Introduction to Regression with Neural Networks in TensorFlow

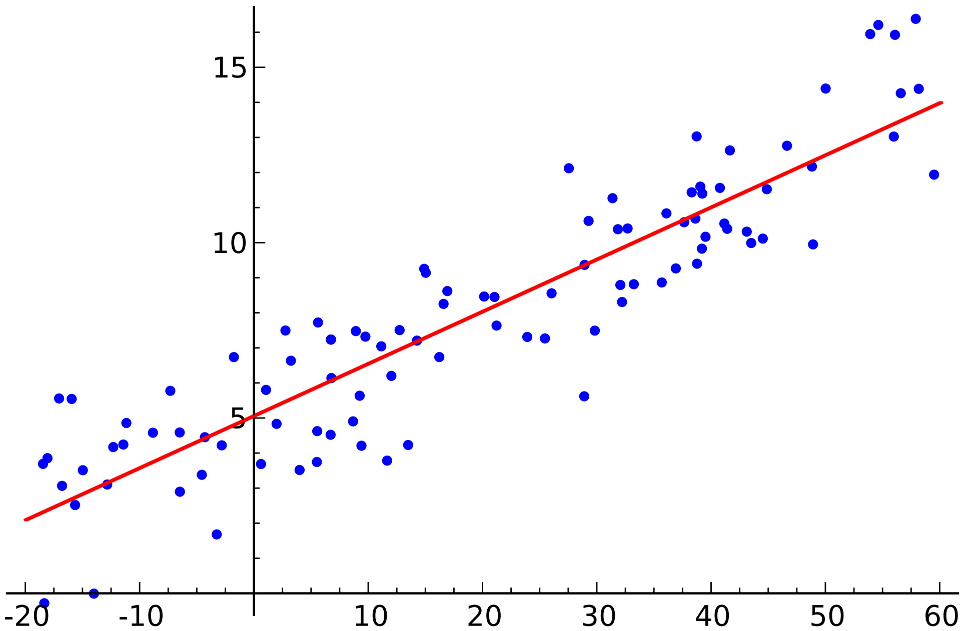
🟢 There are many definitions for a regression problem but in our case, we're going to simplify it: predicting a numerical variable based on some other combination of variables, even shorter... predicting a number.

In [3]:
```
# Import Tensorflow
import tensorflow as tf
print(tf.__version__)
```

```
2.9.1
```

Regression analysis

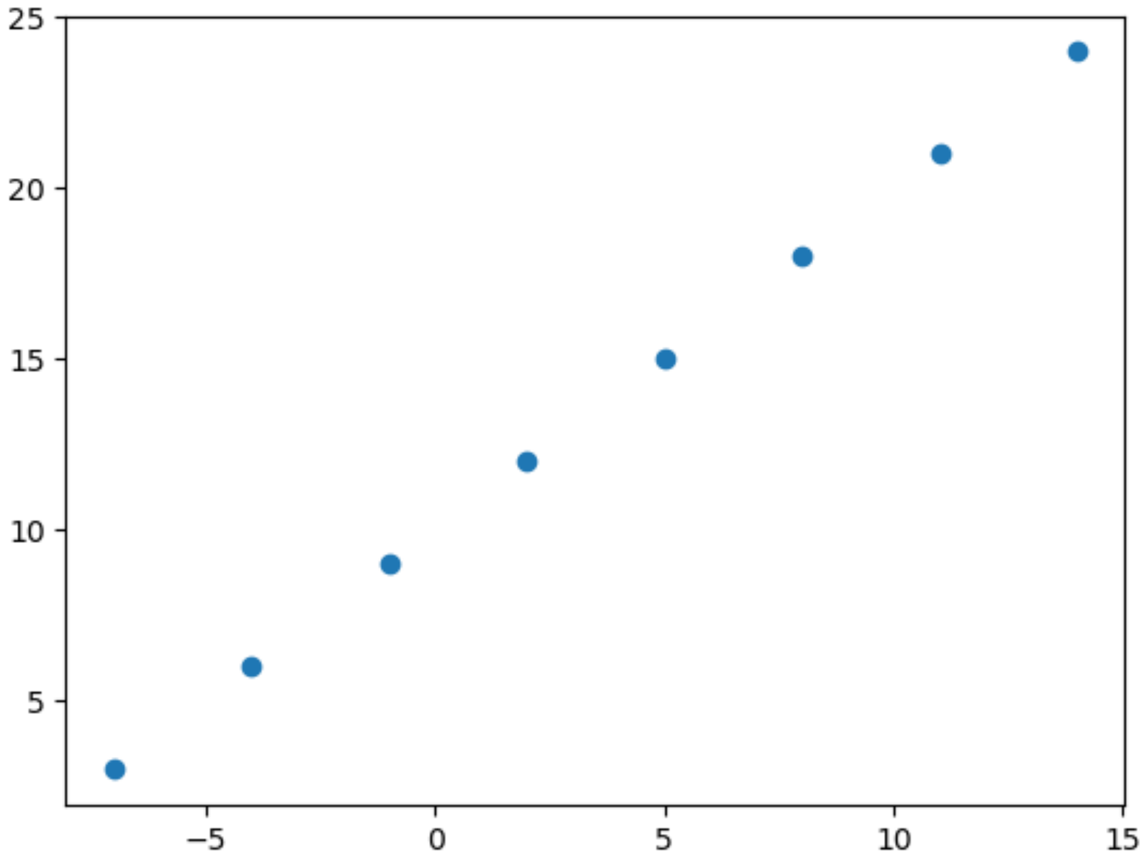
Source: https://en.wikipedia.org/wiki/Regression_analysis



In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome' or 'response' variable, or a 'label' in machine learning parlance) and one or more independent variables (often called 'predictors', 'covariates', 'explanatory variables' or 'features').

Creating data to view and fit

In [4]:
```
import numpy as np
import matplotlib.pyplot as plt

# Create features (Indepent variables)
X = np.array([-7.0, -4.0, -1.0, 2.0, 5.0, 8.0, 11.0, 14.0])

# Create labels (Dependent variables)
y = np.array([3.0, 6.0, 9.0, 12.0, 15.0, 18.0, 21.0, 24.0])

# Visualize it
plt.scatter(X, y);
```



In [5]:
```
# We created the definition above with a relationship
# between X and y as the function X + 10:
X + 10
```

Out[5]:
```
array([ 3.,  6.,  9., 12., 15., 18., 21., 24.])
```

In [6]:
```
# Validating if y == X + 10
y == X + 10
```

Out[6]:
```
array([ True,  True,  True,  True,  True,  True,  True,  True])
```

Input and output shapes

In [7]:
```
# Create a fast demo tensor for our housing price prediction
# problem # to understand how input and output shape is
house_info = tf.constant(["bedroom", "bathroom", "garage"])
house_price = tf.constant([939700])
house_info, house_price
```

```
2022-10-09 20:32:57.601965: I tensorflow/core/platform/cpu_feature_guard.
cc:193] This TensorFlow binary is optimized with oneAPI Deep Neural Netwo
rk Library (oneDNN) to use the following CPU instructions in performance-
critical operations:  SSE4.1 SSE4.2
To enable them in other operations, rebuild TensorFlow with the appropria
te compiler flags.
```

Out[7]:
```
(<tf.Tensor: shape=(3,), dtype=string, numpy=array([b'bedroom', b'bathroo
m', b'garage'], dtype=object)>,
 <tf.Tensor: shape=(1,), dtype=int32, numpy=array([939700], dtype=int32)>
)
```

In [8]:
```
input_shape = X[0].shape
output_shape = y[0].shape
input_shape, output_shape
```

Out[8]:
```
((), ())
```

⚠️ If some error like Input 0 of layer "dense" is incompatible with the layer....

This happens because model.fit() no longer automatically upscales inputs from shape (batch_size,) to (batch_size, 1).

OLD model.fit(X, y, epochs=5)

NEW model.fit(tf.expand_dims(X, axis=-1), y, epochs=5)

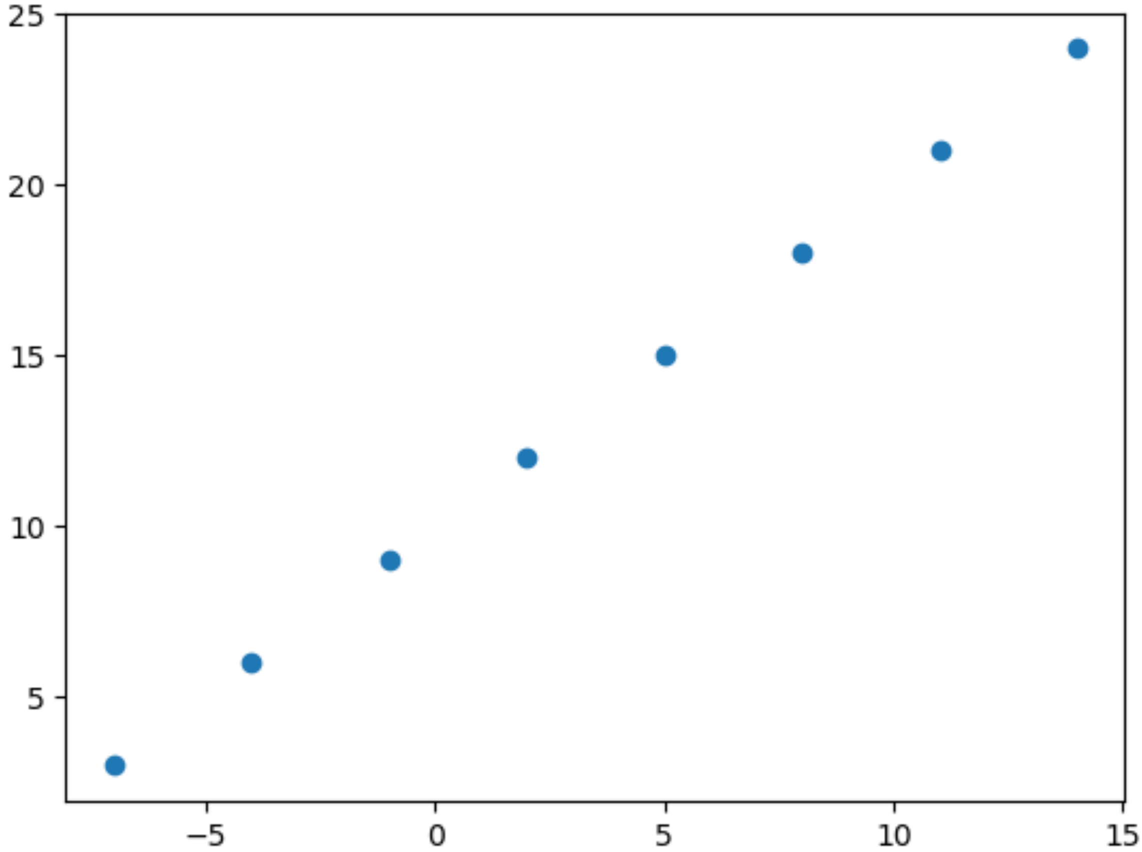
In [9]:
```
# Turn our NumPy arrays into tensors
X = tf.constant(X)
y = tf.constant(y)
X, y
```

Out[9]:
```
(<tf.Tensor: shape=(8,), dtype=float64, numpy=array([-7., -4., -1.,  2.,
5.,  8., 11., 14.])>,
 <tf.Tensor: shape=(8,), dtype=float64, numpy=array([ 3.,  6.,  9., 12.,
15., 18., 21., 24.])>)
```

In [10]:
```
input_shape = X[0].shape
output_shape = y[0].shape
input_shape, output_shape
```

Out[10]:
```
(TensorShape([]), TensorShape([]))
```

In [11]:
```
plt.scatter(X, y);
```



Steps in modelling with TensorFlow

1. **Creating a model** - define the input and output layers, as well as the hidden layers of a deep learning model.
2. **Compile a model** - define the loss function (in other words, the function which tells our model how wrong it is) and the optimizer (tells our model how to improve the patterns its learning) and evaluation metrics (what we can use to interpret the performance of our model).
3. **Fitting a model** - letting the model try to find patterns between X & y (features and labels).

In [12]:
```
# Set random seed
tf.random.set_seed(42)

# 1. Create a model using the Sequential API
# model = tf.keras.Sequential([
#     tf.keras.layers.Dense(1)
# ])
model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(1))

# 2. Compile the model
# Note: Loss MAE is used for comparisons of predicted versus observed

model.compile(
    loss=tf.keras.losses.mae, # mae is short for mean absolute error
    optimizer=tf.keras.optimizers.SGD(), # SGD is short for stochastic gr
    metrics=["mae"]
)

# 3. Fit the model
model.fit(tf.expand_dims(X, axis=-1), y, epochs=5)
```

```
Epoch 1/5
1/1 [==============================] - 0s 174ms/step - loss: 11.5048 - ma
e: 11.5048
Epoch 2/5
1/1 [==============================] - 0s 2ms/step - loss: 11.3723 - mae:
11.3723
Epoch 3/5
1/1 [==============================] - 0s 2ms/step - loss: 11.2398 - mae:
11.2398
Epoch 4/5
1/1 [==============================] - 0s 2ms/step - loss: 11.1073 - mae:
11.1073
Epoch 5/5
1/1 [==============================] - 0s 2ms/step - loss: 10.9748 - mae:
10.9748
```

Out[12]:
```
<keras.callbacks.History at 0x7fae1d943cd0>
```

In [13]:
```
# Check out X an y
X, y
```

Out[13]:
```
(<tf.Tensor: shape=(8,), dtype=float64, numpy=array([-7., -4., -1.,  2.,
5.,  8., 11., 14.])>,
 <tf.Tensor: shape=(8,), dtype=float64, numpy=array([ 3.,  6.,  9., 12.,
15., 18., 21., 24.])>)
```

In [14]:
```
# Try and make a prediction using our model
y_pred = model.predict([17.0])
y_pred
```

```
1/1 [==============================] - 0s 55ms/step
```

Out[14]:
```
array([[12.716021]], dtype=float32)
```

Improving our model

We can improve our model, by altering the steps we took to create a model.

1. **Creating a model** - here we might add more layers, increate the number of hidden units (all called neurons) within each of the hidden layers, change the activation function of each layer.
2. **Compiling a model** - here we might change the optimization function or perhaps the **learning rate** of the optimization function.
3. **Fitting a model** - here we might fit a model for more **ephocs** (leave it training for longer) or on more data (give the model more examples to learn from).

In [15]:
```
# Let's rebuild the model

# 1. Create a model (again)
model = tf.keras.Sequential([
    tf.keras.layers.Dense(1)
])

# 2. Compile the model
model.compile(loss=tf.keras.losses.mae,
              optimizer=tf.keras.optimizers.SGD(),
             metrics=["mae"])

# 3. Fit the model (this time we'll train for longer)
model.fit(tf.expand_dims(X, axis=-1), y, epochs=100)
```

```
Epoch 1/100
1/1 [==============================] - 0s 137ms/step - loss: 11.2219 - ma
e: 11.2219
Epoch 2/100
1/1 [==============================] - 0s 2ms/step - loss: 11.0894 - mae:
11.0894
Epoch 3/100
1/1 [==============================] - 0s 2ms/step - loss: 10.9569 - mae:
10.9569
Epoch 4/100
1/1 [==============================] - 0s 2ms/step - loss: 10.8244 - mae:
10.8244
Epoch 5/100
1/1 [==============================] - 0s 2ms/step - loss: 10.6919 - mae:
10.6919
Epoch 6/100
1/1 [==============================] - 0s 2ms/step - loss: 10.5594 - mae:
10.5594
Epoch 7/100
1/1 [==============================] - 0s 2ms/step - loss: 10.4269 - mae:
10.4269
Epoch 8/100
1/1 [==============================] - 0s 2ms/step - loss: 10.2944 - mae:
10.2944
Epoch 9/100
1/1 [==============================] - 0s 2ms/step - loss: 10.1619 - mae:
```

```
10.1619
Epoch 10/100
1/1 [==============================] - 0s 2ms/step - loss: 10.0294 - mae:
10.0294
Epoch 11/100
1/1 [==============================] - 0s 2ms/step - loss: 9.8969 - mae:
9.8969
Epoch 12/100
1/1 [==============================] - 0s 2ms/step - loss: 9.7644 - mae:
9.7644
Epoch 13/100
1/1 [==============================] - 0s 2ms/step - loss: 9.6319 - mae:
9.6319
Epoch 14/100
1/1 [==============================] - 0s 2ms/step - loss: 9.4994 - mae:
9.4994
Epoch 15/100
1/1 [==============================] - 0s 2ms/step - loss: 9.3669 - mae:
9.3669
Epoch 16/100
1/1 [==============================] - 0s 2ms/step - loss: 9.2344 - mae:
9.2344
Epoch 17/100
1/1 [==============================] - 0s 2ms/step - loss: 9.1019 - mae:
9.1019
Epoch 18/100
1/1 [==============================] - 0s 2ms/step - loss: 8.9694 - mae:
8.9694
Epoch 19/100
1/1 [==============================] - 0s 2ms/step - loss: 8.8369 - mae:
8.8369
Epoch 20/100
1/1 [==============================] - 0s 2ms/step - loss: 8.7044 - mae:
8.7044
Epoch 21/100
1/1 [==============================] - 0s 3ms/step - loss: 8.5719 - mae:
8.5719
Epoch 22/100
1/1 [==============================] - 0s 3ms/step - loss: 8.4394 - mae:
8.4394
Epoch 23/100
1/1 [==============================] - 0s 2ms/step - loss: 8.3069 - mae:
8.3069
Epoch 24/100
1/1 [==============================] - 0s 2ms/step - loss: 8.1744 - mae:
8.1744
Epoch 25/100
1/1 [==============================] - 0s 2ms/step - loss: 8.0419 - mae:
8.0419
Epoch 26/100
1/1 [==============================] - 0s 2ms/step - loss: 7.9094 - mae:
7.9094
Epoch 27/100
1/1 [==============================] - 0s 2ms/step - loss: 7.7769 - mae:
7.7769
Epoch 28/100
1/1 [==============================] - 0s 3ms/step - loss: 7.6444 - mae:
```

```
7.6444
Epoch 29/100
1/1 [==============================] - 0s 2ms/step - loss: 7.5119 - mae: 
7.5119
Epoch 30/100
1/1 [==============================] - 0s 2ms/step - loss: 7.3794 - mae: 
7.3794
Epoch 31/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2750 - mae: 
7.2750
Epoch 32/100
1/1 [==============================] - 0s 3ms/step - loss: 7.2694 - mae: 
7.2694
Epoch 33/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2638 - mae: 
7.2638
Epoch 34/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2581 - mae: 
7.2581
Epoch 35/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2525 - mae: 
7.2525
Epoch 36/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2469 - mae: 
7.2469
Epoch 37/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2412 - mae: 
7.2412
Epoch 38/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2356 - mae: 
7.2356
Epoch 39/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2300 - mae: 
7.2300
Epoch 40/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2244 - mae: 
7.2244
Epoch 41/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2188 - mae: 
7.2188
Epoch 42/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2131 - mae: 
7.2131
Epoch 43/100
1/1 [==============================] - 0s 2ms/step - loss: 7.2075 - mae: 
7.2075
Epoch 44/100
1/1 [==============================] - 0s 3ms/step - loss: 7.2019 - mae: 
7.2019
Epoch 45/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1962 - mae: 
7.1962
Epoch 46/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1906 - mae: 
7.1906
Epoch 47/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1850 - mae: 
```

```
7.1850
Epoch 48/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1794 - mae:
7.1794
Epoch 49/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1737 - mae:
7.1737
Epoch 50/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1681 - mae:
7.1681
Epoch 51/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1625 - mae:
7.1625
Epoch 52/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1569 - mae:
7.1569
Epoch 53/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1512 - mae:
7.1512
Epoch 54/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1456 - mae:
7.1456
Epoch 55/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1400 - mae:
7.1400
Epoch 56/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1344 - mae:
7.1344
Epoch 57/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1287 - mae:
7.1287
Epoch 58/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1231 - mae:
7.1231
Epoch 59/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1175 - mae:
7.1175
Epoch 60/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1119 - mae:
7.1119
Epoch 61/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1062 - mae:
7.1062
Epoch 62/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1006 - mae:
7.1006
Epoch 63/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0950 - mae:
7.0950
Epoch 64/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0894 - mae:
7.0894
Epoch 65/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0838 - mae:
7.0838
Epoch 66/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0781 - mae:
```

```
7.0781
Epoch 67/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0725 - mae:
7.0725
Epoch 68/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0669 - mae:
7.0669
Epoch 69/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0613 - mae:
7.0613
Epoch 70/100
1/1 [==============================] - 0s 3ms/step - loss: 7.0556 - mae:
7.0556
Epoch 71/100
1/1 [==============================] - 0s 3ms/step - loss: 7.0500 - mae:
7.0500
Epoch 72/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0444 - mae:
7.0444
Epoch 73/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0388 - mae:
7.0388
Epoch 74/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0331 - mae:
7.0331
Epoch 75/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0275 - mae:
7.0275
Epoch 76/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0219 - mae:
7.0219
Epoch 77/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0163 - mae:
7.0163
Epoch 78/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0106 - mae:
7.0106
Epoch 79/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0050 - mae:
7.0050
Epoch 80/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9994 - mae:
6.9994
Epoch 81/100
1/1 [==============================] - 0s 3ms/step - loss: 6.9938 - mae:
6.9938
Epoch 82/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9881 - mae:
6.9881
Epoch 83/100
1/1 [==============================] - 0s 3ms/step - loss: 6.9825 - mae:
6.9825
Epoch 84/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9769 - mae:
6.9769
Epoch 85/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9713 - mae:
```

```
6.9713
Epoch 86/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9656 - mae:
6.9656
Epoch 87/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9600 - mae:
6.9600
Epoch 88/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9544 - mae:
6.9544
Epoch 89/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9488 - mae:
6.9488
Epoch 90/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9431 - mae:
6.9431
Epoch 91/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9375 - mae:
6.9375
Epoch 92/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9319 - mae:
6.9319
Epoch 93/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9263 - mae:
6.9263
Epoch 94/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9206 - mae:
6.9206
Epoch 95/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9150 - mae:
6.9150
Epoch 96/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9094 - mae:
6.9094
Epoch 97/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9038 - mae:
6.9038
Epoch 98/100
1/1 [==============================] - 0s 2ms/step - loss: 6.8981 - mae:
6.8981
Epoch 99/100
1/1 [==============================] - 0s 2ms/step - loss: 6.8925 - mae:
6.8925
Epoch 100/100
1/1 [==============================] - 0s 2ms/step - loss: 6.8869 - mae:
6.8869
```

Out[15]:
```
<keras.callbacks.History at 0x7fae1d7460e0>
```

In [16]:
```
# Remind ourselves of the data
X, y
```

Out[16]:
```
(<tf.Tensor: shape=(8,), dtype=float64, numpy=array([-7., -4., -1.,  2.,
5.,  8., 11., 14.])>,
 <tf.Tensor: shape=(8,), dtype=float64, numpy=array([ 3.,  6.,  9., 12.,
15., 18., 21., 24.])>)
```

In [17]:
```
# Let's see if our model's prediction has improved
model.predict([17.0])
```

```
1/1 [==============================] - 0s 34ms/step
```
Out[17]:
```
array([[29.739855]], dtype=float32)
```

In [18]:
```
# Let's see if we can make another change to improve our model

# 1. Create the model (this time with an extra hidden layer with 100 hidd
model = tf.keras.Sequential([
    tf.keras.layers.Dense(50, activation=None),
    tf.keras.layers.Dense(1)
])

# 2 . Compile the model
model.compile(loss=tf.keras.losses.mae,
              optimizer=tf.keras.optimizers.Adam(learning_rate=0.01),
              metrics=["mae"])

# 3. Fit the model
model.fit(tf.expand_dims(X, axis=1), y, epochs=100)
```

```
Epoch 1/100
1/1 [==============================] - 0s 171ms/step - loss: 11.7682 - ma
e: 11.7682
Epoch 2/100
1/1 [==============================] - 0s 2ms/step - loss: 11.0963 - mae:
11.0963
Epoch 3/100
1/1 [==============================] - 0s 2ms/step - loss: 10.4150 - mae:
10.4150
Epoch 4/100
1/1 [==============================] - 0s 2ms/step - loss: 9.7212 - mae:
9.7212
Epoch 5/100
1/1 [==============================] - 0s 2ms/step - loss: 9.0104 - mae:
9.0104
Epoch 6/100
1/1 [==============================] - 0s 2ms/step - loss: 8.2778 - mae:
8.2778
Epoch 7/100
1/1 [==============================] - 0s 2ms/step - loss: 7.5198 - mae:
7.5198
Epoch 8/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9648 - mae:
6.9648
Epoch 9/100
1/1 [==============================] - 0s 2ms/step - loss: 7.0672 - mae:
7.0672
Epoch 10/100
1/1 [==============================] - 0s 2ms/step - loss: 7.3315 - mae:
7.3315
Epoch 11/100
1/1 [==============================] - 0s 2ms/step - loss: 7.4673 - mae:
7.4673
Epoch 12/100
```

```
1/1 [==============================] - 0s 2ms/step - loss: 7.5285 - mae:
7.5285
Epoch 13/100
1/1 [==============================] - 0s 2ms/step - loss: 7.4011 - mae:
7.4011
Epoch 14/100
1/1 [==============================] - 0s 2ms/step - loss: 7.1923 - mae:
7.1923
Epoch 15/100
1/1 [==============================] - 0s 2ms/step - loss: 6.9575 - mae:
6.9575
Epoch 16/100
1/1 [==============================] - 0s 2ms/step - loss: 6.6953 - mae:
6.6953
Epoch 17/100
1/1 [==============================] - 0s 2ms/step - loss: 6.4127 - mae:
6.4127
Epoch 18/100
1/1 [==============================] - 0s 2ms/step - loss: 6.3048 - mae:
6.3048
Epoch 19/100
1/1 [==============================] - 0s 2ms/step - loss: 6.2575 - mae:
6.2575
Epoch 20/100
1/1 [==============================] - 0s 2ms/step - loss: 6.3982 - mae:
6.3982
Epoch 21/100
1/1 [==============================] - 0s 2ms/step - loss: 6.4551 - mae:
6.4551
Epoch 22/100
1/1 [==============================] - 0s 2ms/step - loss: 6.4000 - mae:
6.4000
Epoch 23/100
1/1 [==============================] - 0s 2ms/step - loss: 6.2482 - mae:
6.2482
Epoch 24/100
1/1 [==============================] - 0s 2ms/step - loss: 6.0105 - mae:
6.0105
Epoch 25/100
1/1 [==============================] - 0s 2ms/step - loss: 5.7876 - mae:
5.7876
Epoch 26/100
1/1 [==============================] - 0s 2ms/step - loss: 5.6809 - mae:
5.6809
Epoch 27/100
1/1 [==============================] - 0s 2ms/step - loss: 5.5715 - mae:
5.5715
Epoch 28/100
1/1 [==============================] - 0s 2ms/step - loss: 5.6122 - mae:
5.6122
Epoch 29/100
1/1 [==============================] - 0s 2ms/step - loss: 5.6074 - mae:
5.6074
Epoch 30/100
1/1 [==============================] - 0s 2ms/step - loss: 5.5541 - mae:
5.5541
Epoch 31/100
```

```
1/1 [==============================] - 0s 2ms/step - loss: 5.4568 - mae:
5.4568
Epoch 32/100
1/1 [==============================] - 0s 2ms/step - loss: 5.3199 - mae:
5.3199
Epoch 33/100
1/1 [==============================] - 0s 2ms/step - loss: 5.1477 - mae:
5.1477
Epoch 34/100
1/1 [==============================] - 0s 2ms/step - loss: 4.9442 - mae:
4.9442
Epoch 35/100
1/1 [==============================] - 0s 2ms/step - loss: 4.8239 - mae:
4.8239
Epoch 36/100
1/1 [==============================] - 0s 2ms/step - loss: 4.7389 - mae:
4.7389
Epoch 37/100
1/1 [==============================] - 0s 2ms/step - loss: 4.6657 - mae:
4.6657
Epoch 38/100
1/1 [==============================] - 0s 2ms/step - loss: 4.5846 - mae:
4.5846
Epoch 39/100
1/1 [==============================] - 0s 2ms/step - loss: 4.4027 - mae:
4.4027
Epoch 40/100
1/1 [==============================] - 0s 2ms/step - loss: 4.2653 - mae:
4.2653
Epoch 41/100
1/1 [==============================] - 0s 2ms/step - loss: 4.1212 - mae:
4.1212
Epoch 42/100
1/1 [==============================] - 0s 2ms/step - loss: 3.9702 - mae:
3.9702
Epoch 43/100
1/1 [==============================] - 0s 2ms/step - loss: 3.8272 - mae:
3.8272
Epoch 44/100
1/1 [==============================] - 0s 2ms/step - loss: 3.7041 - mae:
3.7041
Epoch 45/100
1/1 [==============================] - 0s 2ms/step - loss: 3.5320 - mae:
3.5320
Epoch 46/100
1/1 [==============================] - 0s 2ms/step - loss: 3.3664 - mae:
3.3664
Epoch 47/100
1/1 [==============================] - 0s 2ms/step - loss: 3.2116 - mae:
3.2116
Epoch 48/100
1/1 [==============================] - 0s 2ms/step - loss: 3.0463 - mae:
3.0463
Epoch 49/100
1/1 [==============================] - 0s 2ms/step - loss: 2.8705 - mae:
2.8705
Epoch 50/100
```

```
1/1 [==============================] - 0s 2ms/step - loss: 2.6840 - mae:
2.6840
Epoch 51/100
1/1 [==============================] - 0s 2ms/step - loss: 2.4868 - mae:
2.4868
Epoch 52/100
1/1 [==============================] - 0s 2ms/step - loss: 2.2787 - mae:
2.2787
Epoch 53/100
1/1 [==============================] - 0s 2ms/step - loss: 2.0596 - mae:
2.0596
Epoch 54/100
1/1 [==============================] - 0s 2ms/step - loss: 1.8293 - mae:
1.8293
Epoch 55/100
1/1 [==============================] - 0s 2ms/step - loss: 1.5876 - mae:
1.5876
Epoch 56/100
1/1 [==============================] - 0s 2ms/step - loss: 1.3530 - mae:
1.3530
Epoch 57/100
1/1 [==============================] - 0s 2ms/step - loss: 1.0849 - mae:
1.0849
Epoch 58/100
1/1 [==============================] - 0s 2ms/step - loss: 0.8224 - mae:
0.8224
Epoch 59/100
1/1 [==============================] - 0s 2ms/step - loss: 0.5467 - mae:
0.5467
Epoch 60/100
1/1 [==============================] - 0s 2ms/step - loss: 0.2758 - mae:
0.2758
Epoch 61/100
1/1 [==============================] - 0s 2ms/step - loss: 0.1354 - mae:
0.1354
Epoch 62/100
1/1 [==============================] - 0s 2ms/step - loss: 0.4494 - mae:
0.4494
Epoch 63/100
1/1 [==============================] - 0s 2ms/step - loss: 0.6498 - mae:
0.6498
Epoch 64/100
1/1 [==============================] - 0s 2ms/step - loss: 0.6216 - mae:
0.6216
Epoch 65/100
1/1 [==============================] - 0s 2ms/step - loss: 0.8036 - mae:
0.8036
Epoch 66/100
1/1 [==============================] - 0s 2ms/step - loss: 0.7995 - mae:
0.7995
Epoch 67/100
1/1 [==============================] - 0s 2ms/step - loss: 0.7409 - mae:
0.7409
Epoch 68/100
1/1 [==============================] - 0s 2ms/step - loss: 0.7806 - mae:
0.7806
Epoch 69/100
```

```
1/1 [==============================] - 0s 2ms/step - loss: 0.6305 - mae:
0.6305
Epoch 70/100
1/1 [==============================] - 0s 2ms/step - loss: 0.5556 - mae:
0.5556
Epoch 71/100
1/1 [==============================] - 0s 2ms/step - loss: 0.4306 - mae:
0.4306
Epoch 72/100
1/1 [==============================] - 0s 2ms/step - loss: 0.2786 - mae:
0.2786
Epoch 73/100
1/1 [==============================] - 0s 2ms/step - loss: 0.1378 - mae:
0.1378
Epoch 74/100
1/1 [==============================] - 0s 2ms/step - loss: 0.1193 - mae:
0.1193
Epoch 75/100
1/1 [==============================] - 0s 2ms/step - loss: 0.2777 - mae:
0.2777
Epoch 76/100
1/1 [==============================] - 0s 2ms/step - loss: 0.3245 - mae:
0.3245
Epoch 77/100
1/1 [==============================] - 0s 2ms/step - loss: 0.4157 - mae:
0.4157
Epoch 78/100
1/1 [==============================] - 0s 2ms/step - loss: 0.4319 - mae:
0.4319
Epoch 79/100
1/1 [==============================] - 0s 2ms/step - loss: 0.3391 - mae:
0.3391
Epoch 80/100
1/1 [==============================] - 0s 3ms/step - loss: 0.2968 - mae:
0.2968
Epoch 81/100
1/1 [==============================] - 0s 3ms/step - loss: 0.2355 - mae:
0.2355
Epoch 82/100
1/1 [==============================] - 0s 4ms/step - loss: 0.1633 - mae:
0.1633
Epoch 83/100
1/1 [==============================] - 0s 3ms/step - loss: 0.1339 - mae:
0.1339
Epoch 84/100
1/1 [==============================] - 0s 2ms/step - loss: 0.1262 - mae:
0.1262
Epoch 85/100
1/1 [==============================] - 0s 3ms/step - loss: 0.1702 - mae:
0.1702
Epoch 86/100
1/1 [==============================] - 0s 3ms/step - loss: 0.2124 - mae:
0.2124
Epoch 87/100
1/1 [==============================] - 0s 4ms/step - loss: 0.2288 - mae:
0.2288
Epoch 88/100
```

```
1/1 [==============================] - 0s 4ms/step - loss: 0.1901 - mae: 
0.1901
Epoch 89/100
1/1 [==============================] - 0s 2ms/step - loss: 0.1354 - mae: 
0.1354
Epoch 90/100
1/1 [==============================] - 0s 1ms/step - loss: 0.1218 - mae: 
0.1218
Epoch 91/100
1/1 [==============================] - 0s 2ms/step - loss: 0.0382 - mae: 
0.0382
Epoch 92/100
1/1 [==============================] - 0s 2ms/step - loss: 0.2197 - mae: 
0.2197
Epoch 93/100
1/1 [==============================] - 0s 2ms/step - loss: 0.2189 - mae: 
0.2189
Epoch 94/100
1/1 [==============================] - 0s 2ms/step - loss: 0.1427 - mae: 
0.1427
Epoch 95/100
1/1 [==============================] - 0s 2ms/step - loss: 0.1168 - mae: 
0.1168
Epoch 96/100
1/1 [==============================] - 0s 2ms/step - loss: 0.2069 - mae: 
0.2069
Epoch 97/100
1/1 [==============================] - 0s 2ms/step - loss: 0.1524 - mae: 
0.1524
Epoch 98/100
1/1 [==============================] - 0s 2ms/step - loss: 0.2133 - mae: 
0.2133
Epoch 99/100
1/1 [==============================] - 0s 2ms/step - loss: 0.2329 - mae: 
0.2329
Epoch 100/100
1/1 [==============================] - 0s 2ms/step - loss: 0.0780 - mae: 
0.0780
```

Out[18]:

```
<keras.callbacks.History at 0x7fae1db71420>
```

In [19]:

```
# Let's remind ourselves of the data
X, y
```

Out[19]:

```
(<tf.Tensor: shape=(8,), dtype=float64, numpy=array([-7., -4., -1.,  2., 
5.,  8., 11., 14.])>,
 <tf.Tensor: shape=(8,), dtype=float64, numpy=array([ 3.,  6.,  9., 12., 
15., 18., 21., 24.])>)
```

In [20]:

```
model.predict([17.0])
```

```
1/1 [==============================] - 0s 45ms/step
```

Out[20]:

```
array([[26.583532]], dtype=float32)
```

⭐ Common ways to improve a deep model

- Adding layers
- Increase the number of hidden units
- Change the activation functions
- Change the optimization function
- Change the learning rate
- Fitting on more data
- Fitting for longer (epochs)

Evaluating a model

🟢 **When it comes to evaluation... there are 3 words you should memorize:**
"Visualize, visualize, visualize"

It's a good idea to visualize:

- The data - what data are we working with? What does it look like?
- The model itself - What does model look like?
- The training of model - how does a model perform while it learns?
- The predictions of the model - how do the predictions of a model line up against the ground truth (the original labels)?

In [21]:
```
# Make a bigger dataset
X = tf.range(-100, 100, 4) # Numbers between -100 and 100 stepped 4
X
```

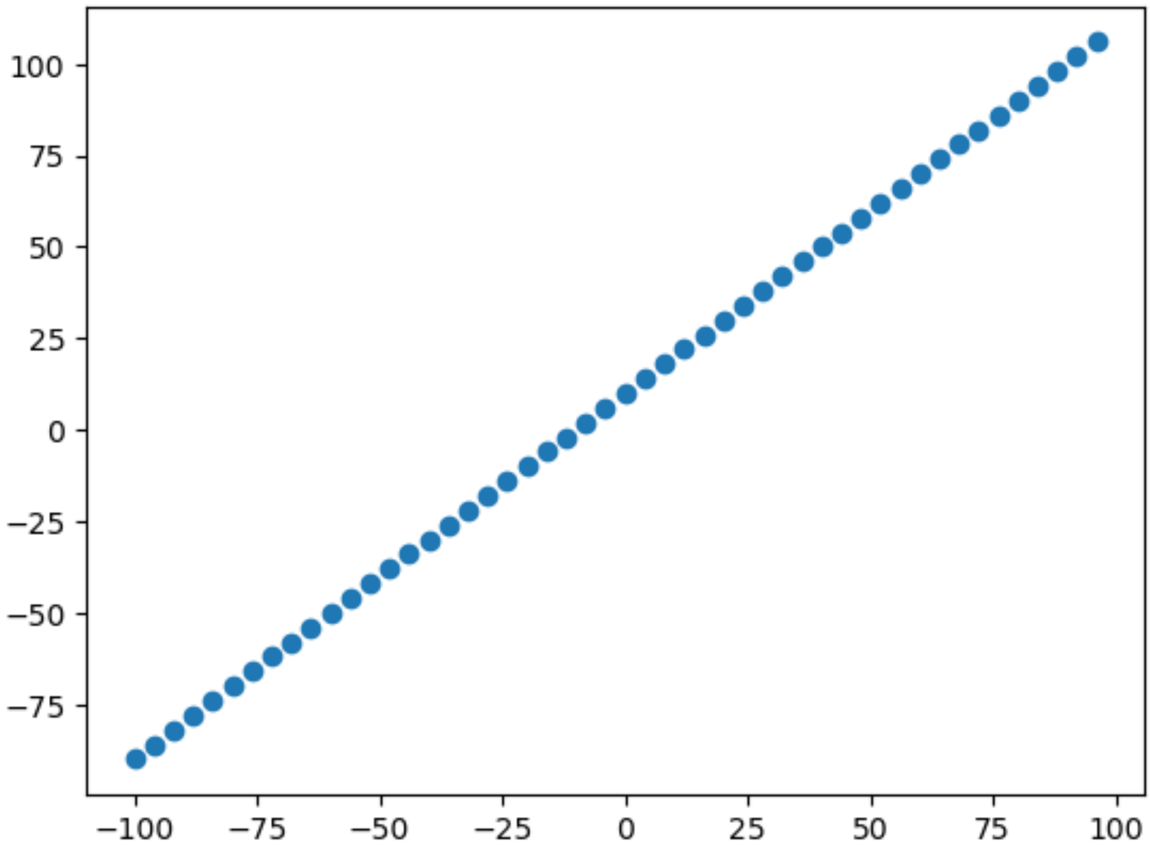
Out[21]:
```
<tf.Tensor: shape=(50,), dtype=int32, numpy=
array([-100,  -96,  -92,  -88,  -84,  -80,  -76,  -72,  -68,  -64,  -60,
        -56,  -52,  -48,  -44,  -40,  -36,  -32,  -28,  -24,  -20,  -16,
        -12,   -8,   -4,    0,    4,    8,   12,   16,   20,   24,   28,
         32,   36,   40,   44,   48,   52,   56,   60,   64,   68,   72,
         76,   80,   84,   88,   92,   96], dtype=int32)>
```

In [22]:
```
# Make labels for the dataset
y = X + 10
y
```

Out[22]:
```
<tf.Tensor: shape=(50,), dtype=int32, numpy=
array([-90, -86, -82, -78, -74, -70, -66, -62, -58, -54, -50, -46, -42,
       -38, -34, -30, -26, -22, -18, -14, -10,  -6,  -2,   2,   6,  10,
        14,  18,  22,  26,  30,  34,  38,  42,  46,  50,  54,  58,  62,
        66,  70,  74,  78,  82,  86,  90,  94,  98, 102, 106], dtype=int3
2)>
```

In [23]:
```
# Visualize the data
import matplotlib.pyplot as plt

plt.scatter(X, y)
```

Out[23]:
```
<matplotlib.collections.PathCollection at 0x7fae1d768610>
```



The 3 sets:

- **Training set** - the model learns from this data, which is tipically 70-80% of the total data you have available.
- **Validation set** - the model gets tuned on this data, which is tipically 10-15% of the total data available.
- **Test set** - the model get evaluated on this data to test what is has learned, this set is tipically 10-15% of the total data available.

Similar to exam

📖 **Course materials** (training set) ➡️ 📝 **Practice exam** (validation set) ➡️ 📝 **Final exam** (test set)

⚙️ Generalization

The ability for a machine learning model to perform well on data it hasn't seen before.

In [24]:
```
# Check the length of how many samples we have
len(X)
```

Out[24]:
```
50
```

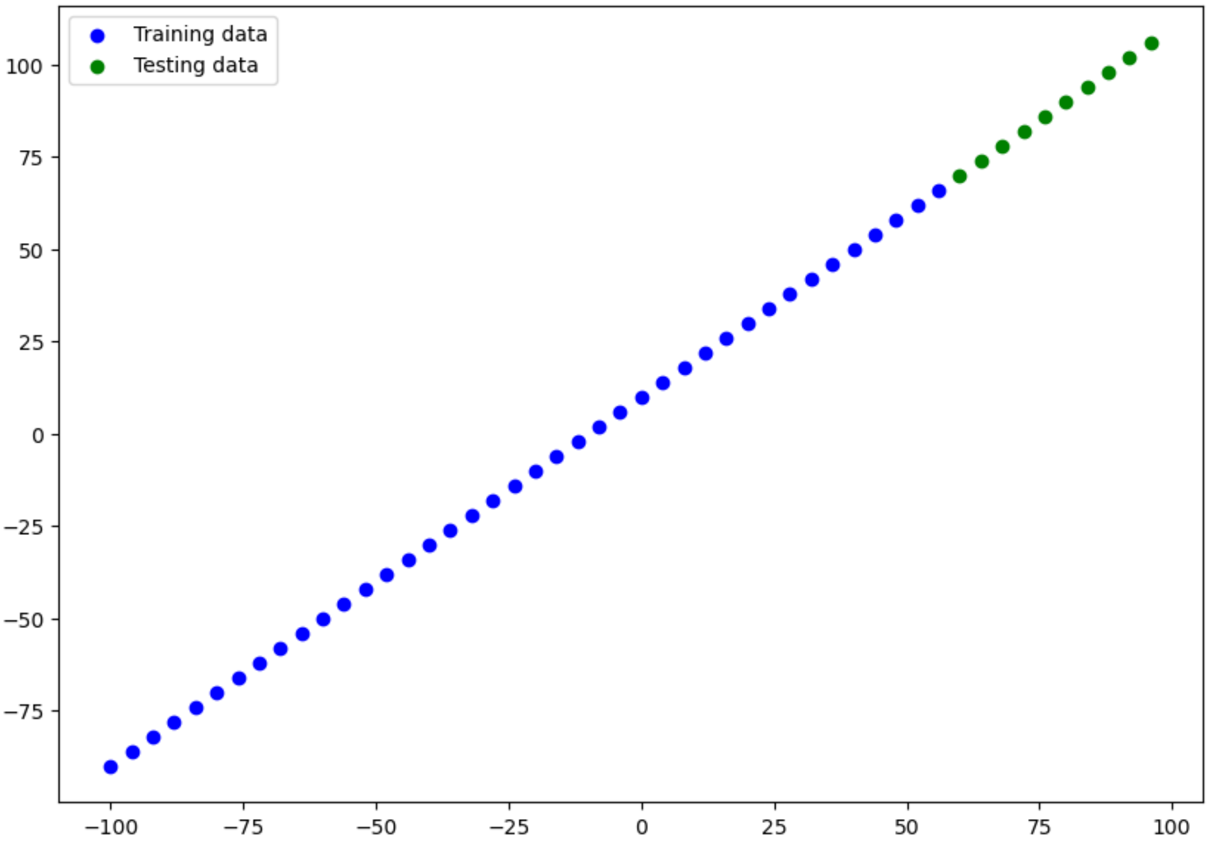
In [25]:
```
# Split the data into train and test sets
X_train = X[:40] # first 40 are training samples (80% of the data)
y_train = y[:40]

X_test  = X[40:] # last 10 samples are testing samples (20% of the data)
y_test  = y[40:]

len(X_train), len(X_test), len(y_train), len(y_test)
```

Out[25]:
```
(40, 10, 40, 10)
```

Visualizing the data

Now we've got our data in training and test sets... let's visualize it again!

In [26]:
```
plt.figure(figsize=(10, 7))

# Plot training data in blue
plt.scatter(X_train, y_train, c="b", label="Training data")

# Plot test data in green
plt.scatter(X_test, y_test, c="g", label="Testing data")

# Show a legend
plt.legend(); # Use this semicolon at and to set end
```



In [27]:
```
# Let's have a look at how to build a neural network for our data

# 1. Create a model
model = tf.keras.Sequential([
    tf.keras.layers.Dense(1)
])

# 2. Compile the model
model.compile(loss=tf.keras.losses.mae,
              optimizer=tf.keras.optimizers.SGD(),
              metrics=["mae"])

# # 3. Fit the model
# model.fit(tf.expand_dims(X_train, axis=1), y_train, epochs=100)
```

Visualizing the model

In [28]:
```
model.summary()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
Input In [28], in <cell line: 1>()
----> 1 model.summary()

File ~/opt/anaconda3/envs/tf/lib/python3.10/site-packages/keras/engine/training.py:2869, in Model.summary(self, line_length, positions, print_fn, expand_nested, show_trainable)
   2847 """Prints a string summary of the network.
   2848 
   2849 Args:
   (...)
   2866     ValueError: if `summary()` is called before the model is built.
   2867 """
   2868 if not self.built:
-> 2869   raise ValueError(
   2870       'This model has not yet been built. '
   2871       'Build the model first by calling `build()` or by calling '
   2872       'the model on a batch of data.')
   2873 layer_utils.print_summary(
   2874     self,
   2875     line_length=line_length,
   (...)
   2878     expand_nested=expand_nested,
   2879     show_trainable=show_trainable)

ValueError: This model has not yet been built. Build the model first by calling `build()` or by calling the model on a batch of data.
```

In [63]:

```
# Let's create a model which builds automatically by defining the
# input_shape argument in the first layer

tf.random.set_seed(42)

# Create a model (same as above)
model = tf.keras.Sequential([
    tf.keras.layers.Dense(10, input_shape=[1], name="input_layer"),
    tf.keras.layers.Dense(1, name="output_layer")
], name="model_1")

# 2. Compile the model (same as above)
model.compile(loss=tf.keras.losses.mae,
              optimizer=tf.keras.optimizers.SGD(),
              metrics=["mae"])
```

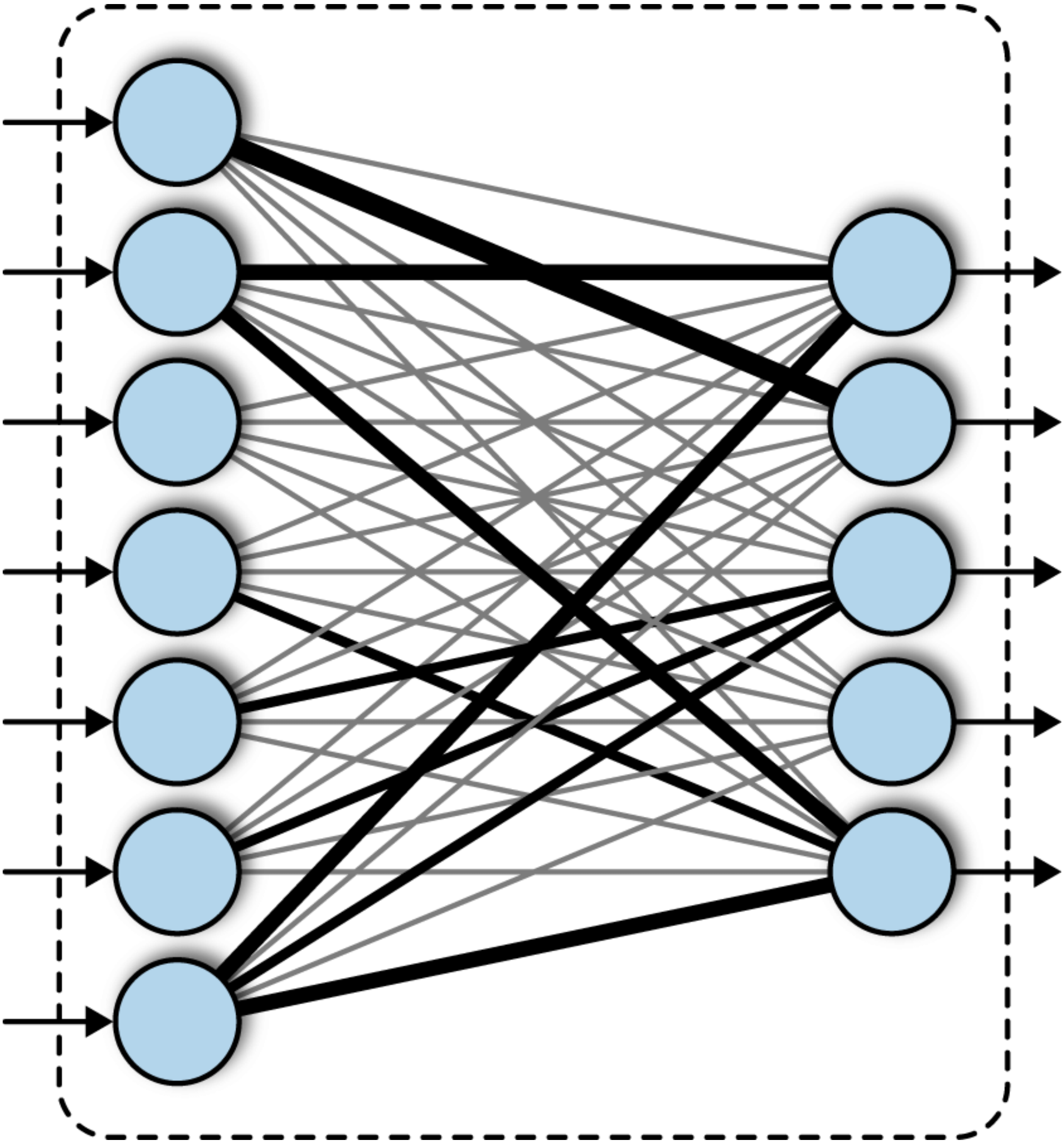
In [64]:

```
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 10)                20

 output_layer (Dense)        (None, 1)                 11

=================================================================
Total params: 31
Trainable params: 31
Non-trainable params: 0
_________________________________________________________________
```

- Total params - total of parameters in the model
- Trainable parameters - these are the parameters (patterns) the model can update as it trains.
- Non-trainable params - these parameters aren't updated during training (this is typical when your bring in already learn patterns or parameters from other models during **transfer learning**).

🟢 Note: Dense means a fully connected neurons layer



In [65]:
```
# Let's fit our model to the training data
model.fit(tf.expand_dims(X_train, axis=1), y_train, epochs=100, verbose=0
```

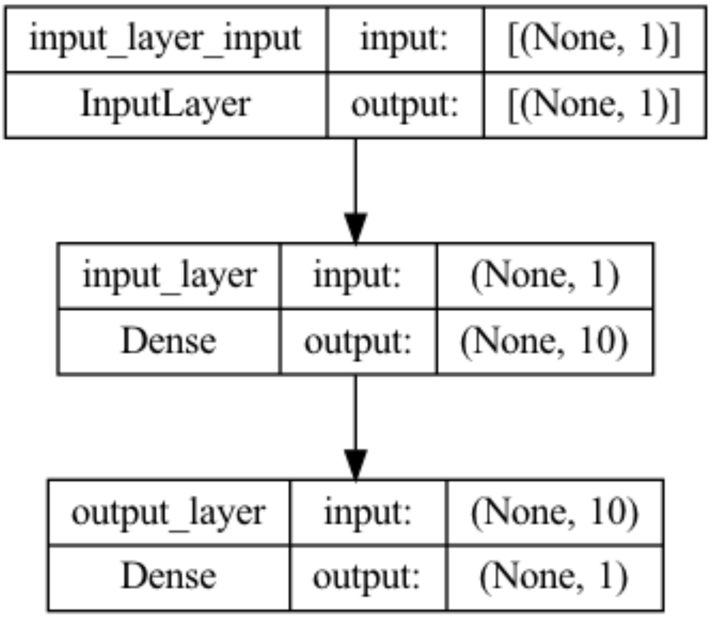
Out[65]:
```
<keras.callbacks.History at 0x7fadf8eddb40>
```

In [66]:
```
model.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 10)                20

 output_layer (Dense)        (None, 1)                 11

=================================================================
Total params: 31
Trainable params: 31
Non-trainable params: 0
_________________________________________________________________
```

In [67]:
```python
from tensorflow.keras.utils import plot_model

plot_model(model=model, show_shapes=True)
```

Out[67]:



Visualizing our model's predictions

To visualize predictions, it's a good idea to plot them against the ground truth labels.

Often you'll see this in the form of `y_test` or `y_true` versus `y_pred` (ground truth versus your model's predictions)

In [70]:
```python
# Make some predictions
y_pred = model.predict(X_test)
y_pred

# In ideal execution y_pred has the same values of y_test
X_test, y_pred, y_test
```

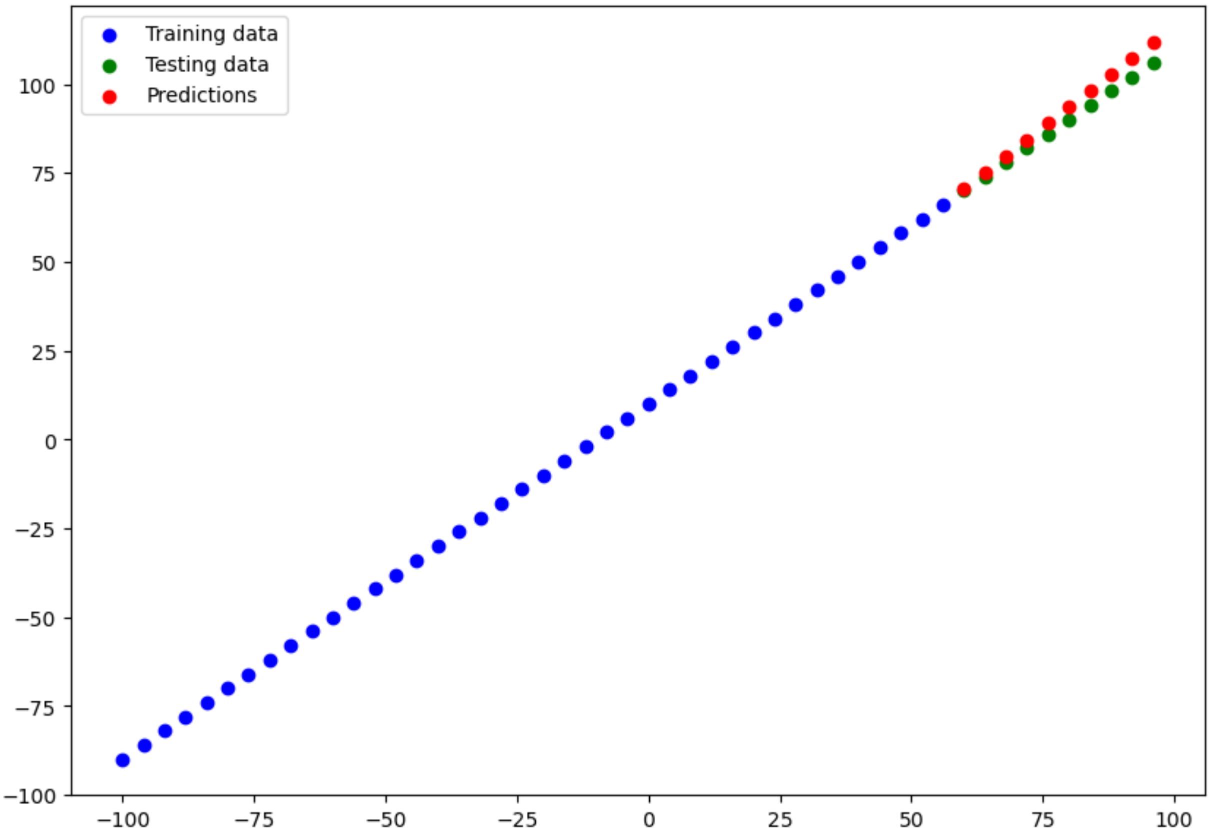
```
1/1 [==============================] - 0s 13ms/step
```

Out[70]:
```
(<tf.Tensor: shape=(10,), dtype=int32, numpy=array([60, 64, 68, 72, 76, 8
0, 84, 88, 92, 96], dtype=int32)>,
 array([[ 70.552185],
        [ 75.13991 ],
        [ 79.72764 ],
        [ 84.315346],
        [ 88.90308 ],
        [ 93.49081 ],
        [ 98.07852 ],
        [102.666245],
        [107.253975],
        [111.84169 ]], dtype=float32),
 <tf.Tensor: shape=(10,), dtype=int32, numpy=array([ 70,  74,  78,  82,
86,  90,  94,  98, 102, 106], dtype=int32)>)
```

🔑 **Note:** Below we will do a plot for predictions. If you feel like you're going to reuse some kind of functionality in the future, it's a good idea to create a function

In [75]:
```
# Let's create a plotting function
def plot_predictions(train_data=X_train,
                     train_labels=y_train,
                     test_data=X_test,
                     test_labels=y_test,
                     predictions=y_pred):
    """
    Plots training data, test data and compares predictions to ground tru
    """
    plt.figure(figsize=(10, 7))

    # Plot training data in blue
    plt.scatter(train_data, train_labels, c="b", label="Training data")

    #Plot testing data in green
    plt.scatter(test_data, test_labels, c="g", label="Testing data")

    #Plot model's predictions in red
    plt.scatter(test_data, predictions, c="r", label="Predictions")

    # Show the legent
    plt.legend();
```

In [77]:
```
# plot_predictions()
plot_predictions(train_data=X_train,
                     train_labels=y_train,
                     test_data=X_test,
                     test_labels=y_test,
                     predictions=y_pred)
```



Evaluating our model's predictions with regression evaluation metrics

Depending on the problem you're working on, there will be different evaluation metrics to evaluate your model's performance.

Since we're working on a regression, two of the main metrics:

- MAE - mean absolute error, "on average, how wrong is each of my model's predictions"
- MSE - mean square error "square the average errors"

In [78]:
```
# Evaluate the model on the test
model.evaluate(X_test, y_test)
```

```
1/1 [==============================] - 0s 86ms/step - loss: 3.1969 - mae:
3.1969
```

Out[78]:
```
[3.1969406604766846, 3.1969406604766846]
```

In [88]:
```
# Calculate the mean absolute error

mae = tf.metrics.mean_absolute_error(y_true=y_test,
                                     y_pred=y_pred)
mae
```

Out[88]:
```
<tf.Tensor: shape=(10,), dtype=float32, numpy=
array([17.558252 , 14.1160555, 11.708944 , 10.336931 , 10.        ,
       10.698161 , 12.447113 , 15.332995 , 19.253975 , 23.84169  ],
      dtype=float32)>
```

In [94]:
```
y_test, tf.constant(y_pred)
```

Out[94]:
```
(<tf.Tensor: shape=(10,), dtype=int32, numpy=array([ 70,  74,  78,  82,
86,  90,  94,  98, 102, 106], dtype=int32)>,
 <tf.Tensor: shape=(10, 1), dtype=float32, numpy=
 array([[ 70.552185],
        [ 75.13991 ],
        [ 79.72764 ],
        [ 84.315346],
        [ 88.90308 ],
        [ 93.49081 ],
        [ 98.07852 ],
        [102.666245],
        [107.253975],
        [111.84169 ]], dtype=float32)>)
```

In [95]:
```
# Calculate the mean absolute error
# keeping the same dimensions y_true and y_pred
# Look that result is the same result of model.evaluate

mae = tf.metrics.mean_absolute_error(y_true=y_test,
                                     y_pred=tf.squeeze(y_pred))
mae
```

Out[95]:
```
<tf.Tensor: shape=(), dtype=float32, numpy=3.19694>
```

In [97]:
```
# Calculate the mean square error

mse = tf.metrics.mean_squared_error(y_true=y_test,
                                     y_pred=tf.squeeze(y_pred))
mse
```

Out[97]:
```
<tf.Tensor: shape=(), dtype=float32, numpy=13.070127>
```

In [109…
```
# Make some functions to reuse MAE and MSE
def mae(y_true, y_pred):
    return tf.metrics.mean_absolute_error(y_true=y_true, y_pred=tf.squeez

def mse(y_true, y_pred):
    return tf.metrics.mean_squared_error(y_true=y_true, y_pred=tf.squeeze
```

Running experiments to improve our model

```
Build a model -> fit it -> evaluate it -> tweak it -> fit
it -> evaluate it -> tweak it -> fit it -> evaluate it ...
```

1. Get more data - get more examples for your model to train on (more opportunities to learn patterns or relationships between features and labels).
2. Make your model larger (using a more complex model) - this might come in the form of more layers or more hidden units in each layer.
3. Train for longer - give your model more of a chance to find patterns in the data.

Let's do 3 modeling experiments:

1. `model_1` - same as the original model, 1 layer, trained for 100 epochs.
2. `model_2` - 2 layers, trained for 100 epochs.
3. `model_3` - 2 layers, trained for 500 epochs.

Build `model_1`

- 1 dense layer, trained for 100 epochs

In [102…

```
# Set random seed
tf.random.set_seed(42)

# 1. Create the model
model_1 = tf.keras.Sequential([
    tf.keras.layers.Dense(1, name="input_layer")
], name="model_1")

# 2. Compile the model
model_1.compile(loss=tf.keras.losses.mae,
                optimizer=tf.keras.optimizers.SGD(),
                metrics=["mae"])


# 3. Fit the model
model_1.fit(tf.expand_dims(X_train, axis=1), y_train, epochs=100, verbose
```

In [104…

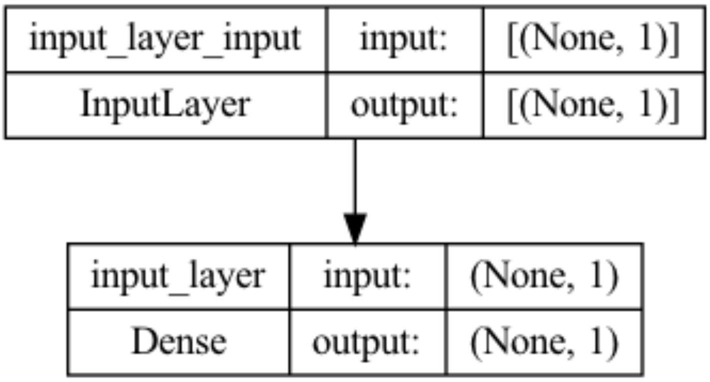
```
model_1.summary()
```

```
Model: "model_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 1)                 2

=================================================================
Total params: 2
Trainable params: 2
Non-trainable params: 0
_________________________________________________________________
```

In [105…

```
plot_model(model=model_1, show_shapes=True)
```

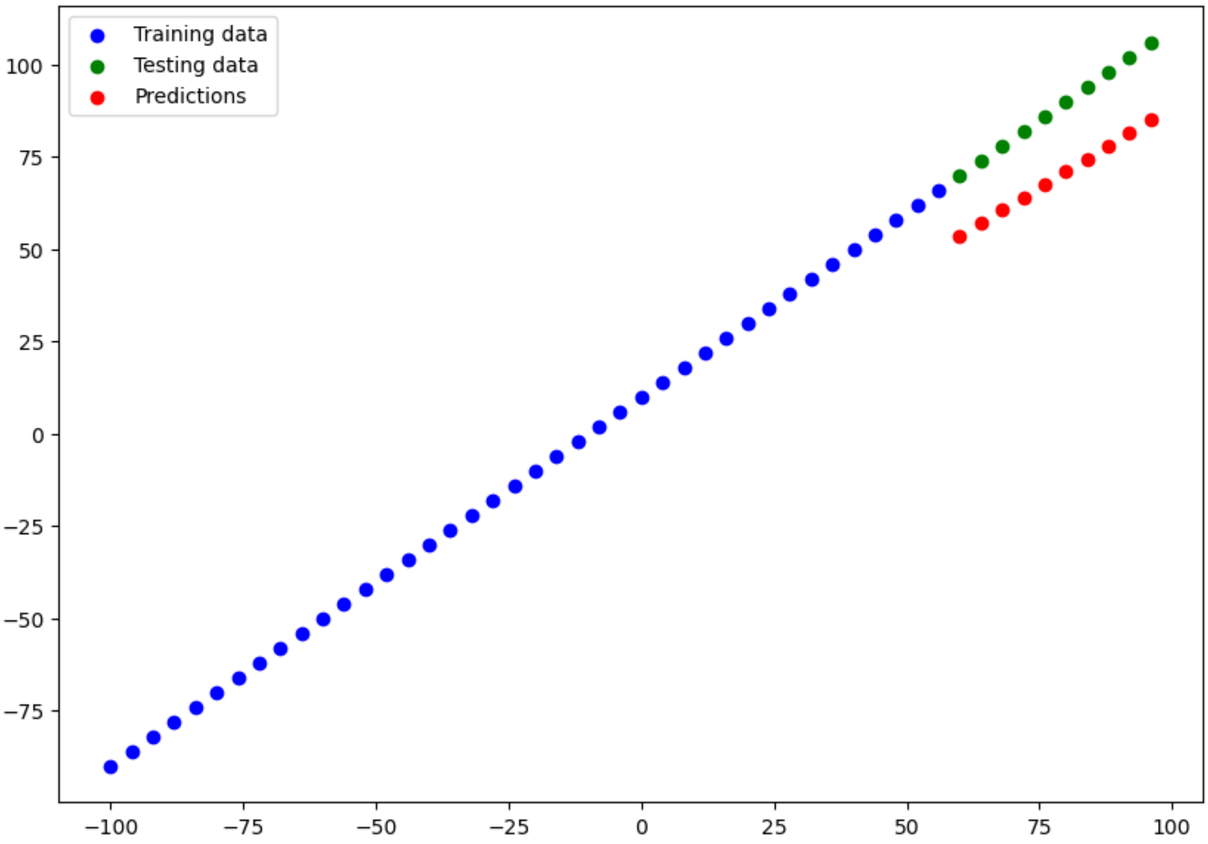
Out[105]:



In [106…

```
# Make and plot predictions for model_1
y_preds_1 = model_1.predict(X_test)
plot_predictions(predictions=y_preds_1)
```

```
WARNING:tensorflow:5 out of the last 7 calls to <function Model.make_pred
ict_function.<locals>.predict_function at 0x7fae298ae290> triggered tf.fu
nction retracing. Tracing is expensive and the excessive number of tracin
gs could be due to (1) creating @tf.function repeatedly in a loop, (2) pa
ssing tensors with different shapes, (3) passing Python objects instead o
f tensors. For (1), please define your @tf.function outside of the loop.
For (2), @tf.function has reduce_retracing=True option that can avoid unn
ecessary retracing. For (3), please refer to https://www.tensorflow.org/g
uide/function#controlling_retracing and https://www.tensorflow.org/api_do
cs/python/tf/function for  more details.
1/1 [==============================] - 0s 28ms/step
```



In [110…

```
# Calculate model_1 evaluation metrics
mae_1 = mae(y_test, y_preds_1)
mse_1 = mse(y_test, y_preds_1)

mae_1, mse_1
```

Out[110]:

```
(<tf.Tensor: shape=(), dtype=float32, numpy=18.745327>,
 <tf.Tensor: shape=(), dtype=float32, numpy=353.57336>)
```

As above metrics results:

- **MAE:** each graph dot is on average 18.745327 far away from where it should be.
- **MSE:** each graph dot is on average 353.57336 far away from where it should be.

Build `model_2`

- 2 dense layers, trained for 100 epochs

In [161…

```
# Set random seed
tf.random.set_seed(42)

# 1. Create the model
model_2 = tf.keras.Sequential([
    tf.keras.layers.Dense(1, name="input_layer"),
    tf.keras.layers.Dense(1, name="output_layer")
], name="model_2")

#2. Compile the model
model_2.compile(loss=tf.keras.losses.mae,
               optimizer=tf.keras.optimizers.SGD(),
               metrics=["mae"])

#3. Fit the model
model_2.fit(tf.expand_dims(X_train, axis=1), y_train, epochs=100, verbose
```

Out[161]:

```
<keras.callbacks.History at 0x7fade85dae90>
```

In [162…

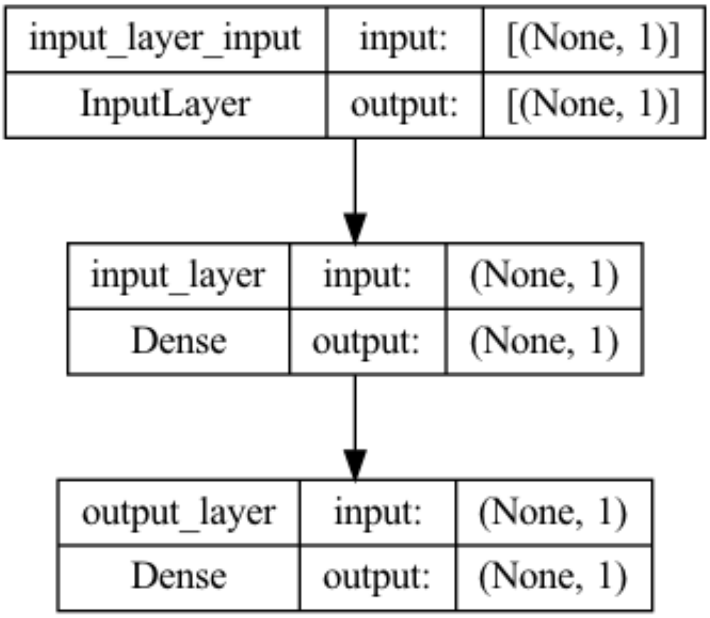
```
model_2.summary()
```

```
Model: "model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 1)                 2

 output_layer (Dense)        (None, 1)                 2

=================================================================
Total params: 4
Trainable params: 4
Non-trainable params: 0
_________________________________________________________________
```

In [163…

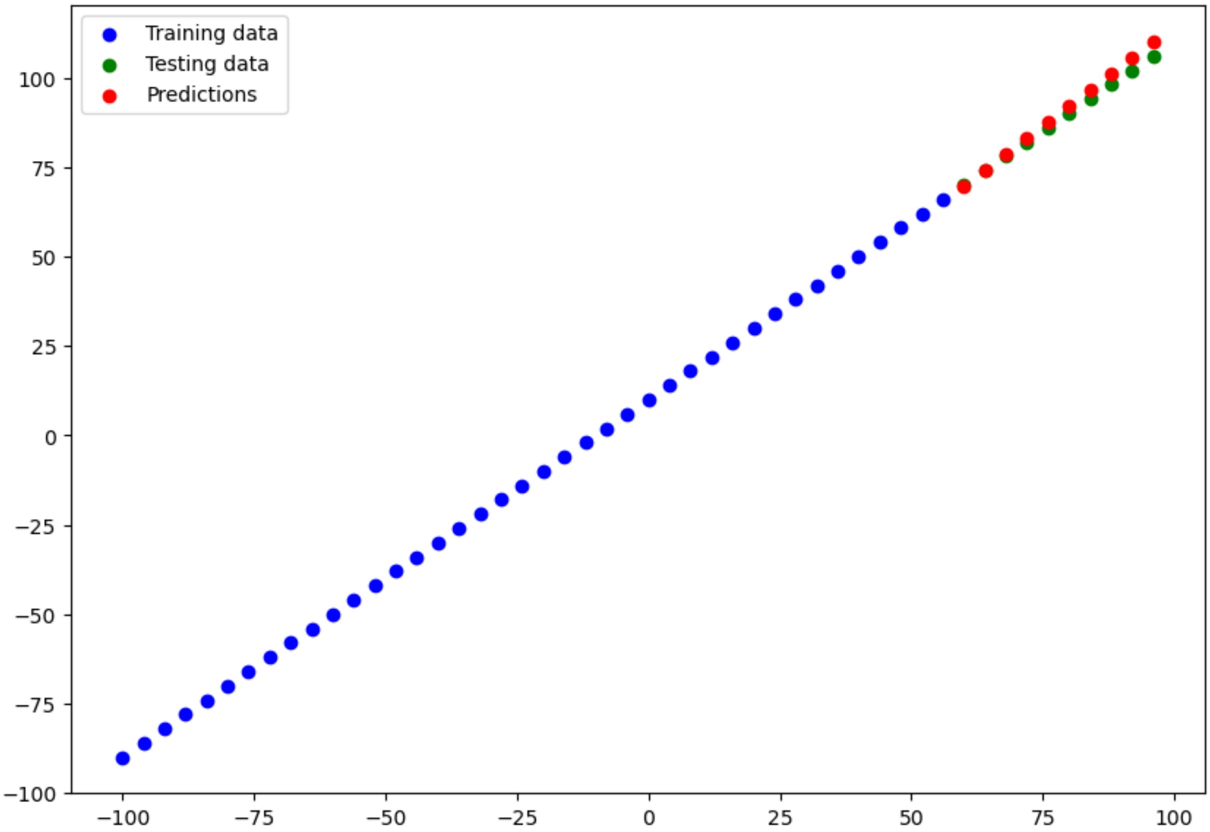
```
plot_model(model_2, show_shapes=True)
```

Out[163]:



In [164…
```
# Make and plot predictions for model_2
y_preds_2 = model_2.predict(X_test)
plot_predictions(predictions=y_preds_2)
```

```
1/1 [==============================] - 0s 32ms/step
```



In [166…
```
# Calculate model_2 evaluation metrics
mae_2 = mae(y_test, y_preds_2)
mse_2 = mse(y_test, y_preds_2)

mae_2, mse_2
```

Out[166]:
```
(<tf.Tensor: shape=(), dtype=float32, numpy=1.9097328>,
 <tf.Tensor: shape=(), dtype=float32, numpy=5.45877>)
```

As above metrics results:

- **MAE:** each graph dot is on average 1.9097328 far away from where it should be.
- **MSE:** each graph dot is on average 5.45877 far away from where it should be.

Build `model_3`

- 2 dense layers, trained for 500 epochs

In [193…

```
# Set random seed
tf.random.set_seed(42)

# 1. Create the model
model_3 = tf.keras.Sequential([
    tf.keras.layers.Dense(1, name="input_layer"),
    tf.keras.layers.Dense(1, name="output_layer")
], name="model_3")

# 2. Compile the model
model_3.compile(loss=tf.keras.losses.mae,
               optimizer=tf.keras.optimizers.SGD(),
               metrics=["mae"])

# 3. Fit the model
model_3.fit(tf.expand_dims(X_train, axis=1), y_train, epochs=500, verbose
```

Out[193]:

```
<keras.callbacks.History at 0x7fadd9a69390>
```

In [194…

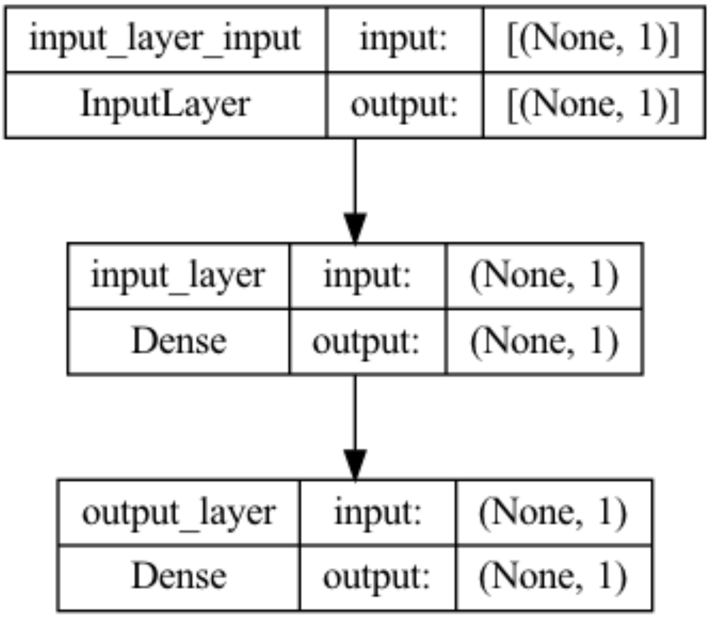
```
model_3.summary()
```

```
Model: "model_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 1)                 2

 output_layer (Dense)        (None, 1)                 2

=================================================================
Total params: 4
Trainable params: 4
Non-trainable params: 0
_________________________________________________________________
```

In [195…

```
plot_model(model_3, show_shapes=True)
```

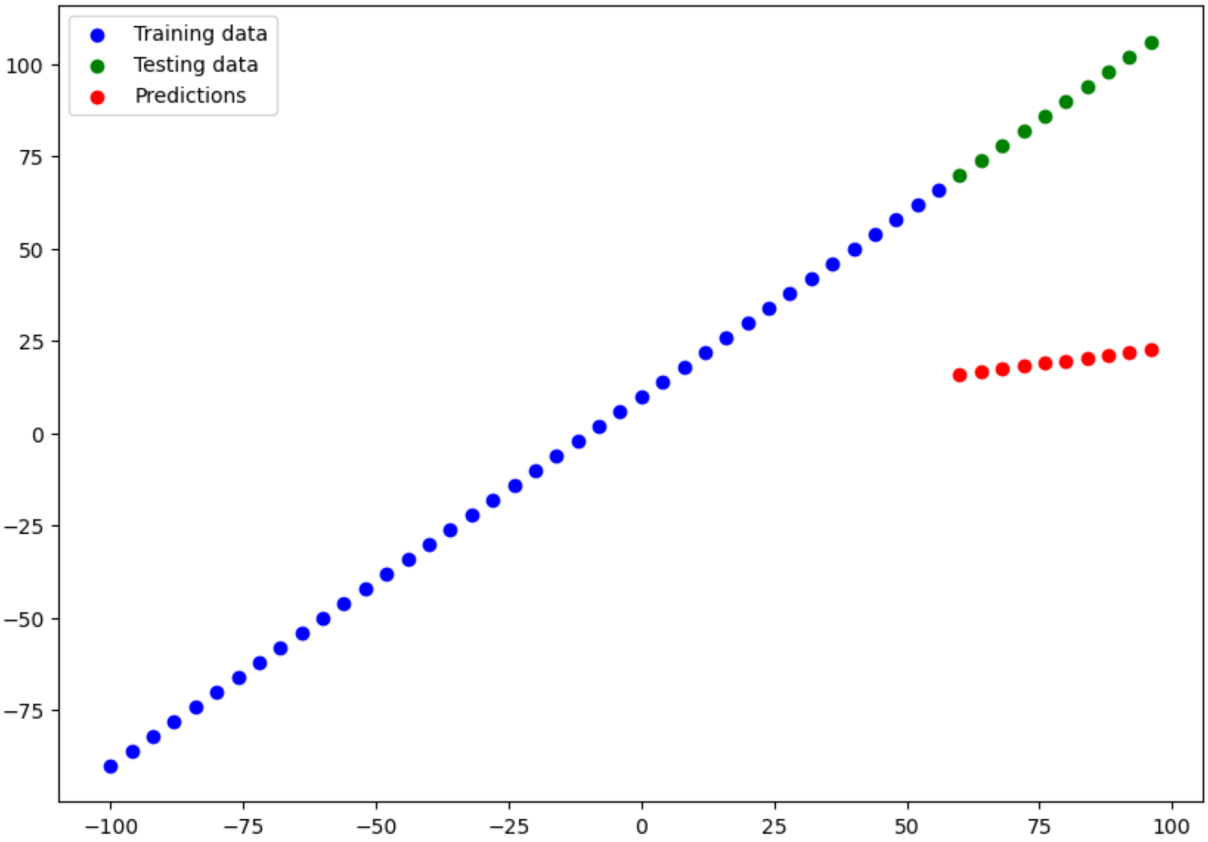
Out[195]:



In [196…

```
# Make and plot predictions for model_3
y_preds_3 = model_3.predict(X_test)
plot_predictions(predictions=y_preds_3)
```

```
1/1 [==============================] - 0s 32ms/step
```



In [198…

```
# Calculate the model_3 evaluation metrics
mae_3 = mae(y_test, y_preds_3)
mse_3 = mse(y_test, y_preds_3)

mae_3, mse_3
```

Out[198]:

```
(<tf.Tensor: shape=(), dtype=float32, numpy=68.68784>,
 <tf.Tensor: shape=(), dtype=float32, numpy=4804.469>)
```

As above metrics results:

- **MAE:** each graph dot is on average 68.68784 far away from where it should be.
- **MSE:** each graph dot is on average 4804.469 far away from where it should be.

Note based on last sections

🔑 **Note:** You want to start with small experiments (samll models) and make sure they work and then increase their scale when necessary.

Comparing the results of our experiments

We've run a few experiments, let's compare the results.

In [199…

```
# Let's compare our model's results using a pandas DataFrame
import pandas as pd

model_results = [["model_1", mae_1.numpy(), mse_1.numpy()],
                 ["model_2", mae_2.numpy(), mse_2.numpy()],
                 ["model_3", mae_3.numpy(), mse_3.numpy()]]


all_results = pd.DataFrame(model_results, columns=["model", "mae", "mse"]

all_results
```

Out[199]:

	model	mae	mse
0	model_1	18.745327	353.573364
1	model_2	1.909733	5.458770
2	model_3	68.687843	4804.469238

Model 2 performed the best

2 dense layers, trained for 100 epochs

In [200…

```
model_2.summary()
```

```
Model: "model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 1)                 2

 output_layer (Dense)        (None, 1)                 2

=================================================================
Total params: 4
Trainable params: 4
Non-trainable params: 0
_________________________________________________________________
```

🔑 **Note:** One of your main goals should be to minimize the time between your experiments. The more experiments you do, the more things you'll figure out which don't work and in turn, get closer to figuring out what does work.

Tracking your experiments

One really good habit in machine learning modelling is to track the results of your experiments.

And when doing so, it can be tedious if you're running lots of experiments.

Luckily, there are tools to help us!

📖 **Reource:** As you build more models, you'll want to look into using:

- TensorBoard (https://www.tensorflow.org/tensorboard) - a component of the TensorFlow library to help track modelling experiments (we'll see this one later).
- Weights & Biases (https://wandb.ai/site) - a tool for tracking all of kinds of machine learning experiments (plugs straight into TensorBoard).

Saving our models

Saving our models allows us to use them outside Jupyter Notebook, Google Colab (or wherever they were trained) such as in a web application or a mobile app.

There are two main formats we can save our model's too:

1. The SavedModel format
2. The HDF5 format - Hierarchical Data Format - Designed to store and organize large amount of data.

In [202…

```
# Save model using the SavedModel format
!mkdir -p saved_model
model_2.save('saved_model/model_2')
```

```
INFO:tensorflow:Assets written to: saved_model/model_2/assets
```

In [203…

```
# Save model using the HDF5 format
!mkdir -p hdf5

# The '.h5' extension indicates that the model should be saved to HDF5
model_2.save('hdf5/model_2.h5')
```

Loading in a saved model

In [210…

```
# Load in a model using the Saved Model format
loaded_SavedModel_format = tf.keras.models.load_model("saved_model/model_
loaded_SavedModel_format.summary()
```

```
Model: "model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 1)                 2

 output_layer (Dense)        (None, 1)                 2

=================================================================
Total params: 4
Trainable params: 4
Non-trainable params: 0
_________________________________________________________________
```

In [211…

```
# Compare model_2 predictions with SavedModel format model predictions
model_2_preds = model_2.predict(X_test)
loaded_SavedModel_format_preds = loaded_SavedModel_format.predict(X_test)

model_2_preds == loaded_SavedModel_format_preds
```

```
1/1 [==============================] - 0s 11ms/step
1/1 [==============================] - 0s 25ms/step
```

Out[211]:

```
array([[ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True]])
```

In [212…

```
# Load in a model using the .h5 format
loaded_h5_format = tf.keras.models.load_model("hdf5/model_2.h5")
loaded_h5_format.summary()
```

```
Model: "model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 1)                 2

 output_layer (Dense)        (None, 1)                 2

=================================================================
Total params: 4
Trainable params: 4
Non-trainable params: 0
_________________________________________________________________
```

In [214…
```
# Compare model_2 predictions with HDF5 format model predictions
model_2_preds = model_2.predict(X_test)
loaded_hdf5_format_preds = loaded_h5_format.predict(X_test)

model_2_preds == loaded_hdf5_format_preds
```

```
1/1 [==============================] - 0s 12ms/step
1/1 [==============================] - 0s 13ms/step
```

Out[214]:
```
array([[ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True],
       [ True]])
```

A larger example

Using a kaggle.com dataset as example - Medical Cost Personal Datasets

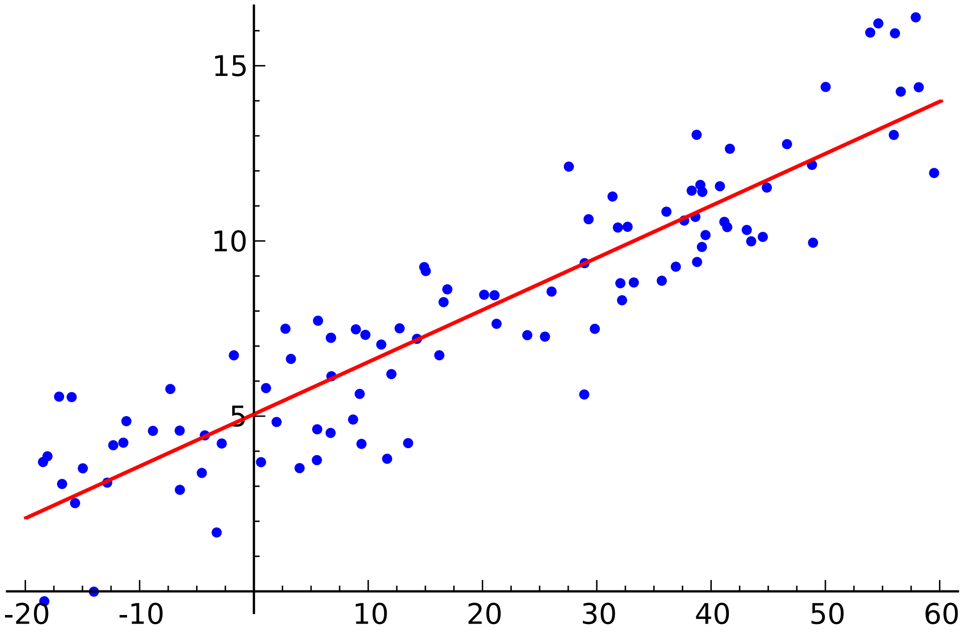
- Details: https://www.kaggle.com/datasets/mirichoi0218/insurance
- Github: https://github.com/stedy/Machine-Learning-with-R-datasets
- Raw data: https://raw.githubusercontent.com/stedy/Machine-Learning-with-R-datasets/master/insurance.csv

Use Linear Regression to discover medical charges based on age, sex, bmi, children, smoker and region.

- **Dependent variable (label):** charges
- **Independent variables (features):** age, sex, bmi, children, smoker and region

Reviewing Regression Analysis Concept

Source: https://en.wikipedia.org/wiki/Regression_analysis



In statistical modeling, regression analysis is a set of statistical processes for estimating the relationships between a dependent variable (often called the 'outcome' or 'response' variable, or a 'label' in machine learning parlance) and one or more independent variables (often called 'predictors', 'covariates', 'explanatory variables' or 'features').

In [227…

```
# Import required libraries

import tensorflow as tf
import pandas as pd
import matplotlib.pyplot as plt
```

In [228…

```
# Read in the insurance dataset
insurance = pd.read_csv("https://raw.githubusercontent.com/stedy/Machine-
insurance
```

Out[228]:

	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520
...	...	...	...	...	...	...	...
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

Transform un-numerical columns to numerical columns to be processsed using one-hot encode

One hot encoding is a process by which categorical variables are converted into a form that could be provided to ML algorithms to do a better job in prediction

Label Encoding

Food Name	Categorical #	Calories
Apple	1	95
Chicken	2	231
Broccoli	3	50

→

One Hot Encoding

Apple	Chicken	Broccoli	Calories
1	0	0	95
0	1	0	231
0	0	1	50

In [233…

```
# Using get_dummies function to convert
# categorial variable into dummy/indicator variables

insurance_one_hot = pd.get_dummies(insurance)
insurance_one_hot.head()
```

Out[233]:

	age	bmi	children	charges	sex_female	sex_male	smoker_no	smoker_yes
0	19	27.900	0	16884.92400	1	0	0	1
1	18	33.770	1	1725.55230	0	1	1	0
2	28	33.000	3	4449.46200	0	1	1	0
3	33	22.705	0	21984.47061	0	1	1	0
4	32	28.880	0	3866.85520	0	1	1	0

In [239…

```
# Create X & y values (features and labels)

# The X (independent variables) will be every column of DataFrame except
X = insurance_one_hot.drop("charges", axis=1)

# The y (dependent or label) is charges column
y = insurance_one_hot["charges"]
```

In [240…

```
# View X (independent variables)
X.head()
```

Out[240]:

	age	bmi	children	sex_female	sex_male	smoker_no	smoker_yes	region_northe
0	19	27.900	0	1	0	0	1	
1	18	33.770	1	0	1	1	0	
2	28	33.000	3	0	1	1	0	
3	33	22.705	0	0	1	1	0	
4	32	28.880	0	0	1	1	0	

In [241…

```
# View y (label)
y.head()
```

Out[241]:

```
0     16884.92400
1      1725.55230
2      4449.46200
3     21984.47061
4      3866.85520
Name: charges, dtype: float64
```

In [245…

```
# Create training and test sets

# Split dataset in random set to train using sklearn
#  Open terminal for environment and rul:
#      conda install -c conda-forge scikit-learn
from sklearn.model_selection import train_test_split

# Separate 20% (0.2) for test and 80% to train
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

len(X), len(X_train), len(X_test)
```

Out[245]: (1338, 1070, 268)

In [276…

```
# Build a neural network (sort of like model_2 above)
tf.random.set_seed(42)

# 1. Create the model
insurance_model = tf.keras.Sequential([
    tf.keras.layers.Dense(10, name="input_layer"),
    tf.keras.layers.Dense(1, name="output_layer")
], name="model")

# 2. Compile the model
insurance_model.compile(loss=tf.keras.losses.mae,
                        optimizer=tf.keras.optimizers.SGD(),
                        metrics=["mae"])

# Fit the model
insurance_model.fit(X_train, y_train, epochs=100, verbose=0)
```

Out[276]: <keras.callbacks.History at 0x7fade885e740>

In [277…

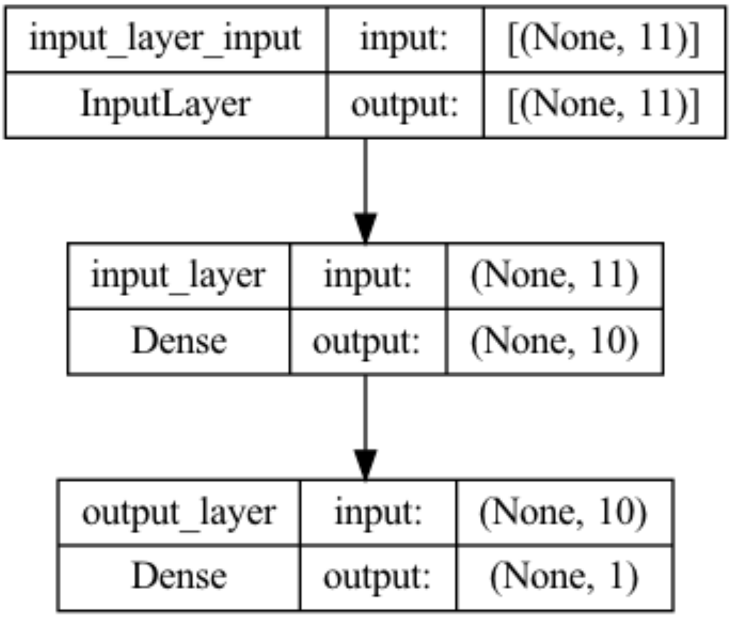
```
# View model summary
insurance_model.summary()
```

```
Model: "model"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_layer (Dense)         (None, 10)                120

 output_layer (Dense)        (None, 1)                 11

=================================================================
Total params: 131
Trainable params: 131
Non-trainable params: 0
_________________________________________________________________
```

In [286…

```
# View model plot
from tensorflow.keras.utils import plot_model

plot_model(model=insurance_model, show_shapes=True)
```

Out[286]:



In [279…

```
# Check the results of the insurance model on the test data (loss value)
insurance_model.evaluate(X_test, y_test)
```

```
9/9 [==============================] - 0s 766us/step - loss: 7023.3281 -
mae: 7023.3281
```

Out[279]:

```
[7023.328125, 7023.328125]
```

In [280…

```
# Check the average and median values to know how far the mae is wrong in
y_train.median(), y_train.mean()

# If the model isn't performing too well... let's try and improve it!
```

Out[280]:

```
(9575.4421, 13346.089736364489)
```

Improve the model

To (try) improve our model, we'll run 2 experiments:

1. Add an extra layer with more hidden units (100 neurons). This amount of neurons requires to use Adam instead of SGD in optimizer
2. Train for longer (200 epochs)

In [315...

```
# Set random seed
tf.random.set_seed(42)

# 1. Create the model
insurance_model_2 = tf.keras.Sequential([
    tf.keras.layers.Dense(100, name="Hidden_layer_1"),
    tf.keras.layers.Dense(10, name="Hidden_layer_2"),
    tf.keras.layers.Dense(1, name="Output_layer")
], name="insurance_model_2")

# Compile the model
insurance_model_2.compile(loss=tf.keras.losses.mae,
                          optimizer=tf.keras.optimizers.Adam(),
                          metrics=["mae"])

# Fit the model
history_training_model_2 = insurance_model_2.fit(X_train, y_train, epochs
```

In [316...

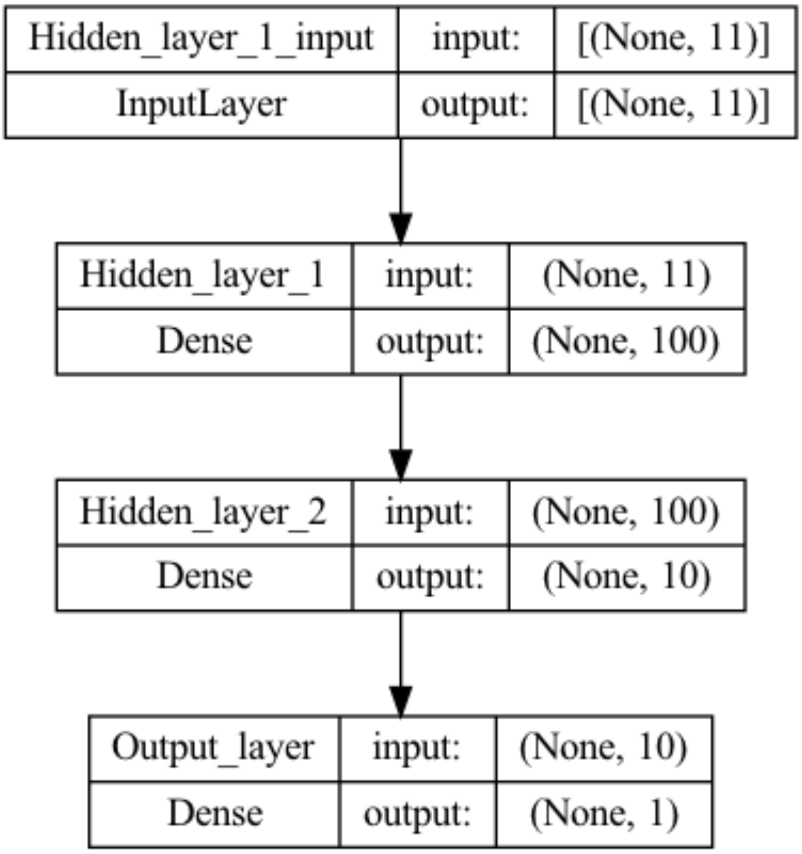
```
insurance_model_2.summary()
```

```
Model: "insurance_model_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 Hidden_layer_1 (Dense)      (None, 100)               1200

 Hidden_layer_2 (Dense)      (None, 10)                1010

 Output_layer (Dense)        (None, 1)                 11

=================================================================
Total params: 2,221
Trainable params: 2,221
Non-trainable params: 0
_________________________________________________________________
```

In [317...

```
plot_model(model=insurance_model_2, show_shapes=True)
```

Out[317]:



In [338…

```
# Evaluate the larger model
insurance_model_2.evaluate(X_test, y_test)
```

```
9/9 [==============================] - 0s 839us/step - loss: 3488.7861 -
mae: 3488.7861
```

Out[338]:

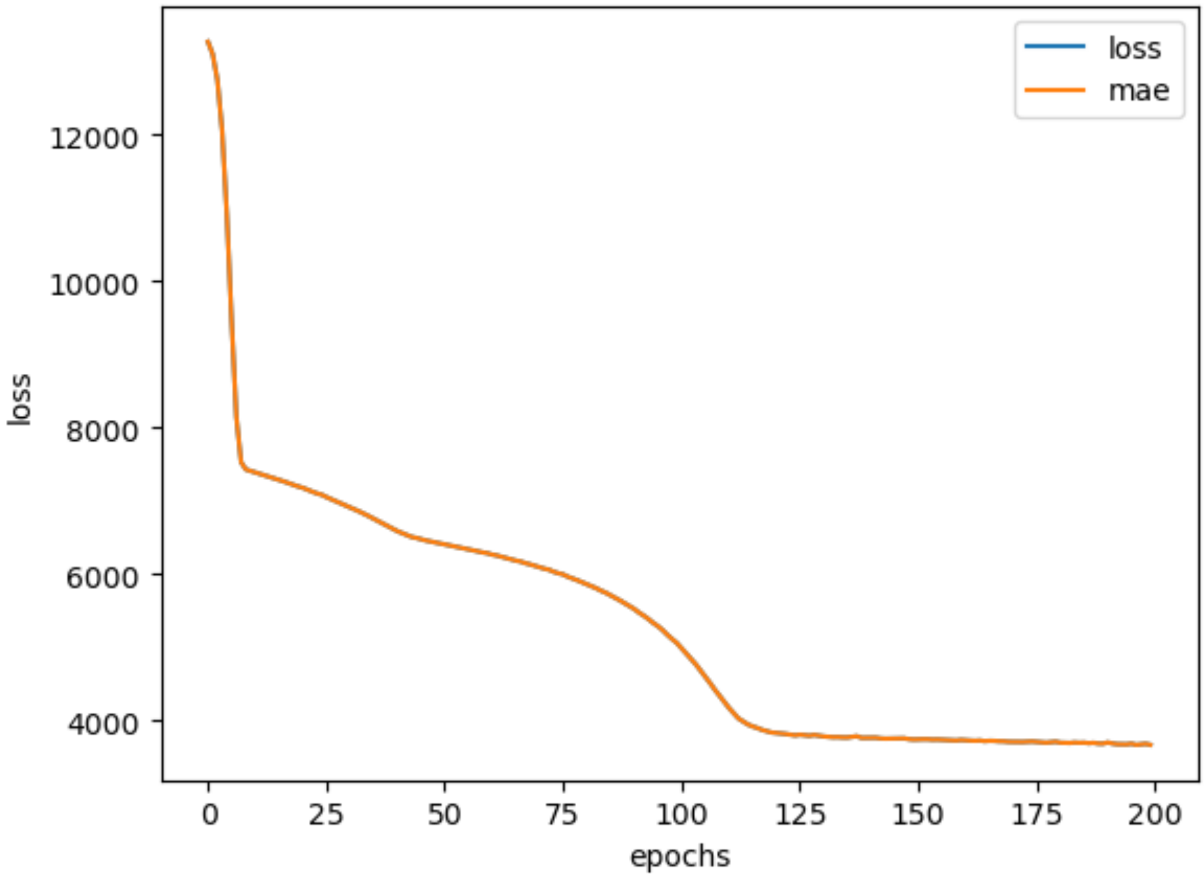
```
[3488.7861328125, 3488.7861328125]
```

In [339…

```
# Plot history (also known as a loss curve or training curve)
pd.DataFrame(history_training_model_2.history).plot()
plt.ylabel("loss")
plt.xlabel("epochs")
```

Out[339]:

```
Text(0.5, 0, 'epochs')
```



🤔 **Question:** How long should you train for?

It depends. Really... it depends on the problem you're working on. However, many people have asked this question before... so Tensorflow has a solution! It's called the [EarlyStopping Callback](), which is a TensorFlow component you can add to your model to stop training once it stops improving a certain metric.

Preprocessing data (normalization and standadization)

In terms of scaling values, neural networkds tend to prefer normalization. Normalization is to change the values of numeric columns in the dataset to a commong scale, without distorting differences in the range of values.

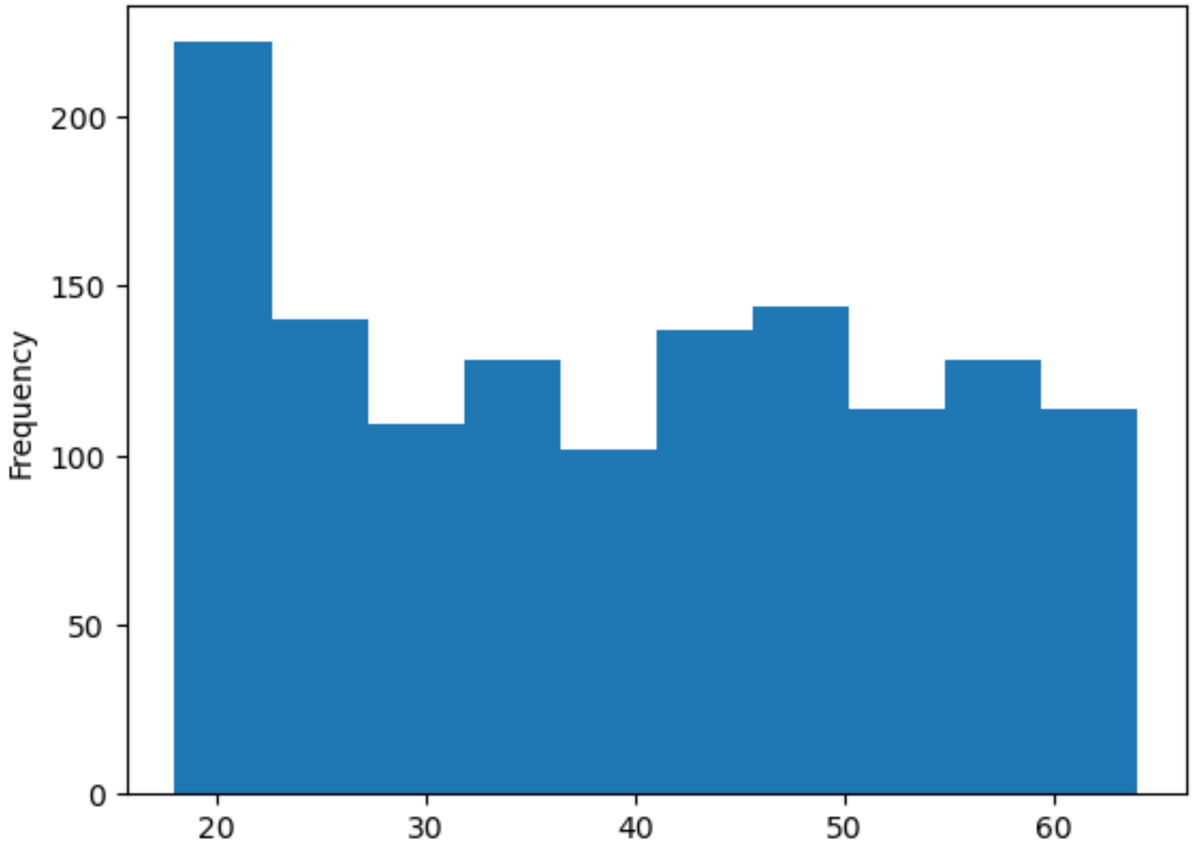
Scaling type

- **Scale (also referred to as normalisation):** Convert all values to between 0 and 1 whilst preserving the original distribution. Scikit-Learn function: **MinMaxScaler**. **When to Use:** Use as default scaler with neural networks.
- **Standarization:** Removes the mean and divides each value by the standard deviation. Scikit-Learn function: **StandardScale**. **When to Use:** Transform a feature to have close to normal distribution (caution: this reduces the effect of outliers).

If you're not sure on which to use, you could try both and see which performs better.

In [352…
```
# Example of columns data distortion is when comparing different
# columns like age, bmi and children as shown in histogram plot
X["age"].plot(kind="hist")
```

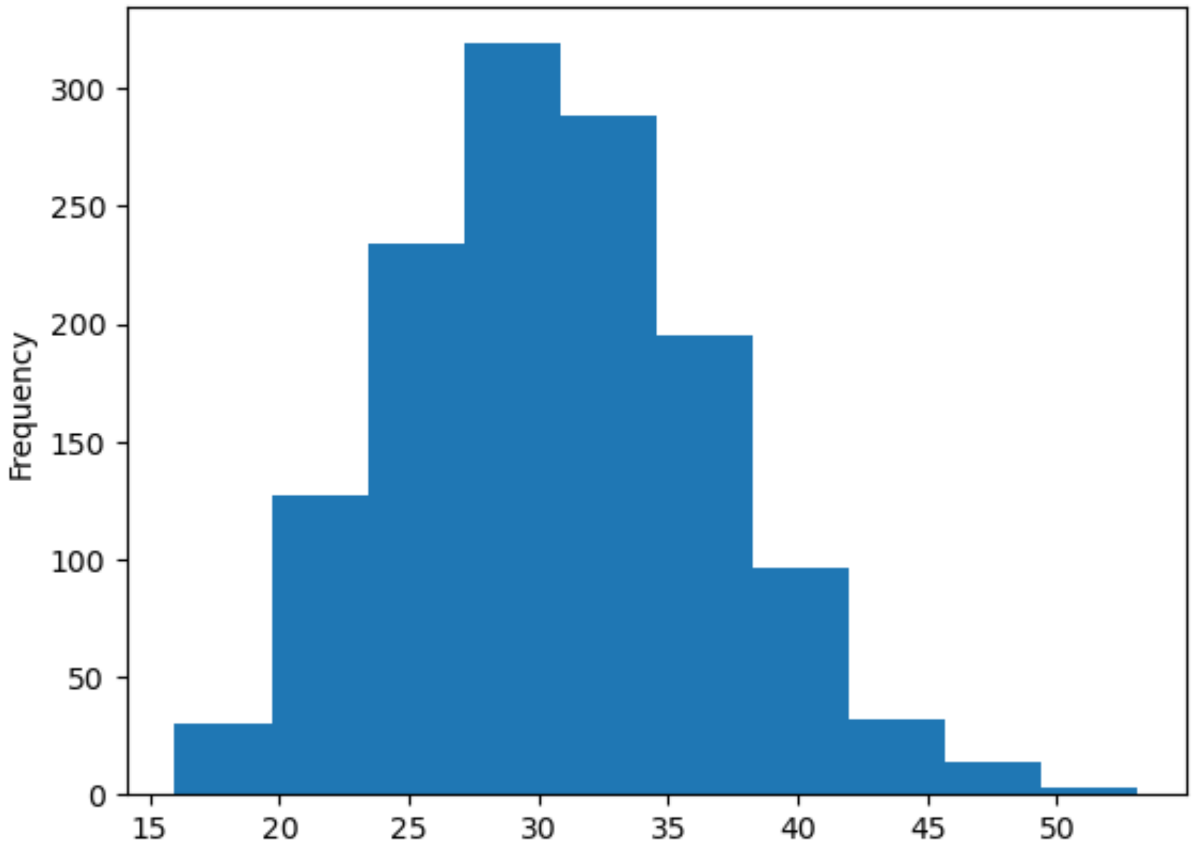
Out[352]:
```
<AxesSubplot:ylabel='Frequency'>
```



In [351…

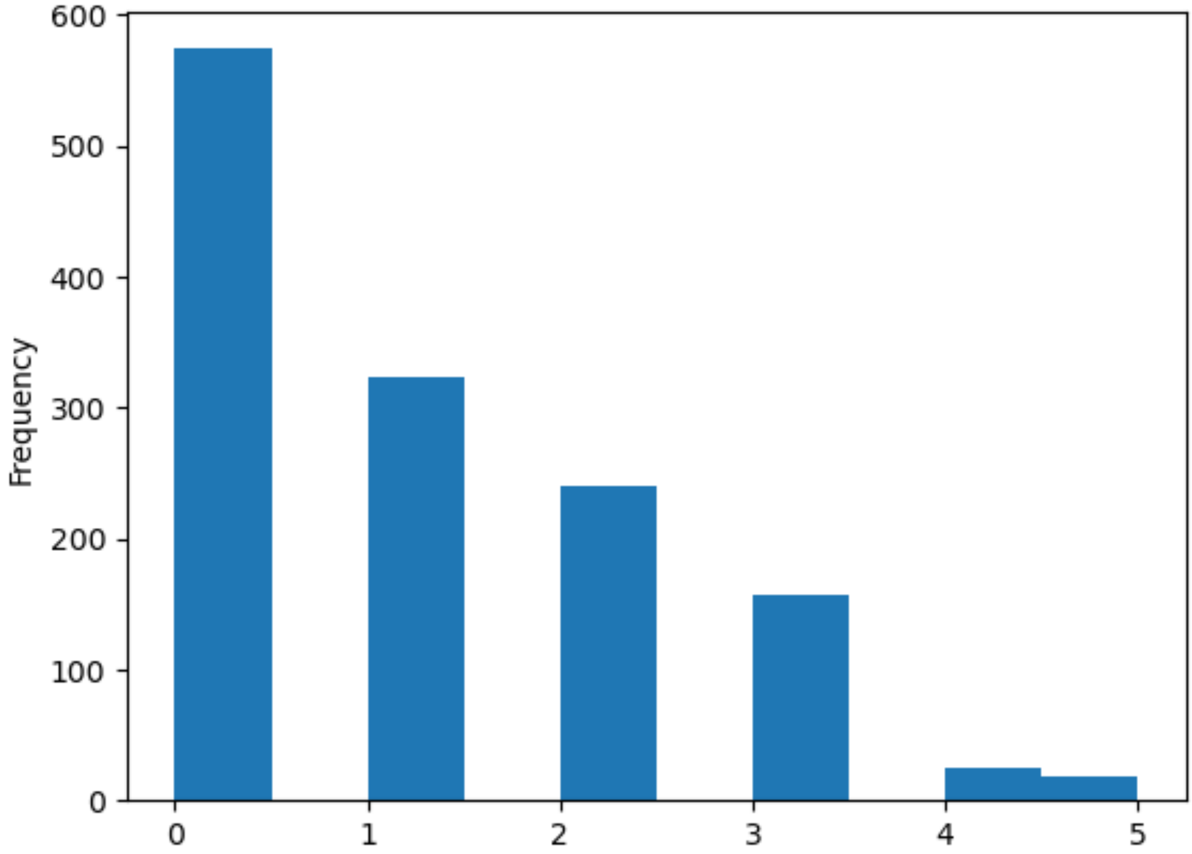
```
X["bmi"].plot(kind="hist")
```

Out[351]: <AxesSubplot:ylabel='Frequency'>



In [353…
```
X["children"].plot(kind="hist")
```

Out[353]: <AxesSubplot:ylabel='Frequency'>



To prepare our data, we can borrow a few classes from Scikit-Learn.

In [358…

```
from sklearn.compose import make_column_transformer
from sklearn.preprocessing import MinMaxScaler, OneHotEncoder
from sklearn.model_selection import train_test_split
#  Open terminal for environment and rul:
#      conda install -c conda-forge scikit-learn


# Create a column transformer
ct = make_column_transformer(
    (MinMaxScaler(), ["age", "bmi", "children"]), # thrn all values in th
    (OneHotEncoder(handle_unknown="ignore"), ["sex", "smoker", "region"])
)

# Create X & y values

# The X (independent variables) will be every column of DataFrame except
X = insurance.drop("charges", axis=1)

# The y (dependent or label) is charges column
y = insurance["charges"]


# Split dataset in random set to train using sklearn
# Separate 20% (0.2) for test and 80% to train
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,

# Fit the column transformer to our training data
ct.fit(X_train)

# Transform training and test data with normalization (MinMaxScaler) and
X_train_normal = ct.transform(X_train)
X_test_normal = ct.transform(X_test)
```

In [361…

```
# What does our data look like now?
X_train.loc[0], X_train_normal[0]
```

Out[361]:

```
(age                19
 sex            female
 bmi              27.9
 children            0
 smoker            yes
 region      southwest
 Name: 0, dtype: object,
 array([0.60869565, 0.10734463, 0.4       , 1.        , 0.        ,
        1.        , 0.        , 0.        , 1.        , 0.        ,
        0.        ]))
```

In [364…

```
# What about the shapes - We can see that original dataset has 6 columns,
# the normalized has 11 columns
X_train.shape, X_train_normal.shape
```

Out[364]:

```
((1070, 6), (1070, 11))
```

Our data has been normalized and one hot encoded.

Now let's build a neural network model on it and see how it goes.

In [432...

```
# Build a neural network model to fit on our normalized data

tf.random.set_seed(42)

# 1. Create the model (based on insurance_model_2)
insurance_model_f = tf.keras.Sequential([
    tf.keras.layers.Dense(100, name="hidden_layer_1"),
    tf.keras.layers.Dense(10, name="hidden_layer_2"),
    tf.keras.layers.Dense(1, name="output_layer")
], name="insurance_model_f")

# 2. Compile the model
insurance_model_f.compile(loss=tf.keras.losses.mae,
                          optimizer=tf.keras.optimizers.Adam(learning_rat
                          metrics=["mae"])

# 3. Fit the model
history_training_model_f = insurance_model_f.fit(X_train_normal, y_train,
```

In [433...

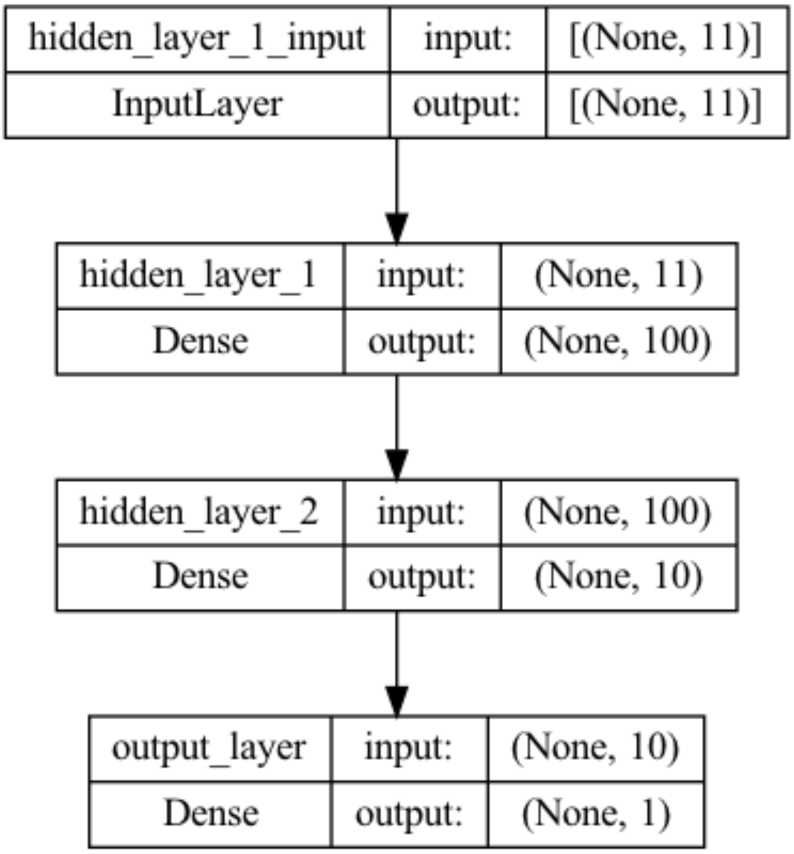
```
insurance_model_f.summary()
```

```
Model: "insurance_model_f"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 hidden_layer_1 (Dense)      (None, 100)               1200

 hidden_layer_2 (Dense)      (None, 10)                1010

 output_layer (Dense)        (None, 1)                 11

=================================================================
Total params: 2,221
Trainable params: 2,221
Non-trainable params: 0
_________________________________________________________________
```

In [434...

```
plot_model(insurance_model_f, show_shapes=True)
```

Out[434]:



In [435...

```
# Evaluate our insurance model trained on normalized data

insurance_model_f.evaluate(X_test_normal, y_test)
```

```
9/9 [==============================] - 0s 852us/step - loss: 3160.6641 -
mae: 3160.6641
```

Out[435]:

```
[3160.6640625, 3160.6640625]
```

Insurance model 2 result:

9/9 [==============================] - 0s 839us/step - loss: 3488.7861 - mae: 3488.7861

Insurance model f result:

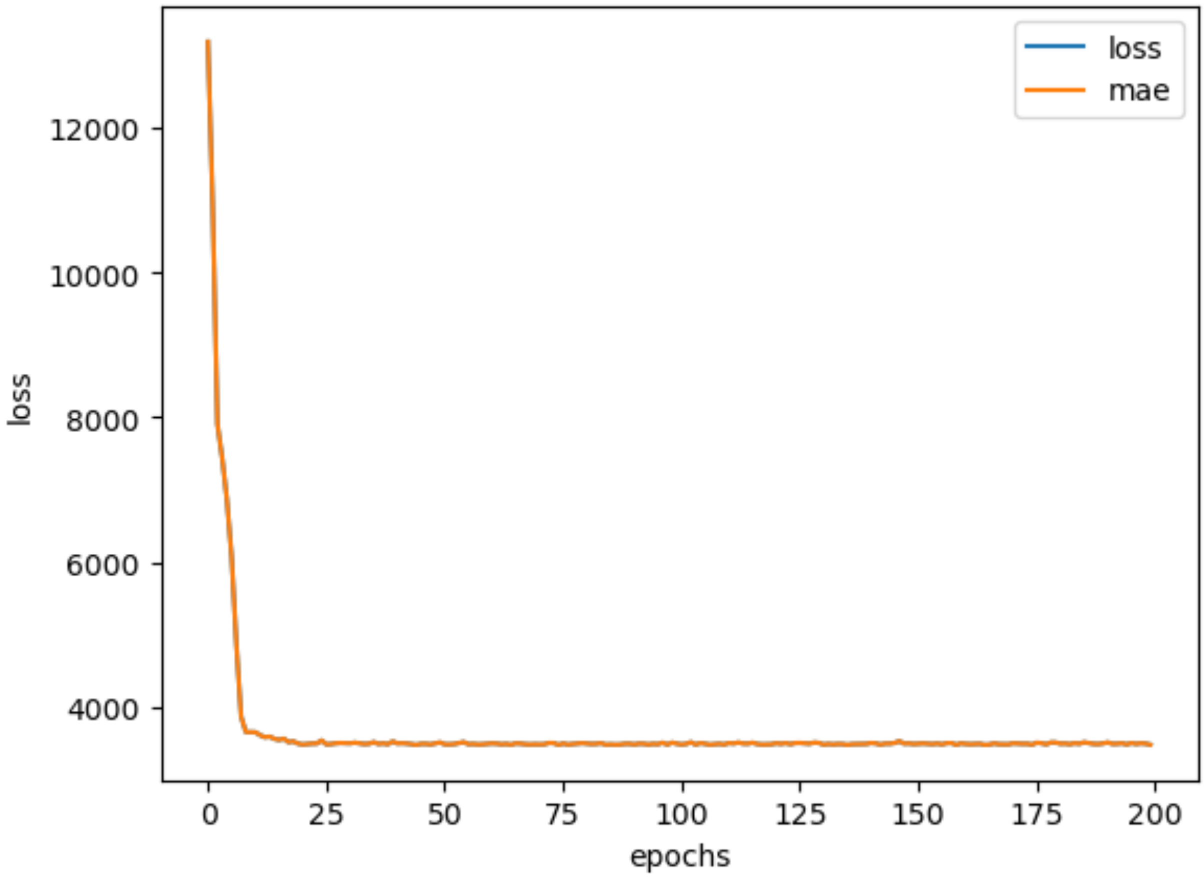
9/9 [==============================] - 0s 852us/step - loss: 3160.6641 - mae: 3160.6641

In [436...

```
# Plot history (also known as a loss curve or training curve)
pd.DataFrame(history_training_model_f.history).plot()
plt.ylabel("loss")
plt.xlabel("epochs")
```

Out[436]:

```
Text(0.5, 0, 'epochs')
```



In [439…

```
# Save model using the SavedModel format
!mkdir -p saved_model
insurance_model_f.save('saved_model/insurance_model_f')
```

```
INFO:tensorflow:Assets written to: saved_model/insurance_model_f/assets
```

In [441…

```
# Save model using the HDF5 format
!mkdir -p hdf5

# The '.h5' extension indicates that the model should be saved to HDF5
insurance_model_f.save('hdf5/insurance_model_f.h5')
```

In [ ]: