q5_hw1

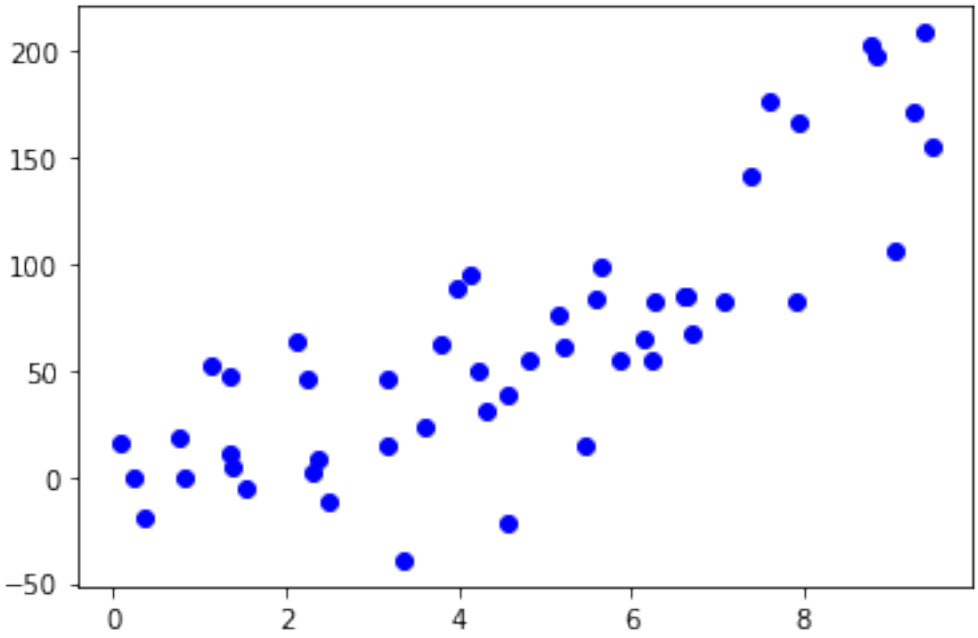
October 25, 2020

[1]:
```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.metrics import r2_score
```

(a) You have the Train and test data below. Visualize them using a scatter plot.

[2]:
```
x_train = np.array([[3.19,9.26,9.38,8.77,7.91,3.79,3.18,7.61,2.36,6.26,6.62,1.
 ↪53,6.25,
          7.93,7.07,4.58,4.14,2.14,9.04,4.56,3.99,6.71,2.51,0.84,6.13,5.22,
          0.25,3.60,1.36,5.59,4.81,1.14,0.36,2.31,1.37,5.86,4.23,9.48,2.26,0.
 ↪77,4.33]]).reshape(-1,1)
y_train = np.array([46.40,172.16,209.00,203.31,82.88,62.57,14.38,177.00,8.01,82.
 ↪35,
          84.84,-5.59,54.96,167.17,83.09,-21.63,94.64,63.97,106.57,38.99,88.
 ↪26,66.99
          ,-11.12,-0.44,65.08,61.47,-0.61,23.85,10.55,83.69,54.35,51.82,-18.
 ↪63,1.98,
          4.90,55.44,50.09,155.66,45.57,18.12,30.58])
x_test = np.array([[5.65,0.07,8.84,5.14,6.65,1.35,5.45,7.39,3.35]]).
 ↪reshape(-1,1)
y_test = np.array([98.52,16.09,198.45,75.90,85.11,47.64,14.76,141.03,-39.13])
```

[3]:
```
plt.scatter(x_train, y_train, c='b')
plt.scatter(x_test, y_test, c='b')
plt.show()
```



(b) Fit the best linear regression model for the training data. Report the model coefficients and both the 2 value and mean square error for the fit of that model for the training data.

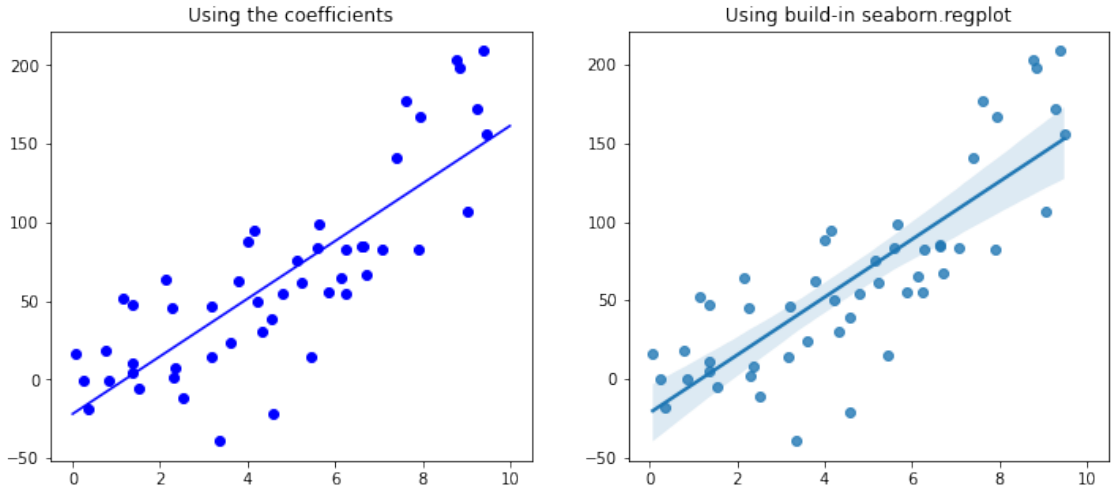
[4]:
```
lr = LinearRegression()
lr.fit(x_train, y_train)
print("The coeficient is {} and the intercept is {}".format(lr.coef_, lr.
 ↪intercept_))
print("The mean squared error is: {}".format(mean_squared_error(y_train, lr.
 ↪predict(x_train))))
print("The R2 score is: {}".format(r2_score(y_train, lr.predict(x_train))))
```

```
The coeficient is [18.30320685] and the intercept is -21.73078292905422
The mean squared error is: 1052.5853662498014
The R2 score is: 0.7014590913812251
```

We can show the regression line using the coefficients or we can just simply use the build-in seaborn.regplot

[5]:
```
fig,axes = plt.subplots(1, 2, sharex=True, figsize = (12,5))

axes[0].scatter(x_train, y_train, c='b')
axes[0].scatter(x_test, y_test, c='b')
a = np.linspace(0,10)
axes[0].plot(a, a*lr.coef_ + lr.intercept_,c='b')

sns.regplot(x = np.concatenate((x_train, x_test)), y = np.concatenate((y_train,␣
 ↪y_test)), ax=axes[1])
```

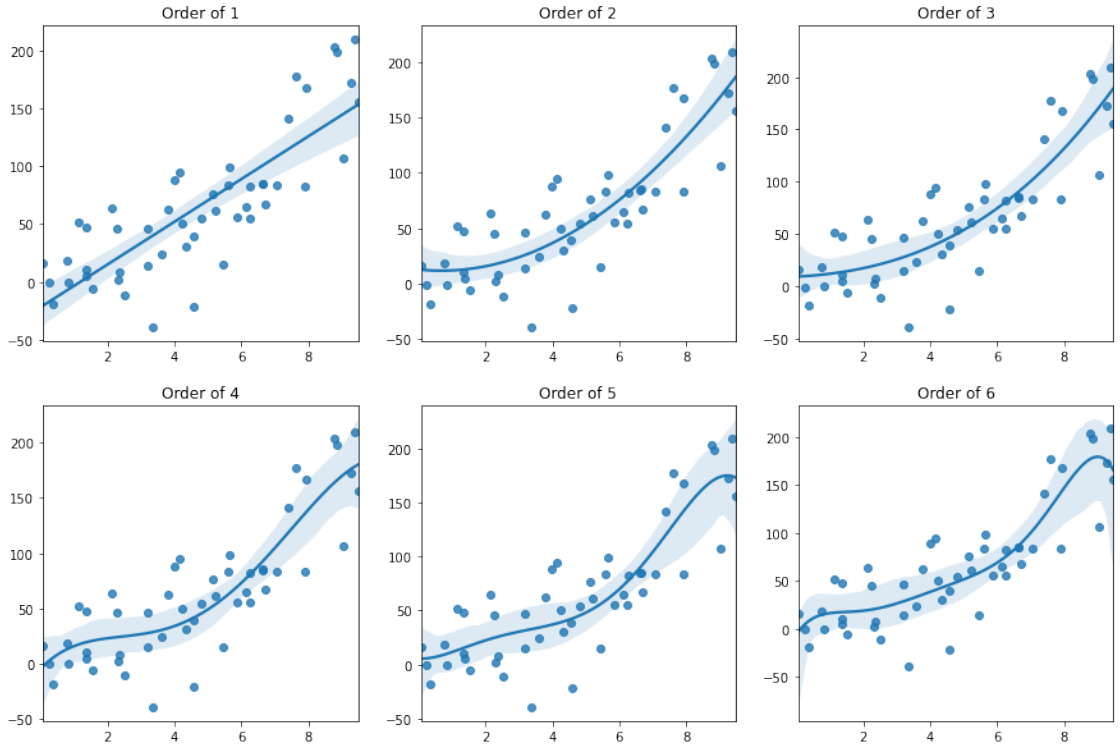
```
axes[0].set_title('Using the coefficients')
axes[1].set_title('Using build-in seaborn.regplot')

plt.show()
```



We can change the order of the polynomial in the seaborn.regplot function to see which one better estimates the model

Considering only up to order 6 of the polynomial

[6]:
```
fig, axes = plt.subplots(2, 3, figsize=(15,10))
order = 1
for i in range(0,2):
    for j in range(0,3):
        sns.regplot(x = np.concatenate((x_train, x_test)), y = np.
 ↪concatenate((y_train, y_test)), order=order, ax=axes[i][j])
        axes[i][j].set_title('Order of {}'.format(order))
        order += 1
plt.show()
```



Looks like order of 2 is a good fit

So we add a new feature i.e. x^2 Then we fit the model on the new training set, and report the mse and R2 score

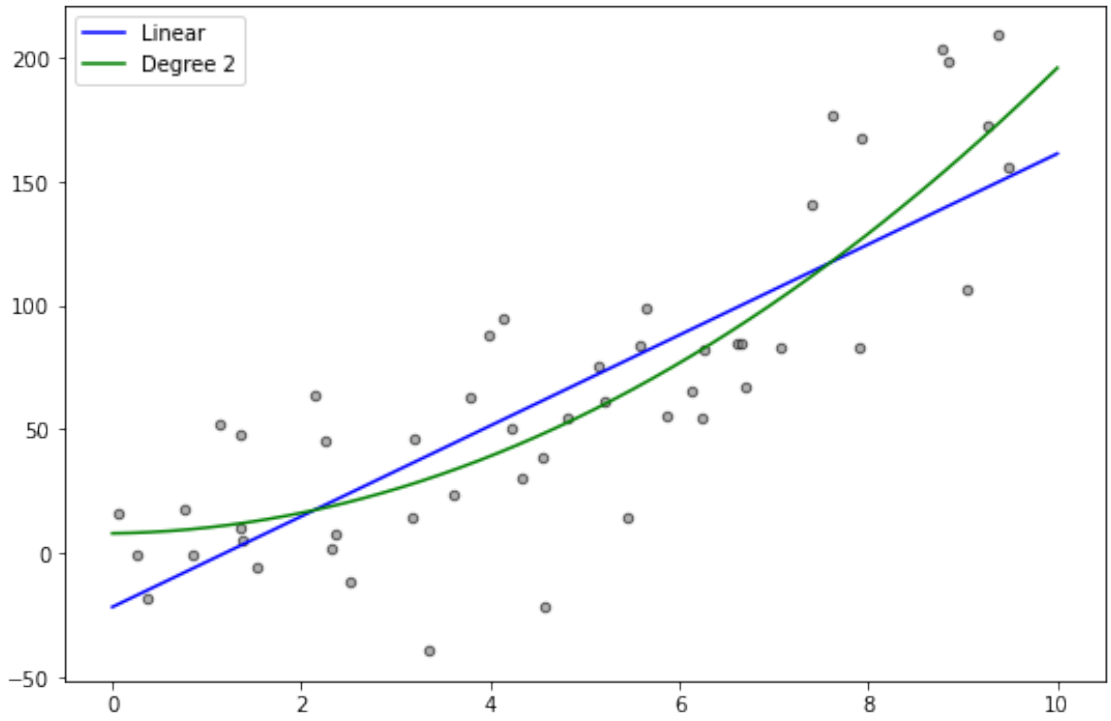
[7]:
```
new_train = np.concatenate((x_train,x_train**2),axis=1)
new_lr = LinearRegression()
new_lr.fit(new_train,y_train)
print("The coeficient is {} and the intercept is {}".format(new_lr.coef_,␣
 ↪new_lr.intercept_))
print("The mean squared error is: {}".format(mean_squared_error(y_train, new_lr.
 ↪predict(new_train))))
print("The R2 score is: {}".format(r2_score(y_train, new_lr.
 ↪predict(new_train))))
```

```
The coeficient is [0.47100686 1.83208191] and the intercept is 8.007337461589657
The mean squared error is: 884.797759660905
The R2 score is: 0.7490480719353505
```

The mse decreased by about 10 percent and the R2 also improved

[8]:
```
plt.figure(figsize=(9,6))
plt.scatter(x = np.concatenate((x_train, x_test)), y = np.concatenate((y_train,␣
 ↪y_test)),
            c='gray', alpha=0.6, s=20, edgecolors='k')
```

```
plt.plot(a, a*lr.coef_ + lr.intercept_, c='b', label='Linear')
plt.plot(a, a*new_lr.coef_[0]+a**2*new_lr.coef_[1] + new_lr.intercept_ , c='g',␣
 ↪label='Degree 2')
plt.legend()
plt.show()
```



(e) Use both model and apply them to the test data and estimate the 2 and mean square error of the test dataset.

[9]:
```
y_pred = lr.predict(x_test)
new_pred = new_lr.predict(np.concatenate((x_test,x_test**2),axis=1))
mean_squared_error(y_test,y_pred)

print("Mean squared error for linear model is {} and for non-linear degree of 2␣
 ↪is {}"
      .format(mean_squared_error(y_test,y_pred),␣
 ↪mean_squared_error(y_test,new_pred)))
print("R2 score for linear model is {} and for non-linear degree of 2 is {}"
      .format(r2_score(y_test,y_pred), r2_score(y_test,new_pred)))
```

```
Mean squared error for linear model is 2023.3121088887128 and for non-linear
degree of 2 is 1398.8817580143948
R2 score for linear model is 0.5556465885794163 and for non-linear degree of 2
is 0.6927820089560344
```

[10]:
```
train_mse=[mean_squared_error(y_train, lr.predict(x_train))]
test_mse=[mean_squared_error(y_test, lr.predict(x_test))]
train=x_train
test=x_test
for i in range(2,8):
    train = np.concatenate((train,x_train**i),axis=1)
    test = np.concatenate((test,x_test**i),axis=1)
    model = LinearRegression()
    model.fit(train,y_train)
    train_mse.append(mean_squared_error(y_train, model.predict(train)))
    test_mse.append(mean_squared_error(y_test, model.predict(test)))
```

[11]:
```
plt.figure(figsize=(10,5))
plt.plot(range(1,8),train_mse,marker='o', label='mean square error of train␣
 ↪set')
plt.plot(range(1,8), test_mse,marker='o', label='mean square error of test set')
plt.xticks(range(1,8,1))
plt.title('train vs test error by degree of polynomial')
plt.xlabel("Degree")
plt.ylabel('Mean square error')
plt.legend()
plt.show()
```