

Development of a multivariate algorithm for the classification of B mesons at the LHCb experiment

Nico Guth **Bachelor talk, 20.07.2022**Arbeitsgruppe Albrecht

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Goal of my thesis:

Develop an algorithm that distinguishes between B_d^0 and B_s^0 mesons based on tracks associated with the signal B meson without tracks of the signal decay. (in pp-collisions at the LHCb detector)

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Structure of this talk:

- Motivation
- B meson production in pp-collisions
- The LHCb detector
- Development of a B meson classifier
 - Identification of same side tracks using a BDT
 - Classification of the B meson using a DeepSet
 - Testing on real LHCb data
- Conclusion and Outlook

Motivation

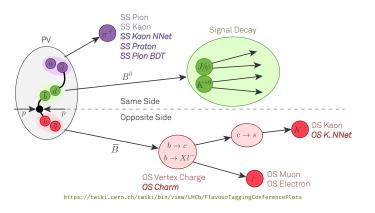
- support background reduction where B_d^0 ($\bar{b}d$) or B_s^0 ($\bar{b}s$) is unwanted
 - partial backgrounds with missing information in the signal decay
 - backgrounds with similar signal kinematics
 - e.g. $B_s^0 \to D_s^+ K^-$ with B_d^0 backgrounds in the signal region

Motivation

- support background reduction where B_d^0 ($\bar{b}d$) or B_s^0 ($\bar{b}s$) is unwanted
 - partial backgrounds with missing information in the signal decay
 - backgrounds with similar signal kinematics
 - \blacksquare e.g. $B_s^0 \to D_s^+ K^-$ with B_d^0 backgrounds in the signal region
- excluding the signal decay
 - → independence of the signal decay channel
- associated event contains enough information (in principle)
 - mass difference of B_d^0 and B_s^0 (87 MeV)
 - different fragmentation processes



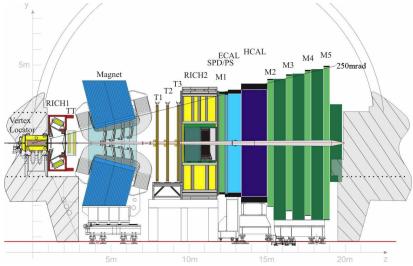
B meson production in pp-collisions



- pp-collisions produce many particles
- gluon-fusion may lead to a *bb*-pair
- hadronisation → B meson and fragmentation particles
- Lorentz boosted signal B → distinguish secondary from primary vertex
- for B_d^0 vs B_s^0 only same side (SS) relevant
- here: exclude the signal decay



The LHCb detector



https://iopscience.iop.org/article/10.1088/1748-0221/3/08/S08005



Development of a B meson classifier

Strategy:

- same side track identification using a BDT
- *B* meson classification using a DeepSet
- test on real LHCb data

Development of a B meson classifier

Strategy:

- same side track identification using a BDT
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Training dataset:

- training with LHCb simulation
- combined dataset:

$$B_d^0 \rightarrow J/\psi K^*$$

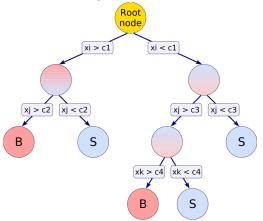
$$B_s^0 \rightarrow D_s^+ \pi^-$$

- found differences by year and simulation version
 - → chose 2016 and same simulation version
- dataset contains 0.4 million events and 18 million tracks



Boosted Decision Tree (BDT)

Simple Decision Tree:

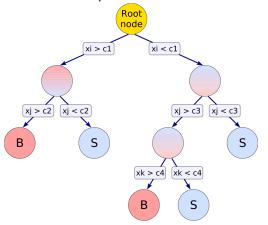


https://arxiv.org/abs/physics/0703039



Boosted Decision Tree (BDT)

Simple Decision Tree:



Boosted Decision Tree:

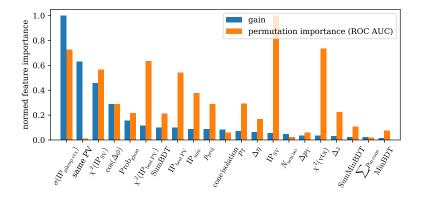
- ensemble of multiple small Decision Trees
- weighted sum transformed with logistic function
 → estimated class probabilities
- iterative training through gradient boosting
 - \rightarrow minimum of a loss function

https://arxiv.org/abs/physics/0703039



SS track identification: Feature Selection

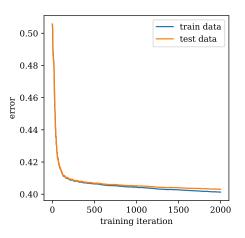
track features	
p_{T}	IP _{SV}
p_{proj}	$\chi^2(IP_{SV})$
Δp_{T}	$\sigma(IP_{pileup vtx})$
Δz	IP _{best PV}
$\Delta\eta$	$\chi^2(IP_{best\ PV})$
$\cos(\Delta\phi)$	IP_{min}
Prob _{ghost}	same PV
$\chi^2(vtx)$	cone isolation
SumBDT	N _{non iso}
MinBDT	$\sum p_{\text{in cone}}$
SumMinBDT	





SS track identification: BDT training and results

Error rate during training

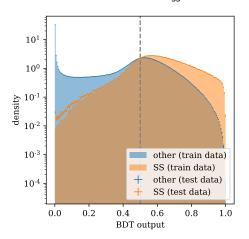


- 60% training data, 40% test data
- 2000 decision trees with maximum tree depth of 4
- loss: logistic regression for binary classification
- output: $Prob_{SS} \in [0, 1]$



SS track identification: BDT training and results

Distribution of Prob_{ss}

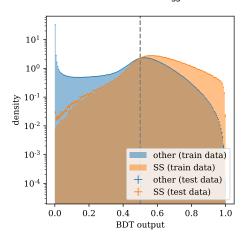


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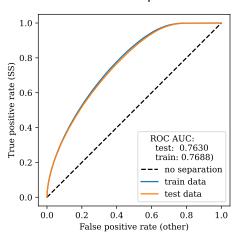


SS track identification: BDT training and results

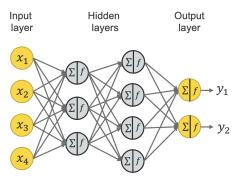
Distribution of Prob_{ss}



ROC curve of the BDT predictions



Neural Network (NN)



https://www.knime.com/blog/a-friendly-introduction-to-deep-neural-networks

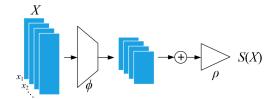
- non-linear transformation $\vec{x} \rightarrow \vec{y}$
- multiple steps called layers of activation $\rightarrow \vec{a}^{(n)} = f^{(n)} \left(W^{(n)} \cdot \vec{a}^{(n-1)} + \vec{b}^n \right)$
- activation functions used here:

 - $f_{\text{Sigmoid}}(z) = \frac{1}{1 + e^{-z}}$
- iterative training through backpropagation (gradient descent)

DeepSet

- extension of NNs to allow inputs of sets of vectors
 - → variable input length
 - → permutation invariant

$$f(X) = \rho \left(\sum_{x_i \in X} \phi(x_i) \right)$$

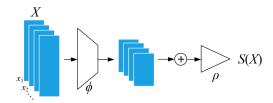


https://arxiv.org/abs/1703.06114

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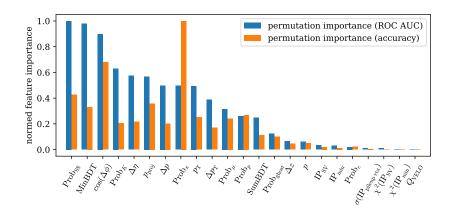
DeepSet for B meson classification:

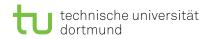
- one set X per event
- one vector *x*; per track
- φ-network layer sizes: 23, 64, 128, 64
- ρ-network layer sizes: 64, 128, 64, 1
- $= f_{ReLU}$ for hidden layers
- lacksquare f_{Sigmoid} for the output layer
- output: $Prob_{B_s} \in [0, 1]$



B meson classification: Feature Selection

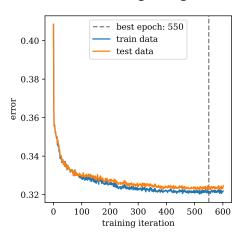
track features	
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p_{T}	$Prob_e$
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Δp	$Prob_{\mathcal{K}}$
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$\cos(\Delta\phi)$	$Prob_{\pi}^{'}$
$\Delta\eta$	$\sigma(IP_{pileup vtx})$
IP_SV	Q_{VELO}
$\chi^2(IP_{SV})$	SumBDT
IP_{min}	MinBDT
$\chi^2(IP_{min})$	





B meson classification: DeepSet training and results

Error rate during training

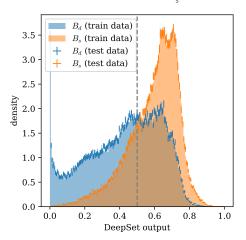


- 60% training data, 40% test data (standard scaled)
- regularisation:
 - early stopping after 50 iterations
 - Dropout of 50%
- loss: binary cross entropy
- optimizer: Adam
- output: $Prob_{B_s} \in [0, 1]$



B meson classification: DeepSet training and results

Distribution of $Prob_{B_a}$

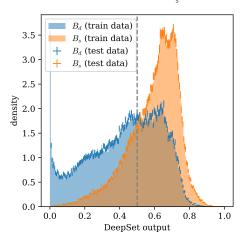


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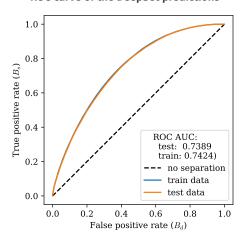


B meson classification: DeepSet training and results

Distribution of $Prob_{B_1}$



ROC curve of the DeepSet predictions



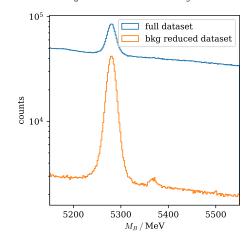


- run 2 LHCb data selected for B_d^0 or $B_s^0 \to J/\psi K_S^0$
- based on an ongoing analysis



- run 2 LHCb data selected for B_d^0 or $B_s^0 \rightarrow J/\psi K_s^0$
- based on an ongoing analysis
- visible B_s^0 peak after background reduction:
 - trained BDT with 13 features on $B_d^0 \to J/\psi K_S^0$ simulation as signal and upper mass sideband (≥ 5450 MeV) as combinatorial background
 - manual cuts for Λ^0 and K^* background that got misidentified as K_c^0

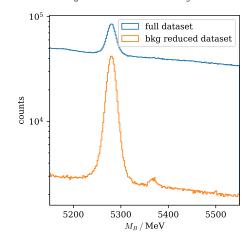
Signal B mass after background reduction (peaks at $M(B_a)$ = 5280 MeV and $M(B_s)$ = 5367 MeV)





- run 2 LHCb data selected for B_d^0 or $B_s^0 \rightarrow J/\psi K_s^0$
- based on an ongoing analysis
- visible B_c peak after background reduction
- testing strategy:
 - apply the developed algorithm
 → Prob_{B₂} for every event
 - estimate counts of B_d^0 and B_s^0 events by fitting the mass distribution and integrating the B_d^0 and B_s^0 components
 - scan through the Prob_{B2} distribution

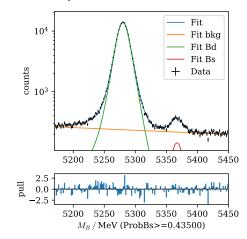
Signal B mass after background reduction (peaks at $M(B_d)$ = 5280 MeV and $M(B_s)$ = 5367 MeV)





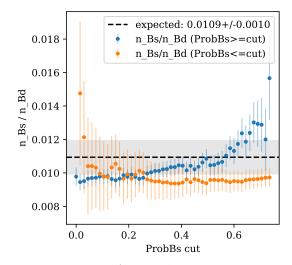
- run 2 LHCb data selected for B_d^0 or $B_s^0 \to J/\psi K_s^0$
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- visible B_s⁰ peak after background reduction
- testing strategy:
 - apply the developed algorithm
 - \rightarrow Prob_{B_c} for every event
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 - \blacksquare scan through the $\mathsf{Prob}_{\mathcal{B}_{\varsigma}}$ distribution

Example fit of the mass distribution





Testing on LHCb data: Results (ratio $n_{B_{\perp}}/n_{B_{\perp}}$ by Prob_{B_{\infty}} cut value)



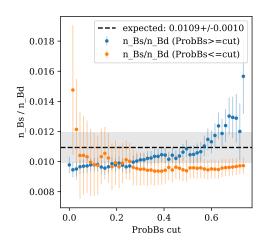


Testing on LHCb data: Animation of $n_{\rm B_c}/n_{\rm B_d}$ and the corresponding fits

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Testing on LHCb data: Results (ratio $n_{B_{\epsilon}}/n_{B_d}$ by $\operatorname{Prob}_{B_{\epsilon}}$ cut value)

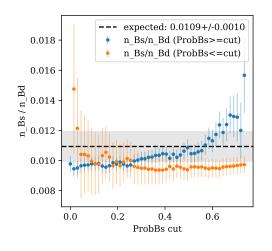


- without separation: constant ratio n_{B_s}/n_{B_d}
- expected value (with perfect selection efficiencies):

$$\frac{{\rm BR}(B_s \to J/\psi \, K_{\rm S}^0)}{{\rm BR}(B_d \to J/\psi \, K_{\rm S}^0)} \cdot f_s/f_d ({\rm 13 \, TeV}) = 0.0109 \pm 0.0010$$



Testing on LHCb data: Results (ratio n_{B_c}/n_{B_d} by $Prob_{B_c}$ cut value)



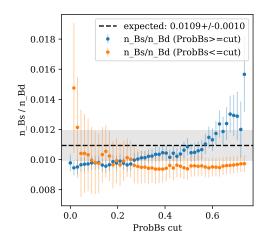
- without separation: constant ratio n_{B_a}/n_{B_d}
- expected value (with perfect selection efficiencies):

$$\frac{{\rm BR}(B_{\rm S} \to J/\psi \, K_{\rm S}^0)}{{\rm BR}(B_d \to J/\psi \, K_{\rm S}^0)} \cdot f_{\rm S}/f_d ({\rm 13 \, TeV}) = 0.0109 \pm 0.0010$$

■ $\operatorname{Prob}_{B_s} \leq x$: mostly constant, no clear B_s^0 peak for low x



Testing on LHCb data: Results (ratio $n_{B_{\epsilon}}/n_{B_d}$ by $\operatorname{Prob}_{B_{\epsilon}}$ cut value)



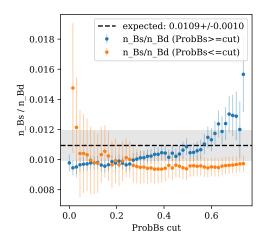
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- $\operatorname{Prob}_{B_s} \leq x$: mostly constant, no clear B_s^0 peak for low x
- $Prob_{B_s} \ge x$: starts constant, then increases



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- $\operatorname{Prob}_{B_s} \leq x$: mostly constant, no clear B_s^0 peak for low x
- $Prob_{B_s} \ge x$: starts constant, then increases
- $lue{}$ clearly achieved some separation between B_d^0 and B_s^0

Conclusion and outlook

Results:

- on simulation:
 - BDT can identify SS tracks (ROC AUC: 0.76) and helps the DeepSet (feature importances)
 - DeepSet achieves a clear separation of B_d^0 and B_s^0 events (ROC AUC: 0.74)
- on LHCb data: prove of concept shown
- reasons for incomplete performance portability unknown:
 - selection differences in training dataset? (combination of $B_d^0 \to J/\psi K^*$ and $B_s^0 \to D_s^+\pi^-$)
 - mismodeled simulation features?



Conclusion and outlook

Results:

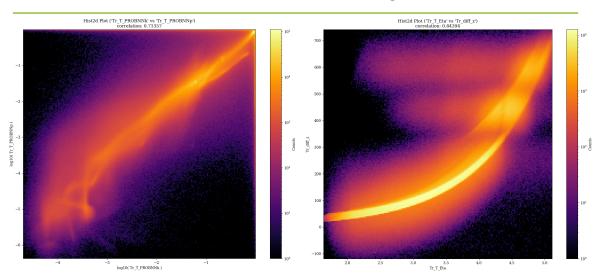
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 - mismodeled simulation features?

Outlook and suggestions:

- feature validation: compare simulation and data
- ensure that kinematic differences originate only from the mass difference:
 - training dataset with the same final-state particles for both *B* mesons
 - reweighting the training data to equalize kinematics
- possible extension to include other *b* hadrons (B^{\pm} , B_c^{\pm} , Λ_b^0 , ...)

Thank you for your attention!

Here is some art I found in the data (2D histograms):



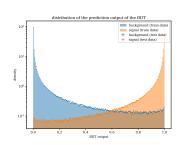


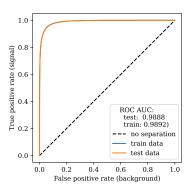


Background BDT

signal	features
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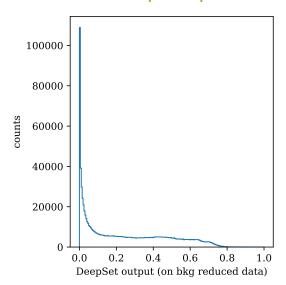
$IP(B^0)$	$p_{T}(\pi^{\scriptscriptstyle +})$
$IP(J/\psi)$	$p_{T}(\pi^{\scriptscriptstyle{-}})$
$IP(K_S^0)$	$p_{T}(K_{S}^{0})$
$IP(\mu^{+})$	$\eta(B^0)$
$IP(\mu^-)$	$\eta(K_S^0)$
$FD(K_S^0)$	$p_z(K_S^0)$
χ^2 (fit)	

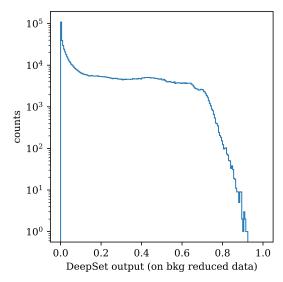






Test on LHCb data: DeepSet output

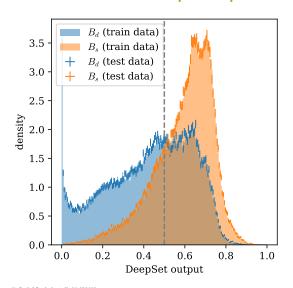


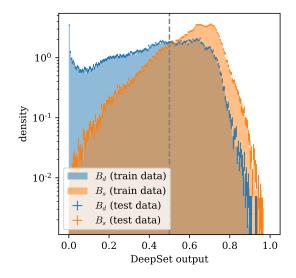


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B meson classification: DeepSet output

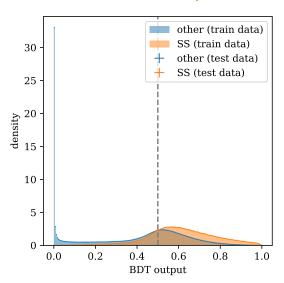


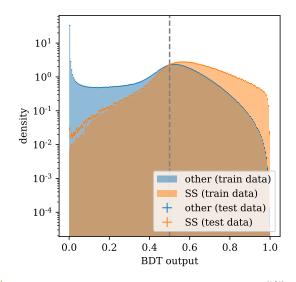


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SS track identification: BDT output

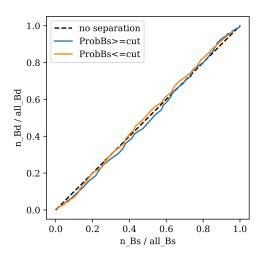




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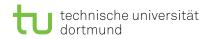


Testing on LHCb data: Results (efficiencies, similar to a ROC curve)



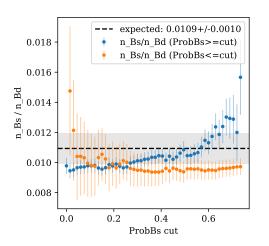
- calculated efficiencies $\varepsilon_B = n_B(x)/n_B$ (no cut)
- plot ε_{B_d} against ε_{B_s}
- should be similar to a ROC curve
- separation not really visible

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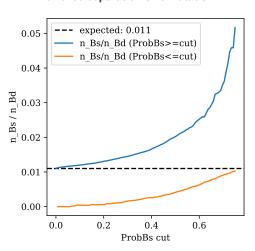


Testing on LHCb data: Results (ratio n_B / n_{B_A} by Prob_{B_B} cut value)

Achieved separation on data



Achieved separation on simulation

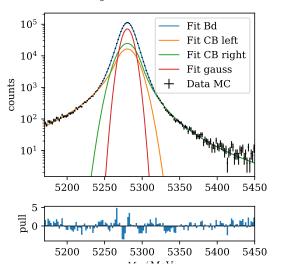


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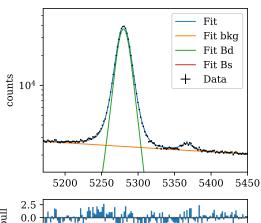


Testing on LHCb data: Fits

Fit of B_d^0 mode on simulation



Fit without ProbBs selection



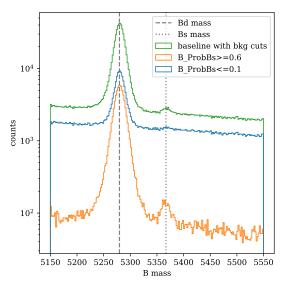
2.5 0.0 -2.5 5200 5250 5300 5350 5400 5450 M₂ / MeV (ProbBs>=0.00000)

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Data cut comparison:



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Fit functions

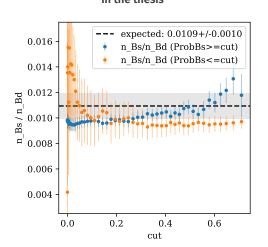
$$\begin{split} F(M_B) &= N_{\text{bkg}} \cdot F_{\text{bkg}}(M_B) + N_{B_d} \cdot F_{B_d}(M_B) + N_{B_s} \cdot F_{B_s}(M_B) \\ &F_{\text{bkg}}(M_B) = \exp(-\lambda \cdot M_B). \\ F_B(M_B) &= f_1 \cdot f_2 \cdot F_{\text{CB}} \left(\frac{M_B - \mu}{\sigma_1}, \beta_1, m_1 \right) \\ &+ (1 - f_1) \cdot f_2 \cdot F_{\text{CB}} \left(-\frac{M_B - \mu}{\sigma_2}, \beta_2, m_2 \right) \\ &+ (1 - f_1) \cdot (1 - f_2) \cdot F_{\text{gauss}} \left(M_B, \mu, \sigma_3 \right), \\ F_{\text{CB}}(x, \beta, m) &= \begin{cases} N \cdot \exp(-\frac{x^2}{2}) & \text{for } x > -\beta \\ N \cdot \left(\frac{m}{|\beta|} \right)^m \cdot \exp\left(-\frac{\beta^2}{2} \right) \cdot \left(\frac{m}{|b|} - |b| - x \right)^{-m} & \text{for } x \leq -\beta \end{cases} \\ F_{\text{gauss}}(x, \mu, \sigma) &= \frac{1}{\sqrt{2}\pi\sigma} \cdot \exp\left(-\frac{1}{2} \left(\frac{x - \mu}{\sigma} \right)^2 \right) \end{split}$$

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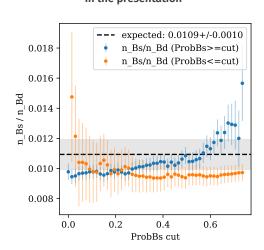


Ratio plot in the thesis and the newest plot (different cut values and slightly different results due to fit instabilities at the edges)

In the thesis



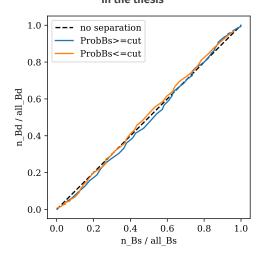
In the presentation



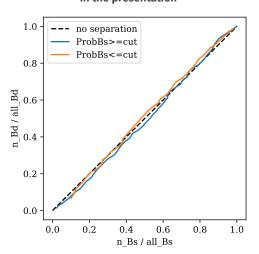
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ROC plot in the thesis and the newest plot In the thesis



In the presentation

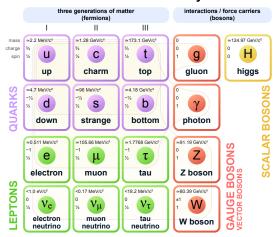


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The Standard Model of particle physics

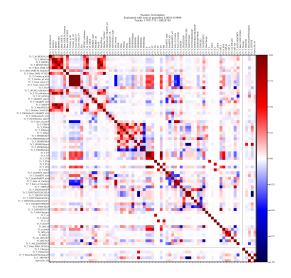
Standard Model of Elementary Particles



https://en.wikipedia.org/wiki/Standard_Model

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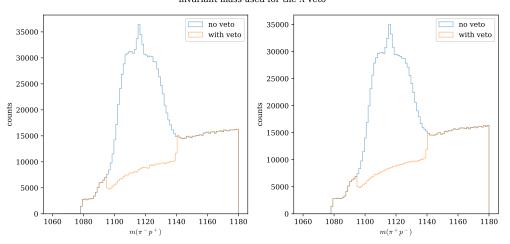
Correlation Matrix





Lambda Veto

invariant mass used for the Λ veto



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