project-asteroids

October 31, 2023

1 Summary

In this study, we utilized the NASA Near-Earth Object Web Service (NeoWs) API to gather data on asteroids. The retrieved asteroid information, presented in JSON format, was then stored in a MongoDB database for further analysis. Leveraging the pymongo library, a series of operations were performed to extract valuable insights from the dataset.

The focus of this analysis centered around two key aspects: asteroid diameter and velocity. These findings provide a deeper understanding of the characteristics and behavior of these celestial objects, contributing to our knowledge of near-Earth asteroids.

2 Requirements and connection

```
import pymongo
import pprint as pp
import pandas as pd
import requests
import numpy as np
import matplotlib.pyplot as plt
import numpy as np
from scipy.optimize import curve_fit
from sklearn.metrics import r2_score
from sklearn.cluster import KMeans
# pandas configuration
pd.set_option('display.precision', 2)
```

Details about the API and database setup

```
[71]: API_URL = "https://api.nasa.gov/neo/rest/v1/feed?

start_date=2015-09-07&end_date=2015-09-08&api_key=DEMO_KEY"

CNX_STR = "mongodb+srv://valleandrea:nosql_andrea@cluster0.puqrqtt.mongodb.net"

DB_NAME = "db_asteroids"

COLL_NAME = "asteroids"
```

3 ELT Process

3.1 Extract

```
[75]: # Conncetion to the database
    client = pymongo.MongoClient(CNX_STR)
    db = client["asteroids_db"]

[78]: # Specify a collection or create it if it does not already exist
    collection_name = "asteroids"

    if collection_name in db.list_collection_names():
        col = db.get_collection(collection_name)
    else:
        col = db.create_collection[collection_name]

# Clean up the collection
    col.delete_many({})
```

[78]: <pymongo.results.DeleteResult at 0x2155840dbe0>

3.2 Load

```
[81]: # Fetcher for the API
def fetcher(data):
    asteroids = {
        'id': int(data['id']),
        'name': data['name'],
        'nasa_jpl_url':data['nasa_jpl_url'],
        'absolute_magnitude_h': data['absolute_magnitude_h'],
        'estimated_diameter': data['estimated_diameter'],
        'is_potentially_hazardous_asteroid':
        'data['is_potentially_hazardous_asteroid'],
        'close_approach_data':data['close_approach_data'],
        'orbital_data':data['orbital_data'],
        'is_sentry_object':data['is_sentry_object']
    }
    return asteroids
```

```
[86]: # Load the dataset
near_earth_objects = []
for i in range(5):
    url = f"https://api.nasa.gov/neo/rest/v1/neo/browse?
    page={i}&size=20&api_key=DEMO_KEY"
    r = requests.get(url)
    data = r.json()
    near_earth_objects.extend(data['near_earth_objects'])
```

```
list_asteroids = []
      for object in near_earth_objects:
          list_asteroids.append(fetcher(object))
[90]: # Insert into the collection
      col.insert_many(list_asteroids)
      # Count elements in the collection
      document_count = col.count_documents({})
      print(f'Number of documents in the collection: {document count}')
     Number of documents in the collection: 100
[95]: # Printing a sample of a document in the collection
      r = col.aggregate([{"$limit":5}])
      pd.DataFrame(r)
[95]:
                                        id
                                                              name
                              id
      0 65416a61d2dd94a9fbceb84d 2000433
                                                433 Eros (A898 PA)
      1 65416a61d2dd94a9fbceb84e
                                   2000719
                                              719 Albert (A911 TB)
      2 65416a61d2dd94a9fbceb84f
                                   2000887
                                              887 Alinda (A918 AA)
      3 65416a61d2dd94a9fbceb850 2001036 1036 Ganymed (A924 UB)
      4 65416a61d2dd94a9fbceb851 2001221
                                              1221 Amor (1932 EA1)
                                          nasa_jpl_url absolute_magnitude_h \
      0 http://ssd.jpl.nasa.gov/sbdb.cgi?sstr=2000433
                                                                       10.41
      1 http://ssd.jpl.nasa.gov/sbdb.cgi?sstr=2000719
                                                                       15.59
      2 http://ssd.jpl.nasa.gov/sbdb.cgi?sstr=2000887
                                                                       13.88
      3 http://ssd.jpl.nasa.gov/sbdb.cgi?sstr=2001036
                                                                        9.26
      4 http://ssd.jpl.nasa.gov/sbdb.cgi?sstr=2001221
                                                                       17.37
                                        estimated_diameter \
      0 {'kilometers': {'estimated diameter min': 22.0...
      1 {'kilometers': {'estimated_diameter_min': 2.02...
      2 {'kilometers': {'estimated diameter min': 4.45...
      3 {'kilometers': {'estimated_diameter_min': 37.3...
      4 {'kilometers': {'estimated_diameter_min': 0.89...
         is_potentially_hazardous_asteroid \
      0
                                     False
                                     False
      1
      2
                                     False
      3
                                     False
      4
                                     False
                                       close_approach_data \
       [{'close_approach_date': '1900-12-27', 'close_...
```

3.3 Transformation

```
[108]: # Extract the average realtive speed based on the osservations
       pipeline = [
           {
               "$unwind": "$close_approach_data"
           },
           {
               "$addFields": {
                   "relativeSpeed": {
                        "$toDouble": "$close_approach_data.relative_velocity.
        ⇔kilometers_per_second"
                   }
               }
           },
           {
               "$group": {
                   "_id": "$_id",
                   "relativeSpeedAvg": { "$avg": "$relativeSpeed" }
               }
           },
               "$project": {
                   " id": 1,
                   "relativeSpeedAvg": 1
           }
       ]
       result = col.aggregate(pipeline)
       for doc in result:
           id = doc["_id"]
           relative_speed_avg = doc["relativeSpeedAvg"]
```

```
col.update_one({"_id": id}, {"$set": {"relativeSpeedAvg":_u
        →relative_speed_avg}})
       pipeline = [
           {"$limit": 5},
           {
               "$project": {
                   "_id": 1,
                   "id": 1,
                   "name": 1,
                   "relativeSpeedAvg": 1
               }
           }
       r = col.aggregate(pipeline)
       pd.DataFrame(r)
[108]:
                                         id
                                                               name relativeSpeedAvg
                               id
                                                 433 Eros (A898 PA)
                                                                                  5.06
       0 65416a61d2dd94a9fbceb84d 2000433
                                                                                 6.20
       1 65416a61d2dd94a9fbceb84e 2000719
                                              719 Albert (A911 TB)
       2 65416a61d2dd94a9fbceb84f 2000887
                                               887 Alinda (A918 AA)
                                                                                10.09
       3 65416a61d2dd94a9fbceb850 2001036 1036 Ganymed (A924 UB)
                                                                                13.98
       4 65416a61d2dd94a9fbceb851 2001221
                                               1221 Amor (1932 EA1)
                                                                                10.46
[107]: # Extract the minimum distance based on the osservations
       pipeline = [
           {
               "$unwind": "$close_approach_data"
           },
           {
               "$addFields": {
                   "missDistance": {
                       "$toDouble": "$close_approach_data.miss_distance.astronomical"
                   }
               }
           },
               "$group": {
                   "_id": "$_id",
                   "missDistance_min": { "$min": "$missDistance" }
               }
           },
```

"\$project": {
 "_id": 1,

}

"missDistance_min": 1

```
}
]
result = col.aggregate(pipeline)
for doc in result:
    unique_id = doc["_id"]
    col.update_one({"_id": unique_id}, {"$set": {"missDistance_min":_

¬doc["missDistance_min"]}})
pipeline = [
    {"$limit": 5},
    {
        "$project": {
            "_id": 1,
            "id": 1,
            "name": 1,
            "missDistance_min": 1
        }
    }
r = col.aggregate(pipeline)
pd.DataFrame(r)
```

```
[107]:
                              id
                                        id
                                                              name missDistance_min
      0 65416a61d2dd94a9fbceb84d 2000433
                                                433 Eros (A898 PA)
                                                                               0.15
                                                                               0.21
      1 65416a61d2dd94a9fbceb84e
                                   2000719
                                              719 Albert (A911 TB)
      2 65416a61d2dd94a9fbceb84f
                                   2000887
                                              887 Alinda (A918 AA)
                                                                               0.08
      3 65416a61d2dd94a9fbceb850 2001036 1036 Ganymed (A924 UB)
                                                                               0.03
      4 65416a61d2dd94a9fbceb851 2001221
                                              1221 Amor (1932 EA1)
                                                                               0.11
```

3.4 Datastructure

4 Orbital analysis

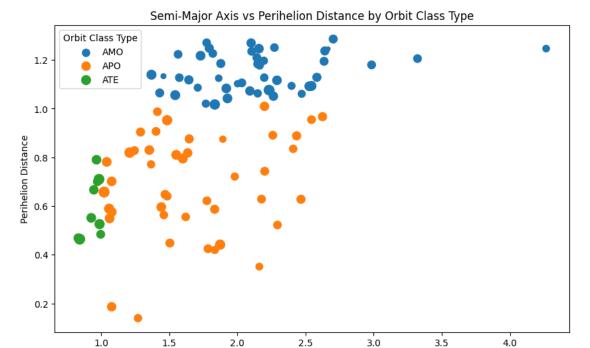
Calculate the distribution of the orbits

```
2 ATE S
```

```
[120]: pipeline = [
           {
               "$project": {
                   "absolute_magnitude_h": 1,
                   "orbital data.perihelion distance": 1,
                   "orbital_data.semi_major_axis": 1,
                   "orbital_data.orbit_class.orbit_class_type": 1,
               }
           }
       ]
       cursor = col.aggregate(pipeline)
       data = []
       for entry in cursor:
           orbital_data = entry.get("orbital_data")
           absolute_magnitude_h = entry.get("absolute_magnitude_h")
           if orbital data:
               perihelion_distance = orbital_data.get("perihelion_distance")
               semi_major_axis = orbital_data.get("semi_major_axis")
               orbit_class = orbital_data.get("orbit_class")
               if perihelion_distance and semi_major_axis and orbit_class:
                   perihelion_distance = float(perihelion_distance)
                   semi_major_axis = float(semi_major_axis)
                   absolute_magnitude_h = float(absolute_magnitude_h)
                   orbit_class_type = orbit_class.get("orbit_class_type")
                   data.append({
                       "perihelion_distance": perihelion_distance,
                       "semi_major_axis": semi_major_axis,
                       "orbit class type": orbit class type,
                       "absolute_magnitude_h": absolute_magnitude_h
                   })
       df = pd.DataFrame(data)
       min_h = df["absolute_magnitude_h"].min()
       max_h = df["absolute_magnitude_h"].max()
        df["normalized_absolute_magnitude_h"] = (df["absolute_magnitude_h"] - min_h) /_{\sqcup} 
        ⇔(max_h - min_h)
       plt.figure(figsize=(10, 6))
       for orbit_class_type, group in df.groupby("orbit_class_type"):
           marker_size = 20 + 100 * group["normalized_absolute_magnitude_h"]
```

```
plt.scatter(
    group["semi_major_axis"],
    group["perihelion_distance"],
    label=orbit_class_type,
    s=marker_size,
)

plt.xlabel('Semi-Major Axis (a)')
plt.ylabel('Perihelion Distance')
plt.title('Semi-Major Axis vs Perihelion Distance by Orbit Class Type')
plt.legend(title='Orbit Class Type')
plt.show()
```



Semi-Major Axis (a)

```
}
    }
]
result = col.aggregate(pipeline)
df = pd.DataFrame(list(result))
estimated diameter min = []
orbit_class_type_list = []
for index, row in df.iterrows():
    orbit_class_type_list.
 →append(row["orbital_data"]["orbit_class"]["orbit_class_type"])
    estimated_diameter = row["absolute_magnitude_h"]
    estimated_diameter_min.append(estimated_diameter)
plt.figure(figsize=(10, 6))
marker_size = 20 + 100 * np.array(estimated_diameter_min)
for i in range(len(df)):
    plt.scatter(
        df["relativeSpeed_Avg"].iloc[i],
        df["missDistance_min"].iloc[i],
        label=orbit_class_type_list[i],
        s=marker_size[i],
        alpha=0.5
    )
plt.xlabel('Relative Speed (km/s)')
plt.ylabel('Miss Distance (astronomical units)')
plt.title('Relative Speed vs Miss Distance')
plt.legend(title='Orbit Class Type', loc='upper right', bbox_to_anchor=(1.3, 1))
plt.show()
```

```
File pandas\_libs\hashtable_class_helper.pxi:7080, in pandas._libs.hashtable.
 →PyObjectHashTable.get_item()
File pandas\ libs\hashtable class helper.pxi:7088, in pandas. libs.hashtable.
 →PyObjectHashTable.get item()
KeyError: 'orbital_data.orbit_class.orbit_class_type'
The above exception was the direct cause of the following exception:
                                          Traceback (most recent call last)
KeyError
Cell In[130], line 18
     15 df = pd.DataFrame(list(result))
     17 # Extract unique orbit class types
---> 18 unique_orbit_classes = df["orbital_data.orbit_class.orbit_class_type"].

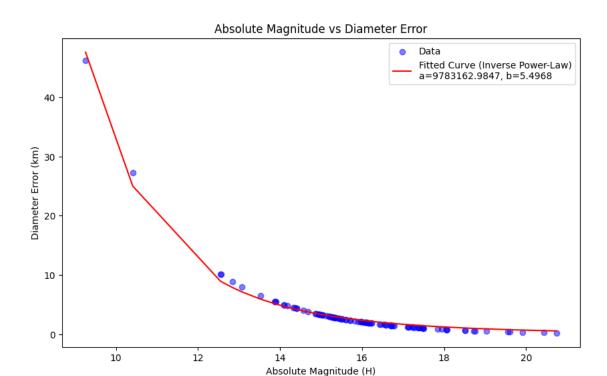
unique()
     20 plt.figure(figsize=(10, 6))
     21 marker_size = 20 + 100 * np.array(estimated_diameter_min)
File ~\OneDrive - Hochschule__
 Luzern\Desktop\AsteroidsDB\venv\lib\site-packages\pandas\core\frame.py:3893,
 →in DataFrame. __getitem__(self, key)
   3891 if self.columns.nlevels > 1:
   3892
            return self._getitem_multilevel(key)
-> 3893 indexer = self.columns.get_loc(key)
   3894 if is_integer(indexer):
            indexer = [indexer]
   3895
File ~\OneDrive - Hochschule__
 Luzern\Desktop\AsteroidsDB\venv\lib\site-packages\pandas\core\indexes\base.py
 ⇒3797, in Index.get_loc(self, key)
            if isinstance(casted_key, slice) or (
   3792
                isinstance(casted_key, abc.Iterable)
   3793
   3794
                and any(isinstance(x, slice) for x in casted_key)
   3795
            ):
   3796
                raise InvalidIndexError(key)
-> 3797
            raise KeyError(key) from err
   3798 except TypeError:
           # If we have a listlike key, _check_indexing_error will raise
   3799
   3800
            # InvalidIndexError. Otherwise we fall through and re-raise
           # the TypeError.
   3801
   3802
            self._check_indexing_error(key)
KeyError: 'orbital_data.orbit_class.orbit_class_type'
```

The number of dangerous asteroids from Nasa: 43

The number of dangerous asteroids from Nasa: 28

Function of absolute error of the diameter based on the velocity

```
result = col.aggregate(pipeline)
# Extract data for plotting
absolute_magnitudes = []
diameter_errors = []
for doc in result:
    absolute_magnitudes.append(doc["absolute_magnitude_h"])
    diameter_errors.append(doc["diameter_error"])
# Define the inverse power-law function
def inverse_power_law(x, a, b):
    return a * np.power(x, -b)
# Sort data for fitting
data_sorted = sorted(zip(absolute_magnitudes, diameter_errors))
x_data_sorted, y_data_sorted = zip(*data_sorted)
# Perform the curve fit
params, covariance = curve_fit(inverse_power_law, x_data_sorted, y_data_sorted)
a_opt, b_opt = params
# Calculate the fitted y values
y_fit_power_law = inverse_power_law(x_data_sorted, a_opt, b_opt)
# Create the combined plot
plt.figure(figsize=(10, 6))
# Scatter plot for data points
plt.scatter(absolute_magnitudes, diameter_errors, c='blue', alpha=0.5,__
 →label='Data')
# Fitted curve (Inverse Power-Law)
plt.plot(x_data_sorted, y_fit_power_law, 'r-', label=f'Fitted Curve (Inverse∟
\neg Power-Law \rangle = \{a_opt:.4f\}, b=\{b_opt:.4f\}'\}
plt.xlabel('Absolute Magnitude (H)')
plt.ylabel('Diameter Error (km)')
plt.title('Absolute Magnitude vs Diameter Error')
plt.legend()
plt.show()
```

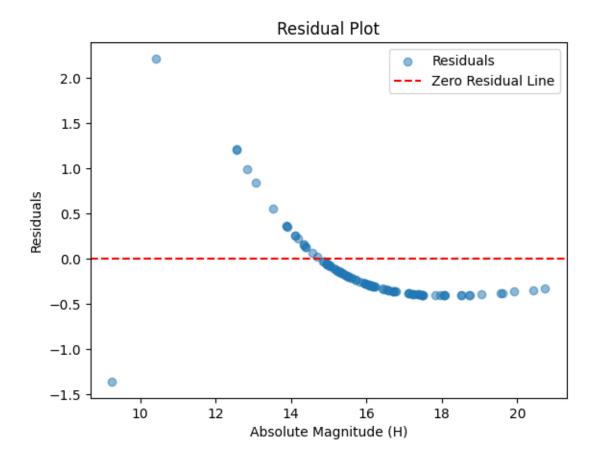


```
[155]: r_squared = r2_score(y_data_sorted, y_fit_power_law)
    residuals = y_data_sorted - y_fit_power_law
# Plot the residuals

plt.scatter(x_data_sorted, residuals, alpha=0.5, label='Residuals')
plt.axhline(y=0, color='r', linestyle='--', label='Zero Residual Line')
plt.xlabel('Absolute Magnitude (H)')
plt.ylabel('Residuals')
plt.title('Residual Plot')
plt.legend()

plt.show()

print(f'R-squared value: {r_squared:.4f}')
```



R-squared value: 0.9930