Using pMSSM Fits to Evaluate the Utility of M_{T_2} Searches

by

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Talk outline

- The M_{T_2} search strategy
- pMSSM fits
- Do pMSSM SUSY searches work?

[a] based on work with AJ Barr, A Dafinca and C Gwenlan (Oxford)

Idea

Many search strategies been optimised for constrained models: are there loopholes?

ATLAS uses $\not{p}_T$ cut strategy, but $\not{p}_T$ could be subject to large systematics in early data. We want to:

- determine how likely M_{T_2}-based searches are to discover SUSY.
- understand the succeses and failures of the searches.
- optimise the searches for a more general MSSM scenario.

Cue M_{T_2}

$$m_T^{(i)^2}(\mathbf{p}_T{}^{(i)}, \not{\mathbf{q}}_T{}^{(i)}) \equiv 2\left|\mathbf{p}_T{}^{(i)}\right|\left|\not{\mathbf{q}}_T{}^{(i)}\right| - 2\mathbf{p}_T{}^{(i)} \cdot \not{\mathbf{q}}_T{}^{(i)}$$

where $\not{\mathbf{q}}_T{}^{(i)}$ is a guess for the true, unknown missing transverse momentum $\not{\mathbf{p}}_T{}^{(i)}$. The variable M_{T2} is defined by:

$$M_{T2}(\mathbf{p}_T{}^{(1)}, \mathbf{p}_T{}^{(2)}, \not{\mathbf{p}}_T) \equiv \min_{\sum \not{\mathbf{q}}_T = \not{\mathbf{p}}_T} \left\{ \max\left(m_T^{(1)}, m_T^{(2)} \right) \right\}$$

The minimization is over all values of $\not{\mathbf{q}}_T{}^{(1,2)}$ consistent with $\sum \not{\mathbf{q}}_T = \not{\mathbf{p}}_T$. For the SUSY search, the unknown undetected particle masses are set to zero in M_{T2}.

Science & Technology Facilities Council

Supersymmetry Cambridge Working group

Backgrounds

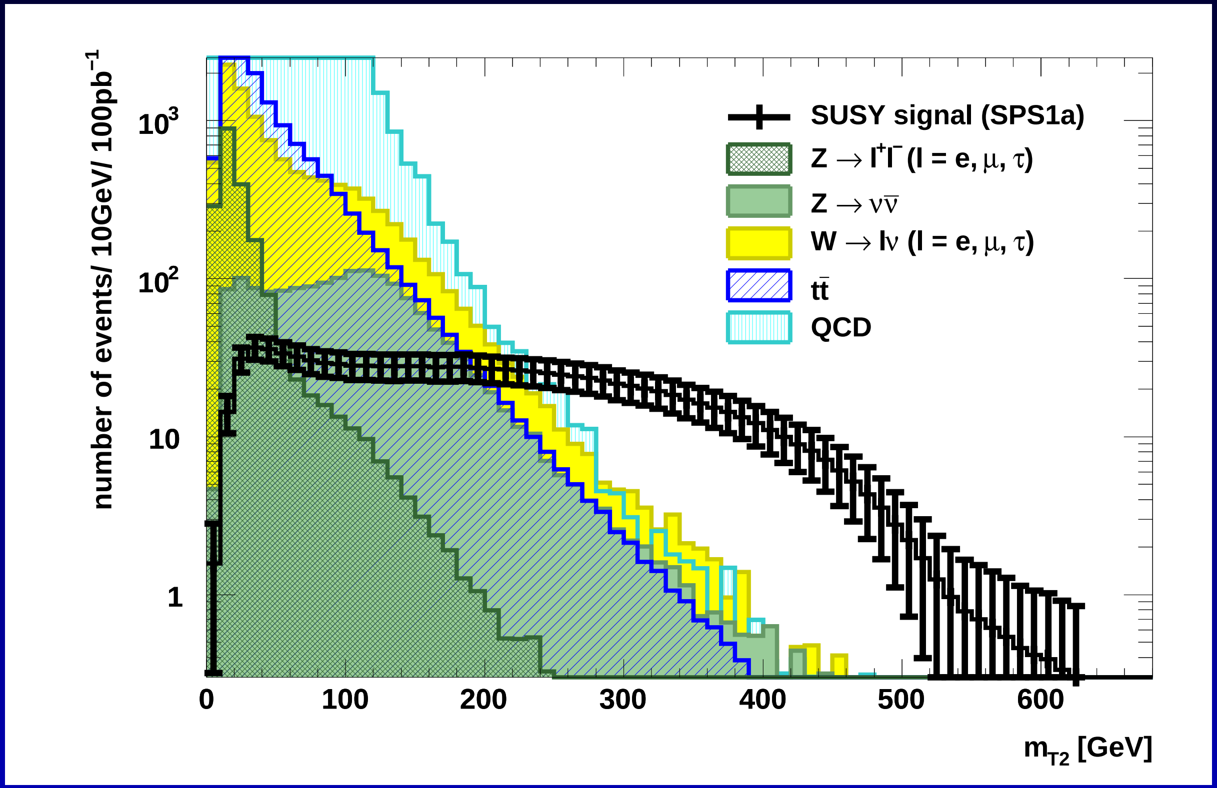


Figure 1: Only cuts: $N_j > 1$, $p_T > 50$ GeV, $\mathcal{L} = 100 pb^{-1}$ at $\sqrt{s} = 7$ TeV. Barr, Gwenlan PRD80 (2009) 074007.

Varying M_{T_2} Cut

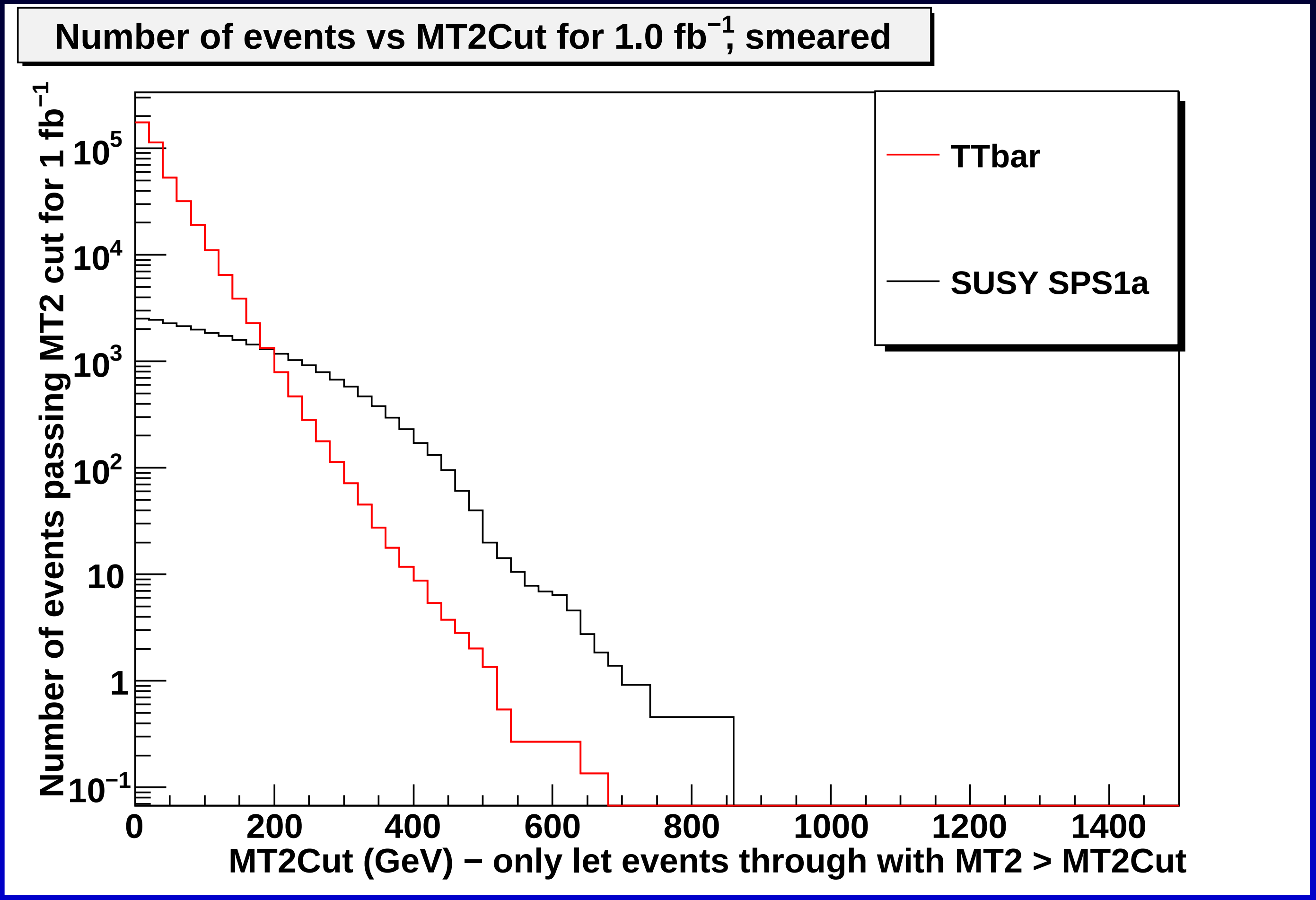


Figure 2: 1 fb^{-1}, $\sqrt{s} = 7$ TeV.

Implementation

We use

- *95% C.L. direct search constraints*
- $\Omega_{DM} h^2 = 0.1143 \pm 0.02$ Boudjema *et al*
- $\delta(g-2)_\mu/2 = (29.5 \pm 8.8) \times 10^{-10}$ Stöckinger *et al*
- $B-$physics observables including $BR[b \rightarrow s\gamma]_{E_\gamma > 1.6\text{ GeV}} = (3.52 \pm 0.38) \times 10^{-4}$
- Electroweak data W Hollik, A Weber *et al*

$$2 \ln \mathcal{L} = -\sum_i \chi_i^2 + c = \sum_i \frac{(p_i - e_i)^2}{\sigma_i^2} + c$$

Priors

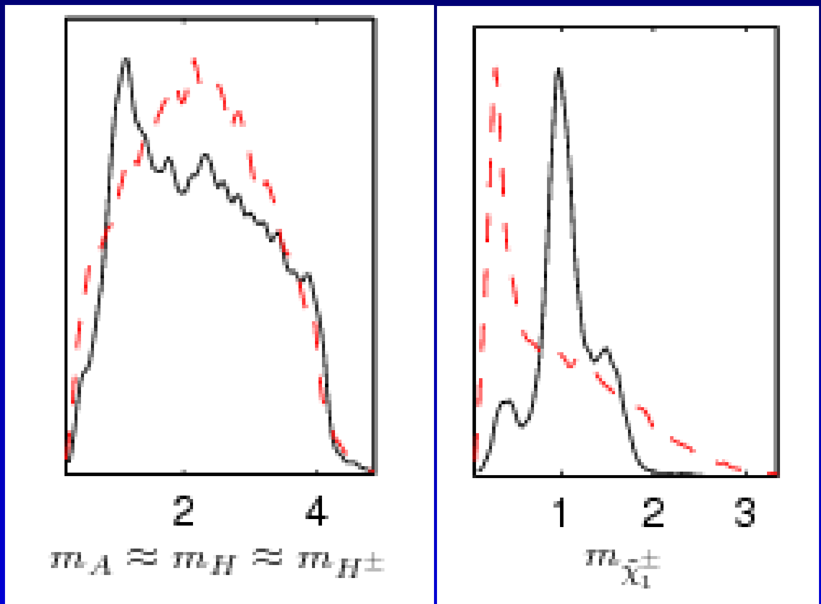
Choose two priors, where $|\mathrm{m}| < 4$ TeV for mass parameters $4m$ and $2 < \tan\beta < 60$:

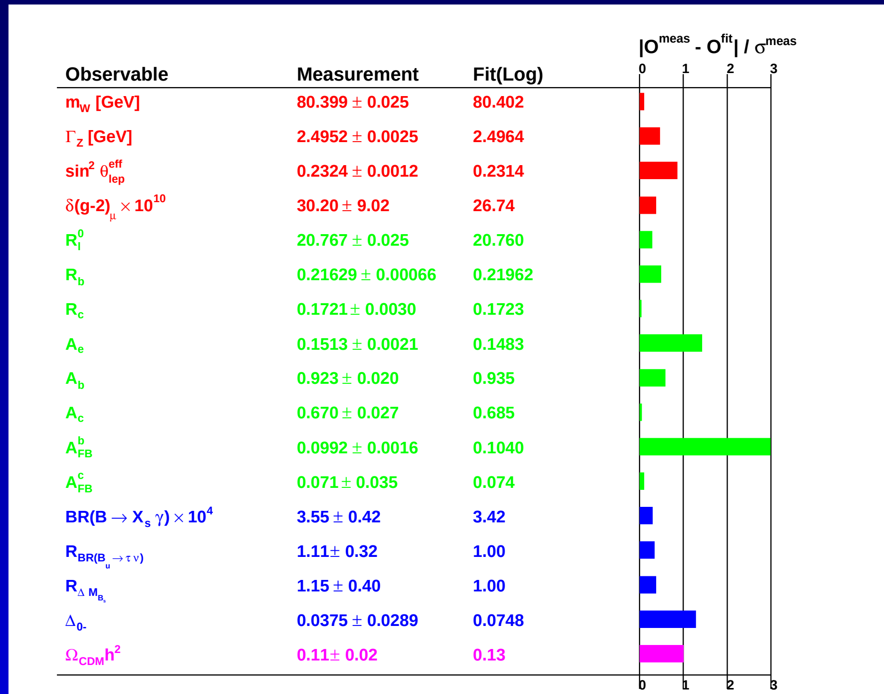
- Linear: *linear in the mass parameters*
- Log: All positive definite parameters set with a log prior, (*scalar masses set to be logarithmic*), all others linear.

SM parameters' priors set to Gaussians with data from the PDG.

pMSSM Fits

25 pMSSM input parameters are: $M_{1,2,3}$, $A_{t,b,\tau,\mu}$, $m_{H_{1,2}}$, $\tan\beta$, $m_{\tilde{d}_{R,L}} = m_{\tilde{s}_{R,L}}$, $m_{\tilde{u}_{R,L}} = m_{\tilde{c}_{R,L}}$, $m_{\tilde{e}_{R,L}} = m_{\tilde{\mu}_{R,L}}$, $m_{\tilde{t},\tilde{b},\tilde{\tau}_{R,L}}$ m_t, $m_b(m_b)$ $\alpha_s(M_Z)^{\overline{MS}}$, $\alpha^{-1}(M_Z)^{\overline{MS}}$, M_Z. Combined Bayesian fit[a]:

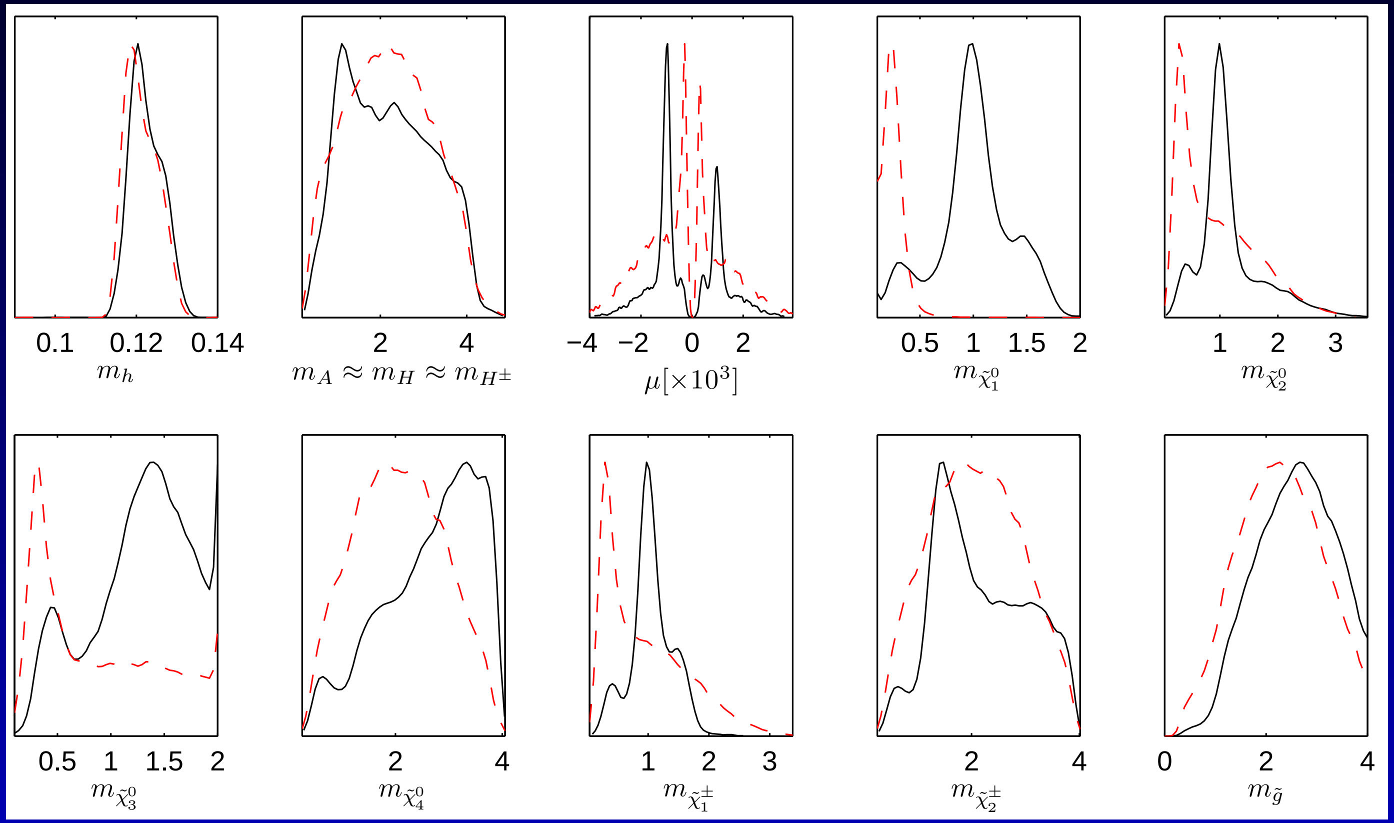




Observable	Measurement	Fit(Log)
m_W [GeV]	80.399 ± 0.025	80.402
Γ_Z [GeV]	2.4952 ± 0.0025	2.4964
$\sin^2\theta^{eff}_{lep}$	0.2324 ± 0.0012	0.2314
$\delta(g-2)_\mu \times 10^{10}$	30.20 ± 9.02	26.74
R_l^0	20.767 ± 0.025	20.760
R_b	0.21629 ± 0.00066	0.21962
R_c	0.1721 ± 0.0030	0.1723
A_e	0.1513 ± 0.0021	0.1483
A_b	0.923 ± 0.020	0.935
A_c	0.670 ± 0.027	0.685
A_{FB}^b	0.0992 ± 0.0016	0.1040
A_{FB}^c	0.071 ± 0.035	0.074
$BR(B \to X_s \gamma) \times 10^4$	3.55 ± 0.42	3.42
$R_{BR(B_u \to \tau\nu)}$	1.11 ± 0.32	1.00
$R_{\Delta M_{B_s}}$	1.15 ± 0.40	1.00
Δ_{0-}	0.0375 ± 0.0289	0.0748
$\Omega_{CDM}h^2$	0.11 ± 0.02	0.13

[a] S.S. AbdusSalam, BCA, F. Quevedo, F. Feroz, M. Hobson, PRD81 (2010) 985012, `arXiv:0904.2548`

Spectrum



Obtained with `MultiNest`[a] algorithm in 16 CPU years. Prior dependence is *useful*: which predictions are robust?

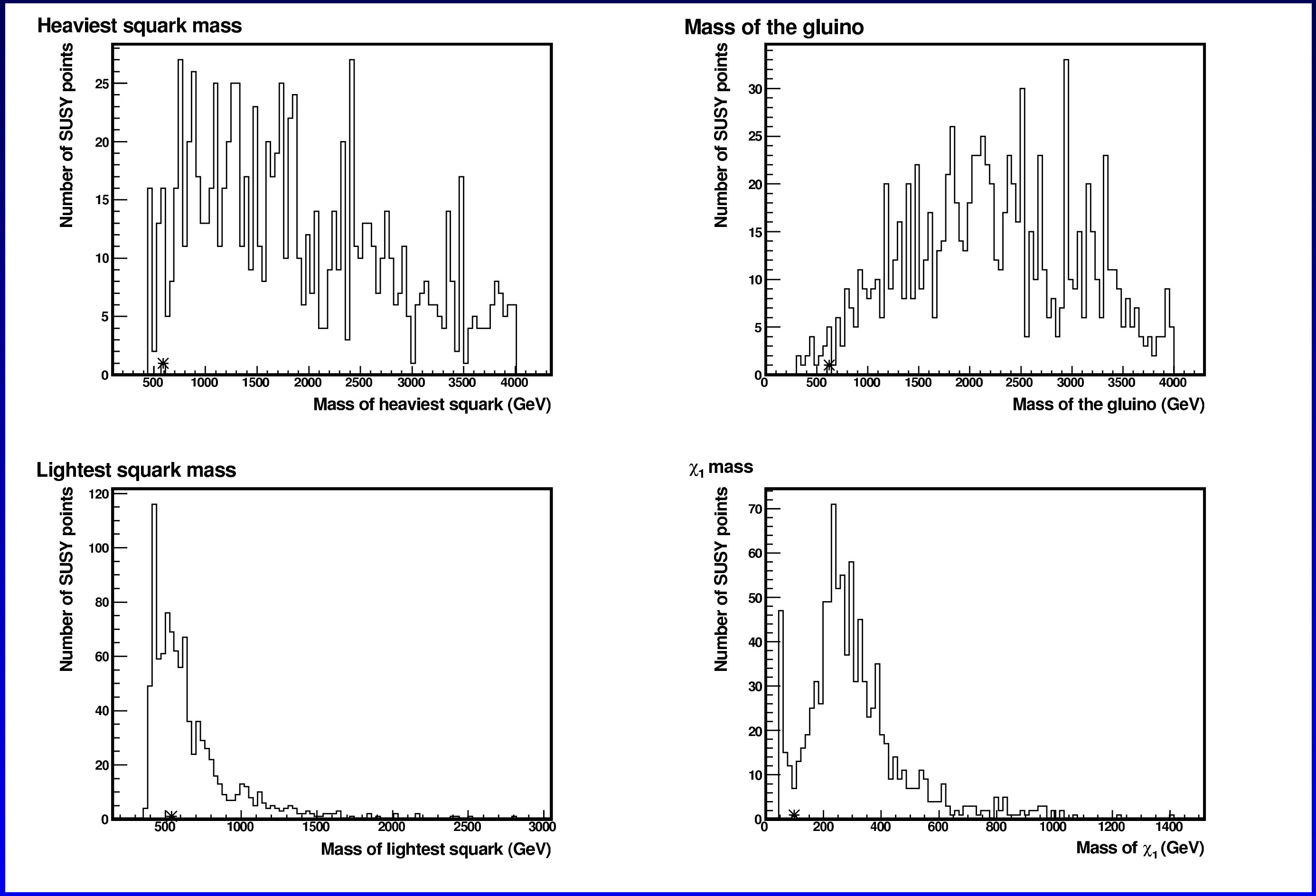
[a] Feroz, Hobson `arxiv:0704.3704`

What's the point?

Despite the fact that fits are extremely prior dependent, this work was a technical demonstration that `MultiNest` can handle ~ 25 parameters. But there is another good use of the fits:

Getting the Point(s)

Examine M_{T2} discoverability with 969 samples from the log prior pMSSM fit. *=SPS1a.



Technical Details

- Used `SOFTSUSY3.1.5` to generate spectra
- `Herwig-2.4.2` generated events.
- Anti-k_T jets with $R = 0.4$ (E combination scheme) have $|\eta| < 5$, $p_T > 10$ GeV and have their 4-momenta scaled by a jet energy response function calculated with full detector simulation (Gaussian with exponential tail).
- M_{T_2} used with hardest 2 jet p_Ts in the event.
- Require $S/\sqrt{B} > 5$ and at least 10 events.

Discoverability

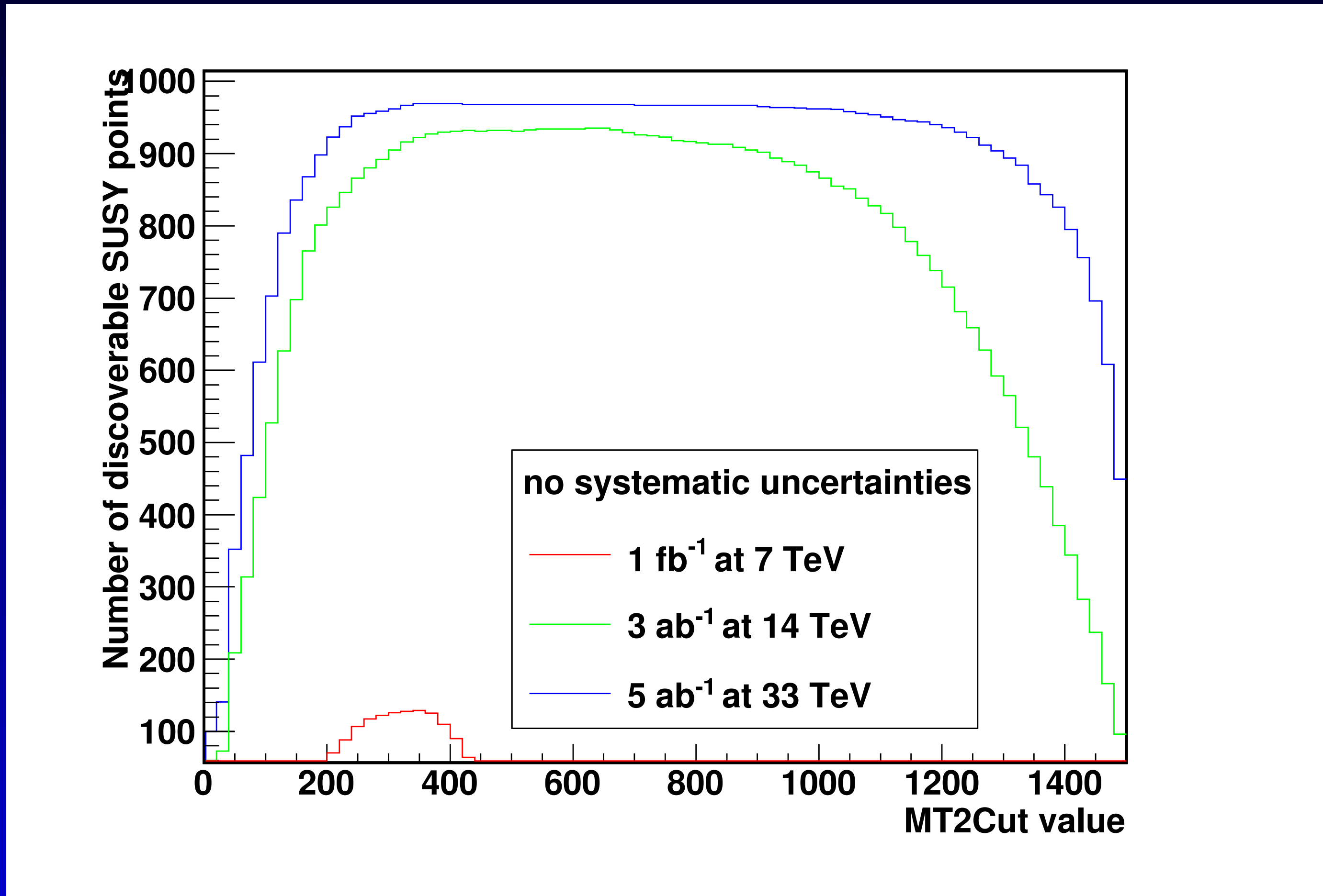
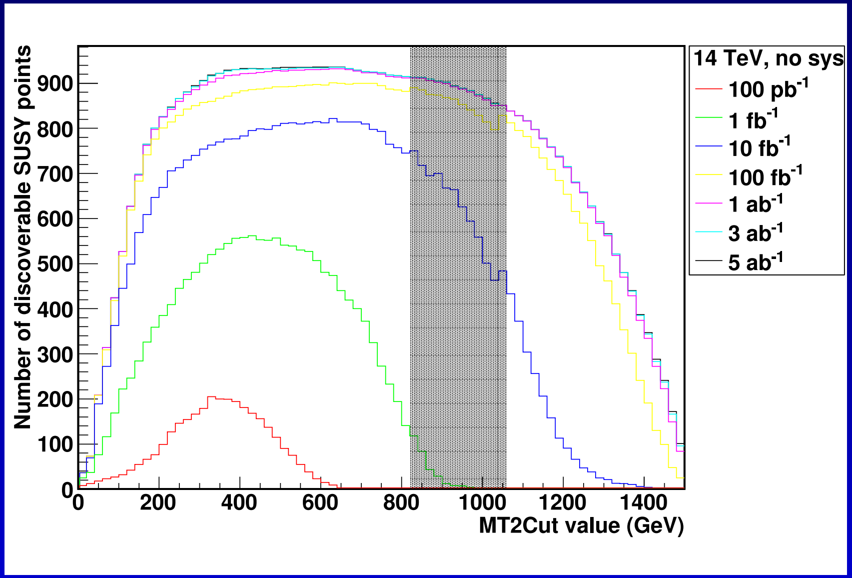
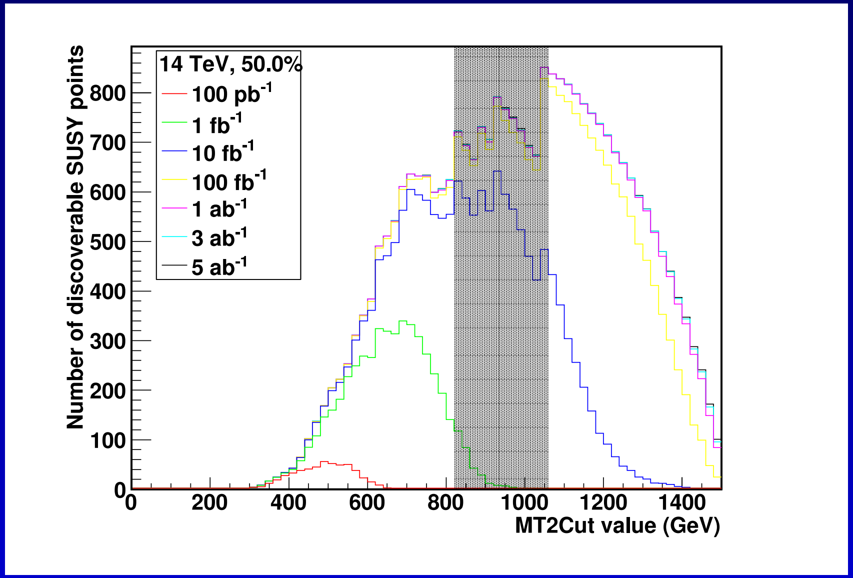


Figure 3: Number of SUSY points (out of 969) discoverable in the lifetime of each LHC period versus M_{T2} cut

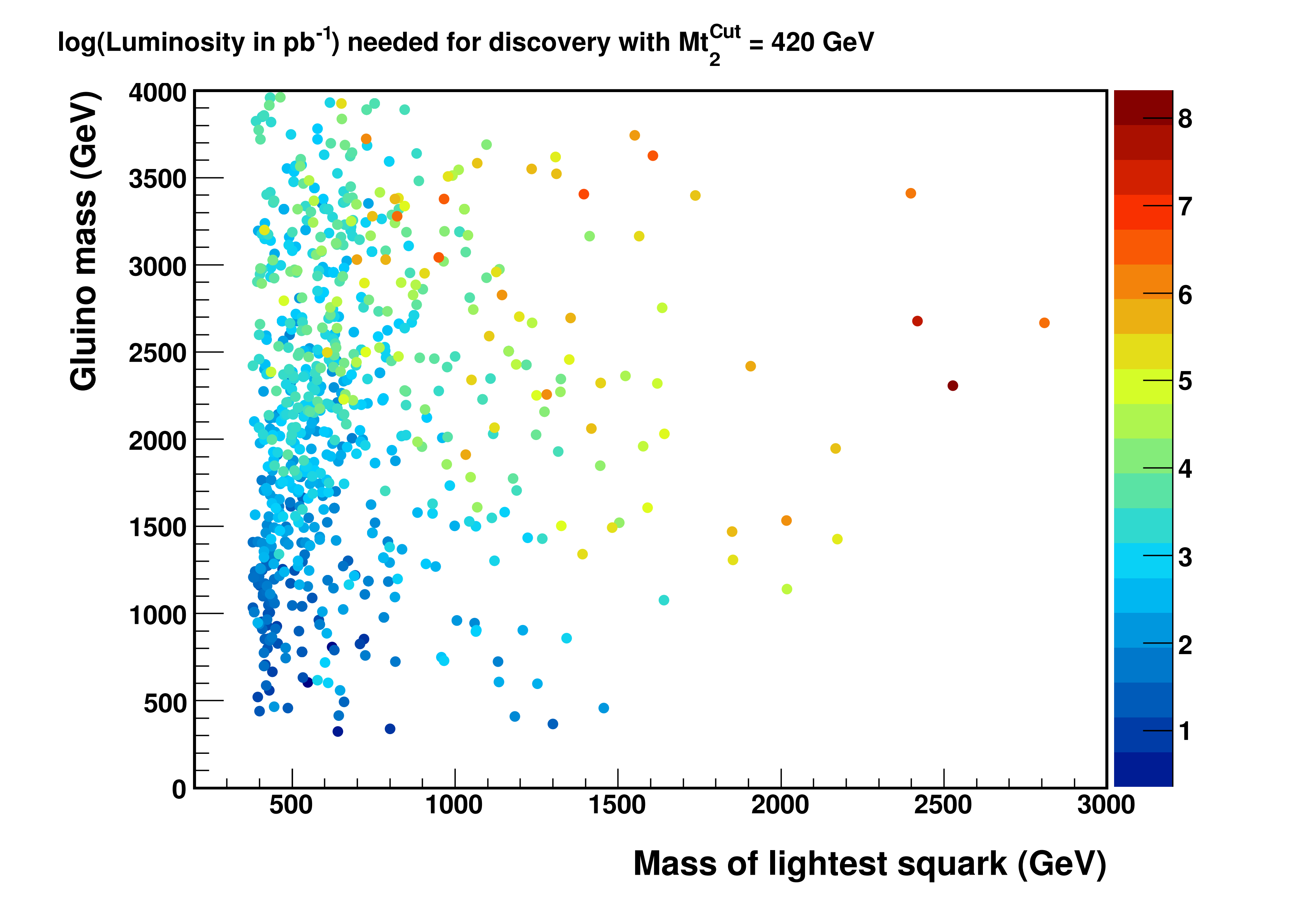
Systematic Effects

Background systematics degrade M_{T2} reach. Effect of a 50% estimated systematic. $\sqrt{s} = 14$ TeV. In shaded region, one can't trust background calculation (low statistics). *SPS1a should have been covered by now!*





Difficult Points



Summary

- M_{T_2} may be a good strategy when searching for SUSY early on.
- pMSSM is of course highly prior dependent. *useful*.
- It's useful to keep a faithful sampling of points for further use! (Cataloguing on web-pages?)
- Intend to pitch ATLAS M_{T2} search vs optimised $\not{p}_T$ with same points to see whether they have relative advantages.
- With systematics, $p(7\ TeV) = 2.8\%$, $p(14\ TeV) = 66\%$, $p(33\ TeV) = 94\%$.

Supplementary Material

Application of Bayes'

$\mathcal{L} \equiv p(\underline{d}|\underline{m}, H)$ is pdf of reproducing data $\underline{d}$ assuming pMSSM hypothesis H and model parameters $\underline{m}$

$$p(\underline{m}|\underline{d}, H) = p(\underline{d}|\underline{m}, H)\frac{p(\underline{m}, H)}{p(\underline{d}, H)}$$

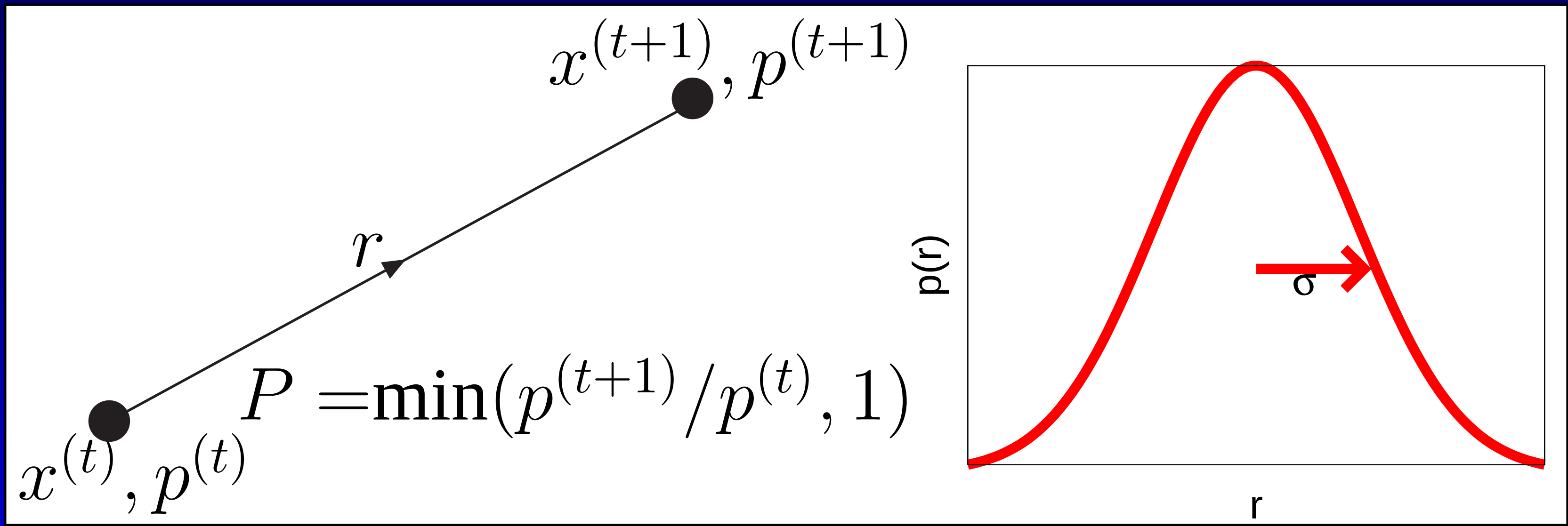
$p(\underline{m}|\underline{d}, H)$ is called the posterior pdf. We will compare $p(\underline{m}, H) = c$ with a *different* prior.

$$p(m_0, M_{1/2}|\underline{d}, H) = \int d\underline{o}\, p(m_0, M_{1/2}, \underline{o}|\underline{d}, H)$$

Called *marginalisation*.

Markov-Chain Monte Carlo

Metropolis-Hastings Markov chain sampling consists of list of parameter points $x^{(t)}$ and associated posterior probabilities $p^{(t)}$.



Final density of x points $\propto p$. Required number of points goes *linearly* with number of dimensions.

Volume Effects

Can't rely on a good χ^2 in non-Gaussian situation

Likelihood and Posterior

Q: What's the chance of observing someone to be pregnant, given that they are female?

Likelihood

p(pregnant | female, human) = 0.01

Posterior

p(female | pregnant, human) = 1.00