BANGIRANA DOUGLAS /00573

LOGISTIC REGRESSION

In [1]:

- 1 #Required libraries
- 2 from sklearn.datasets import make_classification
- 3 from sklearn.model selection import GridSearchCV
- 4 **from** sklearn.linear_model **import** LogisticRegression
- 5 | from sklearn.model_selection import train_test_split
- 6 import pandas as pd
- 7 import numpy as np

In [2]:

df=pd.read_csv("C:\\Users\\Atwongire Vianney\\Desktop\\AI_PRAC\\loan_data.

2 df

Out[2]:

	Gender	Married	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount			
0	Male	Yes	1	Graduate	4583	1508.0	128			
1	Male	Yes	0	Graduate	3000	0.0	66			
2	Male	Yes	0	Not Graduate	2583	2358.0	120			
3	Male	No	0	Graduate	6000	0.0	141			
4	Male	Yes	0	Not Graduate	2333	1516.0	95			
							•••			
376	Male	Yes	3+	Graduate	5703	0.0	128			
377	Male	Yes	0	Graduate	3232	1950.0	108			
378	Female	No	0	Graduate	2900	0.0	71			
379	Male	Yes	3+	Graduate	4106	0.0	40			
380	Female	No	0	Graduate	4583	0.0	133			
381 r	381 rows × 9 columns									

In [3]: 1 df.head()

Out[3]:

	Gender	Married	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount	L
0	Male	Yes	1	Graduate	4583	1508.0	128	_
1	Male	Yes	0	Graduate	3000	0.0	66	
2	Male	Yes	0	Not Graduate	2583	2358.0	120	
3	Male	No	0	Graduate	6000	0.0	141	
4	Male	Yes	0	Not Graduate	2333	1516.0	95	
4								

In [4]: 1 df.tail()

Out[4]:

	Gender	Married	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount
376	Male	Yes	3+	Graduate	5703	0.0	128
377	Male	Yes	0	Graduate	3232	1950.0	108
378	Female	No	0	Graduate	2900	0.0	71
379	Male	Yes	3+	Graduate	4106	0.0	40
380	Female	No	0	Graduate	4583	0.0	133

In [5]:

- 1 #checking for missing values
- 2 print(df.isnull().sum())

5 Gender 0 Married 8 Dependents Education 0 ApplicantIncome 0 CoapplicantIncome 0 LoanAmount 0 Loan_Amount_Term 11 Loan_Status 0

dtype: int64

	Gender	Married	Dependents	ļ	Education	Applica	antIncome	\
0	Male	Yes	1		Graduate		4583	
1	Male	Yes	0		Graduate		3000	
2	Male	Yes	0	Not	Graduate		2583	
3	Male	No	0		Graduate		6000	
4	Male	Yes	0	Not	Graduate		2333	
					• • •		• • •	
376	Male	Yes	3+		Graduate		5703	
377	Male	Yes	0		Graduate		3232	
378	Female	No	0		Graduate		2900	
379	Male	Yes	3+		Graduate		4106	
380	Female	No	0		Graduate		4583	
	Coannl	icantInco	omo LoanAm	ount	Loan Amou	nt Tonm	Loan Stat	
0	соаррт	icantInco 1508		128	LUari_AlliUu	360.0	Loan_Stat	
1).0	66		360.0		N Y
2		2358		120		360.0		Ϋ́
3).0	141		360.0		Ϋ́
4		1516		95		360.0		Ϋ́
4				•••				
376			9.0	128		360.0	•	Υ
377		1956		108		360.0		Y
378			0.0	71		360.0		Υ
379			9.0	40		180.0		Y
380			0.0	133		360.0		N
Γ 2 0 1	10.01.15 1/	0 1	sc l					
Гэот	rows x	9 columr	15]					
[201			Dependents		Education	Applica	antIncome	\
0			-	-	Education Graduate	Applica	antIncome 4583	١
_	Gender	Married	Dependents	١		Applica		١
0	Gender Male	Married Yes	Dependents 1		Graduate	Applica	4583	\
0 1 2 3	Gender Male Male	Married Yes Yes	Dependents 1 0		Graduate Graduate	Applica	4583 3000	\
0 1 2	Gender Male Male Male	Married Yes Yes Yes	Dependents 1 0	Not	Graduate Graduate Graduate	Applica	4583 3000 2583	\
0 1 2 3 4	Gender Male Male Male Male Male	Married Yes Yes Yes No Yes	Dependents 1 0 0 0	Not	Graduate Graduate Graduate Graduate	Applica	4583 3000 2583 6000 2333	\
0 1 2 3 4 	Gender Male Male Male Male Male	Married Yes Yes Yes No Yes	Dependents 1 0 0 3+	Not	Graduate Graduate Graduate Graduate Graduate Graduate	Applica	4583 3000 2583 6000 2333 5703	\
0 1 2 3 4 376 377	Gender Male Male Male Male Male Male	Married Yes Yes Yes No Yes Yes Yes	Dependents 1 0 0 0 3+	Not	Graduate Graduate Graduate Graduate Graduate Graduate Graduate Graduate	Applica	4583 3000 2583 6000 2333 5703 3232	\
0 1 2 3 4 376 377 378	Gender Male Male Male Male Male Male Female	Married Yes Yes No Yes Yes Yes No	Dependents	Not	Graduate Graduate Graduate Graduate Graduate Graduate Graduate Graduate Graduate	Applica	4583 3000 2583 6000 2333 5703 3232 2900	\
0 1 2 3 4 376 377 378 379	Gender Male Male Male Male Male Male Female Male	Married Yes Yes No Yes Yes Yes No Yes	Dependents	Not	Graduate	Applica	4583 3000 2583 6000 2333 5703 3232 2900 4106	\
0 1 2 3 4 376 377 378	Gender Male Male Male Male Male Male Female	Married Yes Yes No Yes Yes Yes No	Dependents	Not	Graduate Graduate Graduate Graduate Graduate Graduate Graduate Graduate Graduate	Applica	4583 3000 2583 6000 2333 5703 3232 2900	\
0 1 2 3 4 376 377 378 379	Gender Male Male Male Male Male Female	Married Yes Yes No Yes Yes Yes No Yes No	Dependents 1 0 0 3+ 0 3+ 0 3+ 0	Not	Graduate		4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes No Yes Yes Yes No Yes No Yes	Dependents 1 0 0 0 3+ 0 3+ 0 ome LoanAm	Not Not ount	Graduate	nt_Term	4583 3000 2583 6000 2333 5703 3232 2900 4106	us
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes No Yes Ves No Yes No Yes No Yes No	Dependents 1 0 0 0 3+ 0 3+ 0 ome LoanAm	Not Not ount 128	Graduate	nt_Term 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes Yes No Yes Yes No Yes No Yes No	Dependents 1 0 0 3+ 0 3+ 0 ome LoanAm 3.0	Not Not ount 128 66	Graduate	nt_Term 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N Y
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes No Yes Yes Yes No Yes No 1508	Dependents 1 0 0 3+ 0 3+ 0 me LoanAm 3.0 3.0 3.0	Not Not 128 66 120	Graduate	nt_Term 360.0 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N Y Y
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes No Yes Yes No Yes No Yes No 2358	Dependents 1 0 0 0 3+ 0 3+ 0 ome LoanAm 3.0 0.0 3.0 0.0	Not Not 128 66 120 141	Graduate	nt_Term 360.0 360.0 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N Y Y Y
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes No Yes Yes Yes No Yes No 1508	Dependents 1 0 0 0 3+ 0 3+ 0 ome LoanAm 3.0 0.0 3.0 0.0	Not Not 128 66 120 141 95	Graduate	nt_Term 360.0 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N Y Y
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes Yes No Yes Yes No Yes No 1508 2358	Dependents 1 0 0 0 3+ 0 3+ 0 ome LoanAm 3.0 0.0 3.0 0.0	Not Not 128 66 120 141	Graduate	nt_Term 360.0 360.0 360.0 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N Y Y Y
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes Yes No Yes Yes No Yes No 1508 2358	Dependents 1 0 0 0 3+ 0 sme LoanAm 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0	Not Not 128 66 120 141 95	Graduate	nt_Term 360.0 360.0 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N Y Y Y
0 1 2 3 4 376 377 378 379 380	Gender Male Male Male Male Male Female	Married Yes Yes Yes No Yes Yes No Yes No 1508	Dependents 1 0 0 0 3+ 0 sme LoanAm 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0	Not Not 128 66 120 141 95 	Graduate	nt_Term 360.0 360.0 360.0 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N Y Y Y Y
0 1 2 3 4 376 377 378 379 380 0 1 2 3 4 376 377	Gender Male Male Male Male Male Female	Married Yes Yes Yes No Yes Yes No Yes No 1508 2358 1516	Dependents 1 0 0 0 3+ 0 3+ 0 me LoanAm 3.0 3.0 3.0 3.0 3.0 3.0 3.0 3.0	Not Not 128 66 120 141 95 128 108	Graduate	nt_Term 360.0 360.0 360.0 360.0 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	us N Y Y Y Y
0 1 2 3 4 376 377 378 379 380 0 1 2 3 4 376 377 378	Gender Male Male Male Male Male Female	Married Yes Yes Yes No Yes No Yes No 1508 1516	Dependents 1 0 0 0 3+ 0 3+ 0 0 3+ 0 0 0 0 0 0 0 0 0 0 0 0 0	Not Not 128 66 120 141 95 128 108 71	Graduate	nt_Term 360.0 360.0 360.0 360.0 360.0 360.0 360.0	4583 3000 2583 6000 2333 5703 3232 2900 4106 4583	xus N Y Y Y Y Y

[358 rows x 9 columns]

In [7]: 1 df.isnull()

Out[7]:

	Gender	Married	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount
0	False	False	False	False	False	False	False
1	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False
3	False	False	False	False	False	False	False
4	False	False	False	False	False	False	False
376	False	False	False	False	False	False	False
377	False	False	False	False	False	False	False
378	False	False	False	False	False	False	False
379	False	False	False	False	False	False	False
380	False	False	False	False	False	False	False

381 rows × 9 columns

In [8]:

1 df_cleaned = df.dropna()

2 df_cleaned

Out[8]:

	Gender	Married	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount	
0	Male	Yes	1	Graduate	4583	1508.0	128	
1	Male	Yes	0	Graduate	3000	0.0	66	
2	Male	Yes	0	Not Graduate	2583	2358.0	120	
3	Male	No	0	Graduate	6000	0.0	141	
4	Male	Yes	0	Not Graduate	2333	1516.0	95	
		•••						
376	Male	Yes	3+	Graduate	5703	0.0	128	
377	Male	Yes	0	Graduate	3232	1950.0	108	
378	Female	No	0	Graduate	2900	0.0	71	
379	Male	Yes	3+	Graduate	4106	0.0	40	
380	Female	No	0	Graduate	4583	0.0	133	
358 rows × 9 columns								
4 =							•	

```
In [9]:
           1 filled_df.to_csv('cleaned_file.csv', index=False)
In [10]:
           1 | x=df_cleaned['LoanAmount'].array.reshape(-1,1)
           2 x
Out[10]: <PandasArray>
          [128],
          [66],
          [120],
          [141],
          [95],
          [70],
          [109],
          [114],
          [17],
          [125],
          [100],
          [76],
          [133],
          [104],
          [116],
          [122],
          [110],
In [11]:
           1 y=df_cleaned['Loan_Amount_Term']
           2 y
Out[11]: 0
                 360.0
          1
                 360.0
          2
                 360.0
          3
                 360.0
                 360.0
          376
                 360.0
          377
                 360.0
          378
                 360.0
          379
                 180.0
          380
                 360.0
         Name: Loan_Amount_Term, Length: 358, dtype: float64
           1 | #splitting the data
In [12]:
           2 x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_st
In [13]:
           1 x_train.shape
Out[13]: (286, 1)
```

```
In [14]:
           1 model=LogisticRegression()
           2 model.fit(x_train,y_train)
         C:\Users\Atwongire Vianney\anaconda3\Lib\site-packages\sklearn\linear model\
         logistic.py:460: ConvergenceWarning: lbfgs failed to converge (status=1):
         STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.
         Increase the number of iterations (max_iter) or scale the data as shown in:
             https://scikit-learn.org/stable/modules/preprocessing.html (https://sciki
         t-learn.org/stable/modules/preprocessing.html)
         Please also refer to the documentation for alternative solver options:
             https://scikit-learn.org/stable/modules/linear model.html#logistic-regres
         sion (https://scikit-learn.org/stable/modules/linear model.html#logistic-regr
         ession)
           n_iter_i = _check_optimize_result(
Out[14]:
          ▼ LogisticRegression
          LogisticRegression()
In [15]:
           1 y_pred=model.predict(x_test)
           2 y_pred
Out[15]: array([360., 360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360.])
           1 | score=model.score(x_train,y_train)
In [16]:
           2 score
Out[16]: 0.8251748251748252
         Fine Tune
In [17]:
             #Defining parameters
           2 param_grid={
           3
                  'penalty':['11','12'],
                  'C':[0.001,0.01,0.1,1,10,100],
           4
           5
                  'solver':['liblinear','saga']
           6
             }
```

```
In [18]:
           1 #performing grid with cross_validation
           2 grid_search=GridSearchCV(estimator=model,param_grid=param_grid,cv=5,n_jobs
           3 grid_search.fit(x_train,y_train)
         C:\Users\Atwongire Vianney\anaconda3\Lib\site-packages\sklearn\model_selectio
         n\_split.py:725: UserWarning: The least populated class in y has only 1 membe
         rs, which is less than n_splits=5.
           warnings.warn(
Out[18]:
                    GridSearchCV
           ▶ estimator: LogisticRegression
                ▶ LogisticRegression
In [19]:
           1 #best parameters and best score
           2 best param=grid search.best params
           3 grid search
Out[19]:
                    GridSearchCV
          ▶ estimator: LogisticRegression
                ▶ LogisticRegression
In [20]:
          1 best_score=grid_search.best_score_
           2 best score
Out[20]: 0.8251663641863279
           1 #evaluating the performance
In [21]:
           2 | score=grid_search.score(x_test,y_test)
           3 score
Out[21]: 0.916666666666666
In [22]:
           1 y_pred=model.predict(x_test)
           2 y_pred
Out[22]: array([360., 360., 360., 360., 360., 360., 360., 360., 360., 360., 360.
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360., 360., 360., 360., 360.,
                360., 360., 360., 360., 360., 360.])
```

LINEAR REGRESSION

- In [23]: 1 import pandas as pd
 2 from sklearn.linear_model import LinearRegression
 3 from sklearn.model_selection import train_test_split
 In [24]: 1 df.head()
- Out[24]:

	Gender	Married	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount	L
0	Male	Yes	1	Graduate	4583	1508.0	128	
1	Male	Yes	0	Graduate	3000	0.0	66	
2	Male	Yes	0	Not Graduate	2583	2358.0	120	
3	Male	No	0	Graduate	6000	0.0	141	
4	Male	Yes	0	Not Graduate	2333	1516.0	95	

In [25]: 1 df.tail()

Out[25]:

	Gender	Married	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount
376	Male	Yes	3+	Graduate	5703	0.0	128
377	Male	Yes	0	Graduate	3232	1950.0	108
378	Female	No	0	Graduate	2900	0.0	71
379	Male	Yes	3+	Graduate	4106	0.0	40
380	Female	No	0	Graduate	4583	0.0	133

In [26]: 1 df.isnull().sum()

Out[26]: Gender 5 Married 0 Dependents 8 Education 0 ApplicantIncome 0 CoapplicantIncome 0 LoanAmount 0 Loan_Amount_Term 11 Loan_Status 0 dtype: int64

```
In [27]: 1 df_cleaned=df.dropna()
2 df_cleaned
```

Out[27]:

	Gender	Married	Dependents	Education	ApplicantIncome	CoapplicantIncome	LoanAmount
0	Male	Yes	1	Graduate	4583	1508.0	128
1	Male	Yes	0	Graduate	3000	0.0	66
2	Male	Yes	0	Not Graduate	2583	2358.0	120
3	Male	No	0	Graduate	6000	0.0	141
4	Male	Yes	0	Not Graduate	2333	1516.0	95
					•••		***
376	Male	Yes	3+	Graduate	5703	0.0	128
377	Male	Yes	0	Graduate	3232	1950.0	108
378	Female	No	0	Graduate	2900	0.0	71
379	Male	Yes	3+	Graduate	4106	0.0	40
380	Female	No	0	Graduate	4583	0.0	133

358 rows × 9 columns

```
Out[28]: <PandasArray>
          [128],
          [66],
          [120],
          [141],
          [95],
          [70],
          [109],
          [114],
          [17],
          [125],
          [100],
          [76],
          [133],
          [104],
          [116],
          [122],
          [110],
           .
ר כ ד
```

```
In [29]:
           1 y=df_cleaned['Loan_Amount_Term']
           2 | y
Out[29]: 0
                 360.0
                 360.0
         2
                 360.0
         3
                 360.0
                 360.0
         376
                 360.0
         377
                 360.0
         378
                360.0
         379
                180.0
         380
                 360.0
         Name: Loan_Amount_Term, Length: 358, dtype: float64
In [30]:
           1 #splitting the data
           2 | x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_st
In [31]:
              model=LinearRegression()
             model.fit(x_train,y_train)
Out[31]:
          LinearRegression
          LinearRegression()
In [32]:
              score=model.score(x_train,y_train)
             score
Out[32]: 0.013044972022888901
In [33]:
           1 model.coef
Out[33]: array([0.28778211])
In [34]:
           1 model.intercept_
Out[34]: 308.4210137519316
         FINE TUNING
In [35]:
           1 #Defining parameters
           2 from sklearn.model_selection import GridSearchCV
           3 from sklearn.metrics import mean_squared_error
```

```
In [36]:
              param_grid={
           2
                  'copy_X':[True,False],
           3
                  'fit_intercept':[True,False],
           4
                  'n_jobs':[True,False],
           5
                  'positive':[True,False]
           6
           7
In [37]:
           1 | #performing grid with cross validation
           2 | grid_search=GridSearchCV(model,param_grid,cv=5,scoring='neg_mean_squared_e
           3 grid_search.fit(x_train,y_train)
Out[37]:
                    GridSearchCV
           ▶ estimator: LinearRegression
                 LinearRegression
In [38]:
           1 #Best model
             best_model=grid_search.best_estimator_
           3 best model
Out[38]:
                         LinearRegression
          LinearRegression(n_jobs=True, positive=True)
In [39]:
              best_score=model.score(x_test,y_test)
           2 best_score
Out[39]: -0.009395552322493339
           1 | y_pred=best_model.predict(x test)
In [40]:
           2 y_pred
Out[40]: array([345.83268771, 341.8037382 , 337.19922449, 348.13494456,
                 346.12046981, 339.21369924, 343.53043085, 331.73136445,
                340.07704556, 337.19922449, 345.5449056, 333.45805709,
                327.70241494, 342.37930242, 325.40015808, 346.12046981,
                321.65899069, 341.5159561, 342.95486663, 339.50148134,
                348.71050878, 347.27159824, 323.67346544, 342.95486663,
                343.81821295, 342.95486663, 334.32140341, 345.25712349,
                321.9467728 , 347.84716246, 340.07704556, 344.39377717,
                325.9757223 , 348.13494456, 334.32140341, 349.86163721,
                349.86163721, 338.92591713, 340.65260977, 342.95486663,
                336.04809606, 342.95486663, 351.01276564, 325.11237598,
                 347.27159824, 342.95486663, 338.35035291, 328.56576127,
                347.55938035, 345.25712349, 346.40825192, 340.94039188,
                 345.83268771, 315.61556644, 332.59471077, 345.83268771,
                 348.99829089, 342.95486663, 329.71688969, 348.13494456,
                 346.12046981, 336.33587816, 337.19922449, 328.56576127,
                 321.08342647, 337.19922449, 350.43720142, 327.70241494,
                 340.94039188, 330.0046718, 340.07704556, 345.83268771])
```