Computational methods applied to Particle Physics

Higgs Boson Machine Learning Challenge

Z. Kassabov

July 2014

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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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- Spin 0.
- Decays $\gamma\gamma$, ZZ and W^+W^- as predicted by SM.
  - The Brout–Englert–Higgs mechanism is responsible for the mass of the W and Z bosons.

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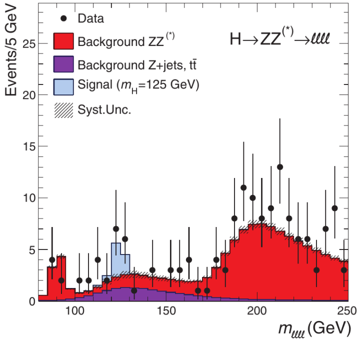

Fermion couplings

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:

$$H \to \tau^+\tau^-$$

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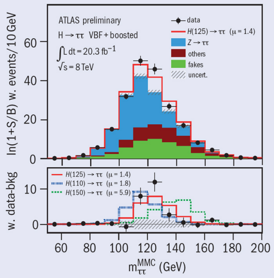

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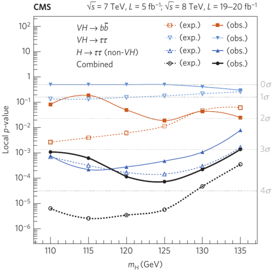

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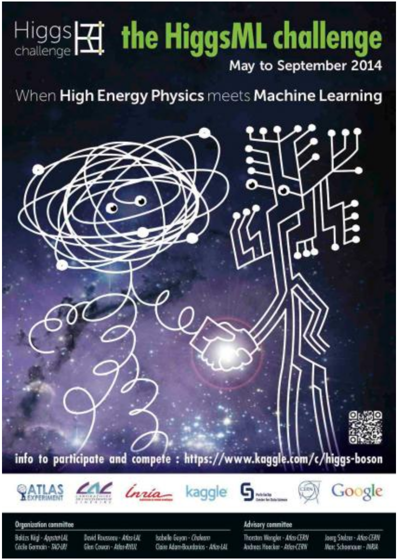

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- Simulated samples of data are provided.
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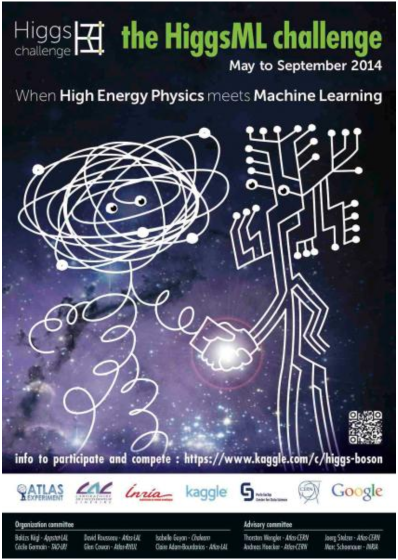

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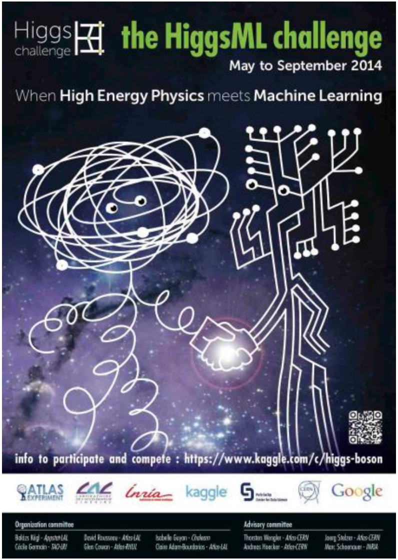

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Example: Regression problem

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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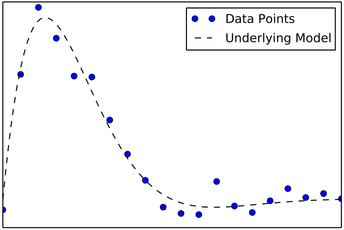

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- Different ML algorithms propose different solutions to finding an appropriate *bias/variance* compromise.

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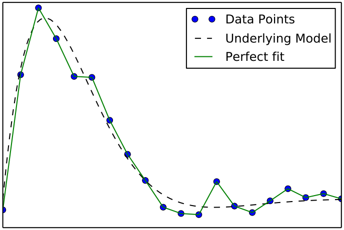

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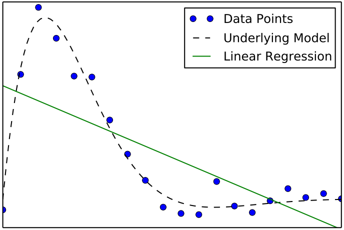

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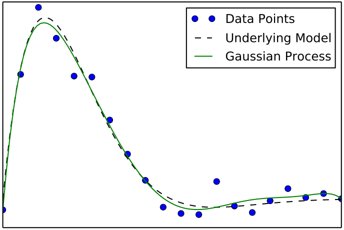

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One of the main challenges of the ML algorithms is to scale with the dimensionality of the feature space.

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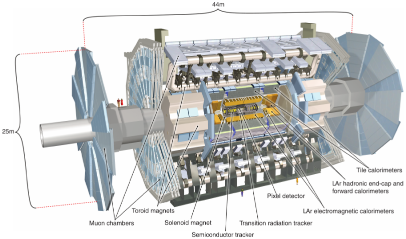

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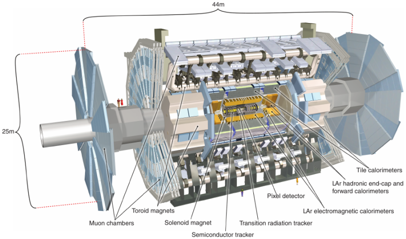

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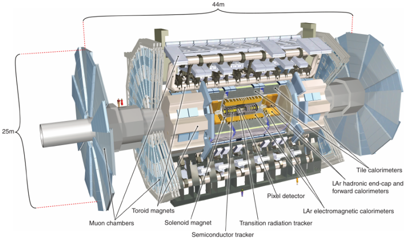

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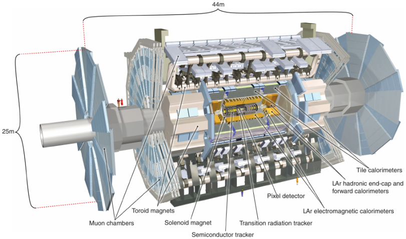

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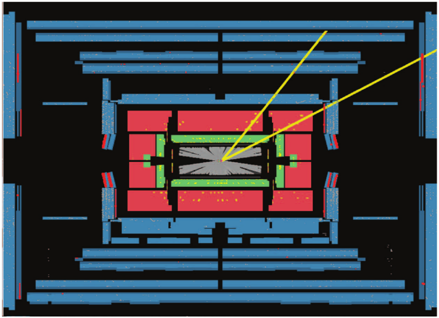

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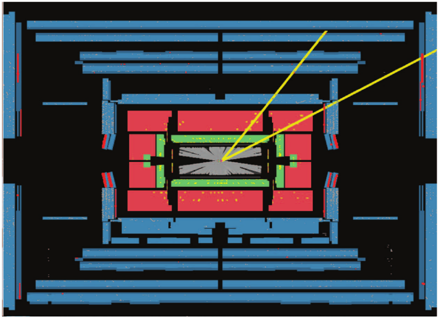

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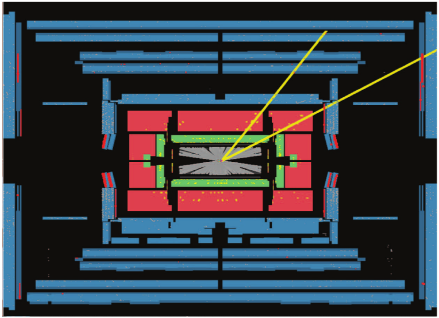

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The data provided for the challenge is simulated:

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

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

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

There are *background* events from:

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The classification problem

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

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.

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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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