Title: Autism Screening Adult Data Set

Informations :

```
Number of Instances:704

Attribute Characteristics: Integer

Number of Attributes:21

Date Donated 2017-12-24

Associated Tasks: Classification

Missing Values? Yes

Number of Web Hits: 84051
```

Dataset Content :

```
     Attribute                         Domain

    1. A1_Score                       {0,1}
    2. A2_Score                       {0,1}
    3. A3_Score                       {0,1}
    4. A4_Score                       {0,1}
    5. A5_Score                       {0,1}
    6. A6_Score                       {0,1}
    7. A7_Score                       {0,1}
    8. A8_Score                       {0,1}
    9. A9_Score                       {0,1}
   10. A10_Score                      {0,1}
   11. age                            numeric
   12. gender                         {f,m}
   13. ethnicity                      {White-
European,Latino,Others,Black,Asian,'Middle Eastern
',Pasifika,'South asian',Hispanic,Turkish,others}
   14.jundice                         {no,yes}
   15.austim                          {no,yes}
   16.contry_of_res                   {'United
States',Brazil,Spain,Egypt,'New
Zealand',Bahamas,Burundi,Austria,Argentina,Jordan,Ireland,'United
 Arab Emirates',Afghanistan,Lebanon,'United Kingdom','South
Africa',Italy,Pakistan,Bangladesh,Chile,France,China,Australia,Canada,

Arabia',Netherlands,Romania,Sweden,Tonga,Oman,India,Philippines,'Sri
 Lanka','Sierra Leone',Ethiopia,'Viet Nam',Iran,'Costa
Rica',Germany,Mexico,Russia,Armenia,Iceland,Nicaragua,'Hong
Kong',Japan,Ukraine,Kazakhstan,AmericanSamoa,Uruguay,Serbia,Portugal,M
 Republic',Cyprus}
   17.used_app_before                 {no,yes}
   18.result                          numeric
   19.age_desc                        {'18 and more'}
   20.relation                        {Self,Parent,'Health care
```

```
professional',Relative,Others}
  21.Class/ASD                        {NO,YES}
```

Dataset Description

```
Feature : Description
index : The participant's ID number
AX_Score: Score based on the Autism Spectrum Quotient (AQ) 10
item screening tool AQ-10
age : Age in years
gender : Male or Female
ethnicity: Ethnicities in text form
jaundice : Whether or not the participant was born with
jaundice?
austsm : Whether or not anyone in tbe immediate family has been
diagnosed with autism?
country_of_res : Countries in text format
used_app_before : Whether the participant has used a screening
app
result  Score from the AQ-10 screening tool
age_desc : Age as categorical
relation : Relation of person who completed the test
Class/ASD : Participant classification
```

Importing Libraries

In [45]:

```python
# For dataframe and visualization
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from scipy.io import arff

# Processing data
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler

# Prepare Data for classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, accuracy_score


# Classification
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn import metrics
from sklearn.metrics import mean_absolute_error

# Comparing Classification
from sklearn.metrics import RocCurveDisplay
```

Reading Data

In [46]:

```python
# Load dataset
```

```
dataset = pd.read_table('Autism-Adult-Data.arff', sep = ',')
```

In [47]:

```
df = dataset.copy()
```

In [48]:

```
# Rename columns
df.columns = ['A1_Score','A2_Score','A3_Score','A4_Score','A5_Score','A6_Scor
```

In [49]:

```
df.head()
```

Out[49]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A8_Score	A9_Scc
0	1	1	0	1	0	0	0	1	
1	1	1	0	1	1	0	1	1	
2	1	1	0	1	0	0	1	1	
3	1	0	0	0	0	0	0	1	
4	1	1	1	1	1	0	1	1	

5 rows × 21 columns

In [50]:

```
df.index #Describe index
```

Out[50]:

```
RangeIndex(start=0, stop=703, step=1)
```

In [51]:

```
df.shape
```

Out[51]:

```
(703, 21)
```

In [52]:

```
df.count() #Number of non-NA values
```

Out[52]:

```
A1_Score           703
A2_Score           703
A3_Score           703
A4_Score           703
A5_Score           703
A6_Score           703
A7_Score           703
A8_Score           703
A9_Score           703
A10_Score          703
age                703
gender             703
ethnicity          703
jundice            703
austim             703
contry_of_res      703
used_app_before    703
resultnumeric      703
age_desc           703
relation           703
```

```
Class/ASD          703
dtype: int64
```

Feature Engineering

In [53]:

```
df.info() #Info on DataFrame
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 703 entries, 0 to 702
Data columns (total 21 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   A1_Score         703 non-null    int64
 1   A2_Score         703 non-null    int64
 2   A3_Score         703 non-null    int64
 3   A4_Score         703 non-null    int64
 4   A5_Score         703 non-null    int64
 5   A6_Score         703 non-null    int64
 6   A7_Score         703 non-null    int64
 7   A8_Score         703 non-null    int64
 8   A9_Score         703 non-null    int64
 9   A10_Score        703 non-null    int64
 10  age              703 non-null    object
 11  gender           703 non-null    object
 12  ethnicity        703 non-null    object
 13  jundice          703 non-null    object
 14  austim           703 non-null    object
 15  contry_of_res    703 non-null    object
 16  used_app_before  703 non-null    object
 17  resultnumeric    703 non-null    int64
 18  age_desc         703 non-null    object
 19  relation         703 non-null    object
 20  Class/ASD        703 non-null    object
dtypes: int64(11), object(10)
memory usage: 115.5+ KB
```

Some columns are object and some of them has string Yes or No, we need to replace them to boolean (0, 1)

In [54]:

```
# Replace columns with number
df = df.replace("yes", 1)
df = df.replace("no", 0)
df = df.replace("YES", 1)
df = df.replace("NO", 0)
df = df.replace("f", 1)
df = df.replace("m", 0)
```

In [55]:

```
df.info() #Info on DataFrame
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 703 entries, 0 to 702
Data columns (total 21 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   A1_Score         703 non-null    int64
 1   A2_Score         703 non-null    int64
 2   A3_Score         703 non-null    int64
 3   A4_Score         703 non-null    int64
 4   A5_Score         703 non-null    int64
 5   A6_Score         703 non-null    int64
 6   A7_Score         703 non-null    int64
 7   A8_Score         703 non-null    int64
 8   A9_Score         703 non-null    int64
 9   A10_Score        703 non-null    int64
```

```
 10  age              703 non-null    object
 11  gender           703 non-null    int64
 12  ethnicity        703 non-null    object
 13  jundice          703 non-null    int64
 14  austim           703 non-null    int64
 15  contry_of_res    703 non-null    object
 16  used_app_before  703 non-null    int64
 17  resultnumeric    703 non-null    int64
 18  age_desc         703 non-null    object
 19  relation         703 non-null    object
 20  Class/ASD        703 non-null    int64
dtypes: int64(16), object(5)
memory usage: 115.5+ KB
```

In [56]:

```
# Show missing values
MissingValues = {col:df[df[col] == "?"].shape[0] for col in df.columns}
MissingValues
```

Out[56]:

```
{'A1_Score': 0,
 'A2_Score': 0,
 'A3_Score': 0,
 'A4_Score': 0,
 'A5_Score': 0,
 'A6_Score': 0,
 'A7_Score': 0,
 'A8_Score': 0,
 'A9_Score': 0,
 'A10_Score': 0,
 'age': 2,
 'gender': 0,
 'ethnicity': 95,
 'jundice': 0,
 'austim': 0,
 'contry_of_res': 0,
 'used_app_before': 0,
 'resultnumeric': 0,
 'age_desc': 0,
 'relation': 95,
 'Class/ASD': 0}
```

Replace '?' values of Age by mean

In [57]:

```
# Replace '?' values by NaN
for j in range(df.shape[0]):
    if(df.iloc[j,10]=='?'):
        df.iloc[j,10]=np.NaN
```

In [58]:

```
# Reaplace NaN value by mean
df.fillna(df.mean(), inplace= True)
```

Replace '?' values of ethnicity by 'Others' and 'others' by 'Others'

In [59]:

```
# There is values that are the same : '?', 'Others' and 'others'
df['ethnicity'].unique()
```

Out[59]:

```
array(['Latino', 'White-European', '?', 'Others', 'Black', 'Asian',
       "'Middle Eastern '", 'Pasifika', "'South Asian'", 'Hispanic',
       'Turkish', 'others'], dtype=object)
```

In [60]:

```
# Replace '?' with 'others'
df['ethnicity'] = df['ethnicity'].replace('?', 'others')
```

In [61]:
```
# Replace '?' with 'Others'
df['ethnicity'] = df['ethnicity'].replace('others', 'Others')
```

In [62]:
```
# Every missing values are now as 'Others'
df['ethnicity'].unique()
```

Out[62]:
```
array(['Latino', 'White-European', 'Others', 'Black', 'Asian',
       "'Middle Eastern '", 'Pasifika', "'South Asian'", 'Hispanic',
       'Turkish'], dtype=object)
```

Replace '?' values of relation by a mode of relation

In [63]:
```
# Here we only have '?' as missing values
df['relation'].unique()
```

Out[63]:
```
array(['Self', 'Parent', '?', "'Health care professional'", 'Relative',
       'Others'], dtype=object)
```

In [64]:
```
# Replace the missing value with modal value of the columns
df['relation'] = df['relation'].replace('?', df['relation'].mode()[0])
```

In [65]:
```
# Show results
df['relation'].unique()
```

Out[65]:
```
array(['Self', 'Parent', "'Health care professional'", 'Relative',
       'Others'], dtype=object)
```

In [66]:
```
# No more missing values !
df.isnull().sum() #Number of NA values
```

Out[66]:
```
A1_Score           0
A2_Score           0
A3_Score           0
A4_Score           0
A5_Score           0
A6_Score           0
A7_Score           0
A8_Score           0
A9_Score           0
A10_Score          0
age                2
gender             0
ethnicity          0
jundice            0
austim             0
contry_of_res      0
used_app_before    0
resultnumeric      0
age_desc           0
relation           0
Class/ASD          0
dtype: int64
```

In [67]:
```
# Now every columns has the right type
df.info() #Info on DataFrame
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 703 entries, 0 to 702
Data columns (total 21 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   A1_Score         703 non-null    int64 
 1   A2_Score         703 non-null    int64 
 2   A3_Score         703 non-null    int64 
 3   A4_Score         703 non-null    int64 
 4   A5_Score         703 non-null    int64 
 5   A6_Score         703 non-null    int64 
 6   A7_Score         703 non-null    int64 
 7   A8_Score         703 non-null    int64 
 8   A9_Score         703 non-null    int64 
 9   A10_Score        703 non-null    int64 
 10  age              701 non-null    object
 11  gender           703 non-null    int64 
 12  ethnicity        703 non-null    object
 13  jundice          703 non-null    int64 
 14  austim           703 non-null    int64 
 15  contry_of_res    703 non-null    object
 16  used_app_before  703 non-null    int64 
 17  resultnumeric    703 non-null    int64 
 18  age_desc         703 non-null    object
 19  relation         703 non-null    object
 20  Class/ASD        703 non-null    int64 
dtypes: int64(16), object(5)
memory usage: 115.5+ KB
```

: number of functions in the data framework
Column: Features header in the Dataframe
Non-null Count: Counter of nonzero values for each Dataframe function
Type: type of data stored for each function of the data frame

Summary

In [68]:
```
df.describe() #Statistical summary of DataFrame
```

Out[68]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A8_
count	703.000000	703.000000	703.000000	703.000000	703.000000	703.000000	703.000000	703.0
mean	0.721195	0.452347	0.456615	0.495021	0.499289	0.284495	0.416785	0.6
std	0.448731	0.498078	0.498469	0.500331	0.500355	0.451495	0.493378	0.4
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.0
50%	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	1.0
75%	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.0
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	1.0

count: number of examples counted for the selected function
mean: arithmetic mean for the selected function
std: standard deviation for the selected function
min: minimum value presented by the examples for the selected function
25%: first quartile calculated on the examples for the selected

```
function
50%: second quartile calculated on the examples for the selected
function
75%: third quartile calculated on examples for selected feature
max: maximum value presented by the examples for the selected
function
```

In [69]:

```
df.head()
```

Out[69]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A8_Score	A9_Sco
0	1	1	0	1	0	0	0	1	
1	1	1	0	1	1	0	1	1	
2	1	1	0	1	0	0	1	1	
3	1	0	0	0	0	0	0	1	
4	1	1	1	1	1	0	1	1	

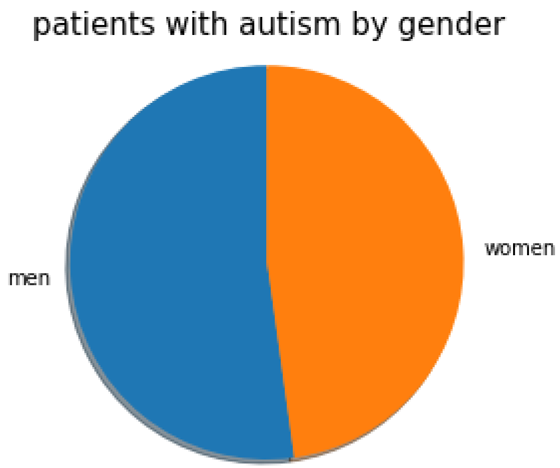
5 rows × 21 columns

Visualization

In [70]:

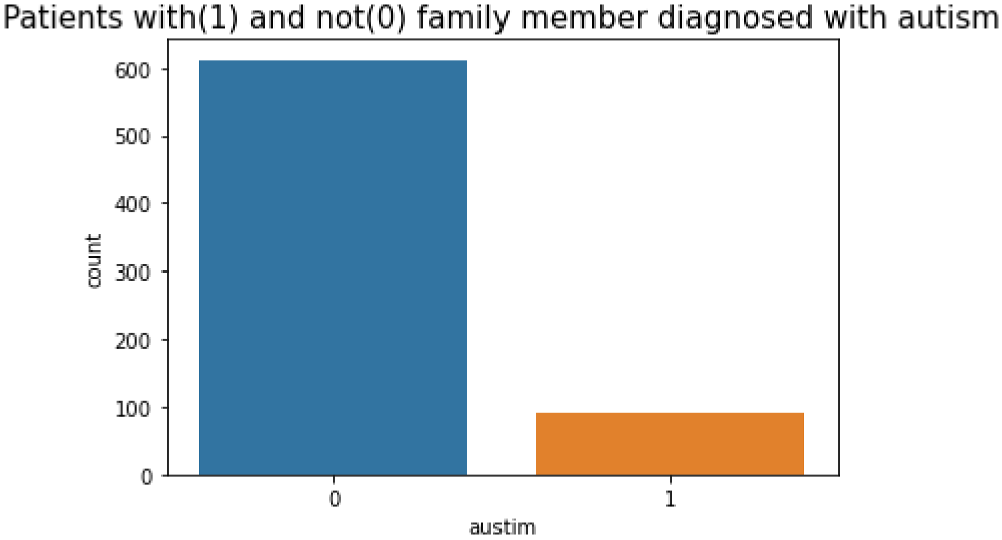
```
# Let's see the diversity of autism
print(df['gender'].value_counts())
men = df.value_counts(["gender"])[0]
women = df.value_counts(["gender"])[1]

name = ['men', 'women']
data = [men, women]
plt.title("patients with autism by gender", fontsize = 15)

plt.pie(data, labels=name, startangle=90, shadow=True)
plt.axis('equal')
plt.show()
```

```
0    367
1    336
Name: gender, dtype: int64
```



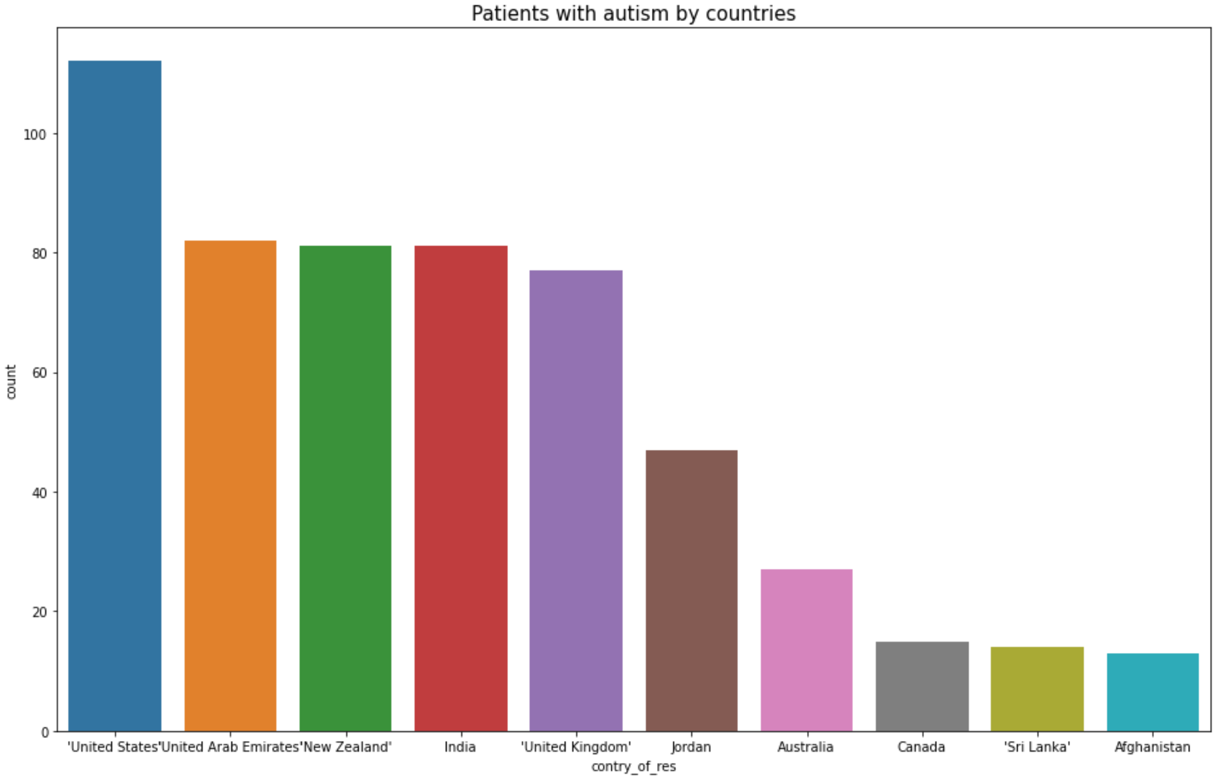
In [71]:
```
# Let's see if Patients has family member diagnosed with autism
print(df['austim'].value_counts())
sns.countplot(x="austim", data=df)
plt.title("Patients with(1) and not(0) family member diagnosed with autism",
plt.show()
```

```
0    612
1     91
Name: austim, dtype: int64
```



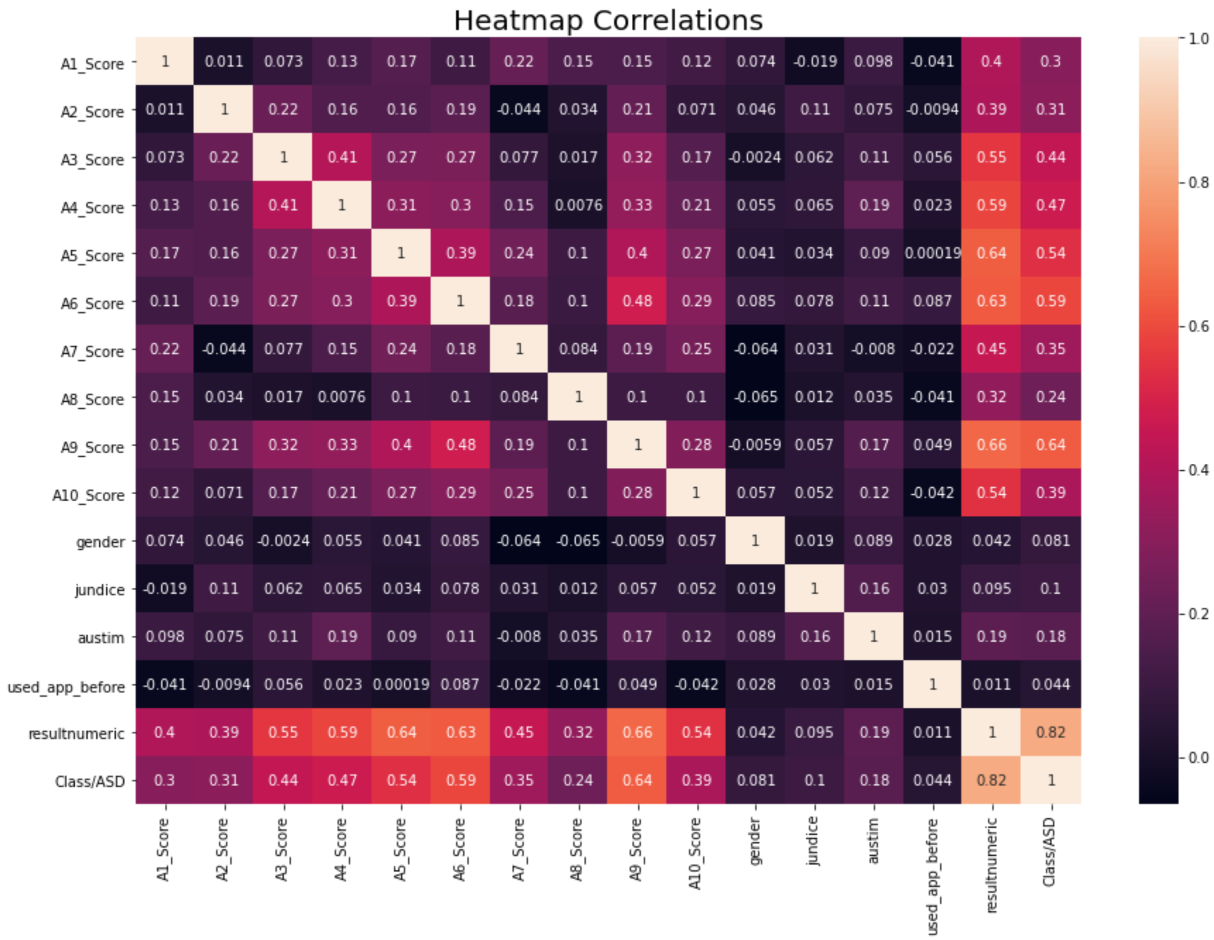
In [72]:
```
# The top 10 countries with autism
plt.figure(figsize = (16, 10))
plt.title("Patients with autism by countries", fontsize = 15)
plt.xlabel('contries')
plt.ylabel('number of austim')
order=df["contry_of_res"].value_counts().nlargest(10).index
# plt.bar(df.value_counts(["contry_of_res"])[1],df['austim'])
sns.countplot(x="contry_of_res", data=df, order=order)
```

Out[72]:
```
<AxesSubplot:title={'center':'Patients with autism by countries'}, xlabel='co
ntry_of_res', ylabel='count'>
```



In [73]:

```python
# Correlation between dataset columns
plt.figure(figsize = (15, 10))
plt.title("Heatmap Correlations", fontsize = 20)
sns.heatmap(df.corr(), annot = True)
plt.show()
```



Pré-processing

In [74]:
```
# Dropp Unwanted columns
df.drop(['age_desc'], axis = 1, inplace = True)
```

Split the data

In [75]:
```
X = df.drop("Class/ASD", axis = 1)    # select all other feature except "Clas
y = df['Class/ASD']
```

Due to the presence of data expressed with different location, normalization must be performed by using the get_dummies() method.

In [76]:
```
X = pd.get_dummies(X)
```

The data need to be split in trainning set and testing set

In [77]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.8)
```

In [78]:
```
print(f"X = {X.shape}")
print(f"Y = {y.shape}")
```

```
X = (703, 143)
Y = (703,)
```

In [79]:
```
print(f"X_train = {X_train.shape}")
print(f"Y_train = {y_train.shape}\n")
print(f"X_test = {X_test.shape}")
print(f"Y_test = {y_test.shape}")
```

```
X_train = (140, 143)
Y_train = (140,)

X_test = (563, 143)
Y_test = (563,)
```

Support Vector Classification

In [36]:
```
# Apply SVC
svc =SVC(random_state=3)
svc.fit(X_train,y_train)
pred_svc = svc.predict(X_test)
print(classification_report(y_test,pred_svc))
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, pred_svc))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, pred_svc))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,
```

```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98       409
           1       1.00      0.88      0.93       154

    accuracy                           0.97       563
   macro avg       0.98      0.94      0.96       563
weighted avg       0.97      0.97      0.97       563

Mean Absolute Error: 0.03374777975133215
```

```
Mean Squared Error: 0.03374777975133215
Root Mean Squared Error: 0.18370568785786723
```

accuracy = 90%

SVC show strong results, we could use SVC to classifie our dataset.

In [37]:

```
A = np.array([ round(metrics.precision_score(y_test, pred_svc),4),
    round(metrics.recall_score(y_test, pred_svc),4),
    round(metrics.f1_score(y_test, pred_svc),4)])
A = np.reshape(A, (1, 3))
A
```

Out[37]:

```
array([[1.    , 0.8766, 0.9343]])
```

Random Forest Classifier

In [38]:

```
# Apply RFC
rfc = RandomForestClassifier(random_state=3)
rfc.fit(X_train, y_train)
pred_RFR = rfc.predict(X_test)
print(classification_report(y_test,pred_RFR))
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, pred_RFR))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, pred_RFR))
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_test,
```

```
              precision    recall  f1-score   support

           0       0.96      1.00      0.98       409
           1       1.00      0.90      0.95       154

    accuracy                           0.97       563
   macro avg       0.98      0.95      0.96       563
weighted avg       0.97      0.97      0.97       563

Mean Absolute Error: 0.028419182948490232
Mean Squared Error: 0.028419182948490232
Root Mean Squared Error: 0.16857990078443585
```

In [39]:

```
B = np.array([ round(metrics.precision_score(y_test, pred_RFR),4),
    round(metrics.recall_score(y_test, pred_RFR),4),
    round(metrics.f1_score(y_test, pred_RFR),4)])
B = np.reshape(B, (1, 3))
B
```

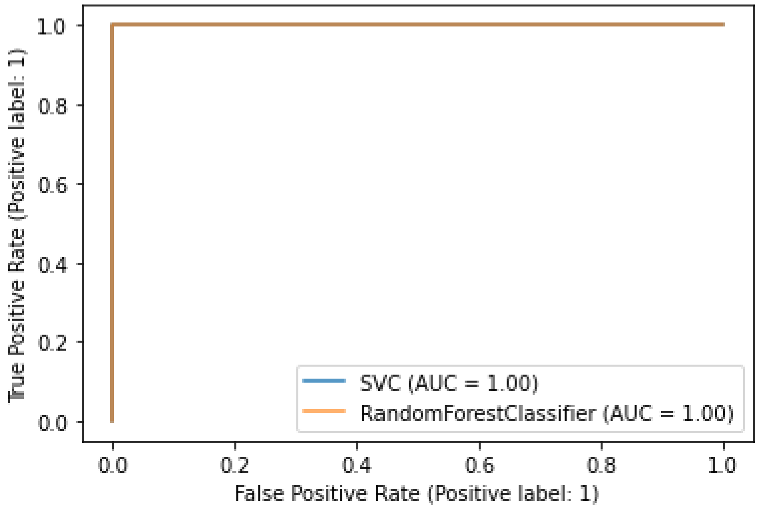
Out[39]:

```
array([[1.    , 0.8961, 0.9452]])
```

Classification Comparison

In [40]:

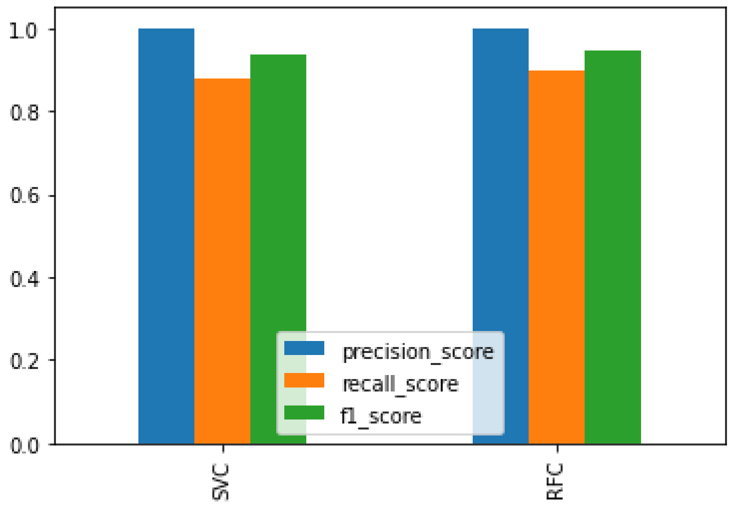
```
svc_disp = RocCurveDisplay.from_estimator(svc, X_test, y_test)
ax = plt.gca()
rfc_disp = RocCurveDisplay.from_estimator(rfc, X_test, y_test, ax=ax, alpha=0
regressor_disp = ()
plt.show()
```



We cannot clearly see the difference with the Roc curve even if we can briefly see that RFC is slightly more eccentric than an RFC.

In [80]:

```
# plot scoring to see the difference
Data = np.reshape([A, B], (2, 3))
fig = pd.DataFrame(Data, columns=["precision_score", "recall_score", "f1_scor
fig.plot.bar();
plt.show()
print([A, B])
```




```
[array([[1.    , 0.8766, 0.9343]]), array([[1.    , 0.8961, 0.9452]])]
```

We will use Random Forest Classifier. He has the best scores and is the most eccentric curve in the ROC curve.