1(a) [4 marks] The exponentially distributed time measurements, $t_{1}, \ldots, t_{n}$, and the Gaussian distributed calibration measurement $y$ are all independent, so the likelihood is simply the product of the corresponding pdfs:

$$
L(\tau, \lambda)=\prod_{i=1}^{n} \frac{1}{\tau+\lambda} e^{-t_{i} /(\tau+\lambda)} \frac{1}{\sqrt{2 \pi} \sigma} e^{-(y-\lambda)^{2} / 2 \sigma^{2}}
$$

The log-likelihood is therefore

$$
\ln L(\tau, \lambda)=-n \ln (\tau+\lambda)-\frac{1}{\tau+\lambda} \sum_{i=1}^{n} t_{i}-\frac{(y-\lambda)^{2}}{2 \sigma^{2}}+C
$$

where $C$ represents terms that do not depend on the parameters and therefore can be dropped. Differentiating $\ln L$ with respect to the parameters gives

$$
\begin{aligned}
& \frac{\partial \ln L}{\partial \tau}=-\frac{n}{\tau+\lambda}+\frac{\sum_{i=1}^{n} t_{i}}{(\tau+\lambda)^{2}} \\
& \frac{\partial \ln L}{\partial \lambda}=-\frac{n}{\tau+\lambda}+\frac{\sum_{i=1}^{n} t_{i}}{(\tau+\lambda)^{2}}+\frac{y-\lambda}{\sigma^{2}}
\end{aligned}
$$

Setting the derivatives to zero and solving for $\tau$ and $\lambda$ gives the ML estimators,

$$
\begin{aligned}
& \hat{\tau}=\frac{1}{n} \sum_{i=1}^{n} t_{i}-y \\
& \hat{\lambda}=y
\end{aligned}
$$

1(b) [4 marks] The variances of $\hat{\lambda}$ and $\hat{\tau}$ and their covariance are

$$
\begin{aligned}
V[\hat{\lambda}] & =V[y]=\sigma^{2} \\
V[\hat{\tau}] & =V\left[\frac{1}{n} \sum_{i=1}^{n} t_{i}-y\right]=\frac{1}{n^{2}} \sum_{i=1}^{n} V\left[t_{i}\right]+V[y]=\frac{(\tau+\lambda)^{2}}{n}+\sigma^{2} \\
\operatorname{cov}[\hat{\tau}, \hat{\lambda}] & =\operatorname{cov}\left[\frac{1}{n} \sum_{i=1}^{n} t_{i}-y, y\right]=-V[y]=-\sigma^{2}
\end{aligned}
$$

For the covariance we used the fact that $t_{i}$ and $y$ are independent and thus have zero covariance.
$\mathbf{1}(\mathbf{c})$ [ $\mathbf{3}$ marks] The standard deviations of $\hat{\tau}$ and $\hat{\lambda}$ can be determined from the contour of $\ln L(\tau, \lambda)=\ln L_{\max }-1 / 2$, as shown in Fig. 1. The standard can be approximated by the distance from the maximum of $\ln L$ to the tangent line to the contour (in either direction).


Figure 1: Illustration of the method to find $\sigma_{\hat{\tau}}$ and $\sigma_{\hat{\lambda}}$ from the contour of $\ln L(\tau, \lambda)=\ln L_{\text {max }}-1 / 2$ (see text).

If $\lambda$ were to be known exactly, then the standard deviation of $\hat{\tau}$ would be less. This can be seen from Fig. 1, for example, since the distance one need to move $\tau$ away from the maximum of $\ln L$ to get to $\ln L_{\max }-1 / 2$ would be less if $\lambda$ were to be fixed at $\hat{\lambda}$.
$\mathbf{1}(\mathbf{d})$ [5 marks] The second derivatives of $\ln L$ are

$$
\begin{aligned}
\frac{\partial^{2} \ln L}{\partial \tau^{2}} & =\frac{n}{(\tau+\lambda)^{2}}-\frac{2 \sum_{i=1}^{n} t_{i}}{(\tau+\lambda)^{3}} \\
\frac{\partial^{2} \ln L}{\partial \lambda^{2}} & =\frac{n}{(\tau+\lambda)^{2}}-\frac{2 \sum_{i=1}^{n} t_{i}}{(\tau+\lambda)^{3}}-\frac{1}{\sigma^{2}} \\
\frac{\partial^{2} \ln L}{\partial \tau \partial \lambda} & =\frac{n}{(\tau+\lambda)^{2}}-\frac{2 \sum_{i=1}^{n} t_{i}}{(\tau+\lambda)^{3}}
\end{aligned}
$$

Using $E\left[t_{i}\right]=\tau+\lambda$ we find the expectation values of the second derivatives,

$$
\begin{aligned}
E\left[\frac{\partial^{2} \ln L}{\partial \tau^{2}}\right] & =\frac{n}{(\tau+\lambda)^{2}}-\frac{2 n(\tau+\lambda)}{(\tau+\lambda)^{3}}=-\frac{n}{(\tau+\lambda)^{2}} \\
E\left[\frac{\partial^{2} \ln L}{\partial \lambda^{2}}\right] & =-\frac{n}{(\tau+\lambda)^{2}}-\frac{1}{\sigma^{2}} \\
E\left[\frac{\partial^{2} \ln L}{\partial \tau \partial \lambda}\right] & =-\frac{n}{(\tau+\lambda)^{2}} .
\end{aligned}
$$

The inverse covariance matrix of the estimators is given by

$$
V_{i j}^{-1}=-E\left[\frac{\partial^{2} \ln L}{\partial \theta_{i} \partial \theta_{j}}\right]
$$

where here we can take, e.g., $\theta_{1}=\tau$ and $\theta_{2}=\lambda$. We are given the formula for the inverse of the corresponding $2 \times 2$ matrix, and by substituting in the ingredients we find

$$
V=\left(\begin{array}{cc}
\frac{(\tau+\lambda)^{2}}{n}+\sigma^{2} & -\sigma^{2} \\
-\sigma^{2} & \sigma^{2}
\end{array}\right)
$$

which are the same as what was found in (c).

$$
\xi_{x} 2
$$

// A simple program to generate exponential random numbers and // store them in a histogram; also optionally writes the individual // values to a file.

```
// Glen Cowan
```

// RhUL Physics
// 2 December 2006
\#include <iostream>
\#include <fstream>
\#include <cstdlib>
\#include <string>
\#include <cmath>
\#include <TFile.h>
\#include <TH1D.h>
\#include <TRandom3.h>
using namespace std;
int main(int argc, char **argv) \{
// Set up output files, book histograms, add to list of histograms.
TFile* histFile = new TFile("expData.root", "RECREATE");
TList* hList $=$ new TList(); // list of histograms to store
TH1D* hl = new TH1D("h1", "mixture of exponentials", 100, 0.0, 10.0);
hList->Add(h1);
string answer;
ofstream dataFile;
// cout << "Also store individual values in a file? (y/n)" << end;
// in >> answer;
answer = "y";
boob makeDataFile = (answer == "Y" || answer == "Y");
if ( makeDataFile ) \{ dataFile.open("expData2.txt"); \}
// Create a TRandom object to generate random numbers uniform in 10,1]
// Use the "Marsenne Twister" algorithm of TRandom3
int seed $=12345$;
TRandom* ran $=$ new TRandom3(seed);
// Fill with exponential random numbers.
const double xi $=1.0 ; \quad / /$ mean value of the exponential
cont double xi $=5.0$;
cont double alpha $=0.2$;
int numval $=0$;
// court << "Enter number of values to generate: ";
// din >> numval;
numVal $=200$;
for (int $i=0 ; i<n u m V a l ;++i)\{$
double $r 1=$ ran $->$ Rndm();
double $r 2=r a n->\operatorname{Rndm}() ;$
double $x$;
if ( ri < alpha ) \{
$\mathrm{x}=-\mathrm{xil}$ * $\log (\mathrm{r} 2)$;
\}
else \{
x = - xi * $\log (\mathrm{r} 2)$;
) new
\}
h1->Fill(x);
if ( makeDataFile ) \{ dataFile << $\mathrm{x} \ll$ endl; \}
\}
// Save all histograms and close up.
hList->Write();
histFile->Close();
if ( makeDataFile ) \{ dataFile.close(); \}
return 0;
\}

```
// A simple C++ program to illustrate the use of ROOT class TMinuit
// for function minimization. The example shows a Maximum Likelihood
// fit for the mean of an exponential pdf in which TMinuit
// minimizes - 2*log(L). The user must specify what to minimize in the
// function fcn, shown in this file below.
// fcn passes back f = -2*ln L by reference; this is the function to minimize.
// The factor of -2 allows MINUIT to get the errors using the same
// recipe as for least squares, i.e., go up from the minimum by 1.
// TMinuit does not allow fcn to be a member function, and the function
// arguments are fixed, so the one of the only ways to bring the data
// into fcn is to declare a pointer to the data (xVecPtr) as global.
// For more info on TMinuit see root.cern.ch/root/html/TMinuit.html .
// Glen Cowan
// RHUL Physics
// 4 December 2006
#include <iostream>
#include <fstream>
#include <cstdlib>
#include <cmath>
#include <string>
#include <vector>
#include <TMinuit.h>
#include <TApplication.h>
#include <TCanvas.h>
#include <TStyle.h>
#include <TROOT.h>
#include <TF1.h>
#include <TAxis.h>
#include <TLine.h>
using namespace std;
// Declare pointer to data as global (not elegant but TMinuit needs this).
vector<double>* xVecPtr = new vector<double>();
// The pdf to be fitted, here an exponential.
// First argument needs to be a pointer in order to plot with the TF1 class.
double expPdf2(double* xPtr, double par[]){
    double x = *xPtr;
    double xi1 = par[0];
    double xi2 = par[1];
    double alpha = par[2];
    double f = 0;
    if ( x >= 0 && xi1 > 0. && xi2 > 0. ) {
        f = alpha * (1.0/xil) * exp(-x/xil) +
            (1.-alpha)*(1.0/xi2) * exp(-x/xi2);
    }
```



```
    // if ( f <= 0. ) {
    // cout << "expPdf2: " << x << " " << xi << " " << f << endl;
    // }
    return f;
}
```

```
//------------------------------------------------------------------------------------
// function to read in the data from a file
void getData(vector<double>* xVecPtr) {
    string infile;
    // cout << "Enter name of input data file: ";
    // cin >> infile;
    infile = "../makeData2/expData2.txt";
    ifstream f;
    f.open(infile.c_str());
    if (f.fail() ){
        cout << "Sorry, couldn't open file" << endl;
        exit(1);
    }
    double x ;
    bool acceptInput = true;
    while ( acceptInput ) {
        f >> x;
        acceptInput = !f.eof();
        if ( acceptInput ) {
            xVecPtr->push_back(x);
        }
    }
    f.close();
}
//-------------------------------------------------------------------------------
// fcn passes back f = - 2*ln(L), the function to be minimized.
void fcn(int& npar, double* deriv, double& f, double par[], int flag){
    vector<double> xVec = *xVecPtr; // xVecPtr is global
    int n = xVec.size();
    double lnL = 0.0;
    for (int i=0; i<n; i++){
        double x = xVec[i];
        double pdf = expPdf2(&x, par);
        if ( pdf > 0.0 ) {
            lnL += log(pdf); // need positive f
        }
        else {
            cout << "WARNING -- pdf is negative!!!" << endl;
        }
    }
    f = -2.0 * lnL; // factor of -2 so minuit gets the errors right
} // end of fon
//---------------------------------------------------------------------------------
int main(int argc, char **argv) {
    TApplication theApp("App", &argc, argv);
    TCanvas* canvas = new TCanvas();
```

/ Set a bunch of parameters to make the plot look nice

```
canvas->SetFillColor(0);
canvas->UseCurrentStyle();
canvas->SetBorderMode(0); // still leaves red frame bottom and right
canvas->SetFrameBorderMode(0); // need this to turn off red hist frame!
gROOT->SetStyle("Plain");
canvas->UseCurrentStyle();
gROOT->ForceStyle();
gStyle->SetOptStat(0);
gStyle->SetTitleBorderSize(0);
gStyle->SetTitleSize(0.04);
gStyle->SetTitleFont(42, "hxy"); // for histogram and axis titles
gStyle->SetLabelFont(42, "xyz"); // for axis labels (values)
gROOT->ForceStyle();
// Read in the data. xVecPtr is global.
```

    getData(xVecPtr);
    // Initialize minuit, set initial values etc. of parameters.
const int npar $=3$; // the number of parameters
TMinuit minuit(npar);
minuit. SetFCN(fon);
double par[npar]; // the start values
double stepSize[npar]; // step sizes
double minVal[npar]; // minimum bound on parameter
double maxVal[npar]; // maximum bound on parameter
string parName[npar];
$\operatorname{par}[0]=1.0 ; \quad / /$ a guess
$\operatorname{par}[1]=5.0$;
par[2] $=0.2$;
stepSize[0] = 0.1; // take e.g. 0.1 of start value
stepSize[1] $=0.5$;
stepsize[2] $=0.02$;
minval[0] $=0.001$; // if min and max values $=0$, parameter is unbounded.
maxVal[0] $=100000000$;
minval[1] $=0.001 ; / /$ if min and max values $=0$, parameter is unbounded.
$\operatorname{maxVal}[1]=100000000$;
minVal[2] = 0.;
maxVal[2] = 1.;
parName[0] = "xil";
parName[1] = "xi2";
parName[2] = "alpha";
for (int $i=0 ; i<n p a r ; i++)\{$
minuit. DefineParameter(i, parName[i].c_str(),
par[i], stepSize[i], minVal[i], maxVal[i]);
\}
// Do the minimization!
minuit.Migrad(); // Minuit's best minimization algorithm
double outpar[npar], err[npar];
for (int $i=0$; $i<n p a r ; i++$ ) $\{$
minuit.GetParameter(i,outpar[i],err[i]);
\}
cout << "fitted values and errors using mnpout..." << endl;

```
        for (int i=0; i<npar; i++){
        TString nam;
        double val;
        double err;
        double xlolim, xuplim;
        int iuint;
    minuit.mnpout(i, nam, val, err, xlolim, xuplim, iuint);
    cout << i << " " << nam << " " << val << " " << err << endl;
    }
    cout << endl;
    cout << "covariance and correlation coefficients..." << endl;
    double covmat[npar][npar];
    minuit.mnemat(&covmat[0][0], npar);
    for (int i=0; i<npar; i++){
        for (int j=0; j<npar; j++){
            double sigma_i = sqrt(covmat[i][i]);
            double sigma_j = sqrt(covmat[j][j]);
            double rho = covmat[i][j]/(sigma_i*sigma_j);
            cout << i << " " << j << " " << covmat[i][j]<< " " << rho << endl;
    }
}
// Plot the result. For this example plot x values as tick marks.
    double xmin = 0.0;
    double xmax = 20.0;
    TF1* func = new TF1("funcplot", expPdf2, xmin, xmax, npar);
    func->SetMinimum(0.);
    func->SetParameters(outpar);
    func->Draw();
    func->SetLineStyle(1); // 1 = solid, 2 = dashed, 3 = dotted
    func->SetLineColor(1); // black (default)
    func->SetLineWidth(1);
    func->GetXaxis()->SetTitle("x");
    func->GetYaxis()->SetTitle("f(x;#xi)");
    vector<double> xVec = *xVecPtr;
    const double tickHeight = 0.03;
    TLine* tick = new TLine();
    for (int i=0; i<xVec.size(); i++){
    tick->DrawLine(xVec[i], 0, xVec[i], tickHeight);
}
cout << "To exit, quit ROOT from the File menu of the plot" << endl;
theApp.Run(true);
canvas->Close();
delete canvas, tick, xVecPtr;
return 0;
```

\}

PARAMETER DEFINITIONS:


FIRST CALL TO USER FUNCTION AT NEW START POINT, WITH IFLAG=4. MINUIT WARNING IN MIGrad
=============== VARIABLE1 IS AT ITS LOWER ALLOWED LIMIT.
START MIGRAD MINIMIZATION. STRATEGY 1. CONVERGENCE WHEN EDM .LT. 1.00e-04 FCN=948.685 FROM MIGRAD STATUS=INITIATE 26 CALLS 27 TOTAL EDM = unknown STRATEGY= 1 NO ERROR MATRIX

| EXT | PARAMETER |  | CURRENT GUESS | STEP | FIRST |
| :---: | :--- | :--- | :---: | :---: | :---: |
| NO. | NAME | VALUE |  | ERROR | SIZE | DERIVATIVE

MIGRAD MINIMIZATION HAS CONVERGED.
MIGRAD WILL VERIFY CONVERGENCE AND ERROR MATRIX.
COVARIANCE MATRIX CALCULATED SUCCESSFULLY


PARAMETER CORRELATION COEFFICIENTS

| NO. | GLOBAL | 1 | 2 | 3 |
| :---: | ---: | ---: | ---: | ---: |
| 1 | 0.67011 | 1.000 | -0.434 | -0.670 |
| 2 | 0.65506 | -0.434 | 1.000 | 0.655 |

fitted

shone Nave

$3 \quad 0.78248$-0.670 0.6551 .000

covariance and correlation coefficients...

| 0 | 0.0976589 | 1 |
| :--- | :--- | :--- |
| 1 | -0.0819479 | -0.434388 |
| 2 | -0.0192495 | -0.67008 |
| 0 | -0.0819479 | -0.434388 |
| 1 | 0.364424 | 1 |
| 2 | 0.0363498 | 0.655032 |
| 0 | -0.0192495 | -0.67008 |
| 1 | 0.0363498 | 0.655032 |




