

Machine learning & deep learning basics

Practice Session 3

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January 22, 2024

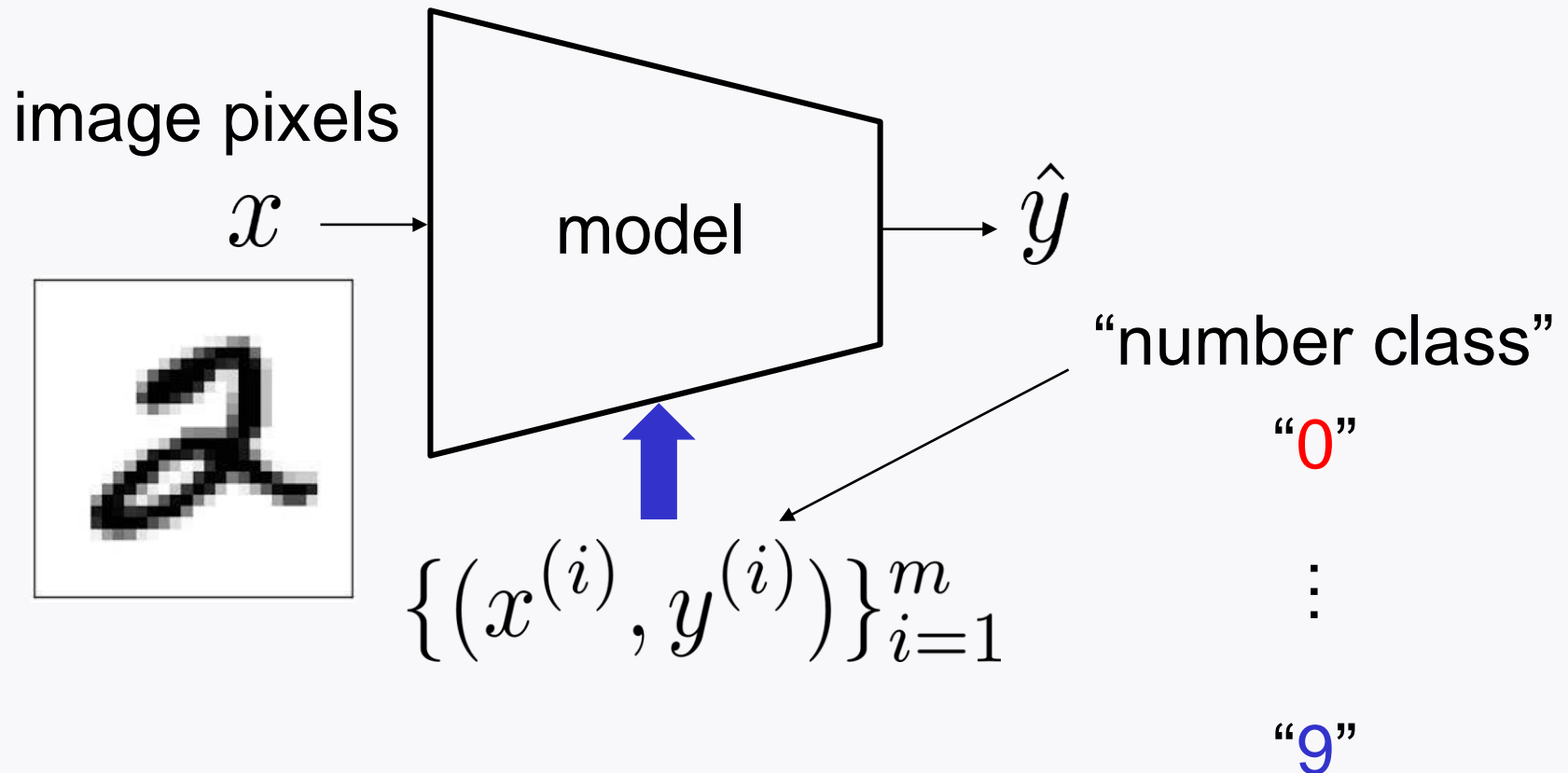
Outline

Will learn how to do **TensorFlow** implementation:

1. Least Squares
2. Logistic regression
3. **Deep learning**

Will do this in the context of **handwritten digit classification**.

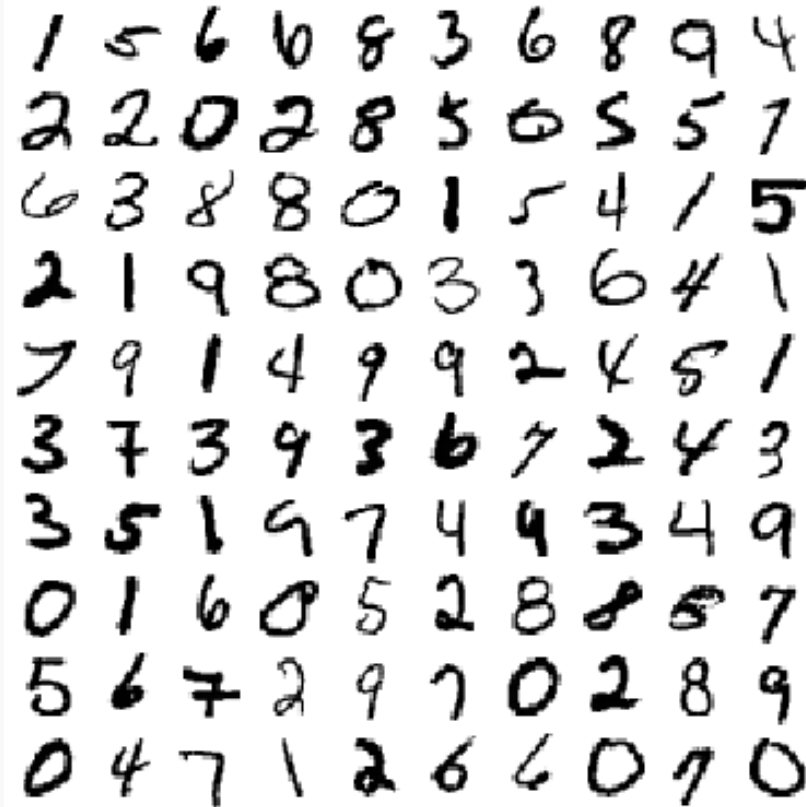
Handwritten digit classification



MNIST dataset

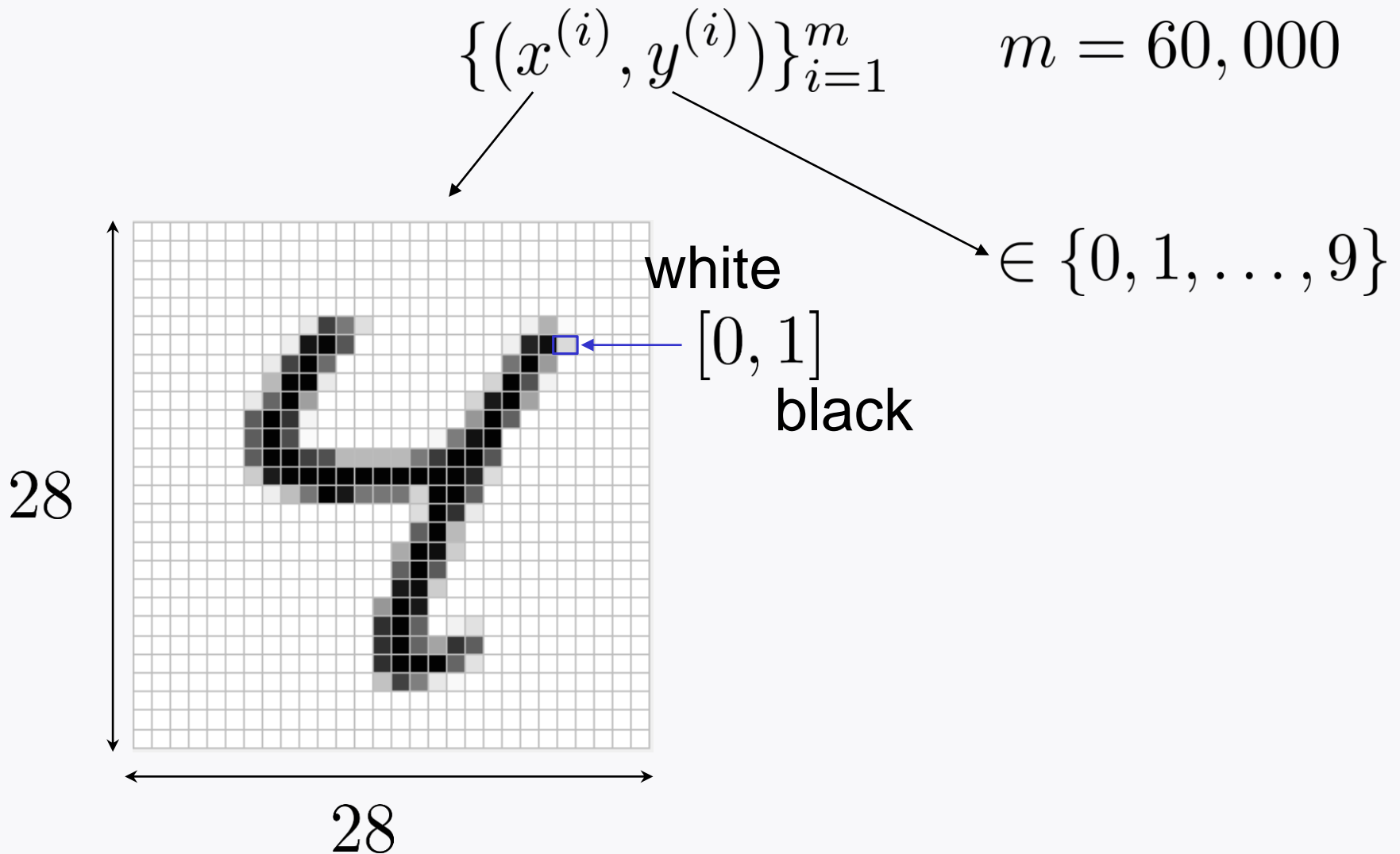
$$\{(x^{(i)}, y^{(i)})\}_{i=1}^m \quad m = 60,000$$

Examples:



Yann LeCun 1998

Input image & label



How to load MNIST dataset

```
from tensorflow.keras.datasets import mnist
```

```
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
print(X_train.shape)  
print(y_train.shape)  
print(X_test.shape)  
print(y_test.shape)
```

```
(60000, 28, 28)  
(60000, )  
(10000, 28, 28)  
(10000, )
```

Pixel data

```
print(X_train[0])
```

```
[[ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
   0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
   0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
   0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
   0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
   0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
   0  0  0  0  0  0  0  0  0  0]
 [ 0  0  0  0  0  0  0  0  0  0  0  0  3  18  18  18 126 136
 175 26 166 255 247 127 0 0 0 0]
 [ 0  0  0  0  0  0  0  0 30 36 94 154 170 253 253 253 253 253
 225 172 253 242 195 64 0 0 0 0]
 [ 0  0  0  0  0  0  0 49 238 253 253 253 253 253 253 253 253 251
 93 82 82 56 39 0 0 0 0 0]
 [ 0  0  0  0  0  0  0 18 219 253 253 253 253 253 198 182 247 241
 0 0 0 0 0 0 0 0 0 0]
 [ 0  0  0  0  0  0  0 0 80 156 107 253 253 205 11 0 43 154
```

Range: 0 ~ 255

Normalization (preprocessing)

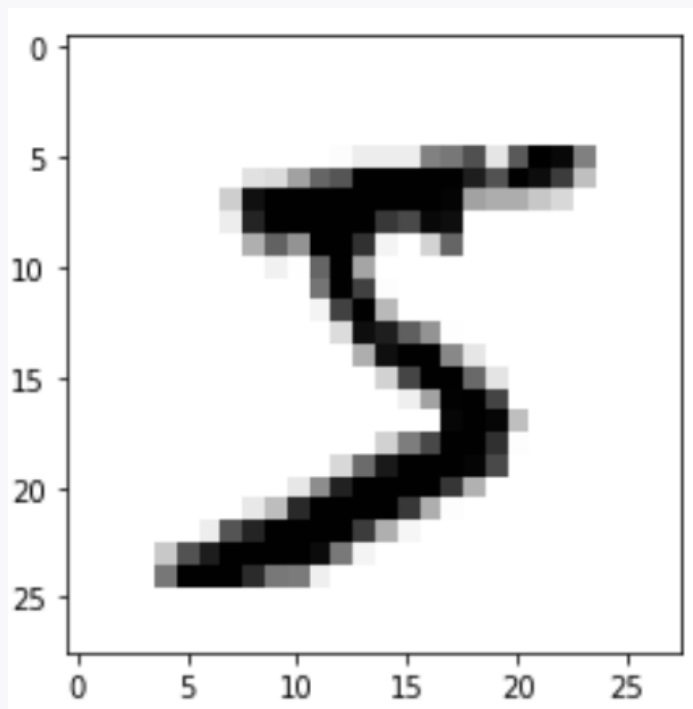
```
X_train, X_test = X_train/255., X_test/255
```


Data visualization

```
import matplotlib.pyplot as plt
```

'gray': background is black

↓
`plt.imshow(X_train[0], cmap='gray_r')` *# gray_r: background is white*

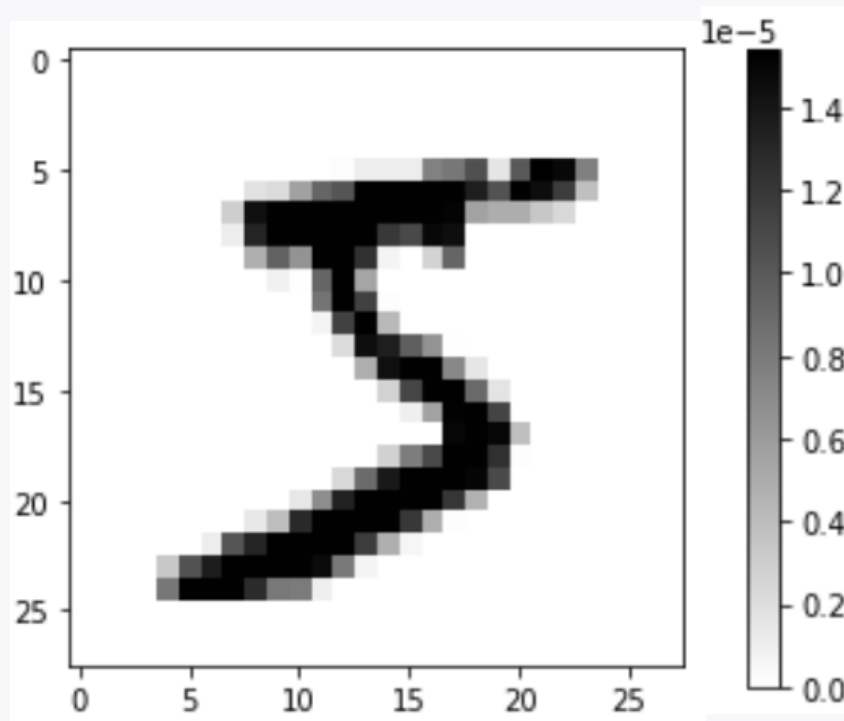


Data visualization

```
import matplotlib.pyplot as plt
```

```
plt.imshow(X_train[0], cmap='gray_r') # gray_r: background is white
```

```
plt.colorbar() # Display a colored bar right next to an image
```



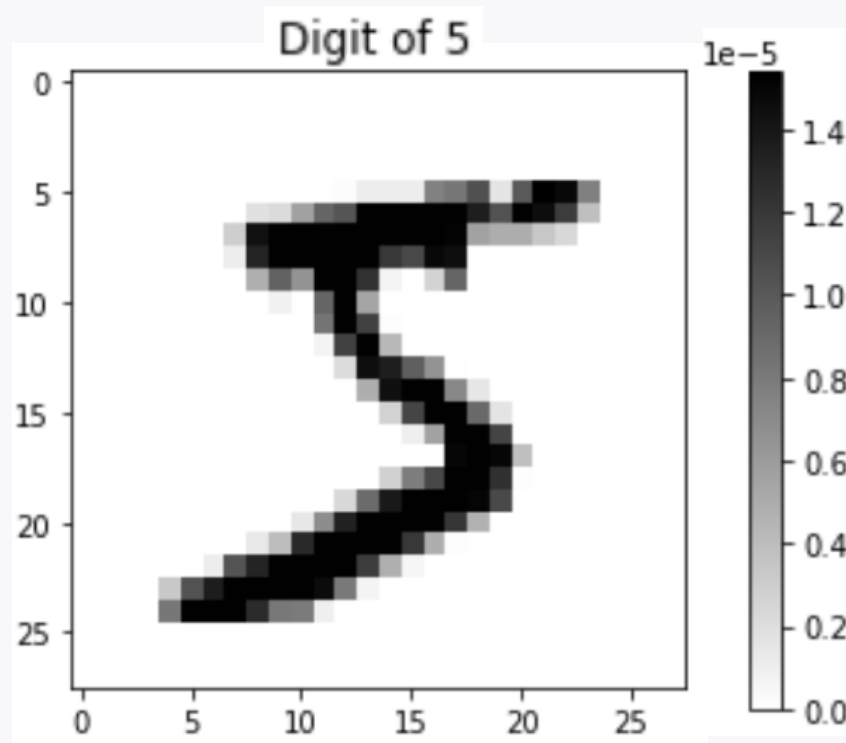
Data visualization

```
import matplotlib.pyplot as plt
```

```
plt.imshow(X_train[0], cmap='gray_r') # gray_r: background is white
```

```
plt.colorbar() # Display a colored bar right next to an image
```

```
plt.title('Digit of {}'.format(y_train[0]))
```



Plotting multiple figures

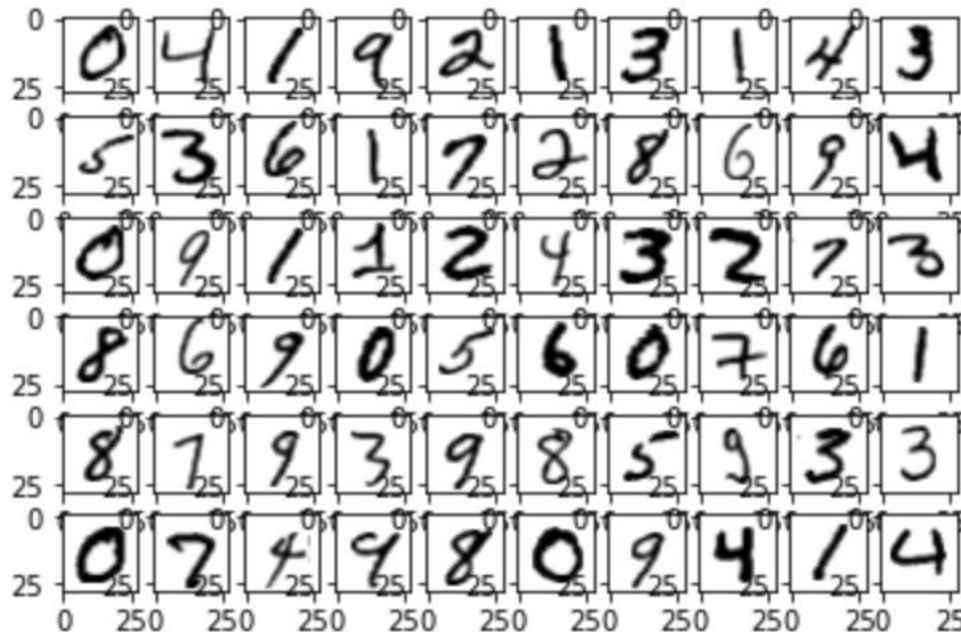
```
import matplotlib.pyplot as plt
```

```
num_of_images = 60
```

```
for index in range(1,num_of_images+1):
```

```
    plt.subplot(6,10,index)
```

```
    plt.imshow(X_train[index], cmap = 'gray_r')
```



Plotting multiple figures

```
import matplotlib.pyplot as plt

num_of_images = 60
for index in range(1, num_of_images+1):
    plt.subplot(6,10,index)
    plt.axis('off')
    plt.imshow(X_train[index], cmap = 'gray_r')
```



Least Squares

```
from sklearn.linear_model import RidgeClassifier
```

```
Model_LS = RidgeClassifier()
```

```
print(X_train.shape)
```

```
(60000, 28, 28)
```

```
print(X_train.reshape(-1, 28*28).shape)
```

```
(60000, 784)
```

Least Squares

```
from sklearn.linear_model import RidgeClassifier

Model_LS = RidgeClassifier()

# training
Model_LS.fit(X_train.reshape(-1, 28*28), y_train)

# prediction on test data
Model_LS.predict(X_test[0].reshape(1, -1))

# evaluate test accuracy
Model_LS.score(X_train.reshape(-1, 28*28), y_train)
```

0.8574

Logistic regression

```
from sklearn.linear_model import LogisticRegression
```

```
Model_LR = LogisticRegression()
```

```
# training
```

```
Model_LR.fit(X_train.reshape(-1, 28*28), y_train)
```

```
# prediction on test data
```

```
Model_LR.predict(X_test[0].reshape(1,-1))
```

```
# evaluate test accuracy
```

```
Model_LR.score(X_test.reshape(-1, 28*28), y_test)
```

```
0.9258
```


Deep learning

```
from tensorflow.keras.models import Sequential
```

```
Model_NN = Sequential()
```

```
from tensorflow.keras.layers import Flatten
```

```
from tensorflow.keras.layers import Dense
```

```
Model_NN.add(Flatten(input_shape=(28,28)))
```

```
Model_NN.add(Dense(128, activation='relu'))
```

```
Model_NN.add(Dense(10, activation='softmax'))
```

```
Model_NN.summary()
```

Deep learning

```
from tensorflow.keras.models import Sequential
```

```
Model_1: Model: "sequential"
```

	Layer (type)	Output Shape	Param #
from t	flatten (Flatten)	(None, 784)	0
from t	dense (Dense)	(None, 128)	100480
Model_1	dense_1 (Dense)	(None, 10)	1290

```
Model_1: =====
```

```
Model_1: Total params: 101,770
```

```
Model_1: Trainable params: 101,770
```

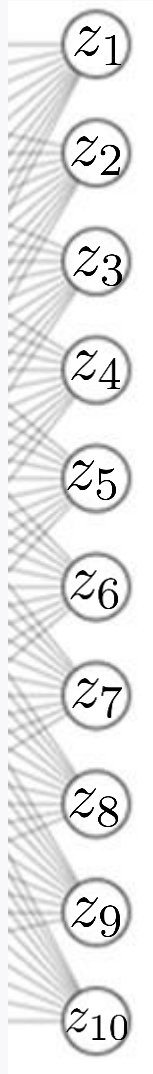
```
Model_1: Non-trainable params: 0
```

```
Model_1: =====
```

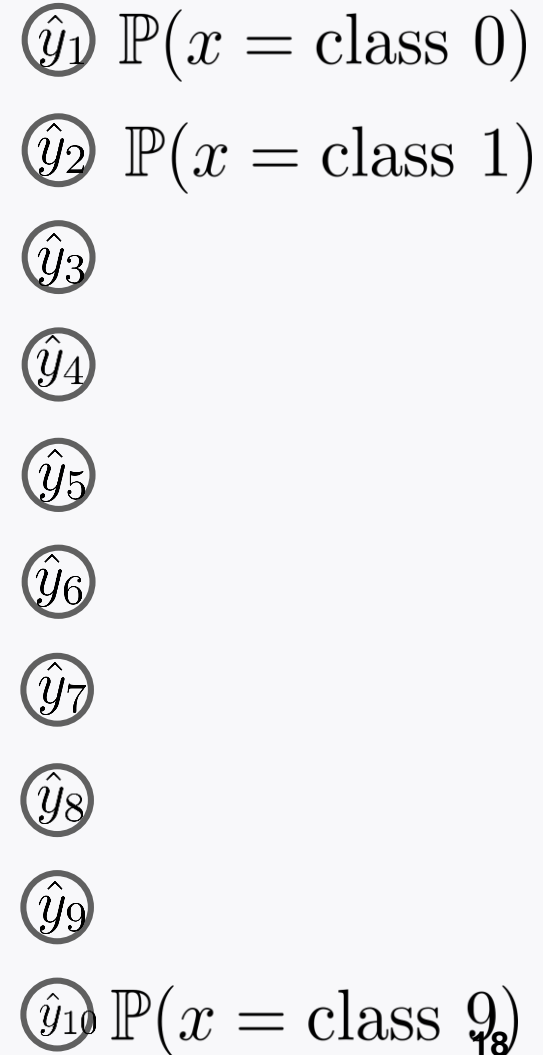
Softmax activation at output layer

output layer

softmax



$$\hat{y}_j = \frac{e^{z_j}}{\sum_{k=1}^{10} e^{z_k}}$$



Optimal loss function

Turns out: The optimal loss function is again cross entropy loss.

$$\ell_{\text{CE}}(y, \hat{y}) = \sum_{j=1}^{10} -y_j \log \hat{y}_j$$

y
 one-hot vector
 (label=2)

$$\begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \begin{matrix} 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \\ 6 \\ 7 \\ 8 \\ 9 \end{matrix}$$

Compile

```
from tensorflow.keras.optimizers import Adam
```

```
opt = Adam(learning_rate=1e-2,  
           beta_1 = 0.9,  
           beta_2 = 0.999)
```

```
Model_NN.compile(optimizer=opt,  
                  loss='sparse_categorical_crossentropy',  
                  metrics=['acc'])
```

Training

```
hist = Model_NN.fit(X_train, y_train, epochs=20)
```

```
Epoch 1/20  
1875/1875 [=====] - 1s 688us/step - loss: 0.2419 - acc:  
0.9285
```

```
Epoch 2/20  
1875/1875 [=====] - 1s 715us/step - loss: 0.1621 - acc:  
0.9545
```

:

```
Epoch 17/20  
1875/1875 [=====] - 1s 678us/step - loss: 0.0892 - acc:  
0.9822
```

```
Epoch 18/20  
1875/1875 [=====] - 1s 707us/step - loss: 0.0875 - acc:  
0.9825
```

```
Epoch 19/20  
1875/1875 [=====] - 1s 673us/step - loss: 0.0807 - acc:  
0.9834
```

```
Epoch 20/20  
1875/1875 [=====] - 1s 659us/step - loss: 0.0931 - acc:  
0.9834
```

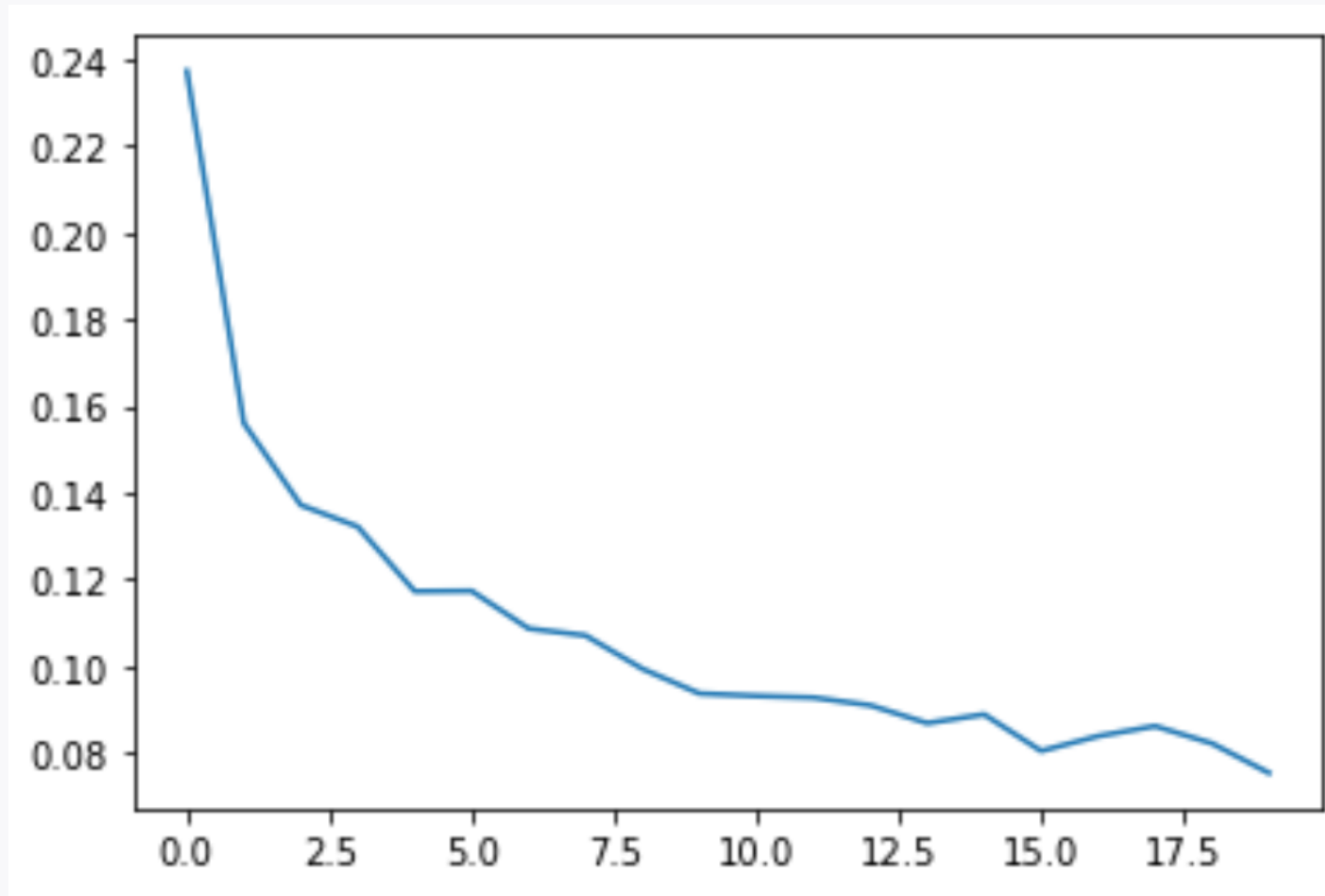
History

```
print(hist.history)
```

```
{ 'loss': [0.23721636831760406, 0.15599527955055237, 0.13709723949432373, 0.13211312890052795, 0.11719996482133865, 0.11729438602924347, 0.10861502587795258, 0.10701850801706314, 0.09931265562772751, 0.09363316744565964, 0.0930742397904396, 0.09269481897354126, 0.09091321378946304, 0.08679905533790588, 0.0888138934969902, 0.08038856834173203, 0.0838022530078888, 0.08611498773097992, 0.08213432878255844, 0.07530936598777771], 'acc': [0.9310500025749207, 0.956166684627533, 0.9624000191688538, 0.964733362197876, 0.9691833257675171, 0.9696999788284302, 0.971916675567627, 0.9732000231742859, 0.9745166897773743, 0.9763166904449463, 0.9783333539962769, 0.9781666398048401, 0.9784166812896729, 0.9793166518211365, 0.9800833463668823, 0.9804999828338623, 0.9807833433151245, 0.9817333221435547, 0.9823166728019714, 0.9836166501045227]}
```

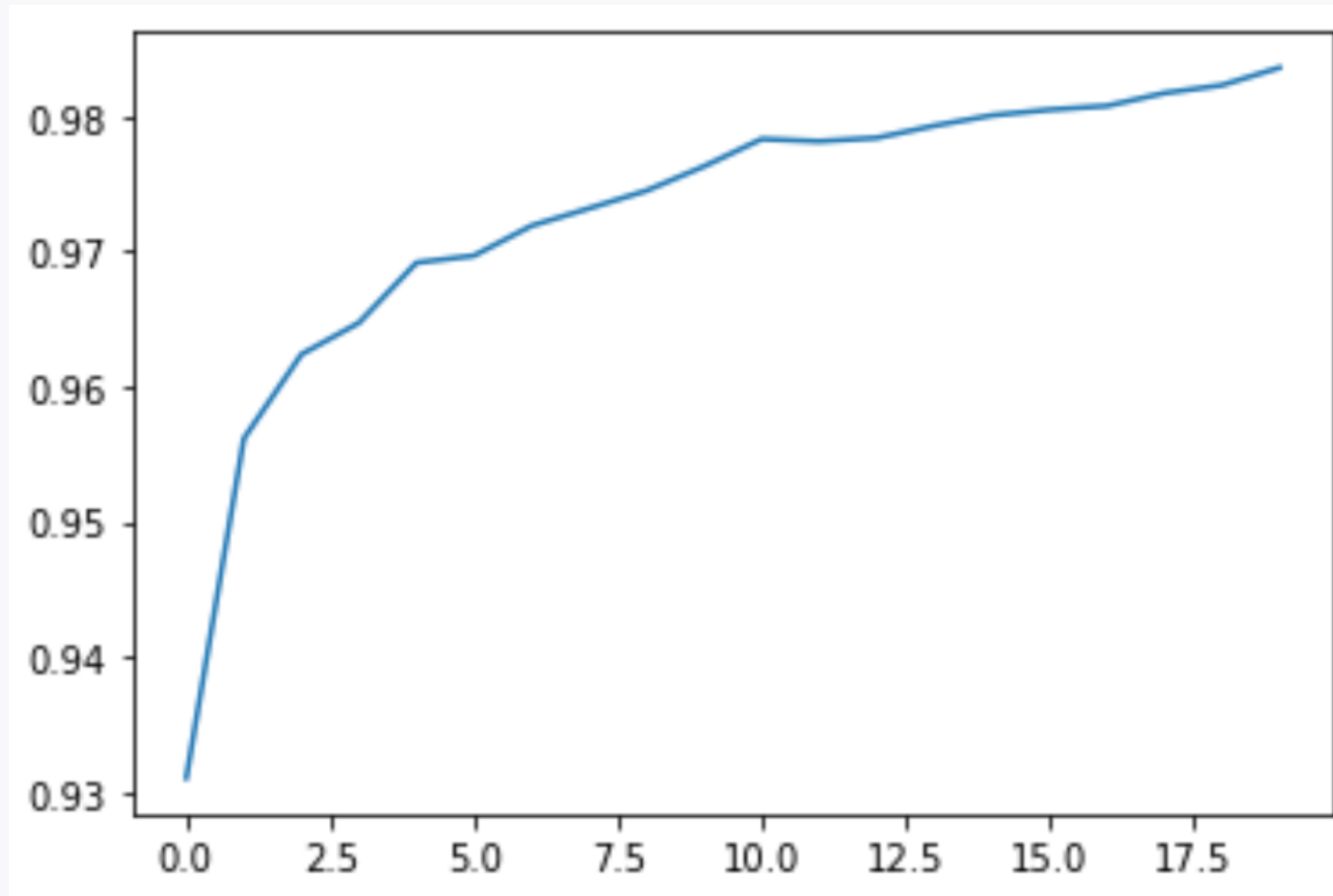
Plotting loss as a function of epoch

```
plt.plot(hist.history['loss'])
```



Plotting accuracy as a function of epoch

```
plt.plot(hist.history['acc'])
```



Testing

```
Model_NN.evaluate(X_test, y_test)
```

```
313/313 [=====] - 0s 559us/step - loss: 0.3107 - acc: 0.9661
```