# gLike 

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MAGIC Dark Matter Workshop, January 16-18, 2019


* gLike is an open source, ROOT-based code framework for the numerical maximization of general-purpose joint likelihood functions.
* The joint likelihood function has one free parameter (named $g$ ) and as many nuisance parameters as wanted, which will be profiled in the maximization process
夫 Non-exhaustive list of examples where gLike is useful (in order of increasingly complexity):
+ Estimating the number of signal events (with uncertainties) and significance in a dataset whose background content is in turn estimated from an independent measurement in a signal-free controlregion (Li\&Ma).
* Same as before, but considering in addition a systematic uncertainty in the estimation of the background or efficiency of signal detection (Rolke).
* Estimating the intensity of a steady source of signal particles in the presence of background particles from datasets obtained under different experimental conditions.
* Same as before, but each dataset actually comes from a different instrument and in different data format.
* Estimating the dark matter annihilation cross-section combining observations of dwarf spheroidal galaxies by different ground-based gamma-ray telescopes, satellite gamma-ray detectors, neutrino telescopes, ....
* Estimating the energy scale of quantum gravity by combining observations of recently measured GRBs, maybe observed by different ground-based gamma-ray telescopes.


## $\square \square \cap$ EXCELENCIA <br> Installation

* gLike is open source, hosted at GitHub (https://github.com/javierrico/gLike)
* At user level you are recommended to download, compile and run the latest stable release, latest one is v00.06.00.
* Once you become an expert you will want to develop your own classes, for which you will need to check out the master (for new developments) or release (for bug fixes) branches. Check the release wiki entry for more information about the gLike repository branch and release structure.
* Define the environment variable GLIKESYS pointing to your main gLike directory, e.g., for bash:
+ export GLIKESYS="/Users/rico/gLike/"
* and include it in the library path, eg. for Mac:
* export DYLD_LIBRARY_PATH="\$\{GLIKESYS\}:\$\{DYLD_LIBRARY_PATH\}"
* Create the gLike library by typing make in the main gLike directory
* [Optional] Create the gLike online documentation with make doc


## 

## gLike distribution structure

* In gLike you find the following directories:
* src: source files (*.cc) with definition of every class,
* include: include files (*.h) with declaration of every class,
* scripts: root macros and scripts with some gLike example applications,
* rcfiles: examples of rcfiles (in principle the only thing a non-expert user should edit and modify),
* data: examples of input data files, e.g. events and corresponding IRFs mimicking a generic IACT telescope of the 2nd generation like MAGIC,
+ DM: files for DM-related analysis, e.g. the dN/dE functions for different masses and annihilation channels,
* logo: the gLike logo
* Other directories are created when compiling/using gLike:
* out: .o files for creating the librar
* lib: contains library libgLike.so
* plots: for storing plots created by macros



##  User levels

* Non-expert user: uses only high-level scripts or executables for solving specific problem (e.g. DM combination of results from different instruments and targets), with virtually no direct access to gLike classes, just a configuration file.
* Expert user: creates gLike classes and directly accesses their methods and functions to solve problems for which there is no existing script yet.
* Developer: develops new gLike classes with new likelihood functions and/or scripts


## 

## gLike expert user

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## Basic expert usage

* Instantiate and configure (e.g. read input files) preferred Lkl-based object
* Configure the minimization algorithm:
* SetErrorDef $\rightarrow$ set the level of -2logL over its minimum that defines the error in $g$
+ SetUnitsOfg $\rightarrow$ results are provided as -2logL vs $g^{*} f U n i t s O f G, ~ c a l l e d ~ " u s e r " ~ u n i t s ~$ (more about why this is extremely useful later)
* SetGIsPositive $\rightarrow$ if we want to restrict $g$ to be definite positive
* Call the minimization method with ComputeLklVsG
* Access the results, e.g.:
* PrintOverview: print results from the minimization process
+ GetLklVsG: TGraph with values of the -2logL function vs $g$
* GetGLklMin: value of $g$ ( $g_{\text {min }}$ ) for which -2logL is minimum (-2logLmin)
* GetGLklMinErr: value of $\Delta g$ for which $-2 \operatorname{logL}\left(g_{\min }+\Delta g\right)=-2 \log L_{m i n}+f E r r o r D e f$


## Example, using PoissonLkl

```
void testPoissonLkl()
{
// create and configure the simplest possible PoissonLkl object
const Int_t Non = 130;
const Int_t Noff = 90;
const Double_t tau = 1.;
PoissonLkl* p = new PoissonLkl(Non,Noff,tau);
// configure the minimization algorithm
const Double_t errorDef = 4;
const Double_t unitsOfG = 2;
p->SetErrorDef(errorDef);
p->SetUnitsOfG(unitsOfG);
// call the minimization
p->(omputeLklVsG();
```


## Define the following Ikl function:

``` Units of \(g\) is 2
// print fit results
cout << endl << "PrintOverview:" << endl;
p->PrintOverview(); // print the details from the fit
p->GetLklVsG()->Draw(); // plot the -2logL vs g curve
Print fit results and draw the curve \(-2 \log L\) vs \(g\)
// access to the gLike results
const Double_t gmin \(=\mathrm{p}->\operatorname{GetGLklMin();} \quad / /\) get the value of \(g\) that minimizes \(-2 l o g \mathrm{~L}\)
const Double_t gerr = p->GetGLklMinErr(); // get the value of gerr such that -2logL(gmin+/-gerr)=-2logLmin+fErrorDef const Double_t sig \(=\) sqrt(p->GetLklVsG() \(->\operatorname{Eval}(0)) ; / /\) compute significance of detection
// compute significance with LiMa formula for comparison
const Double_t LiMasig \(=\operatorname{sqrt}\left(2 . *\left(N o n * \log \left((t a u+1 .)^{*}(1 . * N o n /(N o n+N o f f))\right)+\right.\right.\) Noff* \(\log ((t a u+1) /\) tau*(1.*Noff/(Non+Noff)))));
// compare confidence interval with Rolke method for comparison
TRolke* \(r=\) new TRolke(0.9544);
r->SetPoissonBkgKnownEff(Non,Noff,tau,1);
Double_t low,upp;
r->GetLimits(low,upp);
Double_t grolke \(=\) units0fG*(upp+low)/2;
Double_t grolkeerr \(=\) units0fG*(upp-low) \(/ 2\);
// print and compare results
cout << endl;
cout \(\ll\) "The max lkl value of \(g=" \ll\) gmin \(\ll "\), \t with " \(\ll\) sqrt(errorDef) \(\ll\) "-sigma error bar \(=" \ll\) gerr \(\ll\) endl;
cout << "The Rolke value of \(g=" \ll\) grolke \(\ll "\), \t with 2-sigma error bar \(=" \ll\) grolkeerr << endl;
cout << "The gLike significance of the detection of signal is " << sig \(\ll\) " sigma" << endl;
cout \(\ll\) "The Li\&Ma significande of the detection of signal is " << LiMasig << " sigma" << endl;
\[
\mathcal{L}\left(g ; b \mid N_{\mathrm{on}}, N_{\mathrm{off}}\right)=\frac{(g+b)^{N_{\mathrm{on}}} e^{-(g+b)}}{N_{\mathrm{on}}!} \frac{(\tau b)^{N_{\mathrm{off}}} e^{-\tau b}}{N_{\mathrm{off}}!}
\]

The error is defined for the value of \(g\) with \(-2 \log L=\min +4\)

Call the minimization of the \(-2 \log L\) and scan it around minimum

Compute best fit for g, with error bars and significance, using gLike and standard (Li\&Ma, Rolke) methods, compare results

\section*{gLike output}

\section*{ComputeLklvsG}


1: Name of class and function issuing the log message
2: Name of class issuing the message
3: The message
4: Migrad method in TMinuit is used to find the value of \(g\) minimizing the \(-2 \operatorname{logL}\) function ( \(g_{\text {min }}\) ) and estimating the error for the free and nuisance parameters, which are reported
5: Values of \(g\) always shown in "intrinsic" and "user" (between brackets) units, configurable when one of them must be chosen, like e.g. in axis of plots
6: Status of TMinuit after minimization finished (will try several times looking for convergence, changing e.g. step)

7: The -2 logL function is scanned around \(g_{\min }\), for a configurable number of points in a range that should contain -2logLmin+fErrorDef at both sides of the minimum (several trials might be needed if the -2logL function is not parabolic)
8: From the result of point 5 , the values of best fit for \(g\left(g_{\min }\right)\) and the confidence interval corresponding to fErrorDef are reported


\section*{PrintOverview}
```

root [11] p->PrintOverview(); // print the details from the fit
* Name
* Status
= PoissonLkl
Status =0 (converged)
* Delta(2logL)
=4
\# of parameters =4 (2 free):
g}=39.7917+/- 30.242 (79.5834 +/- 60.4839)
b}=90.0852+/-0.094868
tau =1 (fixed)
eff =1 (fixed)
Units of G
=2

* -2logL min
=13.0464

```

Object-by-object result of the minimization process

GetLkIVsG()->Draw()

Draw the -2logL function vs \(g\) (in "user" units).
Always try to have a look to this plot, specially if you see strange things, most of the times you will get a clue of what is going on


\section*{\(\square \square \cap \bigcirc\)}

\section*{Comparing gLike and "standard" results}
```

// access to the gLike results
const Double_t gmin = p->GetGLklMin(); // get the value of g that minimizes -2logL
const Double_t gerr = p->GetGLklMinErr(); // get the value of gerr such that -2logL(gmin+/-gerr)=-2logLmin+fErrorDef
const Double_t sig = sqrt(p->GetLklVsG()->Eval(0)) ; // compute significance of detection

```
The max lkl value of \(\mathrm{g}=79.5834\), with 2 -sigma error bar \(=60.4839\)
The Rolke value of \(\mathrm{g}=80.4773\), with 2 -sigma error bar \(=59.5622\)
The gLike significance of the detection of signal is 2.70428 sigma
The Li\&Ma significande of the detection of signal is 2.70432 sigma

\section*{Extra nuisance parameters}

\section*{Total implementation of ParabolaLkl likelihood function:}
\[
\mathcal{L}\left(g ; b, \tau, \epsilon \mid N_{\mathrm{on}}, N_{\mathrm{off}}, \mu_{\tau}, \sigma_{\tau}, \sigma_{\epsilon}\right)=\frac{(\epsilon g+b)^{N_{\mathrm{on}}} e^{-(\epsilon g+b)}}{N_{\mathrm{on}}!} \frac{(\tau b)^{N_{\mathrm{on}}} e^{-\tau b}}{N_{\mathrm{off}}!} \frac{1}{\sqrt{2 \pi} \sigma_{\tau}} e^{\frac{\left(\tau-\mu_{\tau}\right)^{2}}{2 \sigma_{\tau}^{2}}} \frac{1}{\sqrt{2 \pi} \sigma_{\epsilon}} e^{\frac{(\epsilon-1)^{2}}{2 \sigma_{\epsilon}^{2}}}
\]
```

Double_t Deff = 0.1;
Double_t Dtau = 0.1;
p->SetDEff(Deff);
p->SetDTau(Dtau);
p->ComputeLklVsG();
p->PrintOverview(); // print the details from the fit
p->GetLklVsG()->Draw("same"); // plot the -2logL vs g curve

```
```

Name
= PoissonLkl

* Status =0 (converged)
* Delta(2logL)
=4
* 
# of parameters

          = 4 (4 free):
          g=39.7475 +/- 37.1452 (79.4951 +/- 74.2905)
          b}=90.1232+/-0.094868
      tau =0.999306 +/- 0.01
    eff =1.00056 +/- 0.01
=2
* Units of G
* -2logL_min =

```


\section*{Building a joint likelihood}
```

void testJointLkl()
{
// define number of PoissonLkl objects that we will use in the JointLkl and their configuration parameters
const Int_t nsamples = 2;
const Int_t Non[nsamples] ={130,90}; . Configuration parameters for the
const Int_t Noff[nsamples] = {105,110};
// create the JointLkl object that will collect the PoissonLkl objects
const Double_t errorDef = 4;
JointLkl* j = new JointLkl;
j->SetErrorDef(errorDef);
// configure samples and introduce them into the JointLkl
PoissonLkl* p[nsamples];
for(Int_t isample=0;isample<nsamples;isample++)
{
p[isample] = new PoissonLkl(Non[isample],Noff[isample]);
p[isample]->SetName(Form("PoissonLkl_%1d",isample));
j->AddSample(p[isample]);
}
// print how JointLkl looks like
j->PrintData();
// call minimization and print/plot results
j->ComputeLklVsG();
j->PrintOverview(); // print the details from the fit
j->GetLklVsG()->Draw(); // plot the -2logL vs g curve
// compare it to each PoissonLkl object separately
for(Int_t isample=0;isample<nsamples;isample++)
{
p[isample]->SetErrorDef(errorDef);
p[isample]->ComputeLklVsG();
p[isample]->PrintOverview(); // print the details from the fit
TGraph* lklvsg = p[isample]->GetLklVsG();
lklvsg->SetLineColor(isample+2); // plot the -2logL vs g curve
lklvsg->Draw("same"); // plot the -2logL vs g curve
}

```

\section*{Results from JointLkl minimisation}

In testJointLkI.C we have built the following Joint likelihood:
\[
\mathcal{L}\left(g ; b_{1}, b_{2}, \mid N_{\text {on } 1}, N_{\text {on } 2}, N_{\text {off } 1}, N_{\text {off } 2}\right)=\underbrace{\operatorname{Pois}\left(N_{\text {on } 1} \mid g+b_{1}\right) \times \operatorname{Pois}\left(N_{\text {off } 1} \mid \tau_{1} b_{1}\right)}_{\text {PoissonLkl_1 }} \times \underbrace{\operatorname{Pois}\left(N_{\text {on } 2} \mid g+b_{2}\right) \times \operatorname{Pois}\left(N_{\text {off } 2} \mid \tau_{2} b_{2}\right)}_{\text {PoissonLkl_2 }}
\]
(note that \(g\) is common to both terms, there is always only 1 free parameter!)

\section*{PrintData}

\section*{PrintOverview}


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\section*{Why user units are so important?}
* Example in testJointLkl.C is only useful if experiments represented by the PoissonLkl objects have the same expectation value for \(g\)
+ e.g. we observe a steady gamma-ray source with the same instrument in exactly the same experimental conditions (i.e. IRF) and for exactly the same amount of time, in that case \(g\) is the expected number of signal events in both On regions. This is a rare case because:
\[
g=T_{\mathrm{obs}} \int_{E_{\min }^{\prime}}^{E_{\max }^{\prime}} d E^{\prime} \int d E \frac{d \Phi}{d E} A_{\mathrm{eff}}(E) G\left(E^{\prime} \mid E\right)
\]
+ Following this example: in many practical cases the spectral shape ( \(d f / d E\) ) can be assumed and the spectral normalization \(k\) is unknown, i.e.:
\[
g=k T_{\mathrm{obs}} \int_{E_{\min }^{\prime}}^{E_{\max }^{\prime}} d E^{\prime} \int d E \frac{d f}{d E} A_{\mathrm{eff}}(E) G\left(E^{\prime} \mid E\right)
\]
+ In such a case (ie. whenever we can refer \(g\) to some global common parameter) we can refer all sample-dependent \(g\) values to common \(k\) parameter by setting units for each sample as:
\[
\text { SetUnits0fG }\left(\frac{1}{T_{\mathrm{obs}} \int_{E_{\min }^{\prime}}^{E_{\max }^{\prime}} d E^{\prime} \int d E \frac{d f}{d E} A_{\mathrm{eff}}(E) G\left(E^{\prime} \mid E\right)}\right)
\]
* The units of each sample are used by JointLkl to compute the value of \(g\) that it passes to it Lkl objects, in such a way that they all refer to the same value of \(g^{*}\) fUnitsOfG

\section*{JointLkl minimisation with units of \(g\) \\ Barcelona Institute of \\ Bist \\ }
* Example: we assume \(g\) is the number of gamma rays measured by some Cherenkov telescope from a given steady source in the On region, during a given known observation time, with known IRF and threshold. The spectrum of the source is a power law with index -2 , and unknown normalization \(k=(d P h i / d E)(E=100 \mathrm{GeV})\)
\(\star\) We consider the following simplifications:
+ constant effective area with energy
+ perfect energy resolution
\(\star\) In such a case fUnitsOfG \(=\frac{1}{T_{\text {obs }} A_{\text {eff }} \int_{E_{\min }}^{E_{\max }} d E \frac{d f}{d E}} \quad\) with \(\int_{E_{\min }}^{E_{\max }} d E \frac{d f}{d E}=(100 \mathrm{GeV})^{2}\left(\frac{1}{E_{\min }}-\frac{1}{E_{\max }}\right)\)
```

// these are the values of observation time, IRF, etc..
const Double_t Emin[nsamples] = {100,200};; // [GeV] energy threshold
const Double_t Emax[nsamples] = {10000,10000}; // [GeV] maximum measurable energy
const Double_t Tobs[nsamples] = {2*60*60,1.8*60*60}; // [s] observation times
const Double_t Aeff[nsamples] ={1e9,0.98e9}; // [cm^2] effective area (considered constant)
Double_t IntegraldFdE[nsamples]; // [GeV] integral of the spectral shape function betwen Emin and Emax
Double_t unitsOfG[nsamples]; // [s-1 cm-2 GeV-1] 1/(Tobs*Aeff*IntegraldFdE)
for(Int_t isample=0;isample<nsamples;isample++)
{
IntegraldFdE[isample] = 100.*100.*(1./Emin[isample]-1./Emax[isample]);
unitsOfG[isample] =1./(Tobs[isample]*Aeff[isample]*IntegraldFdE[isample]);
p[isample]->SetUnitsOfG(unitsOfG[isample]);
}

```
// [GeV] energy threshold
[sel maximum measurable energy
[s] observation times
\(/ /[\mathrm{GeV}]\) integral of the spectral shape function betwen Emin and Emax
\(/ /[s-1 \mathrm{~cm}-2 \mathrm{GeV}-1] 1 /(T o b s * A e f f * I n t e g r a l d F d E)\) array



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\section*{\(-2 \log L\) vs \(g\) with units of \(g\)}

PrintOverview


By construction, \(g\) in JointLkl is identical to \(g\) of the first Lkl-based element of the list (PoissonLkl_0 in this case)
For the rest of the elements of the list, \(g\) is computed so that \(g^{*}\) funitsOfg has the same value for all elements
In other words, the actual common free parameter is \(g^{*}\) fUnitsOfG rather than \(g\)

\section*{GetLkIVsG()->Draw()}



\section*{Iact1dUnbinnedLkl}
* Iact1dUnbinnedLkl implements the following likelihood function*:
\(\mathcal{L}\left(g ; b, \tau \mid\left\{E_{i}^{\prime}\right\}_{i=1, \ldots, N_{\text {on }}}, N_{\text {on }}, N_{\text {off }}, \mu_{\tau}, \sigma_{\tau}\right)=\operatorname{Pois}\left(N_{\text {on }} \mid g+b\right) \times \operatorname{Pois}\left(N_{\text {off }} \mid \tau b\right) \times \operatorname{Gaus}\left(\tau \mid \mu_{\tau}, \sigma_{\tau}\right) \times \prod_{i=1}^{N_{\text {on }}} f\left(E_{i}^{\prime}\right)\)
* with \(f(E)=\frac{g \frac{d N_{g}}{d E^{\prime} d t}\left(E^{\prime}\right)+b \frac{d N_{b}}{d E^{\prime} d t}\left(E^{\prime}\right)}{g+b}\) and \(\mathrm{dN} \mathrm{N}_{\mathrm{g}, \mathrm{b}} / \mathrm{dE}\) 'dt the signal and background rates vs measured E , respectively
* (*) actually the total likelihood is a bit more complex, but in most practical cases reduces to this expression
* As in the PoissonLkl case, \(\mathrm{dNg} / \mathrm{dE}\) 'dt can be computed convoluting the spectrum with IRF and dividing by the observation time, and \(\mathrm{dN}_{\mathrm{s}} / \mathrm{dE}\) 'dt modelled from Off data
* Iact1dUnbinnedLkl is declared with a string containing the name of the input file containing the event list and IRF in a single file, in the IactEventListIRF format (see more later).
* The class is optimised for DM searches:
* One needed input is the average \(\mathrm{dN} / \mathrm{dE}\) of reactions producing gamma rays at the source (which appears in the formula of the DM flux).
* It provides member functions to set the funitsOfg for annihilation and decay processes

\section*{Iact1dBinnedLkl}
* Iact1dBinnedLkl is the binned version of Iact1dUnbinnedLkl, it implements either of these two likelihood functions:
\(\mathcal{L}\left(g ;\left\{b_{i}, \tau_{i}\right\}_{i=1, \ldots, N_{\text {bins }}}\left\{N_{\text {oni }}, N_{\text {off }}\right\}_{i=1, \ldots, \ldots, N_{\text {bins }},}, \mu_{\tau}, \sigma_{\tau}\right)=\prod_{i=1}^{N_{\text {bins }}} \operatorname{Pois}\left(N_{\text {on }} \mid g_{i}(g)+b_{i}\right) \times \operatorname{Pois}\left(N_{\text {off }} \mid \tau_{i} b_{i}\right) \times \operatorname{Gaus}\left(\tau_{i} \mid \mu_{\tau}, \sigma_{\tau}\right)\)
(for energy-dependent systematic uncertainties on background determination), or
\(\mathcal{L}\left(g ;\left\{b_{i}\right\}_{i=1, \ldots, \ldots} N_{\text {bins }}, \tau \mid\left\{N_{\text {oni }}, N_{\text {off }}\right\}_{i=1, \ldots, N_{\text {bins }}}, \mu_{\tau}, \sigma_{\tau}\right)=\operatorname{Gaus}\left(\tau \mid \mu_{\tau}, \sigma_{\tau}\right) \times \prod_{i=1}^{N_{\text {bins }}} \operatorname{Pois}\left(N_{\text {on }} \mid g_{i}(g)+b_{i}\right) \times \operatorname{Pois}\left(N_{\text {off }} \mid \tau_{i} b_{i}\right)\)
(for energy-independent systematic uncertainties on background determination)
* Which one is used (and other details) depends on how we configure the instantiated Iact1dBinnedLkl objects (with constructor and/or Setters)

\section*{Simple DM analysis}
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{
}
```

```
void testDMSearches()
```

void testDMSearches()
// input data
// input data
const Double_t log
const Double_t log
const Double_t DlogJ =0; // [GeV^2 cm^-5] statistical error in log_10 of ]-factor of the assumed DM source
const Double_t DlogJ =0; // [GeV^2 cm^-5] statistical error in log_10 of ]-factor of the assumed DM source
const Double_t mass
const Double_t mass
=19.; // [GeV^2 cm^-5] log_10 of ]-factor of the assumed DM source
=19.; // [GeV^2 cm^-5] log_10 of ]-factor of the assumed DM source
= 1000.; // [GeV] mass of the DM particle
= 1000.; // [GeV] mass of the DM particle
const TString dNdEFileName = TString(Form("./DM/dNdE/Cirelli/dNdESignal_bb_%.1fmass.root",mass)); // dN/dE input file
const TString dNdEFileName = TString(Form("./DM/dNdE/Cirelli/dNdESignal_bb_%.1fmass.root",mass)); // dN/dE input file
const TString inputFile1 = "./data/genericIact_dataIRF_01.root"; // input file with event list and their associated IRF
const TString inputFile1 = "./data/genericIact_dataIRF_01.root"; // input file with event list and their associated IRF
const TString inputFile1 = "./data/genericIact_dataIRF_01.root"; // input file with event list and their associated IRF
const TString inputFile1 = "./data/genericIact_dataIRF_01.root"; // input file with event list and their associated IRF
const Double_t errorDef =4;
const Double_t errorDef =4;
// create and configure an Iact1dUnbinnedLkl object for 1D unbinned likelihood analysis
// create and configure an Iact1dUnbinnedLkl object for 1D unbinned likelihood analysis
Iact1dUnbinnedLkl* unbn = new Iact1dUnbinnedLkl(Form("logJ=%.2f DlogJ=0 inputfile=%s",logJ,inputFile1.Data()));
Iact1dUnbinnedLkl* unbn = new Iact1dUnbinnedLkl(Form("logJ=%.2f DlogJ=0 inputfile=%s",logJ,inputFile1.Data()));
unbn->ReaddNdESignal(dNdEFileName);
unbn->ReaddNdESignal(dNdEFileName);
unbn->SetDMAnnihilationUnitsForG(mass); // set units for DM annihilation <sv>
unbn->SetDMAnnihilationUnitsForG(mass); // set units for DM annihilation <sv>
// create and configure an Iact1dBinnedLkl object for 1D unbinned likelihood analysis
// create and configure an Iact1dBinnedLkl object for 1D unbinned likelihood analysis
Iact1dBinnedLkl* bn = new Iact1dBinnedLkl(Form("logJ=%.2f DlogJ=0 inputfile=%s",logJ,inputFile2.Data()));
Iact1dBinnedLkl* bn = new Iact1dBinnedLkl(Form("logJ=%.2f DlogJ=0 inputfile=%s",logJ,inputFile2.Data()));
bn->ReaddNdESignal(dNdEFileName);
bn->ReaddNdESignal(dNdEFileName);
bn->SetDMAnnihilationUnitsForG(mass); // set units for DM annihilation <sv>
bn->SetDMAnnihilationUnitsForG(mass); // set units for DM annihilation <sv>
// create and fill a JointLkl object for the combined analysis of both datasets
// create and fill a JointLkl object for the combined analysis of both datasets
JointLkl* jointLkl = new JointLkl(Form("DlogJ=%.2f",DlogJ));
JointLkl* jointLkl = new JointLkl(Form("DlogJ=%.2f",DlogJ));
jointLkl->SetErrorDef(errorDef);
jointLkl->SetErrorDef(errorDef);
jointLkl->AddSample(unbn);
jointLkl->AddSample(unbn);
jointLkl->AddSample(bn);
jointLkl->AddSample(bn);
// print how JointLkl looks like
// print how JointLkl looks like
jointLkl->PrintData();
jointLkl->PrintData();
// call minimization and print/plot results
// call minimization and print/plot results
jointLkl->ComputeLklVsG();
jointLkl->ComputeLklVsG();
jointLkl->PrintOverview(); // print the details from the fit
jointLkl->PrintOverview(); // print the details from the fit
TCanvas* c1 = new TCanvas("c1", "",700,500);
TCanvas* c1 = new TCanvas("c1", "",700,500);
jointLkl->GetLklVsG()->Draw(); // plot the -2logL vs g curve

```
    jointLkl->GetLklVsG()->Draw(); // plot the -2logL vs g curve
```

Doing a full DM analysis is repeating this for more masses, allow some options...

## $\square \square \square \quad \bigcirc$ EXCELENCIA

## Output of simple DM analysis

PrintData

|  | ```Object Name : Iact1dUnbinnedLkl \(\mathrm{E}^{\prime}\) range \(=[59.2,10000] \mathrm{GeV}\) Non/Noff \(=11468 / 11526\) Measured tau \(=1.00251+/-0.00574\) Observation time \(=50 \mathrm{~h}\) \(\log (J)=(19+/-0) \mathrm{GeV}^{\wedge} 2 \mathrm{~cm}^{\wedge}-5\) or \(\mathrm{GeV} \mathrm{cm}{ }^{\wedge}-2\) Aeff histo : YES Off Aeff histo : NO E Reso/Bias graphs : YES Migration matrix : NO Background rate histo : YES Foreground rate histo : NO Signal dN/dE histo : YES Signal dN/dE' histo : YES Signal \(\mathrm{dN} / \mathrm{dE}\) ' Off histo : NO Object Name : Iact1dBinnedLkl \(\mathrm{E}^{\prime}\) range \(=[59.2,10000] \mathrm{GeV}\) Non/Noff \(=11576 / 11616\) Measured tau \(=1.00402+/-0.00599\) Observation time \(=45 \mathrm{~h}\) \(\log (J)=(19+/-0) \mathrm{GeV}^{\wedge} 2 \mathrm{~cm}^{\wedge}-5\) or \(\mathrm{GeV} \mathrm{cm}{ }^{\wedge}-2\) Aeff histo : YES Off Aeff histo : NO E Reso/Bias graphs : YES Migration matrix : NO Background rate histo : YES Foreground rate histo : NO Signal dN/dE histo : YES Signal dN/dE' histo : YES Signal \(d N / d E^{\prime}\) Off histo : NO \# of bins \(=10\) Rebinned? = YES (to 1 min entries)``` |
| :---: | :---: |

## PrintOverview



## GetLkIVsG()->Draw()



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## IactEventListIRF data format

## Data members:

| TNtuple* | f0nSample; | //-> ON event list ("Energy:Point_RA:Point_DEC:Delta_RA:Delta_DEC:Arr_time:Hadronness") |
| :---: | :---: | :---: |
| TNtuple* | f0ffSample; | //-> OFF event list ("Energy:Point_RA:Point_DEC:Delta_RA:Delta_DEC:Arr_time:Hadronness") |
| Float_t | fEpmin; | // [GeV] minimum estimated energy |
| Float_t | fEpmax; | // [GeV] maximum estimated energy |
| Float_t | fTau; | // normalization Noff/Non (e.g \# of off regions) |
| Float_t | fDTau; | // statistical error in fTau |
| Float_t | fTauPValue; | // Probability value of agreement between On/Off |
| Float_t | fobsTime; | // [s] observation time |
| TH1F* | fHAeff | //-> Effective area vs E histogram for signal events |
| TH1F* | fHAeffoff | //-> Effective area vs E histogram for signal events IN THE OFF REGION |
| TGraph* | fGEreso | //-> Graph with energy resolution vs energy values |
| TGraph* | fGEbias | //-> Graph with energy bias vs energy values |
| TH2F* | fMigMatrix | //-> Migration matrix (overrides fGEreso and fGEbias) |
| TH1F* | fHdNdEpBkg | //-> $d N / d E$ 'dt vs E' for background events (normalized) |
| TH1F* | fHdNdEpFrg | //-> dN/dE'dt vs E' for foreground (gamma-events from a different source) events (normalized) |

## With fOnSample and fOffSample n-tuples with events formed by structure:

```
// structure to read the events from the NTuple
typedef struct {
    Float_t E; // [GeV] measured energy of event
    Float_t pointRA; // [deg] RA of telescope pointing direction
    Float_t pointDEC; // [deg] DEC of telescope pointing direction
    Float_t dRA; // [deg] distance to pointing direction in the RA axis
    Float_t dDEC; // [deg] distance to pointing direction in the DEC axis
    Float_t t; // [MJD] arrival time
    Float_t had; // [1] hadronness
} IactEvent_t;
```

Data with this format is produced, e.g., by gLikelnputs in MARS

## 

## gLike non-expert user

* Experts are expected to run gLike executables, that read a configuration (rc) file
* So far, no executables, but just one macro: jointLkIDM.C, for DM analyses
* scripts/jointLkIDM.C macro to be run with rcfiles/jointLkIDM.rc
$\star$ As other macros, jointLkIDM.C should always be run in compiled mode
* jointLkIDM.C is nothing but a sophisticated version of testDMSearches.C, where all possible configuration options are available through the rc file
* jointLkIDM.C computes bounds to the DM annihilation <sv> or decay rate 1/ tau, for a given channel, and a list of masses
* Usage (in root command line): jointLklDM.C+(<rcfile>, <rndseed>)
* If random seed is provided, it will produce MonteCarlo mock data according to the observation time and IRFs of all input files. Otherwise it will use the event lists in those input files. This is useful for producing confidence bands.



## \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\# I/O CONFIGURATION \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#

\# Label to indentify this analysis (for naming plots and output files) jointLkIDM.Label: GenericlACT_Annihilation_bb_Unbinned_GisFree_Jisfixed
\# Path (will be added to all specified files and directories in this rcfile) jointLkIDM.path: ./
\# Directory with dN/dE files jointLkIDM.dNdEDir: DM/dNdE/Cirelli/
\# Directory for output plots jointLkIDM.plotsDir: plots
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
ANALYSIS CONFIGURATION
\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\# channel to be analyzed (bb, tautau, mumu, WW, gammagamma, piOpi0 or piOgamma) jointLkIDM.Channel: bb
\# process to be analyzed ("ann" or "dec" for annhilation and decay, respectively, default is annihilation \# (remember to change consistently the list of masses and J-factor value and uncertainty) jointLkIDM.Process: ann
\# list of DM masses to be considered (in GeV)
jointLkIDM.MassList: 100200500100020005000100002000050000100000

## \#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#

## JOINT LIKELIHOOD CONFIGURATION

\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#\#
\# Now include one line per likelihood function term, with the following general syntaxis:
\# jointLkIDM.IkITerm<XXX>: <termType> <parentTerm> [<options>]
\#
jointLkIDM.IkITerm000: JointLkI - DlogJ=0

## PaEnom <br> BIST

## jointLklDM.C output (I/3)

IactldUnbinnedLkl





Iact1dBinnedLkl


Energy resolution and bias



$\mathrm{dN} / \mathrm{dE}$ ' bkg model vs On and Off distributions



## jointLklDM.C output (2/3)



## $\square \square \cap$ EXCELENCIA

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## jointLklDM. C output (3/3)



READY-TO-COPY results
Double $t$ mass [nmass $]=\{100,200,500,1000,2000,5000,10000,20000,50000,100000\}$;
Double t mass[nmass] 1 imit [nmass] $=\{1.43531 \mathrm{e}-22,2.47085 \mathrm{e}-23,5.59858 \mathrm{e}-24,3.5092 \mathrm{e}-24,2.9348 \mathrm{e}-24,3.57842 \mathrm{e}-24,5.89093 \mathrm{e}-24,1.19476 \mathrm{e}-23,3.35726 \mathrm{e}-23,7.30914 \mathrm{e}-23\}$; Double_t snstvt[nmass] $=\{1.43531 \mathrm{e}-22,2.47085 \mathrm{e}-23,5.59858 \mathrm{e}-24,3.5092 \mathrm{e}-24,2.9348 \mathrm{e}-24,3.57842 \mathrm{e}-24,5.89093 \mathrm{e}-24,1.19476 \mathrm{e}-23,3.35726 \mathrm{e}-23,7.30914 \mathrm{e}-23\}$;

Joint likelihood results
Joint likelihood results
***********************************
<sv> limit vs mass
******************************************
mass $=100 \mathrm{GeV},\langle\mathrm{sv}\rangle^{\wedge} \mathrm{UL}=1.43531 \mathrm{e}-22,\langle\mathrm{sv}\rangle$ snstvty $=1.43531 \mathrm{e}-22 \mathrm{~cm}^{\wedge} 3 \mathrm{~s}-1$ mass $=200 \mathrm{GeV},\left\langle\mathrm{sv}>^{\wedge} \mathrm{UL}=2.47085 \mathrm{e}-23,\langle\mathrm{sv}\rangle\right.$ _snstvty $=2.47085 \mathrm{e}-23 \mathrm{~cm} \mathrm{~cm}^{\wedge} 3 \mathrm{~s}-1$ mass $=500 \mathrm{GeV},\langle\mathrm{sv}\rangle{ }^{\wedge} \mathrm{UL}=5.59858 \mathrm{e}-24,\langle\mathrm{sv}\rangle$ _snstvty $=5.59858 \mathrm{e}-24 \mathrm{~cm} \mathrm{~cm}^{\wedge} 3 \mathrm{~s}-1$ mass $=1000 \mathrm{GeV},\left\langle s v>^{\wedge} U L=3.5092 \mathrm{e}-24,<\mathrm{sv}\right\rangle$ snstvty $=3.5092 \mathrm{e}-24 \mathrm{~cm} \mathrm{~cm}^{\wedge} 3 \mathrm{~s}-1$ mass $=2000 \mathrm{Gev}$, ssv>^UL $=2.9348 \mathrm{e}-24$, <sv>_snstvty $=2.9348 \mathrm{e}-24 \mathrm{~cm}$ mass $=5000 \mathrm{GeV}$, <sv>^UL $=3.57842 \mathrm{e}-24$, ssv>_snstvty $=3.57842 \mathrm{e}-24$ Cm Js-1


mass $=100000 \mathrm{GeV},\langle\mathrm{sv}\rangle^{\wedge} \mathrm{UL}=7.30914 \mathrm{e}-23,\langle\mathrm{sv}\rangle$ _snstvty $=7.30914 \mathrm{e}-23 \mathrm{~cm} \mathrm{~cm}^{\wedge} 3 \mathrm{~s}-1$

## Conversion of files into v00.05 and beyond

* To allow for gLike future expansion, several actions have been taken:
+ gLike classes removed from the dark matter oriented mdm library and moved to gitHub
+ Naming convention of classes has changed:

| Old name | New name |
| :---: | :---: |
| MLkl | Lkl |
| MJointLkl | JointLkI |
| MFullLkl | lact1dUnbinnedLkl |
| MBinnedFullLkl | lact1dBinnedLkl |
| MBinnedFluxLkI | FermiTables2016L |
| MPoissonLkl | PoissonLkl |
| MParabolaLkl | ParabolaLkI |
| MIACTEventListl | lactEventListIRF |

* These changes should be transparent to the user except for two aspects:
+ Class names are used in the rcfile, and the new naming convention should be used from now on.
+ Data+IRF input files produced in the format defined by MIACTEventListIRF will not work anymore. New files use format defined in IactEventListIRF. Convert your old files into new ones with the macro convertGLikeInputFiles.c


## computing sensitivity

* The sensitivity (for a given confidence level, CL) is the average limit (with that CL) we would obtain on the free parameter, under the null hypothesis.
$\star$ There are two ways to estimate the sensitivity:
+ More accurate but slower: produce as many independent Monte Carlo simulated samples as needed by the CL and compute for each the limit to $g$. The estimated sensitivity is the average of the obtained limits.
+ Less accurate but faster: take the difference between the value of $g$ for which $-2 \log L$ takes the value corresponding to the CL and the for
 which -2logL minimises. This approach is acceptable if we have a good description of the $-2 \log L$ parabolic shape (i.e. jointLkIDM.isGpositive: FALSE and DlogJ=0).


## 

## gLike developer

## The TemplateLkl class

$\star$ The class TemplateLkl, provided with gLike distribution, provides the minimal skeleton for including your favourite likelihood function

```
class TemplateLkl : public Lkl
{
public:
    // constructors
    TemplateLkl(TString inputString="");
    // destructor
    virtual ~TemplateLkl();
protected:
    Int_t InterpretInputString(TString inputString);
    virtual void SetFunctionAndPars(Double_t ginit=0);
    virtual Int_t MakeChecks();
    virtual void SetMinuitLink();
private:
    ClassDef(TemplateLkl,1) // Full Likelihood (unbinned)
};
```

