NASANearestObjects

July 21, 2022

1 NASA - Nearest Earth Objects

1.1 A cumulative data for Nearest Earth Objects by NASA

https://www.kaggle.com/datasets/sameepvani/nasa-nearest-earth-objects

1.2 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 not 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 classified as the nearest earth object.

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split, RandomizedSearchCV
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.metrics import recall_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import LinearSVC
from sklearn.neighbors import NearestCentroid
```

[2]:
```
neo_df = pd.read_csv('neo_v2.csv')
```

[3]:
```
neo_df.head()
```

[3]:

	id	name	est_diameter_min	est_diameter_max	\
0	2162635	162635 (2000 SS164)	1.198271	2.679415	
1	2277475	277475 (2005 WK4)	0.265800	0.594347	
2	2512244	512244 (2015 YE18)	0.722030	1.614507	
3	3596030	(2012 BV13)	0.096506	0.215794	
4	3667127	(2014 GE35)	0.255009	0.570217	

```
   relative_velocity  miss_distance orbiting_body  sentry_object  \
0       13569.249224   5.483974e+07         Earth          False
1       73588.726663   6.143813e+07         Earth          False
2      114258.692129   4.979872e+07         Earth          False
3       24764.303138   2.543497e+07         Earth          False
4       42737.733765   4.627557e+07         Earth          False

   absolute_magnitude  hazardous
0               16.73      False
1               20.00       True
2               17.83      False
3               22.20      False
4               20.09       True
```

[4]:
```
neo_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 90836 entries, 0 to 90835
Data columns (total 10 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   id                  90836 non-null  int64
 1   name                90836 non-null  object
 2   est_diameter_min    90836 non-null  float64
 3   est_diameter_max    90836 non-null  float64
 4   relative_velocity   90836 non-null  float64
 5   miss_distance       90836 non-null  float64
 6   orbiting_body       90836 non-null  object
 7   sentry_object       90836 non-null  bool
 8   absolute_magnitude  90836 non-null  float64
 9   hazardous           90836 non-null  bool
dtypes: bool(2), float64(5), int64(1), object(2)
memory usage: 5.7+ MB
```

[5]:
```
neo_df.isnull().sum()
```

[5]:
```
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
```

[6]:
```
neo_df.describe()
```

[6]:
```
                 id  est_diameter_min  est_diameter_max  relative_velocity  \
count  9.083600e+04      90836.000000      90836.000000       90836.000000
mean   1.438288e+07          0.127432          0.284947       48066.918918
std    2.087202e+07          0.298511          0.667491       25293.296961
min    2.000433e+06          0.000609          0.001362         203.346433
25%    3.448110e+06          0.019256          0.043057       28619.020645
50%    3.748362e+06          0.048368          0.108153       44190.117890
75%    3.884023e+06          0.143402          0.320656       62923.604633
max    5.427591e+07         37.892650         84.730541      236990.128088

       miss_distance  absolute_magnitude
count   9.083600e+04        90836.000000
mean    3.706655e+07           23.527103
std     2.235204e+07            2.894086
min     6.745533e+03            9.230000
25%     1.721082e+07           21.340000
50%     3.784658e+07           23.700000
75%     5.654900e+07           25.700000
max     7.479865e+07           33.200000
```

[7]:
```
neo_df.nunique()
```

[7]:
```
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
```

This is a Binary classification problem, where **hazardous** is dependent feature. Some of the features like **orbiting_body** and **sentry_object** has only category so it is not that much useful. Also features like **id** and **name** has no relevance to target variable we can remove them too.

[8]:
```
neo_df.drop(columns=['id', 'name', 'orbiting_body', 'sentry_object'],␣
 ↪inplace=True)
num_feats = ['est_diameter_min', 'est_diameter_max', 'relative_velocity',␣
 ↪'miss_distance', 'absolute_magnitude']
```

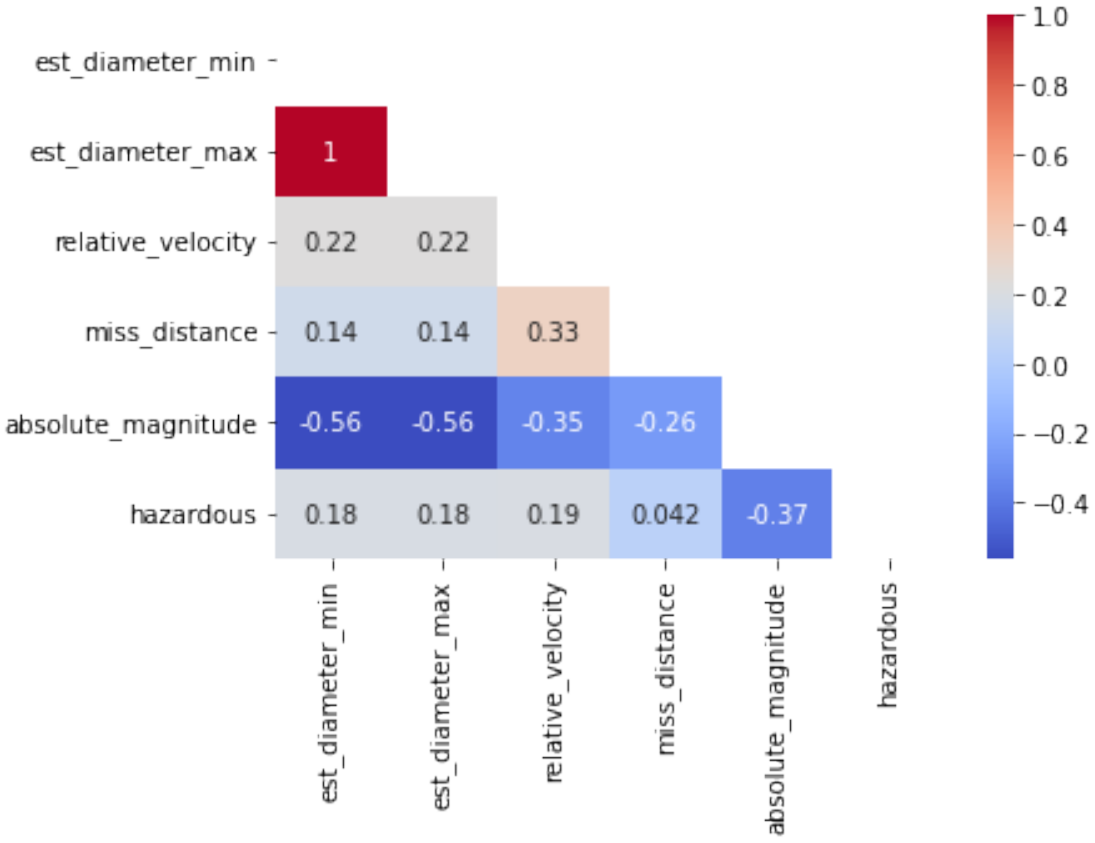
[9]:
```
neo_df.head()
```

[9]:

	est_diameter_min	est_diameter_max	relative_velocity	miss_distance	\
0	1.198271	2.679415	13569.249224	5.483974e+07	
1	0.265800	0.594347	73588.726663	6.143813e+07	
2	0.722030	1.614507	114258.692129	4.979872e+07	
3	0.096506	0.215794	24764.303138	2.543497e+07	
4	0.255009	0.570217	42737.733765	4.627557e+07	

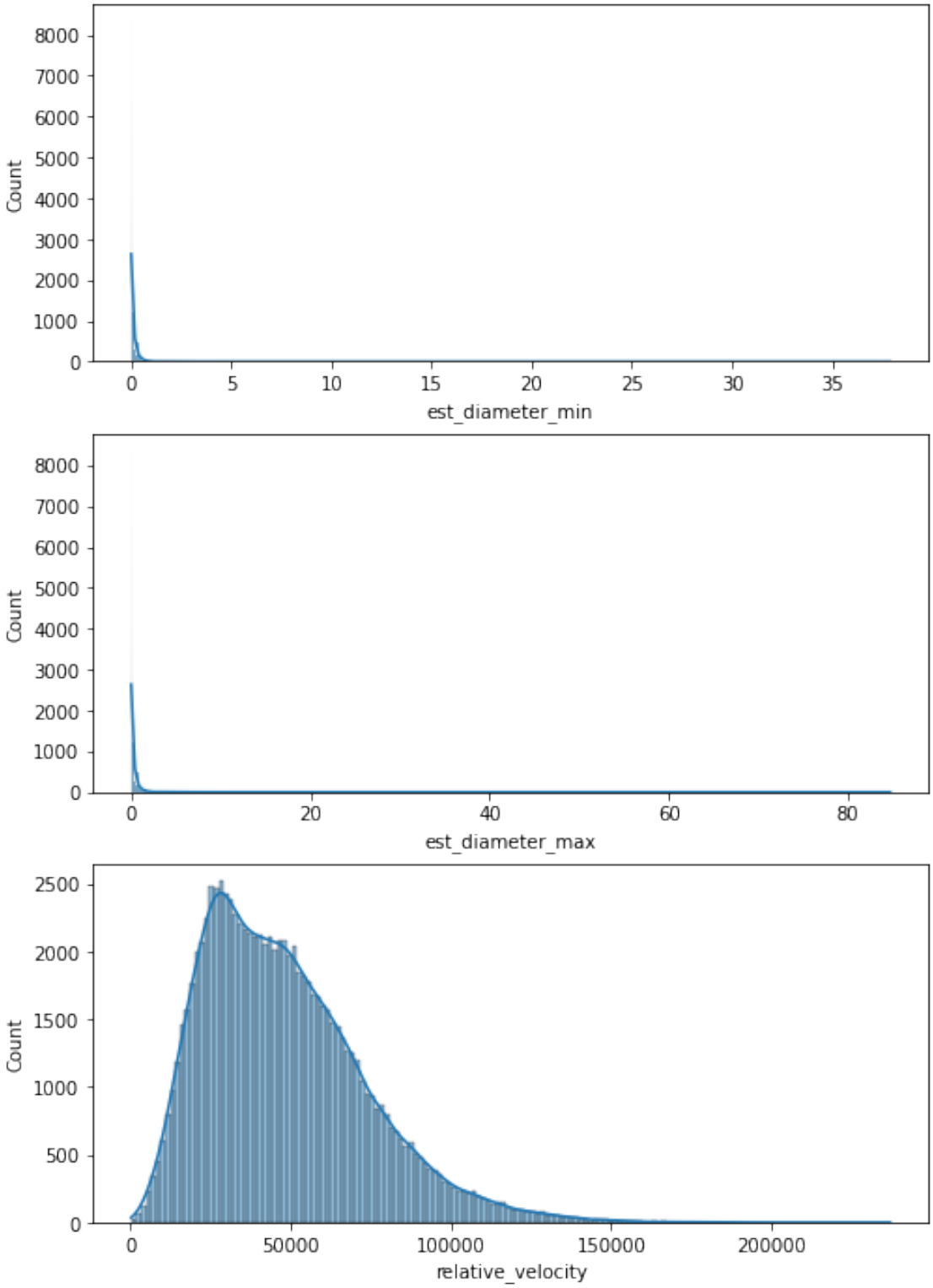
	absolute_magnitude	hazardous
0	16.73	False
1	20.00	True
2	17.83	False
3	22.20	False
4	20.09	True

[10]:
```
corr = neo_df.corr()
mask = np.triu(np.ones_like(corr, dtype=bool))
sns.heatmap(corr, mask=mask, cmap='coolwarm', annot=True);
```



[11]:
```
num_neo_df = neo_df.loc[:, num_feats]
```

[12]:
```
fig, axs = plt.subplots(nrows=3, figsize=(8,12))
sns.histplot(x='est_diameter_min', data=num_neo_df, ax=axs[0], kde=True);
sns.histplot(x='est_diameter_max', data=num_neo_df, ax=axs[1], kde=True);
sns.histplot(x='relative_velocity', data=num_neo_df, ax=axs[2], kde=True);
```



It can be observed from above that there exists skewness in data, in order for the model to train well we need to reduce the skewness.

[13]:
```
skewness = {feat: num_neo_df[feat].skew() for feat in num_neo_df.columns}
skewness
```

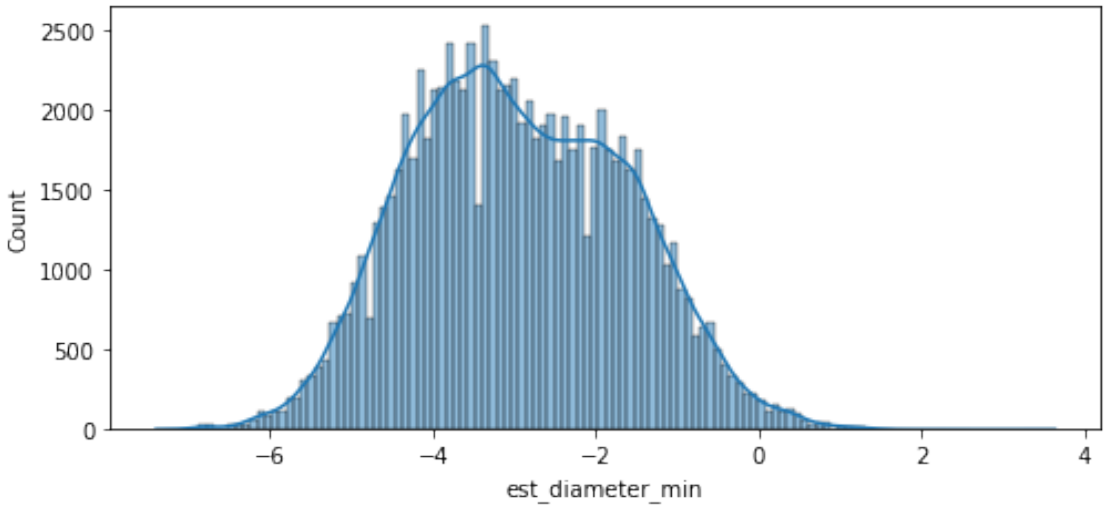
[13]:
```
{'est_diameter_min': 41.13995194872109,
 'est_diameter_max': 41.139951948962064,
 'relative_velocity': 0.9051249321533844,
 'miss_distance': -0.04270598169888327,
 'absolute_magnitude': -0.13741956613464948}
```

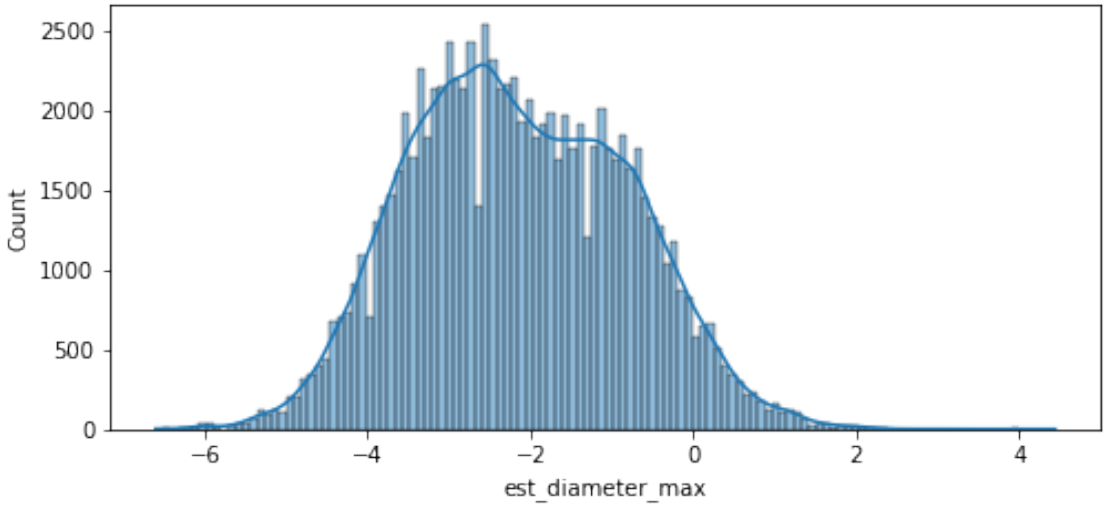
[14]:
```
num_neo_df['est_diameter_min'] = np.log(num_neo_df['est_diameter_min'])
num_neo_df['est_diameter_max'] = np.log(num_neo_df['est_diameter_max'])
num_neo_df['relative_velocity'] = np.sqrt(num_neo_df['relative_velocity'])
```

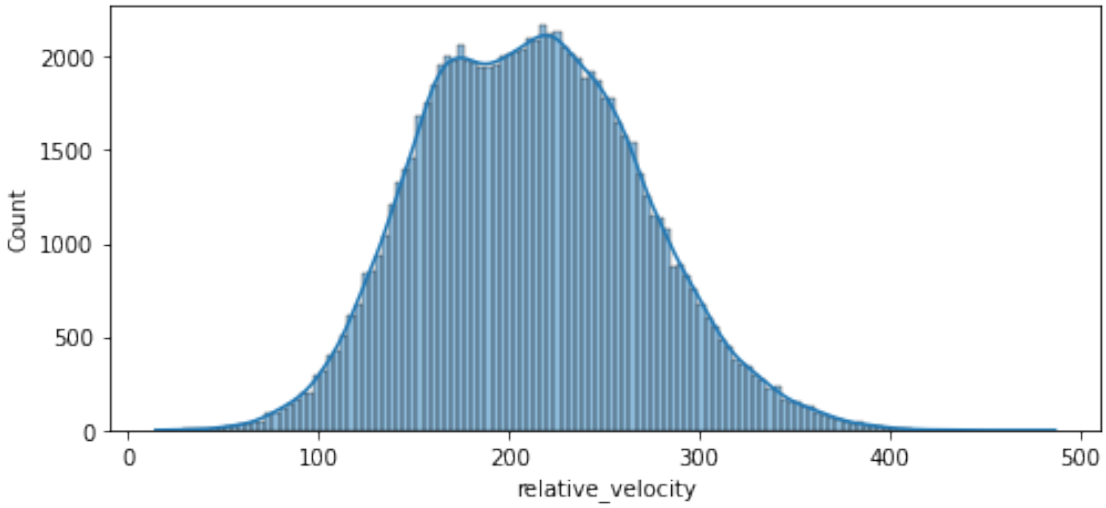
[15]:
```
skewness = {feat: num_neo_df[feat].skew() for feat in num_neo_df.columns}
skewness
```

[15]:
```
{'est_diameter_min': 0.13741956583201068,
 'est_diameter_max': 0.1374195658374031,
 'relative_velocity': 0.1960586412667333,
 'miss_distance': -0.04270598169888327,
 'absolute_magnitude': -0.13741956613464948}
```

[16]:
```
fig, axs = plt.subplots(nrows=3, figsize=(8,12))
sns.histplot(x='est_diameter_min', data=num_neo_df, ax=axs[0], kde=True);
sns.histplot(x='est_diameter_max', data=num_neo_df, ax=axs[1], kde=True);
sns.histplot(x='relative_velocity', data=num_neo_df, ax=axs[2], kde=True);
```







[17]:
```
num_neo_df.head()
```

[17]:
```
   est_diameter_min  est_diameter_max  relative_velocity  miss_distance  \
0          0.180880          0.985598         116.487120   5.483974e+07
1         -1.325011         -0.520292         271.272421   6.143813e+07
2         -0.325689          0.479030         338.021733   4.979872e+07
3         -2.338149         -1.533430         157.366779   2.543497e+07
4         -1.366458         -0.561739         206.731066   4.627557e+07

   absolute_magnitude
0               16.73
1               20.00
2               17.83
3               22.20
4               20.09
```

[18]:
```
X, y = num_neo_df, neo_df['hazardous']
X_train, X_test, y_train, y_test = train_test_split(X, y, shuffle=True,␣
 ↪random_state=4, test_size=0.25)
```

[19]:
```
pipeline_lr = Pipeline([('scaler', StandardScaler()), ('lr',␣
 ↪LogisticRegression())])
pipeline_lv = Pipeline([('scaler', StandardScaler()), ('lv',␣
 ↪LinearSVC(max_iter=4000))])
pipeline_rfc = Pipeline([('scaler', StandardScaler()), ('rfc',␣
 ↪RandomForestClassifier())])
pipeline_nc = Pipeline([('scaler', StandardScaler()), ('nc',␣
 ↪NearestCentroid())])
```

[20]:
```
pipeline_lr.fit(X_train, y_train)
pipeline_lv.fit(X_train, y_train)
pipeline_rfc.fit(X_train, y_train)
pipeline_nc.fit(X_train, y_train);
```

1.2.1 Accuracy Score of Models:

[21]:
```
lr_accuracy_score = pipeline_lr.score(X_test, y_test)
lv_accuracy_score = pipeline_lv.score(X_test, y_test)
rfc_accuracy_score = pipeline_rfc.score(X_test, y_test)
nc_accuracy_score = pipeline_nc.score(X_test, y_test)
print(f"Accuracy score of models ...\nLogisticRegression:␣
 ↪{lr_accuracy_score*100:.2f}\nLinearSVC: {lv_accuracy_score*100:.
 ↪2f}\nRandomForest: {rfc_accuracy_score*100:.2f}\nNearestCentroid:␣
 ↪{nc_accuracy_score*100:.2f}")
```

```
Accuracy score of models ...
LogisticRegression: 89.55
LinearSVC: 90.22
RandomForest: 91.72
NearestCentroid: 76.86
```

For this problem statement accuracy is not the correct metric, since we are more concerned about `False Positive (FP)`. So for this reason we need to opt for Recall.

1.2.2 Recall Score of Models:

[22]:
```
lr_recall_score = recall_score(y_test, pipeline_lr.predict(X_test))
lv_recall_score = recall_score(y_test, pipeline_lv.predict(X_test))
rfc_recall_score = recall_score(y_test, pipeline_rfc.predict(X_test))
nc_recall_score = recall_score(y_test, pipeline_nc.predict(X_test))
print(f"Recall score of models ...\nLogisticRegression: {lr_recall_score*100:.
↪2f}\nLinearSVC: {lv_recall_score*100:.2f}\nRandomForest:␣
↪{rfc_recall_score*100:.2f}\nNearestCentroid: {nc_recall_score*100:.2f}")
```

```
Recall score of models …
LogisticRegression: 7.59
LinearSVC: 1.55
RandomForest: 40.60
NearestCentroid: 95.34
```