In [1]:
```
import numpy as np
import pandas as pd
import scipy.stats as stats
from scipy.stats import ttest_ind
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [3]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

# Analysis of variance (ANOVA)

ANOVA is a hypothesis testing technique tests the equality of two or more population means by examining the variances of samples that are taken.

ANOVA tests the general rather than specific differences among means.

In [4]:
```
A=[30,40,50,60]
B=[25,30,50,55]
C=[25,30,40,45]
D=[43,45,45,47]
E=[37,40,40,43]
F=[34,35,35,36]
```

In [15]:
```
from scipy.stats import f_oneway
```

In [ ]:
```
# one way means comparing the mean with one characteristics
```

In [16]:
```
f_oneway(A,B,C)
```

Out[16]:
```
F_onewayResult(statistic=0.6428571428571429, pvalue=0.5483227164089495)
```

In [17]:
```
f_oneway(D,E,F)
```

Out[17]:
```
F_onewayResult(statistic=32.14285714285714, pvalue=7.970844367886858e-05)
```

In [18]:
```
G1_df=pd.DataFrame()
df1=pd.DataFrame({'group':'A','age':[30,40,50,60]})
df2=pd.DataFrame({'group':'B','age':[25,30,50,55]})
df3=pd.DataFrame({'group':'C','age':[25,30,40,45]})
G1_df=G1_df.append(df1)
G1_df=G1_df.append(df2)
G1_df=G1_df.append(df3)
```

In [20]:
```
G1_df
```

Out[20]:

| | group | age |
|---|---|---|
| **0** | A | 30 |
| **1** | A | 40 |
| **2** | A | 50 |
| **3** | A | 60 |
| **0** | B | 25 |
| **1** | B | 30 |
| **2** | B | 50 |
| **3** | B | 55 |
| **0** | C | 25 |
| **1** | C | 30 |
| **2** | C | 40 |
| **3** | C | 45 |

In [42]:
```
from   statsmodels.formula.api import ols
from   statsmodels.stats.anova import anova_lm
```

In [ ]:
```
# lm means linear model
# ols is ordinary least square
```

In [ ]:
```
m1 = ols('age ~ group', data = G1_df).fit()
aov_table = anova_lm(m1, typ=1)
print(aov_table)
```

```
            df  sum_sq     mean_sq         F    PR(>F)
group      2.0   200.0  100.000000  0.642857  0.548323
Residual   9.0  1400.0  155.555556       NaN       NaN
```

In [22]:
```
G2_df=pd.DataFrame()
Df1=pd.DataFrame({'group':'D','age':[43,45,45,47]})
Df2=pd.DataFrame({'group':'E','age':[37,40,40,43]})
Df3=pd.DataFrame({'group':'F','age':[34,35,35,36]})
G2_df=G2_df.append(Df1)
G2_df=G2_df.append(Df2)
G2_df=G2_df.append(Df3)
```

In [23]:
```
G2_df
```

Out[23]:

| | group | age |
|---|---|---|
| **0** | D | 43 |
| **1** | D | 45 |
| **2** | D | 45 |
| **3** | D | 47 |
| **0** | E | 37 |
| **1** | E | 40 |
| **2** | E | 40 |
| **3** | E | 43 |
| **0** | F | 34 |
| **1** | F | 35 |
| **2** | F | 35 |
| **3** | F | 36 |

In [25]:
```
mod = ols('age ~ group', data = G2_df).fit()
aov_table =anova_lm(mod, typ=1)
print(aov_table)
```

```
           df  sum_sq     mean_sq          F   PR(>F)
group     2.0   200.0  100.000000  32.142857  0.00008
Residual  9.0    28.0    3.111111        NaN      NaN
```

In [ ]:
```
oa=(np.sum(A)+np.sum(B)+np.sum(C))/12
oa
```

Out[97]:
```
40.0
```

In [5]:
```
oa=(np.sum(D)+np.sum(E)+np.sum(F))/12
oa
```

Out[5]: 40.0

In [6]:
```
Abar=np.mean(A)
Bbar=np.mean(B)
Cbar=np.mean(C)
Dbar=np.mean(D)
Ebar=np.mean(E)
Fbar=np.mean(F)
```

In [7]:
```
Avar=np.var(A,ddof=1)
Bvar=np.var(B,ddof=1)
Cvar=np.var(C,ddof=1)
Dvar=np.var(D,ddof=1)
Evar=np.var(E,ddof=1)
Fvar=np.var(F,ddof=1)
```

In [8]:
```
#MSTR Calculation (between sample variability)
sstr=len(A)*(Abar-oa)**2+len(B)*(Bbar-oa)**2+len(C)*(Cbar-oa)**2
sstr
```

Out[8]: 200.0

In [9]:
```
#MSTR Calculation (between sample variability)
sstr=len(D)*(Dbar-oa)**2+len(E)*(Ebar-oa)**2+len(F)*(Fbar-oa)**2
sstr
```

Out[9]: 200.0

In [10]:
```
df1=3-1
mstr=sstr/df1
mstr
```

Out[10]: 100.0

In [11]:
```
#MSE Calculation (within sample variability)
#Within Sample Variability (MSE)=SSE/dof
sse=(len(A)-1)*Avar+(len(B)-1)*Bvar+(len(C)-1)*Cvar
df2=12-3
print(sse)
print(df2)
sse/df2
```

```
1400.0
9
```

Out[11]:
```
155.55555555555554
```

In [12]:
```
F_abc=100/155.55555555555554
F_abc
```

Out[12]:
```
0.6428571428571429
```

In [13]:
```
#MSE Calculation (within sample variability)
#Within Sample Variability (MSE)=SSE/dof
sse=(len(D)-1)*Dvar+(len(E)-1)*Evar+(len(F)-1)*Fvar
df2=12-3
print(sse)
print(df2)
sse/df2
```

```
28.0
9
```

Out[13]:
```
3.111111111111111
```

In [14]:
```
F_def=100/3.1111111111
F_def
```

Out[14]:
```
32.14285714297194
```

- Verify does the salary varies with respect to Dept
- Verify does the salary varies with respect to job_level

In [26]:
```
A=pd.read_csv('/content/drive/My Drive/MSD/fair_pay_data.csv',index_col=0)
A.head()
```

Out[26]:

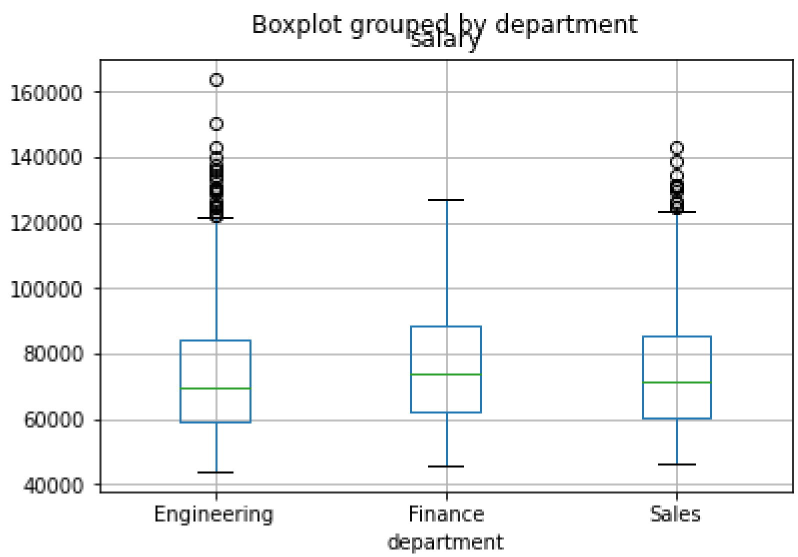
| employee_id | department | salary | new_hire | job_level |
|---|---|---|---|---|
| 1 | Sales | 103263.63550 | No | Salaried |
| 2 | Engineering | 80708.64104 | No | Hourly |
| 4 | Engineering | 60737.04786 | Yes | Hourly |
| 5 | Engineering | 99116.32328 | Yes | Salaried |
| 7 | Engineering | 51021.64386 | No | Hourly |

In [27]:
```
A['department'].value_counts()
```

Out[27]:
```
Engineering    961
Sales          446
Finance         63
Name: department, dtype: int64
```

In [31]:
```
A.boxplot(column='salary',by='department')
```

Out[31]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7efe624ae0f0>
```

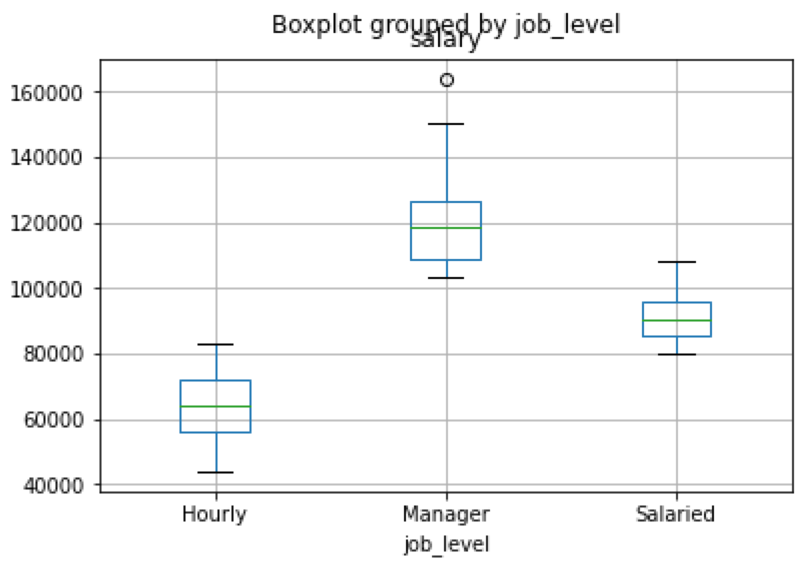



In [28]:
```
A['job_level'].value_counts()
```

Out[28]:
```
Hourly       1039
Salaried      326
Manager       105
Name: job_level, dtype: int64
```

In [32]:
```
A.boxplot(column='salary',by='job_level')
```

Out[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7efe623c18d0>




In [37]:
```
g1=A['salary'][A['department']=='Engineering']
g2=A['salary'][A['department']=='Sales']
g3=A['salary'][A['department']=='Finance']
```

In [38]:
```
g1.mean(),g2.mean(),g3.mean()
```

Out[38]: (73560.73841627462, 75039.9375778251, 76651.66425492064)

In [39]:
```
g1=A['salary'][A['job_level']=='Hourly']
g2=A['salary'][A['job_level']=='Salaried']
g3=A['salary'][A['job_level']=='Manager']
```

In [40]:
```
g1.mean(),g2.mean(),g3.mean()
```

Out[40]: (64251.24077572664, 91143.073100092, 119229.1012304762)

In [43]:
```
m1 = ols('salary ~ department+job_level', data = A).fit()
aov_table = anova_lm(m1, typ=1)
print(aov_table)
```

```
                df        sum_sq       mean_sq            F    PR(>F)
department     2.0  1.081095e+09  5.405473e+08     6.774632  0.001179
job_level      2.0  4.084238e+11  2.042119e+11  2559.369839  0.000000
Residual    1465.0  1.168922e+11  7.978992e+07          NaN       NaN
```

In [44]:
```
data = pd.read_csv("/content/drive/My Drive/Statistics Mahesh Anand/Bank.csv")
data.shape
```

Out[44]: (264, 8)

In [45]:
```
data.head()
```

Out[45]:

| | User I.D | Age | Income | Income2 | Deposit | Deposit2 | Customer_type | Deposit_Scheme |
|---|---|---|---|---|---|---|---|---|
| **0** | ACX570081 | 26 | 32900 | 20230 | 14805.0 | 11935.7 | Irregular | Hal-Yearly |
| **1** | ACX570082 | 43 | 37390 | 21410 | 19442.8 | 10276.8 | Regular | Quaterly |
| **2** | ACX570083 | 35 | 11300 | 22290 | 5989.0 | 9361.8 | Irregular | Monthly |
| **3** | ACX570084 | 27 | 41680 | 26970 | 19589.6 | 15912.3 | Irregular | Quaterly |
| **4** | ACX570085 | 42 | 27170 | 27220 | 14943.5 | 11160.2 | Regular | Quaterly |

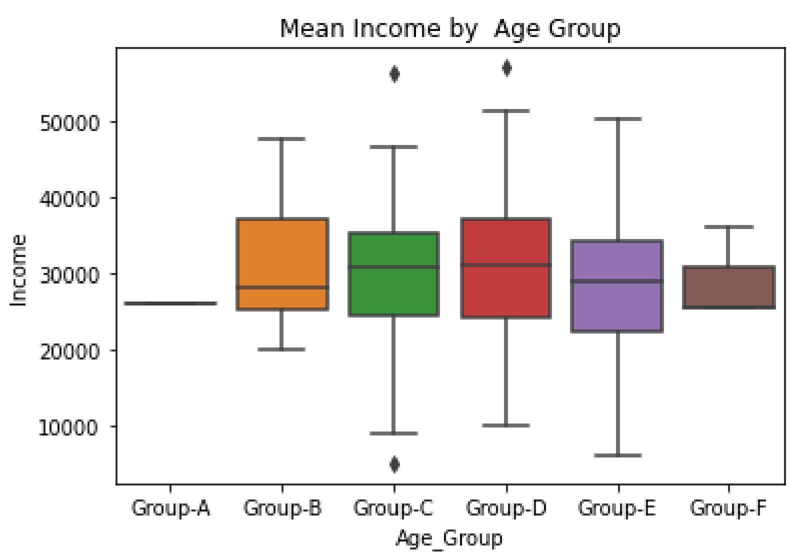
In [46]:
```
bins = [0, 18, 24, 30, 40, 48, np.inf]
names = ["Group-A", "Group-B", "Group-C", "Group-D" , "Group-E" , "Group-F" ]

data['Age_Group'] = pd.cut(data.Age, bins, labels=names)
```

In [47]:
```
data.head()
```

Out[47]:

| | User I.D | Age | Income | Income2 | Deposit | Deposit2 | Customer_type | Deposit_Scheme | Age_Group |
|---|---|---|---|---|---|---|---|---|---|
| **0** | ACX570081 | 26 | 32900 | 20230 | 14805.0 | 11935.7 | Irregular | Hal-Yearly | Group-C |
| **1** | ACX570082 | 43 | 37390 | 21410 | 19442.8 | 10276.8 | Regular | Quaterly | Group-E |
| **2** | ACX570083 | 35 | 11300 | 22290 | 5989.0 | 9361.8 | Irregular | Monthly | Group-D |
| **3** | ACX570084 | 27 | 41680 | 26970 | 19589.6 | 15912.3 | Irregular | Quaterly | Group-C |
| **4** | ACX570085 | 42 | 27170 | 27220 | 14943.5 | 11160.2 | Regular | Quaterly | Group-E |

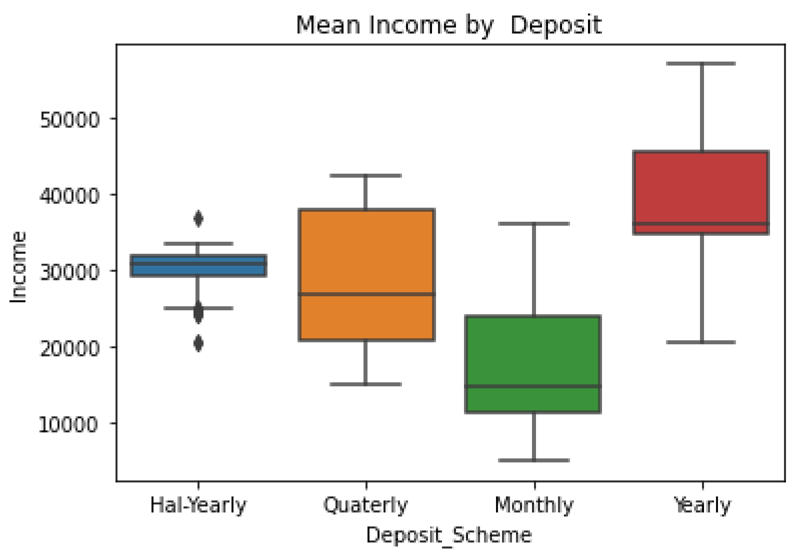
In [48]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.boxplot(x = "Age_Group", y = "Income", data = data)
plt.title('Mean Income by  Age Group')
plt.show()
```



In [49]:
```
import statsmodels.api as sm
from   statsmodels.formula.api import ols

mod = ols('Income ~ Age_Group', data = data).fit()
aov_table = sm.stats.anova_lm(mod, typ=2)
print(aov_table)
```

```
                 sum_sq     df         F    PR(>F)
Age_Group  1.806153e+08    5.0  0.405621  0.844716
Residual   2.297650e+10  258.0       NaN       NaN
```

In [50]:
```
import matplotlib.pyplot as plt
import seaborn as sns
sns.boxplot(x = "Deposit_Scheme", y = "Income", data = data)
plt.title('Mean Income by  Deposit')
plt.show()
```



In [51]:
```
import statsmodels.api as sm
from   statsmodels.formula.api import ols

mod = ols('Income ~ Deposit_Scheme', data = data).fit()
aov_table = sm.stats.anova_lm(mod, typ=2)
print(aov_table)
```

```
                      sum_sq     df         F        PR(>F)
Deposit_Scheme  7.799853e+09    3.0  44.01742  4.891310e-23
Residual        1.535727e+10  260.0       NaN           NaN
```

####Conclussion :

As the p-value (4.891310e-23) is less than alpha (0.05) implies,We reject Null hypothesis.That means mean Income over different Deposit Scheme are not same or in other words different Deposit Schemes are influenced by the Income & the purchasing power of the investor.

**Tukey Test**

Now,we will try to find out for which Deposit scheme the mean income are not same.For that,we will conduct a Tukey test.

Tukey test gives us a way to peep inside the data and find out where the variation is. It will give the permutation combination of several classes and 'reject' column help us identify the variation between the groups.

In [52]:
```
from statsmodels.stats.multicomp import pairwise_tukeyhsd
print(pairwise_tukeyhsd(data['Income'],data['Deposit_Scheme']))
```

```
        Multiple Comparison of Means - Tukey HSD, FWER=0.05
===================================================================
  group1    group2   meandiff  p-adj     lower      upper    reject
-------------------------------------------------------------------
Hal-Yearly  Monthly -11265.787  0.001 -15750.5592 -6781.0149   True
Hal-Yearly Quaterly -1084.7775 0.7602   -4081.533  1911.9779  False
Hal-Yearly   Yearly  9037.4893  0.001   5420.7781 12654.2006   True
   Monthly Quaterly 10181.0095  0.001   5923.9097 14438.1093   True
   Monthly   Yearly 20303.2764  0.001  15589.1534 25017.3993   True
  Quaterly   Yearly 10122.2668  0.001    6792.054 13452.4797   True
-------------------------------------------------------------------
```

####Conclussion: "reject = True" implies there exists significant difference in the Group mean.

Apart from the mean Income of Half-Yearly and Quaterly Deposite Scheme all other Deposit Scheme has significant difference.

```
In [ ]:
```