## **Logistic Regression in Python**

Learning Python

```
In [282]:
           import pandas as pd
           import numpy as np
           import os
           from sklearn.model selection import RepeatedKFold, cross val score
           from sklearn.linear model import LogisticRegression
In [283]:
           os.chdir("C:\\Users\\Matt\\Documents\\Python Projects")
In [284]:
           pwd
Out[284]: 'C:\\Users\\Matt\\Documents\\Python_Projects'
In [285]: | baseball_train = pd.read_csv(r"baseball_train.csv",index_col=0,
                                         dtype={'Opp': 'category', 'Result': 'category',
           'Name': 'category'}, header=0)
           baseball_test = pd.read_csv(r"baseball_test.csv",index_col=0,
                                        dtype={'Opp': 'category', 'Result': 'category', 'N
           ame': 'category'}, header=0)
           print(baseball test.head())
           encoded categories = dict(enumerate(baseball test.Name.cat.categories))
           print(encoded_categories)
                                                                      PO
                 0pp
                      DR
                           ΙP
                                   R
                                       ER
                                           BB
                                               S0
                                                   HR
                                                       HBP
                                                                  CS
                                                                          X2B
                                                                               X3B
                                                                                     IBB
           788
                 DET
                       4
                          4.2
                                3
                                   5
                                        5
                                            7
                                                5
                                                    2
                                                                   0
                                                                       0
                                                                            0
                                                                                  0
                                                                                       0
                       5
                          6.0
                               7
                                   2
                                        2
                                                5
                                                    0
                                                                                       0
           1463
                 DET
                                            1
                                                          0
                                                                   1
                                                                       0
                                                                            1
                                                                                  0
                                        5
           1272
                 TOR
                       4
                          9.0
                               10
                                   5
                                            6
                                                6
                                                    0
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                                                                   1
                                                                       0
                                                                            1
                                                                                  0
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                                            5
           639
                 PIT
                       5 7.0
                                2
                                                6
                                                    0
                                                                   1
                                                                                       0
                                                             . . .
           41
                 ATL
                          2.1
                                0
                                   0
                                            1
                                                0
                                                                   0
                                                                            0
                                                                                  0
                                                                                       0
                       4
                 GDP
                      SF
                          ROE
                               Result
                                         Name
           788
                       0
                   0
                            0
                                     L
                                        Nolan
           1463
                       0
                            0
                                     L
                                        Tommy
           1272
                       0
                            0
                                     L
                                        Tommy
           639
                   1
                       0
                            0
                                     W
                                       Nolan
           41
                   0
                            1
                                     W
                                       Nolan
           [5 rows x 28 columns]
           {0: 'Nolan', 1: 'Tommy'}
```

## Repeated K-Fold Cross Validation

```
In [287]: print(cv_results.min())
    print(np.percentile(cv_results, 25))
    print(cv_results.mean())
    print(np.percentile(cv_results, 50))
    print(np.percentile(cv_results, 75))
    print(cv_results.max())

0.952828605002518
    0.965297585406852
    0.9669297585406852
    0.9662099882688117
    0.9729831391245957
    0.9800403395243298
```

```
In [288]: model = logit.fit(X,y)
          intercept = model.intercept_[0]
          print("intercept = {}".format(intercept))
          for idx, col_name in enumerate(X.columns):
              print("{} = {}".format(col name, model.coef [0][idx]))
          intercept = 1.2946166338126635
          DR = 0.011732883825072156
          IP = -0.23226847104529907
          H = 0.20288283686541814
          R = -0.34776710286808105
          ER = 0.0028960956992052796
          BB = -0.3200886417413454
          SO = -0.3132016093632194
          HR = 0.08526653709614487
          HBP = 0.0710202234769784
          ERA = -0.10336335576210107
          BF = -0.21558563340441994
          GB = 0.726929231994203
          FB = -0.09150477706222566
          LD = 0.30735242703011767
          PU = -0.4865137756269206
          Unk = 0.5177317713205674
          SB = -0.5546505737669927
          CS = 0.25899883409993363
          P0 = -0.8674866862900049
          X2B = 0.0006321819834886793
          X3B = -0.04613833936871116
          IBB = 0.571862684825111
          GDP = 0.19170268600140106
          SF = -0.07018569499658994
          ROE = -0.03986918217233402
```

## Out[289]:

	predicted	truth
788	Nolan	Nolan
1463	Tommy	Tommy
1272	Nolan	Tommy
639	Nolan	Nolan
41	Tommy	Nolan
391	Nolan	Nolan
779	Nolan	Nolan
1457	Tommy	Tommy
496	Nolan	Nolan
678	Nolan	Nolan
358	Nolan	Nolan
67	Nolan	Nolan
1185	Tommy	Tommy
1096	Nolan	Tommy
946	Nolan	Tommy
911	Nolan	Tommy
1542	Tommy	Tommy
324	Nolan	Nolan
955	Tommy	Tommy
206	Nolan	Nolan