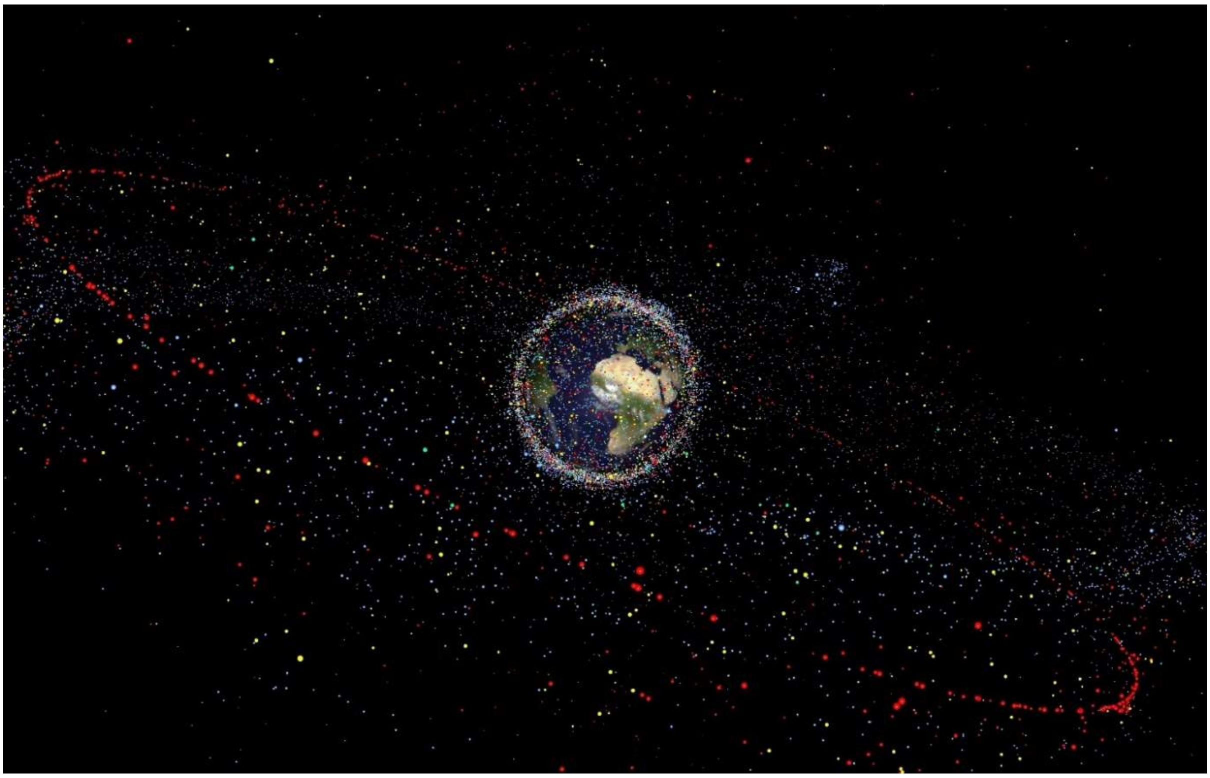
MACHINE LEARNING

18CSC311

PROJECT

NASA - Nearest Earth Objects

A cumulative data for Nearest Earth Objects by NASA



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CONTEXT

There is an infinite number of objects in the outer space. Some of them are closer than we think. Even though we might think that a distance of 70,000 Km can't potentially harm us, but at an astronomical scale, this is a very small distance and can disrupt many natural phenomena. These objects/asteroids can thus prove to be harmful. Hence, it is wise to know what is surrounding us and what can harm us amongst those. Thus, this dataset compiles the list of NASA certified asteroids that are c lassified as the nearest earth object.

ABSTRACT OF THE PROBLEM:

Sentry is a highly automated collision monitoring system that continually scans the most current asteroid catalogue for possibilities of future impact with Earth over the next 100 years. So, this concludes whether that object is hazardous for the earth are not.

Data Set:

There are 90,835 rows and 10 columns in the dataset.

	id	name	est_diameter_min	est_diameter_max	relative_velocity	miss_distance	orbiting_body	sentry_object	absolute_magnitude	hazardous
0	2162635	162635 (2000 SS164)	1.198271	2.679415	13569.249224	5.483974e+07	Earth	False	16.73	False
1	2277475	277475 (2005 WK4)	0.265800	0.594347	73588.726663	6.143813e+07	Earth	False	20.00	True
2	2512244	512244 (2015 YE18)	0.722030	1.614507	114258.692129	4.979872e+07	Earth	False	17.83	False
3	3596030	(2012 BV13)	0.096506	0.215794	24764.303138	2.543497e+07	Earth	False	22.20	False
4	3667127	(2014 GE35)	0.255009	0.570217	42737.733765	4.627557e+07	Earth	False	20.09	True
...	...	...	...	...	...	...	...	...	...	...
90831	3763337	(2016 VX1)	0.026580	0.059435	52078.886692	1.230039e+07	Earth	False	25.00	False
90832	3837603	(2019 AD3)	0.016771	0.037501	46114.605073	5.432121e+07	Earth	False	26.00	False
90833	54017201	(2020 JP3)	0.031956	0.071456	7566.807732	2.840077e+07	Earth	False	24.60	False
90834	54115824	(2021 CN5)	0.007321	0.016370	69199.154484	6.869206e+07	Earth	False	27.80	False
90835	54205447	(2021 TW7)	0.039862	0.089133	27024.455553	5.977213e+07	Earth	False	24.12	False

The columns of the dataset contains “id”, “name”, “est_diameter_min”, “est_diameter_min”, “relative_velocity”, “miss_diatance”, “orbiting_body”, “sentry_object”, “absolute_magnitude”, “hazardous”.

<u>Regressors:</u>

“est_diameter_min”, “est_diameter_min”, “relative_velocity”, “miss_diatance”, “orbiting_body”, “sentry_object”, “absolute_magnitude”.

<u>Response Variable:</u>

“hazardous”

Data Preprocessing:

Data pre-processing can refer to manipulation or dropping of data before it is used in order to ensure or enhance performance, and is an important step in the data mining process.

1. Checking for the null values in the datasets:

```
neo.isnull().sum()
```

```
id                    0
name                  0
est_diameter_min      0
est_diameter_max      0
relative_velocity     0
miss_distance         0
orbiting_body         0
sentry_object         0
absolute_magnitude    0
hazardous             0
dtype: int64
```

There are no null values in the data set, so we proceed to next step.

2. Checking the data types of the data set

```
neo.dtypes
```

```
id                      int64
name                   object
est_diameter_min      float64
est_diameter_max      float64
relative_velocity     float64
miss_distance         float64
orbiting_body          object
sentry_object            bool
absolute_magnitude    float64
hazardous                bool
dtype: object
```

From this we can infer that [‘sentry_object’] and [‘hazardous’] contains the Boolean data type.

Sentry_object:

Sentry is a highly automated collision monitoring system that continually scans the most current asteroid catalog for possibilities of future impact with Earth over the next 100 years.

3. Now we are checking for the unique value sin every column:

Getting unique values for the each column in a dataset

```
unique_values = neo.nunique()
print(unique_values)
```

```
id                   27423
name                 27423
est_diameter_min      1638
est_diameter_max      1638
relative_velocity    90828
miss_distance        90536
orbiting_body            1
sentry_object            1
absolute_magnitude    1638
hazardous                2
dtype: int64
```

From this we can conclude that ['sentry_object'] and ['orbiting_body'] has same value for every row

Oribiting body : Earth

Sentry_object : False

so changing the value into 1

```
neo['sentry_object'] = neo['sentry_object'].astype(int)
print(neo['sentry_object'].head())
```

```
0    0
1    0
2    0
3    0
4    0
Name: sentry_object, dtype: int32
```

```
def my_func(row):
    if row['orbiting_body'] == 'Earth':
        val = 1
    else:
        val = 0
    return val

neo['orbiting_body'] = neo.apply(my_func,axis=1)
neo['orbiting_body'].head()
```

```
0    1
1    1
2    1
3    1
4    1
Name: orbiting_body, dtype: int64
```

4. Now we are changing the datatype [‘hazardous’] into “int”

Changing the bool values into Binary 0 or 1

True = 1, False = 0

```
neo['hazardous'] = neo['hazardous'].astype(int)
print(neo['hazardous'].head())
```

```
0    0
1    1
2    0
3    0
4    1
Name: hazardous, dtype: int32
```

So, now datatype of every column is changed into int or float type, which will be useful for implementing machine learning algorithm

After preprocessing the data types of Attributes are:

```
# Checking for the data types
neo.dtypes
```

```
id                      int64
name                   object
est_diameter_min      float64
est_diameter_max      float64
relative_velocity     float64
miss_distance         float64
orbiting_body           int64
sentry_object           int32
absolute_magnitude    float64
hazardous               int32
dtype: object
```

So, now the data is ready for prediction.
Since the data comes under Supervised learning, we can use both regression and classification.

REGRESSION	CLASSIFICATION
MULTIPLE LINEAR REGRESSION	LOGISTIC REGRESSION
	DECISION TREE
	RANDOM FOREST
	NAIVE BAYE’S
	K -NEAREST NEIGHBORS (KNN)

REGRESSION:

MULTIPLE LINEAR REGRESSION:

We use Multiple linear regression model to estimate the relationship between a quantitative dependent variable ['hazardous'] and independent variables ['est_diameter_min', 'est_diameter_max', 'relative_velocity', 'miss_distance', 'orbiting_body', 'sentry_object', 'absolute_magnitude'] using a straight line.

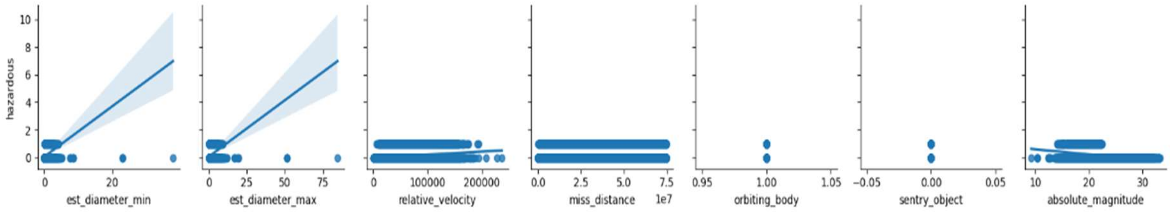
```
#Multiple Linear Regression
from sklearn.linear_model import LinearRegression
regressor = LinearRegression()
regressor.fit(X_train, y_train)
print("Regression co-efficient:", regressor.coef_)
print()
print("Regressor intercept:", regressor.intercept_)
print()
y_pred = regressor.predict(X_test)
print("Predicted values:", y_pred)
print()
print("Actual values:", y_test.values)
```

```
Regression co-efficient: [-5.47944420e-03 -1.22524097e-02  1.09415840e-0
6 -1.06609069e-09
  0.00000000e+00  0.00000000e+00 -3.78551484e-02]

Regressor intercept: 0.9786120177387115

Predicted values: [-0.01736984  0.22216823 -0.06206746 ...  0.0639019
0.15108669
  0.0981872 ]

Actual values: [0 1 0 ... 0 0 0]
```

<u>Visualizing using pair plot</u>

```
sns.pairplot(neo, x_vars = ['est_diameter_min', 'est_diameter_max', 'relative_velocity', 'miss_distance', 'orbiting_body',
                            'sentry_object', 'absolute_magnitude'], y_vars='hazardous', kind = 'reg')
```

```
<seaborn.axisgrid.PairGrid at 0x2d33d893a90>
```



The argument kind='reg' adds a linear regression line to each scatter plot, allowing us to visualize the relationship between the independent and dependent variables.

Now we are doing dimensionality reduction to know which attributes are actually influencing the response variable [“hazardous”]

<u>Dimensionality Reduction</u>

Dimensionality Reduction

```
import statsmodels.regression.linear_model as sm
# add a column of ones as integer data type
X = np.append(arr = np.ones((90836  , 1)).astype(int),
              values = X, axis = 1)
# choose a Significance level usually 0.05, if p>0.05
#  for the highest values parameter, remove that value
X_opt = X[:, [0, 3, 4, 5]]
```

```
ols = sm.OLS(endog = y, exog = X_opt).fit()
ols.summary()
```

OLS Regression Results

Dep. Variable:	hazardous	R-squared:	0.037
Model:	OLS	Adj. R-squared:	0.037
Method:	Least Squares	F-statistic:	1746.
Date:	Tue, 16 May 2023	Prob (F-statistic):	0.00
Time:	09:19:56	Log-Likelihood:	-16714.
No. Observations:	90836	AIC:	3.343e+04
Df Residuals:	90833	BIC:	3.346e+04
Df Model:	2		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-0.0017	0.001	-1.462	0.144	-0.004	0.001
x1	2.327e-06	4.04e-08	57.639	0.000	2.25e-06	2.41e-06
x2	-3.007e-10	4.57e-11	-6.581	0.000	-3.9e-10	-2.11e-10
x3	-0.0017	0.001	-1.462	0.144	-0.004	0.001

Omnibus:	45080.856	Durbin-Watson:	1.901
Prob(Omnibus):	0.000	Jarque-Bera (JB):	195976.752
Skew:	2.570	Prob(JB):	0.00
Kurtosis:	8.036	Cond. No.	1.57e+24

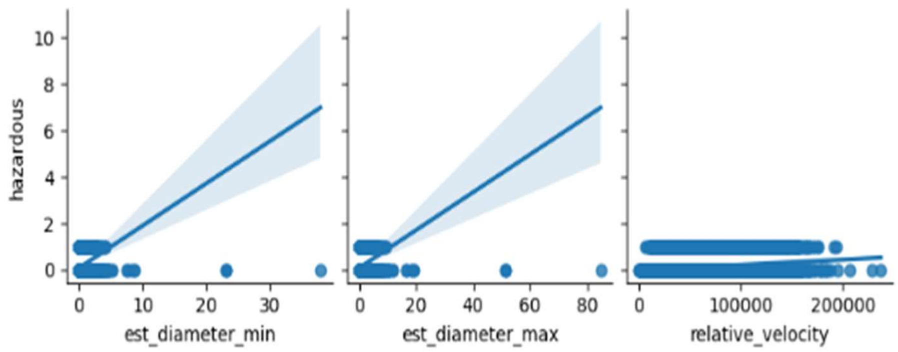
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 6.92e-29. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

From this we can infer that the attributes [“est_diameter_min”, “est_diameter_max”, “relative_velocity”] are influencing the response variable [“hazardous”].

Visualization using pair plot:

```
sns.pairplot(neo, x_vars = ['est_diameter_min', 'est_diameter_max', 'relative_velocity'], y_vars='hazardous', kind = 'reg')
```

```
<seaborn.axisgrid.PairGrid at 0x2d33d893850>
```



INFERENCE FROM MULTIPLE LINEAR REGRESSION:

In multiple linear regression, we aim to establish a relationship between a dependent variable and multiple independent variables. After performing the regression analysis, we conclude that the attributes [“est_diameter_min”, “est_diameter_max”, “relative_velocity”] are influencing the response variable [“hazardous”]. So we can use these three attributes to classify whether the object is hazardous to earth or not.

CLASSIFICATION:
LOGISTIC REGRESSION:

Logistic Regression is a statistical modelling technique used to predict the probability of a binary outcome based on one or more independent variables.

Here the independent variable that has influence on the dependent variable [‘hazardous’] are [‘est_diameter_min’], [‘est_diameter_max’] an d [‘relative_velocity’].

Unlike linear regression, which predicts continuous numeric values, logistic regression models the relationship between the independent variables and the logarithm of the odds of the dependent variable belonging to a particular category. The logistic regression model applies a transformation called the logistic function (also known as the sigmoid function) to convert the linear combination of the independent variables into a probability value between 0 and 1.

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression()
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
print("Accuracy:", logreg.score(X_test, y_test))
```

```
Accuracy: 0.9011999119330691
```

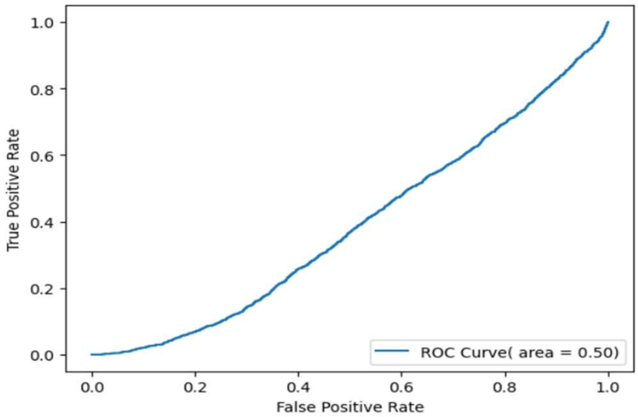
Accuracy:

The proportion of correct predictions over total predictions.

The Accuracy Score of Logistic Regression is**: 0.9011999119330691**

Visualizing:

```python
from sklearn.metrics import confusion_matrix, roc_curve, roc_auc_score
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:, 1])
roc_auc = roc_auc_score(y_test, y_pred)

plt.plot(fpr, tpr, label = 'ROC Curve( area = %0.2f)' %roc_auc)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend(loc = 'lower right')
plt.show()
```



X = False Positive Rate

Y = True Positive Rate

ROC curve and AUC provided a useful way to evaluate and compare the performance of binary classification of the model.

ROC and AUC provide a useful way to evaluate and compare the performance of binary classification the response variable.

INFERENCE FROM LOGISTIC REGRESSION

As with multiple linear regression, the inference aspect for logistic regression will focus on interpretation of coefficients and relationships between explanatory variables. Both p-values and cross-validation will be used for assessing a logistic regression model.

DECISION TREE:

A decision tree is a non-parametric supervised learning algorithm, which is utilized for both classification and regression tasks. It has a hierarchical, tree structure, which consists of a root node, branches, internal nodes and leaf nodes.

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
import graphviz
from sklearn.metrics import accuracy_score
clf = DecisionTreeClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.8937692646411273
```

The Accuracy Score of the Decision Tree is: **0.8937692646411273**

RANDOM FOREST:

Random forest is a Supervised Machine Learning Algorithm that is used widely in Classification and Regression problems. It builds decision trees on different samples and takes their majority vote for classification and average in case of regression.

Random Forest

```
from sklearn.ensemble import RandomForestClassifier
clf = RandomForestClassifier()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
print("Accuracy:", accuracy)
```

```
Accuracy: 0.8937692646411273
```

The Accuracy Score of the Random Forest is: **0.8937692646411273**

NAIYE BAYE'S:

It is a classification technique based on Bayes' Theorem with an independence assumption among predictors. In simple terms, a Naive Bayes classifier assumes that the presence of a particular feature in a class is unrelated to the presence of any other feature.

Naive Baye's

```
from sklearn.naive_bayes import GaussianNB
clf = GaussianNB()
clf.fit(X_train, y_train)
y_pred = clf.predict(X_test)
accuracy = clf.score(X_test, y_test)
print("Accuracy:", accuracy)
```

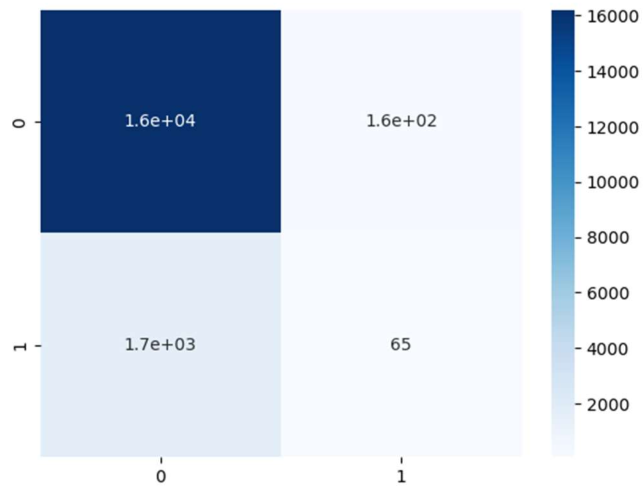
```
Accuracy: 0.895695728753853
```

The Accuracy Score of the Naïve Bye's is: **0.895695728753853**

Visualizing using heat map:

```
from sklearn.metrics import classification_report, confusion_matrix
print("Classification Report:\n", classification_report(y_test, y_pred))
print("Confusion Matrix:\n", confusion_matrix(y_test, y_pred))
sns.heatmap(confusion_matrix(y_test, y_pred), annot = True, cmap = 'Blues')
```

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

           0       0.90      0.99      0.94     16373
           1       0.28      0.04      0.06      1795

    accuracy                           0.90     18168
   macro avg       0.59      0.51      0.50     18168
weighted avg       0.84      0.90      0.86     18168

Confusion Matrix:
 [[16208   165]
 [ 1730    65]]

<Axes: >
```



K – NEAREST NEIGHBORS:

The k-nearest neighbours' algorithm, also known as KNN or k-NN, is a non-parametric, supervised learning classifier, which uses proximity to make classifications or predictions about the grouping of an individual data point.

-

K- Nearest Neighbours(KNN)

```
: from sklearn.neighbors import KNeighborsClassifier
kclassifier = KNeighborsClassifier(n_neighbors = 251)
kclassifier.fit(X_train, y_train)
```

```
:     KNeighborsClassifier
KNeighborsClassifier(n_neighbors=251)
```

```
: kpredict = kclassifier.predict(X_test)
```

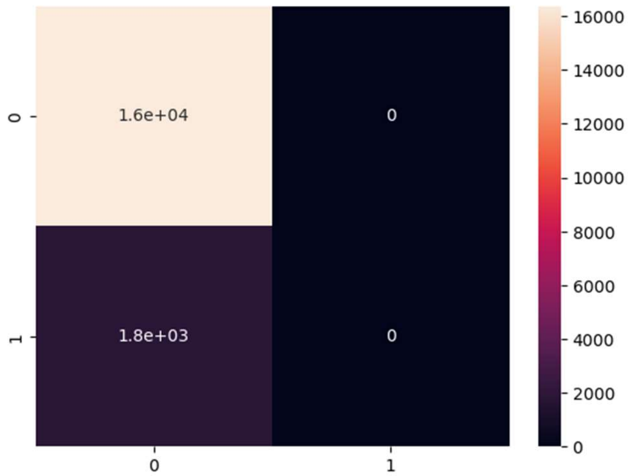
```
: print(classification_report(y_test,kpredict))
```

```
              precision    recall  f1-score   support

           0       0.90      1.00      0.95     16373
           1       0.00      0.00      0.00      1795

    accuracy                           0.90     18168
   macro avg       0.45      0.50      0.47     18168
weighted avg       0.81      0.90      0.85     18168
```

Visualizing using heatmap:

```
from sklearn.metrics import confusion_matrix,classification_report
cm=confusion_matrix(y_test,kpredict)
sns.heatmap(cm,annot=True)
```

```
<Axes: >
```



INFERENCE:

Regression model:

From *Multiple Linear Regression* we concluded that the attributes

[“est_diameter_min”],

[“est_diameter_max”],

[“relative_velocity”]

has the direct influence on the response variable [“hazardous”].

Classification model:

Then, from *classification model* we found various Accuracy Score,

Logistic Regression	**0.9011999119330691**
Decision Tree	**0.8937692646411273**
Random Forest	**0.8937692646411273**
Naïve Baye’s	**0.895695728753853**

The Logistic Regression gives us the best Accuracy Score: **0.9011999119330691.**

From the features [“est_diameter_min”], [“est_diamter_max”], [“relative_velocity”] we can infer that the particular object is hazardous or not to the Earth for the next 100 years. If the response variable [“hazardous”] is **“1” [“True”]** then the object is hazardous if it is **“0” [“False”]** then the object is not hazardous to the Earth.

REFERENCE:

https://www.kaggle.com/code/ishukitty27/nearest-earth-object