```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
```

```
df=pd.read_csv("/content/cardekho_dataset.csv")
```

```
df
```

| | Unnamed: 0 | car_name | brand | model | vehicle_age | km_driven | seller_type | fuel_type | transmission_type | mileage | engine |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 0 | Maruti Alto | Maruti | Alto | 9 | 120000 | Individual | Petrol | Manual | 19.70 | 796 |
| **1** | 1 | Hyundai Grand | Hyundai | Grand | 5 | 20000 | Individual | Petrol | Manual | 18.90 | 1197 |
| **2** | 2 | Hyundai i20 | Hyundai | i20 | 11 | 60000 | Individual | Petrol | Manual | 17.00 | 1197 |
| **3** | 3 | Maruti Alto | Maruti | Alto | 9 | 37000 | Individual | Petrol | Manual | 20.92 | 998 |
| **4** | 4 | Ford Ecosport | Ford | Ecosport | 6 | 30000 | Dealer | Diesel | Manual | 22.77 | 1498 |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| **15406** | 19537 | Hyundai i10 | Hyundai | i10 | 9 | 10723 | Dealer | Petrol | Manual | 19.81 | 1086 |
| **15407** | 19540 | Maruti Ertiga | Maruti | Ertiga | 2 | 18000 | Dealer | Petrol | Manual | 17.50 | 1373 |
| **15408** | 19541 | Skoda Rapid | Skoda | Rapid | 6 | 67000 | Dealer | Diesel | Manual | 21.14 | 1498 |
| **15409** | 19542 | Mahindra XUV500 | Mahindra | XUV500 | 5 | 3800000 | Dealer | Diesel | Manual | 16.00 | 2179 |
| **15410** | 19543 | Honda City | Honda | City | 2 | 13000 | Dealer | Petrol | Automatic | 18.00 | 1497 |

15411 rows × 14 columns

Next steps: Generate code with df New interactive sheet

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15411 entries, 0 to 15410
Data columns (total 14 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         15411 non-null  int64  
 1   car_name           15411 non-null  object 
 2   brand              15411 non-null  object 
 3   model              15411 non-null  object 
 4   vehicle_age        15411 non-null  int64  
 5   km_driven          15411 non-null  int64  
 6   seller_type        15411 non-null  object 
 7   fuel_type          15411 non-null  object 
 8   transmission_type  15411 non-null  object 
 9   mileage            15411 non-null  float64
 10  engine             15411 non-null  int64  
 11  max_power          15411 non-null  float64
 12  seats              15411 non-null  int64  
 13  selling_price      15411 non-null  int64  
dtypes: float64(2), int64(6), object(6)
memory usage: 1.6+ MB
```

```
df.columns
```

```
Index(['Unnamed: 0', 'car_name', 'brand', 'model', 'vehicle_age', 'km_driven',
       'seller_type', 'fuel_type', 'transmission_type', 'mileage', 'engine',
       'max_power', 'seats', 'selling_price'],
      dtype='object')
```

```
df.describe()
```

| | Unnamed: 0 | vehicle_age | km_driven | mileage | engine | max_power | seats | selling_price |
|---|---|---|---|---|---|---|---|---|
| **count** | 15411.000000 | 15411.000000 | 1.541100e+04 | 15411.000000 | 15411.000000 | 15411.000000 | 15411.000000 | 1.541100e+04 |
| **mean** | 9811.857699 | 6.036338 | 5.561648e+04 | 19.701151 | 1486.057751 | 100.588254 | 5.325482 | 7.749711e+05 |
| **std** | 5643.418542 | 3.013291 | 5.161855e+04 | 4.171265 | 521.106696 | 42.972979 | 0.807628 | 8.941284e+05 |
| **min** | 0.000000 | 0.000000 | 1.000000e+02 | 4.000000 | 793.000000 | 38.400000 | 0.000000 | 4.000000e+04 |
| **25%** | 4906.500000 | 4.000000 | 3.000000e+04 | 17.000000 | 1197.000000 | 74.000000 | 5.000000 | 3.850000e+05 |
| **50%** | 9872.000000 | 6.000000 | 5.000000e+04 | 19.670000 | 1248.000000 | 88.500000 | 5.000000 | 5.560000e+05 |
| **75%** | 14668.500000 | 8.000000 | 7.000000e+04 | 22.700000 | 1582.000000 | 117.300000 | 5.000000 | 8.250000e+05 |
| **max** | 19543.000000 | 29.000000 | 3.800000e+06 | 33.540000 | 6592.000000 | 626.000000 | 9.000000 | 3.950000e+07 |

```
df.describe(include='object')
```

| | car_name | brand | model | seller_type | fuel_type | transmission_type |
|---|---|---|---|---|---|---|
| **count** | 15411 | 15411 | 15411 | 15411 | 15411 | 15411 |
| **unique** | 121 | 32 | 120 | 3 | 5 | 2 |
| **top** | Hyundai i20 | Maruti | i20 | Dealer | Petrol | Manual |
| **freq** | 906 | 4992 | 906 | 9539 | 7643 | 12225 |

```
df.isnull().sum()
```

| | 0 |
|---|---|
| **Unnamed: 0** | 0 |
| **car_name** | 0 |
| **brand** | 0 |
| **model** | 0 |
| **vehicle_age** | 0 |
| **km_driven** | 0 |
| **seller_type** | 0 |
| **fuel_type** | 0 |
| **transmission_type** | 0 |
| **mileage** | 0 |
| **engine** | 0 |
| **max_power** | 0 |
| **seats** | 0 |
| **selling_price** | 0 |

**dtype:** int64

```
df.shape
```

```
(15411, 14)
```

```
df.nunique()
```

| | 0 |
|---|---|
| **Unnamed: 0** | 15411 |
| **car_name** | 121 |
| **brand** | 32 |
| **model** | 120 |
| **vehicle_age** | 24 |
| **km_driven** | 3688 |
| **seller_type** | 3 |
| **fuel_type** | 5 |
| **transmission_type** | 2 |
| **mileage** | 411 |
| **engine** | 110 |
| **max_power** | 342 |
| **seats** | 8 |
| **selling_price** | 1086 |

**dtype:** int64

```
df.dtypes
```

| | 0 |
|---|---|
| **Unnamed: 0** | int64 |
| **car_name** | object |
| **brand** | object |
| **model** | object |
| **vehicle_age** | int64 |
| **km_driven** | int64 |
| **seller_type** | object |
| **fuel_type** | object |
| **transmission_type** | object |
| **mileage** | float64 |
| **engine** | int64 |
| **max_power** | float64 |
| **seats** | int64 |
| **selling_price** | int64 |

**dtype:** object

```
df.duplicated().sum()
```

```
np.int64(0)
```

```
null_counts = df.isnull().sum()
print("Null values count per column:")
print(null_counts)


if null_counts.sum() > 0:
    data_no_nulls = df.dropna()
    print(f"Shape after dropping nulls: {data_no_nulls.shape}")
else:
    print("No null values found. No rows were removed.")
    data_no_nulls = df.copy()
```

```
Null values count per column:
Unnamed: 0          0
car_name            0
brand               0
model               0
vehicle_age         0
km_driven           0
seller_type         0
fuel_type           0
transmission_type   0
mileage             0
engine              0
max_power           0
seats               0
selling_price       0
dtype: int64
No null values found. No rows were removed.
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
```

```
numerical_cols = df.select_dtypes(include=np.number).columns

for col in numerical_cols:
    Q1 = df[col].quantile(0.25)
    Q3 = df[col].quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    outliers = df[(df[col] < lower_bound) | (df[col] > upper_bound)]

    print(f"Outliers in '{col}':")
    if not outliers.empty:
        display(outliers[[col]])
    else:
        print("No outliers found.")
    print("-" * 30)
```

```
Outliers in 'Unnamed: 0':
No outliers found.
------------------------------
Outliers in 'vehicle_age':
```

| | vehicle_age |
|---|---|
| 65 | 15 |
| 161 | 15 |
| 245 | 16 |
| 299 | 15 |
| 344 | 16 |
| ... | ... |
| 15019 | 15 |
| 15028 | 15 |
| 15162 | 15 |
| 15316 | 15 |
| 15329 | 25 |

154 rows × 1 columns

```
------------------------------
Outliers in 'km_driven':
```

| | km_driven |
|---|---|
| 33 | 185000 |
| 72 | 160000 |
| 84 | 160000 |
| 151 | 220000 |
| 153 | 170000 |
| ... | ... |
| 15296 | 180000 |
| 15311 | 150000 |
| 15325 | 220000 |
| 15339 | 140000 |
| 15409 | 3800000 |

466 rows × 1 columns

```
------------------------------
Outliers in 'mileage':
```

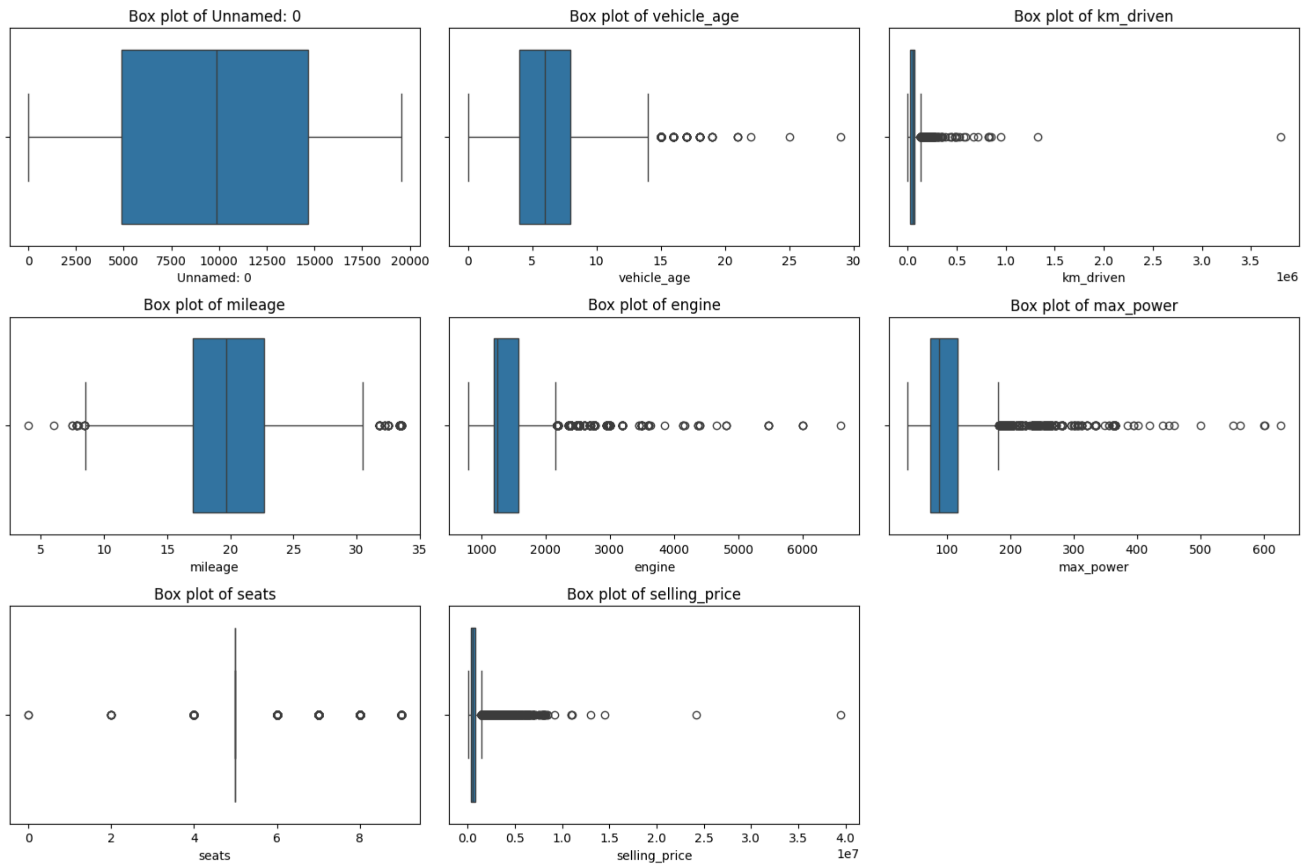
| | mileage |
|---|---|
| 169 | 33.54 |
| 182 | 33.54 |
| 317 | 31.79 |

Start coding or generate with AI.

```
df_no_outliers = df.copy()
for col in numerical_cols:
    Q1 = df_no_outliers[col].quantile(0.25)
    Q3 = df_no_outliers[col].quantile(0.75)
    IQR = Q3 - Q1

    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR

    df_no_outliers = df_no_outliers[(df_no_outliers[col] >= lower_bound) & (df_no_outliers[col] <= upper_bound)]

print("Shape of the dataframe after removing outliers:", df_no_outliers.shape)
```

```
Shape of the dataframe after removing outliers: (11066, 14)
```

```
numerical_cols = df.select_dtypes(include=np.number).columns
plt.figure(figsize=(15, 10))
for i, col in enumerate(numerical_cols):
    plt.subplot(3, 3, i + 1)
    sns.boxplot(x=df[col])
    plt.title(f'Box plot of {col}')
plt.tight_layout()
plt.show()
```




```
Outliers in 'seats':
```

| | seats |
|---|---|
| 24 | 7 |
| 29 | 7 |
| 40 | 7 |
| ... | ... |

```
df.shape
```

```
(15411, 14)
```

```
df_no_outliers.shape
```

```
(11066, 14)
```

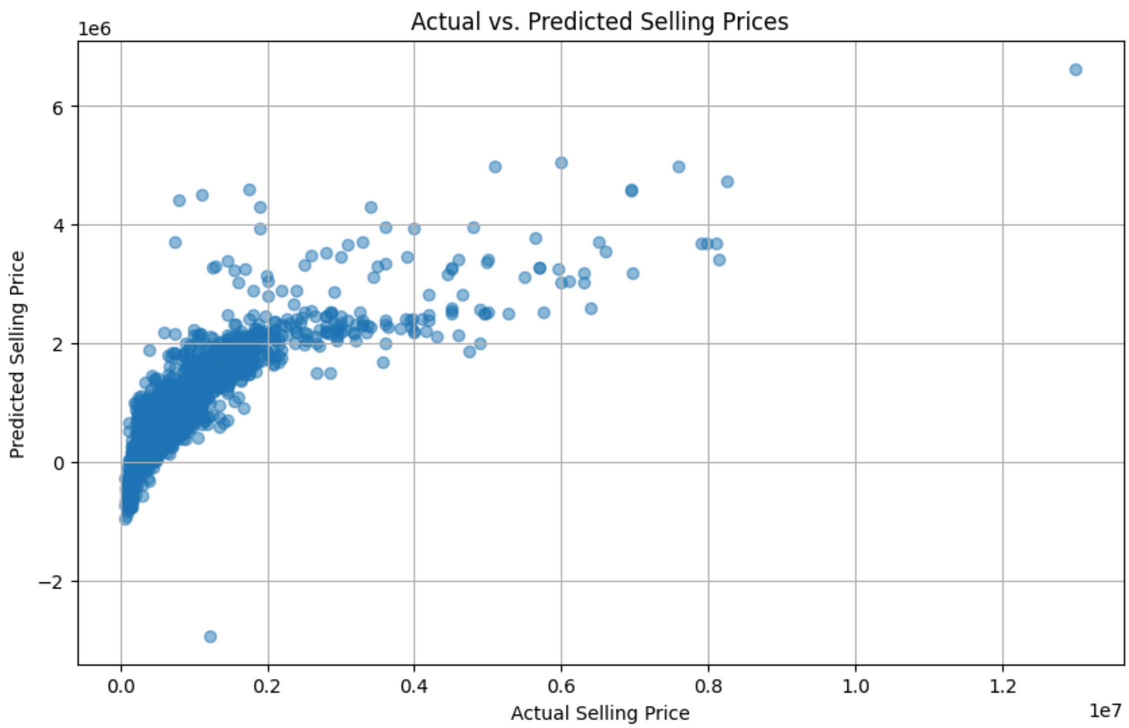
```
#Linear regression
# --- 1. Define Target and Features ---

# Target variable (what we want to predict)
y = df['selling_price']

# Feature matrix (what we use to make the prediction)
# Drop the target, the unnecessary index, and high-cardinality text features
X = df.drop([
    'selling_price',
    'Unnamed: 0',
    'car_name',
    'brand',
    'model'
], axis=1)

print("--- Features and Target defined ---")
print(f"Target (y): 'selling_price'")
print(f"Features (X) columns: {X.columns.tolist()}")

# --- 2. Define Preprocessing Steps ---
```

```
# Identify numerical and categorical features
numerical_features = [
    'vehicle_age',
    'km_driven',
    'mileage',
    'engine',
    'max_power',
    'seats'
]
categorical_features = [
    'seller_type',
    'fuel_type',
    'transmission_type'
]

# Create preprocessing pipeline for numerical features
# 1. StandardScaler: Scales data (e.g., mean=0, std=1)
numerical_transformer = Pipeline(steps=[
    ('scaler', StandardScaler())
])

# Create preprocessing pipeline for categorical features
# 1. OneHotEncoder: Converts categories into binary columns
categorical_transformer = Pipeline(steps=[
    ('onehot', OneHotEncoder(handle_unknown='ignore'))
])

# Combine preprocessing steps using ColumnTransformer
preprocessor = ColumnTransformer(
    transformers=[
        ('num', numerical_transformer, numerical_features),
        ('cat', categorical_transformer, categorical_features)
    ])

print("--- Preprocessing pipeline created ---")

# --- 3. Create and Train the Model ---

# Create the full pipeline: 1. Preprocess, 2. Run Linear Regression
model_pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', LinearRegression())
])

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
print(f"Data split: {len(X_train)} training samples, {len(X_test)} testing samples")

# Train the model
model_pipeline.fit(X_train, y_train)
print("--- Model training complete ---")

# --- 4. Evaluate the Model ---

# Make predictions on the test set
y_pred = model_pipeline.predict(X_test)

# Calculate evaluation metrics
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
r2 = r2_score(y_test, y_pred)

print("\n--- REGRESSION MODEL RESULTS ---")
print(f"Target: Predict 'selling_price'")
print(f"Model: Linear Regression")
print("\nEvaluation Metrics:")
print(f"  Root Mean Squared Error (RMSE): {rmse:.2f}")
print(f"  R-squared (R2): {r2:.4f}")
print("\n(RMSE shows the model's average prediction error in the same units as the target, 'selling_price'.)")
print(f"(R2 score of {r2:.4f} means that {r2*100:.2f}% of the variance in 'selling_price' is predictable from the features.)")
```

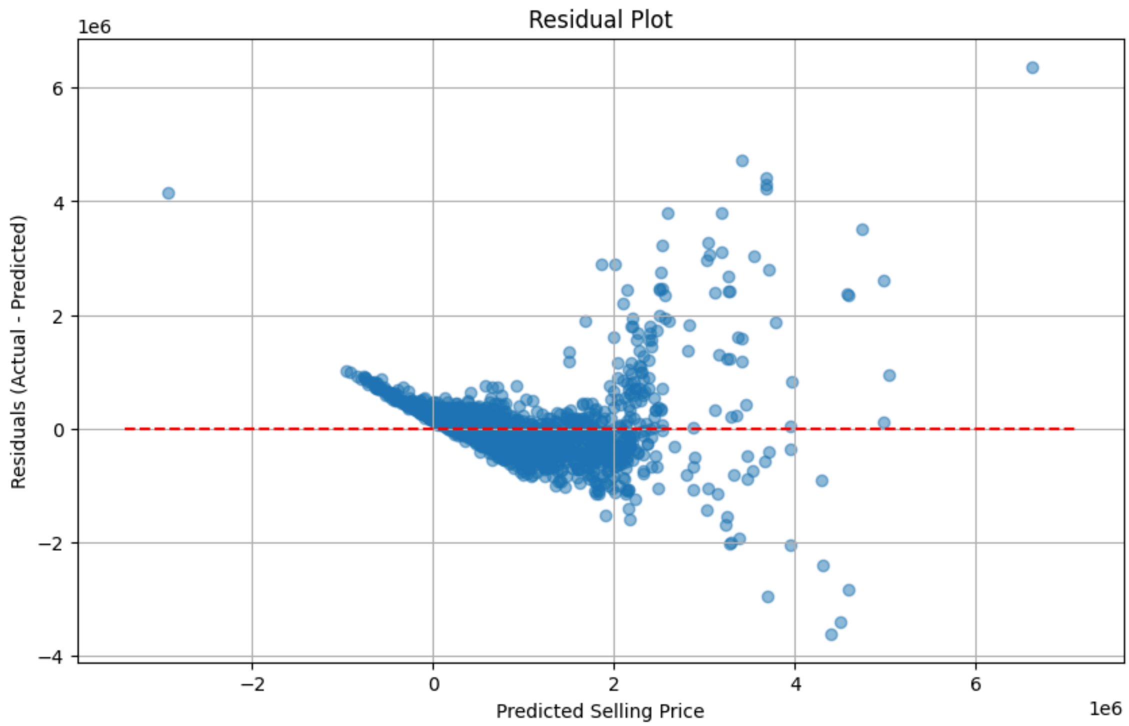
```
--- Features and Target defined ---
Target (y): 'selling_price'
Features (X) columns: ['vehicle_age', 'km_driven', 'seller_type', 'fuel_type', 'transmission_type', 'mileage', 'engine', 'max_
--- Preprocessing pipeline created ---
Data split: 12328 training samples, 3083 testing samples
--- Model training complete ---
```

```
--- REGRESSION MODEL RESULTS ---
Target: Predict 'selling_price'
Model: Linear Regression

Evaluation Metrics:
  Root Mean Squared Error (RMSE): 502095.14
  R-squared (R2): 0.6651

(RMSE shows the model's average prediction error in the same units as the target, 'selling_price'.)
(R2 score of 0.6651 means that 66.51% of the variance in 'selling_price' is predictable from the features.)
```

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred, alpha=0.5)
plt.title('Actual vs. Predicted Selling Prices')
plt.xlabel('Actual Selling Price')
plt.ylabel('Predicted Selling Price')
plt.grid(True)
plt.show()
```




```
residuals = y_test - y_pred

plt.figure(figsize=(10, 6))
plt.scatter(y_pred, residuals, alpha=0.5)
plt.title('Residual Plot')
plt.xlabel('Predicted Selling Price')
plt.ylabel('Residuals (Actual - Predicted)')
plt.hlines(0, plt.xlim()[0], plt.xlim()[1], color='red', linestyle='--')
plt.grid(True)
plt.show()
```



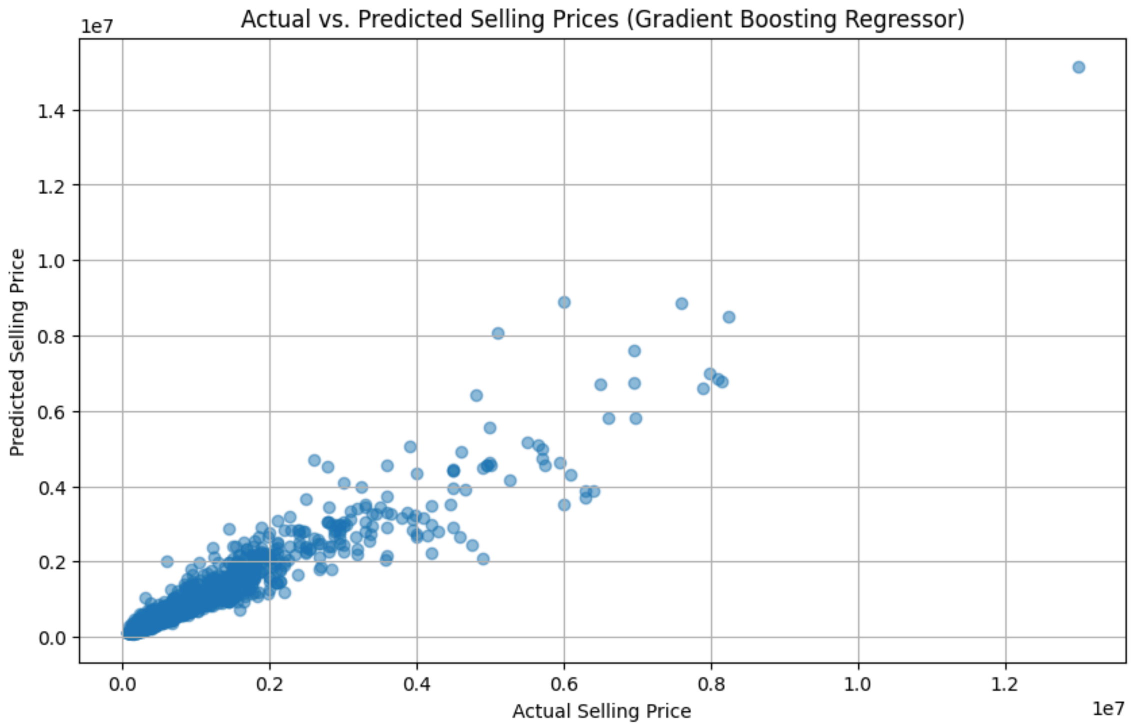

```
from sklearn.ensemble import GradientBoostingRegressor

# Create the full pipeline: 1. Preprocess, 2. Run Gradient Boosting Regressor
model_pipeline_gbr = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', GradientBoostingRegressor(random_state=42)) # Added random_state for reproducibility
])

# Train the Gradient Boosting Regressor model
model_pipeline_gbr.fit(X_train, y_train)
print("--- Gradient Boosting Regressor Model training complete ---")

# Make predictions on the test set
y_pred_gbr = model_pipeline_gbr.predict(X_test)

# Calculate evaluation metrics
rmse_gbr = np.sqrt(mean_squared_error(y_test, y_pred_gbr))
r2_gbr = r2_score(y_test, y_pred_gbr)

print("\n--- GRADIENT BOOSTING REGRESSOR MODEL RESULTS ---")
print(f"Target: Predict 'selling_price'")
print(f"Model: Gradient Boosting Regressor")
print("\nEvaluation Metrics:")
print(f"  Root Mean Squared Error (RMSE): {rmse_gbr:.2f}")
print(f"  R-squared (R2): {r2_gbr:.4f}")
print("\n(Compare these metrics to the Linear Regression results to see if there's an improvement.)")
```

```
--- Gradient Boosting Regressor Model training complete ---

--- GRADIENT BOOSTING REGRESSOR MODEL RESULTS ---
Target: Predict 'selling_price'
Model: Gradient Boosting Regressor

Evaluation Metrics:
  Root Mean Squared Error (RMSE): 263194.22
  R-squared (R2): 0.9080

(Compare these metrics to the Linear Regression results to see if there's an improvement.)
```

Start coding or generate with AI.

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_gbr, alpha=0.5)
plt.title('Actual vs. Predicted Selling Prices (Gradient Boosting Regressor)')
plt.xlabel('Actual Selling Price')
```

```
plt.ylabel('Predicted Selling Price')
plt.grid(True)
plt.show()
```

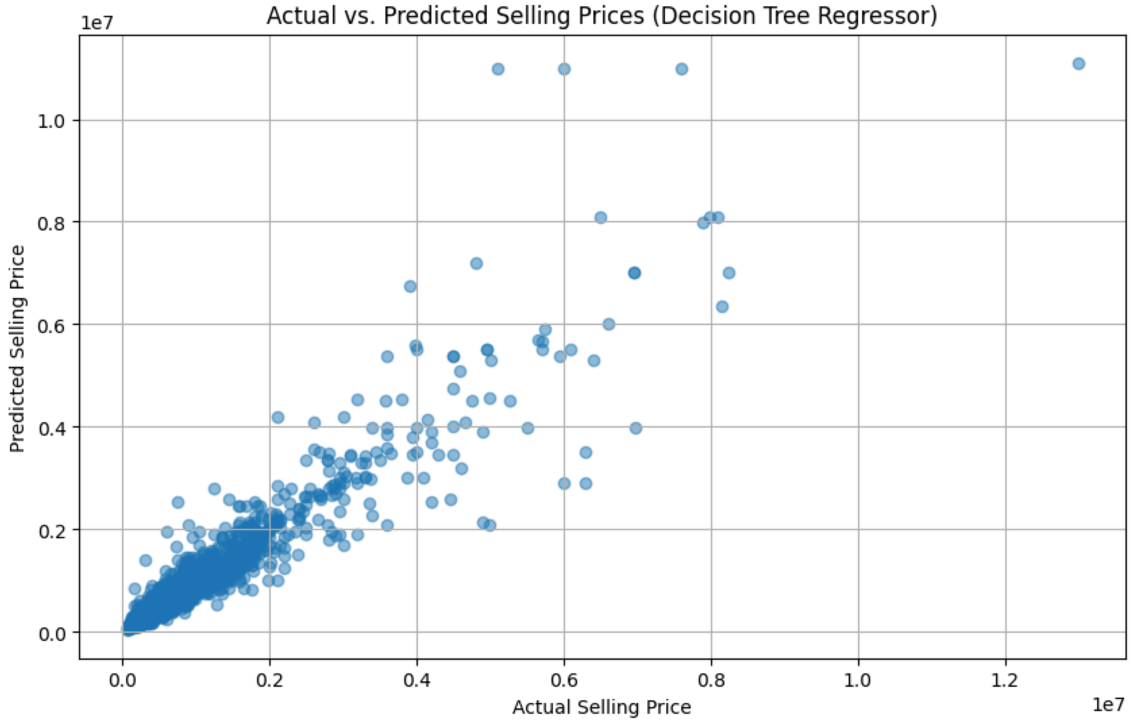



```
from sklearn.tree import DecisionTreeRegressor

# Create the full pipeline for Decision Tree Regression
model_pipeline_dt = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', DecisionTreeRegressor(random_state=42))
])

# Train the Decision Tree Regression model
model_pipeline_dt.fit(X_train, y_train)
print("--- Decision Tree Regressor Model training complete ---")

# Make predictions on the test set
y_pred_dt = model_pipeline_dt.predict(X_test)

# Calculate evaluation metrics for Decision Tree
rmse_dt = np.sqrt(mean_squared_error(y_test, y_pred_dt))
r2_dt = r2_score(y_test, y_pred_dt)

print("\n--- DECISION TREE REGRESSOR MODEL RESULTS ---")
print(f"Target: Predict 'selling_price'")
print(f"Model: Decision Tree Regressor")
print("\nEvaluation Metrics:")
print(f"  Root Mean Squared Error (RMSE): {rmse_dt:.2f}")
print(f"  R-squared (R2): {r2_dt:.4f}")
```

```
--- Decision Tree Regressor Model training complete ---

--- DECISION TREE REGRESSOR MODEL RESULTS ---
Target: Predict 'selling_price'
Model: Decision Tree Regressor

Evaluation Metrics:
  Root Mean Squared Error (RMSE): 307019.78
  R-squared (R2): 0.8748
```

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_dt, alpha=0.5)
plt.title('Actual vs. Predicted Selling Prices (Decision Tree Regressor)')
plt.xlabel('Actual Selling Price')
plt.ylabel('Predicted Selling Price')
plt.grid(True)
```

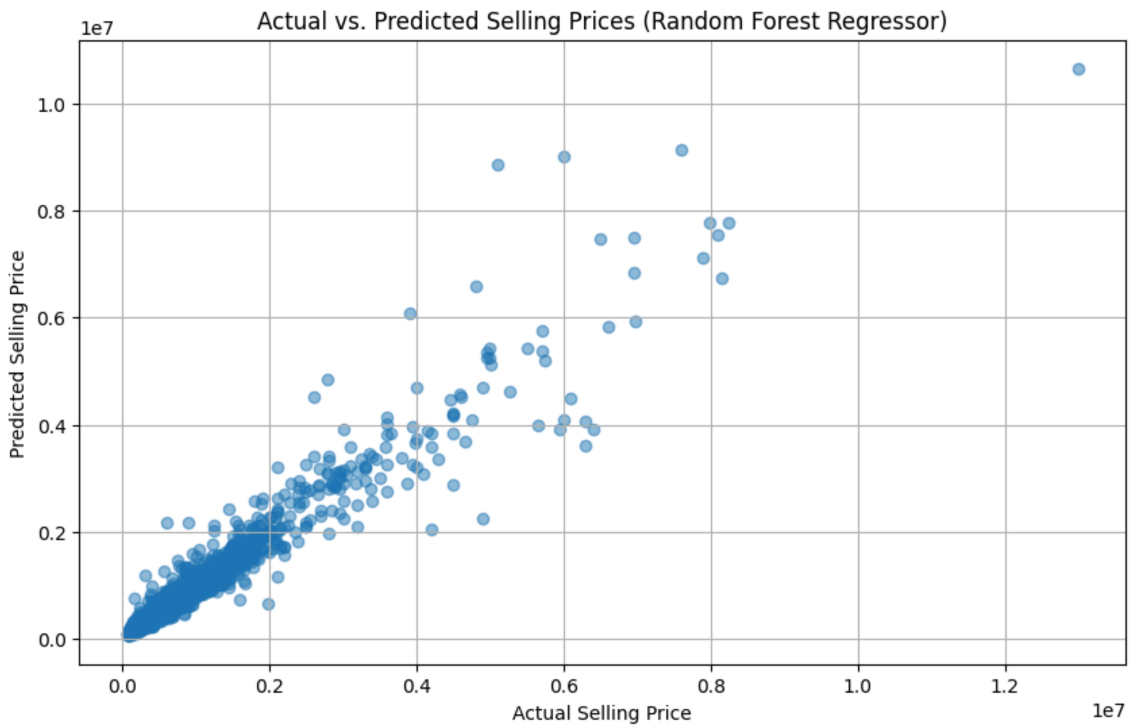
```
plt.show()
```




```
from sklearn.ensemble import RandomForestRegressor

# Create the full pipeline for Random Forest Regression
model_pipeline_rf = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', RandomForestRegressor(random_state=42))
])

# Train the Random Forest Regression model
model_pipeline_rf.fit(X_train, y_train)
print("\n--- Random Forest Regressor Model training complete ---")

# Make predictions on the test set
y_pred_rf = model_pipeline_rf.predict(X_test)

# Calculate evaluation metrics for Random Forest
rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))
r2_rf = r2_score(y_test, y_pred_rf)

print("\n--- RANDOM FOREST REGRESSOR MODEL RESULTS ---")
print(f"Target: Predict 'selling_price'")
print(f"Model: Random Forest Regressor")
print("\nEvaluation Metrics:")
print(f"  Root Mean Squared Error (RMSE): {rmse_rf:.2f}")
print(f"  R-squared (R2): {r2_rf:.4f}")
```

```
--- Random Forest Regressor Model training complete ---

--- RANDOM FOREST REGRESSOR MODEL RESULTS ---
Target: Predict 'selling_price'
Model: Random Forest Regressor

Evaluation Metrics:
  Root Mean Squared Error (RMSE): 236305.45
  R-squared (R2): 0.9258
```

```
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_rf, alpha=0.5)
plt.title('Actual vs. Predicted Selling Prices (Random Forest Regressor)')
plt.xlabel('Actual Selling Price')
plt.ylabel('Predicted Selling Price')
plt.grid(True)
plt.show()
```




```
from sklearn.linear_model import Ridge, Lasso

# Create the full pipeline for Ridge Regression
model_pipeline_ridge = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('regressor', Ridge(random_state=42))
])

# Train the Ridge Regression model
model_pipeline_ridge.fit(X_train, y_train)
print("--- Ridge Regression Model training complete ---")

# Make predictions on the test set
y_pred_ridge = model_pipeline_ridge.predict(X_test)

# Calculate evaluation metrics for Ridge
rmse_ridge = np.sqrt(mean_squared_error(y_test, y_pred_ridge))
r2_ridge = r2_score(y_test, y_pred_ridge)

print("\n--- RIDGE REGRESSION MODEL RESULTS ---")
print(f"Target: Predict 'selling_price'")
print(f"Model: Ridge Regression")
print("\nEvaluation Metrics:")
print(f"  Root Mean Squared Error (RMSE): {rmse_ridge:.2f}")
print(f"  R-squared (R2): {r2_ridge:.4f}")
```

```
--- Ridge Regression Model training complete ---

--- RIDGE REGRESSION MODEL RESULTS ---
Target: Predict 'selling_price'
Model: Ridge Regression

Evaluation Metrics:
  Root Mean Squared Error (RMSE): 502086.74
  R-squared (R2): 0.6651
```

```
# Create the full pipeline for Lasso Regression
model_pipeline_lasso = Pipeline(steps=[
```