

Direct optimization of discovery significance

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Contents

Reminder

Sample weights

Black magic

Binary classification

Multiclass

Summary

Reminder

Statistical significance approximation

- ▶ $s \approx$ True Positive (TP) rate
 $b \approx$ False Negative (FN) rate
 σ_b – background uncertainty
- ▶ Asimov significance:

$$Z_A = \sqrt{2 \left((s+b) \ln \left[\frac{(s+b)(b+\sigma_b^2)}{b^2 + (s+b)\sigma_b^2} \right] - \frac{b^2}{\sigma_b^2} \ln \left[1 + \frac{\sigma_b^2 s}{b(b+\sigma_b^2)} \right] \right)}$$

- ▶ given $b \gg s$, $\sigma_b \propto b$: $Z_A \rightarrow \frac{s}{\sqrt{s+b}}$

Given these approximations for significance, loss functions are defined as:

- ▶ $Z_A \rightarrow l_{Asimov} = \frac{1}{Z_A^2}$
- ▶ $\frac{s}{\sqrt{s+b}} \rightarrow l_{s/\sqrt{s+b}} = \frac{s+b}{s^2} - \underline{\text{but it has been shown that crossentropy is better}}$

Summary

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- ▶ ~~$\frac{s}{\sqrt{s+b}} \rightarrow l = \frac{s}{\sqrt{s+b}} = \frac{s+b}{s^2}$~~

DNN:

- ▶ Two hidden layers with ReLU as activation function.
- ▶ Binary classification:
 - ▶ Sigmoid in output layer.
- ▶ Multiclass
 - ▶ 4 signal classes: $t\bar{t}$ semi-leptonic, $t\bar{t}$ di-leptonic, W jets and actual signal, $t\bar{t} \tilde{\chi}^0$.
 - ▶ Softmax(4) for output layer.

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DNN:

- Two hidden layers with ReLU as activation function.
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 - Softmax(4) for output layer.

To train DNN:

1. Pretrain with crossentropy.
2. Finalize with l_{Asimov} .

Sample weights

Definition for s and b

► $s = W_s \sum_{sig} y^{pred}, W_s = \frac{L\sigma_{sig}\epsilon}{N_{sig}}$

$$b = W_b \sum_{bg} y^{pred}, W_b = \frac{L\sigma_{bg}\epsilon}{N_{bg}}$$

(definition used in research of A. Eldwood and D. Krücker)

Definition for s and b

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- ▶ Resulting equations for s and b :
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 $b = L\sigma_{bg}\epsilon \langle y_{bg}^{pred} \rangle$
- ▶ But in our case we have separate weights per event $\Rightarrow$ must modify equations.

Apply sample weights

$$\begin{aligned}\blacktriangleright \quad s &= W_s \sum_{i=\{sig\}} w_i y_i^{pred}, \quad W_s = \frac{L}{N_{sig}} \\ b &= W_b \sum_{i=\{bg\}} w_i y_i^{pred}, \quad W_b = \frac{L}{N_{bg}}\end{aligned}$$

Apply sample weights

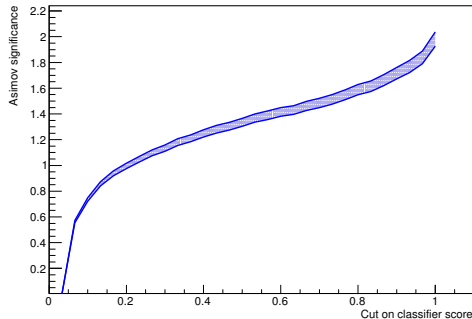
- ▶ $s = W_s \sum_{i=\{sig\}} w_i y_i^{pred}$, $W_s = \frac{L}{N_{sig}}$
 $b = W_b \sum_{i=\{bg\}} w_i y_i^{pred}$, $W_b = \frac{L}{N_{bg}}$

- ▶ Resulting equations for s and b :

$$\begin{aligned} s &= L \frac{\sum_{i=\{sig\}} w_i y_i^{pred}}{N_{sig}} = L \langle w_{sig} \rangle \frac{\sum_{i=\{sig\}} \tilde{w}_i y_i^{pred}}{N_{sig}} \\ &= L \langle w_{sig} \rangle \langle y_{sig}^{pred} \rangle_{weighted} = L \langle \sigma_{sig} \epsilon \rangle \langle y_{sig}^{pred} \rangle_{weighted} \\ b &= L \langle \sigma_{bg} \epsilon \rangle \langle y_{bg}^{pred} \rangle_{weighted} \end{aligned}$$

Apply sample weights

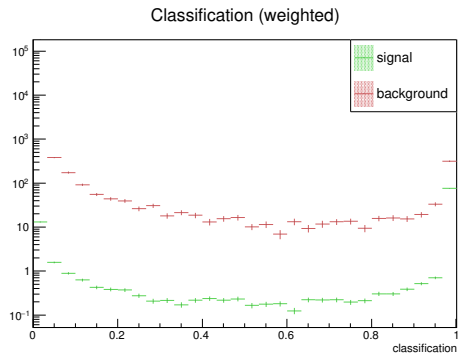
- ▶ $s = W_s \sum_{i=\{sig\}} w_i y_i^{pred}$, $W_s = \frac{L}{N_{sig}}$
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- ▶ ...but it does not work



$$M_{LSP} = 1000 GeV, M_{\tilde{g}} = 1900 GeV, \sigma_b = 10\%$$

Apply sample weights

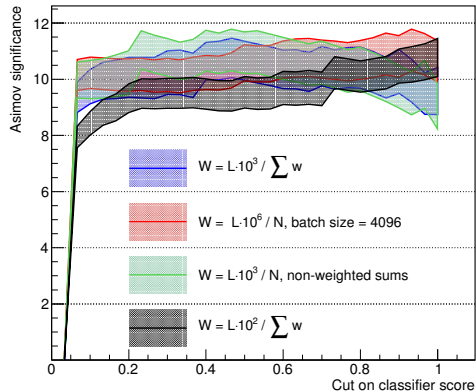
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Black magic

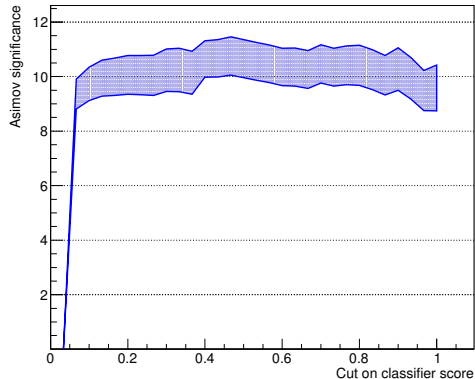
Powerful spells



$M_{LSP} = 1000 \text{ GeV}$, $M_{\tilde{g}} = 1900 \text{ GeV}$, $\sigma_b = 10\%$

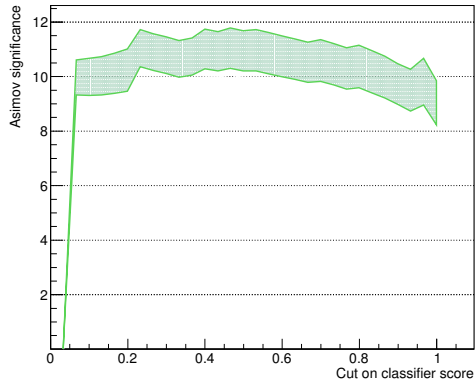
- $s = L \frac{\sum_{i=\{sig\}} w_i y_i^{pred}}{\sum_{i=\{sig\}} w_i} = L \langle y_{sig}^{pred} \rangle_{wtd}$
- $s = L \langle \sigma_{sig} \epsilon \rangle \langle y_{sig}^{pred} \rangle_{wtd} \cdot 10^3$
- $s = L \frac{\sum_{i=\{sig\}} y_i^{pred}}{N_{sig}} = L \langle y_{sig}^{pred} \rangle$
- $s = L \langle y_{sig}^{pred} \rangle_{wtd} \cdot 10^{-1}$

Powerful spells



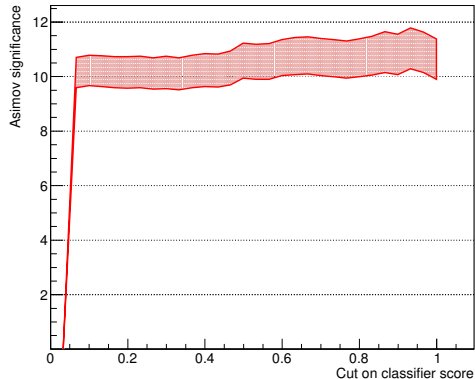
- $s = L \frac{\sum_{i=\{sig\}} w_i y_i^{pred}}{\sum_{i=\{sig\}} w_i} = L \langle y_{sig}^{pred} \rangle_{wtd}$
- For s to represent a number of events, we must have $s \propto L\sigma \Rightarrow s$ is **not** a number of events. And L here is just a magic hyper parameter:
 - $L = 1 \rightarrow Z_A \approx 4.5$
 - $L = (35.9 \cdot 10^3) \cdot 10^{-1} \rightarrow \max(Z_A) > 10$ (**black plot**)

Powerful spells



- $s = L \frac{\sum_{i=\{sig\}} y_i^{pred}}{N_{sig}} = L \langle y_{sig}^{pred} \rangle$
- ▶ Issue is the same as for *blue approach*. But now we don't even use the weights.
- ▶ This is the way Z_A was applied for my previous reports. I.e. just pass sample weights to the Keras, close your eyes and hope it knows what to do.

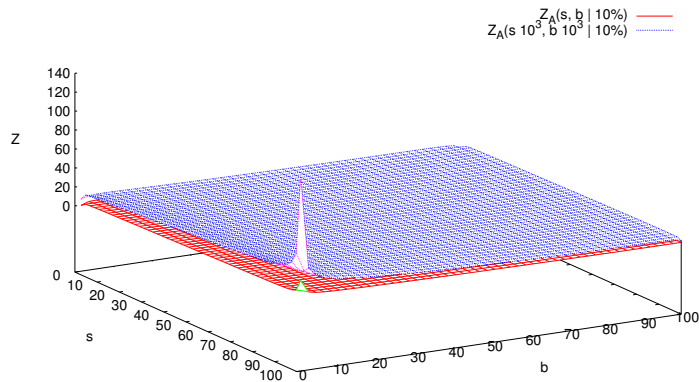
Powerful spells



- $s = L < \sigma_{sig} \epsilon > < y_{sig}^{pred} >_{wtd} \cdot 10^3$
- ▶ *Close to the correct definition, but...*
- ▶ *Issue is in the scale factor, 10^3 :*
 Z_A is non-linear to the scale of s and b ,
 $\forall x, y, \lambda, \sigma_b : Z_A(\lambda x, \lambda y | \sigma_b) \neq \lambda' Z_A(x, y | \sigma_b)$

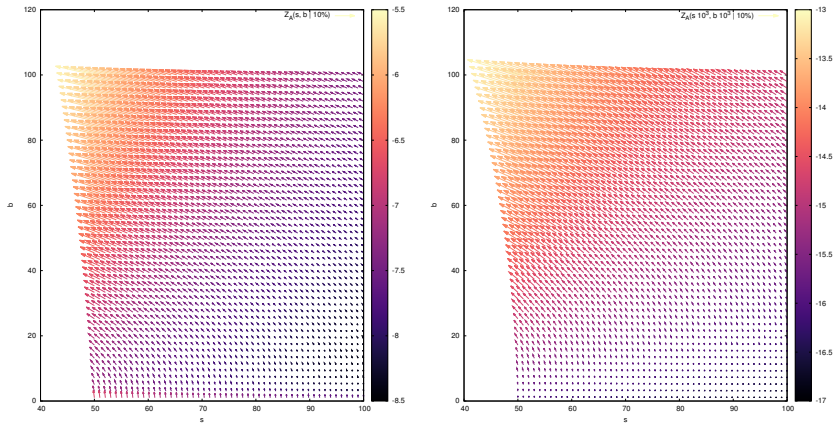
Scaling s and b

But is it really an issue?



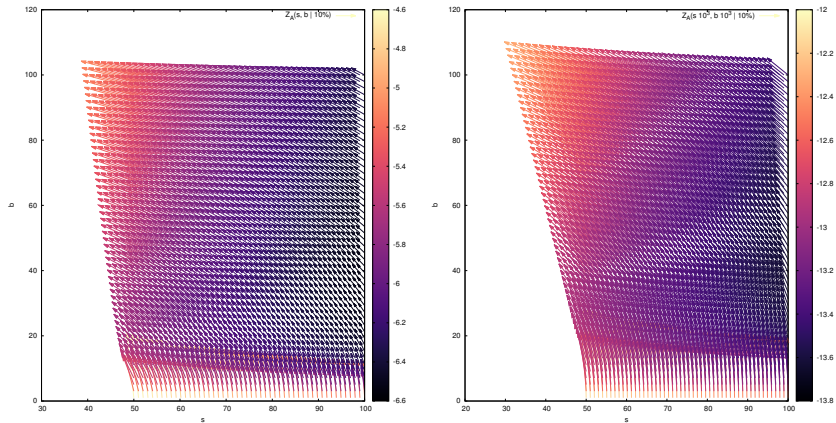
Asimov significance

Scaling s and b



Gradients for $l_{Asimov}(s, b | \sigma = 10\%)$ (left), and $l_{Asimov}(s \cdot 10^3, b \cdot 10^3 | \sigma = 10\%)(right)$

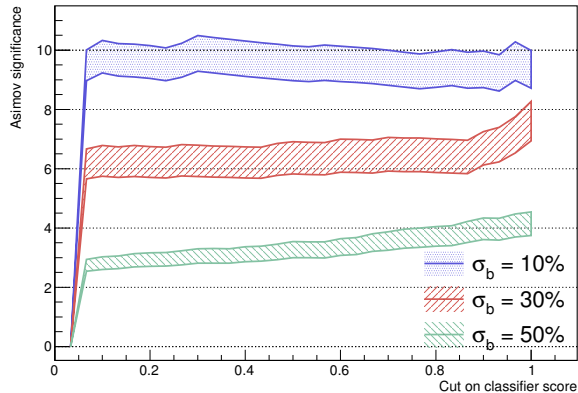
Scaling s and b



Gradients for $1/Z_A(s, b | \sigma = 10\%)$ (left), and $1/Z_A(s \cdot 10^3, b \cdot 10^3 | \sigma = 10\%)(right)$

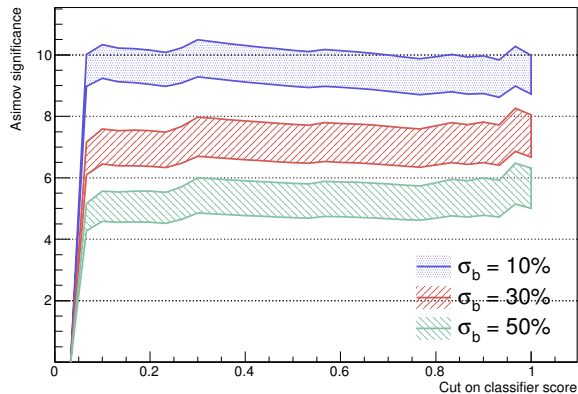
Binary classification

Red approach



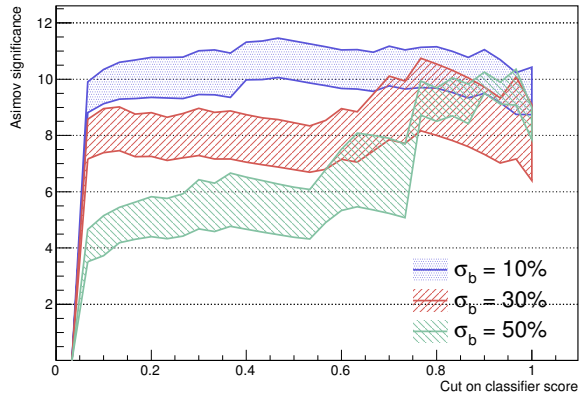
Results for different background uncertainties obtained with red approach.
 $M_{LSP} = 1000\text{GeV}$, $M_{\tilde{g}} = 1900\text{GeV}$, $\sigma_b = 10\%$.

Red approach



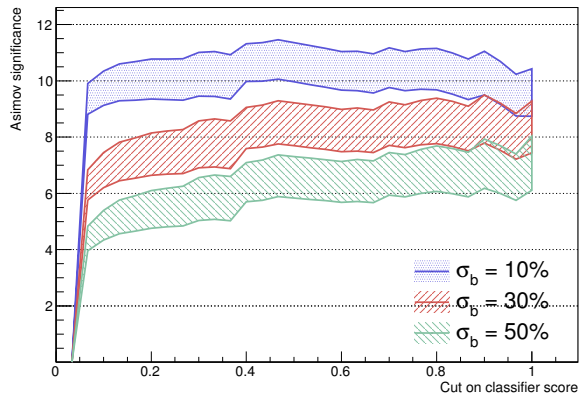
Now all plots are done for DNN trained with $\sigma_b = 10\%$.

Blue approach



Results for different background uncertainties obtained with [blue approach](#).
 $M_{LSP} = 1000\text{GeV}$, $M_{\tilde{g}} = 1900\text{GeV}$, $\sigma_b = 10\%$.

Blue approach



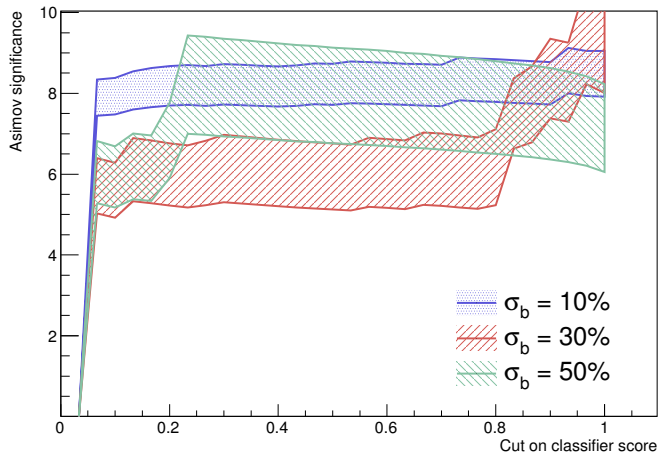
Now all plots are done for DNN trained with $\sigma_b = 10\%$.

Multiclass

Multiclass

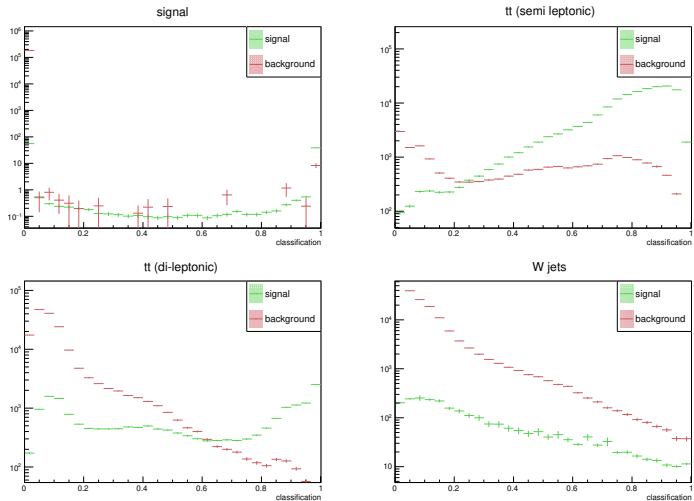
- ▶ $loss = l_{Asimov} \cdot 10^{10} + crossentropy \cdot 10^{-3}$
- ▶ l_{Asimov} is defined as in the [blue approach](#).
- ▶ Coefficients for l_{Asimov} and $crossentropy$ are chosen to weight values of both parts to be of the same order.

Multiclass



Results with different background uncertainties. $M_{LSP} = 1000\text{GeV}$, $M_{\tilde{g}} = 1900\text{GeV}$, $\sigma_b = 10\%$.

Multiclass



Classifier output for different classes. $M_{LSP} = 1000 GeV$, $M_{\tilde{g}} = 1900 GeV$, $\sigma_b = 10\%$.

Summary

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- ▶ Binary classification

- ▶ Asimov significance is decided to be used with:

$$s = L \frac{\sum_{i \in sig} w_i y_i^{pred}}{\sum_{i \in sig} w_i}, \quad b = L \frac{\sum_{i \in bg} w_i y_i^{pred}}{\sum_{i \in bg} w_i}$$

- ▶ ...unless during this meeting it will be decided to use another one.
 - ▶ Obtained significance for test-data set is $\approx 10\sigma$, which impress, since it has only ≈ 99 signal events vs $\approx 182\,627$ background events.
 - ▶ Try $l_{Asimov} = 1/Z_A$.

- ▶ Multiclass

- ▶ Applied combination l_{Asimov} and crossentropy with l_{Asimov} defined as in binary classification.
 - ▶ Obtained significance is lower compared to binary classification -approach. But...
 - ▶ total loss in multiclass is very sensitive to the weighting-coefficients, thus...
 - ▶ hyper-parameter-optimization is the next step.
 - ▶ Maybe “W jets”-class should be removed.

...and sorry for black magic.