HeroSVM Support Vector Machine User Guide

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Chapter 1

Introduction

1.1 What is Support Vector Machine

1.2 Support Vector Machine

Support vector machines (SVM) have recently generated a great interest in the community of machine learning due to its excellent generalization performance in a wide variety of learning problems, such as handwritten digit recognition (see [1] [2]), classification of web pages [3] and face detection [4]. Some classical problems such as multi-local minima, curse of dimensionality and overfitting in neural networks [5], seldom occur in support vector machines. However, training support vector machines is still a bottleneck, especially for a large-scale learning problem [2]. Therefore, it is important to develop a fast training algorithm for SVM in order to apply it to various engineering problems in other fields. HeroSVM package has been implemented based on our recently proposed method [6].

In order to simplify the description of implementation, we give a simple introduction of support vector machine. The details are referred to Burge's tutorial [7]. Given that training samples $\{X_i, y_i\}$, $i = 1, \cdots, N$, $y_i \in \{-1, 1\}$, $X_i \in R^n$ where y_i is the class label, support vector machine first maps the data to the other Hilbert space $\mathcal{H}$ (also called feature space), using a mapping Φ,

$$\Phi : R^n \rightarrow \mathcal{H}. \tag{1.1}$$

The mapping Φ is implemented by a kernel function K that satisfies Mercer's conditions [8] such that $K(X_i, X_j) = \Phi(X_i) \cdot \Phi(X_j)$. Then, in the high-dimensional feature space $\mathcal{H}$, we find an optimal hyperplane by maximizing the margin and bounding the number of training errors. The decision function can be given by

$$\begin{aligned} f(X) &= \theta(W \cdot \Phi(X) - b) \\ &= \theta(\sum_{i=1}^{N} y_i \alpha_i \Phi(X_i) \cdot \Phi(X) - b) \end{aligned} \tag{1.2}$$

$$= \theta(\sum_{i=1}^{N} y_i \alpha_i K(X_i, X) - b).$$

where

$$\theta(u) = \begin{cases} 1 & \text{if } u > 0 \\ -1 & \text{otherwise} \end{cases} \tag{1.3}$$

If α_i is nonzero, the corresponding data x_i is called support vector. Training a SVM is to find $\alpha_i, i = 1, \cdots, N$, which can be achieved by minimizing the following quadratic cost function:

$$\begin{array}{lc} \text{maximize} & L_D(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i\alpha_j y_i y_j K(X_i, X_j). \\ \text{subject to} & 0 \le \alpha_i \le C \quad i = 1 \cdots N \\ & \sum_{i=1}^{N} \alpha_i y_i = 0 \end{array} \tag{1.4}$$

where C is a parameter chosen by the user, a larger C corresponds to a higher penalty allocated to the training errors. Since kernel K is semi-positive definite and constraints define a convex set, the above optimization reduces to a convex quadratic programming. The weight W is uniquely determined, but with respect to the threshold b, there exist several solutions in the special cases (see [9] [10] [11]). Further, an interesting fact is that the solution is not changed if any non-support vector is removed from eq.(1.4).

HeroSvm package is written by Jianxiong Dong, a Ph.D student in CENPARMI. In the next chapter, we describe basic data structure and show user how to use the package. The function reference is given in the chapter 3.

Chapter 2

How to use HeroSVM

2.1 Design philosophy of HeroSVM

HeroSVM was implemented based on our proposed method [6]. In order to facilitate the software portability and maintainess, an object-oriented method has been applied to design the package. Error handling was implemented for the robustness of software. HeroSVM is written using C++ language and developed under Virtual C++ 6.0. In the current version, a dynamical link library of HeroSVM is provided to train SVM on a large-scale learning problem efficiently for research purpose in PC platform. We expect that HeroSVM can facilitate the training of support vector machine and solve some real-world problems in various Engineering fields.

2.2 Basic data structures

2.2.1 Kernel

In HeroSVM, some classical kernels such as radial basis function (RBF), polynomial and linear kernels have been implemented. Users can choose the above kernels or use their own customized kernel. Let a, b, c are kernel parameters. Then three classical kernels can be written as

$$\text{RBF} \quad \exp\left(-\frac{\|X_1 - X_2\|^2}{2c}\right) \tag{2.1}$$

$$\text{Polynomial} \quad ((< X_1, X_2 > +b)/c)^a \tag{2.2}$$

$$\text{Linear} \quad (< X_1, X_2 > +b)/c \tag{2.3}$$

where $X_1 \in R^n$ and $X_2 \in R^n$, $< \cdot >$ and $\| \cdot \|$ denote dot product and Euclidean norm, respectively.

When the user choose to specify his own kernel, he/she has to implement the following function and pass its pointer in the exported function **SvmInit**.

```
float kernel(float* vector1, float* vector2, int dim)
{
 ...
}
```

2.2.2 The size of working set

Usually the total training set is much larger than the number of final support vectors. The size of the working set should be large enough to contain these support vectors. Before the training, the number of support vectors is unknown. Therefore, users can estimate it in terms of the number of training samples. Experiments [6] have shown that generalization performance is insensitive to this paper if it is large enough.

Inside HeroSVM, a kernel caching lower-triangle matrix is dynamically created. It is called caching matrix. suppose that the size of working set is m, then the size of its required memory can be calculated using the formula: $2m^2$ bytes.

2.2.3 Training data format

Training set consists of two files for each class. One sequentially stores the feature vectors of all training samples, which is shared by all classes. The other stores the target values (-1.0 or 1.0). The training method is one-against-the-rest. Note that these files are read or written in binary mode. For example,

```
/* feature vector file */
Input feature vector 1
Input feature vector 2
...
Input feature vector n

/* target file */
Target value of feature vector 1
Target value of feature vector 2
...
Target value of feature vector n
```

2.2.4 Summary information

After training for each class ends, the summary information will be stored in a file . We describe its format with an example as follows:

```
class Label = 0
User-specified kernel is used
```

```
The size of working set is 2000
The size of the training set is 7291
b_low = 0.528602 b_up = 0.507482
cache_hit = 6219030
total kernel evaluations  = 8928917
Actual kernel evaluations = 2709887
cache hit ratio = 0.696504
C= 10.0000
Bias = 0.518042
Iterations = 91
Training time (CPU seconds): 13.390000
Max alpha = 4.608595
Number of support vectors : 330
Number of bounded support vector: 0
|W|^2 = 159.62
margin of separation = 0.158301
```

In the above example, Bias means b in eq.(1.2). The cache hit ratio can be calculated by

$$\text{cache hit ration} = \frac{\text{cache\_hit}}{\text{total kernel evaluations}} \tag{2.4}$$

b_low and b_up are two thresholds in modified SMO [10], and margin is equal to $1/ \parallel W \parallel^2$. If alpha value of one support vector is equal to C, we call it bounded support vector.

2.2.5 Save training results

We save training results into two files. One is used to store kernel paramters, support vectors and the corresponding α. The other (index file) is to store the sequential number of support vectors on the training set in order to merge them during the testing stage and reduce unnecessary kernel re-evaluations. Users can read training results with C language as follows:

```
fp = fopen(file name, ‘‘rb’’);
fread(&C, sizeof(float), 1, fp);
//for user-specified kernel, skip the following three statements.
fread(&kernel_para1, sizeof(float), 1, fp);
fread(&kernel_para2, sizeof(float), 1, fp);
fread(&kernel_para3, sizeof(float), 1, fp);
fread(&threshold, sizeof(float), 1, fp);
fread(&sv, sizeof(int), 1, fp);
for ( i = 0; i < sv; i++, vec += dim)
{
   //read the support vector
   fread(vec, sizeof(float), dim, fp);
   //read the target value of the above support vector
   fread(&target[i], sizeof(float), 1, fp);
   fread(&alpha[i], sizeof(float), 1, fp);
}
```

The format of the index file is illustrated by

```
sequential number of support vector 1
sequential number of support vector 2
...
sequential number of support vector n
```

2.3 Thread issues

Currently only single thread is considered. In the next version, multi-thread will be implemented to speed up the training on multi-processor's platform.

Chapter 3

Function Reference

This chapter describes the interface function reference. These functions are sorted by name. For each routine, we refer to format of xlib reference manual, including declarations of the arguments, return type and description.

3.1 SvmInit

Name

SvmInit – Set SVM training parameters and allocate the memory.

Header file

SVMTrain.h

Synopsis

```
int SvmInit(int nDim,
    int nWorkingSetSize ,
    int nTrainingSetSize ,
    float kernel_Para1,
    float kernel_Para2,
    float kernel_Para3,
    unsigned short int nKernelType,
    float C,
    KernelFunc UserKer,
    int nApplicationType);
```

Parameters

nDim
: The parameter specifies the dimension of input feature vector.

nWorkingSetSize
: Size of working set

nTrainingSetSize
: Number of training samples

kernel_Para1
: Kernel parameter

kernel_Para2
: Kernel parameter

kernel_Para3
: Kernel parameter

nKernelType
: Kernel type. There are four categories as follows:

1	RBF kernel
2	Polynomial kernel
3	Linear kernel
4	User-specified kernel

C
: Upper bound of alpha in eq. (1.4).

UserKer
: a pointer to user-specified kernel function when nKernelType is set to 4.

nApplicationType
: Application type for the output of error message

0	Console application
1	Window application

Return Value

If succeed, return 0; otherwise -1

Remarks

See Also

SvmClean

Example

```
/* create a SVM with RBF kernel */
 SvmInit(400, 2000, 7291, 1.0, 0.0, 0.3, 1, 10.0, NULL, 0);
```

3.2 SvmTrain

Name

SvmTrain – Train support vector machine for classification.

Header file

SVMTrain.h

Synopsis

```
int SvmTrain(char* szDataFilePathName, char* szTargetFilePathName);
```

Parameters

szDataFilePathName
: a pointer to feature vector filename

szTargetFilePathName
: a pointer to target data filename

Return Value

If succeed, return 0; otherwise -1

Remarks

Feature vector and target files are both read/written in binary mode.

See Also

Example

```
SvmTrain(‘‘d:\\data\\feature.dat’’, ‘‘d:\\data\\0.tgt’’)
```

3.3 SvmSaveSummary

Name

SvmSaveSummary – Save useful training information into a file.

Header file

SVMTrain.h

Synopsis

```
int SvmSaveSummary(char* szSummaryFilePathName, int nClass);
```

Parameters

szSummaryFilePathName
    a pointer to summary filename

nClass
    identity number of each class

Return Value

If succeed, return 0; otherwise -1

Remarks

See Also

Example

```
SvmSaveSummary(‘‘d:\\SummaryInfo.txt’’, 1)
```

3.4 SvmSaveResult

Name

SvmSaveResult – Save training results and index of support vectors into files.

Header file

SVMTrain.h

Synopsis

```
int SvmSaveResult(char* szSvFilePathName, char* szSvIndexFilePathName);
```

Parameters

szSvFilePathName
: a pointer to a filename. Support vectors, optimized parameters are stored.

szSvIndexFilePathName
: a pointer to the index filename.

Return Value

If succeed, return 0; otherwise -1

Remarks

Example

```
SvmSaveResult(‘‘d:\\result\\1.res’’, ‘‘d:\\result\\1.idx’’);
```

3.5 SvmClean

Name

SvmClean – Free dynamically allocated memory.

Header file

SVMTrain.h

Synopsis

```
void SvmClean();
```

Parameters

NONE

Return Value

NONE

Remarks

See Also

SvmInit

Example

```
SvmClean( );
```

Chapter 4

Appendix

The chapter contains contact information and an example that shows how to use HeroSvm.

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```
#include "SVMTrain.h"
#include <string.h>
#include <math.h>
#include <stdlib.h>
#include <stdio.h>

#define USER_SPECIFIED_KERNEL

/* This is an example for training support vector machine.
// This example includes RBF and user-specified kernels.
// Note that users need to set the correct path
// Recommendation: first you can try the provided data. Then you can train
// SVM on your own data.
*/

float RBF_cof =  (float)(1.0/(2.0 * 0.3));
```

```
/* user-specified kernel */

float kernel(float* vec1, float* vec2, int n)
{
   float sum;
   float* p1, *p2;
   float temp;
   int i;

   p1 = vec1;
   p2 = vec2;
   sum = 0.0;
   for ( i = 0; i < n; i++, p1++, p2++)
   {
      temp = (*p1) - (*p2);
      sum += temp * temp;
   }
   sum = (float)exp(-sum * RBF_cof);
   return sum;
}

int main( )
{
   int nRes;
   char fname1[200];
   char fname2[200];
   char buf[200];
   char fname3[200];
   int  classNum = 10;
   int  i;

#ifdef USER_SPECIFIED_KERNEL

/* Initialize SVM using user-specified kernel */
   nRes = SvmInit(400, 2000, 7291,
          (float)1.0, (float)0.0, (float)0.3,
   4, 10.0, kernel, 0);
#else

/* Initialize SVM using RBF kernel */
/* size of working set : 2000
```

```
// number of training samples : 7291
// dimension of the feature vector : 400
// kernel parameters: 1.0, 0.0, 0.3
// kernel type: RBF ( radial basis function)
// C: 10.0
// Application type: console
*/
   nRes = SvmInit(400, 2000, 7291,
                 (float)1.0, (float)0.0, (float)0.3,
 1, 10.0, NULL, 0);
   if ( nRes )
   {
      printf("\n Intialization fails");
      return -1;
   }

#endif

   if ( nRes )
   {
      printf("\n Intialization fails");
      return -1;
   }

   for ( i = 0; i < 1; i++)
   {
      itoa(i, fname1, 10);
      strcpy(buf, "g:\\usps\\");
      strcat(fname1, ".tgt");
      strcat(buf, fname1);
      nRes = SvmTrain("g:\\usps\\feature.dat", buf);
      if ( nRes )
      {
         printf("\n SVM training fails");
         SvmClean( );
         return -1;
      }
      nRes = SvmSaveSummary("info.txt", i);
      if ( nRes )
      {
         printf("\n Fail to save the summary information to a file");
```

```
            SvmClean( );
            return -1;
        }
        itoa(i, fname2, 10);
        strcpy(fname3, fname2);
        strcat(fname3, ".index");
        strcat(fname2, "_res.dat");
        nRes = SvmSaveResult(fname2, fname3);
        if ( nRes )
        {
            printf("\n Fail to save the training result to a file");
            SvmClean( );
            return -1;
        }
    }
    SvmClean( );
    return 0;
}
```

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