# IntroToNeuralNetworks - IntroToTensorflow - 2

*One should look for what is and not what he thinks should be. (Albert Einstein)*

# Module completion checklist

| Objective | Complete |
|---|---|
| Prepare data for implementing a neural network | |
| Implement and evaluate the model on test data | |

# Goal for this module

- In this section we will build a **neural network with 2 hidden layers** in TensorFlow using the `tf.keras`
    - We will use a sequential model to create this network
    - We will work with the Credit Card dataset

# Overview of the process

The steps involved in building a neural network are:

1. **Clean and wrangle** the dataset so it is suitable for the neural network model
2. Split the dataset into **train, test, and validation data**
3. Define and compile the **sequential model**
4. **Fit the model** on the training data
5. **Compare** the training/validation accuracy for each epoch
6. Evaluate and make **predictions** on the test data

# Coding in TensorFlow and Keras

Coding fundamentals to keep in mind before starting:

- Whenever we intend to use TensorFlow's native module, we will follow the syntax:
  - `tf.[module_name]`
- When we intend to use Keras, we will will follow the syntax:
  - `tf.keras.[module_name]`
- Or, we can also import specific Keras modules separately and use them directly:
  - `from tensorflow.keras.layers import Dense`
  - then just use `Dense` in our code

# Loading packages

- Let's load the packages we will be using:

```
import os
import pickle
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import math
import seaborn as sns
# Scikit-learn packages.
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn import metrics
# TensorFlow and supporting packages.
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras.models import load_model
from tensorflow.keras.optimizers import Adam
```

# Directory settings

- In order to maximize the efficiency of your workflow, you should encode your directory structure into `variables`
- We will use the `pathlib` library
- Let the `main_dir` be the variable corresponding to your course materials folder
- `data_dir` be the variable corresponding to your `data` folder

```
# Set 'main_dir' to location of the project folder
from pathlib import Path
home_dir = Path(".").resolve()
main_dir = home_dir.parent.parent
print(main_dir)
```

```
data_dir = str(main_dir) + "/data"
print(data_dir)
```

# Load the data

- The `credit_card_data` dataset contains information about **credit card defaulters**

- Our goal is to predict if a customer will **default on a credit card payment**

```
credit_card = pd.read_csv(str(data_dir) + '/credit_card_data.csv')
print(credit_card.head())
```

```
   ID  LIMIT_BAL  SEX  ...  PAY_AMT5  PAY_AMT6  default_payment_next_month
0   1      20000    2  ...         0         0                           1
1   2     120000    2  ...         0      2000                           1
2   3      90000    2  ...      1000      5000                           0
3   4      50000    2  ...      1069      1000                           0
4   5      50000    1  ...       689       679                           0

[5 rows x 25 columns]
```

# Data preparation

- Before starting to implement our neural network, we need to make sure our data is clean and in a suitable form; for that, we need to:
  - check the data for **NAs**
  - transform the data to **numeric values**, and make sure the data is encoded, if it's categorical
  - **split data** into train, test, and validation
  - normalize data
  - examine the target variable imbalance

- **Remember, the order of operations matters!**
  - Ideally, all data transformations should happen after the data has been split
  - In this instance, we will check for NAs and encode categorical variables before the split since this will not significantly affect the results and keep our code more concise

# Data prep: convenience function

- Here is a time-saving function to perform all of the cleaning and split steps on the credit card dataset at once:

```
def data_prep(df):
    df = df.fillna(df.mean()['BILL_AMT1'])
    df = df.drop('ID',axis = 1)
    # Convert 'sex' into dummy variables.
    sex = pd.get_dummies(df['SEX'], prefix = 'sex', drop_first = True)
    # Convert 'education' into dummy variables.
    education = pd.get_dummies(df['EDUCATION'], prefix = 'education', drop_first = True)
    # Convert 'marriage' into dummy variables.
    marriage = pd.get_dummies(df['MARRIAGE'], prefix = 'marriage', drop_first = True)
    # Drop `sex`, `education`, `marriage` from the data.
    df.drop(['SEX', 'EDUCATION', 'MARRIAGE'], axis = 1, inplace = True)
    # Concatenate `sex`, `education`, `marriage` dummies to our dataset.
    df = pd.concat([df, sex, education, marriage], axis=1)
    # Separate predictors from data.
    X = df.drop(['default_payment_next_month'], axis=1)
    y = df['default_payment_next_month']
```

# Data prep: convenience function (cont'd)

```
# Set the seed to 1.
np.random.seed(1)
# Split data into train, test, and validation set, use a 70 - 15 - 15 split.
# First split data into train-test with 70% for train and 30% for test.
X_train, X_test, y_train, y_test = train_test_split(X.values,
                                                    y,
                                                    test_size = .3,
                                                    random_state = 1)
# Then split the test data into two halves: test and validation.
X_test, X_val, y_test, y_val = train_test_split(X_test,
                                                y_test,
                                                test_size = .5,
                                                random_state = 1)
```

# Data prep: convenience function (cont'd)

```
    print("Train shape:", X_train.shape, "Test shape:", X_test.shape, "Val shape:", X_val.shape)

    # Transforms features by scaling each feature to a given range.
    # The default is the range between 0 and 1.
    min_max_scaler = preprocessing.MinMaxScaler()
    X_train_scaled = min_max_scaler.fit_transform(X_train)
    X_test_scaled = min_max_scaler.transform(X_test)
    X_val_scaled = min_max_scaler.transform(X_val)
    return X_train_scaled, X_test_scaled, X_val_scaled, y_train, y_test, y_val
```

# Data prep

```
X_train_scaled, X_test_scaled, X_val_scaled, y_train, y_test, y_val = data_prep(credit_card)
```

```
Train shape: (21000, 30) Test shape: (4500, 30) Val shape: (4500, 30)
```

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# Steps to define your model

Define the input layer and ensure that either:

1. `input_dim` from `Dense` is specified to match the number of inputs to the model or
2. `input_shape` is a tuple of integers, or a shape tuple, where the batch dimension is not included or
3. Pass a list of TF-compatible feature columns, which have the shape, dimensions and data type specified

Determine the number of layers for your model:

1. This is usually done through trial-and-error based on the heuristics of your model
2. You can start with the idea that you need a network large enough to capture the structure of the problem

# Steps to define your model (cont'd)

Use `Dense` to define each layer, specifying:

1. Number of neurons in the given layer as the first argument
2. Activation function using the activation argument

Define the output layer:

1. Number of units to predict (`1` if binary)
2. Choose the activation function for the output, sigmoid if binary

# Implement Sequential model with Dense layers

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

# Let's set the seed so that we can reproduce the results.
tf.random.set_seed(1)

## Set up model.
model = Sequential([
  Dense(32,                                          #<- number of neurons for 1st hidden layer
        input_shape = (X_train_scaled.shape[1], )), #<- input layer shape: `(num_features, )`
  Dense(20,                                          #<- add 2nd hidden layer with 20 neurons
        activation = 'relu'), #<- set activation function for hidden layer
  Dense(1,                    #<- add output layer with single neuron
       activation = 'sigmoid')#<- activation function for output layer
])
```

# Compile the model

- Once the model is initialized, we need to **compile and fit** it
- There are some parameters that we have to choose at this stage:
  - **loss function**: we use it to evaluate the set of weights, in our case it will be the already familiar to us `"binary_crossentropy"`
  - **gradient descent algorithm**: it is a popular and efficient optimization algorithm, in our case `"adam"`, it is popular and efficient
  - **metrics**: the metrics we want as output, let's stick to a simple one `"accuracy"`

```
# Compile the model.
model.compile(optimizer = "adam",
              loss = "binary_crossentropy",
              metrics = ["accuracy"])
```

- Click on the following to review the documentation on: ***loss function***, ***optimization algorithm***, and ***metrics***

# Fit the model

- Finally, we have what we need to **fit the model** to our data
- The training process will run for a fixed number of iterations (“epochs”) through the dataset
- We specify this using the `epochs` argument
- We can also add validation data to compare train and validation metrics and loss

```
model_res = model.fit(X_train_scaled, y_train,                  #<- train data and labels
                      validation_data = (X_val_scaled, y_val), #<- pass val data
                      epochs = 200)                             #<- number of epochs
```

```
Epoch 1/200
657/657 [==============================] - 1s 1ms/step - loss: 0.5129 - accuracy: 0.7841 -
val_loss: 0.4606 - val_accuracy: 0.8049
Epoch 2/200
657/657 [==============================] - 1s 884us/step - loss: 0.4581 - accuracy: 0.8099 -
val_loss: 0.4555 - val_accuracy: 0.8091
...
Epoch 199/200
657/657 [==============================] - 1s 841us/step - loss: 0.4161 - accuracy: 0.8230 -
val_loss: 0.4345 - val_accuracy: 0.8224
Epoch 200/200
657/657 [==============================] - 1s 838us/step - loss: 0.4152 - accuracy: 0.8273 -
val_loss: 0.4328 - val_accuracy: 0.8211
```

# Model evaluation metrics

- We will evaluate our model based on the following metrics:
  - Training/validation **accuracy** for each epoch
  - Training/validation **loss** for each epoch

- At the end of each epoch, the **loss** is calculated by comparing the model's predictions with the original labels
- This is used to update the loss function each time and the weights are adjusted accordingly for every epoch
- For **accuracy**, the ratio of total records that are classified correctly to the total number of records in the dataset

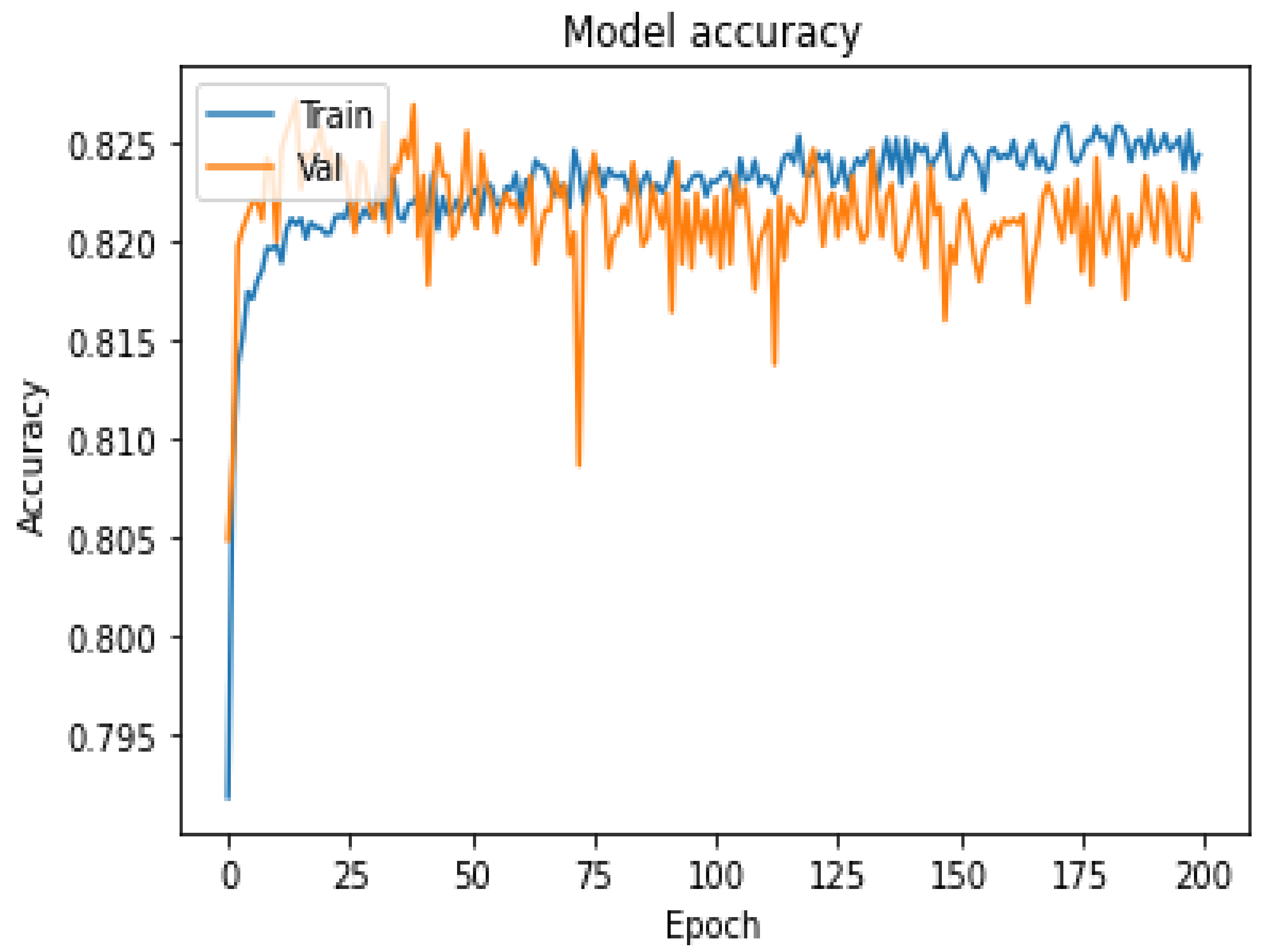
# Model evaluation metrics (cont'd)

- Generally, the model performs well if it gives good accuracy with less loss
- To assess the neural network model, we can quickly visualize and observe the pattern of accuracy and loss for each epoch

# Visualize training/validation accuracy for each epoch

- The `model_res` object contain model results in a `history` dictionary
- You can access accuracy for the train data by calling `model_res.history['accuracy']`
- You can access accuracy for the validation data by calling `model_res.history['val_accuracy']`

```
# Plot training & validation accuracy values
plt.plot(model_res.history['accuracy'])    #<- accuracy
scores
plt.plot(model_res.history['val_accuracy'])#<- get val
accuracy scores from dictionary
plt.title('Model accuracy')
plt.ylabel('Accuracy')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()
```

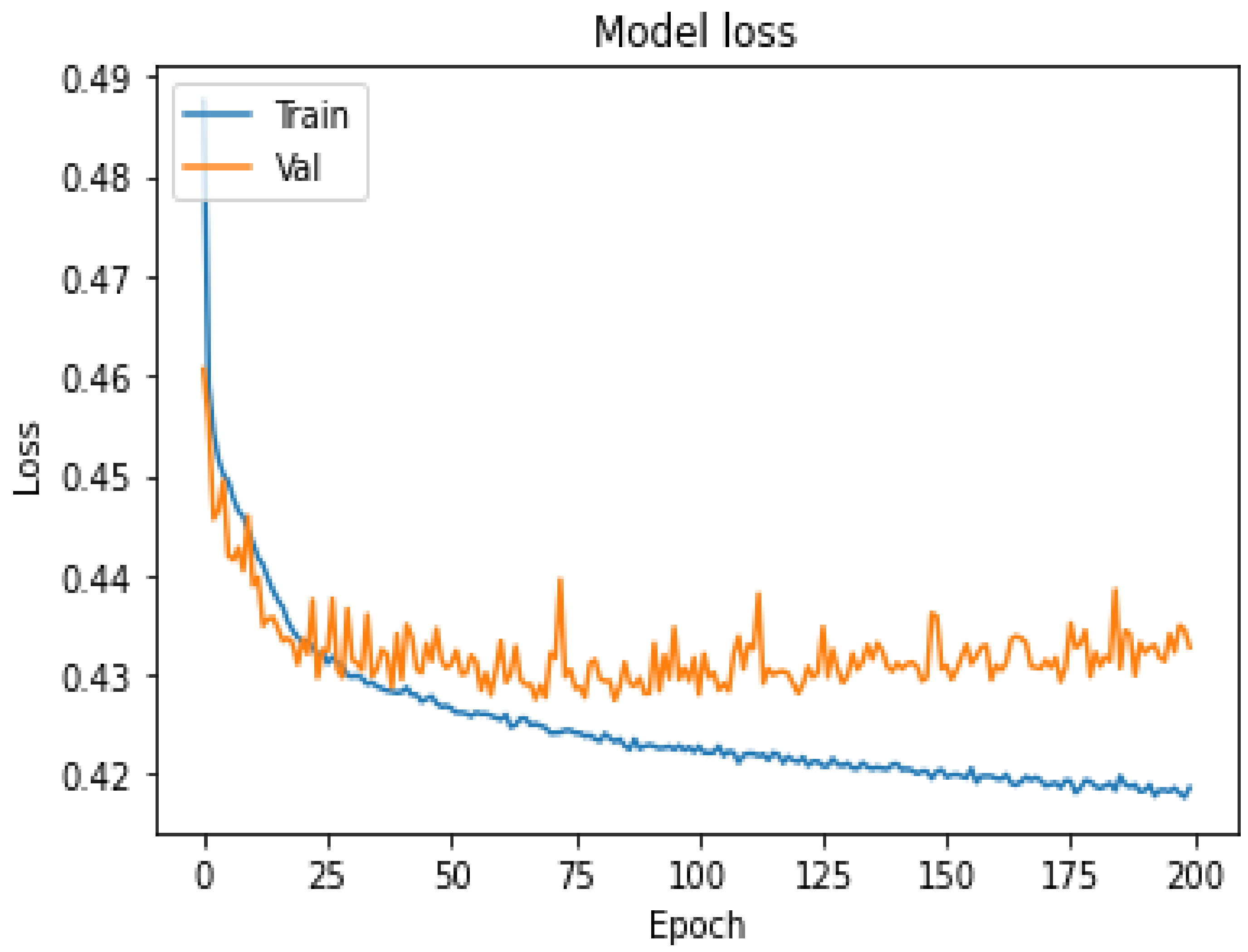



- Overall, the training and the validation accuracy seem to be increasing as the number of epochs increase

# Visualize training/validation loss for each epoch

- You can access loss values for the train data by calling `model_res.history['loss']`
- You can access loss values for the validation data by calling `model_res.history['val_loss']`

```
# Plot training & validation loss values
plt.plot(model_res.history['loss'])
plt.plot(model_res.history['val_loss'])
plt.title('Model loss')
plt.ylabel('Loss')
plt.xlabel('Epoch')
plt.legend(['Train', 'Val'], loc='upper left')
plt.show()
```



# Evaluate loss, accuracy on test data and predict

```
loss, accuracy = model.evaluate(x = X_test_scaled, y = y_test)
```

```
141/141 [==============================] - 0s 611us/step - loss: 0.4448 - accuracy: 0.8127
```

```
print("Loss: {0:6.3f}, Accuracy: {1:6.3f}".format(loss, accuracy))
```

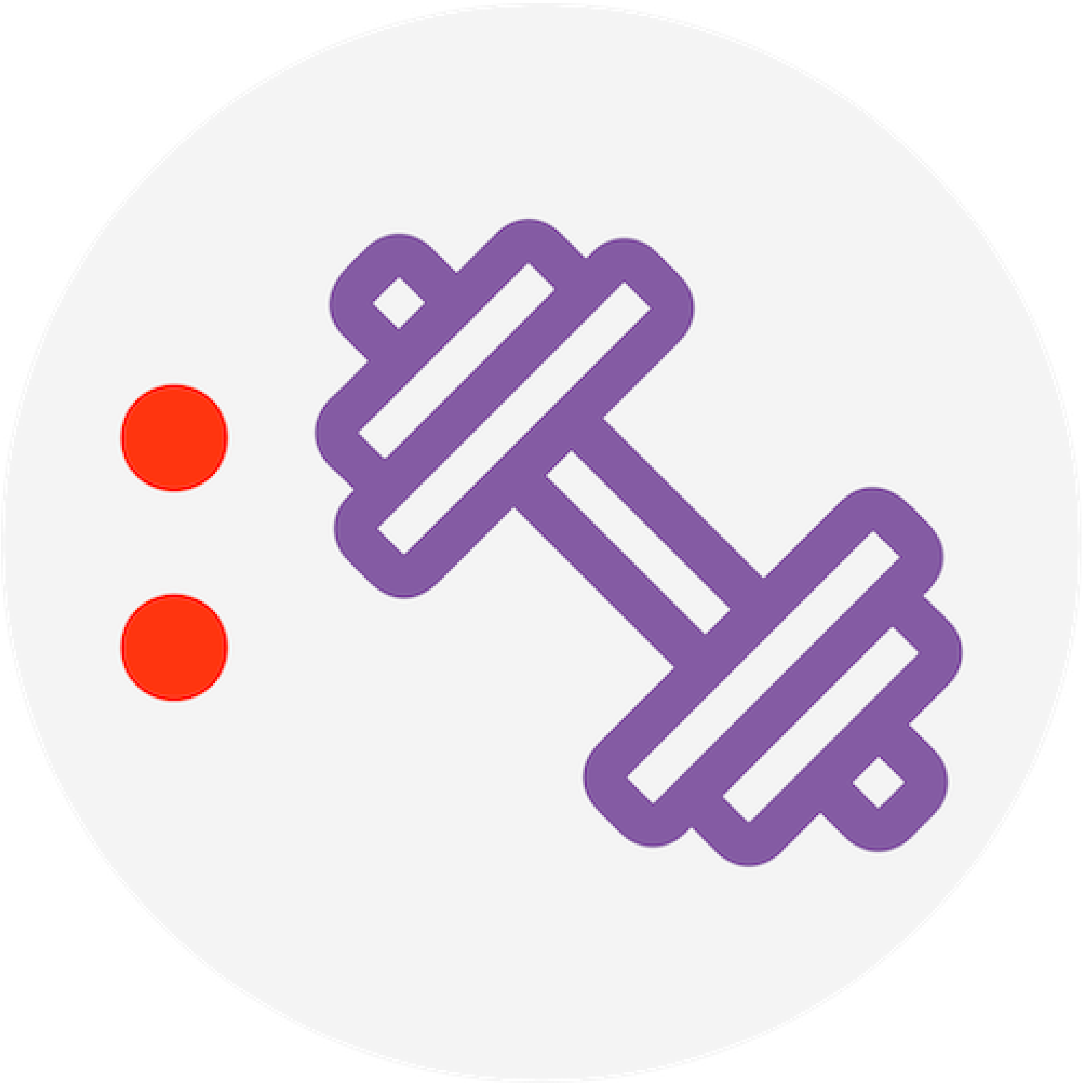
```
Loss:  0.445, Accuracy:  0.813
```

```
y_pred_prob = model.predict(X_test_scaled)
y_pred = (model.predict(X_test_scaled) > 0.5).astype("int32")
print(y_pred)
```

```
[[1]
 [0]
 [0]
 ...
 [1]
 [0]
 [0]]
```

# Knowledge check

# Exercise



You are now ready to try tasks 1-7 in the Exercise for this topic

# Module completion checklist

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|---|---|
| Prepare data for implementing a neural network | ✔ |
| Implement and evaluate the model on test data | ✔ |

# Intro To TensorFlow: Topic summary

In this part of the course, we have covered:

- Overview of TensorFlow / Keras building blocks
- Implement and fit a neural network model using Tensorflow on train data
- Evaluate neural network model on test data

# Congratulations on completing this module!