Interpreting CMS data in the phenomenological MSSM

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1 Introduction

Over most of the CMSSM parameter space $j\ \ j^2\ \ \&\ \ m^2_{1=2}$. The lightest neutralino is then mostly bino, the second-lightest mostly wino, and the heavier ones mostly higgsinos. Light higgsinos and large gaugino–higgsino mixing (mixed bino–higgsino dark matter) occur only in the focus point region, *i.e.* when squarks and sleptons are very heavy. This has a stro73(bi99(impact(bi99(on)-300(squark)-299(and)-299(gluino)-299(cascade)-299(deca group equations to derive model-specific testable predictions. It is expected that once SUSY particles are discovered, measurements of their masses and interactions will allow a partial reconstruction of the Lagrange parameters and thus shed light on the underlying SUSY breaking mechanism.

Happily, not all of the 120 MSSM parameters are of equal relevance. In fact, a couple of reasonable assumptions motivated by experiment serve to simplify the pr6blem considerably. In particular, it is reasonable to restrict

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We perform three blessed CMS analyses, namely the “di-jet $_T$

likelihood ratios. We have demonstrated that the interpretation of CMS data in terms of broad classes of multi-parameter SUSY models is feasible with the currently available computational and statistical tools, and that it is indeed possible to make meaningful statements on the natures of such models and therefore on supersymmetry, in general.

Acknowledgements

We thank JoAnne Hewett and Thomas G. Rizzo for providing us the 6K pMSSM points used in this analysis.

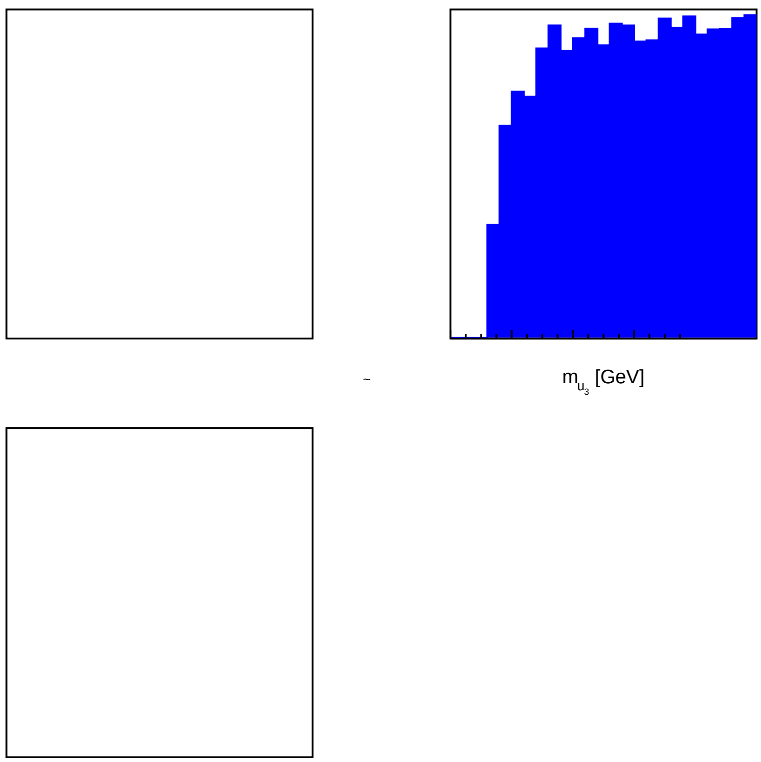

Figure 1: Ratios of profile likelihood L_p to maximum likelihood L

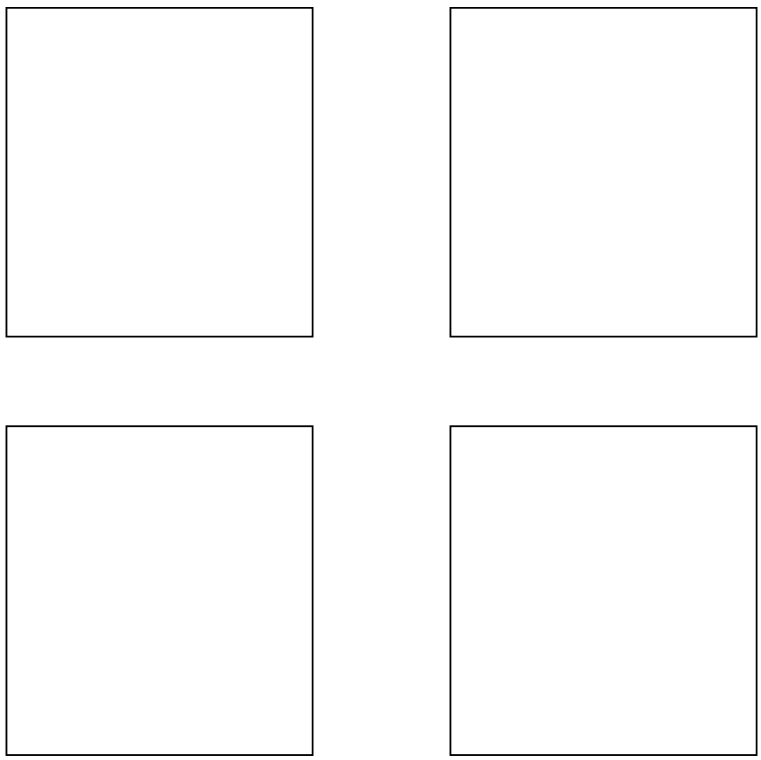

Figure 2: Ratios of profile likelihood L_p to maximum likelihood L

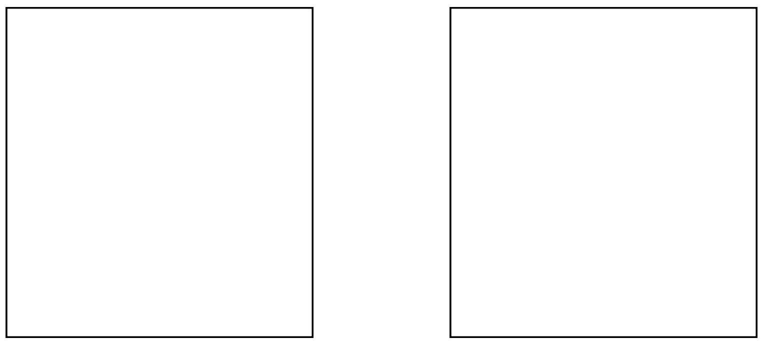

Figure 3: Ratios of profile likelihood L_p

Figure 4: Ratios of profile likelihood L_p to maximum likelihood L_{max} shown for trilinear couplings at SUSY scale. The colored and shaded histograms show the distributions before and after the inclusion of the CMS results.

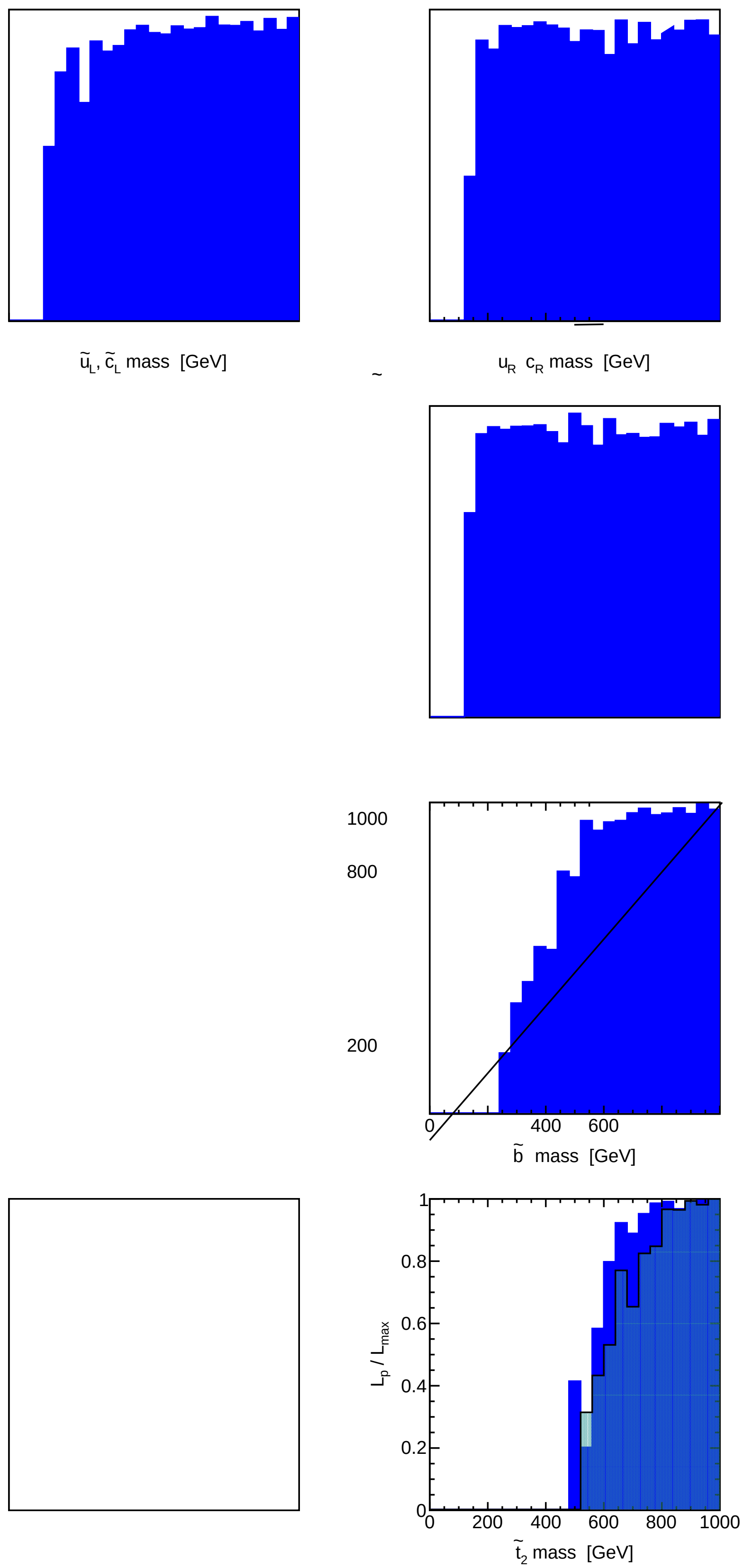

Figure 6: Ratios of profile likelihood L_p to maximum likelihood L

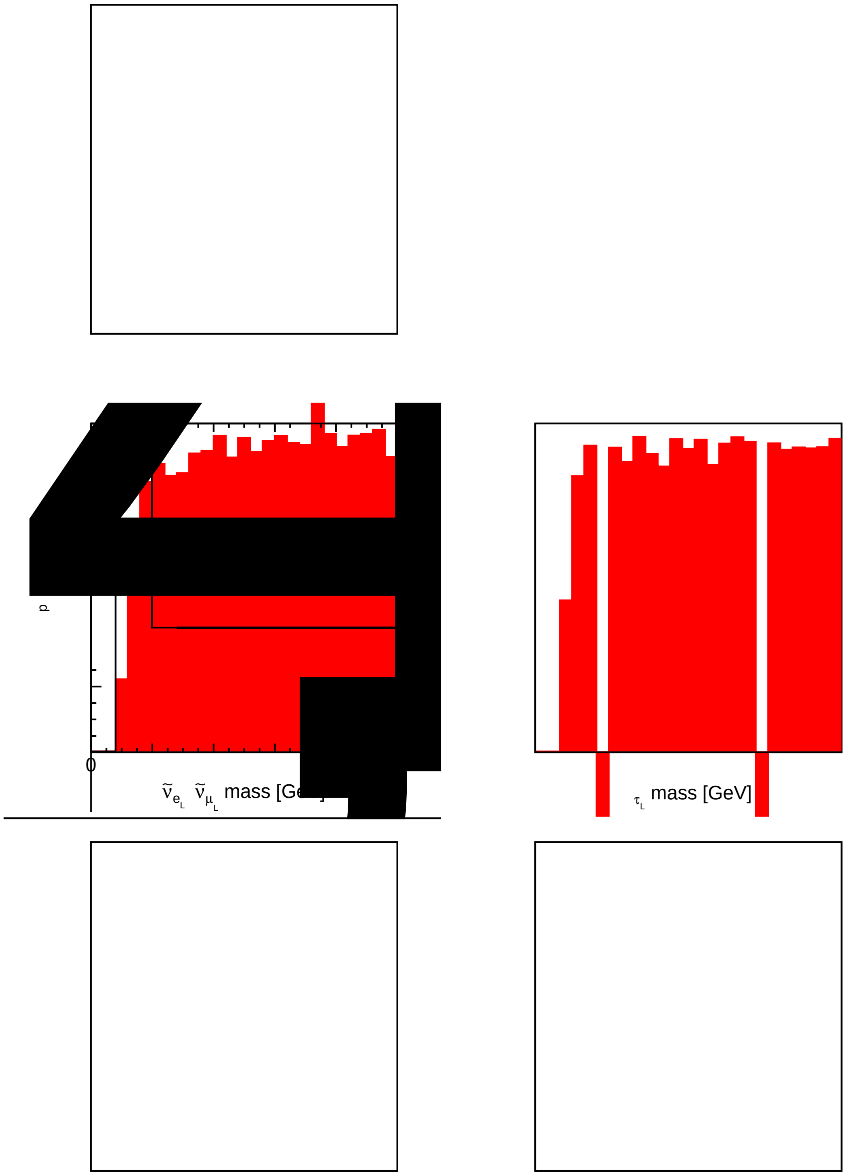

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Figure 10: Ratios of profile likelihood L_p to maximum likelihood L_{max} shown for chargino masses. The colored and shaded histograms show the distributions before and after the inclusion of the CMS results.

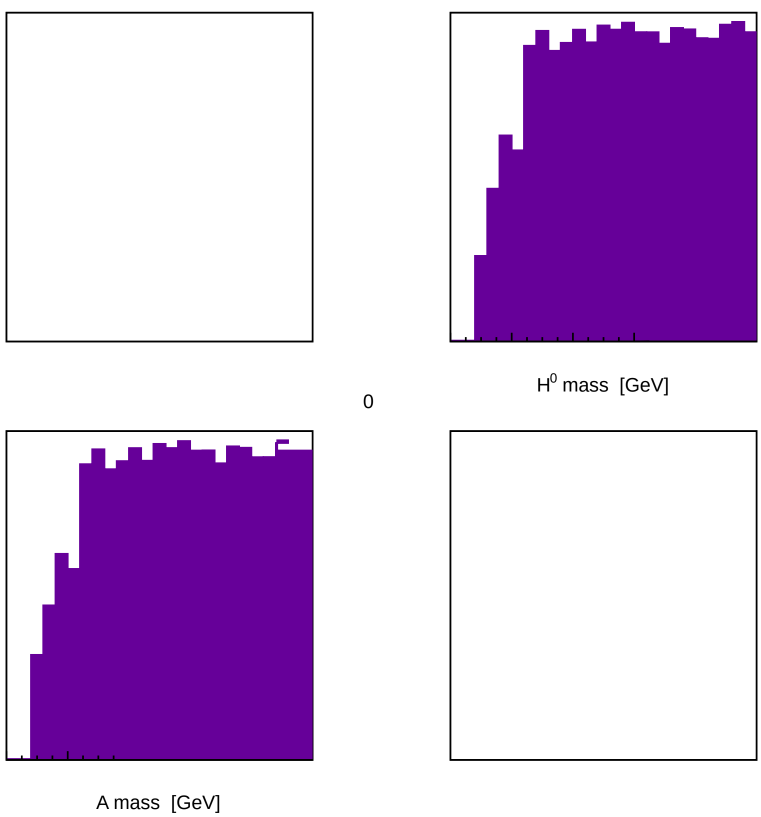

Figure 11: Ratios of profile likelihood L_p to maximum likelihood L_{max} shown for the Higgs masses. The colored and shaded histograms show the distributions before and after the inclusion of the CMS results.

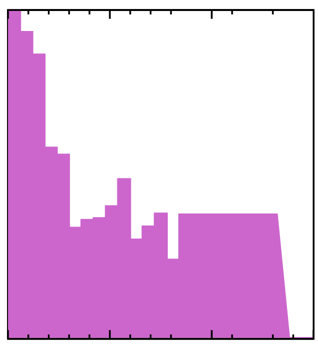

Figure 12: Ratio of profile likelihood L_p to maximum likelihood L_{max} shown for lightest neutralino dark matter relic density. The colored and shaded histograms show theutions before after the inclusion of the CMS results.

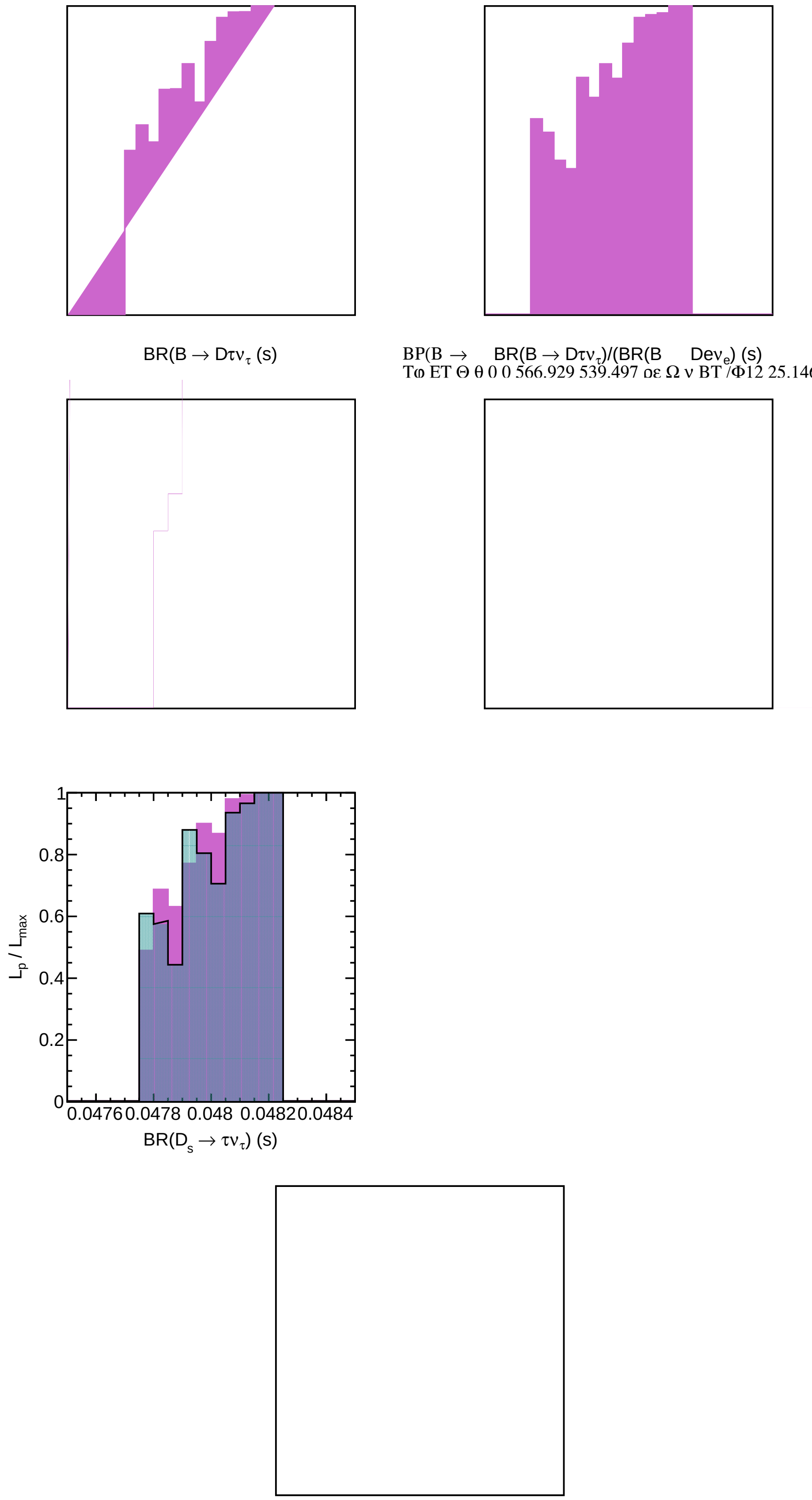

Figure 14: Ratios of profile likelihood L_p L_{max}

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fter the inclusion of the CMS results.

References

[1] K. Choi and H. P. Nilles, JHEP **04**, 006 (2007), hep-ph/0702146.

[2] S. P. Martin, Phys. Rev. **D79**

Appendices

A Comparison of kinematic quantities with full simulation

We compare the important kinematic variables used for the study with the CMSSW full simulation using the LM1 benchmark point. Figures 15, 16, 17 show that the simulation using our `Delphes`-based infrastructure agree well with the full simulation.

Figure 15: Distributions using the CMSSW full simulation and `Delphes` for the LM1 benchmark point as a function of jet multiplicity (left) and H_T (right)

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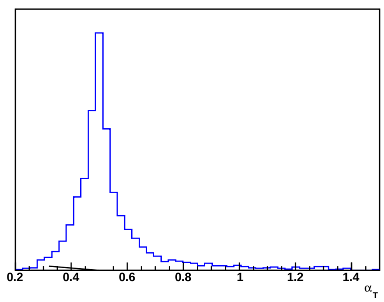

Figure 17: Distributions using the CMSSW full simulation and Delphes for the LM1 benchmark point as a function of

10,11 Find largest density $DMAX$ so far.

12–14 Return average of estimates of profile likelihood.

The above algorithm is implemented in a class we developed called `KDTProfileLikelihood`, which makes use of the multi-dimensional histogrammer `TKDTreeBinning` in Root. The *d*-dimensional histogram is created through recursive binary partitioning of the parameter space in such a way that bins have equal counts. The underlying data structure is a kd-tree [31].