HILL AND VALLEY PREDICTION

Objective: To analyze the hills and valleys

Data Source: YBI Foundation through Github

Import Library

Import Data

In [ ]:
```
import pandas as pd
import numpy as np
df = pd.read_csv(r'https://raw.githubusercontent.com/YBIFoundation/Dataset/main/Hil
df.head()
```

Out[ ]:

	V1	V2	V3	V4	V5	V6	V7	V8	V9
0	39.02	36.49	38.20	38.85	39.38	39.74	37.02	39.53	38.81
1	1.83	1.71	1.77	1.77	1.68	1.78	1.80	1.70	1.75
2	68177.69	66138.42	72981.88	74304.33	67549.66	69367.34	69169.41	73268.61	74465.84
3	44889.06	39191.86	40728.46	38576.36	45876.06	47034.00	46611.43	37668.32	40980.89
4	5.70	5.40	5.28	5.38	5.27	5.61	6.00	5.38	5.34

5 rows × 101 columns

Describe Data

In [ ]:
```
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
```

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

Out[ ]:

	V1	V2	V3	V4	V5	
count	1212.000000	1212.000000	1212.000000	1212.000000	1212.000000	1212.
mean	8169.091881	8144.306262	8192.653738	8176.868738	8128.297211	8173.
std	17974.950461	17881.049734	18087.938901	17991.903982	17846.757963	17927.
min	0.920000	0.900000	0.850000	0.890000	0.880000	0.
25%	19.602500	19.595000	18.925000	19.277500	19.210000	19.
50%	301.425000	295.205000	297.260000	299.720000	295.115000	294.
75%	5358.795000	5417.847500	5393.367500	5388.482500	5321.987500	5328.
max	117807.870000	108896.480000	119031.350000	110212.590000	113000.470000	116848.

8 rows × 101 columns

In [ ]:
```
df.columns
```

Out[ ]:
```
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)
```

In [ ]:
```
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', 'V59', 'V60', 'V61',
'V62', 'V63', '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']
```

In [ ]:
```
df.shape
```

Out[ ]:
```
(1212, 101)
```

In [ ]:
```
df['Class'].value_counts()
```

Out[ ]:
```
0    606
1    606
Name: Class, dtype: int64
```

In [ ]:
```
df.groupby('Class').mean()
```

Out[ ]:

Class	V1	V2	V3	V4	V5	V6	
0	7913.333251	7825.339967	7902.497294	7857.032079	7775.610198	7875.436337	7804.
1	8424.850512	8463.272558	8482.810182	8496.705396	8480.984224	8470.623680	8572.

2 rows × 100 columns

Define Target Variable (y) and Feature Variables (X)

In [ ]:
```
y = df['Class']
y.shape
```

Out[ ]:
```
(1212,)
```

In [ ]:
```
y
```

Out[ ]:
```
0       0
1       1
2       1
3       0
4       0
       ..
1207    1
1208    0
1209    1
1210    1
1211    0
Name: Class, Length: 1212, dtype: int64
```

In [ ]:
```
X = df.drop('Class',axis=1)
X.shape
```

Out[ ]:
```
(1212, 100)
```

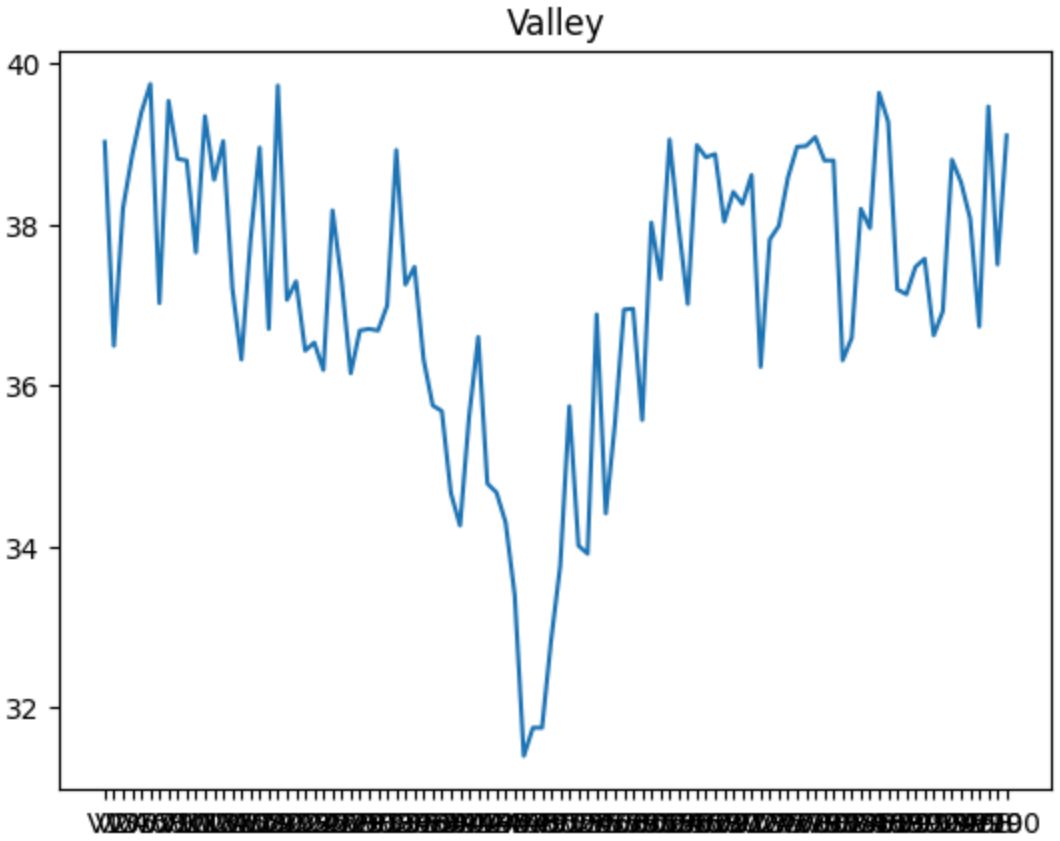
In [ ]:
```
X
```

Out[ ]:

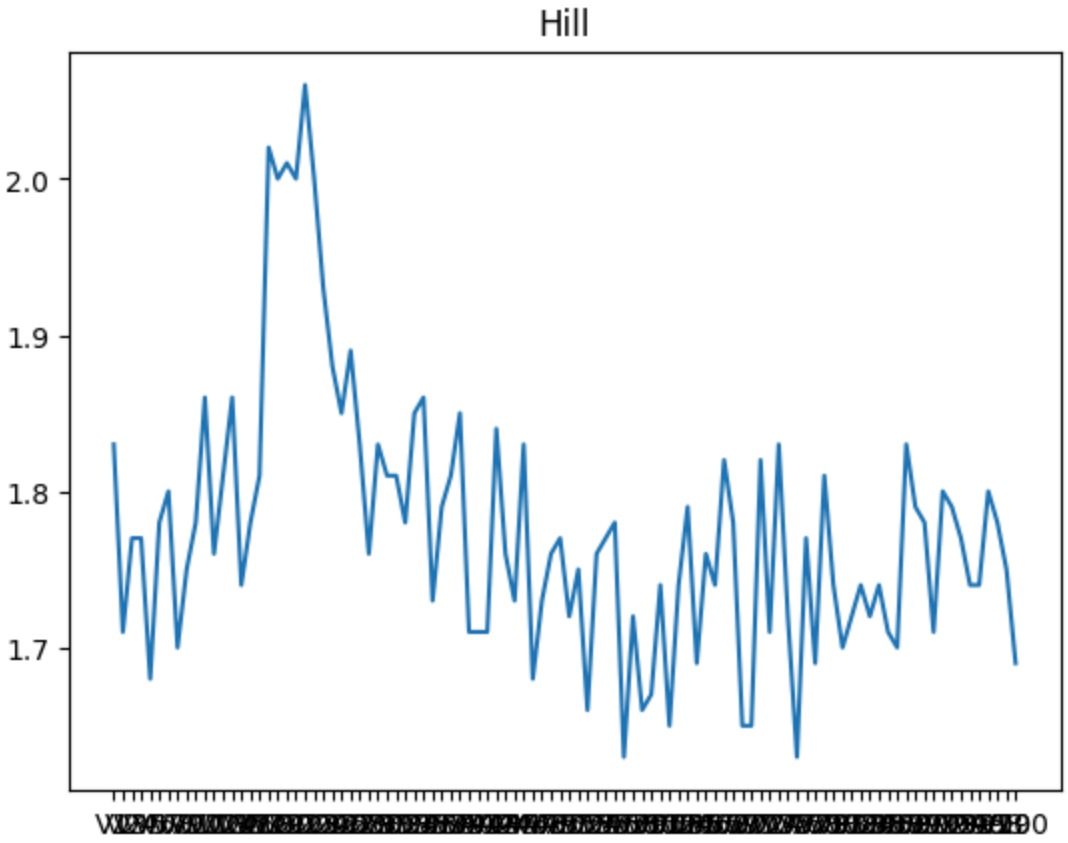
	V1	V2	V3	V4	V5	V6	V7	V8	
0	39.02	36.49	38.20	38.85	39.38	39.74	37.02	39.53	3
1	1.83	1.71	1.77	1.77	1.68	1.78	1.80	1.70	
2	68177.69	66138.42	72981.88	74304.33	67549.66	69367.34	69169.41	73268.61	7446
3	44889.06	39191.86	40728.46	38576.36	45876.06	47034.00	46611.43	37668.32	4098
4	5.70	5.40	5.28	5.38	5.27	5.61	6.00	5.38	
...	...	...	...	...	...	...	...	...	
1207	13.00	12.87	13.27	13.04	13.19	12.53	14.31	13.33	1
1208	48.66	50.11	48.55	50.43	50.09	49.67	48.95	48.65	4
1209	10160.65	9048.63	8994.94	9514.39	9814.74	10195.24	10031.47	10202.28	915
1210	34.81	35.07	34.98	32.37	34.16	34.03	33.31	32.48	3
1211	8489.43	7672.98	9132.14	7985.73	8226.85	8554.28	8838.87	8967.24	863

1212 rows × 100 columns

In [ ]:
```
import matplotlib.pyplot as plt
plt.plot(X.iloc[0,:])
plt.title('Valley');
```



In [ ]:
```
plt.plot(X.iloc[1,:])
plt.title('Hill');
```



Train Test Split

In [ ]:
```
from sklearn.preprocessing import StandardScaler
ss = StandardScaler()
X = ss.fit_transform(X)
X
```

Out[ ]:
```
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],
       [ 0.01782872, -0.02636986,  0.05196137, ...,  0.03036056,
         0.01087365,  0.03123129]])
```

In [ ]:
```
X.shape
```

Out[ ]:
```
(1212, 100)
```

In [ ]:
```
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,
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[ ]:
```
((848, 100), (364, 100), (848,), (364,))
```

In [ ]:
```
from sklearn.linear_model import LogisticRegression
lr = LogisticRegression()
lr.fit(X_train, y_train)
```

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

Prediction

In [ ]:
```
y_pred = lr.predict(X_test)
y_pred.shape
```

Out[ ]:
```
(364,)
```

In [ ]:
```
y_pred
```

Out[ ]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1,
       0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 1,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 0, 0, 1, 1,
       0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1, 1, 0, 0, 1, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 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, 1, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0,
       1, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 0, 0,
       0, 0, 0, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 1, 0, 1])
```

In [ ]:
```
lr.predict_proba(X_test)
```

Out[ ]:
```
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],
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       [0.93595857, 0.06404143],
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       [0.47389171, 0.52610829],
       [0.50781847, 0.49218153],
       [0.50862145, 0.49137855],
       [0.5086342 , 0.4913658 ],
       [0.29771935, 0.70228065],
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       [0.50856525, 0.49143475],
```

```
[0.50860437, 0.49139563],
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```

```
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```

```
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```

```
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```

Explanation

In [ ]:
```
from sklearn.metrics import confusion_matrix, classification_report
print(confusion_matrix(y_test, y_pred))
```

```
[[181   1]
 [106  76]]
```

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

```
              precision    recall  f1-score   support

           0       0.63      0.99      0.77       182
           1       0.99      0.42      0.59       182

    accuracy                           0.71       364
   macro avg       0.81      0.71      0.68       364
weighted avg       0.81      0.71      0.68       364
```

In [ ]:
```
X_new = df.sample(1)
X_new
```

Out[ ]:

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	...	V92	V93	V94	V95	V
409	9.63	8.97	8.48	8.5	9.79	10.15	8.74	9.52	10.18	8.7	...	8.43	8.48	8.81	9.26	8.

1 rows × 101 columns

In [ ]:
```
X_new.shape
```

Out[ ]:
```
(1, 101)
```

In [ ]:
```
X_new = X_new.drop('Class', axis = 1)
X_new
```

Out[ ]:

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	...	V91	V92	V93	V94	V
409	9.63	8.97	8.48	8.5	9.79	10.15	8.74	9.52	10.18	8.7	...	9.05	8.43	8.48	8.81	9.

1 rows × 100 columns

In [ ]:
```
X_new.shape
```

Out[ ]:
```
(1, 100)
```

In [ ]:
```
X_new = ss.fit_transform(X_new)
y_pard_new = lr.predict(X_new)
y_pard_new
```

Out[ ]:
```
array([1])
```

In [ ]:
```
lr.predict_proba(X_new)
```

Out[ ]:
```
array([[0.49714993, 0.50285007]])
```