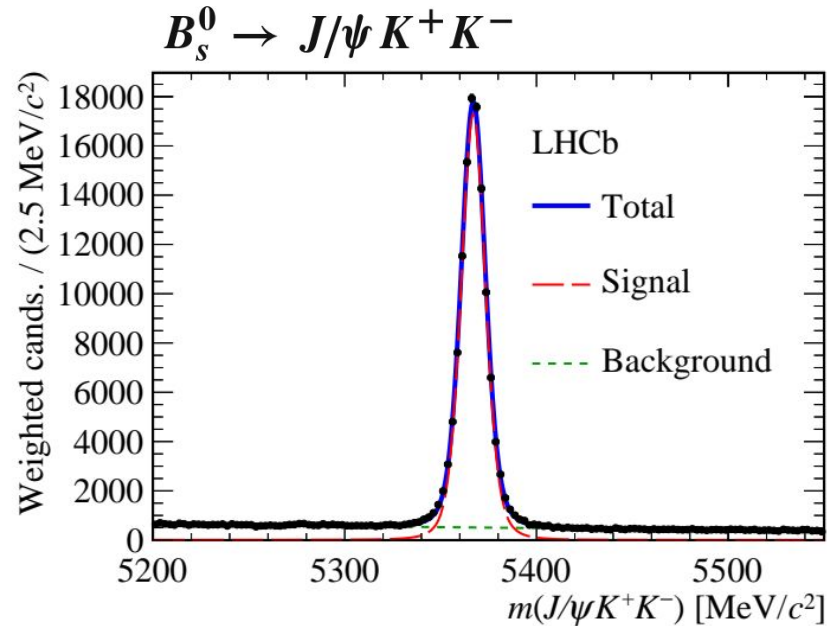
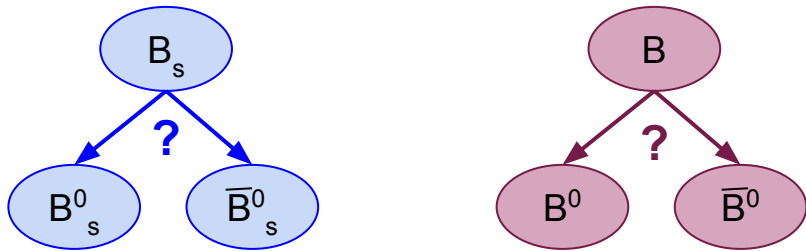


# Fast Inclusive Flavo(u)r Tagging at LHCb

Christoph Hasse, Niklas Nolte, Claire Prouve  
Flavour Tagging Working Group

# Flavour Tagging at LHCb

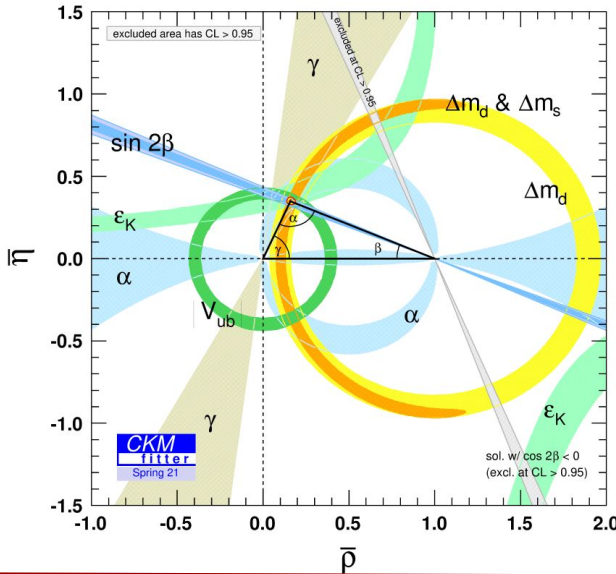
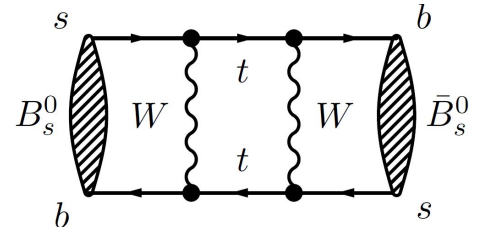
Determining the **flavour** at **production** of neutral B mesons



# Example: $B_s$ meson oscillation

- Neutral  $s, c, b$  mesons can mix into their anti-particles
- Flavour eigenstates  $B_s^0$  and  $\bar{B}_s^0$  are linear combinations of the mass eigenstates  $B_H$  and  $B_L$
- Oscillation frequency  $\Delta m_s = m_H - m_L$  provides powerful constraint on CKM triangle

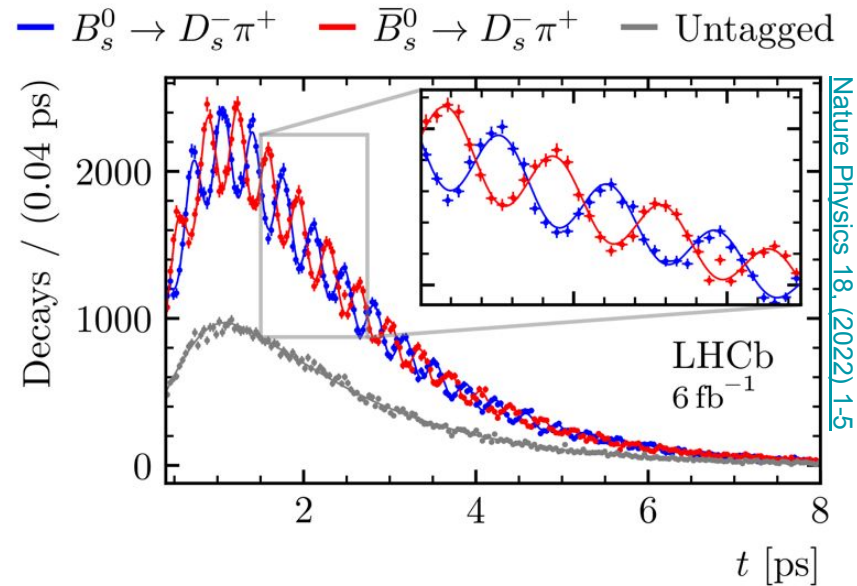
$$P(t) \sim e^{-\Gamma_{st} t} \left[ \cosh \left( \frac{\Delta \Gamma_{st} t}{2} \right) + C \cdot \cos(\Delta m_s t) \right]$$



# Example: $B_s$ meson oscillation

- Reconstruct the  $B_s$  in a flavour-specific final state
- Flavour-tag the  $B_s$  at production
- Measure and fit the decay time distributions

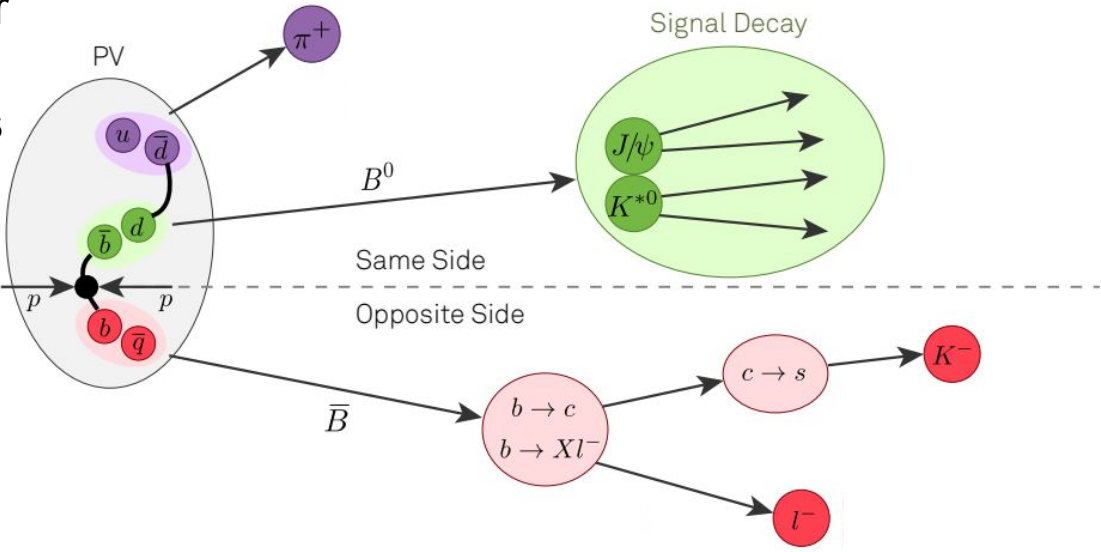
$$P(t) \sim e^{-\Gamma_s t} \left[ \cosh\left(\frac{\Delta\Gamma_s t}{2}\right) + C \cdot \cos(\Delta m_s t) \right]$$



# Flavour Tagging

Opposite side B decay:

- 24% of events have that  $b\bar{b}$  pair in the LHCb acceptance
- look for decay product that tags the other (opposite side) B meson



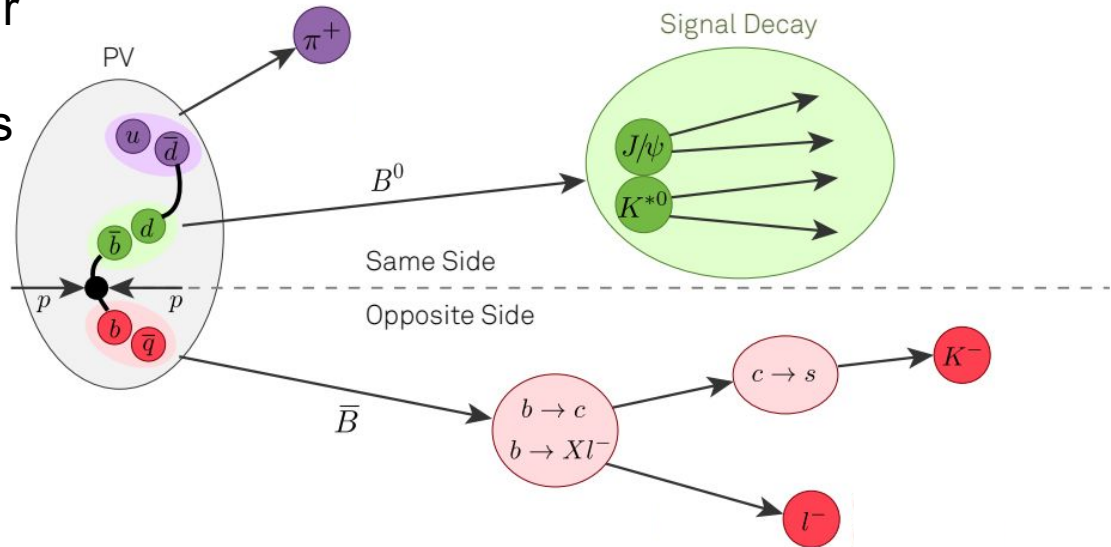
# Flavour Tagging

## Opposite side B decay:

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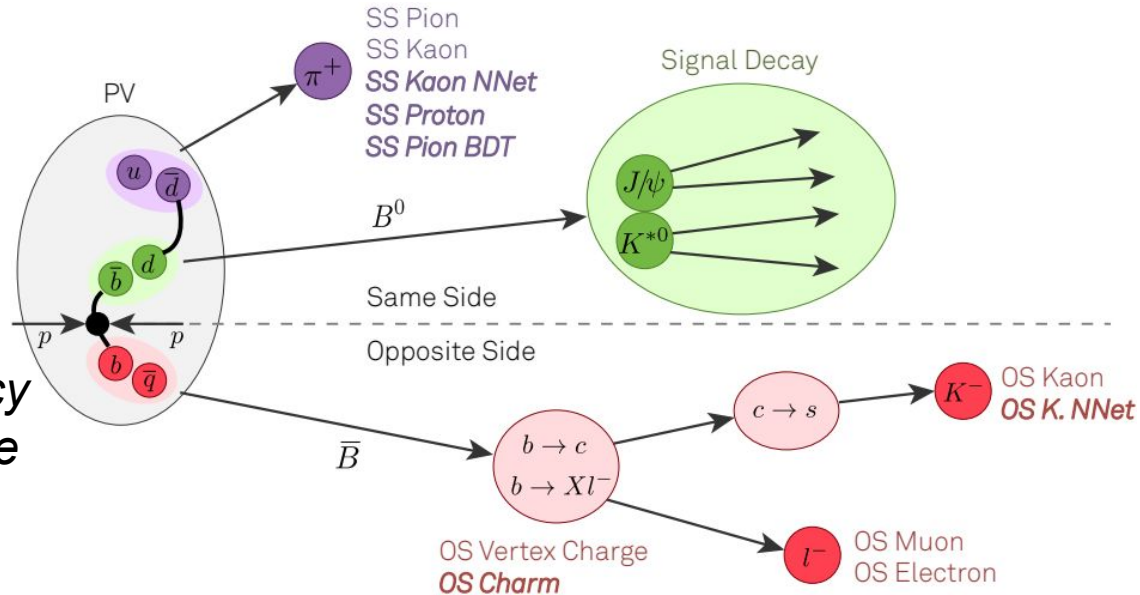
## Same side information:

- additional particles are created during the fragmentation process
- 50% of B are accompanied by a charged pion, 50% of  $B_s$  by a charged kaon



# Classical Taggers

- one tagger per final state species
- selection to find the “tagging particle”
- MVA (usually BDT) to evaluate mistag rate
- low tagging efficiency (*efficiency that a tagging decision could be made*)
- several taggers are combined by picking the one with the smallest predicted mistag

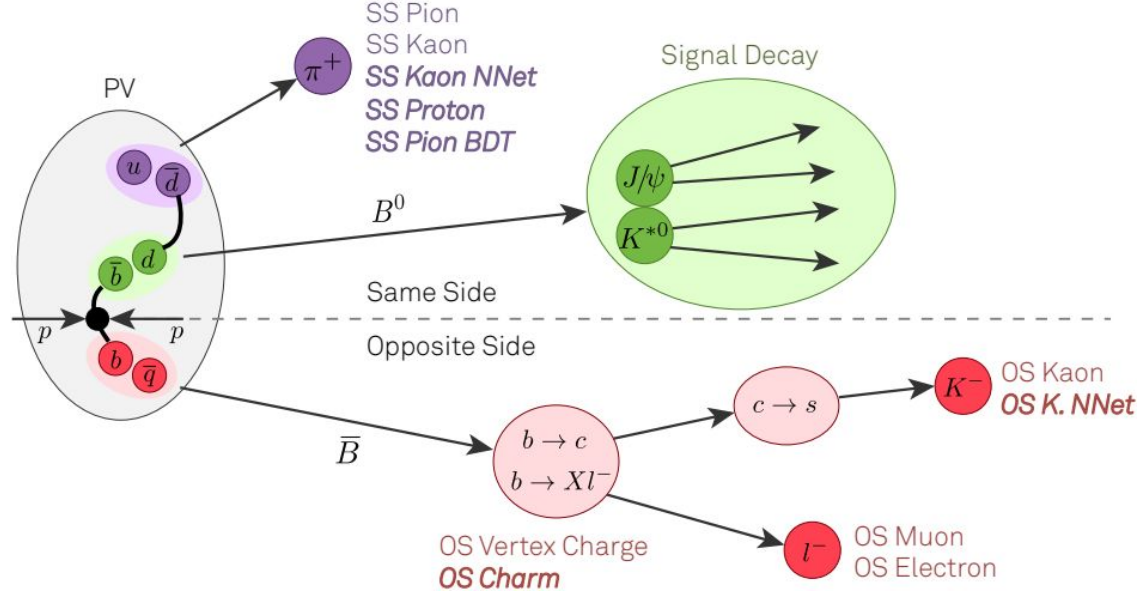


# Inclusive Taggers

- can consider all tracks in the event

Requirements:

- variable number of inputs (number of tracks varies by event)
- permutation invariant
- fast to train and apply for eventual use in real-time environment



RNN inclusive tagger had good performance but was very slow to train/apply, needed input to be sorted and of fixed length



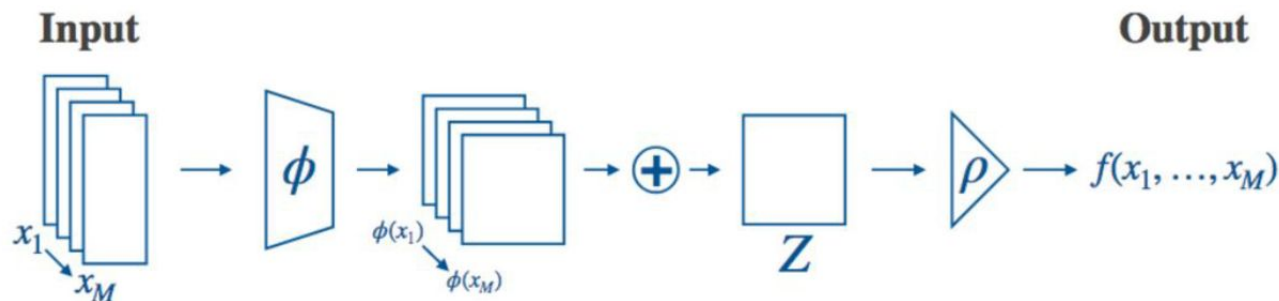
# DeepSet Neural Network

- “every instance (particle) is transformed (possibly by several layers) into some representation  $\phi$ ”
- “the representations  $\phi$  are added up and the output is processed using the  $\rho$  network”

→ permutation invariant, component per particle, component for entire event

→ ~hour to train (while RNN ~days)

→ ~7 $\mu$ s per event to evaluate (while RNN ~5h for 3M events)



# Performance - metrics

**Tagging efficiency  $\epsilon$** : fraction of events that have a tagging decision (not necessarily that the tagging decision is correct)

**Mistag rate/probability  $\omega$** : fraction of events that have a wrong tagging decision / probability that a tagging decision is wrong

**Tagging power  $\epsilon_{\text{eff}} = \epsilon (1 - 2 \cdot \omega)^2$** : statistical precision of the sample

# Performance - Run 2 MC

$B^0 \rightarrow J/\psi K^{*0}$	$\epsilon$	$\epsilon_{\text{eff}}$
OS Combination	38.5 %	3.81 %
SS Combination	80.1 %	1.71 %
<b>Combination</b>	87.0 %	<b>5.39 %</b>

$B^+ \rightarrow J/\psi K^+$	$\epsilon$	$\epsilon_{\text{eff}}$
OS Combination	38.2 %	3.94 %
SS Kaon	67.7 %	1.22
SS Pion	69.9 %	3.94 %
<b>Combination</b>	92.0 %	<b>6.39 %</b>

$B^0 \rightarrow J/\psi K^{*0}$	$\epsilon$	$\epsilon_{\text{eff}}$
<b>DeepSet</b>	100 %	<b>6.38 %</b>

$B^+ \rightarrow J/\psi K^+$	$\epsilon$	$\epsilon_{\text{eff}}$
<b>DeepSet</b>	100 %	<b>8.0 %</b>

$B_s \rightarrow D_s \pi^-$	$\epsilon$	$\epsilon_{\text{eff}}$
<b>DeepSet</b>	100 %	8.7 %

**~ 20 - 25% increase in tagging power wrt classical taggers**

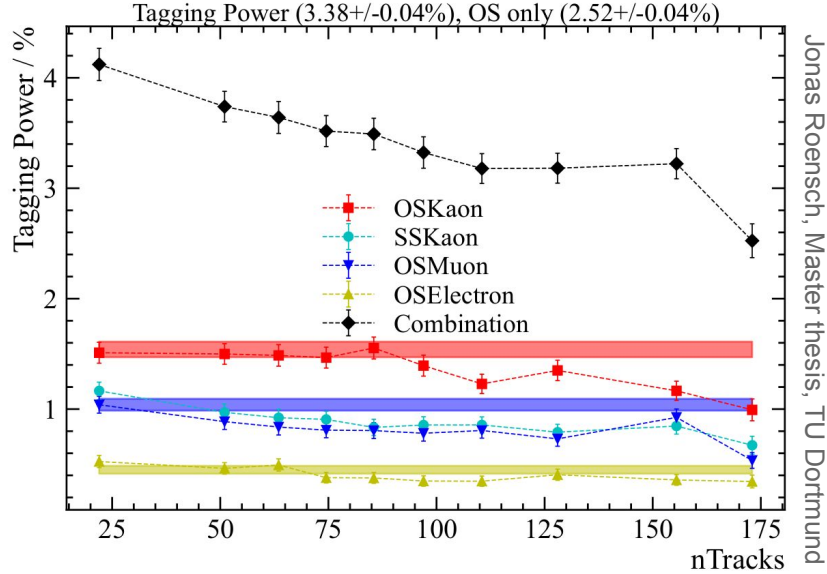
# Performance - Run 3 MC

$B^+ \rightarrow J/\psi K^+$  ( $\mu \sim 7$ )

Tagging algorithm	$\epsilon_{\text{tag}}/\%$	$\bar{\omega}/\%$	$\epsilon_{\text{tag,eff}}/\%$
OSElectron	62.25 $\pm$ 0.06	48.52 $\pm$ 0.08	0.40 $\pm$ 0.03
OSKaon	63.06 $\pm$ 0.06	44.61 $\pm$ 0.08	1.54 $\pm$ 0.03
OSMuon	57.36 $\pm$ 0.06	46.76 $\pm$ 0.09	0.81 $\pm$ 0.02
SSKaon	90.09 $\pm$ 0.04	47.13 $\pm$ 0.07	0.73 $\pm$ 0.02
SSPion	99.9983 $\pm$ 0.0017	47.1 $\pm$ 0.2	0.37 $\pm$ 0.05
SSProton	99.683 $\pm$ 0.007	46.79 $\pm$ 0.07	0.77 $\pm$ 0.04
Combination	100 $\pm$ 0	42.7 $\pm$ 0.2	3.75 $\pm$ 0.15

$B^+ \rightarrow J/\psi K^+$	$\epsilon$	$\epsilon_{\text{eff}}$
DeepSet	100 %	6.36 %
DeepSet presel.	100 %	6.83 %

only use particles associated to the same PV



big increase in tagging power wrt classical taggers (but classical taggers maybe not be optimally trained yet)

# Summary

- Flavour tagging at LHCb is essential for meson mixing measurement and time-dependent CP violation measurements
- Flavour tagging algorithms exploits information from particles that are created with the signal particles
- DeepSet NN can take varying number of tracks, is permutation invariant, fast and yields increased performance wrt the classical taggers
- Possible improvements for Run 3 by cleaning the input
- Looking forward to testing on data :D