EDA ==

```python
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.preprocessing import StandardScaler, OneHotEncoder
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import mean_squared_error, r2_score, accuracy_score,
classification_report, confusion_matrix
from sklearn.feature_selection import SelectKBest, f_regression, f_classif
import scipy.stats as stats
from scipy.stats import zscore

%matplotlib inline

# Set the style for plots
plt.style.use('seaborn-v0_8')
sns.set(font_scale=1.2)

# 1. DATA LOADING AND INITIAL EXPLORATION
print("STEP 1: DATA LOADING AND INITIAL EXPLORATION")
print("-" * 50)

# Load the dataset
df = pd.read_csv('dataset.csv')

# Display basic information
print("Dataset Shape:", df.shape)
print("\nFirst 5 rows of the dataset:")
print(df.head())
```

```
STEP 1: DATA LOADING AND INITIAL EXPLORATION
--------------------------------------------------
Dataset Shape: (958524, 45)

First 5 rows of the dataset:
         id    spkid       full_name pdes     name prefix neo pha     H  \
0  a0000001  2000001         1 Ceres    1    Ceres    NaN   N   N  3.40
1  a0000002  2000002        2 Pallas    2   Pallas    NaN   N   N  4.20
2  a0000003  2000003          3 Juno    3     Juno    NaN   N   N  5.33
3  a0000004  2000004         4 Vesta    4    Vesta    NaN   N   N  3.00
4  a0000005  2000005       5 Astraea    5  Astraea    NaN   N   N  6.90

   diameter  ...       sigma_i      sigma_om       sigma_w      sigma_ma  \
0   939.400  ...  4.608900e-09  6.168800e-08  6.624800e-08  7.820700e-09
1   545.000  ...  3.469400e-06  6.272400e-06  9.128200e-06  8.859100e-06
2   246.596  ...  3.223100e-06  1.664600e-05  1.772100e-05  8.110400e-06
3   525.400  ...  2.170600e-07  3.880800e-07  1.789300e-07  1.206800e-06
4   106.699  ...  2.740800e-06  2.894900e-05  2.984200e-05  8.303800e-06

       sigma_ad       sigma_n      sigma_tp     sigma_per  class      rms
0  1.111300e-11  1.196500e-12  3.782900e-08  9.415900e-09    MBA  0.43301
1  4.961300e-09  4.653600e-10  4.078700e-05  3.680700e-06    MBA  0.35936
2  4.363900e-09  4.413400e-10  3.528800e-05  3.107200e-06    MBA  0.33848
3  1.648600e-09  2.612500e-10  4.103700e-06  1.274900e-06    MBA  0.39980
4  4.729000e-09  5.522700e-10  3.474300e-05  3.490500e-06    MBA  0.52191

[5 rows x 45 columns]
```

```python
print("\nMissing Values Count:")
print(df.isnull().sum())
```

```
Missing Values Count:
id                     0
spkid                  0
full_name              0
pdes                   0
name              936460
prefix            958506
neo                    4
pha                19921
H                   6263
diameter          822315
albedo            823421
diameter_sigma    822443
orbit_id               0
epoch                  0
epoch_mjd              0
epoch_cal              0
equinox                0
e                      0
a                      0
q                      0
i                      0
om                     0
w                      0
ma                     1
ad                     4
n                      0
tp                     0
tp_cal                 0
per                    4
per_y                  1
moid               19921
moid_ld              127
sigma_e            19922
sigma_a            19922
sigma_q            19922
sigma_i            19922
sigma_om           19922
sigma_w            19922
sigma_ma           19922
sigma_ad           19926
sigma_n            19922
sigma_tp           19922
sigma_per          19926
class                  0
rms                    2
dtype: int64
```

Rename Columns --------------------------

```python
# Section 1: Data Description

column_definitions = {
    "id": "Unique identifier for the object",
    "spkid": "Object primary SPK-ID",
    "full_name": "Object full name/designation",
    "pdes": "Object primary designation",
    "name": "Object IAU name",
    "prefix": "Object prefix (if applicable)",
    "neo": "Near-Earth Object (NEO) flag",
```

```python
# Check data types and missing values
print(f"Number of samples in the dataset: {len(df)}\n")
print("Dataset Information:", df.info())
```

```
Number of samples in the dataset: 958524

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 958524 entries, 0 to 958523
Data columns (total 45 columns):
 #   Column          Non-Null Count   Dtype
---  ------          --------------   -----
 0   id              958524 non-null  object
 1   spkid           958524 non-null  int64
 2   full_name       958524 non-null  object
 3   pdes            958524 non-null  object
 4   name            22064 non-null   object
 5   prefix          18 non-null      object
 6   neo             958520 non-null  object
 7   pha             938603 non-null  object
 8   H               952261 non-null  float64
 9   diameter        136209 non-null  float64
 10  albedo          135103 non-null  float64
 11  diameter_sigma  136081 non-null  float64
 12  orbit_id        958524 non-null  object
 13  epoch           958524 non-null  float64
 14  epoch_mjd       958524 non-null  int64
 15  epoch_cal       958524 non-null  float64
 16  equinox         958524 non-null  object
 17  e               958524 non-null  float64
 18  a               958524 non-null  float64
 19  q               958524 non-null  float64
 20  i               958524 non-null  float64
 21  om              958524 non-null  float64
 22  w               958524 non-null  float64
 23  ma              958523 non-null  float64
 24  ad              958520 non-null  float64
 25  n               958524 non-null  float64
 26  tp              958524 non-null  float64
 27  tp_cal          958524 non-null  float64
 28  per             958520 non-null  float64
 29  per_y           958523 non-null  float64
 30  moid            938603 non-null  float64
 31  moid_ld         958397 non-null  float64
 32  sigma_e         938602 non-null  float64
 33  sigma_a         938602 non-null  float64
 34  sigma_q         938602 non-null  float64
 35  sigma_i         938602 non-null  float64
 36  sigma_om        938602 non-null  float64
 37  sigma_w         938602 non-null  float64
 38  sigma_ma        938602 non-null  float64
 39  sigma_ad        938598 non-null  float64
 40  sigma_n         938602 non-null  float64
 41  sigma_tp        938602 non-null  float64
 42  sigma_per       938598 non-null  float64
 43  class           958524 non-null  object
 44  rms             958522 non-null  float64
dtypes: float64(33), int64(2), object(10)
memory usage: 329.1+ MB
Dataset Information: None
```

```python
# Check for duplicate rows
num_duplicates = df.duplicated().sum()
print(f"Number of duplicate rows: {num_duplicates}")
```

```
Number of duplicate rows: 0
```

```python
    "pha": "Potentially Hazardous Asteroid (PHA) flag",
    "H": "Absolute magnitude parameter",
    "diameter": "Object diameter (from equivalent sphere) in km",
    "albedo": "Geometric albedo",
    "diameter_sigma": "1-sigma uncertainty in object diameter (km)",
    "orbit_id": "Orbit solution ID",
    "epoch": "Epoch of osculation in Julian day form",
    "epoch_mjd": "Epoch in modified Julian day form",
    "epoch_cal": "Epoch in calendar date form",
    "e": "Eccentricity",
    "equinox": "Equinox of reference frame",
    "a": "Semi-major axis (au)",
    "q": "Perihelion distance (au)",
    "i": "Inclination; angle with respect to x-y ecliptic plane (degrees)",
    "om": "Longitude of ascending node (degrees)",
    "w": "Argument of perihelion (degrees)",
    "ma": "Mean anomaly (degrees)",
    "ad": "Aphelion distance (au)",
    "n": "Mean motion (degrees/day)",
    "tp": "Time of perihelion passage (Julian day)",
    "tp_cal": "Time of perihelion passage (calendar date)",
    "per": "Orbital period (days)",
    "per_y": "Orbital period (years)",
    "moid": "Minimum Orbit Intersection Distance (au)",
    "moid_ld": "Minimum Orbit Intersection Distance (Lunar Distance)",
    "sigma_e": "1-sigma uncertainty in eccentricity",
    "sigma_a": "1-sigma uncertainty in semi-major axis (au)",
    "sigma_q": "1-sigma uncertainty in perihelion distance (au)",
    "sigma_i": "1-sigma uncertainty in inclination (degrees)",
    "sigma_om": "1-sigma uncertainty in longitude of ascending node (degrees)",
    "sigma_w": "1-sigma uncertainty in argument of perihelion (degrees)",
    "sigma_ma": "1-sigma uncertainty in mean anomaly (degrees)",
    "sigma_ad": "1-sigma uncertainty in aphelion distance (au)",
    "sigma_n": "1-sigma uncertainty in mean motion (degrees/day)",
    "sigma_tp": "1-sigma uncertainty in time of perihelion passage (Julian day)",
    "sigma_per": "1-sigma uncertainty in orbital period (days)",
    "class": "Orbit classification",
    "rms": "Root mean square of orbit fit residuals"
}

rename_dict = {
    'id': 'Asteroid_ID',
    'spkid': 'NASA_SPK_ID',
    'full_name': 'Asteroid_Full_Name',
    'pdes': 'Primary_Designation',
    'name': 'Asteroid_Name',
    'prefix': 'Name_Prefix',
    'neo': 'Near_Earth_Object',
    'pha': 'Potentially_Hazardous',
    'H': 'Brightness',
    'diameter': 'Asteroid_Size_km(Diameter)',
    'albedo': 'Reflectivity',
    'diameter_sigma': 'Size_Uncertainty_km',
    'orbit_id': 'Orbit_Solution_ID',
    'epoch': 'Observation_Date',
    'epoch_mjd': 'Observation_Date_MJD',
    'epoch_cal': 'Observation_Date_Calendar',
    'equinox': 'Reference_Frame',
    'e': 'Orbit_Shape',
    'a': 'Orbit_Distance_AU',
    'q': 'Closest_Sun_Distance_AU',
    'i': 'Orbit_Tilt_Degrees',
    'om': 'Orbit_Angle_1_Degrees',
    'w': 'Orbit_Angle_2_Degrees',
    'ma': 'Orbit_Angle_3_Degrees',
```

```
    'ad': 'Farthest_Sun_Distance_AU',
    'n': 'Orbit_Speed_Degrees_Per_Day',
    'tp': 'Closest_Sun_Date',
    'tp_cal': 'Closest_Sun_Date_Calendar',
    'per': 'Orbit_Period_Days',
    'per_y': 'Orbit_Period_Years',
    'moid': 'Earth_Closest_Distance_AU',
    'moid_ld': 'Earth_Closest_Distance_Lunar',
    'sigma_e': 'Uncertainty_Orbit_Shape',
    'sigma_a': 'Uncertainty_Orbit_Distance',
    'sigma_q': 'Uncertainty_Closest_Sun_Distance',
    'sigma_i': 'Uncertainty_Orbit_Tilt',
    'sigma_om': 'Uncertainty_Orbit_Angle_1',
    'sigma_w': 'Uncertainty_Orbit_Angle_2',
    'sigma_ma': 'Uncertainty_Orbit_Angle_3',
    'sigma_ad': 'Uncertainty_Farthest_Sun_Distance',
    'sigma_n': 'Uncertainty_Orbit_Speed',
    'sigma_tp': 'Uncertainty_Closest_Sun_Date',
    'sigma_per': 'Uncertainty_Orbit_Period',
    'class': 'Asteroid_Class',
    'rms': 'Measurement_Error'
}

non_useful_columns = [
    'Asteroid_ID', 'NASA_SPK_ID', 'Asteroid_Full_Name', 'Primary_Designation',
    'Asteroid_Name', 'Name_Prefix', 'Size_Uncertainty_km', 'Orbit_Solution_ID',
    'Observation_Date', 'Observation_Date_MJD', 'Observation_Date_Calendar',
    'Reference_Frame', 'Closest_Sun_Date', 'Closest_Sun_Date_Calendar',
    'Uncertainty_Orbit_Shape', 'Uncertainty_Orbit_Distance',
'Uncertainty_Closest_Sun_Distance',
    'Uncertainty_Orbit_Tilt', 'Uncertainty_Orbit_Angle_1', 'Uncertainty_Orbit_Angle_2',
    'Uncertainty_Orbit_Angle_3', 'Uncertainty_Farthest_Sun_Distance',
'Uncertainty_Orbit_Speed',
    'Uncertainty_Closest_Sun_Date', 'Uncertainty_Orbit_Period', 'Measurement_Error'
]

df.rename(columns=rename_dict, inplace=True)
print("Dataset - Initial number of features:", df.shape[1])
df = df.drop(columns=non_useful_columns)
print("Dataset - Reduced number of features:", df.shape[1])
```

```
Dataset - Initial number of features: 45
Dataset - Reduced number of features: 19
```

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

```
Near_Earth_Object                  4
Potentially_Hazardous          19921
Brightness                      6263
Asteroid_Size_km(Diameter)    822315
Reflectivity                  823421
Orbit_Shape                        0
Orbit_Distance_AU                  0
Closest_Sun_Distance_AU            0
Orbit_Tilt_Degrees                 0
Orbit_Angle_1_Degrees              0
Orbit_Angle_2_Degrees              0
Orbit_Angle_3_Degrees              1
Farthest_Sun_Distance_AU           4
Orbit_Speed_Degrees_Per_Day        0
Orbit_Period_Days                  4
Orbit_Period_Years                 1
Earth_Closest_Distance_AU      19921
Earth_Closest_Distance_Lunar     127
Asteroid_Class                     0
dtype: int64
```

Creating datafame for Classification

```
original_size = len(df)
print("\nOriginal Size:", original_size)

# Separate PHA classes
df_pha_yes = df[df['Potentially_Hazardous'] == 'Y']
print("\nPHA == Y Size:", len(df_pha_yes))

df_pha_no = df[df['Potentially_Hazardous'] == 'N']
print("PHA == N Size:", len(df_pha_no))

# Filter out rows in the 'N' class to match the non-null features of the 'Y' class
# Drop rows with missing values in 'neo', 'class', and 'H' columns
df_pha_no_clean = df_pha_no.dropna(subset=['Near_Earth_Object',
'Asteroid_Class','Brightness', 'Orbit_Angle_3_Degrees'])
print("\nPHA == N (no missing 'neo', 'class', and 'H') Size:", len(df_pha_no_clean))

# Combine the two classes for classification - balanced dataset
df_classification = pd.concat([df_pha_yes, df_pha_no_clean], ignore_index=True)
# Drop rows with too many missing values in 'diameter' and 'albedo' columns
df_classification =
df_classification.drop(columns=['Asteroid_Size_km(Diameter)','Reflectivity'])
print("\nPercentage of PHA == Y:",
len(df_classification[df_classification['Potentially_Hazardous'] == 'Y']) /
len(df_classification) * 100)
print("Percentage of PHA == N:",
len(df_classification[df_classification['Potentially_Hazardous'] == 'N']) /
len(df_classification) * 100)
print("Classification Dataset Size:",len(df_classification))
```

```
Original Size: 958524

PHA == Y Size: 2066
PHA == N Size: 936537

PHA == N (no missing 'neo', 'class', and 'H') Size: 930270

Percentage of PHA == Y: 0.22159393180141065
Percentage of PHA == N: 99.77840606819859
Classification Dataset Size: 932336
```

```
len(df_classification[df_classification['Potentially_Hazardous'] == 'Y'])
```

```
2066
```

```
len(df_classification[df_classification['Potentially_Hazardous'] == 'N'])
```

```
930270
```

```
df_classification.isnull().sum()
```

```
Near_Earth_Object              0
Potentially_Hazardous          0
Brightness                     0
Orbit_Shape                    0
Orbit_Distance_AU              0
Closest_Sun_Distance_AU        0
Orbit_Tilt_Degrees             0
Orbit_Angle_1_Degrees          0
Orbit_Angle_2_Degrees          0
Orbit_Angle_3_Degrees          0
Farthest_Sun_Distance_AU       0
Orbit_Speed_Degrees_Per_Day    0
Orbit_Period_Days              0
Orbit_Period_Years             0
```

```
Orbit_Distance_AU              0
Closest_Sun_Distance_AU        0
Orbit_Tilt_Degrees             0
Orbit_Angle_1_Degrees          0
Orbit_Angle_2_Degrees          0
Orbit_Angle_3_Degrees          0
Farthest_Sun_Distance_AU       0
Orbit_Speed_Degrees_Per_Day    0
Orbit_Period_Days              0
Orbit_Period_Years             0
Earth_Closest_Distance_AU      0
Earth_Closest_Distance_Lunar   0
Asteroid_Class                 0
dtype: int64
```

```
df_classification.keys()
```

```
Index(['Near_Earth_Object', 'Potentially_Hazardous', 'Brightness',
       'Orbit_Shape', 'Orbit_Distance_AU', 'Closest_Sun_Distance_AU',
       'Orbit_Tilt_Degrees', 'Orbit_Angle_1_Degrees', 'Orbit_Angle_2_Degrees',
       'Orbit_Angle_3_Degrees', 'Farthest_Sun_Distance_AU',
       'Orbit_Speed_Degrees_Per_Day', 'Orbit_Period_Days',
       'Orbit_Period_Years', 'Earth_Closest_Distance_AU',
       'Earth_Closest_Distance_Lunar', 'Asteroid_Class'],
      dtype='object')
```

```
df_classification.head(5)
```

```
  Near_Earth_Object Potentially_Hazardous  Brightness  Orbit_Shape  \
0                 Y                     Y       16.90     0.827021
1                 Y                     Y       15.30     0.335455
2                 Y                     Y       16.25     0.559917
3                 Y                     Y       15.20     0.650352
4                 Y                     Y       18.80     0.763997

   Orbit_Distance_AU  Closest_Sun_Distance_AU  Orbit_Tilt_Degrees  \
0           1.078169                 0.186500           22.822113
1           1.245667                 0.827802           13.337043
2           1.470345                 0.647074            6.354732
3           1.776503                 0.621152           39.829591
4           1.874841                 0.442468            1.322476

   Orbit_Angle_1_Degrees  Orbit_Angle_2_Degrees  Orbit_Angle_3_Degrees  \
0              87.997544              31.393344             192.083181
1             337.186975             276.956068             235.112642
2              35.627131             285.975958              88.546479
3             356.864043             267.822978             312.736110
4             349.486273              43.608203             336.157322

   Farthest_Sun_Distance_AU  Orbit_Speed_Degrees_Per_Day  Orbit_Period_Days  \
0                  1.969838                     0.880387         408.910857
1                  1.663532                     0.708926         507.810053
2                  2.293616                     0.552809         651.219646
3                  2.931855                     0.416251         864.863110
4                  3.307214                     0.383935         937.659578

   Orbit_Period_Years  Earth_Closest_Distance_AU  \
0            1.119537                   0.034245
1            1.390308                   0.030353
2            1.782942                   0.025814
3            2.367866                   0.003568
4            2.567172                   0.011589

   Earth_Closest_Distance_Lunar Asteroid_Class
0                     13.327010            APO
1                     11.812672            APO
2                     10.046073            APO
3                      1.388457            APO
4                      4.510052            APO
```

```
df_classification.isnull().sum()
```

```
Near_Earth_Object              0
Potentially_Hazardous          0
Brightness                     0
Orbit_Shape                    0
```

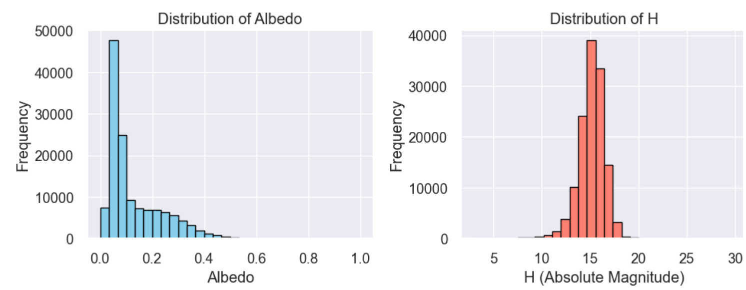
Creating dataframe for Regression

```
#print("\nOriginal Size:", original_size)

df_regression = df.dropna(subset=['Asteroid_Size_km(Diameter)'])
#print("\nSize after dropping rows with missing 'diameter':", len(df_diameter))

df_regression.isnull().sum()
```

```
Near_Earth_Object                 0
Potentially_Hazardous             0
Brightness                     4164
Asteroid_Size_km(Diameter)        0
Reflectivity                   1109
Orbit_Shape                       0
Orbit_Distance_AU                 0
Closest_Sun_Distance_AU           0
Orbit_Tilt_Degrees                0
Orbit_Angle_1_Degrees             0
Orbit_Angle_2_Degrees             0
Orbit_Angle_3_Degrees             0
Farthest_Sun_Distance_AU          0
Orbit_Speed_Degrees_Per_Day       0
Orbit_Period_Days                 0
Orbit_Period_Years                0
Earth_Closest_Distance_AU         0
Earth_Closest_Distance_Lunar      0
Asteroid_Class                    0
dtype: int64
```

```
import matplotlib.pyplot as plt

# Histogram for albedo
plt.figure(figsize=(10, 4))
plt.subplot(1, 2, 1)
plt.hist(df_regression['Reflectivity'].dropna(), bins=30, color='skyblue',
edgecolor='black')
plt.title('Distribution of Albedo')
plt.xlabel('Albedo')
plt.ylabel('Frequency')

# Histogram for H
plt.subplot(1, 2, 2)
plt.hist(df_regression['Brightness'].dropna(), bins=30, color='salmon',
edgecolor='black')
plt.title('Distribution of H')
plt.xlabel('H (Absolute Magnitude)')
plt.ylabel('Frequency')
```

```
plt.tight_layout()
plt.show()
```




```
df_regression[['Brightness', 'Reflectivity']].describe()
```

```
          Brightness  Reflectivity
count  132045.000000  135100.000000
mean       15.132319       0.130625
std         1.387944       0.110323
min         3.000000       0.001000
25%        14.400000       0.053000
50%        15.200000       0.079000
75%        16.000000       0.190000
max        29.900000       1.000000
```

```
#df_regression = df_regression.copy()
df_regression['Reflectivity'] =
df_regression['Reflectivity'].fillna(df_regression['Reflectivity'].median())
df_regression['Brightness'] =
df_regression['Brightness'].fillna(df_regression['Brightness'].mean())


df_regression[['Brightness', 'Reflectivity']].describe()
```

```
          Brightness  Reflectivity
count  136209.000000  136209.000000
mean       15.132319       0.130205
std         1.366564       0.109971
min         3.000000       0.001000
25%        14.400000       0.053000
50%        15.200000       0.079000
75%        16.000000       0.188000
max        29.900000       1.000000
```

```
df_regression.isnull().sum()
```

```
Near_Earth_Object              0
Potentially_Hazardous          0
Brightness                     0
Asteroid_Size_km(Diameter)     0
Reflectivity                   0
Orbit_Shape                    0
Orbit_Distance_AU              0
Closest_Sun_Distance_AU        0
Orbit_Tilt_Degrees             0
Orbit_Angle_1_Degrees          0
Orbit_Angle_2_Degrees          0
```

```
std                  7.998690e-02         2.341159e+06         6.409743e+03
min                  1.608247e-07         1.511918e+02         4.139405e-01
25%                  1.893978e-01         1.348797e+03         3.692806e+00
50%                  2.287358e-01         1.573868e+03         4.309016e+00
75%                  2.669044e-01         1.900761e+03         5.204001e+00
max                  2.381082e+00         2.238462e+09         6.128574e+06

       Earth_Closest_Distance_AU  Earth_Closest_Distance_Lunar
count               9.323360e+05                  932336.000000
mean                1.416253e+00                     551.163122
std                 2.162694e+00                     841.655463
min                 4.544120e-07                       0.000177
25%                 9.802075e-01                     381.467353
50%                 1.241285e+00                     483.070883
75%                 1.593700e+00                     620.220229
max                 7.947660e+01                   30929.908422
```

```
plt.figure(figsize=(16, 12))
correlation_matrix = df_classification[numerical_cols_c].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0, linewidths=0.5)
plt.title('Correlation Matrix of Numerical Features')
plt.tight_layout()
plt.savefig("class_correlation_matrix_heatmap.png", dpi=300, bbox_inches='tight')

import matplotlib.pyplot as plt
import seaborn as sns

# Barcharts of categorical features in the classification dataset
sns.set(style="whitegrid")

for col in categorical_cols_c:
    order = sorted(df_classification[col].dropna().unique())
    plt.figure(figsize=(8, 6))
    ax = sns.countplot(data=df_classification, x=col, hue=col, order=order,
palette="Set2", legend=False)

    # Add number labels on top of each bar
    for container in ax.containers:
        ax.bar_label(container, fmt='%d', label_type='edge', padding=3)

    plt.title(f'Distribution of {col}')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.savefig(f"Distribution of {col}.png", dpi=300, bbox_inches='tight')
    #plt.show()

df_regression.describe()
```

```
          Brightness  Asteroid_Size_km(Diameter)   Reflectivity  \
count  136209.000000               136209.000000  136209.000000
mean       15.132319                    5.506429       0.130205
std         1.366564                    9.425164       0.109971
min         3.000000                    0.002500       0.001000
25%        14.400000                    2.780000       0.053000
50%        15.200000                    3.972000       0.079000
75%        16.000000                    5.765000       0.188000
max        29.900000                  939.400000       1.000000

         Orbit_Shape  Orbit_Distance_AU  Closest_Sun_Distance_AU  \
count  136209.000000      136209.000000            136209.000000
mean        0.145660           2.819158                 2.406130
std         0.077464           1.495980                 0.516931
min         0.000060           0.626210                 0.081820
25%         0.089878           2.542856                 2.072478
50%         0.138919           2.754950                 2.368605
75%         0.191174           3.095029                 2.688275
```

```
Orbit_Angle_3_Degrees          0
Farthest_Sun_Distance_AU       0
Orbit_Speed_Degrees_Per_Day    0
Orbit_Period_Days              0
Orbit_Period_Years             0
Earth_Closest_Distance_AU      0
Earth_Closest_Distance_Lunar   0
Asteroid_Class                 0
dtype: int64
```

Visualization of Classification Dataset

```
# Identify numerical and categorical columns

TARGET_class = 'Potentially_Hazardous'
numerical_cols_c = df_classification.select_dtypes(include=['float64',
'int64']).columns.tolist()
categorical_cols_c = df_classification.select_dtypes(include=['object',
'bool']).columns.tolist()
print(f"{len(numerical_cols_c)} Numerical Features: {numerical_cols_c}")
print(f"{len(categorical_cols_c)} Categorical Features: {categorical_cols_c}")
```

```
14 Numerical Features: ['Brightness', 'Orbit_Shape', 'Orbit_Distance_AU',
'Closest_Sun_Distance_AU', 'Orbit_Tilt_Degrees', 'Orbit_Angle_1_Degrees',
'Orbit_Angle_2_Degrees', 'Orbit_Angle_3_Degrees', 'Farthest_Sun_Distance_AU',
'Orbit_Speed_Degrees_Per_Day', 'Orbit_Period_Days', 'Orbit_Period_Years',
'Earth_Closest_Distance_AU', 'Earth_Closest_Distance_Lunar']
3 Categorical Features: ['Near_Earth_Object', 'Potentially_Hazardous', 'Asteroid_Class']
```

```
df_classification.describe()
```

```
          Brightness    Orbit_Shape  Orbit_Distance_AU  \
count  932336.000000  932336.000000      932336.000000
mean       16.889991       0.156221           2.932615
std         1.801331       0.093001          36.458214
min        -1.100000       0.000003           0.555418
25%        16.000000       0.092160           2.389088
50%        16.900000       0.144933           2.647971
75%        17.700000       0.200589           3.002982
max        33.200000       0.999851       33488.895955

       Closest_Sun_Distance_AU  Orbit_Tilt_Degrees  Orbit_Angle_1_Degrees  \
count            932336.000000       932336.000000          932336.000000
mean                  2.398918            8.996694             168.395442
std                   2.165336            6.606941             102.863946
min                   0.070511            0.007744               0.000025
25%                   1.972209            4.135564              80.528080
50%                   2.227214            7.357849             159.871025
75%                   2.580131           12.332727             251.974334
max                  80.398819          175.082901             359.999793

       Orbit_Angle_2_Degrees  Orbit_Angle_3_Degrees  Farthest_Sun_Distance_AU  \
count          932336.000000          932336.000000             932336.000000
mean              181.381454             177.029125                  3.466313
std               103.909981             105.755423                 72.768214
min                 0.000130             -67.136826                  0.653773
25%                91.490778              83.559427                  2.783887
50%               182.353517             174.966318                  3.048694
75%               271.551530             269.594056                  3.365570
max               359.999646             491.618014              66972.796064

       Orbit_Speed_Degrees_Per_Day  Orbit_Period_Days  Orbit_Period_Years  \
count                 9.323360e+05       9.323360e+05        9.323360e+05
mean                  2.366077e-01       5.181153e+03        1.418522e+01
```

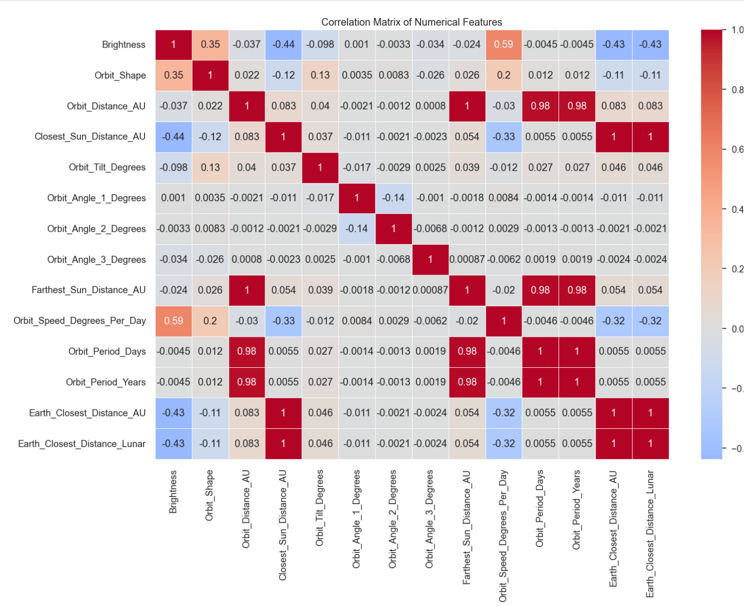
```
max        0.983789         376.133297                40.318477

       Orbit_Tilt_Degrees  Orbit_Angle_1_Degrees  Orbit_Angle_2_Degrees  \
count       136209.000000          136209.000000          136209.000000
mean            10.295360             169.729893             181.808169
std              6.812632             102.715175             103.516287
min              0.022056               0.000418               0.000130
25%              5.088142              82.276476              91.903488
50%              9.335690             160.301343             183.509496
75%             13.670331             255.961202             271.642281
max            170.334595             359.999793             359.998075

       Orbit_Angle_3_Degrees  Farthest_Sun_Distance_AU  \
count          136209.000000             136209.000000
mean              184.529202                  3.232187
std               105.632553                  2.839820
min                 0.005112                  0.999954
25%                91.647097                  2.871056
50%               188.275290                  3.173515
75%               277.821001                  3.472570
max               391.682098                746.169105

       Orbit_Speed_Degrees_Per_Day  Orbit_Period_Days  Orbit_Period_Years  \
count                136209.000000       1.362090e+05       136209.000000
mean                      0.219086       1.787231e+03           4.893173
std                       0.056912       8.965840e+03          24.547132
min                       0.000135       1.809999e+02           0.495551
25%                       0.181012       1.481089e+03           4.055000
50%                       0.215543       1.670202e+03           4.572764
75%                       0.243064       1.988820e+03           5.445092
max                       1.988951       2.664472e+06        7294.925719

       Earth_Closest_Distance_AU  Earth_Closest_Distance_Lunar
count              136209.000000                 136209.000000
mean                    1.423858                    554.122719
std                     0.513029                    199.655301
min                     0.000027                      0.010335
25%                     1.086220                    422.724237
50%                     1.389580                    540.782849
75%                     1.702400                    662.523008
max                    39.360300                  15317.847951
```

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

# Set plot style
sns.set(style="whitegrid")

# Create boxplots for each numerical feature vs the target
for col in numerical_cols_c:
    plt.figure(figsize=(8, 4))
    sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
    plt.title(f"{col} vs {TARGET_class}")
    plt.xlabel(TARGET_class)
    plt.ylabel(col)
    plt.tight_layout()
    plt.savefig(f"{col}_vs_{TARGET_class}.png", dpi=300, bbox_inches='tight')
    #plt.show()
```

```
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:
```

```
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:
```

```python
    plt.tight_layout()
    plt.savefig(f"boxplot_{TARGET_reg} vs {col}.png", dpi=300, bbox_inches='tight')
    plt.show()
```




```
Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\2999458775.py:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0.
Assign the `x` variable to `hue` and set `legend=False` for the same effect.

  sns.boxplot(data=df_classification, x=TARGET_class, y=col, palette="Set2")
```

Visualization of Regression Dataset

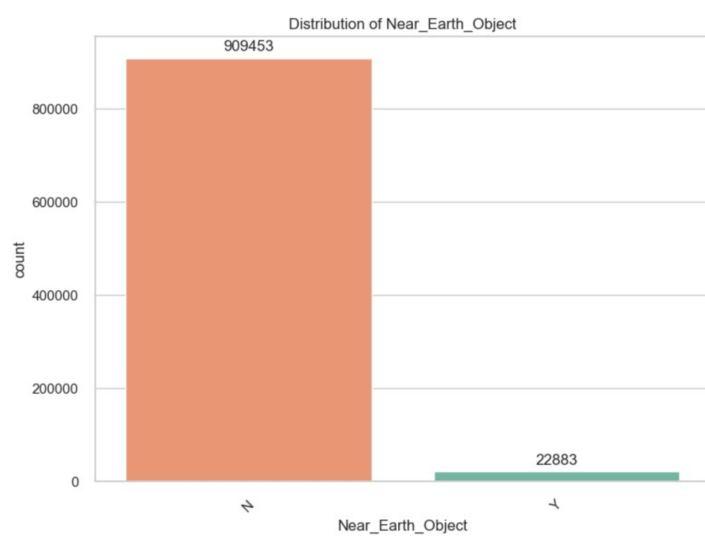
```python
TARGET_reg = 'Asteroid_Size_km(Diameter)'

numerical_cols_r = df_regression.select_dtypes(include=['float64',
'int64']).columns.tolist()
categorical_cols_r = df_regression.select_dtypes(include=['object',
'bool']).columns.tolist()
print(f"Numerical Features: {numerical_cols_r}, {len(numerical_cols_r)}")
print(f"Categorical Features: {categorical_cols_r}, {len(categorical_cols_r)}")
```

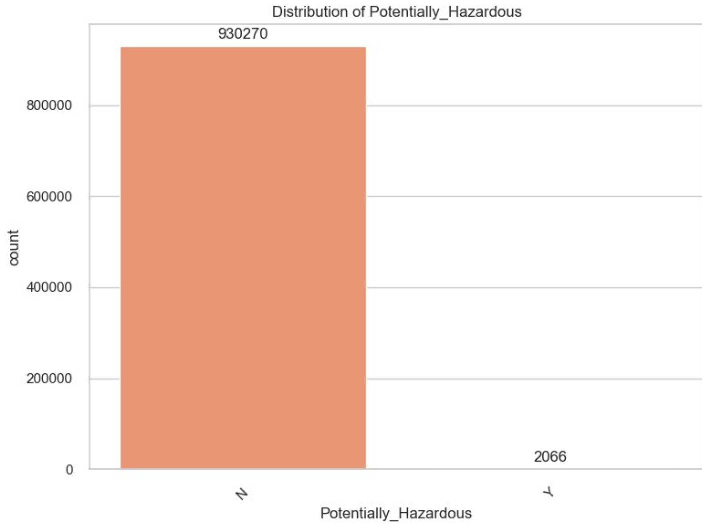
```
Numerical Features: ['Brightness', 'Asteroid_Size_km(Diameter)', 'Reflectivity',
'Orbit_Shape', 'Orbit_Distance_AU', 'Closest_Sun_Distance_AU', 'Orbit_Tilt_Degrees',
'Orbit_Angle_1_Degrees', 'Orbit_Angle_2_Degrees', 'Orbit_Angle_3_Degrees',
'Farthest_Sun_Distance_AU', 'Orbit_Speed_Degrees_Per_Day', 'Orbit_Period_Days',
'Orbit_Period_Years', 'Earth_Closest_Distance_AU', 'Earth_Closest_Distance_Lunar'], 16
Categorical Features: ['Near_Earth_Object', 'Potentially_Hazardous', 'Asteroid_Class'], 3
```

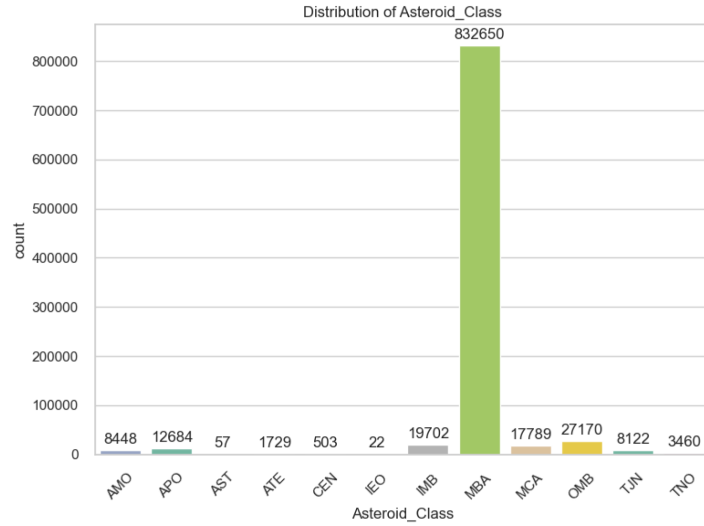
```python
# Barcharts of categorical features in the regression dataset

for col in categorical_cols_r:
    order = sorted(df_regression[col].dropna().unique())
    plt.figure(figsize=(8, 6))
    ax = sns.countplot(data=df_regression, x=col, hue=col, order=order, palette="Set2",
legend=False)

    # Add number labels on top of each bar
    for container in ax.containers:
        ax.bar_label(container, fmt='%d', label_type='edge', padding=3)

    plt.title(f'Distribution of {col}')
    plt.xticks(rotation=45)
    plt.tight_layout()
    plt.savefig(f"Distribution of {col}.png", dpi=300, bbox_inches='tight')
    #plt.show()
```

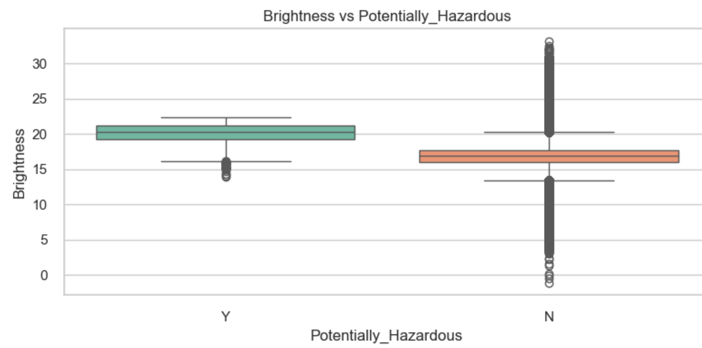
```
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\4000358182.py:5: RuntimeWarning: More
than 20 figures have been opened. Figures created through the pyplot interface
(`matplotlib.pyplot.figure`) are retained until explicitly closed and may consume too
much memory. (To control this warning, see the rcParam `figure.max_open_warning`).
Consider using `matplotlib.pyplot.close()`.
  plt.figure(figsize=(8, 6))
```

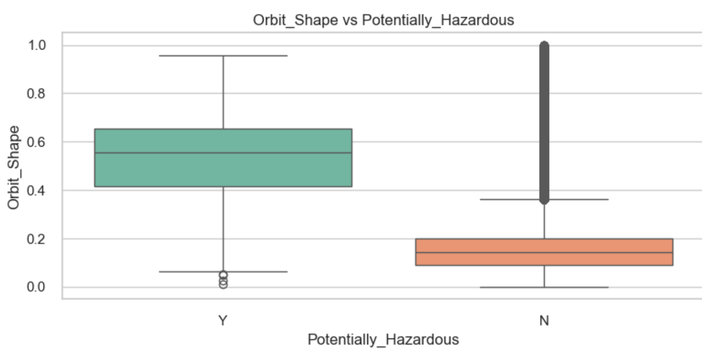
```python
# Boxplots of Categorical Features vs TARGET_reg

for col in categorical_cols_r:
    order = sorted(df_regression[col].dropna().unique())  # or specify a custom list

    plt.figure(figsize=(8, 6))
    sns.boxplot(data=df_regression, x=col, y=TARGET_reg, hue=col, order=order,
palette="Set3")
    plt.title(f'{TARGET_reg} vs {col}')
    plt.xticks(rotation=45)
```

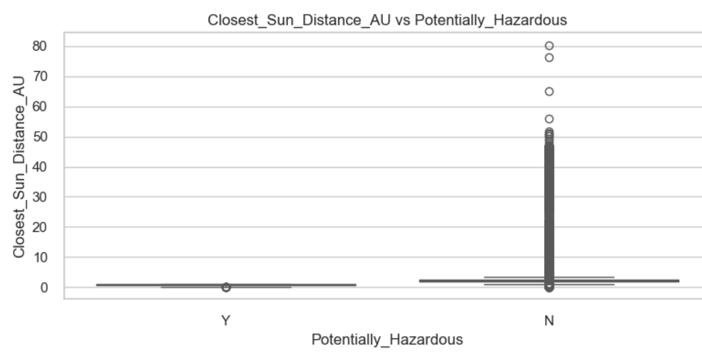


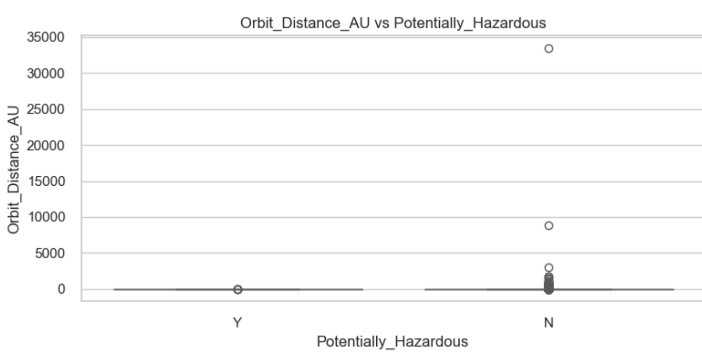

Distribution of Potentially_Hazardous
930270
2066
count
0
200000
400000
600000
800000
N
Y
Potentially_Hazardous

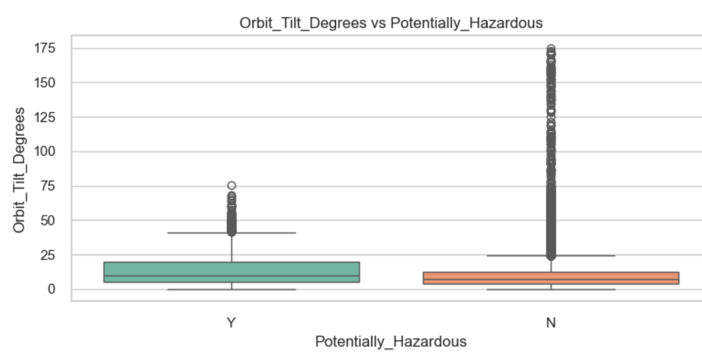

Distribution of Asteroid_Class
832650
8448
12684
57
1729
503
22
19702
17789
27170
8122
3460
count
0
100000
200000
300000
400000
500000
600000
700000
800000
AMO
APO
AST
ATE
CEN
IEO
IMB
MBA
MCA
OMB
TJN
TNO
Asteroid_Class

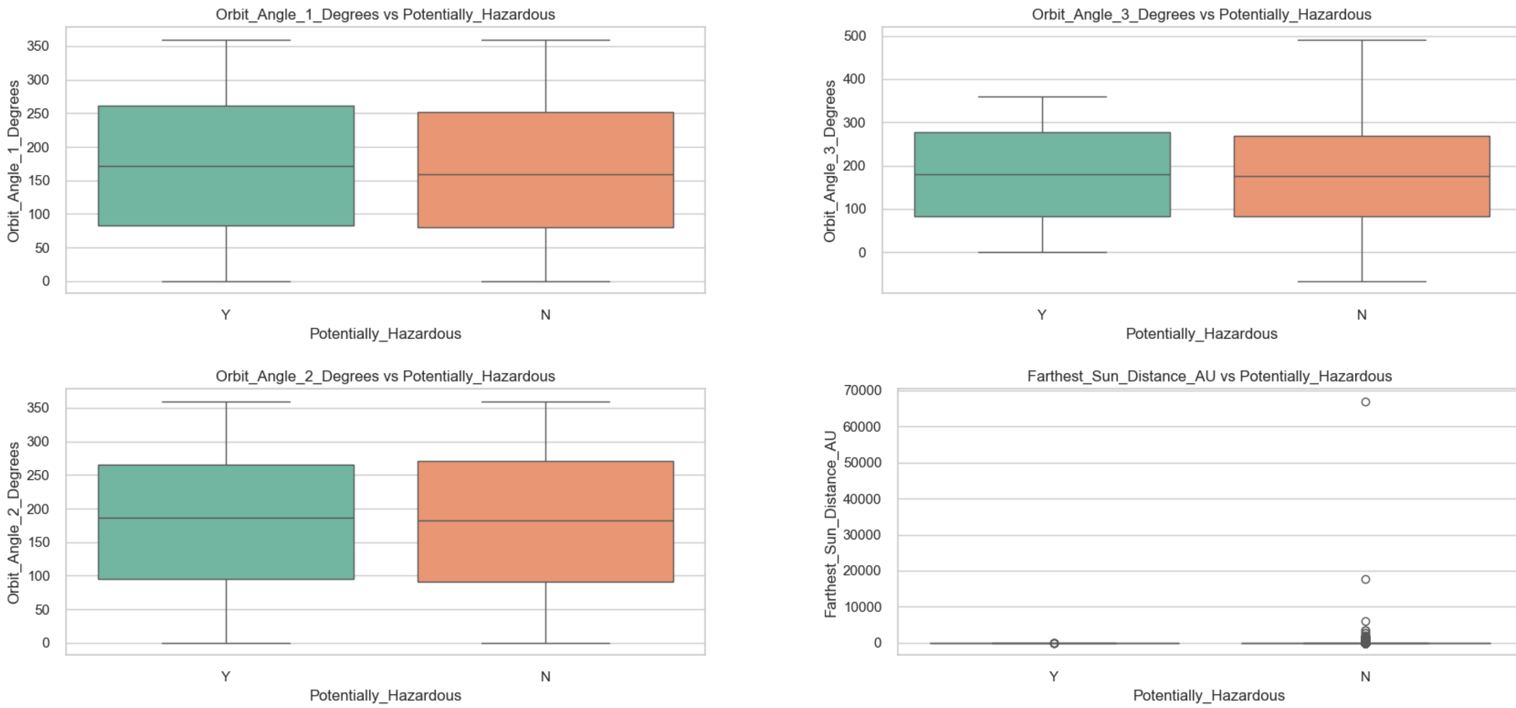

Brightness vs Potentially_Hazardous
Brightness
0
5
10
15
20
25
30
Y
N
Potentially_Hazardous

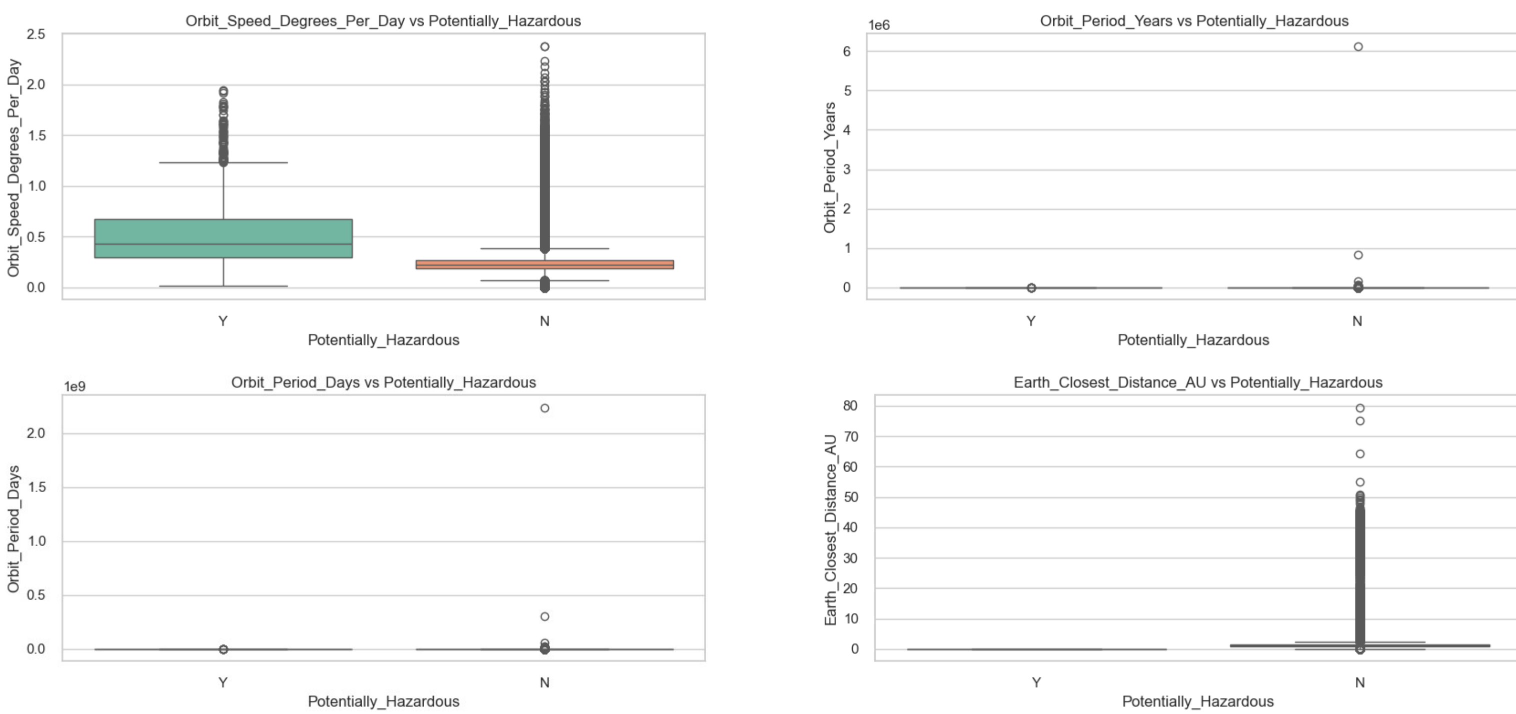

Orbit_Shape vs Potentially_Hazardous
Orbit_Shape
0.0
0.2
0.4
0.6
0.8
1.0
Y
N
Potentially_Hazardous

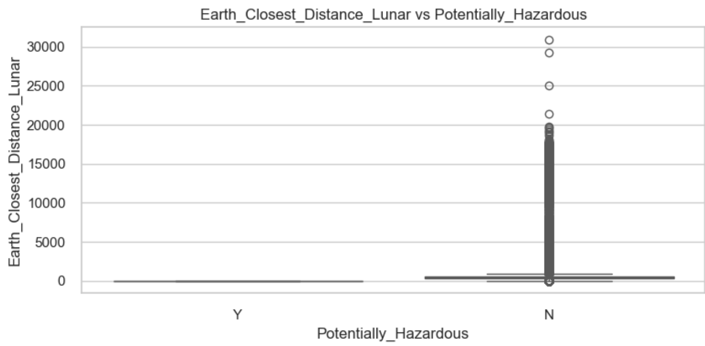

Closest_Sun_Distance_AU vs Potentially_Hazardous
Closest_Sun_Distance_AU
0
10
20
30
40
50
60
70
80
Y
N
Potentially_Hazardous

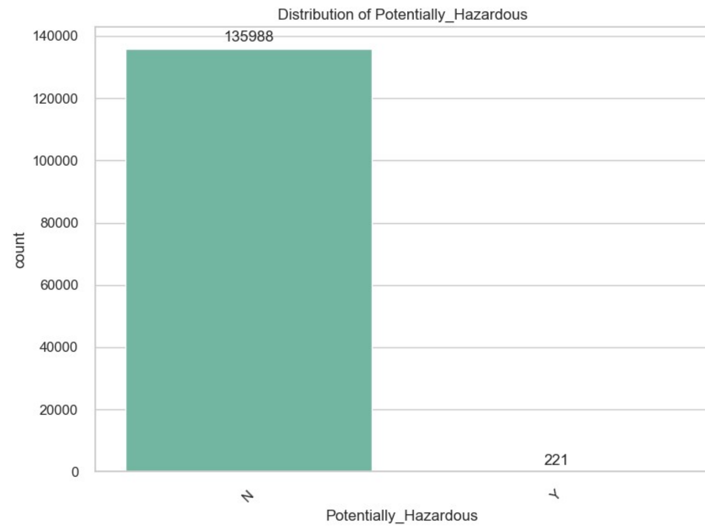

Orbit_Distance_AU vs Potentially_Hazardous
Orbit_Distance_AU
0
5000
10000
15000
20000
25000
30000
35000
Y
N
Potentially_Hazardous

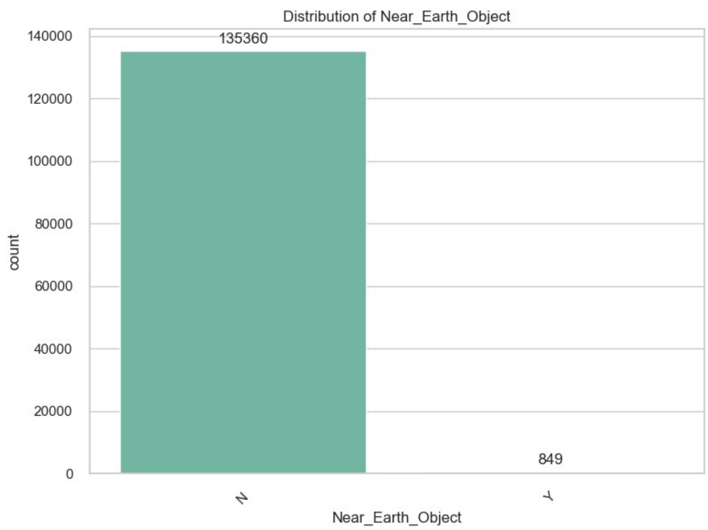

Orbit_Tilt_Degrees vs Potentially_Hazardous
Orbit_Tilt_Degrees
0
25
50
75
100
125
150
175
Y
N
Potentially_Hazardous

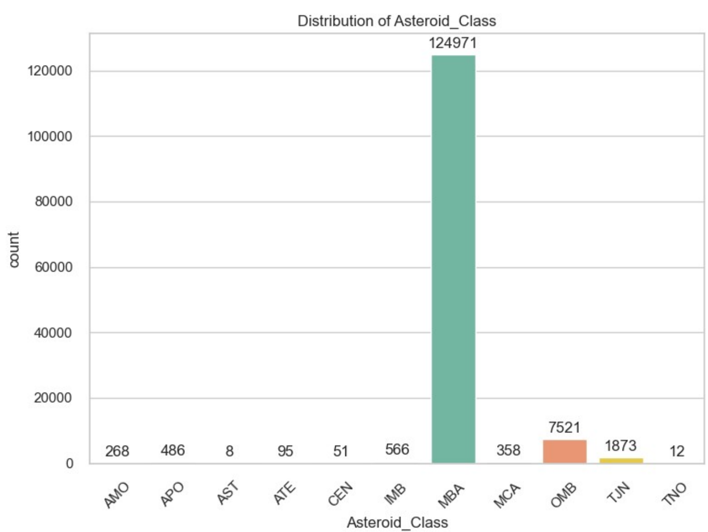

Orbit_Angle_1_Degrees vs Potentially_Hazardous
Orbit_Angle_1_Degrees
Potentially_Hazardous
Y
N
0
50
100
150
200
250
300
350
Orbit_Angle_3_Degrees vs Potentially_Hazardous
Orbit_Angle_3_Degrees
Potentially_Hazardous
0
100
200
300
400
500
Orbit_Angle_2_Degrees vs Potentially_Hazardous
Orbit_Angle_2_Degrees
Potentially_Hazardous
Farthest_Sun_Distance_AU vs Potentially_Hazardous
Farthest_Sun_Distance_AU
Potentially_Hazardous
0
10000
20000
30000
40000
50000
60000
70000

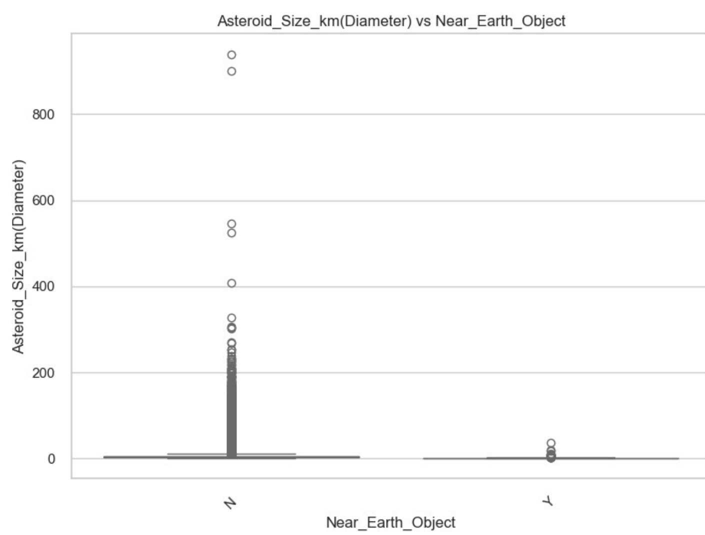

Orbit_Speed_Degrees_Per_Day vs Potentially_Hazardous
Orbit_Speed_Degrees_Per_Day
Potentially_Hazardous
Y
N
0.0
0.5
1.0
1.5
2.0
2.5
Orbit_Period_Years vs Potentially_Hazardous
Orbit_Period_Years
Potentially_Hazardous
1e6
0
1
2
3
4
5
6
Orbit_Period_Days vs Potentially_Hazardous
Orbit_Period_Days
Potentially_Hazardous
1e9
0.0
0.5
1.0
1.5
2.0
Earth_Closest_Distance_AU vs Potentially_Hazardous
Earth_Closest_Distance_AU
Potentially_Hazardous
0
10
20
30
40
50
60
70
80

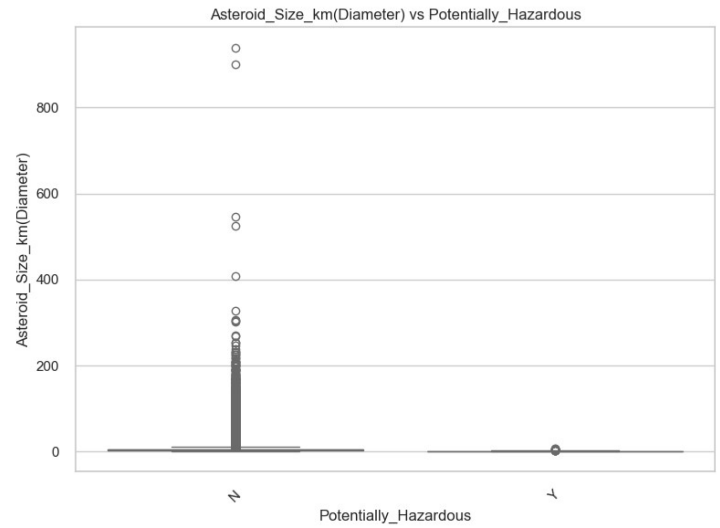

Earth_Closest_Distance_Lunar vs Potentially_Hazardous
Earth_Closest_Distance_Lunar
0
5000
10000
15000
20000
25000
30000
Y
N
Potentially_Hazardous

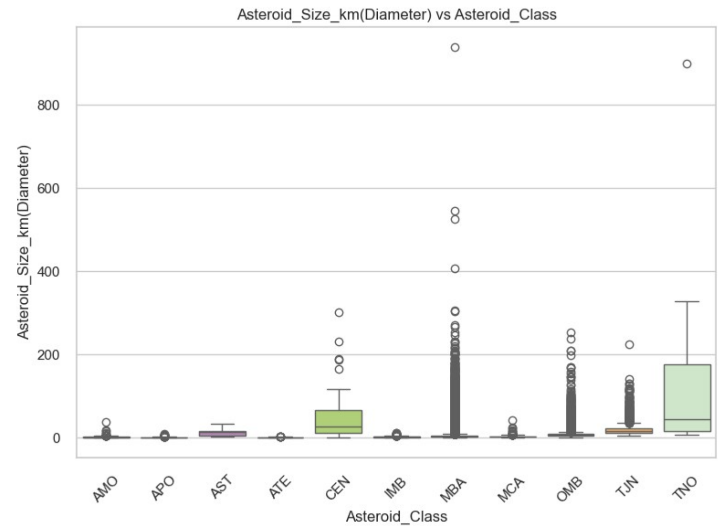

Distribution of Potentially_Hazardous
count
135988
221
N
Y
Potentially_Hazardous


Distribution of Near_Earth_Object
count
135360
849
N
Y
Near_Earth_Object


Distribution of Asteroid_Class
count
268
486
8
95
51
566
124971
358
7521
1873
12
AMO
APO
AST
ATE
CEN
IMB
MBA
MCA
OMB
TJN
TNO
Asteroid_Class


Asteroid_Size_km(Diameter) vs Near_Earth_Object
Asteroid_Size_km(Diameter)
0
200
400
600
800
N
Y
Near_Earth_Object






```python
# Scatter Plots of Numerical Features vs TARGET_reg
for col in numerical_cols_r:
    if col != TARGET_reg:
        plt.figure(figsize=(8, 4))
        sns.scatterplot(data=df_regression, x=col, y=TARGET_reg, alpha=0.6)
        plt.title(f'{TARGET_reg} vs {col}')
        plt.tight_layout()
        plt.savefig(f"scatter_{TARGET_reg} vs {col}.png", dpi=300, bbox_inches='tight')
        #plt.show()

# Histograms of Numerical Variables

for col in numerical_cols_r:
    plt.figure(figsize=(6, 4))
    sns.histplot(data=df_regression, x=col, kde=True, bins=30, color='steelblue')
    plt.title(f'Distribution of {col}')
    plt.tight_layout()
    plt.savefig(f"hist_{TARGET_reg} vs {col}.png", dpi=300, bbox_inches='tight')
    #plt.show()
```

```
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\13780212.py:4: RuntimeWarning: More
than 20 figures have been opened. Figures created through the pyplot interface
(`matplotlib.pyplot.figure`) are retained until explicitly closed and may consume too
much memory. (To control this warning, see the rcParam `figure.max_open_warning`).
Consider using `matplotlib.pyplot.close()`.
  plt.figure(figsize=(6, 4))
```

```python
import pandas as pd

# Step 1: Numerical Summaries
summary_stats = df_regression[numerical_cols_r].describe().T
summary_stats['skewness'] = df_regression[numerical_cols_r].skew()
summary_stats['kurtosis'] = df_regression[numerical_cols_r].kurt()
display(summary_stats)

# Step 2: Corr Matrix
# Compute the correlation_matrix
plt.figure(figsize=(16, 12))
correlation_matrix = df_regression[numerical_cols_r].corr()
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0, linewidths=0.5,
fmt=".2f")
plt.title('Correlation Matrix of Numerical Features')
plt.tight_layout()
plt.savefig("correlation_matrix_heatmap.png", dpi=300, bbox_inches='tight')
#plt.show()

# Step 3: Outlier Detection using IQR
outlier_summary = {}

for col in numerical_cols_r:
    Q1 = df_regression[col].quantile(0.25)
    Q3 = df_regression[col].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = df_regression[(df_regression[col] < lower_bound) | (df_regression[col] >
upper_bound)]
    outlier_count = len(outliers)
    outlier_summary[col] = {
        'lower_bound': lower_bound,
        'upper_bound': upper_bound,
        'outlier_count': outlier_count,
        'outlier_percentage': round(outlier_count / len(df_regression) * 100, 2)
    }

# Convert to DataFrame for display
outlier_df = pd.DataFrame(outlier_summary).T
display(outlier_df)
```

	count	mean	std	min \
Brightness	136209.0	15.132319	1.366564	3.000000
Asteroid_Size_km(Diameter)	136209.0	5.506429	9.425164	0.002500
Reflectivity	136209.0	0.130205	0.109971	0.001000
Orbit_Shape	136209.0	0.145660	0.077464	0.000060
Orbit_Distance_AU	136209.0	2.819158	1.495980	0.626210
Closest_Sun_Distance_AU	136209.0	2.406130	0.516931	0.081820
Orbit_Tilt_Degrees	136209.0	10.295360	6.812632	0.022056
Orbit_Angle_1_Degrees	136209.0	169.729893	102.715175	0.000418
Orbit_Angle_2_Degrees	136209.0	181.808169	103.516287	0.000130
Orbit_Angle_3_Degrees	136209.0	184.529202	105.632553	0.005112
Farthest_Sun_Distance_AU	136209.0	3.232187	2.839820	0.999954
Orbit_Speed_Degrees_Per_Day	136209.0	0.219086	0.056912	0.000135
Orbit_Period_Days	136209.0	1787.231375	8965.839867	180.999945
Orbit_Period_Years	136209.0	4.893173	24.547132	0.495551
Earth_Closest_Distance_AU	136209.0	1.423858	0.513029	0.000027
Earth_Closest_Distance_Lunar	136209.0	554.122719	199.655301	0.010335

	25%	50%	75% \
Brightness	14.400000	15.200000	16.000000
Asteroid_Size_km(Diameter)	2.780000	3.972000	5.765000
Reflectivity	0.053000	0.079000	0.188000
Orbit_Shape	0.089878	0.138919	0.191174
Orbit_Distance_AU	2.542856	2.754950	3.095029
Closest_Sun_Distance_AU	2.072478	2.368605	2.688275
Orbit_Tilt_Degrees	5.088142	9.335690	13.670331
Orbit_Angle_1_Degrees	82.276476	160.301343	255.961202
Orbit_Angle_2_Degrees	91.903488	183.509496	271.642281
Orbit_Angle_3_Degrees	91.647097	188.275290	277.821001
Farthest_Sun_Distance_AU	2.871056	3.173515	3.472570
Orbit_Speed_Degrees_Per_Day	0.181012	0.215543	0.243064
Orbit_Period_Days	1481.088579	1670.202045	1988.819671
Orbit_Period_Years	4.055000	4.572764	5.445092
Earth_Closest_Distance_AU	1.086220	1.389580	1.702400
Earth_Closest_Distance_Lunar	422.724237	540.782849	662.523008

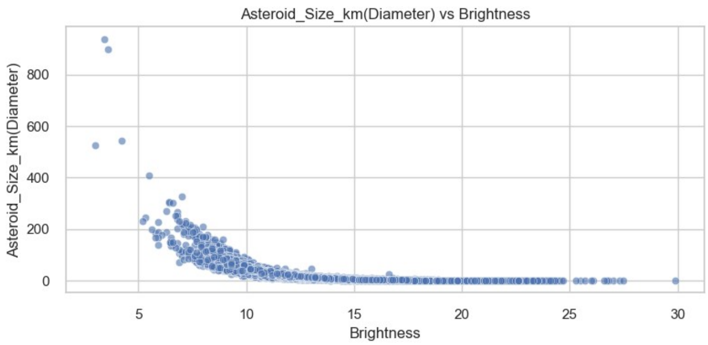
	max	skewness	kurtosis
Brightness	2.990000e+01	-0.698152	4.370548
Asteroid_Size_km(Diameter)	9.394000e+02	25.852418	1634.363104
Reflectivity	1.000000e+00	1.696635	3.958674
Orbit_Shape	9.837890e-01	1.407371	7.034553
Orbit_Distance_AU	3.761333e+02	174.781076	38523.918438
Closest_Sun_Distance_AU	4.031848e+01	7.314837	344.145509
Orbit_Tilt_Degrees	1.703346e+02	1.659299	13.411315
Orbit_Angle_1_Degrees	3.599998e+02	0.185611	-1.131491
Orbit_Angle_2_Degrees	3.599981e+02	-0.027659	-1.203463
Orbit_Angle_3_Degrees	3.916821e+02	-0.069455	-1.241824
Farthest_Sun_Distance_AU	7.461691e+02	199.089250	46160.418336
Orbit_Speed_Degrees_Per_Day	1.988951e+00	6.026977	106.752719
Orbit_Period_Days	2.664472e+06	249.879621	67552.729860
Orbit_Period_Years	7.294926e+03	249.879621	67552.729860
Earth_Closest_Distance_AU	3.936030e+01	7.601012	356.071549
Earth_Closest_Distance_Lunar	1.531785e+04	7.601012	356.071549

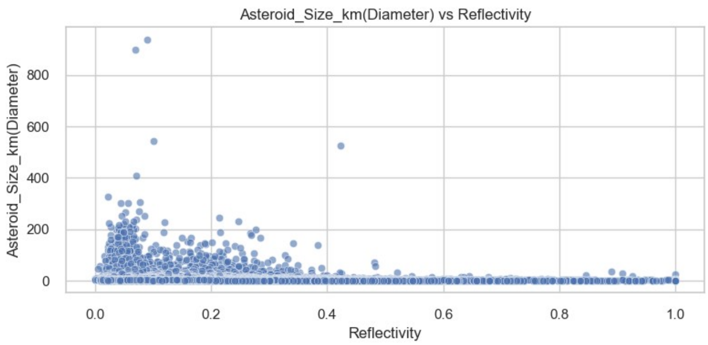
	lower_bound	upper_bound	outlier_count \
Brightness	12.000000	18.400000	3532.0
Asteroid_Size_km(Diameter)	-1.697500	10.242500	9613.0
Reflectivity	-0.149500	0.390500	3809.0
Orbit_Shape	-0.062066	0.343118	1503.0
Orbit_Distance_AU	1.714597	3.923288	3423.0
Closest_Sun_Distance_AU	1.148784	3.611970	2708.0
Orbit_Tilt_Degrees	-7.785143	26.543616	4256.0
Orbit_Angle_1_Degrees	-178.250614	516.488292	0.0
Orbit_Angle_2_Degrees	-177.704700	541.250470	0.0
Orbit_Angle_3_Degrees	-187.613758	557.081856	0.0
Farthest_Sun_Distance_AU	1.968785	4.374841	3567.0
Orbit_Speed_Degrees_Per_Day	0.087933	0.336143	3253.0
Orbit_Period_Days	719.491942	2750.416309	3399.0
Orbit_Period_Years	1.969862	7.530229	3399.0
Earth_Closest_Distance_AU	0.161950	2.626670	2552.0
Earth_Closest_Distance_Lunar	63.026081	1022.221164	2552.0

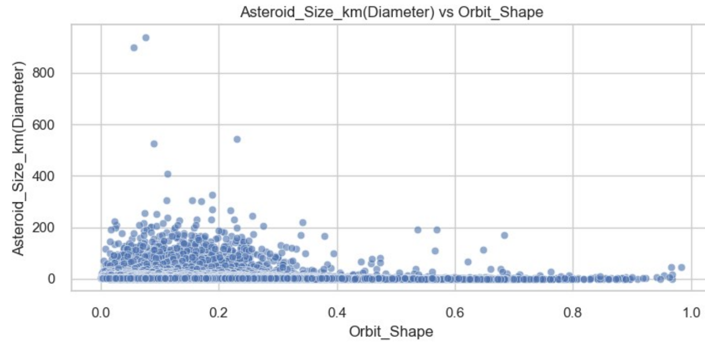
	outlier_percentage
Brightness	2.59
Asteroid_Size_km(Diameter)	7.06
Reflectivity	2.80
Orbit_Shape	1.10
Orbit_Distance_AU	2.51
Closest_Sun_Distance_AU	1.99
Orbit_Tilt_Degrees	3.12
Orbit_Angle_1_Degrees	0.00
Orbit_Angle_2_Degrees	0.00
Orbit_Angle_3_Degrees	0.00
Farthest_Sun_Distance_AU	2.62
Orbit_Speed_Degrees_Per_Day	2.39
Orbit_Period_Days	2.50
Orbit_Period_Years	2.50
Earth_Closest_Distance_AU	1.87
Earth_Closest_Distance_Lunar	1.87

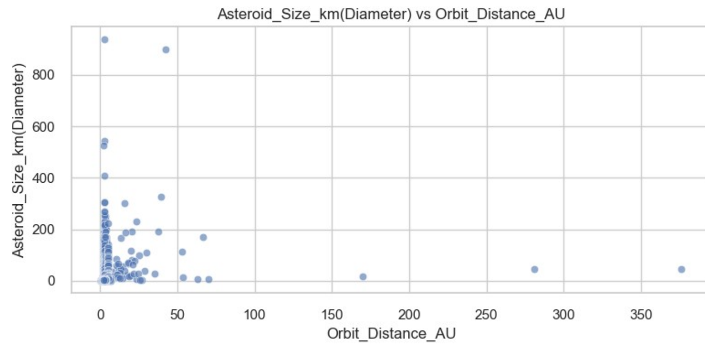
```python
plt.figure(figsize=(16, 12))
correlation_matrix = df_regression[numerical_cols_r].corr()
```

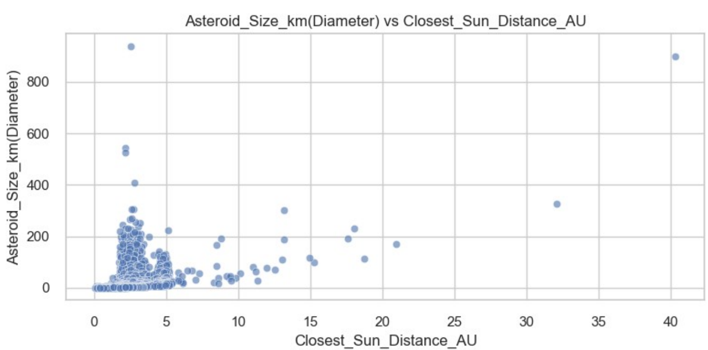
```
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', center=0, linewidths=0.5,
fmt=".2f")
plt.title('Correlation Matrix of Numerical Features')
plt.tight_layout()
plt.savefig("correlation_matrix_heatmap.png", dpi=300, bbox_inches='tight')
plt.show()
```

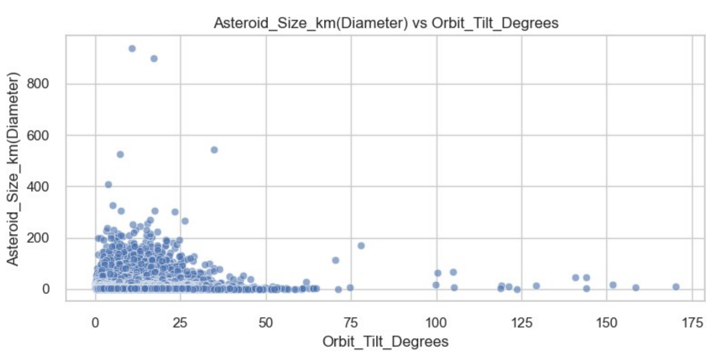


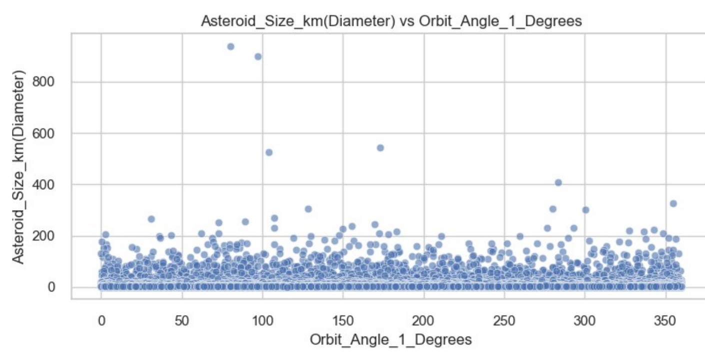


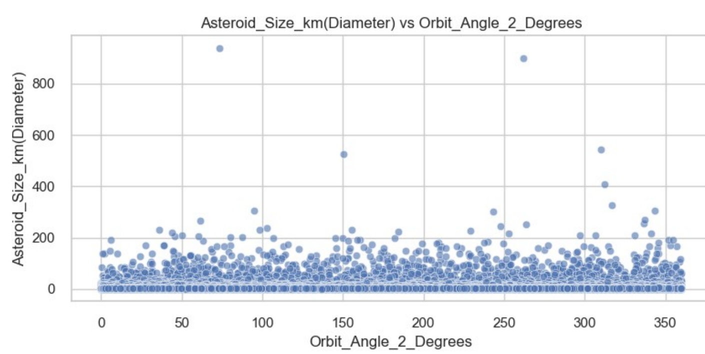


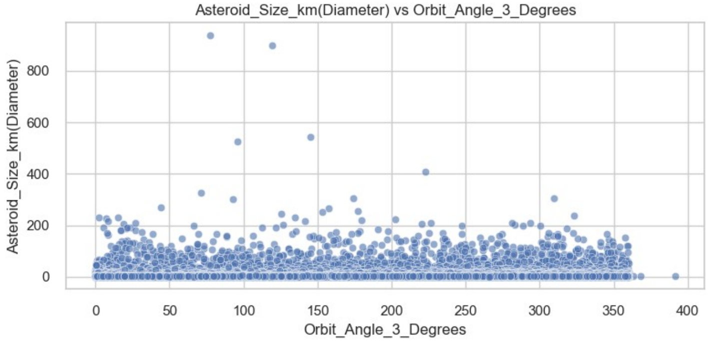


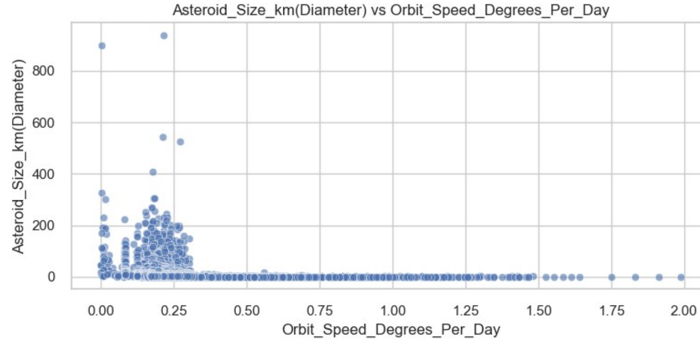


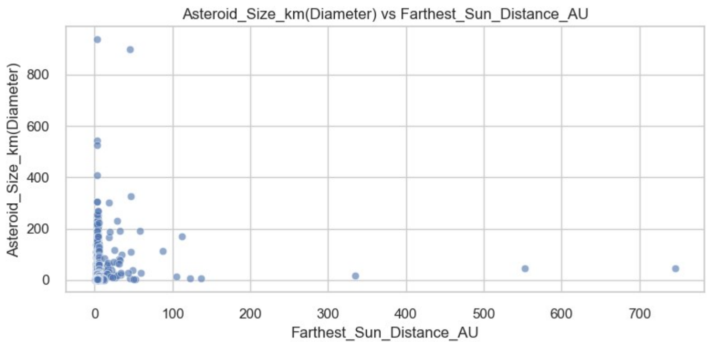


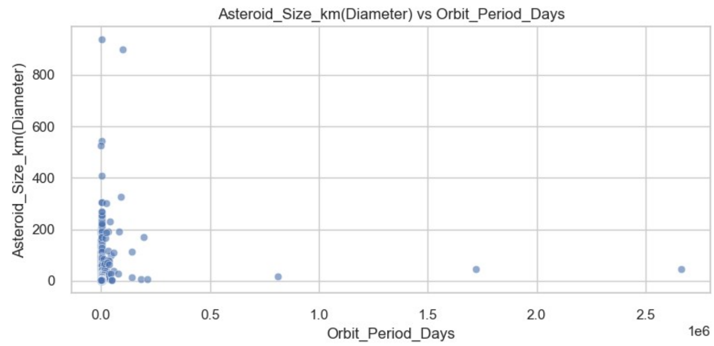


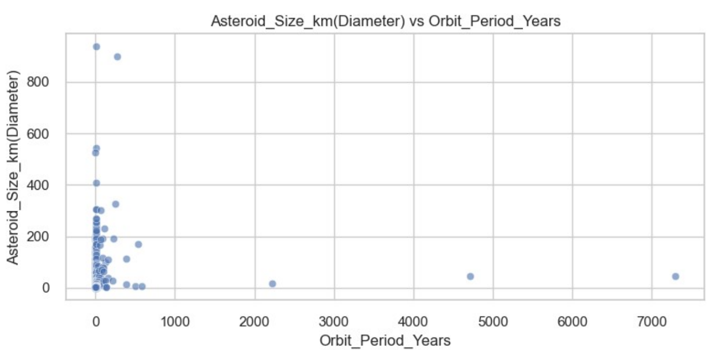


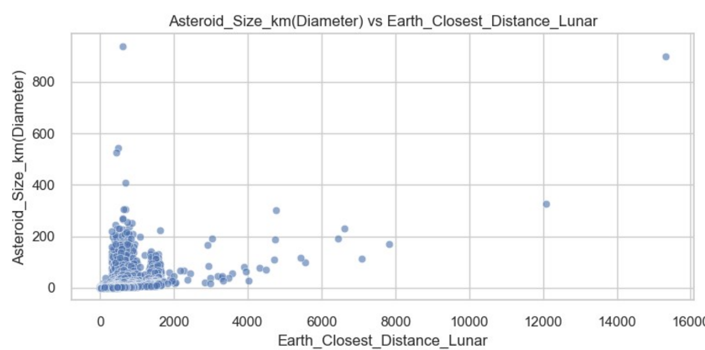

Asteroid_Size_km(Diameter) vs Orbit_Angle_3_Degrees
Asteroid_Size_km(Diameter)
Orbit_Angle_3_Degrees

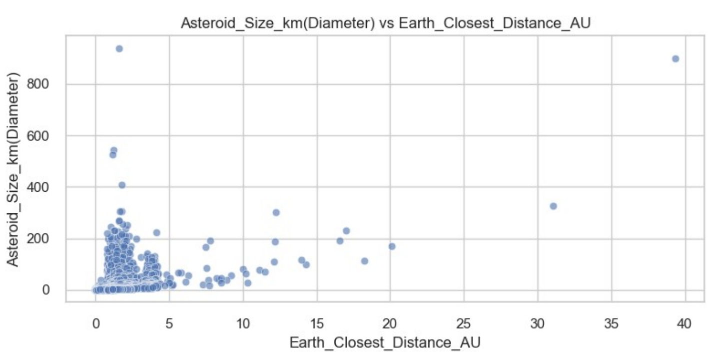

Asteroid_Size_km(Diameter) vs Orbit_Speed_Degrees_Per_Day
Asteroid_Size_km(Diameter)
Orbit_Speed_Degrees_Per_Day

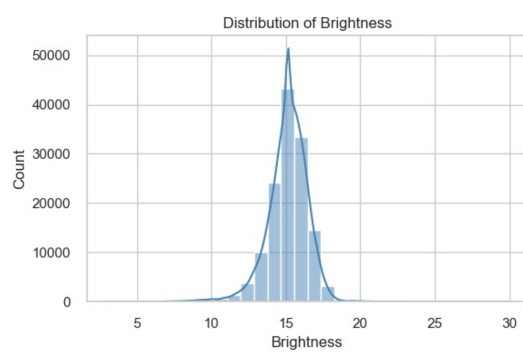

Asteroid_Size_km(Diameter) vs Farthest_Sun_Distance_AU
Asteroid_Size_km(Diameter)
Farthest_Sun_Distance_AU

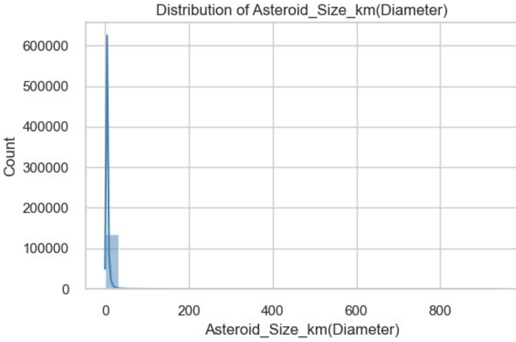

Asteroid_Size_km(Diameter) vs Orbit_Period_Days
Asteroid_Size_km(Diameter)
Orbit_Period_Days
1e6

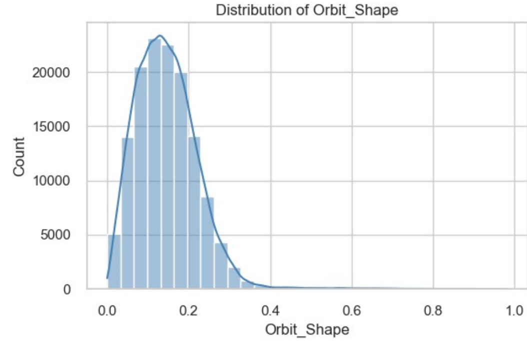

Asteroid_Size_km(Diameter) vs Orbit_Period_Years
Asteroid_Size_km(Diameter)
Orbit_Period_Years

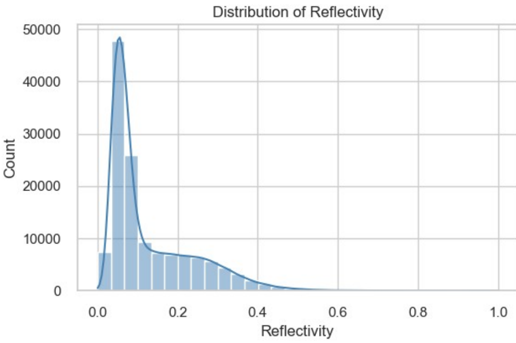

Asteroid_Size_km(Diameter) vs Earth_Closest_Distance_Lunar
Asteroid_Size_km(Diameter)
Earth_Closest_Distance_Lunar

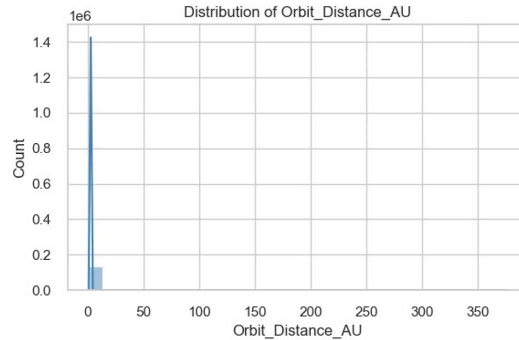

Asteroid_Size_km(Diameter) vs Earth_Closest_Distance_AU
Asteroid_Size_km(Diameter)
Earth_Closest_Distance_AU

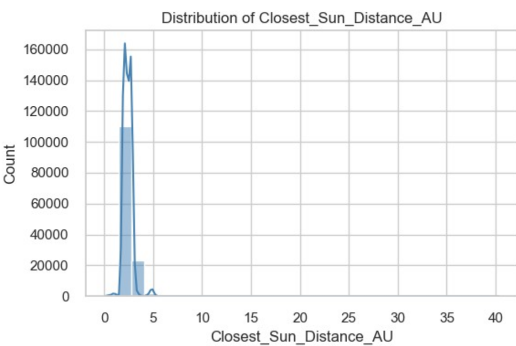

Distribution of Brightness
Count
Brightness

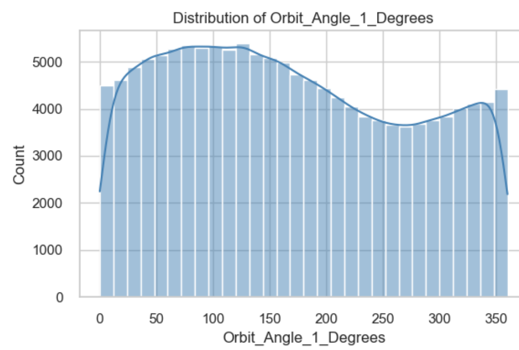

Distribution of Asteroid_Size_km(Diameter)
600000
500000
400000
300000
200000
100000
0
Count
0
200
400
600
800
Asteroid_Size_km(Diameter)

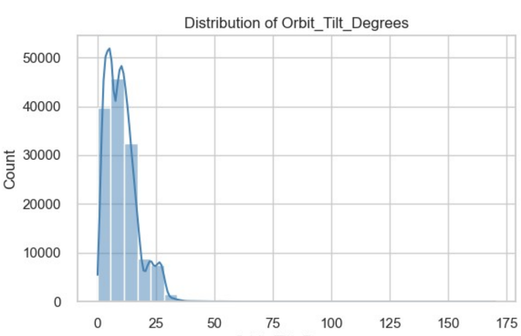

Distribution of Orbit_Shape
20000
15000
10000
5000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
Orbit_Shape

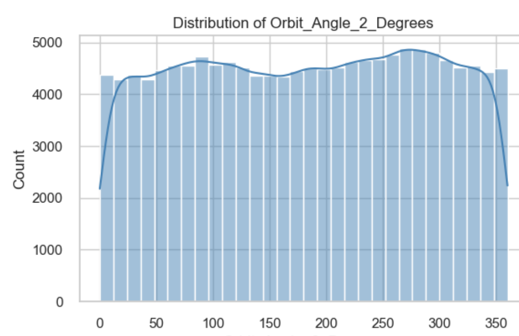

Distribution of Reflectivity
50000
40000
30000
20000
10000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
Reflectivity

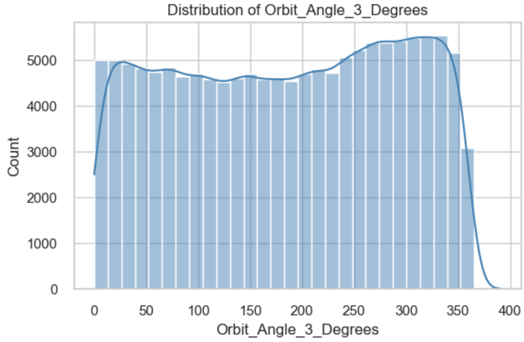

Distribution of Orbit_Distance_AU
1e6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Count
0
50
100
150
200
250
300
350
Orbit_Distance_AU

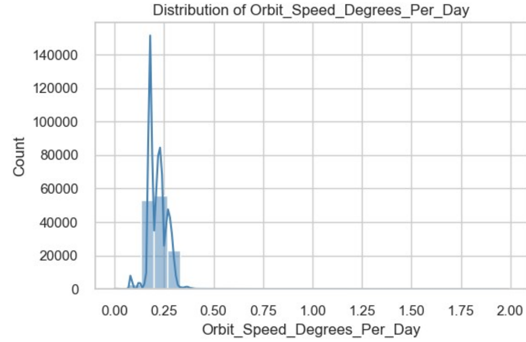

Distribution of Closest_Sun_Distance_AU
160000
140000
120000
100000
80000
60000
40000
20000
0
Count
0
5
10
15
20
25
30
35
40
Closest_Sun_Distance_AU

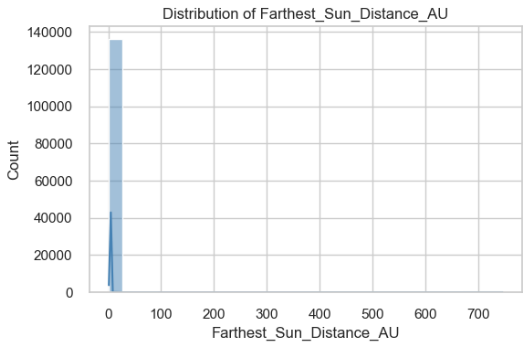

Distribution of Orbit_Angle_1_Degrees
5000
4000
3000
2000
1000
0
Count
0
50
100
150
200
250
300
350
Orbit_Angle_1_Degrees

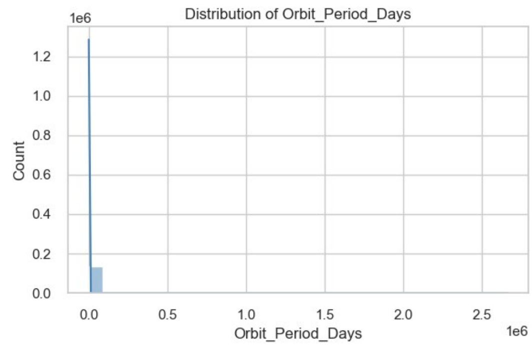

Distribution of Orbit_Tilt_Degrees
50000
40000
30000
20000
10000
0
Count
0
25
50
75
100
125
150
175
Orbit_Tilt_Degrees

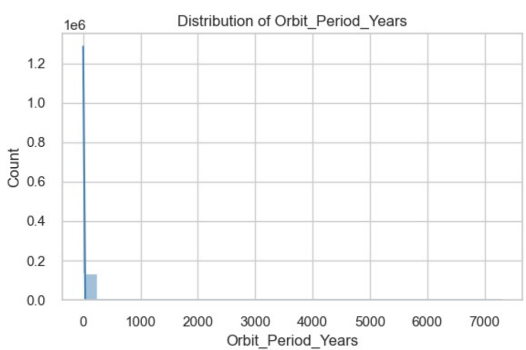

Distribution of Orbit_Angle_2_Degrees
5000
4000
3000
2000
1000
0
Count
0
50
100
150
200
250
300
350
Orbit_Angle_2_Degrees

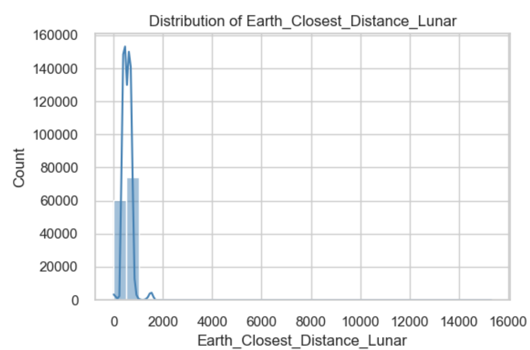

Distribution of Orbit_Angle_3_Degrees
Count
Orbit_Angle_3_Degrees

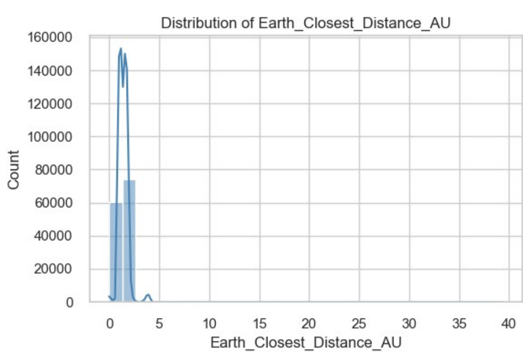

Distribution of Orbit_Speed_Degrees_Per_Day
Count
Orbit_Speed_Degrees_Per_Day

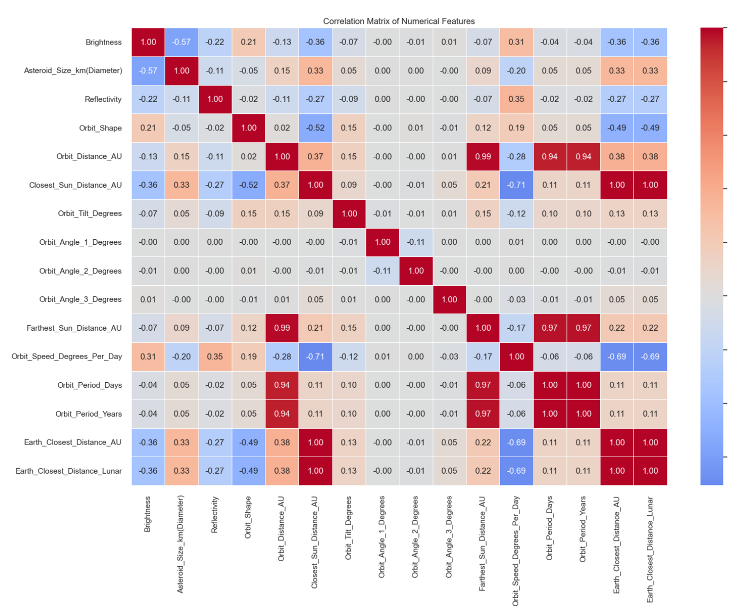

Distribution of Farthest_Sun_Distance_AU
Count
Farthest_Sun_Distance_AU

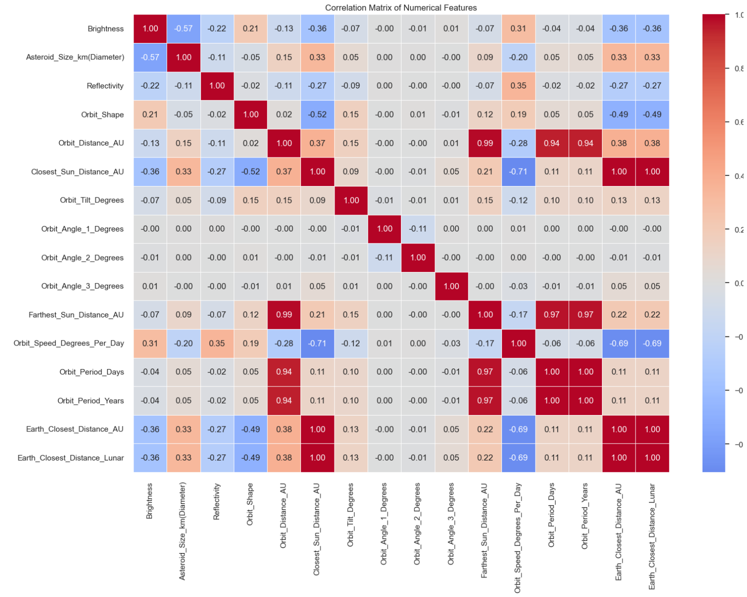

Distribution of Orbit_Period_Days
Count
Orbit_Period_Days


Distribution of Orbit_Period_Years
Count
Orbit_Period_Years


Distribution of Earth_Closest_Distance_Lunar
Count
Earth_Closest_Distance_Lunar


Distribution of Earth_Closest_Distance_AU
Count
Earth_Closest_Distance_AU


Correlation Matrix of Numerical Features
Brightness
Asteroid_Size_km(Diameter)
Reflectivity
Orbit_Shape
Orbit_Distance_AU
Closest_Sun_Distance_AU
Orbit_Tilt_Degrees
Orbit_Angle_1_Degrees
Orbit_Angle_2_Degrees
Orbit_Angle_3_Degrees
Farthest_Sun_Distance_AU
Orbit_Speed_Degrees_Per_Day
Orbit_Period_Days
Orbit_Period_Years
Earth_Closest_Distance_AU
Earth_Closest_Distance_Lunar




```
# #inferential statistics
# from scipy import stats
# from scipy.stats import ttest_ind, f_oneway, chi2_contingency

# # Confidence Interval for Mean Diameter
# diameter_sample = train_df['diameter'].dropna()
# mean_d = diameter_sample.mean()
# std_d = diameter_sample.std()
# n = len(diameter_sample)
# ci_low, ci_high = stats.t.interval(0.95, df=n-1, loc=mean_d, scale=std_d/np.sqrt(n))
# print(f"95% CI for Diameter Mean: ({ci_low:.2f}, {ci_high:.2f})")

# # T-test: Albedo of NEO vs non-NEO
# neo_group = train_df[train_df['neo'] == 'Y']['albedo'].dropna()
# non_neo_group = train_df[train_df['neo'] == 'N']['albedo'].dropna()
# t_stat, p_val = ttest_ind(neo_group, non_neo_group, equal_var=False)
# print(f"T-test for Albedo (NEO vs non-NEO): t={t_stat:.3f}, p={p_val:.3f}")

# # F-test: Variance in Albedo
# f_stat = np.var(neo_group, ddof=1) / np.var(non_neo_group, ddof=1)
# df1 = len(neo_group) - 1
# df2 = len(non_neo_group) - 1
# p_val_f = 1 - stats.f.cdf(f_stat, df1, df2)
# print(f"F-test for Albedo Variance: F={f_stat:.3f}, p={p_val_f:.3f}")

# # Chi-square test: pha vs neo
# contingency = pd.crosstab(train_df['pha'], train_df['neo'])
```

Inferential Statistics

Classification

Point Biseral Correlation Between Potentially_Hazardous and Earth_Closest_Distance_AU

```
# Convert 'Y' to 1 and 'N' to 0
df_biseral = df_classification.copy()
df_biseral['Potentially_Hazardous'] = df_biseral['Potentially_Hazardous'].map({'Y': 1,
'N': 0})

from scipy.stats import pointbiserialr
r, p = pointbiserialr(df_biseral['Earth_Closest_Distance_AU'],
df_biseral['Potentially_Hazardous'])
print(f"Point-Biserial Correlation: r = {r:.3f}, p = {p:.5f}")
```

```
Point-Biserial Correlation: r = -0.030, p = 0.00000
```

Conclusion: There is a statistically significant relationship. But r = -0.03 is so small, it has no practical (real-world) importance

Chi-Square Test between Asteroid_Class and Potentially_Hazardous

```
import pandas as pd
from scipy.stats import chi2_contingency

# Example: df has 'closest_distance_au' and 'hazardous' (0 or 1)
# Bin the distances into categories
print("""
H₀: Asteroid_Class category is independent of orbit Potentially_Hazardous category
H₁: Asteroid_Class category is dependent on Potentially_Hazardous category
""")
# Create a contingency table
contingency_table = pd.crosstab(df['Asteroid_Class'], df['Potentially_Hazardous'])
print("Contingency Table:\n", contingency_table)

# Perform the chi-square test
chi2, p, dof, expected = chi2_contingency(contingency_table)
print(f"\nChi-Square Test:\nChi2 = {chi2:.3f}, p-value = {p:.5f}, dof = {dof}")
```

```
H₀: Asteroid_Class category is independent of orbit Potentially_Hazardous category
H₁: Asteroid_Class category is dependent on Potentially_Hazardous category

Contingency Table:
 Potentially_Hazardous       N     Y
Asteroid_Class
AMO                      8338   118
APO                     10919  1768
AST                        75     0
ATE                      1555   174
CEN                       504     0
HYA                         4     0
IEO                        16     6
IMB                     19903     0
MBA                    837430     0
MCA                     18356     0
OMB                     27815     0
TJN                      8160     0
TNO                      3462     0

Chi-Square Test:
Chi2 = 119576.736, p-value = 0.00000, dof = 12
```

Conclusion: Asteroid_Class is NOT independent of Potentially_Hazardous category.

```
# chi2, chi_p, _, _ = chi2_contingency(contingency)
# print(f"Chi-square test (pha vs neo): χ²={chi2:.2f}, p={chi_p:.4f}")

# # ANOVA: Diameter across asteroid classes
# if 'class' in train_df.columns:
#     groups = [g['diameter'].dropna() for _, g in train_df.groupby('class') if
len(g['diameter'].dropna()) > 2]
#     if len(groups) > 1:
#         a_stat, a_p = f_oneway(*groups)
#         print(f"ANOVA on Diameter by Class: F={a_stat:.2f}, p={a_p:.4f}")

df_classification.describe()
```

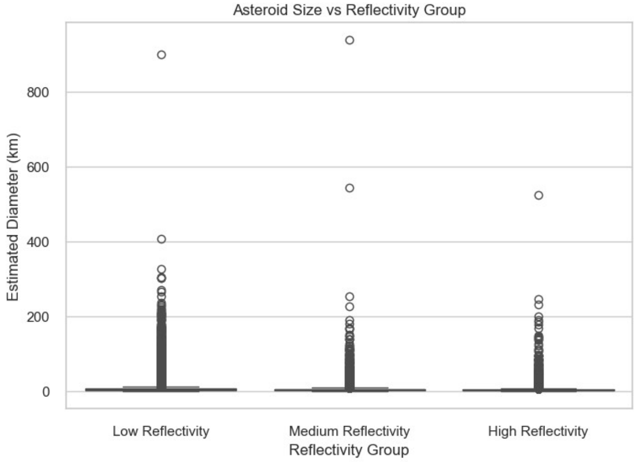
```
         Brightness    Orbit_Shape  Orbit_Distance_AU  \
count  932336.000000  932336.000000      932336.000000
mean       16.889991       0.156221           2.932615
std         1.801331       0.093001          36.458214
min        -1.100000       0.000003           0.555418
25%        16.000000       0.092160           2.389088
50%        16.900000       0.144933           2.647971
75%        17.700000       0.200589           3.002982
max        33.200000       0.999851       33488.895955

       Closest_Sun_Distance_AU  Orbit_Tilt_Degrees  Orbit_Angle_1_Degrees  \
count            932336.000000       932336.000000          932336.000000
mean                  2.398918            8.996694             168.395442
std                   2.165336            6.606941             102.863946
min                   0.070511            0.007744               0.000025
25%                   1.972209            4.135564              80.528080
50%                   2.227214            7.357849             159.871025
75%                   2.580131           12.332727             251.974334
max                  80.398819          175.082901             359.999793

       Orbit_Angle_2_Degrees  Orbit_Angle_3_Degrees  Farthest_Sun_Distance_AU  \
count          932336.000000          932336.000000             932336.000000
mean              181.381454             177.029125                  3.466313
std               103.909981             105.755423                 72.768214
min                 0.000130             -67.136826                  0.653773
25%                91.490778              83.559427                  2.783887
50%               182.353517             174.966318                  3.048694
75%               271.551530             269.594056                  3.365570
max               359.999646             491.618014              66972.796064

       Orbit_Speed_Degrees_Per_Day  Orbit_Period_Days  Orbit_Period_Years  \
count                 9.323360e+05       9.323360e+05        9.323360e+05
mean                  2.366077e-01       5.181153e+03        1.418522e+01
std                   7.998690e-02       2.341159e+06        6.409743e+03
min                   1.608247e-07       1.511918e+02        4.139405e-01
25%                   1.893978e-01       1.348797e+03        3.692806e+00
50%                   2.287358e-01       1.573868e+03        4.309016e+00
75%                   2.669044e-01       1.900761e+03        5.204001e+00
max                   2.381082e+00       2.238462e+09        6.128574e+06

       Earth_Closest_Distance_AU  Earth_Closest_Distance_Lunar
count               9.323360e+05                 932336.000000
mean                1.416253e+00                    551.163122
std                 2.162694e+00                    841.655463
min                 4.544120e-07                      0.000177
25%                 9.802075e-01                    381.467353
50%                 1.241285e+00                    483.070883
75%                 1.593700e+00                    620.220229
max                 7.947660e+01                  30929.908422
```

Regression

1-Way ANOVA: Asteroid Size vs Reflectivity

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import f_oneway

print("""
H₀: μ₁ = μ₂ = μ₃ (Mean reflectivity is the same across small, medium, and large asteroid
groups)
H₁: At least one mean is different
""")
# Example DataFrame columns:
# df_classification['Reflectivity'] (continuous)
# df_classification['Estimated_Diameter_km'] (continuous)
df_anova = df_regression[['Reflectivity', 'Asteroid_Size_km(Diameter)']]

#
# Step 1: Bin Reflectivity into categories
bins = [0.0, 0.08, 0.19, 1.0]  # Adjust based on your data range
labels = ['Low Reflectivity', 'Medium Reflectivity', 'High Reflectivity']
df_anova['Reflectivity_Group'] = pd.cut(df_anova['Reflectivity'], bins=bins,
labels=labels)

# Optional: Check group counts
print(df_anova['Reflectivity_Group'].value_counts())

# Step 2: Boxplot visualization
sns.boxplot(data=df_anova, x='Reflectivity_Group', y='Asteroid_Size_km(Diameter)')
plt.title('Asteroid Size vs Reflectivity Group')
plt.ylabel('Estimated Diameter (km)')
plt.xlabel('Reflectivity Group')
plt.show()

# Step 3: One-Way ANOVA test
groups = [group['Asteroid_Size_km(Diameter)'].dropna() for name, group in
df_anova.groupby('Reflectivity_Group')]
f_stat, p_value = f_oneway(*groups)

print(f"One-Way ANOVA:\nF-statistic = {f_stat:.3f}, p-value = {p_value:.5f}")
```

```
H₀: μ₁ = μ₂ = μ₃ (Mean reflectivity is the same across small, medium, and large asteroid
groups)
H₁: At least one mean is different

Reflectivity_Group
Low Reflectivity       70150
High Reflectivity      33655
Medium Reflectivity    32404
Name: count, dtype: int64

C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\3909619770.py:19:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-
versus-a-copy
  df_anova['Reflectivity_Group'] = pd.cut(df_anova['Reflectivity'], bins=bins,
labels=labels)
```




```
One-Way ANOVA:
F-statistic = 767.230, p-value = 0.00000

C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\3909619770.py:32: FutureWarning: The
default of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to adopt the
future default and silence this warning.
  groups = [group['Asteroid_Size_km(Diameter)'].dropna() for name, group in
df_anova.groupby('Reflectivity_Group')]
```

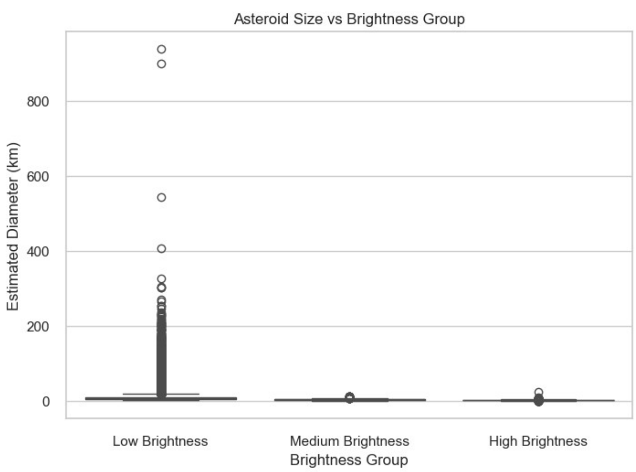
Conclusion: Reflectivity (albedo) has a statistically significant effect on asteroid size.

1-Way ANOVA: Asteroid Size vs Brightness

```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import f_oneway

print("""
H₀: μ₁ = μ₂ = μ₃ (Mean brightness is the same across small, medium, and large asteroid
groups)
H₁: At least one mean is different
""")
# Example DataFrame columns:
# df_classification['Reflectivity'] (continuous)
# df_classification['Estimated_Diameter_km'] (continuous)
df_anova = df_regression[['Brightness', 'Asteroid_Size_km(Diameter)']]

#
# Step 1: Bin Reflectivity into categories
bins = [3.0, 14.4, 16.0, 29.9]  # Adjust based on your data range
labels = ['Low Brightness', 'Medium Brightness', 'High Brightness']
df_anova['Brightness_Group'] = pd.cut(df_anova['Brightness'], bins=bins, labels=labels)
```

```
# Optional: Check group counts
print(df_anova['Brightness_Group'].value_counts())

# Step 2: Boxplot visualization
sns.boxplot(data=df_anova, x='Brightness_Group', y='Asteroid_Size_km(Diameter)')
plt.title('Asteroid Size vs Brightness Group')
plt.ylabel('Estimated Diameter (km)')
plt.xlabel('Brightness Group')
plt.show()

# Step 3: One-Way ANOVA test
groups = [group['Asteroid_Size_km(Diameter)'].dropna() for name, group in
df_anova.groupby('Brightness_Group')]
f_stat, p_value = f_oneway(*groups)

print(f"One-Way ANOVA:\nF-statistic = {f_stat:.3f}, p-value = {p_value:.5f}")
```

```
C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\3583831040.py:19:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-
versus-a-copy
  df_anova['Brightness_Group'] = pd.cut(df_anova['Brightness'], bins=bins, labels=labels)


H₀: μ₁ = μ₂ = μ₃ (Mean brightness is the same across small, medium, and large asteroid
groups)
H₁: At least one mean is different

Brightness_Group
Medium Brightness    70803
Low Brightness       34114
High Brightness      31291
Name: count, dtype: int64
```




```
One-Way ANOVA:
F-statistic = 9415.048, p-value = 0.00000

C:\Users\raiya\AppData\Local\Temp\ipykernel_27560\3583831040.py:32: FutureWarning: The
default of observed=False is deprecated and will be changed to True in a future version
of pandas. Pass observed=False to retain current behavior or observed=True to adopt the
future default and silence this warning.
  groups = [group['Asteroid_Size_km(Diameter)'].dropna() for name, group in
df_anova.groupby('Brightness_Group')]
```

```
import warnings
warnings.filterwarnings('ignore')

import statsmodels.api as sm
from statsmodels.formula.api import ols
df_2way = df_regression[['Asteroid_Class', 'Potentially_Hazardous',
'Asteroid_Size_km(Diameter)']]
df_2way['Potentially_Hazardous'] = df_2way['Potentially_Hazardous'].map({'Y': 1, 'N': 0})
# Make sure Potentially_Hazardous is numeric (0/1)
df_2way['Potentially_Hazardous'] = df_2way['Potentially_Hazardous'].astype(int)
df_2way['Asteroid_Size_km'] = df_2way["Asteroid_Size_km(Diameter)"]
# Two-Way ANOVA model
model = ols('Asteroid_Size_km ~ C(Asteroid_Class) + C(Potentially_Hazardous) +
C(Asteroid_Class):C(Potentially_Hazardous)',
            data=df_2way).fit()

anova_table = sm.stats.anova_lm(model, typ=2)
print(anova_table)
```

```
                                                  sum_sq        df          F  \
C(Asteroid_Class)                           3.358573e+04      10.0  41.011434
C(Potentially_Hazardous)                             NaN       1.0        NaN
C(Asteroid_Class):C(Potentially_Hazardous)  3.553708e+00      10.0   0.004339
Residual                                    1.115349e+07  136195.0        NaN
```

```
                                                  PR(>F)
C(Asteroid_Class)                           1.564306e-18
C(Potentially_Hazardous)                             NaN
C(Asteroid_Class):C(Potentially_Hazardous)  9.956700e-01
Residual                                             NaN

c:\Users\raiya\OneDrive\Desktop\STA301-project\.conda\Lib\site-packages\statsmodels\base\
model.py:1894: ValueWarning: covariance of constraints does not have full rank. The
number of constraints is 10, but rank is 2
  warnings.warn('covariance of constraints does not have full '
c:\Users\raiya\OneDrive\Desktop\STA301-project\.conda\Lib\site-packages\statsmodels\base\
model.py:1894: ValueWarning: covariance of constraints does not have full rank. The
number of constraints is 1, but rank is 0
  warnings.warn('covariance of constraints does not have full '
c:\Users\raiya\OneDrive\Desktop\STA301-project\.conda\Lib\site-packages\statsmodels\base\
model.py:1894: ValueWarning: covariance of constraints does not have full rank. The
number of constraints is 10, but rank is 2
  warnings.warn('covariance of constraints does not have full '
```

Classification Model

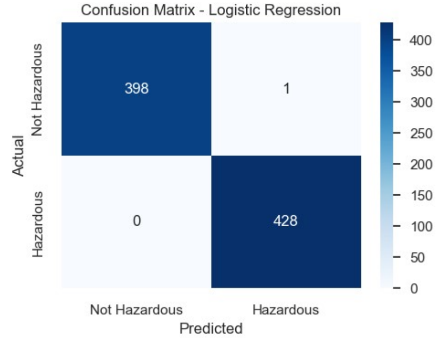
```
df_classification.keys()
```

```
Index(['Near_Earth_Object', 'Potentially_Hazardous', 'Brightness',
       'Orbit_Shape', 'Orbit_Distance_AU', 'Closest_Sun_Distance_AU',
       'Orbit_Tilt_Degrees', 'Orbit_Angle_1_Degrees', 'Orbit_Angle_2_Degrees',
       'Orbit_Angle_3_Degrees', 'Farthest_Sun_Distance_AU',
       'Orbit_Speed_Degrees_Per_Day', 'Orbit_Period_Days',
       'Orbit_Period_Years', 'Earth_Closest_Distance_AU',
       'Earth_Closest_Distance_Lunar', 'Asteroid_Class'],
      dtype='object')
```

```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder
from sklearn.pipeline import Pipeline
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

TARGET_class = 'Potentially_Hazardous'

# Balance the classes
class_Y = df_classification[df_classification[TARGET_class] == 'Y']
class_N = df_classification[df_classification[TARGET_class] ==
'N'].sample(n=len(class_Y), random_state=42)
class_df = pd.concat([class_Y, class_N])

# Define categorical columns from the balanced dataframe
categorical_cols_c = class_df.select_dtypes(include=['object',
'bool']).drop(columns=[TARGET_class]).columns.tolist()

# Drop the target column
X_clf = class_df.drop(columns=[TARGET_class])
y_clf = class_df[TARGET_class]


# One-hot encode categorical features
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(drop='first', handle_unknown='ignore'), categorical_cols_c)
    ],
    remainder='passthrough'  # Keep numerical columns as-is
)

# Create pipeline with preprocessing + logistic regression
```

```python
pipeline = Pipeline(steps=[
    ('preprocessor', preprocessor),
    ('classifier', LogisticRegression(max_iter=1000))
])

# Train/test split
X_train, X_test, y_train, y_test = train_test_split(X_clf, y_clf, test_size=0.2,
random_state=42)

# Fit model
pipeline.fit(X_train, y_train)

# Evaluate
y_pred_clf = pipeline.predict(X_test)
print("\nLogistic Regression Results")
print("Accuracy:", accuracy_score(y_test, y_pred_clf))

import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
# Get confusion matrix
cm = confusion_matrix(y_test, y_pred_clf)
# Plot
plt.figure(figsize=(5, 4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=['Not Hazardous',
'Hazardous'], yticklabels=['Not Hazardous', 'Hazardous'])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix - Logistic Regression')
plt.tight_layout()
plt.savefig("plots/classification/confusion_matrix_logistic_regression.png", dpi=300,
bbox_inches='tight')
plt.show()

print("\nClassification Report:\n", classification_report(y_test, y_pred_clf))

clf_model = pipeline.named_steps['classifier']
feature_names = X_clf.columns

print("Logistic Regression Coefficients:")
for name, coef in zip(feature_names, clf_model.coef_[0]):
    print(f"{name}: {coef:.4f}")
```

```
Logistic Regression Results
Accuracy: 0.9987908101571947
```




```
Classification Report:
               precision    recall  f1-score   support

           N       1.00      1.00      1.00       399
           Y       1.00      1.00      1.00       428

    accuracy                           1.00       827
   macro avg       1.00      1.00      1.00       827
weighted avg       1.00      1.00      1.00       827

Logistic Regression Coefficients:
Near_Earth_Object: 3.0891
Brightness: -0.1592
Orbit_Shape: -2.4773
Orbit_Distance_AU: -0.5973
Closest_Sun_Distance_AU: -0.0001
Orbit_Tilt_Degrees: -0.0006
Orbit_Angle_1_Degrees: -0.0016
Orbit_Angle_2_Degrees: 0.0000
Orbit_Angle_3_Degrees: -0.0000
Farthest_Sun_Distance_AU: -0.0000
Orbit_Speed_Degrees_Per_Day: -1.6077
Orbit_Period_Days: 0.7014
Orbit_Period_Years: 0.3991
Earth_Closest_Distance_AU: 1.6050
Earth_Closest_Distance_Lunar: 0.0102
Asteroid_Class: -0.0019
```

Regression Model

```python
df_regression.keys()
```

```
Index(['Near_Earth_Object', 'Potentially_Hazardous', 'Brightness',
       'Asteroid_Size_km(Diameter)', 'Reflectivity', 'Orbit_Shape',
       'Orbit_Distance_AU', 'Closest_Sun_Distance_AU', 'Orbit_Tilt_Degrees',
       'Orbit_Angle_1_Degrees', 'Orbit_Angle_2_Degrees',
       'Orbit_Angle_3_Degrees', 'Farthest_Sun_Distance_AU',
       'Orbit_Speed_Degrees_Per_Day', 'Orbit_Period_Days',
       'Orbit_Period_Years', 'Earth_Closest_Distance_AU',
       'Earth_Closest_Distance_Lunar', 'Asteroid_Class'],
      dtype='object')
```

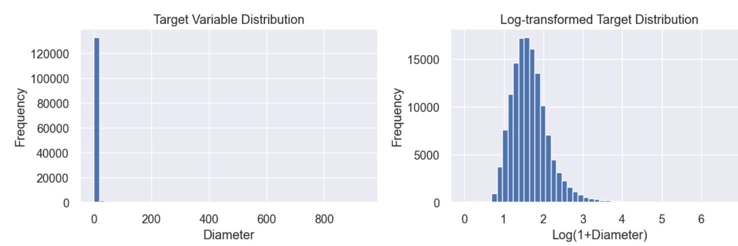
```python
df_regression.describe()
```

```
          Brightness  Asteroid_Size_km(Diameter)   Reflectivity  \
count  136209.000000               136209.000000  136209.000000
mean       15.132319                    5.506429       0.130205
std         1.366564                    9.425164       0.109971
min         3.000000                    0.002500       0.001000
25%        14.400000                    2.780000       0.053000
50%        15.200000                    3.972000       0.079000
75%        16.000000                    5.765000       0.188000
max        29.900000                  939.400000       1.000000

         Orbit_Shape  Orbit_Distance_AU  Closest_Sun_Distance_AU  \
count  136209.000000      136209.000000            136209.000000
mean        0.145660           2.819158                 2.406130
std         0.077464           1.495980                 0.516931
min         0.000060           0.626210                 0.081820
25%         0.089878           2.542856                 2.072478
50%         0.138919           2.754950                 2.368605
75%         0.191174           3.095029                 2.688275
max         0.983789         376.133297                40.318477

       Orbit_Tilt_Degrees  Orbit_Angle_1_Degrees  Orbit_Angle_2_Degrees  \
count       136209.000000          136209.000000          136209.000000
mean            10.295360             169.729893             181.808169
std              6.812632             102.715175             103.516287
min              0.022056               0.000418               0.000130
25%              5.088142              82.276476              91.903488
50%              9.335690             160.301343             183.509496
75%             13.670331             255.961202             271.642281
max            170.334595             359.999793             359.998075

       Orbit_Angle_3_Degrees  Farthest_Sun_Distance_AU  \
count          136209.000000             136209.000000
mean              184.529202                  3.232187
std               105.632553                  2.839820
min                 0.005112                  0.999954
25%                91.647097                  2.871056
50%               188.275290                  3.173515
75%               277.821001                  3.472570
max               391.682098                746.169105

       Orbit_Speed_Degrees_Per_Day  Orbit_Period_Days  Orbit_Period_Years  \
count                136209.000000       1.362090e+05       136209.000000
mean                      0.219086       1.787231e+03            4.893173
std                       0.056912       8.965840e+03           24.547132
min                       0.000135       1.809999e+02            0.495551
25%                       0.181012       1.481089e+03            4.055000
50%                       0.215543       1.670202e+03            4.572764
75%                       0.243064       1.988820e+03            5.445092
max                       1.988951       2.664472e+06         7294.925719

       Earth_Closest_Distance_AU  Earth_Closest_Distance_Lunar
count              136209.000000                 136209.000000
mean                    1.423858                    554.122719
std                     0.513029                    199.655301
min                     0.000027                      0.010335
25%                     1.086220                    422.724237
50%                     1.389580                    540.782849
75%                     1.702400                    662.523008
max                    39.360300                  15317.847951
```

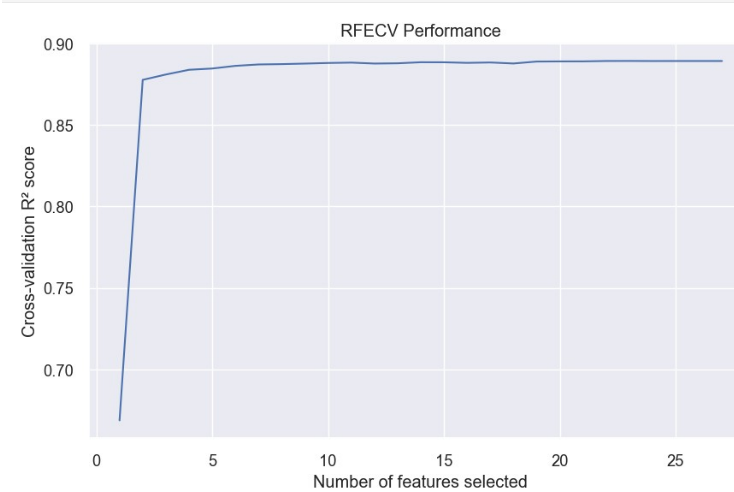
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler, PowerTransformer, OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.feature_selection import RFECV, SelectKBest, f_regression,
mutual_info_regression, SequentialFeatureSelector
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
import scipy.stats as stats
from scipy.stats import normaltest, kstest, shapiro
from sklearn.decomposition import PCA
import warnings
warnings.filterwarnings('ignore')

# Set the style for plots
plt.style.use('seaborn-v0_8')
sns.set(font_scale=1.2)

TARGET_reg = 'Asteroid_Size_km(Diameter)'

# Define categorical columns from the balanced dataframe
categorical_cols_r = df_regression.select_dtypes(include=['object',
'bool']).drop(columns=[TARGET_reg], errors='ignore').columns.tolist()

# Drop the target column
X_reg = df_regression.drop(columns=[TARGET_reg])
y_reg = df_regression[TARGET_reg]

# Create the preprocessor
preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(drop='first', handle_unknown='ignore'), categorical_cols_r)
    ],
    remainder='passthrough'  # Keep numerical columns as-is
)

# Check for data distribution
plt.figure(figsize=(12, 4))
plt.subplot(1, 2, 1)
plt.hist(y_reg, bins=50)
plt.title('Target Variable Distribution')
plt.xlabel('Diameter')
plt.ylabel('Frequency')

plt.subplot(1, 2, 2)
plt.hist(np.log1p(y_reg), bins=50)
plt.title('Log-transformed Target Distribution')
plt.xlabel('Log(1+Diameter)')
plt.ylabel('Frequency')
plt.tight_layout()
plt.savefig('target_distribution.png')
plt.show()

# Apply log transformation to target
y_reg_transformed = np.log1p(y_reg)

# 3.1.1 Traditional Linear Regression
print("\n3.1.1 TRADITIONAL LINEAR REGRESSION")
print("-" * 50)

# Train-test split
X_train_reg, X_test_reg, y_train_reg, y_test_reg = train_test_split(
```

```python
    X_reg, y_reg_transformed, test_size=0.2, random_state=42
)

# Pipeline for preprocessing and model
reg_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('scaler', StandardScaler()),
    ('model', LinearRegression())
])

# Train the model
reg_pipeline.fit(X_train_reg, y_train_reg)

# Predict and evaluate
y_pred_reg = reg_pipeline.predict(X_test_reg)
y_pred_original = np.expm1(y_pred_reg)
y_test_original = np.expm1(y_test_reg)

print("Linear Regression Results (on log scale):")
print("R² Score:", r2_score(y_test_reg, y_pred_reg))
print("RMSE:", np.sqrt(mean_squared_error(y_test_reg, y_pred_reg)))

print("\nLinear Regression Results (original scale):")
print("R² Score:", r2_score(y_test_original, y_pred_original))
print("RMSE:", np.sqrt(mean_squared_error(y_test_original, y_pred_original)))

# 3.1.2 Variable Selection Methods
print("\n3.1.2 VARIABLE SELECTION METHODS")
print("-" * 50)

# Prepare data for variable selection - Apply preprocessing first
X_train_prepared = preprocessor.fit_transform(X_train_reg)
X_train_scaled = StandardScaler().fit_transform(X_train_prepared)
X_test_prepared = preprocessor.transform(X_test_reg)
X_test_scaled = StandardScaler().fit_transform(X_test_prepared)

# Method 1: Recursive Feature Elimination with Cross-Validation
print("1. Recursive Feature Elimination with Cross-Validation (RFECV)")
rfecv = RFECV(estimator=LinearRegression(), cv=5, scoring='r2')
rfecv.fit(X_train_scaled, y_train_reg)

print(f"Optimal number of features: {rfecv.n_features_}")
# Get feature names from preprocessor if possible, otherwise use indices
try:
    feature_names = preprocessor.get_feature_names_out()
    print(f"Selected features: {feature_names[rfecv.support_].tolist()}")
except:
    print(f"Selected feature indices: {np.where(rfecv.support_)[0].tolist()}")

# Plot RFECV results
plt.figure(figsize=(10, 6))
plt.plot(range(1, len(rfecv.cv_results_['mean_test_score']) + 1),
rfecv.cv_results_['mean_test_score'])
plt.xlabel('Number of features selected')
plt.ylabel('Cross-validation R² score')
plt.title('RFECV Performance')
plt.grid(True)
plt.savefig('rfecv_performance.png')
plt.show()

# Method 2: SelectKBest with mutual information
print("\n2. SelectKBest with Mutual Information")
selector_mi = SelectKBest(mutual_info_regression, k=8)
selector_mi.fit(X_train_scaled, y_train_reg)
try:
    feature_names = preprocessor.get_feature_names_out()
    selected_features_mi = feature_names[selector_mi.get_support()].tolist()
    print(f"Selected features (MI): {selected_features_mi}")
except:
    print(f"Selected feature indices (MI): {np.where(selector_mi.get_support())
[0].tolist()}")

# Method 3: Forward Stepwise Selection using sklearn
print("\n3. Forward Stepwise Selection")
# Use SequentialFeatureSelector for forward stepwise selection
sfs = SequentialFeatureSelector(
    LinearRegression(),
    n_features_to_select=8,
    direction='forward',
    cv=5,
    scoring='r2'
)
sfs.fit(X_train_scaled, y_train_reg)
try:
    feature_names = preprocessor.get_feature_names_out()
    stepwise_features = feature_names[sfs.support_].tolist()
    print(f"Selected features (Stepwise): {stepwise_features}")
except:
    print(f"Selected feature indices (Stepwise): {np.where(sfs.support_)[0].tolist()}")

# Perform PCA analysis
print("\nPerforming PCA analysis...")
pca = PCA()
pca.fit(X_train_scaled)

# Calculate explained variance ratio
explained_variance_ratio = pca.explained_variance_ratio_
cumulative_variance = np.cumsum(explained_variance_ratio)

# Find number of components explaining 95% variance
n_components_95 = np.argmax(cumulative_variance >= 0.95) + 1

# Create PCA results dictionary
pca_results = {
    'n_components_95': n_components_95,
    'cumulative_variance': cumulative_variance,
    'explained_variance_ratio': explained_variance_ratio
}

print(f"Number of components explaining 95% variance: {n_components_95}")
print(f"Cumulative variance explained: {cumulative_variance[n_components_95-1]:.4f}")

# Train final model with selected features
print("\n3.1.3 FINAL MODEL WITH PCA")
print("-" * 50)

# Create the final PCA pipeline with optimal number of components
final_pca_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('scaler', StandardScaler()),
    ('pca', PCA(n_components=pca_results['n_components_95'])),
    ('model', LinearRegression())
])

# Train the PCA model
final_pca_pipeline.fit(X_train_reg, y_train_reg)

# Train RFECV model for comparison using feature indices
# Create a mask of selected features after preprocessing
selector_mask = np.zeros(X_train_scaled.shape[1], dtype=bool)
selector_mask[np.where(rfecv.support_)[0]] = True

# Create pipeline for RFECV model
rfecv_pipeline = Pipeline([
    ('preprocessor', preprocessor),
    ('scaler', StandardScaler()),
    ('selector', SelectKBest(mutual_info_regression, k=rfecv.n_features_)),  # Using
SelectKBest as substitute
    ('model', LinearRegression())
])
rfecv_pipeline.fit(X_train_reg, y_train_reg)

# Predict and evaluate both models
print("PCA Model Results:")
y_pred_pca = final_pca_pipeline.predict(X_test_reg)
y_pred_pca_original = np.expm1(y_pred_pca)
print("R² Score (log scale):", r2_score(y_test_reg, y_pred_pca))
print("R² Score (original scale):", r2_score(y_test_original, y_pred_pca_original))
print("RMSE (original scale):", np.sqrt(mean_squared_error(y_test_original,
y_pred_pca_original)))

print("\nRFECV Model Results:")
y_pred_rfecv = rfecv_pipeline.predict(X_test_reg)
y_pred_rfecv_original = np.expm1(y_pred_rfecv)
print("R² Score (log scale):", r2_score(y_test_reg, y_pred_rfecv))
print("R² Score (original scale):", r2_score(y_test_original, y_pred_rfecv_original))
print("RMSE (original scale):", np.sqrt(mean_squared_error(y_test_original,
y_pred_rfecv_original)))

# Use PCA model for residual analysis
best_model = final_pca_pipeline
y_pred_final = y_pred_pca

# 3.1.4 Residual Analysis
print("\n3.1.4 RESIDUAL ANALYSIS")
print("-" * 50)

# Calculate residuals
residuals = y_test_reg - y_pred_final
standardized_residuals = residuals / np.std(residuals)

# Create figure with subplots
fig, axes = plt.subplots(2, 3, figsize=(18, 12))
fig.suptitle('Residual Analysis (PCA Model)', fontsize=16)

# 1. Residuals vs Fitted Values (Linearity and Homoscedasticity)
axes[0, 0].scatter(y_pred_final, residuals, alpha=0.5)
axes[0, 0].axhline(y=0, color='r', linestyle='--')
axes[0, 0].set_xlabel('Fitted Values')
axes[0, 0].set_ylabel('Residuals')
axes[0, 0].set_title('Residuals vs Fitted Values')

# 2. Normal Q-Q Plot (Normality)
stats.probplot(residuals, dist="norm", plot=axes[0, 1])
axes[0, 1].set_title('Normal Q-Q Plot')

# 3. Scale-Location Plot (Homoscedasticity)
axes[0, 2].scatter(y_pred_final, np.sqrt(np.abs(standardized_residuals)), alpha=0.5)
axes[0, 2].set_xlabel('Fitted Values')
axes[0, 2].set_ylabel('√|Standardized Residuals|')
axes[0, 2].set_title('Scale-Location Plot')

# 4. Histogram of Residuals (Normality)
axes[1, 0].hist(residuals, bins=30, edgecolor='black')
axes[1, 0].set_xlabel('Residuals')
axes[1, 0].set_ylabel('Frequency')
axes[1, 0].set_title('Histogram of Residuals')

# 5. Residuals vs Leverage (Outliers and Influence)
# Calculate leverage for PCA-transformed data
X_test_transformed = final_pca_pipeline.named_steps['pca'].transform(
    final_pca_pipeline.named_steps['scaler'].transform(
        final_pca_pipeline.named_steps['preprocessor'].transform(X_test_reg)
    )
)
# Add intercept column
X_with_intercept = np.column_stack([np.ones(X_test_transformed.shape[0]),
X_test_transformed])
# Calculate hat matrix diagonal (leverage values)
hat_matrix = X_with_intercept @ np.linalg.inv(X_with_intercept.T @ X_with_intercept + 1e-
8 * np.eye(X_with_intercept.shape[1])) @ X_with_intercept.T
leverage = np.diag(hat_matrix)

axes[1, 1].scatter(leverage, standardized_residuals, alpha=0.5)
axes[1, 1].axhline(y=0, color='r', linestyle='--')
axes[1, 1].set_xlabel('Leverage')
axes[1, 1].set_ylabel('Standardized Residuals')
axes[1, 1].set_title('Residuals vs Leverage')

# 6. ACF of Residuals (Independence)
from statsmodels.graphics.tsaplots import plot_acf
plot_acf(residuals, ax=axes[1, 2], lags=20)
axes[1, 2].set_title('ACF of Residuals')

plt.tight_layout()
plt.savefig('residual_analysis_pca.png', dpi=300, bbox_inches='tight')
plt.show()

# Formal tests for assumptions
print("\nFORMAL TESTS:")
print("-" * 30)

# 1. Normality of residuals
print("1. Normality Tests:")
if len(residuals) <= 5000:  # Shapiro-Wilk has a limit
    _, p_shapiro = shapiro(residuals)
    print(f"   Shapiro-Wilk test p-value: {p_shapiro:.4f}")
else:
    print("   Shapiro-Wilk test skipped (dataset too large)")
    p_shapiro = np.nan

_, p_normaltest = normaltest(residuals)
print(f"   D'Agostino's K² test p-value: {p_normaltest:.4f}")

# 2. Homoscedasticity (Breusch-Pagan test)
print("\n2. Homoscedasticity Test:")
import statsmodels.stats.api as sms
# Get transformed features for Breusch-Pagan test
X_test_transformed = final_pca_pipeline.named_steps['pca'].transform(
    final_pca_pipeline.named_steps['scaler'].transform(
        final_pca_pipeline.named_steps['preprocessor'].transform(X_test_reg)
    )
)
# Add constant for Breusch-Pagan test
X_test_with_constant = np.column_stack([np.ones(X_test_transformed.shape[0]),
X_test_transformed])
_, p_bp = sms.het_breuschpagan(residuals, X_test_with_constant)[:2]
print(f"   Breusch-Pagan test p-value: {p_bp:.4f}")

# 3. Independence (Durbin-Watson test)
print("\n3. Independence Test:")
from statsmodels.stats.stattools import durbin_watson
```

```python
dw_stat = durbin_watson(residuals)
print(f"   Durbin-Watson statistic: {dw_stat:.4f}")
print("   (Values close to 2 indicate no autocorrelation)")

# 4. Multicollinearity (VIF) - Now with PCA
print("\n4. PCA Component Analysis:")
print(f"   Number of principal components: {n_components_95}")
print(f"   Total variance explained: {cumulative_variance[n_components_95-1]:.4f}")
print("   (By construction, PCA components have VIF = 1)")

# 3.1.5 Transformations and Remedial Measures
print("\n3.1.5 TRANSFORMATIONS AND REMEDIAL MEASURES")
print("-" * 50)

# Check if transformations are needed based on tests
need_transform = False
transformations_applied = []

# Based on residual analysis results
if (not np.isnan(p_shapiro) and p_shapiro < 0.05) or p_normaltest < 0.05:
    print("Non-normality detected in residuals.")
    need_transform = True

if p_bp < 0.05:
    print("Heteroscedasticity detected.")
    need_transform = True

if dw_stat < 1.5 or dw_stat > 2.5:
    print("Potential autocorrelation detected.")

if need_transform:
    print("\nApplying transformations:")

    # 1. Try Box-Cox transformation on target
    from scipy.stats import boxcox

    # Ensure all values are positive for Box-Cox
    y_reg_positive = y_reg + abs(y_reg.min()) + 1 if y_reg.min() <= 0 else y_reg
    y_boxcox, lambda_boxcox = boxcox(y_reg_positive)
    print(f"1. Box-Cox transformation with lambda: {lambda_boxcox:.4f}")

    # 2. Apply power transformation to features
    transformer = PowerTransformer(method='yeo-johnson')

    # Train model with transformed data
    transformed_pipeline = Pipeline([
        ('preprocessor', preprocessor),
        ('scaler', StandardScaler()),
        ('power_transform', transformer),
        ('pca', PCA(n_components=pca_results['n_components_95'])),
        ('model', LinearRegression())
    ])

    # Split with Box-Cox transformed target
    y_train_boxcox = boxcox(y_train_reg + abs(y_train_reg.min()) + 1 if y_train_reg.min()
<= 0 else y_train_reg)[0]
    y_test_boxcox = boxcox(y_test_reg + abs(y_test_reg.min()) + 1 if y_test_reg.min() <=
0 else y_test_reg)[0]

    # Train with transformed target
    transformed_pipeline.fit(X_train_reg, y_train_boxcox)
    y_pred_transformed = transformed_pipeline.predict(X_test_reg)

    # Back-transform predictions - handle the transformation carefully
    if lambda_boxcox != 0:
        y_pred_backtransformed = np.power(y_pred_transformed * lambda_boxcox + 1,
1/lambda_boxcox) - abs(y_reg.min()) - 1
        y_test_backtransformed = np.power(y_test_boxcox * lambda_boxcox + 1,
1/lambda_boxcox) - abs(y_reg.min()) - 1
    else:
        y_pred_backtransformed = np.exp(y_pred_transformed) - abs(y_reg.min()) - 1
        y_test_backtransformed = np.exp(y_test_boxcox) - abs(y_reg.min()) - 1

    # Ensure non-negative predictions
    y_pred_backtransformed = np.maximum(y_pred_backtransformed, 0)
    y_test_backtransformed = np.maximum(y_test_backtransformed, 0)

    print("\nResults after transformations:")
    print("R² Score:", r2_score(y_test_backtransformed, y_pred_backtransformed))
    print("RMSE:", np.sqrt(mean_squared_error(y_test_backtransformed,
y_pred_backtransformed)))

    # Re-check residuals
    residuals_transformed = y_test_boxcox - y_pred_transformed
    if len(residuals_transformed) <= 5000:  # Only run if manageable size
        _, p_shapiro_transformed = shapiro(residuals_transformed)
        print(f"\nShapiro-Wilk test p-value after transformation:
{p_shapiro_transformed:.4f}")

else:
    print("No major violations detected. Current model appears adequate.")

# Summary
print("\n" + "="*50)
print("SUMMARY OF LINEAR REGRESSION ANALYSIS")
print("="*50)
print(f"1. Initial features: {X_train_scaled.shape[1]}")

# For RFECV selected features
try:
    feature_names = preprocessor.get_feature_names_out()
    selected_features = feature_names[rfecv.support_].tolist()
    print(f"2. Selected features (RFECV): {rfecv.n_features_}")
    print(f"3. Selected features names: {selected_features}")
except:
    print(f"2. Selected features (RFECV): {rfecv.n_features_}")
    print(f"3. Selected feature indices: {np.where(rfecv.support_)[0].tolist()}")

print(f"4. Final R² score (log scale): {r2_score(y_test_reg, y_pred_final):.4f}")
y_pred_final_original = np.expm1(y_pred_final)
print(f"5. Final RMSE (original scale): {np.sqrt(mean_squared_error(y_test_original,
y_pred_final_original)):.4f}")
print("\nAssumption Test Results:")
print(f"- Normality (p-value): {p_shapiro:.4f}" if not np.isnan(p_shapiro) else "-
Normality: Test skipped (dataset too large)")
print(f"- Homoscedasticity (p-value): {p_bp:.4f}")
print(f"- Independence (Durbin-Watson): {dw_stat:.4f}")
print(f"- Multicollinearity: Handled by PCA")

# Define final_pipeline for the prediction function
final_pipeline = final_pca_pipeline  # Using PCA pipeline as final model

# Create a prediction function using PCA model
def predict_diameter(features_dict):
    """
    Predict asteroid diameter using the final linear regression model.

    Parameters:
    features_dict (dict): Dictionary with feature names as keys and values as input

    Returns:
    float: Predicted diameter in km
    """
    # Create DataFrame from input
    input_df = pd.DataFrame([features_dict])

    # Make prediction (on log scale)
    y_pred_log = final_pipeline.predict(input_df)

    # Convert back to original scale
    y_pred_original = np.expm1(y_pred_log)

    return y_pred_original[0]

# # Example usage
# example_features = {
#     'H': 15.0,
#     'albedo': 0.1,
#     'e': 0.2,
#     'a': 2.5,
#     'q': 2.0,
#     'i': 5.0,
#     'om': 100.0,
#     'w': 200.0,
#     'ma': 45.0,
#     'ad': 3.0,
#     'n': 0.5,
#     'per': 1000.0,
#     'per_y': 2.7,
#     'moid': 0.1,
#     'moid_ld': 39.0
# }

# print(f"\nExample prediction:")
# print(f"Predicted diameter: {predict_diameter(example_features):.2f} km")
```

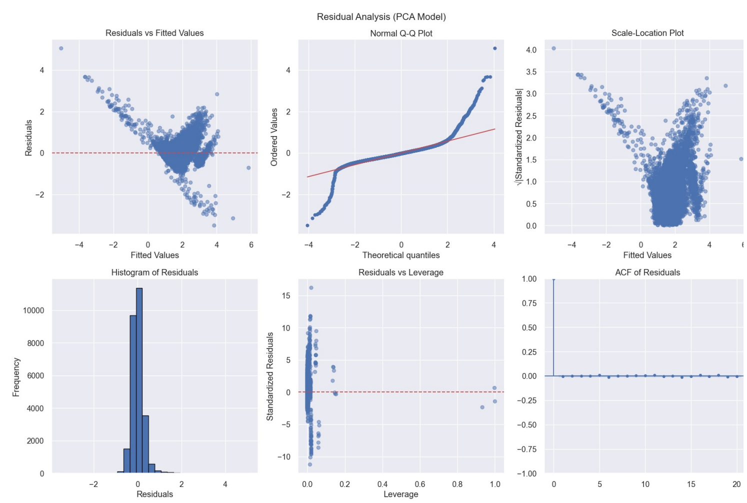



```
3.1.1 TRADITIONAL LINEAR REGRESSION
--------------------------------------------------
Linear Regression Results (on log scale):
R² Score: 0.890359960473653
RMSE: 0.17397465970527956

Linear Regression Results (original scale):
R² Score: 0.7153304912055254
RMSE: 5.358868083410644

3.1.2 VARIABLE SELECTION METHODS
--------------------------------------------------
1. Recursive Feature Elimination with Cross-Validation (RFECV)
Optimal number of features: 23
Selected features: ['cat__Near_Earth_Object_Y', 'cat__Potentially_Hazardous_Y',
'cat__Asteroid_Class_APO', 'cat__Asteroid_Class_ATE', 'cat__Asteroid_Class_CEN',
'cat__Asteroid_Class_IMB', 'cat__Asteroid_Class_MBA', 'cat__Asteroid_Class_MCA',
'cat__Asteroid_Class_OMB', 'cat__Asteroid_Class_TNO', 'remainder__Brightness',
'remainder__Reflectivity', 'remainder__Orbit_Shape', 'remainder__Orbit_Distance_AU',
'remainder__Closest_Sun_Distance_AU', 'remainder__Orbit_Tilt_Degrees',
'remainder__Orbit_Angle_3_Degrees', 'remainder__Farthest_Sun_Distance_AU',
'remainder__Orbit_Speed_Degrees_Per_Day', 'remainder__Orbit_Period_Days',
'remainder__Orbit_Period_Years', 'remainder__Earth_Closest_Distance_AU',
'remainder__Earth_Closest_Distance_Lunar']
```




```
2. SelectKBest with Mutual Information
Selected features (MI): ['remainder__Brightness', 'remainder__Reflectivity',
'remainder__Orbit_Distance_AU', 'remainder__Closest_Sun_Distance_AU',
'remainder__Orbit_Speed_Degrees_Per_Day', 'remainder__Orbit_Period_Years',
'remainder__Earth_Closest_Distance_AU', 'remainder__Earth_Closest_Distance_Lunar']

3. Forward Stepwise Selection
Selected features (Stepwise): ['cat__Near_Earth_Object_Y', 'cat__Asteroid_Class_ATE',
'remainder__Brightness', 'remainder__Reflectivity', 'remainder__Orbit_Shape',
'remainder__Orbit_Tilt_Degrees', 'remainder__Orbit_Speed_Degrees_Per_Day',
'remainder__Earth_Closest_Distance_AU']

Performing PCA analysis...
Number of components explaining 95% variance: 17
Cumulative variance explained: 0.9594

3.1.3 FINAL MODEL WITH PCA
--------------------------------------------------
PCA Model Results:
R² Score (log scale): 0.6499902127433974
R² Score (original scale): 0.27808200226495183
```

```
RMSE (original scale): 8.53387986715992

RFECV Model Results:
R² Score (log scale): 0.8900130265546716
R² Score (original scale): 0.7136876215527479
RMSE (original scale): 5.3743092455567325

3.1.4 RESIDUAL ANALYSIS
--------------------------------------------------
```




```
FORMAL TESTS:
------------------------------
1. Normality Tests:
   Shapiro-Wilk test skipped (dataset too large)
   D'Agostino's K² test p-value: 0.0000

2. Homoscedasticity Test:
   Breusch-Pagan test p-value: 0.0000

3. Independence Test:
   Durbin-Watson statistic: 2.0070
   (Values close to 2 indicate no autocorrelation)

4. PCA Component Analysis:
   Number of principal components: 17
   Total variance explained: 0.9594
   (By construction, PCA components have VIF = 1)

3.1.5 TRANSFORMATIONS AND REMEDIAL MEASURES
--------------------------------------------------
Non-normality detected in residuals.
Heteroscedasticity detected.
```

```
Applying transformations:
1. Box-Cox transformation with lambda: -0.1324

Results after transformations:
R² Score: 0.3995327109764476
RMSE: 0.7212225046742797

==================================================
SUMMARY OF LINEAR REGRESSION ANALYSIS
==================================================
1. Initial features: 27
2. Selected features (RFECV): 23
3. Selected features names: ['cat__Near_Earth_Object_Y', 'cat__Potentially_Hazardous_Y',
'cat__Asteroid_Class_APO', 'cat__Asteroid_Class_ATE', 'cat__Asteroid_Class_CEN',
'cat__Asteroid_Class_IMB', 'cat__Asteroid_Class_MBA', 'cat__Asteroid_Class_MCA',
'cat__Asteroid_Class_OMB', 'cat__Asteroid_Class_TNO', 'remainder__Brightness',
'remainder__Reflectivity', 'remainder__Orbit_Shape', 'remainder__Orbit_Distance_AU',
'remainder__Closest_Sun_Distance_AU', 'remainder__Orbit_Tilt_Degrees',
'remainder__Orbit_Angle_3_Degrees', 'remainder__Farthest_Sun_Distance_AU',
'remainder__Orbit_Speed_Degrees_Per_Day', 'remainder__Orbit_Period_Days',
'remainder__Orbit_Period_Years', 'remainder__Earth_Closest_Distance_AU',
'remainder__Earth_Closest_Distance_Lunar']
4. Final R² score (log scale): 0.6500
5. Final RMSE (original scale): 8.5339

Assumption Test Results:
- Normality: Test skipped (dataset too large)
- Homoscedasticity (p-value): 0.0000
- Independence (Durbin-Watson): 2.0070
- Multicollinearity: Handled by PCA
```

```python
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.preprocessing import StandardScaler, PowerTransformer, OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.feature_selection import RFECV, SelectKBest, f_regression,
mutual_info_regression, SequentialFeatureSelector
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
import scipy.stats as stats
from scipy.stats import normaltest, kstest, shapiro
from sklearn.decomposition import PCA
from scipy import stats
import warnings
warnings.filterwarnings('ignore')

# Set the style for plots
plt.style.use('seaborn-v0_8')
sns.set(font_scale=1.2)

# Function to print model evaluation metrics
def print_metrics(y_true, y_pred, original_scale=True):
    if original_scale:
        print(f"R² Score: {r2_score(y_true, y_pred):.4f}")
        print(f"RMSE: {np.sqrt(mean_squared_error(y_true, y_pred)):.4f}")
    else:
        print(f"R² Score (log scale): {r2_score(y_true, y_pred):.4f}")
        print(f"RMSE (log scale): {np.sqrt(mean_squared_error(y_true, y_pred)):.4f}")
        y_true_orig = np.expm1(y_true)
        y_pred_orig = np.expm1(y_pred)
```

```python
        print(f"R² Score (original scale): {r2_score(y_true_orig, y_pred_orig):.4f}")
        print(f"RMSE (original scale): {np.sqrt(mean_squared_error(y_true_orig,
y_pred_orig)):.4f}")

TARGET_reg = 'Asteroid_Size_km(Diameter)'

# Define a function for outlier detection using z-score
def remove_outliers(df, threshold=3):
    """
    Remove outliers from numerical columns using z-score.

    Parameters:
    -----------
    df : pandas DataFrame
        Input dataframe
    threshold : float
        Z-score threshold to identify outliers

    Returns:
    --------
    pandas DataFrame
        Dataframe with outliers removed
    """
    df_clean = df.copy()

    # Only select numerical columns excluding the target
    num_cols = df_clean.select_dtypes(include=['int64', 'float64']).columns.tolist()
    if TARGET_reg in num_cols:
        num_cols.remove(TARGET_reg)

    # Print initial row count
    print(f"Initial data shape: {df_clean.shape}")

    # Remove outliers for each column
    for col in num_cols:
        z_scores = np.abs(stats.zscore(df_clean[col], nan_policy='omit'))
        df_clean = df_clean[(z_scores < threshold) | np.isnan(z_scores)]

    # Print row count after outlier removal
    print(f"Data shape after outlier removal: {df_clean.shape}")

    return df_clean

# First, let's use the original dataset for the baseline model
X_reg_original = df_regression.drop(columns=[TARGET_reg])
y_reg_original = df_regression[TARGET_reg]

# Define categorical and numerical columns from the original dataframe
categorical_cols_r_original = X_reg_original.select_dtypes(include=['object',
'bool']).columns.tolist()
numerical_cols_r_original = X_reg_original.select_dtypes(include=['int64',
'float64']).columns.tolist()

# Now, remove outliers for the enhanced model
df_regression_clean = remove_outliers(df_regression, threshold=3)

# Proceed with the clean dataset
X_reg_clean = df_regression_clean.drop(columns=[TARGET_reg])
y_reg_clean = df_regression_clean[TARGET_reg]

# Define categorical and numerical columns from the clean dataframe
categorical_cols_r_clean = X_reg_clean.select_dtypes(include=['object',
'bool']).columns.tolist()
numerical_cols_r_clean = X_reg_clean.select_dtypes(include=['int64',
'float64']).columns.tolist()
```

```python
# Visualize data distribution before transformation
plt.figure(figsize=(15, 10))
plt.suptitle('Feature Distributions Before Transformation', fontsize=16)
for i, col in enumerate(numerical_cols_r_clean[:min(9, len(numerical_cols_r_clean))]):
    plt.subplot(3, 3, i+1)
    sns.histplot(X_reg_clean[col], kde=True)
    plt.title(col)
plt.tight_layout()
plt.subplots_adjust(top=0.9)
plt.savefig('before_transformation.png')
plt.show()

# Create preprocessors - simple one for baseline and advanced for enhanced model
basic_preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(drop='first', handle_unknown='ignore'),
categorical_cols_r_original)
    ],
    remainder='passthrough'  # Keep numerical columns as-is
)

enhanced_preprocessor = ColumnTransformer(
    transformers=[
        ('cat', OneHotEncoder(drop='first', handle_unknown='ignore'),
categorical_cols_r_clean),
        ('num', PowerTransformer(method='box-cox', standardize=False),
numerical_cols_r_clean)
    ]
)

# Check for data distribution of target
plt.figure(figsize=(12, 8))
plt.subplot(2, 2, 1)
plt.hist(y_reg_original, bins=50)
plt.title('Original Target Distribution')
plt.xlabel('Diameter')
plt.ylabel('Frequency')

plt.subplot(2, 2, 2)
plt.hist(np.log1p(y_reg_original), bins=50)
plt.title('Log-transformed Original Target')
plt.xlabel('Log(1+Diameter)')
plt.ylabel('Frequency')

plt.subplot(2, 2, 3)
plt.hist(y_reg_clean, bins=50)
plt.title('Clean Target Distribution (Outliers Removed)')
plt.xlabel('Diameter')
plt.ylabel('Frequency')

plt.subplot(2, 2, 4)
plt.hist(np.log1p(y_reg_clean), bins=50)
plt.title('Log-transformed Clean Target')
plt.xlabel('Log(1+Diameter)')
plt.ylabel('Frequency')

plt.tight_layout()
plt.savefig('target_distribution.png')
plt.show()

# Apply log transformation to targets
y_reg_original_transformed = np.log1p(y_reg_original)
y_reg_clean_transformed = np.log1p(y_reg_clean)
```

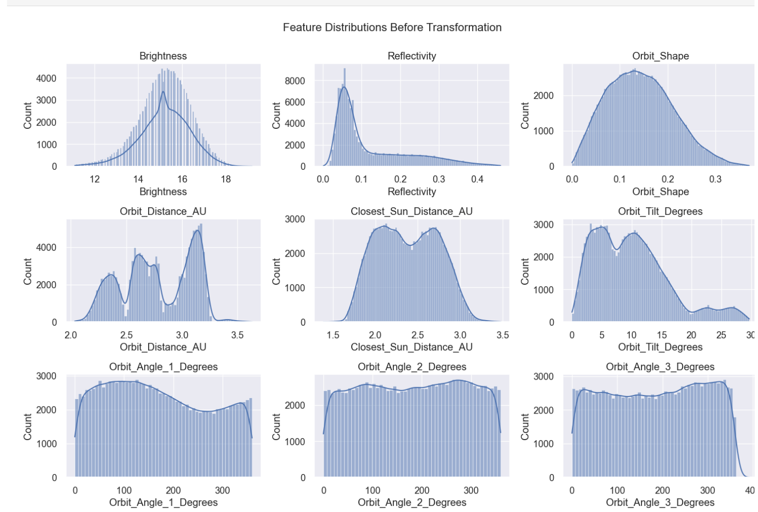
```python
# SECTION 1: BASELINE MODEL (WITHOUT OUTLIER REMOVAL OR BOX-COX)
print("\n" + "="*80)
print("SECTION 1: BASELINE MODEL (WITHOUT OUTLIER REMOVAL OR BOX-COX)")
print("="*80)

# Train-test split for original data
X_train_orig, X_test_orig, y_train_orig, y_test_orig = train_test_split(
    X_reg_original, y_reg_original_transformed, test_size=0.2, random_state=42
)

# Pipeline for baseline model
baseline_pipeline = Pipeline([
    ('preprocessor', basic_preprocessor),
    ('scaler', StandardScaler()),
    ('model', LinearRegression())
])

# Train the baseline model
baseline_pipeline.fit(X_train_orig, y_train_orig)

# Predict and evaluate baseline model
y_pred_baseline = baseline_pipeline.predict(X_test_orig)

print("\nBASELINE MODEL METRICS (NO OUTLIER REMOVAL, NO BOX-COX):")
print("-" * 60)
print_metrics(y_test_orig, y_pred_baseline, original_scale=False)

# SECTION 2: ENHANCED MODEL (WITH OUTLIER REMOVAL AND BOX-COX)
print("\n" + "="*80)
print("SECTION 2: ENHANCED MODEL (WITH OUTLIER REMOVAL AND BOX-COX)")
print("="*80)

# Train-test split for clean data
X_train_clean, X_test_clean, y_train_clean, y_test_clean = train_test_split(
    X_reg_clean, y_reg_clean_transformed, test_size=0.2, random_state=42
)

# Pipeline for enhanced model
enhanced_pipeline = Pipeline([
    ('preprocessor', enhanced_preprocessor),
    ('scaler', StandardScaler()),  # Scale after transformations
    ('model', LinearRegression())
])

# Train the enhanced model
enhanced_pipeline.fit(X_train_clean, y_train_clean)

# Predict and evaluate enhanced model
y_pred_enhanced = enhanced_pipeline.predict(X_test_clean)

print("\nENHANCED MODEL METRICS (WITH OUTLIER REMOVAL AND BOX-COX):")
print("-" * 60)
print_metrics(y_test_clean, y_pred_enhanced, original_scale=False)

# Comparison summary
print("\n" + "="*80)
print("COMPARISON SUMMARY")
print("="*80)
print("Baseline Model (log scale):")
print(f"R² Score: {r2_score(y_test_orig, y_pred_baseline):.4f}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_orig, y_pred_baseline)):.4f}")

print("\nEnhanced Model (log scale):")
print(f"R² Score: {r2_score(y_test_clean, y_pred_enhanced):.4f}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_clean, y_pred_enhanced)):.4f}")
```

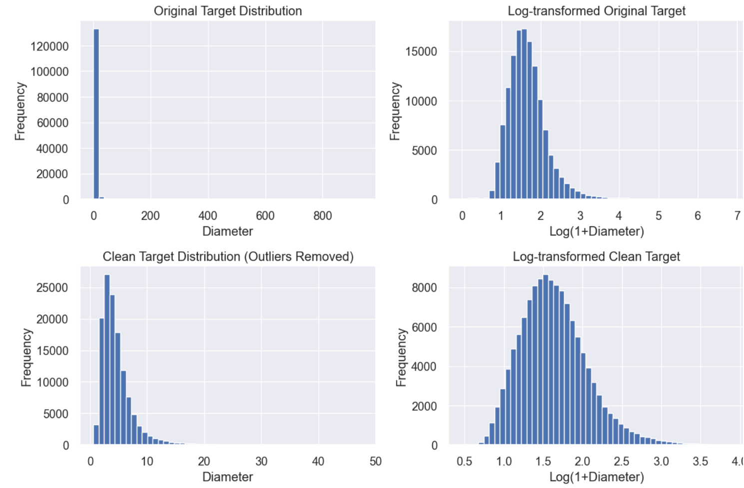
```python
# Calculate improvement percentages
r2_improvement = ((r2_score(y_test_clean, y_pred_enhanced) - r2_score(y_test_orig,
y_pred_baseline)) /
                  max(0.0001, abs(r2_score(y_test_orig, y_pred_baseline)))) * 100
rmse_improvement = ((np.sqrt(mean_squared_error(y_test_orig, y_pred_baseline)) -
                    np.sqrt(mean_squared_error(y_test_clean, y_pred_enhanced))) /
                   np.sqrt(mean_squared_error(y_test_orig, y_pred_baseline))) * 100

print(f"\nR² Improvement: {r2_improvement:.2f}%")
print(f"RMSE Improvement: {rmse_improvement:.2f}%")

# Visualize predictions vs actual values for both models
y_test_orig_unlog = np.expm1(y_test_orig)
y_pred_baseline_unlog = np.expm1(y_pred_baseline)
y_test_clean_unlog = np.expm1(y_test_clean)
y_pred_enhanced_unlog = np.expm1(y_pred_enhanced)

plt.figure(figsize=(16, 8))

# Baseline model scatter plot
plt.subplot(1, 2, 1)
plt.scatter(y_test_orig_unlog, y_pred_baseline_unlog, alpha=0.5, color='blue')
plt.plot([y_test_orig_unlog.min(), y_test_orig_unlog.max()],
         [y_test_orig_unlog.min(), y_test_orig_unlog.max()],
         'r--', lw=2)
plt.xlabel('Actual Diameter')
plt.ylabel('Predicted Diameter')
plt.title('Baseline Model: Actual vs Predicted')
plt.grid(True)

# Enhanced model scatter plot
plt.subplot(1, 2, 2)
plt.scatter(y_test_clean_unlog, y_pred_enhanced_unlog, alpha=0.5, color='green')
plt.plot([y_test_clean_unlog.min(), y_test_clean_unlog.max()],
         [y_test_clean_unlog.min(), y_test_clean_unlog.max()],
         'r--', lw=2)
plt.xlabel('Actual Diameter')
plt.ylabel('Predicted Diameter')
plt.title('Enhanced Model: Actual vs Predicted')
plt.grid(True)

plt.tight_layout()
plt.savefig('prediction_comparison.png')
plt.show()

# Visualize residuals for both models
baseline_residuals = y_pred_baseline - y_test_orig
enhanced_residuals = y_pred_enhanced - y_test_clean

plt.figure(figsize=(16, 8))

# Baseline model residuals
plt.subplot(1, 2, 1)
plt.scatter(y_pred_baseline, baseline_residuals, alpha=0.5, color='blue')
plt.axhline(y=0, color='r', linestyle='--', lw=2)
plt.xlabel('Predicted Values (log scale)')
plt.ylabel('Residuals')
plt.title('Baseline Model: Residual Plot')
plt.grid(True)

# Enhanced model residuals
plt.subplot(1, 2, 2)
plt.scatter(y_pred_enhanced, enhanced_residuals, alpha=0.5, color='green')
plt.axhline(y=0, color='r', linestyle='--', lw=2)
plt.xlabel('Predicted Values (log scale)')
```

```python
plt.ylabel('Residuals')
plt.title('Enhanced Model: Residual Plot')
plt.grid(True)

plt.tight_layout()
plt.savefig('residual_comparison.png')
plt.show()

# Assess residual normality for both models
plt.figure(figsize=(16, 12))

# Baseline model Q-Q plot
plt.subplot(2, 2, 1)
stats.probplot(baseline_residuals, plot=plt)
plt.title('Baseline Model: Q-Q Plot of Residuals')
plt.grid(True)

# Enhanced model Q-Q plot
plt.subplot(2, 2, 2)
stats.probplot(enhanced_residuals, plot=plt)
plt.title('Enhanced Model: Q-Q Plot of Residuals')
plt.grid(True)

# Baseline model residual histogram
plt.subplot(2, 2, 3)
sns.histplot(baseline_residuals, kde=True, color='blue')
plt.axvline(x=0, color='r', linestyle='--', alpha=0.8)
plt.title('Baseline Model: Residual Distribution')
plt.xlabel('Residual')
plt.ylabel('Frequency')
plt.grid(True)

# Enhanced model residual histogram
plt.subplot(2, 2, 4)
sns.histplot(enhanced_residuals, kde=True, color='green')
plt.axvline(x=0, color='r', linestyle='--', alpha=0.8)
plt.title('Enhanced Model: Residual Distribution')
plt.xlabel('Residual')
plt.ylabel('Frequency')
plt.grid(True)

plt.tight_layout()
plt.savefig('residual_normality_check.png')
plt.show()

# Statistical tests for normality
print("\n" + "="*80)
print("RESIDUAL NORMALITY TESTS")
print("="*80)

# Define a function to run normality tests
def test_normality(residuals, model_name):
    print(f"\n{model_name} Residuals:")
    print("-" * 40)

    # Shapiro-Wilk test (better for smaller samples)
    shapiro_test = shapiro(residuals)
    print(f"Shapiro-Wilk Test: W={shapiro_test.statistic:.4f}, p-
value={shapiro_test.pvalue:.6f}")
    if shapiro_test.pvalue < 0.05:
        print("Conclusion: Residuals are NOT normally distributed (reject H0)")
    else:
        print("Conclusion: Residuals appear to be normally distributed (fail to reject
H0)")
```

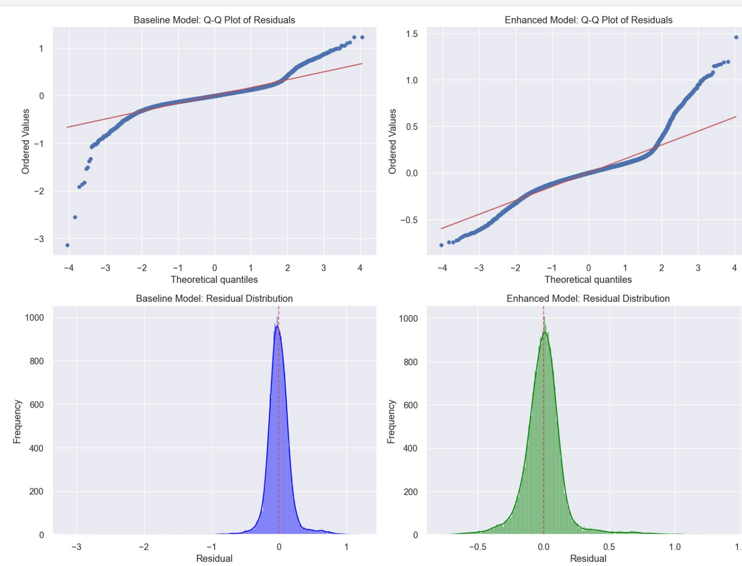
```python
    # D'Agostino's K-squared test
    k2, p = stats.normaltest(residuals)
    print(f"D'Agostino's K² Test: K²={k2:.4f}, p-value={p:.6f}")
    if p < 0.05:
        print("Conclusion: Residuals are NOT normally distributed (reject H0)")
    else:
        print("Conclusion: Residuals appear to be normally distributed (fail to reject
H0)")

    # Kolmogorov-Smirnov test
    ks_test = kstest(residuals, 'norm', args=(np.mean(residuals), np.std(residuals,
ddof=1)))
    print(f"Kolmogorov-Smirnov Test: D={ks_test.statistic:.4f}, p-
value={ks_test.pvalue:.6f}")
    if ks_test.pvalue < 0.05:
        print("Conclusion: Residuals are NOT normally distributed (reject H0)")
    else:
        print("Conclusion: Residuals appear to be normally distributed (fail to reject
H0)")

    # Additional descriptive statistics
    print(f"\nSkewness: {stats.skew(residuals):.4f}")
    print(f"Kurtosis: {stats.kurtosis(residuals):.4f}")
    print(f"Mean: {np.mean(residuals):.6f} (should be close to 0)")
    print(f"Standard Deviation: {np.std(residuals):.6f}")

# Run normality tests for both models
test_normality(baseline_residuals, "Baseline Model")
test_normality(enhanced_residuals, "Enhanced Model")
```

```
Initial data shape: (136209, 19)
Data shape after outlier removal: (128150, 19)
```



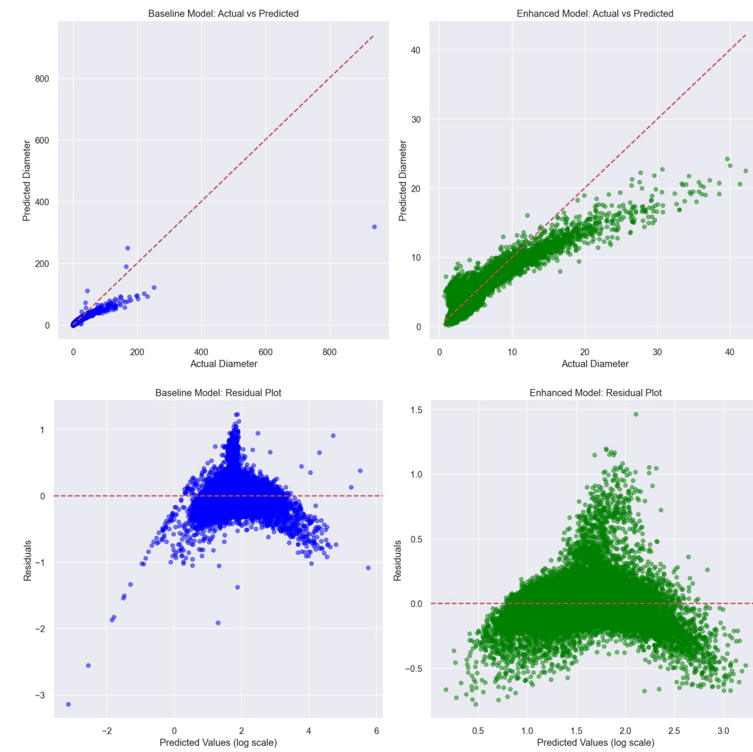



```
================================================================================
SECTION 1: BASELINE MODEL (WITHOUT OUTLIER REMOVAL OR BOX-COX)
================================================================================

BASELINE MODEL METRICS (NO OUTLIER REMOVAL, NO BOX-COX):
------------------------------------------------------------
R² Score (log scale): 0.8904
RMSE (log scale): 0.1740
R² Score (original scale): 0.7153
RMSE (original scale): 5.3589

================================================================================
SECTION 2: ENHANCED MODEL (WITH OUTLIER REMOVAL AND BOX-COX)
================================================================================

ENHANCED MODEL METRICS (WITH OUTLIER REMOVAL AND BOX-COX):
------------------------------------------------------------
R² Score (log scale): 0.8662
RMSE (log scale): 0.1587
R² Score (original scale): 0.8427
RMSE (original scale): 1.2831

================================================================================
COMPARISON SUMMARY
================================================================================
Baseline Model (log scale):
R² Score: 0.8904
RMSE: 0.1740

Enhanced Model (log scale):
R² Score: 0.8662
RMSE: 0.1587
```




```
================================================================================
RESIDUAL NORMALITY TESTS
================================================================================

Baseline Model Residuals:
----------------------------------------
Shapiro-Wilk Test: W=0.8967, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)
D'Agostino's K² Test: K²=5430.4622, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)
Kolmogorov-Smirnov Test: D=0.0784, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)

Skewness: 0.0495
Kurtosis: 12.8693
Mean: 0.000313 (should be close to 0)
Standard Deviation: 0.173974

Enhanced Model Residuals:
----------------------------------------
Shapiro-Wilk Test: W=0.8833, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)
D'Agostino's K² Test: K²=7562.6174, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)
Kolmogorov-Smirnov Test: D=0.1013, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)

Skewness: 1.1430
Kurtosis: 7.8991
```

```
R² Improvement: -2.72%
RMSE Improvement: 8.79%
```




```
Mean: 0.000636 (should be close to 0)
Standard Deviation: 0.158679
```

```python
import statsmodels.api as sm
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.preprocessing import StandardScaler, PowerTransformer, OneHotEncoder
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.impute import SimpleImputer
import scipy.stats as stats
from scipy.stats import normaltest, kstest, shapiro
import warnings
warnings.filterwarnings('ignore')

# Set the style for plots
plt.style.use('seaborn-v0_8')
sns.set(font_scale=1.2)

# Assume df_regression is your dataframe
# If not defined, you'll need to load your data here
# df_regression = pd.read_csv('your_data.csv')

TARGET_reg = 'Asteroid_Size_km(Diameter)'

# Function to print model evaluation metrics
def print_metrics(y_true, y_pred, original_scale=True):
    if original_scale:
        print(f"R² Score: {r2_score(y_true, y_pred):.4f}")
        print(f"RMSE: {np.sqrt(mean_squared_error(y_true, y_pred)):.4f}")
    else:
        print(f"R² Score (log scale): {r2_score(y_true, y_pred):.4f}")
        print(f"RMSE (log scale): {np.sqrt(mean_squared_error(y_true, y_pred)):.4f}")
        y_true_orig = np.expm1(y_true)
        y_pred_orig = np.expm1(y_pred)
        print(f"R² Score (original scale): {r2_score(y_true_orig, y_pred_orig):.4f}")
        print(f"RMSE (original scale): {np.sqrt(mean_squared_error(y_true_orig,
y_pred_orig)):.4f}")

# Define a function for outlier detection using z-score
def remove_outliers(df, threshold=3):
    """
    Remove outliers from numerical columns using z-score.
    """
    df_clean = df.copy()

    # Only select numerical columns excluding the target
    num_cols = df_clean.select_dtypes(include=['int64', 'float64']).columns.tolist()
    if TARGET_reg in num_cols:
        num_cols.remove(TARGET_reg)

    # Print initial row count
    print(f"Initial data shape: {df_clean.shape}")

    # Remove outliers for each column
    for col in num_cols:
        z_scores = np.abs(stats.zscore(df_clean[col], nan_policy='omit'))
        df_clean = df_clean[(z_scores < threshold) | np.isnan(z_scores)]

    # Print row count after outlier removal
    print(f"Data shape after outlier removal: {df_clean.shape}")
```

```python
    return df_clean

# First, let's use the original dataset for the baseline model
X_reg_original = df_regression.drop(columns=[TARGET_reg])
y_reg_original = df_regression[TARGET_reg]

# Define categorical and numerical columns from the original dataframe
categorical_cols_r_original = X_reg_original.select_dtypes(include=['object',
'bool']).columns.tolist()
numerical_cols_r_original = X_reg_original.select_dtypes(include=['int64',
'float64']).columns.tolist()

# Now, remove outliers for the enhanced model
df_regression_clean = remove_outliers(df_regression, threshold=3)

# Proceed with the clean dataset
X_reg_clean = df_regression_clean.drop(columns=[TARGET_reg])
y_reg_clean = df_regression_clean[TARGET_reg]

# Define categorical and numerical columns from the clean dataframe
categorical_cols_r_clean = X_reg_clean.select_dtypes(include=['object',
'bool']).columns.tolist()
numerical_cols_r_clean = X_reg_clean.select_dtypes(include=['int64',
'float64']).columns.tolist()

# Visualize data distribution before transformation
plt.figure(figsize=(15, 10))
plt.suptitle('Feature Distributions Before Transformation', fontsize=16)
for i, col in enumerate(numerical_cols_r_clean[:min(9, len(numerical_cols_r_clean))]):
    plt.subplot(3, 3, i+1)
    sns.histplot(X_reg_clean[col], kde=True)
    plt.title(col)
plt.tight_layout()
plt.subplots_adjust(top=0.9)
plt.savefig('before_transformation.png')
plt.close()

# Create preprocessors with imputation added to handle NaN values
basic_preprocessor = ColumnTransformer(
    transformers=[
        ('num', Pipeline([
            ('imputer', SimpleImputer(strategy='median')),
            ('scaler', StandardScaler())
        ]), numerical_cols_r_original),
        ('cat', Pipeline([
            ('imputer', SimpleImputer(strategy='most_frequent')),
            ('onehot', OneHotEncoder(drop='first', handle_unknown='ignore'))
        ]), categorical_cols_r_original)
    ]
)

enhanced_preprocessor = ColumnTransformer(
    transformers=[
        ('num', Pipeline([
            ('imputer', SimpleImputer(strategy='median')),
            ('transformer', PowerTransformer(method='box-cox', standardize=False)),
            ('scaler', StandardScaler())
        ]), numerical_cols_r_clean),
        ('cat', Pipeline([
            ('imputer', SimpleImputer(strategy='most_frequent')),
            ('onehot', OneHotEncoder(drop='first', handle_unknown='ignore'))
        ]), categorical_cols_r_clean)
    ]
)
```

```python
# Check for data distribution of target
plt.figure(figsize=(12, 8))
plt.subplot(2, 2, 1)
plt.hist(y_reg_original, bins=50)
plt.title('Original Target Distribution')
plt.xlabel('Diameter')
plt.ylabel('Frequency')

plt.subplot(2, 2, 2)
plt.hist(np.log1p(y_reg_original), bins=50)
plt.title('Log-transformed Original Target')
plt.xlabel('Log(1+Diameter)')
plt.ylabel('Frequency')

plt.subplot(2, 2, 3)
plt.hist(y_reg_clean, bins=50)
plt.title('Clean Target Distribution (Outliers Removed)')
plt.xlabel('Diameter')
plt.ylabel('Frequency')

plt.subplot(2, 2, 4)
plt.hist(np.log1p(y_reg_clean), bins=50)
plt.title('Log-transformed Clean Target')
plt.xlabel('Log(1+Diameter)')
plt.ylabel('Frequency')

plt.tight_layout()
plt.savefig('target_distribution.png')
plt.close()

# Apply log transformation to targets
y_reg_original_transformed = np.log1p(y_reg_original)
y_reg_clean_transformed = np.log1p(y_reg_clean)

# SECTION 1: BASELINE MODEL
print("\n" + "="*80)
print("SECTION 1: BASELINE MODEL (WITHOUT OUTLIER REMOVAL OR BOX-COX)")
print("="*80)

# Train-test split for original data
X_train_orig, X_test_orig, y_train_orig, y_test_orig = train_test_split(
    X_reg_original, y_reg_original_transformed, test_size=0.2, random_state=42
)

# Pipeline for baseline model
baseline_pipeline = Pipeline([
    ('preprocessor', basic_preprocessor),
    ('model', LinearRegression())
])

# Train the baseline model
baseline_pipeline.fit(X_train_orig, y_train_orig)

# Predict and evaluate baseline model
y_pred_baseline = baseline_pipeline.predict(X_test_orig)

print("\nBASELINE MODEL METRICS (NO OUTLIER REMOVAL, NO BOX-COX):")
print("-" * 60)
print_metrics(y_test_orig, y_pred_baseline, original_scale=False)

# SECTION 2: ENHANCED MODEL
print("\n" + "="*80)
print("SECTION 2: ENHANCED MODEL (WITH OUTLIER REMOVAL AND BOX-COX)")
print("="*80)

# Train-test split for clean data
```

```python
X_train_clean, X_test_clean, y_train_clean, y_test_clean = train_test_split(
    X_reg_clean, y_reg_clean_transformed, test_size=0.2, random_state=42
)

# Pipeline for enhanced model
enhanced_pipeline = Pipeline([
    ('preprocessor', enhanced_preprocessor),
    ('model', LinearRegression())
])

# Train the enhanced model
enhanced_pipeline.fit(X_train_clean, y_train_clean)

# Predict and evaluate enhanced model
y_pred_enhanced = enhanced_pipeline.predict(X_test_clean)

print("\nENHANCED MODEL METRICS (WITH OUTLIER REMOVAL AND BOX-COX):")
print("-" * 60)
print_metrics(y_test_clean, y_pred_enhanced, original_scale=False)

# Comparison summary
print("\n" + "="*80)
print("COMPARISON SUMMARY")
print("="*80)
print("Baseline Model (log scale):")
print(f"R² Score: {r2_score(y_test_orig, y_pred_baseline):.4f}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_orig, y_pred_baseline)):.4f}")

print("\nEnhanced Model (log scale):")
print(f"R² Score: {r2_score(y_test_clean, y_pred_enhanced):.4f}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test_clean, y_pred_enhanced)):.4f}")

# Calculate improvement percentages
r2_improvement = ((r2_score(y_test_clean, y_pred_enhanced) - r2_score(y_test_orig,
y_pred_baseline)) /
                  max(0.0001, abs(r2_score(y_test_orig, y_pred_baseline)))) * 100
rmse_improvement = ((np.sqrt(mean_squared_error(y_test_orig, y_pred_baseline)) -
                    np.sqrt(mean_squared_error(y_test_clean, y_pred_enhanced))) /
                   np.sqrt(mean_squared_error(y_test_orig, y_pred_baseline))) * 100

print(f"\nR² Improvement: {r2_improvement:.2f}%")
print(f"RMSE Improvement: {rmse_improvement:.2f}%")

# Visualize predictions vs actual values for both models
y_test_orig_unlog = np.expm1(y_test_orig)
y_pred_baseline_unlog = np.expm1(y_pred_baseline)
y_test_clean_unlog = np.expm1(y_test_clean)
y_pred_enhanced_unlog = np.expm1(y_pred_enhanced)

plt.figure(figsize=(16, 8))

# Baseline model scatter plot
plt.subplot(1, 2, 1)
plt.scatter(y_test_orig_unlog, y_pred_baseline_unlog, alpha=0.5, color='blue')
plt.plot([y_test_orig_unlog.min(), y_test_orig_unlog.max()],
         [y_test_orig_unlog.min(), y_test_orig_unlog.max()],
         'r--', lw=2)
plt.xlabel('Actual Diameter')
plt.ylabel('Predicted Diameter')
plt.title('Baseline Model: Actual vs Predicted')
plt.grid(True)

# Enhanced model scatter plot
plt.subplot(1, 2, 2)
plt.scatter(y_test_clean_unlog, y_pred_enhanced_unlog, alpha=0.5, color='green')
plt.plot([y_test_clean_unlog.min(), y_test_clean_unlog.max()],
```

```python
         [y_test_clean_unlog.min(), y_test_clean_unlog.max()],
         'r--', lw=2)
plt.xlabel('Actual Diameter')
plt.ylabel('Predicted Diameter')
plt.title('Enhanced Model: Actual vs Predicted')
plt.grid(True)

plt.tight_layout()
plt.savefig('prediction_comparison.png')
plt.close()

# Visualize residuals for both models
baseline_residuals = y_pred_baseline - y_test_orig
enhanced_residuals = y_pred_enhanced - y_test_clean

plt.figure(figsize=(16, 8))

# Baseline model residuals
plt.subplot(1, 2, 1)
plt.scatter(y_pred_baseline, baseline_residuals, alpha=0.5, color='blue')
plt.axhline(y=0, color='r', linestyle='--', lw=2)
plt.xlabel('Predicted Values (log scale)')
plt.ylabel('Residuals')
plt.title('Baseline Model: Residual Plot')
plt.grid(True)

# Enhanced model residuals
plt.subplot(1, 2, 2)
plt.scatter(y_pred_enhanced, enhanced_residuals, alpha=0.5, color='green')
plt.axhline(y=0, color='r', linestyle='--', lw=2)
plt.xlabel('Predicted Values (log scale)')
plt.ylabel('Residuals')
plt.title('Enhanced Model: Residual Plot')
plt.grid(True)

plt.tight_layout()
plt.savefig('residual_comparison.png')
plt.close()

# Assess residual normality for both models
plt.figure(figsize=(16, 12))

# Baseline model Q-Q plot
plt.subplot(2, 2, 1)
stats.probplot(baseline_residuals, plot=plt)
plt.title('Baseline Model: Q-Q Plot of Residuals')
plt.grid(True)

# Enhanced model Q-Q plot
plt.subplot(2, 2, 2)
stats.probplot(enhanced_residuals, plot=plt)
plt.title('Enhanced Model: Q-Q Plot of Residuals')
plt.grid(True)

# Baseline model residual histogram
plt.subplot(2, 2, 3)
sns.histplot(baseline_residuals, kde=True, color='blue')
plt.axvline(x=0, color='r', linestyle='--', alpha=0.8)
plt.title('Baseline Model: Residual Distribution')
plt.xlabel('Residual')
plt.ylabel('Frequency')
plt.grid(True)

# Enhanced model residual histogram
plt.subplot(2, 2, 4)
```

```
sns.histplot(enhanced_residuals, kde=True, color='green')
plt.axvline(x=0, color='r', linestyle='--', alpha=0.8)
plt.title('Enhanced Model: Residual Distribution')
plt.xlabel('Residual')
plt.ylabel('Frequency')
plt.grid(True)

plt.tight_layout()
plt.savefig('residual_normality_check.png')
plt.close()

# Statistical tests for normality
print("\n" + "="*80)
print("RESIDUAL NORMALITY TESTS")
print("="*80)

# Define a function to run normality tests
def test_normality(residuals, model_name):
    print(f"\n{model_name} Residuals:")
    print("-" * 40)

    # Shapiro-Wilk test (better for smaller samples)
    shapiro_test = shapiro(residuals)
    print(f"Shapiro-Wilk Test: W={shapiro_test.statistic:.4f}, p-
value={shapiro_test.pvalue:.6f}")
    if shapiro_test.pvalue < 0.05:
        print("Conclusion: Residuals are NOT normally distributed (reject H0)")
    else:
        print("Conclusion: Residuals appear to be normally distributed (fail to reject
H0)")

    # D'Agostino's K-squared test
    k2, p = stats.normaltest(residuals)
    print(f"D'Agostino's K² Test: K²={k2:.4f}, p-value={p:.6f}")
    if p < 0.05:
        print("Conclusion: Residuals are NOT normally distributed (reject H0)")
    else:
        print("Conclusion: Residuals appear to be normally distributed (fail to reject
H0)")

    # Additional descriptive statistics
    print(f"\nSkewness: {stats.skew(residuals):.4f}")
    print(f"Kurtosis: {stats.kurtosis(residuals):.4f}")
    print(f"Mean: {np.mean(residuals):.6f} (should be close to 0)")
    print(f"Standard Deviation: {np.std(residuals):.6f}")

# Run normality tests for both models
test_normality(baseline_residuals, "Baseline Model")
test_normality(enhanced_residuals, "Enhanced Model")

# SECTION 3: COEFFICIENT ANALYSIS WITH NUMERICAL VARIABLES ONLY
print("\n" + "="*80)
print("SECTION 3: COEFFICIENT ANALYSIS (NUMERICAL VARIABLES ONLY)")
print("="*80)

def simple_ols_with_numerical_only():
    """
    Build a simpler OLS model using only numerical variables
    with proper index alignment
    """
    # For baseline model
    print("\nBASELINE MODEL - NUMERICAL VARIABLES ONLY:")
    print("-" * 60)

    # Copy data to avoid modifying originals
    X_train_num = X_train_orig[numerical_cols_r_original].copy().reset_index(drop=True)
    y_train_num = y_train_orig.copy().reset_index(drop=True)

    # Handle missing values
    imputer = SimpleImputer(strategy='median')
    X_train_num_imputed = pd.DataFrame(
        imputer.fit_transform(X_train_num),
        columns=numerical_cols_r_original
    )

    # Add constant for intercept
    X_train_num_with_const = sm.add_constant(X_train_num_imputed)

    # Fit OLS model
    baseline_sm_model = sm.OLS(y_train_num, X_train_num_with_const).fit()

    # Print summary
    print(baseline_sm_model.summary())

    # Create DataFrame for coefficients
    baseline_coef_df = pd.DataFrame({
        'Feature': ['const'] + numerical_cols_r_original,
        'Coefficient': baseline_sm_model.params,
        'Std Error': baseline_sm_model.bse,
        't-value': baseline_sm_model.tvalues,
        'p-value': baseline_sm_model.pvalues
    })

    # Add significance markers
    baseline_coef_df['Significance'] = ''
    baseline_coef_df.loc[baseline_coef_df['p-value'] < 0.001, 'Significance'] = '***'
    baseline_coef_df.loc[(baseline_coef_df['p-value'] >= 0.001) & (baseline_coef_df['p-
value'] < 0.01), 'Significance'] = '**'
    baseline_coef_df.loc[(baseline_coef_df['p-value'] >= 0.01) & (baseline_coef_df['p-
value'] < 0.05), 'Significance'] = '*'
    baseline_coef_df.loc[(baseline_coef_df['p-value'] >= 0.05) & (baseline_coef_df['p-
value'] < 0.1), 'Significance'] = '.'

    print("\nBaseline Model Coefficient Table:")
    print(baseline_coef_df)

    # For enhanced model
    print("\nENHANCED MODEL - NUMERICAL VARIABLES ONLY:")
    print("-" * 60)

    # Copy data to avoid modifying originals
    X_train_clean_num =
X_train_clean[numerical_cols_r_clean].copy().reset_index(drop=True)
    y_train_clean_num = y_train_clean.copy().reset_index(drop=True)

    # Handle missing values
    imputer = SimpleImputer(strategy='median')
    X_train_clean_num_imputed = pd.DataFrame(
        imputer.fit_transform(X_train_clean_num),
        columns=numerical_cols_r_clean
    )

    # Add constant for intercept
    X_train_clean_num_with_const = sm.add_constant(X_train_clean_num_imputed)

    # Fit OLS model
    enhanced_sm_model = sm.OLS(y_train_clean_num, X_train_clean_num_with_const).fit()

    # Print summary
    print(enhanced_sm_model.summary())

    # Create DataFrame for coefficients
    enhanced_coef_df = pd.DataFrame({
        'Feature': ['const'] + numerical_cols_r_clean,
        'Coefficient': enhanced_sm_model.params,
        'Std Error': enhanced_sm_model.bse,
        't-value': enhanced_sm_model.tvalues,
        'p-value': enhanced_sm_model.pvalues
    })

    # Add significance markers
    enhanced_coef_df['Significance'] = ''
    enhanced_coef_df.loc[enhanced_coef_df['p-value'] < 0.001, 'Significance'] = '***'
    enhanced_coef_df.loc[(enhanced_coef_df['p-value'] >= 0.001) & (enhanced_coef_df['p-
value'] < 0.01), 'Significance'] = '**'
    enhanced_coef_df.loc[(enhanced_coef_df['p-value'] >= 0.01) & (enhanced_coef_df['p-
value'] < 0.05), 'Significance'] = '*'
    enhanced_coef_df.loc[(enhanced_coef_df['p-value'] >= 0.05) & (enhanced_coef_df['p-
value'] < 0.1), 'Significance'] = '.'

    print("\nEnhanced Model Coefficient Table:")
    print(enhanced_coef_df)

    return baseline_coef_df, enhanced_coef_df

simple_ols_with_numerical_only()

print("\nAnalysis Complete!")
```

```
Initial data shape: (136209, 19)
Data shape after outlier removal: (128150, 19)

================================================================================
SECTION 1: BASELINE MODEL (WITHOUT OUTLIER REMOVAL OR BOX-COX)
================================================================================

BASELINE MODEL METRICS (NO OUTLIER REMOVAL, NO BOX-COX):
------------------------------------------------------------
R² Score (log scale): 0.8904
RMSE (log scale): 0.1740
R² Score (original scale): 0.7153
RMSE (original scale): 5.3589

================================================================================
SECTION 2: ENHANCED MODEL (WITH OUTLIER REMOVAL AND BOX-COX)
================================================================================

ENHANCED MODEL METRICS (WITH OUTLIER REMOVAL AND BOX-COX):
------------------------------------------------------------
R² Score (log scale): 0.8662
RMSE (log scale): 0.1587
R² Score (original scale): 0.8427
RMSE (original scale): 1.2831

================================================================================
COMPARISON SUMMARY
================================================================================
Baseline Model (log scale):
R² Score: 0.8904
RMSE: 0.1740

Enhanced Model (log scale):
R² Score: 0.8662
RMSE: 0.1587
R² Improvement: -2.72%
RMSE Improvement: 8.79%

================================================================================
RESIDUAL NORMALITY TESTS
================================================================================

Baseline Model Residuals:
----------------------------------------
Shapiro-Wilk Test: W=0.8967, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)
D'Agostino's K² Test: K²=5430.4622, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)

Skewness: 0.0495
Kurtosis: 12.8693
Mean: 0.000313 (should be close to 0)
Standard Deviation: 0.173974

Enhanced Model Residuals:
----------------------------------------
Shapiro-Wilk Test: W=0.8833, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)
D'Agostino's K² Test: K²=7562.6152, p-value=0.000000
Conclusion: Residuals are NOT normally distributed (reject H0)

Skewness: 1.1430
Kurtosis: 7.8991
Mean: 0.000636 (should be close to 0)
Standard Deviation: 0.158679

================================================================================
SECTION 3: COEFFICIENT ANALYSIS (NUMERICAL VARIABLES ONLY)
================================================================================

BASELINE MODEL - NUMERICAL VARIABLES ONLY:
------------------------------------------------------------
                            OLS Regression Results
==============================================================================
Dep. Variable:     Asteroid_Size_km(Diameter)   R-squared:                       0.886
Model:                                    OLS   Adj. R-squared:                  0.886
Method:                         Least Squares   F-statistic:                 7.029e+04
Date:                        Mon, 12 May 2025   Prob (F-statistic):               0.00
Time:                                12:55:04   Log-Likelihood:                 34140.
No. Observations:                      108967   AIC:                        -6.825e+04
Df Residuals:                          108954   BIC:                        -6.813e+04
Df Model:                                  12
Covariance Type:                    nonrobust
==============================================================================
=======
                              coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
-------
const                       7.1515      0.023    314.578      0.000       7.107
7.196
Brightness                 -0.3421      0.000   -745.424      0.000      -0.343
-0.341
Reflectivity               -2.0585      0.006   -360.914      0.000      -2.070
-2.047
Orbit_Shape                 0.5108      0.011     44.820      0.000       0.488
0.533
Orbit_Distance_AU          -0.0808      0.006    -13.747      0.000      -0.092
-0.069
Closest_Sun_Distance_AU    -0.1948      0.015    -13.157      0.000      -0.224
```

```
-0.166
Orbit_Tilt_Degrees            -0.0021    9.4e-05    -22.393      0.000      -0.002
-0.002
Orbit_Angle_1_Degrees        1.525e-06   5.24e-06      0.291      0.771   -8.75e-06
1.18e-05
Orbit_Angle_2_Degrees       -1.996e-05   5.21e-06     -3.831      0.000   -3.02e-05   -
9.75e-06
Orbit_Angle_3_Degrees       -2.872e-05   5.09e-06     -5.648      0.000   -3.87e-05   -
1.88e-05
Farthest_Sun_Distance_AU        0.0332      0.003     10.396      0.000       0.027
0.039
Orbit_Speed_Degrees_Per_Day    -0.0049      0.016     -0.316      0.752      -0.036
0.026
Orbit_Period_Days            1.871e-06   3.16e-07      5.915      0.000    1.25e-06
2.49e-06
Orbit_Period_Years           5.118e-09   8.66e-10      5.909      0.000    3.42e-09
6.82e-09
Earth_Closest_Distance_AU    2.346e-06   1.13e-07     20.801      0.000    2.12e-06
2.57e-06
Earth_Closest_Distance_Lunar    0.0009   4.39e-05     20.801      0.000       0.001
0.001
==============================================================================
Omnibus:                    22842.259   Durbin-Watson:                   1.998
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           699438.623
Skew:                          -0.305   Prob(JB):                         0.00
Kurtosis:                      15.397   Cond. No.                     1.44e+19
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 4.01e-26. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Baseline Model Coefficient Table:
                                                   Feature   Coefficient  \
const                                                const  7.151498e+00
Brightness                                      Brightness -3.421083e-01
Reflectivity                                  Reflectivity -2.058477e+00
Orbit_Shape                                    Orbit_Shape  5.107920e-01
Orbit_Distance_AU                        Orbit_Distance_AU -8.078486e-02
Closest_Sun_Distance_AU            Closest_Sun_Distance_AU -1.947769e-01
Orbit_Tilt_Degrees                      Orbit_Tilt_Degrees -2.104840e-03
Orbit_Angle_1_Degrees                Orbit_Angle_1_Degrees  1.525039e-06
Orbit_Angle_2_Degrees                Orbit_Angle_2_Degrees -1.995924e-05
Orbit_Angle_3_Degrees                Orbit_Angle_3_Degrees -2.872467e-05
Farthest_Sun_Distance_AU          Farthest_Sun_Distance_AU  3.320713e-02
Orbit_Speed_Degrees_Per_Day    Orbit_Speed_Degrees_Per_Day -4.941454e-03
Orbit_Period_Days                        Orbit_Period_Days  1.871483e-06
Orbit_Period_Years                      Orbit_Period_Years  5.118202e-09
Earth_Closest_Distance_AU        Earth_Closest_Distance_AU  2.346002e-06
Earth_Closest_Distance_Lunar  Earth_Closest_Distance_Lunar  9.129938e-04

                                 Std Error     t-value        p-value  \
const                         2.273363e-02  314.577886   0.000000e+00
Brightness                    4.589444e-04 -745.424415   0.000000e+00
Reflectivity                  5.703506e-03 -360.914229   0.000000e+00
Orbit_Shape                   1.139650e-02   44.820094   0.000000e+00
Orbit_Distance_AU             5.876363e-03  -13.747425   5.732623e-43
Closest_Sun_Distance_AU       1.480365e-02  -13.157356   1.655036e-39
Orbit_Tilt_Degrees            9.399713e-05  -22.392594  8.279245e-111
Orbit_Angle_1_Degrees         5.241797e-06    0.290938   7.710991e-01
Orbit_Angle_2_Degrees         5.210424e-06   -3.830637   1.278836e-04
Orbit_Angle_3_Degrees         5.085512e-06   -5.648334   1.624125e-08
Farthest_Sun_Distance_AU      3.194296e-03   10.395757   2.663874e-25
```

```
Orbit_Speed_Degrees_Per_Day   -30.3868      0.783    -38.806      0.000     -31.922
-28.852
Orbit_Period_Days               0.0207      0.001     37.863      0.000       0.020
0.022
Orbit_Period_Years           5.666e-05    1.5e-06     37.863      0.000    5.37e-05
5.96e-05
Earth_Closest_Distance_AU    1.281e-06   1.43e-07      8.974      0.000       1e-06
1.56e-06
Earth_Closest_Distance_Lunar    0.0005   5.55e-05      8.974      0.000       0.000
0.001
==============================================================================
Omnibus:                    27287.527   Durbin-Watson:                   1.995
Prob(Omnibus):                  0.000   Jarque-Bera (JB):           157918.627
Skew:                          -1.158   Prob(JB):                         0.00
Kurtosis:                       8.622   Cond. No.                     6.23e+18
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly
specified.
[2] The smallest eigenvalue is 8.88e-27. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

Enhanced Model Coefficient Table:
                                                   Feature  Coefficient  \
const                                                const    40.528418
Brightness                                      Brightness    -0.332125
Reflectivity                                  Reflectivity    -2.163206
Orbit_Shape                                    Orbit_Shape     1.081014
Orbit_Distance_AU                        Orbit_Distance_AU    -7.491520
Closest_Sun_Distance_AU            Closest_Sun_Distance_AU    -7.422976
Orbit_Tilt_Degrees                      Orbit_Tilt_Degrees    -0.002861
Orbit_Angle_1_Degrees                Orbit_Angle_1_Degrees     0.000008
Orbit_Angle_2_Degrees                Orbit_Angle_2_Degrees    -0.000014
Orbit_Angle_3_Degrees                Orbit_Angle_3_Degrees    -0.000043
Farthest_Sun_Distance_AU          Farthest_Sun_Distance_AU    -7.560065
Orbit_Speed_Degrees_Per_Day    Orbit_Speed_Degrees_Per_Day   -30.386841
Orbit_Period_Days                        Orbit_Period_Days     0.020695
Orbit_Period_Years                      Orbit_Period_Years     0.000057
Earth_Closest_Distance_AU        Earth_Closest_Distance_AU     0.000001
Earth_Closest_Distance_Lunar  Earth_Closest_Distance_Lunar     0.000498

                                 Std Error     t-value        p-value  \
const                         8.866023e-01   45.712059   0.000000e+00
Brightness                    4.703495e-04 -706.123079   0.000000e+00
Reflectivity                  5.802717e-03 -372.791870   0.000000e+00
Orbit_Shape                   6.769468e-02   15.968965   2.466210e-57
Orbit_Distance_AU             1.972958e-01  -37.971016   0.000000e+00
Closest_Sun_Distance_AU       1.999568e-01  -37.122890  1.191395e-299
Orbit_Tilt_Degrees            9.712258e-05  -29.452974  7.183578e-190
Orbit_Angle_1_Degrees         4.631565e-06    1.816974   6.922400e-02
Orbit_Angle_2_Degrees         4.595486e-06   -3.066440   2.166805e-03
Orbit_Angle_3_Degrees         4.524106e-06   -9.497098   2.202400e-21
Farthest_Sun_Distance_AU      1.957934e-01  -38.612450   0.000000e+00
Orbit_Speed_Degrees_Per_Day   7.830365e-01  -38.806420   0.000000e+00
Orbit_Period_Days             5.465721e-04   37.863247   0.000000e+00
Orbit_Period_Years            1.496433e-06   37.863247   0.000000e+00
Earth_Closest_Distance_AU     1.427017e-07    8.973967   2.906934e-19
Earth_Closest_Distance_Lunar  5.553521e-05    8.973967   2.906949e-19

                             Significance
const                                 ***
Brightness                            ***
Reflectivity                          ***
Orbit_Shape                           ***
```

```
Orbit_Speed_Degrees_Per_Day   1.561896e-02   -0.316375   7.517183e-01
Orbit_Period_Days             3.163827e-07    5.915250   3.323559e-09
Orbit_Period_Years            8.662112e-10    5.908723   3.457897e-09
Earth_Closest_Distance_AU     1.127807e-07   20.801458   6.457143e-96
Earth_Closest_Distance_Lunar  4.389086e-05   20.801458   6.457174e-96

                             Significance
const                                 ***
Brightness                            ***
Reflectivity                          ***
Orbit_Shape                           ***
Orbit_Distance_AU                     ***
Closest_Sun_Distance_AU               ***
Orbit_Tilt_Degrees                    ***
Orbit_Angle_1_Degrees
Orbit_Angle_2_Degrees                 ***
Orbit_Angle_3_Degrees                 ***
Farthest_Sun_Distance_AU              ***
Orbit_Speed_Degrees_Per_Day
Orbit_Period_Days                     ***
Orbit_Period_Years                    ***
Earth_Closest_Distance_AU             ***
Earth_Closest_Distance_Lunar          ***

ENHANCED MODEL - NUMERICAL VARIABLES ONLY:
------------------------------------------------------------
                            OLS Regression Results
==========================================================================================
Dep. Variable:     Asteroid_Size_km(Diameter)   R-squared:                       0.876
Model:                                    OLS   Adj. R-squared:                  0.876
Method:                         Least Squares   F-statistic:                 6.010e+04
Date:                        Mon, 12 May 2025   Prob (F-statistic):               0.00
Time:                                12:55:04   Log-Likelihood:                 48091.
No. Observations:                      102520   AIC:                        -9.616e+04
Df Residuals:                          102507   BIC:                        -9.603e+04
Df Model:                                  12
Covariance Type:                    nonrobust
==========================================================================================
=======
                                  coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------------------
-------
const                          40.5284      0.887     45.712      0.000      38.791
42.266
Brightness                     -0.3321      0.000   -706.123      0.000      -0.333
-0.331
Reflectivity                   -2.1632      0.006   -372.792      0.000      -2.175
-2.152
Orbit_Shape                     1.0810      0.068     15.969      0.000       0.948
1.214
Orbit_Distance_AU              -7.4915      0.197    -37.971      0.000      -7.878
-7.105
Closest_Sun_Distance_AU        -7.4230      0.200    -37.123      0.000      -7.815
-7.031
Orbit_Tilt_Degrees             -0.0029   9.71e-05    -29.453      0.000      -0.003
-0.003
Orbit_Angle_1_Degrees        8.415e-06   4.63e-06      1.817      0.069   -6.62e-07
1.75e-05
Orbit_Angle_2_Degrees       -1.409e-05    4.6e-06     -3.066      0.002   -2.31e-05   -
5.08e-06
Orbit_Angle_3_Degrees       -4.297e-05   4.52e-06     -9.497      0.000   -5.18e-05   -
3.41e-05
Farthest_Sun_Distance_AU       -7.5601      0.196    -38.612      0.000      -7.944
-7.176
```

```
Orbit_Distance_AU                     ***
Closest_Sun_Distance_AU               ***
Orbit_Tilt_Degrees                    ***
Orbit_Angle_1_Degrees                   .
Orbit_Angle_2_Degrees                  **
Orbit_Angle_3_Degrees                 ***
Farthest_Sun_Distance_AU              ***
Orbit_Speed_Degrees_Per_Day           ***
Orbit_Period_Days                     ***
Orbit_Period_Years                    ***
Earth_Closest_Distance_AU             ***
Earth_Closest_Distance_Lunar          ***

Analysis Complete!
```