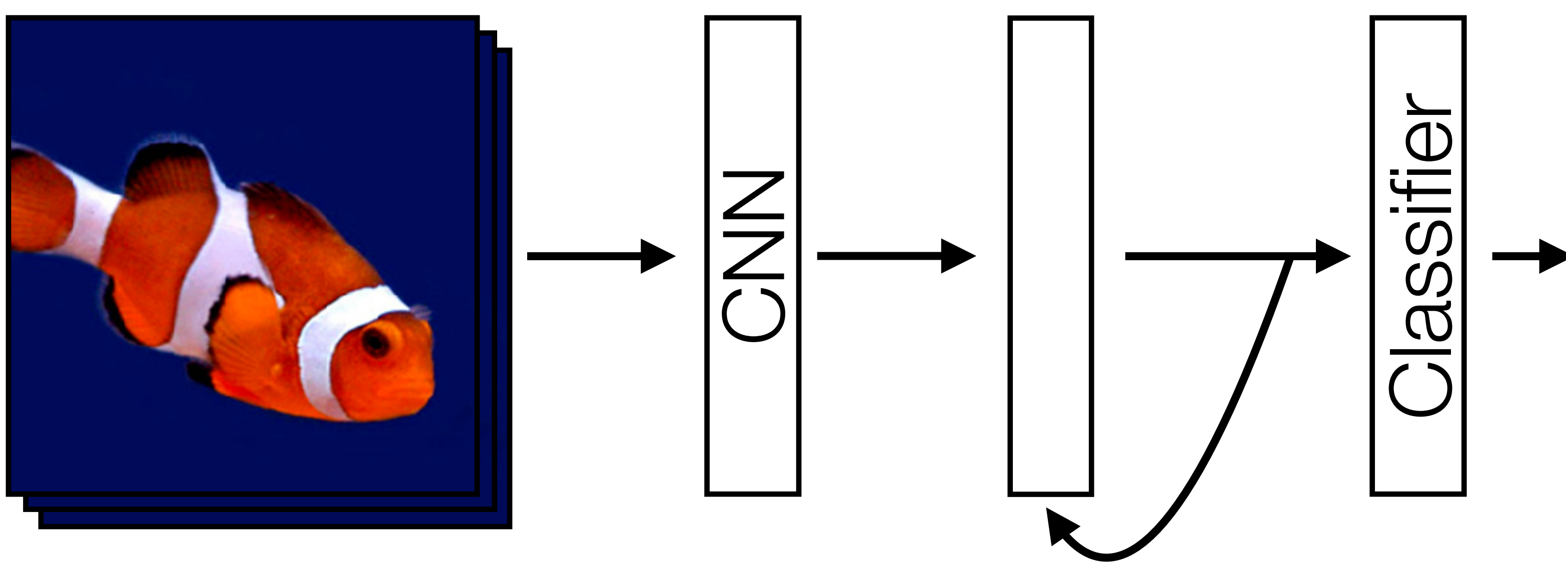

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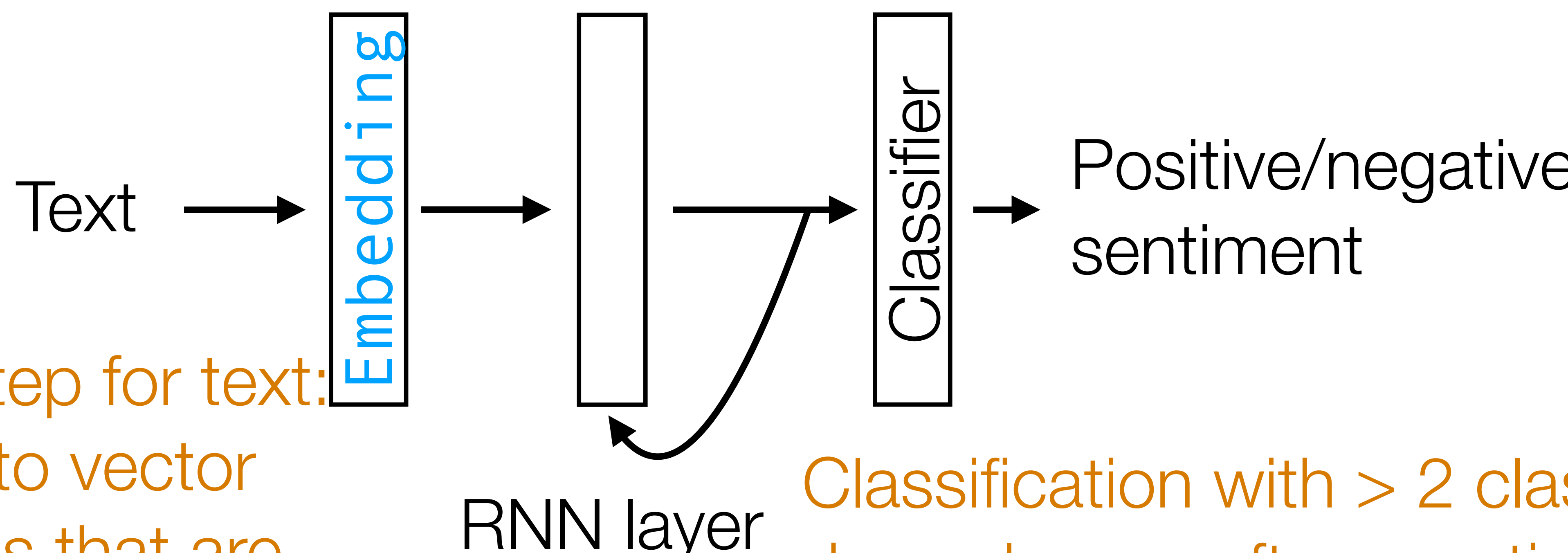
RNNs

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

In `keras`, use the `Embedding` layer

Classification with > 2 classes: dense layer, softmax activation

Classification with 2 classes: dense layer with 1 neuron, sigmoid activation

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

Simple RNN: has trouble remembering things from long ago…

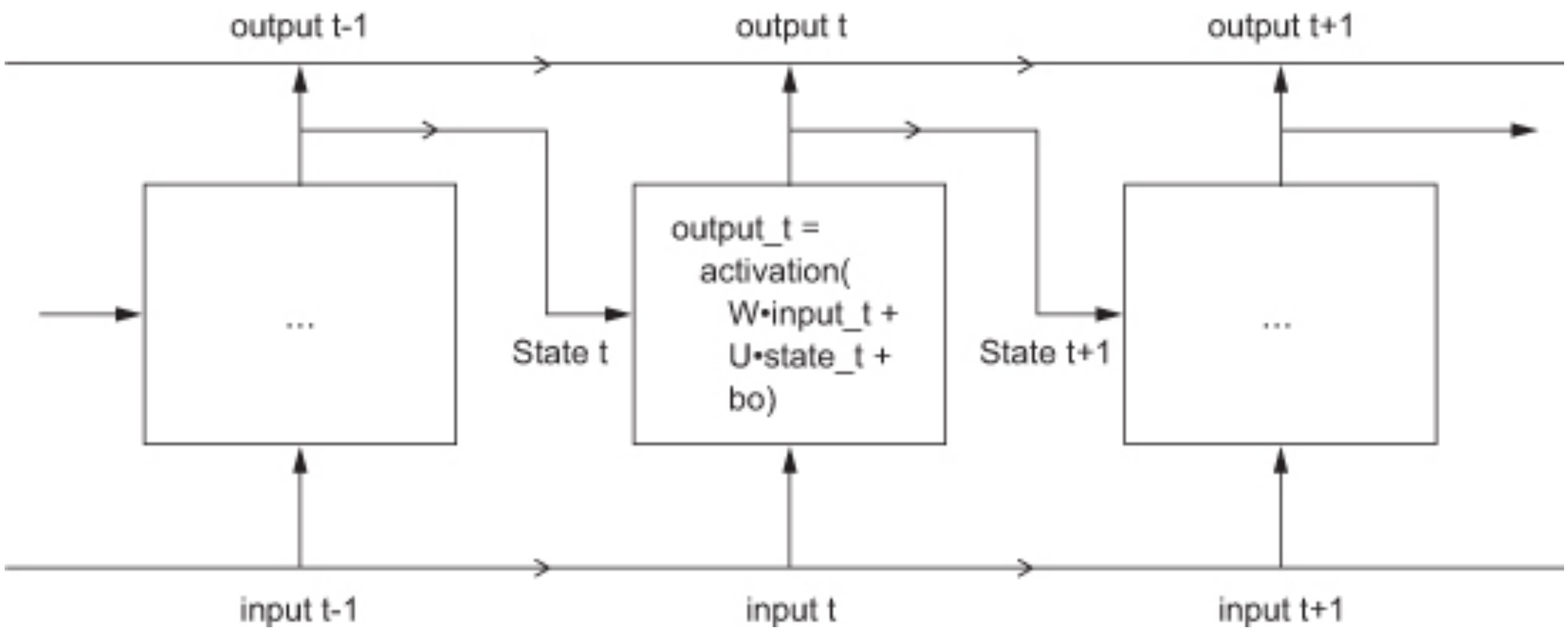


Figure 6.13 from Francois Chollet's book *Deep Learning with Python*

A Little Bit More Detail

Introduce a “carry” state for tracking longer term memory

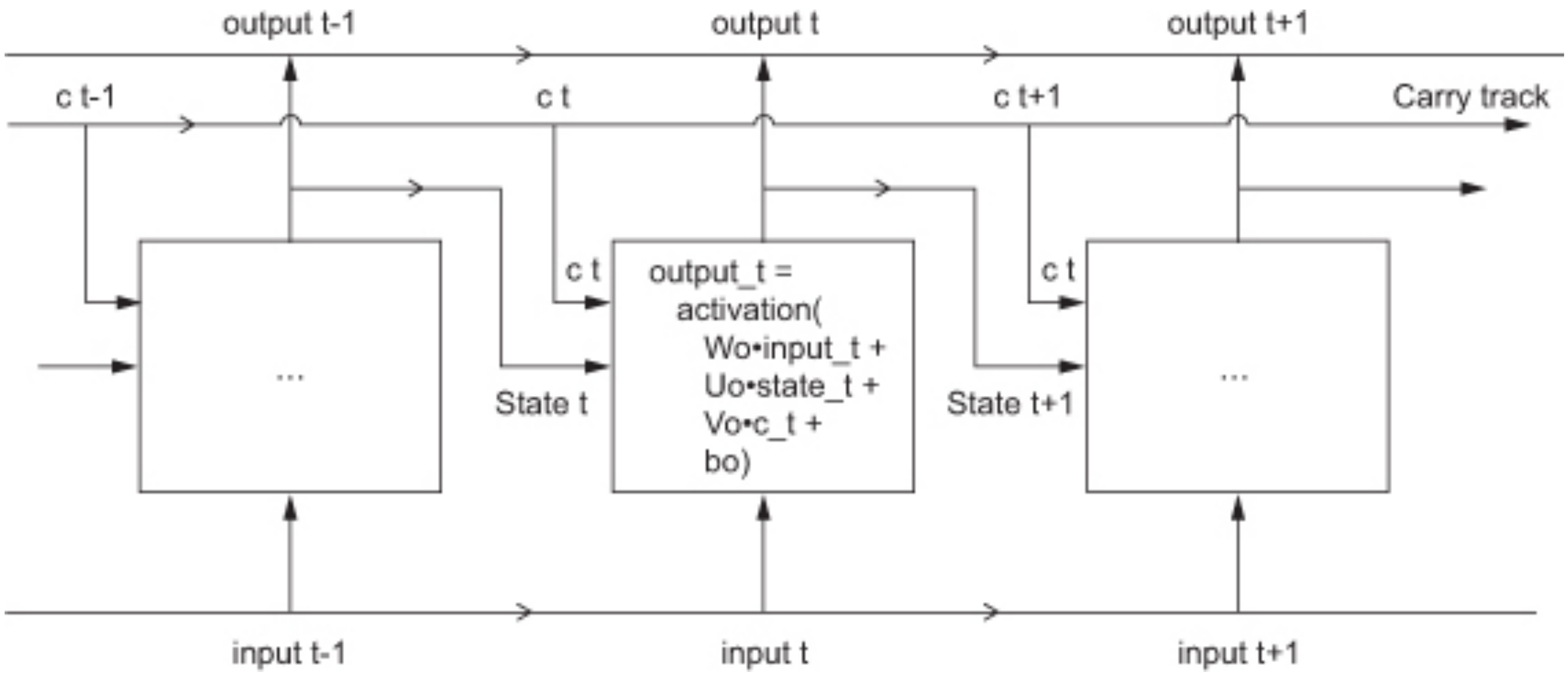


Figure 6.14 from Francois Chollet’s book *Deep Learning with Python*

A Little Bit More Detail

LSTM: figure out how to update “carry” state

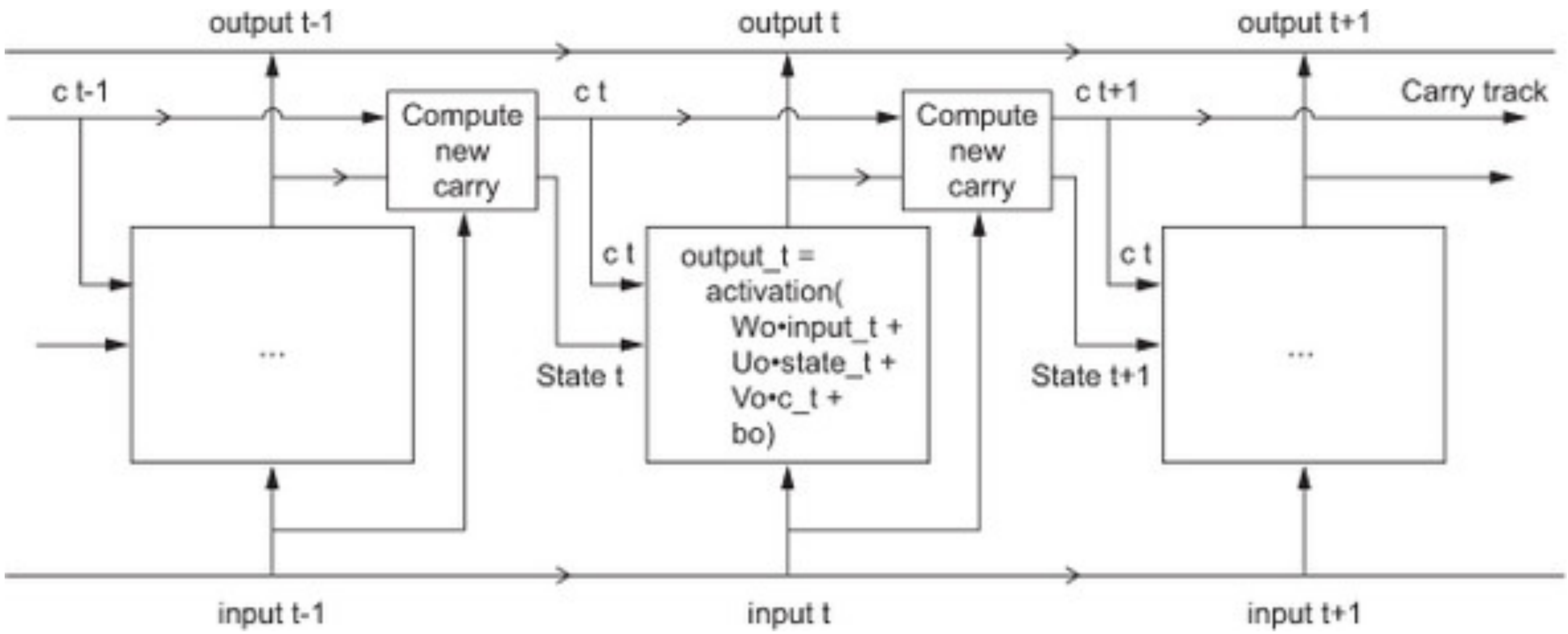
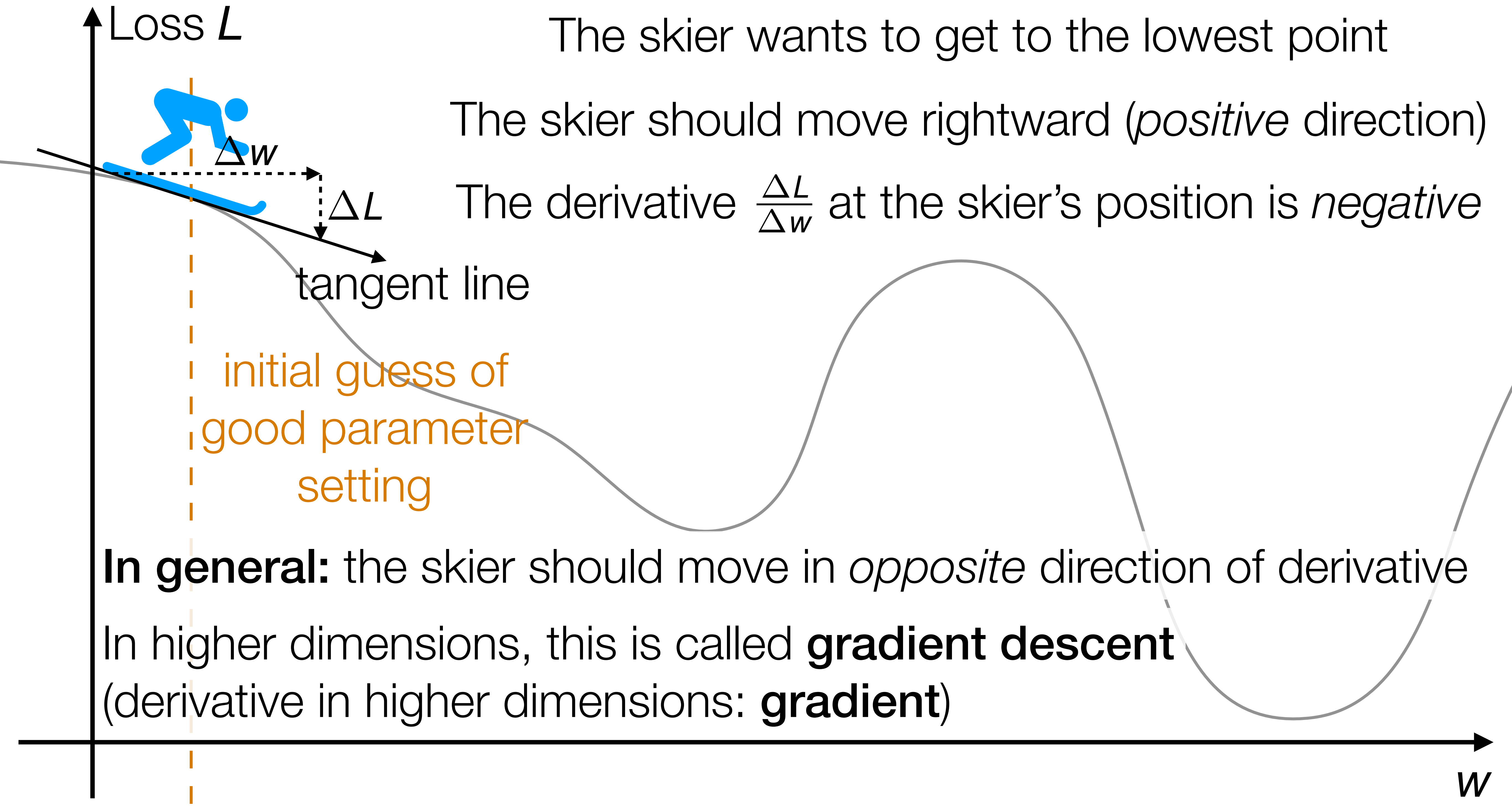


Figure 6.15 from Francois Chollet’s book *Deep Learning with Python*

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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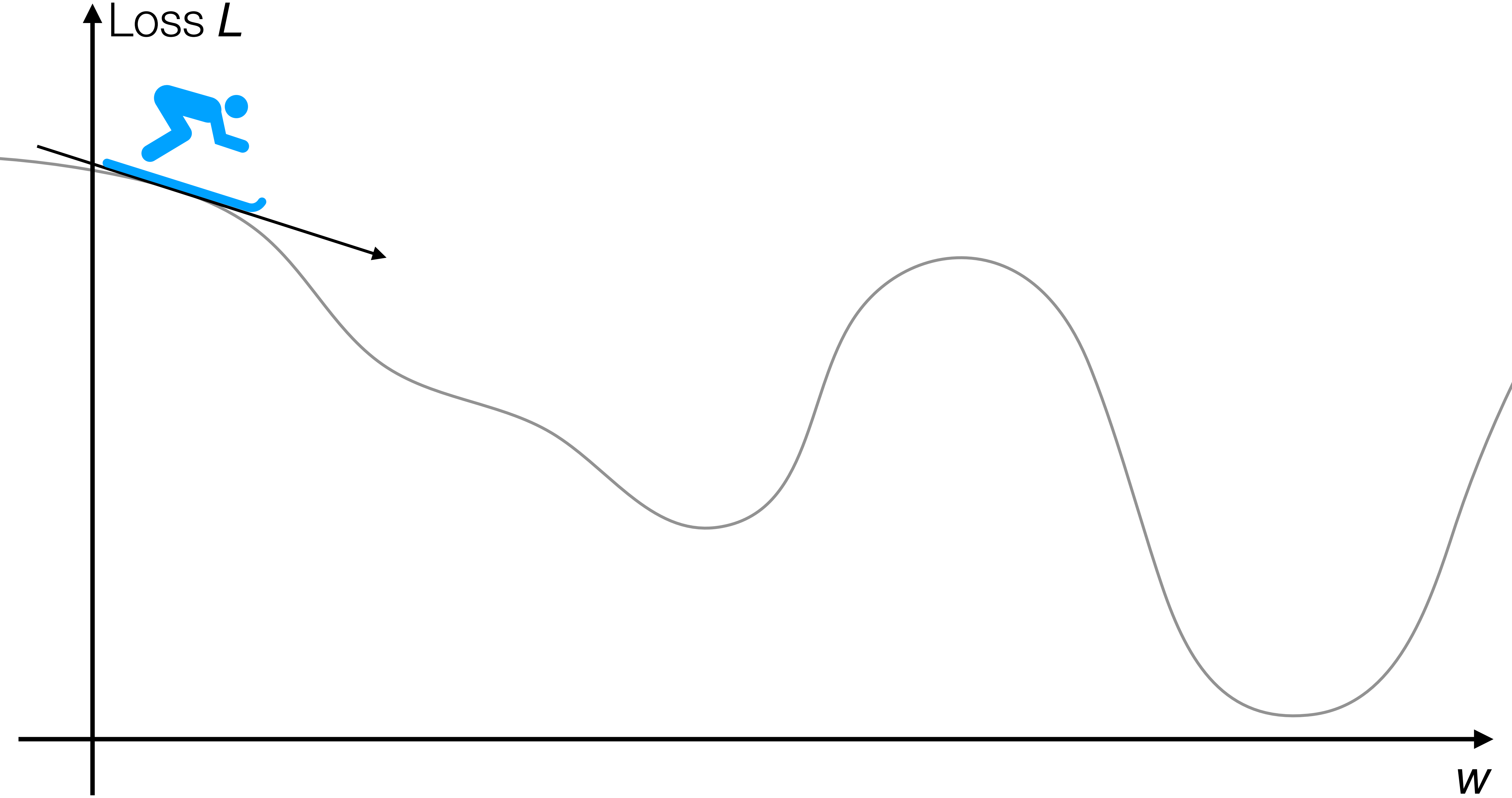

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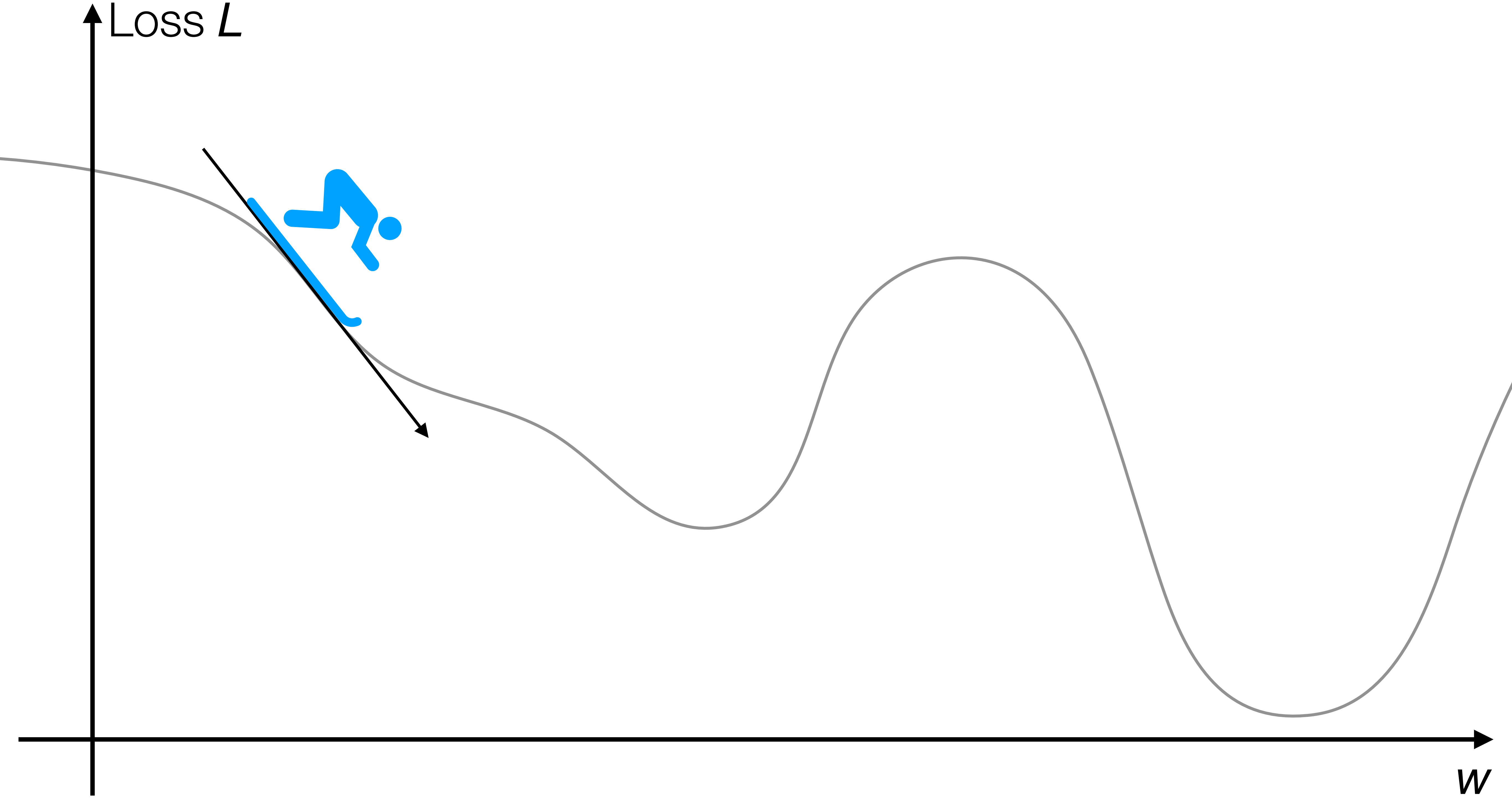
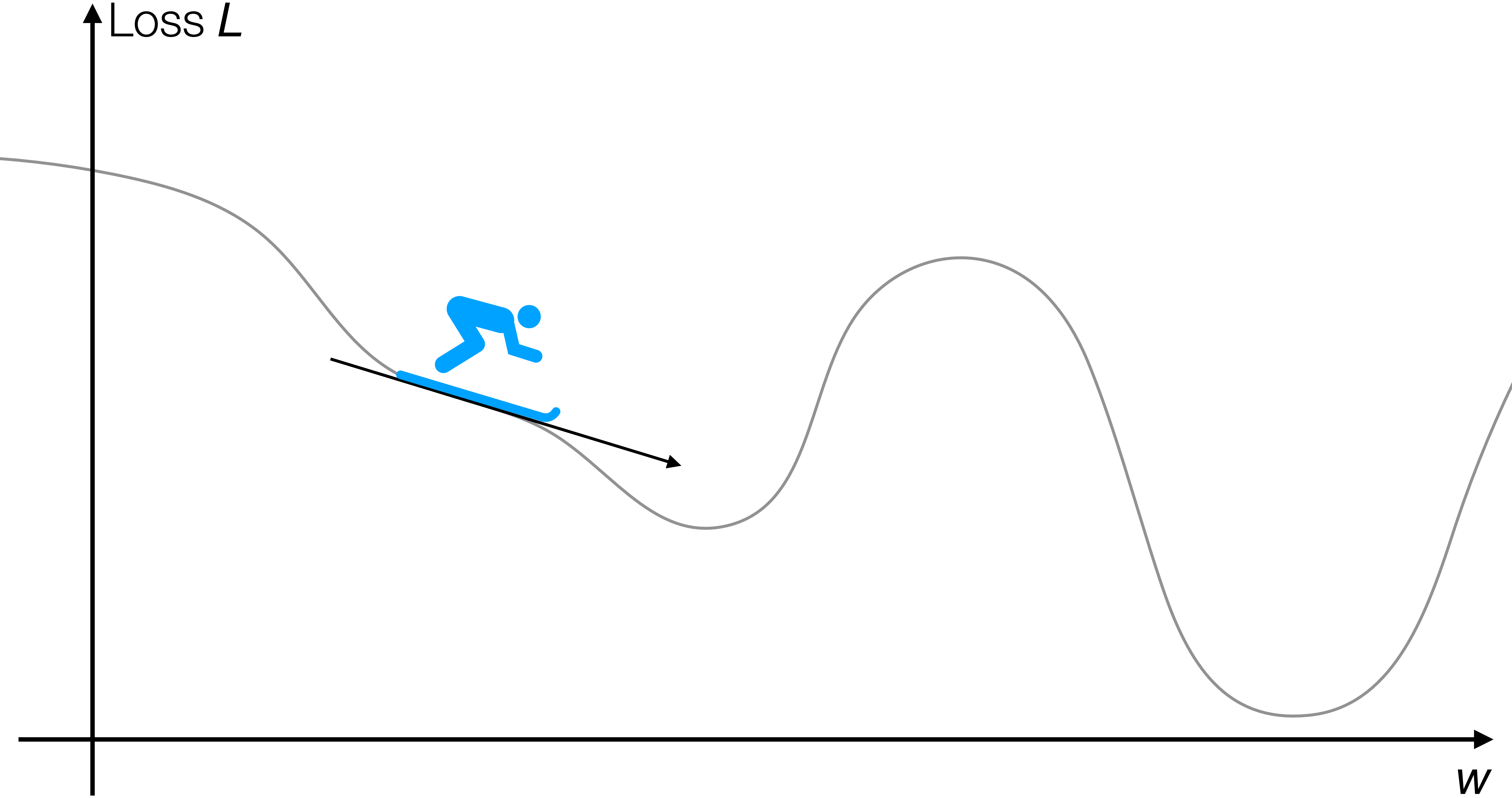


Gradient Descent

Suppose the neural network has a single real number parameter w



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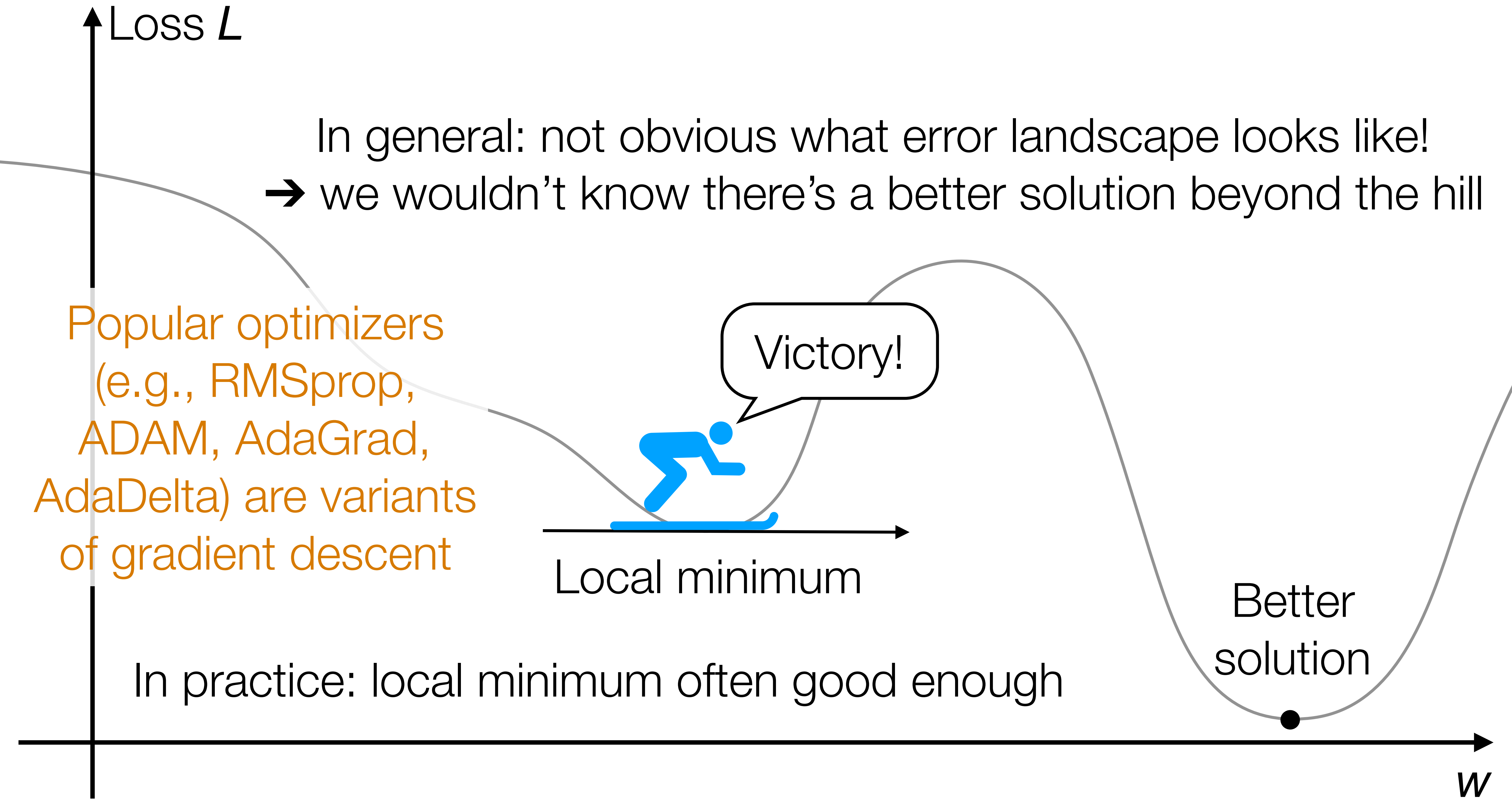
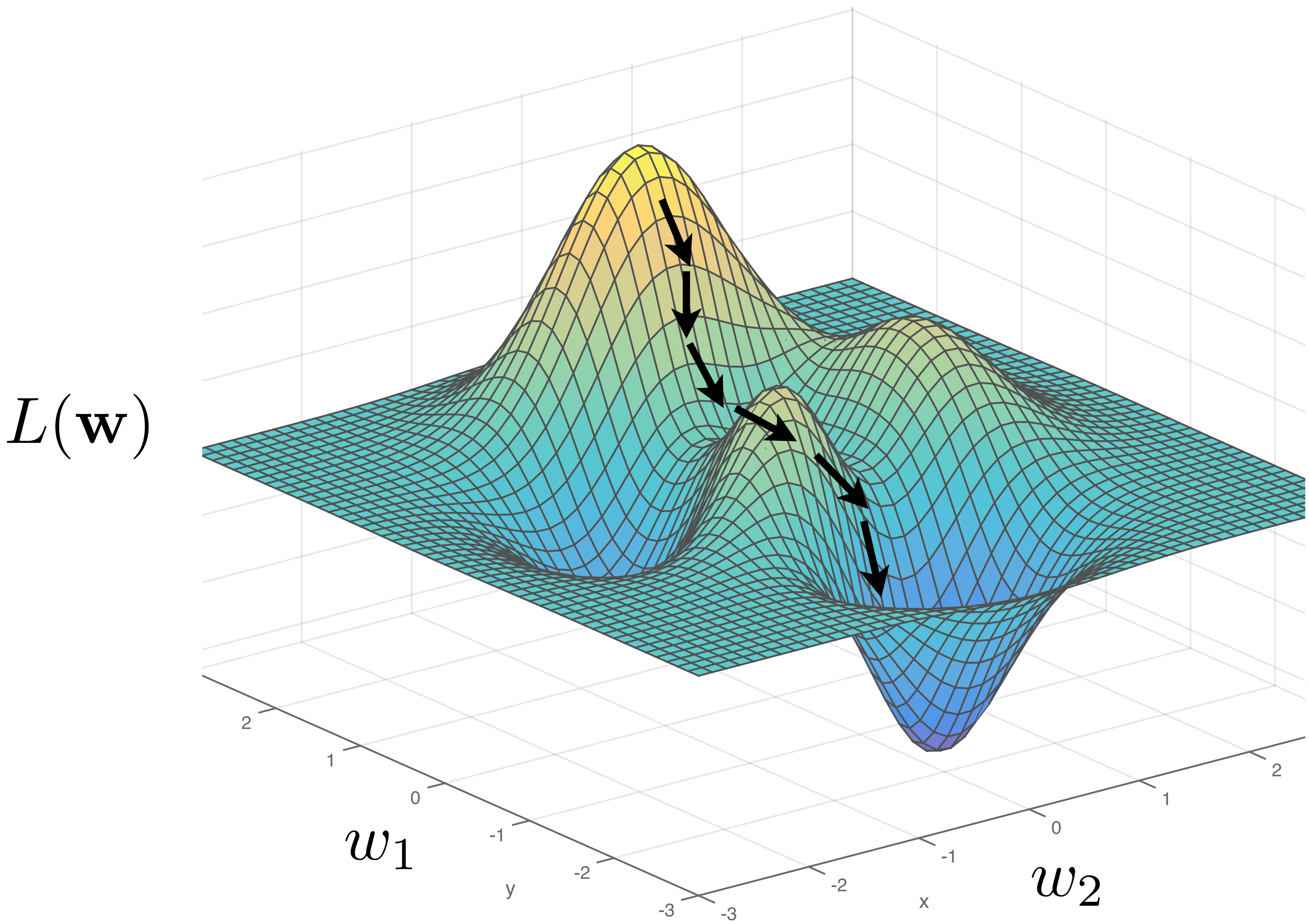


Gradient Descent

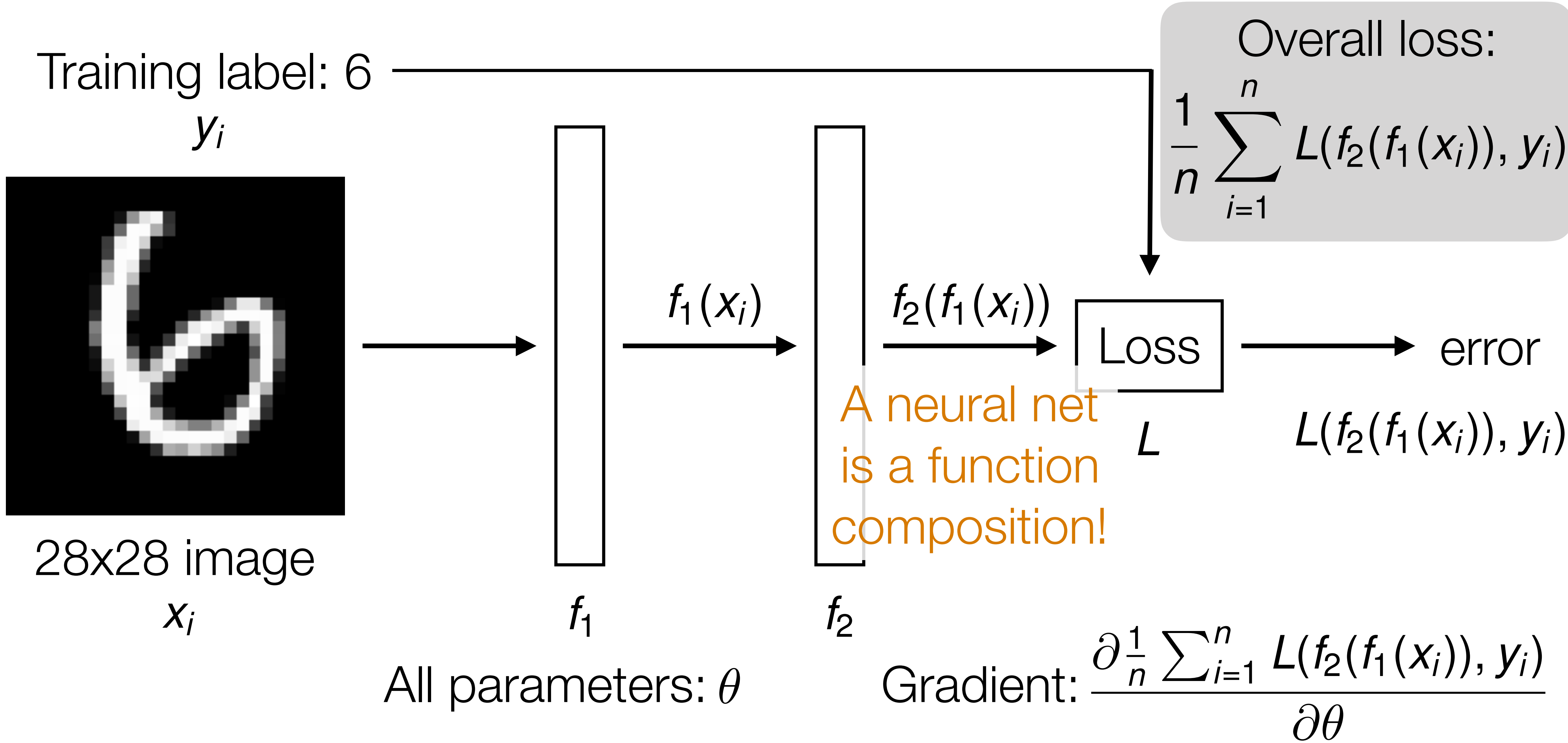
2D example



Slide by Phillip Isola

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

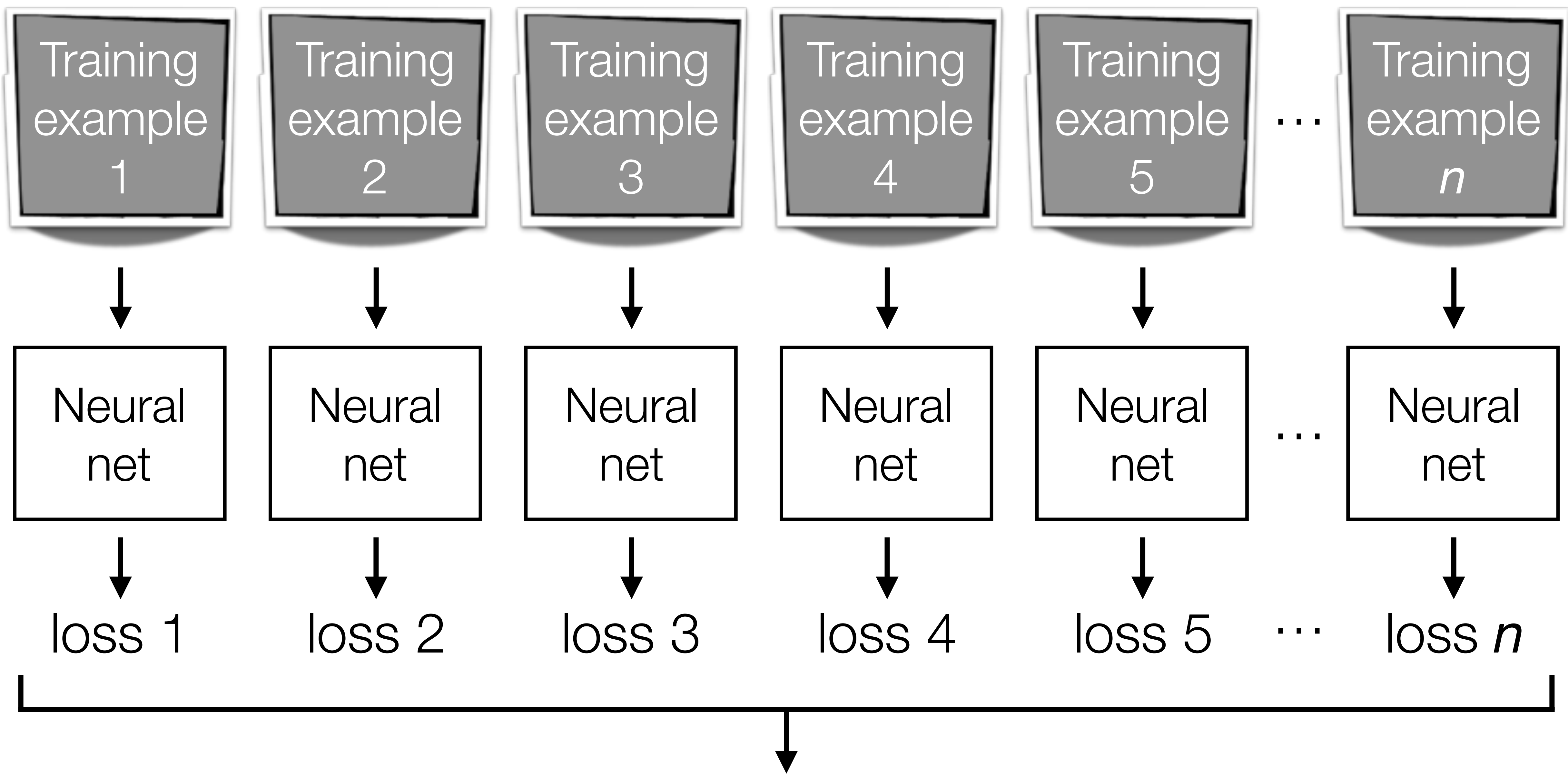
Handwritten Digit Recognition



Automatic differentiation is crucial in learning deep nets!

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

Gradient Descent



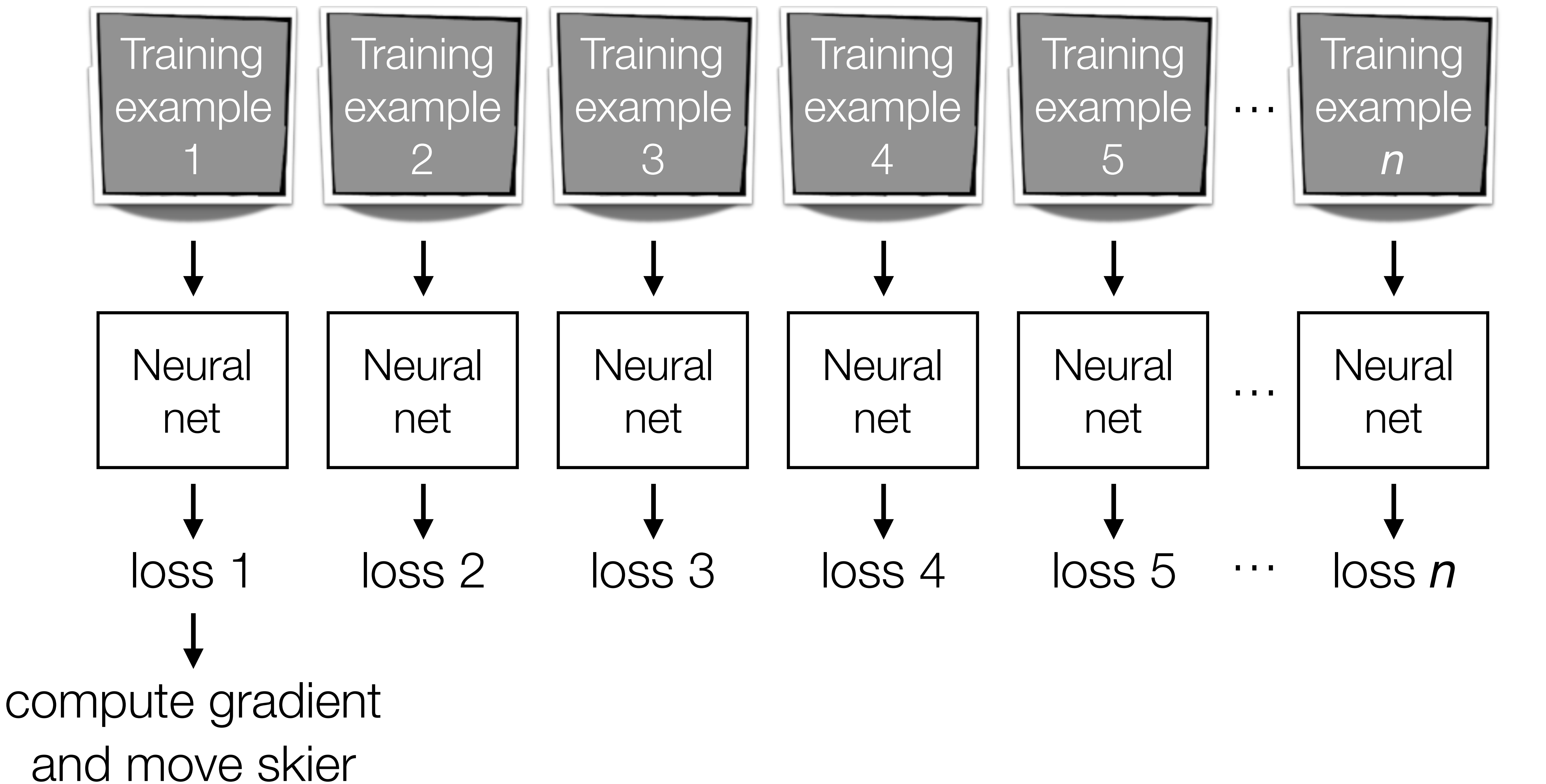
We have to compute lots of gradients to help the skier know where to go!

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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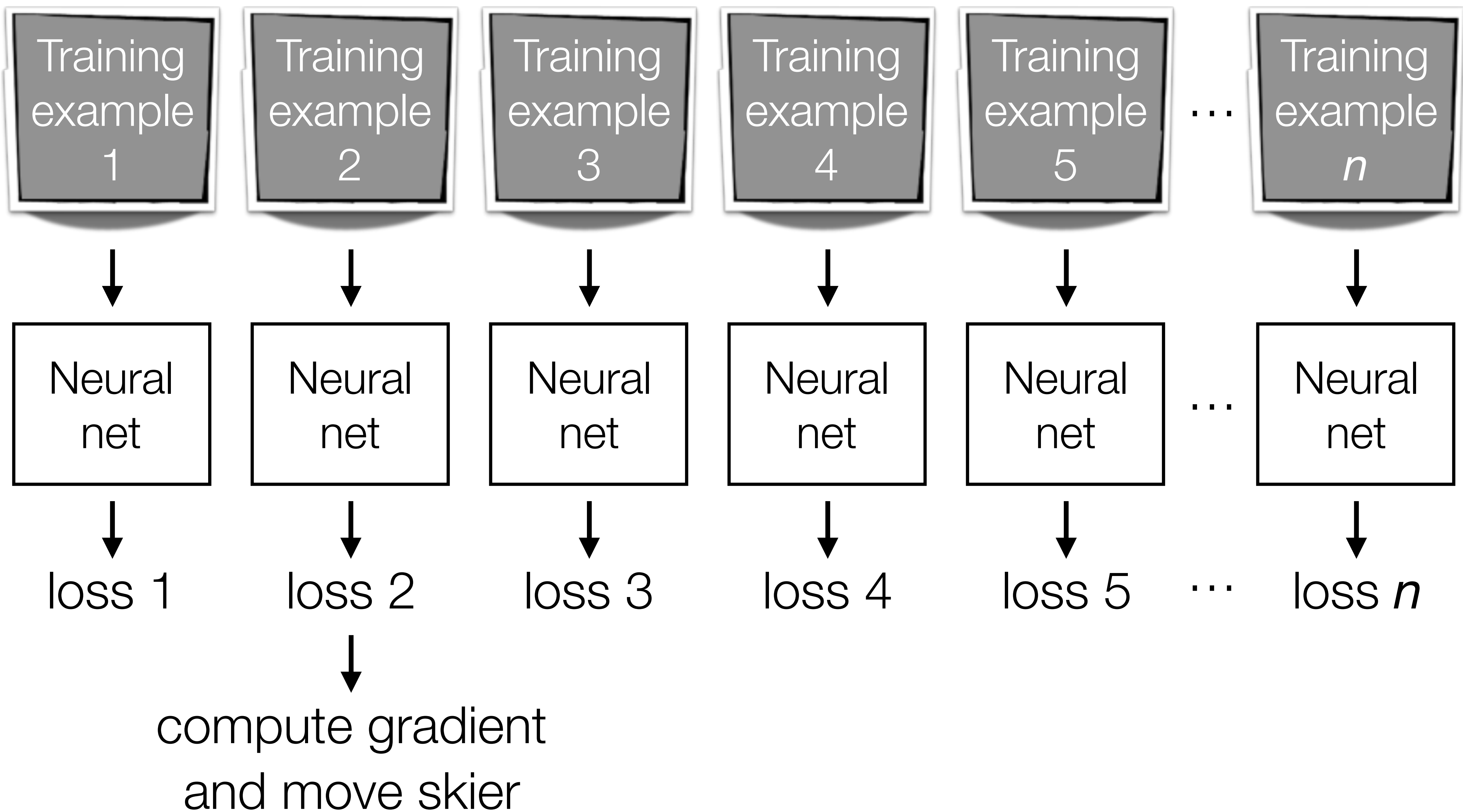

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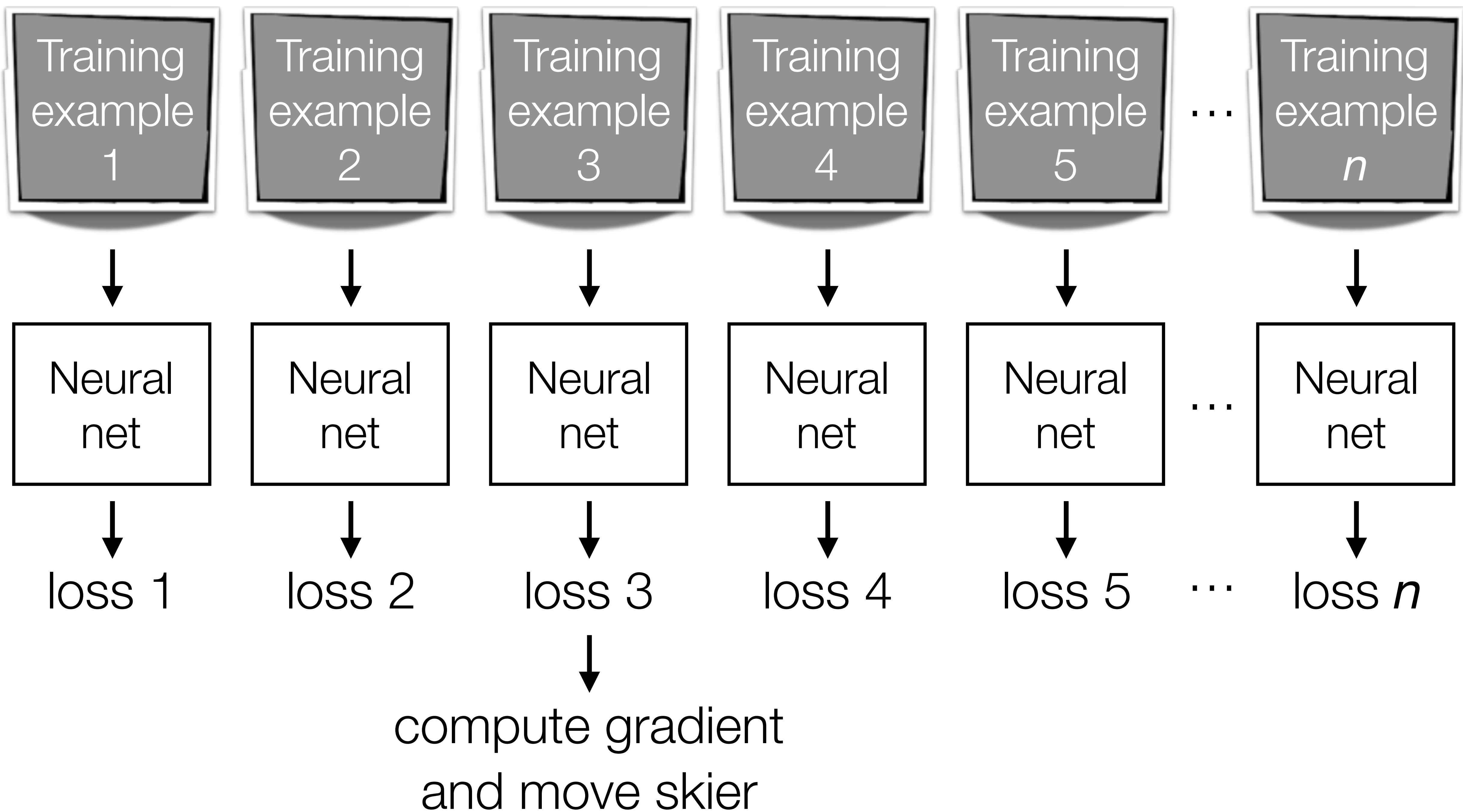

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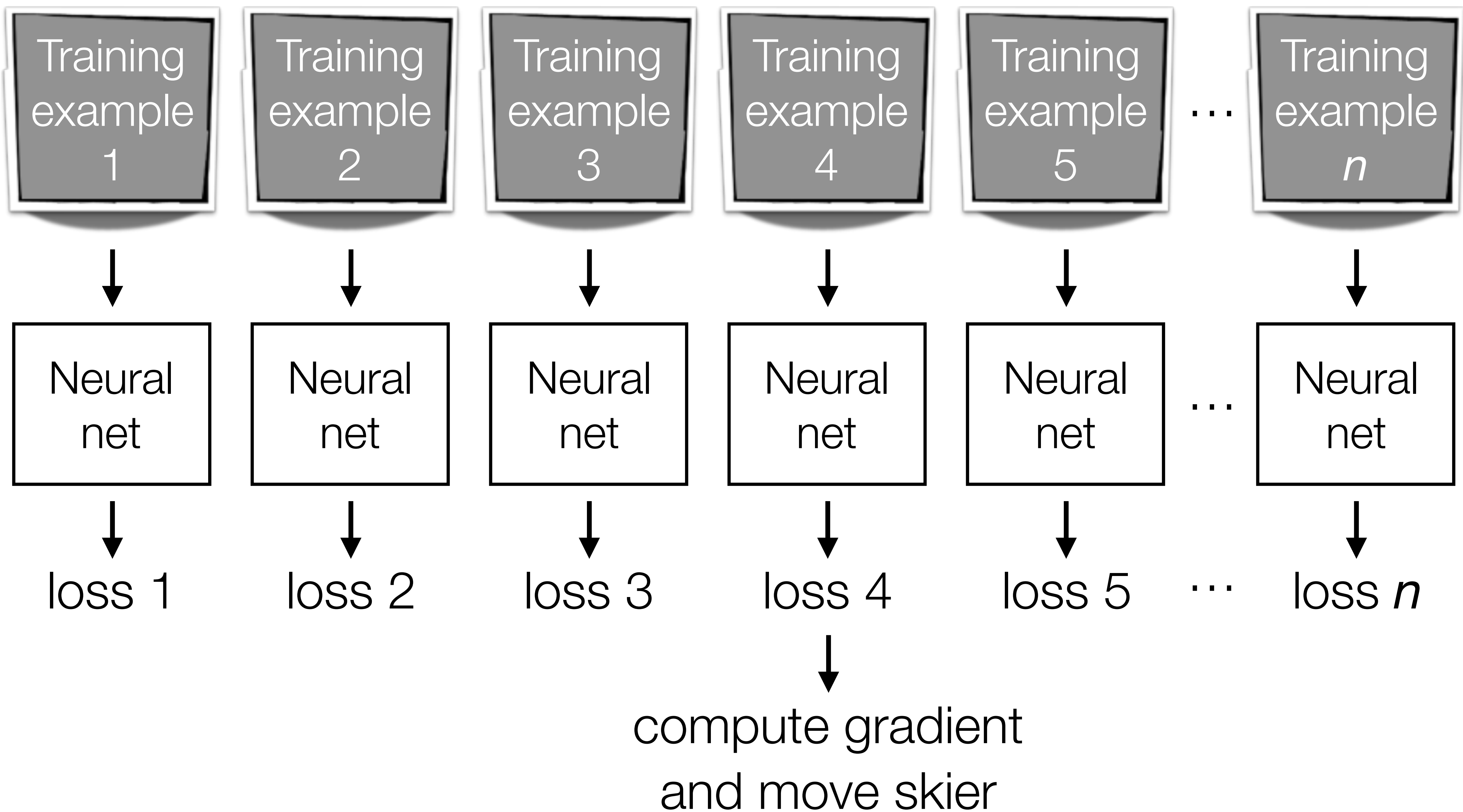

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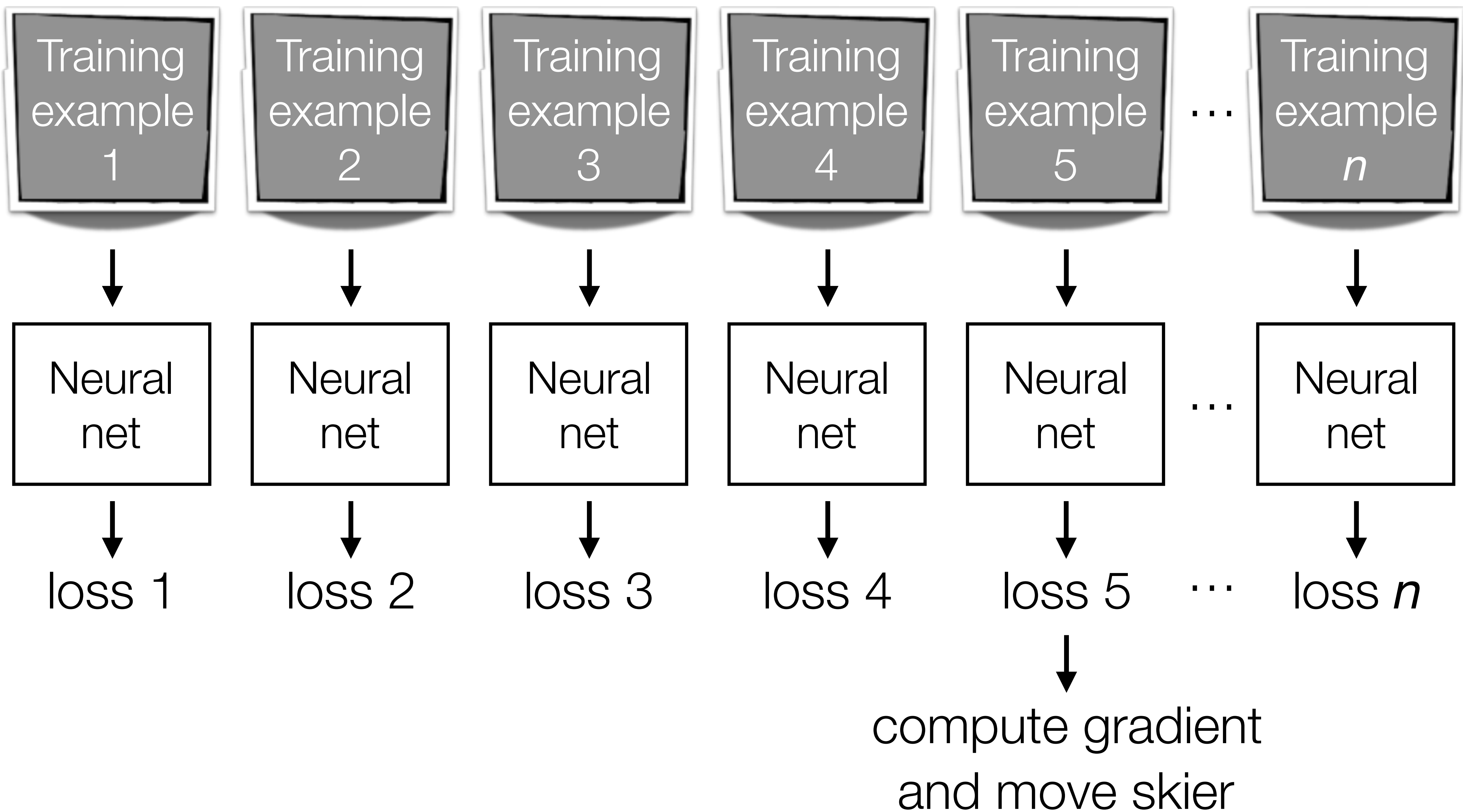

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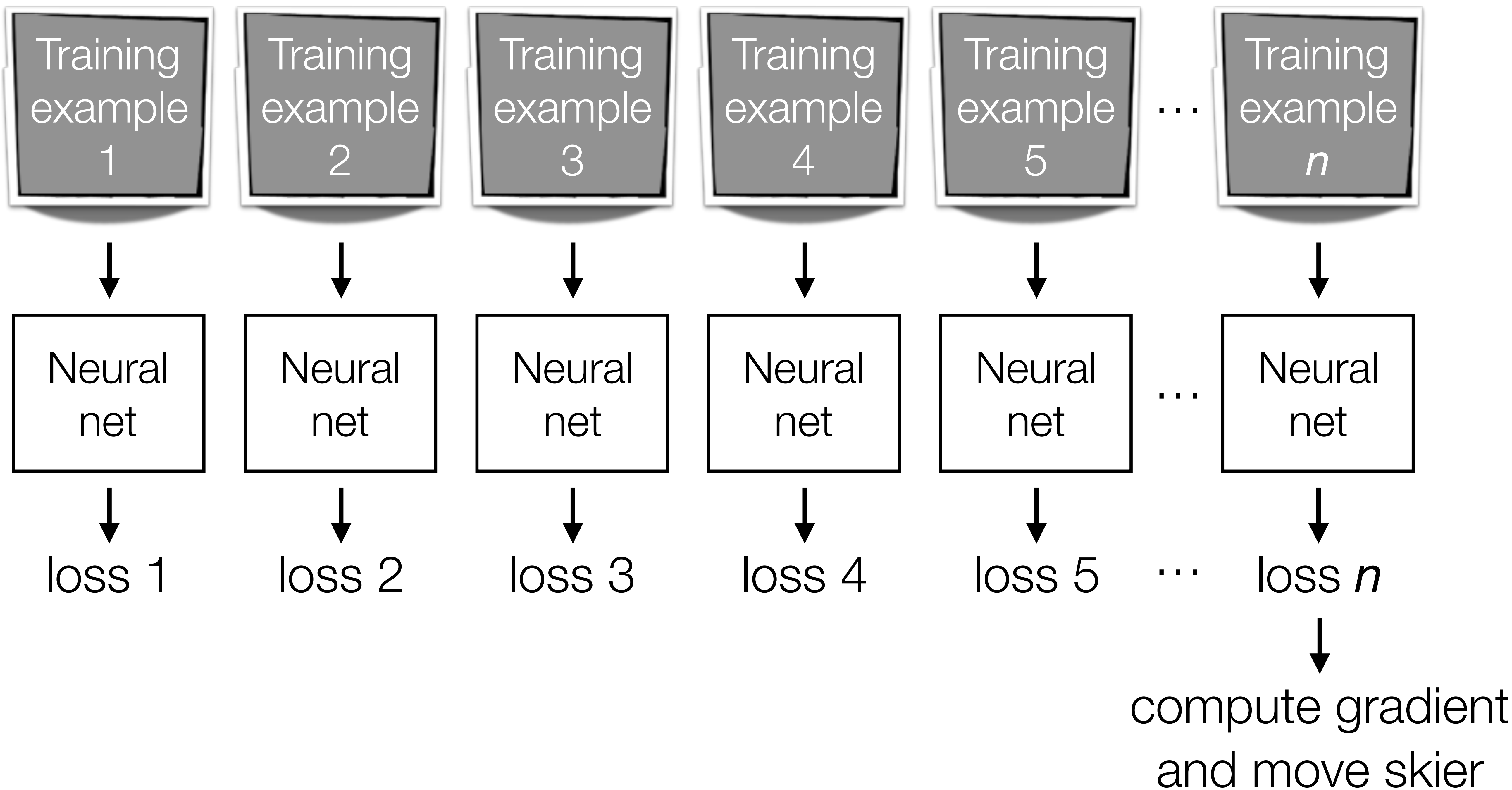

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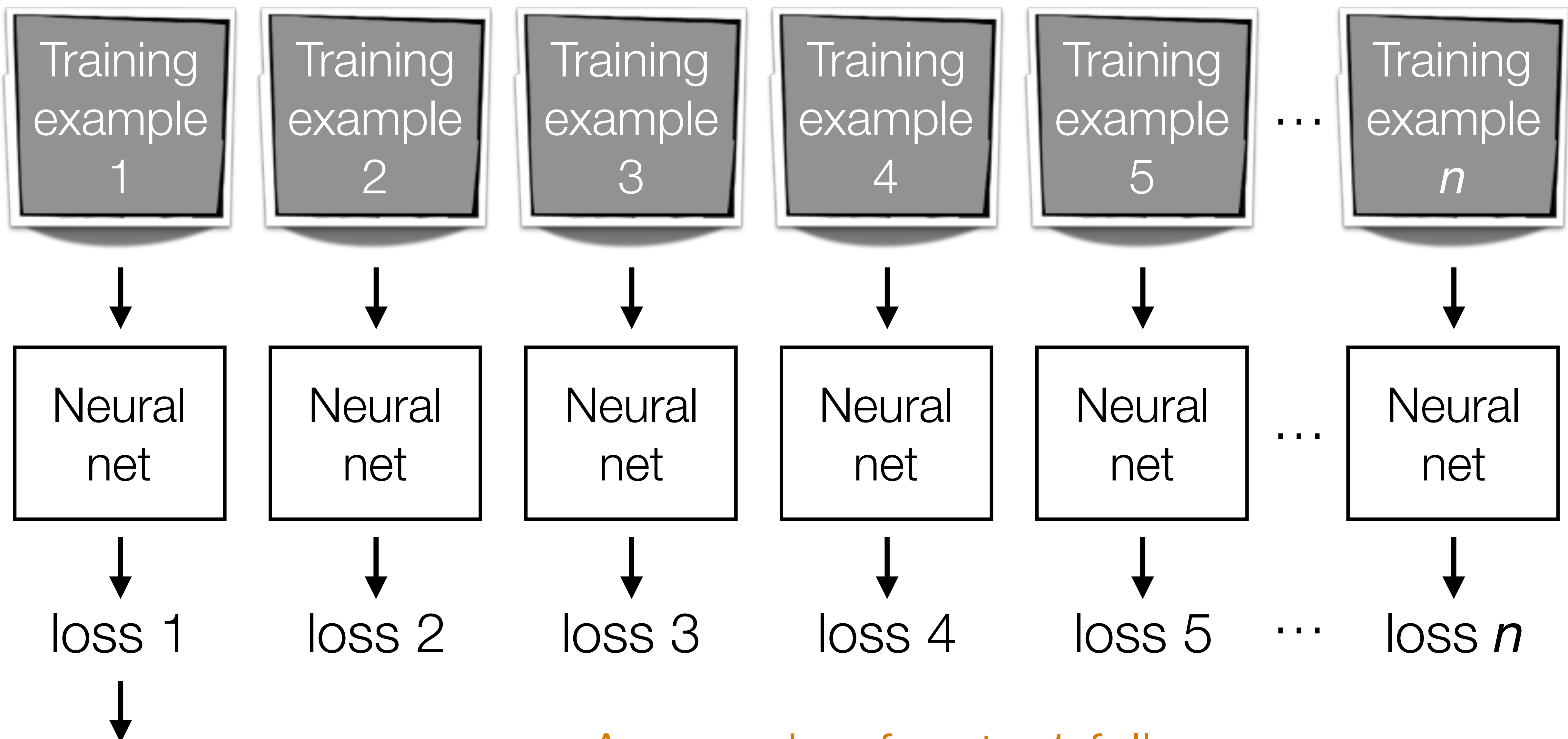

compute gradient
and move skier

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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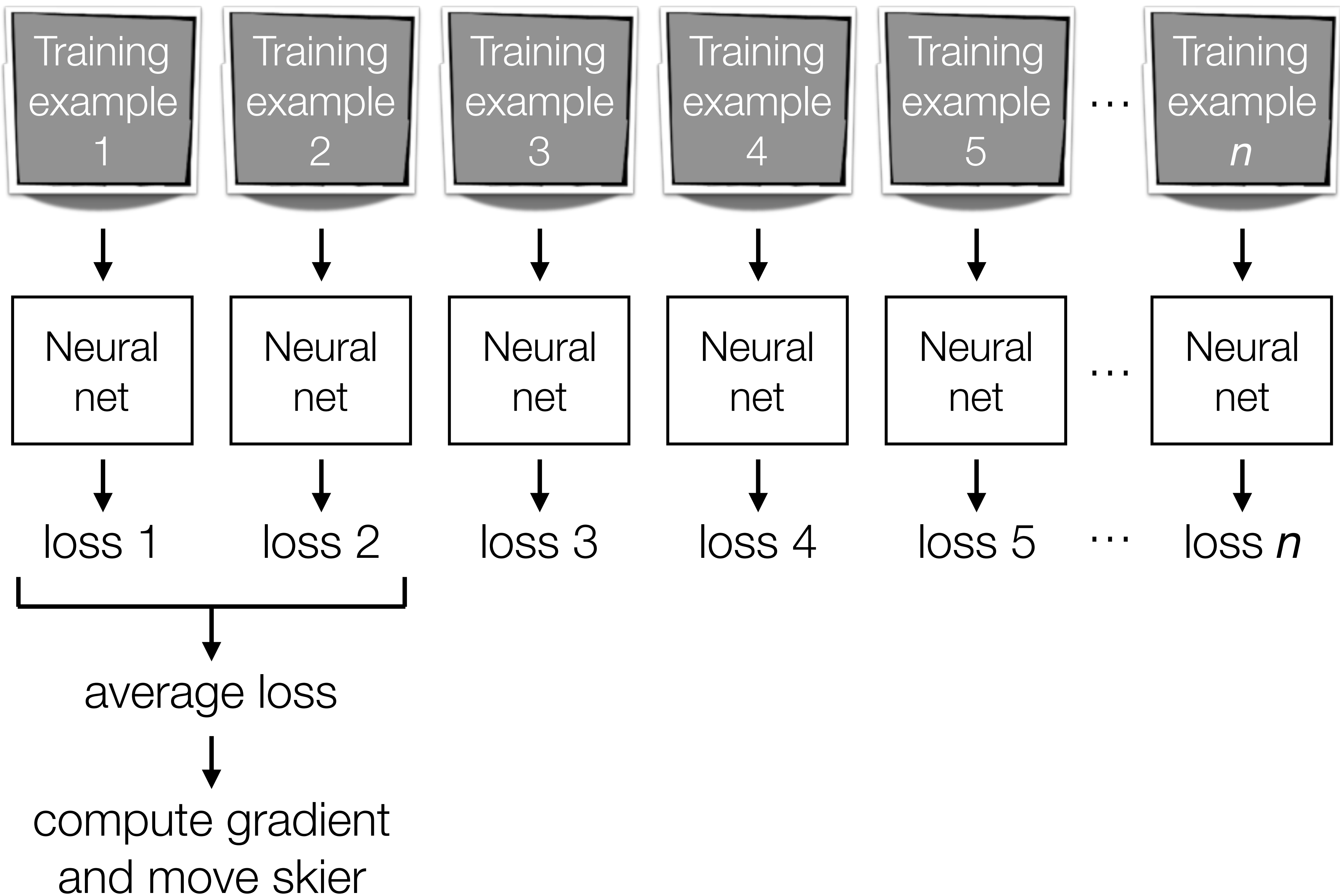
Mini-Batch Gradient Descent



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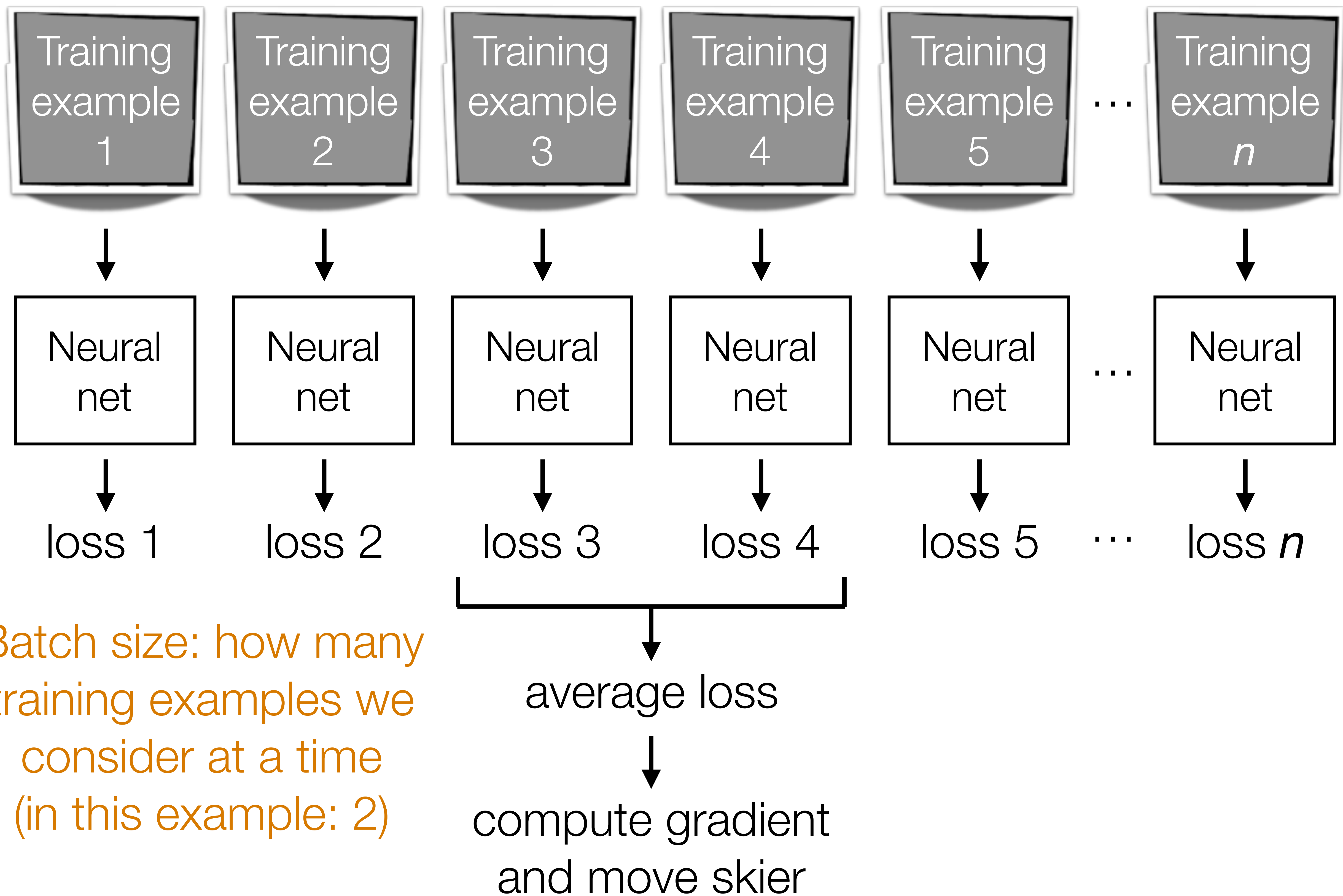

Batch size: how many training examples we consider at a time (in this example: 2)