

50.039 Theory and Practice of Deep Learning

W3-S3 Introduction to Deep Learning using the PyTorch framework

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Introduction (Week 3)

1. What is the **PyTorch library** and its **benefits**?
2. What is a **PyTorch tensor object** and its typical **attributes**?
3. How to implement some typical **tensor operations**?
4. What is **broadcasting** on tensors?
5. What are **tensor locations** in terms of computation?
6. How to **transform our original NumPy shallow Neural Network** class so it uses **PyTorch** now instead?
7. How to implement a **forward, loss** and **accuracy** metric in PyTorch?
8. What are some measurable **performance benefits** of using **PyTorch** over NumPy and **GPUs** over CPUs?

Introduction (Week 3)

9. What is the **autograd/backprop** module in PyTorch, and how does it use a **computational graph** to **compute all derivatives**?
10. How to use the **autograd** to implement **derivatives** and a **vanilla gradient descent**?
11. How to implement **backprop** in PyTorch for our **shallow Neural Network** class?
12. How to use **PyTorch** to implement **advanced optimizers**?
13. How to use **PyTorch** to implement **advanced initializers**?
14. How to use **PyTorch** to implement **regularization**?
15. How to finally revise our **trainer** function to obtain a minimal, yet complete Neural Network in PyTorch?

Introduction (Week 3)

16. What are the **Dataset** and **Dataloader** objects in **PyTorch**?
17. How to implement a custom **Dataloader** and **Dataset** object in PyTorch?
18. How to move from binary classification to **multi-class classification**?
19. How to adjust output probabilities using the **softmax** function?
20. How to change the **cross-entropy loss** so it works in **multi-class classification**?
21. How to implement **building blocks** in PyTorch?
22. How to implement and train our first **Deep Neural Network**?
23. What are **additional good practices** in PyTorch?

To summarize (last two sessions)

We now have a full Neural Network class, in PyTorch, with:

- 2 linear layers, sigmoid activation functions,
- Xavier uniform initialization on trainable parameters,
- Forward pass method,
- Autograd backpropagation and trainer method,
- Adam optimizer,
- Dataloader allowing for stochastic mini-batches,
- Cross entropy loss and accuracies,
- L1 regularization.

And it runs/trains at the speed of light (almost...) on GPU!

```

class ShallowNeuralNet_PT(torch.nn.Module):
    def __init__(self, n_x, n_h, n_y, device):
        super().__init__()
        self.n_x, self.n_h, self.n_y = n_x, n_h, n_y
        self.linear1 = nn.Linear(n_x, n_h, dtype = torch.double)
        self.linear2 = nn.Linear(n_h, n_y, dtype = torch.double)
        self.loss = torch.nn.BCELoss()
        self.accuracy = BinaryAccuracy()
    def forward(self, inputs):
        return torch.sigmoid(self.linear2(torch.sigmoid(self.linear1(inputs))))
    def train(self, inputs, outputs, N_max = 1000, alpha = 1, beta1 = 0.9, beta2 = 0.999, \
              batch_size = 32, lambda_val = 1e-3):
        dataset = torch.utils.data.TensorDataset(inputs, outputs)
        data_loader = torch.utils.data.DataLoader(dataset, batch_size = batch_size, shuffle = True)
        optimizer = torch.optim.Adam(self.parameters(), lr = alpha, betas = (beta1, beta2), eps = 1e-08)
        optimizer.zero_grad()
        self.loss_history = []
        for iteration_number in range(1, N_max + 1):
            for batch in data_loader:
                inputs_batch, outputs_batch = batch
                total_loss = self.loss(self(inputs_batch), outputs_batch.to(torch.float64))\
                    + lambda_val*sum(torch.abs(param).sum() for param in self.parameters()).item()
                self.loss_history.append(total_loss)
                total_loss.backward()
                optimizer.step()
                optimizer.zero_grad()
            if(iteration_number % (N_max//20) == 1):
                pred = self(inputs)
                acc_val = self.accuracy(pred, outputs).item()
                print("Iteration {} - Loss = {} - Accuracy = {}".format(iteration_number, total_loss, acc_val))

```

Writing a custom Dataset object

Most of the time, when demonstrating concepts, we will rely on a "simple" **built-in dataset**, available in the PyTorch library.

In practice, and more specifically in your project, you will often play with a **custom dataset**, fitting your needs.

- Most datasets will be provided by your company, or can be found on dataset search engines, such as **Kaggle**, **Google Dataset Search**, etc.
- Today, we will play with a simplified version of the **Ames Housing Dataset**, which can be found online, here:
<https://www.kaggle.com/datasets/prevek18/ames-housing-dataset?resource=download>

A look at our dataset Excel file

	A	B	C	D	E	F	G	H	I	J	K	
1	Lot Area	Overall Qual	Overall Cond	Year Built	Year Remod/Add	Total Bsmt SF	1st Flr SF	2nd Flr SF	Gr Liv Area	Full Bath	Half Bath	Bedro
2	31770	6	5	1960	1960	1080	1656	0	1656	1	0	
3	11622	5	6	1961	1961	882	896	0	896	1	0	
4	14267	6	6	1958	1958	1329	1329	0	1329	1	1	
5	11160	7	5	1968	1968	2110	2110	0	2110	2	1	
6	13830	5	5	1997	1998	928	928	701	1629	2	1	
7	9978	6	6	1998	1998	926	926	678	1604	2	1	
8	4920	8	5	2001	2001	1338	1338	0	1338	2	0	
9	5005	8	5	1992	1992	1280	1280	0	1280	2	0	
10	5389	8	5	1995	1996	1595	1616	0	1616	2	0	
11	7500	7	5	1999	1999	994	1028	776	1804	2	1	
12	10000	6	5	1993	1994	763	763	892	1655	2	1	
13	7980	6	7	1992	2007	1168	1187	0	1187	2	0	
14	8402	6	5	1998	1998	789	789	676	1465	2	1	
15	10176	7	5	1990	1990	1300	1341	0	1341	1	1	
16	6820	8	5	1985	1985	1488	1502	0	1502	1	1	
17	53504	8	5	2003	2003	1650	1690	1589	3279	3	1	
18	12134	8	7	1988	2005	559	1080	672	1752	2	0	
19	11394	9	2	2010	2010	1856	1856	0	1856	1	1	
20	19138	4	5	1951	1951	864	864	0	864	1	0	
21	13175	6	6	1978	1988	1542	2073	0	2073	2	0	
22	11751	6	6	1977	1977	1844	1844	0	1844	2	0	
23	10625	7	6	1974	1974	1052	1172	0	1172	2	0	

Writing a custom Dataset object

The Ames dataset includes a variety of features for approximately 2,800 houses in Ames, Iowa.

- Features include the size of the house (in square feet), the number of bedrooms and bathrooms, and many more. It also includes the sale price for each house.
- The Ames Housing Dataset is a popular choice for machine learning projects, and it has been used to build AI models for predicting house prices, based on various house features.
- It consists of an Excel file (AmesHousing.xlsx) stored in the ./ames/ folder. The original dataset can be found in the AmesHousing.csv file, but we have simplified it by removing some of its features.

Writing a custom Dataset object

The features we are interested in are:

- **Lot Area:** The area of the lot in square feet.
- **Overall Qual:** A rating of the overall material and finish of the house (1-10).
- **Overall Cond:** A rating of the overall condition of the house (1-10).
- **Year Built:** The year the house was built.
- **Year Remod/Add:** The year the house was remodeled or had an addition added.
- And many more features! (not describing all of them)
- The last column is the selling price, which is our output.

Writing a custom Dataset object

Let us start by loading the **Excel** file into a pandas **DataFrame** first.

*(Note: Not familiar with the **pandas** library? Find 10 minutes to learn it, it will definitely serve you in the long run!*

https://pandas.pydata.org/docs/user_guide/10min.html

```
1 # Load dataset using pandas, and showing the first five entries
2 ames_dataset = pd.read_excel("./ames/AmesHousing.xlsx")
3 print(ames_dataset.head(5))
```

	Lot Area	Overall Qual	Overall Cond	Year Built	Year Remod/Add	\
0	31770	6	5	1960	1960	
1	11622	5	6	1961	1961	
2	14267	6	6	1958	1958	
3	11160	7	5	1968	1968	
4	13830	5	5	1997	1998	

	Total Bsmt SF	1st Flr SF	2nd Flr SF	Gr Liv Area	Full Bath	Half Bath	\
0	1080	1656	0	1656	1	0	
1	882	896	0	896	1	0	
2	1329	1329	0	1329	1	1	
3	2110	2110	0	2110	2	1	
4	928	928	701	1629	2	1	

	Bedroom AbvGr	Kitchen AbvGr	TotRms AbvGrd	Garage Area	Yr Sold	\
0	3	1	7	528	2010	
1	2	1	5	730	2010	
2	3	1	6	312	2010	
3	3	1	8	522	2010	
4	3	1	6	482	2010	

	SalePrice
0	215000
1	105000
2	172000
3	244000
4	189900

Writing a custom Dataset object

To write a custom **dataset class** in PyTorch, we need to:

- Create a **class** that **subclasses** **torch.utils.data.Dataset**.
- Define a an **__init__** that loads the excel file and stores data accordingly.
- Define a **__getitem__** that takes **index** as input, and **returns** the **data** and **label** at that index as an array. This will allow to use the square bracket notation on our dataset object.
- Define a method **__len__** that returns the **number of samples in the dataset**.

```
class AmesHousingDataset(torch.utils.data.Dataset):

    #The init method will simply initialize attributes, which consist
    # of the details related to the dataset.
    def __init__(self, file_path = "./ames/AmesHousing.xlsx"):
        # Whole data as a pandas array
        self.data = pd.read_excel(file_path)
        self.dataset_length = len(self.data) #2928

        # Extract inputs
        self.input_features_number = 16
        self.input_features = self.data.iloc[:, :16]

        # Extract outputs
        self.output_features_number = 1
        self.output_feature = self.data.iloc[:, 16]

    # The getitem method returns the sample with given index
    # x will consist of the 16 input features for the given sample,
    # whereas y will consist of the 1 output feature for the given sample.
    def __getitem__(self, index):
        # Fetch inputs
        x = self.input_features.iloc[index].values
        # Fetch outputs
        y = self.output_feature.iloc[index]
        return x, y

    # Finally, the len special method should return the number of samples,
    # in the dataset. We could use self.dataset_length, but it is more
    # modular to use len(self.data).
    def __len__(self):
        return len(self.data)
```

Writing a custom Dataset object

The `__getitem__()` and `__len__()` special methods will allow for **indexing** and **using for loops** on the dataset object.

- Later on, we could ask for the sample #286 using the square bracket notation, as shown on side.

Similarly, the two special methods are all we need to make a **for loop** that uses the dataset object as the **generator** to be looped over!

```

1 # Instantiate the dataset
2 ames_dataset = AmesHousingDataset('./ames/AmesHousing.xlsx')
3
4 # Fetch sample with index 286
5 sample_input, sample_output = ames_dataset[286]
6 # Input is a (16,) numpy array, with the following values
7 print(type(sample_input), sample_input.shape)
8 print(sample_input)
9 # Output is a single value, of type numpy int64
10 print(type(sample_output), sample_output.shape)
11 print(sample_output)

```

```

<class 'numpy.ndarray'> (16,)
[6858    6    4 1915 1950   806   841   806 1647    1    1    4    1    6
 216 2010]
<class 'numpy.int64'> ()
128000

```

More on the for loop later!

Writing a custom Dataloader

We can then use this custom Dataloader object as the generator in a **for loop**, to generate mini-batches of samples.

- Notice how this Dataloader generates **92** (i.e. $2928/32$, rounded up) **batches** of **32 samples**.
- With the exception of the **last batch** (with index 91), that only contains **16 samples** (that is $2928 \% 32$).

Restricted

```
1 for batch_number, batch in enumerate(ames_dataloader):
2     inputs, outputs = batch
3     print("---")
4     print("Batch number: ", batch_number)
5     print(inputs.shape)
6     print(outputs.shape)
```

```
---
Batch number:  0
torch.Size([32, 16])
torch.Size([32])
```

```
---
Batch number:  1
torch.Size([32, 16])
torch.Size([32])
```

```
---
Batch number:  2
torch.Size([32, 16])
torch.Size([32])
```

```
---
Batch number:  3
torch.Size([32, 16])
torch.Size([32])
```

```
---
Batch number:  4
```

```
---
Batch number:  91
torch.Size([16, 16])
torch.Size([16])
```

Restricted

Writing a custom Dataloader

We can then use this custom Dataloader object as the generator in a **for loop**, to generate mini-batches of samples.

- **Good practice:** the custom Dataset and custom Dataloader definition should be repeated to generate **training, testing** and **validation sets dataloaders**.
- These Dataloaders will then be given to our **trainer** function.

```
1 for batch_number, batch in enumerate(ames_dataloader):
2     inputs, outputs = batch
3     print("---")
4     print("Batch number: ", batch_number)
5     print(inputs.shape)
6     print(outputs.shape)
```

```
---
Batch number:  0
torch.Size([32, 16])
torch.Size([32])
```

```
---
Batch number:  1
torch.Size([32, 16])
torch.Size([32])
```

```
---
Batch number:  2
torch.Size([32, 16])
torch.Size([32])
```

```
---
Batch number:  3
torch.Size([32, 16])
torch.Size([32])
```

```
---
Batch number:  4
```

```
---
Batch number:  91
torch.Size([16, 16])
torch.Size([16])
```


Built-in datasets

Pytorch has a few **built-in datasets**, ready to be downloaded and used on models: typically, the most common ones that have been used in research to demonstrate concepts, such as **MNIST** or **CIFAR-10**.

For more details on the available **built-in datasets** in Pytorch, have a look at the following page:

<https://pytorch.org/vision/stable/datasets.html>.

Built-in datasets

Let us demonstrate using the **FashionMNIST** dataset first.

- This dataset inputs consists of 28 by 28 greyscale images.
- Each input is therefore a 28 by 28 matrix, where each element value represents the grey shade of the pixel at the given location.
- Logic: 0 = black, 1 = white, and anything between 0 and 1 describes a shade of grey.

```
1 # Dictionary of labels and their identification
2 labels_map = {0: "T-Shirt",
3               1: "Trouser",
4               2: "Pullover",
5               3: "Dress",
6               4: "Coat",
7               5: "Sandal",
8               6: "Shirt",
9               7: "Sneaker",
10              8: "Bag",
11              9: "Ankle Boot"}
```

```
1 # Define folder path as string
2 # Dataset will be downloaded and stored there.
3 folder_path = "./data"
4
5 # Download (download = True) training data (train = True)
6 # to folder specified in root parameter.
7 # The transform parameter specifies that the image samples will
8 # be converted to Tensors, ready to be used by models.
9 training_data = datasets.FashionMNIST(root = folder_path, \
10                                     train = True, \
11                                     download = True, \
12                                     transform = ToTensor())
```

Built-in datasets

Let us demonstrate using the **FashionMNIST** dataset first.

- This dataset is used to design image classification models (i.e. models that receive images as inputs) and attempt to predict what is in the image in question.
- The 10 output classes (bag, shirt, etc.) are indexed with 0-9 values, corresponding to the 10 types of fashion objects found in the dataset.

```
1 # Dictionary of labels and their identification
2 labels_map = {0: "T-Shirt",
3               1: "Trouser",
4               2: "Pullover",
5               3: "Dress",
6               4: "Coat",
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10              8: "Bag",
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```

Built-in datasets

Let us demonstrate using the **FashionMNIST** dataset first.

- This dataset is used to design image classification models (i.e. models that receive images as inputs) and attempt to predict what is in the image in question.
- The 10 output classes (bag, shirt, etc.) are indexed with 0-9 values, corresponding to the 10 types of fashion objects found in the dataset.

```
1 # Dataset contains 60000 samples, that are greyscale
2 # images with size 28 by 28 pixels.
3 print(training_data.data.shape)
```

```
torch.Size([60000, 28, 28])
```

```
1 # We can then fetch a sample using the [] notations
2 sample_index = 894
3 img, label = training_data[sample_index]
4 print("Image: ", img.shape)
5 print("Label: ", label)
```

```
Image: torch.Size([1, 28, 28])
```

```
Label: 8
```

```
1 # Display sample
2 sample_index = 894
3 img, label = training_data[sample_index]
4 plt.figure(figsize = (3, 3))
5 plt.axis("off")
6 plt.imshow(img.squeeze(), cmap="gray")
7 plt.title("Image {} - Label = {} ({})"
8           .format(sample_index, \
9                   label, \
10                  labels_map[label]))
10 plt.show()
```

Image 894 - Label = 8 (Bag)



Introducing the MNIST dataset

MNIST is another widely-used dataset for the benchmarking of machine learning and computer vision algorithms.

It consists of

- a **training set** of 60,000 examples,
- and a **testing set** of 10,000 examples.

All samples consist of 28x28 pixel grayscale images of handwritten digits (0 to 9).

MNIST is often used as a "Hello, World!" dataset example, due to its simplicity, which allows for efficient implementations of ML/DL algorithms.



Introducing the MNIST dataset

MNIST is another widely-used dataset for the benchmarking of machine learning and computer vision algorithms.

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- a **training set** of 60,000 examples,
- and a **testing set** of 10,000 examples.

All samples consist of 28x28 pixel grayscale images of handwritten digits (0 to 9).

Careful however: the MNIST dataset is often accused of having been **overused** (which is true) and of **being too simple**.

For now, however, this will do.



Introducing the MNIST dataset

Nevertheless, it is a good dataset to use for testing and comparing the performance of different models, as well as for getting familiar with the basics of machine learning and deep learning algorithms.

- The images serve as inputs, and the task is therefore to predict which of the ten digits appears in the image.

- This is therefore a **classification task**, like before, except that it consists of **10 different classes** (corresponding to the 0-9 digits) **instead of just two like in binary classification**.



Writing the MNIST Dataset and Dataloader

```
1 # Define transform to convert images to tensors and normalize them
2 transform_data = Compose([ToTensor(),
3                             Normalize((0.1307,), (0.3081,))])
4
5 # Load the data
6 batch_size = 64
7 train_dataset = MNIST(root='./mnist/', train = True, download = True, transform = transform_data)
8 test_dataset = MNIST(root='./mnist/', train = False, download = True, transform = transform_data)
9 train_loader = torch.utils.data.DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
10 test_loader = torch.utils.data.DataLoader(test_dataset, batch_size = batch_size, shuffle = False)
```

```
1 # Try the dataloader
2 for batch_number, batch in enumerate(train_loader):
3     inputs, outputs = batch
4     print("---")
5     print("Batch number: ", batch_number)
6     print(inputs.shape)
7     print(outputs.shape)
8     break
```

```
---
Batch number: 0
torch.Size([64, 1, 28, 28])
torch.Size([64])
```


Quick parenthesis: normalizing input data

Good practice: Always a good idea to normalize your inputs!

In general, do the following:

- Scale the data (pixel values) to the $[0,1]$ range.
- Normalize to have zero mean and unit standard deviation.

In MNIST, we will then subtract a mean of 0.1307 and divide by a standard deviation of 0.3081.

These values are the original mean and standard deviation of the dataset before normalization!

```
# Define transform to convert images to tensors and normalize them
transform_data = Compose([ToTensor(),
                           Normalize((0.1307,), (0.3081,))])
```

Writing the MNIST Dataset and Dataloader

```
1 # Define transform to convert images to tensors and normalize them
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9 train_loader = torch.utils.data.DataLoader(train_dataset, batch_size = batch_size, shuffle = True)
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```
1 # Try the dataloader
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6     print(inputs.shape)
7     print(outputs.shape)
8     break
```

```
---
Batch number: 0
torch.Size([64, 1, 28, 28])
torch.Size([64])
```

From binary to multi-class classification

Recall (**Binary classification probabilities as output**):

In **binary classification**, we would produce a single value p as output, with p between 0 and 1.

- This value p would correspond to the **probability of being of class 1**.
- The **probability of being of class 0** would then simply be $1 - p$.
- We would then use a **threshold 0.5** to decide if the sample is predicted of class 0 or 1.

From binary to multi-class classification

Problem: How could we produce multi-class classification probabilities for all possible $N > 2$ classes as outputs?

Unfortunately, when we have more than 2 classes, **we can no longer rely on a single output value p .**

- Instead, it is often preferable to have the model output **10 values:**
$$(p_0, p_1, p_2, \dots p_9)$$
- Where each p_i corresponds to the **probability of being of class i .**
- This could typically be done by asking for **the final layer to produce $n_y = 10$ values** instead of just a single $n_y = 1$ value.

From binary to multi-class classification

Unfortunately, this is not good enough.

- The p_i produced by the network are supposed to represent **probabilities** and **their sum should therefore be equal to 1**, i.e.

$$\sum_{i=0}^9 p_i = 1$$

A **fully connected (or linear) layer** (which implements the $WX + b$ operation) cannot do that on its own, as

- it might produce negative values as probabilities p_i ,
- and those values may not sum up to 1.

From binary to multi-class classification

To normalize the outputs produced by the final fully connected layer, we will use the **softmax** operation, which is a special activation function.

It has two effects:

- It will force the values of the p_i to fall in the range of $[0, 1]$.
- It will force their sum to be equal to 1, that is

$$\sum_{i=0}^9 p_i = 1$$

Softmax function

Definition (the **softmax** function):

The **softmax** operation

$$p_i = s(y_i, y_{-i})$$

is defined, $\forall i$, as:

$$p_i = s(y_i, y_{-i}) = \frac{\exp(y_i)}{\sum_{k=0}^K \exp(y_k)}$$

Note: the y_{-i} notation comes from game theory, and consists of every element in vector Y except y_i , i.e.:

$$y_{-i} = (y_1, \dots, y_{i-1}, y_{i+1}, \dots, y_K)$$

Softmax function

Definition (the softmax function):

The **softmax function** transforms a vector of values

$$Y = (y_0, y_1, y_2, \dots, y_K),$$

into another vector of values

$$P = (p_0, p_1, p_2, \dots, p_K).$$

The new vector **P** is guaranteed to contain positive values, and those values will be summing up to **1**, i.e.

$$\sum_{i=0}^K p_i = 1$$

Softmax function

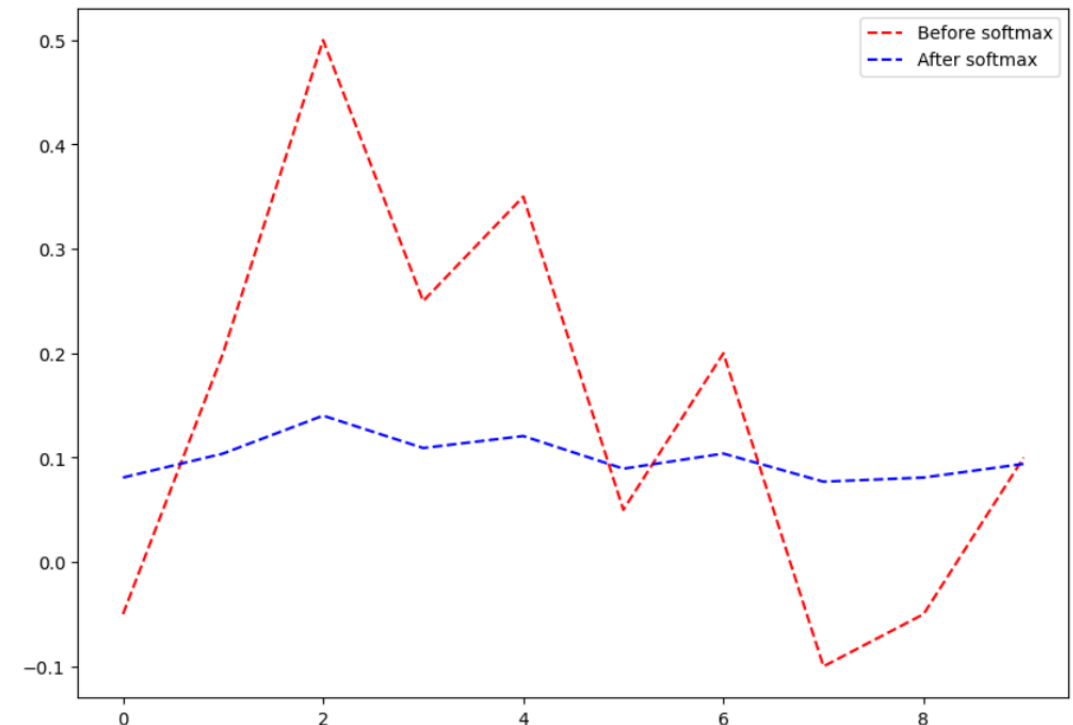
Softmax can be manually implemented as:

```
1 def softmax(x):
2     # Subtract the maximum value from each element of the input vector x
3     # to avoid numerical instability (this is optional, but equivalent)
4     x = x - np.max(x)
5     # Compute the exponent of each element
6     exp_x = np.exp(x)
7     # Normalize the exponentiated values by their sum
8     return exp_x/np.sum(exp_x)
```

```
1 # Ten values that do not sum up to 1
2 Y = np.array([-1, 4, 10, 5, 7, 1, 4, -2, -1, 2])/20
3 print(sum(Y))
4 P = softmax(Y)
5 print(P)
6 print(np.sum(P))
```

```
1.45
[0.08089815 0.10387528 0.14021696 0.10920108 0.12068586 0.08940628
 0.10387528 0.0769527  0.08089815 0.09399024]
0.9999999999999999
```

Softmax effect: It will rescale values so that the trend is preserved, but the new vector consists of positive values that sum up to 1.



Softmax function and prediction

In the case of multi-label classification, we will use the **softmax** operation **as the final activation after the last fully connected layer**.

This will produce a vector of 10 positive values,

$$P = (p_0, p_1, p_2, \dots p_9),$$

Which can be used as the **probabilities for sample of being of class i** .

The **predicted class according to the model** is then defined as the variable ***pred***, corresponding to the index i of the highest probability value p_i , i.e.:

$$pred = \arg \max_i [p_i].$$

Implementation

For instance, this simple neural network consists of **two fully-connected/linear layers**.

A **single ReLU activation** is used between both layers.

No final softmax activation yet.

It also consists of a **flattening** operation, which will transform our input images (2D tensors, size 28 by 28), into a “flattened” 1D tensor with size 784 ($= 28 \times 28$).

```
1 class ShallowNeuralNet(torch.nn.Module):
2     def __init__(self, n_x, n_h, n_y):
3         super().__init__()
4         # Define two layers using the nn.Linear()
5         self.fc1 = torch.nn.Linear(n_x, n_h)
6         self.fc2 = torch.nn.Linear(n_h, n_y)
7
8     def forward(self, x):
9         # Flatten images (transform them from 28x28 2D
10        # matrices to 784 1D vectors)
11        x = x.view(x.size(0), -1)
12        # First Wx + b operation
13        out1 = self.fc1(x)
14        # Using ReLU operation as activation after first layer
15        act1 = torch.relu(out1)
16        # Second Wx + b operation and return
17        out2 = self.fc2(act1)
18        return out2
```

Implementation

Consider a neural network model, with **784 input size**, **128 hidden size**, and **10 output size**, and transferring all the model parameters to a device (e.g. CUDA).

- Next, we get a **single sample** from the **train_loader** iterator and extract sample info in the variables **data** and **target**.
- This can be simply done with the **next** and **iter** functions.

```

1 # Initialize model
2 model = ShallowNeuralNet(n_x = 784, \
3                           n_h = 128, \
4                           n_y = 10).to(device)
5
6 # Get a single sample
7 sample = next(iter(train_loader))
8 data, target = sample
9 print(data.shape)
10 print(target.shape)
11 data1 = data[0].to(device)
12 target1 = target[0].to(device)
13 print(data1.shape)
14 print(target1)
15
16 # Forward pass
17 out2 = model(data1)
18 act2 = torch.nn.functional.softmax(out2, dim = 1)
19 print(out2)
20 print(act2)
21 print(act2.sum())

```

```

torch.Size([64, 1, 28, 28])
torch.Size([64])
torch.Size([1, 28, 28])
tensor(4, device='cuda:0')
tensor([[[-0.2145, -0.0527, -0.1197, -0.0488,  0.2503, -0.1870, -0.1401,  0.1202,
           0.1220,  0.1017]], device='cuda:0', grad_fn=<AddmmBackward0>])
tensor([[0.0812, 0.0954, 0.0892, 0.0958, 0.1292, 0.0834, 0.0874, 0.1134, 0.1136,
          0.1113]], device='cuda:0', grad_fn=<SoftmaxBackward0>])
tensor(1., device='cuda:0', grad_fn=<SumBackward0>)

```

Implementation

- Next, perform a forward pass through the model, storing the **output** in the variable **out2**.
- Apply the **softmax** operation on **out2**. PyTorch offers a functional implementation of the softmax:

torch.nn.functional.softmax()

- We can then verify that **softmax** will adjust the output of the neural network correctly.

```

1 # Initialize model
2 model = ShallowNeuralNet(n_x = 784, \
3                           n_h = 128, \
4                           n_y = 10).to(device)
5
6 # Get a single sample
7 sample = next(iter(train_loader))
8 data, target = sample
9 print(data.shape)
10 print(target.shape)
11 data1 = data[0].to(device)
12 target1 = target[0].to(device)
13 print(data1.shape)
14 print(target1)
15
16 # Forward pass
17 out2 = model(data1)
18 act2 = torch.nn.functional.softmax(out2, dim = 1)
19 print(out2)
20 print(act2)
21 print(act2.sum())

```

```

torch.Size([64, 1, 28, 28])
torch.Size([64])
torch.Size([1, 28, 28])
tensor(4, device='cuda:0')
tensor([[[-0.2145, -0.0527, -0.1197, -0.0488,  0.2503, -0.1870, -0.1401,  0.1202,
          0.1220,  0.1017]], device='cuda:0', grad_fn=<AddmmBackward0>])
tensor([[0.0812, 0.0954, 0.0892, 0.0958, 0.1292, 0.0834, 0.0874, 0.1134, 0.1136,
          0.1113]], device='cuda:0', grad_fn=<SoftmaxBackward0>])
tensor(1., device='cuda:0', grad_fn=<SumBackward0>)

```

Forward Implementation

Our model is however implementing the same forward method as before.

In fact, we will not use the softmax operation as the final activation function in the forward method.

This is normal as **the softmax operation** will be applied in the loss function instead, that is the **cross_entropy() function**, which will be summoned in the **trainer()** later.

```
1 class ShallowNeuralNet(torch.nn.Module):
2     def __init__(self, n_x, n_h, n_y):
3         super().__init__()
4         # Define two layers using the nn.Linear()
5         self.fc1 = torch.nn.Linear(n_x, n_h)
6         self.fc2 = torch.nn.Linear(n_h, n_y)
7
8     def forward(self, x):
9         # Flatten images (transform them from 28x28 2D
10        # matrices to 784 1D vectors)
11        x = x.view(x.size(0), -1)
12        # First Wx + b operation
13        out1 = self.fc1(x)
14        # Using ReLU operation as activation after first layer
15        act1 = torch.relu(out1)
16        # Second Wx + b operation and return
17        out2 = self.fc2(act1)
18        return out2
```

From binary cross entropy...

- Speaking of, in the case of the **binary classification**, we used the following loss function, namely the **log-likelihood binary cross entropy function**.

$$L(x, y) = -\frac{1}{N} \sum_k^N y_k \ln(p(x_k)) + (1 - y_k) \ln(1 - p(x_k))$$

- But in the case of MNIST, **we have more than two classes...**

How does the loss function change now that we have $N > 2$ classes?

...To multi-class cross entropy!

The adjustment is actually quite simple, and the **log-likelihood multi-class cross-entropy loss function** simply rewrites as shown below:

$$L(x, y) = -\frac{1}{N} \sum_k^N \sum_{i=0}^9 y_k^i \ln(p_i(x_k)).$$

In the formula above, $p_i(x_k)$ denotes the **probability for sample x_k of being of being predicted as class i** , according to our model.

In other words, it is the i -th value of the output vector produced by the model for sample x_k , **after softmax has been applied to the output o_i of the forward method of the model.**

...To multi-class cross entropy!

Recall the function in the previous slide:

$$L(x, y) = -\frac{1}{N} \sum_k^N \sum_{i=0}^9 y_k^i \ln(p_i(x_k)).$$

Similarly, we will define the value y_k^i as the ground truth value for the probability of being of class i for sample x_k .

For instance, if the sample x_k is of class $y_k = 2$, we define:

$$Y_k = (y_k^0, y_k^1, y_k^2, y_k^3, \dots, y_k^9) = (0, 0, 1, 0, \dots, 0).$$

We say that Y_k is the **one-hot vector** for the sample k with class 2.

Setting a model in train/eval mode

New good practice: some operations (layers, activations, etc.) in the forward method will have **two different behaviors** depending whether

- the model is currently **training**,
- or if we are using its trained version for **evaluation**.

(Note: at the moment, we have not seen such operations.)

But let us keep this in mind and accept that is good practice to set the model to either **train()** or **eval()** mode.

```
1 # Initialize the model and optimizer
2 model = ShallowNeuralNet(n_x = 784, n_h = 64, n_y = 10).to(device)
3 optimizer = torch.optim.Adam(model.parameters(), lr = 1e-3)
4 # Set model in train mode!
5 model.train()
```

Training our model with Adam GD, as before

```
1 # Training model
2 num_epochs = 5
3 for epoch in range(num_epochs):
4     # Go through all samples in train dataset
5     for i, (images, labels) in enumerate(train_loader):
6         # Get from dataloader and send to device
7         images = images.to(device)
8         labels = labels.to(device)
9         # Forward pass
10        outputs = model(images)
11        # Compute loss
12        loss = torch.nn.functional.cross_entropy(outputs, labels)
13        # Backward and optimize
14        optimizer.zero_grad()
15        loss.backward()
16        optimizer.step()
17        # Display
18        if (i+1) % 300 == 0:
19            print (f'Epoch [{epoch+1}/{num_epochs}], Step [{i+1}/{len(train_loader)}], Loss: {loss.item():.4f}')
```

```
Epoch [1/5], Step [300/938], Loss: 0.2895
Epoch [1/5], Step [600/938], Loss: 0.1588
Epoch [1/5], Step [900/938], Loss: 0.1753
Epoch [2/5], Step [300/938], Loss: 0.0461
Epoch [2/5], Step [600/938], Loss: 0.1251
Epoch [2/5], Step [900/938], Loss: 0.1592
Epoch [3/5], Step [300/938], Loss: 0.1241
Epoch [3/5], Step [600/938], Loss: 0.0511
Epoch [3/5], Step [900/938], Loss: 0.0553
Epoch [4/5], Step [300/938], Loss: 0.0514
Epoch [4/5], Step [600/938], Loss: 0.0339
```

Eval mode and accuracy after training

After training, we will evaluate our trained model to check its accuracy on the test set.

- Set the model in **eval()** mode (good practice for later).
- Predict on **test dataloader**.
- Calculate **accuracy** manually (we could have probably also used a torch function to do that).
- **97% accuracy = a rather nicely trained model!**

```
1 # Evaluate model accuracy on test after training
2 # Set model in eval mode!
3 model.eval()
4 # Evaluate
5 with torch.no_grad():
6     correct = 0
7     total = 0
8     for images, labels in test_loader:
9         # Get images and labels from test loader
10        images = images.to(device)
11        labels = labels.to(device)
12        # Forward pass and predict class using max
13        outputs = model(images)
14        _, predicted = torch.max(outputs.data, 1)
15        # Check if predicted class matches label
16        # and count number of correct predictions
17        total += labels.size(0)
18        correct += (predicted == labels).sum().item()
19 # Compute final accuracy and display
20 accuracy = correct/total
21 print(f'Evaluation after training, Accuracy: {accuracy:.4f}')
```

Evaluation after training, Accuracy: 0.9712

It is now time...

It is now time for us to define and train a **Deep Neural Network**.

Definition (Deep Neural Networks):

By definition, a **deep neural network** is a neural network, which consists of more than two hidden layers.

To demonstrate, we will create a deep neural network with four layers:

- **three linear layers** with **ReLU** activation,
- followed by **one linear layer**, finished with a **softmax activation**.

It is now time...

Reminder: it is good practice to have the size of layers decrease progressively by a factor of at least 2.

- the first layer has inputs size 784 and outputs size 80,
- the second layer has inputs size 80 and outputs size 40,
- the third layer has inputs size 40 and outputs size 20,
- and the fourth layer has inputs size 20 and outputs size 10, matching the number of classes in the dataset.

Note: a layer-by-layer model summary can be seen by printing the model object!

```
1 print(model)
```

```
DeepNeuralNet(  
  (layer1): DenseReLU(  
    (fc): Linear(in_features=784, out_features=80, bias=True)  
  )  
  (layer2): DenseReLU(  
    (fc): Linear(in_features=80, out_features=40, bias=True)  
  )  
  (layer3): DenseReLU(  
    (fc): Linear(in_features=40, out_features=20, bias=True)  
  )  
  (layer4): DenseNoReLU(  
    (fc): Linear(in_features=20, out_features=10, bias=True)  
  )  
)
```

Creating blocks

Good practice: create **building blocks** for modularity.

- The **DenseReLU** class is a custom PyTorch module that consists of a **linear layer** followed by a **ReLU activation** function.
- The **DenseNoReLU** class is similar, but it applies **no activation** function.

Important note: not using softmax as final activation here, for the same reasons as before.

```
1 class DenseReLU(torch.nn.Module):
2     def __init__(self, n_x, n_y):
3         super().__init__()
4         # Define Linear layer using the nn.Linear()
5         self.fc = torch.nn.Linear(n_x, n_y)
6
7     def forward(self, x):
8         # Wx + b operation
9         # Using ReLU operation as activation after
10        return torch.relu(self.fc(x))
```

```
1 class DenseNoReLU(torch.nn.Module):
2     def __init__(self, n_x, n_y):
3         super().__init__()
4         # Define Linear layer using the nn.Linear()
5         self.fc = torch.nn.Linear(n_x, n_y)
6
7     def forward(self, x):
8         # Wx + b operation
9         # No activation function
10        return self.fc(x)
```

Creating blocks

The DeepNeuralNet class will here represent the overall deep neural network.

It starts by initializing four layers:

- Three **DenseReLU** blocks,
- And one **DenseNoReLU** block.

It then combines all blocks into a single PyTorch sequential model using **torch.nn.Sequential()**.

```
class DeepNeuralNet(torch.nn.Module):
    def __init__(self, n_x, n_h, n_y):
        super().__init__()
        # Define three Dense + ReLU layers,
        # followed by one Dense + Softmax layer
        self.layer1 = DenseReLU(n_x, n_h[0])
        self.layer2 = DenseReLU(n_h[0], n_h[1])
        self.layer3 = DenseReLU(n_h[1], n_h[2])
        self.layer4 = DenseNoReLU(n_h[2], n_y)

        # Combine all four layers
        self.combined_layers = torch.nn.Sequential(self.layer1,
                                                    self.layer2,
                                                    self.layer3,
                                                    self.layer4)

    def forward(self, x):
        # Flatten images (transform them from 28x28
        # 2D matrices to 784 1D vectors)
        x = x.view(x.size(0), -1)
        # Pass through all four layers
        out = self.combined_layers(x)
        return out
```

```
# Initialize the model and optimizer
model = DeepNeuralNet(n_x = 784, n_h = [80, 40, 20], n_y = 10).to(device)
optimizer = torch.optim.Adam(model.parameters(), lr = 1e-3)
```


Creating blocks

The forward pass of the network is then simply defined, using the following steps:

- The input image is flattened, transforming a 2D tensor image into a 1D tensor,
- It is then passed through the combined layers/blocks we have assembled in the Sequential().

```
class DeepNeuralNet(torch.nn.Module):
    def __init__(self, n_x, n_h, n_y):
        super().__init__()
        # Define three Dense + ReLU layers,
        # followed by one Dense + Softmax layer
        self.layer1 = DenseReLU(n_x, n_h[0])
        self.layer2 = DenseReLU(n_h[0], n_h[1])
        self.layer3 = DenseReLU(n_h[1], n_h[2])
        self.layer4 = DenseNoReLU(n_h[2], n_y)

        # Combine all four layers
        self.combined_layers = torch.nn.Sequential(self.layer1,
                                                    self.layer2,
                                                    self.layer3,
                                                    self.layer4)

    def forward(self, x):
        # Flatten images (transform them from 28x28
        # 2D matrices to 784 1D vectors)
        x = x.view(x.size(0), -1)
        # Pass through all four layers
        out = self.combined_layers(x)
        return out
```

```
# Initialize the model and optimizer
model = DeepNeuralNet(n_x = 784, n_h = [80, 40, 20], n_y = 10).to(device)
optimizer = torch.optim.Adam(model.parameters(), lr = 1e-3)
```

Creating blocks

Good practice: This modular block-based approach, which

- **Defines blocks of layers,**
- **And eventually assembles them into a larger Deep Neural Network object,**

Is very common and convenient, especially when the architectures are very heavy and include many layers. It helps to organize the mess!

```
class DeepNeuralNet(torch.nn.Module):
    def __init__(self, n_x, n_h, n_y):
        super().__init__()
        # Define three Dense + ReLU layers,
        # followed by one Dense + Softmax layer
        self.layer1 = DenseReLU(n_x, n_h[0])
        self.layer2 = DenseReLU(n_h[0], n_h[1])
        self.layer3 = DenseReLU(n_h[1], n_h[2])
        self.layer4 = DenseNoReLU(n_h[2], n_y)

        # Combine all four layers
        self.combined_layers = torch.nn.Sequential(self.layer1,
                                                    self.layer2,
                                                    self.layer3,
                                                    self.layer4)

    def forward(self, x):
        # Flatten images (transform them from 28x28
        # 2D matrices to 784 1D vectors)
        x = x.view(x.size(0), -1)
        # Pass through all four layers
        out = self.combined_layers(x)
        return out
```

```
# Initialize the model and optimizer
model = DeepNeuralNet(n_x = 784, n_h = [80, 40, 20], n_y = 10).to(device)
optimizer = torch.optim.Adam(model.parameters(), lr = 1e-3)
```

Training our model as before

```
1 # Training model
2 num_epochs = 10
3 for epoch in range(num_epochs):
4     # Go through all samples in train dataset
5     for i, (images, labels) in enumerate(train_loader):
6         # Get from dataloader and send to device
7         images = images.to(device)
8         labels = labels.to(device)
9         # Forward pass
10        outputs = model(images)
11        # Compute loss
12        loss = torch.nn.functional.cross_entropy(outputs, labels)
13        # Backward and optimize
14        optimizer.zero_grad()
15        loss.backward()
16        optimizer.step()
17        # Display
18        if (i+1) % 25 == 0:
19            print (f'Epoch [{epoch+1}/{num_epochs}], Step [{i+1}/{len(train_loader)}], Loss: {loss.item():.4f}')
```

```
Epoch [1/10], Step [25/235], Loss: 2.2469
Epoch [1/10], Step [50/235], Loss: 2.1274
Epoch [1/10], Step [75/235], Loss: 1.9379
Epoch [1/10], Step [100/235], Loss: 1.8415
Epoch [1/10], Step [125/235], Loss: 1.6548
Epoch [1/10], Step [150/235], Loss: 1.4660
Epoch [1/10], Step [175/235], Loss: 1.2895
Epoch [1/10], Step [200/235], Loss: 1.1478
Epoch [1/10], Step [225/235], Loss: 0.9910
Epoch [2/10], Step [25/235], Loss: 0.8251
```

Careful: Deeper does not mean better!

**Shallow Neural Net: 96.5% test acc.
(not too bad in terms of acc.)**

```

1 # Evaluate model accuracy on test after training
2 # Set model in eval mode!
3 model.eval()
4 # Evaluate
5 with torch.no_grad():
6     correct = 0
7     total = 0
8     for images, labels in test_loader:
9         # Get images and labels from test loader
10         images = images.to(device)
11         labels = labels.to(device)
12         # Forward pass and predict class using max
13         outputs = model(images)
14         _, predicted = torch.max(outputs.data, 1)
15         # Check if predicted class matches label
16         # and count number of correct predictions
17         total += labels.size(0)
18         correct += (predicted == labels).sum().item()
19 # Compute final accuracy and display
20 accuracy = correct/total
21 print(f'Evaluation after training, Accuracy: {accuracy:.4f}')
```

Evaluation after training, Accuracy: 0.9649

**Deep Neural Net: 93.7% test acc.
(lower acc., even though we had a lower loss?!)**

```

1 # Evaluate model accuracy on test after training
2 # Set model in eval mode!
3 model.eval()
4 # Evaluate
5 with torch.no_grad():
6     correct = 0
7     total = 0
8     for images, labels in test_loader:
9         # Get images and labels from test loader
10         images = images.to(device)
11         labels = labels.to(device)
12         # Forward pass and predict class using max
13         outputs = model(images)
14         _, predicted = torch.max(outputs.data, 1)
15         # Check if predicted class matches label
16         # and count number of correct predictions
17         total += labels.size(0)
18         correct += (predicted == labels).sum().item()
19 # Compute final accuracy and display
20 accuracy = correct/total
21 print(f'Evaluation after training, test accuracy: {accuracy:.4f}')
```

Evaluation after training, test accuracy: 0.9367

Experimenting on layers numbers and sizes

In fact, in Notebook 7, we trained three DNN models:

- **Model 1:** 6 layers (probably too many layers)

$$n_h = [320, 160, 80, 40, 20],$$

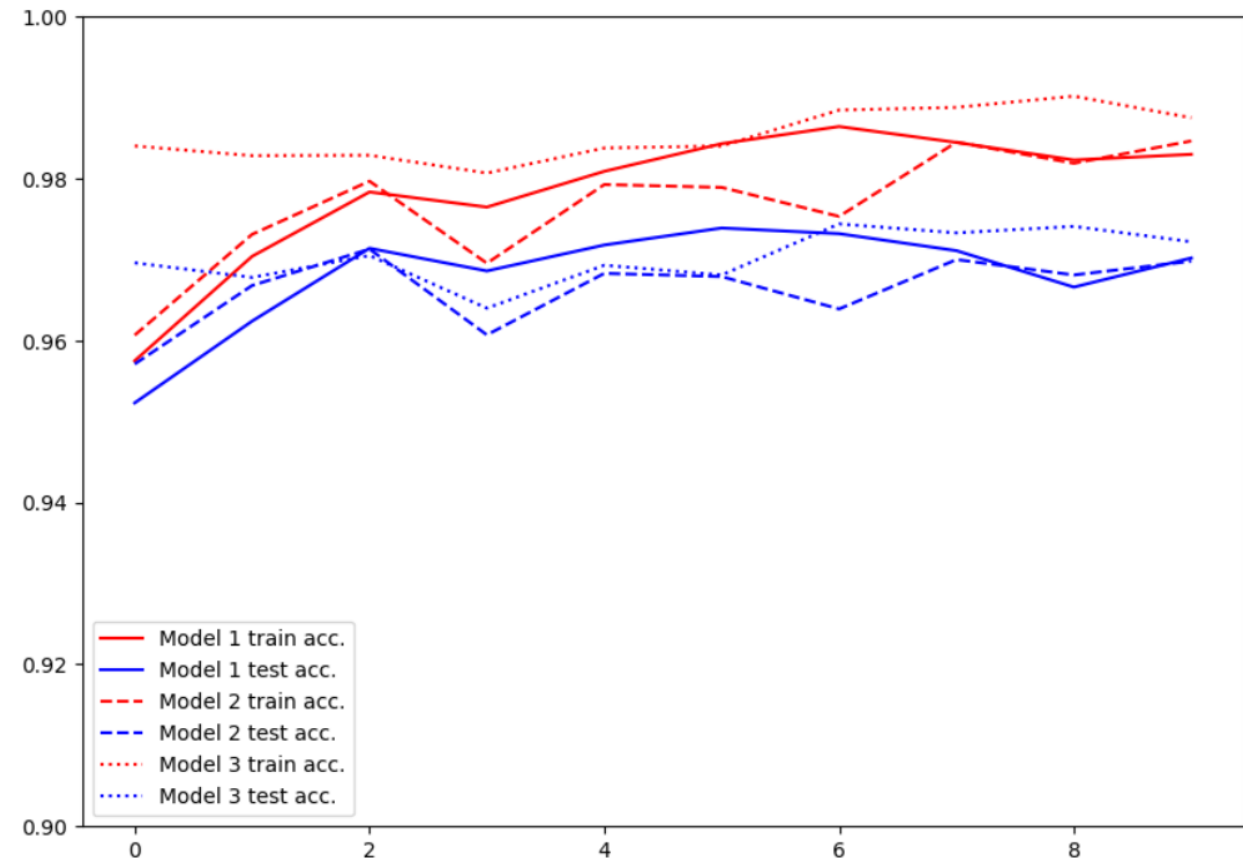
- **Model 2:** 3 layers (layers probably too large)

$$n_h = [400, 200],$$

- **Model 3:** 3 layers (just fine?)

$$n_h = [40, 20].$$

While simpler, model 3 has highest test accuracy!



Important lesson: Larger and deeper network does not necessarily mean better performance! (Deeper and larger models could overfit!)

Conclusion (Week 3)

- PyTorch library and its benefits
- Tensor objects, attributes and operations on tensors
- Converting our NumPy shallow neural network into PyTorch
- Parameter objects
- Forward method implementation
- Performance benefits of GPU acceleration
- Using autograd and computational graphs
- Advanced optimizers in PyTorch
- Initializers in PyTorch
- Regularization in PyTorch
- Dataset and Dataloader objects
- Multi-class classification
- Softmax function and multi-class cross entropy loss
- Building blocks in PyTorch
- Our first Deep Neural Network!
- Network size vs. overfitting tradeoff

Project and HW announcement!

Let us discuss it now.