Carnegie Mellon University
Heinz College

Deep Learning and 95-865 Wrap-Up

nearly all slides by George Chen (CMU)

1 slide by Phillip Isola (OpenAI, UC Berkeley)

CMU 95-865 Fall 2017

Today

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- How learning a deep net works

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- A bunch of deep learning topics we didn’t cover

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- How learning a deep net works
- A bunch of deep learning topics we didn’t cover
- Course wrap-up

Learning a Deep Net

Gradient Descent

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Suppose the neural network has a single real number parameter w

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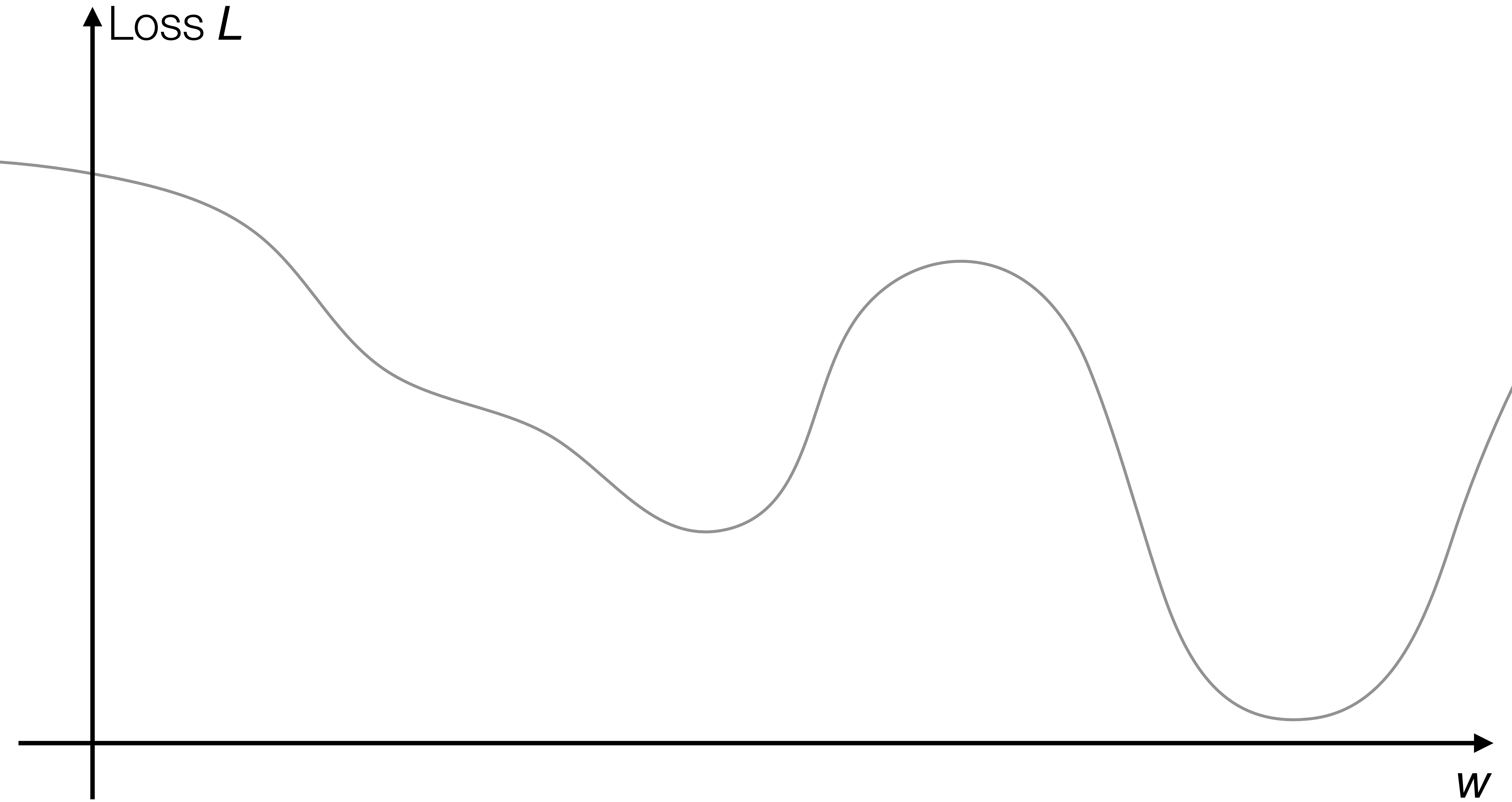

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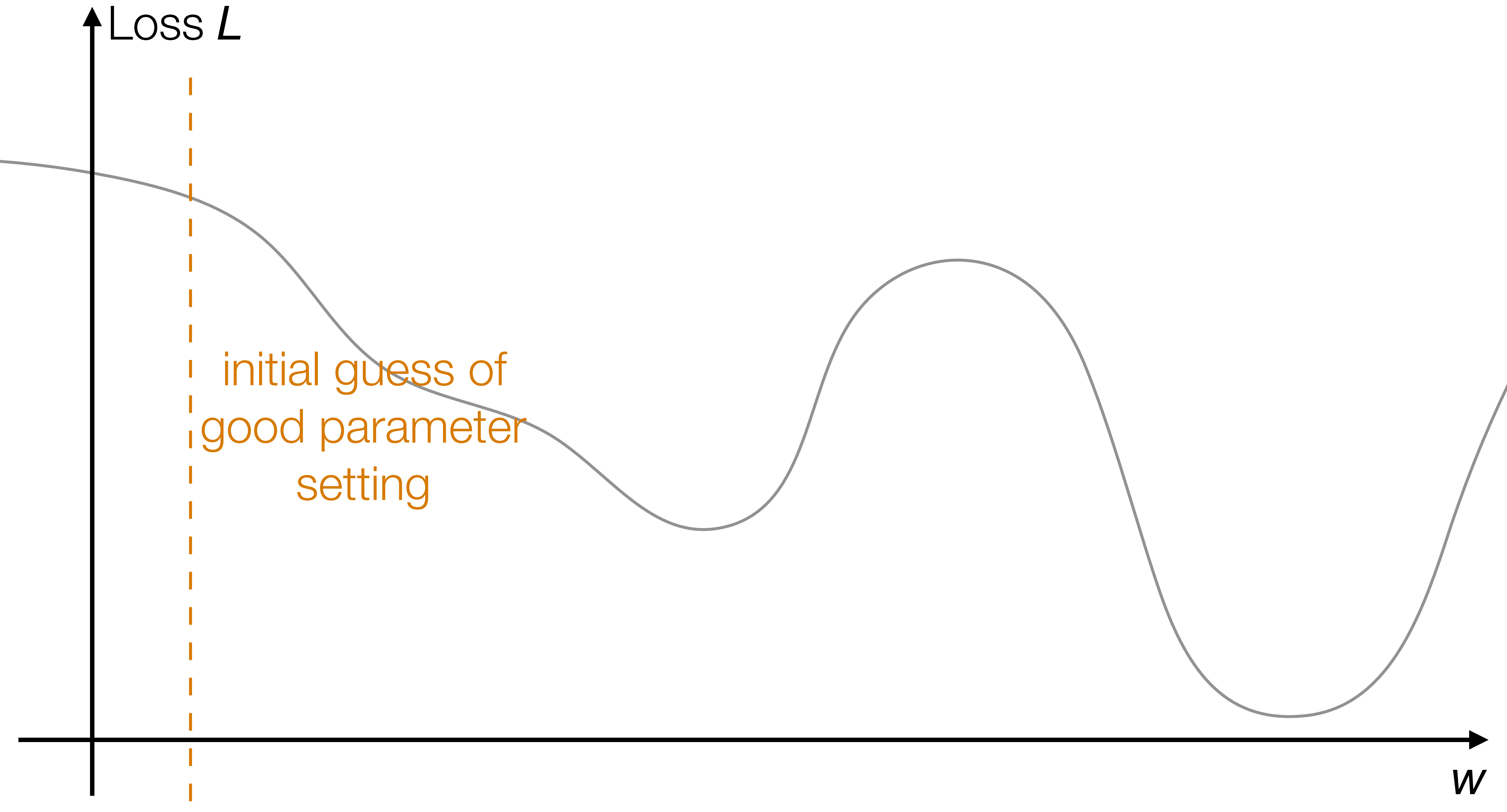

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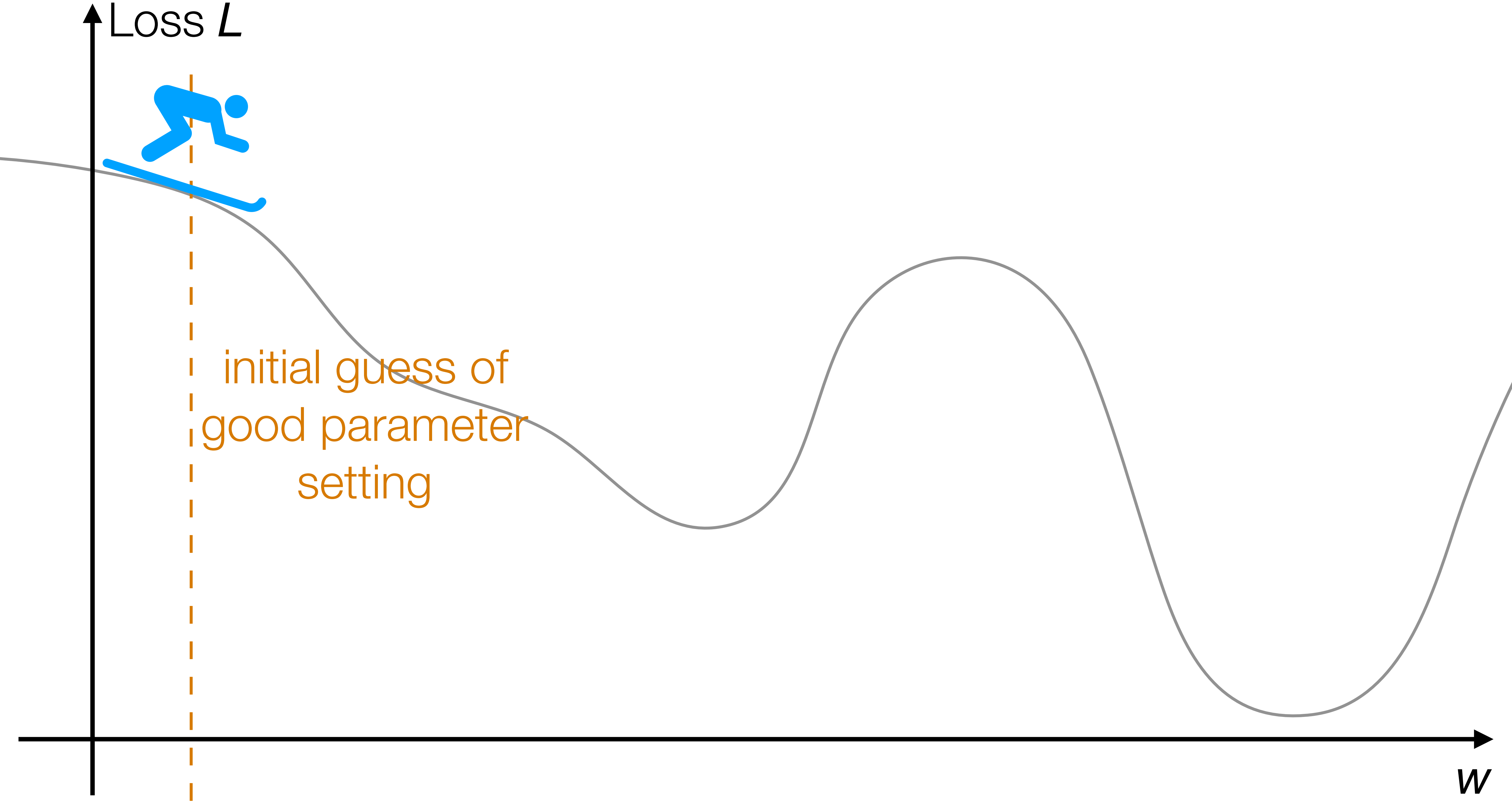

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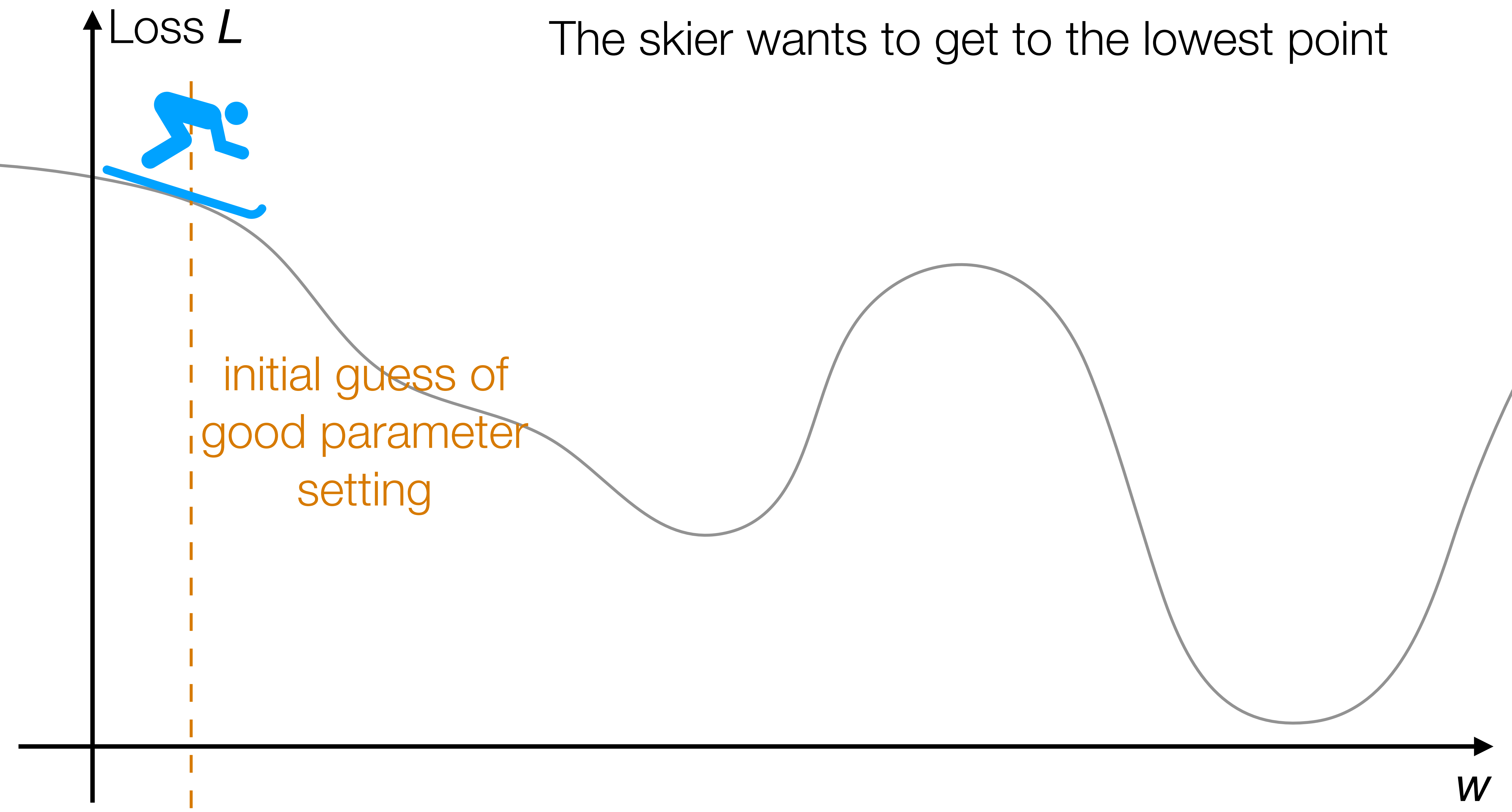

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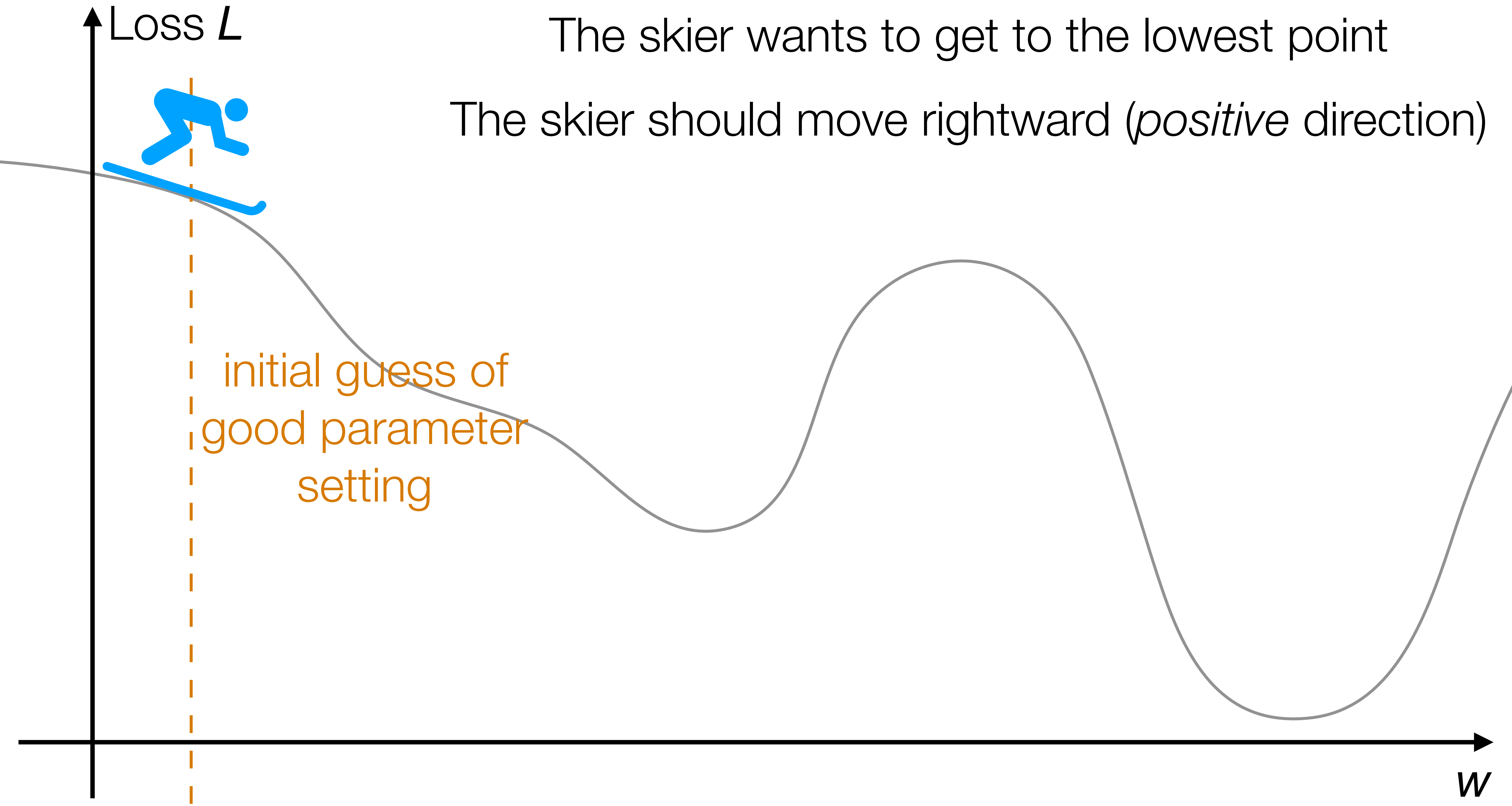

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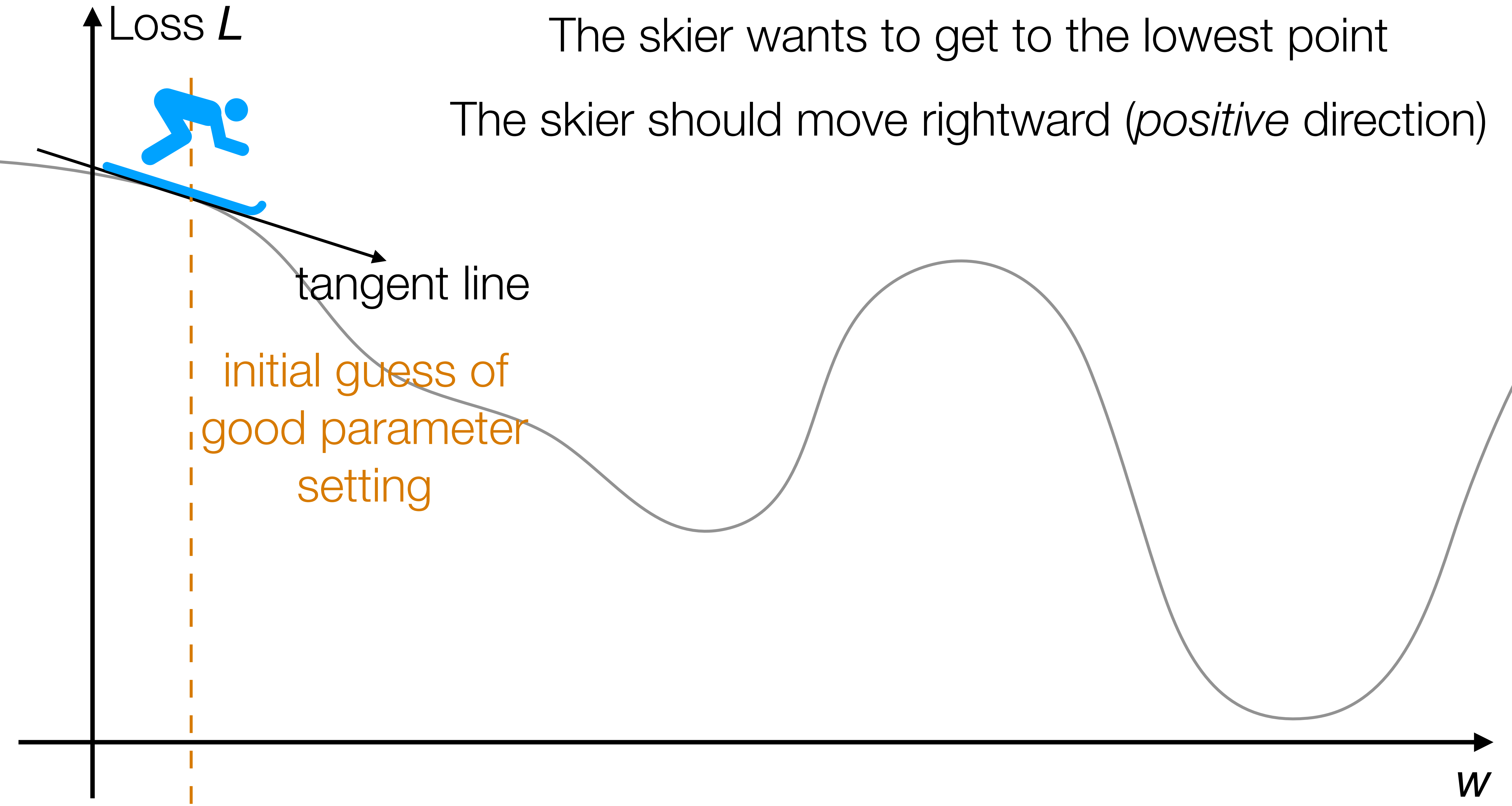
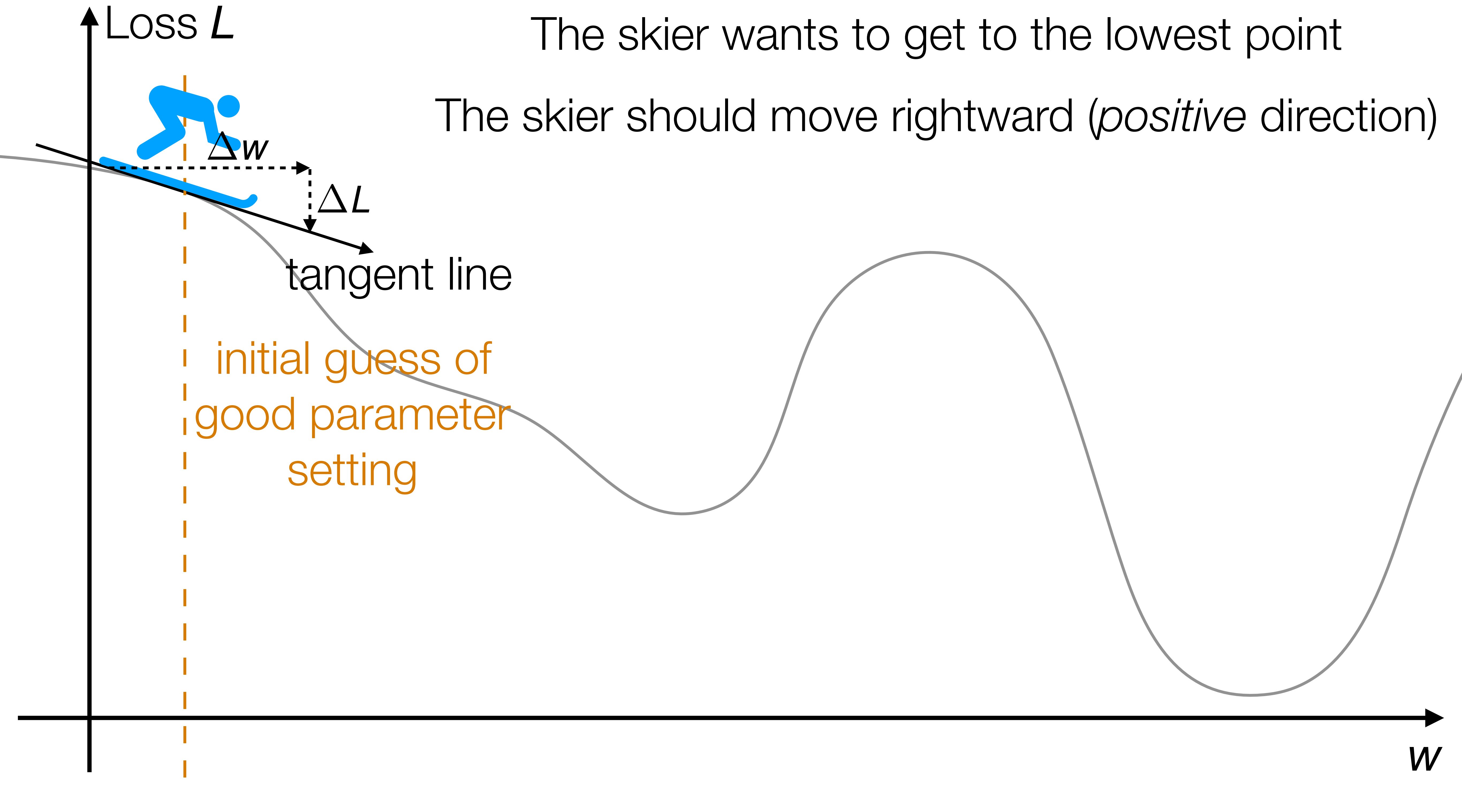


Gradient Descent

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)



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

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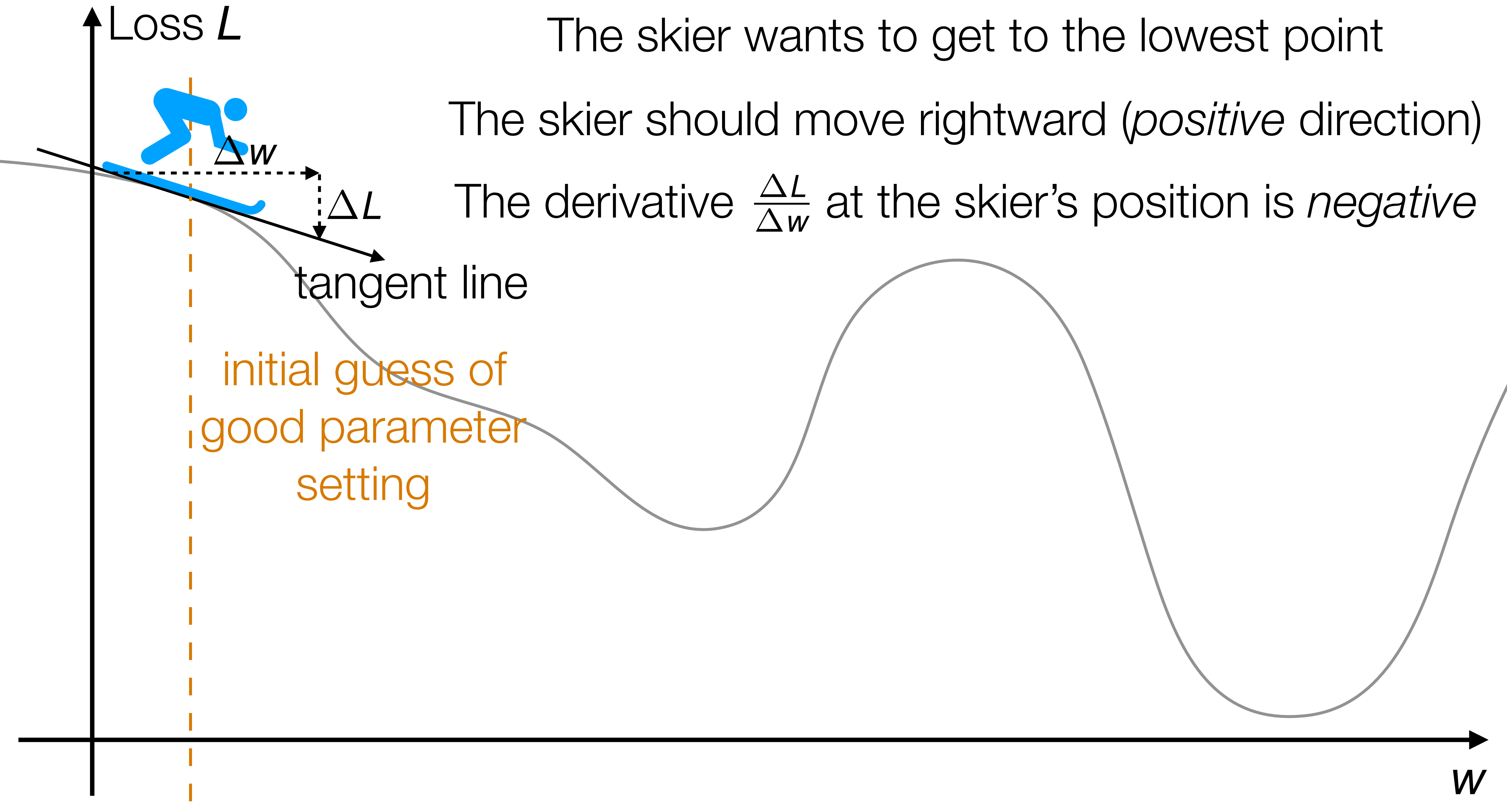
The derivative $\frac{\Delta L}{\Delta w}$ at the skier's position is *negative*



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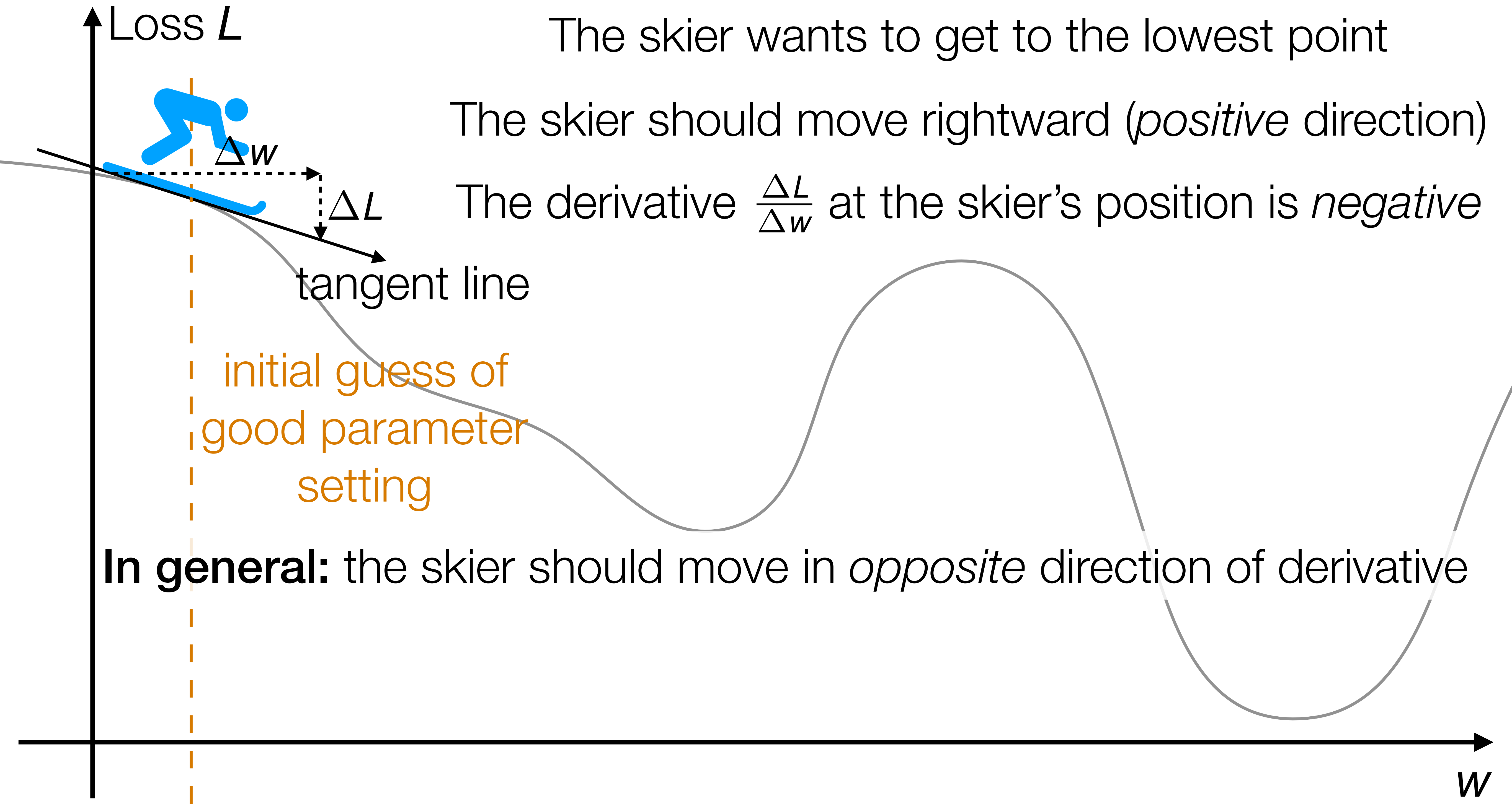

In general: the skier should move in *opposite* direction of derivative

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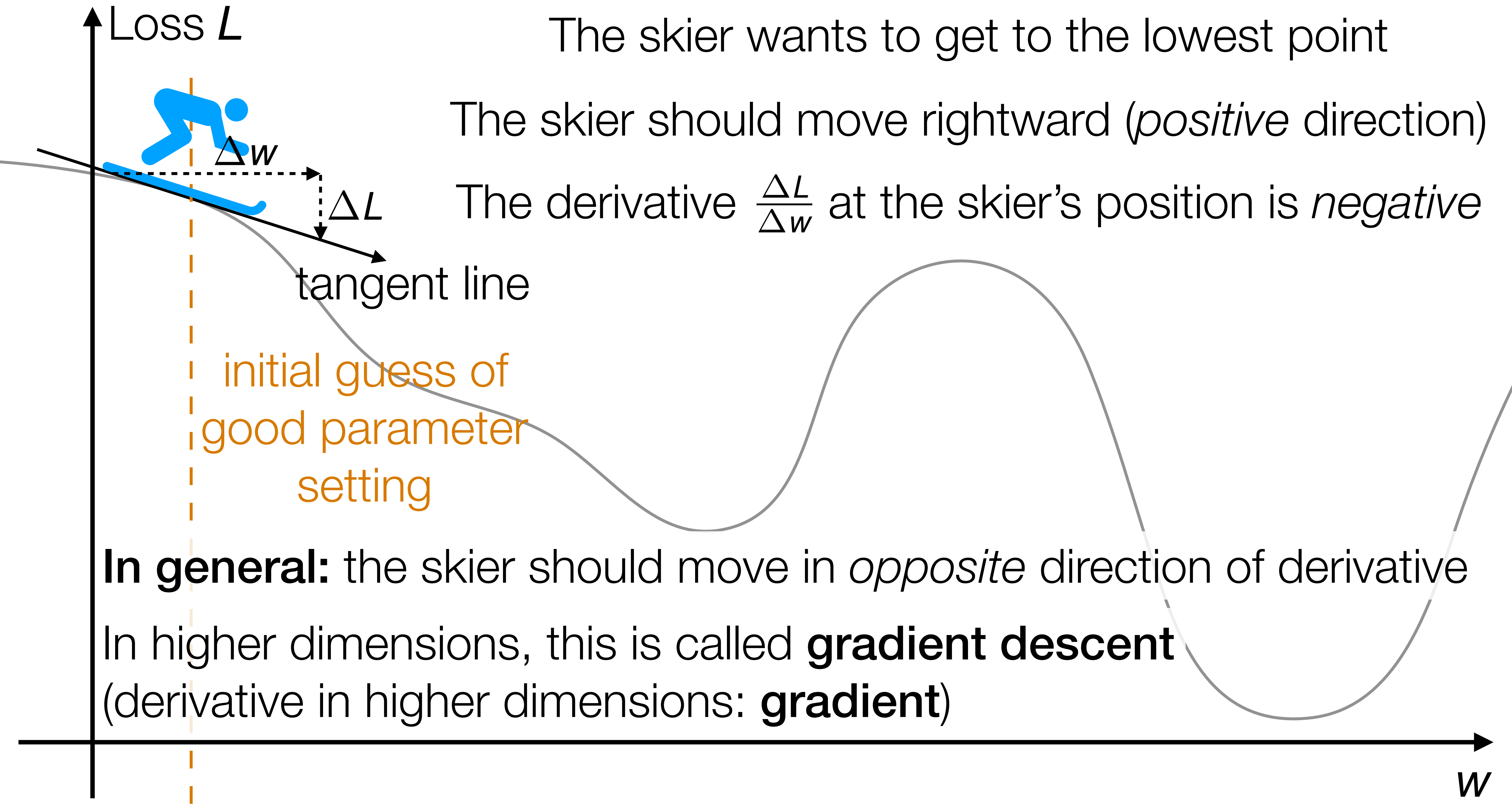

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In general: the skier should move in *opposite* direction of derivative

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

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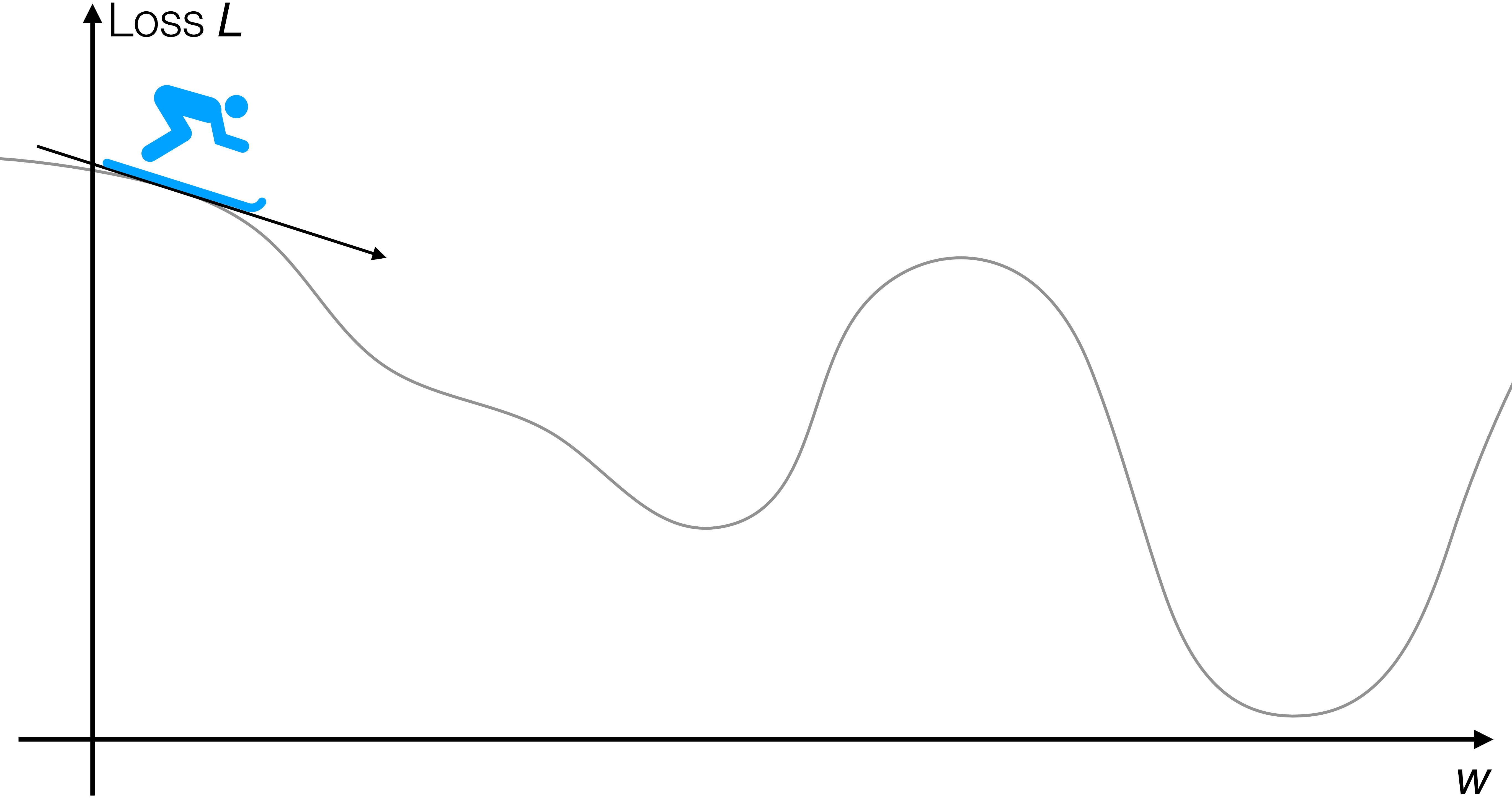

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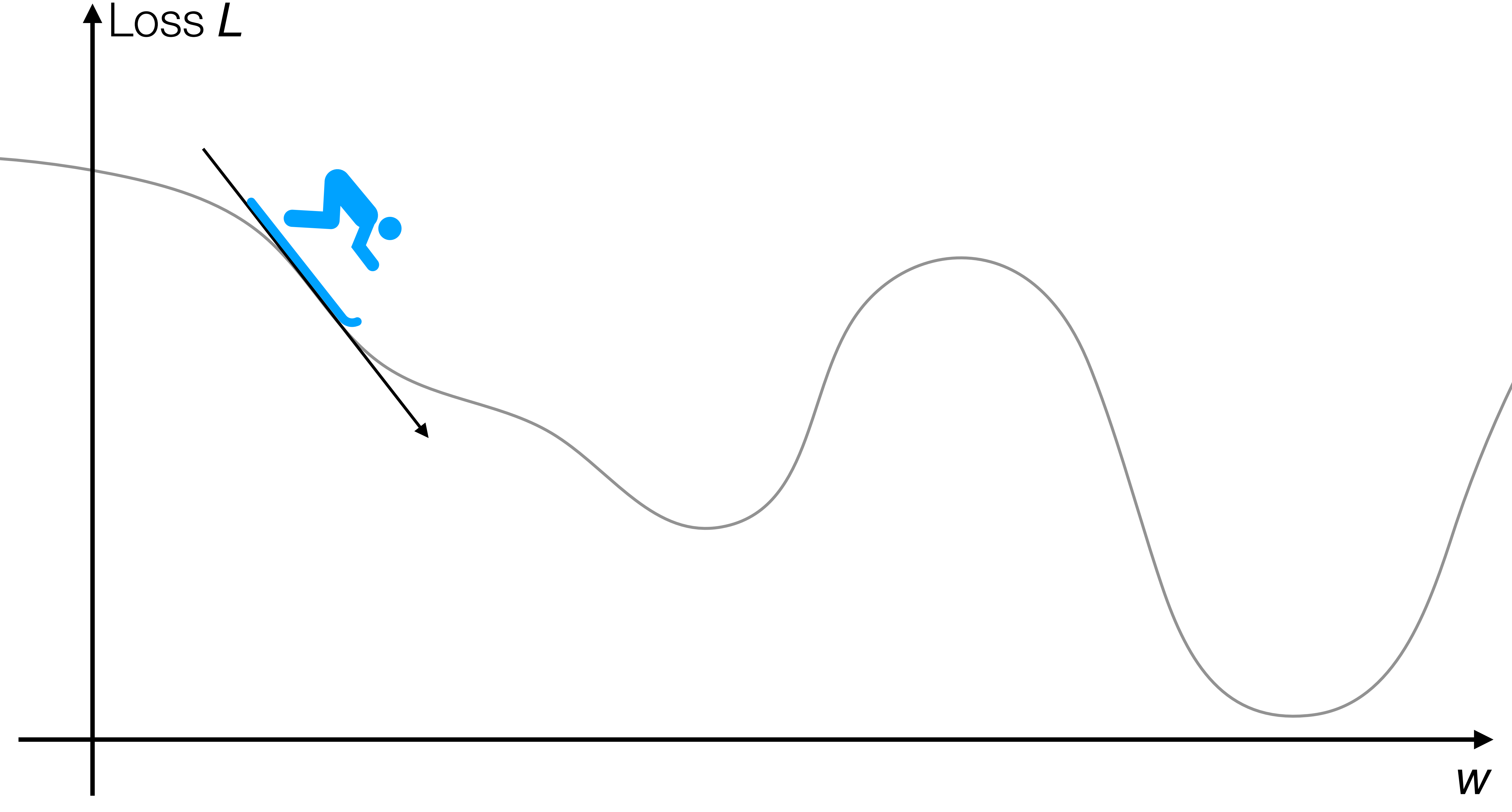

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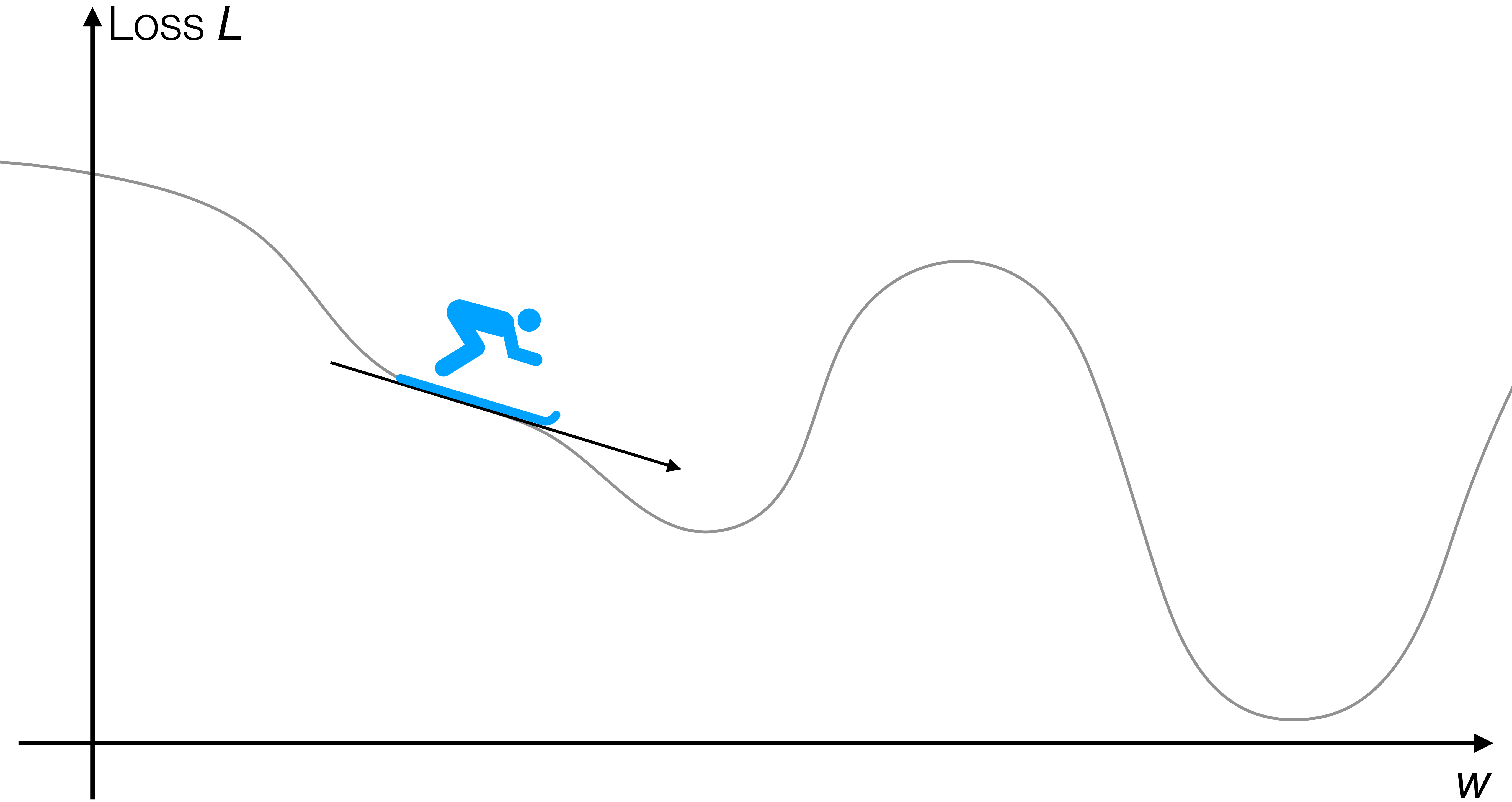

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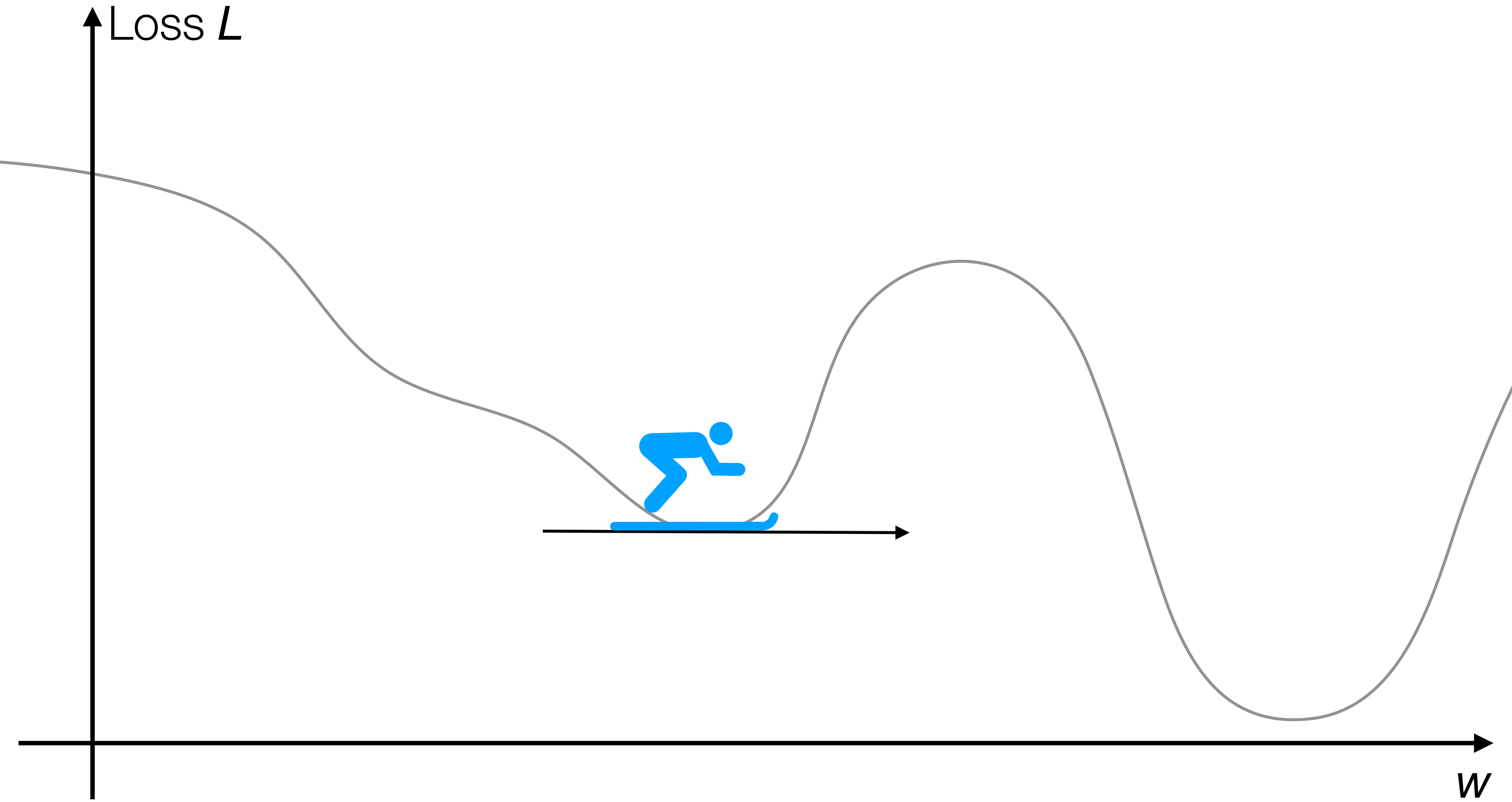

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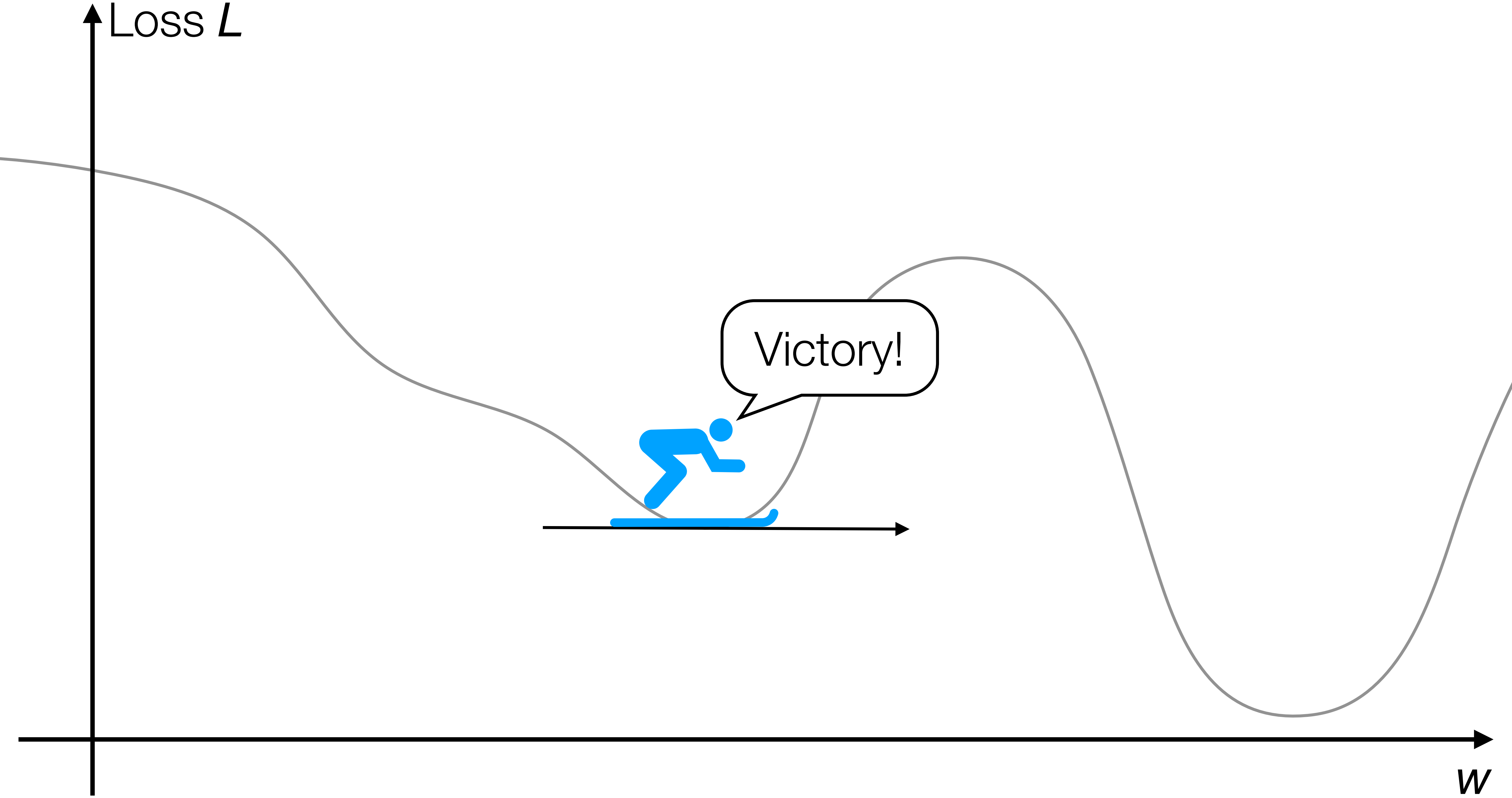

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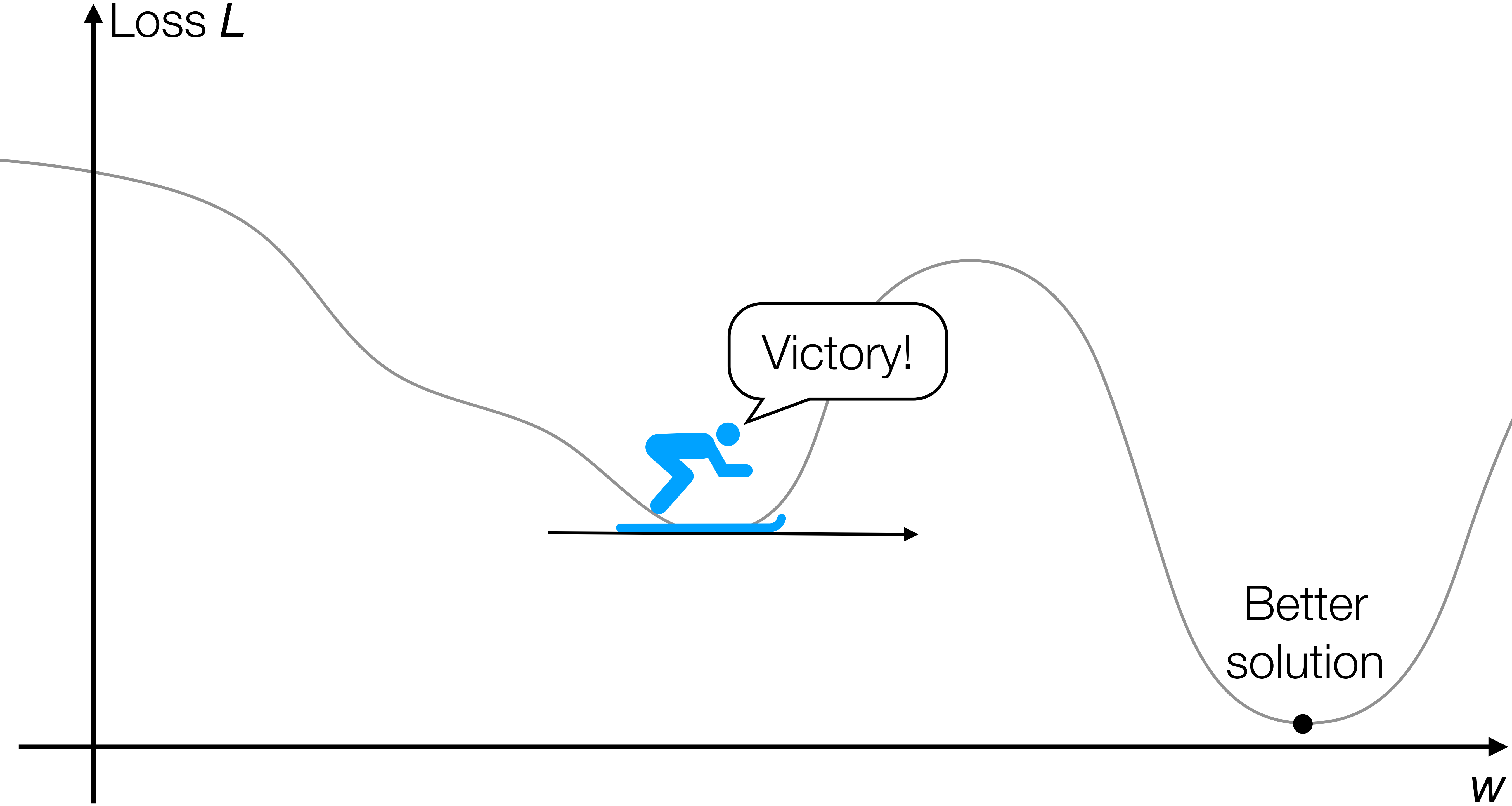

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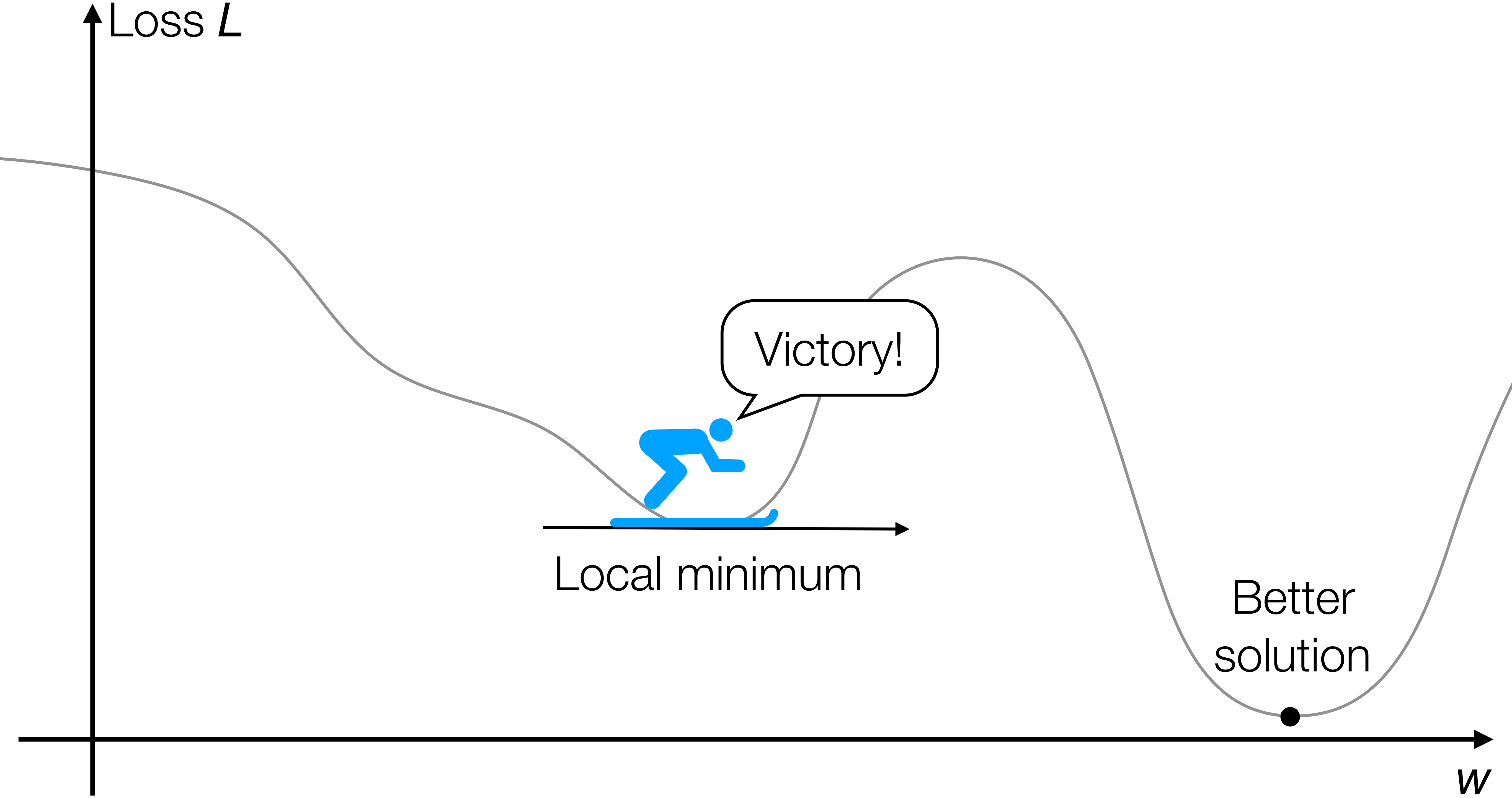

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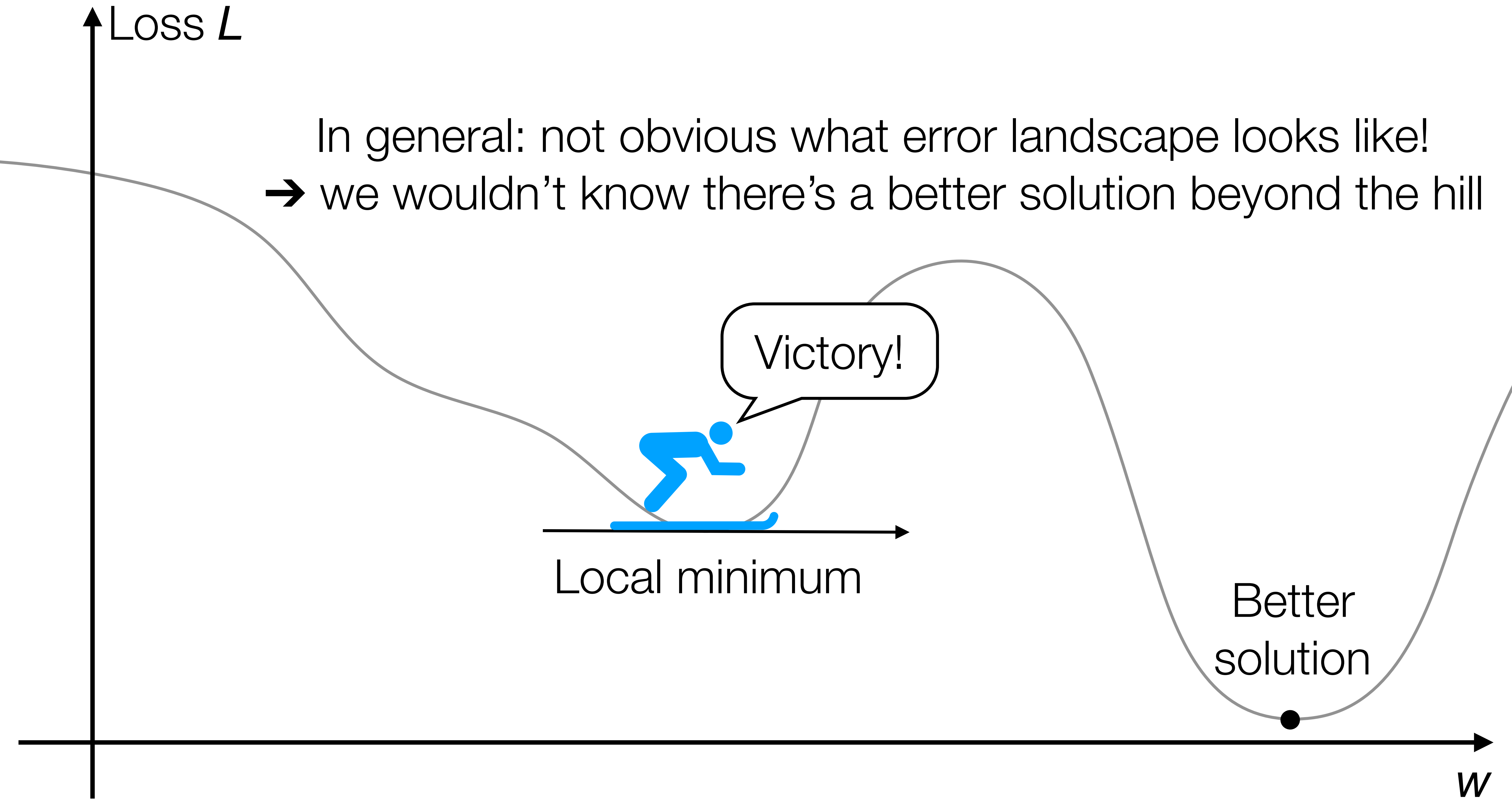

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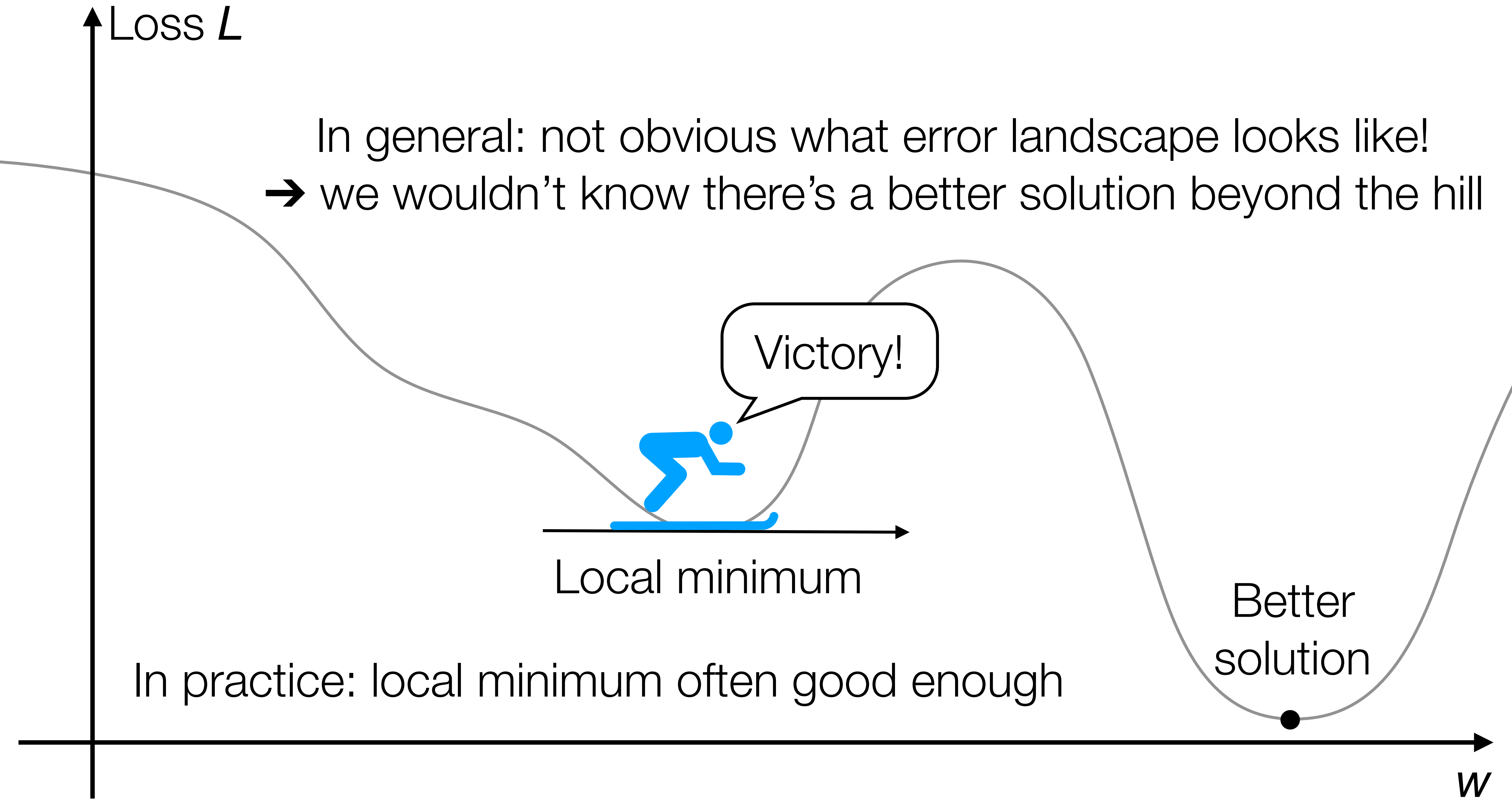

In general: not obvious what error landscape looks like!
➔ we wouldn't know there's a better solution beyond the hill

In practice: local minimum often good enough

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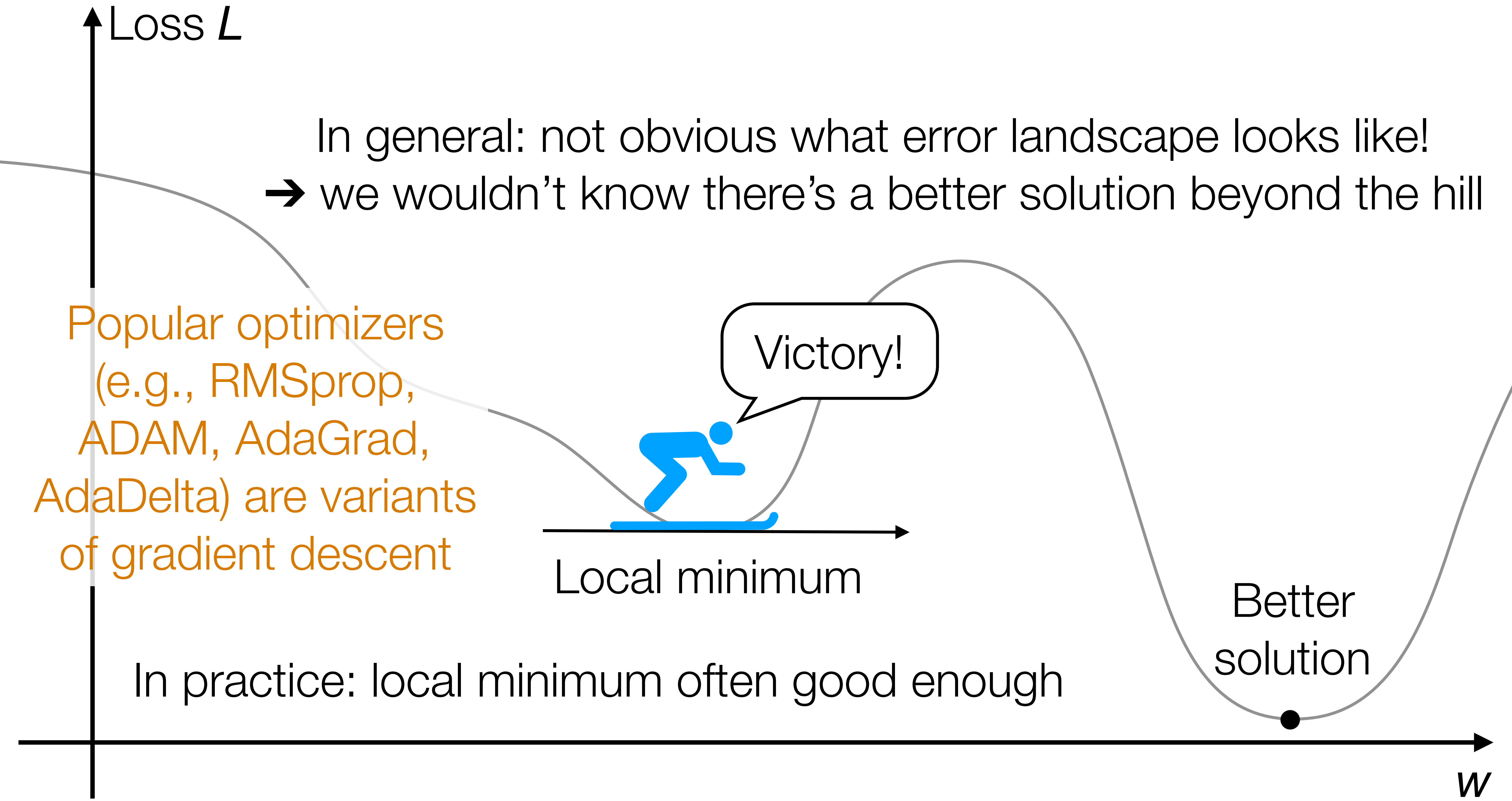
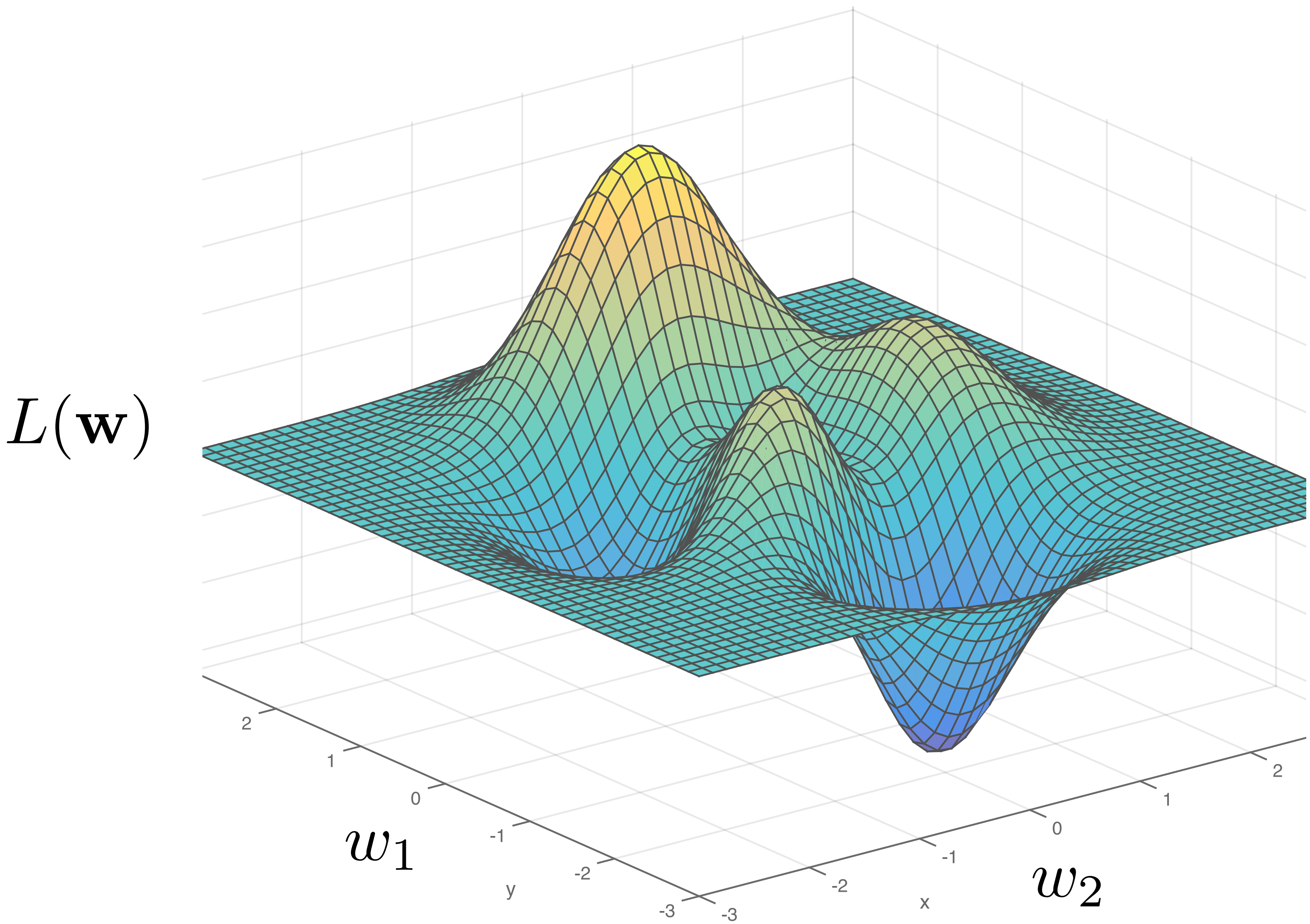


Gradient Descent

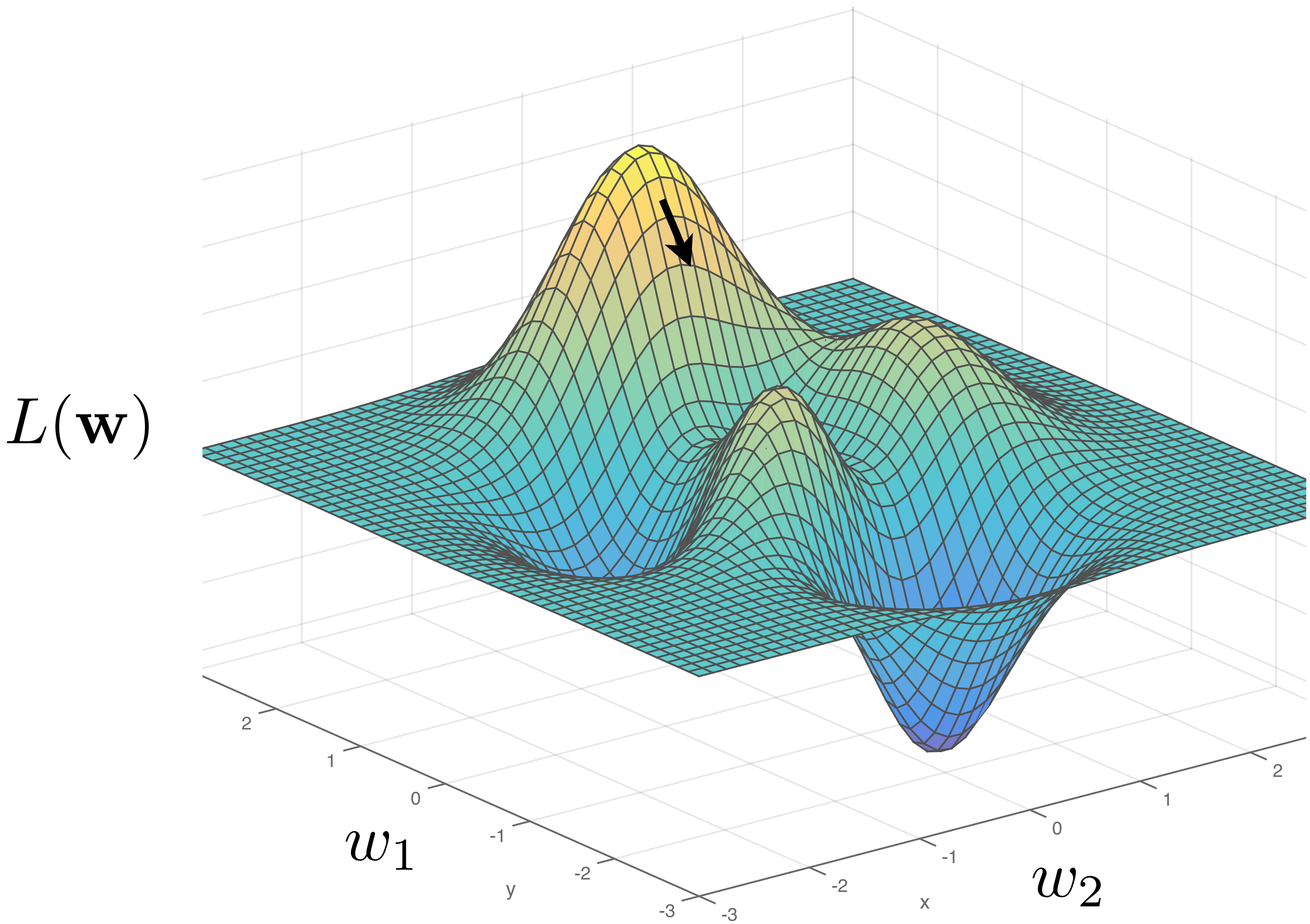
2D example



Slide by Phillip Isola

Gradient Descent

2D example



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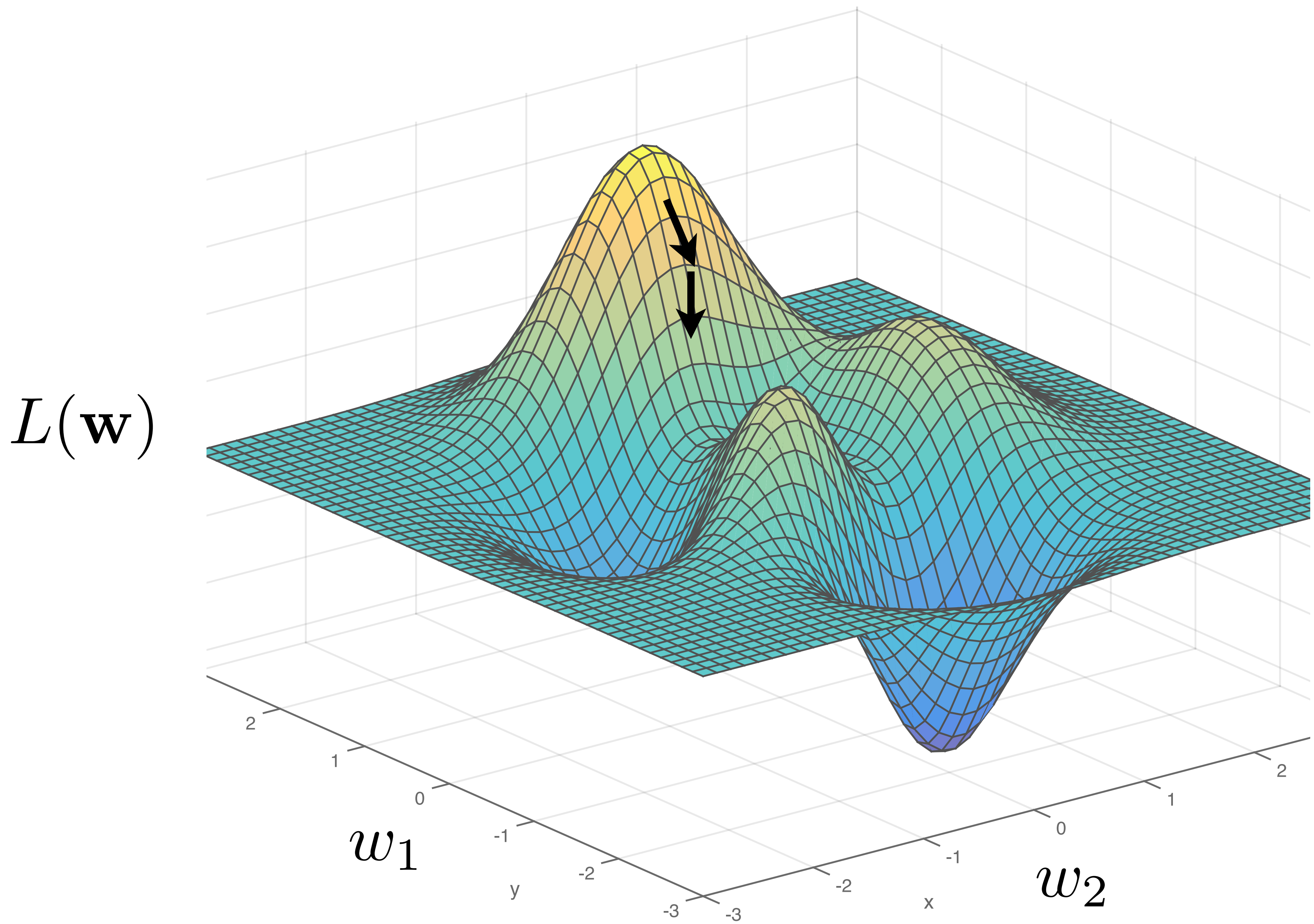

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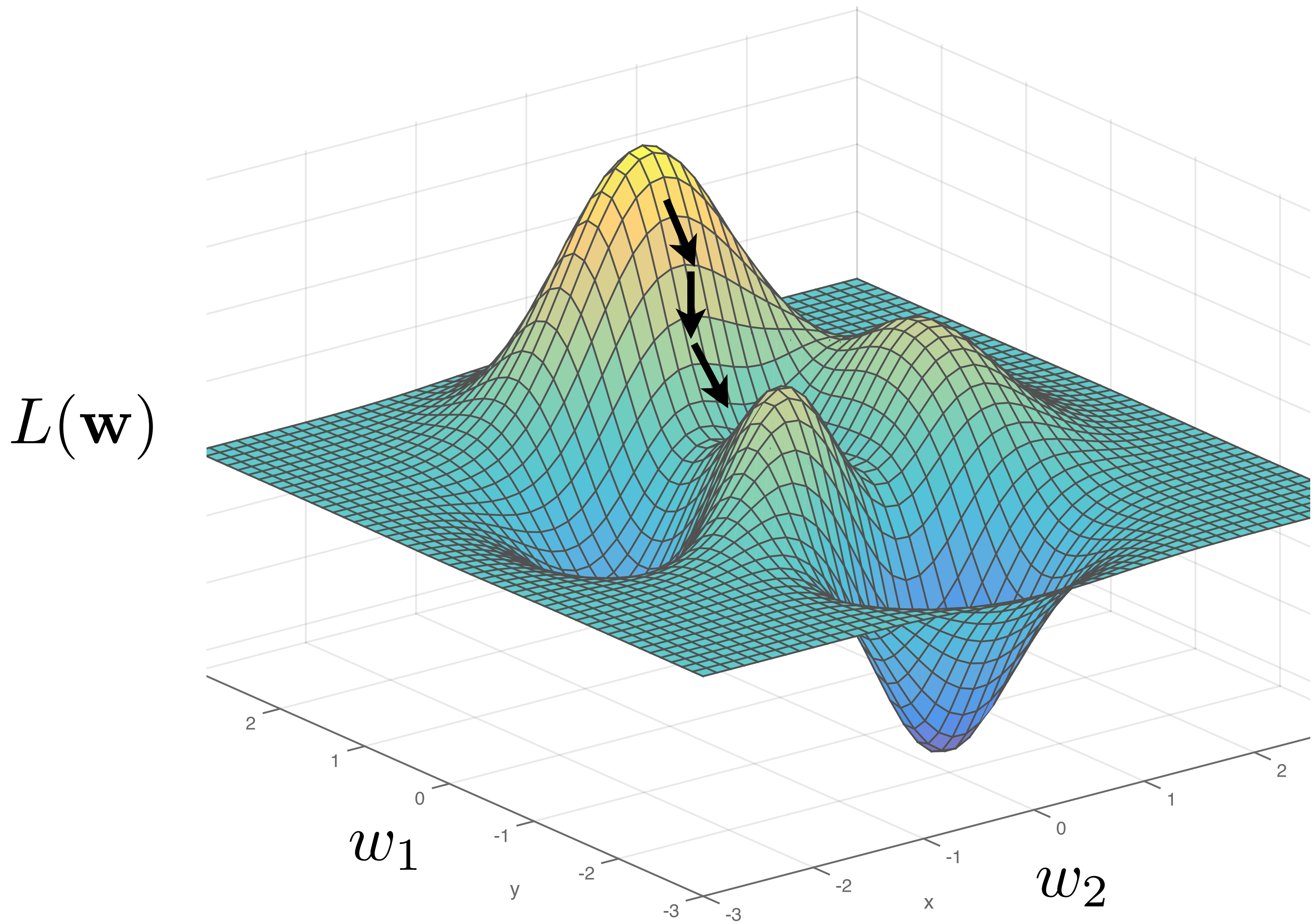

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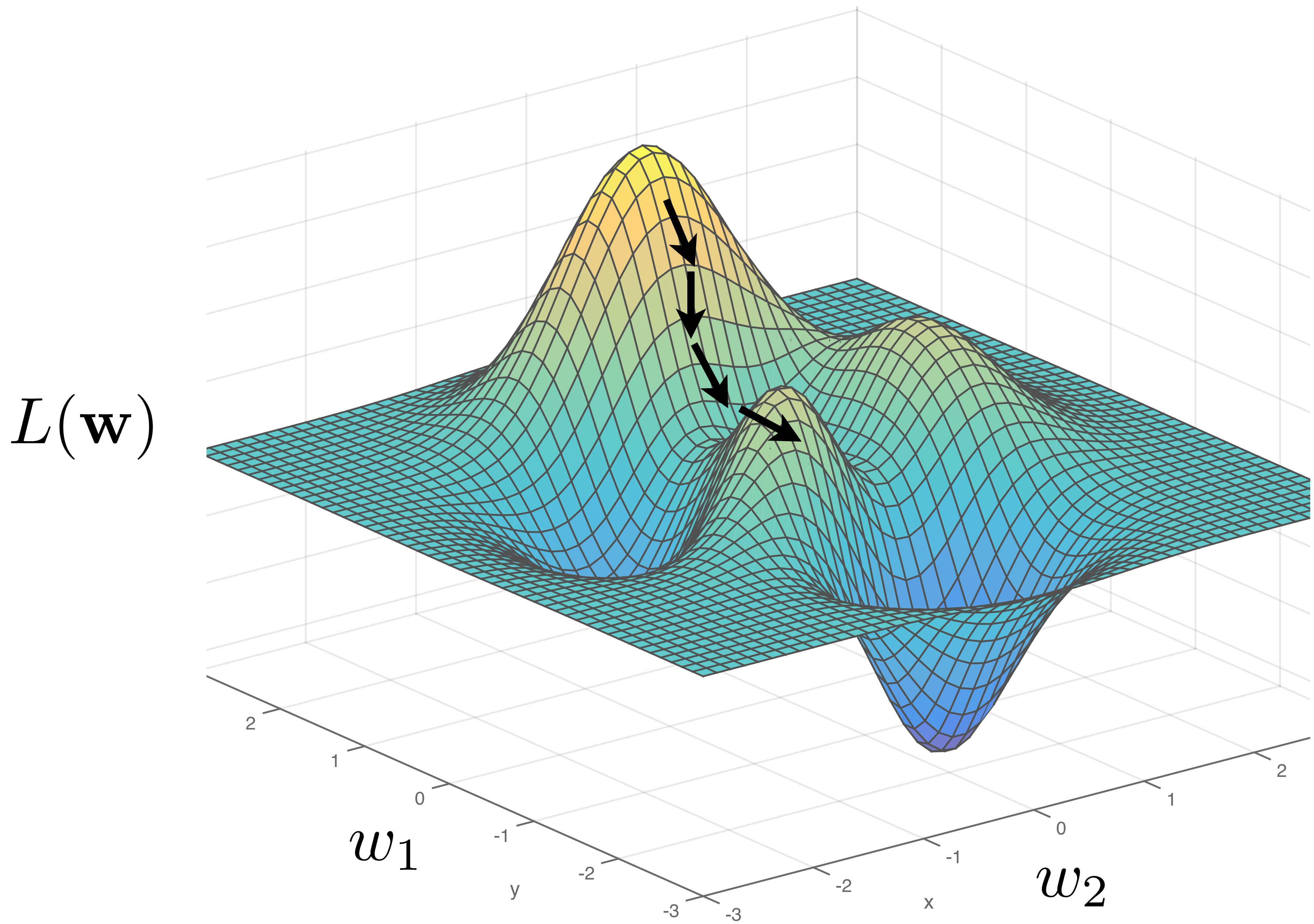

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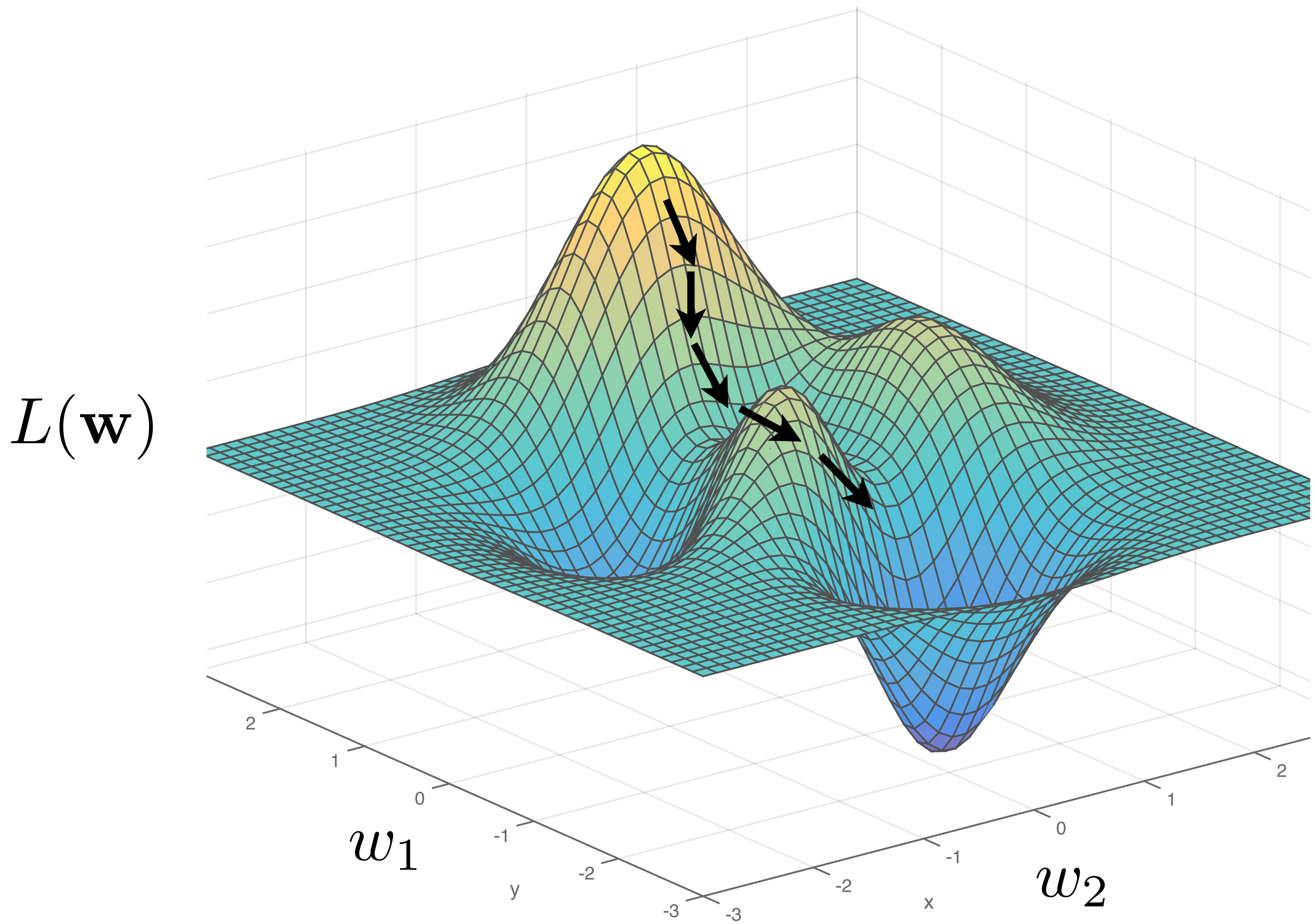

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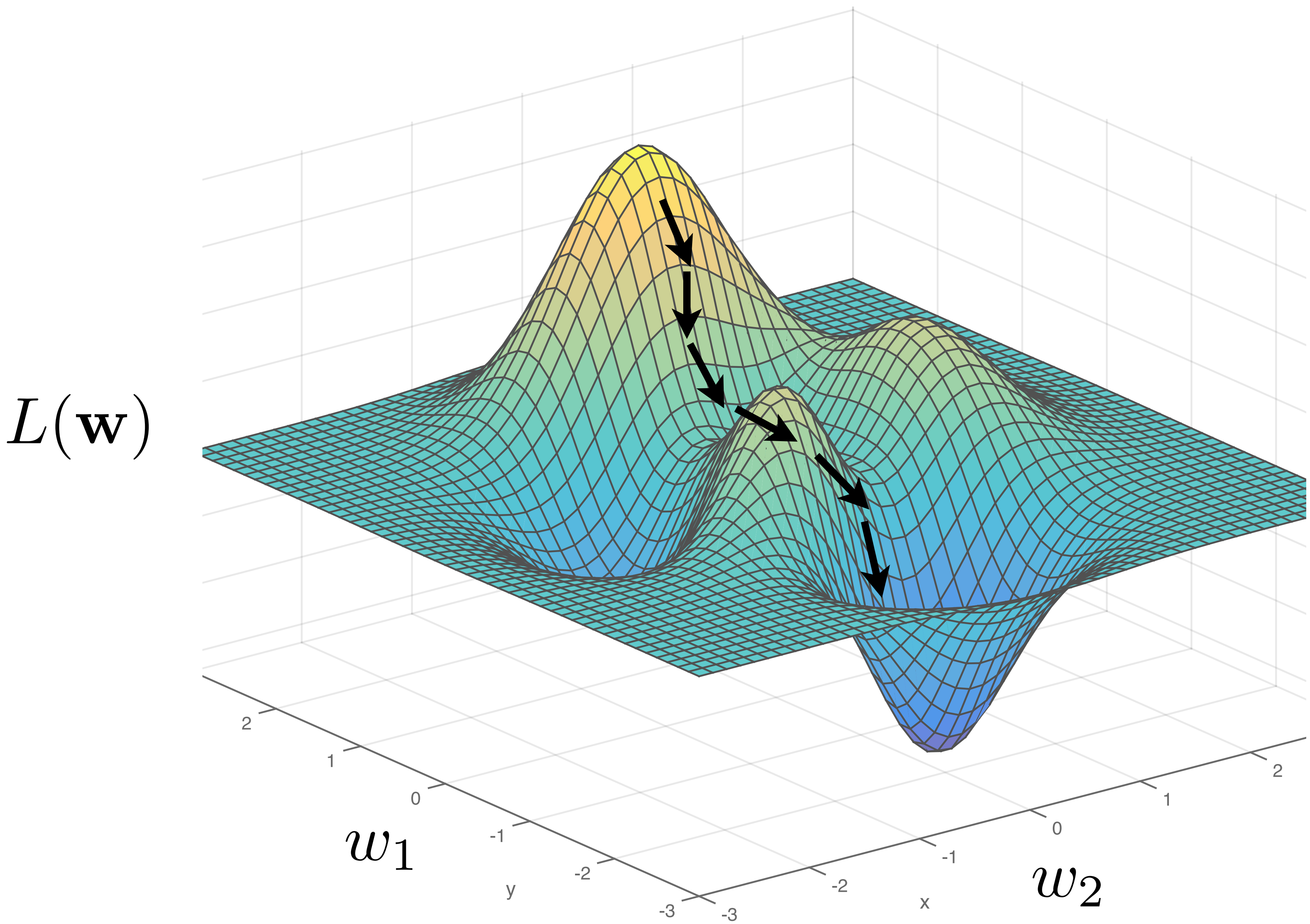

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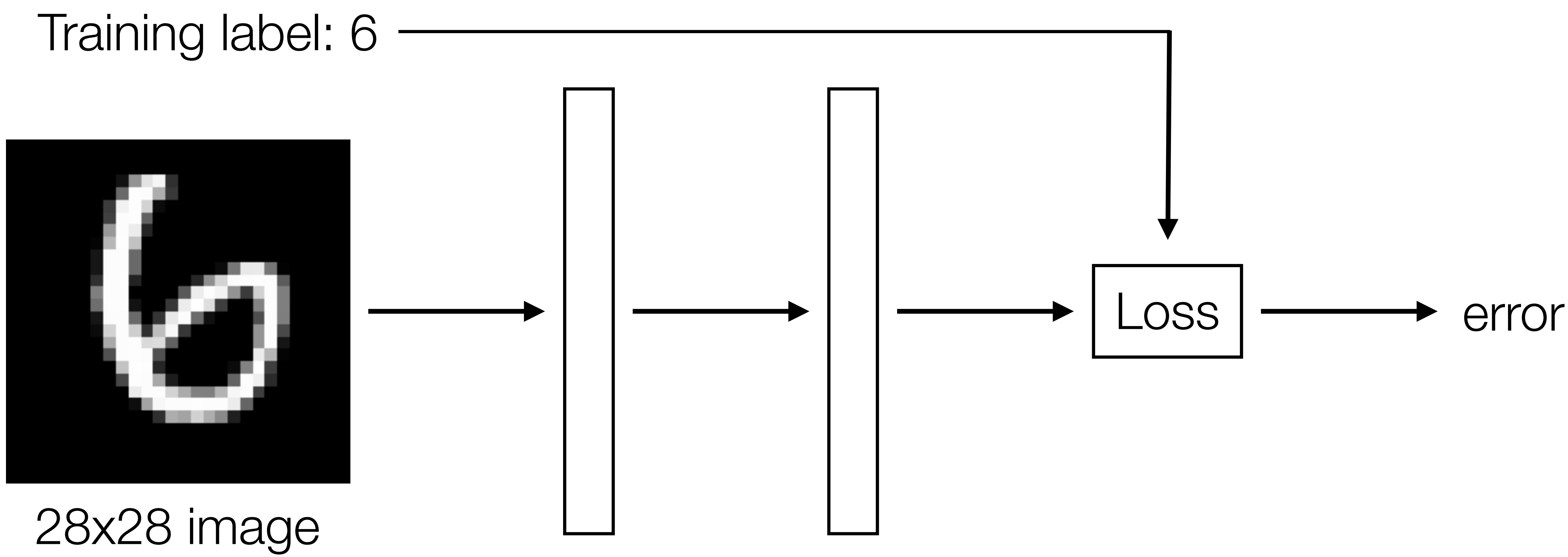
Remark: In practice, deep nets often have > *millions* of parameters, so *very* high-dimensional gradient descent

Handwritten Digit Recognition



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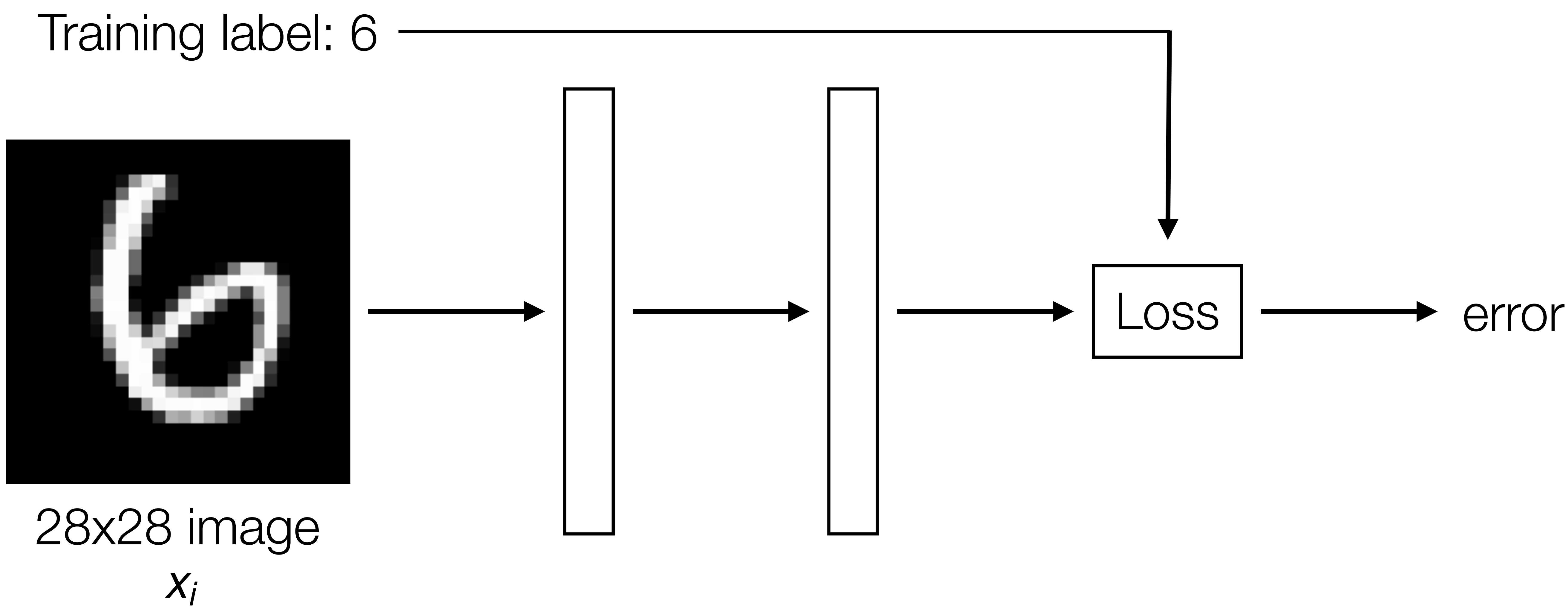

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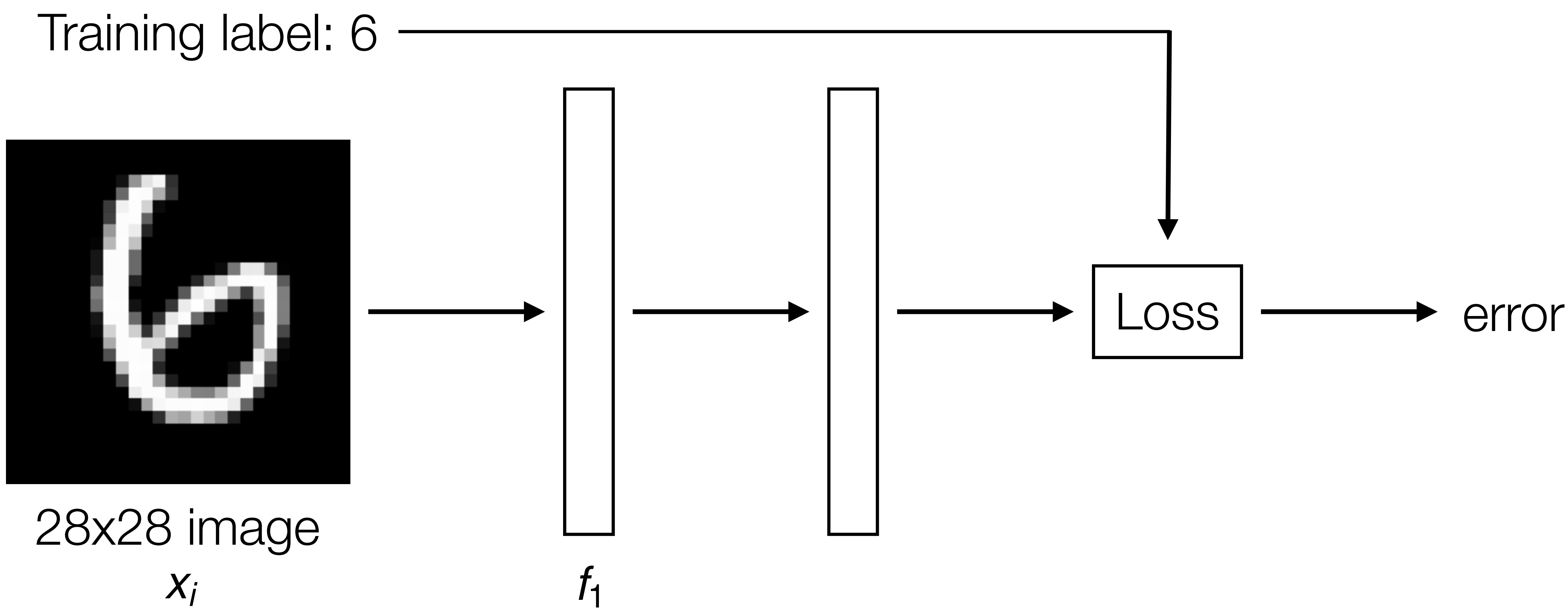

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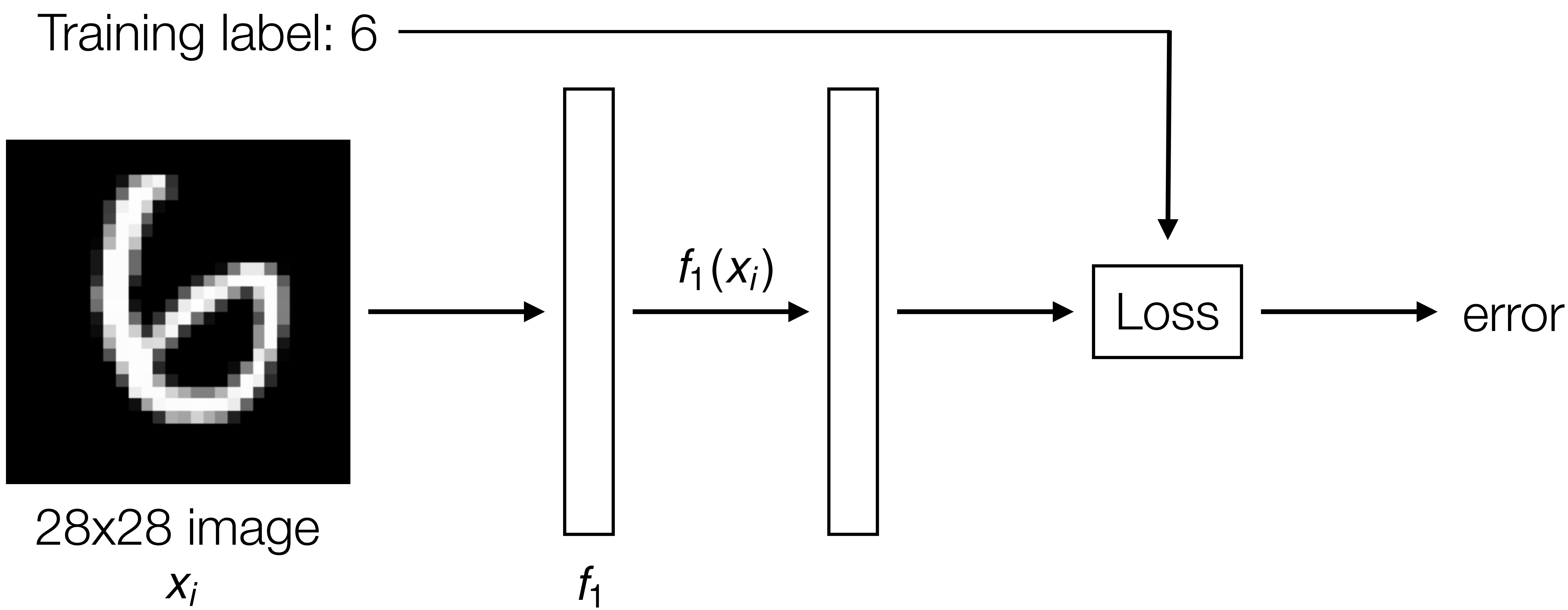

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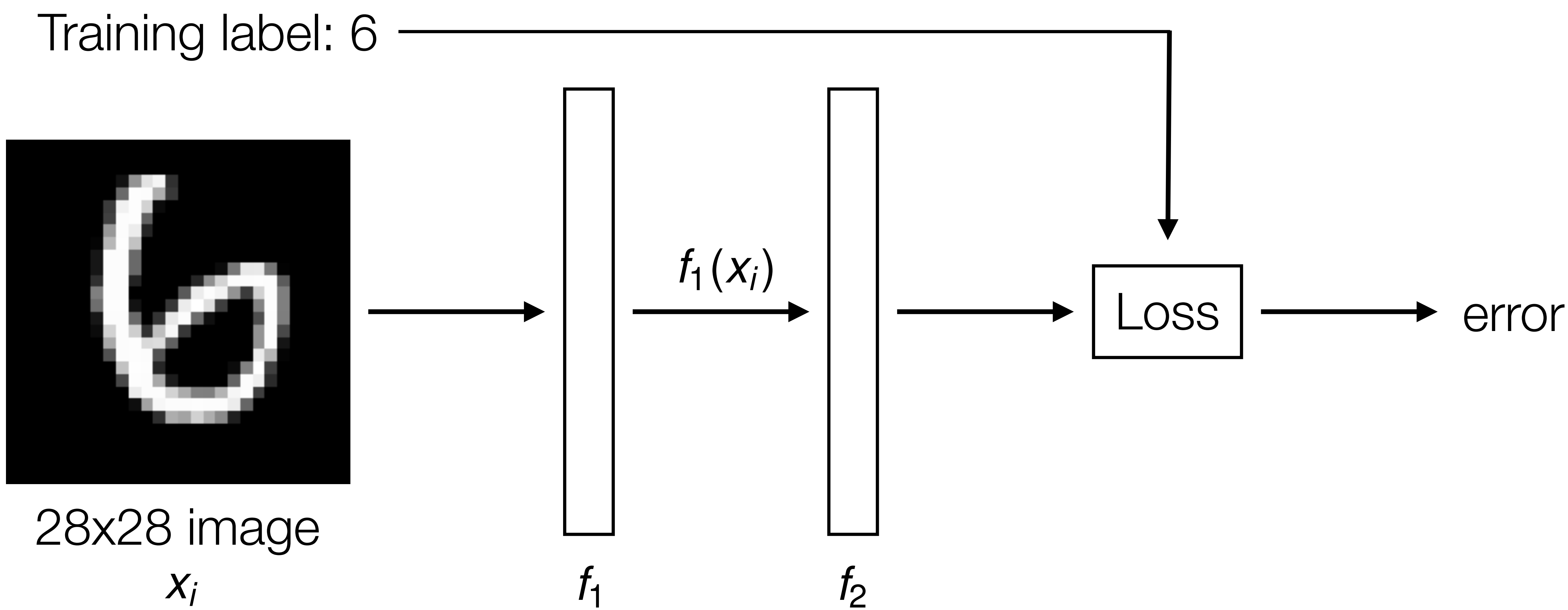

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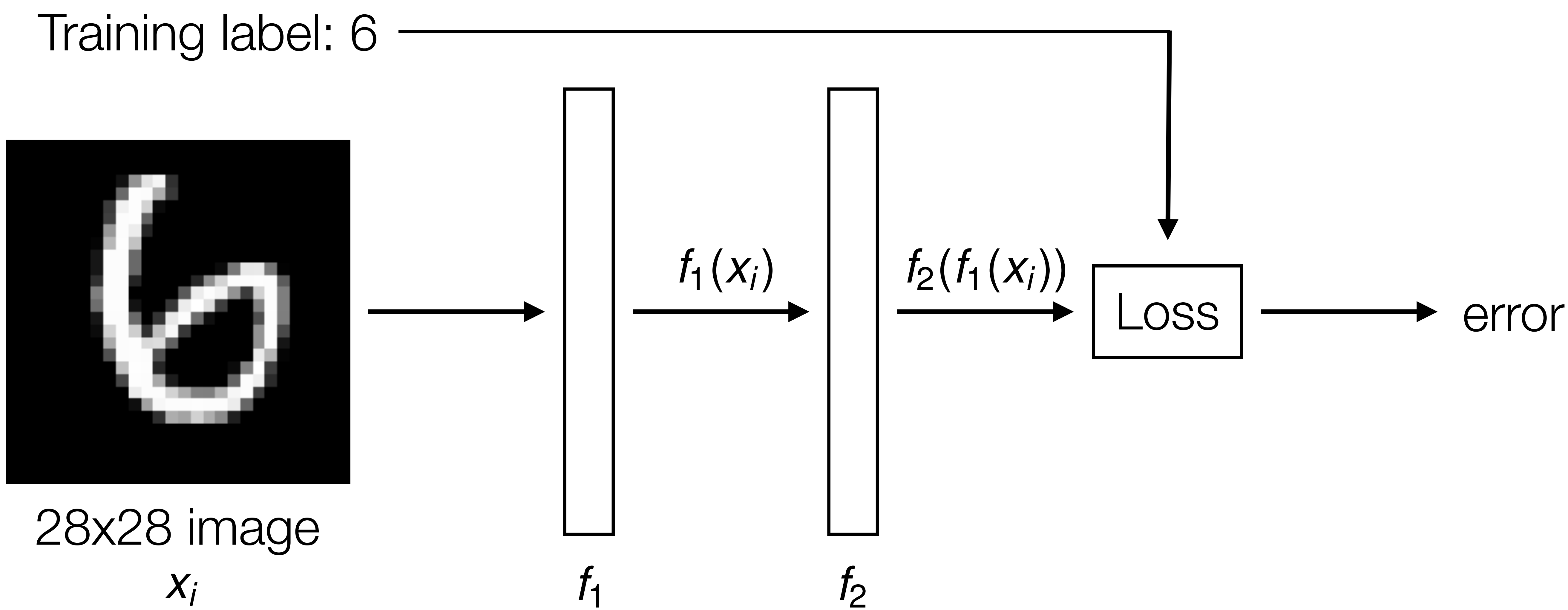

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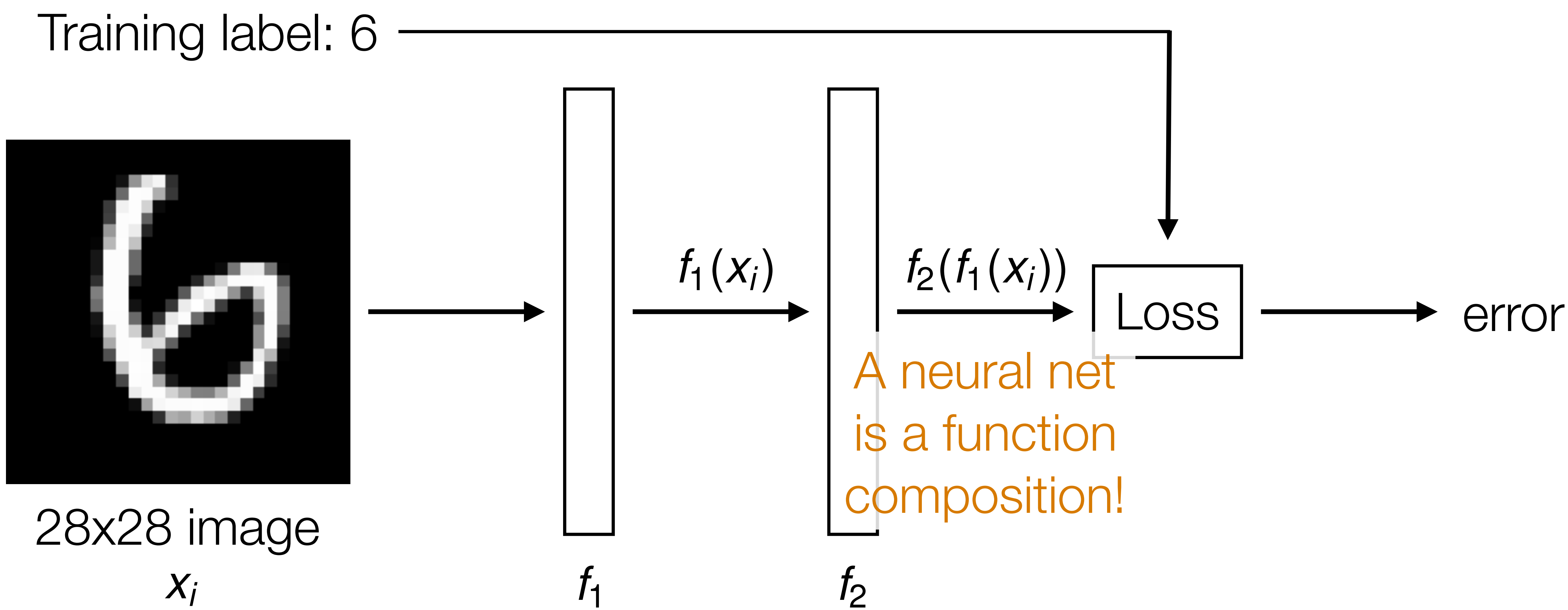

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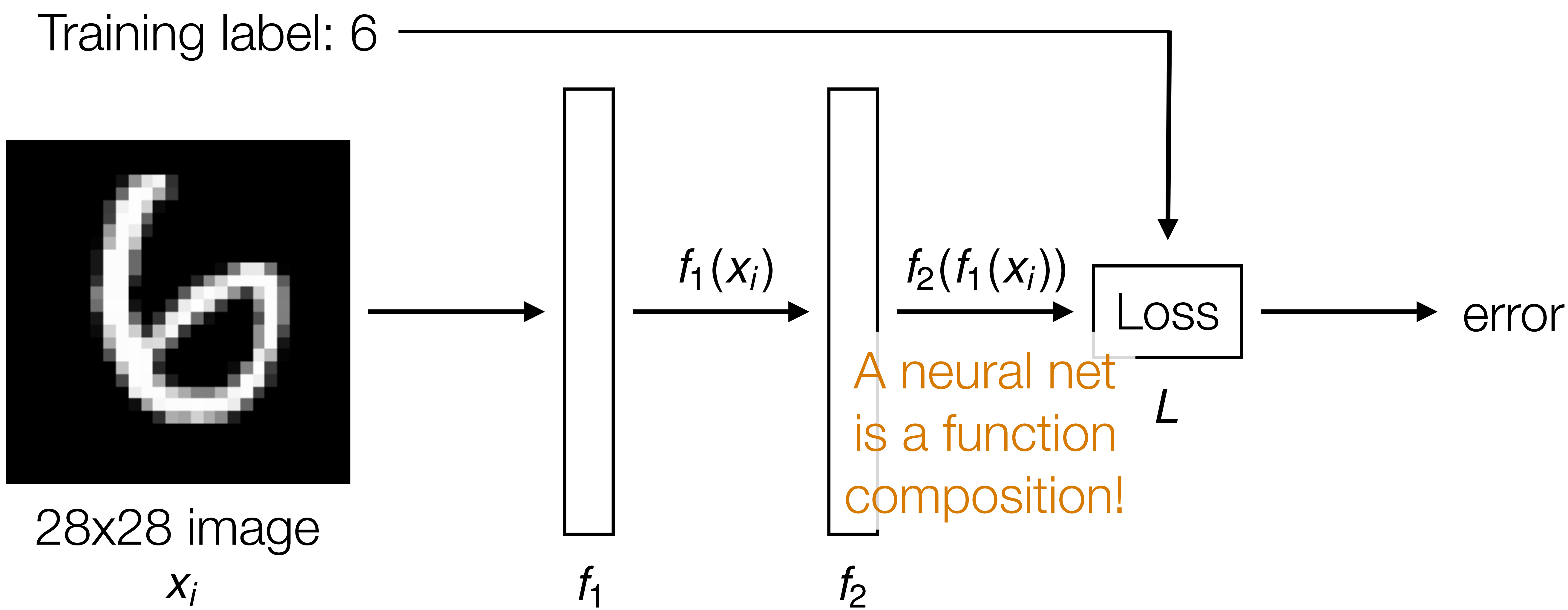

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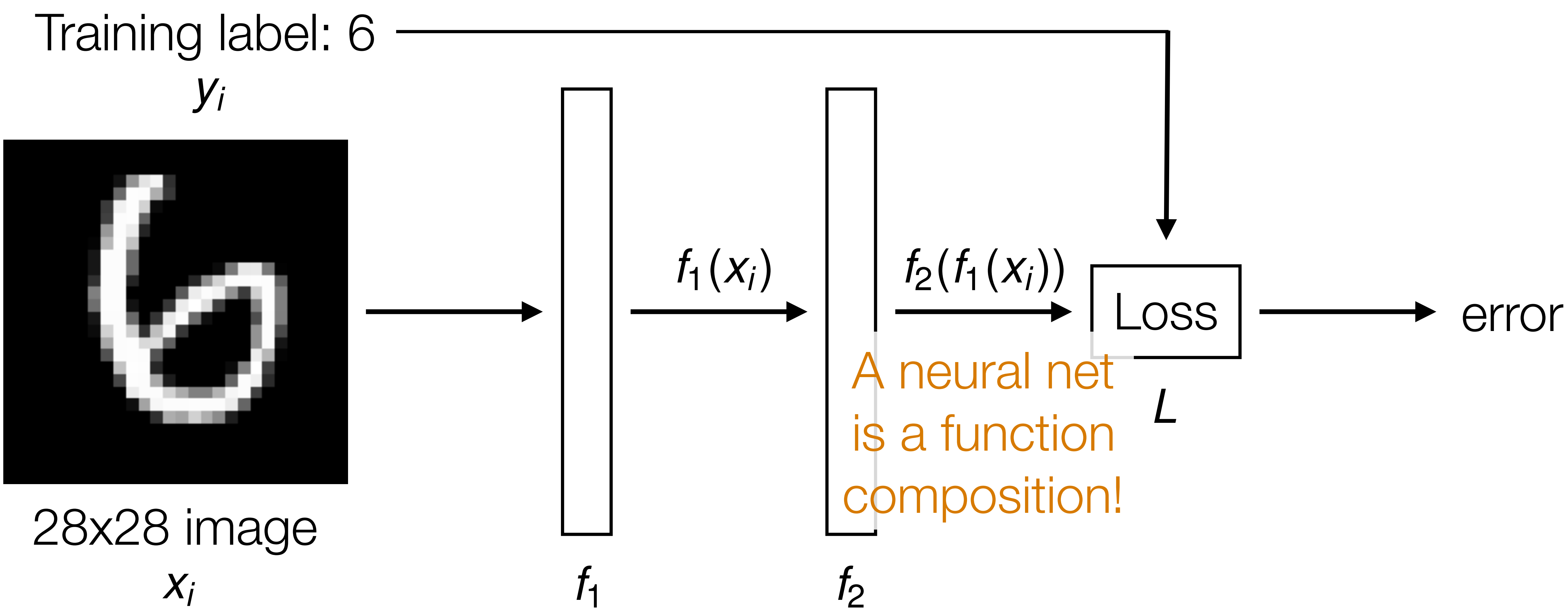

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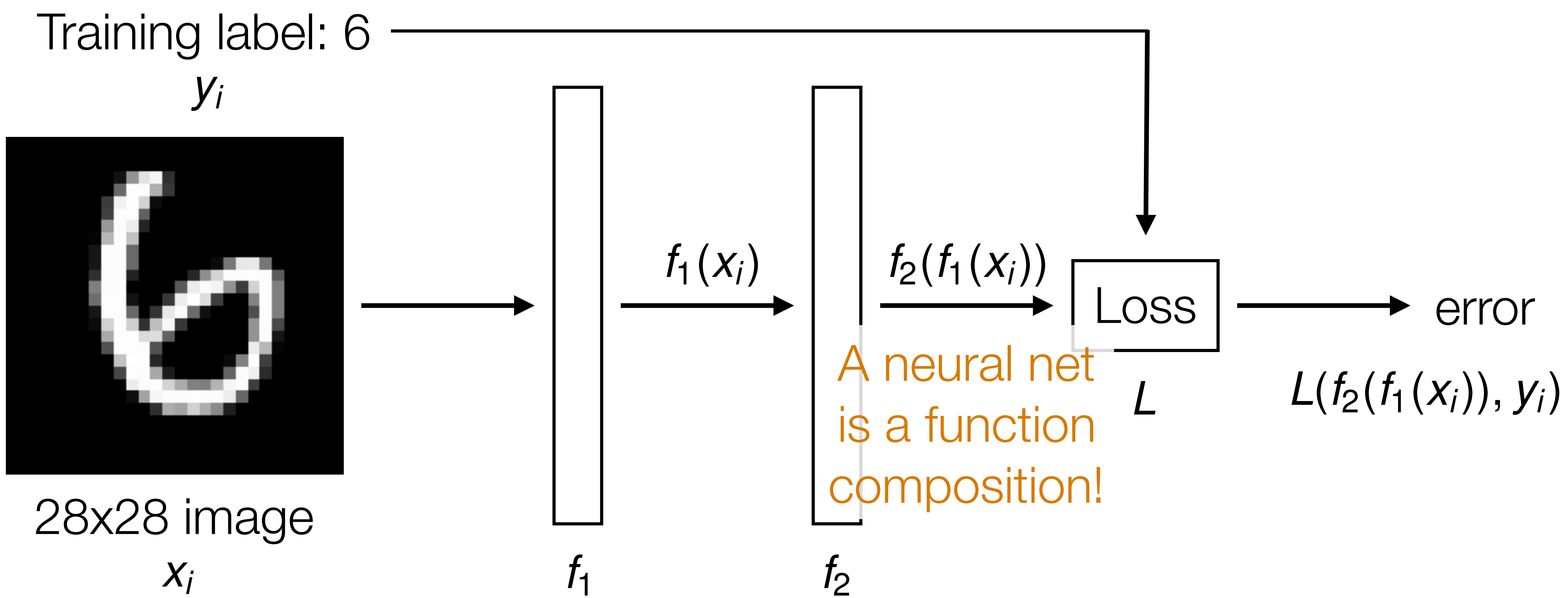

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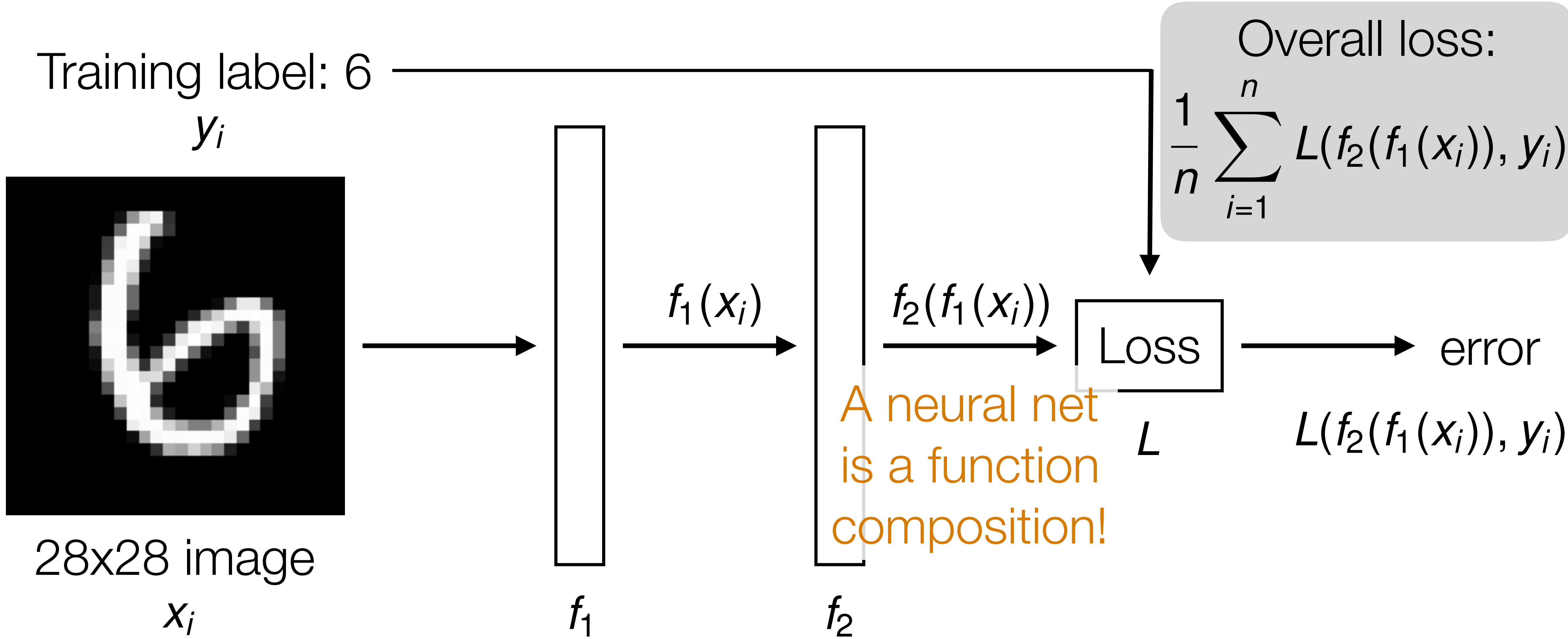

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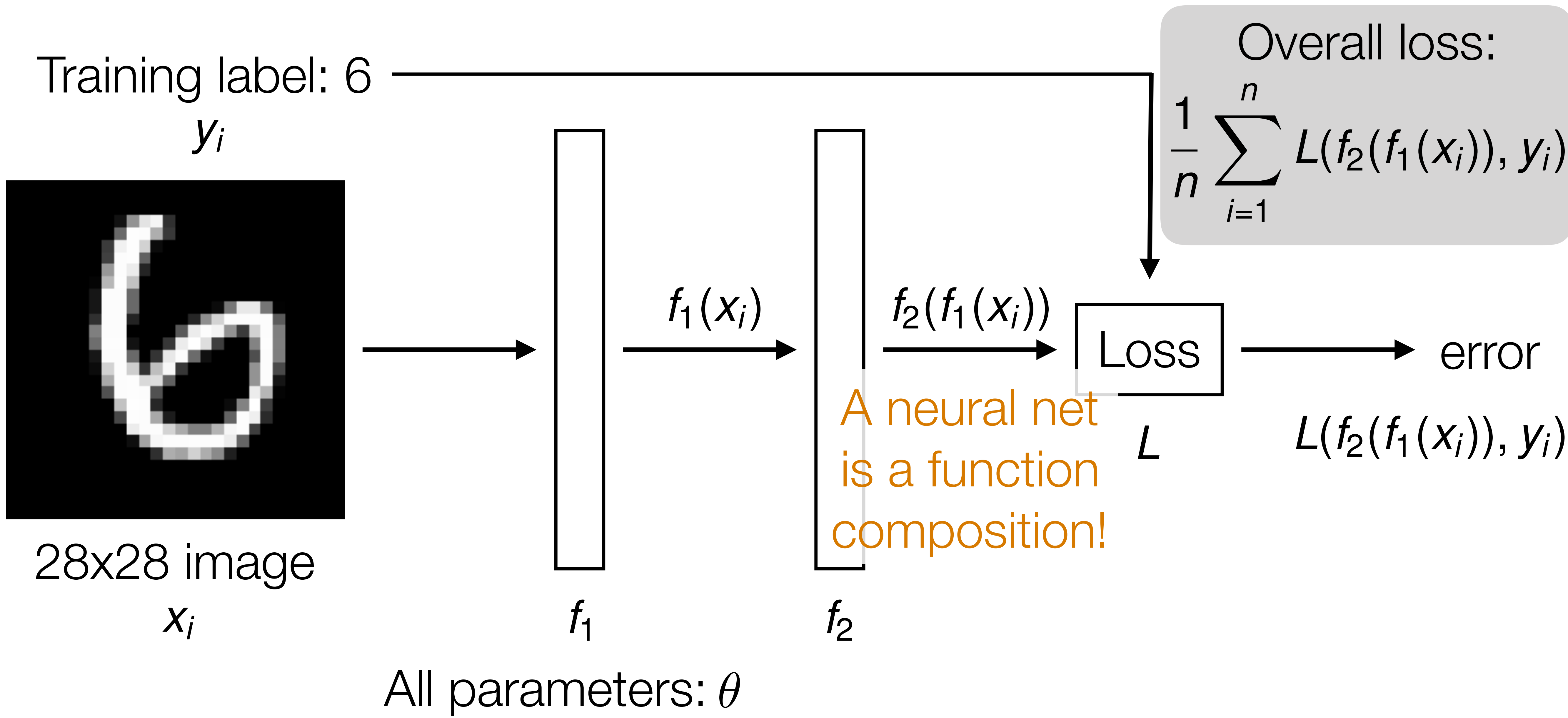

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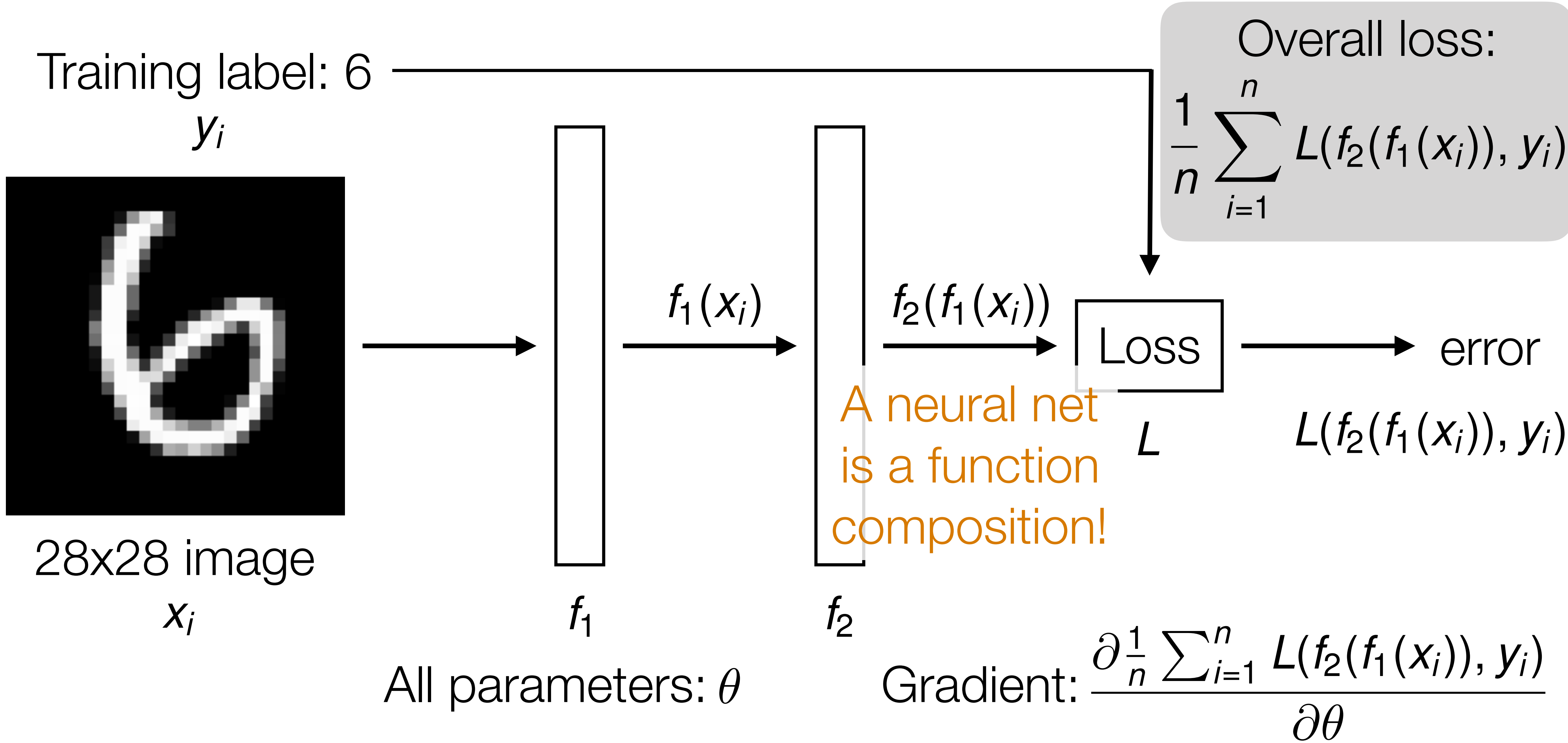

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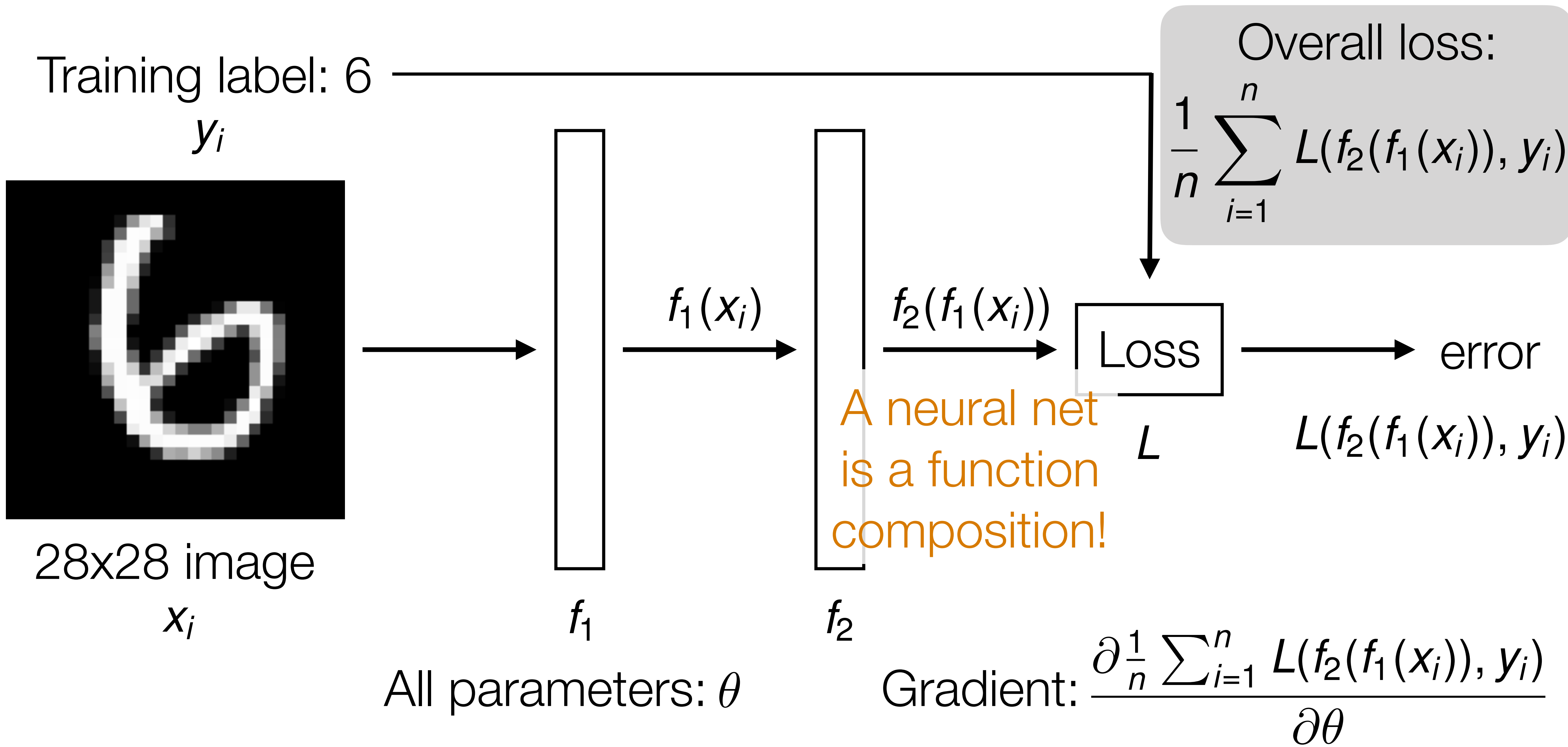
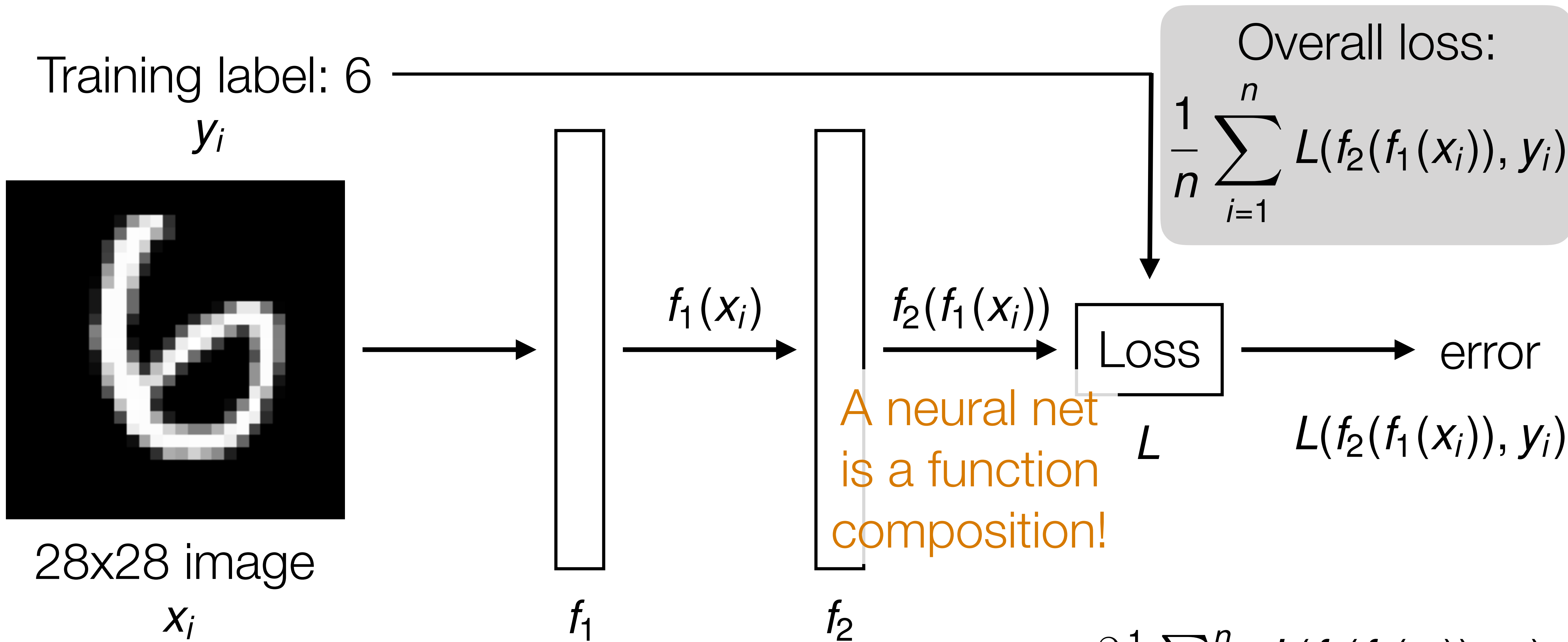


Automatic differentiation is crucial in learning deep nets!

Handwritten Digit Recognition



All parameters: θ

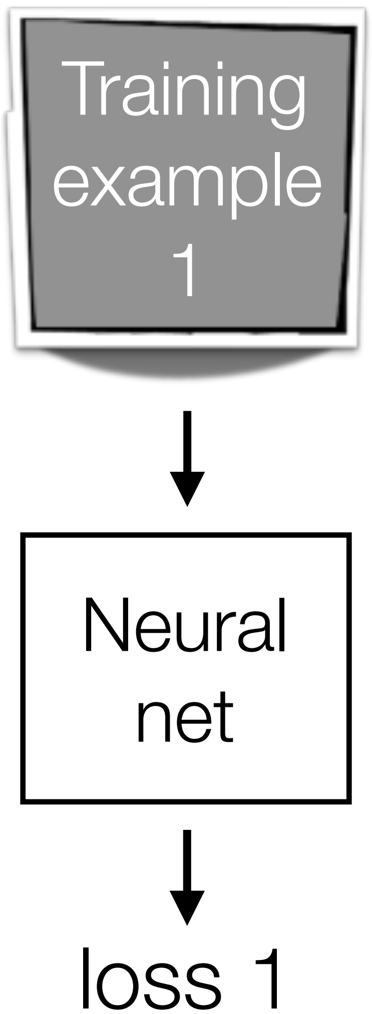
Gradient: $\frac{\partial \frac{1}{n}\sum_{i=1}^{n} L(f_2(f_1(x_i)), y_i)}{\partial \theta}$

Automatic differentiation is crucial in learning deep nets!

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

Gradient Descent

Gradient Descent



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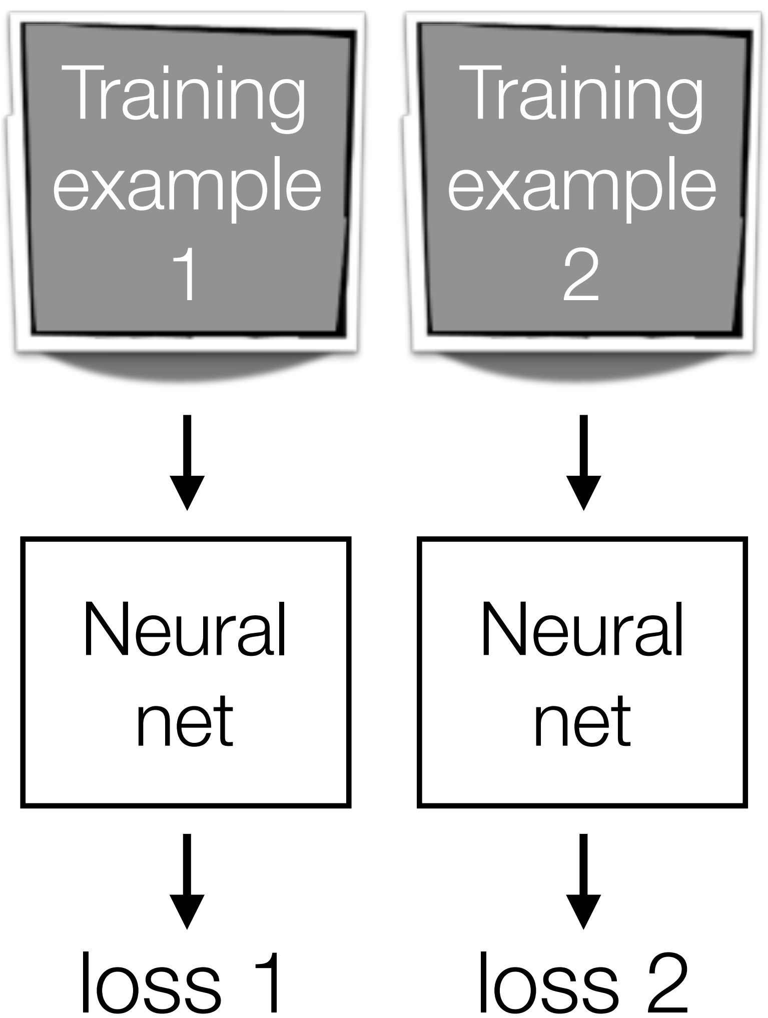

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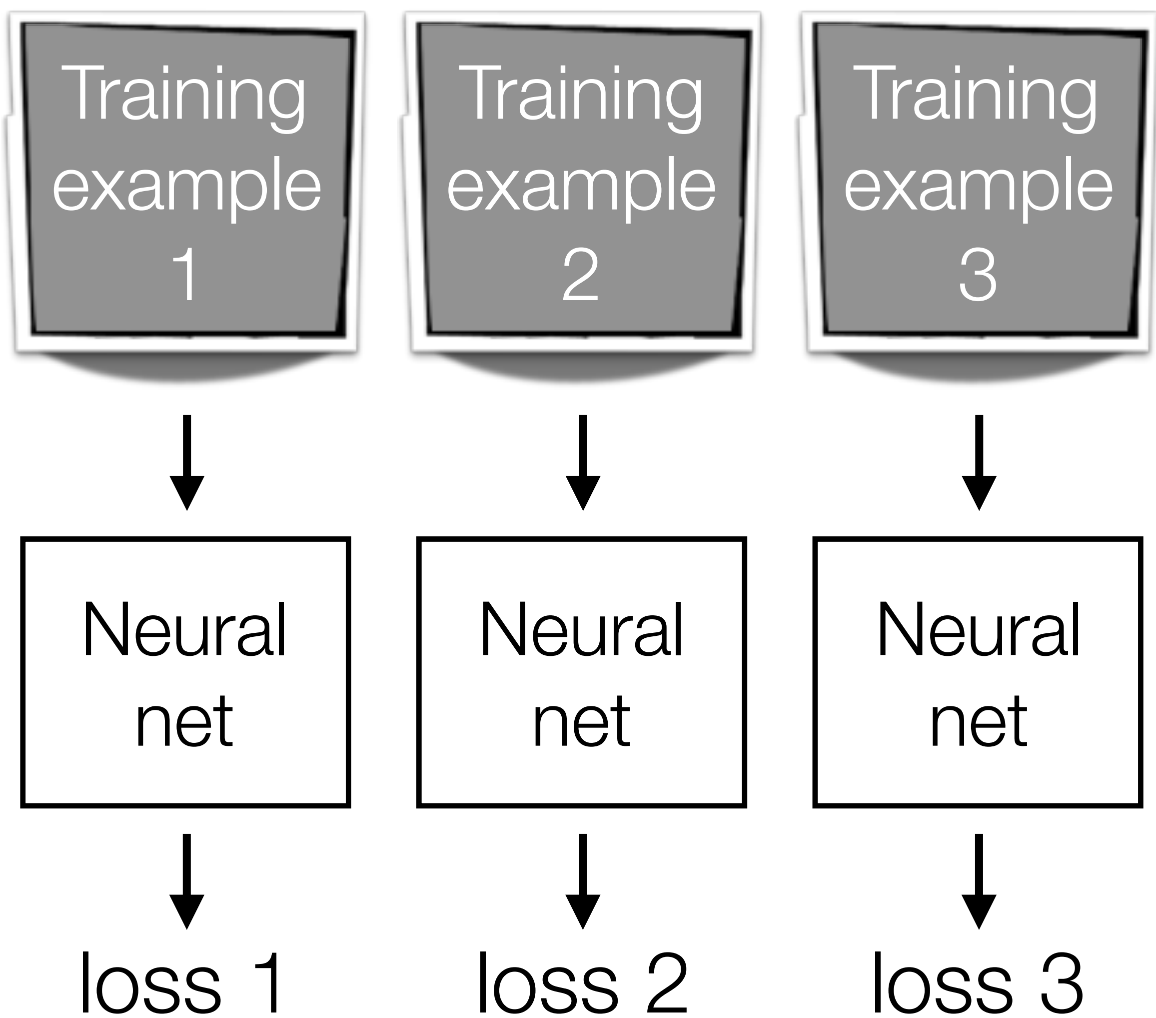

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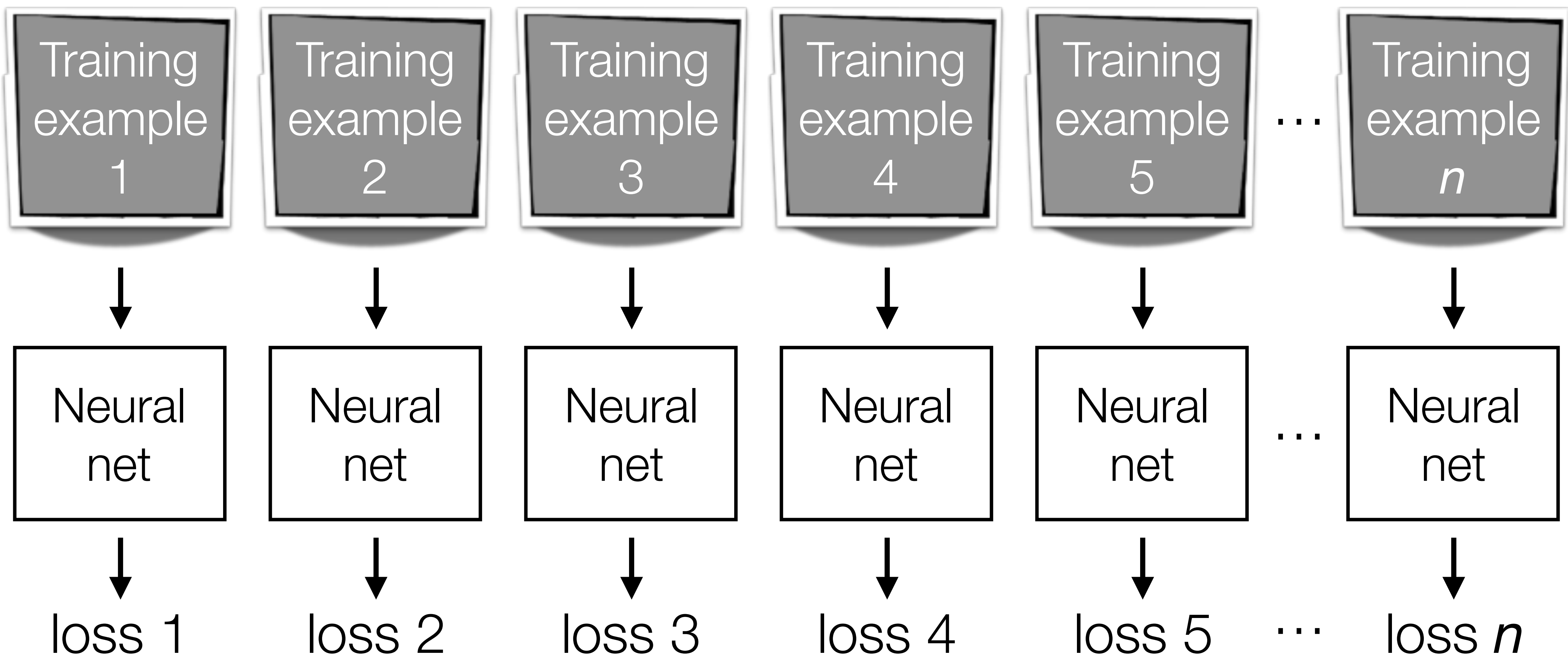

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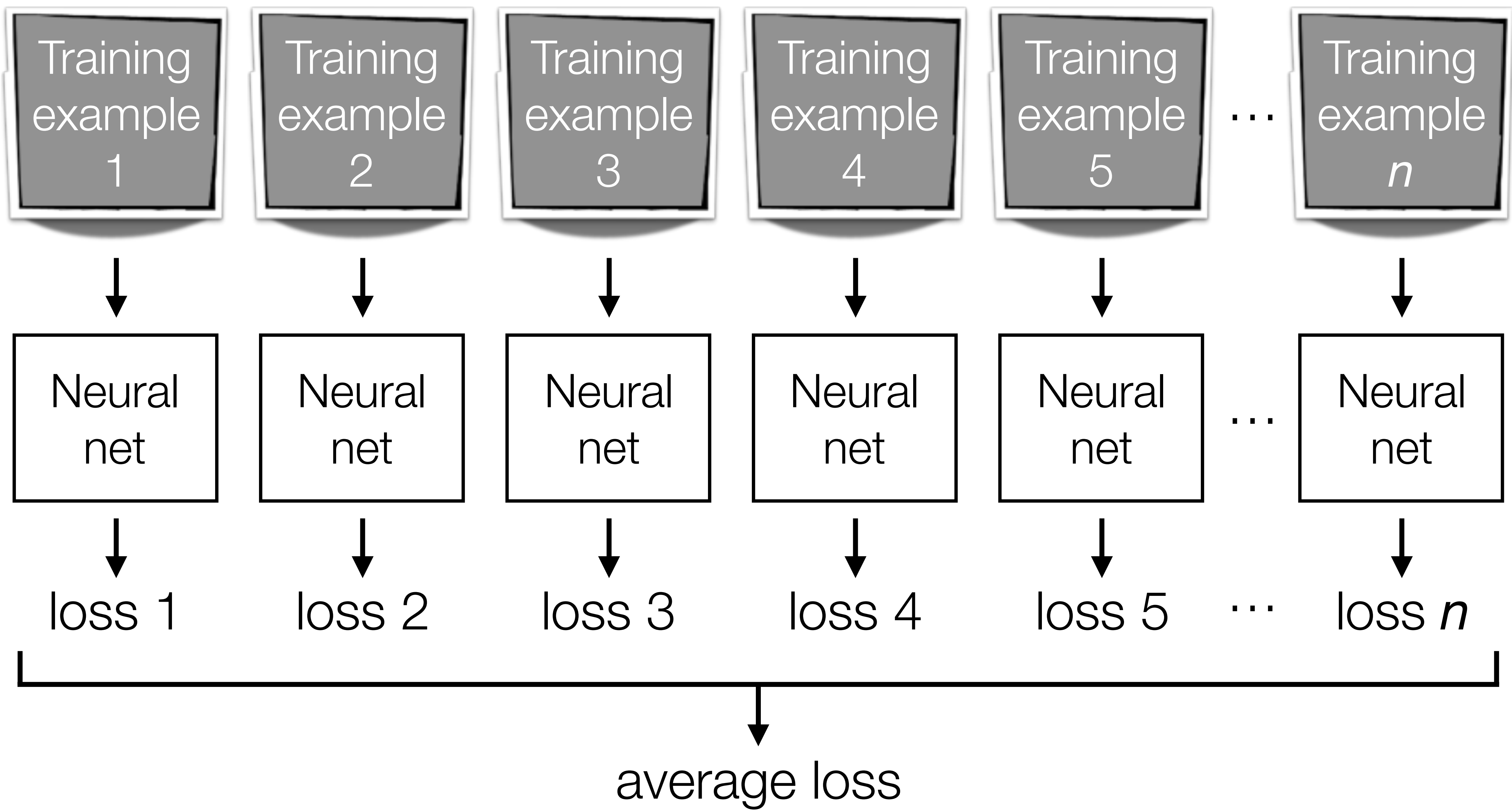

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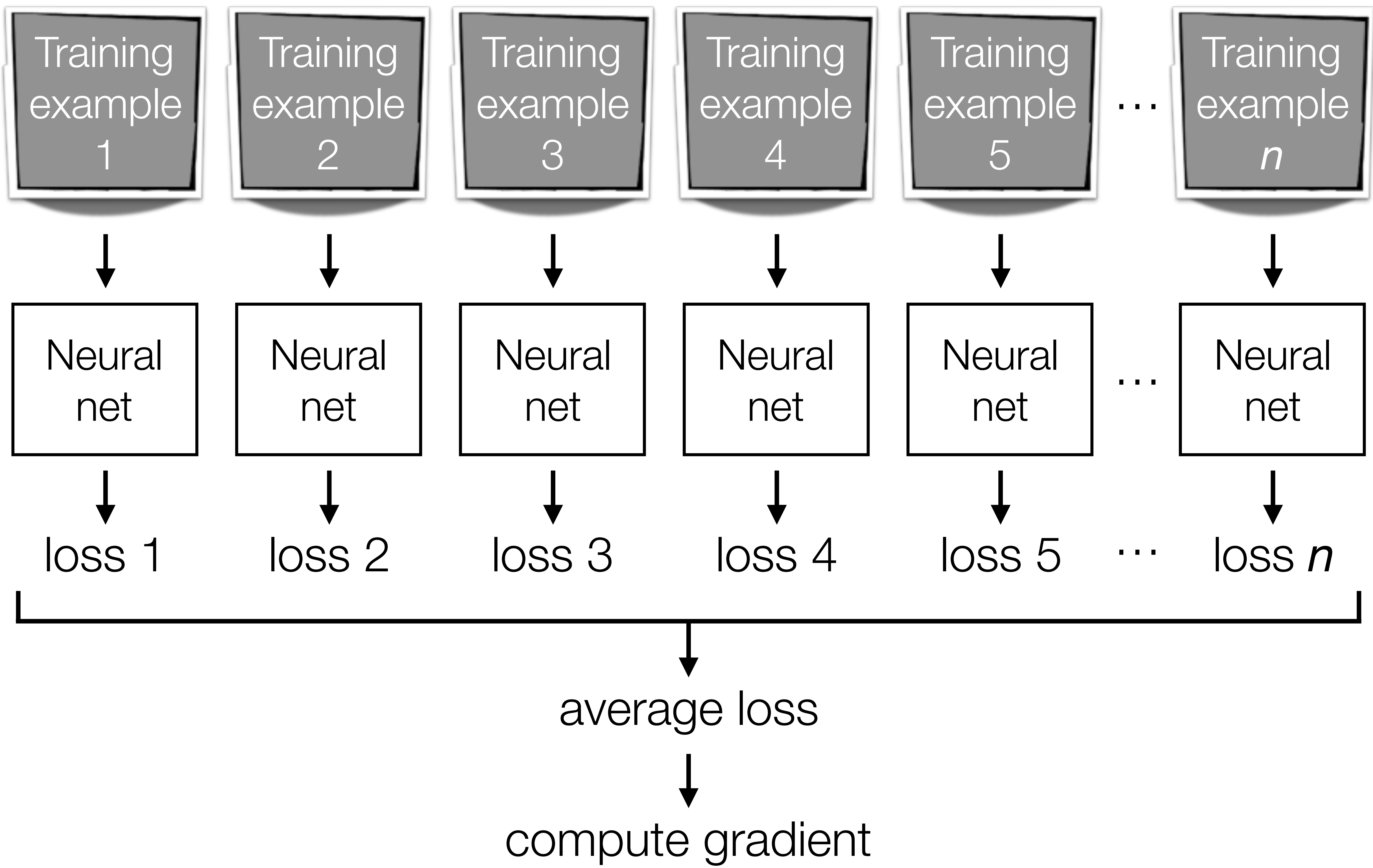

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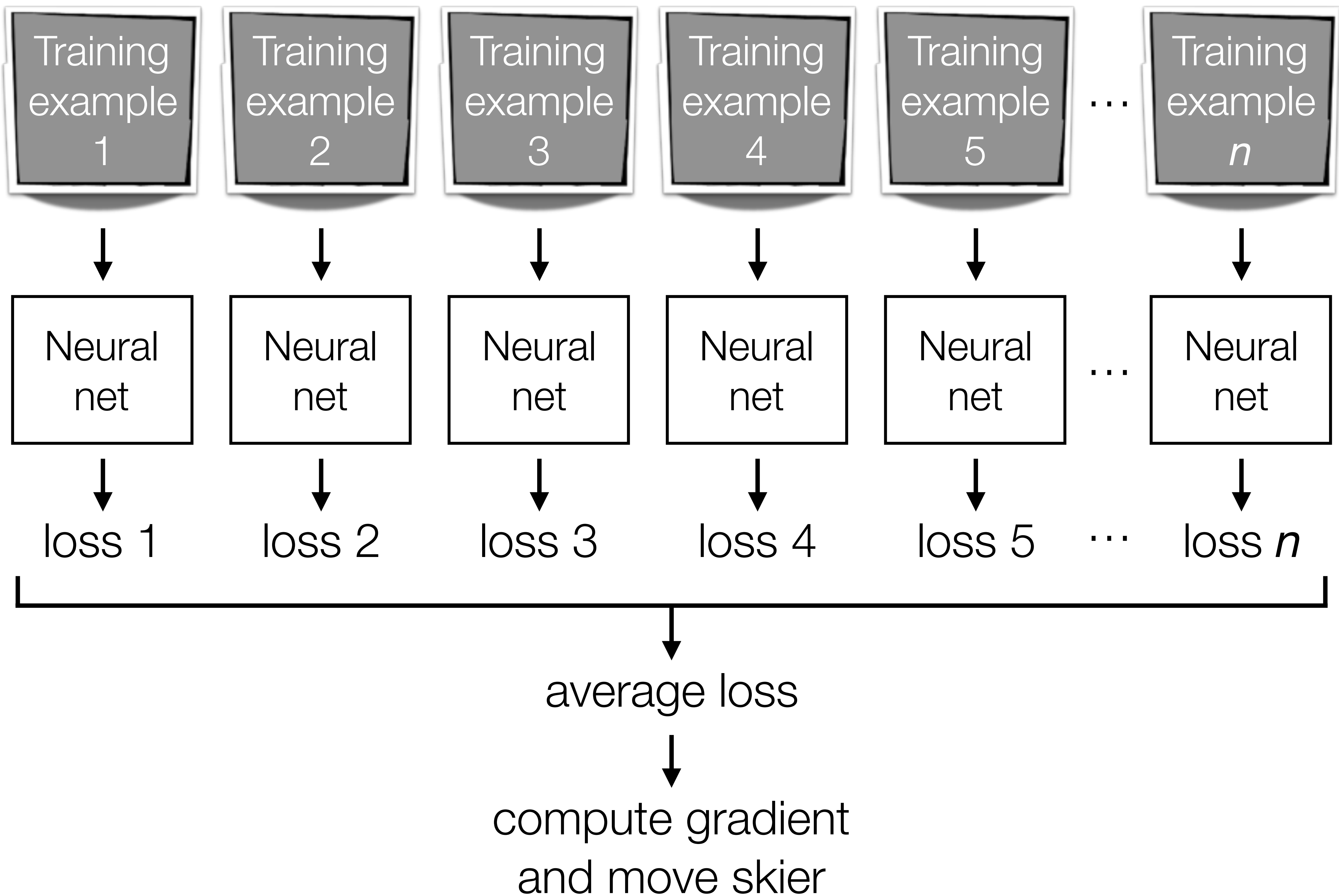

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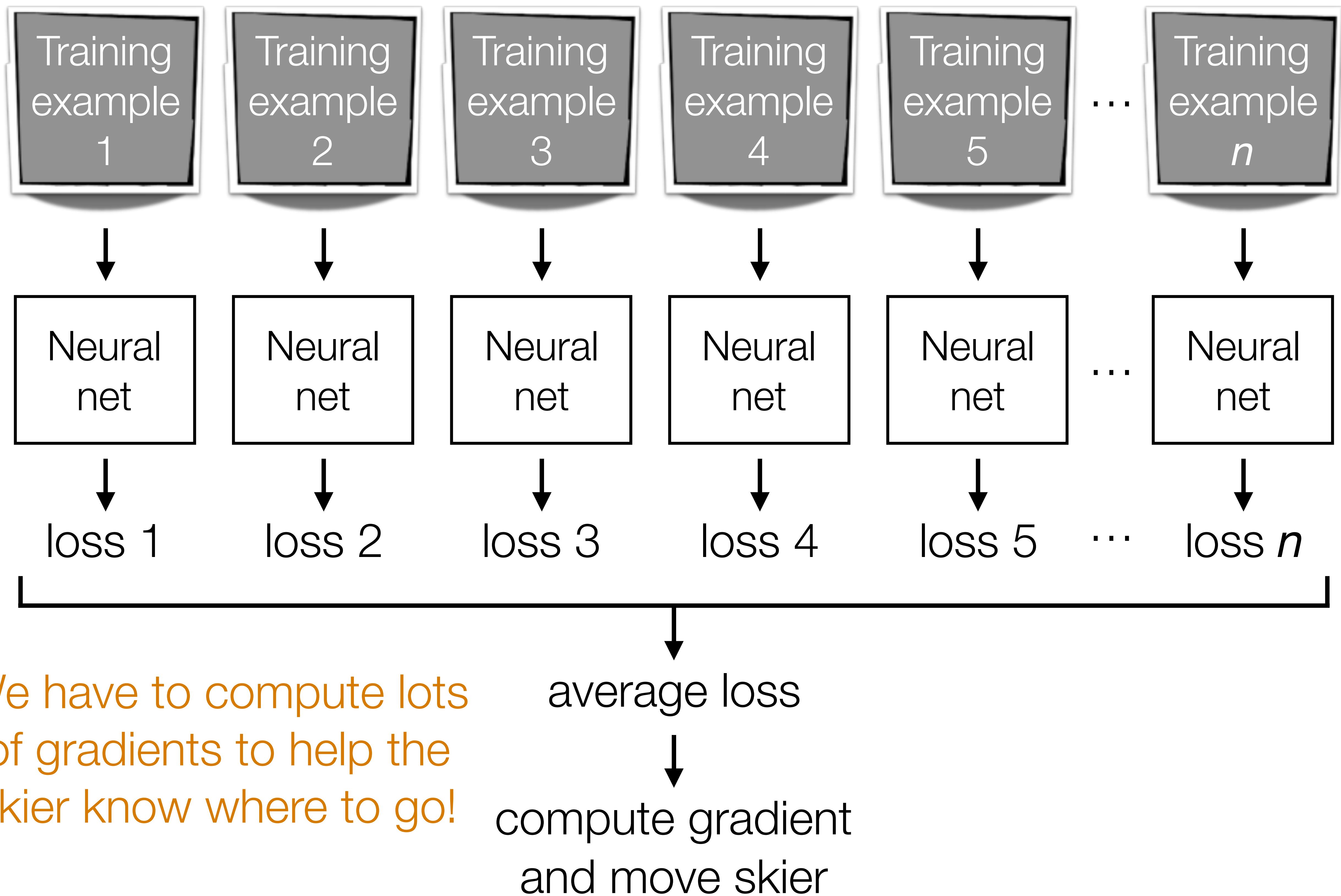

We have to compute lots of gradients to help the skier know where to go!

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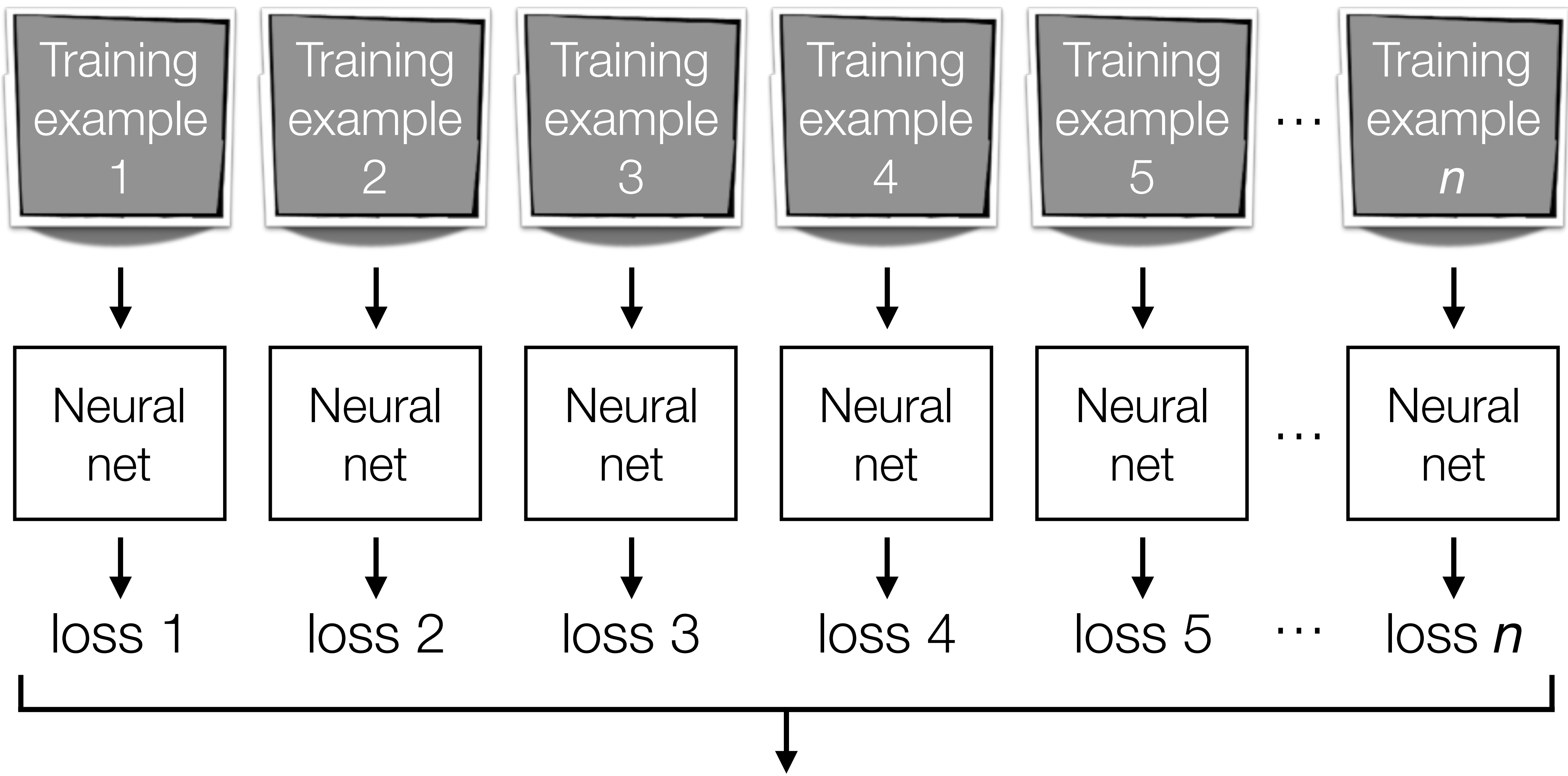


average loss

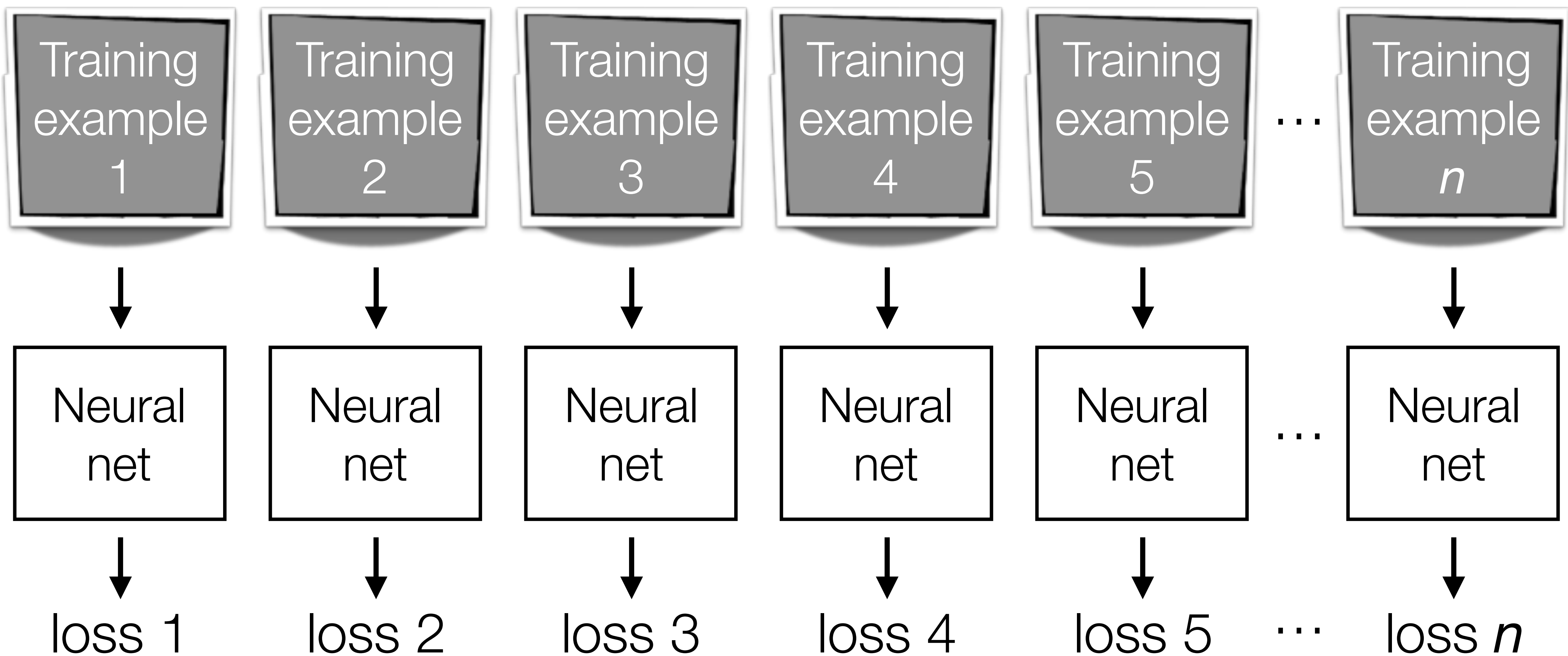
↓

compute gradient and move skier

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

Computing gradients using all the training data seems really expensive!

Stochastic Gradient Descent (SGD)



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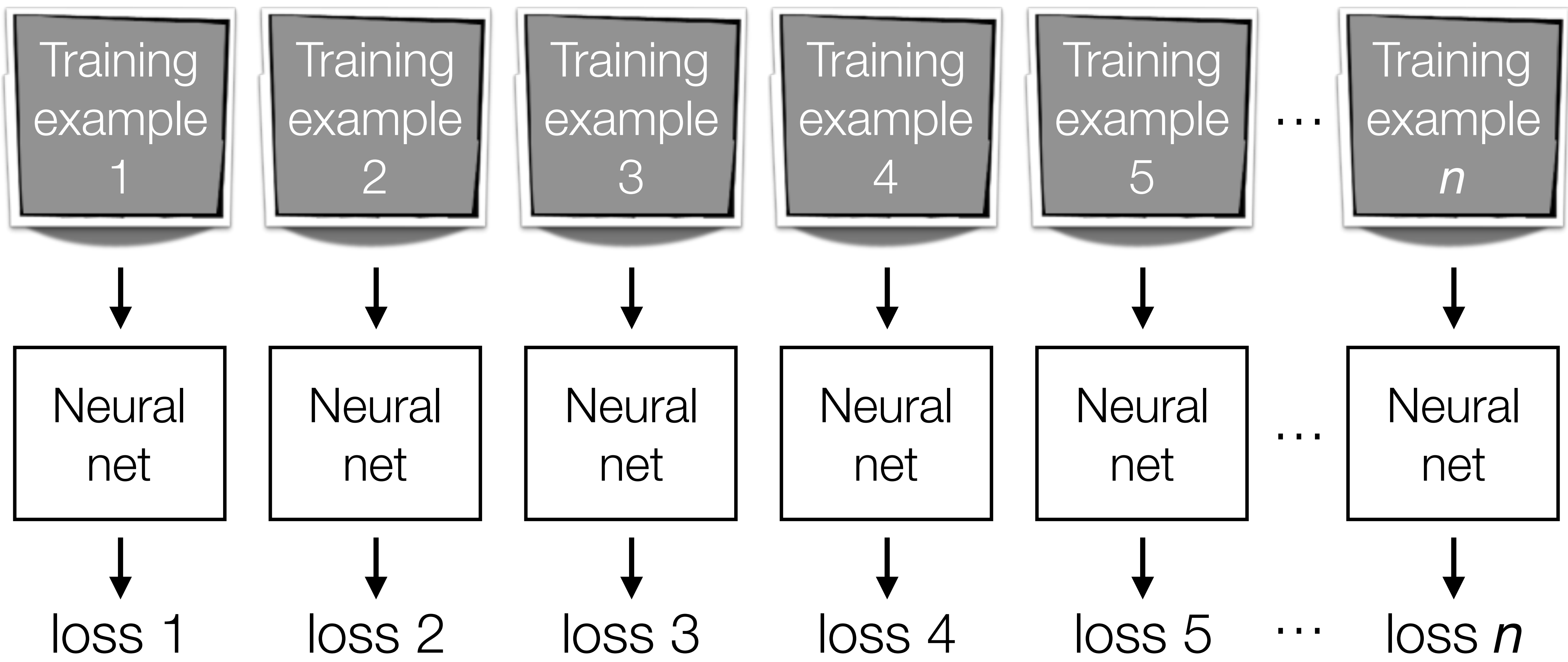

SGD: compute gradient using only 1 training example at a time
(can think of this gradient as a noisy approximation of the “full” gradient)

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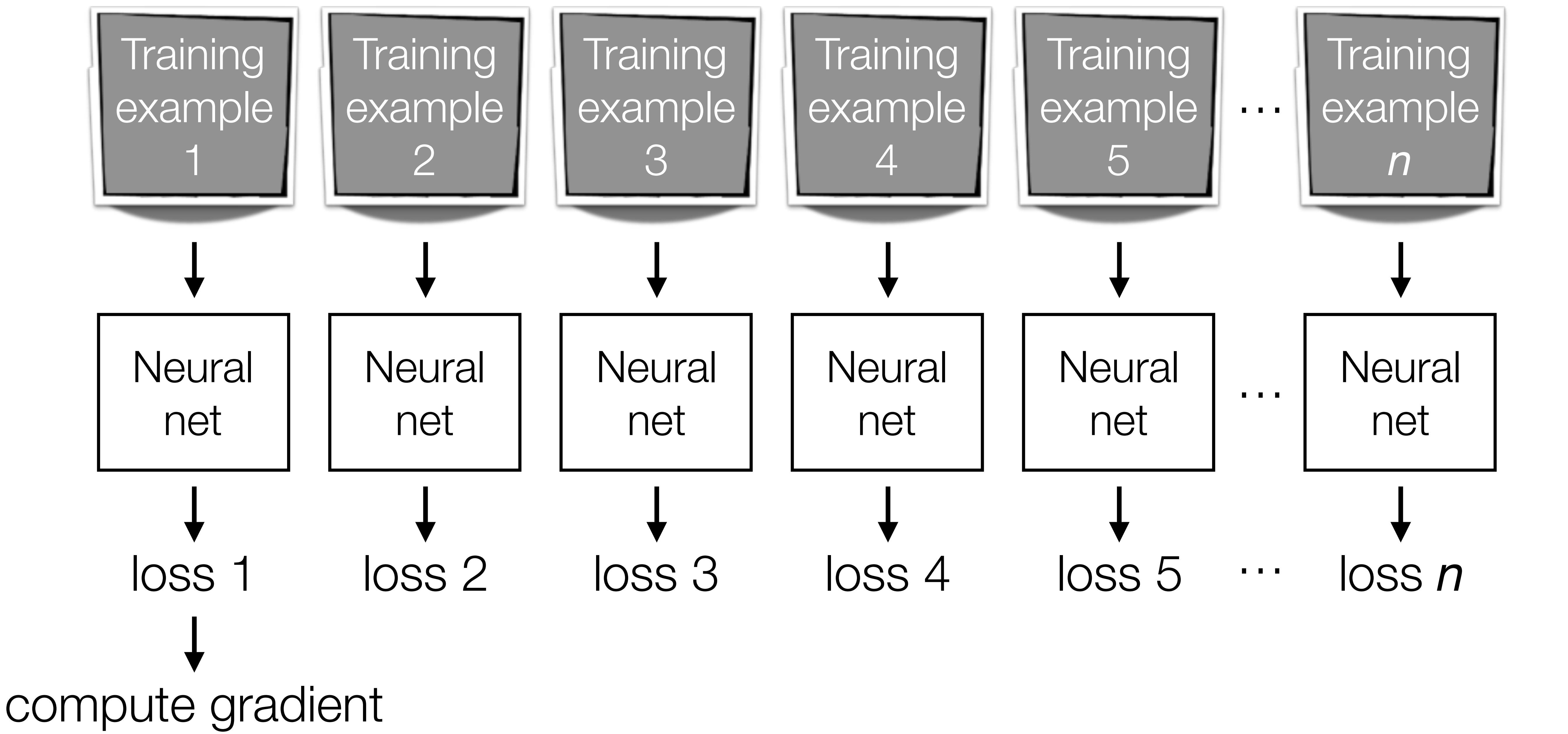

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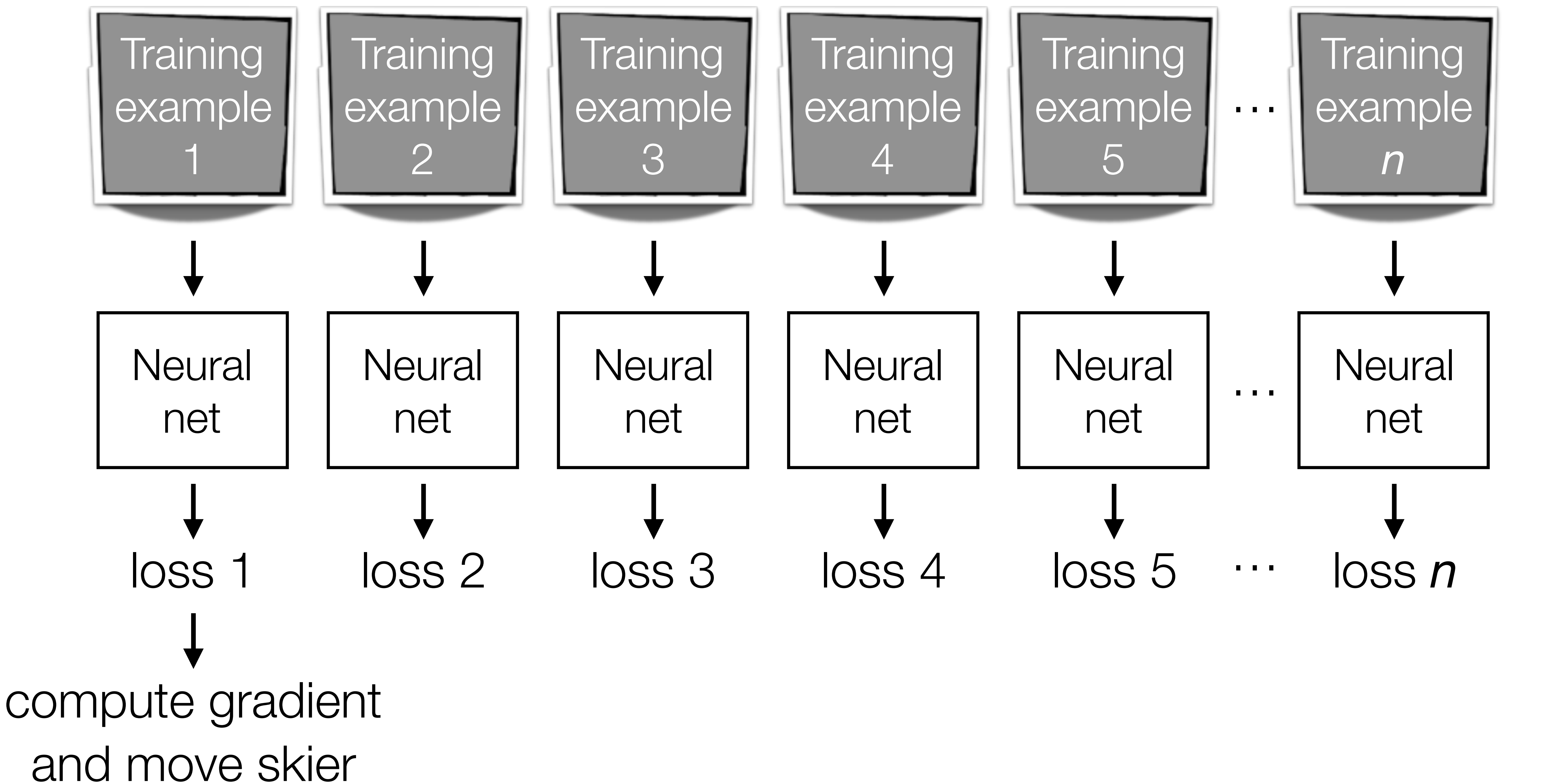

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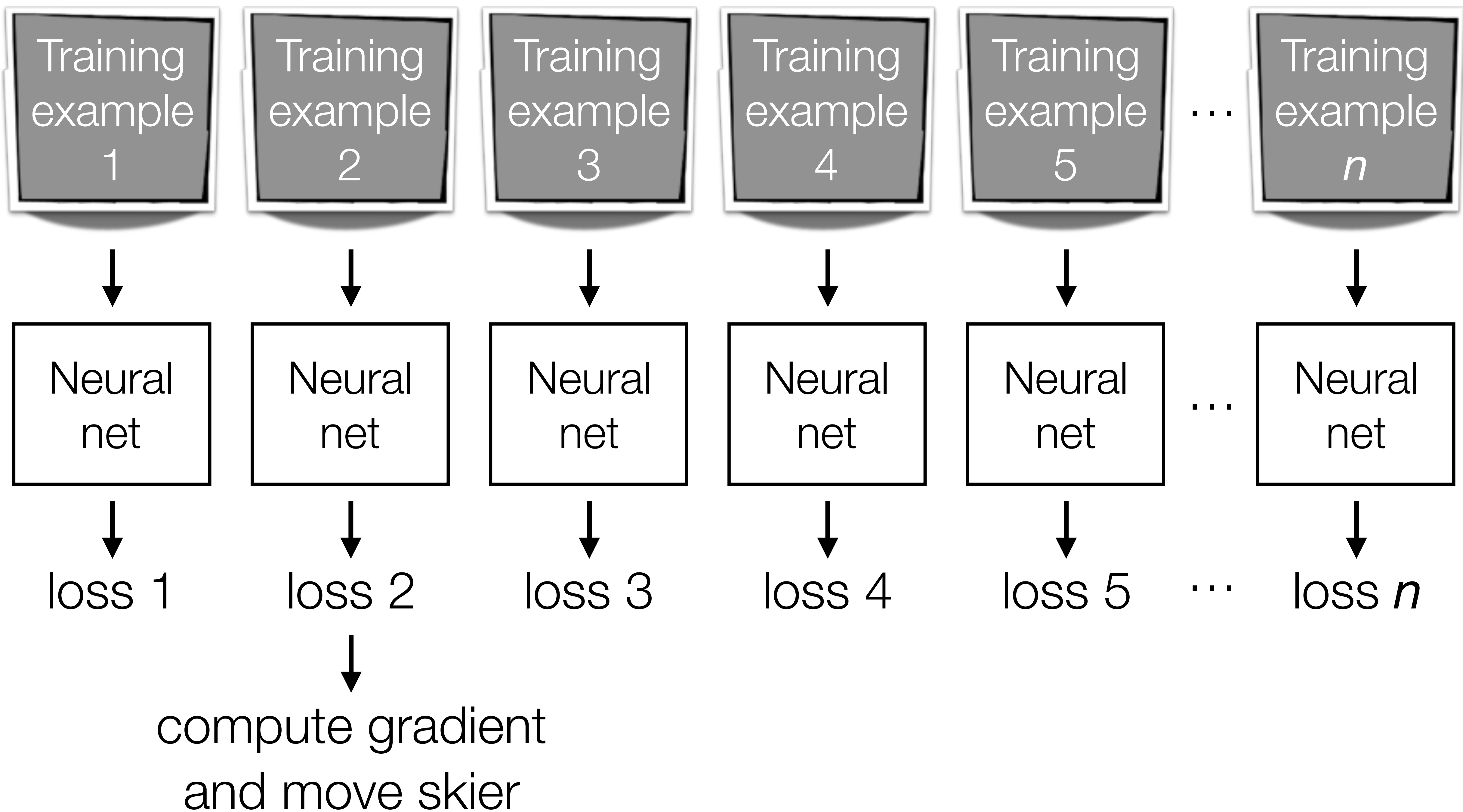

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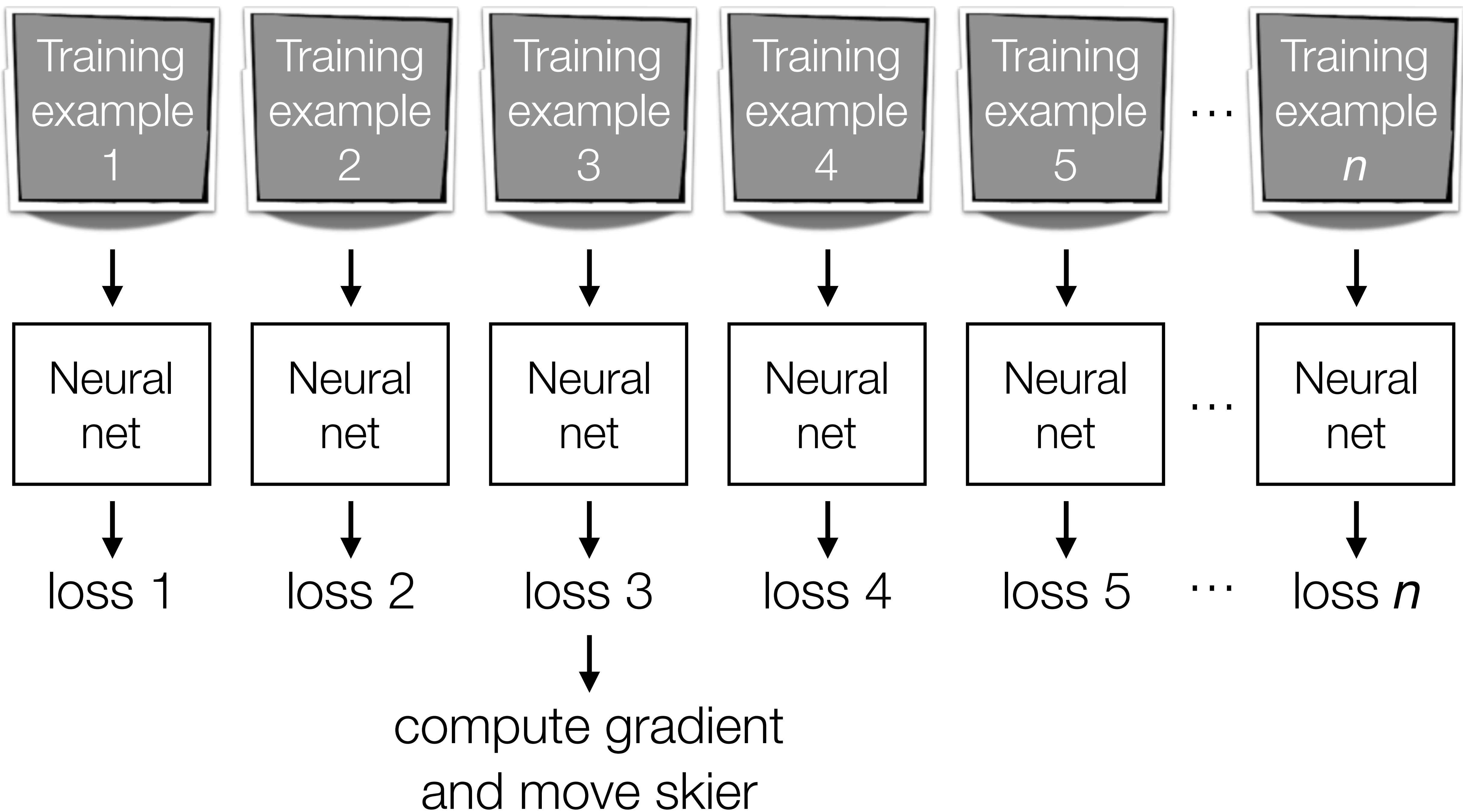

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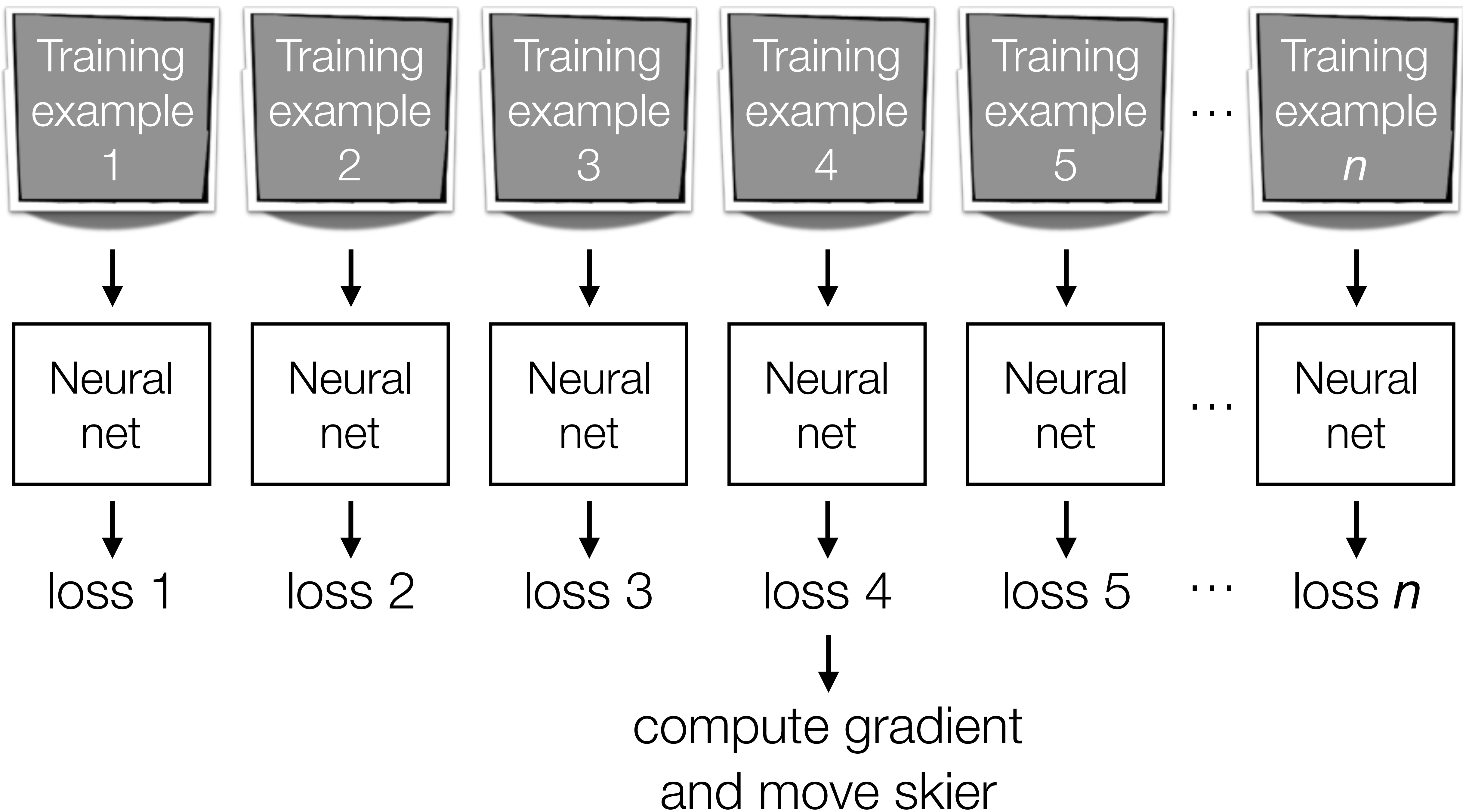

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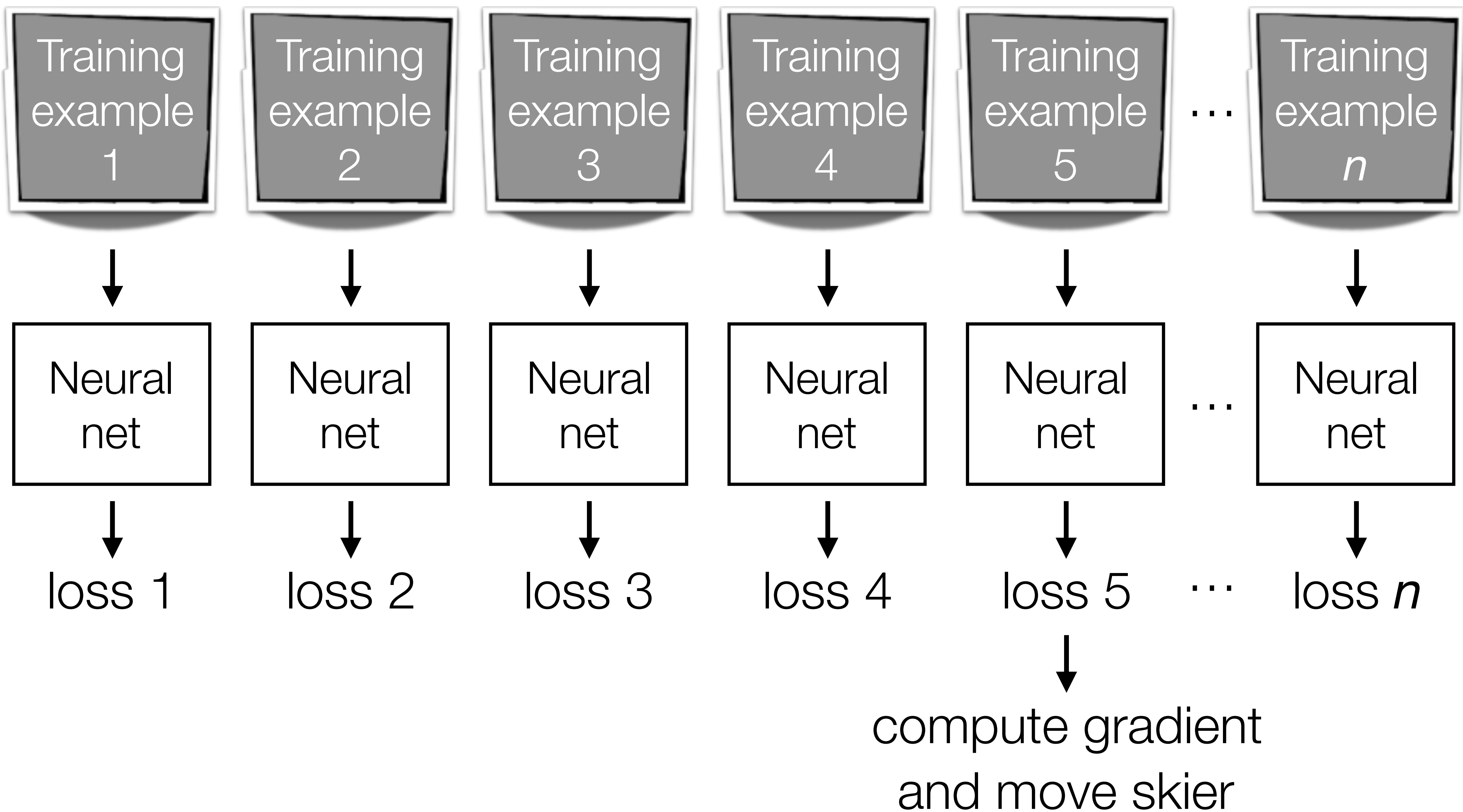

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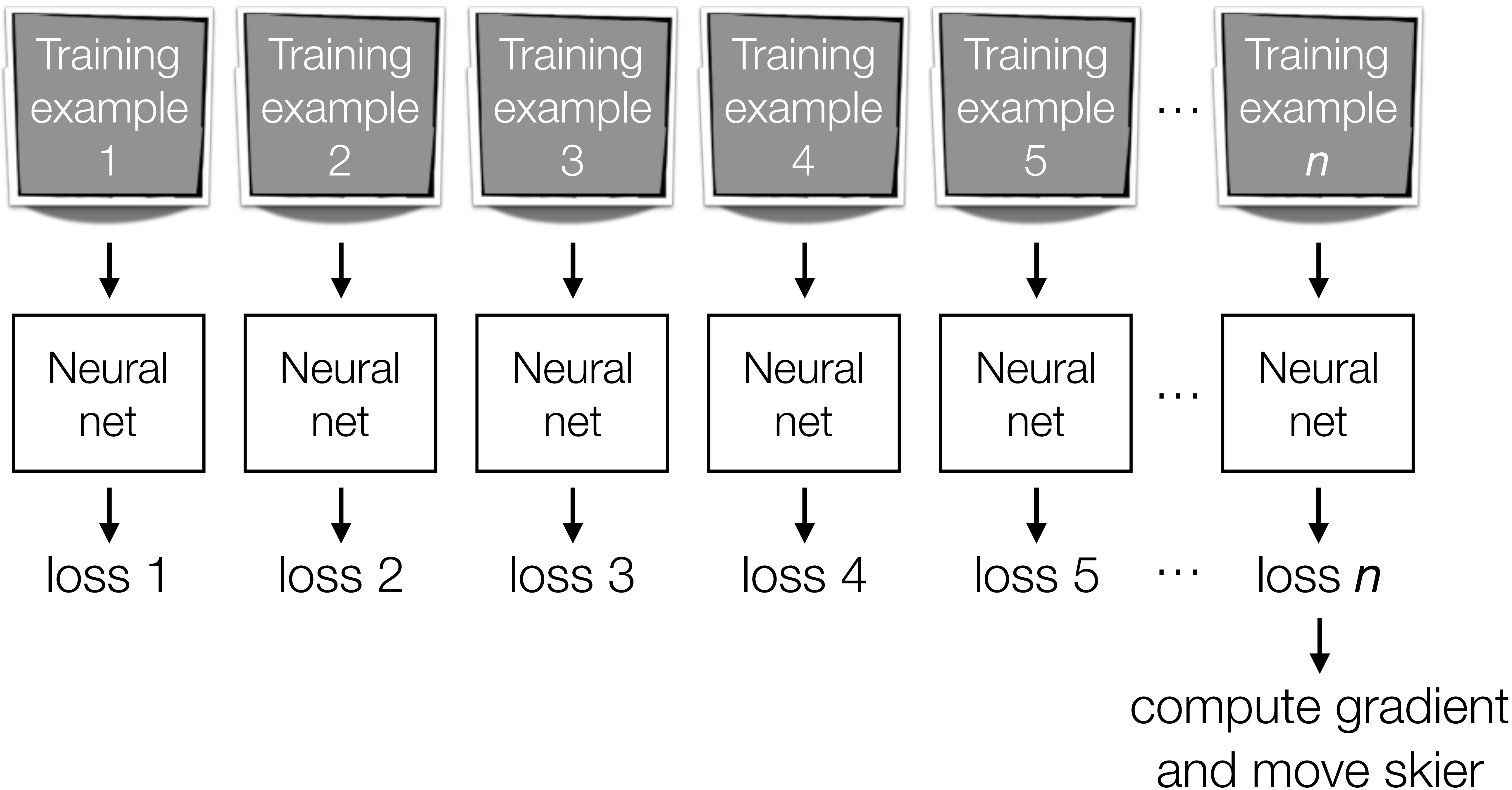

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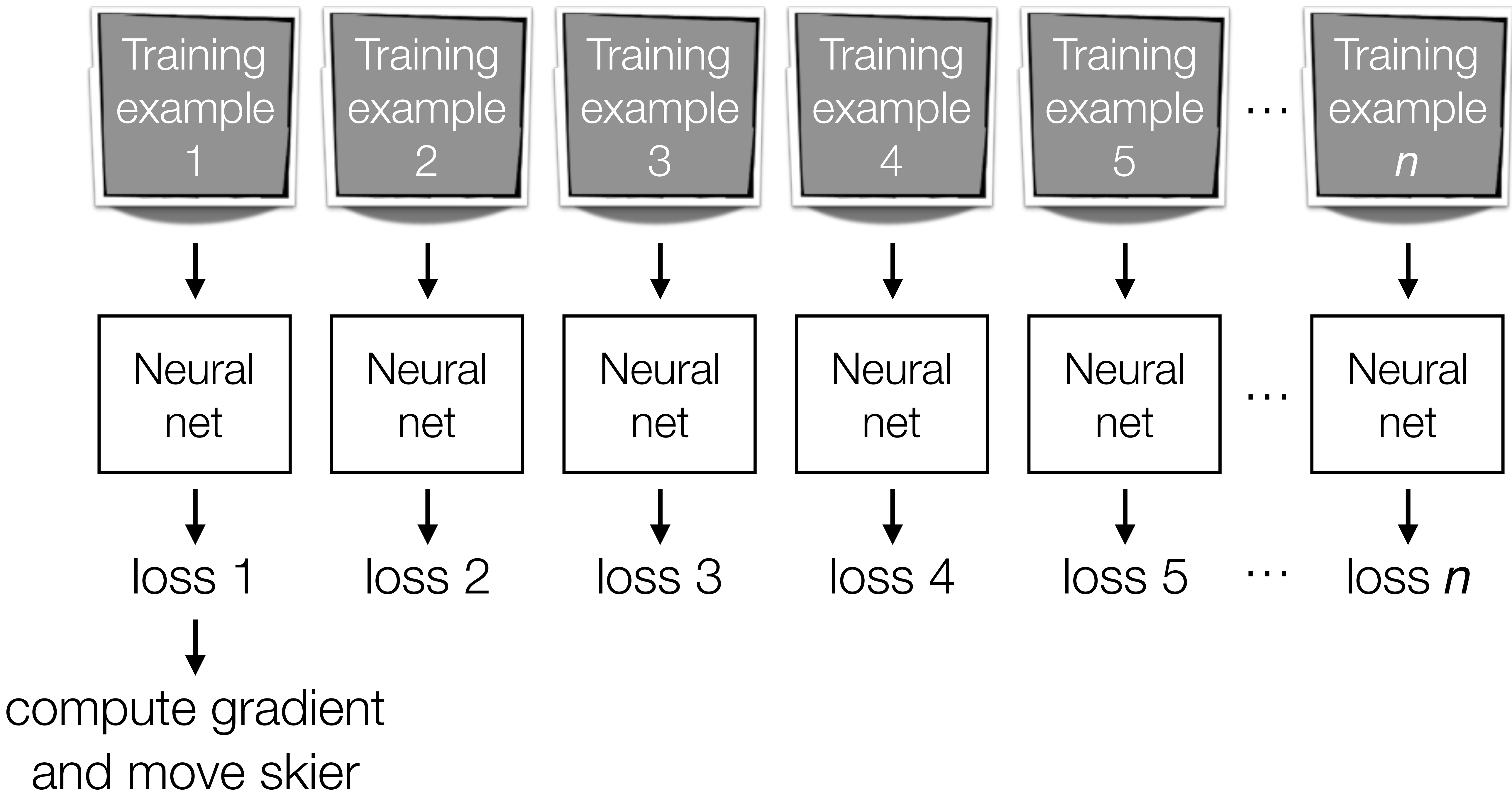

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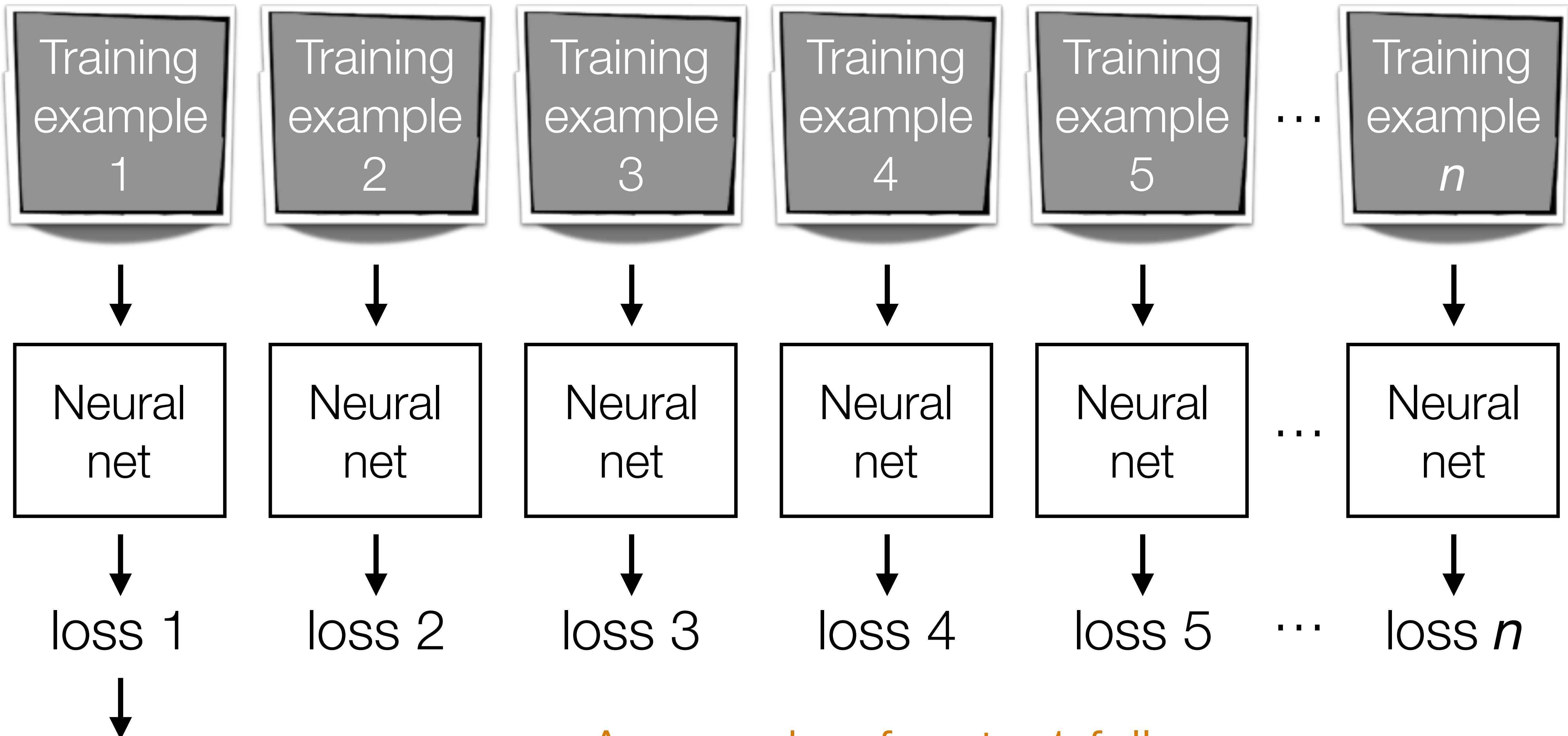
Stochastic Gradient Descent (SGD)

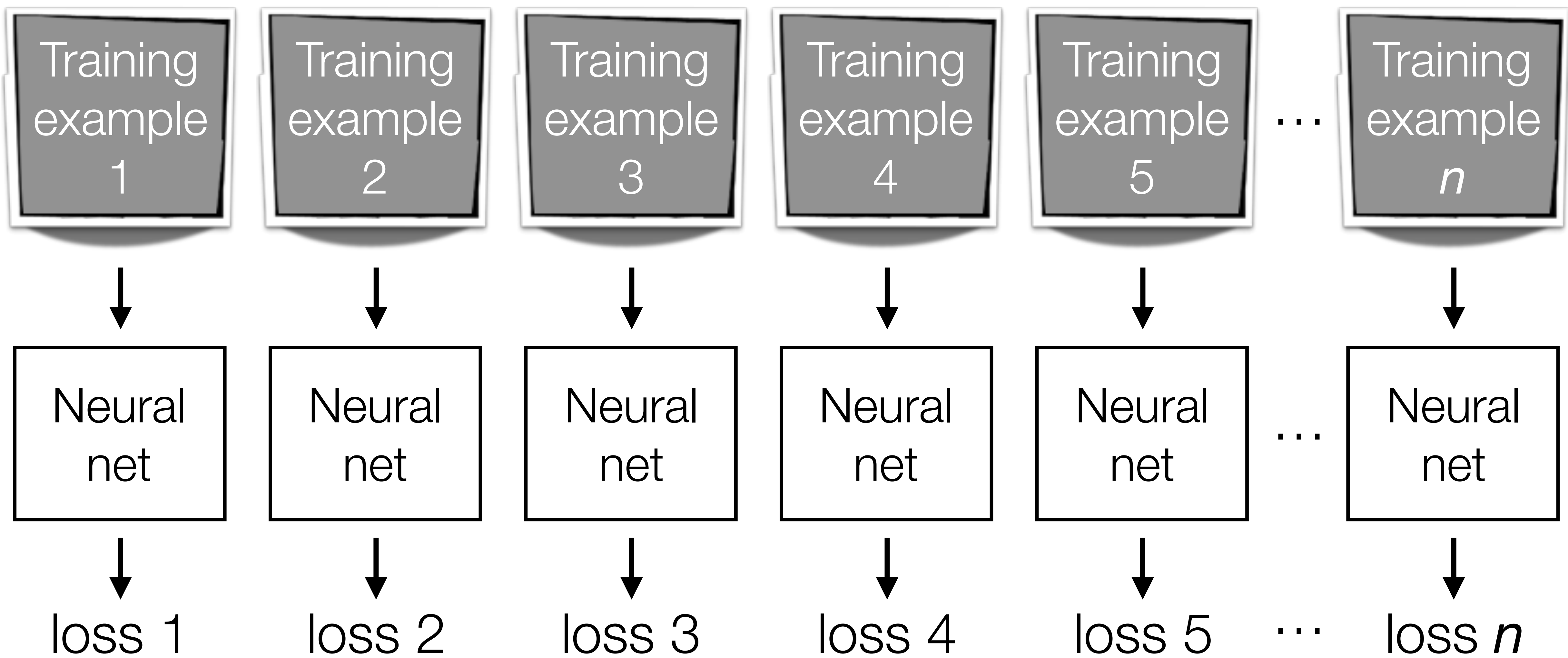


compute gradient
and move skier

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

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

Mini-Batch Gradient Descent



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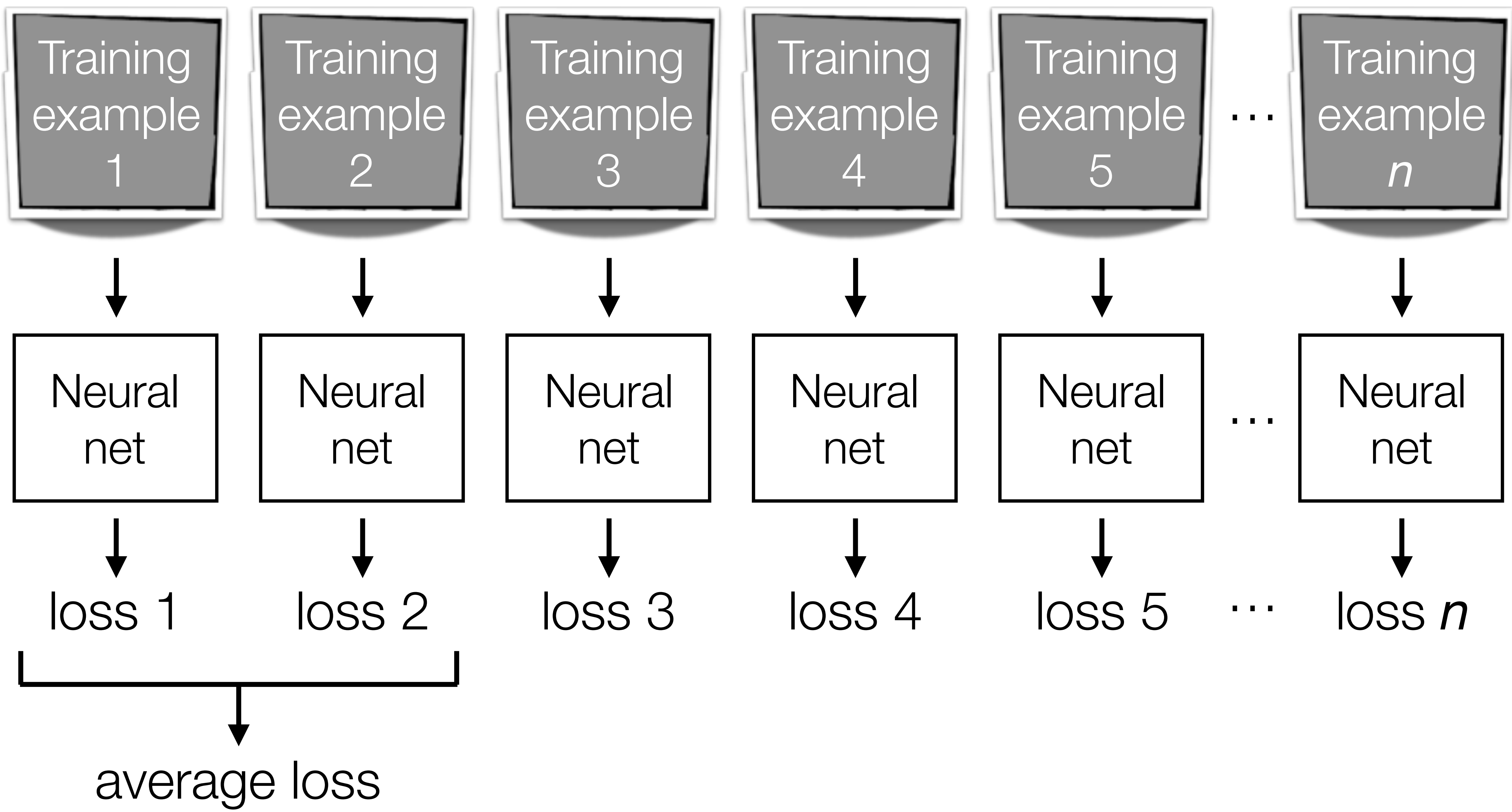

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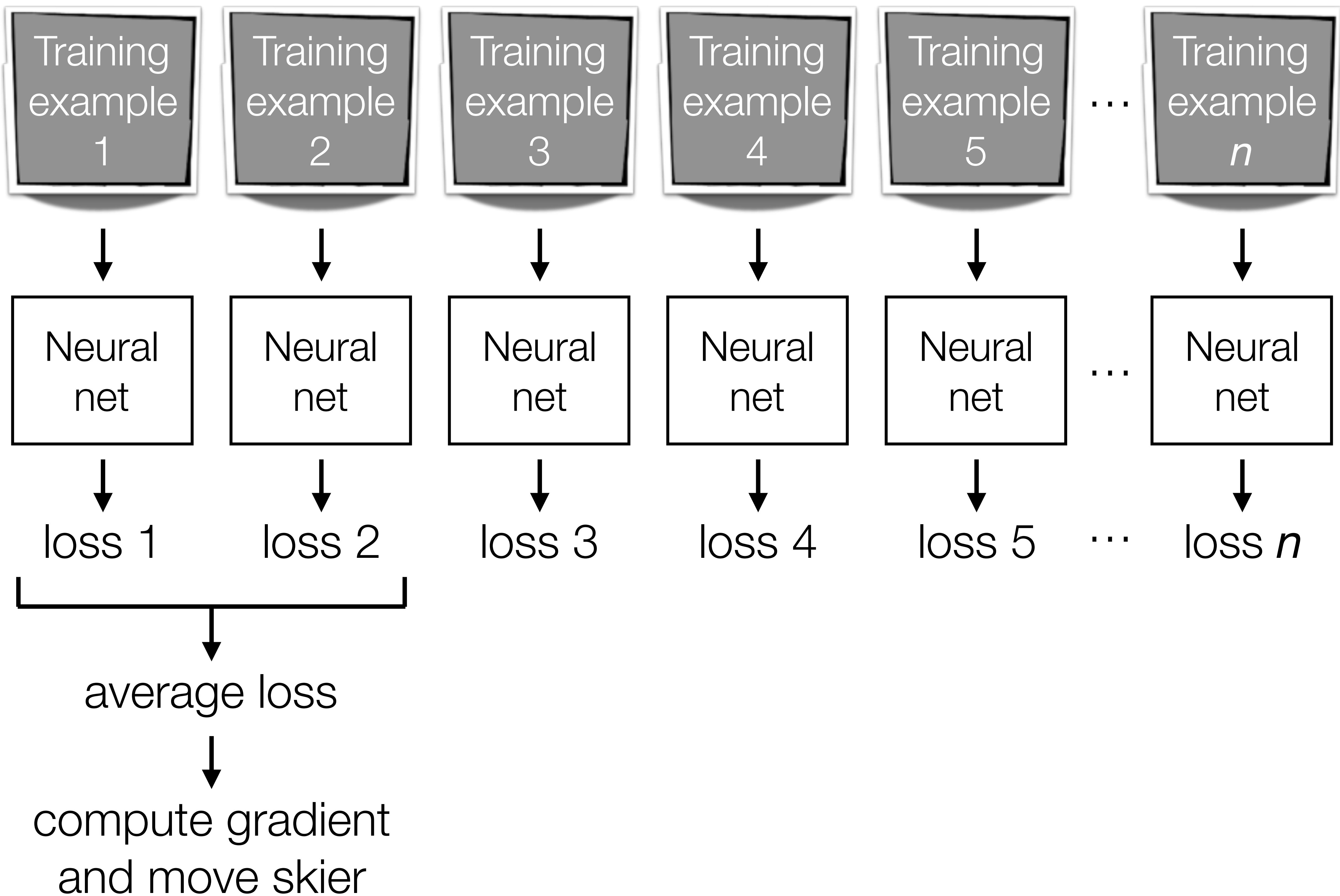

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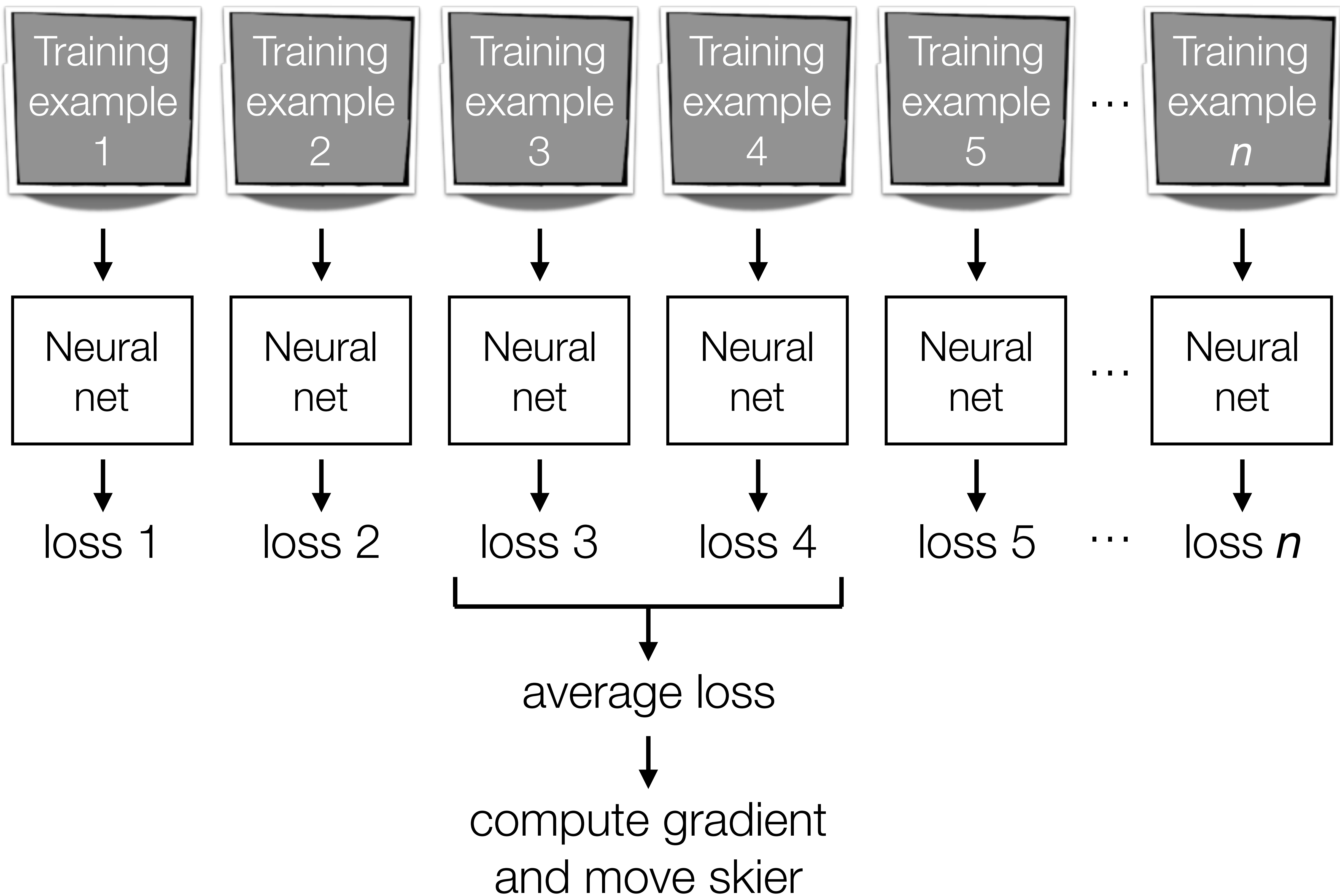

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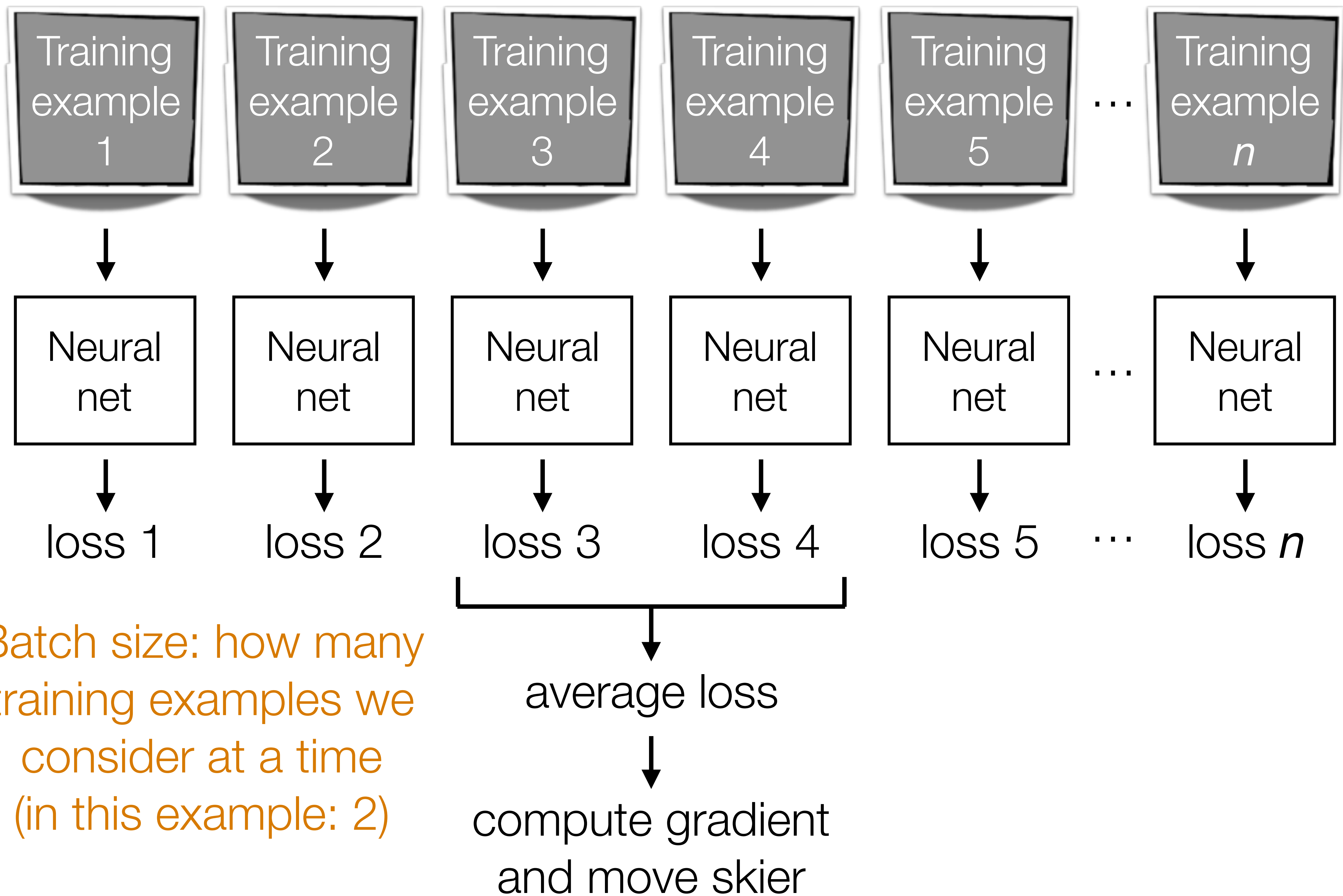

Batch size: how many training examples we consider at a time (in this example: 2)

There's a lot more to deep learning that we didn't cover

Dealing with Small Datasets

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Data augmentation: generate perturbed versions of your training data to get larger training dataset

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Training image

Training label: cat

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Still a cat!

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We just turned 1 training example in 3 training examples

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Training image
Training label: cat

Mirrored
Still a cat!

Rotated & translated
Still a cat!

We just turned 1 training example in 3 training examples

Allowable perturbations depend on data (e.g., for handwritten digits, rotating by 180 degrees would be bad: confuse 6's and 9's)

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Fine tuning: if there’s an existing pre-trained neural net, you could modify it for your problem that has a small dataset

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Example: classify between Tesla's and Toyota's

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You collect photos from the internet of both, but your dataset size is small, on the order of 1000 images

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Example: classify between Tesla's and Toyota's

You collect photos from the internet of both, but your dataset size is small, on the order of 1000 images

Strategy: take existing pre-trained CNN for ImageNet classification and change final layer to do classification between Tesla's and Toyota's rather than classifying into 1000 objects

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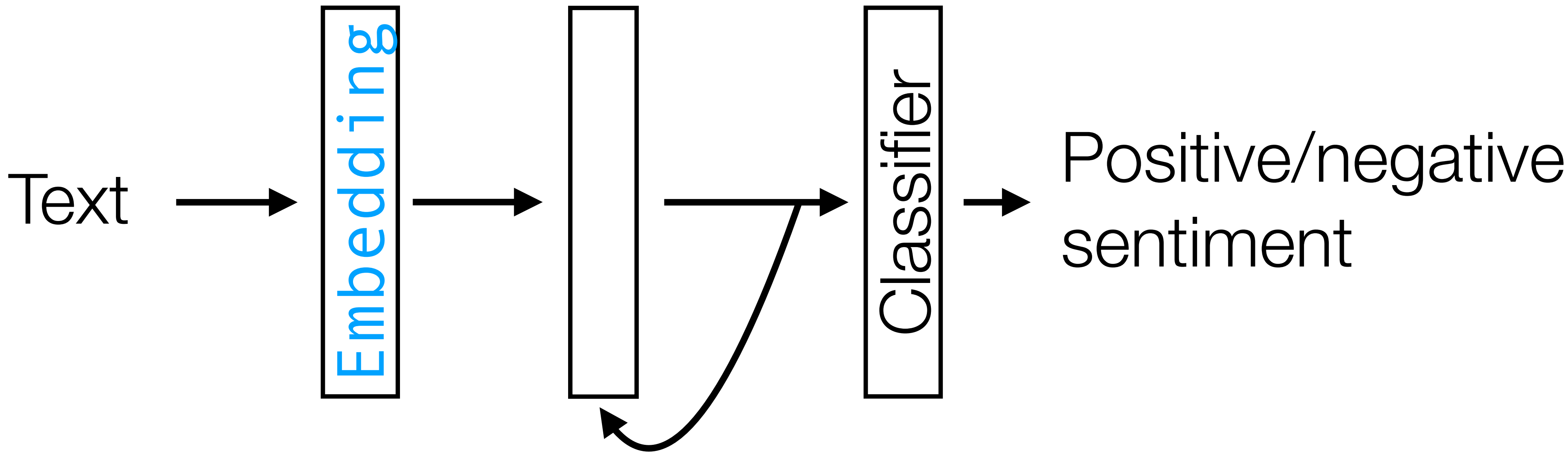

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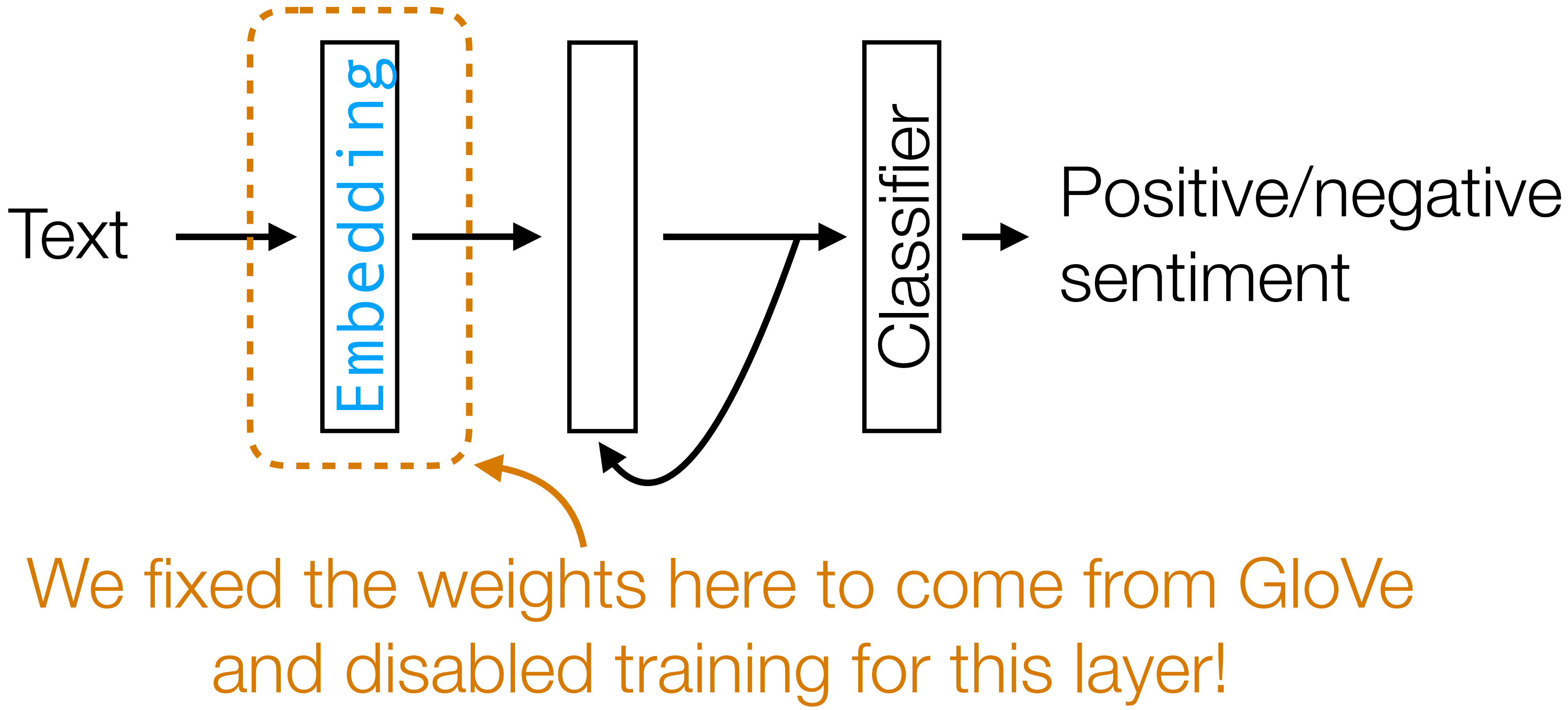

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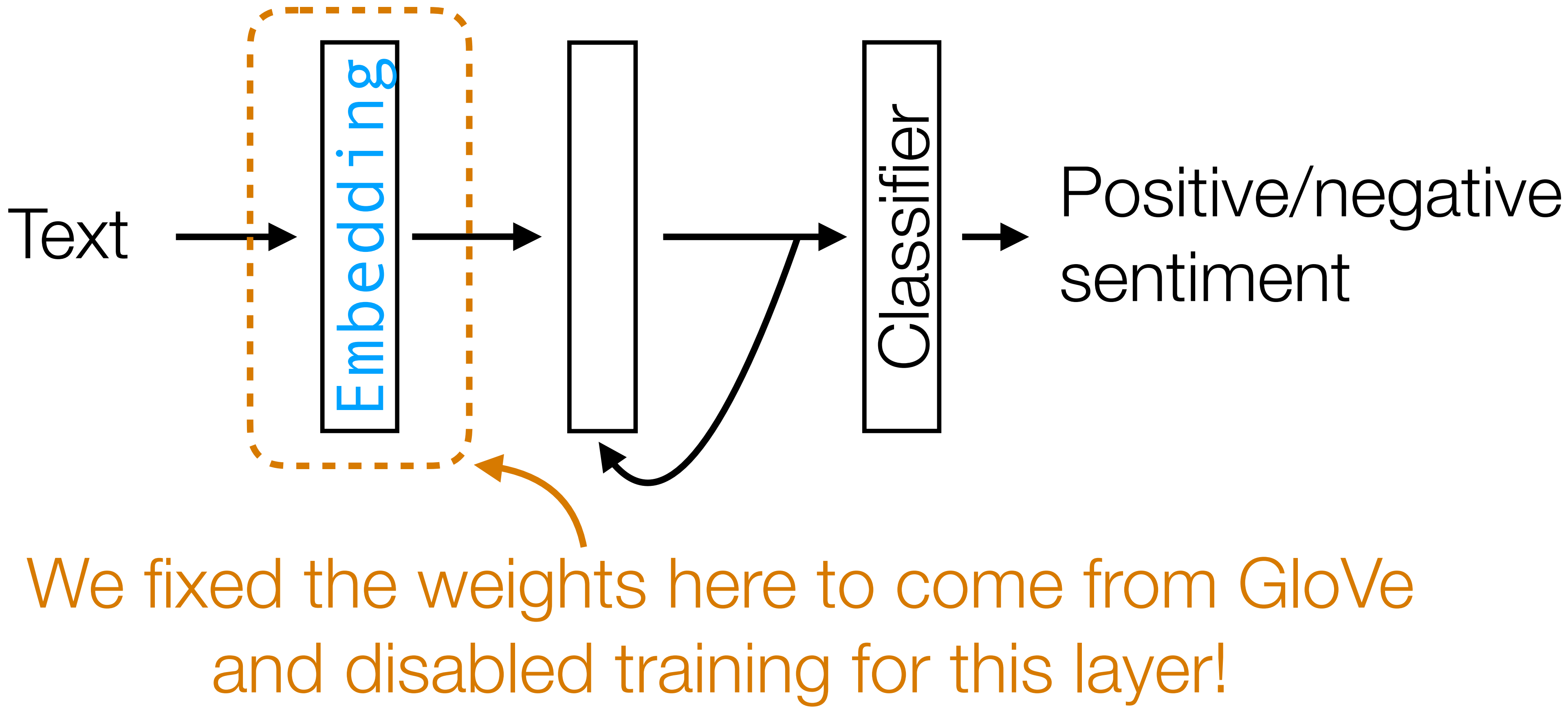

GloVe vectors pre-trained on massive dataset (Wikipedia + Gigaword)

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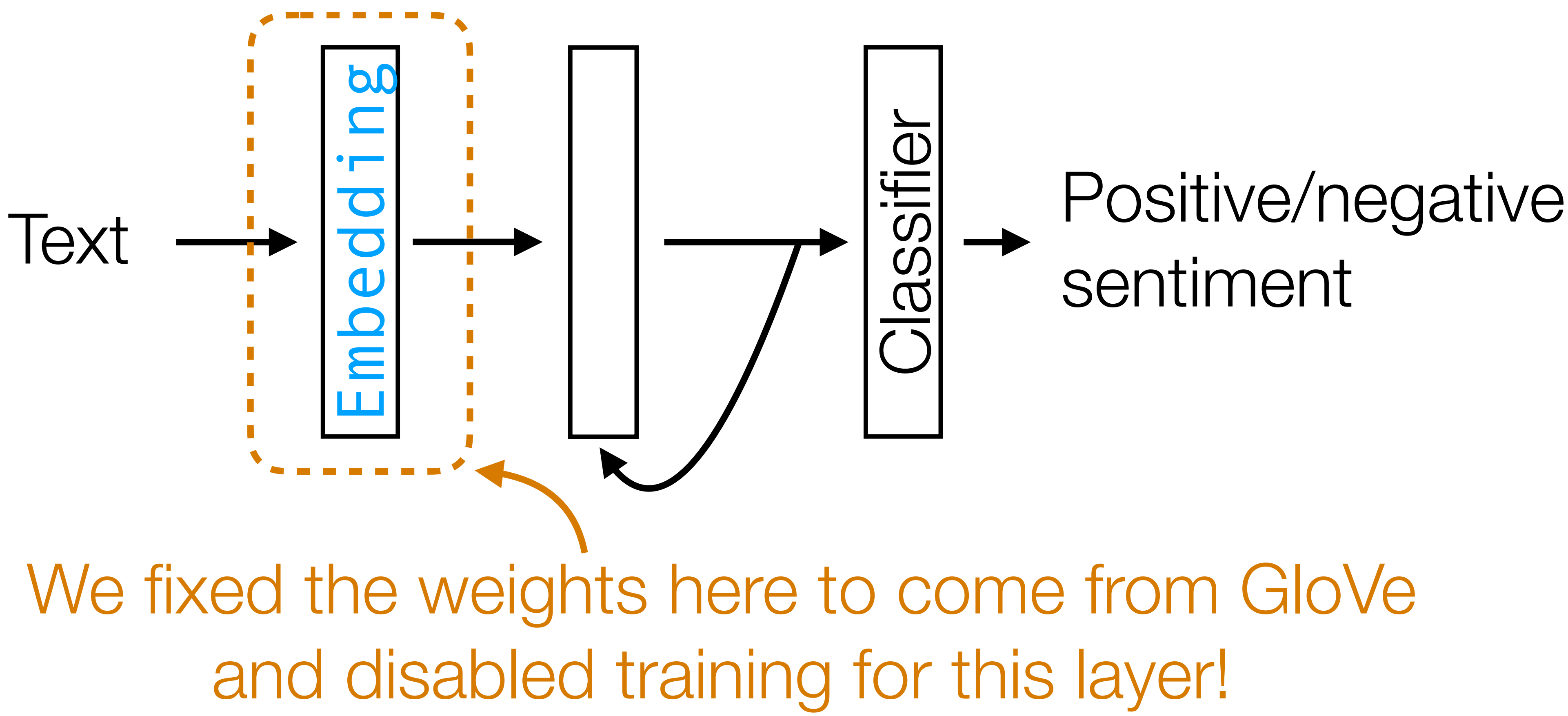

GloVe vectors pre-trained on massive dataset (Wikipedia + Gigaword)

IMDb review dataset is small in comparison

Visualizing What a Deep Net Learned

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- Very straight-forward for CNNs

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  - Plot filter outputs at different layers

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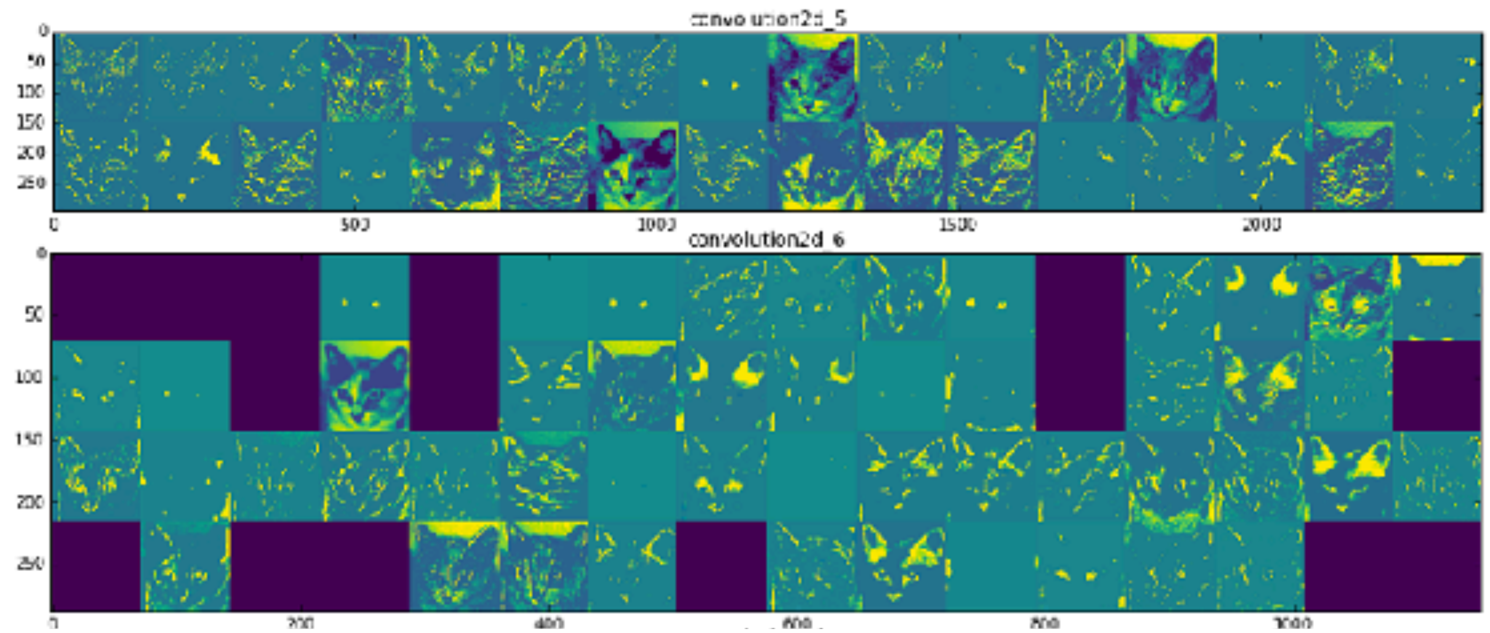

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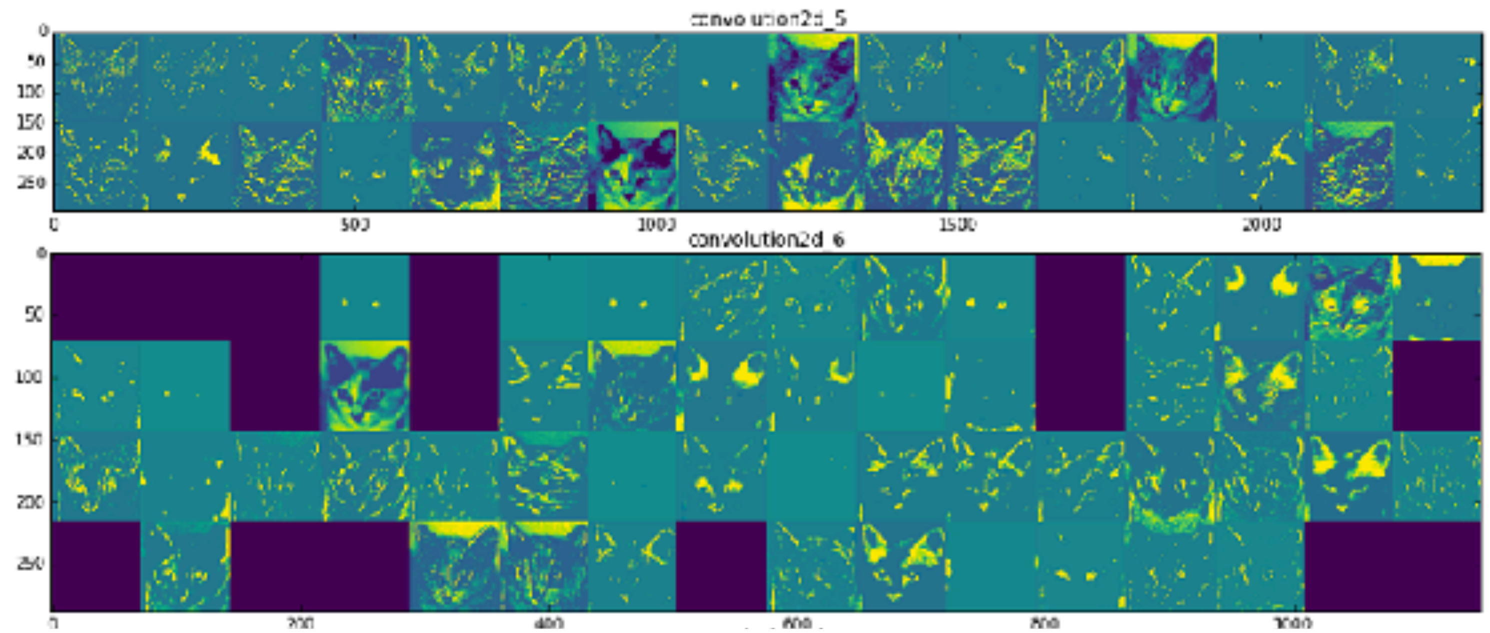

  - Plot regions that maximally activate an output neuron

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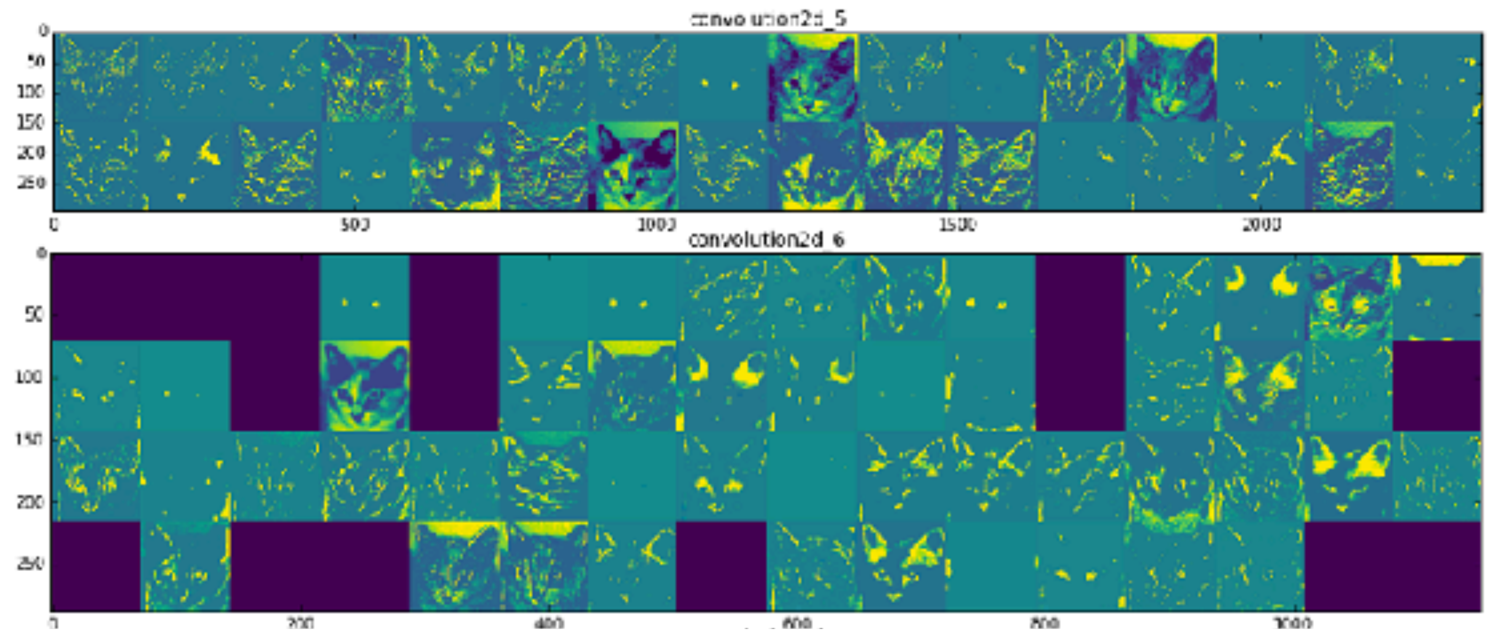

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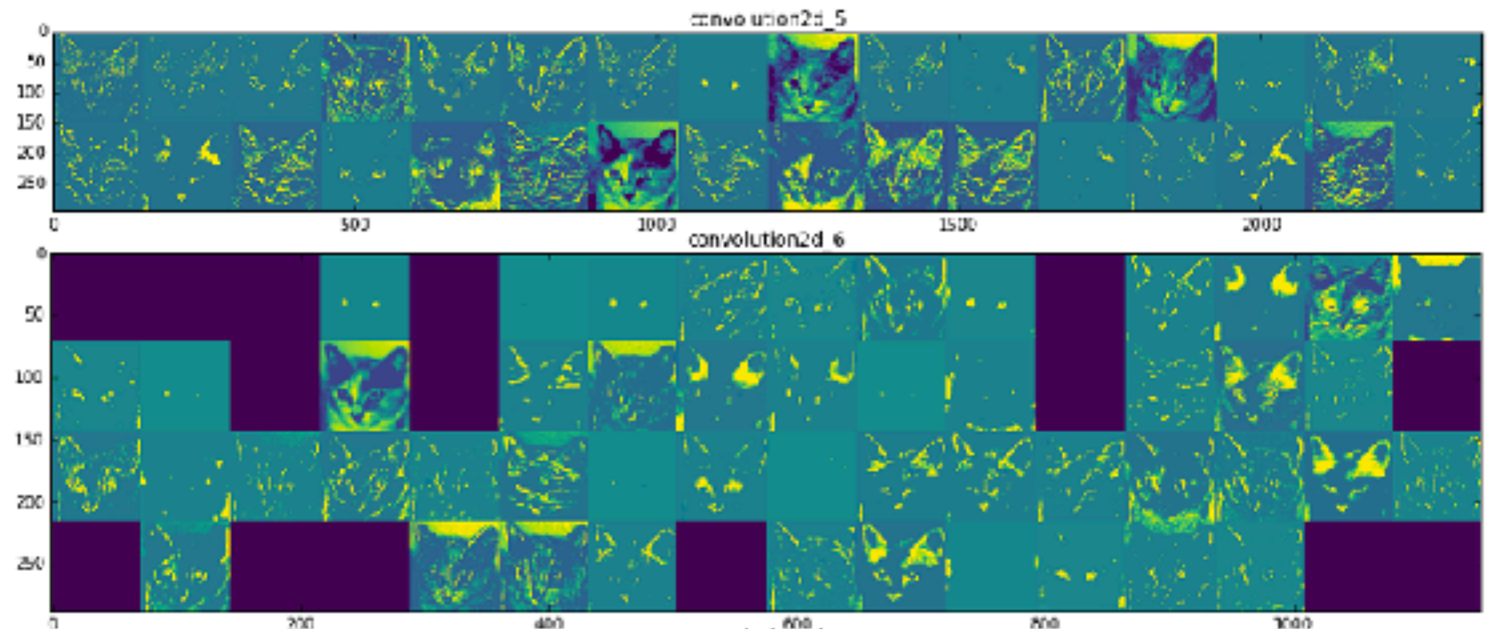

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Images: Francois Chollet's "Deep Learning with Python" Chapter 5

Self-Supervised Learning

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The opioid epidemic or opioid crisis is the rapid increase in the use of prescription and non-prescription opioid drugs in the United States and Canada in the 2010s.

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“Training label”:

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There are “positive” examples of what context words are for “opioid”

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The opioid epidemic or opioid crisis is the rapid increase in the use of prescription and non-prescription opioid drugs in the United States and Canada in the 2010s.

Predict context of each word!

There are "positive" examples of what context words are for "opioid"

Training data point: opioid

"Training label": epidemic, or, crisis, is

Also provide "negative" examples of words that are *not* likely to be context words (e.g., randomly sample words elsewhere in document)

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Input word
(categorical
“one hot”
encoding)

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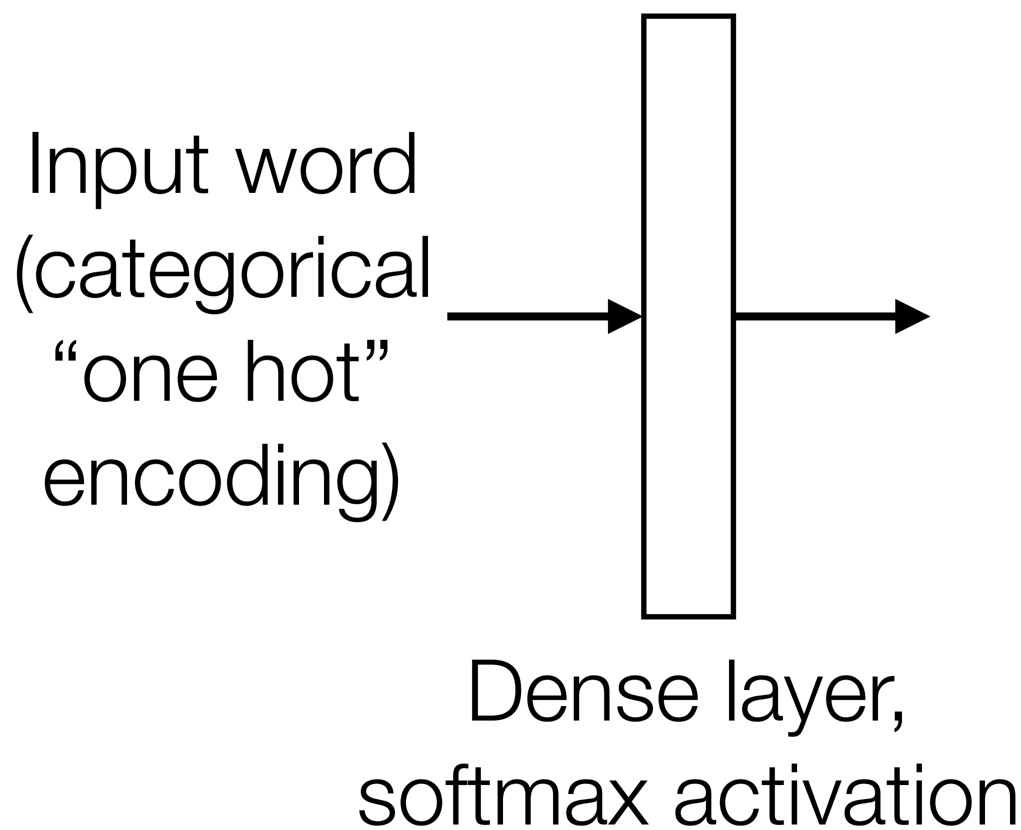

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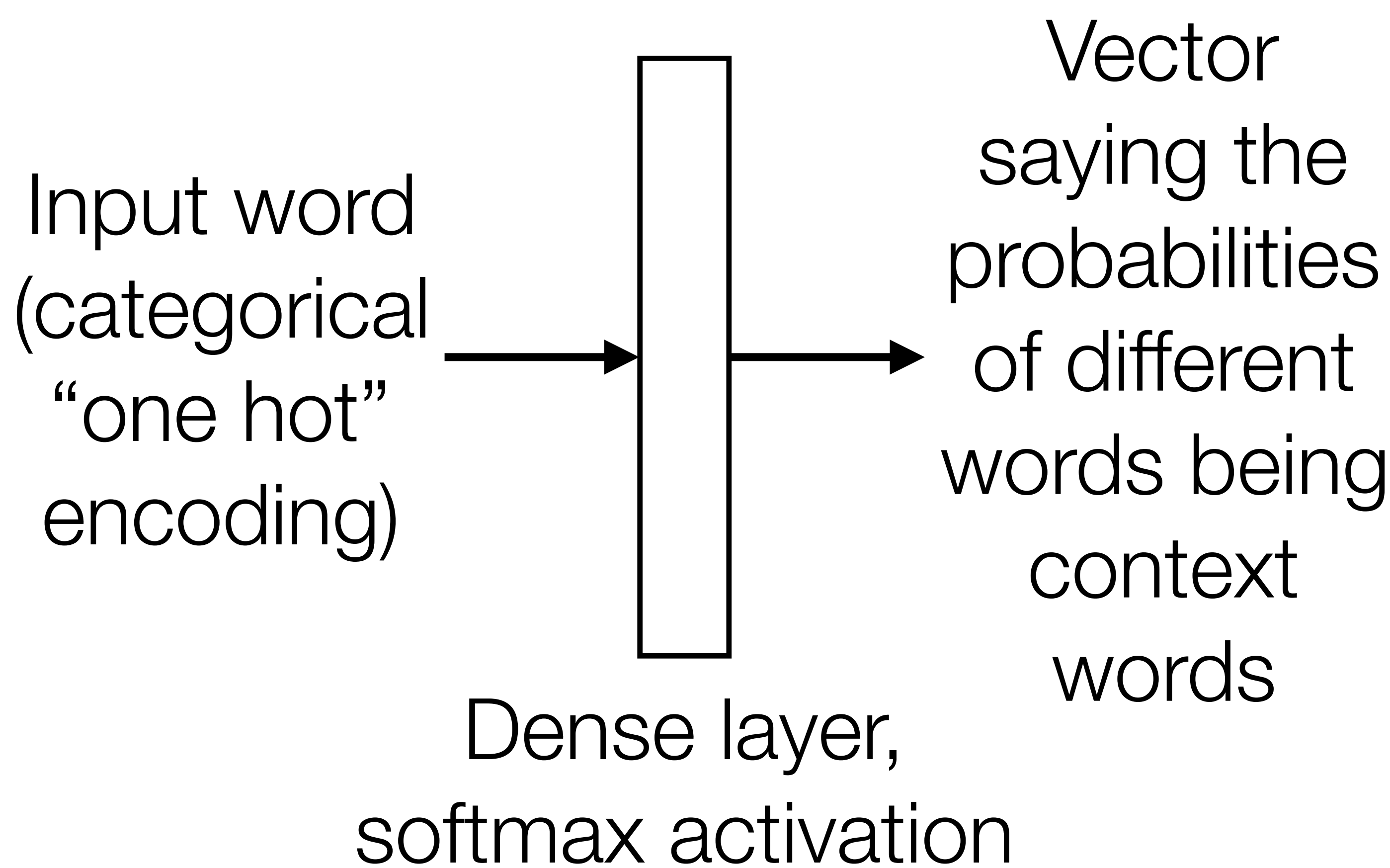

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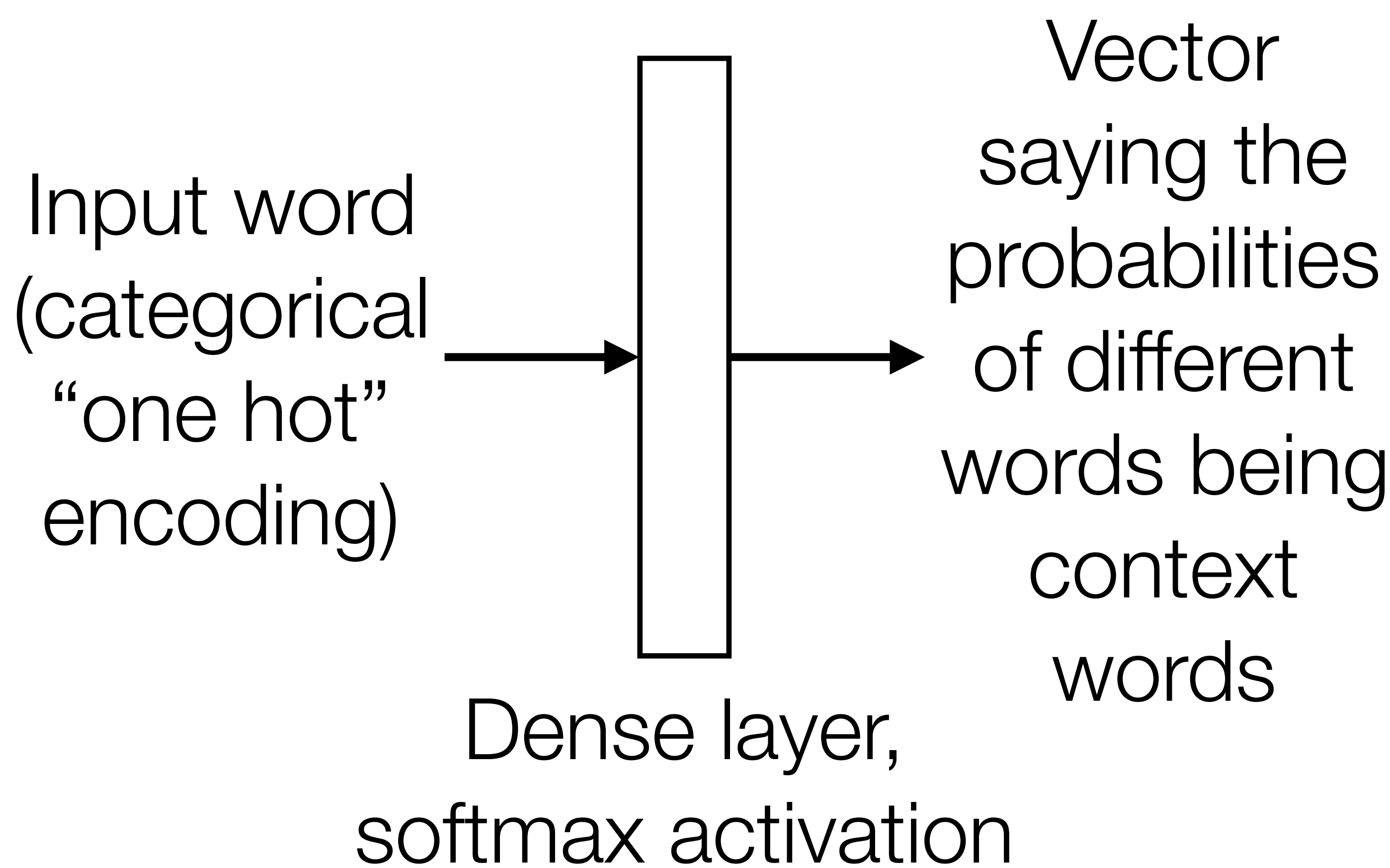

Weight matrix: (# words in vocab) by (# neurons)

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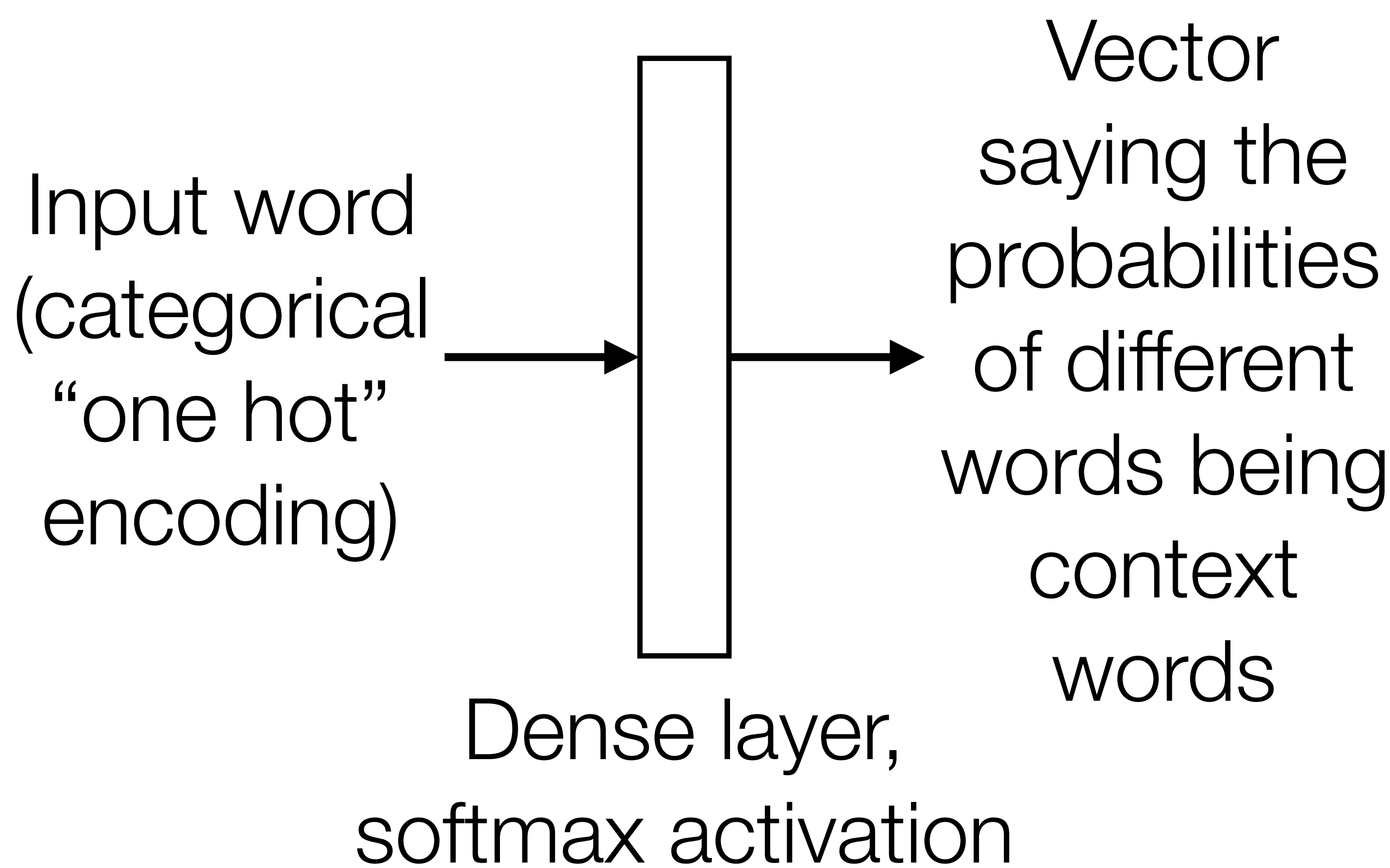

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Dictionary word *i* has "word embedding" given by row *i* of weight matrix

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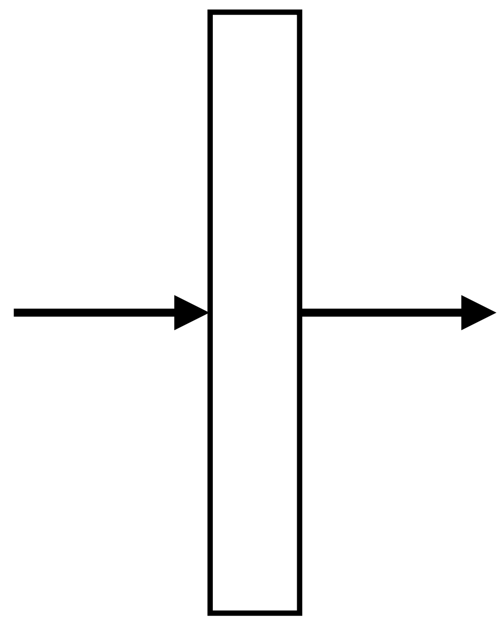

This actually relates to PMI!

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- Key idea: predict part of the training data from other parts of the training data

- No actual training labels required — we are defining what the training labels are just using the unlabeled training data

- This is an *unsupervised* method that sets up a *supervised prediction* task

Learning Distances with Siamese Nets

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Using labeled data, we can learn a distance function

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Data point 1
X_1

Data point 2
X_2

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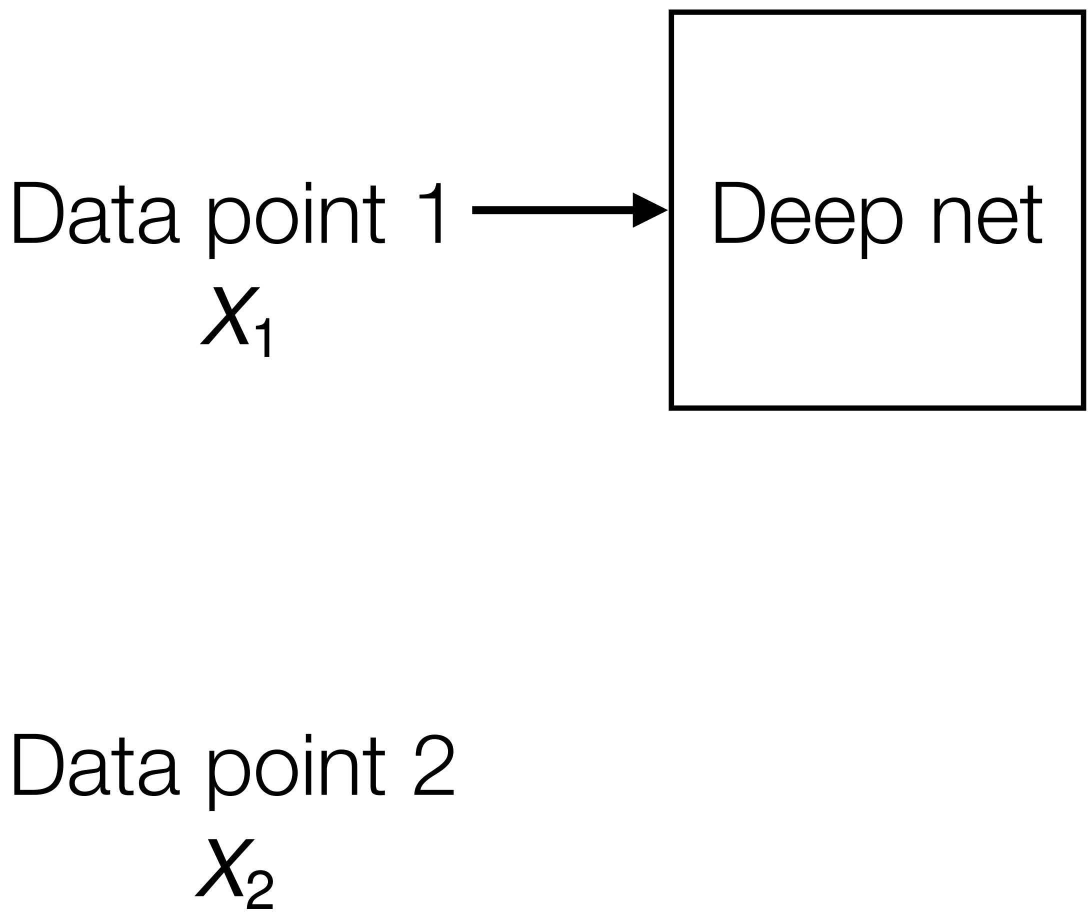

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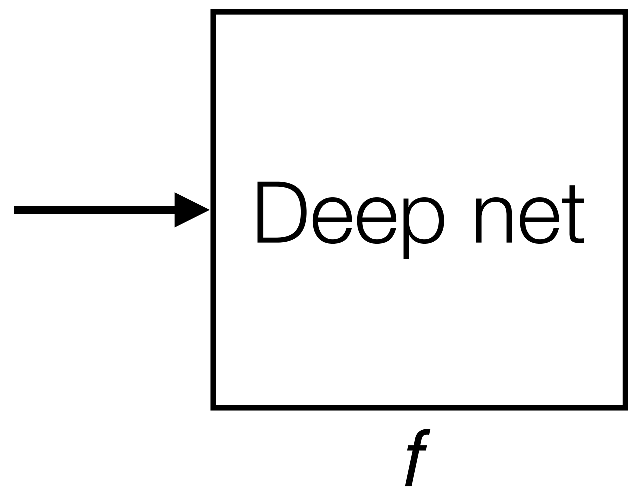

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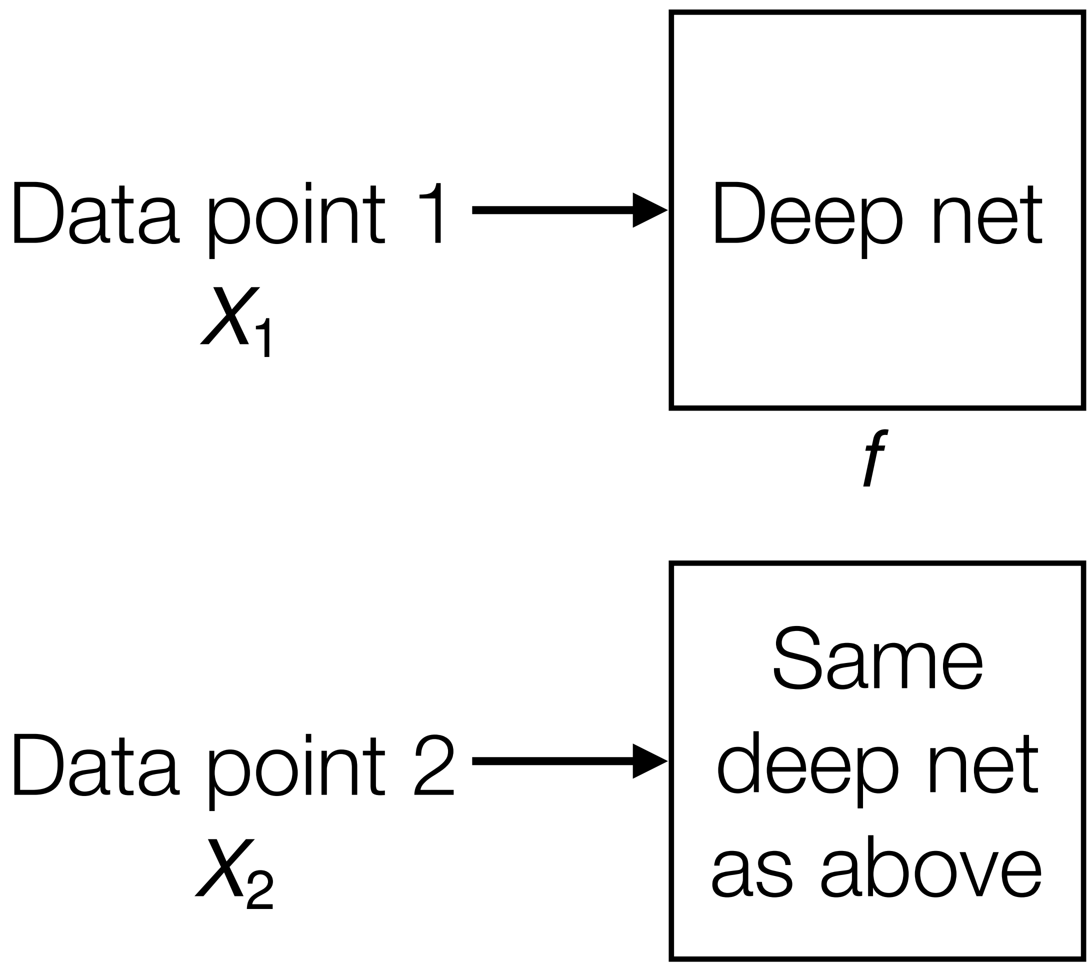

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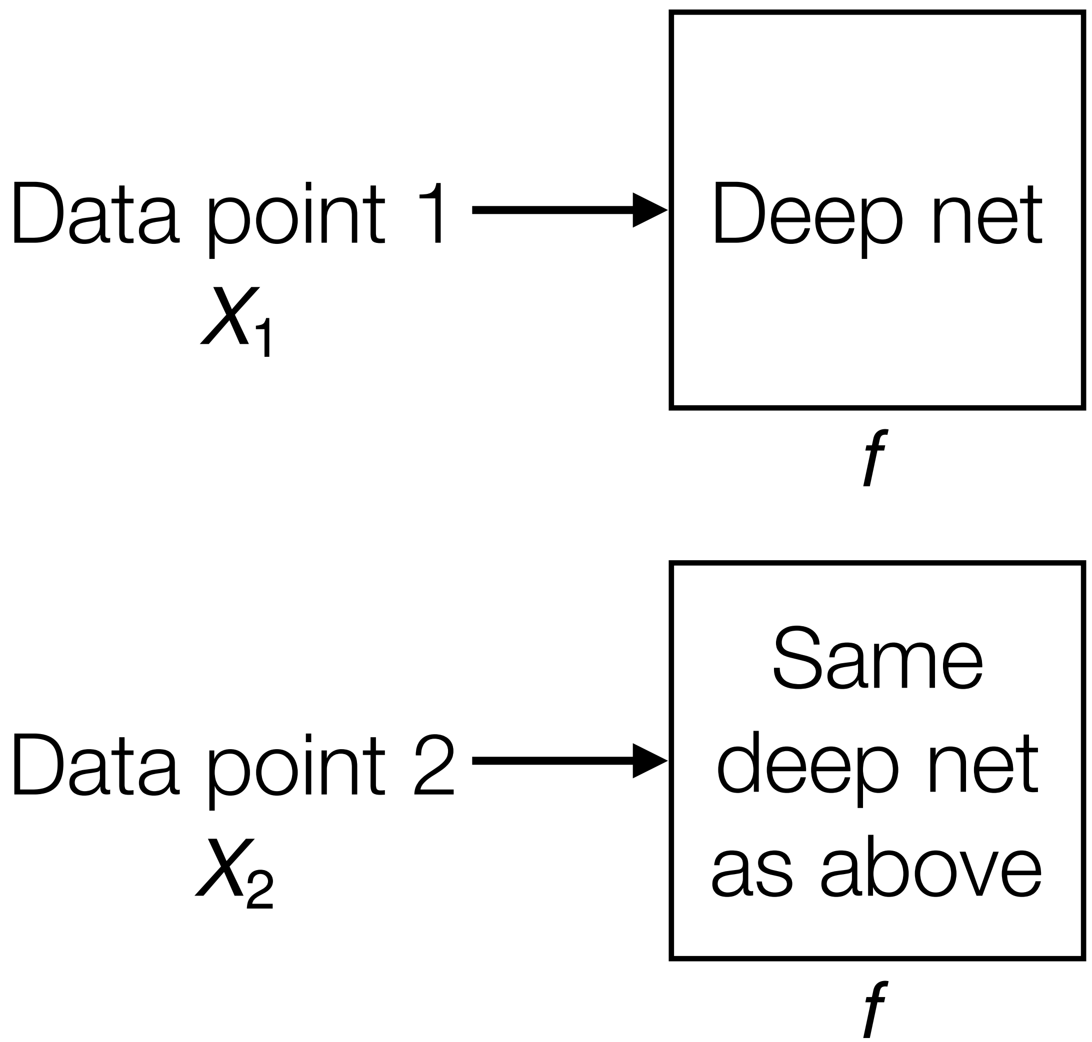

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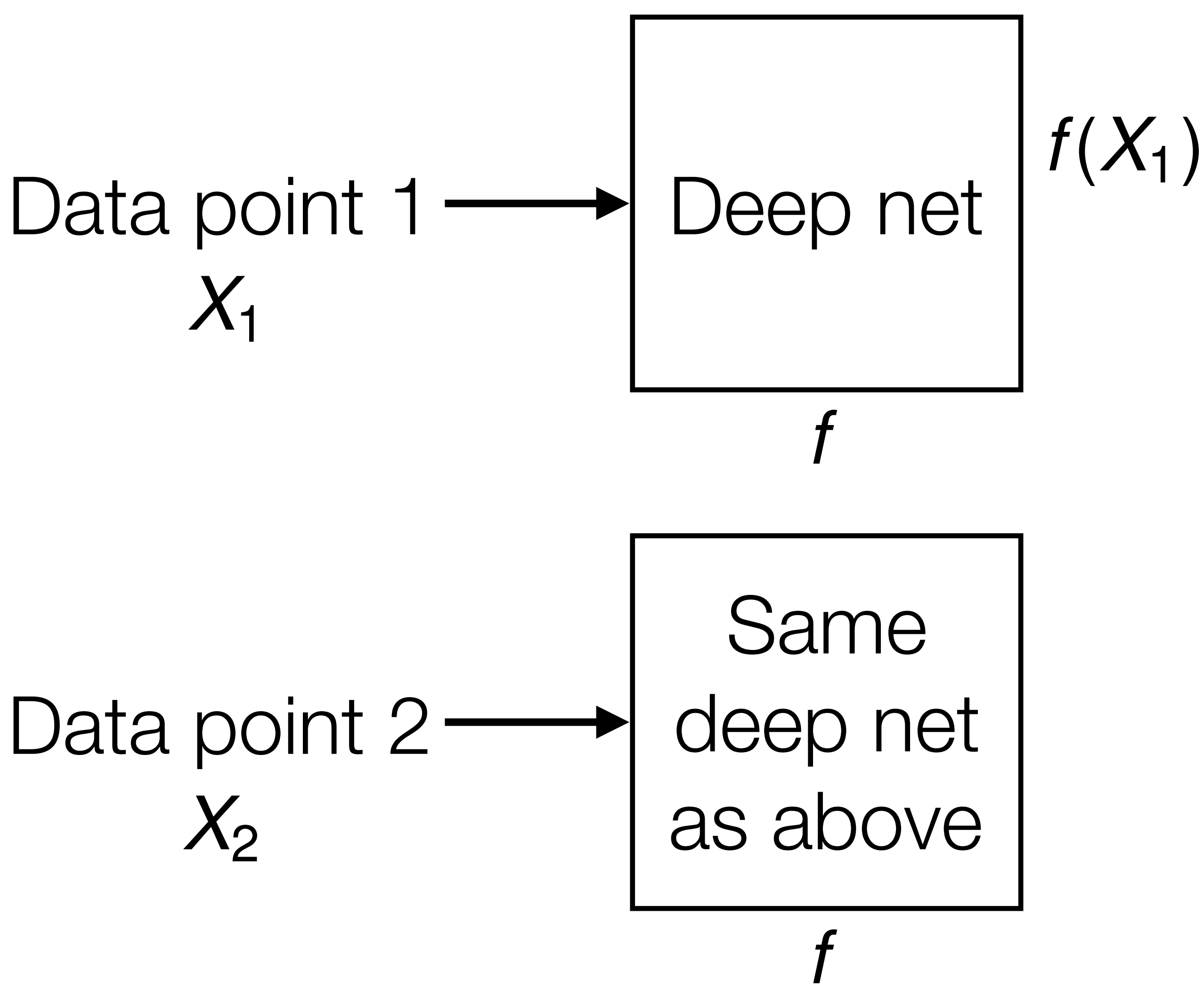

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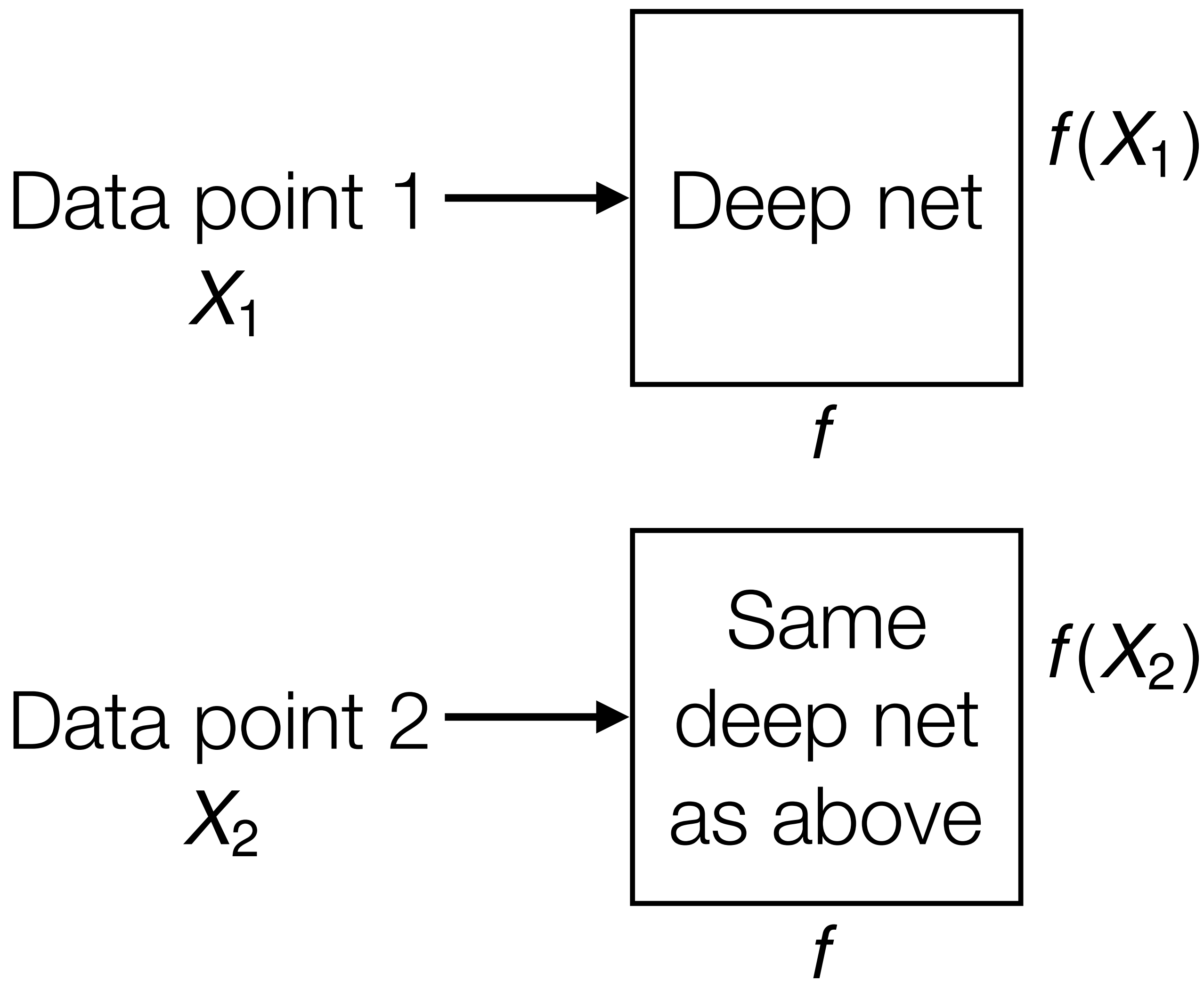

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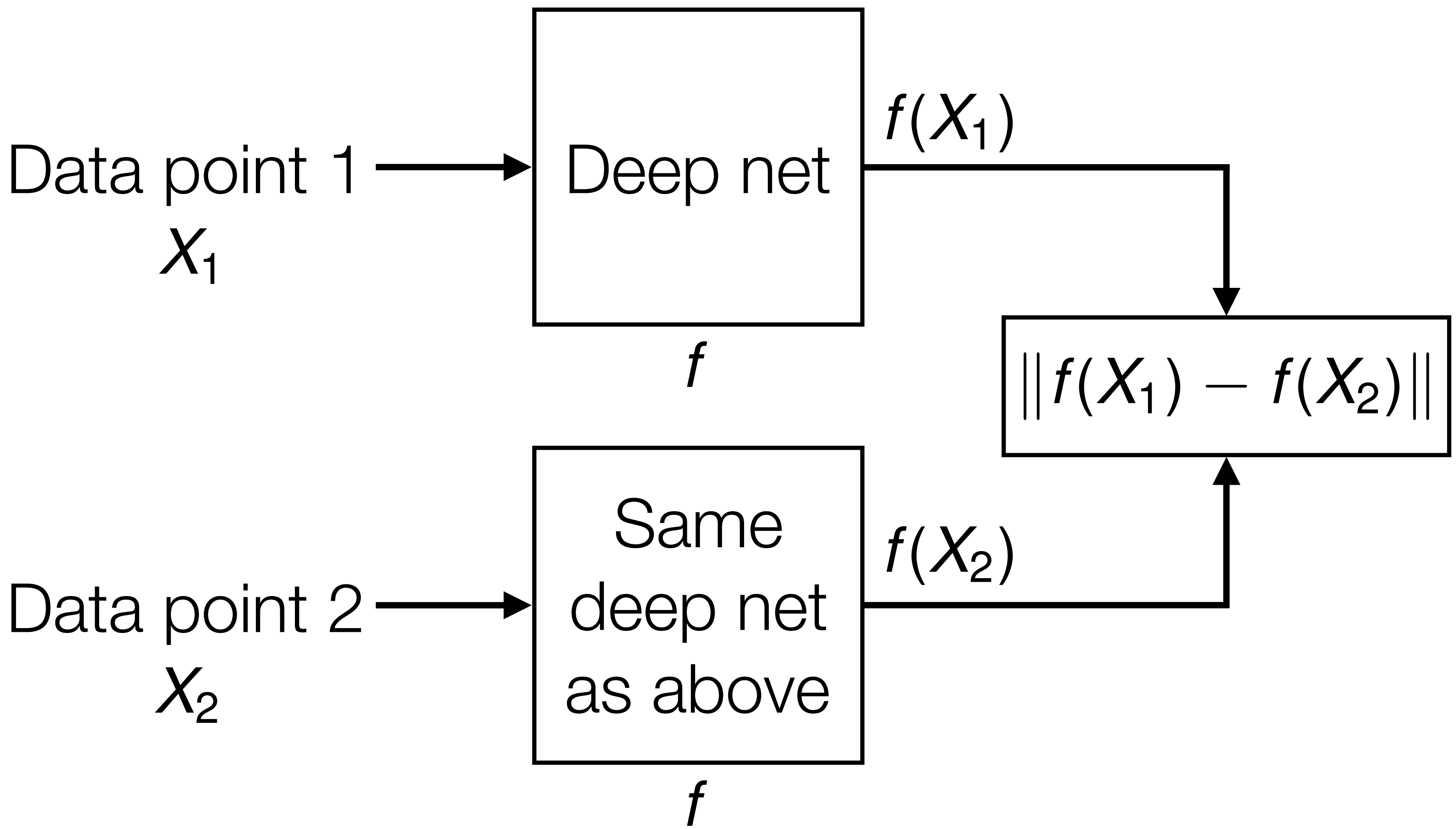

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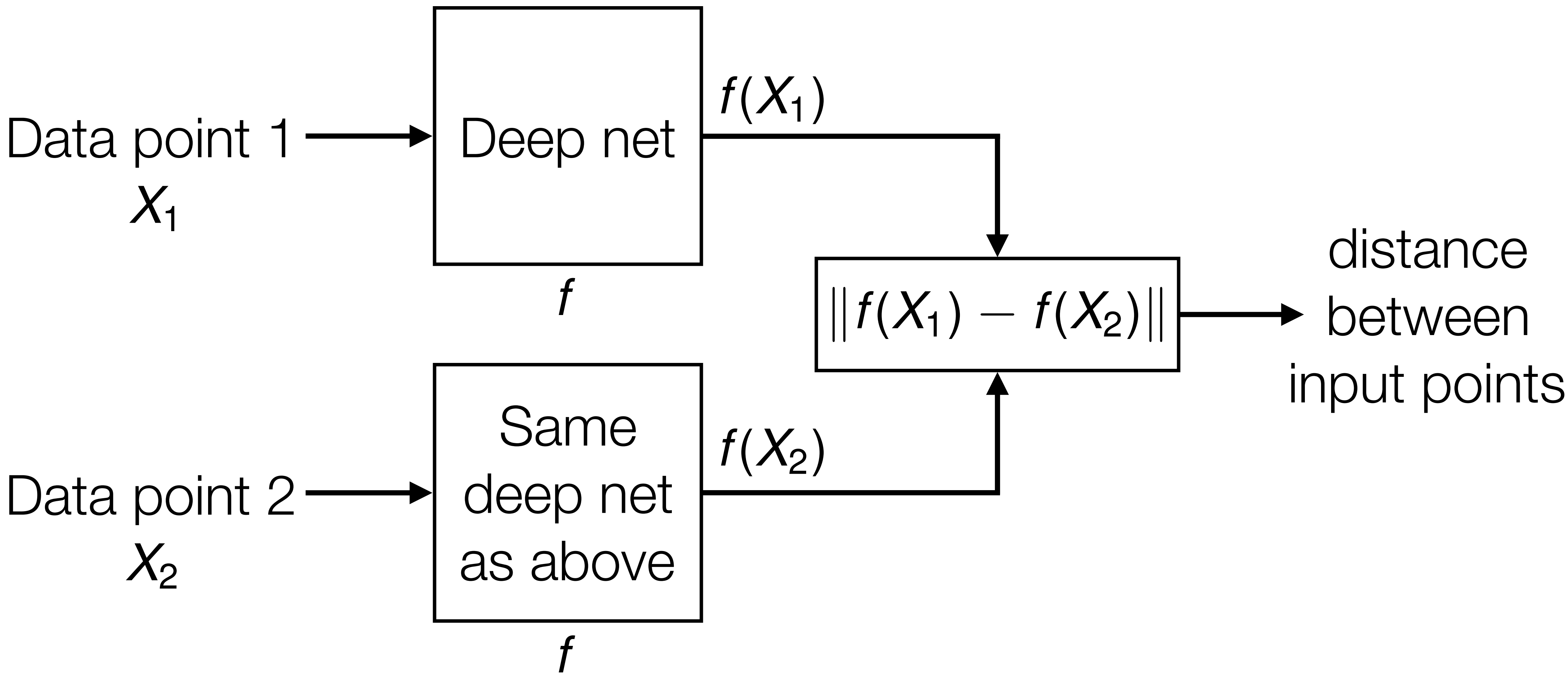

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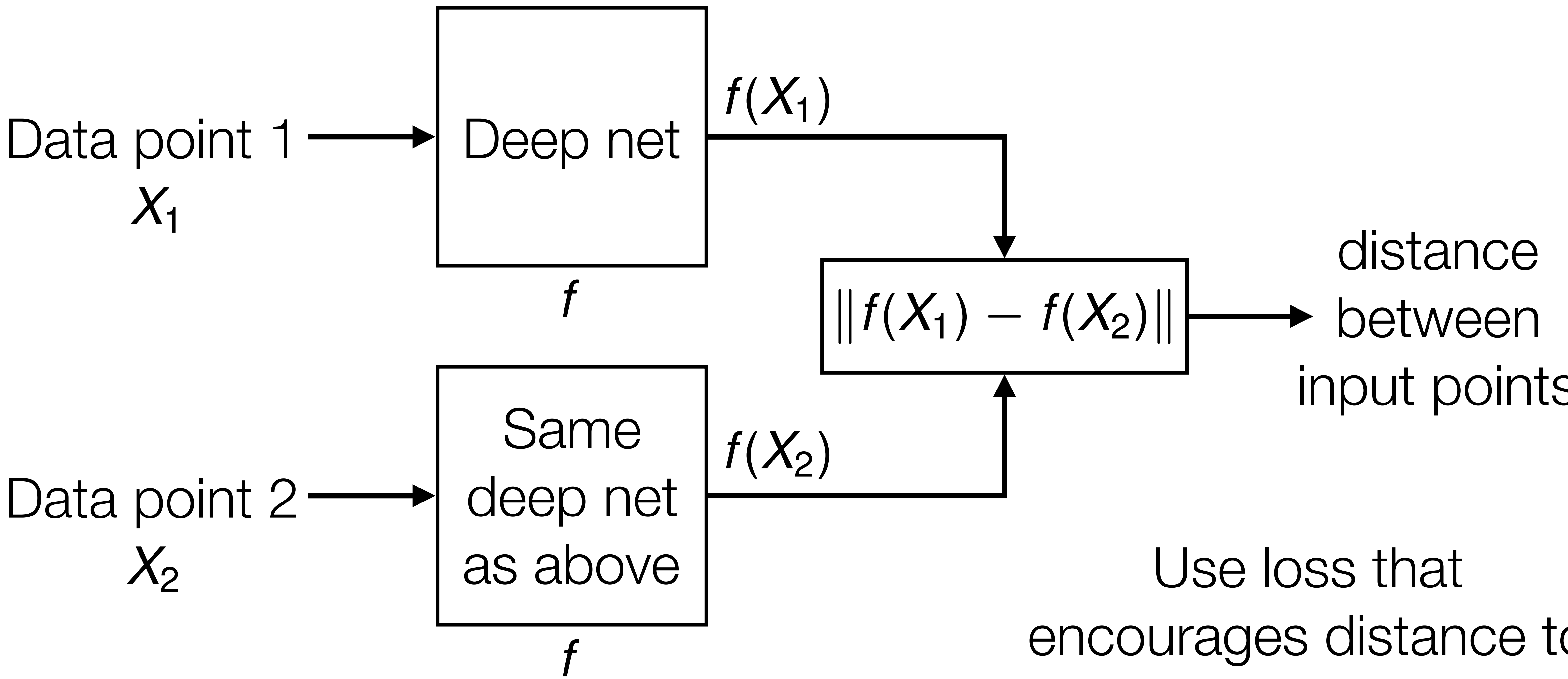

Use loss that encourages distance to be small for data points with same label and large otherwise

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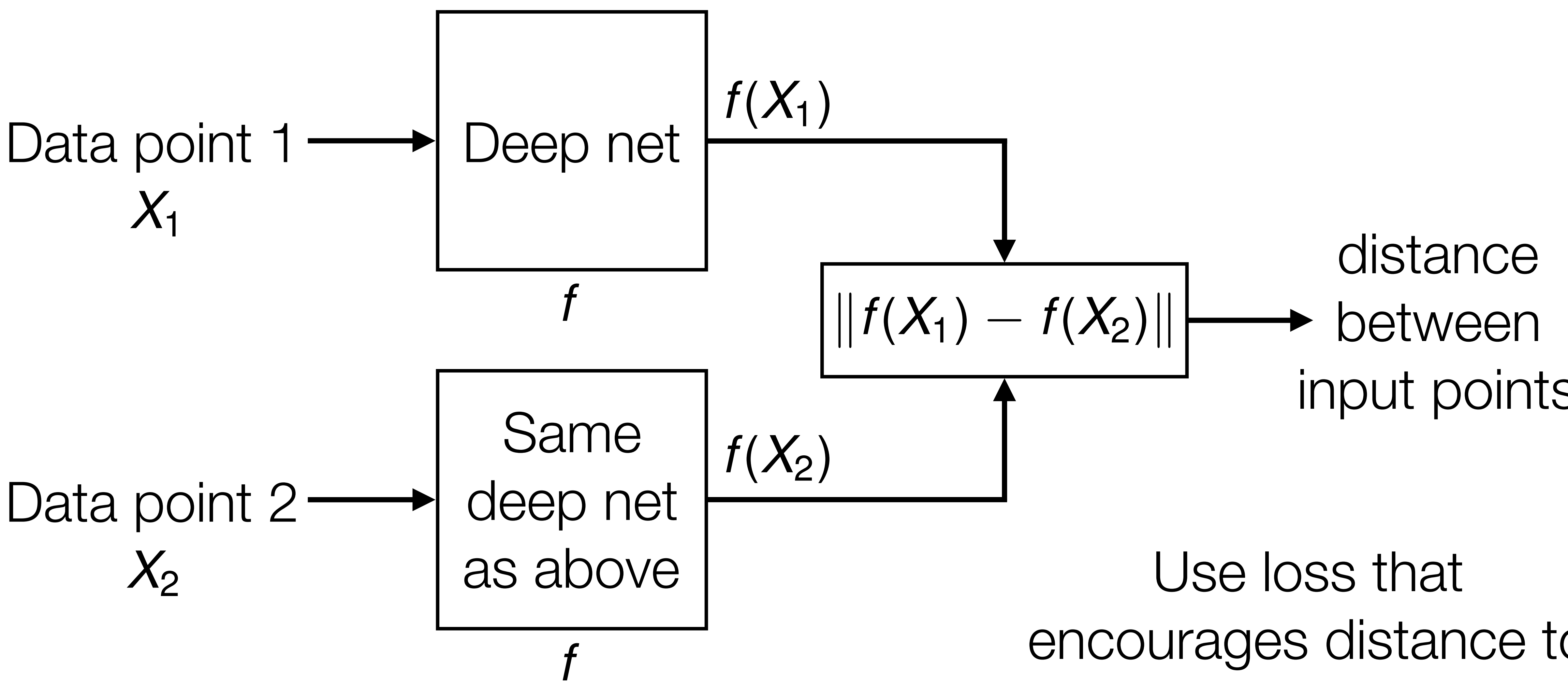

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Note: we are learning the function *f*

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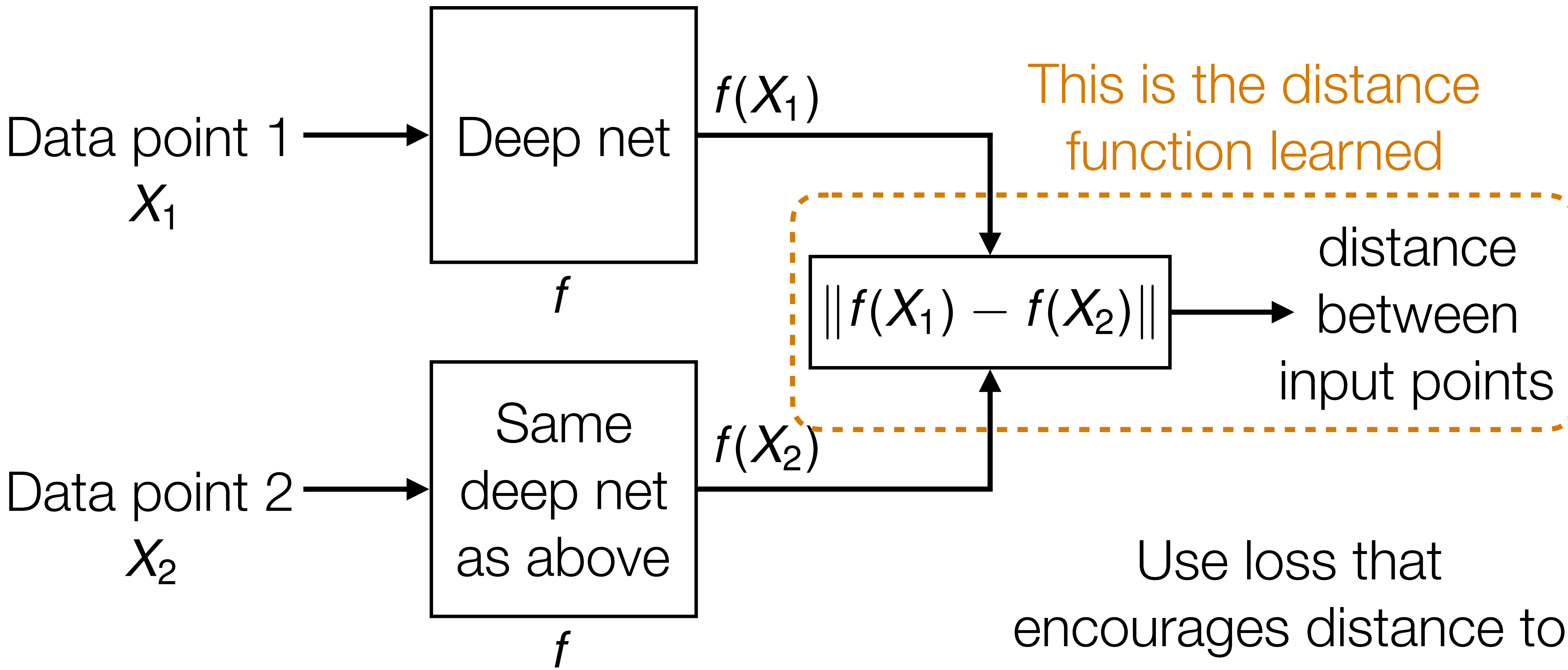

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Unsupervised approach: generate data that look like training data

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Example: Generative Adversarial Network (GAN)

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Real training
example

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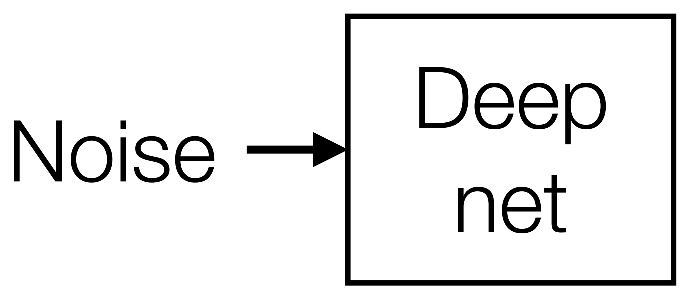

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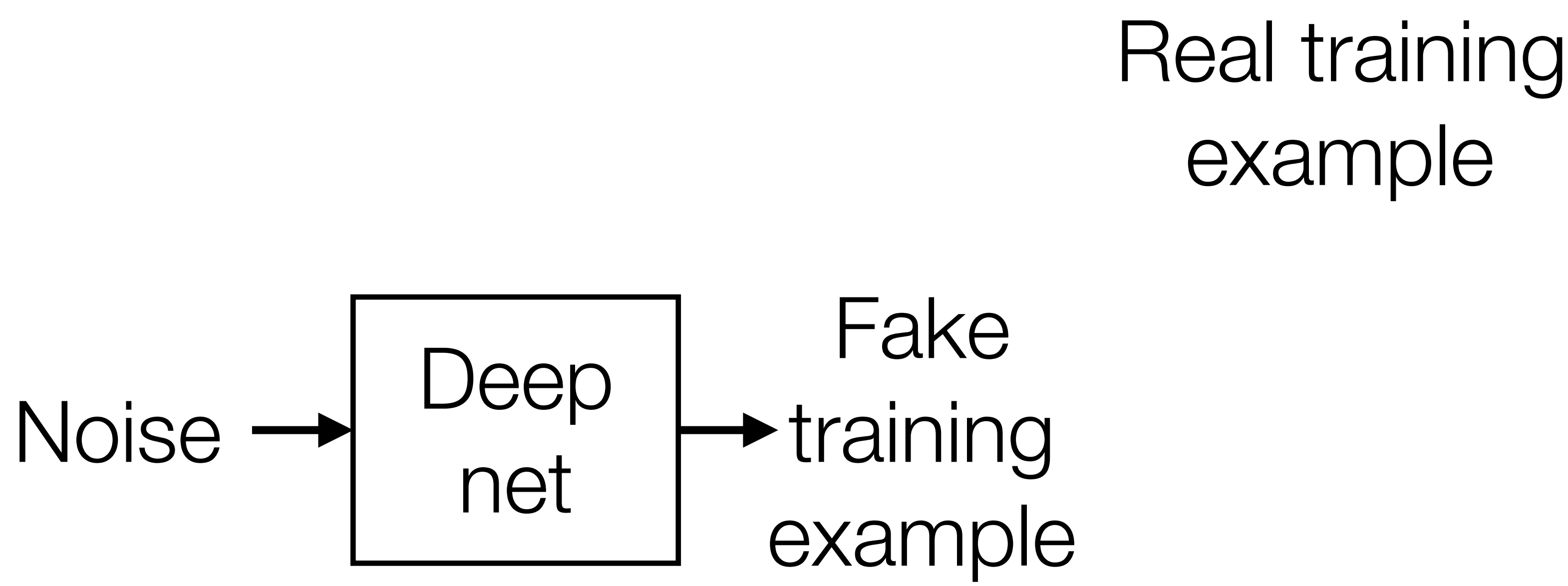

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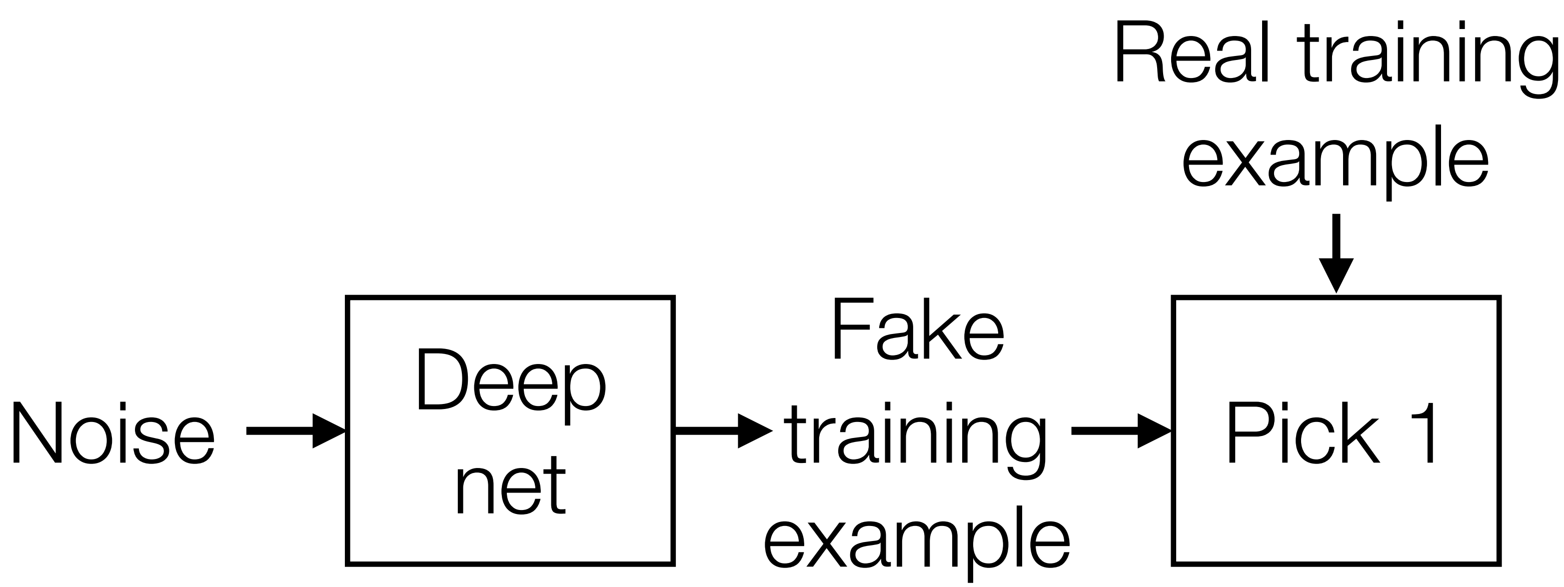

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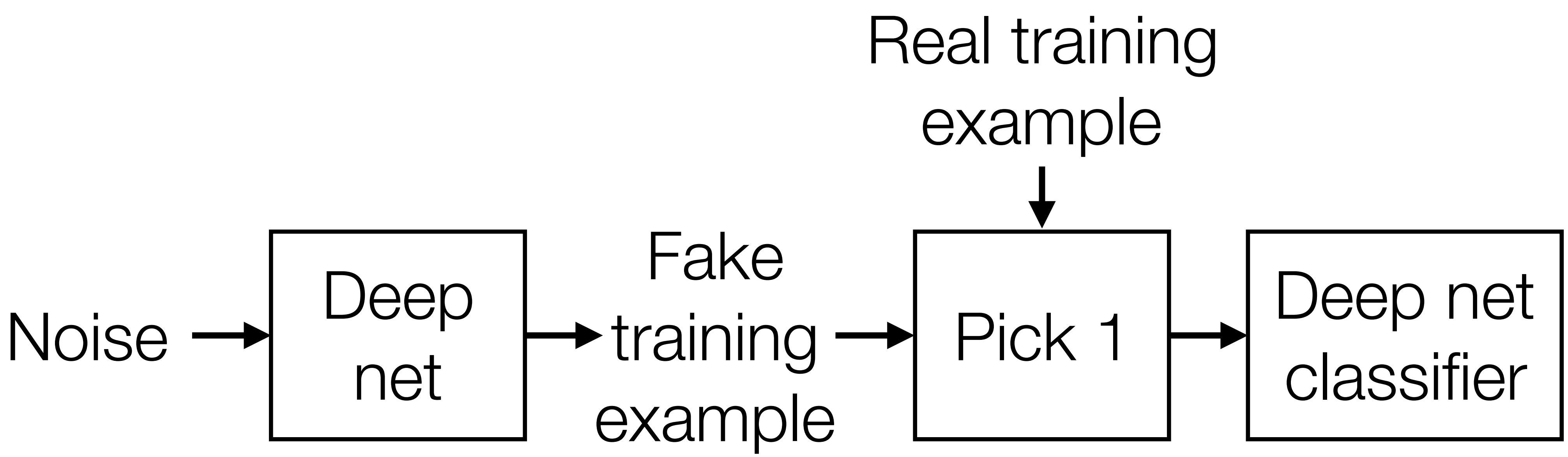

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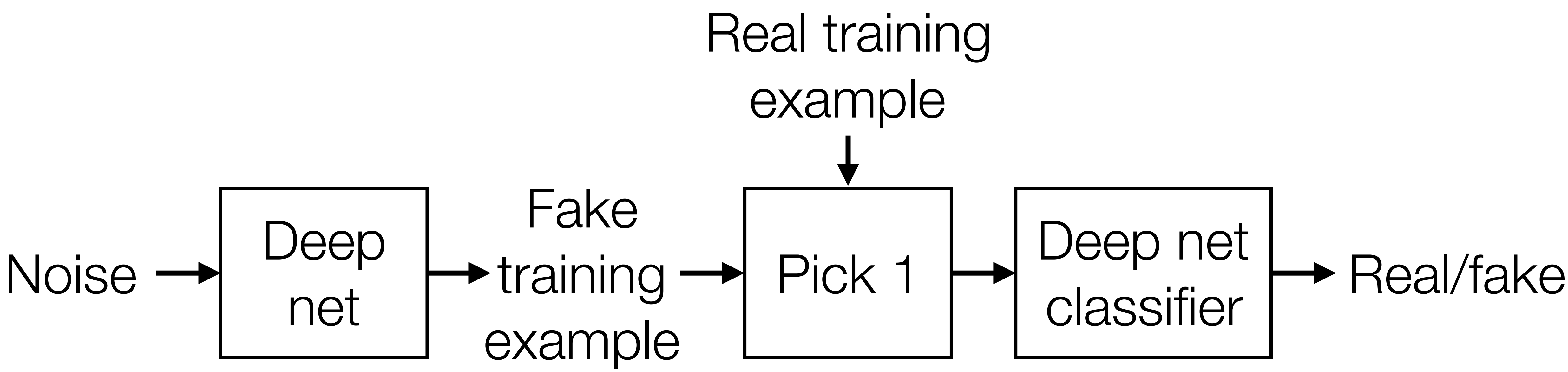

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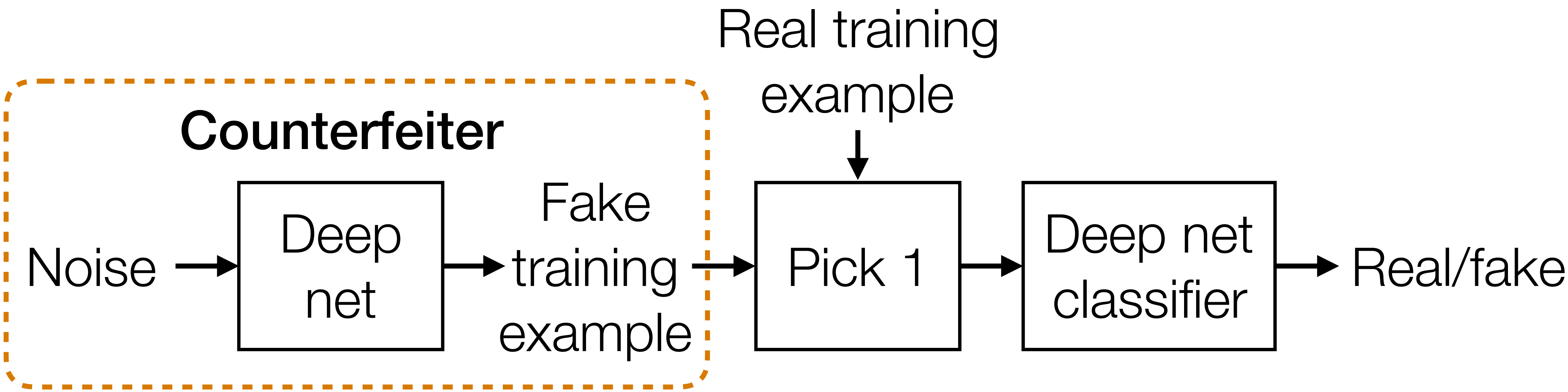

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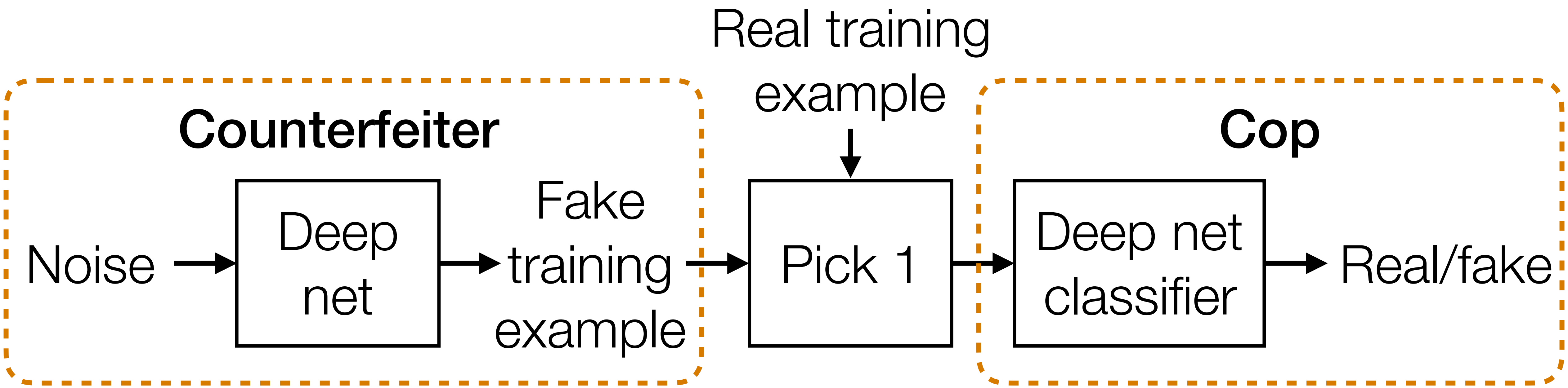

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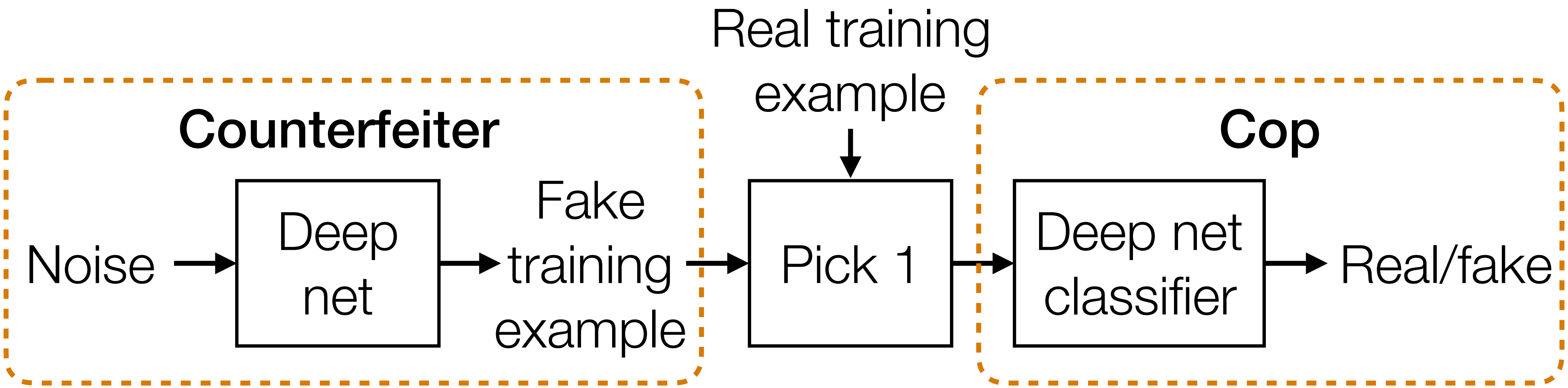

Cop tries to get better at telling which examples are real vs fake

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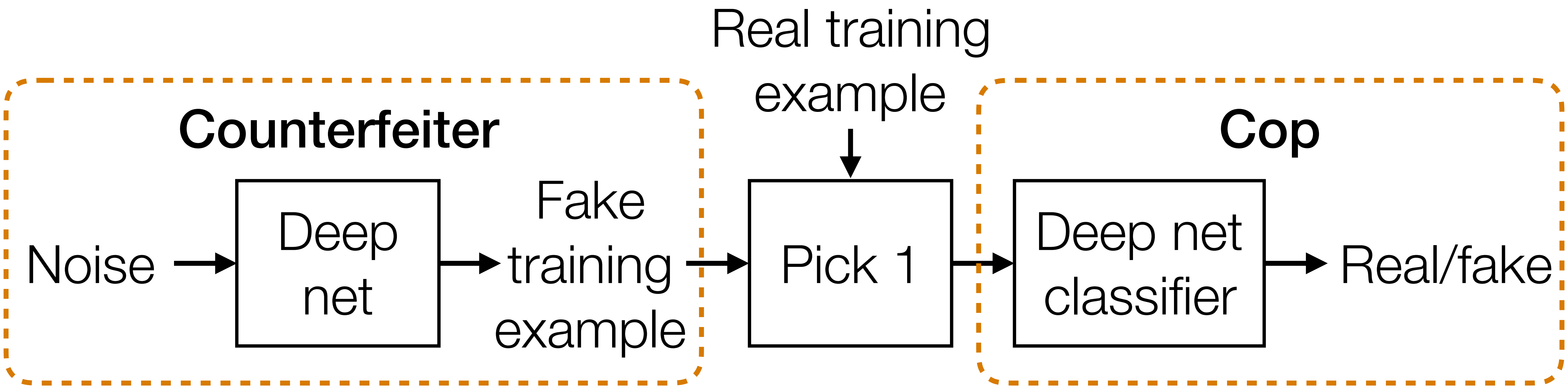

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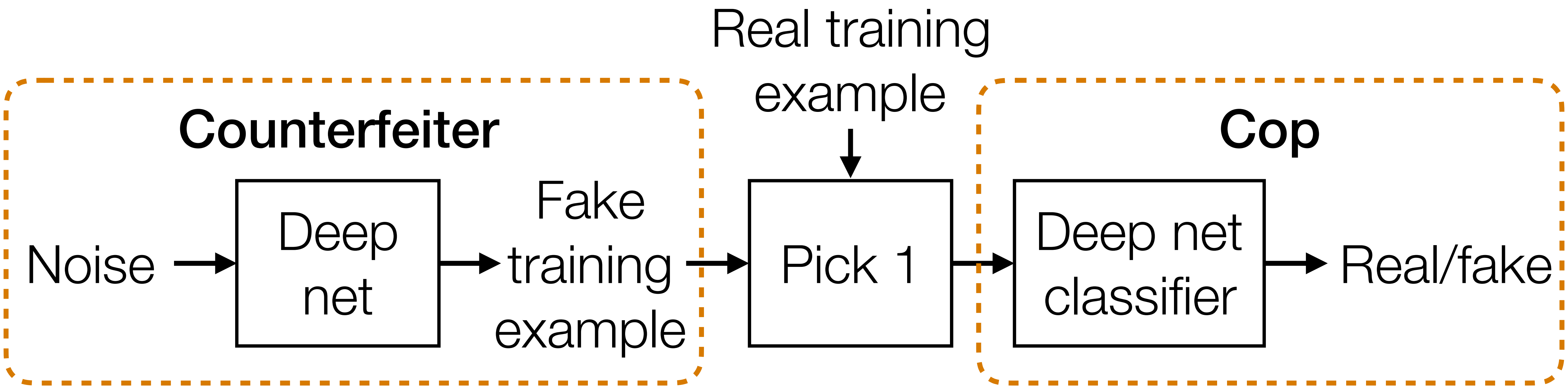

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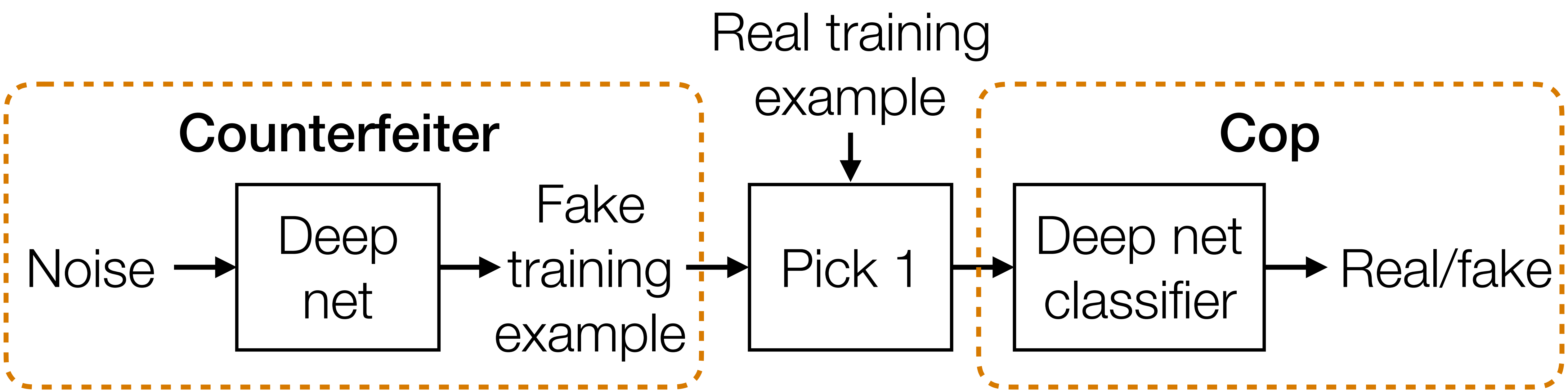

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Other approaches: variational autoencoders, pixelRNNs/pixelCNNs

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Google DeepMind's WaveNet makes fake audio that sounds like whoever you want using pixelRNNs (Oord et al 2016)

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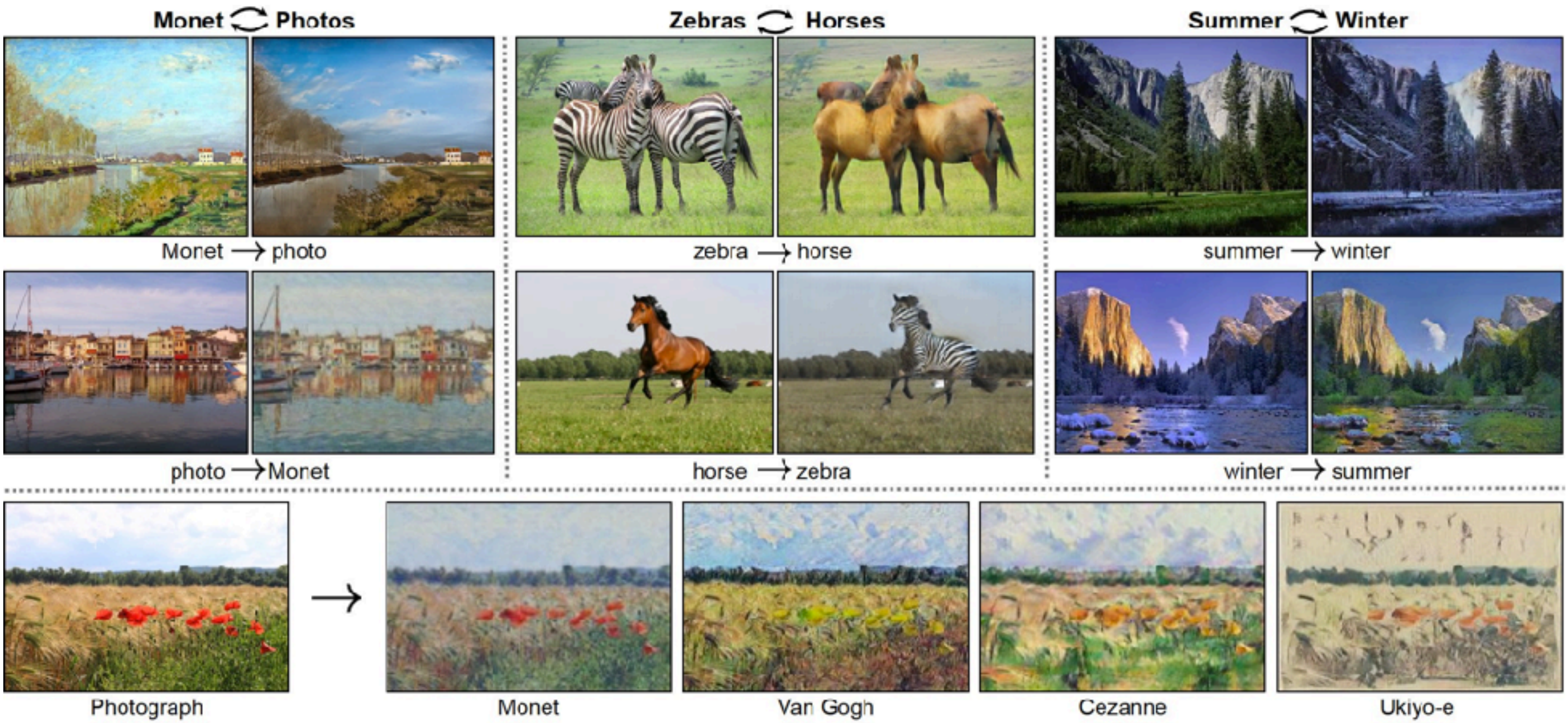

Image-to-image translation results from UC Berkeley using GANs
(Isola et al 2017, Zhu et al 2017)

Deep Reinforcement Learning

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The machinery behind AlphaGo and similar systems

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The machinery behind AlphaGo and similar systems

AI agent

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AI's
current
state

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Environment

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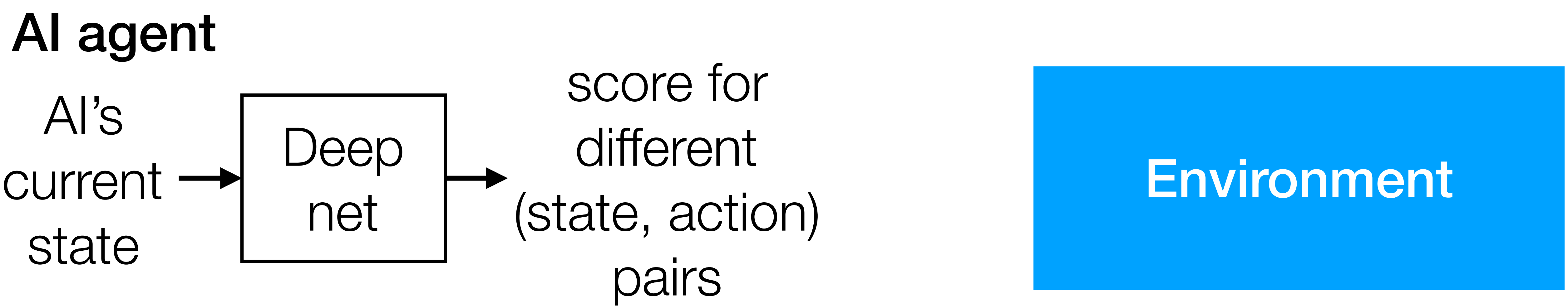

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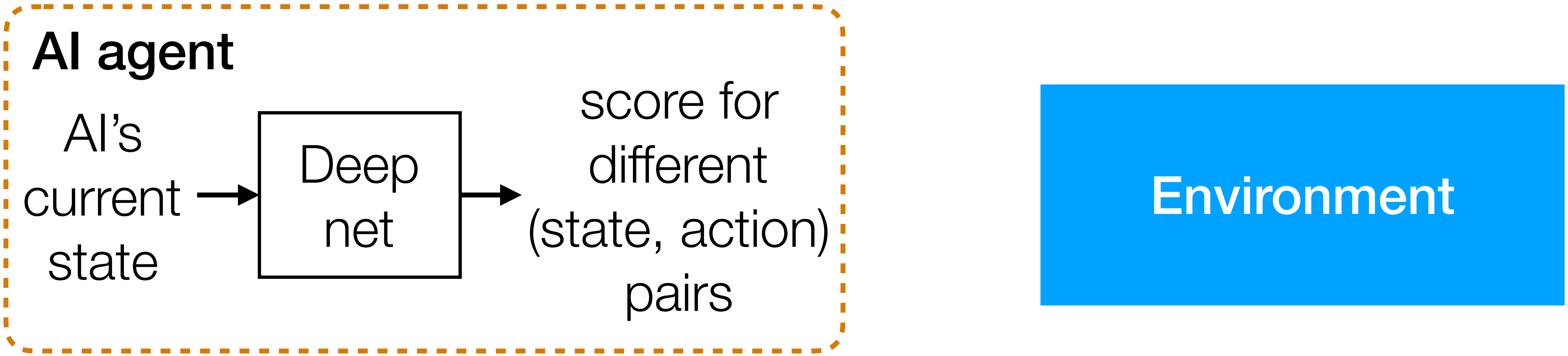
The machinery behind AlphaGo and similar systems



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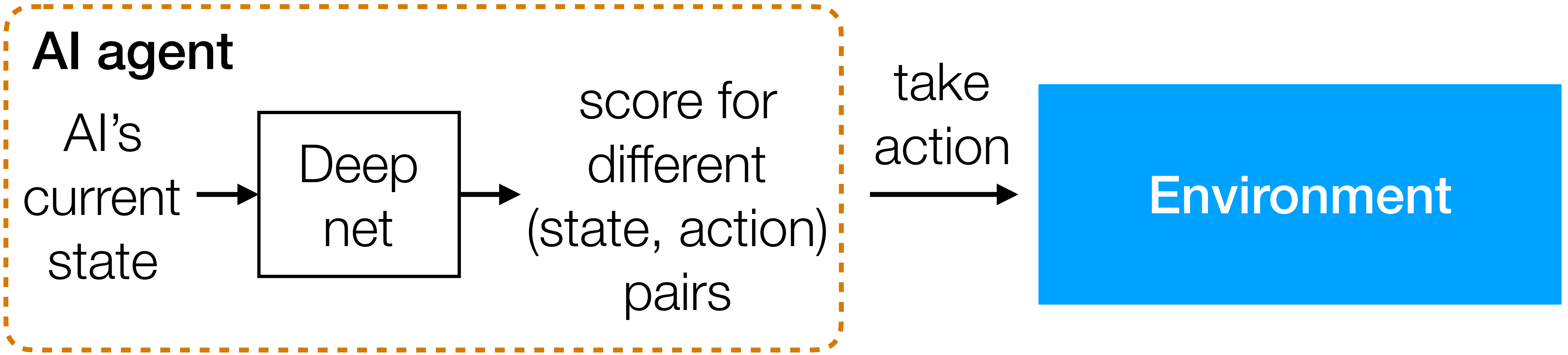

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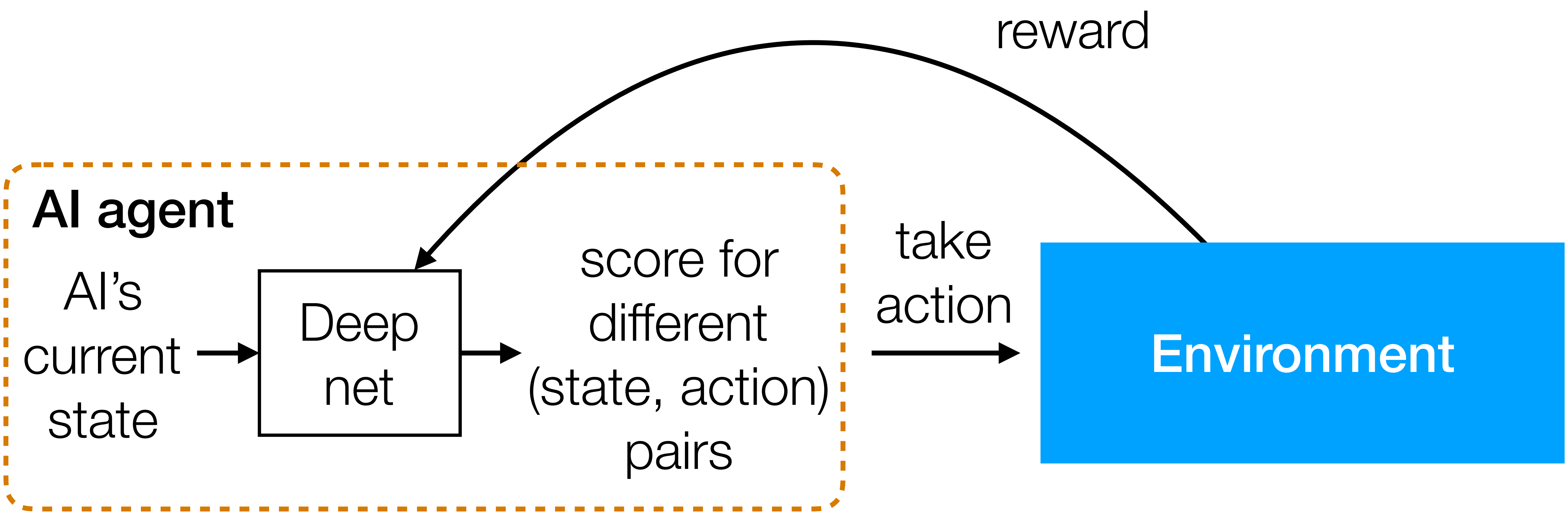

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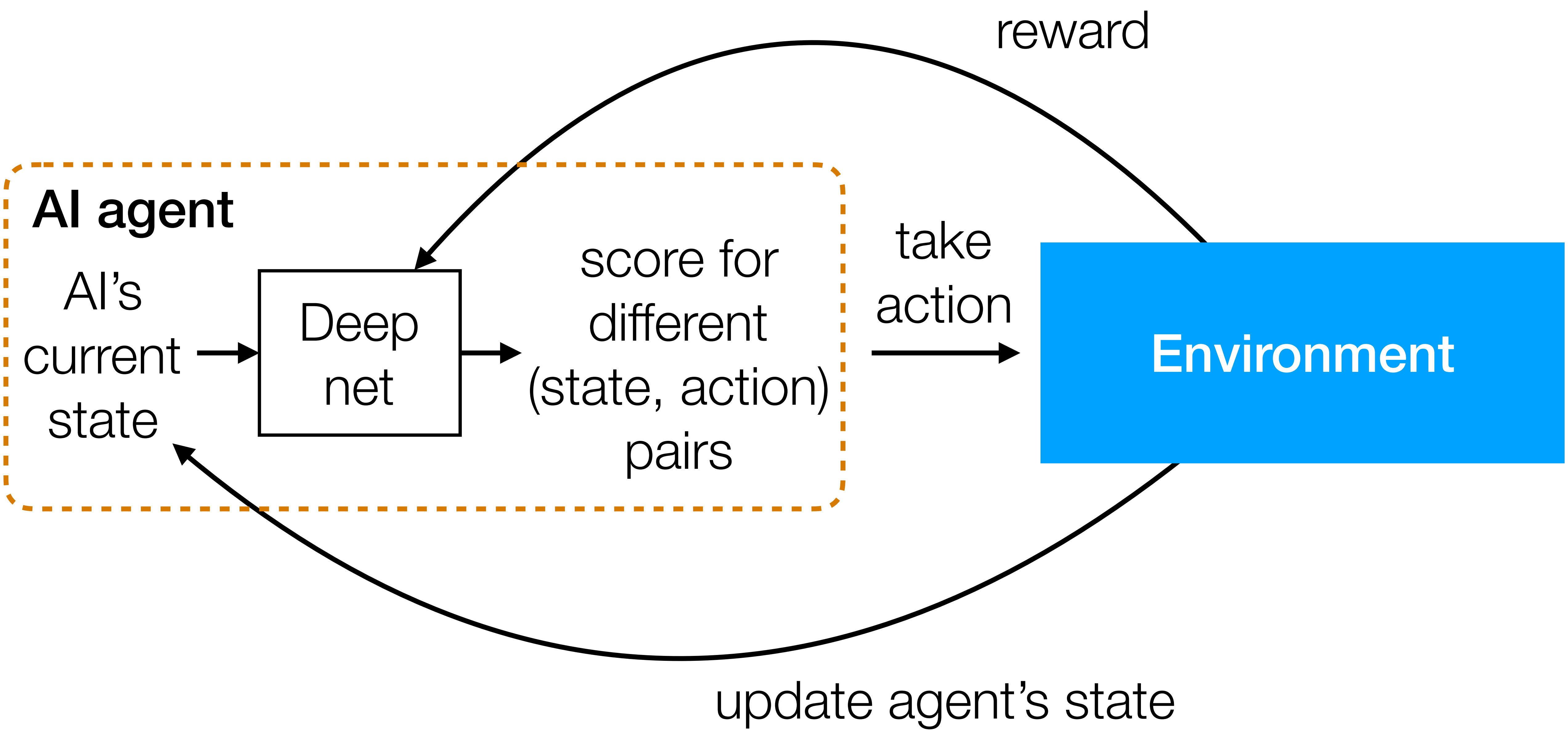

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95-865

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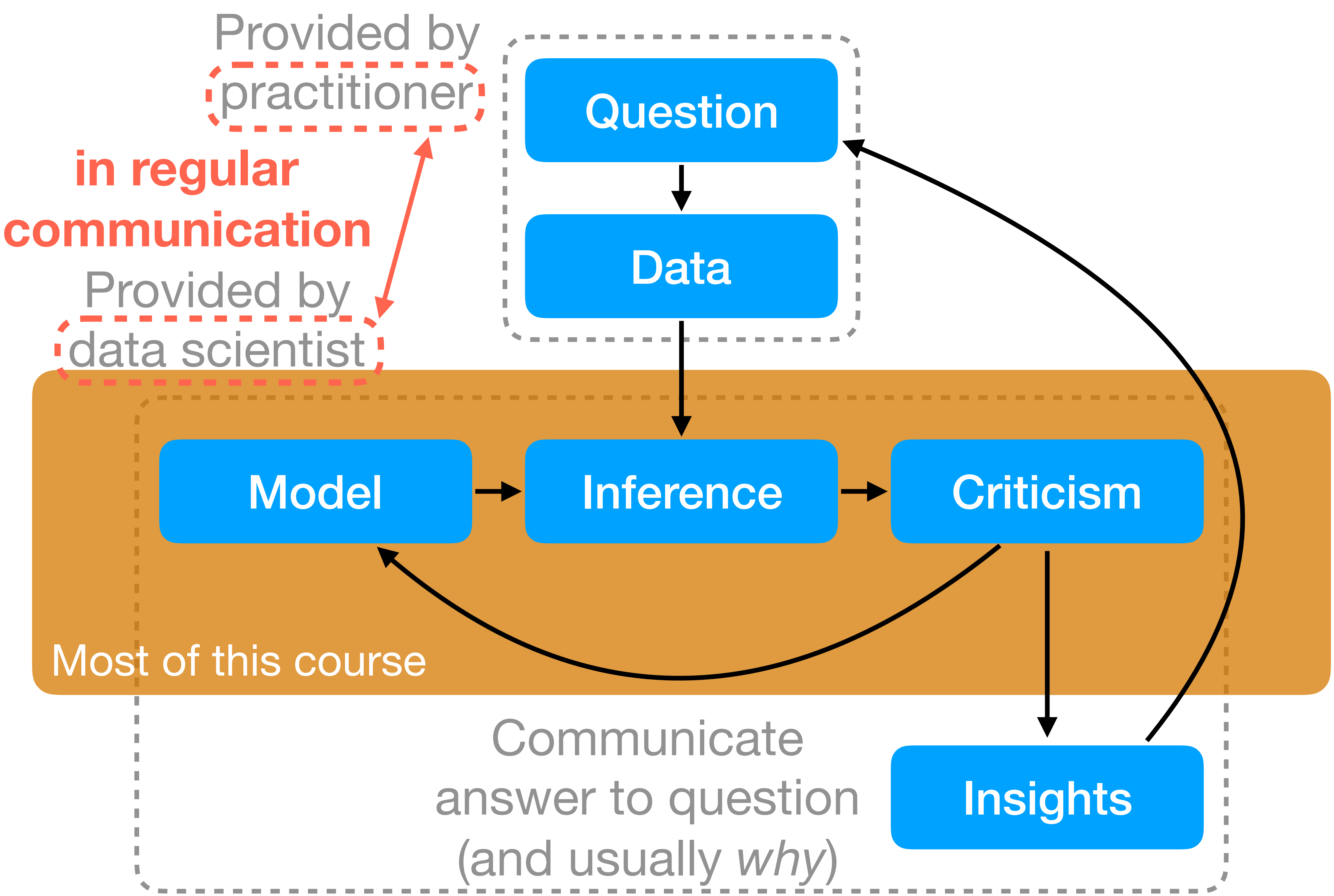
Provided by
practitioner
in regular
communication
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Question
Data
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Most of this course
Communicate
answer to question
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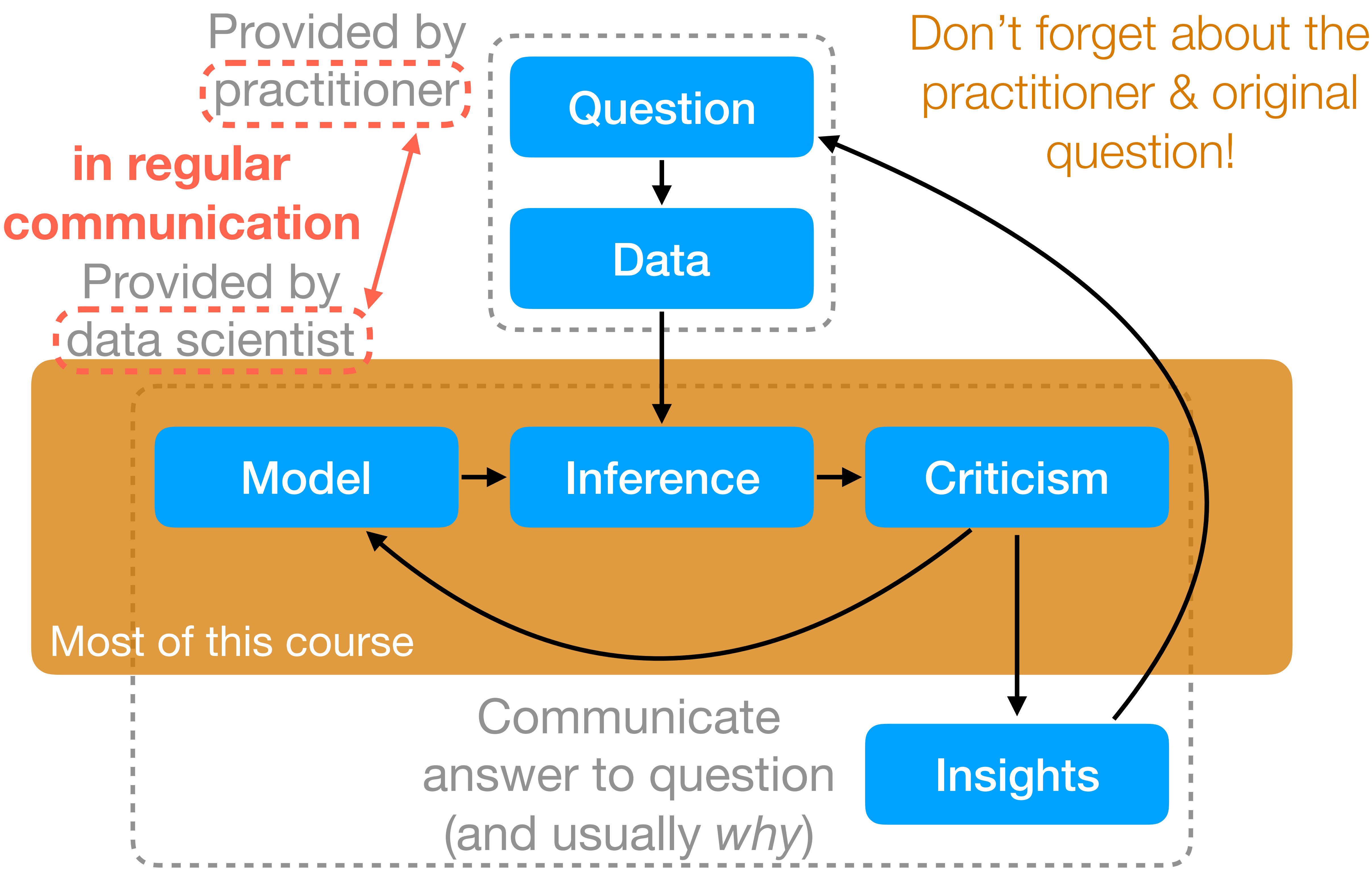
Provided by
practitioner
in regular
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Question
Data
Don't forget about the
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