Introduction to the HistFitter framework

Jeanette Lorenz (LMU)
+ many other people

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Overview

- **<u>Step-0:</u>** define signal/control/validation regions
  - Input TTrees (derived from xAOD), histograms, numbers
- **<u>Step-1:</u>** Construct PDF and the likelihood function

  RooFit or HistFactory + RooFit
  - Result from data is a distribution
  - Model signal and background by PDF (prob. density func.)
  - Construct likelihood(s) by joining data and model(s)
- ↓
- **RooWorkspace**
- ↓
- **<u>Step-2:</u>** Statistical tests on parameter of interest μ

  RooStats
  - Construct test statistic q_μ from likelihoods
  - Obtain expected distributions of q_μ for various μ values
  - Determine discovery p_0 and signal exclusion limit
- **<u>Step-3:</u>** Repeat for each model (assumed value m_H)

HistFitter

- adds steps-0 and 3
- allows full analysis chain from simple configuration file

HistFitter introduction

Introduction

- **HistFitter** is a statistical tool/framework used in (almost) all SUSY WG analyses since 2012 for fitting, interpretation and presentation of fit results
  - Developed in SUSY strong production 1-lepton group, quickly adopted as recommended tool
  - Small core team: Max Baak, Geert-Jan Besjes, David Cote, Alex Koutsman, Jeanette Lorenz and Dan Short
  - Also used (more and more) in Higgs, Exotics and Top WGs

- **HistFitter** is:
  - built on top of RooFit/HistFactory and RooStats
  - consists of Python part for configuration and C++ part for CPU-intensive calculations

- Why HistFitter?
- **HistFitter** extends RooFit/HistFactory and RooStats in four key areas:
  - Programmable framework: performing complete analysis (steps 0-4) from a simple configuration file
  - Analysis strategy: common physics analysis strategy concepts, such as control/signal/validation regions, woven into the fabric of HistFitter design
  - Bookkeeping: can keep track of numerous data models, from histogram production until final statistical tests → handy when working with large collections of signal hypotheses (*signal grids*)
  - Presentation and interpretation: multiple methods are provided to determine statistical significance of signal hypotheses, and produce publication-quality tables and plot summarizing the fit results (*step 4*)

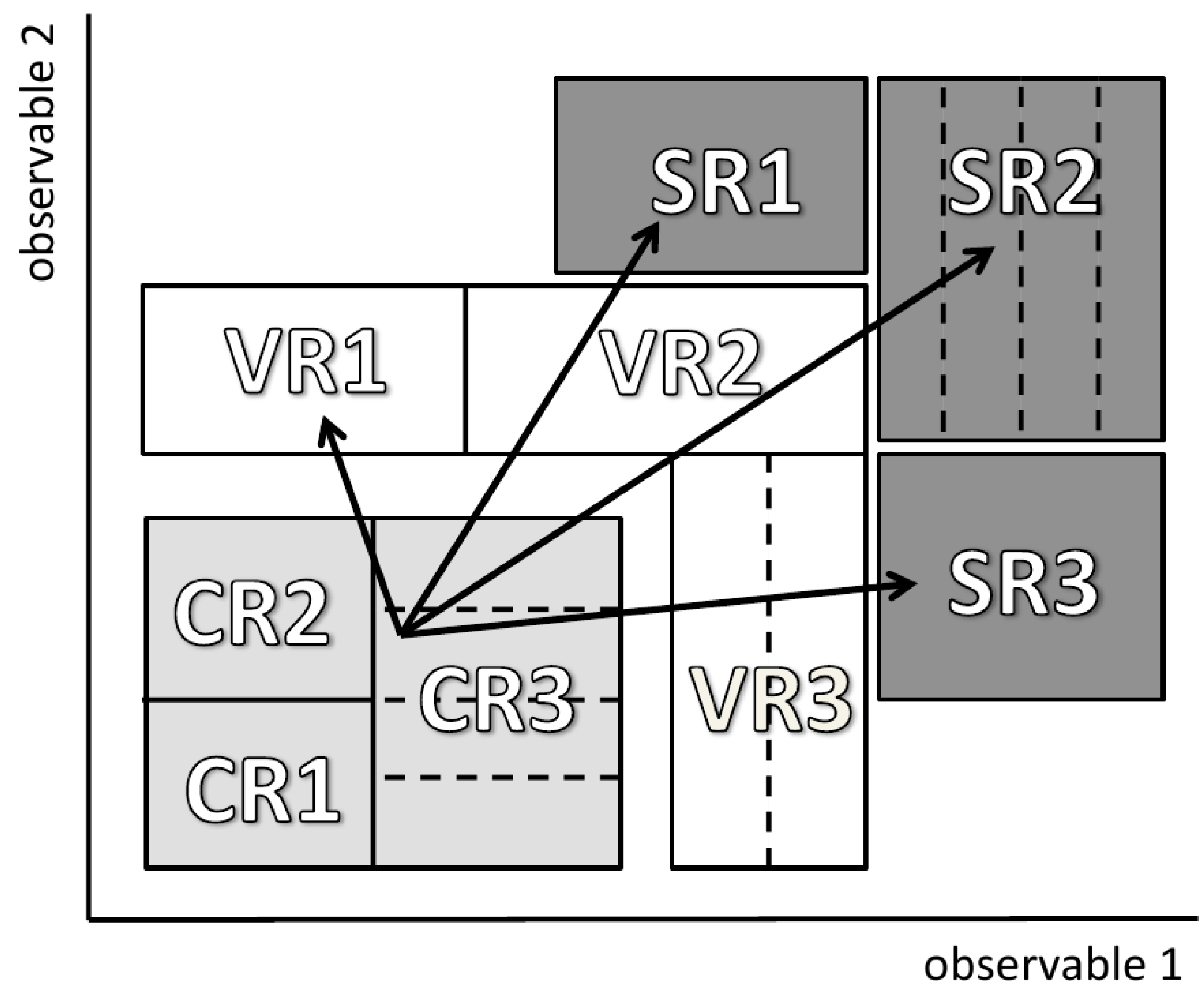
Data analysis strategy

- Particle physics analyze large data samples for measurements of discovery
- Data interpretation relies on using external - simulation, Monte Carlo (MC) - predictions for backgrounds and signal
- HistFitter configures and builds parametric models from these predictions

- Typically one defines several phase space regions to study a specific phenomenon

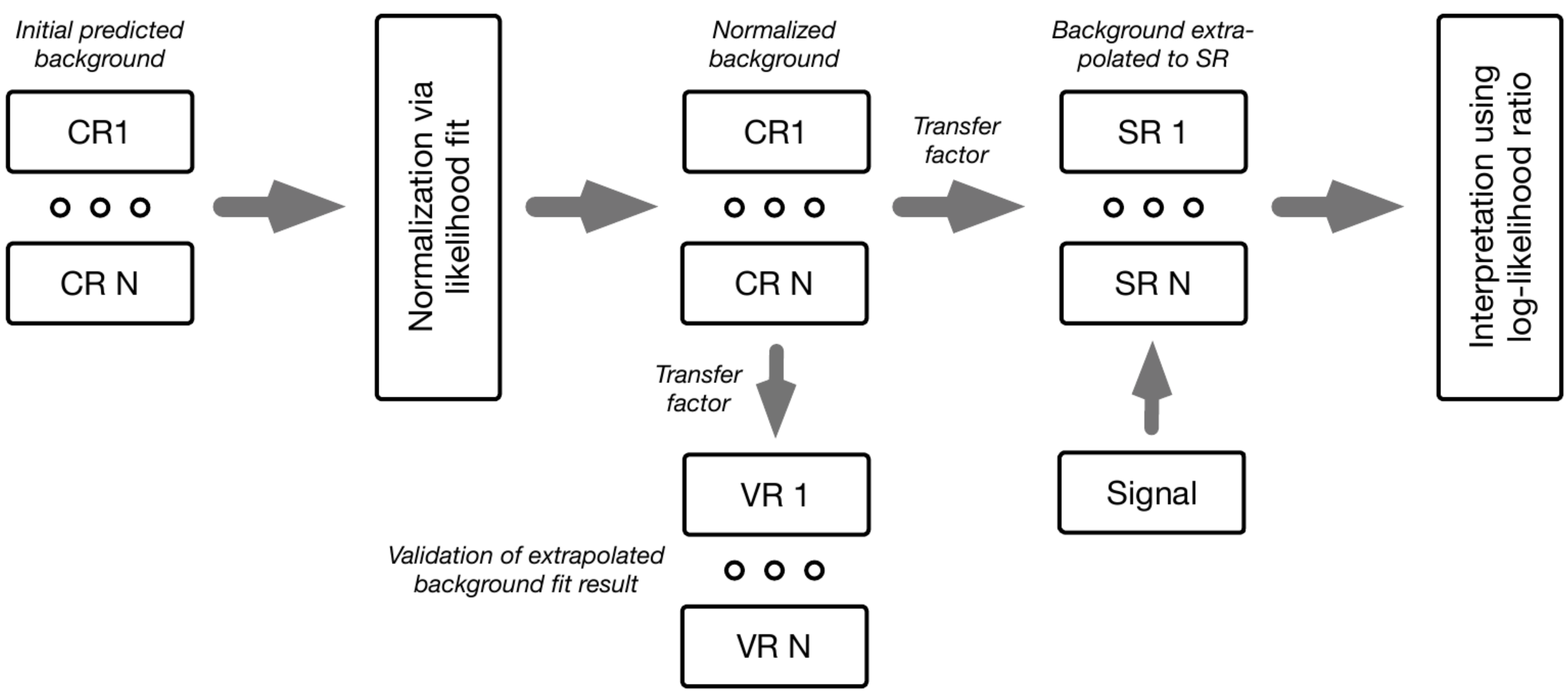
- Definition depends on the purpose:
  - **Signal region:** signal-rich region (SR)
  - **Control region:** background-rich region (CR), fit simulated backgrounds to data
  - **Validation region:** validation of extrapolation (VR)

- Concepts of CR/SR/VR woven into the fabric of HistFitter



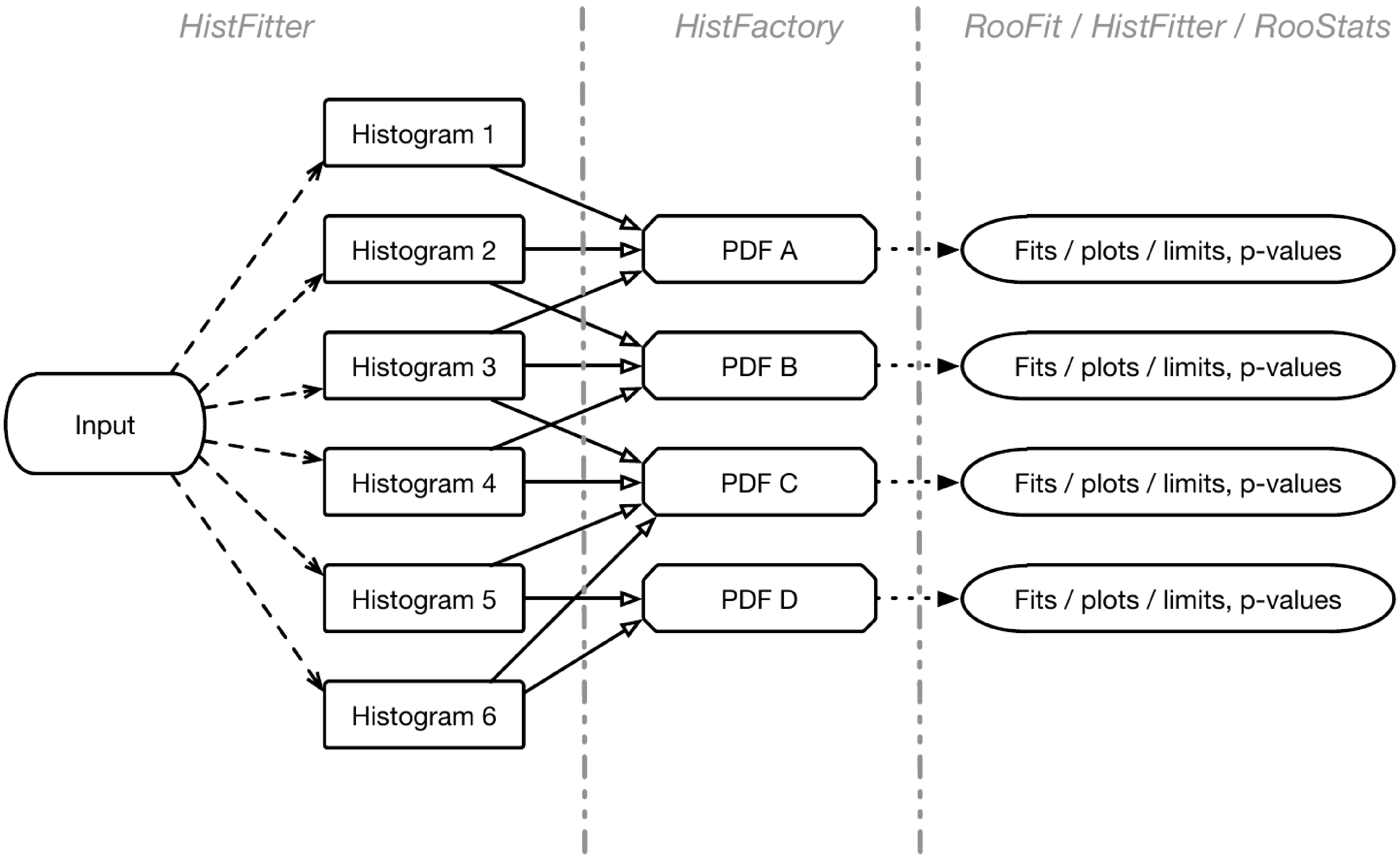
Analysis strategy flow

- Each CR/VR/SR modeled by a separate PDF, combined in a simultaneous fit
- Parameters shared in all regions → consistent background/signal prediction and systematics
  - Sharing user-defined
- Analysis flow:
  - Backgrounds normalized to data in a fit of control regions
  - Extrapolate to validation/signal regions using transfer factors (ratio of events between CR and SR/VR)
  - If good agreement in VR, unblind the SR
  - If no excess, add signal prediction and interpret/set limits



Processing sequence

- Based on user-defined configuration file, processing sequence of HistFitter split in three stages



step-0	**step-1**	**step-2/3**
Histogram production	PDF construction Workspace building	Analysis of models

Model construction

- Models constructed using HistFactory from input histograms
- General form of the constructed likelihood:

$$L(\boldsymbol{n}, \boldsymbol{\theta}^0 | \mu_{\mathrm{sig}}, \boldsymbol{b}, \boldsymbol{\theta}) \;=\; P_{\mathrm{SR}} \times P_{\mathrm{CR}} \times C_{\mathrm{syst}}$$

  - P = Poisson measurements of number of observed events in CR/SR (VR)
  - C = Constraint terms for systematic uncertainties, auxiliary measurements
  - Likelihood depends on number of observed events in all regions (n), predictions for various background processes (b), the nuisance parameter (θ) parametrizing the systematic uncertainties with their central value (θ^0) and signal strength (μ_{SIG})

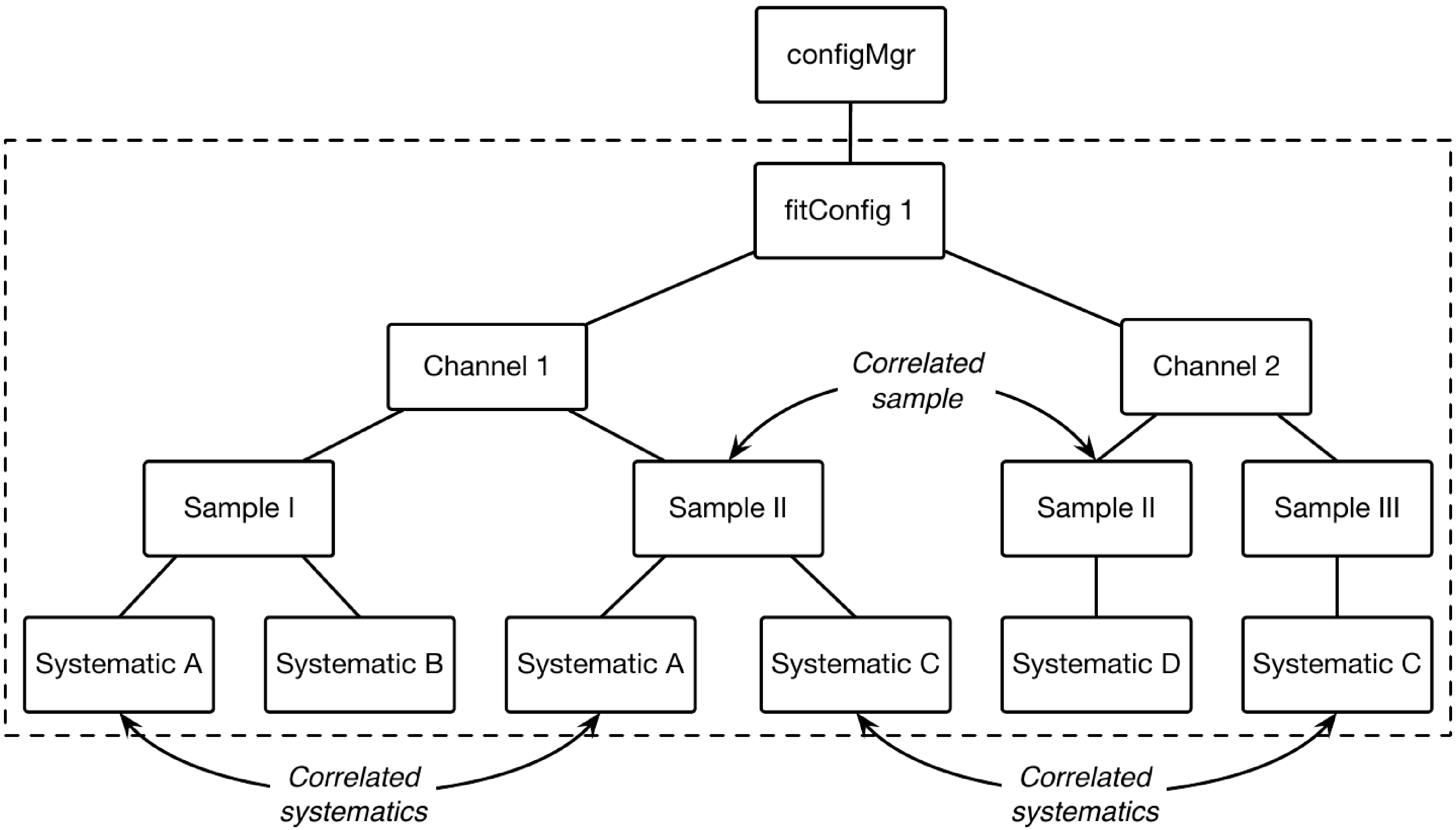
- Likelihood has multiple building blocks:
  - Control/validation/signal regions: called `channel` in HistFitter (HistFactory)
  - Signal and background processes: called `sample` in HistFitter (HistFactory)
  - Uncertainties: called `systematic` in HistFitter (HistFactory)
    - Including statistical/theory/experimental uncertainties

- HistFitter is designed to build and manipulate PDFs of nearly arbitrary complexity
- Bookkeeping/configuration machinery realized through a user-defined Python configuration file

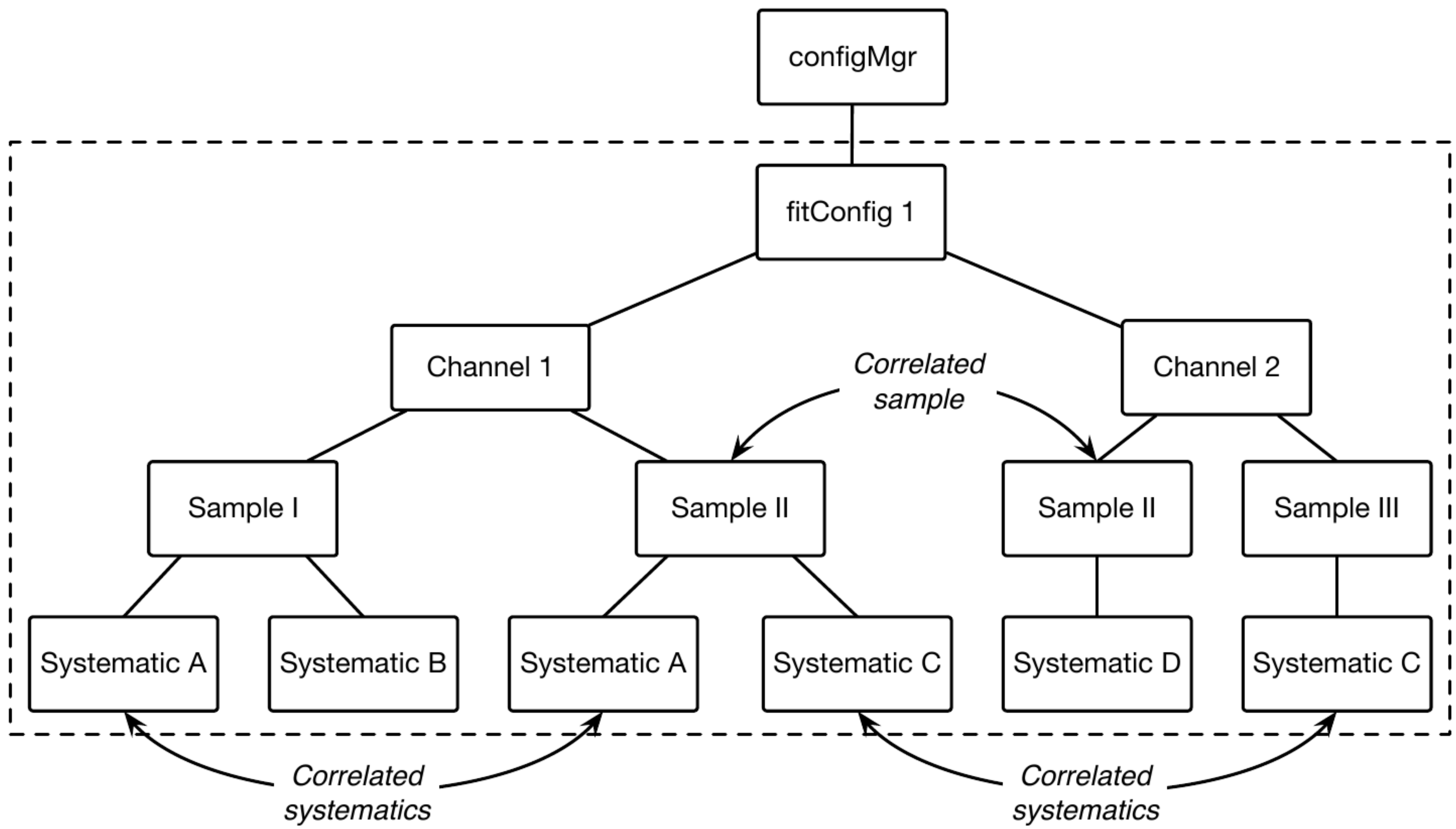
- Configuration manager (`configManager`) highest level (singleton) object in Python and C++
- Manages `fitConfig` objects that contain PDF and meta-data

Fit configuration

- `fitConfig` objects summarize `channels`, `samples` and `systematics` together with corresponding input histograms



Fit configuration properties



- `fitConfig`: can be cloned/extended (see next slide)
- `channels:` either single-bin or multi-bin (shape), property as CR/VR/SR
- `samples:` input from TTree, TH1 or raw (hard-coded) floats, correlated between channels
- `systematics`: provided as ±1σ variation of nominal histogram; input from TTree, TH1 or raw floats; can be correlated between samples and/or channels; many types available extended from HistFactory base types (see later); trickle-down mechanism (see backup)

Common fit strategies

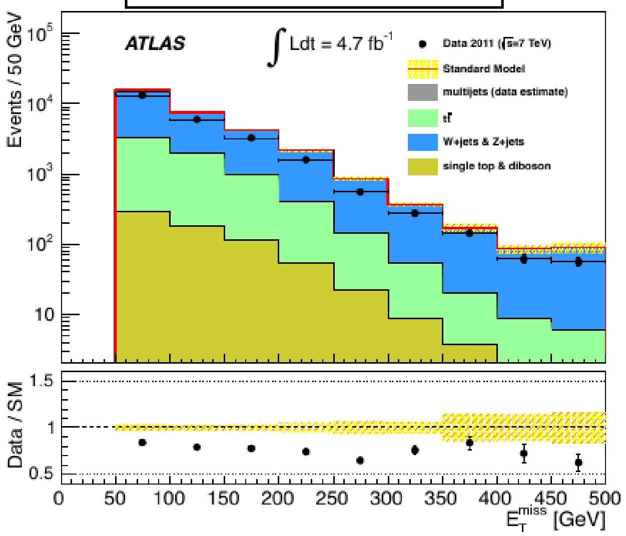
- **Background-only fit**: estimate background yields in validation/signal regions; including *only* CRs in the fit to data; no signal component included in fit configuration
- **Model-dependent signal fit**: set exclusion limit on a specific signal model; possible use of multi-binned (or multi-SR) shape fit for a robust signal estimation - aka ***exclusion fit***
- **Model-*in*dependent signal fit**: to obtain model-independent upper limits on number of BSM events beyond background prediction; only usable with one single-bin SR (otherwise not model-independent) - aka ***discovery fit***

Fit setup	*Background-only fit*	*Model-dependent signal fit*	*Model-independent signal fit*
Samples used	backgrounds	backgrounds + signal	backgrounds + dummy signal
Fit regions	CR(s)	CR(s) + SR(s)	CR(s) + SR

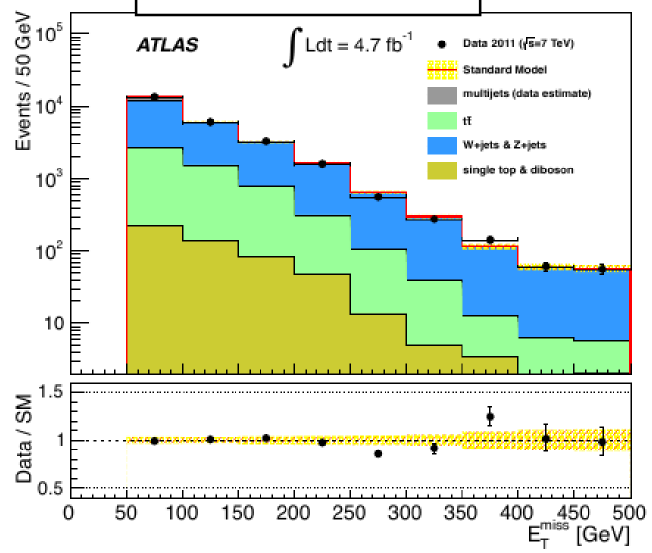
Presentation of results

- HistFitter includes a collection of tools (scripts/functions) to present/understand fit results

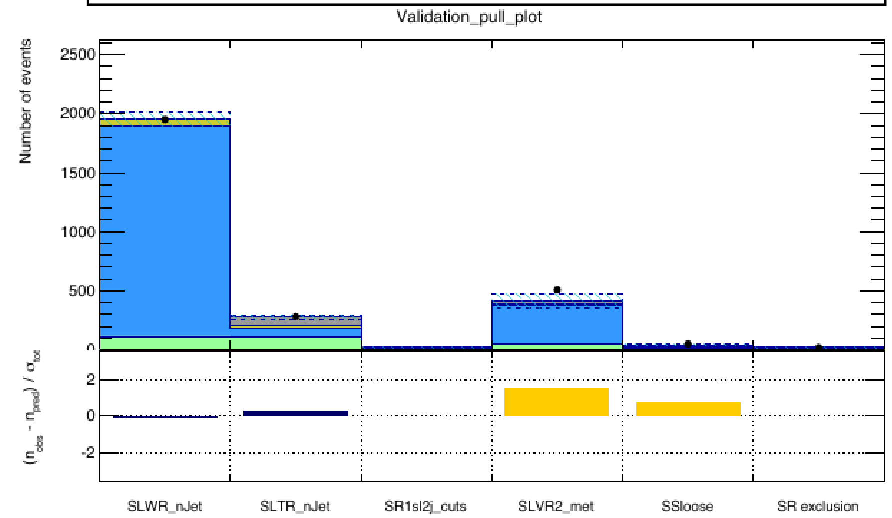
Before Fit



After Fit



After Fit VRs pull plot



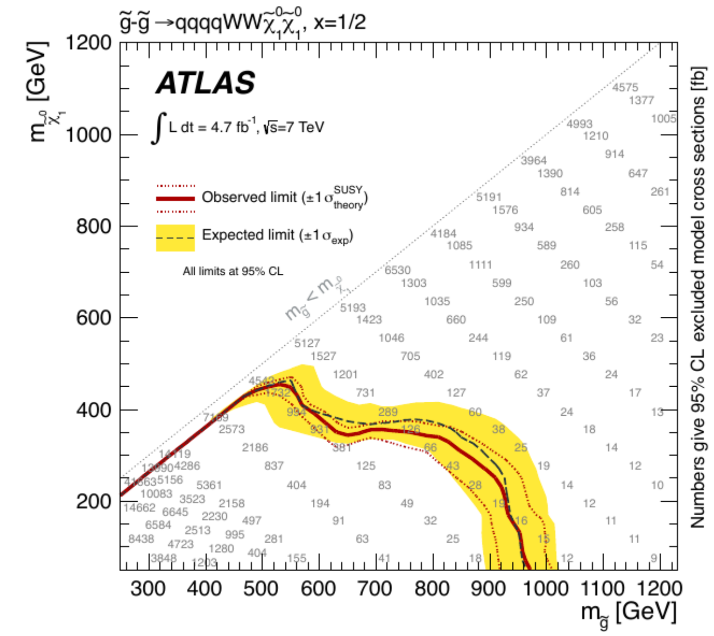
Yields Table

Signal Region	SR1	SR2
Observed events	16	19
Fitted bkg events	19.54 ± 3.93	20.47 ± 5.14
Fitted Top events	4.02 ± 0.96	4.32 ± 1.04
Fitted V+jets events	9.89 ± 1.86	10.47 ± 1.91
Fitted other background events	1.14 ± 0.15	1.19 ± 0.16
Fitted QCD events	4.49 ± 2.72	4.49 ± 4.24
MC exp. SM events	24.85	26.32
MC exp. Top events	8.42	9.11
MC exp. V+jets events	10.82	11.55
MC exp. other background events	1.13	1.17
Data-driven exp. QCD events	4.49	4.49

Systematics Table

Uncertainty of channel	SR1	SR2
Total background expectation	19.54	20.47
Total statistical ($\sqrt{N_{\rm exp}}$)	± 4.42	± 4.52
Total background systematic	± 3.93 [20.14%]	± 5.14 [25.09%]
QCD background	± 2.66	± 4.20
Statistical uncertainties	± 2.54	± 1.86
Jet Energy Scale	± 1.15	± 1.17
Top yield	± 0.82	± 0.88
Renormalization scale (Top)	± 0.34	± 0.39
V+jets yields	± 0.28	± 0.29
Renormalization scale (V+jets)	± 0.14	± 0.03

Exclusion contour with upper limits



Model-independent upper limits

Signal channel	$\langle\sigma_{\rm vis}\rangle^{95}_{\rm obs}$[fb]	$S^{95}_{\rm obs}$	$S^{95}_{\rm exp}$	$p(s=0)$
SR3b	0.19	3.9	$4.4^{+1.7}_{-0.6}$	0.50
SR0b	0.80	16.3	$8.9^{+3.6}_{-2.0}$	0.03

HistFitter & documentation

- HistFitter paper on arXiv: http://arxiv.org/abs/1410.1280
- HistFitter webpage with doxgen documentation: http://cern.ch/histfitter
- Tutorial (to be discussed next): https://twiki.cern.ch/twiki/bin/view/Main/HistFitterTutorialOutsideAtlas
- ACAT 2014 talk on HistFitter: https://indico.cern.ch/event/258092/session/8/contribution/39

HistFitter tutorial

Running HistFitter

- HistFitter.py <options> <configuration_file>

- **-t:** Create histograms in all regions used for all backgrounds, signal, data from TTrees
- **-w**: Build workspaces from histograms
- **-f:** Fit
- **-D**: various drawing options, to be discussed later
- **-L:** log level {VERBOSE,DEBUG,INFO,WARNING,ERROR,FATAL,ALWAYS}
- **-m PARAM**: run Minos for asymmetric error calculation
  - optionally give parameter names comma separated; for all parameters use ‘ALL’ or ‘all’
- **-l**: Calculate upper limit
- **-p**: Calculate the CLs value for a specific signal model (for exclusion)
- **-i**: interactive mode, keeps you in python command line, but shows plots on your screen

- To see all options run: `HistFitter.py --help`

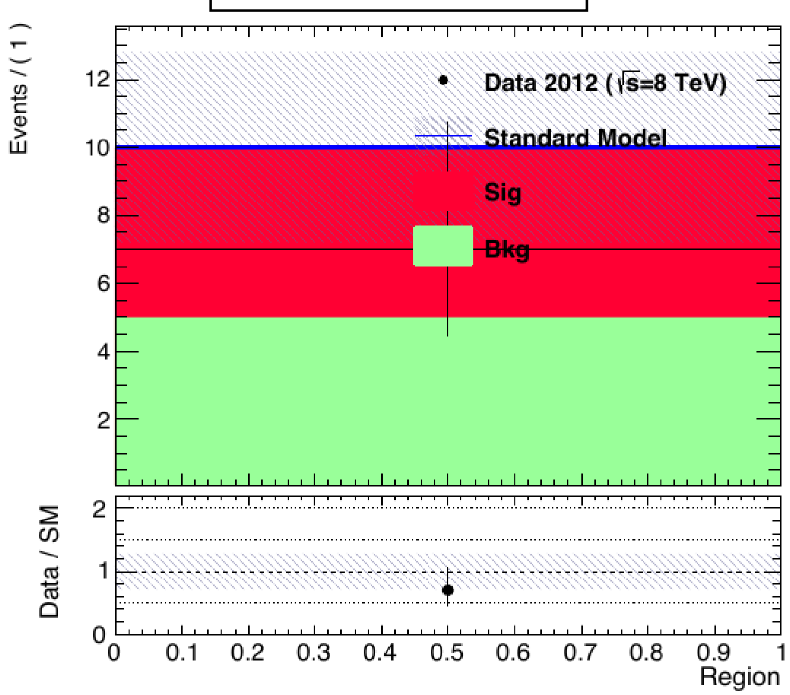
Simple example

- Simple example with one region with one bin:

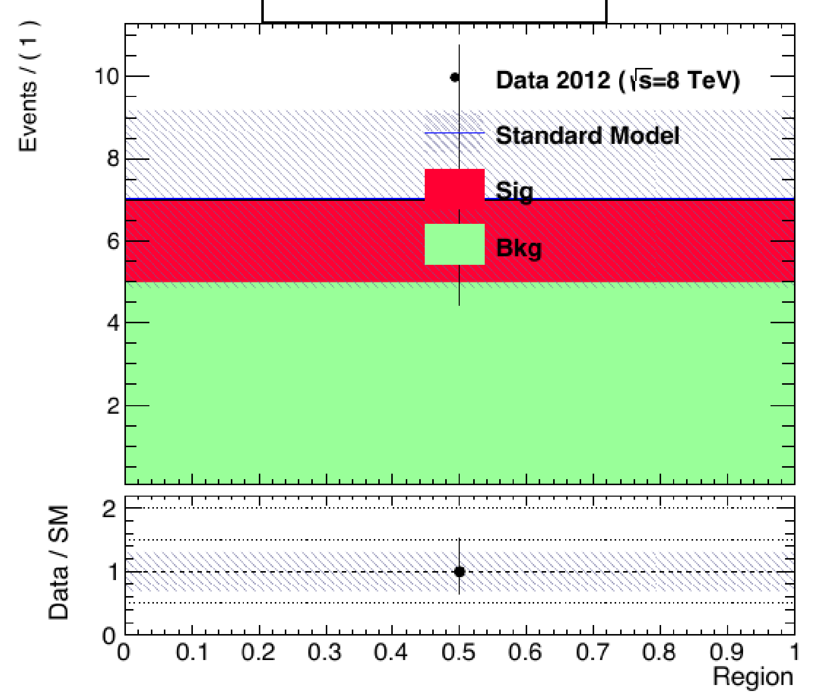
```
HistFitter.py -w -f -D "before,after,corrMatrix" -i
analysis/tutorial/MyUserAnalysis.py
```

- Creates the workspace
- Runs the fit
- Plots before/after fit regions and correlation matrix
- Keeps you in interactive mode

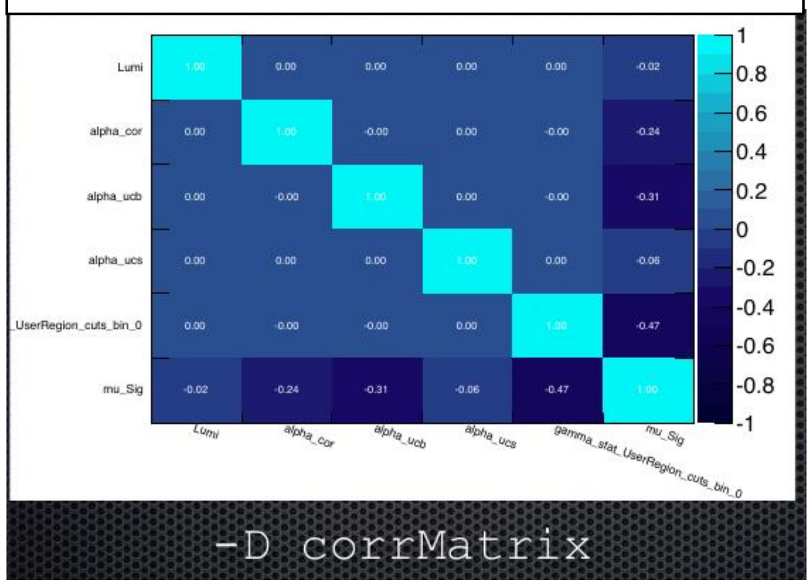
Before Fit



After Fit



correlations matrix



Config file explained - I

- Define a configManager and setup a `fitConfig` ana named SPlusB
- ```
  from configManager import configMgr
  ana = configMgr.addFitConfig("SPlusB")
  ```

- Add one channel/region to the `fitConfig`
- `chan = ana.addChannel("cuts",["UserRegion"],1,0.5,1.5)`

- One defines the region/channel in cutsDict (as one would in ROOT for TTree call)
- Here include all:
- `configMgr.cutsDict["UserRegion"] = "1."`

- Channels can also be binned (shape-fit)
- `chan = ana.addChannel("myObs", ["mySelection"], nBins, varLow, varHigh)`
  ```

Config file explained - II

- Define samples: bkgSample, sigSample and dataSample

- `#` Define samples

`bkgSample = Sample("Bkg",kGreen-9)` # define a background sample with color KGreen-9 if plotting

`bkgSample.setStatConfig(True)` #This sample gets statistical uncertainties

`bkgSample.buildHisto([nbkg],"UserRegion","cuts")` #Build histograms from numbers defined by the user

`bkgSample.buildStatErrors([nbkgErr],"UserRegion","cuts")`

`sigSample = Sample("Sig",kPink)` #A signal sample with color kPink

`sigSample.setNormFactor("mu_Sig",1.,0.,100.)` # This samples receives a normalization parameter

`sigSample.setStatConfig(True)` #This sample gets statistical uncertainties

`sigSample.setNormByTheory()` # and uncertainties due to the luminosity are added

`sigSample.buildHisto([nsig],"UserRegion","cuts")`

`sigSample.buildStatErrors([nsigErr],"UserRegion","cuts")`

`dataSample = Sample("Data",kBlack)` #Data sample

`dataSample.setData()`

`dataSample.buildHisto([ndata],"UserRegion","cuts")`

add all samples to the fitconfig object and thus to all channels

`ana.addSamples([bkgSample,sigSample,dataSample])`

Config file explained - III

- Add systematics to signal/background samples
- Correlating systematics happens by giving them the same name

- # Set uncorrelated systematics for bkg and signal (1 +- relative uncertainties)

```
ucb = Systematic("ucb", configMgr.weights, 1.2,0.8, "user","userOverallSys")
ucs = Systematic("ucs", configMgr.weights, 1.1,0.9, "user","userOverallSys")
```

correlated systematic between background and signal (1 +- relative uncertainties)

```
corb = Systematic("cor",configMgr.weights, [1.1],[0.9], "user","userHistoSys")
cors = Systematic("cor",configMgr.weights, [1.15],[0.85],
"user","userHistoSys")

bkgSample.addSystematic(corb)
bkgSample.addSystematic(ucb)
sigSample.addSystematic(cors)
sigSample.addSystematic(ucs)
```

Table production

- **YieldsTable.py** produces customizable tables of yields before/after fit
- Example: `YieldsTable.py -s Top,WZ,BG,QCD -c SLWR_nJet,SLTR_nJet -w results/MyConfigExample/BkgOnly_combined_NormalMeasurement_model_afterFit.root -o MyYieldsTable.tex`

table.results.yields channel	SLWR_nJet	SLTR_nJet	SR1sl2j	SS_metmeff2Jet
Observed events	1794	269	25	26
Fitted bkg events	1800.73 $\pm$ 39.91	262.45 $\pm$ 11.47	28.53 $\pm$ 5.26	31.74 $\pm$ 8.50
Fitted Top events	117.20 $\pm$ 11.42	113.20 $\pm$ 12.53	6.17 $\pm$ 1.12	6.65 $\pm$ 1.26
Fitted WZ events	1629.37 $\pm$ 42.19	69.75 $\pm$ 6.63	13.95 $\pm$ 2.03	14.57 $\pm$ 1.98
Fitted BG events	43.49 $\pm$ 1.90	23.19 $\pm$ 1.94	0.96 $\pm$ 0.32	1.00 $\pm$ 0.32
Fitted QCD events	10.64 $\pm$ 0.51	56.30 $\pm$ 13.65	7.44 $\pm$ 3.75	9.52 $\pm$ 7.54
MC exp. SM events	1921.26	261.96	32.04	35.35
MC exp. Top events	165.16	153.98	8.75	9.38
MC exp. WZ events	1647.04	66.30	15.26	15.82
MC exp. BG events	40.96	25.03	0.59	0.63
data-driven exp. QCD events	68.06	16.64	7.44	9.52

- **SysTable.py** produces customizable tables of systematic breakdown per region (or sample)
- Example: `SysTable.py -w results/MyConfigExample/BkgOnly_combined_NormalMeasurement_model_afterFit.root -c SR1sl2j -o systable_SR1sl2j.tex`

Uncertainty of channel	SR1sl2j
Total background expectation	28.53
Total statistical ($\sqrt{N_{\rm exp}}$)	$\pm$5.34
Total background systematic	$\pm$5.26 [18.43%]
gamma_stat_SR1sl2j_cuts_bin_0	$\pm$3.63
alpha_QCDNorm_SR1sl2j	$\pm$3.63
alpha_JES	$\pm$0.93
mu_Top	$\pm$0.65
alpha_KtScaleTop	$\pm$0.52
alpha_KtScaleWZ	$\pm$0.37
mu_WZ	$\pm$0.36

Signal model hypothesis test

- Once you have unblinded your SR, one can calculate the CLs/p-value on specific signal models using the exclusion fit (aka model-dependent fit setup)
- As simple in HistFitter as calling:

```
HistFitter.py -p analysis/tutorial/MyUserAnalysis.py
```

- Will calculate:
  - CLs_observed = taking N observed events as data in all regions
  - CLs_expected = taking N expected events as data in all regions
  - CLs_expected ±1sigma experimental uncertainty = N expected as data, ±1sigma fit results
    - yellow band next slide
  - CLs_observed ±1sigma signal theory uncertainty = N observed as data, ±1sigma signal theory
    - need to set the name of the signal theory uncertainty systematic as `Systematic("SigXSec", ...)`
    - red-dotted lines next slide

- Setting calculator and test statistic type can be set in configManager (see backup):

```
## setting the parameters of the hypothesis test
#configMgr.nTOYs=5000
configMgr.calculatorType=2 # 2=asymptotic calculator, 0=frequentist calculator
configMgr.testStatType=3   # 3=one-sided profile likelihood test statistic (LHC default)
configMgr.nPoints=20       # number of values scanned of signal-strength for upper-limit
determination of signal strength.
```

- Result of '-p' stored in a ROOT file with 'hypotest' in the name:

```
results/MySimpleChannelAnalysis_fixSigXSecNominal_hypotest.root
```

Contour plot explained

- https://twiki.cern.ch/twiki/bin/view/AtlasProtected/SUSYLimitPlotting

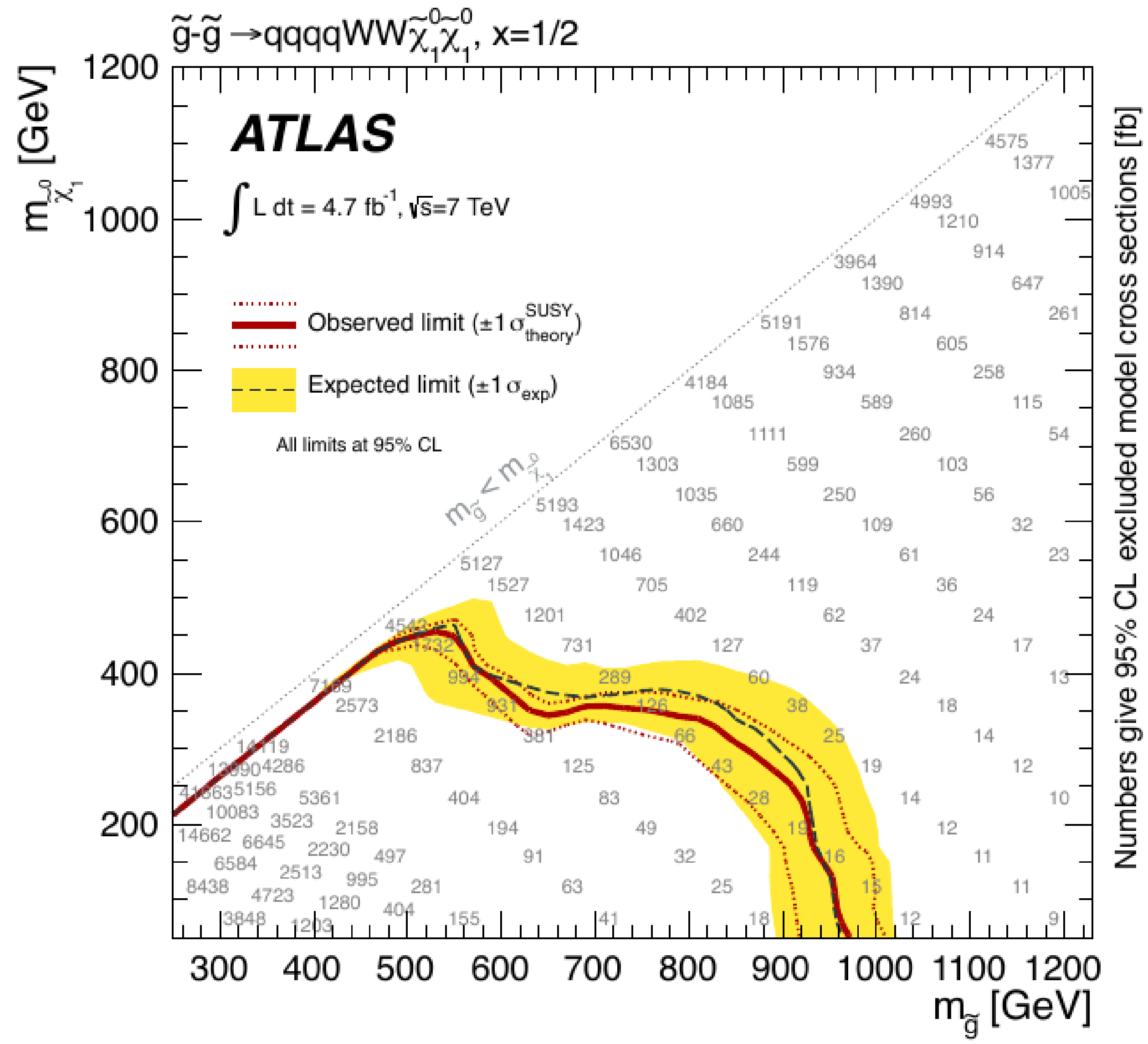
Description of limit lines

The model limits should be computed using the HistFitter package. We present the following limits:

1. **Observed limit** (thick solid dark-red line): all uncertainties are included in the fit as nuisance parameters, with the exception of the theoretical signal uncertainties (PDF, scales).
2. **Expected limit** (less thick long-dashed dark-blue line): all uncertainties are included in the fit as nuisance parameters, with the exception of the theoretical signal uncertainties (PDF, scales).

We present the following uncertainty bands:

- **±1σ lines around observed limit** (1) with style "thin dark-red dotted": re-run limit calculation (1) while increasing or decreasing the signal cross section by the theoretical signal uncertainties (PDF, scales).
- **±1σ band around expected limit** (2) with style "yellow band": the band contours are the ±1σ results of the fit (2).

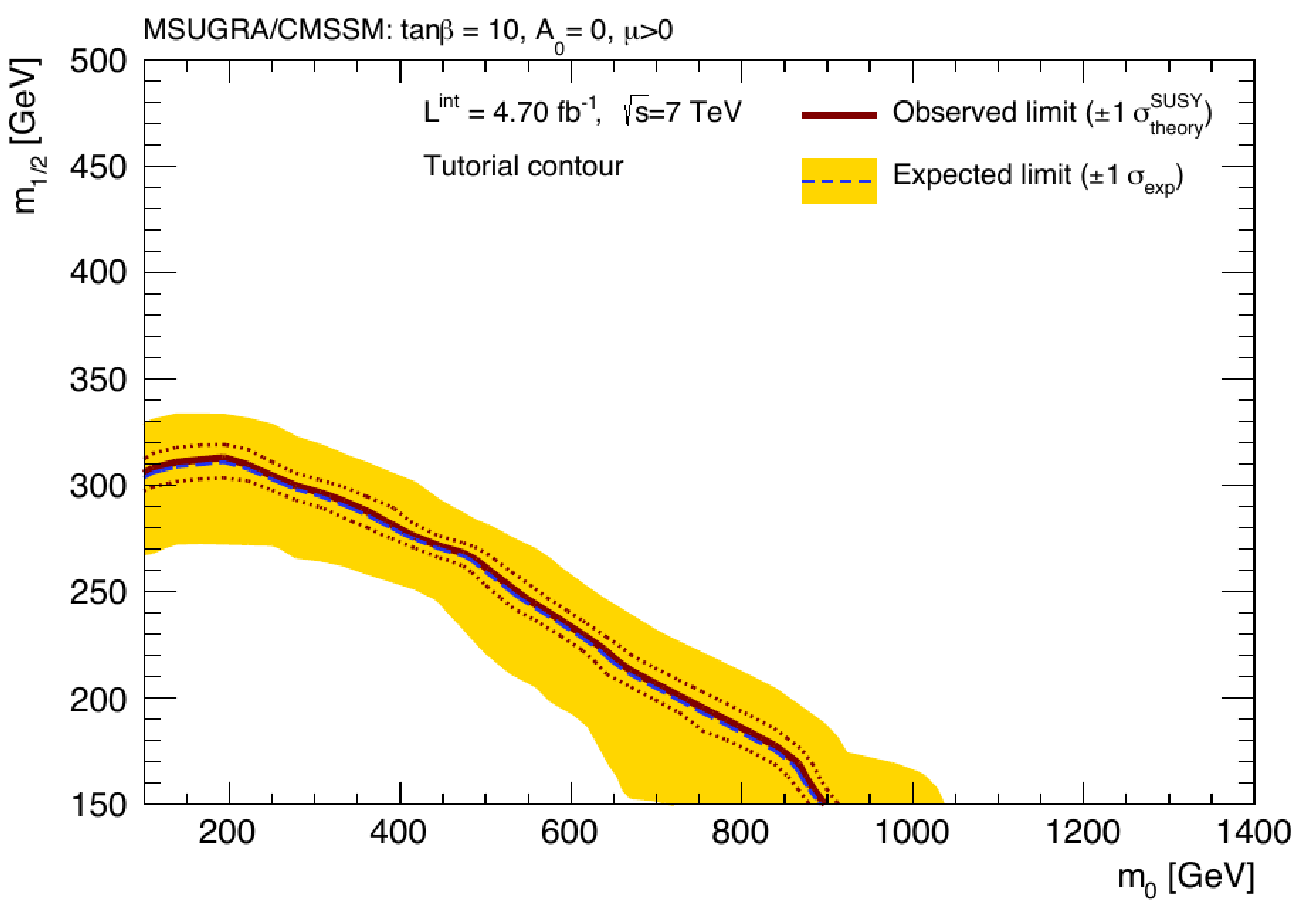


Contour plot production

- Typically a grid of signal model points with varying signal parameters (m_H or m_{gluino}) get processed to produce an exclusion contour
- Five steps to produce (Part 5 of tutorial):

1. run hypothesis tests over all grid points (results saved in multiple *hypotest* files)
2. merge all the output root files into one using `hadd` (if stored in a separate files)
3. transform this set of hypothesis tests into a plain-text file: `makelistfiles.C`
4. create TH2D(s) from the ascii data in this list file: `makecontourhists.C`
5. plot TH2D(s) to draw contour lines and cosmetics: `makecontourplots.C`

- at the requested CLs level, typically 95% CL, CLs<0.05



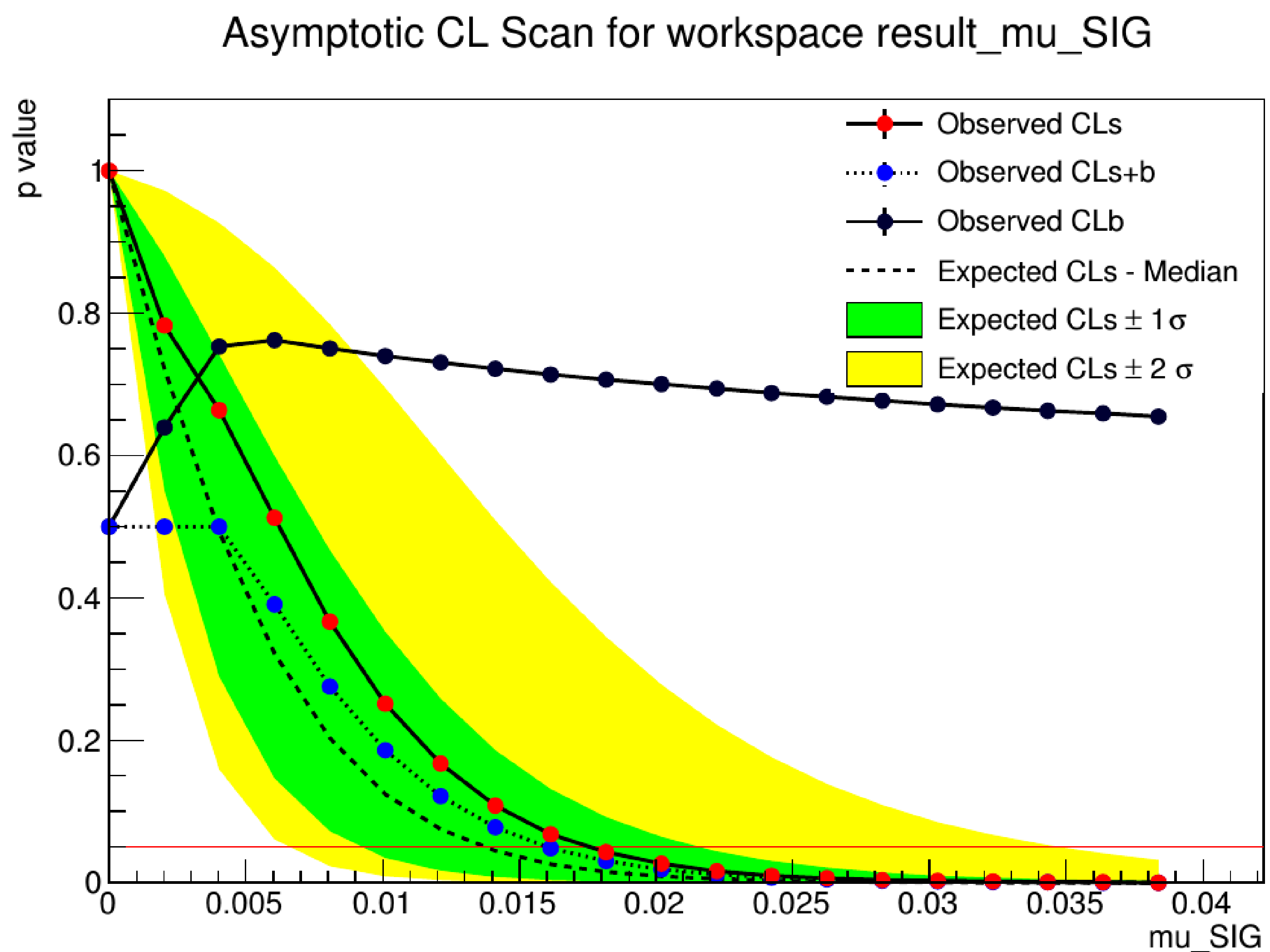
Signal strength upper limit

- Once you have unblinded your SR, one can set upper limits on specific signal models using the exclusion fit (aka model-dependent fit setup)
- As simple in HistFitter as calling:

```
HistFitter.py -l analysis/tutorial/MyUserAnalysis.py
```

  - Technicalities similar to ‘-p’

- Hypothesis test ***inversion***:
  - find the value of mu_SIG for which CLs below 0.05 (or other required value)
    - instead of calculating the p-value for the specific signal
  - run the hypothesis test for increasing values of signal strength mu_SIG
    - scan range determined automatically
    - upper limit on cross section = nominal cross section × upper limit on signal strength (grey numbers in contour plots, run for each signal grid point)



Model-independent upper limit

- Calculate the upper limit on the number of BSM physics events that we exclude in our SR
  - Typically used by theorists to check their favorite BSM model, that we have not looked at
- Requires the model-independent fit setup - aka discovery fit
  - ‘dummy signal’ = exactly one event in signal region (none in CRs)
  - upper limit on this ‘dummy signal’ = upper limit on BSM number of events
- Use the **UpperLimitTable.py** script:

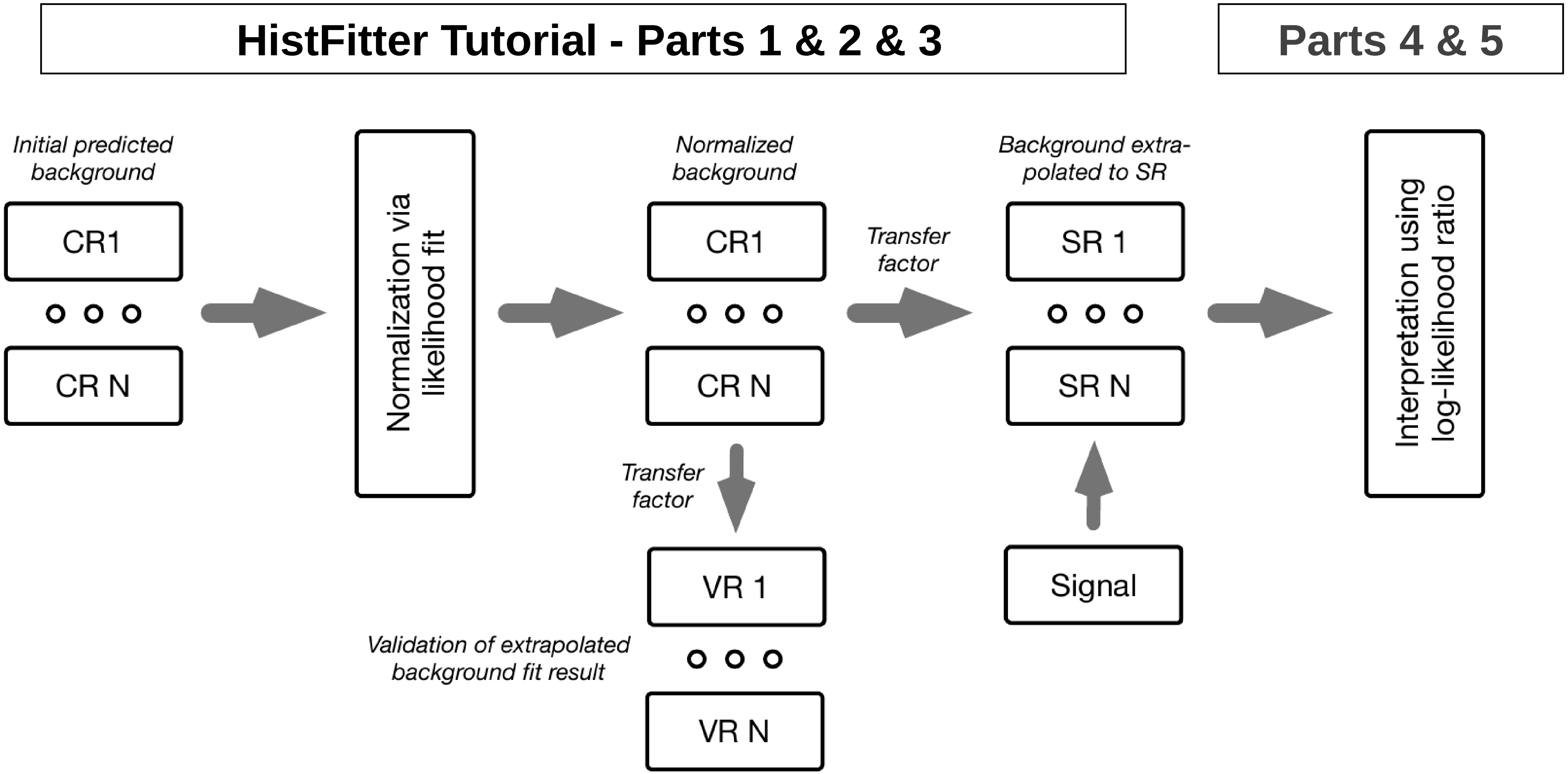
```
UpperLimitTable.py -c SS -w
results/MyUpperLimitAnalysis_SS/SPlusB_combined_NormalMeasurement_model.root -
l 4.713 -n 1000
```

- Results in LaTeX table:

Signal channel	$\langle\epsilon\sigma\rangle^{95}_{\rm obs}$[fb]	$S^{95}_{\rm obs}$	$S^{95}_{\rm exp}$	CL_B	$p(s=0)$
SS	1.73	8.2	$6.1^{+2.3}_{-1.3}$	0.80	0.21

  - ⟨σvis⟩95_obs : 95% CL upper limits on the visible cross section obs
  - S95_obs :95% CL upper limits on the number of signal events obs
  - S95_exp : 95% CL upper limit on the number of signal events, given the expected number (and ±1σ excursions on the expectation) of background events
  - CLB: the confidence level observed for the background-only hypothesis
  - p(s = 0): discovery p-value - the probability, capped at 0.5, that a background-only experiment is more signal-like than the observed number of events in a signal region

HistFitter - tutorial



HistFitter tutorial start up

- A public version is available on the HistFitter webpage:
  http://histfitter.web.cern.ch/histfitter/Software/Install/index.html

  We use HistFitter-2.0.tar.gz for this tutorial.

- **Installation instructions:**
  - Untar the HistFitter package
  - Setup ROOT (if not already done) – use Root 5!
  - Go the HistFitter directory cd HistFitter-2.0
  - Run the HistFitter setup script source setup.sh
  - Go to the src/ directory and compile the C++ side of HistFitter cd src && make
  - Go back to the main HistFitter directory

  - **Input data here**:
    - Link the input data to your HistFitter directory as follows:
    - ln –s /project/etp3/jlorenz/shape_fit/samples/ samples