Assignment -3
Abalone Age
Prediction

Assignment Date	04 October 2022
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Student Roll Number	2127190801065
Maximum Marks	2 Marks

Question-1:

Download and load the dataset into the tool

Solution:
data=pd.read_csv("abalone.csv")
data.head()

```
data=pd.read_csv("abalone.csv")
data.head()
```

	Sex	Length	Diameter	Height	Whole weight	Shucked weight	Viscera weight	Shell weight	Rings
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	15
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	7
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	9
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	10
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	7

Question-2:

Load the dataset into the tool.

Solution:

Age=1.5+data.Rings
data["Age"]=Age
data=data.rename(columns = {'Whole weight':'Whole_weight','Shucked weight': 'Shucked_weight','Viscera weight': 'Viscera_weight',
'Shell weight': 'Shell_weight'})
data=data.drop(columns=["Rings"],axis=1)
data.head()

```
Age=1.5+data.Rings
data["Age"]=Age
data=data.rename(columns = {'Whole weight':'Whole_weight','Shucked weight': 'Shucked_weight','Viscera weight': 'Viscera_weight',
                            'Shell weight': 'Shell_weight'})
data=data.drop(columns=["Rings"],axis=1)
data.head()
```

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	M	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	M	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	F	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	M	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	I	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

Question 3:

Perform Below Visualizations.

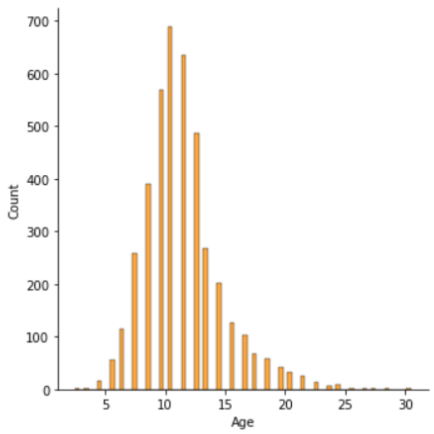
1) Univariate Analysis
2) Bi-variate analysis
3) Multi-variate analysis

Solution:

i) Univariate analysis

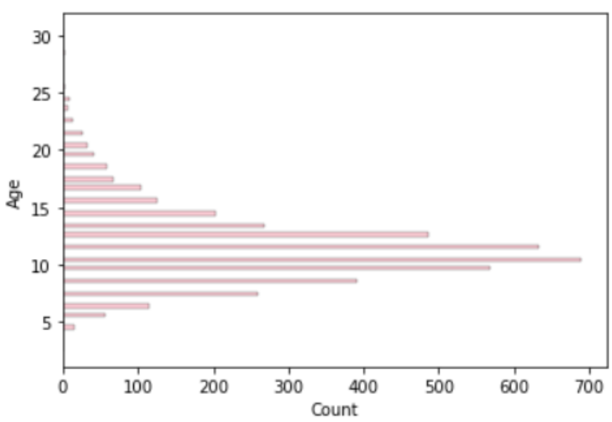
sns.displot(data["Age"], color='darkorange')

<seaborn.axisgrid.FacetGrid at 0x1ac57ab48b0>



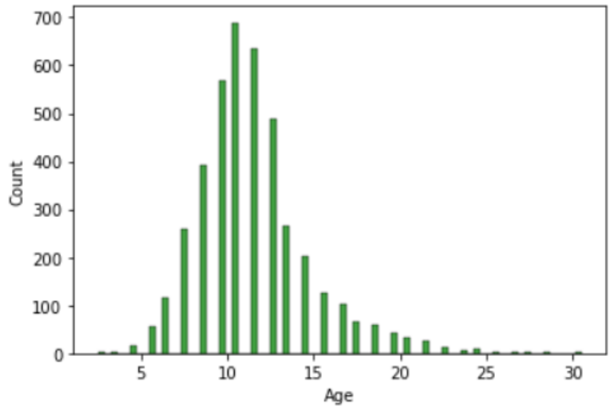
sns.histplot(y=data.Age,color='pink')

<AxesSubplot:xlabel='Count', ylabel='Age'>



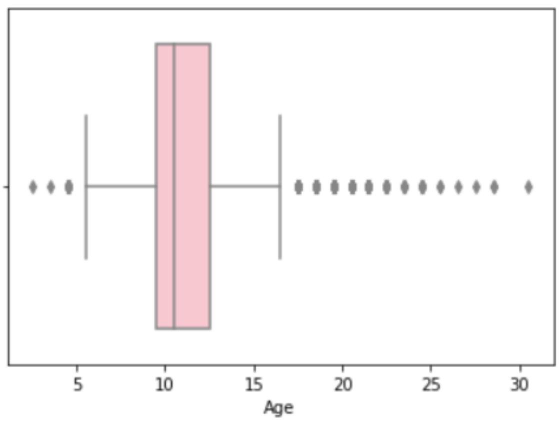
```python
sns.histplot(x=data.Age,color='green')
```

```
<AxesSubplot:xlabel='Age', ylabel='Count'>
```




```python
sns.boxplot(x=data.Age,color='pink')
```

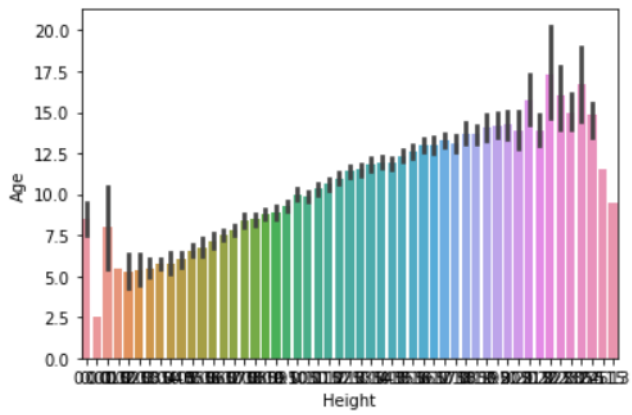
```
<AxesSubplot:xlabel='Age'>
```



ii)Bi-variate analysis

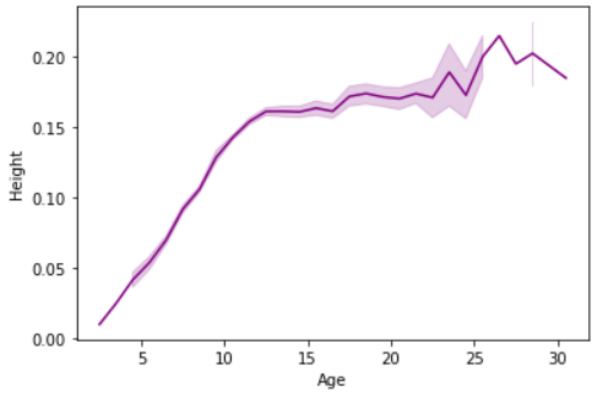
```python
sns.barplot(x=data.Height,y=data.Age)
```

```
<AxesSubplot:xlabel='Height', ylabel='Age'>
```



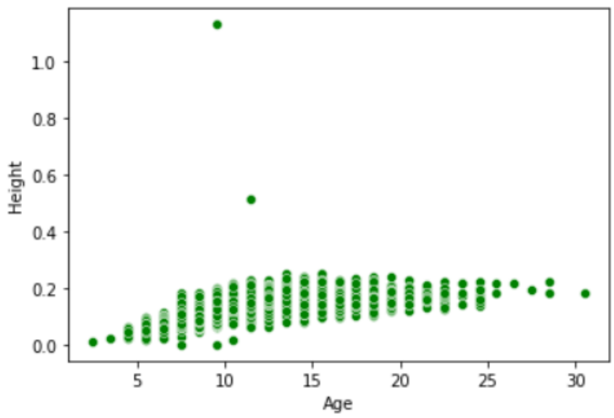
sns.lineplot(x=data.Age,y=data.Height, color='purple')

```
<AxesSubplot:xlabel='Age', ylabel='Height'>
```



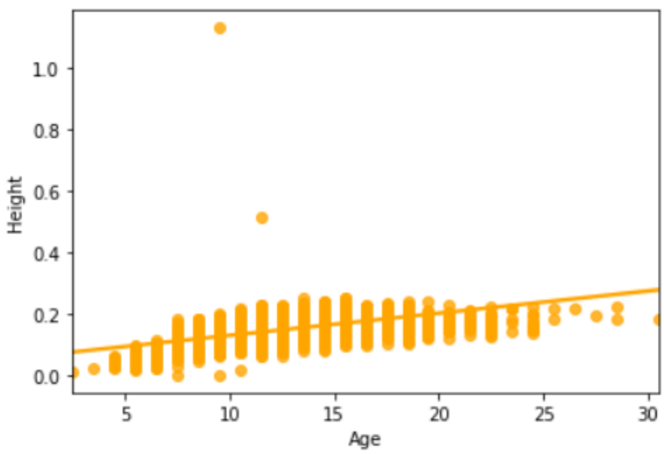
sns.scatterplot(x=data.Age,y=data.Height,color='green')

```
<AxesSubplot:xlabel='Age', ylabel='Height'>
```



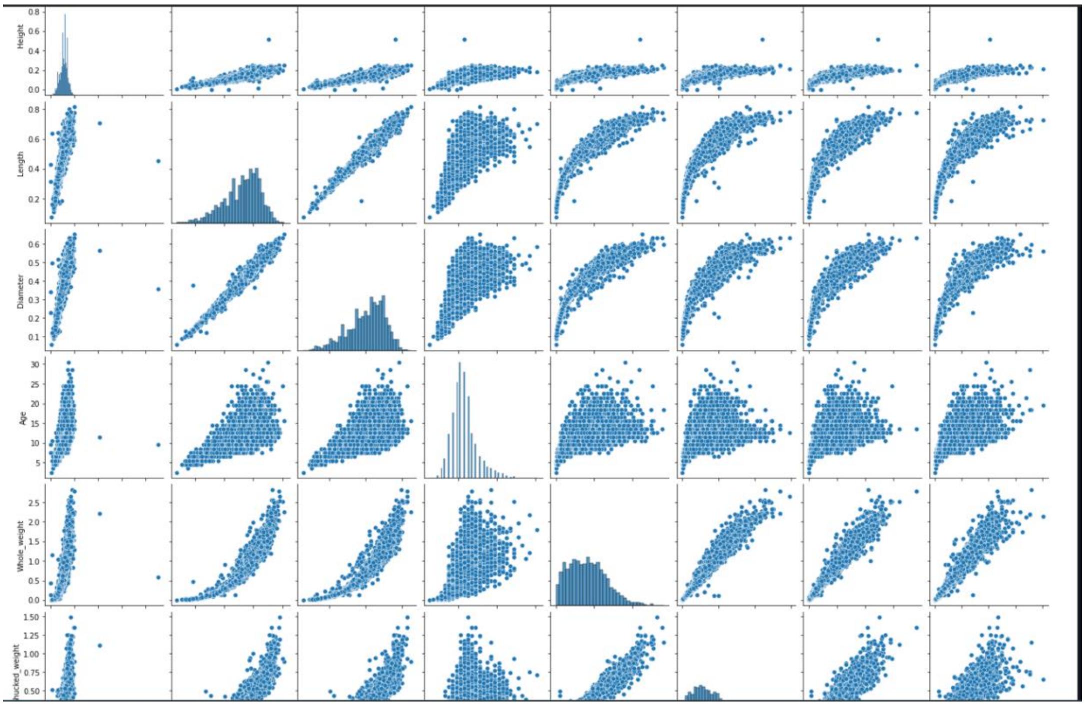
sns.regplot(x=data.Age,y=data.Height,color='orange')

```
<AxesSubplot:xlabel='Age', ylabel='Height'>
```

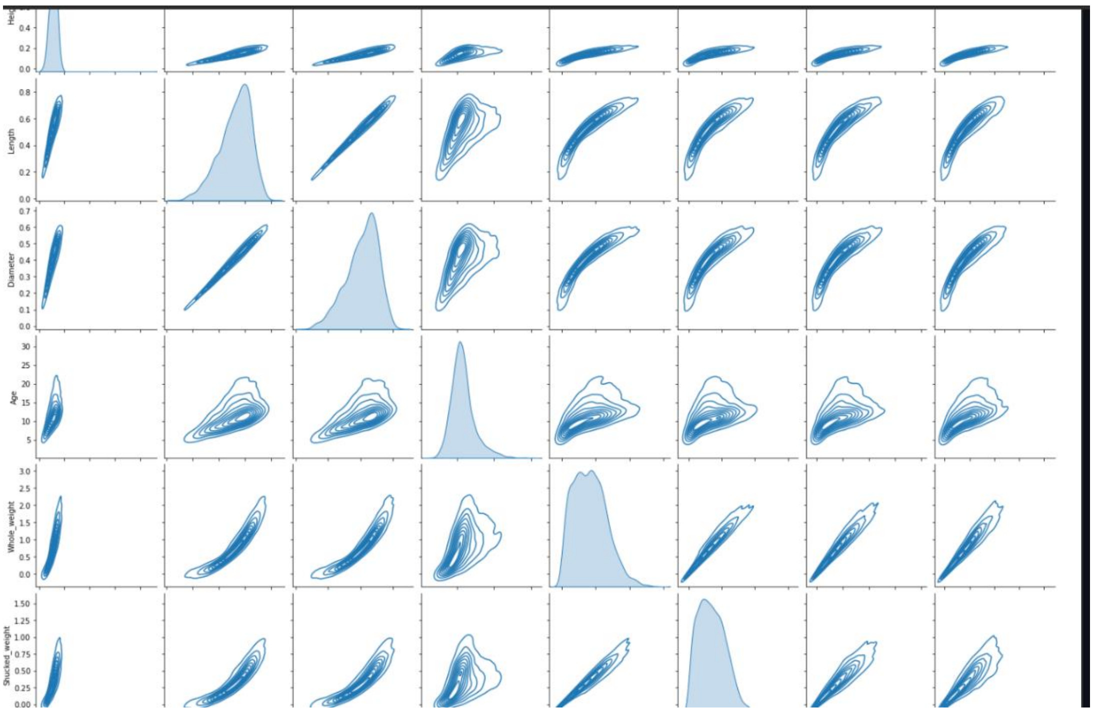


iii)Multivariate analysis

sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","Shucked_weight","Viscera_weight","Shell_weight"]])



sns.pairplot(data=data[["Height","Length","Diameter","Age","Whole_weight","Shucked_weight","Viscera_weight","Shell_weight"]],kind="kde")



Question 4:

Perform descriptive

statistics on dataset

Solution:

data.describe(include='all')

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
count	4177	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000	4177.000000
unique	3	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
top	M	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
freq	1528	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
mean	NaN	0.523992	0.407881	0.139516	0.828742	0.359367	0.180594	0.238831	11.433684
std	NaN	0.120093	0.099240	0.041827	0.490389	0.221963	0.109614	0.139203	3.224169
min	NaN	0.075000	0.055000	0.000000	0.002000	0.001000	0.000500	0.001500	2.500000
25%	NaN	0.450000	0.350000	0.115000	0.441500	0.186000	0.093500	0.130000	9.500000
50%	NaN	0.545000	0.425000	0.140000	0.799500	0.336000	0.171000	0.234000	10.500000
75%	NaN	0.615000	0.480000	0.165000	1.153000	0.502000	0.253000	0.329000	12.500000
max	NaN	0.815000	0.650000	1.130000	2.825500	1.488000	0.760000	1.005000	30.500000

Question 5:

Check for Missing values

and deal with them.

Solution:

data.isnull().sum()

```
data.isnull().sum()
```

```
Sex               0
Length            0
Diameter          0
Height            0
Whole_weight      0
Shucked_weight    0
Viscera_weight    0
Shell_weight      0
Age               0
dtype: int64
```

Question 6:

Find the outliers and replace them outliers

Solution:
outliers=data.quantile(q=(0.25,0.75))
outliers

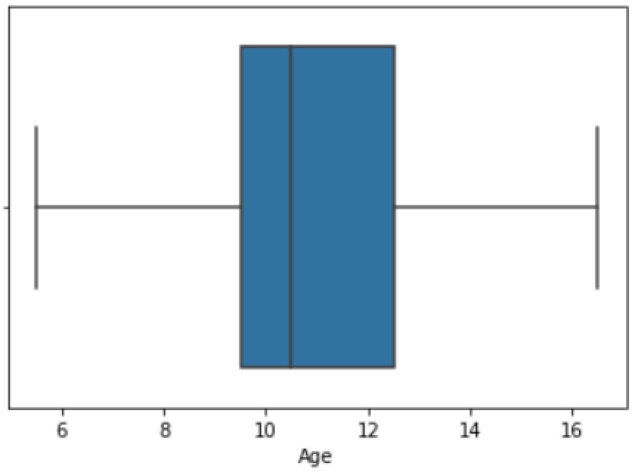
	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0.25	0.450	0.35	0.115	0.4415	0.186	0.0935	0.130	9.5
0.75	0.615	0.48	0.165	1.1530	0.502	0.2530	0.329	12.5

a = data.Age.quantile(0.25)
b = data.Age.quantile(0.75)
c = b - a
lower_limit = a - 1.5 * c
data.median(numeric_only=True)

```
Length             0.5450
Diameter           0.4250
Height             0.1400
Whole_weight       0.7995
Shucked_weight     0.3360
Viscera_weight     0.1710
Shell_weight       0.2340
Age               10.5000
dtype: float64
```

data['Age'] = np.where(data['Age'] < lower_limit, 7, data['Age'])
sns.boxplot(x=data.Age,showfliers = False)

```
<AxesSubplot:xlabel='Age'>
```



Question 7:

Check for Categorical columns and perform encoding.

Solution:
from sklearn.preprocessing import LabelEncoder

lab = LabelEncoder()
data.Sex = lab.fit_transform(data.Sex)

data.head()

	Sex	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	2	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	2	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	0	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	2	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	1	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

Question 8:

Split the data into dependent and independent variables.

Solution:
y = data["Sex"]
y.head()

```
0    2
1    2
2    0
3    2
4    1
Name: Sex, dtype: int32
```

x=data.drop(columns=["Sex"],axis=1)
x.head()

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	0.455	0.365	0.095	0.5140	0.2245	0.1010	0.150	16.5
1	0.350	0.265	0.090	0.2255	0.0995	0.0485	0.070	8.5
2	0.530	0.420	0.135	0.6770	0.2565	0.1415	0.210	10.5
3	0.440	0.365	0.125	0.5160	0.2155	0.1140	0.155	11.5
4	0.330	0.255	0.080	0.2050	0.0895	0.0395	0.055	8.5

Question 9:

Scale the independent variables.

Solution:

```
from sklearn.preprocessing import scale
X_Scaled = pd.DataFrame(scale(x), columns=x.columns)
X_Scaled.head()
```

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
0	-0.574558	-0.432149	-1.064424	-0.641898	-0.607685	-0.726212	-0.638217	1.577830
1	-1.448986	-1.439929	-1.183978	-1.230277	-1.170910	-1.205221	-1.212987	-0.919022
2	0.050033	0.122130	-0.107991	-0.309469	-0.463500	-0.356690	-0.207139	-0.294809
3	-0.699476	-0.432149	-0.347099	-0.637819	-0.648238	-0.607600	-0.602294	0.017298
4	-1.615544	-1.540707	-1.423087	-1.272086	-1.215968	-1.287337	-1.320757	-0.919022

Question 10:

Split the data into training and testing.

Solution:

```
from sklearn.model_selection import train_test_split
X_Train, X_Test, Y_Train, Y_Test = train_test_split(X_Scaled, y, test_size=0.2,
random_state=0)

X_Train.shape,X_Test.shape

Y_Train.shape,Y_Test.shape

X_Train.head()
```

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
3141	-2.864726	-2.750043	-1.423087	-1.622870	-1.553902	-1.583867	-1.644065	-1.543234
3521	-2.573250	-2.598876	-2.020857	-1.606554	-1.551650	-1.565619	-1.626104	-1.387181
883	1.132658	1.230689	0.728888	1.145672	1.041436	0.286552	1.538726	1.577830
3627	1.590691	1.180300	1.446213	2.164373	2.661269	2.330326	1.377072	0.017298
2106	0.591345	0.474853	0.370226	0.432887	0.255175	0.272866	0.906479	1.265723

X_Test.head()

	Length	Diameter	Height	Whole_weight	Shucked_weight	Viscera_weight	Shell_weight	Age
668	0.216591	0.172519	0.370226	0.181016	-0.368878	0.569396	0.690940	0.953617
1580	-0.199803	-0.079426	-0.466653	-0.433875	-0.443224	-0.343004	-0.325685	-0.606915
3784	0.799543	0.726798	0.370226	0.870348	0.755318	1.764639	0.565209	0.329404
463	-2.531611	-2.447709	-2.020857	-1.579022	-1.522362	-1.538247	-1.572219	-1.543234
2615	1.007740	0.928354	0.848442	1.390405	1.415417	1.778325	0.996287	0.641511

Y_Train.head()

```
3141    1
3521    1
883     2
3627    2
2106    2
Name: Sex, dtype: int32
```

Y_Test.head()

```
668     2
1580    1
3784    2
463     1
2615    2
Name: Sex, dtype: int32
```

Question 11:

Build the model.

Solution:
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=10,criterion='entropy')

model.fit(X_Train,Y_Train)

y_predict = model.predict(X_Test)

y_predict_train = model.predict(X_Train)

```
model.fit(X_Train,Y_Train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

Question 12:

Train the model.

Solution:

from sklearn.metrics import accuracy_score,confusion_matrix,classification_report

print('Training accuracy: ',accuracy_score(Y_Train,y_predict_train))

```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

```
print('Training accuracy: ',accuracy_score(Y_Train,y_predict_train))
```

```
Training accuracy:  0.9823406165818617
```

Question 13:

Test the model.

Solution:

print('Testing accuracy: ',accuracy_score(Y_Test,y_predict))

```
print('Testing accuracy: ',accuracy_score(Y_Test,y_predict))
```

```
Testing accuracy:  0.527511961722488
```

Question 14:

Measure the performance using Metrics.

Solution:

pd.crosstab(Y_Test,y_predict)

col_0	0	1	2
Sex			
0	106	27	116
1	37	215	39
2	122	54	120

```
print(classification_report(Y_Test,y_predict))
```

	precision	recall	f1-score	support
0	0.40	0.43	0.41	249
1	0.73	0.74	0.73	291
2	0.44	0.41	0.42	296
accuracy			0.53	836
macro avg	0.52	0.52	0.52	836
weighted avg	0.53	0.53	0.53	836