Perceptron implementation:

Importing panda and numpy:

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
np.random.seed(10)
```

Importing the dataset and converting as panda framework:

In [2]:

```
def import_data (filename):
    """
    This function, imports the train/test data and create the attribute matrix ar
    """
    Matrix = []
    Label = []
    with open(filename) as f:

        for line in f:
            sample = line.split()
            Label.append(float(sample[0]))
            sample.pop(0)
            row = []
            for s in sample:
                feature, value = s.split(':')
                z = len(row)
                nz = int(feature) - (z+1)
                for i in range (nz):
                    row.append(0)
                row.append(float(value))
            Matrix.append(row)
    data =[]
    M = max(len(row) for row in Matrix)
    #print("M:",M)
    for row in Matrix:
        nz = M - (len(row))
        for i in range (nz):
            row.append(0)
        data.append(row)
    Label1 = np.array(Label)
    data1= np.array(data)
    #print("aaa:",Label1, data1.shape)
    S1 = np.concatenate((data1, Label1[:,None]),axis=1)
    attributes = np.arange(1, np.size(data1,1)+2)
    #print(attributes)
    samples = range(0,np.size(data1,0))
    data2 = pd.DataFrame(S1, columns=attributes, index=samples)
    #print('label',data2[6])

    return data2
    #print("data1:",data1.shape)
```

In [3]:

```
def update_label(D):
    x,y = D.shape
    for i in range(x):
        if D[y][i] ==0.0:
            D[y][i] = -1.0
    return (D)
def k_fold(D,k):
    cols = D.columns
    D = D.to_numpy()
    r_n, _ = D.shape
    k_n = (r_n//5)
    lb = (k-1)*k_n
    if k == 5:
        ub = r_n
    else:
        ub = k*k_n-1

    fk = D [lb:ub, :]

    Fk = pd.DataFrame(fk, columns=cols)
    return Fk

def import_label (D, new_feature):
    D = D.to_numpy()
    D = D.copy()
    new_feature = new_feature.to_numpy()
    labels = D[:, -1]
    labels = labels[:,None]

    D_out = np.append(new_feature, labels, axis=1)

    attributes = np.arange(1, np.size(D_out,1)+1)
    D_out = pd.DataFrame(D_out, columns=attributes)
    return D_out

def concat_datasets (D1, D2):
    if type(D1) != np.ndarray:
        D1 = D1.to_numpy()
    if type(D2) != np.ndarray:
        D2 = D2.to_numpy()
    D1 = D1.copy()
    D_out = np.append(D1[:,:-1], D2, axis=1)

    attributes = np.arange(1, np.size(D_out,1)+1)
    D_out = pd.DataFrame(D_out, columns=attributes)
    return D_out
```

Importing the glove datasets:

In [4]:

```
Train_data1 = import_data('glove.train.libsvm')
Train_data_glove = update_label(Train_data1)
Test_data1 = import_data('glove.test.libsvm')
Test_data_glove = update_label(Test_data1)
Eval_data_glove = import_data('glove.eval.anon.libsvm')
```

Importing the bag of words datasets:

In [5]:

```
Train_data1 = import_data('bow.train.libsvm')
Train_data_bow = update_label(Train_data1)
Test_data1 = import_data('bow.test.libsvm')
Test_data_bow = update_label(Test_data1)
Eval_data_bow = import_data('bow.eval.anon.libsvm')
```

Importing the tfidf datasets:

In [6]:

```
Train_data1 = import_data('tfidf.train.libsvm')
Train_data_tfidf = update_label(Train_data1)
Test_data1 = import_data('tfidf.test.libsvm')
Test_data_tfidf = update_label(Test_data1)
Eval_data_tfidf = import_data('tfidf.eval.anon.libsvm')
```

Importing the miscellaneous datasets:

In [7]:

```
misc_train = pd.read_csv ('misc-attributes-train.csv')
train_samples, _ = misc_train.shape
misc_test = pd.read_csv ('misc-attributes-test.csv')
test_samples, _ = misc_test.shape
misc_eval = pd.read_csv ('misc-attributes-eval.csv')
eval_samples, _ = misc_eval.shape
```

In order to convert the database to one hot encoding, all the dataset are concatenated and converted to correlate the cominations.

In [8]:

```
database = pd.concat([misc_train, misc_test, misc_eval], axis=0)
database.head()
```

Out[8]:

	defendant_age	defendant_gender	num_victims	victim_genders	offence_category	offence_subca
0	62	female	1	male	theft	theftFro
1	17	male	1	male	theft	pocke
2	not known	male	1	male	theft	pocke
3	not known	male	1	male	theft	simpleL
4	52	male	1	female	theft	pocke

In [10]:
```
database.dtypes
```

Out[10]:
```
defendant_age          object
defendant_gender       object
num_victims             int64
victim_genders         object
offence_category       object
offence_subcategory    object
dtype: object
```

In [9]:
```
database[database.isnull().any(axis=1)]
# Converting "NaN" to no_gender in victom_genders category:
database = database.fillna({"victim_genders": "no_gender"})
database.head()

# convert all string data in defendant such as not known ,... to Nan and then sul
database['defendant_age'] = pd.to_numeric(database.defendant_age, errors='coerce
database = database.fillna({"defendant_age": 0})
database
```

Out[9]:

	defendant_age	defendant_gender	num_victims	victim_genders	offence_category	offence_su
0	62.0	female	1	male	theft	theft
1	17.0	male	1	male	theft	po
2	0.0	male	1	male	theft	po
3	0.0	male	1	male	theft	sim
4	52.0	male	1	female	theft	po
...	...	...	...	...	...	
5245	0.0	male	1	male	theft	theft
5246	0.0	male	0	no_gender	sexual	
5247	0.0	male	1	male	theft	stealingF
5248	26.0	male	1	male	theft	
5249	16.0	male	1	female	theft	sim

25000 rows × 6 columns

In [10]:
```
# Now that all the data are free of Nan we can convert them to one-hot encoding.
misc_transfered = pd.concat([database.defendant_age, database.num_victims, pd.ge
# for dicision tree i convert all of the featres to one-hot encoding
misc_transfered_all_bin = pd.concat([pd.get_dummies(database.defendant_age), pd.
```

In [13]:

```
misc_transfered
```

Out[13]:

	defendant_age	num_victims	female	indeterminate	male	female	female;female	female;fema
0	62.0	1	1	0	0	0	0	
1	17.0	1	0	0	1	0	0	
2	0.0	1	0	0	1	0	0	
3	0.0	1	0	0	1	0	0	
4	52.0	1	0	0	1	1	0	
...	...	...	...	...	...	...	...	
5245	0.0	1	0	0	1	0	0	
5246	0.0	0	0	0	1	0	0	
5247	0.0	1	0	0	1	0	0	
5248	26.0	1	0	0	1	0	0	
5249	16.0	1	0	0	1	1	0	

25000 rows × 139 columns

In [11]:

```
Train_misc_transfered = misc_transfered.iloc[:train_samples,:]
Test_misc_transfered = misc_transfered.iloc[train_samples:train_samples+test_sam
Eval_misc_transfered = misc_transfered.iloc[train_samples+test_samples:,:]
Train_misc = import_label(Train_data_glove, Train_misc_transfered)
Test_misc = import_label(Test_data_glove, Test_misc_transfered)
Eval_misc = import_label(Eval_data_glove, Eval_misc_transfered)
print(Train_misc.shape)
```

```
(17500, 140)
```

In [12]:

```
def cross_val_ev(f1, f2, f3, f4, f5, max_epoch, learning_rate, perceptron_fcn, ma
    """
    The function calculates the mean accuracy and std based on the 5-fold cross 
    """

    #train_data = pd.DataFrame(columns = f1.columns)
    dataset = []
    acc = []

    for i in range (1,6):
        valid_data = eval("f"+str(i))
        train_name =[]
        val_name = ["f"+str(i)]
        #print(i,val_name)
        #print(valid_data)
        for j in range(1,6):
            if j != i:
                #print(j)
                train_name.append ("f"+str(j))
                dataset.append(eval("f"+str(j)))
        train_data = pd.concat(dataset, ignore_index=True)
        dataset = []
        #print(train_data.shape)
        #print(train_data)
        if perceptron_fcn == 'simple_perceptron':
            w, b, _ = perceptron(train_data, max_epoch, learning_rate)
        elif perceptron_fcn == 'decaying_perceptron':
            w, b, _ = perceptron_decay(train_data, max_epoch, learning_rate)
        elif perceptron_fcn == 'average_perceptron':
            w, b, _ = avg_perceptron(train_data, max_epoch, learning_rate)
        elif perceptron_fcn == 'margin_perceptron':
            w, b, _ = margin_perceptron(train_data, max_epoch, learning_rate, ma

        w = w[-1]
        #print(w)
        b = b [-1]

        #print(train_name)
        acc.append (accuracy (valid_data, w,b))
    #print("accuracy:", acc)
    Std = np.std(acc)
    Mean = np.mean(acc)

    return Mean, Std
```

In [13]:

```
def accuracy (D, w, b):
    """
        This function returns the accuracy of the dataset based on set D and weig
    """
    D = D.to_numpy()
    n_correct_prediction = 0
    n_samples = np.size(D,0)
    label_ix = np.size(D,1)
    for i in range(n_samples):
        sample = D[i,:]
        true_label = sample[-1]
        xi = sample[:-1]
        predicted_label = np.sign (np.dot(xi,w) + b)
        if predicted_label == true_label:
            n_correct_prediction += 1
    acc = n_correct_prediction/n_samples * 100
    return acc
```

In [14]:

```
def prediction (D, w, b):
    """
        This function returns the prediction of the dataset based on set D and we
    """
    D = D.to_numpy()
    n_samples = np.size(D,0)
    label_ix = np.size(D,1)
    pred = []
    for i in range(n_samples):
        sample = D[i,:]
        xi = sample[:-1]
        predicted_label = np.sign (np.dot(xi,w) + b)
        #print(predicted_label[0])
        if predicted_label == -1.0:
            predicted_label = [0.0]
        pred.append([i, predicted_label[0]])

    Pred = pd.DataFrame(pred, columns=['example_id', 'label'])

    return Pred
```

Importing the folded datasets:

Baseline:

In [153]:

```
def frequent_label(D):
    """
    Create common label for set S:
    """
    label_ix = np.size(D,1)
    label = np.unique(D[label_ix])[np.argmax(np.unique(D[label_ix],return_counts

    return label



def baseline_accuracy (D, predicted_label):
    """
        This function returns the baseline accuracy of the dataset for baseline.
    """
    D = D.to_numpy()
    n_correct_prediction = 0
    n_samples = np.size(D,0)
    label_ix = np.size(D,1)
    for i in range(n_samples):
        sample = D[i,:]
        true_label = sample[-1]
        xi = sample[:-1]
        if predicted_label == true_label:
            n_correct_prediction += 1
    acc = n_correct_prediction/n_samples * 100
    return acc
predicted_label = frequent_label(Train_data)

Train_acc = baseline_accuracy (Train_data, predicted_label)
Test_acc = baseline_accuracy (Test_data, predicted_label)


report1 = [{'predicted label':predicted_label, 'Train accuracy(%)':Train_acc,
            'Test accuracy(%)':Test_acc}]

report1 = pd.DataFrame.from_records(report1)
print(report1.to_string(index = False))
```

```
 predicted label  Train accuracy(%)  Test accuracy(%)
            -1.0          50.342857         48.844444
```

Margin Perceptron:

In [15]:

```
def margin_perceptron (D, max_epoch, learning_rate, margin_variable):
    D = D.to_numpy()
    #lr = learning_rate
    u = margin_variable


    w_size = np.size(D,1)-1
    w = -.01 + 0.02 * np.random.rand(w_size)
    ba = 0
    b = -.01 + 0.02 * np.random.rand(1)
    a = 0
    update = 0
    ep_a = []
    ep_ba = []
    ep_update = []
    #ep_w = []
    #ep_b = []
    #ep_update = []
    for epoch in range(1, max_epoch+1):
        lr = learning_rate/epoch
        #1.shuffle the data
        up = 0

        np.random.shuffle(D)
        #2.Update weights:
        for i in range (np.size(D,0)):
            xi = D[i,:-1]
            yi = D[i,-1]
            if yi * (np.dot(xi, w) + b) < u:
                update += 1
                w += lr * yi * xi
                b += lr * yi
            a += w
            ba += b

        #update.append(up)
        #print("w0:", w[0])
        a1 = a
        ba1 = ba
        update1 = update

        #w1 = w
        #b1 = b
        #update1 = update
        #print(b)
        #print(b1)
        ep_a.append(a1.copy())
        ep_ba.append(ba1.copy())
        ep_update.append(update1)
        #print('ep_b:',ep_b)
    #print('update:', update)
    ep_a = np.array(ep_a)
    ep_ba = np.array(ep_ba)
    ep_update = np.array(ep_update)
    return ep_a, ep_ba, ep_update
```

Margin Perceptron over gloves:

In [22]:

```
Data1_gloves = Train_data_glove
cols = Data1_gloves.columns
Data1_gloves = Data1_gloves.to_numpy()
np.random.shuffle(Data1_gloves)
Data1_gloves = pd.DataFrame(Data1_gloves, columns=cols)

f1_gloves = k_fold(Data1_gloves,1)
f2_gloves = k_fold(Data1_gloves,2)
f3_gloves = k_fold(Data1_gloves,3)
f4_gloves = k_fold(Data1_gloves,4)
f5_gloves = k_fold(Data1_gloves,5)
```

In [23]:

```
# Evaluating the network accuracy based on different values for learning rates ar
"""
The cross validation function in previous section is run for different values of
hyper parameter
"""
Learning_rates = [ 0.01, 0.05, 0.001, 0.0001]
margin_variable = [0.2,0.1]

max_epoch = 10
acc_mean = []
acc_std = []
result = []
for lr in Learning_rates:
    for u in margin_variable:
        mean, std = cross_val_ev(f1_gloves, f2_gloves, f3_gloves, f4_gloves, f5_g
        acc_mean.append(mean)
        acc_std.append(std)
        result.append([lr, u, mean, std])
        #print(lr, u)

result = np.array(result)
Best_lr = result[np.argmax(result[:,2]), 0]
Best_u = result[np.argmax(result[:,2]), 1]
best_acc = result[np.argmax(result[:,2]), 2]

print('Cross validation results for different Learning rates and margin variables
result = pd.DataFrame(result, columns=['Learning rate', 'Margin variable', 'accur

pd.set_option('display.max_rows', None)
print(result.to_string(index = False))
print('Best learning rate:', Best_lr)

print('Best margin variable:', Best_u)

report1 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best ac
report1 = pd.DataFrame.from_records(report1)
print(report1.to_string(index = False))
```

```
Cross validation results for different Learning rates and margin variables:
 Learning rate  Margin variable  accuracy mean  accuracy std
        0.0100              0.2      64.466207      0.461541
        0.0100              0.1      64.626233      0.317833
        0.0500              0.2      64.123265      0.376297
        0.0500              0.1      64.340476      0.635709
        0.0010              0.2      64.414794      0.673248
        0.0010              0.1      64.557679      0.594159
        0.0001              0.2      63.660283      0.600437
        0.0001              0.1      64.026148      0.865146
Best learning rate: 0.01
Best margin variable: 0.1
 Best learning rate  Best margin variable  Best accuracy
               0.01                   0.1      64.626233
```

In [24]:

```

max_epoch = 100
w4, b4, ep_update4  = margin_perceptron(Train_data_glove, max_epoch, Best_lr, Be
#print(b)
train_acc = []
train_acc1 =[]
acc = [ 0, 0, 0]
for i in range (max_epoch):
    #print(w[i][0])
    train_acc.append (accuracy (Train_data_glove, w4[i][:],b4[i]))
    acc[0] = i+1
    acc[1] = accuracy (Train_data_glove, w4[i][:],b4[i])
    acc[2] = ep_update4[i]
    train_acc1.append(acc.copy())

#print(train_acc)

train_acc = np.array(train_acc)

best_epoch = np.argmax(train_acc)+1


test_acc =  accuracy (Test_data_glove, w4[best_epoch-1][:],b4[best_epoch-1])

```

In [25]:

```
Epoch = np.arange(1,max_epoch+1)
data2 = pd.DataFrame(train_acc1, columns=['Epoch','Train accuracry', 'number of u
print(data2.to_string(index = False))
train_acc1 = np.array(train_acc1)
plt.plot(train_acc1[:,0], train_acc1[:,1])
plt.xlabel('Epoch')
plt.ylabel('Training accuracy')
```

```
 Epoch  Train accuracry  number of updates
     1        65.468571               8053
     2        65.942857              15771
     3        66.068571              23663
     4        66.005714              31663
     5        66.160000              39889
     6        66.360000              48396
     7        66.491429              57113
     8        66.571429              65876
     9        66.611429              74773
    10        66.760000              83908
    11        66.737143              93210
    12        66.760000             102624
    13        66.725714             112250
    14        66.737143             121885
    15        66.731429             131677
    16        66.714286             141466
    17        66.731429             151545
    18        66.754286             161593
```

In [26]:

```
report4 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best cr
            'Best epoch':best_epoch, 'number of updates':train_acc1[best_epoch-1
            'Train accuracy(%)':train_acc1[best_epoch-1][1],
            'Test accuracy(%)':test_acc}]

report4 = pd.DataFrame.from_records(report4)
print(report4.to_string(index = False))
```

```
 Best learning rate  Best margin variable  Best cross val. acc.(%)  Best epoch
number of updates  Train accuracy(%)  Test accuracy(%)
               0.01                   0.1                64.626233          66
698221.0              66.92         65.111111
```

In [27]:

```
pred4 = prediction (Eval_data_glove,  w4[best_epoch-1][:], b4[best_epoch-1])
pred4.to_csv ('results\Preceptron_result\gloves_labels.csv', index = False, head
```

Margin perceptron with miscalleneous:

In [29]:

```
# generating 5-fold dataset:
Data1 = Train_misc
cols = Data1.columns
Data1 = Data1.to_numpy()
np.random.shuffle(Data1)
Data1 = pd.DataFrame(Data1, columns=cols)
f1_misc = k_fold(Data1,1)
f2_misc = k_fold(Data1,2)
f3_misc = k_fold(Data1,3)
f4_misc = k_fold(Data1,4)
f5_misc = k_fold(Data1,5)
```

In [30]:

```
# Evaluating the network accuracy based on different values for learning rates ar
"""
The cross validation function in previous section is run for different values of
hyper parameter
"""
Learning_rates = [1,0.1, 0.01, 0.001]
margin_variable = [1,0.1, 0.01]

max_epoch = 10
acc_mean = []
acc_std = []
result = []
for lr in Learning_rates:
    for u in margin_variable:
        mean, std = cross_val_ev(f1_misc, f2_misc, f3_misc, f4_misc, f5_misc, ma
        acc_mean.append(mean)
        acc_std.append(std)
        result.append([lr, u, mean, std])
        #print(lr, u)

result = np.array(result)
Best_lr = result[np.argmax(result[:,2]), 0]
Best_u = result[np.argmax(result[:,2]), 1]
best_acc = result[np.argmax(result[:,2]), 2]

print('Cross validation results for different Learning rates and margin variables
result = pd.DataFrame(result, columns=['Learning rate', 'Margin variable', 'accu

pd.set_option('display.max_rows', None)
print(result.to_string(index = False))
print('Best learning rate:', Best_lr)

print('Best margin variable:', Best_u)

report1 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best ac
report1 = pd.DataFrame.from_records(report1)
print(report1.to_string(index = False))
```

```
Cross validation results for different Learning rates and margin variables:
 Learning rate  Margin variable  accuracy mean  accuracy std
         1.000             1.00      78.275050      0.762655
         1.000             0.10      77.612048      0.553744
         1.000             0.01      77.749230      0.703646
         0.100             1.00      78.469388      0.785687
         0.100             0.10      78.200745      0.618433
         0.100             0.01      77.766353      0.715318
         0.010             1.00      78.183590      0.680370
         0.010             0.10      78.457963      0.818276
         0.010             0.01      78.183595      0.631128
         0.001             1.00      77.977837      0.642310
         0.001             0.10      78.177873      0.671491
         0.001             0.01      78.446519      0.728204
Best learning rate: 0.1
Best margin variable: 1.0
```

```
 Best learning rate  Best margin variable  Best accuracy
                0.1                   1.0      78.469388
```

In [36]:

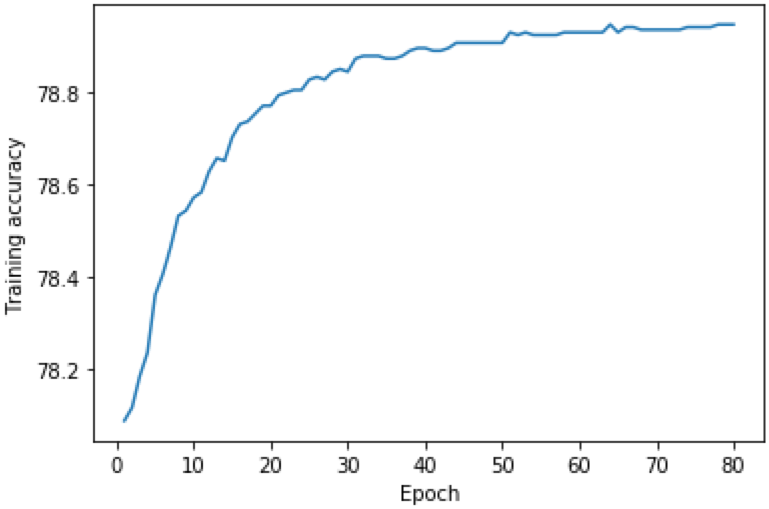
```python

max_epoch = 80
w4, b4, ep_update4  = margin_perceptron(Train_misc, max_epoch, Best_lr, Best_u)
#print(b)
train_acc = []
train_acc1 =[]
acc = [ 0, 0, 0]
for i in range (max_epoch):
    #print(w[i][0])
    train_acc.append (accuracy (Train_misc, w4[i][:],b4[i]))
    acc[0] = i+1
    acc[1] = accuracy (Train_misc, w4[i][:],b4[i])
    acc[2] = ep_update4[i]
    train_acc1.append(acc.copy())

#print(train_acc)

train_acc = np.array(train_acc)

best_epoch = np.argmax(train_acc)+1


test_acc =  accuracy (Test_misc, w4[best_epoch-1][:],b4[best_epoch-1])

```

In [37]:
```
Epoch = np.arange(1,max_epoch+1)
data2 = pd.DataFrame(train_acc1, columns=['Epoch','Train accuracry', 'number of 
print(data2.to_string(index = False))
train_acc1 = np.array(train_acc1)
plt.plot(train_acc1[:,0], train_acc1[:,1])
plt.xlabel('Epoch')
plt.ylabel('Training accuracy')
```

```
 Epoch  Train accuracry  number of updates
     1        78.085714               7402
     2        78.114286              14747
     3        78.182857              22036
     4        78.234286              29357
     5        78.360000              36694
     6        78.405714              44028
     7        78.462857              51314
     8        78.531429              58593
     9        78.542857              65954
    10        78.571429              73252
    11        78.582857              80555
    12        78.628571              87962
    13        78.657143              95373
    14        78.651429             102813
    15        78.702857             110232
    16        78.731429             117736
    17        78.737143             125265
    18        78.754286             132746
    19        78.771429             140302
    20        78.771429             147843
    21        78.794286             155466
    22        78.800000             163025
    23        78.805714             170696
    24        78.805714             178303
    25        78.828571             185999
    26        78.834286             193695
    27        78.828571             201411
    28        78.845714             209142
    29        78.851429             216972
    30        78.845714             224765
    31        78.874286             232570
    32        78.880000             240368
    33        78.880000             248242
    34        78.880000             256082
    35        78.874286             264009
    36        78.874286             272003
    37        78.880000             279926
    38        78.891429             287873
    39        78.897143             295854
    40        78.897143             303796
    41        78.891429             311747
    42        78.891429             319801
    43        78.897143             327843
    44        78.908571             335956
    45        78.908571             344129
    46        78.908571             352290
    47        78.908571             360473
    48        78.908571             368619
```

```
         49        78.908571            376779
         50        78.908571            384981
         51        78.931429            393173
         52        78.925714            401343
         53        78.931429            409552
         54        78.925714            417771
         55        78.925714            425985
         56        78.925714            434234
         57        78.925714            442527
         58        78.931429            450874
         59        78.931429            459161
         60        78.931429            467526
         61        78.931429            475857
         62        78.931429            484251
         63        78.931429            492596
         64        78.948571            500966
         65        78.931429            509365
         66        78.942857            517750
         67        78.942857            526125
         68        78.937143            534556
         69        78.937143            542928
         70        78.937143            551341
         71        78.937143            559794
         72        78.937143            568247
         73        78.937143            576746
         74        78.942857            585234
         75        78.942857            593780
         76        78.942857            602311
         77        78.942857            610834
         78        78.948571            619336
         79        78.948571            627844
         80        78.948571            636359
```

```
Out[37]: Text(0, 0.5, 'Training accuracy')
```



In [38]:
```
report4 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best cı
            'Best epoch':best_epoch, 'number of updates':train_acc1[best_epoch-1
            'Train accuracy(%)':train_acc1[best_epoch-1][1],
            'Test accuracy(%)':test_acc}]

report4 = pd.DataFrame.from_records(report4)
print(report4.to_string(index = False))
```

```
 Best learning rate  Best margin variable  Best cross val. acc.(%)  Best epoch 
number of updates  Train accuracy(%)  Test accuracy(%)
                0.1                   1.0                78.469388          64 
500966.0          78.948571         79.466667
```

In [40]:
```
pred4 = prediction (Eval_misc,  w4[best_epoch-1][:], b4[best_epoch-1])
pred4.to_csv ('results\Preceptron_result\misc_labels.csv', index = False, header:
```

Margin perceptron with bow

In [164]:
```
# generating 5-fold dataset:
Data1 = Train_data_bow
cols = Data1.columns
Data1 = Data1.to_numpy()
np.random.shuffle(Data1)
Data1 = pd.DataFrame(Data1, columns=cols)
f1 = k_fold(Data1,1)
f2 = k_fold(Data1,2)
f3 = k_fold(Data1,3)
f4 = k_fold(Data1,4)
f5 = k_fold(Data1,5)
```

In [165]:

```
# Evaluating the network accuracy based on different values for learning rates ar
"""
The cross validation function in previous section is run for different values of
hyper parameter
"""
Learning_rates = [1,0.1, 0.01, 0.001]
margin_variable = [1,0.1, 0.01]

max_epoch = 10
acc_mean = []
acc_std = []
result = []
for lr in Learning_rates:
    for u in margin_variable:
        mean, std = cross_val_ev(f1, f2, f3, f4, f5, max_epoch, lr, 'margin_perce
        acc_mean.append(mean)
        acc_std.append(std)
        result.append([lr, u, mean, std])
        #print(lr, u)

result = np.array(result)
Best_lr = result[np.argmax(result[:,2]), 0]
Best_u = result[np.argmax(result[:,2]), 1]
best_acc = result[np.argmax(result[:,2]), 2]

print('Cross validation results for different Learning rates and margin variables
result = pd.DataFrame(result, columns=['Learning rate', 'Margin variable', 'accur

pd.set_option('display.max_rows', None)
print(result.to_string(index = False))
print('Best learning rate:', Best_lr)

print('Best margin variable:', Best_u)

report1 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best ac
report1 = pd.DataFrame.from_records(report1)
print(report1.to_string(index = False))
```

```
Cross validation results for different Learning rates and margin variables:
 Learning rate  Margin variable  accuracy mean  accuracy std
         1.000             1.00      68.724277      0.590174
         1.000             0.10      68.227017      0.461414
         1.000             0.01      68.529926      0.805691
         0.100             1.00      69.158649      0.590222
         0.100             0.10      68.604227      0.425621
         0.100             0.01      67.981239      0.337824
         0.010             1.00      70.639012      0.586539
         0.010             0.10      69.181511      0.795419
         0.010             0.01      68.232693      0.483388
         0.001             1.00      70.461843      0.727366
         0.001             0.10      70.330382      0.585036
         0.001             0.01      68.581392      0.224408
Best learning rate: 0.01
Best margin variable: 1.0
```

```
   Best learning rate  Best margin variable  Best accuracy
                 0.01                   1.0      70.639012
```

In [168]:

```
max_epoch = 80
w4, b4, ep_update4  = margin_perceptron(Train_data_bow, max_epoch, Best_lr, Best_
#print(b)
train_acc = []
train_acc1 =[]
acc = [ 0, 0, 0]
for i in range (max_epoch):
    #print(w[i][0])
    train_acc.append (accuracy (Train_data_bow, w4[i][:],b4[i]))
    acc[0] = i+1
    acc[1] = accuracy (Train_data_bow, w4[i][:],b4[i])
    acc[2] = ep_update4[i]
    train_acc1.append(acc.copy())

#print(train_acc)

train_acc = np.array(train_acc)

best_epoch = np.argmax(train_acc)+1


test_acc =  accuracy (Test_data_bow, w4[best_epoch-1][:],b4[best_epoch-1])
```

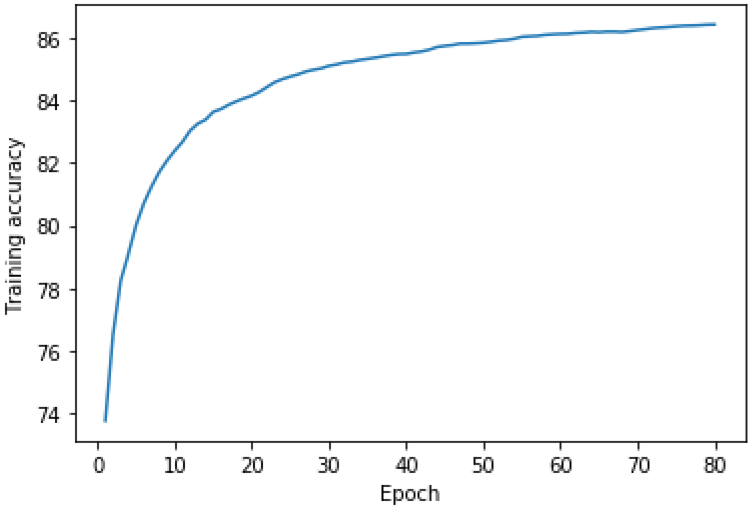
In [169]:

```
Epoch = np.arange(1,max_epoch+1)
data2 = pd.DataFrame(train_acc1, columns=['Epoch','Train accuracry', 'number of
print(data2.to_string(index = False))
train_acc1 = np.array(train_acc1)
plt.plot(train_acc1[:,0], train_acc1[:,1])
plt.xlabel('Epoch')
plt.ylabel('Training accuracy')
```

```
 Epoch  Train accuracry  number of updates
     1        73.754286               9814
     2        76.520000              18113
     3        78.251429              26146
     4        79.097143              34084
     5        80.017143              41855
     6        80.708571              49574
     7        81.245714              57227
     8        81.708571              64853
     9        82.074286              72467
    10        82.388571              79986
    11        82.668571              87452
    12        83.034286              94915
    13        83.257143             102378
    14        83.382857             109833
    15        83.634286             117187
    16        83.725714             124557
    17        83.862857             131931
    18        83.971429             139251
    19        84.068571             146537
    20        84.154286             153818
    21        84.274286             161077
    22        84.434286             168313
    23        84.588571             175537
    24        84.685714             182763
    25        84.765714             189983
    26        84.834286             197197
    27        84.925714             204421
    28        84.982857             211571
    29        85.028571             218756
    30        85.108571             225900
    31        85.154286             233045
    32        85.217143             240176
    33        85.245714             247262
    34        85.297143             254345
    35        85.331429             261441
    36        85.371429             268554
    37        85.417143             275676
    38        85.457143             282764
    39        85.485714             289799
    40        85.491429             296852
    41        85.537143             303907
    42        85.571429             310960
    43        85.628571             317975
    44        85.714286             325021
    45        85.748571             332053
    46        85.777143             339095
    47        85.822857             346078
    48        85.822857             353099
```

```
49          85.834286              360101
50          85.851429              367095
51          85.880000              374115
52          85.920000              381107
53          85.937143              388041
54          85.977143              395000
55          86.040000              401972
56          86.057143              408947
57          86.068571              415861
58          86.102857              422838
59          86.120000              429786
60          86.131429              436718
61          86.137143              443696
62          86.165714              450623
63          86.177143              457515
64          86.200000              464397
65          86.188571              471328
66          86.205714              478262
67          86.205714              485184
68          86.194286              492095
69          86.222857              498964
70          86.257143              505849
71          86.285714              512711
72          86.320000              519619
73          86.337143              526512
74          86.354286              533389
75          86.377143              540232
76          86.394286              547100
77          86.400000              553985
78          86.411429              560852
79          86.428571              567730
80          86.434286              574583
```

```
Out[169]: Text(0, 0.5, 'Training accuracy')
```



In [170]:

```
report4 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best c
            'Best epoch':best_epoch, 'number of updates':train_acc1[best_epoch-1
            'Train accuracy(%)':train_acc1[best_epoch-1][1],
            'Test accuracy(%)':test_acc}]

report4 = pd.DataFrame.from_records(report4)
print(report4.to_string(index = False))
```

```
 Best learning rate  Best margin variable  Best cross val. acc.(%)  Best epoch
number of updates  Train accuracy(%)  Test accuracy(%)
               0.01                   1.0                70.639012          80
574583.0          86.434286         71.244444
```

In [176]:

```
pred4 = prediction (Eval_data_bow,  w4[best_epoch-1][:], b4[best_epoch-1])
pred4.to_csv ('bow_labels.csv', index = False, header=True)
```

Margin perceptron with tfidf

In [19]:

```
# generating 5-fold dataset:
Data1 = Train_data_tfidf
cols = Data1.columns
Data1 = Data1.to_numpy()
np.random.shuffle(Data1)
Data1 = pd.DataFrame(Data1, columns=cols)
f1 = k_fold(Data1,1)
f2 = k_fold(Data1,2)
f3 = k_fold(Data1,3)
f4 = k_fold(Data1,4)
f5 = k_fold(Data1,5)
```

In [20]:

```
# Evaluating the network accuracy based on different values for learning rates an
"""
The cross validation function in previous section is run for different values of
hyper parameter
"""
Learning_rates = [1,0.1, 0.01, 0.001]
margin_variable = [1,0.1, 0.01]

max_epoch = 10
acc_mean = []
acc_std = []
result = []
for lr in Learning_rates:
    for u in margin_variable:
        mean, std = cross_val_ev(f1, f2, f3, f4, f5, max_epoch, lr, 'margin_perce
        acc_mean.append(mean)
        acc_std.append(std)
        result.append([lr, u, mean, std])
        #print(lr, u)

result = np.array(result)
Best_lr = result[np.argmax(result[:,2]), 0]
Best_u = result[np.argmax(result[:,2]), 1]
best_acc = result[np.argmax(result[:,2]), 2]

print('Cross validation results for different Learning rates and margin variables
result = pd.DataFrame(result, columns=['Learning rate', 'Margin variable', 'accur

pd.set_option('display.max_rows', None)
print(result.to_string(index = False))
print('Best learning rate:', Best_lr)

print('Best margin variable:', Best_u)

report1 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best ac
report1 = pd.DataFrame.from_records(report1)
print(report1.to_string(index = False))
```

```
Cross validation results for different Learning rates and margin variables:
 Learning rate  Margin variable  accuracy mean  accuracy std
         1.000             1.00      71.284890      0.443860
         1.000             0.10      70.147487      0.374806
         1.000             0.01      69.936036      0.502691
         0.100             1.00      71.867907      0.636873
         0.100             0.10      71.599239      0.264732
         0.100             0.01      69.838847      0.371118
         0.010             1.00      67.844184      1.132475
         0.010             0.10      71.930798      0.784060
         0.010             0.01      70.953412      0.522366
         0.001             1.00      52.679993      5.426802
         0.001             0.10      68.044222      1.294163
         0.001             0.01      69.758850      0.635772
Best learning rate: 0.01
Best margin variable: 0.1
```

```
 Best learning rate  Best margin variable  Best accuracy
               0.01                   0.1      71.930798
```

In [21]:

```
max_epoch = 80
w4, b4, ep_update4  = margin_perceptron(Train_data_tfidf, max_epoch, Best_lr, Be
#print(b)
train_acc = []
train_acc1 =[]
acc = [ 0, 0, 0]
for i in range (max_epoch):
    #print(w[i][0])
    train_acc.append (accuracy (Train_data_tfidf, w4[i][:],b4[i]))
    acc[0] = i+1
    acc[1] = accuracy (Train_data_tfidf, w4[i][:],b4[i])
    acc[2] = ep_update4[i]
    train_acc1.append(acc.copy())

#print(train_acc)

train_acc = np.array(train_acc)

best_epoch = np.argmax(train_acc)+1


test_acc =  accuracy (Test_data_tfidf, w4[best_epoch-1][:],b4[best_epoch-1])
```

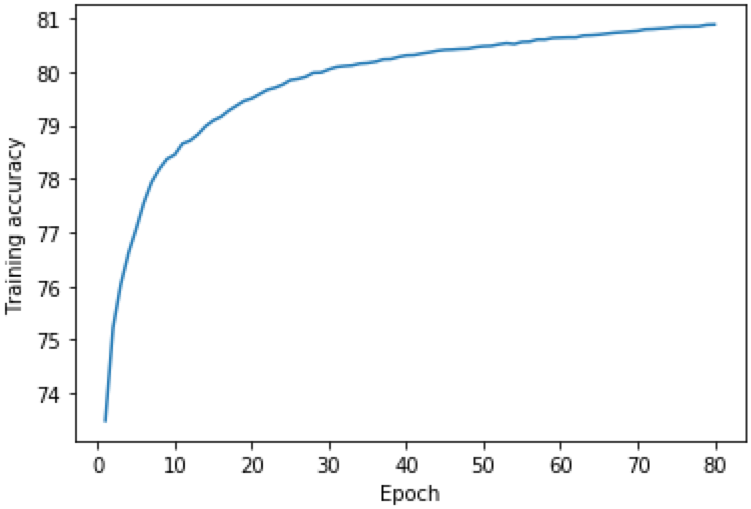
In [22]:

```
Epoch = np.arange(1,max_epoch+1)
data2 = pd.DataFrame(train_acc1, columns=['Epoch','Train accuracry', 'number of 
print(data2.to_string(index = False))
train_acc1 = np.array(train_acc1)
plt.plot(train_acc1[:,0], train_acc1[:,1])
plt.xlabel('Epoch')
plt.ylabel('Training accuracy')
```

```
 Epoch  Train accuracry  number of updates
     1        73.485714              14450
     2        75.222857              26805
     3        76.034286              38674
     4        76.611429              50224
     5        77.062857              61554
     6        77.554286              72823
     7        77.937143              83974
     8        78.182857              94996
     9        78.371429             105986
    10        78.451429             116906
    11        78.657143             127773
    12        78.714286             138604
    13        78.828571             149383
    14        78.982857             160107
    15        79.091429             170779
    16        79.160000             181418
    17        79.274286             192057
    18        79.365714             202657
    19        79.457143             213214
    20        79.502857             223767
    21        79.582857             234291
    22        79.662857             244789
    23        79.702857             255269
    24        79.760000             265735
    25        79.845714             276188
    26        79.868571             286615
    27        79.908571             297053
    28        79.982857             307450
    29        79.988571             317836
    30        80.045714             328193
    31        80.091429             338555
    32        80.108571             348915
    33        80.120000             359240
    34        80.154286             369575
    35        80.165714             379867
    36        80.188571             390173
    37        80.234286             400468
    38        80.240000             410730
    39        80.280000             420984
    40        80.308571             431252
    41        80.314286             441502
    42        80.342857             451738
    43        80.365714             461970
    44        80.394286             472198
    45        80.411429             482410
    46        80.417143             492604
    47        80.428571             502797
    48        80.434286             512969
```

```
49        80.462857           523122
50        80.480000           533290
51        80.485714           543455
52        80.514286           553601
53        80.537143           563743
54        80.520000           573887
55        80.560000           583999
56        80.565714           594102
57        80.605714           604214
58        80.605714           614326
59        80.634286           624394
60        80.640000           634470
61        80.645714           644550
62        80.645714           654600
63        80.680000           664659
64        80.685714           674744
65        80.697143           684801
66        80.714286           694832
67        80.731429           704859
68        80.742857           714885
69        80.754286           724925
70        80.765714           734961
71        80.794286           744998
72        80.800000           755015
73        80.811429           765035
74        80.822857           775039
75        80.840000           785034
76        80.845714           795022
77        80.845714           805024
78        80.851429           815006
79        80.880000           824961
80        80.885714           834932
```

```
Out[22]: Text(0, 0.5, 'Training accuracy')
```



In [23]:

```
report4 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best c
            'Best epoch':best_epoch, 'number of updates':train_acc1[best_epoch-1
            'Train accuracy(%)':train_acc1[best_epoch-1][1],
            'Test accuracy(%)':test_acc}]

report4 = pd.DataFrame.from_records(report4)
print(report4.to_string(index = False))
```

```
 Best learning rate  Best margin variable  Best cross val. acc.(%)  Best epoch
number of updates  Train accuracy(%)  Test accuracy(%)
               0.01                   0.1                71.930798          80
834932.0          80.885714         72.844444
```

In [26]:

```
pred4 = prediction (Eval_data_tfidf,  w4[best_epoch-1][:], b4[best_epoch-1])
pred4.to_csv ('tfidf_labels.csv', index = False, header=True)
```

Margin perceptron with miscalleneous+tfidf:

In [16]:

```
Train_data = concat_datasets(Train_misc, Train_data_tfidf)
Test_data = concat_datasets(Test_misc, Test_data_tfidf)
Eval_data = concat_datasets(Eval_misc, Eval_data_tfidf)
```

In [17]:

```
# generating 5-fold dataset:
Data1 = Train_data
cols = Data1.columns
Data1 = Data1.to_numpy()
np.random.shuffle(Data1)
Data1 = pd.DataFrame(Data1, columns=cols)
f1_misc = k_fold(Data1,1)
f2_misc = k_fold(Data1,2)
f3_misc = k_fold(Data1,3)
f4_misc = k_fold(Data1,4)
f5_misc = k_fold(Data1,5)
```

In [18]:

```
# Evaluating the network accuracy based on different values for learning rates ar
"""
The cross validation function in previous section is run for different values of
hyper parameter
"""
Learning_rates = [1,0.1, 0.01, 0.001]
margin_variable = [1,0.5, 0.1]

max_epoch = 10
acc_mean = []
acc_std = []
result = []
for lr in Learning_rates:
    for u in margin_variable:
        mean, std = cross_val_ev(f1_misc, f2_misc, f3_misc, f4_misc, f5_misc, ma
        acc_mean.append(mean)
        acc_std.append(std)
        result.append([lr, u, mean, std])
        #print(lr, u)

result = np.array(result)
Best_lr = result[np.argmax(result[:,2]), 0]
Best_u = result[np.argmax(result[:,2]), 1]
best_acc = result[np.argmax(result[:,2]), 2]

print('Cross validation results for different Learning rates and margin variables
result = pd.DataFrame(result, columns=['Learning rate', 'Margin variable', 'accu

pd.set_option('display.max_rows', None)
print(result.to_string(index = False))
print('Best learning rate:', Best_lr)

print('Best margin variable:', Best_u)

report1 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best ac
report1 = pd.DataFrame.from_records(report1)
print(report1.to_string(index = False))
```

```
Cross validation results for different Learning rates and margin variables:
 Learning rate  Margin variable  accuracy mean  accuracy std
         1.000              1.0      79.743953      0.376533
         1.000              0.5      79.195274      0.538384
         1.000              0.1      78.892333      0.590322
         0.100              1.0      80.921352      0.657139
         0.100              0.5      80.978528      0.655068
         0.100              0.1      79.789682      0.570851
         0.010              1.0      78.263636      0.748778
         0.010              0.5      78.640866      0.841444
         0.010              0.1      80.864196      0.594491
         0.001              1.0      77.989288      0.695541
         0.001              0.5      78.040728      0.735774
         0.001              0.1      78.303649      0.784628
Best learning rate: 0.1
Best margin variable: 0.5
```

```
 Best learning rate  Best margin variable  Best accuracy
                0.1                   0.5      80.978528
```

In [19]:

```
max_epoch = 100
w4, b4, ep_update4  = margin_perceptron(Train_data, max_epoch, Best_lr, Best_u)
#print(b)
train_acc = []
train_acc1 =[]
acc = [ 0, 0, 0]
for i in range (max_epoch):
    #print(w[i][0])
    train_acc.append (accuracy (Train_data, w4[i][:],b4[i]))
    acc[0] = i+1
    acc[1] = accuracy (Train_data, w4[i][:],b4[i])
    acc[2] = ep_update4[i]
    train_acc1.append(acc.copy())

#print(train_acc)

train_acc = np.array(train_acc)

best_epoch = np.argmax(train_acc)+1


test_acc =  accuracy (Test_data, w4[best_epoch-1][:],b4[best_epoch-1])

```

In [20]:

```
Epoch = np.arange(1,max_epoch+1)
data2 = pd.DataFrame(train_acc1, columns=['Epoch','Train accuracry', 'number of
print(data2.to_string(index = False))
train_acc1 = np.array(train_acc1)
plt.plot(train_acc1[:,0], train_acc1[:,1])
plt.xlabel('Epoch')
plt.ylabel('Training accuracy')
```

```
 Epoch  Train accuracry  number of updates
     1        79.634286               6662
     2        81.240000              13047
     3        81.851429              19153
     4        82.354286              25161
     5        82.857143              31044
     6        83.274286              36877
     7        83.451429              42566
     8        83.628571              48269
     9        83.720000              53951
    10        83.885714              59543
    11        84.028571              65185
    12        84.102857              70743
    13        84.194286              76290
    14        84.245714              81831
    15        84.354286              87378
    16        84.400000              92893
    17        84.520000              98424
    18        84.588571             103913
```

In [21]:
```
report4 = [{'Best learning rate':Best_lr, 'Best margin variable':Best_u, 'Best c
            'Best epoch':best_epoch, 'number of updates':train_acc1[best_epoch-1
            'Train accuracy(%)':train_acc1[best_epoch-1][1],
            'Test accuracy(%)':test_acc}]

report4 = pd.DataFrame.from_records(report4)
print(report4.to_string(index = False))
```

```
 Best learning rate  Best margin variable  Best cross val. acc.(%)  Best epoch
number of updates  Train accuracy(%)  Test accuracy(%)
                0.1                   0.5                80.978528          99
541186.0          86.817143         82.355556
```

In [22]:
```
pred4 = prediction (Eval_data,  w4[best_epoch-1][:], b4[best_epoch-1])
pred4.to_csv ('misc_tfidf_labels.csv', index = False, header=True)
```