Import necessory Libraries

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import GridSearchCV
```

Load the Data

In [ ]:
```
# load data into pandas DataFrame
car_data = pd.read_csv("car data.csv")
```

In [ ]:
```
car_data.head()
```

Out[ ]:

	Car_Name	Year	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_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

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In [ ]:
```
car_data.shape
```

Out[ ]:
```
(301, 9)
```

In [ ]:
```
car_data.isnull().sum()
```

Out[ ]:
```
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
```

In [ ]:
```
car_data.describe()
```

Out[ ]:

	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

In [ ]:
```
car_data.duplicated().sum()
```

Out[ ]:
```
2
```

In [ ]:
```
#Lets remove duplicated data
car_data.drop_duplicates(inplace=True)
car_data.duplicated().sum()
```

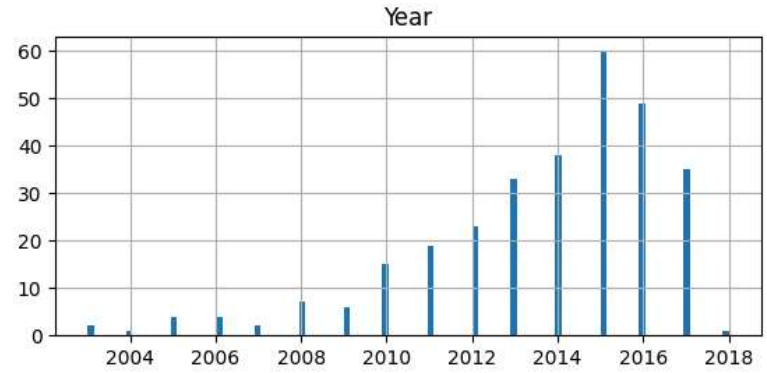
Out[ ]:
```
0
```

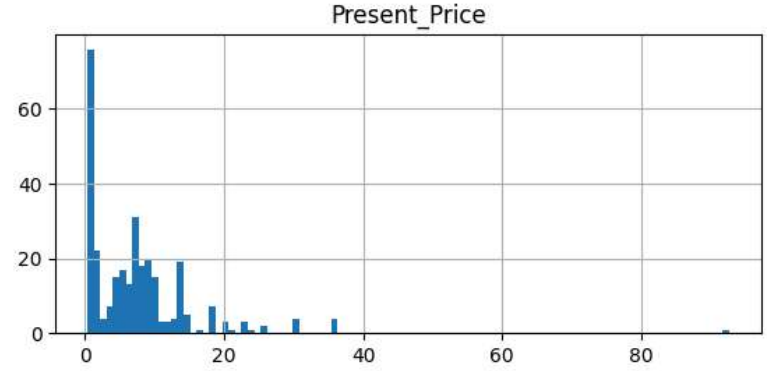
In [ ]:
```
car_data.info()
```

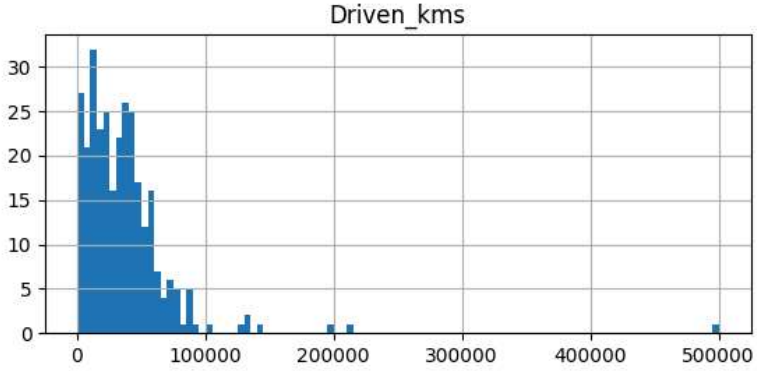
```
<class 'pandas.core.frame.DataFrame'>
Index: 299 entries, 0 to 300
Data columns (total 9 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Car_Name       299 non-null    object 
 1   Year           299 non-null    int64  
 2   Selling_Price  299 non-null    float64
 3   Present_Price  299 non-null    float64
 4   Driven_kms     299 non-null    int64  
 5   Fuel_Type      299 non-null    object 
 6   Selling_type   299 non-null    object 
 7   Transmission   299 non-null    object 
 8   Owner          299 non-null    int64  
dtypes: float64(2), int64(3), object(4)
memory usage: 23.4+ KB
```

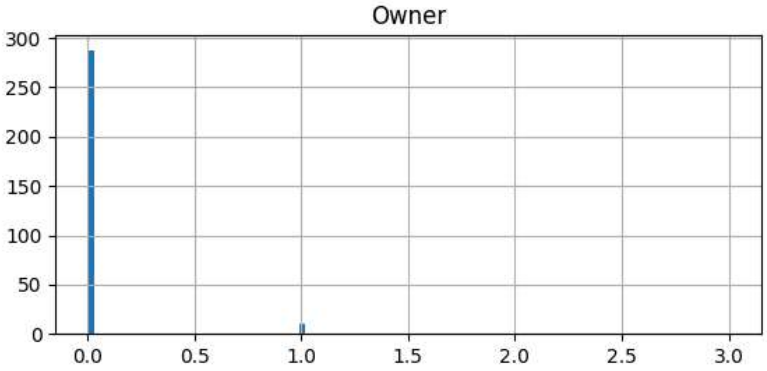
Visualize Data

In [ ]:
```
car_data.hist(bins = 100, figsize =(15,10))
plt.show()
```





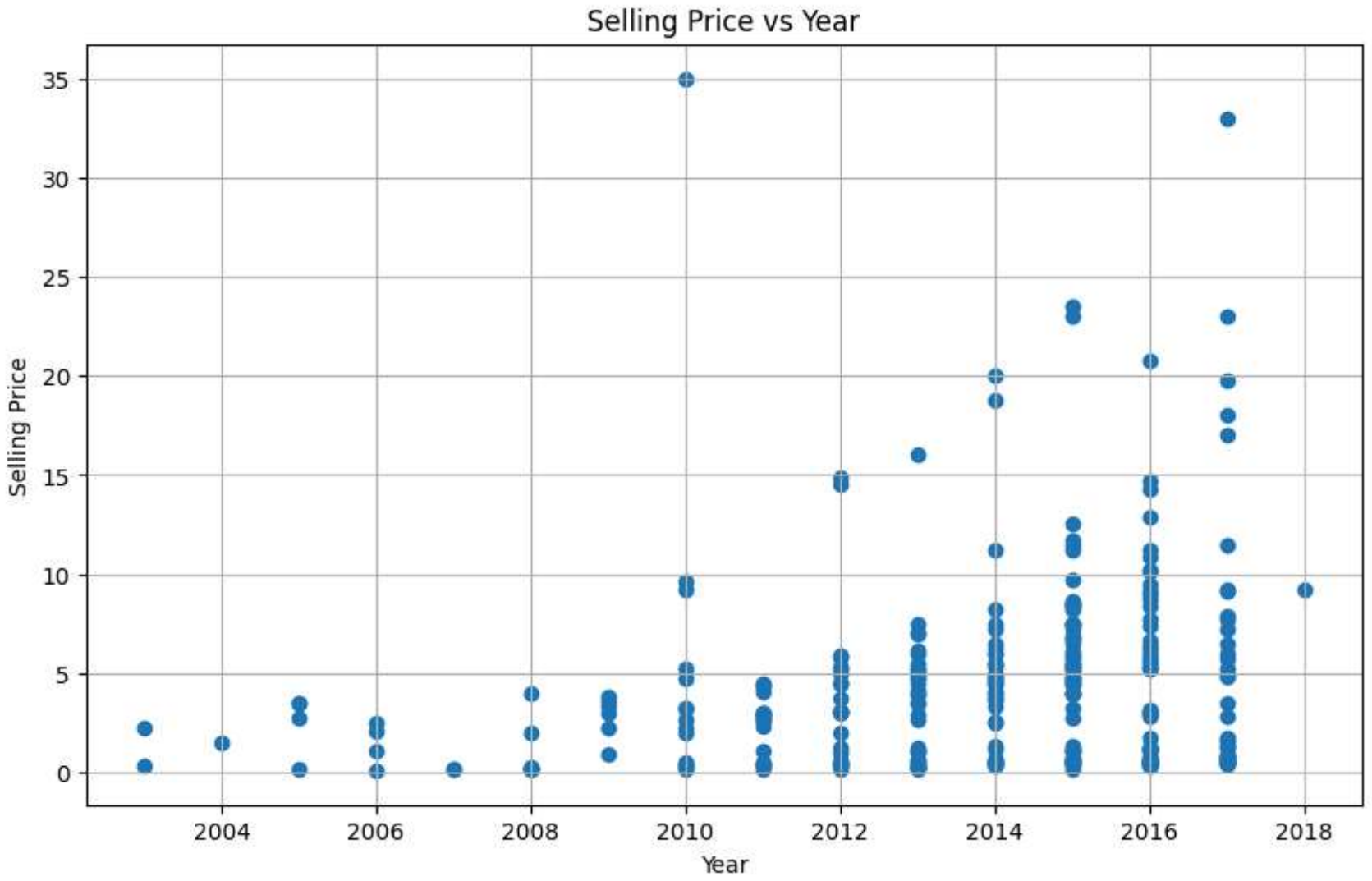




In [ ]:
```
plt.figure(figsize=(10, 6))
plt.scatter(car_data['Year'], car_data['Selling_Price'])
plt.title('Selling Price vs Year')
plt.xlabel('Year')
plt.ylabel('Selling Price')
```

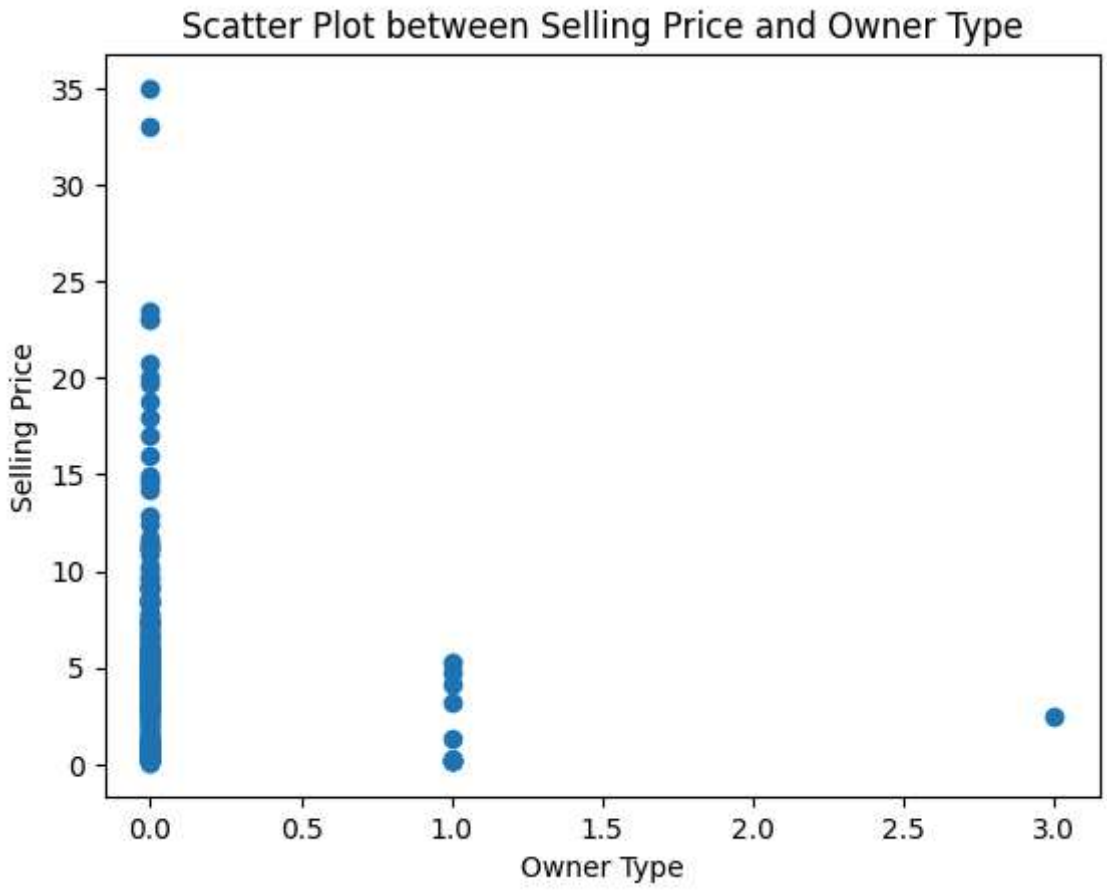
```
plt.grid(True)
plt.show
```

Out[ ]: <function matplotlib.pyplot.show(close=None, block=None)>



In [ ]:
```
plt.scatter(car_data['Owner'], car_data['Selling_Price'])
plt.title('Scatter Plot between Selling Price and Owner Type')
plt.xlabel('Owner Type')
```

```
plt.ylabel('Selling Price')
plt.show()
```



In [ ]:
```
plt.figure(figsize=(10, 6))
plt.scatter(car_data['Driven_kms'], car_data['Selling_Price'], alpha=0.5)
plt.title('Scatter Plot: Selling Price vs Driven Kilometers')
plt.xlabel('Driven Kilometers')
plt.ylabel('Selling Price')
plt.grid(True)
plt.show()
```

Data pre-processing

Label Encoding for Categorical Variables

In [ ]:
```
# create a copy of Original data
data = car_data.copy()
```

In [ ]:
```
le = LabelEncoder()
data["Fuel_Type"] = le.fit_transform(data["Fuel_Type"])
data["Transmission"] = le.fit_transform((data["Transmission"]))
data["Selling_type"] = le.fit_transform(data["Selling_type"])
```

In [ ]:
```
data.head()
```

Out[ ]:

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

Feature Engineering

In [ ]:
```
# Now Create new columns name as car_age
# It is very useful feature because as much as age of car increase then selling price is decreasing
current_year = 2024
data["car_age"] = current_year - data["Year"]
```

In [ ]:
```
# Now drop year columns because "car_age" columns have similar data
new_data = data.drop('Year',axis=1)
```

In [ ]:
```
new_data.head()
```

Out[ ]:

	Car_Name	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner	car_age
0	ritz	3.35	5.59	27000	2	0	1	0	10
1	sx4	4.75	9.54	43000	1	0	1	0	11
2	ciaz	7.25	9.85	6900	2	0	1	0	7
3	wagon r	2.85	4.15	5200	2	0	1	0	13
4	swift	4.60	6.87	42450	1	0	1	0	10

In [ ]:
```
new_data = new_data.drop('Car_Name', axis=1)
```

Feature Scaling

In [ ]:
```
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(new_data)
```

In [ ]:
```
# Convert scaled data back to DataFrame (if needed)
data_scaled = pd.DataFrame(scaled_data, columns=new_data.columns)
```

In [ ]:
```
data_scaled
```

Out[ ]:

	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner	car_age
0	0.093123	0.057109	0.053053	1.0	0.0	1.0	0.0	0.266667
1	0.133238	0.099913	0.085085	0.5	0.0	1.0	0.0	0.333333
2	0.204871	0.103273	0.012813	1.0	0.0	1.0	0.0	0.066667
3	0.078797	0.041504	0.009409	1.0	0.0	1.0	0.0	0.466667
4	0.128940	0.070980	0.083984	0.5	0.0	1.0	0.0	0.266667
...	...	...	...	...	...	...	...	...
294	0.269341	0.122237	0.067043	0.5	0.0	1.0	0.0	0.133333
295	0.111748	0.060468	0.119119	1.0	0.0	1.0	0.0	0.200000
296	0.093123	0.115735	0.175043	1.0	0.0	1.0	0.0	0.600000
297	0.326648	0.131990	0.017017	0.5	0.0	1.0	0.0	0.066667
298	0.148997	0.060468	0.009938	1.0	0.0	1.0	0.0	0.133333

299 rows × 8 columns

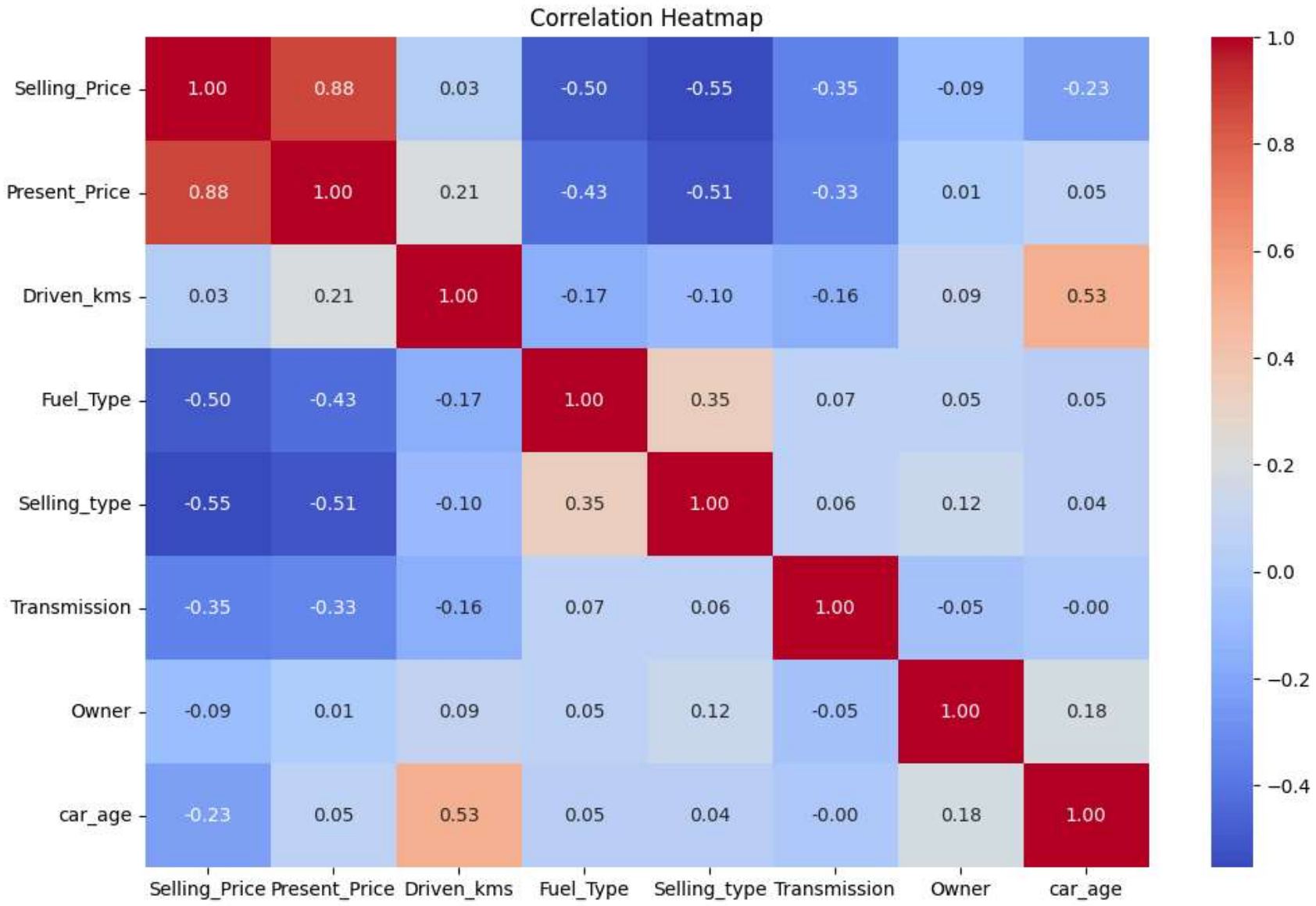
Correlation between data

In [ ]:
```
corr_matrix = data_scaled.corr()
corr_matrix
```

Out[ ]:

	Selling_Price	Present_Price	Driven_kms	Fuel_Type	Selling_type	Transmission	Owner	car_age
Selling_Price	1.000000	0.876305	0.028566	-0.500292	-0.553851	-0.348869	-0.087880	-0.234369
Present_Price	0.876305	1.000000	0.205224	-0.431887	-0.511779	-0.334326	0.009948	0.053167
Driven_kms	0.028566	0.205224	1.000000	-0.167287	-0.101030	-0.163881	0.089367	0.525714
Fuel_Type	-0.500292	-0.431887	-0.167287	1.000000	0.347922	0.068618	0.054174	0.046210
Selling_type	-0.553851	-0.511779	-0.101030	0.347922	1.000000	0.058669	0.123646	0.036820
Transmission	-0.348869	-0.334326	-0.163881	0.068618	0.058669	1.000000	-0.052166	-0.003434
Owner	-0.087880	0.009948	0.089367	0.054174	0.123646	-0.052166	1.000000	0.181639
car_age	-0.234369	0.053167	0.525714	0.046210	0.036820	-0.003434	0.181639	1.000000

In [ ]:
```
# Plot the heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(corr_matrix, annot=True, cmap="coolwarm", fmt=".2f")
plt.title("Correlation Heatmap")
plt.show()
```



Train Machine Learning Model

Split the data

In [ ]:
```
X = data_scaled.drop('Selling_Price', axis=1)
y = data_scaled['Selling_Price']

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=47)
```

Choose and train the model

In [ ]:
```
model = LinearRegression()
```

In [ ]:
```
model.fit(X_train,y_train)
```

Out[ ]:
```
▾ LinearRegression
LinearRegression()
```

Make prediction

In [ ]:
```
# Make predictions on the training set
train_predictions = model.predict(X_train)
```

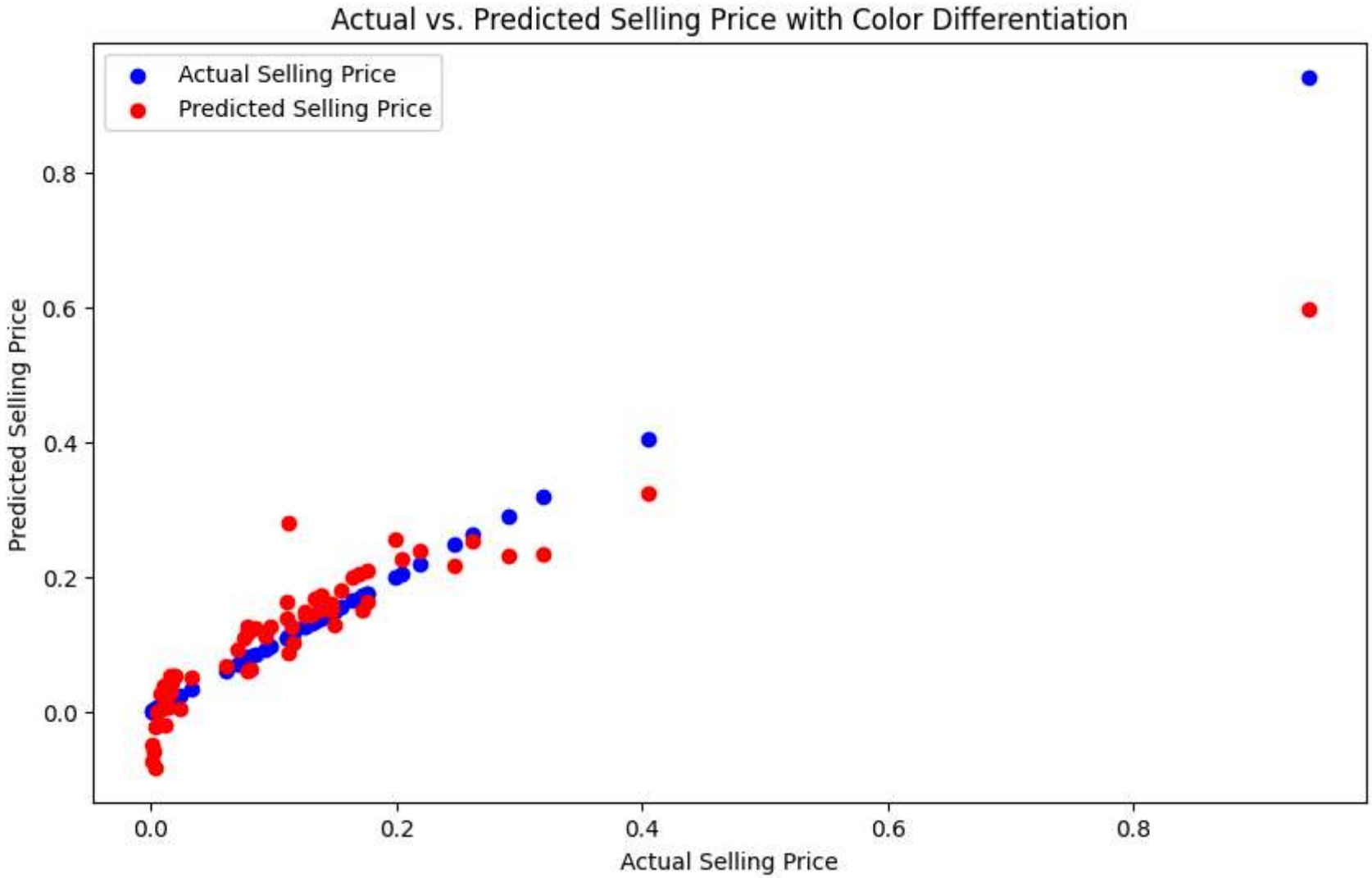
In [ ]:
```
# Make predictions on the testing set
test_predictions = model.predict(X_test)
```

In [ ]:
```
# Example: Visualization of actual vs. predicted values with color differentiation
plt.figure(figsize=(10, 6))

# Scatter plot for actual values (in blue)
plt.scatter(y_test, y_test, color='blue', label='Actual Selling Price')

# Scatter plot for predicted values (in red)
plt.scatter(y_test, test_predictions, color='red', label='Predicted Selling Price')

plt.xlabel('Actual Selling Price')
plt.ylabel('Predicted Selling Price')
plt.title('Actual vs. Predicted Selling Price with Color Differentiation')
plt.legend()
plt.show()
```



Evaluate model

In [ ]:
```
# Make predictions on the test set
y_pred = model.predict(X_test)

# Evaluate the model
```

```
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)

print(f"Mean Squared Error: {mse}")
print(f"Root Mean Squared Error: {rmse}")
print(f"R-squared: {r2}")
```

```
Mean Squared Error: 0.003678816179717397
Root Mean Squared Error: 0.06065324541784551
R-squared: 0.8073225890126082
```