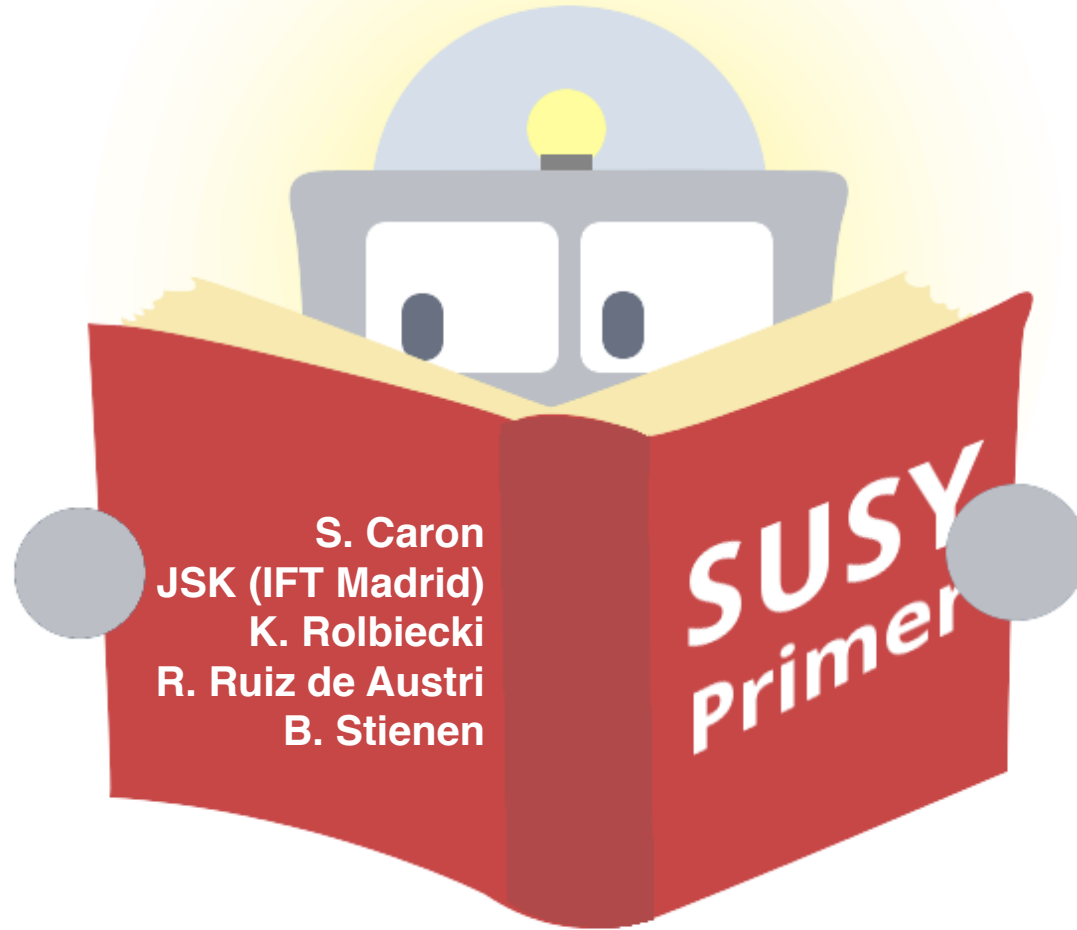


The BSM-AI Project: SUSY-AI



Fit(s) for LHC run-2

Edinburgh, 10.-12. October 2016

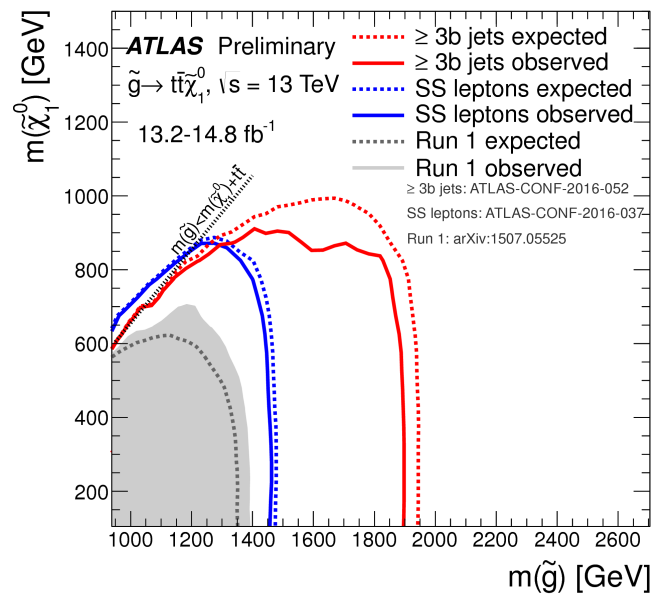
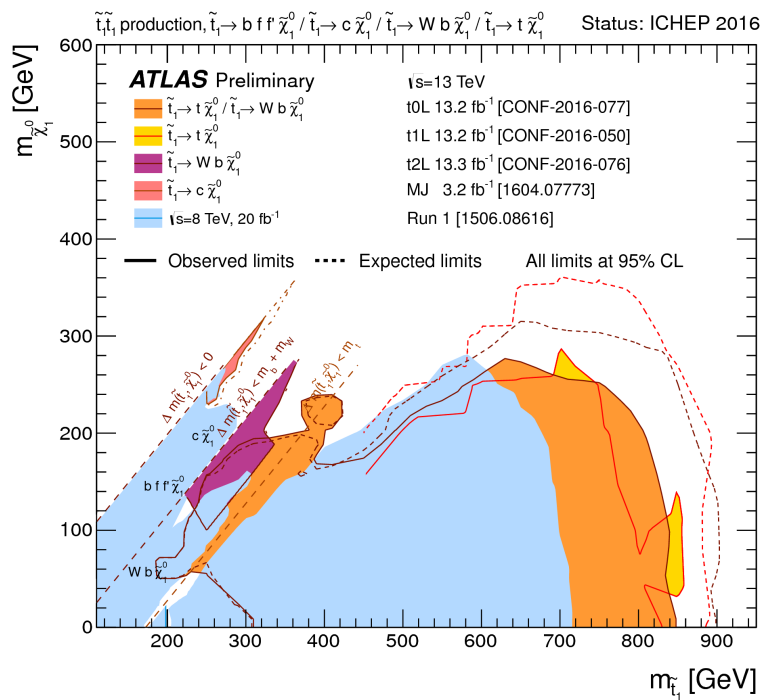
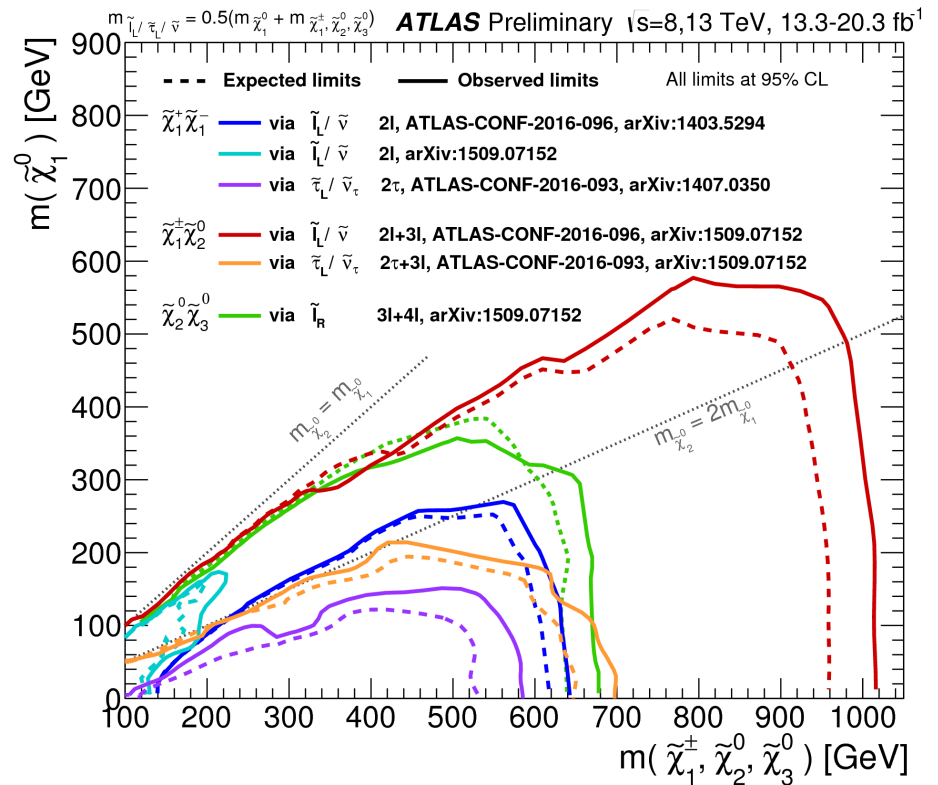
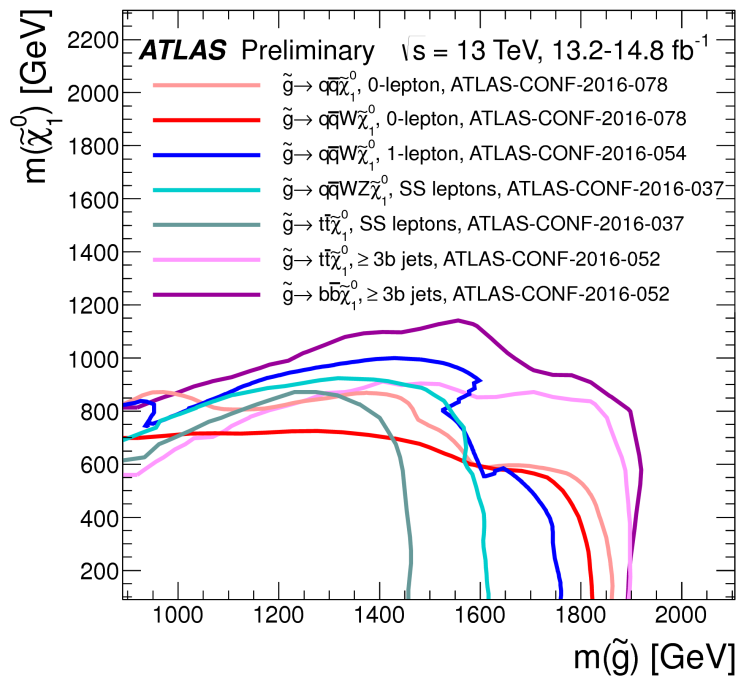
Motivation

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

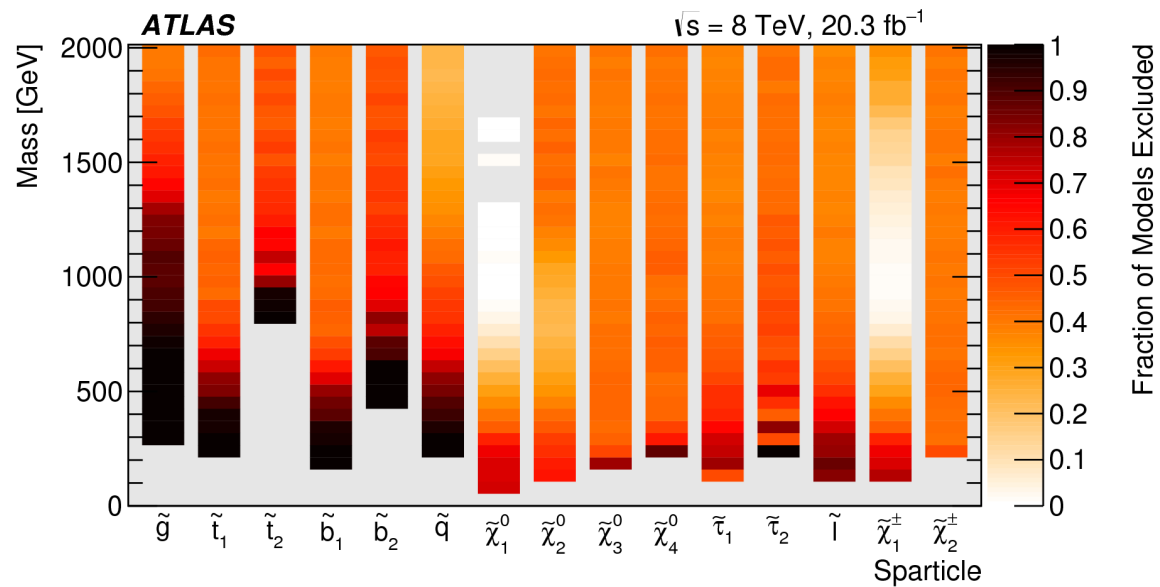
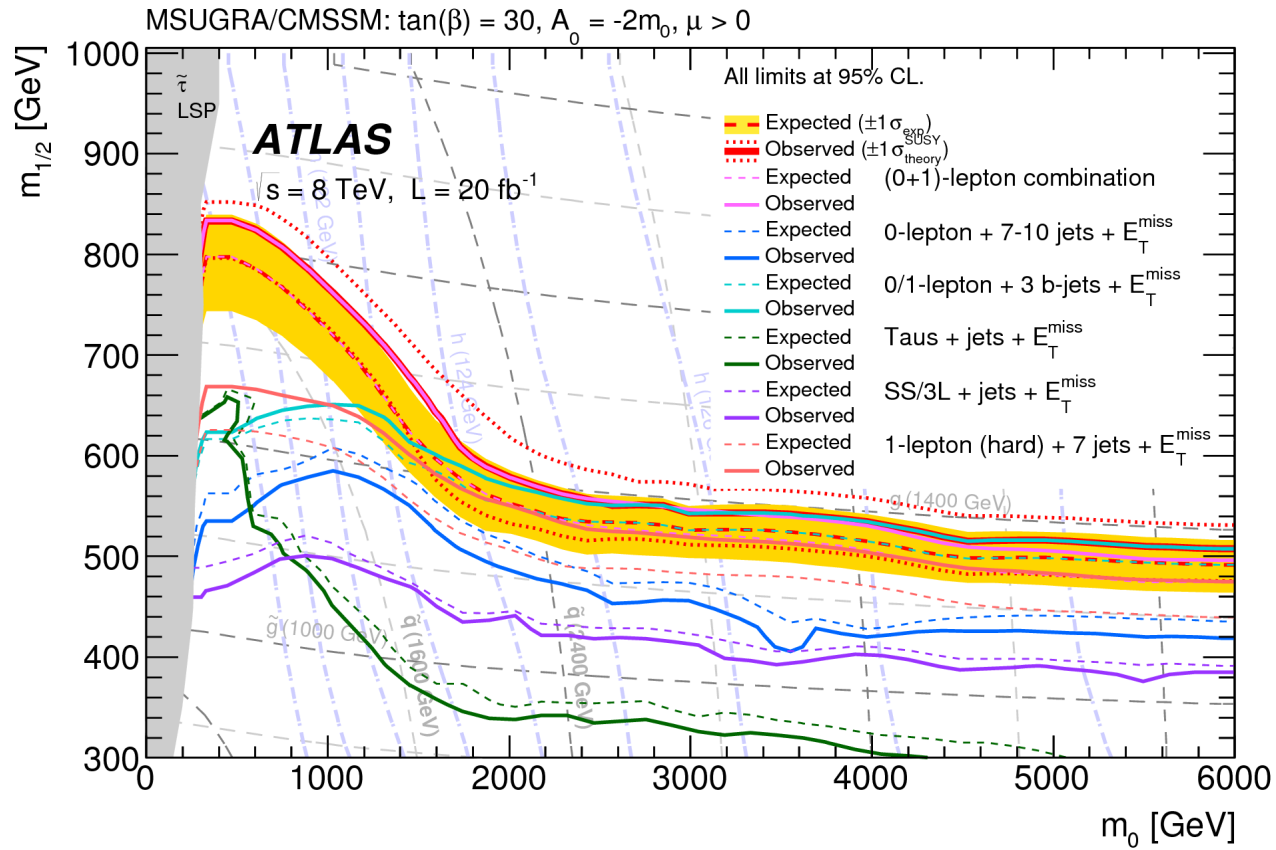
Constraining BSM

- 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!



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



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 to 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)



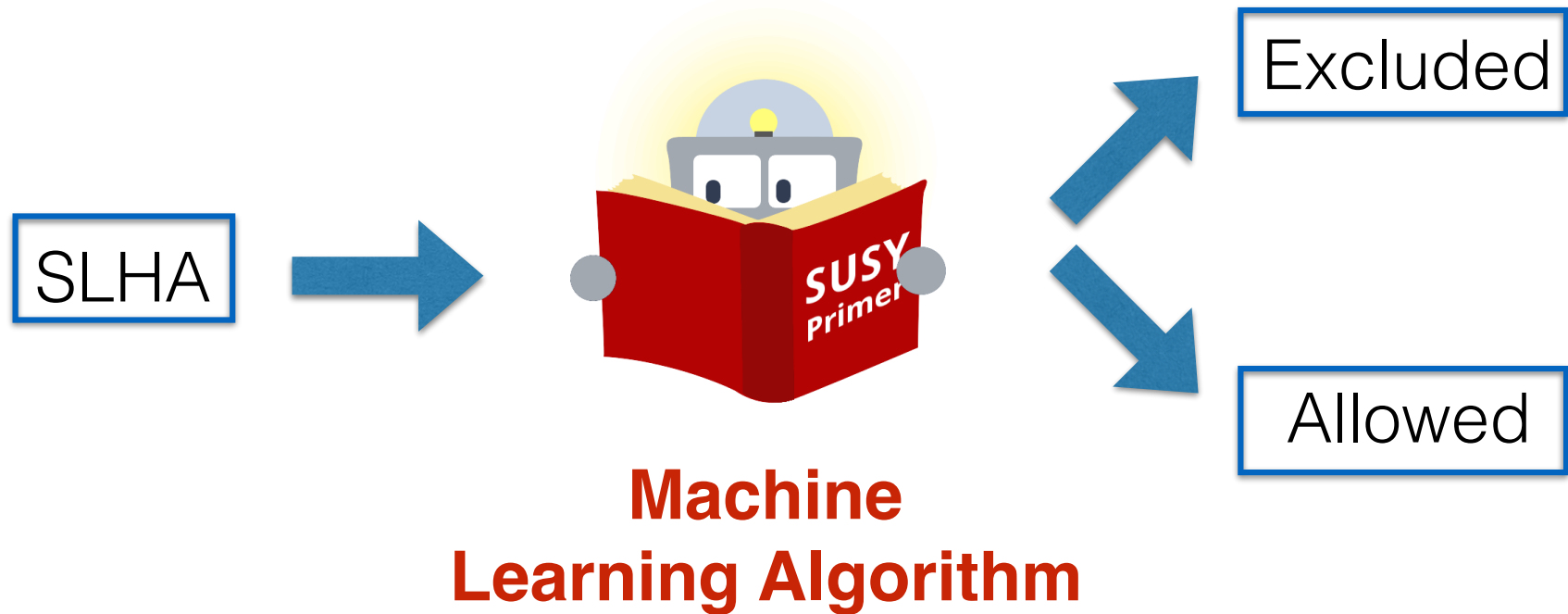
number of parameters

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

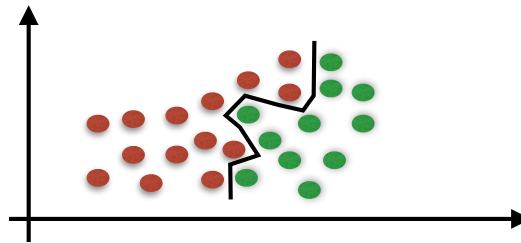
What is Machine Learning?

Machine Learning I

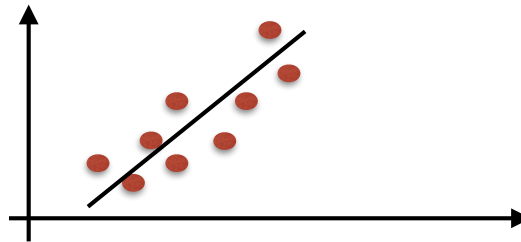
- a ML algorithm can improve its performance using training data
- the algorithm has a large number of fit parameters which can be determined by data
- ML is applied in situations which are very challenging, e.g. face or handwriting recognition

Machine Learning II

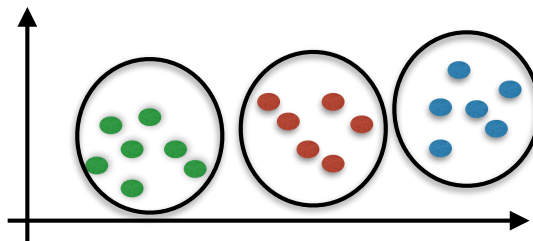
Classification - supervised



Regression - supervised



Unsupervised learning

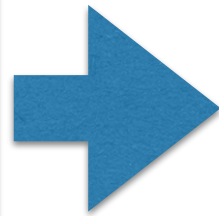


Example

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

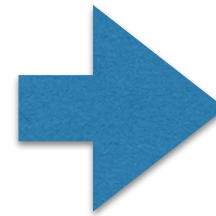
labeled (y)
training
data with
attributes x

(x,y)



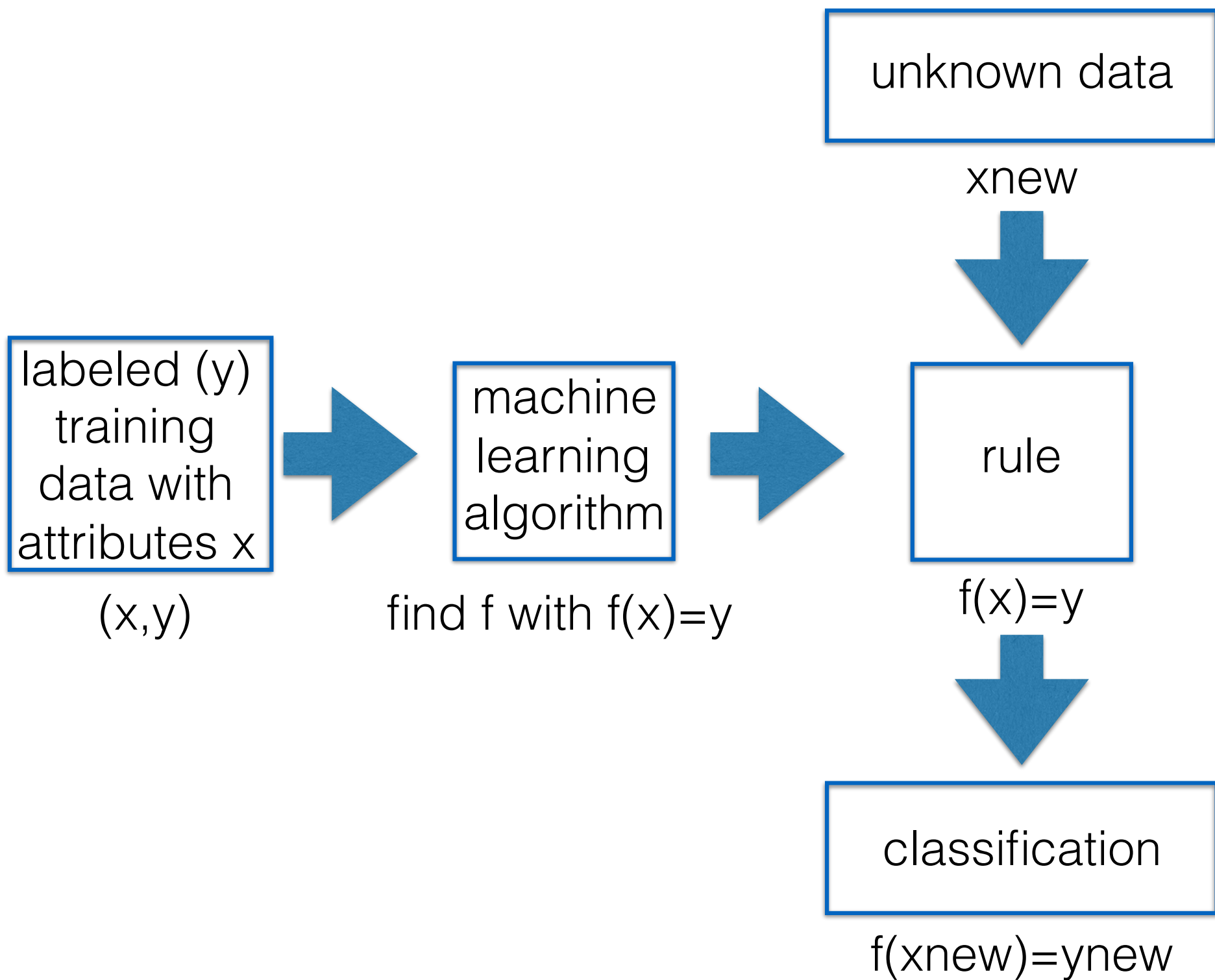
machine
learning
algorithm

find f with $f(x)=y$



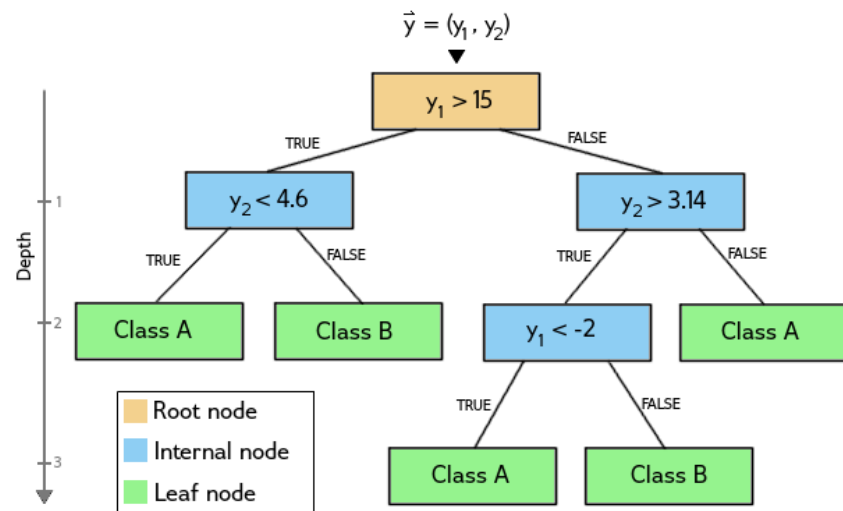
rule

$f(x)=y$



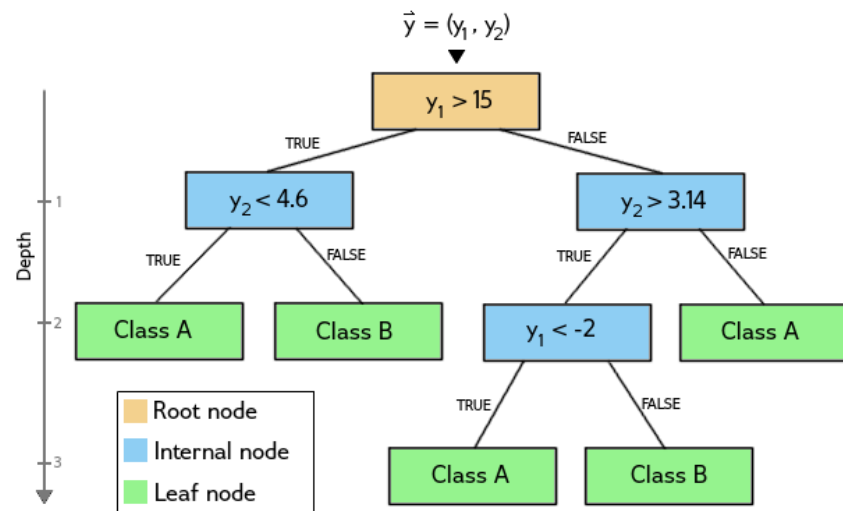
Decision Trees I

- 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



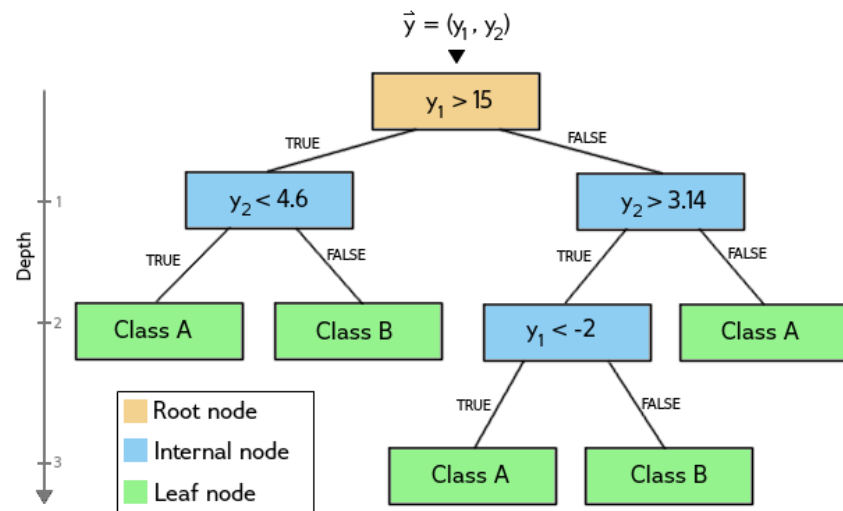
Decision Trees II

- 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

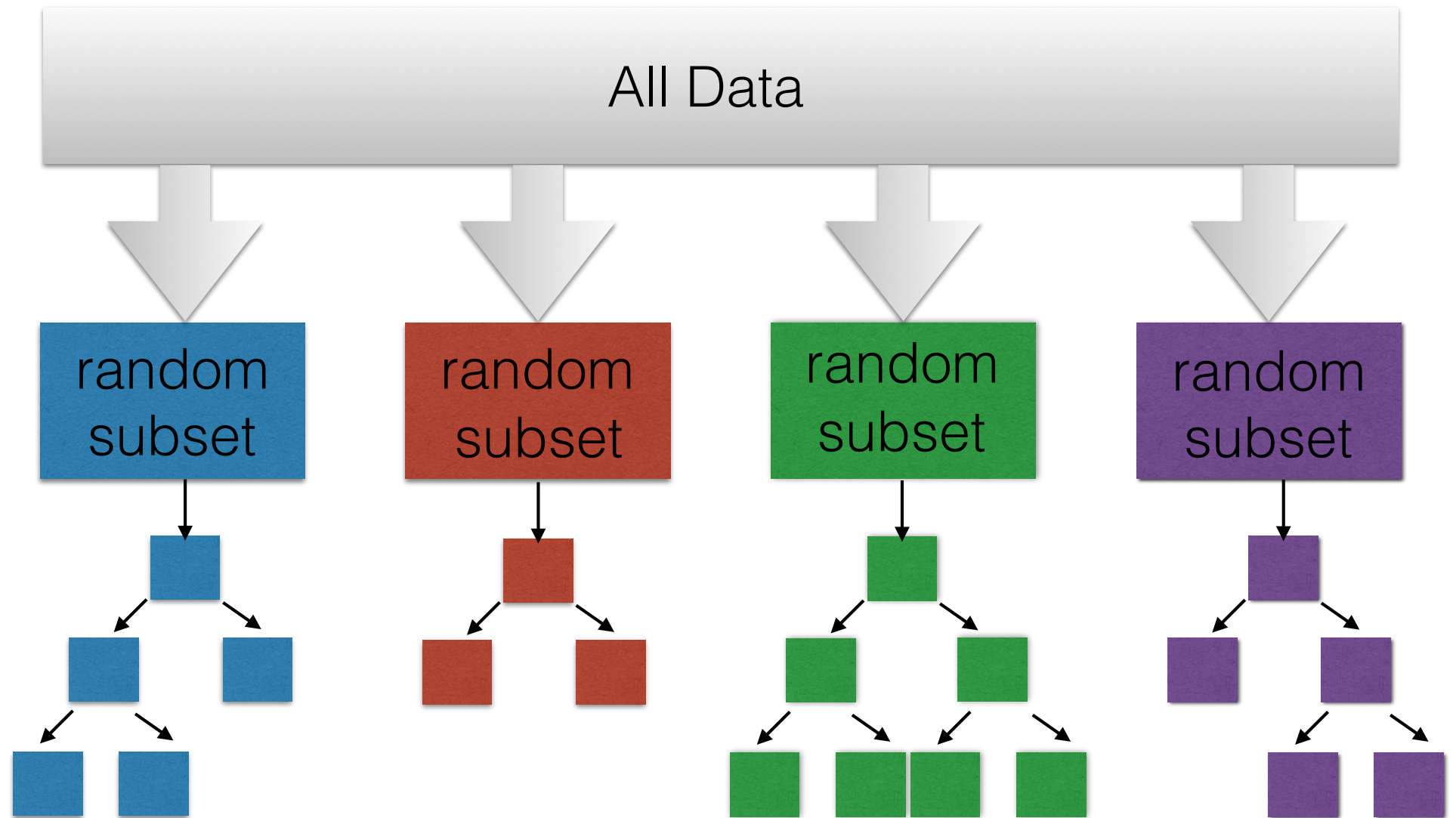
- methods to suppress overtraining
- pruning: training the entire tree but cut away all nodes beyond a certain depth
- boosting: combine multiple DTs into a single classifier
- bagging: for a group of DTs, each decision tree is trained on a random selection of a subset of the attribute set



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
- $R = (\text{\# trees prediction of class } C) / (\text{total number of trees})$
- $R = \text{probability of attribute set belonging to } C$
- 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, $O(100)$ 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

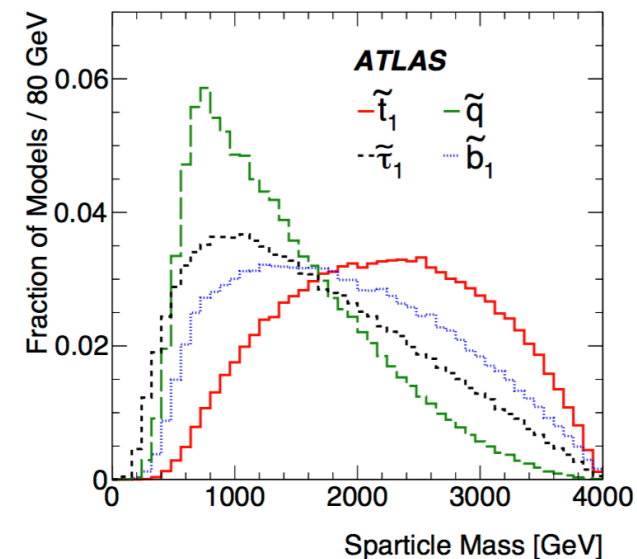
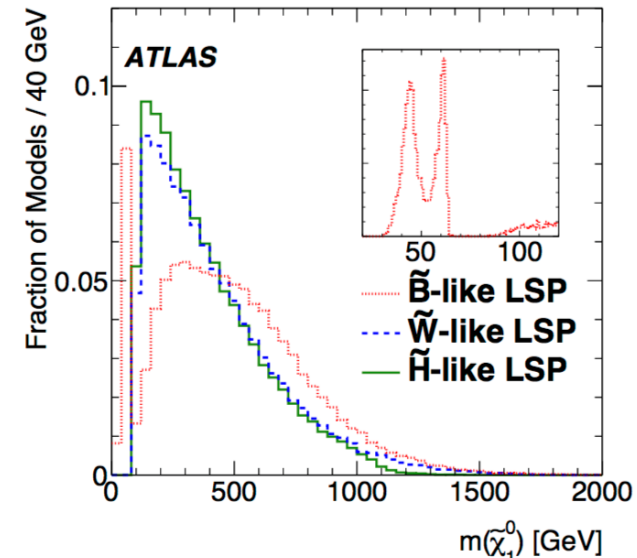
- ATLAS (arXiv:1508.06608) performed a study on the pMSSM-19
- ATLAS considered 5×10^8 model points based on arXiv:1206.4321
- all model points had to satisfy preselection cuts
- 310,327 model points satisfy all theoretical and experimental constraints

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_τ	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
$\Delta(g-2)_\mu$	-17.7×10^{-10}	43.8×10^{-10}
$\text{BR}(b \rightarrow s\gamma)$	2.69×10^{-4}	3.87×10^{-4}
$\text{BR}(B_s \rightarrow \mu^+\mu^-)$	1.6×10^{-9}	4.2×10^{-9}
$\text{BR}(B^+ \rightarrow \tau^+\nu_\tau)$	66×10^{-6}	161×10^{-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

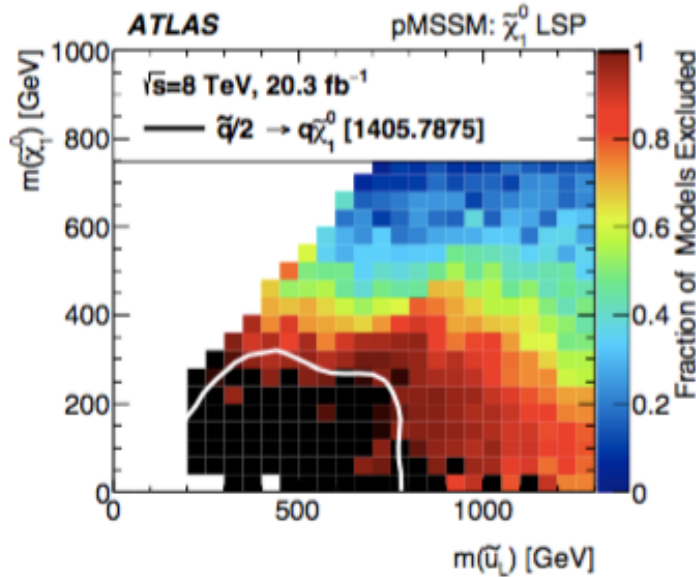


pMSSM-19 and ATLAS III

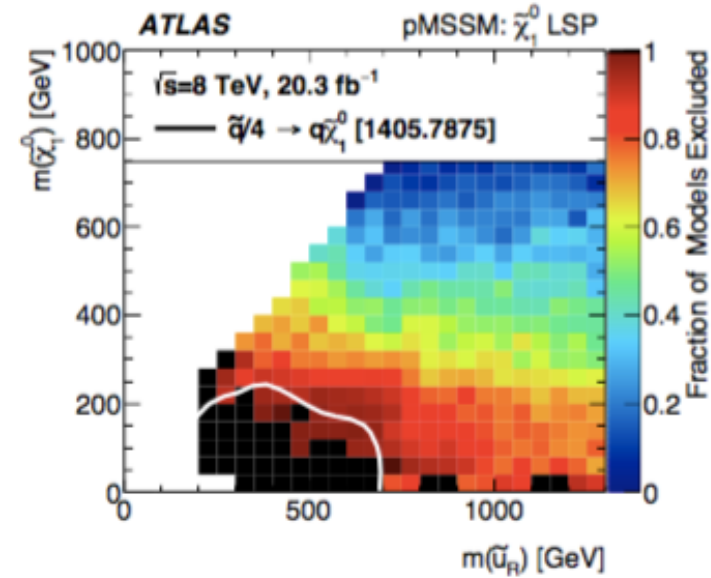
- ATLAS considered 22 separate analyses of Run 1
- a large number of final state topologies are covered
- all relevant processes were generated at truth level
- a fast detector simulation based on GEANT4 were performed

Reference	Final State	Category
[39]	0 lepton + 2 – 6 jets + \cancel{E}_T	Inclusive
[40]	0 lepton + 7 – 10 jets + \cancel{E}_T	
[41]	1 lepton + jets + \cancel{E}_T	
[42]	$\tau(\tau/\ell)$ + jets + \cancel{E}_T	
[43]	SS/3 lepton + jets + \cancel{E}_T	
[44]	b jets + 0/1 lepton + \cancel{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]	2τ final state	
[55]	trilepton final state	
[56]	four-lepton final state	
[57]	disappearing track	
[58, 59]	Long-lived particle search	Other
[60]	$H/A \rightarrow \tau\tau$ search	

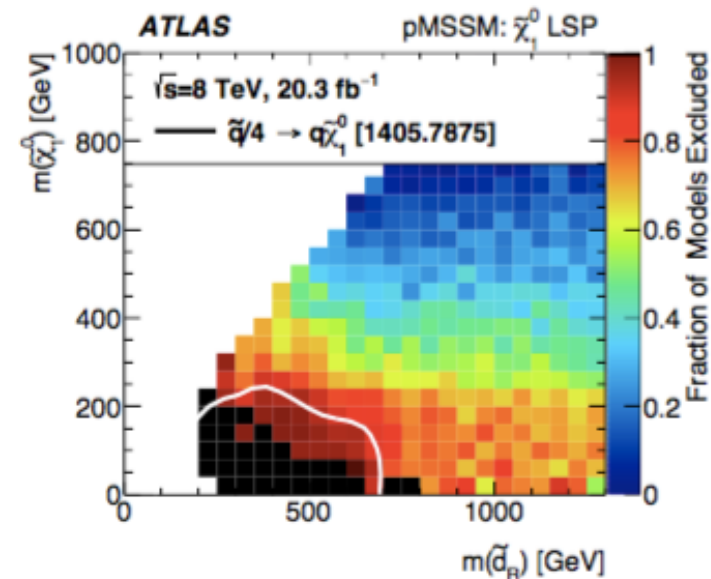
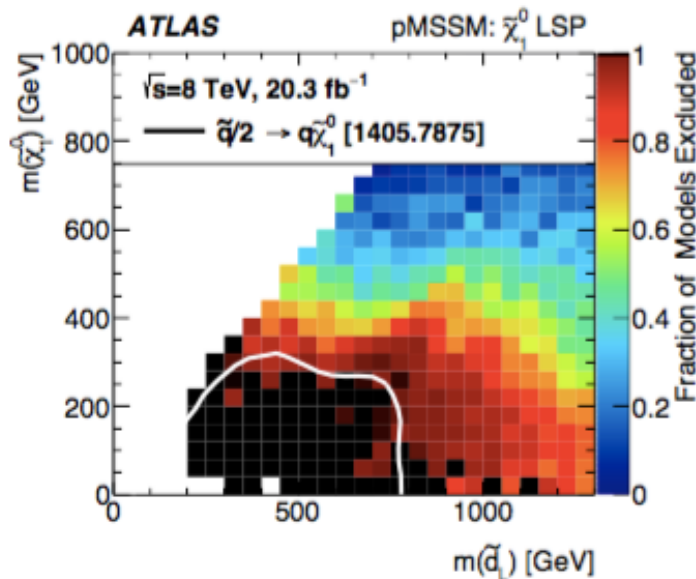
pMSSM-19 and ATLAS IV



(a) Left up squark



(b) Right up squark



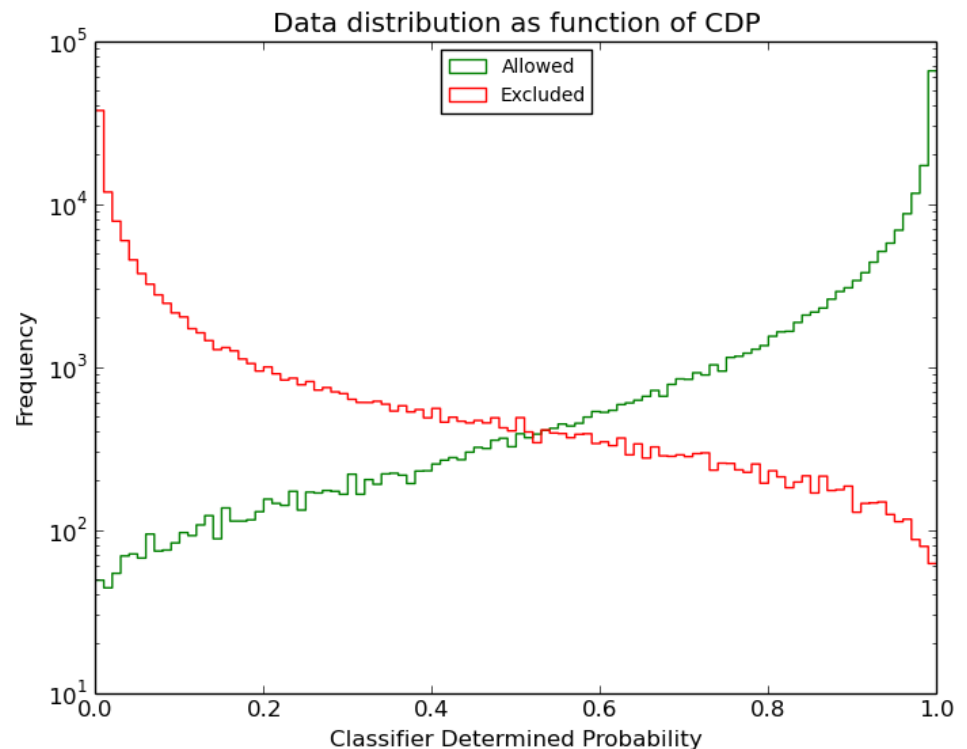
Training

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

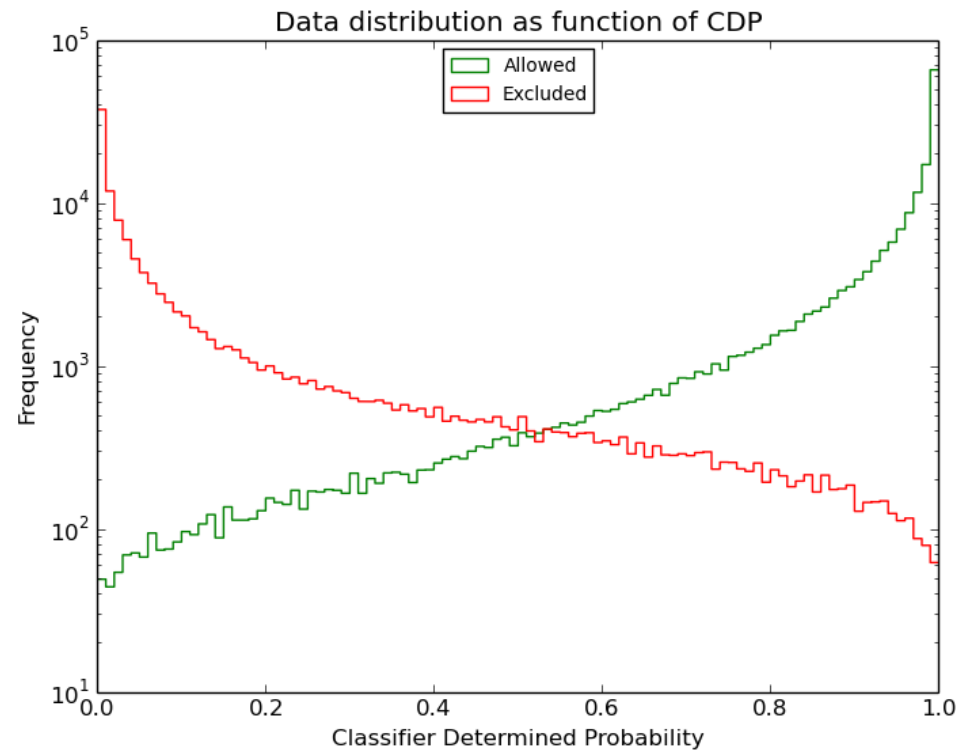
Training of SUSY-AI II

- 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)



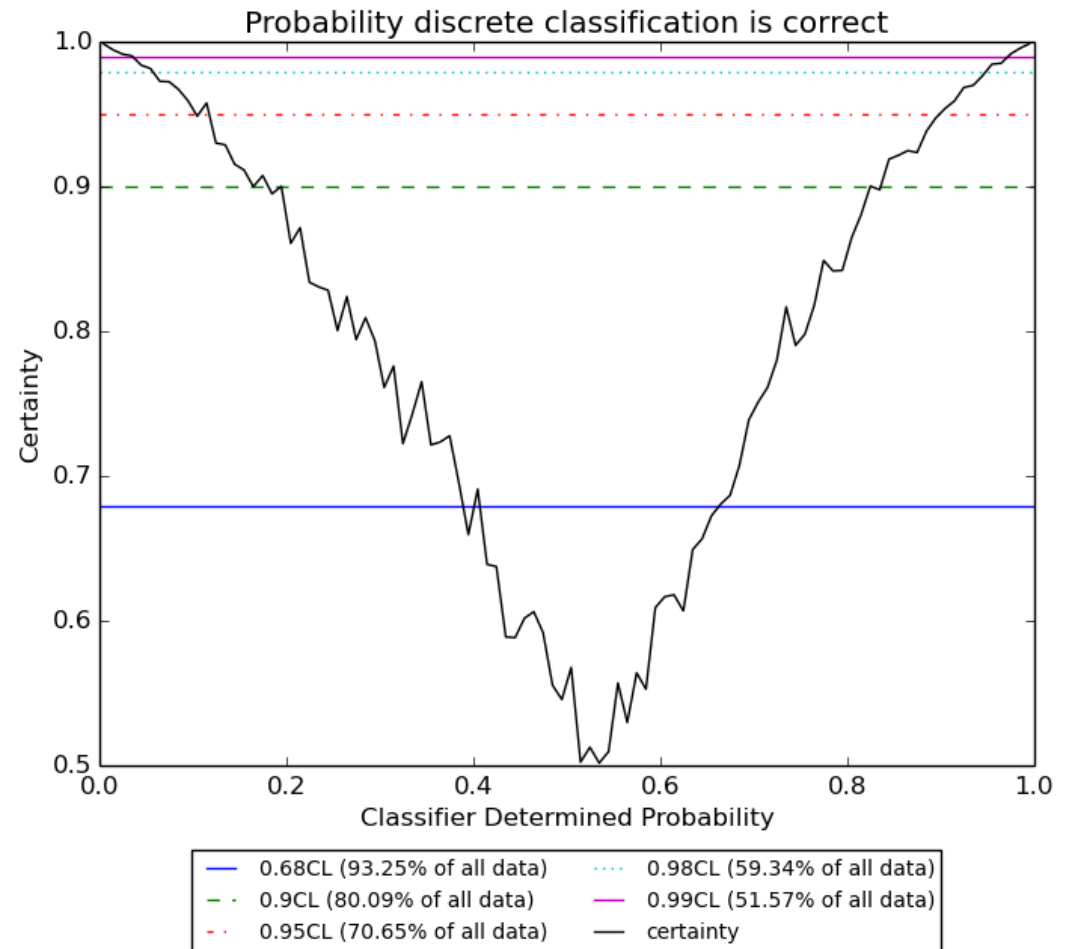
Training of SUSY-AI III

- 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



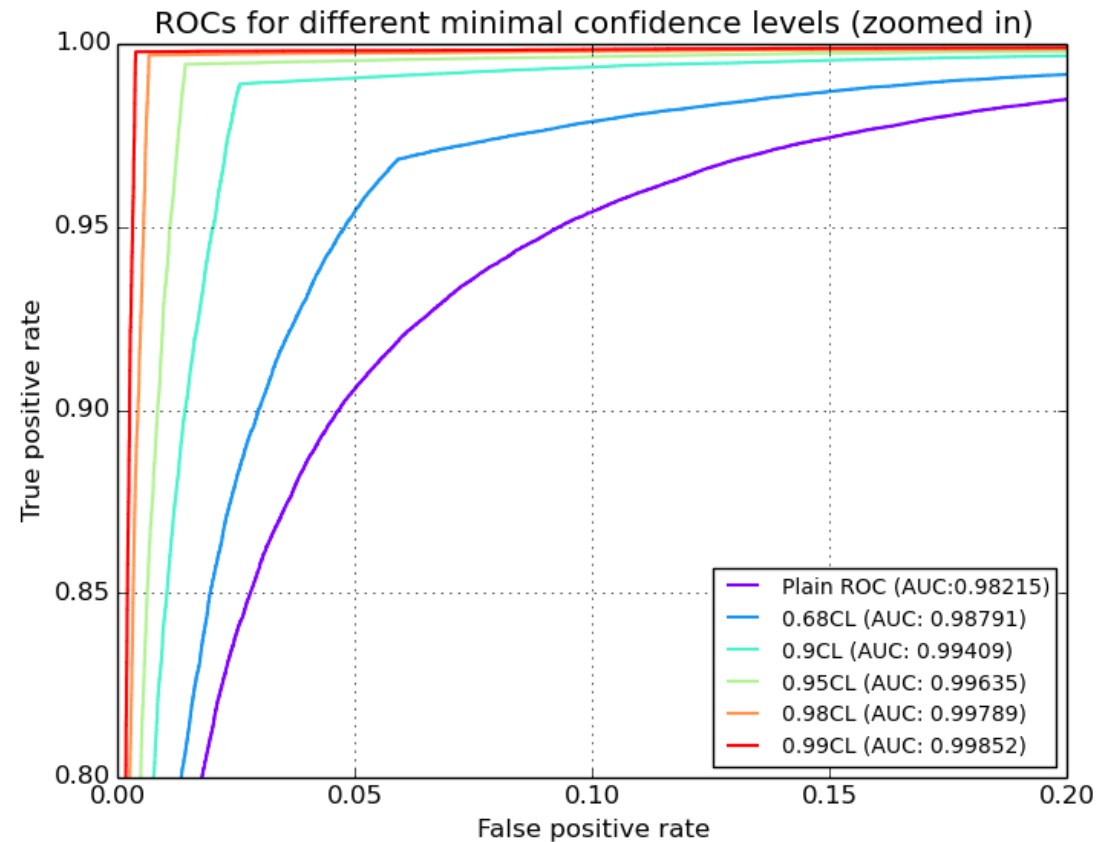
Training of SUSY-AI IV

- 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

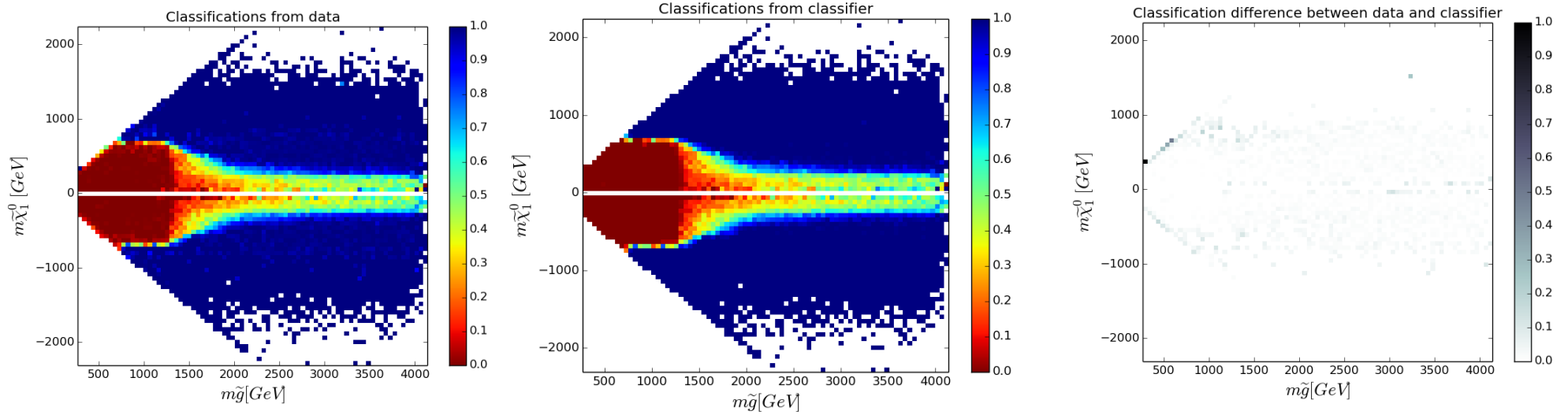
- a “harder” cut provides more reliable results for classification but larger number of points are removed
- the performance can be quantified by the ROC curve
- higher CL cuts increases the AUC



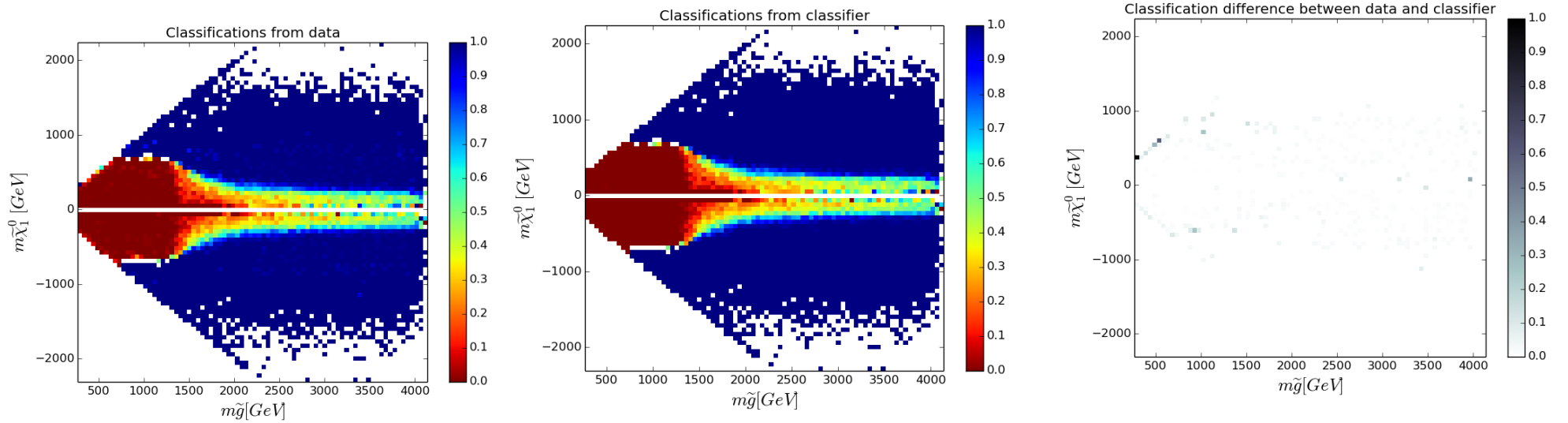
Performance

Performance of SUSY-AI I

No CL cut

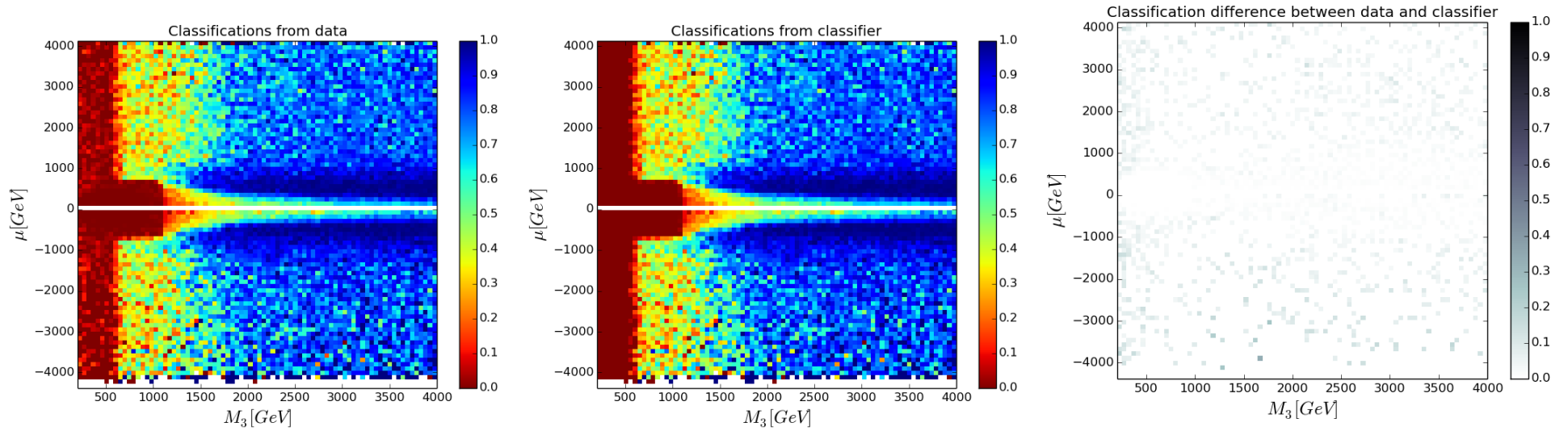


99% CL cut

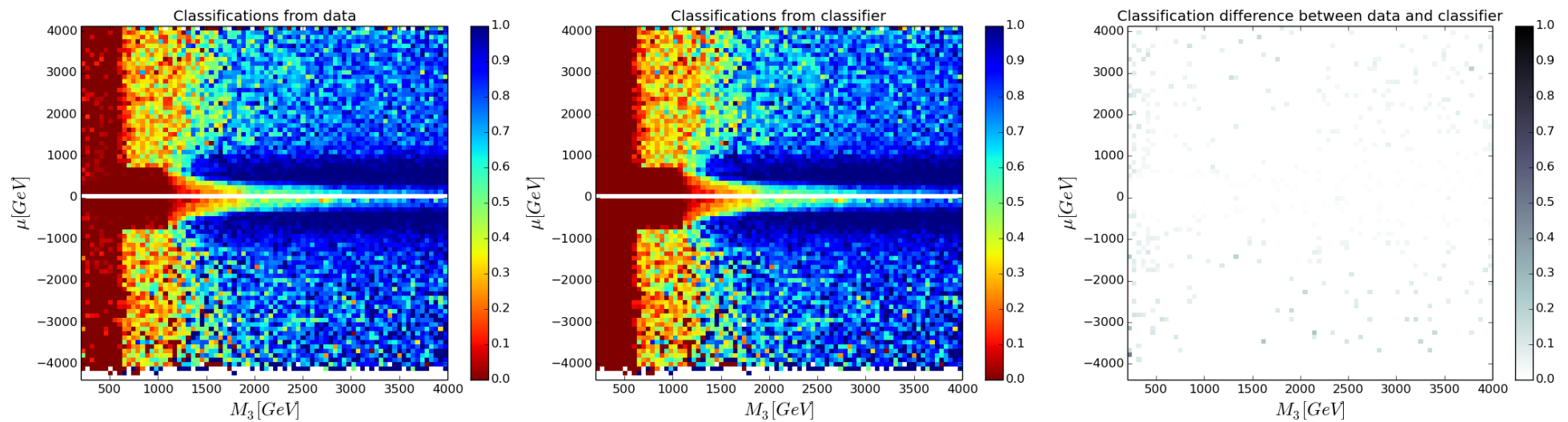


Performance of SUSY-AI II

No CL cut



99% CL cut



Applications

natural SUSY I

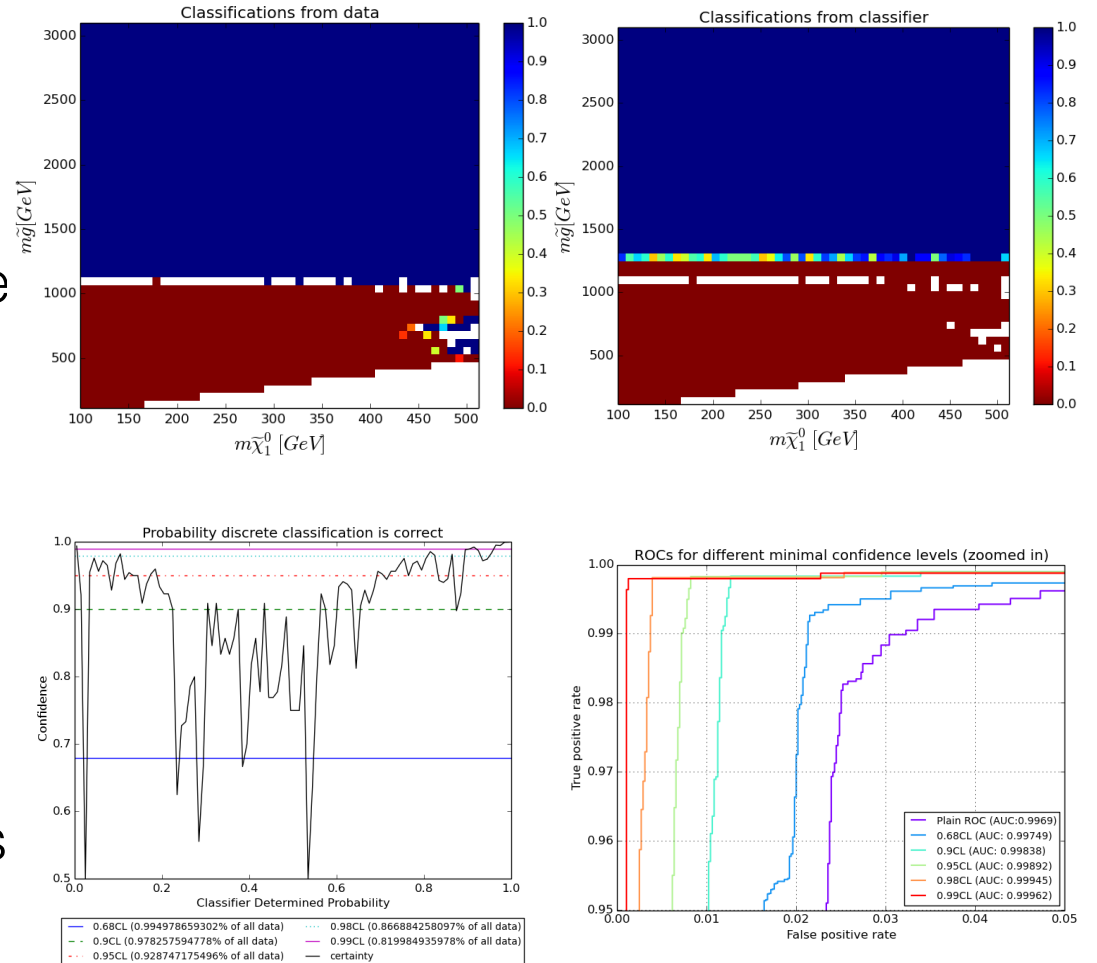
- a minimal natural SUSY scenario consists of light higgsinos, SU(2) doublet third generations squarks, a SU(2) singlet stop and multi-TeV gluinos
- the scenario consists of six input soft breaking parameters
- 22000 benchmark points were generated and the produced MC events analysed with CheckMATE (arXiv: 1511.04461)

Parameter	Description	Scanned range
$m_{\tilde{Q}_3}$	3 rd generation SU(2) doublet soft breaking squark mass	[0.1 TeV, 1.5 TeV]
$m_{\tilde{U}_3}$	3 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]
μ	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 ℓ +2 b jets+ \cancel{E}_T	20.1	6
1403.4853 (ATLAS) [48]	2 ℓ + \cancel{E}_T	20.3	12
1404.2500 (ATLAS) [43]	SS 2 ℓ or 3 ℓ	20.3	5
1407.0583 (ATLAS) [47]	1 ℓ +(b) jets+ \cancel{E}_T	20.0	27
1407.0608 (ATLAS) [49]	monojet+ \cancel{E}_T	20.3	3
1303.2985 (CMS) [89]	α_T + b jets	11.7	59
ATLAS-CONF-2012-104 [90]	1 ℓ + ≥ 4 jets+ \cancel{E}_T	5.8	2
ATLAS-CONF-2013-024 [91]	0 ℓ +6 ($2b$) jets+ \cancel{E}_T	20.5	3
ATLAS-CONF-2013-047 [92]	0 ℓ +2-6 jets+ \cancel{E}_T	20.3	10
ATLAS-CONF-2013-061 [93]	0-1 ℓ + $\geq 3b$ jets+ \cancel{E}_T	20.1	9
ATLAS-CONF-2013-062 [94]	1-2 ℓ +3-6 jets+ \cancel{E}_T	20.0	19
CMS-SUS-13-016 [95]	OS 2 ℓ + $\geq 3b$ jets	19.7	1

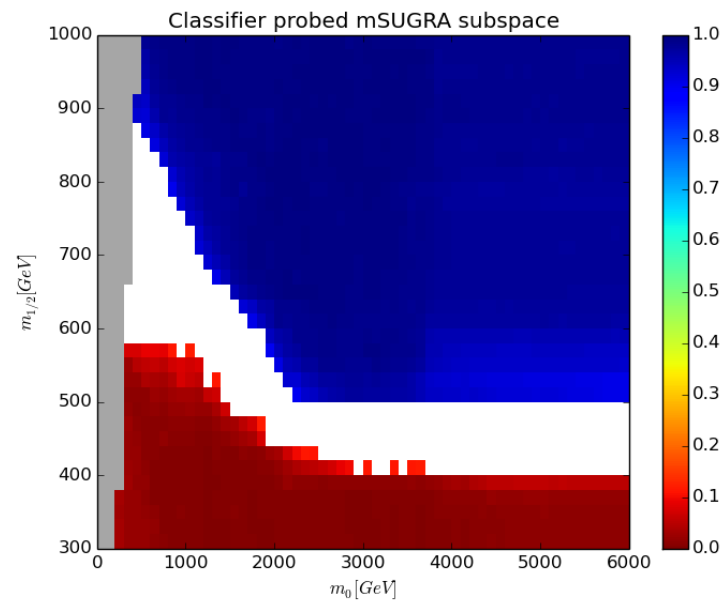
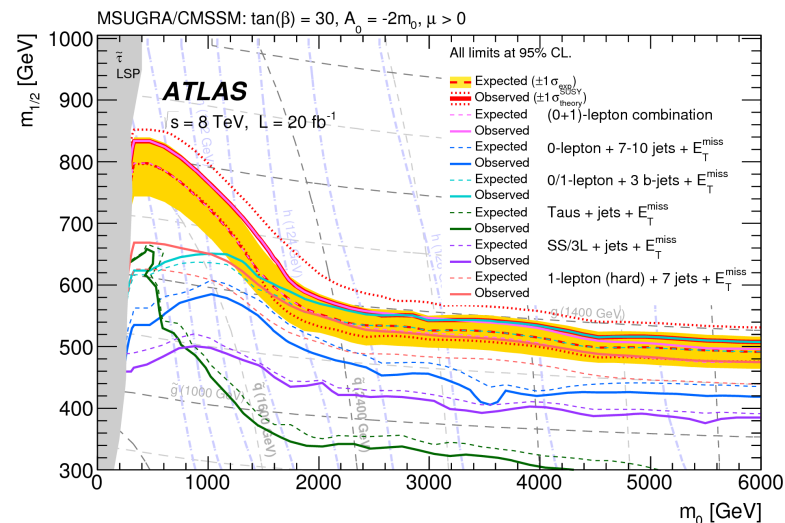
natural SUSY II

- 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:
- m_0 , $m_{1/2}$, A_0 , $\tan \beta$ and $\text{sign } \mu$
- we set $\tan \beta=0$ and $A_0=2m_{1/2}$
- 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

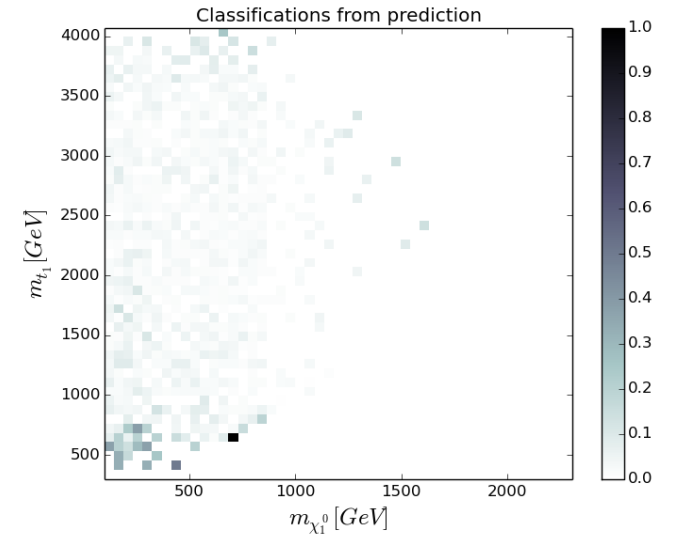
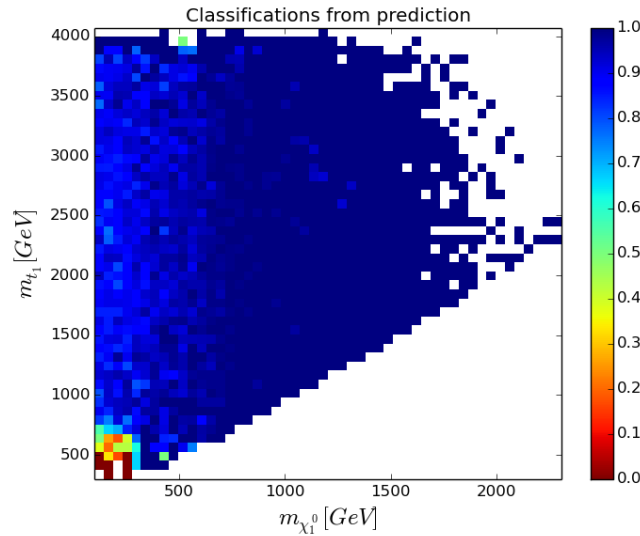
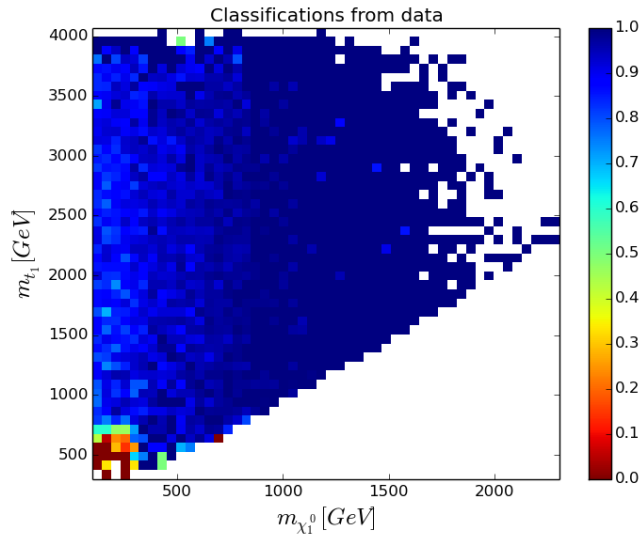
- in order to test this effect, we consider an electroweakino scenario as well as a light stop sector with all remaining sparticles decoupled
- we consider benchmark points which satisfy the cuts given in the table

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_τ	[-4 TeV, 4 TeV]
$ \mu $	[80 GeV, 4 TeV]
$ M_1 $	[600 GeV, 4 TeV]
$ M_2 $	[600 GeV, 4 TeV]
M_3	[1300 GeV, 4 TeV]
M_A	[600 GeV, 4 TeV]
$\tan \beta$	[1, 60]

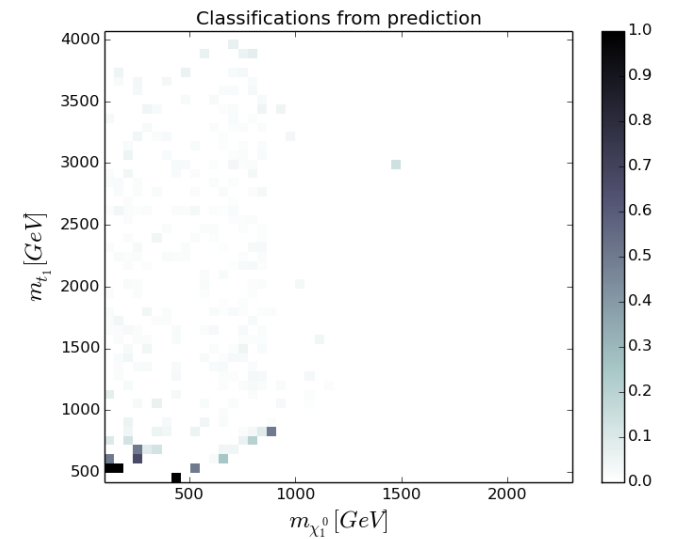
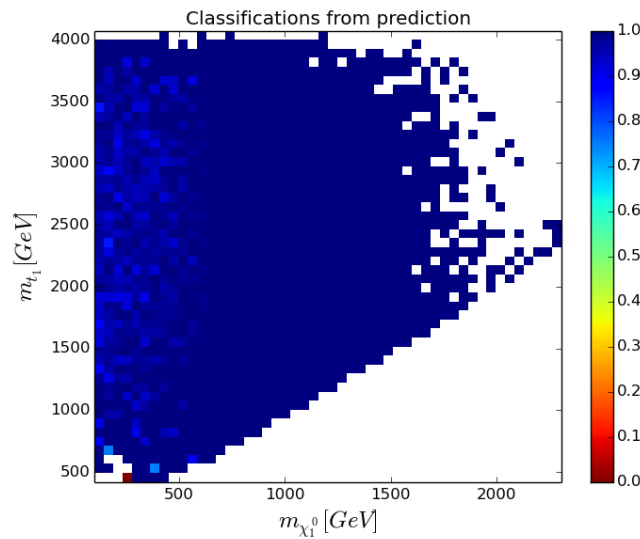
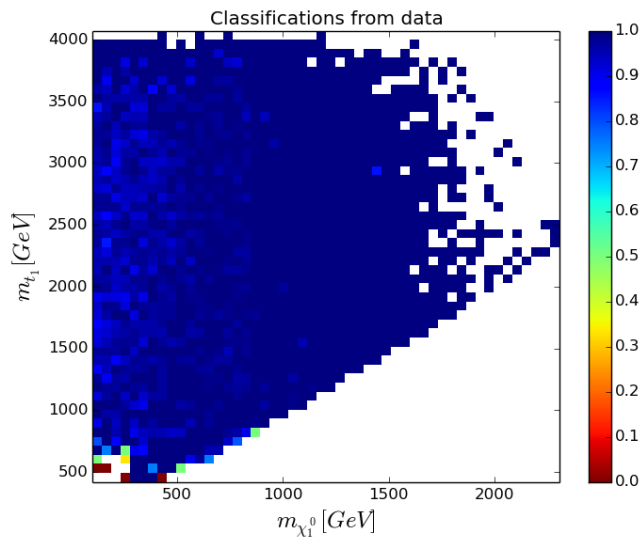
Parameter	Value
$m_{\tilde{L}_1}$	[700 GeV, 4 TeV]
$m_{\tilde{E}_1}$	[700 GeV, 4 TeV]
$m_{\tilde{L}_3}$	[700 GeV, 4 TeV]
$m_{\tilde{E}_3}$	[700 GeV, 4 TeV]
$m_{\tilde{Q}_1}$	[1200 GeV, 4 TeV]
$m_{\tilde{U}_1}$	[1200 GeV, 4 TeV]
$m_{\tilde{D}_1}$	[1200 GeV, 4 TeV]
$m_{\tilde{Q}_3}$	[1200 GeV, 4 TeV]
$m_{\tilde{U}_3}$	[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_τ	[-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

No CL cut

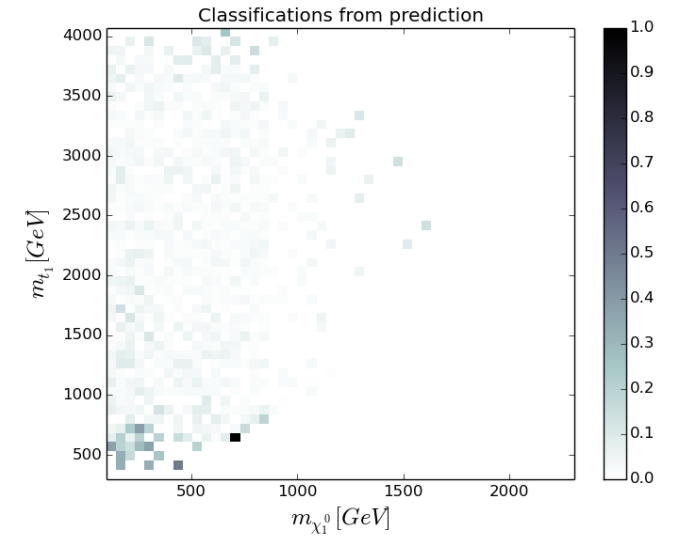
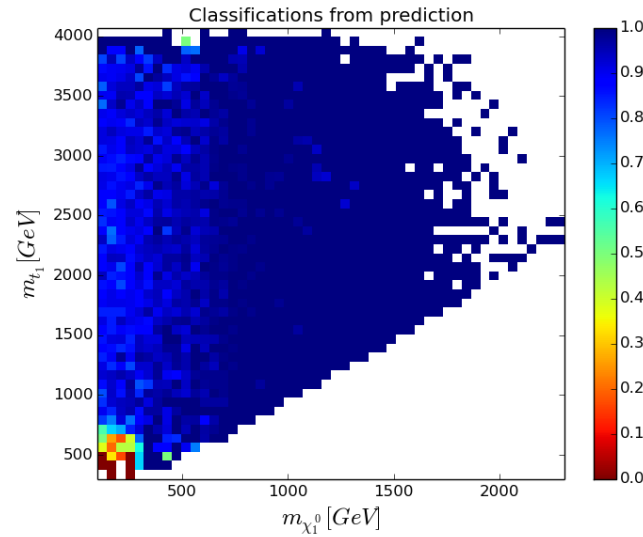
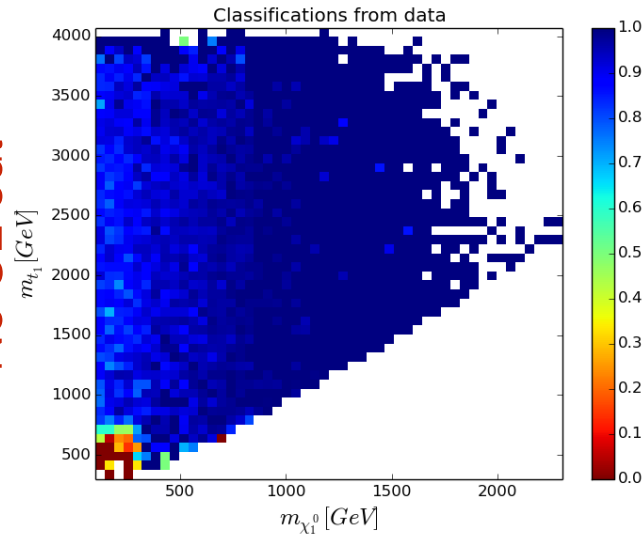


95% CL cut

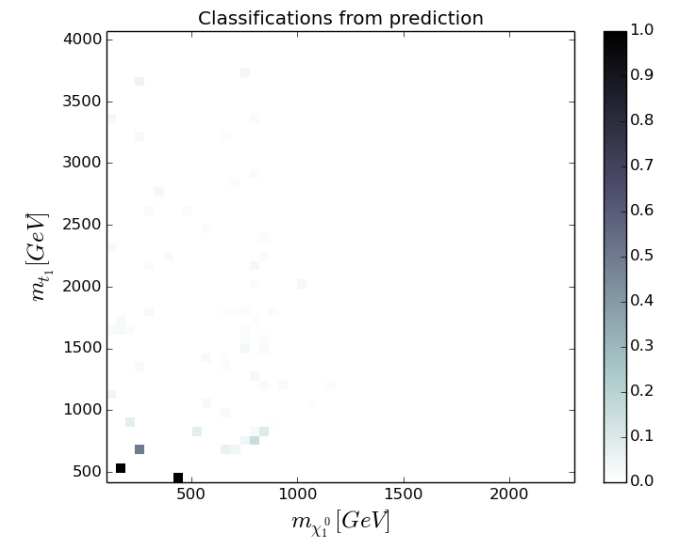
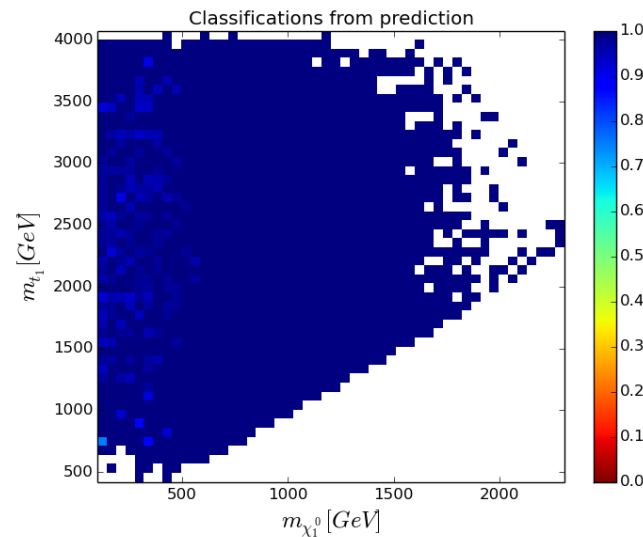
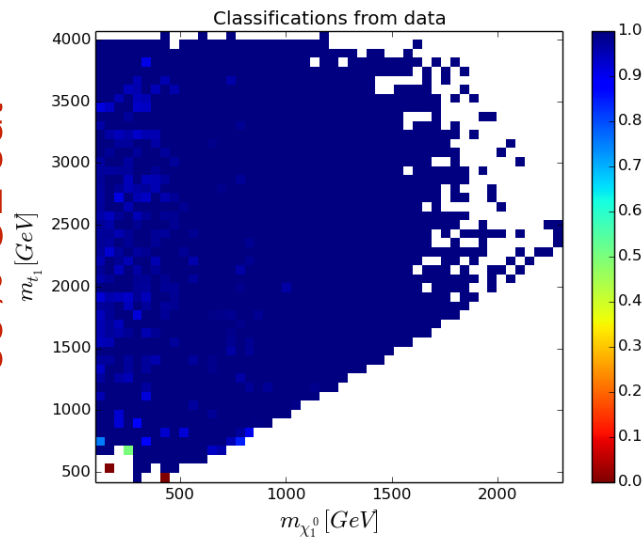


Limited training data IV

No CL cut

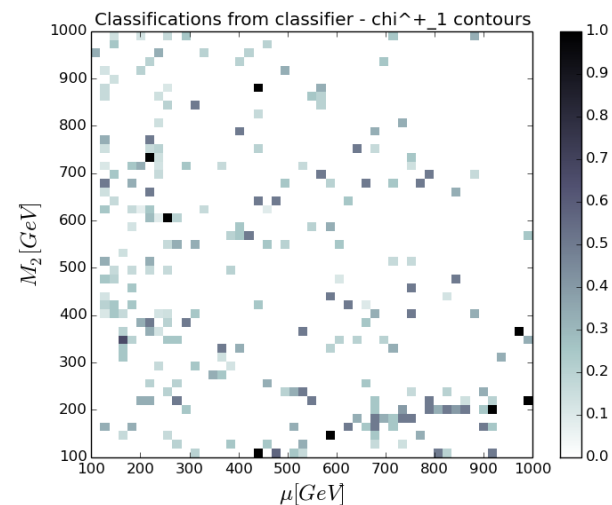
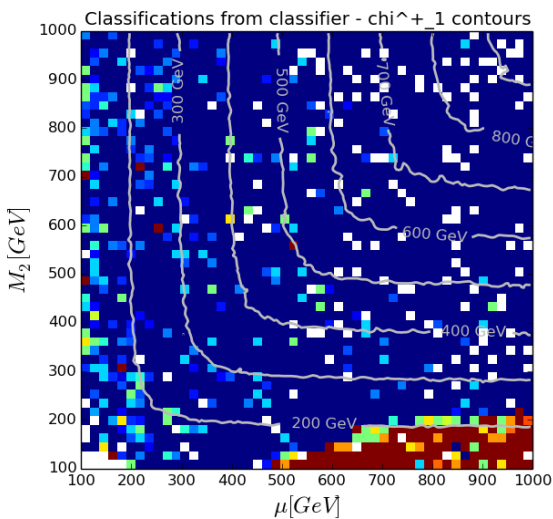
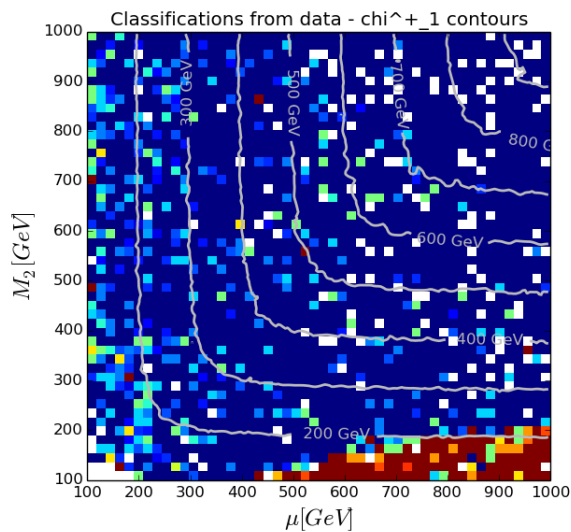


99% CL cut

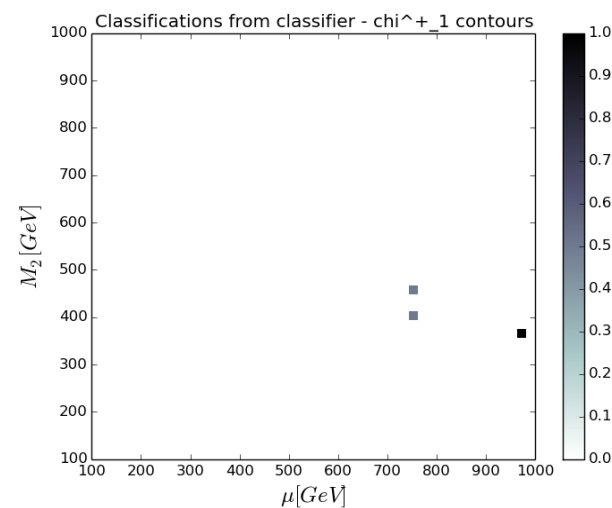
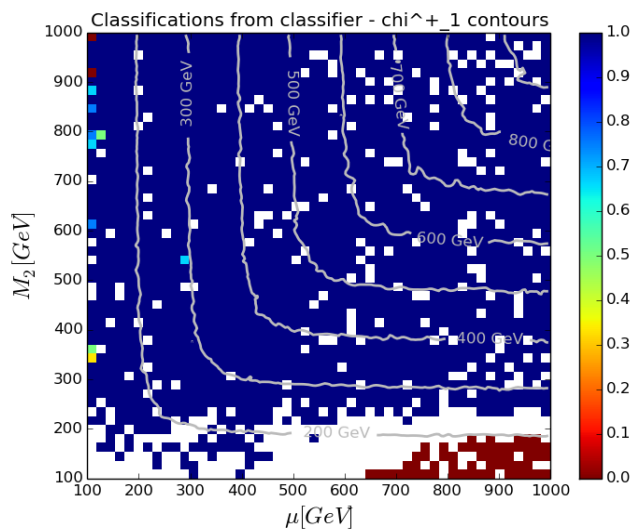
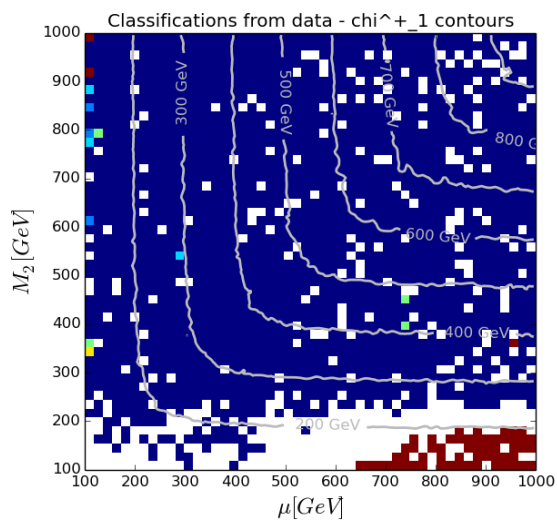


Limited training data V

No CL cut



99% CL cut



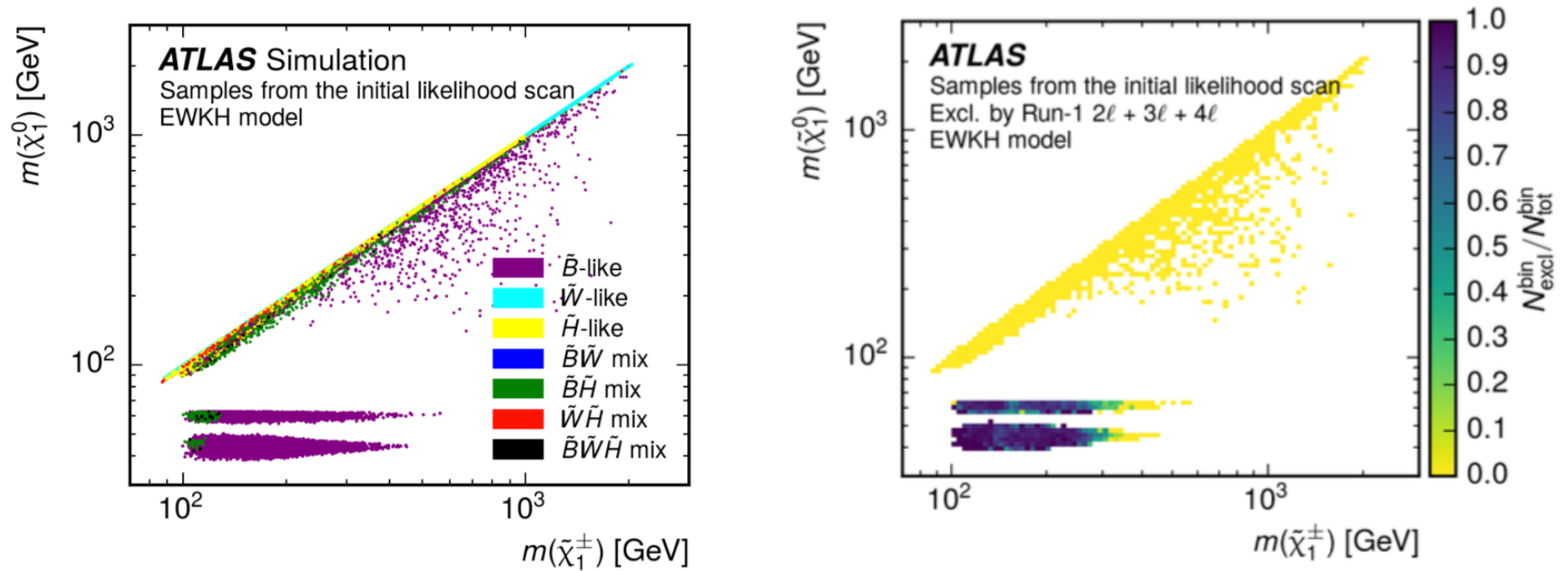
Classifier for corners I

- 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
- M_1 , M_2 , μ , m_A and $\tan\beta$
- 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

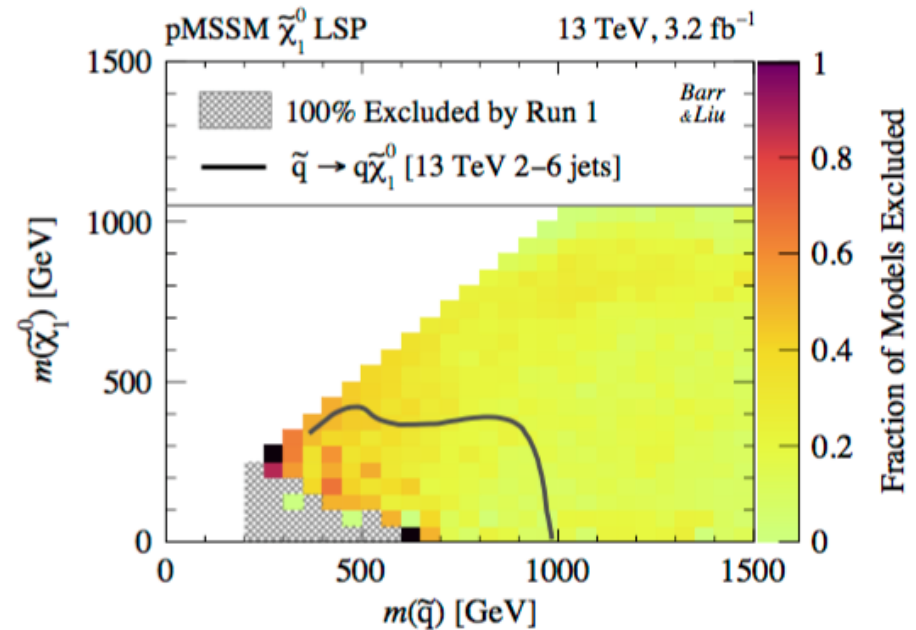
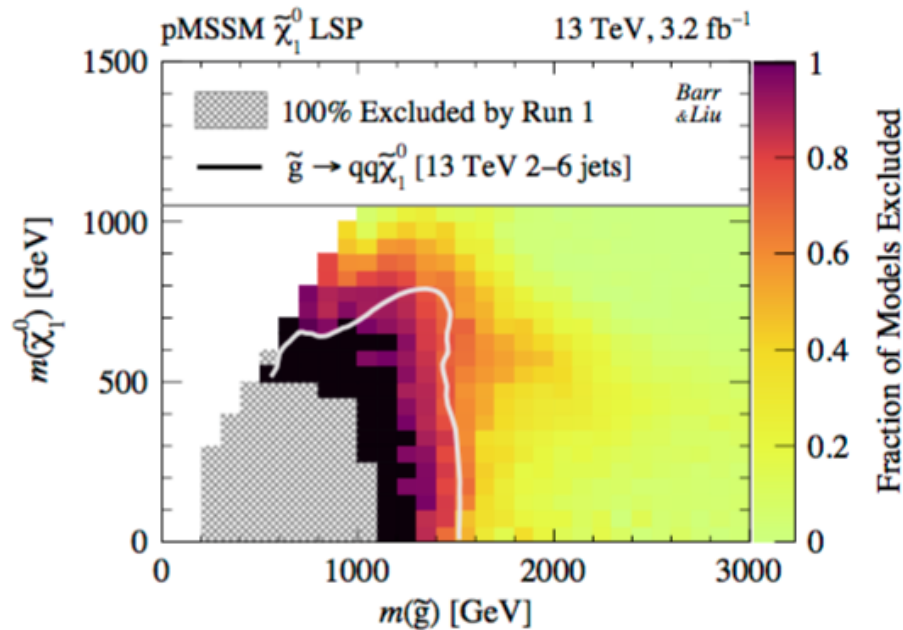


13 TeV constraints I

- 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

SUSY-AI Online SUSY-AI VERSION 2.0.5

S. Caron, J.S. Kim, K. Rolbiecki, R. Ruiz de Austri and B. Stienen,
The BSM-AI project: SUSY-AI - Generalizing LHC limits on Supersymmetry with Machine Learning
[arXiv:1605.02797]



SUSY-AI is a machine learning tool that is able to provide in a fraction of a second the exclusion of a pMSSM (sub)model point. This website provides a simple online interface for quick determination of exclusion of a model point using the results of ATLAS Run-I (8TeV) and ATLAS Run-II (13TeV). The papers associated with this data can be found [here](#).

The full version of SUSY-AI is faster and can provide predictions for multiple modelpoints at the same time. It is under continuing active development and can be downloaded from the hepforge project page.

[Download SUSY-AI](#)

If you use SUSY-AI in your scientific work, don't forget to cite us.

[More about SUSY-AI Online](#)

Direct parameter input

Upload .slha file

Slide the parameters to the requested values or click 'set value' to set a variable manually. Prediction can only be performed if **all parameters** have been set. More information about the parameters (what they are and where they can be found in .slha files) can be found [here](#).

M1	set value	M2	set value	M3	set value	mL1	set value
mL3	set value	mE1	set value	mE3	set value	mQ1	set value
mQ3	set value	mU1	set value	mU3	set value	mD1	set value
mD3	set value	At	set value	Ab	set value	Atau	set value
mu	set value	MA ²	set value	tan(beta)	set value		

[Enter all parameters](#) [How to...](#) [Predict](#)

Analysis **8 TeV** 13 TeV CL **0.0** 0.68 0.90 0.95 0.98 0.99

Upload a file or enter a parameter set above to start predicting

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>