# Car Depriciation model - Madhurima Biswas

In [1]:
```
#Set Working Directory
import os
os.chdir("F:\DS\Projects\Car Dep model")
os.getcwd()
```

Out[1]: 'F:\\DS\\Projects\\Car Dep model'

# Load Libraries

In [2]:
```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.model_selection import train_test_split
from random import randrange, uniform
from scipy.stats import chi2_contingency
from ggplot import *
from fancyimpute import KNN
import seaborn as sns
import statsmodels.api as sm
```

```
C:\Users\sir\Anaconda3\lib\site-packages\ggplot\utils.py:81: FutureWarning: p
andas.tslib is deprecated and will be removed in a future version.
You can access Timestamp as pandas.Timestamp
  pd.tslib.Timestamp,
C:\Users\sir\Anaconda3\lib\site-packages\h5py\__init__.py:36: FutureWarning:
Conversion of the second argument of issubdtype from `float` to `np.floating`
is deprecated. In future, it will be treated as `np.float64 == np.dtype(floa
t).type`.
  from ._conv import register_converters as _register_converters
Using TensorFlow backend.
```

In [3]:
```
#Load the data
data = pd.read_csv("cars.csv")
```

# Exploratory Data Analysis

In [4]:
```
data.shape
```

Out[4]: (2820, 16)

In [5]:
```
#data.head(10)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2820 entries, 0 to 2819
Data columns (total 16 columns):
MMV                 2820 non-null object
Make                2820 non-null object
Model               2820 non-null object
Variant             2820 non-null object
Type                2820 non-null object
Transmission        2820 non-null object
Fuel Type           2820 non-null object
Age                 2820 non-null int64
No of Owners        2820 non-null int64
Color               2820 non-null object
Health Score        2820 non-null float64
Price Score         2820 non-null float64
Distance            2820 non-null object
On Road Price       2820 non-null int64
Current Price       2820 non-null int64
Dep                 2820 non-null float64
dtypes: float64(3), int64(4), object(9)
memory usage: 352.6+ KB
```

In [6]:
```
#Checking the unique values of each column
col = data.columns.values.tolist()
for col in data:
    print (col,":",data[col].nunique())
    #print (data[col].unique())
```

```
MMV : 473
Make : 4
Model : 58
Variant : 398
Type : 6
Transmission : 3
Fuel Type : 8
Age : 12
No of Owners : 6
Color : 34
Health Score : 56
Price Score : 64
Distance : 1128
On Road Price : 448
Current Price : 510
Dep : 690
```

In [7]:
```
'''
Column "Distance" is a numeric type variable, but it has commas ',' which we d
on't need.
Hence, we remove ',' from that column.
'''
data['Distance'] = data['Distance'].str.replace(',','')
```

In [8]:
```
#To change the variables to proper data types
#save numeric & categorical names
catnames = ["MMV","Make","Model","Variant","Type","Fuel Type","Transmission",
"Color","No of Owners"]
numnames = ["Age","Distance","Health Score","Price Score","On Road Price","Cur
rent Price"]
for i in catnames:
    data[i] = data[i].astype('object')
for i in numnames:
    data[i] = data[i].astype('float')
#data.dtypes
```

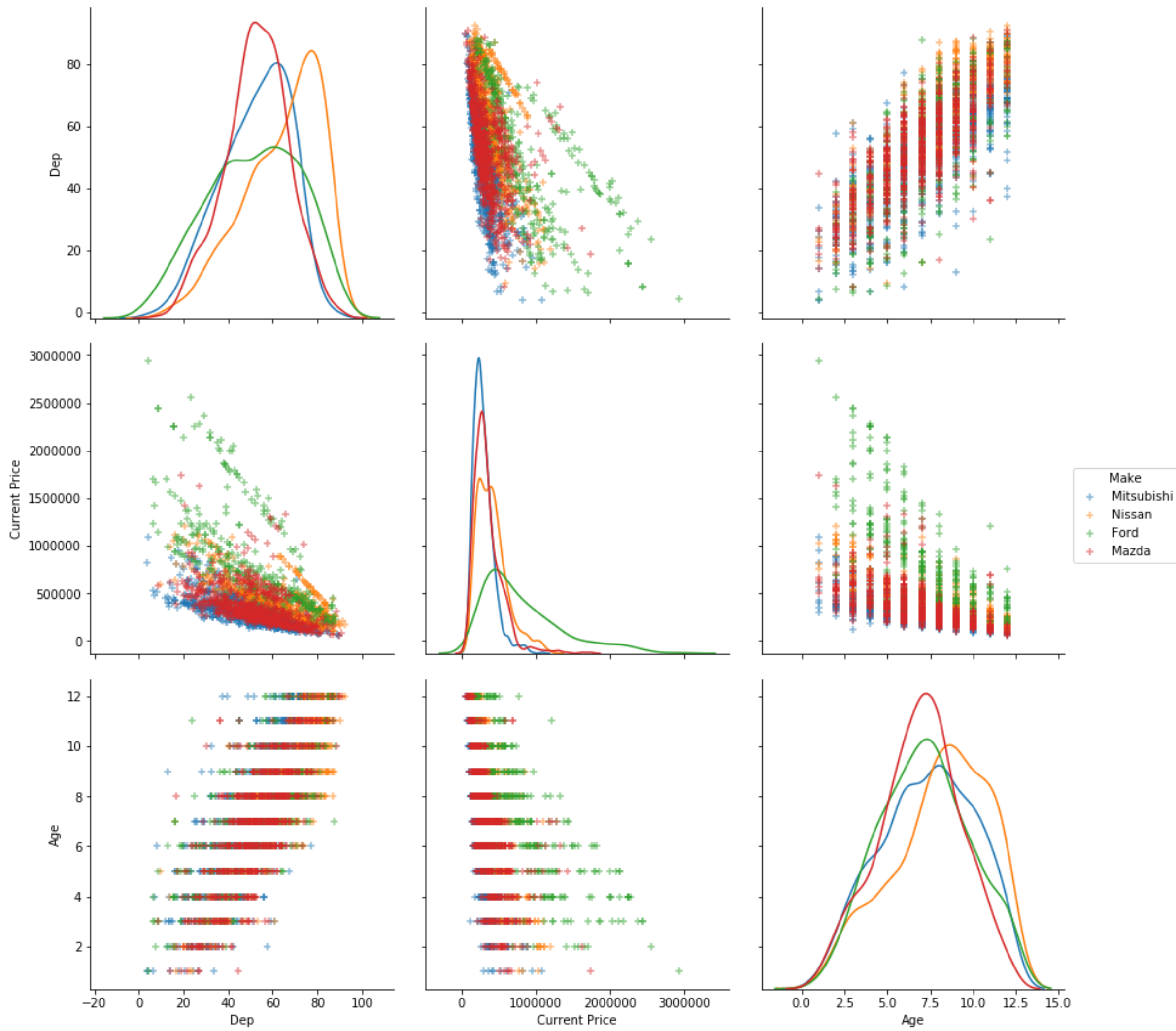
In [9]:
```
#Missing Value Analysis
#Check for missing value
data.isnull().sum()
#No missing values in the dataset
```

Out[9]:
```
MMV              0
Make             0
Model            0
Variant          0
Type             0
Transmission     0
Fuel Type        0
Age              0
No of Owners     0
Color            0
Health Score     0
Price Score      0
Distance         0
On Road Price    0
Current Price    0
Dep              0
dtype: int64
```

# Exploratory Graphical Analysis

In [10]:
```
D = data[["Dep","Current Price","Age","Make"]]
sns.pairplot(D, hue = 'Make', diag_kind = 'kde', markers = '+',
             plot_kws = {'alpha': 0.5, 's': 30, 'edgecolor': 'k'},
             size = 4)
```

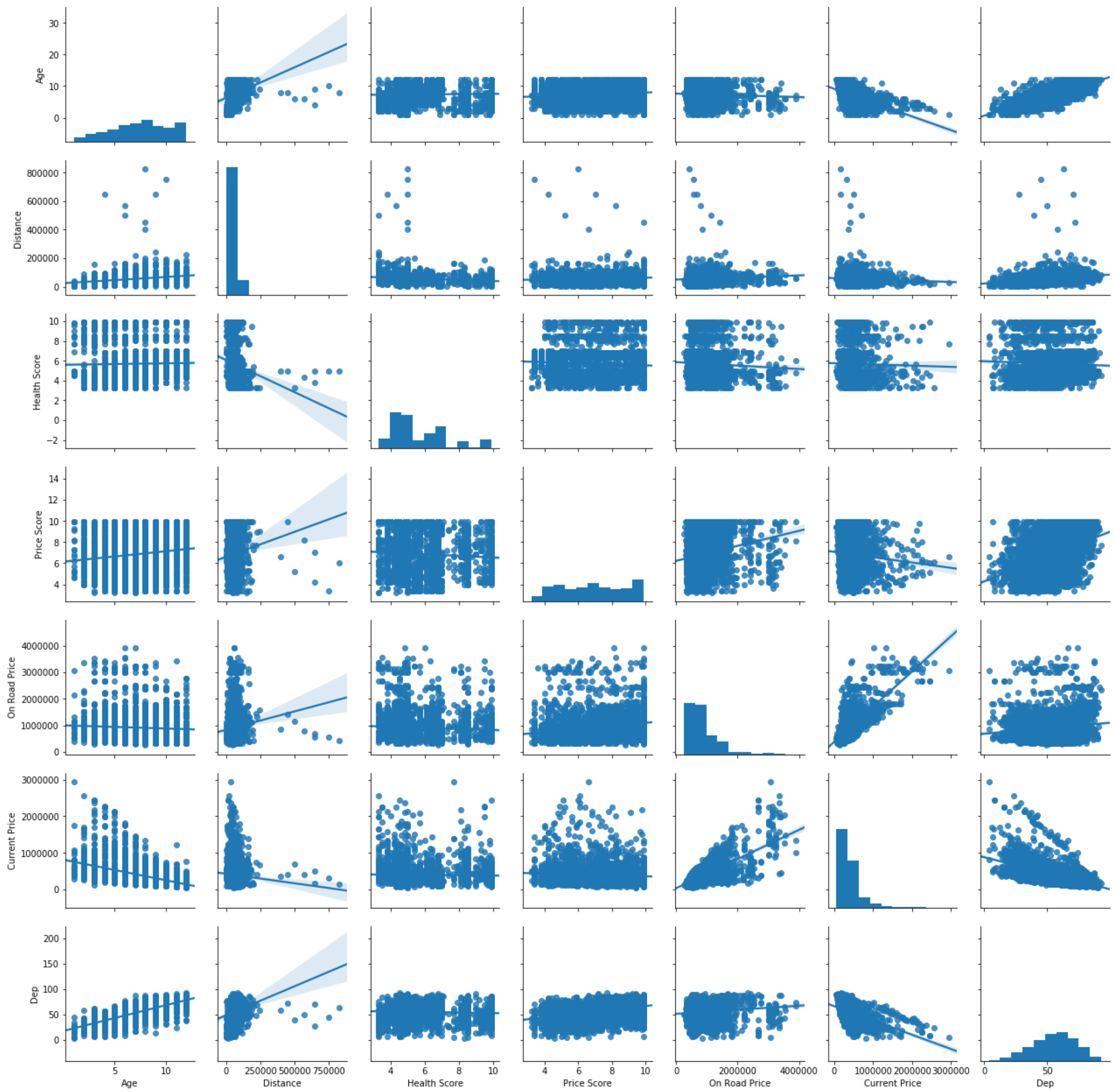
Out[10]: <seaborn.axisgrid.PairGrid at 0x1ae54760828>




In [11]:
```
#Mitsubishi's prices are lower compared to other brands.
#As age of the car increases, Depreciation rate also increases.
```

In [12]:
```
#Plotting Numerical Variables
D = data[["Age","Distance","Health Score","Price Score","On Road Price","Curre
nt Price","Dep"]]
sns.pairplot(D, kind = "reg")
```

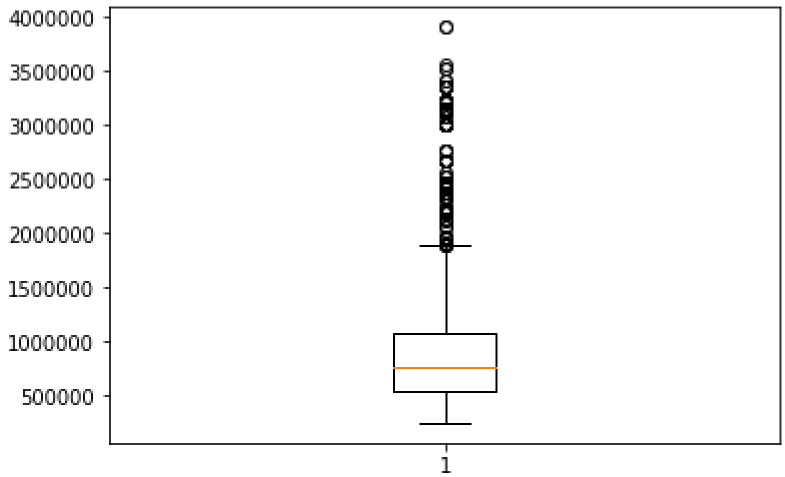
Out[12]: <seaborn.axisgrid.PairGrid at 0x1ae553852e8>




# Outlier Analysis

In [13]:
```
#Plot boxplot to visualize Outliers
%matplotlib inline
plt.boxplot(data['On Road Price'])
```

Out[13]:
```
{'whiskers': [<matplotlib.lines.Line2D at 0x1ae57ccc6d8>,
  <matplotlib.lines.Line2D at 0x1ae57e60160>],
 'caps': [<matplotlib.lines.Line2D at 0x1ae57e609e8>,
  <matplotlib.lines.Line2D at 0x1ae57e60908>],
 'boxes': [<matplotlib.lines.Line2D at 0x1ae57c73240>],
 'medians': [<matplotlib.lines.Line2D at 0x1ae57e41048>],
 'fliers': [<matplotlib.lines.Line2D at 0x1ae57e41eb8>],
 'means': []}
```



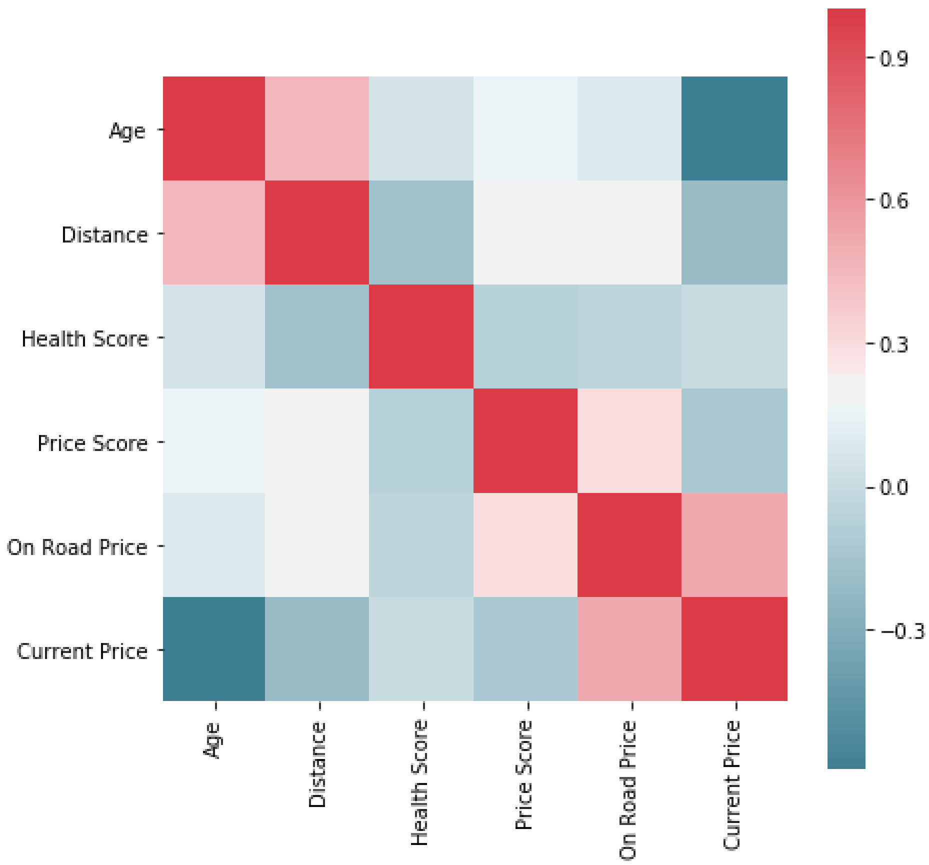

In [14]:
```
#Detect and delete outliers from data
for i in numnames:
     #print(i)
     q75, q25 = np.percentile(data.loc[:,i], [75 ,25])
     iqr = q75 - q25

     min = q25 - (iqr*1.5)
     max = q75 + (iqr*1.5)
     #print(min)
     #print(max)

     #Remove the outliers
     data = data.drop(data[data.loc[:,i] < min].index)
     data = data.drop(data[data.loc[:,i] > max].index)

data.shape          # 13.86% of data is removed, as 391 rows deleted.
```

Out[14]: (2429, 16)

# Feature Selection

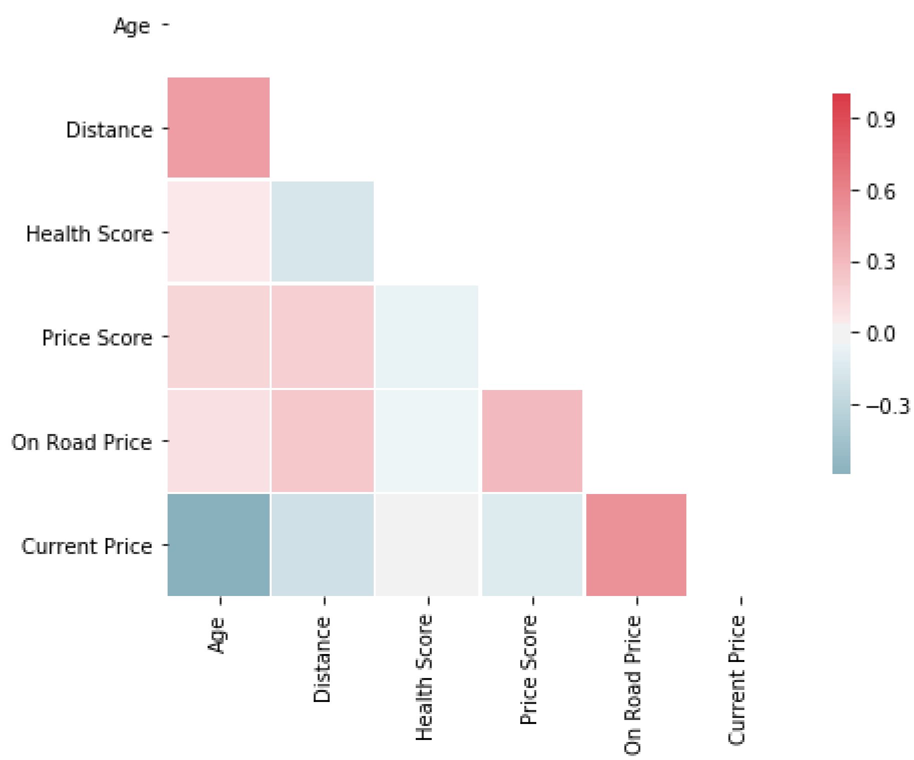
In [15]:
```
##Correlation analysis
#Correlation plot
df_corr = data.loc[:,numnames]
#Set the width and height of the plot
f, ax = plt.subplots(figsize=(7, 7))

#Generate correlation matrix
corr = df_corr.corr()

#Plot using seaborn library
sns.heatmap(corr, mask=np.zeros_like(corr, dtype=np.bool), cmap=sns.diverging_palette(220, 10, as_cmap=True),
            square=True, ax=ax)
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1ae5463e6a0>



In [16]:
```
# Generate a mask for the upper triangle
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True

# Set up the matplotlib figure
f, ax = plt.subplots(figsize=(7, 7))

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

# Draw the heatmap with the mask and correct aspect ratio
sns.heatmap(corr, mask=mask, cmap=cmap, vmax=1, center=0,
            square=True, linewidths=.5, cbar_kws={"shrink": .5})

#We observe, "Distance"-"Age", "Current Price"-"Age" (negatively), "On Road Pr
ice"-"Current Price" are relatively correlated.
```

Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x1ae5862b470>



In [17]:
```
#High Correlation Filter for Independent variables
#Note: The last variable "Dep" is our Output Variable and we don't apple a hig
h correlation filter for that one.
#We can exclude one of variables which are highly correlated |r|>0.7.
data.corr()

#"Current Price"-"Age" & "Current Price"-"on road price" are relatively correl
ated.
```

Out[17]:

| | Age | Health Score | Price Score | Distance | On Road Price | Current Price | Dep |
|---|---|---|---|---|---|---|---|
| **Age** | 1.000000 | 0.052886 | 0.153296 | 0.457501 | 0.092124 | -0.594758 | 0.785177 |
| **Health Score** | 0.052886 | 1.000000 | -0.067988 | -0.169284 | -0.040890 | -0.002803 | -0.038937 |
| **Price Score** | 0.153296 | -0.067988 | 1.000000 | 0.193944 | 0.298484 | -0.124149 | 0.452541 |
| **Distance** | 0.457501 | -0.169284 | 0.193944 | 1.000000 | 0.221885 | -0.207425 | 0.481672 |
| **On Road Price** | 0.092124 | -0.040890 | 0.298484 | 0.221885 | 1.000000 | 0.514747 | 0.354957 |
| **Current Price** | -0.594758 | -0.002803 | -0.124149 | -0.207425 | 0.514747 | 1.000000 | -0.552134 |
| **Dep** | 0.785177 | -0.038937 | 0.452541 | 0.481672 | 0.354957 | -0.552134 | 1.000000 |

In [18]:
```
#Because the 'str' does not have numerical meaning for the classifier:
#we may get Error such as "ValueError: could not convert string to float"
#To encode all the data which are categorized to dtype:object
#data = pd.read_csv("cars_clean.csv")
from sklearn import preprocessing
le = preprocessing.LabelEncoder()
for i in data.columns:
    if data[i].dtype == object:
        data[i] = le.fit_transform(data[i])
    else:
        pass
```

In [19]:
```
#Loop for chi square values of Independent variables wrt each other (within Ca
tegorical Variables)
for i in catnames:
    print ('\n')
    for j in catnames:
        if (i!=j):
            chi2, p, dof, ex = chi2_contingency(pd.crosstab(data[i], data[j]))
            print(i, ' Vs ', j, ':')
            print('p-value =', p)

'''
If p-value<0.05 (Reject Null Hypothesis) => Variables are dependent. : Not imp
ortant for prediction = Redundant (Associated).
If p-value>0.05 (Do Not Reject Null Hypothesis) => Variables are independent.
'''
#'MMV','Make','Model','Variant' are the least favourable features acc. to this
test.
```

```
MMV  Vs  Make :
p-value = 0.0
MMV  Vs  Model :
p-value = 0.0
MMV  Vs  Variant :
p-value = 0.0
MMV  Vs  Type :
p-value = 0.0
MMV  Vs  Fuel Type :
p-value = 0.0
MMV  Vs  Transmission :
p-value = 0.0
MMV  Vs  Color :
p-value = 1.4353628865047457e-110
MMV  Vs  No of Owners :
p-value = 0.9736871872102378


Make  Vs  MMV :
p-value = 0.0
Make  Vs  Model :
p-value = 0.0
Make  Vs  Variant :
p-value = 0.0
Make  Vs  Type :
p-value = 8.065407033558104e-260
Make  Vs  Fuel Type :
p-value = 4.1786571489192645e-51
Make  Vs  Transmission :
p-value = 5.938528301305281e-09
Make  Vs  Color :
p-value = 1.9376671082018443e-20
Make  Vs  No of Owners :
p-value = 0.004119010547295543


Model  Vs  MMV :
p-value = 0.0
Model  Vs  Make :
p-value = 0.0
Model  Vs  Variant :
p-value = 0.0
Model  Vs  Type :
p-value = 0.0
Model  Vs  Fuel Type :
p-value = 1.7933795221577096e-282
Model  Vs  Transmission :
p-value = 8.017453560566174e-235
Model  Vs  Color :
p-value = 2.1817368796251107e-163
Model  Vs  No of Owners :
p-value = 6.038131785679051e-33


Variant  Vs  MMV :
p-value = 0.0
```

```
Variant  Vs  Make :
p-value = 0.0
Variant  Vs  Model :
p-value = 0.0
Variant  Vs  Type :
p-value = 0.0
Variant  Vs  Fuel Type :
p-value = 0.0
Variant  Vs  Transmission :
p-value = 0.0
Variant  Vs  Color :
p-value = 2.2821115225933617e-139
Variant  Vs  No of Owners :
p-value = 0.945408488194952


Type  Vs  MMV :
p-value = 0.0
Type  Vs  Make :
p-value = 8.065407033558104e-260
Type  Vs  Model :
p-value = 0.0
Type  Vs  Variant :
p-value = 0.0
Type  Vs  Fuel Type :
p-value = 7.869059266642349e-42
Type  Vs  Transmission :
p-value = 6.989682365846259e-12
Type  Vs  Color :
p-value = 6.630351640366776e-175
Type  Vs  No of Owners :
p-value = 0.1440675210577128


Fuel Type  Vs  MMV :
p-value = 0.0
Fuel Type  Vs  Make :
p-value = 4.1786571489193856e-51
Fuel Type  Vs  Model :
p-value = 1.7933795221577096e-282
Fuel Type  Vs  Variant :
p-value = 0.0
Fuel Type  Vs  Type :
p-value = 7.869059266642349e-42
Fuel Type  Vs  Transmission :
p-value = 1.9861215884663772e-07
Fuel Type  Vs  Color :
p-value = 1.372893522511756e-07
Fuel Type  Vs  No of Owners :
p-value = 0.00037081576291196806


Transmission  Vs  MMV :
p-value = 0.0
Transmission  Vs  Make :
p-value = 5.938528301305235e-09
Transmission  Vs  Model :
```

```
p-value = 8.017453560566174e-235
Transmission  Vs  Variant :
p-value = 0.0
Transmission  Vs  Type :
p-value = 6.989682365846259e-12
Transmission  Vs  Fuel Type :
p-value = 1.9861215884663632e-07
Transmission  Vs  Color :
p-value = 0.9262271442108017
Transmission  Vs  No of Owners :
p-value = 0.5668569794055609


Color  Vs  MMV :
p-value = 1.4353628865047457e-110
Color  Vs  Make :
p-value = 1.9376671082018443e-20
Color  Vs  Model :
p-value = 2.1817368796251107e-163
Color  Vs  Variant :
p-value = 2.282111522601666e-139
Color  Vs  Type :
p-value = 6.630351640366776e-175
Color  Vs  Fuel Type :
p-value = 1.3728935225116794e-07
Color  Vs  Transmission :
p-value = 0.9262271442108017
Color  Vs  No of Owners :
p-value = 0.9998783258522638


No of Owners  Vs  MMV :
p-value = 0.9736871872102378
No of Owners  Vs  Make :
p-value = 0.0041190105472955529
No of Owners  Vs  Model :
p-value = 6.0381317856787044e-33
No of Owners  Vs  Variant :
p-value = 0.945408488194952
No of Owners  Vs  Type :
p-value = 0.1440675210577128
No of Owners  Vs  Fuel Type :
p-value = 0.00037081576291196844
No of Owners  Vs  Transmission :
p-value = 0.5668569794055605
No of Owners  Vs  Color :
p-value = 0.9998783258522638
```

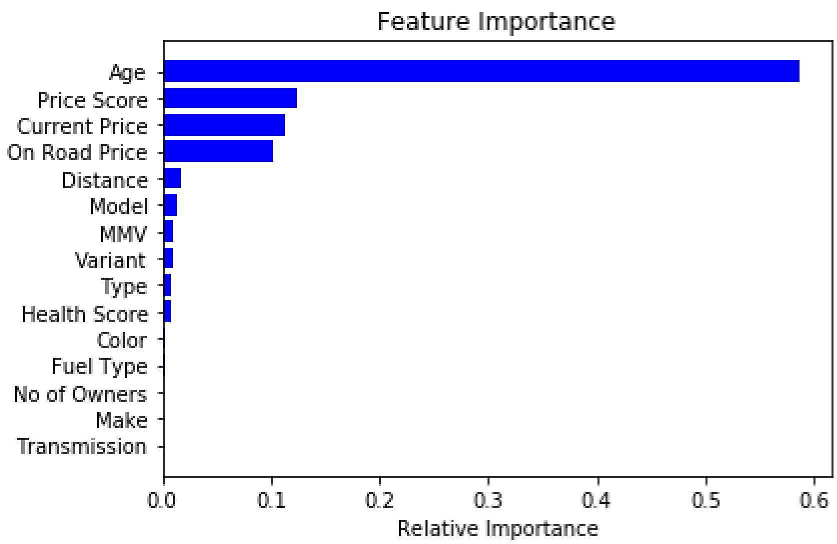
Out[19]:
```
'\nIf p-value<0.05 (Reject Null Hypothesis) => Variables are dependent. : Not
important for prediction = Redundant (Associated).\nIf p-value>0.05 (Do Not R
eject Null Hypothesis) => Variables are independent. \n'
```

In [20]:
```
#Low Variance filter for numerical variables
#We can drop the variables having low variance as variables with a low varianc
e will not affect the target variable.

data.var()

#'Make', 'Transmission' & 'No of Owners' variables have relatively low Varianc
e.
```

Out[20]:
```
MMV              1.048283e+04
Make             7.038547e-01
Model            1.334389e+02
Variant          7.752509e+03
Type             2.247097e+00
Transmission     1.195915e-01
Fuel Type        1.847115e+00
Age              6.485619e+00
No of Owners     3.083306e-01
Color            4.711524e+01
Health Score     2.461460e+00
Price Score      3.666357e+00
Distance         4.508701e+08
On Road Price    1.053479e+11
Current Price    1.960594e+10
Dep              2.417838e+02
dtype: float64
```

In [21]:

```
#Using Random forest's in-built feature importance
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(random_state=1, max_depth=10)
df=data
df = df.drop('Dep', axis=1)
model.fit(df,data.Dep)
#To plot the importance values:
features = data.columns
importances = model.feature_importances_
indices = np.argsort(importances)[-15:]  #displays top 15 features
plt.title('Feature Importance')
plt.barh(range(len(indices)), importances[indices], color='b', align='center')
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()

#'Transmission',Make','No of Owner','Fuel Type' are the least important here.
```



In [22]:
```
#To check multicollinearity
#Define a function to calculate the VIF values

from statsmodels.stats.outliers_influence import variance_inflation_factor

def vif_cal(input_data, target):
    x_vars=input_data.drop([target], axis=1)
    xvar_names=x_vars.columns
    for i in range(0,xvar_names.shape[0]):
        y=x_vars[xvar_names[i]]
        x=x_vars[xvar_names.drop(xvar_names[i])]
        rsq=sm.OLS(y, x).fit().rsquared
        vif=round(1/(1-rsq),2)
        print (xvar_names[i], " VIF = " , vif)

#Calling VIF function
#vif_cal(input_data=data, target="Dep")

'''
MMV  VIF =  131.24
Make  VIF =  127.5
Model  VIF =  16.12
Variant  VIF =  7.66
Type  VIF =  6.37
Transmission  VIF =  24.54
Fuel Type  VIF =  6.35
Age  VIF =  24.99
No of Owners  VIF =  1.34
Color  VIF =  5.03
Health Score  VIF =  14.29
Price Score  VIF =  15.82
Distance  VIF =  10.27
On Road Price  VIF =  23.84
Current Price  VIF =  19.37
'''

#"MMV","Make" have very high multicollinearity.
#Let's check the VIF after removing these two variables.
#dt = data.drop(["Make","MMV"],axis=1)
#vif_cal(input_data=dt, target="Dep")

'''
Model  VIF =  8.2
Variant  VIF =  6.68
Type  VIF =  5.61
Transmission  VIF =  23.2
Fuel Type  VIF =  6.34
Age  VIF =  23.3
No of Owners  VIF =  1.34
Color  VIF =  5.01
Health Score  VIF =  13.81
Price Score  VIF =  14.64
Distance  VIF =  10.18
On Road Price  VIF =  23.6
Current Price  VIF =  18.93
'''
```

```
#"on road price" has high multicollinearity. Let's redo VIF after removing it.
#dt = data.drop(["Make","MMV","On Road Price"],axis=1)
#vif_cal(input_data=dt, target="Dep")

#"Transmission" & "Age" has high multicollinearity. Let's redo VIF after remov
ing it.
dt = data.drop(["Make","MMV","On Road Price","Transmission","Age"],axis=1)
vif_cal(input_data=dt, target="Dep")

#'Age' has high multicollinearity, but it also had high feature importance.
```

```
Model  VIF =  7.57
Variant  VIF =  5.36
Type  VIF =  4.64
Fuel Type  VIF =  6.01
No of Owners  VIF =  1.32
Color  VIF =  4.97
Health Score  VIF =  11.0
Price Score  VIF =  11.52
Distance  VIF =  7.64
Current Price  VIF =  7.29
```

In [23]:

```
#We drop "No of owner", "on road price" & "Transmission" based on previous tes
ts.
#We drop "MMV" as well, because other variables 'Make', "Model" and 'Variant'
 have the same info & it's like an ID for the car.
data = data.drop(["Make","No of Owners","Variant","MMV","On Road Price", "Tran
smission"],axis=1)

#Update numnames & catnames:
numnames.remove("On Road Price")
catnames.remove("Make")
catnames.remove("No of Owners")
catnames.remove("Variant")
catnames.remove("MMV")
catnames.remove("Transmission")
```

In [24]:

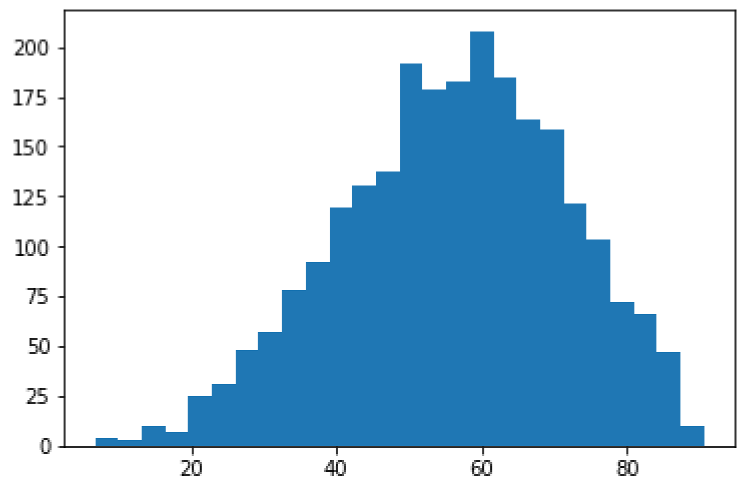
```
#data.head(10)
data.shape
#We have total 10 variables now. (9 -> Independent)
```

Out[24]: (2429, 10)

# Feature Scaling

In [25]:
```
#Normality check
%matplotlib inline
plt.hist(data['Dep'], bins='auto')

#Although the distribution is close to Normal curve, but this could be because
of the outliers removed.
#Future data might not be of such distribution or if we impute the outliers in
stead of removal.
#We go for normalization method.
```

Out[25]:
```
(array([  4.,   3.,  10.,   7.,  25.,  31.,  48.,  57.,  78.,  92., 119.,
        130., 137., 192., 179., 183., 208., 185., 164., 158., 121., 103.,
         72.,  66.,  47.,  10.]),
 array([ 6.7       ,  9.93076923, 13.16153846, 16.39230769, 19.62307692,
        22.85384615, 26.08461538, 29.31538462, 32.54615385, 35.77692308,
        39.00769231, 42.23846154, 45.46923077, 48.7       , 51.93076923,
        55.16153846, 58.39230769, 61.62307692, 64.85384615, 68.08461538,
        71.31538462, 74.54615385, 77.77692308, 81.00769231, 84.23846154,
        87.46923077, 90.7       ]),
 <a list of 26 Patch objects>)
```




In [26]:
```
#Nomalisation
#Only for numeric variables
for i in numnames:
    #print(i)
    data[i] = (data[i] - data[i].min())/(data[i].max() - data[i].min())
```

In [27]:
```
#data.head(10)
print(data.shape)
#12 <- Independent variables.
#Save the cleaned data
#data.to_csv("cars_clean.csv", index=False)
```

```
(2429, 10)
```

# Model Selection

In [28]:
```
#Data Sampling
#Splitting data into train (80%) & test (20%) datasets
nrow = len(data.index)
train, test = train_test_split(data, test_size = 0.2)
#train.shape     #1943 x 10
#test.shape       #486 x 10
```

In [29]:
```
#Making a dataframe just to store and compare each Algorithm's results
results=pd.DataFrame({'Algorithm':["Decision Tree","Random Forest","Linear Reg
ression","KNN"],
                      'RMSE_value':[0.0,0.0,0.0,0.0]})
```

In [30]:
```
#####1.Decision Tree Algortithm#####
#To fit DT on train set
from sklearn.tree import DecisionTreeRegressor
fit_dt= DecisionTreeRegressor(max_depth=2).fit(train.iloc[:,0:9],train.iloc[:,
9])
fit_dt
```

Out[30]:
```
DecisionTreeRegressor(criterion='mse', max_depth=2, max_features=None,
           max_leaf_nodes=None, min_impurity_decrease=0.0,
           min_impurity_split=None, min_samples_leaf=1,
           min_samples_split=2, min_weight_fraction_leaf=0.0,
           presort=False, random_state=None, splitter='best')
```

In [31]:
```
#To predict on test set
predict_dt= fit_dt.predict(test.iloc[:,0:9])
```

In [32]:
```
#Calculate RMSE
def RMSE(actual, pred):
    return np.sqrt(((pred - actual) ** 2).mean())

results.loc[0,'RMSE_value'] = RMSE(test.iloc[:,9],predict_dt)  #RMSE error for
Decision Tree
```

In [33]:
```
######2.Random Forest Algorithm#####
#To fit RF on train set
from sklearn.ensemble import RandomForestRegressor
fit_rf = RandomForestRegressor(n_estimators = 100, random_state = 99).fit(trai
n.iloc[:,0:9],train.iloc[:,9])
fit_rf
```

Out[33]:
```
RandomForestRegressor(bootstrap=True, criterion='mse', max_depth=None,
           max_features='auto', max_leaf_nodes=None,
           min_impurity_decrease=0.0, min_impurity_split=None,
           min_samples_leaf=1, min_samples_split=2,
           min_weight_fraction_leaf=0.0, n_estimators=100, n_jobs=1,
           oob_score=False, random_state=99, verbose=0, warm_start=False)
```

In [34]:
```
#To predict on test set
predict_rf= fit_rf.predict(test.iloc[:,0:9])
```

In [35]:
```
results.loc[1,'RMSE_value'] = RMSE(test.iloc[:,9],predict_rf) #RMSE error for
 Random Forest Algorithm
```

In [36]:
```
#####3.Multiple Linear Regression#####
#Creat dataframe with all numerical variables
df_lr = data[['Dep','Age', 'Distance', 'Health Score', 'Price Score', 'Current
Price']]
#NOTE: Output Variable "Dep" is now the first column (position '0') here.
#create dummies for categorical variables
for i in catnames:
    temp = pd.get_dummies(data[i],prefix = i)
    df_lr = df_lr.join(temp)
```

In [37]:
```
df_lr.shape
```

Out[37]: (2429, 95)

In [38]:
```
#We have 95 variables now.

#We should try to reduce the dimensionality
#Convert to numpy arrays
X = df_lr.iloc[:, 1:94].values
y = df_lr.iloc[:, 0].values

# Split into the Training set and Test set
from sklearn.cross_validation import train_test_split
Xtrain, Xtest, ytrain, ytest = train_test_split(X, y, test_size = 0.2)
```

```
C:\Users\sir\Anaconda3\lib\site-packages\sklearn\cross_validation.py:41: Depr
ecationWarning: This module was deprecated in version 0.18 in favor of the mo
del_selection module into which all the refactored classes and functions are
moved. Also note that the interface of the new CV iterators are different fro
m that of this module. This module will be removed in 0.20.
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [39]:
```
#X.shape                #2429 x 93
#y.shape                #2429 x 1
#Xtrain.shape           #1943 x 93
#Xtest.shape            #486  x 93
#ytrain.shape           #1943 x 1
#ytest.shape            #486 x 1

#We have 108 independent variables now.
```

In [40]:
```
#Using PCA to reduce dimensionality - independent variables
from sklearn.decomposition import PCA
from sklearn.preprocessing import MinMaxScaler
%matplotlib inline

#Scaling the values
sc = MinMaxScaler()
Xtrain = sc.fit_transform(Xtrain)
Xtest = sc.transform(Xtest)
```

In [41]:
```
#To choose no. of components in PCA
from sklearn.preprocessing import scale
X = scale(X)
pca = PCA(n_components=93)
pca.fit(X)
```

Out[41]:
```
PCA(copy=True, iterated_power='auto', n_components=93, random_state=None,
  svd_solver='auto', tol=0.0, whiten=False)
```

In [42]:
```
#The amount of variance that each PC explains
var= pca.explained_variance_ratio_
var
```

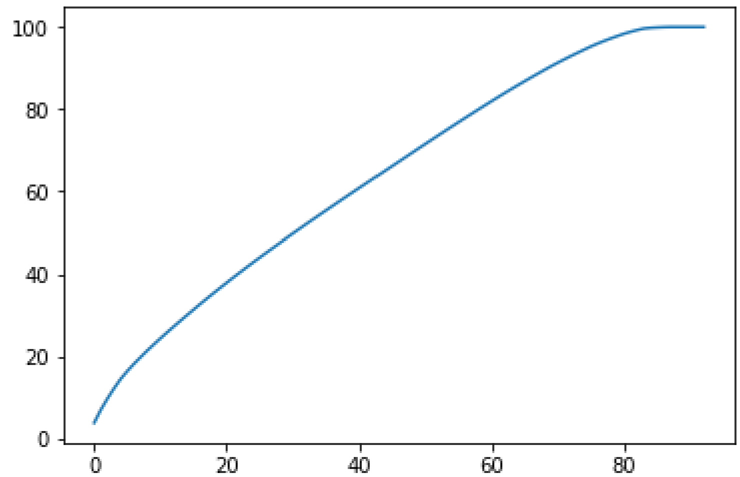
Out[42]:
```
array([3.74102151e-02, 3.15528299e-02, 2.73156351e-02, 2.49874198e-02,
       2.28562793e-02, 1.90978781e-02, 1.74867788e-02, 1.63188393e-02,
       1.59997277e-02, 1.51217748e-02, 1.48625856e-02, 1.44228036e-02,
       1.42326241e-02, 1.38983814e-02, 1.37552344e-02, 1.36444700e-02,
       1.35505348e-02, 1.32983143e-02, 1.29788265e-02, 1.28592858e-02,
       1.27357140e-02, 1.26712536e-02, 1.23194027e-02, 1.22977327e-02,
       1.21207597e-02, 1.19176706e-02, 1.17562535e-02, 1.16463778e-02,
       1.16114050e-02, 1.15544501e-02, 1.13691829e-02, 1.13123804e-02,
       1.12913185e-02, 1.11915059e-02, 1.11082291e-02, 1.10428516e-02,
       1.10063684e-02, 1.09797859e-02, 1.09189018e-02, 1.08669477e-02,
       1.08341404e-02, 1.08222410e-02, 1.08159570e-02, 1.07922481e-02,
       1.07784143e-02, 1.07741990e-02, 1.07705968e-02, 1.07638972e-02,
       1.07608721e-02, 1.07582855e-02, 1.06729196e-02, 1.06664685e-02,
       1.05966627e-02, 1.05559381e-02, 1.05082684e-02, 1.04507407e-02,
       1.04194751e-02, 1.03458977e-02, 1.02511705e-02, 1.01518487e-02,
       1.00634466e-02, 1.00158984e-02, 9.89995225e-03, 9.71094666e-03,
       9.57859239e-03, 9.38730877e-03, 9.32958011e-03, 9.22148798e-03,
       9.05236769e-03, 8.87865035e-03, 8.53017220e-03, 8.30681931e-03,
       8.12813143e-03, 7.80760397e-03, 7.65033508e-03, 7.57117800e-03,
       6.98044892e-03, 6.36469505e-03, 6.09798438e-03, 5.83161799e-03,
       5.56352948e-03, 4.74943584e-03, 4.27349241e-03, 3.62554164e-03,
       1.56889541e-03, 8.98004985e-04, 6.88314818e-04, 3.61315940e-04,
       5.08047285e-06, 5.21892031e-33, 1.27920688e-33, 1.06882066e-33,
       2.91764258e-34])
```

In [43]:
```
#Cumulative Variance explains
var1=np.cumsum(np.round(pca.explained_variance_ratio_, decimals=4)*100)
var1
```

Out[43]:
```
array([  3.74,   6.9 ,   9.63,  12.13,  14.42,  16.33,  18.08,  19.71,
        21.31,  22.82,  24.31,  25.75,  27.17,  28.56,  29.94,  31.3 ,
        32.66,  33.99,  35.29,  36.58,  37.85,  39.12,  40.35,  41.58,
        42.79,  43.98,  45.16,  46.32,  47.48,  48.64,  49.78,  50.91,
        52.04,  53.16,  54.27,  55.37,  56.47,  57.57,  58.66,  59.75,
        60.83,  61.91,  62.99,  64.07,  65.15,  66.23,  67.31,  68.39,
        69.47,  70.55,  71.62,  72.69,  73.75,  74.81,  75.86,  76.91,
        77.95,  78.98,  80.01,  81.03,  82.04,  83.04,  84.03,  85.  ,
        85.96,  86.9 ,  87.83,  88.75,  89.66,  90.55,  91.4 ,  92.23,
        93.04,  93.82,  94.59,  95.35,  96.05,  96.69,  97.3 ,  97.88,
        98.44,  98.91,  99.34,  99.7 ,  99.86,  99.95, 100.02, 100.06,
       100.06, 100.06, 100.06, 100.06, 100.06])
```

In [44]:
```
plt.plot(var1)
```

Out[44]: [<matplotlib.lines.Line2D at 0x1ae5a3ff470>]




In [45]:
```
#Looking at above plot, selecting 82 components can preserve 99.34% of the tot
al variance in data.
```

In [46]:
```
#Build MLR model (With PCA analysis)
pca = PCA(n_components = 82)
Xtrain = pca.fit_transform(Xtrain)
Xtest = pca.transform(Xtest)
explained_variance = pca.explained_variance_ratio_
```

In [47]:
```
#Train regressor
from sklearn.linear_model import LinearRegression
regr = LinearRegression()
regr.fit(Xtrain, ytrain)
```

Out[47]: LinearRegression(copy_X=True, fit_intercept=True, n_jobs=1, normalize=False)

In [48]:
```
#predict for test set
predict_lr = regr.predict(Xtest)
Rsq_lr = regr.score(Xtrain,ytrain)*100
print(Rsq_lr)
#R-squared = 89.12%
#Approx. 89% of the variation in Depreciation rate% is explained by all the in
dependent variables.
```

89.58252440889487

In [49]:
```
predict_lr
```

```
Out[49]: array([66.42793182, 42.5573152 , 62.65437933, 65.60442887, 64.8531598 ,
            44.88002181, 50.98561223, 29.63351529, 67.79763845, 56.68984688,
            55.95165624, 62.02624045, 51.22730484, 62.37959517, 64.94736307,
            49.08637706, 60.81183395, 40.8536289 , 52.08390618, 53.8190211 ,
            74.10845698, 49.86791798, 52.07057562, 44.8206194 , 68.40803452,
            56.19798522, 60.2835308 , 49.48387415, 33.39671796, 68.84784737,
            52.88183446, 48.26796511, 81.62770705, 77.94033238, 51.90492016,
            57.13445868, 60.64834043, 41.04276261, 40.44106708, 53.31849552,
            54.84390421, 48.80954467, 89.43498233, 52.12550425, 58.32999282,
            51.09778005, 59.6894955 , 67.57139723, 60.42827231, 77.08733233,
            48.75428788, 67.2659448 , 72.78297041, 70.90383797, 49.7163556 ,
            56.58511572, 63.88874265, 50.72106707, 61.34423378, 67.1416988 ,
            60.19184941, 67.41225191, 56.05090851, 48.23920147, 78.26807951,
            59.25405873, 41.995296  , 23.95816106, 48.21418418, 50.30330086,
            56.96049471, 40.45481061, 59.15343348, 63.15221308, 58.3954027 ,
            49.7951351 , 62.73088337, 39.05732225, 53.97526128, 39.77034139,
            64.90086619, 71.94255333, 48.24788132, 30.44817694, 25.66964662,
            87.7524352 , 57.01745567, 38.43849579, 55.5424304 , 48.40558427,
            78.44728391, 59.44969461, 54.41157213, 61.34660293, 63.31014024,
            48.96844465, 37.82129355, 34.61108493, 28.50886583, 62.21271625,
            64.7208769 , 46.35409275, 48.13886804, 29.48364346, 69.45852928,
            51.19204499, 68.46286545, 63.56474394, 47.17138985, 79.49228951,
            53.47449639, 69.6848513 , 34.76163821, 46.86140651, 54.67186369,
            40.77013526, 58.63484161, 52.29914069, 66.8627764 , 72.80573023,
            59.93617656, 49.80811157, 54.20742809, 59.46437348, 50.47366262,
            25.45047319, 59.66235532, 76.85222709, 56.20638209, 51.56166187,
            58.09970292, 57.36702838, 49.45815175, 58.04456319, 48.38655077,
            35.82492179, 39.51851817, 65.1227337 , 62.43463197, 52.46578447,
            39.23251453, 33.86336705, 54.04558692, 48.24050858, 58.70089674,
            71.11557755, 61.80512312, 75.30977434, 49.56532587, 47.88852052,
            92.6054841 , 58.45106621, 48.96054268, 55.82756002, 50.3235613 ,
            32.06962553, 47.13492611, 44.73023346, 47.64329648, 78.68200687,
            84.04411971, 49.9254691 , 61.36747074, 77.19002295, 62.57987479,
            38.89891664, 52.25280078, 60.73112242, 69.94902916, 50.17636925,
            39.86067687, 58.80465946, 67.098225  , 53.42253714, 64.21388226,
            66.83925321, 50.67527109, 47.19391345, 50.40498511, 73.35730557,
            68.42759815, 27.1566885 , 89.77440307, 31.86605357, 48.24835892,
            49.79744602, 66.50954663, 43.63711825, 52.60758742, 71.10782485,
            30.21318348, 48.06445828, 90.00641164, 62.28674599, 50.89795472,
            52.58602749, 49.86486071, 36.70983401, 52.60903702, 59.58423041,
            62.77448452, 61.59453704, 48.26489414, 57.52764595, 55.24046389,
            41.34503608, 85.05559652, 54.94050848, 44.22419349, 57.64605241,
            30.38447066, 87.58761315, 29.20542092, 62.39319218, 68.93166324,
            45.03355972, 43.31435238, 52.46755238, 73.70695436, 41.49976646,
            40.62412785, 33.68552646, 74.05535373, 57.92213022, 52.75075095,
            40.65194588, 53.19956443, 63.4410762 , 32.68146679, 76.98034375,
            50.0865351 , 54.37644778, 54.78390783, 34.24836489, 51.66468359,
            44.5133429 , 48.32493936, 60.82204339, 60.34071433, 82.45635626,
            65.29412036, 59.99281136, 69.15066731, 57.31672315, 55.95472729,
            89.89091018, 35.39996303, 41.86326781, 56.32413354, 57.03955902,
            48.98876466, 75.68903942, 59.24234462, 73.20828026, 44.38029058,
            51.59287406, 50.12085194, 41.25607283, 69.90937138, 55.32444237,
            67.61575895, 65.9220308 , 63.84295191, 62.19796512, 71.66504989,
            60.54398886, 35.88538615, 49.67919321, 63.08202011, 50.54317607,
            47.70819839, 44.90252292, 45.75482477, 66.39132287, 49.09289751,
            44.12136195, 36.94944758, 55.77625061, 72.45615516, 42.64679208,
            36.15827058, 47.46426311, 50.1594022 , 61.34719906, 50.24666656,
```

```
       72.82257832, 61.2457838 , 53.39700962, 57.39868305, 48.57293152,
       57.35918979, 57.53669183, 58.81114862, 59.48403566, 43.86471224,
       58.86582956, 62.38397137, 40.25408946, 74.06134299, 59.87113365,
       53.87369092, 23.17348656, 50.36778101, 39.76523396, 39.23507102,
       66.25415475, 76.92465992, 67.08679626, 88.63058721, 69.94709173,
       81.71298596, 60.28424099, 52.87987216, 34.54000653, 69.97328583,
       72.35358167, 69.13945465, 39.00866426, 65.26703103, 59.15808062,
       89.75618753, 48.25489582, 43.69213911, 41.7011117 , 61.29603518,
       46.05738464, 45.1169949 , 51.634607  , 75.3044062 , 37.06750567,
       53.1672226 , 56.05108554, 57.34846351, 68.25304461, 43.80596326,
       49.27520962, 49.47467495, 47.3583425 , 65.92474767, 75.65825002,
       54.82867404, 47.62020652, 59.97488683, 73.07575797, 42.23386784,
       66.8105086 , 63.25886819, 86.21502161, 63.4360195 , 68.40686272,
       57.87305522, 50.62704836, 78.28471823, 71.60733955, 51.50928421,
       41.08084229, 63.82111787, 51.10200687, 63.96651073, 41.1639573 ,
       32.33285274, 64.08450346, 36.88919959, 56.81072933, 45.19939431,
       58.07191256, 78.71220428, 66.43089494, 29.70750469, 46.19887963,
       67.00117591, 45.23811297, 47.27368972, 60.71366812, 86.33861384,
       70.89815472, 38.4820892 , 62.73196784, 40.89591571, 37.91026797,
       71.17302053, 36.12506115, 61.58767009, 71.88359067, 49.78345621,
       38.86272451, 53.19647958, 72.87996529, 56.38284216, 64.07200279,
       48.31881512, 43.29125181, 64.35592147, 88.06253616, 58.879528  ,
       79.68450329, 48.72802429, 36.3189971 , 76.50297122, 61.25895562,
       46.39711157, 76.84190326, 55.44366437, 32.53696138, 57.83790431,
       63.74665666, 60.78084331, 53.16823033, 40.39254882, 59.14857011,
       55.86347701, 55.2977982 , 55.86353526, 38.84675798, 66.00669633,
       72.85294804, 67.81487278, 77.66552524, 61.07634237, 65.6148375 ,
       53.33254721, 64.81747102, 49.44472136, 71.5511384 , 59.55365522,
       50.2457662 , 77.40612221, 42.50652197, 64.98579687, 58.52711976,
       53.31610045, 35.75531901, 87.19576928, 35.19850916, 84.04728214,
       38.93817235, 67.14299255, 46.33690863, 34.77126929, 47.30777209,
       37.203648  , 90.3481817 , 33.79485456, 47.69396343, 64.92355751,
       69.49657404, 37.57768388, 38.52610628, 62.73968131, 45.927574  ,
       71.23387161, 51.18590346, 45.91561667, 57.11703166, 25.06178871,
       85.47551246, 46.66168228, 60.25913549, 68.04758523, 39.49739738,
       69.31233103, 38.22372255, 54.21354943, 72.69702481, 40.97799105,
       56.54659667, 66.00232945, 81.44625287, 75.53109146, 53.37048451,
       43.24140884, 66.19250831, 58.189171  , 79.96606507, 42.83011538,
       53.32685392, 67.62305981, 38.54144946, 44.74161753, 52.13749064,
       44.27736361, 88.04206223, 74.94097036, 34.94348624, 58.21459323,
       54.73945652])
```

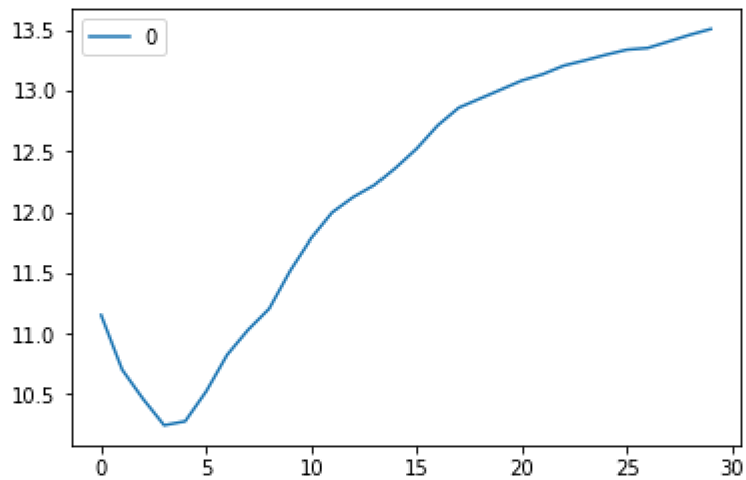
In [50]:
```
#Calculate RMSE for MLR
results.loc[2,'RMSE_value'] = RMSE(ytest,predict_lr)
```

In [51]:
```
######4.KNN Implementation#####
#To find the optimum no. of k-neighbors
from sklearn import neighbors
rmse_val = []           #to store rmse values for different k
for K in range(30):
    K = K+1
    fit_knn = neighbors.KNeighborsRegressor(n_neighbors = K)

    fit_knn.fit(train.iloc[:,0:9], train.iloc[:,9]) #fit the model

    predict_knn = fit_knn.predict(test.iloc[:,0:9]) #make prediction on test s
et
    error = RMSE(test.iloc[:,9] , predict_knn) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K , 'is:', error)
```

```
RMSE value for k=  1 is: 11.153251569660375
RMSE value for k=  2 is: 10.703598535302893
RMSE value for k=  3 is: 10.461502793337868
RMSE value for k=  4 is: 10.24520928393388
RMSE value for k=  5 is: 10.278038395094114
RMSE value for k=  6 is: 10.524313332699125
RMSE value for k=  7 is: 10.826334677524088
RMSE value for k=  8 is: 11.03296342007458
RMSE value for k=  9 is: 11.206334101539445
RMSE value for k=  10 is: 11.519038722324876
RMSE value for k=  11 is: 11.784640198915543
RMSE value for k=  12 is: 11.996732546506557
RMSE value for k=  13 is: 12.122633184369034
RMSE value for k=  14 is: 12.221470708875344
RMSE value for k=  15 is: 12.363980034205687
RMSE value for k=  16 is: 12.52249374017559
RMSE value for k=  17 is: 12.713882778245173
RMSE value for k=  18 is: 12.859580386913121
RMSE value for k=  19 is: 12.93410101306262
RMSE value for k=  20 is: 13.008329341352274
RMSE value for k=  21 is: 13.083646686083835
RMSE value for k=  22 is: 13.13591593120292
RMSE value for k=  23 is: 13.206576035119262
RMSE value for k=  24 is: 13.249855792399245
RMSE value for k=  25 is: 13.295892311617898
RMSE value for k=  26 is: 13.337907696810568
RMSE value for k=  27 is: 13.352222725476311
RMSE value for k=  28 is: 13.406065673578256
RMSE value for k=  29 is: 13.460588607956604
RMSE value for k=  30 is: 13.508655980403478
```

In [52]:
```
#plotting the rmse values against k values
curve = pd.DataFrame(rmse_val)
curve.plot()
#K=3 is the value of neighbors for least RMSE.
```

Out[52]: <matplotlib.axes._subplots.AxesSubplot at 0x1ae5a41b470>




In [53]:
```
#For K=3:
fit_knn = neighbors.KNeighborsRegressor(n_neighbors = 3)
fit_knn.fit(train.iloc[:,0:9], train.iloc[:,9]) #fit the model
predict_knn = fit_knn.predict(test.iloc[:,0:9]) #make prediction on test set
results.loc[3,'RMSE_value'] = RMSE(test.iloc[:,9] , predict_knn) #RMSE error f
or KNN
```

In [54]:
```
#Comparing the RMSE errors of all algorithms:
results
```

Out[54]:

| | Algorithm | RMSE_value |
|---|---|---|
| 0 | Decision Tree | 10.356044 |
| 1 | Random Forest | 5.785979 |
| 2 | Linear Regression | 5.158987 |
| 3 | KNN | 10.461503 |

In [55]:
```
'''
After comparing the errors or RMSE for each algorithm, we find Multivariate Li
near Regression to be most appropriate as it gives the least error.
Also, linear Models have fewer parametersRa compared to Random Forests and so
 Random Forests might overfit more easily than a Linear Regression model.
-> Hence, We can choose "Multivariate Linear Regression" for modelling this da
taset.
'''
```

Out[55]:
```
'\nAfter comparing the errors or RMSE for each algorithm, we find Multivariat
e Linear Regression to be most appropriate as it gives the least error.\nAls
o, linear Models have fewer parametersRa compared to Random Forests and so Ra
ndom Forests might overfit more easily than a Linear Regression model.\n-> He
nce, We can choose "Multivariate Linear Regression" for modelling this datase
t.\n'
```