

```
In [1]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.preprocessing import LabelEncoder, OneHotEncoder, StandardScaler
import warnings
warnings.filterwarnings('ignore')
from sklearn.tree import DecisionTreeRegressor
from sklearn.feature_selection import RFE
from sklearn.preprocessing import MinMaxScaler, StandardScaler
import joblib
import datetime
from sklearn.feature_selection import SelectFromModel
from sklearn.model_selection import cross_val_score, GridSearchCV
from sklearn.linear_model import Ridge, Lasso
```

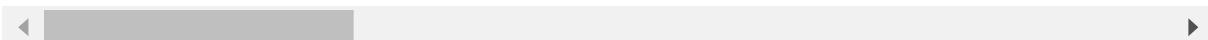
```
In [2]: df = pd.read_csv('HR.csv')
```

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

Out[3]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	E
0	41	Yes	Travel_Rarely	1102	Sales	1	2	
1	49	No	Travel_Frequently	279	Research & Development	8	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	
4	27	No	Travel_Rarely	591	Research & Development	2	1	
...
1465	36	No	Travel_Frequently	884	Research & Development	23	2	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	
1468	49	No	Travel_Frequently	1023	Sales	2	3	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	

1470 rows × 35 columns



In [4]: df.head()

Out[4]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	Educ
0	41	Yes	Travel_Rarely	1102	Sales	1	2	Lif
1	49	No	Travel_Frequently	279	Research & Development	8	1	Lif
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	Lif
4	27	No	Travel_Rarely	591	Research & Development	2	1	

5 rows × 35 columns



In [5]: df.tail()

Out[5]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	E
1465	36	No	Travel_Frequently	884	Research & Development	23	2	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	
1468	49	No	Travel_Frequently	1023	Sales	2	3	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	

5 rows × 35 columns

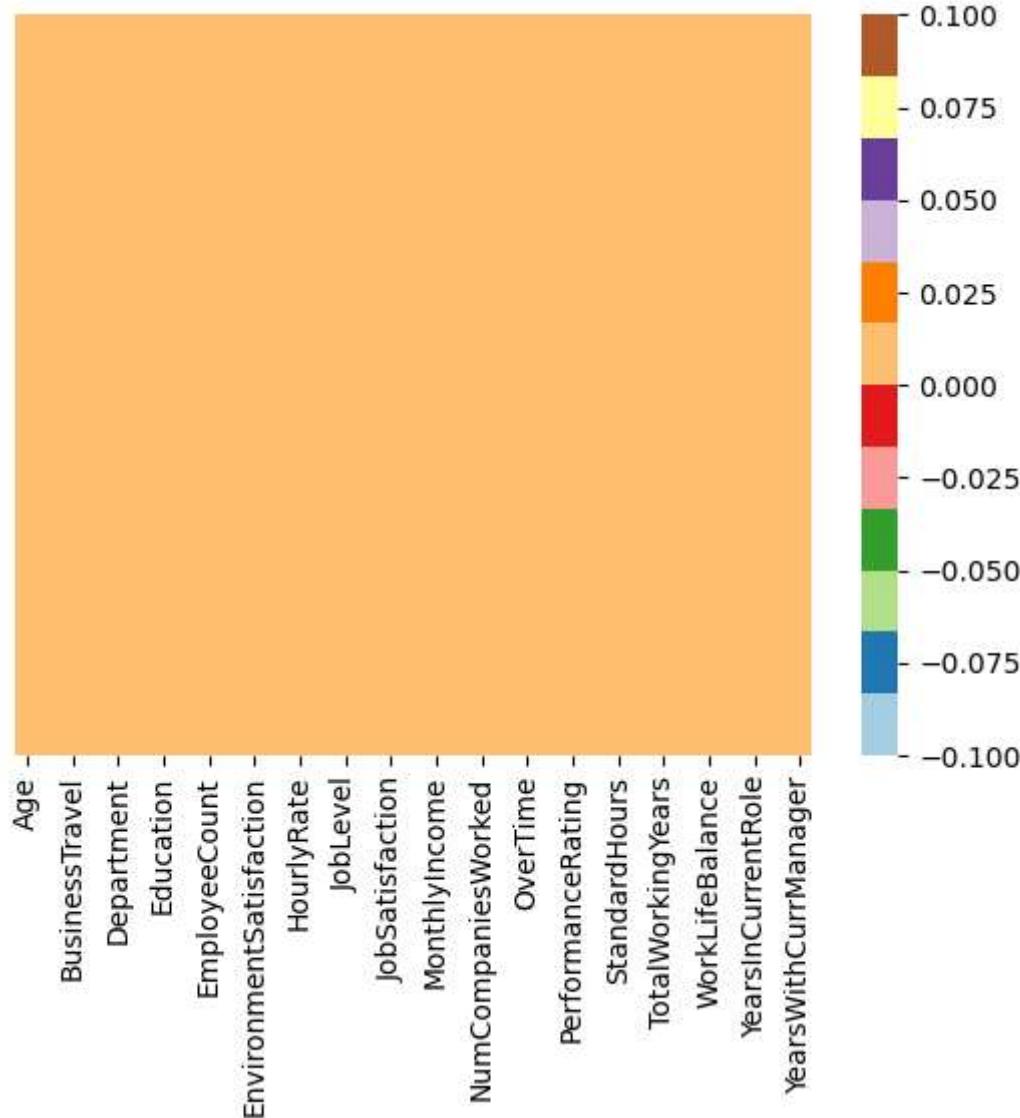


```
In [6]: df.isnull().sum()
```

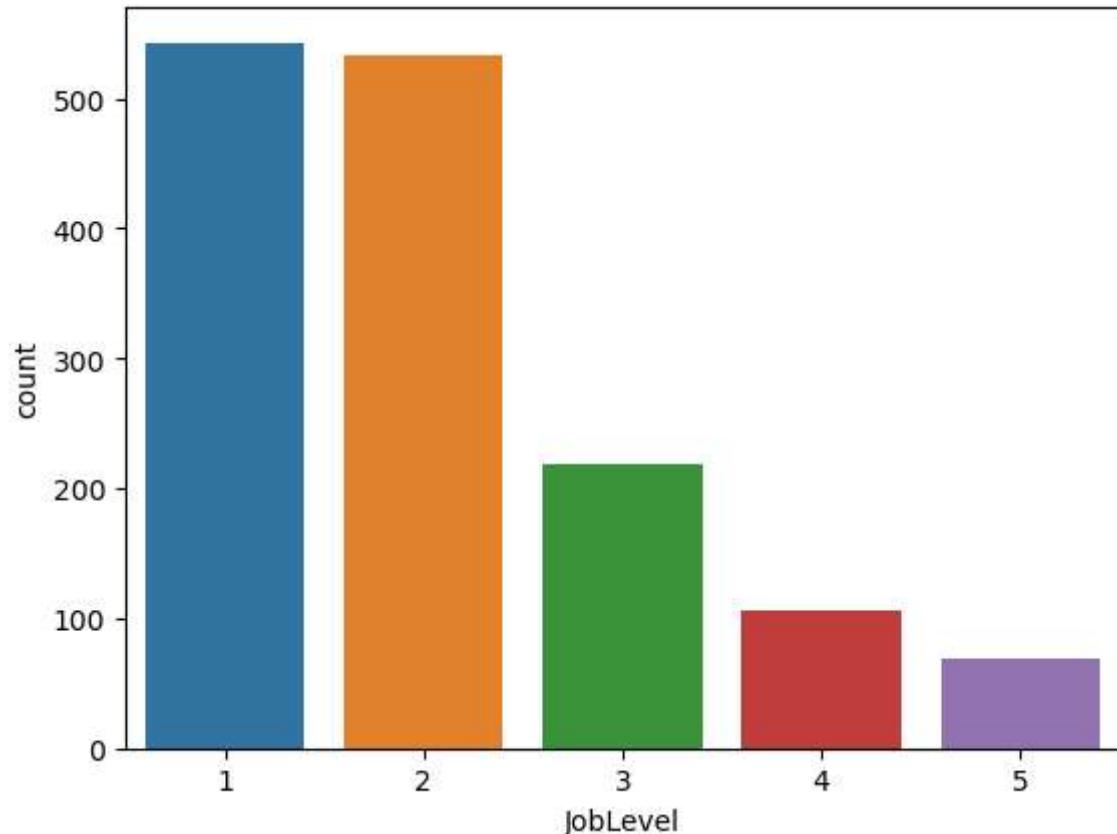
```
Out[6]: Age          0  
Attrition      0  
BusinessTravel  0  
DailyRate       0  
Department      0  
DistanceFromHome 0  
Education        0  
EducationField    0  
EmployeeCount     0  
EmployeeNumber    0  
EnvironmentSatisfaction 0  
Gender          0  
HourlyRate       0  
JobInvolvement    0  
JobLevel         0  
JobRole          0  
JobSatisfaction   0  
MaritalStatus     0  
MonthlyIncome     0  
MonthlyRate       0  
NumCompaniesWorked 0  
Over18           0  
OverTime          0  
PercentSalaryHike 0  
PerformanceRating 0  
RelationshipSatisfaction 0  
StandardHours     0  
StockOptionLevel   0  
TotalWorkingYears  0  
TrainingTimesLastYear 0  
WorkLifeBalance    0  
YearsAtCompany     0  
YearsInCurrentRole 0  
YearsSinceLastPromotion 0  
YearsWithCurrManager 0  
dtype: int64
```

```
In [7]: sns.heatmap(df.isnull(),yticklabels=False,cmap="Paired")
```

```
Out[7]: <Axes: >
```

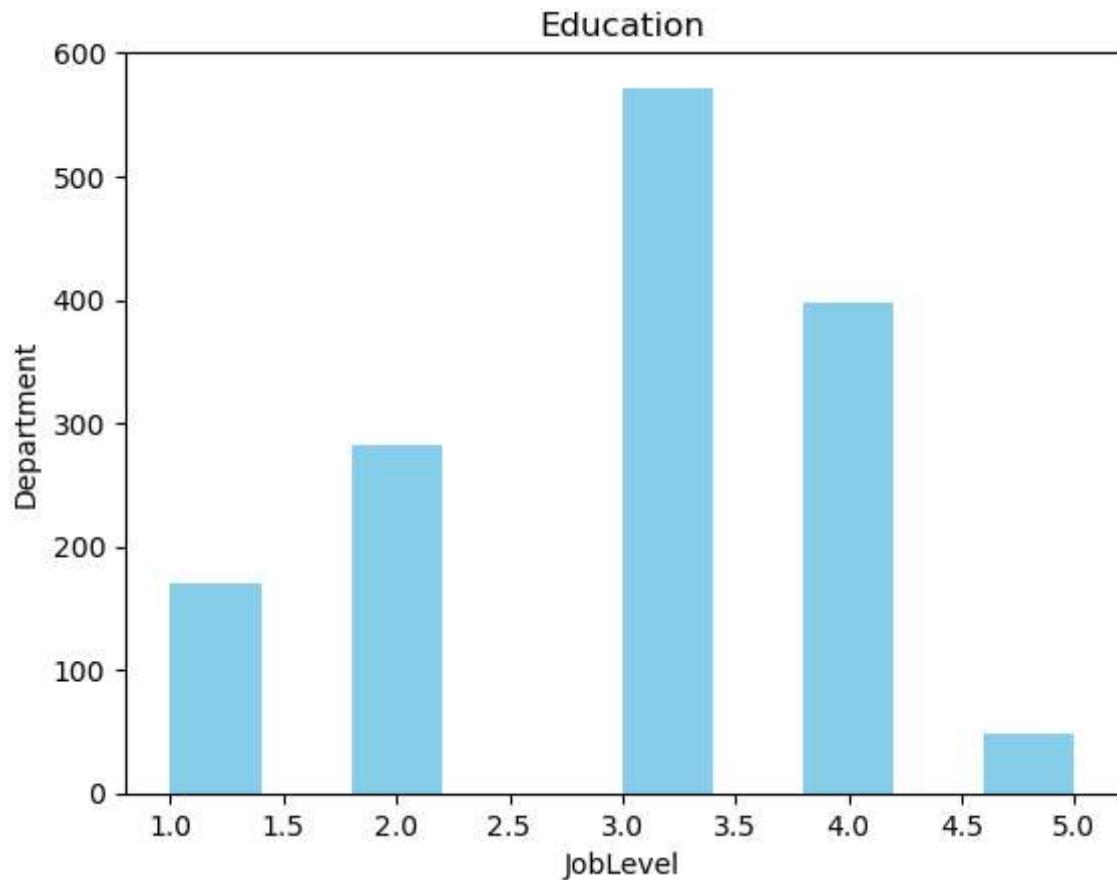


```
In [8]: sns.countplot(x=df['JobLevel'])
plt.show()
```



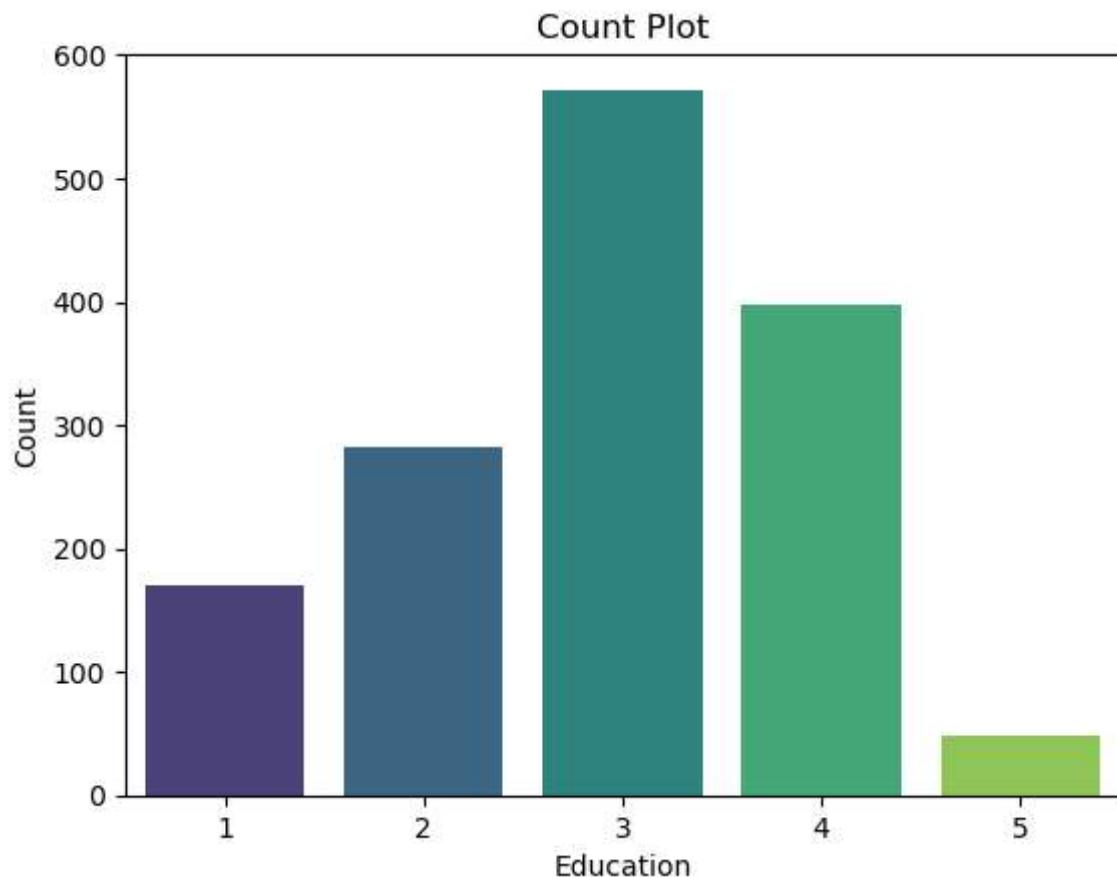
```
In [9]: plt.hist(df[ 'Education' ], bins=10, color='skyblue')

plt.xlabel('JobLevel')
plt.ylabel('Department')
plt.title('Education')
plt.show()
```



```
In [10]: sns.countplot(x='Education', data=df, palette='viridis')
plt.xlabel('Education')
plt.ylabel('Count')
plt.title('Count Plot')

plt.show()
```

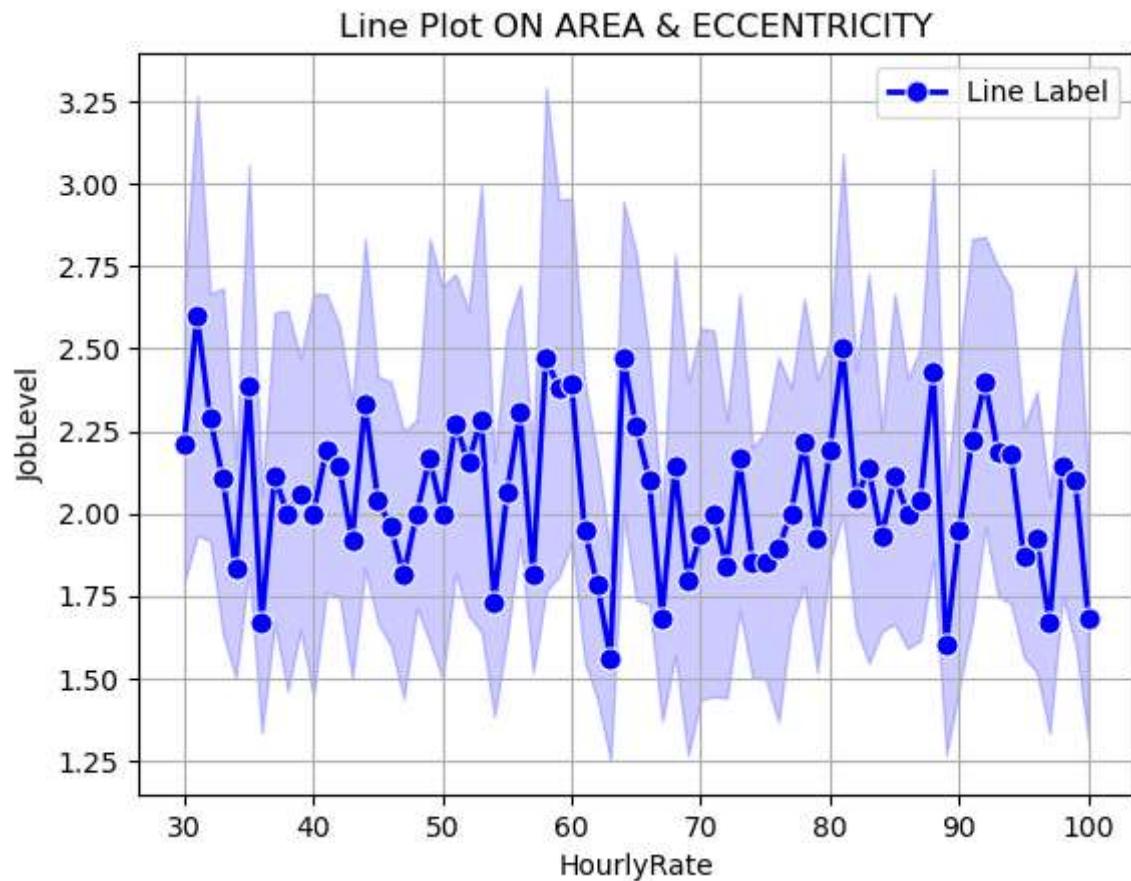


```
In [11]: df_area=df['HourlyRate'].value_counts()
```

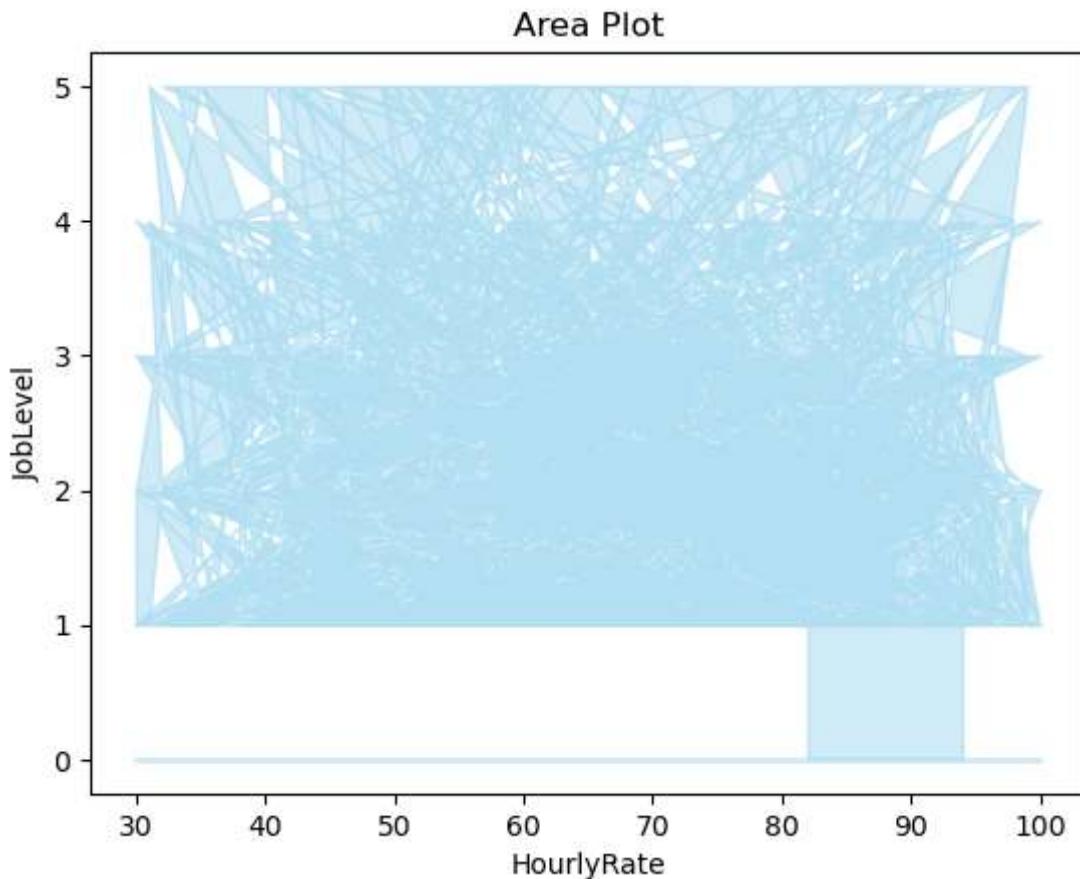
```
In [12]: df_area
```

```
Out[12]: 66    29
98    28
42    28
48    28
84    28
...
31    15
53    14
68    14
38    13
34    12
Name: HourlyRate, Length: 71, dtype: int64
```

```
In [13]: sns.lineplot(x='HourlyRate', y='JobLevel', data=df, marker='o', color='b', lin  
plt.xlabel('HourlyRate')  
plt.ylabel('JobLevel')  
plt.title('Line Plot ON AREA & ECCENTRICITY')  
plt.legend()  
plt.grid(True)  
plt.show()
```



```
In [14]: plt.fill_between(df['HourlyRate'], df['JobLevel'], color='skyblue', alpha=0.4)
plt.xlabel('HourlyRate')
plt.ylabel('JobLevel')
plt.title('Area Plot')
plt.show()
```

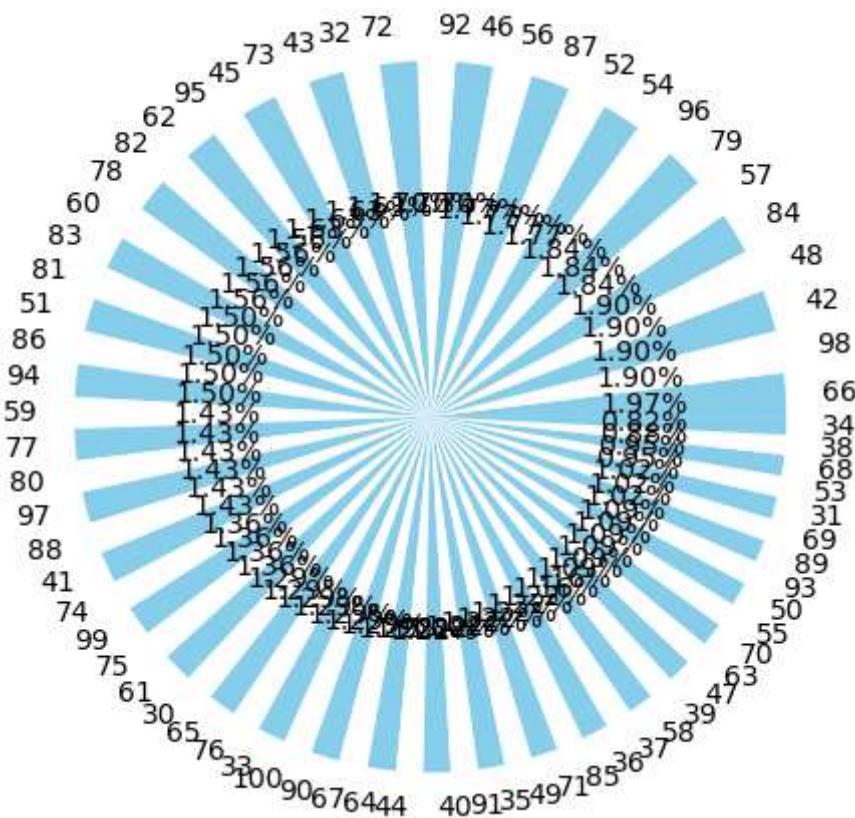


```
In [15]: df_pie =df['HourlyRate'].value_counts()
```

```
In [16]: df_pie
```

```
Out[16]: 66    29
98    28
42    28
48    28
84    28
...
31    15
53    14
68    14
38    13
34    12
Name: HourlyRate, Length: 71, dtype: int64
```

```
In [17]: plt.pie(df_pie, labels=df_pie.index, autopct=".2f%%", radius =1.2, colors=['skyblue', 'red', 'green', 'yellow', 'purple', 'brown', 'pink', 'orange', 'grey', 'lightblue'])  
plt.show()
```



In [18]: df.dtypes

Out[18]:

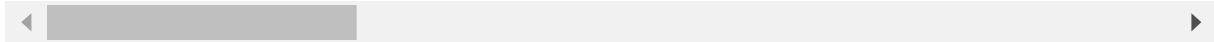
Age	int64
Attrition	object
BusinessTravel	object
DailyRate	int64
Department	object
DistanceFromHome	int64
Education	int64
EducationField	object
EmployeeCount	int64
EmployeeNumber	int64
EnvironmentSatisfaction	int64
Gender	object
HourlyRate	int64
JobInvolvement	int64
JobLevel	int64
JobRole	object
JobSatisfaction	int64
MaritalStatus	object
MonthlyIncome	int64
MonthlyRate	int64
NumCompaniesWorked	int64
Over18	object
Overtime	object
PercentSalaryHike	int64
PerformanceRating	int64
RelationshipSatisfaction	int64
StandardHours	int64
StockOptionLevel	int64
TotalWorkingYears	int64
TrainingTimesLastYear	int64
WorkLifeBalance	int64
YearsAtCompany	int64
YearsInCurrentRole	int64
YearsSinceLastPromotion	int64
YearsWithCurrManager	int64
dtype:	object

In [19]: df

Out[19]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	E
0	41	Yes	Travel_Rarely	1102	Sales	1	2	
1	49	No	Travel_Frequently	279	Research & Development	8	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	
4	27	No	Travel_Rarely	591	Research & Development	2	1	
...
1465	36	No	Travel_Frequently	884	Research & Development	23	2	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	
1468	49	No	Travel_Frequently	1023	Sales	2	3	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	

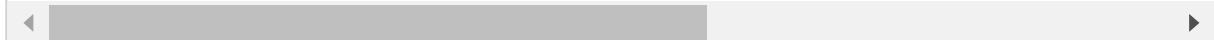
1470 rows × 35 columns



ENCODING

In [20]: encoder=LabelEncoder()

In [21]: categorical_col = ['Attrition', 'BusinessTravel', 'Department', 'EducationField',
encoder = OneHotEncoder(drop='first', sparse=False)
encoder_cols = pd.DataFrame(encoder.fit_transform(df[categorical_col]), columns



In [22]: encoder_cols

Out[22]:

	Attrition_Yes	BusinessTravel_Travel_Frequently	BusinessTravel_Travel_Rarely	Department_& Dev
0	1.0		0.0	1.0
1	0.0		1.0	0.0
2	1.0		0.0	1.0
3	0.0		1.0	0.0
4	0.0		0.0	1.0
...
1465	0.0		1.0	0.0
1466	0.0		0.0	1.0
1467	0.0		0.0	1.0
1468	0.0		1.0	0.0
1469	0.0		0.0	1.0

1470 rows × 22 columns

In [23]: numerical_col = ['Age', 'DailyRate', 'DistanceFromHome', 'Education', 'EmployeeCount', 'EmployeeNumber', 'Gender', 'JobRole', 'MaritalStatus', 'OverTime', 'RelationshipSatisfaction', 'StandardHours', 'TotalWorkingYears', 'WorkLifeBalance', 'YearsAtCompany', 'YearsInCurrentRole', 'YearsOnLastPromotion', 'YearsSinceLastPromotion', 'YearsWithCurrManager']
Scaled = StandardScaler()
Scaled = pd.DataFrame(Scaled.fit_transform(df[numerical_col]), columns=numerical_col)

In [24]: Scaled

Out[24]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	R
0	0.446350	0.742527		-1.010909	-0.891688	0.0	-1.701283
1	1.322365	-1.297775		-0.147150	-1.868426	0.0	-1.699621
2	0.008343	1.414363		-0.887515	-0.891688	0.0	-1.696298
3	-0.429664	1.461466		-0.764121	1.061787	0.0	-1.694636
4	-1.086676	-0.524295		-0.887515	-1.868426	0.0	-1.691313
...
1465	-0.101159	0.202082		1.703764	-0.891688	0.0	1.721670
1466	0.227347	-0.469754		-0.393938	-1.868426	0.0	1.723332
1467	-1.086676	-1.605183		-0.640727	0.085049	0.0	1.726655
1468	1.322365	0.546677		-0.887515	0.085049	0.0	1.728317
1469	-0.320163	-0.432568		-0.147150	0.085049	0.0	1.733302

1470 rows × 15 columns

In [25]: `x = pd.concat([encoder_cols, Scaled], axis=1)`
`y = df['YearsWithCurrManager']`

In [26]: `x`

Out[26]:

	Attrition_Yes	BusinessTravel_Travel_Frequently	BusinessTravel_Travel_Rarely	Department_L & Dev
0	1.0	0.0	1.0	
1	0.0	1.0	0.0	
2	1.0	0.0	1.0	
3	0.0	1.0	0.0	
4	0.0	0.0	1.0	
...
1465	0.0	1.0	0.0	
1466	0.0	0.0	1.0	
1467	0.0	0.0	1.0	
1468	0.0	1.0	0.0	
1469	0.0	0.0	1.0	

1470 rows × 37 columns



In [27]: `y`

Out[27]:

0	5
1	7
2	0
3	0
4	2
..	
1465	3
1466	7
1467	3
1468	8
1469	2

Name: YearsWithCurrManager, Length: 1470, dtype: int64

LINEAR

In [28]: `x.shape`

Out[28]: (1470, 37)

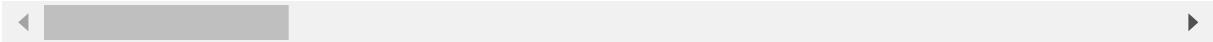
```
In [29]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=
```

```
In [30]: x_train
```

Out[30]:

	Attrition_Yes	BusinessTravel_Travel_Frequently	BusinessTravel_Travel_Rarely	Department_& Dev
1097	0.0	0.0	1.0	
727	0.0	0.0	0.0	
254	0.0	0.0	1.0	
1175	0.0	0.0	1.0	
1341	0.0	0.0	1.0	
...	
1130	0.0	0.0	1.0	
1294	0.0	0.0	1.0	
860	1.0	1.0	0.0	
1459	0.0	0.0	1.0	
1126	0.0	0.0	1.0	

1176 rows × 37 columns



```
In [31]: model=LinearRegression()
model.fit(x_train,y_train)
y_pred=model.predict(x_test)
```

```
In [32]: from sklearn.metrics import r2_score, mean_squared_error,mean_absolute_error
```

```
In [33]: R2= r2_score(y_test,y_pred)
```

```
In [34]: mae = mean_absolute_error(y_test,y_pred)
mse = mean_squared_error(y_test,y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test,y_pred)
```

```
In [35]: print('Mean Absolute Error',mae)
print('Mean Squared error',rmse)
print('Root Mean Squared Error',rmse)
print('R2 Score',r2)
```

Mean Absolute Error 1.557335466097933
 Mean Squared error 2.0962789390706984
 Root Mean Squared Error 2.0962789390706984
 R2 Score 0.6798528904675876

```
In [36]: lr_model = LinearRegression()
lr_scores = cross_val_score(lr_model,x_train,y_train,cv=5)
```

```
In [37]: ridge_model= Ridge(alpha=1.0)
ridge_scores = cross_val_score(ridge_model , x_train , y_train , cv = 5)
```

```
In [38]: Lasso_model= Lasso(alpha=1.0)
Lasso_scores = cross_val_score(Lasso_model , x_train , y_train , cv = 5)
```

```
In [39]: lr_model.fit(x_train,y_train)
lr_prediction = lr_model.predict(x_test)
lr_mae = mean_absolute_error(y_test,lr_prediction)
lr_mse = mean_squared_error(y_test,lr_prediction)
lr_r2 = r2_score(y_test,lr_prediction)
```

```
In [40]: print('Linear MAE',lr_mae)
print('Linear MSE',lr_mse)
print('Linear R2',lr_r2)
```

Linear MAE 1.557335466097933
 Linear MSE 4.394385390391372
 Linear R2 0.6798528904675876

```
In [41]: Lasso_model.fit(x_train , y_train)
Lasso_prediction = Lasso_model.predict(x_test)
Lasso_mae = mean_absolute_error(y_test , Lasso_prediction)
Lasso_mse = mean_squared_error(y_test , Lasso_prediction)
Lasso_r2 = r2_score(y_test , Lasso_prediction)
```

```
In [42]: print('Lasso MAE',Lasso_mae)
print('Lasso MSE',Lasso_mse)
print('Lasso R2',Lasso_r2)
```

Lasso MAE 2.0235815126568895
 Lasso MSE 6.188584184887578
 Lasso R2 0.5491389209462796

```
In [43]: ridge_model.fit(x_train , y_train)
ridge_prediction = ridge_model.predict(x_test)
ridge_mae = mean_absolute_error(y_test , ridge_prediction)
ridge_mse = mean_squared_error(y_test , ridge_prediction)
ridge_r2 = r2_score(y_test , ridge_prediction)
```

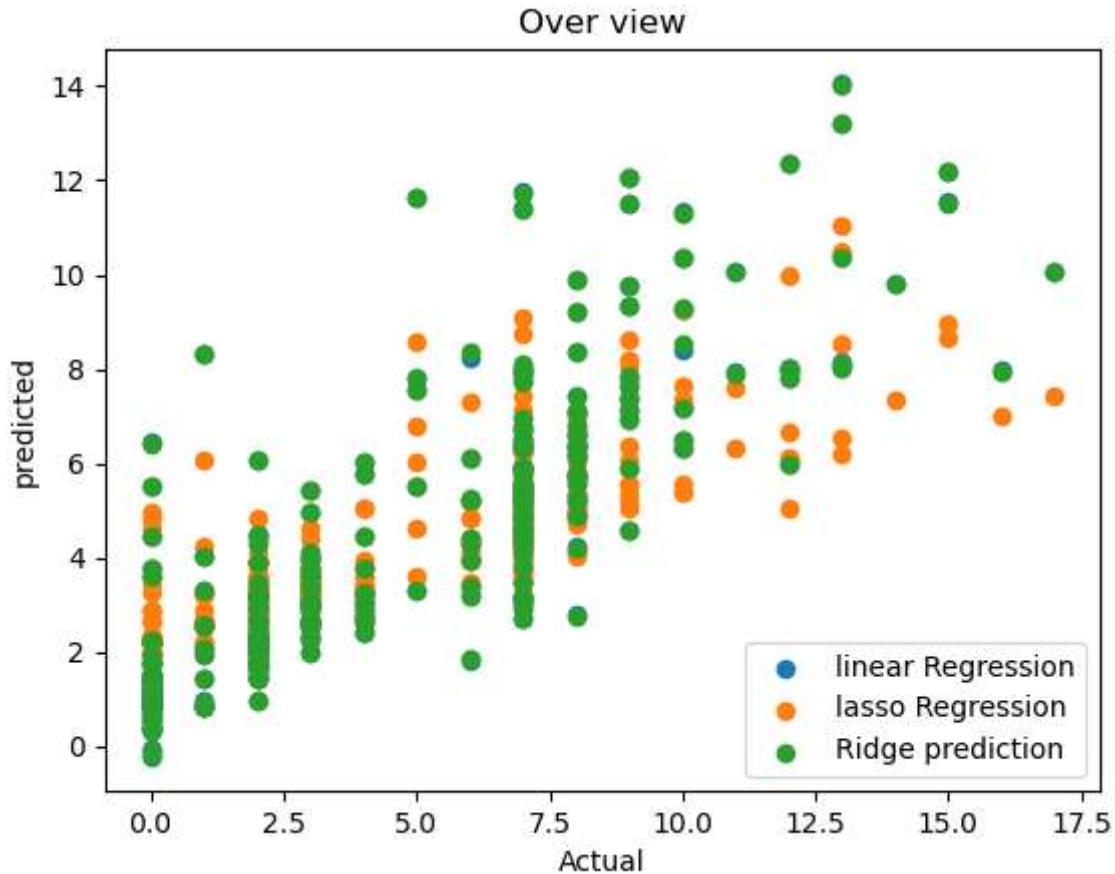
```
In [44]: print('Ridge MAE',ridge_mae)
print('Ridge MSE',ridge_mse)
print('Ridge R2',ridge_r2)
```

Ridge MAE 1.5567969339805532
 Ridge MSE 4.394584864652236
 Ridge R2 0.6798383580353204

```
In [45]: plt.scatter(y_test,lr_prediction,alpha = 1.0,label='linear Regression')
plt.scatter(y_test,Lasso_prediction,alpha=1.0,label= 'lasso Regression')
plt.scatter(y_test,ridge_prediction,alpha=1.0,label='Ridge prediction')

plt.xlabel('Actual')
plt.ylabel('predicted')
plt.title('Over view')
plt.legend()
```

Out[45]: <matplotlib.legend.Legend at 0x199b6381250>



LOGISTIC REGRESSION

```
In [46]: def YearsWithManager (row):
    return 1 if row['YearsWithCurrManager'] >= 78.800082 else 0
```

```
In [47]: df[ 'YearsWithManager' ] = df.apply(YearsWithManager, axis=1)
```

```
In [48]: df[ 'YearsWithManager' ].value_counts()
```

Out[48]: 0 1470
Name: YearsWithManager, dtype: int64

```
In [49]: numerical_col = ['Age', 'DailyRate', 'DistanceFromHome', 'Education', 'EmployeeCount', 'EmployeeNumber', 'Rate', 'Salary', 'Score', 'Tenure', 'WorkLifeBalance', 'WorkRate', 'WorkSatisfaction', 'WorkType', 'Year', 'YearEndBonus', 'YearInCompany']
Scaled = StandardScaler()
Scaled= pd.DataFrame(Scaled.fit_transform(df[numerical_col]),columns=numerical_col)
```

```
In [50]: Scaled
```

Out[50]:

	Age	DailyRate	DistanceFromHome	Education	EmployeeCount	EmployeeNumber	Rate	Salary	Score	Tenure	WorkLifeBalance	WorkRate	WorkSatisfaction	WorkType	Year	YearEndBonus	YearInCompany
0	0.446350	0.742527		-1.010909	-0.891688		0.0			-1.701283							
1	1.322365	-1.297775		-0.147150	-1.868426		0.0			-1.699621							
2	0.008343	1.414363		-0.887515	-0.891688		0.0			-1.696298							
3	-0.429664	1.461466		-0.764121	1.061787		0.0			-1.694636							
4	-1.086676	-0.524295		-0.887515	-1.868426		0.0			-1.691313							
...
1465	-0.101159	0.202082		1.703764	-0.891688		0.0			1.721670							
1466	0.227347	-0.469754		-0.393938	-1.868426		0.0			1.723332							
1467	-1.086676	-1.605183		-0.640727	0.085049		0.0			1.726655							
1468	1.322365	0.546677		-0.887515	0.085049		0.0			1.728317							
1469	-0.320163	-0.432568		-0.147150	0.085049		0.0			1.733302							

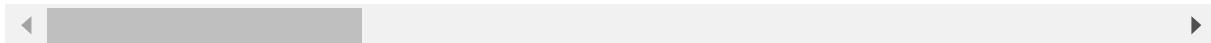
1470 rows × 16 columns

In [51]: df

Out[51]:

	Age	Attrition	BusinessTravel	DailyRate	Department	DistanceFromHome	Education	E
0	41	Yes	Travel_Rarely	1102	Sales	1	2	
1	49	No	Travel_Frequently	279	Research & Development	8	1	
2	37	Yes	Travel_Rarely	1373	Research & Development	2	2	
3	33	No	Travel_Frequently	1392	Research & Development	3	4	
4	27	No	Travel_Rarely	591	Research & Development	2	1	
...
1465	36	No	Travel_Frequently	884	Research & Development	23	2	
1466	39	No	Travel_Rarely	613	Research & Development	6	1	
1467	27	No	Travel_Rarely	155	Research & Development	4	3	
1468	49	No	Travel_Frequently	1023	Sales	2	3	
1469	34	No	Travel_Rarely	628	Research & Development	8	3	

1470 rows × 36 columns



In [52]: `x = pd.concat([encoder_cols, Scaled], axis=1)`
`y = df['StockOptionLevel']`

In [53]: `x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)`

In [54]: `from sklearn.linear_model import LogisticRegression`

In [55]: `log = LogisticRegression()`

In [56]: `log.fit(x_train, y_train)`

Out[56]: `LogisticRegression()`

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [57]: print("TrainScore",log.score(x_train,y_train))
```

TrainScore 1.0

```
In [58]: print("Test Score",log.score(x_test,y_test))
```

Test Score 1.0

```
In [59]: pred_train = log.predict(x_train)
pred_test = log.predict(x_test)
```

```
In [60]: from sklearn import metrics
print(metrics.classification_report(y_train,pred_train))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	493
1	1.00	1.00	1.00	483
2	1.00	1.00	1.00	128
3	1.00	1.00	1.00	72
accuracy			1.00	1176
macro avg	1.00	1.00	1.00	1176
weighted avg	1.00	1.00	1.00	1176

```
In [65]: from sklearn.metrics import matthews_corrcoef
mcc = matthews_corrcoef(y_test, pred_test)
print('MCC: ',mcc)
```

MCC: 1.0

```
In [66]: from sklearn.model_selection import GridSearchCV
```

```
In [67]: from sklearn.model_selection import GridSearchCV
param_grid ={
    'penalty':["l1", "l2"],
    'C': [0.1,0.5,1,5,10]
}
grid=GridSearchCV(estimator=log, param_grid=param_grid, cv=5)
grid.fit(x_train,y_train)
```

Out[67]: GridSearchCV(cv=5, estimator=LogisticRegression(),
param_grid={'C': [0.1, 0.5, 1, 5, 10], 'penalty': ['l1', 'l2']})

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```
In [68]: best_param = grid.best_params_
best_model = grid.best_estimator_
```

```
In [69]: y_pred=best_model.predict(x_test)
```

```
In [70]: from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_
```

```
In [72]: from sklearn.linear_model import Lasso, Ridge

lasso = Lasso(alpha=0.1)
lasso.fit(x_train, y_train)

ridge = Ridge(alpha=0.1)
ridge.fit(x_train, y_train)
```

Out[72]: Ridge(alpha=0.1)

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```
In [73]: from sklearn.model_selection import cross_val_score

scores = cross_val_score(model, x_train, y_train, cv=5)
print("Cross-validated accuracy: %0.2f (+/- %0.2f)" % (scores.mean(), scores.s
```

Cross-validated accuracy: 1.00 (+/- 0.00)

PERFORMING SVM

```
In [74]: from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, classification_report
from sklearn.metrics import confusion_matrix
```

```
In [75]: scaler = StandardScaler()
```

```
In [76]: x_train = scaler.fit_transform(x_train)
x_test = scaler.fit_transform(x_test)
```

```
In [77]: svcm = SVC(kernel='linear')
```

```
In [78]: svcm.fit(x_train,y_train)
```

Out[78]: SVC(kernel='linear')

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```
In [79]: y_pred = svcm.predict(x_test)
```

In [80]: y_pred

```
Out[80]: array([0, 2, 1, 1, 0, 2, 0, 3, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 2, 0, 3,
   1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 0, 3, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1,
   0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 1, 3, 0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0,
   1, 1, 0, 0, 2, 0, 1, 0, 2, 3, 1, 1, 1, 2, 1, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0,
   1, 0, 1, 0, 0, 1, 0, 0, 2, 2, 1, 1, 0, 3, 2, 1, 0, 2, 0, 0, 0, 1, 1,
   2, 0, 1, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 3, 0, 0, 0, 0, 3, 0, 1, 0, 0, 0, 1, 0, 0,
   0, 0, 1, 2, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0,
   2, 1, 1, 1, 2, 1, 2, 0, 2, 1, 1, 0, 0, 3, 1, 0, 2, 1, 1, 0, 0, 1, 0, 0, 1, 1,
   1, 1, 1, 0, 1, 0, 0, 2, 3, 0, 0, 1, 0, 1, 0, 0, 1, 2, 0, 0, 0, 1, 2, 0, 0, 1,
   1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 3, 0, 0, 0, 0, 3, 0, 1, 0, 0, 0, 3, 0, 2,
   1, 1, 2, 0, 1, 2, 2, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 0,
   0, 2, 1, 0, 1, 1, 1, 0, 0, 3, 0, 1, 1, 2, 0, 0, 0, 1, 1, 2, 1, 2, 1, 2, 1,
   0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 1, 2, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 0,
   0, 0, 1, 0, 1, 0, 0, 1], dtype=int64)
```

```
In [81]: acc = accuracy_score(y_test,y_pred)
        print('Accuracy:{:.2f}%'.format(acc*100))
```

Accuracy:100.00%

```
In [82]: print(classification_report(y_test,y_pred))
```

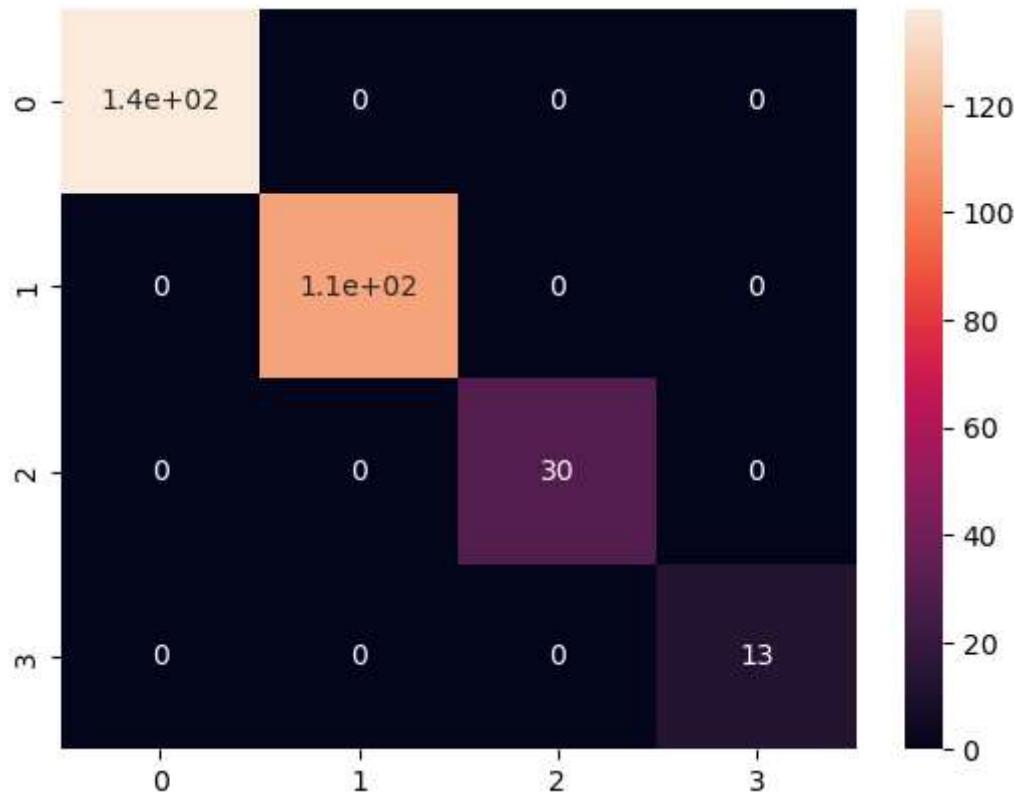
	precision	recall	f1-score	support
0	1.00	1.00	1.00	138
1	1.00	1.00	1.00	113
2	1.00	1.00	1.00	30
3	1.00	1.00	1.00	13
accuracy			1.00	294
macro avg	1.00	1.00	1.00	294
weighted avg	1.00	1.00	1.00	294

```
In [83]: cm = confusion_matrix(y_test,y_pred)
print('confusion matrix:')
print(cm)
```

```
confusion matrix:
[[138  0  0  0]
 [ 0 113  0  0]
 [ 0  0 30  0]
 [ 0  0  0 13]]
```

```
In [84]: sns.heatmap(cm,annot=True)
```

```
Out[84]: <Axes: >
```



```
In [85]: from sklearn.metrics import roc_curve, auc
from sklearn.preprocessing import label_binarize
from sklearn.multiclass import OneVsRestClassifier
```

```
In [86]: yb = label_binarize(y,classes=[0,1])
```

```
In [87]: nc = yb.shape[1]
```

```
In [88]: classifier = OneVsRestClassifier(SVC(kernel='linear',probability=True,random_s
```

```
In [89]: y_score = classifier.fit(x_train,y_train).decision_function(x_test)
```

```
In [90]: y_score_2d = y_score.reshape(-1, 1)
```

```
In [92]: from sklearn.metrics import confusion_matrix
```

```
In [93]: cm = confusion_matrix(y_test,y_pred)
print('confusion matrix:')
print(cm)
```

```
confusion matrix:
[[138  0  0  0]
 [ 0 113  0  0]
 [ 0  0 30  0]
 [ 0  0  0 13]]
```

TUNING WITH GRID SEARCH CV

```
In [94]: from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
param_grid = {
    'C': [0.1, 1, 10, 100],
    'kernel': ['linear'],
}
svm = SVC()
grid_search = GridSearchCV(svm, param_grid, cv=5, n_jobs=-1)
grid_search.fit(x_train, y_train)
print("Best hyperparameters found: ", grid_search.best_params_)
print("Best accuracy on the validation set: {:.2f}".format(grid_search.best_sc
```

```
Best hyperparameters found: {'C': 0.1, 'kernel': 'linear'}
Best accuracy on the validation set: 1.00
```

```
In [95]: grid_search = GridSearchCV(svm, param_grid, cv=5, n_jobs=-1)
grid_search.fit(x_train, y_train)
```

```
Out[95]: GridSearchCV(cv=5, estimator=SVC(), n_jobs=-1,
                      param_grid={'C': [0.1, 1, 10, 100], 'kernel': ['linear']})
```

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```
In [96]: print("Best hyperparameters found: ", grid_search.best_params_)
print("Best accuracy on the validation set: {:.2f}".format(grid_search.best_sc
```

```
Best hyperparameters found: {'C': 0.1, 'kernel': 'linear'}
Best accuracy on the validation set: 1.00
```

```
In [97]: best_svm = grid_search.best_estimator_
best_svm.fit(x_train, y_train)
```

Out[97]: SVC(C=0.1, kernel='linear')

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```
In [98]: test_accuracy = best_svm.score(x_test, y_test)
print("Test accuracy: {:.2f}".format(test_accuracy))
```

Test accuracy: 1.00

```
In [99]: test_accuracy = best_svm.score(x_train, y_train)
print("Test accuracy: {:.2f}".format(test_accuracy))
```

Test accuracy: 1.00

PERFORMING NAIVE BAYES

```
In [100]: from sklearn import model_selection, naive_bayes, svm, metrics, feature_extraction
```

```
In [101]: x = pd.concat([encoder_cols, Scaled], axis=1)
y = df['StockOptionLevel']
```

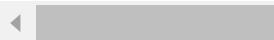
```
In [102]: x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2, random_state=42)
```

In [103]: `x_train`

Out[103]:

	Attrition_Yes	BusinessTravel_Travel_Frequently	BusinessTravel_Travel_Rarely	Department_& Dev
1097	0.0		0.0	1.0
727	0.0		0.0	0.0
254	0.0		0.0	1.0
1175	0.0		0.0	1.0
1341	0.0		0.0	1.0
...
1130	0.0		0.0	1.0
1294	0.0		0.0	1.0
860	1.0		1.0	0.0
1459	0.0		0.0	1.0
1126	0.0		0.0	1.0

1176 rows × 38 columns



In [104]: `from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)`

In [105]: `bayes = naive_bayes.MultinomialNB()`

In [106]: `bayes.fit(x_train,y_train)`

Out[106]: `MultinomialNB()`

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In [107]: `y_pred_nb=bayes.predict(x_test)`

In [108]: `accuracy=metrics.accuracy_score(y_test,y_pred_nb)
accuracy`

Out[108]: `0.7687074829931972`

```
In [109]: print(metrics.classification_report(y_test, y_pred_nb))
```

	precision	recall	f1-score	support
0	1.00	0.82	0.90	138
1	0.62	1.00	0.77	113
2	0.00	0.00	0.00	30
3	0.00	0.00	0.00	13
accuracy			0.77	294
macro avg	0.41	0.45	0.42	294
weighted avg	0.71	0.77	0.72	294

```
In [110]: cm=confusion_matrix(y_test,y_pred)  
cm
```

```
Out[110]: array([[138,  0,  0,  0],  
                  [ 0, 113,  0,  0],  
                  [ 0,  0, 30,  0],  
                  [ 0,  0,  0, 13]], dtype=int64)
```

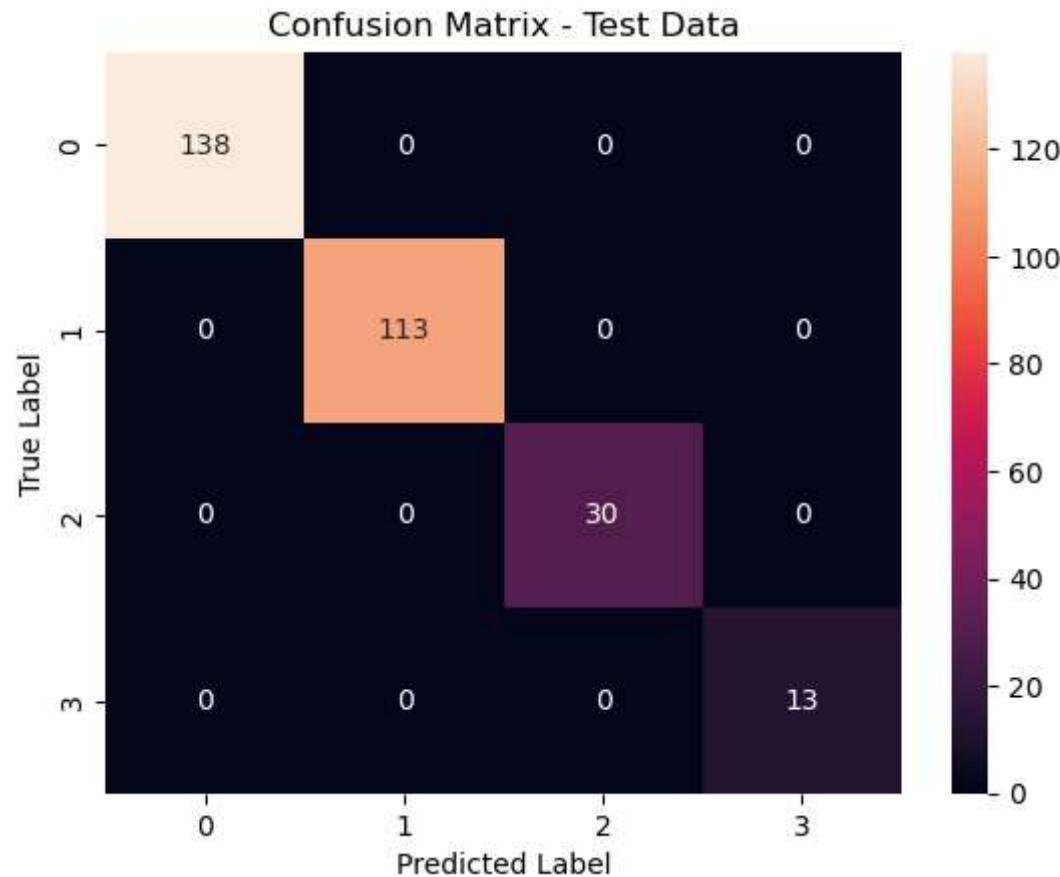
```
In [111]: yb=label_binarize(y, classes=[0,1,2])  
nc = yb.shape[1]
```

```
In [112]: classifier = OneVsRestClassifier(bayes)
```

```
In [113]: y_score=classifier.fit(x_train,y_train).predict(x_test)
```

```
In [116]: cm=confusion_matrix(y_test,y_pred)
print(cm)
sns.heatmap(cm, annot=True, fmt='.3g')
plt.title('Confusion Matrix - Test Data')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
[[138  0  0  0]
 [ 0 113  0  0]
 [ 0  0  30  0]
 [ 0  0  0  13]]
```



TUNING IN NAIVE BAYES

```
In [117]: param_grid = {
    'alpha': [0.1, 1, 10, 100],
    'fit_prior': [True, False]
}
```

```
In [118]: bayes = naive_bayes.MultinomialNB()
grid_search = GridSearchCV(bayes, param_grid, cv=5)
grid_search.fit(x_train, y_train)
```

```
Out[118]: GridSearchCV(cv=5, estimator=MultinomialNB(),
param_grid={'alpha': [0.1, 1, 10, 100],
'fit_prior': [True, False]})
```

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```
In [119]: best_param = grid_search.best_params_
best_nb = naive_bayes.MultinomialNB(alpha = best_param['alpha'], fit_prior = b
best_nb.fit(x_train, y_train)
y_pred_1 = best_nb.predict(x_test)
```

```
In [120]: print("Best Hyperparameter : ", best_param)
```

```
Best Hyperparameter : {'alpha': 0.1, 'fit_prior': True}
```

```
In [121]: acc = accuracy_score(y_test, y_pred_1)
acc
```

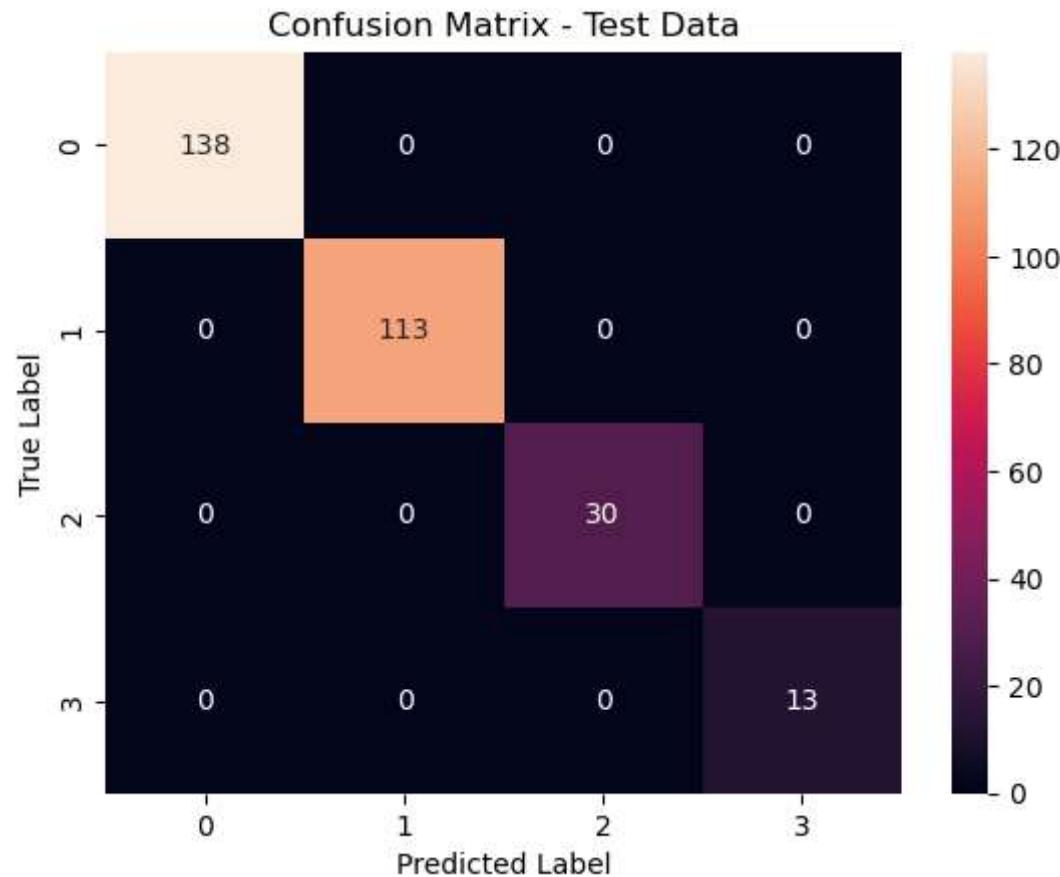
```
Out[121]: 0.7687074829931972
```

```
In [122]: print (classification_report(y_test,y_pred_1))
```

	precision	recall	f1-score	support
0	1.00	0.82	0.90	138
1	0.62	1.00	0.77	113
2	0.00	0.00	0.00	30
3	0.00	0.00	0.00	13
accuracy			0.77	294
macro avg	0.41	0.45	0.42	294
weighted avg	0.71	0.77	0.72	294

```
In [123]: cm=confusion_matrix(y_test,y_pred)
print(cm)
sns.heatmap(cm, annot=True, fmt='.3g')
plt.title('Confusion Matrix - Test Data')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

```
[[138  0  0  0]
 [ 0 113  0  0]
 [ 0  0  30  0]
 [ 0  0  0  13]]
```



```
In [124]: from sklearn.model_selection import RandomizedSearchCV
from scipy.stats import uniform
```

```
In [125]: svm=SVC(kernel='linear')
param_dist={
    'C':uniform(loc=0,scale=10),
    'gamma':['scale','auto']+list(uniform(loc=0,scale=1).rvs(10)),
}
```

```
In [126]: n_iter_search=20
random_search = RandomizedSearchCV(svc, param_distributions=param_dist, n_iter=n_iter_search)
random_search.fit(x_train,y_train)
```

```
Out[126]: RandomizedSearchCV(cv=5, estimator=SVC(kernel='linear'), n_iter=20, n_jobs=-1,
                             param_distributions={'C': <scipy.stats._distn_infrastructure.rv_continuous_frozen object at 0x00000199B89DF490>,
                                                  'gamma': ['scale', 'auto'],
                                                  0.9361641890683409,
                                                  0.19628102401003744,
                                                  0.5284108463087878,
                                                  0.8132920126128795,
                                                  0.1381782095844173,
                                                  0.45161984754437445,
                                                  0.9180837631471861,
                                                  0.8587795855275844,
                                                  0.3758360165992314,
                                                  0.9279744367311602],
                             random_state=42)
```

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```
In [127]: best_param = random_search.best_params_
best_model = random_search.best_estimator_
y_pred_2=best_model.predict(x_test)
```

```
In [128]: print(classification_report(y_test,y_pred))
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	138
1	1.00	1.00	1.00	113
2	1.00	1.00	1.00	30
3	1.00	1.00	1.00	13
accuracy			1.00	294
macro avg	1.00	1.00	1.00	294
weighted avg	1.00	1.00	1.00	294

```
In [129]: cm= confusion_matrix(y_test,y_pred_2)
print(cm)
```

```
[[138  0  0  0]
 [ 0 113  0  0]
 [ 0  0  30  0]
 [ 0  0  0  13]]
```

