# HILL VALLEY PREDICTION

# **Objective:**

To develop a predictive model using logistic regression that accurately classifies the given data points in the Hill Valley Dataset into one of two classes (0 or 1). The model aims to identify whether a given sequence of data points corresponds to a "valley" (class 0) or a "hill" (class 1) based on the provided features (V1 to V100).

### **Data source**

Github

# **Import Library**

```
[ ]: import pandas as pd
[ ]: import numpy as np
```

### **Import Data**

```
[]: df=pd_read_csv("https://github.com/YBIFoundation/Dataset/raw/main/

\( \text{Hill%20Valley%20Dataset.csv"} \)
```

```
[ ]: df.head()
```

E

]:		V1	V2	V3	V4	V5	V6	V7 \	
	0	39.02	36.49	38.20	38.85	39.38	39.74	37.02	
	1	1.83	1.71	1.77	1.77	1.68	1.78	1.80	
	2	68177.69	66138.42	72981.88	74304.33	67549.66	69367.34	69169.41	
	3	44889.06	39191.86	40728.46	38576.36	45876.06	47034.00	46611.43	
	4	5.70	5.40	5.28	5.38	5.27	5.61	6.00	
		V8	V9	V10	V	92 V	93 V	94 V95	\
	0	39.53	38.81	38.79	36.	62 36.	92 38.	80 38.52	
	1	1.70	1.75	1.78	1.	80 1.1	79 1.:	77 1.74	
	2	73268.61	74465.84	72503.37	73438.	88 71053.	35 71112.	62 74916.48	
	3	37668.32	40980.89	38466.15	42625.	67 40684.	20 46960.	73 44546.80	
	4	5.38	5.34	5.87	5.	17 5.0	67 5.0	5.94	
		V96	V97	V98					
	0	38.07	36.73	39.46	37.50	39.10	0		
	1	1.74	1.80	1.78	1.75	1.69	1		
	2	72571.58	66348.97	71063.72	67404.27	74920.24	1		
	3	45410.53	47139.44	43095.68	40888.34	39615.19	0		
	4	5.73	5.22	5.30	5.73	5.91	0		

[5 rows x 101 columns]

# []: df.info()

<class 'pandas.core.frame.DataFrame'> RangeIndex: 1212 entries, 0 to 1211 Columns: 101 entries, V1 to Class dtypes: float64(100), int64(1) memory usage: 956.5 KB

# **Describe Data**

# []: df.describe()

[]:		V1	V2	V3	V4	\
	count	1212.000000	1212.000000	1212.000000	1212.000000	
	mean	8169.091881	8144.306262	8192.653738	8176.868738	
	std	17974.950461	17881.049734	18087.938901	17991.903982	
	min	0.920000	0.900000	0.850000	0.890000	
	25% 50%	19.602500 301.425000	19.595000 295.205000	18.925000 297.260000	19.277500 299.720000	
	75%	5358.795000	5417.847500	5393.367500	5388.482500	
	max	117807.870000	108896.480000	119031.350000	110212.590000	
						,
	count	V5	V6	V7	V8	\
	count	1212.000000 8128.297211	1212.000000 8173.030008	1212.000000 8188.582748	1212.000000 8183.641543	
	mean std	17846.757963	17927.114105	18029.562695	18048.582159	
	min	0.880000	0.860000	0.870000	0.650000	
	25%	19.210000	19.582500	18.690000	19.062500	
	50%	295.115000	294.380000	295.935000	290.850000	
	75%	5321.987500	5328.040000	5443.977500	5283.655000	
	max	113000.470000	116848.390000	115609.240000	118522.320000	
		V9	V10	V	92 V	93 \
	count	V9 1212.000000	V10 1212.000000	V		,
	count mean				1212.0000	00
		1212.000000 8154.670066 17982.390713	1212.000000	1212.0000 8120.0568 17773.1906	000 1212.0000 315 8125.9174 321 17758.1824	00 09
	mean std min	1212.000000 8154.670066 17982.390713 0.650000	1212.000000 8120.767574 17900.798206 0.620000	1212.0000 8120.0568 17773.1906 0.8700	1212.0000 115 8125.9174 17758.1824 100 0.9000	00 09 03 00
	mean std min 25%	1212.000000 8154.670066 17982.390713 0.650000 19.532500	1212.000000 8120.767574 17900.798206 0.620000 19.285000	1212.0000 8120.0568 17773.1906 0.8700 19.1975	1212.0000 115 8125.9174 17758.1824 100 0.9000 18.8950	00 09 03 00 00
	mean std min 25% 50%	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450	1212.0000 115 8125.9174 17758.1824 100 0.9000 18.8950 100 295.4200	00 09 03 00 00
	mean std min 25% 50% 75%	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450 5355.3550	1212.0000 115 8125.9174 17758.1824 100 0.9000 18.8950 100 295.4200 100 5386.0375	00 09 03 00 00 00
	mean std min 25% 50%	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450	1212.0000 115 8125.9174 17758.1824 100 0.9000 18.8950 100 295.4200 100 5386.0375	00 09 03 00 00 00
	mean std min 25% 50% 75%	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000 112895.900000	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500 117798.300000	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450 5355.3550 113858.6800	1212.0000 115 8125.9174 17758.1824 100 0.9000 18.8950 100 295.4200 100 5386.0375 112948.8300 112948.8300	00 09 03 00 00 00 00 00
	mean std min 25% 50% 75%	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000 112895.900000 V94 1212.000000	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500 117798.300000	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450 5355.3550 113858.6800 V96 1212.000000	1212.00000 115 8125.91740 121 17758.18240 100 0.9000 18.8950 100 295.42000 100 5386.03750 112948.83000 V97 1212.000000	00 09 03 00 00 00 00 00
	mean std min 25% 50% 75% max	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000 112895.900000 V94 1212.000000 8158.793812	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500 117798.300000 V95 1212.000000 8140.885421	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450 5355.3550 113858.6800  V96 1212.000000 8213.480611	1212.00000 15 8125.91740 15 17758.18240 100 0.9000 18.8950 100 295.42000 100 5386.03750 112948.83000 V97 1212.000000 8185.594002	00 09 03 00 00 00 00 00
	mean std min 25% 50% 75% max count mean std	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000 112895.900000 V94 1212.000000 8158.793812 17919.510371	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500 117798.300000 V95 1212.000000 8140.885421 17817.945646	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450 5355.3550 113858.6800  V96 1212.000000 8213.480611 18016.445265	1212.00006 15 8125.91746 15 8125.91746 100 0.9000 18.8950 100 295.42006 100 5386.03756 112948.83006 112948.83006 V97 1212.000000 8185.594002 17956.084223	00 09 03 00 00 00 00 00
	mean std min 25% 50% 75% max count mean std min	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000 112895.900000 V94 1212.000000 8158.793812 17919.510371 0.870000	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500 117798.300000 V95 1212.000000 8140.885421 17817.945646 0.880000	1212.0000 17773.1906 17773.1906 19.1975 19.1975 19.355.3550 113858.6800  V96 1212.000000 8213.480611 18016.445265 0.890000	000 1212.00000 015 8125.91740 021 17758.18240 000 0.9000 00 18.8950 000 295.42000 000 5386.03750 00 112948.83000 V97 1212.000000 8185.594002 17956.084223 0.890000	00 09 03 00 00 00 00 00
	mean std min 25% 50% 75% max count mean std min 25%	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000 112895.900000 V94 1212.000000 8158.793812 17919.510371 0.870000 19.237500	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500 117798.300000 V95 1212.000000 8140.885421 17817.945646 0.880000 19.385000	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450 5355.3550 113858.6800  V96 1212.000000 8213.480611 18016.445265 0.890000 19.027500	000 1212.00000 015 8125.91740 021 17758.18240 000 0.9000 00 18.8950 000 295.42000 000 5386.03750 000 112948.83000 V97 1212.000000 8185.594002 17956.084223 0.890000 19.135000	00 09 03 00 00 00 00 00
	mean std min 25% 75% max count mean std min 25% 50%	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000 112895.900000 V94 1212.000000 8158.793812 17919.510371 0.870000 19.237500 299.155000	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500 117798.300000 V95 1212.000000 8140.885421 17817.945646 0.880000 19.385000 293.355000	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450 5355.3550 113858.6800  V96 1212.000000 8213.480611 18016.445265 0.890000 19.027500 301.370000	000 1212.00000 015 8125.91740 021 17758.18240 000 0.9000 00 18.8950 000 295.42000 000 5386.03750 000 112948.83000 V97 1212.000000 8185.594002 17956.084223 0.890000 19.135000 296.960000	00 09 03 00 00 00 00 00
	mean std min 25% 50% 75% max count mean std min 25%	1212.000000 8154.670066 17982.390713 0.650000 19.532500 294.565000 5378.180000 112895.900000 V94 1212.000000 8158.793812 17919.510371 0.870000 19.237500	1212.000000 8120.767574 17900.798206 0.620000 19.285000 295.160000 5319.097500 117798.300000 V95 1212.000000 8140.885421 17817.945646 0.880000 19.385000	1212.0000 8120.0568 17773.1906 0.8700 19.1975 297.8450 5355.3550 113858.6800  V96 1212.000000 8213.480611 18016.445265 0.890000 19.027500	000 1212.00000 015 8125.91740 021 17758.18240 000 0.9000 00 18.8950 000 295.42000 000 5386.03750 000 112948.83000 V97 1212.000000 8185.594002 17956.084223 0.890000 19.135000	00 09 03 00 00 00 00 00

 V98
 V99
 V100
 Class

 count
 1212.000000
 1212.000000
 1212.000000
 1212.000000

```
8140.195355
                            8192.960891
                                           8156.197376
                                                           0.500000
     mean
     std
            17768.356106 18064.781479
                                         17829.310973
                                                           0.500206
                0.860000
                               0.910000
                                              0.890000
                                                           0.000000
     min
     25%
               19.205000
                              18.812500
                                             19.145000
                                                           0.000000
              300.925000
     50%
                             299.200000
                                            302.275000
                                                           0.500000
     75%
             5390.850000
                            5288.712500
                                           5357.847500
                                                           1.000000
     max
           116431.960000 113291.960000 114533.760000
                                                           1.000000
     [8 rows x 101 columns]
[ ]: df.columns
[]: Index(['V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10',
            'V92', "V93', 'V94', 'V95', 'V96', 'V97', 'V98', 'V99', 'V100',
            'Class'],
           dtype='object', length=101)
[]: print(df.columns.tolist())
    ['V1', 'V2', 'V3', 'V4', 'V5', 'V6', 'V7', 'V8', 'V9', 'V10', 'V11', 'V12',
    'V13', 'V14', 'V15', 'V16', 'V17', 'V18', 'V19', 'V20', 'V21', 'V22', 'V23',
    'V24', 'V25', 'V26', 'V27', 'V28', 'V29', 'V30', 'V31', 'V32', 'V33', 'V34',
    'V35', 'V36', 'V37', 'V38', 'V39', 'V40', 'V41', 'V42',
                                                            'V43', 'V44'
                                                                          'V45'.
    'V46'. 'V47'. 'V48'. 'V49'. 'V50'. 'V51'.
                                              'V52'. 'V53'.
                                                            'V54'. 'V55'.
                                                                          'V56'.
    'V57', 'V58',
                         'V60', 'V61',
                                       'V62',
                                              'V63',
                 'V59'.
                                                     'V64'
                                                            'V65'.
                                                                   'V66'.
                                                                          'V67'.
    'V68', 'V69', 'V70', 'V71', 'V72', 'V73',
                                              'V74', 'V75', 'V76', 'V77', 'V78',
    'V79', 'V80', 'V81', 'V82', 'V83', 'V84', 'V85', 'V86', 'V87', 'V88', 'V89',
    'V90', 'V91', 'V92', 'V93', 'V94', 'V95', 'V96', 'V97', 'V98', 'V99', 'V100',
    'Class'l
[]: df.shape
[]: (1212, 101)
[]: df["Class"]_value_counts()
[ ]: Class
     0
          606
     1
          606
     Name: count, dtype: int64
[ ]: df_groupby("Class")_mean()
[ ]:
                     V1
                                  V2
                                               V3
                                                            V4
                                                                         V5 \
     Class
            7913.333251 7825.339967 7902.497294 7857.032079 7775.610198
     0
```

```
1
           8424.850512 8463.272558 8482.810182 8496.705396 8480.984224
                    ۷6
                                ٧7
                                             ٧8
                                                         ۷9
                                                                     V10 ... \
     Class
           7875.436337 7804.166584 7722.324802 7793.328416 7686.782046
     0
           8470.623680 8572.998911 8644.958284 8516.011716 8554.753102 ....
     1
                   V91
                               V92
                                            V93
                                                        V94
                                                                     V95 \
     Class
           7753.427244 7737.843366 7799.332079 7825.211700 7791.354010
     0
     1
           8478.513399 8502.270264 8452.502739 8492.375924 8490.416832
                   V96
                               V97
                                            V98
                                                        V99
                                                                   V100
     Class
           7927.237112 7874.502343 7844.227459 7875.338713 7855.181172
     1
           8499,724109 8496,685660 8436,163251 8510,583069 8457,213581
     [2 rows x 100 columns]
[]: y=df["Class"]
[]: y.shape
[]: (1212,)
[ ]: y
[]: 0
            0
     2
            1
     3
            0
            0
    1207
            1
    1208
    1209
    1210
            1
     1211
     Name: Class, Length: 1212, dtype: int64
[ ]:
```

### [ ]: x.shape

2

### []: (1212, 100)

[ ]: X [ ]: V2 V3 ٧4 V5 ۷7 \ V1 ۷6 38.85 0 39.02 36.49 38.20 39.38 39.74 37.02 1 1.83 1.71 1.77 1.77 1.68 1.78 1.80 2 68177.69 66138.42 72981.88 74304.33 67549.66 69367.34 69169.41 3 44889.06 39191.86 40728.46 38576.36 45876.06 47034.00 46611.43 4 5.70 5.40 5.28 5.38 5.27 5.61 6.00 12.87 1207 13.00 13.27 13.04 13.19 12.53 14.31 50.11 50.43 49.67 1208 48.66 48.55 50.09 48.95 1209 10160.65 9048.63 8994.94 9814.74 10195.24 10031.47 9514.39 1210 34.81 35.07 34.98 32.37 34.16 34.03 33.31 1211 8489.43 7672.98 9132.14 7985.73 8226.85 8554.28 8838.87 ٧8 ۷9 V10 V91 V92 V93 \ 0 39.53 38.79 37.57 36.62 36.92 38.81 1 1.70 1.75 1.78 1.71 1.79 1.80 2 73268.61 74465.84 72503.37 ... 69384.71 73438.88 71053.35 3 37668.32 40980.89 38466.15 47653.60 42625.67 40684.20 4 5.38 5.34 5.87 5.52 5.17 5.67 1207 13.33 13.63 14.55 12.89 12.48 12.15 1208 48.65 48.63 48.61 47.45 46.93 49.61 1209 10202.28 9152.99 9591.75 ... 10413.41 9068.11 9191.80 1210 32.48 35.63 32.48 ... 33.18 32.76 35.03 1211 8967.24 8635.14 8544.37 ... 7747.70 8609.73 9209.48 V100 V94 V95 V96 V97 V98 V99 0 38.80 38.52 38.07 36.73 39.46 37.50 39.10 1 1.74 1.77 1.74 1.80 1.78 1.75 1.69

71112.62 74916.48 72571.58 66348.97 71063.72 67404.27 74920.24

3	46960.73	44546.80	45410.53	47139.44	43095.68	40888.34	39615.19
4	5.60	5.94	5.73	5.22	5.30	5.73	5.91
1207	13.15	12.35	13.58	13.86	12.88	13.87	13.51
1208	47.16	48.17	47.94	49.81	49.89	47.43	47.77
1209	9275.04	9848.18	9074.17	9601.74	10366.24	8997.60	9305.77
1210	32.89	31.91	33.85	35.28	32.49	32.83	34.82
1211	8496.33	8724.01	8219.99	8550.86	8679.43	8389.31	8712.80

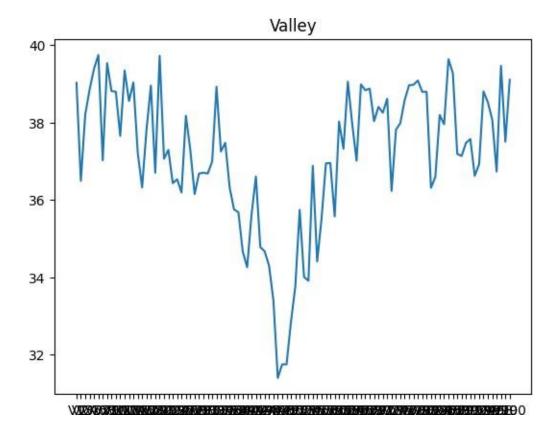
[1212 rows x 100 columns]

# **Data Visualization**

[ ]: import matplotlib.pyplot as plt

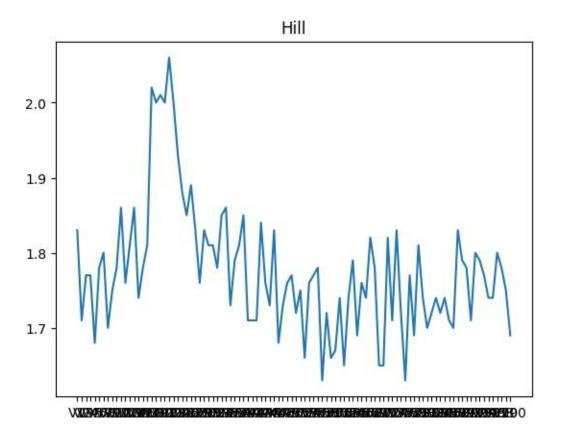
[]: plt.plot(x.iloc[0,:]) plt.title("Valley")

[]: Text(0.5, 1.0, 'Valley')



[ ]: plt.plot(x.iloc[1,:]) plt.title('Hill')

### []: Text(0.5, 1.0, 'Hill')



```
[]: from sklearn_preprocessing import StandardScaler

[]: ss=StandardScaler()

[]: x=ss.fit_transform(x)

[]: x

[]: array([[-0.45248681, -0.45361784, -0.45100881, ..., -0.45609618, -0.45164274, -0.45545496], [-0.45455665, -0.45556372, -0.45302369, ..., -0.45821768, -0.45362255, -0.45755405], [ 3.33983504, 3.24466709, 3.58338069, ..., 3.5427869, 3.27907378, 3.74616847], ..., [ 0.11084204, 0.0505953, 0.04437307, ..., 0.12533312, 0.04456025, 0.06450317], [-0.45272112, -0.45369729, -0.45118691, ..., -0.45648861, -0.45190136, -0.45569511],
```

```
0.01087365, 0.03123129]])
 []: x.shape
 []: (1212, 100)
Train Test Split
     from sklearn.model selection import train_test_split
[]:
 x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.
      →3, stratify=y, random_state=2529)
 [ ]: x_train.shape,x_test.shape,y_train.shape,y_test.shape
 []: ((848, 100), (364, 100), (848,), (364,))
 Modeling
      from sklearn.linear model import LogisticRegression
 [ ]:
 []: Ir=LogisticRegression()
 [ ]: | Ir.fit(x_train,y_train)
 []: LogisticRegression()
 Model Evaluation
 y_pred=Ir_predict(x_test)
 [ ]: y_pred.shape
 []: (364,)
 [ ]: y_pred
 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
           0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0,
           0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0,
           0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
```

[0.01782872, -0.02636986, 0.05196137, ..., 0.03036056,

# **Prediction**

```
[ ]: Ir.predict_proba(x_test)
```

```
[ ]: array([[0.56336744, 0.43663256],
           [0.50327039, 0.49672961],
           [0.57446514, 0.42553486],
           [0.50737525, 0.49262475],
           [0.50767478, 0.49232522],
           [0.5087066, 0.4912934],
           [0.50793217, 0.49206783],
           [0.60357917, 0.39642083],
           [0.51009655, 0.48990345],
           [0.50964836, 0.49035164],
           [0.50721213, 0.49278787],
           [0.51503419, 0.48496581],
           [0.93595857, 0.06404143],
           [0.50968822, 0.49031178],
           [0.52004959, 0.47995041],
           [0.73731198, 0.26268802],
           [0.47389171, 0.52610829],
           [0.50781847, 0.49218153],
           [0.50862145, 0.49137855],
           [0.5086342, 0.4913658],
           [0.29771935, 0.70228065],
           [0.38273299, 0.61726701],
           [0.50865396, 0.49134604],
           [0.28367974, 0.71632026],
           [0.50873182, 0.49126818],
           [0.50707761, 0.49292239],
           [0.50896136, 0.49103864],
           [0.50811697, 0.49188303],
           [0.50861558, 0.49138442],
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from sklearn.metrics import confusion_matrix,classification_report
print(confusion_matrix(y_test,y_pred))
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[]: print(classification_report(y_test,y_pred))
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                             recall f1-score
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                                         0.77
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                               0.42
                                         0.59
                                                   182
        accuracy
                                         0.71
                                                   364
                      0.81
                               0.71
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                                                   364
       macro avq
    weighted avg
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                               0.71
                                         0.68
                                                   364
[]: x_new=df_sample(1)
[ ]: x_new
[]:
           V1
                 V2
                      V3
                            V4
                                  ٧5
                                       V6
                                             ٧7
                                                   ٧8
                                                         ۷9
                                                             V10 ... V92 \
    792 6.82 6.23 6.42 6.44 6.78
                                     7.01
                                           6.52 6.23
                                                      6.82
                                                            6.51 ... 7.0
          V93
                V94 V95
                          V96
                                V97
                                      V98
                                           V99 V100 Class
    792 6.56 6.73 6.5
                        7.01 6.94 6.36 6.98 6.27
    [1 rows x 101 columns]
[]: x_new.shape
[]: (1, 101)
[]: x_new=x_new_drop("Class",axis=1)
[ ]: x_new
[ ]:
                 V2
                      V3
                                  ٧5
                                       ۷6
                                                   ٧8
                                                             V10 ... V91 \
    792 6.82 6.23 6.42 6.44 6.78 7.01 6.52 6.23 6.82 6.51 ... 7.0
         V92 V93 V94 V95
                              V96 V97 V98 V99 V100
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    [1 rows x 100 columns]
[]: x_new.shape
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[ ]: x_new=ss_fit_transform(x_new)
[ ]: y_pred_new=lr_predict(x_new)
```

- [ ]: y\_pred\_new
  [ ]: array([1])
  [ ]: lr.predict\_proba(x\_new)
- []: array([[0.49714993, 0.50285007]])