



神经网络

王思广

北京大学物理学院



讲课内容



- 多层感知器MLP（Multi-Layer Perceptron）
 - 对类型进行识别
 - 对连续函数进行描述
- 多变量分析TMVA（Multi-Variate-Analysis类）



多层感知器MLP（Multi-Layer Perceptron）



对类型进行识别

siguang@pku.edu.cn

3



人的识别能力

● 校园中，大家识别男、女同学的准确率应该很高。我常用的依据如下：

- 衣服：颜色艳丽的是女同学的概率大
- 头发：头发长的是女同学的概率大
- 说话：音调高的是女同学的概率大
-

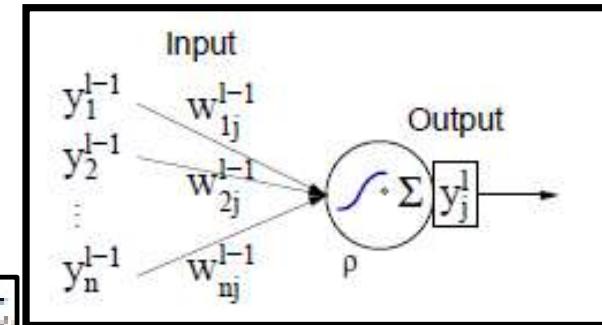
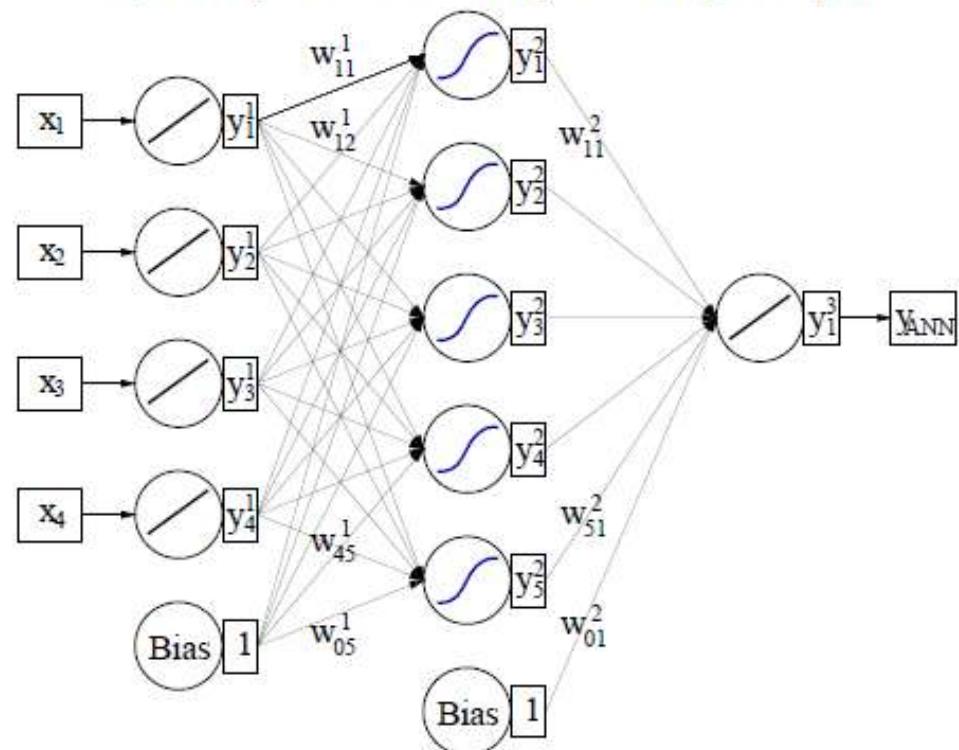
将以上所有概率在心中默默加合在一起，最后给出判断。

● 神经网络就是要模拟人的这个过程



一个隐藏层的多层感知器MLP工作示意图

Input Layer Hidden Layer Output Layer



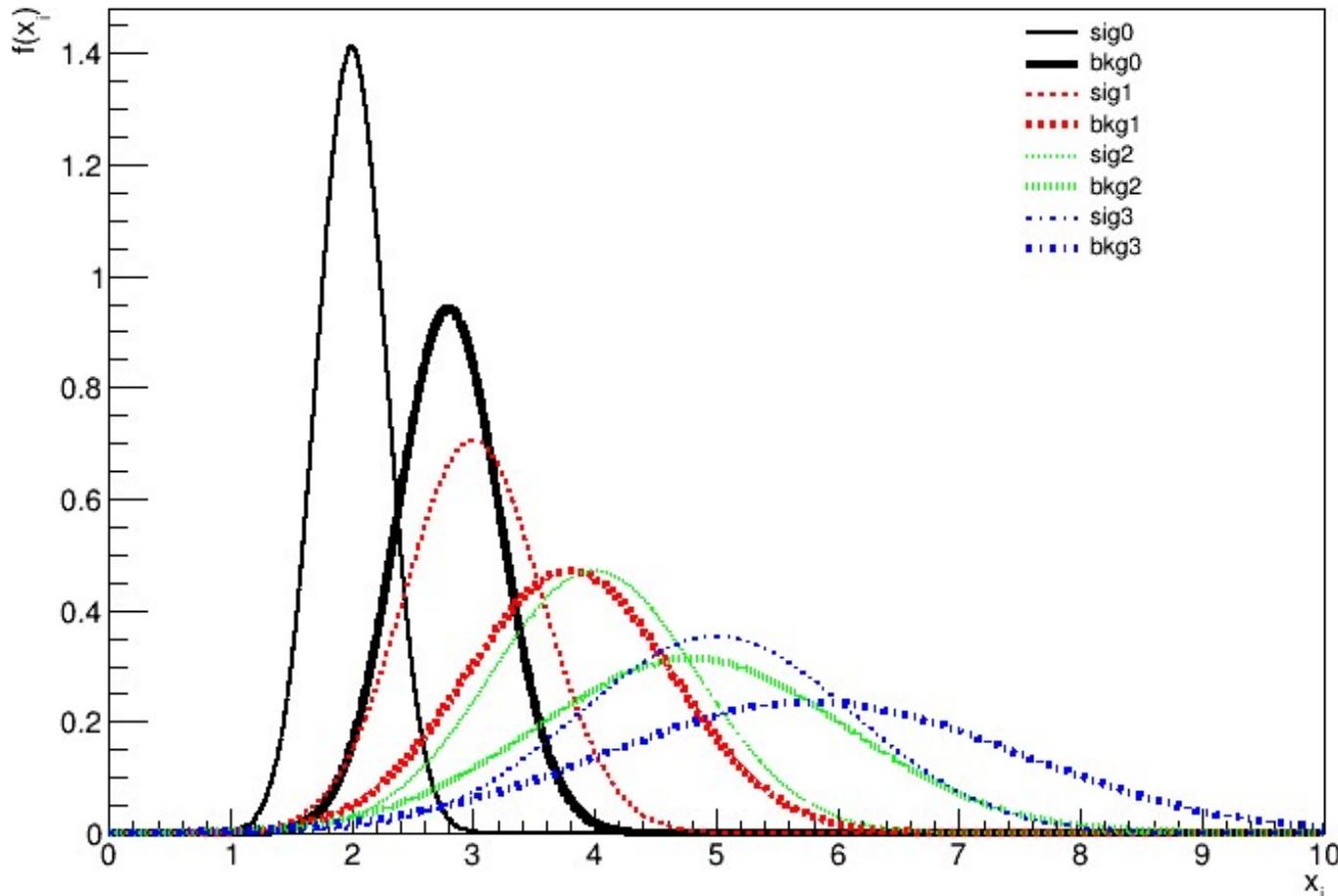
$$\rho = \alpha \circ \kappa$$

$$\kappa: (y_1^{(\ell)}, \dots, y_n^{(\ell)} | w_{0j}^{(\ell)}, \dots, w_{nj}^{(\ell)}) \rightarrow \begin{cases} w_{0j}^{(\ell)} + \sum_{i=1}^n y_i^{(\ell)} w_{ij}^{(\ell)} & \text{Sum,} \\ w_{0j}^{(\ell)} + \sum_{i=1}^n (y_i^{(\ell)} w_{ij}^{(\ell)})^2 & \text{Sum of squares,} \\ w_{0j}^{(\ell)} + \sum_{i=1}^n |y_i^{(\ell)} w_{ij}^{(\ell)}| & \text{Sum of absolutes,} \end{cases}$$

$$\alpha: x \rightarrow \begin{cases} x & \text{Linear,} \\ \frac{1}{1+e^{-kx}} & \text{Sigmoid,} \\ \frac{e^x - e^{-x}}{e^x + e^{-x}} & \text{Tanh,} \\ e^{-x^2/2} & \text{Radial.} \end{cases}$$



产生训练神经网络的数据



- 分为两类：
 - 细线表示信号
 - 粗线表示本底
 - 如果产生信号，用细的4个函数分别产生一个随机数赋给变量1到4
 - 如果产生本底，用粗的4个函数分别产生一个随机数赋给变量1到4
- 具体函数形式见代码



数据产生实现代码 (createData.C)

```
#include "TMultiLayerPerceptron.h"
#include "TRandom3.h"
#include "TFile.h"
#include "TTree.h"
#include "TF1.h"
#include "TSystem.h"
#include "TMath.h"
#include "TROOT.h"
#include "TLegend.h"
#include "TCanvas.h"

void createData(Int_t tot=50000,Int_t nSeed=2){
    const Int_t Nx = 4;
    TF1 *fsig[Nx];
    TF1 *fbkg[Nx];
    const Double_t xmin=0;
    const Double_t xmax=10;
    const Double_t sqPi = sqrt(TMath::Pi());
    for(Int_t i=0; i<Nx; i++){
        fsig[i] = new TF1(Form("fsig%d",i),"[0]*exp(-(x-[1])*(x-[1])/[2]/[2])",xmin,xmax);
        fbkg[i] = new TF1(Form("fbkg%d",i),"[0]*exp(-(x-[1])*(x-[1])/[2]/[2])",xmin,xmax);
    }
}
```

siguang@pku.edu.cn



数据产生实现代码（createData.C 续）

```
Double_t MeanS = i+2.0;
Double_t MeanB = i+2.8;
Double_t sigmaS = (i+1.)*0.4;
Double_t sigmaB = (i+1.)*0.6;
fsig[i]->SetParameters(1/(sqPi*sigmaS),MeanS,sigmaS);
fbkg[i]->SetParameters(1/(sqPi*sigmaB),MeanB,sigmaB);
fsig[i]->SetNpx(10000);
fbkg[i]->SetNpx(10000);
fsig[i]->SetLineColor(i+1);
fbkg[i]->SetLineColor(i+1);
fsig[i]->SetLineStyle(i+1);
fbkg[i]->SetLineStyle(i+1);
fsig[i]->SetLineWidth(2);
fbkg[i]->SetLineWidth(4);
}
```



数据产生实现代码（createData.C 续）

```
TCanvas *c1 = new TCanvas("c1","");
c1->SetTopMargin(0.03);
c1->SetRightMargin(0.03);
TLegend *lg = new TLegend(0.75,0.7,0.96,0.96);
for(Int_t i=0; i<Nx; i++){
  if(i==0){
    fsig[i]->Draw();
    fsig[i]->SetTitle(";x_{i};f(x_{i})");
  }else{
    fsig[i]->Draw("same");
  }
  fbkg[i]->Draw("same");
  lg->AddEntry(fsig[i],Form("sig%d",i),"l");
  lg->AddEntry(fbkg[i],Form("bkg%d",i),"l");
}
lg->SetFillColor(0);
lg->SetLineWidth(0);
lg->SetLineColor(0);
lg->Draw();
```



数据产生实现代码 (createData.C 续)

```
//create data
TFile *fout = new TFile(Form("data%d.root",nSeed),"recreate");
TTree *T = new TTree("T","Tree for Sig and Background");
Double_t x[Nx];
Int_t N;
Int_t iType;
Double_t w;

T->Branch("iType",&iType,"iType/I");
T->Branch("N",&N,"N/I");
T->Branch("x",x,"x[N]/D");
T->Branch("w",&w,"w/D");
N = Nx;
gRandom->SetSeed(nSeed);
```

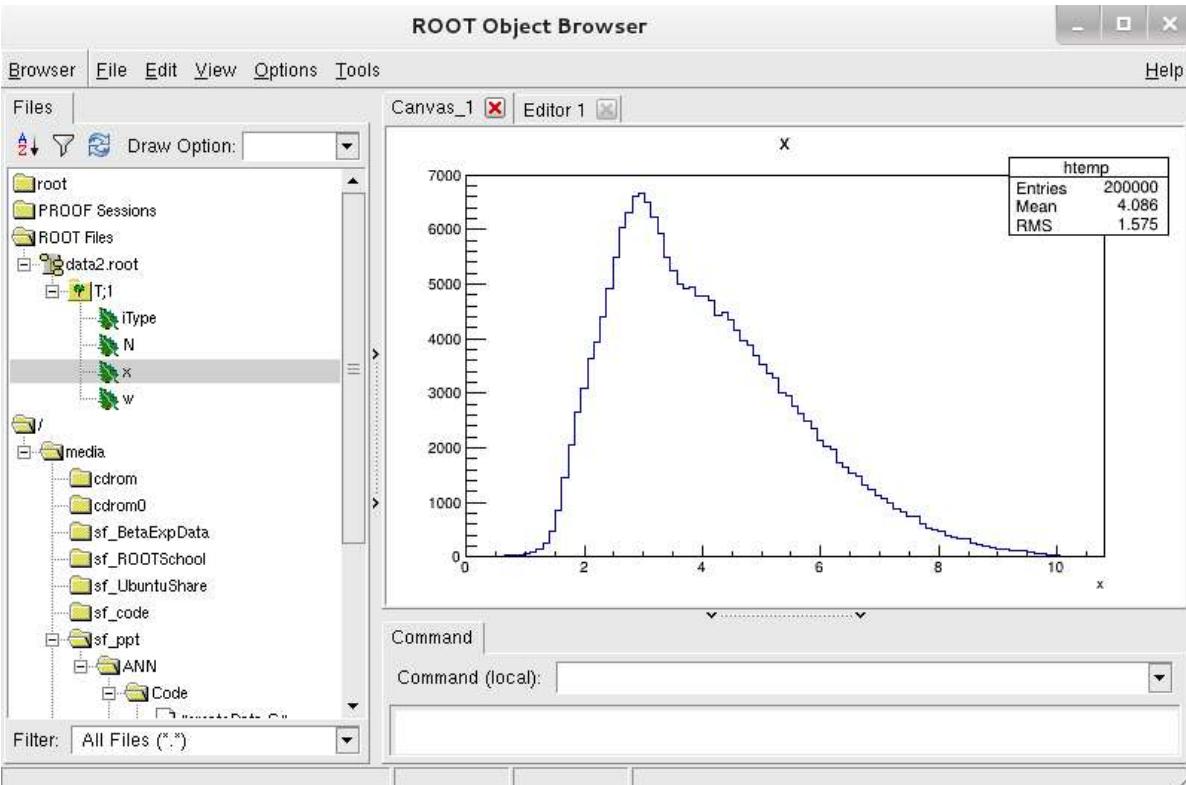


数据产生实现代码 (createData.C 续)

```
for(Int_t i=0; i<tot; i++){
    if(gRandom->Rndm()<0.75) iType = 0; //background 75% weight=0.25
    else iType = 1; //signal
    if(iType==1) {
        w = 0.75; // 25% signal, 1 event with 75% weight
        for(Int_t j=0; j<N; j++){
            x[j] = fsig[j]->GetRandom();
        }
    }else{
        w = 0.25; // 75% background, 1 event with 25% weight
        for(Int_t j=0; j<N; j++){
            x[j] = fbkg[j]->GetRandom();
        }
    }
    T->Fill();
}
T->Write();
fout->Close();
}
```



训练数据文件的内容检查



练习：

```
>root data2.root
Root[1]new TBrowser
root [2] T->Draw("x")
root [3] T->Draw("x[0]")
root [4] T->Draw("x[0]", "iType==0")
root [5] T->Draw("x[0]", "iType==1")
root [6] T->Draw("x[0]:x[1]", "iType==1")
root [7] T->Draw("x[0]:x[1]", "iType==1", "surf")
root [8] T->Draw("x[0]:x[1]", "iType==1", "surf1")
root [9] T->Draw("x[0]:x[1]", "iType==1", "surf2")
root [10] T->Draw("x[0]:x[1]", "iType==1", "surf3")
root [11] T->Draw("x[0]:x[1]", "iType==1", "surf4")
root [12] T->Draw("x[0]:x[1]", "iType==1", "box")
root [13] T->Draw("x[0]:x[1]:x[3]", "iType==1")
root [14] .q
```



多层感知器MLP（Multi-Layer Perceptron）



对类型进行识别
之
训练神经网络

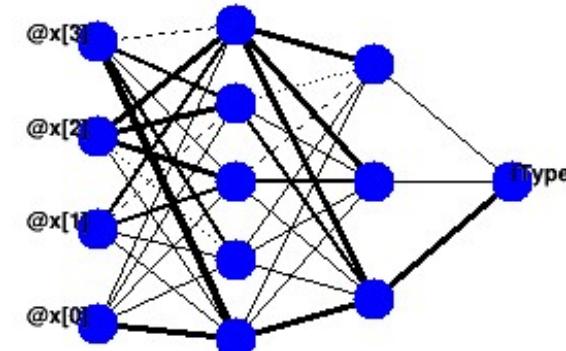
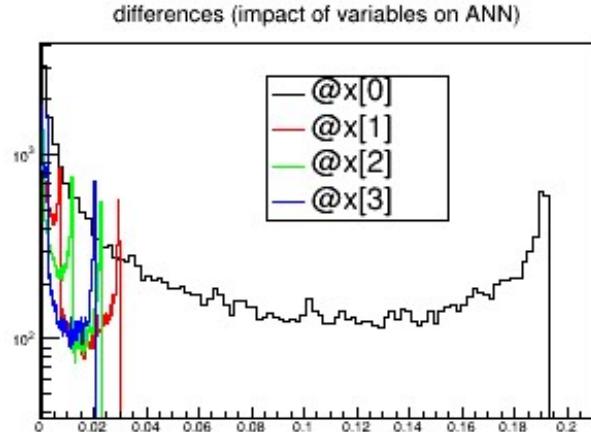
siguang@pku.edu.cn

13



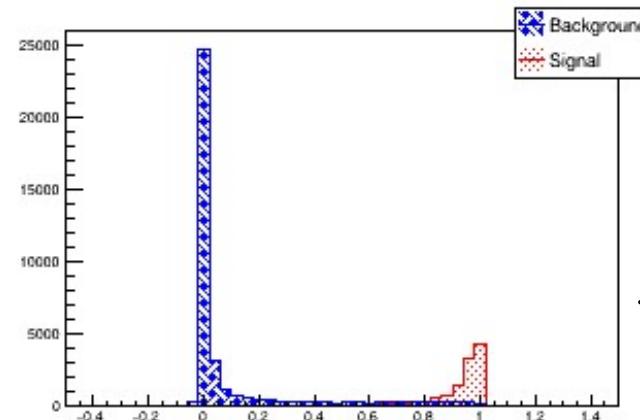
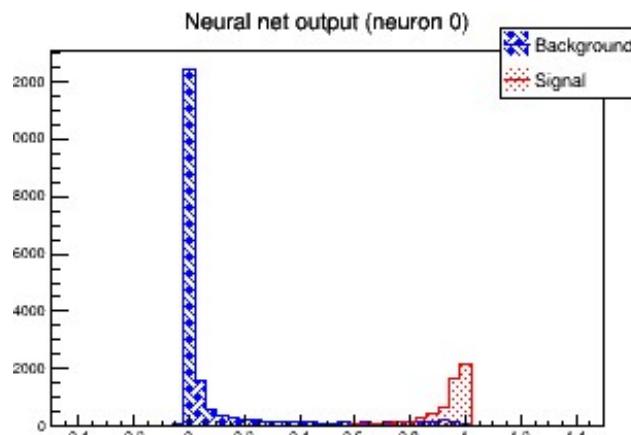
MLP神经网络结构及训练输出

各参量对最后结果的影响



神经网络的结构。
线的粗细反映权重大小

训练后的神经网络对测试数据的输出结果



训练后的神经网络对训练及测试数据的输出结果



MLP神经网络训练代码 (toTrain.C)

```
#include "TMultiLayerPerceptron.h"
#include "TMLPAnalyzer.h"
#include "TRandom3.h"
#include "TFile.h"
#include "TTree.h"
#include "TF1.h"
#include "TSystem.h"
#include "TMath.h"
#include "TROOT.h"
#include "TLegend.h"
#include "TCanvas.h"
#include "TH1F.h"
#include "THStack.h"

//Note: part of code from mlpHiggs.C under ROOT's tutorials/mlp
void toTrain(Int_t NumTrain=1000){
    if (!gROOT->GetClass("TMultiLayerPerceptron")) {
        gSystem->Load("libMLP");
    }

    TFile *f = new TFile("../createDataForTrain/data2.root"); //where the data is
    TTree *T;
    f->GetObject("T",T);
```



MLP神经网络训练代码 (toTrain.C 续)

```
//Declaration of leaves types
Int_t          iType;
Int_t          N;
Double_t       x[4];
Double_t       w; //weight of each event
// Set branch addresses.
T->SetBranchAddress("iType",&iType);
T->SetBranchAddress("N",&N);
T->SetBranchAddress("x",x);
T->SetBranchAddress("w",&w);

TMultiLayerPerceptron *mlp =
  new TMultiLayerPerceptron("@x[0],@x[1],@x[2],@x[3]:5:3:iType","w",T,"Entry%2","(Entry+1)%2");
//@--- to normalize the variation before taking part in the training.
//5:3---number of neurons in each layers
// "w"---weight
//T---TTree pointer
// "Entry%2" and "(Entry+1)%2"--training and test list

mlp->Train(NumTrain, "text,graph,update=10");
mlp->Export("TClassANN","C++");
```

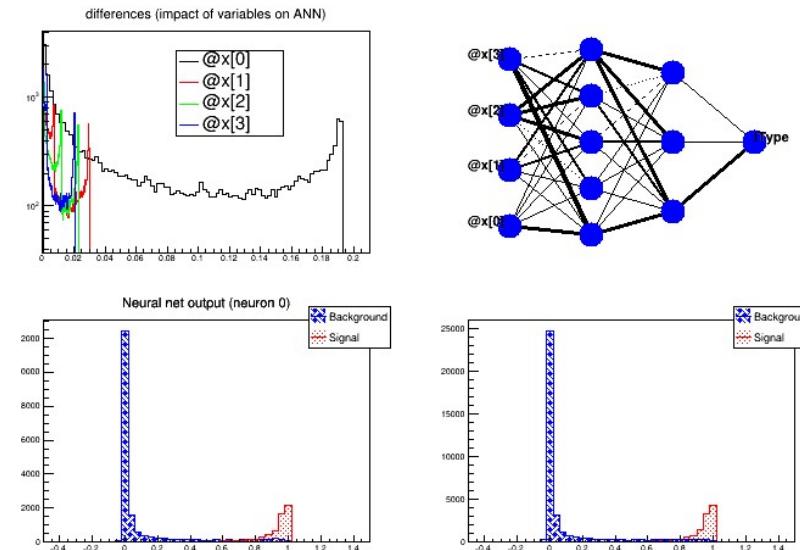
核心3句话！



MLP神经网络训练代码 (toTrain.C 续)

```
// Use TMLPAnalyzer to check more information
TCanvas* cTrain = new TCanvas("cTrain","Network analysis");
cTrain->Divide(2,2);
TMLPAnalyzer ana(mlp);
// Initialisation
ana.GatherInformations();
//
// output to the console
ana.CheckNetwork();
cTrain->cd(1);
// shows how each variable influences the network
ana.DrawDInputs();
cTrain->cd(2);
// shows the network structure
mlp->Draw();
cTrain->cd(3);
// draws the resulting network
ana.DrawNetwork(0,"iType==1","iType==0");
```

Network with structure: @x[0],@x[1],@x[2],@x[3]:5:3:iType
inputs with low values in the differences plot may not be needed
@x[0] -> 0.0158814 +/- 0.00631877
@x[1] -> 0.00728075 +/- 0.00291779
@x[2] -> 0.000366171 +/- 0.00022766
@x[3] -> 0.00112137 +/- 0.000837734





MLP神经网络训练代码 (toTrain.C 续)

```
cTrain->cd(4);
// Use the NN to plot the results for each sample
// This will give approx. the same result as DrawNetwork.
// All entries are used, while DrawNetwork focuses on the test sample.
TH1F *bg = new TH1F("bgh", "NN output", 50, -0.5, 1.5);
TH1F *sig = new TH1F("sigh", "NN output", 50, -0.5, 1.5);
Double_t params[4];
for (Int_t i = 0; i < T->GetEntries(); i++) {
    T->GetEntry(i);
    for(Int_t j=0;j<N; j++) params[j] = x[j];
    if(iType==0) bg->Fill(mlp->Evaluate(0, params));
    else sig->Fill(mlp->Evaluate(0, params));
}
bg->SetLineColor(kBlue);
bg->SetLineStyle(3008);    bg->SetFillColor(kBlue);
sig->SetLineColor(kRed);
sig->SetLineStyle(3003); sig->SetFillColor(kRed);
bg->SetStats(0);
sig->SetStats(0);
```



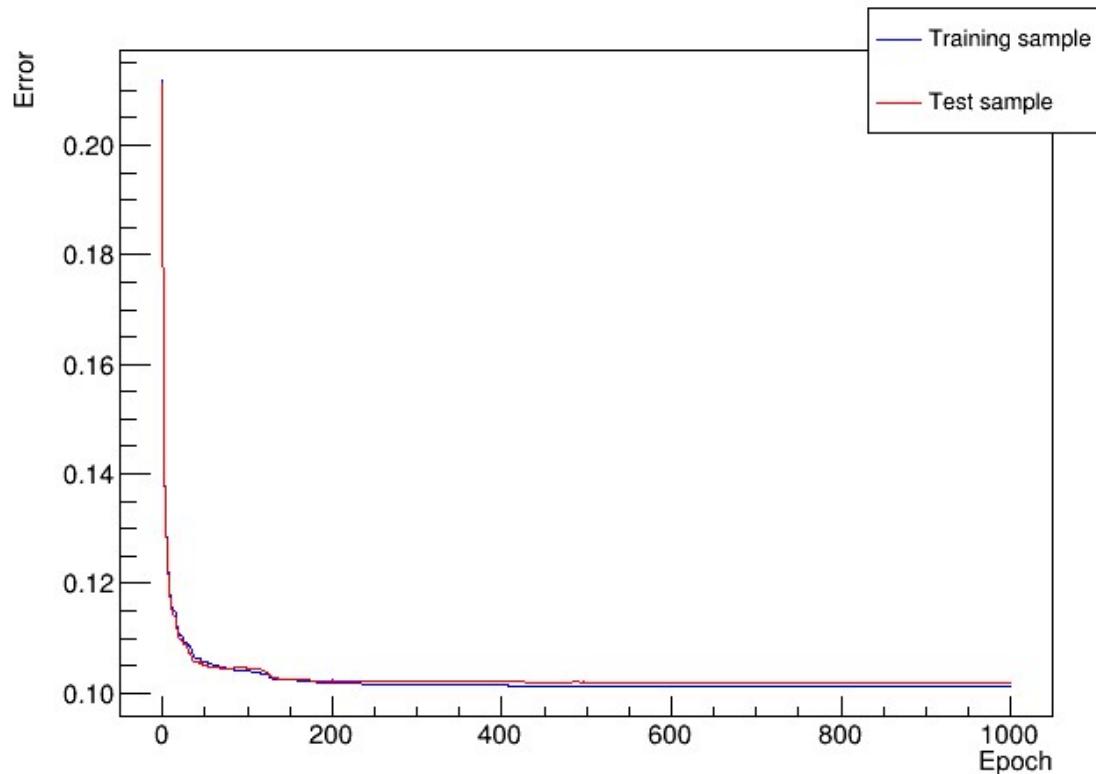
MLP神经网络训练代码 (toTrain.C 续)

```
THStack *ht = new THStack();
ht->Add(sig);
ht->Add(bg);
ht->Draw("nostack");

TLegend *legend = new TLegend(.75, .80, .95, .95);
legend->AddEntry(bg, "Background");
legend->AddEntry(sig, "Signal");
legend->Draw();
cTrain->cd(0);
```

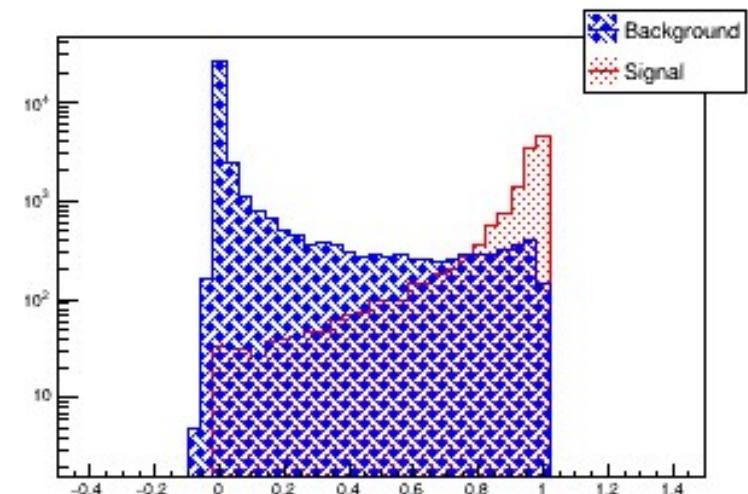


训练过程中错误率的显示



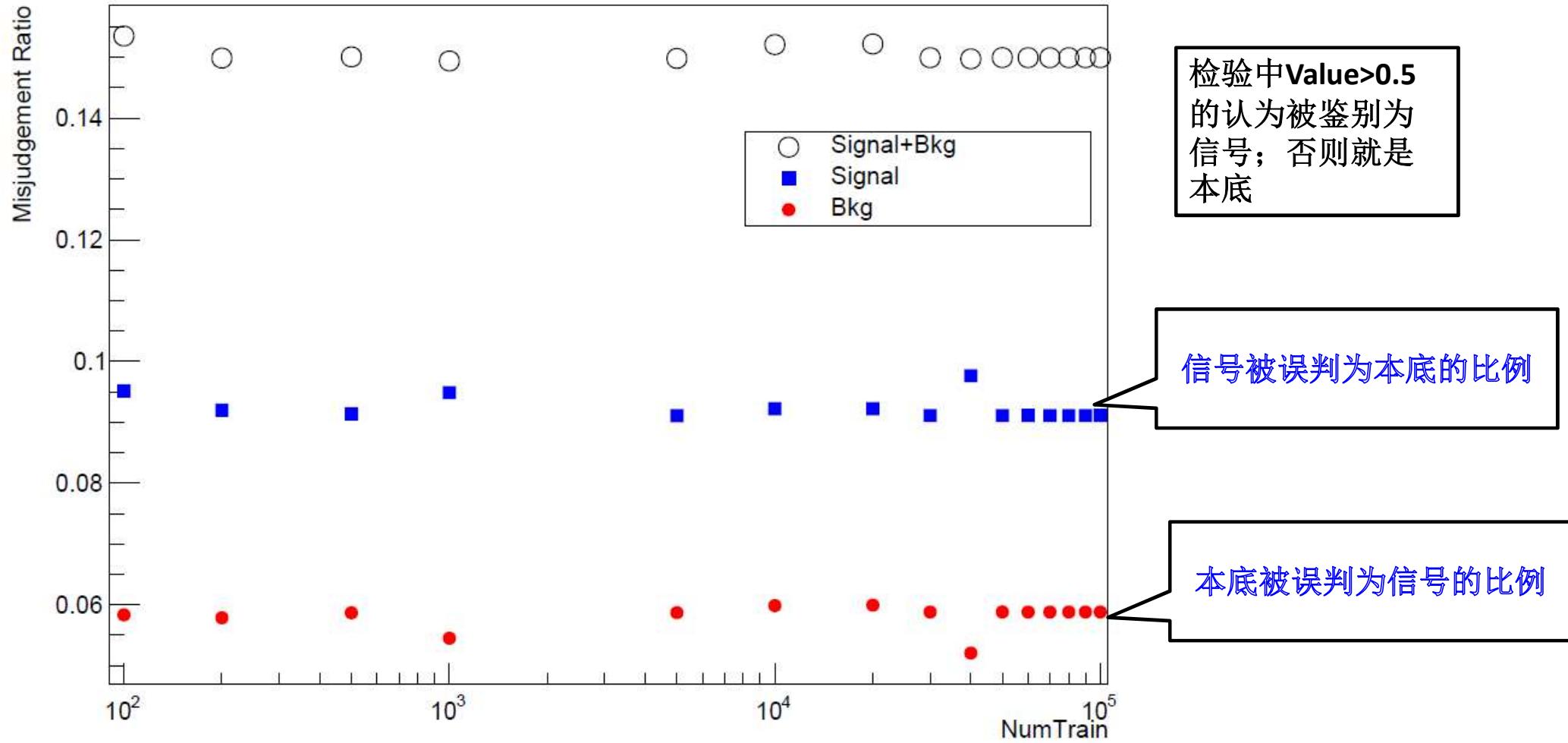
在训练的过程中，程序给出错误率的显示（如左图）。

如果随着训练代数的增加，错误率变大了，说明过度训练。建议改变层数及各层的神经元数目重新训练！





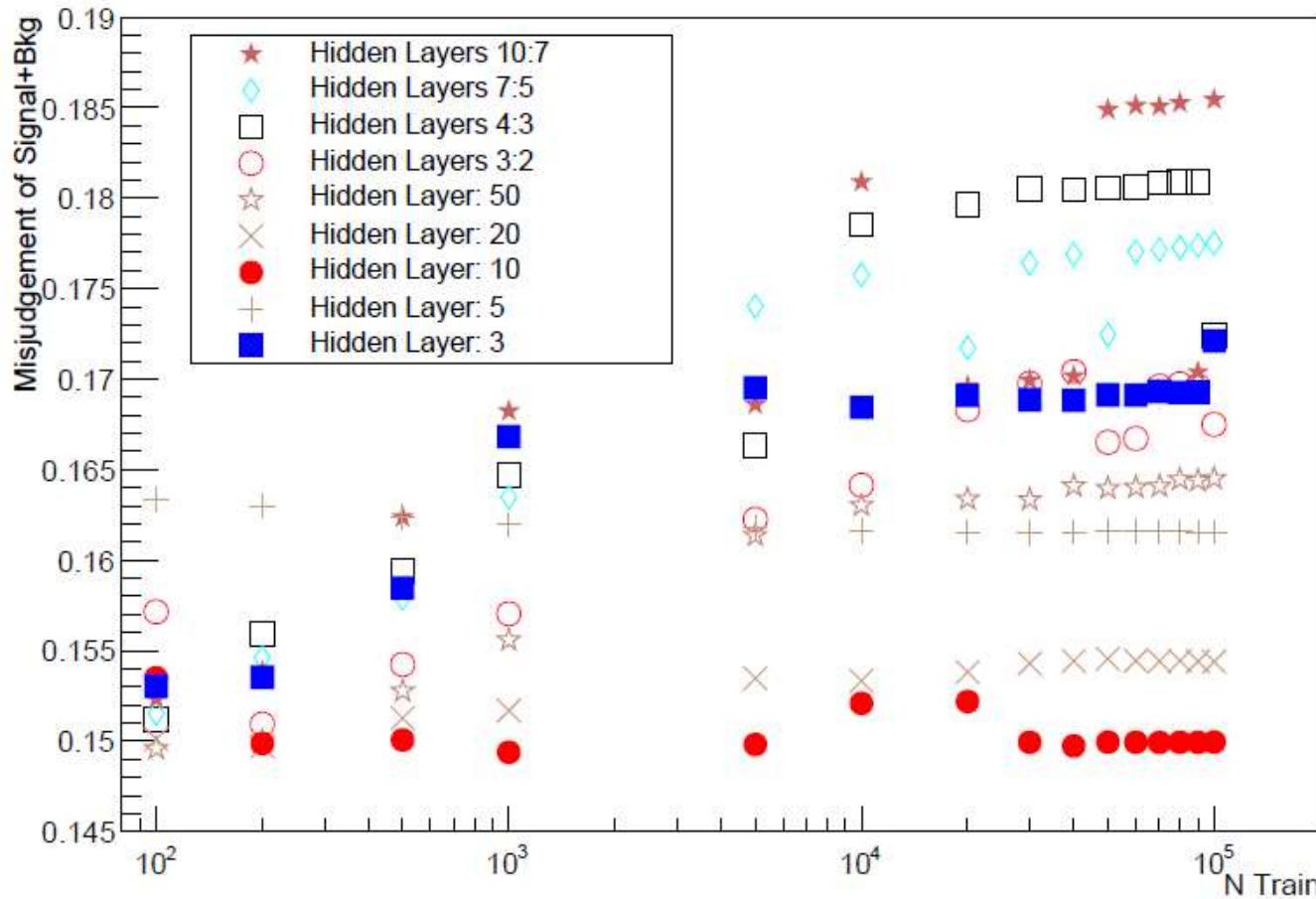
对不同训练总代数的类进行检验





MLP层数及各层神经元数目的确定

对于一个固定问题，需要用多少层及每层的神经元数目多少怎么确定？



对不同层数、不同神经元数目，由简单到复杂的神经网络结构进行不同训练代数的测试，找出
1) 信号+本底错误率最小
2) 随训练代数的增加比较稳定的结构！



MLP神经网络训练生成的类 (TClassANN.h)

```
#ifndef TClassANN_h
#define TClassANN_h

class TClassANN {
public:
    TClassANN() {}
    ~TClassANN() {}
    double Value(int index,double in0,double in1,double in2,double in3);
    double Value(int index, double* input);
private:
    double input0;
    double input1;
    double input2;
    double input3;
    double neuron0x2054d50();
    double neuron0x2055090();
    double neuron0x20553d0();
    double neuron0x2055710();
    double input0x2055b80();
    double neuron0x2055b80();
    double input0x2055ef0();
    double neuron0x2055ef0();

....
```



MLP神经网络训练生成的类 (TClassANN.hxx)

```
#include "TClassANN.h"
#include <cmath>

double TClassANN::Value(int index,double in0,double in1,double in2,double in3) {
    input0 = (in0 - 2.59797)/0.526293;
    input1 = (in1 - 3.59619)/0.861869;
    input2 = (in2 - 4.58778)/1.22867;
    input3 = (in3 - 5.56243)/1.58495;
    switch(index) {
        case 0:
            return neuron0x2057f90();
        default:
            return 0.;
    }
}
```

```
double TClassANN::neuron0x2057f90() {
    double input = input0x2057f90();
    return (input * 1)+0;
}
```

```
double TClassANN::input0x2057f90() {
    double input = 0.0208308;
    input += synapse0x2058240();
    input += synapse0x2058280();
    input += synapse0x20582c0();
    return input;
}
```



MLP神经网络训练生成的类 (TClassANN.hxx)

```
double TClassANN::Value(int index, double* input) {  
    input0 = (input[0] - 2.59797)/0.526293;  
    input1 = (input[1] - 3.59619)/0.861869;  
    input2 = (input[2] - 4.58778)/1.22867;  
    input3 = (input[3] - 5.56243)/1.58495;  
    switch(index) {  
        case 0:  
            return neuron0x2057f90();  
        default:  
            return 0.;  
    }  
}
```

对训练出来的类，可以独立使用！



多层感知器MLP（Multi-Layer Perceptron）

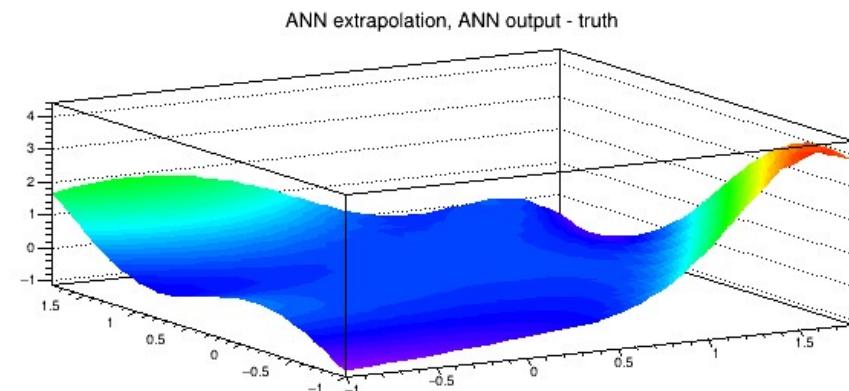
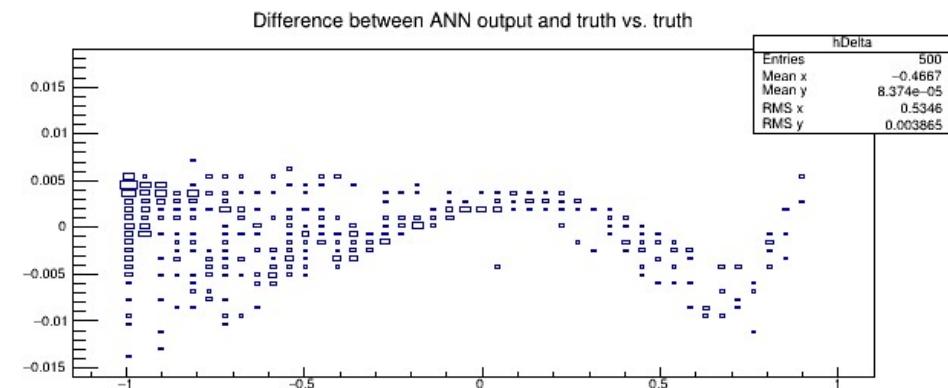
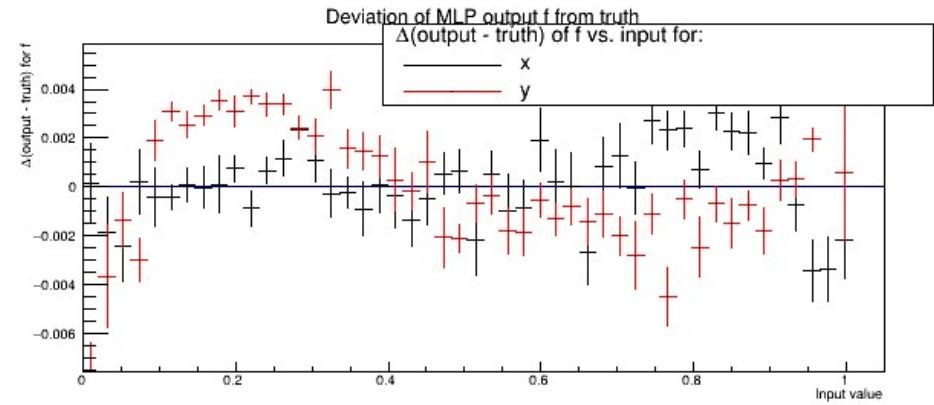
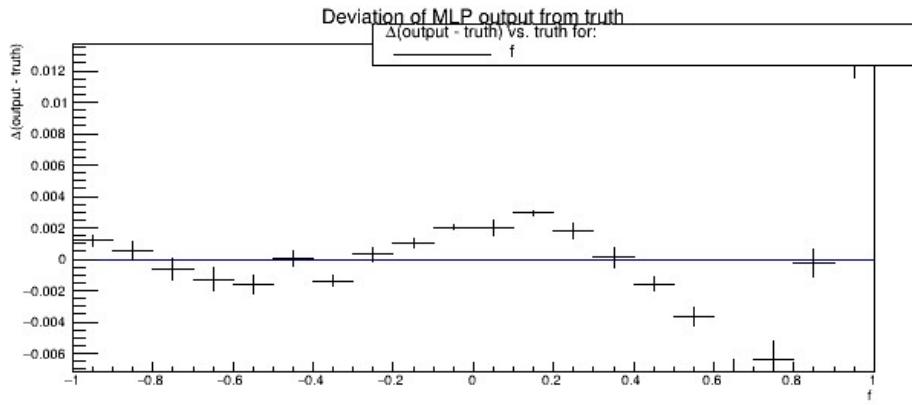


对连续函数进行描述



mlpRegression.C

● \$ROOTSYS/tutorials/mlp\$ emacs mlpRegression.C

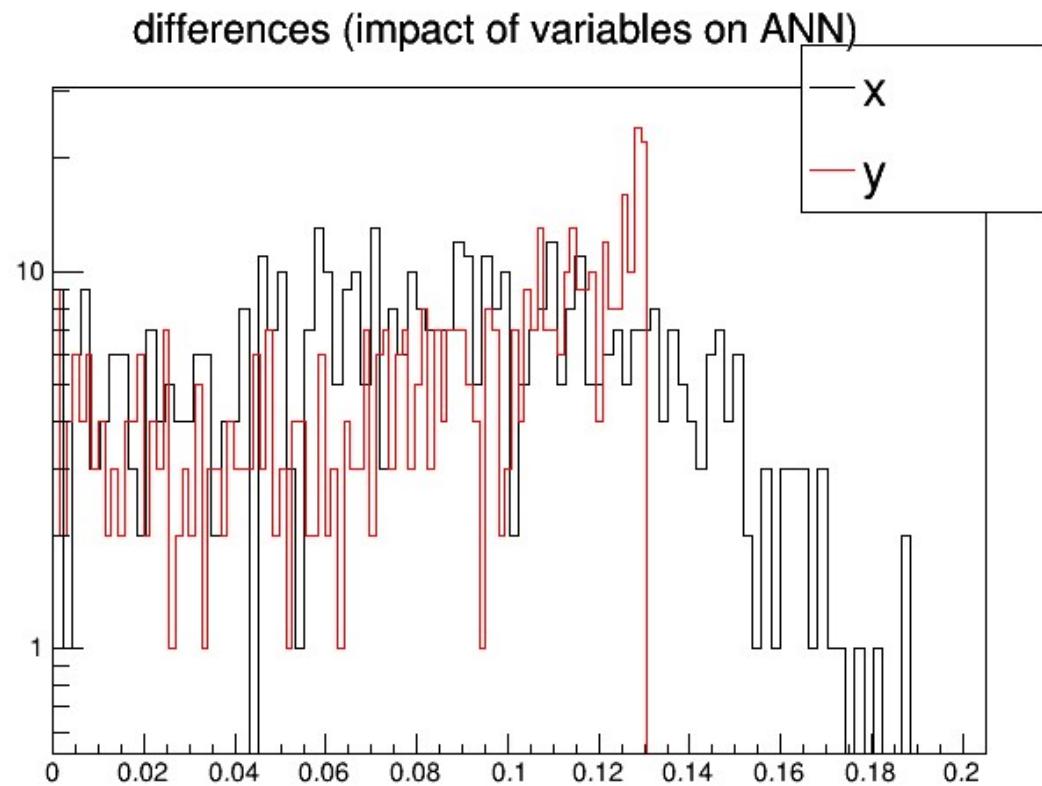


siguang@pku.edu.cn

27



mlpRegression.C (继续)





mlpRegression.C (继续)

```
//This macro shows the use of an ANN for regression analysis:  
//given a set {i} of input vectors i and a set {o} of output vectors o,  
//one looks for the unknown function f(i)=o.  
//The ANN can approximate this function; TMLPAnalyzer::DrawTruthDeviation  
//methods can be used to evaluate the quality of the approximation.  
//  
//For simplicity, we use a known function to create test and training data.  
//In reality this function is usually not known, and the data comes e.g.  
//from measurements.  
//  
//Axel Naumann, 2005-02-02  
  
Double_t theUnknownFunction(Double_t x, Double_t y) {  
    return sin((1.7+x)*(x-0.3)-2.3*(y+0.7));  
}
```



mlpRegression.C (继续)

```
void mlpRegression() {
    // create a tree with train and test data.
    // we have two input parameters x and y,
    // and one output value f(x,y)
    TNtuple* t=new TNtuple("tree","tree","x:y:f");
    TRandom r;
    for (Int_t i=0; i<1000; i++) {
        Float_t x=r.Rndm();
        Float_t y=r.Rndm();
        // fill it with x, y, and f(x,y) - usually this function
        // is not known, and the value of f given an x and a y comes
        // e.g. from measurements
        t->Fill(x,y,theUnknownFunction(x,y));
    }

    // create ANN
    TMultiLayerPerceptron* mlp=new TMultiLayerPerceptron("x,y:10:8:f",t,
        "Entry$%2","(Entry$%2)==0");
    mlp->Train(150,"graph update=10");
```

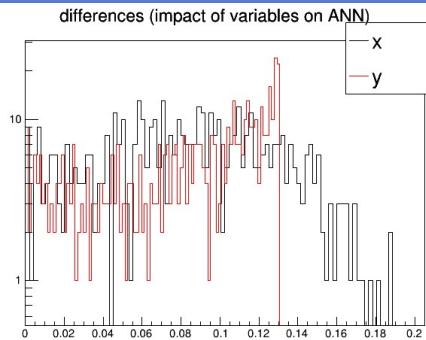


mlpRegression.C (继续)

```
// analyze it  
TMLPAnalyzer* mlpa=new TMLPAnalyzer(mlp);  
mlpa->GatherInformations();  
mlpa->CheckNetwork();  
mlpa->DrawDInputs();
```



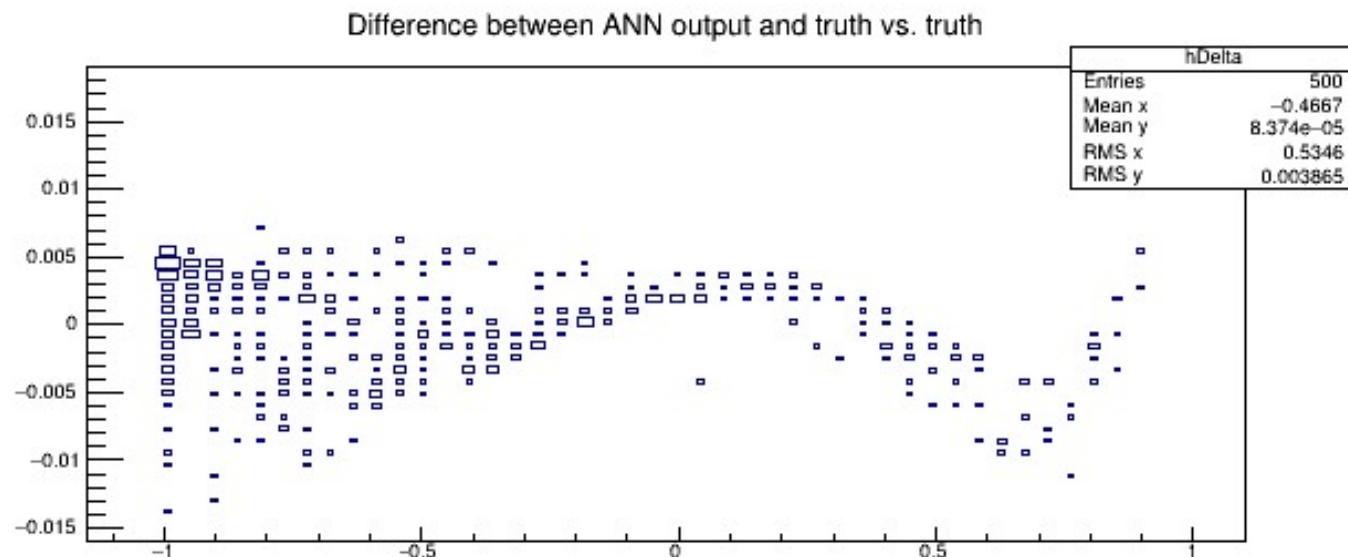
```
// draw statistics shows the quality of the ANN's approximation  
TCanvas* cI0=new TCanvas("TruthDeviation", "TruthDeviation");  
cI0->Divide(2,2);  
cI0->cd(1);  
// draw the difference between the ANN's output for (x,y) and  
// the true value f(x,y), vs. f(x,y), as TProfiles  
mlpa->DrawTruthDeviations();  
  
cI0->cd(2);  
// draw the difference between the ANN's output for (x,y) and  
// the true value f(x,y), vs. x, and vs. y, as TProfiles  
mlpa->DrawTruthDeviationInsOut();
```





mlpRegression.C (继续)

```
cI0->cd(3);
// draw a box plot of the ANN's output for (x,y) vs f(x,y)
mlpa->GetIOTree()->Draw("Out.Out0-True.True0:True.True0>>hDelta","","goff");
TH2F* hDelta=(TH2F*)gDirectory->Get("hDelta");
hDelta->SetTitle("Difference between ANN output and truth vs. truth");
hDelta->Draw("BOX");
```





mlpRegression.C (继续)

```
cI0->cd(4);
// draw difference of ANN's output for (x,y) vs f(x,y) assuming the ANN can extrapolate
Double_t vx[225];
Double_t vy[225];
Double_t delta[225];
Double_t v[2];
for (Int_t ix=0; ix<15; ix++) {
    v[0]=ix/5.-1.;
    for (Int_t iy=0; iy<15; iy++) {
        v[1]=iy/5.-1.;
        Int_t idx=ix*15+iy;
        vx[idx]=v[0];
        vy[idx]=v[1];
        delta[idx]=mlp->Evaluate(0, v)-theUnknownFunction(v[0],v[1]);
    }
}
TGraph2D* g2Extrapolate=new TGraph2D("ANN extrapolation",
                                         "ANN extrapolation, ANN output - truth",
                                         225, vx, vy, delta);
g2Extrapolate->Draw("TRI2");
}
```



多变量分析TMVA (Multi-Variate-Analysis类)

		MVA METHOD									
CRITERIA		Cuts	Likeli-hood	PDE-RS / k-NN	PDE-Foam	H-Matrix	Fisher / LD	MLP	BDT	Rule-Fit	SVM
Performance	No or linear correlations	★	★★	★	★	★	★★	★★	★	★★	★
	Nonlinear correlations	○	○	★★	★★	○	○	★★	★★	★★	★★
Speed	Training	○	★★	★★	★★	★★	★	○	★	○	
	Response	★★	★★	○	★	★★	★★	★★	★	★★	★
Robustness	Overtraining	★★	★	★	★	★★	★★	★	○	★	★★
	Weak variables	★★	★	○	○	★★	★★	★	★★	★	★
Curse of dimensionality		○	★★	○	○	★★	★★	★	★	★	
Transparency		★★	★★	★	★	★★	★★	○	○	○	○

siguang@pku.edu.cn



ROOT有TMVA软件包: [\\$ROOTSYS/tmva/test](#)

在自学的时候建议先读该目录下的**README**

学习入口:

`TMVAClassification.C` 进行训练

`TMVAClassificationApplication.C` 展示怎么使用训练后的结果

因为`TMVAClassification.C`涉及到多种区分本底与信号的方法，为简便，本课对以上两程序进行简化：
展现BDT（Boosted Decision Trees 增强决策森林）和MLP（Multilayer Perceptron多层感知机）两种训练算法的使用



TMVA的训练

siguang@pku.edu.cn

36



TrainTMVA.C (简化后的TMVAClassification.C)

```
void TrainTMVA(Int_t totEvt=10000, Int_t NumTrain=200, Int_t nSeed=1){
    const Int_t Nx = 4;
    TF1 *fsig[Nx];
    TF1 *fbkg[Nx];
    const Double_t xmin=0;
    const Double_t xmax=10;
    const Double_t sqPi = sqrt(TMath::Pi());
    Int_t N = Nx;
    //prepare signal and background functions
    for(Int_t i=0; i<N; i++){
        fsig[i] = new TF1(Form("fsig%d",i),"[0]*exp(-(x-[1])*(x-[1])/[2]/[2])",xmin,xmax);
        fbkg[i] = new TF1(Form("fbkg%d",i),"[0]*exp(-(x-[1])*(x-[1])/[2]/[2])",xmin,xmax);
        Double_t MeanS = i+2.0;
        Double_t MeanB = i+2.8;
        Double_t sigmaS = (i+1.)*0.4;
        Double_t sigmaB = (i+1.)*0.6;
        fsig[i]->SetParameters(1/(sqPi*sigmaS),MeanS,sigmaS);
        fbkg[i]->SetParameters(1/(sqPi*sigmaB),MeanB,sigmaB);
        fsig[i]->SetNpx(10000);
        fbkg[i]->SetNpx(10000);
        fsig[i]->SetLineColor(i+1);
        fbkg[i]->SetLineColor(i+1);
```



TrainTMVA.C (续)

```
fsig[i]->SetLineStyle(i+1);
fbkg[i]->SetLineStyle(i+1);
fsig[i]->SetLineWidth(2);
fbkg[i]->SetLineWidth(4);
}

//  
//create data

TTree *Tsig = new TTree("Tsig","Tree for Signal and Background");
Double_t var1,var2,var3,var4;
Double_t w;
Tsig->Branch("var1",&var1,"var1/D");
Tsig->Branch("var2",&var2,"var2/D");
Tsig->Branch("var3",&var3,"var3/D");
Tsig->Branch("var4",&var4,"var4/D");
Tsig->Branch("w",&w,"w/D");

TTree *Tbkq = Tsig->CloneTree(0);
```

不拷贝内容，
只克隆结构



TrainTMVA.C (续)

```
gRandom->SetSeed(nSeed);
Int_t nSig = totEvt/(1+3);
Int_t nBkg = totEvt - nSig;
for(Int_t i=0; i<nSig; i++){
    w = 3.0; // signal weight 3
    var1 = fsig[0]->GetRandom();
    var2 = fsig[1]->GetRandom();
    var3 = fsig[2]->GetRandom();
    var4 = fsig[3]->GetRandom();
    Tsig->Fill();
}

for(Int_t i=0; i<nBkg; i++){
    w = 1.0; // background weight 1
    var1 = fbkg[0]->GetRandom();
    var2 = fbkg[1]->GetRandom();
    var3 = fbkg[2]->GetRandom();
    var4 = fbkg[3]->GetRandom();
    Tbkg->Fill();
}
```



TrainTMVA.C (续)

```
//define TMVA factory-----  
// Create a ROOT output file where TMVA will store ntuples, histograms, etc.  
TString outfileName( "TMVAoutput.root" );  
TFile* outputFile = TFile::Open( outfileName, "RECREATE" );  
  
TMVA::Factory *factory = new TMVA::Factory( "TrainTMVA", outputFile,  
                                         "!V:!Silent:Color:DrawProgressBar:  
                                         Transformations=I;D;P;G,D:AnalysisType=Classification" );  
//V---Verbose flag  
//Silent---Batch mode: boolean silent flag inhibiting any output from TMVA  
//after the creation of the factory class object (default: False)  
//Color---Flag for coloured screen output (default: True, if in batch mode: False)  
//DrawProgressBar---Draw progress bar to display training, testing and evaluation schedule (default: True)  
//Transformations---List of transformations to test; formatting example: "Transformations=I;D;P;G,D",  
//for identity, decorrelation, PCA, and Gaussianisation followed by decorrelation transformations"  
  
factory->AddVariable( "var1", "Variable 1", "units", 'F' );  
factory->AddVariable( "var2", "Variable 2", "units", 'F' );  
factory->AddVariable( "var3", "Variable 3", "units", 'F' );  
factory->AddVariable( "var4", "Variable 4", "units", 'F' );  
//AddVariable(const TString& expression, const TString& title, const TString& unit, char type = 'F',  
// Double_t min = 0, Double_t max = 0)
```

PCA (Principal Component Analysis) 是一种常用的数据分析方法。PCA通过线性变换将原始数据变换为一组各维度线性无关的表示，可用于提取数据的主要特征分量，常用于高维数据的降维。



TrainTMVA.C (续)

```
// Add signal or background trees
factory->AddSignalTree    ( Tsig );
factory->AddBackgroundTree( Tbkg);
factory->SetSignalWeightExpression("w");
factory->SetBackgroundWeightExpression("w");

// Apply additional cuts on the signal and background samples (can be different)
TCut mycuts = ""; // for example: TCut mycuts = "abs(var1)<0.5 && abs(var2-0.5)<1";
TCut mycutb = ""; // for example: TCut mycutb = "abs(var1)<0.5";
factory->PrepareTrainingAndTestTree( mycuts, mycutb,
                                     "nTrain_Signal=0:nTrain_Background=0:
                                     SplitMode=Random:NormMode=NumEvents:!V" );
```



TrainTMVA.C (续)

```
// Adaptive Boost
factory->BookMethod( TMVA::Types::kBDT, "BDT",
                      "!H:!V:NTrees=850:MinNodeSize=2.5%:MaxDepth=3:BoostType=AdaBoost:
                      AdaBoostBeta=0.5:UseBaggedBoost:BaggedSampleFraction=0.5:
                      SeparationType=GiniIndex:nCuts=20" );
//BDT options (http://tmva.sourceforge.net/optionRef.html):
//H---Print method-specific help, (default False)
//V---Verbose output, (False)
//NTrees---Number of trees in the forest, default 800
//MinNodeSize--Minimum percentage of training events required in a leaf node
//                         (default: Classification: 5%, Regression: 0.2%)
//MaxDepth---Max depth of the decision tree allowed (3)
//BoostType--- Boosting type for the trees in the forest (AdaBoost)
//AdaBoostBeta---Learning rate for AdaBoost algorithm(0.5)
//UseBaggedBoost---Use only a random subsample of all events for growing the trees in each iteration (False)
//BaggedSampleFraction---Relative size of bagged event sample to original size of the data sample
//                         (used whenever bagging is used (i.e. UseBaggedGrad, Bagging,) (0.6)
//SeparationType---Separation criterion for node splitting (GiniIndex)
//nCuts---Number of grid points in variable range used in finding optimal cut in node splitting (20)
```



TrainTMVA.C (续)

```
// Tmlp(Root)ANN
factory->BookMethod( TMVA::Types::kTMLpANN, "TMLpANN", "!H:!V:NCycles=200:HiddenLayers=N+1,N:LearningMethod=BFGS:ValidationFraction=0.3" );
//OPtions of TMLpANN (http://tmva.sourceforge.net/optionRef.html)
//HiddenLayers---Specification of hidden layer architecture (N stands for number of variables; any integers may also be used)
//ValidationFraction---Fraction of events in training tree used for cross validation(0.5)

// ---- Now you can tell the factory to train, test, and evaluate the MVAs

// Train MVAs using the set of training events
factory->TrainAllMethods();

// ---- Evaluate all MVAs using the set of test events
factory->TestAllMethods();

// ----- Evaluate and compare performance of all configured MVAs
factory->EvaluateAllMethods();

// -----
// Save the output
outputFile->Close();

delete factory;
}
```



TrainTMVA.C 训练结果

训练后会在当前目录下生成weights子目录，该目录下针对BDT和MLP两种方法，生成训练后可独立使用的c++类和xml文件。

MLP的C++类文件名：TrainTMVA_TMLpANN.cxx 及头文件TrainTMVA_TMLpANN.h

MLP的xml文件名：TrainTMVA_TMLpANN.weights.xml

```
#ifndef TrainTMVA_TMLpANN_h
#define TrainTMVA_TMLpANN_h

class TrainTMVA_TMLpANN {
public:
    TrainTMVA_TMLpANN() {}
    ~TrainTMVA_TMLpANN() {}
    double Value(int index,double in0,double in1,double in2,double in3);
    double Value(int index, double* input);
private:
    double input0;
    double input1;
    double input2;
    double input3;
```

MLP通过TMVA训练处的类
与root自带的
TMultiLayerPerceptron训
练出类的类一样。



TrainTMVA.C 训练结果

BDT的C++类文件名：TrainTMVA_BDT.class.C

BDT的xml文件名： TrainTMVA_BDT.weights.xml

TrainTMVA_BDT.class.C

```
class ReadBDT : public IClassifierReader {  
  
public:  
  
    // constructor  
    ReadBDT( std::vector<std::string>& theInputVars )  
    ....  
  
    double GetMvaValue__( const std::vector<double>& inputValues ) const;  
    ....
```

>0 信号
否则本底



TMVA的训练结果的应用：用xml文件测试训练结果

siguang@pku.edu.cn

46



训练后的Xml的内容 --TrainTMVA_TMLpANN.weights.xml



```
<?xml version="1.0"?>
<MethodSetup Method="TMLpANN::TMLpANN">
  <GeneralInfo>
    <Info name="TMVA Release" value="4.2.0 [262656]" />
    <Info name="ROOT Release" value="5.34/36 [336420]" />
    <Info name="Creator" value="wsg" />
    <Info name="Date" value="Mon Jul 31 03:42:06 2017" />
    <Info name="Host" value="Linux debian 3.2.0-4-amd64 #1 SMP Debian 3.2.78-1 x86_64 GNU/Linux" />
    <Info name="Dir" value="/media/sf_UbuntuShare/rootEduBOOK/chapter3/tmva" />
    <Info name="Training events" value="5000" />
    <Info name="TrainingTime" value="6.33900785e+00" />
    <Info name="AnalysisType" value="Classification" />
  </GeneralInfo>
  <Options>
    <Option name="V" modified="Yes">False</Option>
    <Option name="VerbosityLevel" modified="No">Default</Option>
    <Option name="VarTransform" modified="No">None</Option>
    <Option name="H" modified="Yes">False</Option>
    <Option name="CreateMVAPdfs" modified="No">False</Option>
    <Option name="IgnoreNegWeightsInTraining" modified="No">False</Option>
    <Option name="NCycles" modified="Yes">200</Option>
    <Option name="HiddenLayers" modified="Yes">N+1,N</Option>
    <Option name="ValidationFraction" modified="Yes">3.000000e-01</Option>
    <Option name="LearningMethod" modified="Yes">bfgs</Option>
  </Options>
  <Variables NVar="4">
    <Variable VarIndex="0" Expression="var1" Label="var1" Title="Variable 1" Unit="units" Internal="var1" Type="F" Min="9.57743347e-01" Max="4.37795401e+00" />
    <Variable VarIndex="1" Expression="var2" Label="var2" Title="Variable 2" Unit="units" Internal="var2" Type="F" Min="5.56589127e-01" Max="6.46939230e+00" />
    <Variable VarIndex="2" Expression="var3" Label="var3" Title="Variable 3" Unit="units" Internal="var3" Type="F" Min="1.47316948e-01" Max="8.63263226e+00" />
    <Variable VarIndex="3" Expression="var4" Label="var4" Title="Variable 4" Unit="units" Internal="var4" Type="F" Min="2.01887488e-01" Max="9.99827957e+00" />
  </Variables>
```



训练后的Xml的内容--TrainTMVA_TMLpANN.weights.xml (续)



```
<Spectators NSpec="0"/>
<Classes NClass="2">
  <Class Name="Signal" Index="0"/>
  <Class Name="Background" Index="1"/>
</Classes>
<Transformations NTransformations="0"/>
<MVAPdfs/>
<Weights>
  <Architecture BuildOptions="@var1,@var2,@var3,@var4:5:4:type"/>
  <input>
    0.524228 2.59941 0.855831 3.60237 1.21668 4.5976 1.58965 5.57355
  </input>
  <output>
    1 0
  </output>
  <neurons>
    -0.485791 0.240646 0.0774717 -0.0232713 0.861459 2.53571 3.17827 0.568858 -0.0317327 1.55842 -0.737349 0.275889 -6.63192 -0.0816457
  </neurons>
  <synapses>
    -1.02722 -2.63409 -1.46141 -2.63127 -1.27809 -0.494163 -0.120283 -0.212213 -3.23353 0.459102 1.72003 -1.3362 -3.00814 -2.72479 0.697151 1.48738 -3.16787 0.166163 -1.80745 -0.220989 -2.37366 -1.3176 0.48645 -0.421324 1.64198 -0.332904 0.457442 -0.55447 0.0389644 -1.29349 -0.55402 0.60312 0.840831 -0.359233 -0.780982 1.9062 -3.16468 3.03454 1.57723 2.35888 0.0588785 0.397996 -0.113308 3.65965
  </synapses>
  </Weights>
</MethodSetup>
```



训练后的xml---TrainTMVA_BDT.weights.xml

```
<?xml version="1.0"?>
<MethodSetup Method="BDT::BDT">
  <GeneralInfo>
    <Info name="TMVA Release" value="4.2.0 [262656]" />
    <Info name="ROOT Release" value="5.34/36 [336420]" />
    <Info name="Creator" value="wsg" />
    <Info name="Date" value="Mon Jul 31 03:41:57 2017" />
    <Info name="Host" value="Linux debian 3.2.0-4-amd64 #1 SMP Debian 3.2.78-1 x86_64 GNU/Linux" />
    <Info name="Dir" value="/media/sf_UbuntuShare/rootEduBOOK/chapter3/tmva" />
    <Info name="Training events" value="5000" />
    <Info name="TrainingTime" value="1.81201911e+00" />
    <Info name="AnalysisType" value="Classification" />
  </GeneralInfo>
  <Options>
    <Option name="V" modified="Yes">False</Option>
    <Option name="VerbosityLevel" modified="No">Default</Option>
    <Option name="VarTransform" modified="No">None</Option>
    <Option name="H" modified="Yes">False</Option>
    <Option name="CreateMVPdfs" modified="No">False</Option>
    <Option name="IgnoreNegWeightsInTraining" modified="No">False</Option>
    <Option name="NTrees" modified="Yes">850</Option>
  </Options>

```

○ ○ ○ ○ ○ ○



训练后的xml---TrainTMVA_BDT.weights.xml (续)

```
<Weights NTrees="850" AnalysisType="0">
  <BinaryTree type="DecisionTree" boostWeight="9.9781444396469765e-01" itree="0">
    <Node pos="s" depth="0" NCoef="0" IVar="0" Cut="2.3041086196899414e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="5.0131785869598389e-01" nType="0">
      <Node pos="l" depth="1" NCoef="0" IVar="1" Cut="3.9850797653198242e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="8.7936508655548096e-01" nType="0">
        <Node pos="l" depth="2" NCoef="0" IVar="-1" Cut="5.4512405395507812e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="9.1946703195571899e-01" nType="1"/>
        <Node pos="r" depth="2" NCoef="0" IVar="-1" Cut="0.000000000000000e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="4.5731708407402039e-01" nType="-1"/>
      </Node>
      <Node pos="r" depth="1" NCoef="0" IVar="-1" Cut="2.6019032001495361e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="1.2605041265487671e-01" nType="-1"/>
    </Node>
  </BinaryTree>
  . . . . .

```

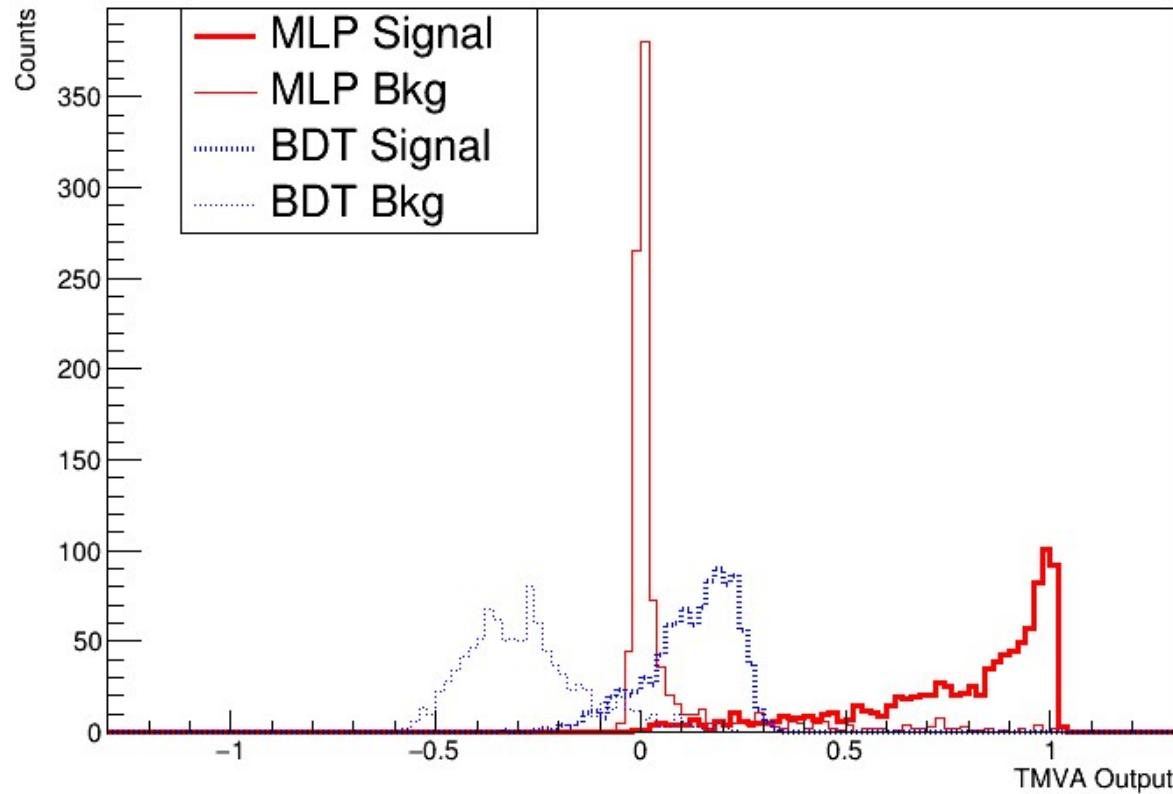
第850个 (从序号0开始)

```
<BinaryTree type="DecisionTree" boostWeight="1.4243556483244563e-01" itree="849">
  <Node pos="s" depth="0" NCoef="0" IVar="2" Cut="2.5716927051544189e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="4.4853436946868896e-01" nType="0">
    <Node pos="l" depth="1" NCoef="0" IVar="-1" Cut="0.000000000000000e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="8.2950592041015625e-01" nType="1"/>
    <Node pos="r" depth="1" NCoef="0" IVar="3" Cut="4.8414001464843750e+00" cType="0" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="4.3779209256172180e-01" nType="0">
      <Node pos="l" depth="2" NCoef="0" IVar="3" Cut="6.5428924560546875e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="4.7115877270698547e-01" nType="0">
        <Node pos="l" depth="3" NCoef="0" IVar="-1" Cut="0.000000000000000e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="5.0120848417282104e-01" nType="1"/>
        <Node pos="r" depth="3" NCoef="0" IVar="-1" Cut="0.000000000000000e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="3.3787220716476440e-01" nType="-1"/>
      </Node>
      <Node pos="r" depth="2" NCoef="0" IVar="-1" Cut="3.7366983890533447e+00" cType="1" res="-9.900000000000000e+01" rms="0.000000000000000e+00" purity="3.8180994987487793e-01" nType="-1"/>
    </Node>
  </Node>
</BinaryTree>
</Weights>
</MethodSetup>
```



xml文件的应用例子： UseXMLOutput.C

UseXMLOutput.C的输出



siguang@pku.edu.cn

51



UseXMLOutput.C

```
#include <cstdlib>
#include <vector>
#include <iostream>
#include <map>
#include <string>

using namespace TMVA;
void UseOutput(){
// part of codes are from /tmva/test$ emacs TMVAClassificationApplication.C
#ifndef __CINT__
    gROOT->ProcessLine( ".00" ); // turn off optimization in CINT
#endif
// This loads the library
TMVA::Tools::Instance();

// --- Create the Reader object
TMVA::Reader *reader = new TMVA::Reader( "!Color:!Silent" );
...}
```



UseXMLOutput.C (续)

```
// Create a set of variables and declare them to the reader
// - the variable names MUST corresponds in name and type to
//   those given in the weight file(s) used
Float_t var1, var2;
Float_t var3, var4;
reader->AddVariable( "var1", &var1 );
reader->AddVariable( "var2", &var2 );
reader->AddVariable( "var3", &var3 );
reader->AddVariable( "var4", &var4 );

//book the method and weightfile
TString methodName = "TMlpANN method"; //MUST exactly
TString weightfile = "weights/TrainTMVA_TMlpANN.weights.xml";
reader->BookMVA( methodName, weightfile );

methodName = "BDT method";
weightfile = "weights/TrainTMVA_BDT.weights.xml";
reader->BookMVA( methodName, weightfile );
```



UseXMLEOutput.C (续)

```
//prepare signal and background functions
const Int_t Nx = 4;
TF1 *fsig[Nx];
TF1 *fbkg[Nx];
const Double_t xmin=0;
const Double_t xmax=10;
const Double_t sqPi = sqrt(TMath::Pi());
Int_t N = Nx;

for(Int_t i=0; i<N; i++){
    fsig[i] = new TF1(Form("fsig%d",i),"[0]*exp(-(x-[1])*(x-[1])/[2]/[2])",xmin,xmax);
    fbkg[i] = new TF1(Form("fbkg%d",i),"[0]*exp(-(x-[1])*(x-[1])/[2]/[2])",xmin,xmax);
    Double_t MeanS = i+2.0;
    Double_t MeanB = i+2.8;
    Double_t sigmaS = (i+1.)*0.4;
    Double_t sigmaB = (i+1.)*0.6;
    fsig[i]->SetParameters(1/(sqPi*sigmaS),MeanS,sigmaS);
    fbkg[i]->SetParameters(1/(sqPi*sigmaB),MeanB,sigmaB);
    fsig[i]->SetNpx(10000);
    fbkg[i]->SetNpx(10000);
}
```



UseXMLOutput.C (续)

```
//create data
// Book output histograms
UInt_t nbin = 130;
TH1F* hSigMlp    = new TH1F( "hSigMlp",           "MVA_TMlpANN",      nbin, -1.3, 1.3 );
TH1F* hBkgMlp    = new TH1F( "hBkgMlp",           "MVA_TMlpANN",      nbin, -1.3, 1.3 );

TH1F* hSigBdt    = new TH1F( "hSigBdt",           "MVA_BDT",          nbin, -1.3, 1.3 );
TH1F* hBkgBdt    = new TH1F( "hBkgBdt",           "MVA_TBD",          nbin, -1.3, 1.3 );

Int_t nSig = 1000;
Int_t nBkg = 1000;
for(Int_t i=0; i<nSig; i++){
    var1 = fsig[0]->GetRandom();
    var2 = fsig[1]->GetRandom();
    var3 = fsig[2]->GetRandom();
    var4 = fsig[3]->GetRandom();
    hSigMlp->Fill(reader->EvaluateMVA( "TMlpANN method" ));
    hSigBdt->Fill(reader->EvaluateMVA( "BDT method" ));
}
```



UseXMLOutput.C (续)

```
for(Int_t i=0; i<nBkg; i++){
    var1 = fbkg[0]->GetRandom();
    var2 = fbkg[1]->GetRandom();
    var3 = fbkg[2]->GetRandom();
    var4 = fbkg[3]->GetRandom();
    hBkgMlp->Fill(reader->EvaluateMVA( "TMlpANN method"));
    hBkgBdt->Fill(reader->EvaluateMVA( "BDT method"));
}

TCanvas *c1 = new TCanvas("c1","");
gPad->SetTopMargin(0.03);
gPad->SetRightMargin(0.03);
THStack *hs = new THStack();
hs->Add(hSigMlp);
hs->Add(hBkgMlp);
hs->Add(hSigBdt);
hs->Add(hBkgBdt);
```



UseXMLOutput.C (续)

```
hSigMlp->SetLineColor(kRed);
hSigMlp->SetLineWidth(3);
hSigMlp->SetLineStyle(1);
hBkgMlp->SetLineColor(kRed);
hBkgMlp->SetLineWidth(1);
hBkgMlp->SetLineStyle(1);

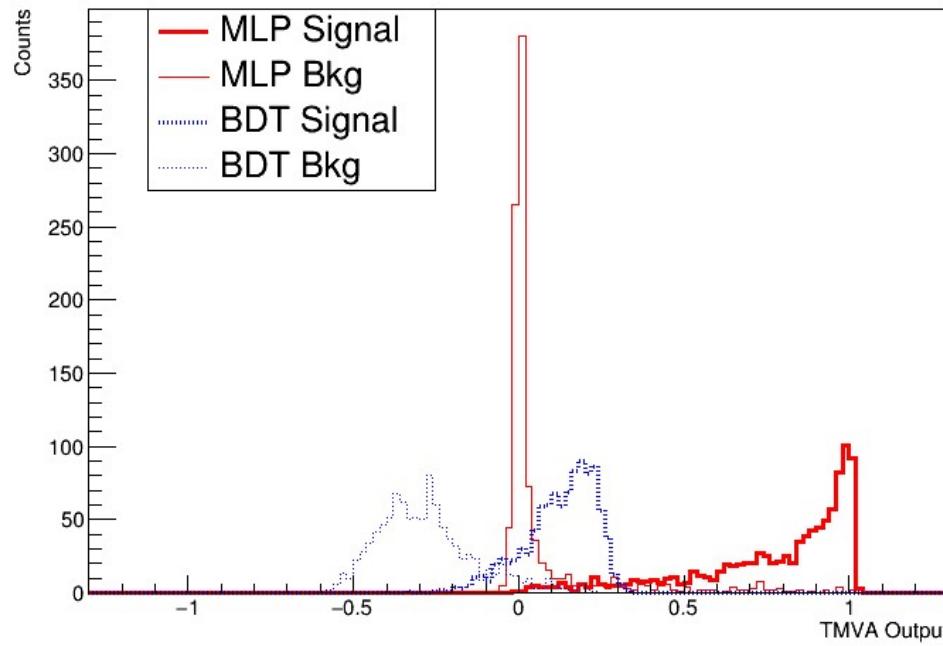
hSigBdt->SetLineColor(kBlue);
hSigBdt->SetLineWidth(3);
hSigBdt->SetLineStyle(3);
hBkgBdt->SetLineColor(kBlue);
hBkgBdt->SetLineWidth(1);
hBkgBdt->SetLineStyle(3);

hs->Draw("nostack");
hs->SetTitle("TMVA Output; Counts");
hs->GetYaxis()->SetTitleOffset(1.2);
```



UseXMLOutput.C (续)

```
hs->GetYaxis()->SetTitleOffset(1.2);
TLegend *lg = new TLegend(0.16,0.7,0.45,0.97);
lg->AddEntry(hSigMlp,"MLP Signal","L");
lg->AddEntry(hBkgMlp,"MLP Bkg","L");
lg->AddEntry(hSigBdt,"BDT Signal","L");
lg->AddEntry(hBkgBdt,"BDT Bkg","L");
lg->Draw();
}
```



siguang@pku.edu.cn



TMVA的训练结果的应用：用C++文件测试训练结果

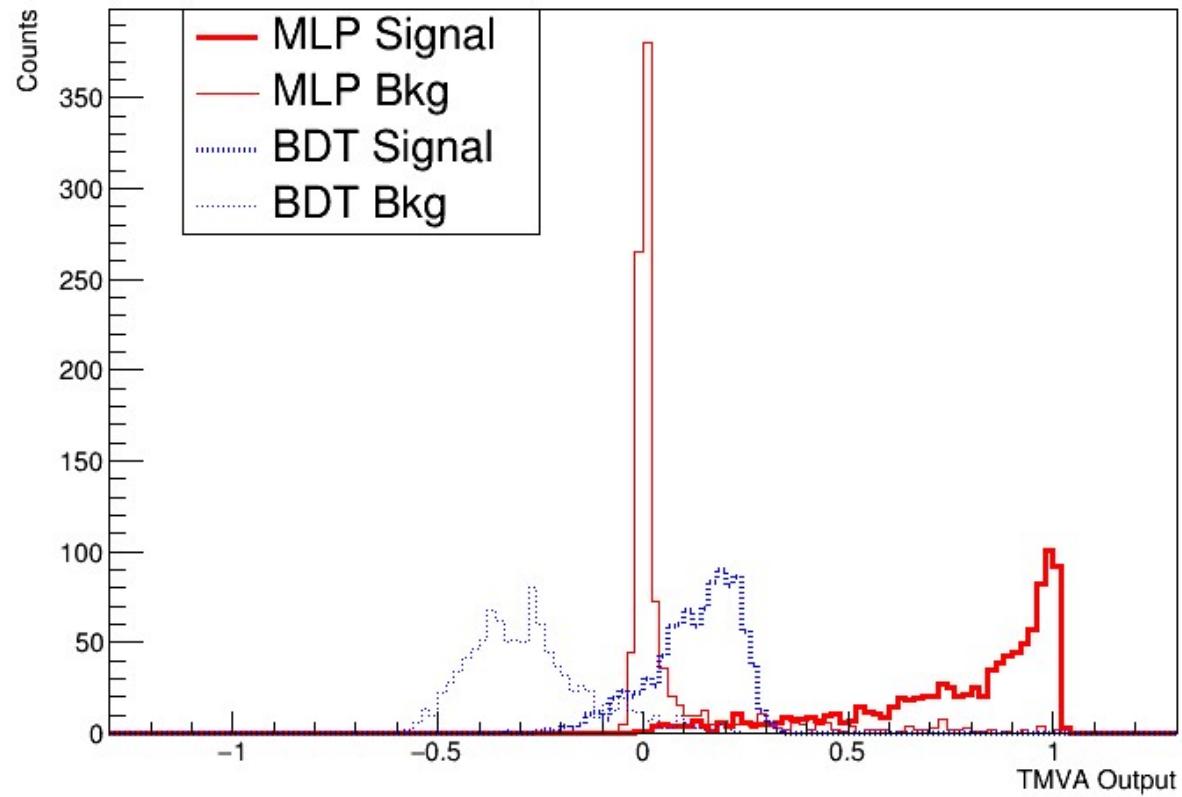
siguang@pku.edu.cn

59



UseCppOutput.C输出

利用TMVA输出的C++文件进行测试



展示出怎么使用TMVA
训练的类



编译TMVA的C++输出成库文件

在运行TMVA训练程序的目录下（含有**weights**子目录的文件夹！），启动root，运行：

```
[] .L weights/TrainTMVA_TMLpANN.cxx++
```

生成TrainTMVA_TMLpANN_cxx.so（weights内）

注意：因为TrainTMVA_TMLpANN.cxx文件中含有#include
“weights/TrainTMVA_TMLpANN.h”，如在weights子目录内运行，找不到.h头文件。
报错如下：

```
/media/sf_code/chapter3/tmva/weights/.TrainTMVA_TMLpANN.cxx:1:39: fatal error:  
weights/TrainTMVA_TMLpANN.h: No such file or directory  
#include "weights/TrainTMVA_TMLpANN.h"
```

故必须在**weights**上级目录运行！

```
[] .L weights/TrainTMVA_BDT.class.C++
```

生成：TrainTMVA_BDT.class_C.so



UseCppOutput.C 代码（续）

```
#include "weights/TrainTMVA_BDT.class_C.so"
#include "weights/TrainTMVA_TMLpANN_cxx.so"
#include "weights/TrainTMVA_TMLpANN.h"
```

解释运行的条件下
可直接include .so可以！

```
void UseCppOutput(){
    ...
    //prepare ReadBDT
    std::vector<std::string> theInputVars;
    theInputVars.push_back("var1");
    theInputVars.push_back("var2");
    theInputVars.push_back("var3");
    theInputVars.push_back("var4");
    ReadBDT *rBDT = new ReadBDT(theInputVars);

    //prepare Read Mlp
    TrainTMVA_TMLpANN *rMlp = new TrainTMVA_TMLpANN();
```



UseCppOutput.C 代码（续）

```
//prepare signal and background functions
const Int_t Nx = 4;
TF1 *fsig[Nx];
TF1 *fbkg[Nx];
const Double_t xmin=0;
const Double_t xmax=10;
const Double_t sqPi = sqrt(TMath::Pi());
Int_t N = Nx;

for(Int_t i=0; i<N; i++){
    fsig[i] = new TF1(Form("fsig%d",i),"[0]*exp(-(x-[1])*(x-[1])/[2]/[2])",xmin,xmax);
    fbkg[i] = new TF1(Form("fbkg%d",i),"[0]*exp(-(x-[1])*(x-[1])/[2]/[2])",xmin,xmax);
    Double_t MeanS = i+2.0;
    Double_t MeanB = i+2.8;
    Double_t sigmaS = (i+1.)*0.4;
    Double_t sigmaB = (i+1.)*0.6;
    fsig[i]->SetParameters(1/(sqPi*sigmaS),MeanS,sigmaS);
    fbkg[i]->SetParameters(1/(sqPi*sigmaB),MeanB,sigmaB);
    fsig[i]->SetNpx(10000);
    fbkg[i]->SetNpx(10000);
}
```

测试数据函数准备与xml代码同，可以忽略



UseCppOutput.C 代码（续）

```
// output histograms
UInt_t nbin = 130;
TH1F* hSigMlp = new TH1F( "hSigMlp",
TH1F* hBkgMlp = new TH1F( "hBkgMlp",
                           "MVA_TMlpANN",           nbin, -1.3, 1.3 );
                           "MVA_TMlpANN",           nbin, -1.3, 1.3 );

TH1F* hSigBdt = new TH1F( "hSigBdt",
TH1F* hBkgBdt = new TH1F( "hBkgBdt",
                           "MVA_BDT",             nbin, -1.3, 1.3 );
                           "MVA_TBD",              nbin, -1.3, 1.3 );

Int_t nSig = 1000;
Int_t nBkg = 1000;
std::vector<double> vVar;
Double_t var1,var2,var3,var4;
for(Int_t i=0; i<nSig; i++){
    var1 = fsig[0]->GetRandom();
    var2 = fsig[1]->GetRandom();
    var3 = fsig[2]->GetRandom();
    var4 = fsig[3]->GetRandom();
    vVar.clear();
    vVar.push_back(var1);
    vVar.push_back(var2);
    vVar.push_back(var3);
    vVar.push_back(var4);
    hSigMlp->Fill(rMlp->Value(0,var1,var2,var3,var4));
    hSigBdt->Fill(rBDT->GetMvaValue(vVar));
}
```



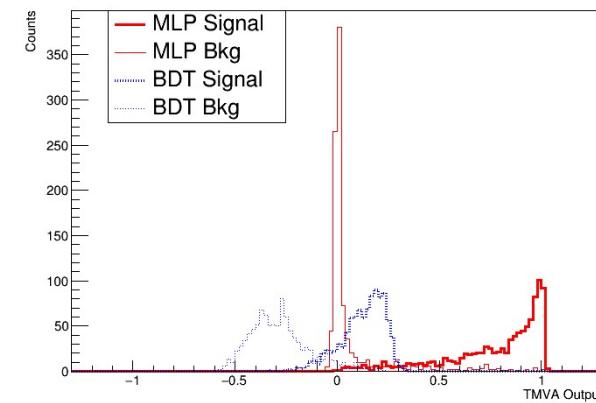
UseCppOutput.C 代码（续）

```
TCanvas *c1 = new TCanvas("c1","");
gPad->SetTopMargin(0.03);
gPad->SetRightMargin(0.03);
THStack *hs = new THStack();
hs->Add(hSigMlp);
hs->Add(hBkgMlp);
hs->Add(hSigBdt);
hs->Add(hBkgBdt);
hSigMlp->SetLineColor(kRed);
hSigMlp->SetLineWidth(3);
hSigMlp->SetLineStyle(1);
hBkgMlp->SetLineColor(kRed);
hBkgMlp->SetLineWidth(1);
hBkgMlp->SetLineStyle(1);

hSigBdt->SetLineColor(kBlue);
hSigBdt->SetLineWidth(3);
hSigBdt->SetLineStyle(3);
hBkgBdt->SetLineColor(kBlue);
hBkgBdt->SetLineWidth(1);
hBkgBdt->SetLineStyle(3);
```

画图代码与xml文件的应用同，可以忽略

```
hs->Draw("nostack");
hs->SetTitle(";TMVA Output; Counts");
hs->GetYaxis()->SetTitleOffset(1.2);
TLegend *lg = new TLegend(0.16,0.7,0.45,0.97);
lg->AddEntry(hSigMlp,"MLP Signal","L");
lg->AddEntry(hBkgMlp,"MLP Bkg","L");
lg->AddEntry(hSigBdt,"BDT Signal","L");
lg->AddEntry(hBkgBdt,"BDT Bkg","L");
lg->Draw();
}
```



siguang@pku.edu.cn

65



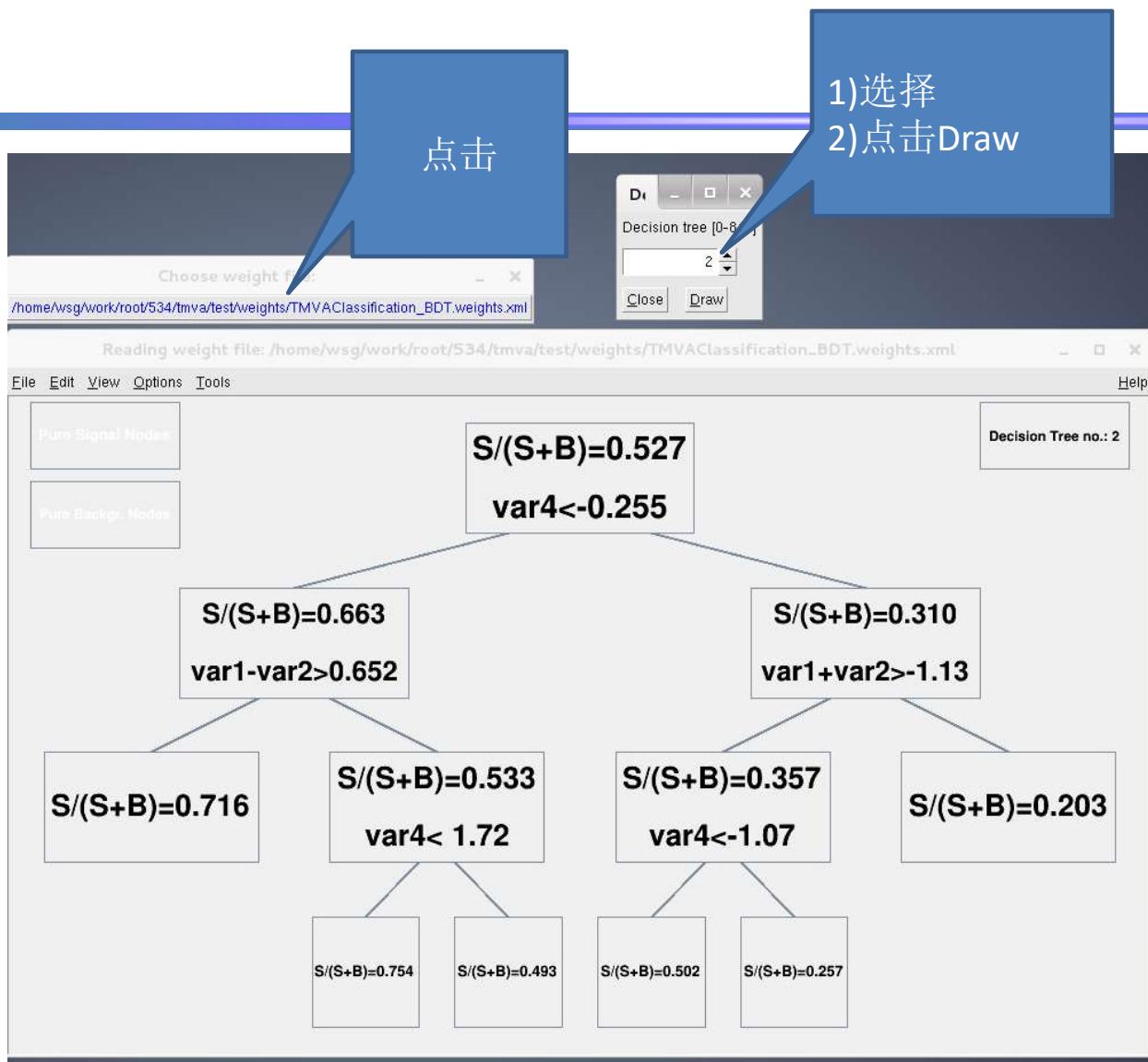
TMVA软件包结果分析程序

运行：
>root TMVAClassification.C
会弹出右边的窗口
(TMVAGui.C文件运行结果), 点击文字将运行不同的代码

TMVA Plotting Macros For Classification	
(1a)	Input variables (training sample)
(1b)	Input variables 'Deco'-transformed (training sample)
(1c)	Input variables 'PCA'-transformed (training sample)
(1d)	Input variables 'Gauss_Decode'-transformed (training sample)
(2a)	Input variable correlations (scatter profiles)
(2b)	Input variable correlations 'Deco'-transformed (scatter profiles)
(2c)	Input variable correlations 'PCA'-transformed (scatter profiles)
(2d)	Input variable correlations 'Gauss_Decode'-transformed (scatter profiles)
(3)	Input Variable Linear Correlation Coefficients
(4a)	Classifier Output Distributions (test sample)
(4b)	Classifier Output Distributions (test and training samples superimposed)
(4c)	Classifier Probability Distributions (test sample)
(4d)	Classifier Rarity Distributions (test sample)
(5a)	Classifier Cut Efficiencies
(5b)	Classifier Background Rejection vs Signal Efficiency (ROC curve)
(5b)	Classifier 1/(Backgr. Efficiency) vs Signal Efficiency (ROC curve)
(6)	Parallel Coordinates (requires ROOT-version >= 5.17)
(7)	PDFs of Classifiers (requires "CreateMVAPdfs" option set)
(8)	Likelihood Reference Distributions
(9a)	Network Architecture (MLP)
(9b)	Network Convergence Test (MLP)
(10)	Decision Trees (BDT)
(11)	Decision Tree Control Plots (BDT)
(12)	Plot Foams (PDEFoam)
(13)	General Boost Control Plots
(14)	Quit

点击

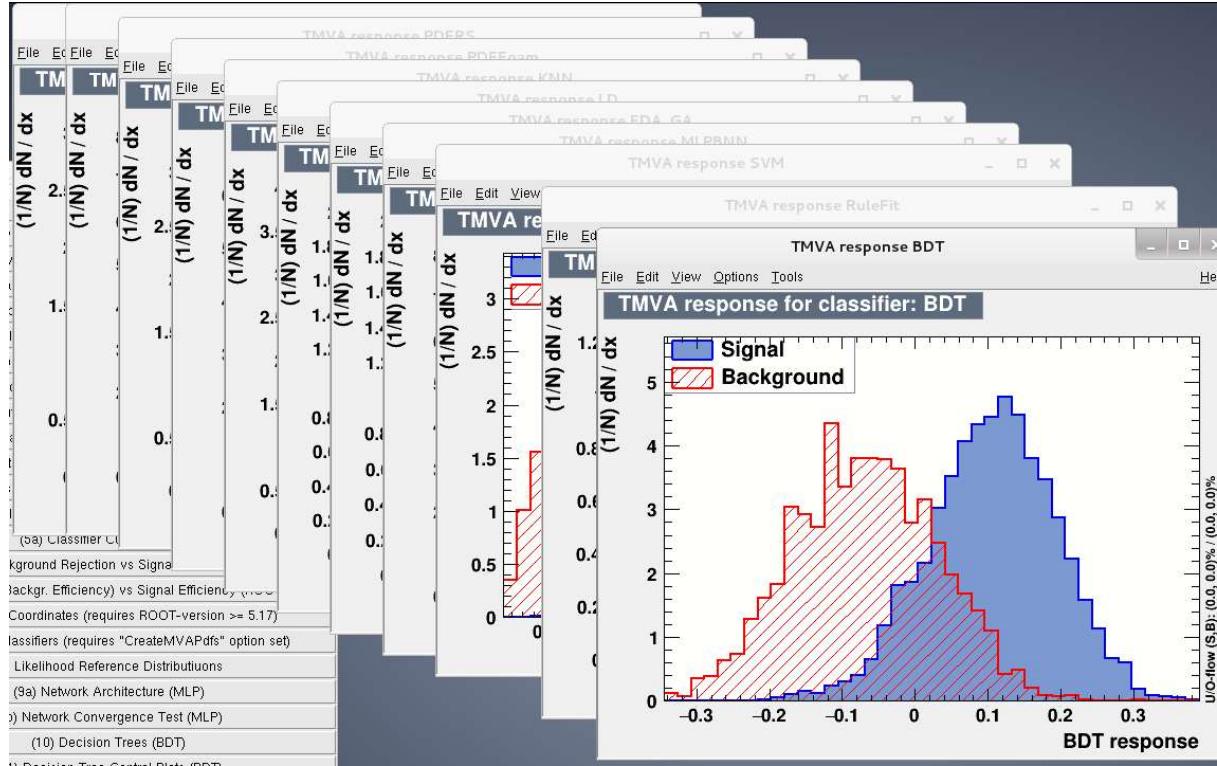
siguang@pku.edu.cn



siguang@pku.edu.cn



点击 (4a) 画出各种算法对信号与本底的分布图



可以打开TMVAGui.C，找出来画图的程序文件名进行参考(mvas.C):

```
ActionButton( cbar,
               title,
               Form( ".x mvas.C(\"%s\",1)", fName ),
               "Plots the probability of each classifier for the test data (macro mvas.C(...,1))",
               buttonType, defaultRequiredClassifier );
```

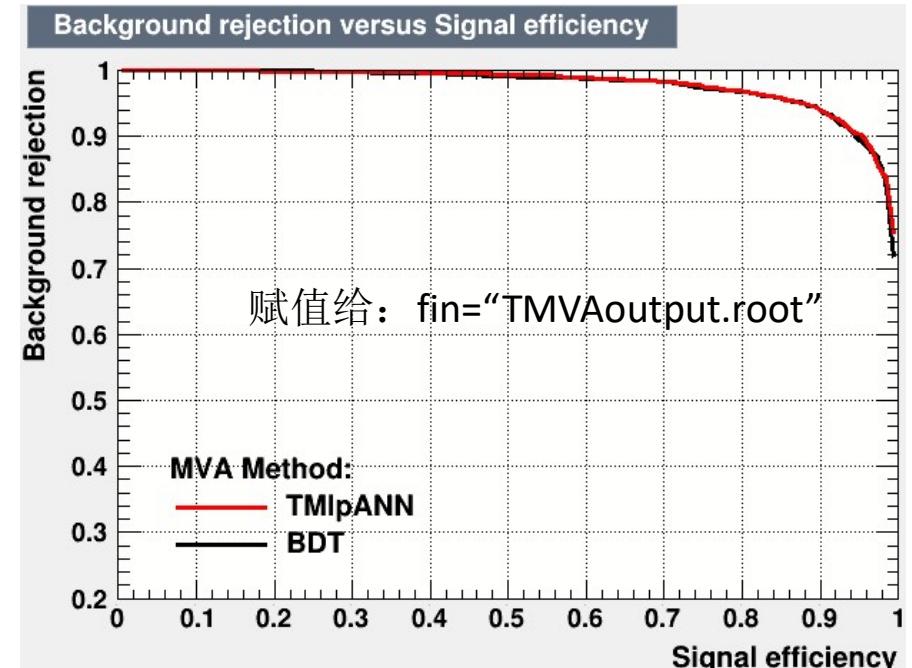
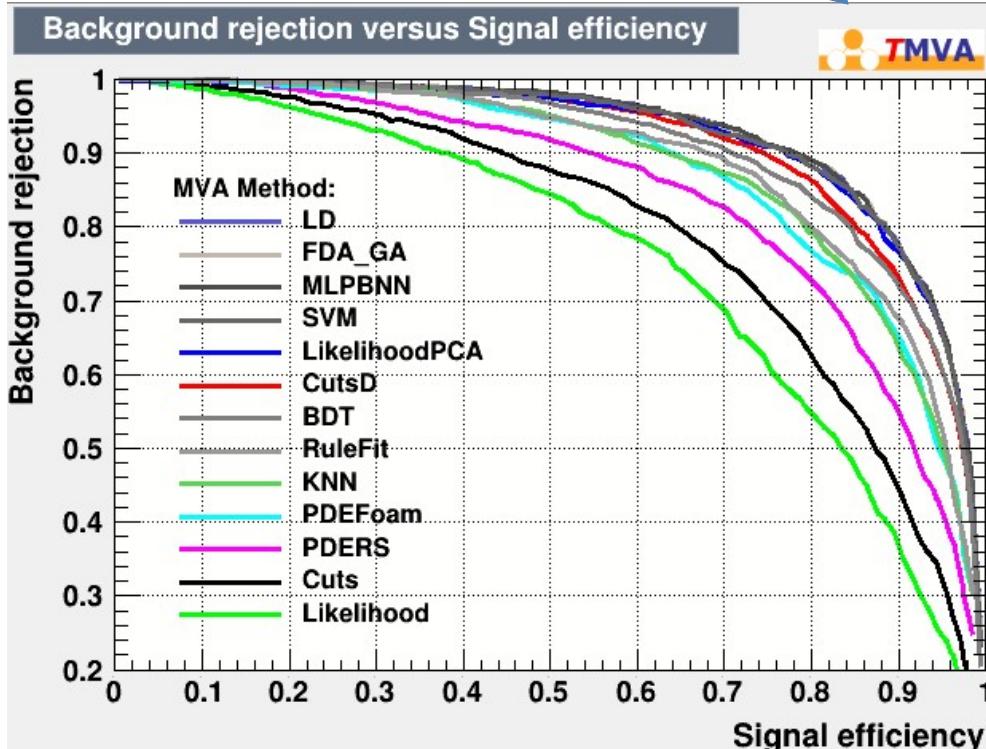
siguang@pku.edu.cn



点击(5b)TMVA的训练结果识别信号与压制本底的效率

\$ROOTSYS/tmva/test/efficiencies.C

```
void efficiencies( TString fin = "TMVA.root",
```



左图：运行\$ROOTSYS/tmva/test/TMVAClassification.C生成TMVA.root，然后运行efficiencies.C

右图：运行本讲座程序TrainTMVA.C，生成TMVAoutput.root,然后运行efficiencies.C，注意输入的root文件名差异

siguang@pku.edu.cn