```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn import metrics
from sklearn.svm import SVC
from xgboost import XGBClassifier
from sklearn.linear_model import LogisticRegression
from imblearn.over_sampling import RandomOverSampler

import warnings
warnings.filterwarnings('ignore')
```

```
df = pd.read_csv('/content/train.csv')
print(df.head())
```

```
   ID  A1_Score  A2_Score  A3_Score  A4_Score  A5_Score  A6_Score  A7_Score  \
0   1         1         0         1         1         1         1         0
1   2         0         0         0         0         0         0         0
2   3         1         1         1         1         1         1         0
3   4         0         0         0         1         0         0         0
4   5         0         0         0         0         1         0         0

   A8_Score  A9_Score  ...  gender       ethnicity jaundice austim  \
0         1         1  ...       f  White-European       no     no
1         0         0  ...       f     South Asian       no     no
2         0         1  ...       f  White-European       no     no
3         0         0  ...       f     South Asian       no     no
4         0         1  ...       m           Black       no    yes

    contry_of_res used_app_before     result     age_desc  relation Class/ASD
0   United States              no   7.819715  18 and more      Self         0
1       Australia              no  10.544296  18 and more         ?         0
2  United Kingdom              no  13.167506  18 and more      Self         1
3     New Zealand              no   1.530098  18 and more         ?         0
4           Italy              no   7.949723  18 and more      Self         0

[5 rows x 22 columns]
```

```
df.shape
```

```
(800, 22)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 800 entries, 0 to 799
Data columns (total 22 columns):
 #   Column           Non-Null Count  Dtype
---  ------           --------------  -----
 0   ID               800 non-null    int64
 1   A1_Score         800 non-null    int64
 2   A2_Score         800 non-null    int64
 3   A3_Score         800 non-null    int64
 4   A4_Score         800 non-null    int64
 5   A5_Score         800 non-null    int64
 6   A6_Score         800 non-null    int64
 7   A7_Score         800 non-null    int64
 8   A8_Score         800 non-null    int64
 9   A9_Score         800 non-null    int64
 10  A10_Score        800 non-null    int64
 11  age              800 non-null    float64
 12  gender           800 non-null    object
 13  ethnicity        800 non-null    object
 14  jaundice         800 non-null    object
 15  austim           800 non-null    object
 16  contry_of_res    800 non-null    object
 17  used_app_before  800 non-null    object
 18  result           800 non-null    float64
 19  age_desc         800 non-null    object
 20  relation         800 non-null    object
 21  Class/ASD        800 non-null    int64
```

```
dtypes: float64(2), int64(12), object(8)
memory usage: 137.6+ KB
```

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

	count	mean	std	min	25%	50%	75%
ID	800.0	400.500000	231.084400	1.000000	200.750000	400.500000	600.250000
A1_Score	800.0	0.582500	0.493455	0.000000	0.000000	1.000000	1.000000
A2_Score	800.0	0.286250	0.452290	0.000000	0.000000	0.000000	1.000000
A3_Score	800.0	0.321250	0.467249	0.000000	0.000000	0.000000	1.000000
A4_Score	800.0	0.415000	0.493030	0.000000	0.000000	0.000000	1.000000
A5_Score	800.0	0.457500	0.498502	0.000000	0.000000	0.000000	1.000000
A6_Score	800.0	0.208750	0.406670	0.000000	0.000000	0.000000	0.000000
A7_Score	800.0	0.273750	0.446161	0.000000	0.000000	0.000000	1.000000
A8_Score	800.0	0.717500	0.450497	0.000000	0.000000	1.000000	1.000000
A9_Score	800.0	0.316250	0.465303	0.000000	0.000000	0.000000	1.000000
A10_Score	800.0	0.460000	0.498709	0.000000	0.000000	0.000000	1.000000
age	800.0	28.612306	12.872373	9.560505	19.282082	25.479960	33.154755
result	800.0	7.058530	3.788969	-2.594654	4.527556	6.893472	9.892981
Class/ASD	800.0	0.231250	0.421896	0.000000	0.000000	0.000000	0.000000

```
df['ethnicity'].value_counts()
```

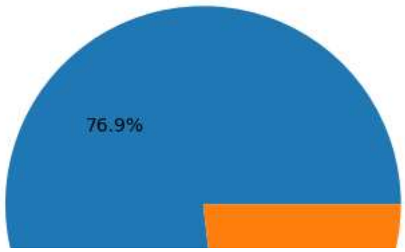
```
White-European     211
?                  151
Asian              134
Middle Eastern     116
Black               45
Latino              44
South Asian         35
Others              24
Pasifika            18
Hispanic            16
Turkish              4
others               2
Name: ethnicity, dtype: int64
```

```
df['relation'].value_counts()
```

```
Self                        617
?                            77
Parent                       49
Relative                     43
Health care professional      7
Others                        7
Name: relation, dtype: int64
```

```
df = df.replace({'yes':1, 'no':0, '?':'Others', 'others':'Others'})
```

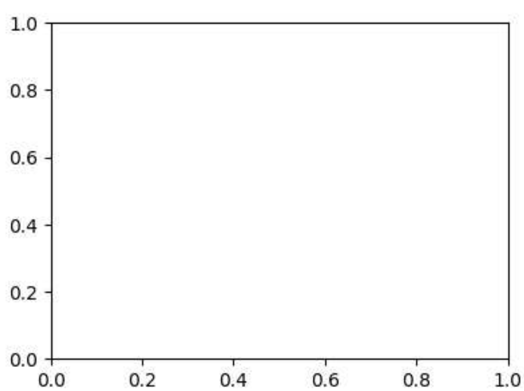
```
plt.pie(df['Class/ASD'].value_counts().values, autopct='%1.1f%%')
plt.show()
```



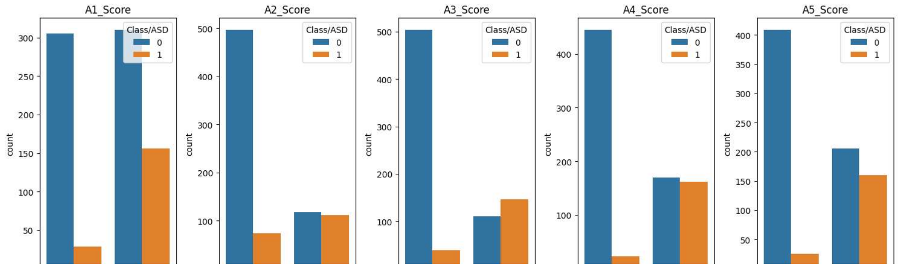

```
ints = []
objects = []
floats = []

for col in df.columns:
  if df[col].dtype == int:
    ints.append(col)
  elif df[col].dtype == object:
    objects.append(col)
  else:
    floats.append(col)



ints.remove('ID')
ints.remove('Class/ASD')



plt.subplots(figsize=(15,15))

for i, col in enumerate(ints):
  plt.subplot(4,3,i+1)
  sb.countplot(df[col], hue=df['Class/ASD'])
plt.tight_layout()
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-29-06ca6660f100> in <cell line: 3>()
      3 for i, col in enumerate(ints):
      4   plt.subplot(4,3,i+1)
----> 5   sb.countplot(df[col], hue=df['Class/ASD'])
      6 plt.tight_layout()
      7 plt.show()

                                  2 frames
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py in
establish_variables(self, x, y, hue, data, orient, order, hue_order, units)
    435             if hue is not None:
    436                 error = "Cannot use `hue` without `x` and `y`"
--> 437                 raise ValueError(error)
    438
    439             # No hue grouping with wide inputs

ValueError: Cannot use `hue` without `x` and `y`
```

SEARCH STACK OVERFLOW



```
import seaborn as sb
import matplotlib.pyplot as plt
import math

# Assuming you have a list of integer columns to plot (ints)
# For example:


# Assuming 'Class/ASD' is the target variable, and 'df' is your DataFrame

# Calculate the number of rows and columns based on the number of columns you want to plot
n_cols = 5  # Number of columns in the grid
n_rows = math.ceil(len(ints) / n_cols)  # Calculate the number of rows based on the number of columns

plt.figure(figsize=(15, 15))

# Create a grid of count plots for each integer column
for i, col in enumerate(ints):
    plt.subplot(n_rows, n_cols, i + 1)
    ax = sb.countplot(x=col, data=df, hue='Class/ASD', ax=plt.gca())
    ax.set_title(col)

# Adjust the layout and show the plot
plt.tight_layout()
plt.show()
```



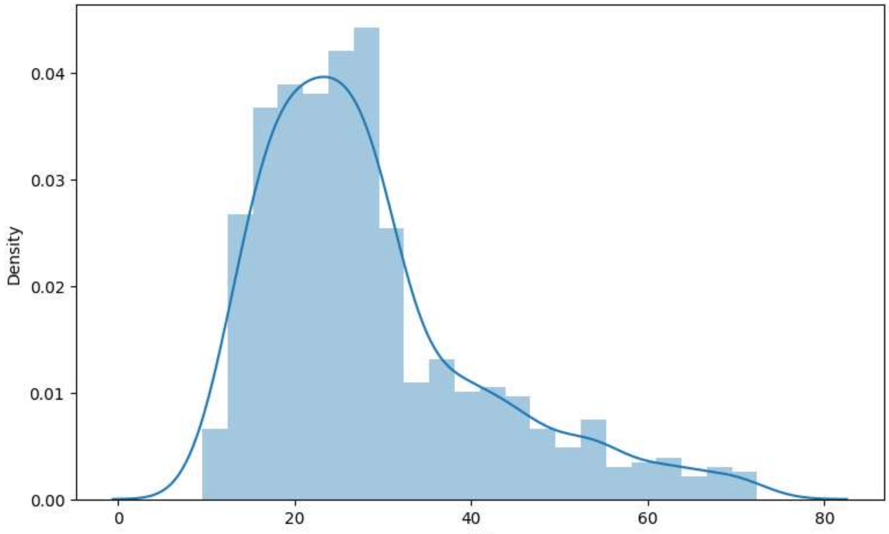

```
plt.figure(figsize=(15,5))
sb.countplot(data=df, x='country_of_res', hue='Class/ASD')
plt.xticks(rotation=90)
plt.show()
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-23-80f9c38c5c06> in <cell line: 2>()
      1 plt.figure(figsize=(15,5))
----> 2 sb.countplot(data=df, x='country_of_res', hue='Class/ASD')
      3 plt.xticks(rotation=90)
      4 plt.show()

                              2 frames
/usr/local/lib/python3.10/dist-packages/seaborn/categorical.py in
establish_variables(self, x, y, hue, data, orient, order, hue_order, units)
    539                 if isinstance(var, str):
    540                     err = f"Could not interpret input '{var}'"
--> 541                     raise ValueError(err)
    542 
    543             # Figure out the plotting orientation

ValueError: Could not interpret input 'country_of_res'
```

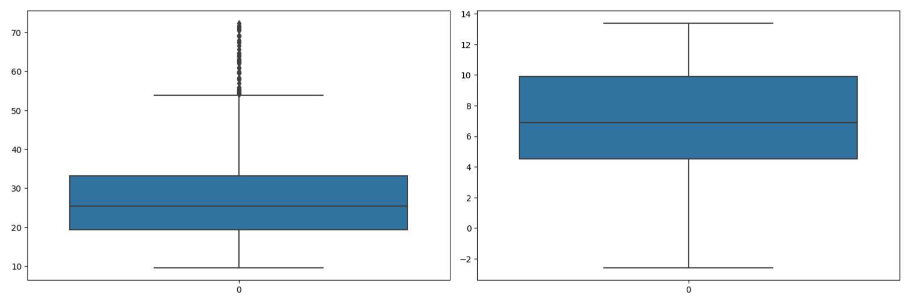
SEARCH STACK OVERFLOW

```
<Figure size 1500x500 with 0 Axes>
```

```
plt.subplots(figsize=(15,5))

for i, col in enumerate(floats):
  plt.subplot(1,2,i+1)
  sb.distplot(df[col])
  plt.tight_layout()
  plt.show()
```




```
plt.subplots(figsize=(15,5))

for i, col in enumerate(floats):
  plt.subplot(1,2,i+1)
  sb.boxplot(df[col])
plt.tight_layout()
plt.show()
```

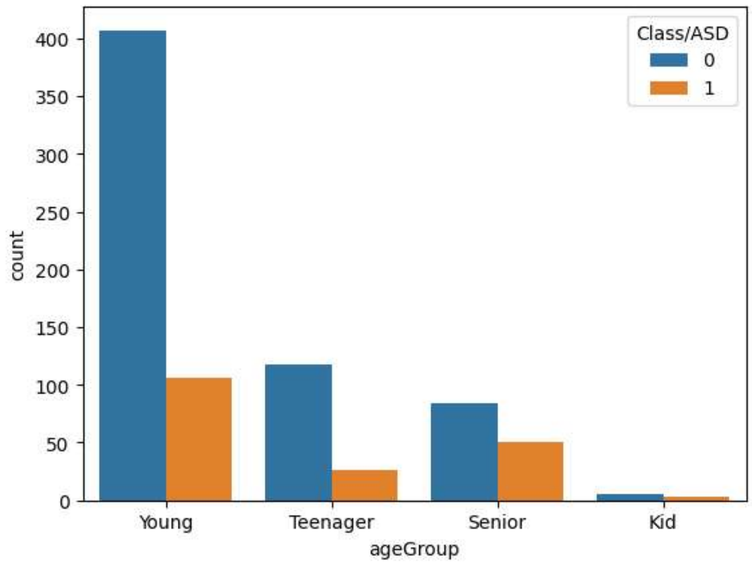


```
df = df[df['result']>-5]
df.shape
```

```
(800, 23)
```

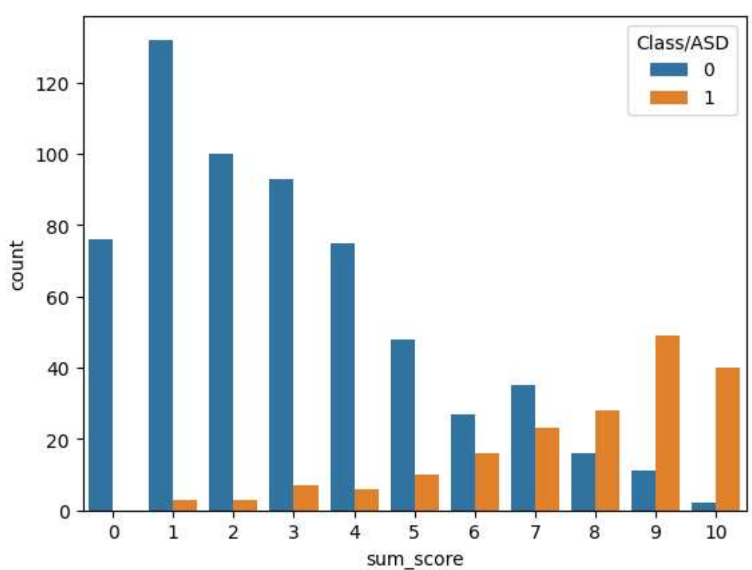
```
# This functions make groups by taking
# the age as a parameter
def convertAge(age):
    if age < 4:
        return 'Toddler'
    elif age < 12:
        return 'Kid'
    elif age < 18:
        return 'Teenager'
    elif age < 40:
        return 'Young'
    else:
        return 'Senior'

df['ageGroup'] = df['age'].apply(convertAge)
```

```
sb.countplot(x=df['ageGroup'], hue=df['Class/ASD'])
plt.show()
```



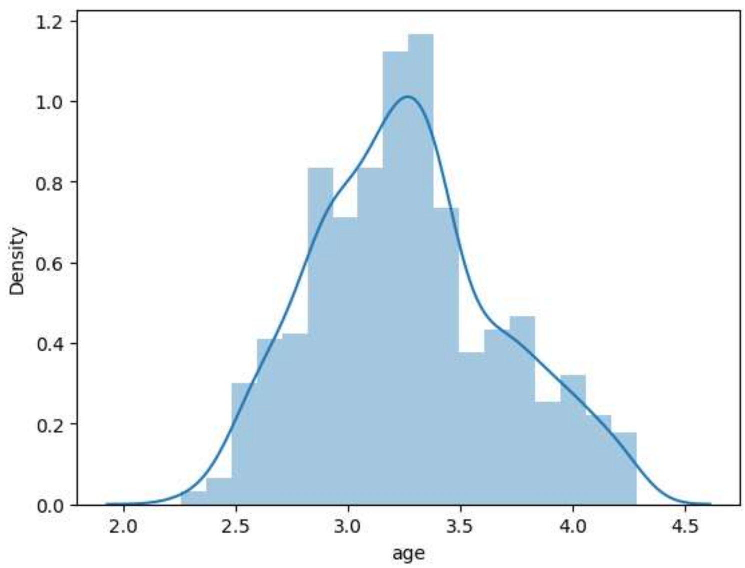

```
def add_feature(data):

# Creating a column with all values zero
  data['sum_score'] = 0
  for col in data.loc[:,'A1_Score':'A10_Score'].columns:

    # Updating the 'sum_score' value with scores
    # from A1 to A10
    data['sum_score'] += data[col]

  # Creating a random data using the below three columns
  data['ind'] = data['austim'] + data['used_app_before'] + data['jaundice']

  return data

df = add_feature(df)
```

```
sb.countplot(x=df['sum_score'], hue=df['Class/ASD'])
plt.show()
```

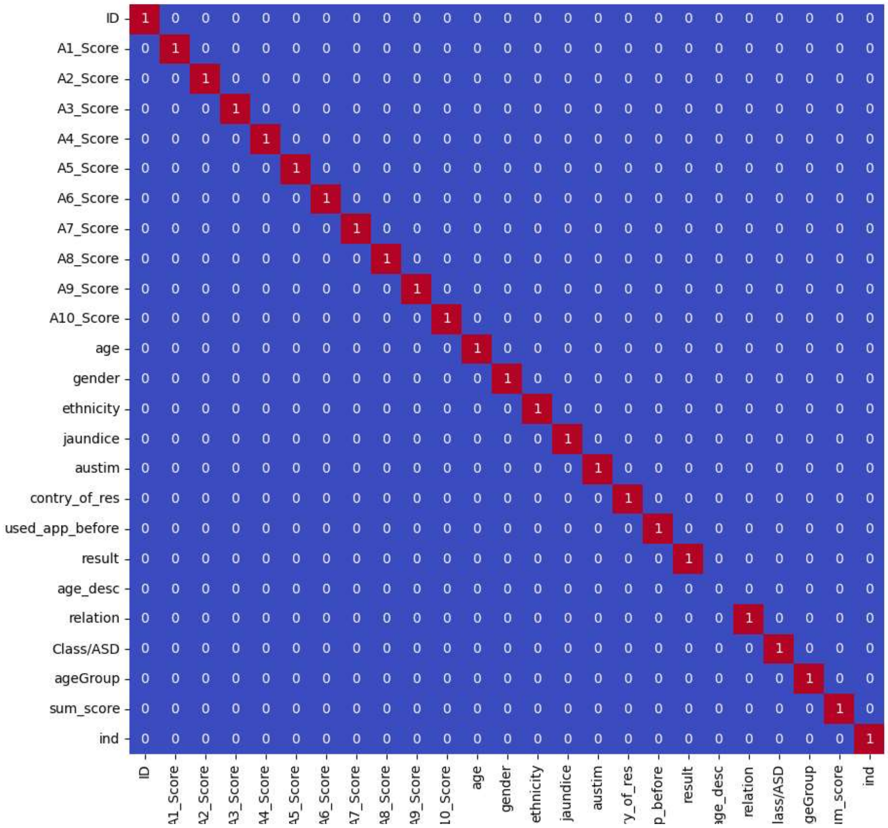



```
# Applying log transformations to remove the skewness of the data.
df['age'] = df['age'].apply(lambda x: np.log(x))
```

```
sb.distplot(df['age'])
plt.show()
```




```
from sklearn.preprocessing import LabelEncoder
import seaborn as sb
import matplotlib.pyplot as plt

def encode_labels(data):
    for col in data.columns:
        if data[col].dtype == 'object':
            le = LabelEncoder()
            data[col] = le.fit_transform(data[col])
    return data

# Assuming you have a DataFrame 'df'
df = encode_labels(df)

# Create a correlation matrix
correlation_matrix = df.corr()

# Set a threshold for correlation values to highlight
threshold = 0.8  # You can adjust this threshold as needed

# Create a mask to hide the upper triangle of the correlation matrix
mask = correlation_matrix.where(abs(correlation_matrix) > threshold, 0)

# Making a heatmap to visualize the correlation matrix
plt.figure(figsize=(10, 10))
sb.heatmap(mask, annot=True, cbar=False, cmap='coolwarm')  # Adjust the colormap as needed
plt.show()
```




```
removal = ['ID', 'age_desc', 'used_app_before', 'austim']
features = df.drop(removal + ['Class/ASD'], axis=1)
target = df['Class/ASD']
```

```
X_train, X_val, Y_train, Y_val = train_test_split(features, target, test_size = 0.2, random_state=10)

# As the data was highly imbalanced we will balance it by adding repetitive rows of minority class.
ros = RandomOverSampler(sampling_strategy='minority',random_state=0)
X, Y = ros.fit_resample(X_train,Y_train)
X.shape, Y.shape
```

```
((992, 20), (992,))
```

```
# Normalizing the features for stable and fast training.
scaler = StandardScaler()
X = scaler.fit_transform(X)
X_val = scaler.transform(X_val)
```

```
models = [LogisticRegression(), XGBClassifier(), SVC(kernel='rbf')]

for model in models:
  model.fit(X, Y)

  print(f'{model} : ')
  print('Training Accuracy : ', metrics.roc_auc_score(Y, model.predict(X)))
  print('Validation Accuracy : ', metrics.roc_auc_score(Y_val, model.predict(X_val)))
  print()
```

```
LogisticRegression() :
Training Accuracy :  0.845766129032258
Validation Accuracy :  0.8348022135683542

XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
```

```
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=None, n_jobs=None,
              num_parallel_tree=None, random_state=None, ...) :
Training Accuracy :  1.0
Validation Accuracy :  0.836441893830703

SVC() :
Training Accuracy :  0.9203629032258065
Validation Accuracy :  0.8398237343717975
```