In [103]:
```
# Supress Warnings
import warnings
warnings.filterwarnings('ignore')
```

In [104]:
```
# Importing all required packages

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
from sklearn.preprocessing import scale
from sklearn.model_selection import train_test_split
from sklearn.linear_model import Ridge, Lasso
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import GridSearchCV

# Importing RFE and LinearRegression
from sklearn.feature_selection import RFE
from sklearn.linear_model import LinearRegression
```

Step 1: Reading and Understanding the Data

In [105]:
```
df = pd.read_csv("auto-mpg-1.csv")
```

In [106]:
```
df.head()
```

Out[106]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	torque	seats
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.4 kmpl	1248 CC	74 bhp	190Nm@ 2000rpm	5.0
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14 kmpl	1498 CC	103.52 bhp	250Nm@ 1500-2500rpm	5.0
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	17.7 kmpl	1497 CC	78 bhp	12.7@ 2,700(kgm@ rpm)	5.0
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	23.0 kmpl	1396 CC	90 bhp	22.4 kgm at 1750-2750rpm	5.0
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	16.1 kmpl	1298 CC	88.2 bhp	11.5@ 4,500(kgm@ rpm)	5.0

In [107]:
```
df = df.drop(['torque'], axis = 1)
```

In [108]:
```python
print("*********************************  Info *******************************************")
print(df.info())
print("*********************************  Shape ******************************************")
print(df.shape)
print("**************************** Columns having null values *****************************")
print(df.isnull().any())
print("**************************** Describe *****************************")
df.describe()
```

```
*********************************  Info *******************************************
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8128 entries, 0 to 8127
Data columns (total 12 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   name           8128 non-null   object
 1   year           8128 non-null   int64
 2   selling_price  8128 non-null   int64
 3   km_driven      8128 non-null   int64
 4   fuel           8128 non-null   object
 5   seller_type    8128 non-null   object
 6   transmission   8128 non-null   object
 7   owner          8128 non-null   object
 8   mileage        7907 non-null   object
 9   engine         7907 non-null   object
 10  max_power      7913 non-null   object
 11  seats          7907 non-null   float64
dtypes: float64(1), int64(3), object(8)
memory usage: 762.1+ KB
None
*********************************  Shape ******************************************
(8128, 12)
**************************** Columns having null values *****************************
name             False
year             False
selling_price    False
km_driven        False
fuel             False
seller_type      False
transmission     False
owner            False
mileage           True
engine            True
max_power         True
seats             True
dtype: bool
**************************** Describe *****************************
```

Out[108]:

	year	selling_price	km_driven	seats
count	8128.000000	8.128000e+03	8.128000e+03	7907.000000
mean	2013.804011	6.382718e+05	6.981951e+04	5.416719
std	4.044249	8.062534e+05	5.655055e+04	0.959588
min	1983.000000	2.999900e+04	1.000000e+00	2.000000
25%	2011.000000	2.549990e+05	3.500000e+04	5.000000
50%	2015.000000	4.500000e+05	6.000000e+04	5.000000
75%	2017.000000	6.750000e+05	9.800000e+04	5.000000
max	2020.000000	1.000000e+07	2.360457e+06	14.000000

In [109]:
```python
df.select_dtypes(include='object').isnull().sum()[df.select_dtypes(include='object').isnull().sum()>0]
```

Out[109]:
```
mileage      221
engine       221
max_power    215
dtype: int64
```

In [110]:
```python
df = df.dropna()
```

In [111]:
```
df.select_dtypes(include='object').isnull().sum()[df.select_dtypes(include='object').isnull().sum()>0]
```
Out[111]:
```
Series([], dtype: int64)
```

No more null values

In [112]:
```
df['mileage'] = df['mileage'].str.replace('kmpl', '')
df['mileage'] = df['mileage'].str.replace('km/kg', '')
df['engine'] = df['engine'].str.replace('CC', '')
df['max_power'] = df['max_power'].str.replace('bhp', '')
```

In [113]:
```
#deleting rows that had a unit but no numeric values and converting all values to type float
df['mileage'] = pd.to_numeric(df['mileage'],errors = 'coerce')
df['engine'] = pd.to_numeric(df['engine'],errors = 'coerce')
df['max_power'] = pd.to_numeric(df['max_power'],errors = 'coerce')
```

In [114]:
```
df = df.dropna()
```

In [115]:
```
df
```
Out[115]:

	name	year	selling_price	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	seats
0	Maruti Swift Dzire VDI	2014	450000	145500	Diesel	Individual	Manual	First Owner	23.40	1248	74.00	5.0
1	Skoda Rapid 1.5 TDI Ambition	2014	370000	120000	Diesel	Individual	Manual	Second Owner	21.14	1498	103.52	5.0
2	Honda City 2017-2020 EXi	2006	158000	140000	Petrol	Individual	Manual	Third Owner	17.70	1497	78.00	5.0
3	Hyundai i20 Sportz Diesel	2010	225000	127000	Diesel	Individual	Manual	First Owner	23.00	1396	90.00	5.0
4	Maruti Swift VXI BSIII	2007	130000	120000	Petrol	Individual	Manual	First Owner	16.10	1298	88.20	5.0
...	...	...	...	...	...	...	...	...	...	...	...	...
8123	Hyundai i20 Magna	2013	320000	110000	Petrol	Individual	Manual	First Owner	18.50	1197	82.85	5.0
8124	Hyundai Verna CRDi SX	2007	135000	119000	Diesel	Individual	Manual	Fourth & Above Owner	16.80	1493	110.00	5.0
8125	Maruti Swift Dzire ZDi	2009	382000	120000	Diesel	Individual	Manual	First Owner	19.30	1248	73.90	5.0
8126	Tata Indigo CR4	2013	290000	25000	Diesel	Individual	Manual	First Owner	23.57	1396	70.00	5.0
8127	Tata Indigo CR4	2013	290000	25000	Diesel	Individual	Manual	First Owner	23.57	1396	70.00	5.0

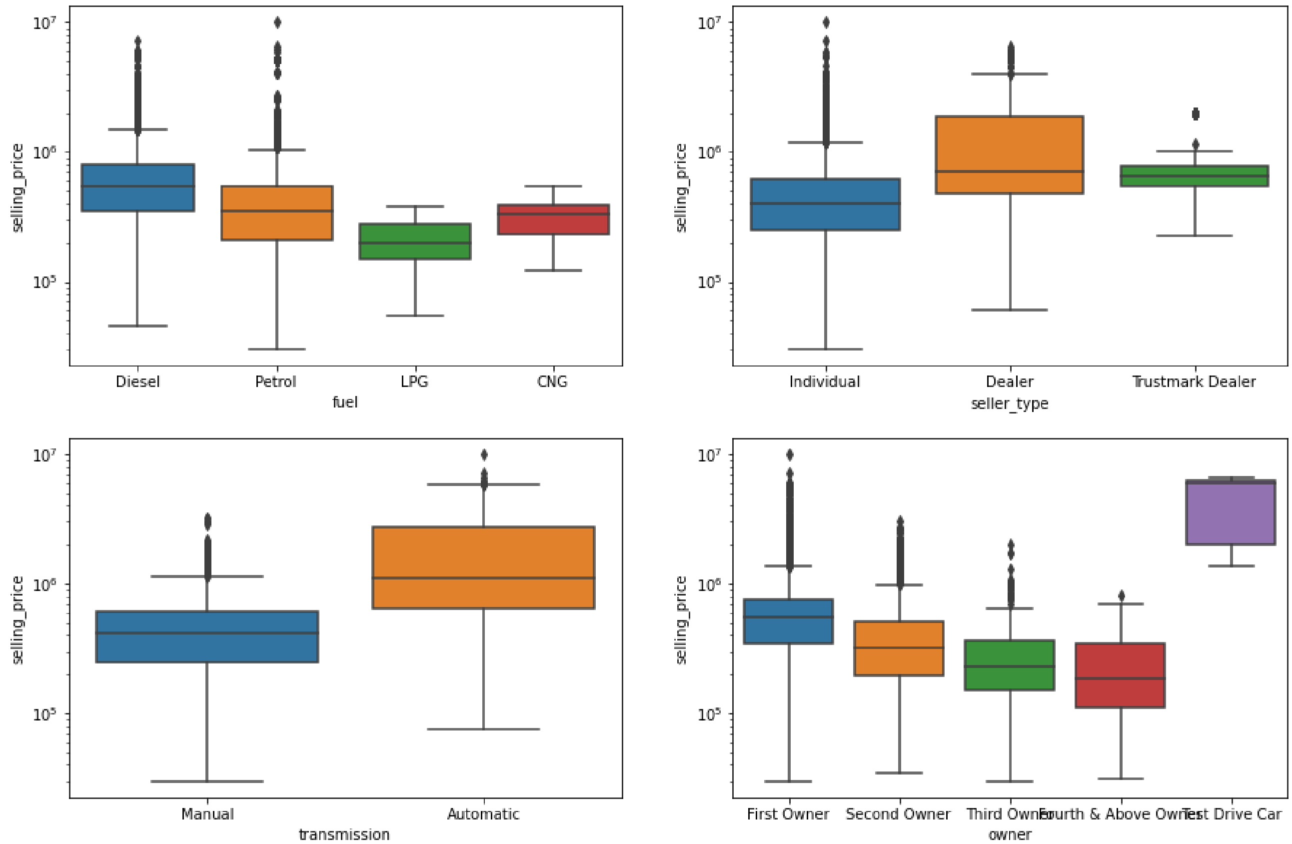
7906 rows × 12 columns

In [116]:
```
X = df.drop(columns=['selling_price'])
y = df['selling_price']
```

Plotting the relationships between the label (Selling Price) and the discrete features (fuel type, Seller type, transmission) using a small multiple of box plots

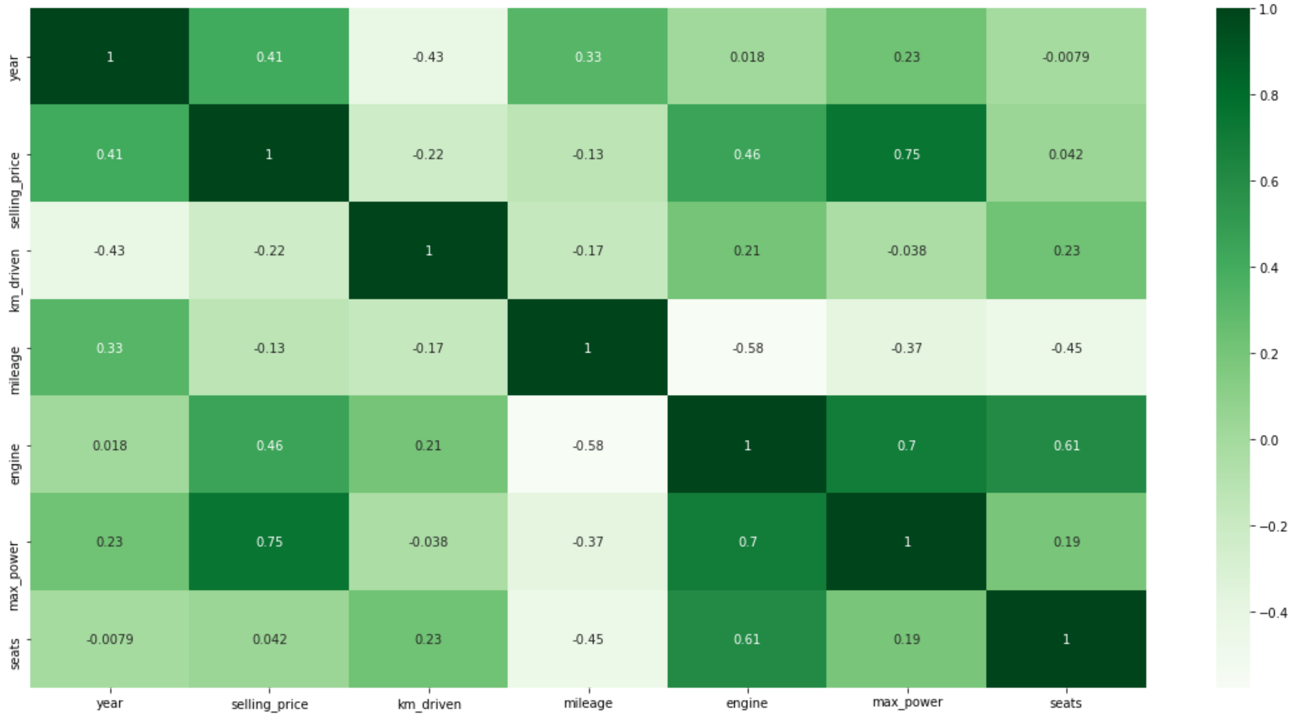
In [117]:
```
disc_features = ['fuel', 'seller_type', 'transmission', 'owner']
df1 = X[disc_features]
target = y
```

In [118]:
```
fig, ax = plt.subplots(2,2,figsize=(15,10))
for var, subplot in zip(disc_features, ax.flatten()):
    plot = sns.boxplot(x=var, y=target, data = df1, ax=subplot)
    plot.set_yscale("log")
```



From the plots for the continuous variable, we observe a linear relationship as stated earlier. Additionally, the discrete features also can potentially be modeled in a linear fashion. Hence, linear regressions seem to be a suitable model for the given problem.

In [119]:
```python
# Check the correlation of numerical columns

plt.figure(figsize = (20, 10))
sns.heatmap(df.corr(), annot = True, cmap="Greens")
plt.show()
```



In [120]:
```
X
```

Out[120]:

	name	year	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	seats
0	Maruti Swift Dzire VDI	2014	145500	Diesel	Individual	Manual	First Owner	23.40	1248	74.00	5.0
1	Skoda Rapid 1.5 TDI Ambition	2014	120000	Diesel	Individual	Manual	Second Owner	21.14	1498	103.52	5.0
2	Honda City 2017-2020 EXi	2006	140000	Petrol	Individual	Manual	Third Owner	17.70	1497	78.00	5.0
3	Hyundai i20 Sportz Diesel	2010	127000	Diesel	Individual	Manual	First Owner	23.00	1396	90.00	5.0
4	Maruti Swift VXI BSIII	2007	120000	Petrol	Individual	Manual	First Owner	16.10	1298	88.20	5.0
...	...	...	...	...	...	...	...	...	...	...	...
8123	Hyundai i20 Magna	2013	110000	Petrol	Individual	Manual	First Owner	18.50	1197	82.85	5.0
8124	Hyundai Verna CRDi SX	2007	119000	Diesel	Individual	Manual	Fourth & Above Owner	16.80	1493	110.00	5.0
8125	Maruti Swift Dzire ZDi	2009	120000	Diesel	Individual	Manual	First Owner	19.30	1248	73.90	5.0
8126	Tata Indigo CR4	2013	25000	Diesel	Individual	Manual	First Owner	23.57	1396	70.00	5.0
8127	Tata Indigo CR4	2013	25000	Diesel	Individual	Manual	First Owner	23.57	1396	70.00	5.0

7906 rows × 11 columns

In [121]:
```
X['year'] =  2020 - X['year']
```

In [122]:
```
#dropping the car name as it is irrelevant.
X.drop(["name"],axis = 1,inplace=True)

#check out the dataset with new changes
X.head()
```

Out[122]:

	year	km_driven	fuel	seller_type	transmission	owner	mileage	engine	max_power	seats
0	6	145500	Diesel	Individual	Manual	First Owner	23.40	1248	74.00	5.0
1	6	120000	Diesel	Individual	Manual	Second Owner	21.14	1498	103.52	5.0
2	14	140000	Petrol	Individual	Manual	Third Owner	17.70	1497	78.00	5.0
3	10	127000	Diesel	Individual	Manual	First Owner	23.00	1396	90.00	5.0
4	13	120000	Petrol	Individual	Manual	First Owner	16.10	1298	88.20	5.0

In [123]:
```
fuel_ohc = pd.get_dummies(X['fuel'])
seller_type_ohc = pd.get_dummies(X['seller_type'])
transmission_ohc = pd.get_dummies(X['transmission'])
owner_ohc = pd.get_dummies(X['owner'])

X = pd.concat([X, fuel_ohc,seller_type_ohc,transmission_ohc,owner_ohc], axis=1)
X = X.drop(columns=['seller_type','fuel','owner','transmission'])
```

In [124]:
```
#dataframe after one hot encoding for categorical variables
X.head()
```

Out[124]:

	year	km_driven	mileage	engine	max_power	seats	CNG	Diesel	LPG	Petrol	Dealer	Individual	Trustmark Dealer	Automatic	Manual	Fi Owr
0	6	145500	23.40	1248	74.00	5.0	0	1	0	0	0	1	0	0	1	
1	6	120000	21.14	1498	103.52	5.0	0	1	0	0	0	1	0	0	1	
2	14	140000	17.70	1497	78.00	5.0	0	0	0	1	0	1	0	0	1	
3	10	127000	23.00	1396	90.00	5.0	0	1	0	0	0	1	0	0	1	
4	13	120000	16.10	1298	88.20	5.0	0	0	0	1	0	1	0	0	1	

In [125]:
```
y
```

Out[125]:
```
0       450000
1       370000
2       158000
3       225000
4       130000
         ...
8123    320000
8124    135000
8125    382000
8126    290000
8127    290000
Name: selling_price, Length: 7906, dtype: int64
```

Train-test-split

In [126]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

In [127]:
```
lm = LinearRegression()
lm.fit(X_train, y_train)

# running RFE
rfe = RFE(lm, 10)
rfe = rfe.fit(X_train, y_train)
```

In [128]:
```
col = X_train.columns[rfe.support_]

# assign the 10 features selected using RFE to a dataframe and view them

temp_df = pd.DataFrame(list(zip(X_train.columns,rfe.support_,rfe.ranking_)), columns=['Variable', 'rfe_su
temp_df = temp_df.loc[temp_df['rfe_support'] == True]
temp_df.reset_index(drop=True, inplace=True)

temp_df
```

Out[128]:

	Variable	rfe_support	rfe_ranking
0	Dealer	True	1
1	Individual	True	1
2	Trustmark Dealer	True	1
3	Automatic	True	1
4	Manual	True	1
5	First Owner	True	1
6	Fourth & Above Owner	True	1
7	Second Owner	True	1
8	Test Drive Car	True	1
9	Third Owner	True	1

In [129]:
```
# Assign the 10 columns to X_train_rfe

X_train_rfe = X_train[col]
```

In [130]:
```
# Associate the new 10 columns to X_train and X_test for further analysis

X_train = X_train_rfe[X_train_rfe.columns]
X_test =  X_test[X_train.columns]
```

Model Building and Evaluation

In [131]:
```python
# list pf alphas

params = {'alpha': [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0, 4.0
                    9.0, 10.0, 20, 50, 100, 500, 1000 ]}

ridge = Ridge()

# cross validation

folds = 5
ridge_model_cv = GridSearchCV(estimator = ridge,
                        param_grid = params,
                        scoring= 'neg_mean_absolute_error',
                        cv = folds,
                        return_train_score=True,
                        verbose = 1)
ridge_model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 27 candidates, totalling 135 fits
```

Out[131]:
```
GridSearchCV(cv=5, estimator=Ridge(),
             param_grid={'alpha': [0.0001, 0.001, 0.01, 0.1, 0.2, 0.3, 0.4, 0.5,
                                   0.6, 0.7, 0.8, 0.9, 1.0, 2.0, 3.0, 4.0, 5.0,
                                   6.0, 7.0, 8.0, 9.0, 10.0, 20, 50, 100, 500,
                                   1000]},
             return_train_score=True, scoring='neg_mean_absolute_error',
             verbose=1)
```

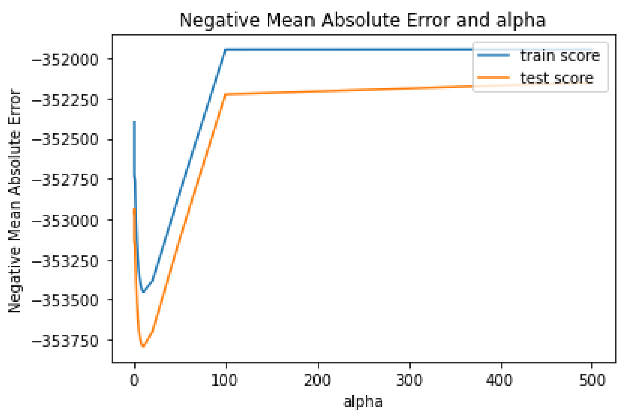
In [132]:

```python
# display the mean scores

ridge_cv_results = pd.DataFrame(ridge_model_cv.cv_results_)
ridge_cv_results = ridge_cv_results[ridge_cv_results['param_alpha']<=500]
ridge_cv_results[['param_alpha', 'mean_train_score', 'mean_test_score', 'rank_test_score']].sort_values(b
```

Out[132]:

	param_alpha	mean_train_score	mean_test_score	rank_test_score
25	500	-351943.427660	-352149.911672	1
24	100	-351944.111765	-352223.388635	2
5	0.3	-352519.917714	-352942.440142	3
4	0.2	-352477.818126	-352943.355404	4
3	0.1	-352433.127534	-352952.400830	5
2	0.01	-352401.019199	-352961.852665	6
1	0.001	-352397.879777	-352962.874129	7
0	0.0001	-352397.564952	-352962.977083	8
6	0.4	-352559.656170	-352978.732596	9
7	0.5	-352597.257289	-353013.466791	10
8	0.6	-352632.842121	-353046.388068	11
9	0.7	-352666.582104	-353077.686892	12
10	0.8	-352698.742403	-353107.585754	13
23	50	-352834.013288	-353122.281073	14
11	0.9	-352729.358281	-353136.115526	15
12	1.0	-352758.495660	-353163.348321	16
13	2.0	-352987.839185	-353377.488084	17
14	3.0	-353139.774391	-353517.935661	18
15	4.0	-353244.114353	-353613.767038	19
16	5.0	-353317.188349	-353680.566119	20
22	20	-353384.213679	-353701.776255	21
17	6.0	-353368.595657	-353727.069423	22
18	7.0	-353404.217586	-353758.430509	23
19	8.0	-353428.808274	-353778.624775	24
20	9.0	-353445.042192	-353790.353159	25
21	10.0	-353454.233247	-353795.603748	26

In [133]:
```
# plotting mean test and train scoes with alpha

ridge_cv_results['param_alpha'] = ridge_cv_results['param_alpha'].astype('int32')

# plotting

plt.plot(ridge_cv_results['param_alpha'], ridge_cv_results['mean_train_score'])
plt.plot(ridge_cv_results['param_alpha'], ridge_cv_results['mean_test_score'])
plt.xlabel('alpha')
plt.ylabel('Negative Mean Absolute Error')
plt.title("Negative Mean Absolute Error and alpha")
plt.legend(['train score', 'test score'], loc='upper right')
plt.show()
```



In [134]:
```
# get the best estimator for lambda

ridge_model_cv.best_estimator_
```

Out[134]: Ridge(alpha=500)

In [135]:
```
# check the coefficient values with lambda = 10

alpha = 500
ridge = Ridge(alpha=alpha)

ridge.fit(X_train, y_train)
ridge.coef_
```

Out[135]:
```
array([ 238767.39832227, -175765.31695917,  -63002.0813631 ,
        449820.57748154, -449820.57748154,  138455.66268397,
        -40899.26938719,  -58164.510249  ,   27902.33582309,
        -67294.21887086])
```

In [136]:
```
# Put the Features and coefficienst in a dataframe

ridge_df = pd.DataFrame({'Features':X_train.columns, 'Coefficient':ridge.coef_.round(4)})
ridge_df.reset_index(drop=True, inplace=True)
ridge_df
```

Out[136]:

	Features	Coefficient
0	Dealer	238767.3983
1	Individual	-175765.3170
2	Trustmark Dealer	-63002.0814
3	Automatic	449820.5775
4	Manual	-449820.5775
5	First Owner	138455.6627
6	Fourth & Above Owner	-40899.2694
7	Second Owner	-58164.5102
8	Test Drive Car	27902.3358
9	Third Owner	-67294.2189

In [137]:
```python
# Assign the Features and their coefficient values to a dictionary which would be used while plotting the

ridge_coeff_dict = dict(pd.Series(ridge.coef_.round(4), index = X_train.columns))
ridge_coeff_dict
```

Out[137]:
```
{'Dealer': 238767.3983,
 'Individual': -175765.317,
 'Trustmark Dealer': -63002.0814,
 'Automatic': 449820.5775,
 'Manual': -449820.5775,
 'First Owner': 138455.6627,
 'Fourth & Above Owner': -40899.2694,
 'Second Owner': -58164.5102,
 'Test Drive Car': 27902.3358,
 'Third Owner': -67294.2189}
```

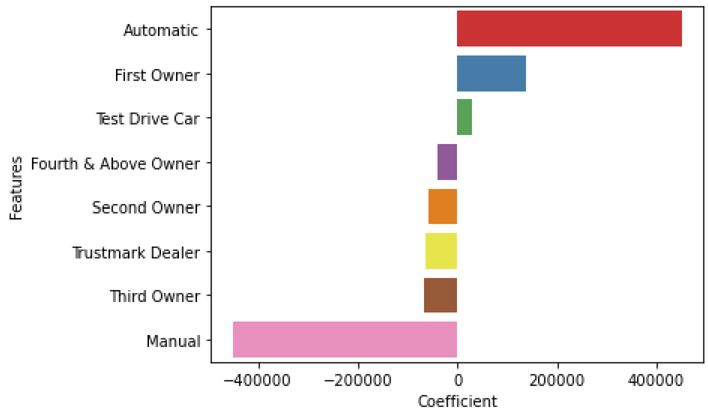
In [138]:
```python
# Do an RFE to minimise the features to 8
X_train_ridge = X_train[ridge_df.Features]

lm = LinearRegression()
lm.fit(X_train_ridge, y_train)

# running RFE
rfe = RFE(lm, 8)
rfe = rfe.fit(X_train_ridge, y_train)
```

In [139]:
```python
# Method to get the coefficient values

def find(x):
    return ridge_coeff_dict[x]

# Assign top 10 features to a temp dataframe for further display in the bar plot

temp1_df = pd.DataFrame(list(zip( X_train_ridge.columns, rfe.support_, rfe.ranking_)), columns=['Features
temp1_df = temp1_df.loc[temp1_df['rfe_support'] == True]
temp1_df.reset_index(drop=True, inplace=True)

temp1_df['Coefficient'] = temp1_df['Features'].apply(find)
temp1_df = temp1_df.sort_values(by=['Coefficient'], ascending=False)
temp1_df = temp1_df.head(10)
temp1_df
```

Out[139]:

	Features	rfe_support	rfe_ranking	Coefficient
1	Automatic	True	1	449820.5775
3	First Owner	True	1	138455.6627
6	Test Drive Car	True	1	27902.3358
4	Fourth & Above Owner	True	1	-40899.2694
5	Second Owner	True	1	-58164.5102
0	Trustmark Dealer	True	1	-63002.0814
7	Third Owner	True	1	-67294.2189
2	Manual	True	1	-449820.5775

In [140]:
```python
# bar plot to determine the variables that would affect pricing most using ridge regression

plt.figure(figsize=(20,20))
plt.subplot(4,3,1)
sns.barplot(y = 'Features', x='Coefficient', palette='Set1', data = temp1_df)
plt.show()
```



Lasso

In [141]:
```python
lasso = Lasso()

# list of alphas

params = {'alpha': [0.0001, 0.0002, 0.0003, 0.0004, 0.0005, 0.001, 0.002, 0.003, 0.004, 0.005, 0.01]}

# cross validation

folds = 5
lasso_model_cv = GridSearchCV(estimator = lasso,
                        param_grid = params,
                        scoring= 'neg_mean_absolute_error',
                        cv = folds,
                        return_train_score=True,
                        verbose = 1)

lasso_model_cv.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 11 candidates, totalling 55 fits
```

Out[141]:
```
GridSearchCV(cv=5, estimator=Lasso(),
             param_grid={'alpha': [0.0001, 0.0002, 0.0003, 0.0004, 0.0005,
                                   0.001, 0.002, 0.003, 0.004, 0.005, 0.01]},
             return_train_score=True, scoring='neg_mean_absolute_error',
             verbose=1)
```

In [142]:
```python
# display the mean scores

lasso_cv_results = pd.DataFrame(lasso_model_cv.cv_results_)
lasso_cv_results[['param_alpha', 'mean_train_score', 'mean_test_score', 'rank_test_score']].sort_values(
```

Out[142]:

	param_alpha	mean_train_score	mean_test_score	rank_test_score
10	0.01	-352397.533197	-352962.985755	1
9	0.005	-352397.531579	-352962.987143	2
8	0.004	-352397.531256	-352962.987420	3
7	0.003	-352397.530932	-352962.987698	4
6	0.002	-352397.530609	-352962.987976	5
5	0.001	-352397.530285	-352962.988253	6
4	0.0005	-352397.530123	-352962.988392	7
3	0.0004	-352397.530091	-352962.988420	8
2	0.0003	-352397.530059	-352962.988448	9
1	0.0002	-352397.530026	-352962.988475	10
0	0.0001	-352397.529994	-352962.988503	11

In [143]:
```python
lasso_cv_results['param_alpha'] = lasso_cv_results['param_alpha'].astype('float64')
```

In [144]:
```python
# get the best estimator for lambda

lasso_model_cv.best_estimator_
```

Out[144]:
```
Lasso(alpha=0.01)
```

In [145]:
```python

alpha = 0.01

lasso = Lasso(alpha=alpha)

lasso.fit(X_train, y_train)
lasso.coef_
```

Out[145]:
```
array([ 468827.51521879,   29696.28429588, -119603.5397049 ,
       1203787.83059786,      -0.        ,  217243.44913252,
       -112922.03676589,   15582.03475208, 3371031.66951676,
        -52946.59414298])
```

In [146]:
```python
# Put the shortlisted Features and coefficienst in a dataframe

lasso_df = pd.DataFrame({'Features':X_train.columns, 'Coefficient':lasso.coef_.round(4)})
lasso_df = lasso_df[lasso_df['Coefficient'] != 0.00]
lasso_df.reset_index(drop=True, inplace=True)
lasso_df
```

Out[146]:

	Features	Coefficient
0	Dealer	4.688275e+05
1	Individual	2.969628e+04
2	Trustmark Dealer	-1.196035e+05
3	Automatic	1.203788e+06
4	First Owner	2.172434e+05
5	Fourth & Above Owner	-1.129220e+05
6	Second Owner	1.558203e+04
7	Test Drive Car	3.371032e+06
8	Third Owner	-5.294659e+04

In [147]:
```
# Put the Features and Coefficients in dictionary

lasso_coeff_dict = dict(pd.Series(lasso.coef_, index = X_train.columns))
lasso_coeff_dict
```

Out[147]:
```
{'Dealer': 468827.51521878934,
 'Individual': 29696.284295879646,
 'Trustmark Dealer': -119603.53970490451,
 'Automatic': 1203787.8305978617,
 'Manual': -0.0,
 'First Owner': 217243.44913252094,
 'Fourth & Above Owner': -112922.03676589063,
 'Second Owner': 15582.034752076945,
 'Test Drive Car': 3371031.6695167557,
 'Third Owner': -52946.594142984024}
```

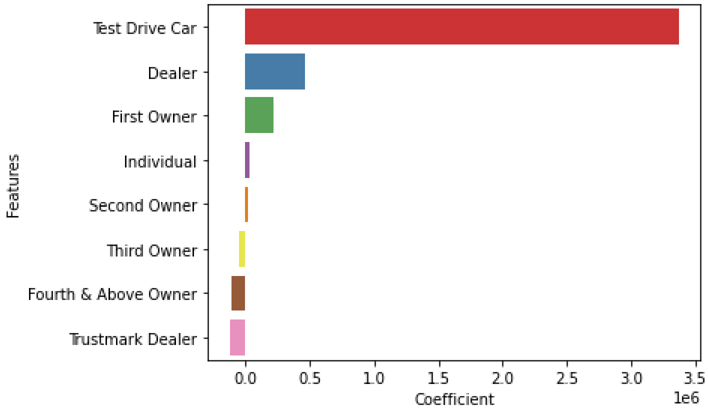
In [148]:
```
# Do an RFE to minimise the features to 8

X_train_lasso = X_train[lasso_df.Features]

lm = LinearRegression()
lm.fit(X_train_lasso, y_train)

# running RFE

rfe = RFE(lm, 8)
rfe = rfe.fit(X_train_lasso, y_train)
```

In [149]:
```
# Method to get the coefficient values

def find(x):
    return lasso_coeff_dict[x]

# Assign top 8 features to a temp dataframe for further display in the bar plot

temp2_df = pd.DataFrame(list(zip( X_train_lasso.columns, rfe.support_, rfe.ranking_)), columns=['Features
temp2_df = temp2_df.loc[temp2_df['rfe_support'] == True]
temp2_df.reset_index(drop=True, inplace=True)

temp2_df['Coefficient'] = temp2_df['Features'].apply(find)
temp2_df = temp2_df.sort_values(by=['Coefficient'], ascending=False)
temp2_df = temp2_df.head(10)
temp2_df
```

Out[149]:

	Features	rfe_support	rfe_ranking	Coefficient
6	Test Drive Car	True	1	3.371032e+06
0	Dealer	True	1	4.688275e+05
3	First Owner	True	1	2.172434e+05
1	Individual	True	1	2.969628e+04
5	Second Owner	True	1	1.558203e+04
7	Third Owner	True	1	-5.294659e+04
4	Fourth & Above Owner	True	1	-1.129220e+05
2	Trustmark Dealer	True	1	-1.196035e+05

In [150]:
```
# bar plot to determine the variables that would affect pricing most using ridge regression

plt.figure(figsize=(20,20))
plt.subplot(4,3,1)
sns.barplot(y = 'Features', x='Coefficient', palette='Set1', data = temp2_df)
plt.show()
```



In [151]:
```
# Check the mean squared error
mean_squared_error(y_test, ridge.predict(X_test))
```

Out[151]: 417808486827.479

In [152]:
```
# Check the mean squared error
mean_squared_error(y_test, lasso.predict(X_test))
```

Out[152]: 403341306275.08484

Conclusion :

- The optimal lambda value in case of Ridge and Lasso is as below:
  - Ridge - 10
  - Lasso - 0.01
- The mean squared error for the dataset is really high. Hence, `linear regression` may not a model to apply on this dataset.
- The mean squared error of Lasso is slightly lower than that of Ridge
- Therefore, the variables predicted by Lasso in the above bar chart are significant variables for predicting the price of the car