Stockholm University

Genetic Algorithms: New Tools to Explore SUSY Parameter Spaces

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In collaboration with:

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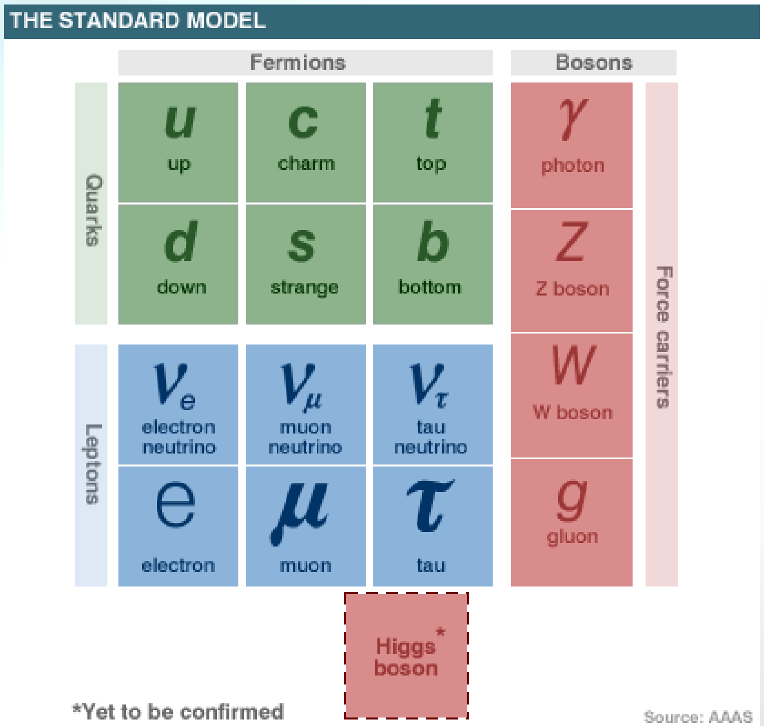
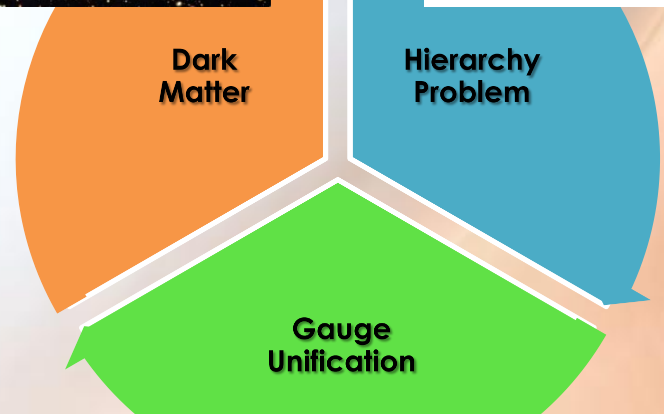
JHEP 04, 057 (2010) [arXiv:0910.3950]

Oskar Klein centre

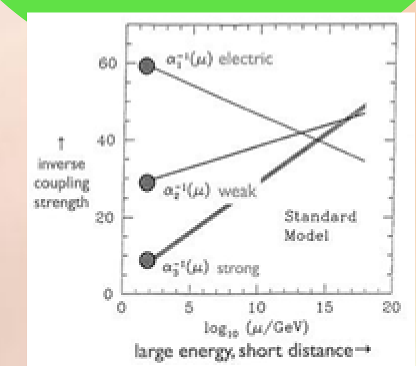
Oskar Klein Center for Cosmoparticle Physics (OKC)

Demands for New Physics at TeV Scales





$$\Delta m_h^2 \sim \frac{\lambda^2}{16\pi^2}\int^{\Lambda}\frac{d^4p}{p^2} \sim \frac{\lambda^2}{16\pi^2}\Lambda^2$$



Weak-Scale SUSY

can solve the problems

Minimal Supersymmetric Standard Model

Field Content:

$\tilde{e}_{L,R}, \tilde{\mu}_{L,R}, \tilde{\tau}_{L,R}$	[Sleptons (Spin 0)]
$\tilde{\nu}_e, \tilde{\nu}_\mu, \tilde{\nu}_\tau$	
$\tilde{u}_{L,R}, \tilde{c}_{L,R}, \tilde{t}_{L,R}$	[Squarks (Spin 0)]
$\tilde{d}_{L,R}, \tilde{s}_{L,R}, \tilde{b}_{L,R}$	
$\tilde{B}, \tilde{W}^0, \tilde{H}_u^0, \tilde{H}_d^0$	[Neutralinos (Spin 1/2)]
$\tilde{W}^+, \tilde{H}_u^+$	[Charginos (Spin 1/2)]
$\tilde{W}^-, \tilde{H}_d^-$	
$\tilde{g}$	[Gluinos (Spin 1/2)]
$\tilde{G}$	[Gravitino (Spin 3/2)]

After EW Symmetry Breaking:

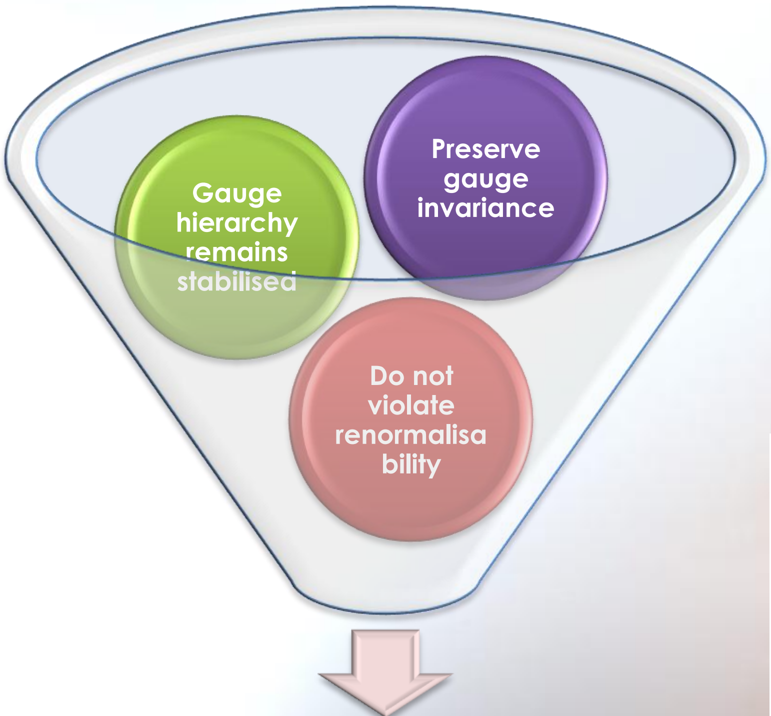
$h, H, A, H^{\pm}$ [Higgs Bosons (Spin 0)]

Minimal Supersymmetric Standard Model

Free Parameters:

Superpotential:

$$W = \lambda_u H_u Q \bar{U} + \lambda_d H_d Q \bar{D} + \lambda_e H_d L \bar{E} + \mu H_u H_d$$



Soft SUSY-breaking Terms:

$$\begin{aligned} & m^2_{\tilde{Q}}|\tilde{Q}|^2 + m^2_{\tilde{U}}|\tilde{U}|^2 + m^2_{\tilde{D}}|\tilde{D}|^2 + m^2_{\tilde{L}}|\tilde{L}|^2 + m^2_{\tilde{E}}|\tilde{E}|^2 \\ & + \frac{1}{2}\left\{\left[M_1 \tilde{B}\tilde{B} + M_2 \tilde{W}^j \tilde{W}^j + M_3 \tilde{g}^k \tilde{g}^k\right] + \text{h.c.}\right\} \\ & + \lambda_u A_U H_u \tilde{Q}\tilde{U} + \lambda_d A_D H_d \tilde{Q}\tilde{D} + \lambda_e A_E H_d \tilde{L}\tilde{E} \\ & + m^2_{H_u}|H_u|^2 + m^2_{H_d}|H_d|^2 + (B H_u H_d + \text{h.c.}) \end{aligned}$$

Minimal Supersymmetric Standard Model

Free Parameters:

Superpotential:

$$W = \lambda_u H_u Q\bar{U} + \lambda_d H_d Q\bar{D} + \lambda_e H_d L\bar{E} + \mu H_u H_d$$

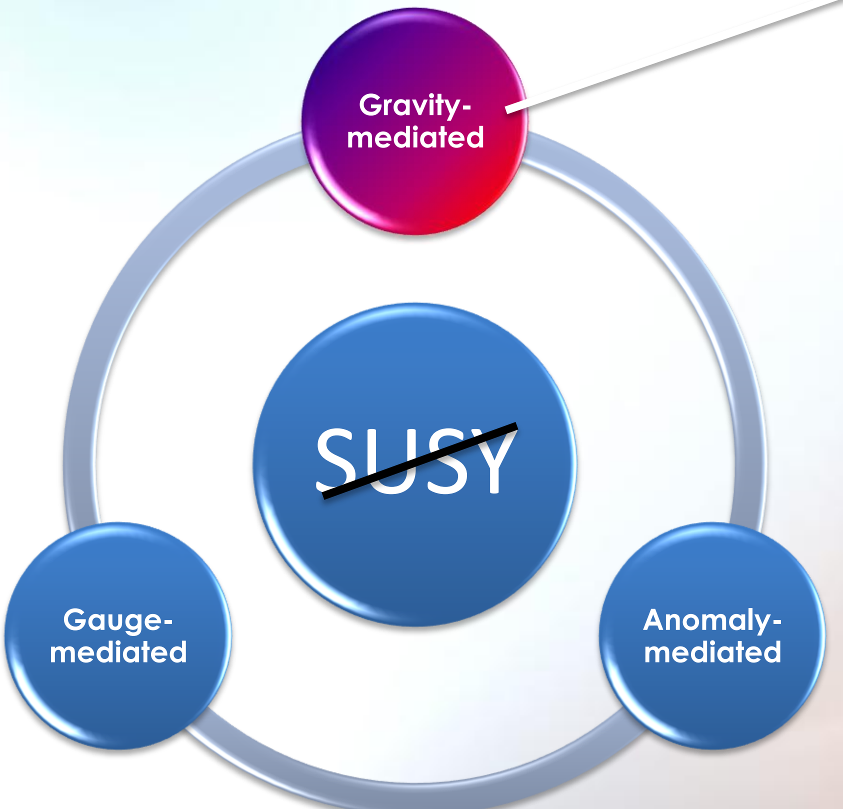
Soft SUSY-breaking terms:

$$\begin{aligned} & m^2_{\tilde{Q}}|\tilde{Q}|^2 + m^2_{\tilde{U}}|\tilde{U}|^2 + m^2_{\tilde{D}}|\tilde{D}|^2 + m^2_{\tilde{L}}|\tilde{L}|^2 + m^2_{\tilde{E}}|\tilde{E}|^2 \\ & + \frac{1}{2}\left\{\left[M_1 \tilde{B}\tilde{B} + M_2 \tilde{W}^j\tilde{W}^j + M_3 \tilde{g}^k\tilde{g}^k\right] + \text{h.c.}\right\} \\ & + \lambda_u A_U H_u \tilde{Q}\tilde{U} + \lambda_d A_D H_d \tilde{Q}\tilde{D} + \lambda_e A_E H_d \tilde{L}\tilde{E} \\ & + m^2_{H_u}|H_u|^2 + m^2_{H_d}|H_d|^2 + (BH_u H_d + \text{h.c.}) \end{aligned}$$

105 new parameters

Constraints on FCNCs and CP-violation can help

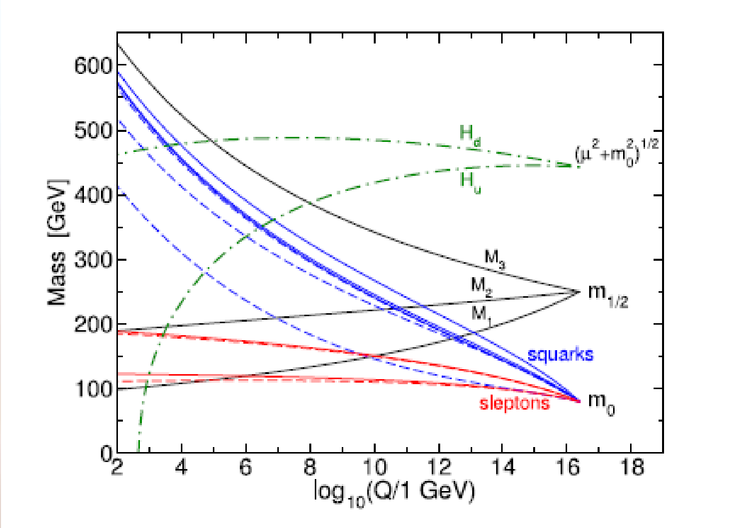
Minimal Supersymmetric Standard Model



mSUGRA/CMSSM

Unified at GUT Scale

$$\{\underbrace{m_0, m_{1/2}, A_0}, \tan\beta, \mathrm{sign}(\mu)\}$$



S. P. Martin [arXiv:hep-ph/9709356]

At EW scale: $M_1 : M_2 : M_3 \simeq 1 : 2 : 7$

Scanning Supersymmetric Parameter Spaces

Goal: given a particular version of supersymmetry, determine which parameter combinations fit all experiments, and how well

SUSY Global Fit

Issue 1: Combining fits to different experiments
Easy – composite likelihood $(L_1 \times L_2 \equiv \chi_1^2 + \chi_2^2)$

- dark matter relic density from WMAP
- precision electroweak tests at LEP
- LEP limits on sparticle masses
- B-factory data (rare decays, $b \to s\gamma$)
- muon anomalous magnetic moment

Issue 2: Finding the points with the best likelihoods
Tough – grid scans, MCMCs, nested sampling or genetic algorithms

Public codes: **SuperBayeS, SFitter, Fittino**

Statistical Framework

Two fundamentally different approaches:

- **Bayesian statistics:** — **prior dependent**

We are interested in the **marginal posterior** for the parameters:

$$p(\theta_i|D) = \int p(\Theta|D)d\theta_1 ... d\theta_{i-1}d\theta_{i+1} ... d\theta_m$$

- **Frequentist statistics:** — **in principle independent of priors**

We are interested in the **profile likelihood** for the parameters:

$$\mathbb{L}(\theta_i) \equiv \max_{\theta_1,...,\theta_{i-1},\theta_{i+1},...,\theta_m} \mathcal{L}(\Theta)$$

Thus in the profile likelihood one maximizes the value of the likelihood along the hidden dimensions, rather than integrating it out as in the marginal posterior.

Statistical Framework

Bayes' Theorem:

$$p(\Theta|D) = \frac{p(D|\Theta)p(\Theta)}{p(D)}$$

likelihood

prior probability density function

posterior probability density function

evidence or model likelihood

(just a renormalization factor for our purpose)

- One practically interesting consequence of Bayesian inference is that it gives a powerful way of estimating **how robust a fit is**, i.e., if the **posterior** is strongly **dependent** on **different priors**, this actually means that **the data** are **not sufficient or accurate enough** to constrain the model parameters.

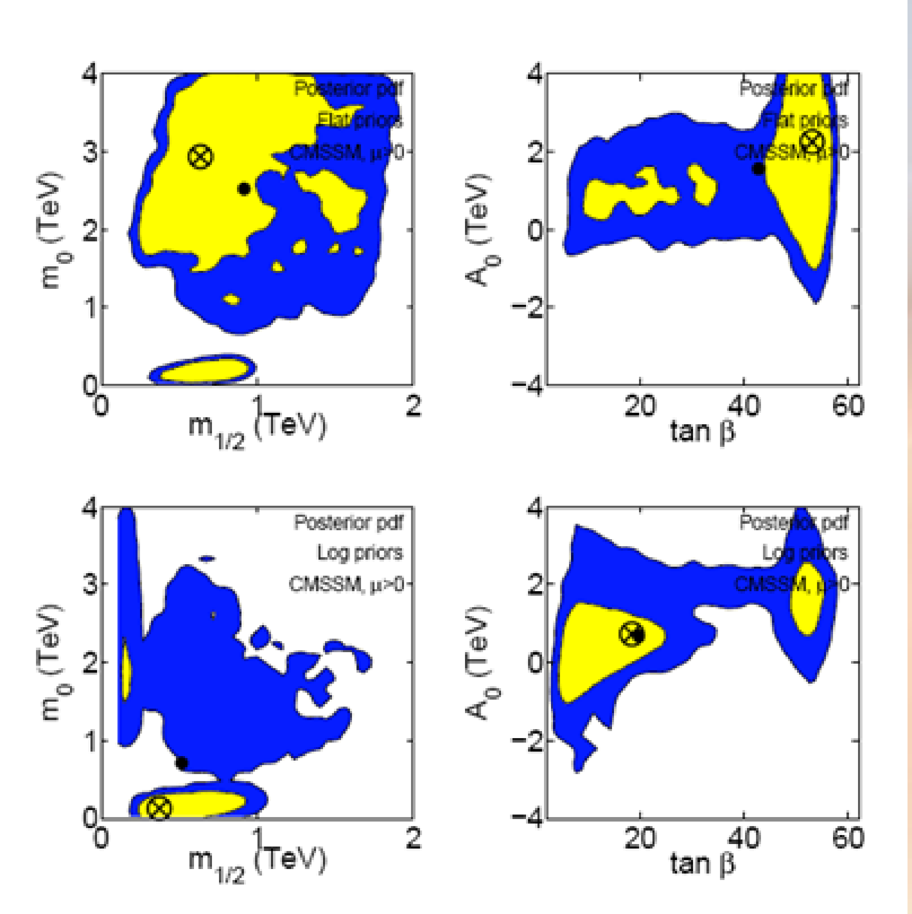
- If a fit is robust, the Bayesian and frequentist methods should result in similar confidence regions of the parameter space. This is **NOT** the case for **SUSY models**.

Statistical Framework

Some CMSSM Scans with SuperBayeS:

Flat Prior:

Log Prior:



R. Trotta, F. Feroz, M.P. Hobson, L. Roszkowski and R. Ruiz de Austri, *The impact of priors and observables on parameter inferences in the Constrained MSSM*, JHEP 12 (2008) 024 [arXiv:0809.3792]

SuperBayes
(www.superbayes.org)

New version v1.5 now available (June 2010)

- Developed by **Roberto Ruiz de Austri**, **Roberto Trotta**, **Farhan Feroz**, **Leszek Roszkowski**, and **Mike Hobson**.

- It is a package for **fast** and **efficient** sampling of the CMSSM.

- Compares SUSY predictions with observable quantities, including **sparticle masses**, **collider observables, B-factory data, dark matter relic abundance**, **direct detection cross sections**, **indirect detection quantities** etc.

- The package combines **SoftSusy**, **DarkSusy**, **FeynHiggs**, **Bdecay** and **MicrOMEGAs**.

- It uses **Bayesian** techniques to explore multidimensional SUSY parameter spaces. Scanning can be performed using **Markov Chain Monte Carlo (MCMC)** technology or more efficiently by employing the new scanning technique called **nested sampling (MultiNest algorithm)**.

- Although these methods have been used for the **profile likelihood** analysis of the model, they are essentially **optimized for the marginal posterior analysis** of the model.

200 times faster

SuperBay

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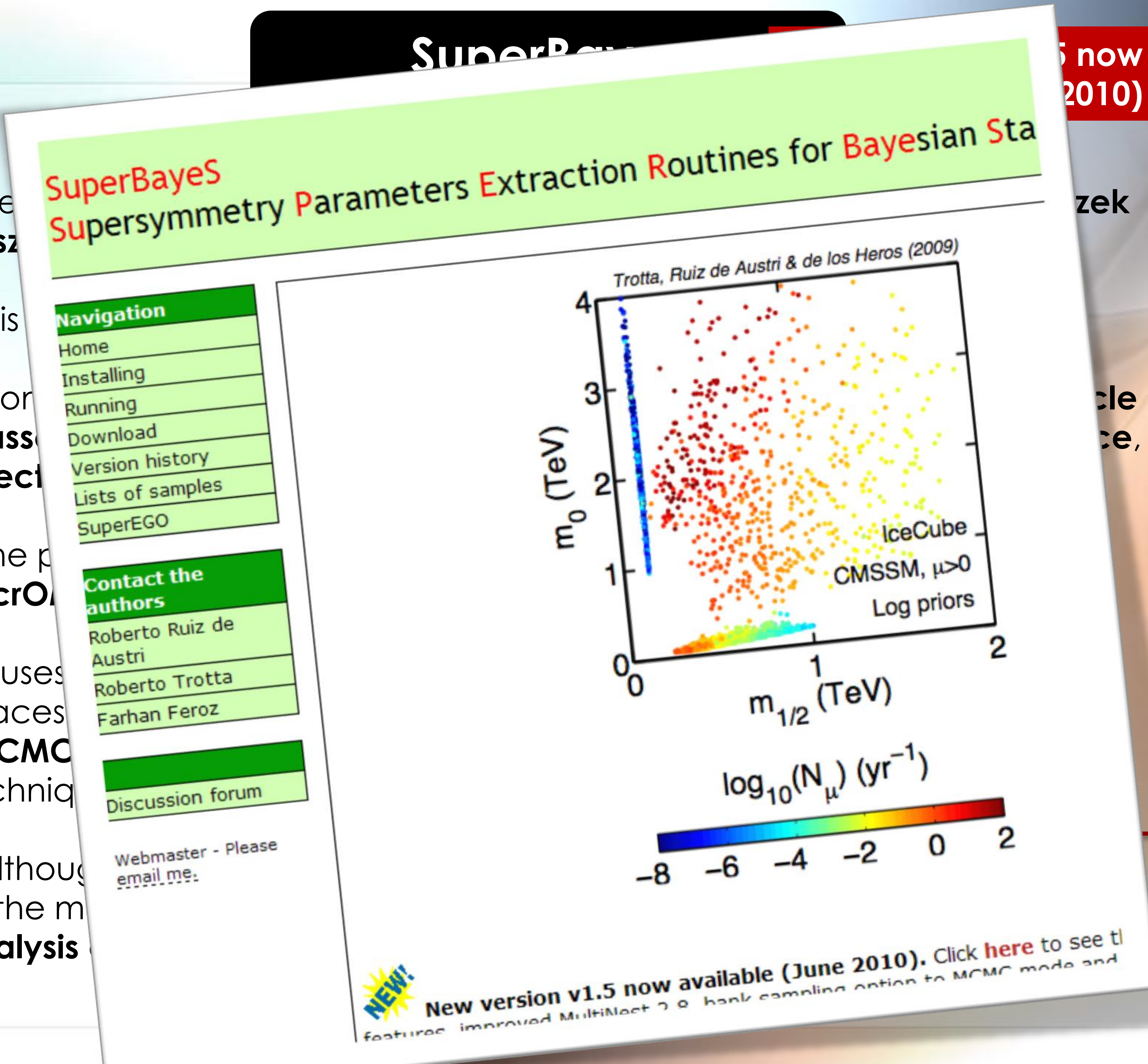

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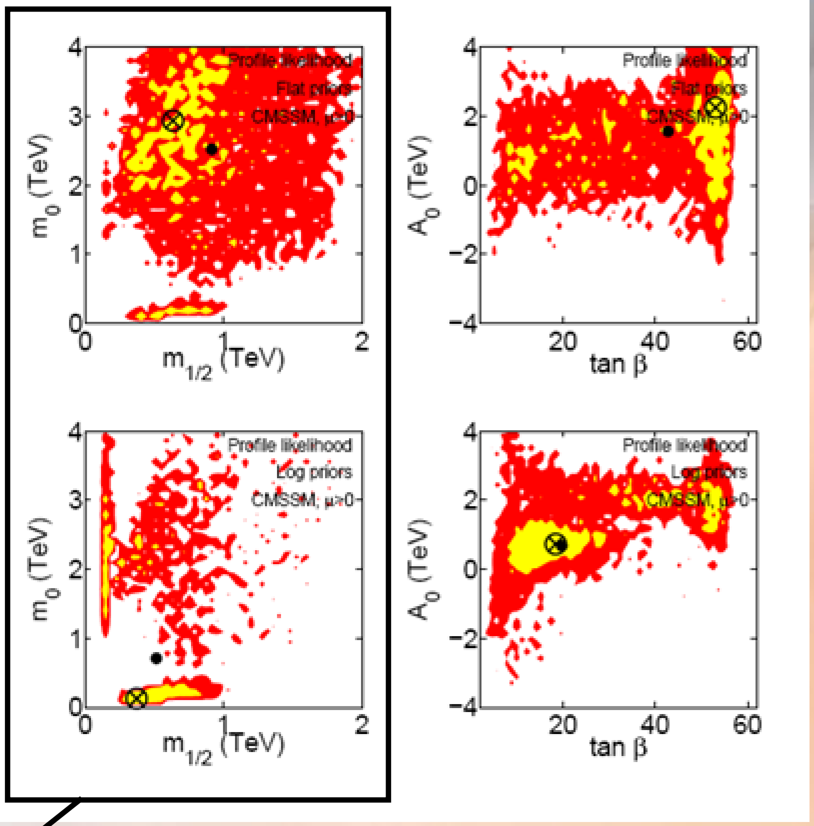
200 times faster

CMSSM + SuperBayes (MultiNest)

Profile Likelihoods:

Flat Prior:

Log Prior:



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Look very different: **prior dependent** **?!!**

Not a very interesting technique for profile likelihood approach

According to the SB people, MCMC scans give similar results up to some statistical noise

Complex Parameter Spaces

Marginal Posterior vs. Profile Likelihood:

Spike-like best-fit region
(problematic)

- **Posterior Mass**
- **Highest Likelihood**

In thermodynamic language:

- **Thermal Energy**
- **Temperature**

In order to make a profile likelihood analysis of a model correctly, it is extremely important to know, with enough accuracy, the highest value of the likelihood function in the parameter space of the model. Otherwise, the calculated confidence regions might be very far from the real ones.

Genetic Algorithms (GAs)

GAs can be helpful, because:

- The actual use of these algorithms is to **maximize/minimize** a specific function; **this is exactly what we need in the case of a profile likelihood scan.**

- GAs are usually considered as **powerful methods** in probing global extrema when the parameter space is **very large**, **complex** or **poorly understood**; **these are precisely what we have in the case of the supersymmetric models including the CMSSM.**

Genetic Algorithms (GAs)

GAs are a class of **adaptive heuristic search techniques** that incorporate the **evolutionary ideas of natural selection and survival of the fittest** in biology. As such, they represent an intelligent random search within a defined search space to solve a complex problem.

- Selection
- Crossover
- Mutation
- Elitism

Generation 1

Generation 1

Average fitness of the whole population increases. (Survival of the Fittest)

Genetic Algorithms (GAs)

General Structure:

Genetic Operator: $\mathbb{G} = \mathbb{RMCS}$

- **R**eproduction
- **M**utation
- **C**rossover
- **S**election

initialisation:

$P^0 := \{\Theta_i^0\}, \ \forall i \in [1, I]$

$k := 0$

reproduction loop:

do while not $\mathbb{T}$

$\quad k := k + 1$

$\quad$ generating new population through genetic operators:

$\quad P^k := \mathbb{G} P^{k-1}$

end do

reading the best-fit point:

$\Theta_{max} := \Theta_l^m$ where $\mathcal{L}(\Theta_l^m) = \max\{\mathcal{L}(\Theta_i^k)\}, \ \forall i \in [1, I], \ \forall k \in [1, K]$

SuperBayes v1.35 + PIKAIA 1.2*

* Developed by P. Charbonneau *et. al.*, can be downloaded from http://www.hao.ucar.edu/modeling/pikaia/pikaia.php

Model + Nuisance Parameters

- **CMSSM:** GUT-scale parameterisation

m_0: scalar mass parameter
$m_{1/2}$: gaugino mass parameter
$\tan\beta$: ratio of Higgs VEVs
A_0: trilinear coupling
sgn μ: Higgs mass parameter (+ve in our scans)

Just a testbed – techniques are applicable to any MSSM parameterisation

- **SM nuisances:** reflecting our imperfect knowledge of the values of relevant SM parameters

m_t: pole top quark mass
m_b: bottom quark mass
α_{em}: EM coupling constant
α_s: strong coupling constant

Data and Other Constraints Included

Observable	Mean value	Uncertainties (standard deviations) experimental	theoretical
SM nuisance parameters			
m_t	172.6 GeV	1.4 GeV	-
$m_b(m_b)^{\overline{MS}}$	4.20 GeV	0.07 GeV	-
$\alpha_s(m_Z)^{\overline{MS}}$	0.1176	0.002	-
$1/\alpha_{\rm em}(m_Z)^{\overline{MS}}$	127.955	0.03	-
measured			
m_W	80.398 GeV	25 MeV	15 MeV
$\sin^2\theta_{\rm eff}$	0.23153	16×10^{-5}	15×10^{-5}
$\delta a_\mu^{\rm SUSY}\times10^{10}$	29.5	8.8	1.0
$BR(\overline{B}\to X_s\gamma)\times10^4$	3.55	0.26	0.21
ΔM_{B_s}	17.77 ps^{-1}	0.12 ps^{-1}	2.4 ps^{-1}
$BR(\overline{B}_u\to\tau\nu)\times10^4$	1.32	0.49	0.38
$\Omega_\chi h^2$	0.1099	0.0062	$0.1\,\Omega_\chi h^2$
limits only (95% CL)			
$BR(\overline{B}_s\to\mu^+\mu^-)$	$<5.8\times10^{-8}$		14%
m_h	>114.4 GeV (SM-like Higgs)		3 GeV
ζ_h^2	$f(m_h)$ (see Ref. 21)		negligible
$m_{\tilde\chi_1^0}$	>50 GeV		5%
$m_{\tilde\chi_1^\pm}$	>103.5 GeV (>92.4 GeV)		5%
$m_{\tilde e_R}$	>100 GeV (>73 GeV)		5%
$m_{\tilde\mu_R}$	>95 GeV (>73 GeV)		5%
$m_{\tilde\tau_1}$	>87 GeV (>73 GeV)		5%
$m_{\tilde\nu}$	>94 GeV (>43 GeV)		5%
$m_{\tilde t_1}$	>95 GeV (>65 GeV)		5%
$m_{\tilde b_1}$	>95 GeV (>59 GeV)		5%
$m_{\tilde q}$	>375 GeV		5%
$m_{\tilde g}$	>289 GeV		5%

+

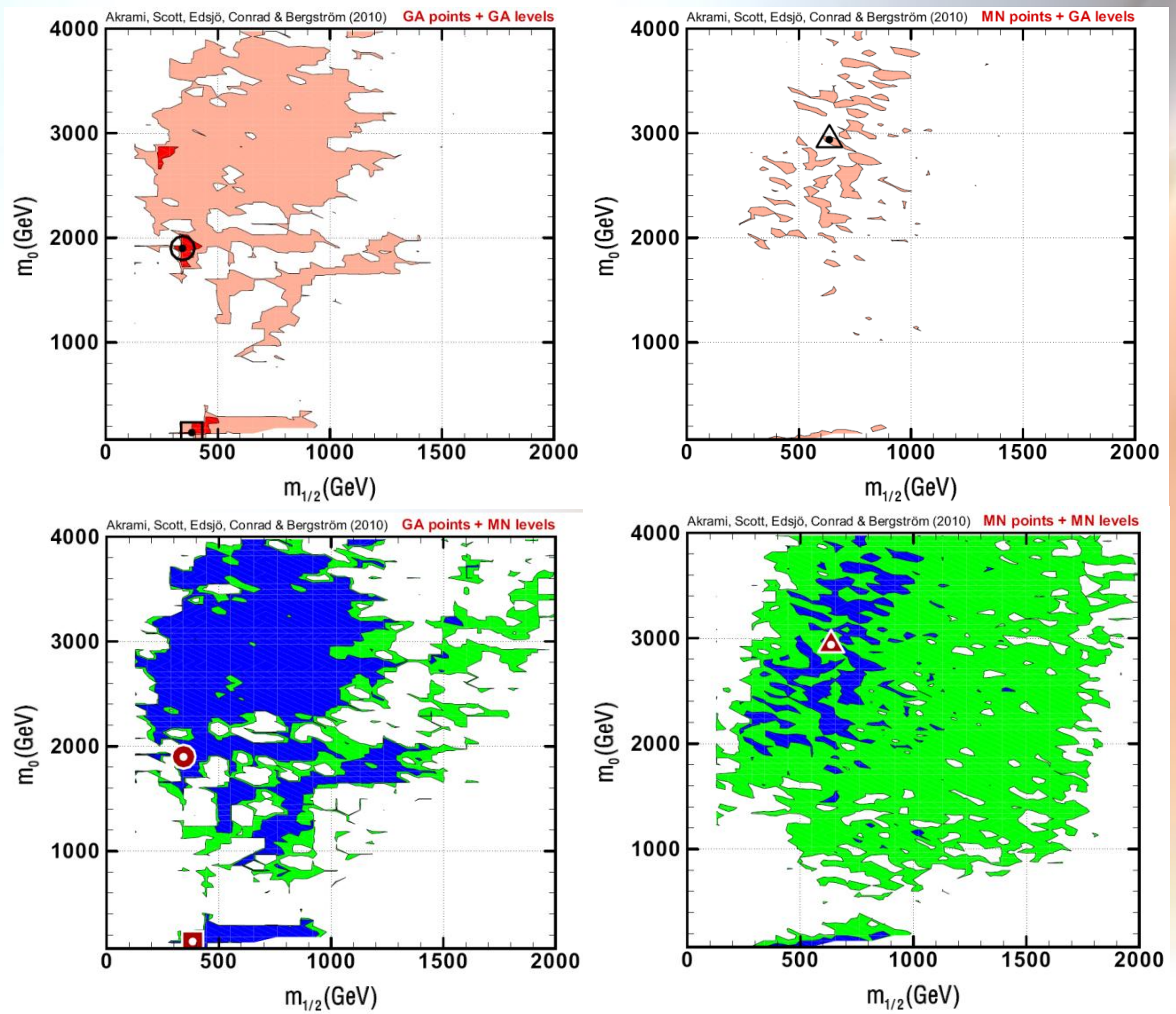
- **Physicality**
  - self-consistent solutions to the RGEs exist
  - conditions of EW symmetry breaking are satisfied
  - no masses become tachyonic)
- **Neutralino is the LSP**

2D Profile Likelihoods in m_0-$m_{1/2}$ Plane

GAs find better fits than nested sampling (χ^2 = 9.35 vs. χ^2 = 13.51).

Contours based on GA best-fit point:

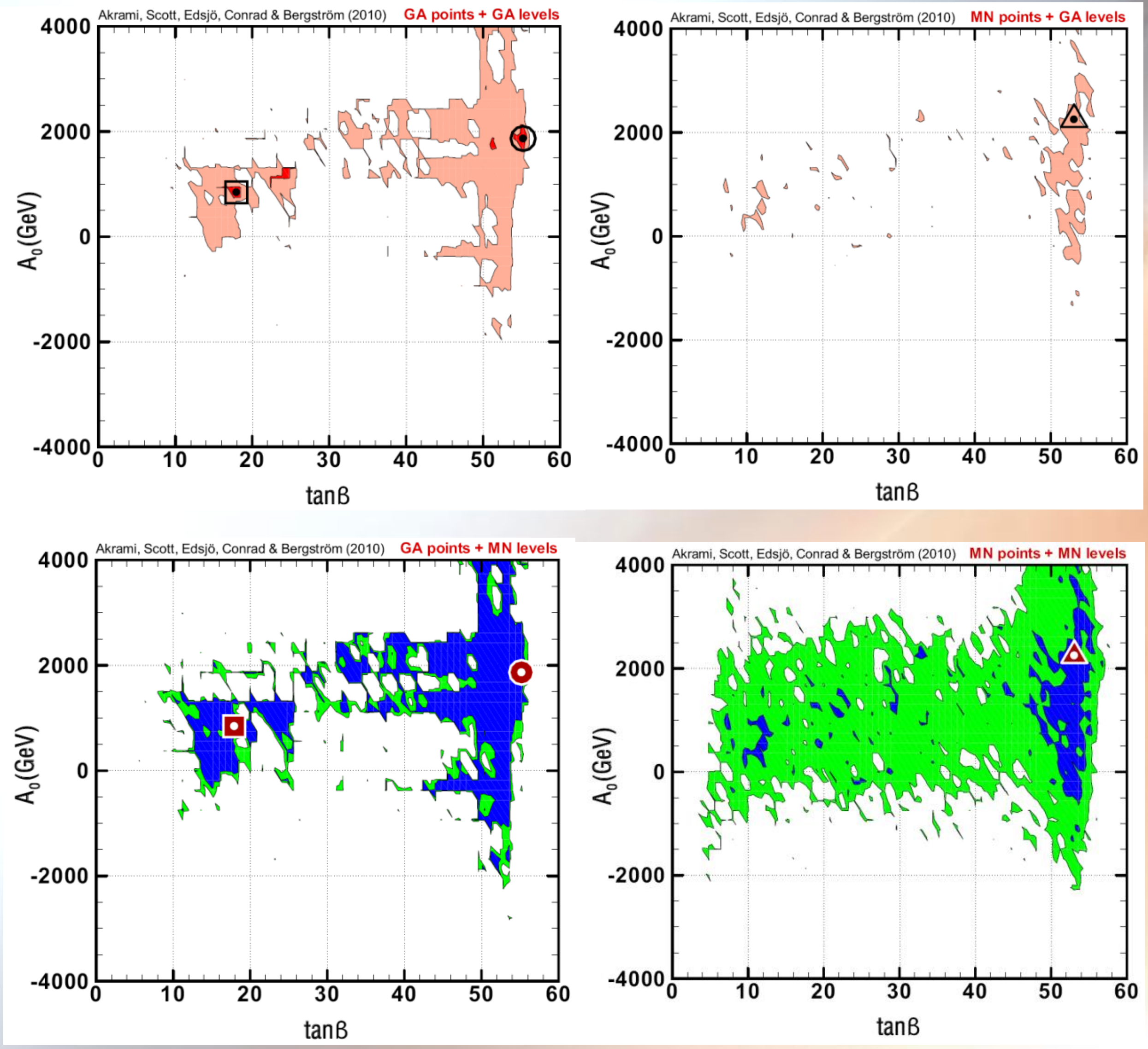
Contours based on MN best-fit point:



2D Profile Likelihoods in A_0-tanβ Plane

Contours based on GA best-fit point:

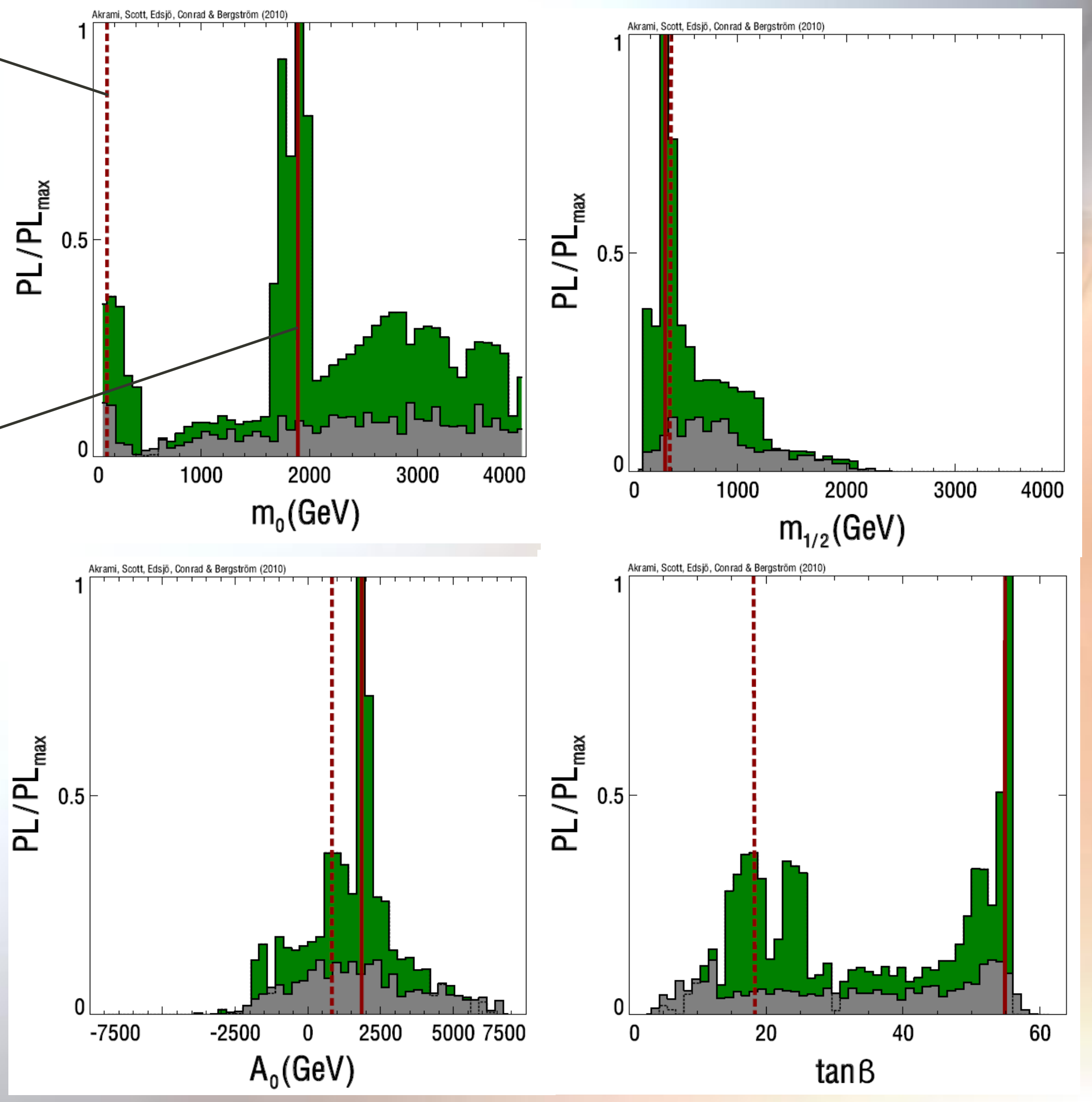
Contours based on MN best-fit point:



1D Profile Likelihoods for CMSSM Parameters

GA COA BFP

GA Global (FP) BFP



Best-fit Parameter Values

model (+nuisance) parameters		
	GA global BFP (located in FP region)	GA COA BFP
m_0	1900.5 GeV	133.9 GeV
$m_{1/2}$	342.8 GeV	383.1 GeV
A_0	1873.9 GeV	840.6 GeV
$\tan\beta$	55.0	17.9
m_t	172.9 GeV	173.3 GeV
$m_b(m_b)^{\overline{MS}}$	4.19 GeV	4.20 GeV
$\alpha_s(m_Z)^{\overline{MS}}$	0.1172	0.1183
$1/\alpha_{\rm em}(m_Z)^{\overline{MS}}$	127.955	127.955
observables		
	GA global BFP (located in FP region)	GA COA BFP
m_W	80.366 GeV	80.371 GeV
$\sin^2\theta_{\rm eff}$	0.23156	0.23153
$\delta a_\mu^{\rm SUSY}\times 10^{10}$	5.9	14.5
$BR(\overline{B}\to X_s\gamma)\times 10^4$	3.58	2.97
ΔM_{B_s}	17.37 ps^{-1}	19.0 ps^{-1}
$BR(\overline{B}_u\to\tau\nu)\times 10^4$	1.32	1.46
$\Omega_\chi h^2$	0.10949	0.10985
$BR(\overline{B}_s\to\mu^+\mu^-)$	4.34×10^{-8}	3.87×10^{-8}

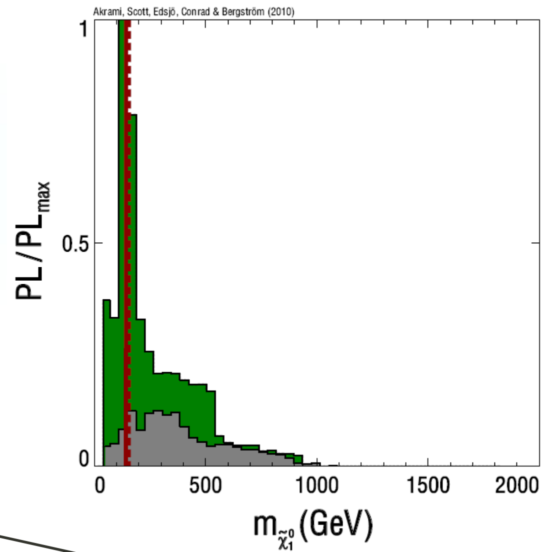
Best-fit Parameter Values

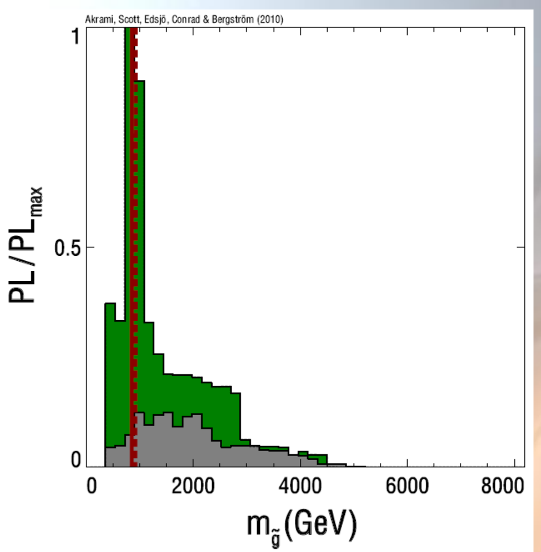
observable	partial χ^2 (fractional contribution to the total χ^2 in %)			
	GA global BFP located in FP region	GA COA BFP	MN global BFP with flat priors	MN global BFP with log priors
nuisance parameters	0.12 (1.27%)	0.35 (3.10%)	0.48 (3.56%)	0.81 (6.78%)
mw	1.21 (12.95%)	0.83 (7.29%)	1.48 (10.92%)	0.69 (5.83%)
$\sin^2\theta_{\text{eff}}$	0.024 (0.26%)	$\sim 10^{-4}$ (0.001%)	0.07 (0.49%)	0.0040 (0.034%)
$\delta a_\mu^{\text{SUSY}}$	7.09 (75.79%)	2.86 (25.21%)	9.21 (68.20%)	2.40 (20.18%)
$BR(\overline{B}\to X_s\gamma)$	0.010 (0.11%)	3.03 (26.76%)	0.10 (0.74%)	3.83 (32.20%)
ΔM_{B_s}	0.028 (0.30%)	0.26 (2.31%)	0.09 (0.66%)	0.29 (2.41%)
$BR(\overline{B}_u\to\tau\nu)$	$\sim 10^{-5}$ (10^{-4}%)	0.050 (0.44%)	1.91 (14.14%)	0.043 (0.36%)
$\Omega_\chi h^2$	0.0011 (0.012%)	$\sim 10^{-5}$ (10^{-4}%)	0.03 (0.2%)	0.13 (1.07%)
$BR(\overline{B}_s\to\mu^+\mu^-)$	0.016 (0.17%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)
m_h	0.85 (9.14%)	3.96 (34.88%)	0.15 (1.09%)	3.70 (31.13%)
sparticles	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)	0.00 (0.00%)
all	**9.35 (100 %)**	**11.34 (100 %)**	**13.51 (100 %)**	**11.90 (100 %)**

Mass Spectrum at Best-fit Points

(GeV)	GA global BFP located in FP region	GA COA BFP
$m_{\tilde{e}_L}$	1908	294.1
$m_{\tilde{e}_R}$	1903	202
$m_{\tilde{\mu}_L}$	1907	294.1
$m_{\tilde{\mu}_R}$	1901	201.9
$m_{\tilde{\tau}_1}$	1100	160.1
$m_{\tilde{\tau}_2}$	1560	289.2
$m_{\tilde{\nu}_e}$	1906	283.3
$m_{\tilde{\nu}_\mu}$	1905	283.3
$m_{\tilde{\nu}_\tau}$	1560	272.5
$m_{\tilde{u}_L}$	1998	826.1
$m_{\tilde{u}_R}$	1996	805.4
$m_{\tilde{c}_L}$	1998	826.1
$m_{\tilde{c}_R}$	1996	805.4
$m_{\tilde{t}_1}$	1194	672.8
$m_{\tilde{t}_2}$	1364	803
$m_{\tilde{d}_L}$	2001	832.4
$m_{\tilde{d}_R}$	1994	798.1
$m_{\tilde{s}_L}$	2000	832.4
$m_{\tilde{s}_R}$	1994	798.1
$m_{\tilde{b}_1}$	1354	765
$m_{\tilde{b}_2}$	1492	793.4
$m_{\tilde{\chi}_1^0}$	140.4	152.6
$m_{\tilde{\chi}_2^0}$	269.9	285.4
$m_{\tilde{\chi}_3^0}$	519.7	451.1
$m_{\tilde{\chi}_4^0}$	529.7	469.6
$m_{\tilde{\chi}_1^\pm}$	270.4	286.9
$m_{\tilde{\chi}_2^\pm}$	530.3	468.5
m_h	115.55	111.11
m_H	179.93	504.24
m_A	179.83	504.04
$m_{H^\pm}$	201.14	510.67
$m_{\tilde{g}}$	877.1	898.8

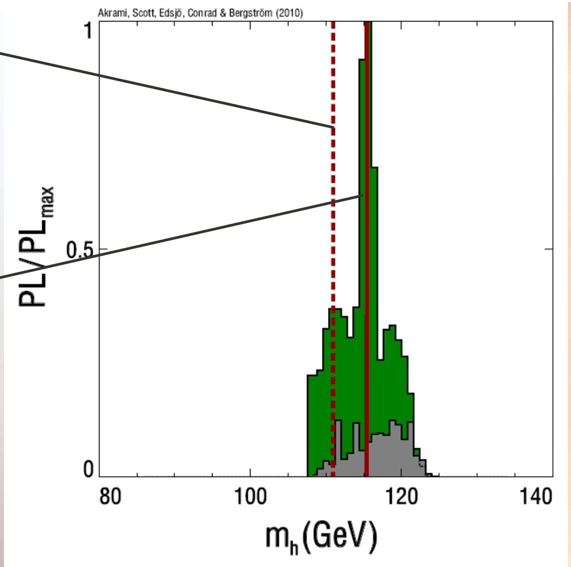
1D Profile Likelihoods for Some Observables





GA COA BFP

GA Global (FP) BFP

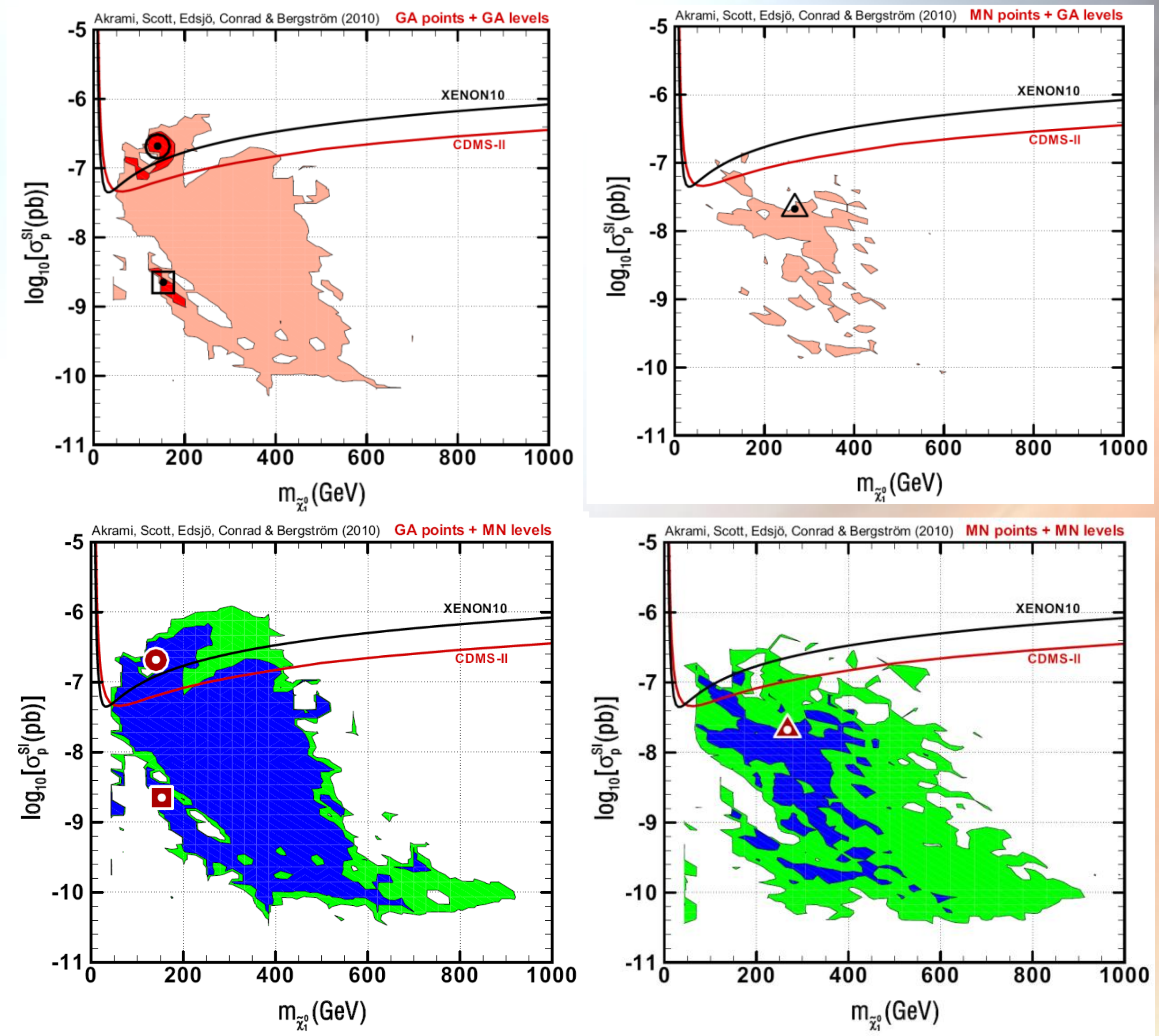


- **The LHC is in principle able to investigate a large fraction of the high-likelihood points in the CMSSM parameter space if it explores sparticle masses up to around 3 TeV.**

2D Profile Likelihoods in DM Direct Detection Plane (SI)

Contours based on GA best-fit point:

Contours based on MN best-fit point:

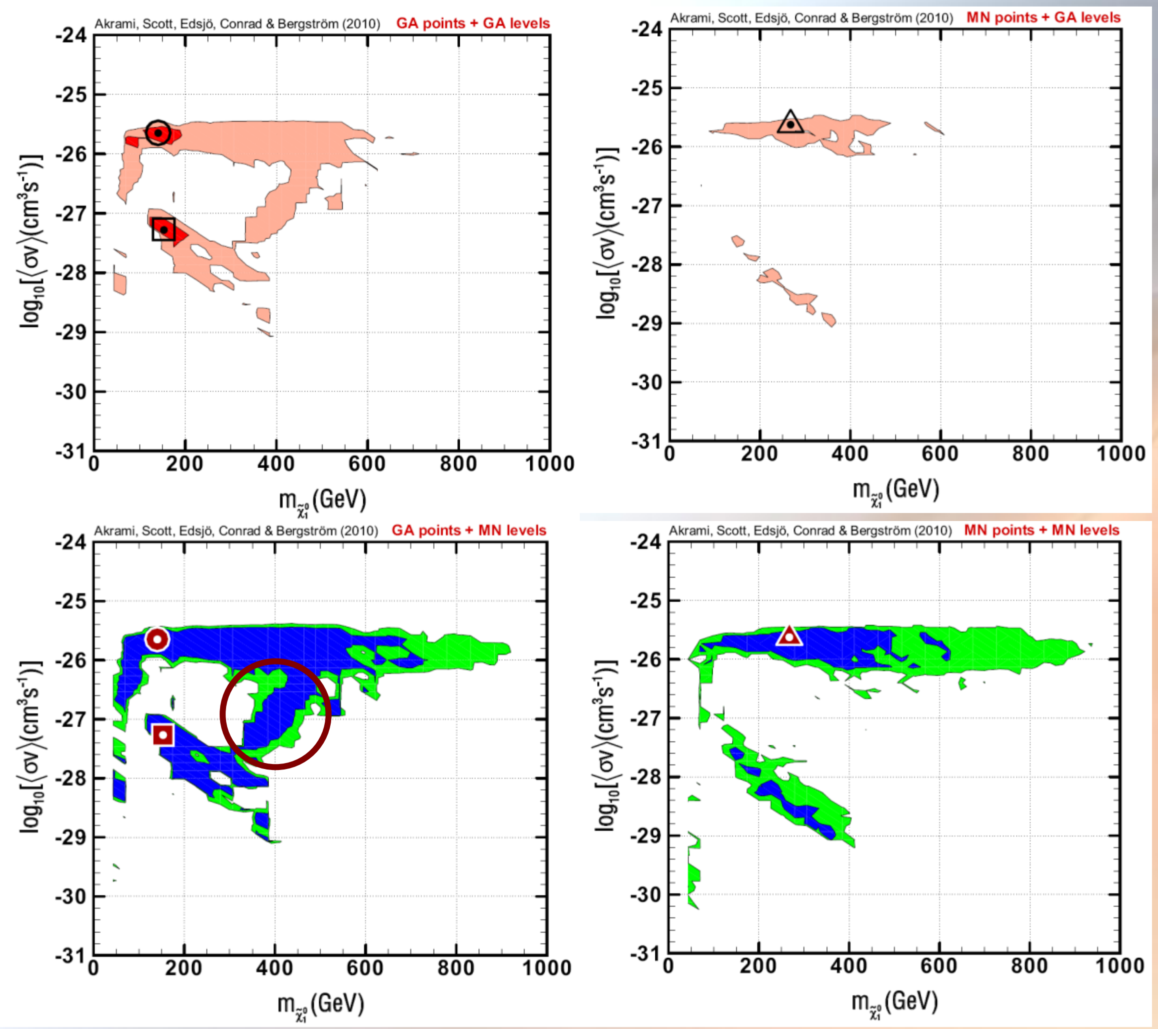


- Best-fit point is actually ruled out by direct detection (under standard halo assumptions).
- Secondary maximum still OK.

2D Profile Likelihoods in DM Indirect Detection Plane

Contours based on GA best-fit point:

Contours based on MN best-fit point:



- **Global best-fit point should be probed soon by *Fermi* (**See e.g. P. Scott, J. Conrad, J. Edsjö, L. Bergström, C. Farnier & **YA**. *Direct Constraints on Minimal Supersymmetry from Fermi-LAT Observations of the Dwarf Galaxy Segue 1*, JCAP 01, 031 (2010) [arXiv:0909.3300]**)**
- **The GA turns up a 'new' region at moderate <σv>, around 400 GeV. This region is a high-m_0 stau coannihilation region, apparently missed in other scans.**

Summary and Conclusions

1. Constraining the parameter space of the MSSM using existing data is under no circumstances an easy or straightforward task. **Even in the case of the CMSSM, a highly simplified and economical version of the model, the present data are not sufficient to constrain the parameters in a way completely independent of computational and statistical techniques.**

1. Many recent activities in this field have used scanning methods optimised for calculating the Bayesian evidence and posterior PDF. **Highly successful in revealing the complex structure of SUSY models, demonstrating that some patience will be required before we can place any strong constraints on their parameters.**

2. Bayesian scanning methods have also been employed for frequentist analyses of the problem, particularly in the framework of the profile likelihood. **These methods are not optimised for such frequentist analyses, so care should be taken in applying them to such tasks.**

3. We have employed a completely new scanning algorithm, based on GAs. **They seem to be a powerful tool for frequentist approaches to the problem of scanning the CMSSM parameter space. We compared the outcomes of GA scans directly with those of the state-of-the-art Bayesian algorithm MultiNest, in the framework of the CMSSM.**

4. We found many new high-likelihood CMSSM points, which have a strong impact on the final statistical conclusions of the study. **These not only influence considerably the inferred high-likelihood regions and confidence levels on the parameter values, but also indicate that the applicability of the conventional Bayesian scanning techniques is highly questionable in a frequentist context.**

Summary and Conclusions

5. Although our initial motivation in using GAs was to gain a correct estimate of the likelihood at the global best-fit point, which is crucial in a profile likelihood analysis, we also realised that they can find many new and interesting points in almost all the relevant regions of parameter space. **These points strongly affect the inferred confidence regions around the best-t point. Even though we cannot be confident of exactly how completely our algorithm is really mapping these high-likelihood regions, it has certainly covered large parts of them better than any previous algorithm.**

6. By improving the different ingredients of GAs, such as the crossover and mutation schemes, this ability might even be enhanced further. **We largely employed the standard, simplest versions of the genetic operators in our analysis, as well as very typical genetic parameters. These turned out to work sufficiently well for our purposes. Although we believe that tuning the algorithm might produce even more interesting results, it is good news that satisfactory results can be produced even with a very generic version. This likely means that one can apply the method to more complicated SUSY models without extensive ne-tuning.**

7. We have also compared our algorithm with MultiNest in terms of speed and convergence, and argued that GAs are no worse than MultiNest in this respect. **GAs have a large potential for parallelisation, reducing considerably the time required for a typical run. This property, as well as the fact that the computational eort scales linearly (i.e. as kN for an N-dimensional parameter space), also makes GAs an excellent method for the frequentist exploration of higher-dimensional SUSY parameter spaces.**

Summary and Conclusions

8. The focus point region is favoured in our analysis over the co-annihilation region, in contrast to findings from some other MCMC studies, where the opposite is claimed. We also found a rather large part of the stau co-annihilation region, consistent with all experimental data, located at high m_0. **That is, at least in our particular setup, high masses, corresponding either to the FP or the COA regions, are by no means disfavoured by current data (except perhaps direct detection of dark matter). The discrepancy might originate in the different scanning algorithms employed, or in the different physics and likelihood calculations performed in each analysis. We have however shown, by comparing our results with others produced using exactly the same setup except for the scanning algorithm, that one should not be at all confident that all the relevant points for a frequentist analysis can be found by scanning techniques optimised for Bayesian statistics, such as nested sampling and MCMCs.**

Summary and Conclusions

The **bottom line** of our work is that:

We once again see that even the CMSSM, despite its simplicity, possesses a highly complex and poorly-understood structure, with many small, fine-tuned regions. This makes investigation of the model parameter space very difficult and still very challenging for modern statistical scanning techniques. Although the method proposed in this paper seems to outperform the usual Bayesian techniques in a frequentist analysis, it is important to remember that it may by no means be the final word in this direction. Dependence of the results on the chosen statistical framework, measure and method calls for caution in drawing strong conclusions based on such scans. The situation will of course improve significantly with additional constraints provided by forthcoming data.

OKC PROSPECTS WORKSHOP

(http://agenda.albanova.se/conferenceDisplay.py?confId=1983)

AlbaNova

OKC PROSPECTS Workshop

15-17 September 2010

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PROSPECTS - PROblems in Statistical Parameter Estimation and ConsTraints for Supersymmetry

With a new energy frontier opening up we all want to be ready to set out on the road to discoveries. We know that along the way we will face hordes of data, the constraining shackles of statistical error bars and the nefarious plotting of systematic errors, we know we must endure the hardships of complicated parameter interdependencies. All this to perhaps, finally, reach the undiscovered country of New Physics.

The aim of this workshop is to investigate approaches to constraining the parameters of New Physics models with data from current collider and astrophysics experiments, with some emphasis on models with Supersymmetry. This is a field which has seen a lot of activity over the past few years, and our goal is to gather experts to discuss some of the issues involved in interpreting data and applying statistical methods. Furthermore, we want to have brief reviews of current methods and the tools available, and finally some PROSPECTS for the future.

Topics:

- Statistics & Algorithms (Talks on statistical methods and scanning algorithms)
- Packages & Codes (Presentations of available tools and recent tool developments)
- Experimental Constraints (Summaries of current and expected near-future experimental results)
- Phenomenology/Results (Updates on current parameter scans and their phenomenological consequences)

List of Speakers:

- Ben Allanach (DAMTP, Cambridge)
- Geneviéve Bélanger (LAPTH, Annecy)
- Fawzi Boudjema (LAPTH, Annecy)*
- Klaus Desch (Bonn)
- John Ellis (CERN)
- Farhan Feroz (Cavendish, Cambridge)
- Michael Hobson (Cavendish, Cambridge)
- Tilman Plehn (Heidelberg)
- Roberto Ruiz de Austri (IFIC, Valencia)
- Roberto Trotta (Imperial College)*
- Martin White (Cavendish, Cambridge)

* To be confirmed

The workshop will be a small-scale event with ample time for discussions. Note that there is no registration fee for the workshop, but there is a fee for those who wish to participate at the workshop dinne on Thursday the 16th of September.

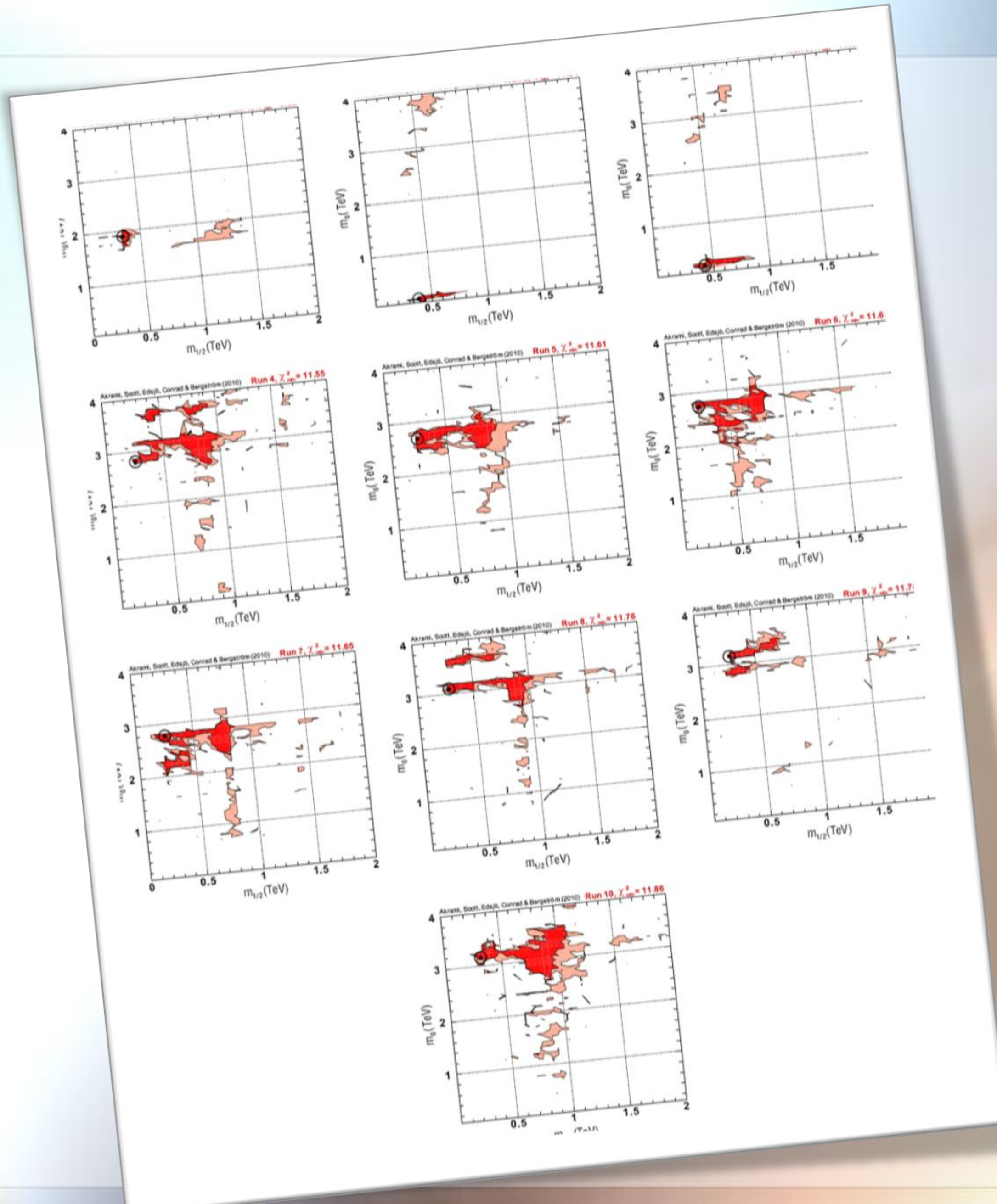
Local Organizing Committee

A. Raklev (co-chair, Stockholm University), P. Scott (co-chair, Stockholm University), Y. Akrami (Stockholm University), J. Edsjö (Stockholm University), J. Conrad (Stockholm University), A. Putze (Stockholm University/KTH), J. Ripken (Stockholm University), C. Savage (Stockholm University).

Thank You

for your attention

direct detection		
	GA global BFP	GA BFP in COA region
σ_p^{SI}	2.057×10^{-7} pb	2.236×10^{-9} pb
σ_p^{SD}	2.435×10^{-6} pb	4.231×10^{-6} pb
σ_n^{SD}	1.644×10^{-6} pb	3.142×10^{-6} pb
indirect detection		
	GA global BFP	GA BFP in COA region
$\langle\sigma v\rangle$	$2.260 \times 10^{-26} \mathrm{cm}^3\mathrm{s}^{-1}$	$5.385 \times 10^{-28} \mathrm{cm}^3\mathrm{s}^{-1}$



Akrami, Scott, Edsjö, Conrad & Bergström (2010)
Run 4, χ^2_{min} = 11.55
Run 5, χ^2_{min} = 11.61
Run 6, χ^2_{min} = 11.6
Run 7, χ^2_{min} = 11.65
Run 8, χ^2_{min} = 11.76
Run 9, χ^2_{min} = 11.7
Run 10, χ^2_{min} = 11.86
m_0(TeV)
$m_{1/2}$(TeV)

	m_0 (GeV)	$m_{1/2}$ (GeV)	A_0 (GeV)	$\tan\beta$	m_t (GeV)	$m_b(m_b)^{\overline{MS}}$ (GeV)	$\alpha_s(m_Z)^{\overline{MS}}$	$1/\alpha_{\rm em}(m_Z)^{\overline{MS}}$	χ^2_{min}
Run 1	1900.5	342.8	1873.9	55.0	172.9	4.20	0.1172	127.955	**9.35**
Run 2	133.9	383.1	840.6	17.9	173.3	4.20	0.1183	127.955	**11.34**
Run 3	198.8	426.3	1059.4	22.6	173.3	4.20	0.1183	127.955	**11.45**
Run 4	2817.3	244.6	1712.9	51.2	172.9	4.20	0.1179	127.954	**11.55**
Run 5	2693.1	240.0	1706.0	51.0	172.6	4.20	0.1179	127.954	**11.61**
Run 6	2737.8	238.7	1692.6	51.0	172.6	4.20	0.1176	127.954	**11.63**
Run 7	2775.1	248.2	1780.2	51.1	172.6	4.20	0.1179	127.954	**11.65**
Run 8	3102.3	287.3	1976.8	51.2	172.8	4.20	0.1176	127.954	**11.76**
Run 9	3158.9	276.6	1901.2	51.1	173.1	4.21	0.1174	127.955	**11.78**
Run 10	3159.3	317.0	2136.8	51.2	172.7	4.20	0.1180	127.955	**11.86**