EDA

Dataset: https://www.kaggle.com/sakhawat18/asteroid-dataset

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Basic Column Definition

- **SPK-ID**: Object primary SPK-ID
- **Object ID**: Object internal database ID
- **Object fullname**: Object full name/designation. Combination of provisional and permanent designation. Some asteroids do not yet have a permanent designation.
- **pdes**: Object primary designation (most recent designation). Provisional designation or permanent designation (if available). When a new object is found that cannot be identified with an already-known object, Minor Planet Center (MPC) assigns a provisional designation- year of discovery, two letters, and further digits if needed (eg. 1989 AC). When orbit is well enough determined, object is assigned permanent designation- a number. https://web.archive.org/web/20060216182947/http://www.iau.org/MINOR_PLANETS_NAMING.2
- **name**: Object IAU name. Discoverer is invited to suggest a name only after object receives permanent designation.
- **NEO**: Near-Earth Object (NEO) flag
- **PHA**: Potentially Hazardous Asteroid (PHA) flag. Target.
- **H**: Absolute magnitude parameter. Visual magnitude an observer would record if the asteroid were placed 1 Astronomical Unit (au) away, and 1 au from the Sun and at a zero phase angle (the magnitude of an asteroid at zero phase angle and at unit heliocentric and geocentric distances)
- **Diameter**: object diameter (from equivalent sphere) km Unit
- **Albedo**: Geometric albedo. Shininess/reflectiveness of the surface. https://www.nasa.gov/mission_pages/WISE/multimedia/gallery/neowise/pia14733.html
- **Diameter_sigma**: 1-sigma uncertainty in object diameter km Unit
- **Orbit_id**: Orbit solution ID
- **Epoch**: Epoch of osculation in modified Julian day form
- **Equinox**: Equinox of reference frame
- **e**: Orbit eccentricity. Amount by which orbit deviates from a perfect circle (0 - circular, 0 to 1 - elliptic, 1 - parabolic escape, < 1 - hyperbola
- **a**: Semi-major axis au Unit. One half of the major axis of the elliptical orbit; also the mean distance from the Sun
- **q**: perihelion distance au Unit. Perihelion is orbit’s closest point to the Sun
- **i**: inclination; angle with respect to x-y ecliptic plane
- **tp**: Time of perihelion passage TDB Unit. The time at which an object is closest to the sun.

- **moid_ld**: Earth Minimum Orbit Intersection Distance au Unit. Distance between closest points of orbits of asteroid and Earth. Direct measure of close approach/collision risk.
- **class**: orbit classification

Class values (orbit classifications)

- AMO Amor: Near-Earth asteroid orbits similar to that of 1221 Amor (a > 1.0 AU; 1.017 AU < q < 1.3 AU).
- APO Apollo: Near-Earth asteroid orbits which cross the Earth's orbit similar to that of 1862 Apollo (a > 1.0 AU; q < 1.017 AU).
- AST Asteroid: Asteroid orbit not matching any defined orbit class.
- ATE Aten: Near-Earth asteroid orbits similar to that of 2062 Aten (a < 1.0 AU; Q > 0.983 AU).
- CEN Centaur: Objects with orbits between Jupiter and Neptune (5.5 AU < a < 30.1 AU).
- HYA Hyperbolic Asteroid: Asteroids on hyperbolic orbits (e > 1.0).
- IEO Interior Earth Object: An asteroid orbit contained entirely within the orbit of the Earth (Q < 0.983 AU).
- IMB Inner Main-belt Asteroid: Asteroids with orbital elements constrained by (a < 2.0 AU; q > 1.666 AU).
- MBA Main-belt Asteroid: Asteroids with orbital elements constrained by (2.0 AU < a < 3.2 AU; q > 1.666 AU).
- MCA Mars-crossing Asteroid: Asteroids that cross the orbit of Mars constrained by (1.3 AU < q < 1.666 AU; a < 3.2 AU).
- OMB Outer Main-belt Asteroid: Asteroids with orbital elements constrained by (3.2 AU < a < 4.6 AU).
- PAA Parabolic Asteroid: Asteroids on parabolic orbits (e = 1.0).
- TJN Jupiter Trojan: Asteroids traped in Jupiter's L4/L5 Lagrange points (4.6 AU < a < 5.5 AU; e < 0.3).
- TNO TransNeptunian Object: Objects with orbits outside Neptune (a > 30.1 AU).

Additional notes

- The astronomical unit (au) is defined by the IAU as exactly 149,597,870,700 m. Based on avg distance between Earth and Sun.
- NEO: An asteroid or comet with a perihelion distance less than or equal to 1.3 au. 99% of NEOs are asteroids.
- 1 sigma uncertainty means 1 standard deviation.

In [2]:
```python
data = pd.read_csv('data/dataset.csv')

data.info()
```

```
/Users/lauramiller/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/IPyt
hon/core/interactiveshell.py:3145: DtypeWarning: Columns (3,4,5) have mixed type
s.Specify dtype option on import or set low_memory=False.
  has_raised = await self.run_ast_nodes(code_ast.body, cell_name,
<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
```

In [3]:
```
data.shape
```

Out[3]:
```
(958524, 45)
```

In [4]:
```
data.head()
```

Out[4]:

	id	spkid	full_name	pdes	name	prefix	neo	pha	H	diameter	...	sigm
0	a0000001	2000001	1 Ceres	1	Ceres	NaN	N	N	3.40	939.400	...	4.60890(
1	a0000002	2000002	2 Pallas	2	Pallas	NaN	N	N	4.20	545.000	...	3.46940(
2	a0000003	2000003	3 Juno	3	Juno	NaN	N	N	5.33	246.596	...	3.22310(

	id	spkid	full_name	pdes	name	prefix	neo	pha	H	diameter	...	sigma
3	a0000004	2000004	4 Vesta	4	Vesta	NaN	N	N	3.00	525.400	...	2.170600
4	a0000005	2000005	5 Astraea	5	Astraea	NaN	N	N	6.90	106.699	...	2.740800

5 rows × 45 columns

In [5]:
```
data.describe()
```

Out[5]:

	spkid	H	diameter	albedo	diameter_sigma	epo
count	9.585240e+05	952261.000000	136209.000000	135103.000000	136081.000000	9.585240e+
mean	3.810114e+06	16.906411	5.506429	0.130627	0.479184	2.458869e+
std	6.831541e+06	1.790405	9.425164	0.110323	0.782895	7.016716e-
min	2.000001e+06	-1.100000	0.002500	0.001000	0.000500	2.425052e+
25%	2.239632e+06	16.100000	2.780000	0.053000	0.180000	2.459000e+
50%	2.479262e+06	16.900000	3.972000	0.079000	0.332000	2.459000e+
75%	3.752518e+06	17.714000	5.765000	0.190000	0.620000	2.459000e+
max	5.401723e+07	33.200000	939.400000	1.000000	140.000000	2.459000e+

8 rows × 35 columns

Examine columns

In [6]:
```
print(data.id.value_counts(normalize=True))
print('\nUnique Values:')
data.id.nunique()
```

```
a0447626    0.000001
bK15TO5P    0.000001
bK16CR1A    0.000001
bK10FD8K    0.000001
bK16F34O    0.000001
              ...
bK08T87U    0.000001
a0109100    0.000001
bK14OE8G    0.000001
a0238766    0.000001
a0208807    0.000001
Name: id, Length: 958524, dtype: float64

Unique Values:
```

Out[6]:
```
958524
```

In [7]:
```
print(data.full_name.value_counts(normalize=True))
print('\nUnique Values:')
data.full_name.nunique()
```

```
  2082 Galahad (7588 P-L)     0.000001
314752 (2006 SA239)           0.000001
157631 (2005 WA159)           0.000001
```

```
        (2015 GG34)          0.000001
        (2017 BY75)          0.000001
                               ...
        (2015 FD324)         0.000001
        (2014 RE18)          0.000001
 63094  (2000 WP142)         0.000001
        (2005 RW31)          0.000001
        (2018 AC12)          0.000001
Name: full_name, Length: 958524, dtype: float64

Unique Values:
```

Out[7]:
```
958524
```

In [8]:
```python
print(data.name.value_counts(normalize=True))
print('\nUnique Values:')
data.name.nunique()
```

```
Zsigmond          0.000045
Spacesora         0.000045
MacGregor         0.000045
Wilkens           0.000045
Hamra             0.000045
                    ...
Gavioliremo       0.000045
Novotroitskoe     0.000045
Pholus            0.000045
Meslier           0.000045
Scorzelli         0.000045
Name: name, Length: 22064, dtype: float64

Unique Values:
```

Out[8]:
```
22064
```

In [9]:
```python
print(data.pdes.value_counts(normalize=True))
print('\nUnique_Values')
data.pdes.nunique()
```

```
2014 GS55      0.000001
319503         0.000001
319515         0.000001
319514         0.000001
319513         0.000001
                 ...
2015 OA18      0.000001
2006 SR154     0.000001
2014 KZ17      0.000001
2001 FR208     0.000001
2016 FD4       0.000001
Name: pdes, Length: 958524, dtype: float64

Unique_Values
```

Out[9]:
```
958524
```

The above features appear to be unique identifiers for each row, not properties that will be effective in a classification model.

In [10]:
```python
print(data.orbit_id.value_counts(normalize=True))
print('\nUnique_Values')
data.orbit_id.nunique()
```

```
1             0.052312
JPL 1         0.049549
```

```
JPL 2         0.036064
JPL 3         0.031226
12            0.030397
                ...
MPO490516     0.000001
MPO478183     0.000001
MPO479019     0.000001
MPO485984     0.000001
MPO481628     0.000001
Name: orbit_id, Length: 4690, dtype: float64

Unique_Values
```

Out[10]:
```
4690
```

In [11]:
```
print(data.equinox.value_counts(normalize=True))
print('\nUnique_Values')
data.equinox.nunique()
```

```
J2000    1.0
Name: equinox, dtype: float64

Unique_Values
```

Out[11]:
```
1
```

In [12]:
```
print(data['class'].value_counts(normalize=True))
print('\nUnique_Values')
data['class'].nunique()
```

```
MBA    0.892992
OMB    0.029582
IMB    0.021241
MCA    0.019494
APO    0.013236
AMO    0.008823
TJN    0.008577
TNO    0.003618
ATE    0.001804
CEN    0.000528
AST    0.000079
IEO    0.000023
HYA    0.000004
Name: class, dtype: float64

Unique_Values
```

Out[12]:
```
13
```

In [13]:
```
data.prefix.value_counts(normalize=True)
```

Out[13]:
```
A    1.0
Name: prefix, dtype: float64
```

In [14]:
```
print(data['moid_ld'].value_counts(normalize=True))
print('\nUnique_Values')
data['moid_ld'].nunique()
```

```
0.000000      0.020653
390.563229    0.000026
454.702336    0.000026
482.236114    0.000025
456.009947    0.000023
                ...
197.488987    0.000001
```

```
795.506289    0.000001
376.472550    0.000001
333.391042    0.000001
248.113777    0.000001
Name: moid_ld, Length: 314301, dtype: float64

Unique_Values
```

Out[14]:
```
314301
```

In [15]:
```
# What percent of asteroids are near earth objects?

data.neo.value_counts(normalize=True)
```

Out[15]:
```
N    0.976114
Y    0.023886
Name: neo, dtype: float64
```

In [16]:
```
# Check for class imbalance. What percent of asteroids are hazardous?

data.pha.value_counts(normalize=True)
```

Out[16]:
```
N    0.997799
Y    0.002201
Name: pha, dtype: float64
```

Data displays a heavy class imbalance. ~ 99.8% of asteroids are non-hazardous. There are far, far fewer potentially hazardous asteroids. A naive classifier that always predicts a negative ("N") label will be accurate 99.8% of the time. I will address class imbalances after selecting a best-performing model.

Furthermore, a metric like recall (sensitivity, or `true positives / (true positives + false negatives`) should take priority in model evaluation, as we want to make sure we identify every potentially hazardous asteroid. The cost of missing one potentially hazardous body can be quite disastrous.

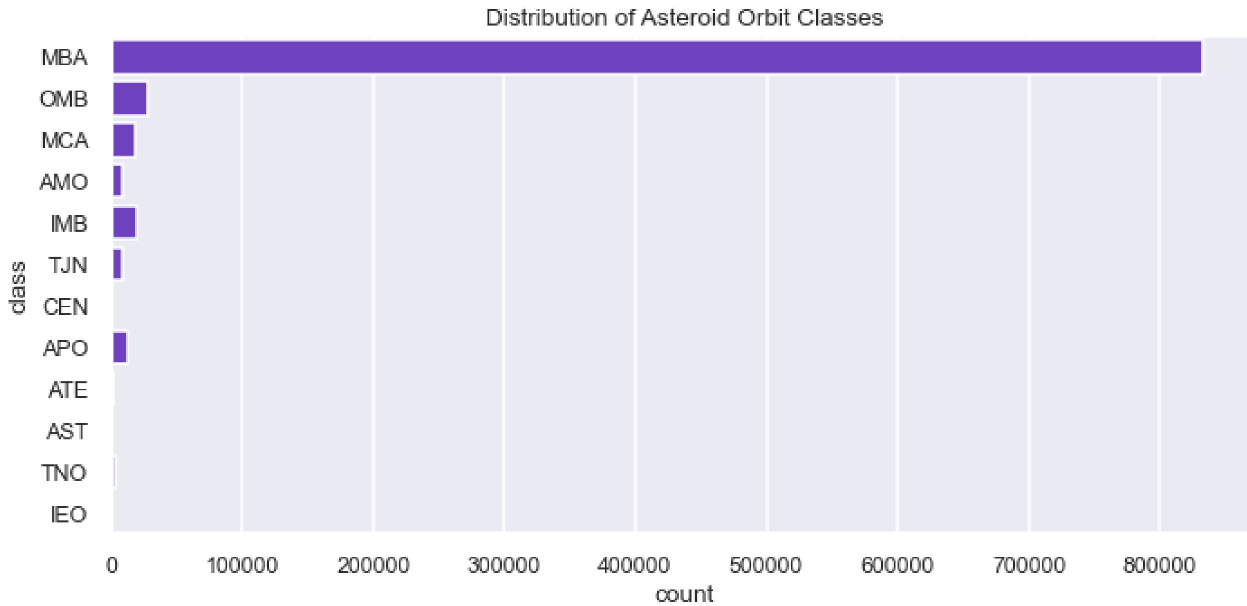
In [39]:
```
data['class'].value_counts()
```

Out[39]:
```
MBA    832650
OMB     27170
IMB     19702
MCA     17789
APO     12684
AMO      8448
TJN      8122
TNO      3459
ATE      1729
CEN       503
AST        57
IEO        22
Name: class, dtype: int64
```

In [8]:
```
sns.set_context('talk', font_scale=0.75)
sns.set_style('darkgrid')
colors = ['#682dd3', '#fe4134', '#fe5448']
```

In [148…
```
# What are the counts of various asteroid classes? Which class contains the most

plt.figure(figsize=(10, 5))
ax = sns.countplot(y='class', data=data, color='#682dd3')
```

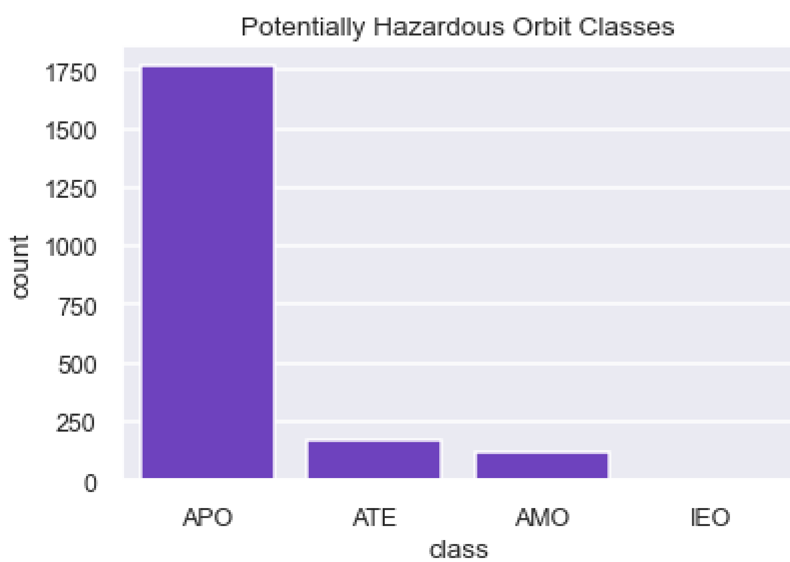
```
plt.title('Distribution of Asteroid Orbit Classes')
plt.tight_layout()
plt.savefig('images/class-dist.png', bbox_inches='tight')
plt.savefig('images/class-dist-hr.png', dpi=200, bbox_inches='tight');
```



Most asteroids are MBA, or main belt asteroids (asteroids with orbital elements constrained by (2.0 AU < a < 3.2 AU; q > 1.666 AU). They are within the asteroid belt, orbiting between Mars and Jupiter. The fewest asteroids are IE0 (interior earth objects), which have orbits contained within the orbit of earth(Q < 0.983 AU)

In [155…

```
# What are the orbit classifications of potentially hazardous asteroids?

sns.countplot(x='class', data=data[data['pha'] == 'Y'], color='#682dd3')
plt.title('Potentially Hazardous Orbit Classes')
plt.savefig('images/pha-class.png', bbox_inches='tight')
plt.savefig('images/pha-class-hr.png', dpi=200, bbox_inches='tight');
```



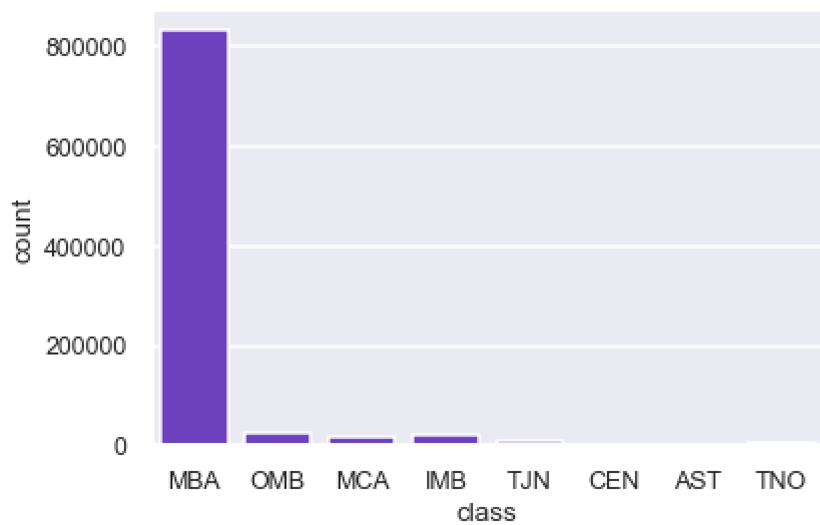
Most potentially hazardous asteroids are of the APO (Apollo) class (Near-Earth asteroid orbits which cross the Earth's orbit with orbits similar to that of 1862 Apollo (a > 1.0 AU; q < 1.017 AU).

In [147…

```
# What are the orbit classes of near earth objects?

sns.countplot(x='class', data=data[data['neo'] == 'Y'], color='#682dd3');
```

In [157…

```
# Are there asteroids that are not NEOs in the 4 classes above?

sns.countplot(x='class', data=data[data['neo'] == 'N'], color='#682dd3');
```



The 4 NEO-containing classes do not appear in the plot above, so they are entirely comprised of Near Earth Objects.

In [19]:

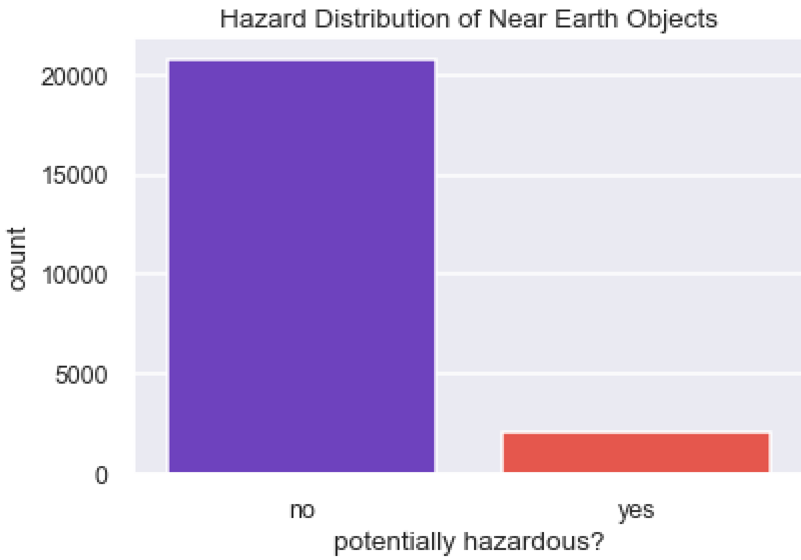
```
# Of NEOs, what percentage are potentially hazardous?

data[data['neo'] == 'Y']['pha'].value_counts(normalize=True)
```

Out[19]:

```
N    0.909758
Y    0.090242
Name: pha, dtype: float64
```

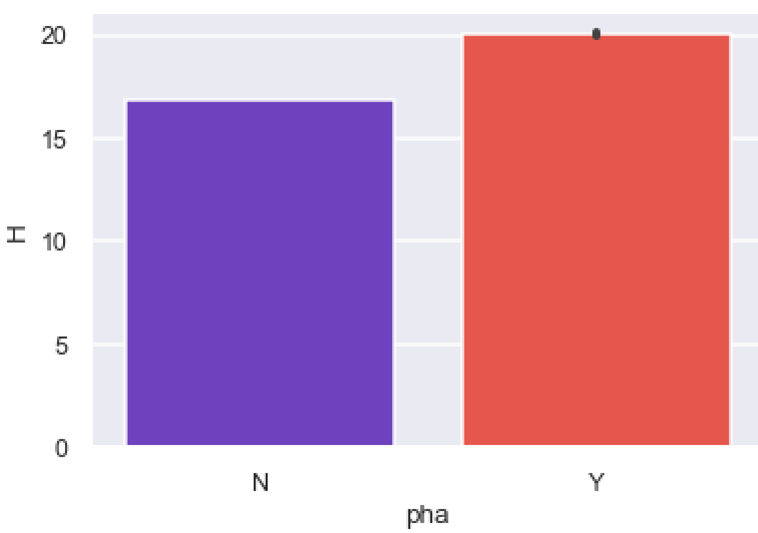
In [11]:

```
sns.countplot(x='pha', data = data[data['neo'] == 'Y'], palette=colors)
plt.title('Hazard Distribution of Near Earth Objects')
plt.xlabel('potentially hazardous?')
plt.xticks([0, 1], labels=['no', 'yes'])
plt.savefig('images/neo-pha.png', bbox_inches='tight')
plt.savefig('images/neo-pha-hr.png', dpi=200, bbox_inches='tight');
```



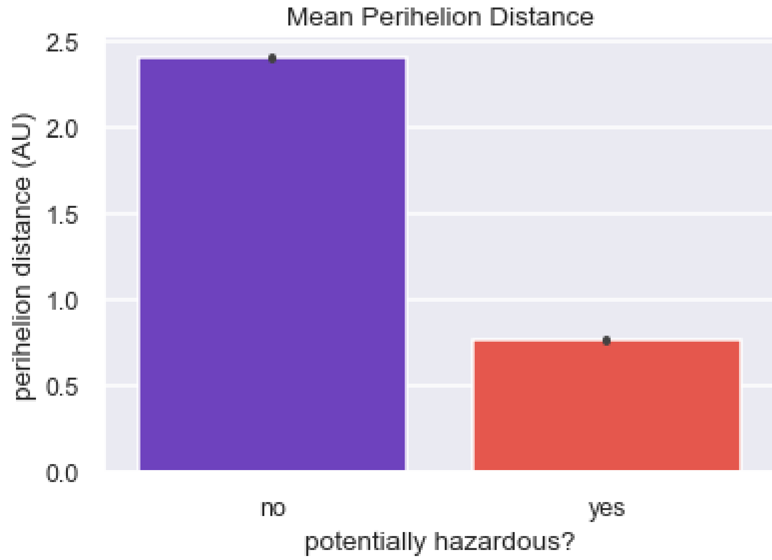
Most NEOs are non-hazardous (~91%) while 9% are potentially hazardous. While all phas are NEOs, not all NEOs are potentially hazardous.

In [9]:
```
# Mean H (visual magnitude) of non-hazardous/ potentially hazardous asteroids

sns.barplot(x=data['pha'], y=data['H'], data=data.groupby('pha').mean().reset_in
```



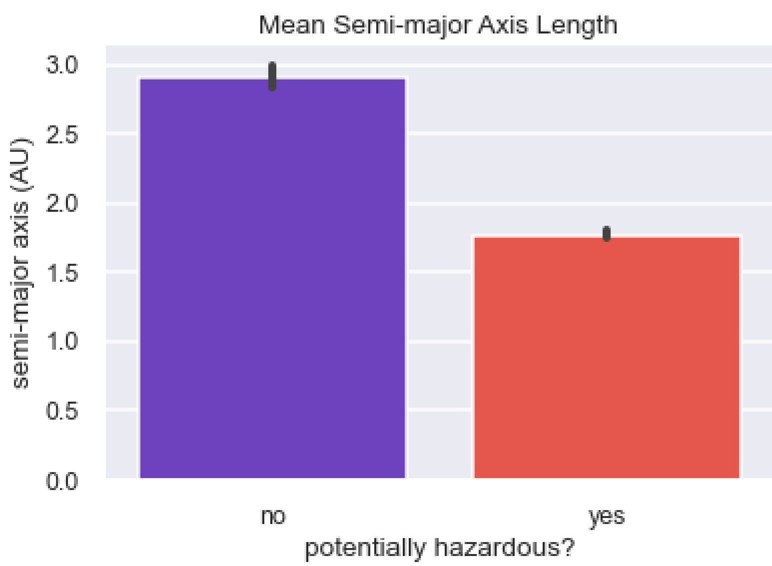
On average, phas have a greater visual magnitude than non-hazardous asteroids.

In [10]:
```
# Mean q (perihelion distance) for non-hazardous/potentially hazardous asteroids

sns.barplot(x=data['pha'], y=data['q'], data=data, palette=colors)
plt.title('Mean Perihelion Distance')
plt.xlabel('potentially hazardous?')
plt.ylabel('perihelion distance (AU)')
plt.xticks([0, 1], labels=['no', 'yes'])
plt.savefig('Images/q-pha.png', bbox_inches='tight')
plt.savefig('Images/q-pha-hr.png', dpi=200, bbox_inches='tight');
```



The mean perihelion distance is lower for phas, which means that their orbits come closer to the sun.

In [7]:
```
# Mean a for non-hazardous/potentially hazardous asteroids

sns.barplot(x="pha", y='a', data=data, palette=colors)
plt.title('Mean Semi-major Axis Length')
plt.xlabel('potentially hazardous?')
plt.ylabel('semi-major axis (AU)')
plt.xticks([0, 1], labels=['no', 'yes'])
plt.savefig('Images/a-pha.png', bbox_inches='tight')
plt.savefig('Images/a-pha-hr.png', dpi=200, bbox_inches='tight');
```



phas have smaller semi-major axis lengths. On average, their orbits are tighter than that of non-hazardous asteroids

In [89]:
```
# Mean moid_ld values for non-hazardous and potentially hazardous asteroids by c

crosstab = pd.crosstab(index=data['class'], columns=data['pha'], values=data['mo
crosstab
```

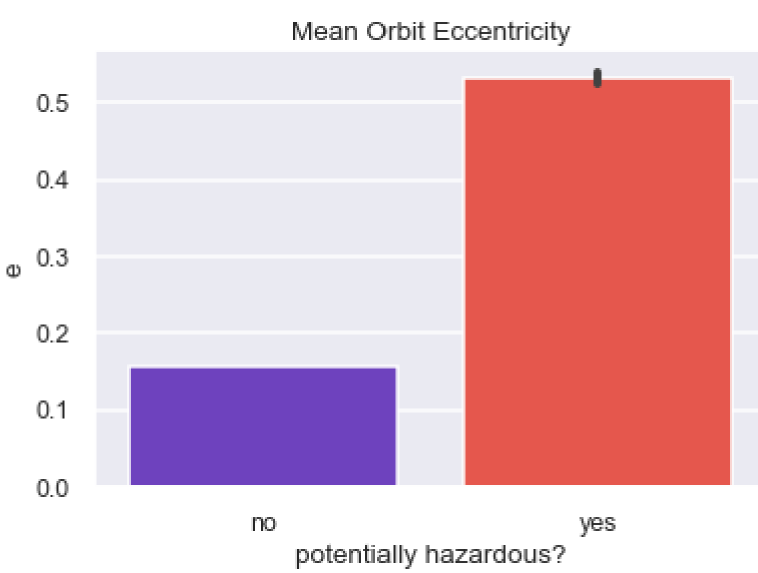
Out[89]:

pha	N	Y

pha	N	Y
class		
AMO	65.541659	13.689846
APO	21.674208	8.905461
AST	657.901061	NaN
ATE	18.056258	9.072017
CEN	3129.367152	NaN
IEO	57.550358	15.348035
IMB	314.225552	NaN
MBA	506.401837	NaN
MCA	234.240645	NaN
OMB	743.152499	NaN
TJN	1494.498062	NaN
TNO	13608.816204	NaN

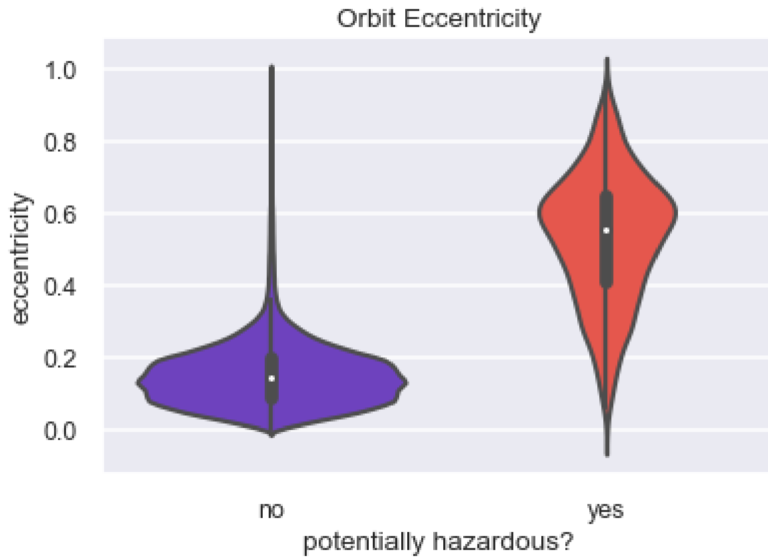
The 4 classes containing containing potentially hazardous asteroids also have the smallest mean values for `moid_ld` , as expected.

In [10]:
```
# Mean eccentricity of non-hazardous and potentially hazardous asteroids?

sns.barplot(x="pha", y="e", data=data, palette=colors)
plt.title('Mean Orbit Eccentricity')
plt.xlabel('potentially hazardous?')
plt.xticks([0, 1], labels=['no', 'yes'])
plt.savefig('images/e-pha.png', bbox_inches='tight')
plt.savefig('images/e-pha-hr.png', dpi=200, bbox_inches='tight');
```



In [162…
```
# Distribution of eccentricity for non-hazardous/ potentially hazardous asteroid

sns.violinplot(x="pha", y="e", data=data, palette=colors)
plt.title('Orbit Eccentricity')
```

```
plt.xlabel('potentially hazardous?')
plt.ylabel('eccentricity')
plt.xticks([0, 1], labels=['no', 'yes'])
plt.savefig('images/e-pha-violin.png', bbox_inches='tight')
plt.savefig('images/e-pha-violin-hr.png', dpi=200, bbox_inches='tight');
```



Address missing values

In [22]:
```
data.isna().sum()
```

Out[22]:
```
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
```

In [23]:
```
data.isna().any().sum()
```

Out[23]:
```
26
```

In [24]:
```
# NEOs

# Check perihelion distances. If <= 1.3 au, the object is NEO

data[data.neo.isna()]['q']
```

Out[24]:
```
741612    5.260067
929462    0.255912
946657    5.858539
950563    8.820993
Name: q, dtype: float64
```

One missing entry is a NEO, the others are not.

In [25]:
```
data.at[929462, 'neo'] = 'Y'
```

In [26]:
```
data.neo.fillna(value='N', inplace=True)
```

In [27]:
```
# Drop ID cols & cols with 800K+ missing values

data.columns
```

Out[27]:
```
Index(['id', 'spkid', 'full_name', 'pdes', 'name', 'prefix', 'neo', 'pha', 'H',
       'diameter', 'albedo', 'diameter_sigma', 'orbit_id', 'epoch',
       'epoch_mjd', 'epoch_cal', 'equinox', 'e', 'a', 'q', 'i', 'om', 'w',
       'ma', 'ad', 'n', 'tp', 'tp_cal', 'per', 'per_y', 'moid', 'moid_ld',
       'sigma_e', 'sigma_a', 'sigma_q', 'sigma_i', 'sigma_om', 'sigma_w',
       'sigma_ma', 'sigma_ad', 'sigma_n', 'sigma_tp', 'sigma_per', 'class',
       'rms'],
      dtype='object')
```

In [28]:
```
# Equinox is the same for every entry, so this is also uninformative

# Class provides orbit information, but in broader categories. Drop orbit_id ins

cols = ['id', 'spkid', 'full_name', 'pdes', 'name', 'prefix', 'diameter', 'albed

data = data.drop(cols, axis=1)
```

In [29]:
```
data.isna().sum()
```

Out[29]:
```
neo             0
pha         19921
```

```
H               6263
epoch              0
epoch_mjd          0
epoch_cal          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
```

In [30]:

```
data = data.dropna()
```

In [31]:

```
data.shape
```

Out[31]:

```
(932335, 34)
```

Even after dropping the remaining rows with missing data, we still have ~932K entries.

In [32]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 932335 entries, 0 to 958523
Data columns (total 34 columns):
 #   Column     Non-Null Count   Dtype  
---  ------     --------------   -----  
 0   neo        932335 non-null  object 
 1   pha        932335 non-null  object 
 2   H          932335 non-null  float64
 3   epoch      932335 non-null  float64
 4   epoch_mjd  932335 non-null  int64  
 5   epoch_cal  932335 non-null  float64
 6   e          932335 non-null  float64
 7   a          932335 non-null  float64
 8   q          932335 non-null  float64
 9   i          932335 non-null  float64
 10  om         932335 non-null  float64
 11  w          932335 non-null  float64
 12  ma         932335 non-null  float64
 13  ad         932335 non-null  float64
 14  n          932335 non-null  float64
```

```
 15  tp         932335 non-null  float64
 16  tp_cal     932335 non-null  float64
 17  per        932335 non-null  float64
 18  per_y      932335 non-null  float64
 19  moid       932335 non-null  float64
 20  moid_ld    932335 non-null  float64
 21  sigma_e    932335 non-null  float64
 22  sigma_a    932335 non-null  float64
 23  sigma_q    932335 non-null  float64
 24  sigma_i    932335 non-null  float64
 25  sigma_om   932335 non-null  float64
 26  sigma_w    932335 non-null  float64
 27  sigma_ma   932335 non-null  float64
 28  sigma_ad   932335 non-null  float64
 29  sigma_n    932335 non-null  float64
 30  sigma_tp   932335 non-null  float64
 31  sigma_per  932335 non-null  float64
 32  class      932335 non-null  object
 33  rms        932335 non-null  float64
dtypes: float64(30), int64(1), object(3)
memory usage: 249.0+ MB
```

In [34]:
```
data.to_csv('data/data_cleaned.csv')
```