



Learning (from) High-dimensional Models with PhenoAI and iDarkSurvey

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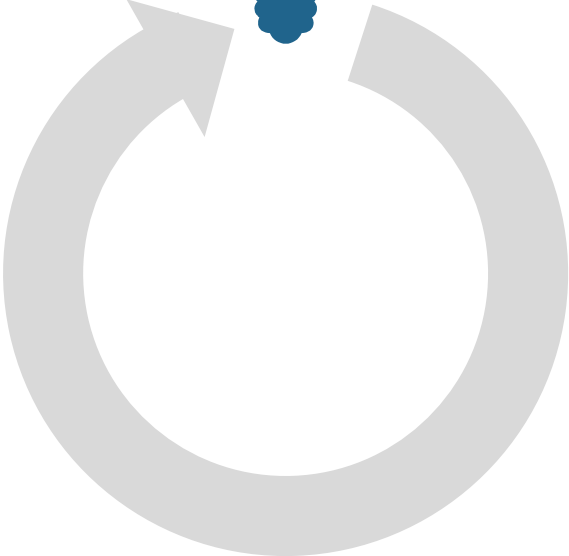
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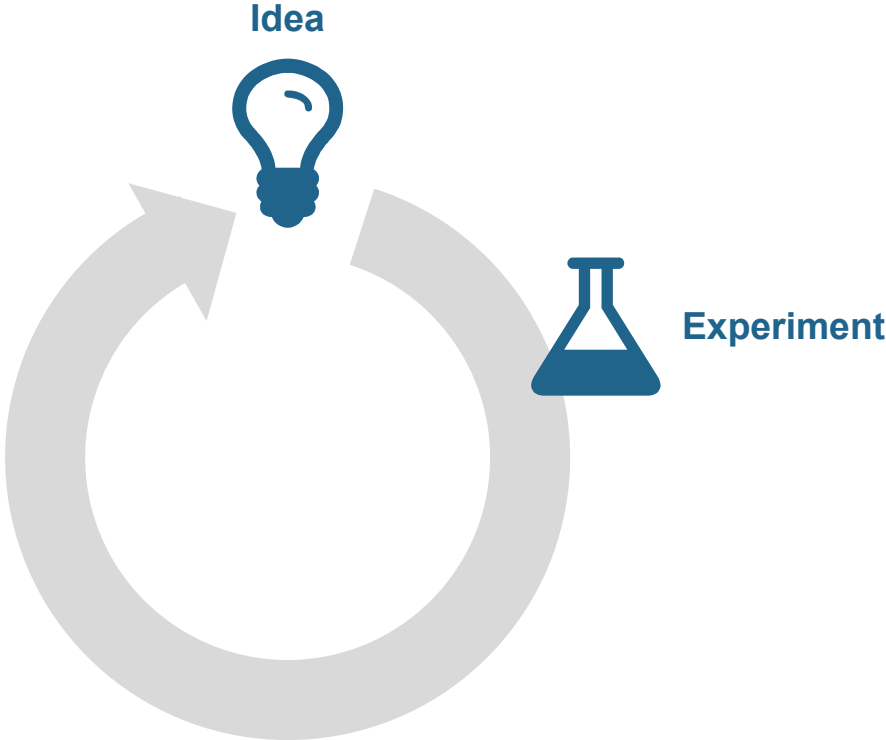
How do we do (particle) physics?

The Circle of Physics

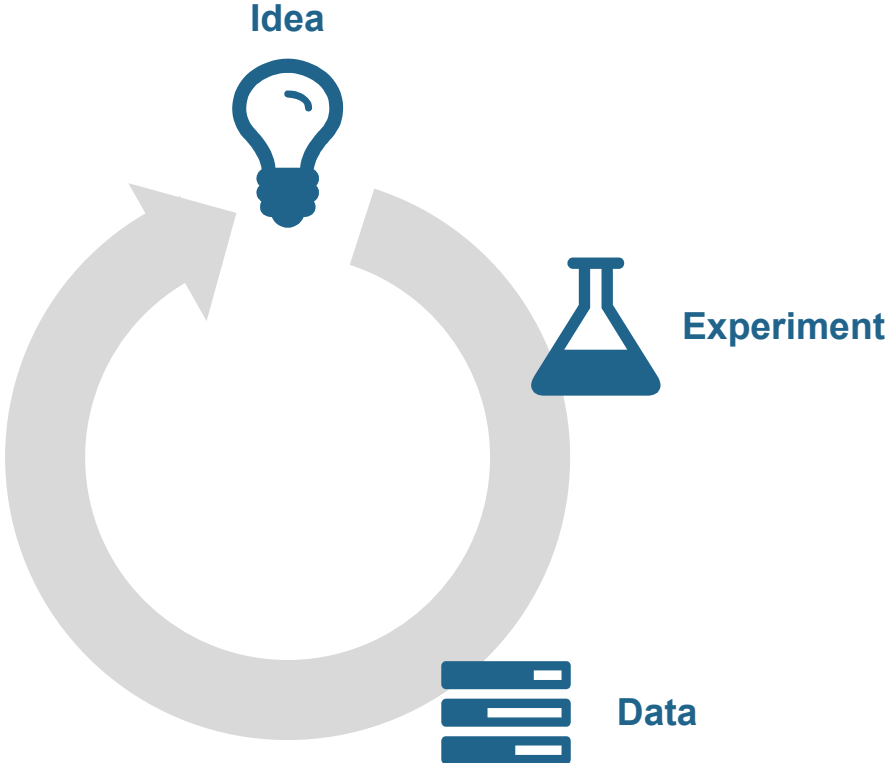
Idea



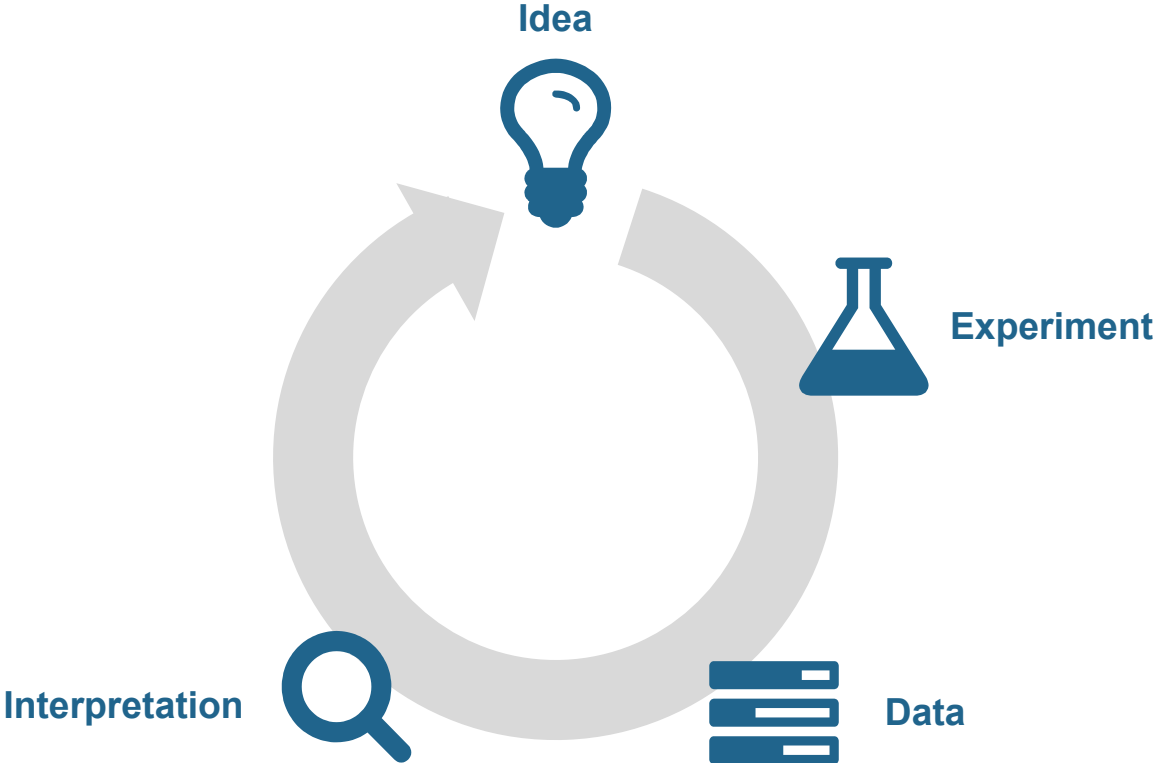
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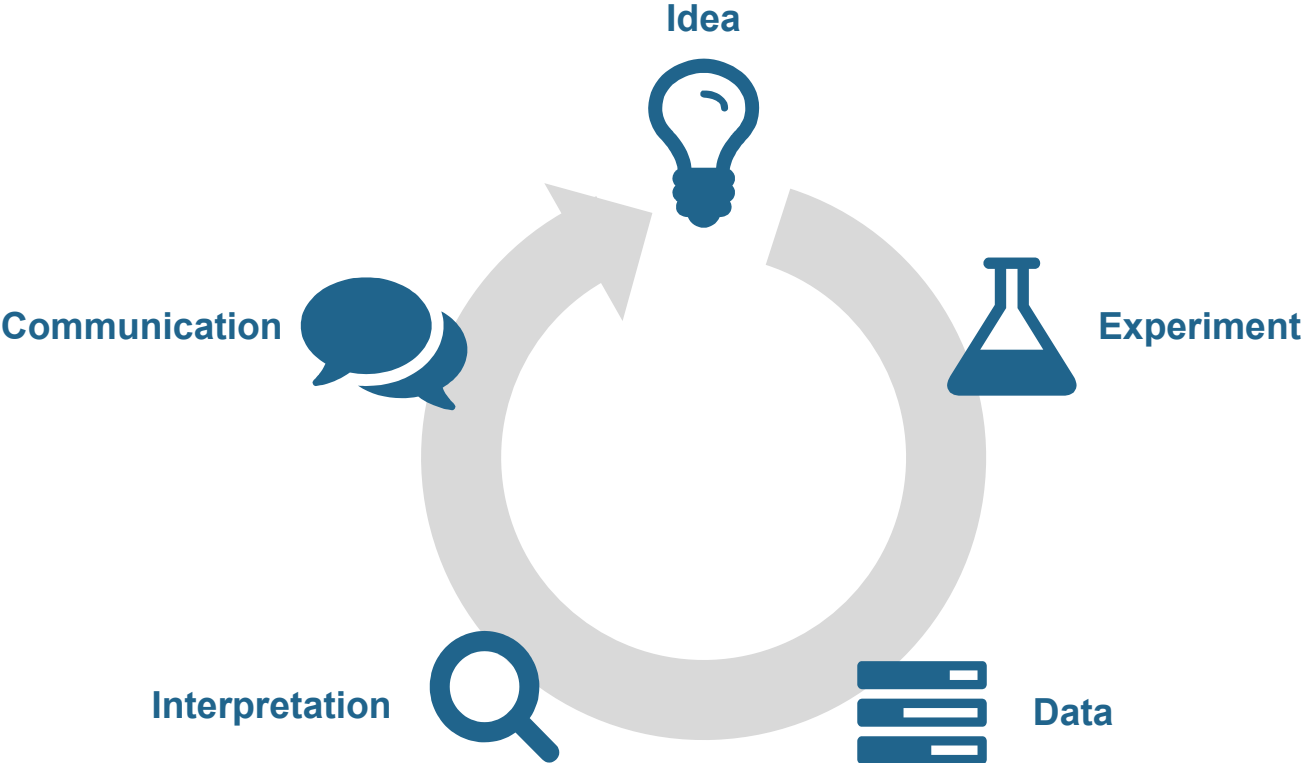
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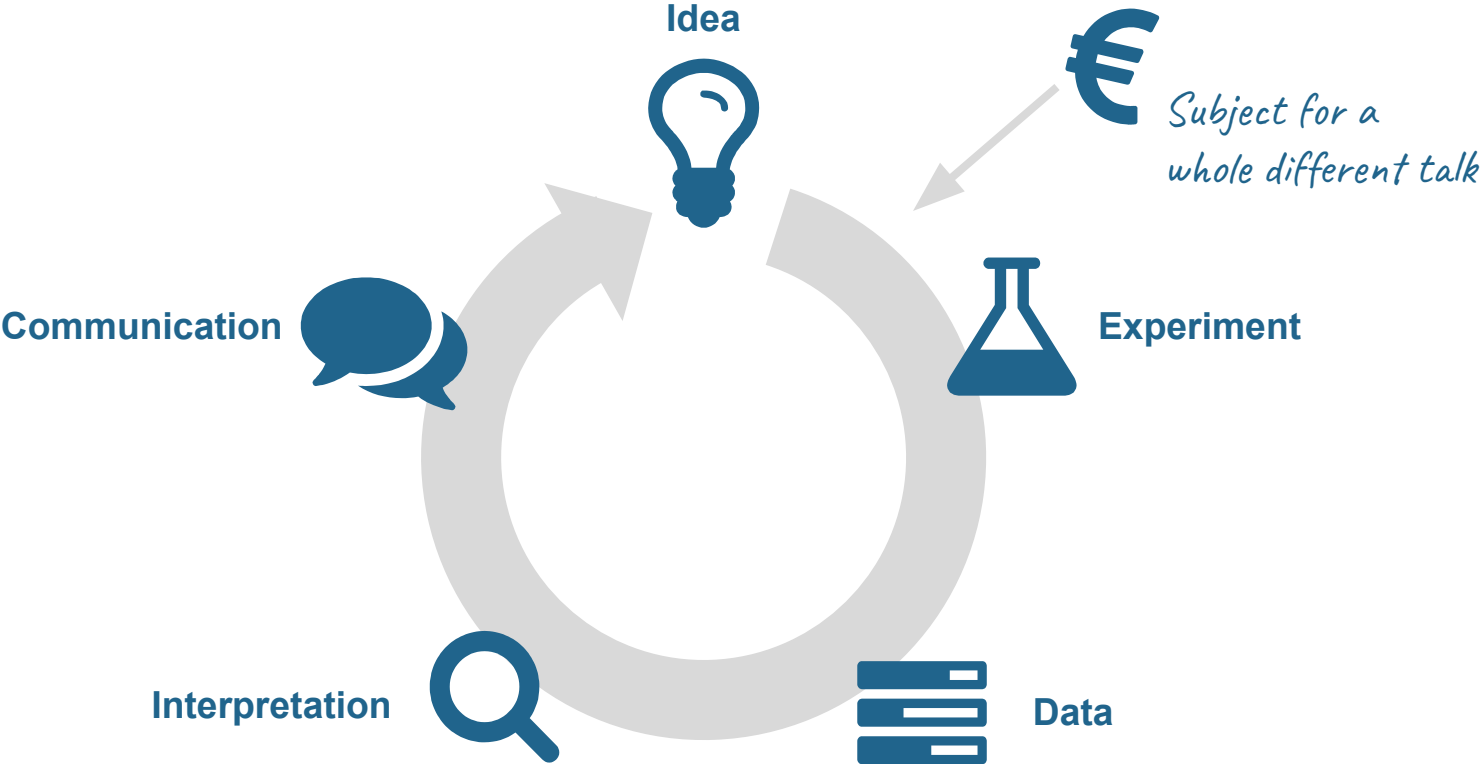
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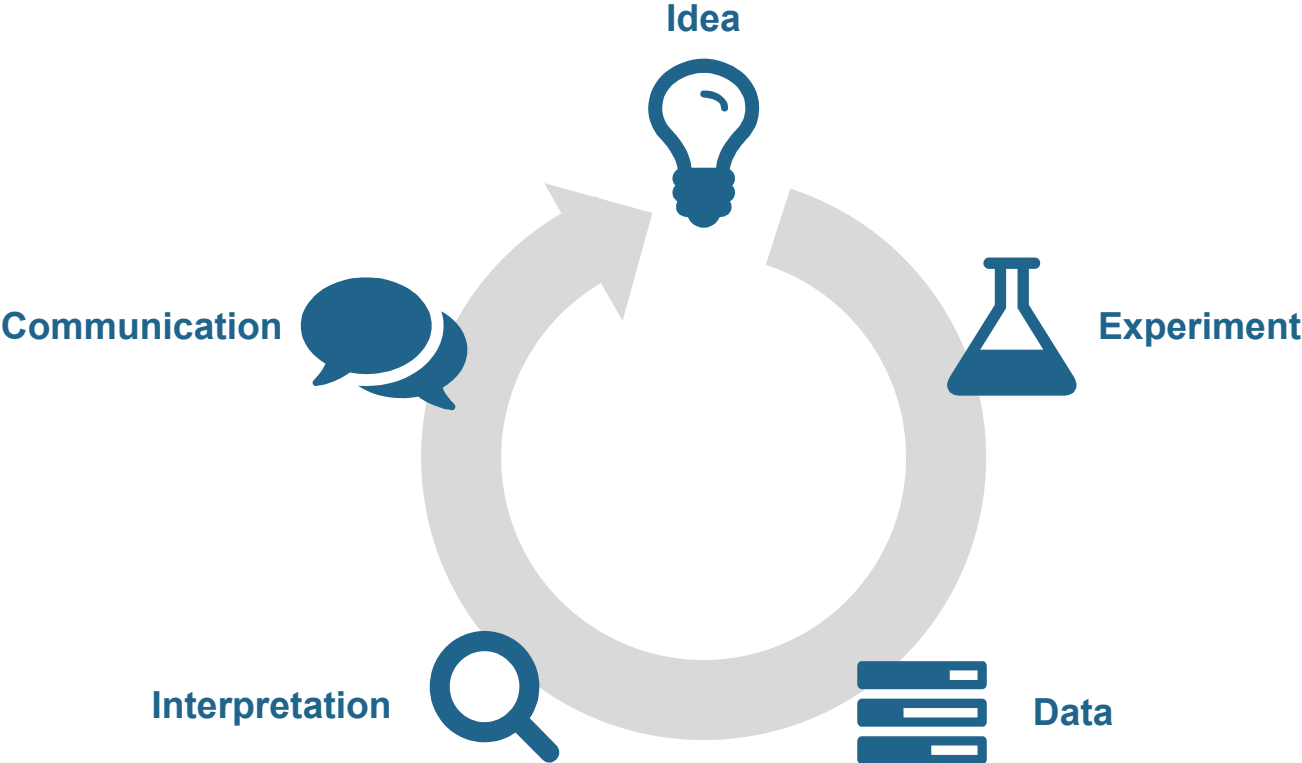
The Circle of Physics



The Circle of Physics



The Circle of Physics



The Circle of Physics

Communication



Interpretation

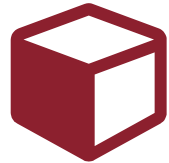


Idea

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



N^*



The Circle of Physics

Communication



Interpretation

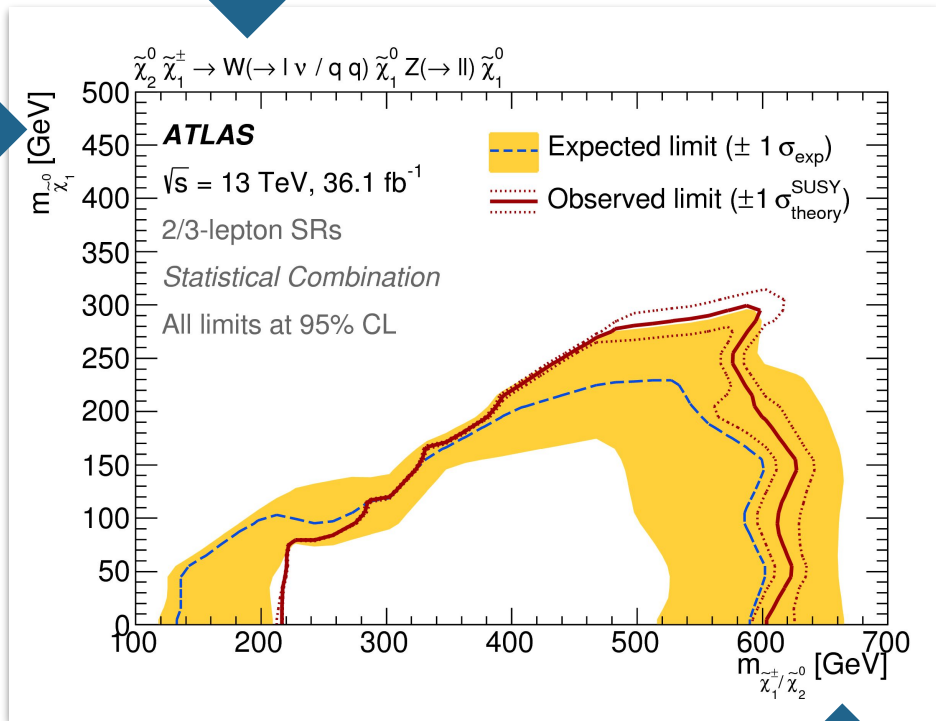


Idea

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

Experiment





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**

The Circle of Physics

Communication



Interpretation



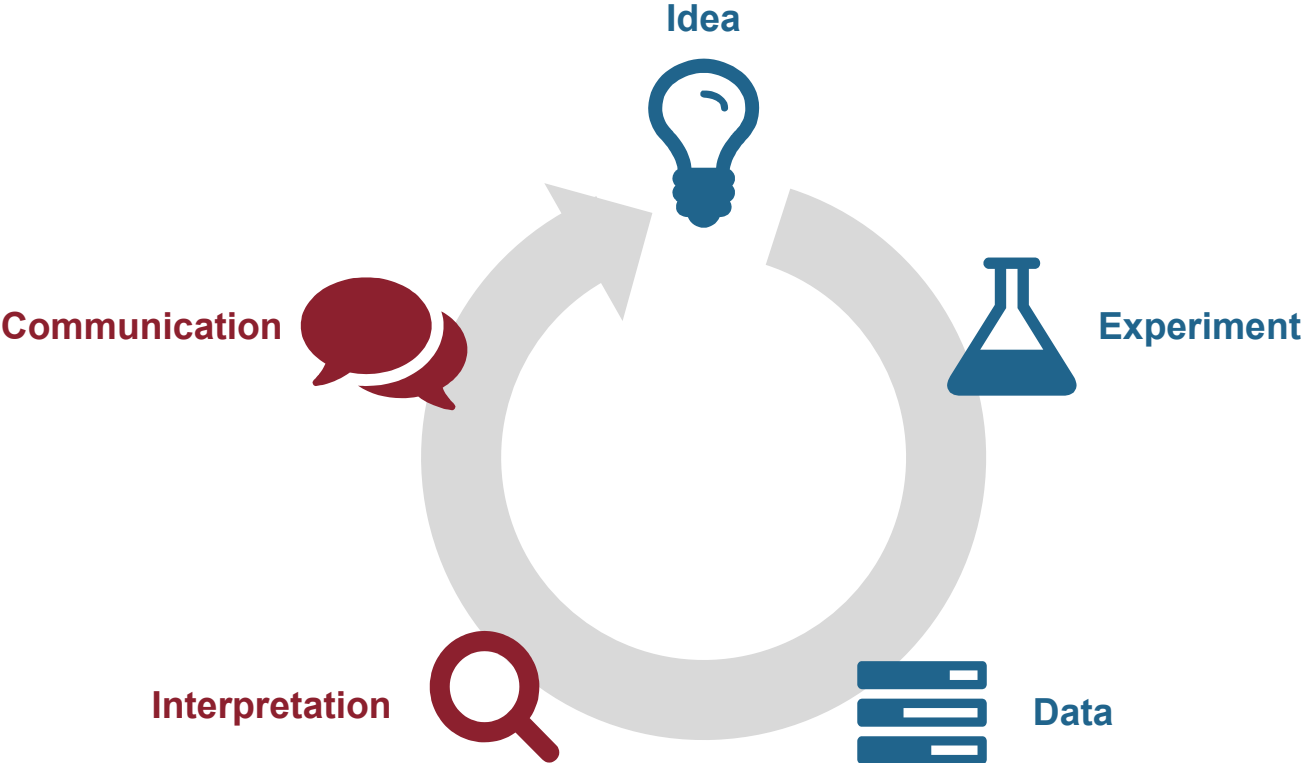
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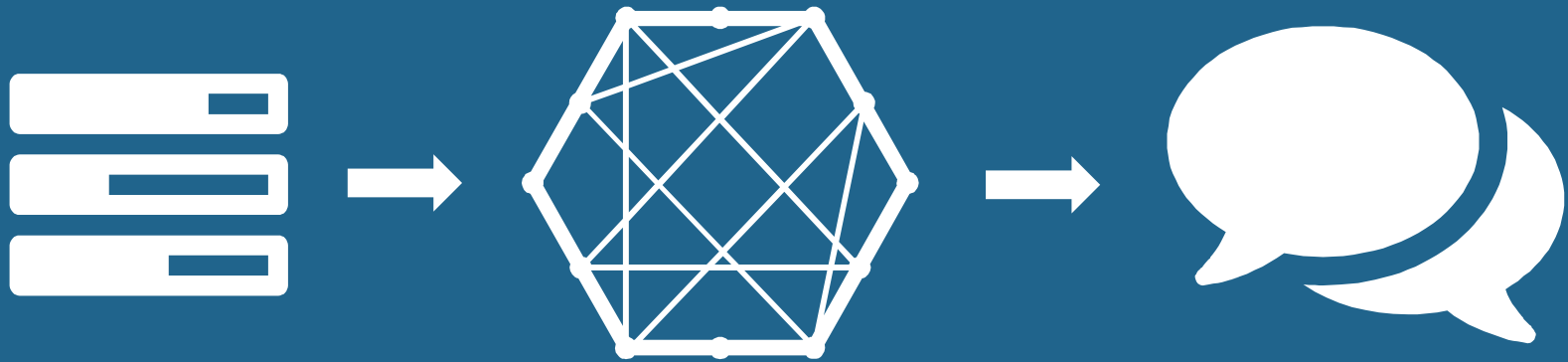
Experiment



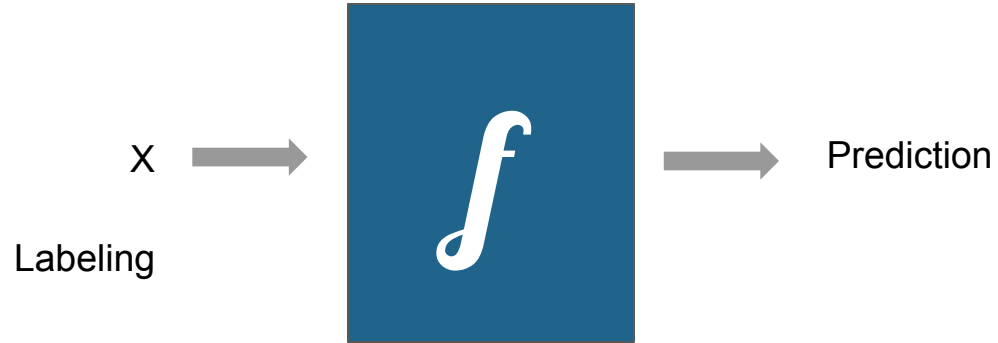
The Circle of Physics



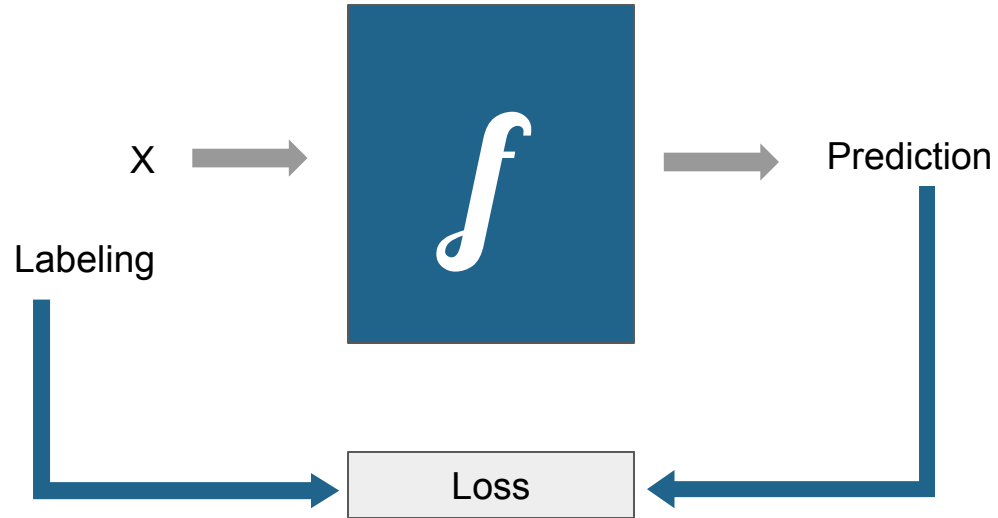
*How to manage our information
to retain most of it?*



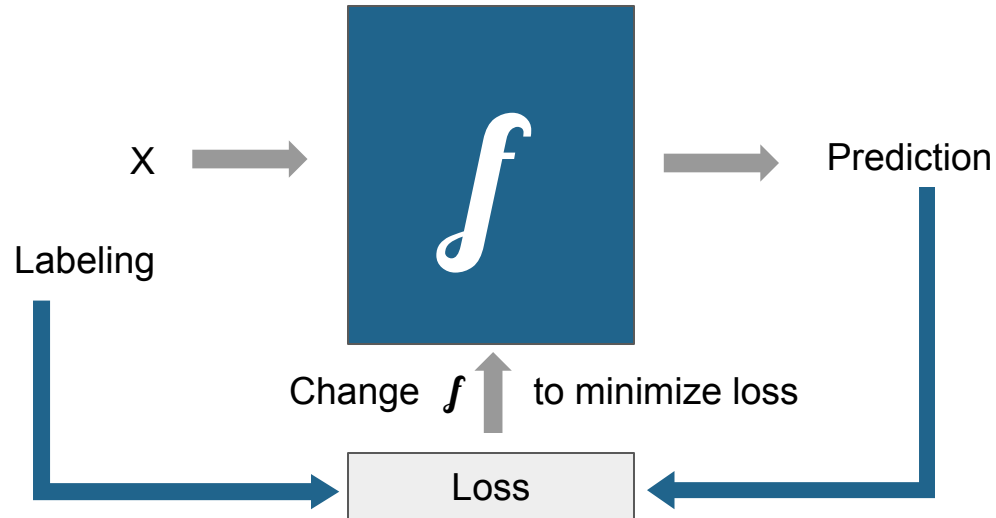
Machine Learning as a solution



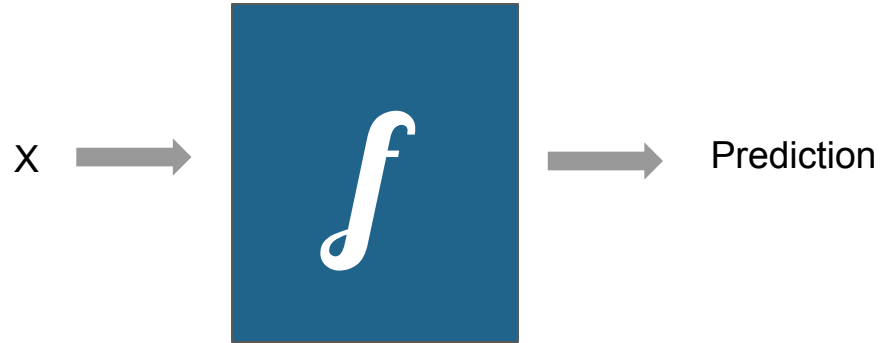
Machine Learning as a solution



Machine Learning as a solution



Machine Learning as a solution



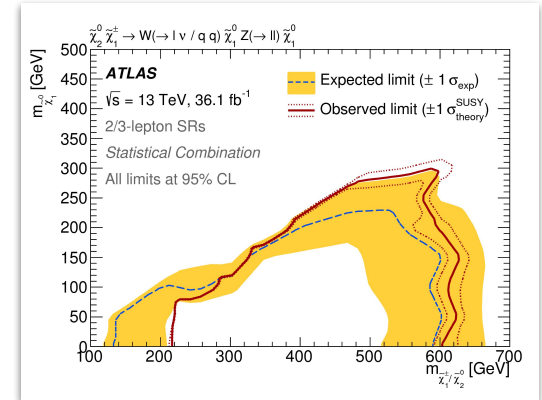
Encodes our model and entire
analysis workflow

Machine Learning as a solution

Example



m_{chargino}
 $m_{\text{neutralino}}$

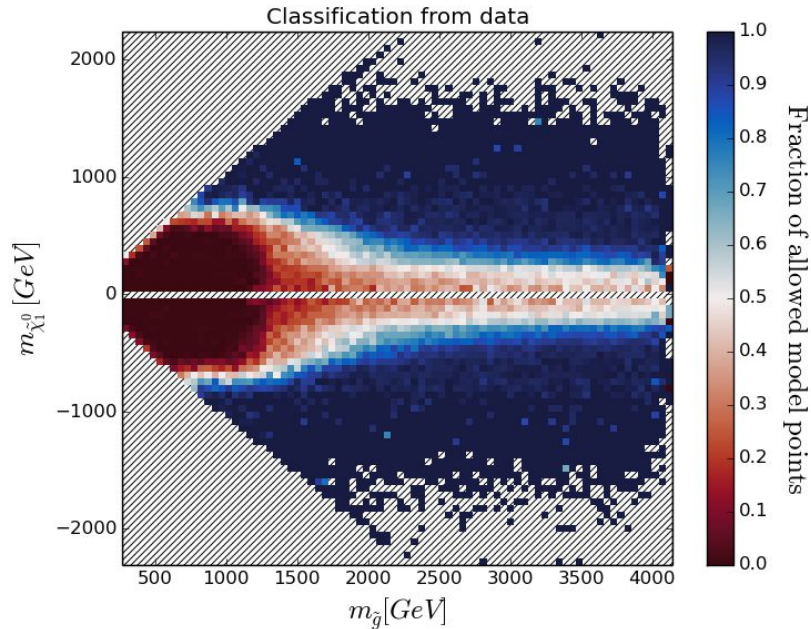


Encodes our model and entire analysis workflow

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

SUSY-AI as proof-of-principle

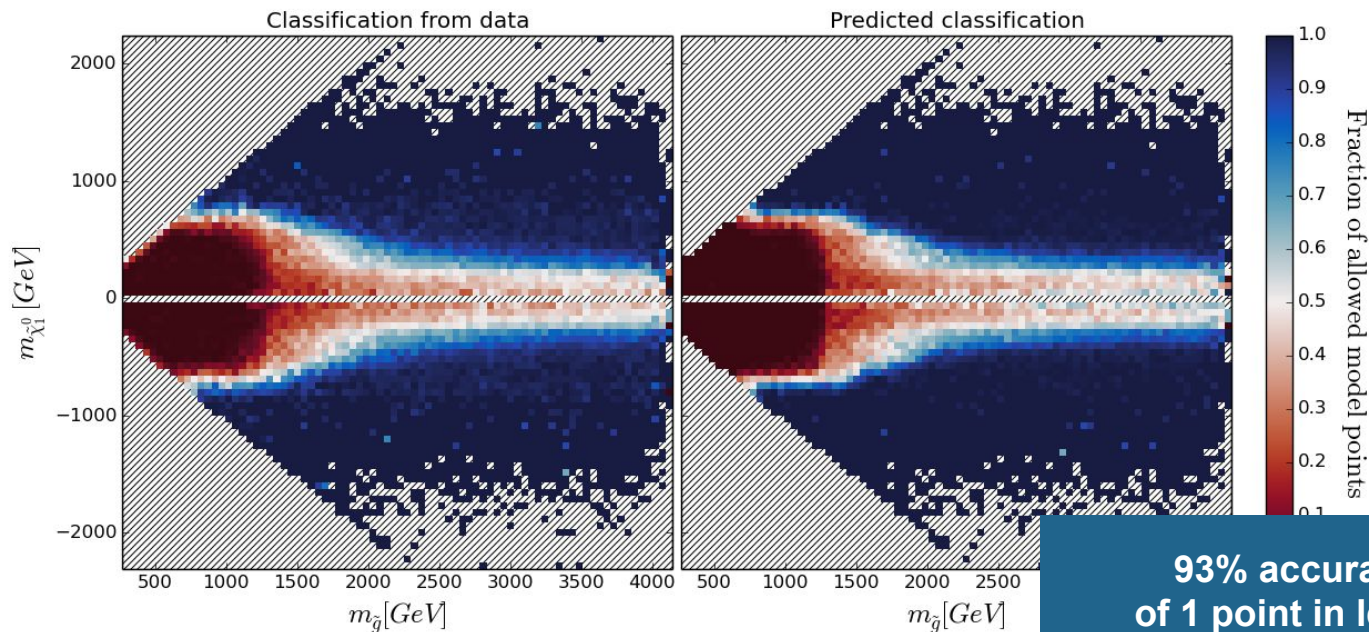
DOI: 10.1140/epjc/s10052-017-4814-9



- pMSSM19
- 300,000 training points
[10.1007/JHEP10\(2015\)134](https://arxiv.org/abs/1507.06454)
- Exclusion determined by 22 different analyses
- RandomForest (for the *connaisseurs*)

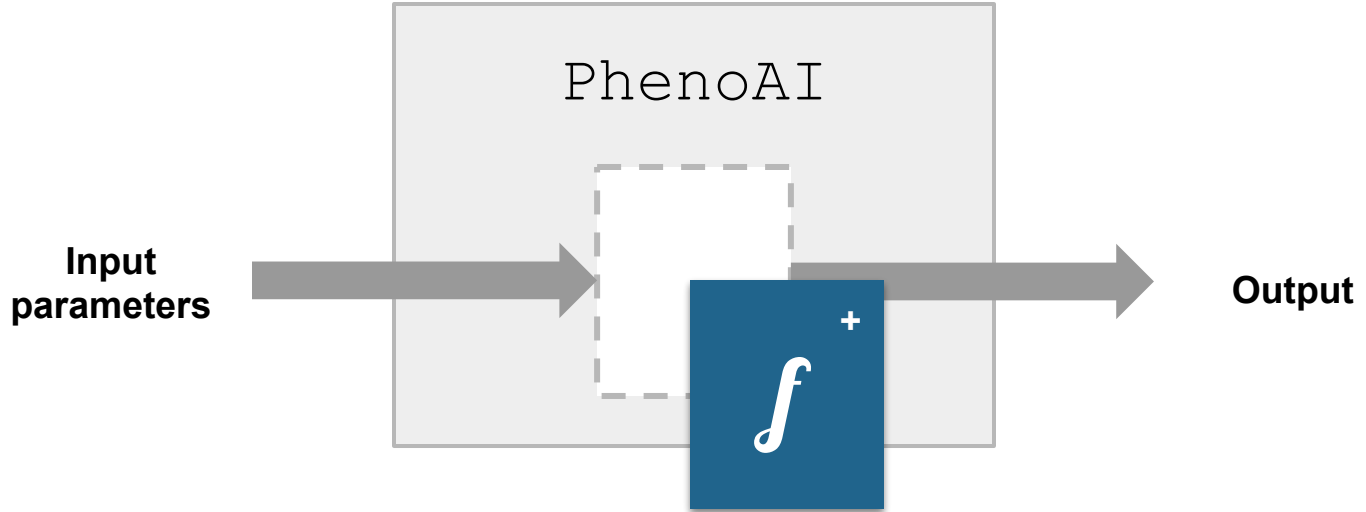
SUSY-AI as proof-of-principle

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**93% accuracy at a rate
of 1 point in less than a ms
in a full 19-dimensional model**

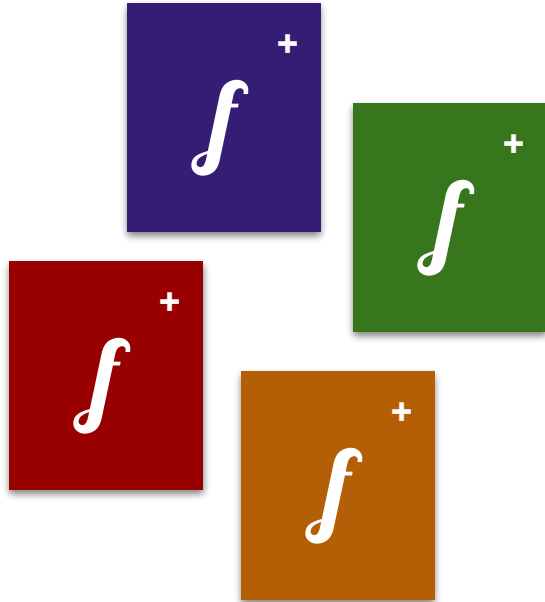
PhenoAI as natural evolution



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

PhenoAnalyses



- Trained algorithms (**Analyses**) still need to be made. You can do this yourself, or ...
- ... download one from the Analysis library on the PhenoAI website
- Currently working on Analyses for:
 - Cross Sections << *See S. Otten's talk tomorrow*
 - Electroweakino
 - Likelihoods from Gambit

PhenoAI *“Pheno for the masses”*

- PhenoAI is available via pip3 (`phenoai`) and via the website <http://hef.ru.nl/~bstienen/phenoai>
- Extensive documentation available
- Feedback is more than welcome!
- Paper will be out soon

The screenshot shows the PhenoAI website homepage. The header is dark blue with the text 'PhenoAI' in white. Below the header is a navigation menu with links for 'About', 'Download', 'Quick Start', and 'Documentation'. The main content area features a large image of a computer keyboard with the text 'Machine Learning for High Energy Physics Phenomenology' overlaid. Below this text are two buttons: 'Learn more' and 'Download'. The current version is listed as '0.1.2 (July 17, 2018)'. A paragraph below describes PhenoAI as a Python package for using, creating, and sharing machine learning algorithms. At the bottom, there are three columns with icons and text: 'Use' (importing algorithms), 'Create' (making own algorithms), and 'Share' (collaborating with others). Each column has a 'More information >>' link.

PhenoAI

About
Download
Quick Start
Documentation

Library
Analyses

Other
FAQ

Machine Learning for
High Energy Physics Phenomenology

Learn more Download

Current version: 0.1.2 (July 17, 2018)

PhenoAI is a Python package that allows the user to easily use, create and share machine learning algorithms from a variety of libraries. This allows ease of use, but also the communication scientific results in high-dimensional parameter spaces.

Use
Import trained Machine Learning algorithms out-of-the-box within the consistent framework of BSM-AI.
[More information >>](#)

Create
Make your own algorithms and convert them to a BSM-AI format to easily use them in a production environment.
[More information >>](#)

Share
Collaborate with others and share your results in algorithm format to allow use of your full-dimensional results.
[More information >>](#)

But what about data?

Data publishing

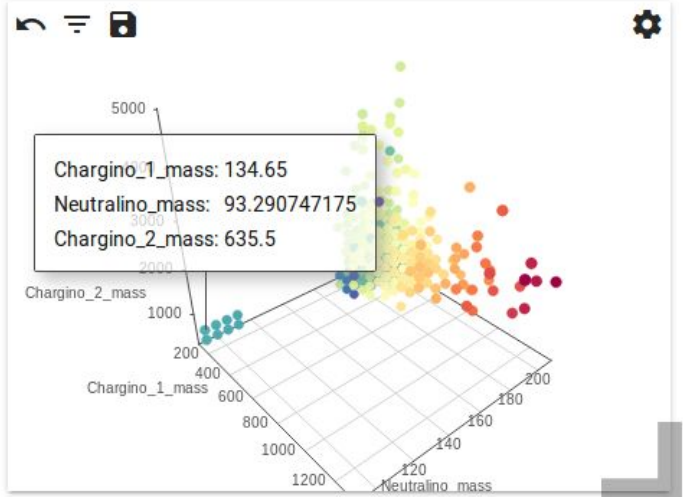
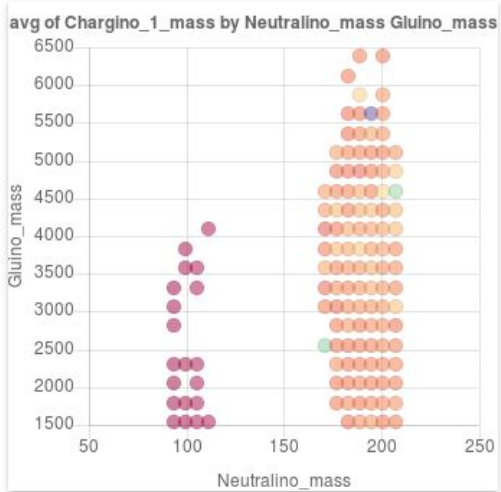
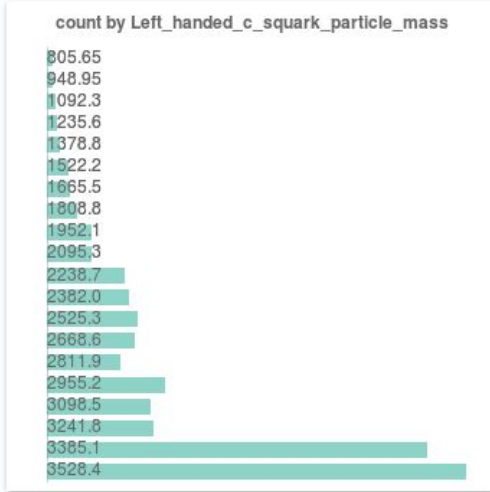
- Individual data points (e.g. model points) are not really informative on their own
- Data can be published on HEPData, but...
 - ... lacks an easy interface to navigate and explore the data
 - ... data sets can not be easily compared

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

iDarkSurvey for Data Publishing

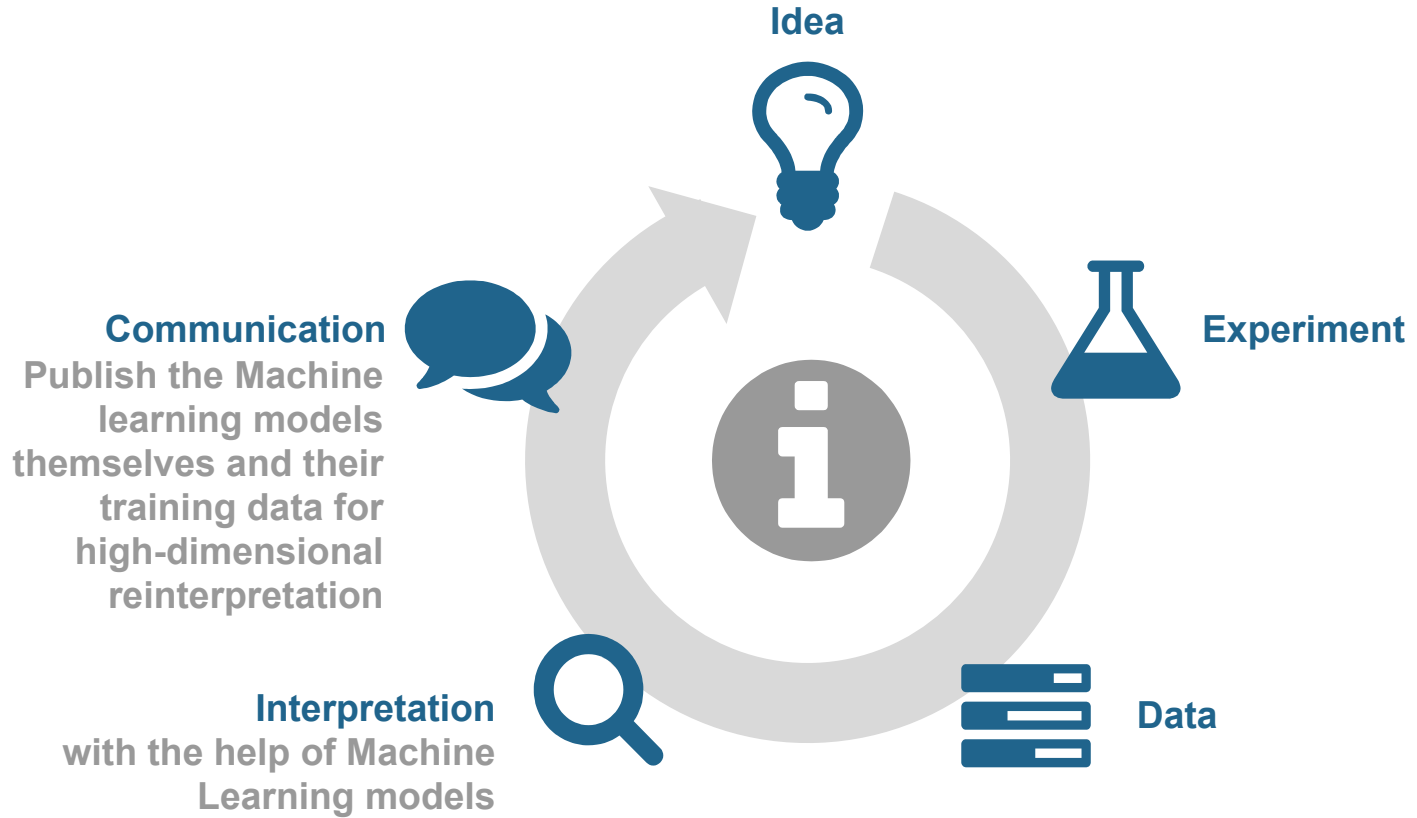
- Online data storage for high energy physics data
- Has online plotting interface to explore data
- Multiple data sets can easily be compared within the same plots
- Own data can be viewed alongside the data in the database
- Online demo at <http://www.idarksurvey.org/>

iDarkSurvey for Data Publishing



<http://www.idarksurvey.org/>

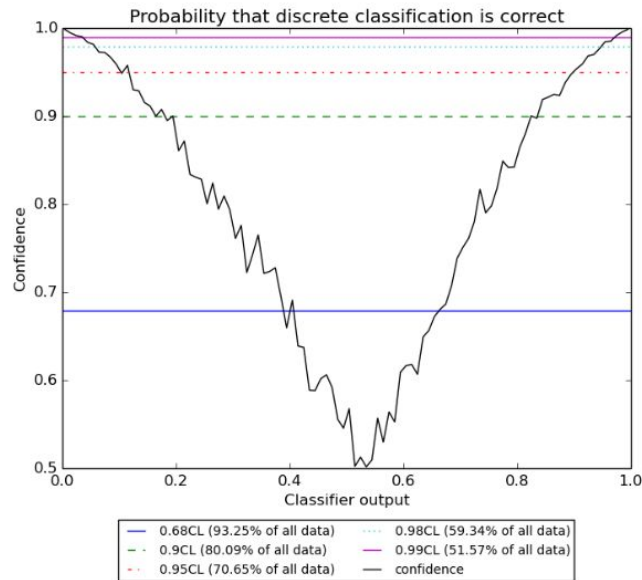
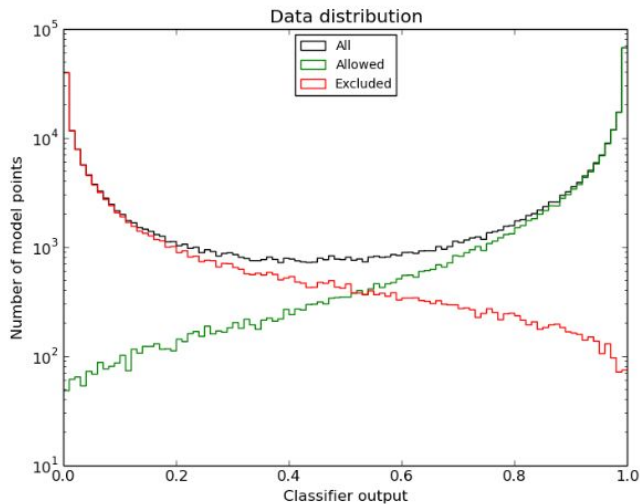
Conclusion



Extra slides

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 PhenoAI

PhenoAI 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.

Supported ML libraries

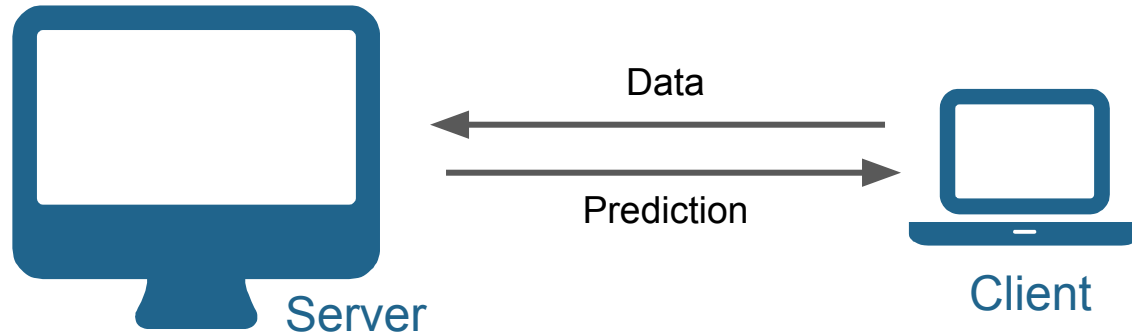
All estimators and models created with Keras/tensorflow and scikit-learn are supported within PhenoAI. We are in the process of adding support for ROOT TMVA models as well.



Server-client structure

PhenoAI has a built-in ability to create a server-client structure. The server has the Analyses 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.

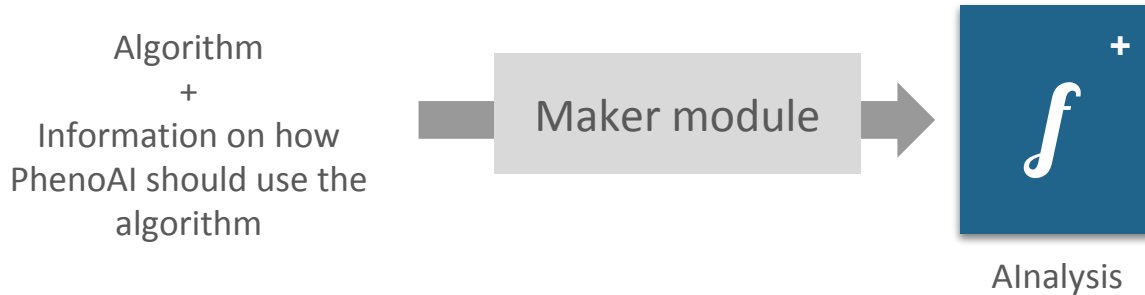
Server and client can of course just be the same machine



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 Analysis 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 available.



DarkMachines

PhenoAI 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 darkmachines.org for more information.

Dark Machines

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About Dark Machines

Dark Machines is a research collective of physicists and data scientists. We are curious about the universe and want to answer cutting edge questions about Dark Matter with the most advanced techniques that data science provides us with.

