Logistic Regression

winglok

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Download the dataset "a9a&a9a.t":

```
In [1]: import requests
        r1 = requests.get("https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/binary/a9a")
        r2 = requests.get("https://www.csie.ntu.edu.tw/~cjlin/libsvmtools/datasets/binary/a9a.t")
```

Load the dataset to X_train&y_train,X_val&y_val:

```
In [2]: from sklearn.datasets import load_svmlight_file
        from io import BytesIO
        X_train, y_train = load_svmlight_file(BytesIO(r1.content), n_features=123)
        X_train = X_train.toarray()

        X_val, y_val = load_svmlight_file(BytesIO(r2.content), n_features=123)
        X_val = X_val.toarray()
```

Preprocess, change the shape of X_train&y_train,X_val&y_val:

```
In [3]: import numpy
        n_samples, n_features = X_train.shape
        X_train = numpy.column_stack((X_train, numpy.ones((n_samples, 1))))
        y_train = y_train.reshape((-1, 1))

        n_samples, n_features = X_val.shape
        X_val = numpy.column_stack((X_val, numpy.ones((n_samples, 1))))
        y_val = y_val.reshape((-1, 1))
```

Define max iterations, learning rate and batch size:

```
In [4]: max_epoch = 1500
        learning_rate = 0.03
        batch_size=497

        losses_train = []
        losses_val = []
```

Initialize w by different ways(using normal initialization where $\mu = 0.1, \sigma = 0.1$):

```
In [5]: #w = numpy.zeros((n_features + 1, 1))  # initialize with zeros
        #w = numpy.random.random((n_features + 1, 1))  # initialize with random numbers
        w = numpy.random.normal(0.1, 0.1, size=(n_features + 1, 1))  # initialize with zero normal distribution
```

Define sigmoid function:

$$sigmoid(x) = \frac{1}{1+e^{-x}}$$

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

Log-Likehood loss function:

$$J(w) = -\frac{1}{m}\sum_{i=1}^{m}[y_i log h_\omega(X_i) + (1-y_i) log(1-h_\omega(X_i))]$$

Gradient:

$$\frac{\partial J(\omega)}{\partial \omega_j} = -\frac{1}{m}\sum_{i=1}^{m}[y_i(1-h_\omega(X_i))(-X_{i,j}) + (1-y_i)h_\omega(X_i)(X_{i,j})]$$

$$= -\frac{1}{m}\sum_{i=1}^{m}(-y_i X_{i,j} + h_\omega(X_i)X_{i,j})$$

$$= -\frac{1}{m}\sum_{i=1}^{m}(h_\omega(X_i) - y_i)X_{i,j}$$

So we get:

$$\omega := \omega - \frac{1}{n}\sum_{i=1}^{m}\alpha(h_\omega(X_i) - y_i)X_i$$

Where α is learning rate. And thats how we to update ω

Training nad iterations:

```
In [7]: from sklearn.model_selection import train_test_split
        for epoch in range(max_epoch):
            X_t, X_v, y_t, y_v = train_test_split(X_train, y_train, test_size=1-batch_size/y_train.size)#split X_train
            # and y_train to batch size
            y_s=(y_t+1)/2#preprocess the dataset
            y_s2=(y_val+1)/2
            nums=X_t.shape[0]
            w=w-learning_rate*numpy.dot(X_t.transpose(),(sigmoid(numpy.dot(X_t,w))-y_s))/nums #update

            loss_train = -numpy.average(y_s*numpy.log(sigmoid(numpy.dot(X_t,w)))+(1-y_s)*numpy.log(1-sigmoid(numpy.dot(X_t,w))))
            losses_train.append(loss_train)#loss of training set of batch size

            loss_val = -numpy.average(y_s2*numpy.log(sigmoid(numpy.dot(X_val,w)))+(1-y_s2)*numpy.log(1-sigmoid(numpy.dot(X_val,w))))
            losses_val.append(loss_val)#loss of validation set
```

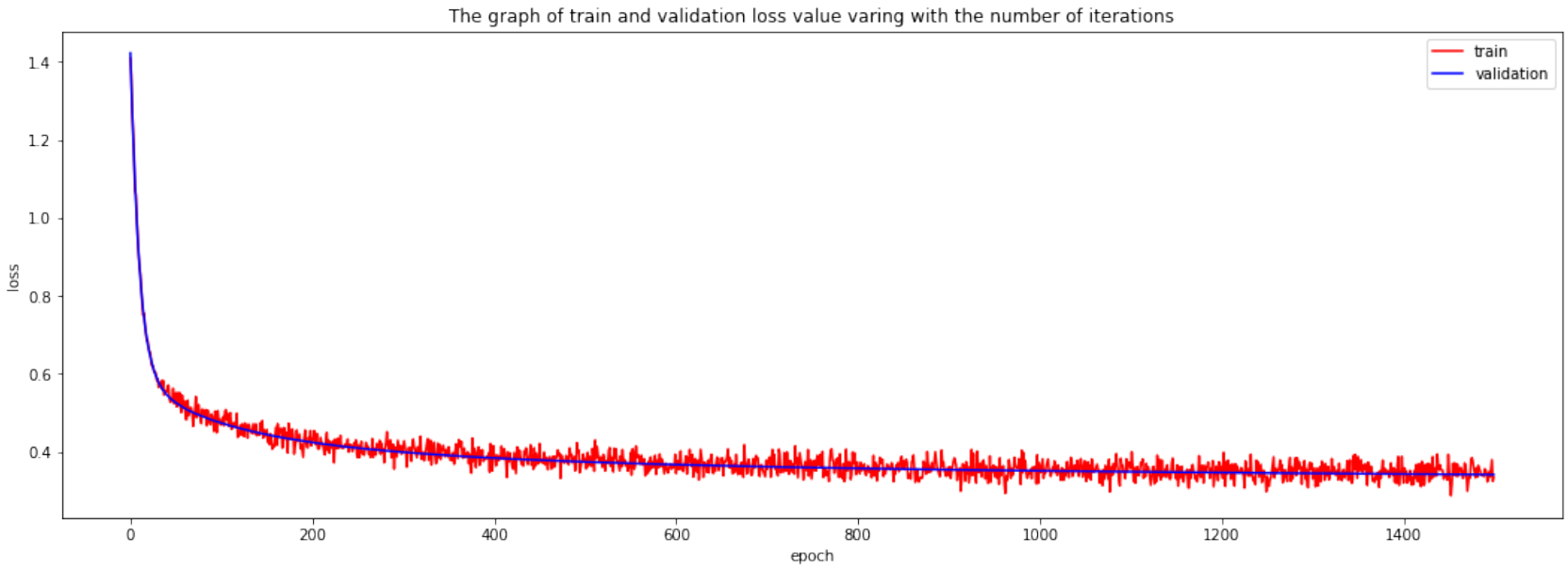
Show the precision recall and f1-score rate:

```
In [8]: from sklearn.metrics import classification_report
        print(classification_report(y_s2, numpy.where(numpy.dot(X_val, w) >= 0, 1, 0),
                                    target_names=["positive", "negative"], digits=4))
```

```
             precision    recall  f1-score   support

   positive     0.8655    0.9389    0.9007     12435
   negative     0.7278    0.5283    0.6122      3846

avg / total     0.8330    0.8419    0.8326     16281
```

Plot train loss and validation loss with diff iterations:

```
In [9]: %matplotlib inline
        import matplotlib.pyplot as plt
        plt.figure(figsize=(18, 6))
        plt.plot(losses_train, color="r", label="train")
        plt.plot(losses_val, color="b", label="validation")
        plt.legend()
        plt.xlabel("epoch")
        plt.ylabel("loss")
        plt.title("The graph of train and validation loss value varing with the number of iterations")

Out[9]: Text(0.5,1,'The graph of train and validation loss value varing with the number of iterations')
```



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