Deep Learning Architectures

Introduction to Machine Learning, Day 4

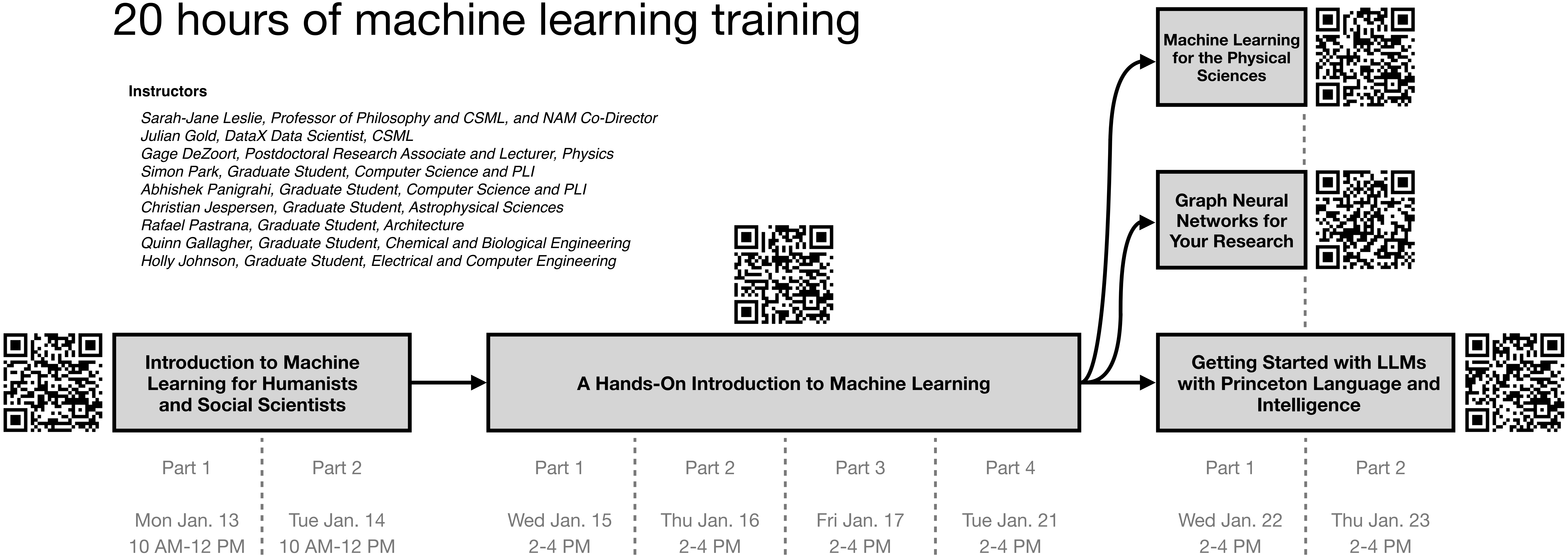
Gage DeZoort

Wintersession 2025 with PICSciE/RC

20 hours of machine learning training

Instructors

Sarah-Jane Leslie, Professor of Philosophy and CSML, and NAM Co-Director
Julian Gold, DataX Data Scientist, CSML
Gage DeZoort, Postdoctoral Research Associate and Lecturer, Physics
Simon Park, Graduate Student, Computer Science and PLI
Abhishek Panigrahi, Graduate Student, Computer Science and PLI
Christian Jespersen, Graduate Student, Astrophysical Sciences
Rafael Pastrana, Graduate Student, Architecture
Quinn Gallagher, Graduate Student, Chemical and Biological Engineering
Holly Johnson, Graduate Student, Electrical and Computer Engineering



Introduction to Machine Learning for Humanists and Social Scientists

Part 1 — Mon Jan. 13, 10 AM-12 PM

Part 2 — Tue Jan. 14, 10 AM-12 PM

A Hands-On Introduction to Machine Learning

Part 1 — Wed Jan. 15, 2-4 PM

Part 2 — Thu Jan. 16, 2-4 PM

Part 3 — Fri Jan. 17, 2-4 PM

Part 4 — Tue Jan. 21, 2-4 PM

Machine Learning for the Physical Sciences

Graph Neural Networks for Your Research

Getting Started with LLMs with Princeton Language and Intelligence

Part 1 — Wed Jan. 22, 2-4 PM

Part 2 — Thu Jan. 23, 2-4 PM

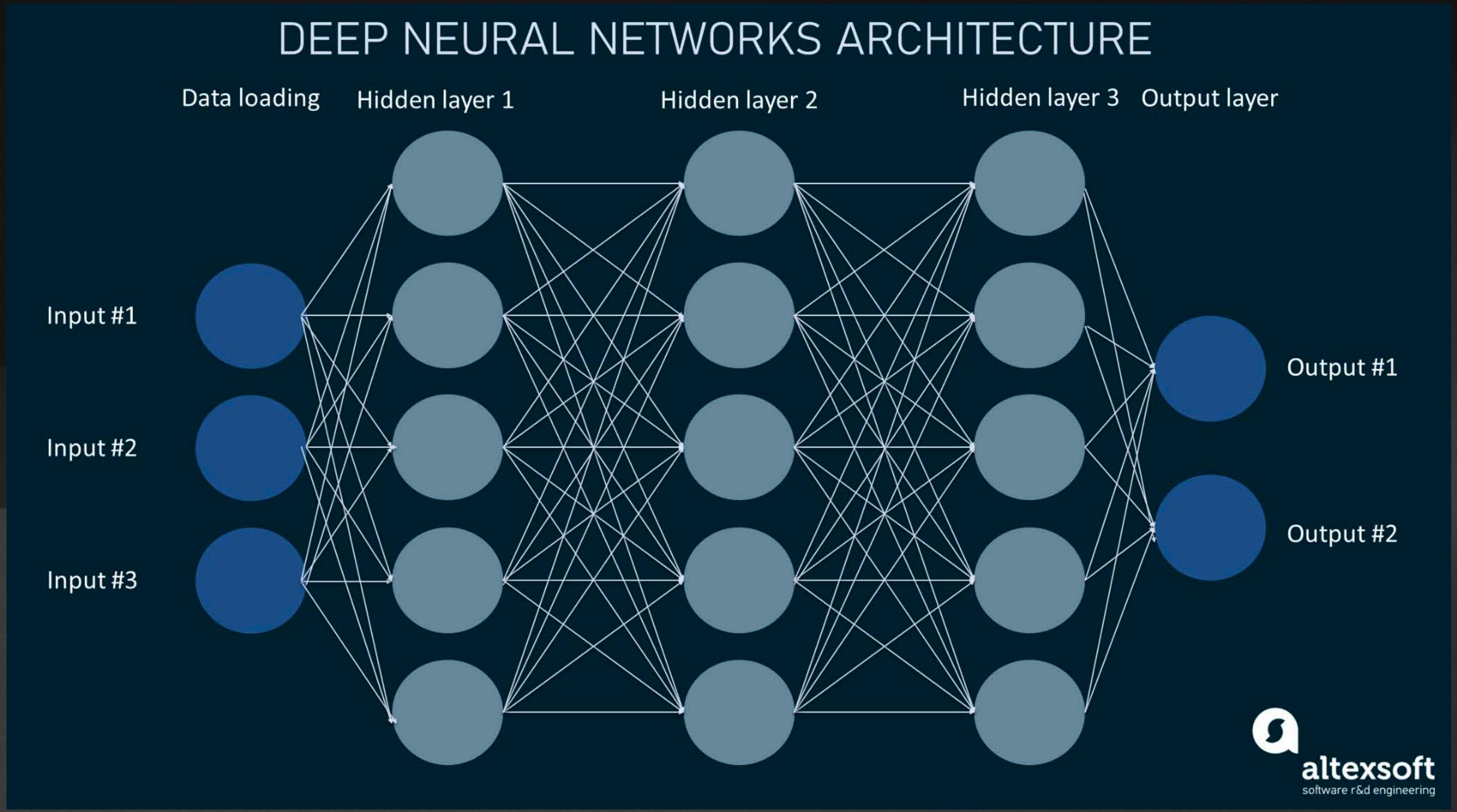
NATURAL & ARTIFICIAL MINDS

CENTER FOR STATISTICS AND MACHINE LEARNING

DataX
Accelerating Scientific Discovery at Princeton

PLI PRINCETON Language + Intelligence

`https://researchcomputing.princeton.edu/workshops`



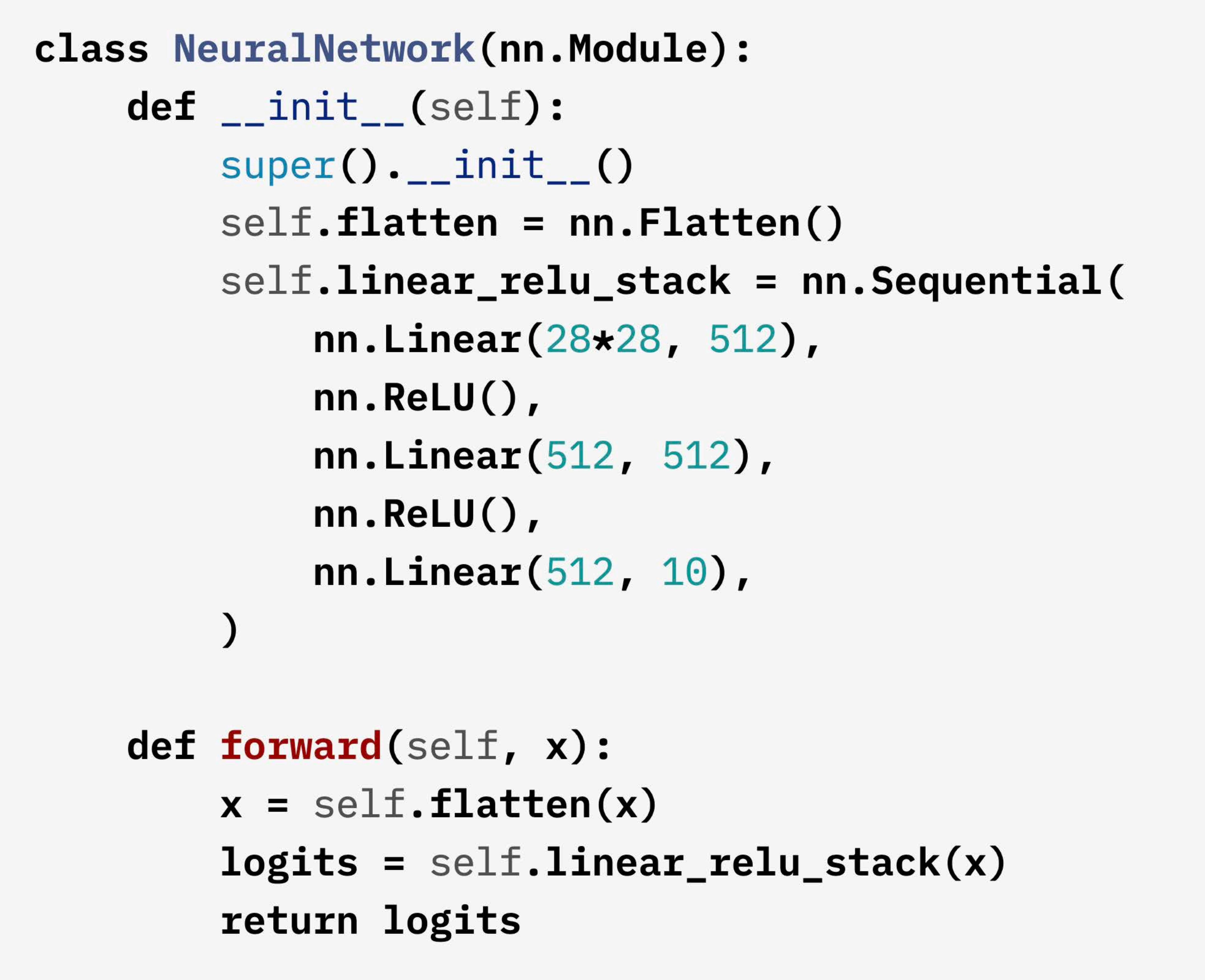
- Forward pass:

$$z_i^{(\ell+1)} = \sum_{i=1}^{n_\ell} W_{ij}^{(\ell+1)} \sigma(z_j^{(\ell)}) + b_i^{(\ell+1)}$$

- Backward pass:

$$W_{ij}^{(\ell+1)} = W_{ij}^{(\ell)} - \gamma \frac{\partial L}{\partial W_{ij}} \Big|_{W_{ij}^{(\ell)}}$$

$$b_i^{(\ell+1)} = b_i^{(\ell)} - \gamma \frac{\partial L}{\partial b_i} \Big|_{b_i^{(\ell)}}$$



```python
class NeuralNetwork(nn.Module):
    def __init__(self):
        super().__init__()
        self.flatten = nn.Flatten()
        self.linear_relu_stack = nn.Sequential(
            nn.Linear(28*28, 512),
            nn.ReLU(),
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    def forward(self, x):
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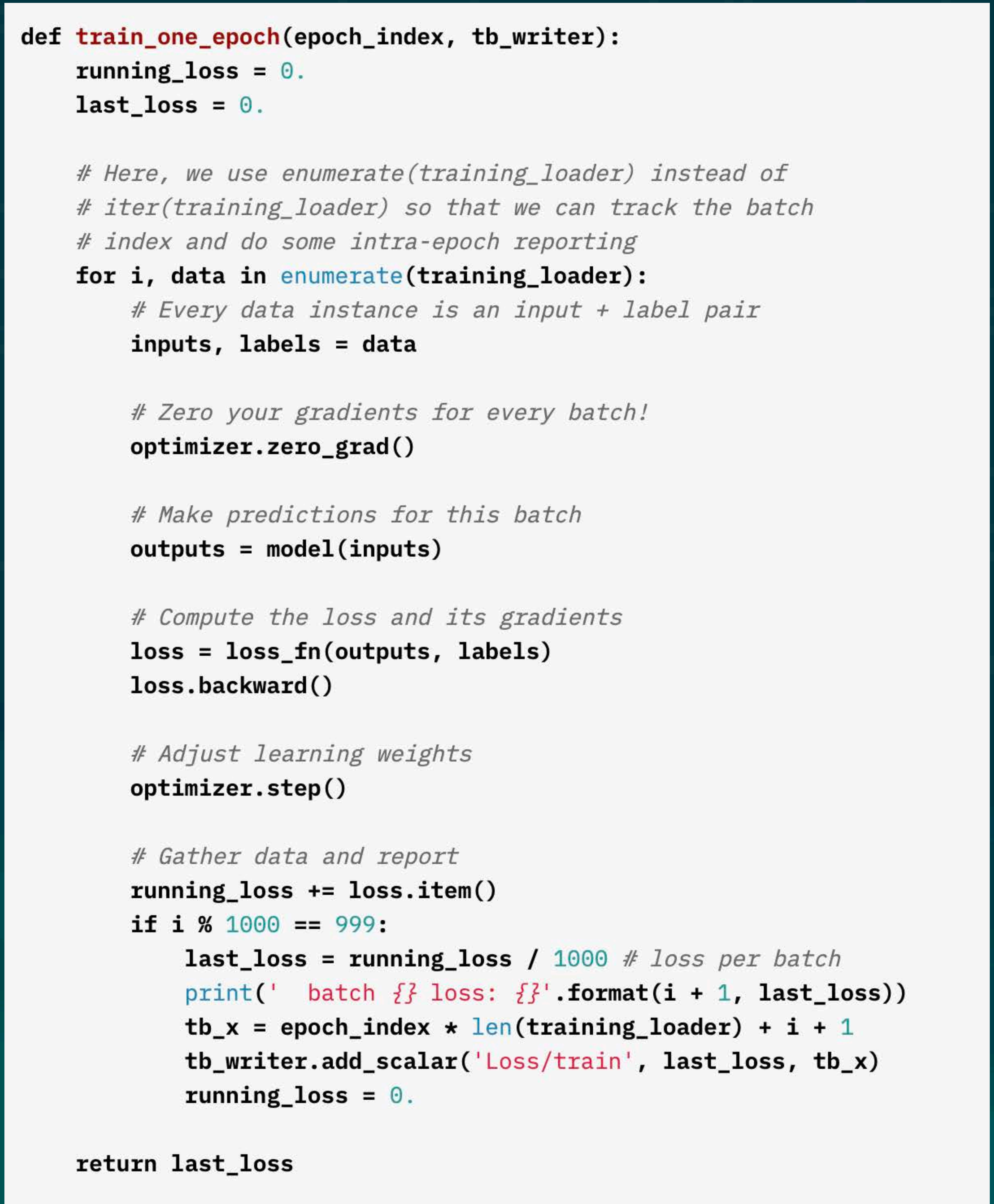

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def train_one_epoch(epoch_index, tb_writer):
    running_loss = 0.
    last_loss = 0.

    # Here, we use enumerate(training_loader) instead of
    # iter(training_loader) so that we can track the batch
    # index and do some intra-epoch reporting
    for i, data in enumerate(training_loader):
        # Every data instance is an input + label pair
        inputs, labels = data

        # Zero your gradients for every batch!
        optimizer.zero_grad()

        # Make predictions for this batch
        outputs = model(inputs)

        # Compute the loss and its gradients
        loss = loss_fn(outputs, labels)
        loss.backward()

        # Adjust learning weights
        optimizer.step()

        # Gather data and report
        running_loss += loss.item()
        if i % 1000 == 999:
            last_loss = running_loss / 1000 # loss per batch
            print('  batch {} loss: {}'.format(i + 1, last_loss))
            tb_x = epoch_index * len(training_loader) + i + 1
            tb_writer.add_scalar('Loss/train', last_loss, tb_x)
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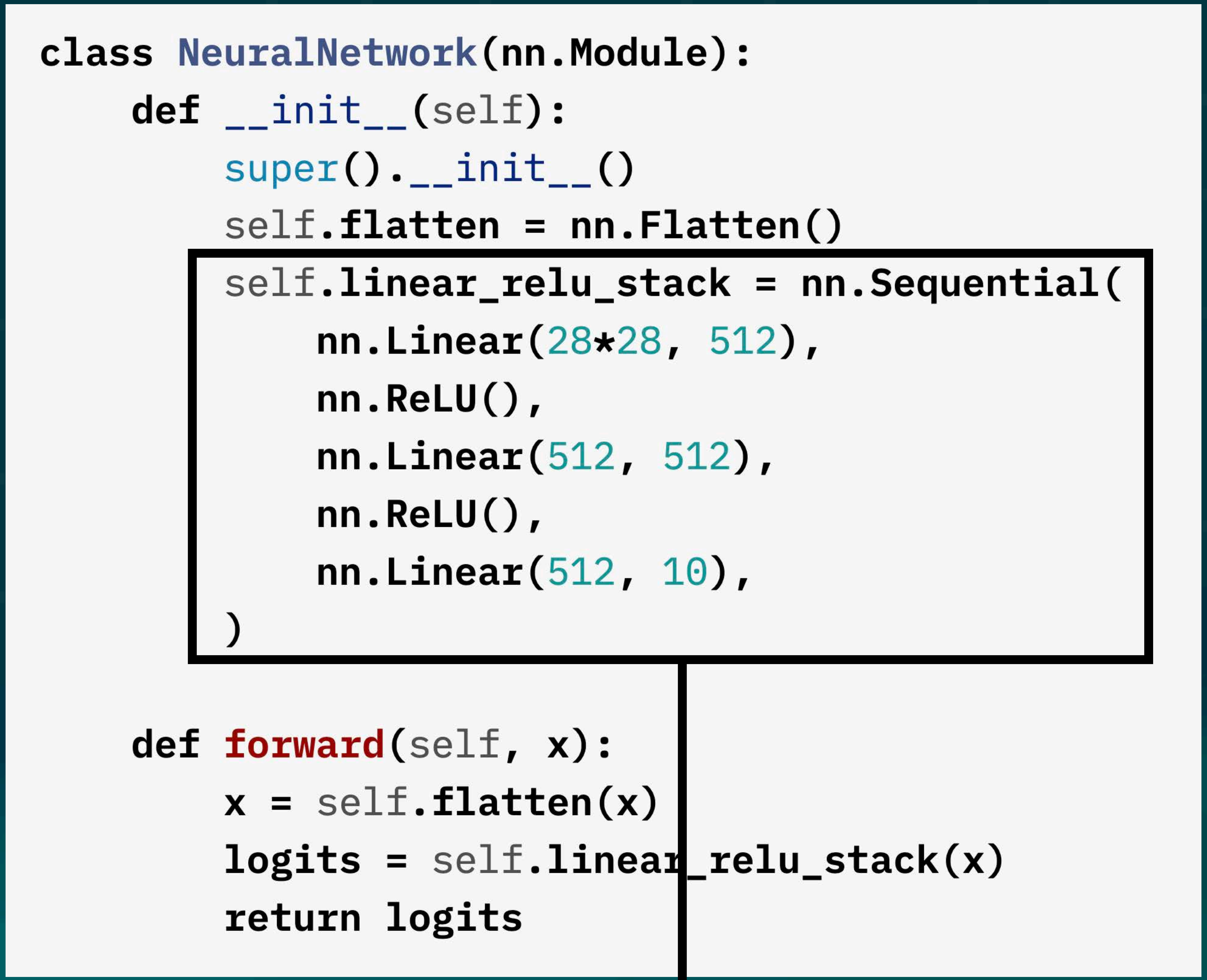

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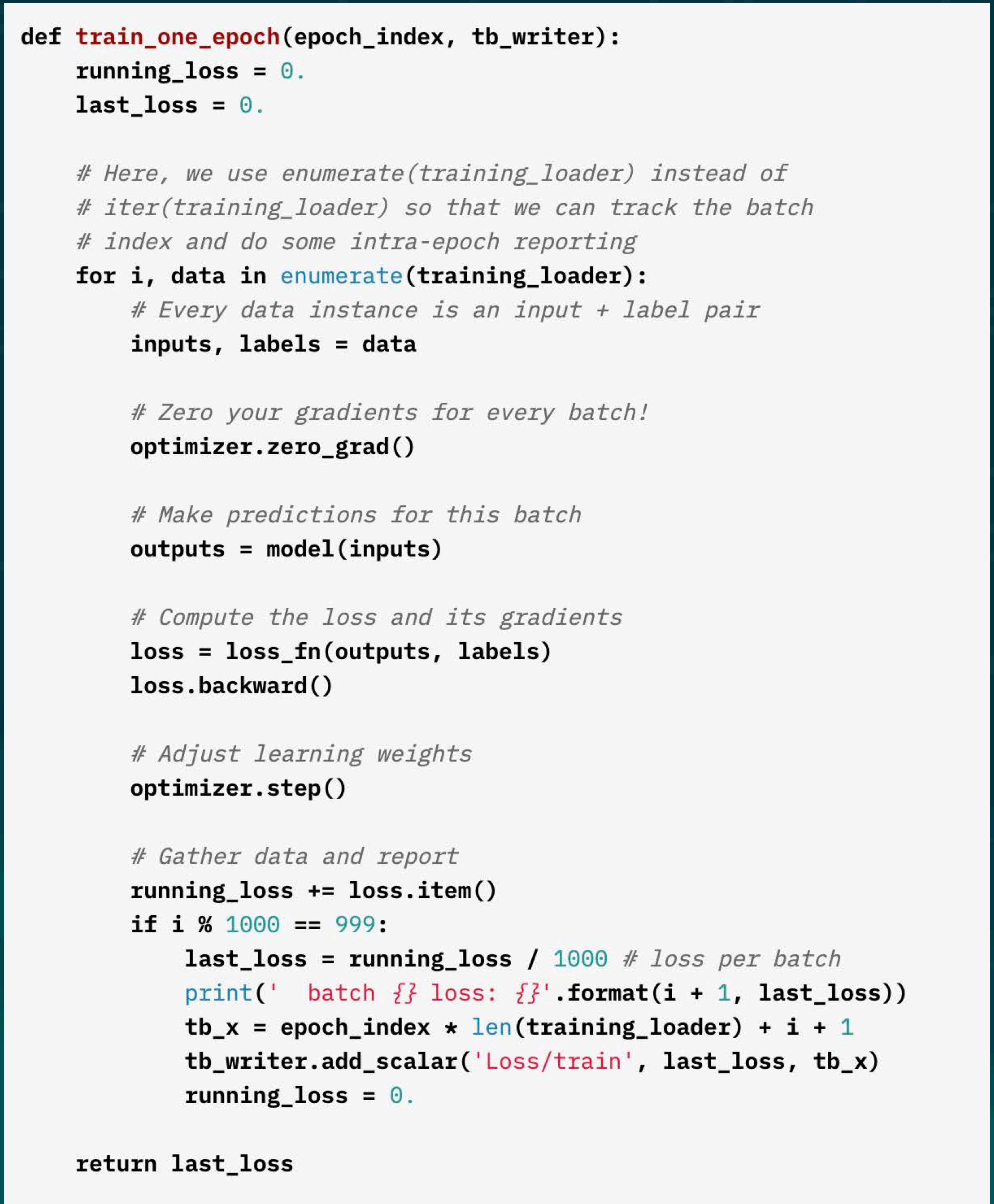

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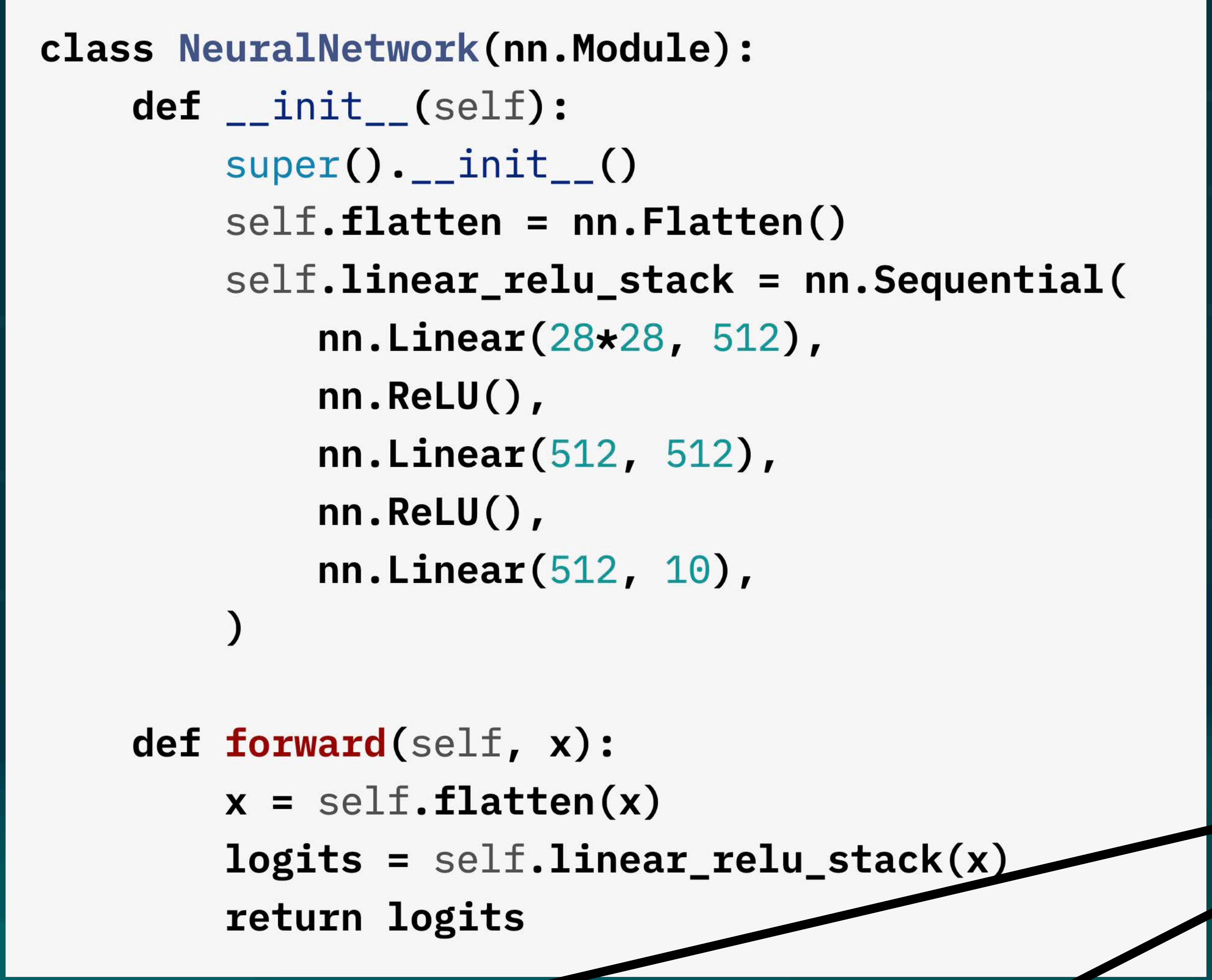

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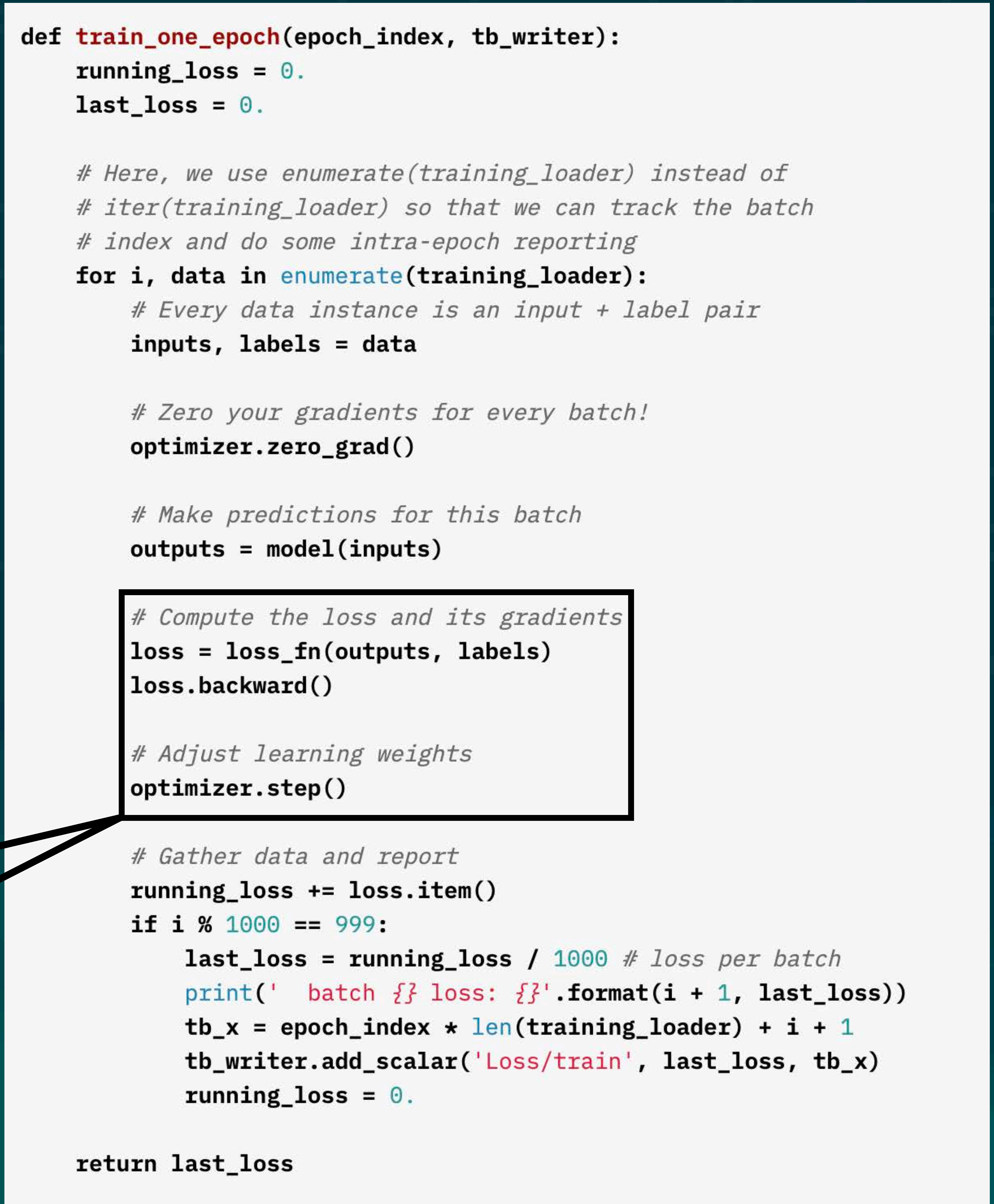

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$$W_{ij}^{(\ell+1)} = W_{ij}^{(\ell)} - \gamma \frac{\partial L}{\partial W_{ij}}\bigg|_{W_{ij}^{(\ell)}} \qquad b_i^{(\ell+1)} = b_i^{(\ell)} - \gamma \frac{\partial L}{\partial b_i}\bigg|_{b_i^{(\ell)}}$$

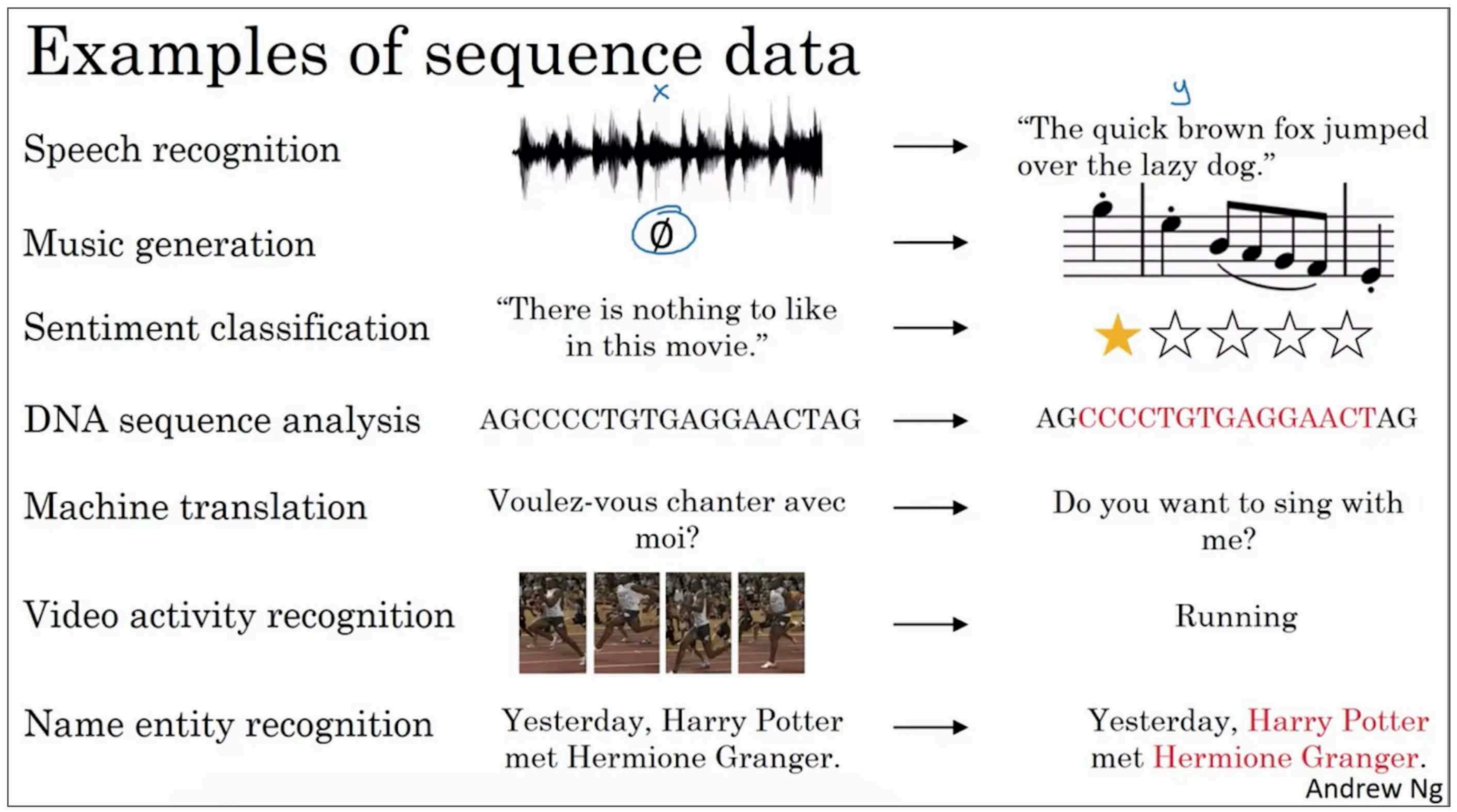
Beyond Simple DNNs

Survey of Deep Learning Architectures

- Deep NN (DNN) $\leftrightarrow$ Feed-Forward NN (FFNN) $\leftrightarrow$ Fully-Connected NN (FCNN)
- Many other architectures exist:
  - Recurrent NNs (RNNs): process sequential data
  - Convolutional NNs (CNNs): process data on a grid
  - Graph Neural Networks (GNNs): process data on a graph / attention
  - Generative Models: produce new data
  - … and more!

Recurrent Neural Networks

Designed to Process Sequential Data



Examples of sequence data

	x		y
Speech recognition		→	"The quick brown fox jumped over the lazy dog."
Music generation	∅	→	
Sentiment classification	"There is nothing to like in this movie."	→	★☆☆☆☆
DNA sequence analysis	AGCCCCTGTGAGGAACTAG	→	AGCCCCTGTGAGGAACTAG
Machine translation	Voulez-vous chanter avec moi?	→	Do you want to sing with me?
Video activity recognition		→	Running
Name entity recognition	Yesterday, Harry Potter met Hermione Granger.	→	Yesterday, Harry Potter met Hermione Granger.

Andrew Ng

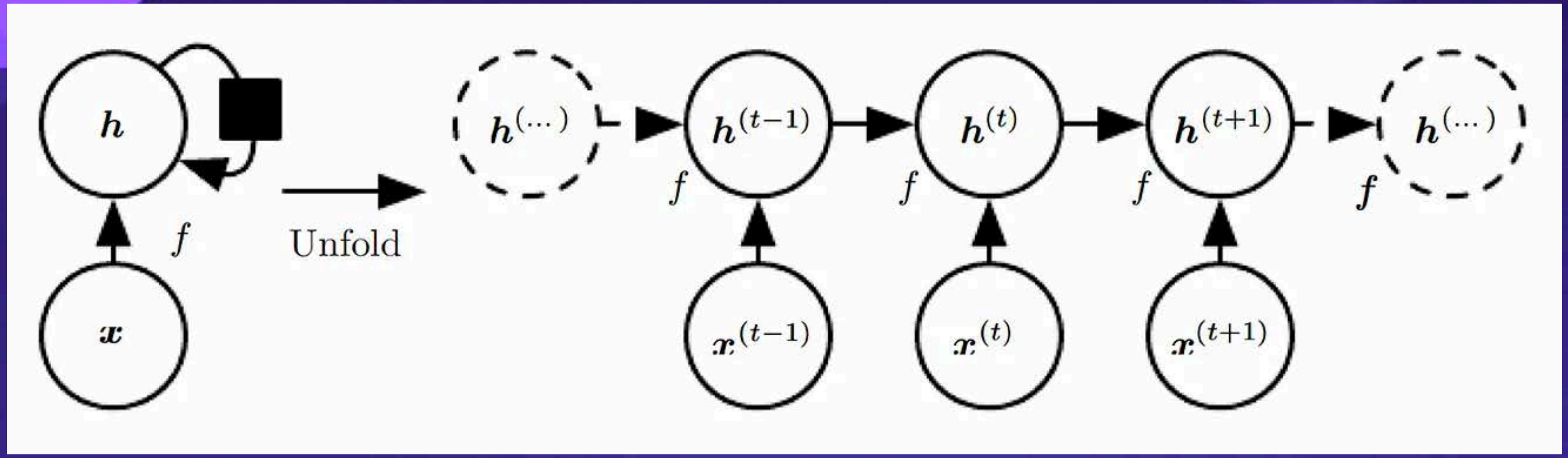
https://aiml.com/what-does-sequential-data-mean-which-models-are-best-suited-for-handling-sequential-data/

Recurrent Neural Networks

Basic Idea

- Time-indexed inputs: $\mathbf{x}^{(1)}, \mathbf{x}^{(2)}, \ldots, \mathbf{x}^{(T)}$
- Parameter sharing: apply the same set of learnable weights to all values of the time index
- Given a set of learnable parameters θ, the hidden units in many RNNs are calculated via. $\mathbf{h}^{(t)} = f(\mathbf{h}^{(t-1)}, \mathbf{x}^{(t)}; \theta)$

Image from *Deep Learning* by Goodfellow et al.



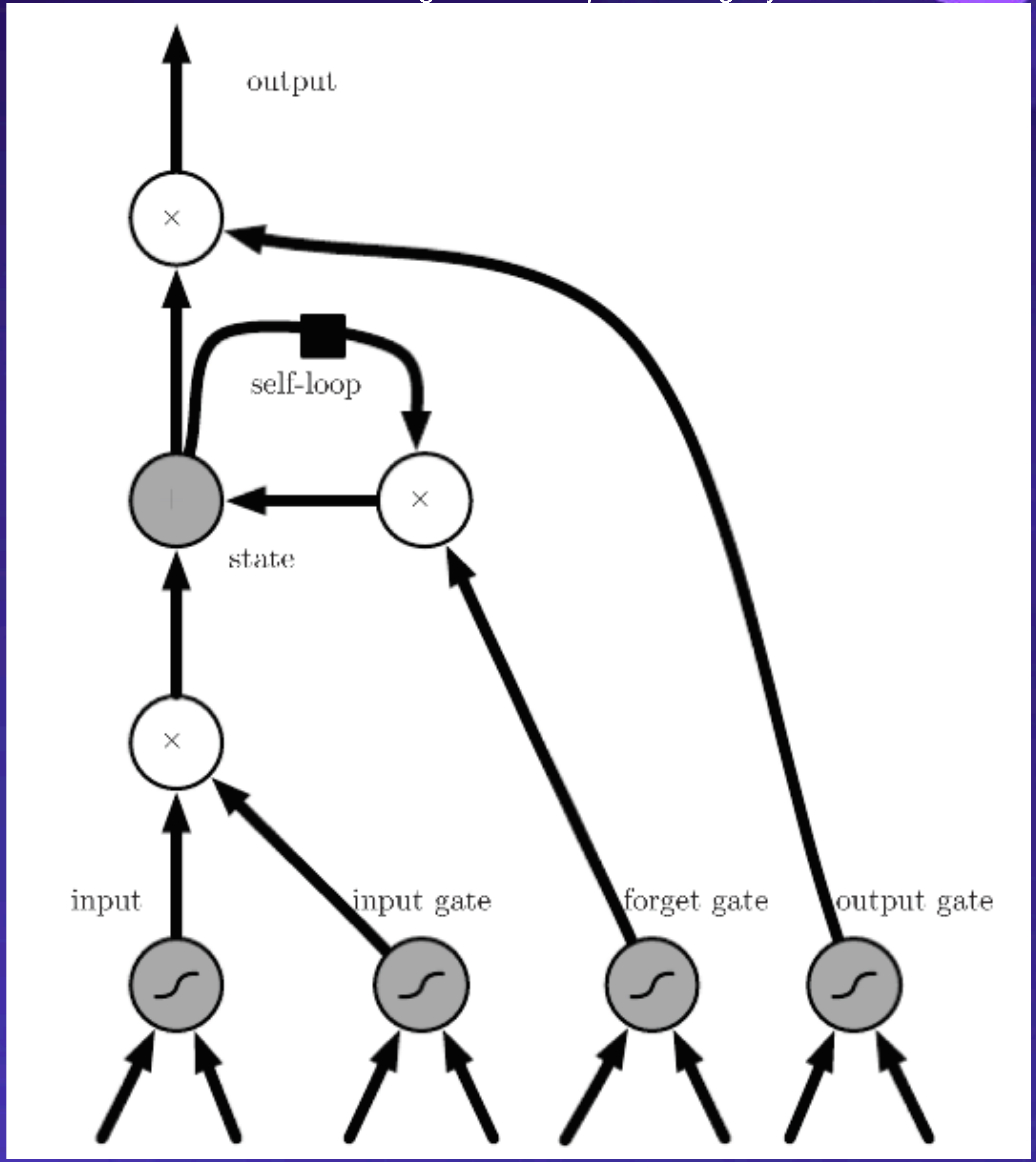
RNN with no outputs; information is processed sequentially, taking into account both $\mathbf{x}^{(t)}$ and $h^{(t-1)}$ but applying the *same function* $f(\,\cdot\,;\theta)$ *at each tilmestep*

Long Short-Term Memory (LSTM)

An Upgraded RNN Module

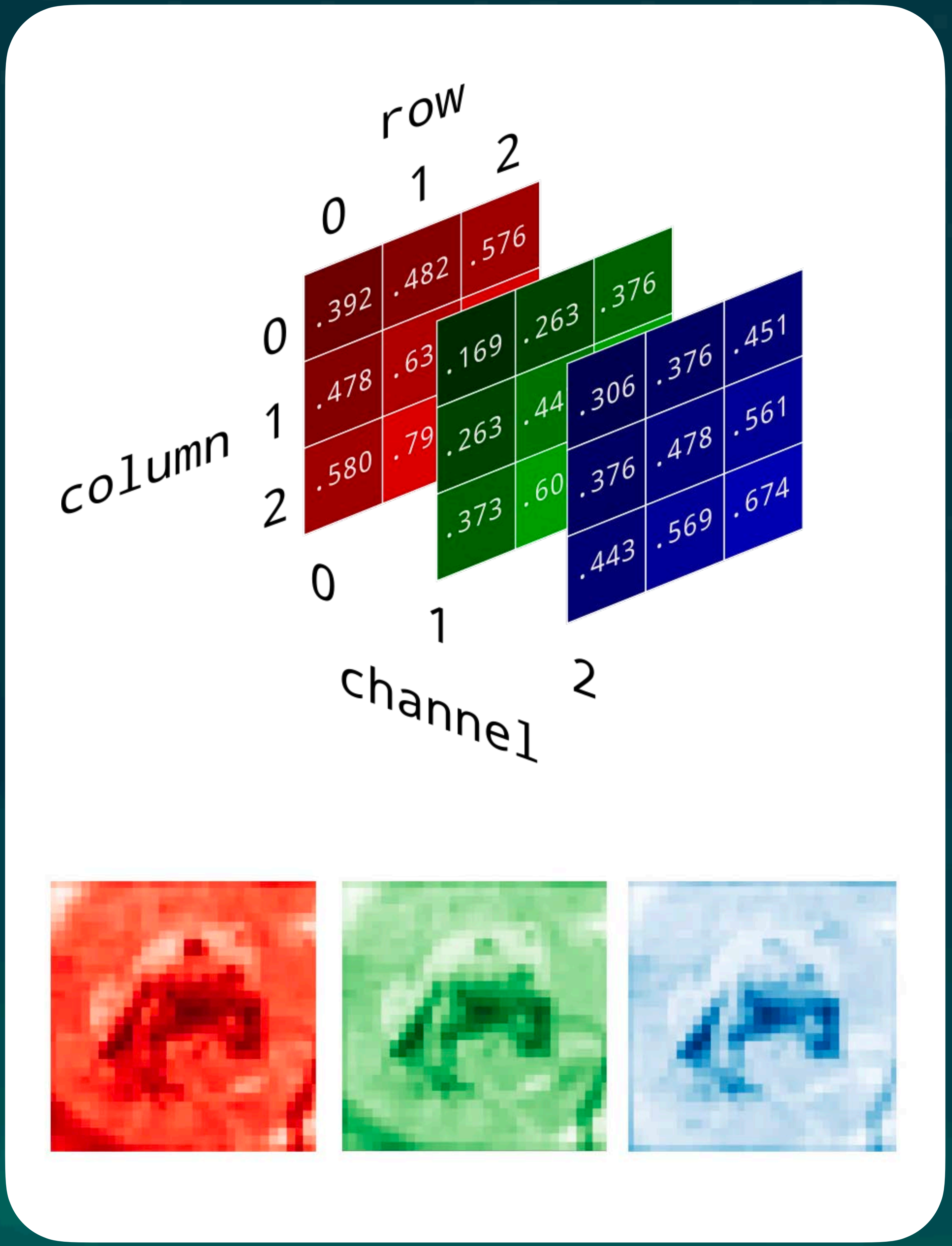
- RNNs are finicky to train; they often suffer from exploding/vanishing gradients
- This has motivated the development of more advanced RNNs like LSTMs
- The LSTM is a recurrent "cell" that is applied to all timesteps equally

Image from *Deep Learning* by Goodfellow et al.



Convolutional Neural Networks (CNNs)

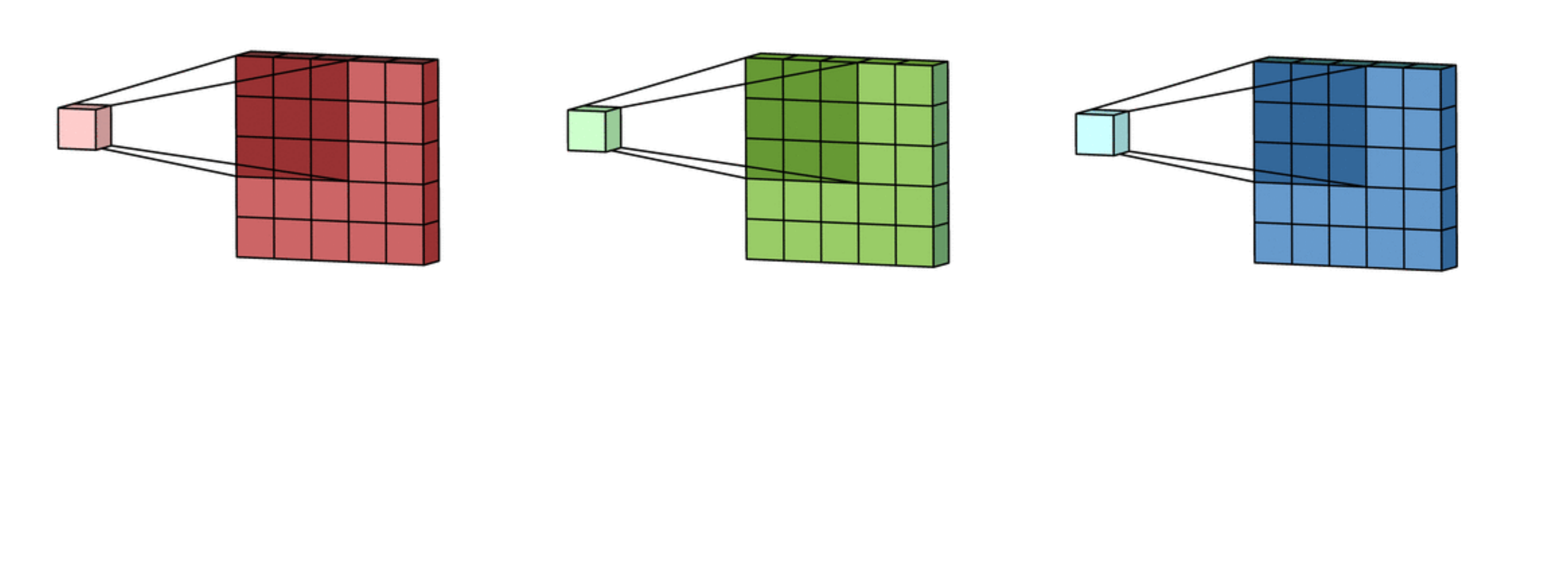
- Deep learning applied to images (data on a grid)
    - For square images, inputs are $I \in \mathbb{R}^{n_{\text{pixels}} \times n_{\text{pixels}} \times n_{\text{features}}}$

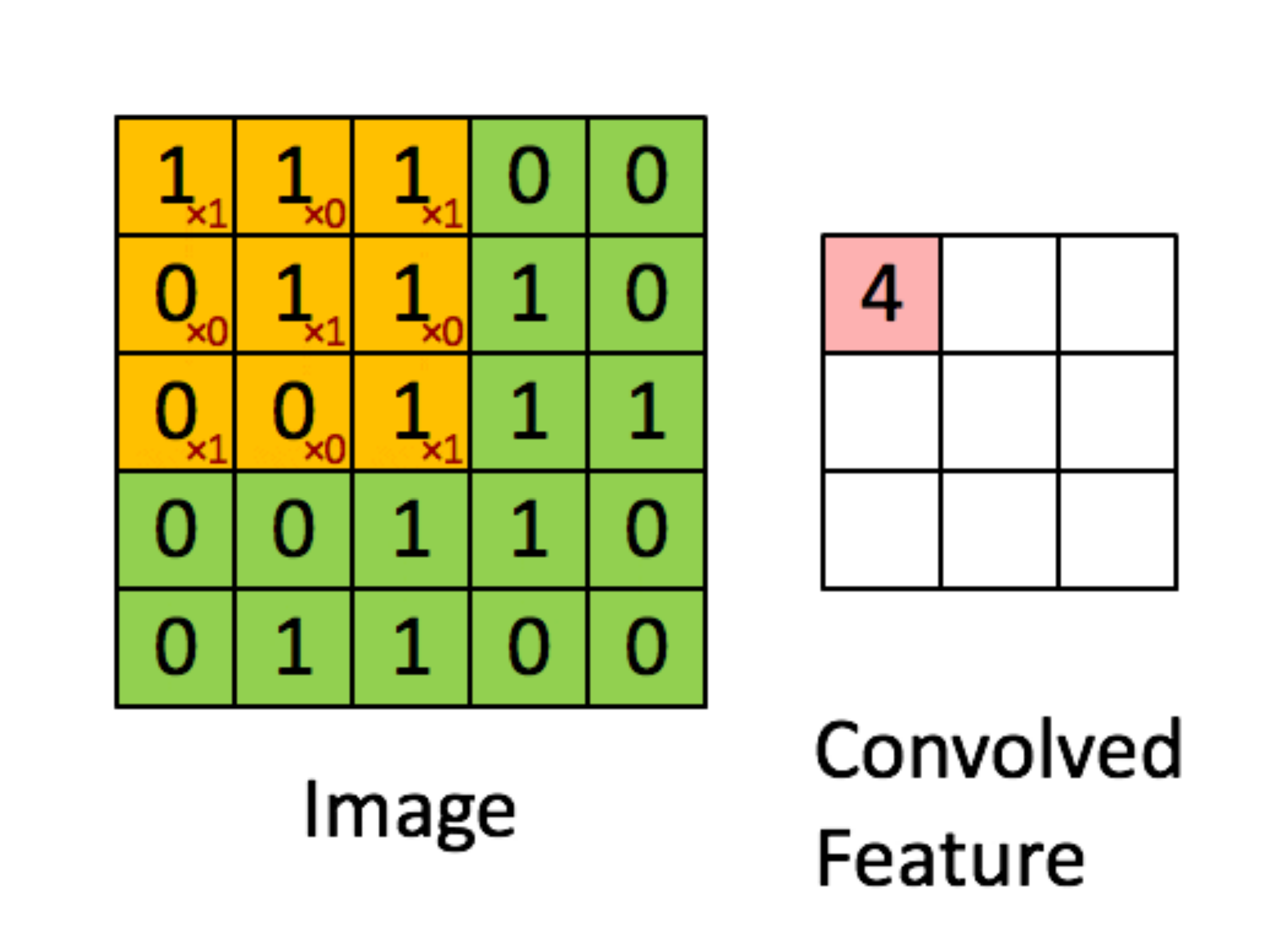


https://ai.plainenglish.io/complete-guide-image-classification-on-cifar-10-chapter-i-multiclass-logistic-regression-525daee0775b

Convolutional Neural Networks (CNNs)

- Very similar approach to DNNs (non-sequential inputs, feed-forward approach), except now we use *convolutional* layers
  - Convolution: filter is *convolved* (weighted sum with learnable weights) with the input image
  - Again, parameter sharing!





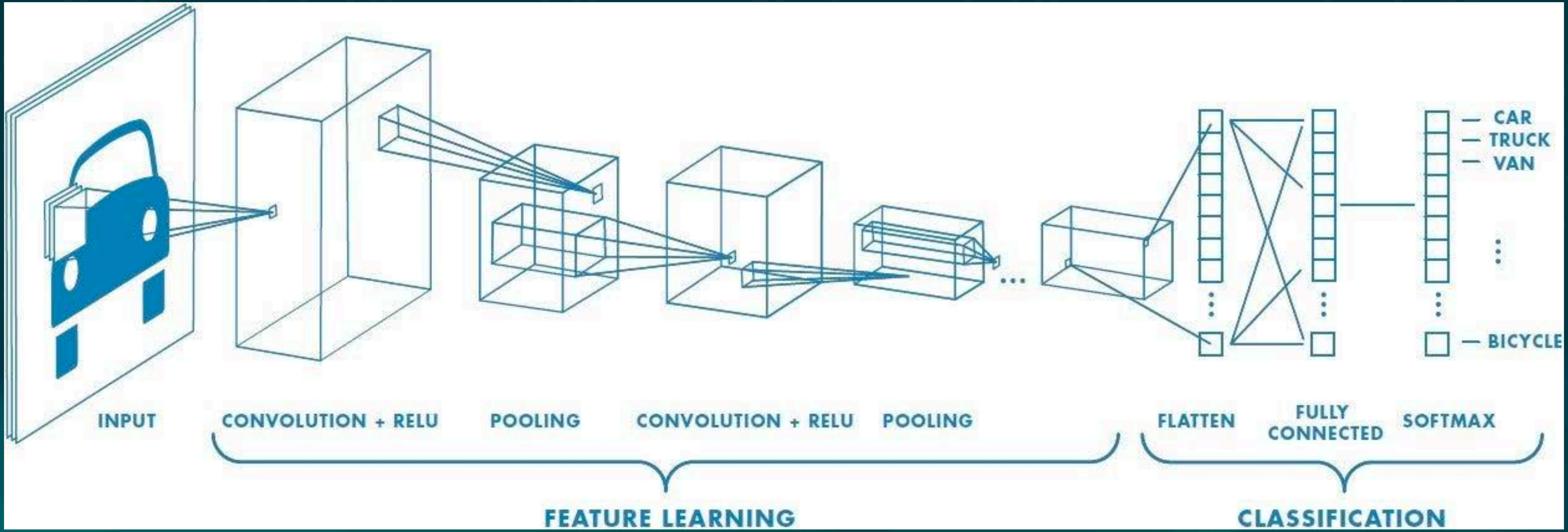
1 ×1	1 ×0	1 ×1	0	0
0 ×0	1 ×1	1 ×0	1	0
0 ×1	0 ×0	1 ×1	1	1
0	0	1	1	0
0	1	1	0	0

Image

4		

Convolved Feature

Convolutional Neural Networks (CNNs)

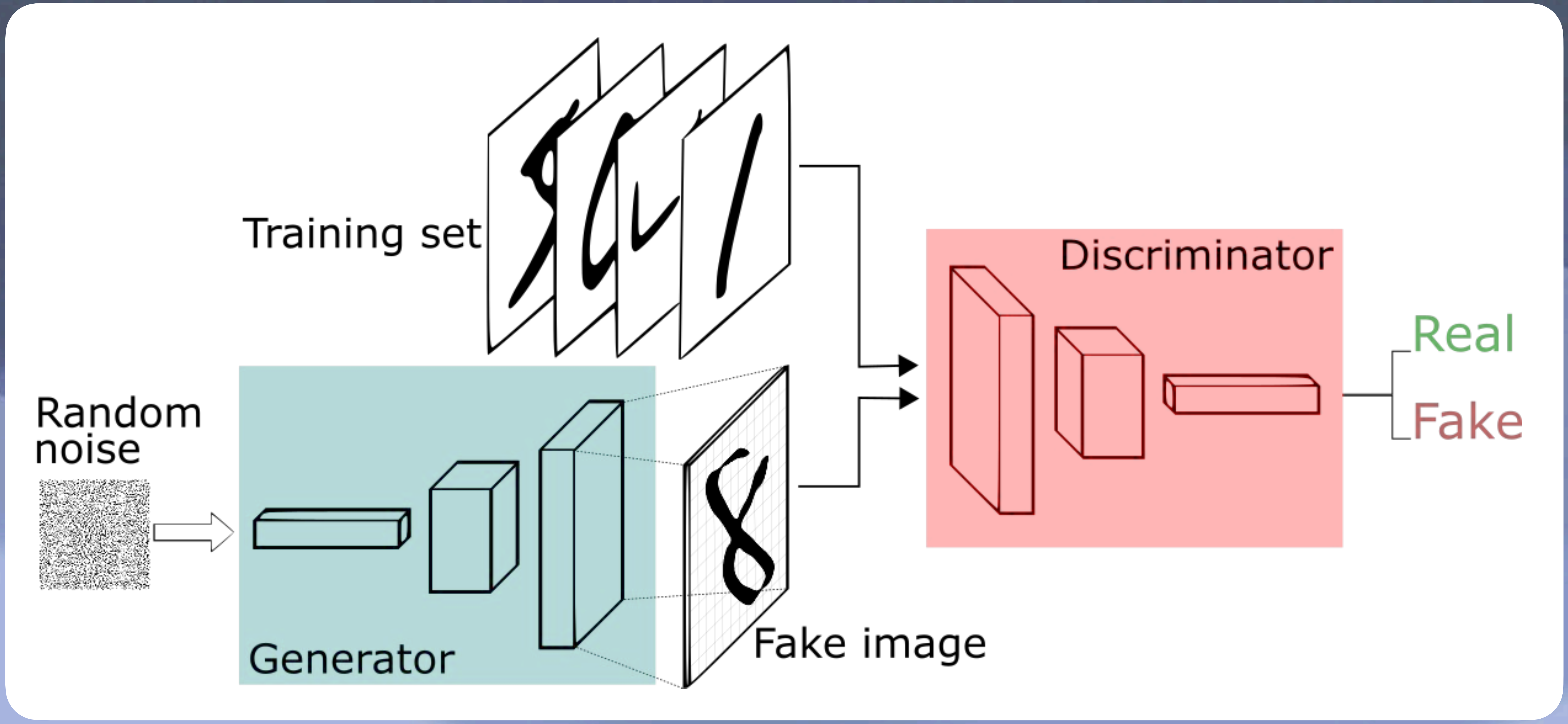


https://miro.medium.com/v2/resize:fit:1358/1*vkQ0hXDaQv57sALXAJquxA.jpeg

Generative Adversarial Networks (GANs)

Survey of Deep Learning Architectures

- “Generative” AI: use ML to create new images, sounds, etc.
- GANs: two agents (the *generator* and the *discriminator*) are given competing tasks:

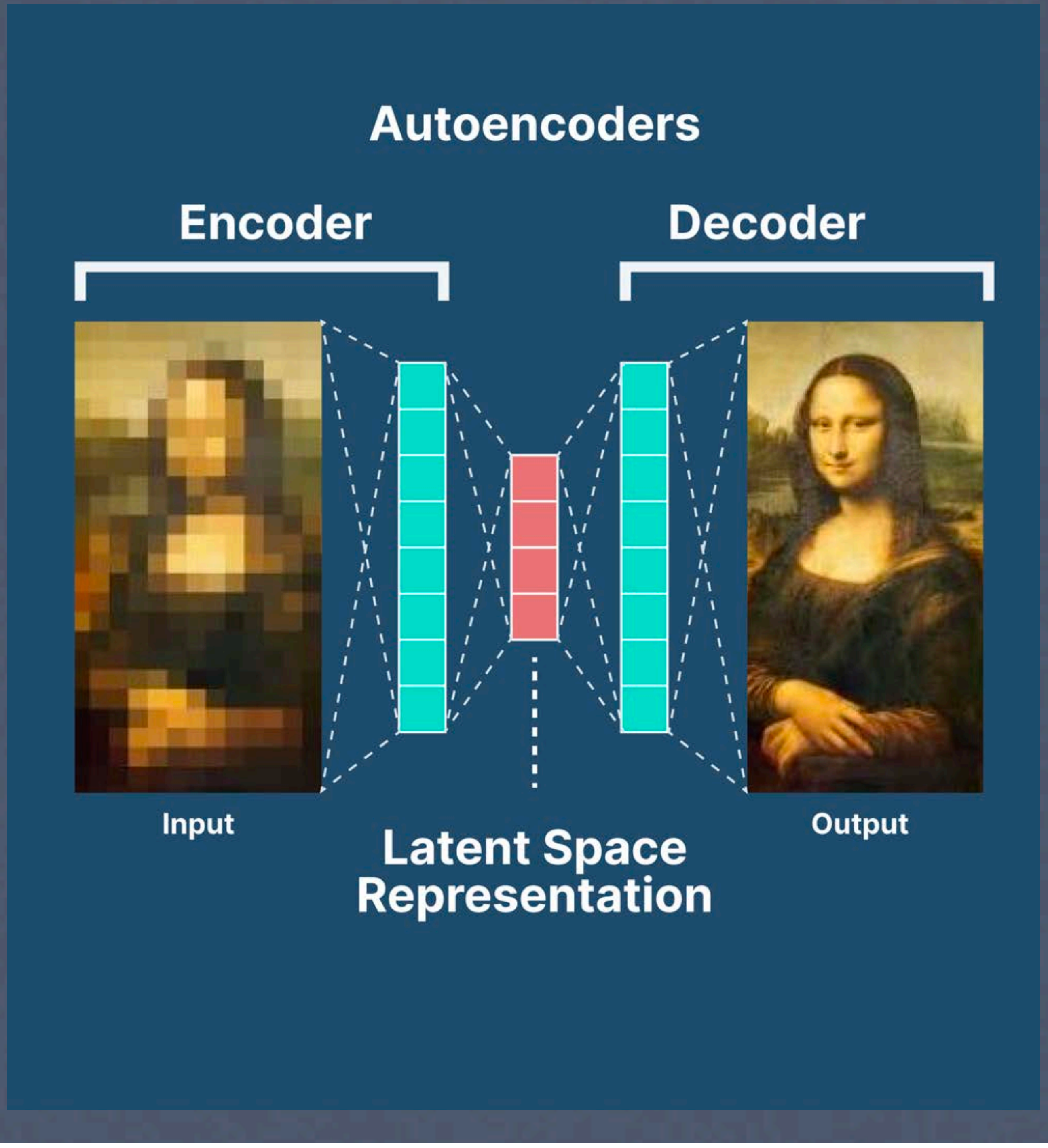


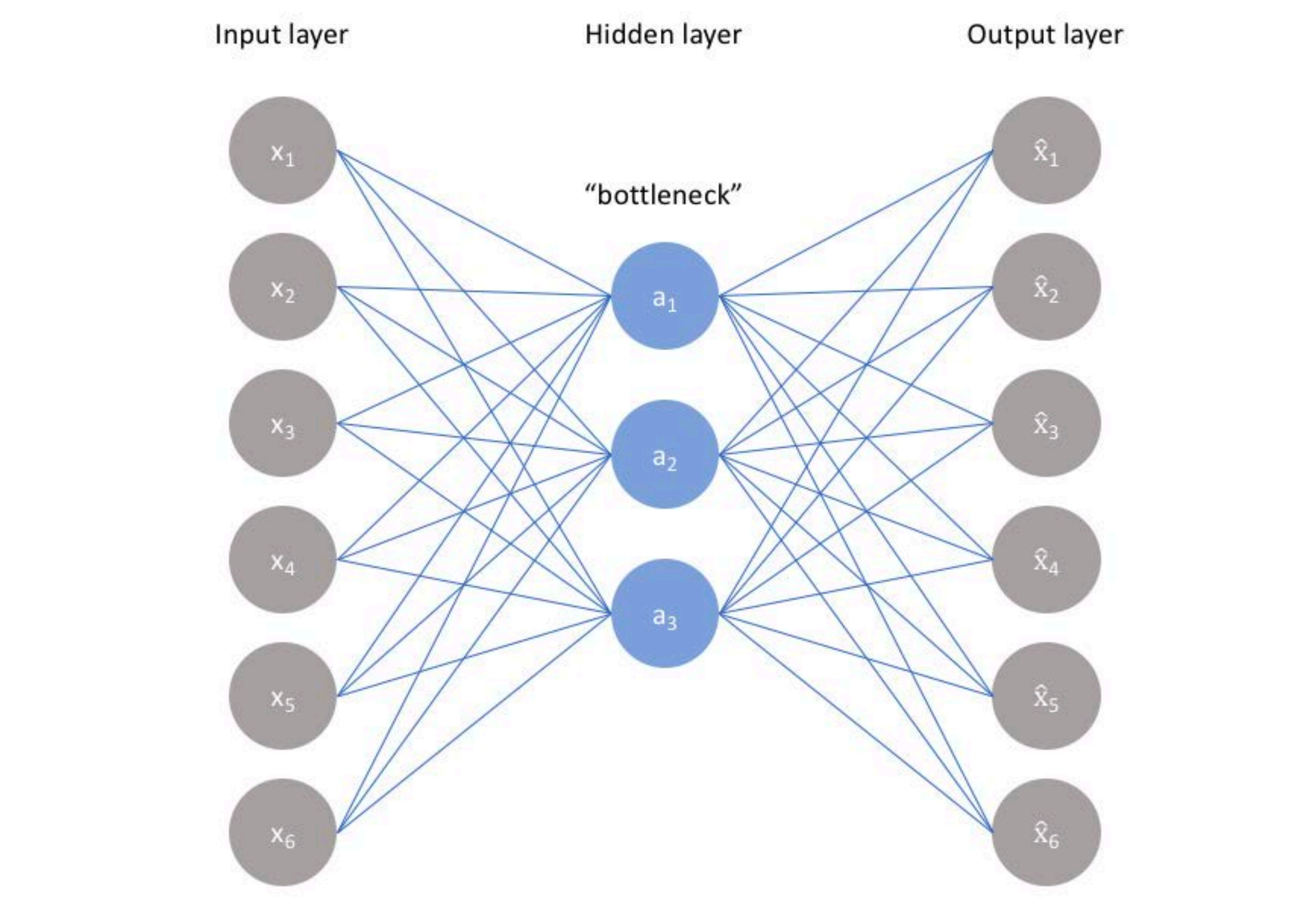
https://sthalles.github.io/intro-to-gans/

Autoencoders

Learning Efficient Codings

- Autoencoders are used to produce compressed data representations
  - **Encoder**: produces a lower-dimensional (compressed) “latent” representation of the input data
  - **Decoder**: given the compressed representation, reconstruct the original data
- Decoded representations typically less noisy,
- Uses: efficient encoding, image denoting, generative modeling, anomaly detection



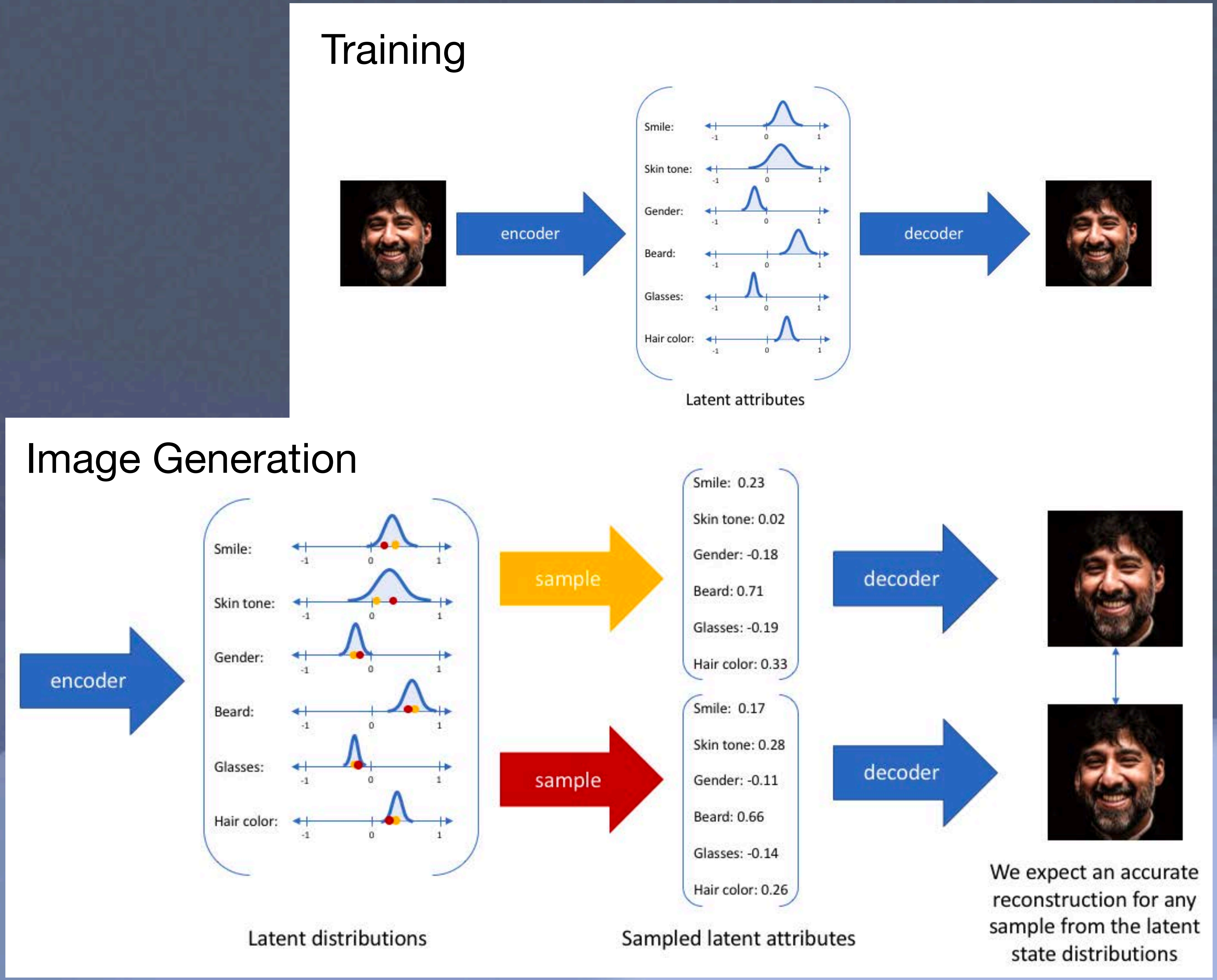


https://www.v7labs.com/blog/autoencoders-guide#:~:text=An%20autoencoder%20is%20an%20unsupervised,even%20generation%20of%20image%20data.

Variational Autoencoder (VAEs)

Generative Modeling via Autoencoders

- Generate realistic images from random noise
  - **Encoder**: predict means and standard deviations of a *probability distribution* over the latent features
  - **Decoder:** given a random sample from the latent distributions, produce the corresponding output



We expect an accurate reconstruction for any sample from the latent state distributions

https://www.jeremyjordan.me/variational-autoencoders/

SCAN ME