Support Vector Machines

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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 io import BytesIO
        from sklearn.datasets import load_svmlight_file

        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_train_samples, n_features = X_train.shape
        X_train = numpy.column_stack((X_train, numpy.ones((n_train_samples, 1))))
        y_train = y_train.reshape((-1, 1))

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

Define max iterations, learning rate batch size and coefficient C:

```
In [4]: import random
        max_epoch=1000
        learning_rate = 0.0001
        batch_size=1500
        C = 0.5

        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(0.6, 0.6, size=(n_features + 1, 1))  # initialize with zero normal distributi
```

Here are some formulas we needed:

Loss function(target):

$$L = min\frac{||\omega||_2^2}{2} + C\sum_{i=1}^{m} max(0, 1 - y_i(X_i\omega))$$

Through simple derivation,we get:

$$\frac{\partial L(\omega)}{\partial \omega} = \omega - C(X^T y_i(or0))$$

If $1 - y_i(X_i\omega) > 0$ here is y_i,otherwise is 0

So, we know how to update ω:

$$\omega := \omega - \alpha\frac{\partial L(\omega)}{\partial \omega}$$

Training nad iterations:

```
In [6]: 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
            h = 1 - y_t * numpy.dot(X_t, w)
            y_d = numpy.where(h > 0, y_t, 0)#derivation for whether exits y_i
            w -= learning_rate * (w - C * numpy.dot(X_t.transpose(), y_d))

            loss_train = numpy.sum(w * w) + C * numpy.sum(numpy.maximum(1 - y_t * numpy.dot(X_t, w), 0))
            losses_train.append(loss_train/X_t.shape[0])#divided by m for get similar scale(loss)

            loss_val = numpy.sum(w * w) + C * numpy.sum(numpy.maximum(1 - y_val * numpy.dot(X_val, w), 0))
            losses_val.append(loss_val/X_val.shape[0])#divided by m for get similar scale(loss)
```

Show the precision recall and f1-score rate:

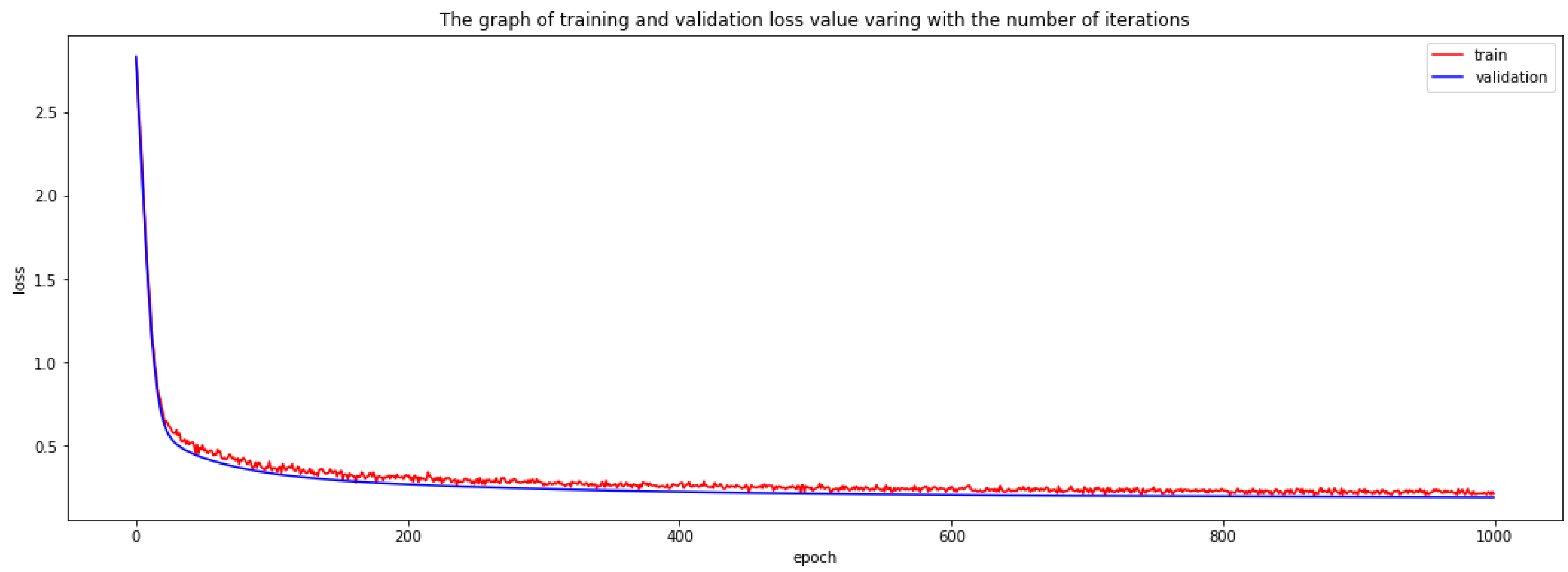
```
In [7]: from sklearn.metrics import classification_report
        print(classification_report(y_val, numpy.where(numpy.dot(X_val, w) > 0, 1, -1),
                                    target_names=["positive", "negative"], digits=4))
```

```
             precision    recall  f1-score   support

   positive     0.8727    0.9253    0.8982     12435
   negative     0.7000    0.5637    0.6245      3846

avg / total     0.8319    0.8399    0.8336     16281
```

Plot train loss and validation loss with diff iterations:

```
In [8]: %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 training and validation loss value varing with the number of iterations")
```

```
Out[8]: Text(0.5,1,'The graph of training and validation loss value varing with the number of iterations')
```



References:
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4. 理解 Hinge Loss (折页损失函数、铰链损失函数)[EB/OL]. https://blog.csdn.net/fendegao/article/details/79968994.
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