Logistic Regression with Sigmoid

Reference

[1] Machine Learning by Andrew Ng (https://www.coursera.org/learn/machine-learning (https://www.coursera.org/learn/machine-learning))

In [63]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call
drive.mount("/content/drive", force_remount=True).
```

In [64]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [65]:
```
data = pd.read_csv('/content/drive/My Drive/Competition/train.csv')
```

In [66]:
```
len_data = data.shape[0]
len_data
```

Out[66]:
```
47760
```

In [67]:
```
y_all_train = data.iloc[:, -1]
y_all_train
```

Out[67]:
```
0        0
1        1
2        0
3        0
4        0
        ..
47755    2
47756    2
47757    0
47758    0
47759    0
Name: LABELS, Length: 47760, dtype: int64
```

In [68]:
```
y_all_train.shape
```

Out[68]:
```
(47760,)
```

In [69]:
```
def label_percentages(labels):
  n0 = 0
  n1 = 0
  n2 = 0
  total = labels.shape[0]
  for label in labels:
    if label == 0:
      n0 += 1
    elif label == 1:
      n1 += 1
    elif label == 2:
      n2 += 1

  return (n0, n1, n2), (n0/total, n1/total, n2/total)
```

In [70]:
```
label_percentages(y_all_train)
```

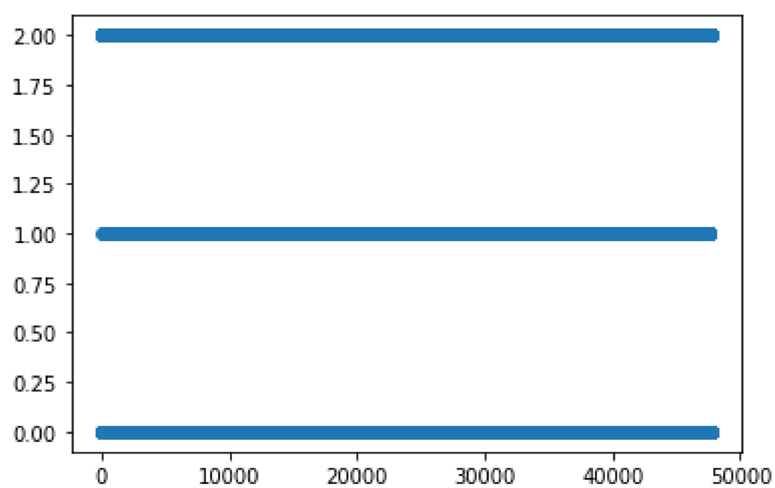
Out[70]:
```
((37535, 2002, 8223),
 (0.7859087102177554, 0.04191792294807370, 0.17217336683417087))
```

In [71]:
```
# distribution of labels
labels = y_all_train.copy().to_numpy()
labels.shape
```

Out[71]:
```
(47760,)
```

In [72]:
```
plt.scatter([i for i in range(labels.shape[0])], labels)
```

Out[72]:
```
<matplotlib.collections.PathCollection at 0x7fb4404cb890>
```



In [73]:
```
test = pd.read_csv('/content/drive/My Drive/Competition/test.csv')
```

In [74]:
```
all_features = pd.concat([data.iloc[:, :-1], test]).reset_index(drop=True)
```

In [75]:
```
all_features
```

Out[75]:

	S.No	lat	lon	TMQ	U850	V850	UBOT	VBOT	QRE
0	0	-24.758801	242.1875	16.019615	-4.391696	4.777769	-6.388222	7.725320	0.01(
1	1	23.820078	277.8125	47.802036	8.623652	9.308566	4.596105	9.938286	0.01ξ
2	2	23.820078	276.8750	11.556691	-2.483993	-6.009627	-3.503036	-5.921963	0.007
3	3	13.494133	253.1250	53.186630	0.150933	-1.319407	3.757741	-2.172120	0.01ξ
4	4	-24.524120	241.2500	23.353998	-7.467506	-5.113565	-9.545109	-4.691221	0.01
...	...	...	...	...	...	...	...	...	
55075	7315	24.054759	276.5625	51.415295	-1.095974	-8.194263	2.484773	-10.520496	0.02(
55076	7316	24.054759	276.8750	52.377407	-0.265653	-8.730537	3.783044	-10.748092	0.02
55077	7317	24.054759	277.1875	54.639217	0.775797	-9.646189	5.087689	-10.786784	0.02
55078	7318	24.054759	277.5000	56.121231	1.813888	-10.849813	6.442380	-10.859090	0.02
55079	7319	24.054759	277.8125	56.888420	2.819084	-12.172881	7.671317	-10.641853	0.022

55080 rows × 20 columns

Preprocessing data

(1) Remove non-significant features

(2) Standarlise data

(3) Add bias term

(4) Split train and test

In [ ]:
```
def preprocessing(features):
  X = features.copy()
  X = X.iloc[:, 1:19]
  X = X.drop(columns="PS")
  X.insert(0, 'bias', 1)
  X_means = np.mean(X)
  X_std = np.std(X)
  X_scale = (X - X_means) / X_std
  X_scale.iloc[:, 0] = np.ones((X_scale.shape[0], 1))
  return X_scale
```

In [ ]:
```
features_scale = preprocessing(all_features)
features_scale
```

Out[ ]:

	bias	lat	lon	TMQ	U850	V850	UBOT	VBOT	QREFH
0	1.0	-0.952799	-0.659826	-1.456660	-0.544970	1.082394	-0.689690	1.750971	-1.01902
1	1.0	1.167947	0.208099	0.980482	1.330311	2.126323	1.095283	2.212530	1.02801
2	1.0	1.167947	0.185259	-1.798887	-0.270104	-1.403102	-0.220842	-1.095445	-1.71571
3	1.0	0.717160	-0.393358	1.393384	0.109542	-0.322441	0.959048	-0.313340	1.09709
4	1.0	-0.942553	-0.682666	-0.894244	-0.988140	-1.196643	-1.202690	-0.838749	-0.67312
...	...	...	...	...	...	...	...	...	.
55075	1.0	1.178192	0.177646	1.257555	-0.070115	-1.906459	0.752188	-2.054562	1.62259
55076	1.0	1.178192	0.185259	1.331331	0.049520	-2.030020	0.963159	-2.102031	1.73687
55077	1.0	1.178192	0.192872	1.504772	0.199574	-2.240993	1.175167	-2.110102	1.82509
55078	1.0	1.178192	0.200486	1.618416	0.349145	-2.518317	1.395306	-2.125182	1.84868
55079	1.0	1.178192	0.208099	1.677245	0.493976	-2.823162	1.595011	-2.079873	1.94768

55080 rows × 18 columns

In [ ]:
```
# separate data and test data
train_data = features_scale.iloc[0:len_data, :]
test_data = features_scale.iloc[len_data:features_scale.shape[0], :]
train_data.shape, test_data.shape
```

Out[ ]: ((47760, 18), (7320, 18))

In [ ]:
```
train_data
```

Out[ ]:

	bias	lat	lon	TMQ	U850	V850	UBOT	VBOT	QREFH
0	1.0	-0.952799	-0.659826	-1.456660	-0.544970	1.082394	-0.689690	1.750971	-1.01902
1	1.0	1.167947	0.208099	0.980482	1.330311	2.126323	1.095283	2.212530	1.02801
2	1.0	1.167947	0.185259	-1.798887	-0.270104	-1.403102	-0.220842	-1.095445	-1.71571
3	1.0	0.717160	-0.393358	1.393384	0.109542	-0.322441	0.959048	-0.313340	1.09709
4	1.0	-0.942553	-0.682666	-0.894244	-0.988140	-1.196643	-1.202690	-0.838749	-0.67312
...	...	...	...	...	...	...	...	...	.
47755	1.0	-1.208927	2.050537	-1.559338	0.542162	0.960851	0.282271	0.865639	-1.50132
47756	1.0	-0.963044	-0.659826	-0.419844	1.410663	-0.103645	1.506244	-1.000442	-0.18382
47757	1.0	-1.208927	2.050537	-1.075436	1.198620	-1.466387	0.950071	-1.395281	-0.95668
47758	1.0	1.157701	0.177646	0.818513	-0.347110	0.046155	-0.779050	0.281748	1.55431
47759	1.0	1.178192	0.185259	1.114539	-0.284359	-0.212958	-0.678358	-0.274555	0.78549

47760 rows × 18 columns

In [ ]:
```
test_data
```

Out[ ]:

	bias	lat	lon	TMQ	U850	V850	UBOT	VBOT	QREFHT
47760	1.0	-1.229417	2.042923	-0.969527	-0.199640	-0.019019	-0.908190	-0.249263	-1.53332
47761	1.0	-1.229417	2.050537	-1.033650	-0.208858	0.073115	-1.022537	-0.056414	-1.61189
47762	1.0	-1.229417	2.058150	-1.115755	-0.218882	0.146943	-1.088501	0.171496	-1.65935
47763	1.0	-1.229417	2.065764	-1.153955	-0.218557	0.240390	-1.077335	0.400787	-1.70300
47764	1.0	-1.229417	2.073377	-1.182211	-0.208022	0.401727	-1.028380	0.603821	-1.75904
...	...	...	...	...	...	...	...	...	..
55075	1.0	1.178192	0.177646	1.257555	-0.070115	-1.906459	0.752188	-2.054562	1.62259
55076	1.0	1.178192	0.185259	1.331331	0.049520	-2.030020	0.963159	-2.102031	1.73687
55077	1.0	1.178192	0.192872	1.504772	0.199574	-2.240993	1.175167	-2.110102	1.82509
55078	1.0	1.178192	0.200486	1.618416	0.349145	-2.518317	1.395306	-2.125182	1.84868
55079	1.0	1.178192	0.208099	1.677245	0.493976	-2.823162	1.595011	-2.079873	1.94768

7320 rows × 18 columns

Logistic Regression Model

$$g(z) = \frac{1}{1 + e^{-z}}$$

In [ ]:
```
def sigmoid(z):
  return 1.0/(1 + np.exp(-z))
```

$$h_\theta(x) = g(\theta^T x),$$

$$X\theta = \begin{bmatrix} -(x^{(1)})^T\theta - \\ -(x^{(2)})^T\theta - \\ \vdots \\ -(x^{(m)})^T\theta - \end{bmatrix} = \begin{bmatrix} -\theta^T(x^{(1)}) - \\ -\theta^T(x^{(2)}) - \\ \vdots \\ -\theta^T(x^{(m)}) - \end{bmatrix}$$

Cost function

$$J(\theta) = \frac{1}{m}\sum_{i=1}^{m} \left[-y^{(i)} \log(h_\theta(x^{(i)})) - (1 - y^{(i)}) \log(1 - h_\theta(x^{(i)}))\right] + \frac{\lambda}{2m}\sum_{j=1}^{n} \theta_j^2,$$

Note that you should not regularize the parameter θ_0.

In [ ]:
```
def cost(X, y, theta, lambda_):
  # m: number of examples
  # n: number of features with bias term

  # X: (m, n), y (one col of y_onehot): (m, 1),
  # theta: (n, 1)
  m = X.shape[0]
  n = X.shape[1]

  h = sigmoid(np.dot(X, theta))
  # h: (m, nb_classes)

  log_h = np.log(h)  # (m, 1)
  log_one_minusH = np.log(1 - h) # (m, 1)

  yT = np.transpose(y)  # (1, m)
  one_minus_yT = np.transpose(1 - y)  # (1, m)

  sum_ = np.dot(-yT, log_h) - np.dot(one_minus_yT, log_one_minusH)
  # (1, m) * (m, 1) - (1, m) * (m, 1)

  theta_without_bias = theta[1:n]
  reg = (lambda_ / (2*m)) * np.sum(theta_without_bias ** 2)

  return sum_/ m + reg
```

Gradient

$$\frac{\partial J(\theta)}{\partial \theta_j} = \frac{1}{m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)x_j^{(i)} \qquad \text{for } j = 0,$$

$$\frac{\partial J(\theta)}{\partial \theta_j} = \left(\frac{1}{m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)x_j^{(i)}\right) + \frac{\lambda}{m}\theta_j \qquad \text{for } j \geq 1,$$

To vectorize this operation over the dataset, we start by writing out all the partial derivatives explicitly for all θ_j,

$$\begin{bmatrix} \frac{\partial J(\theta)}{\partial \theta_0} \\ \frac{\partial J(\theta)}{\partial \theta_1} \\ \frac{\partial J(\theta)}{\partial \theta_2} \\ \vdots \\ \frac{\partial J(\theta)}{\partial \theta_n} \end{bmatrix} = \frac{1}{m}\begin{bmatrix} \sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)x_0^{(i)} \\ \sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)x_1^{(i)} \\ \sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)x_2^{(i)} \\ \vdots \\ \sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)x_n^{(i)} \end{bmatrix} = \frac{1}{m}\sum_{i=1}^{m}\left(h_\theta(x^{(i)}) - y^{(i)}\right)x^{(i)} = \frac{1}{m}X^T(h_\theta(x) - y) \qquad (1)$$

In [ ]:
```
def gradient(X, y, theta, lambda_):
  m = X.shape[0]
  n = X.shape[1]
  h = sigmoid(np.dot(X, theta))

  sum_ = np.transpose(X).dot(h - y)  # (n, m) * (m, 1)
  gradient = sum_ / m

  theta_without_bias = theta[1:n]
  reg = lambda_ / m * theta_without_bias

  gradient[1:n] = gradient[1:n] + reg
  return gradient
```

In [ ]:
```
def gradient_descent(X, y, theta, lambda_, eps, alpha, max_iter): # alpha is l
earning rate
  losses = []
  i = 0
  print("Iteration: Cost")

  while(i < max_iter):
    i += 1
    grad = gradient(X, y, theta, lambda_)
    theta -= alpha * grad
    loss = cost(X, y, theta, lambda_)
    if (i % 1000 == 0):
      print("{}: {:.8f}".format(i, loss))

    len_losses = len(losses)
    if (len_losses == 0):
      diff = np.abs(loss)
    else :
      diff = np.abs(losses[len_losses-1] - loss)

    losses.append(loss)
    if(diff < eps):
      return theta, losses

  return theta, losses
```

Training Model

In [ ]:
```
y_all_train.shape
```

Out[ ]:
```
(47760,)
```

In [ ]:
```
def split_train_test(X, y, training_size, val_size):
    m = X.shape[0]
    nb_train = int(m * training_size)
    X_train = X.iloc[0:nb_train, :]
    y_train = y[0:nb_train]

    nb_val = int(m * val_size)

    val_index = nb_train + nb_val
    X_val = X.iloc[nb_train: val_index, :]
    y_val = y[nb_train: val_index]

    X_test = X.iloc[val_index: m, :]
    y_test = y[val_index: m]
    return X_train, y_train, X_val, y_val, X_test, y_test
```

In [ ]:
```
X_train, y_train, X_val, y_val, X_test, y_test = split_train_test(train_data,
y_all_train, 0.7, 0.15)
```

In [ ]:
```
X_train.shape, y_train.shape, X_val.shape, y_val.shape, X_test.shape, y_test.s
hape
```

Out[ ]:
```
((33432, 18), (33432,), (7164, 18), (7164,), (7164, 18), (7164,))
```

In [ ]:
```
def onehot_y(labels, classes):
    size = labels.shape[0]
    result = np.zeros((size, classes))
    for i in range(size):
        cl = int(labels[i])
        result[i][cl] = 1
    return result
```

In [ ]:
```
y_label = pd.Series.to_numpy(y_train.copy())
```

In [ ]:
```
y_onehot = onehot_y(y_label, 3)
y_onehot
```

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

In [ ]:
```
y_onehot.shape
```

Out[ ]:
```
(33432, 3)
```

In [ ]:
```
X_train_array = X_train.copy().to_numpy()
X_train_array
```

Out[ ]:
```
array([[ 1.        , -0.95279851, -0.65982622, ...,  1.42921582,
        -0.4285615 , -0.9506135 ],
       [ 1.        ,  1.16794656,  0.20809904, ..., -1.47779616,
         1.27702377,  1.39059963],
       [ 1.        ,  1.16794656,  0.1852589 , ...,  0.56987529,
        -1.43640373, -1.10560504],
       ...,
       [ 1.        ,  1.16794656,  0.20048566, ..., -0.34950255,
         0.18667299,  0.62839043],
       [ 1.        , -0.93230821, -0.67505298, ...,  1.42888277,
        -2.08529432, -1.45474775],
       [ 1.        ,  1.08598539, -0.60653257, ..., -0.99833767,
         0.85495341,  0.07425633]])
```

In [ ]:
```
# y_train: onehot of y
# lambda_: hyperparameter for regularization (or penalty)
# alpha: learning rate
# theta0: dim is (n, nb_classes) n is number of features including bias term
# return theta
# X, y, theta, lambda_, eps, alpha, max_iter, batch_size for sgd

def train(X_train, y_train, theta0, lambda_, eps, alpha, max_iter, nb_classes
):
  n = X_train.shape[1]  # number of features including bias term
  theta = np.zeros((n, 3))
  loss_dict = {}
  for i in range(nb_classes):
    print("Cost for {}th column of theta".format(i))
    losses = []
    theta[:, i], losses = gradient_descent(X_train,
                                           y_train[:, i],
                                           theta0[:, i],
                                           lambda_,
                                           eps,
                                           alpha,
                                           max_iter)
    loss_dict[i] = losses
  return theta, loss_dict
```

Hyperparameter Tuning

In [ ]:
```
def calculate_accuracy(X_test, y_test, theta):
  X_test_array = X_test.to_numpy()
  mat = X_test_array.dot(theta)
  y_pred = np.argmax(mat, axis=1)
  y_test_array = y_test.to_numpy()
  accuracy_rate = np.sum(y_test_array == y_pred) / y_test_array.shape[0]
  return accuracy_rate
```

In [ ]:
```python
def hyperparameter_tuning(lambda_list, X_train, y_onehot, X_test, y_test, eps,
alpha, max_iter, nb_classes):
  n = X_train.shape[1]
  all_theta = {}
  all_losses = {}
  print("Hyperparameter tuning: Lambda")
  for each_lambda in lambda_list:
    theta0 = np.zeros((n, nb_classes))
    print(each_lambda)
    theta, loss_dict = train(X_train, y_onehot, theta0, each_lambda, eps, alph
a, max_iter, nb_classes)
    all_theta[each_lambda] = theta
    all_losses[each_lambda] = loss_dict
    accuracy = calculate_accuracy(X_test, y_test, theta)
    print("accuracy for lambda = {}: {:.8f}".format(each_lambda, accuracy))
    print("--------------------------------------------------")

  return all_theta, all_losses
```

In [ ]:
```python
X_test.shape, y_test.shape
```

Out[ ]:
```
((7164, 18), (7164,))
```

Prediction

In [ ]:
```python
test_data
```

Out[ ]:

	bias	lat	lon	TMQ	U850	V850	UBOT	VBOT	QREFHT
47760	1.0	-1.229417	2.042923	-0.969527	-0.199640	-0.019019	-0.908190	-0.249263	-1.53332
47761	1.0	-1.229417	2.050537	-1.033650	-0.208858	0.073115	-1.022537	-0.056414	-1.61189
47762	1.0	-1.229417	2.058150	-1.115755	-0.218882	0.146943	-1.088501	0.171496	-1.65935
47763	1.0	-1.229417	2.065764	-1.153955	-0.218557	0.240390	-1.077335	0.400787	-1.70300
47764	1.0	-1.229417	2.073377	-1.182211	-0.208022	0.401727	-1.028380	0.603821	-1.75904
...	...	...	...	...	...	...	...	...	..
55075	1.0	1.178192	0.177646	1.257555	-0.070115	-1.906459	0.752188	-2.054562	1.62259
55076	1.0	1.178192	0.185259	1.331331	0.049520	-2.030020	0.963159	-2.102031	1.73687
55077	1.0	1.178192	0.192872	1.504772	0.199574	-2.240993	1.175167	-2.110102	1.82509
55078	1.0	1.178192	0.200486	1.618416	0.349145	-2.518317	1.395306	-2.125182	1.84868
55079	1.0	1.178192	0.208099	1.677245	0.493976	-2.823162	1.595011	-2.079873	1.94768

7320 rows × 18 columns

In [ ]:
```
def plot_loss(losses):
  plt.figure(figsize=(8, 6))
  for i in range(3):
    plt.plot([i for i in range(len(losses[i]))], losses[i])
  plt.show()
```

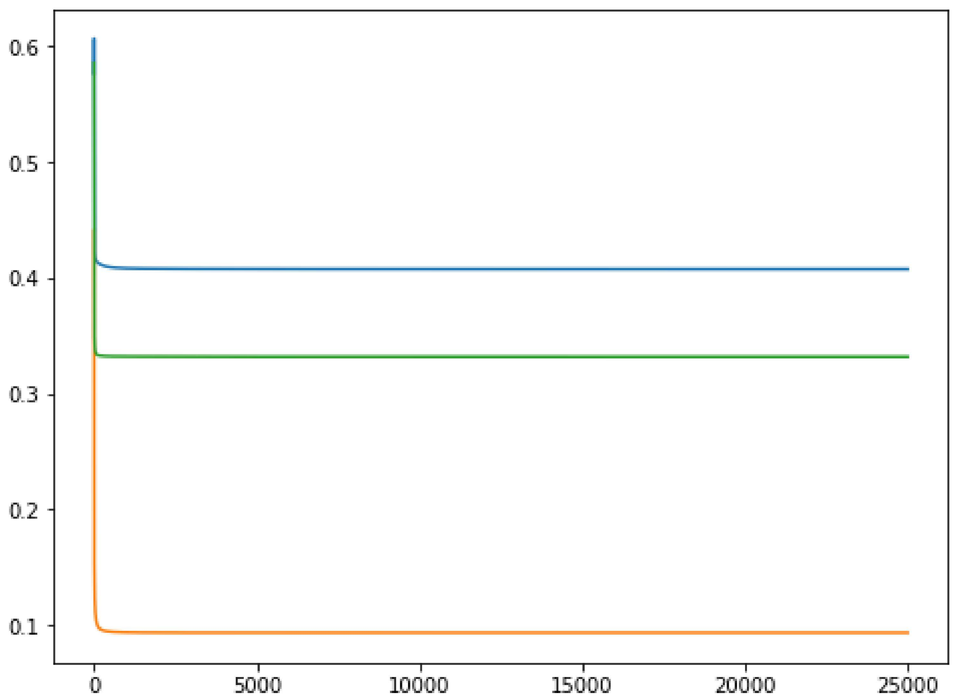
In [ ]:
```
n = test_data.shape[1]
nb_classes = 3
theta0 = np.zeros((n, nb_classes))

lambda_ = 3.5
eps = 10^-6
alpha = 1.5
max_iter = 25000
final_theta, loss_dict_final = train(X_train, y_onehot, theta0, lambda_, eps,
alpha, max_iter, nb_classes)
```

```
Cost for 0th column of theta
Iteration: Cost
1000: 0.40827548
2000: 0.40789532
3000: 0.40777280
4000: 0.40769939
5000: 0.40765096
6000: 0.40761863
7000: 0.40759702
8000: 0.40758257
9000: 0.40757292
10000: 0.40756646
11000: 0.40756215
12000: 0.40755927
13000: 0.40755734
14000: 0.40755605
15000: 0.40755519
16000: 0.40755461
17000: 0.40755423
18000: 0.40755397
19000: 0.40755380
20000: 0.40755369
21000: 0.40755361
22000: 0.40755356
23000: 0.40755352
24000: 0.40755350
25000: 0.40755349
Cost for 1th column of theta
Iteration: Cost
1000: 0.09352998
2000: 0.09325629
3000: 0.09320555
4000: 0.09319153
5000: 0.09318557
6000: 0.09318218
7000: 0.09317995
8000: 0.09317842
9000: 0.09317734
10000: 0.09317657
11000: 0.09317602
12000: 0.09317562
13000: 0.09317534
14000: 0.09317513
15000: 0.09317499
16000: 0.09317488
17000: 0.09317481
18000: 0.09317475
19000: 0.09317471
20000: 0.09317469
21000: 0.09317467
22000: 0.09317465
23000: 0.09317464
24000: 0.09317463
25000: 0.09317463
Cost for 2th column of theta
Iteration: Cost
1000: 0.33206051
```

```
2000: 0.33195964
3000: 0.33189458
4000: 0.33185035
5000: 0.33182025
6000: 0.33179977
7000: 0.33178583
8000: 0.33177634
9000: 0.33176989
10000: 0.33176549
11000: 0.33176250
12000: 0.33176047
13000: 0.33175909
14000: 0.33175814
15000: 0.33175750
16000: 0.33175707
17000: 0.33175677
18000: 0.33175657
19000: 0.33175643
20000: 0.33175634
21000: 0.33175627
22000: 0.33175623
23000: 0.33175620
24000: 0.33175618
25000: 0.33175617
```

In [ ]:

```
plot_loss(loss_dict_final)
```



In [ ]:

```
# accuracy on X_train
calculate_accuracy(X_train, y_train, final_theta)
```

Out[ ]: 0.8192151232352237

In [ ]:
```
# accuracy on split X_val
calculate_accuracy(X_val, y_val, final_theta)
```

Out[ ]: 0.8164433277498604

In [ ]:
```
# accuracy on split X_test
calculate_accuracy(X_test, y_test, final_theta)
```

Out[ ]: 0.8104410943606923

In [ ]:
```
mat_prob_test = test_data.dot(final_theta)
mat_prob_test
```

Out[ ]:

	0	1	2
47760	1.302737	-13.424771	-1.367839
47761	1.323159	-13.540540	-1.370454
47762	1.400580	-13.719122	-1.399481
47763	1.459107	-13.803240	-1.431322
47764	1.449182	-13.707072	-1.451464
...	...	...	...
55075	2.808538	-1.239371	-4.427883
55076	2.641542	-1.147226	-4.441608
55077	2.409571	-1.011491	-4.336809
55078	2.199825	-0.873350	-4.249391
55079	2.106112	-0.861428	-4.240929

7320 rows × 3 columns

In [ ]:
```
mat_prob_test_array = mat_prob_test.to_numpy()
mat_prob_test_array
```

Out[ ]:
```
array([[  1.30273674, -13.42477076,  -1.36783944],
       [  1.32315888, -13.54053973,  -1.37045396],
       [  1.40057968, -13.71912249,  -1.39948076],
       ...,
       [  2.40957123,  -1.0114905 ,  -4.33680941],
       [  2.19982524,  -0.87335026,  -4.24939078],
       [  2.10611199,  -0.86142788,  -4.24092889]])
```

In [ ]:
```
pred_test = np.argmax(mat_prob_test_array, axis=1)
pred_test
```

Out[ ]: array([0, 0, 0, ..., 0, 0, 0])

In [ ]:
```
label_percentages(pred_test)
```

Out[ ]:
```
((6534, 126, 660),
 (0.8926229508196721, 0.01721311475409836, 0.09016393442622951))
```

In [ ]:
```
submission = pd.read_csv('/content/drive/My Drive/Competition/sample_submissio
n.csv')
submission
```

Out[ ]:

	S.No	LABELS
0	0	1
1	1	1
2	2	1
3	3	1
4	4	1
...	...	...
7315	7315	1
7316	7316	1
7317	7317	1
7318	7318	1
7319	7319	1

7320 rows × 2 columns

In [ ]:
```
submission.iloc[:,1] = pred_test
submission
```

Out[ ]:

	S.No	LABELS
0	0	0
1	1	0
2	2	0
3	3	0
4	4	0
...	...	...
7315	7315	0
7316	7316	0
7317	7317	0
7318	7318	0
7319	7319	0

7320 rows × 2 columns

In [ ]:
```
from google.colab import files
submission.to_csv('submission_sigmoid.csv', index=False)
files.download('submission_sigmoid.csv')
```

In [ ]: