Lab 1 – Machine Learning

Linear and Polynomial regression with TensorFlow and Keras

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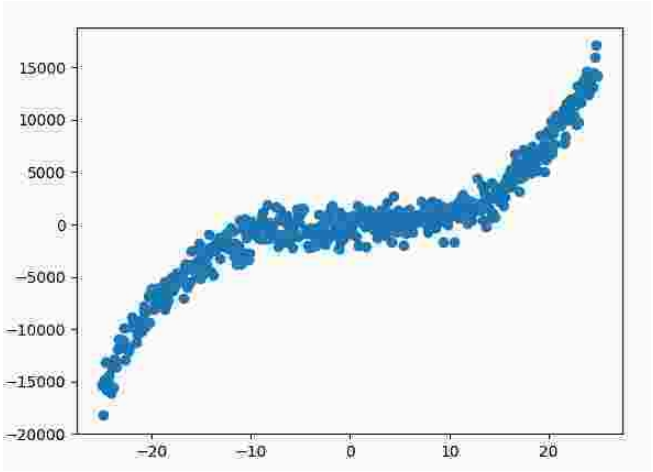
1. Linear Regression on Non-Linear Data

- Get X and y from **`dataset()`** function
- Train a Linear Regression model for this **dataset**.
- Visualize the model prediction

1.1 Dataset

Call **`dataset()`** function to get **`X,y`**

```
import numpy as np
import matplotlib.pyplot as plt

def dataset(show=True):
    X = np.arange(-25, 25, 0.1)
    # Try changing y to a different function
    y = X**3 + 20 + np.random.randn(500)*1000
    if show:
        plt.scatter(X, y)
        plt.show()
    return X, y

X, y = dataset()
```

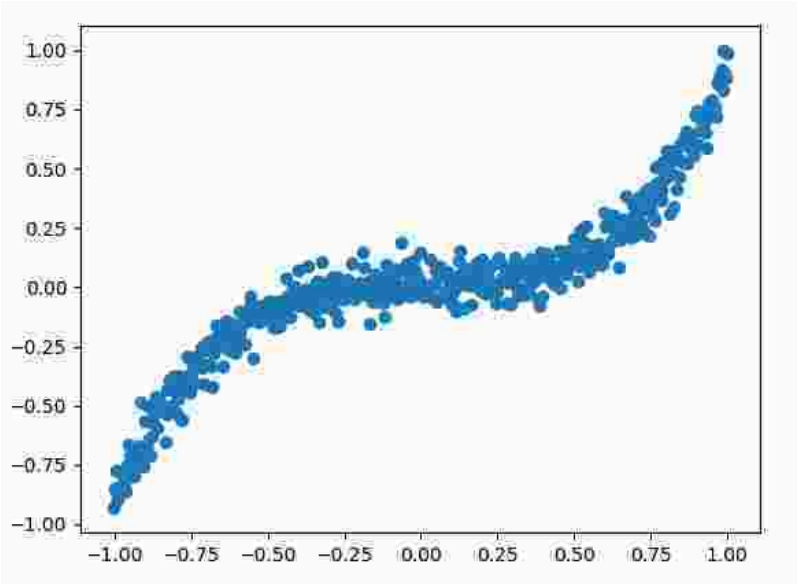


1.1.1 Scaling Dataset

The maximum value of y in the dataset goes upto 15000 and the minimum values is less than -15000. The range of y is very large which makes the convergence/loss reduction slower. So will we scale the data, scaling the data will help the model converge faster. If all the features and target are in the same range, there will be symmetry in the curve of Loss vs weights/bias, which makes the convergence faster.
We will do a very simple type of scaling, we will divide all the values of the data with the maximum values for X and y respectively.

```
X, y = dataset()
print(max(X), max(y), min(X), min(y))
X = X/max(X)
y = y/max(y)
print(max(X), max(y), min(X), min(y))
```

This is not a great scaling method, but good to start. We will see many more scaling/normalization methods later.



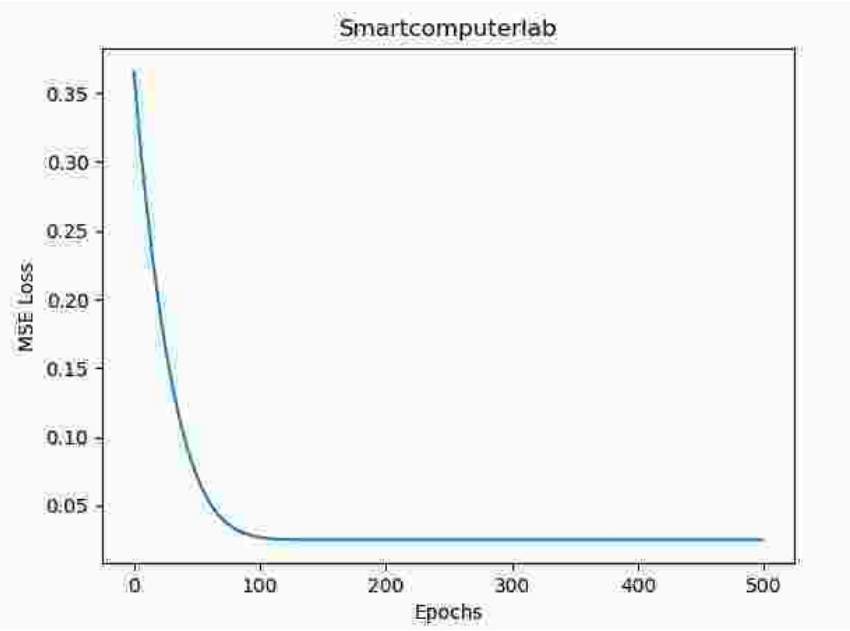
Try training the model with and without scaling and see the difference yourself.

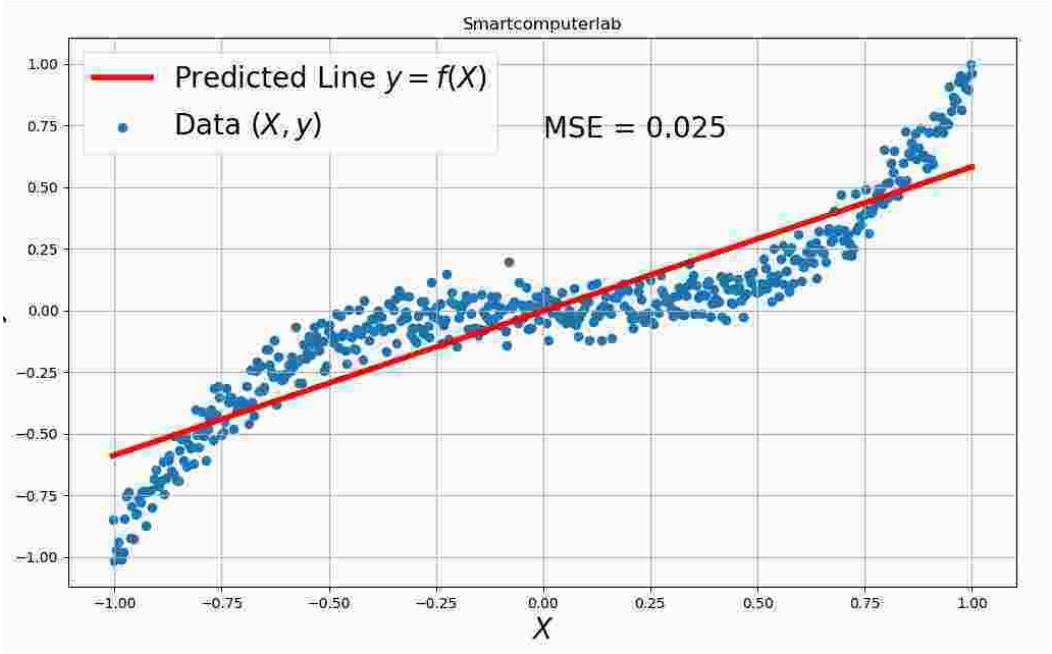
1.2 Linear Regression in TensorFlow

The example is run with 500 epochs.

```
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
import numpy as np

def dataset(show=True):
    X = np.arange(-25, 25, 0.1)
    # Try changing y to a different function
    y = X**3 + 20 + np.random.randn(500)*1000
    if show:
        plt.scatter(X, y)
        plt.show()
    return X, y

X, y = dataset(show=False)
X_scaled = X/max(X)
```

```
y_scaled = y/max(y)

model = tf.keras.Sequential([keras.layers.Dense(units=1, input_shape=[1])])

# you can also define optimizers in this way, so you can change parameters like
lr.
optimizer = tf.keras.optimizers.Adam(learning_rate=1e-3)
model.compile(optimizer=optimizer, loss='mean_squared_error')
tf_history = model.fit(X_scaled, y_scaled, epochs=500, verbose=True)

plt.plot(tf_history.history['loss'])
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.show()

mse = tf_history.history['loss'][-1]
y_hat = model.predict(X_scaled)

plt.figure(figsize=(12,7))
plt.title('TensorFlow Model')
plt.scatter(X_scaled, y_scaled, label='Data $(X, y)$')
plt.plot(X_scaled, y_hat, color='red', label='Predicted Line $y = f(X)
$',linewidth=4.0)
plt.xlabel('$X$', fontsize=20)
plt.ylabel('$y$', fontsize=20)
plt.text(0,0.70,'MSE = {:.3f}'.format(mse), fontsize=20)
plt.grid(True)
plt.legend(fontsize=20)
plt.show()
```





1.3 Exercise

Change number of epochs to 10 and observe the result.

2. Polynomial Regression

When the dataset is not linear, linear regression cannot learn the dataset and make good predictions.
We need here a polynomial model which considered the polynomial terms as well.
We need terms like x^2 , x^3, ..., x^n for the model to learn a polynomial of nth degree.

$$y=w0+w1*x+w2*x^2+...+wn*x^n$$

One down side of this model is that, we have to decide the value of **n**. But this is better than a linear regression model. We can get an idea of the value of **n** by visualizing a dataset, but for multi variable dataset, we will have to try different values of **n** and check which is better.

2.1 Polynomial Features

We can calculate the polynomial features for each feature by programming it or we can try **`sklearn.preprocessing.PolynomialFeatures`** which allows us to make polynomial terms of our data.

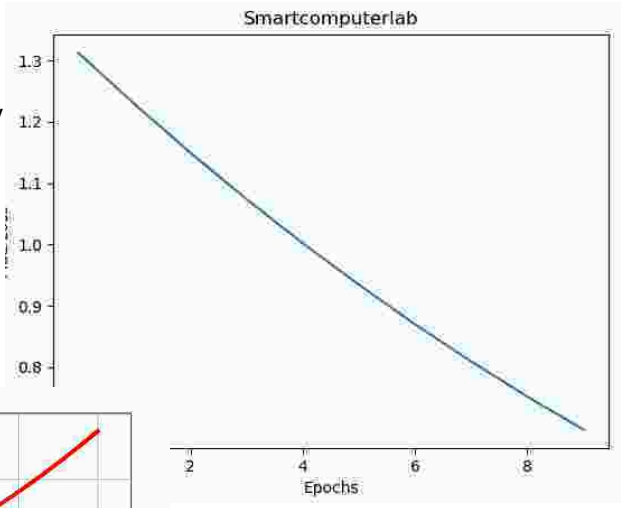
We will try degree 2, 3 and 4

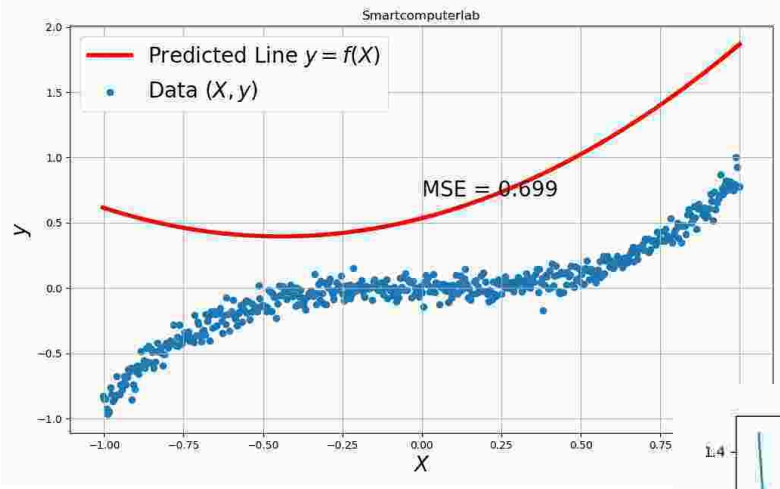
```
X, y = dataset(show=False)
X_scaled = X/max(X)
y_scaled = y/max(y)
from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree=2)

X_2 = poly.fit_transform(X_scaled.reshape(-1,1))
print(X_2.shape)
print(X_2[0])


from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree=3)

X_3 = poly.fit_transform(X_scaled.reshape(-1,1))
print(X_3.shape)
print(X_3[0])

from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree=4)

X_4 = poly.fit_transform(X_scaled.reshape(-1,1))
print(X_4.shape)
print(X_4[0])
```

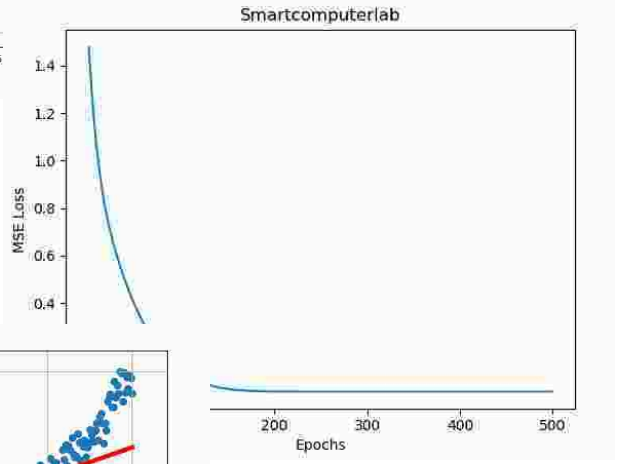
2.2 Polynomial Regression – degree 2

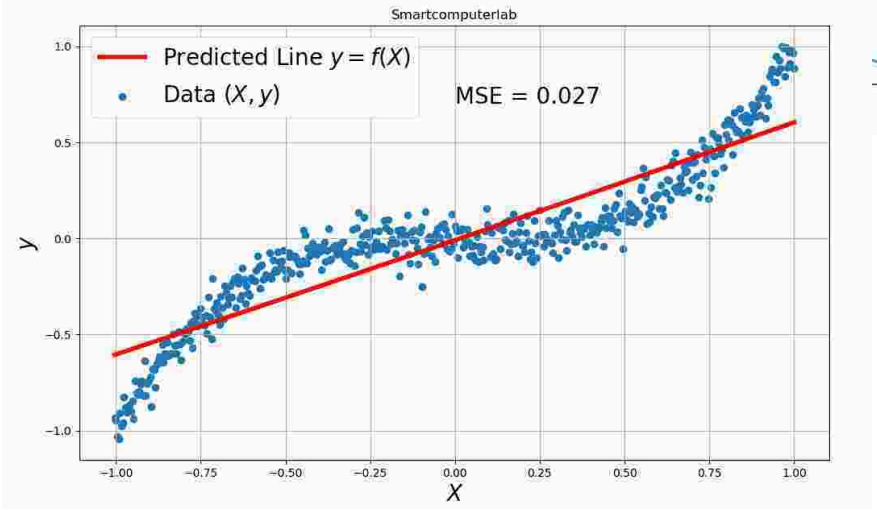
```
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
import numpy as np

def dataset(show=True):
    X = np.arange(-25, 25, 0.1)
    # Try changing y to a different function
    y = X**3 + 20 + np.random.randn(500)*1000
    if show:
        plt.scatter(X, y)
        plt.show()
    return X, y

X, y = dataset(show=False)
X_scaled = X/max(X)
y_scaled = y/max(y)

from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree=2)

X_2 = poly.fit_transform(X_scaled.reshape(-1,1))
print(X_2.shape)
print(X_2[0])

model = tf.keras.Sequential([keras.layers.Dense(units=1, input_shape=[3])])

optimizer = tf.keras.optimizers.Adam(learning_rate=1e-3)

model.compile(optimizer=optimizer, loss='mean_squared_error')
#tf_history = model.fit(X_2, y_scaled, epochs=500, verbose=True)
tf_history = model.fit(X_2, y_scaled, epochs=10, verbose=True)

plt.plot(tf_history.history['loss'])
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.title('Smartcomputerlab')
plt.show()

mse = tf_history.history['loss'][-1]
y_hat = model.predict(X_2)

plt.figure(figsize=(12,7))
plt.title('Smartcomputerlab')
plt.scatter(X_2[:, 1], y_scaled, label='Data $(X, y)$')
plt.plot(X_2[:, 1], y_hat, color='red', label='Predicted Line $y = f(X)
$',linewidth=4.0)
plt.xlabel('$X$', fontsize=20)
plt.ylabel('$y$', fontsize=20)
plt.text(0,0.70,'MSE = {:.3f}'.format(mse), fontsize=20)
plt.grid(True)
```

Note that the obtained result (for only 10 epochs) is much worse than that for the linear regression. Let us try to improve it with the training run with 500 epochs.





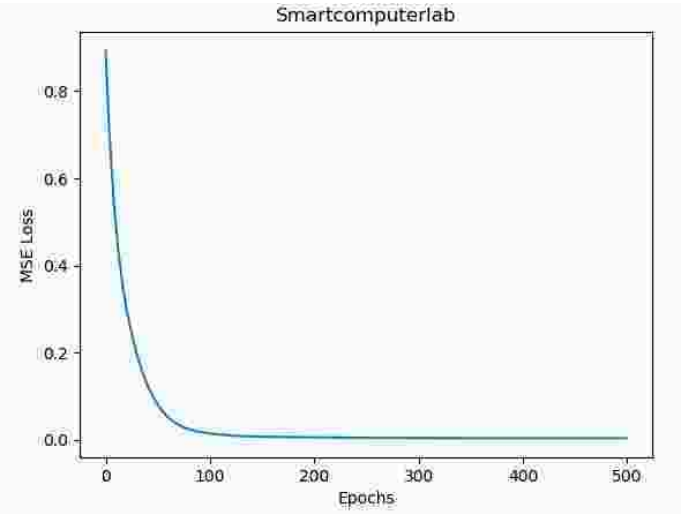


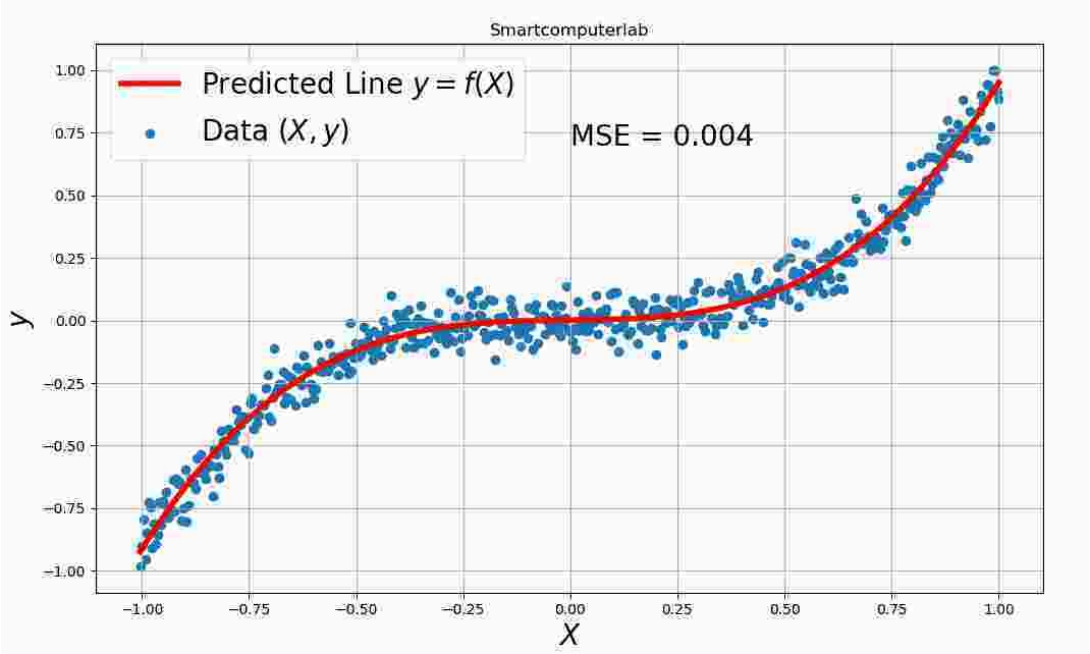


Why is the polynomial regression with 2-d features look like a straight line?
Well because the model thinks that a straight line better fits the dataset than a parabola. If you train the model for less epochs you can notice the model tries to fit the data with a parabola but it improves as it moves to a line.

2.3 Tensorflow Model with 3rd Degree

```
import tensorflow as tf
from tensorflow import keras
import matplotlib.pyplot as plt
import numpy as np

def dataset(show=True):
    X = np.arange(-25, 25, 0.1)
    # Try changing y to a different function
    y = X**3 + 20 + np.random.randn(500)*1000
    if show:
        plt.scatter(X, y)
        plt.show()
    return X, y

X, y = dataset(show=False)
X_scaled = X/max(X)
y_scaled = y/max(y)

from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree=3)
X_3 = poly.fit_transform(X_scaled.reshape(-1,1))
print(X_3.shape)
print(X_3[0])

model = tf.keras.Sequential([keras.layers.Dense(units=1, input_shape=[4])])

optimizer = tf.keras.optimizers.Adam(learning_rate=1e-3)

model.compile(optimizer=optimizer, loss='mean_squared_error')
tf_history = model.fit(X_3, y_scaled, epochs=500, verbose=True)

plt.plot(tf_history.history['loss'])
plt.xlabel('Epochs')
plt.ylabel('MSE Loss')
plt.title('Smartcomputerlab')
plt.show()

mse = tf_history.history['loss'][-1]
y_hat = model.predict(X_3)

plt.figure(figsize=(12,7))
plt.title('Smartcomputerlab')
plt.scatter(X_3[:, 1], y_scaled, label='Data $(X, y)$')
plt.plot(X_3[:, 1], y_hat, color='red', label='Predicted Line $y = f(X)
$',linewidth=4.0)
plt.xlabel('$X$', fontsize=20)
plt.ylabel('$y$', fontsize=20)
plt.text(0,0.70,'MSE = {:.3f}'.format(mse), fontsize=20)
plt.grid(True)
plt.legend(fontsize=20)
plt.show()
```





2.4 Exercise:

Try to develop the Model with 4th degree and test it with different epochs values (500,10,..)