

Potential applications of machine learning in particle physics

See http://gambit.hepforge.org/

Andrew Fowlie 19 March 2018. Machine Learning Symposium

Monash University

Particle physics

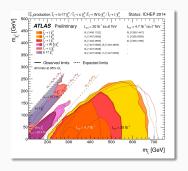
We study the most fundamental particles — building blocks of matter



The most recent discovery was the Higgs boson at the LHC. We have many theories involving new undiscovered states!

Finding new physics

We are struggling to find them, though, which is ruling out parameter space in our models.



The GAMBIT collaboration is checking which models remain allowed, and what they predict.

GAMBIT: The Global And Modular BSM Inference Tool

gambit.hepforge.org

- Fast definition of new datasets and theoretical models
- Plug and play scanning, physics and likelihood packages
- Extensive model database not just SUSY
- Extensive observable/data libraries

- Many statistical and scanning options (Bayesian & frequentist)
- Fast LHC likelihood calculator
- Massively parallel
- Fully open-source

ATLAS
F. Bernlochner, A. Buckley, P. Jackson, M. White
LHCb M. Chrząszcz, N. Serra
Belle-II F. Bernlochner, P. Jackson
Fermi-LAT J. Conrad, J. Edsjö, G. Martinez, P. Scott
CTA C. Balázs, T. Bringmann, M. White
CMS C. Rogan
I. Edsjö, P. Scott

M. White, S. Wild





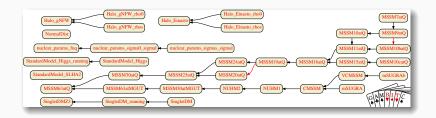


31 Members in 9 Experiments, 12 major theory codes, 11 countries

Global fits in particle physics

Testing whether a point is allowed or ruled out is slow — $\mathcal{O}(\text{seconds})$ — as it requires Monte Carlo simulations.

We have many models with many parameters — the simplest models have a couple of parameters and a few nuisance parameters. The most complicated ones have $\mathcal{O}(100)$.



Global fits in particle physics

Exploring the high-dimensional parameter spaces requires millions of evaluations.

Every point must be classified as allowed or forbidden, or assigned a likelihood.

Classification?

Is this screaming ML to you?

We could train a ML algorithm to classify points as excluded or allowed.

We could train ML regression to predict the likelihood of a point.

This would accelerate our work!

Visualise high-dimensional space

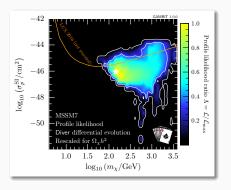
Once we have the results, we want to understand them.

The allowed/excluded regions may involve complicated relations in many dimensions.

How can we understand it?

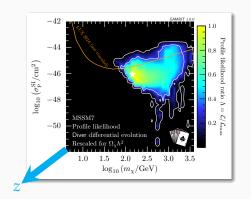
Visualise high-dimensional space

We can profile onto two dimensions.



Visualise high-dimensional space

We can profile onto two dimensions.



What about the others?

Clustering & Dimensional reduction?

Can we use clustering to understand distinct types of allowed points and their properties?

Can we use dimensional reduction to see the important relationships?

Going forward

Some work already on this in the literature.

Let's discuss at the coffee breaks! Have a look at our public codes and datasets if you are interested

http://gambit.hepforge.org/pubs