Exploratory Data Analysis(EDA)

EDA is an approach of analyzing data sets to summarize their main characteristics, often using statistical graphics and other data visualization methods. In simple words The process of getting to know the data in depth is called Exploratory Data Analysis.

Steps:-

1. Data Collection. It is an essential part of exploratory data analysis.

2. Data Cleaning. It refers to the process of removing unwanted variables, values from dataset and getting rid of any irregularities in it.

3. Univariate Analysis. Statistical analysis of single variable and summarize the outcome of only one variable at a time.

4. Bivariate Analysis. Statistical analysis with two variables and comparing whether a relationship exists between them.

1. Data Collection

In [1]:
```
#Library files Load
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
#Dataset Load
dataset=pd.read_csv("Placement.csv")
```

In [3]:
```
dataset.head()
```

Out[3]:

	sl_no	gender	ssc_p	ssc_b	hsc_p	hsc_b	hsc_s	degree_p	degree_t	workex	etest_p	specialisati
0	1	M	67.00	Others	91.00	Others	Commerce	58.00	Sci&Tech	No	55.0	Mkt&I
1	2	M	79.33	Central	78.33	Others	Science	77.48	Sci&Tech	Yes	86.5	Mkt&I
2	3	M	65.00	Central	68.00	Central	Arts	64.00	Comm&Mgmt	No	75.0	Mkt&I
3	4	M	56.00	Central	52.00	Central	Science	52.00	Sci&Tech	No	66.0	Mkt&I
4	5	M	85.80	Central	73.60	Central	Commerce	73.30	Comm&Mgmt	No	96.8	Mkt&I

2. Data Cleaning

Find Missing or Null and NaN Values

In [4]:
```
dataset.shape     # it reveals no.of rows(215) and columns(15)
```

Out[4]:
```
(215, 15)
```

In [5]:
```
dataset.isnull().head(2)              #find null values and show entire dataset
```

Out[5]:

	sl_no	gender	ssc_p	ssc_b	hsc_p	hsc_b	hsc_s	degree_p	degree_t	workex	etest_p	specialisation	mba_p
0	False	False	False	False	False	False	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False	False	False	False	False	False	False

In [6]:
```
dataset.isnull().sum()              #Get the sum of null values in each column of dataset
```

Out[6]:
```
sl_no               0
gender              0
ssc_p               0
ssc_b               0
hsc_p               0
hsc_b               0
hsc_s               0
degree_p            0
degree_t            0
workex              0
etest_p             0
specialisation      0
mba_p               0
status              0
salary             67
dtype: int64
```

In [7]:
```
dataset.isna().sum()       #Likewise, Get the sum of NaN values in each column of dataset
```

Out[7]:
```
sl_no               0
gender              0
ssc_p               0
ssc_b               0
hsc_p               0
hsc_b               0
hsc_s               0
degree_p            0
degree_t            0
workex              0
etest_p             0
specialisation      0
mba_p               0
status              0
salary             67
dtype: int64
```

In [8]:
```
dataset.isna().sum().max()            #maximum of NaN values count
```

Out[8]:
```
67
```

Percentage of Missing or Null and NaN values

In [9]:
```
dataset=pd.read_csv("Placement.csv")
```

In [10]:
```
#Finding missing data in percentage
total = dataset.isnull().sum().sort_values(ascending=False)
percent = (dataset.isnull().sum()/dataset.isnull().count()).sort_values(ascending=False)
missing_data = pd.concat([total,percent],axis=1,keys=['total','percent'])
missing_data.head()
```

Out[10]:

	total	percent
salary	67	0.311628
sl_no	0	0.000000

gender	0	0.000000
ssc_p	0	0.000000
ssc_b	0	0.000000

To drop Missing or Null and NaN values

In [11]:
```
#dataset=dataset.drop((missing_data[missing_data['total']>1]).index,axis=1)   #It will d
#dataset=dataset.drop(dataset.loc[dataset['salary'].isnull()].index)           #drop all
#dataset=dataset.dropna()                                                     #drop all
#dataset.isna().sum().max()                                                   #Cross che
```

To drop unwanted columns

In [12]:
```
dataset=dataset.drop("sl_no",axis=1)                  # It will drop "Sl_No" column entir
                                                        #if axis=0 Row wise delete if the
```

To fill Missing or Null and NaN values

In [13]:
```
dataset["salary"]=dataset["salary"].fillna(0)           # fill null/NaN by 0 or any valu
#dataset=dataset.fillna(0)                                # fill null/NaN by 0 or any va
```

In [14]:
```
dataset.isna().sum().max()   #Cross Checking after fill null values
```

Out[14]:
```
0
```

3. Univariate Analysis

In [15]:
```
dataset.describe()      # Statistical values for all the quantitative columns in the whol
```

Out[15]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
count	215.000000	215.000000	215.000000	215.000000	215.000000	215.000000
mean	67.303395	66.333163	66.370186	72.100558	62.278186	198702.325581
std	10.827205	10.897509	7.358743	13.275956	5.833385	154780.926716
min	40.890000	37.000000	50.000000	50.000000	51.210000	0.000000
25%	60.600000	60.900000	61.000000	60.000000	57.945000	0.000000
50%	67.000000	65.000000	66.000000	71.000000	62.000000	240000.000000
75%	75.700000	73.000000	72.000000	83.500000	66.255000	282500.000000
max	89.400000	97.700000	91.000000	98.000000	77.890000	940000.000000

In [16]:
```
dataset.info()        # Get Basic informations about all column indexes in the whole Dat
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 215 entries, 0 to 214
Data columns (total 14 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   gender          215 non-null    object 
 1   ssc_p           215 non-null    float64
 2   ssc_b           215 non-null    object 
 3   hsc_p           215 non-null    float64
 4   hsc_b           215 non-null    object 
 5   hsc_s           215 non-null    object 
```

```
 6   degree_p        215 non-null    float64
 7   degree_t        215 non-null    object
 8   workex          215 non-null    object
 9   etest_p         215 non-null    float64
 10  specialisation  215 non-null    object
 11  mba_p           215 non-null    float64
 12  status          215 non-null    object
 13  salary          215 non-null    float64
dtypes: float64(6), object(8)
memory usage: 23.6+ KB
```

In [17]:
```
dataset['ssc_p'].dtypes     # Get datatype of selected column index from the Dataset
```

Out[17]:
```
dtype('float64')
```

In [18]:
```
dataset.columns              # Get column index names of the Dataset
```

Out[18]:
```
Index(['gender', 'ssc_p', 'ssc_b', 'hsc_p', 'hsc_b', 'hsc_s', 'degree_p',
       'degree_t', 'workex', 'etest_p', 'specialisation', 'mba_p', 'status',
       'salary'],
      dtype='object')
```

In [19]:
```
# Code to separate Quantitative & Qualitative Columns
Quan=[]
Qual=[]
for column in dataset.columns:
    if(dataset[column].dtypes=='object'):
        Qual.append(column)
    else:
        Quan.append(column)
```

In [20]:
```
Quan
```

Out[20]:
```
['ssc_p', 'hsc_p', 'degree_p', 'etest_p', 'mba_p', 'salary']
```

In [21]:
```
Qual
```

Out[21]:
```
['gender',
 'ssc_b',
 'hsc_b',
 'hsc_s',
 'degree_t',
 'workex',
 'specialisation',
 'status']
```

In [22]:
```
# Converting as User defined function to find Quantitative & Qualitative Columns
def QuanQual(dataset):
    Quan=[]
    Qual=[]
    for column in dataset.columns:

        if(dataset[column].dtypes=='object'):
            Qual.append(column)
        else:
            Quan.append(column)

    return Quan, Qual
```

In [23]:
```
quan,qual = QuanQual(dataset)          # Calling user defined function 'QuanQual' & Assi
```

In [24]:
```
quan
```

```
['ssc_p', 'hsc_p', 'degree_p', 'etest_p', 'mba_p', 'salary']
```

Out[24]:

In [25]:
```
qual
```

Out[25]:
```
['gender',
 'ssc_b',
 'hsc_b',
 'hsc_s',
 'degree_t',
 'workex',
 'specialisation',
 'status']
```

In [26]:
```
dataset['ssc_p'].value_counts()          # Get no.of unique values and its counts separat
                                         # Here the Total Unique Value counts is = 103.
```

Out[26]:
```
62.00    11
63.00    10
67.00     9
52.00     9
73.00     9
         ..
69.70     1
80.92     1
83.00     1
86.50     1
80.60     1
Name: ssc_p, Length: 103, dtype: int64
```

In [27]:
```
dataset['ssc_p'].value_counts().index       # Show all the unique values alone as like co
```

Out[27]:
```
Float64Index([ 62.0,  63.0,  67.0,  52.0,  73.0,  74.0,  65.0,  69.0,  77.0,
                58.0,
               ...
                81.7,  64.6,  52.6, 84.86,  75.0,  69.7, 80.92,  83.0,  86.5,
                80.6],
              dtype='float64', length=103)
```

In [28]:
```
dataset['ssc_p'].value_counts().values      # Get all the unique value counts alone as l
                                               #(it's nothing but Frequency)
```

Out[28]:
```
array([11, 10,  9,  9,  9,  7,  7,  7,  6,  6,  4,  4,  4,  4,  3,  3,  3,
        3,  3,  3,  3,  3,  3,  3,  2,  2,  2,  2,  2,  2,  2,  2,  2,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,  1,
        1], dtype=int64)
```

In [29]:
```
len(dataset['ssc_p'].value_counts().values)          # The length of unique values , i.e
```

Out[29]:
```
103
```

In [30]:
```
len(dataset["ssc_p"])                        # Total length of a column values,  i.e  21
```

Out[30]:
```
215
```

In [31]:
```
dataset['ssc_p'].value_counts().values/len(dataset["ssc_p"])*100       #Percentage of ea
                                                                          #(it's nothin
```

Out[31]:
```
array([5.11627907, 4.65116279, 4.18604651, 4.18604651, 4.18604651,
       3.25581395, 3.25581395, 3.25581395, 2.79069767, 2.79069767,
       1.86046512, 1.86046512, 1.86046512, 1.86046512, 1.39534884,
       1.39534884, 1.39534884, 1.39534884, 1.39534884, 1.39534884,
       1.39534884, 1.39534884, 1.39534884, 1.39534884, 0.93023256,
```

```
       0.93023256, 0.93023256, 0.93023256, 0.93023256, 0.93023256,
       0.93023256, 0.93023256, 0.93023256, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628, 0.46511628, 0.46511628,
       0.46511628, 0.46511628, 0.46511628])
```

In [32]:
```
dataset['ssc_p'].cumsum()              # Cumulative sum of all the values a single colu
```

Out[32]:
```
0         67.00
1        146.33
2        211.33
3        267.33
4        353.13
          ...
210    14209.23
211    14267.23
212    14334.23
213    14408.23
214    14470.23
Name: ssc_p, Length: 215, dtype: float64
```

Creating a User defined Table to tabulate the Frequencies of Unique Values

In [33]:
```
 frq=pd.DataFrame()           # Creating a Table named 'freq' using Pandas
```

In [34]:
```
frq                    # 'freq' Table has no values
```

Out[34]: —

In [35]:
```
frq["Unique_Values"]=dataset['ssc_p'].value_counts().index       # Creating a column inde
```

In [36]:
```
frq.head()            # Now the 'freq' Table has a column index and values
```

Out[36]:

	Unique_Values
0	62.0
1	63.0
2	67.0
3	52.0
4	73.0

In [37]:
```
frq["Frequency"]=dataset['ssc_p'].value_counts().values          # Adding second column
```

In [38]:
```
frq.head()
```

Out[38]:

	Unique_Values	Frequency
0	62.0	11

1	63.0	10
2	67.0	9
3	52.0	9
4	73.0	9

In [39]:
```
frq["Relative_Freq"]=dataset['ssc_p'].value_counts().values/len(dataset["ssc_p"])*100
```

In [40]:
```
frq.head()
```

Out[40]:

	Unique_Values	Frequency	Relative_Freq
0	62.0	11	5.116279
1	63.0	10	4.651163
2	67.0	9	4.186047
3	52.0	9	4.186047
4	73.0	9	4.186047

In [41]:
```
frq["Cumulative_Freq"]=frq["Relative_Freq"].cumsum()            # Adding fourth column t
```

In [42]:
```
frq.head()
```

Out[42]:

	Unique_Values	Frequency	Relative_Freq	Cumulative_Freq
0	62.0	11	5.116279	5.116279
1	63.0	10	4.651163	9.767442
2	67.0	9	4.186047	13.953488
3	52.0	9	4.186047	18.139535
4	73.0	9	4.186047	22.325581

In [43]:
```
# All the above 'freq' Table creation steps are defined as a function
def FreqTable(columnName,dataset):
    frq=pd.DataFrame()
    frq["Unique_Values"]=dataset[columnName].value_counts().index
    frq["Frequency"]=dataset[columnName].value_counts().values
    frq["Relative_Freq"]=dataset[columnName].value_counts().values/len(dataset[columnNam
    frq["Cumulative_Freq"]=frq["Relative_Freq"].cumsum()
    return frq
```

In [44]:
```
FreqTable('ssc_p',dataset).head()              # 'FreqTable' Function called to get Freque
```

Out[44]:

	Unique_Values	Frequency	Relative_Freq	Cumulative_Freq
0	62.0	11	5.116279	5.116279
1	63.0	10	4.651163	9.767442
2	67.0	9	4.186047	13.953488
3	52.0	9	4.186047	18.139535
4	73.0	9	4.186047	22.325581

In [45]:
```
FreqTable('mba_p',dataset).head()                    # 'FreqTable' Function called to get F
```

Out[45]:

	Unique_Values	Frequency	Relative_Freq	Cumulative_Freq
0	56.70	3	1.395349	1.395349
1	66.94	2	0.930233	2.325581
2	59.47	2	0.930233	3.255814
3	60.44	2	0.930233	4.186047
4	68.07	2	0.930233	5.116279

Get the Statistical informations for desired individual columns in the dataset

In [46]:
```
dataset['ssc_p'].mean()              #Get the Mean of entire column
```

Out[46]:
```
67.30339534883721
```

In [47]:
```
dataset['ssc_p'].median()    #Get the Median of entire column & There is no outliers beca
```

Out[47]:
```
67.0
```

In [48]:
```
dataset['ssc_p'].mode()[0]           #Get the Mode of entire column
```

Out[48]:
```
62.0
```

In [49]:
```
univariate=pd.DataFrame(index=["Mean","Median","Mode"],columns=Quan)              #Creatin
```

In [50]:
```
univariate
```

Out[50]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
Mean	NaN	NaN	NaN	NaN	NaN	NaN
Median	NaN	NaN	NaN	NaN	NaN	NaN
Mode	NaN	NaN	NaN	NaN	NaN	NaN

In [51]:
```
univariate["ssc_p"]["Mean"]
```

Out[51]:
```
nan
```

In [52]:
```
for column in Quan:
    univariate[column]["Mean"]=dataset[column].mean()
    univariate[column]["Median"]=dataset[column].median()
    univariate[column]["Mode"]=dataset[column].mode()[0]
```

In [53]:
```
univariate
```

Out[53]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
Mean	67.303395	66.333163	66.370186	72.100558	62.278186	198702.325581
Median	67.0	65.0	66.0	71.0	62.0	240000.0
Mode	62.0	63.0	65.0	60.0	56.7	0.0

In [54]:
```
np.percentile(dataset['ssc_p'],0)
```

```
40.89
```

Out[54]:

In [55]:
```
np.percentile(dataset['ssc_p'],100)
```

Out[55]:
```
89.4
```

In [56]:
```
dataset['ssc_p'].min()
```

Out[56]:
```
40.89
```

In [57]:
```
dataset['ssc_p'].max()
```

Out[57]:
```
89.4
```

In [58]:
```
univariate=pd.DataFrame(index=["Mean","Median","Mode","Min","25%","50%","75%","Max"],col
for column in Quan:
    univariate[column]["Mean"]=dataset[column].mean()
    univariate[column]["Median"]=dataset[column].median()
    univariate[column]["Mode"]=dataset[column].mode()[0]

    univariate[column]["Min"]=dataset[column].min()
    univariate[column]["25%"]=np.percentile(dataset[column],25)
    univariate[column]["50%"]=np.percentile(dataset[column],50)
    univariate[column]["75%"]=np.percentile(dataset[column],75)
    univariate[column]["Max"]=dataset[column].max()
```

In [59]:
```
dataset['salary'].mode()[0]
```

Out[59]:
```
0.0
```

In [60]:
```
univariate
```

Out[60]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
Mean	67.303395	66.333163	66.370186	72.100558	62.278186	198702.325581
Median	67.0	65.0	66.0	71.0	62.0	240000.0
Mode	62.0	63.0	65.0	60.0	56.7	0.0
Min	40.89	37.0	50.0	50.0	51.21	0.0
25%	60.6	60.9	61.0	60.0	57.945	0.0
50%	67.0	65.0	66.0	71.0	62.0	240000.0
75%	75.7	73.0	72.0	83.5	66.255	282500.0
Max	89.4	97.7	91.0	98.0	77.89	940000.0

In [61]:
```
univariate=pd.DataFrame(index=["Mean","Median","Mode","Min","25%","50%","75%","Max","IQR
for column in Quan:

    univariate[column]["Mean"]=dataset[column].mean()
    univariate[column]["Median"]=dataset[column].median()
    univariate[column]["Mode"]=dataset[column].mode()[0]


    univariate[column]["Min"]=dataset[column].min()
    univariate[column]["25%"]=np.percentile(dataset[column],25)
    univariate[column]["50%"]=np.percentile(dataset[column],50)
    univariate[column]["75%"]=np.percentile(dataset[column],75)
    univariate[column]["Max"]=dataset[column].max()
```

```
    univariate[column]["IQR"]=univariate[column]["75%"]-univariate[column]["25%"]
    univariate[column]["1.5*IQR"]=1.5*univariate[column]["IQR"]
    univariate[column]["Lesser"]=univariate[column]["25%"]-univariate[column]["1.5*IQR"]
    univariate[column]["Greater"]=univariate[column]["75%"]+univariate[column]["1.5*IQR"]
```

In [62]:
```
univariate
```

Out[62]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
Mean	67.303395	66.333163	66.370186	72.100558	62.278186	198702.325581
Median	67.0	65.0	66.0	71.0	62.0	240000.0
Mode	62.0	63.0	65.0	60.0	56.7	0.0
Min	40.89	37.0	50.0	50.0	51.21	0.0
25%	60.6	60.9	61.0	60.0	57.945	0.0
50%	67.0	65.0	66.0	71.0	62.0	240000.0
75%	75.7	73.0	72.0	83.5	66.255	282500.0
Max	89.4	97.7	91.0	98.0	77.89	940000.0
IQR	15.1	12.1	11.0	23.5	8.31	282500.0
1.5*IQR	22.65	18.15	16.5	35.25	12.465	423750.0
Lesser	37.95	42.75	44.5	24.75	45.48	-423750.0
Greater	98.35	91.15	88.5	118.75	78.72	706250.0

In [63]:
```
Lesserr=[]
Greaterr=[]
for column in Quan:

    if(univariate[column]["Min"]<univariate[column]["Lesser"]):
        Lesserr.append(column)
    if(univariate[column]["Max"]>univariate[column]["Greater"]):
        Greaterr.append(column)

print("Lesserr Columns: ",Lesserr)
print("Greaterr Columns: ",Greaterr)
```

```
Lesserr Columns:  ['hsc_p']
Greaterr Columns:  ['hsc_p', 'degree_p', 'salary']
```

In [64]:
```
univariate['hsc_p']['Lesser']
```

Out[64]:
```
42.75
```

In [65]:
```
dataset['hsc_p']
```

Out[65]:
```
0      91.00
1      78.33
2      68.00
3      52.00
4      73.60
       ...
210    82.00
211    60.00
212    67.00
213    66.00
```

```
214    58.00
Name: hsc_p, Length: 215, dtype: float64
```

In [66]:
```
dataset['hsc_p']<=42.75
```

Out[66]:
```
0      False
1      False
2      False
3      False
4      False
       ...
210    False
211    False
212    False
213    False
214    False
Name: hsc_p, Length: 215, dtype: bool
```

In [67]:
```
dataset['hsc_p']<=42.75
dataset.head()
```

Out[67]:

	gender	ssc_p	ssc_b	hsc_p	hsc_b	hsc_s	degree_p	degree_t	workex	etest_p	specialisation	mb
0	M	67.00	Others	91.00	Others	Commerce	58.00	Sci&Tech	No	55.0	Mkt&HR	5
1	M	79.33	Central	78.33	Others	Science	77.48	Sci&Tech	Yes	86.5	Mkt&Fin	6
2	M	65.00	Central	68.00	Central	Arts	64.00	Comm&Mgmt	No	75.0	Mkt&Fin	5
3	M	56.00	Central	52.00	Central	Science	52.00	Sci&Tech	No	66.0	Mkt&HR	5
4	M	85.80	Central	73.60	Central	Commerce	73.30	Comm&Mgmt	No	96.8	Mkt&Fin	5

In [68]:
```
dataset[dataset['hsc_p']<=42.75]
```

Out[68]:

	gender	ssc_p	ssc_b	hsc_p	hsc_b	hsc_s	degree_p	degree_t	workex	etest_p	specialisation	mb
42	M	49.00	Others	39.00	Central	Science	65.00	Others	No	63.00	Mkt&Fin	5
49	F	50.00	Others	37.00	Others	Arts	52.00	Others	No	65.00	Mkt&HR	5
120	M	58.00	Others	40.00	Others	Science	59.00	Comm&Mgmt	No	73.00	Mkt&HR	5
169	M	59.96	Others	42.16	Others	Science	61.26	Sci&Tech	No	54.48	Mkt&HR	6
206	M	41.00	Central	42.00	Central	Science	60.00	Comm&Mgmt	No	97.00	Mkt&Fin	5

In [69]:
```
dataset['hsc_p']<univariate['hsc_p']['Lesser']
```

Out[69]:
```
0      False
1      False
2      False
3      False
4      False
       ...
210    False
211    False
212    False
213    False
```

```
214    False
Name: hsc_p, Length: 215, dtype: bool
```

In [70]:
```
dataset['hsc_p'][dataset['hsc_p']<univariate['hsc_p']['Lesser']]
```

Out[70]:
```
42     39.00
49     37.00
120    40.00
169    42.16
206    42.00
Name: hsc_p, dtype: float64
```

In [71]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [72]:
```
dataset['hsc_p'][dataset['hsc_p']<univariate['hsc_p']['Lesser']]=univariate['hsc_p']['Le
```

In [73]:
```
dataset['hsc_p'][dataset['hsc_p']<univariate['hsc_p']['Lesser']]
```

Out[73]:
```
Series([], Name: hsc_p, dtype: float64)
```

In [74]:
```
for less in Lesserr:
    dataset[less][dataset[less]<univariate[less]['Lesser']]=univariate[less]['Lesser']
for less in Greaterr:
    dataset[less][dataset[less]>univariate[less]['Greater']]=univariate[less]['Greater']
```

In [75]:
```
univariate=pd.DataFrame(index=["Mean","Median","Mode","Min","25%","50%","75%","Max","IQR
for column in Quan:
    univariate[column]["Mean"]=dataset[column].mean()
    univariate[column]["Median"]=dataset[column].median()
    univariate[column]["Mode"]=dataset[column].mode()[0]

    univariate[column]["Min"]=dataset[column].min()
    univariate[column]["25%"]=np.percentile(dataset[column],25)
    univariate[column]["50%"]=np.percentile(dataset[column],50)
    univariate[column]["75%"]=np.percentile(dataset[column],75)
    univariate[column]["Max"]=dataset[column].max()

    univariate[column]["IQR"]=univariate[column]["75%"]-univariate[column]["25%"]
    univariate[column]["1.5*IQR"]=1.5*univariate[column]["IQR"]
    univariate[column]["Lesser"]=univariate[column]["25%"]-univariate[column]["1.5*IQR"]
    univariate[column]["Greater"]=univariate[column]["75%"]+univariate[column]["1.5*IQR"
```

In [76]:
```
Lesserr=[]
Greaterr=[]
for column in Quan:

    if(univariate[column]["Min"]<univariate[column]["Lesser"]):
        Lesserr.append(column)
    if(univariate[column]["Max"]>univariate[column]["Greater"]):
        Greaterr.append(column)

print("Lesserr Columns: ",Lesserr)
print("Greaterr Columns: ",Greaterr)
```

```
Lesserr Columns:  []
Greaterr Columns:  []
```

In [77]:
```
univariate
```

Out[77]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary

Mean	67.303395	66.334744	66.358558	72.100558	62.278186	197615.116279
Median	67.0	65.0	66.0	71.0	62.0	240000.0
Mode	62.0	63.0	65.0	60.0	56.7	0.0
Min	40.89	42.75	50.0	50.0	51.21	0.0
25%	60.6	60.9	61.0	60.0	57.945	0.0
50%	67.0	65.0	66.0	71.0	62.0	240000.0
75%	75.7	73.0	72.0	83.5	66.255	282500.0
Max	89.4	91.15	88.5	98.0	77.89	706250.0
IQR	15.1	12.1	11.0	23.5	8.31	282500.0
1.5*IQR	22.65	18.15	16.5	35.25	12.465	423750.0
Lesser	37.95	42.75	44.5	24.75	45.48	-423750.0
Greater	98.35	91.15	88.5	118.75	78.72	706250.0

In [78]:
```
#dir(dataset['hsc_p'])
```

In [79]:
```
dataset['hsc_p'].var()
```

Out[79]:
```
112.0637306585525
```

In [80]:
```
dataset['hsc_p'].std()
```

Out[80]:
```
10.586015806645694
```

In [81]:
```
dataset['hsc_p'].kurtosis()
```

Out[81]:
```
0.08690077018906717
```

In [82]:
```
dataset['hsc_p'].skew()
```

Out[82]:
```
0.16261050623024148
```

In [83]:
```
univariate=pd.DataFrame(index=["Mean","Median","Mode","Min","25%","50%","75%","Max","IQR

for column in Quan:

    univariate[column]["Mean"]=dataset[column].mean()
    univariate[column]["Median"]=dataset[column].median()
    univariate[column]["Mode"]=dataset[column].mode()[0]

    univariate[column]["Min"]=dataset[column].min()
    univariate[column]["25%"]=np.percentile(dataset[column],25)
    univariate[column]["50%"]=np.percentile(dataset[column],50)
    univariate[column]["75%"]=np.percentile(dataset[column],75)
    univariate[column]["Max"]=dataset[column].max()

    univariate[column]["IQR"]=univariate[column]["75%"]-univariate[column]["25%"]
    univariate[column]["1.5*IQR"]=1.5*univariate[column]["IQR"]
    univariate[column]["Lesser"]=univariate[column]["25%"]-univariate[column]["1.5*IQR"]
    univariate[column]["Greater"]=univariate[column]["75%"]+univariate[column]["1.5*IQR"

    univariate[column]["Variance"]=dataset[column].var()
    univariate[column]["Std"]=dataset[column].std()
```

```
    univariate[column]["Kurtosis"]=dataset[column].kurtosis()
    univariate[column]["Skew"]=dataset[column].skew()
```

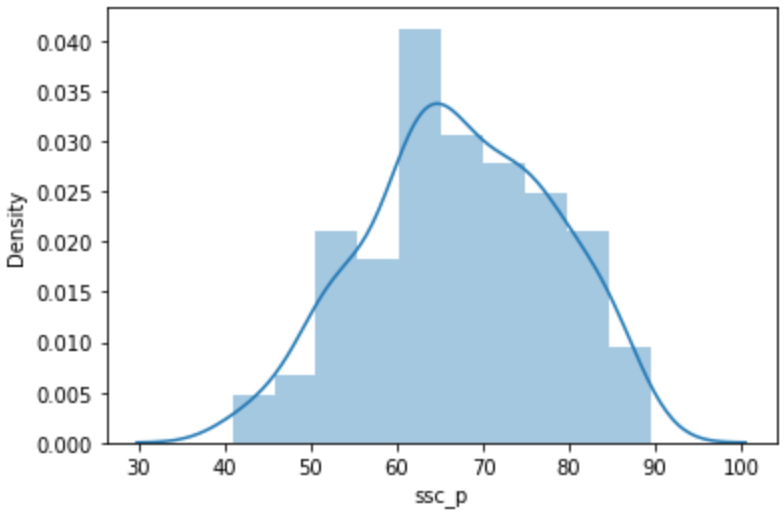
In [84]:
```
univariate
```

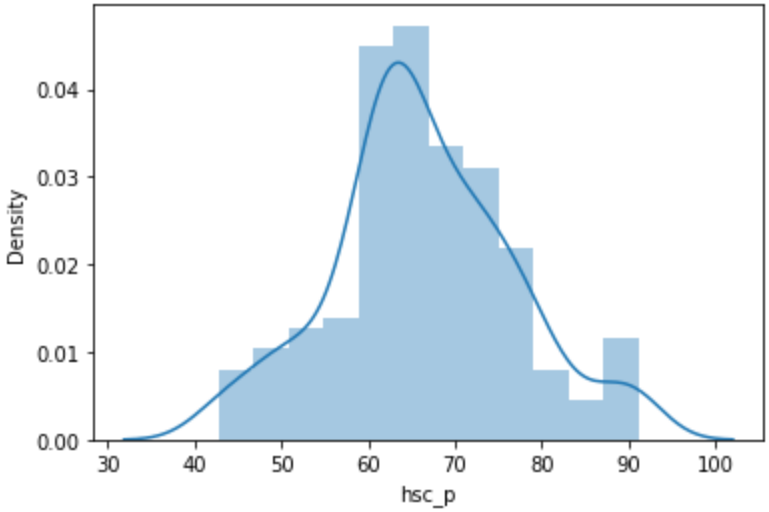
Out[84]:

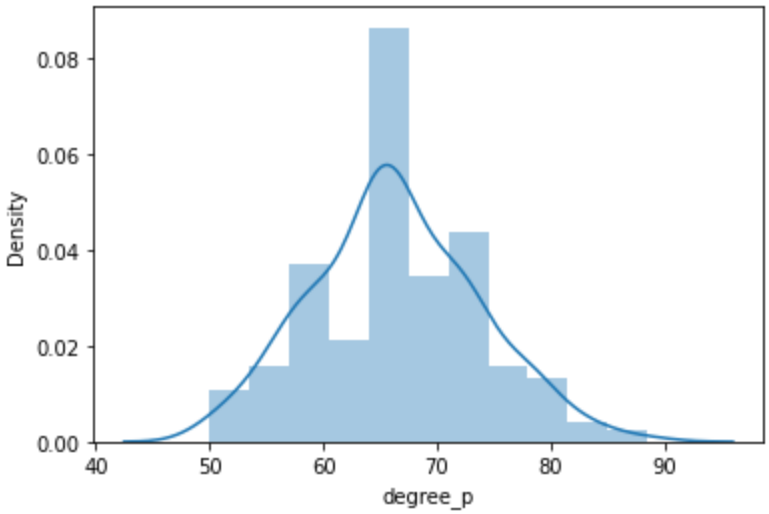
	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
Mean	67.303395	66.334744	66.358558	72.100558	62.278186	197615.116279
Median	67.0	65.0	66.0	71.0	62.0	240000.0
Mode	62.0	63.0	65.0	60.0	56.7	0.0
Min	40.89	42.75	50.0	50.0	51.21	0.0
25%	60.6	60.9	61.0	60.0	57.945	0.0
50%	67.0	65.0	66.0	71.0	62.0	240000.0
75%	75.7	73.0	72.0	83.5	66.255	282500.0
Max	89.4	91.15	88.5	98.0	77.89	706250.0
IQR	15.1	12.1	11.0	23.5	8.31	282500.0
1.5*IQR	22.65	18.15	16.5	35.25	12.465	423750.0
Lesser	37.95	42.75	44.5	24.75	45.48	-423750.0
Greater	98.35	91.15	88.5	118.75	78.72	706250.0
Variance	117.228377	112.063731	53.60471	176.251018	34.028376	22591846791.458374
Std	10.827205	10.586016	7.321524	13.275956	5.833385	150305.844169
Kurtosis	-0.60751	0.086901	-0.09749	-1.08858	-0.470723	0.025787
Skew	-0.132649	0.162611	0.204164	0.282308	0.313576	0.125415

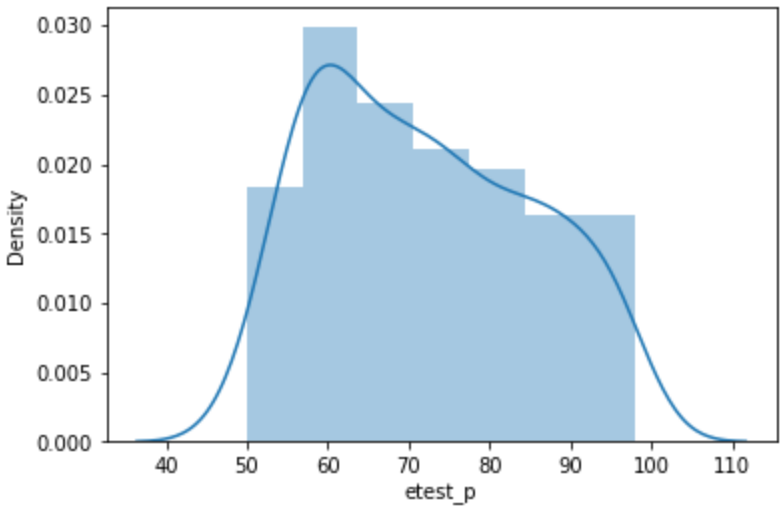
Histogram with Distribution Plots

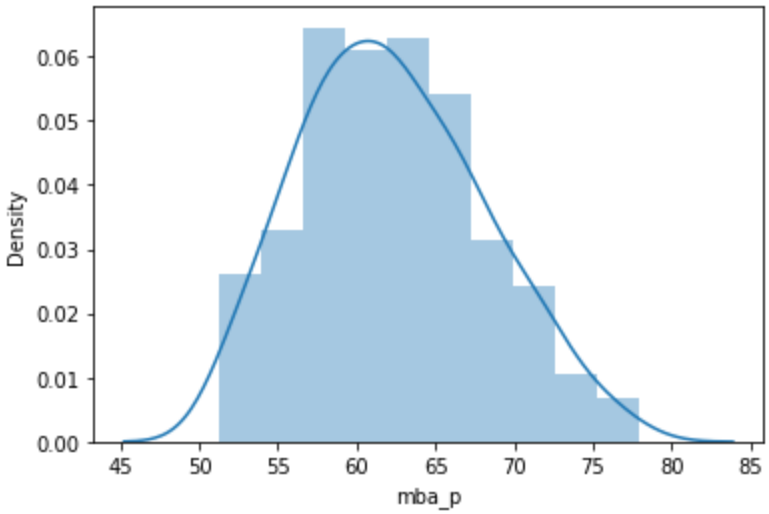
In [85]:
```
# Distribution Plots with histogram for all the quantitative columns data variables
for column in Quan:
    sns.distplot(dataset[column])
    plt.figure()             #it describes Overall distribution of continuous data variab
```

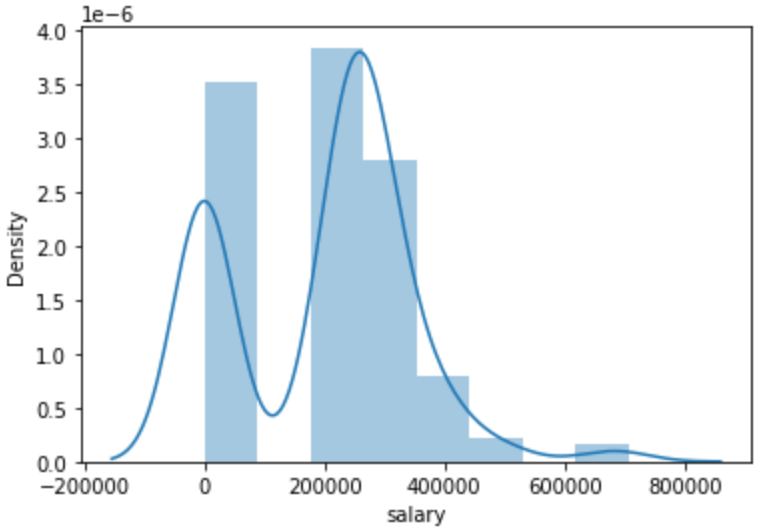



Density
0.04
0.03
0.02
0.01
0.00
30
40
50
60
70
80
90
100
hsc_p


Density
0.08
0.06
0.04
0.02
0.00
40
50
60
70
80
90
degree_p


Density
0.030
0.025
0.020
0.015
0.010
0.005
0.000
40
50
60
70
80
90
100
110
etest_p





<Figure size 432x288 with 0 Axes>

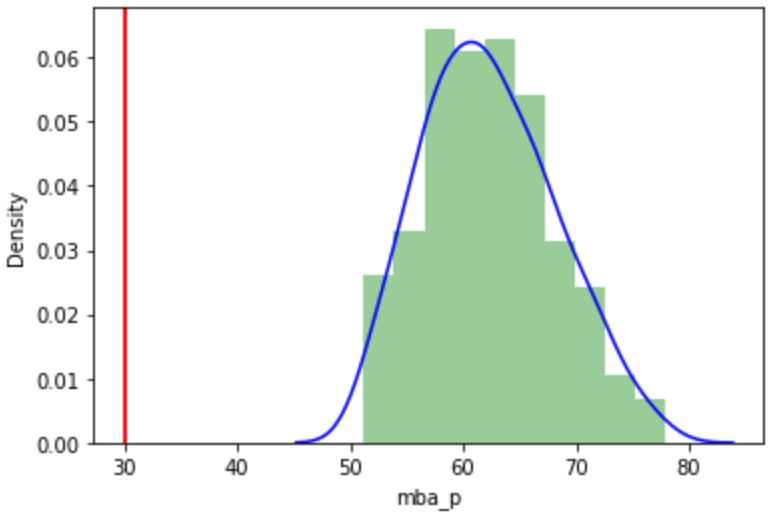
Probability Densiy Function

In [86]:
```
def get_pdf_probability(dataset,startrange,endrange):
    from matplotlib import pyplot
    from scipy.stats import norm
    import seaborn as sns
    ax=sns.distplot(dataset,kde=True,kde_kws={'color':'blue'},color='Green')
    pyplot.axvline(startrange,color='Red')
    pyplot.axvline(endrange,color='Red')

    # generate a sample
    sample=dataset
    #calculate parameters
    sample_mean=sample.mean()
    sample_std=sample.std()
    print('Mean=%.3f, Standard Deviation=%.3f' %(sample_mean, sample_std))
    #define the distribution
    dist=norm(sample_mean, sample_std)

    #sample probalities for a range of outcomes
    values=[value for value in range(startrange, endrange)]          #One-Liner for loop
    probabilities=[dist.pdf(value) for value in values]
    prob=sum(probabilities)
    print('The area between range({},{}):{}'.format(startrange,endrange,sum(probabilitie
    return prob
```

In [87]:
```
get_pdf_probability(dataset['mba_p'],30,30)
```

```
Mean=62.278, Standard Deviation=5.833
The area between range(30,30):0
0
```

Out[87]:



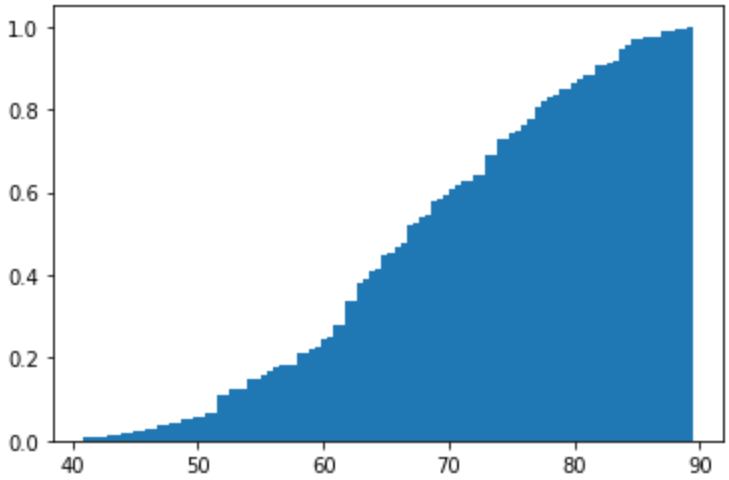
Cumulative Probability Density Function

In [88]:
```
import matplotlib.pyplot as plt
x=dataset['ssc_p']
plt.hist(x,cumulative=True, density=True, bins=100)
```

Out[88]:

```
(array([0.00930233, 0.00930233, 0.00930233, 0.00930233, 0.01395349,
        0.01395349, 0.01860465, 0.01860465, 0.02325581, 0.02325581,
        0.02790698, 0.02790698, 0.0372093 , 0.0372093 , 0.04186047,
        0.04186047, 0.05116279, 0.05116279, 0.05581395, 0.05581395,
        0.06511628, 0.06511628, 0.11162791, 0.11162791, 0.1255814 ,
        0.1255814 , 0.1255814 , 0.14883721, 0.14883721, 0.15813953,
        0.16744186, 0.17674419, 0.18139535, 0.18139535, 0.18139535,
        0.20930233, 0.20930233, 0.22325581, 0.22790698, 0.24651163,
        0.25116279, 0.27906977, 0.27906977, 0.33488372, 0.33488372,
        0.38139535, 0.39069767, 0.40930233, 0.41395349, 0.44651163,
        0.45116279, 0.46511628, 0.47906977, 0.52093023, 0.5255814 ,
        0.53953488, 0.54418605, 0.57674419, 0.58139535, 0.59534884,
        0.60930233, 0.61860465, 0.62790698, 0.62790698, 0.64186047,
        0.64186047, 0.68837209, 0.68837209, 0.73023256, 0.73023256,
        0.74418605, 0.74883721, 0.7627907 , 0.77674419, 0.80465116,
        0.81860465, 0.82790698, 0.83255814, 0.84651163, 0.85116279,
        0.86511628, 0.8744186 , 0.88372093, 0.88372093, 0.90697674,
        0.90697674, 0.91162791, 0.91627907, 0.94418605, 0.95348837,
        0.96744186, 0.96744186, 0.97209302, 0.97209302, 0.97674419,
        0.99069767, 0.99069767, 0.99534884, 0.99534884, 1.        ]),
 array([40.89  , 41.3751, 41.8602, 42.3453, 42.8304, 43.3155, 43.8006,
        44.2857, 44.7708, 45.2559, 45.741 , 46.2261, 46.7112, 47.1963,
        47.6814, 48.1665, 48.6516, 49.1367, 49.6218, 50.1069, 50.592 ,
        51.0771, 51.5622, 52.0473, 52.5324, 53.0175, 53.5026, 53.9877,
        54.4728, 54.9579, 55.443 , 55.9281, 56.4132, 56.8983, 57.3834,
        57.8685, 58.3536, 58.8387, 59.3238, 59.8089, 60.294 , 60.7791,
        61.2642, 61.7493, 62.2344, 62.7195, 63.2046, 63.6897, 64.1748,
        64.6599, 65.145 , 65.6301, 66.1152, 66.6003, 67.0854, 67.5705,
        68.0556, 68.5407, 69.0258, 69.5109, 69.996 , 70.4811, 70.9662,
        71.4513, 71.9364, 72.4215, 72.9066, 73.3917, 73.8768, 74.3619,
        74.847 , 75.3321, 75.8172, 76.3023, 76.7874, 77.2725, 77.7576,
        78.2427, 78.7278, 79.2129, 79.698 , 80.1831, 80.6682, 81.1533,
        81.6384, 82.1235, 82.6086, 83.0937, 83.5788, 84.0639, 84.549 ,
        85.0341, 85.5192, 86.0043, 86.4894, 86.9745, 87.4596, 87.9447,
```

```
        88.4298, 88.9149, 89.4   ]),
 <BarContainer object of 100 artists>)
```



In [89]:
```
from statsmodels.distributions.empirical_distribution import ECDF
ecdf = ECDF(dataset['ssc_p'])
```

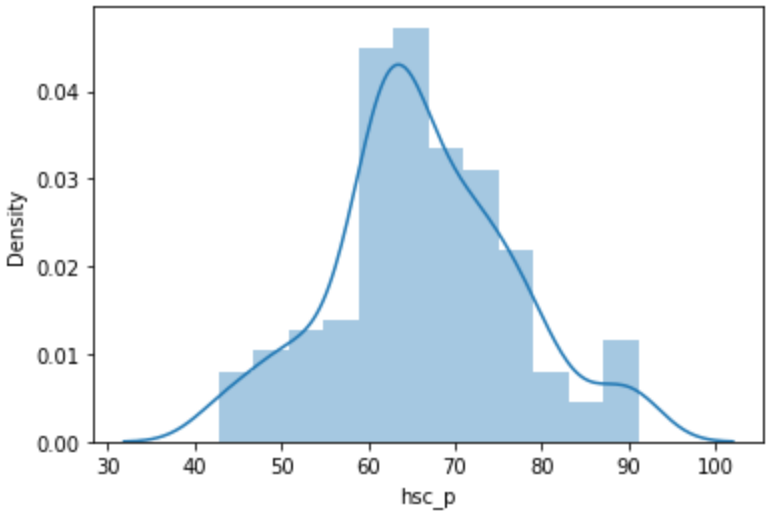
In [90]:
```
ecdf(89)
```

Out[90]:
```
0.9953488372093023
```

Converting Normal Distribution to Standard Normal Distribution

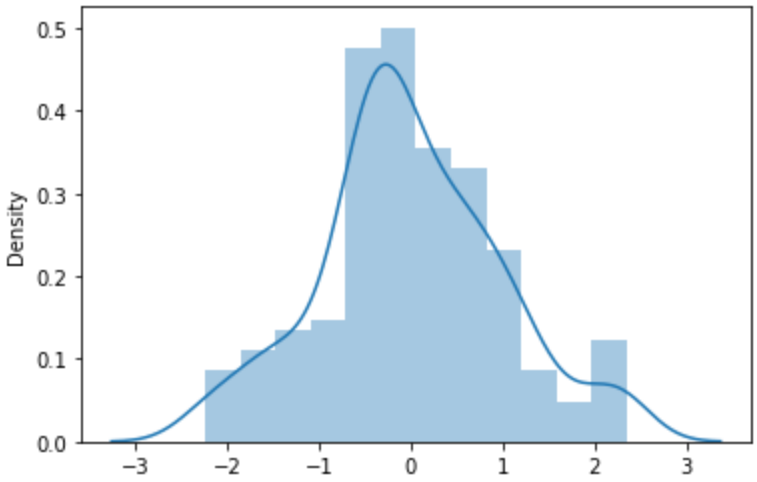
In [91]:
```
sns.distplot(dataset['hsc_p'])
```

Out[91]:
```
<AxesSubplot:xlabel='hsc_p', ylabel='Density'>
```



In [92]:
```
#Normal Distribution to Standard Normal Distribution
mean=dataset['hsc_p'].mean()
std=dataset['hsc_p'].std()
values=[i for i in dataset['hsc_p']]

z_score=[((x-mean)/std) for x in values]

sns.distplot(z_score,kde=True)
```

Out[92]:
```
<AxesSubplot:ylabel='Density'>
```



In [93]:
```
sum(z_score)
```

Out[93]:
```
-1.8596235662471372e-13
```

In [94]:
```
len(z_score)
```

Out[94]:
```
215
```

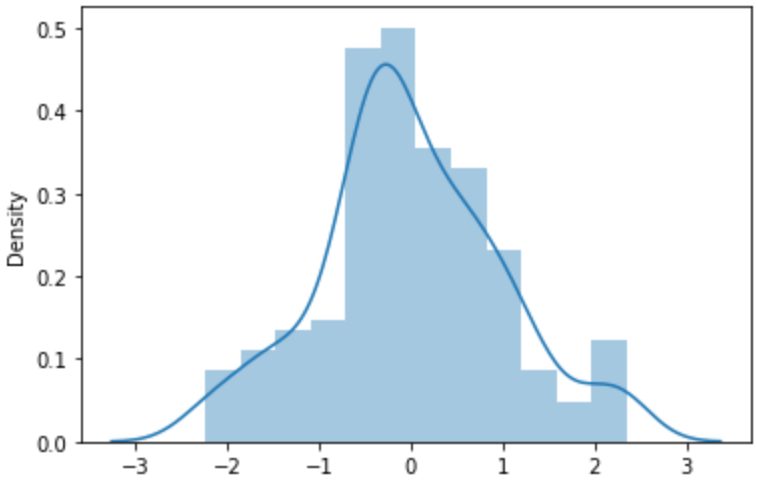
In [95]:
```
sum(z_score)/len(z_score)        # Mean for Z-Score
```

Out[95]:
```
-8.649411936033196e-16
```

Converting Normal Distribution to Standard Normal Distribution By User Defined function

In [96]:
```
# Creating as function from above steps
def standardNDFBgraph(dataset):
    mean=dataset.mean()              #It automatically calculate Mean for all the quantit
    std=dataset.std()                #It automatically calculate std for all the quantita
    values=[i for i in dataset]

    z_score=[((x-mean)/std) for x in values]

    sns.distplot(z_score,kde=True)

    sum(z_score)/len(z_score)
```

In [97]:
```
standardNDFBgraph(dataset['hsc_p'])
```



4. Bivariate Analysis

Covariance

In [98]:
```
dataset.cov()              # Finding Covariances
```

Out[98]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
ssc_p	117.228377	58.853253	42.702550	37.659225	24.535952	9.088585e+05
hsc_p	58.853253	112.063731	33.684453	33.838355	21.517688	7.310079e+05
degree_p	42.702550	33.684453	53.604710	22.078774	17.185200	4.663363e+05
etest_p	37.659225	33.838355	22.078774	176.251018	16.886973	3.727004e+05
mba_p	24.535952	21.517688	17.185200	16.886973	34.028376	1.239934e+05
salary	908858.485818	731007.850848	466336.264888	372700.449468	123993.387361	2.259185e+10

Correlation

In [99]:
```
dataset.corr()             # Finding Correlations
```

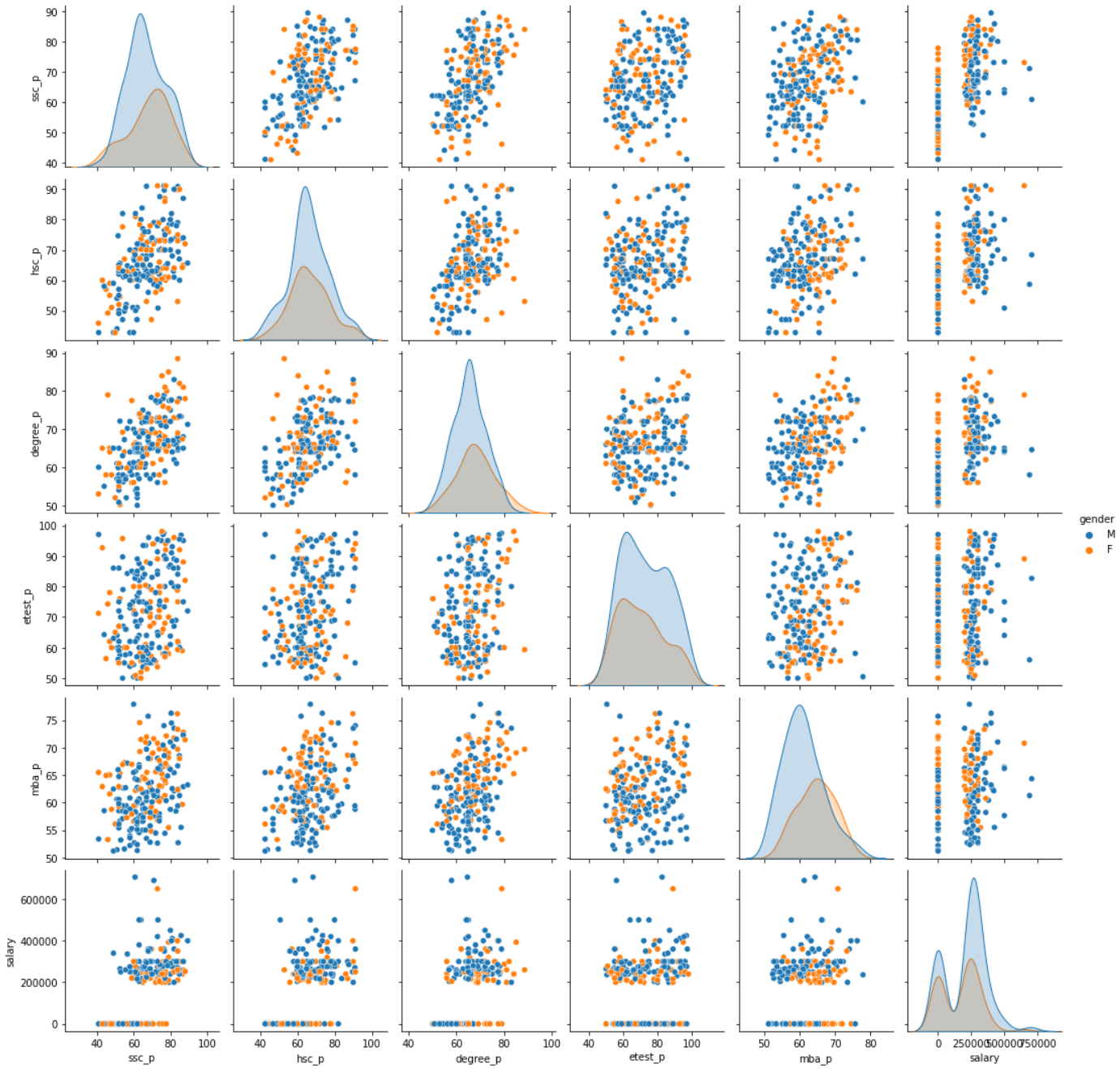
Out[99]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
ssc_p	1.000000	0.513478	0.538686	0.261993	0.388478	0.558475
hsc_p	0.513478	1.000000	0.434606	0.240775	0.348452	0.459424
degree_p	0.538686	0.434606	1.000000	0.227147	0.402376	0.423762
etest_p	0.261993	0.240775	0.227147	1.000000	0.218055	0.186775
mba_p	0.388478	0.348452	0.402376	0.218055	1.000000	0.141417
salary	0.558475	0.459424	0.423762	0.186775	0.141417	1.000000

Visualization of the Pairs

In [100…
```
sns.pairplot(dataset,hue='gender')          # By assiging value to hue, can get difference
#plt.savefig('Pairplot.png')                #save the graph separately
```

Out[100]:
```
<seaborn.axisgrid.PairGrid at 0x2799b0fb048>
```



In [101…
```
dataset.corrwith(dataset['mba_p'])    # Find Correlation with each column for a give colu
```

Out[101]:
```
ssc_p       0.388478
hsc_p       0.348452
degree_p    0.402376
etest_p     0.218055
mba_p       1.000000
salary      0.141417
dtype: float64
```

User defined function to separate Quantitative data columns alone

In [102…
```
# User defined function to find Quantitative & Qualitative Columns
def QuanQual(dataset):
    Quan=[]
    Qual=[]
    for column in dataset.columns:

        if(dataset[column].dtypes=='object'):
            Qual.append(column)
        else:
```

```
            Quan.append(column)
    return Quan
    return Qual
```

In [103…
```
quan =QuanQual(dataset)
Quan_data=dataset[quan]    # Load Quanditative datas alone as a separate dataset
```

In [104…
```
Quan_data.head()
```

Out[104]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
0	67.00	91.00	58.00	55.0	58.80	270000.0
1	79.33	78.33	77.48	86.5	66.28	200000.0
2	65.00	68.00	64.00	75.0	57.80	250000.0
3	56.00	52.00	52.00	66.0	59.43	0.0
4	85.80	73.60	73.30	96.8	55.50	425000.0

Variance Inflaion Factor - (IVF)

In [105…
```
from statsmodels.stats.outliers_influence import variance_inflation_factor

def calc_vif(x):

    #Calculating VIF
    vif=pd.DataFrame()
    vif['VARIABLES']=x.columns
    vif['VIF']=[ variance_inflation_factor(x.values,i) for i in range(x.shape[1])]
    return (vif)     # or  return vif
```

In [106…
```
calc_vif(Quan_data)
```

Out[106]:

	VARIABLES	VIF
0	ssc_p	78.168671
1	hsc_p	61.882196
2	degree_p	114.820554
3	etest_p	32.720365
4	mba_p	116.034378
5	salary	4.171783

In [107…
```
Quan_data=dataset[['ssc_p','hsc_p']]
```

In [108…
```
calc_vif(Quan_data)
```

Out[108]:

	VARIABLES	VIF
0	ssc_p	41.494645
1	hsc_p	41.494645

In [109…
```
Quan_data=dataset[['ssc_p','mba_p']]
calc_vif(Quan_data)
```

Out[109]:

	VARIABLES	VIF
0	ssc_p	44.929108
1	mba_p	44.929108

--

In [110…
```
# To know the difference between the usage of with .values method and without .values me
dataset['ssc_p']  # It results values with index, i.e it mentionning the Row index numbe
```

Out[110]:
```
0      67.00
1      79.33
2      65.00
3      56.00
4      85.80
       ...
210    80.60
211    58.00
212    67.00
213    74.00
214    62.00
Name: ssc_p, Length: 215, dtype: float64
```

In [111…
```
# To know the difference between the usage of with .values method and without .values me
dataset['ssc_p'].values   # resuls will be in array or play with values only, without in
```

Out[111]:
```
array([67.  , 79.33, 65.  , 56.  , 85.8 , 55.  , 46.  , 82.  , 73.  ,
       58.  , 58.  , 69.6 , 47.  , 77.  , 62.  , 65.  , 63.  , 55.  ,
       63.  , 60.  , 62.  , 79.  , 69.8 , 77.4 , 76.5 , 52.58, 71.  ,
       63.  , 76.76, 62.  , 64.  , 67.  , 61.  , 87.  , 62.  , 69.  ,
       51.  , 79.  , 73.  , 81.  , 78.  , 74.  , 49.  , 87.  , 77.  ,
       76.  , 70.89, 63.  , 63.  , 50.  , 75.2 , 54.4 , 40.89, 80.  ,
       74.  , 60.4 , 63.  , 68.  , 74.  , 52.6 , 74.  , 84.2 , 86.5 ,
       61.  , 80.  , 54.  , 83.  , 80.92, 69.7 , 73.  , 82.  , 75.  ,
       84.86, 64.6 , 56.6 , 59.  , 66.5 , 64.  , 84.  , 69.  , 69.  ,
       81.7 , 63.  , 84.  , 70.  , 83.84, 62.  , 59.6 , 66.  , 84.  ,
       85.  , 52.  , 60.23, 52.  , 58.  , 73.  , 76.  , 70.5 , 69.  ,
       54.  , 45.  , 63.  , 77.  , 73.  , 69.  , 59.  , 61.08, 82.  ,
       61.  , 52.  , 69.5 , 51.  , 58.  , 73.96, 65.  , 73.  , 68.2 ,
       77.  , 76.  , 60.8 , 58.  , 64.  , 66.5 , 74.  , 67.  , 84.  ,
       79.  , 72.  , 80.4 , 76.7 , 62.  , 74.9 , 67.  , 73.  , 77.44,
       72.  , 47.  , 67.  , 82.  , 77.  , 65.  , 66.  , 85.  , 77.67,
       52.  , 89.4 , 62.  , 70.  , 77.  , 44.  , 71.  , 65.  , 75.4 ,
       49.  , 53.  , 51.57, 84.2 , 66.5 , 67.  , 52.  , 87.  , 55.6 ,
       74.2 , 63.  , 67.16, 63.3 , 62.  , 67.9 , 48.  , 59.96, 63.4 ,
       80.  , 73.  , 52.  , 73.24, 63.  , 59.  , 73.  , 68.  , 77.8 ,
       65.  , 62.  , 52.  , 65.  , 56.28, 88.  , 52.  , 78.5 , 61.8 ,
       54.  , 64.  , 67.  , 65.2 , 60.  , 52.  , 66.  , 72.  , 83.96,
       67.  , 69.  , 69.  , 54.2 , 70.  , 55.68, 74.  , 61.  , 41.  ,
       83.33, 43.  , 62.  , 80.6 , 58.  , 67.  , 74.  , 62.  ])
```

T - Test (Paired & Unpaired T-Tests)

Paired T-Test (Independent Sample)

Is there a Similarity between Male and Female candidates of Salary?

Different Group(i.e., Male, Female) But Same Condition(i.e., Salary)

```
#Paired T-Test is a statistical test that compares the means of two samples
```

In [112…
```
from scipy.stats import ttest_ind
#dataset=dataset.dropna()
male=dataset[dataset['gender']=='M']['salary']
female=dataset[dataset['gender']=='F']['salary']
ttest_ind(male, female)
```

Out[112]:
```
Ttest_indResult(statistic=2.0937842507001165, pvalue=0.03746230397067219)
```

Hypothesis Test

In [113…
```
def hypo_test(pvalue):
    message = []
    if(pvalue <= 0.05):
        print("For the given problem the pvalue is {}".format(pvalue) + " i.e. <= 0.05 \
        messageBox = "Alternate Hypothesis Accpeted"
    else:
        print("For the given problem the pvalue is {}".format(pvalue) + " i.e. > 0.05 \n
        messageBox = "Null Hypothesis Accpeted"
    message.append(messageBox)
    return message
```

In [114…
```
test_ans = ttest_ind(male, female)
pvalue = round(test_ans.pvalue, 2)
pvalue
```

Out[114]:
```
0.04
```

In [115…
```
hypo_test(pvalue)
```

```
For the given problem the pvalue is 0.04 i.e. <= 0.05
So reject the null hypothesis and can take alternate hypothesis.

Hence Either there is a Similarity Or Significant difference between given variables.
```
Out[115]:
```
['Alternate Hypothesis Accpeted']
```

(For the above problem the pvalue is <=0.05 so reject the null hypothesis and can take alternate hypothesis. Hence There is a similarity between male and female candidates of Salary.)

Unpaired T-Test (Dependent Sample)

Is there Similarity between Male candidates of ssc_p, hsc_p marks?

Same Group(i.e., Male) But Different Condition(i.e., ssc_p, hsc_p)

In [116…
```
#T-Test is a statistical test that compares the means of two samples
from scipy.stats import ttest_rel
#dataset=dataset.dropna()
male=dataset[dataset['gender']=='M']['ssc_p']
male1=dataset[dataset['gender']=='M']['hsc_p']
ttest_rel(male,male1)
```

Out[116]:
```
Ttest_relResult(statistic=0.6842940392688153, pvalue=0.4949370716000775)
```

Hypothesis Test

In [117…
```
test_ans = ttest_rel(male,male1)
pvalue1 = round(test_ans.pvalue, 2)
```

```
pvalue1
```

Out[117]:
```
0.49
```

In [118…
```
hypo_test(pvalue1)
```

```
For the given problem the pvalue is 0.49 i.e. > 0.05
so, alternate hypothesis is weak, null can't be rejected.

Hence Either there is No Similarity Or No Significant difference between given variable
s.
```

Out[118]:
```
['Null Hypothesis Accpeted']
```

(For the above problem the pvalue is >0.05 so, alternate hypothesis is weak, null can't be rejected. Hence There is no similarity between male candidates of ssc_p, hsc_p marks.)

ANAVO : Analysis of Variance

One-Way Classification (ANAVO)

In [119…
```
import scipy.stats as stats
stats.f_oneway(dataset['ssc_p'],dataset['hsc_p'],dataset['degree_p'])
```

Out[119]:
```
F_onewayResult(statistic=0.695991304348204, pvalue=0.49895574725815317)
```

Hypothesis Test

In [120…
```
test_ans = stats.f_oneway(dataset['ssc_p'],dataset['hsc_p'],dataset['degree_p'])
pvalue2 = round(test_ans.pvalue, 2)
pvalue2
```

Out[120]:
```
0.5
```

In [121…
```
hypo_test(pvalue2)
```

```
For the given problem the pvalue is 0.5 i.e. > 0.05
so, alternate hypothesis is weak, null can't be rejected.

Hence Either there is No Similarity Or No Significant difference between given variable
s.
```

Out[121]:
```
['Null Hypothesis Accpeted']
```

(For the above problem the pvalue is >0.05 so, alternate hypothesis is weak, null can't be rejected. Hence There is no significant difference between ssc_p, hsc_p and degree_p marks.)

Two-Way Classification (ANAVO)

In [122…
```
quan =QuanQual(dataset)
Quan_data=dataset[quan]
Quan_data.shape
```

Out[122]:
```
(215, 6)
```

In [123…
```
Quan_data.head(6)
```

Out[123]:

	ssc_p	hsc_p	degree_p	etest_p	mba_p	salary
0	67.00	91.00	58.00	55.0	58.80	270000.0
1	79.33	78.33	77.48	86.5	66.28	200000.0
2	65.00	68.00	64.00	75.0	57.80	250000.0
3	56.00	52.00	52.00	66.0	59.43	0.0
4	85.80	73.60	73.30	96.8	55.50	425000.0
5	55.00	49.80	67.25	55.0	51.58	0.0

In [124…
```
Quan_data.iloc[0].values
```

Out[124]:
```
array([6.70e+01, 9.10e+01, 5.80e+01, 5.50e+01, 5.88e+01, 2.70e+05])
```

In [125…
```
rowValues_1 = Quan_data.iloc[0].values
rowValues_2 = Quan_data.iloc[1].values
rowValues_3 = Quan_data.iloc[2].values
rowValues_4 = Quan_data.iloc[3].values
rowValues_5 = Quan_data.iloc[4].values
rowValues_6 = Quan_data.iloc[5].values
```

In [126…
```
listA = []
listB = []
listC = []
listD = []
listE = []
listF = []

for columnName_1 in rowValues_1:
    listA.append(columnName_1)
for columnName_2 in rowValues_2:
    listB.append(columnName_2)
for columnName_3 in rowValues_3:
    listC.append(columnName_3)
for columnName_4 in rowValues_4:
    listD.append(columnName_4)
for columnName_5 in rowValues_5:
    listE.append(columnName_5)
for columnName_6 in rowValues_6:
    listF.append(columnName_6)
```

In [127…
```
listB
```

Out[127]:
```
[79.33, 78.33, 77.48, 86.5, 66.28, 200000.0]
```

In [128…
```
Quan_data = pd.DataFrame({"student_1" : listA, "student_2" : listB, "student_3": listC,
```

In [129…
```
Quan_data
```

Out[129]:

	student_1	student_2	student_3	student_4	student_5	student_6
0	67.0	79.33	65.0	56.00	85.8	55.00
1	91.0	78.33	68.0	52.00	73.6	49.80
2	58.0	77.48	64.0	52.00	73.3	67.25
3	55.0	86.50	75.0	66.00	96.8	55.00
4	58.8	66.28	57.8	59.43	55.5	51.58

5	270000.0	200000.00	250000.0	0.00	425000.0	0.00

In [130…
```
import scipy.stats as stats
stats.f_oneway(Quan_data["student_1"], Quan_data["student_2"], Quan_data["student_3"])
```

Out[130]:
```
F_onewayResult(statistic=0.022207760671763402, pvalue=0.9780691103580185)
```

Hypothesis test

In [131…
```
#Test for Student 1,  Student 2 and Student 3
test_ans = stats.f_oneway(Quan_data["student_1"], Quan_data["student_2"], Quan_data["stu
pvalue3 = round(test_ans.pvalue, 2)
pvalue3
```

Out[131]:
```
0.98
```

In [132…
```
hypo_test(pvalue3)
```

Out[132]:
```
For the given problem the pvalue is 0.98 i.e. > 0.05
so, alternate hypothesis is weak, null can't be rejected.

Hence Either there is No Similarity Or No Significant difference between given variable
s.
['Null Hypothesis Accpeted']
```

(For the above problem the pvalue is >0.05 so, alternate hypothesis is weak, null can't be rejected. Hence There is no significant difference between Student 1, Student 2, and Student 3.)

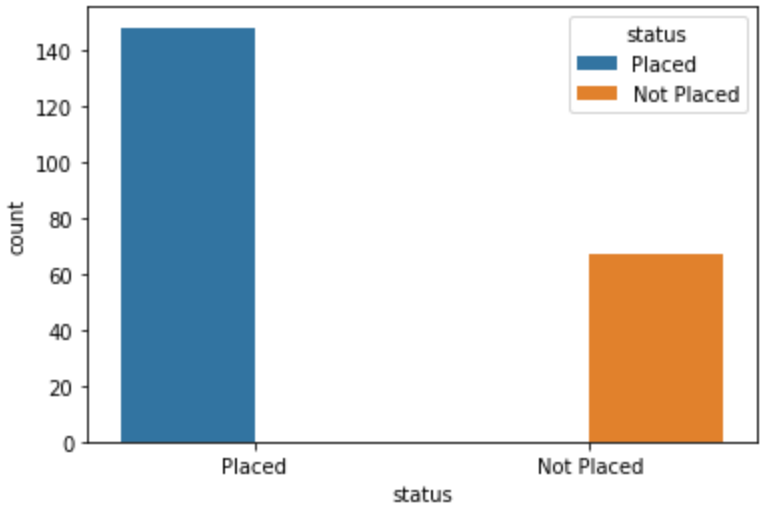
~~ Inferential Analysis (Conclusions)

~Placed and Not Placed Candidates Count.

In [133…
```
dataset["status"].value_counts()              #By value counts to status we found that 14
```

Out[133]:
```
Placed        148
Not Placed     67
Name: status, dtype: int64
```

In [134…
```
#Countplot of status/status
sns.countplot(x ="status",hue="status",data = dataset)
plt.show()
```



~Reasons behind Non Placement of Candidates

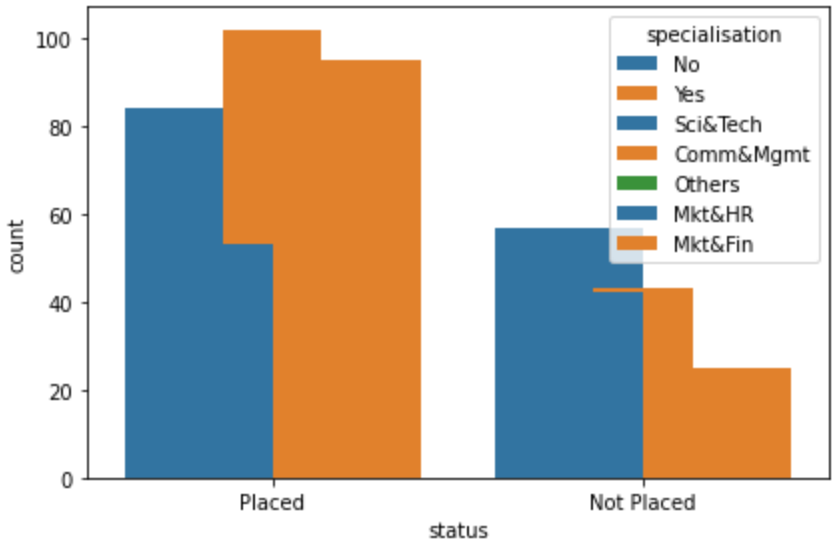
In [135…
```
Not_Placed=dataset.groupby(["status","workex","degree_t","specialisation"])
#Not_Placed.count()
Not_Placed.size()
```

Out[135]:

status	workex	degree_t	specialisation	
Not Placed	No	Comm&Mgmt	Mkt&Fin	17
			Mkt&HR	20
		Others	Mkt&Fin	1
			Mkt&HR	4
		Sci&Tech	Mkt&Fin	3
			Mkt&HR	12
	Yes	Comm&Mgmt	Mkt&Fin	1
			Mkt&HR	5
		Others	Mkt&Fin	1
		Sci&Tech	Mkt&Fin	2
			Mkt&HR	1
Placed	No	Comm&Mgmt	Mkt&Fin	37
			Mkt&HR	26
		Others	Mkt&Fin	1
			Mkt&HR	1
		Sci&Tech	Mkt&Fin	10
			Mkt&HR	9
	Yes	Comm&Mgmt	Mkt&Fin	31
			Mkt&HR	8
		Others	Mkt&Fin	1
			Mkt&HR	2
		Sci&Tech	Mkt&Fin	15
			Mkt&HR	7

dtype: int64

In [136…
```
#Countplot of status/workex, status/degree_t and status/specialisation
sns.countplot(x ="status",hue="workex",data = dataset)
sns.countplot(x ="status",hue="degree_t",data = dataset)
sns.countplot(x ="status",hue="specialisation",data = dataset)
plt.tight_layout()
plt.show()
```



From the Status Totally 67 Candidates were not placed.

In the Total 67 Mostly due to no experience, 57 Candidates were not placed.

And also 15 more Sci&Tech degree_t candidates is not fit for Mkt&HR and Mkt&Fin specialisations

and few of the 4 more Others degree_t candidates is also not fit for Mkt&HR specialisations

~Relationship between salary and mba_p

In [137…
```
dataset[["salary","mba_p"]].corr()
```

Out[137]:

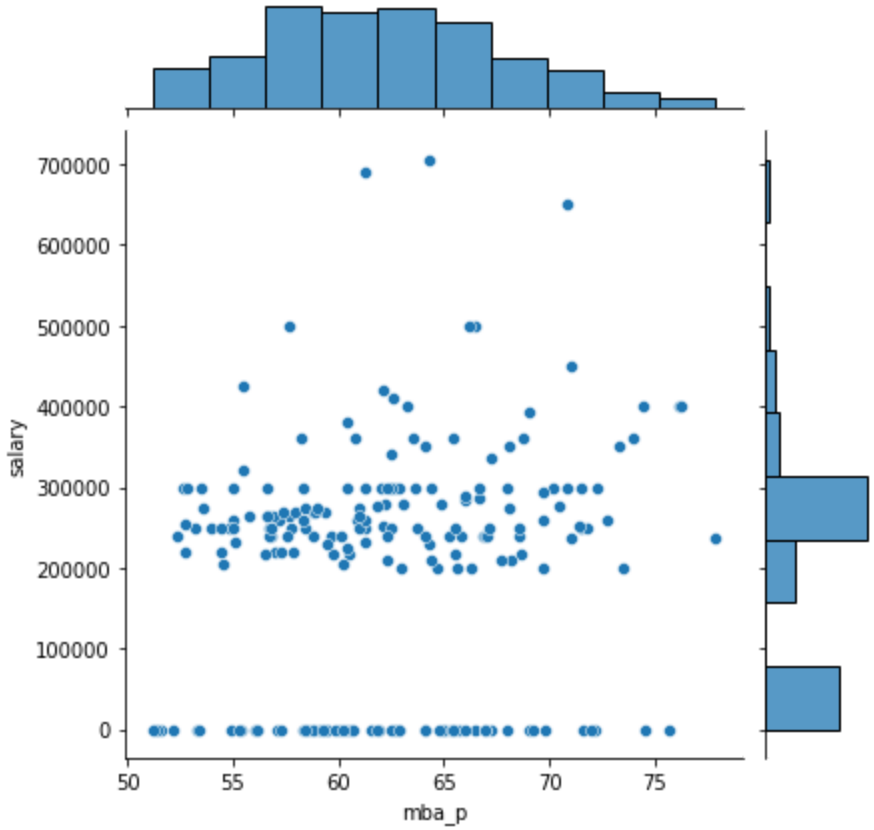
	salary	mba_p
salary	1.000000	0.141417
mba_p	0.141417	1.000000

In [138…
```
dataset["mba_p"].corr(dataset["salary"])  #Salary and mba_p is weakly correlated with ea
```

Out[138]:
```
0.14141713944325937
```

In [139…
```
sns.jointplot(x="mba_p",y="salary",data=dataset)   #Salary ranges between 2-4 lakhs for
plt.show
```

Out[139]:
```
<function matplotlib.pyplot.show(close=None, block=None)>
```



~Minimum Salary is drawn by which Specialisation

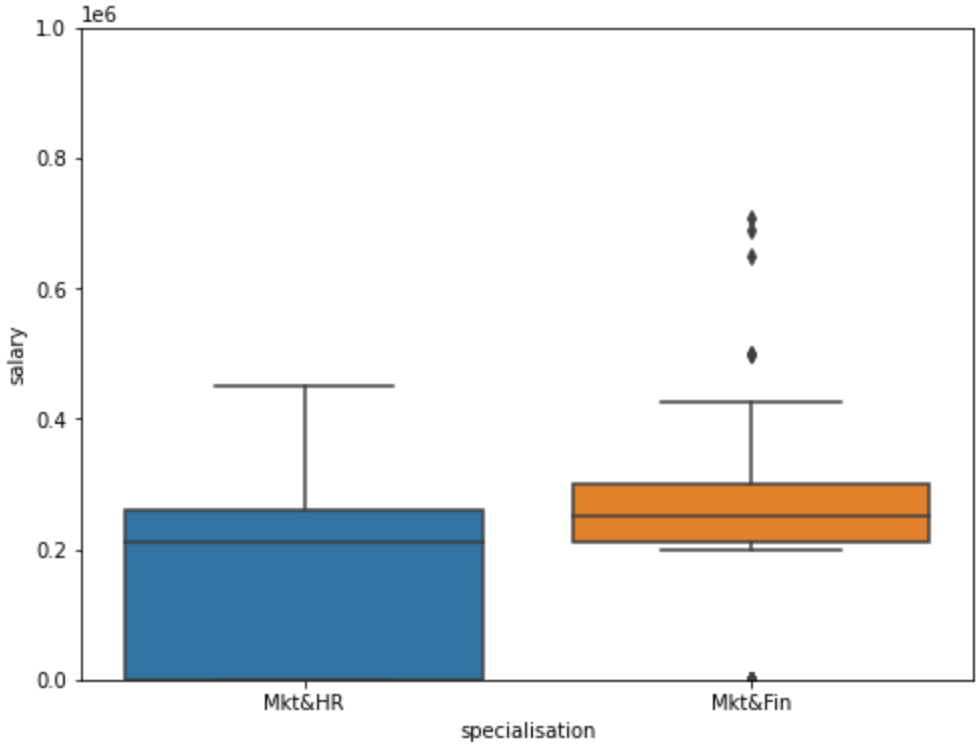
In [140…
```
pd.pivot_table(dataset,values="salary",index=["specialisation"]) # Comparition made by P
                                                                 #First Mkt&HR, Minim
                                                                 #Second Mkt&Fin, Min
```

Out[140]:

specialisation	salary
Mkt&Fin	234643.750000
Mkt&HR	150842.105263

In [141…
```
#boxplot of specialisation/salary
var = 'specialisation'
data = pd.concat([dataset['salary'],dataset[var]],axis=1)
f, ax = plt.subplots(figsize=(8,6))
fig = sns.boxplot(x=var,y='salary',data=data)
fig.axis(ymin=0,ymax=1000000)
```

Out[141]:
```
(-0.5, 1.5, 0.0, 1000000.0)
```



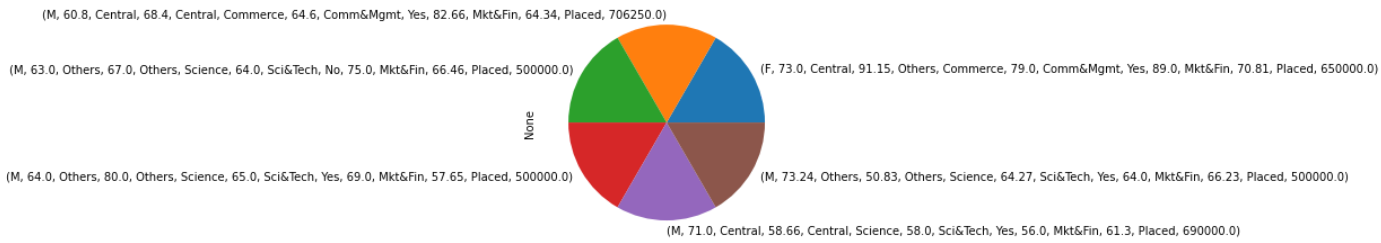
~Howmany of them drawn Salary above 5 lakhs

In [142…
```
dataset[dataset["salary"]>=500000]
len(dataset[dataset["salary"]>=500000])    # Six Candidates drawn above 5 lakhs salary
```

Out[142]:
```
6
```

In [143…
```
dataset[dataset["salary"]>=500000].value_counts().plot.pie(autopct=None)
```

Out[143]:
```
<AxesSubplot:ylabel='None'>
```



~ANAVO(Analysis of Variance) between etest_p and mba_p at signifance level 5%.

In [144…
```
#Analysis of Variance By One-Way Classification
import scipy.stats as stats
stats.f_oneway(dataset['etest_p'],dataset['mba_p'])
```

Out[144]:
```
F_onewayResult(statistic=98.64487057324706, pvalue=4.672547689133573e-21)
```

Hypothesis Test

In [145…
```
test_ans = stats.f_oneway(dataset['etest_p'],dataset['mba_p'])
pvalue4 = round(test_ans.pvalue, 2)
pvalue4
```

Out[145]: 0.0

In [146…
```
hypo_test(pvalue4)
```

```
For the given problem the pvalue is 0.0 i.e. <= 0.05
So reject the null hypothesis and can take alternate hypothesis.

Hence Either there is a Similarity Or Significant difference between given variables.
['Alternate Hypothesis Accpeted']
```

Out[146]:

(For the above problem the pvalue is <=0.05 so reject the null hypothesis and can take alternate hypothesis. Hence There is a significant difference between etest_p and mba_p marks.)

Test the similarity between the degree_t(Sci&Tech) and specialisation(Mkt&HR) w.r.t salary at significance level of 5%. (Take the decision using Hypothesis Testing)

In [147…
```
#Paired T-Test(Independent Sample)
from scipy.stats import ttest_ind
deg = dataset[dataset['degree_t']=='Sci&Tech']['salary']
spc = dataset[dataset['specialisation']=='Mkt&HR']['salary']
ttest_ind(deg,spc)
```

Out[147]: Ttest_indResult(statistic=2.692041243555374, pvalue=0.007897969943471179)

In [148…
```
test_ans = ttest_ind(deg,spc)
pvalue5 = round(test_ans.pvalue, 2)
pvalue5
```

Out[148]: 0.01

In [149…
```
hypo_test(pvalue5)                # There is a similarity
```

```
For the given problem the pvalue is 0.01 i.e. <= 0.05
So reject the null hypothesis and can take alternate hypothesis.

Hence Either there is a Similarity Or Significant difference between given variables.
['Alternate Hypothesis Accpeted']
```

Out[149]:

(For the above problem the pvalue is <=0.05 so reject the null hypothesis and can take alternate hypothesis. Hence There is a similarity between degree_t(Sci&Tech) and specialisation(Mkt&HR))

~Test the similarity between the degree_t(Sci&Tech)with respect to etest_p and mba_p at significance level of 5%. (Take the decision using Hypothesis Testing)

In [150…
```
#Unpaired T-Test(Dependent sample)
from scipy.stats import ttest_rel
deg = dataset[dataset['degree_t']=='Sci&Tech']['etest_p']
deg1 = dataset[dataset['degree_t']=='Sci&Tech']['mba_p']
ttest_rel(deg, deg1)
```

Out[150]: Ttest_relResult(statistic=5.0049844583693615, pvalue=5.517920600505392e-06)

In [151…
```
test_ans = ttest_rel(deg, deg1)
pvalue6 = round(test_ans.pvalue, 2)
pvalue6
```

```
0.0
```

Out[151]:

In [152…
```
hypo_test(pvalue6)
```

```
For the given problem the pvalue is 0.0 i.e. <= 0.05
So reject the null hypothesis and can take alternate hypothesis.

Hence Either there is a Similarity Or Significant difference between given variables.
```

Out[152]:
```
['Alternate Hypothesis Accpeted']
```

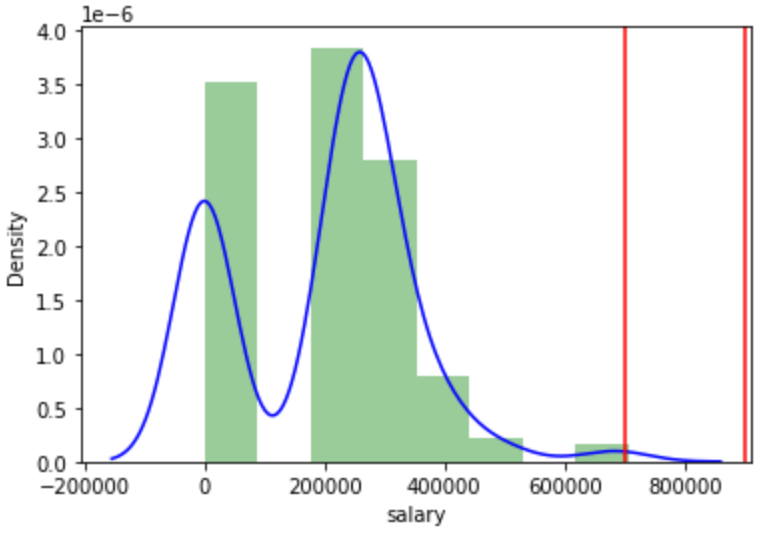
~PDF for the salary range from 700000 - 900000

In [153…
```
def get_pdf_probability(dataset,startrange,endrange):
    from matplotlib import pyplot
    from scipy.stats import norm
    import seaborn as sns
    ax = sns.distplot(dataset,kde=True,kde_kws={'color':'blue'},color='Green')
    pyplot.axvline(startrange,color='Red')
    pyplot.axvline(endrange,color='Red')
    # generate a sample
    sample = dataset
    # calculate parameters
    sample_mean =sample.mean()
    sample_std = sample.std()
    print('Mean=%.3f, Standard Deviation=%.3f' % (sample_mean, sample_std))
    # define the distribution
    dist = norm(sample_mean, sample_std)

    # sample probabilities for a range of outcomes
    values = [value for value in range(startrange, endrange)]
    probabilities = [dist.pdf(value) for value in values]
    prob=sum(probabilities)
    print("The area between range({},{}):{}".format(startrange,endrange,sum(probabilitie
    return prob
```

In [154…
```
get_pdf_probability(dataset['salary'],700000,900000)
```

```
Mean=197615.116, Standard Deviation=150305.844
The area between range(700000,900000):0.0004137812663830048
```

Out[154]:
```
0.0004137812663830048
```



~Highly Correlated Columns with Salary

High degree:- If the coefficient value lies between ± 0.50 and ± 1, then it is said to be a high correlation.

Moderate degree:- If the value lies between ± 0.30 and ± 0.49, then it is said to be a medium correlation.

Low degree:- When the value lies below + .29, then it is said to be a low correlation.

No correlation:- When the value is zero.

In [155…
```
correlationTable=pd.DataFrame(index=["ssc_p","hsc_p","degree_p","mba_p","etest_p"],colum
for i in correlationTable.index:
    correlationTable["salary"][i]=dataset[i].corr(dataset["salary"])
```

In [156…
```
correlationTable
```

Out[156]:

	salary
ssc_p	0.558475
hsc_p	0.459424
degree_p	0.423762
mba_p	0.141417
etest_p	0.186775

In [157…
```
correlationTable.sort_values('salary',ascending=False)   # Highly correlated columns with
                                                          # In the row ssc_p is highly co
```

Out[157]:

	salary
ssc_p	0.558475
hsc_p	0.459424
degree_p	0.423762
etest_p	0.186775
mba_p	0.141417