

# Masterthesis: analysis of $B \rightarrow K^* \mu \mu$ decay

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Here comes the abstract

## 1 Introduction

### 1.1 $B \rightarrow K^* \mu \mu$ decay

The Decay is a flavor changing neutral current (FCNC) with four charged particles in the final state: The  $K^+$  and  $\pi^-$  from the  $K^*$  decay and two leptons from the loop or box digrams:

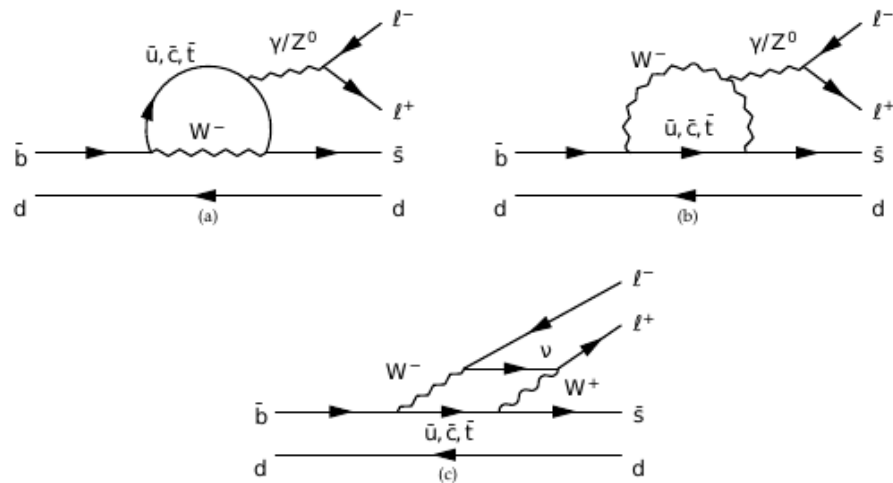


Figure 1: Feynman diagrams for decay  $B_d \rightarrow \mu^+ \mu^-$  at lowest order

The kinematics of the decay are defined by the three angles  $\theta_K$ ,  $\theta_L$  and  $\phi$ :

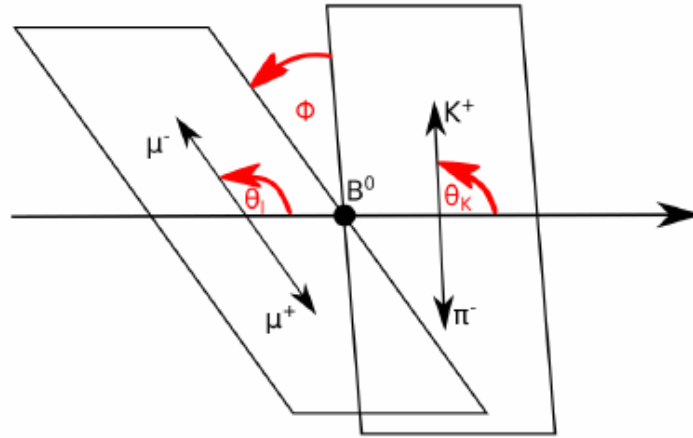


Figure 2: kinematic variables of the decay  $B^0 \rightarrow K^{*0} \mu \mu$

## 1.2 The LHCb Experiment

The Large Hadron Collider beauty experiment (LHCb) is one of four large experiments based at the CERN laboratory near Geneva in Switzerland. It is part of the Large Hadron Collider (LHC), a proton-proton accelerator and collider located in a vast underground tunnel with 26.7 km circumference beneath the Swiss-French countryside. The other three experiments are CMS and ATLAS which are dedicated to a wide range of physics and have therefore very large detectors. ALICE investigates quark-gluon plasma and therefore needs heavy ion collisions, instead of proton collisions.

The protons in the LHC have a kinetic energy of 7 TeV, which allows a collision energy, in the LHCb detector, of 13 TeV. In the year 2016 the LHCb had a recorded luminosity of  $1906 \text{ pb}^{-1}$ . For this thesis  $2280 \text{ pb}^{-1}$  of data, collected at LHCb during the years 2011 to 2016 are used. LHCb is dedicated to flavour physics. It therefore investigates rare decays and CP violation in beauty and charm hadrons.

CERN's Accelerator Complex

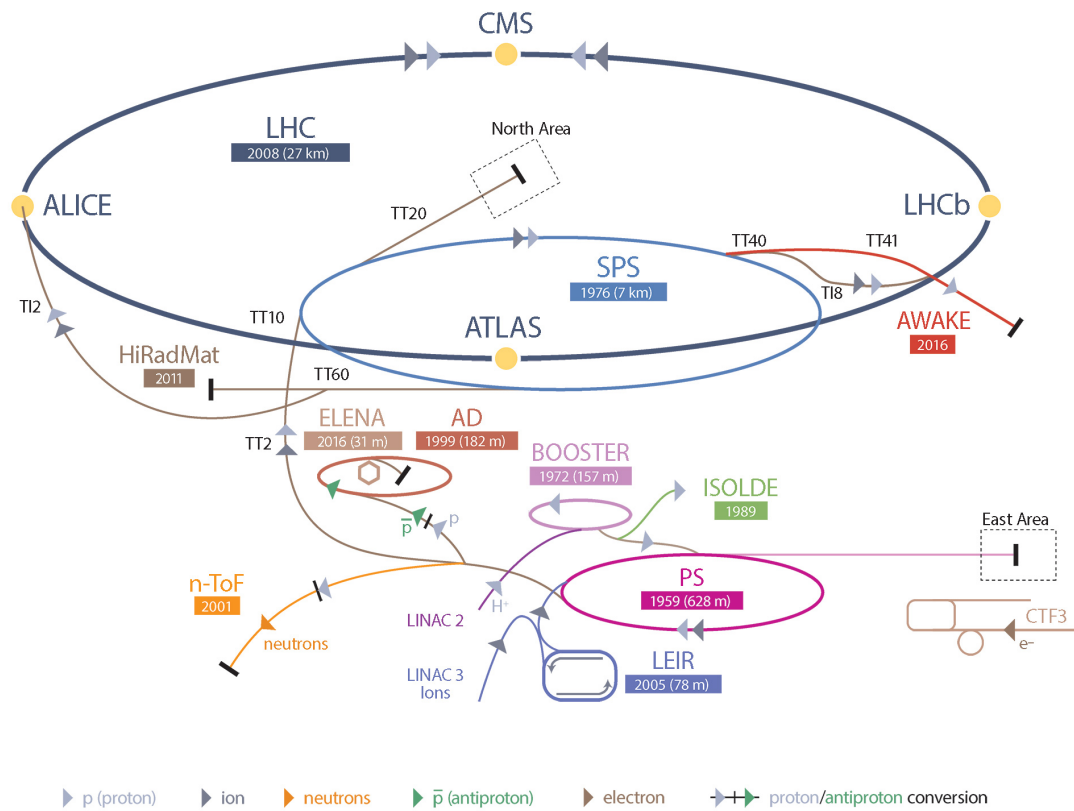


Figure 3: CERN's Accelerator Complex.[1] The protons get injected in the lineare accelerator LINAC2. Then they get pre-accelerated in 3 synchrotrons (BOOSTER,PS,SPS) where the protons reach a kinetic energy of 450 GeV. That is the entering energy of the LHC which accelerates them futher up to 7 TeV, before they collide at the four detectors: CMS, ATLAS, LHCb and ALICE.

### 1.2.1 The LHCb Detector

The LHCb Detector has a fix target geometry, because beauty hadrons are manily produced at small angeles with respect to the beam pipe.

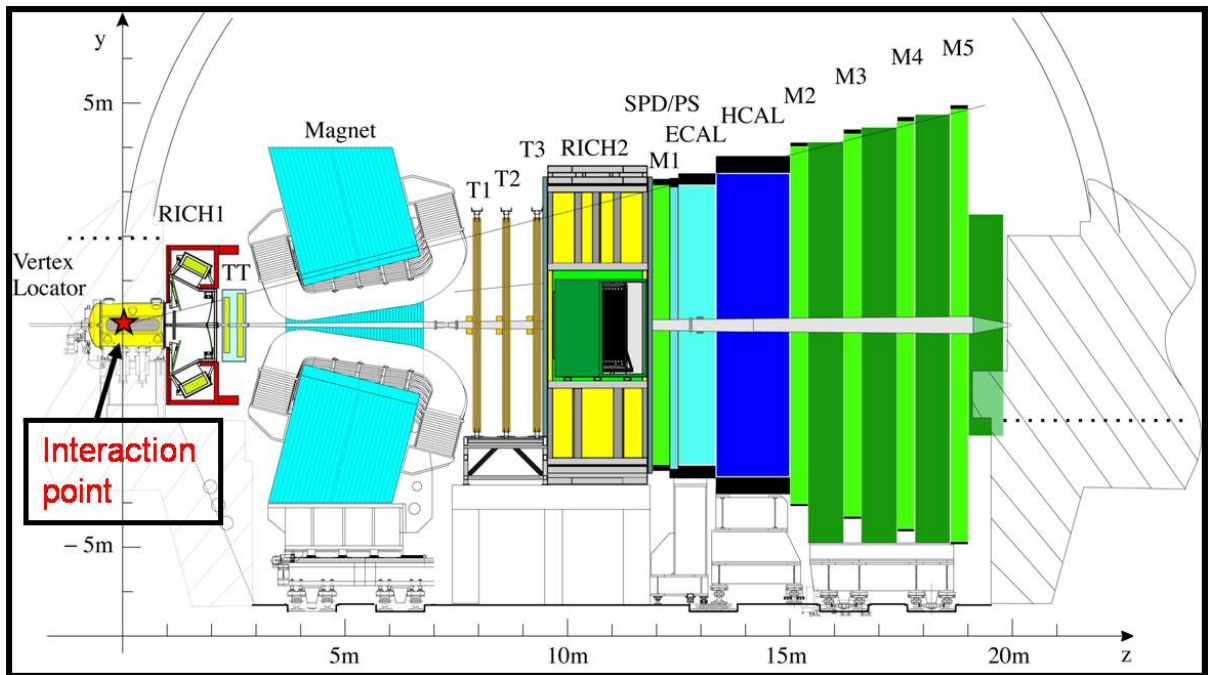


Figure 4: Basic layout of the LHCb detector [2]. The interaction point is inside the vertex detector and the beam pipe passes through the center. The different subdetectors are the two Ring Imaging Cherenkov Detectors (RICH1 and RICH2), the tracking stations (TT and T1 to T3), the scintillator pad detector (SPD), the preshower electromagnetic calorimeter (ECAL), the hadronic calorimeter (HCAL) and the muon stations (M1-M5).

**Vertex Locator (VELO) [3] :** Velo picks out B mesons from the multitude of other particles produced. This is a complex task since B mesons have very short lifetimes spent close to the beam. The VELO's silicon detector elements must be placed at a distance of just five millimetres to the interaction point. To prevent damage to the detector during beam injection and stabilization it is mechanically moved to a safe distance. Velo measures B mesons indirectly by detecting its decay particles, nevertheless it has a resolution of 10 microns. .

**Ring Imaging Cherenkov (RICH) detectors [4] :** The RICH detectors measure the emission of Cherenkov radiation, which happens when a charged particle passes through a medium faster than light does. It is a similar effect like the sonic boom an aircraft produces by breaking the sound barrier. The shape of the light cone depends on the particle's velocity, enabling the detector to determine its speed.

**Magnet [5] :** The big magnet of the LHCb experiment weighs 27 tonnes and is mounted inside a 1,450 tonne steel frame. This powerful magnet forces all charged particles to change their trajectory. By examining the curvature of the path one can calculate its momentum.

**Trackers [6] :** The LHCb's tracking system consists of a series of four large rectangular stations, each covering an area of  $40 \text{ m}^2$ . While flying through this area charged particles will leave a trace, therefore one can estimate the trajectory of a particle. The trajectory is used to link the signals left in other detector elements to the corresponding particle. In LHCb two different tracker technologies are used: The silicon tracker placed close to the beam pipe, uses silicon microstrips. If a charged particle passes such a stripe it collides with the silicon atoms, liberating electrons and creating an electric current, which is then recorded. The outer tracker situated further from the beam pipe consists of gas-filled tubes. The gas ionizes when a charged particle hits a gas molecule, producing electrons. These reach an anode wire situated in the centre of each tube. The position of the track is found by timing how long it takes

electrons to reach it.

**Calorimeters [7] :** Calorimeters stop particles as they pass through, measuring the amount of energy lost. In LHCb there are two different types: The electromagnetic calorimeter responsible for light particles like electrons and photons and the hadronic calorimeter responsible for heavier particles containing quarks. Both have a sandwich-like structure, with alternating layers of metal and plastic plates. If a particle hits a metal plate it produces a shower of secondary particles. These will excite polystyrene molecules in the plastic plates, which then emit ultraviolet light. The energy lost by the particle in the metal plate is proportional to the amount of UV light produced in the plastic plates.

**Muon System [8] :** The muon system consists of 5 rectangular stations, which cover an area of  $435 \text{ m}^2$ . Each station has chambers filled with three gases: carbon dioxide, argon and tetrafluoromethane. Passing muons react with the mixture and electrodes detect the result.

### 1.2.2 The LHCb trigger system

The rate of events at the LHCb interaction point is 40 MHz. But the rate to have a B meson contained in the detector is 15 kHz. But the offline computing power just allows 2 kHz to be recorded. The LHCb trigger system aims to 'fill' this 2 kHz with interesting B decays and important control decays like  $J/\psi$  decays. The trigger has two levels:

The **Level Zero (L0)** trigger reduces the beginning 40 MHz to 1 MHz. To get this high rate it can only rely on fast sub-detectors as the calorimeters and the muon system. The L0 trigger looks for events with high transverse momentum with respect to the particle beam axis (pT), because particles from a B decay have this attribute, since B Mesons are always produced almost parallel to the beam axis. In addition the L0 trigger performs a simplified vertex reconstruction with the signal of two silicon layers of the VELO to identify events with multiple proton-proton collisions. They are rejected because for this kind of events it is much more difficult to reconstruct B meson decays, since it is harder to distinguish primary and secondary vertex of the B decay.

The **High Level Trigger (HLT)** is an algorithm that runs on a farm of 1000 16-core computers. It has two stages: HLT1 which reduces the event rate to a few tens of kHz and HLT2 which reduces the rate to the 2 kHz which are recorded. HLT1 gets all the candidates of the L0 trigger and uses the full detector information on them to search for particles with a high impact parameter with respect to the proton-proton collision. These particles are most likely decay products from B mesons, because of its relatively long life-time. They typically fly 1 cm away from the collision before decaying resulting in a high impact parameter for the decay products. HLT2 does a complete reconstruction of the events. It starts with the track of the VELO and connects them to the tracks in the other sub-detectors. Most important are displaced vertices, since they are strong indicator for B decays. The selection is divided into two parts. The inclusive selection searches for resonance decays like  $D^*$  or  $J/\psi$ . The exclusive selection is designed to provide the highest possible efficiency to fully reconstruct B decays of interest. It therefore uses all information available such as mass and vertex quality and intermediate resonances.

## 2 Analysis

### 2.1 Classification

#### 2.1.1 Introduction

To eliminate combinatorial background Machine Learning algorithms called classifiers are used. They can separate data into two or more parts, depending on certain parameters. For example separating colors depending on their share of magenta, cyan and yellow. But first they need to be trained on so called labeled data. In a labeled data set it is known which entries corresponds to which category, like colors. While training the algorithm will learn to separate data into the pre defined categories. That is the reason it is called Machine learning. In this thesis the classification should separate signal from combinatorial background.

To do so Monte Carlo data which contains only  $B \rightarrow K^* \mu \mu$  decays is labeled with probability 1 to be signal. Then it is merged with real data and used to train the classifiers. But since the classification becomes naturally biased if the data to classify is the same as the training data, a technique called K-folding is used. K-folding separates the data Monte Carlo mix into several parts called folds. To classify one fold all the other folds are used for training. After iterating over all the folds one has a completely classified data set without any bias.

#### 2.1.2 classifiers test

In this thesis the classifiers themselves are used as a black box and are not explained further. First the following list of classifiers were tested and compared in terms of performance:

- Ada Boost
- uGB + knnAda
- uBoost
- uGB + FI
- xgb
- sk\_bdtg
- sk\_bdt

The test was performed with 30000 events from the 2016 LHCb  $B \rightarrow K^* \mu \mu$  data and 10000 events from the Monte Carlo simulation. The following list of parameters are used in brackets are the names of the parameters in the root files.

- Decay vertex location for reconstructed particles (ENDVERTEX)
- Primary vertex location (OWNPV)
- Impact parameter (IP\_OWNPV)
- Flight distance (FD\_OWNPV)
- The cosine of the angle between primary vertex and decay vertex and recorded momentum (DIRA\_OWNPV)

To compare the different classifiers the ROC curves and the correlations to the kinematic variables of the decay (see 2) are used. First let's inspect the ROC curve. Since the curves for the different folds all look alike only one is presented here 5. One can find the other nine curves in the appendix ?? . It turns

out that all the classifiers classify the data correctly with just some minor variances. The ROC curve is in that case not a good tool to compare the different classifiers.

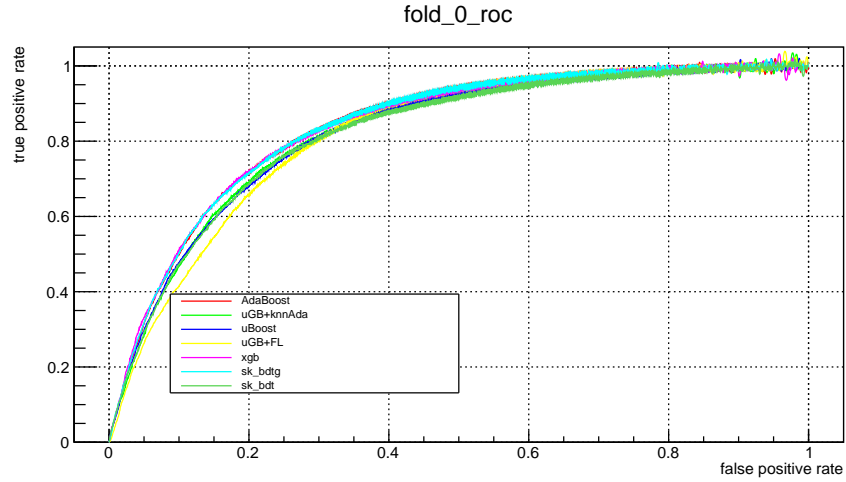


Figure 5: ROC curve of the first fold. One can see that all the classifiers are competitive in terms of classifying correctly

The next step is to check for unwanted correlations, only the correlations with the mass are shown here. The others can be found in appendix ??.

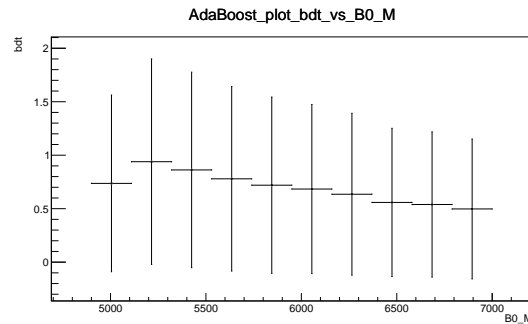


Figure 6: This plot shows the correlation between the bdt decision of the AdaBoost classifier and the  $B_0$  mass.

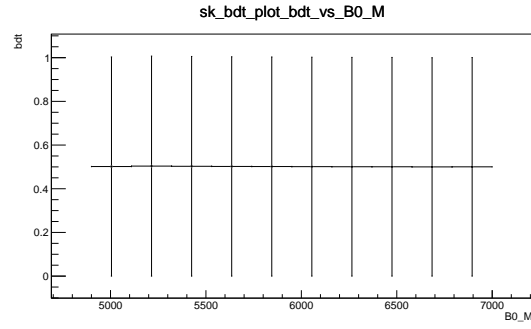


Figure 7: This plot shows the correlation between the bdt decision of the sk\_bdt classifier and the  $B_0$  mass.

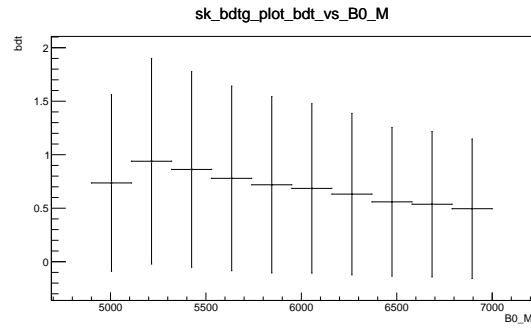


Figure 8: This plot shows the correlation between the bdt decision of the sk\_bdtg classifier and the  $B_0$  mass.

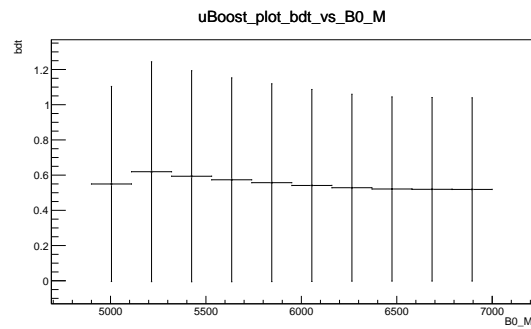


Figure 9: This plot shows the correlation between the bdt decision of the uBoost classifier and the  $B_0$  mass.



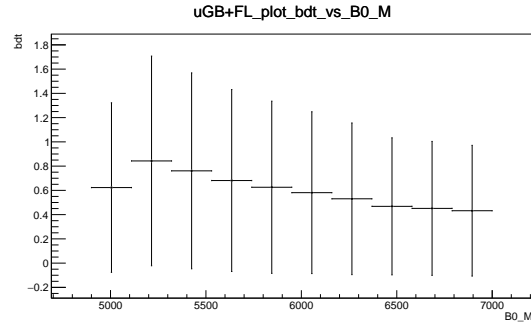


Figure 10: This plot shows the correlation between the bdt decision of the uGB+FL classifier and the  $B_0$  mass.

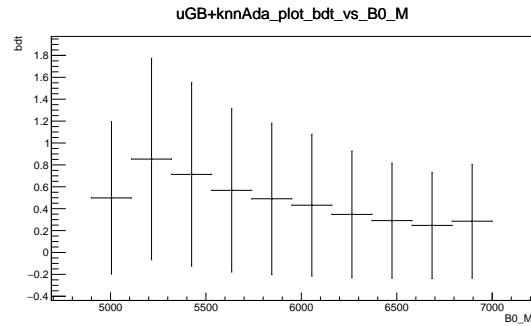


Figure 11: This plot shows the correlation between the bdt decision of the uGB+knnAda classifier and the  $B_0$  mass.

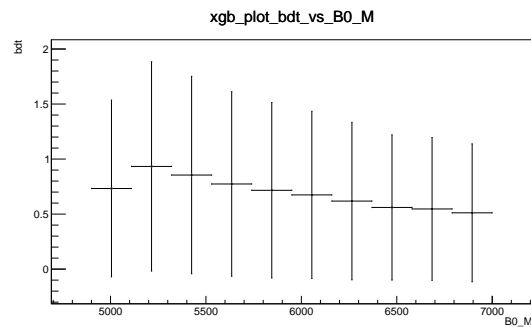


Figure 12: This plot shows the correlation between the bdt decision of the xgb classifier and the  $B_0$  mass.

The two classifiers with the least correlation are the sk\_bdt and the uBoost classifiers. Therefore they were used to do the separation between signal and background in the  $B \rightarrow K^* \mu \mu$  data.

## 2.2 SPlot

### 2.2.1 Likelihood method

Consider an analysis of a data sample, which consists of several types of events. These types represent signal components and background components, for example from different experiments. The log-likelihood of such a data sample is expressed as:

$$L = \sum_{i=1}^N \ln \left[ \sum_{j=1}^{N_S} N_j f_j(y_i) \right] - \sum_{j=1}^{N_S} N_j \quad (1)$$

- $N$  = total number of events
- $N_S$  = number of types
- $N_i$  = expected average number of events for type  $i$
- $y$  = set of discriminating variables
- $f_j$  = PDF of the  $i$ th type
- $f_j(y_i)$  = value of PDF for event  $y_i$
- $x$  = control variable, not a part of  $L$  by construction

The yields  $N_i$  and the free parameters of the PDF are obtained by maximizing the above log-likelihood (eq 1).

### 2.2.2 *inPlot* technique

Consider a variable  $x$  which can be expressed as a function of the discriminating variables  $y$  used in the fit. Furthermore a fit has been performed to determine the yields  $N_i$  for all types. From the knowledge of the PDF and the values of  $N_i$  a naive weight can be defined as:

$$P_n(y_i) = \frac{N_n f_n(y_i)}{\sum_{k=1}^{N_S} N_k f_k(y_i)} \quad (2)$$

which will lead to the  $x$ -distribution  $\tilde{M}_n$  defined by:

$$N_n \tilde{M}_n(\bar{x}) = \sum_{i \in \delta x} P_n(y_i) \quad (3)$$

where  $\sum_{i \in \delta x}$  contains all events for which  $x_i$  lies in the interval centered on  $\bar{x}$  and of total width  $\delta x$ . Therefore  $N_n \tilde{M}_n(\bar{x}) \delta x$  is the  $x$ -distribution of the histogrammed events, using the weights of eq 2. With this procedure one can on average reproduce the true distribution  $\mathbf{M}_n(x)$ . One can even replace the sum in eq 3 by an integral:

$$\left\langle \sum_{i \in \delta x} \right\rangle \rightarrow \int dy \sum_{j=1}^{N_S} N_j f_j(y) \delta(x(y) - \bar{x}) \delta x \quad (4)$$

Furthermore through identifying the number of events  $N_i$  from the fit one gets:

$$\langle N_n \rangle \tilde{M}_n(\bar{x}) = \int dy \sum_{j=1}^{N_s} N_j f_j(y) \delta(x(y) - \bar{x}) P_n(y) \quad (5)$$

$$= \int dy \sum_{j=1}^{N_s} N_j f_j(y) \delta(x(y) - \bar{x}) \cdot \frac{N_n f_n(y)}{\sum_{k=1}^{N_s} N_k f_k(y)} \quad (6)$$

$$= N_n \int dy \delta(x(y) - \bar{x}) f_n(y) \quad (7)$$

$$= N_n \mathbf{M}_n(\bar{x}) \quad (8)$$

One can see that the sum over events of the naive weight  $P_n$  provides a direct estimate of the  $x$ -distribution for the  $n$ th type. But this procedure has a major drawback, since  $x$  is correlated to  $y$ , the PDFs of  $x$  enter implicitly in the definition of the naive weight. Therefore the  $\tilde{M}_n$  distributions are a bad estimate for the quality of the fit, since these distributions are biased in a difficult way, when the PDFs  $f_i(y)$  are not accurate.

Consider for example a data sample where one of the types has events on the tail of the  $x$ -distribution. Such events require the true distribution to account for the tail. But since the events are averaged the weights on the tail are going to be very small missing those events in the estimated true distribution. Only the core of the  $x$ -distribution can be examined with *inPlots*.

### 2.2.3 $s$ Plot technique

In the previous section it was shown that if a variable  $x$  belongs to a set  $y$  of discriminating variables, one can reconstruct the expected  $x$  distribution. Consider now two sets of variables  $x$  and  $y$ , where  $x$  does not belong to  $y$  and which are uncorrelated, hence the total PDFs  $f_i(x, y)$  all factorize into products  $\mathbf{M}_i(x) f_i(y)$ . The equation 8 does not hold anymore because, when summing over the events the  $x$ -PDFs  $\mathbf{M}_j(x)$  appear:

$$\langle N_n \rangle \tilde{M}_n(\bar{x}) = \int \int dy dx \sum_{j=1}^{N_s} N_j \mathbf{M}_j(x) f_j(y) \delta(x - \bar{x}) P_n \quad (9)$$

$$= \int dy \sum_{j=1}^{N_s} N_j \mathbf{M}_j(\bar{x}) f_j(y) \frac{N_n f_n(y)}{\sum_{k=1}^{N_s} N_k f_k(y)} \quad (10)$$

$$= N_n \sum_{j=1}^{N_s} \mathbf{M}_j(\bar{x}) \left( N_j \int dy \frac{f_n(y) f_j(y)}{\sum_{k=1}^{N_s} N_k f_k(y)} \right) \quad (11)$$

$$\neq N_n \mathbf{M}_n(\bar{x}). \quad (12)$$

The correction term

$$N_j \int dy \frac{f_n(y) f_j(y)}{\sum_{k=1}^{N_s} N_k f_k(y)} \quad (13)$$

is not identical to the Kronecker delta  $\delta_{jn}$ . In fact the  $N_n \tilde{M}_n$  distribution obtained by the naive weight is a linear combination of the true distribution  $\mathbf{M}_j$ .

To go forward one has to realize that the correction term is related to the inverse of the covariance matrix, given by the second derivatives of  $-L$ , after the minimization.

$$\mathbf{V}_{nj}^{-1} = \frac{\partial^2(-L)}{\partial N_n \partial N_j} = \sum_{i=1}^N \frac{f_n(y_i) f_j(y_i)}{\left( \sum_{k=1}^{N_s} N_k f_k(y_i) \right)^2} \quad (14)$$

If one averages and is replacing the sum over events by intergals (eq 4) the varaince matrix reads:

$$\langle \mathbf{V}_{nj}^{-1} \rangle = \int \int dy dx \sum_{e=1}^{N_s} N_e \mathbf{M}_e(x) f_e(y) \frac{f_n(y) f_j(y)}{\left( \sum_{k=1}^{N_s} N_k f_k(y) \right)^2} \quad (15)$$

$$= \int dy \sum_{e=1}^{N_s} N_e f_e(y) \frac{f_n(y) f_j(y)}{\left( \sum_{k=1}^{N_s} N_k f_k(y) \right)^2} \cdot \int dx \mathbf{M}_l(x) \quad (16)$$

$$= \int dy \frac{f_n(y) f_j(y)}{\sum_{k=1}^{N_s} N_k f_k(y)} \quad (17)$$

Therefor equation 9 can be rewritten as:

$$\langle \tilde{M}_n(\bar{x}) \rangle = \sum_{j=1}^{N_s} \mathbf{M}_j(\bar{x}) N_j \langle \mathbf{V}_{nj}^{-1} \rangle. \quad (18)$$

To get the distribution of intrest one has to invert this matrix equation:

$$N_n \mathbf{M}_n(\bar{x}) = \sum_{j=1}^{N_s} \langle \mathbf{V}_{nj} \rangle \langle \tilde{M}_j(\bar{x}) \rangle \quad (19)$$

The true distribution of  $x$  can still be reconstructed using the naive weight (eq 2), through a linear combination of  $_{in}Plots$ . In other words: When  $x$  does not belong to the set  $y$ , the weights are not given by equation 2, they are given by a covariance-weighted quantity called  $sWeight$  defined by:

$$_sP_n(y_i) = \frac{\sum_{j=1}^{N_s} \mathbf{V}_{nj} f_j(y_i)}{\sum_{k=1}^{N_s} N_k f_k(y_i)} \quad (20)$$

With the  $sWeights$  on can obtain the distribution of the  $x$  variable by histogramming the  $_sPlot$ :

$$N_{ns} \tilde{M}_n(\bar{x}) \delta x = \sum_{i \in \delta x} _sP_n(y_i) \quad (21)$$

On average it reproduced the true distribution:

$$\langle N_{ns} \tilde{M}_n(x) \rangle = N_n \mathbf{M}_n(x) \quad (22)$$

In the case were  $x$  is significantly correlated with  $y$ , the  $_sPlots$  from equation 21 connt be compared with the pure distributions of the various types. To solve that problem one can perform a Monte Carlo simulation of the procedure and obtain the expected distributions to which the  $_sPlots$  should be compared with.

For more information on  $_sPlots$  consider reading [9].

### 2.3 Reweighting

The infomation needed in an analysis is not all contained inside the data. For example efficiencies can not be recorded by a detector. But they can be simulated by a Monte Carlo simulation of the particle

decay. The problem is that the simulation has to be the same as data to get the correct answers. Since resimulating everything with different parameters until one hits the data distribution would take too much resources. One can simply reweight the simulation to match the data. As an initial weight the sWeights see equation 20 are used. The parameters used to reweight the MC samples are applied in the following order: 'nTracks', ' $B_0 p_T$ ' and the quality of the  $K\pi\mu\mu$  vertex. The new weights derived by the difference in data and simulation of these parameters are used to weight all the MC samples. For this analysis the MC and Data of the  $K^* \rightarrow J/\Psi K^{*0}$  are used, because it is a very clean channel.

## References

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