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19BCP130

Logistics Regression

Import Libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.datasets import *
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
sns.set()
```

Load the data

```
data = load_breast_cancer() #refer: http://scikit-learn.org/stable/modules/generated/sklearn.dataset

# data with features
X = data.data

# data class labels
y = data.target
```

Print the number of data points, number of features and number of classes in the given data set.

```
print(f'Number of data points = {data.data.shape[0]}')
print(f'Number of features = {len(data.feature_names)}')
print(f'Number of classes = {len(data.target_names)}')
```

```
Number of data points = 569
Number of features = 30
Number of classes = 2
```

Splitting data into Train and test sets with Stratified Sampling using train_test_split()

```
X_train, X_test, y_train, y_test = train_test_split(X, y, stratify=y, test_size=0.2, random_state=42
```

```
def getShape(name, dataset):
  print(f'Shape of {name} is {dataset.shape[0]} * {dataset.shape[1]}')

getShape('X', X)
```

```
getShape('X_train', X_train)
getShape('X_test', X_test)
```

```
Shape of X is 569 * 30
Shape of X_train is 455 * 30
Shape of X_test is 114 * 30
```

Data Preprocessing using column standardisation. Use sklearn.preprocessing.StandardScaler().

```
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

Implement Logistic Regression Using Gradient Descent: without using sklearn.

In this algorithm, n is the total number of datapoints in dataset. α is the learning rate to be used in gradient descent. For this work, just fix $\alpha = 0.001$.

The predicted value for data point x is $y_{pred} = \sigma(w^T x + b)$, where σ is a sigmoid function.

ALGORITHM:

- Initialize the weight_vector and intercept term to zeros (Write your code in def initialize_weights())
- Create a loss function (Write your code in def logloss())
  $logloss = -1 * \frac{1}{n}\Sigma_{for each y_{true}, y_{pred}}(y_{true}log(y_{pred}) + (1 - y_{true})log(1 - y_{pred}))$
- for each epoch:
  - for each data point say x_i in train:
    - calculate the gradient of loss function w.r.t each weight in weight vector (write your code in def gradient_dw())
      $dw^{(t)} = \frac{1}{n}(x_i(\sigma((w^{(t)})^T x_i + b^t) - y_i))$
    - Calculate the gradient of the intercept (write your code in def gradient_db())
      $db^{(t)} = \frac{1}{n}(\sigma((w^{(t)})^T x_i + b^t) - y_i))$
    - Update weights and intercept using gradient descent
      $w^{(t+1)} \leftarrow w^{(t)} - \alpha(dw^{(t)})$
      $b^{(t+1)} \leftarrow b^{(t)} - \alpha(db^{(t)})$
  - predict the output for all test data points with updated weights. (write your function in def prediction())
  - calculate the log loss for train and test data points separately with the updated weights. Store these losses in the lists, train_loss and test_loss.

- And if you wish, you can compare the previous train loss and the current train loss, if it is not updating, then you can stop the training
- return the updated weights, training and test loss lists.

```
def logloss(y_true, y_pred):
    # you have been given two arrays y_true and y_pred and you have to calculate the logloss
    sum_ind = 0

    for i in range(len(y_true)):
      sum_ind += (y_true[i] * np.log(y_pred[i]) + (1 - y_true[i]) * np.log(1 - y_pred[i]))

    logloss = (-1) * ( 1 / len(y_true) ) * sum_ind

    return logloss
```

```
def initialize_weights(inVec):
    #initialize the weights as 1d array consisting of all zeros similar to the dimensions of input v
    weights = np.zeros_like(inVec)

    #initialize bias to zero
    bias = 0

    return weights, bias
```

```
def sigmoid(z):
    ''' In this function, we will return sigmoid of z'''
    # compute sigmoid(z) and return
    return 1 / (1 + np.exp(-z))
```

```
# w should be a vector of size as input data point. Size of w and dw be same.
def gradient_dw(x, y, w, b, n):
  # In this function, we will compute the gradient w.r.to w
  dw = (1/n) * x * ( sigmoid(np.dot(w, x) + b) - y)

  return dw
```

```
#b should be a scalar value
def gradient_db(x, y, w, b, n):
  # In this function, we will compute gradient w.r.to b
  db = (1/n) * ( sigmoid(np.dot(w, x) + b) - y )

  return db
```

For the prediction, if activation_value > 0.5 then assign label = 1 else label = 0

```
def getPredictions(y_true, y_pred):
  true_pos = 0

  for i in range(len(y_true)):
    if y_pred[i] > 0.5:
      y_pred[i] = 1
```

```
    else:
      y_pred[i] = 0

    if y_true[i] == y_pred[i]:
      true_pos += 1

  return true_pos, round((true_pos/len(y_true)) * 100, 2)
```

```
def predict(w, b, X):
  n = len(X)
  z = np.dot(w, X) + b

  return sigmoid(z)
```

```
def logistic_regression(X_train, y_train, X_test, y_test, epochs, lr):
  # implement your algorithm
  weights, bias = initialize_weights(X_train[0])

  train_loss = []
  test_loss = []
  train_true_pos = []
  test_true_pos = []
  train_acc = []
  test_acc = []
  epoch_list = []
  n = len(X_train)

  loss_last = -1

  for epoch in range(epochs): # Running epochs for training
    for batch in range(n):
      # Finding differentiations against weight and bias
      dw = gradient_dw(X_train[batch], y_train[batch], weights, bias, n)
      db = gradient_db(X_train[batch], y_train[batch], weights, bias, n)

      # Changing weights and biases as per differences calculated above
      weights -= lr * dw
      bias -= lr * db

    train_predict, test_predict = [], []

    for batch in range(len(X_train)):
      train_predict.append( predict(weights, bias, X_train[batch]) )

    for batch in range(len(X_test)):
      test_predict.append( predict(weights, bias, X_test[batch]) )

    curr_train_loss = logloss(y_train, train_predict)

    if curr_train_loss == loss_last or curr_train_loss==1:
      break
    else:
      epoch+=1
      epoch_list.append(epoch)

      loss_last = curr_train_loss
      train_loss.append( curr_train_loss )
      test_loss.append( logloss(y_test, test_predict) )
```

```
        train_pred, train_accuracy = getPredictions(y_train, train_predict)
        train_true_pos.append(f'{train_pred}')
        train_acc.append(train_accuracy)

        test_correct_pred, test_accuracy = getPredictions(y_test, test_predict)
        test_true_pos.append(f'{test_correct_pred}')
        test_acc.append(test_accuracy)

    results = pd.DataFrame({ "Epochs": epoch_list,
                             "Train Loss": train_loss,
                             "Test Loss": test_loss,
                             "Train Accuracy": train_acc,
                             "Test Accuracy": test_acc })

    return results, weights, bias
```

Plot your train and test loss vs epochs. Plot epoch number on X-axis and loss on Y-axis and make sure that the curve is converging

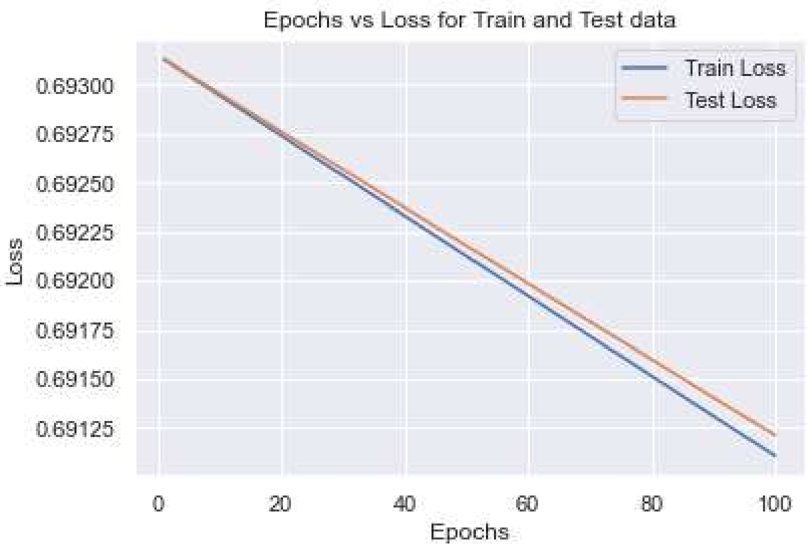
```
epochs = 100
learning_rate = 0.00001

main_results, weights, bias = logistic_regression(X_train, y_train, X_test, y_test, epochs, learning
```

```
main_results
```

	Epochs	Train Loss	Test Loss	Train Accuracy	Test Accuracy
0	1	0.693127	0.693128	93.85	90.35
1	2	0.693106	0.693108	93.85	90.35
2	3	0.693086	0.693089	93.85	90.35
3	4	0.693065	0.693070	93.85	90.35
4	5	0.693045	0.693050	93.85	90.35
...	...	...	...	...	...
95	96	0.691189	0.691290	93.85	90.35
96	97	0.691168	0.691270	93.85	90.35
97	98	0.691148	0.691251	93.85	90.35
98	99	0.691128	0.691232	93.85	90.35
99	100	0.691107	0.691212	93.85	90.35

100 rows × 5 columns

```
main_results.plot(x='Epochs', y=['Train Loss', 'Test Loss'], kind="line")
plt.ylabel('Loss')
plt.title('Epochs vs Loss for Train and Test data')
plt.show()
```



Compute the final accuracy on test dataset.

```
def getTestAccuracy(weights, bias, X_test, y_test):
  n = len(X_test)

  y_pred = []

  for batch in range(n):
    y_pred.append( predict(weights, bias, X_test[batch]) )

  correct_preds, accuracy = getPredictions(y_test, y_pred)

  return correct_preds, accuracy
```

```
correct_preds, accuracy = getTestAccuracy(weights, bias, X_test, y_test)

print(f'For Test Dataset:')
print(f'    Accuracy = {accuracy} %')
print(f'    Correct Predictions = {correct_preds}/{len(X_test)}')
```

```
For Test Dataset:
    Accuracy = 90.35 %
    Correct Predictions = 103/114
```

BONUS: Train your model with varying values of learning rates say ranging in $[0.1, 0.01, 0.001, 0.0001]$ **and plot the performances.**

```
learning_rates = [0.1, 0.01, 0.001, 0.0001]

for curr_learning_rate in learning_rates:
  results, weights, bias = logistic_regression(X_train, y_train, X_test, y_test, epochs, curr_learni
  print(results['Train Loss'])
  plt.plot(results['Epochs'].to_numpy(), results['Train Loss'].to_numpy())

plt.legend([str(i) for i in learning_rates], loc='upper right')
plt.xlabel('Epochs')
plt.ylabel('Train Loss')
plt.title('Epochs vs Train Loss for different learning rates')
plt.show()
```

```
for curr_learning_rate in learning_rates:
  results, weights, bias = logistic_regression(X_train, y_train, X_test, y_test, epochs, curr_learni
  print(results['Test Loss'])
  plt.plot(results['Epochs'].to_numpy(), results['Test Loss'].to_numpy())

plt.legend([str(i) for i in learning_rates], loc='upper right')
plt.xlabel('Epochs')
plt.ylabel('Test Loss')
plt.title('Epochs vs Test Loss for different learning rates')
plt.show()
```

```
0     0.549519
1     0.467568
2     0.414485
3     0.376954
4     0.348784
        ...
95    0.127685
96    0.127340
97    0.127000
98    0.126666
99    0.126337
Name: Test Loss, Length: 100, dtype: float64
0     0.674360
1     0.656781
2     0.640322
3     0.624899
4     0.610429
        ...
95    0.274937
96    0.273881
97    0.272840
98    0.271813
```