RNN Demo

list of length-2 tuples each containing (review, label 0 or 1)

1. Load in training data (25000 IMDb reviews) `train_dataset`
2. Do a 80/20 split of the training data into:
   - proper training data (20000 reviews) `proper_train_dataset`
   - validation data (5000 reviews) `val_dataset`
3. Convert each <u>proper training</u> review into tokens using spaCy **(the demo was updated so that after spaCy's tokenization, we convert each token to lowercase)**

"Master cinéaste Alain Resnais likes to work with those actors"

↓ (using the new `tokenizer_lowercase` function)

['master', 'cinéaste', 'alain', 'resnais', 'likes', 'to', 'work', 'with', 'those', 'actors']

4. Build a vocabulary using the proper training reviews `vocab`

behaves like a function (input: list of strings, output: list of integers)

- proper training data (20000 reviews) `proper_train_dataset`
- validation data (5000 reviews) `val_dataset`

3. Convert each <u>proper training</u> review into tokens using spaCy **(the demo was updated so that after spaCy's tokenization, we convert each token to lowercase)**

"Master cinéaste Alain Resnais likes to work with those actors"

(using the new `tokenizer_lowercase` function)

['master', 'cinéaste', 'alain', 'resnais', 'likes', 'to', 'work', 'with', 'those', 'actors']

4. Build a vocabulary using the proper training reviews `vocab`

behaves like a function (input: list of strings, output: list of integers)

5. Compute each proper training review's encoded version

(using the `vocab` function)

[1259, 59266, 11261, 16475, 1225, 7, 171, 20, 162, 169]

`proper_train_dataset_encoded`
`val_dataset_encoded`

list of length-2 tuples each containing (encoded review, label 0 or 1)

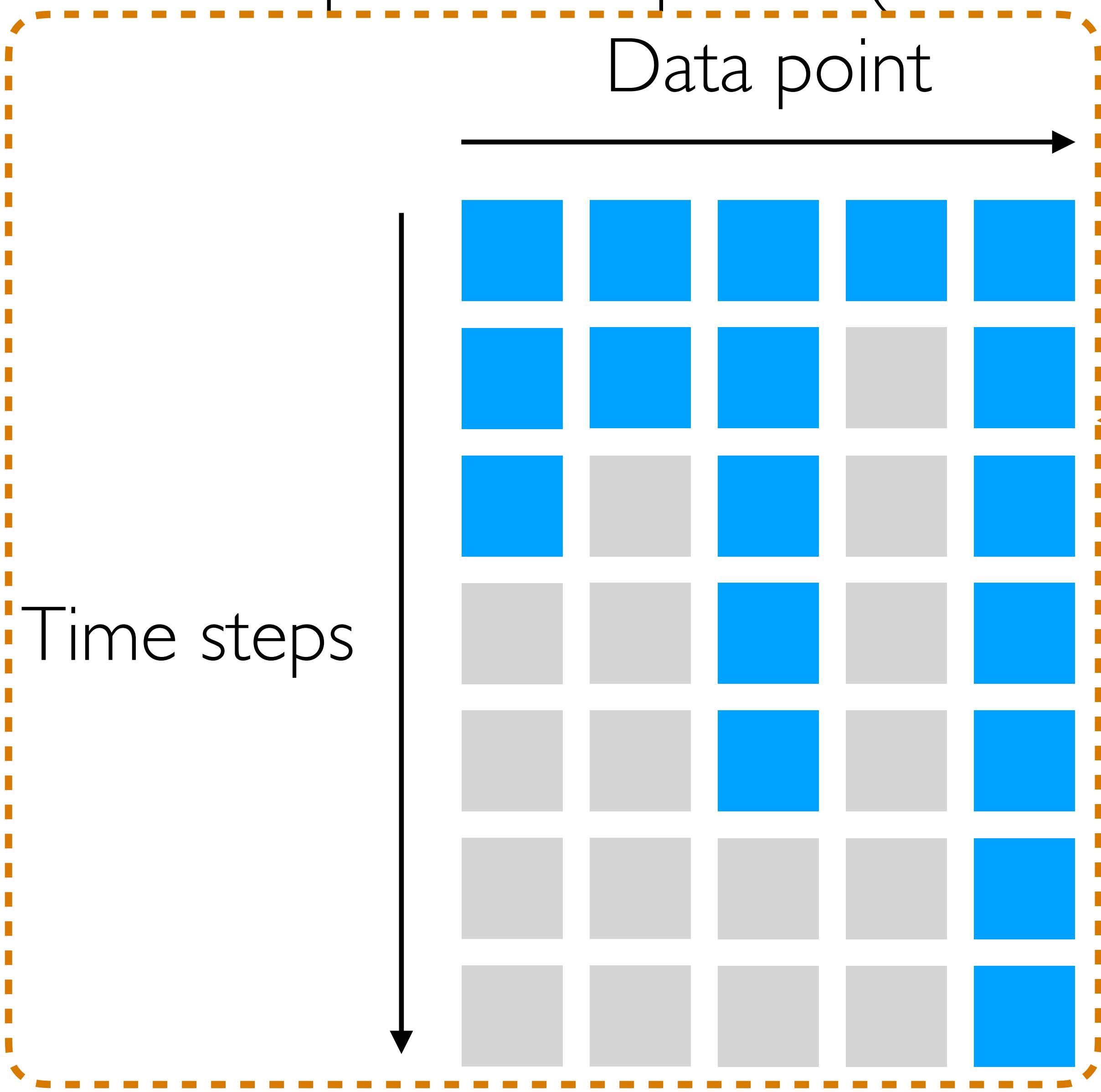
`proper_train_dataset_encoded`
`val_dataset_encoded`

list of length-2 tuples each containing (encoded review, label 0 or 1)

6. Construct neural net (instead of `nn.Sequential`, we make a class that inherits from `nn.module`)

PyTorch convention: the `forward` function specifies how a neural net actually processes a batch of input data

Example: 5 data points (each one is a time series) of lengths 3, 2, 5, 1, 7

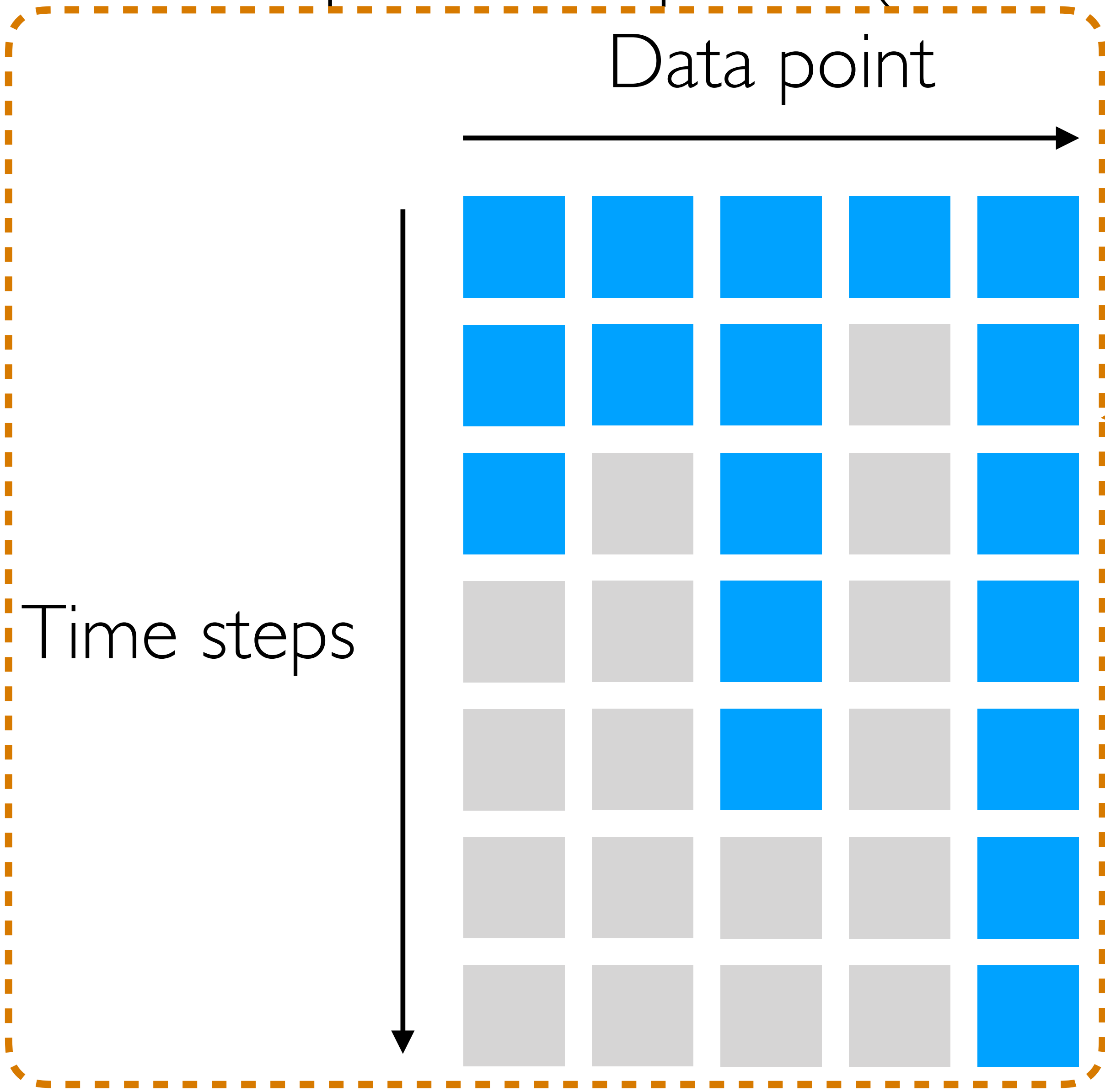


The neural net we constructed has a `forward` function with two inputs:
- a 2D table
  (each column is for 1 data point)
- a 1D table
  (specifies length for each time series)

Blue entries contain actual values from the 5 time series

Gray entries contain padded values (e.g., zeros)

Example: 5 data points (each one is a time series) of lengths 3, 2, 5, 1, 7



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  (each column is for 1 data point)
- a 1D table
  (specifies length for each time series)

Blue entries contain actual values from the 5 time series

Gray entries contain padded values (e.g., zeros)

```
In [30]: # example where there are 5 input time series of lengths 3, 2, 5, 1, 7;
         # we specify these time series using a 2D table that is padded and a
         # 1D table of lengths (see lecture slides for details)
         summary(simple_lstm_model,
                 input_data=[torch.zeros((7, 5), dtype=torch.long),
                             torch.tensor([3, 2, 5, 1, 7], dtype=torch.long)])
```

Data types matter in PyTorch (torch.long means these tables store integers)

Gray entries contain
padded values (e.g., zeros)

```
In [30]: # example where there are 5 input time series of lengths 3, 2, 5, 1, 7;
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                             torch.tensor([3, 2, 5, 1, 7], dtype=torch.long)])
```

Data types matter in PyTorch (torch.long means these tables store integers)

7. Train the neural net some max number of epochs

8. Automatically tune on one hyperparameter:
   choose # of epochs to be the one achieving highest validation accuracy

9. Load in the saved neural net from the best # of epochs

10. Finally load in test data, tokenize and convert each test review into
    a list of integers, and use the trained neural net to predict

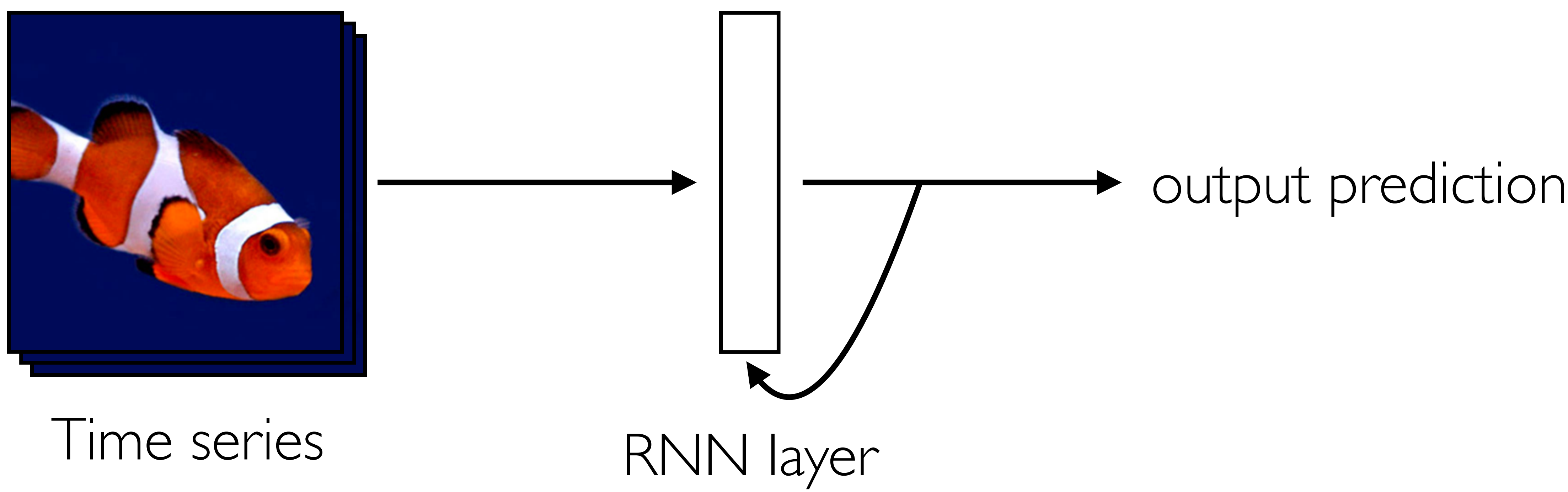
A special kind of RNN: an “LSTM”

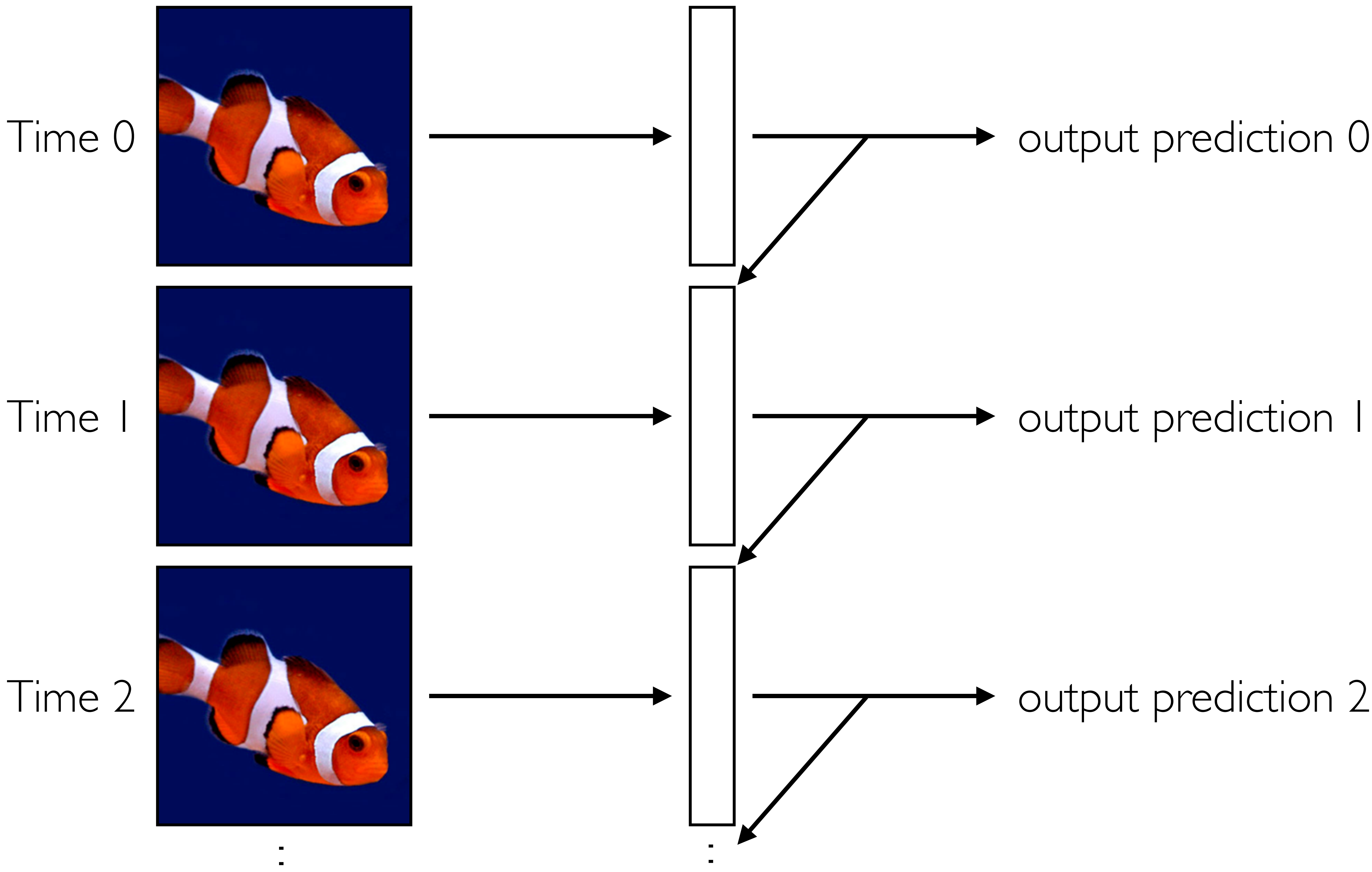
(Flashback) Vanilla ReLU RNN

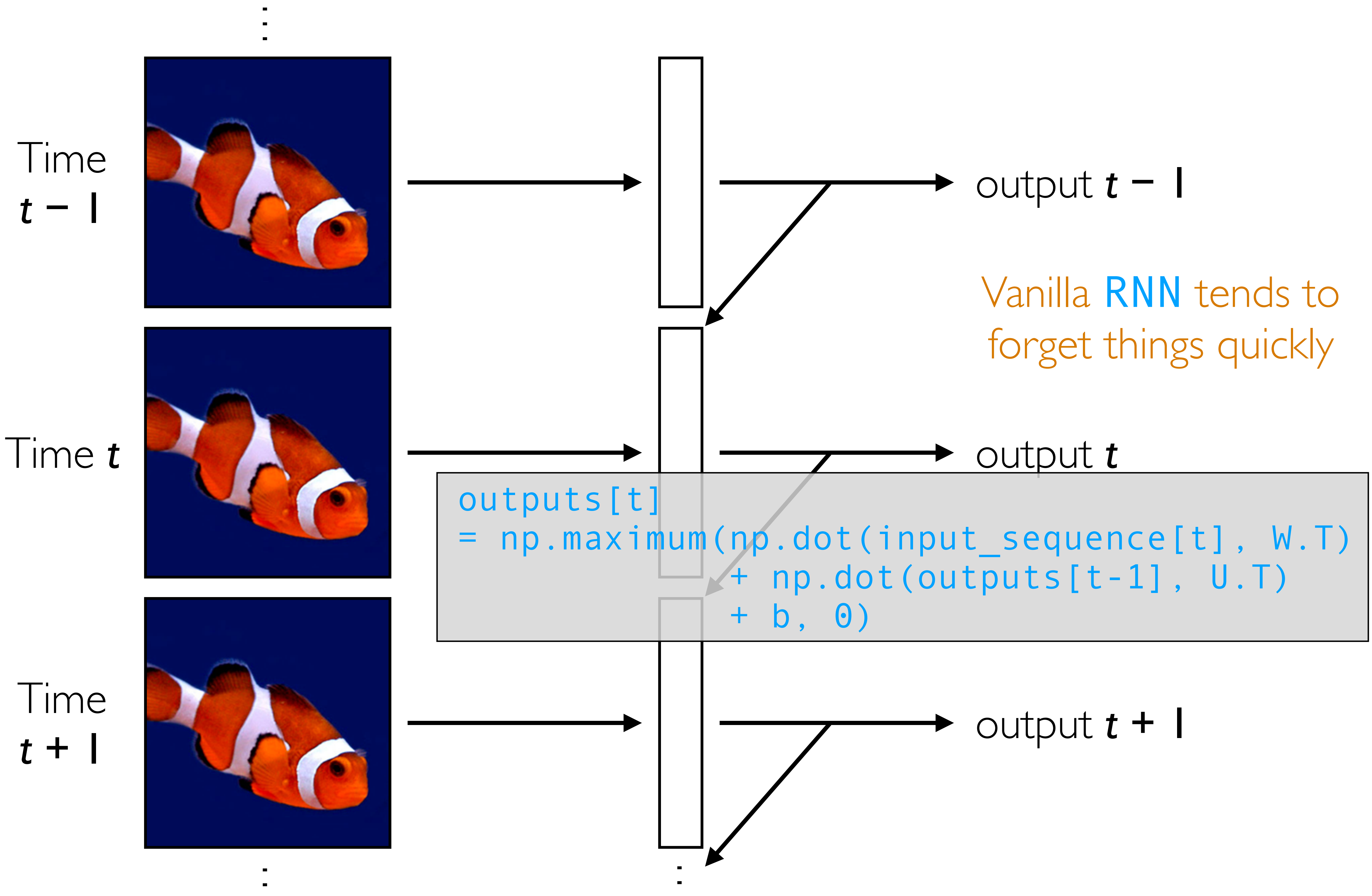
```
current_state = np.zeros(num_nodes)

outputs = []

for input in input_sequence:

  linear = np.dot(input, W.T) + b   \
           + np.dot(current_state, U.T)

  output = np.maximum(0, linear) # ReLU

  outputs.append(output)

  current_state = output
```

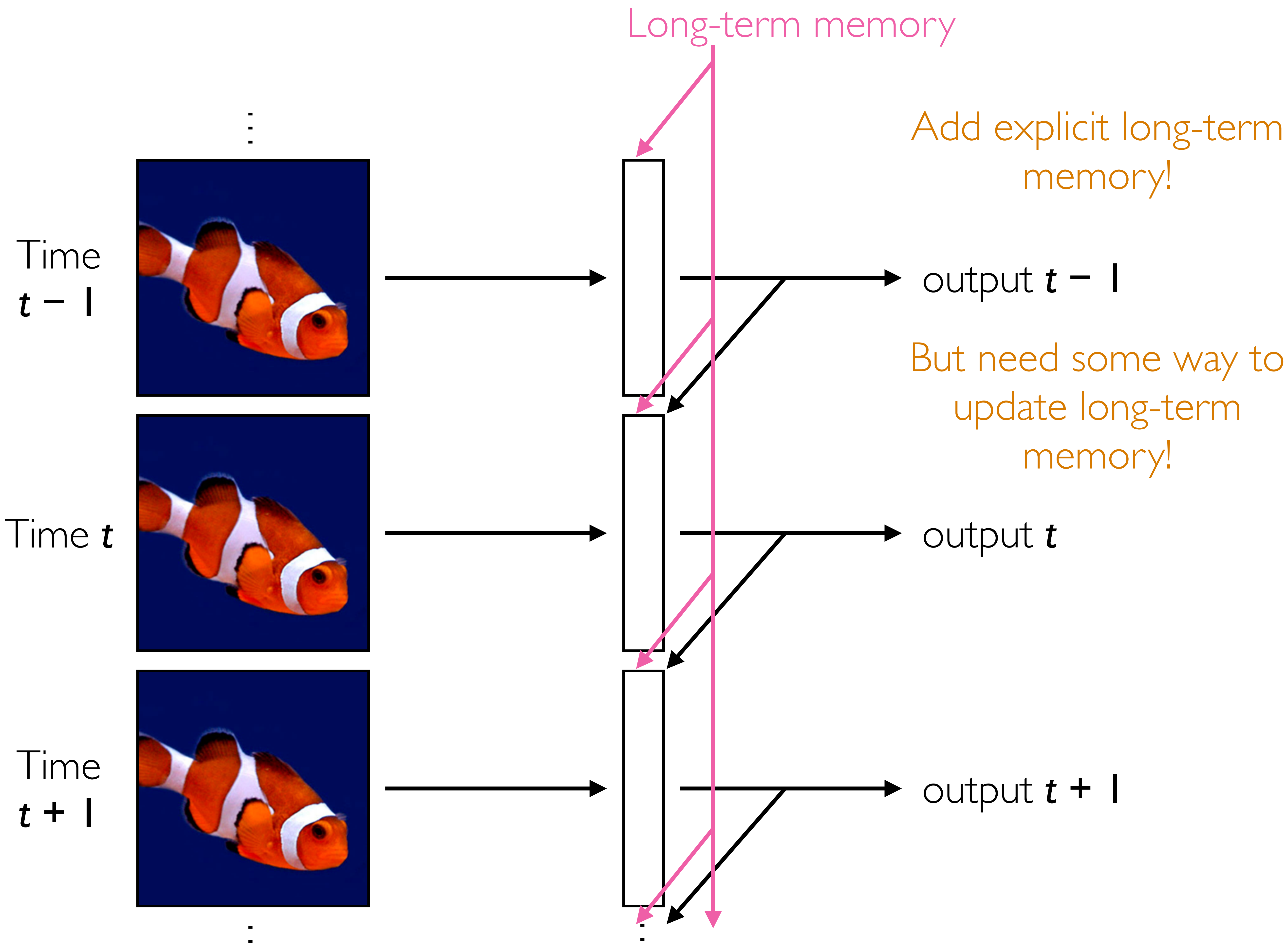
In general: there is an output at every time step

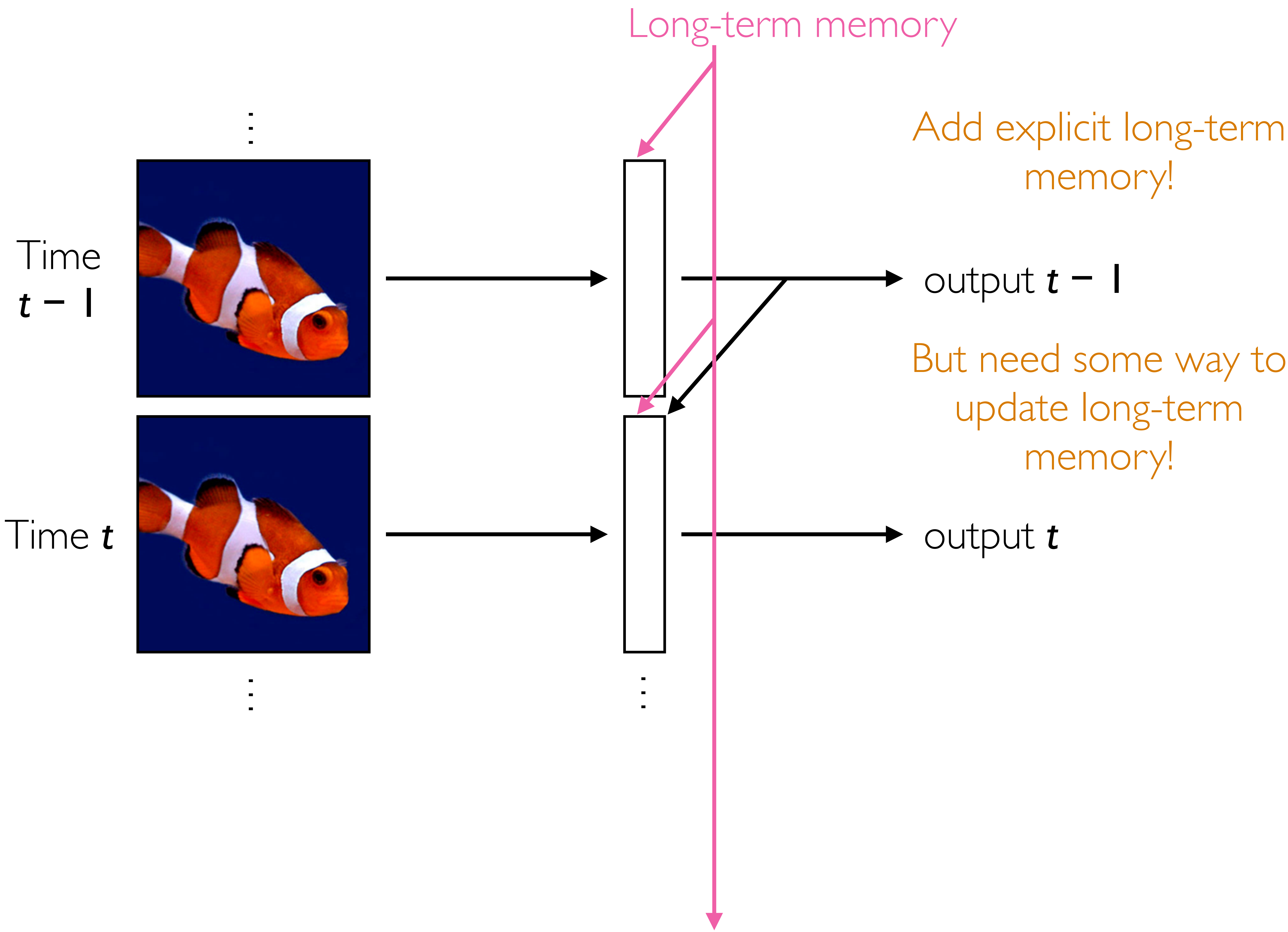
For simplicity, in today's lecture, we only use the very last time step's output


Time series
RNN layer
output prediction

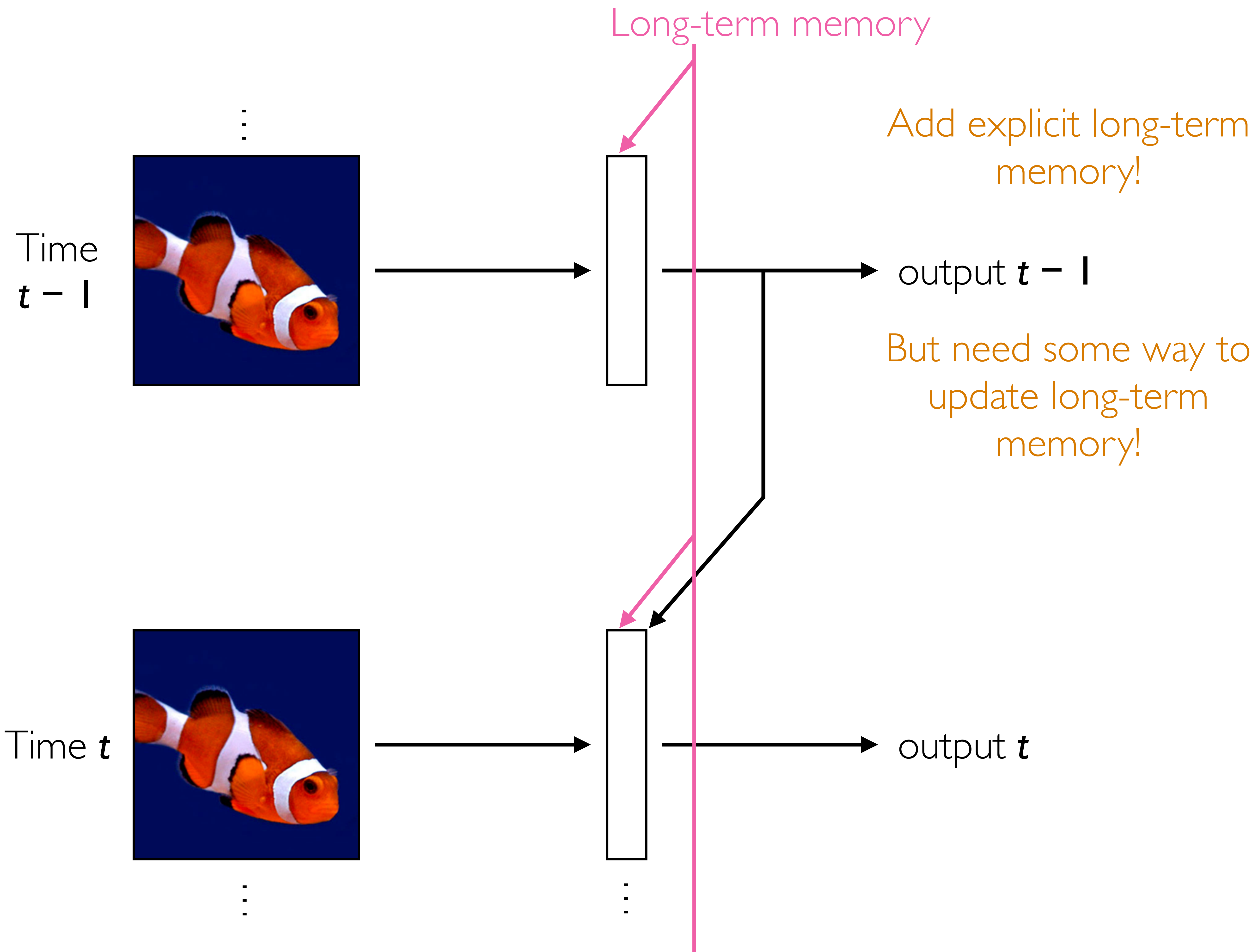

Time 0
output prediction 0
Time 1
output prediction 1
Time 2
output prediction 2

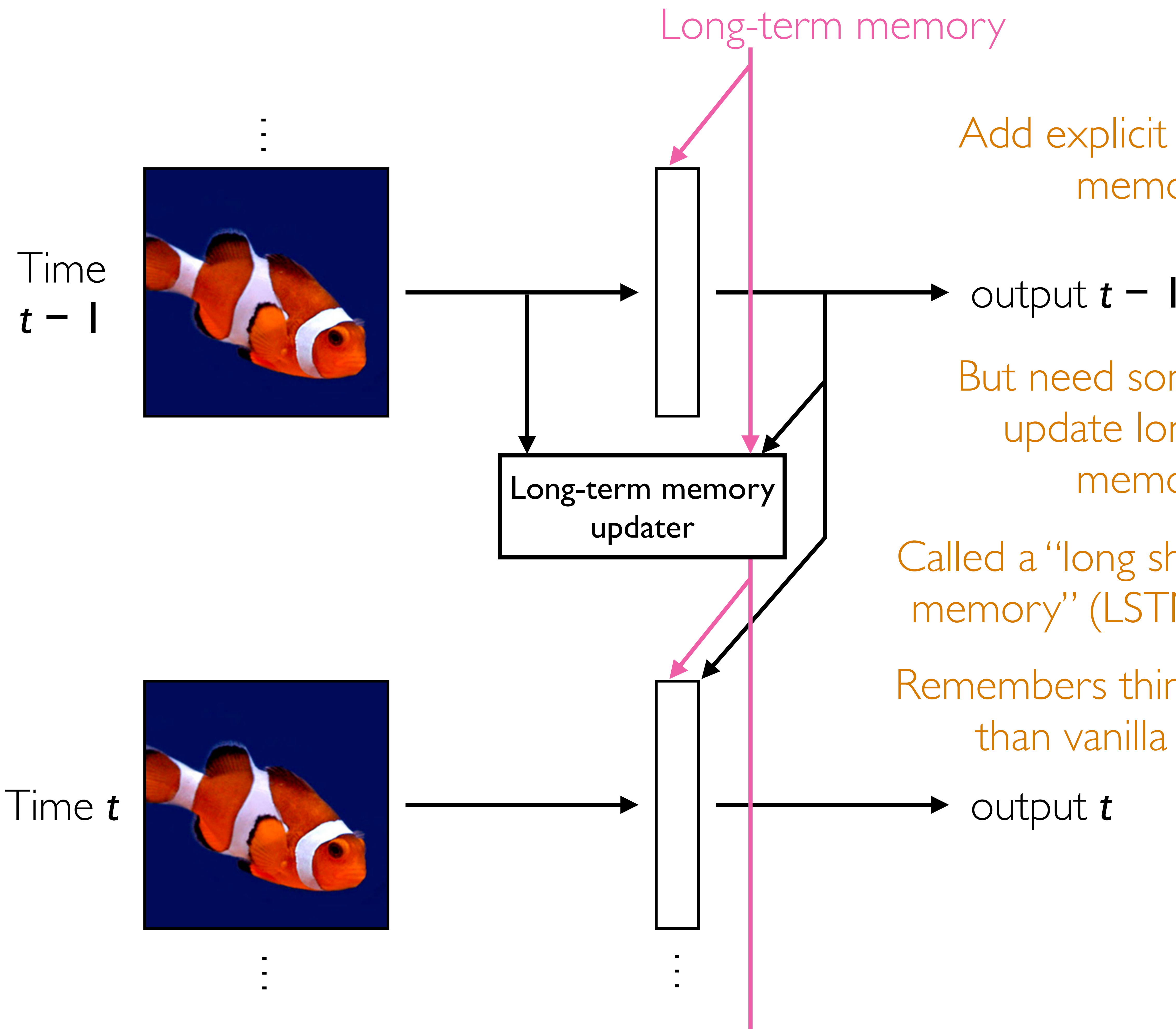

Time
t − 1
Time t
Time
t + 1
output t − 1
Vanilla RNN tends to
forget things quickly
output t
outputs[t]
= np.maximum(np.dot(input_sequence[t], W.T)
+ np.dot(outputs[t-1], U.T)
+ b, 0)
output t + 1


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



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


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



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 vanilla RNN

Analyzing Times Series with CNNs

- Think about an image with 1 column, and where the rows index time steps: this is a time series!
- Think about a 2D image where rows index time steps, and the columns index features: this is a multivariate time series (feature vector that changes over time!)
- CNNs can be used to analyze time series *but inherently the size of the filters used say how far back in time we look*
- If your time series data all have the same length (same number of time steps) and do not have long-range dependencies that require long-term memory, CNNs can do well already!

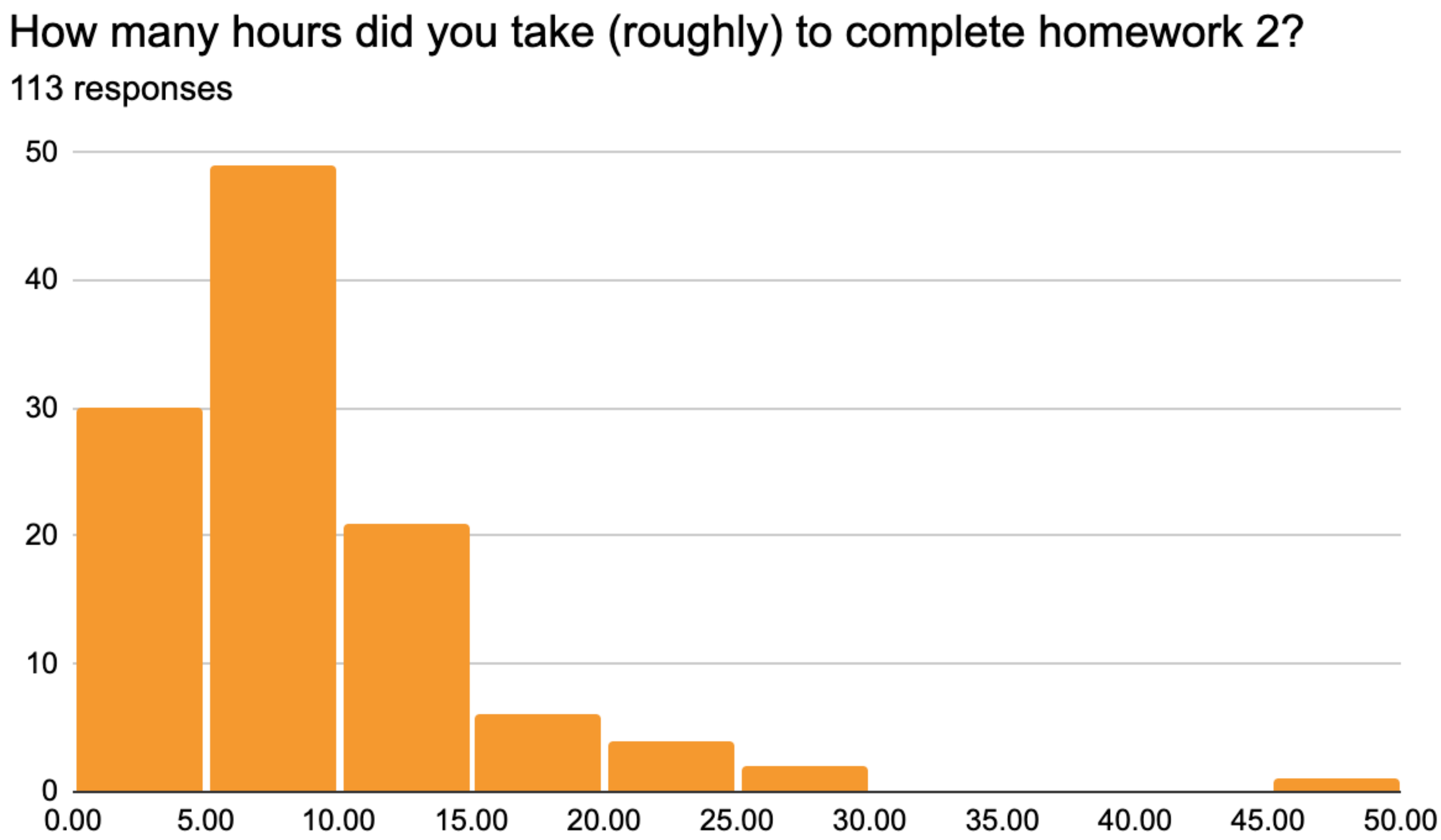
  ⇒ If you need long-term memory or time series with different lengths, use RNNs
- Note: while it is possible to have a CNN take in inputs that vary in size, we did not cover this in lecture

95-865 Unstructured Data Analytics

Last lecture: Additional deep learning topics; course wrap-up

Slides by George H. Chen

HW2 Questionnaire (1/3)



HW2 Questionnaire (2/3)

Free response comments/feedback

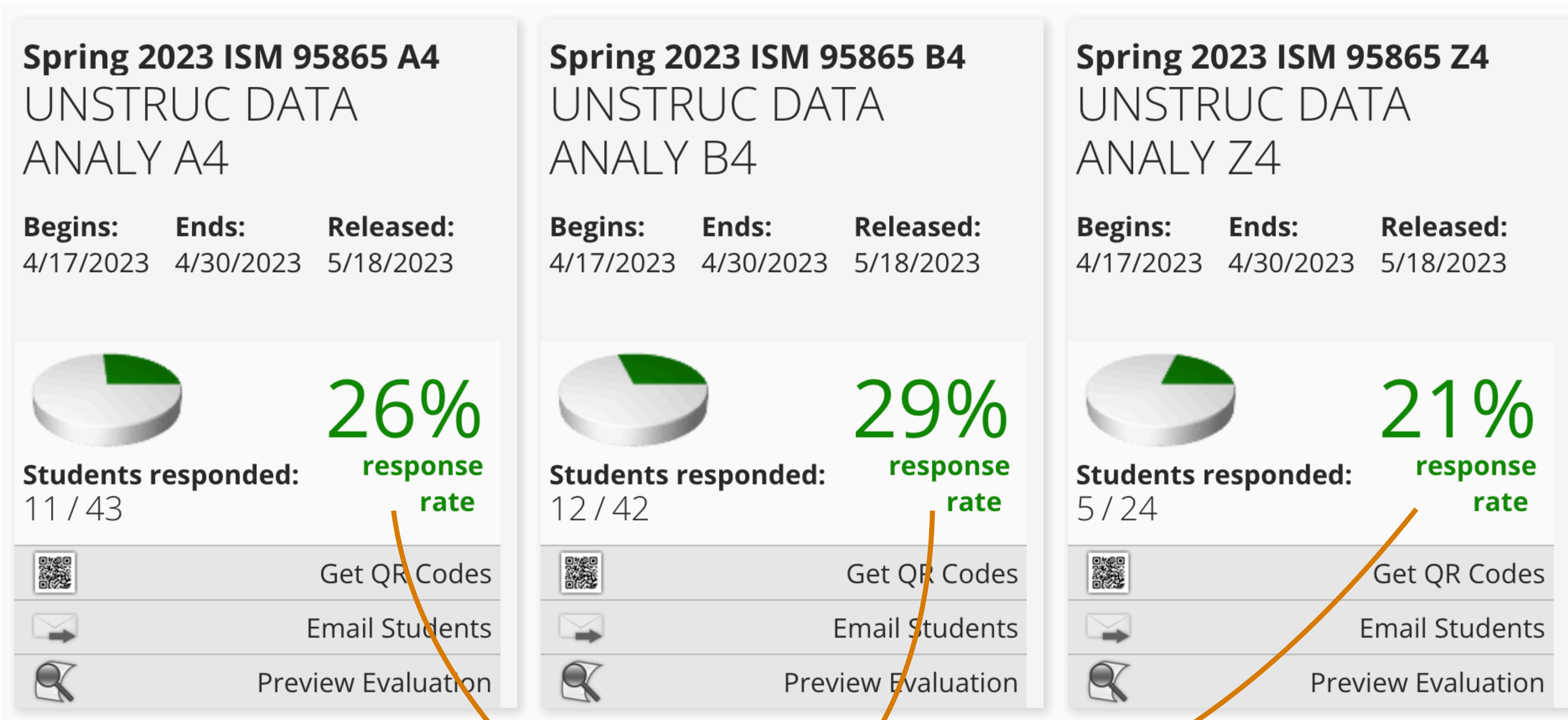
- Reading material and notes:
  - I realize that the current situation is not great (i.e., there's no single textbook/easy to understand resource that covers all the topics of 95-865 at the same level of detail)
  - Many students said they use StatQuest
- There was a comment saying that asking ChatGPT to explain concepts has been very helpful and that, basically, ChatGPT's office hours slots are 24/7 (nice!)
  - Careful! ChatGPT had a high error rate on Quiz 1 Problem 1
- I got several requests from students saying that they wish I provided problems like the ones from your real quizzes
  - This is precisely why we provide many practice quizzes — these <u>are</u> real past quizzes!

HW2 Questionnaire (3/3)

- A number of students are still asking for more demos
  - As I stated in Lecture 11 (in my thoughts on the HW1 questionnaire): it's important that you learn to not only find other demos yourself **but to create your own demos**
    - For example, start with a demo that already exists using a dataset you find interesting, and think about other possible analyses that you can do on the same dataset
      - In fact, a number of demos from my lectures are like this where I have cited the original demo that I modified
  - I think it's important to recognize that getting better at data analysis (unstructured or not) *requires practice*
  - Analogy: it's like learning how to swim
    - Sure, you can watch more and more demonstrations of people swimming, *but to get good yourself, you have to practice*

Faculty Course Evaluations

Please fill out faculty course evaluations to provide feedback on the course!



Let's get these response rates higher! 😃

Outline

- How learning a deep net roughly works
- Dealing with small datasets
  - Data augmentation
  - Fine-tuning
- Self-supervised learning (word embeddings are a special case)
- Some other deep learning topics that are good to know about
- Course wrap-up

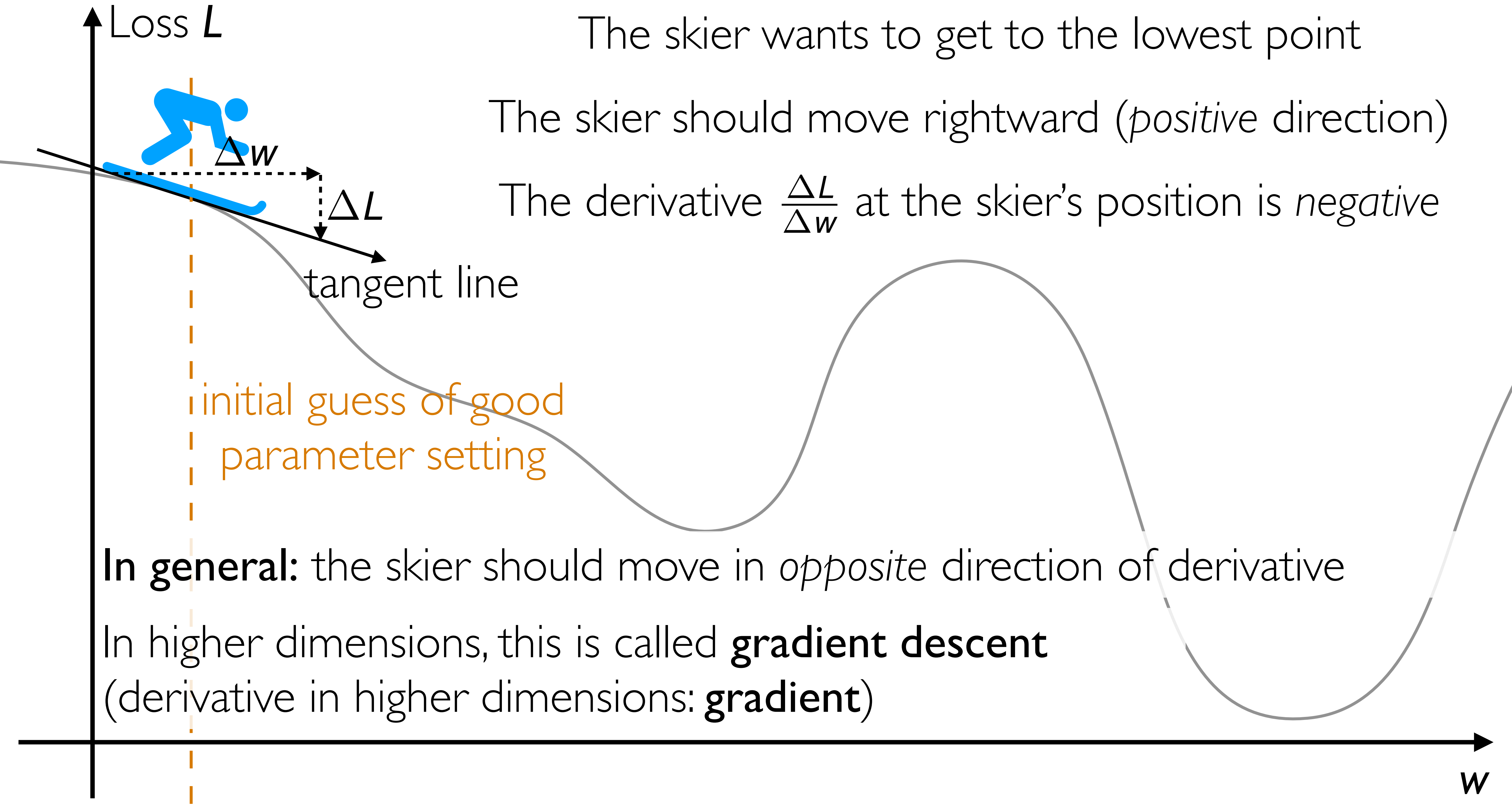
Learning a Deep Net

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*

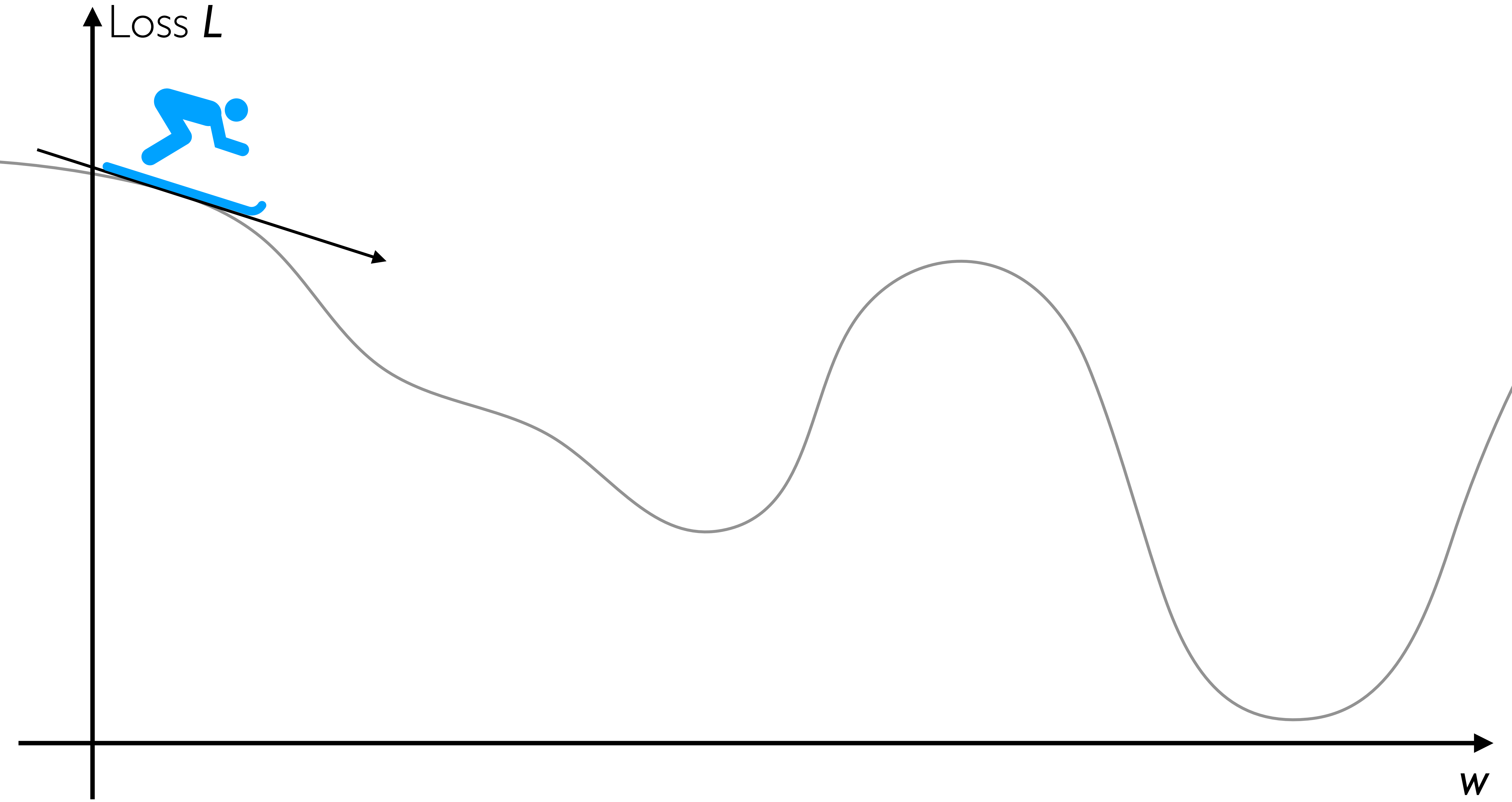


In general: the skier should move in *opposite* direction of derivative

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

Learning a Deep Net

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



Learning a Deep Net

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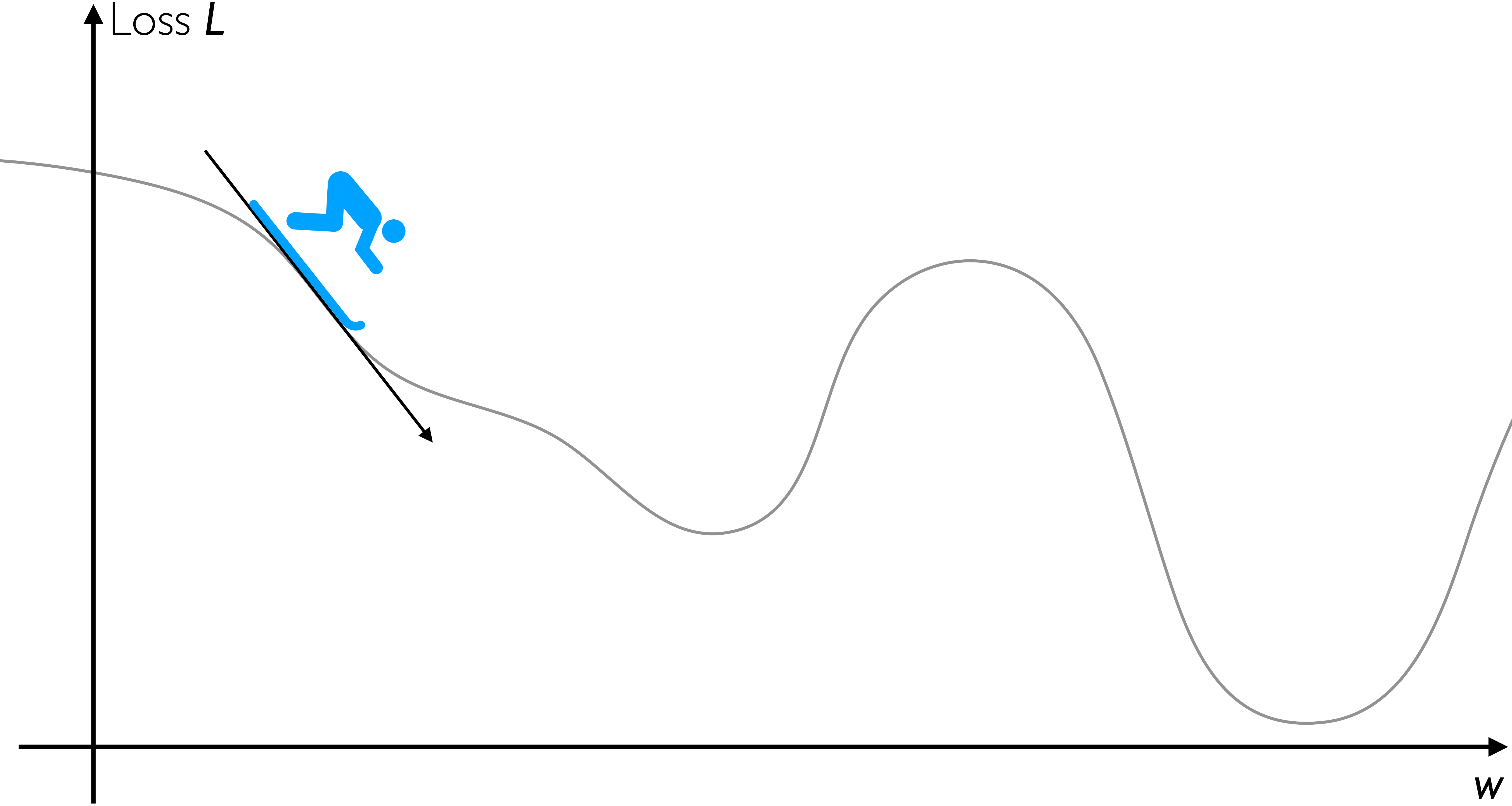
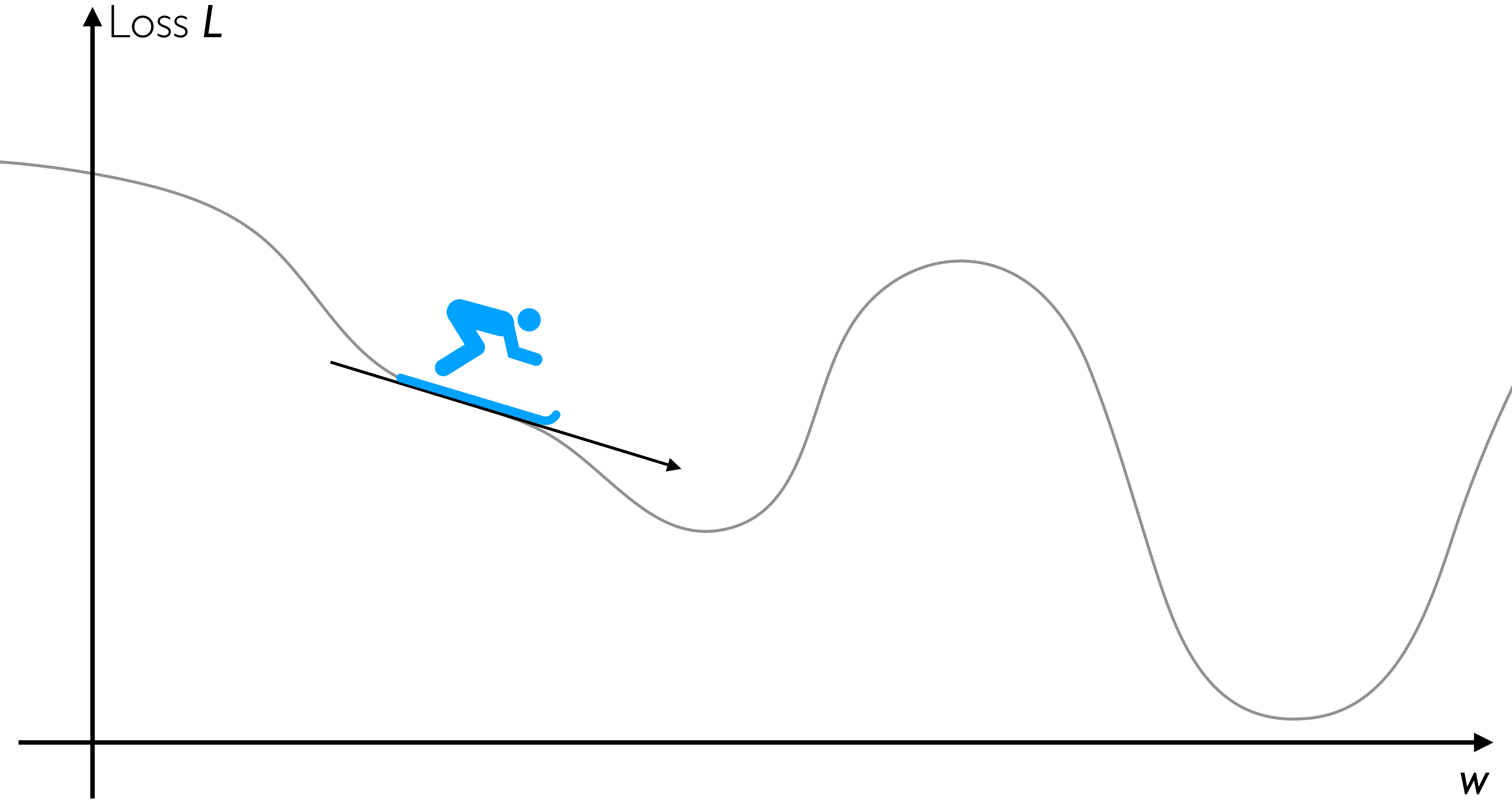


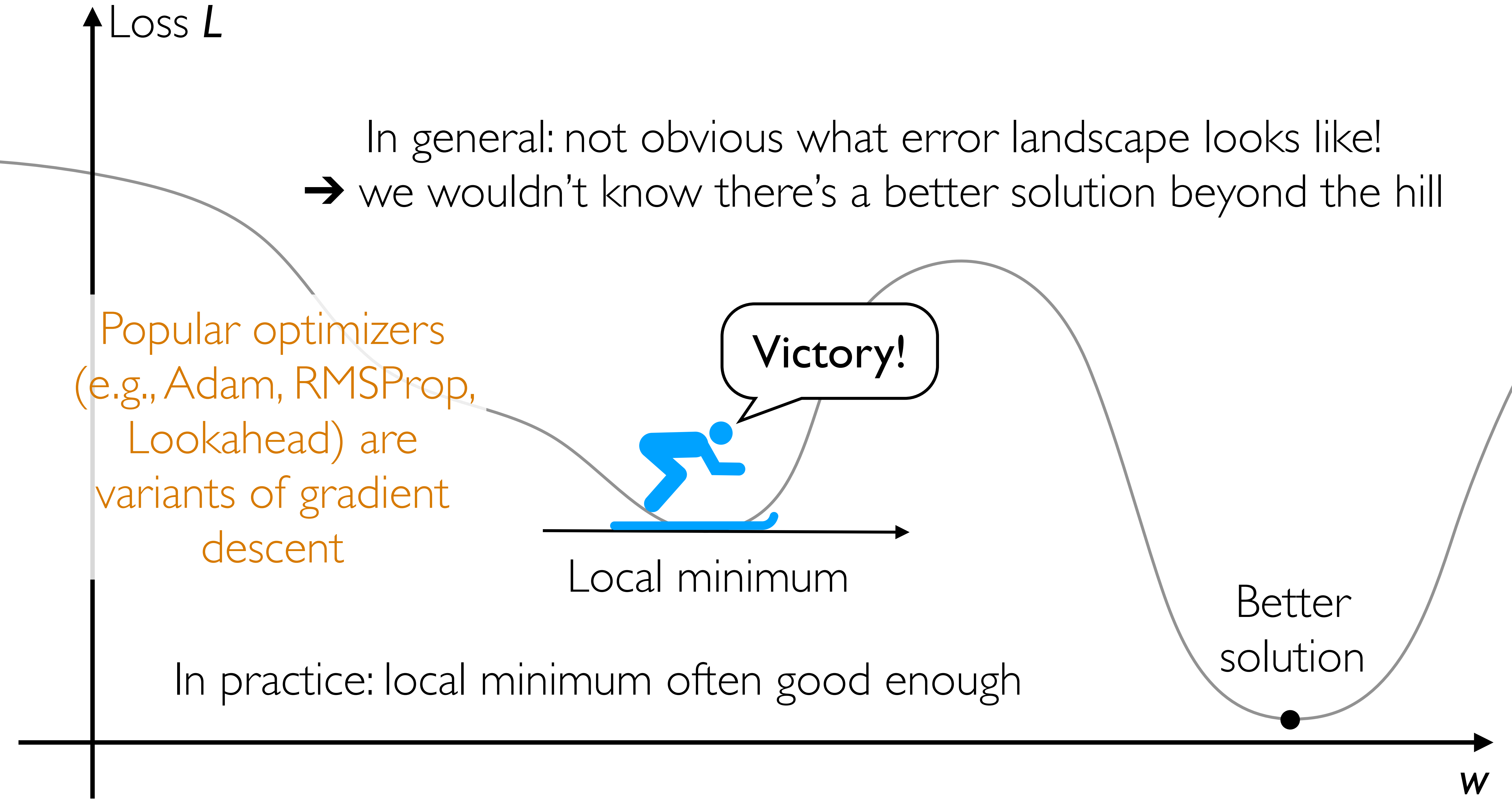
Learning a Deep Net

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

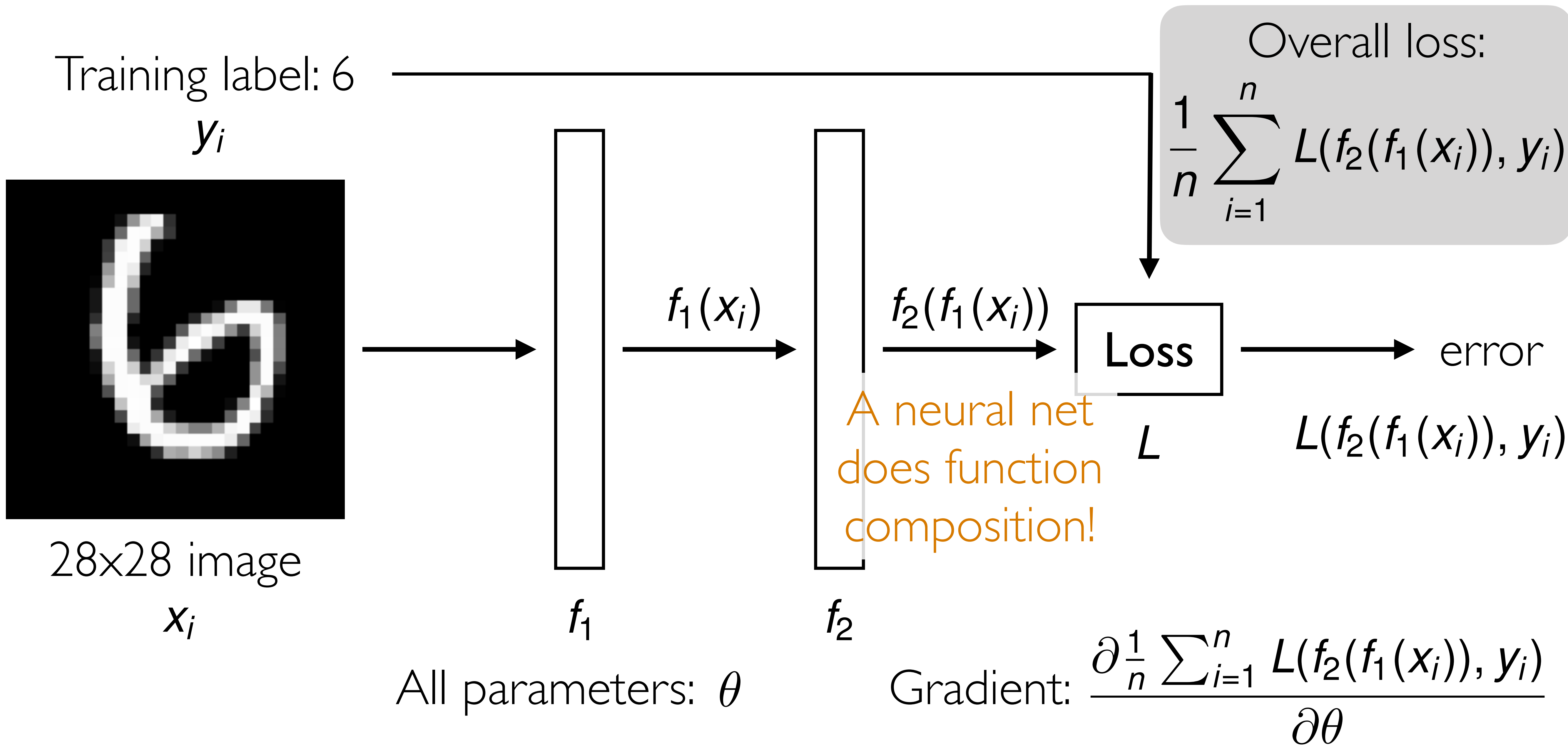


Learning a Deep Net

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



Handwritten Digit Recognition



Automatic differentiation is crucial in learning deep nets!

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

Gradient Descent

Training example 1 · Training example 2 · Training example 3 · Training example 4 · Training example 5 · … · Training example *n*

loss 1 · loss 2 · loss 3 · loss 4 · loss 5 · … · loss ***n***

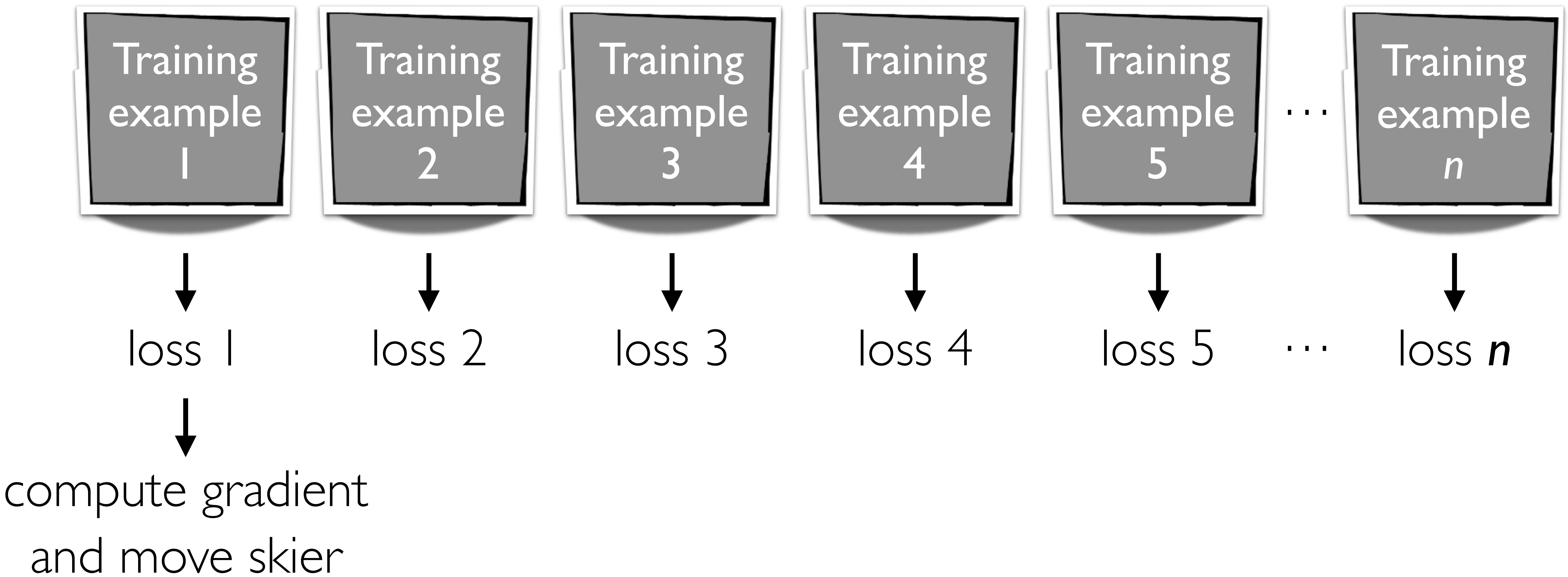
average loss

compute gradient and move skier

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

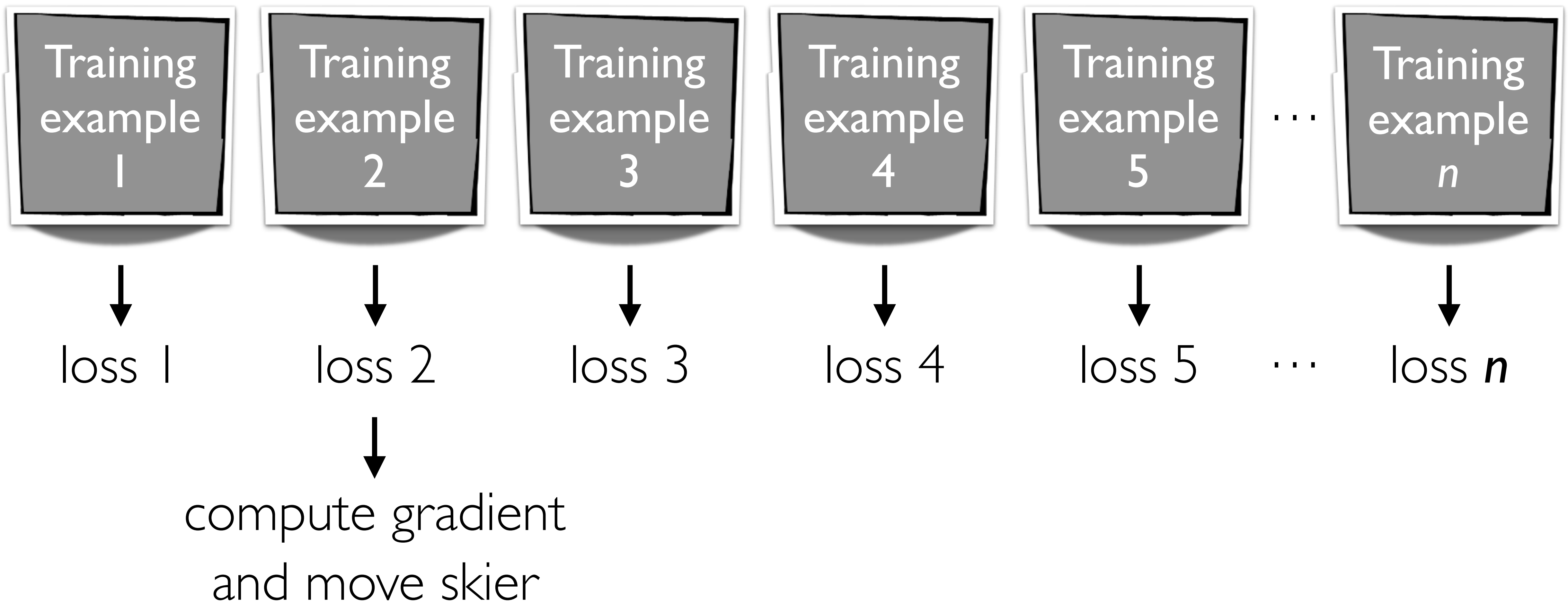
Computing gradients using all the training data seems really expensive!

Stochastic Gradient Descent (SGD)



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

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)

Stochastic Gradient Descent (SGD)

Training example 1	Training example 2	Training example 3	Training example 4	Training example 5	. . .	Training example *n*
↓	↓	↓	↓	↓		↓
loss 1	loss 2	loss 3	loss 4	loss 5	. . .	loss ***n***
		↓				
		compute gradient and move skier				

SGD: compute gradient using only 1 training example at a time
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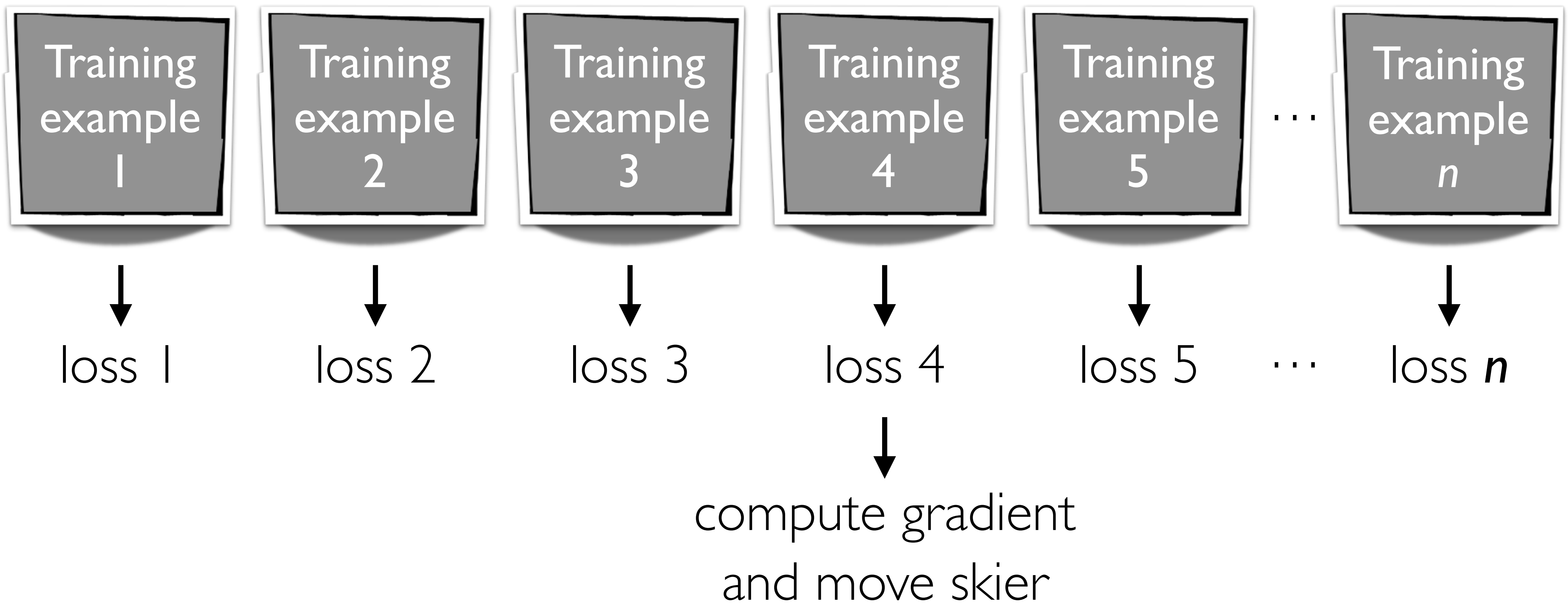
Stochastic Gradient Descent (SGD)



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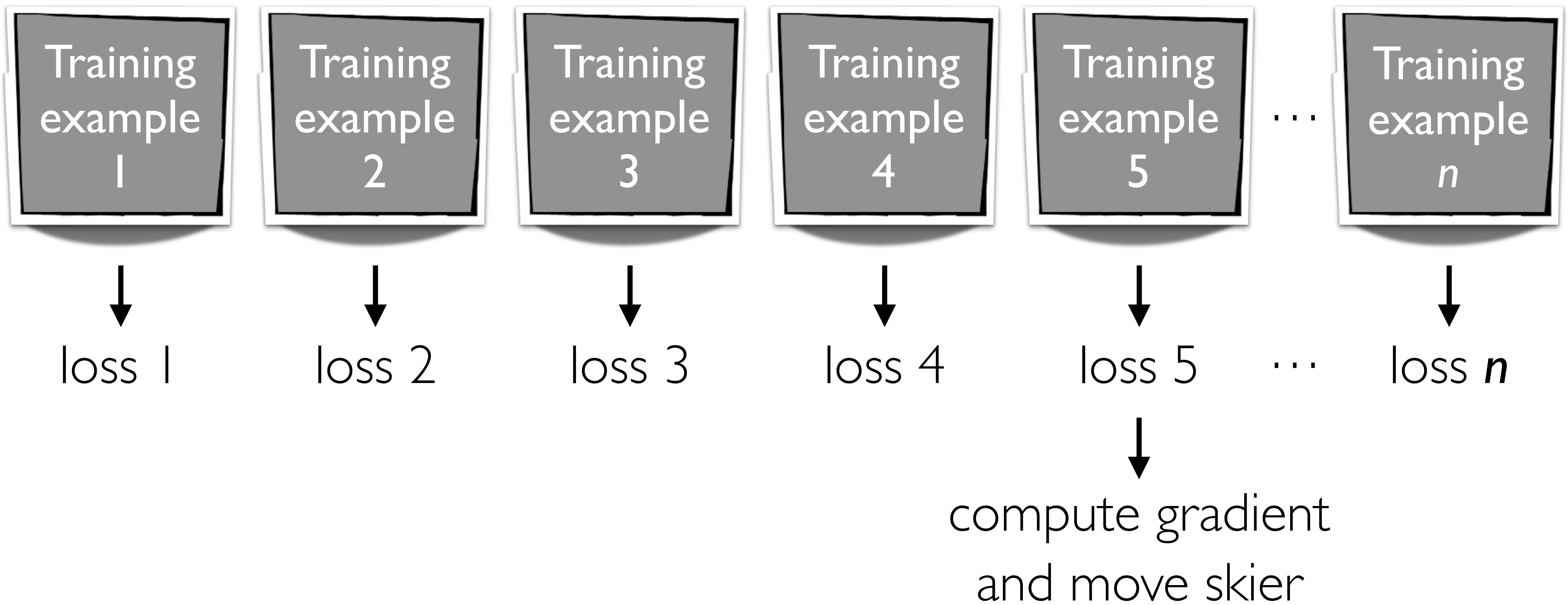

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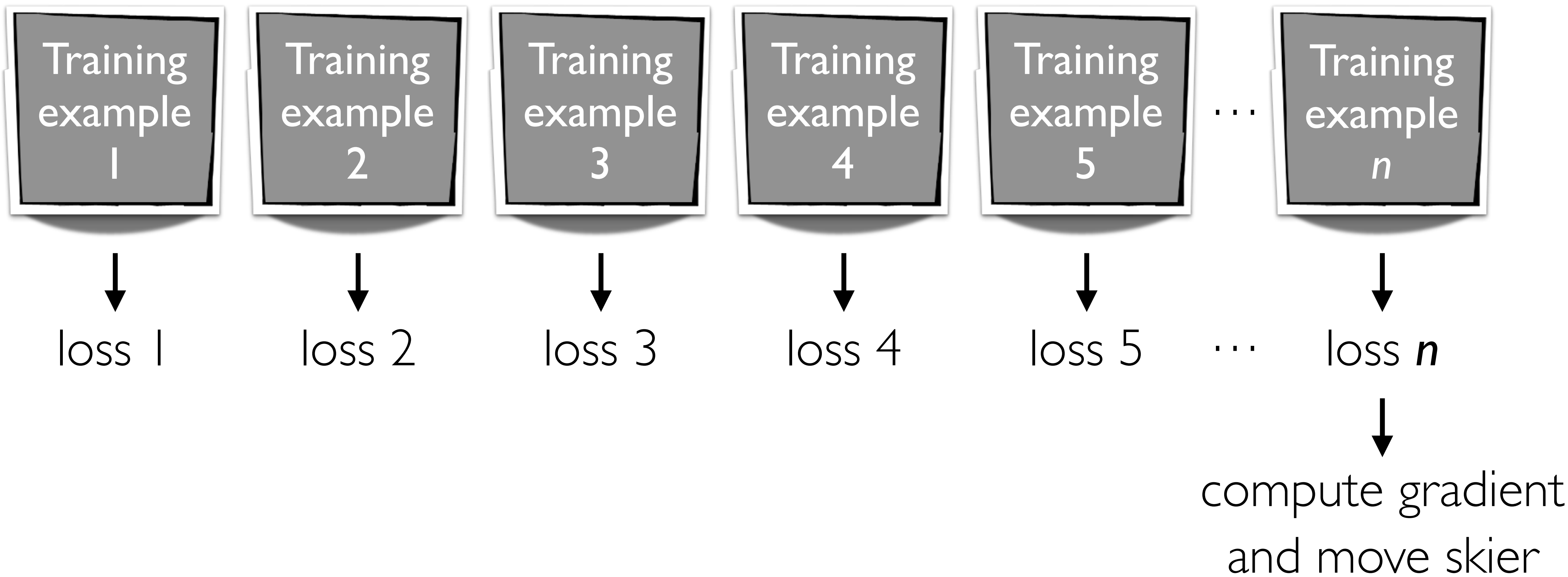
Stochastic Gradient Descent (SGD)



SGD: compute gradient using only 1 training example at a time
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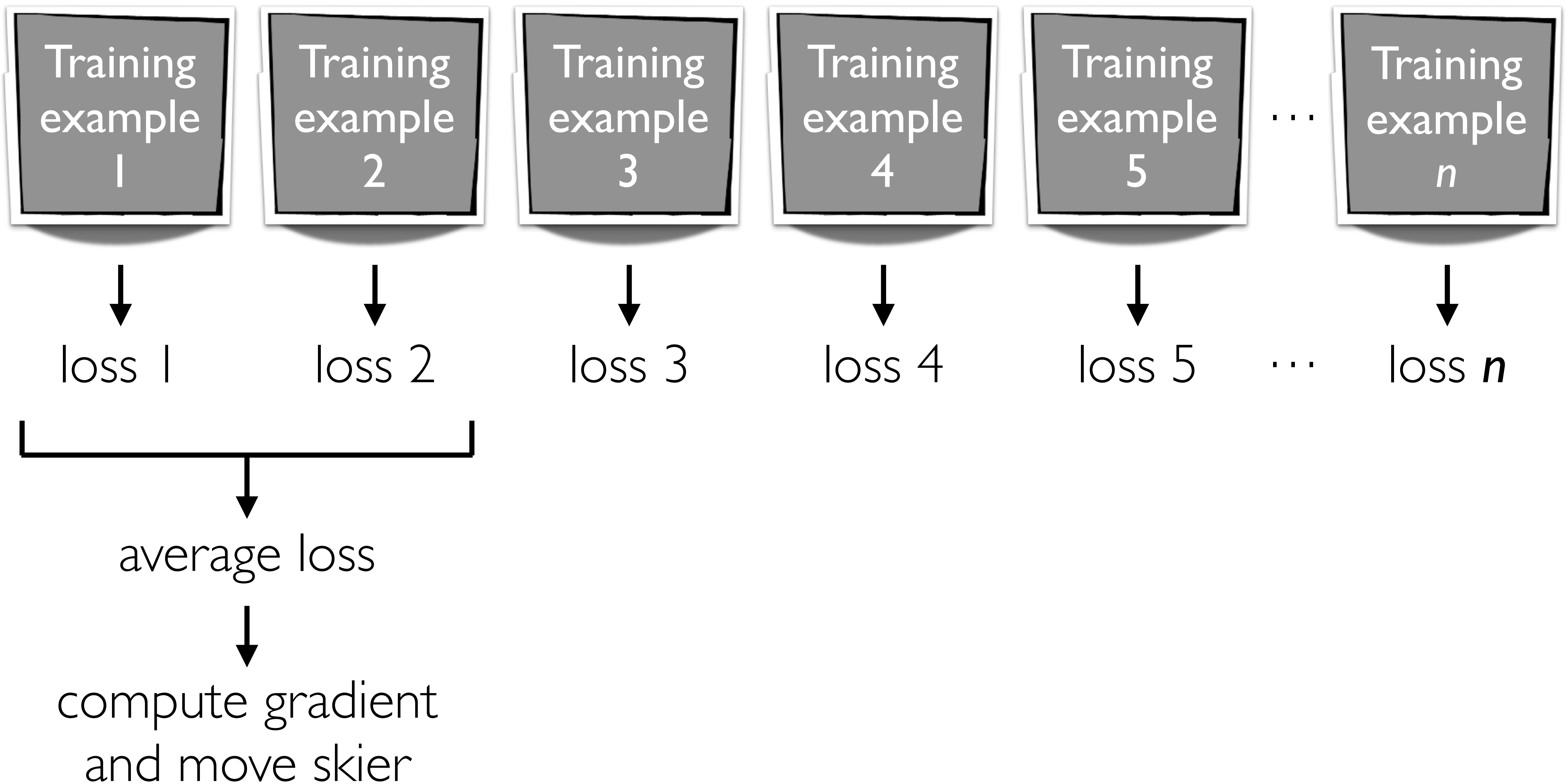
Stochastic Gradient Descent (SGD)

Training example 1	Training example 2	Training example 3	Training example 4	Training example 5	…	Training example n
↓	↓	↓	↓	↓		↓
loss 1	loss 2	loss 3	loss 4	loss 5	…	loss n
↓						
compute gradient and move skier						

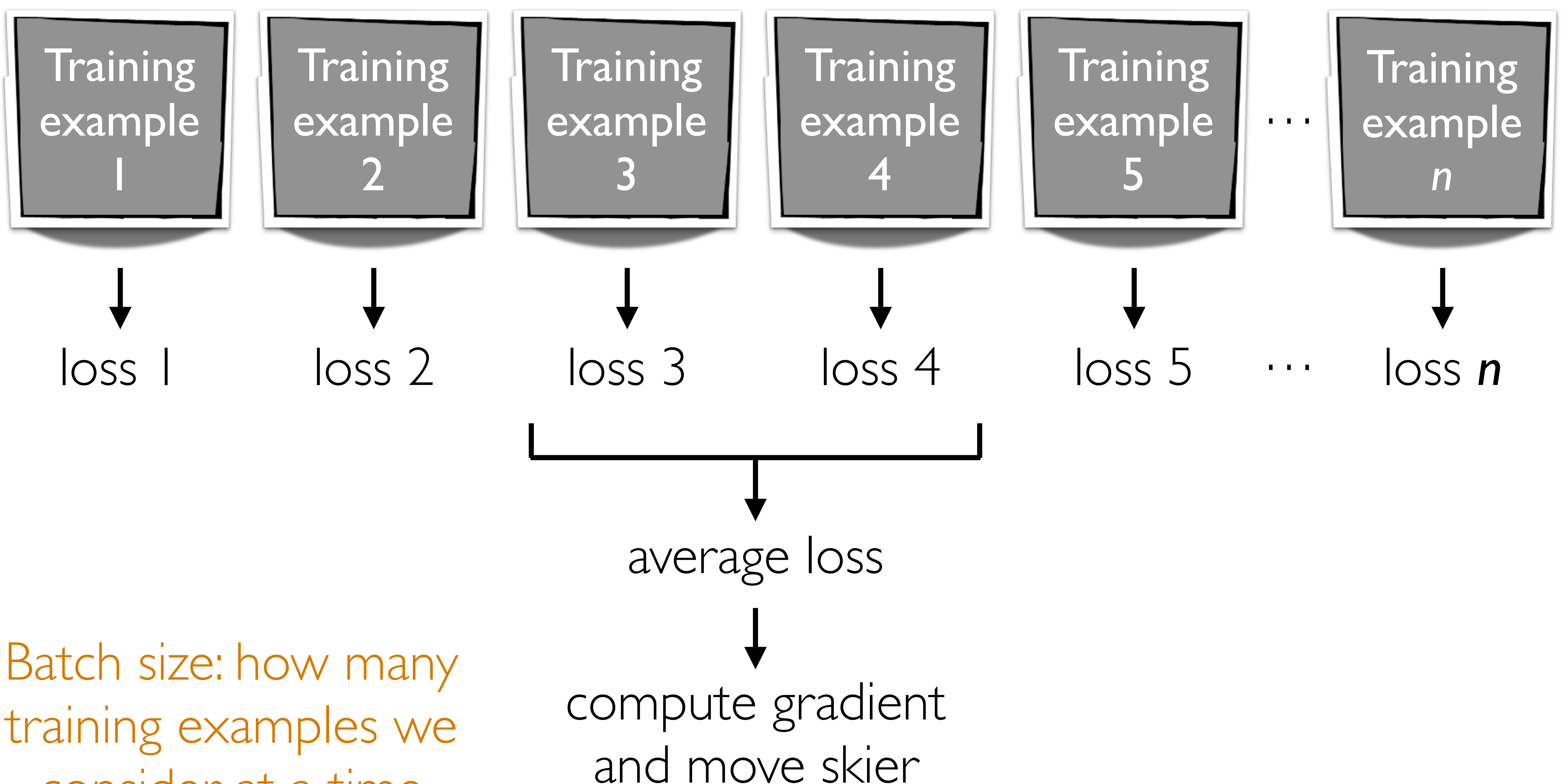
An epoch refers to 1 full pass through all the training data

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

Minibatch Gradient Descent



Minibatch Gradient Descent



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

Best optimizer? Best learning rate? 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!!!

A Look Under the Hood

UDA_pytorch_utils.py

Dealing with Small Datasets

Data Augmentation

Generate perturbed versions of your training data to get a larger training dataset

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)

Fine Tuning

If there's an existing pre-trained neural net, you could modify it for your problem that has a small dataset

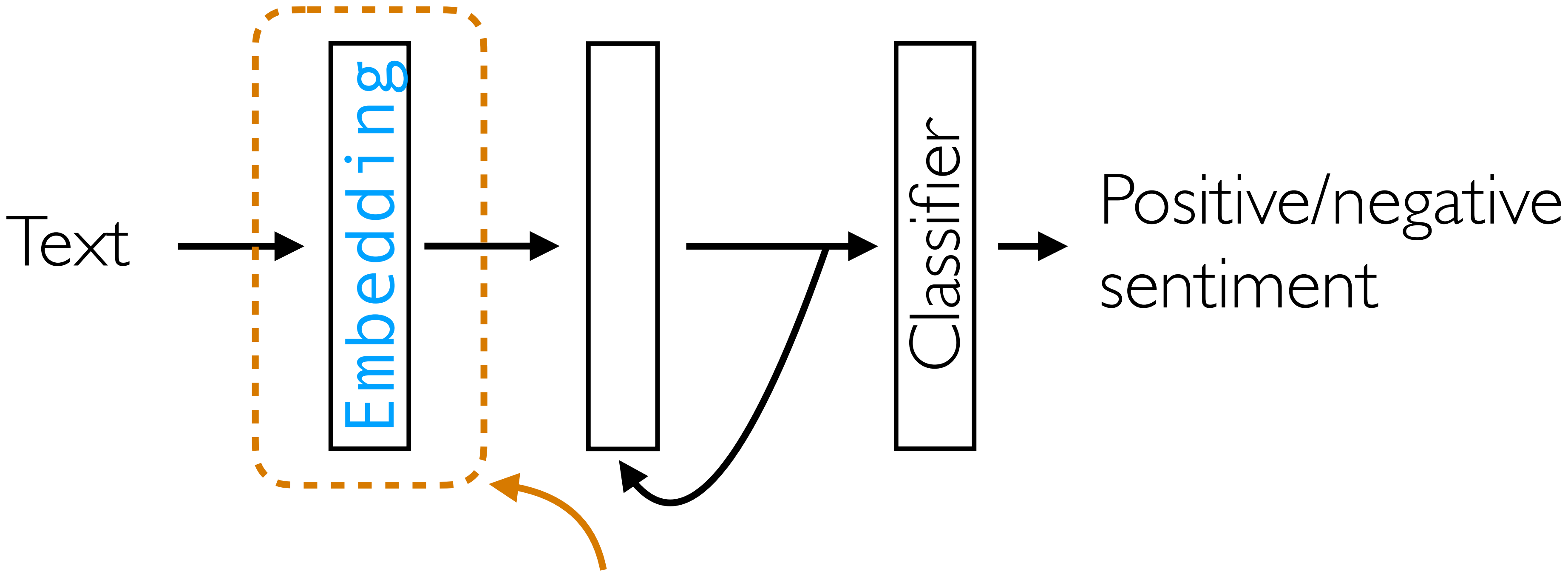
Example: classify between Tesla's and Toyota's

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

Strategy: take pre-trained convnet (such as a state-of-the-art one like ResNet, trained to classify between 1000 objects) and change final layers to do classification between Tesla's and Toyota's

Fine Tuning

Sentiment analysis RNN demo



Weights here are treated as fixed & come from pre-trained GloVe word embeddings

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

IMDb review dataset is small in comparison

Word Embeddings: Even without labels, we can set up a prediction problem!

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

Word Embeddings: word2vec

Can solve tasks like the following:

Man is to King as Woman is to **???**

Word Embeddings: word2vec

Can solve tasks like the following:

Man is to King as Woman is to <u>Queen</u>

Word Embeddings: word2vec

Can solve tasks like the following:

Man is to King as Woman is to <u>Queen</u>

Which word doesn't belong?
blue, red, green, crimson, transparent

Word Embeddings: word2vec

Can solve tasks like the following:

Man is to King as Woman is to <u>Queen</u>

Which word doesn't belong?
blue, red, green, crimson, <u>transparent</u>

Word Embeddings: word2vec

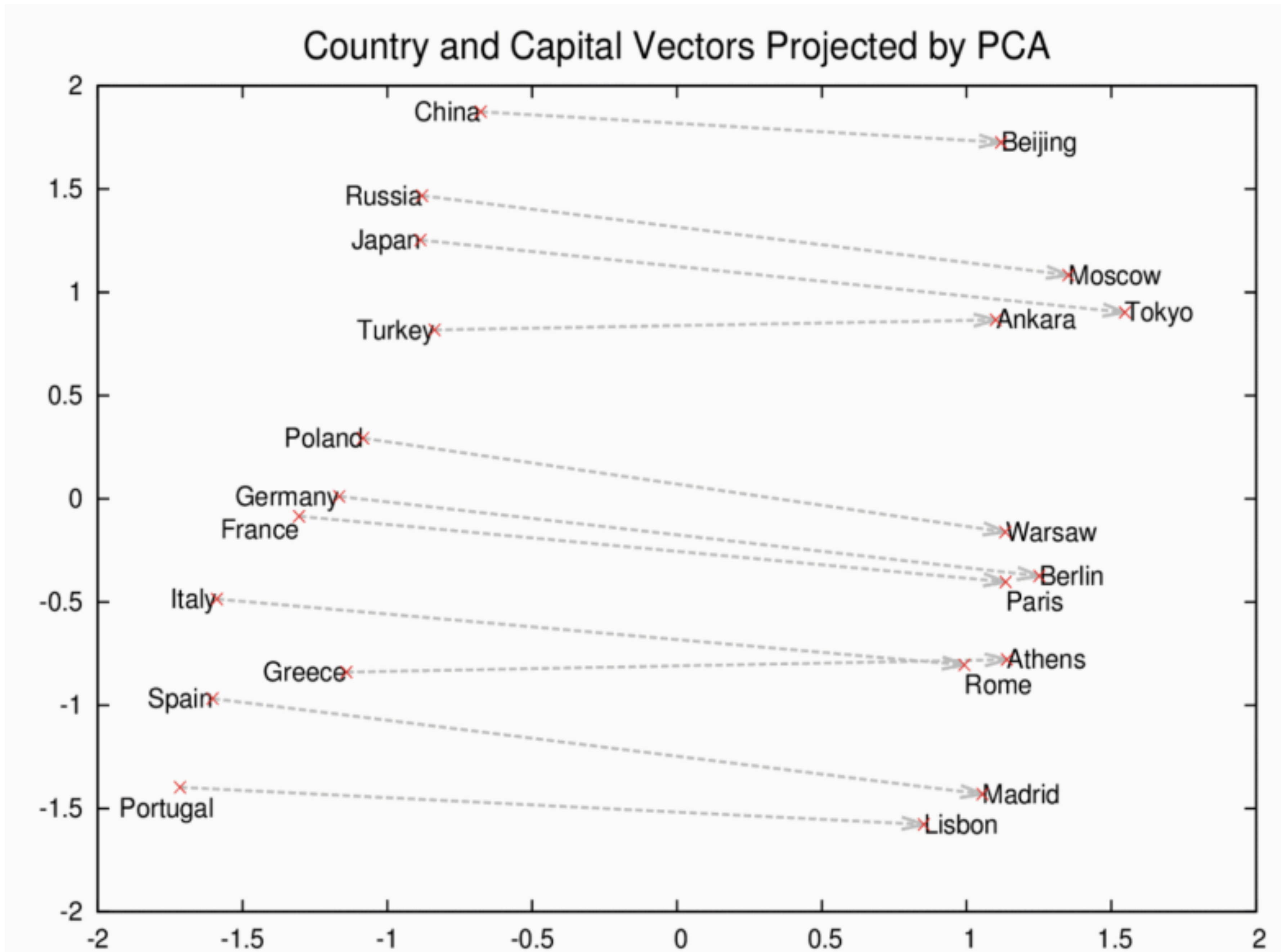


Image source: https://deeplearning4j.org/img/countries_capitals.png

Word Embeddings: word2vec

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!

Training data point: epidemic

"Training labels": the, opioid, or, opioid

Word Embeddings: word2vec

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!

Training data point: or

"Training labels": opioid, epidemic, opioid, crisis

Word Embeddings: word2vec

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!

These are "positive" (correct) examples of what context words are for "opioid"

Training data point: opioid

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

Also provide "negative" examples of words that are *not* likely to be context words (by randomly sampling words elsewhere in document)

Word Embeddings: word2vec

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.

randomly sampled word

Predict context of each word!

Training data point: opioid

"Negative training label": 2010s

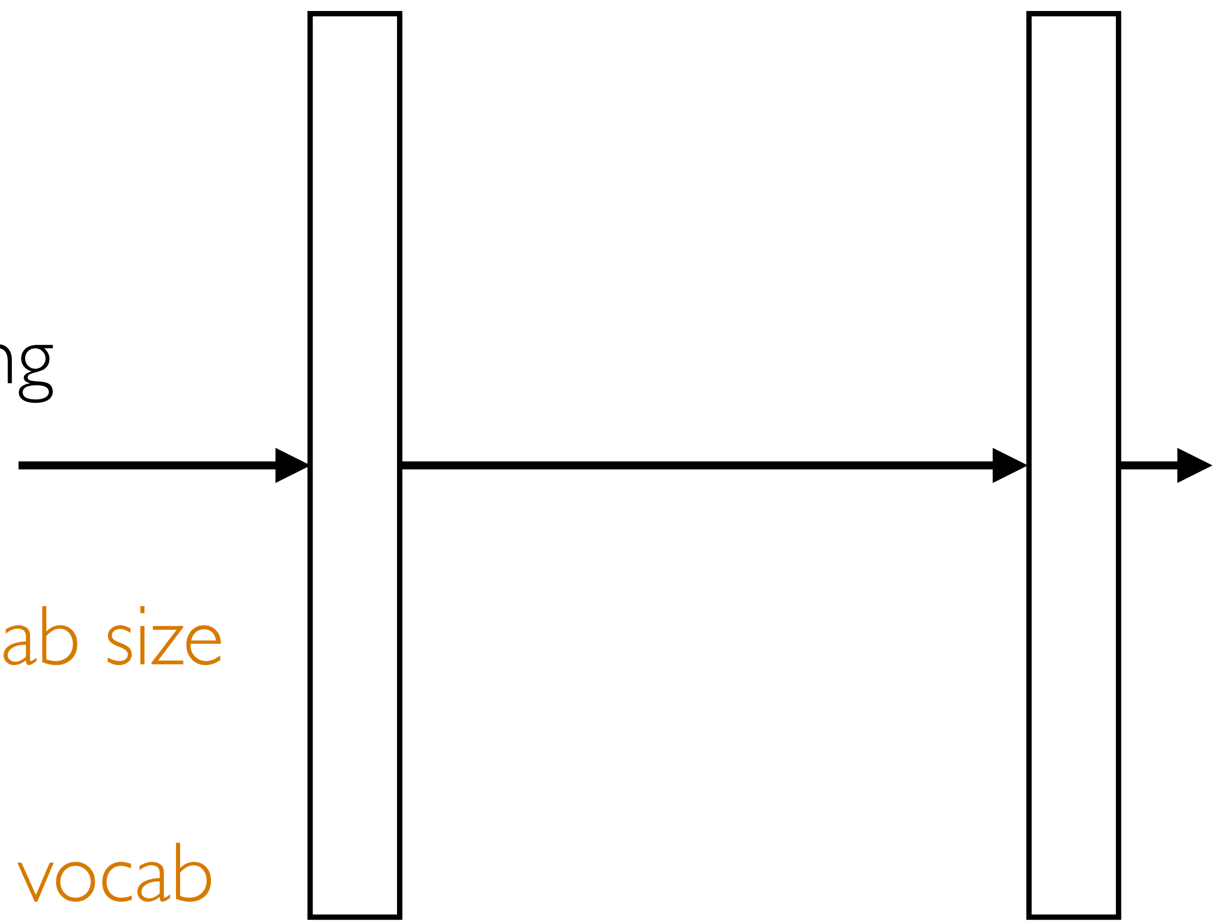
Also provide "negative" examples of words that are *not* likely to be context words (by randomly sampling words elsewhere in document)

Word2vec Neural Net

"opioid"
Use one-hot encoding
[0, 0, . . ., 1, . . ., 0]

vector length = vocab size

index of "opioid" in vocab



Want real context words (e.g., "epidemic", "crisis") to have high probability

Linear
(100 nodes)

Linear
(# nodes = vocab size),
Softmax

Learned weight matrix used as word embedding!

(Treat ***i***-th col of weight matrix as word embedding for ***i***-th word)

Word Embeddings as a Special Case of *Self-Supervised Learning*

- Key idea: hide part of the training data and try to predict hidden part using 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
- Other word embeddings methods are possible

(Flashback)

What about a word that has multiple meanings?

Challenging: try to split up word into multiple words depending on meaning (requires inferring meaning from context)

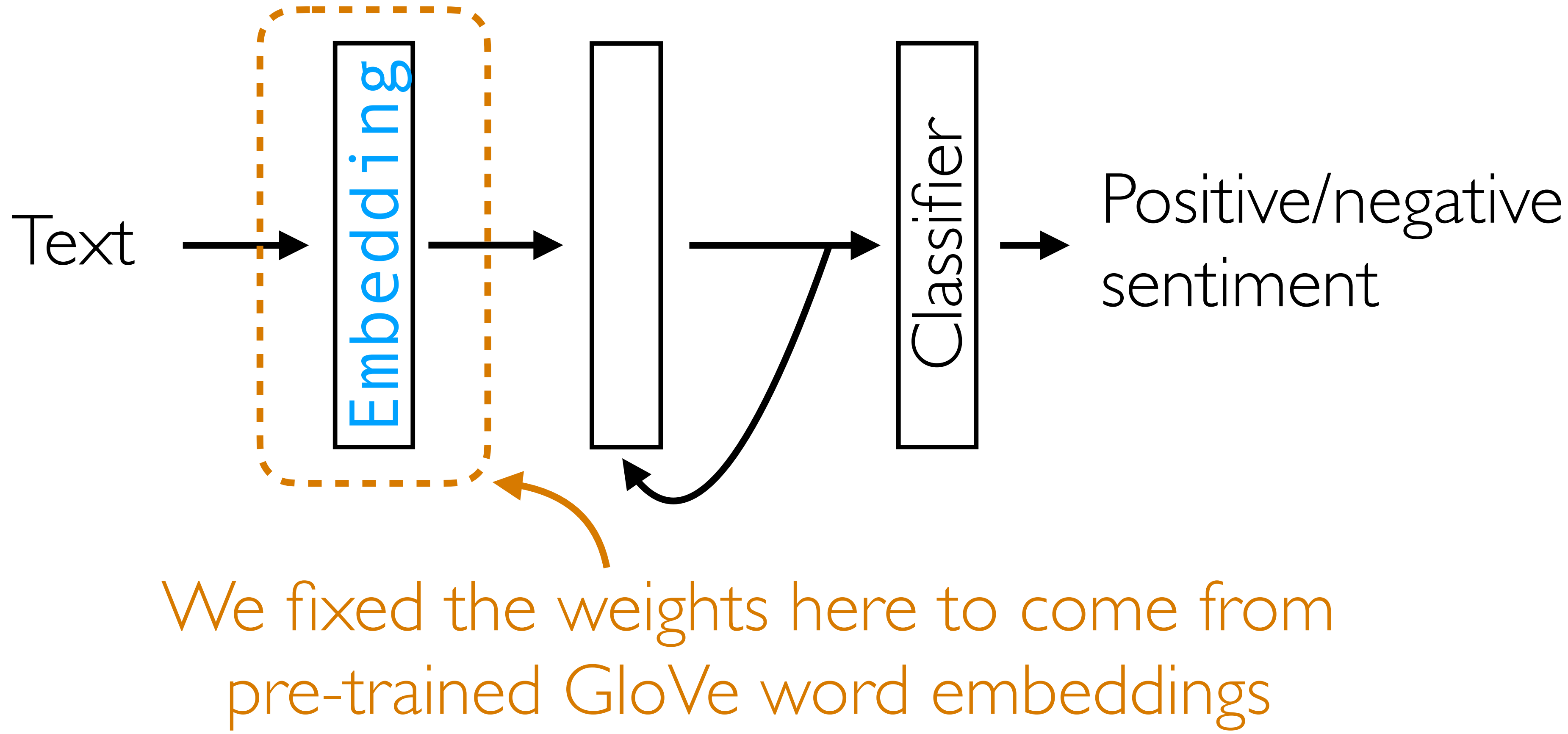
This problem is called **word sense disambiguation** (WSD)

Word Embeddings as a Special Case of *Self-Supervised Learning*

- Key idea: hide part of the training data and try to predict hidden part using 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
- Other word embeddings methods are possible
  - Word embedding that handles word-sense disambiguation: BERT (to figure out embedding for word, provide sentence the word is used in)

(Flashback) Fine Tuning

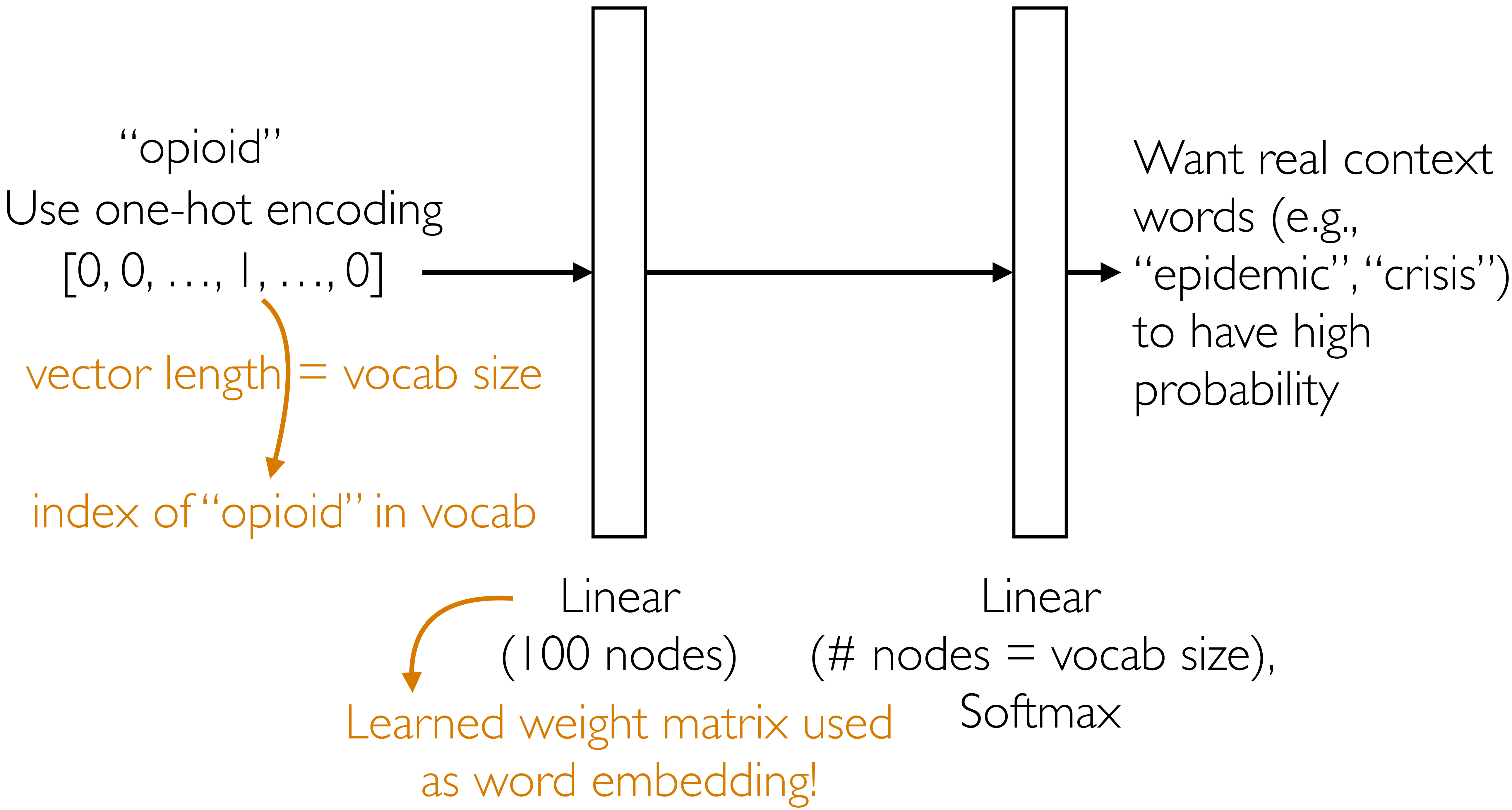
Sentiment analysis RNN demo



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

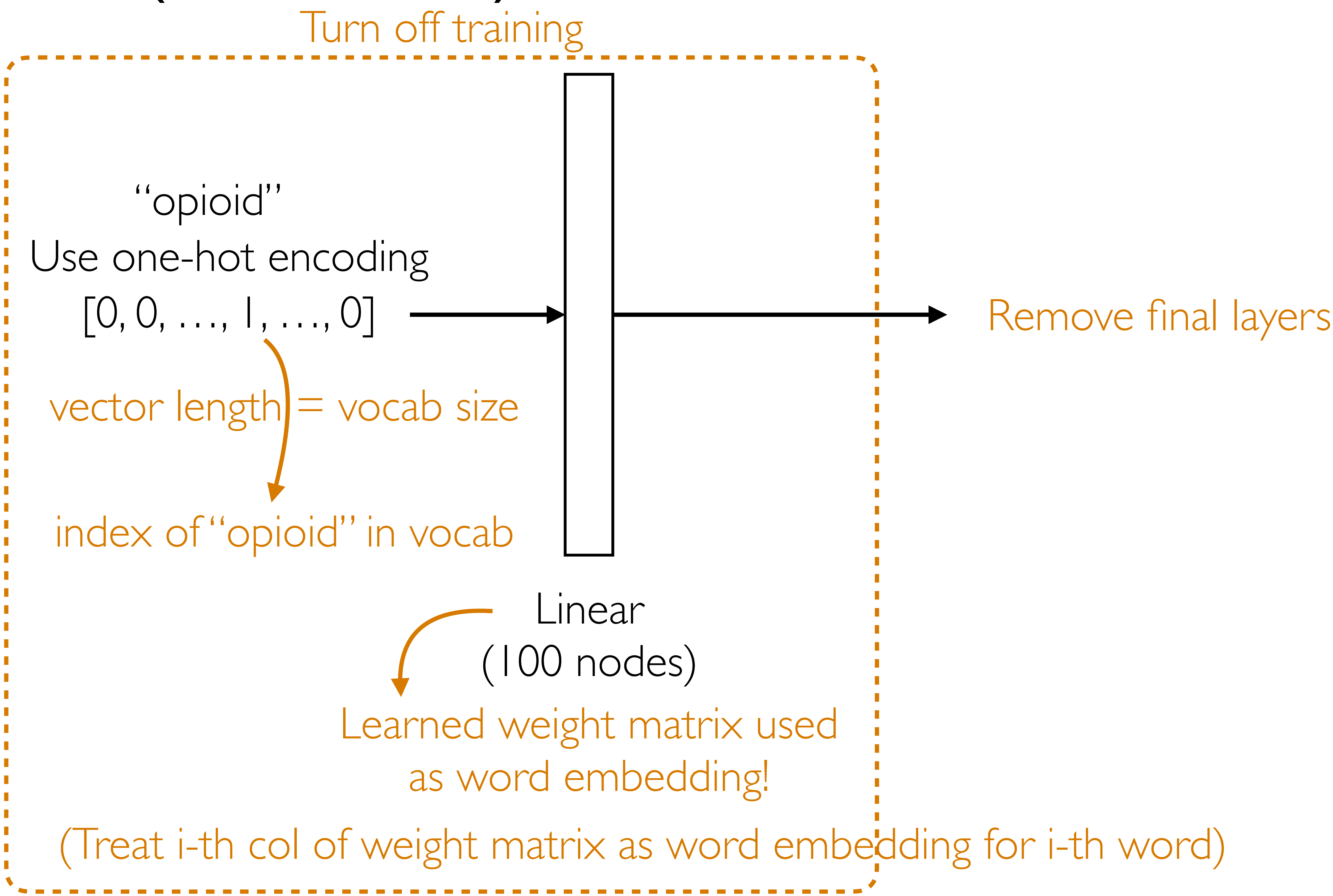
IMDb review dataset is small in comparison

(Flashback) Word2vec Neural Net

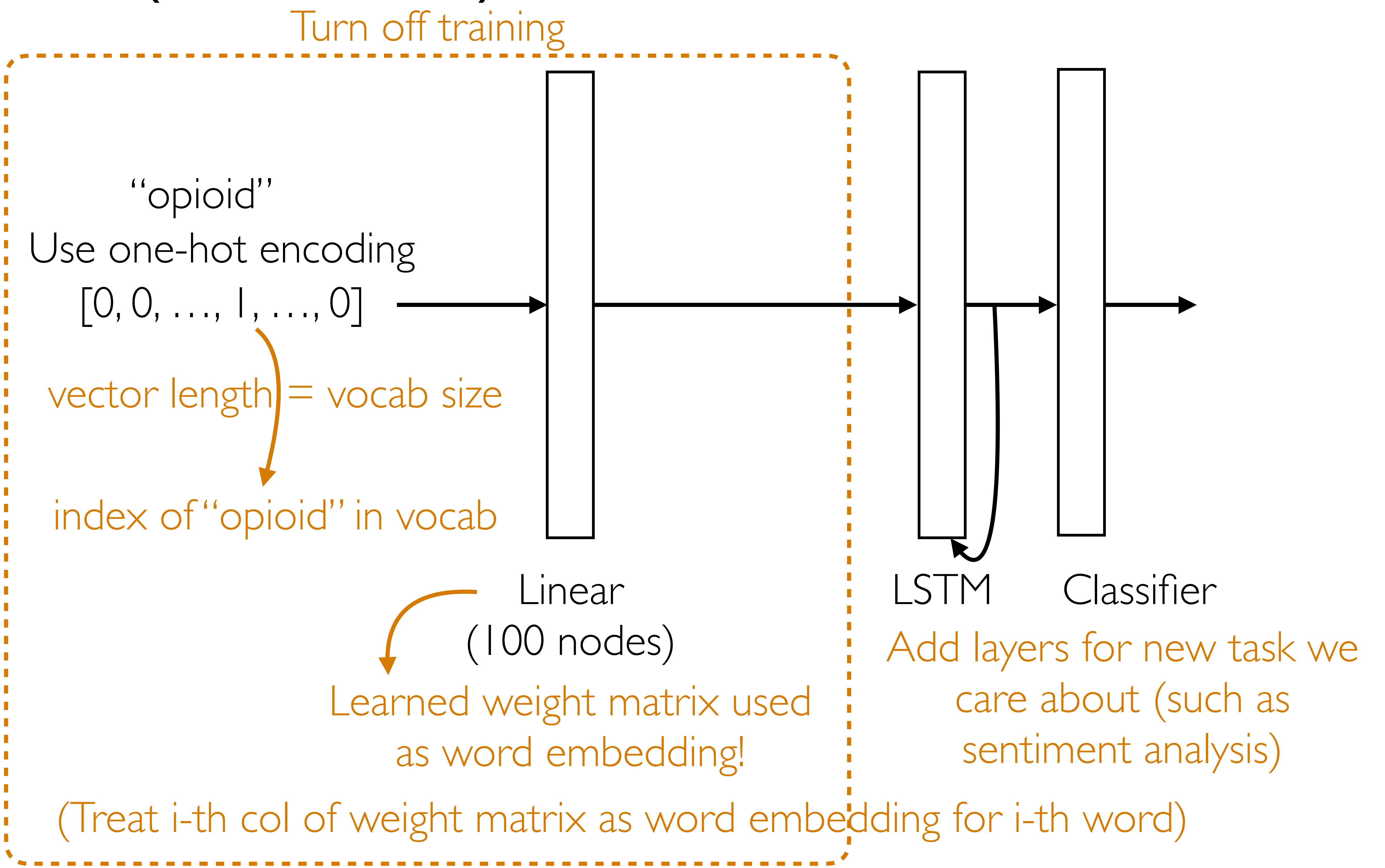


(Treat i-th col of weight matrix as word embedding for i-th word)

(Flashback) Word2vec Neural Net



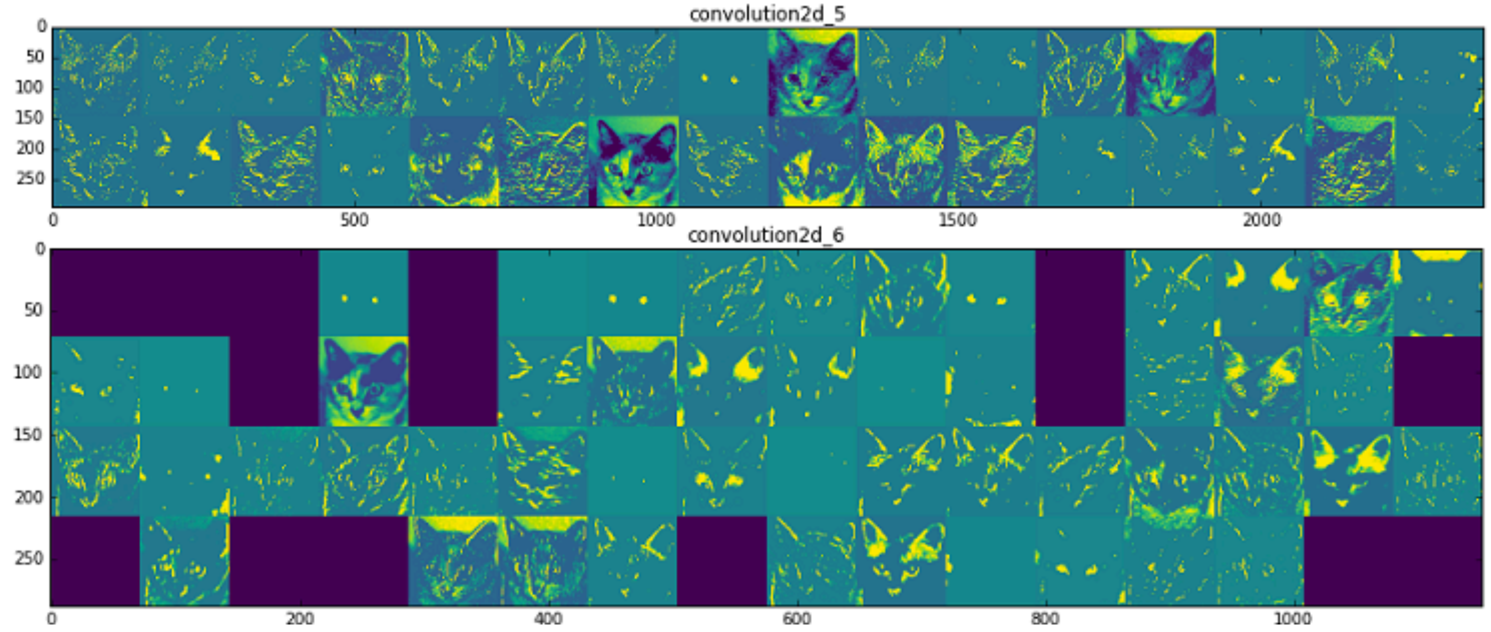
(Flashback) Word2vec Neural Net



Interpreting/explaining deep nets

Visualizing What a CNN Learned

- Plot filter outputs at different layers



- Plot regions that maximally activate an output neuron

There are many ways to do this!

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

Example: Wolves vs Huskies

(a) Husky classified as wolf (b) Explanation

Turns out the deep net learned that wolves are wolves because of snow…

➔ visualization is crucial!

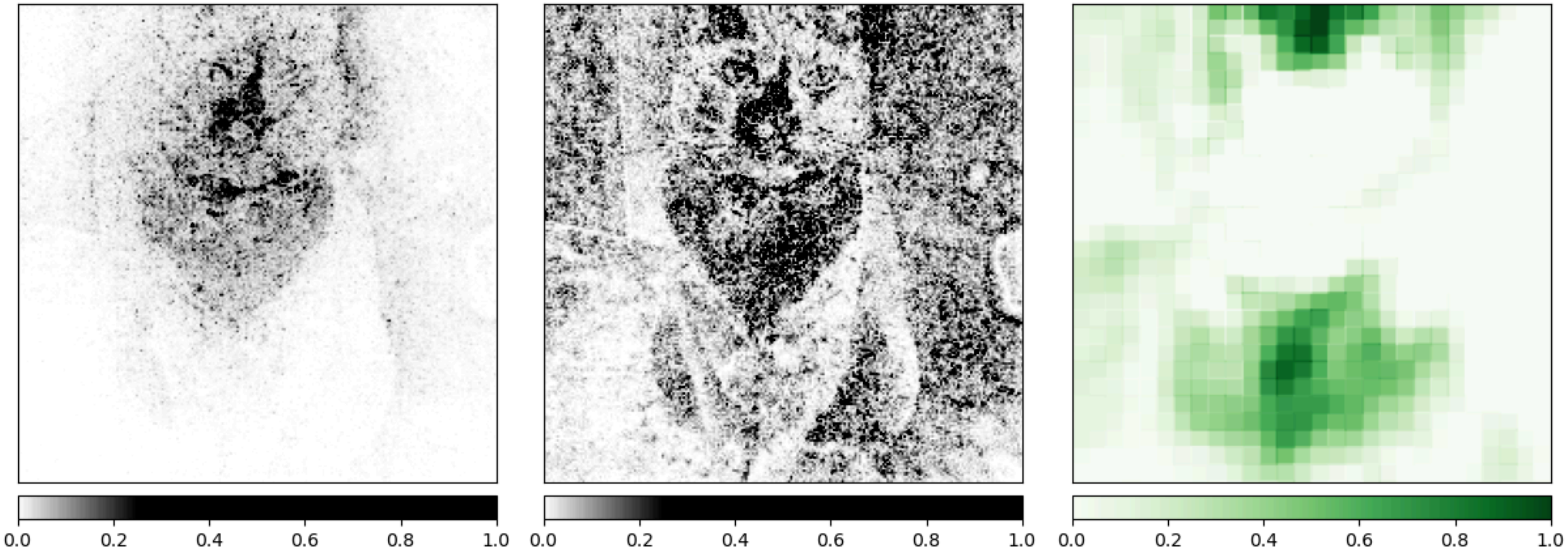
Source: Ribeiro et al. "Why should I trust you? Explaining the predictions of any classifier." KDD 2016.

Interpretability/Explainability: Current State of Affairs

- There are *lots* of "explanation" approaches that can be used after learning a deep net to try to understand what has been learned
  - Many of these are implemented in the Python package Captum developed by Facebook/Meta: https://captum.ai/

ResNet-18 (a CNN) predicts my cat to be an "Egyptian cat"

What pixels are important for prediction?



Crop image (many CNN's require image to be a specific size)

These are the answers from 3 different explanation models (they give different answers!)

Warning: there's a *lot* of debate as to how much we should actually trust these explanations, as **they can often be misleading**

Interpretability/Explainability: Current State of Affairs

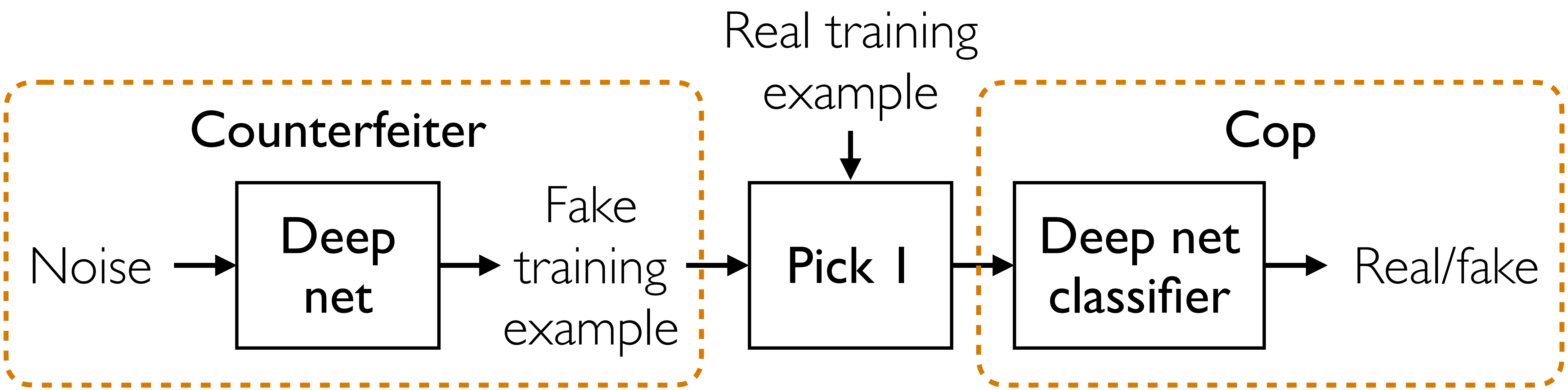
- There are neural net architectures that *by design are interpretable* (e.g., prototypical part networks, neural topic models, …)
    - No separate explanation approach needed since model directly provides explanation
    - My opinion: if you really care about interpretability/explainability, then you're better off using this sort of model

Generating Fake Data That Look Real

Generate Fake Data that Look Real

Example: Generative Adversarial Network (GAN)

Basic version is unsupervised: generate fake data that look like training data



Counterfeiter tries to get better at tricking the cop

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

Terminology: counterfeiter is the **generator**, cop is the **discriminator**

Generate Fake Data that Look Real

Generate images of <u>synthetic</u> people
(StyleGAN3 by Karras et al 2021)

Generate Fake Data that Look Real

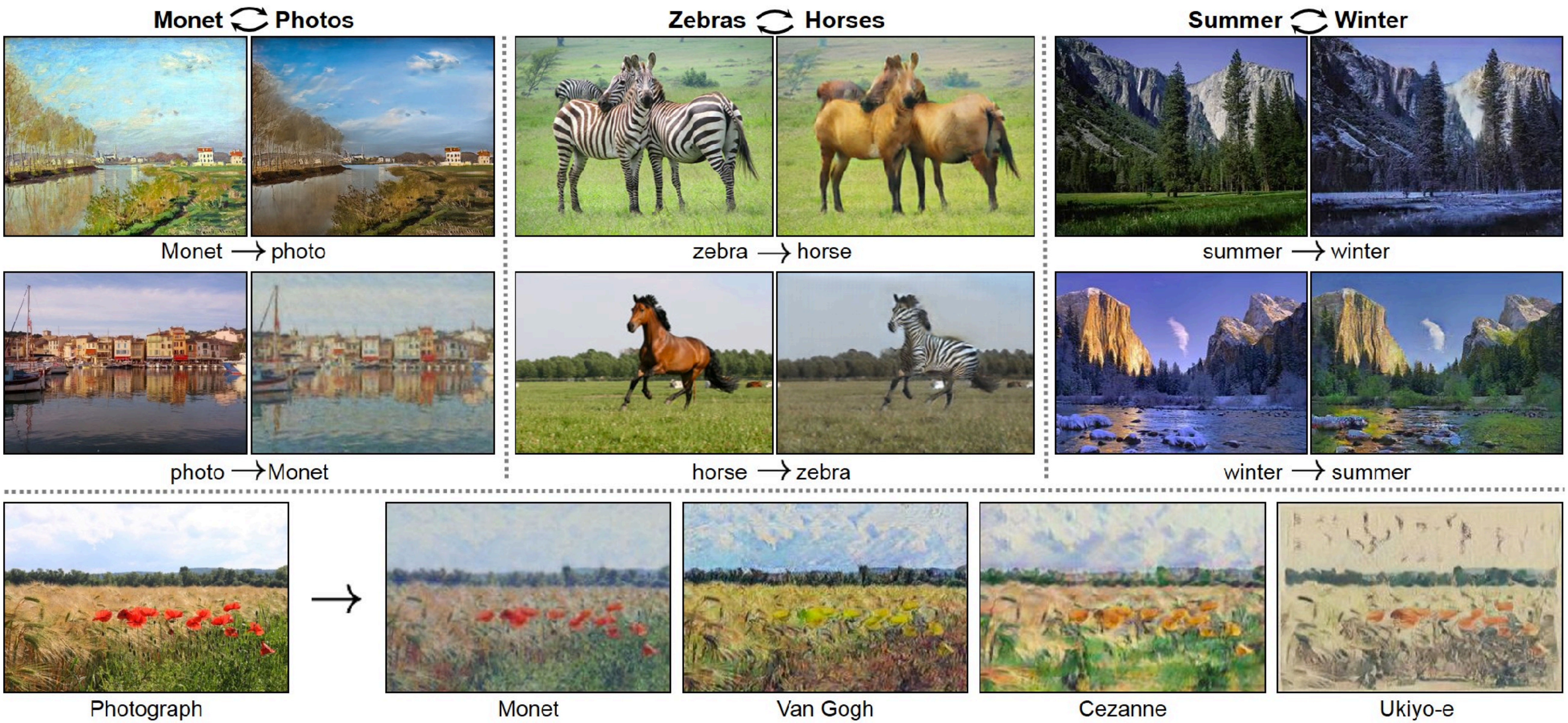


Image-to-image translation results using GANs
(Isola et al 2017, Zhu et al 2017)

Concluding Thoughts on Deep Learning

- Deep learning learns computer programs
  - We have only seen simple examples of these computer programs in this class, but the programs that can be learned are becoming increasingly sophisticated (e.g., GPT 4.0)
- All the best ideas that lead to amazing prediction results incorporate problem-specific structure
  - For example, think about how CNNs and RNNs incorporate structure of images/time series
- How do we automatically discover & incorporate important problem structure?
- How do we do lifelong learning?
- How do we reason about causality?

Unstructured Data Analysis

Question	Data	Finding Structure	Insights
			

Becoming good at data scientist requires you to think like a detective!

The dead body	*The evidence*	*Puzzle solving,*	*When? Where?*
Th			?
by			
	more evidence!	analysis	*catchable?*
			Answer original question

Much like how some murder mysteries are hard to solve, many data analysis problems (unstructured or not) are hard to solve too!

<u>There isn't always a follow-up prediction problem to solve</u>

Some Parting Thoughts

- Remember to **visualize steps of your data analysis pipeline**
  - Helpful in debugging & interpreting intermediate/final outputs
- Very often there are *tons* of models/design choices to try
  - Come up with **quantitative metrics** that make sense for your problem, and use these metrics to **evaluate models (think about how we chose hyperparameters!)**
  - But don't blindly rely on metrics without **interpreting results in the context of your original problem!**
- Often times you won't have labels! If you really want labels:
  - Manually obtain labels (either you do it or crowdsource)
  - Set up "self-supervised" learning task
- There is a *lot* we did not cover — **keep learning!**

Want to Learn More?

- Some courses at CMU:
  - Natural language processing (analyze text): 11-611
  - Computer vision (analyze images): 16-720
  - Deep learning: 11-785, 10-707
  - Deep reinforcement learning: 10-703
  - Math for machine learning: 10-606, 10-607
  - Intro to machine learning at different levels of math: 10-601, 10-701, 10-715
  - Machine learning with large datasets: 10-605

- One of the best ways to learn material is to teach it!

  Apply to be a TA for me next term!