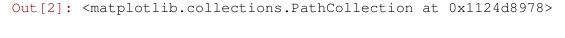
## HW5

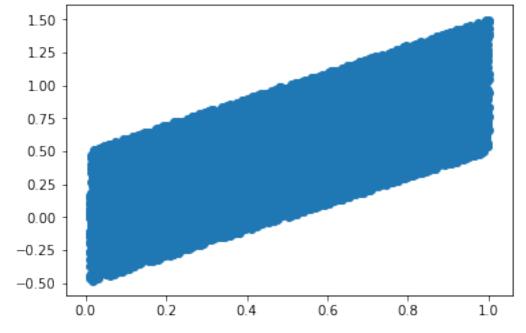
## June 2, 2017

```
In [1]: from sklearn.linear_model import LinearRegression
    import numpy as np
    import matplotlib.pylab as plt
    %matplotlib inline
    from sklearn import linear_model

In [2]: n = 10000
    x = np.linspace(0.01, 1, n).reshape(-1, 1)
    y = np.linspace(0.01, 1, n) + np.random.rand(n) - .5

plt.scatter(x,y)
```





Assignment 5 1. Create and fit a Linear Regression Model Calculate the Training error and Testing error using sklearn with a .50 split

```
In [4]: from sklearn import cross_validation
        from sklearn.metrics import mean_squared_error
        X_train, X_test , y_train, y_test = cross_validation.train_test_split(x, y,
        ML = linear_model.LinearRegression()
        ML.fit(X_train,y_train)
        predtrain = ML.predict(X_train)
        print('the training error is:' ,mean_squared_error(y_train, predtrain))
        predtest = ML.predict(X_test)
        print('the test error is: ', mean_squared_error(y_test, predtest))
the training error is: 0.0833385727281
the test error is: 0.0849722787711
  2. Repeat #1 for a Ridge Regression
In [7]: MR = linear_model.Ridge(alpha = 0.5)
        MR.fit(X_train,y_train)
        predtrainR = MR.predict(X_train)
        print('the training error is:' ,mean_squared_error(y_train, predtrainR))
        predtestR = MR.predict(X_test)
        print('the test error is: ', mean_squared_error(y_test, predtestR))
the training error is: 0.0833386924379
the test error is: 0.0849775236424
  3. Vary the split size from .01 to .99 with at least 10 values (the more the merrier!). Plot the
    resulting Training error and Testing error vs. split size. Create separate plots for Linear and
    Ridge¶
In [50]: split = np.linspace(0.01,0.99,100)
         ErrortrainL = []
         ErrortestL = []
         ErrortrainR = []
         ErrortestR = []
         for i in split:
             X_train, X_test , y_train, y_test = cross_validation.train_test_split
             ML.fit(X_train,y_train)
             predtrain = ML.predict(X_train)
```

predtest = ML.predict(X\_test)

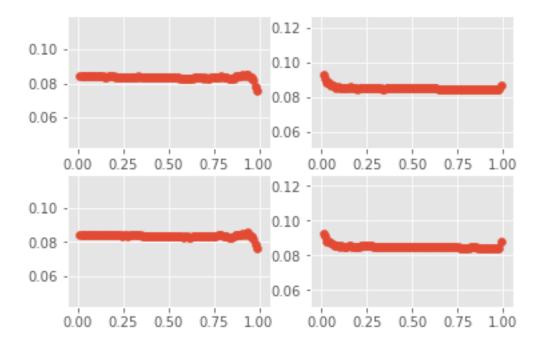
```
ErrortrainL.append(mean_squared_error(y_train, predtrain))
ErrortestL.append(mean_squared_error(y_test, predtest))

MR.fit(X_train,y_train)
predtrainR = MR.predict(X_train)
predtestR = MR.predict(X_test)
ErrortrainR.append(mean_squared_error(y_train, predtrainR))
ErrortestR.append(mean_squared_error(y_test, predtestR))
```

```
plt.style.use('ggplot')

fig, ax = plt.subplots(2,2)
ax[0,0].scatter(split,ErrortrainL)
ax[0,1].scatter(split,ErrortestL)
ax[1,0].scatter(split,ErrortrainR)
ax[1,1].scatter(split,ErrortestR)

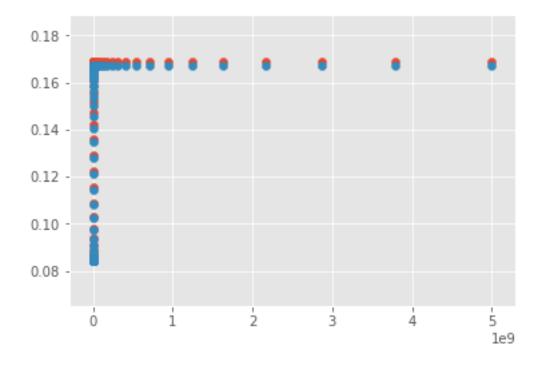
plt.show()
```



4. Chose an ideal split size based on the previous plot for Ridge. Vary the Ridge parameter

alpha from 0 to any value you'd like above 1. Plot the Train and Test error. Describe what you see based on the alpha parameter's stiffness.

```
In [58]: 'locate the minimum test error for the ridge regression'
         minIndextest = ErrortestR.index(min(ErrortestR))
         print(split[minIndextest])
         minIndextrain = ErrortrainR.index(min(ErrortrainR))
         print(split[minIndextrain])
         'use 91%'
         X_train, X_test , y_train, y_test = cross_validation.train_test_split(x, y_
         alphas = 10 **np.linspace(10, -2, 100) *0.5
         RidgeErrortrain = []
         RidgeErrortest = []
         for i in alphas:
             MR = linear_model.Ridge(alpha = i)
             MR.fit(X_train,y_train)
             predtrainR = MR.predict(X_train)
             RidgeErrortrain.append(mean_squared_error(y_train, predtrainR))
             predtestR = MR.predict(X_test)
             RidgeErrortest.append(mean_squared_error(y_test, predtestR))
         print(alphas[RidgeErrortrain.index(min(RidgeErrortrain))])
         print (alphas[RidgeErrortest.index(min(RidgeErrortest))])
         plt.scatter(alphas, RidgeErrortrain)
         plt.scatter(alphas, RidgeErrortest)
0.910808080808
0.99
0.005
0.005
Out[58]: <matplotlib.collections.PathCollection at 0x112b28b00>
```



Based on a test size of 91%, the optimal ridge parameter is 0.005, very close to zero which means that the ridge regression gives similar results to a linear regression

In [ ]: