# Lecture 4 Artificial Neural Networks

May 11, 2022

## 1 Neural Network Workbook

Welcome to the Neural Network Workbook. Remember, ideally we would like to use TensorFlow or Keras for Deep Learning as they enable more features. In case you had trouble installing TensorFlow we will start with sklearn.

[1]:
```
import numpy as np
import pandas as pd

from matplotlib import pyplot as plt
%matplotlib inline

import seaborn as sns
sns.set_style('darkgrid')

import tensorflow as tf

%matplotlib inline
```

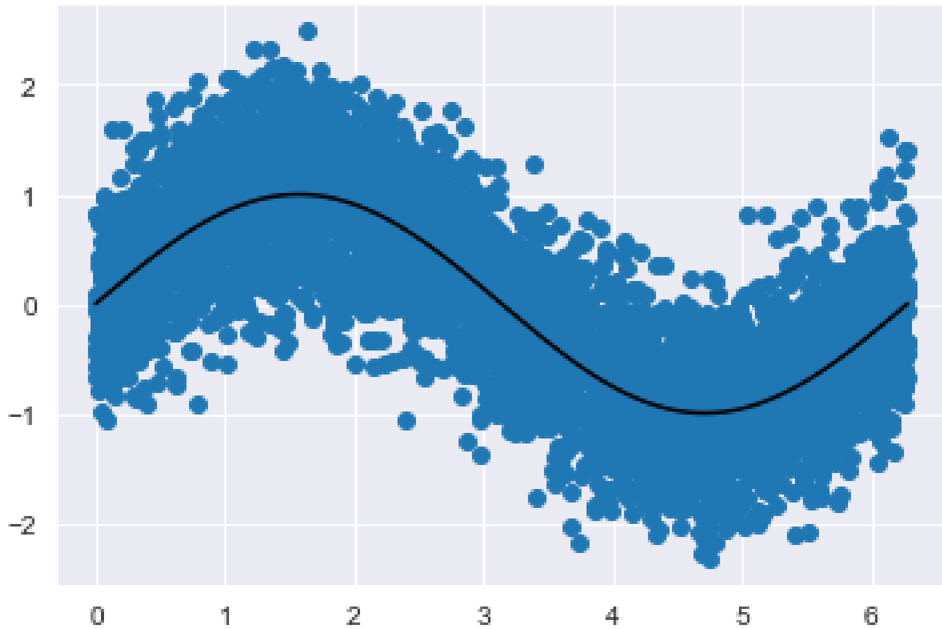
Let's start with creating a data set with noise.

[26]:
```
x = np.linspace(0, 2*np.pi, 5000)
# noise
np.random.seed(321)
noise = np.random.normal(0, .5, 5000)
# target variable
y = np.sin(x) + noise
```

We will plot the x and y to see how the data set looks.

[27]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

# Scatterplot of x and y
ax.scatter(x, y)

# Overlay the sine wave
ax.plot(x, np.sin(x), color='k')
```

```
plt.show()
```




[28]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
x_scaled = scaler.fit_transform(x.reshape(-1, 1))
```

We are now going to split our data set into train and test sets.

[29]:
```
from sklearn.model_selection import train_test_split
```

[30]:
```
X_train, X_test, y_train, y_test = train_test_split(x_scaled, y, test_size=0.3)
```

### 1.1 MLP Regressor

Now we import the MLPRegressor from sklearn.neural network library.

[31]:
```
from sklearn.neural_network import MLPRegressor
```

[32]:
```
mlp = MLPRegressor(random_state=5)
```

[33]:
```
mlp.fit(X_train.reshape(-1, 1), y_train)
```

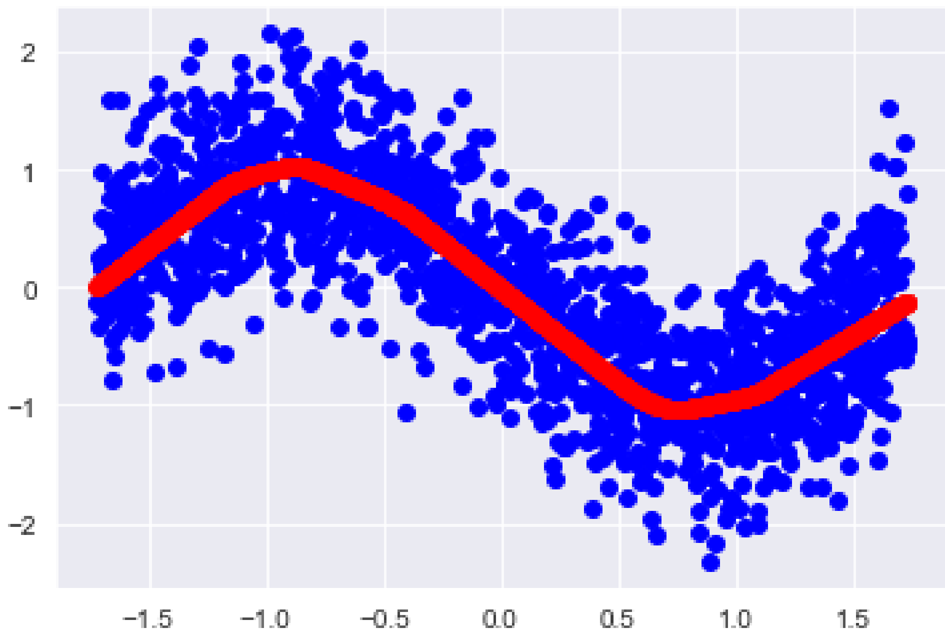
[33]:
```
MLPRegressor(random_state=5)
```

Neural networks work with special shapes. Don't forget to reshape your input data set.

```
[34]: y_pred = mlp.predict(X_test.reshape(-1, 1))
```

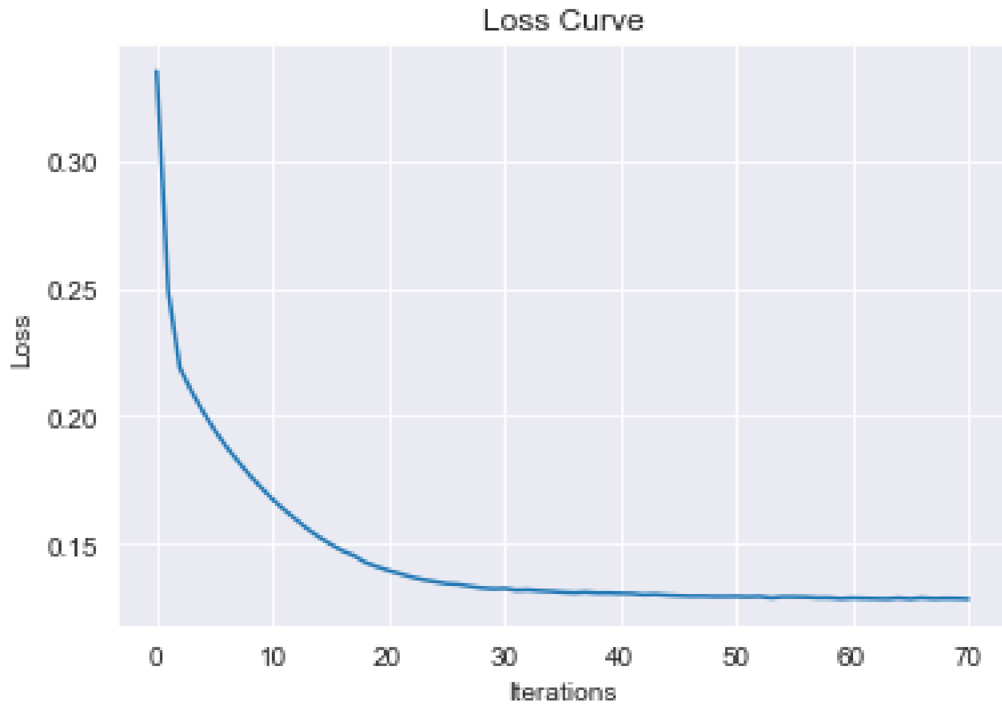
Let's see how our first prediction looks like.

```
[35]: fig = plt.figure(figsize=[6,4])
      ax = plt.subplot(111)


      # Overlay the sine wave
      ax.scatter(X_test, y_test, color='b')
      # Overlay the sine wave
      ax.scatter(X_test, y_pred, color='r')

      plt.show()
```




```
[36]: plt.plot(mlp.loss_curve_)
      plt.xlabel('Iterations')
      plt.ylabel('Loss')
      plt.title('Loss Curve')
```

```
[36]: Text(0.5, 1.0, 'Loss Curve')
```



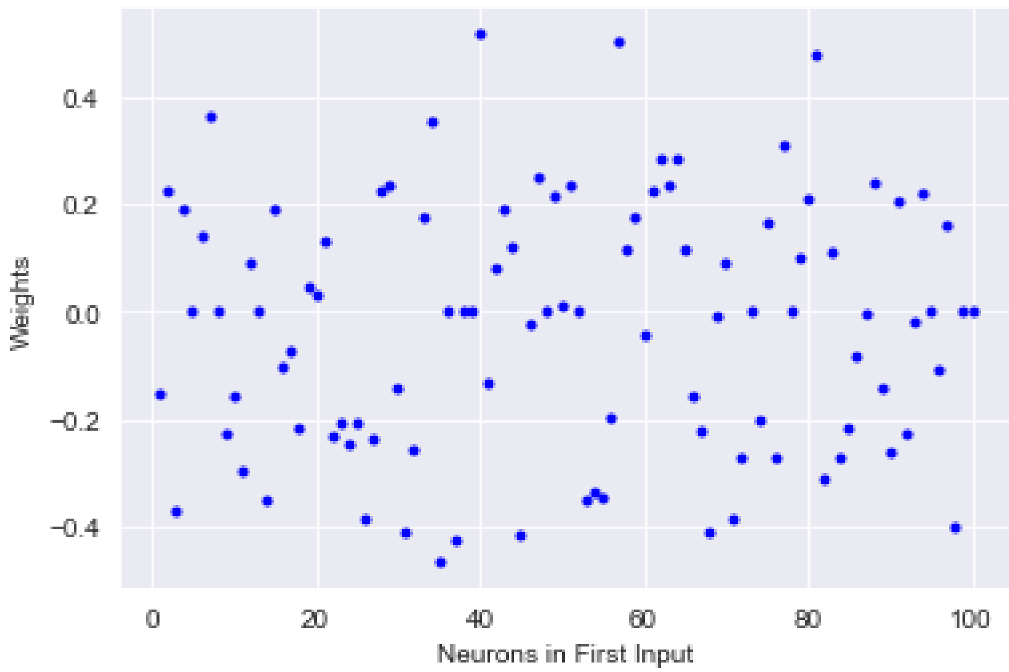

[37]:
```
print(np.shape(mlp.coefs_), np.shape(mlp.coefs_[0]))
```

```
(2,) (1, 100)
```

```
/Users/dsozturk/Library/Python/3.8/lib/python/site-
packages/numpy/core/fromnumeric.py:2007: VisibleDeprecationWarning: Creating an
ndarray from ragged nested sequences (which is a list-or-tuple of lists-or-
tuples-or ndarrays with different lengths or shapes) is deprecated. If you meant
to do this, you must specify 'dtype=object' when creating the ndarray.
  result = asarray(a).shape
```

[38]:
```
plt.plot(np.arange(1,101,1).reshape(1,100),mlp.coefs_[0],'b.')
plt.ylabel('Weights')
plt.xlabel('Neurons in First Input')
```

[38]:
```
Text(0.5, 0, 'Neurons in First Input')
```




We can do better, but how? ### Changing Neuron Number Let's try changing the neuron number.

[39]:
```
mlp2 = MLPRegressor(random_state=5, hidden_layer_sizes=[10])
```

[40]:
```
mlp2.fit(X_train.reshape(-1, 1), y_train)
```

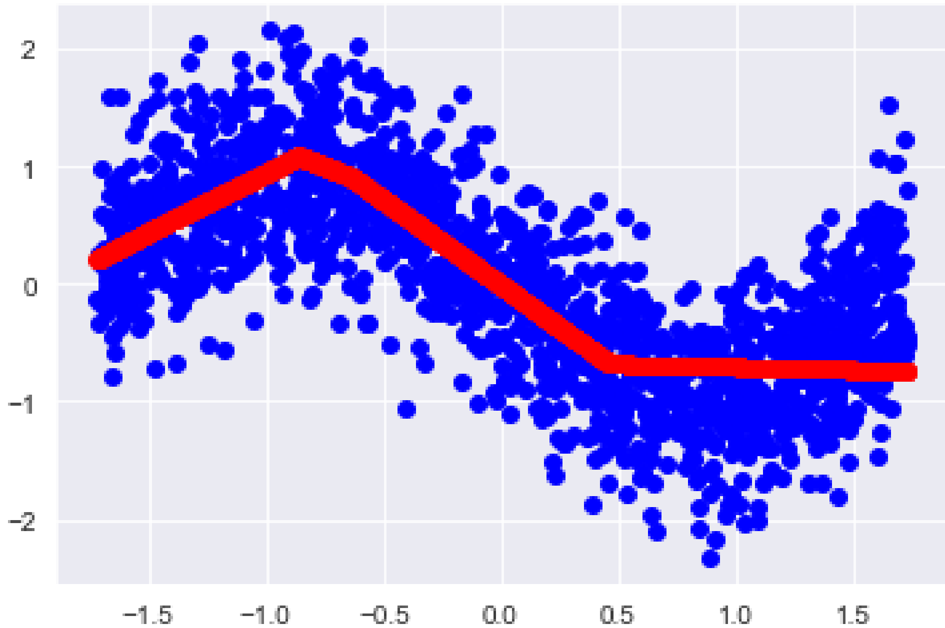
```
/Users/dsozturk/Library/Python/3.8/lib/python/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:582:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[40]:
```
MLPRegressor(hidden_layer_sizes=[10], random_state=5)
```

[41]:
```
y_pred2 = mlp2.predict(X_test.reshape(-1, 1))
```

[42]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)


# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred2, color='r')
```

```
plt.show()
```




We certainly didn't do any better. Let's increate the neuron size above the default value.

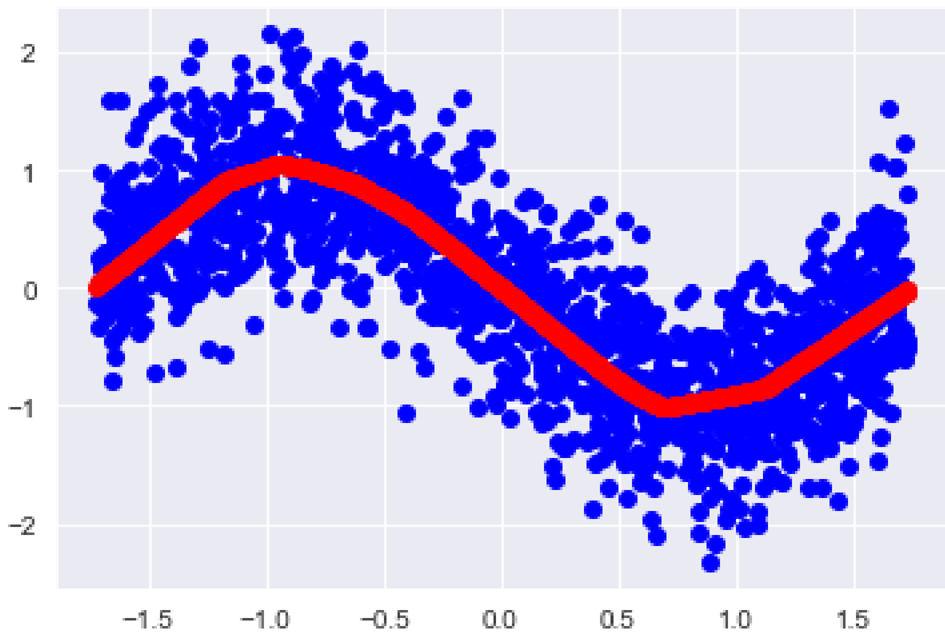
[43]:
```
mlp3 = MLPRegressor(random_state=5, hidden_layer_sizes=[200])
```

[44]:
```
mlp3.fit(X_train.reshape(-1, 1), y_train)
```

[44]:
```
MLPRegressor(hidden_layer_sizes=[200], random_state=5)
```

[45]:
```
y_pred3 = mlp3.predict(X_test.reshape(-1, 1))
```

[46]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)


# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred3, color='r')

plt.show()
```




It is somewhat better, but nowhere close to what people say about neural networks. ### Changing Layer Number Let's add another layer.

[47]:
```
mlp4 = MLPRegressor(random_state=5, hidden_layer_sizes=[100,100])
```

[48]:
```
mlp4.fit(X_train.reshape(-1, 1), y_train)
```

[48]: MLPRegressor(hidden_layer_sizes=[100, 100], random_state=5)

[49]:
```
mlp4.n_layers_
```

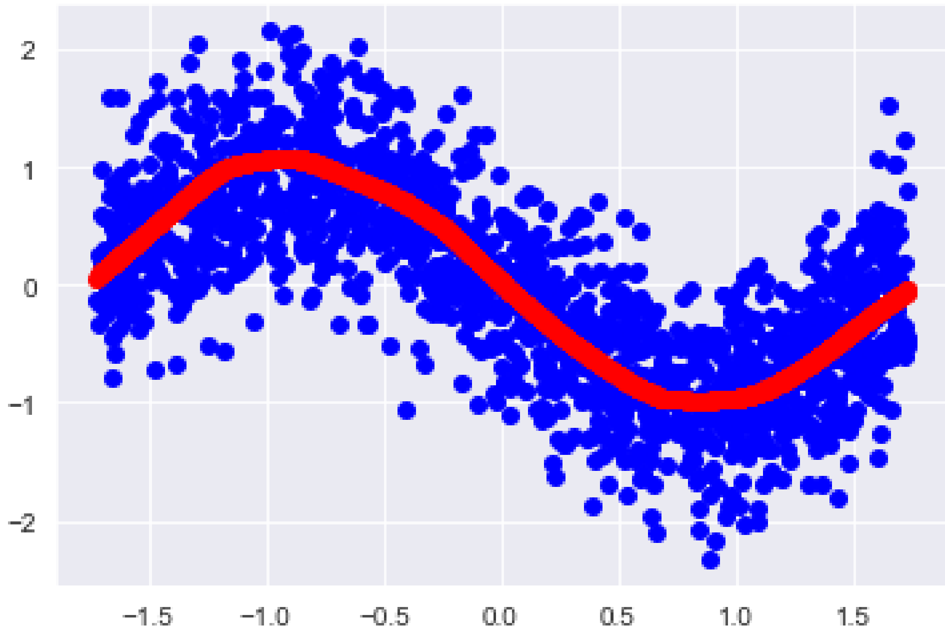
[49]: 4

We have only added one more layer, why are there 4 layers?

[50]:
```
y_pred4 = mlp4.predict(X_test.reshape(-1, 1))
```

[51]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)


# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred4, color='r')
```

```
plt.show()
```




The tail looks better, will adding even more layers help?

[52]:
```
mlp5 = MLPRegressor(random_state=5, hidden_layer_sizes=[100,80,60,40,20])
```

[53]:
```
mlp5.fit(X_train.reshape(-1, 1), y_train)
```

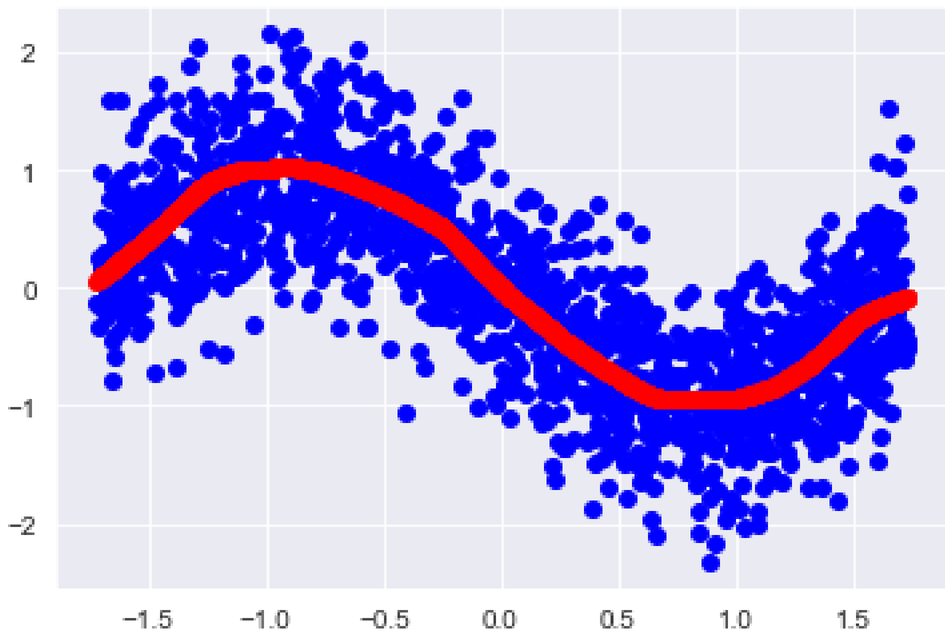
[53]:
```
MLPRegressor(hidden_layer_sizes=[100, 80, 60, 40, 20], random_state=5)
```

[54]:
```
mlp5.n_layers_
```

[54]:
```
7
```

[55]:
```
y_pred5 = mlp5.predict(X_test.reshape(-1, 1))
```

[56]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)


# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred5, color='r')

plt.show()
```




This doesn't seem like a monumental gain. ### Changing Activation Function We can try the way the neurons are activated.

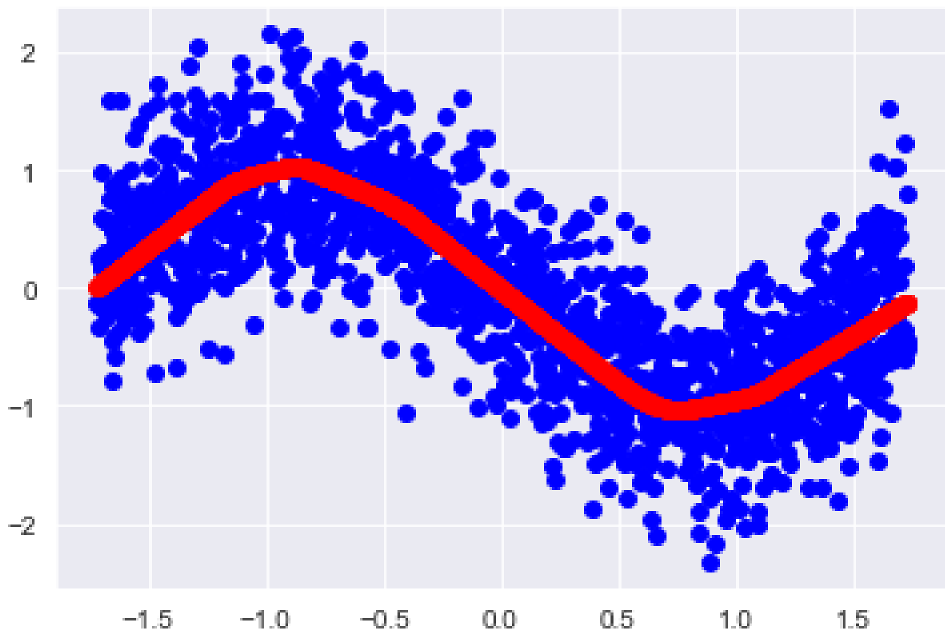
[59]:
```
mlp6 = MLPRegressor(random_state=5, activation='relu')
```

[60]:
```
mlp6.fit(X_train.reshape(-1, 1), y_train)
```

[60]:
```
MLPRegressor(random_state=5)
```

[61]:
```
y_pred6 = mlp6.predict(X_test.reshape(-1, 1))
```

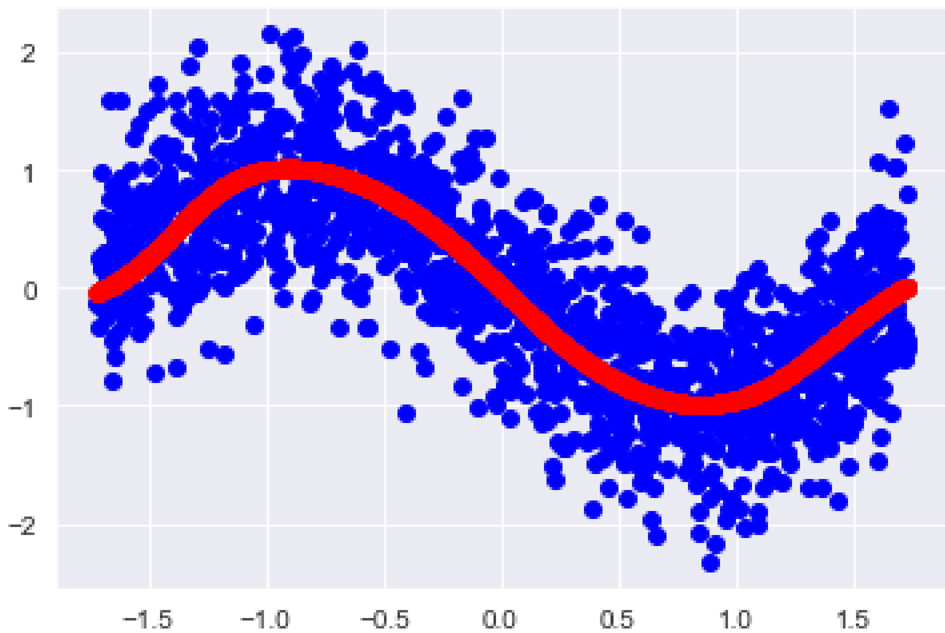
[62]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)


# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred6, color='r')

plt.show()
```




Let's combine it with adding more layers.

[63]:
```
mlp7 = MLPRegressor(random_state=5, activation='tanh', ␣
  ↪hidden_layer_sizes=[100,80,60,40,20])
mlp7.fit(X_train.reshape(-1, 1), y_train)
y_pred7 = mlp7.predict(X_test.reshape(-1, 1))
```

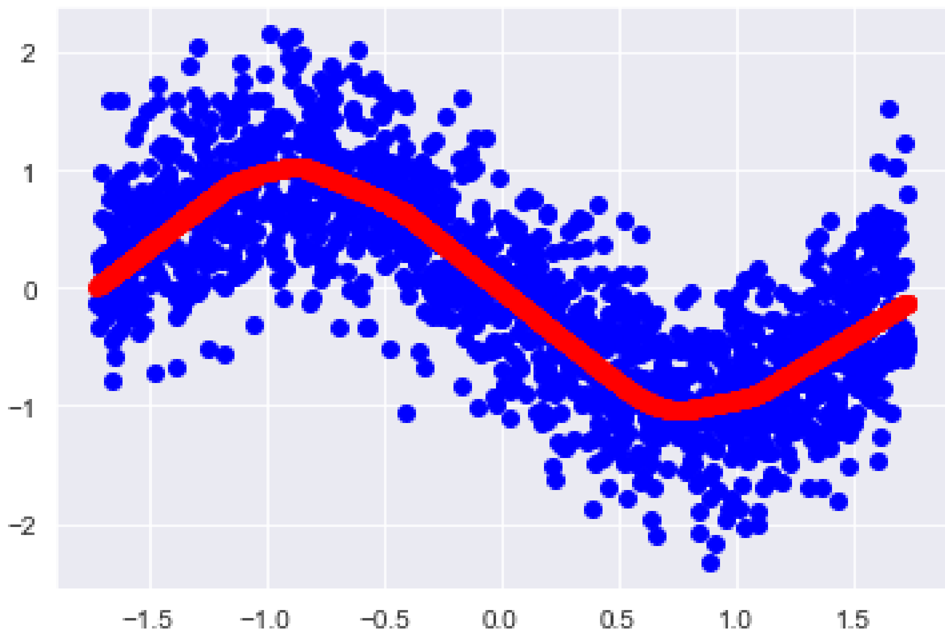
[64]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)


# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred7, color='r')

plt.show()
```




Oh hello, neural network performance! ### Changing Learning Rate Can we do even better?

[67]:
```
mlp8 = MLPRegressor(random_state=5, alpha=0.01)
mlp8.fit(X_train.reshape(-1, 1), y_train)
y_pred8 = mlp8.predict(X_test.reshape(-1, 1))
```

[68]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)



# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred8, color='r')

plt.show()
```

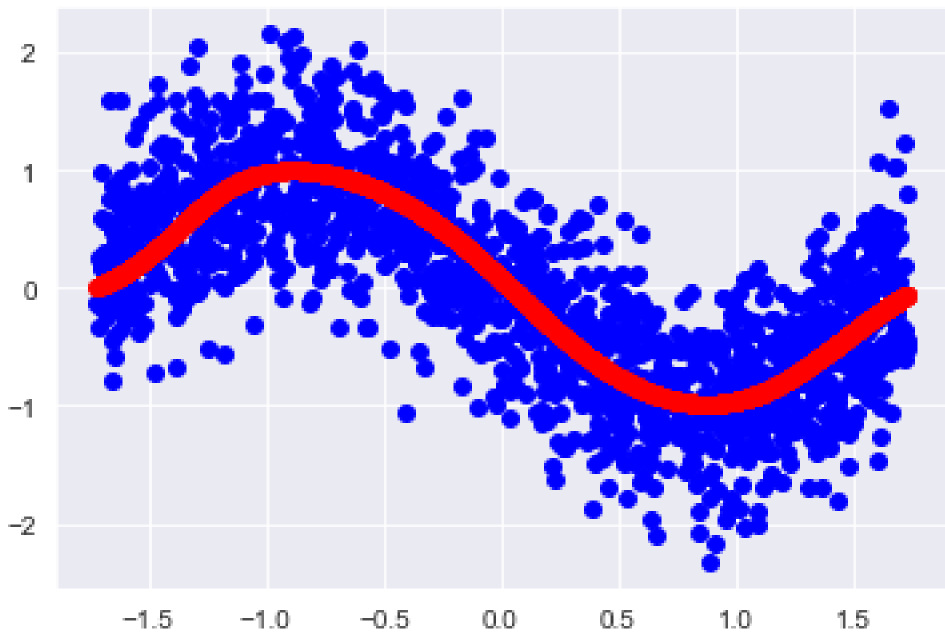



Let's combine all the approaches that worked.

[69]:
```
mlp9 = MLPRegressor(random_state=5, activation='tanh', ␣
    ↪hidden_layer_sizes=[100,80,60,40,20], alpha = 0.1)
mlp9.fit(X_train.reshape(-1, 1), y_train)
y_pred9 = mlp9.predict(X_test.reshape(-1, 1))
```

```
/Users/dsozturk/Library/Python/3.8/lib/python/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:582:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[70]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)


# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred9, color='r')

plt.show()
```

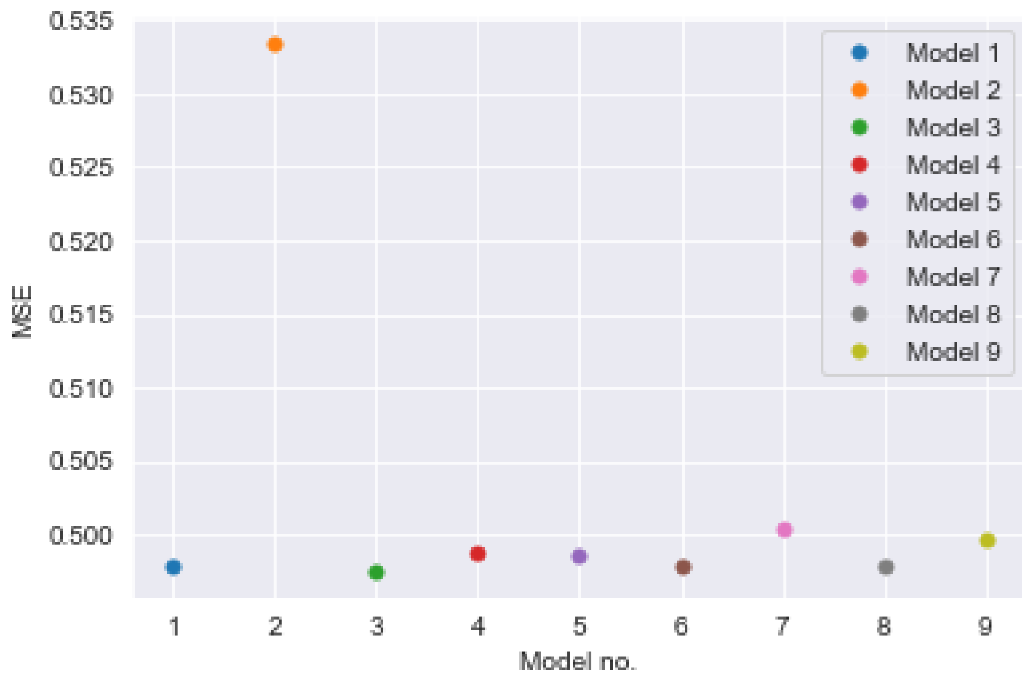


Seems like a better fit, but to be sure we need to quantify the performance. ### Evaluation an MLP Regressor Remember how we used to evaluate a regressor?

[71]:
```
from sklearn.metrics import mean_squared_error as mse
```

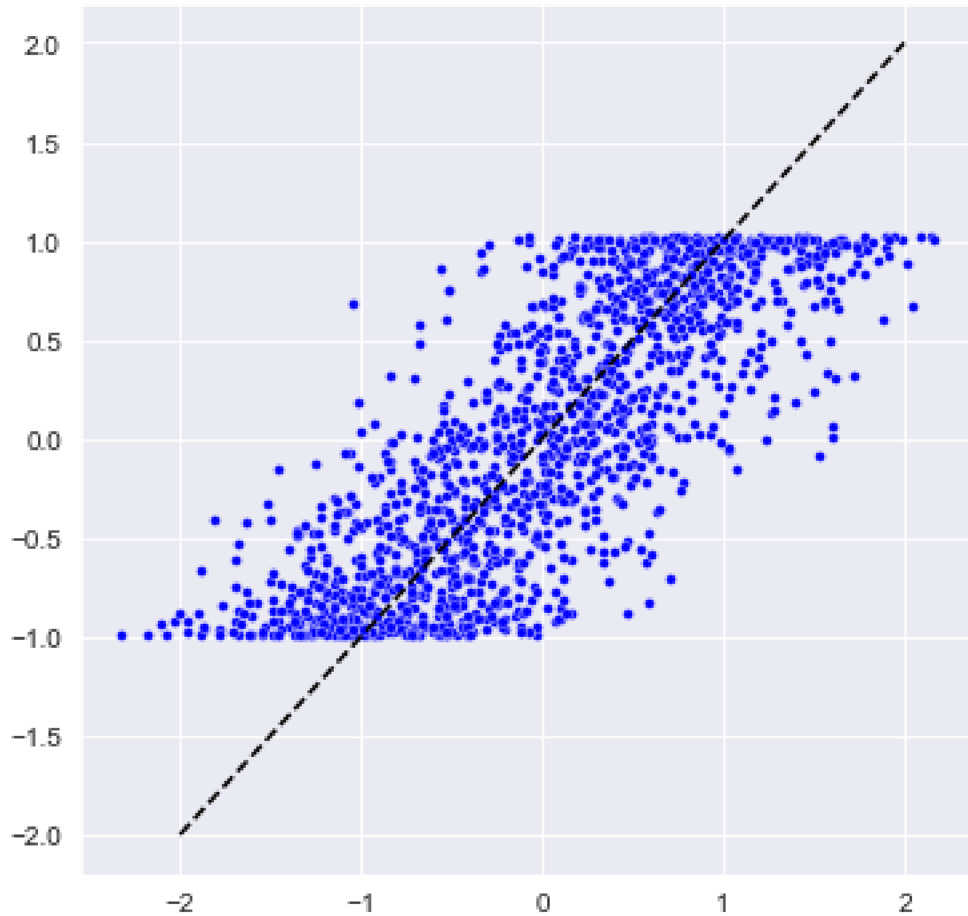
[72]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

# Overlay the sine wave
ax.plot(1,mse(y_test,y_pred,squared=False), '.', markersize=10, label='Model 1')
ax.plot(2,mse(y_test,y_pred2,squared=False), '.', markersize=10, label='Model␣
↪2')
ax.plot(3,mse(y_test,y_pred3,squared=False), '.', markersize=10, label='Model␣
↪3')
ax.plot(4,mse(y_test,y_pred4,squared=False), '.', markersize=10, label='Model␣
↪4')
ax.plot(5,mse(y_test,y_pred5,squared=False), '.', markersize=10, label='Model␣
↪5')
ax.plot(6,mse(y_test,y_pred6,squared=False), '.', markersize=10, label='Model␣
↪6')
ax.plot(7,mse(y_test,y_pred7,squared=False), '.', markersize=10, label='Model␣
↪7')
ax.plot(8,mse(y_test,y_pred8,squared=False), '.', markersize=10, label='Model␣
↪8')
```

```
ax.plot(9,mse(y_test,y_pred9,squared=False), '.', markersize=10, label='Model␣
↪9')

ax.set_ylabel('MSE')
ax.set_xlabel('Model no.')
ax.legend()
plt.show()
```




[73]:
```
f, ax = plt.subplots(figsize=(6, 6))
sns.scatterplot(x=y_test, y=y_pred7, s=15, color="b")
#sns.kdeplot(x=y_test, y=y_pred7, levels=5, color="w", linewidths=1)
ax.plot(np.linspace(-2,2,100),np.linspace(-2,2,100),'k--')
```

[73]: [<matplotlib.lines.Line2D at 0x164615a90>]




### 1.1.1 TensorFlow representation for MLPRegressor

1. The sklearn MLPRegressor uses 0.1 of the training set for validation, for TensorFlow we would define the validation set separately.
2. MLPRegressor uses mean_squared_error by default, so we are going to define this as our loss function in TensorFlow too.

[75]:
```
X_train1, X_val, y_train1, y_val = train_test_split(X_train, y_train,␣
↪test_size=0.1, random_state=1) # 0.25 x 0.8 = 0.2
```

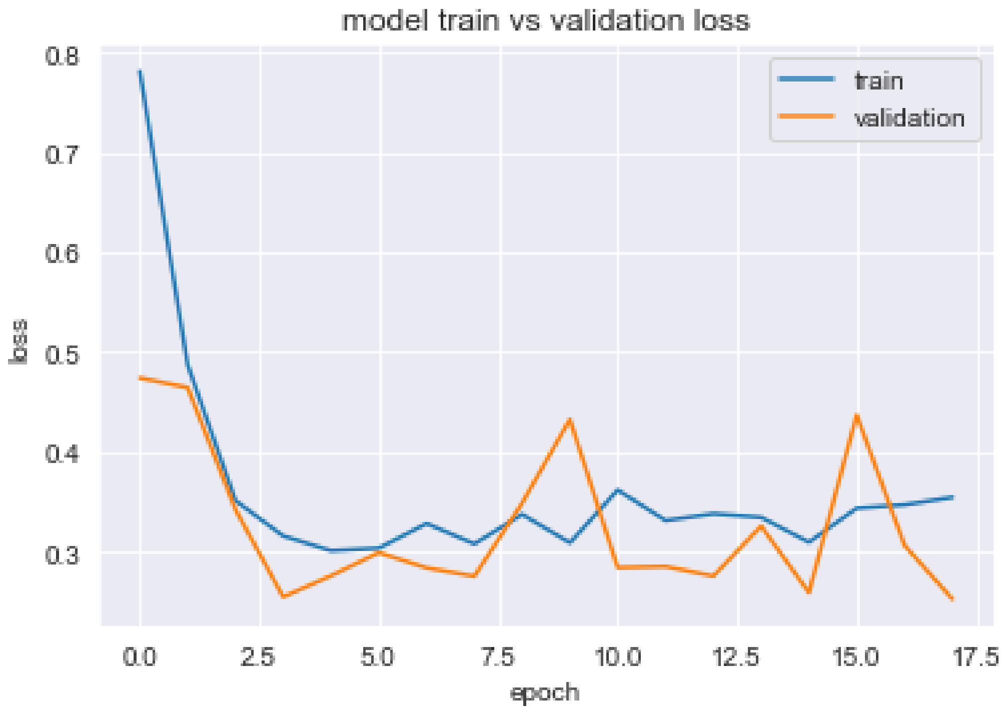
[77]:
```
#activation='tanh',  hidden_layer_sizes=[100,80,60,40,20], alpha = 0.1

model = tf.keras.Sequential()
model.add(tf.keras.layers.Dense(200, input_shape=X_train1.shape[1:],␣
↪activation='tanh'))
#model.add(tf.keras.layers.Dense(80, activation='tanh'))
#model.add(tf.keras.layers.Dense(60, activation='tanh'))
#model.add(tf.keras.layers.Dense(40, activation='tanh'))
```

```python
#model.add(tf.keras.layers.Dense(20, activation='tanh'))
model.add(tf.keras.layers.Dense(1))

model.summary()

model.compile(loss='mean_squared_error', optimizer=tf.keras.optimizers.
 ↪Adam(learning_rate=0.1))

history = model.fit(X_train1, y_train1, validation_data=(X_val, y_val),␣
 ↪epochs=18)

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model train vs validation loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
```

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_2 (Dense)             (None, 200)               400

 dense_3 (Dense)             (None, 1)                 201

=================================================================
Total params: 601
Trainable params: 601
Non-trainable params: 0
_________________________________________________________________
Epoch 1/18
99/99 [==============================] - 0s 2ms/step - loss: 0.7813 - val_loss:
0.4742
Epoch 2/18
99/99 [==============================] - 0s 1ms/step - loss: 0.4874 - val_loss:
0.4645
Epoch 3/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3513 - val_loss:
0.3424
Epoch 4/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3158 - val_loss:
0.2546
Epoch 5/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3011 - val_loss:
0.2758
Epoch 6/18
```

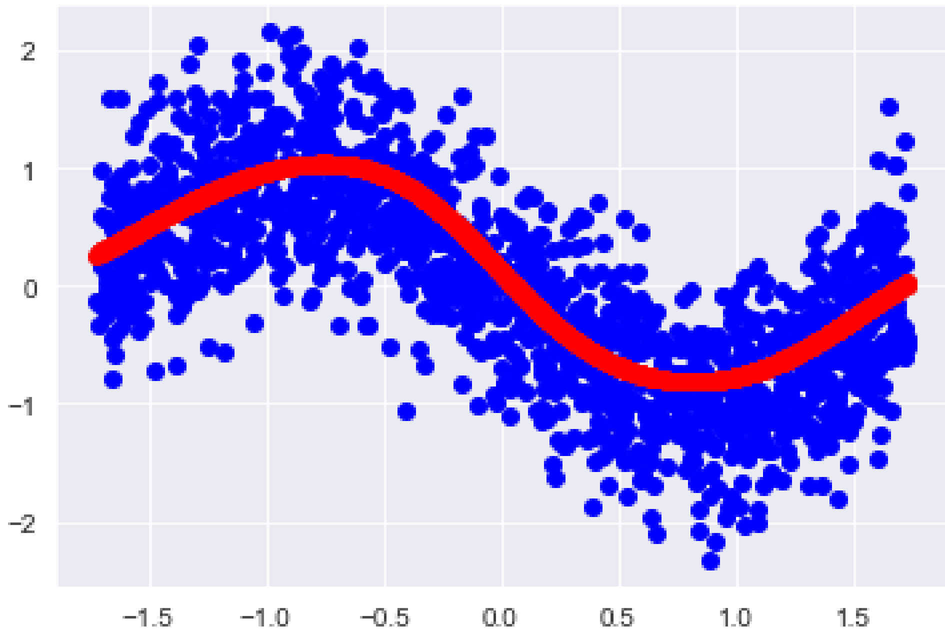
```
99/99 [==============================] - 0s 1ms/step - loss: 0.3036 - val_loss:
0.2990
Epoch 7/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3283 - val_loss:
0.2838
Epoch 8/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3078 - val_loss:
0.2754
Epoch 9/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3375 - val_loss:
0.3487
Epoch 10/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3090 - val_loss:
0.4325
Epoch 11/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3617 - val_loss:
0.2842
Epoch 12/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3313 - val_loss:
0.2851
Epoch 13/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3380 - val_loss:
0.2756
Epoch 14/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3345 - val_loss:
0.3257
Epoch 15/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3095 - val_loss:
0.2590
Epoch 16/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3436 - val_loss:
0.4369
Epoch 17/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3471 - val_loss:
0.3063
Epoch 18/18
99/99 [==============================] - 0s 1ms/step - loss: 0.3544 - val_loss:
0.2526
```

```
[77]: <matplotlib.legend.Legend at 0x1645cfa90>
```




[78]:

```
y_pred10 = model.predict(X_test)
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)


# Overlay the sine wave
ax.scatter(X_test, y_test, color='b')
# Overlay the sine wave
ax.scatter(X_test, y_pred10, color='r')

plt.show()
```

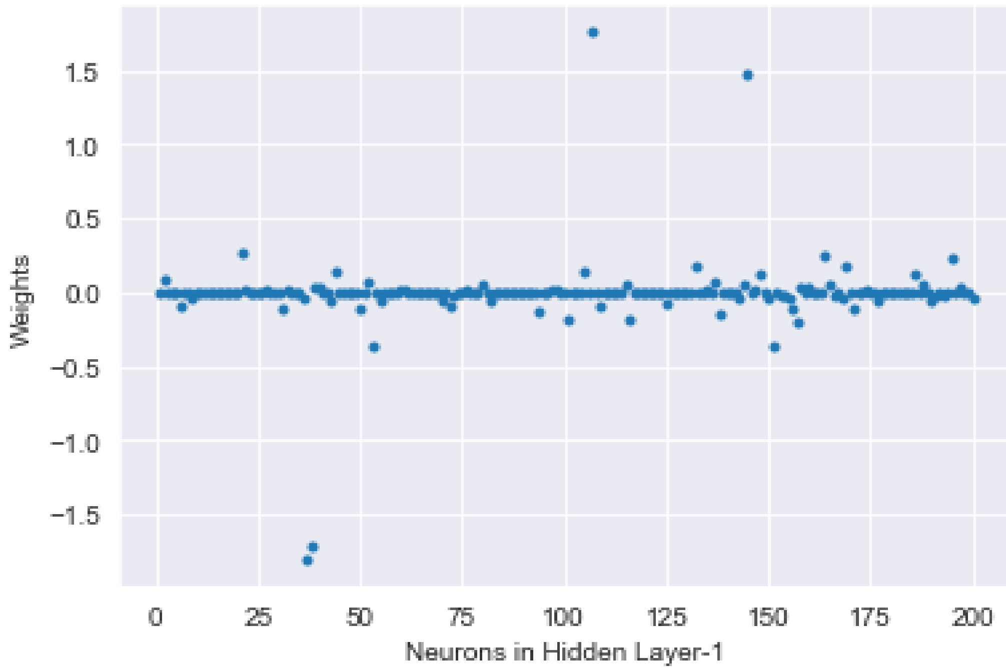



[79]:
```
mse(y_test,model.predict(X_test),squared=False)
```

[79]: 0.5117901998618909

[80]:
```
plt.plot(np.arange(1,201,1), np.asarray(model.weights[0]).reshape(-1,1),'.')
plt.ylabel('Weights')
plt.xlabel('Neurons in Hidden Layer-1')
```

[80]: Text(0.5, 0, 'Neurons in Hidden Layer-1')




There are other ways we can evaluate the performance.

## 1.2 MLP Classifier

Now, let's look at how we can use Multi-layer perceptrons for classification problems. First we will recreate that difficult data set using make_moons.

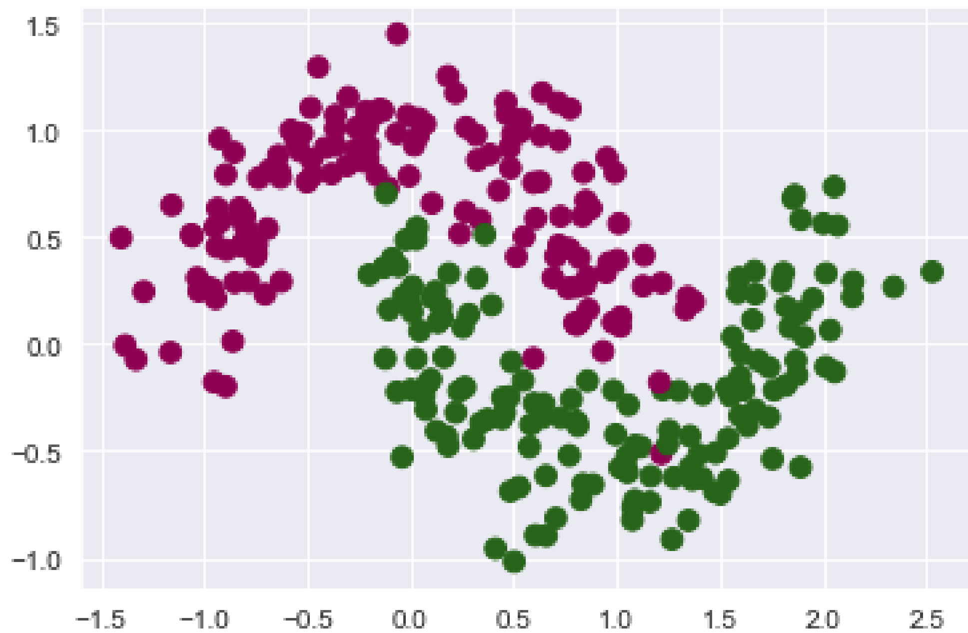
[81]:
```
from sklearn.datasets import make_moons
```

[82]:
```
X_moon, y_moon = make_moons(n_samples=300, noise=0.2, random_state=0)
```

[83]:
```
scaler_moon = StandardScaler()
x_scaled_moon = scaler_moon.fit_transform(X_moon)
```

[84]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_moon[:,0], X_moon[:,1], c=y_moon, cmap='PiYG', s=60)
```

[84]:
```
<matplotlib.collections.PathCollection at 0x1648a4f40>
```



Import the MLPClassifier library.

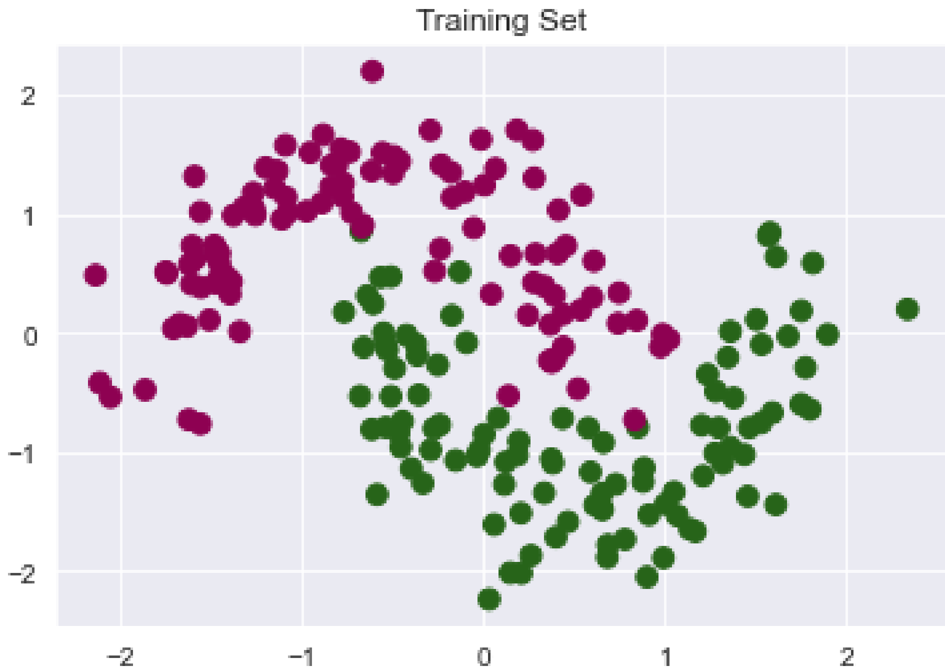
[86]:
```
from sklearn.neural_network import MLPClassifier
```

Now, let's separate the data set into training and test sets.

[87]:
```
X_train, X_test, y_train, y_test = train_test_split(x_scaled_moon, y_moon,␣
↪test_size=0.3)
```

[88]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_train[:,0], X_train[:,1], c=y_train, cmap='PiYG', s=60)
plt.title('Training Set')
```

[88]:
```
Text(0.5, 1.0, 'Training Set')
```




[89]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_test[:,0], X_test[:,1], c=y_test, cmap='PiYG', s=60)
plt.title('Test Set')
```

[89]: Text(0.5, 1.0, 'Test Set')


Create the MLPClassifier.

[90]:
```
mlp = MLPClassifier(random_state=5)
```

[91]:
```
mlp.fit(X_train, y_train)
```

```
/Users/dsozturk/Library/Python/3.8/lib/python/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:582:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[91]:
```
MLPClassifier(random_state=5)
```

[92]:
```
y_pred = mlp.predict(X_test)
```

[93]:
```
y_test
```

[93]:
```
array([1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 1, 0, 1,
       0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 0,
       1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 0,
       0, 1])
```

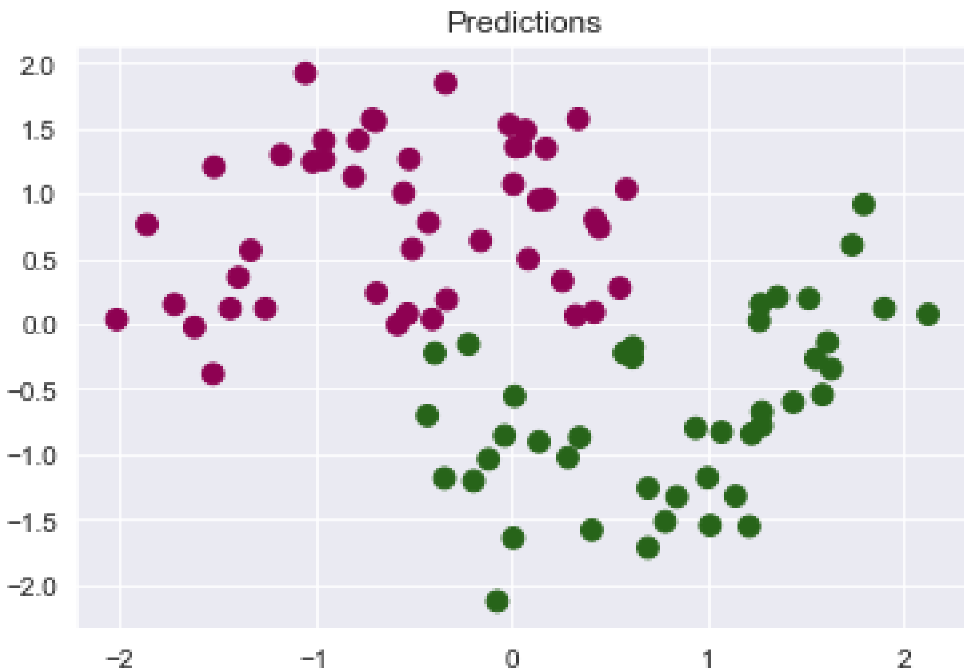
[94]:
```
y_pred
```

```
[94]: array([1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1,
             0, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
             1, 0, 0, 1, 0, 1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0,
             1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 0,
             0, 1])
```

Let's see how the predictions look like.

```
[95]: fig = plt.figure(figsize=[6,4])
      ax = plt.subplot(111)

      ax.scatter(X_test[:,0], X_test[:,1], c=y_pred, cmap='PiYG', s=60)
      plt.title('Predictions')
```

```
[95]: Text(0.5, 1.0, 'Predictions')
```




```
[96]: mlp.hidden_layer_sizes
```

```
[96]: (100,)
```

There are subtle differences. ### Changing Neuron Number Let's see if changing the neuron number will help.

```
[97]: mlp2 = MLPClassifier(random_state=5, hidden_layer_sizes=[10])
```

[98]:
```
mlp2.fit(X_train, y_train)
```

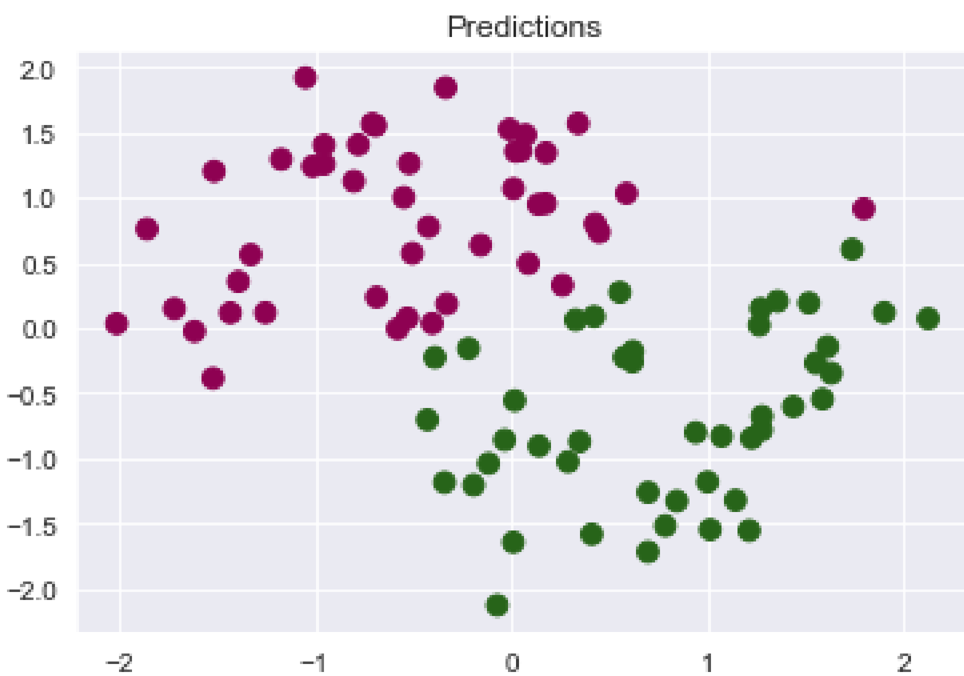
```
/Users/dsozturk/Library/Python/3.8/lib/python/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:582:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[98]:
```
MLPClassifier(hidden_layer_sizes=[10], random_state=5)
```

[99]:
```
y_pred2 = mlp2.predict(X_test)
```

[100]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_test[:,0], X_test[:,1], c=y_pred2, cmap='PiYG', s=60)
plt.title('Predictions')
```

[100]:
```
Text(0.5, 1.0, 'Predictions')
```




Still, there are some differences. ### Changing Layer Number Let's see if adding layers will help.

[101]:
```
mlp3 = MLPClassifier(random_state=5, hidden_layer_sizes=[100,100])
```

[102]:
```
mlp3.fit(X_train, y_train)
```

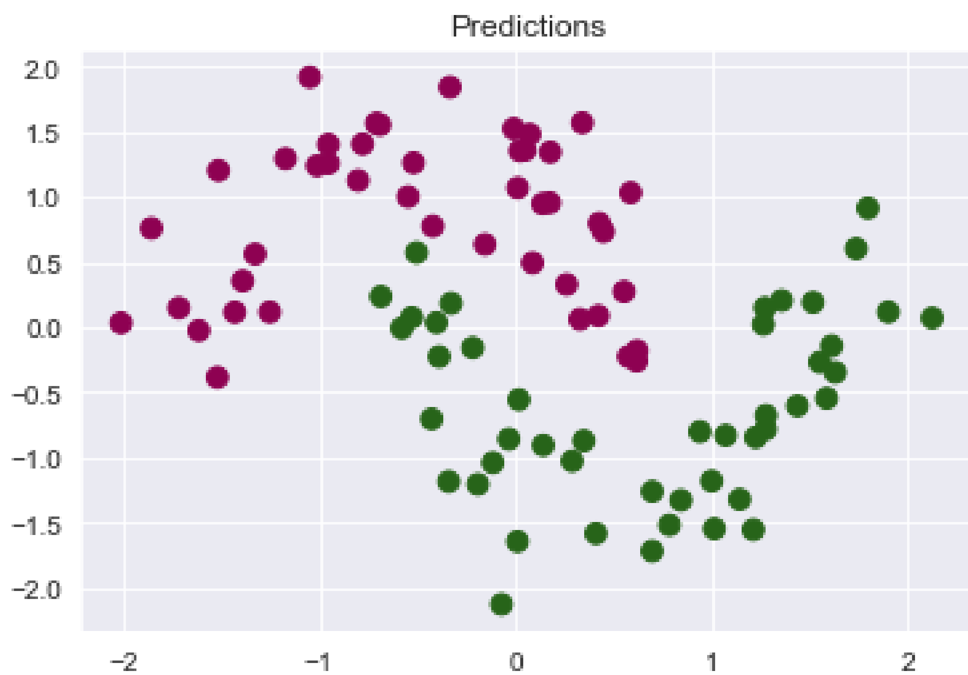
```
/Users/dsozturk/Library/Python/3.8/lib/python/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:582:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[102]:
```
MLPClassifier(hidden_layer_sizes=[100, 100], random_state=5)
```

[103]:
```
y_pred3 = mlp3.predict(X_test)
```

[104]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_test[:,0], X_test[:,1], c=y_pred3, cmap='PiYG', s=60)
plt.title('Predictions')
```

[104]:
```
Text(0.5, 1.0, 'Predictions')
```




### 1.2.1 Changing Activation Function

Let's see how to change the activation function.

[105]:
```
mlp4 = MLPClassifier(random_state=5, hidden_layer_sizes=[10], activation='tanh')
```

[106]:
```
mlp4.fit(X_train, y_train)
```

```
/Users/dsozturk/Library/Python/3.8/lib/python/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:582:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[106]:
```
MLPClassifier(activation='tanh', hidden_layer_sizes=[10], random_state=5)
```

[107]:
```
y_pred4 = mlp4.predict(X_test)
```

[108]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_test[:,0], X_test[:,1], c=y_pred4, cmap='PiYG', s=60)
plt.title('Predictions')
```

[108]:
```
Text(0.5, 1.0, 'Predictions')
```


[109]:
```
mlp.alpha
```

[109]:
```
0.0001
```

### 1.2.2 Changing Learning Rate/Regularization

Another parameter we can tune is the learning rate.

[110]:
```
mlp5 = MLPClassifier(random_state=5, hidden_layer_sizes=[10], alpha=0.01)
```

[111]:
```
mlp5.fit(X_train, y_train)
```

```
/Users/dsozturk/Library/Python/3.8/lib/python/site-
packages/sklearn/neural_network/_multilayer_perceptron.py:582:
ConvergenceWarning: Stochastic Optimizer: Maximum iterations (200) reached and
the optimization hasn't converged yet.
  warnings.warn(
```

[111]:
```
MLPClassifier(alpha=0.01, hidden_layer_sizes=[10], random_state=5)
```

[112]:
```
y_pred5 = mlp5.predict(X_test)
```

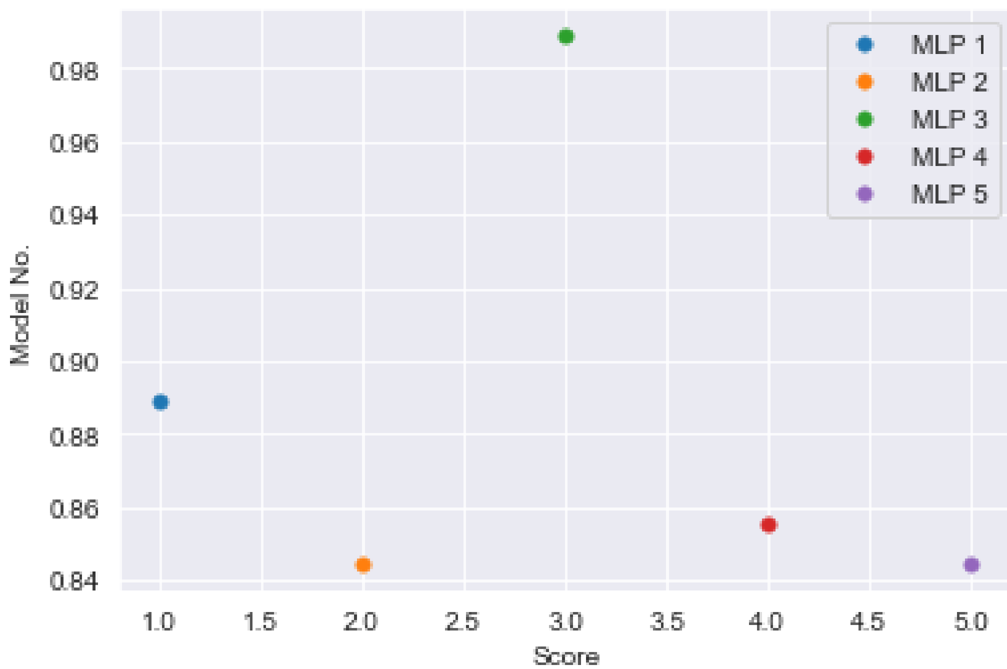
[113]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_test[:,0], X_test[:,1], c=y_pred5, cmap='PiYG', s=60)
plt.title('Predictions')
```

[113]:
```
Text(0.5, 1.0, 'Predictions')
```


It is hard to evaluate by eye. ### Evaluation an MLP Classifier Remember how we used to evaluate a classifier?

[114]:
```python
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.plot(1, mlp.score(X_test,y_test),'.', markersize=10, label='MLP 1')
ax.plot(2, mlp2.score(X_test,y_test),'.', markersize=10, label='MLP 2')
ax.plot(3, mlp3.score(X_test,y_test),'.', markersize=10, label='MLP 3')
ax.plot(4, mlp4.score(X_test,y_test),'.', markersize=10, label='MLP 4')
ax.plot(5, mlp5.score(X_test,y_test),'.', markersize=10, label='MLP 5')

ax.set_ylabel('Model No.')
ax.set_xlabel('Score')
ax.legend()
```

[114]:
```
<matplotlib.legend.Legend at 0x165272f40>
```

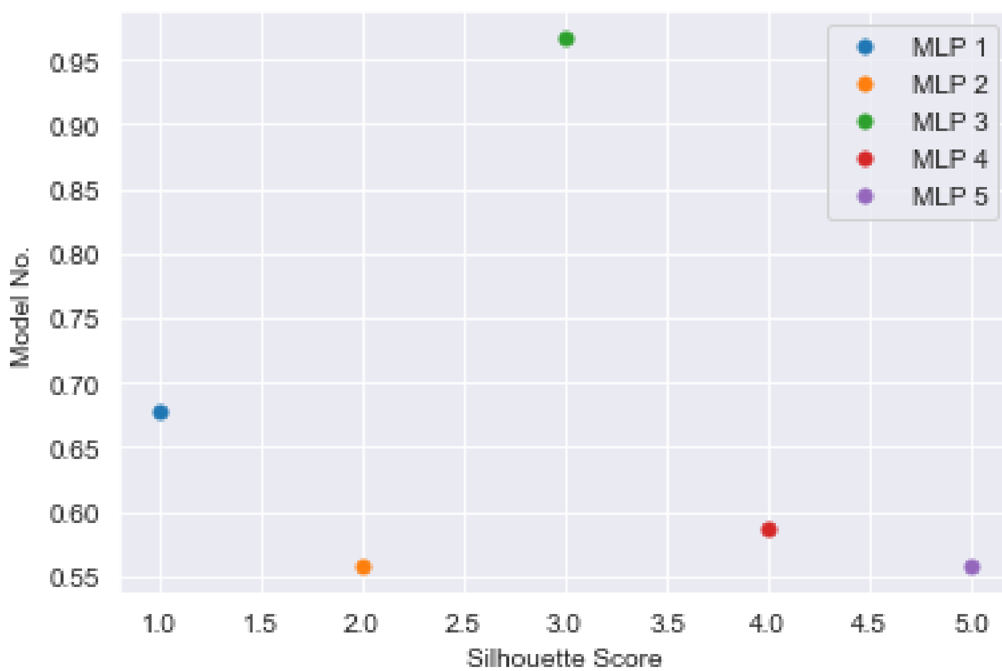



[115]:
```python
from sklearn.metrics import silhouette_score
```

[116]:
```python
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.plot(1,silhouette_score(y_test.reshape(-1, 1),y_pred),'.', markersize=10,␣
 ↪label='MLP 1')
ax.plot(2,silhouette_score(y_test.reshape(-1, 1),y_pred2),'.', markersize=10,␣
 ↪label='MLP 2')
```

```
ax.plot(3,silhouette_score(y_test.reshape(-1, 1),y_pred3),'.', markersize=10,␣
    ↪label='MLP 3')
ax.plot(4,silhouette_score(y_test.reshape(-1, 1),y_pred4),'.', markersize=10,␣
    ↪label='MLP 4')
ax.plot(5,silhouette_score(y_test.reshape(-1, 1),y_pred5),'.', markersize=10,␣
    ↪label='MLP 5')
ax.set_ylabel('Model No.')
ax.set_xlabel('Silhouette Score')

ax.legend()
```

[116]: <matplotlib.legend.Legend at 0x1652fcf40>




### 1.2.3 TensorFlow representation for MLPClassifier

1. The sklearn MLPClassifier uses 0.1 of the training set for validation, for TensorFlow we would define the validation set separately.
2. MLPClassifier uses log-loss by default, so we are going to define this as our loss function in TensorFlow too.

[117]:
```
X_train1, X_val, y_train1, y_val = train_test_split(X_train, y_train,␣
    ↪test_size=0.1, random_state=1) # 0.25 x 0.8 = 0.2
```

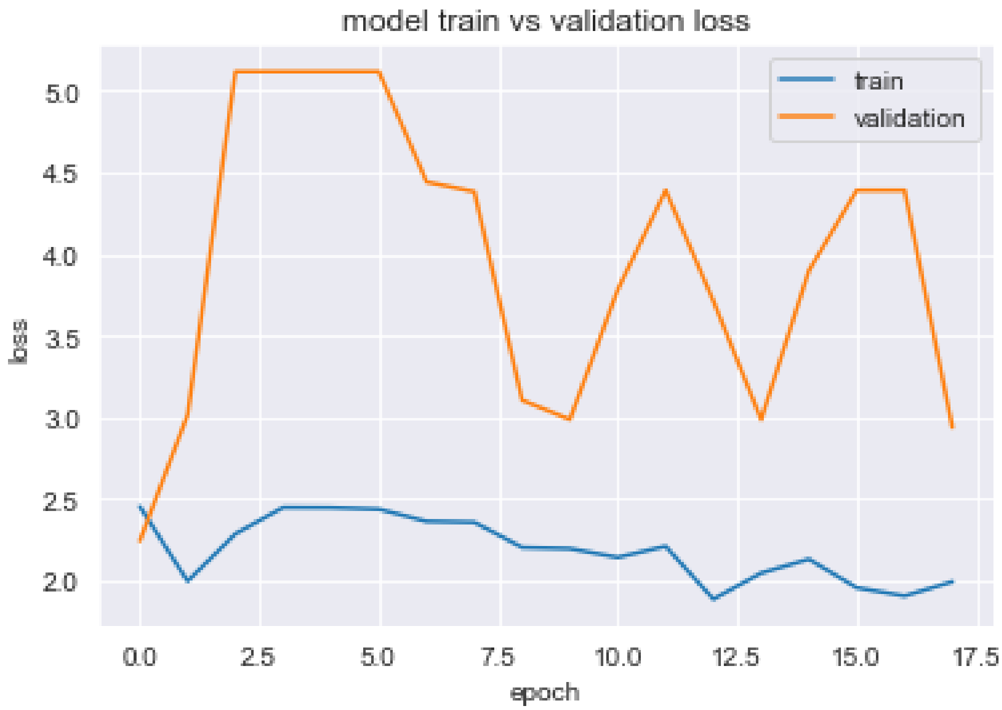
[121]:
```
#activation='tanh',  hidden_layer_sizes=[100,80,60,40,20], alpha = 0.1
```

```
model3 = tf.keras.Sequential()
model3.add(tf.keras.layers.Dense(200, input_shape=X_train1.shape[1:],␣
 ↪activation='tanh'))
#model3.add(tf.keras.layers.BatchNormalization())
#model3.add(tf.keras.layers.Dropout(0.1))
model3.add(tf.keras.layers.Dense(100, activation='tanh'))
#model.add(tf.keras.layers.Dense(60, activation='tanh'))
#model.add(tf.keras.layers.Dense(40, activation='tanh'))
#model.add(tf.keras.layers.Dense(20, activation='tanh'))
model3.add(tf.keras.layers.Dense(1))

model3.summary()

model3.compile(loss='binary_crossentropy', optimizer=tf.keras.optimizers.
 ↪Adam(learning_rate=0.01))

history = model3.fit(X_train1, y_train1, validation_data=(X_val, y_val),␣
 ↪epochs=18, batch_size=32)

plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model train vs validation loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'validation'], loc='upper right')
```

```
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_10 (Dense)            (None, 200)               600

 dense_11 (Dense)            (None, 100)               20100

 dense_12 (Dense)            (None, 1)                 101

=================================================================
Total params: 20,801
Trainable params: 20,801
Non-trainable params: 0
_________________________________________________________________
Epoch 1/18
6/6 [==============================] - 0s 27ms/step - loss: 2.4528 - val_loss:
2.2418
Epoch 2/18
6/6 [==============================] - 0s 6ms/step - loss: 1.9961 - val_loss:
3.0146
```

```
Epoch 3/18
6/6 [==============================] - 0s 6ms/step - loss: 2.2850 - val_loss:
5.1165
Epoch 4/18
6/6 [==============================] - 0s 6ms/step - loss: 2.4472 - val_loss:
5.1165
Epoch 5/18
6/6 [==============================] - 0s 6ms/step - loss: 2.4459 - val_loss:
5.1165
Epoch 6/18
6/6 [==============================] - 0s 6ms/step - loss: 2.4366 - val_loss:
5.1165
Epoch 7/18
6/6 [==============================] - 0s 6ms/step - loss: 2.3612 - val_loss:
4.4415
Epoch 8/18
6/6 [==============================] - 0s 6ms/step - loss: 2.3559 - val_loss:
4.3820
Epoch 9/18
6/6 [==============================] - 0s 6ms/step - loss: 2.2026 - val_loss:
3.1043
Epoch 10/18
6/6 [==============================] - 0s 6ms/step - loss: 2.1956 - val_loss:
2.9858
Epoch 11/18
6/6 [==============================] - 0s 6ms/step - loss: 2.1417 - val_loss:
3.7802
Epoch 12/18
6/6 [==============================] - 0s 6ms/step - loss: 2.2100 - val_loss:
4.3904
Epoch 13/18
6/6 [==============================] - 0s 6ms/step - loss: 1.8861 - val_loss:
3.7121
Epoch 14/18
6/6 [==============================] - 0s 6ms/step - loss: 2.0459 - val_loss:
2.9856
Epoch 15/18
6/6 [==============================] - 0s 6ms/step - loss: 2.1309 - val_loss:
3.8983
Epoch 16/18
6/6 [==============================] - 0s 6ms/step - loss: 1.9559 - val_loss:
4.3904
Epoch 17/18
6/6 [==============================] - 0s 6ms/step - loss: 1.9055 - val_loss:
4.3904
Epoch 18/18
6/6 [==============================] - 0s 6ms/step - loss: 1.9927 - val_loss:
2.9381
```

[121]: <matplotlib.legend.Legend at 0x165533f40>



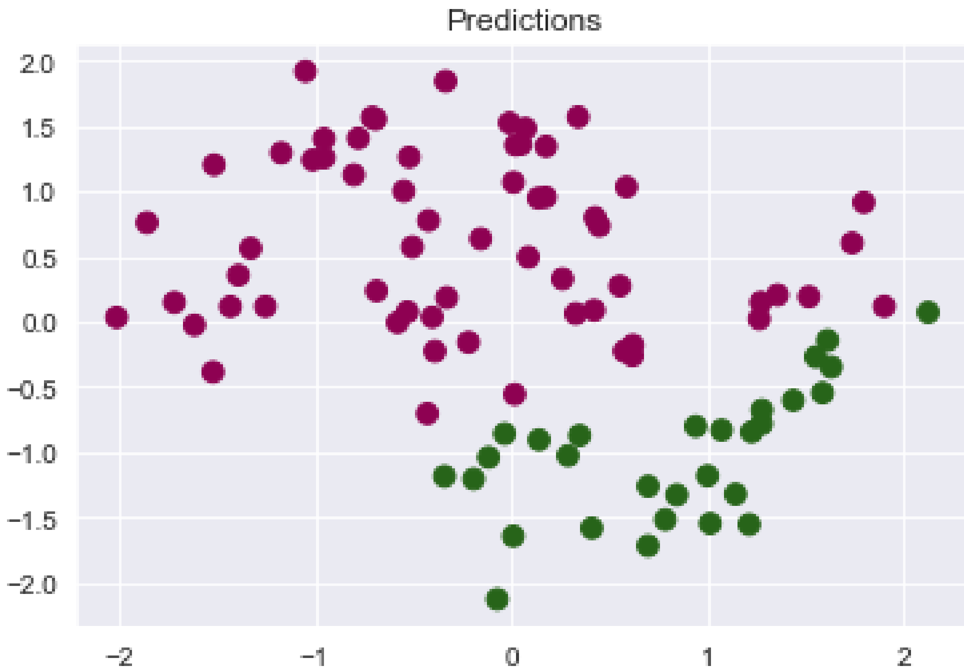

[122]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_test[:,0], X_test[:,1], c=[model3.predict(X_test)], cmap='PiYG',␣
 ↪s=60)
plt.title('Predictions')
```

[122]: Text(0.5, 1.0, 'Predictions')


TensorFlow returns the prediction probabilities once again. Therefore, let's apply the threshold.

[123]:
```
fig = plt.figure(figsize=[6,4])
ax = plt.subplot(111)

ax.scatter(X_test[:,0], X_test[:,1], c=[model3.predict(X_test)> 0.5],␣
  ↪cmap='PiYG', s=60)
plt.title('Predictions')
```

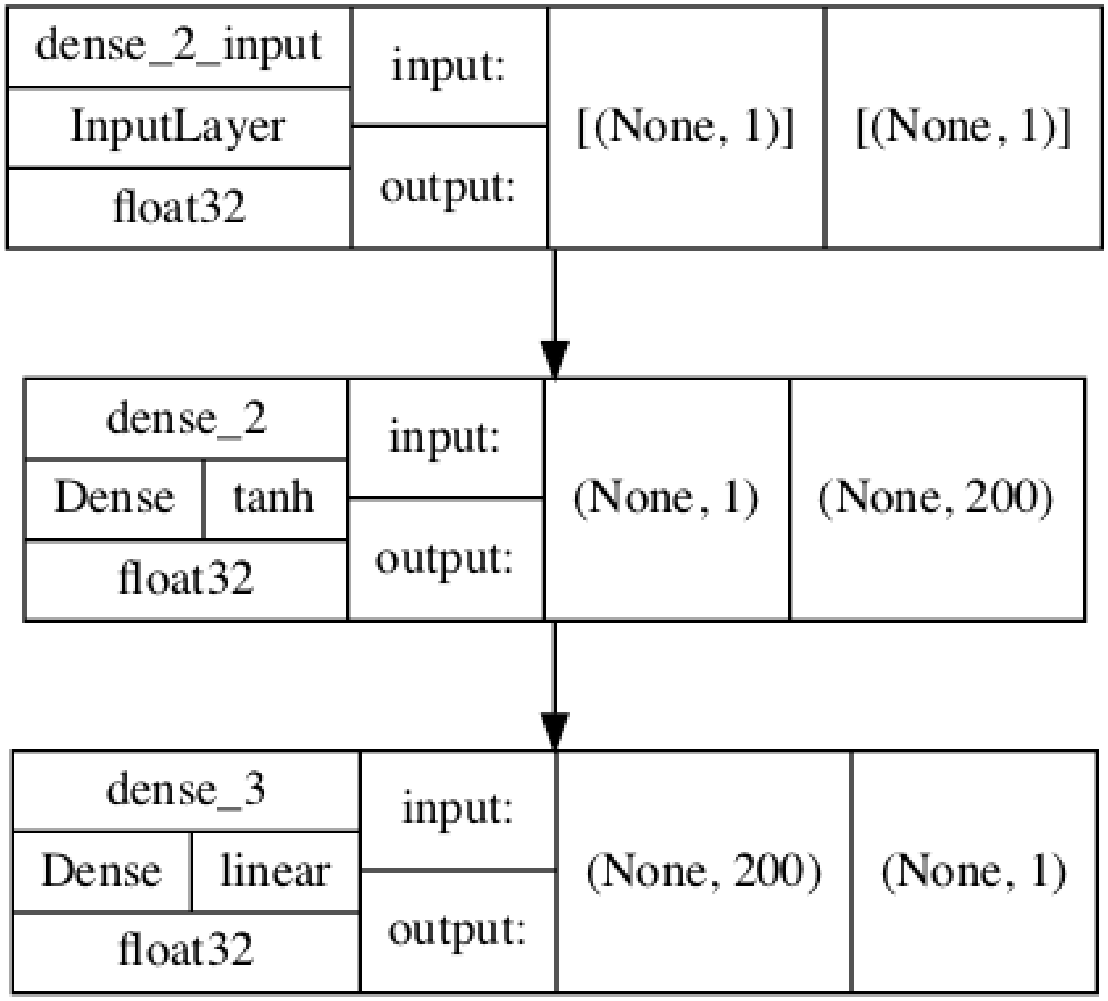
[123]:
```
Text(0.5, 1.0, 'Predictions')
```




### 1.2.4 Visualization of TensorFlow Models

[124]:
```
dot_img_file = './model.png'
tf.keras.utils.plot_model(model,
                          to_file=dot_img_file,
                          show_shapes=True,
                          show_dtype=True,
                          show_layer_activations=True)
```

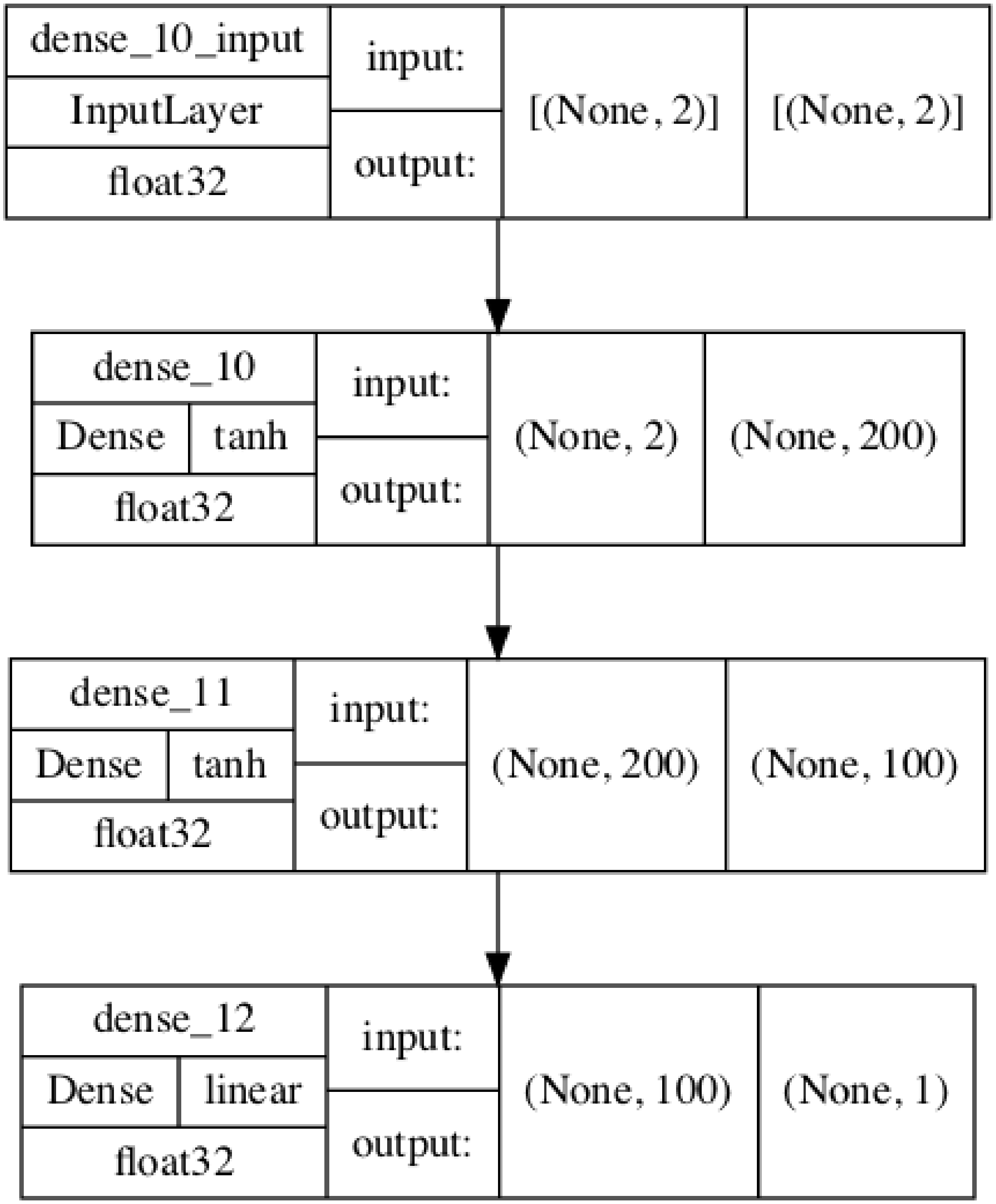
[124]:




[125]:

```
dot_img_file = './model3.png'
tf.keras.utils.plot_model(model3,
                          to_file=dot_img_file,
                          show_shapes=True,
                          show_dtype=True,
                          show_layer_activations=True)
```

[125]:




[126]:

```
y_pred = model3.predict(X_test)>0.5

from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[44  1]
 [17 28]]
```

[126]:
```
0.8
```

[127]:
```
cm2 = confusion_matrix(y_test, y_pred3)
print(cm2)
accuracy_score(y_test, y_pred3)
```

```
[[44  1]
 [ 0 45]]
```

[127]:
```
0.9888888888888889
```

Congratulations, you have completed the Neural Network Workbook!

[ ]:
```

```