In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
df=pd.read_csv('Attrition Data.csv')
```

In [3]:
```
df
```

Out[3]:

	Age	Attrition	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumC
0	41	Yes	Sales	1	2	Life Sciences	2	4	Single	5993	
1	49	No	Research & Development	8	1	Life Sciences	3	2	Married	5130	
2	37	Yes	Research & Development	2	2	Other	4	3	Single	2090	
3	33	No	Research & Development	3	4	Life Sciences	4	3	Married	2909	
4	27	No	Research & Development	2	1	Medical	1	2	Married	3468	
...	...	...	...	...	...	...	...	...	...	...	
1465	36	No	Research & Development	23	2	Medical	3	4	Married	2571	
1466	39	No	Research & Development	6	1	Medical	4	1	Married	9991	
1467	27	No	Research & Development	4	3	Life Sciences	2	2	Married	6142	
1468	49	No	Sales	2	3	Medical	4	2	Married	5390	
1469	34	No	Research & Development	8	3	Medical	2	3	Married	4404	

1470 rows × 13 columns

Here below we check for any missing null values present in the columns using df.info() function

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1470 entries, 0 to 1469
Data columns (total 13 columns):
 #   Column                   Non-Null Count  Dtype 
---  ------                   --------------  ----- 
 0   Age                      1470 non-null   int64 
 1   Attrition                1470 non-null   object
 2   Department               1470 non-null   object
 3   DistanceFromHome         1470 non-null   int64 
 4   Education                1470 non-null   int64 
 5   EducationField           1470 non-null   object
 6   EnvironmentSatisfaction  1470 non-null   int64 
 7   JobSatisfaction          1470 non-null   int64 
 8   MaritalStatus            1470 non-null   object
 9   MonthlyIncome            1470 non-null   int64 
 10  NumCompaniesWorked       1470 non-null   int64 
 11  WorkLifeBalance          1470 non-null   int64 
 12  YearsAtCompany           1470 non-null   int64 
dtypes: int64(9), object(4)
memory usage: 149.4+ KB
```

Here we check for descriptive statistics and to check the skewness (distribution) of the data

In [5]:
```
df.describe()
```

Out[5]:

	Age	DistanceFromHome	Education	EnvironmentSatisfaction	JobSatisfaction	MonthlyIncome	NumCompaniesWorked	WorkLifeBalance	YearsA
count	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	1470.000000	14
mean	36.923810	9.192517	2.912925	2.721769	2.728571	6502.931293	2.693197	2.761224	
std	9.135373	8.106864	1.024165	1.093082	1.102846	4707.956783	2.498009	0.706476	
min	18.000000	1.000000	1.000000	1.000000	1.000000	1009.000000	0.000000	1.000000	
25%	30.000000	2.000000	2.000000	2.000000	2.000000	2911.000000	1.000000	2.000000	
50%	36.000000	7.000000	3.000000	3.000000	3.000000	4919.000000	2.000000	3.000000	
75%	43.000000	14.000000	4.000000	4.000000	4.000000	8379.000000	4.000000	3.000000	
max	60.000000	29.000000	5.000000	4.000000	4.000000	19999.000000	9.000000	4.000000	

In [6]:
```
#distance from home, monthly income,years at company
```

Splitting the features and target to train the model

In [7]:
```
x=df.iloc[:,[0,2,3,4,5,6,7,8,9,10,11,12]]
```

In [8]:
```
x
```

Out[8]:

	Age	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompanies
0	41	Sales	1	2	Life Sciences	2	4	Single	5993	
1	49	Research & Development	8	1	Life Sciences	3	2	Married	5130	
2	37	Research & Development	2	2	Other	4	3	Single	2090	
3	33	Research & Development	3	4	Life Sciences	4	3	Married	2909	
4	27	Research & Development	2	1	Medical	1	2	Married	3468	
...	...	...	...	...	...	...	...	...	...	
1465	36	Research & Development	23	2	Medical	3	4	Married	2571	
1466	39	Research & Development	6	1	Medical	4	1	Married	9991	
1467	27	Research & Development	4	3	Life Sciences	2	2	Married	6142	
1468	49	Sales	2	3	Medical	4	2	Married	5390	
1469	34	Research & Development	8	3	Medical	2	3	Married	4404	

1470 rows × 12 columns

In [9]:
```
y=df.iloc[:,1:2]
y
```

Out[9]:

	Attrition
0	Yes
1	No
2	Yes
3	No
4	No
...	...
1465	No
1466	No
1467	No
1468	No
1469	No

1470 rows × 1 columns

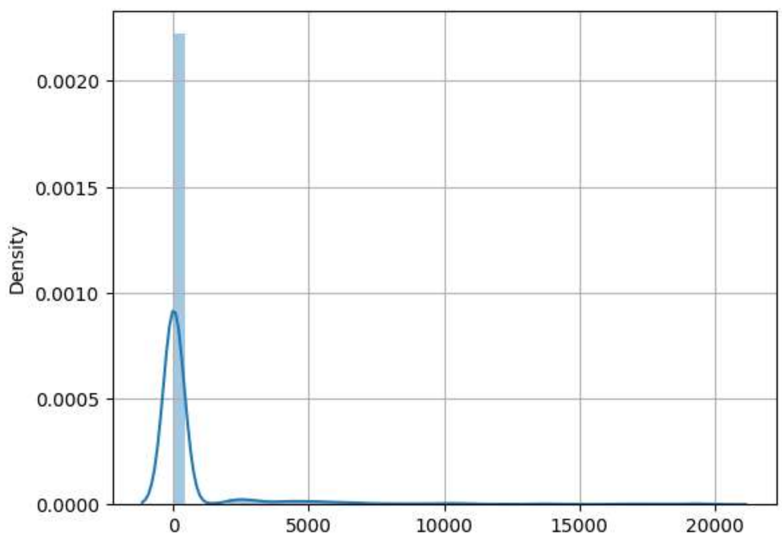
In [10]:
```
a=x.select_dtypes('int64').columns
a
```

Out[10]:
```
Index(['Age', 'DistanceFromHome', 'Education', 'EnvironmentSatisfaction',
       'JobSatisfaction', 'MonthlyIncome', 'NumCompaniesWorked',
       'WorkLifeBalance', 'YearsAtCompany'],
      dtype='object')
```

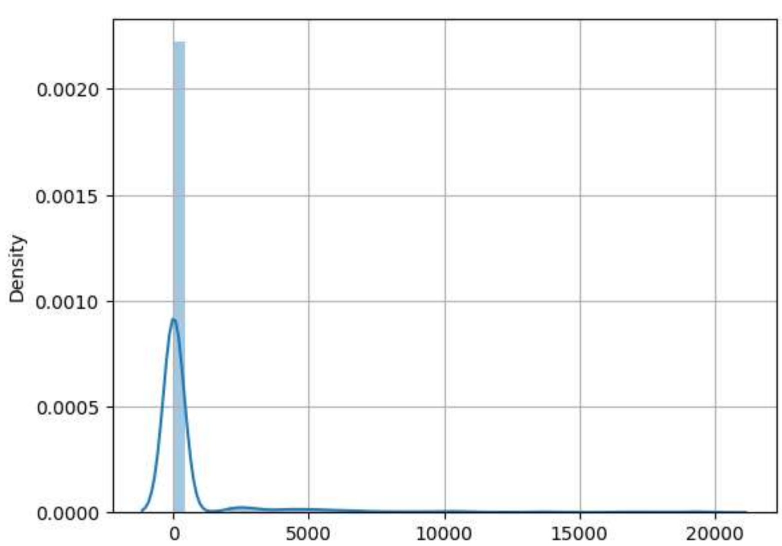
Checking the skewness to check for outliers

In [12]:
```
for i in x[a]:
    print(i)
    print(x[a].mean())
    print(x[a].median())
    sns.distplot(x[a])
    plt.grid()
    plt.show()
```

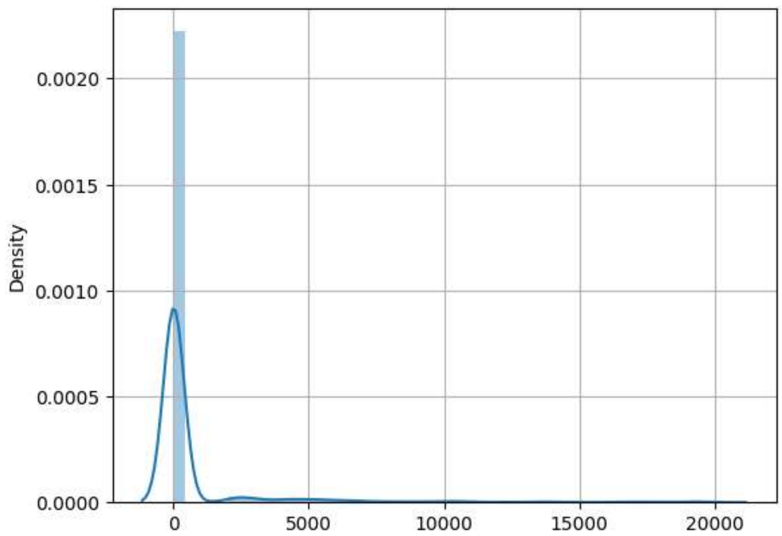
```
Age
Age                          36.923810
DistanceFromHome              9.192517
Education                     2.912925
EnvironmentSatisfaction       2.721769
JobSatisfaction               2.728571
MonthlyIncome              6502.931293
NumCompaniesWorked            2.693197
WorkLifeBalance               2.761224
YearsAtCompany                7.008163
dtype: float64
Age                          36.0
DistanceFromHome              7.0
Education                     3.0
EnvironmentSatisfaction       3.0
JobSatisfaction               3.0
MonthlyIncome              4919.0
NumCompaniesWorked            2.0
WorkLifeBalance               3.0
YearsAtCompany                5.0
dtype: float64
```



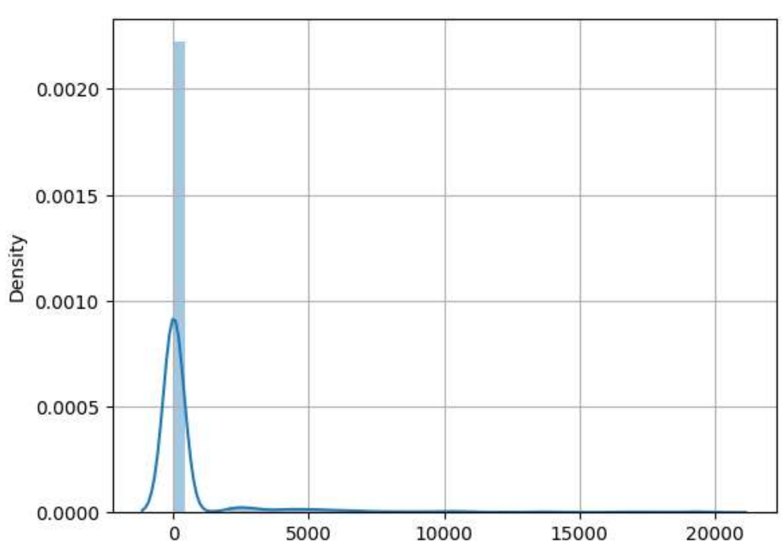

```
DistanceFromHome
Age                          36.923810
DistanceFromHome              9.192517
Education                     2.912925
EnvironmentSatisfaction       2.721769
JobSatisfaction               2.728571
MonthlyIncome              6502.931293
NumCompaniesWorked            2.693197
WorkLifeBalance               2.761224
YearsAtCompany                7.008163
dtype: float64
Age                          36.0
DistanceFromHome              7.0
Education                     3.0
EnvironmentSatisfaction       3.0
JobSatisfaction               3.0
MonthlyIncome              4919.0
NumCompaniesWorked            2.0
WorkLifeBalance               3.0
YearsAtCompany                5.0
dtype: float64
```



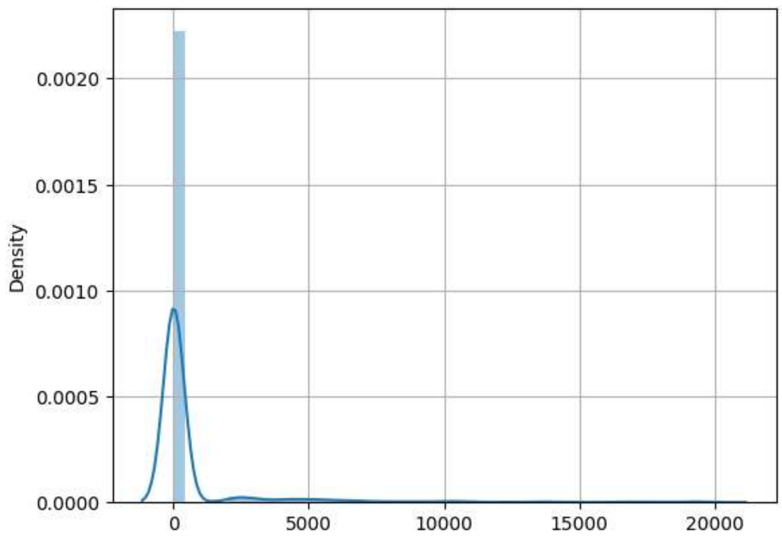
```
Education
Age                          36.923810
DistanceFromHome              9.192517
Education                     2.912925
EnvironmentSatisfaction       2.721769
JobSatisfaction               2.728571
MonthlyIncome              6502.931293
NumCompaniesWorked            2.693197
WorkLifeBalance               2.761224
YearsAtCompany                7.008163
dtype: float64
Age                          36.0
DistanceFromHome              7.0
Education                     3.0
EnvironmentSatisfaction       3.0
JobSatisfaction               3.0
MonthlyIncome              4919.0
NumCompaniesWorked            2.0
WorkLifeBalance               3.0
YearsAtCompany                5.0
dtype: float64
```



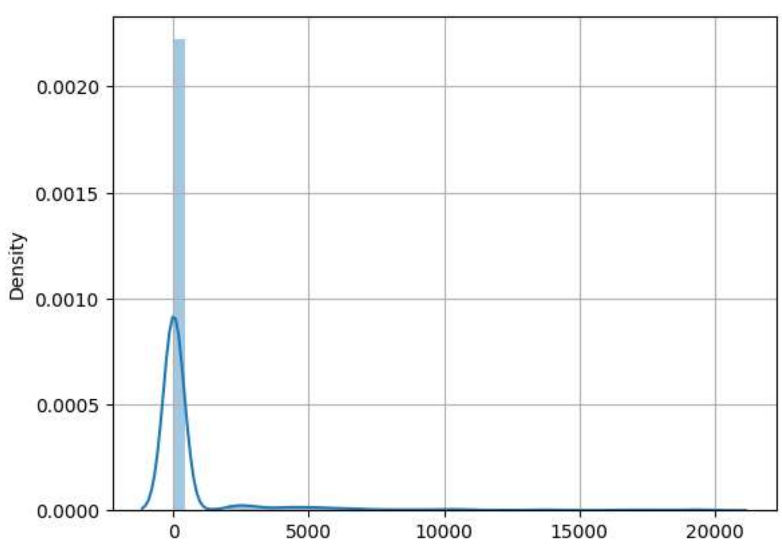

```
EnvironmentSatisfaction
Age                          36.923810
DistanceFromHome              9.192517
Education                     2.912925
EnvironmentSatisfaction       2.721769
JobSatisfaction               2.728571
MonthlyIncome              6502.931293
NumCompaniesWorked            2.693197
WorkLifeBalance               2.761224
YearsAtCompany                7.008163
dtype: float64
Age                          36.0
DistanceFromHome              7.0
Education                     3.0
EnvironmentSatisfaction       3.0
JobSatisfaction               3.0
MonthlyIncome              4919.0
NumCompaniesWorked            2.0
WorkLifeBalance               3.0
YearsAtCompany                5.0
dtype: float64
```



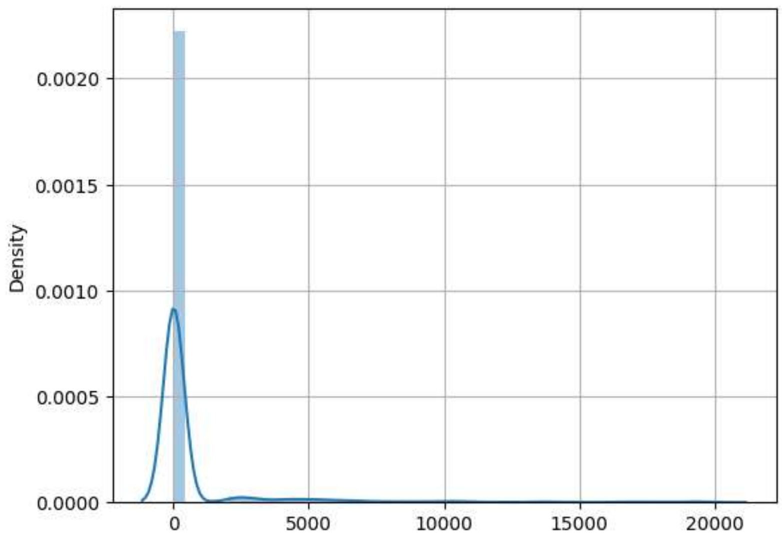
```
JobSatisfaction
Age                          36.923810
DistanceFromHome              9.192517
Education                     2.912925
EnvironmentSatisfaction       2.721769
JobSatisfaction               2.728571
MonthlyIncome              6502.931293
NumCompaniesWorked            2.693197
WorkLifeBalance               2.761224
YearsAtCompany                7.008163
dtype: float64
Age                          36.0
DistanceFromHome              7.0
Education                     3.0
EnvironmentSatisfaction       3.0
JobSatisfaction               3.0
MonthlyIncome              4919.0
NumCompaniesWorked            2.0
WorkLifeBalance               3.0
YearsAtCompany                5.0
dtype: float64
```



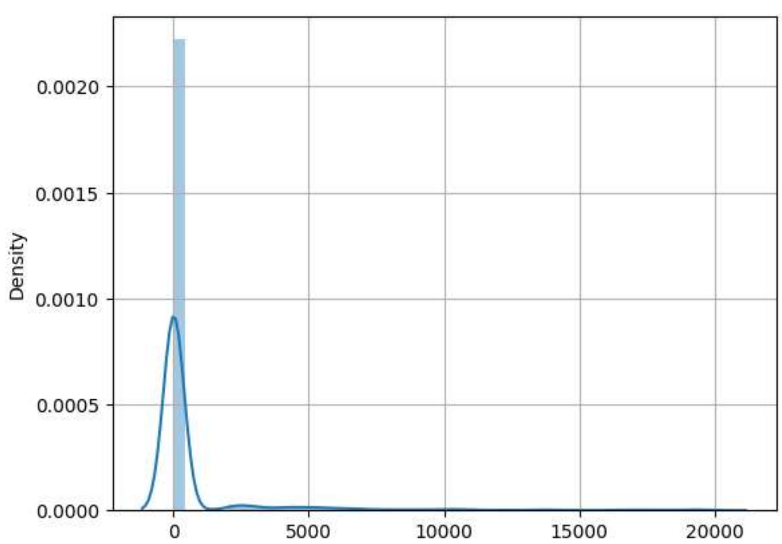

```
MonthlyIncome
Age                          36.923810
DistanceFromHome              9.192517
Education                     2.912925
EnvironmentSatisfaction       2.721769
JobSatisfaction               2.728571
MonthlyIncome              6502.931293
NumCompaniesWorked            2.693197
WorkLifeBalance               2.761224
YearsAtCompany                7.008163
dtype: float64
Age                          36.0
DistanceFromHome              7.0
Education                     3.0
EnvironmentSatisfaction       3.0
JobSatisfaction               3.0
MonthlyIncome              4919.0
NumCompaniesWorked            2.0
WorkLifeBalance               3.0
YearsAtCompany                5.0
dtype: float64
```



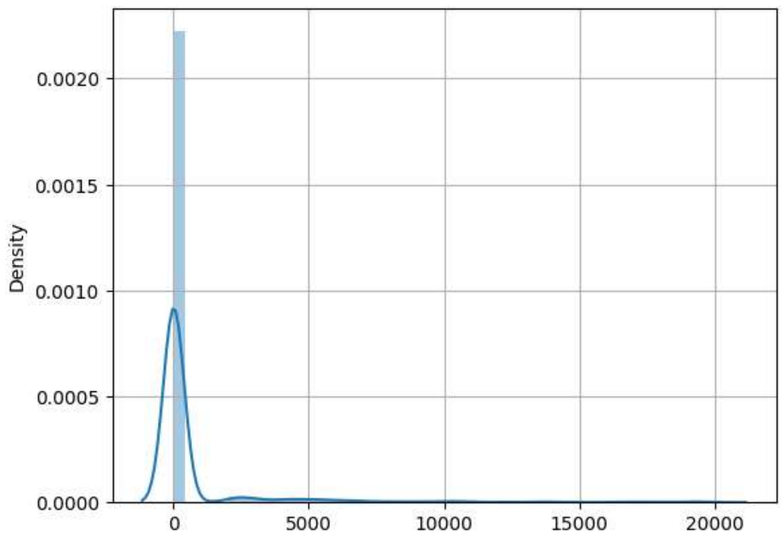
```
NumCompaniesWorked
Age                          36.923810
DistanceFromHome              9.192517
Education                     2.912925
EnvironmentSatisfaction       2.721769
JobSatisfaction               2.728571
MonthlyIncome              6502.931293
NumCompaniesWorked            2.693197
WorkLifeBalance               2.761224
YearsAtCompany                7.008163
dtype: float64
Age                          36.0
DistanceFromHome              7.0
Education                     3.0
EnvironmentSatisfaction       3.0
JobSatisfaction               3.0
MonthlyIncome              4919.0
NumCompaniesWorked            2.0
WorkLifeBalance               3.0
YearsAtCompany                5.0
dtype: float64
```




```
WorkLifeBalance
Age                          36.923810
DistanceFromHome              9.192517
Education                     2.912925
EnvironmentSatisfaction       2.721769
JobSatisfaction               2.728571
MonthlyIncome              6502.931293
NumCompaniesWorked            2.693197
WorkLifeBalance               2.761224
YearsAtCompany                7.008163
dtype: float64
Age                          36.0
DistanceFromHome              7.0
Education                     3.0
EnvironmentSatisfaction       3.0
JobSatisfaction               3.0
MonthlyIncome              4919.0
NumCompaniesWorked            2.0
WorkLifeBalance               3.0
YearsAtCompany                5.0
dtype: float64
```

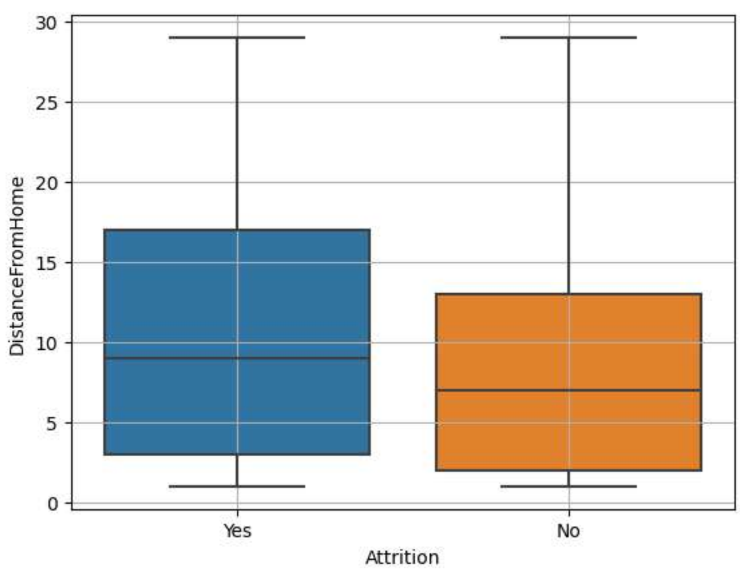


```
YearsAtCompany
Age                           36.923810
DistanceFromHome               9.192517
Education                      2.912925
EnvironmentSatisfaction        2.721769
JobSatisfaction                2.728571
MonthlyIncome               6502.931293
NumCompaniesWorked             2.693197
WorkLifeBalance                2.761224
YearsAtCompany                 7.008163
dtype: float64
Age                           36.0
DistanceFromHome               7.0
Education                      3.0
EnvironmentSatisfaction        3.0
JobSatisfaction                3.0
MonthlyIncome               4919.0
NumCompaniesWorked             2.0
WorkLifeBalance                3.0
YearsAtCompany                 5.0
dtype: float64
```

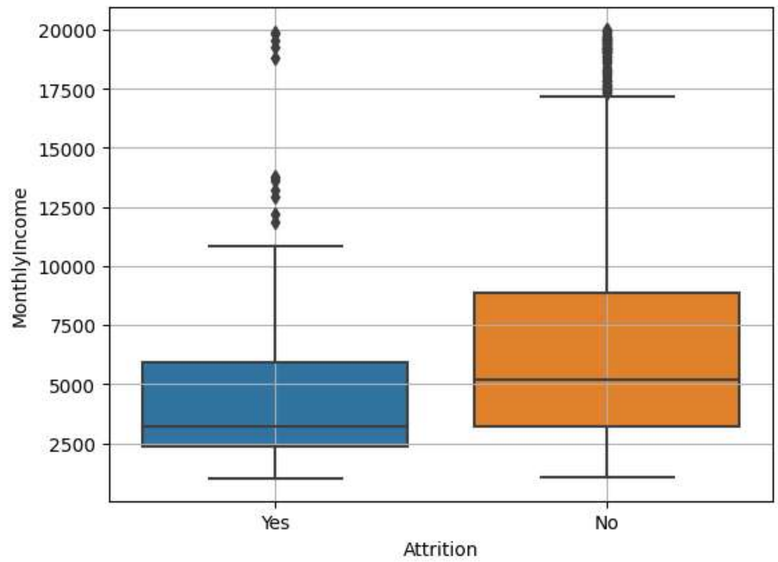


Step 2: Outlier Removal

In [13]:
```
sns.boxplot(data=df,x='Attrition',y='DistanceFromHome')
plt.grid()
plt.show()
```



In [14]:
```
sns.boxplot(data=df,x='Attrition',y='MonthlyIncome')
plt.grid()
plt.show()
```



In [15]:
```
a=x[(x["MonthlyIncome"]>11000) & (y['Attrition']=='Yes')].index
a
```

Out[15]:
```
Int64Index([45, 271, 435, 568, 595, 706, 749, 813, 838, 913, 975, 1223], dtype='int64')
```

In [16]:
```
b=x[(x["MonthlyIncome"]>17000) & (y['Attrition']=='No')].index
b
```

Out[16]:
```
Int64Index([  25,   29,   62,  105,  106,  112,  123,  147,  165,  186,  187,
             190,  231,  233,  237,  244,  257,  270,  279,  280,  290,  314,
             326,  329,  392,  400,  411,  417,  425,  429,  473,  477,  497,
             535,  538,  584,  588,  609,  653,  699,  710,  714,  716,  741,
             746,  755,  766,  770,  799,  810,  814,  851,  858,  861,  867,
             869,  894,  898,  899,  904,  907,  916,  918,  922,  936,  937,
             954,  955,  956, 1008, 1009, 1024, 1055, 1116, 1126, 1129, 1135,
            1140, 1154, 1184, 1185, 1242, 1264, 1277, 1330, 1331, 1351, 1374,
            1377, 1401, 1437, 1443],
           dtype='int64')
```

In [17]:
```
x.drop(a,inplace=True)
```

In [18]:
```
y.drop([45, 271, 435, 568, 595, 706, 749, 813, 838, 913, 975, 1223],inplace=True)
```

In [19]:
```
x.drop(b,inplace=True)
```

In [20]:
```
y.drop([25,   29,   62,  105,  106,  112,  123,  147,  165,  186,  187,
             190,  231,  233,  237,  244,  257,  270,  279,  280,  290,  314,
             326,  329,  392,  400,  411,  417,  425,  429,  473,  477,  497,
             535,  538,  584,  588,  609,  653,  699,  710,  714,  716,  741,
             746,  755,  766,  770,  799,  810,  814,  851,  858,  861,  867,
             869,  894,  898,  899,  904,  907,  916,  918,  922,  936,  937,
             954,  955,  956, 1008, 1009, 1024, 1055, 1116, 1126, 1129, 1135,
            1140, 1154, 1184, 1185, 1242, 1264, 1277, 1330, 1331, 1351, 1374,
            1377, 1401, 1437, 1443],inplace=True)
```

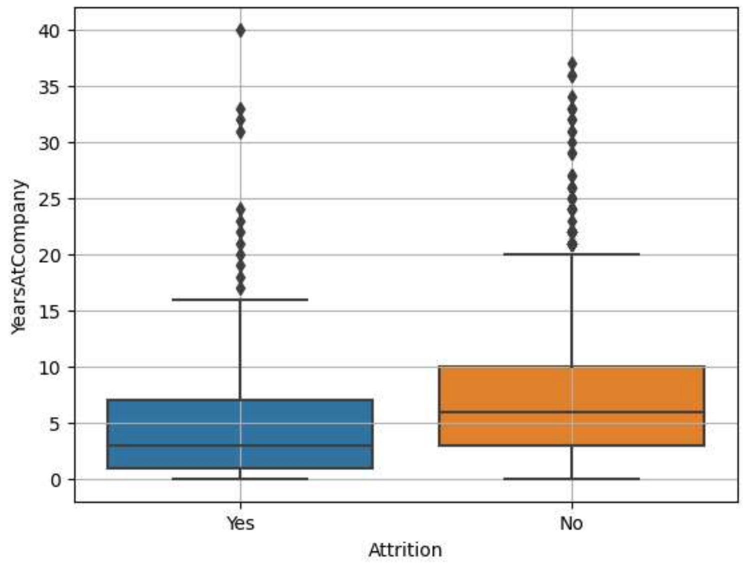
In [21]:
```
x
```

Out[21]:

	Age	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompanies
0	41	Sales	1	2	Life Sciences	2	4	Single	5993	
1	49	Research & Development	8	1	Life Sciences	3	2	Married	5130	
2	37	Research & Development	2	2	Other	4	3	Single	2090	
3	33	Research & Development	3	4	Life Sciences	4	3	Married	2909	
4	27	Research & Development	2	1	Medical	1	2	Married	3468	
...	...	...	...	...	...	...	...	...	...	
1465	36	Research & Development	23	2	Medical	3	4	Married	2571	
1466	39	Research & Development	6	1	Medical	4	1	Married	9991	
1467	27	Research & Development	4	3	Life Sciences	2	2	Married	6142	
1468	49	Sales	2	3	Medical	4	2	Married	5390	
1469	34	Research & Development	8	3	Medical	2	3	Married	4404	

1366 rows × 12 columns

In [22]:
```
sns.boxplot(data=df,x='Attrition',y='YearsAtCompany')
plt.grid()
plt.show()
```



In [23]:
```
c=x[(x["YearsAtCompany"]>16) & (y['Attrition']=='Yes')].index
c
```

Out[23]:
```
Int64Index([126, 752, 789, 1111], dtype='int64')
```

In [24]:
```
d=x[(x["YearsAtCompany"]>20) & (y['Attrition']=='No')].index
d
```

Out[24]:
```
Int64Index([  18,   28,   63,   90,   98,  119,  178,  300,  311,  390,  544,
             561,  592,  677,  738,  753,  914,  926,  962, 1086, 1096, 1138,
            1221, 1225, 1295, 1303],
           dtype='int64')
```

In [25]:
```
x.drop(c,inplace=True)
```

In [26]:
```
y.drop([126, 752, 789, 1111],inplace=True)
```

In [27]:
```
x.drop(d,inplace=True)
```

In [28]:
```
y.drop([18,   28,   63,   90,   98,  119,  178,  300,  311,  390,  544,
             561,  592,  677,  738,  753,  914,  926,  962, 1086, 1096, 1138,
            1221, 1225, 1295, 1303],inplace=True)
```

In [29]:
```
x
```

Out[29]:

	Age	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompanies
0	41	Sales	1	2	Life Sciences	2	4	Single	5993	
1	49	Research & Development	8	1	Life Sciences	3	2	Married	5130	
2	37	Research & Development	2	2	Other	4	3	Single	2090	
3	33	Research & Development	3	4	Life Sciences	4	3	Married	2909	
4	27	Research & Development	2	1	Medical	1	2	Married	3468	
...	...	...	...	...	...	...	...	...	...	
1465	36	Research & Development	23	2	Medical	3	4	Married	2571	
1466	39	Research & Development	6	1	Medical	4	1	Married	9991	
1467	27	Research & Development	4	3	Life Sciences	2	2	Married	6142	
1468	49	Sales	2	3	Medical	4	2	Married	5390	
1469	34	Research & Development	8	3	Medical	2	3	Married	4404	

1336 rows × 12 columns

Checking the correlation of the columns

In [30]:
```
df.corr().style.background_gradient()
```

Out[30]:

	Age	DistanceFromHome	Education	EnvironmentSatisfaction	JobSatisfaction	MonthlyIncome	NumCompaniesWorked	WorkLifeBa
Age	1.000000	-0.001686	0.208034	0.010146	-0.004892	0.497855	0.299635	-0.02
DistanceFromHome	-0.001686	1.000000	0.021042	-0.016075	-0.003669	-0.017014	-0.029251	-0.02
Education	0.208034	0.021042	1.000000	-0.027128	-0.011296	0.094961	0.126317	0.00
EnvironmentSatisfaction	0.010146	-0.016075	-0.027128	1.000000	-0.006784	-0.006259	0.012594	0.02
JobSatisfaction	-0.004892	-0.003669	-0.011296	-0.006784	1.000000	-0.007157	-0.055699	-0.01
MonthlyIncome	0.497855	-0.017014	0.094961	-0.006259	-0.007157	1.000000	0.149515	0.03
NumCompaniesWorked	0.299635	-0.029251	0.126317	0.012594	-0.055699	0.149515	1.000000	-0.00
WorkLifeBalance	-0.021490	-0.026556	0.009819	0.027627	-0.019459	0.030683	-0.008366	1.00
YearsAtCompany	0.311309	0.009508	0.069114	0.001458	-0.003803	0.514285	-0.118421	0.01

In [31]:
```
y
```

Out[31]:

	Attrition
0	Yes
1	No
2	Yes
3	No
4	No
...	...
1465	No
1466	No
1467	No
1468	No
1469	No

1336 rows × 1 columns

In [32]:
```
x
```

Out[32]:

	Age	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompanies
0	41	Sales	1	2	Life Sciences	2	4	Single	5993	
1	49	Research & Development	8	1	Life Sciences	3	2	Married	5130	
2	37	Research & Development	2	2	Other	4	3	Single	2090	
3	33	Research & Development	3	4	Life Sciences	4	3	Married	2909	
4	27	Research & Development	2	1	Medical	1	2	Married	3468	
...	...	...	...	...	...	...	...	...	...	
1465	36	Research & Development	23	2	Medical	3	4	Married	2571	
1466	39	Research & Development	6	1	Medical	4	1	Married	9991	
1467	27	Research & Development	4	3	Life Sciences	2	2	Married	6142	
1468	49	Sales	2	3	Medical	4	2	Married	5390	
1469	34	Research & Development	8	3	Medical	2	3	Married	4404	

1336 rows × 12 columns

Step 4:- Convert Categorical Data into Numerical Data

In [34]:
```
from sklearn.preprocessing import OrdinalEncoder
oe=OrdinalEncoder()
x[['Department','EducationField','MaritalStatus']]=oe.fit_transform(x[['Department','EducationField','MaritalStatus']])
```

In [35]:
```
x
```

Out[35]:

	Age	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompaniesV
0	41	2.0	1	2	1.0	2	4	2.0	5993	
1	49	1.0	8	1	1.0	3	2	1.0	5130	
2	37	1.0	2	2	4.0	4	3	2.0	2090	
3	33	1.0	3	4	1.0	4	3	1.0	2909	
4	27	1.0	2	1	3.0	1	2	1.0	3468	
...	...	...	...	...	...	...	...	...	...	
1465	36	1.0	23	2	3.0	3	4	1.0	2571	
1466	39	1.0	6	1	3.0	4	1	1.0	9991	
1467	27	1.0	4	3	1.0	2	2	1.0	6142	
1468	49	2.0	2	3	3.0	4	2	1.0	5390	
1469	34	1.0	8	3	3.0	2	3	1.0	4404	

1336 rows × 12 columns

In [36]:
```
y
```
Out[36]:

	Attrition
0	Yes
1	No
2	Yes
3	No
4	No
...	...
1465	No
1466	No
1467	No
1468	No
1469	No

1336 rows × 1 columns

In [37]:
```
from sklearn.preprocessing import OrdinalEncoder
le=OrdinalEncoder()
y.iloc[:,:]=le.fit_transform(y.iloc[:,:])
```
In [38]:
```
y
```
Out[38]:

	Attrition
0	1.0
1	0.0
2	1.0
3	0.0
4	0.0
...	...
1465	0.0
1466	0.0
1467	0.0
1468	0.0
1469	0.0

1336 rows × 1 columns

In [39]:
```
y['Attrition']=y['Attrition'].astype('int64')
```
In [40]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=1)
```
In [41]:
```
xtrain
```
Out[41]:

	Age	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompaniesW
10	35	1.0	16	3	3.0	1	2	1.0	2426	
1094	40	2.0	9	2	3.0	1	1	1.0	5473	
924	35	1.0	6	1	1.0	3	3	1.0	3506	
740	35	1.0	10	3	4.0	2	4	0.0	3917	
350	42	0.0	2	1	5.0	3	3	0.0	2696	
...	...	...	...	...	...	...	...	...	...	
788	28	1.0	10	3	4.0	3	3	2.0	3660	
1007	29	1.0	14	1	4.0	3	4	2.0	7553	
1214	44	1.0	2	3	1.0	3	4	1.0	7879	
261	38	2.0	2	2	1.0	4	4	1.0	5249	
1177	50	1.0	17	5	1.0	4	1	0.0	13269	

935 rows × 12 columns

In [42]:
```
ytrain
```
Out[42]:

	Attrition
10	0
1094	0
924	0
740	0
350	0
...	...
788	0
1007	1
1214	0
261	0
1177	0

935 rows × 1 columns

In [43]:
```
xtest
```

Out[43]:

	Age	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompaniesW
1430	38	1.0	10	3	3.0	2	3	1.0	13206	
1203	53	1.0	24	4	3.0	2	4	1.0	7005	
317	52	1.0	8	4	3.0	3	2	1.0	4941	
662	20	2.0	2	3	3.0	3	3	2.0	2044	
632	42	1.0	2	1	3.0	2	4	2.0	2515	
...	...	...	...	...	...	...	...	...	...	
150	40	1.0	26	3	3.0	2	2	0.0	5605	
704	35	2.0	3	4	1.0	4	4	0.0	7823	
999	42	0.0	10	3	0.0	3	1	1.0	16799	
804	48	1.0	1	4	3.0	1	4	2.0	16885	
402	30	2.0	12	3	5.0	2	3	2.0	6577	

401 rows × 12 columns

In [44]:
```
ytest
```

Out[44]:

	Attrition
1430	0
1203	0
317	1
662	1
632	0
...	...
150	0
704	0
999	0
804	0
402	0

401 rows × 1 columns

Step 5 :- Model Building

In [45]:
```
from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression()
```

In [46]:
```
logreg.fit(xtrain,ytrain)
```

Out[46]:
```
▾ LogisticRegression
LogisticRegression()
```

In [47]:
```
ypred=logreg.predict(xtest)
```

In [48]:
```
ypred
```

Out[48]:
```
array([0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0], dtype=int64)
```

In [49]:
```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [50]:
```
ac=accuracy_score(ytest,ypred)
cm=confusion_matrix(ytest,ypred)
cr=classification_report(ytest,ypred)
print(f'Accuracy:- {ac}\n {cm}\n {cr}')
```

```
Accuracy:- 0.8778054862842892
 [[346   1]
 [ 48   6]]
               precision    recall  f1-score   support

           0       0.88      1.00      0.93       347
           1       0.86      0.11      0.20        54

    accuracy                           0.88       401
   macro avg       0.87      0.55      0.57       401
weighted avg       0.88      0.88      0.83       401
```

In [51]:
```
train=logreg.score(xtrain,ytrain)
test=logreg.score(xtest,ytest)
print(f'Training accuracy:- {train}\ntesting accuracy:- {test}')
```

```
Training accuracy:- 0.8352941176470589
testing accuracy:- 0.8778054862842892
```

In [52]:
```
y['Attrition'].value_counts()
```

Out[52]:
```
0    1115
1     221
Name: Attrition, dtype: int64
```

Improving accuracy

In [53]:
```
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(x,y,test_size=0.3,random_state=1,stratify=y)
```

In [54]:
```
ac=accuracy_score(ytest,ypred)
cm=confusion_matrix(ytest,ypred)
cr=classification_report(ytest,ypred)
print(f'Accuracy:- {ac}\n {cm}\n {cr}')
```

```
Accuracy:- 0.8329177057356608
 [[331   4]
 [ 63   3]]
               precision    recall  f1-score   support

           0       0.84      0.99      0.91       335
           1       0.43      0.05      0.08        66

    accuracy                           0.83       401
   macro avg       0.63      0.52      0.50       401
weighted avg       0.77      0.83      0.77       401
```

In [55]:
```
train=logreg.score(xtrain,ytrain)
test=logreg.score(xtest,ytest)
print(f'Training accuracy:- {train}\ntesting accuracy:- {test}')
```

```
Training accuracy:- 0.8502673796791443
testing accuracy:- 0.8428927680798005
```

In [56]:
```
x
```

Out[56]:

	Age	Department	DistanceFromHome	Education	EducationField	EnvironmentSatisfaction	JobSatisfaction	MaritalStatus	MonthlyIncome	NumCompaniesW
0	41	2.0	1	2	1.0	2	4	2.0	5993	
1	49	1.0	8	1	1.0	3	2	1.0	5130	
2	37	1.0	2	2	4.0	4	3	2.0	2090	
3	33	1.0	3	4	1.0	4	3	1.0	2909	
4	27	1.0	2	1	3.0	1	2	1.0	3468	
...	...	...	...	...	...	...	...	...	...	
1465	36	1.0	23	2	3.0	3	4	1.0	2571	
1466	39	1.0	6	1	3.0	4	1	1.0	9991	
1467	27	1.0	4	3	1.0	2	2	1.0	6142	
1468	49	2.0	2	3	3.0	4	2	1.0	5390	
1469	34	1.0	8	3	3.0	2	3	1.0	4404	

1336 rows × 12 columns

Prediction of new observation fed to the model

In [57]:
```
def attrition():
    age=int(input('Enter Age:-'))
    department=input('Enter department:-')
    distancefromhome=int(input('Enter distance from home:-'))
    education=int(input('Enter Education level:- '))
    educationfield=input('Enter Education Field:-')
    environmentalsatisfaction=int(input('Enter Environmental Satisifaction score:-'))
    jobsatisfaction=int(input('Enter jobsatisfaction:-'))
    maritalstatus=input('Enter marital Status:- ')
    monthlyincome=int(input('Enter MonthlyIncome:-'))
    numcompaniesworked=int(input('Enter Number of Companies Worked:- '))
    worklifebalance=int(input('Enter work life balance score:- '))
    yearsatcompany=int(input('Enter years at company:- '))


    newob=[age,department,distancefromhome,education,educationfield,environmentalsatisfaction,
          jobsatisfaction,maritalstatus,monthlyincome,numcompaniesworked,worklifebalance,
           yearsatcompany]
    newob[1],newob[4],newob[7]=oe.fit_transform([[newob[1],newob[4],newob[7]]])[0]
    a=logreg.predict([newob])[0]
    return a
```

In [58]:
```
attrition()
```

```
Enter Age:-35
Enter department:-Sales
Enter distance from home:-10
Enter Education level:- 3
Enter Education Field:-Life Sciences
Enter Environmental Satisifaction score:-5
Enter jobsatisfaction:-5
Enter marital Status:- Single
Enter MonthlyIncome:-15000
Enter Number of Companies Worked:- 5
Enter work life balance score:- 5
Enter years at company:- 5
```

Out[58]:
```
0
```

Here 0 means the employee will not leave the company and if we get 1 in the output that means the employee will leave the company

In [ ]:
```

```