idark project
Utilizing Multi-parametric (model) DataSets

idarksurvey visualization and database: escience center
(Faruk Diblen, Jisk Attema, Rena Bakshi, Luc Hendriks)
BSM-AI: *with Jong Soo Kim, Krzysztof Rolbiecki, Roberto Ruiz de Austri, Bob Stienen,*
first result is SUSY-AI: [1605.02797]

netherlands eScience center

Sascha Caron (Radboud University and Nikhef)

This talk is about publishing , releasing and utilizing (HEP/DM) model data (e.g. Likelihoods, constraints) in high-dimensional parameter spaces.

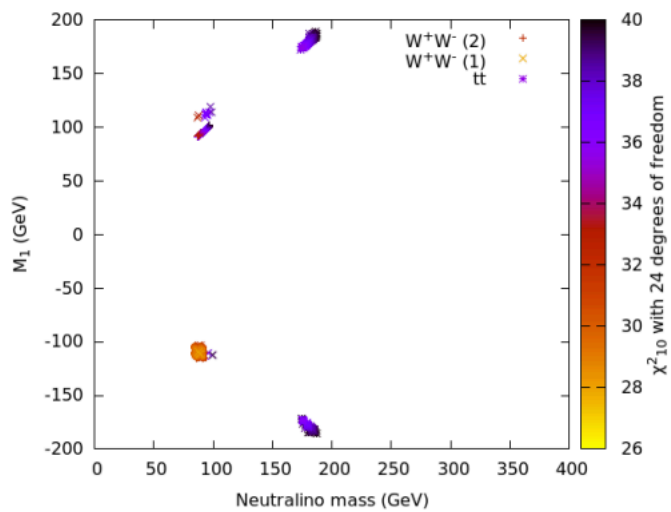
… proposing a tool/framework for very simple minded experiment/phenomenology people to analysis data beyond the end of the analysis (i.e. after submitting to arxiv)…

In 10 minutes I hope to have convinced you that this is useful…and hope to get some people interested…

Theory community … A typical example …

What is Dark Matter ? …

Let's determine the best parameter sets of a Dark Matter model ?



$$-103\,\mathrm{GeV} < \mathrm{M}_1 < -119\,\mathrm{GeV},$$

$$240 < M_2 < 660\,\mathrm{GeV},$$

$$108\,\mathrm{GeV} < \mu < 142\,\mathrm{GeV},$$

$$8 < \tan\beta < 50.$$

Everybody (plots are actually from our own paper) gives 2 dimensional Information.
We can not compare solution 1 of paper X with solution 2 of paper Y
We do not get the full parameter-set of the solutions …

Simple reminder…

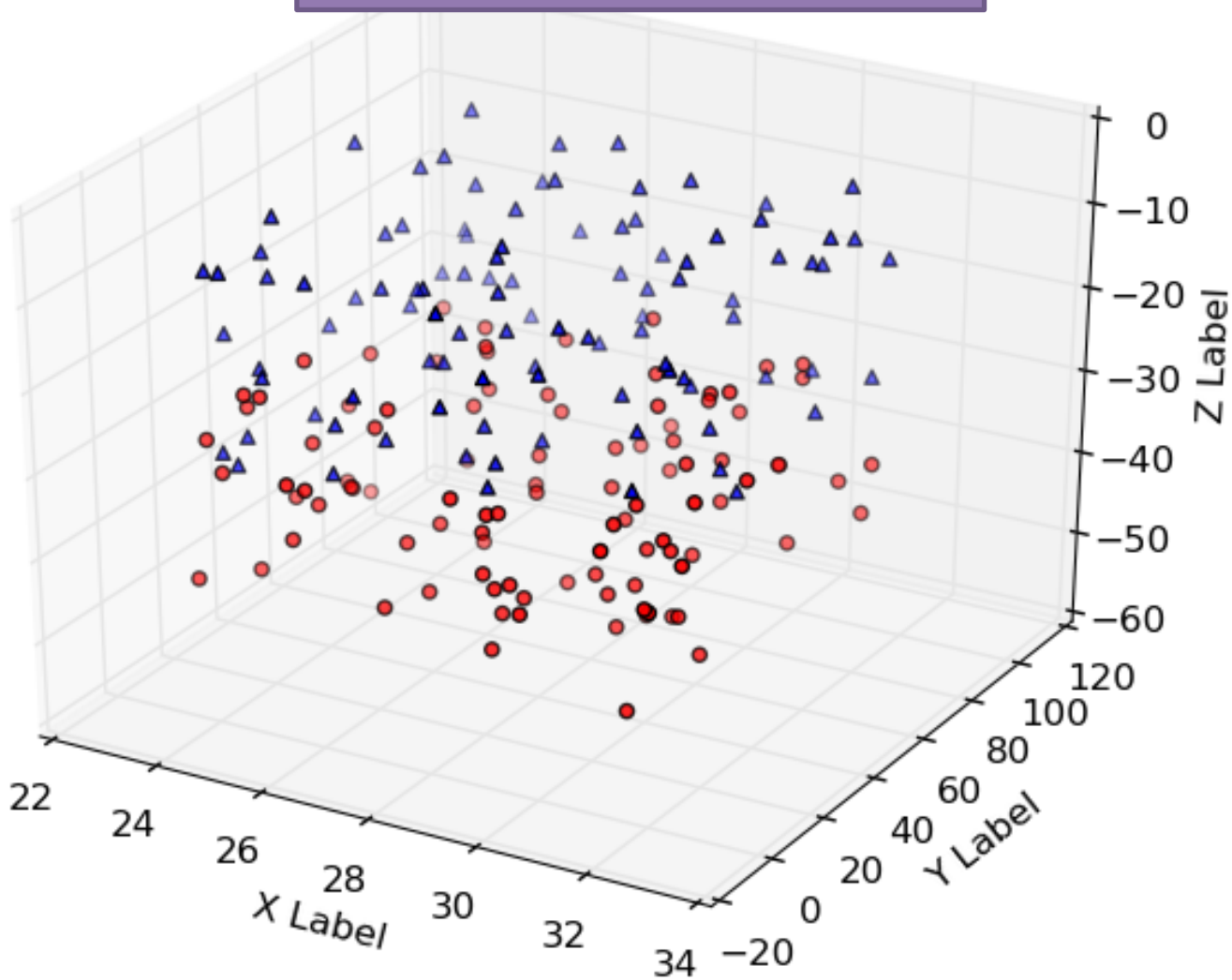
Simplified models * number of models

not equal

Full model

Do not be afraid of models > 2 parameters ! We need them !

Publish model evaluations in N-dim
➔ There are 3 dimensions ;)



idarksurvey
(Faruk Diblen, Jisk Attema, Rena Bakshi, Luk Hendriks)

Can we collect/store the multidimensional model datasets ?

Prototypes at www.idarksurvey.com and http://54.93.46.86/

Idea :

- Provide a database (postgresql for the moment)
  for multi-dimensional theory model solutions (or HEP data)
- Connect the database with web-based visualization tools as frontend
  (developing SPOT with Dutch escience center, also quick demo using highcharts)
- Connecting to arxiv (maybe with hepdata?)

Let us have a look….

SPOT visualisation

- **"SPOT"** started as tool in Summer in the City project (https://github.com/jiskattema/spot)
- plans to be useful as scientific tool: provenance, downloading of data
- **multi-dimensional** data using linked, animated & interactive **low dimensional** plots
- two contributors: Jisk Attema, Faruk Diblen
- Chart.js using html5 canvas (no DOM, gpu accelerated drawing)
- Uses modern web technologies: quick development (crossfilter, node.js, ampersand.js, chart.js, vis.js)
- two possible backends: crossfilter (fully client side) and PostgreSQL
- Responsive interface: material design (google)
- **documented** (jsdoc) and **tested** (jasmine)
- three types of data: numerical, categorial (labels or text), dates and duration

SPOT visualisation

- exploration sessions can be saved or restored as json file
- mostly a data viewer, modification not supported. Some changes for displaying purposes are possible (change strings labels, format dates)
- works with grouping, all plots performant (canvas is often **openGL accelerated**)

Why is such high-dimensional (model) data useful ?

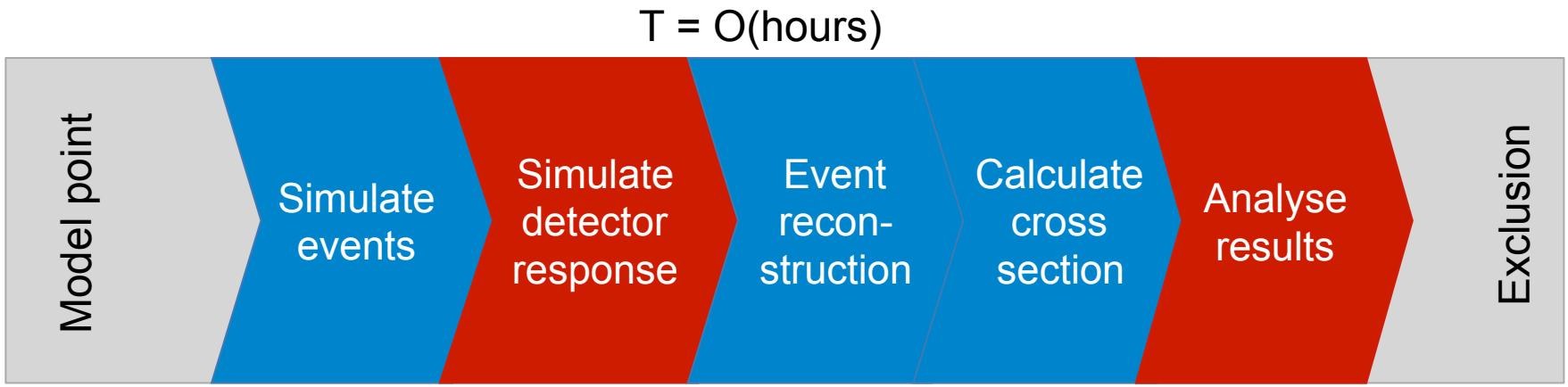
1. Data preservation
2. Exclude/Update theory predictions
3. Compare solutions of theory papers
4. “Machine” Learning limits in high dimensions
5. Training tools…
6. …?

Example of n-dimensional model evaluations:

ATLAS released > 300000 model evaluations in the 19 dimensional MSSM
http://arxiv.org/abs/arXiv:1508.06608

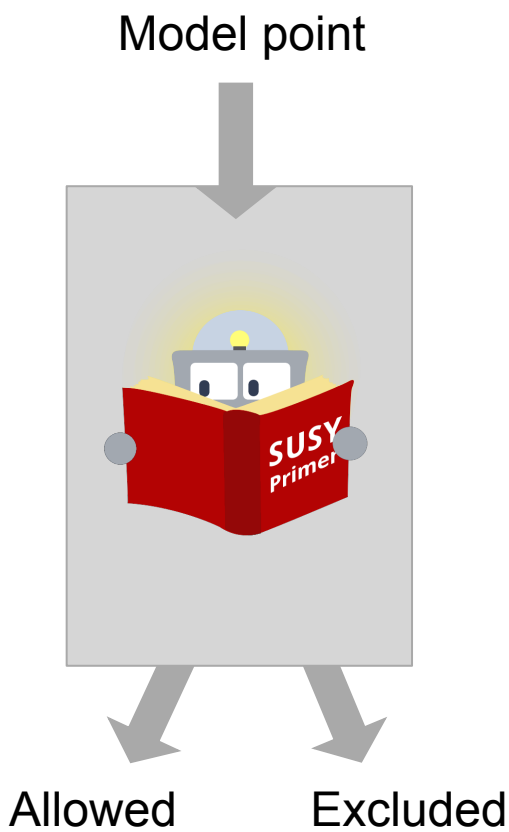
Can we "learn" the full 19-dim pMSSM exclusion range with
300000 models ?
Is this enough to populate a 19 dimensional parameter space ?

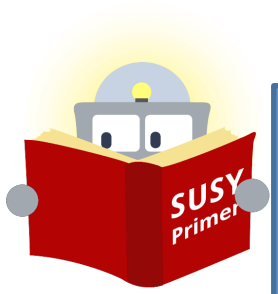
ATLAS analysis chain for each of the 300000 model points



Machine Learning Applied

- Training data: model points in supersymmetric model with only phenomenologically relevant parameters (pMSSM)
  source: ATLAS [1508.06608]
- Testing data: independent (unseen) data

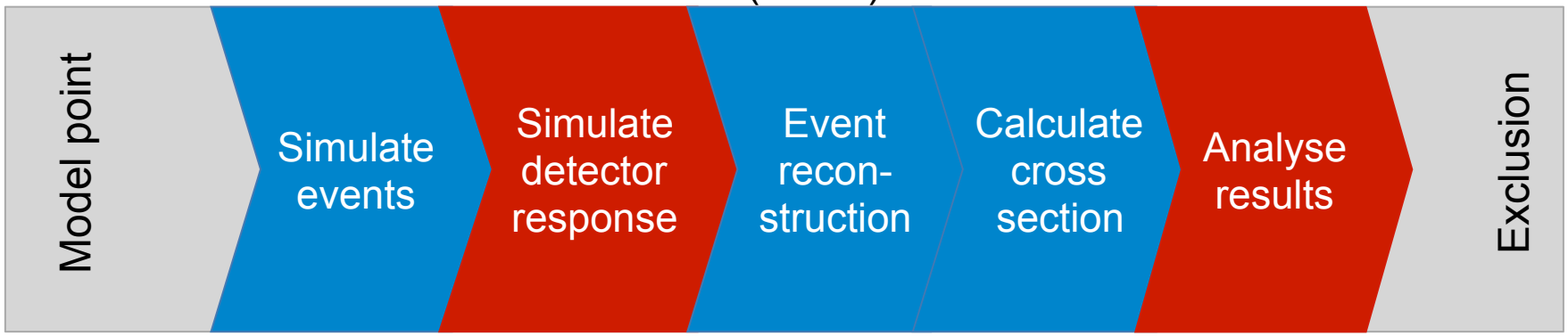


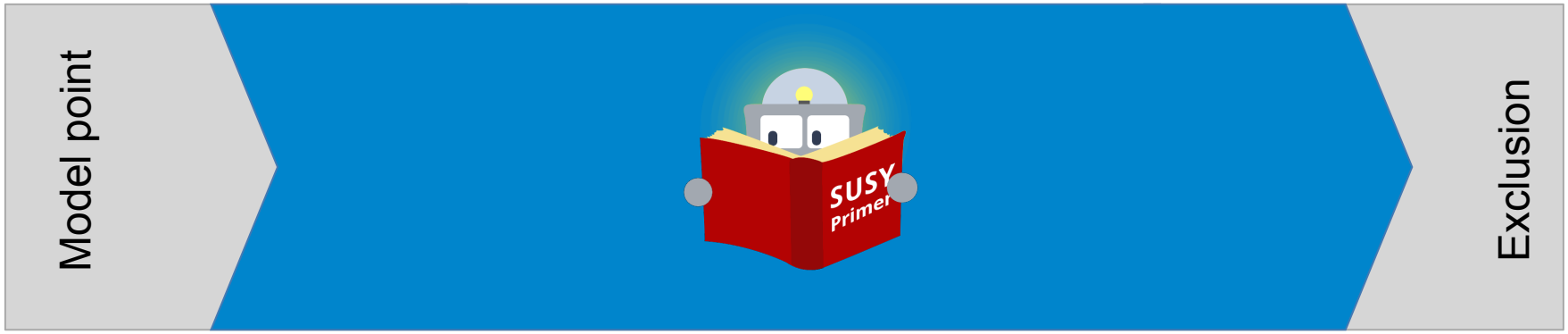


Is currently a classification algorithm using scikit-learn (a Random Forest)

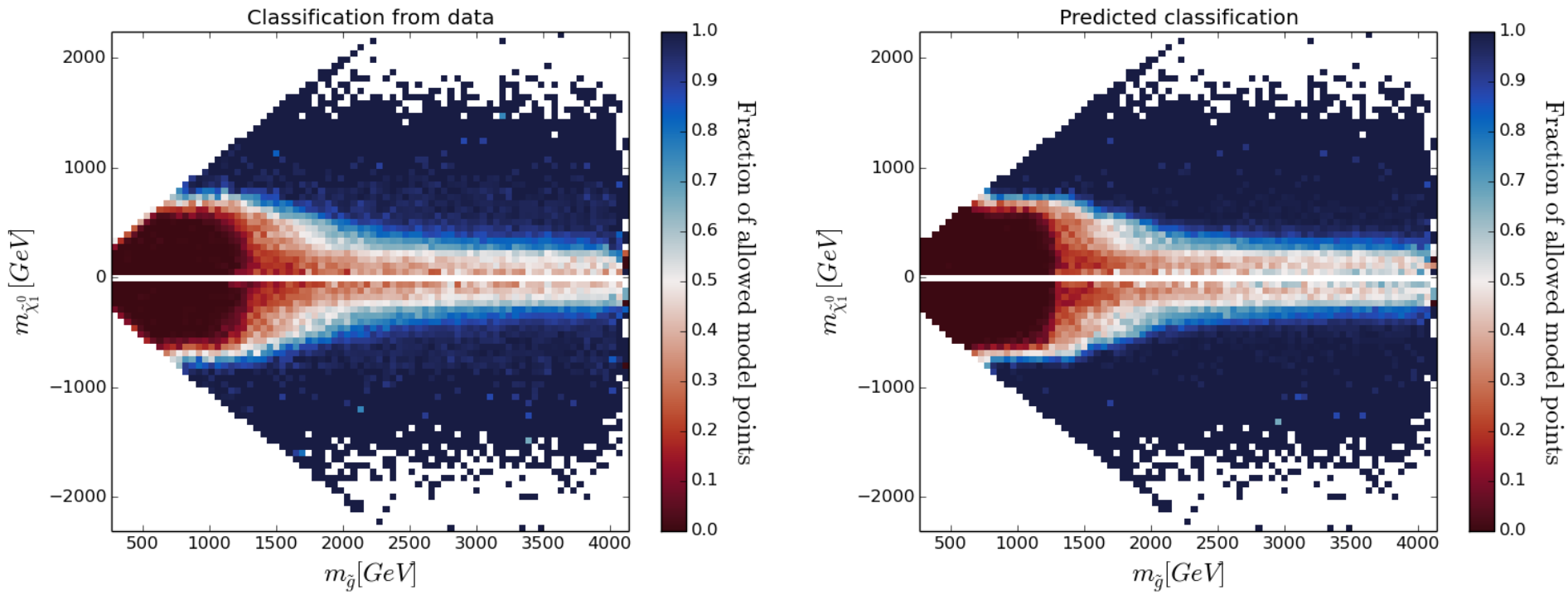
Exclusion analysis

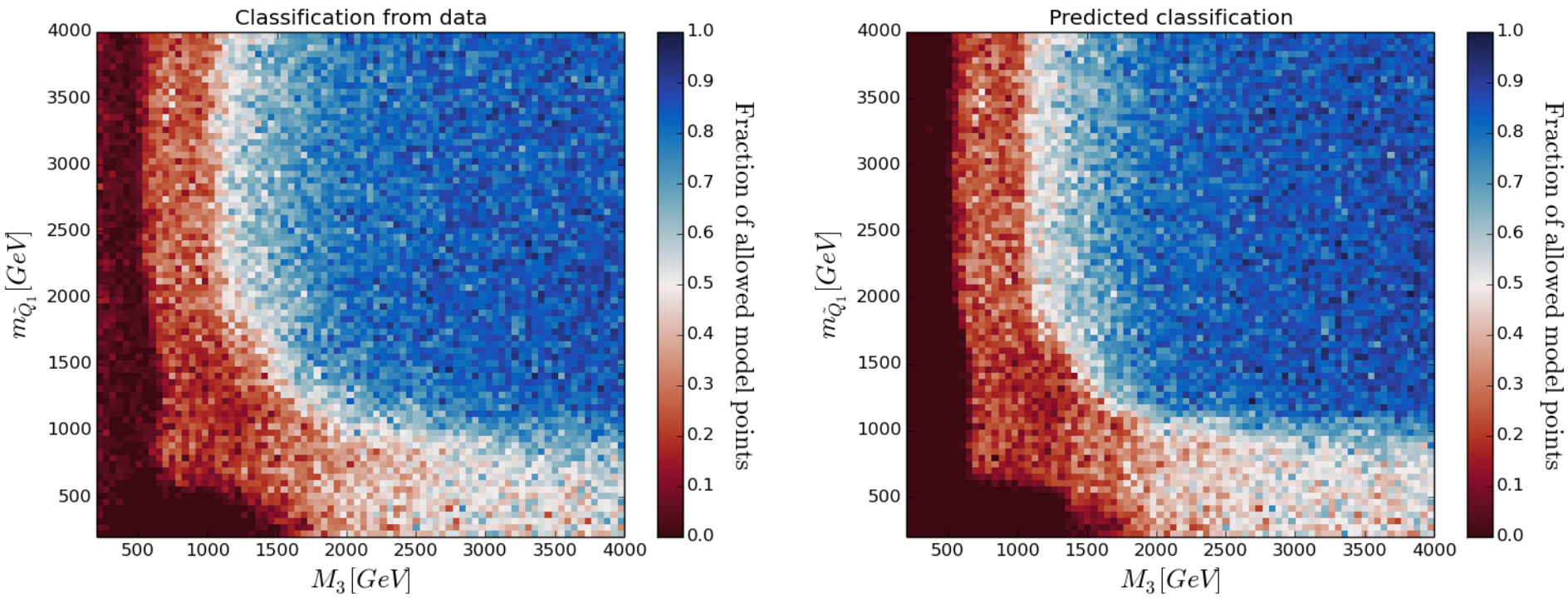
T = O(hours)





T = < O(1 ms)


Classification from data
Predicted classification
$m_{\tilde{\chi}_1^0}$ [GeV]
$m_{\tilde{g}}$[GeV]
Fraction of allowed model points
2000
1000
0
−1000
−2000
500
1000
1500
2000
2500
3000
3500
4000
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0


Classification from data
Predicted classification
$m_{\tilde{Q}_1}\,[GeV]$
$M_3\,[GeV]$
Fraction of allowed model points
4000
3500
3000
2500
2000
1500
1000
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Why use SUSY-AI / Machine Learning

- Fast statistical results based on earlier analyses
- High accuracy by learning hard-to-see relations in data
- Works also in submodels of the learned model (e.g. mSUGRA)
- Providing confidence levels on prediction

- New way to publish and recast multivariate data
- Creating plots not present in paper
- Re-usability and persistence of analysis and results

Summary

Idark project

1. idarksurvey: Database and Online data visualisation
2. Generalizing Likelihoods and Limits for the HEP community with Machine Learning (first tool is www.susy-ai.com)

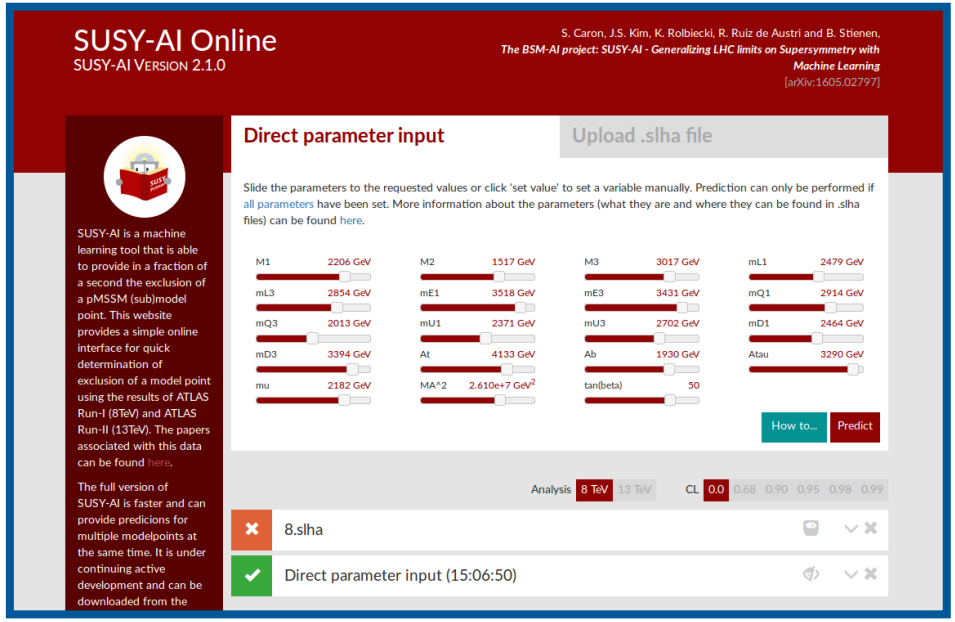
3. Next steps: Discussing tools with community …

Extra Slides

SUSY-AI (Online)

- Tool has been published
  https://susyai.hepforge.org
  - Python interface to classifier
  - Scikit-learn package for ML implementation

- Online interface
  http://susy-ai.org/
  - All functionalities except batch predictions
  - Predictions in < 2 seconds



Summary and Conclusions

- High-speed + high accuracy prediction of ATLAS exclusion
- Applicable to phenomenological supersymmetry and its submodels
- Programmatic and online interface (http://www.susy-ai.org)

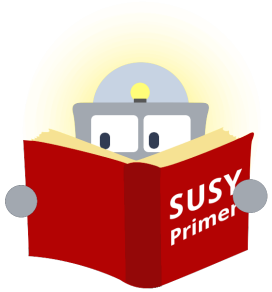
- First time use of Machine Learning for publishing and extrapolating multivariate results
- More models will be done
  - Dark Matter models
  - Higgs couplings
  - Effective Field Theories
  - …

  Development can be accelerated with more public data

➔ **New "initiative" to release multivariate model likelihood evaluations !**

More people highly welcome !

Non-polite summary: STOP WORKING ONLY ON SIMPLIFIED MODELS!



Used training data to learn classification

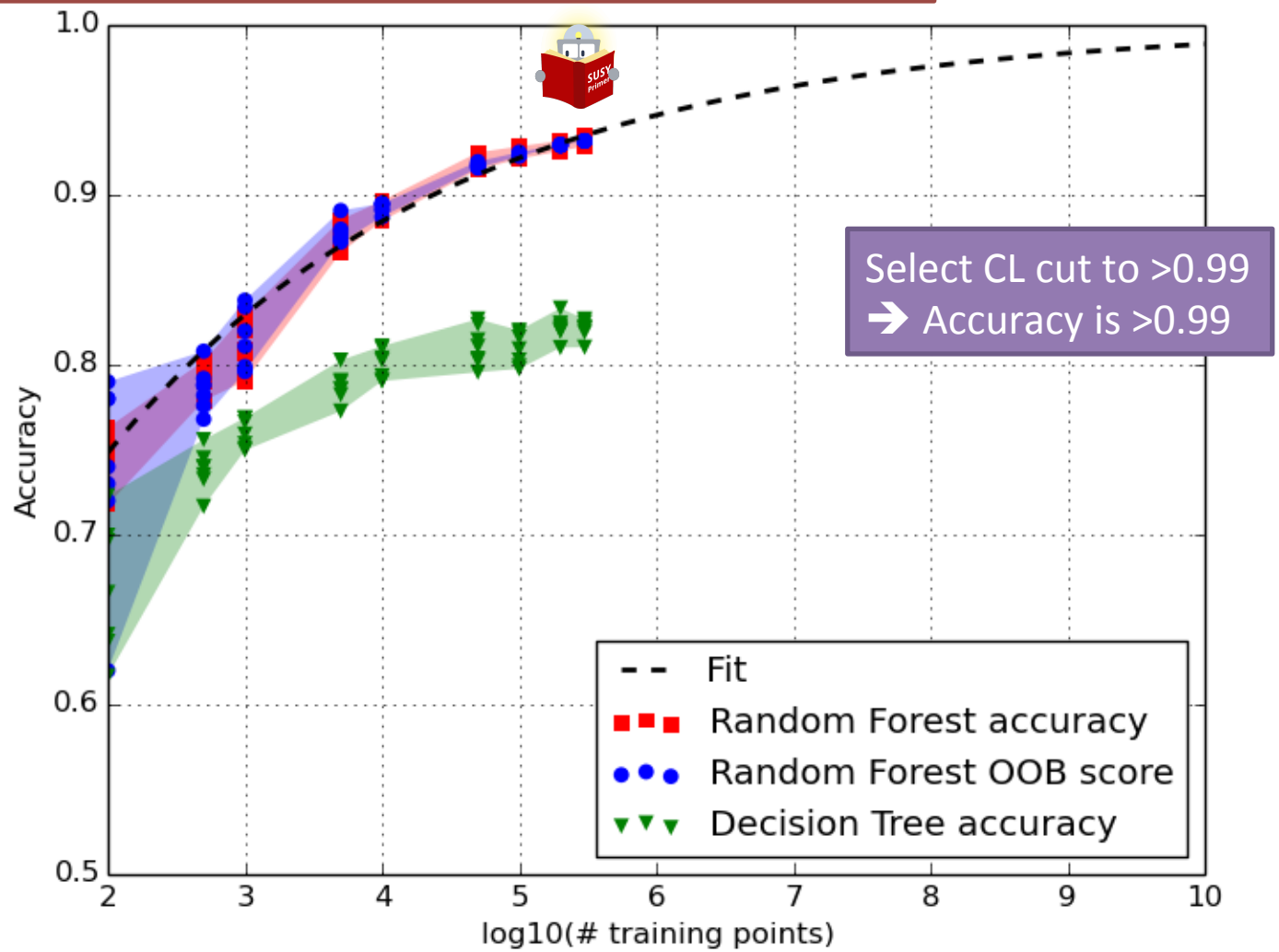
It determines a confidence level of
its classification using the training data.

Low confidence level
➔ Higher chance of misclassification

Confidence level : "Chance for misclassification"
➔ Can also be selected by the user

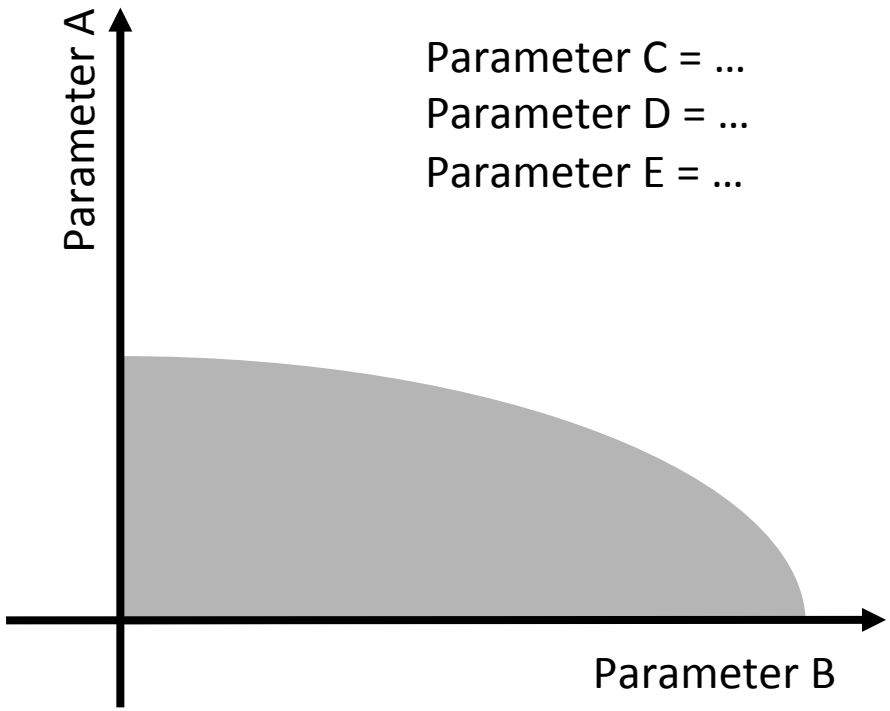
(CL by estimating signal / total as function of classifier output)

Accuracy (no confidence cut) as a function of training data points:
Note that we can do better by “active learning”, i.e. adding points at difficult places.
Conclusion: Machine Learning (SUSY-AI) works
already fantastic in **19** dimensions with 300000 training points
(especially it knows its own confidence)



Model exclusion in Particle Physics

- Consider a model of new physics with parameters A, B, C, D and E
- Assume Supersymmetry or a model to fit the Higgs couplings
- Usually such models have many parameters (e.g. pMSSM can have 19, Higgs couplings has >5-8).



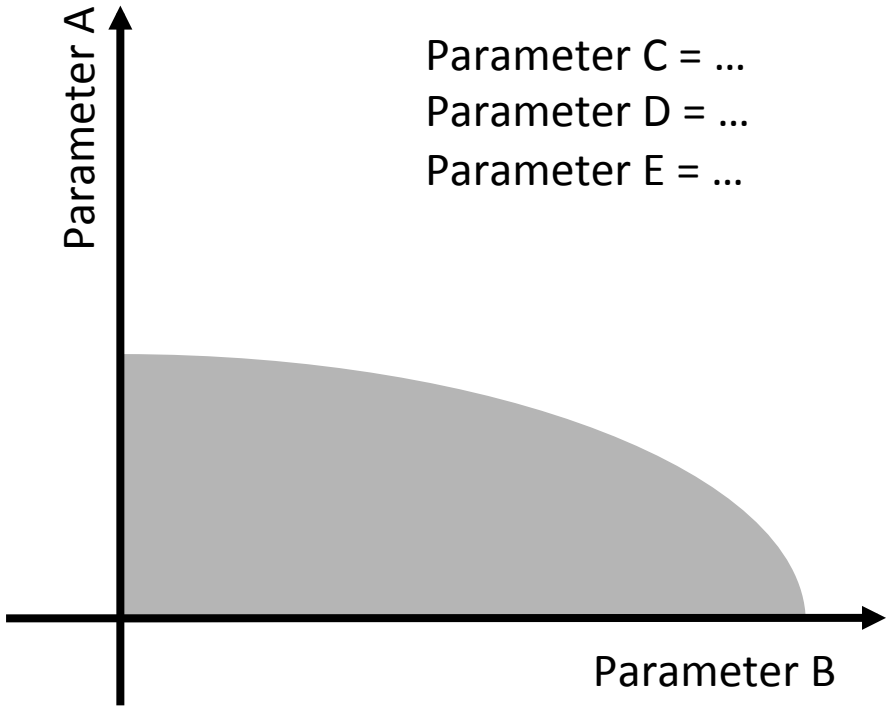
Our Goal: Set limits on models and its parameters

Model exclusion in Particle Physics

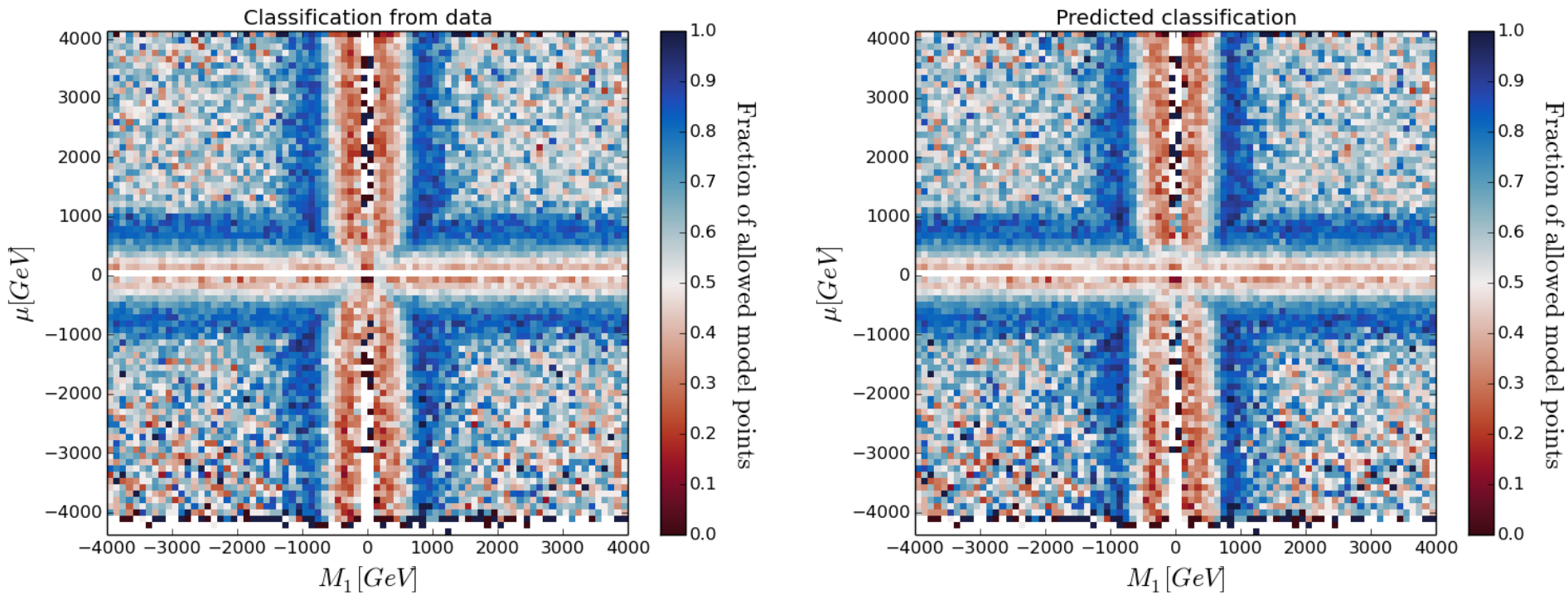
We are used to publish on a piece of paper…
i.e. in 2 dimensions.

<u>What we usually do in HEP?</u>

a) Forget about the 6 dimensional model, take a "simplified" model with only A and B
b) Set parameter C= …, D= …, E=… and plot A vs B
c) More sophisticated: Show projections (profiling) of the model likelihood on parameters A, B as well as C,D etc.



This is the experimentalists…
What about the theory community ?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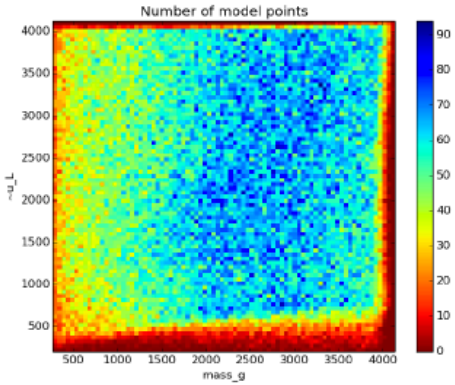
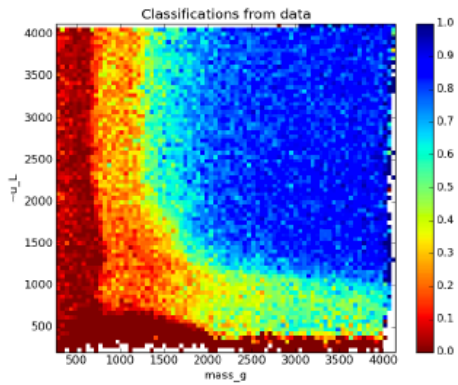
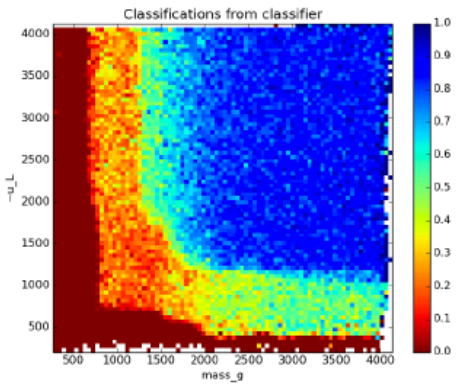
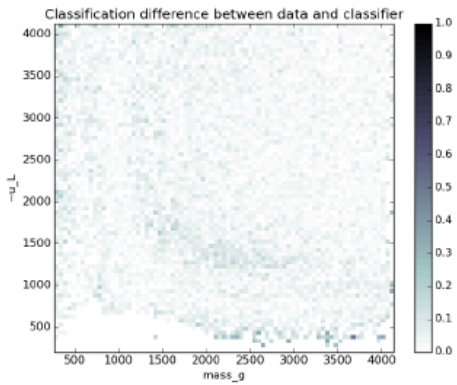
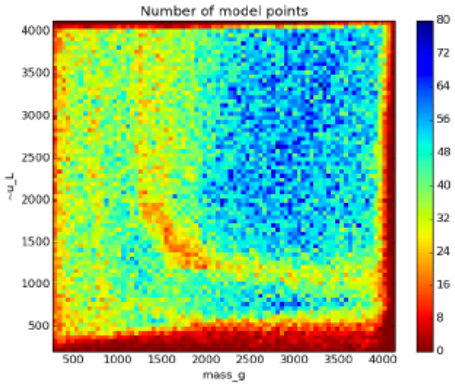
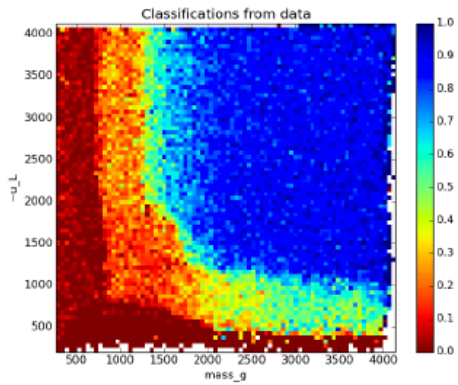
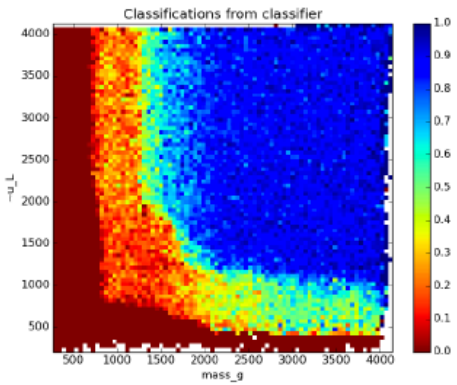
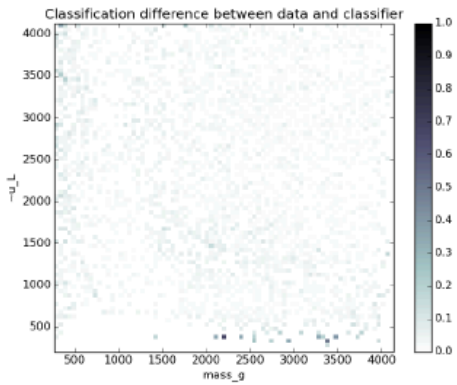
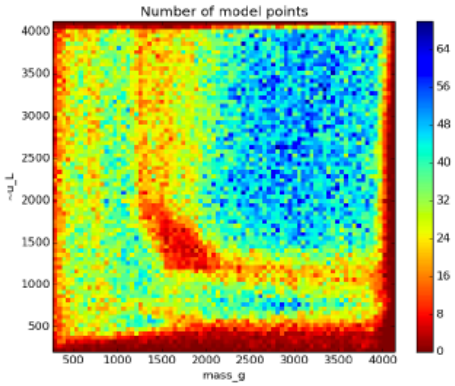
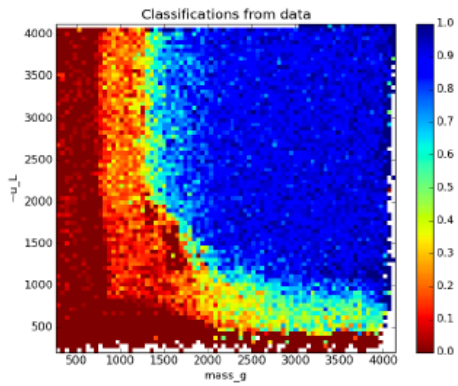
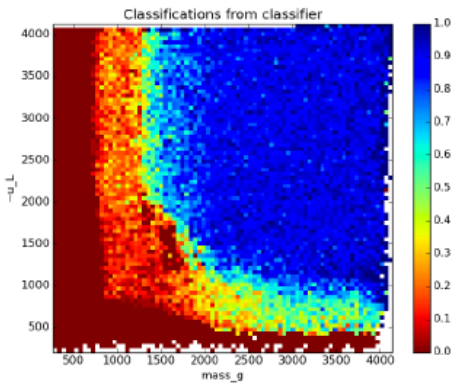
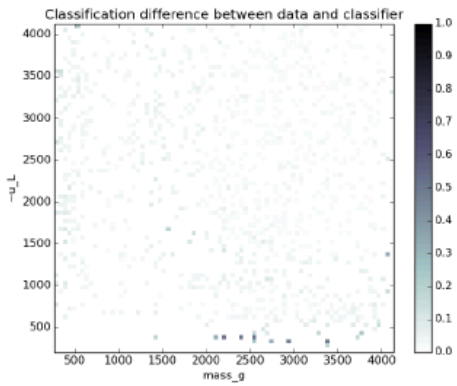
	Number of model points	True classification	Prediction by classifier	Difference between classification and prediction
All data				
95CL				
99CL				

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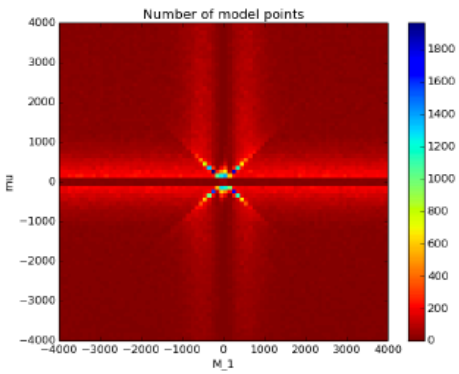
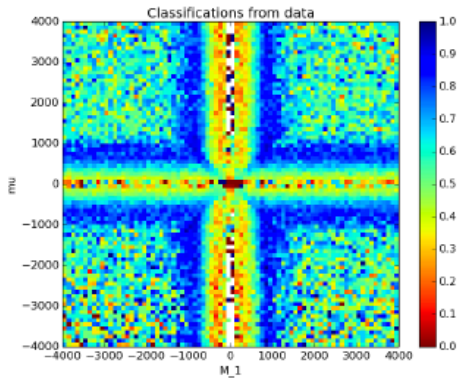
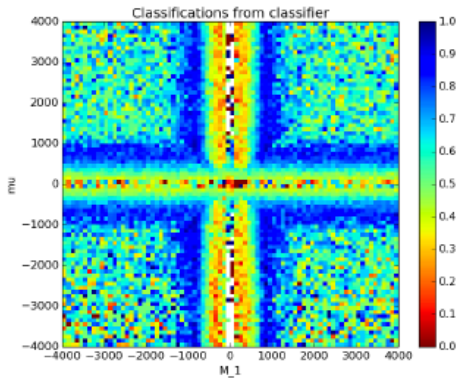
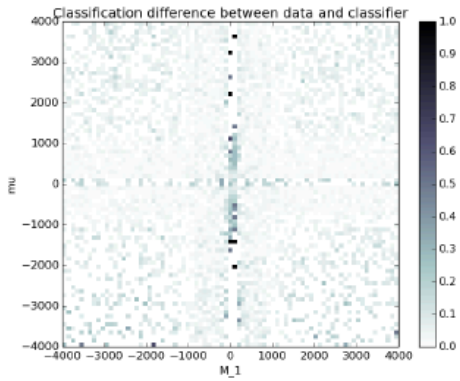
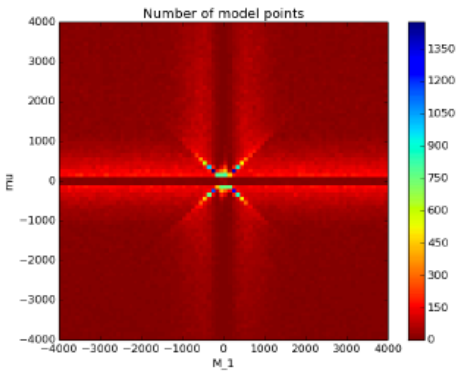
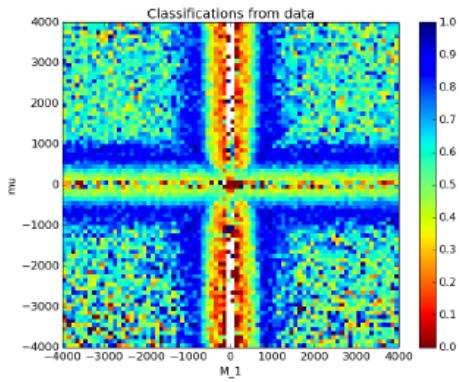
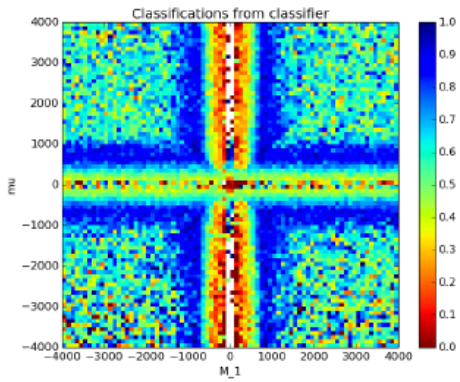
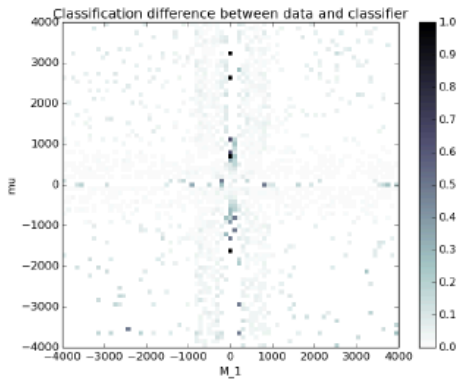
All data				
95CL				
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