or-was-discovered-after-its-impact

June 25, 2024

[ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

The dataset contains the following variables:

name: the name of the meteorite (typically a location, often modified with a number, year, composition, etc) **id**: a unique identifier for the meteorite

nametype: one of:

– valid: a typical meteorite

– relict: a meteorite that has been highly degraded by weather on Earth

recclass: the class of the meteorite; one of a large number of classes based on physical, chemical, and other characteristics (see the Wikipedia article on meteorite classification for a primer)

mass: the mass of the meteorite, in grams

fall: whether the meteorite was seen falling, or was discovered after its impact; one of:

– Fell: the meteorite's fall was observed

– Found: the meteorite's fall was not observed

year: the year the meteorite fell, or the year it was found (depending on the value of fell)

reclat: the latitude of the meteorite's landing

reclong: the longitude of the meteorite's landing

GeoLocation: a parentheses-enclose, comma-separated tuple that combines reclat and reclong

[ ]:
```
from PIL import Image
import matplotlib.pyplot as plt
plt.figure(figsize=(11,11))

# Specify the path to your image file
image_path = '/content/image.png'  # Replace with your image file path

# Open the image file
img = Image.open(image_path)
```

```
# Display the image using matplotlib
plt.imshow(img)
plt.axis('off')  # Turn off axis numbers and ticks
plt.show()
```

[ ]:
```
df=pd.read_csv('/content/meteorite-landings.csv')
df.head()
```

[ ]:

	name	id	nametype	recclass	mass	fall	year	reclat	reclong	GeoLocation
0	Aachen	1	Valid	L5	21.0	Fell	1880.0	50.77500	6.08333	(50.775000, 6.083330)
1	Aarhus	2	Valid	H6	720.0	Fell	1951.0	56.18333	10.23333	(56.183330, 10.233330)
2	Abee	6	Valid	EH4	107000.0	Fell	1952.0	54.21667	-113.00000	(54.216670, -113.000000)
3	Acapulco	10	Valid	Acapulcoite	1914.0	Fell	1976.0	16.88333	-99.90000	(16.883330, -99.900000)
4	Achiras	370	Valid	L6	780.0	Fell	1902.0	-33.16667	-64.95000	(-33.166670, -64.950000)

DATA PREPROCSSING

[ ]:
```
df.isnull().sum()
```

```
name              0
id                0
nametype          0
recclass          0
mass            131
fall              0
year            288
reclat         7315
reclong        7315
GeoLocation    7315
dtype: int64
```

```
df.shape
```

```
(45716, 10)
```

```
df.describe()
```

```
                id          mass          year        reclat       reclong
count  45716.000000  4.558500e+04  45428.000000  38401.000000  38401.000000
mean   26889.735104  1.327808e+04   1991.772189    -39.122580     61.074319
std    16860.683030  5.749889e+05     27.181247     46.378511     80.647298
min        1.000000  0.000000e+00    301.000000    -87.366670   -165.433330
25%    12688.750000  7.200000e+00   1987.000000    -76.714240      0.000000
50%    24261.500000  3.260000e+01   1998.000000    -71.500000     35.666670
75%    40656.750000  2.026000e+02   2003.000000      0.000000    157.166670
max    57458.000000  6.000000e+07   2501.000000     81.166670    354.473330
```

```
df.columns
```

```
Index(['name', 'id', 'nametype', 'recclass', 'mass', 'fall', 'year', 'reclat',
       'reclong', 'GeoLocation'],
      dtype='object')
```

```
df.name.value_counts()
```

```
name
Aachen                    1
Northwest Africa 7463     1
Northwest Africa 741      1
Northwest Africa 7410     1
Northwest Africa 7412     1
                         ..
Grove Mountains 052256    1
Grove Mountains 052259    1
Grove Mountains 052260    1
Grove Mountains 052263    1
```

```
Zulu Queen                1
Name: count, Length: 45716, dtype: int64
```

[ ]:
```
df.columns
```

[ ]:
```
Index(['name', 'id', 'nametype', 'recclass', 'mass', 'fall', 'year', 'reclat',
       'reclong', 'GeoLocation'],
      dtype='object')
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45716 entries, 0 to 45715
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   name         45716 non-null  object
 1   id           45716 non-null  int64
 2   nametype     45716 non-null  object
 3   recclass     45716 non-null  object
 4   mass         45585 non-null  float64
 5   fall         45716 non-null  object
 6   year         45428 non-null  float64
 7   reclat       38401 non-null  float64
 8   reclong      38401 non-null  float64
 9   GeoLocation  38401 non-null  object
dtypes: float64(4), int64(1), object(5)
memory usage: 3.5+ MB
```

[ ]:
```
df.head()
```

[ ]:

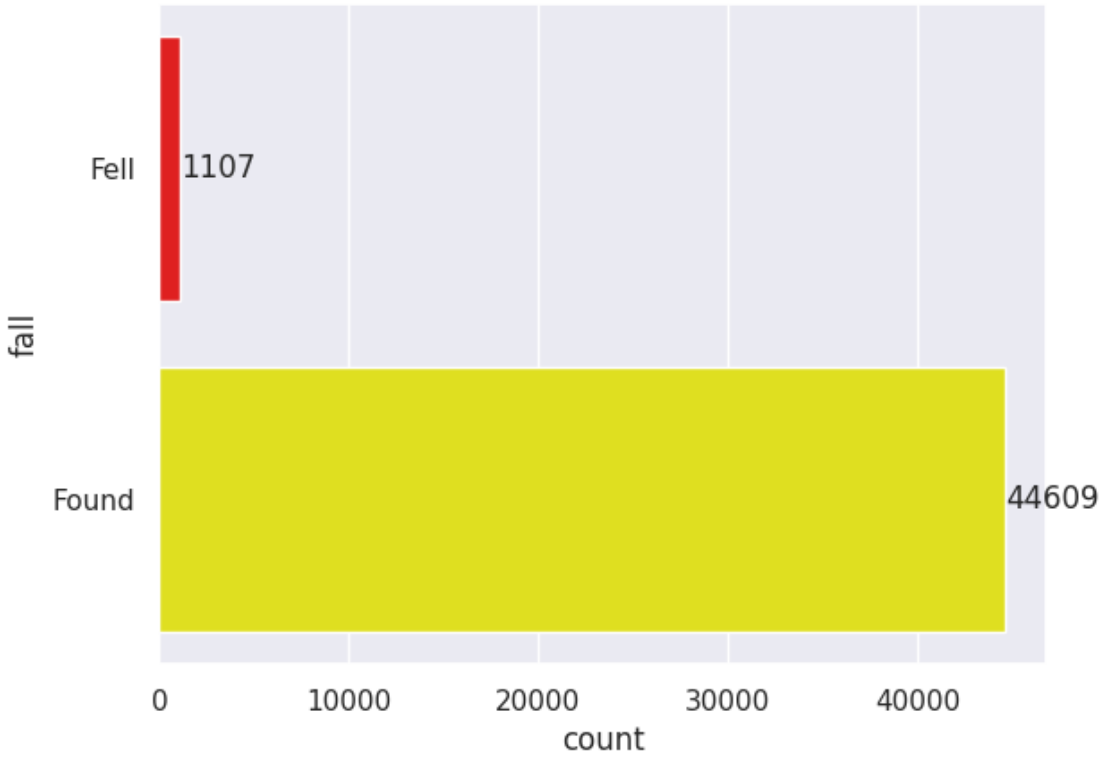
	name	id	nametype	recclass	mass	fall	year	reclat	reclong	GeoLocation
0	Aachen	1	Valid	L5	21.0	Fell	1880.0	50.77500	6.08333	(50.775000, 6.083330)
1	Aarhus	2	Valid	H6	720.0	Fell	1951.0	56.18333	10.23333	(56.183330, 10.233330)
2	Abee	6	Valid	EH4	107000.0	Fell	1952.0	54.21667	-113.00000	(54.216670, -113.000000)
3	Acapulco	10	Valid	Acapulcoite	1914.0	Fell	1976.0	16.88333	-99.90000	(16.883330, -99.900000)
4	Achiras	370	Valid	L6	780.0	Fell	1902.0	-33.16667	-64.95000	(-33.166670, -64.950000)

[ ]:
```
df['recclass'].value_counts()
```

[ ]:
```
recclass
L6          8285
H5          7142
L5          4796
H6          4528
H4          4211
            …
EL7            1
CH/CBb         1
H/L~4          1
LL3.7-6        1
L/LL           1
Name: count, Length: 466, dtype: int64
```

[ ]:
```
sns.set()
palette=['red','yellow']
a=sns.countplot(df['fall'],palette=palette)
for ax in a.containers:
  a.bar_label(ax)
```

```
<ipython-input-442-8c775c10d5dd>:3: FutureWarning:

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

  a=sns.countplot(df['fall'],palette=palette)
```



[ ]:
```
df.isnull().sum()
```

[ ]:
```
name              0
id                0
nametype          0
recclass          0
mass            131
fall              0
year            288
reclat         7315
reclong        7315
GeoLocation    7315
dtype: int64
```

[ ]:
```
df['mass']=df['mass'].fillna(df['mass'].mean())
df.isnull().sum()
```

[ ]:
```
name              0
id                0
nametype          0
recclass          0
mass              0
```

```
fall              0
year            288
reclat         7315
reclong        7315
GeoLocation    7315
dtype: int64
```

[ ]:
```
df.head()
```

[ ]:
```
       name   id nametype     recclass      mass  fall    year    reclat  \
0    Aachen    1    Valid           L5      21.0  Fell  1880.0  50.77500
1    Aarhus    2    Valid           H6     720.0  Fell  1951.0  56.18333
2      Abee    6    Valid          EH4  107000.0  Fell  1952.0  54.21667
3  Acapulco   10    Valid  Acapulcoite    1914.0  Fell  1976.0  16.88333
4   Achiras  370    Valid           L6     780.0  Fell  1902.0 -33.16667

     reclong              GeoLocation
0    6.08333     (50.775000, 6.083330)
1   10.23333    (56.183330, 10.233330)
2 -113.00000  (54.216670, -113.000000)
3  -99.90000   (16.883330, -99.900000)
4  -64.95000  (-33.166670, -64.950000)
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
name              0
id                0
nametype          0
recclass          0
mass              0
fall              0
year            288
reclat         7315
reclong        7315
GeoLocation    7315
dtype: int64
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 45716 entries, 0 to 45715
Data columns (total 10 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   name         45716 non-null  object
 1   id           45716 non-null  int64
 2   nametype     45716 non-null  object
```

```
 3   recclass     45716 non-null  object
 4   mass         45716 non-null  float64
 5   fall         45716 non-null  object
 6   year         45428 non-null  float64
 7   reclat       38401 non-null  float64
 8   reclong      38401 non-null  float64
 9   GeoLocation  38401 non-null  object
dtypes: float64(4), int64(1), object(5)
memory usage: 3.5+ MB
```

[ ]:
```
df['year'].value_counts()
```

[ ]:
```
year
2003.0    3323
1979.0    3046
1998.0    2697
2006.0    2456
1988.0    2296
          …
1741.0       1
1519.0       1
1671.0       1
1779.0       1
1792.0       1
Name: count, Length: 268, dtype: int64
```

[ ]:
```
df.head()
```

[ ]:
```
       name   id nametype     recclass      mass  fall    year    reclat  \
0    Aachen    1    Valid           L5      21.0  Fell  1880.0  50.77500
1    Aarhus    2    Valid           H6     720.0  Fell  1951.0  56.18333
2      Abee    6    Valid          EH4  107000.0  Fell  1952.0  54.21667
3  Acapulco   10    Valid  Acapulcoite    1914.0  Fell  1976.0  16.88333
4   Achiras  370    Valid           L6     780.0  Fell  1902.0 -33.16667

     reclong              GeoLocation
0    6.08333     (50.775000, 6.083330)
1   10.23333    (56.183330, 10.233330)
2 -113.00000  (54.216670, -113.000000)
3  -99.90000   (16.883330, -99.900000)
4  -64.95000  (-33.166670, -64.950000)
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
name              0
id                0
nametype          0
```

```
recclass          0
mass              0
fall              0
year            288
reclat         7315
reclong        7315
GeoLocation    7315
dtype: int64
```

[ ]:
```
df=df.drop(columns=['GeoLocation'],axis=1)
df.head()
```

[ ]:
```
       name   id nametype     recclass      mass  fall    year    reclat  \
0    Aachen    1    Valid           L5      21.0  Fell  1880.0  50.77500
1    Aarhus    2    Valid           H6     720.0  Fell  1951.0  56.18333
2      Abee    6    Valid          EH4  107000.0  Fell  1952.0  54.21667
3  Acapulco   10    Valid  Acapulcoite    1914.0  Fell  1976.0  16.88333
4   Achiras  370    Valid           L6     780.0  Fell  1902.0 -33.16667

     reclong
0    6.08333
1   10.23333
2 -113.00000
3  -99.90000
4  -64.95000
```

[ ]:
```
df=df.drop(columns=['id'],axis=1)
df.head()
```

[ ]:
```
       name nametype     recclass      mass  fall    year    reclat    reclong
0    Aachen    Valid           L5      21.0  Fell  1880.0  50.77500    6.08333
1    Aarhus    Valid           H6     720.0  Fell  1951.0  56.18333   10.23333
2      Abee    Valid          EH4  107000.0  Fell  1952.0  54.21667 -113.00000
3  Acapulco    Valid  Acapulcoite    1914.0  Fell  1976.0  16.88333  -99.90000
4   Achiras    Valid           L6     780.0  Fell  1902.0 -33.16667  -64.95000
```

[ ]:
```
df.isnull().sum()
```

[ ]:
```
name           0
nametype       0
recclass       0
mass           0
fall           0
year         288
reclat      7315
reclong     7315
dtype: int64
```

```
[ ]: df['year'].dtype
```

```
[ ]: dtype('float64')
```

```
[ ]:
```

```
[ ]: df['year'].dtype
```

```
[ ]: dtype('float64')
```

```
[ ]: df['year'].value_counts()
```

```
[ ]: year
     2003.0    3323
     1979.0    3046
     1998.0    2697
     2006.0    2456
     1988.0    2296
               …
     1741.0       1
     1519.0       1
     1671.0       1
     1779.0       1
     1792.0       1
     Name: count, Length: 268, dtype: int64
```

```
[ ]:
```

```
[ ]: df.head()
```

```
[ ]:        name nametype     recclass      mass  fall    year    reclat    reclong
     0    Aachen    Valid           L5      21.0  Fell  1880.0  50.77500     6.08333
     1    Aarhus    Valid           H6     720.0  Fell  1951.0  56.18333    10.23333
     2      Abee    Valid          EH4  107000.0  Fell  1952.0  54.21667  -113.00000
     3  Acapulco    Valid  Acapulcoite    1914.0  Fell  1976.0  16.88333   -99.90000
     4   Achiras    Valid           L6     780.0  Fell  1902.0 -33.16667   -64.95000
```

```
[ ]: df.year.value_counts()
```

```
[ ]: year
     2003.0    3323
     1979.0    3046
     1998.0    2697
     2006.0    2456
     1988.0    2296
               …
     1741.0       1
```

```
1519.0       1
1671.0       1
1779.0       1
1792.0       1
Name: count, Length: 268, dtype: int64
```

[ ]:
```
df=df.dropna()
df
```

[ ]:
```
             name nametype              recclass      mass   fall    year  \
0          Aachen    Valid                    L5      21.0   Fell  1880.0
1          Aarhus    Valid                    H6     720.0   Fell  1951.0
2            Abee    Valid                   EH4  107000.0   Fell  1952.0
3        Acapulco    Valid           Acapulcoite    1914.0   Fell  1976.0
4         Achiras    Valid                    L6     780.0   Fell  1902.0
…           …      …                        …       …     …     …
45711  Zillah 002    Valid               Eucrite     172.0  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped      46.0  Found  1999.0
45713        Zlin    Valid                    H4       3.3  Found  1939.0
45714   Zubkovsky    Valid                    L6    2167.0  Found  2003.0
45715  Zulu Queen    Valid                  L3.7     200.0  Found  1976.0

         reclat    reclong
0      50.77500    6.08333
1      56.18333   10.23333
2      54.21667 -113.00000
3      16.88333  -99.90000
4     -33.16667  -64.95000
…         …         …
45711  29.03700   17.01850
45712  13.78333    8.96667
45713  49.25000   17.66667
45714  49.78917   41.50460
45715  33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
df.shape
```

[ ]:
```
(38226, 8)
```

[ ]:
```
df.isnull().sum()
```

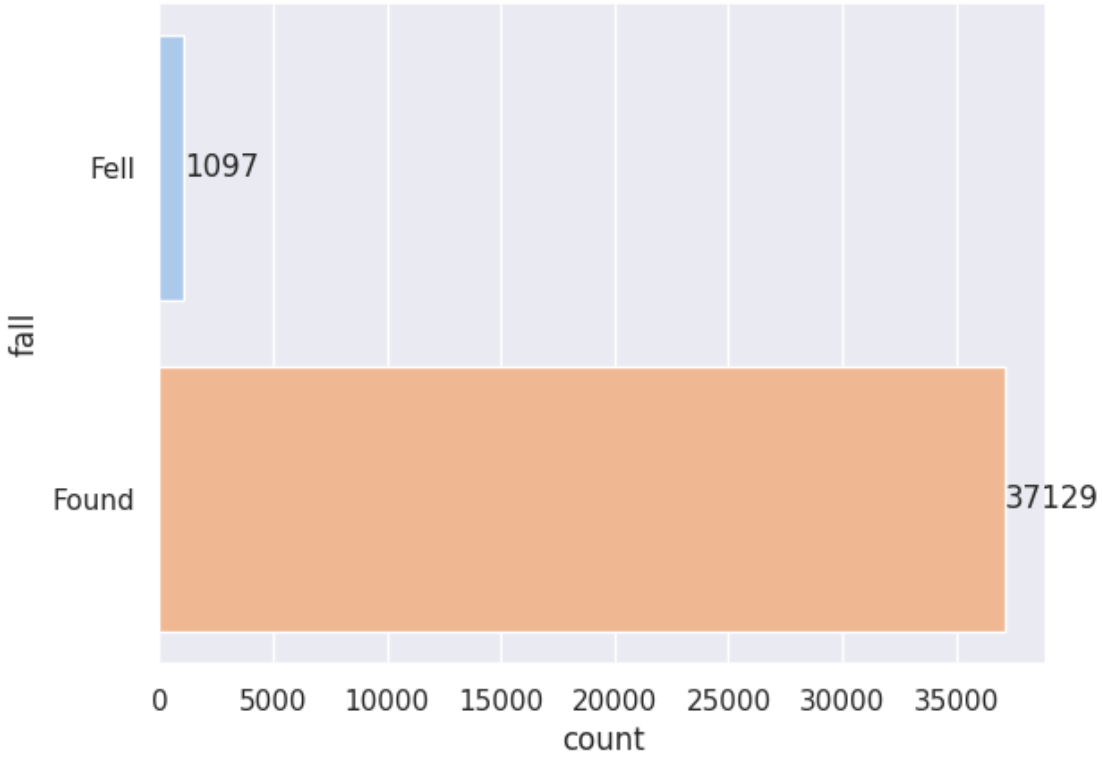
[ ]:
```
name        0
nametype    0
recclass    0
mass        0
```

```
fall        0
year        0
reclat      0
reclong     0
dtype: int64
```

Data analysis

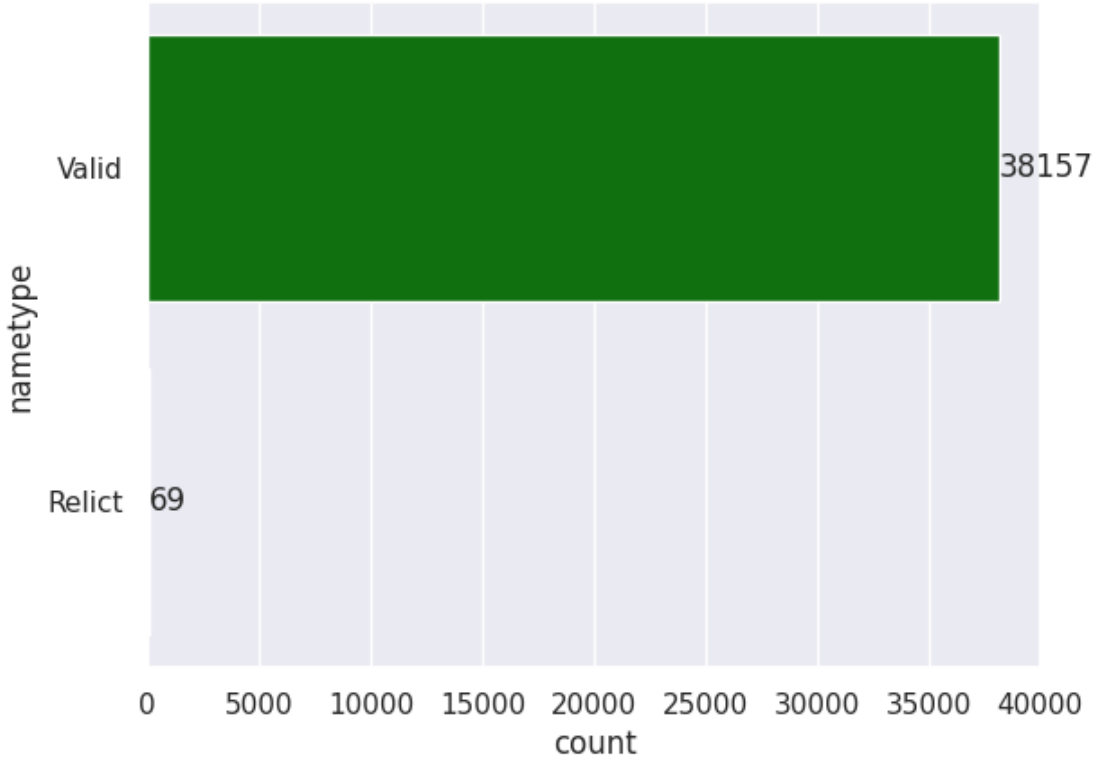
[ ]:
```
a=sns.countplot(df['fall'],palette='pastel')
for ax in a.containers:
  a.bar_label(ax)
```

```
<ipython-input-462-de95e54789ab>:1: FutureWarning:

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

  a=sns.countplot(df['fall'],palette='pastel')
```



[ ]:
```
a=sns.countplot(df['nametype'],palette=['green','yellow'])
for ax in a.containers:
  a.bar_label(ax)
```

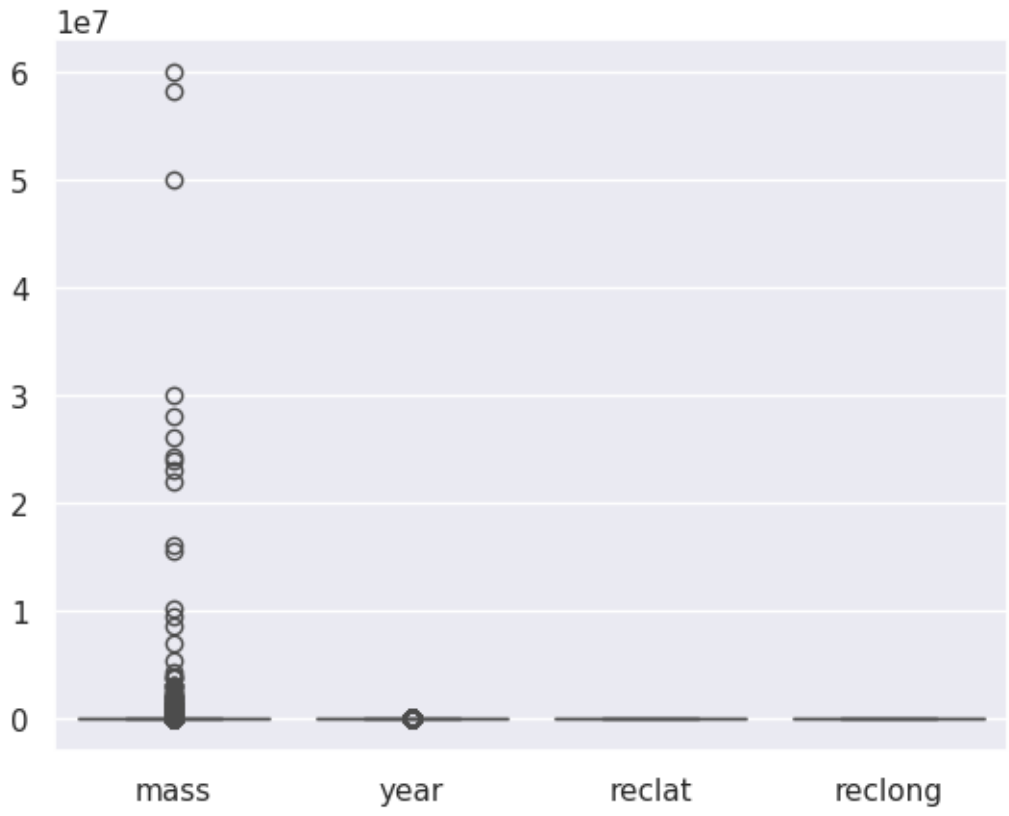
```
<ipython-input-463-3874a169ec8d>:1: FutureWarning:

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

  a=sns.countplot(df['nametype'],palette=['green','yellow'])
```



OUTLIER DETECTION AND REMOVE USING IQR

[ ]:
```
sns.boxplot(df)
```

[ ]:
```
<Axes: >
```



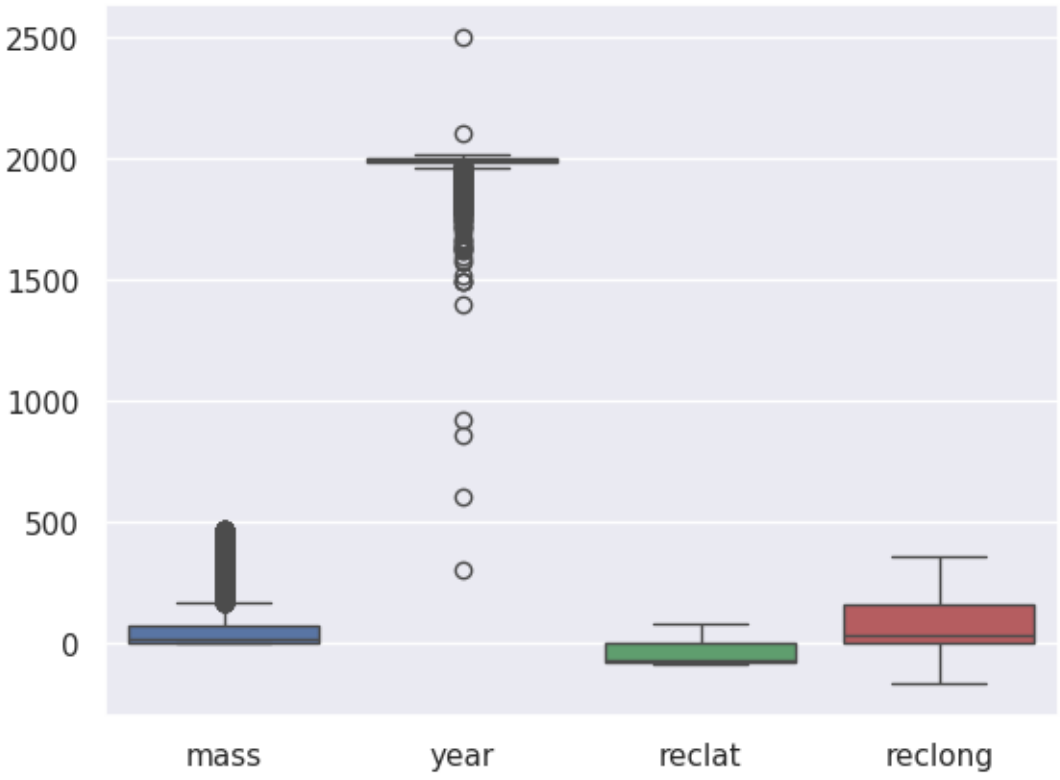
[ ]:
```
Q1 = df['mass'].quantile(0.25)
Q3 = df['mass'].quantile(0.75)
IQR = Q3 - Q1

# Define limits for outlier removal
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR

# Filter out outliers and assign back to the original column
df['mass'] = df[(df['mass'] >= lower_limit) & (df['mass'] <=␣
 ↪upper_limit)]['mass']

print("DataFrame after removing outliers:")
print(df)
```

```
DataFrame after removing outliers:
             name nametype              recclass   mass   fall    year  \
0          Aachen    Valid                    L5   21.0   Fell  1880.0
1          Aarhus    Valid                    H6    NaN   Fell  1951.0
2            Abee    Valid                   EH4    NaN   Fell  1952.0
3        Acapulco    Valid           Acapulcoite    NaN   Fell  1976.0
```

```
4         Achiras    Valid                    L6    NaN   Fell  1902.0
…           …      …                      …    …    …     …
45711  Zillah 002    Valid                Eucrite  172.0  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped   46.0  Found  1999.0
45713        Zlin    Valid                    H4    3.3  Found  1939.0
45714   Zubkovsky    Valid                    L6    NaN  Found  2003.0
45715  Zulu Queen    Valid                 L3.7  200.0  Found  1976.0

         reclat    reclong
0      50.77500    6.08333
1      56.18333   10.23333
2      54.21667 -113.00000
3      16.88333  -99.90000
4     -33.16667  -64.95000
…         …         …
45711  29.03700   17.01850
45712  13.78333    8.96667
45713  49.25000   17.66667
45714  49.78917   41.50460
45715  33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
sns.boxplot(df)
```

[ ]:
```
<Axes: >
```



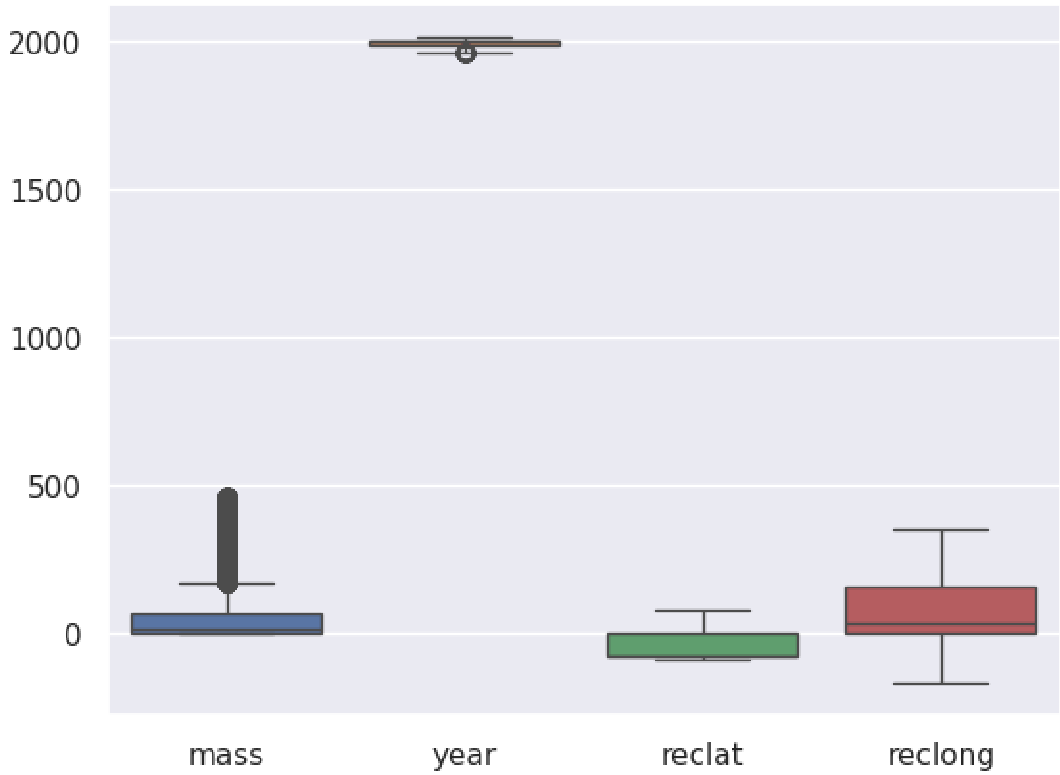
[ ]:
```
Q1 = df['year'].quantile(0.25)
Q3 = df['year'].quantile(0.75)
IQR = Q3 - Q1

# Define limits for outlier removal
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR

# Filter out outliers and assign back to the original column
df['year'] = df[(df['year'] >= lower_limit) & (df['year'] <=␣
 ↪upper_limit)]['year']

print("DataFrame after removing outliers:")
print(df)
```

```
DataFrame after removing outliers:
             name nametype              recclass   mass   fall    year  \
0          Aachen    Valid                    L5   21.0   Fell     NaN
1          Aarhus    Valid                    H6    NaN   Fell     NaN
2            Abee    Valid                   EH4    NaN   Fell     NaN
3        Acapulco    Valid           Acapulcoite    NaN   Fell  1976.0
4         Achiras    Valid                    L6    NaN   Fell     NaN
```

```
...            ...      ...                  ...    ...    ...     ...
45711  Zillah 002    Valid               Eucrite  172.0  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped   46.0  Found  1999.0
45713        Zlin    Valid                    H4    3.3  Found     NaN
45714   Zubkovsky    Valid                    L6    NaN  Found  2003.0
45715  Zulu Queen    Valid                  L3.7  200.0  Found  1976.0

          reclat    reclong
0       50.77500    6.08333
1       56.18333   10.23333
2       54.21667 -113.00000
3       16.88333  -99.90000
4      -33.16667  -64.95000
...          ...        ...
45711   29.03700   17.01850
45712   13.78333    8.96667
45713   49.25000   17.66667
45714   49.78917   41.50460
45715   33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
sns.boxplot(df)
```

[ ]: <Axes: >

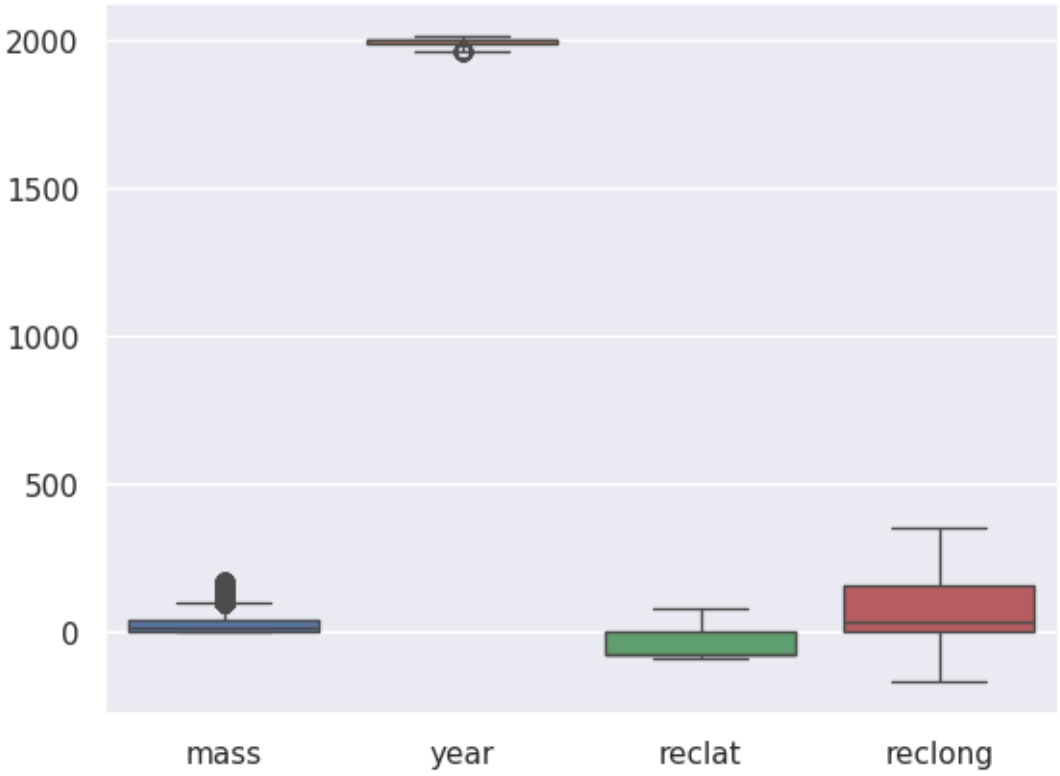


[ ]:
```
Q1 = df['mass'].quantile(0.25)
Q3 = df['mass'].quantile(0.75)
IQR = Q3 - Q1

# Define limits for outlier removal
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR

# Filter out outliers and assign back to the original column
df['mass'] = df[(df['mass'] >= lower_limit) & (df['mass'] <=
 ↪upper_limit)]['mass']

print("DataFrame after removing outliers:")
print(df)
```

```
DataFrame after removing outliers:
             name nametype              recclass  mass   fall    year  \
0          Aachen    Valid                    L5  21.0   Fell     NaN
1          Aarhus    Valid                    H6   NaN   Fell     NaN
2            Abee    Valid                   EH4   NaN   Fell     NaN
3        Acapulco    Valid           Acapulcoite   NaN   Fell  1976.0
4         Achiras    Valid                    L6   NaN   Fell     NaN
…           …      …                     …    …    …     …
45711  Zillah 002    Valid               Eucrite   NaN  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped  46.0  Found  1999.0
45713        Zlin    Valid                    H4   3.3  Found     NaN
45714   Zubkovsky    Valid                    L6   NaN  Found  2003.0
45715  Zulu Queen    Valid                  L3.7   NaN  Found  1976.0

         reclat    reclong
0      50.77500    6.08333
1      56.18333   10.23333
2      54.21667 -113.00000
3      16.88333  -99.90000
4     -33.16667  -64.95000
…          …         …
45711  29.03700   17.01850
45712  13.78333    8.96667
45713  49.25000   17.66667
45714  49.78917   41.50460
45715  33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
sns.boxplot(df)
```

[ ]: <Axes: >



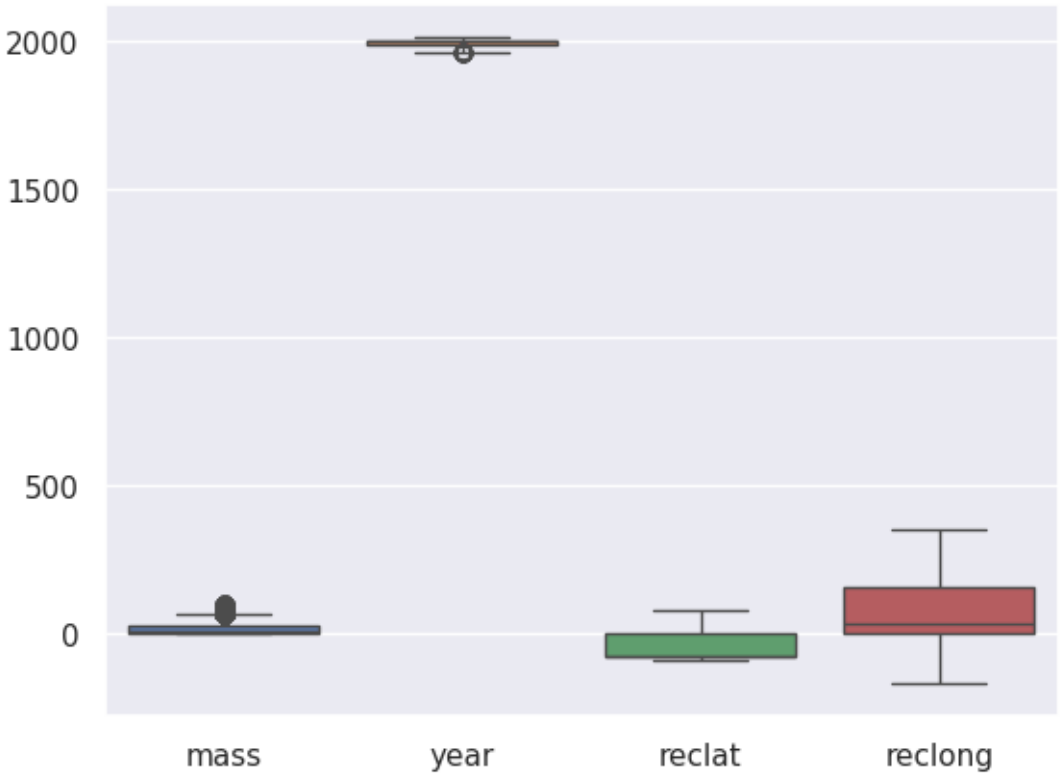
[ ]:
```
Q1 = df['mass'].quantile(0.25)
Q3 = df['mass'].quantile(0.75)
IQR = Q3 - Q1

# Define limits for outlier removal
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR

# Filter out outliers and assign back to the original column
df['mass'] = df[(df['mass'] >= lower_limit) & (df['mass'] <=␣
 ↪upper_limit)]['mass']

print("DataFrame after removing outliers:")
print(df)
```

```
DataFrame after removing outliers:
             name nametype              recclass  mass   fall    year  \
0          Aachen    Valid                    L5  21.0   Fell     NaN
1          Aarhus    Valid                    H6   NaN   Fell     NaN
2            Abee    Valid                   EH4   NaN   Fell     NaN
```

```
3         Acapulco    Valid           Acapulcoite   NaN   Fell  1976.0
4          Achiras    Valid                    L6   NaN   Fell     NaN
…             …        …                     …    …     …      …
45711  Zillah 002    Valid               Eucrite   NaN  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped  46.0  Found  1999.0
45713        Zlin    Valid                    H4   3.3  Found     NaN
45714   Zubkovsky    Valid                    L6   NaN  Found  2003.0
45715  Zulu Queen    Valid                  L3.7   NaN  Found  1976.0

         reclat    reclong
0      50.77500    6.08333
1      56.18333   10.23333
2      54.21667 -113.00000
3      16.88333  -99.90000
4     -33.16667  -64.95000
…           …         …
45711  29.03700   17.01850
45712  13.78333    8.96667
45713  49.25000   17.66667
45714  49.78917   41.50460
45715  33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
sns.boxplot(df)
```

[ ]: <Axes: >



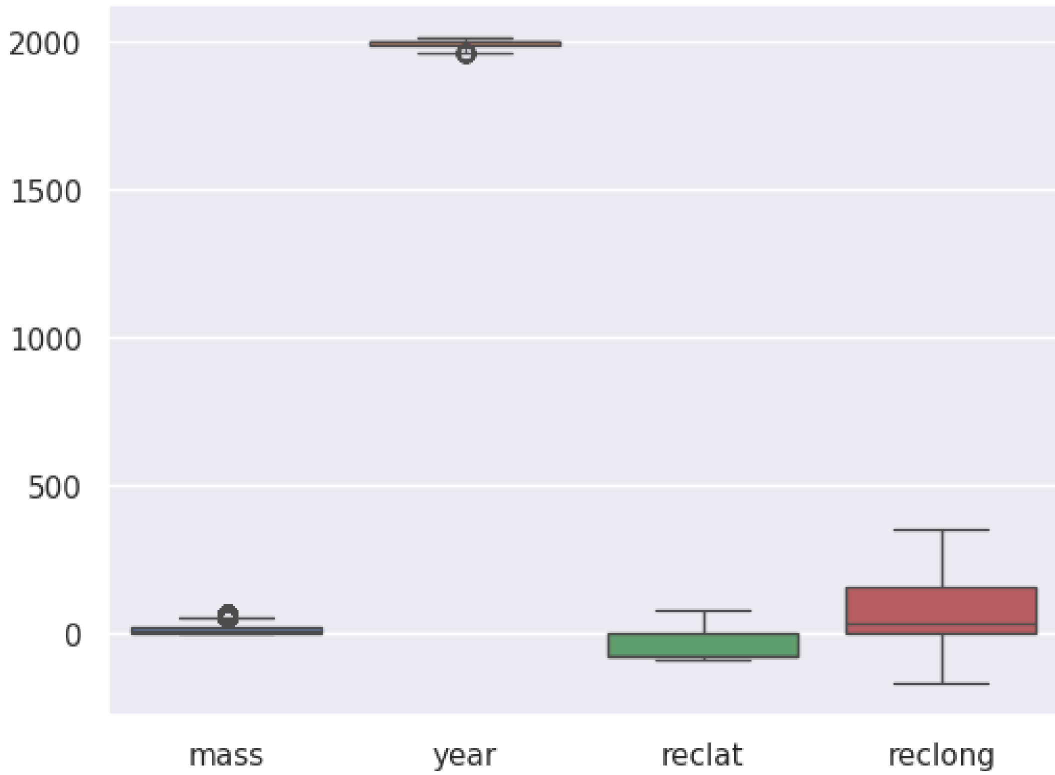
[ ]:
```
Q1 = df['mass'].quantile(0.25)
Q3 = df['mass'].quantile(0.75)
IQR = Q3 - Q1

# Define limits for outlier removal
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR

# Filter out outliers and assign back to the original column
df['mass'] = df[(df['mass'] >= lower_limit) & (df['mass'] <=␣
 ↪upper_limit)]['mass']

print("DataFrame after removing outliers:")
print(df)
```

```
DataFrame after removing outliers:
             name nametype              recclass  mass   fall    year  \
0          Aachen    Valid                    L5  21.0   Fell     NaN
1          Aarhus    Valid                    H6   NaN   Fell     NaN
2            Abee    Valid                  EH4    NaN   Fell     NaN
3        Acapulco    Valid          Acapulcoite    NaN   Fell  1976.0
4         Achiras    Valid                    L6   NaN   Fell     NaN
```

```
…             …      …                     …    …     …       …
45711  Zillah 002    Valid                Eucrite   NaN  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped  46.0  Found  1999.0
45713        Zlin    Valid                     H4   3.3  Found     NaN
45714   Zubkovsky    Valid                     L6   NaN  Found  2003.0
45715  Zulu Queen    Valid                   L3.7   NaN  Found  1976.0

         reclat    reclong
0      50.77500    6.08333
1      56.18333   10.23333
2      54.21667 -113.00000
3      16.88333  -99.90000
4     -33.16667  -64.95000
…           …          …
45711  29.03700   17.01850
45712  13.78333    8.96667
45713  49.25000   17.66667
45714  49.78917   41.50460
45715  33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
sns.boxplot(df)
```

[ ]: <Axes: >

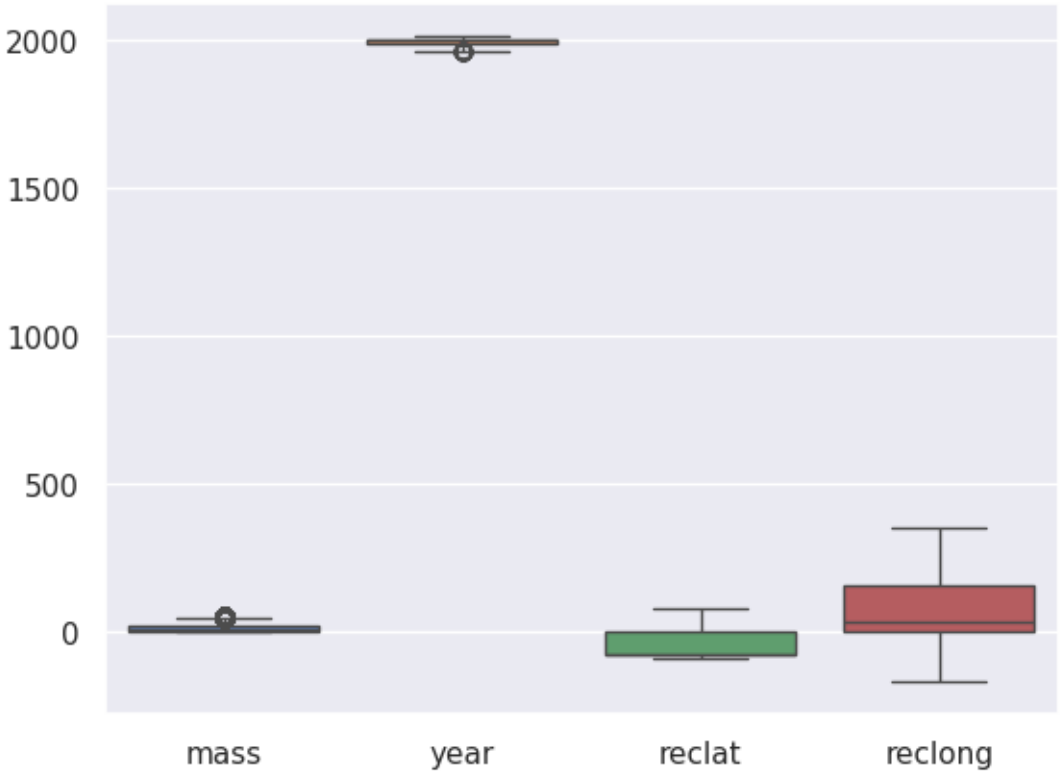


[ ]:
```
Q1 = df['mass'].quantile(0.25)
Q3 = df['mass'].quantile(0.75)
IQR = Q3 - Q1

# Define limits for outlier removal
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR

# Filter out outliers and assign back to the original column
df['mass'] = df[(df['mass'] >= lower_limit) & (df['mass'] <=␣
 ↪upper_limit)]['mass']

print("DataFrame after removing outliers:")
print(df)
```

```
DataFrame after removing outliers:
             name nametype              recclass  mass   fall    year  \
0          Aachen    Valid                    L5  21.0   Fell     NaN
1          Aarhus    Valid                    H6   NaN   Fell     NaN
2            Abee    Valid                   EH4   NaN   Fell     NaN
3        Acapulco    Valid           Acapulcoite   NaN   Fell  1976.0
4         Achiras    Valid                    L6   NaN   Fell     NaN
…           …      …                       …    …     …      …
45711  Zillah 002    Valid               Eucrite   NaN  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped  46.0  Found  1999.0
45713        Zlin    Valid                    H4   3.3  Found     NaN
45714   Zubkovsky    Valid                    L6   NaN  Found  2003.0
45715  Zulu Queen    Valid                  L3.7   NaN  Found  1976.0

         reclat    reclong
0      50.77500    6.08333
1      56.18333   10.23333
2      54.21667 -113.00000
3      16.88333  -99.90000
4     -33.16667  -64.95000
…          …         …
45711  29.03700   17.01850
45712  13.78333    8.96667
45713  49.25000   17.66667
45714  49.78917   41.50460
45715  33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
sns.boxplot(df)
```

[ ]: <Axes: >



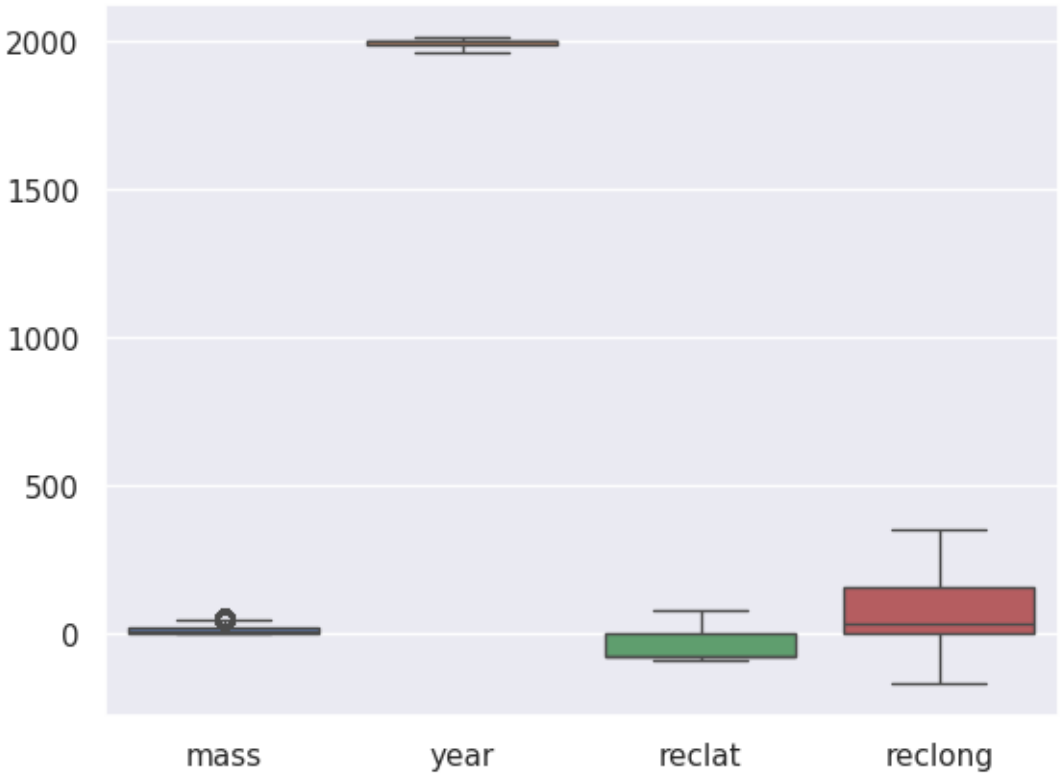
[ ]:
```
Q1 = df['year'].quantile(0.25)
Q3 = df['year'].quantile(0.75)
IQR = Q3 - Q1

# Define limits for outlier removal
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR

# Filter out outliers and assign back to the original column
df['year'] = df[(df['year'] >= lower_limit) & (df['year'] <=␣
 ↪upper_limit)]['year']

print("DataFrame after removing outliers:")
print(df)
```

```
DataFrame after removing outliers:
             name nametype              recclass  mass   fall    year  \
0          Aachen    Valid                    L5  21.0   Fell     NaN
1          Aarhus    Valid                    H6   NaN   Fell     NaN
2            Abee    Valid                   EH4   NaN   Fell     NaN
```

```
3        Acapulco    Valid           Acapulcoite   NaN   Fell  1976.0
4         Achiras    Valid                    L6   NaN   Fell     NaN
…           …      …                     …   …    …     …
45711  Zillah 002    Valid                Eucrite   NaN  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped  46.0  Found  1999.0
45713        Zlin    Valid                    H4   3.3  Found     NaN
45714   Zubkovsky    Valid                    L6   NaN  Found  2003.0
45715  Zulu Queen    Valid                  L3.7   NaN  Found  1976.0

         reclat    reclong
0      50.77500    6.08333
1      56.18333   10.23333
2      54.21667 -113.00000
3      16.88333  -99.90000
4     -33.16667  -64.95000
…         …         …
45711  29.03700   17.01850
45712  13.78333    8.96667
45713  49.25000   17.66667
45714  49.78917   41.50460
45715  33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
sns.boxplot(df)
```

[ ]:
```
<Axes: >
```



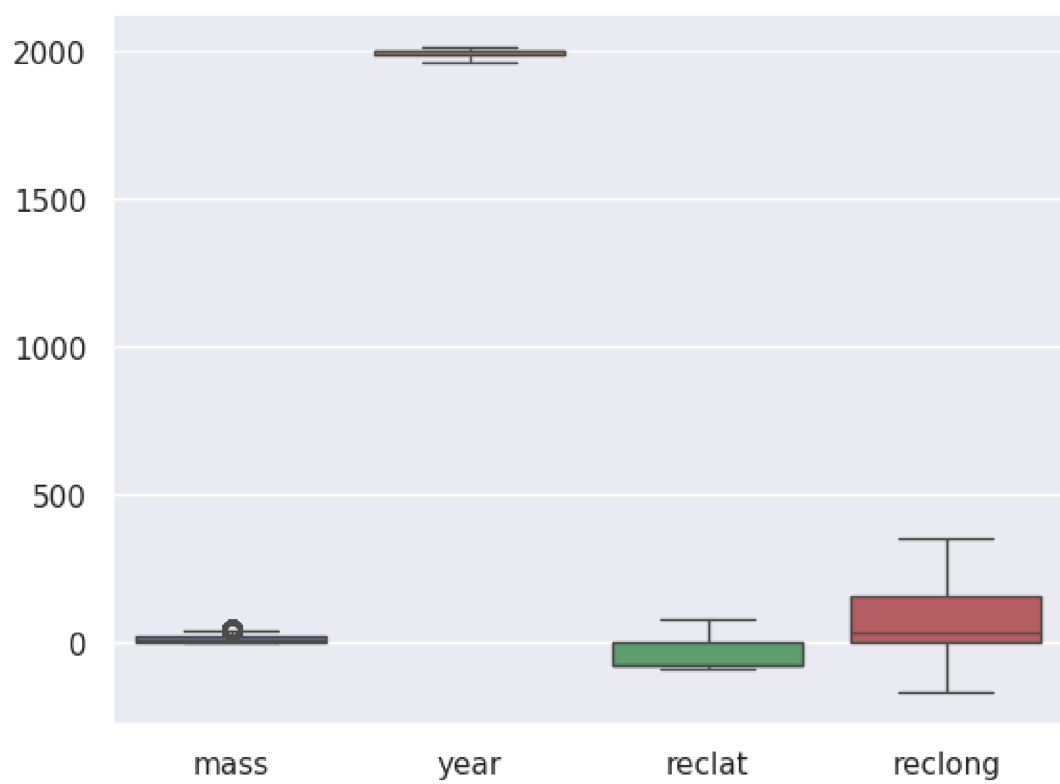
[ ]:
```
Q1 = df['mass'].quantile(0.25)
Q3 = df['mass'].quantile(0.75)
IQR = Q3 - Q1

# Define limits for outlier removal
lower_limit = Q1 - 1.5 * IQR
upper_limit = Q3 + 1.5 * IQR

# Filter out outliers and assign back to the original column
df['mass'] = df[(df['mass'] >= lower_limit) & (df['mass'] <=␣
 ↪upper_limit)]['mass']

print("DataFrame after removing outliers:")
print(df)
```

```
DataFrame after removing outliers:
             name nametype              recclass  mass   fall    year  \
0          Aachen    Valid                    L5  21.0   Fell     NaN
1          Aarhus    Valid                    H6   NaN   Fell     NaN
2            Abee    Valid                   EH4   NaN   Fell     NaN
3        Acapulco    Valid           Acapulcoite   NaN   Fell  1976.0
4         Achiras    Valid                    L6   NaN   Fell     NaN
```

```
…              …       …                     …    …     …      …
45711  Zillah 002    Valid              Eucrite   NaN  Found  1990.0
45712      Zinder    Valid  Pallasite, ungrouped  46.0  Found  1999.0
45713        Zlin    Valid                   H4   3.3  Found     NaN
45714   Zubkovsky    Valid                   L6   NaN  Found  2003.0
45715  Zulu Queen    Valid                 L3.7   NaN  Found  1976.0

         reclat    reclong
0      50.77500    6.08333
1      56.18333   10.23333
2      54.21667 -113.00000
3      16.88333  -99.90000
4     -33.16667  -64.95000
…           …          …
45711  29.03700   17.01850
45712  13.78333    8.96667
45713  49.25000   17.66667
45714  49.78917   41.50460
45715  33.98333 -115.68333

[38226 rows x 8 columns]
```

[ ]:
```
sns.boxplot(df)
```

[ ]: <Axes: >



[ ]:
```
#finally outlier has been removed after performing multiple times of IQR
```

[ ]:
```
df.head()
```

[ ]:

	name	nametype	recclass	mass	fall	year	reclat	reclong
0	Aachen	Valid	L5	21.0	Fell	NaN	50.77500	6.08333
1	Aarhus	Valid	H6	NaN	Fell	NaN	56.18333	10.23333
2	Abee	Valid	EH4	NaN	Fell	NaN	54.21667	-113.00000
3	Acapulco	Valid	Acapulcoite	NaN	Fell	1976.0	16.88333	-99.90000
4	Achiras	Valid	L6	NaN	Fell	NaN	-33.16667	-64.95000

[ ]:
```
df.head()
```

[ ]:

	name	nametype	recclass	mass	fall	year	reclat	reclong
0	Aachen	Valid	L5	21.0	Fell	NaN	50.77500	6.08333
1	Aarhus	Valid	H6	NaN	Fell	NaN	56.18333	10.23333
2	Abee	Valid	EH4	NaN	Fell	NaN	54.21667	-113.00000
3	Acapulco	Valid	Acapulcoite	NaN	Fell	1976.0	16.88333	-99.90000
4	Achiras	Valid	L6	NaN	Fell	NaN	-33.16667	-64.95000

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 38226 entries, 0 to 45715
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype
---  ------     --------------  -----
 0   name       38226 non-null  object
 1   nametype   38226 non-null  object
 2   recclass   38226 non-null  object
 3   mass       21967 non-null  float64
 4   fall       38226 non-null  object
 5   year       36257 non-null  float64
 6   reclat     38226 non-null  float64
 7   reclong    38226 non-null  float64
dtypes: float64(4), object(4)
memory usage: 2.6+ MB
```

[ ]:
```
df=df.dropna()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 21887 entries, 260 to 45712
Data columns (total 8 columns):
 #   Column     Non-Null Count  Dtype
```

```
---  ------     --------------  -----
 0   name       21887 non-null  object
 1   nametype   21887 non-null  object
 2   recclass   21887 non-null  object
 3   mass       21887 non-null  float64
 4   fall       21887 non-null  object
 5   year       21887 non-null  float64
 6   reclat     21887 non-null  float64
 7   reclong    21887 non-null  float64
dtypes: float64(4), object(4)
memory usage: 1.5+ MB
```

[ ]:
```
df.head()
```

[ ]:

	name	nametype	recclass	mass	fall	year	reclat	reclong
260	Dunbogan	Valid	L6	30.00	Fell	1999.0	-31.66667	152.83333
337	Grefsheim	Valid	L5	45.50	Fell	1976.0	60.66667	11.00000
509	Kutais	Valid	H5	23.00	Fell	1977.0	44.51667	39.30000
587	Maribo	Valid	CM2	25.81	Fell	2009.0	54.76183	11.46745
596	Mason Gully	Valid	H5	24.54	Fell	2010.0	0.00000	0.00000

[ ]:
```
df=df.drop(columns=['name'],axis=1)
df.head()
```

[ ]:

	nametype	recclass	mass	fall	year	reclat	reclong
260	Valid	L6	30.00	Fell	1999.0	-31.66667	152.83333
337	Valid	L5	45.50	Fell	1976.0	60.66667	11.00000
509	Valid	H5	23.00	Fell	1977.0	44.51667	39.30000
587	Valid	CM2	25.81	Fell	2009.0	54.76183	11.46745
596	Valid	H5	24.54	Fell	2010.0	0.00000	0.00000

[ ]:
```
df.isnull().sum()
```

[ ]:
```
nametype    0
recclass    0
mass        0
fall        0
year        0
reclat      0
reclong     0
dtype: int64
```

[ ]:
```
df['year'].value_counts()
```

[ ]:
```
year
1979.0    2394
1998.0    1549
```

1988.0	1420
2003.0	1321
1986.0	1179
2006.0	1057
1990.0	1003
1999.0	966
1997.0	963
2009.0	852
1993.0	774
2000.0	639
2007.0	626
1974.0	558
1994.0	550
2001.0	548
1987.0	528
2002.0	509
2008.0	491
2010.0	470
1991.0	422
1981.0	322
1996.0	275
1975.0	273
1977.0	264
1985.0	239
1992.0	231
1984.0	227
2011.0	226
1982.0	224
1983.0	168
1978.0	134
2004.0	121
1995.0	110
1980.0	73
2005.0	69
2012.0	26
1969.0	16
1973.0	12
1968.0	11
1989.0	8
1963.0	7
1971.0	7
1970.0	6
1965.0	4
1976.0	4
1966.0	3
1967.0	3
2013.0	3

```
1964.0       1
1972.0       1
Name: count, dtype: int64
```

[ ]:
```
df['years'] = np.where(df['year'] >= 2000, 'latest',
                       np.where((df['year'] >= 1980) & (df['year'] < 2000),␣
 ↪'normal', 'older'))
```

[ ]:
```
df['years'].value_counts()
```

[ ]:
```
years
normal    11231
latest     6958
older      3698
Name: count, dtype: int64
```

[ ]:
```
df=df.drop(columns='year',axis=1)
df
```

[ ]:
```
      nametype                recclass   mass   fall    reclat    reclong  \
260      Valid                      L6  30.00   Fell -31.66667  152.83333
337      Valid                      L5  45.50   Fell  60.66667   11.00000
509      Valid                      H5  23.00   Fell  44.51667   39.30000
587      Valid                     CM2  25.81   Fell  54.76183   11.46745
596      Valid                      H5  24.54   Fell   0.00000    0.00000
…        …                       …     …      …        …         …
45673    Valid                      L6   4.50  Found  39.55801 -114.42715
45687    Valid                H-metal   3.00  Found  34.81970 -114.27610
45688    Valid                      H5  25.90  Found  34.82658 -114.27763
45699    Valid                      L4  27.70  Found  18.33333  -97.50000
45712    Valid  Pallasite, ungrouped  46.00  Found  13.78333    8.96667

        years
260    normal
337     older
509     older
587    latest
596    latest
…       …
45673  latest
45687  latest
45688  latest
45699  normal
45712  normal

[21887 rows x 7 columns]
```

```
[ ]: df['recclass'].value_counts()
```

```
[ ]: recclass
     L6                       4204
     H5                       3826
     H6                       2557
     H4                       2551
     L5                       1817
                              …
     K3                          1
     LL-imp melt                 1
     R                           1
     L~4                         1
     Pallasite, ungrouped        1
     Name: count, Length: 250, dtype: int64
```

```
[ ]: df['reclat'] = np.where(df['reclat'] >= 0, 'Northen Hemisphere','Southern␣
      ↪Hemisphere')
     df
```

```
[ ]:       nametype              recclass   mass   fall              reclat  \
     260      Valid                    L6  30.00   Fell  Southern Hemisphere
     337      Valid                    L5  45.50   Fell   Northen Hemisphere
     509      Valid                    H5  23.00   Fell   Northen Hemisphere
     587      Valid                   CM2  25.81   Fell   Northen Hemisphere
     596      Valid                    H5  24.54   Fell   Northen Hemisphere
     …        …                     …    …    …                    …
     45673    Valid                    L6   4.50  Found   Northen Hemisphere
     45687    Valid                H-metal   3.00  Found   Northen Hemisphere
     45688    Valid                    H5  25.90  Found   Northen Hemisphere
     45699    Valid                    L4  27.70  Found   Northen Hemisphere
     45712    Valid  Pallasite, ungrouped  46.00  Found   Northen Hemisphere

              reclong   years
     260    152.83333  normal
     337     11.00000   older
     509     39.30000   older
     587     11.46745  latest
     596      0.00000  latest
     …           …     …
     45673 -114.42715  latest
     45687 -114.27610  latest
     45688 -114.27763  latest
     45699  -97.50000  normal
     45712    8.96667  normal

     [21887 rows x 7 columns]
```

```
[ ]: df['reclong'] = np.where(df['reclong'] < 0, 'Western Hemisphere','Eastern␣
      ↪Hemisphere')
     df
```

```
[ ]:       nametype              recclass   mass   fall              reclat  \
     260      Valid                    L6  30.00   Fell  Southern Hemisphere
     337      Valid                    L5  45.50   Fell   Northen Hemisphere
     509      Valid                    H5  23.00   Fell   Northen Hemisphere
     587      Valid                   CM2  25.81   Fell   Northen Hemisphere
     596      Valid                    H5  24.54   Fell   Northen Hemisphere
     …        …                      …    …     …                    …
     45673    Valid                    L6   4.50  Found   Northen Hemisphere
     45687    Valid                H-metal   3.00  Found   Northen Hemisphere
     45688    Valid                    H5  25.90  Found   Northen Hemisphere
     45699    Valid                    L4  27.70  Found   Northen Hemisphere
     45712    Valid  Pallasite, ungrouped  46.00  Found   Northen Hemisphere

                     reclong   years
     260    Eastern Hemisphere  normal
     337    Eastern Hemisphere   older
     509    Eastern Hemisphere   older
     587    Eastern Hemisphere  latest
     596    Eastern Hemisphere  latest
     …                    …     …
     45673  Western Hemisphere  latest
     45687  Western Hemisphere  latest
     45688  Western Hemisphere  latest
     45699  Western Hemisphere  normal
     45712  Eastern Hemisphere  normal

     [21887 rows x 7 columns]
```

```
[ ]: df['mass'] = np.where((df['mass'] >= 0) & (df['mass'] <= 10), 'small',
                           np.where((df['mass'] > 10) & (df['mass'] < 30),␣
      ↪'medium',
                                    np.where((df['mass'] >= 30) &␣
      ↪(df['mass'] < 50), 'large', 'very large')))
```

```
[ ]: df.head()
```

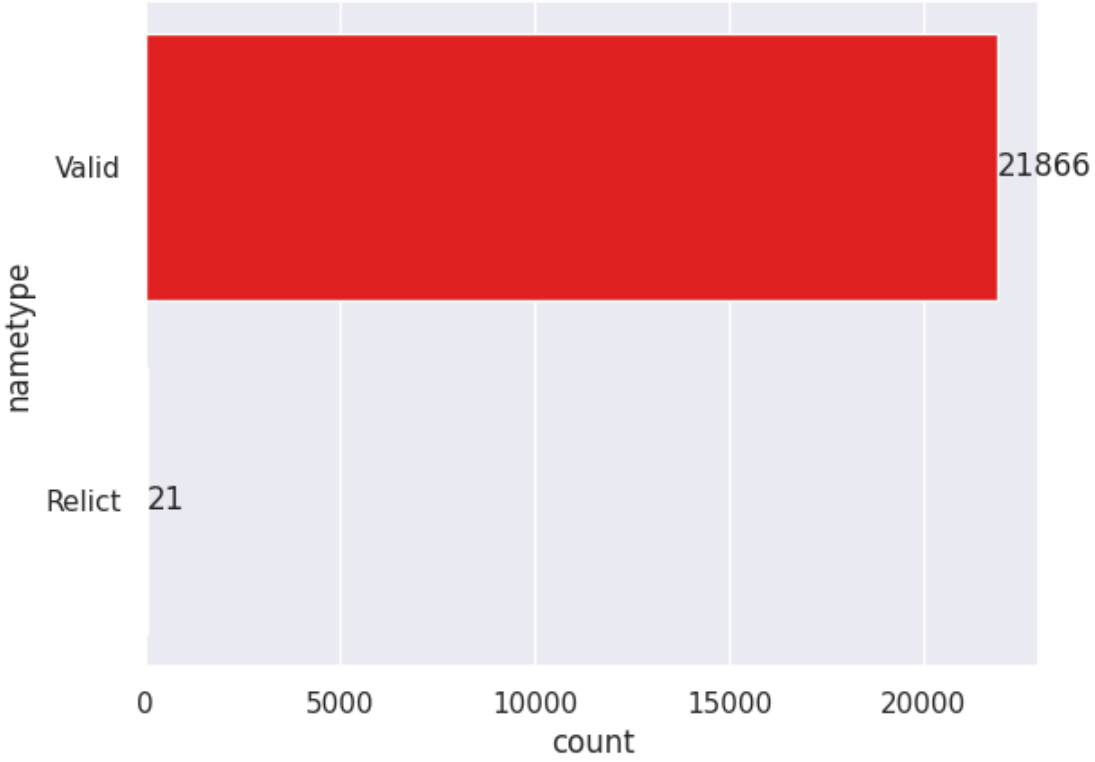
```
[ ]:     nametype recclass    mass  fall              reclat             reclong  \
     260    Valid       L6   large  Fell  Southern Hemisphere  Eastern Hemisphere
     337    Valid       L5   large  Fell   Northen Hemisphere  Eastern Hemisphere
     509    Valid       H5  medium  Fell   Northen Hemisphere  Eastern Hemisphere
     587    Valid      CM2  medium  Fell   Northen Hemisphere  Eastern Hemisphere
     596    Valid       H5  medium  Fell   Northen Hemisphere  Eastern Hemisphere
```

```
      years
260  normal
337   older
509   older
587  latest
596  latest
```

Data Visualization

[ ]:
```
a=sns.countplot(df['nametype'],palette=['red','yellow'])
for ax in a.containers:
  a.bar_label(ax)
```

```
<ipython-input-498-ce66c0cadf14>:1: FutureWarning:

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

  a=sns.countplot(df['nametype'],palette=['red','yellow'])
```

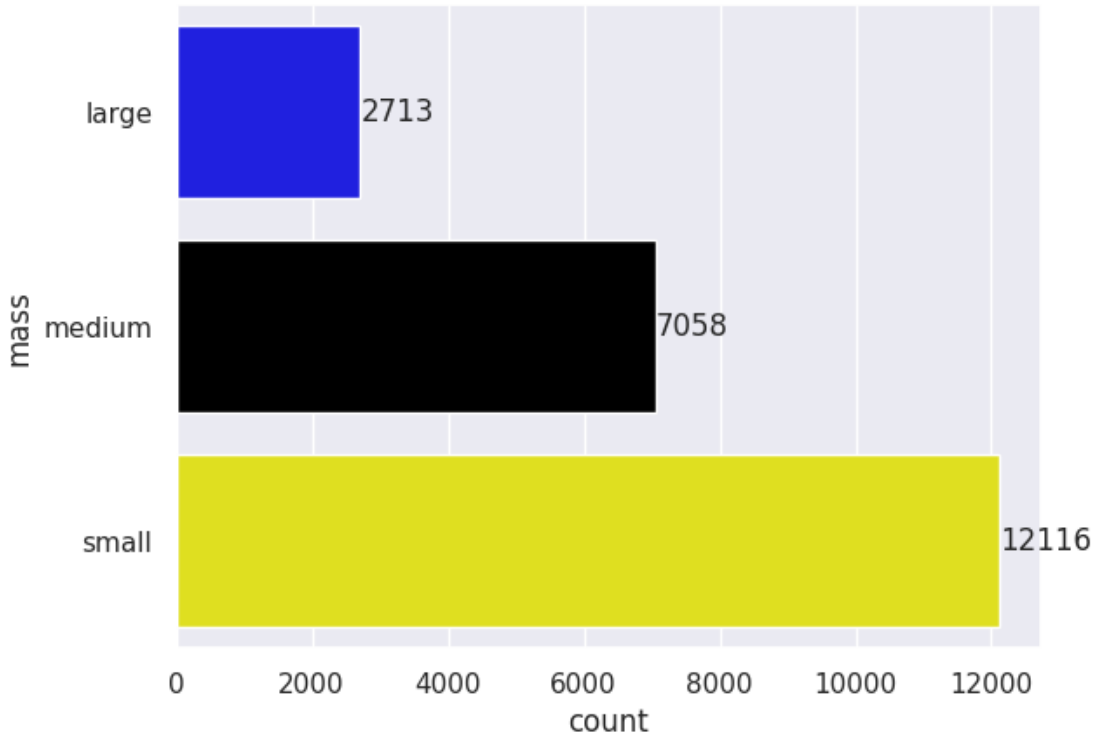


[ ]:
```
df['mass'].value_counts()
```

[ ]:
```
mass
small     12116
medium     7058
large      2713
Name: count, dtype: int64
```

[ ]:
```
a=sns.countplot(df['mass'],palette=['blue','black','yellow'])
for ax in a.containers:
  a.bar_label(ax)
```

```
<ipython-input-500-4f1fa7e6bbd4>:1: FutureWarning:

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

  a=sns.countplot(df['mass'],palette=['blue','black','yellow'])
```

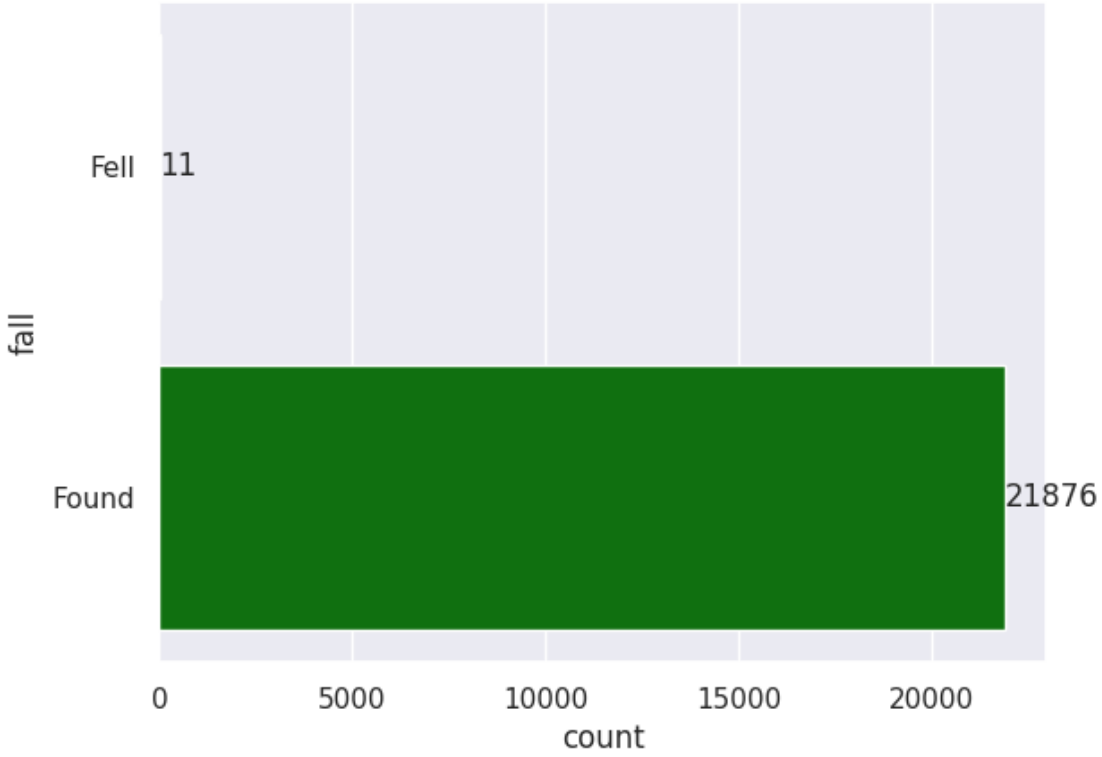


[ ]:
```
df.columns #mass , nametype , fall,reclat
```

[ ]:
```
Index(['nametype', 'recclass', 'mass', 'fall', 'reclat', 'reclong', 'years'],
dtype='object')
```

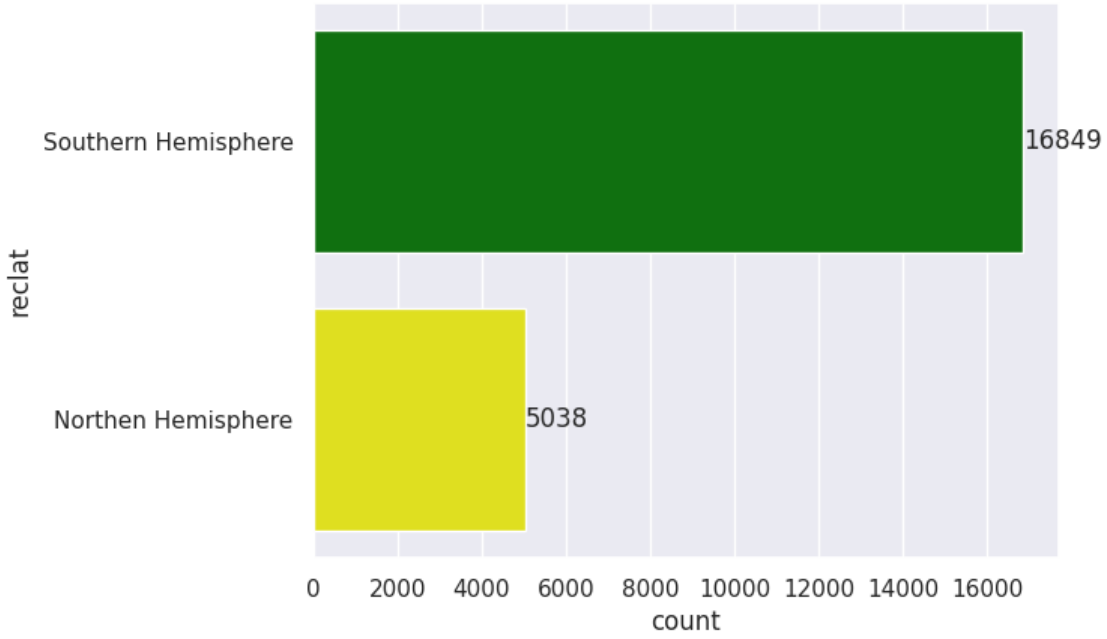
[ ]:
```
a=sns.countplot(df['fall'],palette=['yellow','green'])
for ax in a.containers:
  a.bar_label(ax)
```

```
<ipython-input-502-d685611a9610>:1: FutureWarning:

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

  a=sns.countplot(df['fall'],palette=['yellow','green'])
```



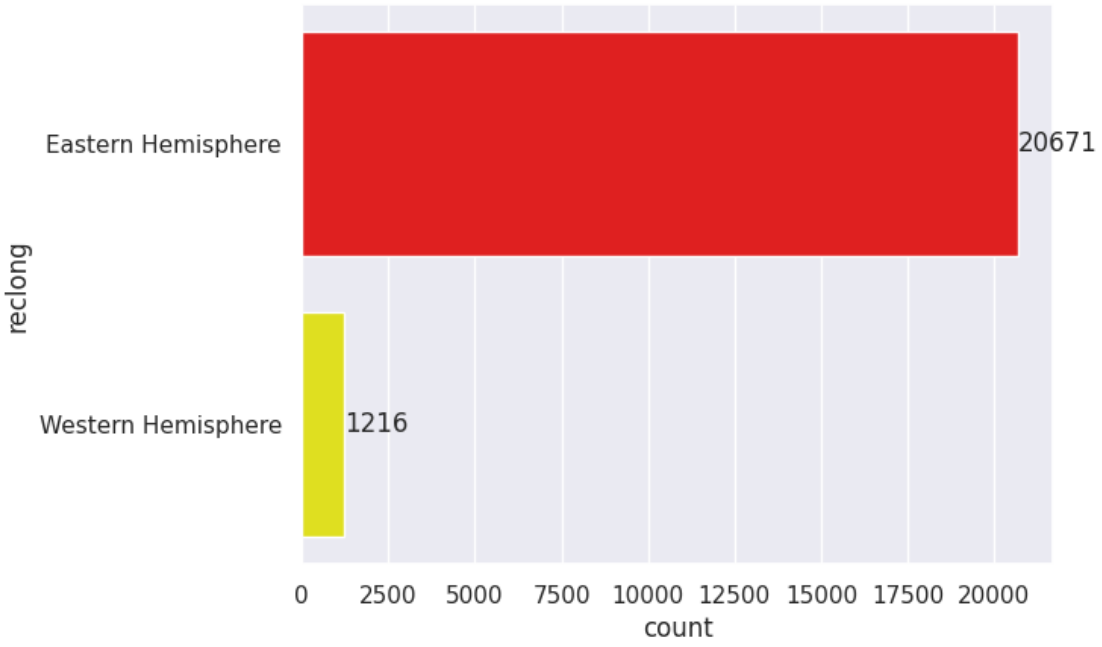
[ ]:
```
a=sns.countplot(df['reclat'],palette=['green','yellow'])
for ax in a.containers:
  a.bar_label(ax)
```

```
<ipython-input-503-f454ee67b9f8>:1: FutureWarning:

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

  a=sns.countplot(df['reclat'],palette=['green','yellow'])
```



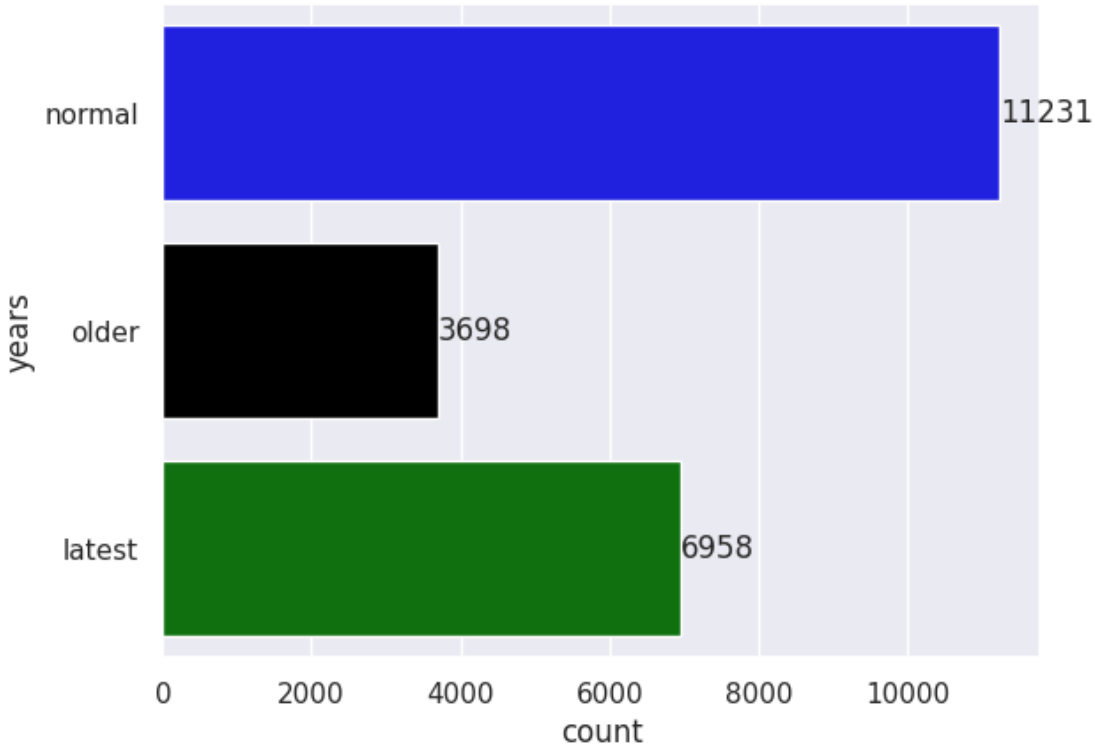
[ ]:
```
a=sns.countplot(df['reclong'],palette=['red','yellow'])
for ax in a.containers:
  a.bar_label(ax)
```

```
<ipython-input-504-23c2dc1d1e1a>:1: FutureWarning:

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

  a=sns.countplot(df['reclong'],palette=['red','yellow'])
```



[ ]:
```
a=sns.countplot(df['years'],palette=['blue','black','green'])
for ax in a.containers:
  a.bar_label(ax)
```

```
<ipython-input-505-a271d47953a8>:1: FutureWarning:

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

  a=sns.countplot(df['years'],palette=['blue','black','green'])
```



[ ]:
```
df.head()
```

[ ]:
```
    nametype recclass    mass  fall              reclat            reclong  \
260    Valid       L6   large  Fell  Southern Hemisphere  Eastern Hemisphere
337    Valid       L5   large  Fell   Northen Hemisphere  Eastern Hemisphere
509    Valid       H5  medium  Fell   Northen Hemisphere  Eastern Hemisphere
587    Valid      CM2  medium  Fell   Northen Hemisphere  Eastern Hemisphere
596    Valid       H5  medium  Fell   Northen Hemisphere  Eastern Hemisphere

      years
260  normal
337   older
509   older
587  latest
596  latest
```

[ ]:
```
df.columns
```

[ ]:
```
Index(['nametype', 'recclass', 'mass', 'fall', 'reclat', 'reclong', 'years'],
dtype='object')
```

MACHINE LEARNING MODEL

```
[ ]: df.head()
```

```
[ ]:     nametype recclass    mass  fall              reclat             reclong  \
     260    Valid       L6   large  Fell  Southern Hemisphere  Eastern Hemisphere
     337    Valid       L5   large  Fell   Northen Hemisphere  Eastern Hemisphere
     509    Valid       H5  medium  Fell   Northen Hemisphere  Eastern Hemisphere
     587    Valid      CM2  medium  Fell   Northen Hemisphere  Eastern Hemisphere
     596    Valid       H5  medium  Fell   Northen Hemisphere  Eastern Hemisphere

           years
     260  normal
     337   older
     509   older
     587  latest
     596  latest
```

```
[ ]: from sklearn.preprocessing import LabelEncoder
     le=LabelEncoder()
```

```
[ ]: df['nametype'].value_counts()
```

```
[ ]: nametype
     Valid     21866
     Relict       21
     Name: count, dtype: int64
```

```
[ ]: df['nametype']=le.fit_transform(df['nametype'])
     df['nametype'].value_counts() #valid=1 , relict = 0
```

```
[ ]: nametype
     1    21866
     0       21
     Name: count, dtype: int64
```

```
[ ]: df['mass'].value_counts()
```

```
[ ]: mass
     small     12116
     medium     7058
     large      2713
     Name: count, dtype: int64
```

```
[ ]: df['mass']=le.fit_transform(df['mass'])
     df['mass'].value_counts() # small = 2 , medium = 1, large = 0
```

```
[ ]: mass
     2    12116
```

```
1     7058
0     2713
Name: count, dtype: int64
```

[ ]:
```
df['fall'].value_counts()
```

[ ]:
```
fall
Found    21876
Fell        11
Name: count, dtype: int64
```

[ ]:
```
df['fall']=le.fit_transform(df['fall'])
df['fall'].value_counts() # found = 1 , fell = 0
```

[ ]:
```
fall
1    21876
0       11
Name: count, dtype: int64
```

[ ]:
```
df['reclat'].value_counts()
```

[ ]:
```
reclat
Southern Hemisphere    16849
Northen Hemisphere      5038
Name: count, dtype: int64
```

[ ]:
```
df['reclat']=le.fit_transform(df['reclat'])
df['reclat'].value_counts() # southern hemisphere=1 , northern hemisphere= 0
```

[ ]:
```
reclat
1    16849
0     5038
Name: count, dtype: int64
```

[ ]:
```
df['reclong'].value_counts()
```

[ ]:
```
reclong
Eastern Hemisphere    20671
Western Hemisphere     1216
Name: count, dtype: int64
```

[ ]:
```
df['reclong']=le.fit_transform(df['reclong'])
df['reclong'].value_counts() # eastern hemisphere=0 , western hemisphere= 1
```

[ ]:
```
reclong
0    20671
1     1216
```

```
Name: count, dtype: int64
```

[ ]:
```
df['years'].value_counts()
```

[ ]:
```
years
normal    11231
latest     6958
older      3698
Name: count, dtype: int64
```

[ ]:
```
df['years']=le.fit_transform(df['years'])
df['years'].value_counts() # normal = 1 , latest=0 ,older =2
```

[ ]:
```
years
1    11231
0     6958
2     3698
Name: count, dtype: int64
```

[ ]:
```
#to predict the fall
```

[ ]:
```
X=df.drop('fall',axis=1)
y=df['fall']
```

[ ]:
```
df.columns
```

[ ]:
```
Index(['nametype', 'recclass', 'mass', 'fall', 'reclat', 'reclong', 'years'],
dtype='object')
```

[ ]:
```
df.head()
```

[ ]:

	nametype	recclass	mass	fall	reclat	reclong	years
260	1	L6	0	0	1	0	1
337	1	L5	0	0	0	0	2
509	1	H5	1	0	0	0	2
587	1	CM2	1	0	0	0	0
596	1	H5	1	0	0	0	0

[ ]:
```
df.head()
```

[ ]:

	nametype	recclass	mass	fall	reclat	reclong	years
260	1	L6	0	0	1	0	1
337	1	L5	0	0	0	0	2
509	1	H5	1	0	0	0	2
587	1	CM2	1	0	0	0	0
596	1	H5	1	0	0	0	0

[ ]:
```
df.to_csv('nasa.csv', index=False)
```

MACHINE LERNING MODEL

[ ]:
```
from sklearn.model_selection import train_test_split
```

[ ]:
```
df=pd.read_csv('nasa.csv')
```

[ ]:
```
df=df.drop(columns=['recclass'],axis=1)
```

[ ]:
```
df.head()
```

[ ]:

	nametype	mass	fall	reclat	reclong	years
0	1	0	0	1	0	1
1	1	0	0	0	0	2
2	1	1	0	0	0	2
3	1	1	0	0	0	0
4	1	1	0	0	0	0

[ ]:
```
X=df.drop(columns='fall',axis=1)
y=df['fall']
```

[ ]:
```
X_train,X_test,y_train,y_test= train_test_split(X,y,test_size=0.
↪2,random_state=42)
```

[ ]:
```
len(X_train)
```

[ ]: 17509

[ ]:
```
len(X_test)
```

[ ]: 4378

LOGISTIC REGRESSION

[ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report


model1 = LogisticRegression()


model1.fit(X_train, y_train)
print("model score train :",model1.score(X_train,y_train))
print("model score test :",model1.score(X_test,y_test))


y_pred = model1.predict(X_test)
```

```python
# Example: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f'Accuracy: {accuracy:.2f}')
print(f'Classification Report:\n{report}')
```

```
model score train : 0.9994859786395568
model score test : 0.9995431703974418
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       1.00      1.00      1.00      4376

    accuracy                           1.00      4378
   macro avg       0.50      0.50      0.50      4378
weighted avg       1.00      1.00      1.00      4378


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

DECISION TREE CLASSIFIER

[ ]:
```python
from sklearn.tree import DecisionTreeClassifier


model2 = DecisionTreeClassifier()


model2.fit(X_train, y_train)
print("model train score :",model2.score(X_train,y_train))
```

```
print("model test score :",model2.score(X_test,y_test))


y_pred = model2.predict(X_test)


accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f'Accuracy: {accuracy:.2f}')
print(f'Classification Report:\n{report}')
```

```
model train score : 0.9994859786395568
model test score : 0.9995431703974418
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       1.00      1.00      1.00      4376

    accuracy                           1.00      4378
   macro avg       0.50      0.50      0.50      4378
weighted avg       1.00      1.00      1.00      4378


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

RANDOM FOREST CLASSIFIER

[ ]:
```
from sklearn.ensemble import RandomForestClassifier


model3 = RandomForestClassifier()
```

```python
model3.fit(X_train, y_train)
print("model train score :",model3.score(X_train,y_train))
print("model test score :",model3.score(X_test,y_test))


y_pred = model3.predict(X_test)

# Example: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f'Accuracy: {accuracy:.2f}')
print(f'Classification Report:\n{report}')
```

```
model train score : 0.9994859786395568
model test score : 0.9995431703974418
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       1.00      1.00      1.00      4376

    accuracy                           1.00      4378
   macro avg       0.50      0.50      0.50      4378
weighted avg       1.00      1.00      1.00      4378

/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

SVM

[ ]:
```
from sklearn.svm import SVC

# Example: Instantiate the model
model4 = SVC()

# Example: Fit the model on training data
model4.fit(X_train, y_train)
print("model train score :",model4.score(X_train,y_train))
print("model test score :",model4.score(X_test,y_test))

# Example: Predict on test data
y_pred = model4.predict(X_test)

# Example: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f'Accuracy: {accuracy:.2f}')
print(f'Classification Report:\n{report}')
```

```
model train score : 0.9994859786395568
model test score : 0.9995431703974418
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       1.00      1.00      1.00      4376

    accuracy                           1.00      4378
   macro avg       0.50      0.50      0.50      4378
weighted avg       1.00      1.00      1.00      4378


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
```

```
  _warn_prf(average, modifier, msg_start, len(result))
```

[ ]:
```
from sklearn.neighbors import KNeighborsClassifier

# Example: Instantiate the model
model = KNeighborsClassifier()

# Example: Fit the model on training data
model.fit(X_train, y_train)
print("model train score :",model4.score(X_train,y_train))
print("model test score :",model4.score(X_test,y_test))

# Example: Predict on test data
y_pred = model.predict(X_test)

# Example: Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f'Accuracy: {accuracy:.2f}')
print(f'Classification Report:\n{report}')
```

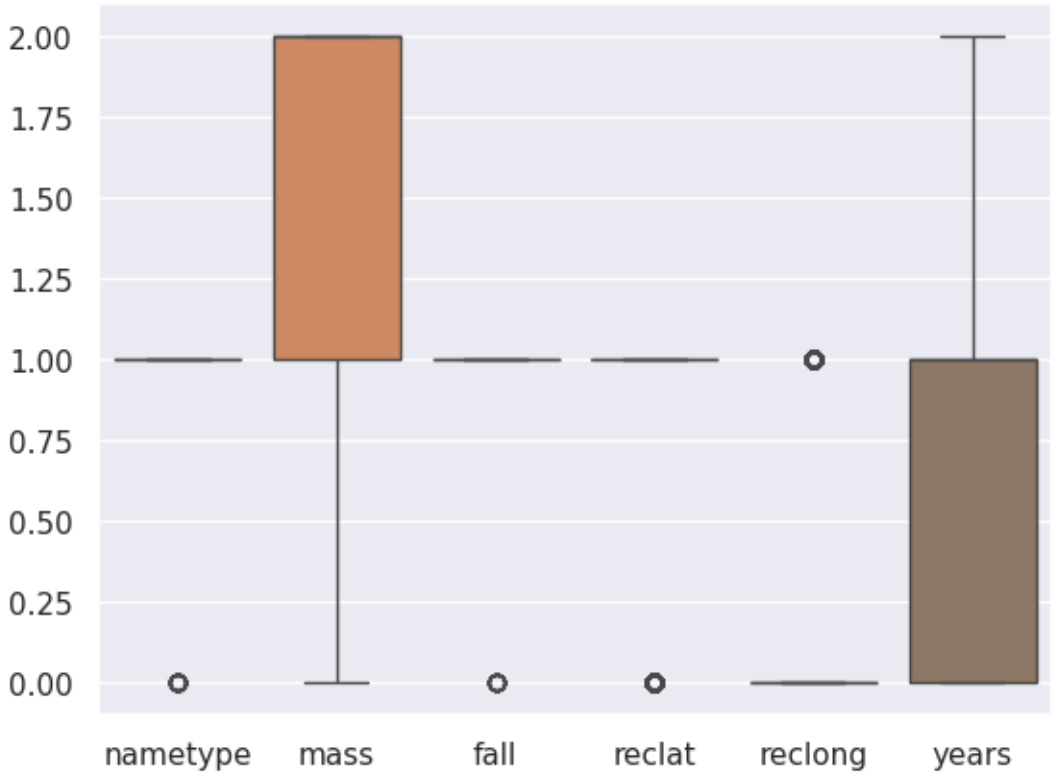
```
model train score : 0.9994859786395568
model test score : 0.9995431703974418
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       1.00      1.00      1.00      4376

    accuracy                           1.00      4378
   macro avg       0.50      0.50      0.50      4378
weighted avg       1.00      1.00      1.00      4378


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
```

```
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[ ]:
```
#all models work better in case of this dataset
```

[ ]:
```
sns.boxplot(df) # no outler present
```

[ ]:
```
<Axes: >
```



CROSS VALIDATION

[ ]:
```
from sklearn.model_selection import cross_val_score

# Example with 5-fold cross-validation
scores = cross_val_score(model, X, y, cv=5)
print(f"Cross-Validation Scores: {scores}")
print(f"Mean CV Accuracy: {scores.mean():.4f}")
```

```
Cross-Validation Scores: [0.99931476 0.99954317 0.99954307 0.99954307
0.99954307]
Mean CV Accuracy: 0.9995
```

Learning Curves:

USING OF ANN

[ ]:
```
from sklearn.preprocessing import StandardScaler
```

[ ]:
```
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[ ]:
```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout

# Initialize the ANN
model = Sequential()

# Add the input layer and the first hidden layer
model.add(Dense(units=128, activation='relu', input_shape=(X_train.shape[1],)))

# Add dropout regularization
model.add(Dropout(0.2))  # 20% dropout

# Add the second hidden layer
model.add(Dense(units=64, activation='relu'))

# Add dropout regularization
model.add(Dropout(0.2))  # 20% dropout

# Add the output layer
model.add(Dense(units=1, activation='sigmoid'))  # Sigmoid activation for␣
 ↪binary classification

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy',␣
 ↪metrics=['accuracy'])

# Print a summary of the model
model.summary()
```

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 128)               768

 dropout (Dropout)           (None, 128)               0

 dense_1 (Dense)             (None, 64)                8256
```

```
 dropout_1 (Dropout)         (None, 64)                0

 dense_2 (Dense)             (None, 1)                 65

=================================================================
Total params: 9089 (35.50 KB)
Trainable params: 9089 (35.50 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

[ ]:
```
# Train the model
history = model.fit(X_train_scaled, y_train, epochs=50, batch_size=32,␣
 ↪validation_data=(X_test_scaled, y_test))
```

```
Epoch 1/50
548/548 [==============================] - 9s 13ms/step - loss: 0.0247 -
accuracy: 0.9978 - val_loss: 0.0036 - val_accuracy: 0.9995
Epoch 2/50
548/548 [==============================] - 5s 9ms/step - loss: 0.0041 -
accuracy: 0.9995 - val_loss: 0.0038 - val_accuracy: 0.9995
Epoch 3/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0035 -
accuracy: 0.9995 - val_loss: 0.0041 - val_accuracy: 0.9995
Epoch 4/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0046 - val_accuracy: 0.9995
Epoch 5/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0045 - val_accuracy: 0.9995
Epoch 6/50
548/548 [==============================] - 2s 4ms/step - loss: 0.0036 -
accuracy: 0.9995 - val_loss: 0.0044 - val_accuracy: 0.9995
Epoch 7/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0047 - val_accuracy: 0.9995
Epoch 8/50
548/548 [==============================] - 1s 2ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0050 - val_accuracy: 0.9995
Epoch 9/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0032 -
accuracy: 0.9995 - val_loss: 0.0050 - val_accuracy: 0.9995
Epoch 10/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0050 - val_accuracy: 0.9995
Epoch 11/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0035 -
accuracy: 0.9995 - val_loss: 0.0049 - val_accuracy: 0.9995
```

```
Epoch 12/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0036 -
accuracy: 0.9995 - val_loss: 0.0051 - val_accuracy: 0.9995
Epoch 13/50
548/548 [==============================] - 1s 2ms/step - loss: 0.0037 -
accuracy: 0.9995 - val_loss: 0.0049 - val_accuracy: 0.9995
Epoch 14/50
548/548 [==============================] - 2s 4ms/step - loss: 0.0031 -
accuracy: 0.9995 - val_loss: 0.0054 - val_accuracy: 0.9995
Epoch 15/50
548/548 [==============================] - 2s 4ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0052 - val_accuracy: 0.9995
Epoch 16/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0037 -
accuracy: 0.9995 - val_loss: 0.0054 - val_accuracy: 0.9995
Epoch 17/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0032 -
accuracy: 0.9995 - val_loss: 0.0051 - val_accuracy: 0.9995
Epoch 18/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0032 -
accuracy: 0.9995 - val_loss: 0.0054 - val_accuracy: 0.9995
Epoch 19/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0037 -
accuracy: 0.9995 - val_loss: 0.0049 - val_accuracy: 0.9995
Epoch 20/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0053 - val_accuracy: 0.9995
Epoch 21/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0052 - val_accuracy: 0.9995
Epoch 22/50
548/548 [==============================] - 2s 4ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0052 - val_accuracy: 0.9995
Epoch 23/50
548/548 [==============================] - 2s 4ms/step - loss: 0.0035 -
accuracy: 0.9995 - val_loss: 0.0054 - val_accuracy: 0.9995
Epoch 24/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0035 -
accuracy: 0.9995 - val_loss: 0.0051 - val_accuracy: 0.9995
Epoch 25/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0037 -
accuracy: 0.9995 - val_loss: 0.0055 - val_accuracy: 0.9995
Epoch 26/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0058 - val_accuracy: 0.9995
Epoch 27/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0058 - val_accuracy: 0.9995
```

```
Epoch 28/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0035 -
accuracy: 0.9995 - val_loss: 0.0053 - val_accuracy: 0.9995
Epoch 29/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0051 - val_accuracy: 0.9995
Epoch 30/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0056 - val_accuracy: 0.9995
Epoch 31/50
548/548 [==============================] - 2s 4ms/step - loss: 0.0035 -
accuracy: 0.9995 - val_loss: 0.0054 - val_accuracy: 0.9995
Epoch 32/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0050 - val_accuracy: 0.9995
Epoch 33/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0054 - val_accuracy: 0.9995
Epoch 34/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0031 -
accuracy: 0.9995 - val_loss: 0.0056 - val_accuracy: 0.9995
Epoch 35/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0056 - val_accuracy: 0.9995
Epoch 36/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0032 -
accuracy: 0.9995 - val_loss: 0.0055 - val_accuracy: 0.9995
Epoch 37/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0030 -
accuracy: 0.9995 - val_loss: 0.0052 - val_accuracy: 0.9995
Epoch 38/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0031 -
accuracy: 0.9995 - val_loss: 0.0057 - val_accuracy: 0.9995
Epoch 39/50
548/548 [==============================] - 2s 4ms/step - loss: 0.0032 -
accuracy: 0.9995 - val_loss: 0.0052 - val_accuracy: 0.9995
Epoch 40/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0031 -
accuracy: 0.9995 - val_loss: 0.0054 - val_accuracy: 0.9995
Epoch 41/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0030 -
accuracy: 0.9995 - val_loss: 0.0063 - val_accuracy: 0.9995
Epoch 42/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0030 -
accuracy: 0.9995 - val_loss: 0.0050 - val_accuracy: 0.9995
Epoch 43/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0032 -
accuracy: 0.9995 - val_loss: 0.0051 - val_accuracy: 0.9995
```

```
Epoch 44/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0032 -
accuracy: 0.9995 - val_loss: 0.0054 - val_accuracy: 0.9995
Epoch 45/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0036 -
accuracy: 0.9995 - val_loss: 0.0059 - val_accuracy: 0.9995
Epoch 46/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0050 - val_accuracy: 0.9995
Epoch 47/50
548/548 [==============================] - 2s 4ms/step - loss: 0.0034 -
accuracy: 0.9995 - val_loss: 0.0051 - val_accuracy: 0.9995
Epoch 48/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0031 -
accuracy: 0.9995 - val_loss: 0.0053 - val_accuracy: 0.9995
Epoch 49/50
548/548 [==============================] - 2s 3ms/step - loss: 0.0028 -
accuracy: 0.9995 - val_loss: 0.0057 - val_accuracy: 0.9995
Epoch 50/50
548/548 [==============================] - 1s 3ms/step - loss: 0.0033 -
accuracy: 0.9995 - val_loss: 0.0051 - val_accuracy: 0.9995
```

[ ]:
```python
# Predict on test data
y_pred = (model.predict(X_test_scaled) > 0.5).astype("int32")

# Calculate accuracy and other metrics
accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

print(f'Accuracy: {accuracy:.2f}')
print(f'Classification Report:\n{report}')
```

```
137/137 [==============================] - 1s 3ms/step
Accuracy: 1.00
Classification Report:
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         2
           1       1.00      1.00      1.00      4376

    accuracy                           1.00      4378
   macro avg       0.50      0.50      0.50      4378
weighted avg       1.00      1.00      1.00      4378


/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
```

```
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.10/dist-packages/sklearn/metrics/_classification.py:1344:
UndefinedMetricWarning: Precision and F-score are ill-defined and being set to
0.0 in labels with no predicted samples. Use `zero_division` parameter to
control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

[ ]: