Data Sources: WHO, CDC, World Bank and UN.

```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

from catboost import CatBoostClassifier


#importing plotly and cufflinks in offline mode
import cufflinks as cf
import plotly.offline
cf.go_offline()
cf.set_config_file(offline=False, world_readable=True)

import plotly
import plotly.express as px
import plotly.graph_objs as go
import plotly.offline as py
from plotly.offline import iplot
from plotly.subplots import make_subplots
import plotly.figure_factory as ff
import matplotlib.pyplot as plt
import matplotlib as mpl

import missingno as msno
from p5 import *


import datetime as dt
from datetime import timedelta

from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.cluster import KMeans

from sklearn.linear_model import LinearRegression,Ridge,Lasso
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize']=20,10

from sklearn.preprocessing import MinMaxScaler
std=StandardScaler()
import warnings
warnings.filterwarnings("ignore")
```

```python
df = pd.read_csv('Leading Causes of Death in Egypt.csv')
df.head()
```

	Death Causes	Deaths	Percentage%	Rate per 100,000	World Rank/183	Cause Effect
0	Coronary Heart Disease	163171.0	29.38	271.69	15	NO
1	Liver Disease	68866.0	12.40	116.08	1	NO
2	Stroke	59445.0	10.70	101.05	53	NO
3	Alzheimers & Dementia	17957.0	3.23	36.09	29	NO
4	Kidney Disease	18279.0	3.29	29.87	32	NO

```python
df = df.replace({'Cause Effect': {'YES':1, 'NO':0}})
df.head()
```

	Death Causes	Deaths	Percentage%	Rate per 100,000	World Rank/183	Cause Effect
0	Coronary Heart Disease	163171.0	29.38	271.69	15	0
1	Liver Disease	68866.0	12.40	116.08	1	0
2	Stroke	59445.0	10.70	101.05	53	0
3	Alzheimers & Dementia	17957.0	3.23	36.09	29	0
4	Kidney Disease	18279.0	3.29	29.87	32	0

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51 entries, 0 to 50
Data columns (total 6 columns):
 #   Column            Non-Null Count  Dtype
---  ------            --------------  -----
 0   Death Causes      51 non-null     object
 1   Deaths            51 non-null     float64
 2   Percentage%       51 non-null     float64
 3   Rate per 100,000  51 non-null     float64
 4   World Rank/183    51 non-null     int64
 5   Cause Effect      51 non-null     int64
dtypes: float64(3), int64(2), object(1)
memory usage: 2.5+ KB
```

```python
df.duplicated().sum()
```

0

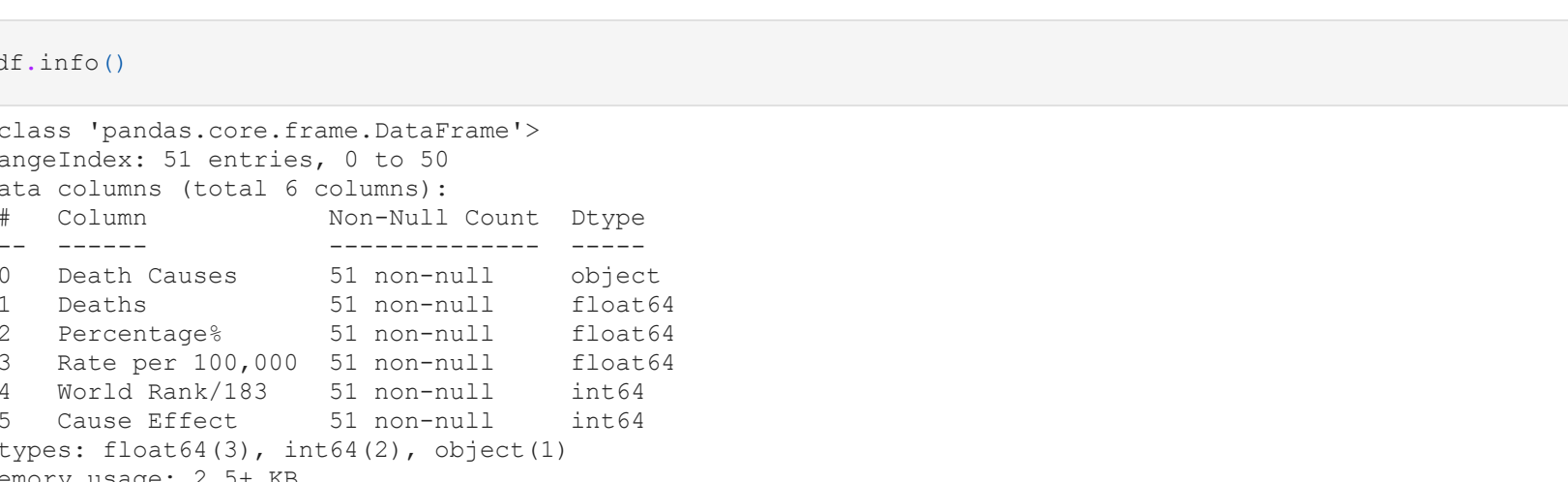
```python
def missing (df):
    missing_number = df.isnull().sum().sort_values(ascending=False)
    missing_percent = (df.isnull().sum()/df.isnull().count()).sort_values(ascending=False)
    missing_values = pd.concat([missing_number, missing_percent], axis=1, keys=['Missing_Number', 'Missing_Perc
    return missing_values

missing(df)
```

	Missing_Number	Missing_Percent
Cause Effect	0	0.0
World Rank/183	0	0.0
Rate per 100,000	0	0.0
Percentage%	0	0.0
Deaths	0	0.0
Death Causes	0	0.0

```python
msno.matrix(df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x1d1e73a3988>

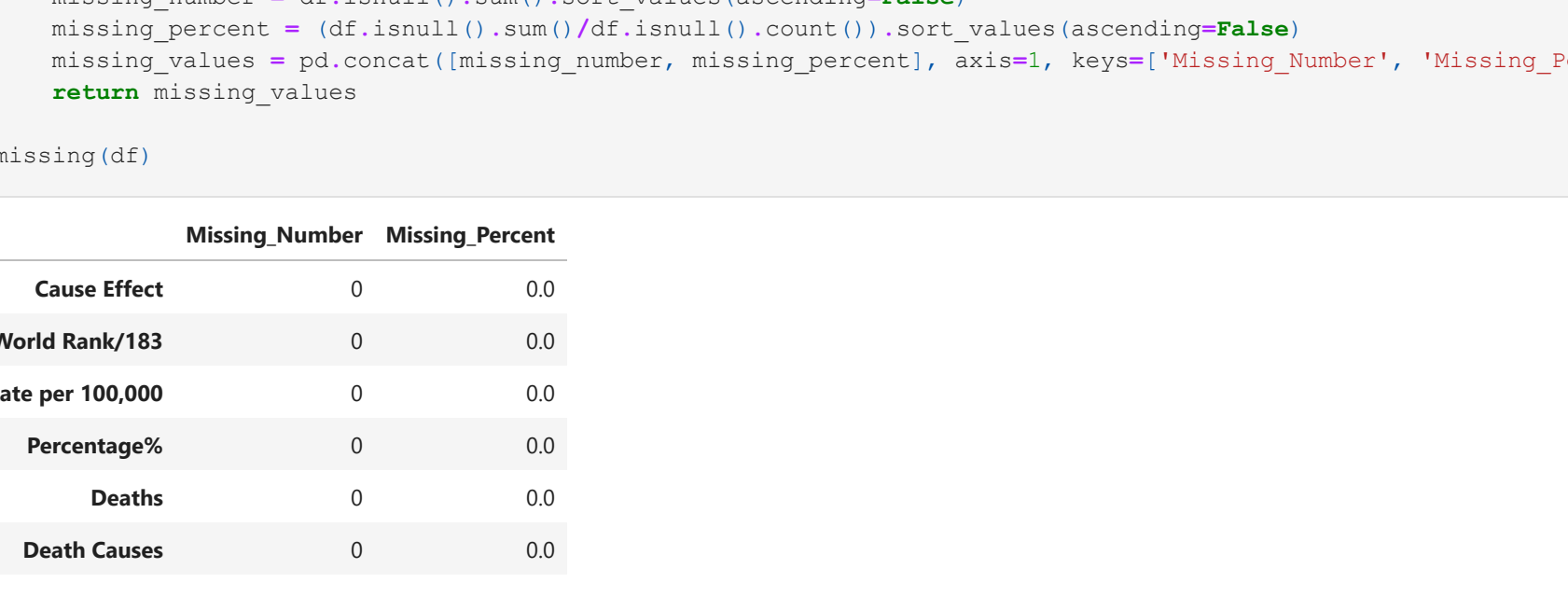



```python
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
Deaths	51.0	10722.275471	25346.977791	5.049	1334.500	3667.00	7071.50	163171.00
Percentage%	51.0	2.010196	4.552531	0.070	0.280	0.68	1.88	29.38
Rate per 100,000	51.0	23.040000	58.704917	0.560	2.125	5.19	11.08	308.00
World Rank/183	51.0	81.372549	46.926735	1.000	49.000	82.00	103.00	179.00
Cause Effect	51.0	0.137255	0.347540	0.000	0.000	0.00	0.00	1.00

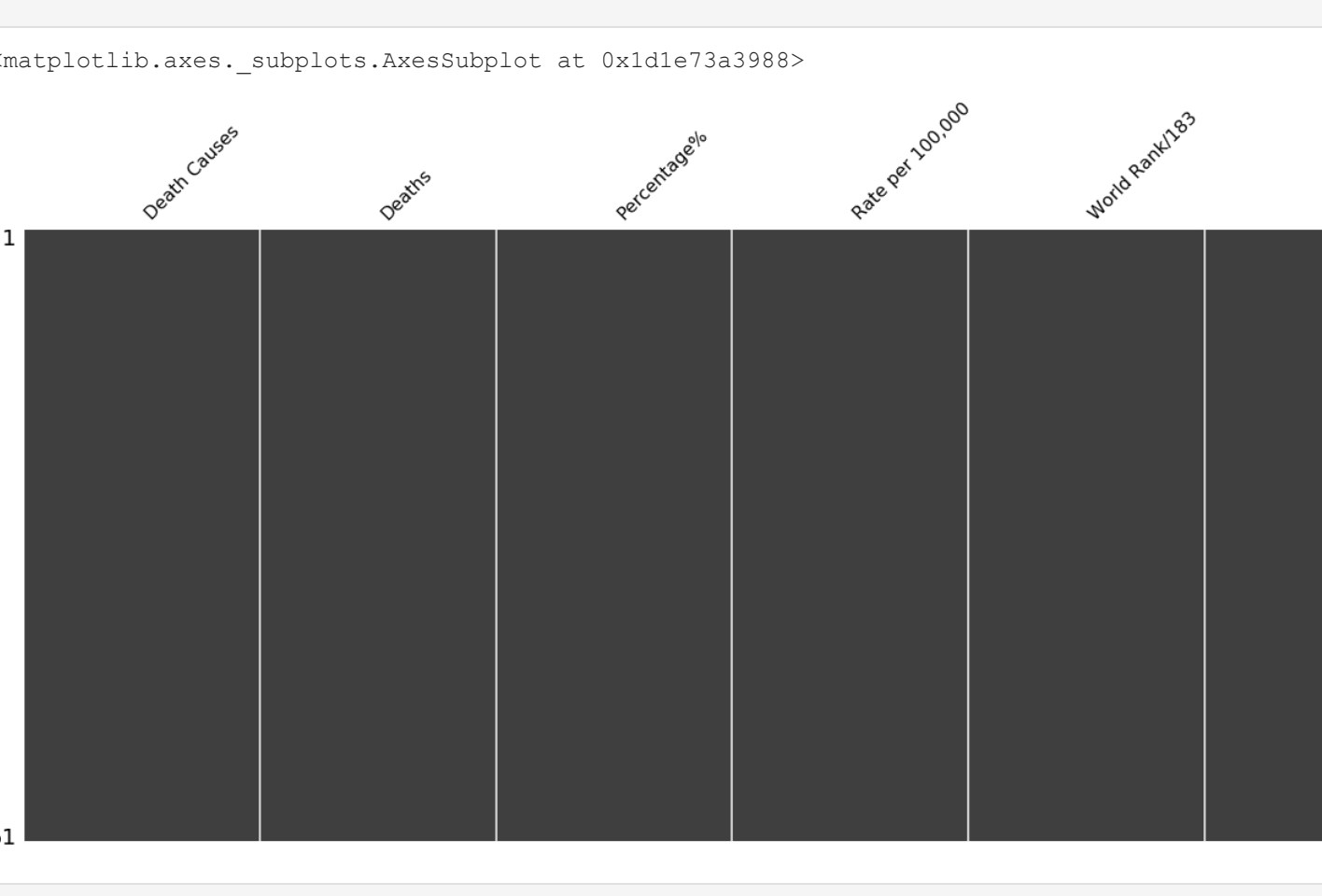
```python
df.describe().plot()
```

<matplotlib.axes._subplots.AxesSubplot at 0x1d1e74132c8>



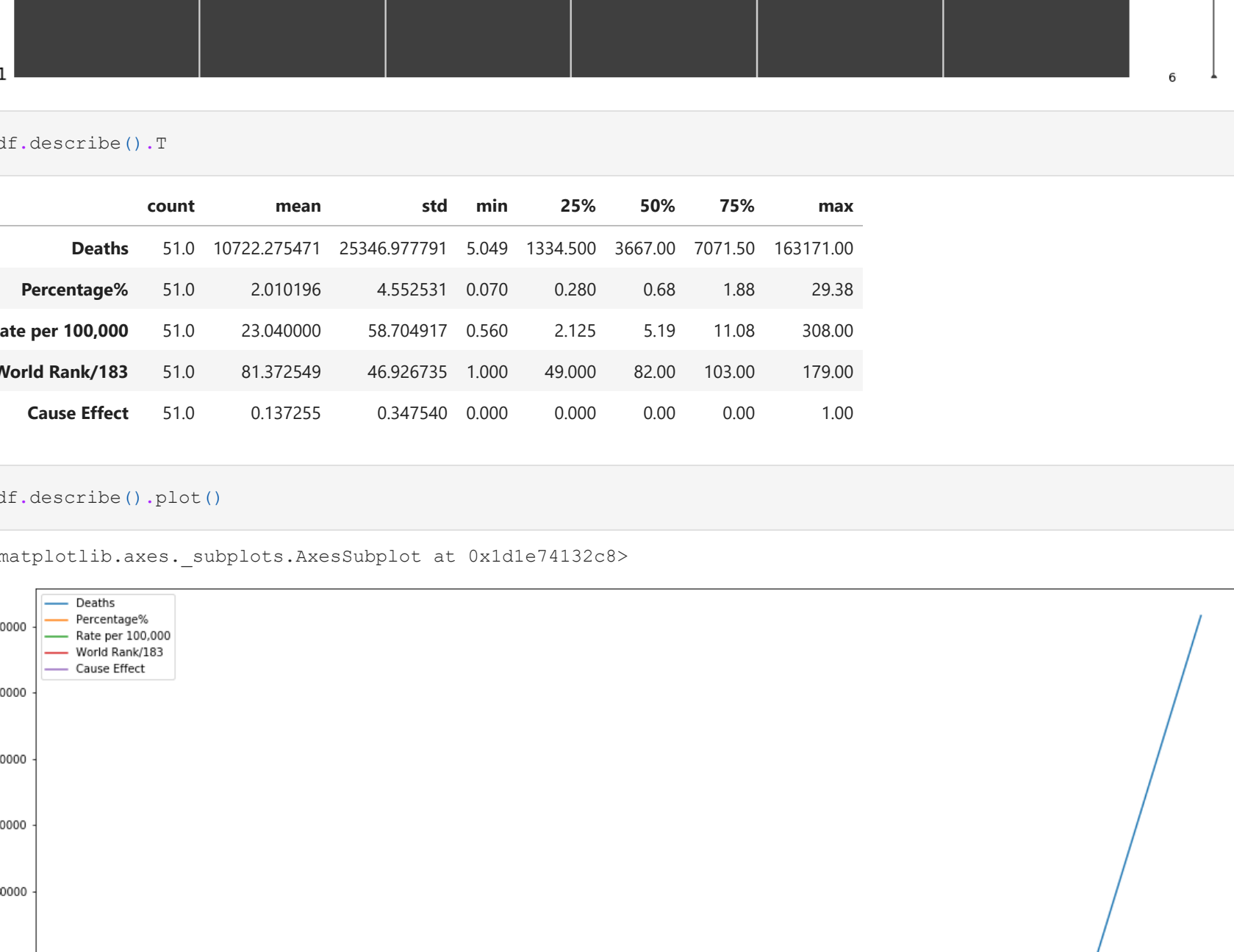

```python
sns.pairplot(df, hue='Rate per 100,000')
```

<seaborn.axisgrid.PairGrid at 0x1d1e76c08c8>

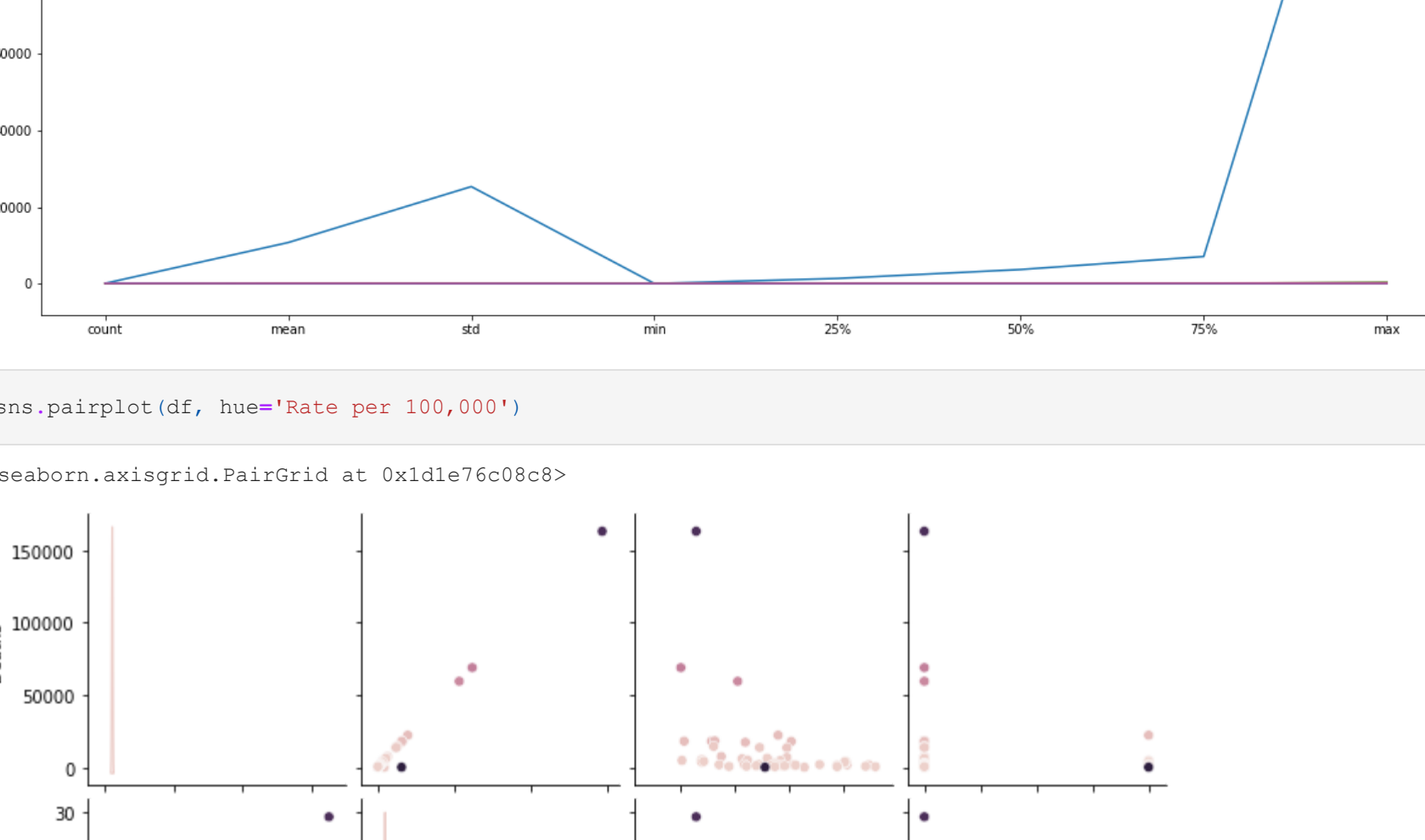



```python
sns.pairplot(df, kind='kde')
```

<seaborn.axisgrid.PairGrid at 0x1d1e066a448>




```python
df.hist(figsize=(15,8))
plt.show()
```




```python
px.treemap(df, path=['Percentage%','Deaths','Rate per 100,000'], values='Rate per 100,000')
```

```python
y = df['Cause Effect']
print(f"There is:  {round(y.value_counts(normalize=True)[1]*100,2)}%  --> ({y.value_counts()[1]} of the death I
```

```
There is:  13.73%  --> (7 of the death Leading Causes affect others)
While: 86.27%  --> (44 doesn't affect)
```

```python
df['Cause Effect'].iplot(kind='hist')
```

```python
numerical= df.select_dtypes('number').columns

categorical = df.select_dtypes('object').columns


print(f'Numerical Columns:  {df[numerical].columns}')
print('\n')
print(f'Categorical Columns: {df[categorical].columns}')
```

```
Numerical Columns:  Index(['Deaths', 'Percentage%', 'Rate per 100,000', 'World Rank/183',
       'Cause Effect'],
      dtype='object')


Categorical Columns: Index(['Death Causes'], dtype='object')
```

Target Variable

Numerical Features

```python
df[numerical].describe()
```

	Deaths	Percentage%	Rate per 100,000	World Rank/183	Cause Effect
count	51.000000	51.000000	51.000000	51.000000	51.000000
mean	10722.275471	2.010196	23.040000	81.372549	0.137255
std	25346.977791	4.552531	58.704917	46.926735	0.347540
min	5.049000	0.070000	0.560000	1.000000	0.000000
25%	1334.500000	0.280000	2.125000	49.000000	0.000000
50%	3667.000000	0.680000	5.190000	82.000000	0.000000
75%	7071.500000	1.880000	11.080000	103.000000	0.000000
max	163171.000000	29.380000	308.000000	179.000000	1.000000

```python
df[numerical].iplot(kind='hist');
```

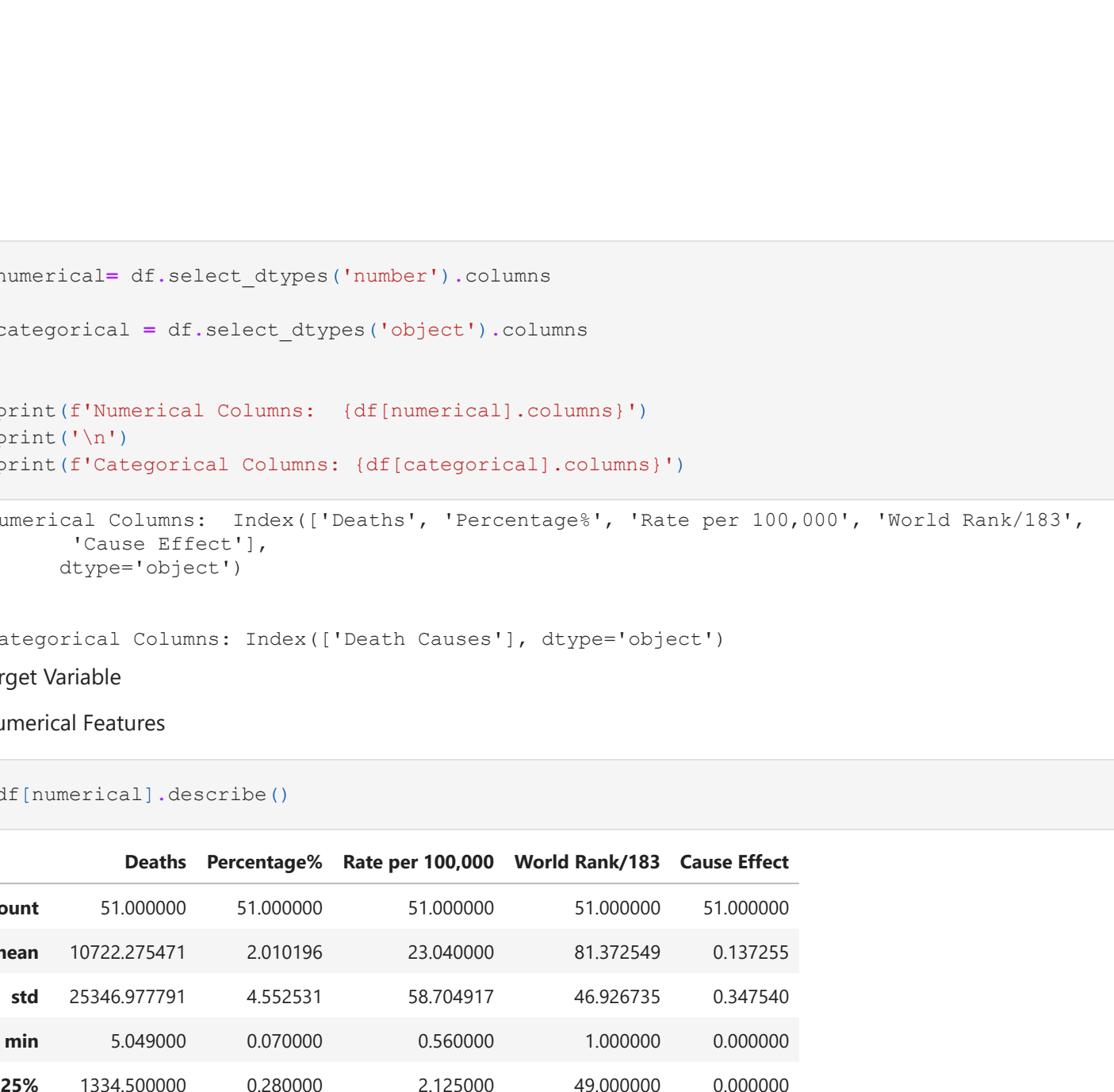
```python
df[numerical].iplot(kind='histogram',subplots=True,bins=50)
```

```python
skew_limit = 0.2 # This is our threshold-limit to evaluate skewness. Overall below abs(5) seems acceptable for
skew_vals = df[numerical].skew()
skew_cols= skew_vals[abs(skew_vals)> skew_limit].sort_values(ascending=False)
skew_cols
```

```
Deaths              4.901379
Percentage%         4.886697
Rate per 100,000    4.065901
Cause Effect        2.172703
World Rank/183      0.268354
dtype: float64
```

```python
numerical1= df.select_dtypes('number').columns


matrix = np.triu(df[numerical1].corr())
fig, ax = plt.subplots(figsize=(14,10))
sns.heatmap (df[numerical1].corr(), annot=True, fmt= '.2f', vmin=-1, vmax=1, center=0, cmap='coolwarm',mask=mat
```



Categorical Features

```python
df[categorical].head()
```

	Death Causes
0	Coronary Heart Disease
1	Liver Disease
2	Stroke
3	Alzheimers & Dementia
4	Kidney Disease

```python
df[categorical].describe()
```

	Death Causes
count	51
unique	51
top	Inflammatory/Heart
freq	1

```python
df[categorical].nunique()
```

```
Death Causes    51
dtype: int64
```

    So far so good. No zero variance and no extremely high variance compared with the high rate of data.

MODEL SELECTION

Prediction using Different Machine Learning Models

    first We'll use dummy Catboost module to hyperparameter tuning for Catboost

CATBOOST

```python
accuracy =[]
model_names =[]


X= df.drop('Cause Effect', axis=1)
y= df['Cause Effect']
categorical_features_indices = np.where(X.dtypes != np.float)[0]

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

model = CatBoostClassifier(verbose=False,random_state=0,
                          objective= 'CrossEntropy',
    colsample_bylevel= 0.04292240490294766,
    depth= 10,
    boosting_type= 'Plain',
    bootstrap_type= 'MVS')

model.fit(X_train, y_train,cat_features=categorical_features_indices,eval_set=(X_test, y_test))
y_pred = model.predict(X_test)
accuracy.append(round(accuracy_score(y_test, y_pred),4))
print(classification_report(y_test, y_pred))

model_names = ['Catboost_tuned']
result_df6 = pd.DataFrame({'Accuracy':accuracy}, index=model_names)
result_df6
```

```
              precision    recall  f1-score   support

           0       0.88      1.00      0.93        14
           1       0.00      0.00      0.00         2

    accuracy                           0.88        16
   macro avg       0.44      0.50      0.47        16
weighted avg       0.77      0.88      0.82        16
```

	Accuracy
Catboost_tuned	0.875

    second we will use sklearn.model_selection to get the Label Distributions:

```python
Rate = df['Cause Effect']
Percentage = df['Percentage%']


df.drop(['Cause Effect', 'Percentage%'], axis=1, inplace=True)
df.insert(0, 'Cause Effect', Rate)
df.insert(1, 'Percentage%', Percentage)


# Rate and Percentage are Scaled!

df.head()
```

	Cause Effect	Percentage%	Death Causes	Deaths	Rate per 100,000	World Rank/183
0	0	29.38	Coronary Heart Disease	163171.0	271.69	15
1	0	12.40	Liver Disease	68866.0	116.08	1
2	0	10.70	Stroke	59445.0	101.05	53
3	0	3.23	Alzheimers & Dementia	17957.0	36.09	29
4	0	3.29	Kidney Disease	18279.0	29.87	32

Splitting the Data (Original DataFrame)

```python
from sklearn.model_selection import train_test_split
from sklearn.model_selection import KFold, StratifiedKFold

print(round(df['Cause Effect'].value_counts()[0]/len(df) * 100,2), '% of the dataset are not contagious')
print(round(df['Cause Effect'].value_counts()[1]/len(df) * 100,2), '% of the dataset are contagious')

X = df.drop('Cause Effect', axis=1)
y = df['Cause Effect']

sss = StratifiedKFold(n_splits=5, random_state=None, shuffle=False)

for train_index, test_index in sss.split(X, y):
    print("Train:", train_index, "Test:", test_index)
    original_Xtrain, original_Xtest = X.iloc[train_index], X.iloc[test_index]
    original_ytrain, original_ytest = y.iloc[train_index], y.iloc[test_index]

# We already have X_train and y_train for undersample data thats why I am using original to distinguish and to
# original_Xtrain, original_Xtest, original_ytrain, original_ytest = train_test_split(X, y, test_size=0.2, ranc

# Check the Distribution of the labels


# Turn into an array
original_Xtrain = original_Xtrain.values
original_Xtest = original_Xtest.values
original_ytrain = original_ytrain.values
original_ytest = original_ytest.values

# See if both the train and test label distribution are similarly distributed
train_unique_label, train_counts_label = np.unique(original_ytrain, return_counts=True)
test_unique_label, test_counts_label = np.unique(original_ytest, return_counts=True)
print('-' * 100)

print('Label Distributions: \n')
print(train_counts_label/ len(original_ytrain))
print(test_counts_label/ len(original_ytest))
```

```
86.27 % of the dataset are not contagious
13.73 % of the dataset are contagious
Train: [10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 26 27 28 29 30 31 32 33 34
 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50] Test: [ 0  1  2  3  4  5  6  7  8  9 25]
Train: [ 0  1  2  3  4  5  6  7  8  9 19 20 21 22 23 24 25 26 27 28 29 31 32 33
 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50] Test: [10 11 12 13 14 15 16 17 18 30]
Train: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 25 29 30 31 32
 33 34 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50] Test: [19 20 21 22 23 24 26 27 28 35]
Train: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 30 35 40 42 43 44 45 46 47 48 49 50] Test: [29 31 32 33 34 36 37 38 39 41]
Train: [ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 16 17 18 19 20 21 22 23
 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 41] Test: [40 42 43 44 45 46 47 48 49 50]
----------------------------------------------------------------------------------------------------
Label Distributions:

[0.87804878 0.12195122]
[0.8 0.2]
```

Let's predict the increase of average rate using KNeighborsRegressor model

```python
# example of evaluating a knn model on the housing regression dataset
from pandas import read_csv
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_absolute_error
from sklearn.neighbors import KNeighborsRegressor

# load the dataset
df = read_csv('Leading Causes of Death in Egypt.csv', header=None)
data = df.values
X, y = data[:, :-1], data[:, -1]
print(X.shape, y.shape)
# split dataset
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
try:
    # define model
    model = KNeighborsRegressor()
    # fit model
    model.fit(X_train, y_train)
    # make predictions
    yhat = model.predict(X_test)
    # evaluate predictions
    mae = mean_absolute_error(y_test, yhat)
except ValueError:
    print('Mean Absolute Error (mae)')
    print('Rate Of Increase: %.3f' % mae,'%')
```

```
(52, 5) (52,)
(36, 5) (16, 5) (36,) (16,)
Mean Absolute Error (mae)
Rate Of Increase: 4.488 %
```

```python
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier
from sklearn import datasets
Accuracy = datasets.load_wine()
X = Accuracy.data
y = Accuracy.target
dtree = DecisionTreeClassifier()
Model_Accuracy = cross_val_score(dtree, X, y, scoring="accuracy").mean()
print('Model Accuracy:',Model_Accuracy *100, '%')
```

```
Model Accuracy: 86.52380952380952 %
```

important mention

This statistics had been recorded in 2018 from the WORLD HEALTH RANKINGS of the world life expectancy in details such as(world rank, percentage, rate and deaths) as we can see in the previous dataset, since the last recorded statics listed in 2020 with the Total cases rate only without any details as we can see in the following blank, Hence from the the previous and following statics of 2018 and 2020 we can check the module accuracy in a specific row only as an example:

Coronary Heart Disease in egypt in 2018: 271,690 cases as we saw earlier the model shown the Rate Of Increase as: 4.433 % so 4.433 of 271.690 = 12044.0177 cases

So, 12044.0177 + (271690 Last record state) = 283,734.0177 cases.

And the last recorded cases in 2020 for Coronary Heart Disease was 288,790 cases, which is almost nearly expectation record between the model and the real recorded cases as the model has a 86.52% of Accuracy.

Coronary Heart Disease 288,790 Liver Disease 121,883 Stroke 105,209 Influenza and Pneumonia 39,130 Kidney Disease 32,350 Liver Cancer 31,873 Alzheimers & Dementia 31,781 Diabetes Mellitus 31,593 Lung Disease 30,520 Low Birth Weight 24,134 Road Traffic Accidents 23,848 COVID-19 17,545 Breast Cancer 13,086 Hypertension 11,944 Birth Trauma 10,974 Lymphomas 9,144 Lung Cancers 8,936 Endocrine Disorders 8,719 Bladder Cancer 8,375 Violence 8,177 Diarrhoeal diseases 7,917 Leukemia 7,159 Suicide 6,724 Inflammatory/Heart 6,501 Other Neoplasms 6,355 Colon-Rectum Cancers 5,042