<pre>In [1]: In [2]: Out[2]:</pre>	import pandas as pd import numpy as np import matplotlib.pyplot as plt import seaborn as sns %matplotlib inline df=pd.read_csv("car data.csv") df.head() Car Name Year Selling Price Present Price Kms Driven Fuel Type Seller Type Transmission Owner 0 ritz 2014 3.35 5.59 27000 Petrol Dealer Manual 0 1 sx4 2013 4.75 9.54 43000 Diesel Dealer Manual 0 2 ciaz 2017 7.25 9.85 6900 Petrol Dealer Manual 0 3 wagon r 2011 2.85 4.15 5200 Petrol Dealer Manual 0
In [4]:	(301, 9) df.isnull().sum() Car_Name
<pre>In [5]: In [6]: Out[6]:</pre>	<pre>print(df['Seller_Type'].unique()) print(df['Fuel_Type'].unique()) print(df['Transmission'].unique()) print(df['Owner'].unique()) ['Dealer' 'Indivaual'] ['Petrol' 'Diesel' 'CNG'] ['Manual' 'Automatic'] [0 1 3] df.describe() Year Selling_Price Present_Price Kms_Driven Owner count 301.000000 301.000000 301.000000 301.000000</pre>
In [7]: In [8]: Out[8]:	0 2014 3.35 5.59 27000 Petrol Dealer Manual 0 1 2013 4.75 9.54 43000 Diesel Dealer Manual 0 2 2017 7.25 9.85 6900 Petrol Dealer Manual 0 3 2011 2.85 4.15 5200 Petrol Dealer Manual 0
<pre>In [9]: In [10]: Out[10]: In [11]: In [12]: Out[12]:</pre>	0 2014 3.35 5.59 27000 Petrol Dealer Manual 0 2022 1 2013 4.75 9.54 43000 Diesel Dealer Manual 0 2022 2 2017 7.25 9.85 6900 Petrol Dealer Manual 0 2022 3 2011 2.85 4.15 5200 Petrol Dealer Manual 0 2022 4 2014 4.60 6.87 42450 Diesel Dealer Manual 0 2022 final_dataset['no_year']=final_dataset['Current Year']- final_dataset['Year'] final_dataset.head()
In [13]: In [14]: Out[14]: In [15]: In [16]:	0 3.35 5.59 27000 Petrol Dealer Manual 0 8 1 4.75 9.54 43000 Diesel Dealer Manual 0 9 2 7.25 9.85 6900 Petrol Dealer Manual 0 5 3 2.85 4.15 5200 Petrol Dealer Manual 0 11 4 4.60 6.87 42450 Diesel Dealer Manual 0 8 final_dataset=pd.get_dummies(final_dataset,drop_first=True)
<pre>In [17]: Out[17]:</pre>	3 2.85 4.15 5200 0 11 0 1 0 1 4 4.60 6.87 42450 0 8 1 0 0 0 1 final_dataset.corr() Elling_Price Present_Price Km_Driven Owner no.year Fuel_Type_Diesel Fuel_Type_Petrol Selling_Price Present_Price Nm_Driven 0.089983 0.029187 0.088344 0.236141 0.0550724 0.0540671 -0.550724 -0.550724 -0.367128 Present_Price 0.878983 1.00000 0.089147 0.008547 0.046524 0.47336 -0.465244 -0.51203 -0.348715 Km_Driven 0.029187 0.089147 0.050047 0.052442 0.172515 -0.172814 -0.101491 -0.162510 Owner -0.088344 0.00857 0.08916 0.052442 0.053469 0.053469 0.059999 0.03986 -0.00394 </th
In [18]: Out[18]:	Transmission_Manual
In [19]:	top_corr_features = corrmat.index plt.figure(figsize=(20,20)) #plot heat map g=sns.heatmap(final_dataset[top_corr_features].corr(), annot=True, cmap="RdY1Gn")
	94 0029 02 1 0089 0.52 0.17 0.17 0.1 0.16
	1 0.089 0.52 0.17 -0.17 -0.1 -0.16 1 - 0.088 0.0081 0.089 1 0.18 -0.053 0.056 0.12 -0.05 - 0.24 0.048 0.52 0.18 1 -0.064 0.06 0.04 -0.0039 - 0.00
	The state of the
<pre>In [20]: In [21]: Out[21]:</pre>	x=final_dataset.drop(['Selling_Price'], axis=1) y=final_dataset('Selling_Price'] x.head() Present_Price Kms_Driven Owner no_year Fuel_Type_Diesel Fuel_Type_Petrol Seller_Type_Individual Transmission_Manual
In [22]: Out[22]:	0 5.59 27000 0 8 0 1 0 1 1 9.54 43000 0 9 1 0 0 1 2 9.85 6900 0 5 0 1 0 1 3 4.15 5200 0 11 0 1 0 1 4 6.87 42450 0 8 1 0 0 1
In [23]: In [24]: In [25]:	Feature importance checking Extra Tree Regressor is use to check which are the importance feature in this datasets & which are not. from sklearn.ensemble import ExtraTreesRegressor model=ExtraTreesRegressor() model.fit(x,y)
In [26]: In [27]:	print(model.feature_importances_) [3.96234216e-01 4.06737581e-02 2.94386327e-04 7.79593949e-02 2.16200228e-01 8.57559231e-03 1.23728867e-01 1.36333558e-01] #plot graph of feature importances for better visualization feat_importances = pd.Series(model.feature_importances_, index=x.columns) feat_importances.nlargest(5).plot(kind='barh') plt.show() **Seller_Type_Individual
In [28]: In [29]:	Fuel_Type_Diesel - Present_Price - 0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 from sklearn.model_selection import train_test_split X_train, X_test, y_train, y_test=train_test_split(x, y, test_size=0.2) from sklearn.ensemble import RandomForestRegressor
	HYPERPARAMETER TUNING n_estimators=[int (x) for x in np.linspace(start = 100, stop = 1200, num = 12)] print(n_estimators) [100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200] from sklearn.model_selection import RandomizedSearchCV #Randomized Search CV # Number of trees in random forest n_estimators = [int(x) for x in np.linspace(start = 100, stop = 1200, num = 12)] #Number of features to consider at every split
In [33]:	<pre>max_features = ['auto', 'sqrt'] # Maximum number of levels in tree max_depth = [int(x) for x in np.linspace(5, 30, num = 6)] # max_depth.append(None) # Minimum number of samples required to split a node min_samples_split = [2, 5, 10, 15, 100] # Minimum number of samples required at each leaf node min_samples_leaf = [1, 2, 5, 10] # Create the random grid random_grid = {'n_estimators': n_estimators,</pre>
<pre>In [34]: In [35]: In [36]: Out[36]:</pre>	<pre>{'n_estimators': [100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200], 'max_features': ['auto', 'sqrt'], 'max_depth': [5, 10, 15, 20, 25, 30], 'min_samples_split': [2, 5, 10]] rf = RandomForestRegressor() rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, scoring='neg_mean_squared_error', n_iter = 10, cv = 5, verbose=2, random_state=42, n_jobs = -1) rf_random.fit(X_train,y_train) Fitting 5 folds for each of 10 candidates, totalling 50 fits RandomizedSearchCV(cv=5, estimator=RandomForestRegressor(), n_jobs=-1, param_distributions=('max_depth': [5, 10, 15, 20, 25, 30],</pre>
<pre>In [37]: Out[37]: In [38]: Out[39]:</pre>	rf_random.best_params_ {'n_estimators': 1000, 'min_samples.split': 2, 'min_samples.leaf': 1, 'max_features': 'sqrt', 'max_depth': 25} predition = rf_random.predict(X_test) predition array([4.4422 , 4.1966 , 2.8974 , 3.75851 , 0.94295 , 4.83198 , 4.63995 , 0.51226 , 4.63238 , 7.69968 , 1.4181 , 0.47679 , 19.7588 , 9.41492 , 0.96747 , 8.4545 , 0.66626 , 0.61162 , 13.10156 , 0.9198 , 0.88532 , 0.74289 , 1.0072 , 4.88912 , 6.86339 , 10.2402 , 5.6373 , 6.22873 , 2.83336 , 11.02798 , 0.54862 , 0.4558 , 6.11584 , 4.42008 , 3.7779 , 0.68074 , 2.31865 , 3.43232 , 0.95022 , 1.33602 , 0.74304 , 3.4631 , 0.54592 , 2.53845 , 2.35074 , 9.54179 , 1.2443 , 0.67101 , 8.19261 , 4.2226 , 5.40478 , 8.57167 , 2.8195 , 4.59 ,
<pre>In [40]: Out[40]:</pre>	0.60865, 3.73006, 6.25788, 0.47274, 7.4058, 6.48212, 1.21582]) sns.distplot(y_test-predition) C:\Users\lenovo\anaconda3\lib\site-packages\seaborn\distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed in a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms). warnings.warn(msg, FutureWarning)
In [41]: Out[41]:	plt.scatter(y_test, predition) <matplotlib.collections.pathcollection 0x2068e309400="" at=""> 20.0 17.5</matplotlib.collections.pathcollection>
In [42]: In [43]:	print('MAE:', metrics.mean_absolute_error(y_test, predition)) print('MSE:', metrics.mean_squared_error(y_test, predition))
	print('MMSE:', np.sqrt(metrics.mean_squared_error(y_test, predition))) MAE: 0.5547409836065497 MSE: 0.9344097436622749 RMSE: 0.9666487179230493