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

Corentin Santos
Under the supervision of Isabelle Ripp-Baudot and Giulio Dujany

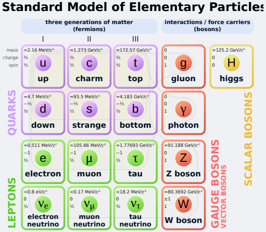
IPHC,
CNRS,
University of Strasbourg,

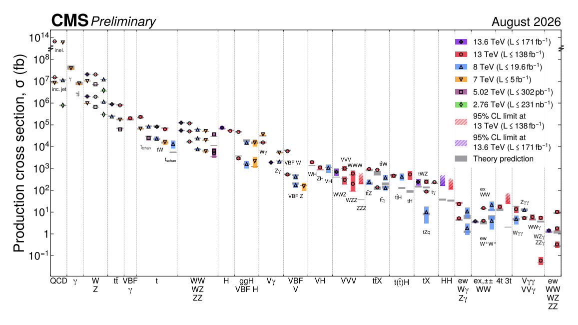
17 September 2026

The standard model of particle physics

Standard Model (SM) of particle physics:

- Mathematical framework
- Describes elementary particles and their interactions
- Predicts interaction probabilities (cross-section, **branching fraction/ratio**) . . .
- Successful in its predictions

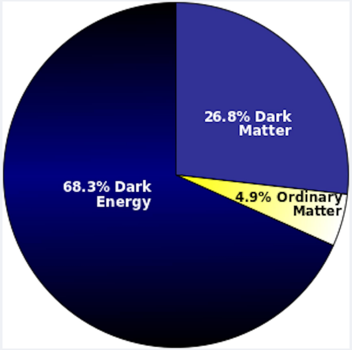




Beyond the standard model of particle physics

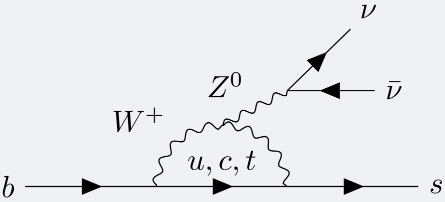
SM cannot explain:

- Matter/anti-matter asymmetry of the universe
- Dark matter/energy



$b \to s\nu\bar{\nu}$ transitions

- Sensitive to:
  - **High energy new physics** contributions [Bečirević, Piazza, Sumensari, 2023]
  - **Light new particles** [Bolton, Fajfer, Kamenik, Novoa-Brunet, 2025]
- $b \to s$ transition = **Flavor Changing Neutral Current**
- **Rare decay** (suppressed by Glashow–Iliopoulos–Maiani mechanism): Branching ratio $\leq \mathcal{O}\left(10^{-5}\right)$
- **Well described** by the Standard Model (SM)

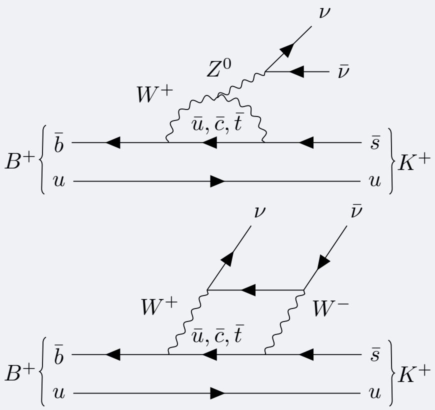


$\pm$

The $B \to K^{(*)}\nu\bar{\nu}$ decays

Many possible $b \to s\nu\bar{\nu}$ decays:

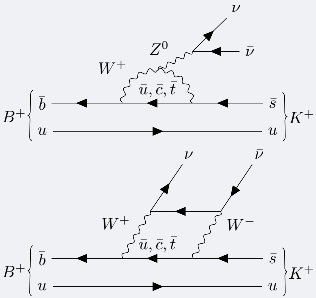
- $B^{\pm} \to K^{\pm}\nu\bar{\nu}$
- $B^{0} \to K^{0}_{S}\nu\bar{\nu}$
- $B^{\pm} \to K^{*\pm}\nu\bar{\nu}$
- $B^{0} \to K^{*0}\nu\bar{\nu}$
- ...



$\longrightarrow$ Focus on the $B^{\pm} \to K^{\pm}\nu\bar{\nu}$ decay channel

The $B \to K^{(*)}\nu\bar{\nu}$ decays - Standard Model

Decay	SM Prediction $[\times 10^{-6}]$
$B^\pm \to K^\pm \nu\bar{\nu}$	4.44 ± 0.30
$B^0 \to K^0_S \nu\bar{\nu}$	2.05 ± 0.14
$B^\pm \to K^{*\pm} \nu\bar{\nu}$	9.8 ± 1.4
$B^0 \to K^{*0} \nu\bar{\nu}$	9.05 ± 1.37



- For K modes: 7% precision, mainly due to CKM matrix elements uncertainties
- For K^* modes: 14% precision, mainly due to form factor uncertainties

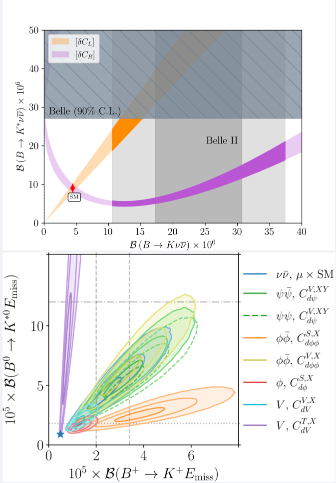
The $B \to K^{(*)}\nu\bar{\nu}$ decays - New physics models

Heavy new particles contributions[Bečirević, Piazza, Sumensari, 2023]:

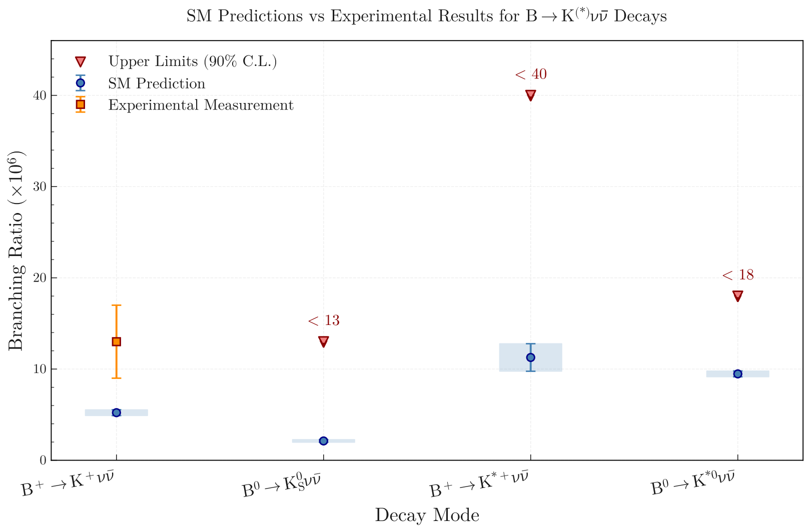
- Z' mediator
- Leptoquark mediator
- ...

Light new particles contributions[Bolton, Fajfer, Kamenik, Novoa-Brunet, 2025]:

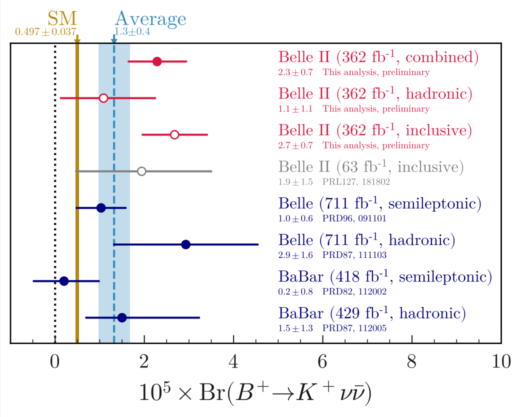
- Axion like particles
- Scalar
- ...



The $B \to K^{(*)}\nu\bar{\nu}$ decays - State of the art



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



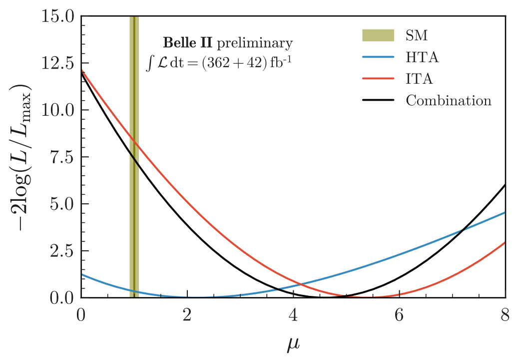


Figure: $\mu = \frac{BF}{BF_{SM}}$ [PhysRevD11.112006]

Goal: Carry an independent measurement using **semileptonic tagging strategy**

Why semileptonic tagging strategy?

- Higher efficiency than hadronic method
- Higher purity than inclusive method
- Complementary to the other two Belle II analyses
- Complementary to the Belle and BaBar analyses

Analysis	**Naively scaled to 487.72 fb^{-1}** $(\times 10^6)$
BaBar HTA	12
BaBar STA	7
Belle HTA	19
Belle STA	7
Belle II ITA	6
Belle II HTA	10
Belle II HTA + ITA	6

1. Analysis context
2. Belle II toolbox
   - CP-violation at Belle II
   - $B \to K^{(*)}\nu\bar{\nu}$ at Belle II
3. $B^{\pm} \to K^{\pm}\nu\bar{\nu}$ analysis strategy
   - Reconstruction and preselection
   - Data/simulation discrepancy corrections
   - Selection
   - Backgrounds studies
   - Statistical model and uncertainties
4. Results and discussion
5. Summary and prospects

Experimental constraints

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

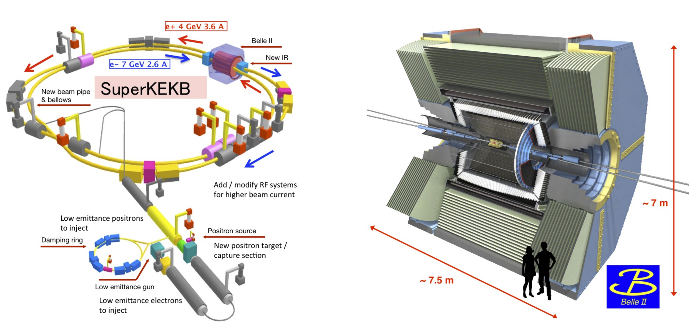
Only experiment capable of measuring the branching ratio of this decay: **Belle II**

Why Belle II?

- e^+e^- collisions $\longrightarrow$ **Clean environment** ✓
- Detector covering a $\approx 4\pi$ solid angle $\longrightarrow$ Almost **complete angular acceptance** ✓
- Bonus: integrated luminosity at the ab^{-1} level $\longrightarrow$ **High statistics** ✓

The Belle II experiment

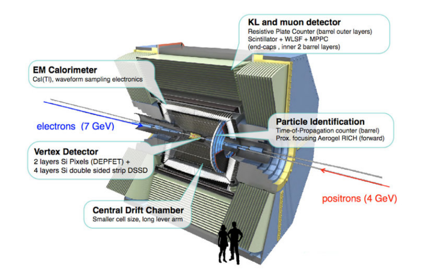
- International collaboration
- Taking data on the SuperKEKB accelerator, in Japan, since 2019
- $e^{+}e^{-} \to \Upsilon(4S) \to B\bar{B} \longrightarrow B$-**factory**
- Record for highest instantaneous luminosity: 5.3×10^{34} cm^{2}/s



The Belle II detector

Composed of layered sub-detectors, designed for specific tasks

- Tracking:
  - Vertex detector
  - Central Drift Chamber
- Particle Identification (PID):
  - Time Of Propagation
  - Aerogel Ring-Imaging Cherenkov
- Clustering:
  - Electromagnetic Calorimeter (ECL)
- K_L^0 and μ detector

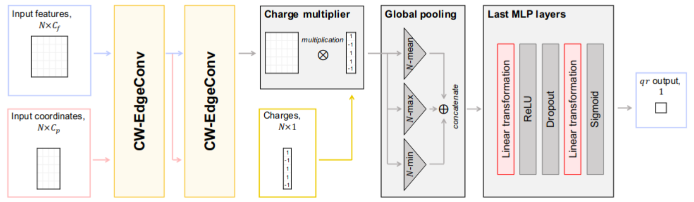


CP-violation studies

- Want to measure the *CP*-asymmetry:

$$a^{CP} = \frac{N_{B^0} - N_{\bar{B}^0}}{N_{B^0} + N_{\bar{B}^0}}$$

- Need to know the *flavour* of the B meson at the time of its decay (B^0 or $\bar{B}^0$)
  $\Longrightarrow$ **Flavour tagging** algorithm
- Role of the `GFlaT`, a graph neural network



Parameters

- `GFlaT` characterised by its **tagging efficiency**:

$$\varepsilon = \frac{N^{\text{tag}}_{B^0} + N^{\text{tag}}_{\bar{B}^0}}{N_{B^0} + N_{\bar{B}^0}}$$

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

$$N^{\text{tag}}_{B^0} = \varepsilon\left(\left(1-w\right)N_{B^0} + wN_{\bar{B}^0}\right)$$
$$N^{\text{tag}}_{\bar{B}^0} = \varepsilon\left(wN_{B^0} + \left(1-w\right)N_{\bar{B}^0}\right)$$

Calibration and optimisation

Goal:

- Implement a calibration strategy for the `GFlaT` in a *time-integrated* way
- Automatise and optimise the calibration process

My work:

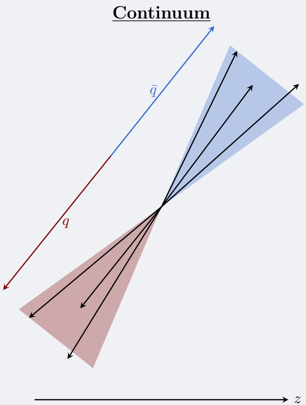
- Parallelised the fits necessary for the calibration
- Transformed the independent fits into a simultaneous fit
- Reduced the continuum background
- Automatised the workflow using B2LUIGI

Results:

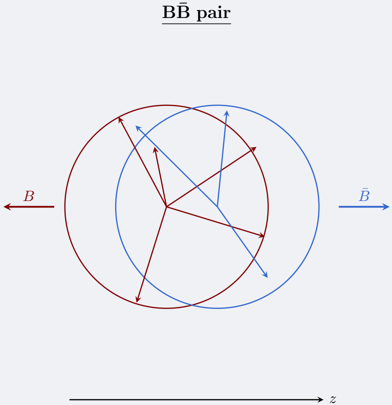
- Effective tagging efficiency on data: $\varepsilon = 37.3 \pm 1.0\%$

Selecting the signal - Events geometry

- e^+e^- collision $\Rightarrow \Upsilon(4S) \longrightarrow B\bar{B}$ **OR** $q\bar{q}$
- How to discriminate?
  $\Longrightarrow$ Geometry of the decay



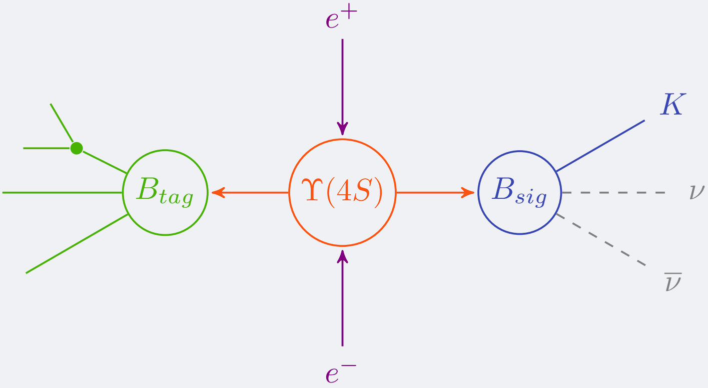
$\mathrm{p}(q) \approx 5\,\mathrm{GeV}/c$
$e^+e^- \to q\bar{q} \quad (q \in \{u, d, s, c\})$



$\mathrm{p}(B) \approx 0.3\,\mathrm{GeV}/c$
$e^+e^- \to \Upsilon(4S) \to B\bar{B}$

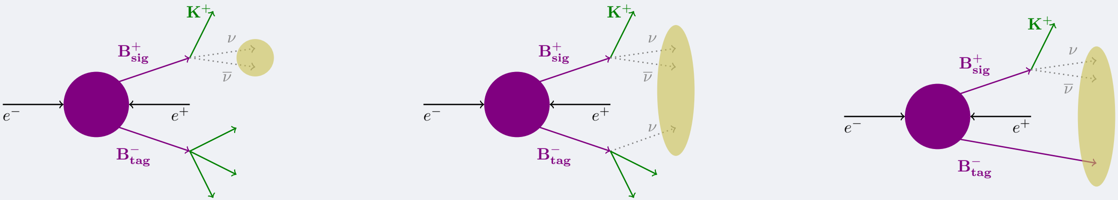
Selecting the signal - Handling invisible particles

- Only two particles are produced: signal B_{sig} and partner B_{tag}
  $\implies$ Infer information about B_{sig} from B_{tag}



Selecting the signal - Tagging strategies

Hadronic Tagged Analysis (HTA) Semileptonic Tagged Analysis (STA) Inclusive Tagged Analysis (ITA)



Tagging efficiency

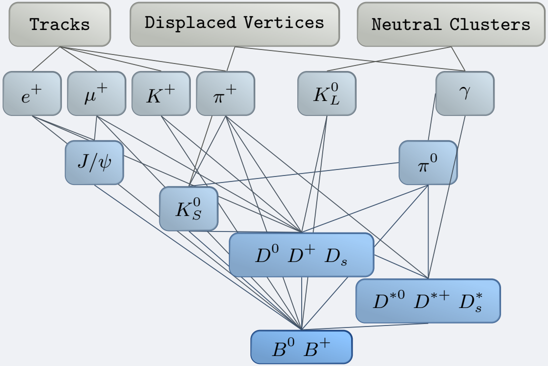
$\mathcal{O}\,(0.1\%)$ $\mathcal{O}\,(10\%)$

Tagging purity

$80\% - 20\%$ $\mathcal{O}\,(1\%)$

Full Event Interpretation (FEI)

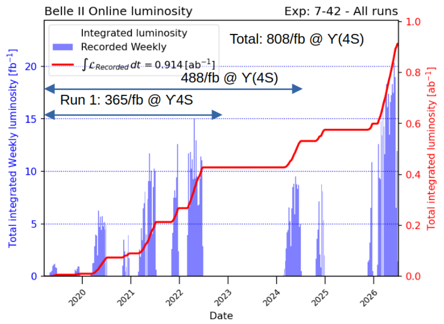
- **Tagging algorithm**: reconstruct the tag side
- Based on **Boosted Decision Trees** (BDT)
- Can be hadronic or **semileptonic**
- For the semileptonic, we consider the following B_{tag} decays:
  - $B \longrightarrow De\nu$
  - $B \longrightarrow D\mu\nu$
  - $B \longrightarrow D^{*}e\nu$
  - $B \longrightarrow D^{*}\mu\nu$



Analysis overview

- Analysis is **blinded**: not looking at signal in data sample $\longrightarrow$ **Monte-Carlo (MC) simulation**
  $\Rightarrow$ Need to control data/simulation discrepancies (**control samples**)

- **Dataset:** 488fb^{-1} at the $\Upsilon(4S)$ resonance
- **Simulated samples:**
  - $B\bar{B}$ and $q\bar{q}$: $4\times$ dataset luminosity each
  - $B^{\pm} \to K^{\pm}\nu\bar{\nu}$, $B^0 \to K^0_S\nu\bar{\nu}$, $B^{\pm} \to K^{*\pm}\nu\bar{\nu}$, $B^0 \to K^{*0}\nu\bar{\nu}$ channels: 10×10^6 events each



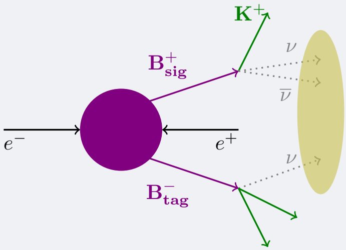
- **Important variable:** q^2, squared invariant mass of the $\nu\bar{\nu}$ system

$$q^2 = (E_{\nu} + E_{\bar{\nu}})^2 - (\vec{p}_{\nu} + \vec{p}_{\bar{\nu}})^2$$

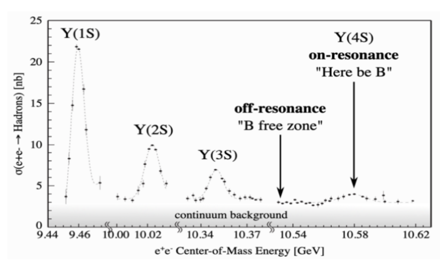
Reconstruction and preselection

Overview:

1. Reconstruct the B_{tag} using FEI
2. Reconstruct the signal-side K
3. Combine the corresponding tracks
4. Remove events with extra "*good*" tracks or remaining π^0, Λ, K_S^0



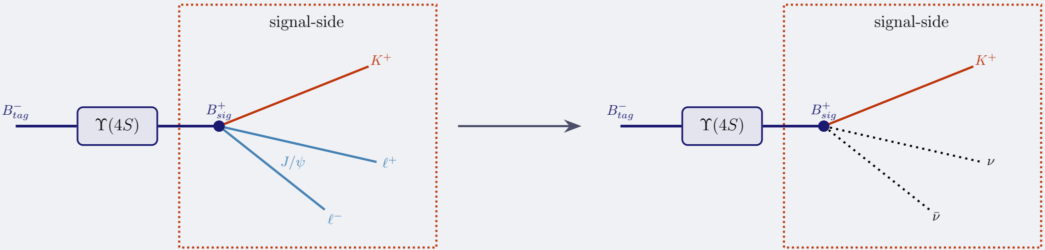
Control samples - backgrounds



- For $q\bar{q}$: **off-resonance** sample
  - 60 MeV below the $\Upsilon(4S)$ resonance
  - 59 fb^{-1} of data, 4× for simulation
- For $B\bar{B}$: **wrong charge** and **extra tracks** samples
  - **Wrong charge**: the two B mesons must have the same charge
  - **Extra tracks**: at least one extra "*acceptable*" track in the rest of event

Control samples - signal

- For signal: **embedding**
  1. Choose a channel with good kinematics knowledge and a K
     e.g. $B^+ \to K^+ J/\psi\,(\to \ell^+\ell^-)$
  2. Reconstruct in simulation and data
  3. Remove the signal-side ($B^+ \to K^+ J/\psi$) from reconstructed samples
  4. Replace with our simulated signal $B^{\pm} \to K^{\pm}\nu\bar{\nu}$



Corrections overview

Corrections	Method	Applied to
PID	Syscorr framework	All samples
FEI	Calibration from $B \to D^{*}\ell\nu$	Signal and $B\bar{B}$
Signal Form Factors	Correct from latest theory paper	Signal
Backgrounds	Correct branching fractions to PDG value	$B\bar{B}$
Specific backgrounds	Correct q^2 distribution ($B \to KK_L^0K_L^0$ and $B \to Kn\bar{n}$)	$B\bar{B}$
$q\bar{q}$ normalisation	Correct $\frac{data}{MC}$ from off-resonance sideband	$q\bar{q}$
Badly-tagged $B\bar{B}$ normalisation	Correct $\frac{data}{MC}$ from extra-tracks sideband	$B\bar{B}$
Backgrounds shape corrections	Train BDTs to separate data and MC in sidebands	$B\bar{B}$ and $q\bar{q}$

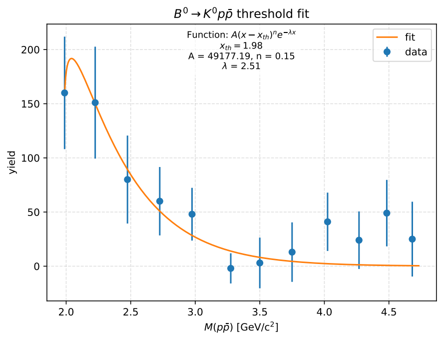
Special backgrounds - $B^{\pm} \to K^{\pm} n\bar{n}$ and $B^{\pm} \to K^{\pm} K_L^0 K_L^0$

- Some modes can easily mimic our signal, *e.g.* $B^{\pm} \to K^{\pm} n\bar{n}$ and $B^{\pm} \to K^{\pm} K_L^0 K_L^0$
  $\Longrightarrow$ Need proper q^2 description $\longrightarrow$ correct q^2 distribution
- No measurement for $B^{\pm} \to K^{\pm} n\bar{n}$ and $B^{\pm} \to K^{\pm} K_L^0 K_L^0$
  $\Longrightarrow$ Use isospin symmetry with ...

Special backgrounds - $B^{\pm} \longrightarrow K^{\pm}n\bar{n}$ and $B^{\pm} \longrightarrow K^{\pm}K_L^0K_L^0$

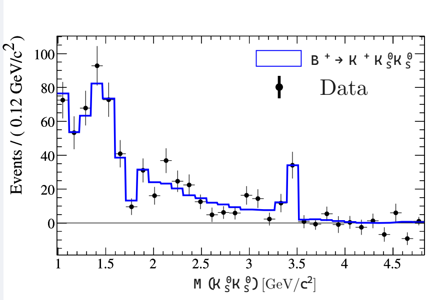
$B^{\pm} \longrightarrow K^{\pm}n\bar{n}$

- $B^0 \longrightarrow K^0 p\bar{p}$: measured by BaBar [PhysRevD76.092004]
- Model: $A\,(x - x_{th})^n\, e^{-\lambda x}$



$B^{\pm} \longrightarrow K^{\pm}K_L^0K_L^0$

- $B^{\pm} \longrightarrow K^{\pm}K_S^0K_S^0$: measured by BaBar [PhysRevD85.112010]
- Reweight to obtain a similar binned q^2 distribution as BaBar

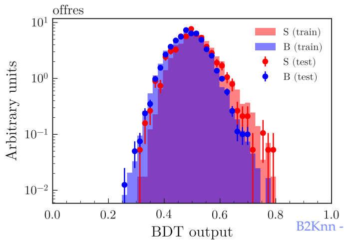


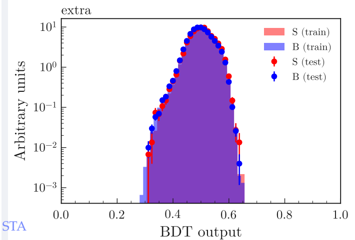
Backgrounds shape corrections

- **Goal**: correct the shape of the variables which will be used for the background suppression
  $\Longrightarrow$ **Issue:** 18 variables = 18 weights
- **Idea**: use a **multi-variate** algorithm (18 inputs $\rightarrow$ 1 output)
- **Method**: train a BDT to separate data and simulation
  - BDT output = $P\,(\text{data})$ = probability to be a data event
  - $1 - P\,(\text{data}) = P\,(\text{simulation})$ = probability to be a simulation event
  - Weight:

$$w_{BDT_{sb}} = \frac{P\,(\text{data})}{P\,(\text{simulation})}$$

- Train two BDTs: one on off-resonance (for $q\bar{q}$) sample **and** one on extra tracks sample (for $B\bar{B}$)



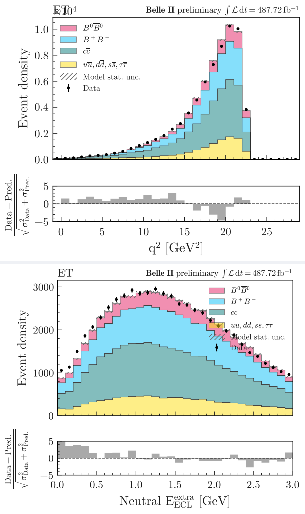


Other corrections

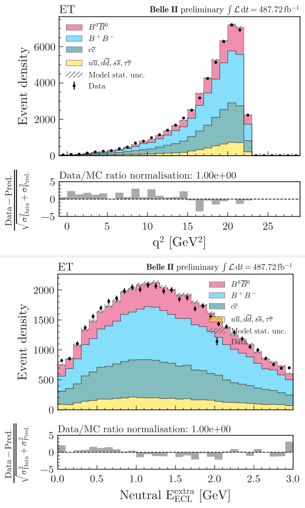
- **PID and FEI**: calibration factors from the collaboration
- **Signal form factors**: reweight q^2 distribution
- **Backgrounds**: compute weight to update branching ratio to state of the art
- $q\bar{q}$ **normalisation**: compute weight from off-resonance sample to unity
- **Baddly-tagged** $B\bar{B}$ **normalisation**: compute weight from baddly-tagged extra-tracks sample

Corrections validation

Before corrections

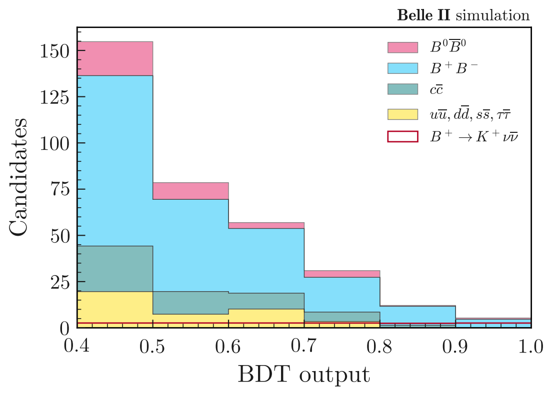


After corrections



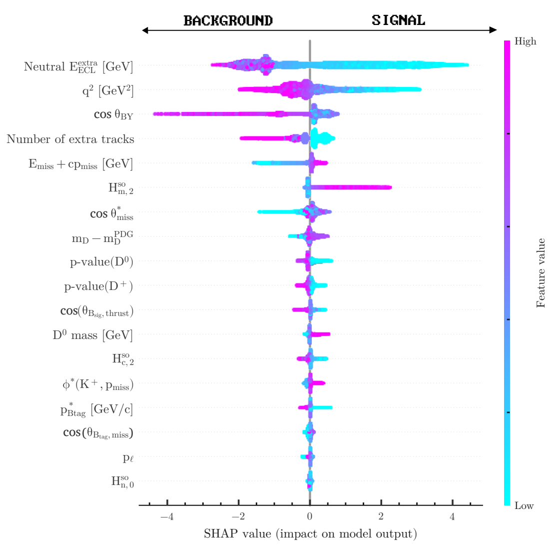
Selection

- Input: 18 variables
- Chosen using Shapley values for feature importance
- **Signal region**:
  - BDT output > 0.4
  - Signal efficiency: 0.7%
  - Purity: 6%



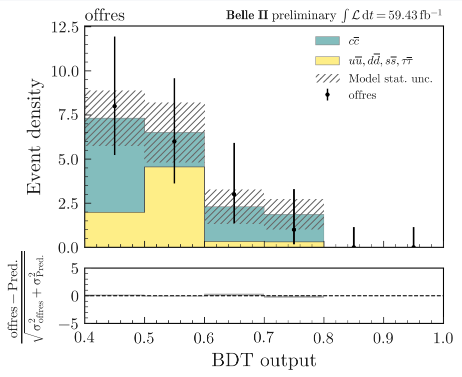
BDT input variables

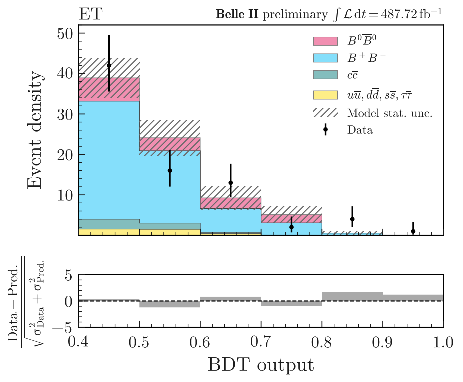
- The color gradient indicates the value of the feature
- The *x*-axis is the **Shapley value**
  - Shapley value > 0 = contributes to the "signal" prediction
  - Shapley value < 0 = contributes to the "background" prediction



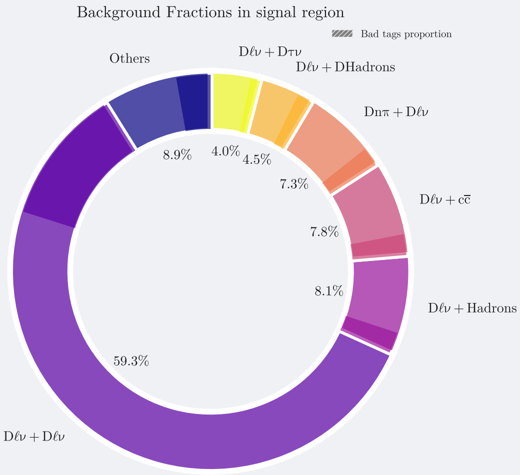
Validation

Sideband	data/MC signal region	Valid? ($\leq 2\sigma$)
offres	1.25 ± 0.35 (18 data evts)	✓
wc	1.18 ± 0.24 (39 data evts)	✓
extra	1.32 ± 0.20 (78 data evts)	✓





Backgrounds

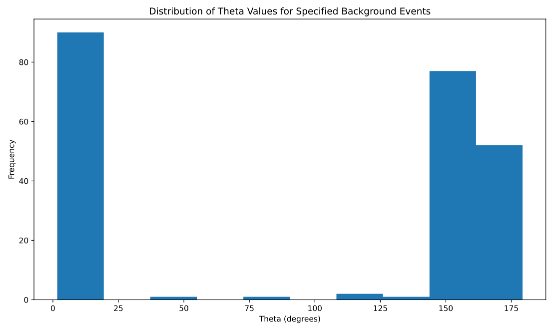


$B \to D\ell\nu$ studies

- **Most important decay:** $B \to D\ell\nu$
  - For $1\text{ab}^{-1} \approx 42 \times 10^6$ events
  - How does it mimic our signal $B^{\pm} \to K^{\pm}\nu\bar{\nu}$?
  - Can we reduce its contribution?
- Full decay is: $B^{\pm} \to D^{(*)0}(\to K^{\pm}X^{\mp})\ell^{\pm}\nu$

  $\Rightarrow$ X^{-} and ℓ are lost/not reconstructed

$\Longrightarrow$ It is deemed as **irreducible**



Statistical model - context

- **Goal:** Extract the branching fraction $\mathcal{B}\left(B^{\pm} \to K^{\pm}\nu\bar{\nu}\right)$

  $\Longrightarrow$ We work with the **signal strength** μ

$$\mu = \frac{\mathcal{B}\left(B^{\pm} \to K^{\pm}\nu\bar{\nu}\right)}{\mathcal{B}\left(B^{\pm} \to K^{\pm}\nu\bar{\nu}\right)_{SM}}$$

- **Contributions:**
  - **Signal:** $B^{\pm} \to K^{\pm}\nu\bar{\nu}$
  - **Generic backgrounds:** $B^{+}B^{-}$, $B^{0}\bar{B}^{0}$, light-$q\bar{q}$ ($u\bar{u}, d\bar{d}, s\bar{s}, \tau\bar{\tau}$), $c\bar{c}$
  - **Crossfeeds:** $B^{0} \to K^{0}_{S}\nu\bar{\nu}$, $B^{\pm} \to K^{*\pm}\nu\bar{\nu}$, $B^{0} \to K^{*0}\nu\bar{\nu}$
- 8 contributions

Statistical model - framework and strategy

- Create histograms in signal region (BDT > 0.4) with $b = 6$ bins
- Run a maximum likelihood fit

Definition (`HistFactory` framework)

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

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 normalisation constant
- π is a prior acting as a constraint on the nuisance parameters

- Compute the profile likelihood ratio with the signal strength μ as the parameter of interest
- Get the expected uncertainty on branching fraction and expected upper limits

Statistical model - systematic uncertainties

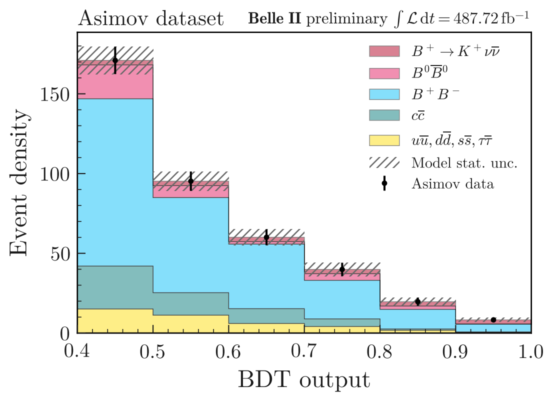
Source	Contribution(s)	Treatment	Number of NP
PID	All samples	Bin-correlated	22
Signal Form Factors	Signal	Bin-correlated	3
Continuum	$q\bar{q}$	Bin-correlated	1
Backgrounds	$B\bar{B}$	Bin-correlated	77
Specific backgrounds	$B\bar{B}$	Bin-correlated	5
Sgn eff (incl. FEI)	Signal	Normalisation	1
$q\bar{q}$ normalisation	$q\bar{q}$	Normalisation	2
$B\bar{B}$ normalisation	$B\bar{B}$	Normalisation	2
Crossfeed normalisation	$B\bar{B}$	Normalisation	3
B meson counting	Signal, $B\bar{B}$ and crossfeed	Contribution-correlated	1
MC statistical	All samples	Uncorrelated	8×6

Statistical model - uncertainties contributions

- Based on [Pinto,Wu,2023]
- For **statistical uncertainty**:
  - For each bin, vary the content n_b by $\pm\sqrt{n_b}$
  - Repeat the fit leaving everything free $\longrightarrow$ get a new μ_{var}
  - Compute $\Delta\mu = \mu_{var} - \mu_{nom}$
  - Sum in quadrature to get the full statistical uncertainty
- For **systematic uncertainty**:
  - For nuisance parameter, vary the value a_i by $\pm\sigma_i$
  - Repeat the fit leaving everything free $\longrightarrow$ get a new μ_{var}
  - Compute $\Delta\mu = \mu_{var} - \mu_{nom}$
  - Sum in quadrature to get the full systematic uncertainty

Asimov fit - results

- **Asimov dataset:** observed data = expected data
- Allows us to
  - Get an estimate of the correlations
  - Get an estimate of the uncertainties



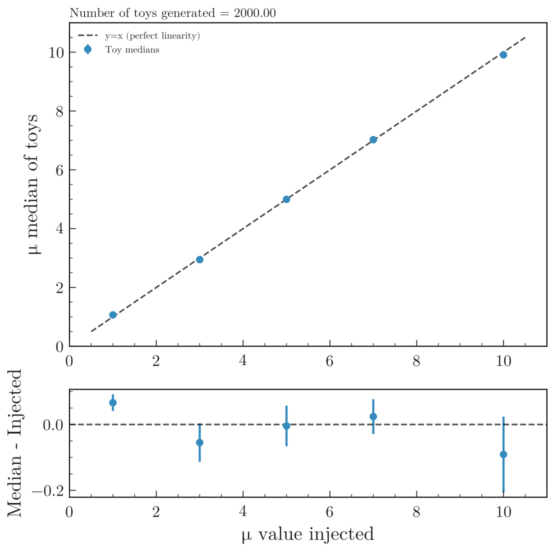
Asimov fit - uncertainties decomposition

- **Statistically dominated**
- Most important systematics:
  - Limited simulation statistics
    - $\longrightarrow$ More simulation
  - Backgrounds normalisation
  - Backgrounds branching fractions
    - $\longrightarrow$ Could improve with new measurements of unknown decays

Systematic Category	Absolute contribution on branching fraction ($\times 10^{-6}$)
StatMC	2.2
KL	1.0
Continuum	0.8
bkg norm	0.6
sgn eff + tracking	0.5
Backgrounds	0.4
KKLKL	0.3
nBB	0.2
Data/MC extra	0.1
FF	0.1
PID	0.1
D2KL	0.0
KX2nn	0.0
Kneutrons	0.0
Total systematic	**2.7**
Total statistical	**4.3**
Total	**5.1**

Discussions - closure test

- Test different signal injections to see how the model behaves
- For each signal injection:
  - Generate 2000 toys datasets
  - Perform a fit
  - Compare the median to the injected signal
- Test at various signal strength: $[1, 3, 5, 7, 10]$



Discussions - sensitivity at $\mu = 4.6$

- **Goal:** Compare sensitivity to previous Belle II analysis if same observation
- **Test:** Injection of signal $\mu = 4.6$ ($\mathcal{B}\left(B^{\pm} \to K^{\pm}\nu\bar{\nu}\right) = 2.3 \times 10^{-5}$)
- Uncertainty from previous analysis: 7.0×10^{-6}
- **Uncertainty from this analysis:** $\sigma_{BF} = 7.0 \times 10^{-6}$
  - On par with previous analysis
  - Could not get evidence if $\mathcal{B}\left(B^{\pm} \to K^{\pm}\nu\bar{\nu}\right) = 2.3 \times 10^{-5}$

Systematic Category	Absolute contribution on branching fraction ($\times 10^{-6}$)
sgn eff + tracking	2.3
StatMC	2.1
bkg norm	1.7
KL	1.4
Continuum	0.9
nBB	0.6
Backgrounds	0.5
FF	0.4
KKLKL	0.3
Data/MC extra	0.2
PID	0.2
D2KL	0.0
KX2nn	0.0
Kneutrons	0.0
Total systematic	**4.0**
Total statistical	**5.7**
Total	**7.0**

Summary

- The strategy is working and gives encouraging results
- Current sensitivity is on par with state of the art and better than previous occurence of semileptonic tagged analyses

Analysis	**Absolute uncertainty** $(\times 10^{6})$	**Naively scaled to 487.72 fb**$^{-1}$ $(\times 10^{6})$
BaBar HTA	13	12
BaBar STA	8	7
Belle HTA	16	19
Belle STA	6	7
Belle II ITA	7	6
Belle II HTA	12	10
Belle II HTA + ITA	7	6
This analysis	6	6

Prospects

- **TODOs**:
  - Add other $B \to K^{(*)}\nu\bar{\nu}$ channels as crossfeeds
  - Add other $B^{\pm} \to X_{su}\nu\bar{\nu}$ and $B^0 \to X_{sd}\nu\bar{\nu}$ as crossfeeds
- **Unblinding** = results on real data
- Combined fit with $B^0 \to K^{*0}\nu\bar{\nu}$ channel
- Combination with other analyses on the same channels (inclusive and hadronic tagging)
- Improvement expected thanks to higher statistics for future analyses

6 Supplementary Material

Effective field theory

Effective field theory:

- Approximation of the theory at lower energy scale
- Two ingredients:
  - Operators O (encode lower energy scale)
  - Wilson coefficients C (encode higher energy scale)
- Hamiltonian of the system, energy μ:

$$\mathcal{H}_{eff} = \sum_{i=1}^{N} C_i\left(\mu\right) O_i\left(\mu\right)$$

6. Supplementary Material
   - Analysis context
   - Belle II toolbox
   - Calibration of the Flavour Tagger
   - Preselection cuts
   - Shapley values

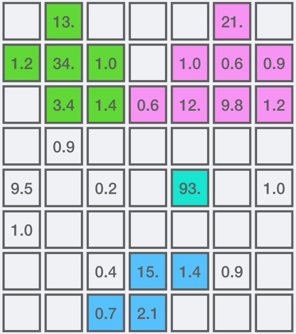
Reconstruction - tracks and clusters

Tracks:

- Charged particles leave *hits* in the VXD and CDC
- Bundle hits together via pattern recognition algorithms
- Extrapolate VXD and CDC tracks together
- Obtain trajectory, momentum and charged via a Kalman filter

Clusters:

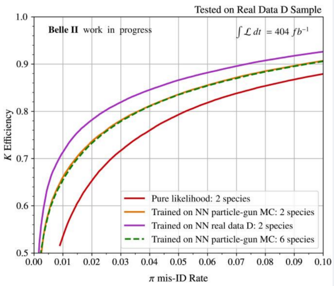
- Neutral particles leave *energy deposits* in the ECL
- Bundle deposits together via nearest neighbour algorithm
- Extrapolate CDC tracks to the reconstructed cluster



Reconstruction - particle identification

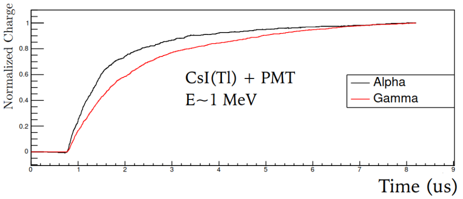
Charged particles identification:

- Each subdetector gives a likelihood for each particle hypotheses
- Likelihoods and momenta are used as inputs for a neural networks
- Gives a probability for each charged particle hypotheses: K, π, e, μ, p, d



Neutral particles identification:

- Look at shower shapes and use *pulse shape discrimination*



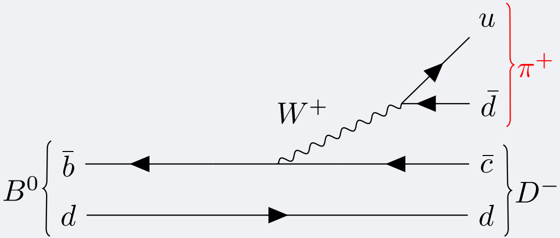
CP-asymmetry

- Want to measure the *CP*-asymmetry:

$$a^{CP} = \frac{N_{B^0} - N_{\bar{B}^0}}{N_{B^0} + N_{\bar{B}^0}}$$

$\longrightarrow$ 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 ?*

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^+
Kinetic Lepton	ℓ^-
Intermediate Kinetic Lepton	ℓ^+
Kaon	K^-
Kaon-Pion	K^-, π^+
Slow Pion	π^+
Fast Hadron	π^+, K^-
Maximum p	ℓ^-, π^-
Fast-Slow-Correlated	ℓ^-, π^+
Lambda	Λ
Total = 13	

- Categories $\longrightarrow$ Classification $\longrightarrow$ Classifier $\longrightarrow$ Machine Learning

$\Longrightarrow$ Introducing the Flavour Tagger

Parameters

- Flavour tagger characterized by its **tagging efficiency**:

Definition (Tagging efficiency)

$$\varepsilon = \frac{N^{\text{tag}}_{B^0} + N^{\text{tag}}_{\bar{B}^0}}{N_{B^0} + N_{\bar{B}^0}}$$

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

Definition (Wrong tag fraction)

$$N^{\text{tag}}_{B^0} = \varepsilon \left((1 - w) N_{B^0} + w N_{\bar{B}^0} \right)$$
$$N^{\text{tag}}_{\bar{B}^0} = \varepsilon \left(w N_{B^0} + (1 - w) N_{\bar{B}^0} \right)$$

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)

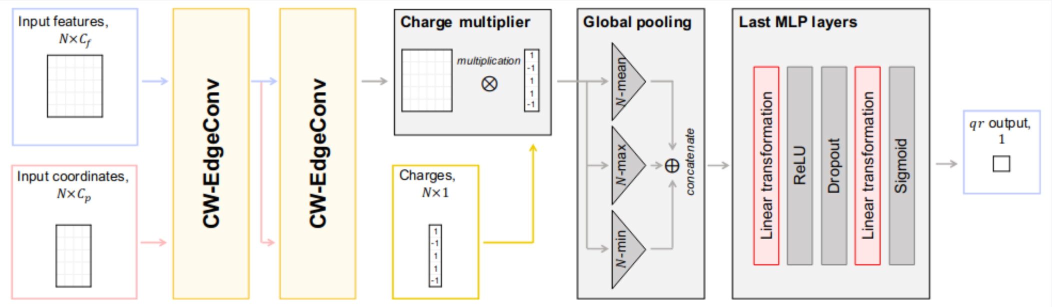
$$r \equiv |1 - 2w| \in [0, 1]$$

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]
- 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

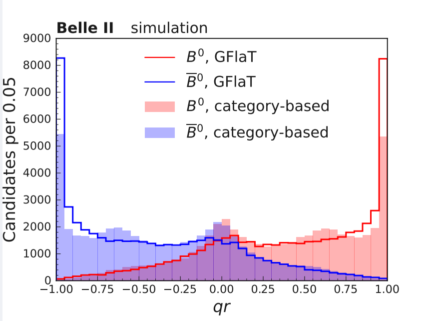
Goal:

- Implement a calibration strategy for the Flavour Tagger in a *time-integrated* way
- Automatize and optimise 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



Calibration strategy: ersatz

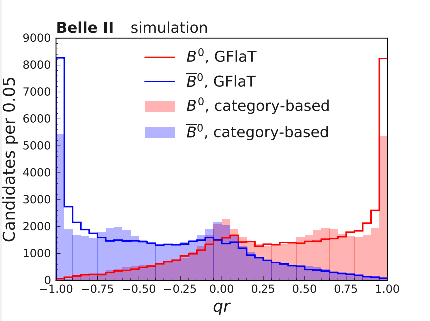
Goal:

- Implement a calibration strategy for the Flavour Tagger in a *time-integrated* way
- Automatize and optimise 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



Calibration strategy: ersatz

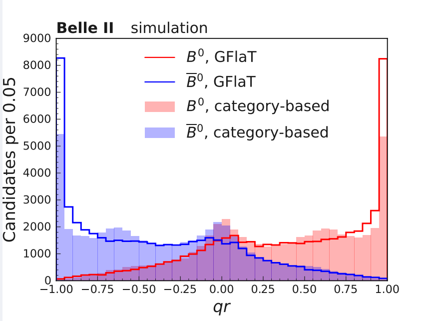
Goal:

- Implement a calibration strategy for the Flavour Tagger in a *time-integrated* way
- Automatize and optimise 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



Calibration strategy: ersatz

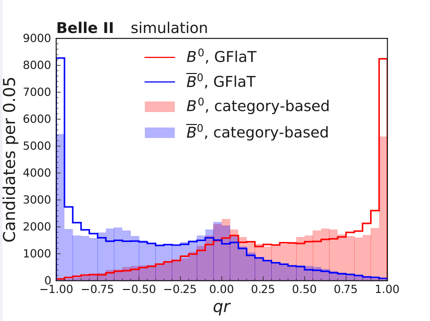
Goal:

- Implement a calibration strategy for the Flavour Tagger in a *time-integrated* way
- Automatize and optimise 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



Calibration strategy: ersatz

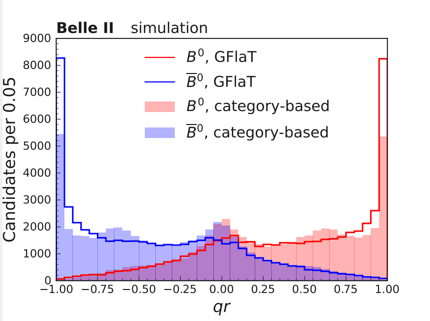
Goal:

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



Calibration strategy: ersatz

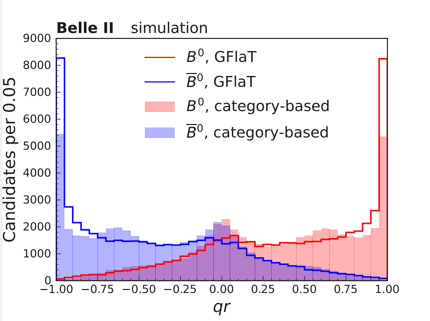
Goal:

- Implement a calibration strategy for the Flavour Tagger in a *time-integrated* way
- Automatize and optimise 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



Calibration strategy: ersatz

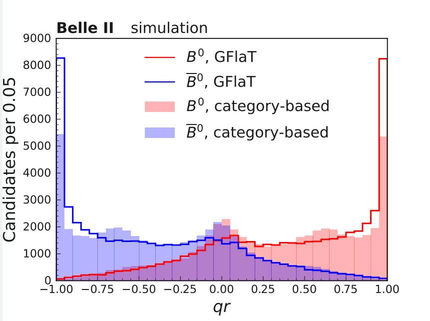
Goal:

- Implement a calibration strategy for the Flavour Tagger in a *time-integrated* way
- Automatize and optimise 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

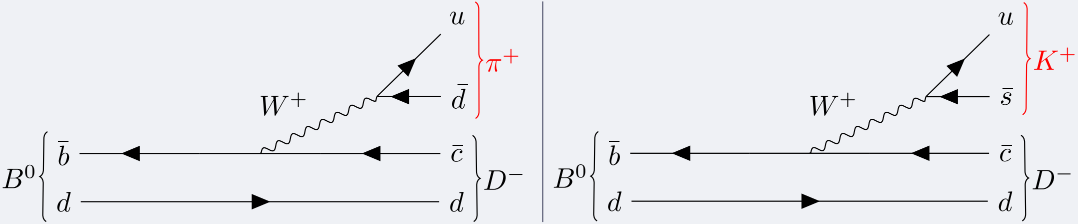


Calibration strategy: signal

- Need self-tagged decays:

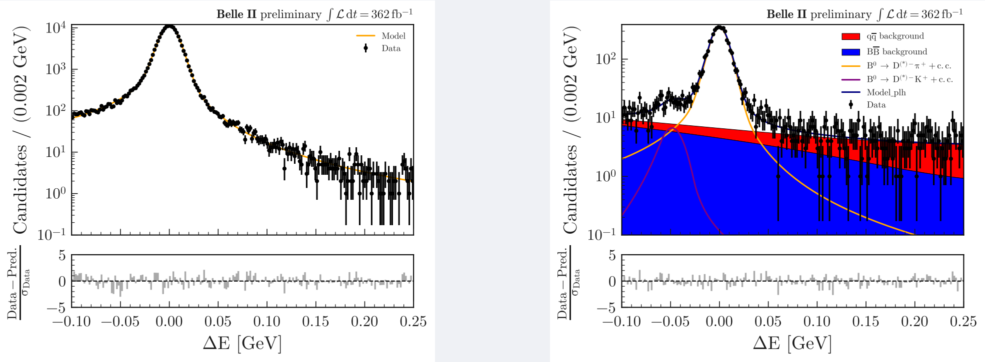
$$B^0 \longrightarrow D^- \pi^+$$
$$B^0 \longrightarrow D^{*-}(\longrightarrow \bar{D}^0(K^+\pi^-)\pi^-)\pi^+$$
$$B^0 \longrightarrow D^{*-}(\longrightarrow \bar{D}^0(K^+\pi^-\pi^0)\pi^-)\pi^+$$
$$B^0 \longrightarrow D^{*-}(\longrightarrow \bar{D}^0(K^+\pi^-\pi^-\pi^+)\pi^-)\pi^+$$

- Also consider $B \longrightarrow D^{(*)-}K^+$ 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 $i \in [\![0, 6]\!]$

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

with

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

and deduce

$$\boxed{w_i = \frac{1}{2}\left(w_i^{+} + w_i^{-}\right), \Delta w_i = w_i^{+} - w_i^{-}}$$

Calibration strategy: tagging efficiency

- Define a tagging efficiency for each bin $i \in [\![0, 6]\!]$

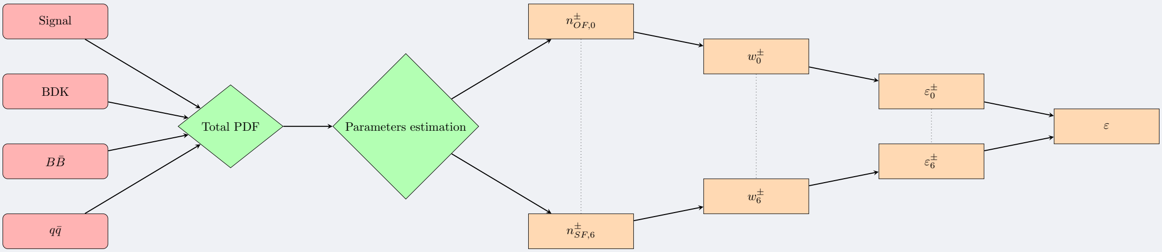
$$\varepsilon_i^{\pm} = \frac{n_{\mathrm{OF},i}^{\pm} + n_{\mathrm{SF},i}^{\pm}}{N_{B^0}^{\mathrm{tag}} + N_{\bar{B}^0}^{\mathrm{tag}}}$$

and compute the *effective* tagging efficiency

Definition (Effective tagging efficiency)

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

Calibration workflow

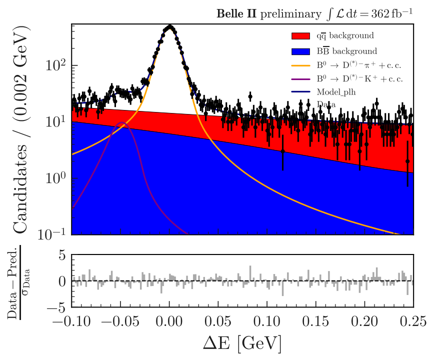


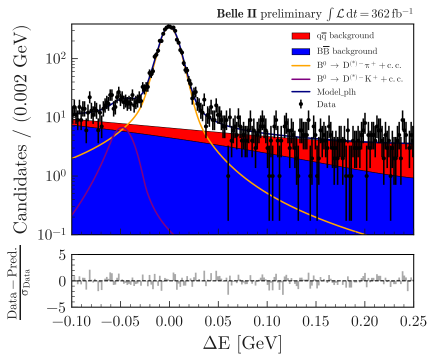
Calibration optimisation: parallelisation and automation

- **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
- Automatize 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 optimisation: 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)





Calibration optimisation: summary

- Parallelised the fits of the shapes
- Transformed the independent fits into a simultaneous fit
- Reduced the continnum background
- Automatised the workflow using B2LUIGI

Results:

- Effective tagging efficiency on data: $\varepsilon = 37.3 \pm 1.0\%$

Calibration optimisation: summary

Quantity	MC [%]	Data [%]
w_1^+	47.06 ± 0.78	46.96 ± 1.51
w_1^-	47.98 ± 0.78	48.87 ± 1.47
w_2^+	41.70 ± 0.68	39.36 ± 1.29
w_2^-	41.99 ± 0.68	43.80 ± 1.32
w_3^+	32.54 ± 0.63	32.57 ± 1.20
w_3^-	33.07 ± 0.63	35.52 ± 1.14
w_4^+	22.59 ± 0.72	22.27 ± 1.34
w_4^-	23.93 ± 0.73	28.99 ± 1.40
w_5^+	15.77 ± 0.76	14.12 ± 1.46
w_5^-	17.19 ± 0.78	19.16 ± 1.44
w_6^+	11.71 ± 0.64	11.38 ± 1.19
w_6^-	8.72 ± 0.61	12.62 ± 1.16

Preselection

"Good Track":

- $p_t > 0.2$ GeV/c
- $E < 5.5$ GeV
- thetaInCDCAcceptace
- $dr < 2$ cm
- $|dz| < 4$ cm

K^+ :

- "Good Track"
- $dr < 0.5$ cm
- $|dz| < 2$ cm
- Kaon ID > 0.9[a]

π^0 :(pi0eff30_May2020)

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

[a] will 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
- |clusterTiming| `< 200 ns`
- `0.2967 < clusterTheta < 2.6180 rad`

FEI cuts:

- $\cos(\theta_{BY}) \in]-4, 3[$
- `cosTBTO < 0.9`
- `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:

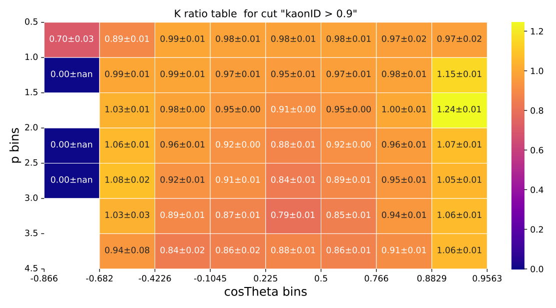
- `minC2TDist>50` cm
- `beamBackgroundSuppression > 0.5` and `fakePhotonSuppression > 0.5`

Ask for:

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

FEI and PID corrections

- PID and FEI corrections based on recommendations from collaboration
- PID calibrated with $D^{*+} \longrightarrow D^0 (\longrightarrow K^-\pi^+) \pi^+$
- FEI calibrated with $B^+ \longrightarrow D^{*0} \ell^+ \nu_\ell$



Mode	Calibration factor	Uncertainty
$De\nu$	1.14	0.11
$D\mu\nu$	1.10	0.11
$D^*e\nu$	0.87	0.10
$D^*\mu\nu$	0.850	0.098

Branching fractions corrections

- Branching fractions used for simulation are not always up-to-date

$\Longrightarrow$ Compute **weight** $w_{BF} = \frac{BF_{PDG}}{BF_{simulation}}$

- Exceptions:
  - $B \longrightarrow X_s \nu\bar{\nu}, B^{\pm} \longrightarrow K^{\pm}K^0_L K^0_L$ special backgrounds
  - PYTHIA modes and modes not present in the PDG $w_{BF} = 1$
  - $B^{\pm} \longrightarrow K^{\pm}\pi^{+}\pi^{-}, B^{\pm} \longrightarrow K^{\pm}K^{\pm}K^{0}$ $w_{BF} = 1$
- **Global correction for not corrected decays:**

$$w_{\text{global BF}} = \frac{1 - \sum_{i \in \text{corrected}} \text{BF}_i^{\text{PDG}}}{\sum_{i \in \text{not corrected}} \text{BF}_i^{\text{simulation}}}$$

  - For B^+B^-: $w_{\text{global BF}} = 1.07$
  - For $B^0\bar{B}^0$: $w_{\text{global BF}} = 1.00$

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

```python
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