```
import pandas as pd
import numpy as np
# libraries for plotting
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings("ignore")
import seaborn as sns
sns.set(style="whitegrid")
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
df_long = pd.read_csv('/content/oasis_longitudinal.csv')
```

```
df_long.head()
```

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12

```
# lets see the summary stats of numerical columns
df_long.describe(include=[np.number])
```

	Visit	MR Delay	Age	EDUC	SES	MMSE	
count	373.000000	373.000000	373.000000	373.000000	354.000000	371.000000	373.0
mean	1.882038	595.104558	77.013405	14.597855	2.460452	27.342318	0.2
std	0.922843	635.485118	7.640957	2.876339	1.134005	3.683244	0.3
min	1.000000	0.000000	60.000000	6.000000	1.000000	4.000000	0.0
25%	1.000000	0.000000	71.000000	12.000000	2.000000	27.000000	0.0
50%	2.000000	552.000000	77.000000	15.000000	2.000000	29.000000	0.0
75%	2.000000	873.000000	82.000000	16.000000	3.000000	30.000000	0.5
max	5.000000	2639.000000	98.000000	23.000000	5.000000	30.000000	2.0

```
# lets see the summary of categorical columns
df_long.describe(include=[np.object])
```

	Subject ID	MRI ID	Group	M/F	Hand
count	373	373	373	373	373
unique	150	373	3	2	1
top	OAS2_0070	OAS2_0001_MR1	Nondemented	F	R
freq	5	1	190	213	373

```
# dropping irrelevant columns
df_long=df_long.drop(['Subject ID','MRI ID','Hand'],axis=1)
```

```
df_long.head()
```

Group	Visit	MR Delay	M/F	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF

```
# checking missing values in each column
df_long.isna().sum()
```

```
Group        0
Visit        0
MR Delay     0
M/F          0
Age          0
EDUC         0
SES         19
MMSE         2
CDR          0
eTIV         0
nWBV         0
ASF          0
dtype: int64
```

```
round(df_long.isnull().sum()/len(df_long.index), 2)*100
```

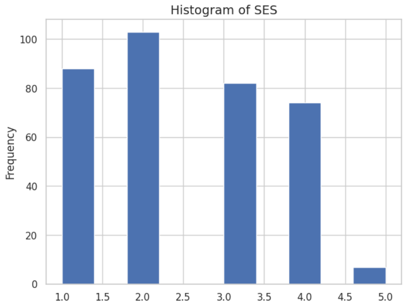
```
Group       0.0
Visit       0.0
MR Delay    0.0
M/F         0.0
Age         0.0
EDUC        0.0
SES         5.0
MMSE        1.0
CDR         0.0
eTIV        0.0
nWBV        0.0
ASF         0.0
dtype: float64
```

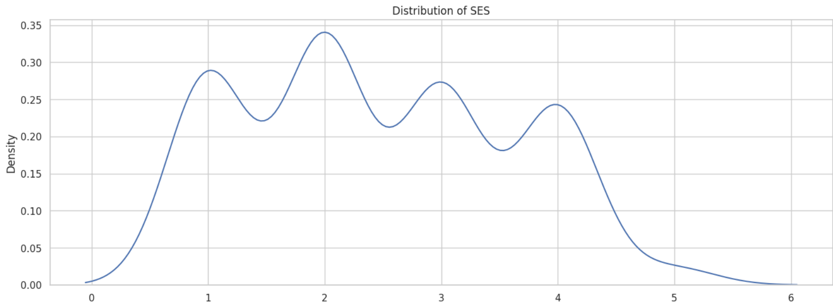
So, we have to impute missing values in SES and MMSE. Lets analyze SES column

#

```
# Plotting distribution of SES
def univariate_mul(var):
    fig = plt.figure(figsize=(16,12))
    cmap=plt.cm.Blues
    cmap1=plt.cm.coolwarm_r
    ax1 = fig.add_subplot(221)
    ax2 = fig.add_subplot(212)
    df_long[var].plot(kind='hist',ax=ax1, grid=True)
    ax1.set_title('Histogram of '+var, fontsize=14)

    ax2=sns.distplot(df_long[[var]],hist=False)
    ax2.set_title('Distribution of '+ var)
    plt.show()
```

```
# lets see the distribution of SES to decide which value we can impute in place of missing values.
univariate_mul('SES')
df_long['SES'].describe()
```





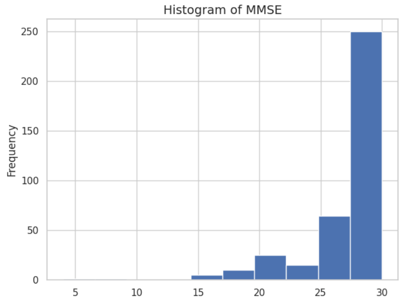

```
count    354.000000
mean       2.460452
std        1.134005
min        1.000000
25%        2.000000
```

As SES has values of integer type so we cannot impute float value of mean¶ we can impute median in place as both median and mean have very close values and median in this case is most representative value of SES.¶

```
# imputing missing value in SES with median
df_long['SES'].fillna((df_long['SES'].median()), inplace=True)
```

Next we will analyze another column having missing values i.e., MMSE¶

```
univariate_mul('MMSE')
df_long['MMSE'].describe()
```



MMSE also has integer values so we cannot impute float. So we will impute it with median value

```
# imputing MMSE with median values
df_long['MMSE'].fillna((df_long['MMSE'].median()), inplace=True)
```

```
# Now, lets check the percentage of missing values in each column
round(df_long.isnull().sum()/len(df_long.index), 2)*100
```

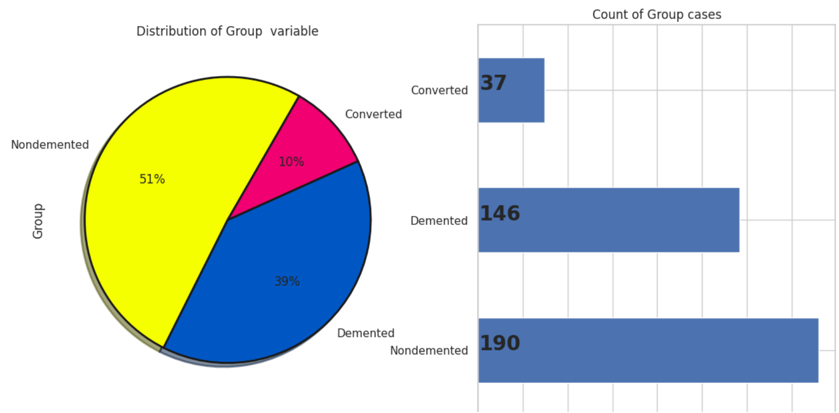
```
Group       0.0
Visit       0.0
MR Delay    0.0
M/F         0.0
Age         0.0
EDUC        0.0
SES         0.0
MMSE        0.0
CDR         0.0
eTIV        0.0
nWBV        0.0
ASF         0.0
dtype: float64
```

Univariate Analysis

```
# Defining function to create pie chart and bar plot as subplots
def plot_piechart(var):
  plt.figure(figsize=(14,7))
  plt.subplot(121)
  label_list = df_long[var].unique().tolist()
  df_long[var].value_counts().plot.pie(autopct = "%1.0f%%",colors = sns.color_palette("prism",7),startangle = 60,labels=label_
  wedgeprops={"linewidth":2,"edgecolor":"k"},shadow =True)
  plt.title("Distribution of "+ var +"  variable")

  plt.subplot(122)
  ax = df_long[var].value_counts().plot(kind="barh")

  for i,j in enumerate(df_long[var].value_counts().values):
    ax.text(.7,i,j,weight = "bold",fontsize=20)

  plt.title("Count of "+ var +" cases")
  plt.show()
```

First, we will analyze categorical column named Group

```
plot_piechart('Group')
```



As we can see from the above plot, there are around 39% demented cases in the dataset i.e., majority of the data is of Non Demented cases while 10% of the data is of Converted. So lets analyze numerical features and perform univariate analysis on those features to see if we find any pattern or some interesting insights. So, we first begin with analyzing the most important categorical feature i.e., Clinical Dementia Rating (CDR).

```
df_long['CDR'].describe()
```

```
count    373.000000
mean       0.290885
std        0.374557
min        0.000000
25%        0.000000
50%        0.000000
75%        0.500000
max        2.000000
Name: CDR, dtype: float64
```

The CDR™ Scoring Table provides descriptive anchors that guide the clinician in making appropriate ratings based judgment. This score is useful for characterizing and tracking a patient's level of impairment/dementia:

0 = Normal 0.5 = Very Mild Dementia or Questionable 1 = Mild Dementia 2 = Moderate Dementia 3 = Severe Dementia

Clinical Dementia Rating (CDR) Score Interpretations

Particulars	None (0)	Questionable (0.5)	Mild (1)	Moderate (2)	Severe (3)
Memory	No memory loss or slight inconsistent forgetfulness	Consistent slight forgetfulness; partial recollection of events; "benign" forgetfulness	Moderate memory loss; more marked for recent events; defect interferes with everyday activities	Severe memory loss; only highly learned material retained; new material rapidly lost	Severe memory loss; only fragments remain
Judgment & Problem Solving	Solves everyday problems & handles business & financial affairs well;	Slight impairment in solving problems, similarities, and differences	Moderate difficulty in handling problems, similarities, and differences;	Severely impaired in handling problems, similarities, and differences;	Unable to make judgments or solve problems
Personal Care	Fully capable of Self-Care		Needs prompting	Requires assistance in dressing, hygiene, keeping of personal effects	Requires much help with personal care; frequent incontinence

Source: https://knightadrc.wustl.edu/ (Washington University in St. Louis Missouri)

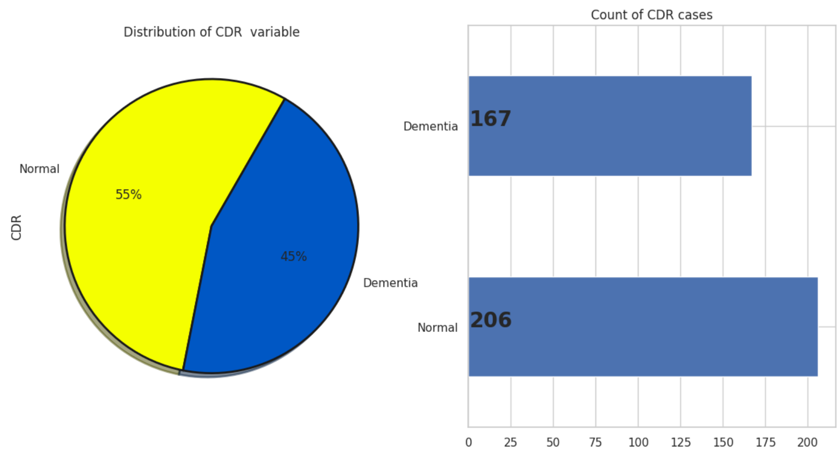
After seeing from the above table, it has been observed that except Normal score all other score including 0.5 have dementia symptoms because it is very crucial to detect dementia in early stages. So, we are grouping cases having 0 score as Normal and all other score >=0.5 as dementia.

```
# Plotting CDR with other variable
def univariate_percent_plot(cat):
    fig = plt.figure(figsize=(18,12))
    cmap=plt.cm.Blues
    cmap1=plt.cm.coolwarm_r
    ax1 = fig.add_subplot(221)
    ax2 = fig.add_subplot(222)

    result = df_long.groupby(cat).apply (lambda group: (group.CDR == 'Normal').sum() / float(group.CDR.count())
```

```
        ).to_frame('Normal')
    result['Dementia'] = 1 -result.Normal
    result.plot(kind='bar', stacked = True,colormap=cmap1, ax=ax1, grid=True)
    ax1.set_title('stacked Bar Plot of '+ cat +' (in %)', fontsize=14)
    ax1.set_ylabel('% Dementia status (Normal vs Dementia)')
    ax1.legend(loc="lower right")
    group_by_stat = df_long.groupby([cat, 'CDR']).size()
    group_by_stat.unstack().plot(kind='bar', stacked=True,ax=ax2,grid=True)
    ax2.set_title('stacked Bar Plot of '+ cat +' (in %)', fontsize=14)
    ax2.set_ylabel('Number of Cases')
    plt.show()
```

```
# Categorizing feature CDR
def cat_CDR(n):
    if n == 0:
        return 'Normal'

    else:                                        # As we have no cases of sever dementia CDR score=3
        return 'Dementia'

df_long['CDR'] = df_long['CDR'].apply(lambda x: cat_CDR(x))
```

```
plot_piechart('CDR')
```



As we can see majority of the cases are Normal while very few cases are of Mild and Moderate dementia.

Next we will analyse another feature named MMSE.

About MMSE (Mini Mental State Examination) Mini-mental state : A practical method for grading the cognitive state of patients for the clinician study especially for older adults. It is a 30-point questionnaire that is used extensively in clinical and research settings to measure cognitive impairment.

Interpretations: Any score of 24 or more (out of 30) indicates a normal cognition. Below this, scores can indicate severe (≤9 points), moderate (10–18 points) or mild (19–23 points) cognitive impairment.That is, even a maximum score of 30 points can never rule out dementia. Low to very low scores correlate closely with the presence of dementia, although other mental disorders can also lead to abnormal findings on MMSE testing.

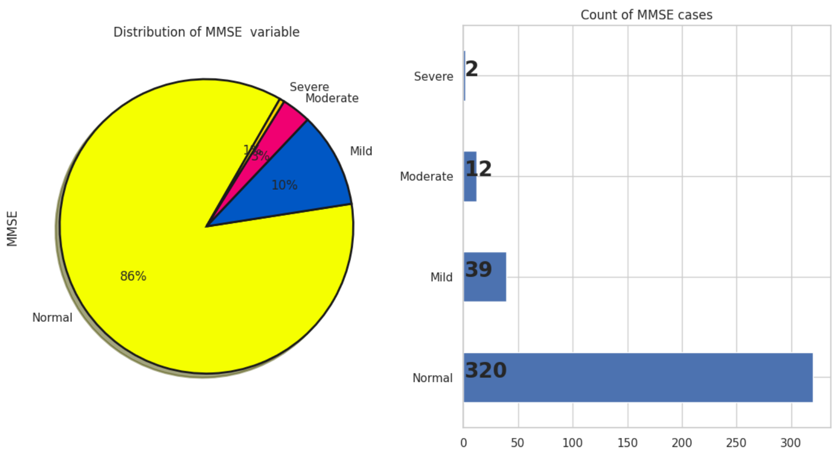
```
df_long['MMSE'].describe()
```

```
count    373.000000
mean      27.351206
std        3.675329
min        4.000000
```

```
25%        27.000000
50%        29.000000
75%        30.000000
max        30.000000
Name: MMSE, dtype: float64
```

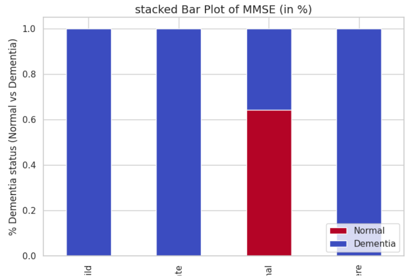
```
# Categorizing feature MMSE
def cat_MMSE(n):
    if n >= 24:
        return 'Normal'
    elif n <= 9:
        return 'Severe'
    elif n >= 10 and n <= 18:
        return 'Moderate'
    elif n >= 19 and n <= 23:                                       # As we have no cases of sever dementia CDR score=3
        return 'Mild'

df_long['MMSE'] = df_long['MMSE'].apply(lambda x: cat_MMSE(x))
```

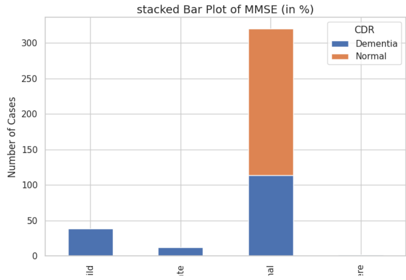
```
plot_piechart('MMSE')
```



Here, also there are majority of cases of normal cognitive impairment whereas very few cases of Mild, Moderate and Severe cognitive Impairment.

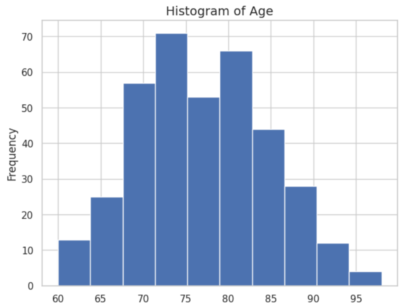
```
univariate_percent_plot('MMSE')
```

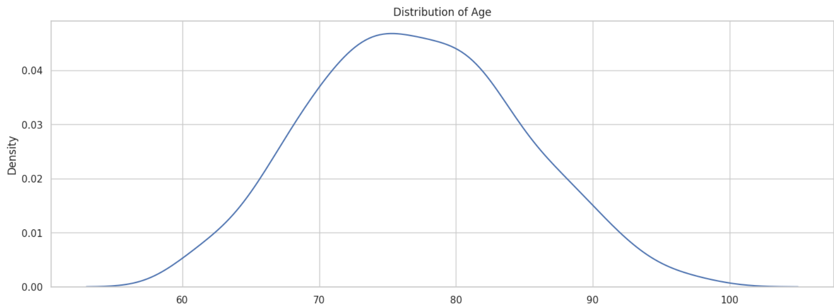




As we can see from the above plot, there are around 40% of the cases in Normal MMSE status are of dementia cases accroding to CDR scoring. Next we will analyze Age feature to see how age is impacting the dementia status.

```
univariate_mul('Age')
df_long['Age'].describe()
```






```
count    373.000000
mean      77.013405
std        7.640957
min       60.000000
25%       71.000000
50%       77.000000
75%       82.000000
max       98.000000
Name: Age, dtype: float64
```

Age in this dataset is uniformly distributed ranging from 60 years to 98 years.

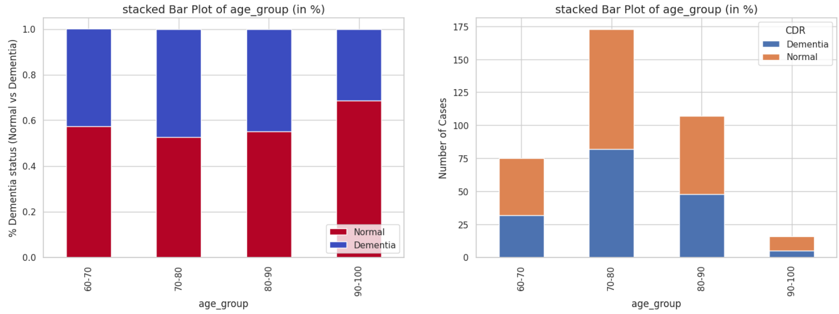
```
df_long['age_group'] = pd.cut(df_long['Age'], [60, 70, 80,90, 100], labels=['60-70', '70-80', '80-90','90-100'])
df_long['age_group'].value_counts()
```

```
70-80     173
80-90     107
60-70      75
```

```
90-100     16
Name: age_group, dtype: int64
```

Now plotting age group to see dementia distribution

```
univariate_percent_plot('age_group')
```



Majority of cases of Dementia are in the age group of 70-80 years (around 45%) while second most highest cases are in 80-90 years of age.

Bivariate Analysis

```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="M/F", y="Age",hue="CDR",split=True, data=df_long)
plt.show()
```

As we can observe from the above plot, in case of Male most number of dementia cases are reported in the age of around 80 years while in case of females dementia is prevalent in 75 years of Age. One more observation suggests that in case of Males dementia starts early even before 60 years of age while in case of females demetia generally after 60 years of age.

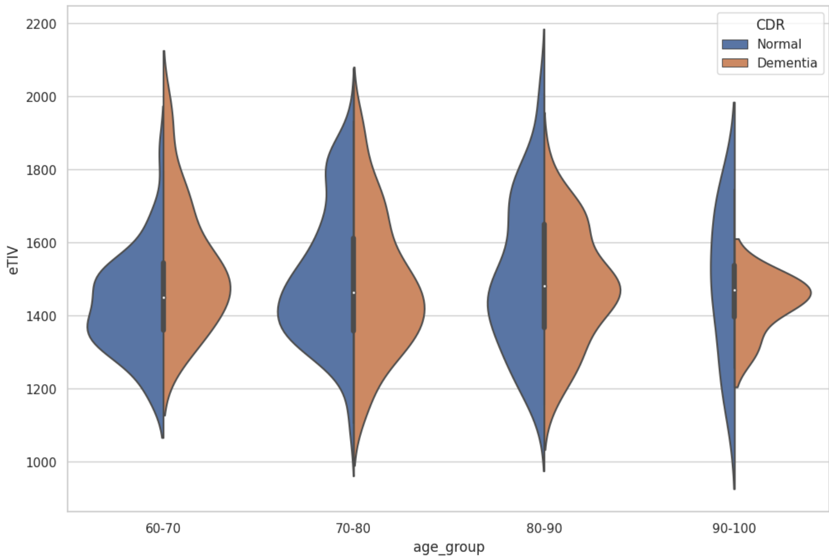
Next we will analyze another important feature named eTIV.

Estimated total intracranial volume (eTIV):¶ Intracranial volume (ICV) is an important normalization measure used in morphometric analyses to correct for head size in studies of Alzheimer Disease (AD). ICV is often used in studies involved with analysis of the cerebral structure under different imaging modalities, such as Magnetic Resonance (MR).

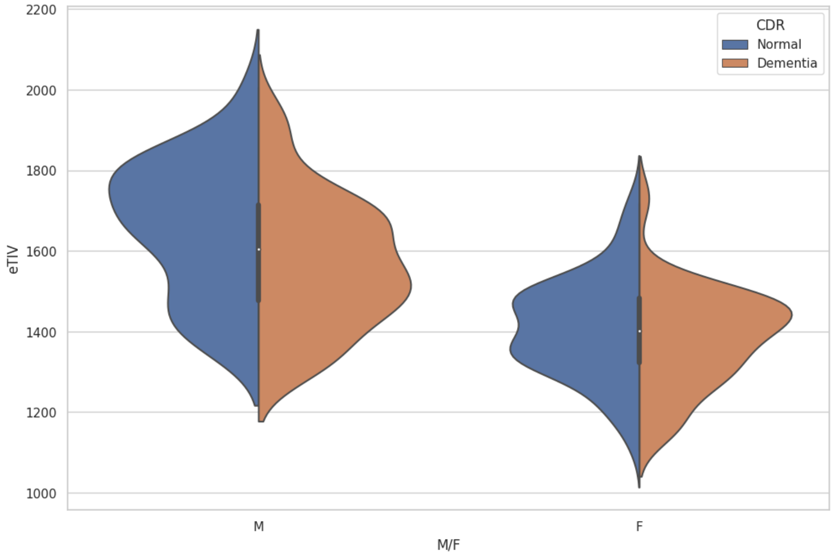
```
df_long['eTIV'].describe()
```

```
count     373.000000
mean     1488.128686
std       176.139286
min      1106.000000
25%      1357.000000
50%      1470.000000
75%      1597.000000
max      2004.000000
Name: eTIV, dtype: float64
```

```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="age_group", y="eTIV",hue="CDR",split=True, data=df_long)
plt.show()
```

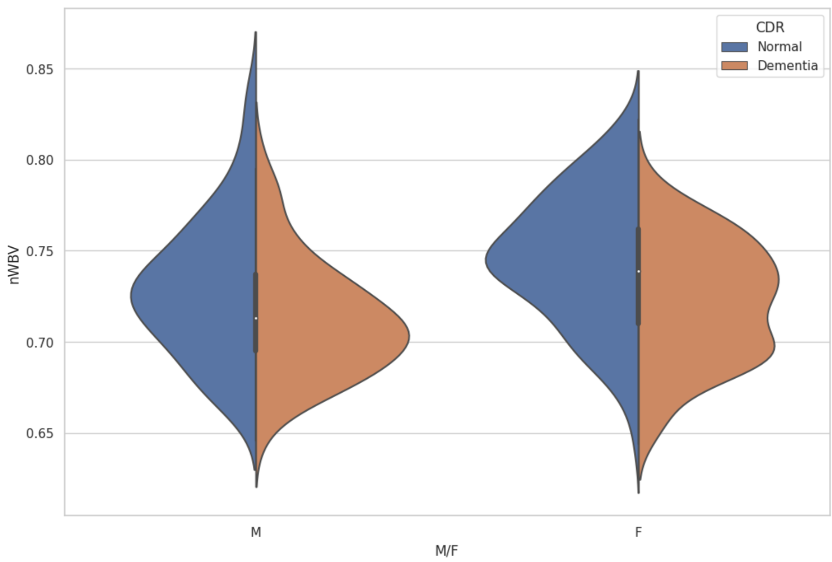



```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="M/F", y="eTIV",hue="CDR",split=True, data=df_long)
plt.show()
```



Normalized whole-brain volume, expressed as a percent of all voxels in the atlas-masked image that are labeled as gray or white matter by the automated tissue segmentation process

```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="M/F", y="nWBV",hue="CDR",split=True, data=df_long)
plt.show()
```

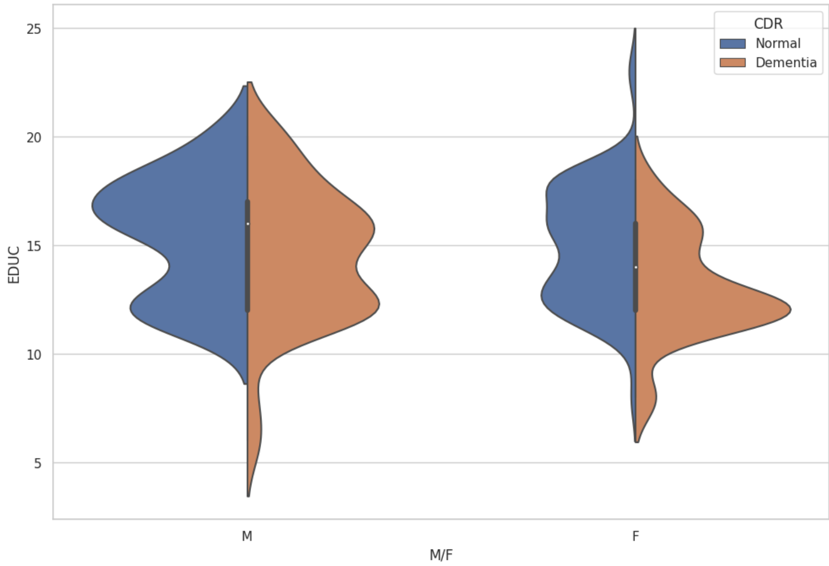



```
df_long['EDUC'].describe()
```

```
count    373.000000
mean      14.597855
std        2.876339
min        6.000000
25%       12.000000
```

```
50%       15.000000
75%       16.000000
max       23.000000
Name: EDUC, dtype: float64
```

```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="M/F", y="EDUC",hue="CDR",split=True, data=df_long)
plt.show()
```



Observation: As we can observe from the above plot,Mens having education level between 10 and 17 have higher level of dementia cases and mens started to show dymentia symptoms with less education levels starting from 4 years whereas females starts showing dymentia symptoms after 6 years of education level having highest peak at 13 years of age.

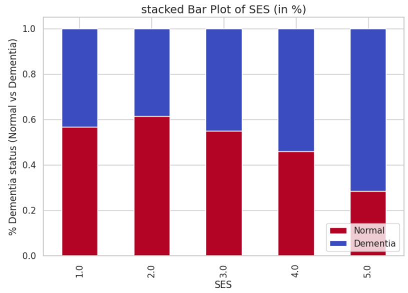
SES - Socioeconomic status, classified into categories from 1 (highest status) to 5 (lowest status)

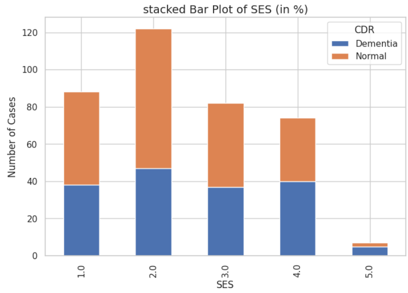
```
df_long['SES'].describe()
```

```
count    373.000000
mean       2.436997
std        1.109307
min        1.000000
25%        2.000000
50%        2.000000
75%        3.000000
max        5.000000
Name: SES, dtype: float64
```

Now plotting socio economic status to see dementia distribution

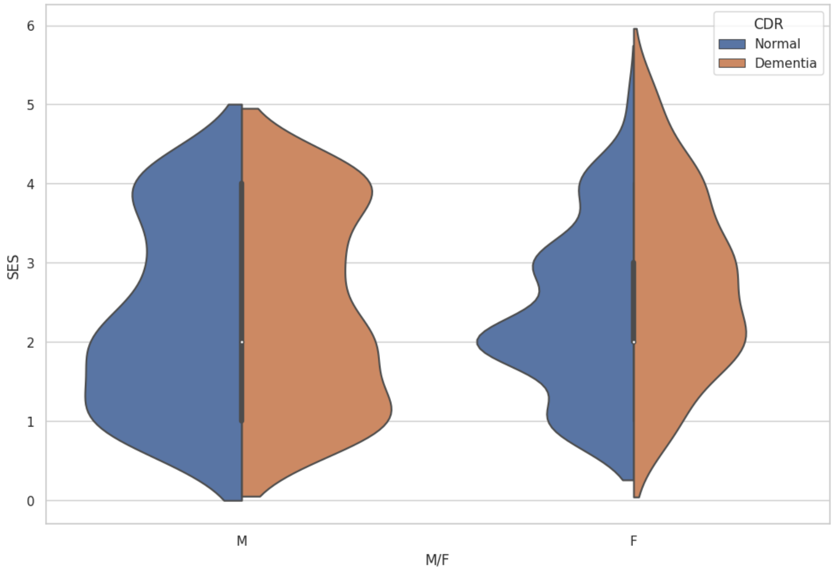
```
univariate_percent_plot('SES')
```





Observation: At lowest level of socio economic status there is a highest probability of dementia which may be due to lower economic condition which results in depression, mental sufferings which in turn results in dementia.

```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="M/F", y="SES",hue="CDR",split=True, data=df_long)
plt.show()
```



Observation: Interesting pattern observed from the above plot that in mens there are two peaks of highest dementia cases one at 1 (Highest status) and 4(lower status) and in between 1 and 4 there less instances of dementia cases whereas in case of females highest peak is at 2 whereas at 1 and 5 there are slightly less dementia cases reported. It suggests that womens have less dementia probability at extreme higher and extreme lower level of socio economic status while mens have exactly opposite phenomenon.

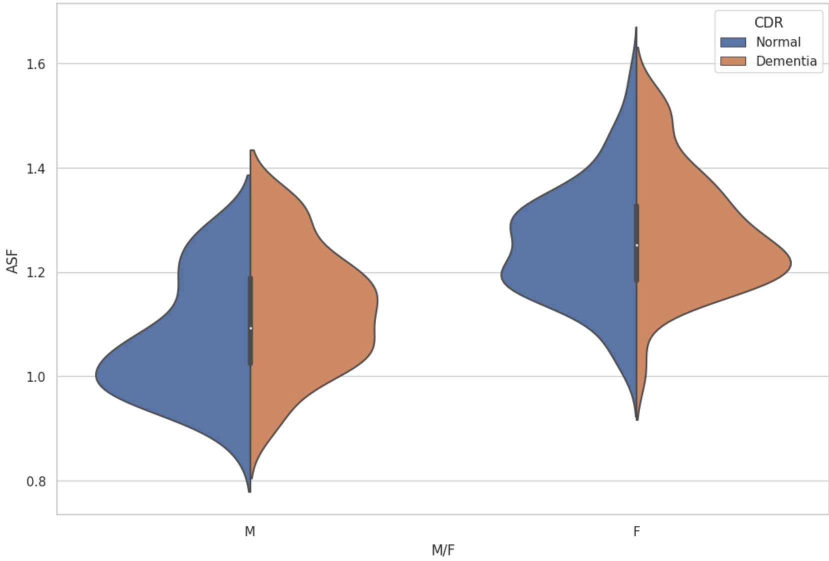
ASF - Atlas scaling factor (unitless). Computed scaling factor that transforms native-space brain and skull to the atlas target

```
df_long['ASF'].describe()
```

```
count    373.000000
mean       1.195461
std        0.138092
min        0.876000
25%        1.099000
50%        1.194000
```

```
75%        1.293000
max        1.587000
Name: ASF, dtype: float64
```

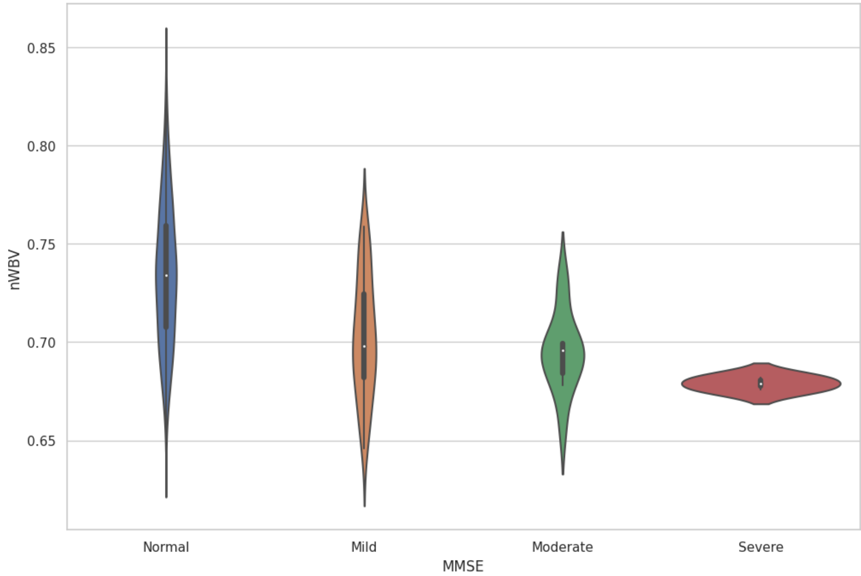
```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="M/F", y="ASF",hue="CDR",split=True, data=df_long)
plt.show()
```




```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="MMSE", y="ASF",split=True, data=df_long)
plt.show()
```

From the above plot we can get the intuition about ASF as in case of normal patients the value of ASF distributed between 0.8 and 1.6 but as the patients started showing dementia cases its value centered around 1 as in case of Mild, Moderate and Severe it shrinks down to 1.1

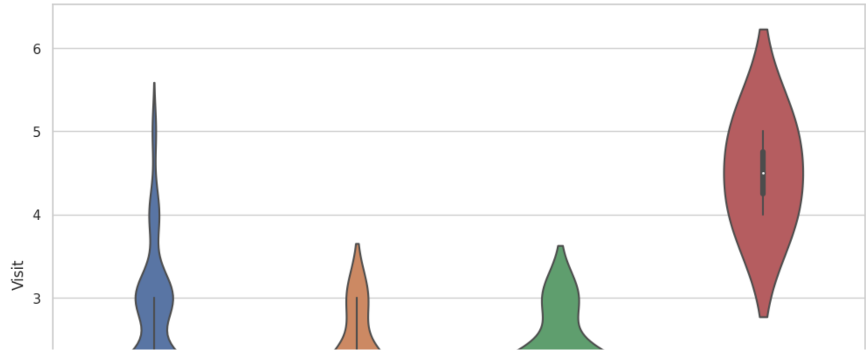
```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="MMSE", y="nWBV",split=True, data=df_long)
plt.show()
```



Observation:

Same pattern observed in case of nWBV as the dementia level increases nWBV centered between 0.65 and 0.70.

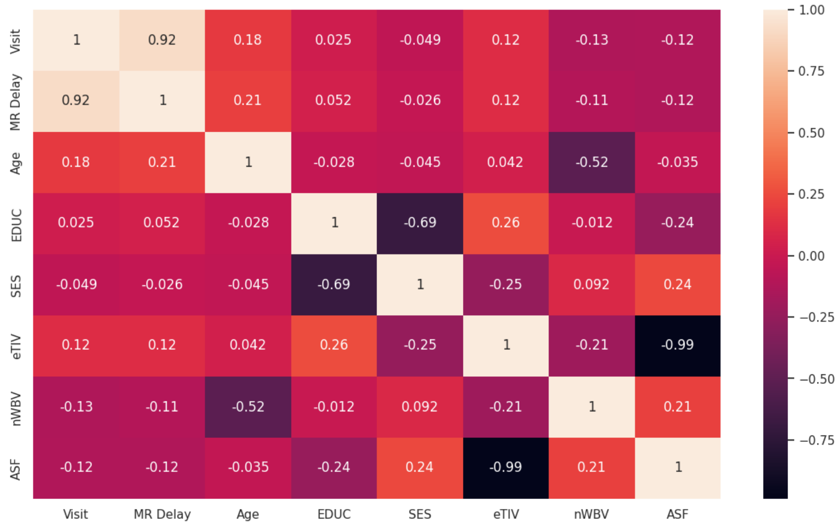
```
plt.figure(figsize=(12, 8))
ax = sns.violinplot(x="MMSE", y="Visit",split=True, data=df_long)
plt.show()
```



Observation: Severe Dementia cases starts reporting as the number of visits increases to more than 3 whereas normal cases are also reported after higher number of visits more than 3 but they are very few in number.

Multicollinearity In this step, we will see how much variables are correlated with another

```
plt.figure(figsize=(14, 8))
sns.heatmap(df_long.corr(), annot=True)
plt.show()
```



Key Insights: Most of the cases of dementia observed in the age group of 70 - 80 years of Age. Mens develop dementia at early age before 60 years while womens have tendency of dementia at later age of later than 60 years In mens dementia starts at an education level of 4 years and most prevalent at education level of 12 years and 16 years and it can also extend upto more than 20 years of education level, while in womens dementia starts after 5 years of education level and most prevalent around 12 to 13 years of education level and it started to decrease as womens education level increase Dementia is prevalent in Mens having highest and lowest socio economic status while womens having medium socio economic status have higher dementia cases. Lower values of ASF close to 1 corresponds to severe dementia cases. Severe dementia is diagnosed after minnimum 3 number of visits.

Double-click (or enter) to edit