```
In [155...
          import pandas as pd
          from sklearn.model selection import train test split
          from sklearn.ensemble import RandomForestClassifier
          from sklearn import metrics
          import seaborn as sn
          import matplotlib.pyplot as p
           import matplotlib.pyplot as plt
           import seaborn as sns
          %matplotlib inline
          import numpy as np
           from numpy import math
          from sklearn.model selection import train test split
          from sklearn.linear_model import LinearRegression
           from sklearn.metrics import r2 score
           from sklearn.metrics import mean squared error
          import matplotlib.pyplot as plt
          import seaborn as sns
          %matplotlib inline
In [156...
          data_scaled.head()
                                             3
Out[156...
          0 -1.688194 -1.283841 -1.040015 -1.921745 -2.012674 -2.265684 -2.045899 1.924965
                                                                                   0.156393
                                                                                           0.790569
          1 -1.599342 -0.957113 -1.109625 -1.632743 -1.166557 -2.166566 -0.640595 0.517334 -0.061440
                                                                                           0.790569
          2 -1.510490 -1.067904 -1.072393 -0.767781 -1.200402 -1.848324 -1.265175 0.204528
                                                                                   1.463390 -1.264911
          3 -1.421637 -0.957951 -0.813364 -0.649612 -1.196171 -1.485358 -1.109030 0.830141
                                                                                   0.374226
                                                                                            0.790569
          4 -1.332785 -1.019325 -0.599586 -0.073184 -1.416162 -1.087486 -1.733610 1.142948
                                                                                   1.681223 0.790569
In [157...
          data_scaled['class'] = df.target
          AttributeError
                                                      Traceback (most recent call last)
          <ipython-input-157-70fe323a6b93> in <module>
          ----> 1 data_scaled['class'] = df.target
          ~\anaconda3\lib\site-packages\pandas\core\generic.py in __getattr__(self, name)
             5463
                               if self. info axis. can hold identifiers and holds name(name):
             5464
                                   return self[name]
          -> 5465
                               return object. getattribute (self, name)
             5466
             5467
                      def __setattr__(self, name: str, value) -> None:
          AttributeError: 'DataFrame' object has no attribute 'target'
In [158...
          df = pd.read_csv("d.csv")
          print (df)
              year agriculture industries services
                                                          GGRP
          0
              2012
                          76123
                                      104218
                                                209540
                                                         12.00
                         150200
              2013
                                       92458
                                                265878 14.00
              2014
                         125081
                                       98748
                                                434494 13.92
              2015
                         150010
                                      142509
                                                457530
         3
                                                         13.93
              2016
                         136095
                                      178625
                                                569899
                                                         13.41
          5
                         144803
                                      222031
                                                598520 13.49
              2017
          6
              2018
                         176107
                                      185890
                                                616374 14.76
              2019
                         230424
                                      125456
                                                315256
                                                         14.25
         8
              2020
                         325123
                                      312522
                                                658123
                                                         14.58
                         450222
                                      325456
                                                752963 14.25
         9
              2021
          10
             2022
                         545486
                                      456963
                                                754963 14.47
          11
             2023
                         325123
                                      252156
                                                645856
                                                         15.47
          12
             2024
                         325478
                                      212123
                                                445456
                                                         15.47
          13
             2025
                         125456
                                      123342
                                                345587 15.68
          14
             2026
                         454222
                                      345477
                                                558647 15.47
          15
              2027
                         214569
                                      212547
                                                345798
                                                         15.98
          16
             2028
                         125456
                                      121547
                                                314547
                                                         15.34
          17
             2029
                         456321
                                      314214
                                                478458 16.58
          18
             2030
                         125693
                                      114458
                                                254478 16.47
          19
              2031
                         325489
                                      214578
                                                547987
                                                         17.45
                                                614789 14.68
          20
             2032
                         456189
                                      347458
          21
              2033
                         345666
                                      214547
                                                612478 17.15
                                                812487 17.59
                         615235
          22
              2034
                                      412457
```

721587 17.56

```
125478 612478 17.78
            154236
25 2037
                        421547 824145 18.57
521478 921457 18.54
26
   2038
             752963
27
   2039
            815856
28 2040
            641523
                        512478 725458 18.78
                               947125 18.98
29
   2041
            915236
                        712687
            521326
456282
                               614798 19.12
512698 19.65
30
   2042
                       412478
31
   2043
                        345789
                      512358 725894 19.65
32 2044
            614236
                               514654 19.47
33 2045
            125123
                        111547
             215236
34
   2046
                        125145
                                 514364
                                        19.58
                                 812749 20.12
35
   2047
             452456
                        345795
36
   2048
             325456
                        245794
                               412789 20.36
   2049
             912156
                        812547
                               987215 20.45
37
                               812457 20.56
38
   2050
             325456
                        245784
    increased GSDP growth(crores) COA COI COS target increase growth
0
                         552854
                                14
                                     26
                                         60
                                                  1
                                                               2.3
1
                         577902
                                 23
                                     17
                                          59
                                                               -1.2
2
                         658325
                                 19
                                     15
                                          66
                                                  0
                                                               -1.6
                         750050
                                 20
                                     19 61
                                                               2.6
                         850596
                                     21 67
4
                                 16
                                                  1
                                                               3.2
                         965355
                                 15
                                     23
                                          62
                                                  0
                                     19 63
                                                               2.1
                         978373
                                 18
6
                                                  1
                         945231
                                 20
                                                               -4.5
                                     20
                         934634
                                 18
                                                  1
                                                               2.0
8
                                          62
9
                         934653
                                 30
                                     20
                                          50
                                                  0
                                                               -6.0
                                     22
                         934876
                                 25
                                          53
                                                               3.6
10
                                                  1
                        1012343 26
11
                                                               2.0
                        1023432
                                     14 57
16 54
12
                                29
                                                  0
                                                              -5.6
13
                        1043432
                                 30
                                                  1
                                                               2.3
                                     16
                                     9 58
14
                        943234
                                33
                                                  1
                                                               2.6
15
                        1043634 26
                                    15 59
                                                  0
                                                              -3.0
                                     14 64
                         954345 22
                                                  0
16
                                                               -5.3
17
                        1123432
                                 31
                                      4
                                          65
                                                  0
                                                               -6.0
                                     3 62
                        1520236
18
                                 35
                                                               6.0
                                                  1
19
                        1134876 28
                                                  0
                                                               -4.0
                                    11
                        912754
20
                                 23
                                     14 63
                                                  0
                                                               -3.0
21
                        1134876
                                 28
                                      5
                                          67
                                                  0
                                                               -2.3
22
                        1256345
                                 25
                                     16 59
                                                               6.0
                                                  1
23
                        1298689
                                 27
                                     18
                                          55
                                                  0
                                                               -4.0
24
                        1287957
                                 26
                                     23
                                          51
                                                  1
                                                               3.0
25
                        1276987
                                 21
                                     20
                                          59
                                                  1
                                                               4.0
                        1289565
                                     16
                                                               3.0
26
                                 32
                                          52
                                                  1
27
                        1252564 34
                                     13 53
                                                  0
                                                               -6.0
                                     14
12
                        1376965
28
                                 29
                                          57
                                                               4.0
                                                  1
                                          53
                        1356345
                                                               3.0
29
                                 35
                                                  1
30
                        1345653 33
                                     8 59
                                                               4.0
                                                  1
31
                        1389567 27
                                    12 61
                                                  0
                                                               -8.0
                                     5 67
5 63
                        1398348
                                 28
                                                               4.0
32
                                                  1
33
                        1368947
                                 32
                                      5
                                          63
                                                  1
                                                               6.0
                                     3 59
                        1345764
                                                               4.0
34
                                 38
                                                  1
35
                        1398064
                                 36
                                     1 63
                                                  1
                                                               5.0
36
                        1355765
                                 35
                                     11
                                          54
                                                  0
                                                               -4.0
37
                        1465736
                                 35
                                     12
                                          53
                                                  1
                                                               6.0
                        1498457
                                 35
                                          61
                                                               7.0
```

24 2036

y_pred=classifier.predict(X_test)

512478 17.98

```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
X_train=sc.fit_transform(X_train)
X_test=sc.transform(X_test)
#fit logistic regression to the training set
from sklearn.linear_model import LogisticRegression
classifier=LogisticRegression(random_state = 0)
classifier.fit(X_train, y_train)
#predict the test set results
```

C:\Users\Moulya Janjarla\anaconda3\lib\site-packages\sklearn\utils\validation.py:63: DataConversionWarning: A col
umn-vector y was passed when a 1d array was expected. Please change the shape of y to (n_samples,), for example
using ravel().
 return f(*args, **kwargs)

```
accept_large_sparse=solver != 'liblinear')
             1346
                           check classification_targets(y)
          -> 1347
             1348
                           self.classes_ = np.unique(y)
             1349
          ~\anaconda3\lib\site-packages\sklearn\utils\multiclass.py in check_classification_targets(y)
                       181
              182
                           raise ValueError("Unknown label type: %r" % y_type)
          --> 183
              184
               185
          ValueError: Unknown label type: 'continuous'
In [160...
          X = df[['GGRP','target','COS','COI','COA']]
           v = df['target']
           X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train}_{\text{test}}, split(X, y, \text{test}_{\text{size}}=0.25, \text{random}_{\text{state}}=0)
In [161...
           #loading the data
           x = data_scaled.iloc[:,0:9]
           y = data_scaled.iloc[:,9:10]
In [162...
           clf = RandomForestClassifier(n estimators=20)
           clf.fit(X_train,y_train)
Out[162... RandomForestClassifier(n estimators=20)
In [163...
           y_pred=clf.predict(X_test)
In [164...
           #generate confusion matrix
           print('Accuracy: ', 100 * metrics.accuracy_score(y_test, y_pred))
group_names = ['True Negative','False Positive','False Negative','TruePositive']
           labels = [f'{v1}' for v1 in zip(group_names)]
           confusion_matrix = pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Predicted'])
           sn.heatmap(confusion_matrix, annot=True)
          Accuracy: 100.0
Out[164... <AxesSubplot:xlabel='Predicted', ylabel='Actual'>
                                           0
                                           9
                        ò
                              Predicted
In [165...
           print (X_test)
               GGRP target COS COI
                                          COA
              13.41
                           1
                              67
                                     21
                                           16
          28 18.78
                                57
                                           29
                           1
                                     14
```

 $$$ \sim \alpha_3 \le \beta_x \le \beta_x$

10 y_pred=classifier.predict(X_test)

29

10

18.98

14.47

33 19.47

34 19.58

25 17.78

53

63

59

59

1

1

1 53

12

5

20

22

35

32

38

21

25

```
    22
    17.59
    1
    59
    16
    25

    11
    15.47
    1
    60
    14
    26

    27
    18.54
    0
    53
    13
    34

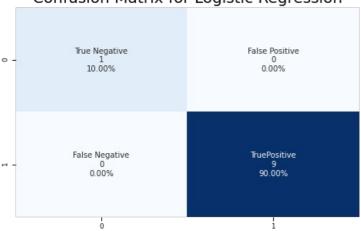
In [166...
            print(y pred)
           [1 1 1 1 1 1 1 1 1 0]
In [167...
            from sklearn import metrics
            print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pred))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred))
            print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test, y_pred)))
           Mean Absolute Error: 0.0
           Mean Squared Error: 0.0
           Root Mean Squared Error: 0.0
In [168...
            from sklearn.svm import SVC
            svc = SVC(kernel = 'rbf')
            svc.fit(X_train,y_train)
Out[168... SVC()
In [169...
           from sklearn.metrics import confusion_matrix
            y_pred_RSVM = svc.predict(X_test)
            cm = confusion_matrix(y_test,y_pred_RSVM)
            print('confusion matrix:\n',cm)
           confusion matrix:
            [[0 1]
            [0 9]]
In [170...
            from sklearn.metrics import accuracy_score
            sva2 = accuracy_score(y_test,y_pred_RSVM)
print('accuracy_score = ',sva2)
           accuracy score = 0.9
In [171_ from sklearn.preprocessing import StandardScaler
            sc = StandardScaler()
            X_train = sc.fit_transform(X_train)
            X test = sc.transform(X test)
In [172...
            from sklearn.linear_model import LogisticRegression
            lr = LogisticRegression()
            lr.fit(X train,y train)
Out[172... LogisticRegression()
In [173...
            from sklearn.metrics import confusion matrix
            y_pred_log = lr.predict(X_test)
            cm = confusion_matrix(y_test,y_pred_log)
            print('confusion matrix:\n',cm)
            #generate confusion matrix
            cm = confusion_matrix(y_test, y_pred)
            group_names = ['True Negative', 'False Positive', 'False Negative', 'TruePositive']
            group_counts = ['{0:0.0f}'.format(value) for value in cm.flatten()]
            group_percentages = ['{0:.2%}'.format(value) for value in cm.flatten()/np.sum(cm)]
labels = [f'{v1}\n{v2}\n{v3}' for v1, v2, v3 in zip(group_names,group_counts,group_percentages)]
            labels = np.asarray(labels).reshape(2,2)
            sns.heatmap(cm, annot = labels, fmt = '', cmap='Blues', cbar = False)
            plt.gcf().set_size_inches(8,5)
```

```
plt.title('Confusion Matrix for Logistic Regression', fontsize = 20)
plt.show()
```

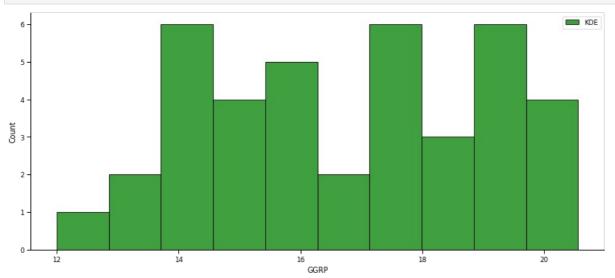
confusion matrix:
 [[1 0]

[0 9]]

Confusion Matrix for Logistic Regression



```
sns.displot(df['GGRP'],bins=10,color='green',label='KDE')
plt.legend()
plt.gcf().set_size_inches(12,5)
```



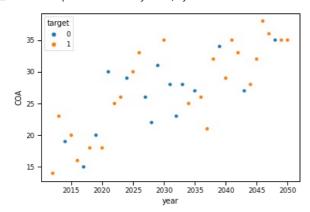
In [116... df.describe()

Out[116		year	agriculture	industries	services	GGRP	increased GSDP growth(crores)	COA	COI	cos	target	incre gro
	count	39.000000	39.000000	39.000000	39.000000	39.000000	3.900000e+01	39.000000	39.000000	39.000000	39.000000	39.000
	mean	2031.000000	367199.871795	279920.256410	584165.487179	16.757436	1.125414e+06	27.102564	13.692308	59.282051	0.615385	0.512
	std	11.401754	229687.253443	171150.469612	197488.656473	2.394638	2.560132e+05	6.488025	6.477304	4.650686	0.492864	4.327
	min	2012.000000	76123.000000	92458.000000	209540.000000	12.000000	5.528540e+05	14.000000	1.000000	50.000000	0.000000	-8.000
	25%	2021.500000	152218.000000	125467.000000	451493.000000	14.630000	9.442325e+05	22.500000	10.000000	56.000000	0.000000	-3.600
	50%	2031.000000	325456.000000	222031.000000	598520.000000	16.580000	1.134876e+06	28.000000	14.000000	60.000000	1.000000	2.300
	75%	2040.500000	456423.000000	346626.500000	725676.000000	18.880000	1.350764e+06	32.500000	19.000000	62.500000	1.000000	4.000
	max	2050.000000	915236.000000	812547.000000	987215.000000	20.560000	1.520236e+06	38.000000	26.000000	67.000000	1.000000	7.000

```
In [177... sns.violinplot(data=df,x='target',y='GGRP')
```

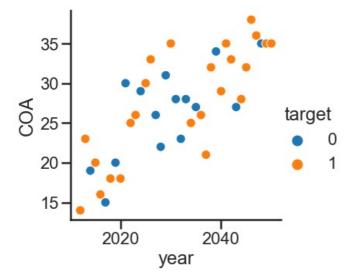
```
sns.set_context("paper")
sns.scatterplot(x='year', y='COA',data=df, hue='target')
```

Out[180... <AxesSubplot:xlabel='year', ylabel='COA'>



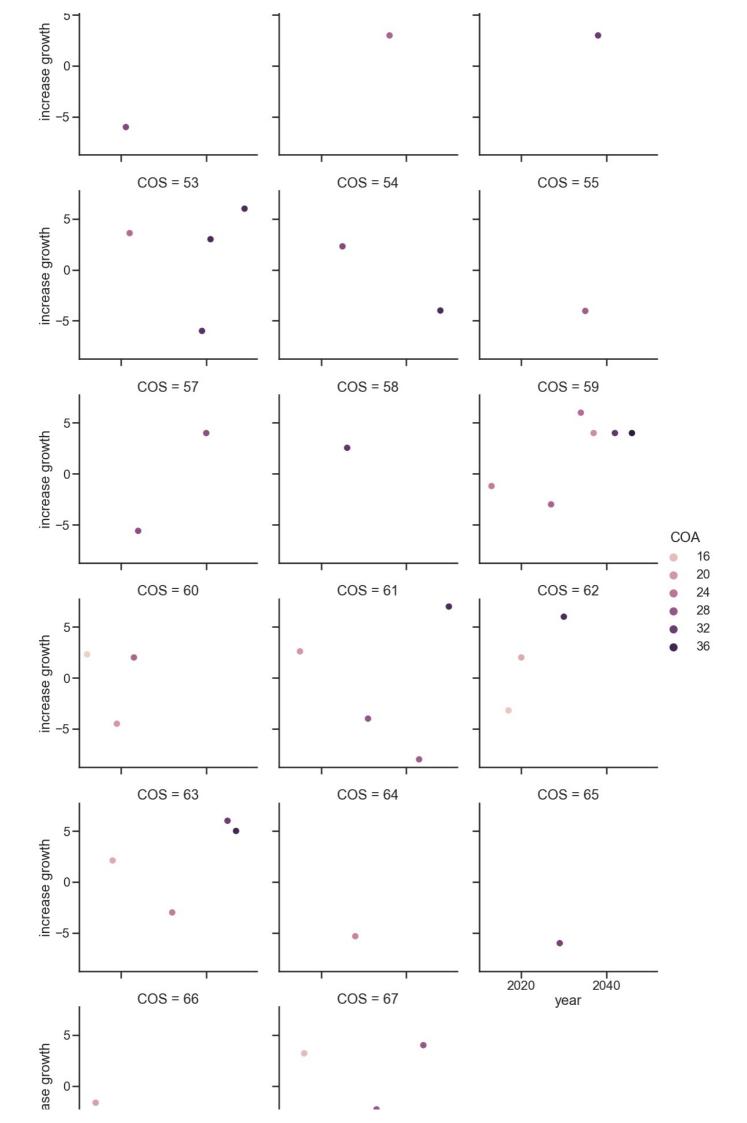
```
#Generate relation ship plot between contribution of agriculture and target sns.set_context("poster") sns.relplot(data=df, x='year', y='COA', hue='target')
```

Out[196... <seaborn.axisgrid.FacetGrid at 0x1ff31d5fd90>

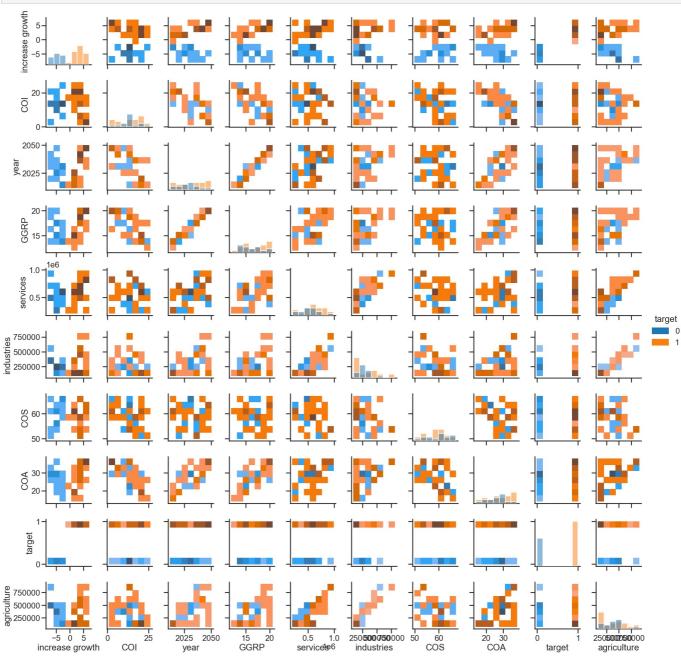


```
sns.set_context("poster")
sns.relplot(data=df, x='year', y='increase growth',hue='COA',col='COS',col_wrap=3)
```

Out[197... <seaborn.axisgrid.FacetGrid at 0x1ff2ded3f10>

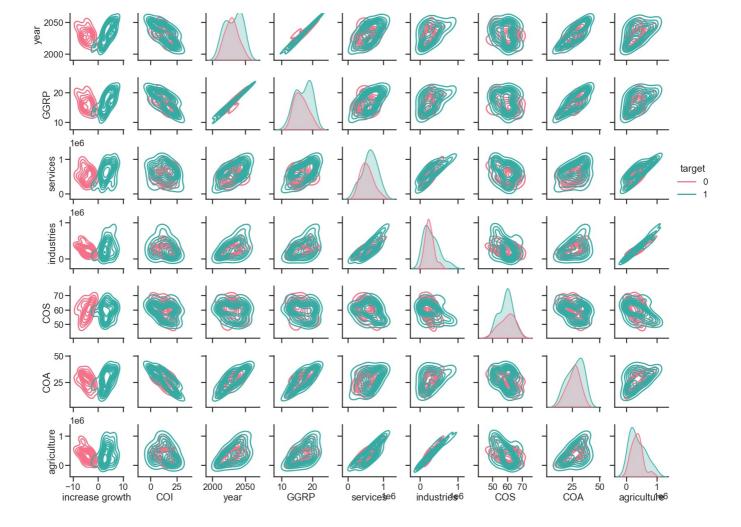


In [198...
sns.set_style("ticks")
sns.pairplot(df,x_vars={"year","agriculture","industries","services","GGRP","COA","COI","COS","target","increase
plt.show()



sns.set_style("ticks")
sns.pairplot(df,x_vars={"year","agriculture","industries","services","GGRP","COA","COI","COS","increase growth"},
plt.show()

25



In []:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js