

Search for the $B \rightarrow K^{(*)}\nu\bar{\nu}$ decays at Belle II

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1 Analysis context

2 Belle II toolbox

3 Calibration of the FLAVOUR TAGGER

4 $B \rightarrow K\nu\bar{\nu}$ search

- Reconstruction and preselection
- Corrections
- Selection
- Backgrounds studies
- Fit

5 Conclusion and outlook

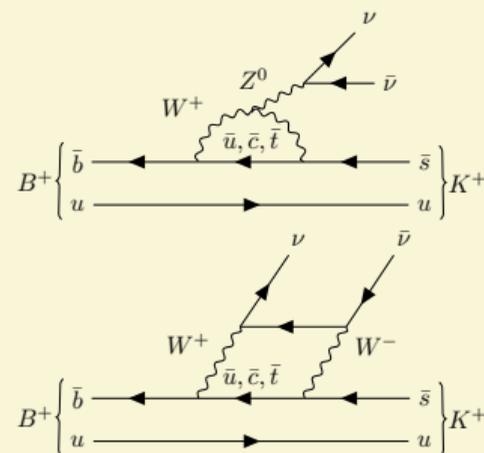
Motivations

Why $B \rightarrow K^{(*)}\nu\bar{\nu}$?

- $b \rightarrow s\nu\bar{\nu}$ transition = **Flavor Changing Neutral Current**
- **Rare decay** (suppressed by Glashow–Iliopoulos–Maiani mechanism): Branching Ratio (BR) $\sim \mathcal{O}(10^{-5})$
- **Well described** by the Standard Model (SM)

\Rightarrow **Sensitive to high energy new physics** contributions
[\[arXiv:2301.06990\]](#)

\Rightarrow Since neutrinos are never measured, also **sensitive to light new particles** [\[arXiv:2503.19025\]](#)



Definition (Signal strength)

$$\mu = \frac{BR(B \rightarrow K^{(*)}\nu\bar{\nu})_{\text{measured}}}{BR(B \rightarrow K^{(*)}\nu\bar{\nu})_{\text{expected}}} \quad (1)$$

Decay channels

$B \rightarrow K^{(*)} \nu \bar{\nu}$ is a generic term for many possible decays:

- $B^\pm \rightarrow K^\pm \nu \bar{\nu}$
- $B^0 \rightarrow K_S^0 \nu \bar{\nu}$
- $B^\pm \rightarrow (K^{*\pm} \rightarrow K^\pm \pi^0) \nu \bar{\nu}$
- $B^\pm \rightarrow (K^{*\pm} \rightarrow K_S^0 \pi^\pm) \nu \bar{\nu}$
- $B^0 \rightarrow (K^{*0} \rightarrow K^\pm \pi^\mp) \nu \bar{\nu}$

→ Focus on the $B^\pm \rightarrow K^\pm \nu \bar{\nu}$ decay channel in this presentation, but the goal of the analysis is to measure the BR of all the decays listed above.

Experimental constraints

- Two neutrinos in a 3-body decay = cannot simply reconstruct the signal
- Lack of kinematic constraints \implies **Complete angular acceptance**
- Only signature is a $K \implies$ **Clean environment**

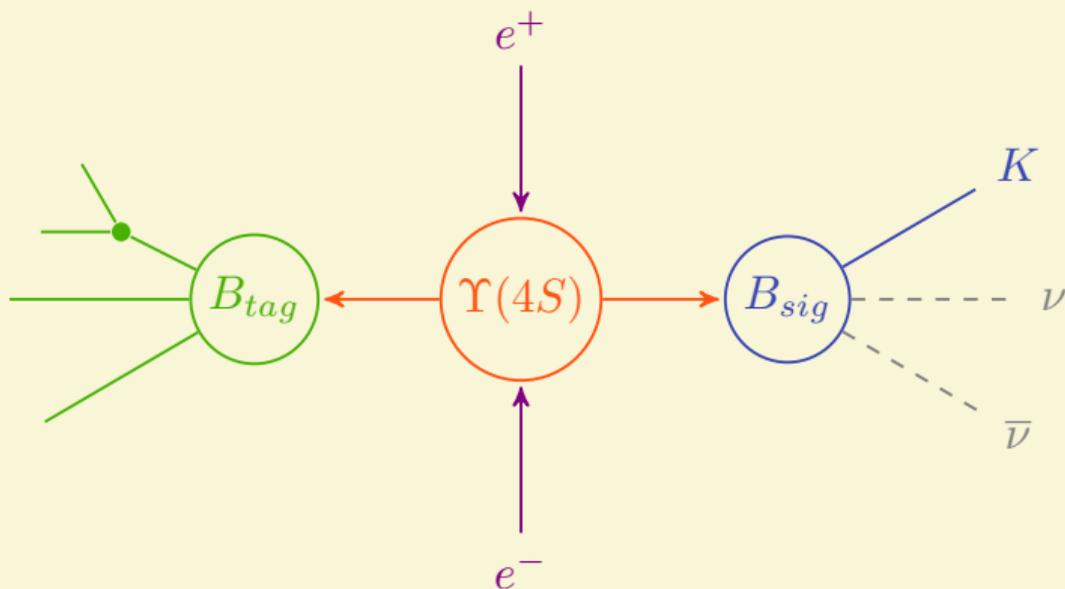
Only experiment capable of measuring the BR of this decay: **Belle II**

Why Belle II?

- e^+e^- collisions \longrightarrow **Clean environment** ✓
- Current integrated luminosity $\mathcal{L} = 365 \text{ fb}^{-1} \longrightarrow$ **High statistics** ✓
- Detector covering a 4π solid angle \longrightarrow **Complete angular acceptance** ✓

What about the almost invisible signal?

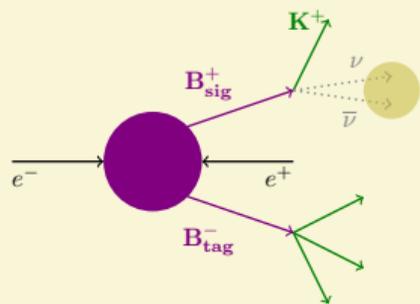
Handling the invisible signal



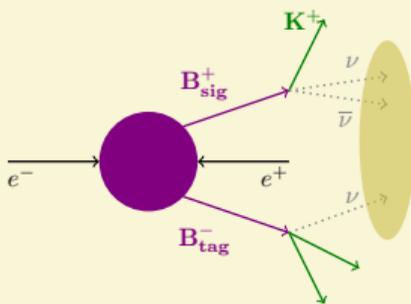
→ We infer information about the B_{sig} from the B_{tag} since they are *entangled*

Tagging strategies

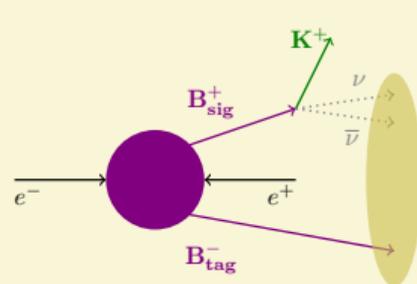
Hadronic Tagged Analysis (HTA)



Semileptonic Tagged Analysis (STA)



Inclusive Tagged Analysis (ITA)



Tagging efficiency

$\mathcal{O}(0.1\%)$

$\mathcal{O}(10\%)$

Tagging purity

80% – 20%

$\mathcal{O}(1\%)$

Previous $B^+ \rightarrow K^+ \nu\bar{\nu}$ analyses

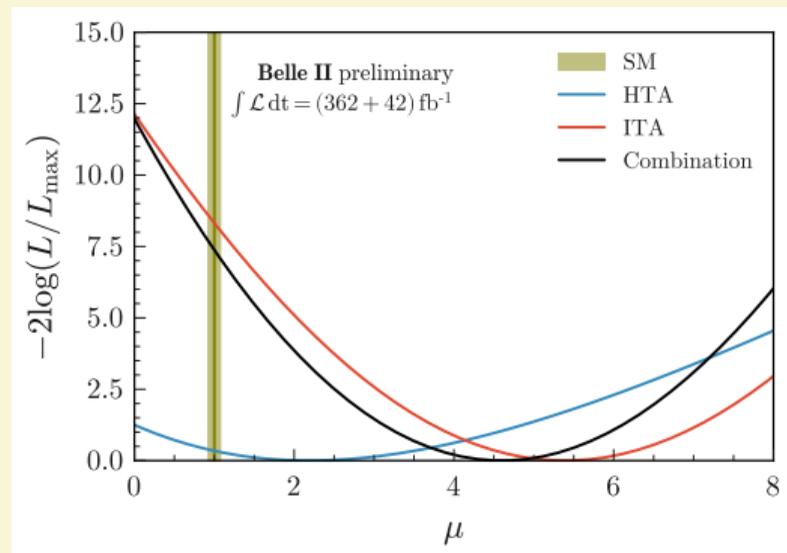
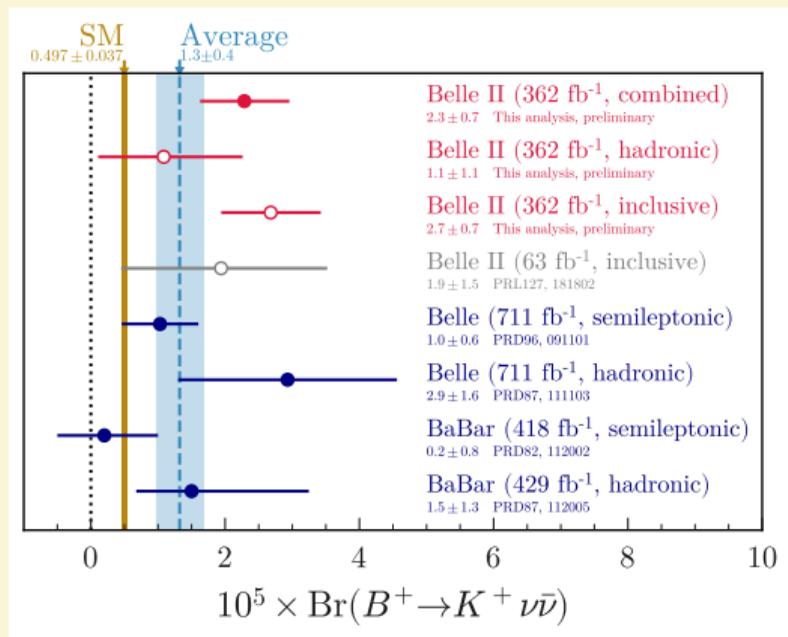


Figure: from [arXiv:2311.14647](https://arxiv.org/abs/2311.14647)

Goal: Carry an independent measurement using *semileptonic tagging*

Why semileptonic tagging?

- Higher efficiency than HTA
- Higher purity than ITA
- Complementary to the other two Belle II analyses
- Complementary to the Belle and BaBar analyses

Analysis	Uncertainty on the BF naively scaled to 362 fb^{-1}
Belle HTA	2.29×10^{-5}
Belle STA	0.80×10^{-5}
BaBar HTA	1.41×10^{-5}
BaBar STA	0.81×10^{-5}
Belle II HTA	1.20×10^{-5}
Belle II ITA	0.71×10^{-5}

Table: Comparison of the uncertainties on the branching fraction of the various analyses, scaled to 362 fb^{-1}

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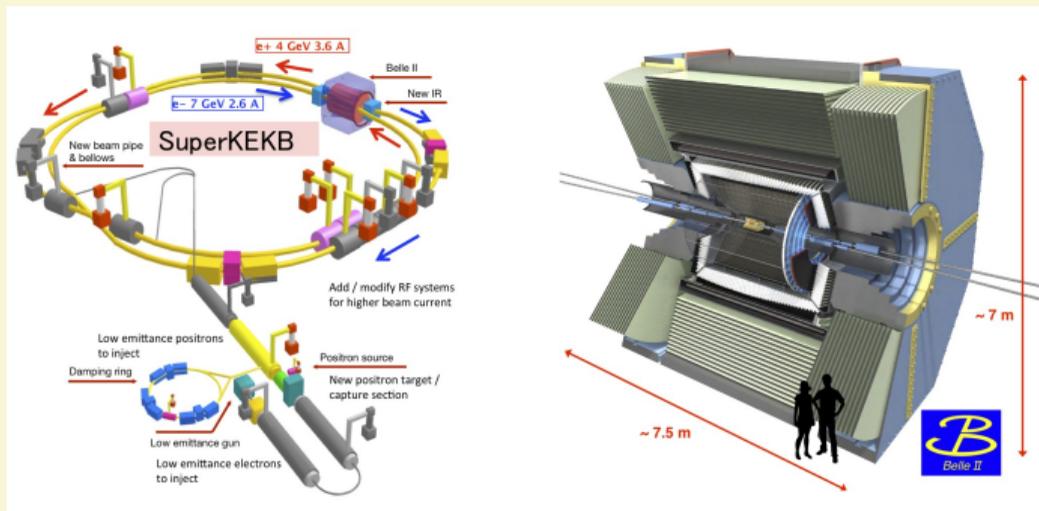
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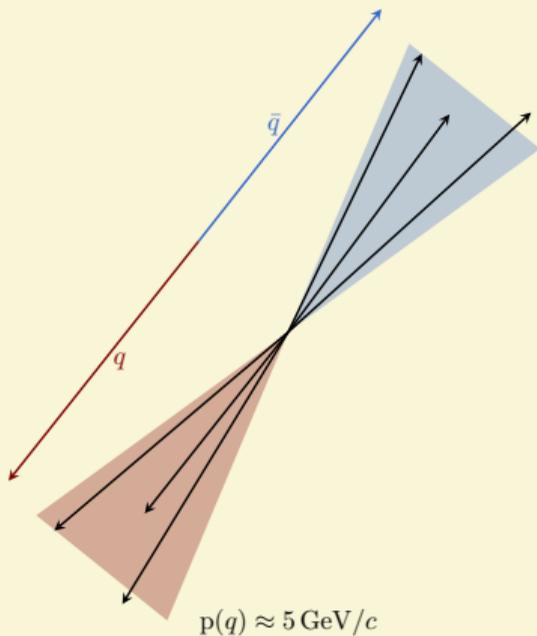
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The Belle II experiment

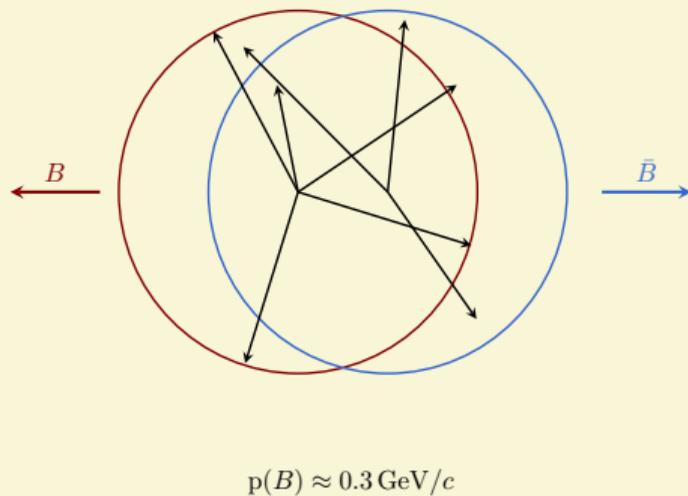
- International collaboration
- Taking data on the SuperKEKB accelerator, in Japan, since 2019
- e^+e^- collisions at $\sqrt{s} = 11$ GeV
- Record for highest instantaneous luminosity: 5.1×10^{34} cm²/s



Event geometries



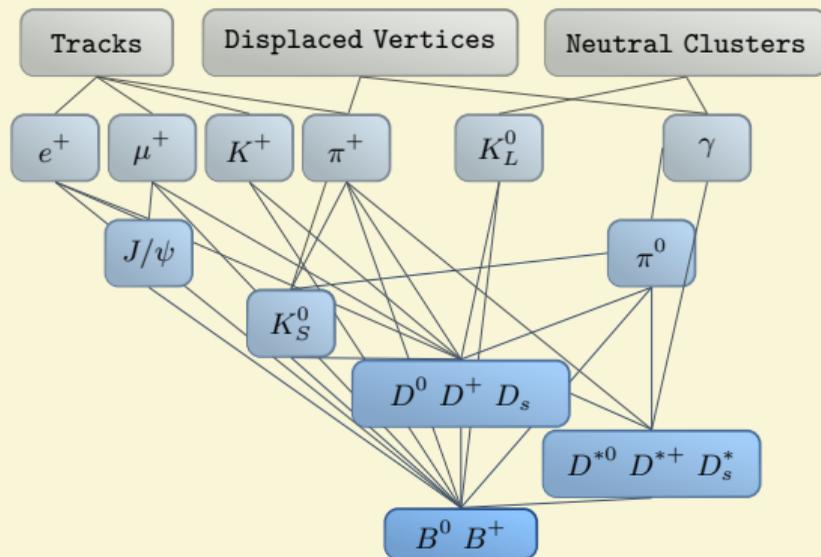
$$e^+e^- \rightarrow q\bar{q} \quad (q \in \{u, d, s, c\})$$



$$e^+e^- \rightarrow \Upsilon(4S) \rightarrow B\bar{B}$$

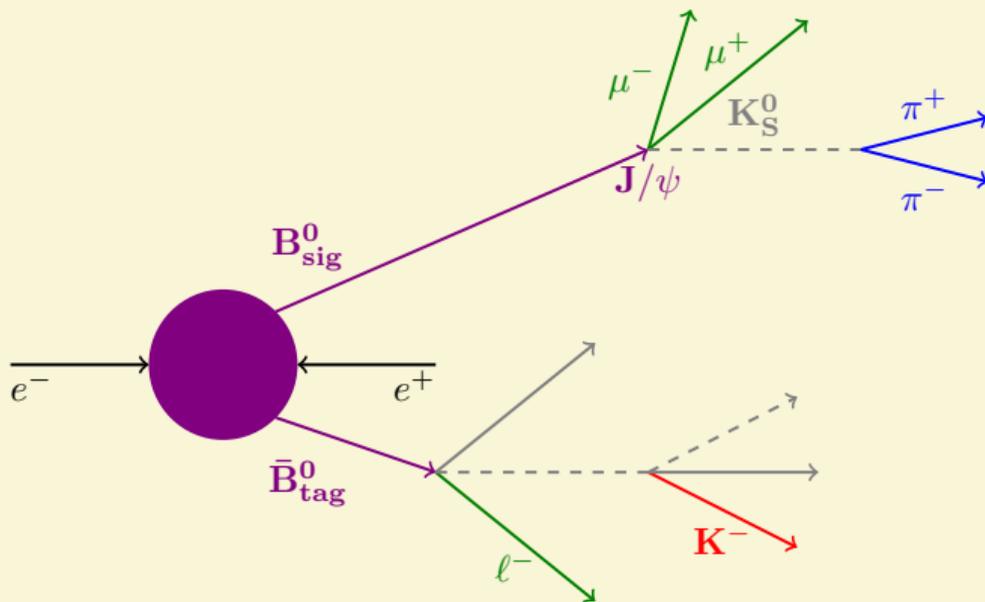
Full Event Interpretation (FEI)

- **Tagging algorithm:** reconstruct the tag side
- Based on **Boosted Decision Trees (BDT)**
- Can be *hadronic* or **semileptonic**
- For the semileptonic, we consider the following B_{tag} decays:
 - $B \rightarrow D e \nu$
 - $B \rightarrow D \mu \nu$
 - $B \rightarrow D^* e \nu$
 - $B \rightarrow D^* \mu \nu$
 - $B \rightarrow D^{(*)} \ell \nu \pi$, $\ell \in \{e, \mu\}$, also available, but not used



About tagging

- **Tagging** is an important technique when no direct information on the signal side is available
 - Essential for the $B \rightarrow K^{(*)}\nu\bar{\nu}$ search, since quasi-invisible
- Can also be used for study of CP violation in complex B decays



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CP-asymmetry

- Want to measure the CP-asymmetry

Definition (CP-asymmetry)

$$a^{CP} = \frac{N_{B^0} - N_{\bar{B}^0}}{N_{B^0} + N_{\bar{B}^0}} \quad (2)$$

→ Need to know the *flavour* of the B meson at the time of its decay (B^0 or \bar{B}^0)

- **Self-tagged** decays: one of the final state particles gives away the flavour of the B meson
- *What if the signal is not self-tagged?*

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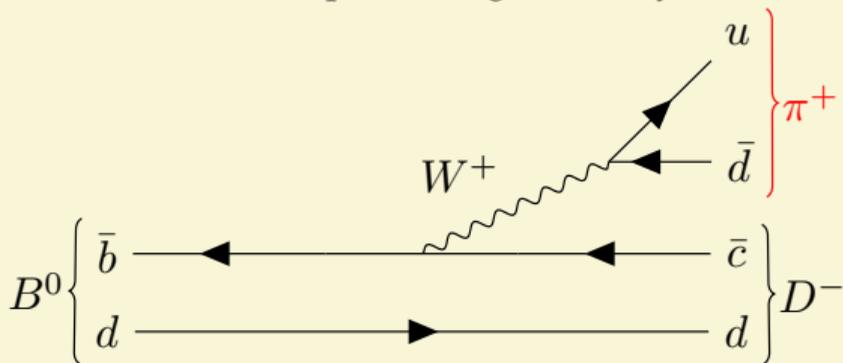
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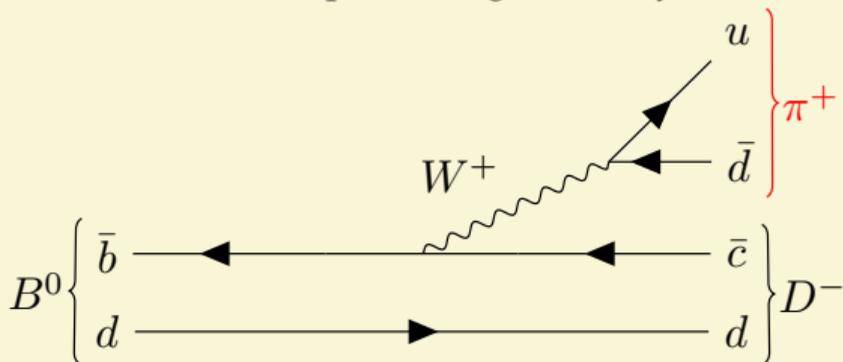
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- **Self-tagged** decays: one of the final state particles gives away the flavour of the B meson



- What if the signal is not self-tagged ?

Tagging (again)

- Can rely on self-tagging B_{tag} decays
- 13 signature categories were define:

Categories	Targets
Electron	e^-
Intermediate Electron	e^+
Muon	μ^-
Intermediate Muon	μ^+
KinLepton	e^-
Intermediate KinLepton	ℓ^+
Kaon	K^-
KaonPion	K^-, π^+
SlowPion	π^+
FastHadron	π^-, K^-
MaximumP	ℓ^-, π^-
FSC	ℓ^-, π^+
Lambda	Λ
Total= 13	

- Categories \rightarrow Classification \rightarrow Classifier \rightarrow Machine Learning \Rightarrow Introducing the FLAVOUR TAGGER

Parameters

- FLAVOUR TAGGER characterized by its **tagging efficiency**:

Definition (Tagging efficiency)

$$\varepsilon = \frac{N_{B^0}^{\text{tag}} + N_{\bar{B}^0}^{\text{tag}}}{N_{B^0} + N_{\bar{B}^0}} \quad (3)$$

- Mistagging quantified by the **wrong tag fraction**, w :

Definition (Wrong tag fraction)

$$N_{B^0}^{\text{tag}} = \varepsilon ((1 - w) N_{B^0} + w N_{\bar{B}^0}) \quad (4)$$

$$N_{\bar{B}^0}^{\text{tag}} = \varepsilon (w N_{B^0} + (1 - w) N_{\bar{B}^0}) \quad (5)$$

Observed vs True CP -asymmetry

- Observed CP -asymmetry written as

$$\begin{aligned}
 a_{\text{obs}}^{CP} &= \frac{N_{B^0}^{\text{tag}} - N_{\bar{B}^0}^{\text{tag}}}{N_{B^0}^{\text{tag}} + N_{\bar{B}^0}^{\text{tag}}} \\
 &= (1 - 2w) a^{CP}
 \end{aligned}$$

Definition (Dilution factor)

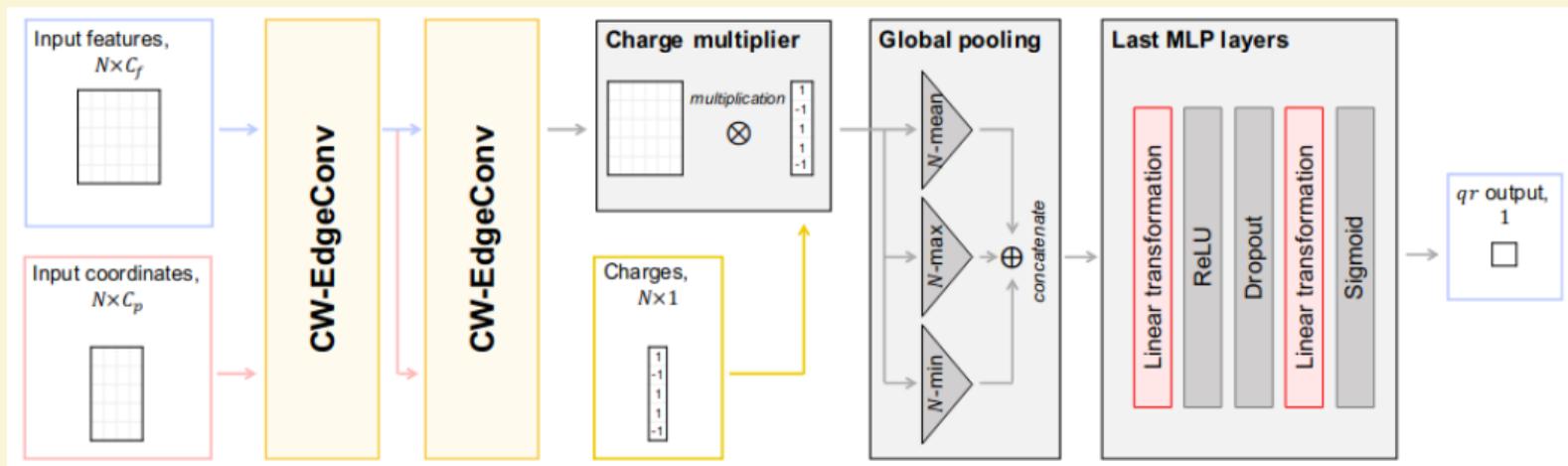
$$r \equiv |1 - 2w| \in [0, 1] \quad (6)$$

Interpretation:

- If $w = \frac{1}{2}$, then $r = 0$ and it gives us no information
- If $w = 0$ or $w = 1$, then $r = 1$ and it gives us the full information

FLAVOUR TAGGER algorithm: GFLAT

- Based on a Graph Neural Network [[arXiv:2402.17260](https://arxiv.org/abs/2402.17260)]
- Procedure:
 1. Reconstructs and classifies the tracks among the 13 categories with a probability
 2. Takes into consideration all the probabilities and computes qr , where $q \in \{-1, 1\}$ is the flavour of the particle



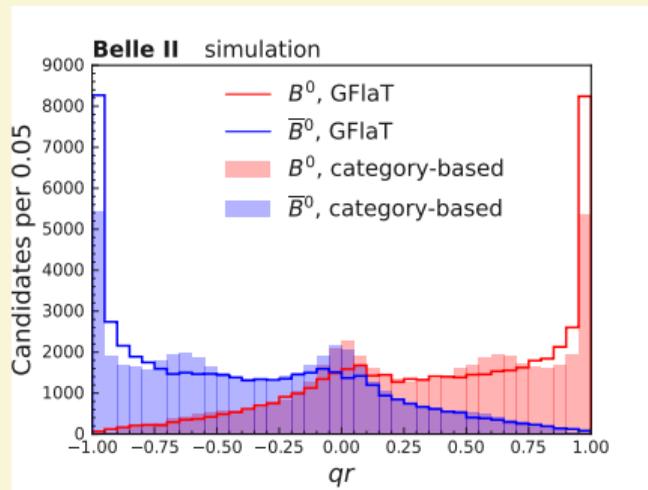
Calibration strategy: ersatz

Goal:

- Implement a calibration strategy for the FLAVOUR TAGGER in a *time-integrated* way
- Automatize and optimize the calibration process

Strategy:

- Want to measure the tagging efficiency and the wrong tag fraction
1. Work with events with self-tagged decays for the B_{sig}
 2. Use the FLAVOUR TAGGER on those events to get qr
 3. Create 7 bins of $|qr|$
 4. Fit the overall ΔE PDF
 5. Extract the N^{tag} for B^0 and \bar{B}^0
 6. Compute the wrong tag fraction and the tagging efficiency



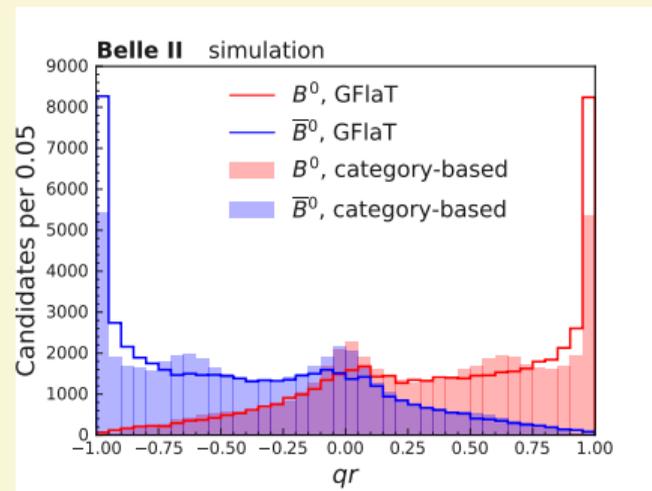
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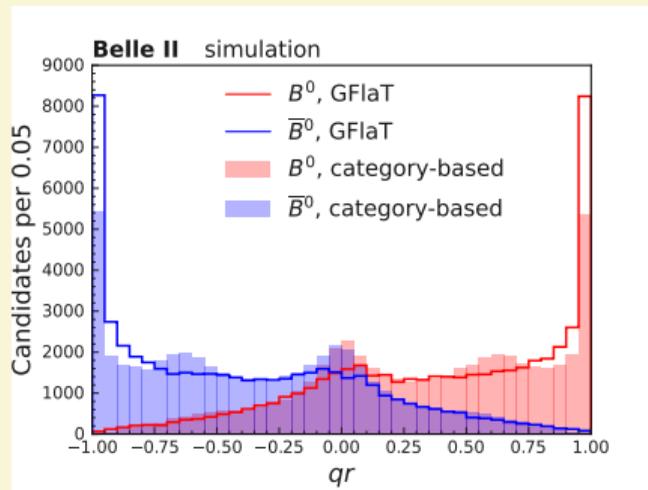
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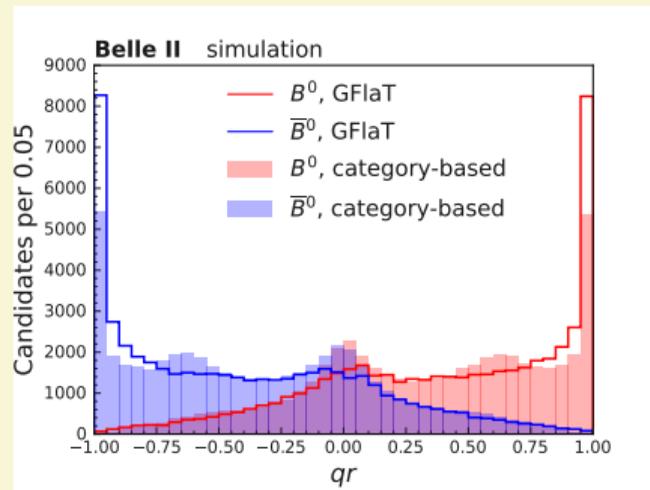
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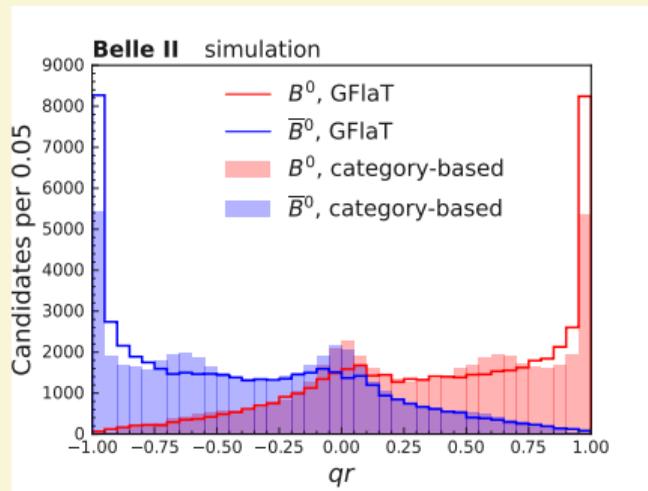
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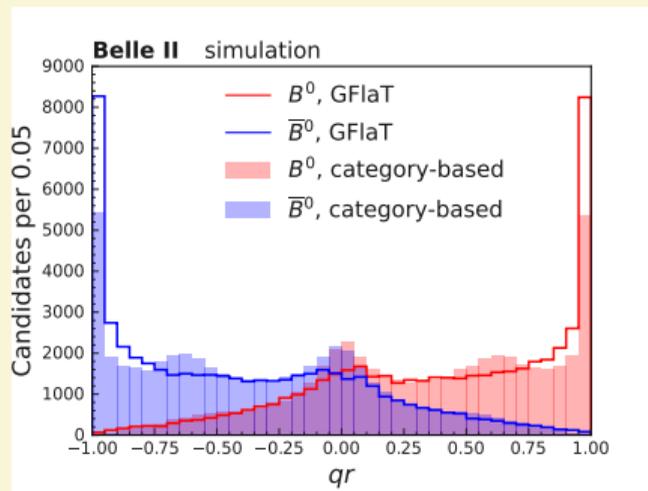
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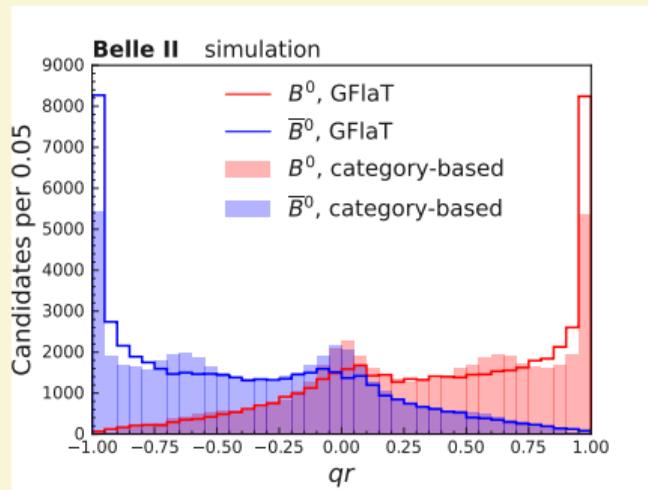
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Calibration strategy: signal

- Need self-tagged decays:

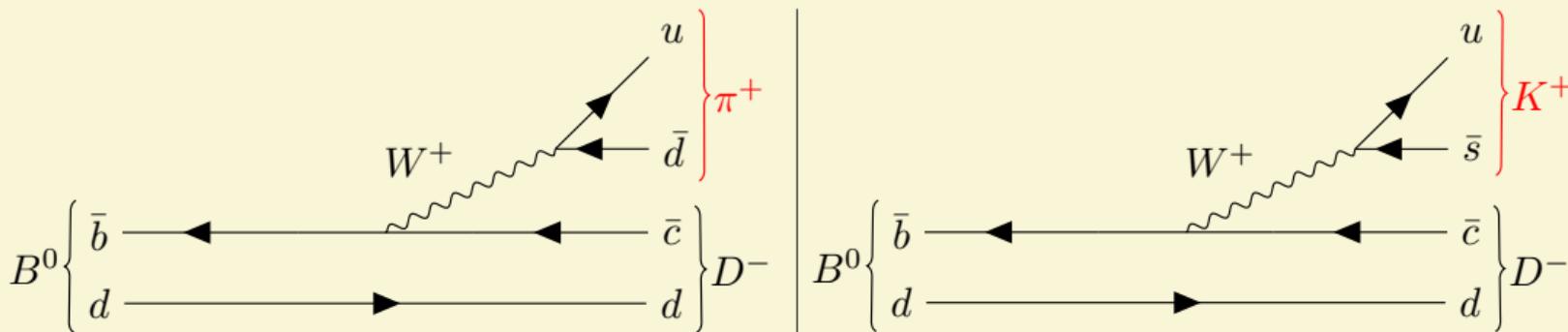
$$B^0 \rightarrow D^- \pi^+$$

$$B^0 \rightarrow D^{*-} (\rightarrow \bar{D}^0 (K^+ \pi^-) \pi^-) \pi^+$$

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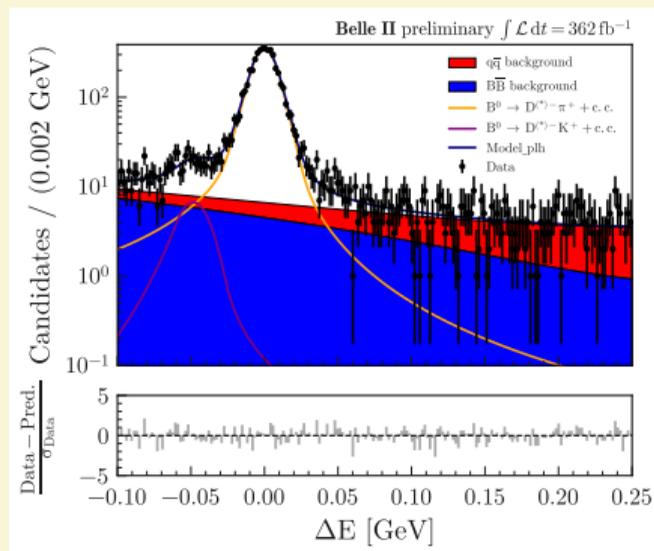
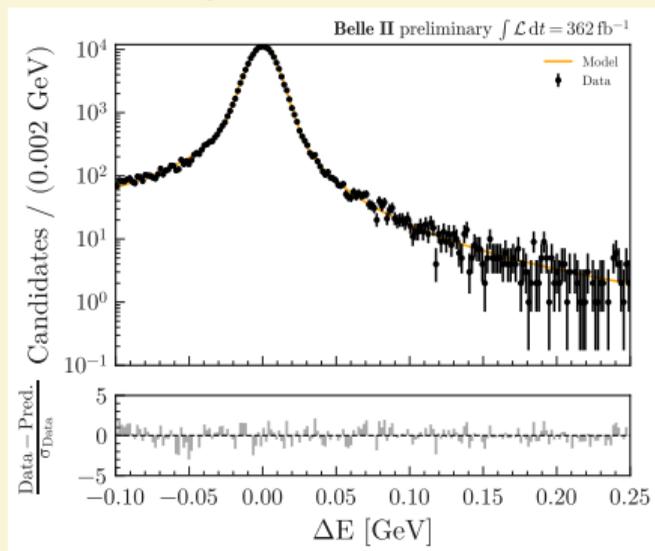
$$B^0 \rightarrow D^{*-} (\rightarrow \bar{D}^0 (K^+ \pi^- \pi^- \pi^+) \pi^-) \pi^+$$

- Also consider $B \rightarrow D^{(*)-} K^+$ equivalents, called "BDK"s



Calibration strategy: extracting the yields

- Important kinematic variable for signal selection: $\Delta E = E_B - E_{\text{beam}}$
- Fit the ΔE distributions on MC for the signals $BD\pi$ and BDK , as well as the $B\bar{B}$ and $q\bar{q}$ backgrounds
- Sum all the shapes and fit the overall ΔE PDF
- Extract the yield



Calibration strategy: wrong tag fraction

- Need to discriminate between:
 - Same or Opposite Flavours (SF or OF)
 - Flavour of the B_{tag} (+ or -)
- Define 7 bins of $|qr|$
- Compute the wrong tag fractions w_i^\pm for each bin $i \in \llbracket 0, 6 \rrbracket$

$$w_i^\pm = \frac{f_i^\pm - R}{(1 - R)(1 + f_i^\pm)}$$

with

$$f_i^\pm = \frac{n_{\text{OF},j}^\pm}{n_{\text{SF},j}^\pm}, \quad R = \frac{\chi_d}{1 - \chi_d}, \quad \chi_d = 0.1860 \pm 0.0011[2]$$

and deduce

$$w_i = \frac{1}{2} (w_i^+ + w_i^-)$$

Calibration strategy: tagging efficiency

- Define a tagging efficiency for each bin $i \in \llbracket 0, 6 \rrbracket$

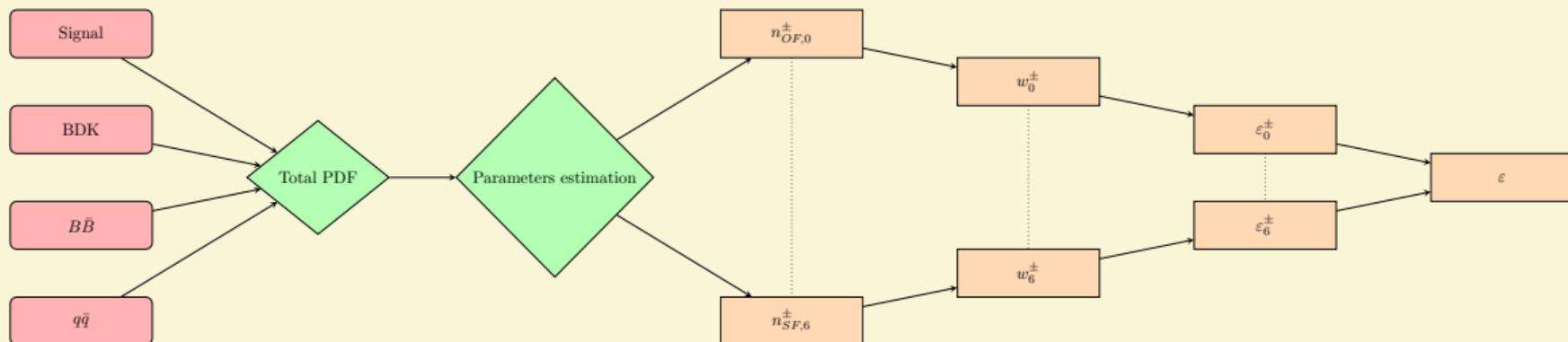
$$\varepsilon_i^\pm = \frac{n_{\text{OF},i}^\pm + n_{\text{SF},i}^\pm}{N_{B^0}^{\text{tag}} + N_{\bar{B}^0}^{\text{tag}}}$$

and compute the *effective* tagging efficiency

Definition (Effective tagging efficiency)

$$\varepsilon = \sum_{i=0}^6 \varepsilon_i (1 - 2w_i)^2 \quad (7)$$

Calibration workflow



Calibration optimization: simultaneous fit

- **Before this work:**

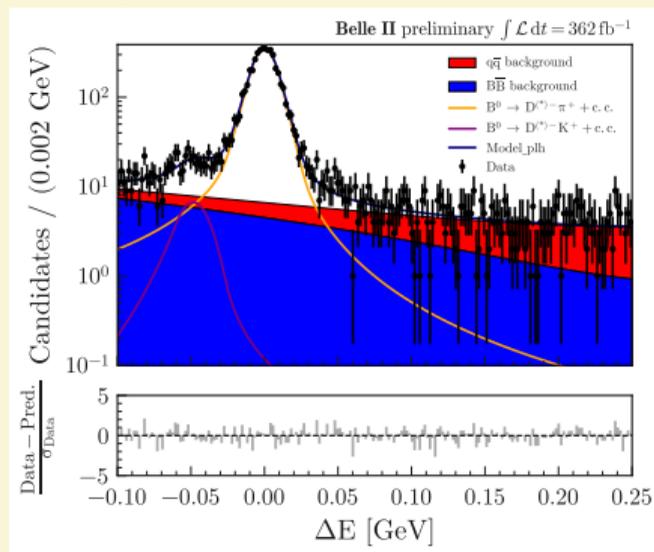
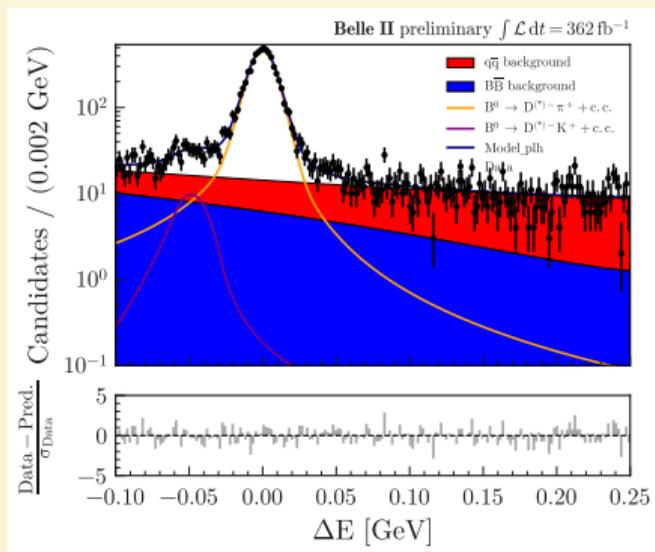
- Fits of the various shapes (signal, BDK, $B\bar{B}$, $q\bar{q}$) were done sequentially
- Fits were independent on the the bins and the categories

- **Idea:**

- Parallelize the fits of the shapes
- Simultaneously fit the 7 bins and the 4 categories

Calibration optimization: backgrounds studies

- $q\bar{q}$: reduced continuum background
 - Via a cut on a geometric variable ✓
 - Via a BDT (worked on MC but not on data)
- $B\bar{B}$: studied the bump observed at $\Delta E = 0$
 - due to signal events wrongly considered as background at MC level



Calibration optimization: automatization

- Automate the processes using **B2LUIGI**
- **Pros:** Parallelize processes and easy to use
- **Whole workflow automated:**
 - Reconstruction of the events, management of the dataset and pre-processing
 - Calibration strategy and visualization

Calibration optimization: summary

- Parallelized the fits of the shapes
- Transform the independent fits into a simultaneous fit
- Reduced the continuum background
- Studied the $B\bar{B}$ background
- Automatized the workflow using B2LUIGI

Results:

- Wrong tag fractions (bin-by-bin): 48%, 42%, 35%, 24%, 18%, 11%, 3%
- Effective tagging efficiency on data: $\varepsilon = 36.90 \pm 0.8\%$

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Analysis flow

1. Preselection
2. Apply data/MC corrections
3. Train and apply Boosted Decision Tree (BDT) for selection
4. Compute systematics uncertainties
5. Fit to get the signal strength μ

Control samples:

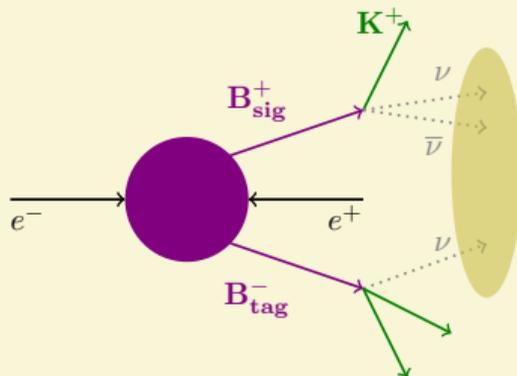
- For $q\bar{q}$ continuum: off-resonance data and MC
- For $B\bar{B}$ background: wrong charged and pion-enriched sample
- For signal: **embedding**

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Reconstruction and preselection

Overview:

1. Reconstruct the B_{tag} using FEI
2. Reconstruct the signal-side Kaon (see details on the cut in the appendix 1)
3. Combine the corresponding tracks
4. Remove all extra "good" tracks and remaining π^0, Λ, K_S^0



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Corrections overview

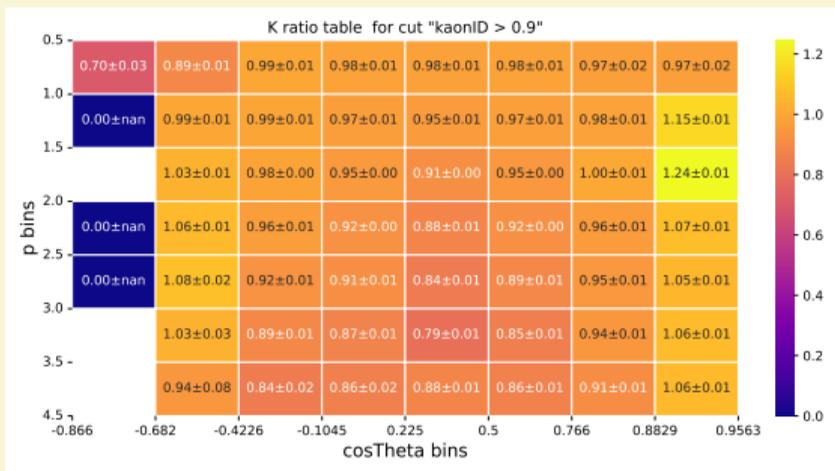
Corrections	Status
Particle Identification (PID)	✓
FEI	✓
Signal Form Factors	<i>to be improved</i>
Continuum	✓
ECLCluster ¹ Extra Energy (EEXTRA)	<i>to be improved</i>
Specific backgrounds	<i>to be improved</i>

Table: Table of the corrections and their status

¹ECL = Electromagnetic Calorimeter

FEI and PID corrections

- PID and FEI corrections based on recommendations
- May switch to **SYSVAR**



mode	labels	cal factor	error
mode0	$D_{e\nu}$	1.18	0.09
mode1	$D_{\mu\nu}$	1.03	0.08
mode2	$D^*_{e\nu}$	0.97	0.07
mode3	$D^*_{\mu\nu}$	0.91	0.06

Table: Calibration factors and errors for FEI, with sgn probability cut > 0.004, on B^+

Continuum correction (BDTc)

Computed by reweighting the MC to the data based on the BDTc output in the off-resonance sample, $weight = \frac{BDTc}{1-BDTc}$.

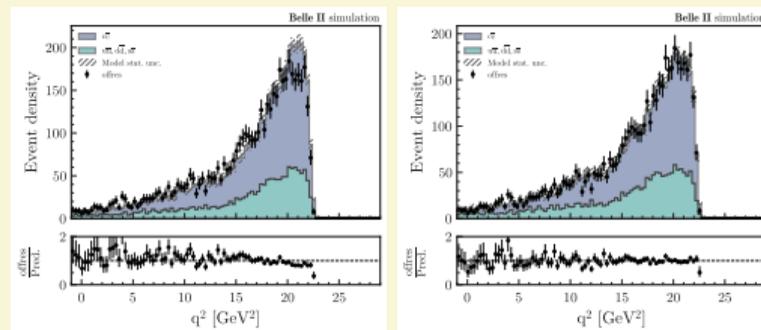
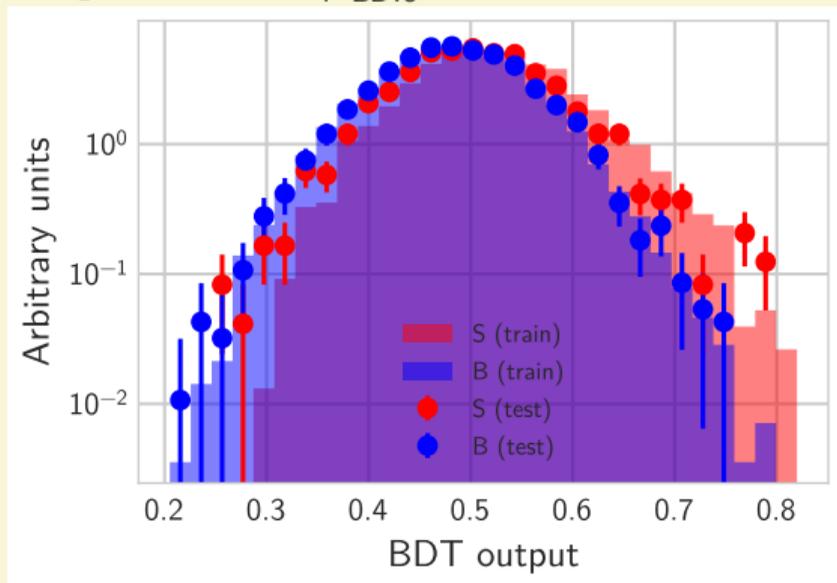


Figure: Plots of q^2 before and after correction

Figure: BDT output for offres data (in red) and offres MC (in blue)

1 Analysis context

2 Belle II toolbox

3 Calibration of the FLAVOUR TAGGER

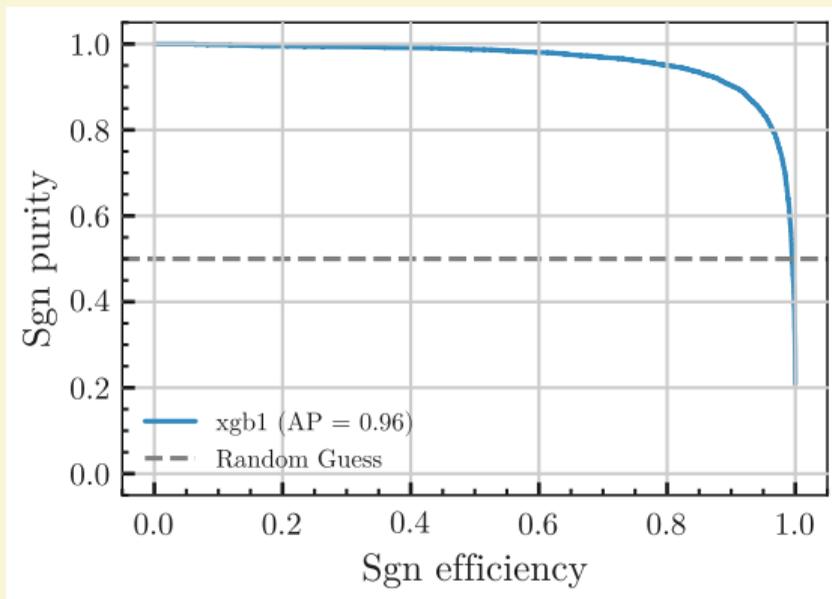
4 $B \rightarrow K\nu\bar{\nu}$ search

- Reconstruction and preselection
- Corrections
- Selection
- Backgrounds studies
- Fit

5 Conclusion and outlook

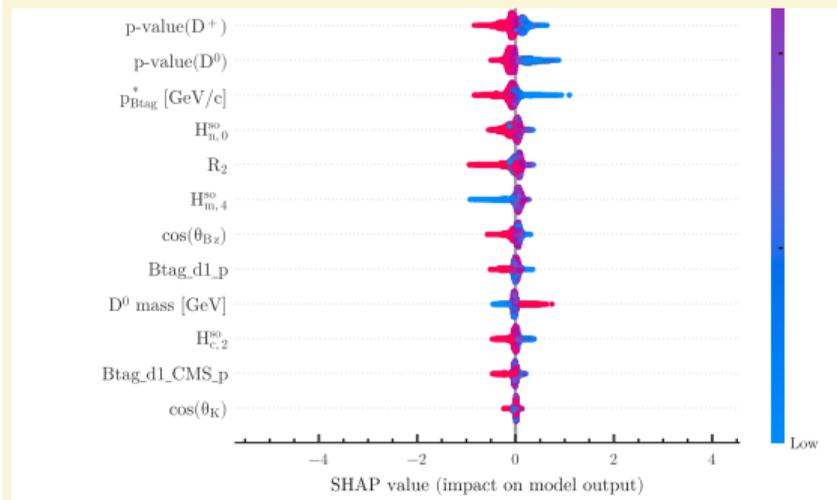
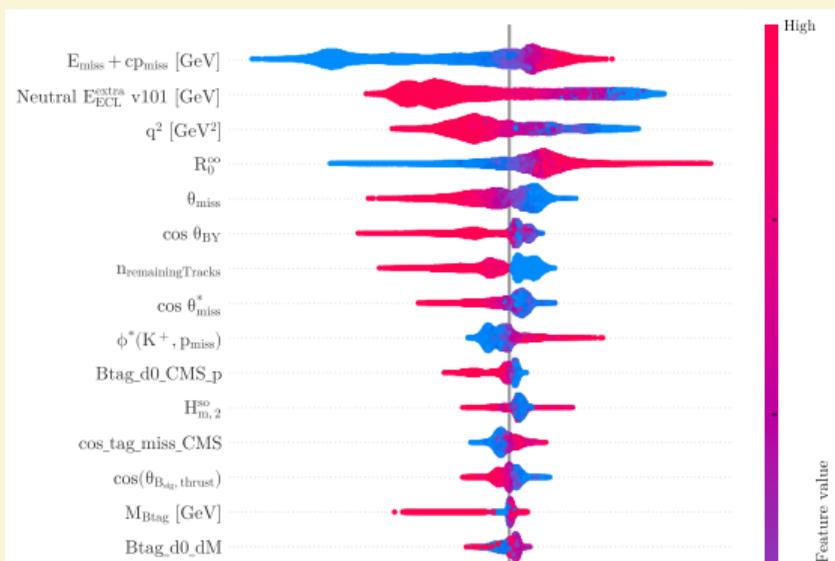
Selection

- Using XGBClassifier
- Using **Shapley values** for feature importance
- F_1 -score for signal on validation data: 97%
- **Signal region:** BDT output > 0.4
- Efficiency after cut on BDT output > 0.4 : 77.5×10^{-4}



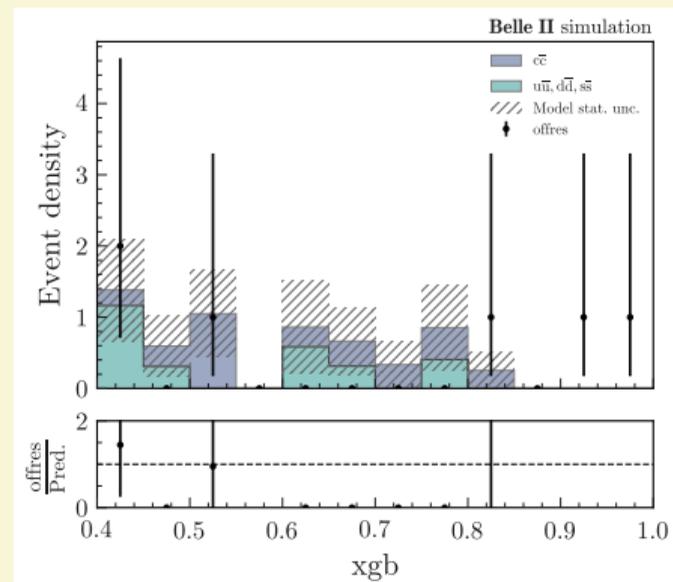
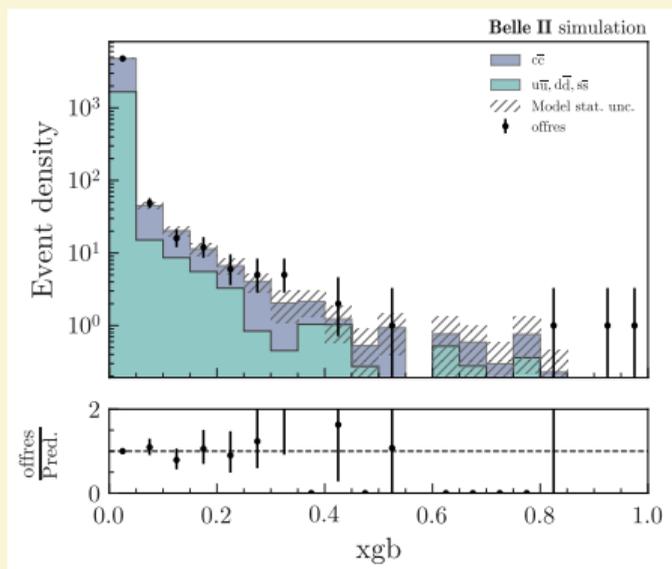
BDT input variables

- The color gradient indicates the value of the feature
- The x-axis is the Shapley value (see Slide 74); the more on the right(left) it is, the more it contributes to the signal(background) prediction



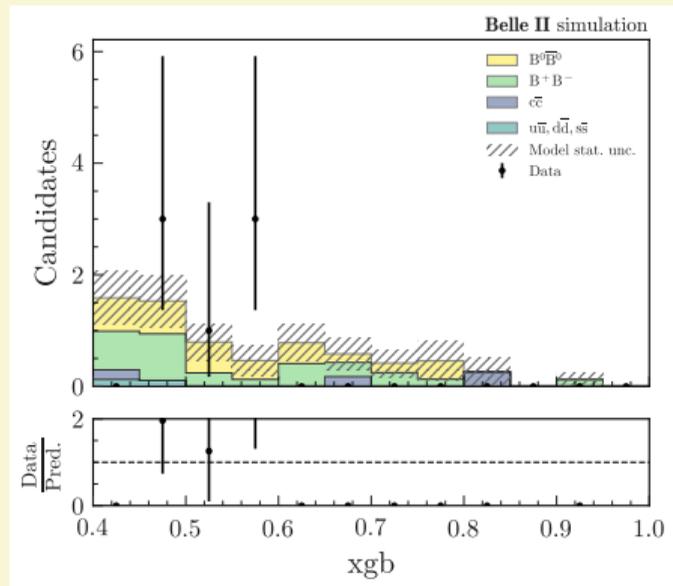
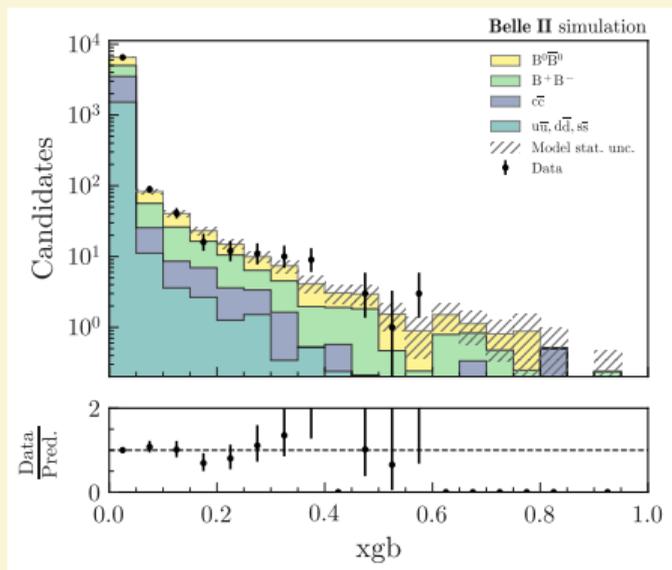
Selection on sidebands (offres)

Sideband	data/MC in preselection	data/MC in signal region
offres	1.114 ± 0.021 (4900data events)	0.7 ± 0.5 (6data events)



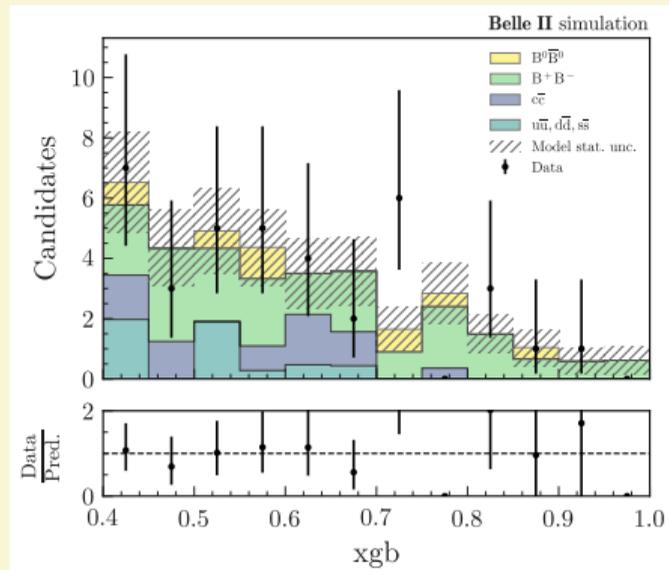
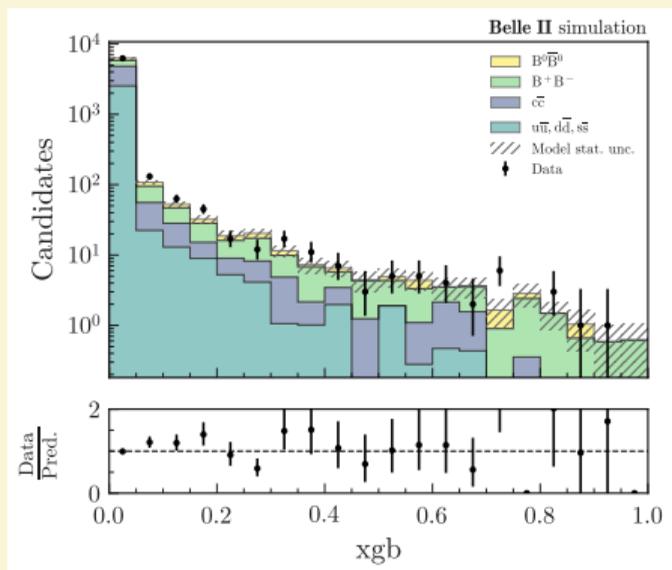
Selection on sidebands (wc)

Sideband	data/MC in preselection	data/MC in signal region
wc	0.963 ± 0.019 (6721 data events)	1.1 ± 0.5 (7 data events)



Selection on sidebands (kid)

Sideband	data/MC in preselection	data/MC in signal region
kid	1.101 ± 0.012 (6588data events)	1.8 ± 0.5 (37data events)



New possible sideband: extra tracks

- Based on "Measurement of $B \rightarrow \tau\nu$ Branching Ratio with Hadronic FEI Tagging in the Run1 dataset"
- Will use events with extra tracks to validate the E^{extra} corrections on $B\bar{B}$
- Still need to work on the details of the selection

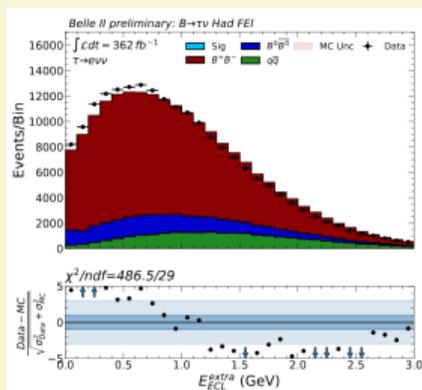


Figure: E^{EXTRA} distribution for the extra tracks sideband

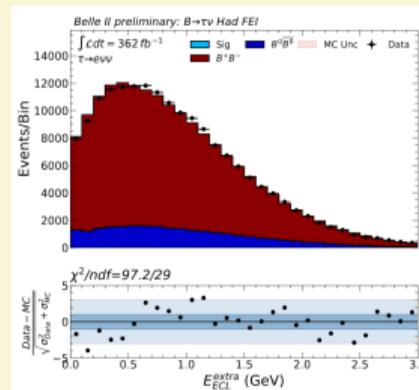


Figure: E^{EXTRA} distribution for the extra tracks sideband after continuum subtraction and bin-by-bin correction

1 Analysis context

2 Belle II toolbox

3 Calibration of the FLAVOUR TAGGER

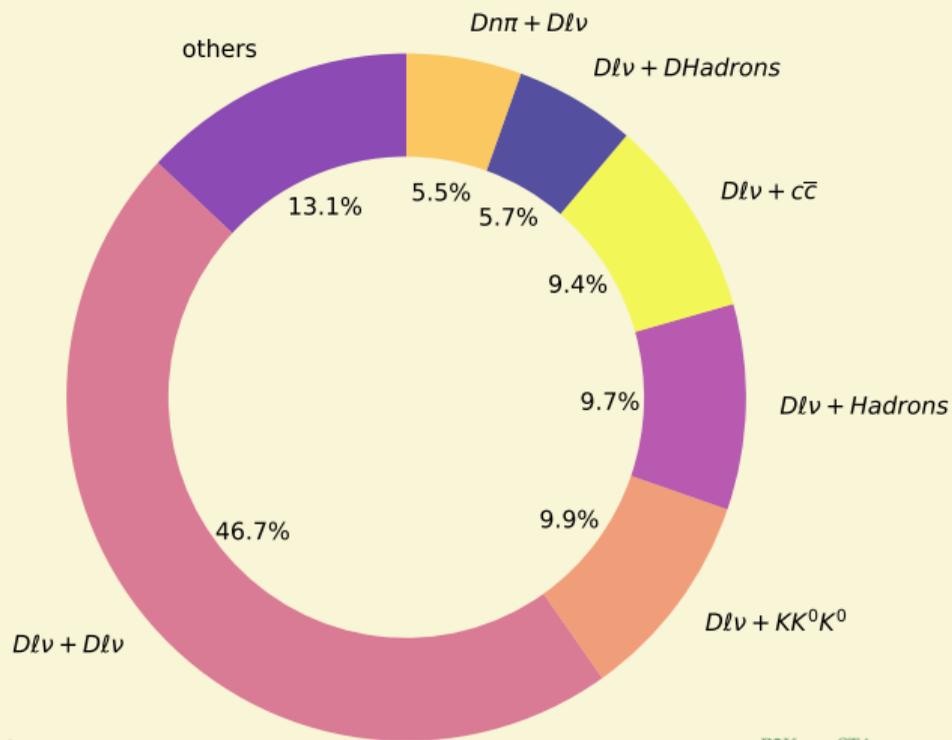
4 $B \rightarrow K\nu\bar{\nu}$ search

- Reconstruction and preselection
- Corrections
- Selection
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- Fit

5 Conclusion and outlook

Backgrounds

Background Fractions in signal region



Specific corrections and systematics for the following backgrounds:

- $D \rightarrow K_L^0 X$
- $B \rightarrow D^{**}$
- $B^+ \rightarrow K^+ K_L^0 K_L^0$
- $B^+ \rightarrow K^+ n\bar{n}$

- 1 Analysis context
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- 4 $B \rightarrow K\nu\bar{\nu}$ search
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Methodology

- Create histograms in signal region (BDT > 0.4) with 12 bins
- Run a maximum likelihood fit with `pyhf` on the data
- Compute the profile likelihood ratio with the signal strength μ as the parameter of interest
- Get the expected error on BR and expected upper limits

Definition (Likelihood function)

$$\mathcal{L}(\mu, \theta | \mathbf{n}) = \frac{1}{Z} \prod_{b=1}^{12} \text{Poisson}(n_b | \nu_b(\mu, \theta)) \rho(\theta) \quad (8)$$

with:

$\theta \in \mathbb{R}^N$ is a vector of N nuisance parameters;

n_b is the number of events in bin b , ν_b the expected number of events in bin b ;

Z a normalization constant;

ρ is a prior acting as a constraint on the nuisance parameters.

1 Analysis context

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Next steps

The whole machinery is present for the analysis flow, we now plan to optimize and study in details each steps:

- Detailed study of the backgrounds
- Embedding samples for signal efficiency validation
- Optimize BDTs features and hyperparameters
- Improve systematics evaluations

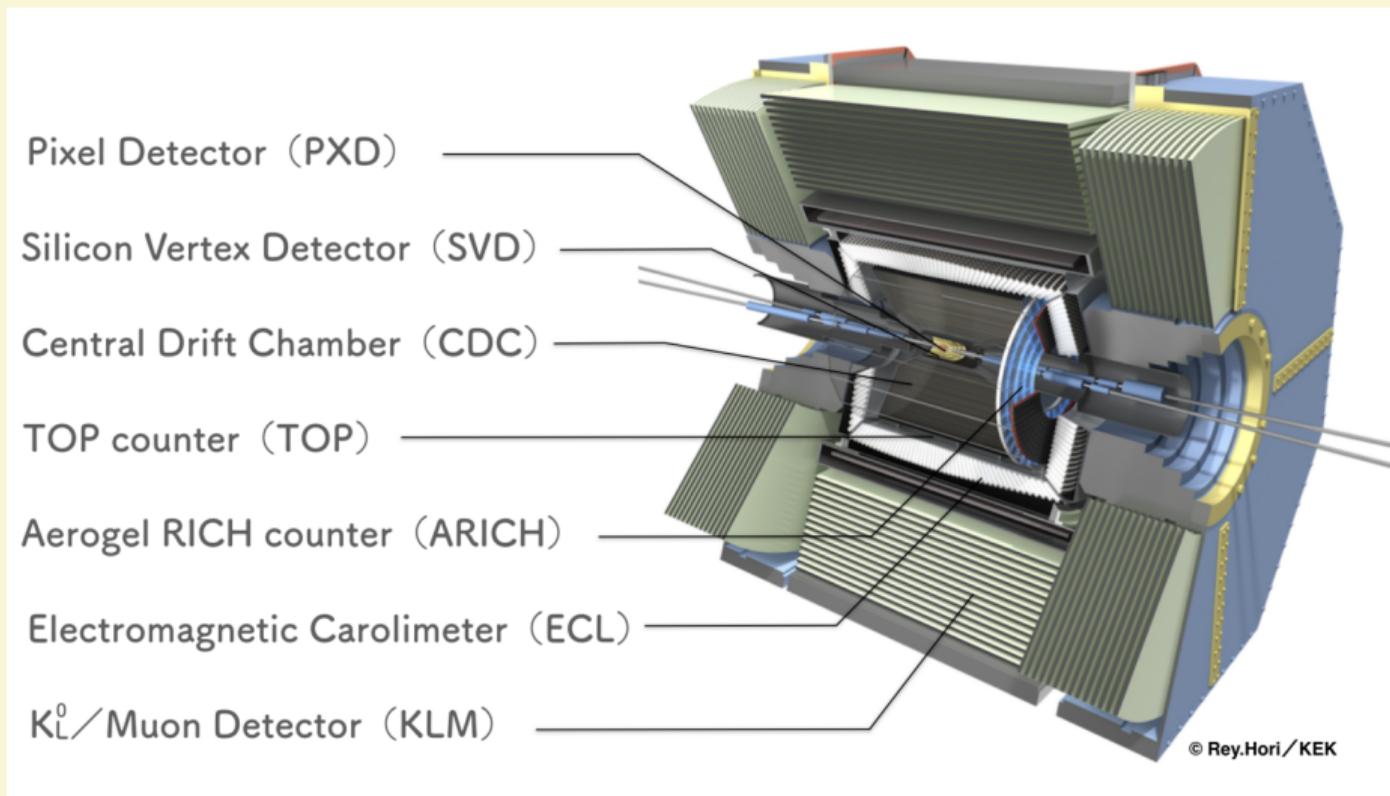
Trainings, conferences and publications

- Scientific trainings: 54h
- Transversal trainings: 55h
- International conference already attended: CHEP 2024
- Other conferences expected in Winter 2026
- Article: proceedings of CHEP 2024 [[arxiv:2503.09401](https://arxiv.org/abs/2503.09401)]
- Poster: soon presenting at the Congrès Annuel de la Société Française de Physique (SFP) 2025

6 Supplementary Material

- Preselection cuts
- PID corrections
- Selection
- EExtra corrections
- Shapley values
- Backgrounds

Belle II subdetectors



6 Supplementary Material

- Preselection cuts
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- Backgrounds

Preselection

"Good Track":

- $p_t > 0.2 \text{ GeV}/c$
- $E < 5.5 \text{ GeV}$
- thetaInCDCAcceptance
- $dr < 2 \text{ cm}$
- $|dz| < 4 \text{ cm}$

K^+ :

- "Good Track"
- $dr < 0.5 \text{ cm}$
- $|dz| < 2 \text{ cm}$
- Kaon ID $> 0.9^a$

π^0 :(pi0eff30_May2020)

- $\text{InvM} \in]0.120, 0.145[\text{ GeV}/c^2$
- $\text{daughterDiffOfPhi} \in] - 1.5, 1.5[\text{ rad}$
- $\text{daughterAngle} < 1.4 \text{ rad}$

^awill switch to Neural Network PIDs when ready

Preselection

ROE Mask: for signal and tag

- "Good Track"
- `clusterReg==1` and $E > 0.08$ GeV
or `clusterReg==2` and $E > 0.03$ GeV
or `clusterReg==3` and $E > 0.06$ GeV
- `clusterNHits > 1.5`
- $|\text{clusterTiming}| < 200$ ns
- $0.2967 < \text{clusterTheta} < 2.6180$ rad

FEI cuts:

- $\cos(\theta_{BY}) \in]-4, 3[$
- $\cos\text{TBT0} < 0.9$
- $\text{SignalProbability} > 0.004$

Rest Of Event

ROE Cluster Cuts: (for EExtra)

- "Good Track"
- `clusterReg == 1` and `clusterE > 0.100 GeV`
or `clusterReg == 2` and `clusterE > 0.060 GeV`
or `clusterReg == 3` and `clusterE > 0.150 GeV`
- `0.2967 < clusterTheta < 2.6180`

Two masks studied for now:

- `minC2TDist > 50 cm`
- `beamBackgroundSuppression > 0.5` and `fakePhotonSuppression > 0.5`

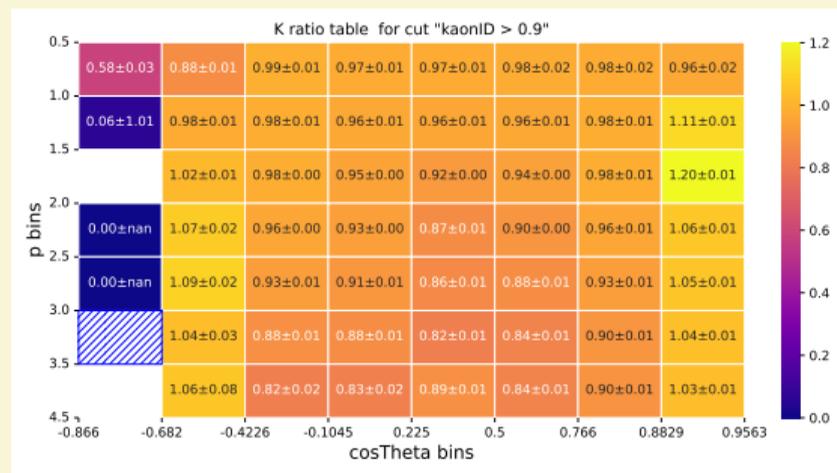
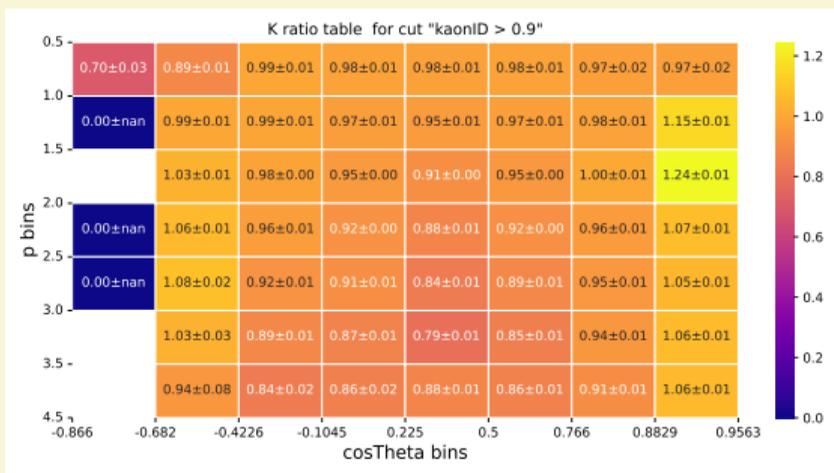
Ask for:

- No extra good track in the event
- No extra K_S , Λ or π^0 in the event

6 Supplementary Material

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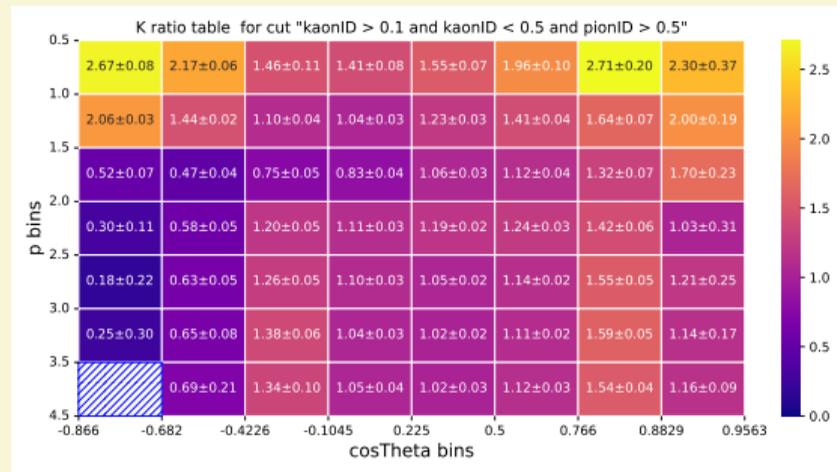
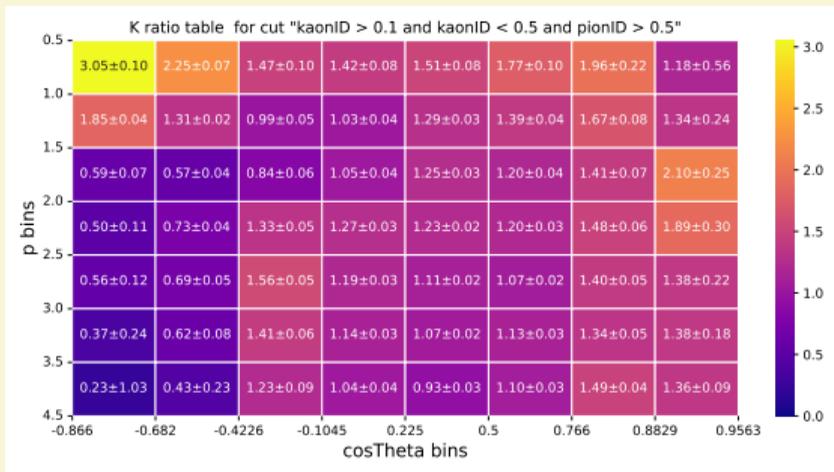
PID corrections - Kaon



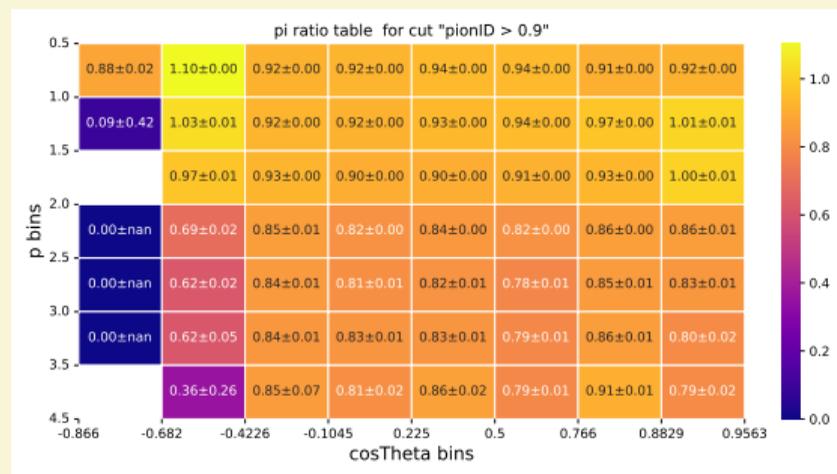
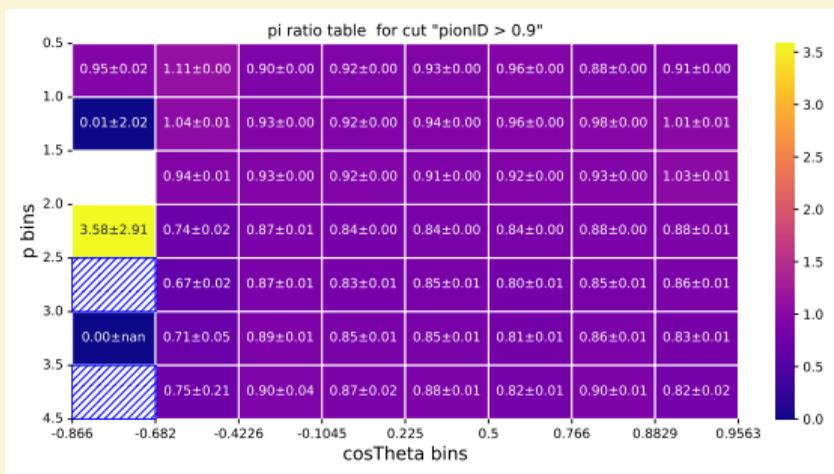
→ Cut: $\cos(\theta_K) > -0.682$

→ Efficiency of 99.9%

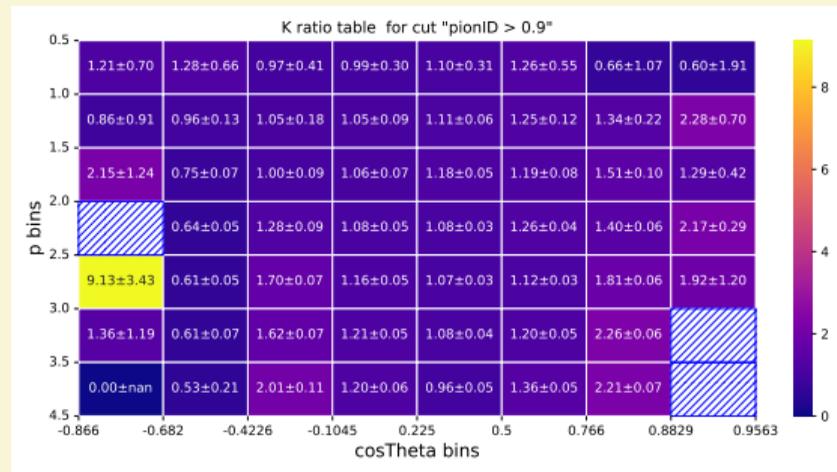
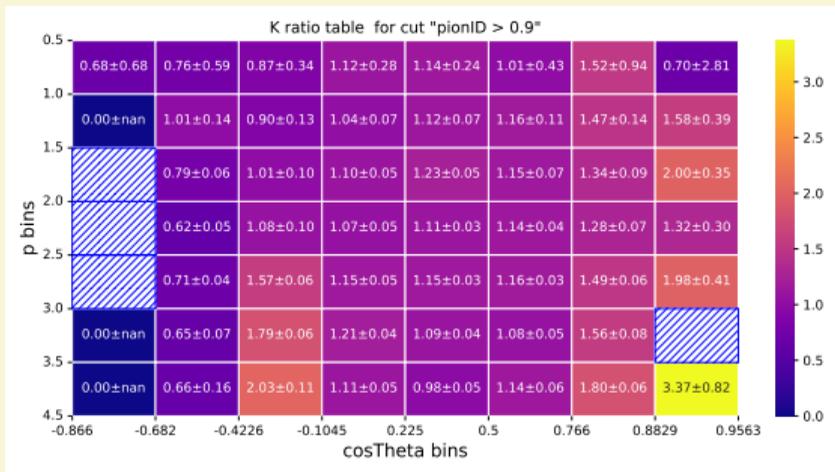
PID corrections - Kaon sideband



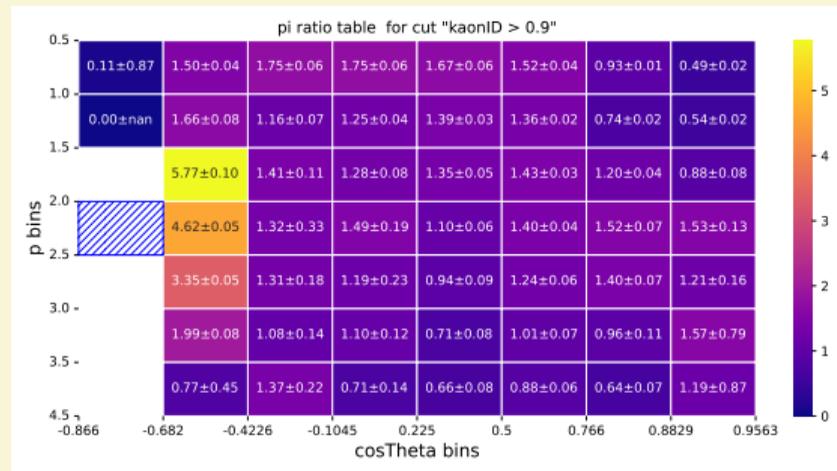
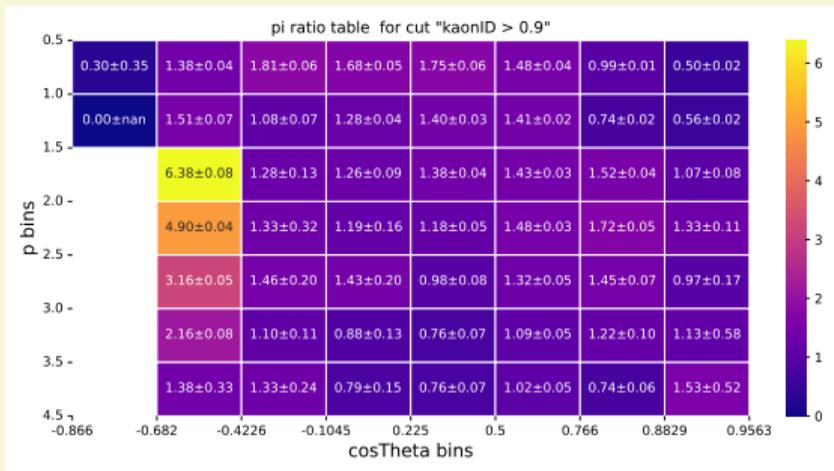
PID corrections - Pion sideband



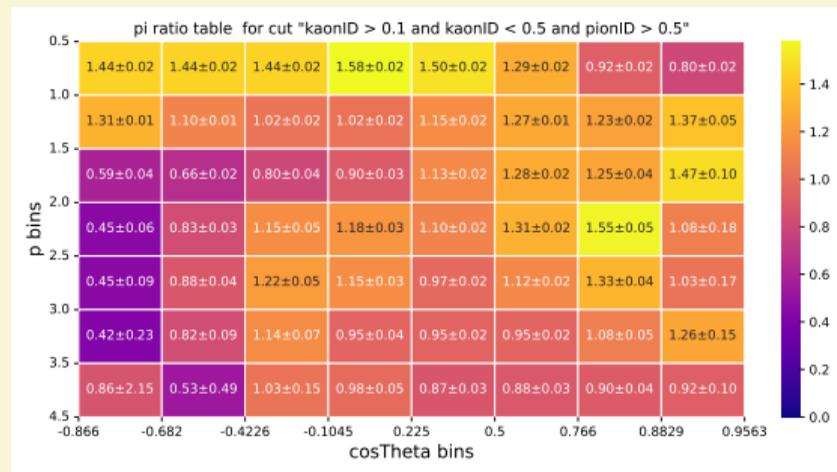
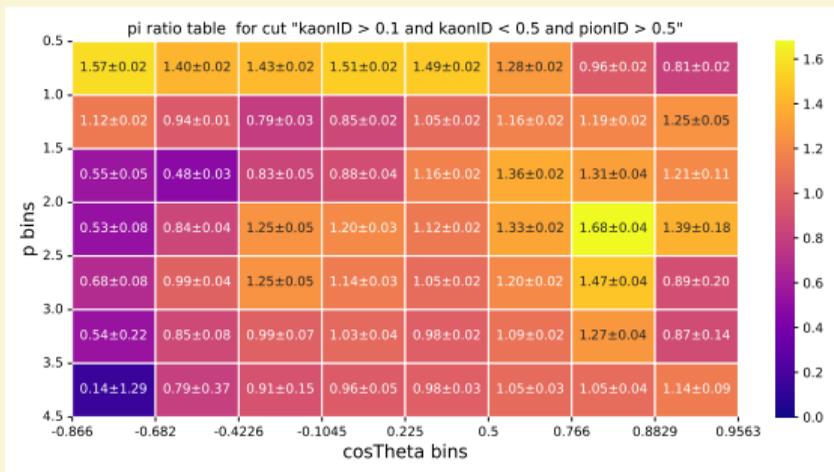
PID corrections - Pion sideband



PID corrections - Pion



PID corrections - Pion



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Continuum suppression pre-BDT

Summary:

Cut	Efficiency after Signal probability > 0.01	Purity [%]	Sigma minuit [$\times 10^{-5}$]
Original cuts	74.2	12	0.4
$-1.75 < \cos(\theta_{BY}) < 1.1$	66.1	14	0.4
$-1.9 < \cos(\theta_{BY}) < 1.2$	65.6	13	0.4
NREMAININGTRACKS	58.4	14	0.5
R2	53.1	13	0.4
Signal probability > 0.01	65.0	14	0.4
Signal probability > 0.1	26.5	17	0.6

Table: Table summarizing the cuts applied and their consequences on the various metrics

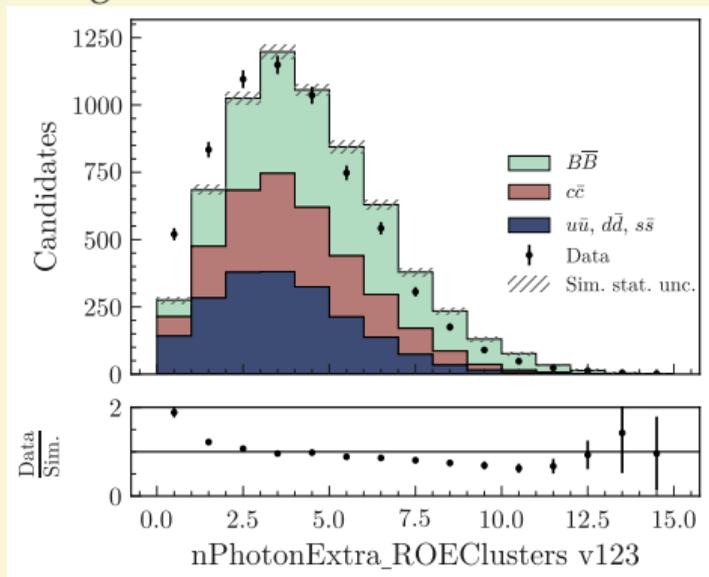
6 Supplementary Material

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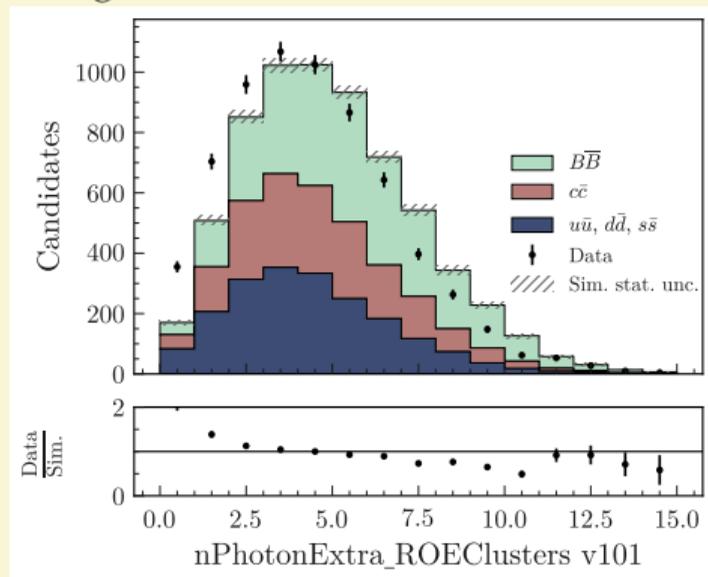
EEExtra corrections (in pion-enriched sideband, before corrections)

Computed by reweighting the MC to the data on n_{PHOTONS} in the wrong charged control sample.

Using BDT variables:



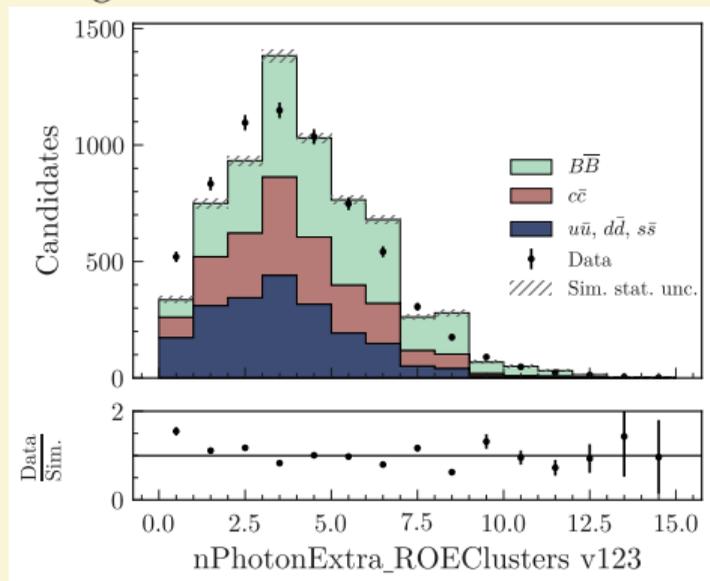
Using MINC2TDIST :



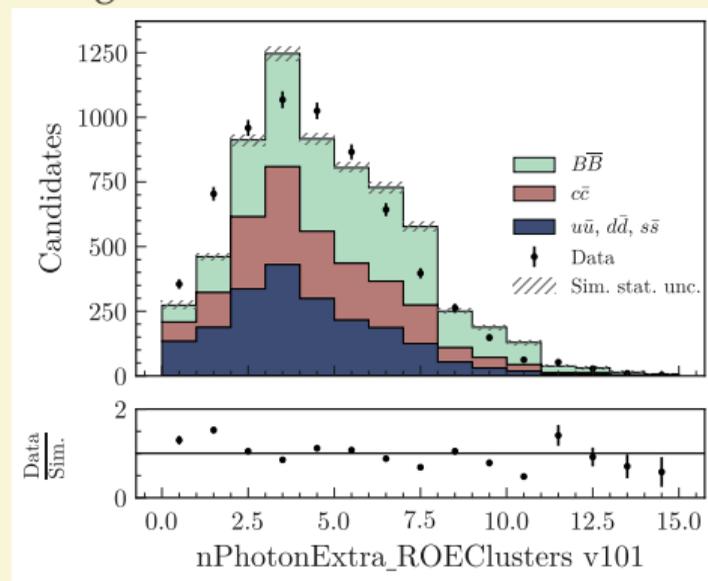
EEExtra corrections (in pion-enriched sideband, after corrections)

Computed by reweighting the MC to the data on n_{PHOTONS} in the wrong charged control sample.

Using BDT variables:



Using MINC2TDIST :

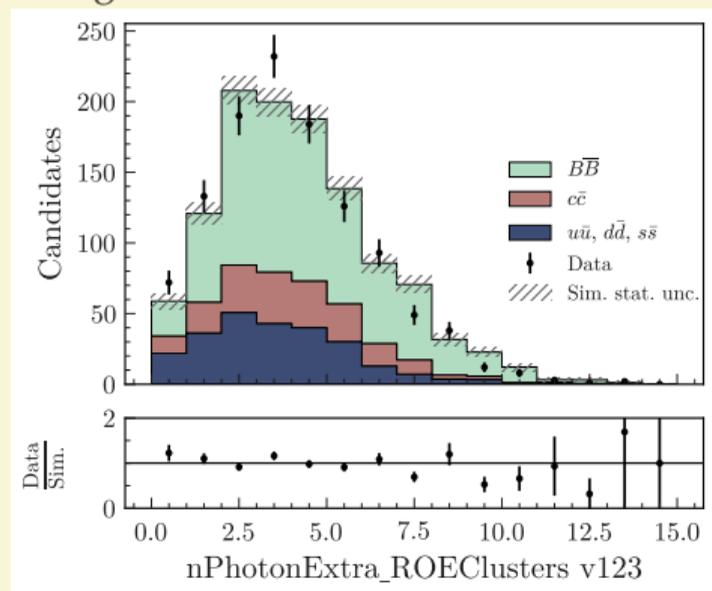


→ Need to study the wrong charged control sample in details

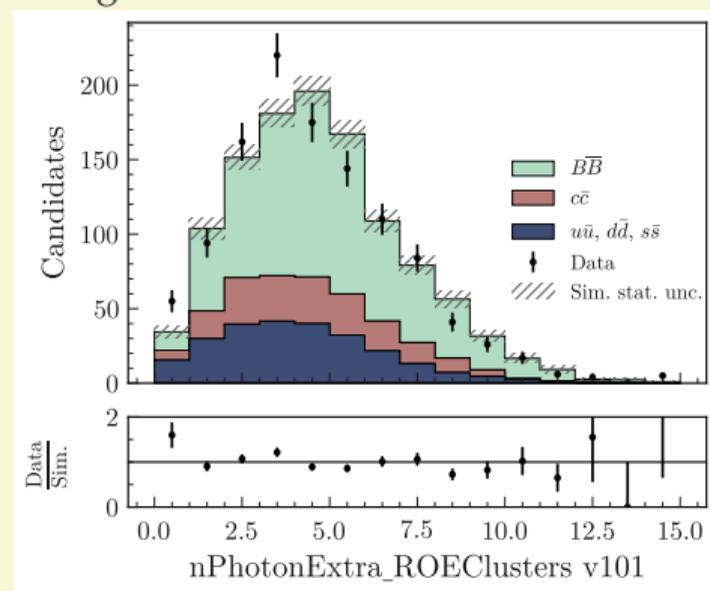
Extra corrections (in wrong charged pion-enriched sideband before corrections)

Computed by reweighting the MC to the data on n_{PHOTONS} in the wrong charged control sample.

Using BDT variables:



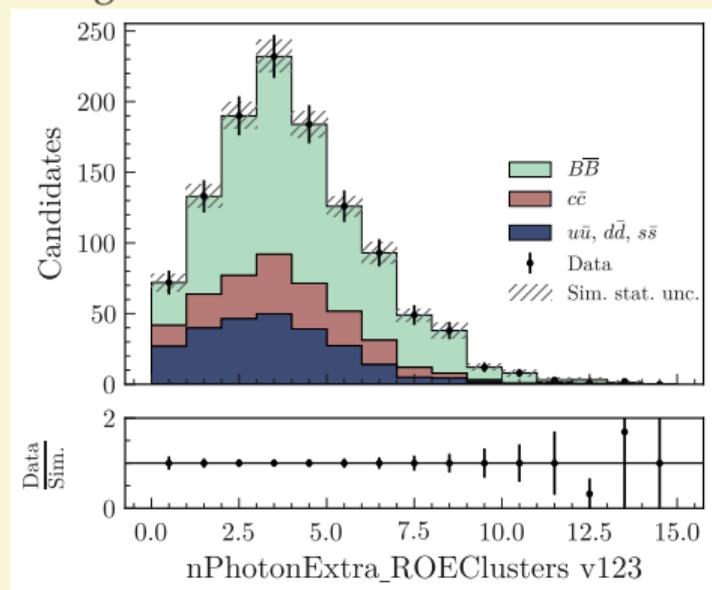
Using MINC2DIST :



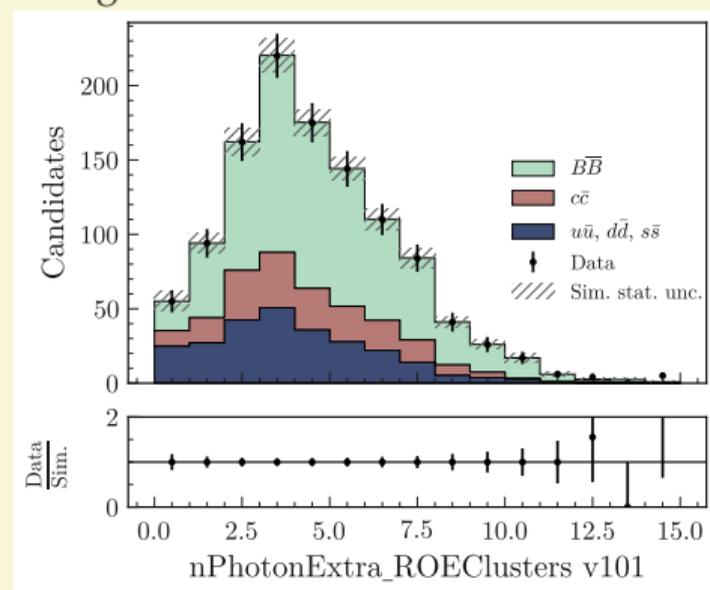
Extra corrections (in wrong charged pion-enriched sideband after corrections)

Computed by reweighting the MC to the data on n_{PHOTONS} in the wrong charged control sample.

Using BDT variables:



Using MINC2DIST :



6 Supplementary Material

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Shapley values - Explanation

- Method to attribute the prediction of a model to its features
- Originates from cooperative game theory:
 - Imagine a set N (of n players) and a gain function v that assigns a value to each coalition S
 - Question: How to fairly distribute the total gain among the players?
 - Answer: Shapley values

$$\varphi_i(v) = \frac{1}{n} \sum_{S \subseteq N \setminus \{i\}} \binom{n-1}{|S|}^{-1} (v(S \cup \{i\}) - v(S))$$

Shapley values - Example

```
import xgboost as xgb
import shap as sh

# ----- XGBoost Classifier ----- #
bdt = xgb.XGBClassifier(**param)
bdt.fit(X_train, y_train, sample_weight=weights_train)

# ----- Shapley Values ----- #
explainer_xgb = sh.TreeExplainer(bdt)
explanation = explainer_xgb(X_test)

# ----- SHAP Interpreter Plot ----- #
sh.plots.beeswarm(explanation, max_display=len(branches))
```

Listing: Example Python Code

6 Supplementary Material

- Preselection cuts
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Backgrounds

Channel 1 sl charged evt type	occurrence (398 evts)
misID K_{sig}	3.77% (15)
at least 1 K_L	24.62% (98)
$D\ell\nu + D\ell\nu$	46.74% (179)
$D\ell\nu + KK^0K^0$	9.92% (38)
$D\ell\nu + Hadrons$	9.66% (37)
$D\ell\nu + c\bar{c}$	9.40% (36)
$D\ell\nu + DHadrons$	5.74% (22)
$Dn\pi + D\ell\nu$	5.48% (21)
$D\ell\nu + DD$	2.09% (8)
$Dn\pi + DHadrons$	1.04% (4)
$D\ell\nu + D\tau\nu$	1.04% (4)
$Dn\pi + c\bar{c}$	0.78% (3)
$Dn\pi + Dn\pi$	0.26% (1)
$Dn\pi + D\tau\nu$	0.26% (1)
$KK^0K^0 + DD$	0.26% (1)
$DHadrons + DHadrons$	0.26% (1)
other	6.78% (27)

- [1] Belle II Collaboration, *Evidence for $B^+ \rightarrow K^+ \nu \bar{\nu}$ decays*, (2024), [arXiv:2311.14647](https://arxiv.org/abs/2311.14647).
- [2] B^0 - \bar{B}^0 Mixing, <https://pdg.lbl.gov/2024/reviews/rpp2024-rev-b-bar-mixing.pdf>.