

Fast Inclusive Flavour Tagging at LHCb

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Abstract. The task of identifying B meson flavor at the primary interaction point in the LHCb detector is crucial for measurements of mixing and time-dependent CP violation. Flavor tagging is usually done with a small number of expert systems that find important tracks to infer the B meson flavor from. Recent advances show that replacing all of those expert systems with one ML algorithm that considers all tracks in an event yields an increase in tagging power. However, training the current classifier takes a long time and it is not suitable for use in real time triggers. In this work we present a new classifier, based on the DeepSet architecture. With the right inductive bias of permutation invariance, we achieve great speedups in training (multiple hours vs 10 minutes), a factor of 4-5 speed-up in inference for use in real time environments like the trigger and less tagging asymmetry. For the first time we investigate and compare performances of these “Inclusive Flavor Taggers” on simulation of the upgraded LHCb detector for the third run of the LHC.

1 Introduction

The identification of the flavour of B^0 and B_s^0 mesons at production is crucial for many B -mixing and time-dependent CP -violation measurements [1] [2]. The identification of the B meson flavour at production relies on analysing information from the rest of the event. The procedure of determining the flavour of a B meson at the time of its production utilising information from the rest of the event is called *flavour tagging*.

At the B Factories, flavour tagging is done with high efficiency since the vast majority of B mesons are produced as quantum-correlated pairs via the decay of $\Upsilon(4S)$ or $\Upsilon(5S)$ resonances. If the flavour of one B meson is identified, then the other can be inferred. At proton-proton colliders this is more difficult as not all B mesons are produced in $B\bar{B}$ pairs, and of those produced in pairs, most are not produced in quantum-correlation. Additionally, unlike at the B Factories, the reconstruction of the second B meson - if it exists - cannot be performed with high efficiency. Combined with the necessarily higher background from uninformative ‘background’ particles stemming from the proton-proton collision, this makes flavour tagging at LHCb considerably more difficult.

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In these proceedings we lay out the general way flavour tagging works at LHCb as well as the specific algorithms used in the past. Then we present the new approach of the inclusive tagger in the specific implementation using a DeepSet Neutral Network as well as its advantages and compare its performances to past taggers. We end with a summary and conclusion.

2 Flavour Tagging Information in the Event

Information on the flavour of the signal B meson can be present in different ways in the event. This is illustrated in Figure 1. The signal B meson decay is pictured on the top half of the illustration. The top half is therefore referred to as the *same side*. The bottom half is called the *opposite side* and contains another B meson decay, referred to as the *opposite-side B meson*.

Even in proton-proton collision b quarks are usually produced in $b\bar{b}$ pairs. At LHCb 24% of events have both, b and \bar{b} quarks, produced within the detector acceptance. The b and \bar{b} quarks hadronise to produce two B hadrons – the signal B and the opposite-side B – of opposite flavour. By determining the flavour of the opposite-side B meson, the flavour of the signal B meson can be inferred as being the opposite. This strategy is also employed by the B Factories.

In addition to the opposite side information, same side information is present uniquely in environments in which B mesons are produced via the strong interaction, such as proton-proton colliders, but not the B Factories. In the hadronisation process of the signal b quark, additional particles are produced which are correlated in phase-space with the signal decay itself. These particles are called *same-side tagging particles*. If the same-side particles can be reconstructed and identified the flavour of the signal B meson can be inferred from the charge of the same-side *tagging particle*. For B^0 mesons, the same-side tagging particle is a pion, formed from the $d\bar{d}$ quark pair from the hadronisation process. The d quark is used with the \bar{b} to form the B^0 meson, and the left over \bar{d} forms a positively charged pion (equivalently a \bar{B} meson is produced together with a negatively charged pion). Similarly, for B_s^0 mesons, the light meson associated with the hadronisation is a positively charged kaon, produced with the s quark from the $s\bar{s}$ quark pair from the hadronisation process (and a negatively charged kaon for the \bar{B}_s^0). About 50% of B^0 mesons are accompanied by a charged pion and 50% of B_s^0 mesons by a charged kaon.

3 Classical Taggers

The traditional approach to flavour tagging at LHCb is what we call the *classical taggers* [3] [4]. Each of the classical taggers is an algorithm that attempts to identify *one* specific tagging particle in the event that carries information about the flavour of the signal B meson. The same side taggers search for charged particles that were produced during the hadronisation process of the signal B meson. These charged particles are kinematically correlated with the signal decay. The opposite side taggers search for specific decay products from the opposite-side B meson. All classical taggers perform a selection on all charged particles in the event. Then a multivariate analysis tool (usually a Boosted Decision Tree) is used to determine the probability that the selected particle yields the correct tagging decision.

For each signal B meson all classical taggers that apply for that B meson species are run. Table 1 shows a list of all different classical taggers and the B mesons species they can be used for¹. If several taggers yield a tagging decision for the same signal B meson,

¹Charged B^\pm mesons are self-tagging and don't require flavour tagging algorithms. They can therefore be used to train, validate and calibrate the taggers.

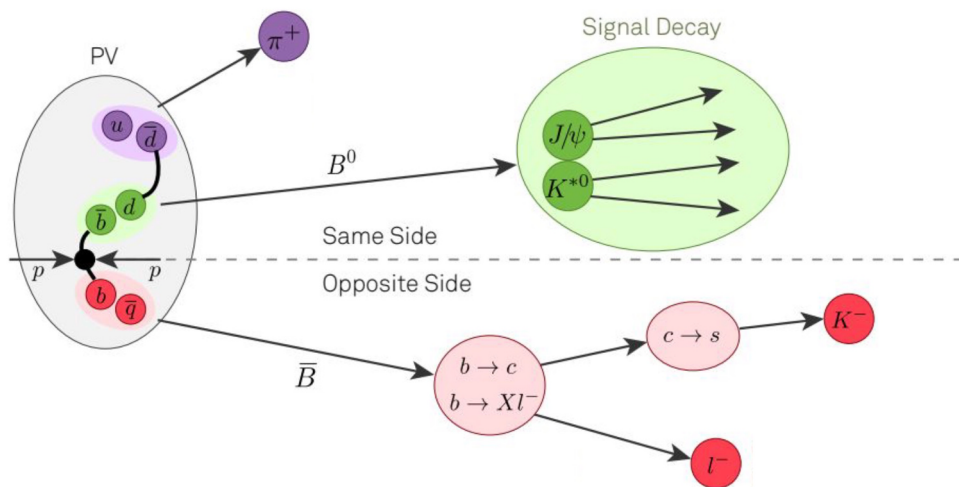


Figure 1. Illustration of the flavour tagging information present in the event.

Table 1. List of classical taggers and the B meson species they can be used for.

Opposite side kaon tagger	B^0, B^\pm, B_s^0
Opposite side muon tagger	B^0, B^\pm, B_s^0
Opposite side electron tagger	B^0, B^\pm, B_s^0
Same side kaon tagger	B_s^0
Same side pion tagger	B^0, B^\pm
Same side proton tagger	B^0

the tagging decision of the tagger with the smallest predicted probability of being wrong is chosen. One disadvantage of the classical tagger is that each taggers aims at identifying only one specific particle in the event. That particle might not be found – either because it was not created in the first place or because it was not produced within the detector acceptance, or because it could not be reconstructed and identified by the corresponding algorithm. As is shown in Section 5.3, even when combining all taggers, no tagging decision can be reached for a significant fraction of the events. Additionally the classical taggers require the training, validation and calibration of an entire list of individual taggers.

4 DeepSet Neutral Network Inclusive Tagger

In order to address the disadvantages of the classical taggers the concept of the *inclusive tagger* is introduced. The inclusive tagger considers all particles in the event simultaneously and has therefore an increased probability of reaching a tagging decision with respect to the classical taggers. Since the number of additional particles in the event varies from event to event the inclusive tagger has to be able to take a variable number of input particles. Additionally, the tagging decision should not depend on the order of the inputs, therefore the inclusive tagging algorithm has to be invariant under the permutation of the inputs. Lastly,

the inclusive tagging algorithm should be fast to train and to evaluate since in the future we will want to use it in the real-time environment of the LHCb software trigger.

An algorithm that fulfills these requirements is the DeepSet Neutral Network (DeepSet NN). The functionality of the DeepSet NN is illustrated in Figure 2 and presented in rigorous detail in Reference [5]. In a first step, the representation x_i of each charged particle i in the event² is transformed individually by a neutral net ϕ into some representation $\phi(x_i)$. The representations $\phi(x_i)$ are then summed up. The sum is processed by another network ρ to give the output of the DeepSet NN $f(x_1, \dots, x_M)$. Therefore the structure of the DeepSet NN can be expressed as

$$f(x_1, \dots, x_M) = \rho\left(\sum_i^M \phi(x_i)\right) \quad (1)$$

for an event with M charged particles that do not belong to the signal B meson decay, where x_i is the representation of charged particle i and ϕ and ρ are neutral networks.

The construction of the DeepSet NN has one component for each input particle individually (in the form of ϕ) and one component that acts on the event as a whole (in the form of ρ). Due to the summing of the $\phi(x_i)$ the DeepSet output is invariant under the permutation of the input particles. Additionally, the architecture of the DeepSet NN makes it easy to parallelise the training and the evaluation. Notably, it takes about an hour to train on a statically significant sample and $7\mu\text{s}$ to evaluate per event³.

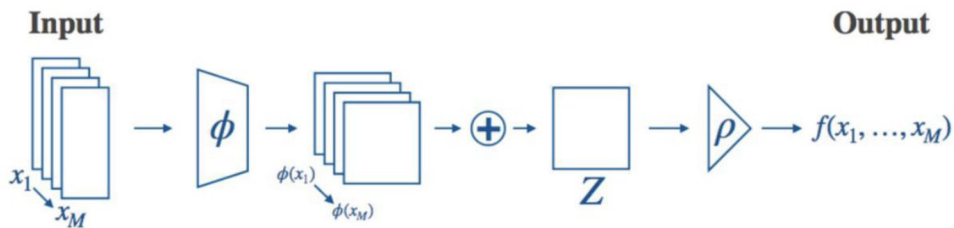


Figure 2. Illustration of the DeepSet Neutral Network (DeepSet NN). The DeepSet NN acts on a list of inputs (x_1, \dots, x_M) where M can vary between different events, and ϕ and ρ are neural networks.

5 Flavour Tagging Performance

In this section the performance of the DeepSet NN tagger is compared to the performance of the classical taggers. First the performance metrics used in flavour tagging is introduced and the data-samples used for training and evaluation are presented. Then a summary of the performance numbers is given.

5.1 Performance Metrics

The tagging performance is evaluated in terms of three parameters, namely the *tagging efficiency*, the *mistag rate* and the *tagging power*.

²Excluding charged particles that belong to the signal B meson decay.

³Previous implementations of the inclusive tagger using a different architecture took several days to train and $100\mu\text{s}$ per event to evaluate.

The tagging efficiency ϵ_{tag} is the fraction of events for which a tagging decision can be reached⁴. This quantity is especially important for the classical taggers since the tagging particle for a specific tagger might not be present or identifiable in the event, e.g. not all events have the opposite side B meson in the detector acceptance. The tagging efficiency is defined as

$$\epsilon_{tag} = \frac{N_{tagged}}{N_{tagged} + N_{untagged}} \quad (2)$$

where N_{tagged} is the number of signal events where a tagging decision is reached and $N_{untagged}$ is the number of signal events for which a tagging decision can not be reached.

The mistag rate ω is the fraction of tagged events for which the tagging decision is wrong. The mistag rate is calculated as

$$\omega = \frac{N_{tagged}^{incorrect}}{N_{tagged}} = \frac{N_{tagged}^{incorrect}}{N_{tagged}^{correct} + N_{tagged}^{incorrect}} \quad (3)$$

where $N_{tagged}^{incorrect}$ is the number of signal events where the tagging decision reached by the tagger is incorrect and $N_{tagged}^{correct}$ is the number of signal events where the tagging decision is correct.

The tagging power ϵ_{eff} combines the tagging efficiency and the mistag rate into a quantity that represents the effective power of the signal sample after tagging. The tagging power is defined as

$$\epsilon_{eff} = \epsilon_{tag} \cdot (1 - 2 \cdot \omega)^2 \quad (4)$$

Due to the imperfect tagging efficiency and mistag rate – i.e. the lack of knowledge of the true flavour of the signal B meson at production – the statistical power of a sample of N events is reduced to $\epsilon_{eff} \cdot N$. This in turn affects measurements of e.g. CP -violating quantities whose uncertainties scale like $1/\sqrt{\epsilon_{eff} \cdot N}$. Therefore, the larger the tagging power, the more precise the measurement.

Typically, opposite-side tagging algorithms have a low tagging efficiency, as these require that the opposite-side B meson (and its decay products) are present and reconstructible in the event and identified by the algorithm; but also have a low mistag rate, as once these requirements are met, identification of the signal B meson flavour is comparatively easy. Conversely, a pion (kaon) track close to the B^0 (B_s^0) meson signal vertex can be identified in most events, however the conversion of this to a correct tag is more difficult, and therefore the same-side tagging algorithms have a generally high tagging efficiency but also a high mistag rate.

5.2 Training and Evaluation Datasets

In our study all taggers are trained and evaluated on simulated data that represents the data-taking conditions of Run 2 (2015 - 2018) and Run 3 (2022 - 2025) of the LHC and the LHCb experiment. During Run 2, the LHCb experiment collected data from proton-proton collisions at a fixed pileup⁵ of ~ 1 . For Run 3, the LHCb experiment underwent an upgrade where many parts of the detector were replaced to meet the requirements of running at a higher instantaneous luminosity and at a pileup of ~ 6 .

Different signal decays are simulated and used for testing and training. The decays⁶ are $B^0 \rightarrow J/\psi K^{*0}$, $B^+ \rightarrow J/\psi K^+$ and $B_s^0 \rightarrow D_s^+ \pi^-$ for Run 2 and $B^+ \rightarrow J/\psi K^+$ for Run 3.

⁴Note that the tagging efficiency only encapsulates that the taggers have produced a decision, not if the decision is correct.

⁵Pileup is the average number of proton-proton interactions per collision.

⁶Charge conjugation is implied throughout.

5.3 Flavour Tagging Performance

The comparison of tagging efficiency and tagging power between the classical taggers and the DeepSet NN tagger are shown in Tables 2 and 3 for the Run 2 and Run 3 data-taking conditions, respectively. The Deepset NN tagger consistently performs better than the combination of all classical taggers. Due to its inclusive nature the DeepSet NN tagger reaches a tagging efficiency of 100% throughout. The tagging power of the DeepSet NN is about 20 to 25% increased with respect to the combination of classical taggers for the Run 2 samples and even more for the Run 3 sample.

The tables also show an overall reduced tagging power on the Run 3 with respect to the Run 2 samples. This is due to the higher pileup in Run 3, that leads to more particles in the event that are neither associated with the signal B meson, nor do they carry information about its flavour. While the number of particles carrying information about the signal B meson flavour stays the same between Run 2 and Run 3, the number of "background" particles increases significantly. In order to facilitate the DeepSet NN's task, we perform a selection on the input particles. Instead of using all charged particles in the event as inputs to the DeepSet NN, we select those that can be associated to the same primary vertex (PV)⁷ as the signal B meson. Table 3 shows that this purification of the inputs leads to an increase in tagging power of $\sim 7\%$.

Table 2. Comparison of the performance of the DeepSet NN tagger with the Classical taggers for the Run 2 data-taking conditions of the LHC and the LHCb experiment. The tagging efficiency ϵ_{tag} and the tagging power ϵ_{eff} are shown for different signal B meson decays.

	$\epsilon_{\text{tag}}[\%]$	$\epsilon_{\text{eff}}[\%]$
$B^0 \rightarrow J/\psi K^{*0}$		
OS Combination	38.5	3.81
SS Combination	80.1	1.71
Classical Taggers Combination	87.0	5.39
DeetSet NN	100	6.38
$B^+ \rightarrow J/\psi K^+$		
OS Combination	38.2	3.94
SS Kaon	67.7	1.22
SS Pion	69.9	3.94
Classical Taggers Combination	92.0	6.39
DeepSet NN	100	8.0
$B_s^0 \rightarrow D_s^+ \pi^-$		
DeepSet NN	100	8.7

Table 3. Comparison of the performance of the DeepSet NN tagger with the Classical taggers for the Run 3 data-taking conditions of the LHC and the LHCb experiment. The tagging efficiency ϵ_{tag} and the tagging power ϵ_{eff} are shown for $B^+ \rightarrow J/\psi K^+$ meson decays.

	$\epsilon_{\text{tag}}[\%]$	$\epsilon_{\text{eff}}[\%]$
$B^+ \rightarrow J/\psi K^+$		
Classical Taggers Combination	100	3.75
DeepSet NN	100	6.36
DeepSet NN same PV	100	6.83

⁷The primary vertex is where the proton-proton interaction took place.

6 Summary, Conclusion and Outlook

Determining the flavour of neutral B mesons at production is essential for meson mixing and time-dependent CP violation measurements. The flavour tagging exploits information from particles that are created in correlation with the signal B meson to obtain its flavour at production. The classical approach to flavour tagging is a set of individual algorithms that each look for only one specific particle that carries information about the flavour of the signal B meson. These classical taggers suffer from a low tagging efficiency and require the training and evaluation of several different algorithms. In these proceedings, we propose an inclusive tagger which can consider the entire event as a whole. A suitable architecture for such an inclusive tagger is the DeepSet NN, which can take a list of inputs of variable length (since the number of input particles varies between events) and is invariant under the permutation of its inputs (since the ordering of the input particles should have no influence on the predicted flavour of the signal B meson). In addition, the DeepSet NN architecture lends itself to parallelisation and is faster in training and evaluation than any previous flavour tagging algorithms. When compared on simulated data samples the flavour tagging performance of the DeepSet NN is consistently increased with respect to the combination of classical taggers. We also found that the tagging power of the DeepSet NN can be increased in the high-background environment of Run 3 by performing a selection on the particles in the event prior to inputting them into the DeepSet NN. In conclusion it can be said that the DeepSet NN shows very promising performances for the flavour tagging. It is also fast to train and to evaluate, which makes it suitable for future application in the real-time software trigger of the LHCb experiment. The next steps are to evaluate and compare its performance on data and use it as part of a physics measurement.

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References

- [1] LHCb collaboration, Precise determination of the B_s^0 - \bar{B}_s^0 oscillation frequency, *Nat. Phys.* **18**, 1–5 (2022)
- [2] LHCb collaboration, Updated measurement of time-dependent CP -violating observables in $B_s^0 \rightarrow J/\psi KK$ decays, *Eur.Phys.J.C* **79** (2019) 8, 706, *Eur.Phys.J.C* **80** (2020) 7, 601 (erratum)
- [3] LHCb collaboration, Optimization and calibration of the same-side kaon tagging algorithm using hadronic B_s^0 decays in 2011 data, *Hadron Collider Physics Symposium 2012*, Kyoto, Japan, 12 - 16 Nov 2012
- [4] LHCb collaboration, Opposite-side flavour tagging of B mesons at the LHCb experiment, *Eur. Phys. J. C* **72** (2012) 2022
- [5] Manzil Zaheer, Satwik Kottur, Siamak Ravanbakhsh, Barnabás Póczos, Ruslan Salakhutdinov and Alexander J. Smola, Deep Sets, arXiv:1703.06114v3 [cs.LG]