Predicting Car Prices

May 26, 2018

0.0.1 Introduction

```
In [1]: import math as m
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        from operator import itemgetter
        from sklearn.model_selection import KFold
        from sklearn.metrics import mean_squared_error
        from sklearn.neighbors import KNeighborsRegressor
        %matplotlib inline

        # Decide about the database column headers by getting detail data insight at: https://
        col_name = ['symboling', 'normalized-losses', 'make', 'fuel-type', 'aspiration', 'num-
                    'drive-wheels', 'engine-location', 'wheel-base', 'length', 'width', 'heigh
                    'num-of-cylinders', 'engine-size', 'fuel-system', 'bore', 'stroke', 'compr
                    'city-mpg', 'highway-mpg', 'price']
```

0.0.2 Getting Information About the Dataset

```
In [2]: cars = pd.read_csv(r"./databank/import-85.csv", names=col_name)
        cars.head(5)
```

```
Out[2]:    symboling normalized-losses         make fuel-type aspiration num-of-doors  \
        0          3                 ?  alfa-romero       gas        std          two
        1          3                 ?  alfa-romero       gas        std          two
        2          1                 ?  alfa-romero       gas        std          two
        3          2               164         audi       gas        std         four
        4          2               164         audi       gas        std         four

            body-style drive-wheels engine-location  wheel-base  ...    engine-size  \
        0  convertible          rwd           front        88.6  ...            130
        1  convertible          rwd           front        88.6  ...            130
        2    hatchback          rwd           front        94.5  ...            152
        3        sedan          fwd           front        99.8  ...            109
        4        sedan          4wd           front        99.4  ...            136

           fuel-system  bore  stroke compression-rate horsepower  peak-rpm city-mpg  \
```

```
0          mpfi  3.47    2.68               9.0        111      5000        21
1          mpfi  3.47    2.68               9.0        111      5000        21
2          mpfi  2.68    3.47               9.0        154      5000        19
3          mpfi  3.19     3.4              10.0        102      5500        24
4          mpfi  3.19     3.4               8.0        115      5500        18

  highway-mpg  price
0          27  13495
1          27  16500
2          26  16500
3          30  13950
4          22  17450

[5 rows x 26 columns]
```

```
In [3]: print(cars.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 26 columns):
symboling            205 non-null int64
normalized-losses    205 non-null object
make                 205 non-null object
fuel-type            205 non-null object
aspiration           205 non-null object
num-of-doors         205 non-null object
body-style           205 non-null object
drive-wheels         205 non-null object
engine-location      205 non-null object
wheel-base           205 non-null float64
length               205 non-null float64
width                205 non-null float64
height               205 non-null float64
curb-weight          205 non-null int64
engine-type          205 non-null object
num-of-cylinders     205 non-null object
engine-size          205 non-null int64
fuel-system          205 non-null object
bore                 205 non-null object
stroke               205 non-null object
compression-rate     205 non-null float64
horsepower           205 non-null object
peak-rpm             205 non-null object
city-mpg             205 non-null int64
highway-mpg          205 non-null int64
price                205 non-null object
dtypes: float64(5), int64(5), object(16)
memory usage: 41.7+ KB
```

```
None
```

0.0.3 Select Columns with Continuous Data Values

```
In [4]: # Using data info available at: http://archive.ics.uci.edu/ml/machine-learning-databas
        col_vals = ['normalized-losses', 'wheel-base', 'length', 'width', 'height', 'curb-weig
                    'compression-rate', 'horsepower', 'peak-rpm', 'city-mpg', 'highway-mpg', '
        cars_num = cars[col_vals]
        cars_num.head(5)
```

```
Out[4]:   normalized-losses  wheel-base  length  width  height  curb-weight  bore  \
        0                 ?        88.6   168.8   64.1    48.8         2548  3.47
        1                 ?        88.6   168.8   64.1    48.8         2548  3.47
        2                 ?        94.5   171.2   65.5    52.4         2823  2.68
        3               164        99.8   176.6   66.2    54.3         2337  3.19
        4               164        99.4   176.6   66.4    54.3         2824  3.19

          stroke  compression-rate horsepower peak-rpm  city-mpg  highway-mpg  price
        0   2.68               9.0        111     5000        21           27  13495
        1   2.68               9.0        111     5000        21           27  16500
        2   3.47               9.0        154     5000        19           26  16500
        3    3.4              10.0        102     5500        24           30  13950
        4    3.4               8.0        115     5500        18           22  17450
```

0.0.4 Prepare Data for Missing Value Fill-up by Replacing Special Characters

```
In [5]: # As seen above, the dataframe carries "?". Replace it with null value
        cars_num = cars_num.replace("?", np.NaN)
        cars_num.head(5)
```

```
Out[5]:   normalized-losses  wheel-base  length  width  height  curb-weight  bore  \
        0               NaN        88.6   168.8   64.1    48.8         2548  3.47
        1               NaN        88.6   168.8   64.1    48.8         2548  3.47
        2               NaN        94.5   171.2   65.5    52.4         2823  2.68
        3               164        99.8   176.6   66.2    54.3         2337  3.19
        4               164        99.4   176.6   66.4    54.3         2824  3.19

          stroke  compression-rate horsepower peak-rpm  city-mpg  highway-mpg  price
        0   2.68               9.0        111     5000        21           27  13495
        1   2.68               9.0        111     5000        21           27  16500
        2   3.47               9.0        154     5000        19           26  16500
        3    3.4              10.0        102     5500        24           30  13950
        4    3.4               8.0        115     5500        18           22  17450
```

0.0.5 Convert All Values to Same Data Type

```
In [6]: # Convert all columns of the dataframe to float data type
        cars_num = cars_num.astype('float64')
```

```
# Check for all columns data type
cars_num.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 205 entries, 0 to 204
Data columns (total 14 columns):
normalized-losses    164 non-null float64
wheel-base           205 non-null float64
length               205 non-null float64
width                205 non-null float64
height               205 non-null float64
curb-weight          205 non-null float64
bore                 201 non-null float64
stroke               201 non-null float64
compression-rate     205 non-null float64
horsepower           203 non-null float64
peak-rpm             203 non-null float64
city-mpg             205 non-null float64
highway-mpg          205 non-null float64
price                201 non-null float64
dtypes: float64(14)
memory usage: 22.5 KB
```

0.0.6 Select Target Column

```
In [7]: target_col = cars_num['price']
```

0.0.7 Remove Null Values from Target Columns

```
In [8]: cars_num = cars_num.dropna(subset=['price'], axis=0)
        cars_num['price'].isnull().sum()
```

```
Out[8]: 0
```

0.0.8 Check for Null Values in Other Columns

```
In [9]: cars_num.isnull().sum()
```

```
Out[9]: normalized-losses    37
        wheel-base            0
        length                0
        width                 0
        height                0
        curb-weight           0
        bore                  4
        stroke                4
        compression-rate      0
        horsepower            2
```

```
peak-rpm             2
city-mpg             0
highway-mpg          0
price                0
dtype: int64
```

0.0.9 Fill out Missing Column Values

```
In [10]: # Fill out the missing values with column mean
         cars_num = cars_num.fillna(cars_num.mean())
         # Check for no null values
         cars_num.isnull().sum().sum()
```

```
Out[10]: 0
```

0.0.10 Feature Scaling

```
In [11]: temp_target = cars_num['price']
         cars_num = (cars_num - cars_num.mean())/(cars_num.max() - cars_num.min())
         cars_num['price'] = temp_target
         cars_num.head(5)
```

```
Out[11]:    normalized-losses  wheel-base    length     width    height  curb-weight  \
         0           0.000000   -0.297289 -0.080612 -0.152911 -0.413889    -0.002974
         1           0.000000   -0.297289 -0.080612 -0.152911 -0.413889    -0.002974
         2           0.000000   -0.125277 -0.044791 -0.033253 -0.113889     0.103698
         3           0.219895    0.029242  0.035806  0.026577  0.044444    -0.084820
         4           0.219895    0.017580  0.035806  0.043671  0.044444     0.104086

                bore    stroke  compression-rate  horsepower  peak-rpm  city-mpg  \
         0  0.099492 -0.274716         -0.072767    0.035528 -0.047995 -0.116086
         1  0.099492 -0.274716         -0.072767    0.035528 -0.047995 -0.116086
         2 -0.464793  0.101474         -0.072767    0.236463 -0.047995 -0.171642
         3 -0.100508  0.068141         -0.010267   -0.006528  0.156087 -0.032753
         4 -0.100508  0.068141         -0.135267    0.054220  0.156087 -0.199420

            highway-mpg    price
         0    -0.097015  13495.0
         1    -0.097015  16500.0
         2    -0.123331  16500.0
         3    -0.018068  13950.0
         4    -0.228594  17450.0
```

0.0.11 Develop Univariate Model

```
In [12]: # Set up a function that develop model and return RMSE

         def knn_train_test(train_col, test_col, data):
```

```
    # Randomize the data
        np.random.seed(1)
        shuflled_idx = np.random.permutation(data.index)
        data_rand = data.reindex(shuflled_idx)

    # Divide the data set 50/50 between the training and test set
        break_pt = int(round(len(data)/2, 0))
        train_df = data_rand.iloc[:break_pt]
        test_df = data_rand.iloc[break_pt+1:]

    # Defining the Training and Test Set
        train_features = train_df[[train_col]]
        train_target = train_df[test_col]
        test_features = test_df[[train_col]]
        test_target = test_df[test_col]

    # Develop KNeighbor Regression
        knn = KNeighborsRegressor()
        knn.fit(train_features, train_target)
        predictions = knn.predict(test_features)

    # Calculate the model error matrix
        mse_val = mean_squared_error(test_target, predictions)
        rmse = m.sqrt(mse_val)
        return rmse

    trn_col = cars_num.drop(labels='price', axis=1).columns
    tst_col = 'price'
    rmse_dict = {}

    for col in trn_col:
        rmse_dict[col] = knn_train_test(col, 'price', cars_num)
    rmse_dict
```

```
Out[12]: {'bore': 6822.548760309449,
          'city-mpg': 4998.449685132381,
          'compression-rate': 6628.568722823954,
          'curb-weight': 4422.255745566961,
          'height': 7857.62725440702,
          'highway-mpg': 4675.883732044671,
          'horsepower': 4011.999335643016,
          'length': 5455.571648177668,
          'normalized-losses': 7338.850271289094,
          'peak-rpm': 7698.121918961792,
          'stroke': 7965.733340477825,
          'wheel-base': 5486.805326526539,
          'width': 4931.242155725067}
```

0.0.12 Univariate Model with Multiple Clusters

In [13]:
```
# Defining the number of split values as variable
cluster_num = [1, 3, 5, 7, 9]

# Set up function that develop model that can handle multiple split values and genera
def knn_train_test_splits(train_col, test_col, data):

# Randomize the data
    np.random.seed(1)
    shuflled_idx = np.random.permutation(data.index)
    data_rand = data.reindex(shuflled_idx)

# Divide the data set 50/50 between the training and test set
    break_pt = int(round(len(data)/2, 0))
    train_df = data.iloc[:break_pt]
    test_df = data.iloc[break_pt+1:]

# Defining the Training and Test Set
    train_features = train_df[[train_col]]
    train_target = train_df[test_col]
    test_features = test_df[[train_col]]
    test_target = test_df[test_col]

# Develop KNeighbor Regression
    rmse_val = {}
    for i in cluster_num:
        knn = KNeighborsRegressor(n_neighbors = i)
        knn.fit(train_features, train_target)
        predictions = knn.predict(test_features)

# Calculate the model error matrix
        mse_val = mean_squared_error(test_target, predictions)
        rmse_val[i] = m.sqrt(mse_val)
    return rmse_val

# Establish RMSE dictionary with varying clusters for every feature of the dataset
RMSE_MC = {}
trn_col = cars_num.drop(labels='price', axis=1).columns
tst_col = 'price'
for i in trn_col:
    RMSE_MC[i] = knn_train_test_splits(i, tst_col, cars_num)

RMSE_MC
```

Out[13]:
```
{'bore': {1: 16584.92378245978,
  3: 13996.721161043395,
  5: 13420.66013722127,
  7: 11079.213535955796,
```

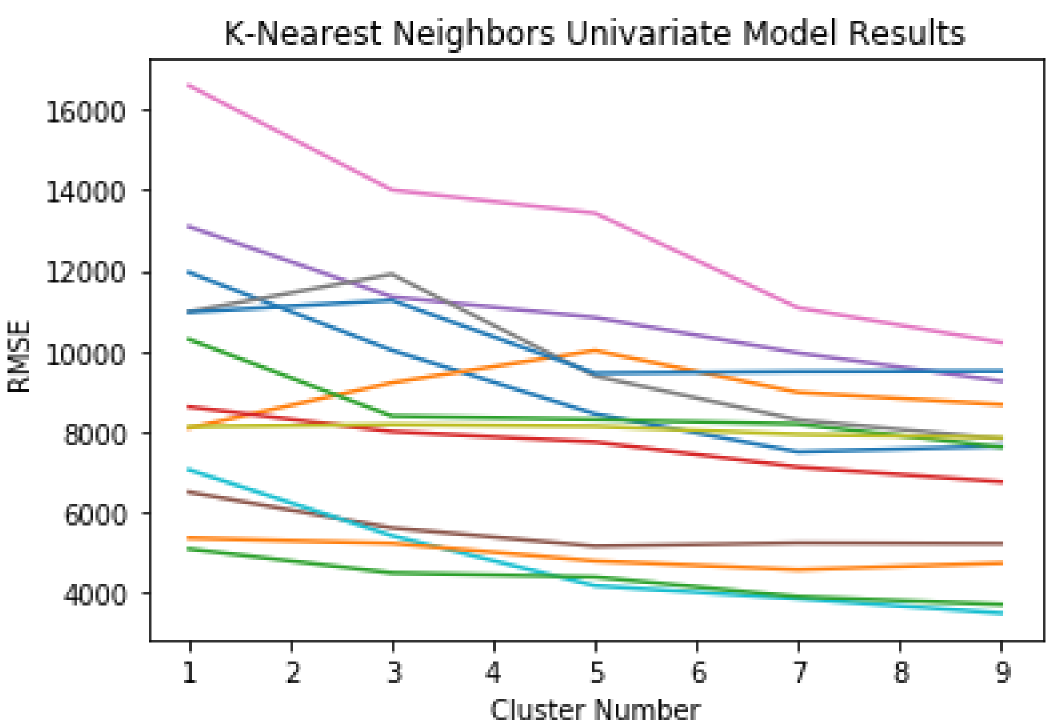
```
 9: 10217.599521613385},
'city-mpg': {1: 5365.433446609883,
 3: 5234.360540484174,
 5: 4796.381435749246,
 7: 4579.778132559413,
 9: 4743.612991690856},
'compression-rate': {1: 8125.434180399223,
 3: 8178.550223059776,
 5: 8136.40761621491,
 7: 7934.111996902223,
 9: 7856.87625370601},
'curb-weight': {1: 6506.062797114703,
 3: 5618.008230878825,
 5: 5164.381316866522,
 7: 5245.599869783965,
 9: 5228.853464251726},
'height': {1: 13086.66478901328,
 3: 11351.195125967035,
 5: 10835.39508699152,
 7: 9957.21417984294,
 9: 9258.219431789274},
'highway-mpg': {1: 5095.432138690496,
 3: 4500.45206963824,
 5: 4398.904134031566,
 7: 3911.670503683529,
 9: 3718.106564511261},
'horsepower': {1: 7062.084135720843,
 3: 5424.37770347899,
 5: 4182.751064168175,
 7: 3861.016243484218,
 9: 3503.520831998422},
'length': {1: 10295.140528909744,
 3: 8388.354331982458,
 5: 8304.747817098361,
 7: 8190.342248499205,
 9: 7620.134422350525},
'normalized-losses': {1: 11951.82024421385,
 3: 10023.50956878655,
 5: 8443.070564077978,
 7: 7500.093728489162,
 9: 7638.045516110313},
'peak-rpm': {1: 10968.678615494211,
 3: 11263.00163026417,
 5: 9454.169136439225,
 7: 9495.13848893641,
 9: 9508.025552742532},
'stroke': {1: 10980.078241979882,
 3: 11907.399436811456,
```

```
 5: 9383.411544614251,
 7: 8295.568471005641,
 9: 7825.851999780543},
'wheel-base': {1: 8091.709810664245,
 3: 9216.785562102321,
 5: 10016.733728895862,
 7: 8978.328387232203,
 9: 8674.610712274423},
'width': {1: 8616.242079352227,
 3: 8004.028103745985,
 5: 7744.931063502115,
 7: 7126.92195030325,
 9: 6761.684721627543}}
```

0.0.13 Plot the Univariate Multicluster Model Results

In [14]:
```
# Developing the plot series
for k, v in RMSE_MC.items():
    X = list(v.keys())
    y = list(v.values())

    plt.plot(X, y)
    plt.xlabel("Cluster Number")
    plt.ylabel("RMSE")
    plt.title("K-Nearest Neighbors Univariate Model Results")
plt.show()
```



0.0.14 Develop Multivariate Model (Default Clusters)

```
In [15]: # Develop Multivariate Model with Single Default Neighbor Value as 5 from scikit-lear

         def knn_train_test_mv(train_col, test_col, data):

         # Randomize the data
             np.random.seed(1)
             shuflled_idx = np.random.permutation(data.index)
             data_rand = data.reindex(shuflled_idx)

         # Divide the data set 50/50 between the training and test set
             break_pt = int(round(len(data)/2, 0))
             train_df = data_rand.iloc[:break_pt]
             test_df = data_rand.iloc[break_pt+1:]

         # Defining the Training and Test Set
             train_features = train_df[train_col]
             train_target = train_df[test_col]
             test_features = test_df[train_col]
             test_target = test_df[test_col]

         # Develop KNeighbor Regression
             knn = KNeighborsRegressor()
             knn.fit(train_features, train_target)
             predictions = knn.predict(test_features)

         # Calculate the model error matrix
             mse_val = mean_squared_error(test_target, predictions)
             rmse = m.sqrt(mse_val)
             return rmse

         # Trying different best features and verify how RMSE varies
         # To identify the preference of top 5 best features, let's extract
         # the RMSE value in ascending order from the previous Univariate Model

         best_features = {}
         for k, v in RMSE_MC.items():
             best_features[k] = sum(v.values())/len(v.values())

         top5_nn = sorted(best_features.items(), key=itemgetter(1))
         print(top5_nn)

         rmse_mv = {}
```

```
two_best_features = ['horsepower', 'highway-mpg']
three_best_features = ['horsepower', 'highway-mpg', 'city-mpg']
four_best_features = ['horsepower', 'highway-mpg', 'city-mpg','curb-weight']
five_best_features = ['horsepower', 'highway-mpg', 'city-mpg','curb-weight', 'width']
six_best_features = ['horsepower', 'highway-mpg', 'city-mpg','curb-weight', 'width',

rmse_mv_keys = ['two_best_features', 'three_best_features', 'four_best_features', 'fi
rmse_mv_vals = [two_best_features, three_best_features, four_best_features, five_best_

for i in range(len(rmse_mv_keys)):
    rmse_mv[rmse_mv_keys[i]] = knn_train_test_mv(rmse_mv_vals[i], 'price', cars_num)

rmse_mv
```

```
[('highway-mpg', 4324.913082111018), ('horsepower', 4806.74999577013), ('city-mpg', 4943.91330
```

Out[15]:
```
{'five_best_features': 3354.768120153761,
 'four_best_features': 3497.917667698884,
 'six_best_features': 3542.0349199295024,
 'three_best_features': 3353.1645428758793,
 'two_best_features': 3280.770311801788}
```

0.0.15 Multivariate Model With Multiple Clusters

In [16]:
```
# Develop Multivariate Model with Multiple Neighbor Values Using the Top 6 Best Featu

def knn_train_test_mvc(train_col, test_col, data):

# Randomize the data
    np.random.seed(1)
    shuflled_idx = np.random.permutation(data.index)
    data_rand = data.reindex(shuflled_idx)

# Divide the data set 50/50 between the training and test set
    break_pt = int(round(len(data)/2, 0))
    train_df = data_rand.iloc[:break_pt]
    test_df = data_rand.iloc[break_pt+1:]

# Defining the Training and Test Set
    train_features = train_df[train_col]
    train_target = train_df[test_col]
    test_features = test_df[train_col]
    test_target = test_df[test_col]

# Defining the cluster values from 1 - 25
    k_val = [x for x in range(25)]
    rmse_val_mvc = {}
```

```python
    # Develop KNeighbor Regression
        for k in k_val:
            knn = KNeighborsRegressor(n_neighbors = k + 1)
            knn.fit(train_features, train_target)
            predictions = knn.predict(test_features)

    # Calculate the model error matrix
            mse_val_mvc = mean_squared_error(test_target, predictions)
            rmse_val_mvc[k + 1] = m.sqrt(mse_val_mvc)
        return rmse_val_mvc

    rmse_mvc = {}

    two_best_features = ['horsepower', 'highway-mpg']
    three_best_features = ['horsepower', 'highway-mpg', 'city-mpg']
    four_best_features = ['horsepower', 'highway-mpg', 'city-mpg','curb-weight']
    five_best_features = ['horsepower', 'highway-mpg', 'city-mpg','curb-weight', 'width']
    six_best_features = ['horsepower', 'highway-mpg', 'city-mpg','curb-weight', 'width',

    rmse_mvc_keys = ['two_best_features', 'three_best_features', 'four_best_features', 'fi
    rmse_mvc_vals = [two_best_features, three_best_features, four_best_features, five_bes

    for i in range(len(rmse_mvc_keys)):
        rmse_mvc[rmse_mvc_keys[i]] = knn_train_test_mvc(rmse_mvc_vals[i], 'price', cars_nu

    rmse_mvc
```

```
Out[16]: {'five_best_features': {1: 2522.34322803222,
  2: 2901.265709565396,
  3: 3194.7981612476106,
  4: 3179.8159698125614,
  5: 3354.768120153761,
  6: 3554.219122903245,
  7: 3835.365094826338,
  8: 4023.857588049837,
  9: 4011.8186578325463,
  10: 4159.130326354297,
  11: 4363.387571221952,
  12: 4437.940498042607,
  13: 4516.051228751735,
  14: 4485.415098427801,
  15: 4496.478315936694,
  16: 4575.928353273997,
  17: 4619.454166523248,
  18: 4678.060992505203,
  19: 4710.954185222263,
  20: 4735.107799200563,
```

```
 21: 4779.058044867539,
 22: 4811.659056250249,
 23: 4830.614628012334,
 24: 4903.95236785043,
 25: 4948.054413629665},
'four_best_features': {1: 2726.3392488830145,
 2: 2686.8332410106887,
 3: 3053.8303944027048,
 4: 3140.17829688857,
 5: 3497.917667698884,
 6: 3812.048222339854,
 7: 3975.2003164004454,
 8: 4134.100658603846,
 9: 4354.96304487446,
 10: 4461.40887272171,
 11: 4583.420441228841,
 12: 4645.517198952543,
 13: 4732.750936891872,
 14: 4682.136018819241,
 15: 4721.437077595007,
 16: 4739.036601157389,
 17: 4675.760410159827,
 18: 4685.1937887572885,
 19: 4765.525999904079,
 20: 4766.812732518448,
 21: 4804.353110482626,
 22: 4777.348096200728,
 23: 4812.925938989358,
 24: 4868.485129423389,
 25: 4894.183427872723},
'six_best_features': {1: 2538.4777052398945,
 2: 2924.6141501914403,
 3: 3219.4941802504736,
 4: 3128.693080584927,
 5: 3542.0349199295024,
 6: 3785.0061070330894,
 7: 3947.2993226834396,
 8: 4163.821567326252,
 9: 4204.946471217258,
 10: 4374.062519054797,
 11: 4476.530484843764,
 12: 4610.950479308891,
 13: 4634.299160153433,
 14: 4668.066965767281,
 15: 4696.9484222654855,
 16: 4786.570710184249,
 17: 4796.05119509285,
 18: 4841.6860291478715,
```

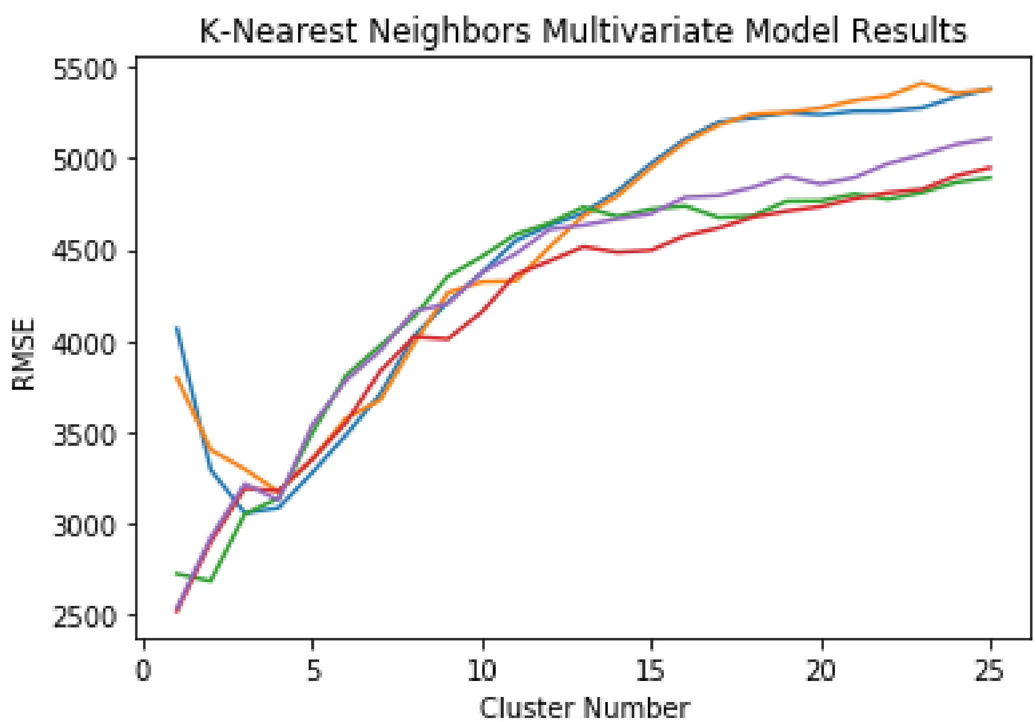
```
 19: 4901.528662231396,
 20: 4859.5147476317015,
 21: 4894.557734298004,
 22: 4971.79654319457,
 23: 5019.791601839455,
 24: 5075.9531785621175,
 25: 5109.0777740034455},
'three_best_features': {1: 3799.769910139297,
 2: 3404.7266545935813,
 3: 3299.680963366003,
 4: 3175.940592564666,
 5: 3353.1645428758793,
 6: 3578.5343852461287,
 7: 3677.877630412099,
 8: 3987.164656392748,
 9: 4266.181276759444,
 10: 4325.012368618152,
 11: 4329.087107344366,
 12: 4514.762731076426,
 13: 4685.552416611788,
 14: 4792.746961837655,
 15: 4948.364890039717,
 16: 5088.9756313241405,
 17: 5183.157343472917,
 18: 5243.67548595213,
 19: 5252.323817410374,
 20: 5274.804570813501,
 21: 5315.959357356891,
 22: 5340.986903057933,
 23: 5411.307325656456,
 24: 5355.620460655679,
 25: 5377.999202860484},
'two_best_features': {1: 4069.5789892813236,
 2: 3296.250909745798,
 3: 3059.664965137341,
 4: 3086.983107035897,
 5: 3280.770311801788,
 6: 3486.6901349592595,
 7: 3710.1524880373577,
 8: 4028.4231578171502,
 9: 4212.909096931993,
 10: 4373.115326240551,
 11: 4548.201200102252,
 12: 4634.007734132519,
 13: 4699.956358534638,
 14: 4820.089955131671,
 15: 4971.794442497039,
 16: 5105.347339761456,
```

```
17: 5199.833188440995,
18: 5222.006810306045,
19: 5248.867052278337,
20: 5238.98718269333,
21: 5258.264146380113,
22: 5259.896089833629,
23: 5276.498097004657,
24: 5335.944753816446,
25: 5379.758333683029}}
```

0.0.16 Plot the Multivariate Multicluster Model Result

In [17]:
```
# Developing the plot series
for k, v in rmse_mvc.items():
    X = list(v.keys())
    y = list(v.values())

    plt.plot(X, y)
    plt.xlabel("Cluster Number")
    plt.ylabel("RMSE")
    plt.title("K-Nearest Neighbors Multivariate Model Results")
plt.show()
```



Let's improve model performance by using KFold Cross Validation Method.

0.0.17 Develop Univariate Model Using KFold Cross Validation

```
In [18]: # Develop Univariate KFold Model with default Split Value and default number of neigh

         def kfold_train_test(train_col, test_col, data):

         # Divide the data set 50/50 between the training and test set & randomize the data
             kfd = KFold(n_splits = 3, shuffle=True)

         # Develop KNeighbor Regression
             knn = KNeighborsRegressor(n_neighbors=5)
             for train_index, test_index, in kfd.split(data):
                 train_kf = data.iloc[train_index]
                 test_kf = data.iloc[test_index]

                 train_features = train_kf[[train_col]]
                 train_target = train_kf[test_col]
                 test_features = test_kf[[train_col]]
                 test_target = test_kf[test_col]

                 knn.fit(train_features, train_target)
                 predictions = knn.predict(test_features)

         # Calculate the model error matrix

                 mse_val_kfd = mean_squared_error(test_target, predictions)
                 rmse_val_kfd = m.sqrt(mse_val_kfd)
             return rmse_val_kfd

         trn_col = cars_num.drop(labels='price', axis=1).columns
         tst_col = 'price'
         rmse_val_kfd = {}

         for col in trn_col:
             rmse_val_kfd[col] = kfold_train_test(col, 'price', cars_num)
         rmse_val_kfd
```

```
Out[18]: {'bore': 5315.196622470554,
          'city-mpg': 3970.033239907463,
          'compression-rate': 5887.687591180707,
          'curb-weight': 3501.748088146236,
          'height': 8786.4885851355,
          'highway-mpg': 5220.101166058049,
          'horsepower': 3046.2973485072644,
          'length': 5788.265244775899,
          'normalized-losses': 7441.517813641668,
          'peak-rpm': 7973.661074521746,
          'stroke': 6494.111632741422,
```

```
 'wheel-base': 5116.804072506383,
 'width': 5293.788718133621}
```

0.0.18 Univariate Model Using KFold Cross Validation with Multiple Clusters

```
In [19]: # Set up a KFold cross validation that develop model with multiple clusters, 5 data f
         clusters = [1, 3, 5, 7, 9]

         def kfold_train_test_mc(train_col, test_col, data):

         # Divide the data set between the training and test set & randomize the data
             kfd = KFold(n_splits = 5, shuffle=True)
             kfold_rmse = []
             rmse_kfd = {}

         # Develop KNeighbor Regression.
             for i in clusters:
                 knn = KNeighborsRegressor(n_neighbors=i)
                 for train_index, test_index, in kfd.split(data):
                     train_kf = data.iloc[train_index]
                     test_kf = data.iloc[test_index]

                     train_features = train_kf[[train_col]]
                     train_target = train_kf[test_col]
                     test_features = test_kf[[train_col]]
                     test_target = test_kf[test_col]

                     knn.fit(train_features, train_target)
                     predictions = knn.predict(test_features)

         # Calculate the model error matrix
                     mse_val_kfd = mean_squared_error(test_target, predictions)
                     kfold_rmse.append(m.sqrt(mse_val_kfd))
                 rmse_kfd[i] = np.mean(kfold_rmse)
             return rmse_kfd

         trn_col = cars_num.drop(labels='price', axis=1).columns
         tst_col = 'price'
         rmse_kfd_mc = {}

         for col in trn_col:
             rmse_kfd_mc[col] = kfold_train_test_mc(col, 'price', cars_num)
         rmse_kfd_mc
```

```
Out[19]: {'bore': {1: 8327.580323142378,
           3: 7720.6813663367575,
           5: 7492.325530997303,
           7: 7374.399857383169,
```

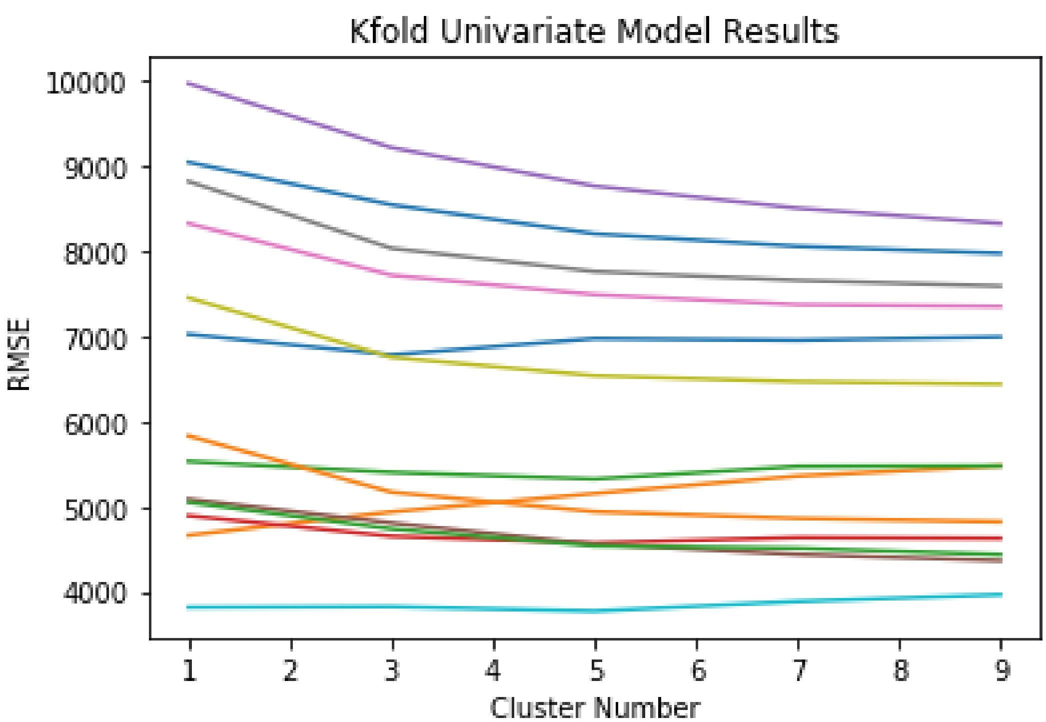
```
 9: 7352.568758535477},
'city-mpg': {1: 5828.667481490455,
 3: 5168.2724354332095,
 5: 4938.520978279707,
 7: 4859.184409918129,
 9: 4820.060025184927},
'compression-rate': {1: 7454.196136549045,
 3: 6754.529212345032,
 5: 6537.510448639073,
 7: 6467.330432243976,
 9: 6437.81121532997},
'curb-weight': {1: 5085.238679780281,
 3: 4804.846374645145,
 5: 4554.712194791633,
 7: 4435.020606905218,
 9: 4363.053844653614},
'height': {1: 9973.755654217723,
 3: 9221.338751721212,
 5: 8768.746580435898,
 7: 8507.875765205785,
 9: 8329.161769481676},
'highway-mpg': {1: 5048.597895835071,
 3: 4735.764950214003,
 5: 4535.664067908839,
 7: 4507.060816581736,
 9: 4433.2881070163685},
'horsepower': {1: 3812.5600141720306,
 3: 3820.459679685042,
 5: 3767.518513405144,
 7: 3881.778373023022,
 9: 3960.244843781488},
'length': {1: 5527.271226810661,
 3: 5401.698797360317,
 5: 5322.310785736173,
 7: 5471.055077313072,
 9: 5475.90951502706},
'normalized-losses': {1: 7025.474989283388,
 3: 6781.831129144508,
 5: 6975.020555416428,
 7: 6954.86055970077,
 9: 6994.240269971826},
'peak-rpm': {1: 9048.768851047611,
 3: 8548.007972277152,
 5: 8206.705945749827,
 7: 8058.816957346031,
 9: 7976.49526761935},
'stroke': {1: 8822.554705097678,
 3: 8035.706924006006,
```

```
 5: 7762.252454332899,
 7: 7659.684430701302,
 9: 7592.209381424959},
'wheel-base': {1: 4660.672666772243,
 3: 4935.564645168429,
 5: 5152.369687718226,
 7: 5357.7380743761005,
 9: 5477.7092437934025},
'width': {1: 4890.756592218648,
 3: 4648.868058891875,
 5: 4569.99425459647,
 7: 4633.839322926813,
 9: 4624.431609367567}}
```

0.0.19 Plot Univariate Multicluster Kfold Cross Validation Result

In [20]:
```
# Developing the Kfold plot series
for k, v in rmse_kfd_mc.items():
    X = list(v.keys())
    y = list(v.values())

    plt.plot(X, y)
    plt.xlabel("Cluster Number")
    plt.ylabel("RMSE")
    plt.title("Kfold Univariate Model Results")
plt.show()
```



0.0.20 Identify the Top 5 Best Features from KFold Cross Validation

In [21]:
```
best_kfd_features = {}
for k, v in rmse_kfd_mc.items():
    best_kfd_features[k] = sum(v.values())/len(v.values())

# Print features in ascending order of error values
top5_kfd = sorted(best_kfd_features.items(), key=itemgetter(1))
print(top5_kfd)
```

```
[('horsepower', 3848.5122848133456), ('curb-weight', 4648.574340155178), ('highway-mpg', 4652.(
```

0.0.21 Multivariate KFold Cross Validation With Multiple Clusters

In [22]:
```
# Set up a KFold cross validation that develop model with multiple clusters, 10 data
clusters_mvmc = [x for x in range(1, 26)]

def kfold_train_test_mvmc(train_col, test_col, data):

# Divide the data set between the training and test set & randomize the data
    kfd = KFold(n_splits = 10, shuffle=True)
    kfold_rmse_mvmc = []
    rmse_kfd_mvmc = {}

# Develop KNeighbor Regression
    for k in clusters_mvmc:
        knn = KNeighborsRegression(n_neighbors= k)
        for train_index, test_index, in kfd.split(data):
            train_kf = data.iloc[train_index]
            test_kf = data.iloc[test_index]

            train_features = train_kf[[train_col]]
            train_target = train_kf[test_col]
            test_features = test_kf[[train_col]]
            test_target = test_kf[test_col]

            knn.fit(train_features, train_target)
            predictions = knn.predict(test_features)

# Calculate the model error matrix
            mse_val_mvmc = mean_squared_error(test_target, predictions)
            kfold_rmse_mvmc.append(m.sqrt(mse_val_mvmc))
        rmse_kfd_mvmc[i] = np.mean(kfold_rmse_mvmc)
    return rmse_kfd_mvmc
```

```
rmse_mvmc = {}

two_best_features = ['horsepower', 'curb-weight']
three_best_features = ['horsepower', 'curb-weight', 'width']
four_best_features = ['horsepower', 'curb-weight', 'width','city-mpg']
five_best_features = ['horsepower', 'curb-weight', 'width','city-mpg', 'highway-mpg']
six_best_features = ['horsepower', 'curb-weight', 'width','city-mpg', 'highway-mpg',

rmse_mvmc_keys = ['two_best_features', 'three_best_features', 'four_best_features', 'f
rmse_mvmc_vals = [two_best_features, three_best_features, four_best_features, five_bes

for i in range(len(rmse_mvmc_keys)):
    rmse_mvmc[rmse_mvmc_keys[i]] = knn_train_test_mvc(rmse_mvmc_vals[i], 'price', cars

rmse_mvmc
```

Out[22]:
```
{'five_best_features': {1: 2522.34322803222,
  2: 2901.265709565396,
  3: 3194.7981612476106,
  4: 3179.8159698125614,
  5: 3354.768120153761,
  6: 3554.219122903245,
  7: 3835.365094826338,
  8: 4023.857588049837,
  9: 4011.8186578325463,
  10: 4159.130326354297,
  11: 4363.387571221952,
  12: 4437.940498042607,
  13: 4516.051228751735,
  14: 4485.415098427801,
  15: 4496.478315936694,
  16: 4575.928353273997,
  17: 4619.454166523248,
  18: 4678.060992505203,
  19: 4710.954185222263,
  20: 4735.107799200563,
  21: 4779.058044867539,
  22: 4811.659056250249,
  23: 4830.614628012334,
  24: 4903.95236785043,
  25: 4948.054413629665},
 'four_best_features': {1: 2508.700263084452,
  2: 2825.099184984485,
  3: 3027.53402953625,
  4: 3141.306046356356,
  5: 3296.1910519871267,
  6: 3496.133159291848,
```

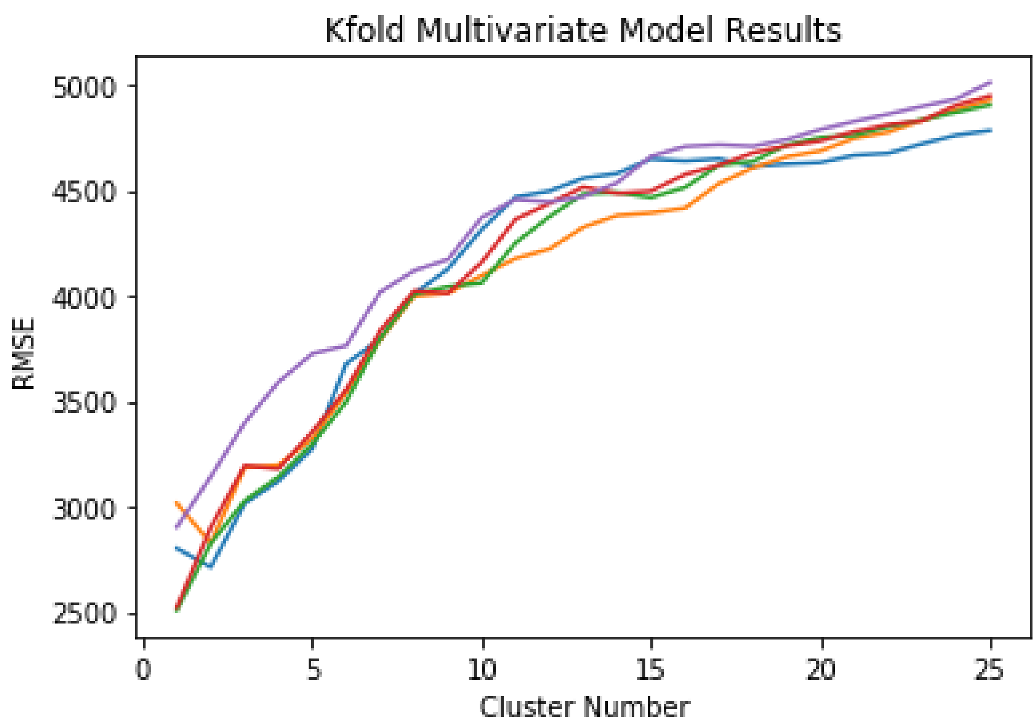
```
 7: 3799.5898375847823,
 8: 4007.828333730906,
 9: 4043.7752590925943,
 10: 4061.585955153479,
 11: 4250.79245548248,
 12: 4375.286951938759,
 13: 4483.370742747367,
 14: 4489.915257063572,
 15: 4465.819253360897,
 16: 4514.011766770981,
 17: 4619.620820963662,
 18: 4637.760207681141,
 19: 4715.269069975908,
 20: 4750.881405165783,
 21: 4761.378934168045,
 22: 4801.650405910296,
 23: 4835.278211081895,
 24: 4870.355670638882,
 25: 4905.289873639682},
'six_best_features': {1: 2903.4532043757827,
 2: 3142.0018968803947,
 3: 3396.8392455340004,
 4: 3590.8558216496244,
 5: 3725.481343021328,
 6: 3763.0956998342617,
 7: 4018.294441066015,
 8: 4119.172252994981,
 9: 4172.055347099227,
 10: 4371.63023444344,
 11: 4457.404384164281,
 12: 4445.475644014685,
 13: 4470.007393710047,
 14: 4536.375387630525,
 15: 4661.429680106499,
 16: 4708.5231406809635,
 17: 4716.842957763243,
 18: 4709.737146383511,
 19: 4741.016094269443,
 20: 4789.170634956015,
 21: 4827.856239976242,
 22: 4861.782713820617,
 23: 4899.037844053352,
 24: 4933.098839716593,
 25: 5011.346646521272},
'three_best_features': {1: 3015.5526093901926,
 2: 2827.2230399280493,
 3: 3185.8503572655272,
 4: 3196.0885968242496,
```

```
 5: 3321.910837816091,
 6: 3539.8708979911185,
 7: 3793.0856521425662,
 8: 3998.8041253370366,
 9: 4012.833999083133,
 10: 4096.527942160287,
 11: 4176.949918321417,
 12: 4221.982450413221,
 13: 4325.052659466676,
 14: 4381.325736607027,
 15: 4393.354922111853,
 16: 4416.152056677319,
 17: 4532.682224970172,
 18: 4606.920384749421,
 19: 4659.545413256474,
 20: 4687.480138640591,
 21: 4747.607147042925,
 22: 4776.151009226352,
 23: 4832.640363945995,
 24: 4883.133452450838,
 25: 4928.990953226837},
'two_best_features': {1: 2802.056360960643,
 2: 2712.806615850087,
 3: 3015.006126951578,
 4: 3121.398744653589,
 5: 3273.867152710996,
 6: 3677.646990490885,
 7: 3794.1271291622397,
 8: 4009.539237614311,
 9: 4126.992051493002,
 10: 4314.186932632845,
 11: 4468.543354706605,
 12: 4496.775761425253,
 13: 4558.046484044459,
 14: 4580.507460964231,
 15: 4649.5206564930495,
 16: 4639.7379678714415,
 17: 4650.666519701671,
 18: 4614.284748928866,
 19: 4625.033325282348,
 20: 4632.395383133331,
 21: 4666.650528395322,
 22: 4676.108846142386,
 23: 4721.055147421024,
 24: 4761.630442851292,
 25: 4784.2029310003145}}
```

0.0.22 Plot Multivariate Multicluster KFold Cross Validation Result

```
In [23]: # Developing the Kfold plot series
         for k, v in rmse_mvmc.items():
             X = list(v.keys())
             y = list(v.values())

             plt.plot(X, y)
             plt.xlabel("Cluster Number")
             plt.ylabel("RMSE")
             plt.title("Kfold Multivariate Model Results")
         plt.show()
```



0.0.23 Compare Results of Two Different Model Approaches

Univariate Model Errors

```
In [24]: UVE = pd.DataFrame.from_dict(rmse_dict, orient='index')
         UVE.columns = ["Nearest Neighbors"]
         UVE["KFold"] = pd.DataFrame.from_dict(rmse_val_kfd, orient='index')
         uve_delta = ((UVE['KFold'] - UVE['Nearest Neighbors'])*100/UVE['Nearest Neighbors']).r
         print("Overall change in the error matrix = " + str(round(uve_delta, 2)) + "%\n")
         UVE
```

```
Overall change in the error matrix = -6.31%
```

Out[24]:

	Nearest Neighbors	KFold
normalized-losses	7338.850271	7441.517814
wheel-base	5486.805327	5116.804073
length	5455.571648	5788.265245
width	4931.242156	5293.788718
height	7857.627254	8786.488585
curb-weight	4422.255746	3501.748088
bore	6822.548760	5315.196622
stroke	7965.733340	6494.111633
compression-rate	6628.568723	5887.687591
horsepower	4011.999336	3046.297349
peak-rpm	7698.121919	7973.661075
city-mpg	4998.449685	3970.033240
highway-mpg	4675.883732	5220.101166

Multivariate Model Errors for Multiclusters

In [25]:

```
multiclusters_nn = {}
mutliclusters_kfd = {}

for k, v in RMSE_MC.items():
    multiclusters_nn[k] = sum(v.values())/len(v.values())

for k, v in rmse_kfd_mc.items():
    mutliclusters_kfd[k] = sum(v.values())/len(v.values())

MCE = pd.DataFrame.from_dict(multiclusters_nn, orient='index')
MCE.columns = ["Nearest Neighbors"]
MCE["KFold"] = pd.DataFrame.from_dict(mutliclusters_kfd, orient='index')
mce_delta = ((MCE['KFold'] - MCE['Nearest Neighbors'])*100/MCE['Nearest Neighbors']).r
print("Overall change in the error matrix = " + str(round(mce_delta, 2)) + "%\n")
MCE
```

```
Overall change in the error matrix = -21.37%
```

Out[25]:

	Nearest Neighbors	KFold
normalized-losses	9111.307924	6946.285501
wheel-base	8995.633640	5116.810864
length	8559.743870	5439.649080
width	7650.761584	4673.577968
height	10897.737723	8960.175704
curb-weight	5552.581136	4648.574340

bore	13059.823628	7653.511167
stroke	9678.461939	7974.481579
compression-rate	8046.276054	6730.275489
horsepower	4806.749996	3848.512285
peak-rpm	10137.802685	8367.758999
city-mpg	4943.913309	5122.941066
highway-mpg	4324.913082	4652.075168

Multivariate Model Errors for Top 5 Best Features

In [26]:
```
# Getting the average value of each of the top 5 best features
multivariate_nn = {}
mutlivariate_kfd = {}

for k, v in rmse_mvc.items():
    multivariate_nn[k] = sum(v.values())/len(v.values())

for k, v in rmse_mvmc.items():
    mutlivariate_kfd[k] = sum(v.values())/len(v.values())

MVE = pd.DataFrame.from_dict(multivariate_nn, orient='index')
MVE.columns = ["Nearest Neighbors"]
MVE["KFold"] = pd.DataFrame.from_dict(mutlivariate_kfd, orient='index')
mve_delta = ((MVE['KFold'] - MVE['Nearest Neighbors'])*100/MVE['Nearest Neighbors']).r
print("Overall change in the error matrix = " + str(round(mve_delta, 2)) + "%\n")
MVE
```

```
Overall change in the error matrix = -3.82%
```

Out[26]:

	Nearest Neighbors	KFold
two_best_features	4512.159647	4174.911476
three_best_features	4519.335087	4142.308676
four_best_features	4279.908275	4147.376966
five_best_features	4185.179948	4185.179948
six_best_features	4326.870948	4318.879369

0.0.24 Conclusion

We can summarize our findings from the project outcome as:

1. Reducing the data noise by eliminating the data gaps, 2. effective data cleaning with proper understanding of the data, 3. filling out the missing data properly feature mean values, 4. careful selection of various features of high significance value, 5. reasonably increasing the number data points/clusters, and 6. use of proper model validation technique

can help to improve the predictive models accuracy for care sale price.