# The BSM-AI Project: SUSY-AI


Fit(s) for LHC run-2

Edinburgh, 10.-12. October 2016

# Motivation

# LHC Run 2

- Run 2 is very impressive. 35 inverse fb has been collected so far

- 3 + 14 inverse fb of data has been analysed and no significant excess above SM expectation has been observed

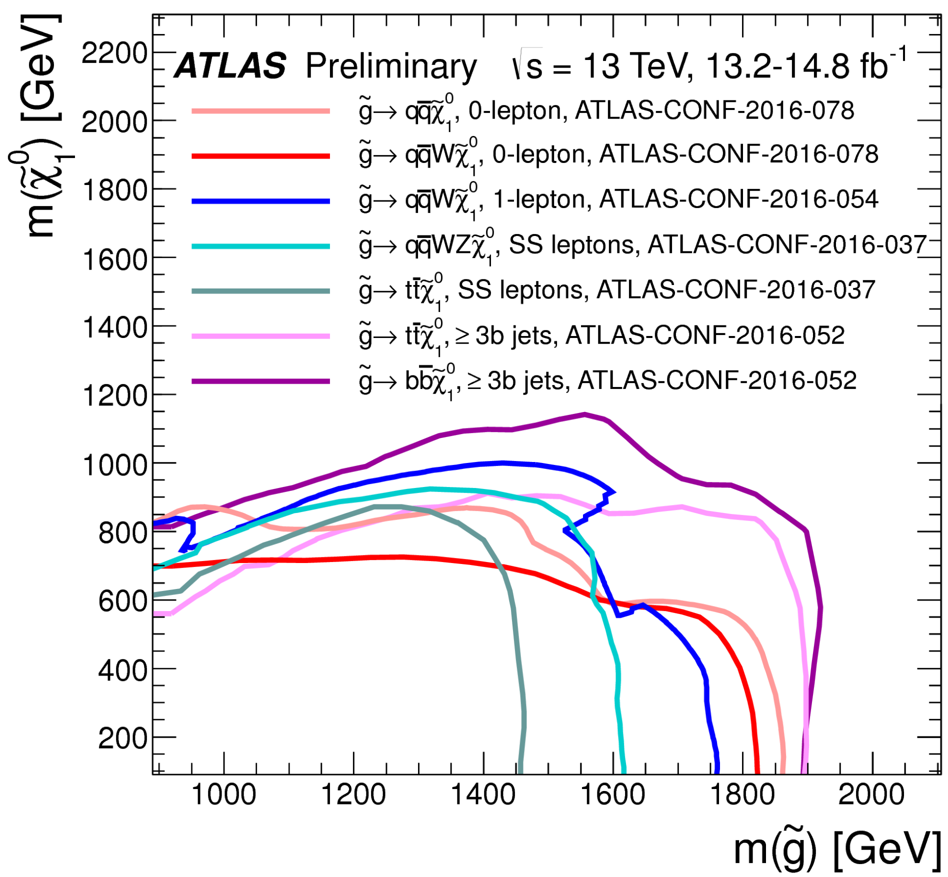
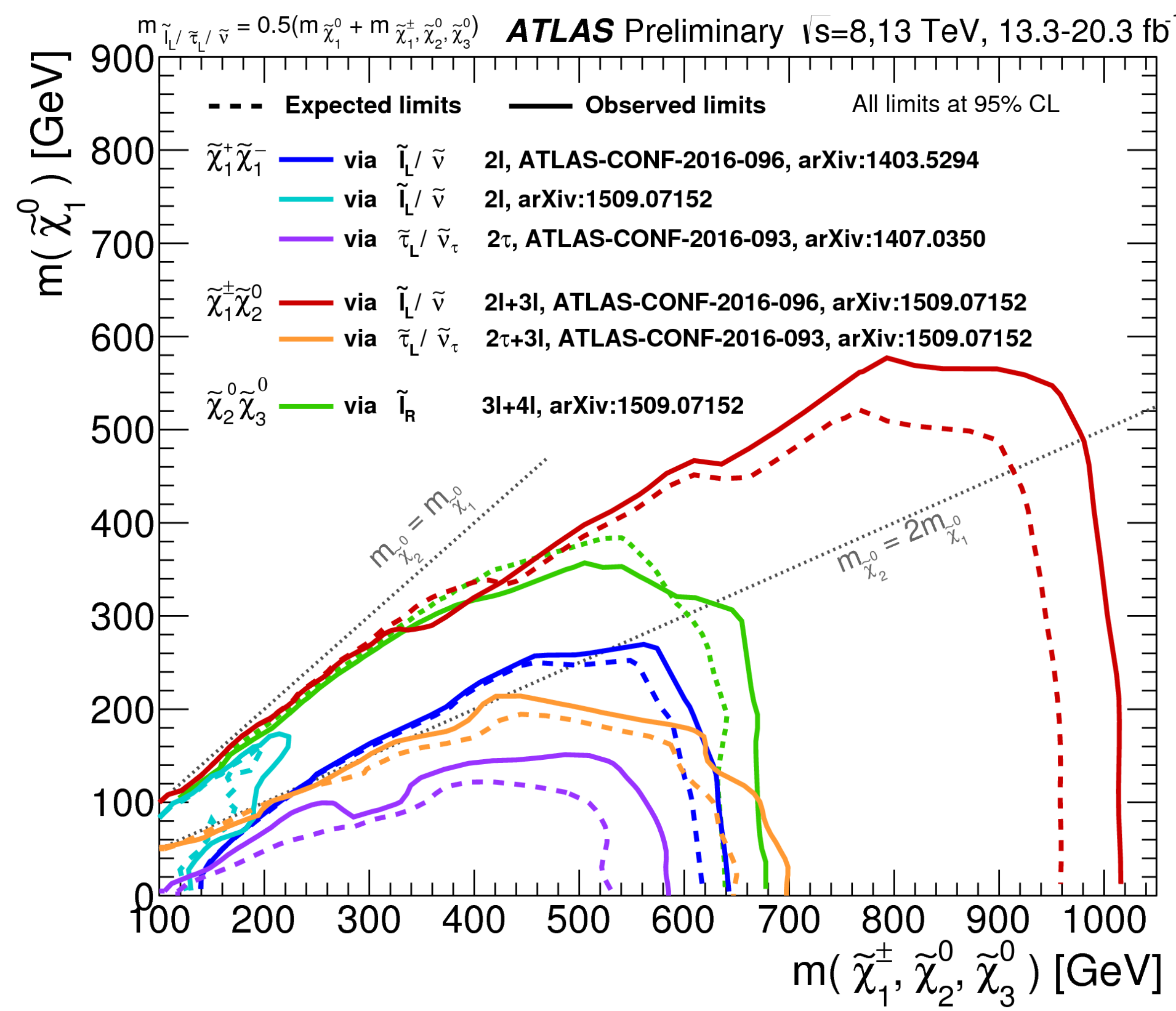
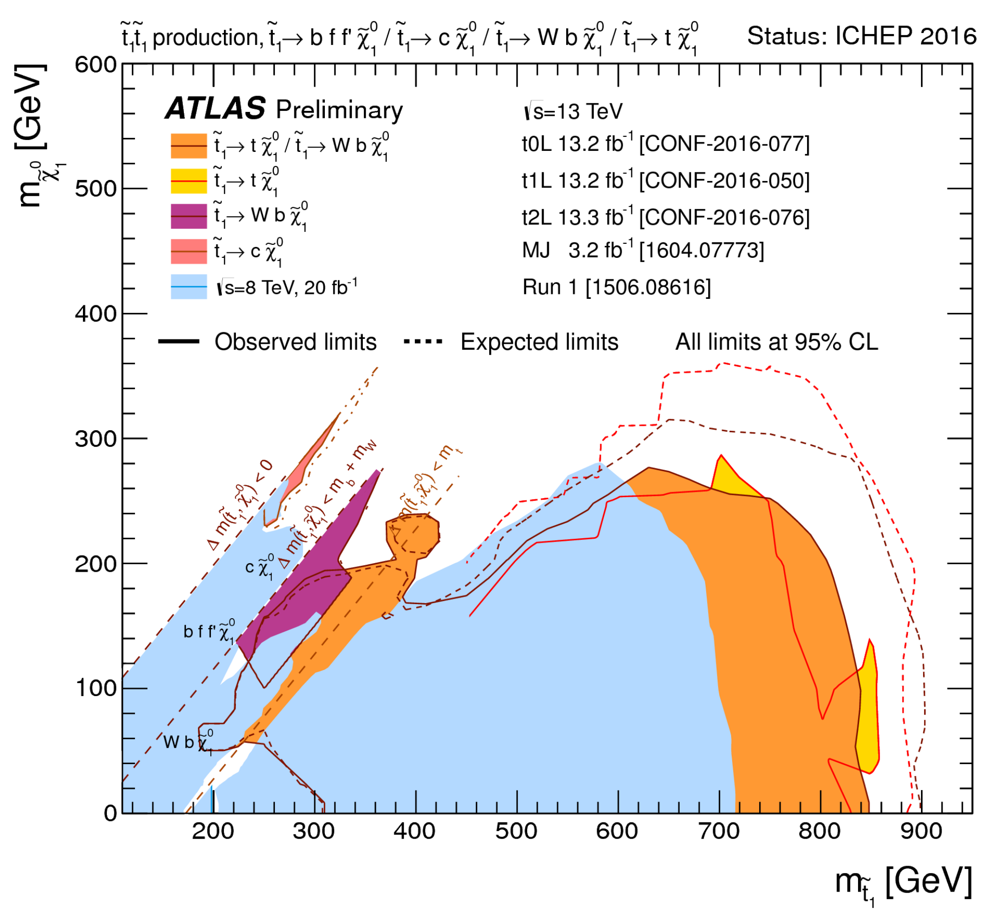
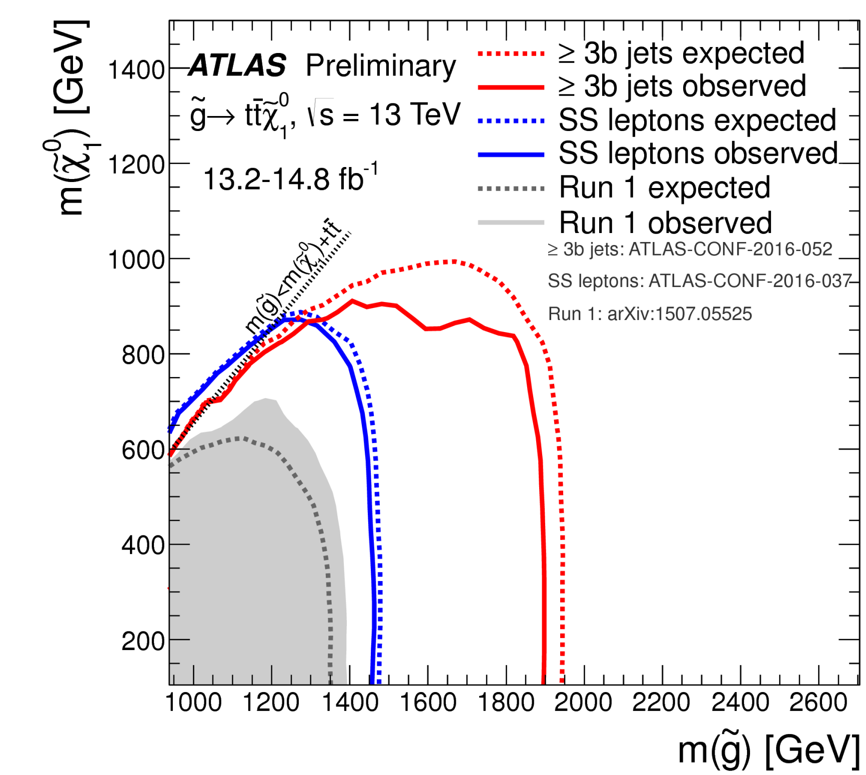
- null results can be translated in strong limits on BSM scenarios

# Constraining BSM

- experimentalists mostly interpret exclusion in simplified models assuming a few BSM particles accessible at the LHC

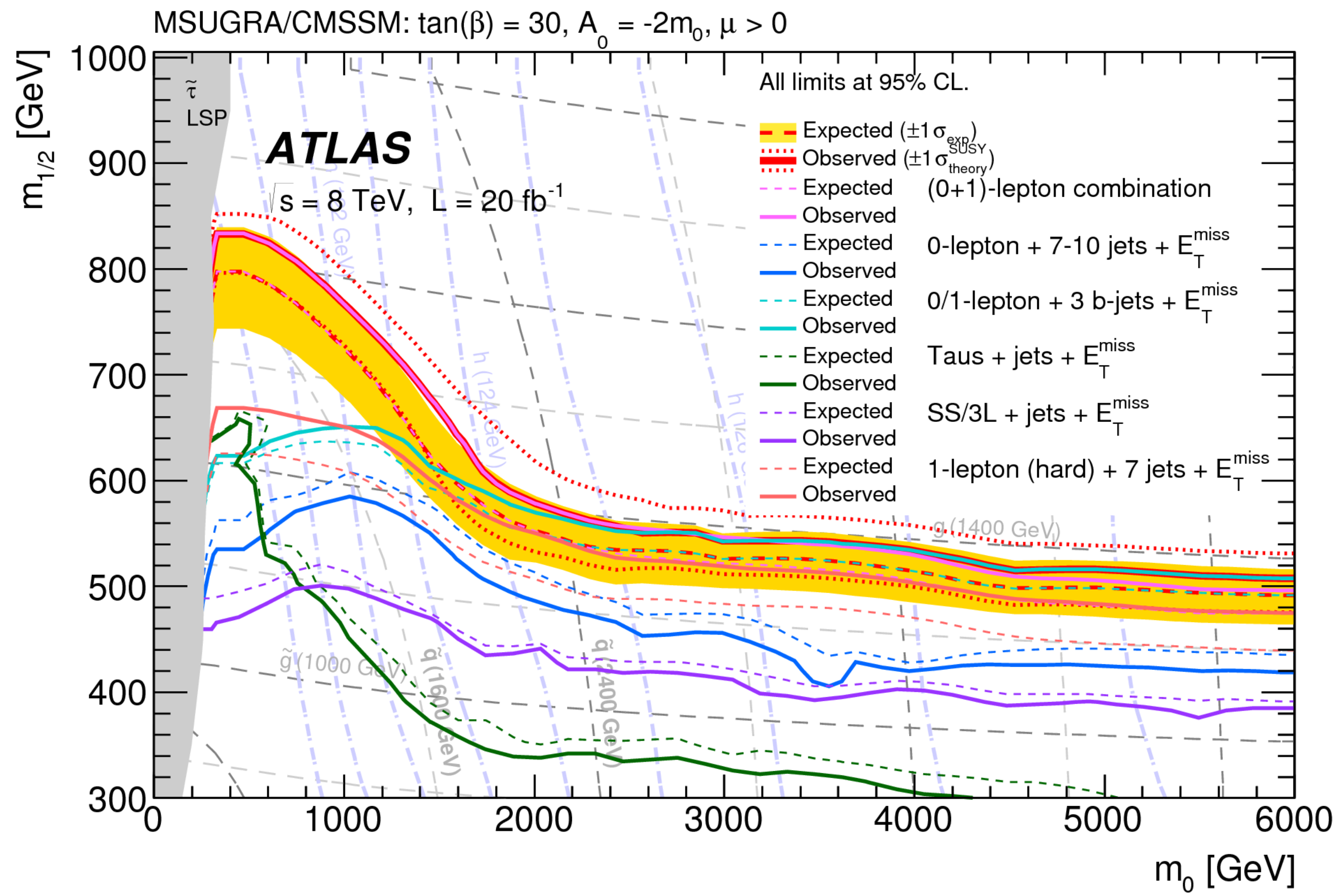
- in the past constrained models such as mSUGRA with its full parameter space were investigated

- the derived results are very impressive and many SUSY particles below the multi TeV scale are seemingly excluded!

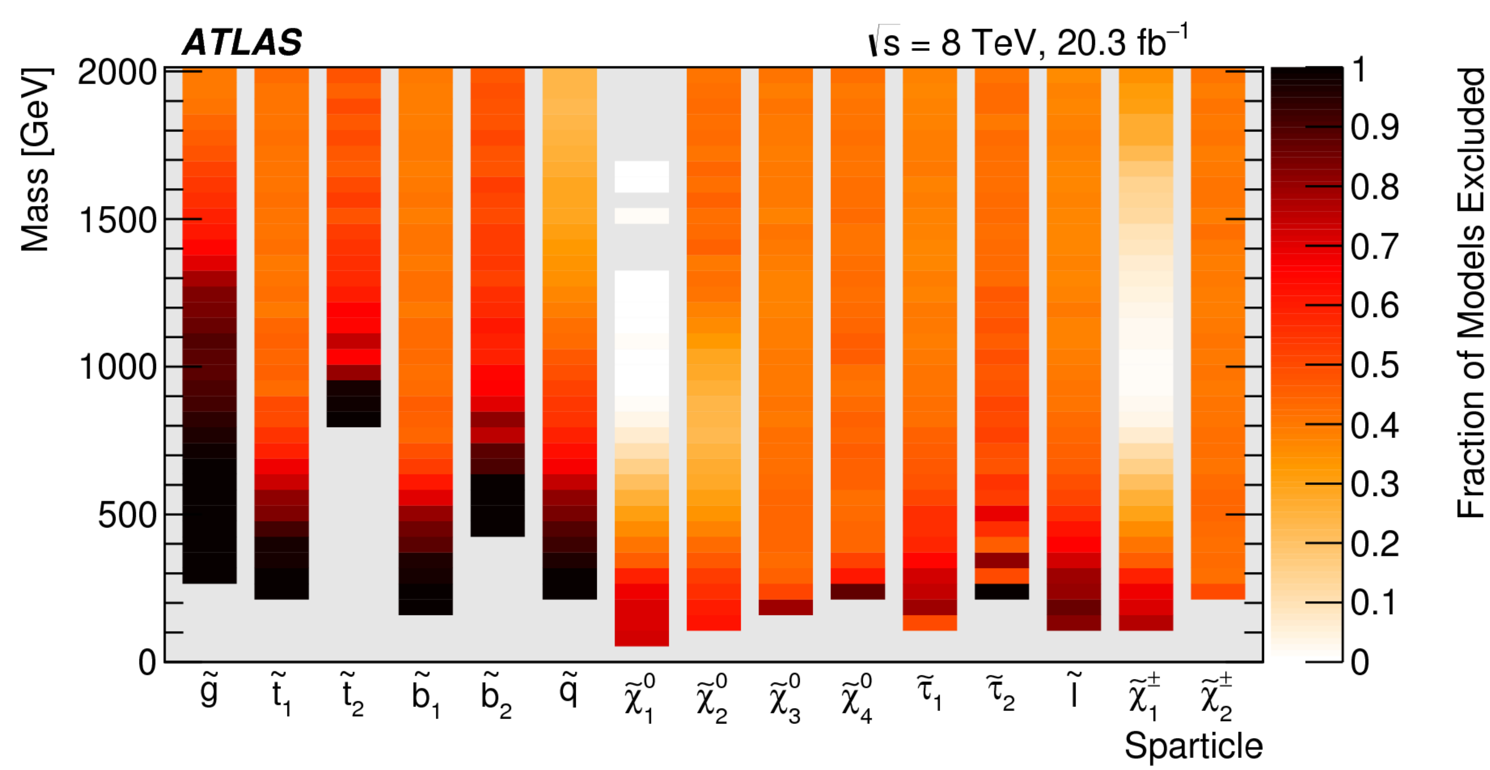

ATLAS Preliminary √s = 13 TeV, 13.2-14.8 fb-1
g̃→ qq̄χ̃10, 0-lepton, ATLAS-CONF-2016-078
g̃→ qq̄Wχ̃10, 0-lepton, ATLAS-CONF-2016-078
g̃→ qq̄Wχ̃10, 1-lepton, ATLAS-CONF-2016-054
g̃→ qq̄WZχ̃10, SS leptons, ATLAS-CONF-2016-037
g̃→ tt̄χ̃10, SS leptons, ATLAS-CONF-2016-037
g̃→ tt̄χ̃10, ≥ 3b jets, ATLAS-CONF-2016-052
g̃→ bb̄χ̃10, ≥ 3b jets, ATLAS-CONF-2016-052
m(χ̃10) [GeV]
m(g̃) [GeV]

ATLAS Preliminary √s=8,13 TeV, 13.3-20.3 fb-1
Expected limits
Observed limits
All limits at 95% CL
via l̃L/ ν̃ 2l, ATLAS-CONF-2016-096, arXiv:1403.5294
via l̃L/ ν̃ 2l, arXiv:1509.07152
via τ̃L/ ν̃τ 2τ, ATLAS-CONF-2016-093, arXiv:1407.0350
via l̃L/ ν̃ 2l+3l, ATLAS-CONF-2016-096, arXiv:1509.07152
via τ̃L/ ν̃τ 2τ+3l, ATLAS-CONF-2016-093, arXiv:1509.07152
via l̃R 3l+4l, arXiv:1509.07152
m(χ̃10) [GeV]
m(χ̃1±, χ̃20, χ̃30) [GeV]

Status: ICHEP 2016
ATLAS Preliminary
√s=13 TeV
t0L 13.2 fb-1 [CONF-2016-077]
t1L 13.2 fb-1 [CONF-2016-050]
t2L 13.3 fb-1 [CONF-2016-076]
MJ 3.2 fb-1 [1604.07773]
√s=8 TeV, 20 fb-1
Run 1 [1506.08616]
Observed limits
Expected limits
All limits at 95% CL
mt̃1 [GeV]

ATLAS Preliminary
g̃→ tt̄χ̃10, √s = 13 TeV
13.2-14.8 fb-1
≥ 3b jets expected
≥ 3b jets observed
SS leptons expected
SS leptons observed
Run 1 expected
Run 1 observed
≥ 3b jets: ATLAS-CONF-2016-052
SS leptons: ATLAS-CONF-2016-037
Run 1: arXiv:1507.05525
m(χ̃10) [GeV]
m(g̃) [GeV]

# Drawbacks…

- however, many simplified models are unrealistic
- constrained models have a small number of parameters and therefore their whole parameter space can be tested against all phenomenological constraints but the conclusions are not *universal*
- even slight generalisation of the model invalidates the limits



MSUGRA/CMSSM: tan(β) = 30, $A_0 = -2m_0$, μ > 0
$m_{1/2}$ [GeV]
$m_0$ [GeV]
ATLAS
$\sqrt{s}$ = 8 TeV, L = 20 fb$^{-1}$
$\tilde{\tau}$ LSP
All limits at 95% CL.
Expected ($\pm 1\sigma_{exp}$)
Observed ($\pm 1\sigma^{SUSY}_{theory}$)
Expected
Observed
(0+1)-lepton combination
0-lepton + 7-10 jets + $E_T^{miss}$
0/1-lepton + 3 b-jets + $E_T^{miss}$
Taus + jets + $E_T^{miss}$
SS/3L + jets + $E_T^{miss}$
1-lepton (hard) + 7 jets + $E_T^{miss}$
$\tilde{g}$ (1400 GeV)
$\tilde{g}$ (1000 GeV)
$\tilde{q}$ (1600 GeV)
$\tilde{q}$ (2400 GeV)
h (124 GeV)
h (122 GeV)
h (126 GeV)

ATLAS
$\sqrt{s}$ = 8 TeV, 20.3 fb$^{-1}$
Mass [GeV]
Fraction of Models Excluded
$\tilde{g}$ $\tilde{t}_1$ $\tilde{t}_2$ $\tilde{b}_1$ $\tilde{b}_2$ $\tilde{q}$ $\tilde{\chi}^0_1$ $\tilde{\chi}^0_2$ $\tilde{\chi}^0_3$ $\tilde{\chi}^0_4$ $\tilde{\tau}_1$ $\tilde{\tau}_2$ $\tilde{l}$ $\tilde{\chi}^\pm_1$ $\tilde{\chi}^\pm_2$
Sparticle

How can we constrain the most general realization of a model against experimental data?

# Derive my own limits…

- generate parton level events with Madgraph
- hadronize events with Pythia, Herwig, Sherpa
- calculate the NLO cross section
- simulate detector response with Delphes, PGS
- code up the relevant searches with up to hundreds of SRs

# There are no free lunches

- validation can be really painful
- a huge number of ATLAS and CMS searches are on the market
- the implementation of all those searches is time consuming
- several attempts to recast LHC limits, e.g. Atom, CheckMATE, FastLim, MadAnalysis 5, SModels and many others

# Simplified vs General

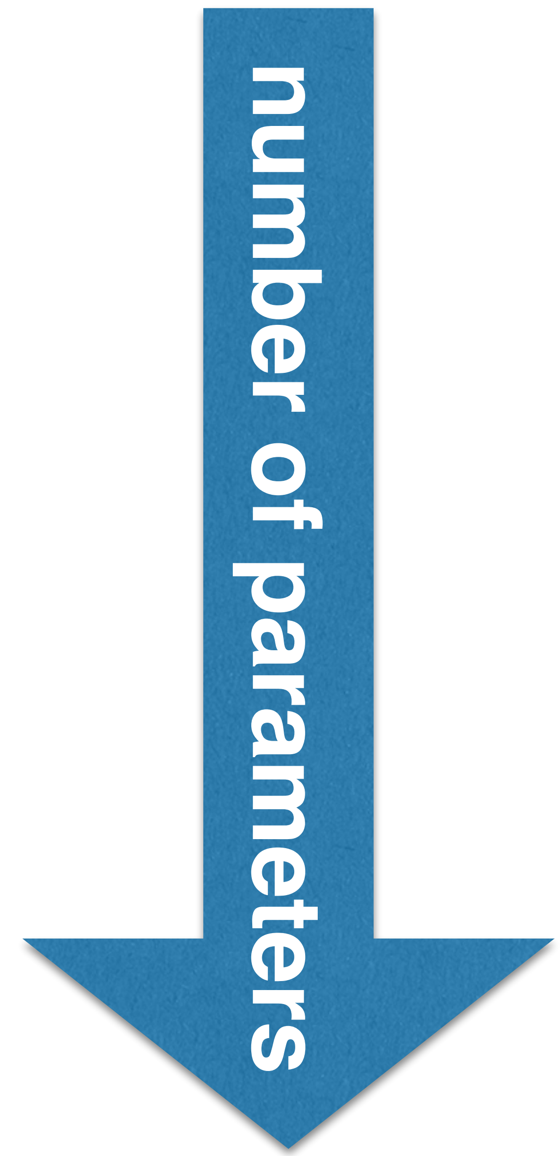
| | Pro | Con |
|---|---|---|
| **FastLim, SModels** | very fast, very easy too use | only for simplified models |
| **Atom, CheckMATE, MadAnalysis 5** | are very generic | relatively slow since they depend on MC input |

# Model complexity

simplified models
(1-3 parameters)

constrained models, e.g. mSUGRA
(4-6 parameters)

general models, e.g. pMSSM
(7-20 parameters)

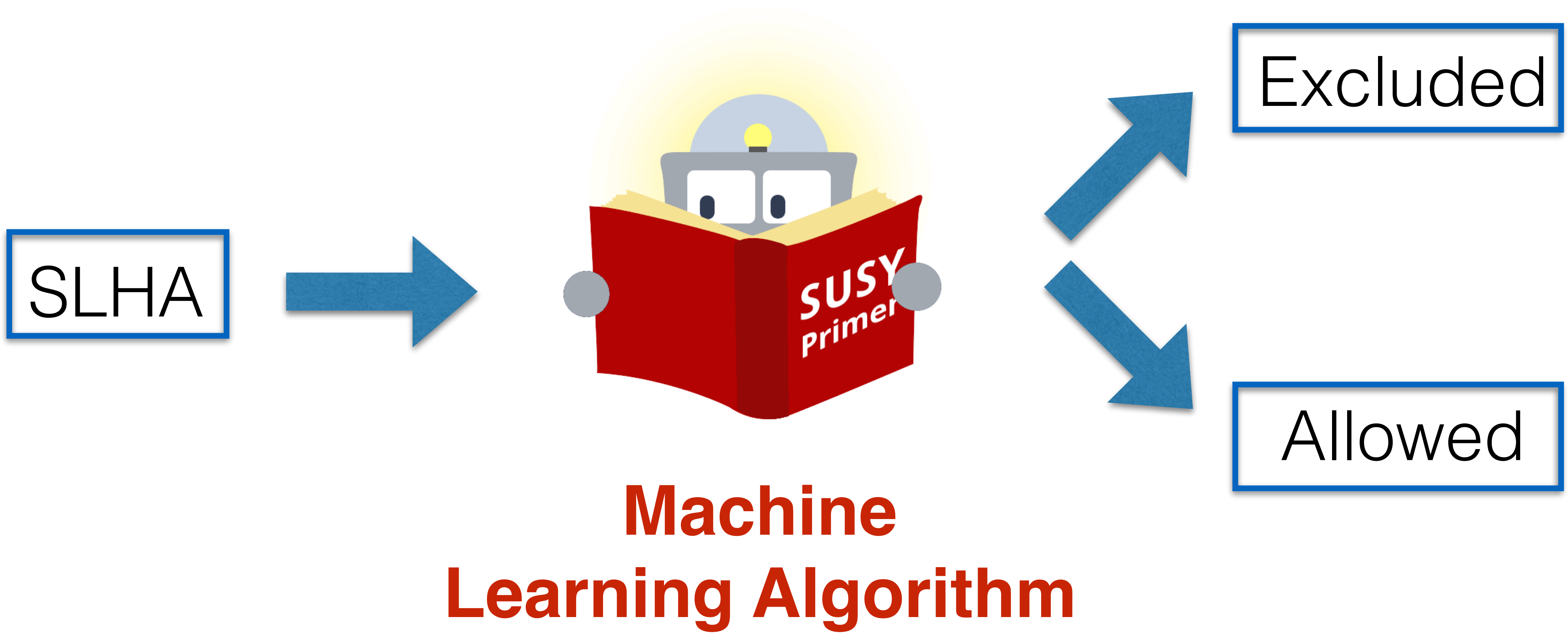



with increasing complexity, a general scan of parameter space becomes impractical (curse of dimensionality)

# Global fits

- we want to test a model against EWPO, DD and ID DM, Higgs precision measurements, *b* physics,…
- however, testing a complex model against collider data is difficult if the parameter space has a high dimensional volume
- e.g., in arXiv:1507.07008, we presented a new global fit of the pMSSM-19 compatible with all DM and collider constraints while accomodating the gamma ray excess from the Galactic centre
- testing the collider constraints was computationally expensive
- how can we speed up collider tests for complex models?

# Our idea: SUSY-AI




≈ 5000 predictions / CPU second

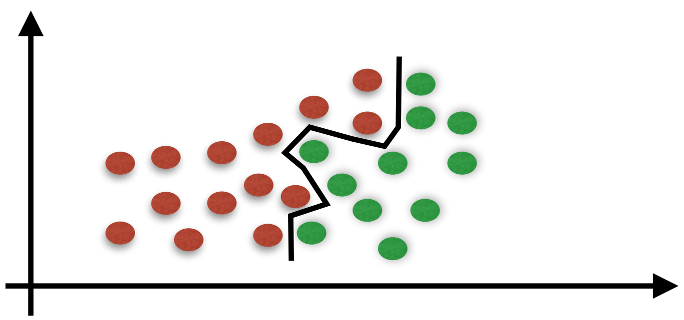
# What is Machine Learning?

# Machine Learning I

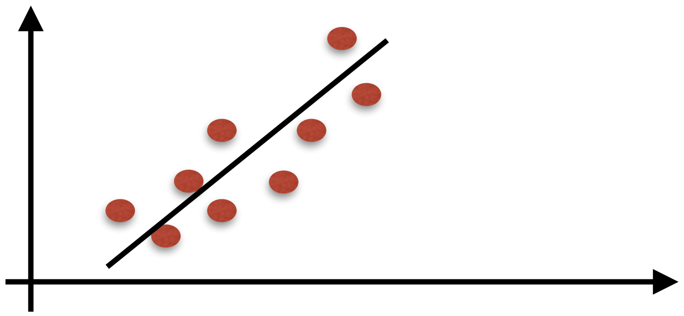
- a ML algorithm can improve its performance using training data
- the algorithm has a large number of fit parameters which can be determined by data
- ML is applied in situations which are very challenging, e.g. face or handwriting recognition

# Machine Learning II

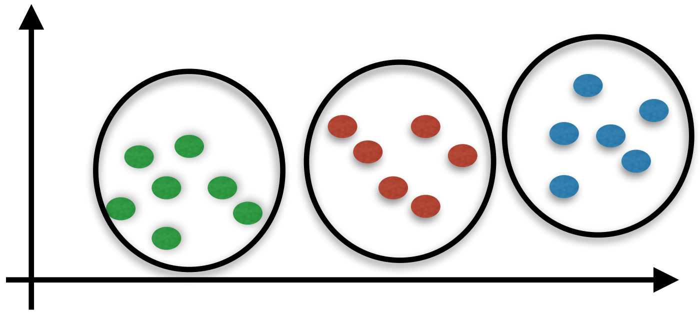
Classification - supervised



Regression - supervised

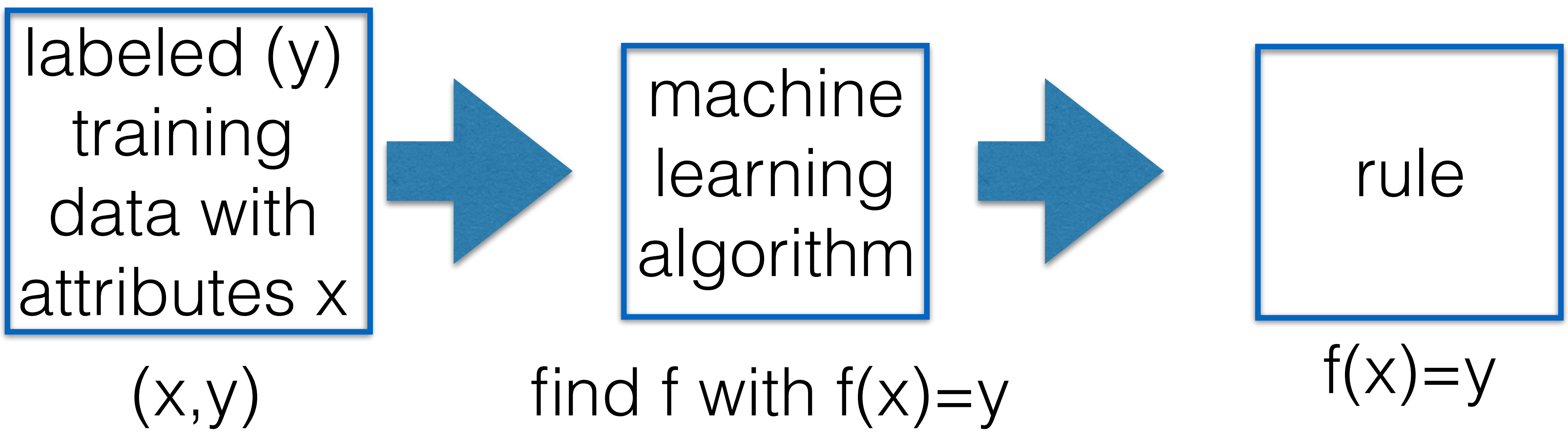


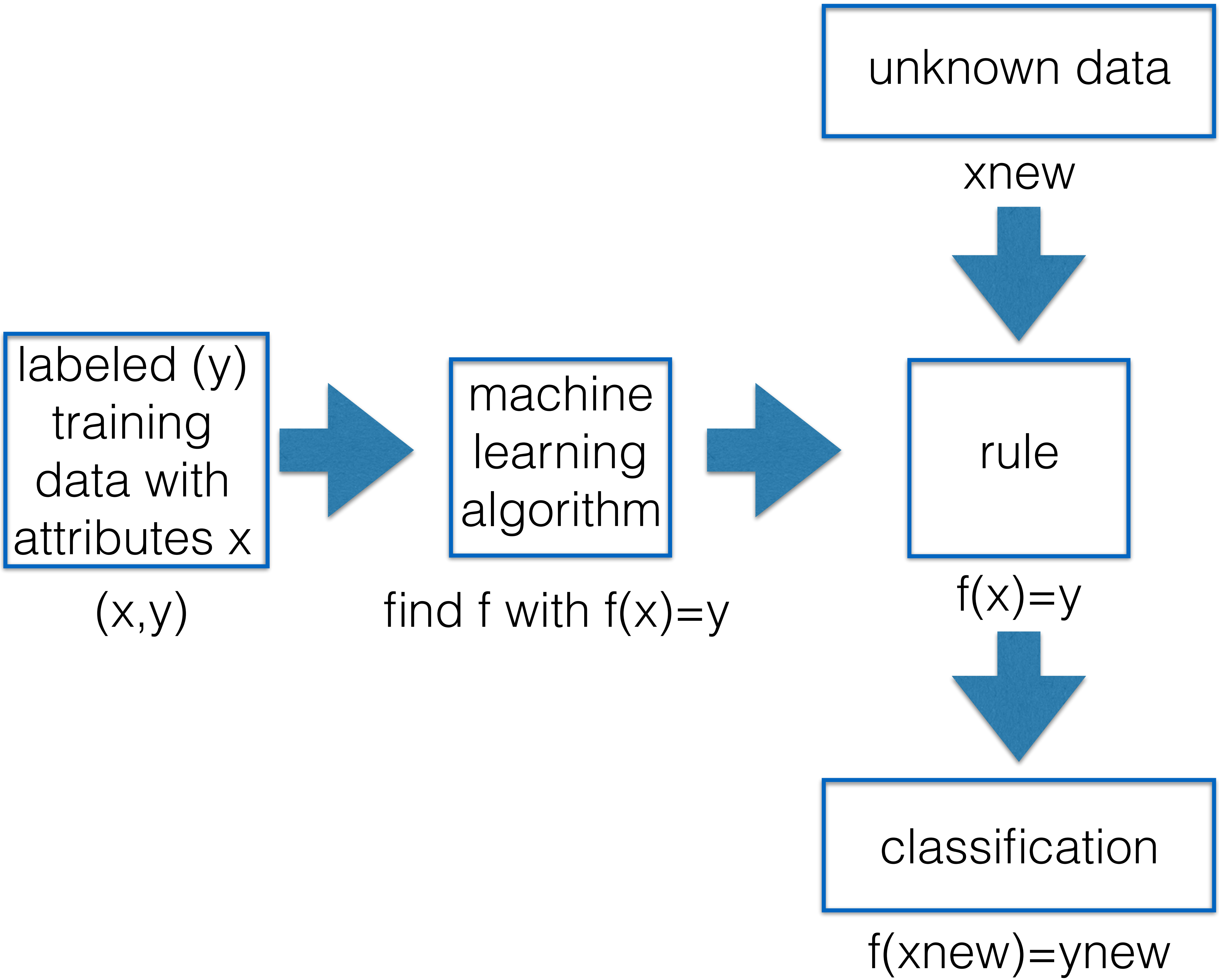
Unsupervised learning



# Example

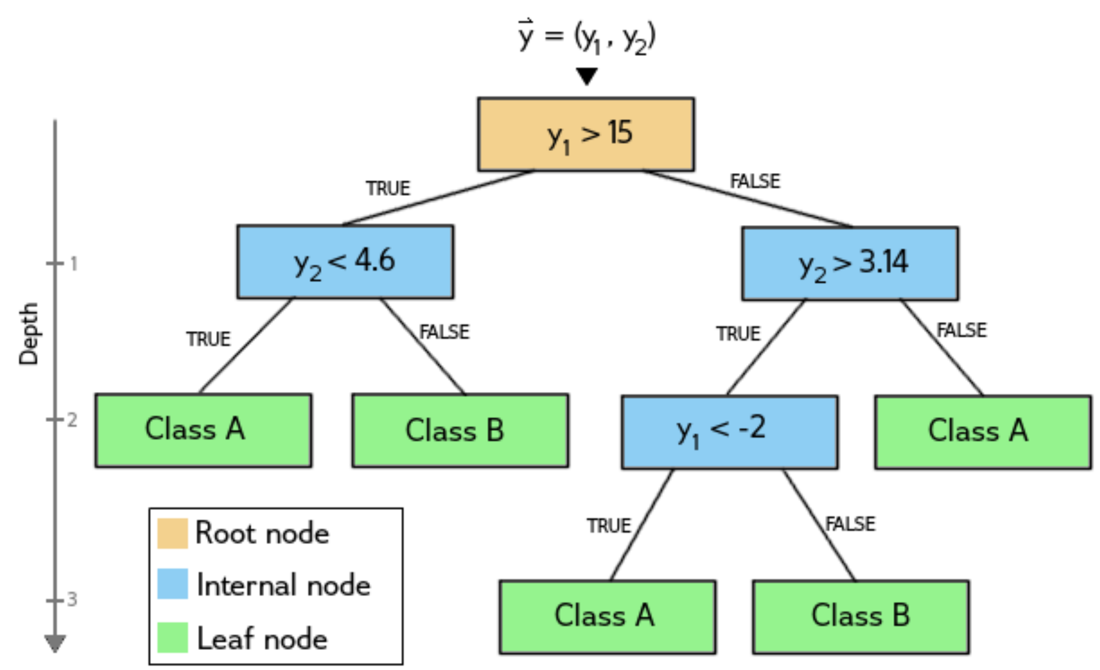
| example | attribute 1 | attribute 2 | label |
|---|---|---|---|
| banana | … | … | 1 |
| tomato | … | … | 0 |
| cherry | … | … | 1 |
| apple | … | … | 1 |
| onion | … | … | 0 |
| cucumber | … | … | 0 |
| orange | … | … | 1 |
| water melon | … | … | ? |
| turnip | … | … | ? |
| maiz | … | … | ? |


labeled (y) training data with attributes x
(x,y)
machine learning algorithm
find f with f(x)=y
rule
f(x)=y


unknown data
xnew
labeled (y) training data with attributes x
(x,y)
machine learning algorithm
find f with f(x)=y
rule
f(x)=y
classification
f(xnew)=ynew

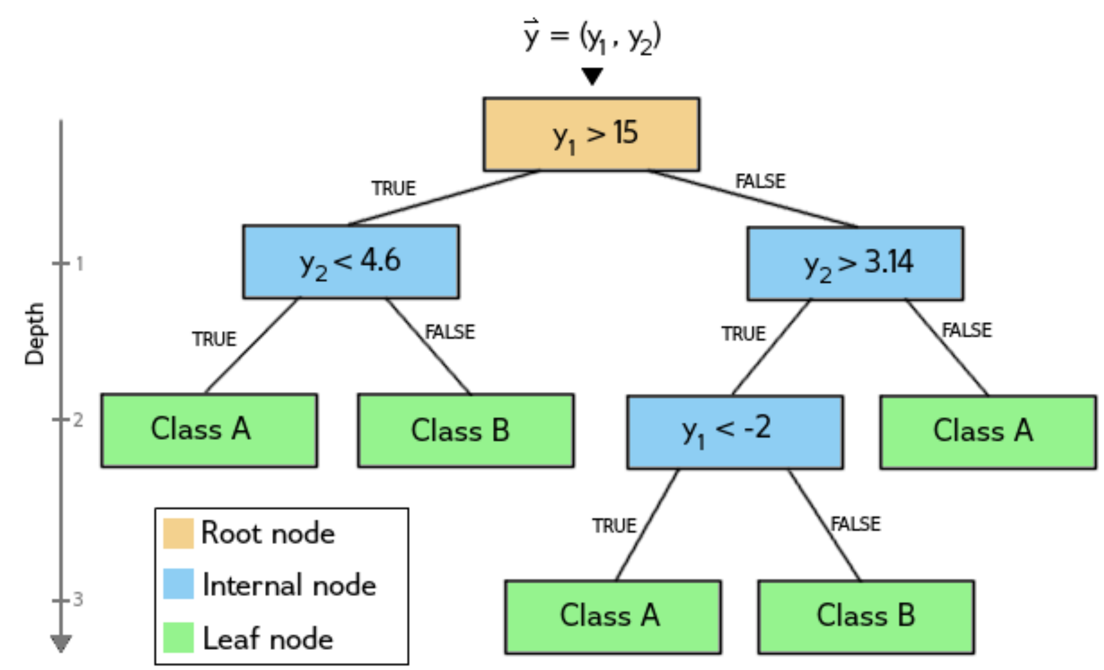
# Decision Trees I

- a Decision Tree is a commonly used classification algorithm
- DT consists of several nodes and at each node a test is performed
- the attribute set moves down the tree until the final leaf node is reached
- at the final leaf node, a class label is assigned to the attribute set



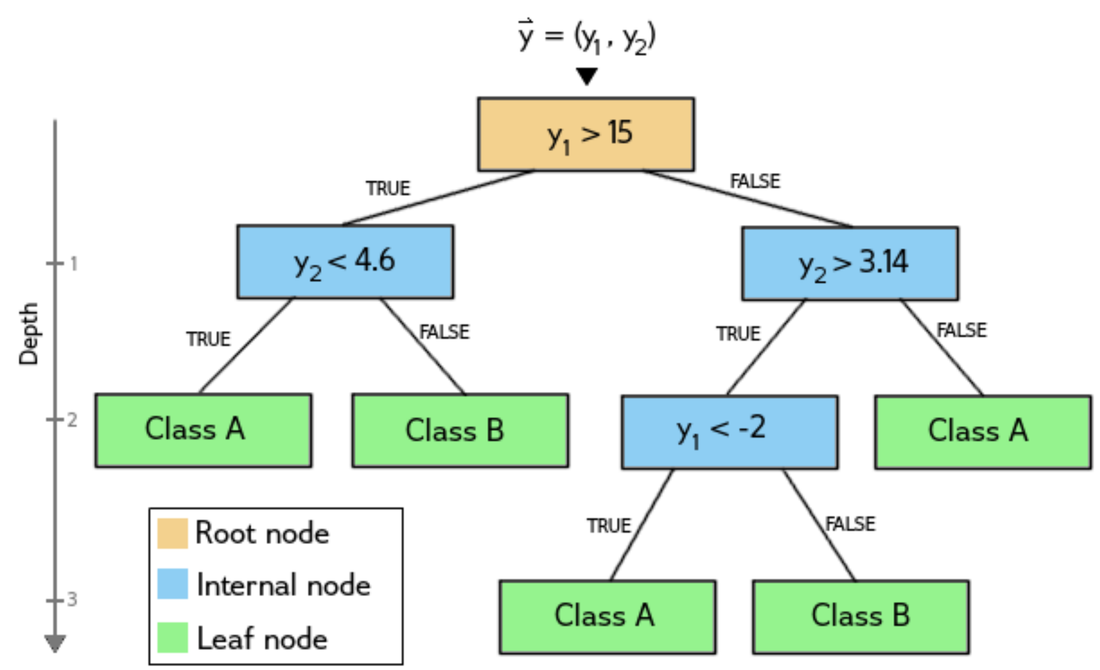
# Decision Trees II

- the DT works on the whole attribute set
- every test corresponds to a cut in this parameter space
- a DT split the attribute set into disjunct regions
- disadvantage: tendency of overtraining, i.e. DT learns the noise



# Decision Trees III

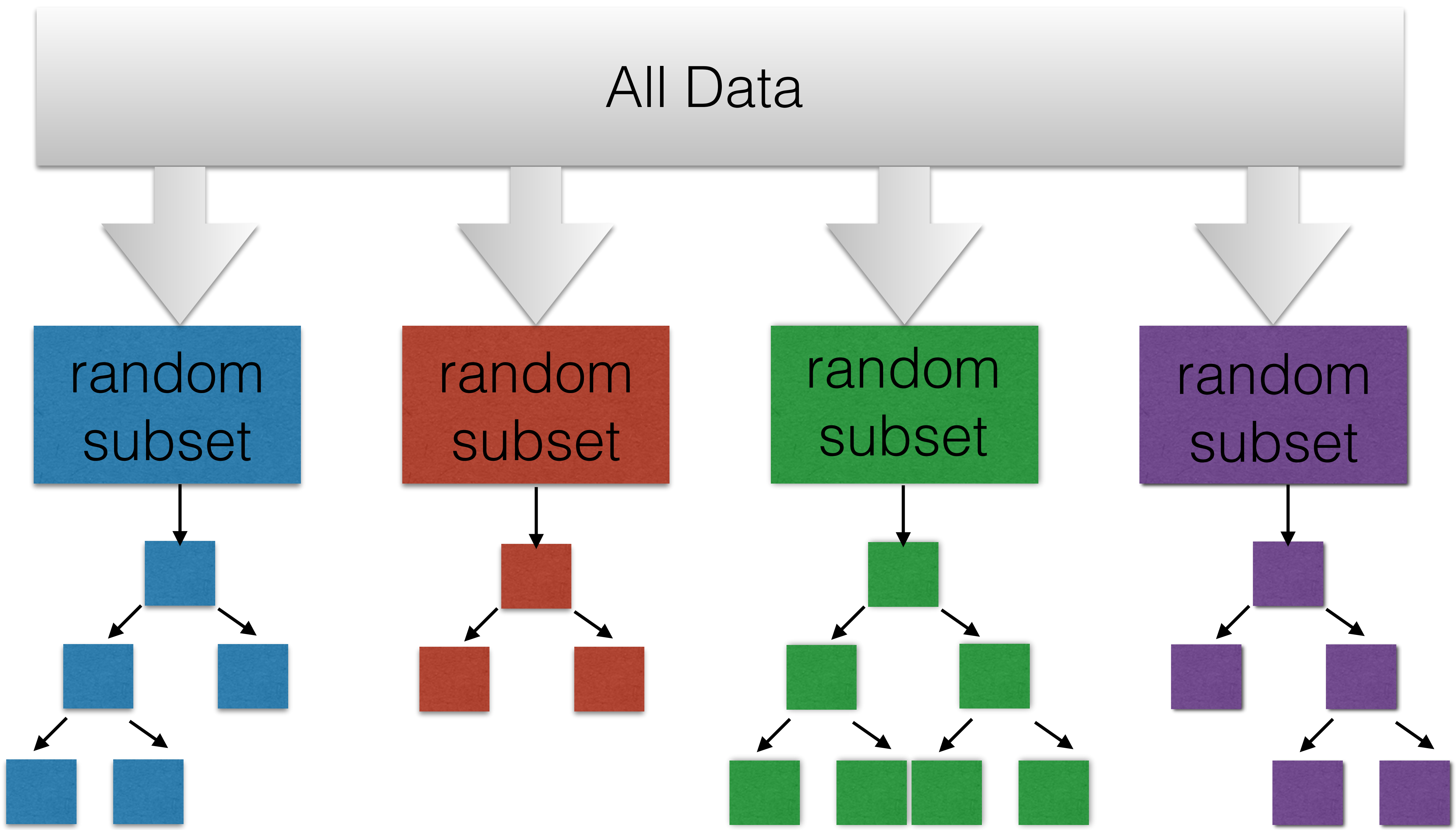
- methods to suppress overtraining
- pruning: training the entire tree but cut away all nodes beyond a certain depth
- boosting: combine multiple DTs into a single classifier
- bagging: for a group of DTs, each decision tree is trained on a random selection of a subset of the attribute set



# Random Forest I

- trees are weak learners but a forest is a strong learner
- a random forest combines trees (boosting)
- draw *N* bootstrap samples from original sample
- fit a classification tree to each bootstrap sample
- randomly preselect *M* attribute variables at each node (bagging)

# Random Forest II




at each node a random subset of the attribute set is chosen

# Random Forest III

- output the ensemble of trees
- *R*=( # trees prediction of class *C )* / ( total number of trees )
- *R*=probability of attribute set belonging to *C*
- classification in RF is done by majority vote

# pMSSM-19 & ATLAS

# pMSSM-19 I

- the most general MSSM has a large number of input parameters, $\mathcal{O}(100)$ soft breaking parameters!
- it is unfeasible for a dedicated collider study
- assumptions on the soft breaking sector heavily reduces number of free parameters, e.g. mSUGRA
- however, this approach might be too constraining
- consider a MSSM taking into account all constraints from particle physics experiments

# pMSSM-19 II

- consider the most general and CP conserving MSSM

- assume minimal flavour violation

- demand that the lightest neutralino is the LSP

- require the first two generation sfermions are degenerate and decoupled

- 19 weak scale parameters = pMSSM-19

# pMSSM-19 and ATLAS I

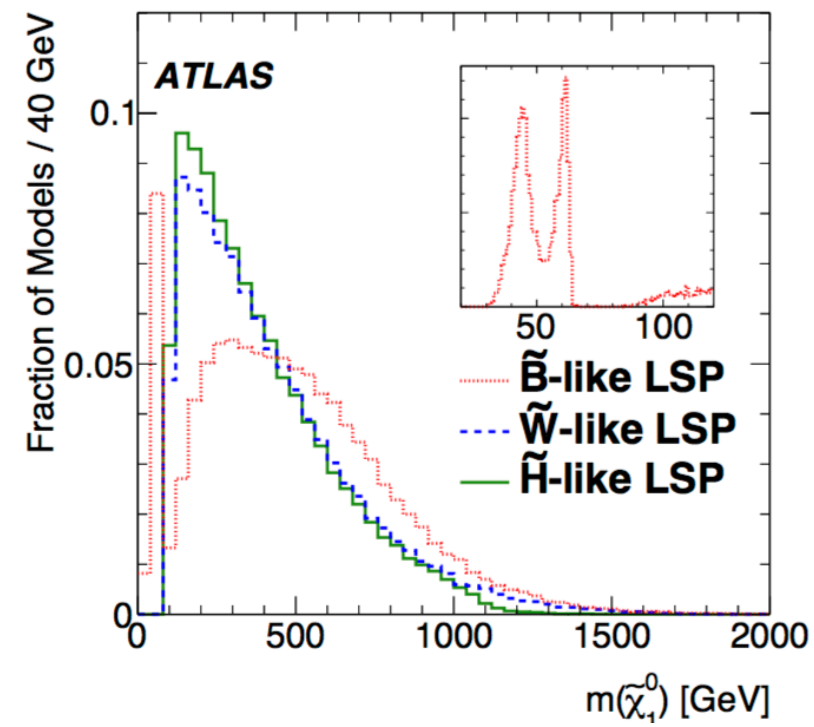
- ATLAS (arXiv:1508.06608) performed a study on the pMSSM-19
- ATLAS considered 5x10^8 model points based on arXiv:1206.4321
- all model points had to satisfy preselection cuts
- 310,327 model points satisfy all theoretical and experimental constraints

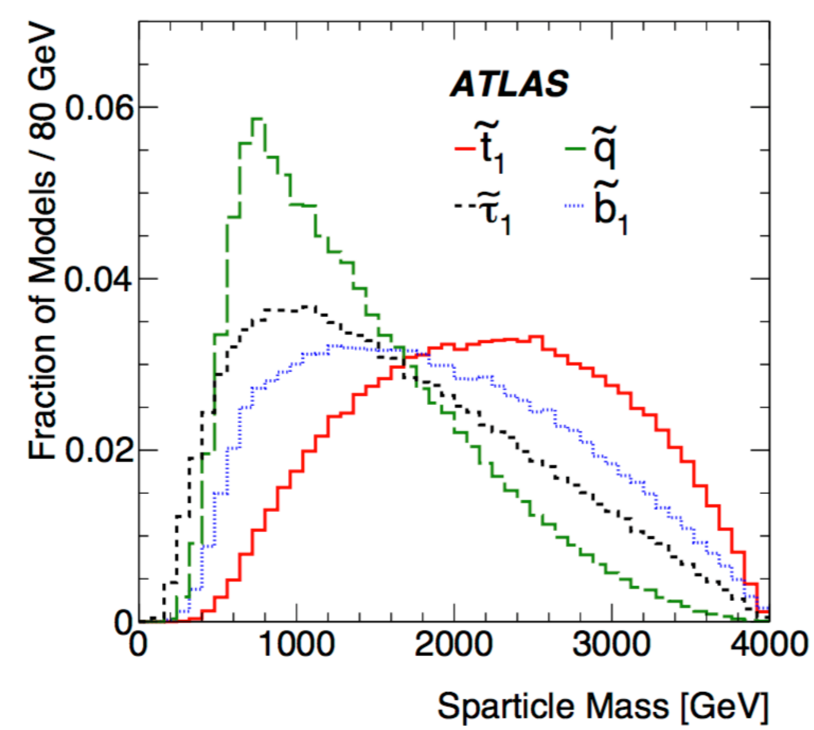
| Parameter | Description | Scanned range |
|---|---|---|
| $m_{\tilde{L}_1}$ | $1^{st}/2^{nd}$ gen. $SU(2)$ doublet soft breaking slepton mass | [90 GeV, 4 TeV] |
| $m_{\tilde{E}_1}$ | $1^{st}/2^{nd}$ gen. $SU(2)$ singlet soft breaking slepton mass | [90 GeV, 4 TeV] |
| $m_{\tilde{L}_3}$ | $3^{rd}$ gen. $SU(2)$ doublet soft breaking slepton mass | [90 GeV, 4 TeV] |
| $m_{\tilde{E}_3}$ | $3^{rd}$ gen. $SU(2)$ singlet soft breaking slepton mass | [90 GeV, 4 TeV] |
| $m_{\tilde{Q}_1}$ | $1^{st}/2^{nd}$ gen. $SU(2)$ doublet soft breaking squark mass | [200 GeV, 4 TeV] |
| $m_{\tilde{U}_1}$ | $1^{st}/2^{nd}$ gen. $SU(2)$ singlet soft breaking squark mass | [200 GeV, 4 TeV] |
| $m_{\tilde{D}_1}$ | $1^{st}/2^{nd}$ gen. $SU(2)$ singlet soft breaking squark mass | [200 GeV, 4 TeV] |
| $m_{\tilde{Q}_3}$ | $3^{rd}$ gen. $SU(2)$ doublet soft breaking squark mass | [100 GeV, 4 TeV] |
| $m_{\tilde{U}_3}$ | $3^{rd}$ gen. $SU(2)$ singlet soft breaking squark mass | [100 GeV, 4 TeV] |
| $m_{\tilde{D}_3}$ | $3^{rd}$ gen. $SU(2)$ singlet soft breaking squark mass | [100 GeV, 4 TeV] |
| $A_t$ | Stop trilinear coupling | [−8 TeV, 8 TeV] |
| $A_b$ | Sbottom trilinear coupling | [−4 TeV, 4 TeV] |
| $A_\tau$ | Stau trilinear coupling | [−4 TeV, 4 TeV] |
| $\|\mu\|$ | Higgsino mass parameter | [80 GeV, 4 TeV] |
| $\|M_1\|$ | Bino mass parameter | [0 TeV, 4 TeV] |
| $\|M_2\|$ | Wino mass parameter | [70 GeV, 4 TeV] |
| $M_3$ | Gluino mass parameter | [200 GeV, 4 TeV] |
| $M_A$ | Pseudoscalar Higgs mass | [100 GeV, 4 TeV] |
| $\tan\beta$ | Ratio of vacuum expectation values | [1, 60] |

| Parameter | Minimum Value | Maximum Value |
|---|---|---|
| $\Delta\rho$ | $-0.0005$ | $0.0017$ |
| $\Delta(g-2)_\mu$ | $-17.7 \times 10^{-10}$ | $43.8 \times 10^{-10}$ |
| $\mathrm{BR}(b \to s\gamma)$ | $2.69 \times 10^{-4}$ | $3.87 \times 10^{-4}$ |
| $\mathrm{BR}(B_s \to \mu^+\mu^-)$ | $1.6 \times 10^{-9}$ | $4.2 \times 10^{-9}$ |
| $\mathrm{BR}(B^+ \to \tau^+\nu_\tau)$ | $66 \times 10^{-6}$ | $161 \times 10^{-6}$ |
| $\Omega_{\tilde{\chi}_1^0} h^2$ | – | 0.1208 |
| $\Gamma_{\text{invisible}}(Z)$ | – | 2 MeV |
| Masses of charged sparticle | 100 GeV | – |
| $m_{\tilde{\chi}_1^\pm}$ | 103 GeV | – |
| $m_h$ | 124 GeV | 128 GeV |

# pMSSM-19 and ATLAS II

- low mass SUSY models overproduce DM
- e.g. bino LSP tend to overclose universe unless it annihilates via resonances
- benchmark points are sampled such that the number of bino, higgsino and wino LSP DM is roughly the same



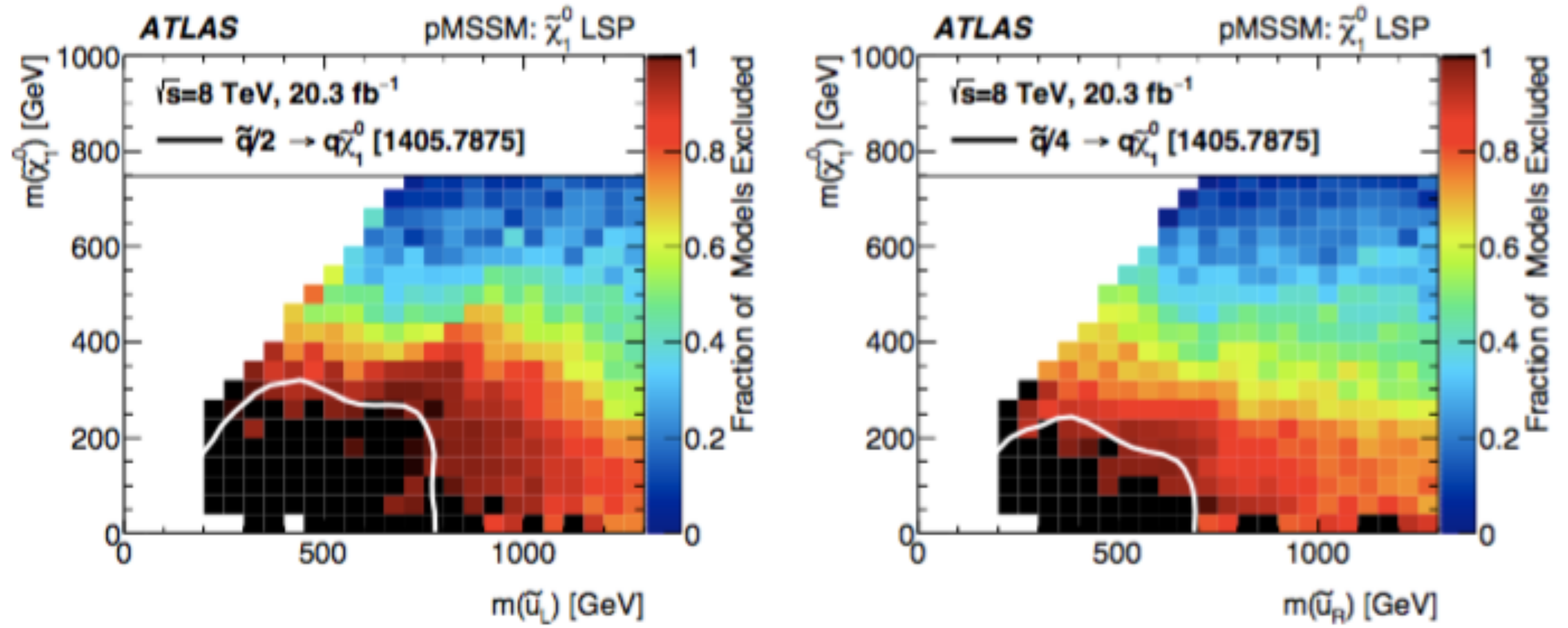



# pMSSM-19 and ATLAS III

- ATLAS considered 22 separate analyses of Run 1
- a large number of final state topologies are covered
- all relevant processes were generated at truth level
- a fast detector simulation based on GEANT4 were performed

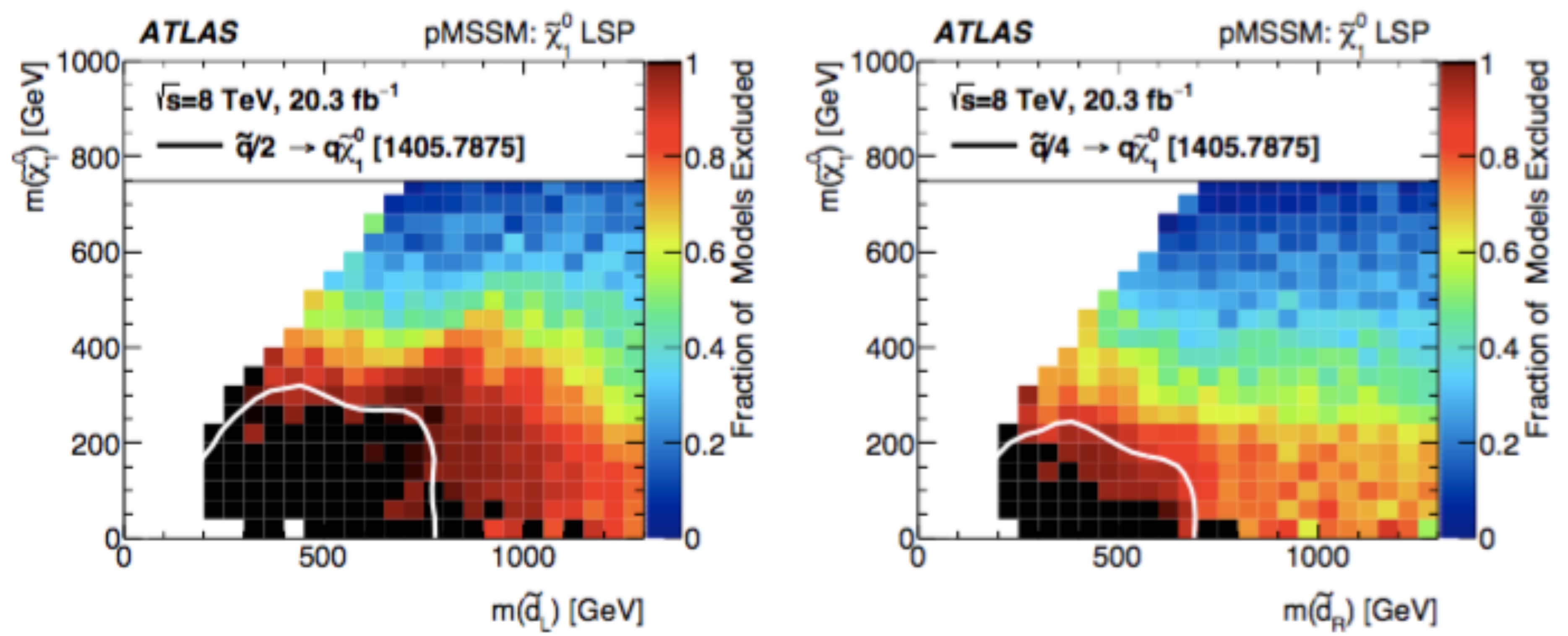
| Reference | Final State | Category |
|---|---|---|
| [39] | 0 lepton + $2-6$ jets + $\not{E}_T$ | Inclusive |
| [40] | 0 lepton + $7-10$ jets + $\not{E}_T$ | |
| [41] | 1 lepton + jets + $\not{E}_T$ | |
| [42] | $\tau(\tau/\ell)$ + jets + $\not{E}_T$ | |
| [43] | SS/3 lepton + jets + $\not{E}_T$ | |
| [44] | $b$ jets + 0/1 lepton + $\not{E}_T$ | |
| [45] | monojet | |
| [46] | 0 lepton stop search | Third generation squarks |
| [47] | 1 lepton stop search | |
| [48] | 2 lepton stop search | |
| [49] | monojet search | |
| [50] | stop search with $Z$ in final state | |
| [51] | $2b$ jet sbottom search | |
| [4] | asymmetric stop search | |
| [52] | 1 lepton plus Higgs final state | Electroweak |
| [53] | dilepton final state | |
| [54] | $2\tau$ final state | |
| [55] | trilepton final state | |
| [56] | four-lepton final state | |
| [57] | disappearing track | |
| [58, 59] | Long-lived particle search | Other |
| [60] | $H/A \to \tau\tau$ search | |

# pMSSM-19 and ATLAS IV




(a) Left up squark

(b) Right up squark



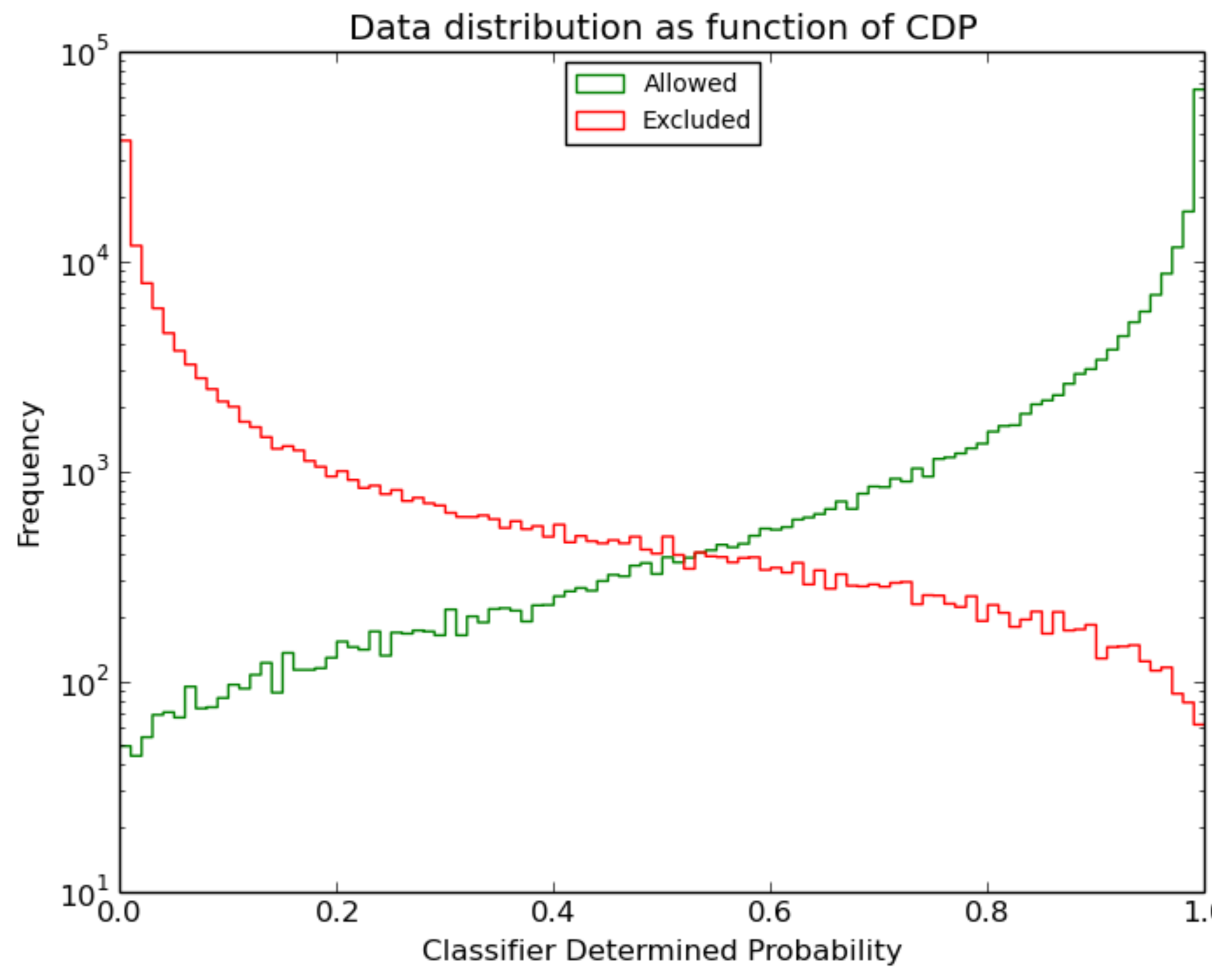
# Training

# Training of SUSY-AI I

- we used the Python package *scikit-learn-0.17.1*
- we trained our RF classifier with the ATLAS data points
- we determined the optimal classifier configuration in a grid search
- 900 DT with a maximal depth of 30 nodes and a maximum number of features considered at each node of 12

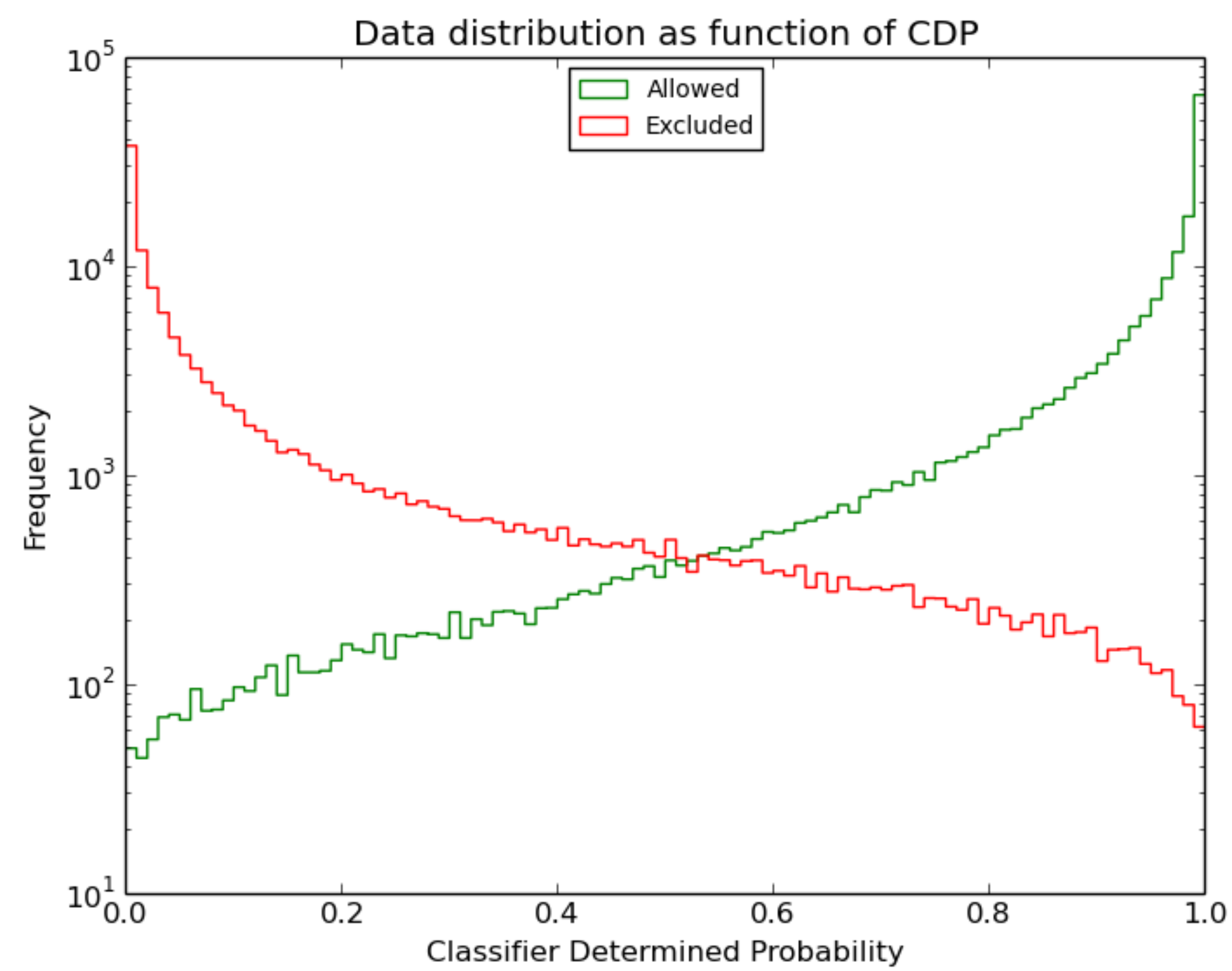
# Training of SUSY-AI II

- all predicted data points are assigned with a classification probability by the RF classifier
- the green histogram includes all points which are truly allowed
- the red histogram includes all truly excluded points
- the x-axis corresponds to the classifier determined probability (CDP)



# Training of SUSY-AI III

- CDP is the probability that the model point is allowed
- majority of points are correctly classified
- however, perfect classification is not possible
- a cut makes the classification binary, e.g. a cut at 0.5, i.e. for ≥0.5, point is allowed



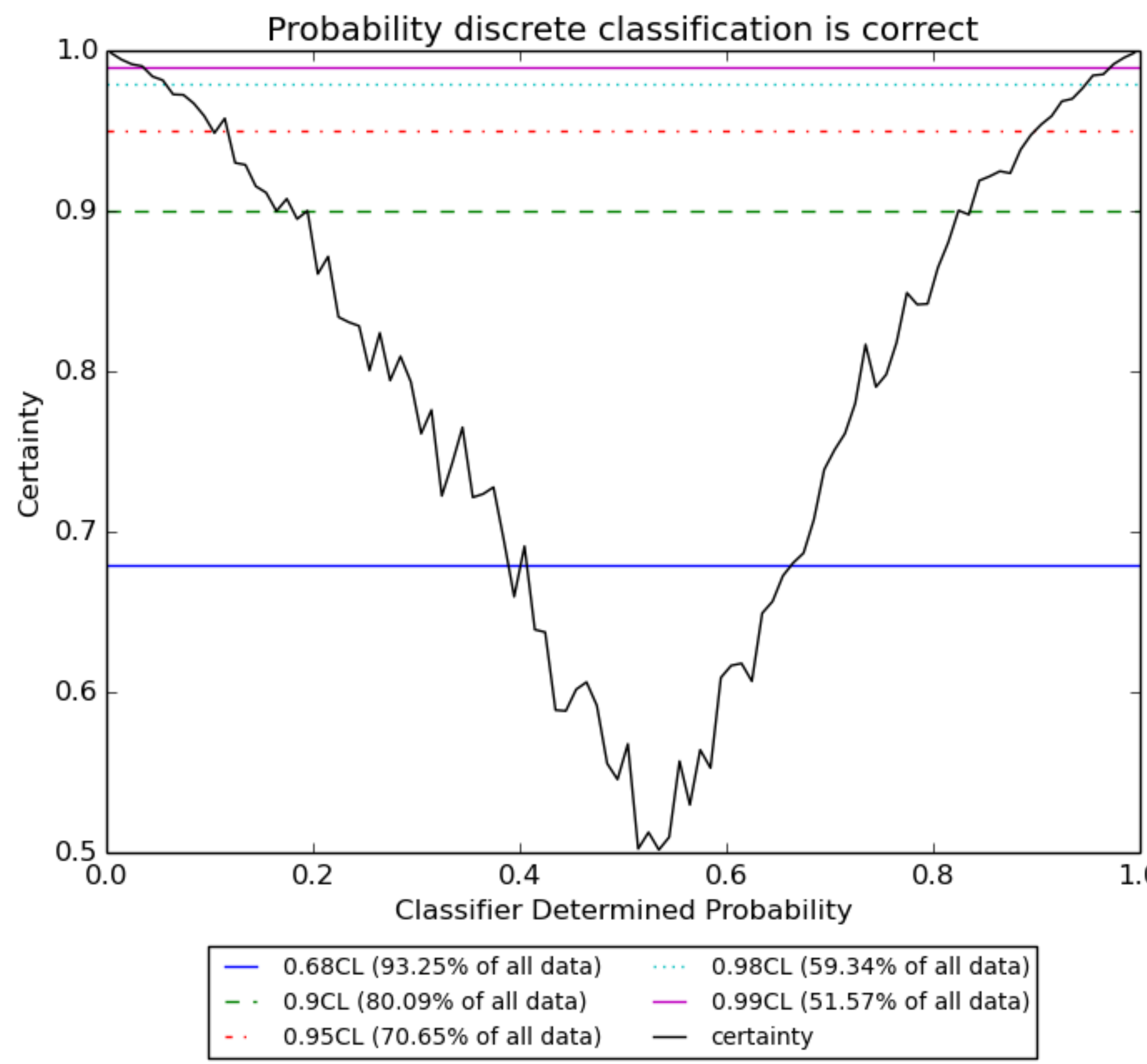
# Training of SUSY-AI IV

- take ratio of upper histogram and total number of points in each bin

- it allows a frequentist confidence level that a point with given CDP is allowed or excluded

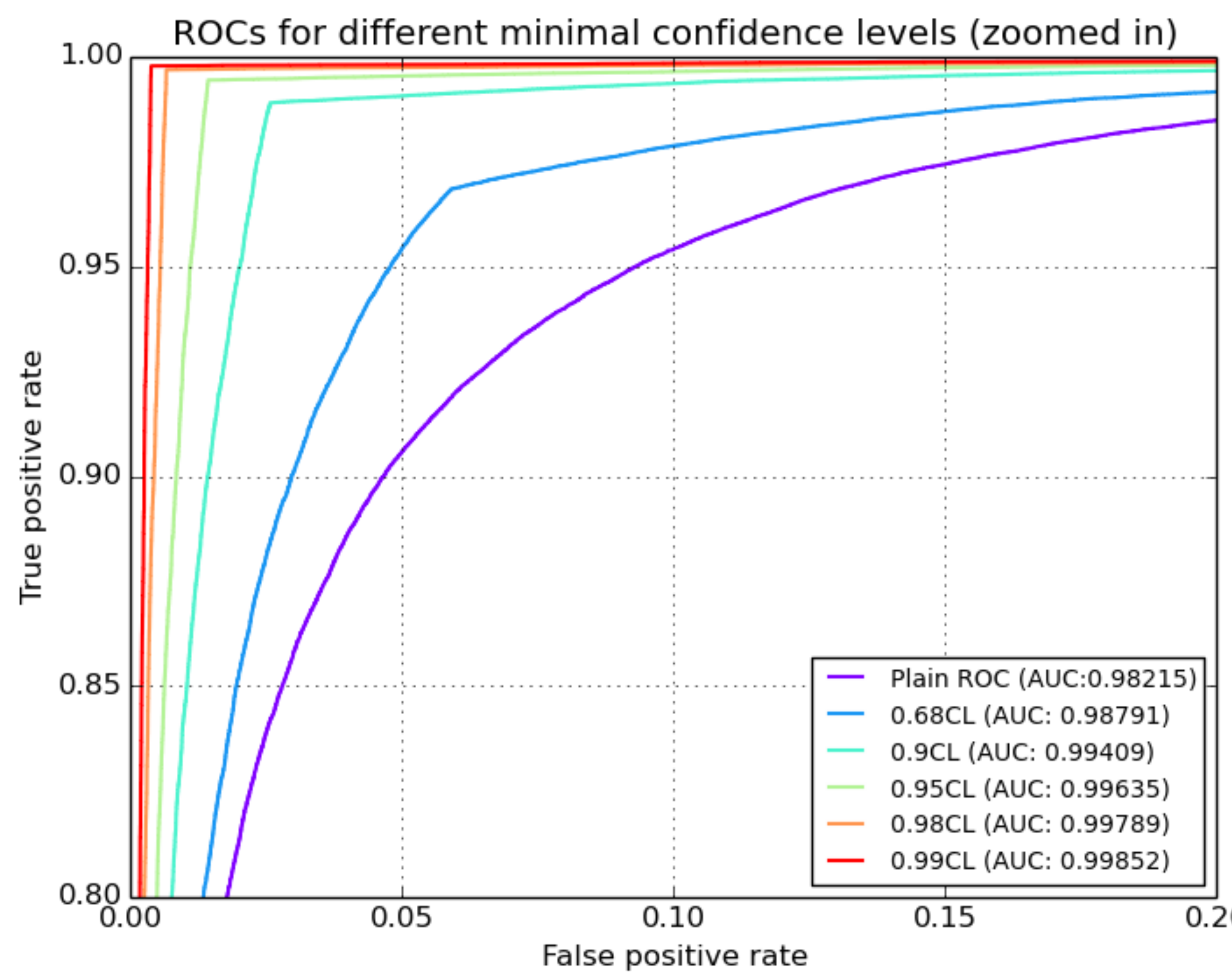
- e.g.: a CL of 98% corresponds to a CDP of below 0.05 or above 0.95

- a CL of 95% corresponds to predicted probabilities below 0.133 or above 0.9



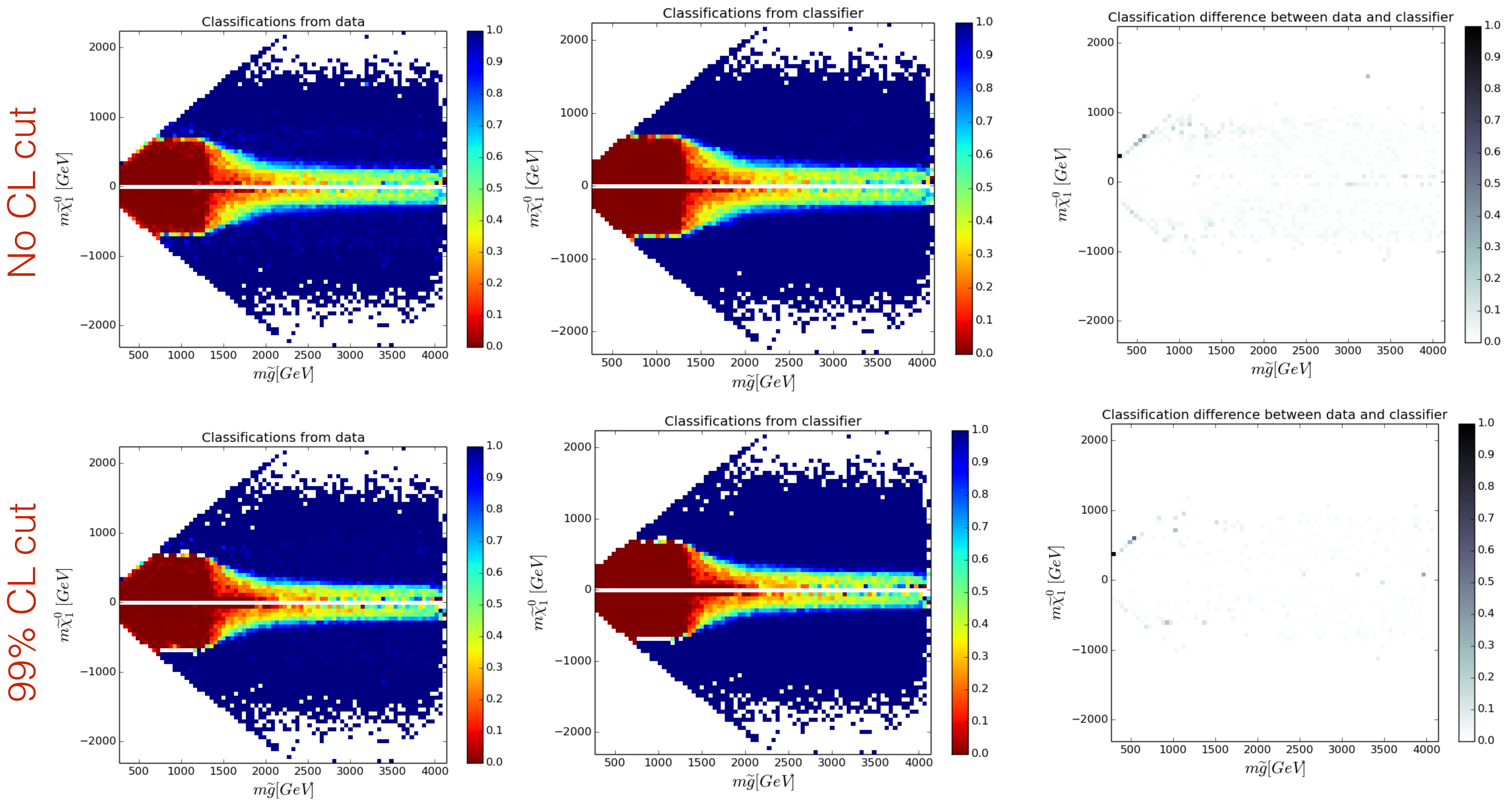
# Training of SUSY-AI V

- a "harder" cut provides more reliable results for classification but larger number of points are removed
- the performance can be quantified by the ROC curve
- higher CL cuts increases the AUC



# Performance

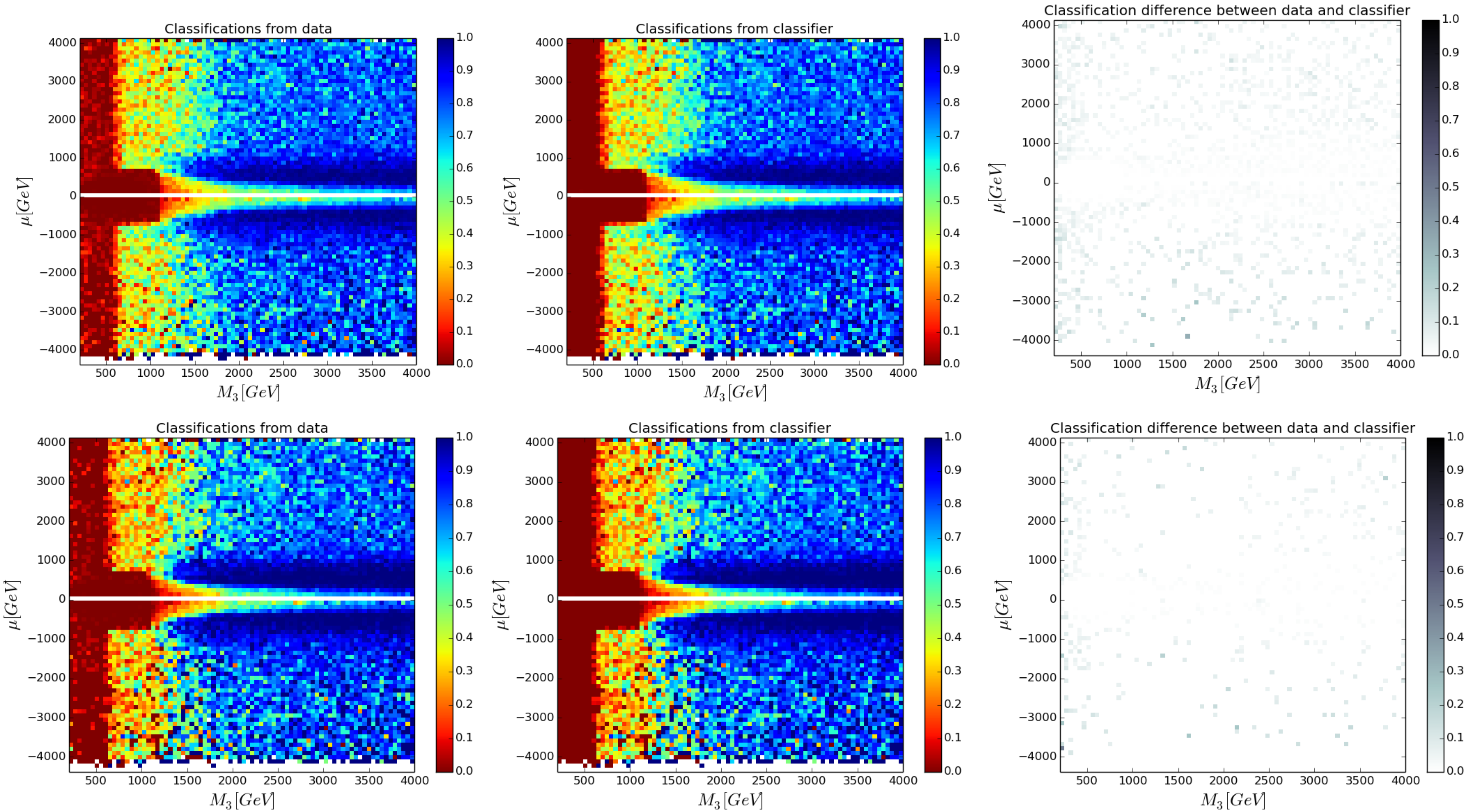
# Performance of SUSY-AI I



# Performance of SUSY-AI II

No CL cut

99% CL cut



# Applications

# natural SUSY I

- a minimal natural SUSY scenario consists of light higgsinos, SU(2) doublet third generations squarks, a SU(2) singlet stop and multi-TeV gluinos

- the scenario consists of six input soft breaking parameters

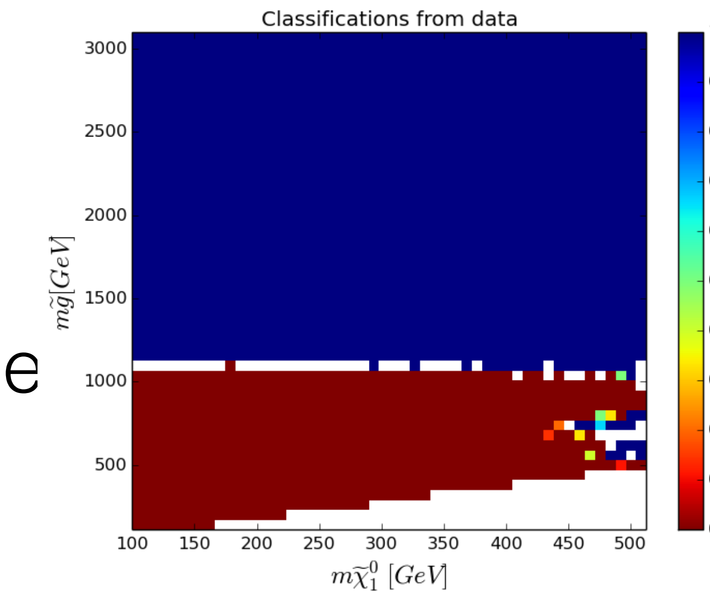
- 22000 benchmark points were generated and the produced MC events analysed with CheckMATE (arXiv: 1511.04461)

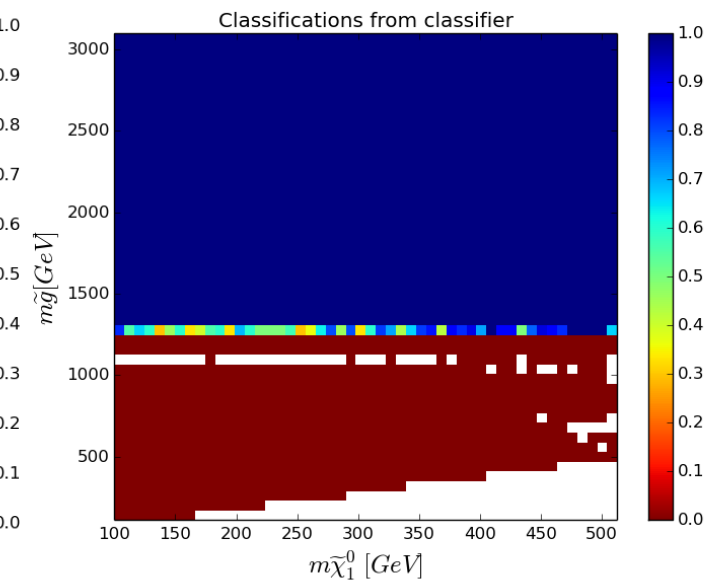
| Parameter | Description | Scanned range |
|---|---|---|
| $m_{\tilde{Q}_3}$ | 3$^{\rm rd}$ generation $SU(2)$ doublet soft breaking squark mass | [0.1 TeV, 1.5 TeV] |
| $m_{\tilde{U}_3}$ | 3$^{\rm rd}$ generation $SU(2)$ singlet soft breaking squark mass | [0.1 TeV, 1.5 TeV] |
| $M_3$ | Gluino mass parameter | [0.1 TeV, 3.0 TeV] |
| $A_t$ | Stop trilinear coupling | [−3.0 TeV, 3.0 TeV] |
| $\mu$ | Higgsino mass parameter | [0.1 TeV, 0.5 TeV] |
| $\tan\beta$ | Ratio of vacuum expectation values | [1, 20] |

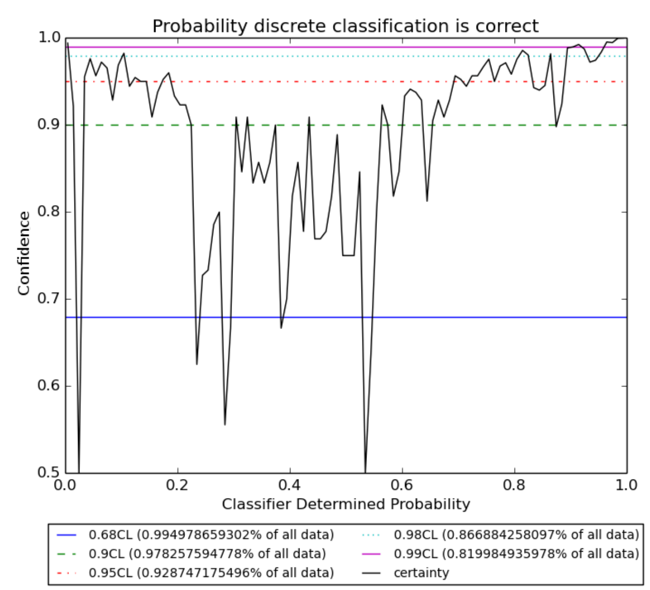
| Reference | Final State | $\mathcal{L}$ [fb$^{-1}$] | #SR |
|---|---|---|---|
| 1308.2631 (ATLAS) [51] | $0\ell+2b$ jets+$\not{E}_T$ | 20.1 | 6 |
| 1403.4853 (ATLAS) [48] | $2\ell+\not{E}_T$ | 20.3 | 12 |
| 1404.2500 (ATLAS) [43] | SS $2\ell$ or $3\ell$ | 20.3 | 5 |
| 1407.0583 (ATLAS) [47] | $1\ell+(b)$ jets+$\not{E}_T$ | 20.0 | 27 |
| 1407.0608 (ATLAS) [49] | monojet+$\not{E}_T$ | 20.3 | 3 |
| 1303.2985 (CMS) [89] | $\alpha_T+b$ jets | 11.7 | 59 |
| ATLAS-CONF-2012-104 [90] | $1\ell+\geq 4$ jets+$\not{E}_T$ | 5.8 | 2 |
| ATLAS-CONF-2013-024 [91] | $0\ell+6$ $(2b)$ jets+$\not{E}_T$ | 20.5 | 3 |
| ATLAS-CONF-2013-047 [92] | $0\ell+2$-6 jets+$\not{E}_T$ | 20.3 | 10 |
| ATLAS-CONF-2013-061 [93] | 0-$1\ell+\geq 3b$ jets+$\not{E}_T$ | 20.1 | 9 |
| ATLAS-CONF-2013-062 [94] | 1-$2\ell+3$-6 jets+$\not{E}_T$ | 20.0 | 19 |
| CMS-SUS-13-016 [95] | OS $2\ell+\geq 3b$ jets | 19.7 | 1 |

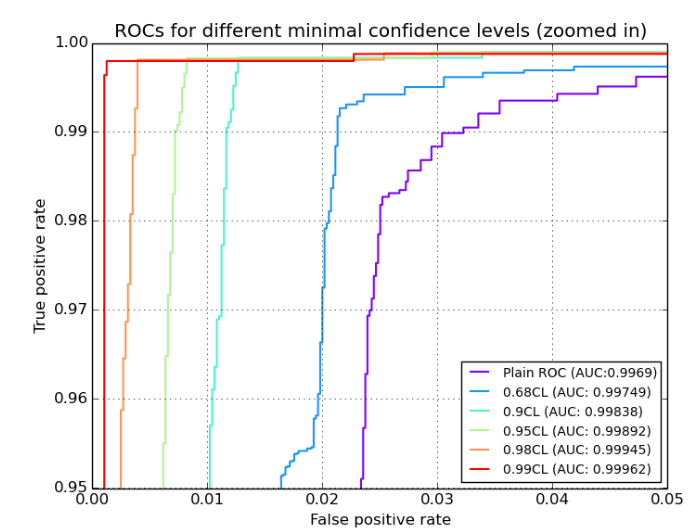
# natural SUSY II

- we tested all 22k benchmark points with SUSY-AI
- we were able to reproduce the limits
- we derived somewhat better results since the procedure with CheckMATE was conservative
- there are wrong classifications but a confidence level cut provides reliable results



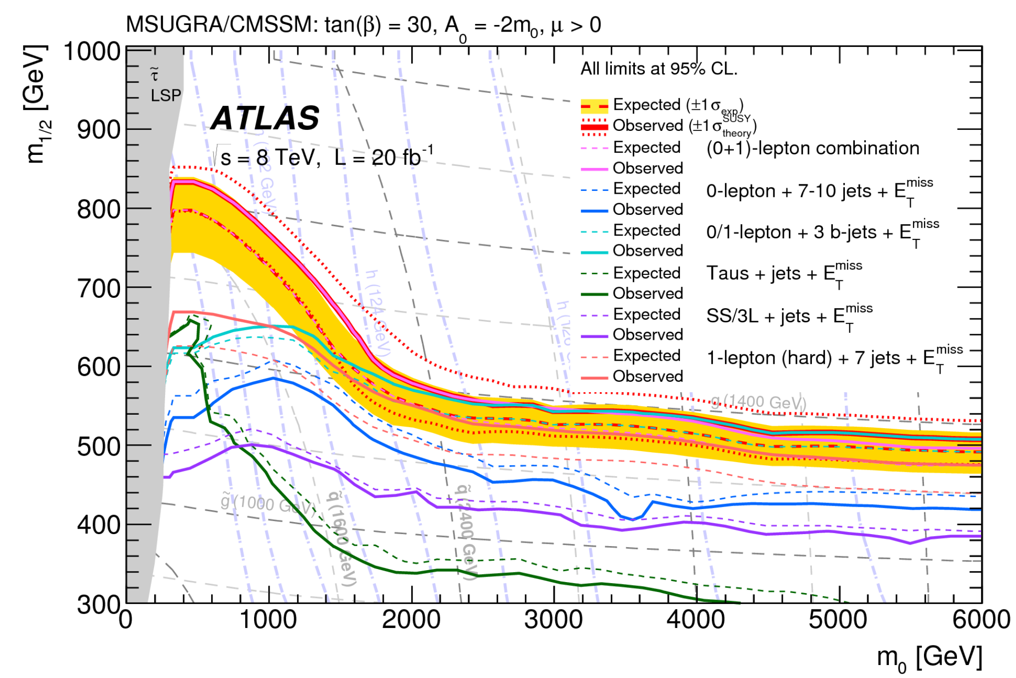



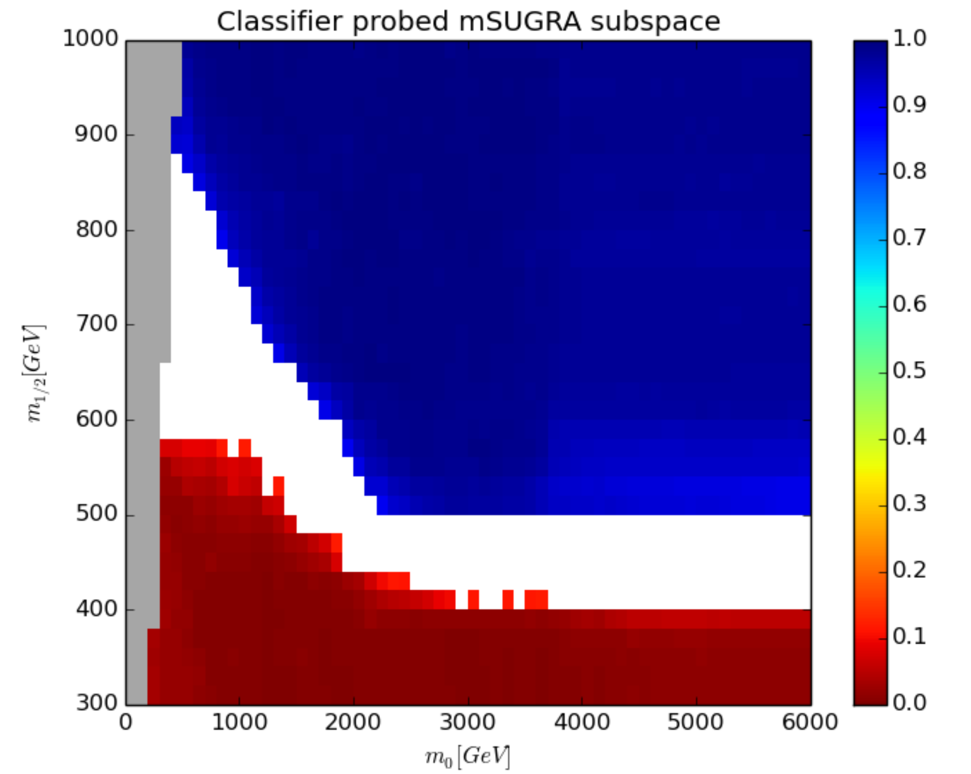



# mSUGRA

- we performed a test with the constrained SUGRA model
- it has 4 and 1/2 parameters:
- m0, m12, A0, tan β and sign μ
- we set tan β=0 and A0=2m12
- all points outside of the sampling range were relocated into the sampling region



# Limited training data I

- SUSY-AI performs very well
- however, there are a few limitations
- corner of parameter space which are not well covered, e.g. very light stops
- lack of training data turns into a lower value of C.L.
- a cut on the C.L. will remove incorrectly classified points

# Limited training data II

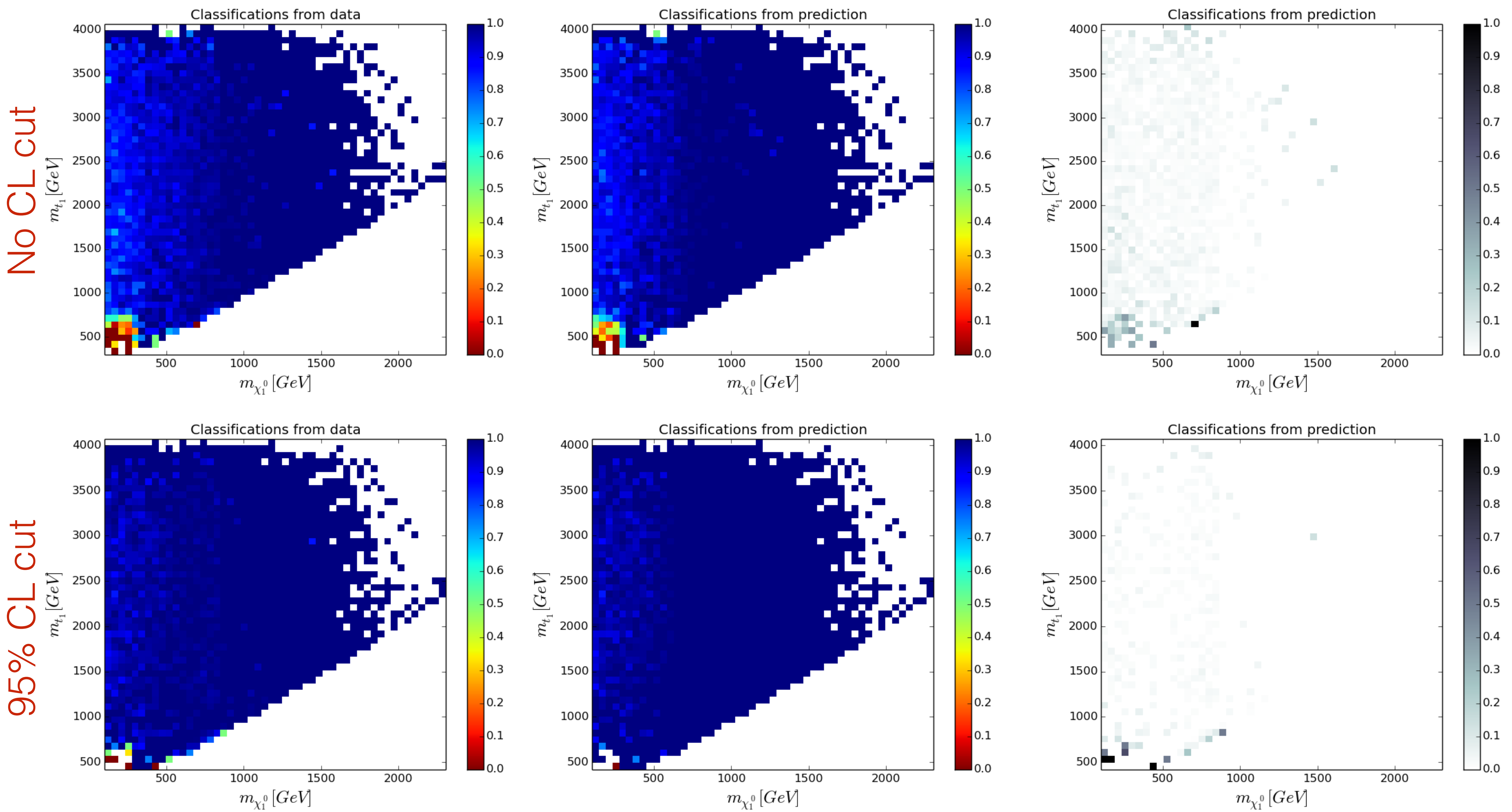
- in order to test this effect, we consider an electroweakino scenario as well as a light stop sector with all remaining sparticles decoupled

- we consider benchmark points which satisfy the cuts given in the table

| Parameter | Value |
|---|---|
| $m_{\tilde{L}_1}$ | [600 GeV, 4 TeV] |
| $m_{\tilde{E}_1}$ | [600 GeV, 4 TeV] |
| $m_{\tilde{L}_3}$ | [600 GeV, 4 TeV] |
| $m_{\tilde{E}_3}$ | [600 GeV, 4 TeV] |
| $m_{\tilde{Q}_1}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{U}_1}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{D}_1}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{Q}_3}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{U}_3}$ | [100 GeV, 4 TeV] |
| $m_{\tilde{D}_3}$ | [100 GeV, 4 TeV] |
| $A_t$ | [−8 TeV, 8 TeV] |
| $A_b$ | [−4 TeV, 4 TeV] |
| $A_\tau$ | [−4 TeV, 4 TeV] |
| $\|\mu\|$ | [80 GeV, 4 TeV] |
| $\|M_1\|$ | [600 TeV, 4 TeV] |
| $\|M_2\|$ | [600 GeV, 4 TeV] |
| $M_3$ | [1300 GeV, 4 TeV] |
| $M_A$ | [600 GeV, 4 TeV] |
| $\tan\beta$ | [1, 60] |

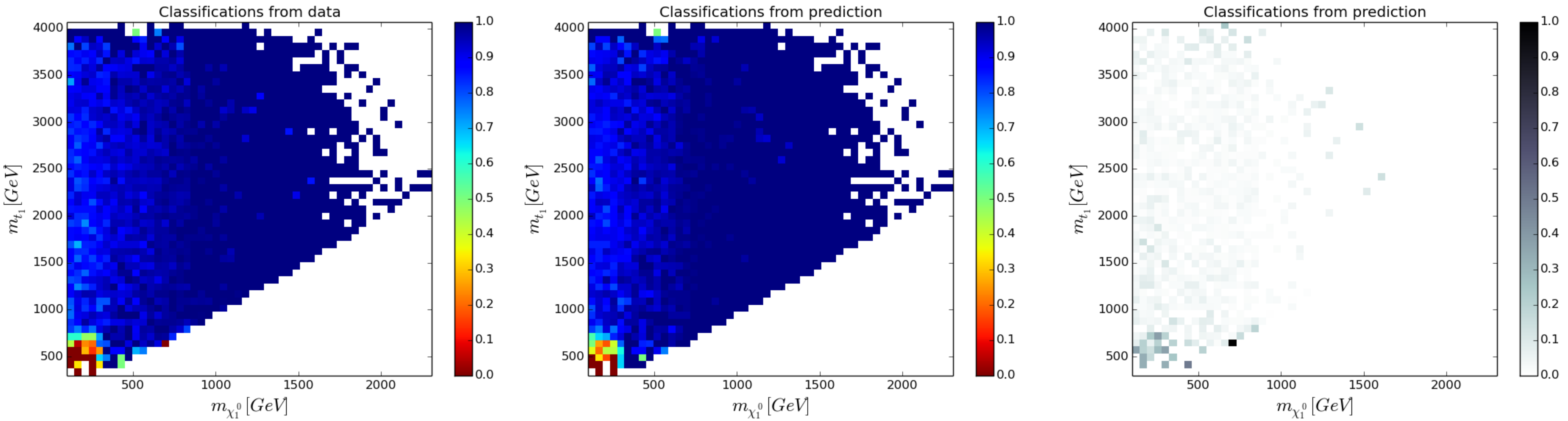
| Parameter | Value |
|---|---|
| $m_{\tilde{L}_1}$ | [700 GeV, 4 TeV] |
| $m_{\tilde{E}_1}$ | [700 GeV, 4 TeV] |
| $m_{\tilde{L}_3}$ | [700 GeV, 4 TeV] |
| $m_{\tilde{E}_3}$ | [700 GeV, 4 TeV] |
| $m_{\tilde{Q}_1}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{U}_1}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{D}_1}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{Q}_3}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{U}_3}$ | [1200 GeV, 4 TeV] |
| $m_{\tilde{D}_3}$ | [1200 GeV, 4 TeV] |
| $A_t$ | [−8 TeV, 8 TeV] |
| $A_b$ | [−4 TeV, 4 TeV] |
| $A_\tau$ | [−4 TeV, 4 TeV] |
| $\|\mu\|$ | [80 GeV, 4 TeV] |
| $\|M_1\|$ | [0 TeV, 4 TeV] |
| $\|M_2\|$ | [70 GeV, 4 TeV] |
| $M_3$ | [1300 GeV, 4 TeV] |
| $M_A$ | [700 GeV, 4 TeV] |
| $\tan\beta$ | [1, 60] |

# Limited training data III

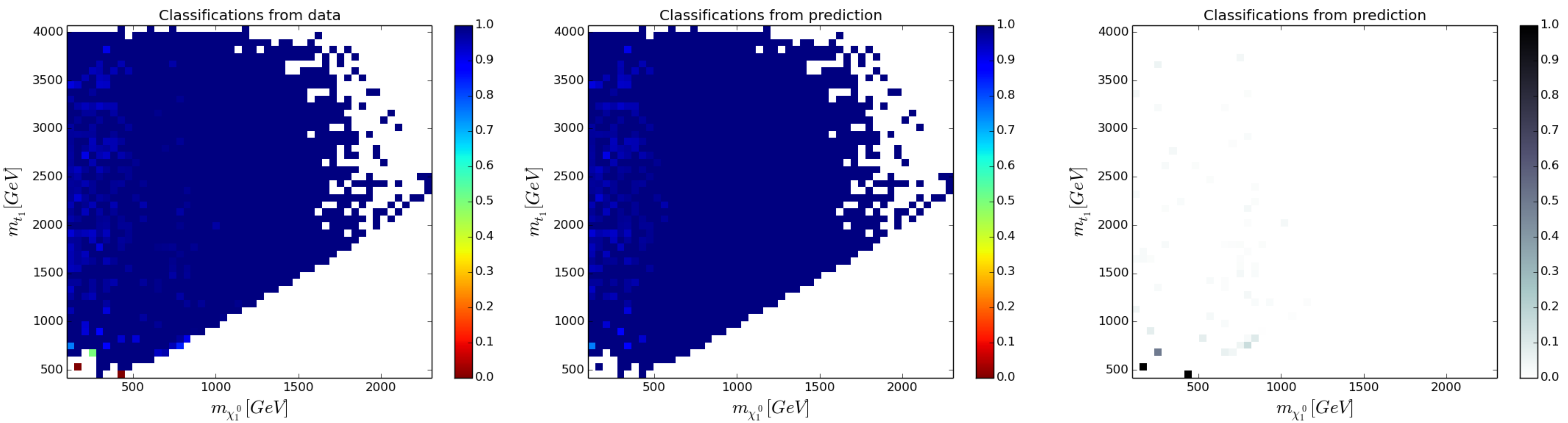


# Limited training data IV

No CL cut

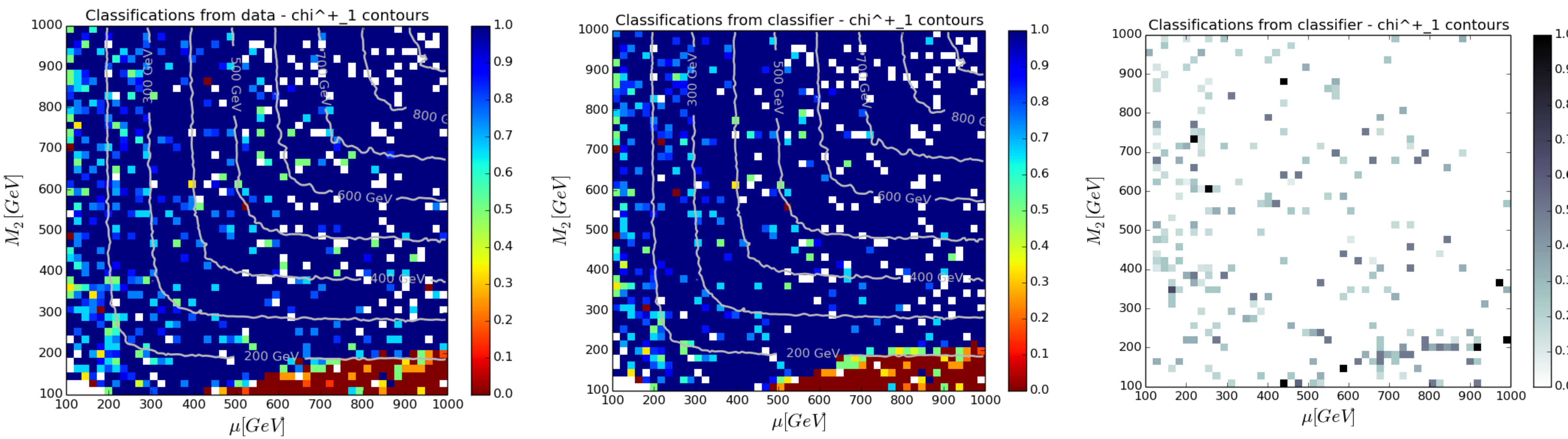



99% CL cut

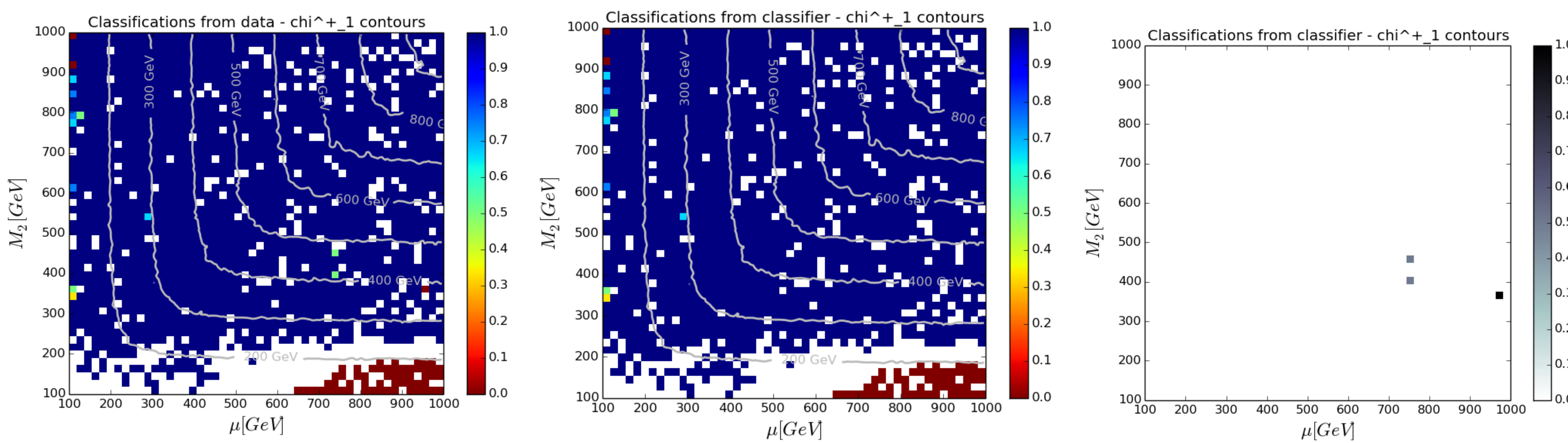


# Limited training data V

No CL cut




99% CL cut



# Classifier for corners I

- we provide two new classifier at 8 TeV which cover these two specific subsets of the pMSSM

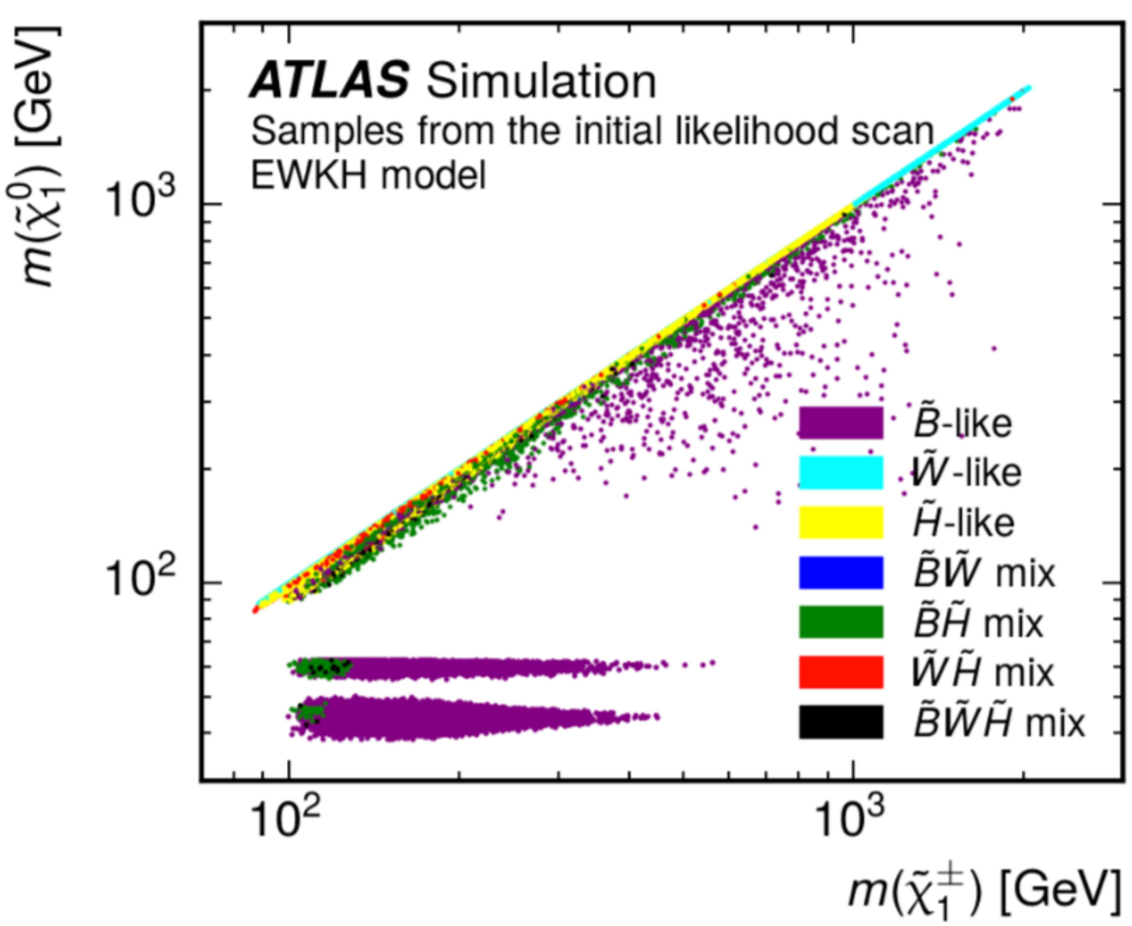
- one is based on an official ATLAS analysis of the five dimensional electroweakino sector of the pMSSM, arXiv: 1608.00872

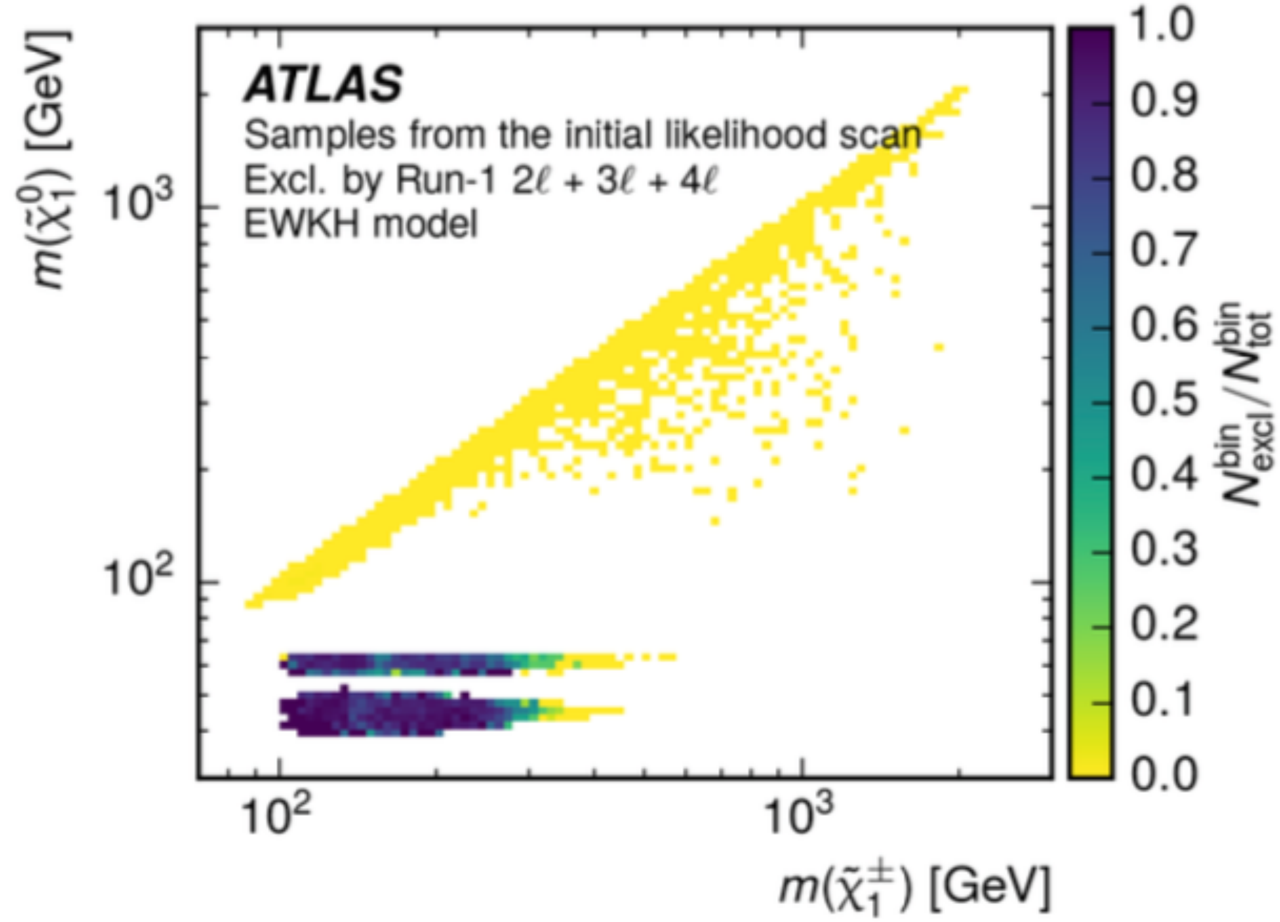
- the second classifier is based on a six dimensional natural SUSY study at 8 TeV, arXiv:1511.04461

# Classifier for corners II

- the ATLAS electroweakino study considers a five dimensional pMSSM scenario with
- M1, M2, mu, mA and tanbeta
- the parameter space is sampled with flat and with log priors for the initial likelihood scan
- 570k model points were considered
- 2 lepton, 2 tau, 3 lepton and 4 lepton study are employed

# Classifier for corners III



# 13 TeV constraints I

- Alan Barr and Jesse Liu did the first interpretation of 13 TeV SUSY searches in the pMSSM (arxiv: 1605.09502) with 3.2 inverse fb

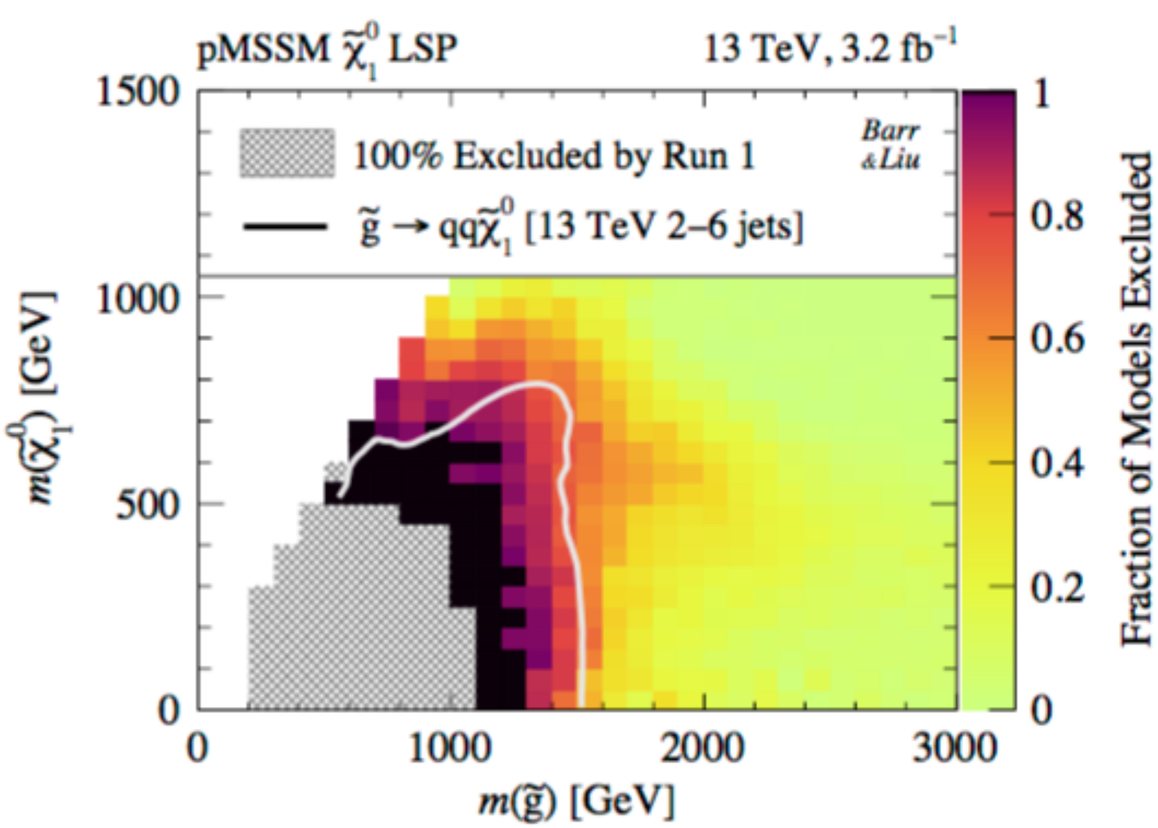
- they took the 310k ATLAS pMSSM points and tested 183k model points which survived Run 1

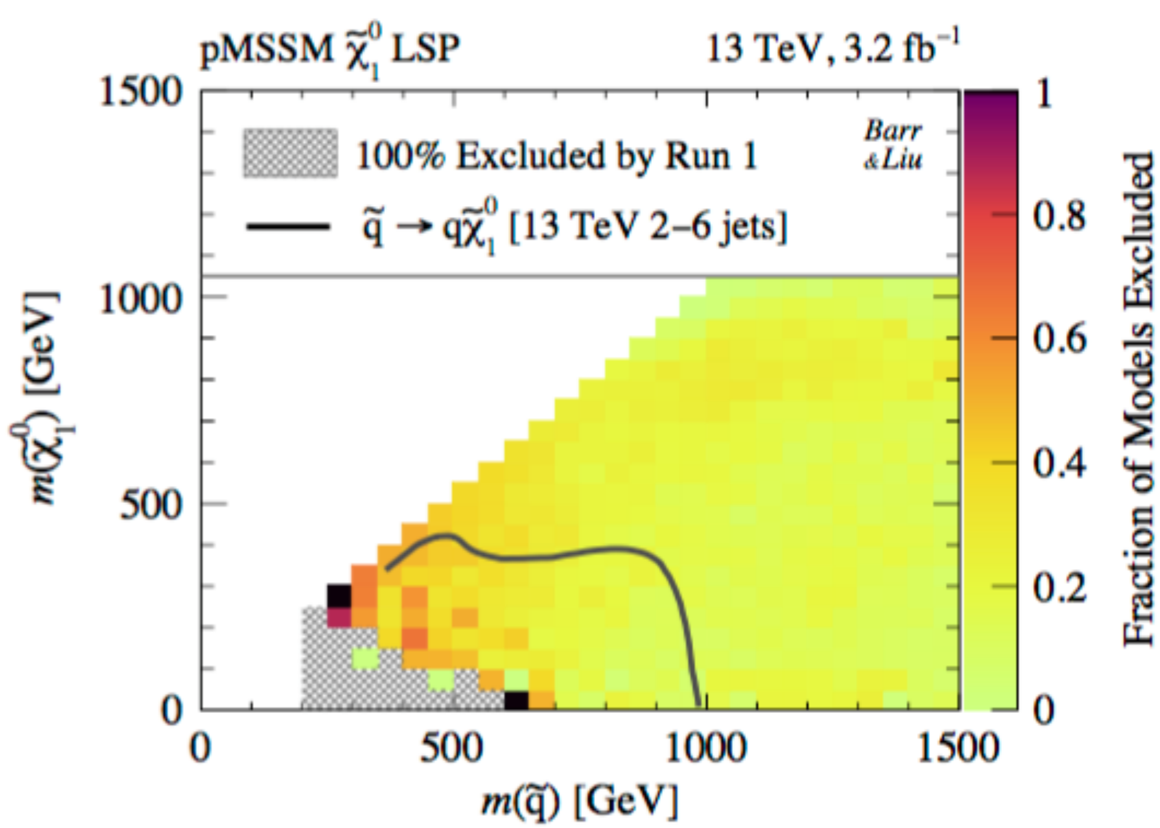
- benchmark points with long lived sparticles were not considered

- they recasted six 3.2 Run 2 searches

# 13 TeV constraints II

| Analysis | All LSPs | Bino | Wino | Higgsino |
|---|---|---|---|---|
| 2–6 jets [1] | 12.6% | 17.2% | 10.8% | 10.1% |
| 7–10 jets [2] | 0.6% | 0.5% | 0.5% | 0.7% |
| 1-lepton [3] | 1.0% | 0.8% | 1.1% | 1.1% |
| Multi-b [4] | 4.2% | 3.0% | 4.0% | 5.2% |
| SS/3L [5] | 0.5% | 0.1% | 1.6% | 0.1% |
| Monojet [6] | 1.3% | 3.3% | 0.2% | 0.2% |
| All analyses | 15.7% | 18.8% | 14.9% | 13.8% |



# 13 TeV constraints III

- Alan Barr and Jesse Liu made their detailed analysis public under http://www-pnp.physics.ox.ac.uk/~jesseliu/pmssm/
- we used this information to update our classifier with results at 13 TeV with 3.2 inverse fb

# The Tool

# The Tool I

```
from susyai import susyai
import numpy as np

sa = susyai("susyai_classifier_python_v3.pkl")
data = np.array([[30, 4.0276e2, 7.3196e2, 2.1862e3, 1.0,
          4.0713e3, 4.4890e3, 4.4752e3, 4.4743e3, 2.8806e3,
          3.7855e3, 1.3240e3, 2.9076e3, 4.2226e3, 4.2056e3,
          3.4290e3, 3.8608e3, -4.3154e3, -8.1538e3, -7.3680e3]])
clas, pred, cert = sa.predict(data)
```

```
from susyai import susyai
import numpy as np

sa = susyai("susyai_classifier_python_v3.pkl")
sa.set_coordinate_selector(1)

files = ['spectrum.slha']
clas, pred, cert, coords = sa.predict_files(files)
```

# The Tool II

```
from susyai import susyai
import numpy as np

sa = susyai("susyai_classifier_python_v3.pkl")
sa.set_coordinate_selector(1)
sa.set_id_selector('filename')

files = ['spectrum1.slha', 'spectrum2.slha']
clas, pred, cert, coords, ids = sa.predict_files(files)
```

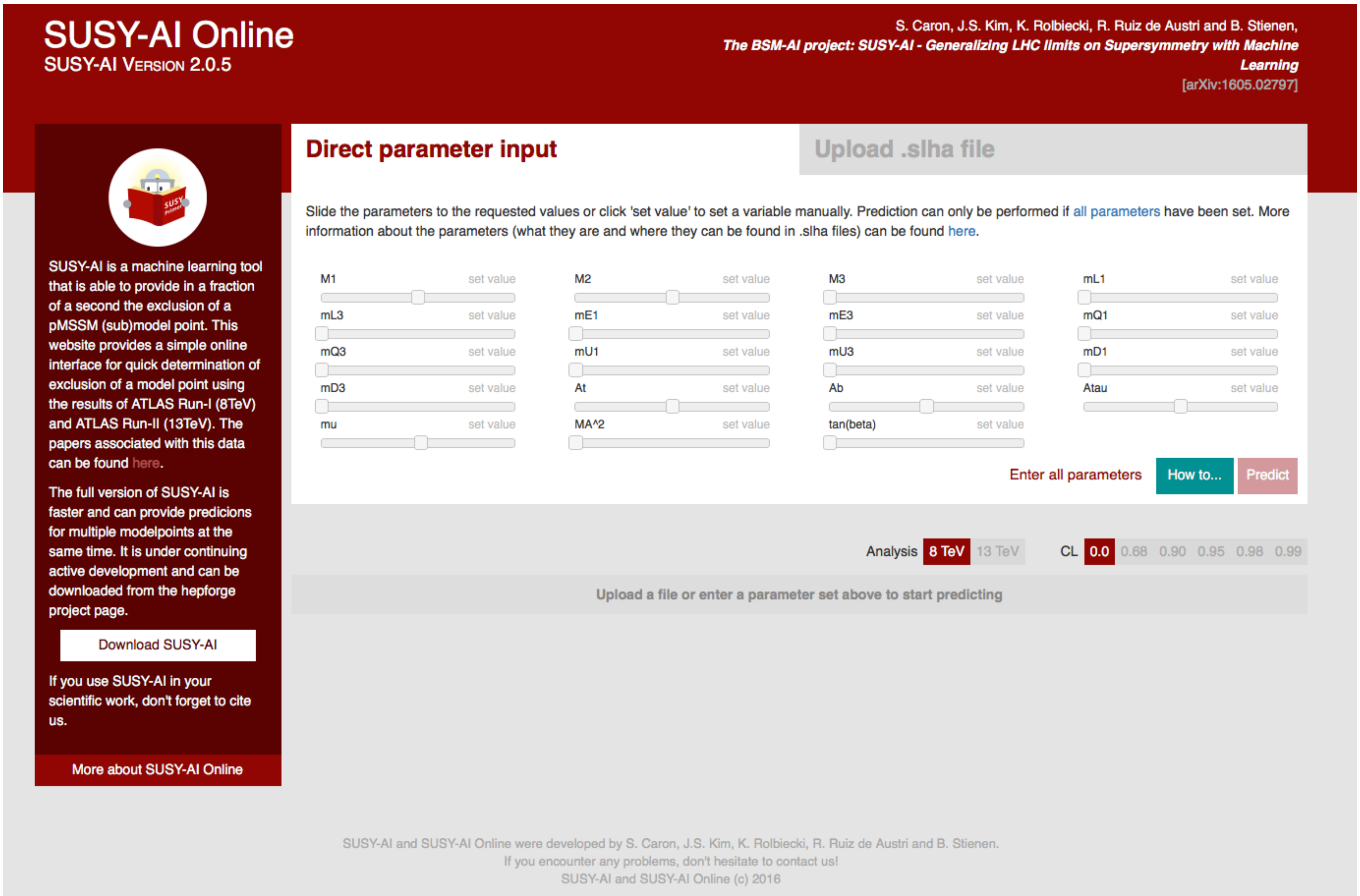
```
from susyai import susyai
import numpy as np

def xsel(spectrum, filepath):
    x = np.zeros(3)
    x[0] = spectrum.blocks['MASS'][1000002]
    x[1] = spectrum.blocks['MASS'][1000021]
    x[2] = spectrum.blocks['MASS'][1000022]
    return x

sa = susyai("susyai_classifier_python_v3.pkl")
sa.set_coordinate_selector(1)
sa.set_xtra_selector(xsel)
sa.set_id_selector('filename')

files = ['spectrum_01.slha', 'spectrum_02.slha']
clas, pred, cert, coords, xtras, ids = sa.predict_files(files)
```

# Online presence



# Outlook

# BSM-AI and SUSY-AI

- we will provide classifiers for the MSSM and the NMSSM updated with 13 TeV data based on a larger training set
- we want to perform the difficult task of predicting the efficiencies/likelihoods (interesting for people performing a global fit)
- we want to include non collider constraints
- we work on providing classifiers for non-SUSY models
- ultimate goal is to consider a generic model independent approach

# Conclusion

- we trained a RF classifier on over 310,000 data points of the pMSSM-19
- we used the results from the ATLAS (arXiv:1508.06608) pMSSM study
- we obtain the correct classification with an accuracy of at least 93.8%
- we will continuously update SUSY-AI with future LHC results
- we want to provide classifiers for other BSM

http://susyai.hepforge.org

http://amia.nikhef.nl