A deeper dive into loading data

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Maham Faisal Khan
Senior Data Scientist

Back to our animals dataset

```python
import pandas as pd
pd.read_csv('animals.csv')
```

animal_name	hair	feathers	eggs	milk	predator	fins	legs	tail	type
skimmer	0	1	1	0	1	0	2	1	2
gull	0	1	1	0	1	0	2	1	2
seahorse	0	0	1	0	0	1	0	1	4
tuatara	0	0	1	0	1	0	4	1	3
squirrel	1	0	0	1	0	0	2	1	1

Type key: **mammal** (1), **bird** (2), **reptile** (3), **fish** (4), **amphibian** (5), **bug** (6), **invertebrate** (7).

Back to our animals dataset: defining features

```python
import numpy as np
# Define input features
features = animals.iloc[:, 1:-1]
X = features.to_numpy()
print(X)
```

```
array([[0, 1, 1, 0, 1, 0, 2, 1],
       [0, 0, 1, 0, 0, 1, 0, 1],
       [0, 1, 1, 0, 1, 0, 2, 1],
       [1, 0, 0, 1, 0, 0, 2, 1],
       [0, 0, 1, 0, 1, 0, 4, 1]])
```

Back to our animals dataset: defining target values

```python
# Define target features (ground truth)
target = animals.iloc[:, -1]
y = target.to_numpy()
```

```
array([2, 2, 4, 3, 1])
```

Recalling TensorDataset

```python
import torch
from torch.utils.data import TensorDataset
```

```python
# Instantiate dataset class
dataset = TensorDataset(torch.tensor(X).float(), torch.tensor(y).float())
```

```python
# Access an individual sample
sample = dataset[0]
input_sample, label_sample = sample
print('input sample:', input_sample)
print('label_sample:', label_sample)
```

```
input sample: tensor([0., 1., 1., 0., 1., 0., 2., 1.])
label_sample: tensor(2.)
```

Recalling DataLoader

```python
from torch.utils.data import DataLoader
```

```python
batch_size = 2
shuffle = True

# Create a DataLoader
dataloader = DataLoader(dataset, batch_size=batch_size, shuffle=shuffle)
```

Recalling DataLoader

```python
# Iterate over the dataloader
for batch_inputs, batch_labels in dataloader:
    print('batch inputs', batch_inputs)
    print('batch labels', batch_labels)
```

```
batch inputs: tensor([[0., 0., 1., 0., 0., 1., 0., 1.],
                      [0., 1., 1., 0., 1., 0., 2., 1.]])
batch labels: tensor([4., 2.])
batch inputs: tensor([[0., 1., 1., 0., 1., 0., 2., 1.],
                      [1., 0., 0., 1., 0., 0., 2., 1.]])
batch labels: tensor([2., 1.])
batch inputs: tensor([[0., 0., 1., 0., 1., 0., 4., 1.]])
batch labels: tensor([3.])
```

Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Evaluating model performance

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Maham Faisal Khan
Senior Data Scientist

Training, validation and testing

- Raw dataset is usually split in three subsets:

	Percent of data	Role
Training	80-90%	Used to adjust the model's parameters
Validation	10-20%	Used for hyperparameter tuning
Testing	5-10%	Only used once to calculate final metrics

Model evaluation metrics

- In this video, we'll focus on evaluating:
  - **Loss**
    - Training
    - Validation
  - **Accuracy**
    - Training
    - Validation

- In classification, **accuracy** measures how well model correctly predicts ground truth labels

Calculating training loss

- For each epoch:
  - we sum up the loss for each iteration of the training set dataloader
  - at the end of the epoch, we calculate the mean training loss

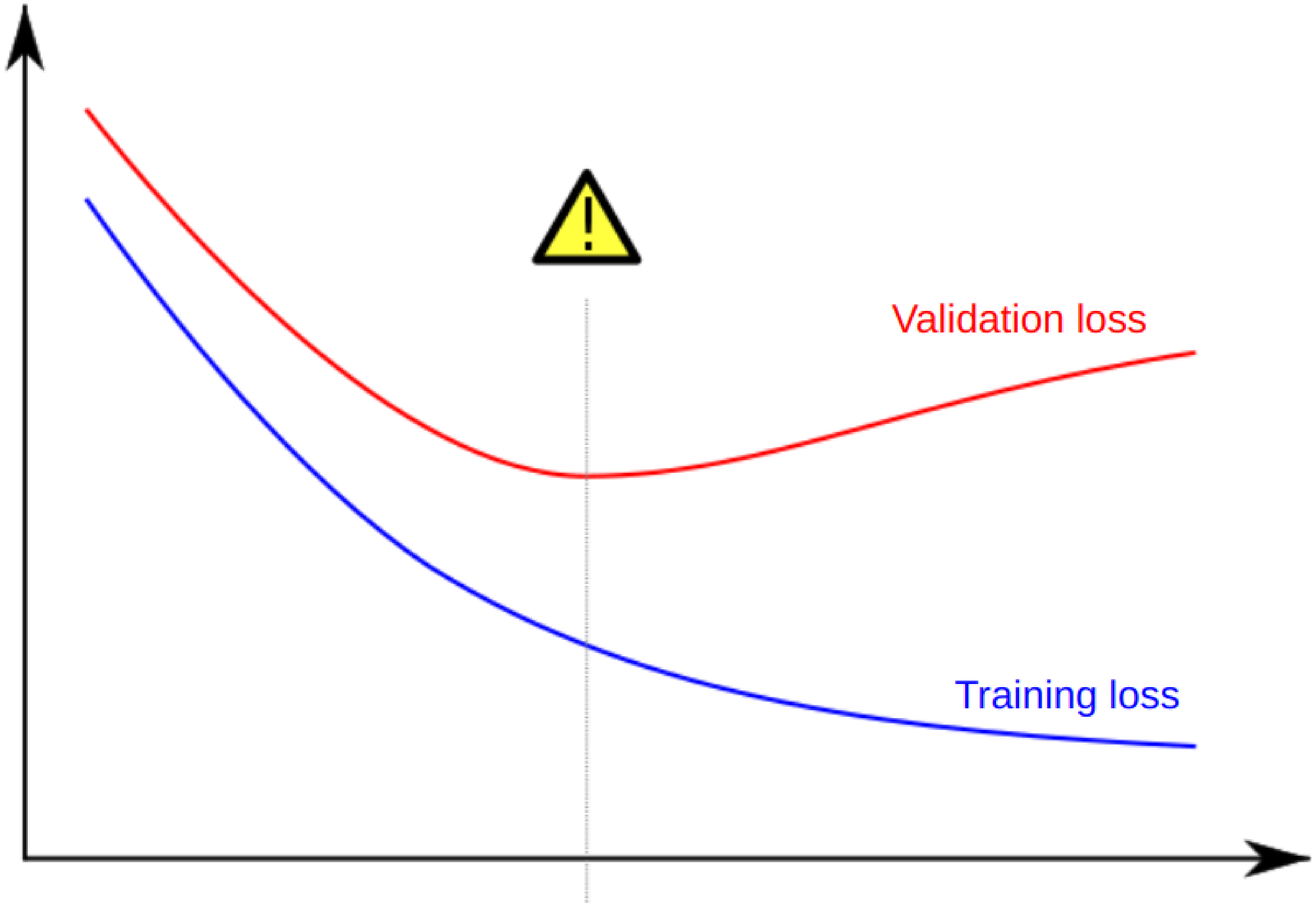
```
training_loss = 0.0
for i, data in enumerate(trainloader, 0):
    # Run the forward pass
    ...

    # Calculate the loss
    loss = criterion(outputs, labels)
    # Calculate the gradients
    ...
    # Calculate and sum the loss
    training_loss += loss.item()
epoch_loss = training_loss / len(trainloader)
```

Calculating validation loss

- After the training epoch, we iterate over the validation set and calculate the average validation loss

```
validation_loss = 0.0
model.eval() # Put model in evaluation mode
with torch.no_grad(): # Speed up the forward pass
  for i, data in enumerate(validationloader, 0):
      # Run the forward pass
      ...
      # Calculate the loss
      loss = criterion(outputs, labels)
      validation_loss += loss.item()
epoch_loss = validation_loss / len(validationloader)
model.train()
```

Overfitting



Calculating accuracy with torchmetrics

```python
import torchmetrics

# Create accuracy metric using torch metrics
metric = torchmetrics.Accuracy(task="multiclass", num_classes=3)
for i, data in enumerate(dataloader, 0):
    features, labels = data
    outputs = model(features)
    # Calculate accuracy over the batch
    acc = metric(output, labels.argmax(dim=-1))
# Calculate accuracy over the whole epoch
acc = metric.compute()
print(f"Accuracy on all data: {acc}")
# Reset the metric for the next epoch (training or validation)
metric.reset()
```

Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Fighting overfitting

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Maham Faisal Khan
Senior Data Scientist

Reasons for overfitting

- **Overfitting:** the model does not generalize to unseen data.
  - model memorizes training data
  - good performances on the training set / poor performances on the validation set
- Possible causes:

Problem	Solutions
Dataset is not large enough	Get more data / use data augmentation
Model has too much capacity	Reduce model size / add dropout
Weights are too large	Weight decay

Fighting overfitting

Strategies:

- Reducing model size or adding dropout layer
- Using weight decay to force parameters to remain small
- Obtaining new data or augmenting data

"Regularization" using a dropout layer

- Randomly zeroes out elements of the input tensor **during training**

```
model = nn.Sequential(nn.Linear(8, 4),
                      nn.ReLU(),
                      nn.Dropout(p=0.5))
features = torch.randn((1, 8))
model(i)
```

```
tensor([[1.4655, 0.0000, 0.0000, 0.8456]], grad_fn=<MulBackward0>)
```

- Dropout is added **after** the activation function
- Behaves differently during training and evaluation; we must remember to switch modes using `model.train()` and `model.eval()`

Regularization with weight decay

```
optimizer = optim.SGD(model.parameters(), lr=1e-3, weight_decay=1e-4)
```

- Optimizer's `weight_decay` parameter takes values between zero and one
  - Typically small value, e.g. 1e-3
- Weight decay adds penalty to loss function to discourage large weights and biases
- The higher the parameter, the less likely the model is to overfit

Data augmentation

Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Improving model performance

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Maham Faisal Khan
Senior Data Scientist

Steps to maximize performance

- Overfit the training set
  - can we solve the problem?
  - sets a performance baseline
- Reduce overfitting
  - improve performances on the validation set
- Fine-tune hyperparameters

Step 1:

Overfit the training set

Step 2:

Reduce overfitting

Step 3:

Fine-tune the hyperparameters

Step 1: overfit the training set

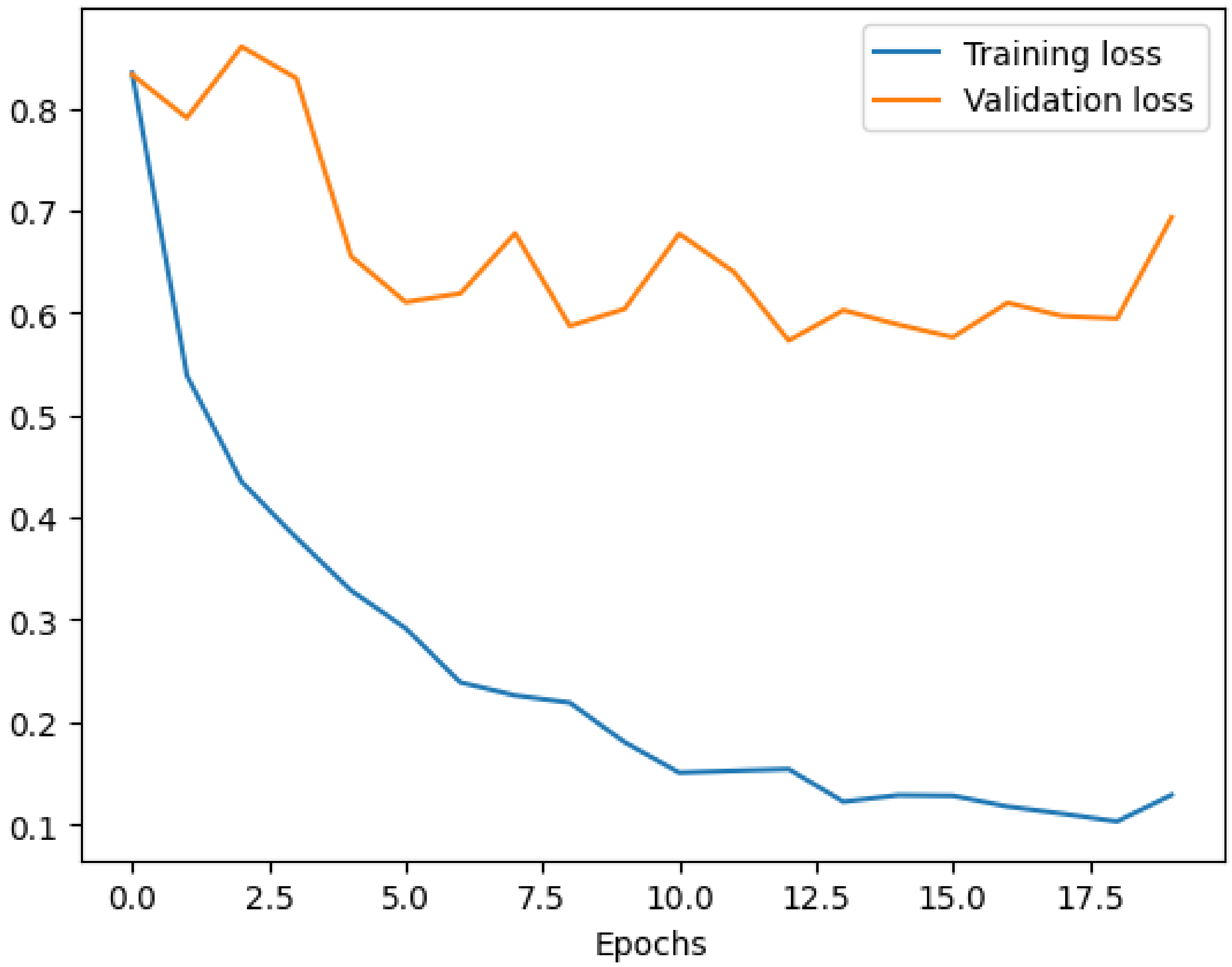
- Modify the training loop to overfit a single data point (batch size of 1)

```
features, labels = next(iter(trainloader))
for i in range(1e3):
  outputs = model(features)
  loss = criterion(outputs, labels)
  loss.backward()
  optimizer.step()
```

  - should reach 1.0 accuracy and 0 loss
  - helps findings bugs in the code
- **Goal:** minimize the training loss
  - create large enough model
  - use a default learning rate

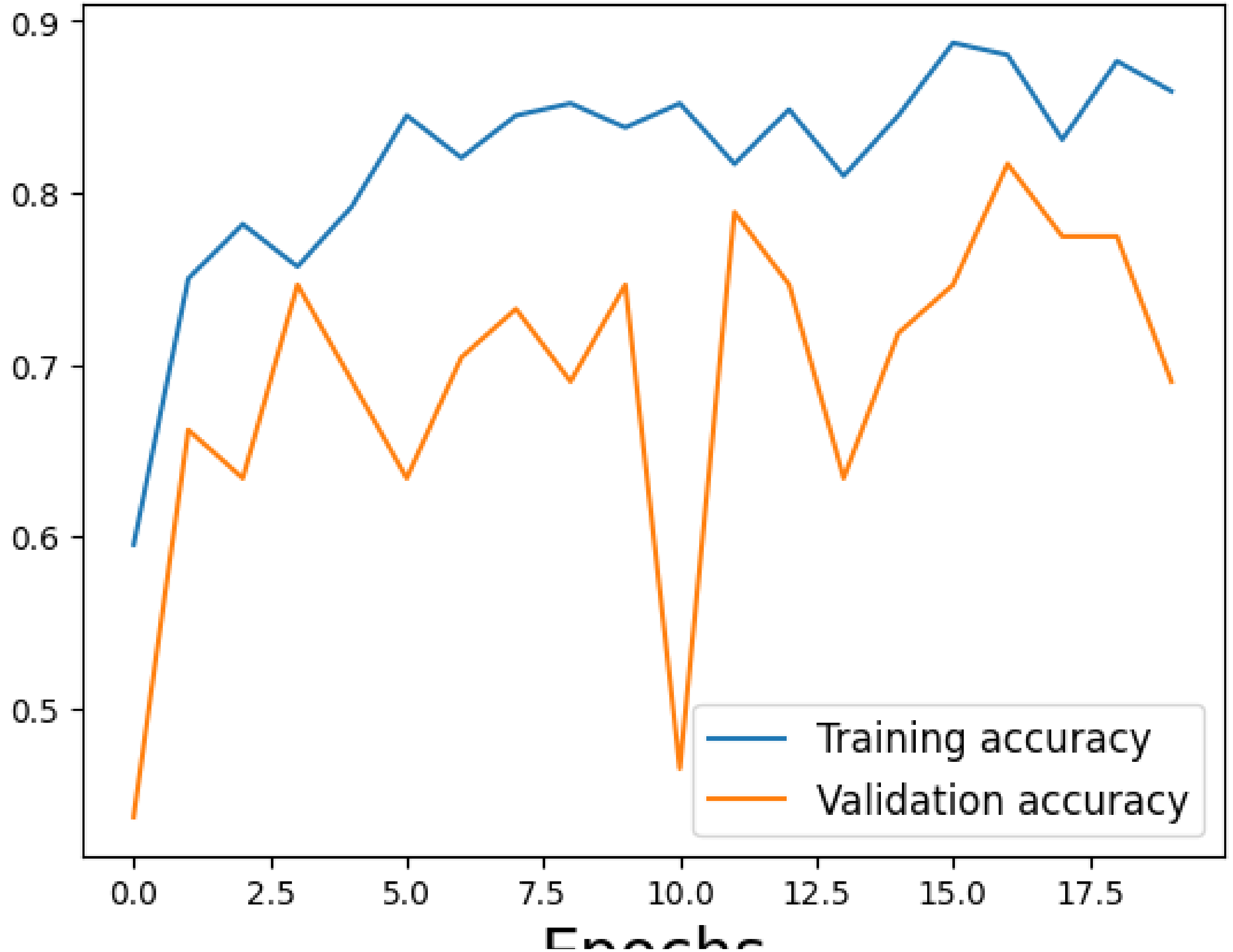
Step 2: reduce overfitting

- **Goal:** maximize the validation accuracy
- Experiment with:
  - Dropout
  - Data augmentation
  - Weight decay
  - Reducing model capacity
- Keep track of each hyperparameter and report maximum validation accuracy

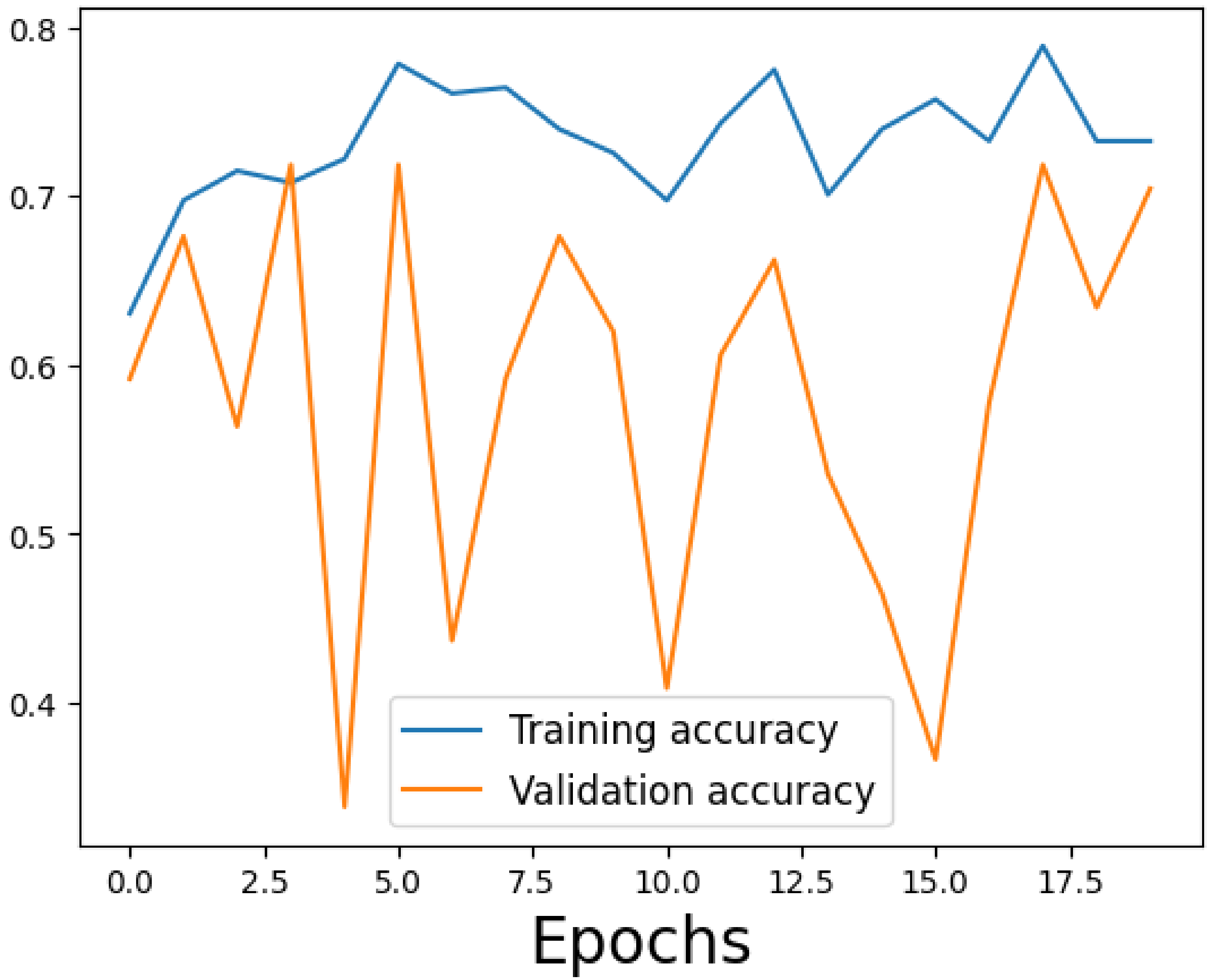


Step 2: reduce overfitting

Original model overfitting the training data



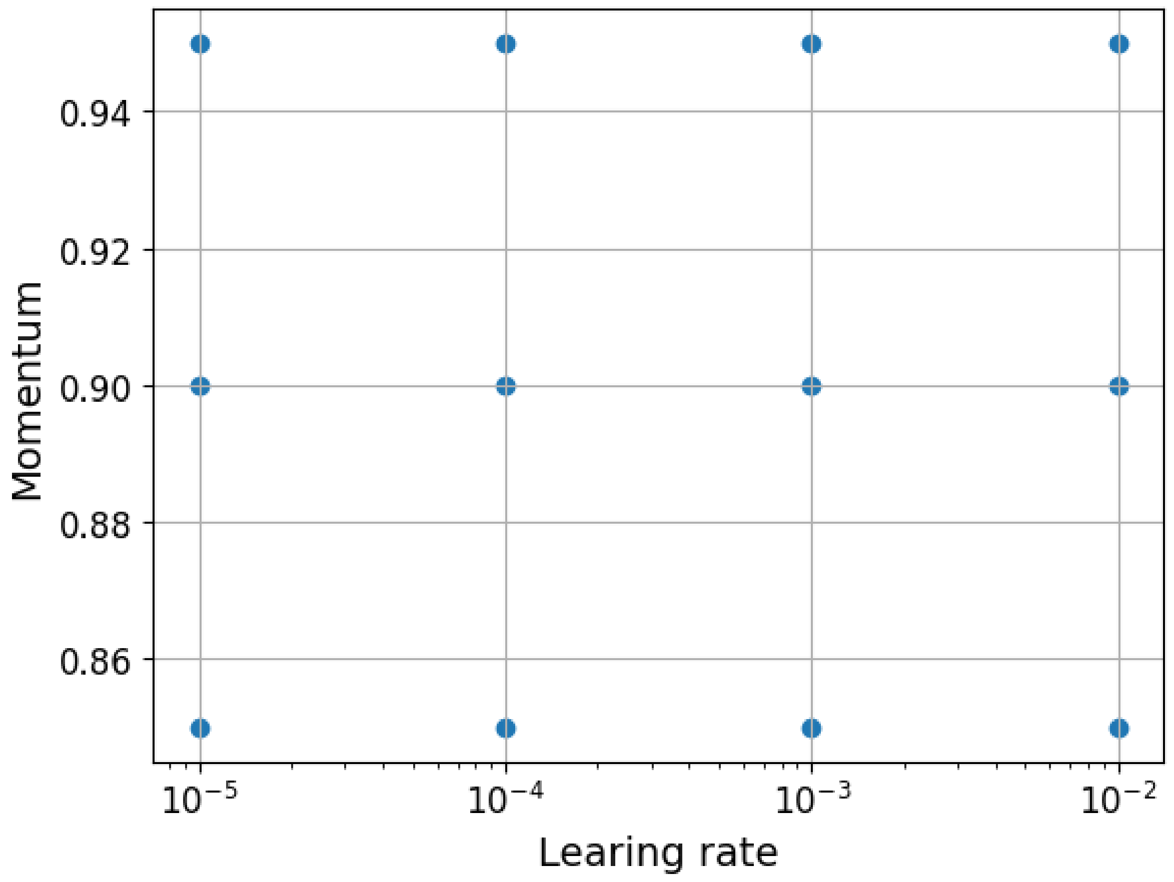
Model with too much regularization



Step 3: fine-tune hyperparameters

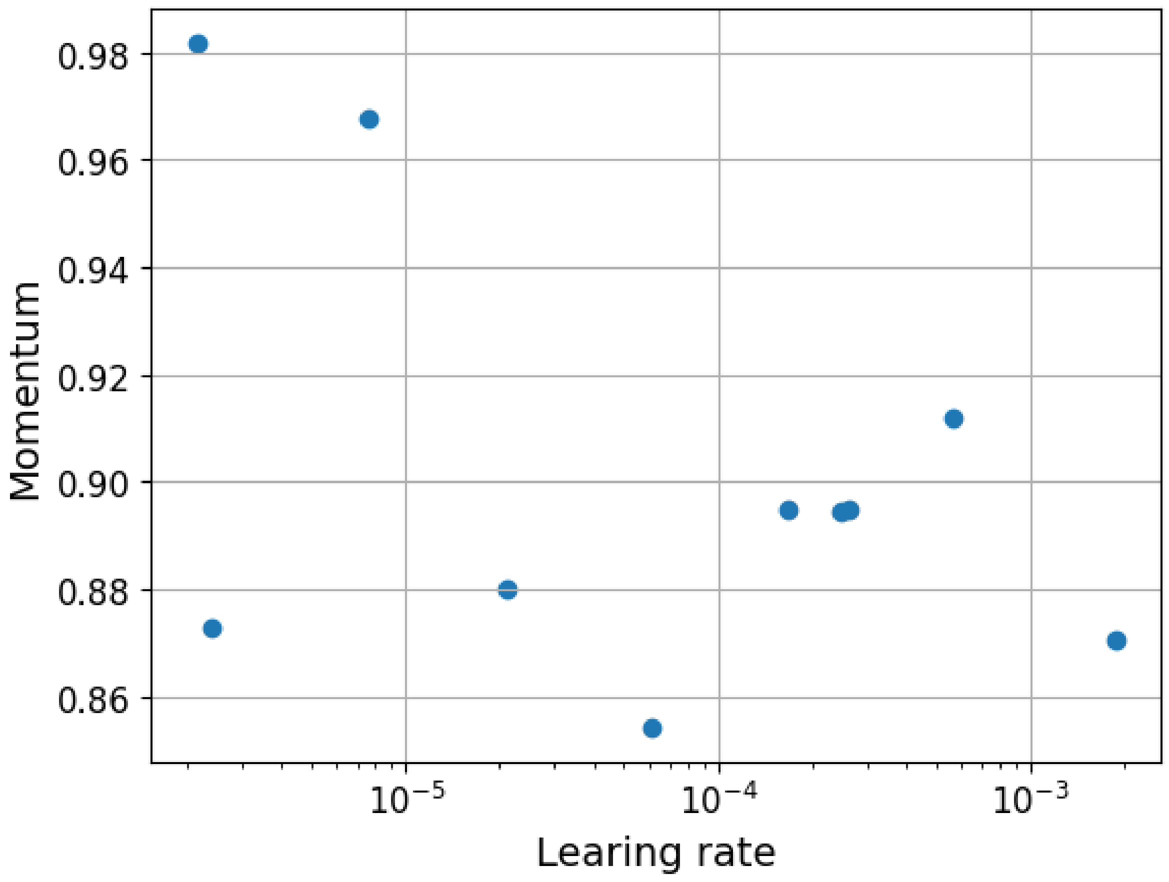
- Grid search

```python
for factor in range(2, 6):
    lr = 10 ** -factor
```



- Random search

```python
factor = np.random.uniform(2, 6)
lr = 10 ** -factor
```



Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

Wrap-up video

INTRODUCTION TO DEEP LEARNING WITH PYTORCH

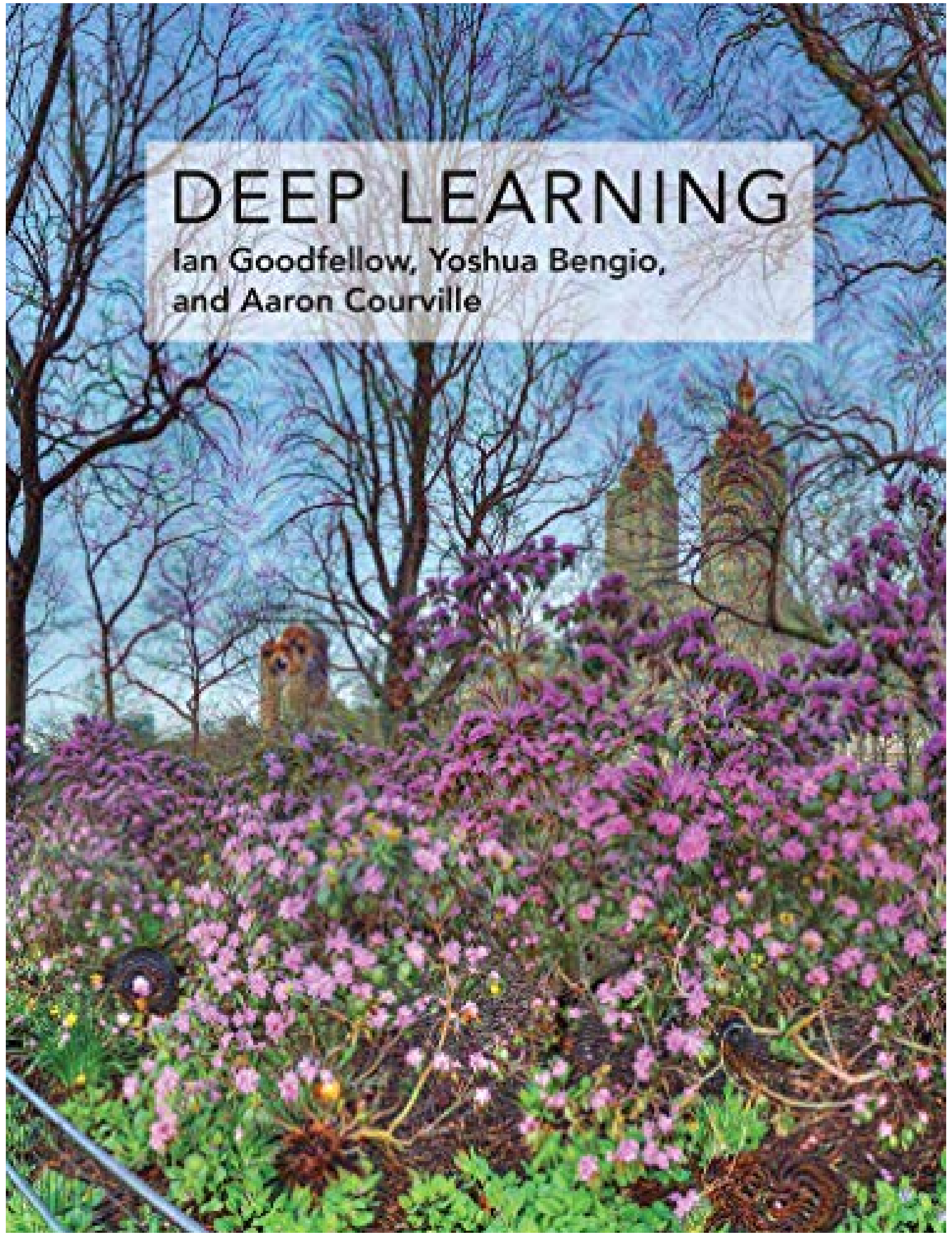
Maham Faisal Khan
Senior Data Scientist

Summary

- **Chapter 1**
  - Discovered deep learning
  - Created small neural networks
  - Discovered linear layers and activation functions
- **Chapter 2**
  - Created and used loss functions
  - Calculated derivatives and use backpropagation
  - Trained a neural network
- **Chapter 3**
  - Manipulated the architecture of a neural network
  - Played with learning rate and momentum
  - Learned about transfer learning
- **Chapter 4**
  - Learned about dataloaders
  - Reduced overfitting
  - Evaluated model performance

Next steps

- Course
  - Intermediate Deep Learning with PyTorch
- Learn
  - Probability and statistics
  - Linear algebra
  - Calculus
- Practice
  - Pick a dataset on Kaggle
  - Check out DataCamp workspace
  - Train a neural network



Let's practice!

INTRODUCTION TO DEEP LEARNING WITH PYTORCH