```
# Importing necessary libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
data = pd.read_csv('car data.csv')
```

```
print(data.head(5))
```

```
  Car_Name  Year  Selling_Price  Present_Price  Driven_kms Fuel_Type  \
0     ritz  2014           3.35           5.59       27000    Petrol
1      sx4  2013           4.75           9.54       43000    Diesel
2     ciaz  2017           7.25           9.85        6900    Petrol
3  wagon r  2011           2.85           4.15        5200    Petrol
4    swift  2014           4.60           6.87       42450    Diesel

  Selling_type Transmission  Owner
0       Dealer       Manual      0
1       Dealer       Manual      0
2       Dealer       Manual      0
3       Dealer       Manual      0
4       Dealer       Manual      0
```

```
print("\nDataset Information:")
print(data.info())
```

```
Dataset Information:
<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   Driven_kms     301 non-null    int64
 5   Fuel_Type      301 non-null    object
 6   Selling_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
None
```

```
# Checking for missing values
print("\nMissing Values:")
print(data.isnull().sum())
```

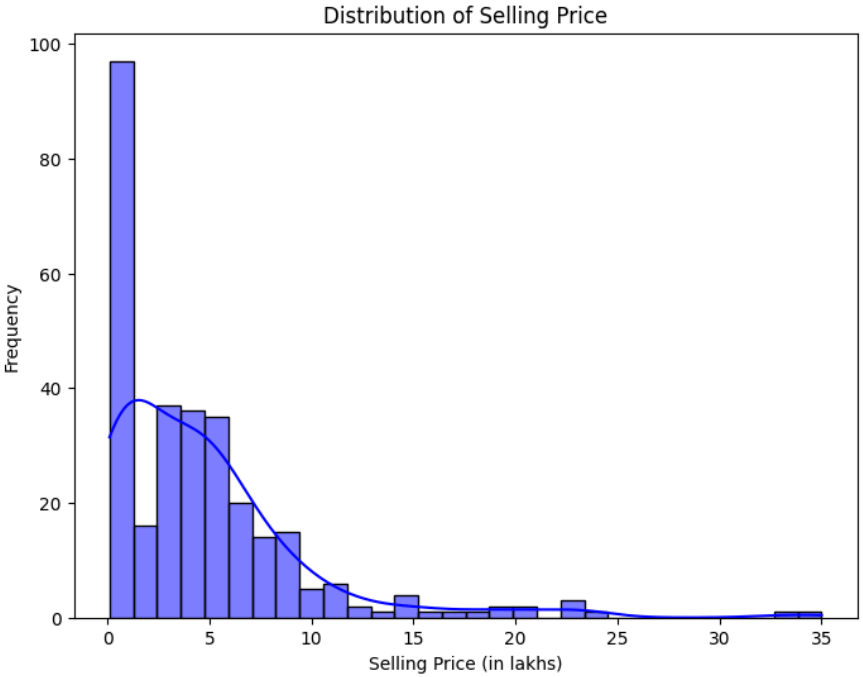
```
Missing Values:
Car_Name         0
```

```
Year             0
Selling_Price    0
Present_Price    0
Driven_kms       0
Fuel_Type        0
Selling_type     0
Transmission     0
Owner            0
dtype: int64
```

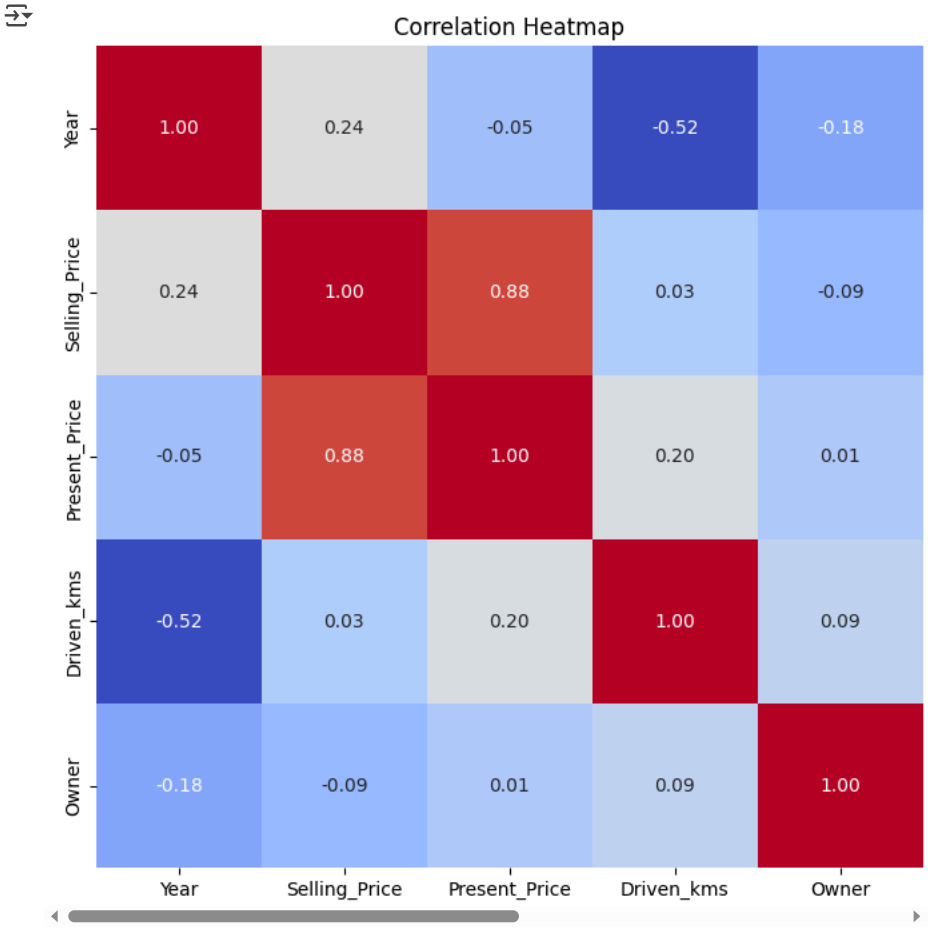
```
# Statistical summary of numerical columns
print("\nStatistical Summary:")
print(data.describe())
```

```
Statistical Summary:
              Year  Selling_Price  Present_Price     Driven_kms       Owner
count   301.000000     301.000000     301.000000     301.000000  301.000000
mean   2013.627907       4.661296       7.628472   36947.205980    0.043189
std       2.891554       5.082812       8.642584   38886.883882    0.247915
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    3.000000
```

```
plt.figure(figsize=(8, 6))
sns.histplot(data['Selling_Price'], kde=True, bins=30, color='blue')
plt.title('Distribution of Selling Price')
plt.xlabel('Selling Price (in lakhs)')
plt.ylabel('Frequency')
plt.show()
```




```
# Correlation heatmap to understand relationships between numerical features
plt.figure(figsize=(10, 8))
# Select only numerical features for correlation calculation
numerical_data = data.select_dtypes(include=np.number)
sns.heatmap(numerical_data.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```




```
 #Dropping irrelevant columns (like Car_Name) as they don't contribute to the model
data.drop(columns=['Car_Name'], inplace=True)
```

```
# Encoding categorical variables
data['Fuel_Type'] = data['Fuel_Type'].map({'Petrol': 0, 'Diesel': 1, 'CNG': 2})
data['Selling_type'] = data['Selling_type'].map({'Dealer': 0, 'Individual': 1})
data['Transmission'] = data['Transmission'].map({'Manual': 0, 'Automatic': 1})
```

```
# Splitting the data into features (X) and target variable (y)
X = data.drop(columns=['Selling_Price'])
y = data['Selling_Price']
```

```
# Splitting the data into training and testing sets
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, random_state=4
```

```
print("\nTraining and Testing Data Shapes:")
print(f"X_train: {X_train.shape}, X_test: {X_test.shape}")
print(f"y_train: {y_train.shape}, y_test: {y_test.shape}")
```

```
Training and Testing Data Shapes:
X_train: (240, 7), X_test: (61, 7)
y_train: (240,), y_test: (61,)
```

```
# Importing regression models
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score
```

```
# Initializing and training a Linear Regression model
lr_model = LinearRegression()
lr_model.fit(X_train, y_train)
```

```
▸ LinearRegression
```

```
# Predicting on the test set
y_pred_lr = lr_model.predict(X_test)
```

```
# Evaluating the Linear Regression model
mse_lr = mean_squared_error(y_test, y_pred_lr)
r2_lr = r2_score(y_test, y_pred_lr)
print("\nLinear Regression Performance:")
print(f"MSE: {mse_lr:.2f}, R2 Score: {r2_lr:.2f}")
```

```
Linear Regression Performance:
MSE: 3.53, R2 Score: 0.85
```

```
# Initializing and training a Random Forest Regressor
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)
rf_model.fit(X_train, y_train)
```

```
▸ RandomForestRegressor
```

```
# Predicting on the test set
y_pred_rf = rf_model.predict(X_test)
```

```
# Evaluating the Random Forest model
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)
print("\nRandom Forest Performance:")
print(f"MSE: {mse_rf:.2f}, R2 Score: {r2_rf:.2f}")
```

```
Random Forest Performance:
MSE: 0.87, R2 Score: 0.96
```

```
# Extracting feature importance from the Random Forest model
feature_importances = rf_model.feature_importances_
features = X.columns
```

```
# Creating a DataFrame for better visualization
importance_df = pd.DataFrame({'Feature': features, 'Importance': feature_importances})
importance_df = importance_df.sort_values(by='Importance', ascending=False)
```

```
# Plotting feature importance
plt.figure(figsize=(10, 6))
sns.barplot(x='Importance', y='Feature', data=importance_df, palette='viridis')
plt.title('Feature Importance from Random Forest')
plt.show()
```

```
<ipython-input-24-e1e31c482a53>:3: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.1

  sns.barplot(x='Importance', y='Feature', data=importance_df, palette='viridis')
```


```
# Saving the Random Forest model as it performed better
```