School Summary: what I've learnt and hope to use (and maybe you have too)

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PHYSICS AT THE TERA SCALE
Helmholtz Alliance

From Glen

Bayes theorem is not just for Bayesians.
Bayesians & Frequentists have learnt to co-exist. Each has useful insights.

p-values are a key tool for hypothesis testing (more exciting than it sounds)
You need to be able to translate fluently between p-values and Z-values

```
in python (scipy.stats):
p = 1 - norm.cdf(Z) = norm.sf(Z)
Z = norm.ppf(1-p)
```

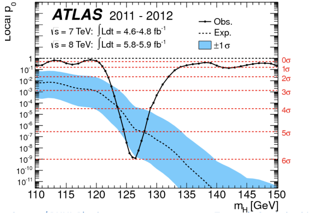
Neyman-Pearson Lemma: test on $t(x) = \frac{P(x|H_1)}{P(x|H_0)}$
Seems obvious. Point is that it can reduce a multidimensional boundary problem to a 1-dimensional cut.

If you see nothing, that gives an upper limit of 3.0 events. "If the true strength is 3.0 or more, the Poisson probability of getting a downward fluctuation this far [or further] is only 5% or less." This 3.0 is then translated into a cross section or BR or whatever

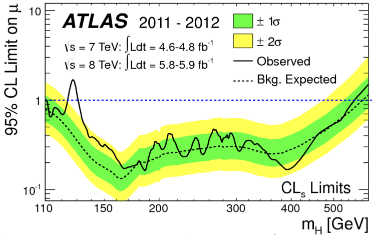
Use of the Likelihood Ratio and Wilks' theorem for discoveries and limits
Both are in the framework of hypothesis testing and use the same apparatus, from the CCGV paper, EPJC 21 (2011) 1554

Discovery: null hypothesis is no signal. But $L(\hat{\mu}) >> L(\mu = 0)$ so $q (\sim \chi^2)$ is large so p is small so Z is large and you have a discovery

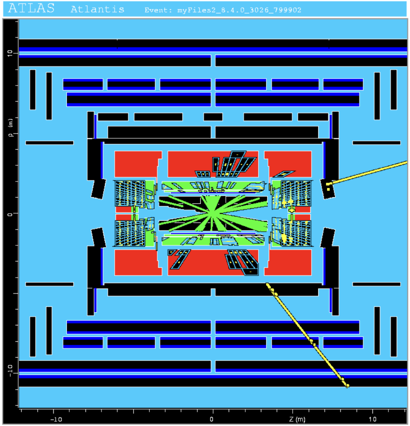
Upper limit: find μ_{hi} with $L(\mu_{hi}) < L(\hat{\mu})$ by an amount such that q is large but not too large, giving p of 0.05 (or whatever)



ATLAS, Phys. Lett. B 716 (2012) 1-29



From Glen – a ‘background’ event (!)



This event from Standard Model ttbar production also has high p_{T} jets and muons, and some missing transverse energy.

→ can easily mimic a signal event.

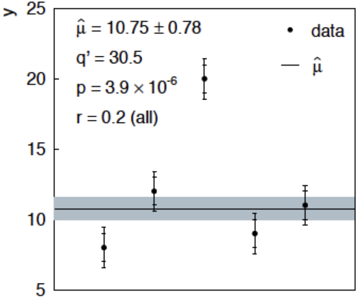
From Glen ("Errors on Errors")

This is very cutting-edge stuff

Motivational validity not entirely clear (to me): does make sense in a hybrid Bayesian plus Frequentist picture. But never mind, use it anyway.

Gamma distribution is likewise an assumption. But it works.

$f(v; \alpha, \beta) = \frac{\beta^\alpha}{\Gamma(\alpha)} v^{\alpha-1} e^{-\beta v}$



Gives a methodical way of disfavouring results which are clearly out of line.

Do we need to deploy it?

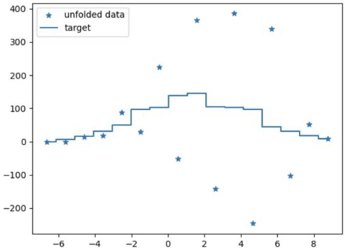
I think not, for most of us. This is a tool for meta-analysis (PDG, and HFLAV). Not our responsibility to put errors on our errors. But must not object if this is done for us.

From Vince

"You can get it wrong and still you think that it's alright"

John Lennon, quoted by Volker Blobel

- Don't do it unless you really have to.
- Never, ever use 'correction factors'
- Matrix inversion gives scary results.
- Regularisation - applying smoothing
- Unfolding is not just 'cleaning up the data to remove detector effects'



RooUnfold and RooFitUnfold

Several methods on offer - user-friendly and written by experts.
Broadly: smoothing-type and iterative-Bayesian.
Try more than one (important for legacy-type analyses)

From the Combine team

Real connection with real data and real tools. Many thanks to CMS for sharing their software with outsiders

```
imax    1 number of bins
jmax    4 number of processes minus 1
kmax    * number of nuisance parameters
--------------------------------------------------------------------------------
--------------------------------------------------------------------------------
bin          signal_region
observation  10.0
--------------------------------------------------------------------------------
bin                          signal_region   signal_region   signal_region   signal_region   signal_re
process                      ttbar           diboson         Ztautau         jetFakes        bbHtautau
process                      1               2               3               4               0
rate                         4.43803         3.18309         3.7804          1.63396         0.711064
--------------------------------------------------------------------------------
CMS_eff_b           lnN      1.02            1.02            1.02            -               1.02
CMS_eff_t           lnN      1.12            1.12            1.12            -               1.12
CMS_eff_t_highpt    lnN      1.1             1.1             1.1             -               1.1
acceptance_Ztautau  lnN      -               -               1.08            -               -
acceptance_bbH      lnN      -               -               -               -               1.05
acceptance_ttbar    lnN      1.005           -               -               -               -
norm_jetFakes       lnN      -               -               -               1.2             -
xsec_diboson        lnN      -               1.05            -               -               -
```

Very powerful. So many options to choose and values to adjust.
(I found Higgs signal with 20x SM significance - probably wrong)
Those of you on CMS will doubtless take this further
Those of us not on CMS will be doing the same things with different tools
Green and yellow (Brazilian Flag) plots NOT always drawn beforehand

From Tilman

Neural Networks/Machine Learning/AI becomes increasingly powerful thanks to CPU and GPU development

- I learnt what an affine transformation is - not sure that's going to be useful;...
- And that Machine learning is cool (already knew). And a good place for students to get jobs
- Training works by dumbing-down procedures for finding maximum

Heteroscedastic networks

New (to me) and really exciting.
Network can learn about errors
Downplay rogue data values - and / or areas where the model doesn't work well

Not just a network but an ensemble

Consider not just 'a network' but a whole cloud of networks, evolving through time/training using fluid mechanics, with mutual repulsion

$$\frac{d\theta}{dt} = -\nabla_\theta \log \frac{\rho(\theta,t)}{\pi(\theta)}$$

$$\frac{\partial\rho(\theta,t)}{\partial t} = \nabla_\theta \left[\rho(\theta,t)\nabla_\theta \log \frac{\rho(\theta,t)}{\pi(\theta)}\right]$$

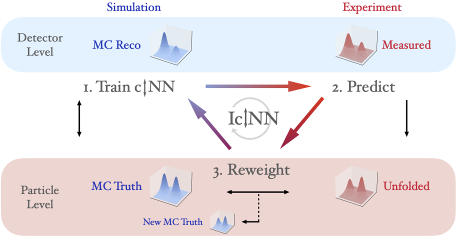
$$= -\nabla_\theta \left[\rho(\theta,t)\nabla_\theta \log \pi(\theta)\right] + \nabla_\theta^2 \log \rho(\theta,t) \ .$$

giving understanding of the variance of the outputs/results
(Also Bayesian networks, which are not Bayesian so we can use them without feeling guilty)

Classification and Unfolding

NNs beat everything else available
Classification basically the same as regression, just a different loss function
Unsupervised classification is already happening
VAEs not useful. GANs work better but they cheat.
INN / NF both ways: same dimensionality.. Network encodes the Jacobian between the data and noise: 'latent' multi-Gaussian
Normalising flows and diffusion netwroks
CFMs are the cool networks today -
Reweighting (1) Nachman OmniFold: reweighting . Train a classifier over phase space and find Neyman-Pearson factor

Reweighting (2) Conditional Generative networks



Further reading...

Modern Machine Learning for LHC Physicists

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Theo Heimel[a], Claudius Krause[c], and Ramon Winterhalder[d]

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April 3, 2024

Some of us will be getting our hands dirty developing and improving networks and other ML tools. Transformers?
The rest of us will be using them

About uncertainties, asymmetric or not

- The Neyman Construction really helps you conceptualise errors
- Systematic errors are not scary
- $\Delta \ln L = -\frac{1}{2}$ errors are not infallible
- Asymmetric errors should be avoided if possible
- If not possible, there are methods, but you have to think about what you're trying to do

Final thoughts

We have a lot of data (at the LHC and other experiments) and we're going to get a lot more.

New useful statistical ideas and techniques continue to emerge and we need to use the latest technology

The Standard Model has got to crack one day

There is lots of work to be done – let's get on with it

Big thank-you to Olaf and the team for all the organisation

Goodbye