# Learning (from) High-dimensional Models

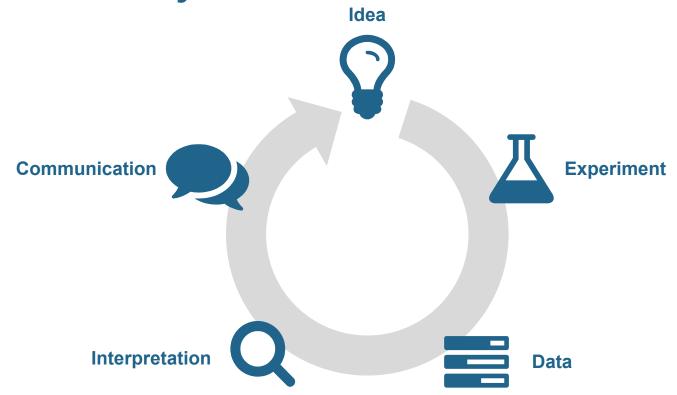
Jisk Attema Tom Heskes Roberto Ruiz de Austri Sascha Caron Sydney Otten Jong Soo Kim Faruk Diblen Krzysztof Rolbiecki <u>Bob Stienen</u>

netherlands





# How do we do (particle) physics?



Communication

# Interpretation

#### Idea

- Inherently model dependent
  - → different model = different interpretation

#### **Experiment**

- Interpretation of the results in the context of a single model point is computationally very expensive
  - → Simplified models are often used, but



#### Communication



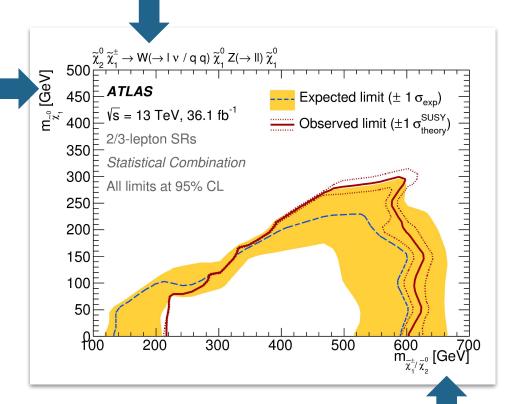
Interpretation

#### Idea

- Images in papers are inherently 2-dimensional
  - → displaying more than 4 dimensions in a plot is difficult

#### Experiment

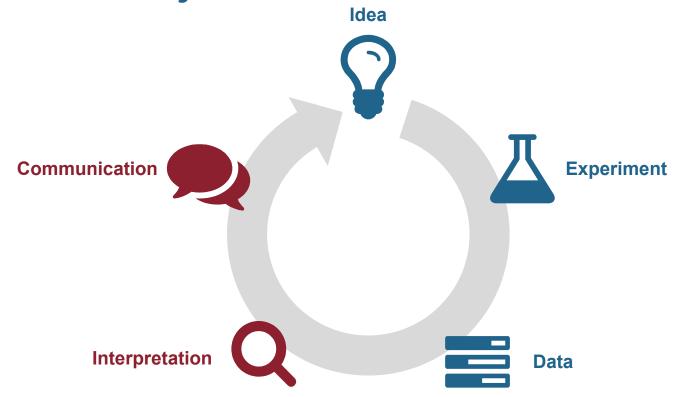
- Simplified models are often used, but at the cost of information loss
- Raw data can be published (e.g. model points + evaluations)
  - → Individual results are not extremely useful



#### What if...

- i don't have a 100% BR to the specified final state?
- i want to know the exclusion in another projection?
- i have the other free parameters set differently?

Core of the problem: Plotting N>2 dimensions is hard

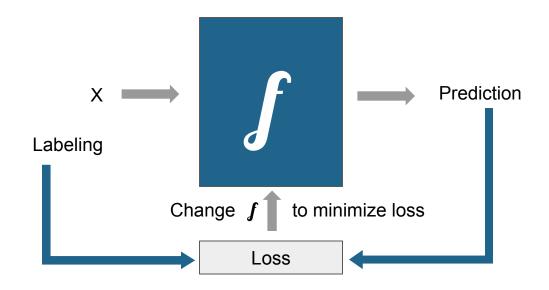


# How to manage our information to retain most of it?



#### Machine Learning as a solution

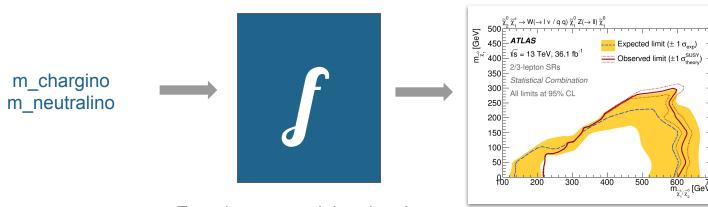




#### Machine Learning as a solution

Example





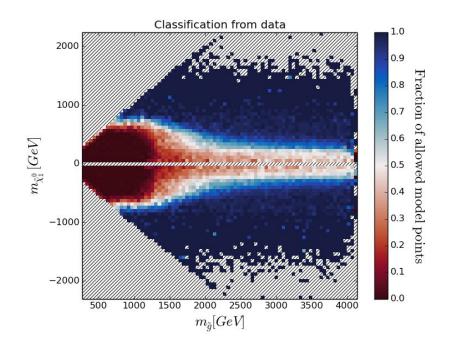
Encodes our model and entire analysis workflow

But... can be N>2...

#### SUSY-AI as proof-of-principle

DOI: 10.1140/epjc/s10052-017-4814-9



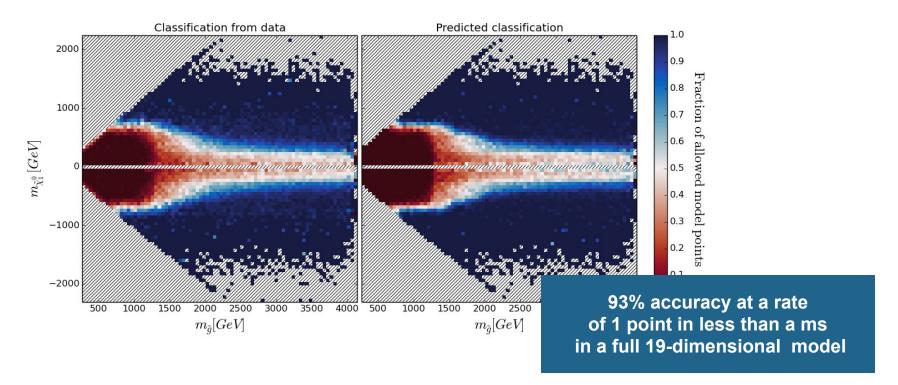


- pMSSM19
- 300,000 training points 10.1007/JHEP10(2015)134
- Exclusion determined by 22 different analyses
- RandomForest (for the connaisseurs)

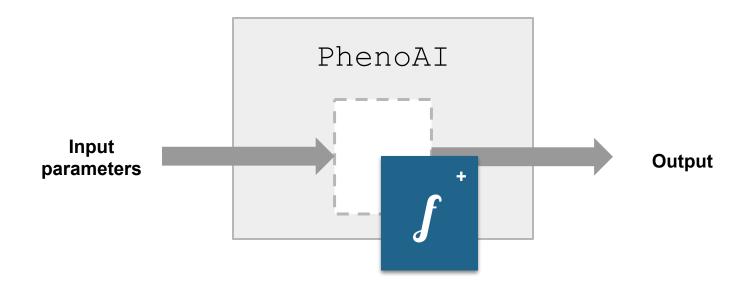
#### SUSY-AI as proof-of-principle

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#### PhenoAI as natural evolution

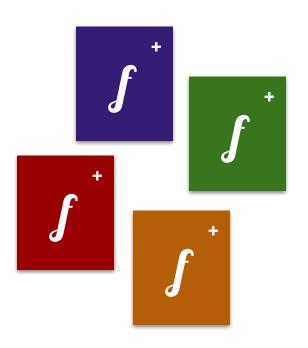


Machine Learning is abstracted away: anyone with Python knowledge can use the trained models

Communication of high-dimensional results becomes possible:

publish a trained algorithm

#### **PhenoAlnalyses**



- Trained algorithms (Alnalyses) still need to be made. You can do this yourself, or...
- ... download one from the Alnalysis library on the PhenoAl website
- Currently working on Alnalyses for:
  - **Cross Sections**
  - Electroweakino
  - Likelihoods from Gambit

#### Supported ML libraries

All estimators and models created with Keras/tensorflow and scikit-learn are supported within PhenoAl. We are in the process of adding support for ROOT TMVA models as well.

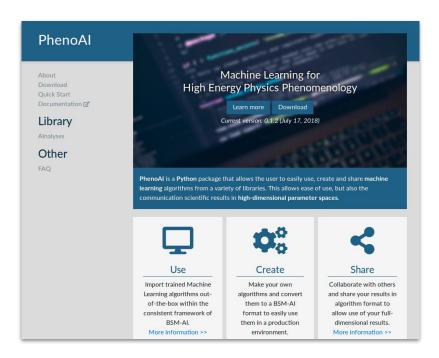






#### Pheno for the masses"

- Stable beta PhenoAI is available via pip3 (phenoai) and via the website <a href="http://hef.ru.nl/~bstienen/phenoai">http://hef.ru.nl/~bstienen/phenoai</a>
- Extensive documentation available
- Started to collect algorithms for Alnalysis library



## But what about data?

#### Data publishing

- Individual data points (e.g. model points) are not really informative on their own
- Data can be published on HEPData, but...
  - ... lacks an easy interface to navigate and explore the data
  - ... data sets can not be easily compared

**Result**: Publishing information like model point evaluations is still not extremely common in our field.

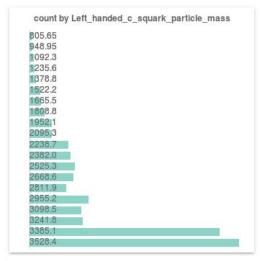
#### iDarkSurvey for Data Publishing

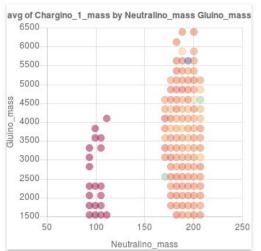


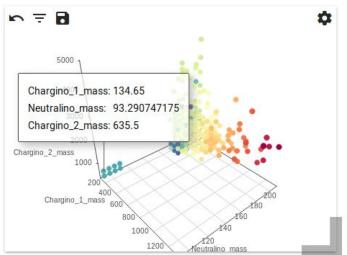
- iDarkSurvey is an instance of SPOT, a plotting and data collection tool
- Online data storage for high energy physics data
- Has online plotting interface to explore data
- Multiple data sets can easily be compared within the same plots
- Own data can be viewed alongside the data in the database
- Online demo at <a href="http://www.idarksurvey.org/">http://www.idarksurvey.org/</a>

#### iDarkSurvey for Data Publishing







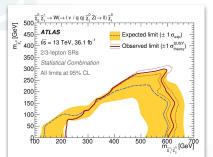


http://www.idarksurvey.org/

Idea



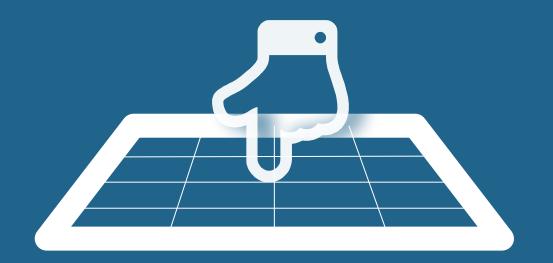
- Sampling in particle physics is most commonly grid sampling, which is intractable for high-dimensional spaces
- Evaluation of truth label can take O(hour)
- In ideal world we want "most bang for our buck":
   get most informative points only



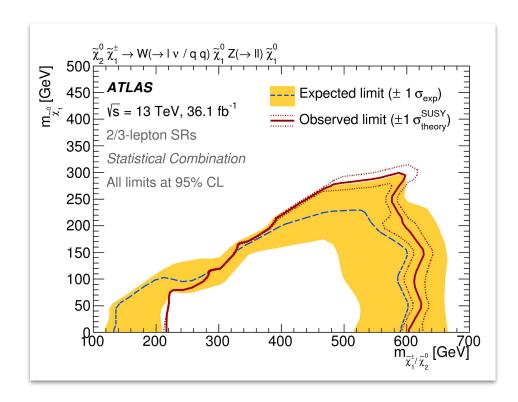




# Can we aim our sampling?



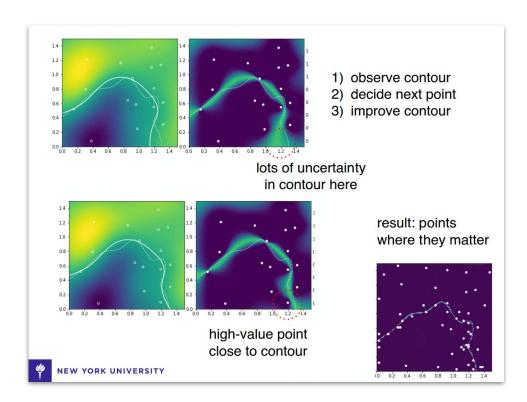
#### Where to aim?



Depends on case, e.g.

- Binary exclusion
   Around decision boundary
- Global regression
   Regions with highest 'uncertainty', could basically be anywhere in the parameter space

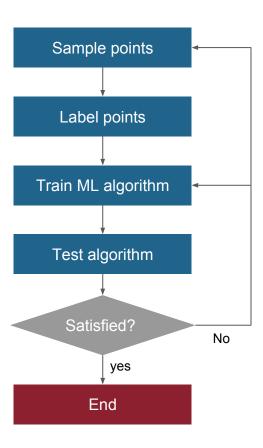
#### **Gaussian Processes**



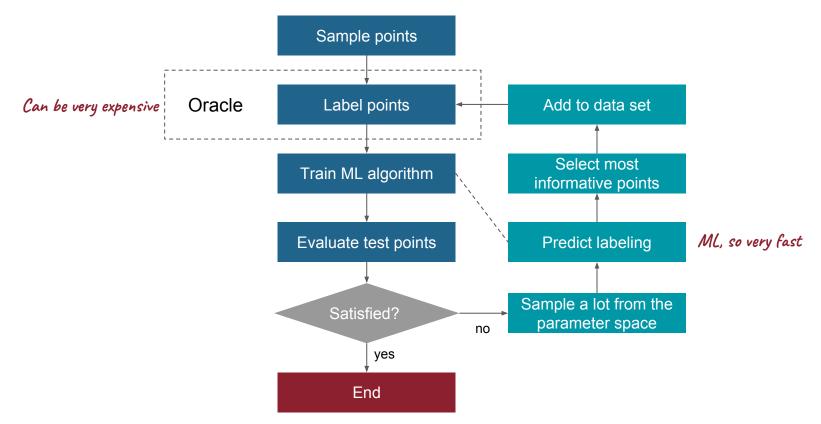
#### Levelset Estimation by Bayesian Optimization

K. Cranmer, L. Heinrich, G. Louppe https://indico.cern.ch/event/702612/timetable/

#### Optimization of Machine Learning algorithm



#### **Active Learning**



#### **Active Learning**

Select most informative points

#### **Uncertainty sampling**

Use output of algorithm as probability:

- Softmax output layer
- Platt scaling
- Other calibration methods

Select points with lowest associated probability.

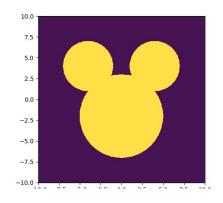
#### **Query by Committee**

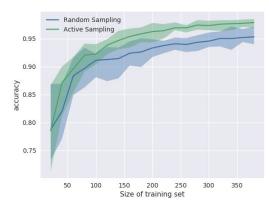
Train multiple algorithms on same data with natural variation:

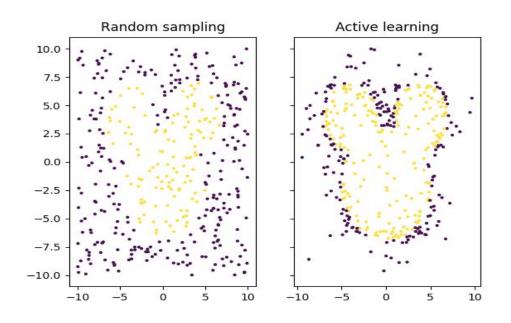
- Bagging
- Vary the algorithms themselves (e.g. different NN architectures)

Let all algorithms make predictions on points, select those points with largest spread in the prediction.

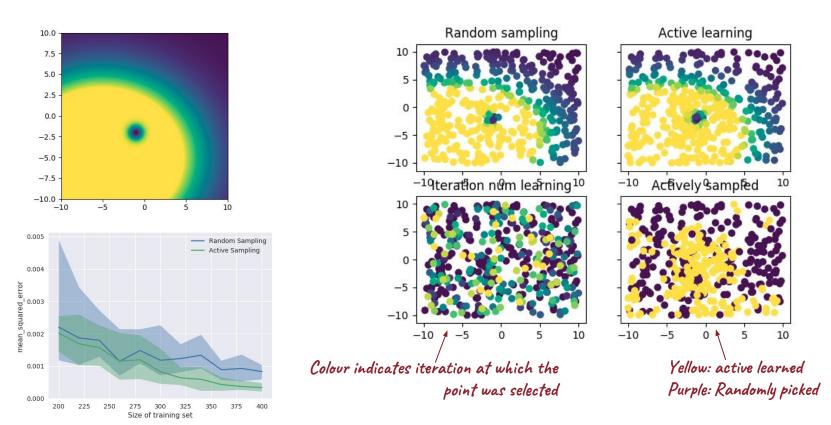
#### Simplified example I



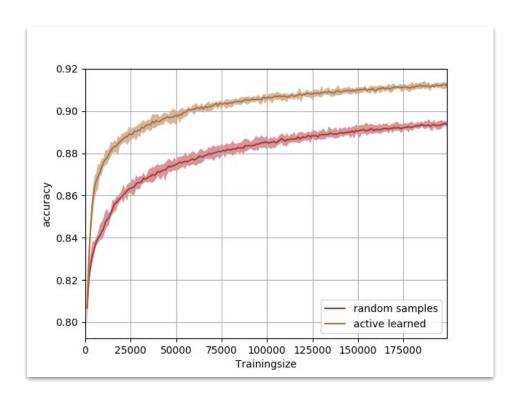




#### Simplified example II



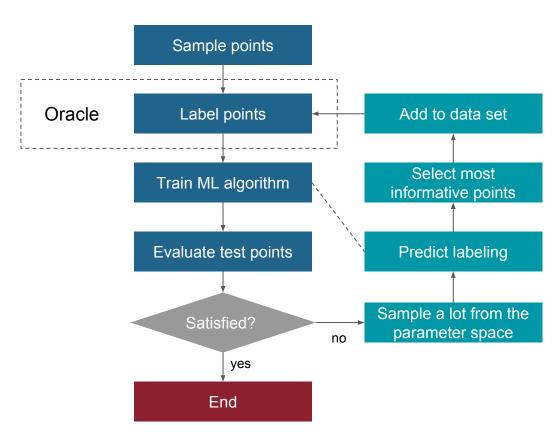
#### Real-life example



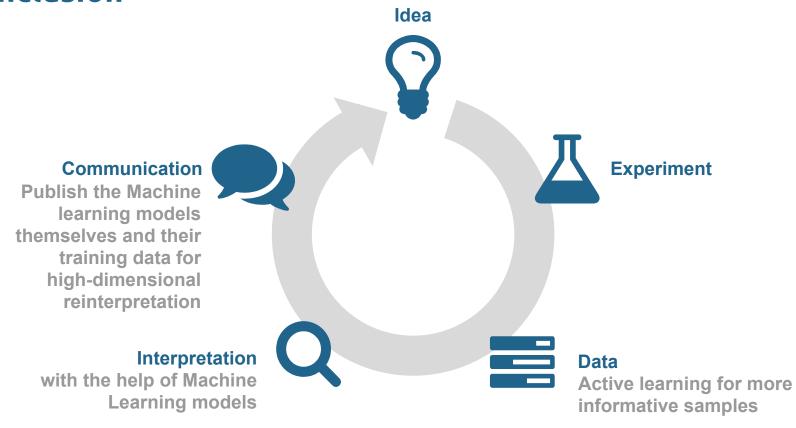
- ATLAS pMSSM-19 data (source for SUSY-AI) to train a neural network
- This NN is the oracle (mimicking the true simulation chain)
- 3. Use Active Learning with RandomForests to get accuracy development plot

#### Active learning

- Works for any dimensionality, as long as ML algorithm is chosen accordingly
- Working on the Gambit MSSM7 data as second real-life example
- Working on first applications



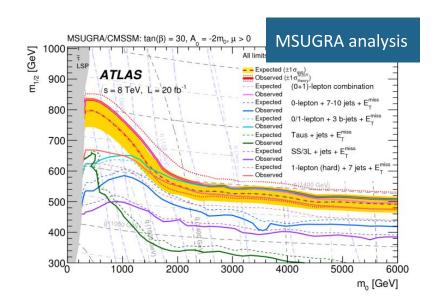
#### **Conclusion**

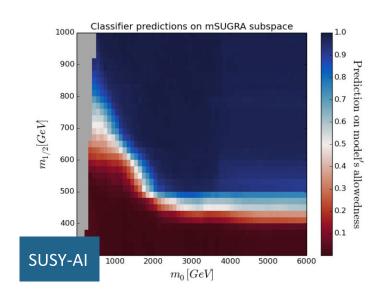


### Extra slides

#### What about my simplified model?

Training on a full model still allows access to submodels. SUSY-AI was trained on the pMSSM19, of which MSUGRA/CMSSM is a submodel.

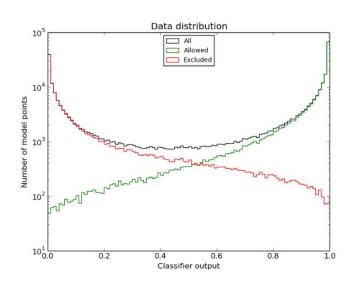


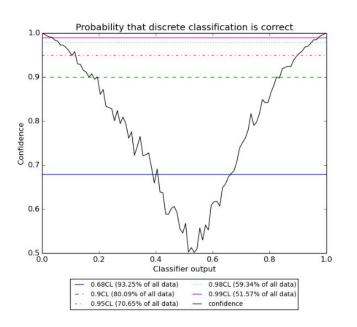


Comparison not entirely fair: the dedicated MSUGRA/CMSSM scan combined signal regions in a smart way, whereas the exclusion of the SUSY-AI dataset uses the simple: "if excluded by any analysis -> excluded"

#### Confidence construction from SUSY-AI

SUSY-AI is a classifier, but outputs a continuous value between 0 (excluded) and 1 (allowed). It can *not* be interpreted as a probability, but can be transformed into one.





#### Is PhenoAI really that simple?

```
1 from phenoai.phenoai import PhenoAI
2
3 master = PhenoAI()
4 master.add("./example_ainalysis", "example")
5 result = master.run(X)
```

Yes

#### Learning to use PhenoAl

PhenoAl aims to be as easy to use as possible. To this end we have created:

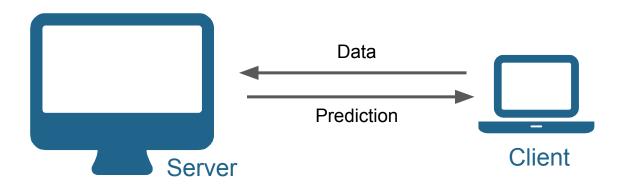
- online documentation
- in-code documentation
- example scripts
- a quick start manual

We are busy optimizing the learning experience of PhenoAI even further, making material as a tutorial and a cheat sheet.

#### Server-client structure

PhenoAI has a built-in ability to create a server-client structure. The server has the Alnalyses loaded, the client can be added to any script and will query the server for prediction on a specific data set. In this way, the loading and configuration overhead are needed only once.

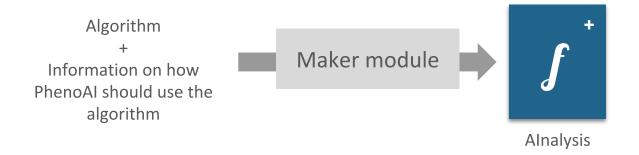
Server and client can of course just be the same machine



#### Maker module

In order to use a trained algorithm within PhenoAI, it needs to be stored within a folder with a PhenoAI configuration file. This collective as files is called an AInalysis and can, in principle, be made by hand. It is however more convenient to use the phenoai.maker module. Which will indicate if errors are made.

Example scripts on how to use the maker module are availble.



#### **DarkMachines**

PhenoAl is connected to the DarkMachines initiative as well, a research collective aiming to unravel the mystery that is dark matter with the help of machine learning. See <u>darkmachines.org</u> for more information.

