

Data set:  $D = \{(x_1, y_1, w_1), \dots, (x_n, y_n, w_n)\}$

$\downarrow$        $\downarrow$   
 $x_i \in \mathbb{R}^d$      $y_i \in \{b, s\}$       "sign" label  
 "d-dimensional feature vector"      "background"  
 $w_i \in \mathbb{R}^+$       non negative weight

define  $S = \{i : y_i = s\}$  and  $B = \{i : y_i = b\}$ , and  $\begin{cases} n_s = |S| \\ n_b = |B| \end{cases}$  number of signal/background events

for the simulated data set:

$n_s/n_b \neq P(y=s)/P(y=b)$  for naturally collected data, as we can simulate as many events as we wish  
 - this is good because normally  $P(y=s) \ll P(y=b) \rightarrow$  so we would have very few ( $y=s$ ) points to train our model / i.e. unbalanced data set

importance-weighted events:  $\rightarrow$  to make the setup invariant to the number of events

$$\sum_{i \in S} w_i = n_s \quad \sum_{i \in B} w_i = n_b, \quad \text{where } n_s \text{ and } n_b \text{ are normalization constants} \approx \text{"expected total number of } s/b \text{ events"}$$

$$w_i \sim \begin{cases} p_s(x_i) / q_s(x_i) & \text{if } y_i = s \\ p_b(x_i) / q_b(x_i) & \text{if } y_i = b \end{cases} \quad \text{where } \begin{aligned} p_s(x_i) &= p(x_i | y=s) \\ p_b(x_i) &= p(x_i | y=b) \end{aligned} \quad \begin{matrix} q_s, q_b \\ \text{are} \\ \text{intrinsic} \\ \text{densities} \end{matrix}$$

$(p: \text{probability density})$

define "g" as classifier, "G" =  $\{x : g(x) = s\}$  selection region,  $\hat{G}$  index set points that  $g$  selects

$$\hat{G} = \{i : x_i \in G\} = \{i : g(x_i) = s\}$$

$$S = \sum_{i \in S \cap \hat{G}} w_i : \text{Unbiased estimator of the expected number of signal events selected by } g, \quad S \cap \hat{G} : \text{the index set of events captured by the classifier } g$$

$$n_s = n_s \int_G p_s(x) dx \quad \text{and}$$

$$b = \sum_{i \in B \cap \hat{G}} w_i : \text{Unbiased estimator of the expected number of background events selected by } g$$

$$n_b = n_b \int_G p_b(x) dx$$

in machine learning terminology:

$S$ : true positive

$b$ : false positive

## AMS (approximate median significance)

$$\text{AMS} = \sqrt{2 \left( (s + b + b_{\text{reg}}) \ln \left( 1 + \frac{s}{b + b_{\text{reg}}} \right) - s \right)}$$

where  $b_{\text{reg}} = \text{cnst} = 10$ , regularization term  
to reduce the variance of the AMS

### **TASK:**

- train classifier  $g$  to MAXIMIZE AMS !

## The data

events of Higgs bosons + 3 background processes

importance - sampling flavor:

- the sum of weights of events falling in the region is an unbiased estimate of the expected number of events
- weights are not part of the input to the classifier

- 1) Z bosons - similar event to Higgs bosons
- 2) top quarks
- 3) W boson decay

$d=30$  features' details are given in Appendix B