Computational methods applied to Particle Physics

Higgs Boson Machine Learning Challenge

Z. Kassabov

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Discovery of the Higgs boson

In 2013 ATLAS and CMS experiments confirmed that the boson found in 2012 is compatible with a Higgs boson.

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- Decays $\gamma\gamma$, ZZ and W^+W^- as predicted by SM.
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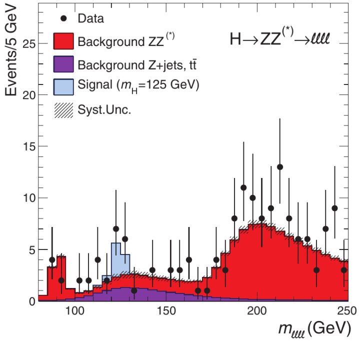

Fermion couplings

The SM Higgs couples to fermions, via Yukawa couplings.

- Branching ratios predicted to scale with the mass squared of the decay products.
    - Most abundant fermionic decay channels:

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  - Significance of 4.1σ in the $\tau\tau$ channel.
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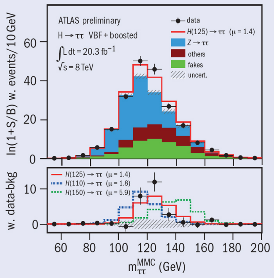

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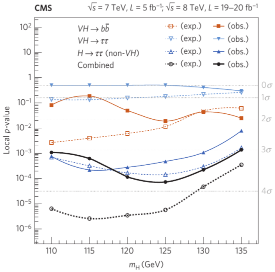

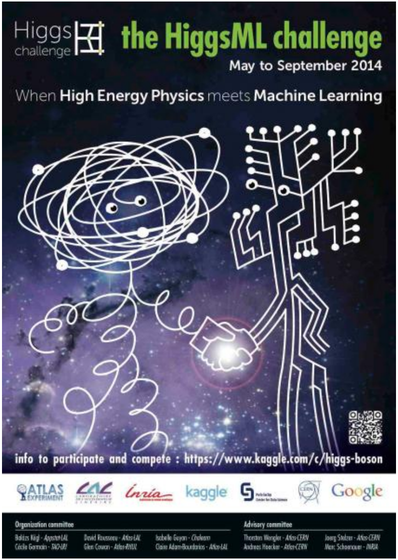

The goal of the challenge is to explore the use of Machine Learning tools to improve the discovery significance of the experiment.

- Simulated samples of data are provided.
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Signal $\tau\tau$ decay of a Higgs boson.

Background W, Z decays, $t\bar{t}$ products.

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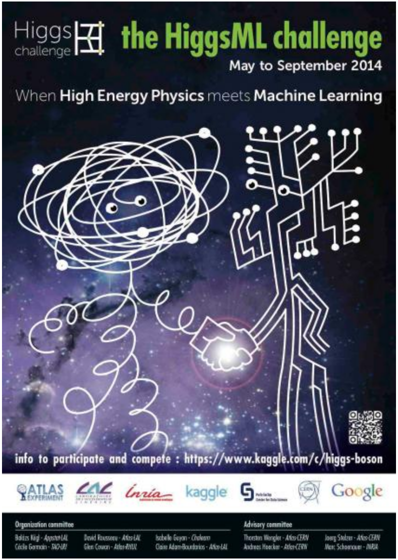

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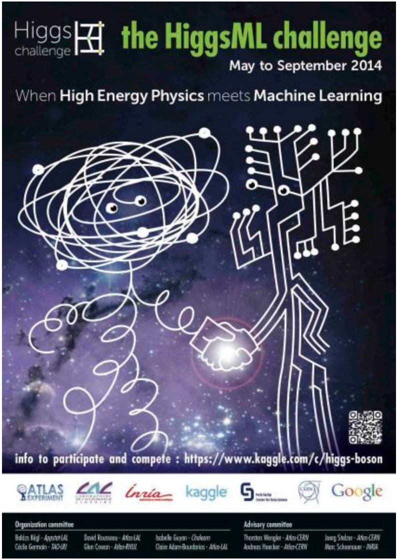

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Example: Regression problem

Given the set of data points $\mathcal{D} = \{(x_1, y_1), ..., (x_n, y_n)\}$ with $x_i, y_i \in \mathbb{R}$, find a function $f(x) \to \mathbb{R}$ that *generalizes* them (ie is able to make a *good* prediction for new points generated by the same underlying model).

Good Maximize some score function.

- Typically split the known points into a *training set* and a *test set*.

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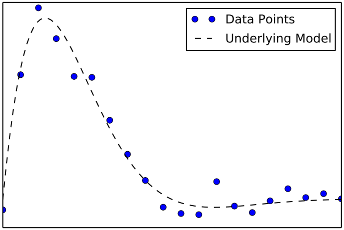

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- Different ML algorithms propose different solutions to finding an appropriate *bias/variance* compromise.

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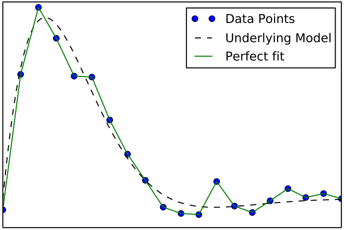

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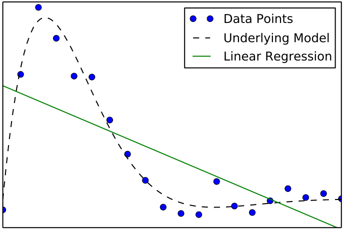

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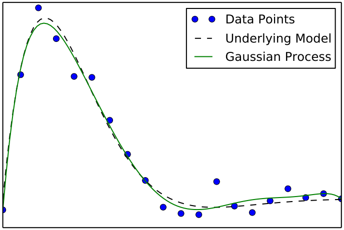

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One of the main challenges of the ML algorithms is to scale with the dimensionality of the feature space.

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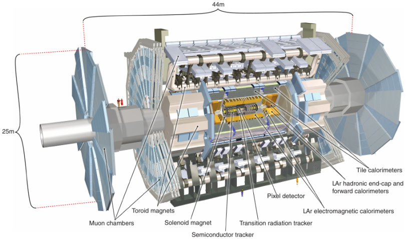

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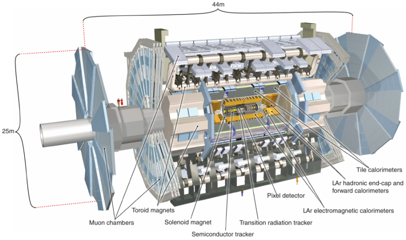

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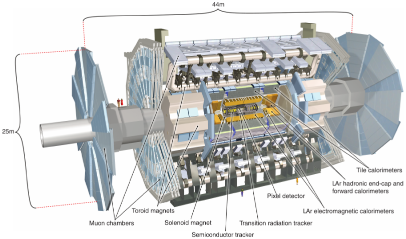

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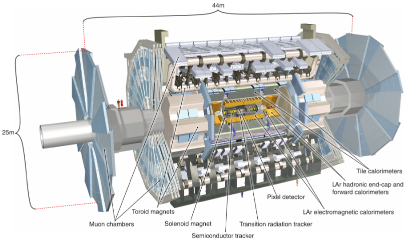

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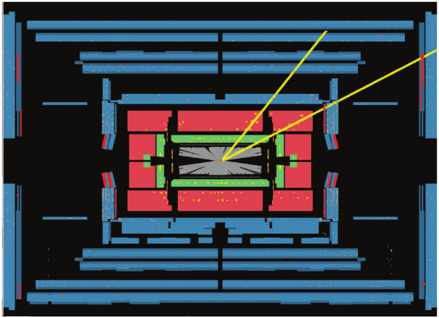

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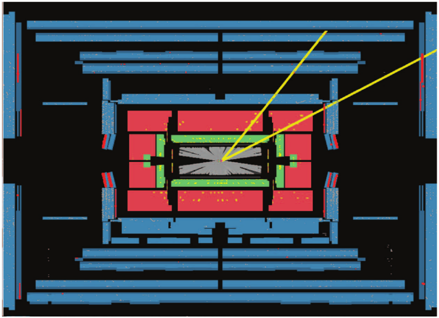

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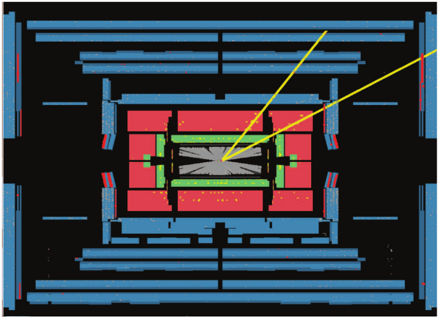

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The data provided for the challenge is simulated:

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In the challenge, we are interested in the process (*signal*):

$$H \longrightarrow \tau^-\tau^+ \longrightarrow (l + 2\nu) + (\text{hadrons} + \nu)$$

$$l \in \{e^\pm, \mu^\pm), \nu \in \{\nu_e, \nu_\mu, \nu_\tau, \overline{\nu_e}, \overline{\nu_\mu}, \overline{\nu_\tau}\}$$

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The classification problem

Let $\mathcal{D}$ be the training sample:

$$\mathcal{D} = \{(x_1, y_1, w_1), ..., (x_n, y_n, w_n)\}$$

where:

- $x_i \in \mathbb{R}^d$: Feature vector.
- $y_i \in \{b = \text{"}background\text{"}, s = \text{"}signal\text{"}\}$: Label
- $w_i \in \mathbb{R}^+$: Weight.

Find a classifier $g : \mathbb{R}^d \to \{b, s\}$ that maximizes the *Approximate Median Significance*.

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Gradient Boosting Classifier Formulation

$$g(x) = \sum_{m=1}^{M} \gamma_m h_m(x)$$

- h_m weak learners (decision trees).
- h_m chosen to minimize some loss function $L(y_i, x_i)$ at each iteration:

$$g_m(x) = g_{m-1}(x) + \arg\min_h \sum_{i=1}^{n} L(y_i, g_{m-1}(x_i) - h(x))$$

- The minimization is performed by the steepest descent method:

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Results

The first submission obtained an AMS score of 3.376.

	Score
Random Submission	0.58
Simple Window	1.54
Naive Bayes	2.06
Simple Boosted Trees	3.25
AdaBoost	3.34
My submission	3.38
Best submission	3.81
ATLAS (real significance)	4.1

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