Inclusive Flavour Tagging at LHCb

FSP Meeting Bonn
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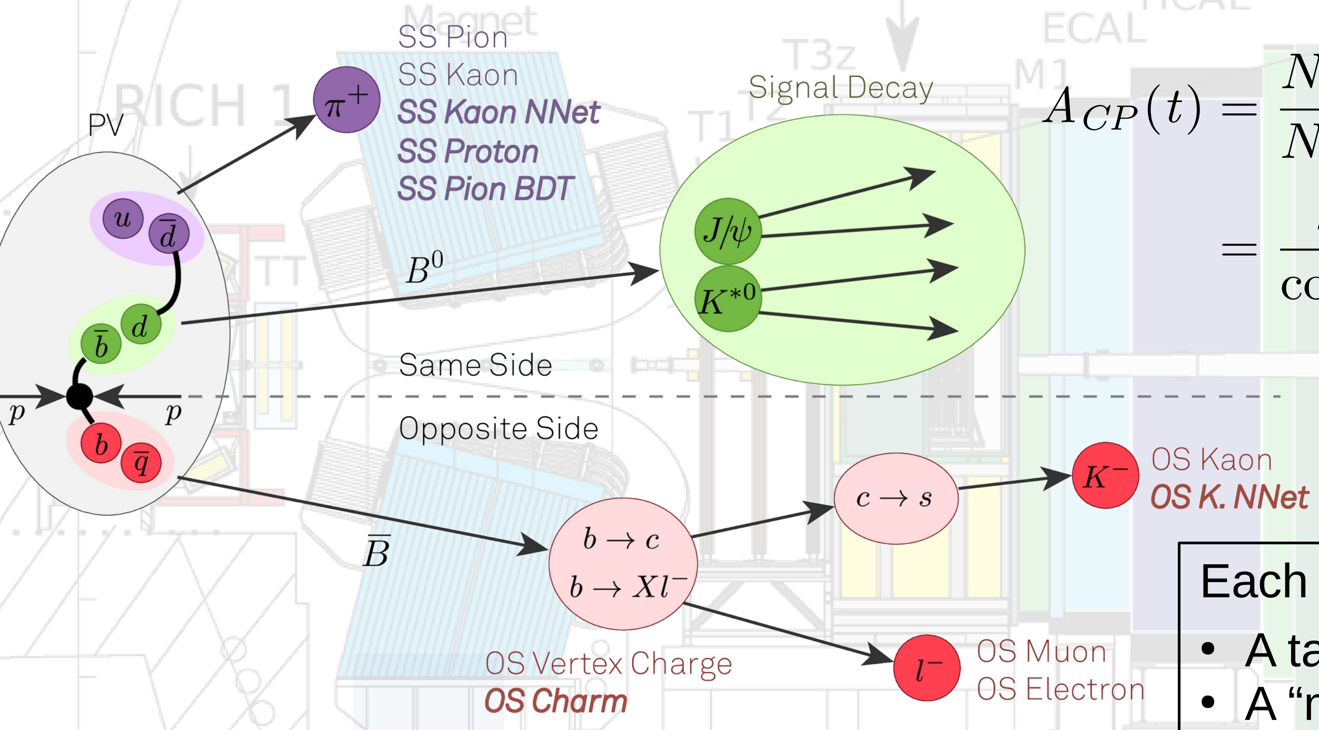
on behalf of the Flavour Tagging working group

Technische Universität Dortmund

Flavour Tagging Technique

Time dependent measurements of mixing parameters / CP violation require knowledge about initial B flavour



$$A_{CP}(t) = \frac{N(\bar{B}^0 \to f)(t) - N(B^0 \to f)(t)}{N(\bar{B}^0 \to f)(t) + N(B^0 \to f)(t)} = \frac{S_f \sin(\Delta m_q t) - C_f \cos(\Delta m_q t)}{\cosh(\frac{1}{2}\Delta\Gamma_q t) + \mathcal{A}_{\Delta\Gamma} \sinh(\frac{1}{2}\Delta\Gamma_q t)}$$

Each tagging algorithm provides:

- A tag decision (b or $\bar{b}$ or unknown)
- A “mistag probability” η

Flavour Tagging Technique

$$A_{CP}^{\text{measured}}(t) = \frac{N(\bar{B}^0 \to f)(t) - N(B^0 \to f)(t)}{N(\bar{B}^0 \to f)(t) + N(B^0 \to f)(t)}$$

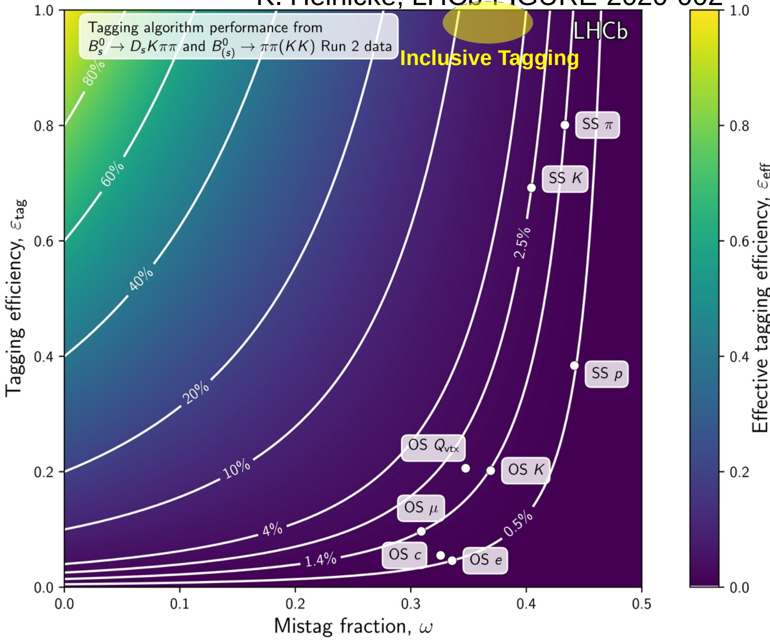
$$= (1 - 2\omega) A_{CP}^{\text{true}}(t)$$

$$\omega = \frac{N_{\text{wrong}}}{N_{\text{wrong}} + N_{\text{right}}} \qquad \varepsilon_{\text{tag}} = \frac{N_{\text{right}} + N_{\text{wrong}}}{N_{\text{tot}}}$$

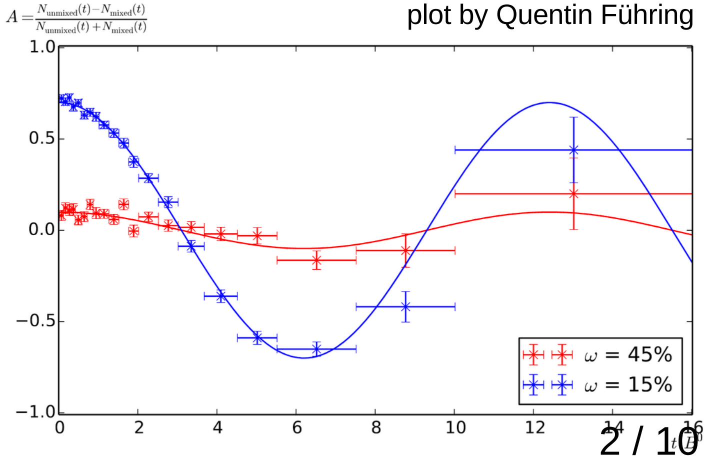
Measurement sensitivity:

$$\sigma^{-1}_{A_{CP}^{\text{true}}} \propto \sqrt{\varepsilon_{\text{tag}}(1 - 2\omega)^2 N} = \sqrt{\varepsilon_{\text{eff}} N}$$

K. Heinicke, LHCb-FIGURE-2020-002

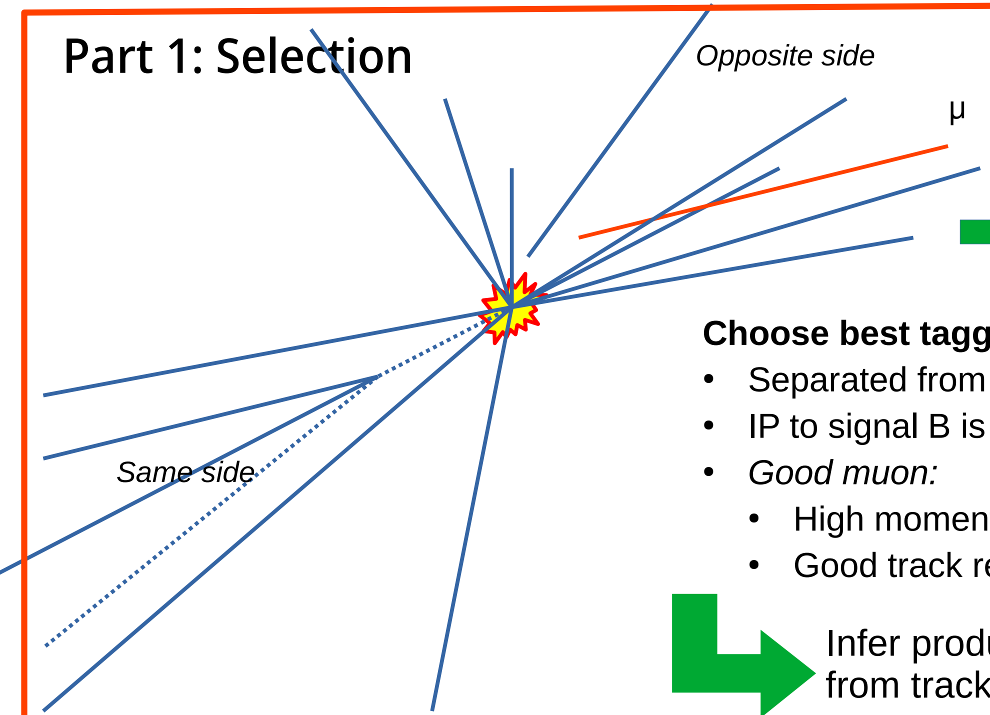


plot by Quentin Führing



Standard Flavour Tagging Approach Example
The opposite side muon tagger

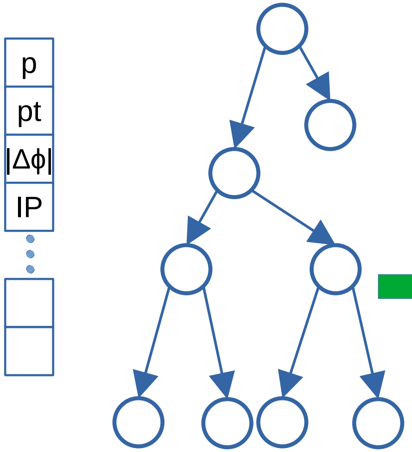
Part 1: Selection



Choose best tagging muon:
- Separated from signal in phi
- IP to signal B is large
- *Good muon:*
  - High momentum
  - Good track reconstruction

Infer production flavour from track charge

Part 2: Tagging via BDT



Mistag probability
η

Inclusive Tagging Approach

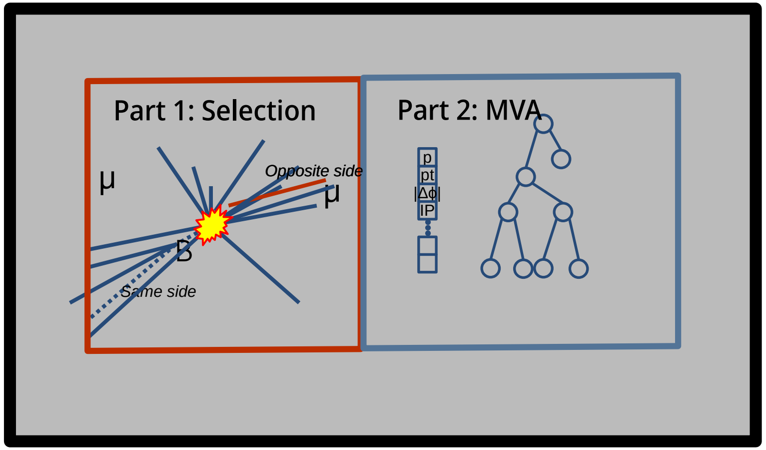
Full event interpretation

Full event

i.e. **all reconstructed tracks** with union of all single tagger track features including

- **Track charge**
- Particle identification
- Track momenta
- Topological information like
  - Phi + eta angle difference w.r.t. B meson

"Inclusive Tagger"



Tag decision

Mistag probability

(d, η)

This idea is not completely new, but has never been fully implemented / optimized for LHCb

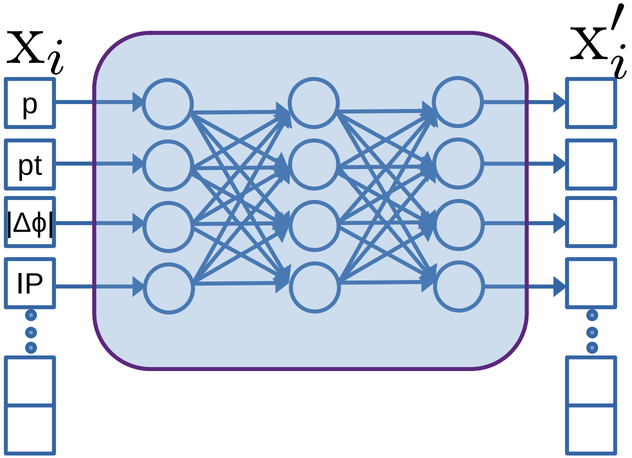
- T. Likhomanenko, D. Derkach, A. Rogozhnikov: "*Inclusive Flavour Tagging Algorithm*", ***J. Phys. Conf. Ser.*** *762 (2016) 012045*

The network architecture was then further optimized by

- *S. Akar, A. Camboni, D. P. O'Hanlon, B. Khanji* ***et al.*** → *Usage of long-short-term-memory units*

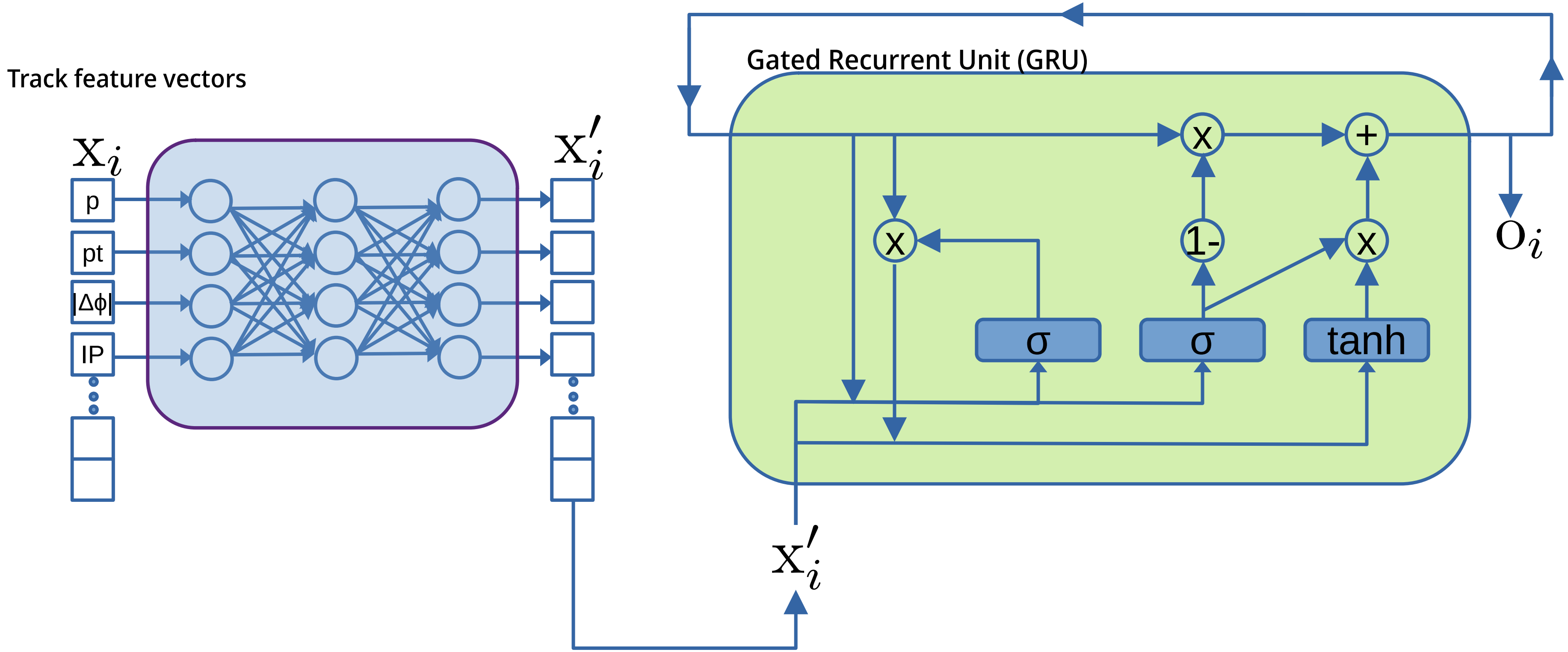
Current Inclusive Tagger Architecture

Track feature vectors

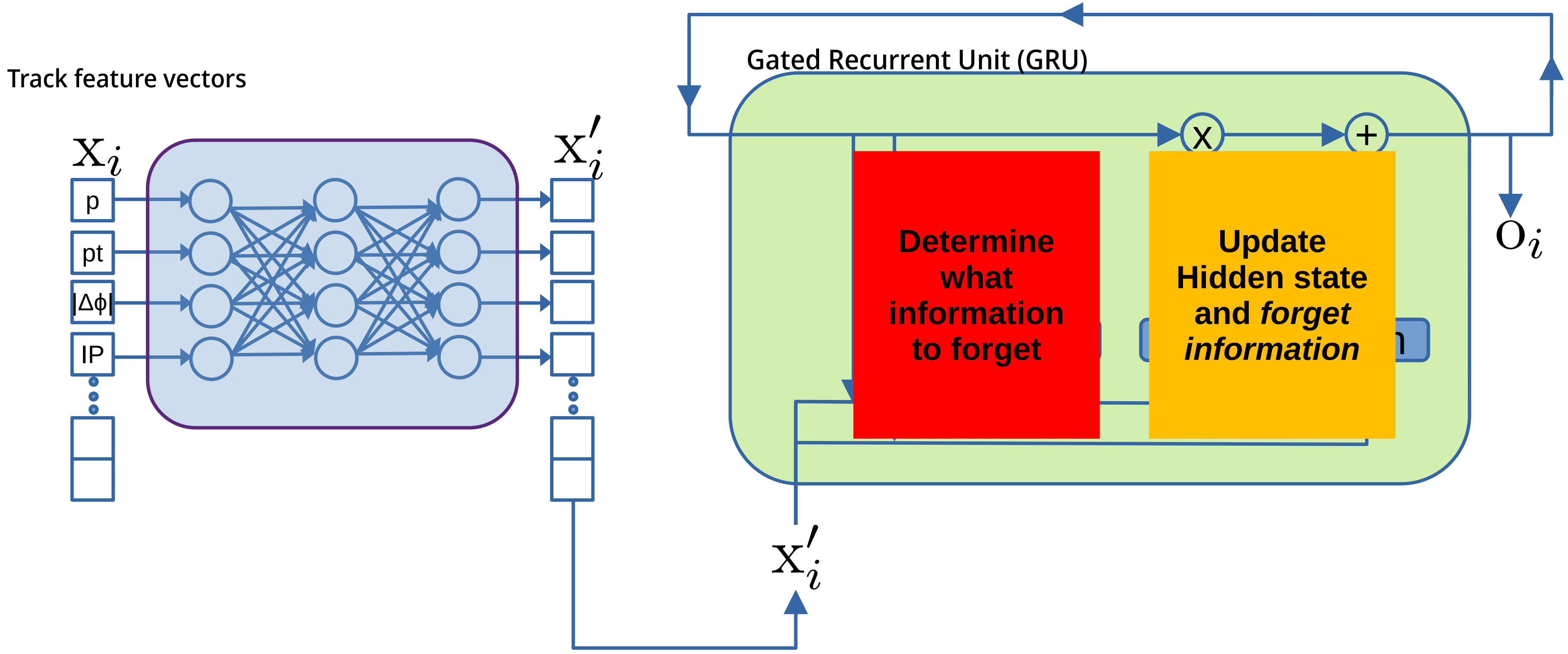


S. Akar
D. P. O'Hanlon
V. Chobanova
Q. Führing
M. Schiller
V. J.

Current Inclusive Tagger Architecture



Current Inclusive Tagger Architecture



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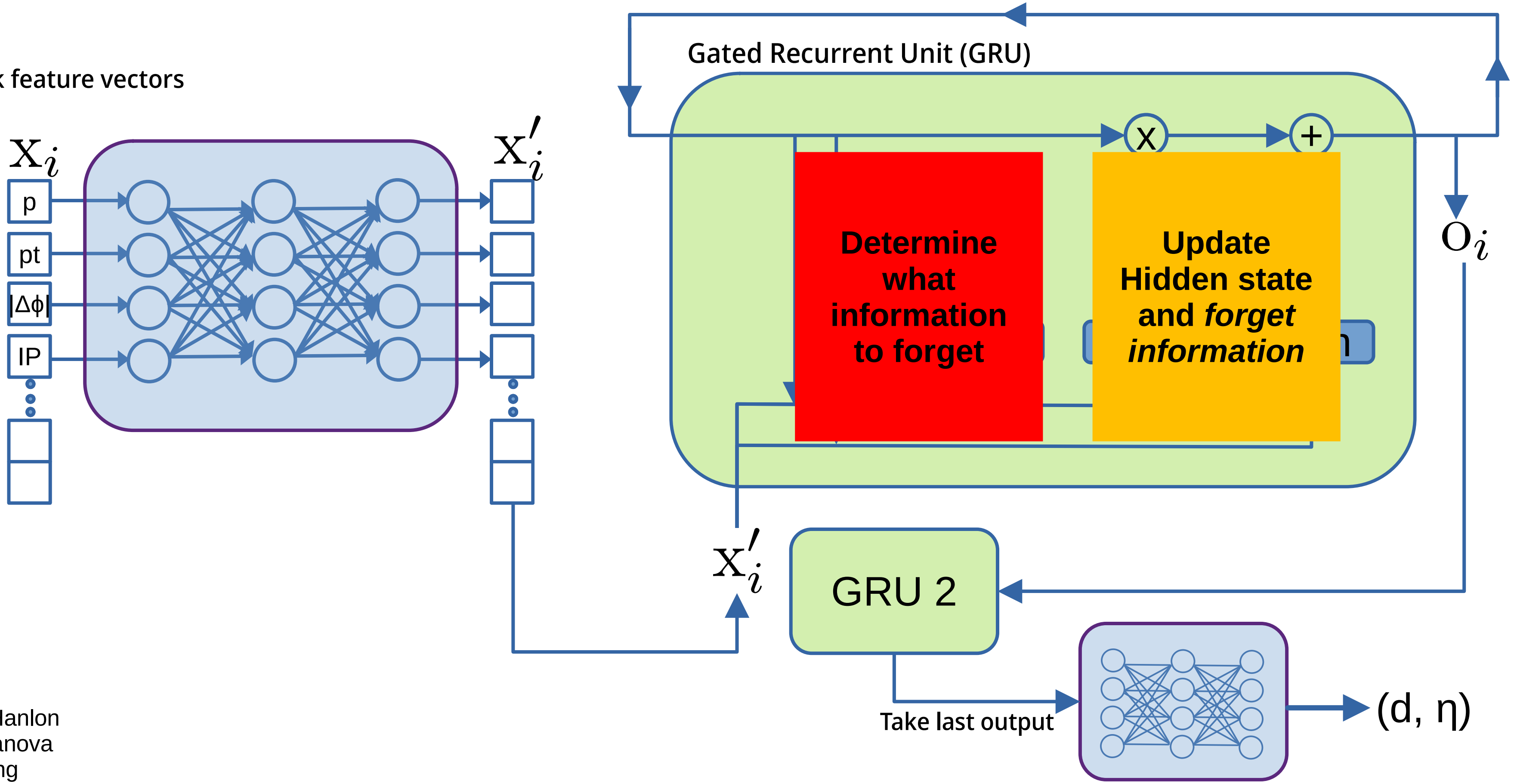
Current Inclusive Tagger Architecture



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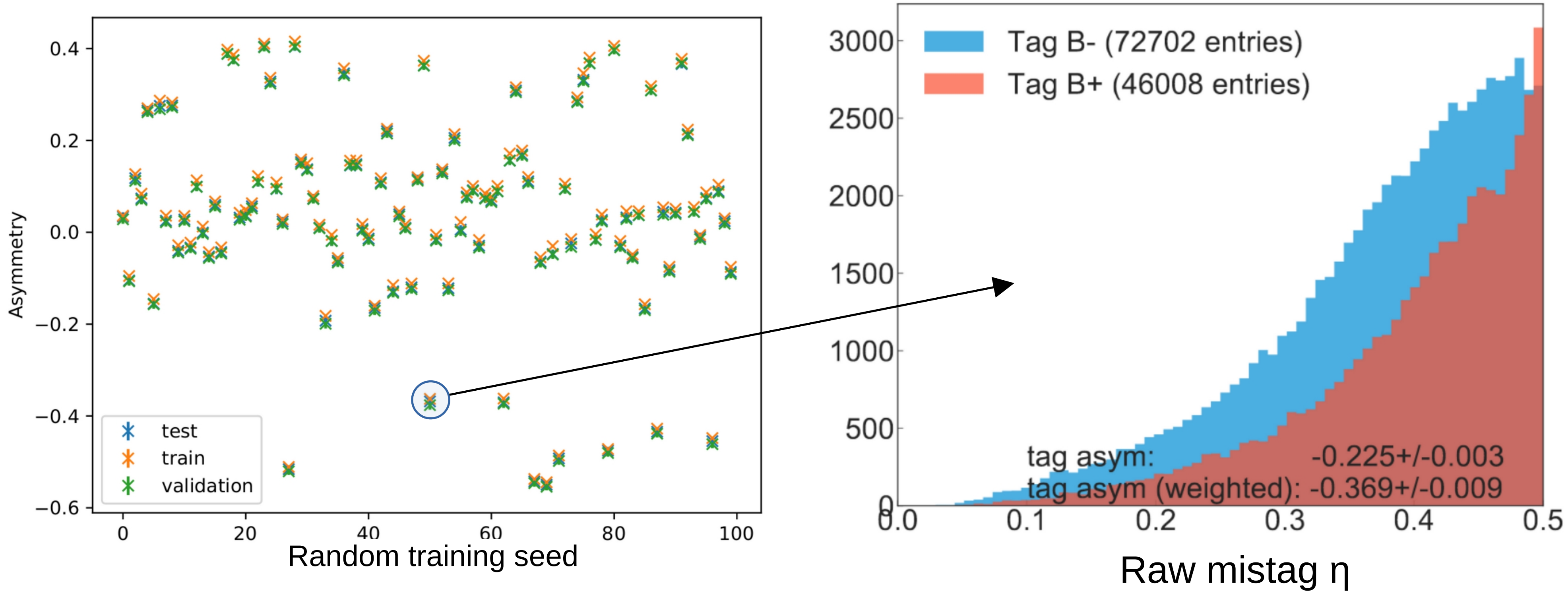
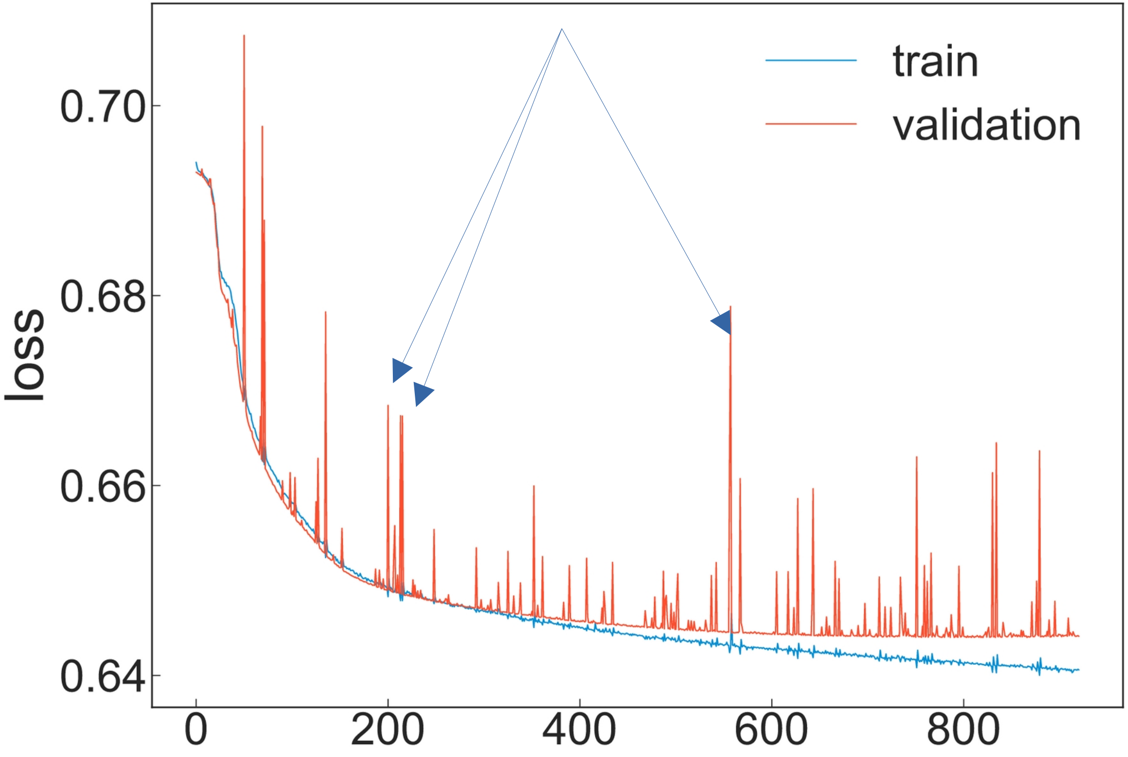
Training the network in practise has been quite a challenge...

Show stopper: Correlation between random seed and tag asymmetry



Happy end of asymmetry issues

Loss function “glitches” are strongly correlated to tag asymmetry



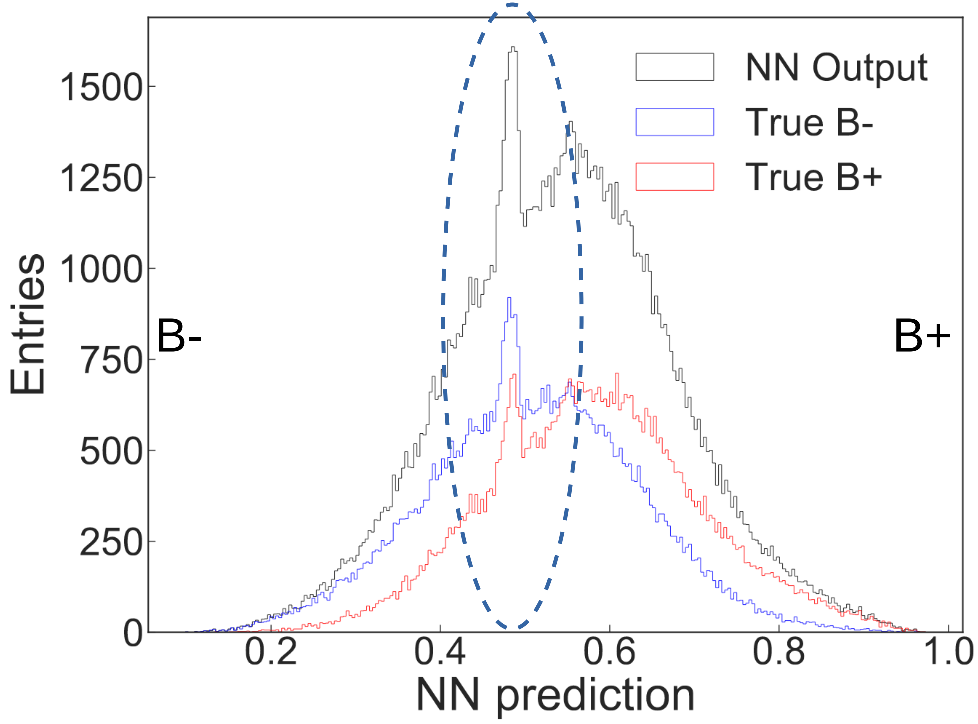
- Issue was that Network chose last training state instead of “best” state.
- Combined with these spikes, this resulted in huge asymmetries (still somewhat surprising to us)

But…

- Choosing best Network state still produced asymmetries of up to 10% though.
- Reduced to up to 1% by choosing perfectly balanced training samples, i.e. 100% balanced instead of 99.9% balanced. Quite surprising as well…

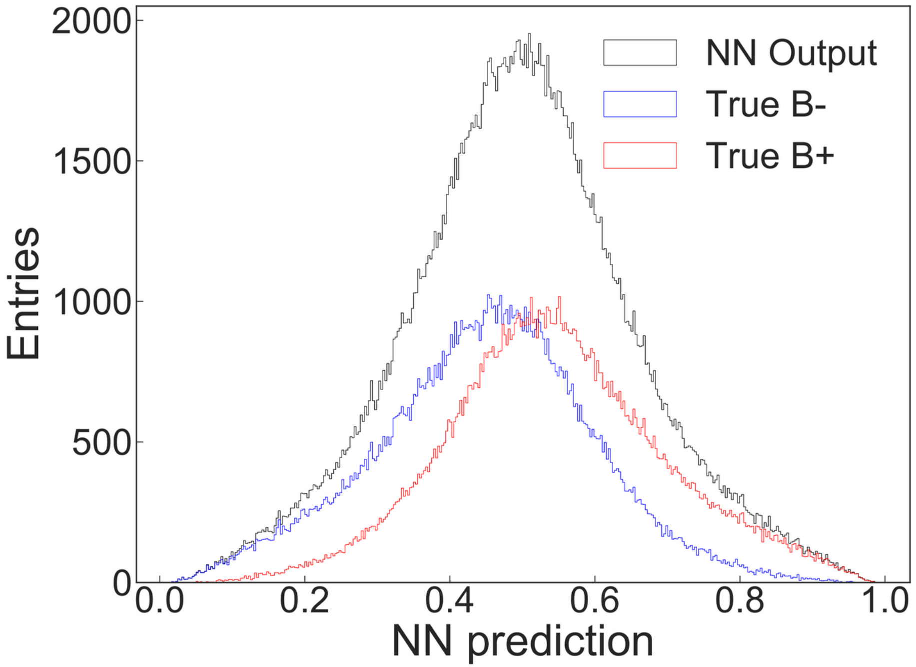
Issue Nr 2: Inconsistent features in the neural network output

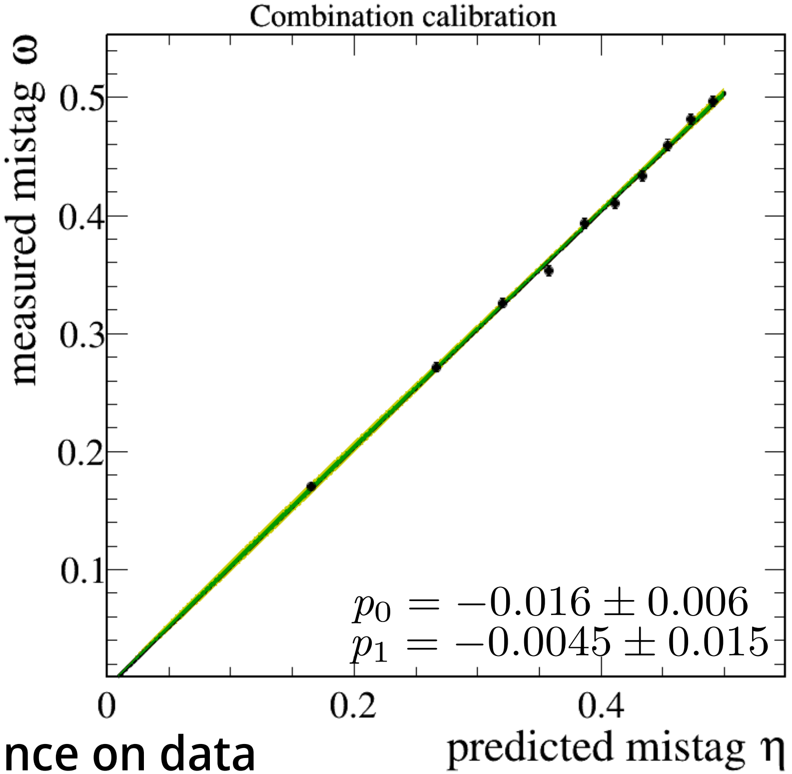
- Neural network output often contained one, sometimes multiple sharper spikes
- The higher the resolution, (i.e. the more statistics), the more such features could be observed
- In addition, these were very inconsistent between trainings



Solved by using smooth activation function instead of ReLU

Results on $B^+ \to J/\psi K^+$ Simulation





Tagging power $\varepsilon_{\text{eff}} \approx 9.7\%$, very similar performance on data

Tagging efficiency: 100%

Classical tagger combination: $\varepsilon_{\text{eff}} \approx 6\%$

Factor 1.6 improvement

Summary

- Inclusive tagging models have been developed and trained successfully
- Observed tagging performance on B+2JpsiK+ improvement is promising
- Major show-stoppers have been understood
  - Development of taggers for neutral modes + Bs mode in progress

Run 3

- Work is ongoing to make the IFT (and classical taggers) run efficiently in the HLT
- If validation studies are convincing, inclusive Tagger could replace classical taggers? → Easier to maintain
- Decision will be made soon