In [1]:

```
import pandas as pd
from numpy import mean
from numpy import std
from sklearn.datasets import make_classification
from sklearn.metrics import f1_score
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.metrics import f1_score
from sklearn import preprocessing
```

In [2]:

```
# reading csv files
data =  pd.read_csv("C:/Users/Mohsen/Desktop/Autism-Adult-Data.csv")
df=pd.DataFrame(data)
print(df)
```

```
     A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Sco
re  A7_Score  \
0           1         1         1         1         0         
0         1  
1           1         1         0         1         0         
0         0  
2           1         1         0         1         1         
0         1  
3           1         1         0         1         0         
0         1  
4           1         0         0         0         0         
0         0  
..        ...       ...       ...       ...       ...       
...       ...  
699         0         1         0         1         1         
0         1  
700         1         0         0         0         0         
0         0  
701         1         0         1         1         1         
0         1  
702         1         0         0         1         1         
0         1  
703         1         0         1         1         1         
0         1  

     A8_Score  A9_Score  A10_Score  ... gender       ethnicit
y jundice austim  \
0           1         0          0  ...      f  White-Europea
n      no     no  
1           1         0          1  ...      m          Latin
o      no    yes  
2           1         1          1  ...      m          Latin
o     yes    yes  
3           1         0          1  ...      f  White-Europea
n      no    yes  
4           1         0          0  ...      f              
?      no     no  
..        ...       ...        ...  ...    ...            
```

```
...       ...     ...
699          1         1          1  ...      f  White-Europea
n      no     no
700          1         0          1  ...      m        Hispani
c      no     no
701          1         0          1  ...      f
?      no     no
702          0         1          1  ...      m      South Asia
n      no     no
703          1         1          1  ...      f  White-Europea
n      no     no

     contry_of_res used_app_before result     age_desc relati
on Class/ASD
0    United States              no       6  18 and more      Se
lf         NO
1           Brazil              no       5  18 and more      Se
lf         NO
2            Spain              no       8  18 and more    Pare
nt        YES
3    United States              no       6  18 and more      Se
lf         NO
4            Egypt              no       2  18 and more
?         NO
..             ...             ...     ...          ...
...        ...
699         Russia              no       7  18 and more      Se
lf        YES
700         Mexico              no       3  18 and more    Pare
nt         NO
701         Russia              no       7  18 and more
?        YES
702       Pakistan              no       6  18 and more      Se
lf         NO
703         Cyprus              no       8  18 and more      Se
lf        YES

[704 rows x 21 columns]
```

In [3]:

```
print(df)
```

```
     A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Sco
re  A7_Score  \
0           1         1         1         1         0
0         1
1           1         1         0         1         0
0         0
2           1         1         0         1         1
0         1
3           1         1         0         1         0
0         1
4           1         0         0         0         0
0         0
..        ...       ...       ...       ...       ...
...       ...
699         0         1         0         1         1
0         1
700         1         0         0         0         0
0         0
```

```
0        0
701        1        0        1        1        1
0        1
702        1        0        0        1        1
0        1
703        1        0        1        1        1
0        1

     A8_Score  A9_Score  A10_Score  ... gender       ethnicit
y jundice austim  \
0           1         0          0  ...      f  White-Europea
n      no     no
1           1         0          1  ...      m          Latin
o      no    yes
2           1         1          1  ...      m          Latin
o     yes    yes
3           1         0          1  ...      f  White-Europea
n      no    yes
4           1         0          0  ...      f
?      no     no
..        ...       ...        ...  ...    ...
...     ...    ...
699         1         1          1  ...      f  White-Europea
n      no     no
700         1         0          1  ...      m        Hispani
c      no     no
701         1         0          1  ...      f
?      no     no
702         0         1          1  ...      m     South Asia
n      no     no
703         1         1          1  ...      f  White-Europea
n      no     no

     contry_of_res used_app_before result     age_desc relati
on Class/ASD
0    United States              no      6  18 and more     Se
lf        NO
1           Brazil              no      5  18 and more     Se
lf        NO
2            Spain              no      8  18 and more   Pare
nt       YES
3    United States              no      6  18 and more     Se
lf        NO
4            Egypt              no      2  18 and more
?        NO
..             ...             ...    ...          ...
...       ...
699         Russia              no      7  18 and more     Se
lf       YES
700         Mexico              no      3  18 and more   Pare
nt        NO
701         Russia              no      7  18 and more
?       YES
702       Pakistan              no      6  18 and more     Se
lf        NO
703         Cyprus              no      8  18 and more     Se
lf       YES

[704 rows x 21 columns]
```

In [4]:

```
df.shape
```

Out[4]:

```
(704, 21)
```

In [5]:

```
df.head(10)
```

Out[5]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A8_
0	1	1	1	1	0	0	1	
1	1	1	0	1	0	0	0	
2	1	1	0	1	1	0	1	
3	1	1	0	1	0	0	1	
4	1	0	0	0	0	0	0	
5	1	1	1	1	1	0	1	
6	0	1	0	0	0	0	0	
7	1	1	1	1	0	0	0	
8	1	1	0	0	1	0	0	
9	1	1	1	1	0	1	1	

10 rows × 21 columns

In [ ]:

```

```

In [6]:

```
df.loc[:,"austim"].mode()
```

Out[6]:

```
0    no
dtype: object
```

In [7]:

```
df.loc[:,"austim"].replace("?", "White-European",inplace=True)
```

In [8]:

```
df.loc[:,"ethnicity"].mode()
```

Out[8]:

```
0    White-European
dtype: object
```

In [9]:

```
df.loc[:,"ethnicity"].replace("?", "White-European",inplace=True)
```

In [10]:

```
df.loc[:,"relation"].mode()
```

Out[10]:

```
0    Self
dtype: object
```

In [11]:

```
df.loc[:,"relation"].replace("?", "Self",inplace=True)
```

In [12]:

```
df.isnull().sum()
```

Out[12]:

```
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                0
gender             0
ethnicity          0
jundice            0
austim             0
contry_of_res      0
used_app_before    0
result             0
age_desc           0
relation           0
Class/ASD          0
dtype: int64
```

In [13]:

```
df.describe()
```

Out[13]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A
count	704.000000	704.000000	704.000000	704.000000	704.000000	704.000000	70
mean	0.721591	0.453125	0.457386	0.495739	0.498580	0.284091	
std	0.448535	0.498152	0.498535	0.500337	0.500353	0.451301	
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
50%	1.000000	0.000000	0.000000	0.000000	0.000000	0.000000	
75%	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.000000	

In [14]:

```
#Which attributes seem to be correlated
correlation =df.corr(method='pearson')
correlation
```

Out[14]:

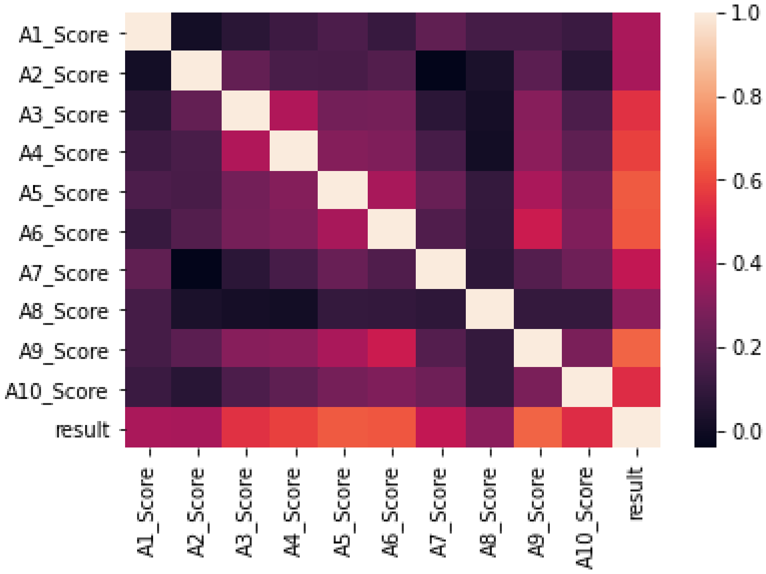
	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_S
A1_Score	1.000000	0.011539	0.074096	0.127814	0.169369	0.110199	0.217
A2_Score	0.011539	1.000000	0.223921	0.158998	0.153821	0.185864	-0.04
A3_Score	0.074096	0.223921	1.000000	0.412722	0.264927	0.268846	0.07
A4_Score	0.127814	0.158998	0.412722	1.000000	0.306806	0.295152	0.15
A5_Score	0.169369	0.153821	0.264927	0.306806	1.000000	0.392354	0.23
A6_Score	0.110199	0.185864	0.268846	0.295152	0.392354	1.000000	0.17
A7_Score	0.217538	-0.041768	0.078216	0.151236	0.238589	0.175489	1.00
A8_Score	0.147640	0.035408	0.017771	0.008617	0.102086	0.100123	0.08
A9_Score	0.145452	0.205421	0.315113	0.327673	0.396582	0.479422	0.18
A10_Score	0.118413	0.068883	0.168454	0.210968	0.267561	0.294435	0.25
result	0.397454	0.392540	0.552356	0.586025	0.639706	0.630012	0.45

In [15]:

```
import seaborn as sns
sns.heatmap(correlation)
```

Out[15]:

<matplotlib.axes._subplots.AxesSubplot at 0x1c3b35b92b0>

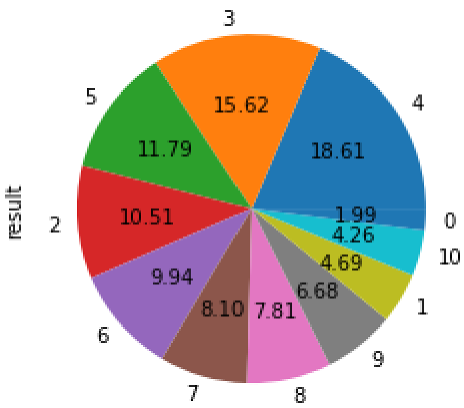


In [16]:

```
# balanced dataset and Normalize the dataset
df['result'].value_counts()
# dataset is imbalanced
df['result'].value_counts().plot.pie(autopct='%.2f')
```

Out[16]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x1c3b3dd0820>
```



In [17]:

```
import pandas as pd
credithistory_dataset = pd.DataFrame(df)
credithistory_dataset
```

Out[17]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A
0	1	1	1	1	0	0	1	
1	1	1	0	1	0	0	0	
2	1	1	0	1	1	0	1	
3	1	1	0	1	0	0	1	
4	1	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	
699	0	1	0	1	1	0	1	
700	1	0	0	0	0	0	0	
701	1	0	1	1	1	0	1	
702	1	0	0	1	1	0	1	
703	1	0	1	1	1	0	1	

704 rows × 21 columns

In [18]:

```
df['gender'] = df['gender'].replace(['m'],'0')
df['gender'] = df['gender'].replace(['f'],'1')
df['jundice']=df['jundice'].replace(['no'],'1')
df['jundice']=df['jundice'].replace(['yes'],'1')
df['Class/ASD']=df['Class/ASD'].replace(['NO'],'0')
df['Class/ASD']=df['Class/ASD'].replace(['YES'],'1')
df['relation']=df['relation'].replace(['Self'],'1')
df['relation']=df['relation'].replace(['Parent'],'0')
df['used_app_before']=df['used_app_before'].replace(['no'],'0')
df['used_app_before']=df['used_app_before'].replace(['yes'],'1')
df['austim']=df['austim'].replace(['no'],'0')
df['austim']=df['austim'].replace(['yes'],'1')
df
```

Out[18]:

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

...	...	...	...	...	...	...	...
699	0	1	0	1	1	0	1
700	1	0	0	0	0	0	0
701	1	0	1	1	1	0	1
702	1	0	0	1	1	0	1
703	1	0	1	1	1	0	1

704 rows × 21 columns

In [ ]:

```
X = df.drop(['austim', 'ethnicity', 'contry_of_res','age_desc'], axis=1)
X.head
```

In [29]:

```
X = df[['A1_Score' ,'A2_Score','A3_Score' ,'A4_Score' ,'A5_Score' ,'A6_Sco
re' ,'A7_Score','A8_Score', 'A9_Score' ,'A10_Score','result']]
```

In [30]:

```
X
```

Out[30]:

	A1_Score	A2_Score	A3_Score	A4_Score	A5_Score	A6_Score	A7_Score	A
0	1	1	1	1	0	0	1	
1	1	1	0	1	0	0	0	
2	1	1	0	1	1	0	1	
3	1	1	0	1	0	0	1	
4	1	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	
699	0	1	0	1	1	0	1	
700	1	0	0	0	0	0	0	
701	1	0	1	1	1	0	1	
702	1	0	0	1	1	0	1	
703	1	0	1	1	1	0	1	

704 rows × 11 columns

In [31]:

```
Y = df['austim']
Y.head(20)
```

Out[31]:

```
0     0
1     1
2     1
3     1
4     0
5     0
6     0
7     0
8     0
9     1
10    0
11    0
12    0
13    0
14    0
15    1
16    0
17    0
18    1
19    0
Name: austim, dtype: object
```

In [32]:

```
# Split data set
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size=0.30, r
andom_state=1)
Y_test
```

Out[32]:

```
402    0
422    0
331    0
189    0
185    0
      ..
459    0
346    0
582    0
103    0
323    1
Name: austim, Length: 212, dtype: object
```

In [33]:

```
# Normalize data set
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

In [35]:

```
#Random Forests
# Feature Scaling
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
```

```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
#Create a Gaussian Classifier
clf=RandomForestClassifier(n_estimators=100)
#Train the model using the training sets y_pred=clf.predict(X_test)
model = clf.fit(X_train,Y_train)
Y_pred=clf.predict(X_test)
Y_test.shape
Y_pred.shape
#Import scikit-learn metrics module for accuracy calculation
#Evaluating the Algorithm
from sklearn import metrics
import numpy as np
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_tes
t, Y_pred)))
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(Y_test, Y_pred))
```

```
Mean Absolute Error: 0.13679245283018868
Mean Squared Error: 0.13679245283018868
Root Mean Squared Error: 0.36985463743231434
Accuracy: 0.8632075471698113
```

In [37]:

```
# Evaluate a Random Forest model using k-fold cross-validation
# prepare the cross-validation procedure
from numpy import mean
from numpy import std
from sklearn.datasets import make_classification
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
cv = KFold(n_splits=10, random_state=1, shuffle=True)
# Evaluate model
scores = cross_val_score(model, X_test, Y_test, scoring='accuracy', cv=cv,
n_jobs=-1)
# report performance
print('Accuracy: %.3f (%.3f)' % (mean(scores), std(scores)))
```

```
Accuracy: 0.915 (0.077)
```

In [44]:

```
#Support Vector Machine
Y_train=Y_train.astype(float)
from sklearn.svm import SVC
svclassifier = SVC(kernel='poly', degree=8)
svclassifier.fit(X_train, Y_train)
# Accuracy with Cross validation for SVM
from numpy import mean
from numpy import std
from sklearn.datasets import make_classification
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
from sklearn.linear_model import LogisticRegression
# prepare the cross-validation procedure
```

```
cv = KFold(n_splits=10, random_state=1, shuffle=True)
# create model
# Instantiate the Support Vector Classifier (SVC)
svc = SVC(C=1.0, random_state=1, kernel='linear')
model = svc.fit(X_train, Y_train)
# evaluate model
scores = cross_val_score(model, X_test, Y_test, scoring='accuracy', cv=cv,
n_jobs=-1)
# report performance
print('Accuracy: %.3f (%.3f)' % (mean(scores), std(scores)))
```

```
Accuracy: 0.915 (0.075)
```

In [48]:

```
#Evaluate a logistic regression model using k-fold cross-validation
from sklearn.linear_model import LogisticRegression
# prepare the cross-validation procedure
cv = KFold(n_splits=10, random_state=1, shuffle=True)
# create model
model = LogisticRegression()
# Evaluate model
scores = cross_val_score(model, X_test, Y_test, scoring='accuracy', cv=cv,
n_jobs=-1)
# report performance
print('Accuracy: %.3f (%.3f)' % (mean(scores), std(scores)))
```

```
Accuracy: 0.906 (0.078)
```

In [51]:

```
#the Naive Bayes Algorithm
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
# Accuracy and Cross validation
from sklearn.model_selection import cross_val_score
# use the same model as before
clf = clf.fit(X_train,Y_train)
# X,y will automatically devided by 3 folder, the scoring I will still use
the accuracy
scores = cross_val_score(model, X_train, Y_train, cv=10, scoring='accurac
y')
# print all 5 times scores
print(scores)
# then I will do the average about these five scores to get more accuracy
 score.
print('Accuracy',scores.mean())
```

```
[0.62       0.7        0.73469388 0.71428571 0.79591837 0.755
10204
 0.85714286 0.85714286 0.73469388 0.75510204]
Accuracy 0.752408163265306
```