

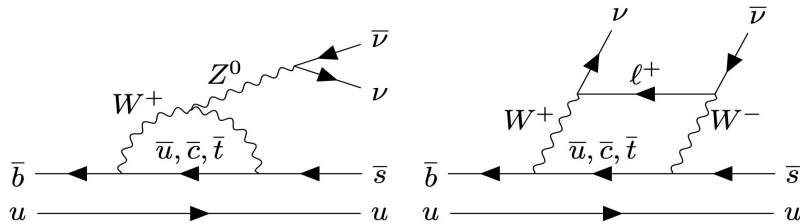
# **b- $\rightarrow$ svv with inclusive tag**

## **status and updates**

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# Motivation

- b- $\rightarrow$  svv: a FCNC transition, offers a powerful opportunity to probe the SM
  - Highly suppressed in SM
  - Branching fraction precisely predicted: no charged leptons in the final state
  - Highly sensitive to non-SM contributions
- B- $\rightarrow$  K(\*)vv @Belle II
  - B<sup>+</sup>/B<sup>0</sup> decays into a pseudo-scalar (K<sup>+</sup>/K<sub>s</sub><sup>0</sup>) or a vector meson (K<sup>\*+</sup>/K<sup>\*0</sup>)



Example of lowest-order quark-level diagrams for b- $\rightarrow$ svv transition

Decay	SM total (x10 <sup>-6</sup> )
$B^+ \rightarrow K^+ \nu \bar{\nu}$	$5.06 \pm 0.31$
$B^0 \rightarrow K_s^0 \nu \bar{\nu}$	$2.05 \pm 0.14$
$B^+ \rightarrow K^{*+} \nu \bar{\nu}$	$10.86 \pm 1.43$
$B^0 \rightarrow K^{*0} \nu \bar{\nu}$	$9.05 \pm 1.37$

<https://arxiv.org/abs/2301.06990>

# Where we were

- Previous measurements:

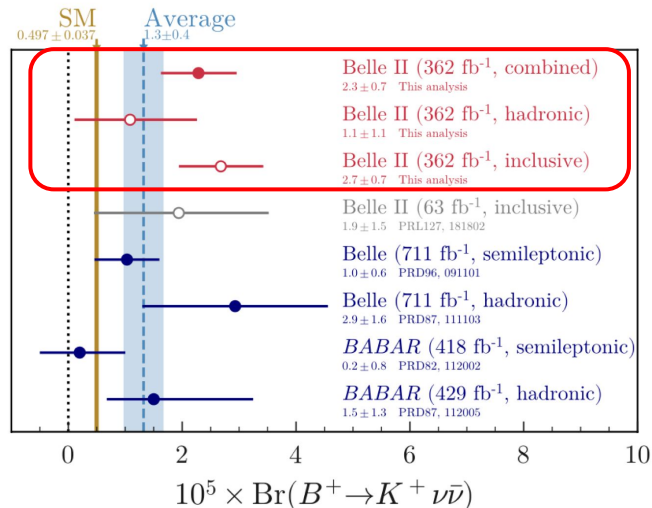
- $B^+ \rightarrow K^+ \nu \bar{\nu}$  measurement with Belle II Run 1 data
  - Inclusive tag, Hadronic tag and combined
  - $3.5\sigma$  wrt to null hypothesis and  $2.7\sigma$  wrt SM
  - First evidence of  $B^+ \rightarrow K^+ \nu \bar{\nu}$

[PhysRevD.109.112006](https://arxiv.org/abs/1907.07802)

- Extend to  $K^*$ ,  $K_S^0$  channels

- Use the data sample collected in Run1
- Challenge: low efficiency of final states with  $K_S^0$ s and  $\pi^0$ s
- Follow similar strategies with potential improvements
  - Selections, background suppression, new ML tools, etc.

- Target: moriond 2025



# Workflow and Outline

## Recap

The analyses follow a similar workflow as the last iteration:

- 1) Basic selection:
  - Object selection and event cleanup
  - Signal candidate selection
- 2) Main background suppression
  - BDT1 for event selection
  - Background suppression: e.g from D
  - Final selection using BDT2
- 3) Validation with control channels
- 4) Statistic interpretation

# Workflow and Outline

## Improvements wrt previous iteration

The analyses follow a similar workflow as the last iteration:

- 1) Basic selection:
  - Object selection and event cleanup
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Samples:

MC15ri, MC15rd exp18

Gitlab repository:

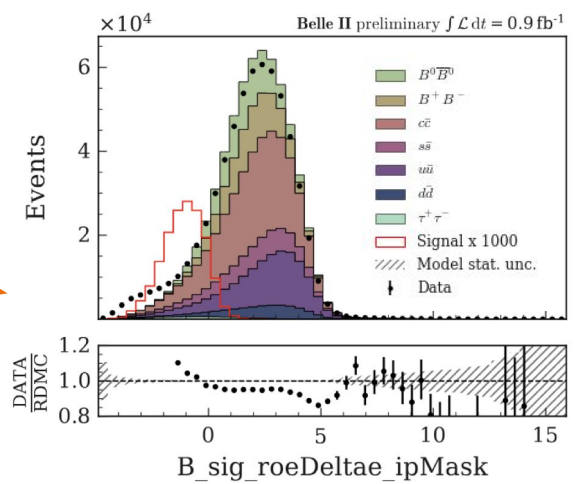
[https://gitlab.desy.de/belle2/physics/ewp/b2hnunubar\\_ITA](https://gitlab.desy.de/belle2/physics/ewp/b2hnunubar_ITA)

1. Candidate selection
2. Optimize D veto
3. Explore new ML tools: DNN LNN
4. Look into important background components

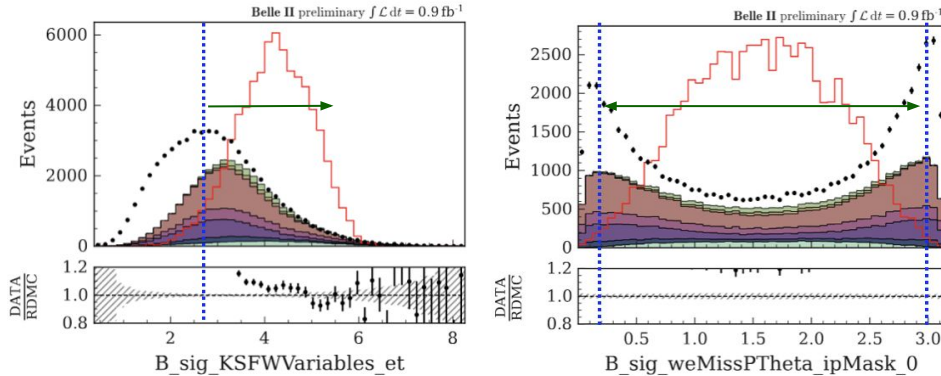
# Reject low-multiplicity tracks

e.g. KS0 channel

- Discrepancy in the low DeltaE range comes from the low-multiplicity tracks: **not well modeled in simulation**
- Reject using selections on event variables: angle of missing momentum direction and transverse energy

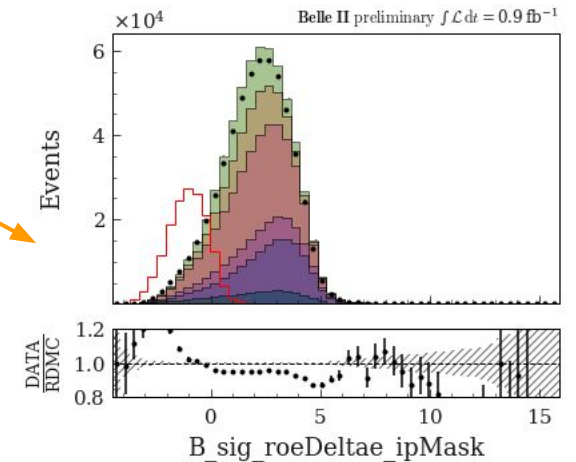


Zoomed in the low-multiplicity abundant region



Efficiency loss: 2.34%

→ Unify these selections for all channels: study ongoing



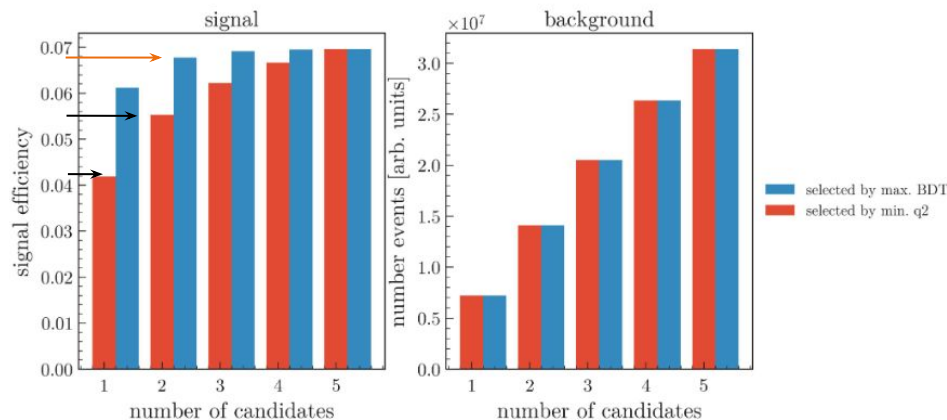
# Candidates selection strategy

Multi-candidates to improve the signal efficiency:

- KS0/K+:
  - Apply best candidate selection at the basic selection step  
-> BDT1, etc...
- K\*0/K\*+: postponed best candidate selection to a later stage
  - Two candidates at the basic selection step  
-> BDT1  
-> Background Suppression  
-> Best candidate selection at BDT2

e.g. multi-candidates in the K\*+ channel:

- Based on the BDT1 and  $q^2$  info
- Improved signal efficiency while keeping background level under control



Signal efficiency and background events in K\*+ channel as a function of multiple candidates

# Improvements related to D veto

Dominating background in signal region:

**K<sup>+</sup>, K<sub>S</sub><sup>0</sup>**: kaon from D

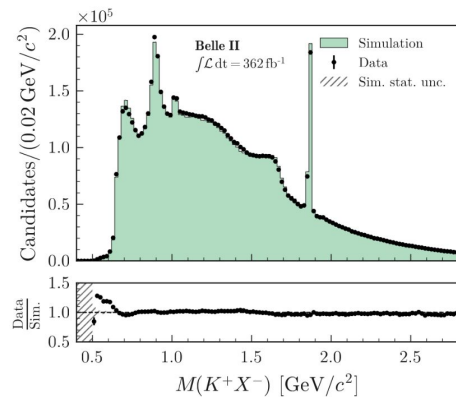
**K<sup>\*</sup>**: D → K<sup>\*</sup>X and combinatorial background (kaon from D)

Previously, we suppressed with the reconstructed D<sup>0</sup>/D<sup>+</sup> candidates:

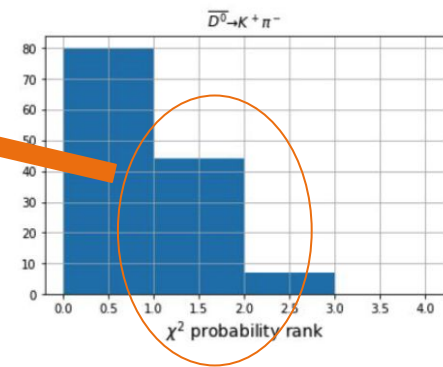
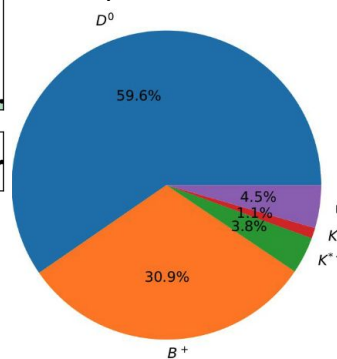
- (K<sub>S</sub><sup>0</sup>) D<sub>p</sub> → π<sup>+</sup>K<sub>S</sub>, D<sub>0</sub> → π<sup>+</sup>π<sup>-</sup>K<sub>S</sub>
- (K<sup>\*0</sup>) D<sub>p</sub> → K<sup>\*0</sup> e/μ, D<sub>0</sub> → K<sup>\*0</sup> π<sup>+</sup>π<sup>-</sup>, D<sub>0</sub> → K<sup>+</sup> X, D<sub>p</sub> → K<sup>\*0</sup> X
- (K<sup>\*+</sup>) D<sub>p</sub> → K<sup>\*+</sup> π<sup>+</sup>π<sup>-</sup>, D<sub>0</sub> → K<sup>\*+</sup> π<sup>-</sup>, D<sub>0</sub> → K<sup>\*-</sup> X, D<sub>p</sub> → K<sup>\*+</sup> X X (X: charged tracks)
- Keep candidate with highest vertex fitting chiProb : **can be improved**

Ongoing studies and developments for improvement:

- Detailed categorization of the background
- Exploration of new methods and additional variables for improving background suppression



Background composition of K<sup>+</sup> channel in charged B sample





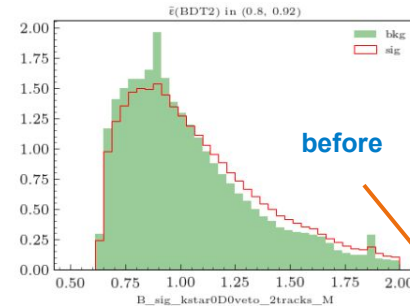
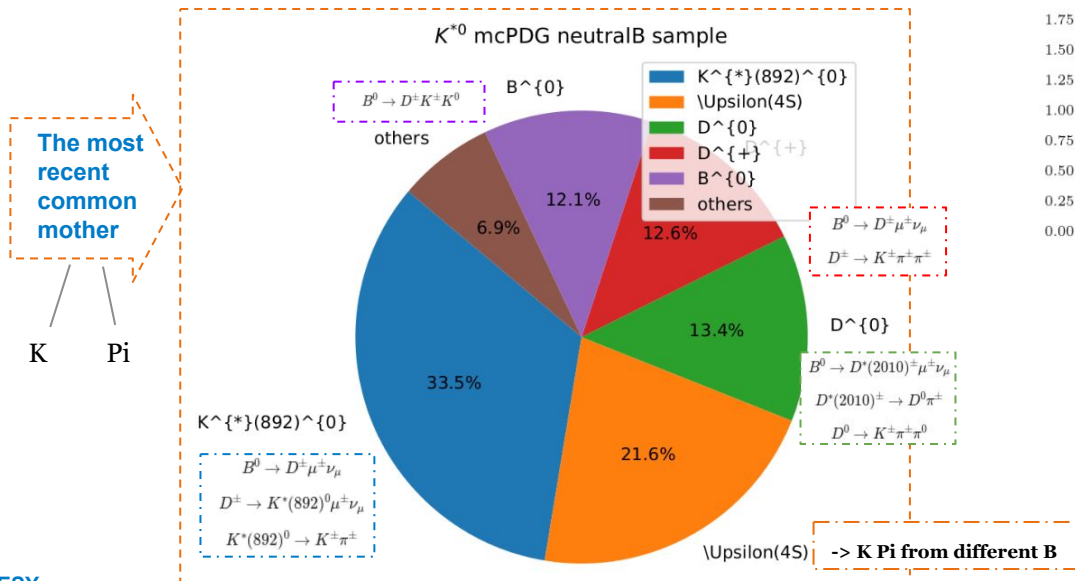
# Optimization of the D veto

e.g.  $K^*0$

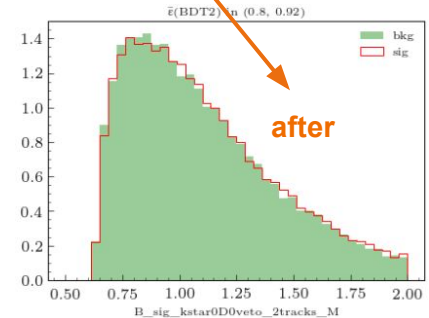
- 1) Background composition -> which particle is mimicking signal  $K^*0$
- 2) Veto strategy:
  - a) Reconstruct the particles mimicking  $K^*0$
  - b) Save and pass the variables to BDT2
- 3) Check the background composition again



Optimization is ongoing  
(also for other channels)

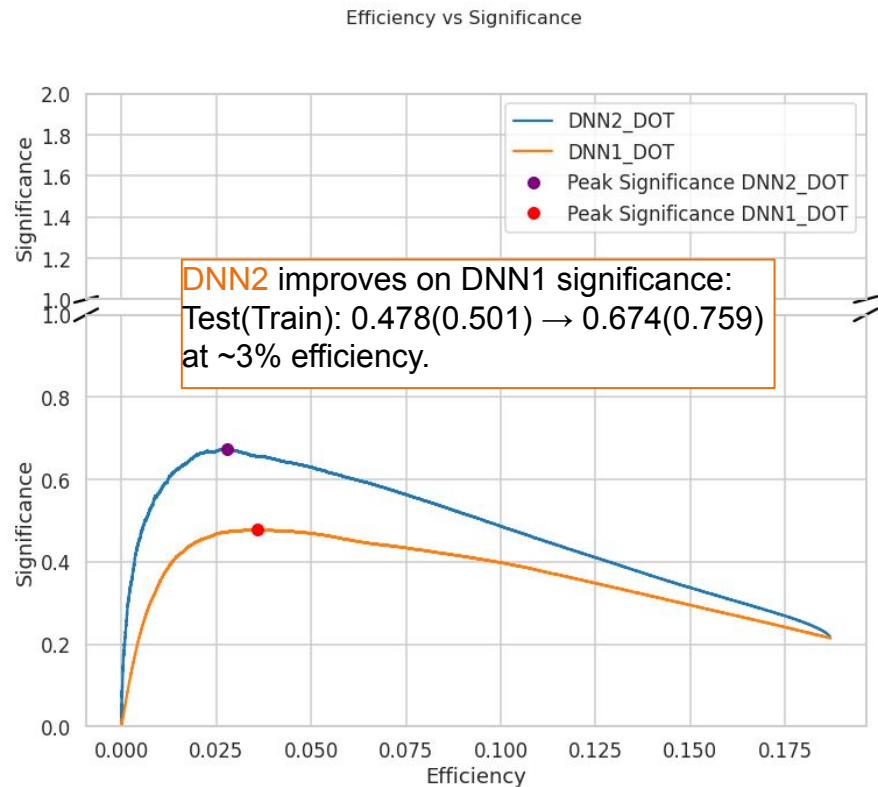


BDT2 retrained



# Explore other ML tools: DNN

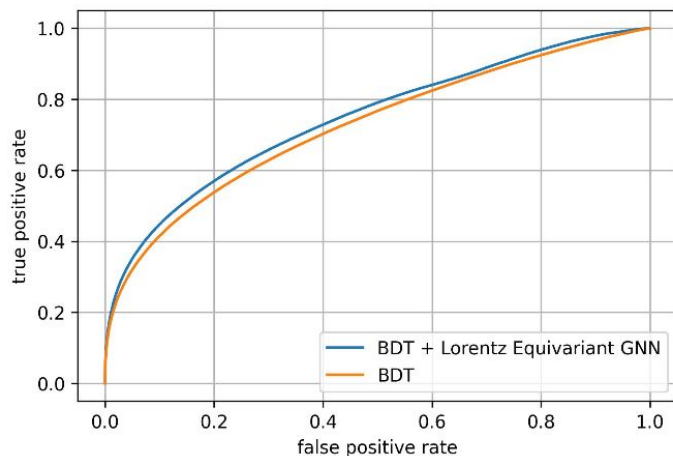
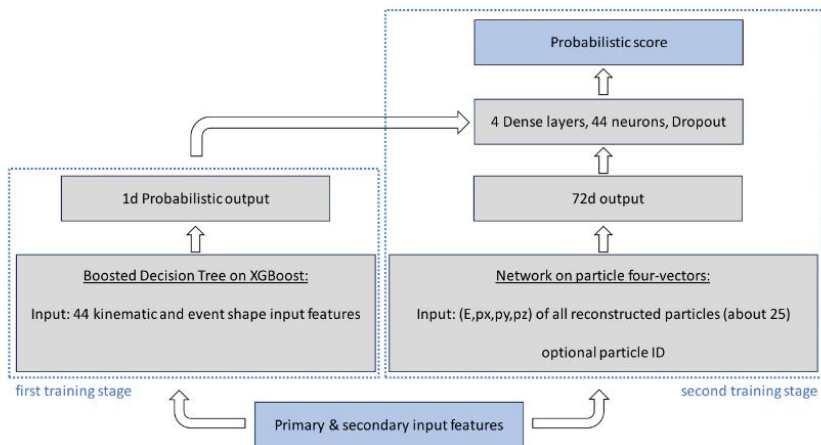
- Performance is being checked in **K\*0 channel**
  - Train **DNN1** and **DNN2** as potential alternatives to BDT1/BDT2
  - **Good discriminating power**
- **Promising starting point, can be further optimised in the future!**



# Explore new chance with new architecture

## BDT combined with Lorentz equivariant architecture

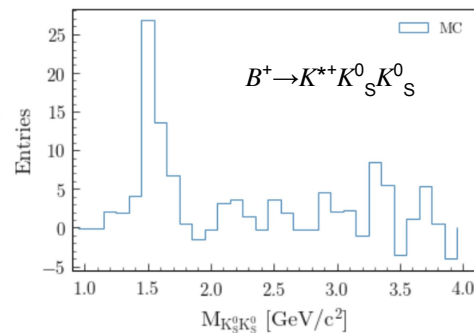
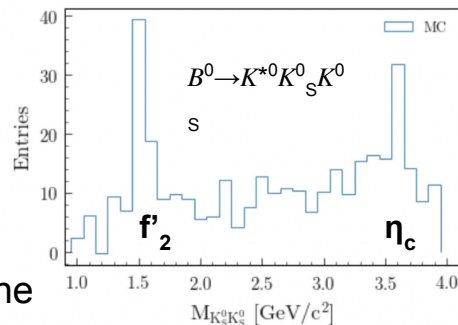
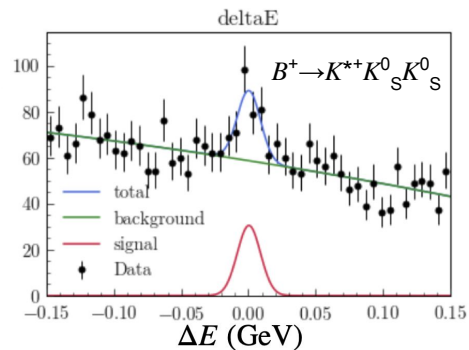
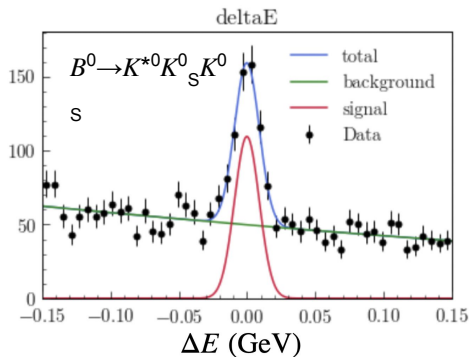
- Lorentz equivariant Net, similar to a GNN, respects the Lorentz group symmetries of 4-momenta
- Combine BDT1,2 and a LNN on particle 4-vectors for signal-background classification:
  - Looks promising with initial setup, and further investigation is ongoing ...
  - [Talk @EWP](#)



# Background from $B \rightarrow K^* K^0 K^0$

- $B \rightarrow K^* K^0 K^0$  can **mimic our signal**  
=> Essential to constrain and model them well
- Use  $B \rightarrow K^* K^0_S K^0_S$  decays to model  $B \rightarrow K^* K^0_L K^0_L$
- $B \rightarrow K^* K^0_S K^0_S$  have never been measured before  
=> **Measure them ourselves**
- For now, use generic  $400 \text{ fb}^{-1}$  MC15ri sample
  - Reconstruct  $B \rightarrow K^* K^0_S K^0_S$
  - Fit  $\Delta E$  distribution
  - Apply sPlot technique to obtain signal-only  $M(K^0_S K^0_S)$  distributions  
=> In simulation, prominent  $f'_2$  resonance  
=> However, no  $B \rightarrow K^* f'_2$  in PDG
  - Use the obtained model from data to reweight the phase space

=> Now preparing to look in data



# Modeling of K0K0K0

## Replace the relevant decays before BDT2 training

B0->KS0K0K0 is an important background for KS0 channel and not well modeled in simulation

=> highly **overestimated** in rel-06

=> **double counting** of K0K0K0 is fixed in rel-08

```
Belle2 Decay file (rel6)
1606 # PPP
1607 #
1608 0.000006200 K_S0 K_S0 K_S0 PHSP; #Measured, inclusive
1609 0.000006200 K_L0 K_L0 K_L0 PHSP; #Same as KsKsKs
1610 0.000007400 K_S0 K_S0 K_L0 PHSP; #UL
1611 0.000007400 K_S0 K_L0 K_L0 PHSP; #Same as KsKsKL
...
1030 0.000048000 K0 anti-K0 K0 PHSP; #Assume 8*BF(KsKsKs)~=48 (8 is a guess).
```



```
BF used to generate signal MC
0.000006000 K_S0 K_S0 K_S0 K0K0K0
0.000002460 K_S0 K_S0 K_L0 K0K0K0
0.000002460 K_S0 K_L0 K_L0 K0K0K0
```

(BarBar)  
[PhysRevD.85.054023](https://arxiv.org/abs/1505.05402)

- Correction before BDT2 training
  - ◆ Replace the relevant decays in generic simulation with K0K0K0 (Dalitz) and up-to-date branching fractions
  - ◆ B->Φ KL/KS is scaled to the latest PDG value
  - ◆ Improves background modeling

# Summary and outlook

The analyses follow a similar workflow as the last iteration:

- 1) Basic selection:
  - Basic event selection
  - Signal candidate selection
- 2) Main background suppression
  - BDT1 for event selection
  - Background suppression: e.g from D
  - Final selection using BDT2
- 3) Validation with the control channel
- 4) Statistic interpretation

**The analysis is progressing efficiently, with efforts aimed at improving various areas.**

**Target: moriond 2025**

# Where we were

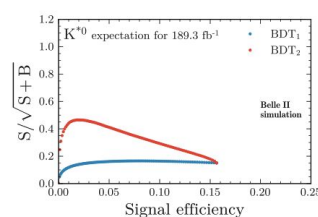
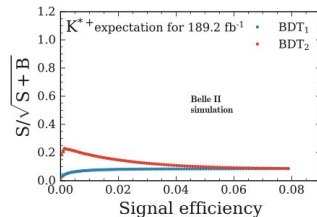
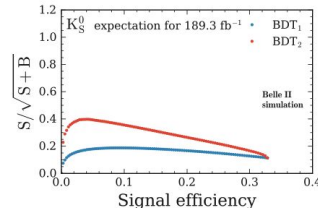
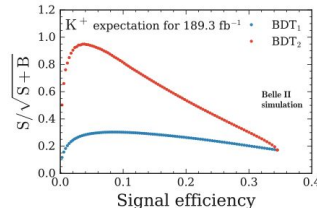
B<sup>+</sup> → K<sup>+</sup> nunu

Previously:

- B<sup>0</sup> → K<sup>\*0</sup>, B<sup>+</sup> → K<sup>\*+</sup> and B<sup>0</sup> → KS<sup>0</sup> were studied pretty detailed for Moriond 2022
- **Data sample:** (collected by summer 2021) 189.2 fb<sup>-1</sup> and 17.9 fb<sup>-1</sup> on- and off-resonance samples
- **MC14ri** samples
- The measurements were almost ready to be unblinded and code machinery is well developed

Follow similar workflow as last iteration:

- 1) Basic selection:
  - Signal candidate selection
  - Basic event selection
- 2) Main background suppression
  - BDT1 for event selection
  - Final selection using BDT2 or BDT2+GraphNN (K<sup>\*+</sup>)
- 3) Validation with control channel
- 4) Statistic interpretation



# Explore new chance with NN

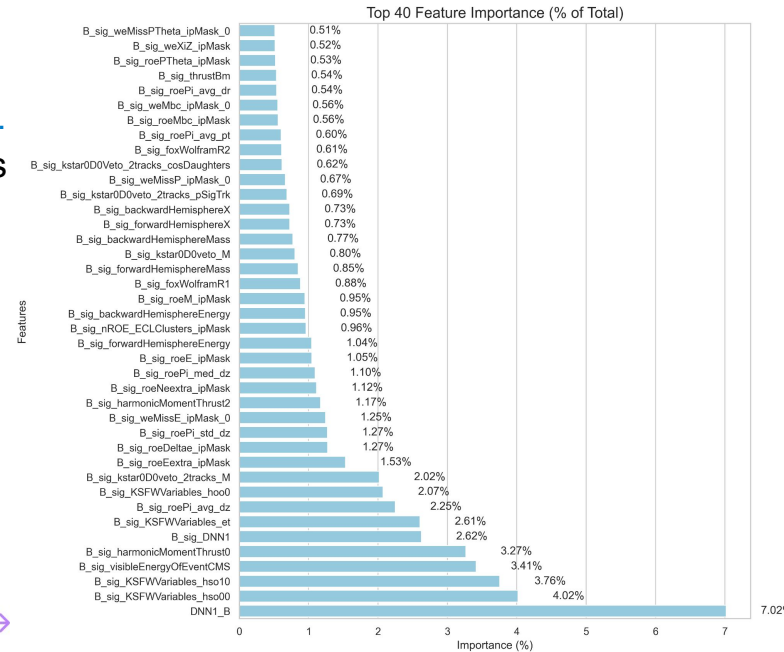
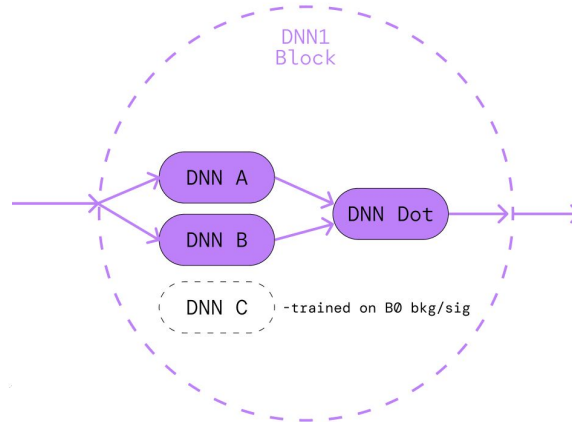
## DNN Architecture: 16 Layers, 279 Features.

```

1 class NeuralNetwork(nn.Module):
2     def __init__(
3         self,
4         input_dim,
5         hidden_layers=[1024, 512, 512, 256],
6         dropout_rate=0.4,
7         alpha=0.01, # for LeakyReLU
8     ):
9         super(NeuralNetwork, self).__init__()
10        self.input_dim = input_dim
11        self.hidden_layers = hidden_layers
12        self.dropout_rate = dropout_rate
13
14        layers = []
15        prev_dim = input_dim
16        for units in hidden_layers:
17            layers.extend(
18                [
19                    nn.Linear(prev_dim, units),
20                    nn.LeakyReLU(alpha),
21                    nn.BatchNorm1d(units),
22                    nn.Dropout(dropout_rate),
23                ]
24            )
25            prev_dim = units
26        layers.append(nn.Linear(prev_dim, 1))
27        self.model = nn.Sequential(*layers)
28
29    def forward(self, x):
30        return self.model(x)
31

```

- BatchNorm and Dropout layers reduce model overfitting.
- Use appropriate model complexity.
- ReLU family of activation functions fix vanishing gradient problem.
- DNN1 is composed of 3 models dnn1a, dnn1b and dnn1dot which combines their scores.

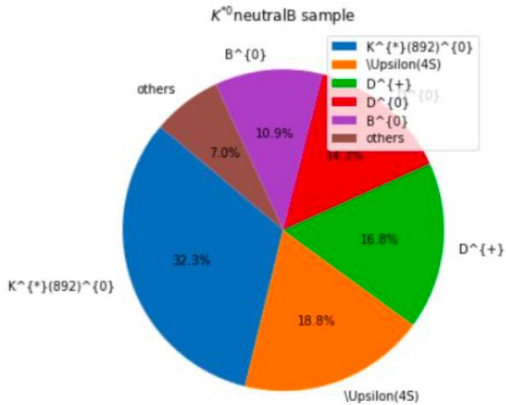




# Which particles(decays) mimic signal $K^0$ (decays) in neutral B background

BDT2 > 0.92

**D-veto**



formatted_dec	multiplicity
$\Upsilon(4S) \rightarrow D^*(2010)^{\pm} \mu^{\pm} \nu_{\mu}$	0.091503
$\Upsilon(4S) \rightarrow D^*(2010)^{\pm} e^{\pm} \nu_e$	0.069350
$\Upsilon(4S) \rightarrow D^*(2010)^{\pm} \tau^{\pm} \nu_{\tau}$	0.045198
$\Upsilon(4S) \rightarrow D^{\pm} \mu^{\pm} \nu_{\mu}$	0.031073
$\Upsilon(4S) \rightarrow D^*(2010)^{\pm} \tau^{\pm} \nu_{\tau}$	0.028249
$\Upsilon(4S) \rightarrow D^*(2010)^{\pm} e^{\pm} \nu_e \gamma$	0.028249
$B^0 \rightarrow D^{\pm} K^{\pm} K^0$	0.045198
$B^0 \rightarrow D^*(2010)^{\pm} e^{\pm} \nu_e$	0.031073
$B^0 \rightarrow D^*(2010)^{\pm} \tau^{\pm} \nu_{\tau}$	0.028249
$B^0 \rightarrow D^{\pm} \tau^{\pm} \nu_{\tau}$	0.028249
$B^0 \rightarrow D^*(2010)^{\pm} K^{\pm} K^0$	0.028249

currently no idea

formatted_dec	multiplicity
$B^0 \rightarrow D^{\pm} \mu^{\pm} \nu_{\mu}$	0.040913
$D^{\pm} \rightarrow K^*(892)^0 \mu^{\pm} \nu_{\mu}$	0.040913
$K^*(892)^0 \rightarrow K^{\pm} \pi^{\pm}$	0.040913
$B^0 \rightarrow D^{\pm} \mu^{\pm} \nu_{\mu}$	0.035205
$D^{\pm} \rightarrow K^*(892)^0 e^{\pm} \nu_e$	0.035205
$K^*(892)^0 \rightarrow K^{\pm} \pi^{\pm}$	0.035205
$B^0 \rightarrow K^0 K^0 K^*(892)^0$	0.030447
$K^*(892)^0 \rightarrow K^{\pm} \pi^{\pm}$	0.030447
$B^0 \rightarrow D^{\pm} e^{\pm} \nu_e$	0.029496
$D^{\pm} \rightarrow K^*(892)^0 e^{\pm} \nu_e$	0.029496
$K^*(892)^0 \rightarrow K^{\pm} \pi^{\pm}$	0.029496

$B^0 \rightarrow D^{\pm} \mu^{\pm} \nu_{\mu}$	0.023787
$D^{\pm} \rightarrow K^*(892)^0 \pi^{\pm} \pi^0$	0.023787
$K^*(892)^0 \rightarrow K^{\pm} \pi^{\pm}$	0.023787

true  $K^0$  from  $D \rightarrow K^0 l \nu$ :  
 new possible veto:  
 $K^0$ :sig + ml lepton/pion

formatted_dec	multiplicity
$B^0 \rightarrow D^{\pm} \mu^{\pm} \nu_{\mu}$	0.170330
$D^{\pm} \rightarrow K^{\pm} \pi^{\pm} \pi^{\pm}$	0.170330
$B^0 \rightarrow D^{\pm} e^{\pm} \nu_e$	0.093407
$D^{\pm} \rightarrow K^{\pm} \pi^{\pm} \pi^{\pm}$	0.093407
$B^0 \rightarrow D^{\pm} e^{\pm} \nu_e \gamma$	0.049451
$D^{\pm} \rightarrow K^{\pm} \pi^{\pm} \pi^{\pm}$	0.049451
$B^0 \rightarrow D^*(2010)^{\pm} \mu^{\pm} \nu_{\mu}$	0.045788
$D^*(2010)^{\pm} \rightarrow D^{\pm} \pi^0$	0.045788
$D^{\pm} \rightarrow K^{\pm} \pi^{\pm} \pi^{\pm}$	0.045788
$B^0 \rightarrow D^{\pm} \tau^{\pm} \nu_{\tau}$	0.042125
$D^{\pm} \rightarrow K^{\pm} \pi^{\pm} \pi^{\pm}$	0.042125

new possible veto:  
 $D_p \rightarrow (\text{sig}) K + 2(\text{roe}) \pi$

formatted_dec	multiplicity
$B^0 \rightarrow D^*(2010)^{\pm} \mu^{\pm} \nu_{\mu}$	0.126882
$D^*(2010)^{\pm} \rightarrow D^0 \pi^{\pm}$	0.126882
$D^0 \rightarrow K^{\pm} \pi^{\pm} \pi^0$	0.126882
$B^0 \rightarrow D^*(2010)^{\pm} e^{\pm} \nu_e$	0.070968
$D^*(2010)^{\pm} \rightarrow D^0 \pi^{\pm}$	0.070968
$D^0 \rightarrow K^{\pm} \pi^{\pm} \pi^0$	0.070968
$B^0 \rightarrow D^*(2010)^{\pm} \mu^{\pm} \nu_{\mu} \gamma$	0.032258
$D^*(2010)^{\pm} \rightarrow D^0 \pi^{\pm}$	0.032258
$D^0 \rightarrow K^{\pm} \pi^{\pm} \pi^0$	0.032258
$B^0 \rightarrow D^*(2010)^{\pm} e^{\pm} \nu_e \gamma$	0.030108
$D^*(2010)^{\pm} \rightarrow D^0 \pi^{\pm}$	0.030108
$D^0 \rightarrow K^{\pm} \pi^{\pm} \pi^0$	0.030108
$B^0 \rightarrow D^*(2010)^{\pm} \tau^{\pm} \nu_{\tau}$	0.030108
$D^*(2010)^{\pm} \rightarrow D^0 \pi^{\pm}$	0.030108
$D^0 \rightarrow K^{\pm} \pi^{\pm} \pi^0$	0.030108

new possible veto:  
 $D^0 \rightarrow (\text{sig}) K (\text{roe}) \pi \pi^0$

# Basic selection

e.g.  $K^*0$  channel

- Signal selection efficiency drops a lot for  $K^*0$  channels (initial starting point)
  - Good tracks:  $|dr| < 0.5$  cm,  $|dz| < 3$  cm,  $p_T > 0.1$  GeV/c,  $E < 5.5$  GeV,  $\theta \in \text{CDC}$
  - Cuts on inv.mass of  $K^*0$
  - $\text{KaonID} > 0.9$ : reduce the multiplicity
  - Number of PXD hits: accurate vertex
  - Best candidate selection

Selection efficiency drops from 45.6% to 23.7%

	efficiency	candidate multiplicity
Track clean up	45.6%	13.9
+ $0.8 < K_{\text{star\_M}} < 1.0$	39.7%	5.2
+ $K_{\text{star\_K\_kaonID}} > 0.9$	30.2%	1.8
+ $K_{\text{star\_K\_nPXDHits}} > 0$	28.7%	1.8
+ $K_{\text{star\_Pi\_nPXDHits}} > 0$	27.4%	1.7
+ Best candidate (lowest $q_2$ )	23.7%	1.0

