Genetic Algorithms in the search for the Higgs boson

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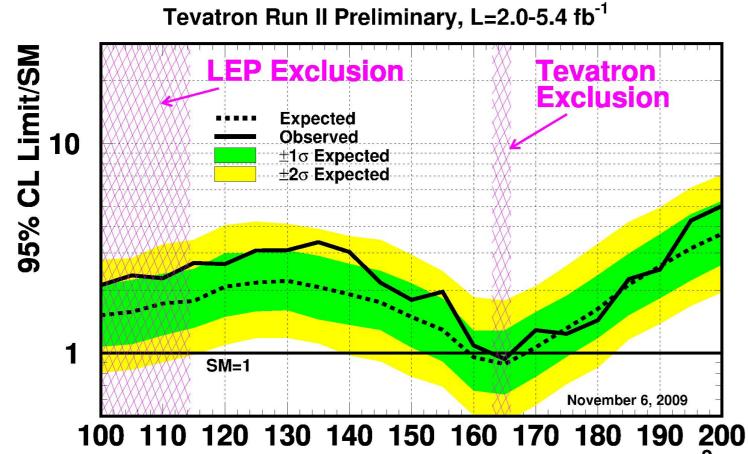
Why is the Higgs boson important?

The Standard Model is the most accurate theory to date that characterizes fundamental particles and their interactions. The Higgs boson is the only fundamental particle predicted by the Standard Model whose existence has not been experimentally verified. The Higgs boson is the particle associated with the Higgs field, which, unlike the other fields of the Standard Model, is postulated to have a non-zero value in empty space. This implies that the ground state of the Standard Model breaks the electroweak symmetry. The symmetry breakdown causes the W and Z bosons to acquire mass. Furthermore, the postulated interaction between the Higgs field and the charged lepton and quark fields, as well as the Higgs field itself, causes the charged leptons, the quarks, and the Higgs to acquire mass. In effect, this interaction "slows down" these otherwise massless particles. The Standard Model does not provide an explanation for the symmetry breakdown, nor does it predict the mass of the Higgs boson, but it does predict all other aspects of the Higgs boson including how it decays. The experiment at the Large Hadron Collider (LHC) would offer many insights into our understanding of the Standard Model, and what we can learn depend on what is seen. In addition to the high energies needed to create the Higgs boson, the unknown parameters make the search even more difficult. The Tevatron at Fermilab and CERN's precursor to the LHC, the LEP, have probed possible mass ranges for the Higgs boson, experimentally narrowing the bounds of the Higgs mass, as seen in Figure 1. In addition, the case of a single Higgs boson in the Standard Model would indicate an upper bound on the Higgs mass at about 190 GeV.

Computational Methods

Neural networks and genetic algorithms appeal to the difficult problem of discerning Higgs events at the LHC due to their ability to model any smooth function. With any input parameters, the systems can output a desired value or set of values. These attributes can be utilized for the binary classification of Higgs events against background events [2]. Currently, Bayesian neural networks are applied to classify Higgs events from background and this current work aims to compare the success of a genetic algorithm fitting the identical function of the neural network, as displayed in equation 1.

$$f(\mathbf{x}, \mathbf{w}) = \mathbf{b} + \sum_{i=1}^{H} \mathbf{v}_{i} \tanh \left(\mathbf{a}_{i} + \sum_{i=1}^{P} \mathbf{u}_{ij} \mathbf{x}_{i}\right)$$
(1)



where H is the number of hidden nodes in the neural network and P is the number of inputs, which are the four-momenta of the Higgs' decay products in our case. The coefficients are the weights of the neural network, which make up the chromosome of the genetic algorithm. The function the genetic algorithm attempts to minimize is

$$f = \frac{1}{N} \sum_{i=1}^{N} (y(w_i) - f(x_i, w_i))^2$$
(2)

Where $y(w_i)$ is 0 for background and 1 for a Higgs event. The parameters **w** are the chromosome parameters in the genetic algorithm and the node weights in the neural network.

Genetic algorithms are, in general, a search algorithm that uses evolutionary techniques such as "mutation" and "crossover" of parameter data to search the function space for the desired result of the function to be fit, equation 2. Genetic algorithms are appealing because a "population" of parameters are generated so the algorithm searches the entire function space, which saves the solution from being stuck in a local minima, as neural networks can do. Results will offer a direct comparison of the two methods and what parameters in both methods affect computation time, accuracy of results, and other computational interests. Because this genetic algorithm is designed to mimic the neural network function, this genetic algorithm can be applied to many function-fitting and classification problems.

Figure: Where the Tevatron has probed as a function of Higgs mass. y = 1 indicates the cross-section at which the Standard Model predicts the Higgs boson to be produced.

Why do we need advanced computational techniques?

In addition to not knowing its mass, the Higgs is expected to be created in an environment that is extremely difficult to probe experimentally. With an integrated luminosity of about 100pb^{-1} expected over the next twelve months at the LHC, we expect about 10 Higgs boson events in the Higgs decay channel, $H \rightarrow ZZ^*$, that is, in the channel in which the Higgs decays to a pair of Z bosons, one of which is on-shell. Of the many decay channels of the Higgs boson, as seen in Figure 2, the **ZZ**^{*} has the most desirable experimental signature combined with a higher branching ration at energies of interest. The rarity of the signal combined with an overwhelming amount of background reactions places background mitigation at a primary concern in finding the Higgs boson. The necessity for optimum signal to background discrimination requires advanced computational techniques. If the Higgs mass is < 130 GeV, as suggested indirectly by all the available data, the difficulties of discriminating the signal from background become even more severe.

Discussion

Due to the extremely low production rate of the Higgs boson and the immense amount of background events, combined with not knowing the mass of the Higgs boson, highly sophisticated computational techniques are necessary for appropriate signal identification. Advanced techniques utilizing genetic algorithms and neural networks have already been successfully applied at the TeVatron at Fermilab. Future work includes testing the genetic algorithm on classification of simulated Higgs and background data and comparing the computational results to the Bayesian neural networks currently in use. Genetic algorithms provide a great testing ground for the accuracy needed for Higgs identification at the LHC, and this work aims to explore the optimal genetic algorithm for the task.

References

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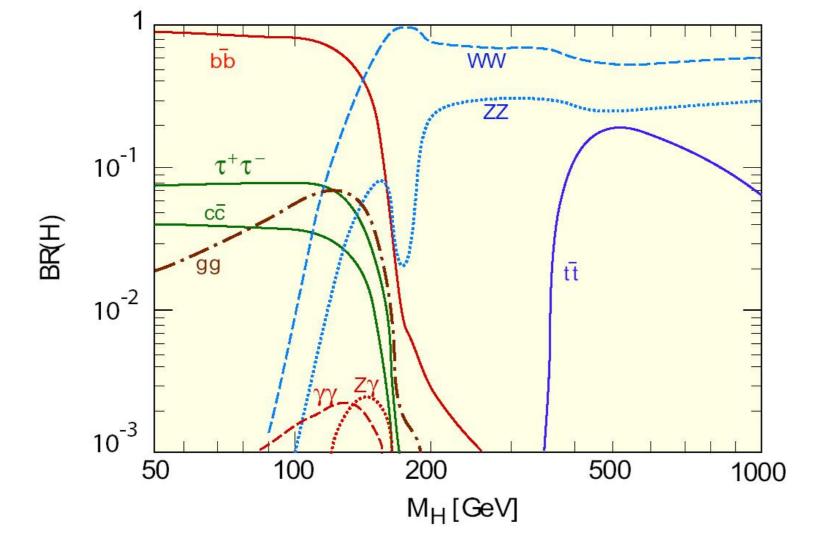


Figure: Higgs boson production at different decay channels as a function of mass. Branching ratio is a measure of how likely the Higgs boson is to decay to those particles. Figure from Reference [4]

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