# Open and prepare the data set

```
data = pd.read_csv('countries of the world.csv')
2
  data
                                                                                       Infant
                                                      Pop.
                                                               Coastline
                                                                                    mortality
                                                                                                 GDP
                                                                                                                Phones
                                                   Density
                                              Area
                                                                               Net
                                                                                                      Literacy
                                                                                                                         Arable
                                                                                                                                 Crops
                                                                                                                                         Other
        Country
                      Region Population
                                                             (coast/area
                                                                                        (per
1000
                                                                                              ($ per
capita)
                                                                                                                  (per
1000)
                                                                                                                                                Climate Birthr
                                           (sq. mi.)
                                                                                                                                           (%)
                                                                          migration
                                                                  ratio)
                                                       mi.)
                                                                                       births)
                    ASIA (EX.
     Afghanistan
                       NEAR
                                31056997
                                           647500
                                                       48 0
                                                                   0.00
                                                                             23.06
                                                                                       163.07
                                                                                                 700
                                                                                                          36.0
                                                                                                                    3.2
                                                                                                                          12 13
                                                                                                                                   0.22
                                                                                                                                          87 65
                                                                                                                                                     1.0
                                                                                                                                                             46
                    EASTERN
 1
         Albania
                                 3581655
                                            28748
                                                      124.6
                                                                   1.26
                                                                              -4.93
                                                                                       21.52
                                                                                                4500
                                                                                                          86.5
                                                                                                                   71.2
                                                                                                                          21.09
                                                                                                                                   4.42
                                                                                                                                         74.49
                                                                                                                                                     3.0
                                                                                                                                                             15.
                    EUROPE
                  NORTHERN
 2
                               32930091 2381740
                                                                                                                                                             17.
          Algeria
                                                       13.8
                                                                   0.04
                                                                              -0.39
                                                                                       31.00
                                                                                                6000
                                                                                                          70.0
                                                                                                                   78.1
                                                                                                                           3.22
                                                                                                                                   0.25
                                                                                                                                          96.53
                                                                                                                                                     1.0
                      AFRICA
                    OCEANIA
                                   57794
                                               199
                                                     290.4
                                                                  58.29
                                                                             -20.71
                                                                                        9.27
                                                                                                8000
                                                                                                          97.0
                                                                                                                  259.5 10.00 15.00 75.00
                                                                                                                                                     2.0
                                                                                                                                                             22.
         Samoa
```

# Test the correlation between GDP and Phones and draw the variables for linear regression

```
print('GDP - Phones')
   print('\nComparing linear regression values:')
   print('-'*47)
   print('{:15} {:>15} {:>15}'.format('Statistic', 'From Scipy', 'From Scratch'))
   for name, sc_val, sp_val in [("alpha", intercept_phone, alpha_phone),
                                 ("beta", slope_phone, beta_phone),
                                  ("r-squared", r_squared_value_phone, r_v_phone**2)]:
       print('{:15} {:15.2f} {:15.2f}'.format(name, sc_val, sp_val))
10 print('-'*47)
   from scipy.stats import pearsonr
   print('\nCorrelation from scipy: {:.3f}'.format(pearsonr(data[GDP], data[Phones])[0]))
13
   print('Correlation from scratch: {:.3f}\n'.format(correlation(data[GDP], data[Phones])))
Comparing linear regression values:
Statistic
                    From Scipy
                                 From Scratch
alpha
                           0.02
                                           0.02
beta
r-squared
                           0.72
Correlation from scipy: 0.849
Correlation from scratch: 0.849
```

# Illustrate the linear regression graph using variables found above

# Compare correlation values using the heat-map

```
sns.heatmap(data=data[[GDP,Phones,Migration,Infant,Birthrate]].corr(), annot=True, cmap="YlGnBu")
label = ["GDP","Phones","Migration","Infant","Birthrate"]
index = np.arange(len(label))
plt.xticks(index+0.5, label)|
plt.yticks(index+0.5, label)
plt.show()
```

# Split the data into Training data and Test data

```
X = data[[GDP,Phones,Birthrate,Deathrate,Infant,Migration]]
Y = data[[Region]]
print(X.shape)
print(Y.shape)

(203, 6)
(203, 1)

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, random_state=1)
print("Train X data:", X_train.shape)
print("Train Y data:", Y_train.shape)
print("Test X data:", X_test.shape)
print("Test Y data:", Y_test.shape)

('Train X data:', (142, 6))
('Train Y data:', (61, 6))
('Test X data:', (61, 6))
('Test Y data:', (61, 1))
```

# Fit the data to decision tree model and check the accuracy

```
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier(random_state=1)
model.fit(X_train, Y_train)

print("Training set Accuracy: {:.3f}".format(model.score(X_train, Y_train)))
print("Test set Accuracy: {:.3f}".format(model.score(X_test, Y_test)))

Training set Accuracy: 1.000
Test set Accuracy: 0.607
```

# Fit the data to logistic regression model and check the accuracy

```
logreg = LogisticRegression()
   _ = logreg.fit(X_train, Y_train)

print("Test set Accuracy: {:.3f}".format(logreg.score(X_test, Y_test)))

Test set Accuracy: 0.607
```

# Declare 'key' for connecting with the targets(regions)

```
region_groups = data.groupby('Region')
key=', '.join(['{}={}'.format(i,name) for i,name in enumerate(region_group)])
key
```

'0=AFRICA, 1=ASIA, 2=EAST ASIA, 3=EASTERN EUROPE, 4=LATIN AMER. & CARIB, 5=NORTHERN AMERICA, 6=OCEANIA, 7=WESTERN EUR OPE'

# Estimate intercept/coefficients/splitter and illustrate classification report and confusion matrix

```
Intercept:
[-0.02621052 0.03265841 0.1010144 0.13584803 0.04020111 -0.05868455 0.01594544 -0.11620712]

Coefficients:
[-4.07840105e-04 -4.97840778e-03 7.75371758e-03 2.64356527e-01 -2.66124205e-02 7.56774974e-03]
[ 2.51369699e-05 -1.60289657e-03 1.25401738e-02 -4.53743798e-01 4.43585181e-02 9.20866284e-02]
[ 4.20370288e-05 4.52984310e-03 -7.75586040e-02 -4.45196698e-01 -3.44661932e-01 2.2858284e0-02]
[ -6.66338607e-05 5.62148281e-04 -2.37455844e-01 1.29190659e-01 18 EASTERN EUROPE 3.37149195e-02 -9.99127859e-02 -1.13588531e-01 -3.78716764e-02 4.59362839e-03]
[ -3.53968248e-05 2.19909912e-02 -6.49615786e-01 -1.00838028e+00 -3.64758019e-02 -4.94222049e-01]
[ 3.30056128e-04 2.69258705e-03 -2.77112282e-01 4.81408617e-01 -1.01865524e+00 -2.33406671e-01]]
```

# Find the best parameter for logistic regression and print the classification report and the confusion matrix with new parameters

```
from sklearn.model_selection import GridSearchCV
   # Perform grid search
   param_grid = [
       {'C': [1, 10, 100, 1000, 1e4, 1e5, 1e6, 1e7], 'penalty': ['11', '12']}
5
   logreg = GridSearchCV(LogisticRegression(), param grid)
   logreg.fit(X_train, Y_train)
10 # Print grid search results
11
   print('Grid search mean and stdev:\n')
    #for mean, std, params in zip(means, stds, tree.cv_results_['params']):
13 | for mean_score, scores, params in zip (logreg.cv_results_['mean_score_time'],logreg.cv_results_['mean_test_score'],
14
      print("{:0.3f} (+/-{:0.03f}) for {}".format(
15
               mean score, scores.std() * 2, params))
16
17 # Print best params
print('\nBest parameters:', logreg.best_params_)
20 print('\nClassification report ({}):\n'.format(key))
21 print(classification_report(Y_test, logreg.predict(X_test)))
22 print('Confusion matrix ({}):\n'.format(key))
23 _ = plt.matshow(confusion_matrix(Y_test, logreg.predict(X_test)), cmap=plt.cm.PuRd, interpolation='nearest')
24 = plt.colorbar()
25 = plt.ylabel('true label')
26 _ = plt.xlabel('predicted label')
```

```
0.002 (+/-0.000) for {'penalty': 'l1', 'C': 1}
0.002 (+/-0.000) for {'penalty': 'l2', 'C': 1}
0.002 (+/-0.000) for {'penalty': 'l1', 'C': 10}
                                                                                                               precision
                                                                                                                                 recall f1-score
                                                                                                                                                          support
0.002 (+/-0.000) for ('penalty': '12', 'C': 10)
0.001 (+/-0.000) for ('penalty': '11', 'C': 100)
                                                                                                    AFRICA
                                                                                                                                    0.79
                                                                                                                      1.00
                                                                                                                                                 0.88
                                                                                                                                                                  19
                                                                                                      ASIA
                                                                                                                                    0.62
                                                                                                                      0.56
                                                                                                                                                  0.59
0.002 (+/-0.000) for {'penalty': '12', 'C': 100}
                                                                                                EAST ASIA
                                                                                                                                                  0.40
0.002 (+/-0.000) for {
                               penalty': 'l1', 'C': 1000}
                                                                                         EASTERN EUROPE
                                                                                                                      0.73
                                                                                                                                    0.80
                                                                                                                                                  0.76
                                                                                                                                                                  10
                               penalty': '12', 'C': 1000}
'penalty': '11', 'C': 10000.0}
'penalty': '12', 'C': 10000.0}
0.003 (+/-0.000) for
                                                                                  LATIN AMER. & CARIB
                                                                                                                      0.55
                                                                                                                                    1.00
                                                                                                                                                 0.71
                                                                                                                                                                   6
0.002 (+/-0.000) for {
                                                                                                                      0.00
                                                                                      NORTHERN AMERICA
                                                                                                                                    0.00
                                                                                                                                                 0.00
                                                                                                                                                                   2
0.003 (+/-0.000) for {
0.002 (+/-0.000) for { penalty: '11', 'C': 100000.0}
0.001 (+/-0.000) for { 'penalty': '12', 'C': 100000.0}
                                                                                                   OCEANIA
                                                                                                                      0.00
                                                                                                                                    0.00
                                                                                                                                                 0.00
                                                                                         WESTERN EUROPE
                                                                                                                                    0.70
                                                                                                                                                 0.64
                                                      'C': 100000.0}
                               'penalty': '11', 'C': 1000000.0}
0.001 (+/-0.000) for {
                                                                                                micro avg
                                                                                                                      0.69
                                                                                                                                    0.69
                                                                                                                                                  0.69
                                                                                                                                                                  61
0.001 (+/-0.000) for {
                               'penalty': '12', 'C': 1000000.0}
                                                                                                macro avq
                                                                                                                      0.47
                                                                                                                                    0.55
                                                                                                                                                 0.50
                                                                                                                                                                  61
0.002 (+/-0.000) for {'penalty': '11', 'C': 10000000.0}
0.002 (+/-0.000) for {'penalty': '12', 'C': 10000000.0}
('\nBest parameters:', {'penalty': '11', 'C': 100000.0})
                                                                                            weighted avg
                                                                                                                      0.66
                                                                                                                                    0.69
                                                                                                                                                 0.66
```

# Test how the accuracy changes according to different parameters

```
1 train_result = []
    test_result = []
   model_criterion = []
   model_max_depth = []
 5 parameter_min_leaf = []
   insert_criterion = ['gini', 'entropy']
   max depth = 5
   list_min_leaf = [i for i in range(1,10)]
   for i in insert criterion:
10
11
       for n in list min leaf:
            tree = DecisionTreeClassifier(criterion=i, max_depth=max_depth, min_samples_leaf=n, random_state=1)
12
             tree.fit(X_train, Y_train)
14
             train_result.append(tree.score(X_train,Y_train))
15
             test_result.append(tree.score(X_test,Y_test))
16
            model_criterion.append(i)
17
            model_max_depth.append(max_depth)
18
            parameter_min_leaf.append(n)
19
20 result = pd.DataFrame()
21 result["Criterion"] = model_criterion
22 result["Depth"] = max_depth
23 result["MinLeafSize"] = parameter_min_leaf
24 result["TrainAccuracy"] = train_result
25 result["TestAccuracy"] = test_result
26 result
27
```

	Criterion	Depth	MinLeafSize	TrainAccuracy	TestAccuracy
0	gini	5	1	0.697183	0.557377
1	gini	5	2	0.676056	0.540984
2	gini	5	3	0.669014	0.573770
3	gini	5	4	0.654930	0.524590
4	gini	5	5	0.647887	0.524590
5	gini	5	6	0.633803	0.590164
6	gini	5	7	0.633803	0.590164
7	gini	5	8	0.626761	0.606557
8	gini	5	9	0.647887	0.622951

9	entropy	5	1	0.795775	0.639344
10	entropy	5	2	0.760563	0.639344
11	entropy	5	3	0.760563	0.639344
12	entropy	5	4	0.732394	0.672131
13	entropy	5	5	0.676056	0.672131
14	entropy	5	6	0.661972	0.639344
15	entropy	5	7	0.654930	0.590164
16	entropy	5	8	0.633803	0.622951
17	entropy	5	9	0.626761	0.557377

# Visualise the test result and determine the best parameter

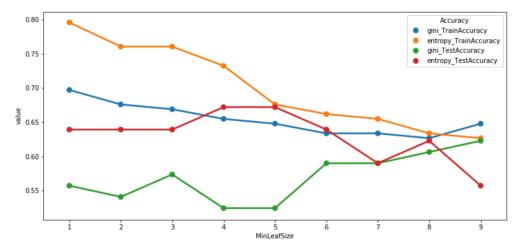
```
plt.figure(figsize=(13,6))

result_melt = pd.melt(result, id_vars=['Criterion', 'Depth', 'MinLeafSize'])

result_melt['Accuracy'] = result_melt['Criterion']+'_'+result_melt['variable']

sns.pointplot(data=result_melt, x='MinLeafSize', y='value', hue='Accuracy')
```

<matplotlib.axes.\_subplots.AxesSubplot at 0x1a1a462d90>



# Fit the new model with the best parameter that chosen according to the test above and see how the accuracy has changed

```
1 model_new = DecisionTreeClassifier(criterion='entropy', max_depth=5, min_samples_leaf=5, random_state=1)
 2 model_new.fit(X_train,Y_train)
 3 print("Training set Accuracy: {:.3f}".format(model_new.score(X_train, Y_train)))
 4 print("Test set Accuracy: {:.3f}\n".format(model_new.score(X_test, Y_test)))
 6 from sklearn.metrics import classification report
 7 print(classification_report(Y_test, model_new.predict(X_test)))
Training set Accuracy: 0.676
Test set Accuracy: 0.672
                   precision recall f1-score support
                                0.84
            AFRICA
                         0.84
                                            0.84
                                                       19
             ASIA
                         0.40
                                 0.75
                                            0.52
                                                        8
                                0.50
0.60
         EAST ASIA
                        0.50
                                            0.50
    EASTERN EUROPE
                        1.00
                                            0.75
                                                       10
                                0.67
0.00
LATIN AMER. & CARIB
                        0.57
                                            0.62
                                                        6
                      0.57
  NORTHERN AMERICA
                                            0.00
                                                        2
           OCEANIA
                                  0.00
                        0.00
                                            0.00
                      0.67
                              0.80
    WESTERN EUROPE
                                           0.73
                                                      10
                      0.67
                              0.67
                                            0.67
         micro avq
         macro avg
                        0.50
                                  0.52
                                            0.49
      weighted avg
                        0.66
                                  0.67
                                            0.65
```

# McNemar test to find out if there a big different in the error rate between logistic regression model and decision tree model and determine if my null hypothesis should be rejected or not

```
1 from scipy.stats import chi2
  def mcnemar(x, y):
    n1 = np.sum(x < y)
      n2 = np.sum(x > y)
      stat = (np.abs(n1-n2)-1)**2 / (n1+n2)
6
     df = 1
     pval = chi2.sf(stat,1)
     return stat, pval
10 # Calculate whether each test prediction is correct
12 t_yn = np.array([int(p==t) for p,t in zip(model_new.predict(X_test), Y_test.values)])
13
14 print(l_yn)
15 print(t_yn)
17 print('Can we reject HO?', 'Yes' if mcnemar(l_yn, t_yn)[1]<0.05 else 'No')
```

# Draw the decision tree with final model