HW2_STAT760

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1 HW 2: Apply Linear Regression to Construct a Prostate Cancer Model

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STAT 760
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Prostrate Data Info: http://web.stanford.edu/~hastie/ElemStatLearn/datasets/prostate.info.txt
Data Set: http://web.stanford.edu/~hastie/ElemStatLearn/datasets/prostate.data
Given a training set of prostate cancer linear data, estimate the model parameters using subset selection.

1.1 STEPS

1. import data
2. break data into two groups: train and test
3. break the training set into two matrices X : design matrix (add column of 1s at beginning) y : vector of responses
4. convert the X and y data frames into numpy arrays
5. standardize the predictors to have unit variance
6. estimate weights
7. calculate RSS for training set for all possible models
8. Graph k by RSS

- Fxn evaluates RSS for given X, y, beta
- Fxn trains models given list of columns
- Fxn generates all possible list of columns
- Fxn plot dictionary

1.2 Imports

```
In [1]: import numpy as np
        import pandas as pd
        import itertools
        import matplotlib.pyplot as plt
```

1.3 Load Data

```
In [2]: data = pd.read_csv('prostate.data', delimiter='\t')
```

1.4 Functions

```
In [3]: def evaluateRSS(df, predictor_subset, beta):

            # generate predictor df
            predictor_df = df[predictor_subset]

            # generate response df
            response_df = df["lpsa"]

            # convert predictor df to ndarray
            predictor_matrix = predictor_df.as_matrix()

            # normalize predictors
            predictor_matrix = (predictor_matrix - np.mean(predictor_matrix, axis=0))/np.std(pre

            # adds constant term 1s to predictor matrix
            predictor_matrix = np.c_[np.ones(len(predictor_matrix)), predictor_matrix]

            # convert response df to ndarray
            response_matrix = response_df.as_matrix()

            # compute error
            e = response_matrix - np.dot(predictor_matrix, beta)

            # return error
            return np.dot(e,e)
```

```
In [4]: def train(df, predictors_subset):

            # generate predictor df
            predictor_df = df[predictors_subset]

            # generate response df
            response_df = df["lpsa"]

            # convert predictor df to ndarray
            predictor_matrix = predictor_df.as_matrix()

            # normalize predictors
            predictor_matrix = (predictor_matrix - np.mean(predictor_matrix, axis=0))/np.std(pre

            # adds constant term 1s to predictor matrix
            predictor_matrix = np.c_[np.ones(len(predictor_matrix)), predictor_matrix]

            # convert response df to ndarray
            response_matrix = response_df.as_matrix()

            # fit model by pinv:
```

```
        # calculate psuedo-inverse
        predictor_inverse = np.linalg.pinv(predictor_matrix)

        # multiply pseudo-inverse by response matrix
        beta = np.dot(predictor_inverse, response_matrix)

        # return weights
        return beta
```

```
In [5]: def generate_columns(predictors):
            # return all possible subset of predictors - n choose k
            n = len(predictors)

            subsets = []

            for k in range(1, n+1):
                x = list(itertools.combinations(predictors, k))
                x = [list(y) for y in x]
                subsets += x
            return subsets
```

```
In [6]: def plot(rss_dict):
            # plots subset by rss
            fig = plt.figure()
            ax = fig.add_subplot(1, 1, 1)
            x = rss_dict[:,0]
            y = rss_dict[:,1]
            ax.scatter(x,y)
            plt.show()
```

1.5 Train Models

```
In [7]: predictors = list(data.columns.values[1:9])
```

```
In [8]: train_data = data[data.train == 'T']
        test_data = data[data.train == 'F']
```

```
In [9]: predictor_subsets = generate_columns(predictors)
        rss_values = {k:[] for k in range(1,9)}
```

```
In [10]: for p in predictor_subsets:
             beta = train(train_data, p)
             rss = evaluateRSS(train_data, p, beta)
             rss_values[len(p)].append(rss)
```

```
In [11]: rss_values
```

```
Out[11]: {1: [44.52858265645385,
           73.613540185775335,
```

```
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```

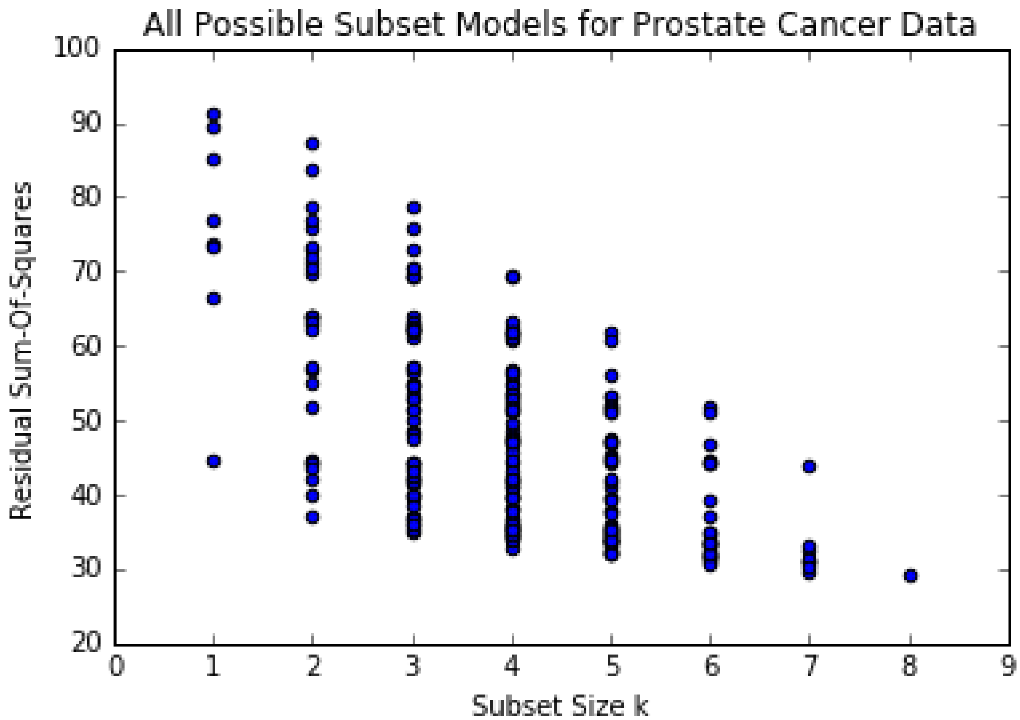
1.6 Plot RSS for Subsets

In [12]:
```
# set x values according to the key and corresponding length of its dictionary
x = [j for j in range(1,9) for k in range(len(rss_values[j]))]

# set y values to k subsets(1-8)
y = []
for k in rss_values.keys():
    y += rss_values[k]

# graph scatter plot
plt.scatter(x,y)
plt.title("All Possible Subset Models for Prostate Cancer Data")
plt.xlabel("Subset Size k")
plt.ylabel("Residual Sum-Of-Squares")
```

Out[12]:
```
<matplotlib.text.Text at 0x7f71a9387450>
```


All Possible Subset Models for Prostate Cancer Data
Residual Sum-Of-Squares
Subset Size k
100
90
80
70
60
50
40
30
20
0
1
2
3
4
5
6
7
8
9