

EVENT CLASSIFICATION

INFORMATION EXTRACT

The LHC experiments are expensive

$\sim \$10^{10}$ (accelerator and experiments)

the competition is intense

(ATLAS vs. CMS) vs. Tevatron

and the stakes are high:



4 sigma effect

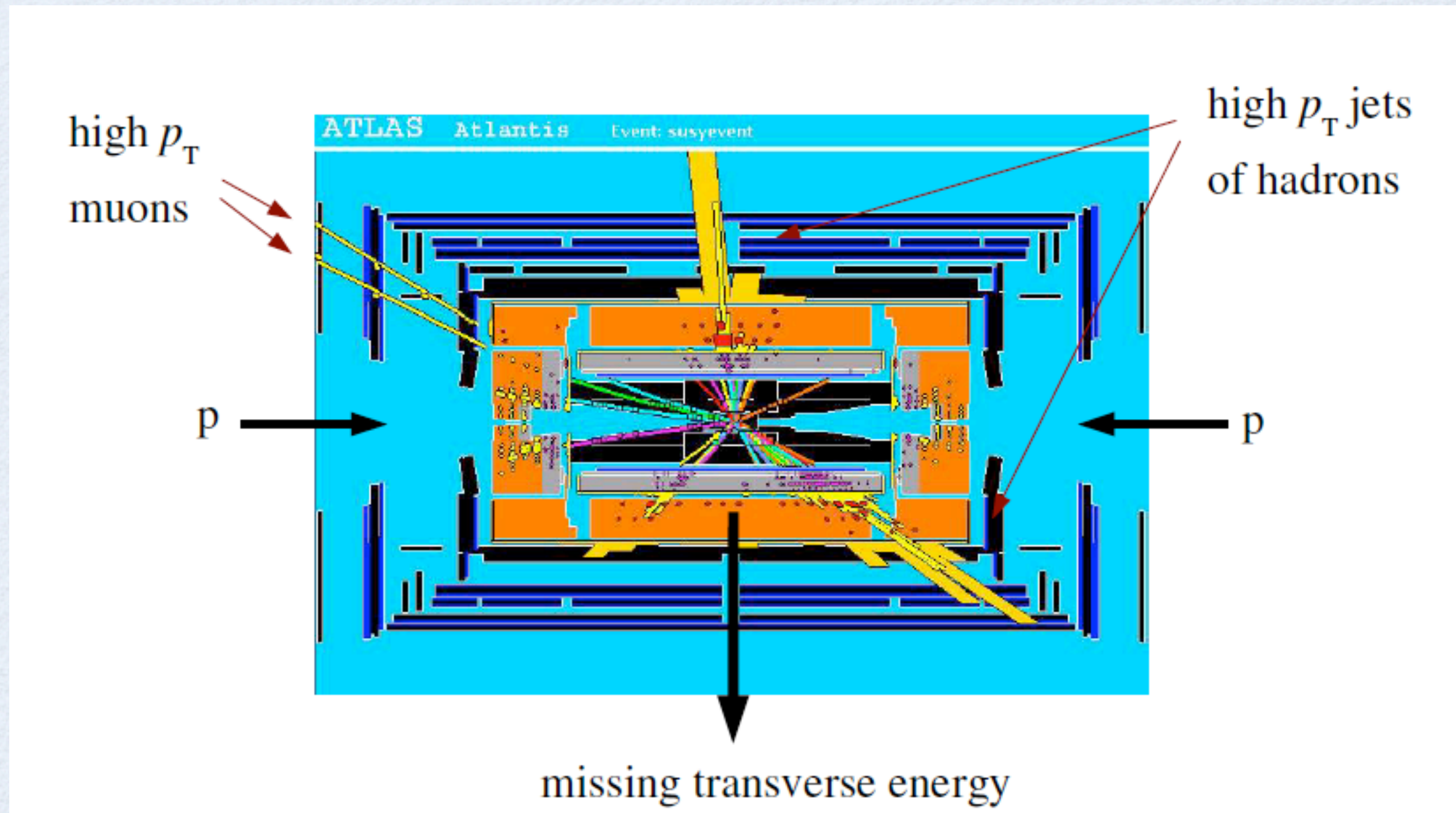


5 sigma effect



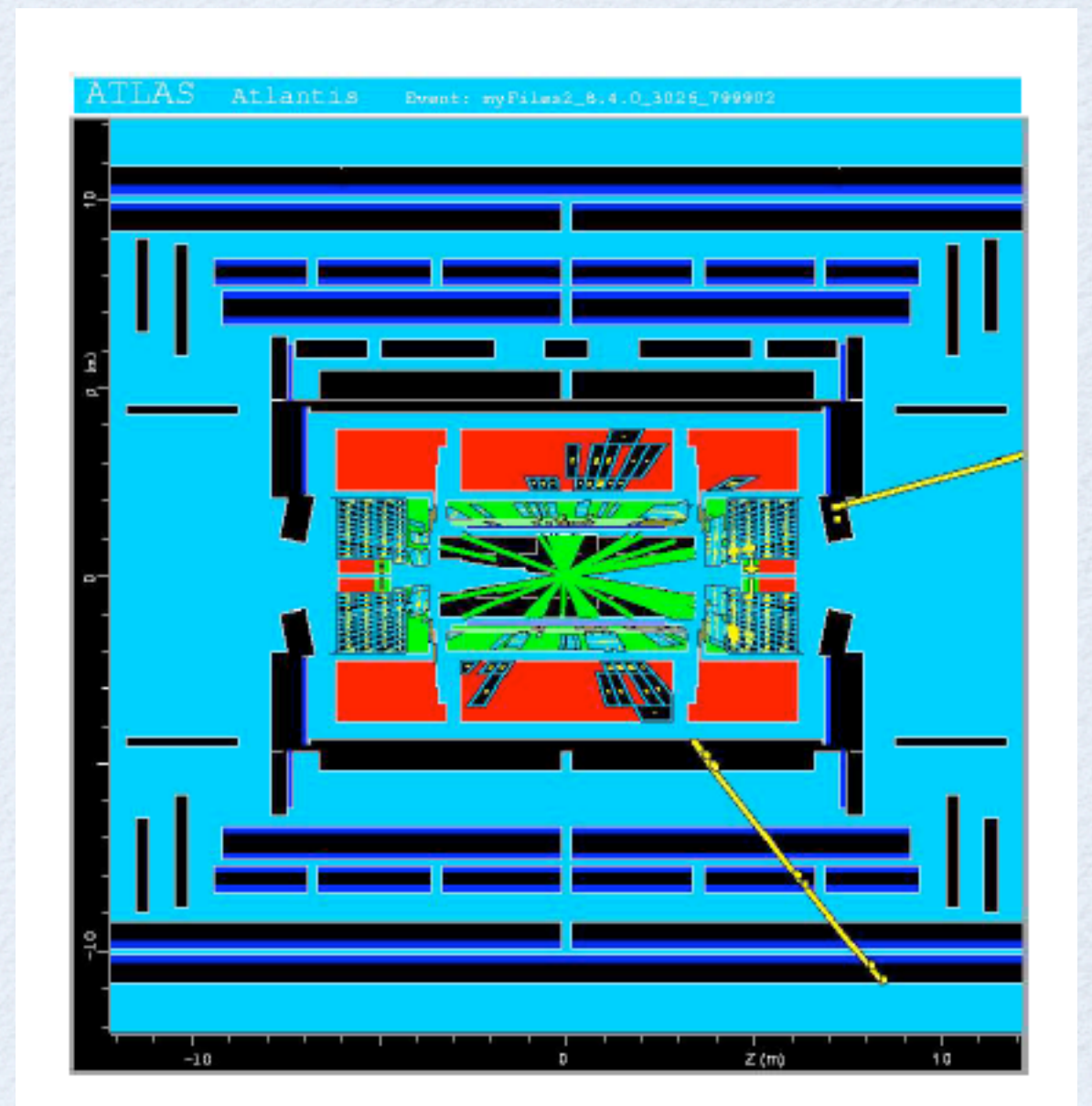
So there is a strong motivation to extract all possible information from the data.

SIGNAL EVENT: SUSY



BACKGROUND EVENT

- top quark event



BASIC PROBLEM

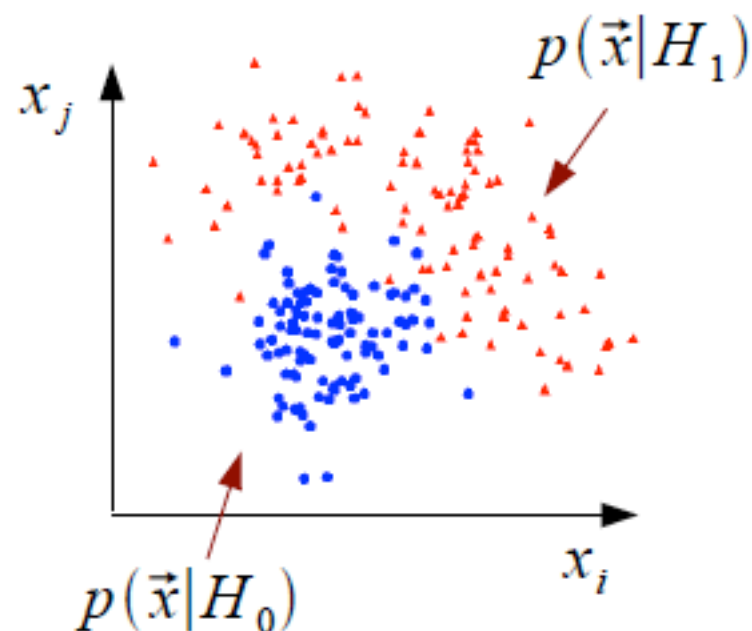
Suppose for each event we measure a set of numbers $\vec{x} = (x_1, \dots, x_n)$

$$x_1 = \text{jet } p_T$$

$$x_2 = \text{missing energy}$$

$$x_3 = \text{particle i.d. measure, ...}$$

\vec{x} follows some n -dimensional joint probability density, which depends on the type of event produced, i.e., was it $pp \rightarrow t \bar{t}$, $pp \rightarrow \tilde{g} \tilde{g}, \dots$



E.g. hypotheses (class labels) H_0, H_1, \dots

Often simply “signal”, “background”

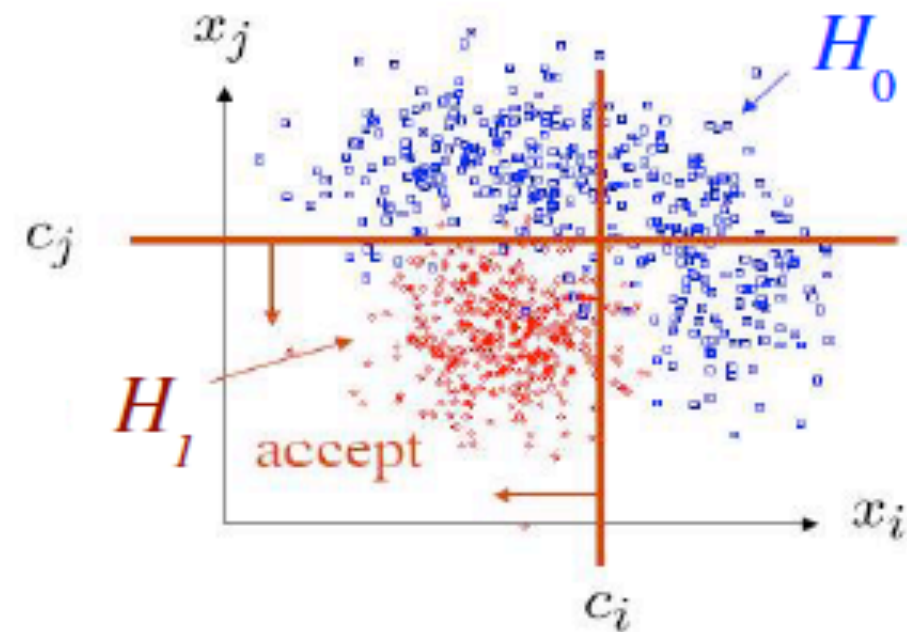
We want to separate (classify) the event types in a way that exploits the information carried in many variables.

GOAL

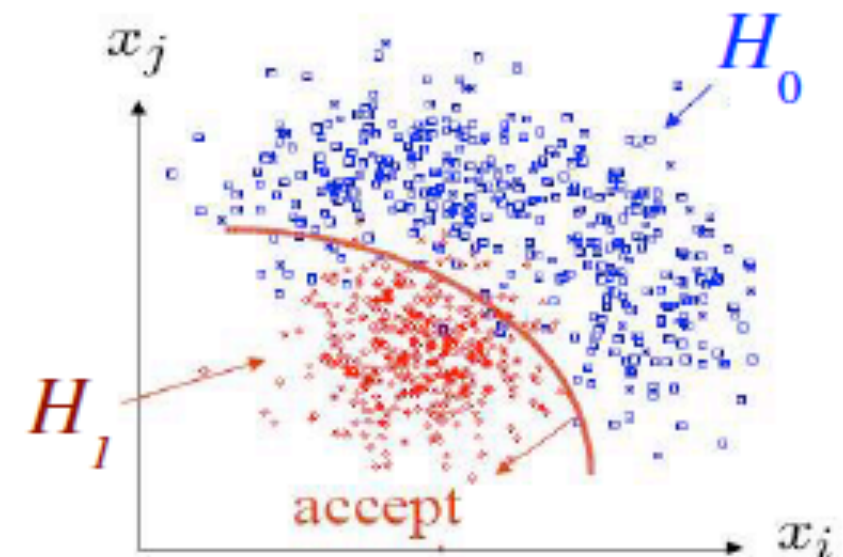
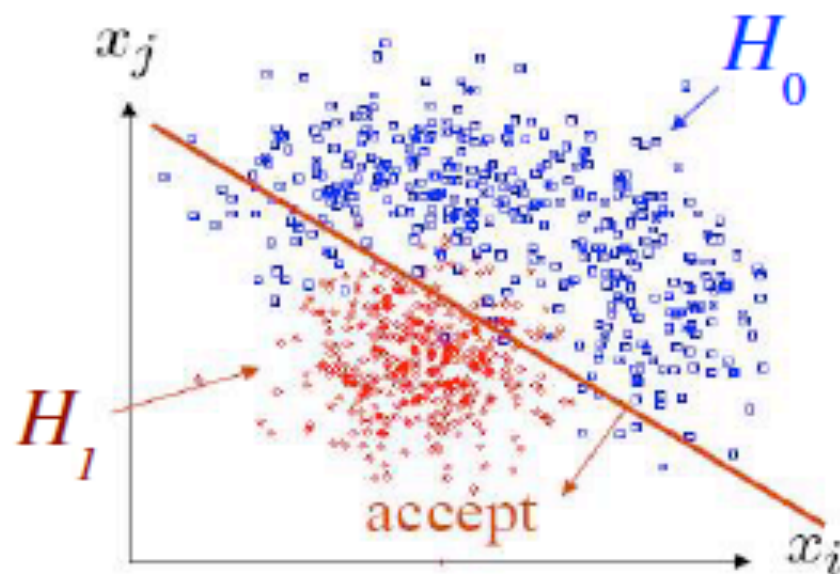
Maybe select events with “cuts”:

$$x_i < c_i$$

$$x_j < c_j$$

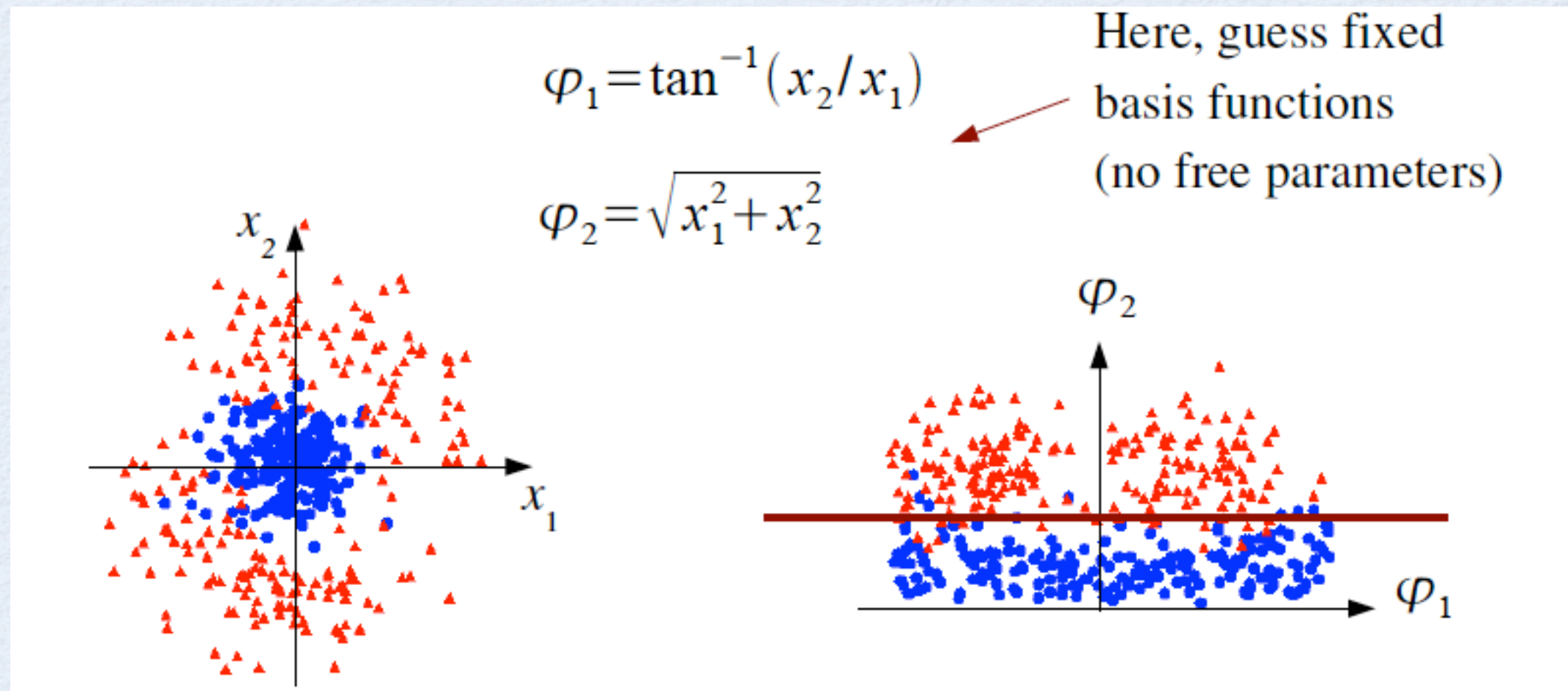


Or maybe use some other type of decision boundary:



Goal of multivariate analysis is to do this in an “optimal” way.

- We can try to find a transformation so that the transformed “feature space” variables can be separated better by a linear boundary:



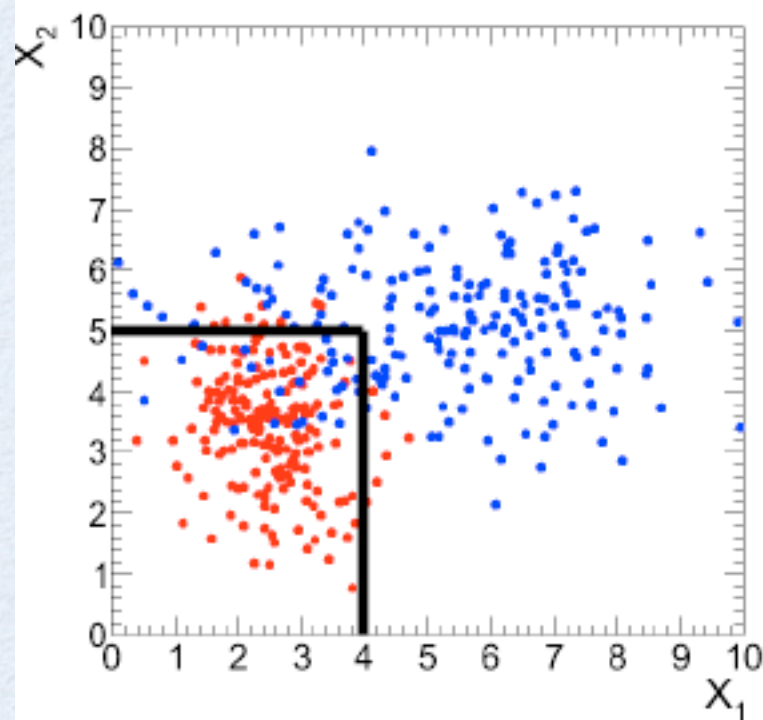
POSSIBLE SOLUTIONS

optimized
cuts

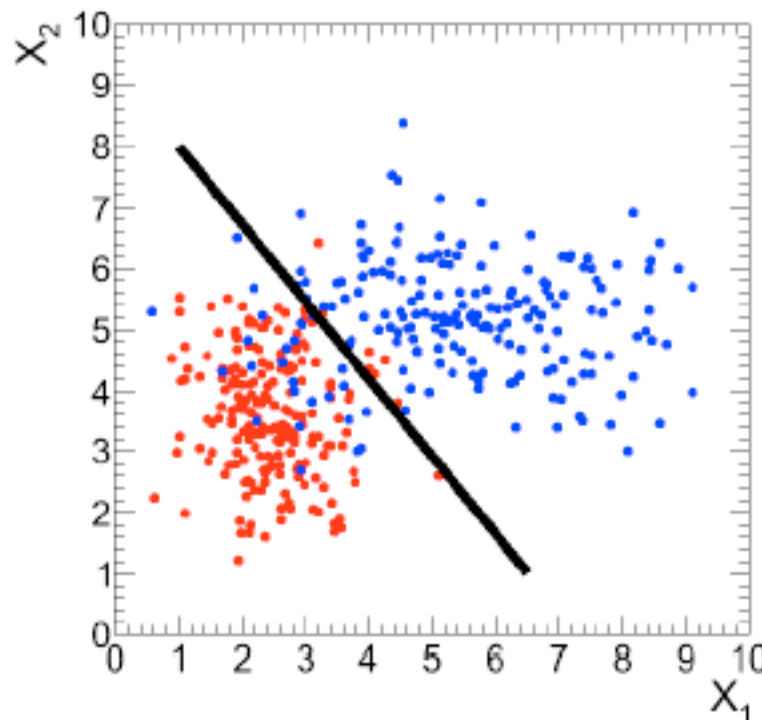
transform or
find relation

optimized
solution

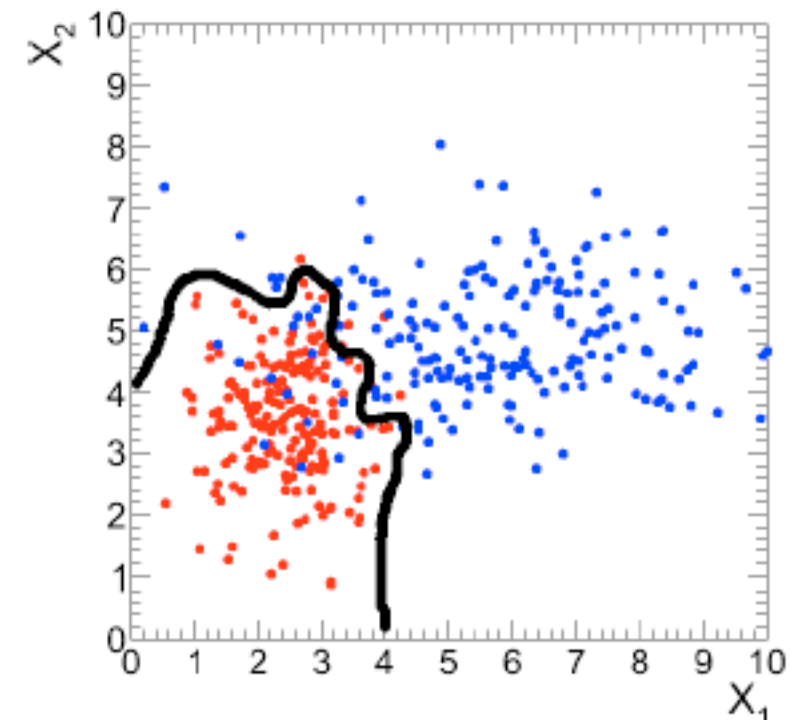
Rectangular cuts



Linear (Fisher)



**Non-linear
(BDT, NN...)**



RECTANGULAR CUTS

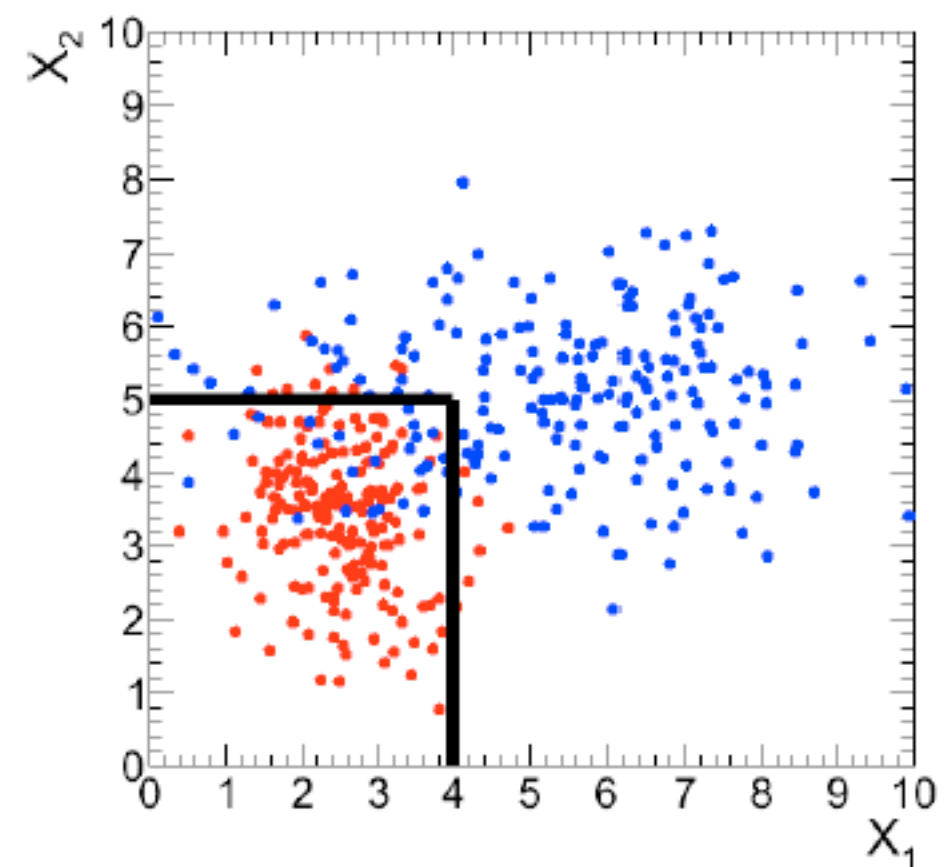
- Simplest multivariate method, very intuitive
- All HEP analyses are using rectangular cuts, not always completely optimized

Rectangular cuts optimization :

- Grid search, Monte-Carlo sampling
- Genetic algorithm
- Simulated annealing

Characteristics :

- Difficult to discriminate signal from background if too much correlations
- Optimization difficult to handle with high number of variables



Define the signal region :

$$a1 < x1 < a2,$$

$$b1 < x2 < b2$$

...

CHOOSING CUTS

How to find the best set of cuts for a given criterion ?

Grid search

- Try N points (usually very large) of the phase-space equally spaced in each dimensions
- => Impossible with high number of variables (too much CPU time)

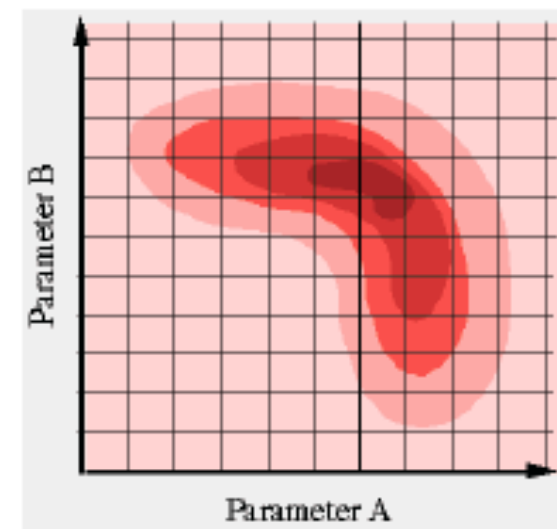
Monte-Carlo sampling

- Try N points randomly chosen in the phase space
- => Usually performs better, but still non optimal

Both are good global minimum finder but have poor accuracy

Examples of criterion :

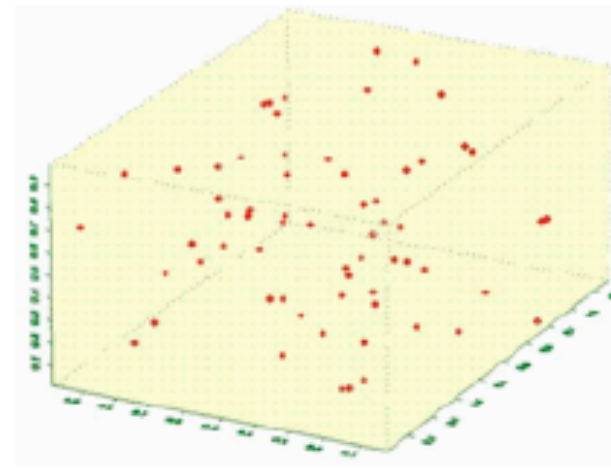
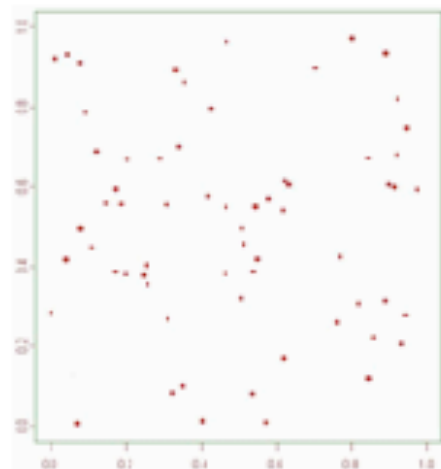
- Maximize the signal efficiency for a given background rejection
- Maximize the significance



DIMENSIONALITY

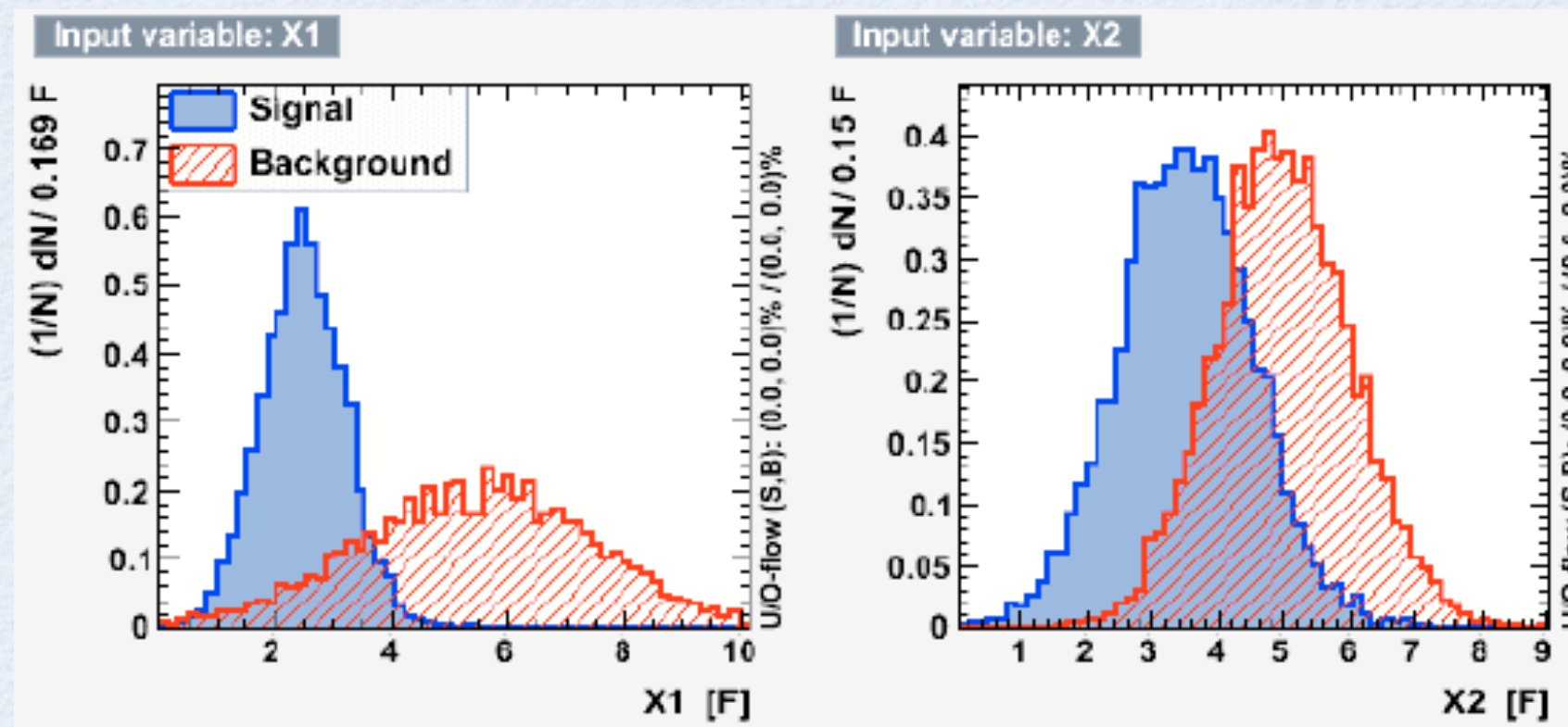
Grid search and Monte-Carlo sampling suffer from the curse of dimensionality :

- For one variables, trying 100 working points is easy
- For two variables, 100 working points will lead to not well covered phase-space because each points have more distance between them
- 100x100 points should be used
- Increasing number of variables will lead this algorithm to be impossible in practice



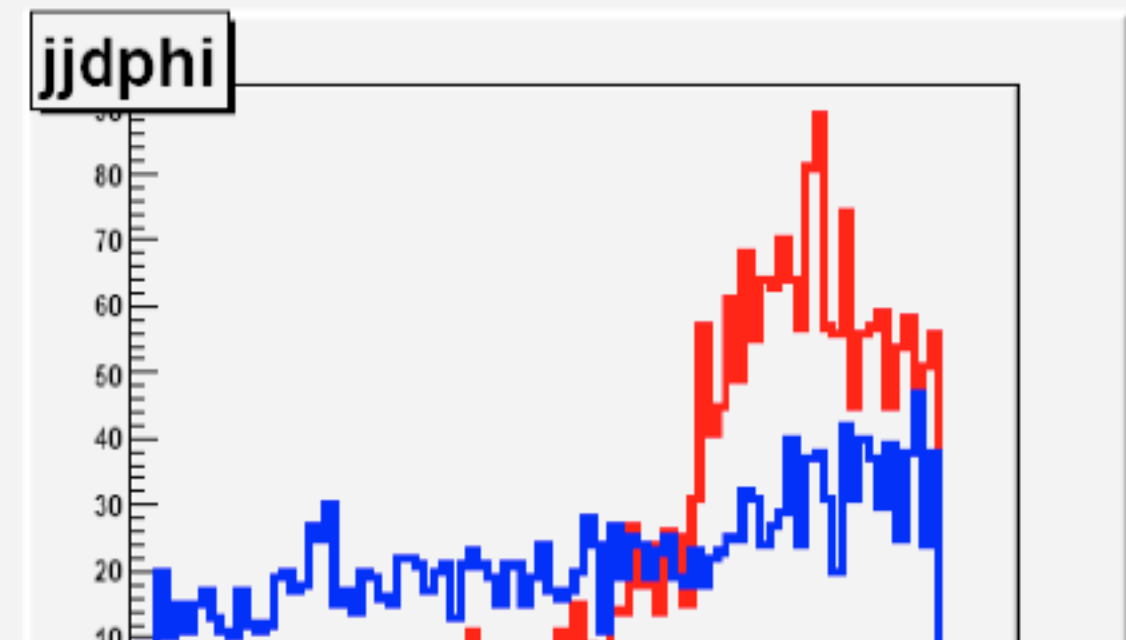
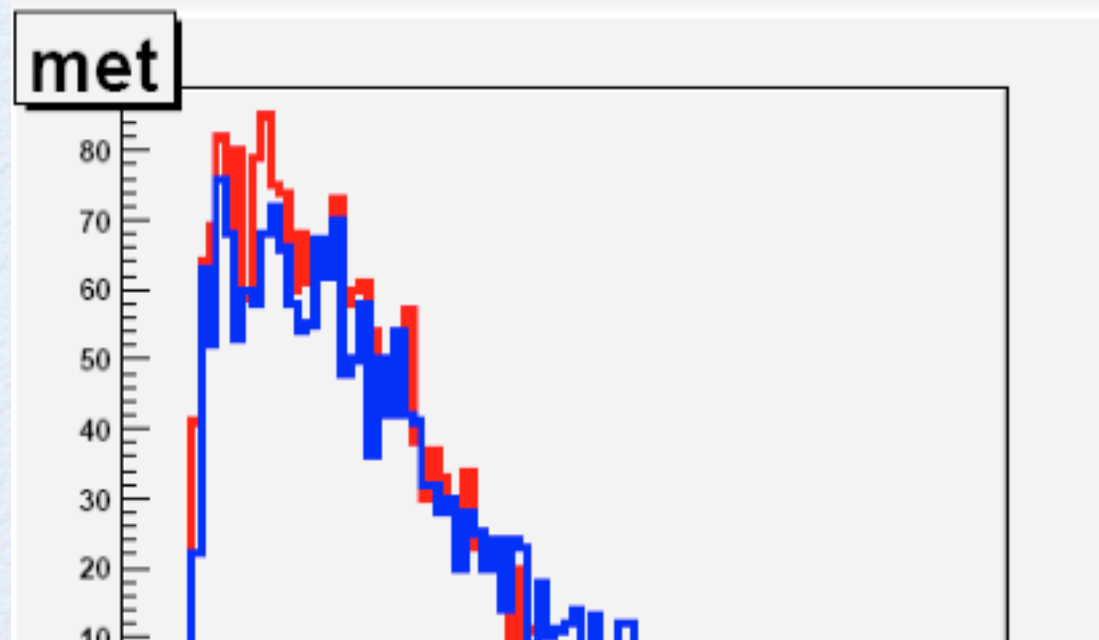
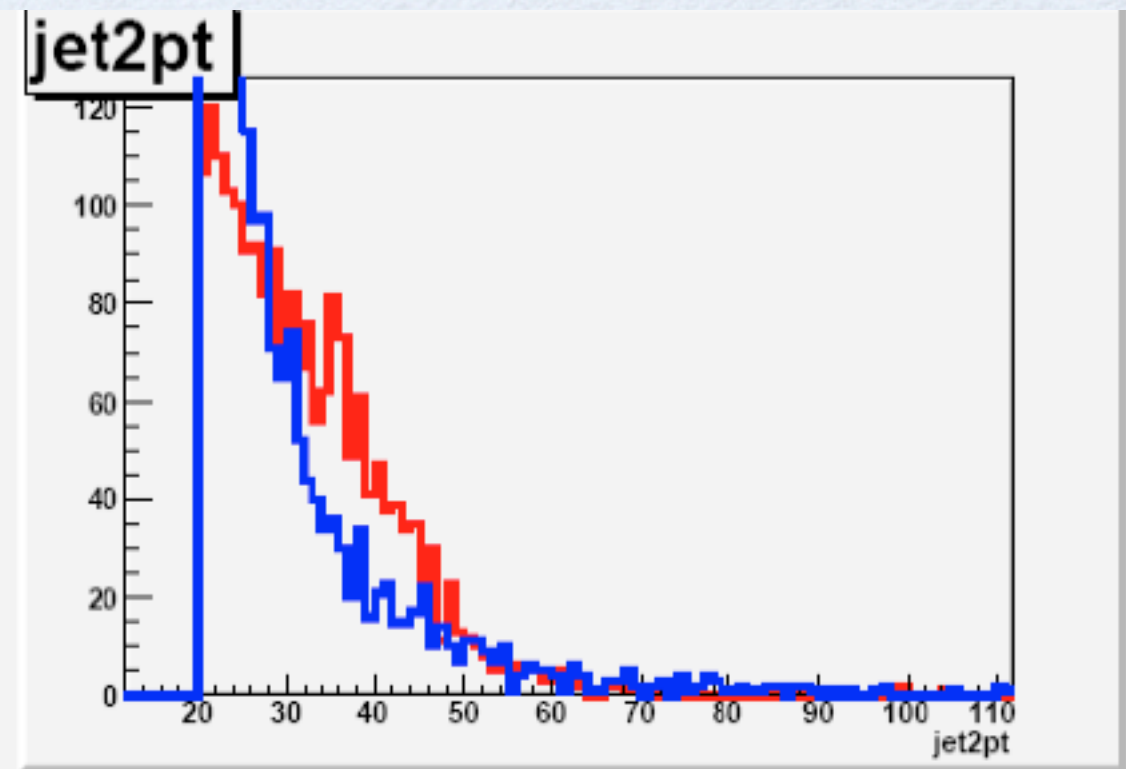
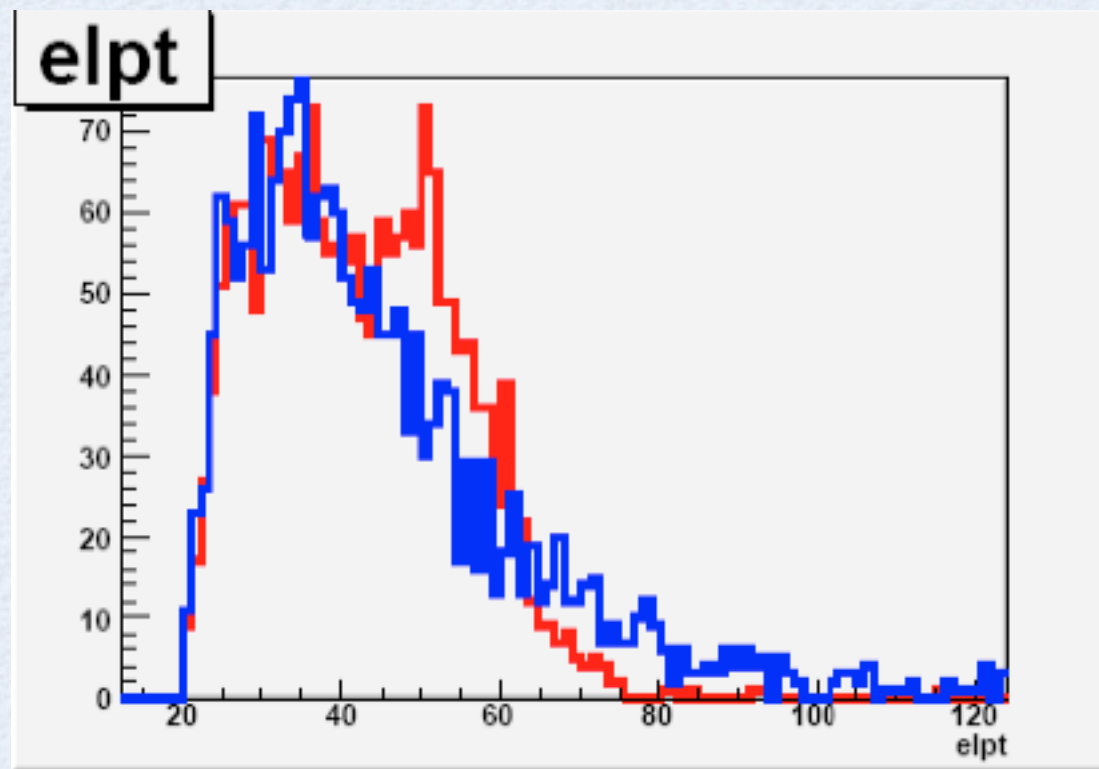
MULTIPLE VARIABLES

Might be able to use 'square cuts'
if your distributions look like

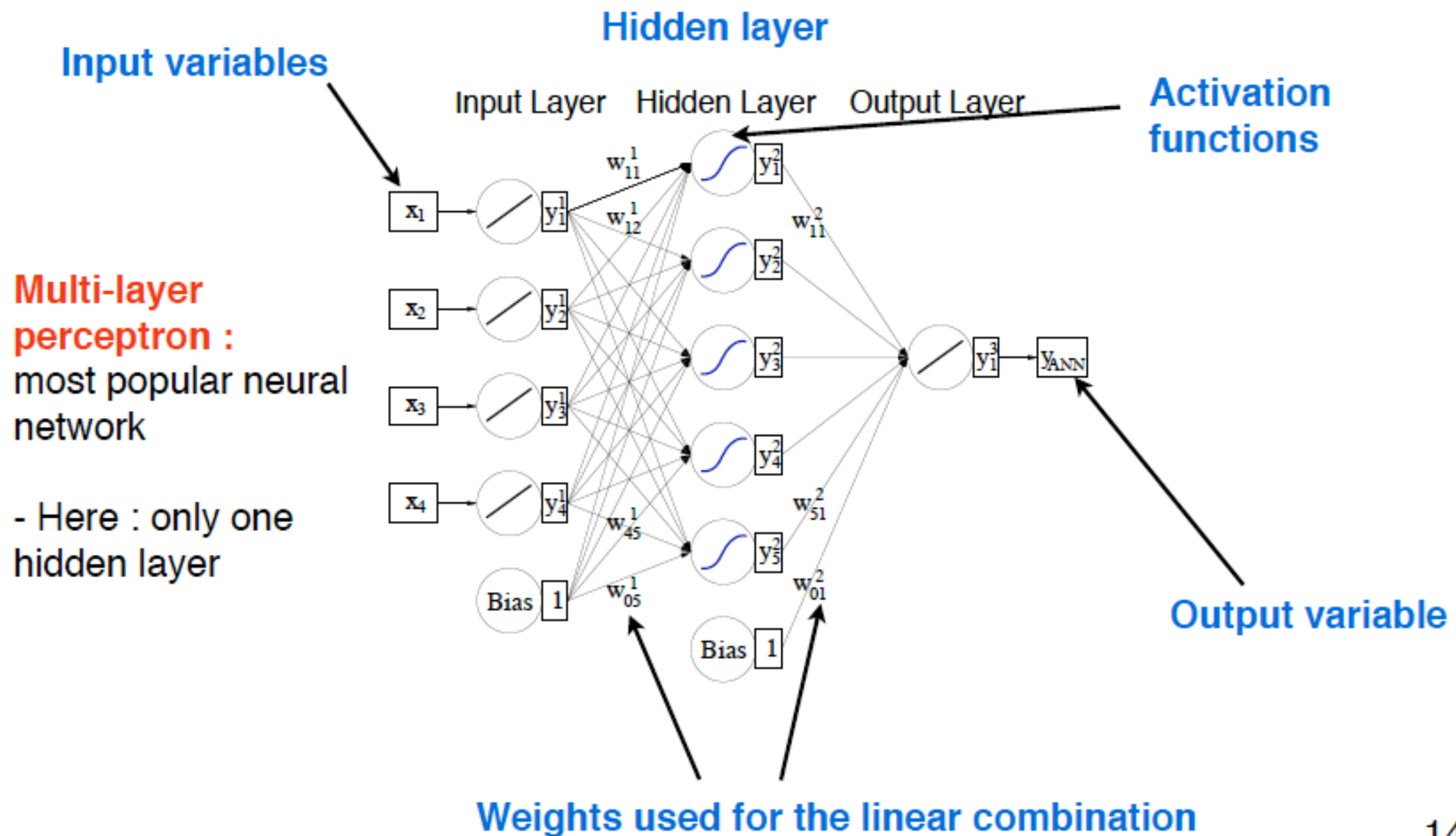


MULTIVARIATE METHODS

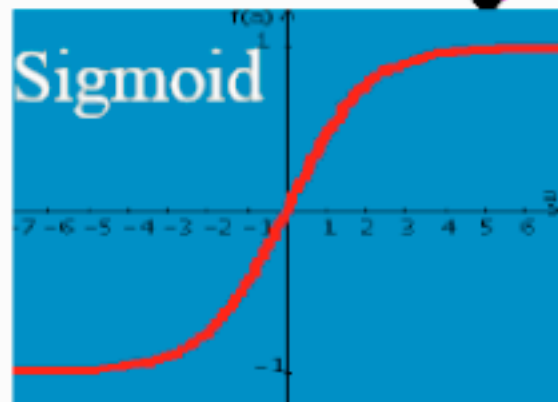
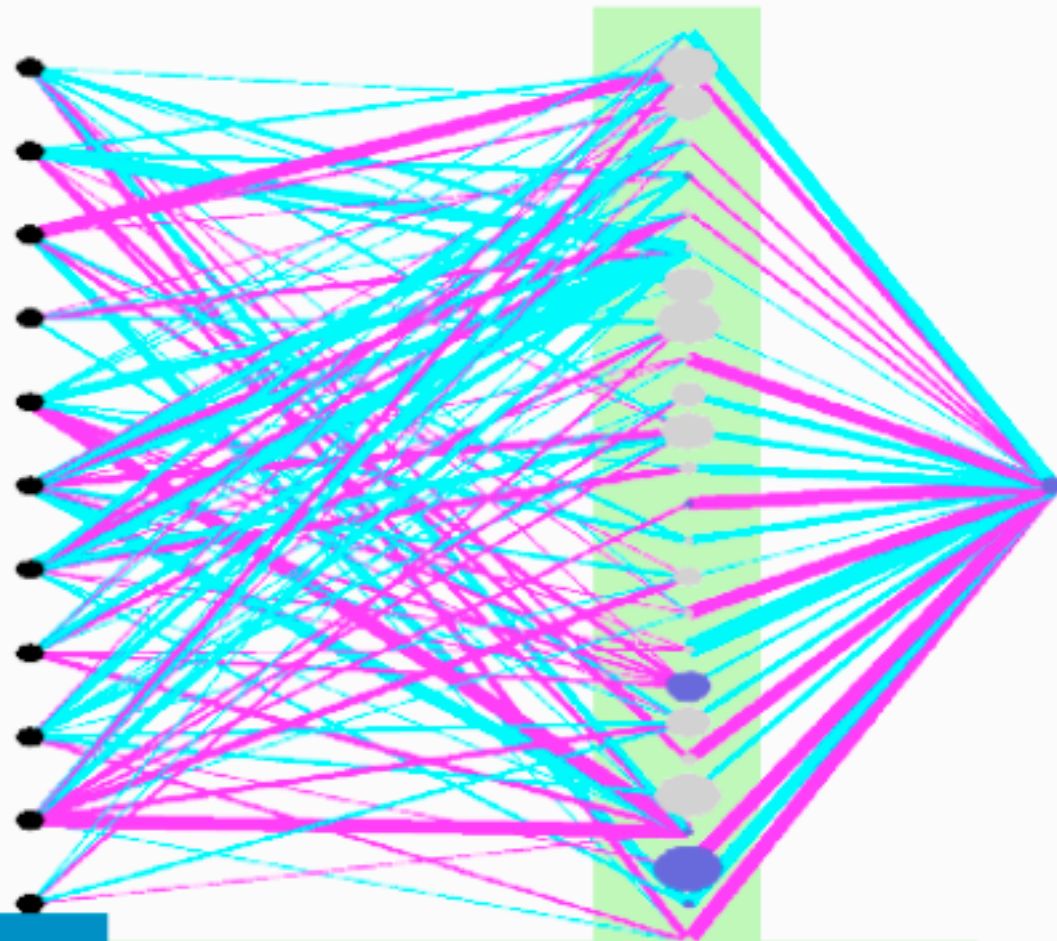
But what if?



NEURAL NETWORKS



AT THE NODE, TRANSFORM



Hidden Nodes: Each is a sigmoid dependent on the input variables

$$n_k(\vec{x}, \vec{w}_k) = \frac{1}{1 + e^{-\sum w_{ik} x_i}}$$

FROM MANY ...ONE

Input Nodes: One for each variable x_i

$M_T(\text{jet1, jet2})$

$M(\text{all jets})$

$p_T(\text{jet1, jet2})$

$p_T(\text{notbest2})$

$p_T(\text{notbest1})$

$\cos(\angle Q(l) \times z)_{\text{besttop}}$

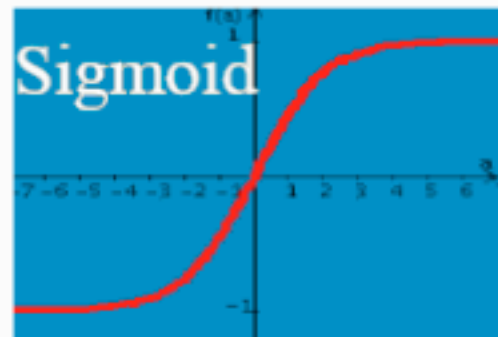
$M(W, \text{best})$

$M(W, \text{tag1})$

$\Delta R(\text{jet1, jet2})$

\sqrt{s}

$p_T(\text{tag1})$

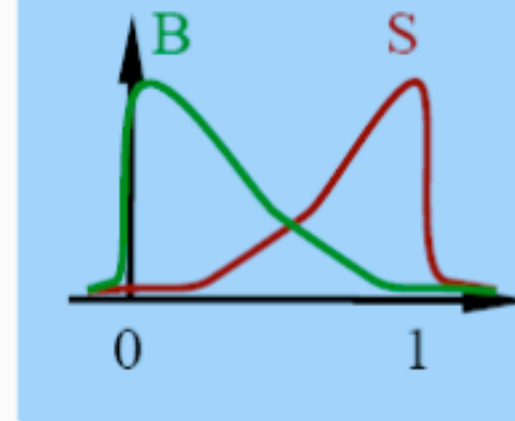


Hidden Nodes: Each is a sigmoid dependent on the input variables

$$n_k(\vec{x}, \vec{w}_k) = \frac{1}{1 + e^{-\sum w_{ik} x_i}}$$

Output Node: linear combination of hidden nodes

$$f(\vec{x}) = \sum w'_k n_k(\vec{x}, \vec{w}_k)$$



EXAMPLE

- ROOT tutorial file placed on blackboard.
- Download and run it - it will go download a file from the web and create a neural network