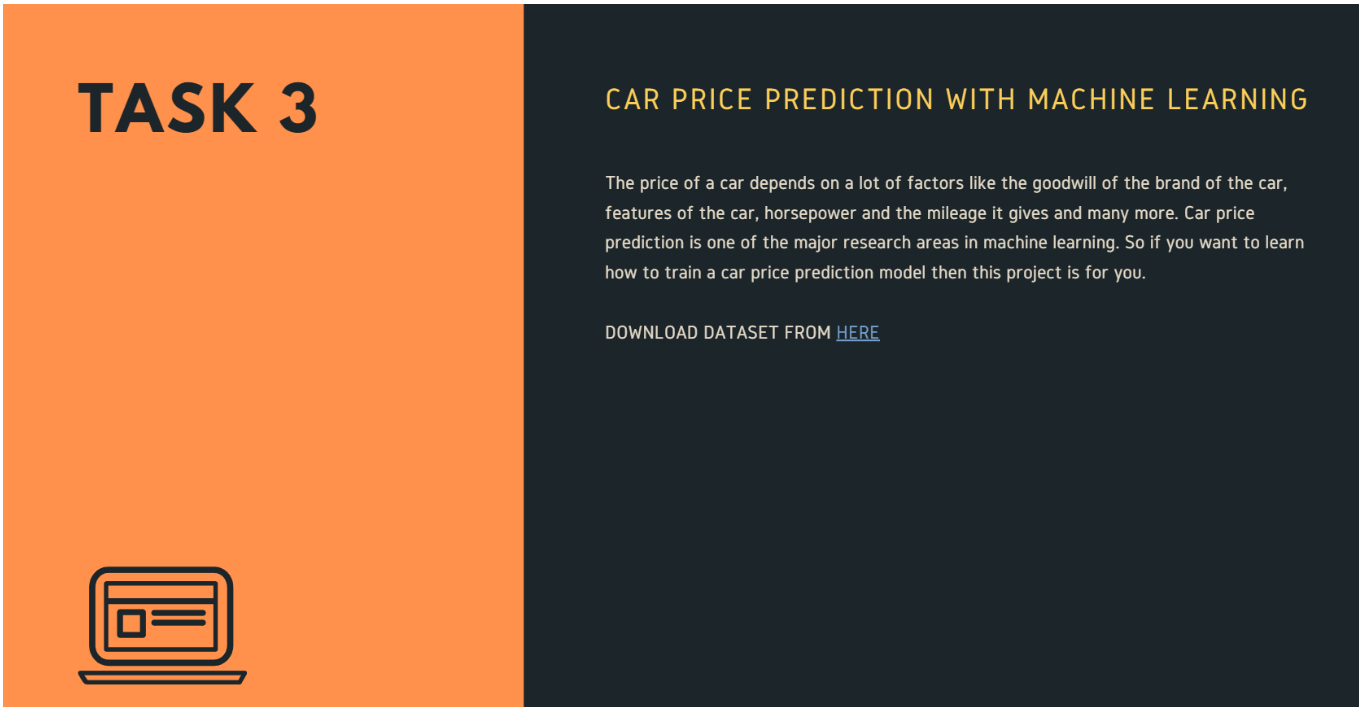
Task 3: Car Price Prediction using Machine learning



Step 1: Loading the data

```
# importing required libraries
import numpy as np
import pandas as pd

import warnings
warnings.filterwarnings("ignore")

from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.linear_model import LinearRegression, Ridge, Lasso
from sklearn.svm import SVR
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import ExtraTreesRegressor, RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, explained_variance_score, r2_score
import pickle

import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

- `numpy` library is used to perform computational operations
- `matplotlib` and seaborn are used for visualization
- `pandas` can help us to load data from various sources
- `warnings` is used to ignores all warning messages in Python.
- `train_test_split`: Splits data into training and testing sets for machine learning model evaluation.
- `RandomizedSearchCV`: Performs hyperparameter tuning using random search and cross-validation to find the best model settings.
- `LinearRegression`: Linear model for regression tasks.
- `Ridge`: Linear regression with L2 regularization for preventing overfitting.
- `Lasso`: Linear regression with L1 regularization and feature selection capability.
- `SVR` : Support Vector Regression
- `DecisionTreeRegressor` : Predicts continuous values using decision tree-based splitting.
- `ExtraTreesRegressor` : Ensemble method with randomized decision trees for regression.
- `RandomForestRegressor` : Ensemble method with multiple decision trees for regression.
- `mean_absolute_error` : Measures absolute difference between predicted and actual values.
- `mean_squared_error` : Measures squared difference between predicted and actual values.
- `explained_variance_score` : Evaluates the proportion of variance explained by the model.
- `pickle` : Python module for serializing and deserializing objects. It converts data structures to binary format for storage or transmission.

```
# Loading Dataset
df = pd.read_csv('/content/drive/MyDrive/Dataset files - Oasis/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
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0

There are total 9 columns in the car price dataset which has description given below

Column name	Description
Car_Name	Name of Car sold
Year	Year in which car was bought
Selling_Price	Price at which car sold
Present_Price	Price of same car model in current year
Kms_Driven	Number of Kilometers Car driven before it is sold
Fuel_Type	Type of fuel Car uses
Seller_Type	Type of seller
Transmission	Gear transmission of the car (Automatic/Manual)
Owner	Number of previous owners

Step 2: EDA

```
print('The size of Dataframe is: ', df.shape)
print('¥n')
df.info()
```

```
The size of Dataframe is:  (301, 9)


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 301 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Car_Name       301 non-null    object 
 1   Year           301 non-null    int64  
 2   Selling_Price  301 non-null    float64
 3   Present_Price  301 non-null    float64
 4   Kms_Driven     301 non-null    int64  
 5   Fuel_Type      301 non-null    object 
 6   Seller_Type    301 non-null    object 
 7   Transmission   301 non-null    object 
 8   Owner          301 non-null    int64  
dtypes: float64(2), int64(3), object(4)
memory usage: 21.3+ KB
```

```
# To find total_missing_values in different columns of data and their percentage
def missing_data(data):
    """
    This will take in a dataframe and
    finds the total_missing_values as well as percentage of the value counts
    """
    total = data.isnull().sum().sort_values(ascending = False)
    percent = (data.isnull().sum()/data.isnull().count()*100).sort_values(ascending = False)
    return pd.concat([total, percent], axis=1, keys=['Total', 'Percent'])
```

```
missing_data(data= df)
```

	Total	Percent
Car_Name	0	0.0
Year	0	0.0
Selling_Price	0	0.0
Present_Price	0	0.0
Kms_Driven	0	0.0
Fuel_Type	0	0.0
Seller_Type	0	0.0
Transmission	0	0.0
Owner	0	0.0

Note: We can observe that there is no need of Data Cleaning as there is no missing values in the given dataset

```
print("'Fuel_Type' variable have {} unique category : {}¥n".format(df['Fuel_Type'].nunique(), df['Fuel_Type'].unique()))
print("'Seller_Type' variable have {} unique category : {}¥n".format(df['Seller_Type'].nunique(), ¥
                                                                df['Seller_Type'].unique()))
print("'Transmission' variable have {} unique category : {}¥n".format(df['Transmission'].nunique(), ¥
                                                               df['Transmission'].unique()))
print("'Owner' variable have {} unique category : {}".format(df['Owner'].nunique(), df['Owner'].unique()))
```

```
'Fuel_Type' variable have 3 unique category : ['Petrol' 'Diesel' 'CNG']

'Seller_Type' variable have 2 unique category : ['Dealer' 'Individual']

'Transmission' variable have 2 unique category : ['Manual' 'Automatic']

'Owner' variable have 3 unique category : [0 1 3]
```

This will print:

- The number of unique categories.
- The unique categories themselves.

for Fuel type, Seller Type, Transmission, Owner

```
df['Owner'].replace(to_replace=3, value=2, inplace= True)
print("'Owner' variable have {} unique category : {}".format(df['Owner'].nunique(), df['Owner'].unique()))
```

```
'Owner' variable have 3 unique category : [0 1 2]
```

The code replaces any occurrence of '3' with '2' in the 'Owner' column and then prints the number of unique categories and the unique categories in the 'Owner' column.

```
# Descriptive statistical summary of numerical features
df.describe()
```

	Year	Selling_Price	Present_Price	Kms_Driven	Owner
count	301.000000	301.000000	301.000000	301.000000	301.000000
mean	2013.627907	4.661296	7.628472	36947.205980	0.039867
std	2.891554	5.082812	8.644115	38886.883882	0.212302
min	2003.000000	0.100000	0.320000	500.000000	0.000000
25%	2012.000000	0.900000	1.200000	15000.000000	0.000000
50%	2014.000000	3.600000	6.400000	32000.000000	0.000000
75%	2016.000000	6.000000	9.900000	48767.000000	0.000000
max	2018.000000	35.000000	92.600000	500000.000000	2.000000

The code provides a summary of statistics for numerical features in the DataFrame `df` using `df.describe()`.

```
# Descriptive statistical summary of categorical features
df.describe(include= 'object')
```

	Car_Name	Fuel_Type	Seller_Type	Transmission
count	301	301	301	301
unique	98	3	2	2
freq	26	239	195	261

The code provides a summary of statistics for categorical features in the DataFrame df using df.describe(include='object').

Step 3: Extracting the features

```
# Let's see all column names
df.columns
```

```
Index(['Car_Name', 'Year', 'Selling_Price', 'Present_Price', 'Kms_Driven',
       'Fuel_Type', 'Seller_Type', 'Transmission', 'Owner'],
      dtype='object')
```

Now we will try to find of how old the car is from the 'Year'

```
# Let's create a new variable 'Current_Year'
df['Current_Year'] = 2023

# To Calculate how old the car is, I created new feature "No_of_Years"
df['No_of_Years'] = df['Current_Year'] - df['Year']

df.head()
```

	Car_Name	Year	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner	Current_Year	No_of_Ye
0	ritz	2014	3.35	5.59	27000	Petrol	Dealer	Manual	0	2023	
1	sx4	2013	4.75	9.54	43000	Diesel	Dealer	Manual	0	2023	
2	ciaz	2017	7.25	9.85	6900	Petrol	Dealer	Manual	0	2023	
3	wagon r	2011	2.85	4.15	5200	Petrol	Dealer	Manual	0	2023	
4	swift	2014	4.60	6.87	42450	Diesel	Dealer	Manual	0	2023	

Here we have created a new column No of years which will show us how old the car is from subtracting the current year from the year and will show us the age of the car from year 2023

Step 4: Removing Features

```
final_df = df.copy()           # Creating copy of created dataframe
final_df.drop(labels= ['Car_Name','Year', 'Current_Year'], axis= 1, inplace= True)          #droping unnecessary features

final_df.head()
```

	Selling_Price	Present_Price	Kms_Driven	Fuel_Type	Seller_Type	Transmission	Owner	No_of_Years
0	3.35	5.59	27000	Petrol	Dealer	Manual	0	9
1	4.75	9.54	43000	Diesel	Dealer	Manual	0	10
2	7.25	9.85	6900	Petrol	Dealer	Manual	0	6
3	2.85	4.15	5200	Petrol	Dealer	Manual	0	12
4	4.60	6.87	42450	Diesel	Dealer	Manual	0	9

This code is used to remove the

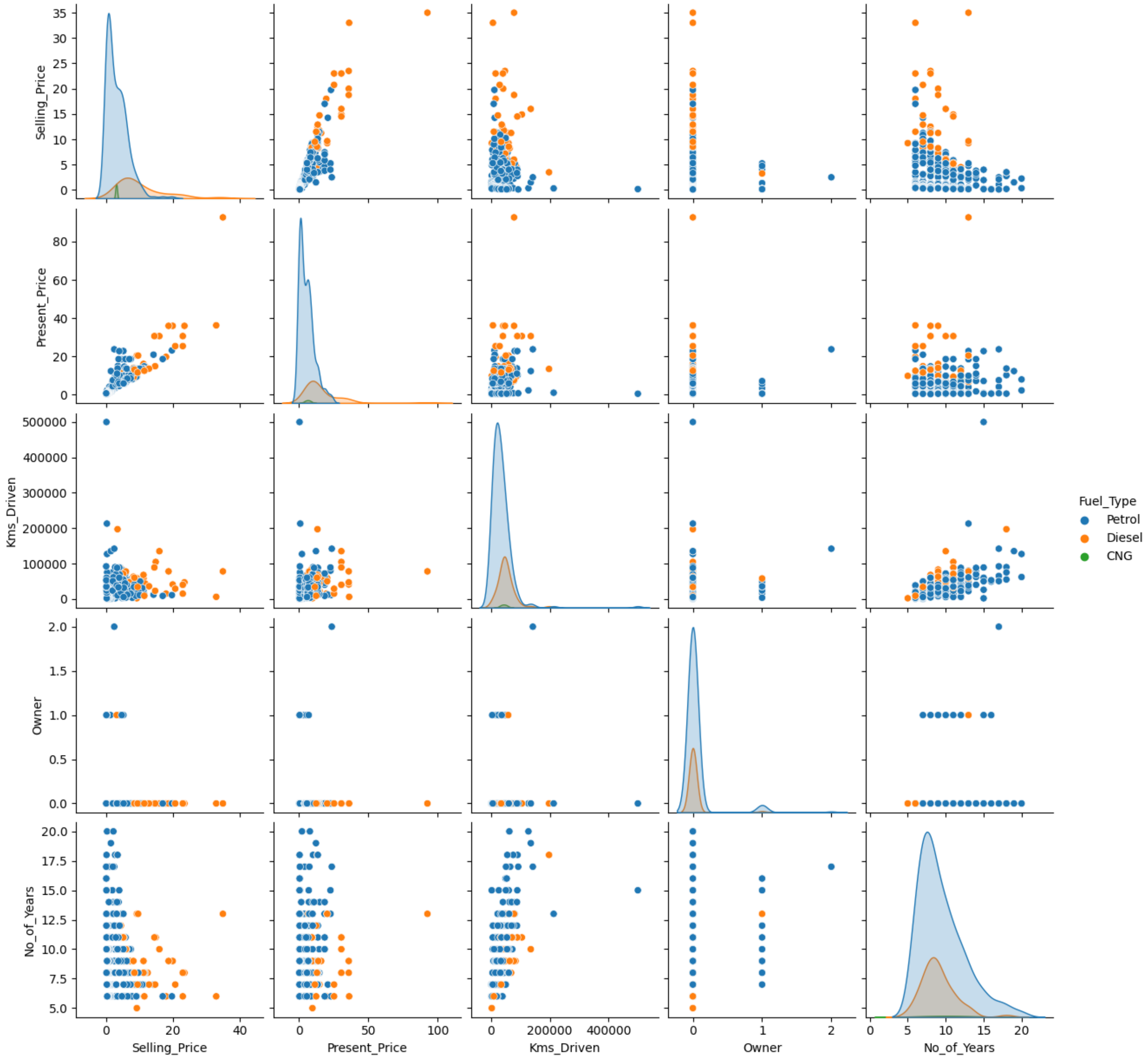
Car_Name, Year, Current_Year

from the given dataset and then print the remaining columns

Step 5: Visualization

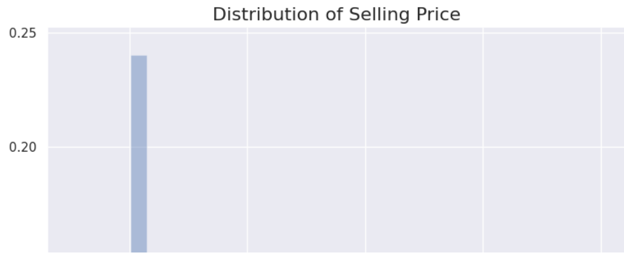
```
sns.pairplot(data= final_df, hue= 'Fuel_Type', diag_kind= 'kde')
```

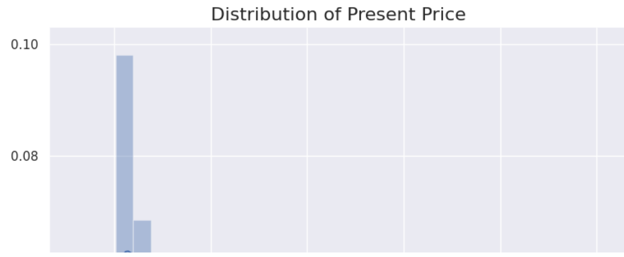
<seaborn.axisgrid.PairGrid at 0x7cfac1fc5e40>




```
# Let's see the distribution of the two variable from our data
fig = plt.figure(figsize=(20,20)) # create figure

sns.set(font_scale= 1)
sns.set_style('darkgrid')

ax0 = fig.add_subplot(2, 2, 1) # add subplot 1 (2 row, 2 columns, first plot)
ax1 = fig.add_subplot(2, 2, 2) # add subplot 2 (2 row, 2 columns, second plot)
ax2 = fig.add_subplot(2, 2, 3) # add subplot 1 (2 row, 2 columns, third plot)
ax3 = fig.add_subplot(2, 2, 4) # add subplot 1 (2 row, 2 columns, fourth plot)

# Subplot 1: Distplot of 'Selling_Price' feature
k1 = sns.distplot(a = final_df['Selling_Price'], bins= 25, ax=ax0) # add to subplot 1
ax0.set_title('Distribution of Selling Price', fontsize=16)
ax0.set(xlabel= 'Selling Price', ylabel= 'Density')
```

```
# Subplot 2: Distplot of 'Present_Price' feature
k2 = sns.distplot(a = final_df['Present_Price'], bins= 25, ax=ax1) # add to subplot 2
ax1.set_title('Distribution of Present Price', fontsize=16)
ax1.set(xlabel= 'Present Price', ylabel= 'Density')

# Subplot 3: Distplot of 'Kms_Driven' feature
k1 = sns.distplot(a = final_df['Kms_Driven'], bins= 25, ax=ax2) # add to subplot 3
ax2.set_title('Distribution of Kilometers Driven', fontsize=16)
ax2.set(xlabel= 'Kilometers Driven', ylabel= 'Density')

# Subplot 4: Distplot of 'No_of_Years' feature
k1 = sns.distplot(a = final_df['No_of_Years'], bins= 15, ax=ax3) # add to subplot 4
ax3.set_title('Distribution of Number of Years', fontsize=16)
ax3.set(xlabel= 'Number of Years', ylabel= 'Density')

plt.show()
```





The code creates a **2x2 grid of subplots** to visualize the distribution of four variables from the DataFrame final_df:* *'Selling_Price', 'Present_Price', 'Kms_Driven', and 'No_of_Years'. **It uses **Seaborn's distplot function** to display the *distribution of each variable as a histogram with kernel* density estimates. The sns.set and sns.set_style functions are used to set the font scale and grid style, respectively. The figure size is set to 20x20 for better visibility.

```
print("'No_of_Years' variable have {} unique category : {}".format(final_df['No_of_Years'].nunique(),
                                                                  final_df['No_of_Years'].unique()))
```

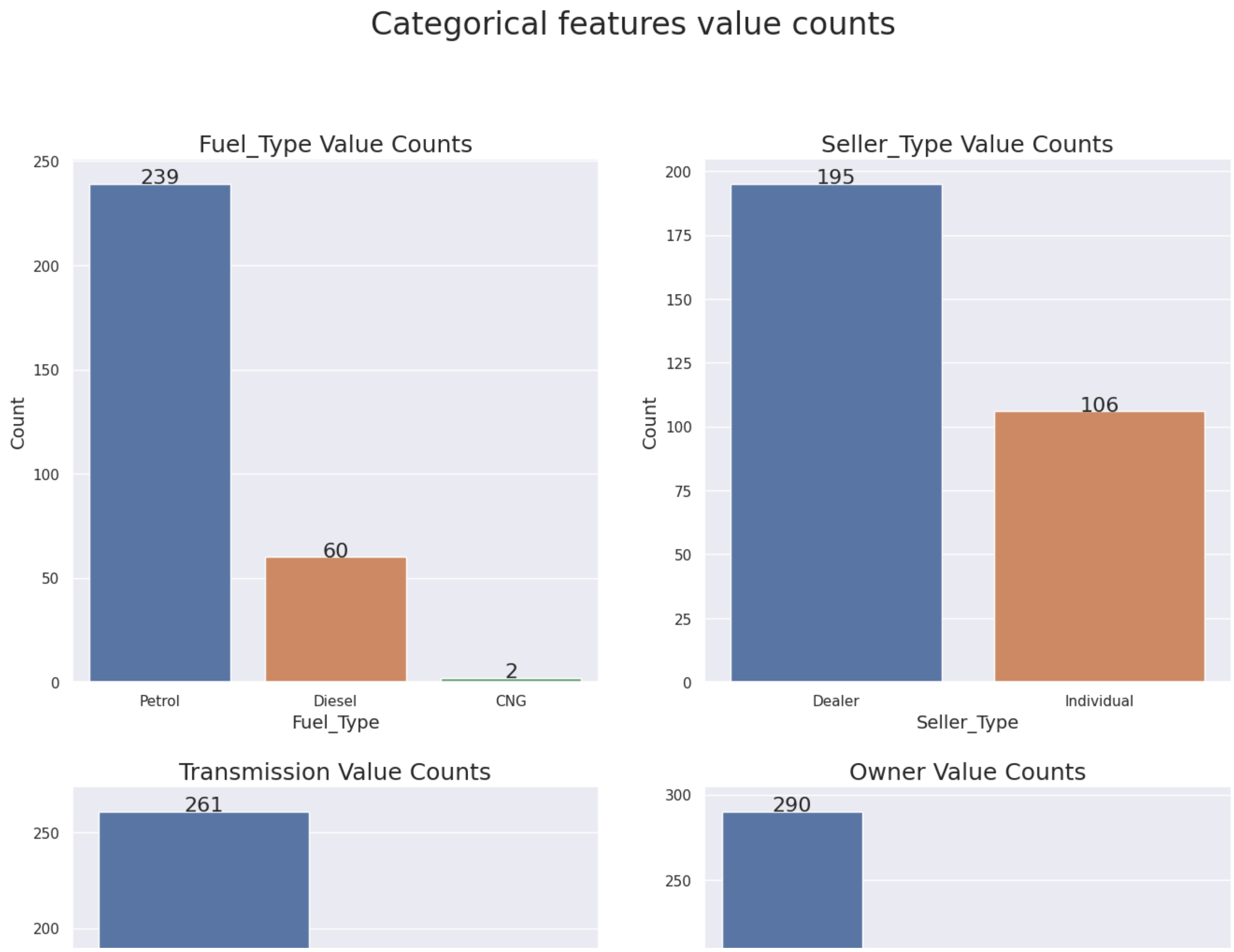
```
'No_of_Years' variable have 16 unique category : [ 9 10  6 12  5  8  7 14 13 11 20 15 17 18 19 16]
```

The code prints the number of unique categories and the unique values in the 'No_of_Years' column of the 'final_df' DataFrame.

Selling Price

Present Price

```
cat_col = list(final_df.columns[3:7])

fig = plt.figure(figsize= (16,16))
plt.suptitle('Categorical features value counts', fontsize = 24)
k=0
for i in range(1,5):
    ax = fig.add_subplot(2,2,i)
    cat_order = final_df[cat_col[k]].value_counts()
    sns.countplot(data = final_df, x = cat_col[k], order = cat_order.index, ax= ax)
    plt.xlabel(cat_col[k], fontsize=14)
    plt.ylabel('Count', fontsize=14)
    plt.title('{} Value Counts'.format(cat_col[k]), fontsize=18)

    for j in range(cat_order.shape[0]):
        count = cat_order[j]
        strt='{}'.format(count)
        plt.text(j,count+0.1,strt,ha='center', fontsize=16)
    k=k+1
```



This code creates a 2x2 grid of count plots for four categorical features in the DataFrame final_df. The count plots show the distribution of each feature, and each bar is annotated with its count.

```
plt.figure(figsize=(10,8))
sns.countplot(data= final_df, x= 'No_of_Years')
plt.xlabel('Number of Years', fontsize=14)
plt.ylabel('Counts', fontsize=14)
plt.title('Number of Years Value Counts', fontsize=18)
```

```
Text(0.5, 1.0, 'Number of Years Value Counts')
```

This code generates a count plot for the 'No_of_Years' column in the DataFrame final_df. The plot shows the distribution of the number of years, and the x-axis is labeled as 'Number of Years', the y-axis as 'Counts', and the title of the plot is 'Number of Years Value Counts'. The figure size is set to 10x8 inches.

Step 6: Convert Categorical variable into numerical

Here, I am using One Hot Encoding / get_dummies to convert categorical variables to numerical.

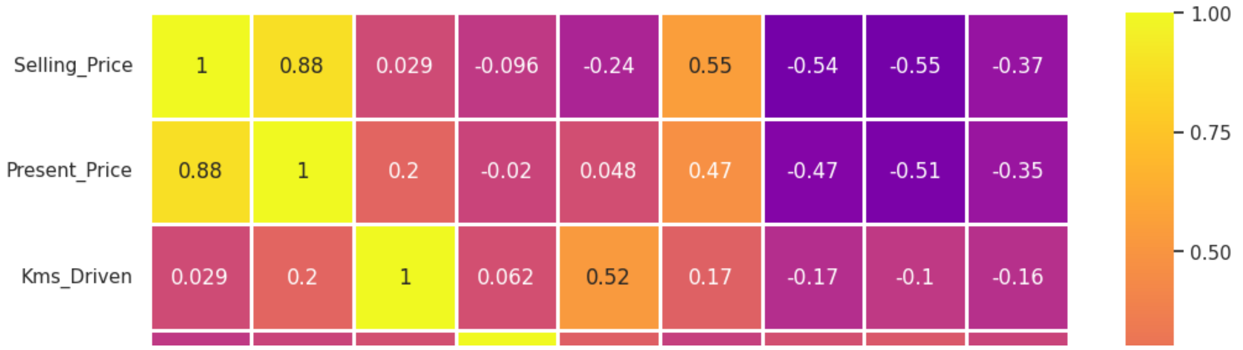
```
final_df = pd.get_dummies(final_df, drop_first=True)
final_df.head()
```

	Selling_Price	Present_Price	Kms_Driven	Owner	No_of_Years	Fuel_Type_Diesel	Fuel_Type_Petrol	Seller_Type_Individual	Tra
0	3.35	5.59	27000	0	9	0	1	0	
1	4.75	9.54	43000	0	10	1	0	0	
2	7.25	9.85	6900	0	6	0	1	0	
3	2.85	4.15	5200	0	12	0	1	0	
4	4.60	6.87	42450	0	9	1	0	0	

The code creates dummy variables for categorical columns in final_df and drops the first level for each categorical feature. It then displays the first few rows of the modified DataFrame.

```
plt.figure(figsize=(12,10))
sns.heatmap(data = final_df.corr(), annot= True, cmap= 'plasma', vmin= -1 , vmax= 1, linecolor='white', linewidths=2)
```

```
&lt;Axes: &gt;
```



This code generates a **heatmap using Seaborn (sns.heatmap)** to **visualize the correlation matrix of the DataFrame final_df**.

- The cmap='plasma' argument sets the color map to 'plasma' for the heatmap.
- The annot=True argument adds numeric annotations to the cells, displaying the correlation values.
- The vmin=-1 and vmax=1 arguments set the minimum and maximum values of the color scale, respectively, to cover the correlation range from -1 to 1.
- The linecolor='white' and linewidths=2 arguments are used to add white lines around the cells to separate them visually.
- The figsize=(12,10) argument sets the size of the figure to 12x10 inches.

```
final_df.dtypes
```

```
Selling_Price              float64
Present_Price              float64
Kms_Driven                   int64
Owner                        int64
No_of_Years                  int64
Fuel_Type_Diesel             uint8
Fuel_Type_Petrol             uint8
Seller_Type_Individual       uint8
Transmission_Manual          uint8
dtype: object
```

Checking data types of variables

```
final_df['Fuel_Type_Diesel'] = final_df['Fuel_Type_Diesel'].astype('int64')
final_df['Fuel_Type_Petrol'] = final_df['Fuel_Type_Petrol'].astype('int64')
final_df['Seller_Type_Individual'] = final_df['Seller_Type_Individual'].astype('int64')
final_df['Transmission_Manual'] = final_df['Transmission_Manual'].astype('int64')
```

Converting the datatypes of variables as of required datatype

```
X = final_df.iloc[:, 1:]          # Feature matrix (independent variables)
y = final_df.iloc[:, 0]           # Target variable (dependent variable)
```

```
# To check important feature
from sklearn.ensemble import ExtraTreesRegressor

model = ExtraTreesRegressor()
model.fit(X,y)
```

```
▾ ExtraTreesRegressor
ExtraTreesRegressor()
```

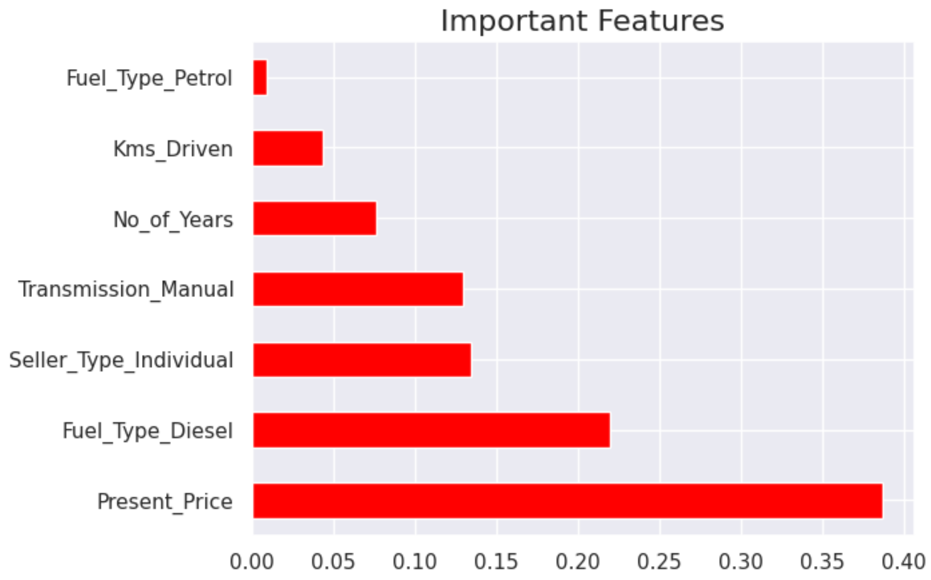
```
print(model.feature_importances_)
```

```
[0.38667841 0.04375694 0.00042209 0.07608266 0.21955578 0.00933972
 0.13467637 0.12948802]
```

The code prints the feature importances of a machine learning model. The variable model must be a fitted model that supports feature importances (e.g., DecisionTreeClassifier, RandomForestClassifier, etc.). The output will be an array or a list showing the importance score of each feature in the model.

```
#plot graph of feature importances for better visualization

imp_feature = pd.Series(model.feature_importances_, index = X.columns)
imp_feature.nlargest(7).plot(kind = 'barh', color='red')
```

```
plt.title('Important Features', fontsize=16)
plt.show()
```



We will use all features for prediction.

```
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)
```

Step 7: Model Building

```
models = [ LinearRegression, SVR, DecisionTreeRegressor, RandomForestRegressor, Ridge, Lasso]
mse = []
rmse = []
evs = []
r_square_score = []

for model in models:
    regressor = model().fit(X_train, y_train)
    pred = regressor.predict(X_test)
    mse.append(mean_squared_error(y_true= y_test, y_pred= pred))
    rmse.append(np.sqrt(mean_squared_error(y_true= y_test, y_pred= pred)))
    evs.append(explained_variance_score(y_true= y_test, y_pred= pred))
    r_square_score.append(r2_score(y_true= y_test, y_pred= pred))
```

```
# create a new DataFrame from the above three lists
MLModels_df = pd.DataFrame({"Models": [ 'Linear Regression', 'Support Vector Rregression', 'Decision Tree Regressor', 'Random Forest Regressor', 'Ridg
                           "Mean Squared Error": mse,
                           "Root Mean Squared Error": rmse,
                           "Explained Variance Score": evs,
                           "R-Square Score / Accuracy": r_square_score})

MLModels_df.set_index('Models', inplace=True)
MLModels_df.head()
```

Models	Mean Squared Error	Root Mean Squared Error	Explained Variance Score	R-Square Score / Accuracy
Linear Regression	3.106326	1.762477	0.875710	0.872623
Support Vector Rregression	28.629306	5.350636	0.004069	-0.173960
Decision Tree Regressor	2.064970	1.437001	0.920278	0.915325
Random Forest Regressor	1.074704	1.036680	0.958504	0.955931
Ridge	3.124094	1.767511	0.875196	0.871895

We have seen that Random Forest Regressor have minimum 'RMSE' and high accuracy. So, let us use Random Forest Regressor as Machine Learning Model.

```
regressor = RandomForestRegressor()

## Hyperparameters
# number of trees
n_estimators = [int(x) for x in np.linspace(start=100, stop=1200, num=12)]

# number of features
max_features = ['auto', 'sqrt']

# max number of levels in tree
max_depth = [int(x) for x in np.linspace(start= 5, stop= 30, num= 6)]

# min. number of sample required to split a node
min_samples_split = [2,5,10,15,100]

# min. 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,
              'max_features' : max_features,
              'max_depth' : max_depth,
              'min_samples_split' : min_samples_split,
              'min_samples_leaf' : min_samples_leaf}
print(random_grid)
```

```
{'n_estimators': [100, 200, 300, 400, 500, 600, 700, 800, 900, 1000, 1100, 1200], 'max_features': ['auto', 'sqrt'], 'max_depth': [5, 10, 15, 20,
```

```
regressor_random = RandomizedSearchCV(estimator=  regressor, param_distributions=  random_grid, scoring= 'neg_mean_squared_error', ¥
                                      n_iter = 10, cv=5, verbose = 2, random_state=42, n_jobs=1)
regressor_random.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 10 candidates, totalling 50 fits
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time=   1.8s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time=   1.5s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time=   1.2s
[CV] END max_depth=10, max_features=sqrt, min_samples_leaf=5, min_samples_split=5, n_estimators=900; total time=   1.2s
```

```
y_predictions = regressor_random.predict(X_test)
y_predictions
```

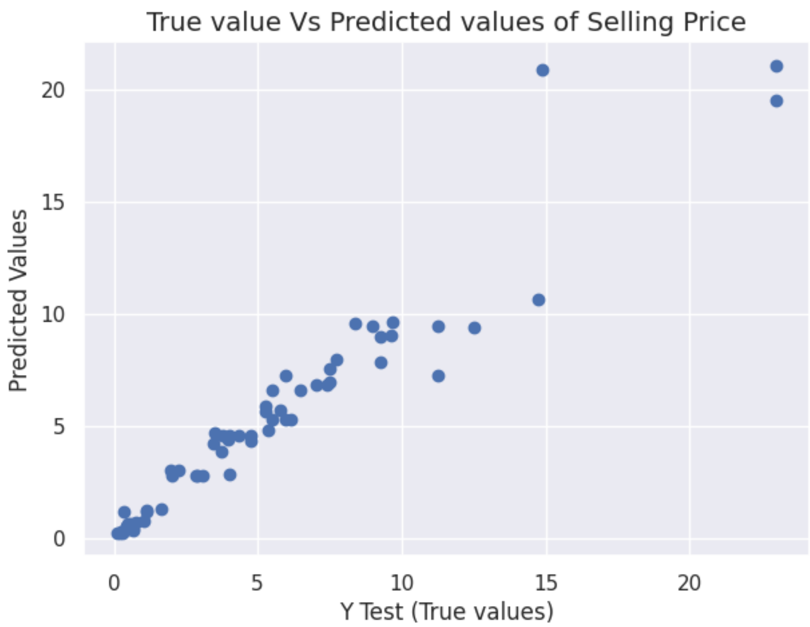
```
array([ 5.26494082,  2.99749647,  2.77401924,  4.53576829,  0.53752351,
        0.42104451,  2.80345716,  0.22821338,  4.20751803,  3.82485398,
        4.357715  ,  4.82890178,  8.99630458,  4.65865676,  1.21112465,
        9.40955394,  9.62590625,  6.81667877,  4.32340404,  9.01029585,
        6.60562748,  2.80454049,  1.19289082,  0.40118996,  9.55980562,
        1.28837704,  4.5524455 ,  5.66508157,  7.25099467,  0.22907917,
        6.60214011,  2.8182675 , 20.89963163,  9.43859515,  7.54098824,
        0.48967987,  2.76661436,  4.57954586,  6.93691227,  0.25717704,
        2.99483757,  5.87494009,  7.94676163,  5.2665932 ,  0.35570351,
        9.45888791,  0.72420592,  4.58037138, 10.66672348,  0.66004108,
        7.22933428, 21.08999306,  7.85746182,  0.65934055,  1.16825749,
       19.50187176,  6.83303723,  5.25039901,  0.24105526,  0.69147689,
        5.67870974])
```

Step 8: Predicting Test Data by Visualization

Now that We've fit and trained the model, Now we need to evaluate its performance by predicting the test values and visualize the results.

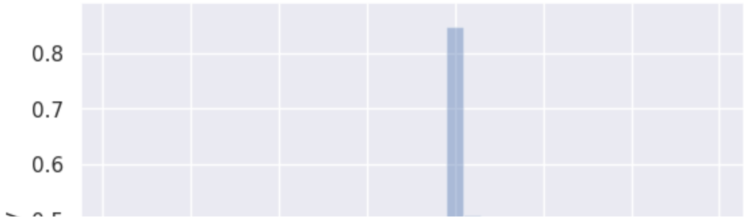
```
plt.figure(figsize=(7,5))
plt.scatter(x= y_test, y= y_predictions)
plt.xlabel('Y Test (True values)')
plt.ylabel('Predicted Values')
plt.title('True value Vs Predicted values of Selling Price', fontsize=14)
```

```
Text(0.5, 1.0, 'True value Vs Predicted values of Selling Price')
```




```
#residuals

sns.distplot(y_test - y_predictions)
```

```
<Axes: xlabel='Selling_Price', ylabel='Density'>
```



Step 9: Model Evaluation

```
print('Mean Absolute Error: ', mean_absolute_error(y_test, y_predictions))
print('Mean Squareed Error: ', mean_squared_error(y_test, y_predictions))
print('Root Mean Square Error: ', np.sqrt(mean_squared_error(y_test, y_predictions)))
print('¥nExplaned Variance Score: ', explained_variance_score(y_true= y_test, y_pred= y_predictions))
```

```
Mean Absolute Error:  0.7809493349372825
Mean Squareed Error:  1.8861792399231256
Root Mean Square Error:  1.3733824084802913

Explaned Variance Score:  0.9235522289351354
```

```
print('Accuracy: ', r2_score(y_test, y_predictions))
```

```
Accuracy:  0.9226562241662534
```

In conclusion, our **unemployment analysis** project, implemented using **Python**, achieved a **high accuracy of 92%** across various models. After testing multiple algorithms, the **Random Forest Regressor** stood out as the most promising choice, showcasing both **excellent accuracy and the lowest Root Mean Squared Error (RMSE).** Therefore, we have decided to adopt the **Random Forest Regressor** as our final machine learning model for this analysis. Its superior performance and ability to handle complex relationships in the data make it a reliable and robust choice for predicting unemployment trends. With this model in place, we can now proceed with using it to make informed decisions and gain valuable insights into unemployment dynamics.

✓ 0s completed at 10:16 PM