Machine learning techniques in LHCb

Patrick Owen
MLHEP summer school
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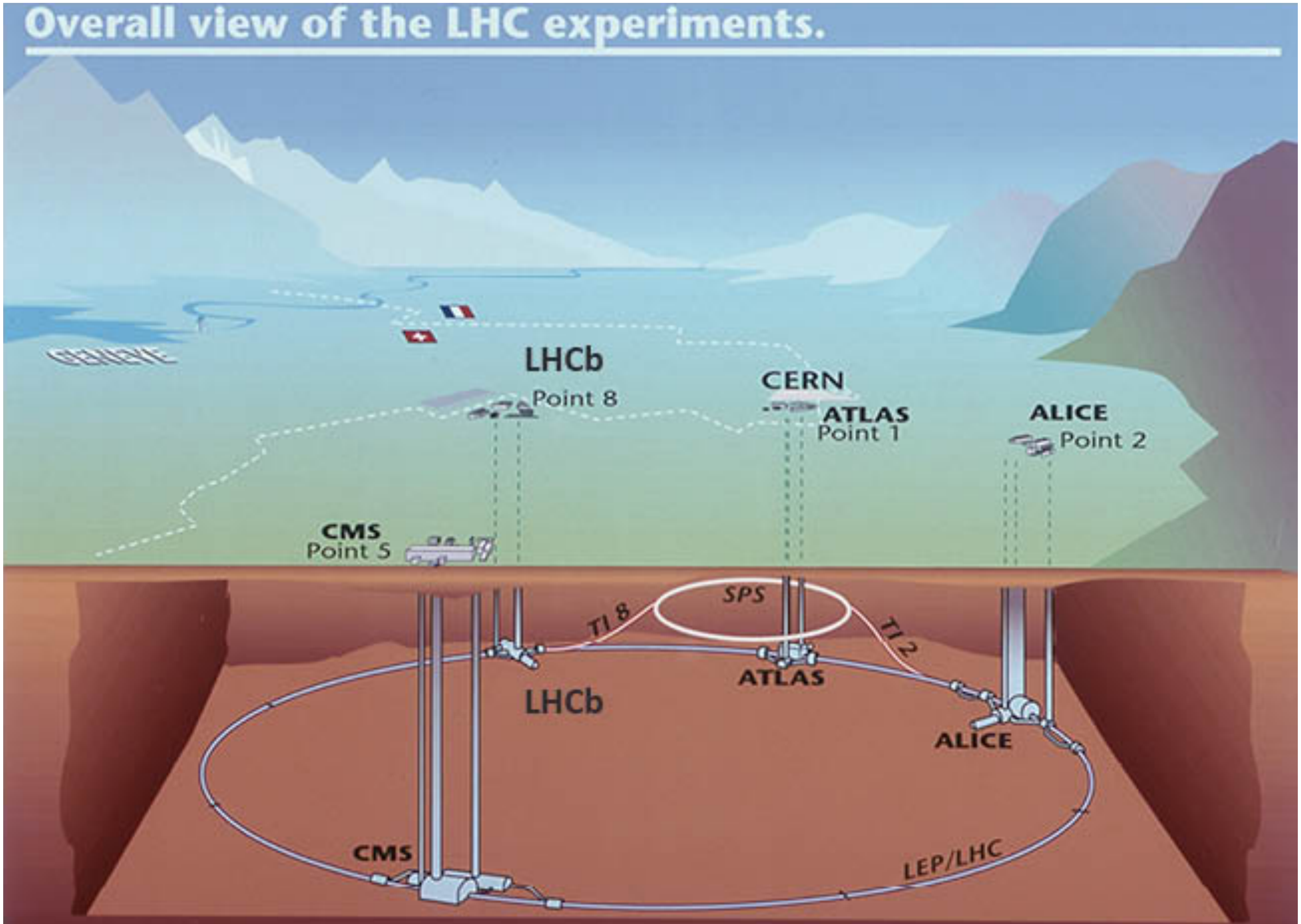
Imperial College London
LHCb

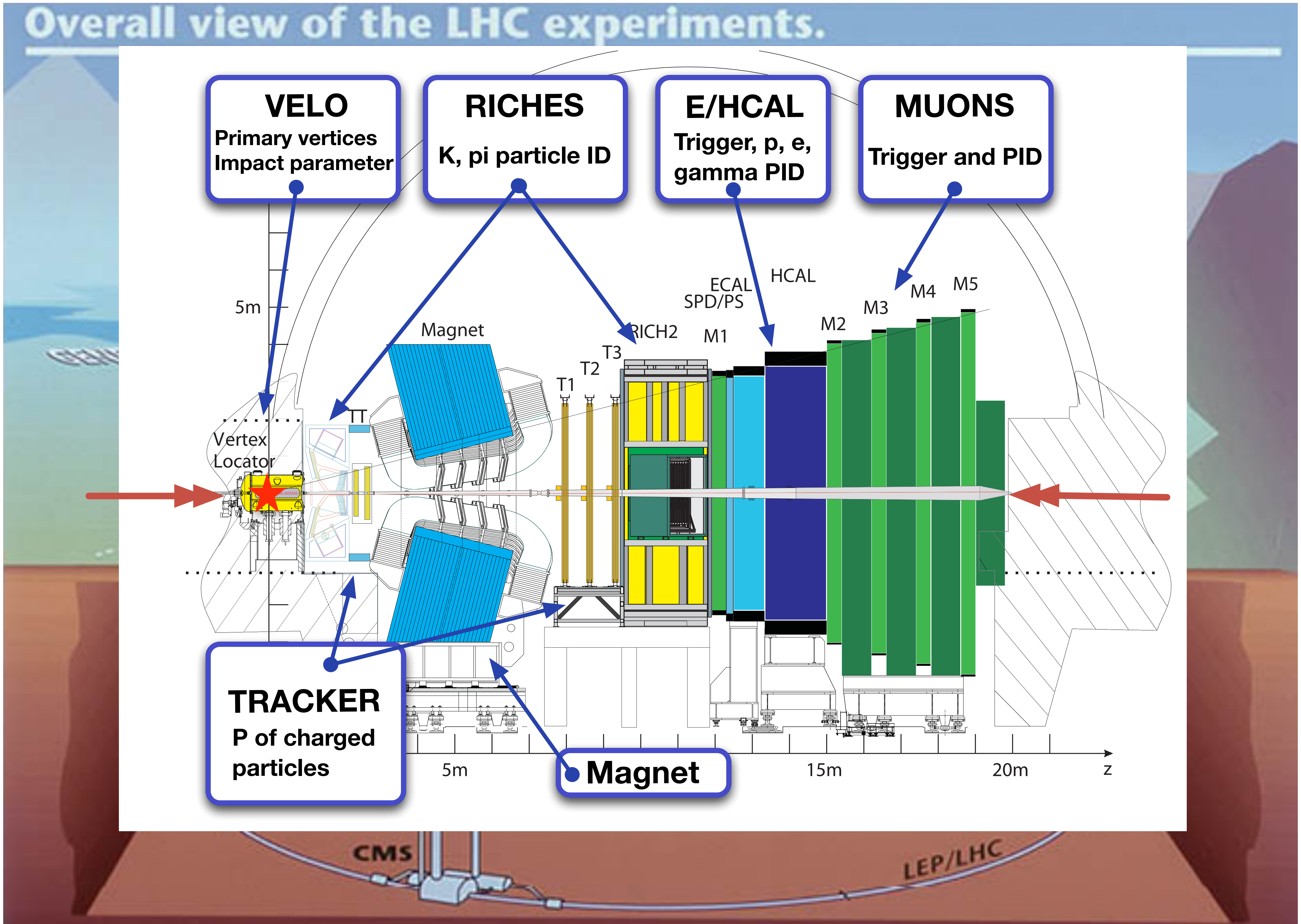
Jargon transformation

- Overfitting —> Overtraining
- Feature —> Variable
- Model —> classifier
- Bias/correlation to POI —> feature selection (?)
- Model ensembling —> ‘blending’
- k-Fold cross-validation —> k-Fold cross-validation (?)

The LHCb experiment



The LHCb experiment



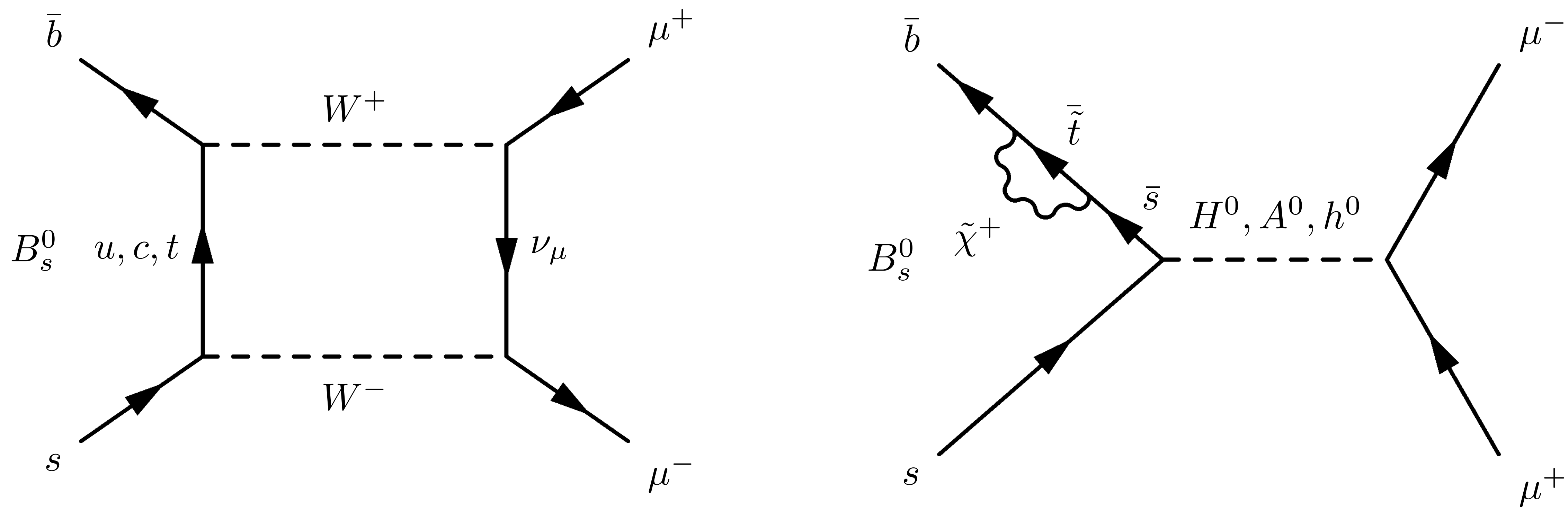
Physics beyond the SM

- There are many problems with our theoretical description of the universe, the Standard Model (SM).
  - Only 5% of matter accounted for by SM.
  - SM CP violation ~10 orders of magnitude too small to account for observed matter/anti-matter asymmetry.
  - Nothing to do with gravity.
  - + some fine tuning problems.
- The hope is that we find some new particles at LHC to fix some of this.

The goal of LHCb

- Core physics programme: Indirect searches for new physics in heavy flavour decays.

- Example: $B_s^0 \to \mu^+\mu^-$



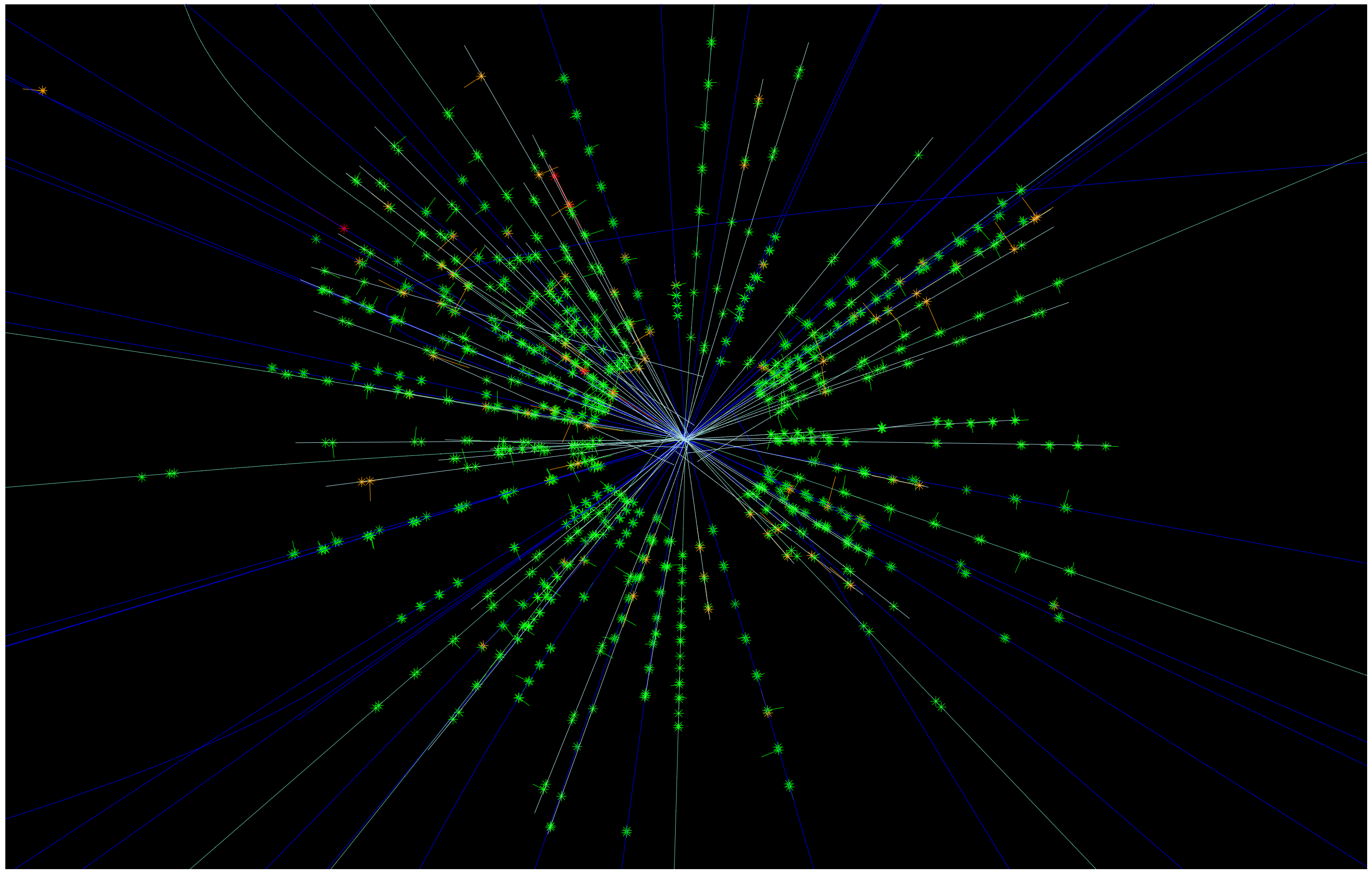
- Measuring properties of B decays can tell us about NP way beyond accelerator energy.

Hadronic environment

- Many precise B physics results have been made at e^+e^- colliders.
  - Very clean environment to work in, typically only 2B mesons produced in the detector.

- Roughly 1000 times more B-mesons produced so far at LHCb interaction point compared to B-factories

- However, hadronic environment much more difficult to work with.

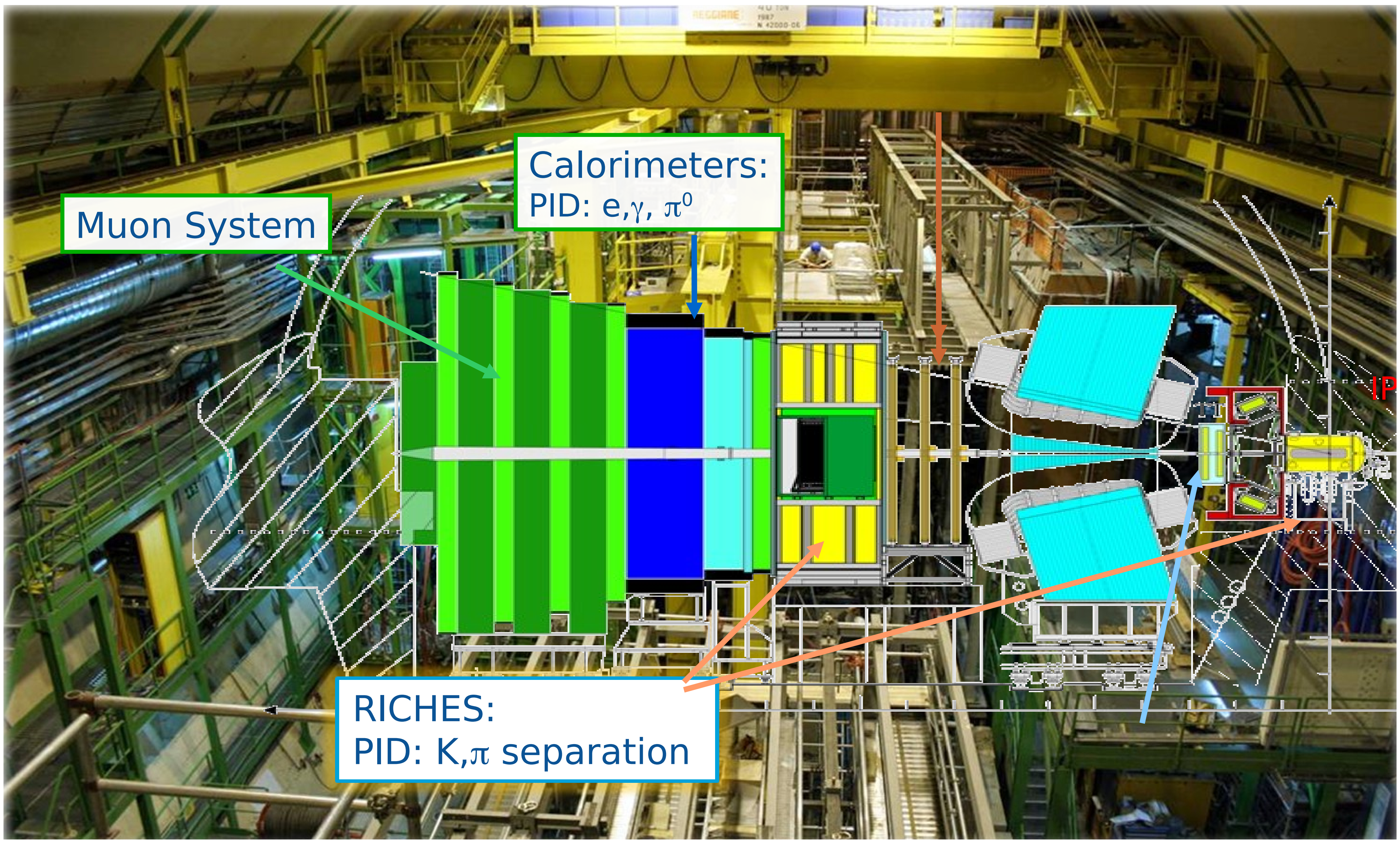


Outline

- Lower level information:
  - Particle ID
  - Tracking
  - Flavour tagging
- Physics analyses (most use MVA):
  - Canonical example: $B_s^0 \to \mu^+\mu^-$
  - Bias to observables of interest: Dark boson search
  - Badly modelled variables: $B^0 \to K^{*0}\mu^+\mu^-$
  - Choice of classifier: $\tau^+ \to \mu^+\mu^-\mu^+$

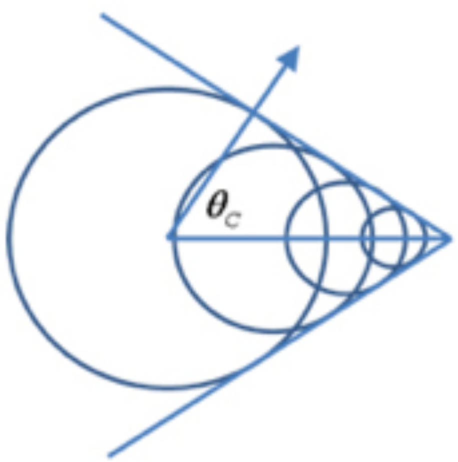
Particle ID at LHCb

- Several sub-detectors provide particle ID information.

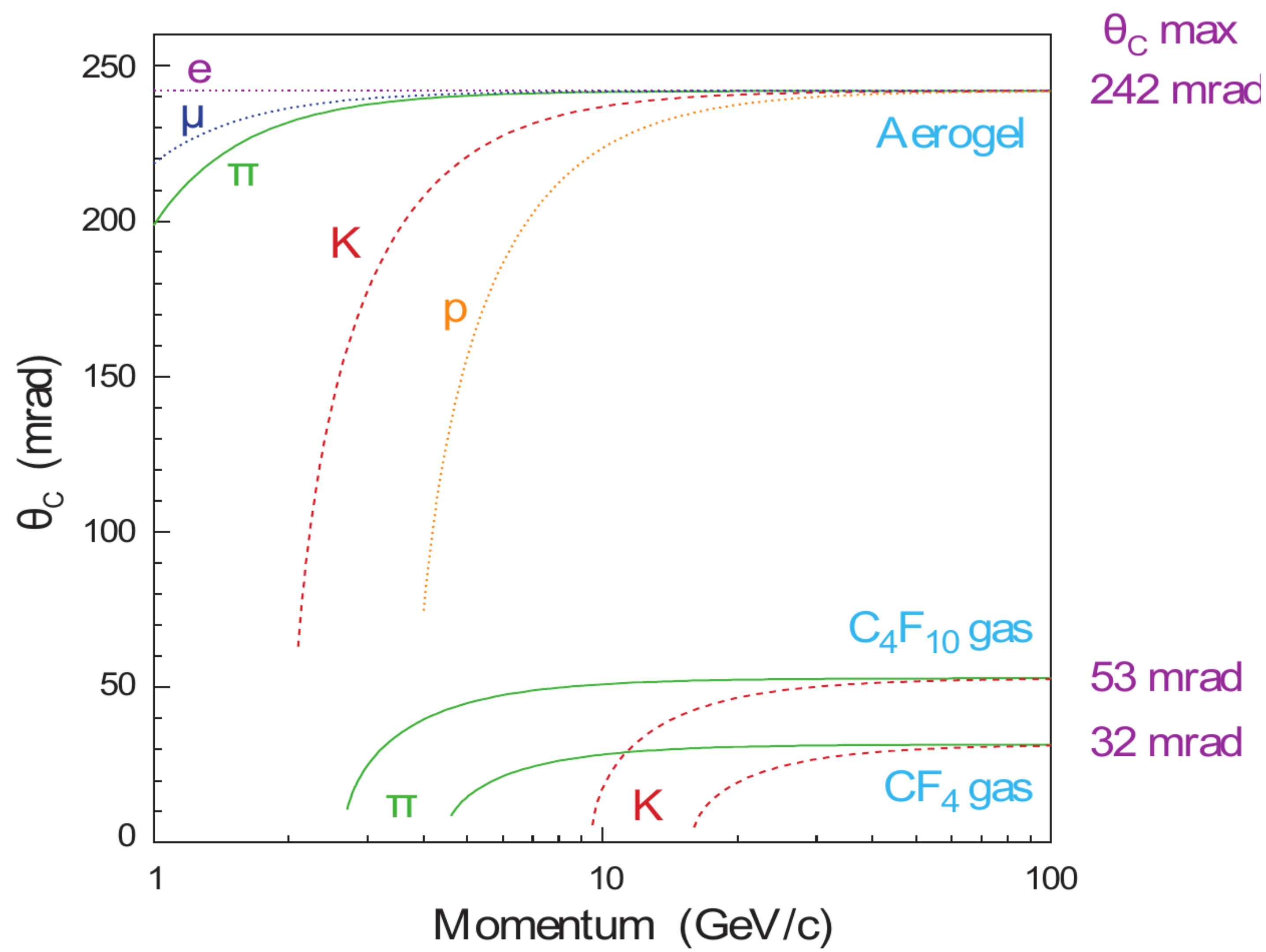


RICH detectors

- Particles that travel faster than the speed of light will emit a cone of light, known as Cherenkov radiation.



$$\theta_C = \cos^{-1}\left(\frac{1}{\beta n}\right)$$

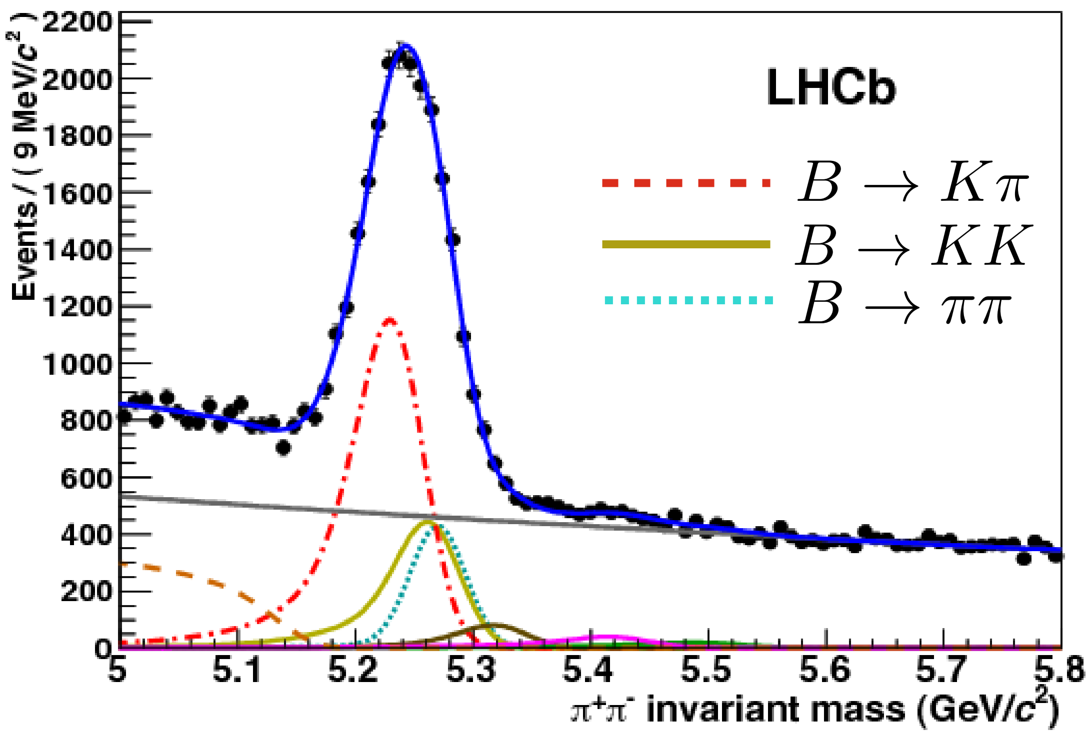


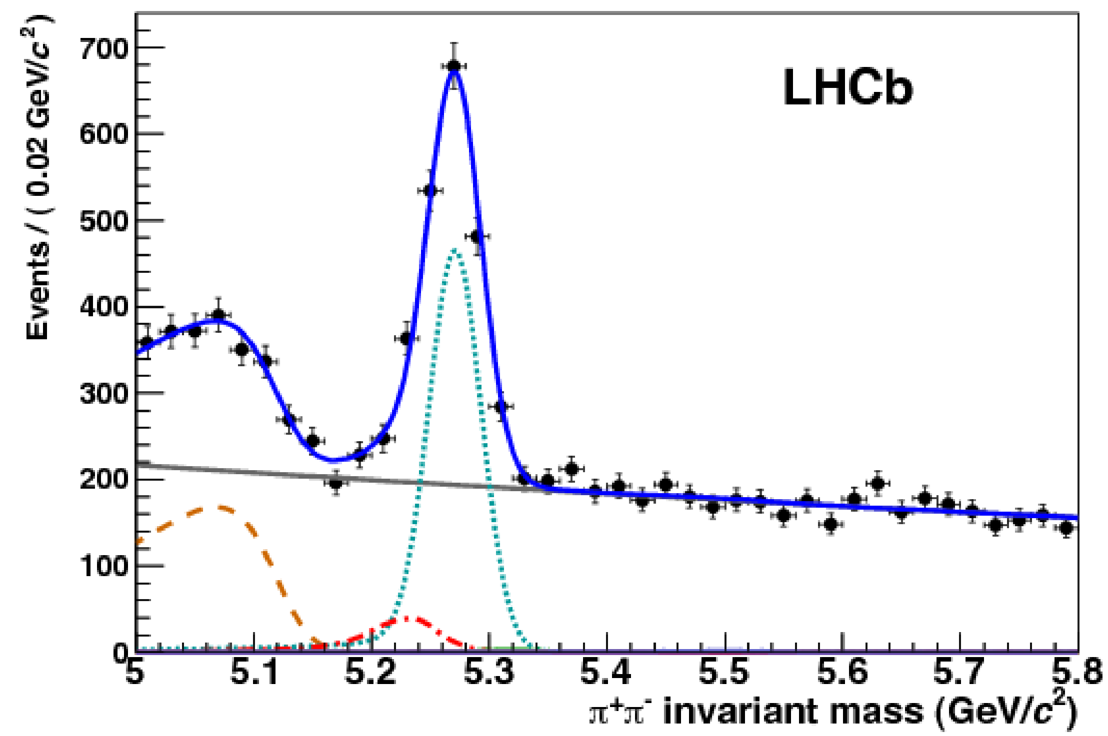
- Allows LHCb to distinguish between pions and kaons.
- Criteria used in analysis combines likelihood information from each sub detector (combined DLLs).

Particle ID in action

- Particle ID crucial for most LHCb analyses.

From RICH performance paper, arXiv:1211.6759





- Most commonly used criteria is the combined DLL information.

Limitations with combined DLL

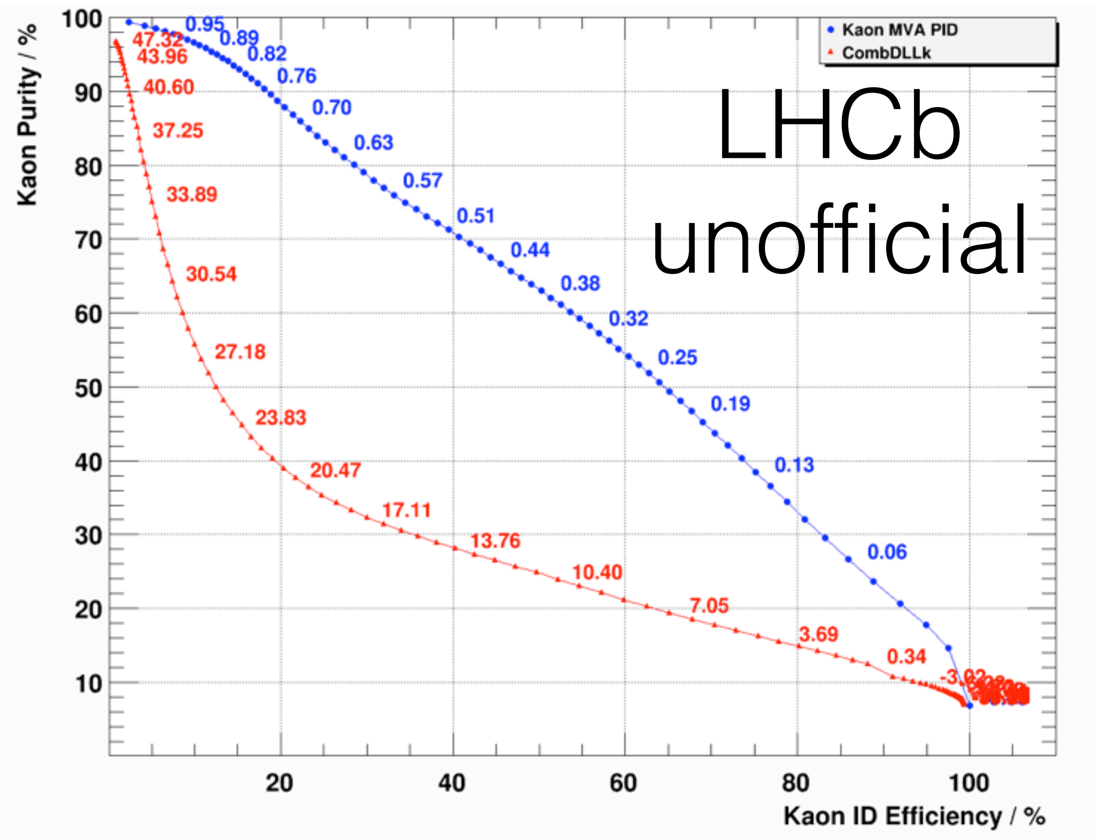
- Not all information can be represented as a likelihood.
  - Binary, or discrete variables, e.g. detector acceptance flags.
  - Combining likelihoods not always mathematically defined (sometimes need to re-scale input).
- Instead, use MVA.
  - Train on simulation (all tracks).
  - Combine tracking information with PID information.

Performance compared with DLLs

- Various models are tested, and the Multi-layered perceptron is most performant.

- MVA looks to be much more performant than CombDLL.

- However, this problem is not always what analysts want to solve.

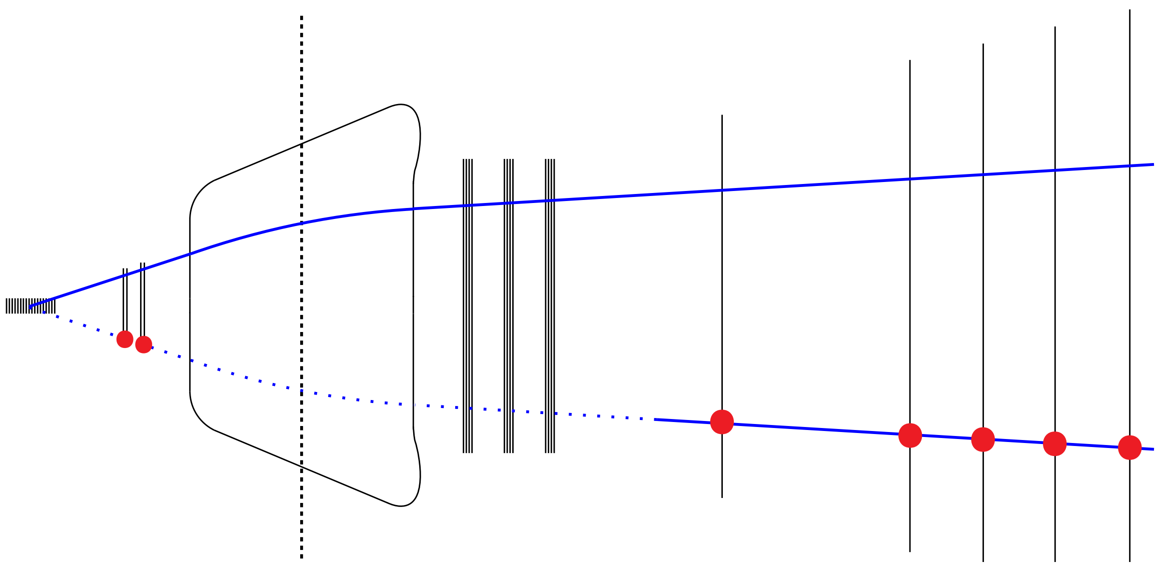


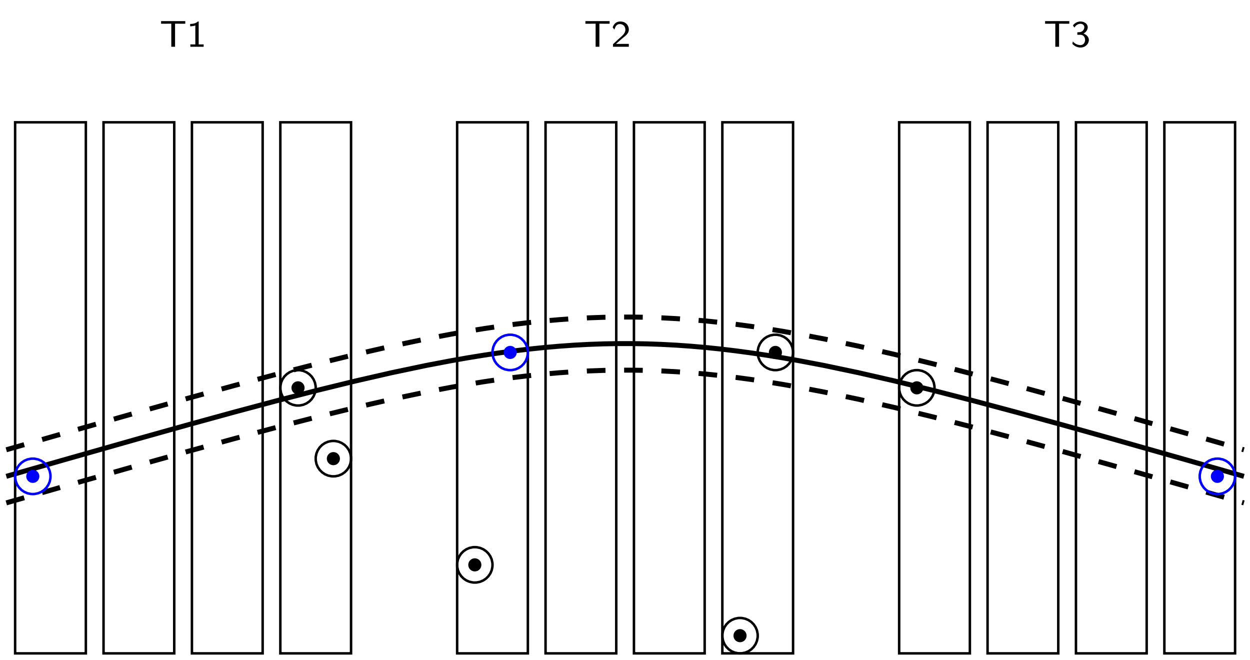
- They often really care about K-pi separation, in that case often the CombDLLs have similar performance, despite plot on right.

- MVA PID better at getting rid of combinatorial background.

Tracking in LHCb

- Measure direction of tracks before and after dipole magnet - measure momentum.

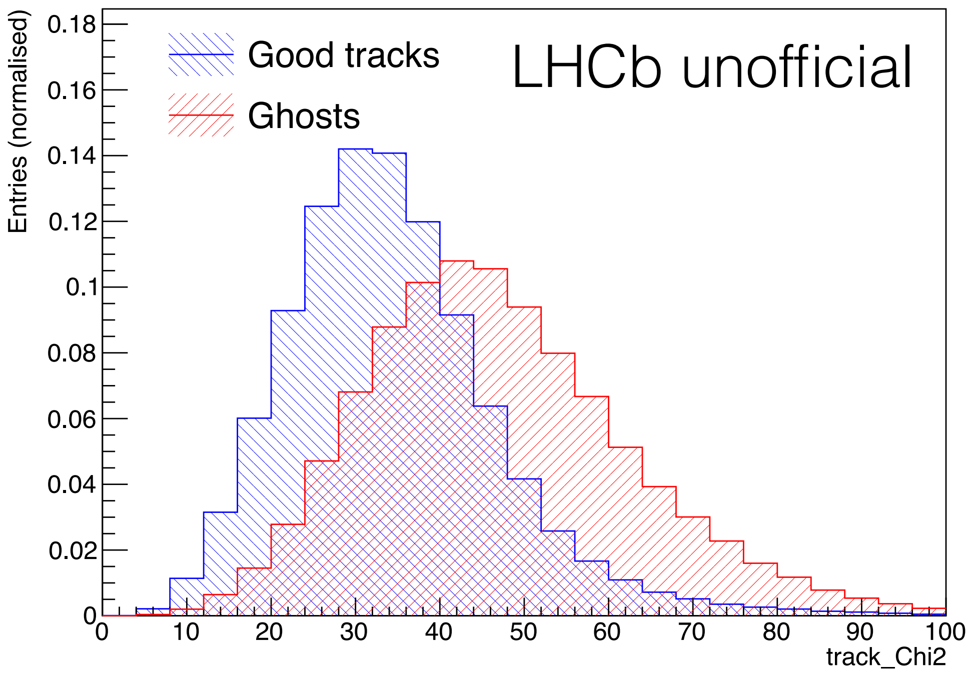


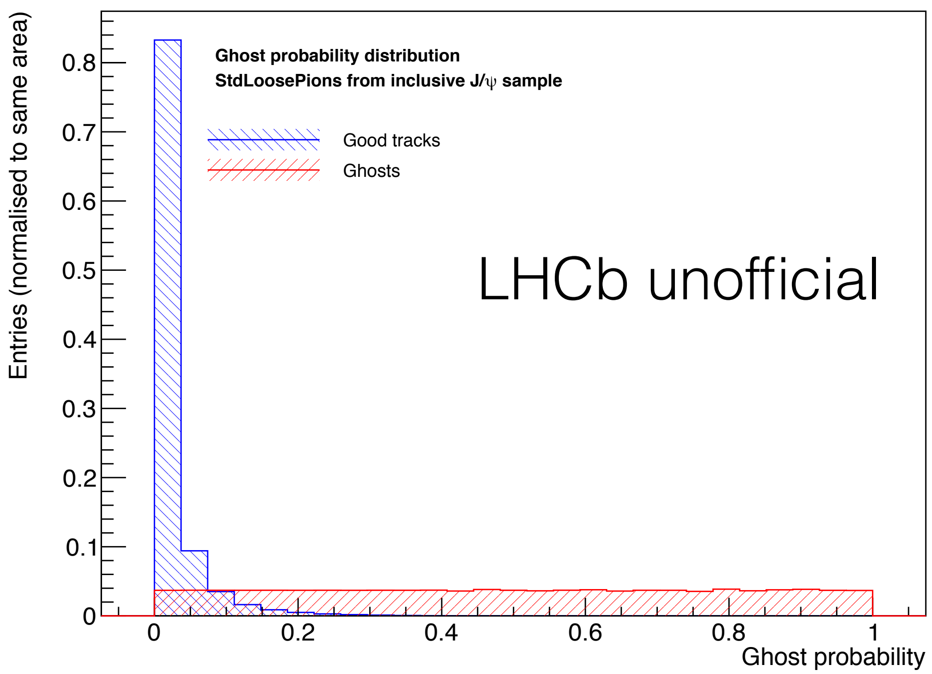


- Tracks are formed by adding hits which are consistent with a parabola.
- If noise hits are added, or hits from other particle, it is called a 'ghost'.

Ghost probability tool

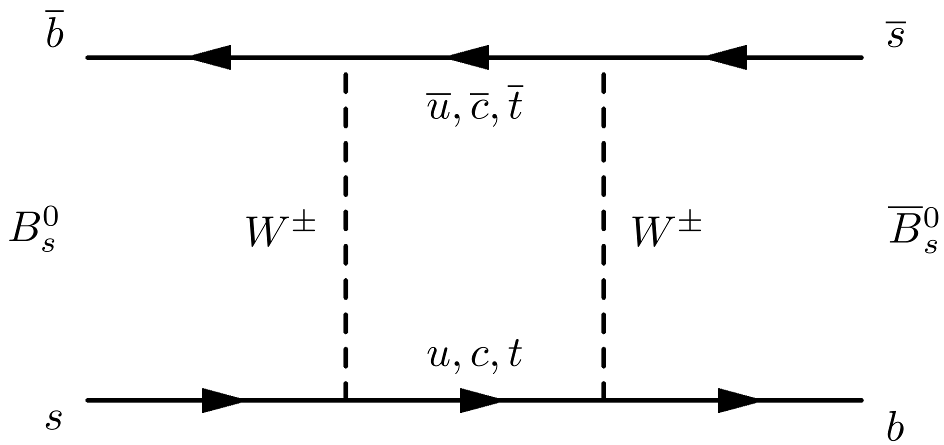
- Artificial neural network.
  - Trained on simulation.
  - Use various properties of the track (# hits in sub-stations, quality etc ..).

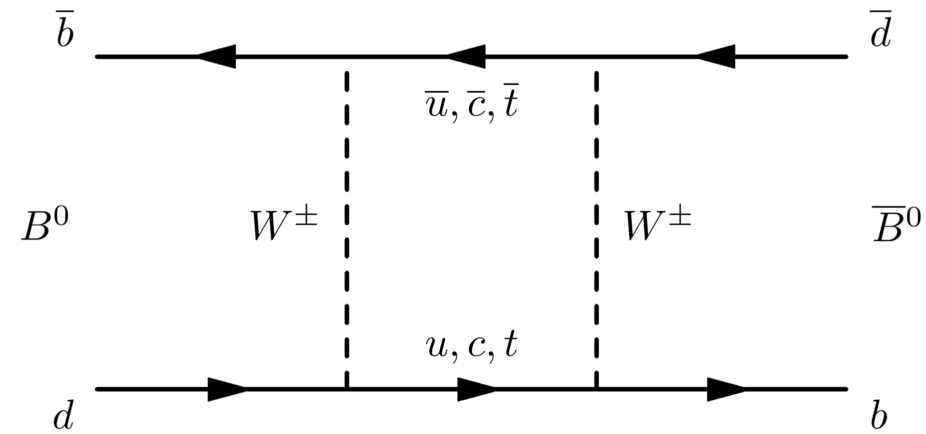




Flavour tagging

- Neutral B mesons oscillate into their anti-partners, and vice versa.

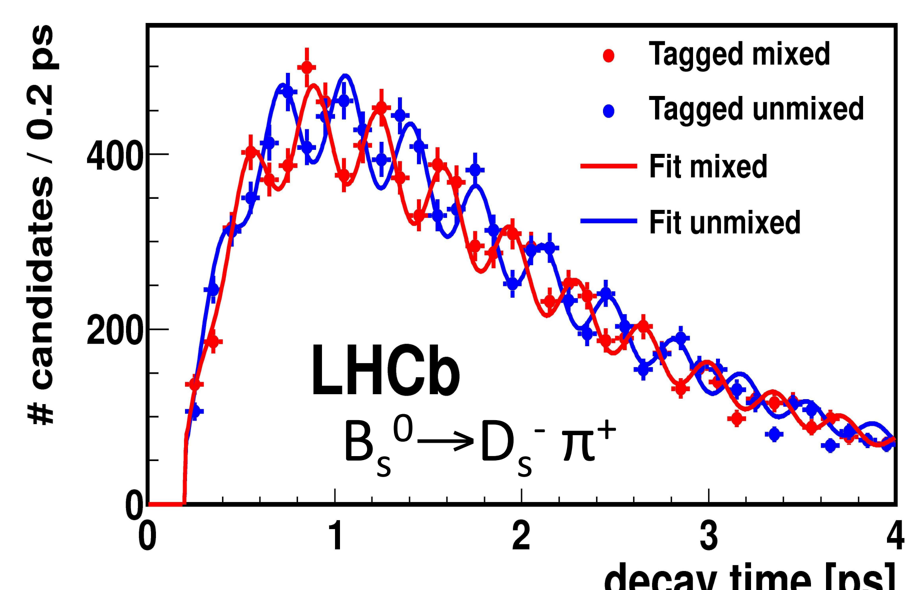




- Flavour tagging is the ability to tell the flavour of a neutral B meson at the time of production.

NJP 15 (2013) 053021

- Crucial for probing NP inside these box diagrams.



How it works

Same side (SS): Fragmentation of b-quarks leads to correlation between spectator quark and nearby particles

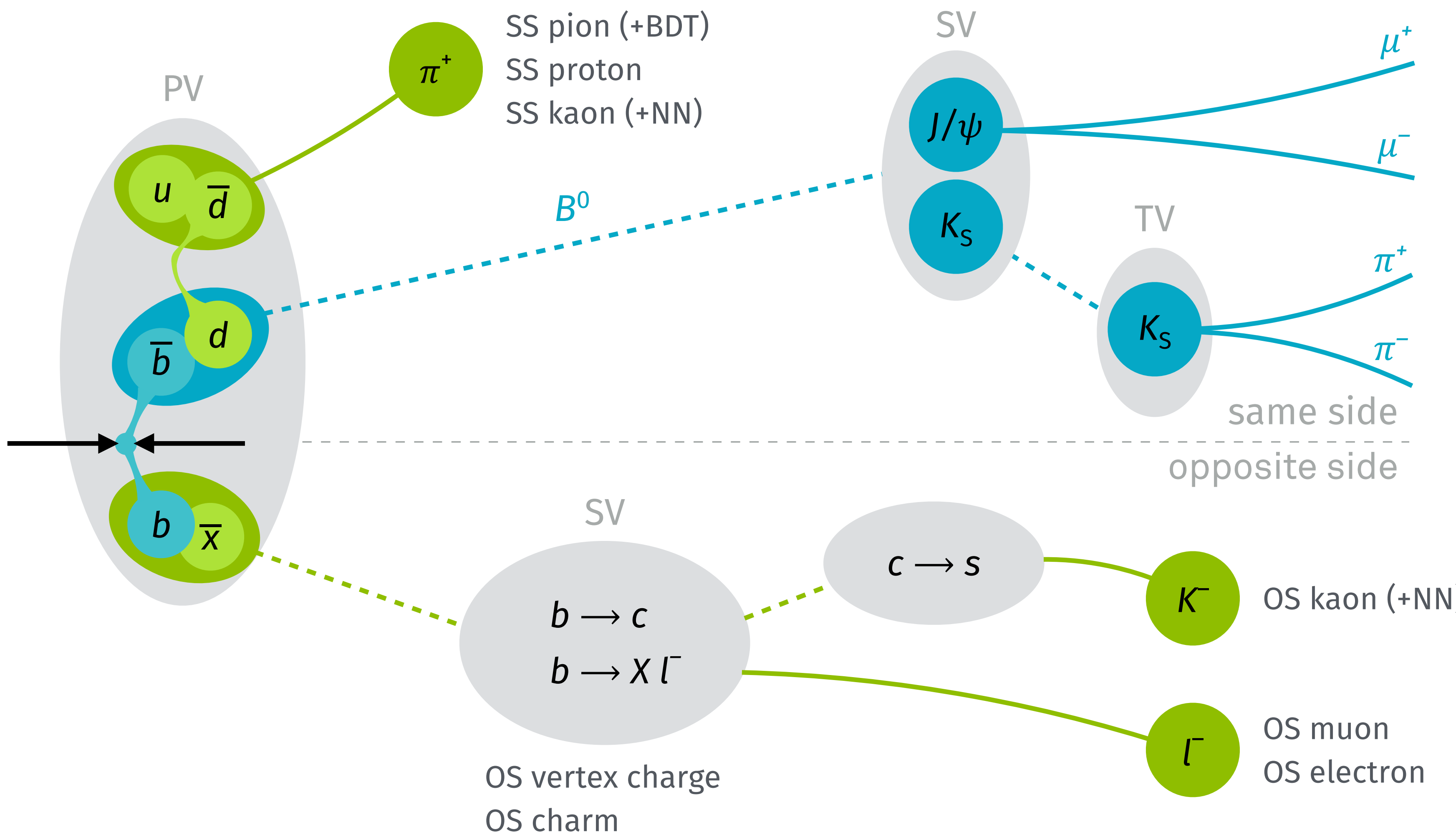


Diagram from J. Wishahi

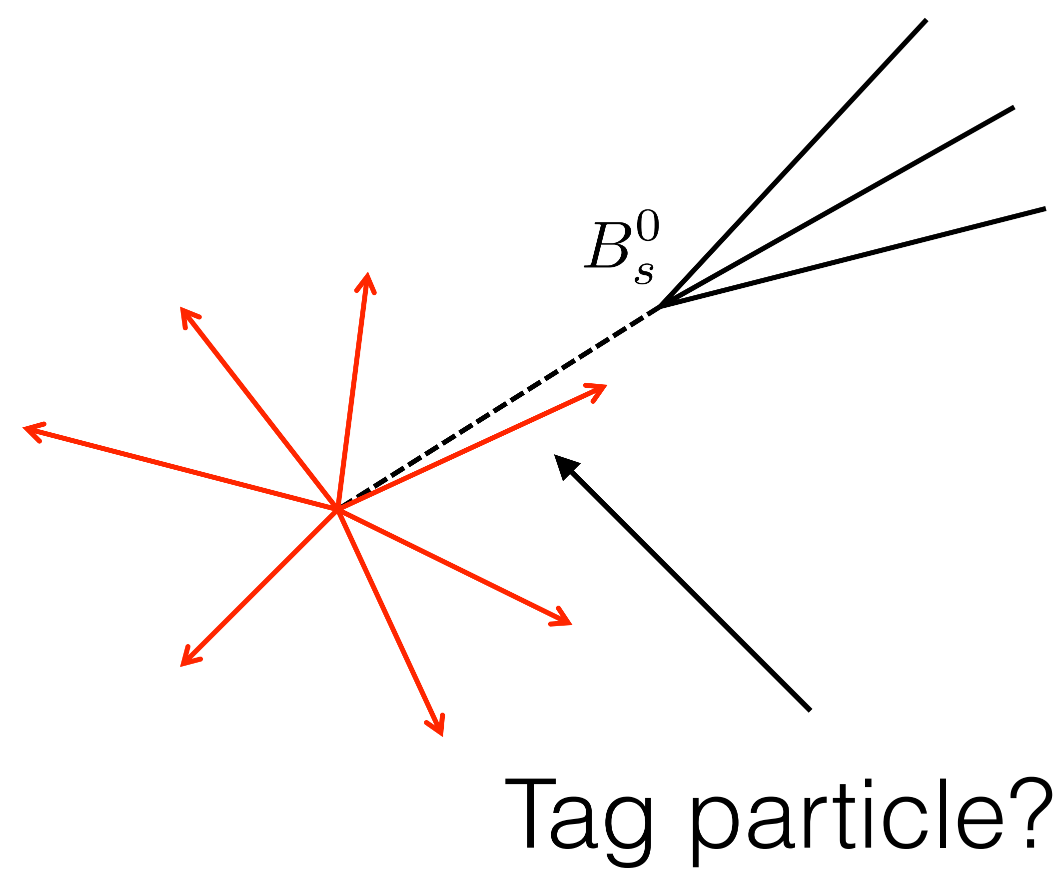
Opposite side (OS): Exploit the fact that there are always two b-quarks produced with opposite flavour.

Same-side tagging

- Tagging is a classification problem:
  - Distinguish between particles originating from fragmentation (signal), and those from elsewhere (background).

- Select several good quality tracks, with kaon PID from the RICH detectors.

- Choose tagging particle based on how close it is to the Bs phase-space (pseudo-rapidity difference, phi, BsK mass etc).

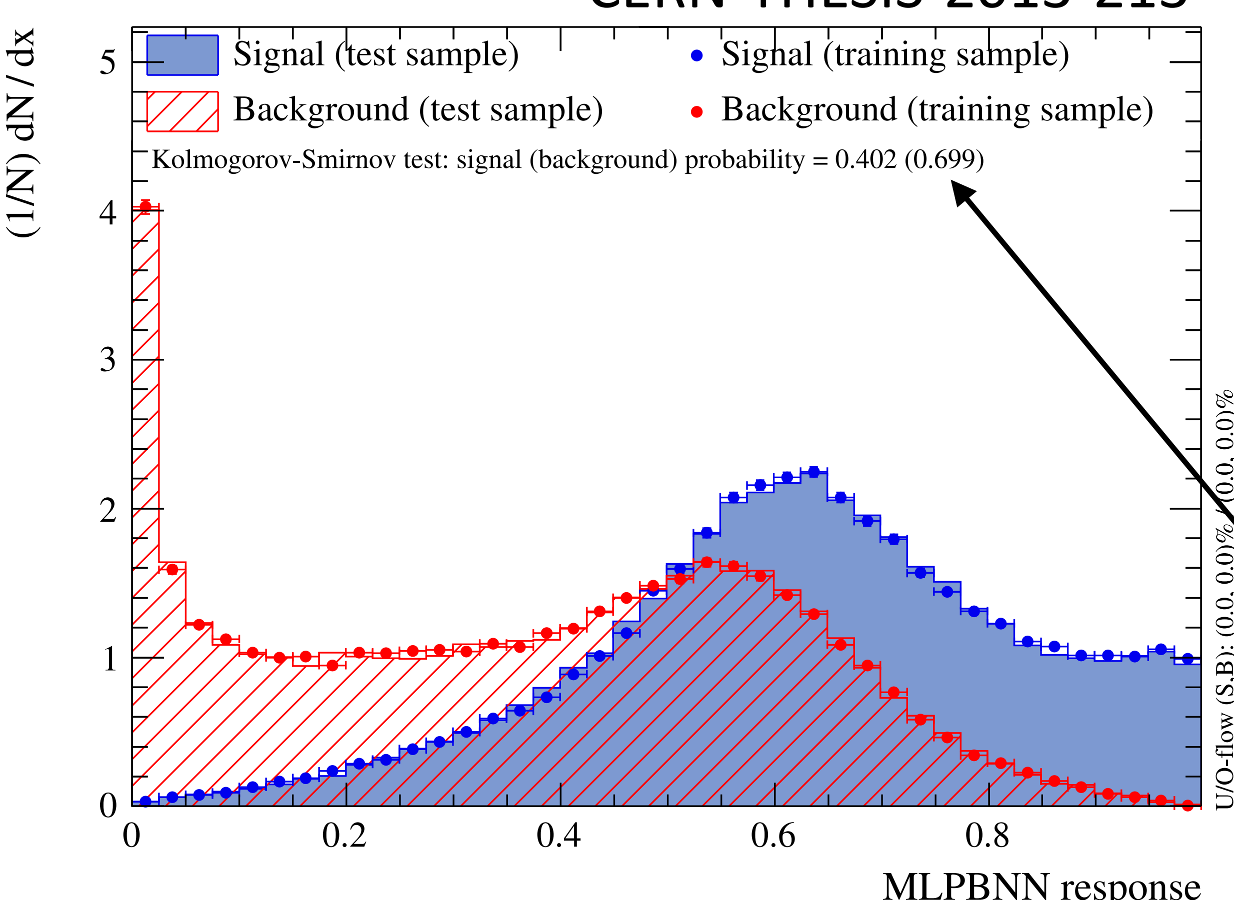


Neutral Net tagger

- Initially cut based selection used to choose tag particle [LHCb-CONF-2012-033].

- Now use Neutral Net, combining information from the entire event (track multiplicity particularly useful).

CERN-THESIS-2013-213



- Improvement in tagging power equivalent to having 40% more data!
- Can calculate mis-tag probability on event-by-event basis.

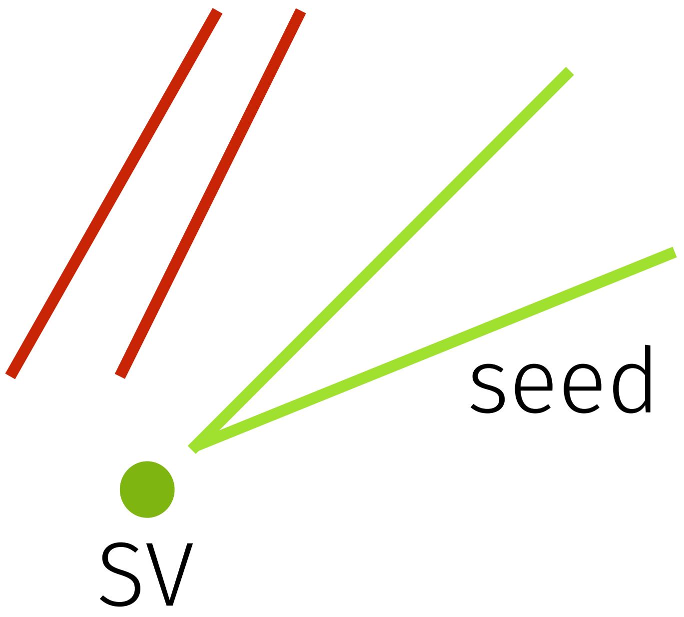
Btw, these numbers never make any sense.

Opposite side taggers

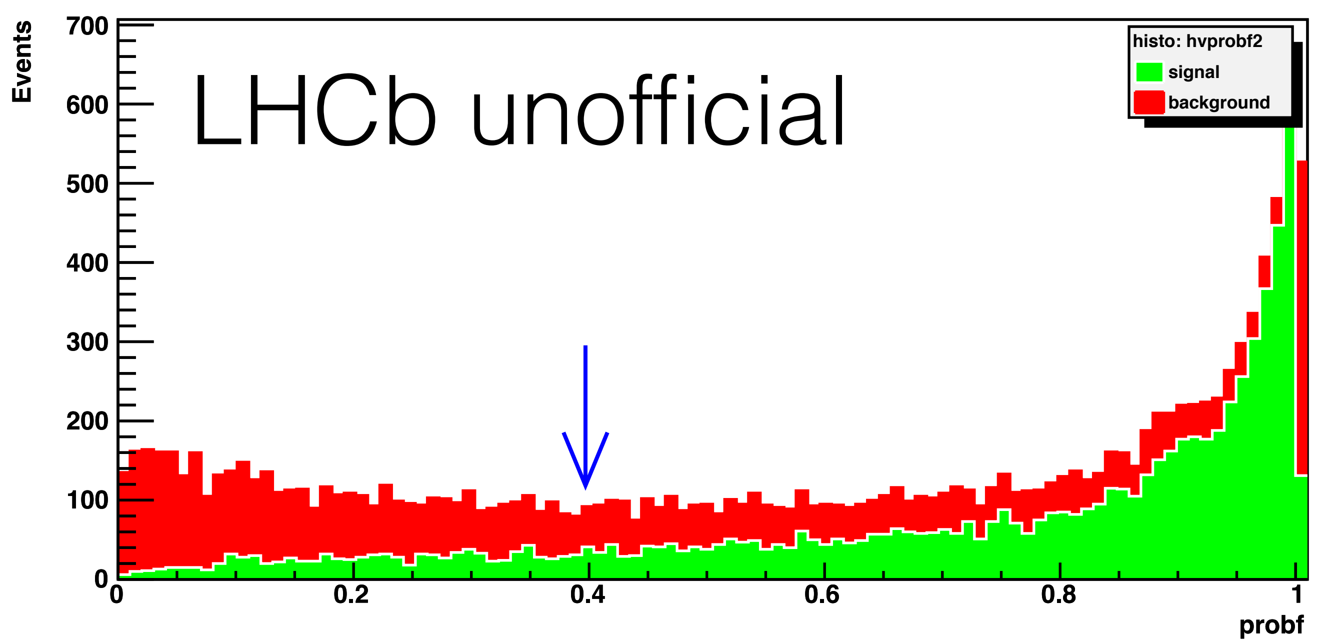
- To exploit opposite side, need to think about common B decays.
    - $B \to DX$ 85%
    - $B \to \ell\nu X$ 25%
- Find flavour of lepton/charm to get flavour of other B in event.
- Diluted by opposite side oscillations.
    - 30 (100)% B^0(B_s^0) oscillate before they decay

OS vertex tagger

- A more inclusive way to is to calculate charge of a detached vertex on other side.
  - Best detached vertex chosen by NN classification.



- Tracks added to this candidate, NN response updated.



- Calculate vertex charge, mark as untagged if too low.

$$Q_{\mathrm{vtx}} = \frac{\Sigma_i Q_i p_{\mathrm{Ti}}^{\kappa}}{\Sigma_i p_{\mathrm{Ti}}^{\kappa}}$$

$$B_s^0 \to \mu^+ \mu^-$$

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Science & Environment

Ultra-rare decay confirmed in LHC

By Melissa Hogenboom
Science reporter, BBC News

24 July 2013 | Science & Environment

Huge background, small signal

- Lets look at the expected rate for $B_s^0 \to \mu^+\mu^-$

$$\mathcal{B}(B_s^0 \to \mu^+\mu^-) \sim 3 \times 10^{-9}$$

- Background originates from two separate B decays, both decaying

$$\mathcal{B}(\bar{b} \to \mu^+ X) \times \mathcal{B}(b \to \mu^- X) \sim 1 \times 10^{-2}$$

- Before any selection, the background is seven orders of magnitude bigger than the signal.

Training samples

- First job, decide on samples to train on, which represent signal and background.

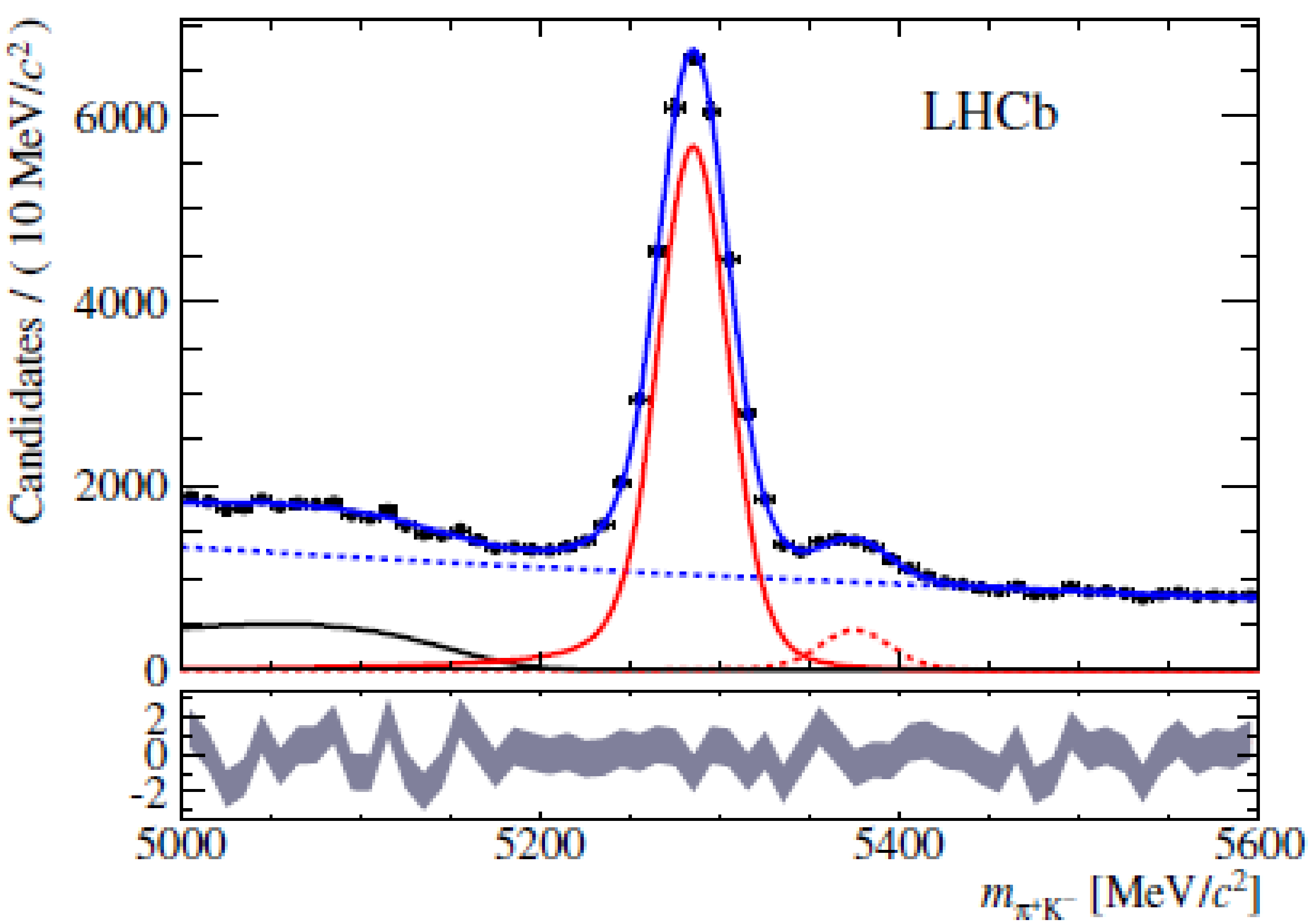
Simulation	Real data
Easily test for bias	Guaranteed to be realistic
No worry about overtraining	Typically bigger than simulation samples

- For $B_s^0 \to \mu^+\mu^-$, understand background well enough to use simulation for both.

Calibration

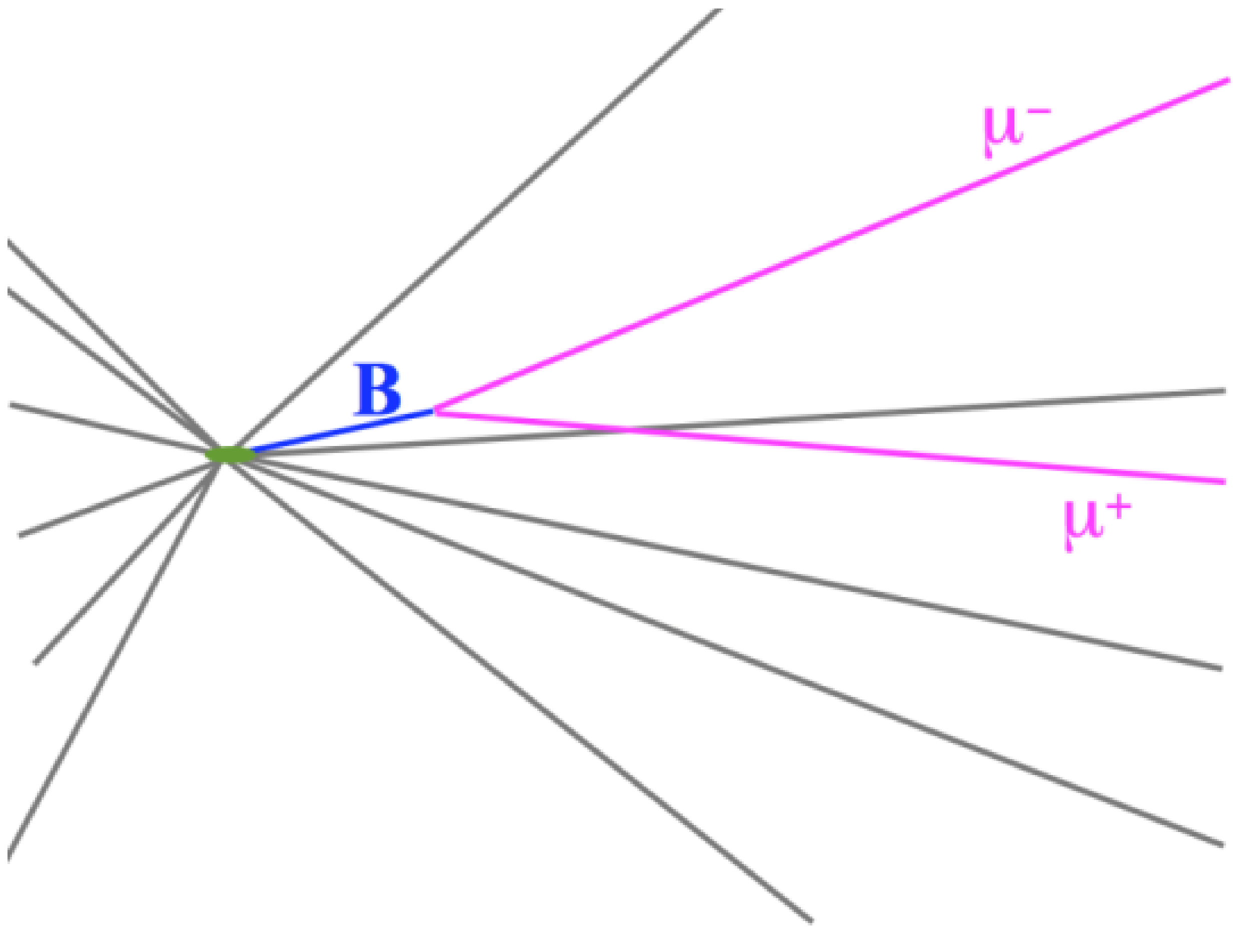
- Calibrate response of MVA on B—>hh, same topology.

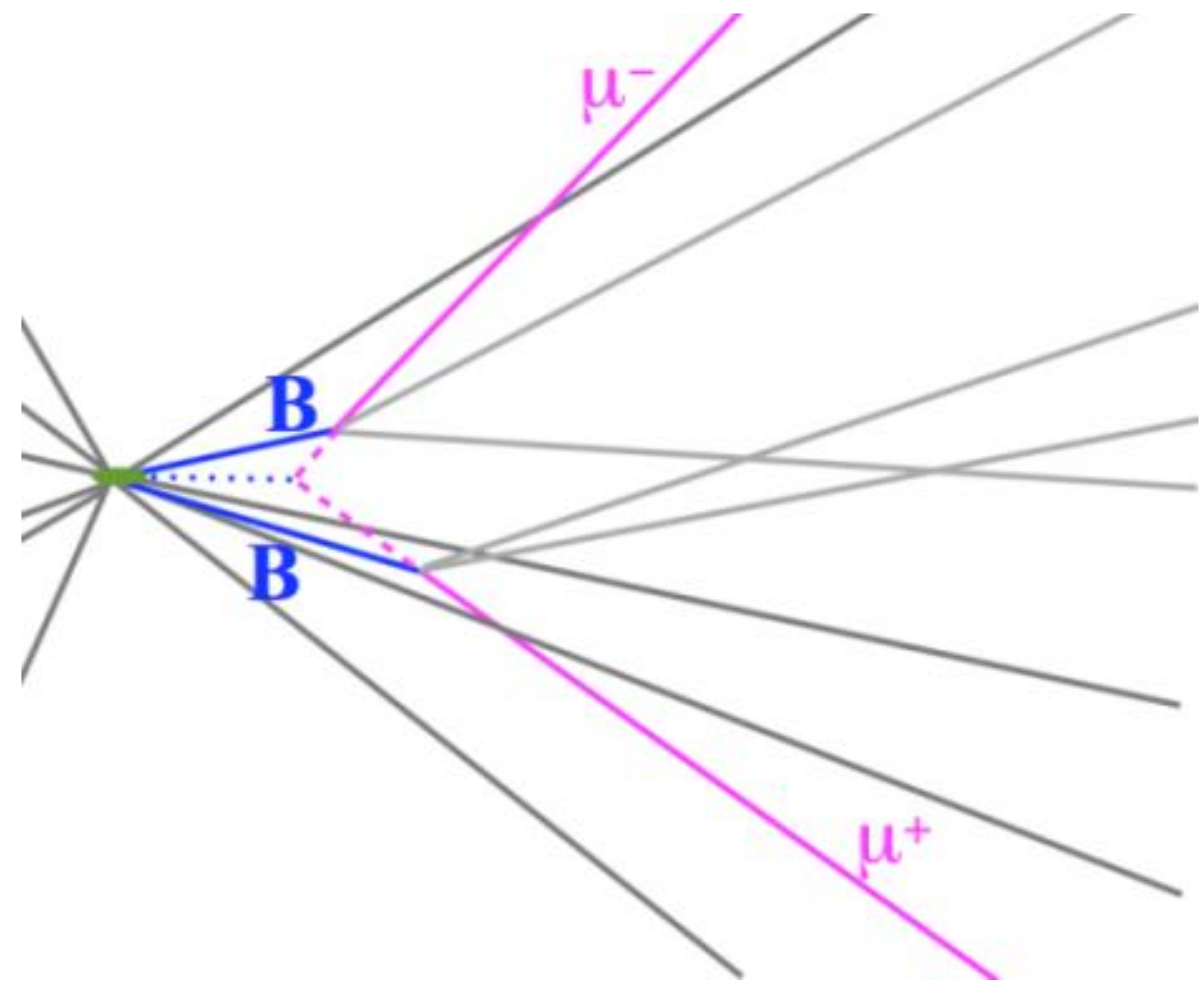
  - In order for this to work, omit particle ID from list of variables.



- For background, can use data outside the signal region to check response.

Topologies

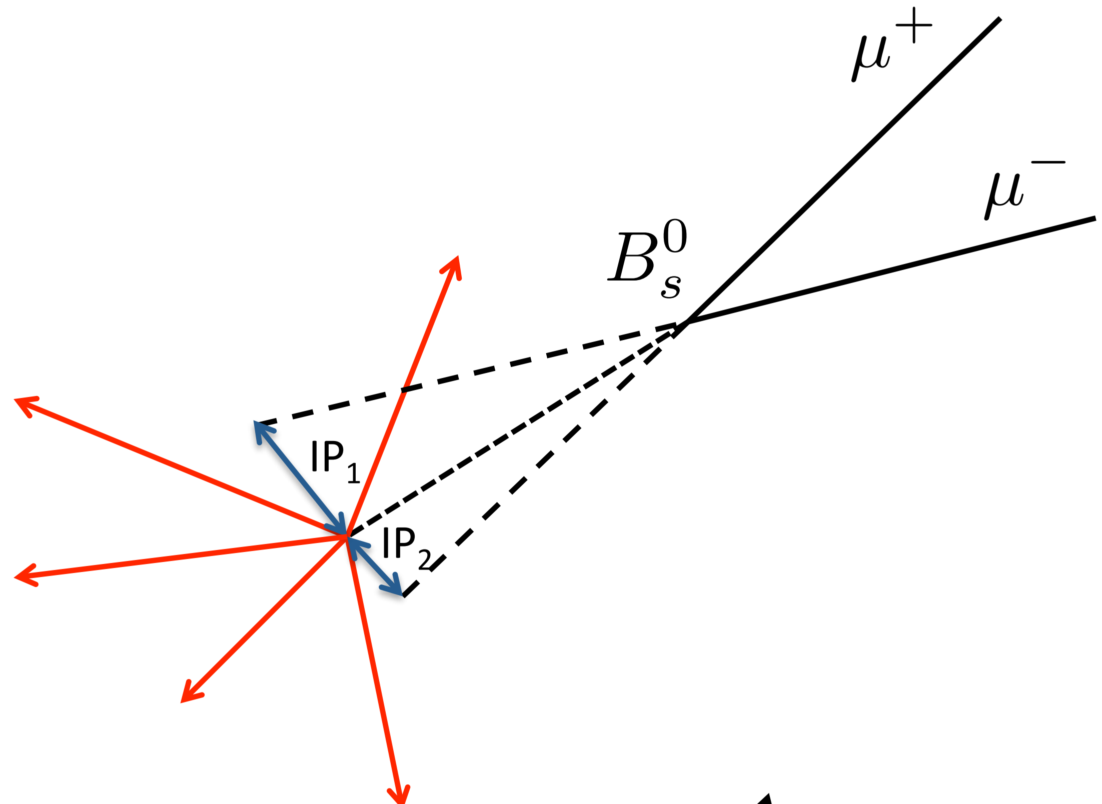




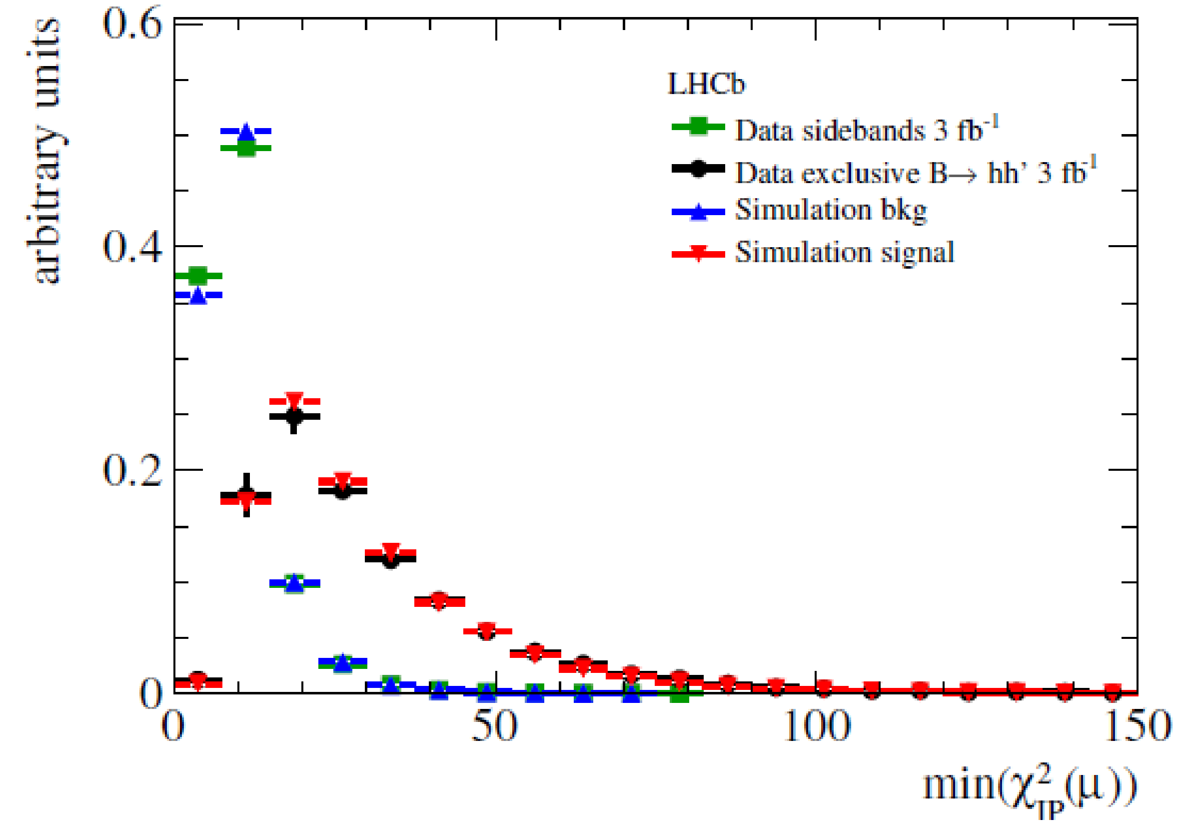
Desirable variable qualities:

- Have physical reason to distinguish
- Well reproduced in simulation
- Not correlated with dimuon mass

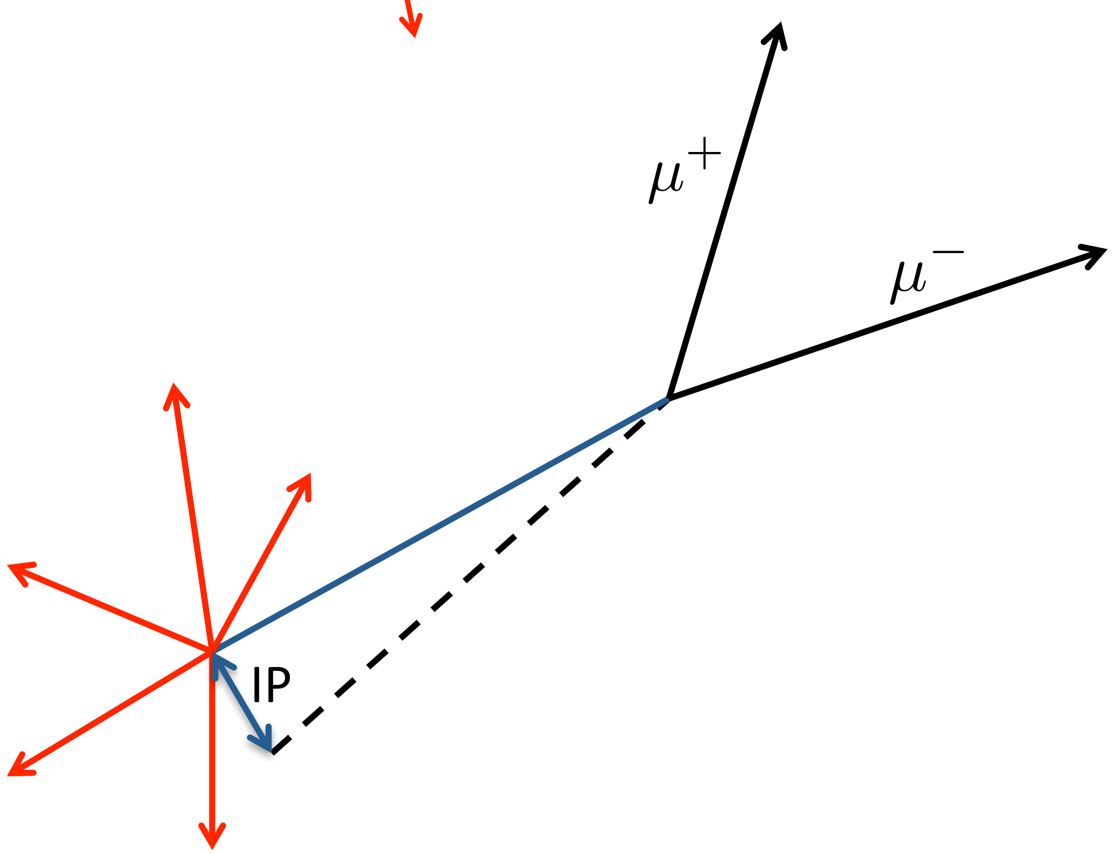
Variables



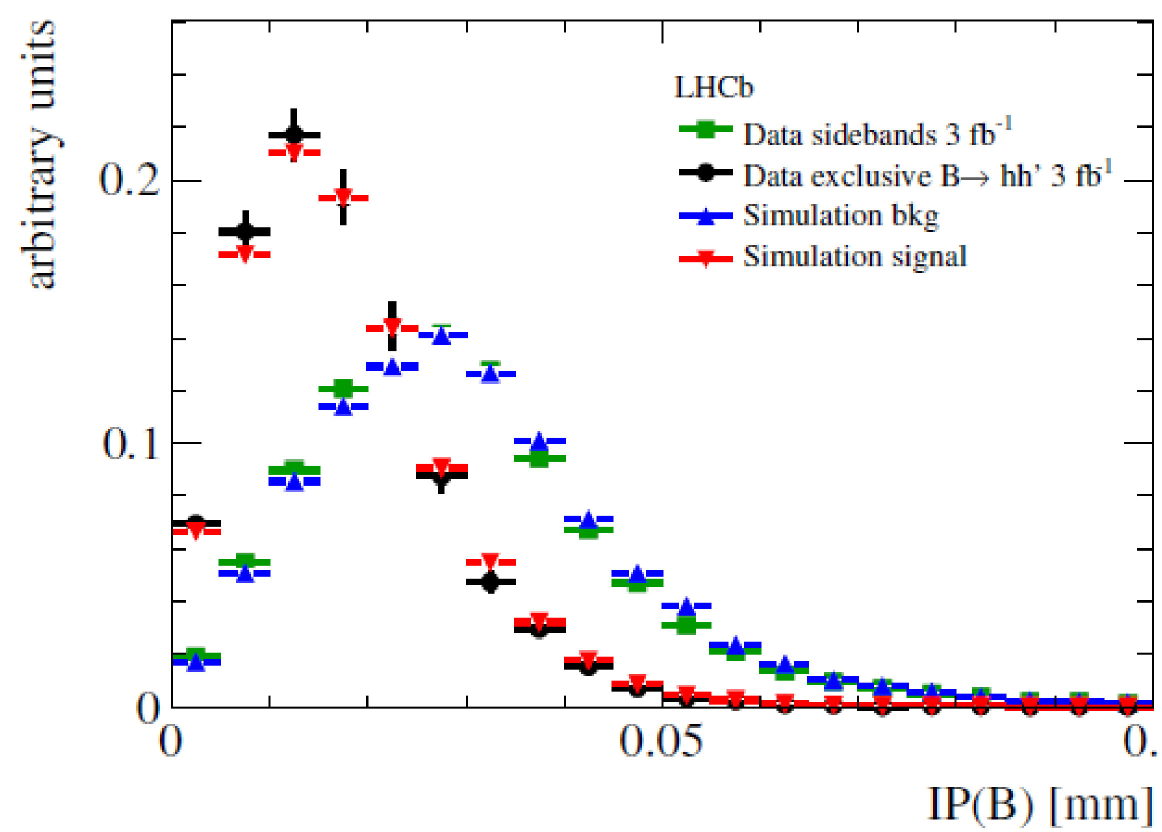
μ^+
μ^-
B_s^0
IP_1
IP_2



arbitrary units
LHCb
Data sidebands 3 fb^{-1}
Data exclusive B→ hh' 3 fb^{-1}
Simulation bkg
Simulation signal
0.6
0.4
0.2
0
0
50
100
150
$\min(\chi^2_{IP}(\mu))$

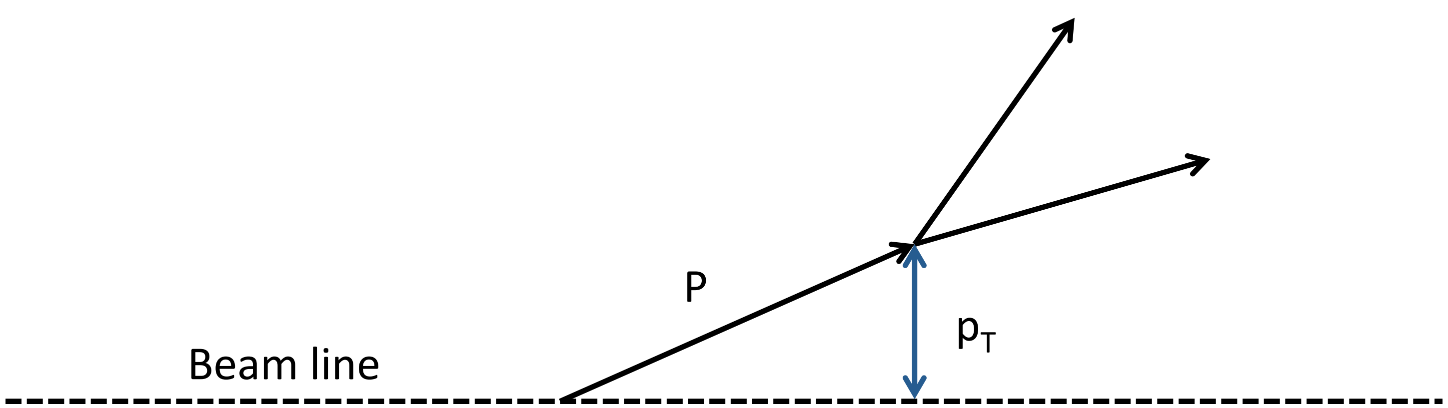


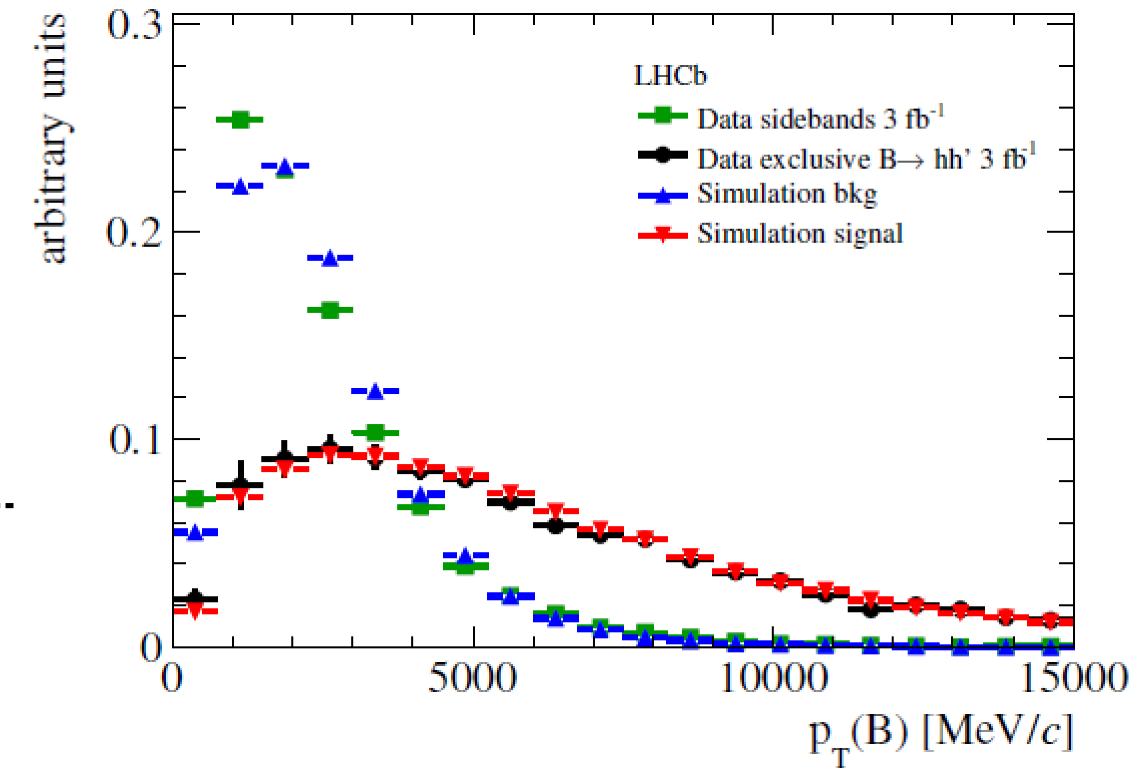
μ^+
μ^-
IP

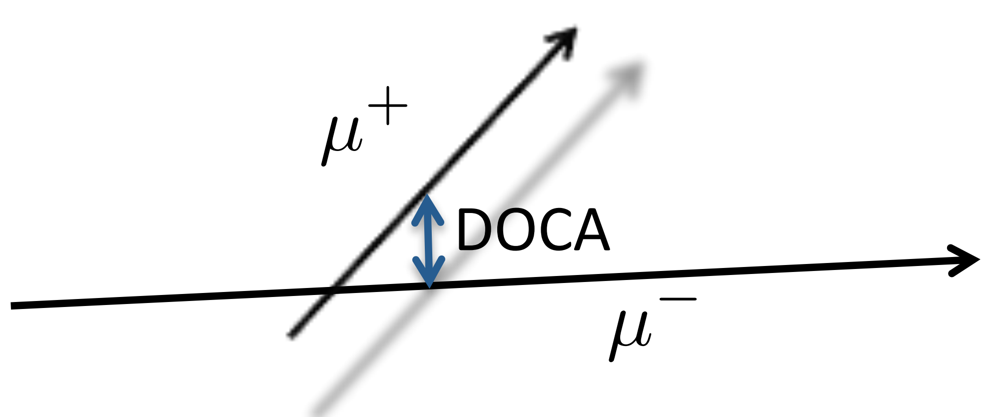


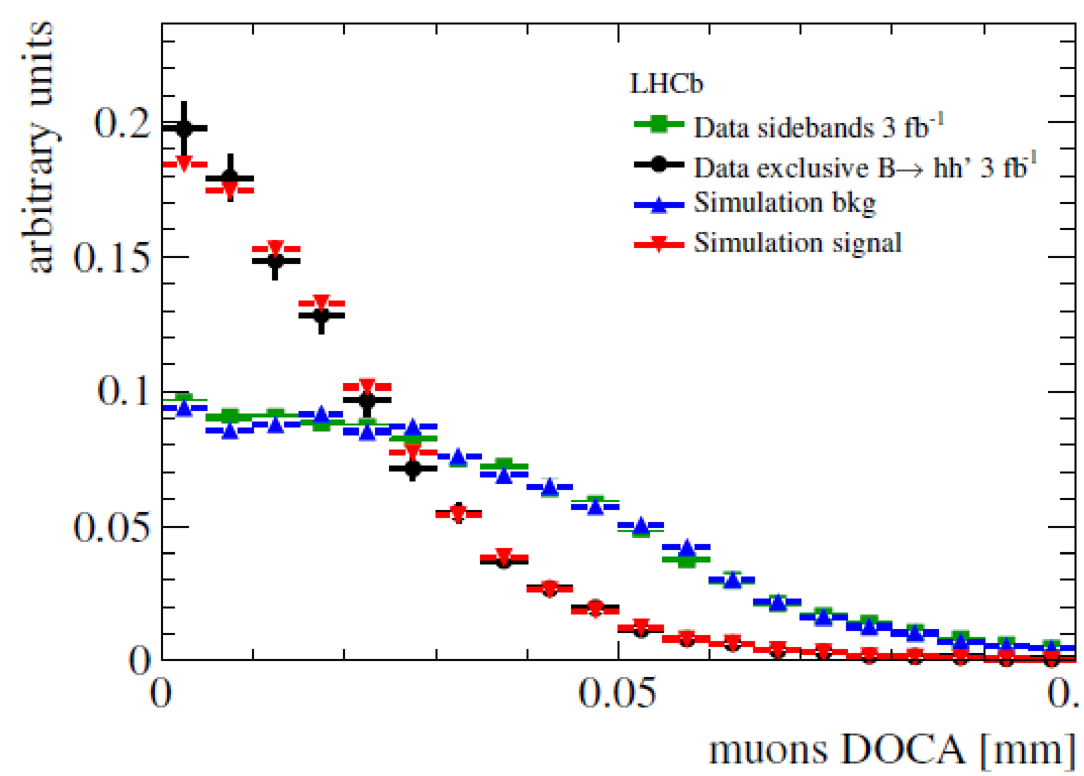
arbitrary units
LHCb
Data sidebands 3 fb^{-1}
Data exclusive B→ hh' 3 fb^{-1}
Simulation bkg
Simulation signal
0.2
0.1
0
0
0.05
0.1
IP(B) [mm]

Variables


P
p_T
Beam line


arbitrary units
LHCb
Data sidebands 3 fb[-1]
Data exclusive B→ hh' 3 fb[-1]
Simulation bkg
Simulation signal
p_T(B) [MeV/c]

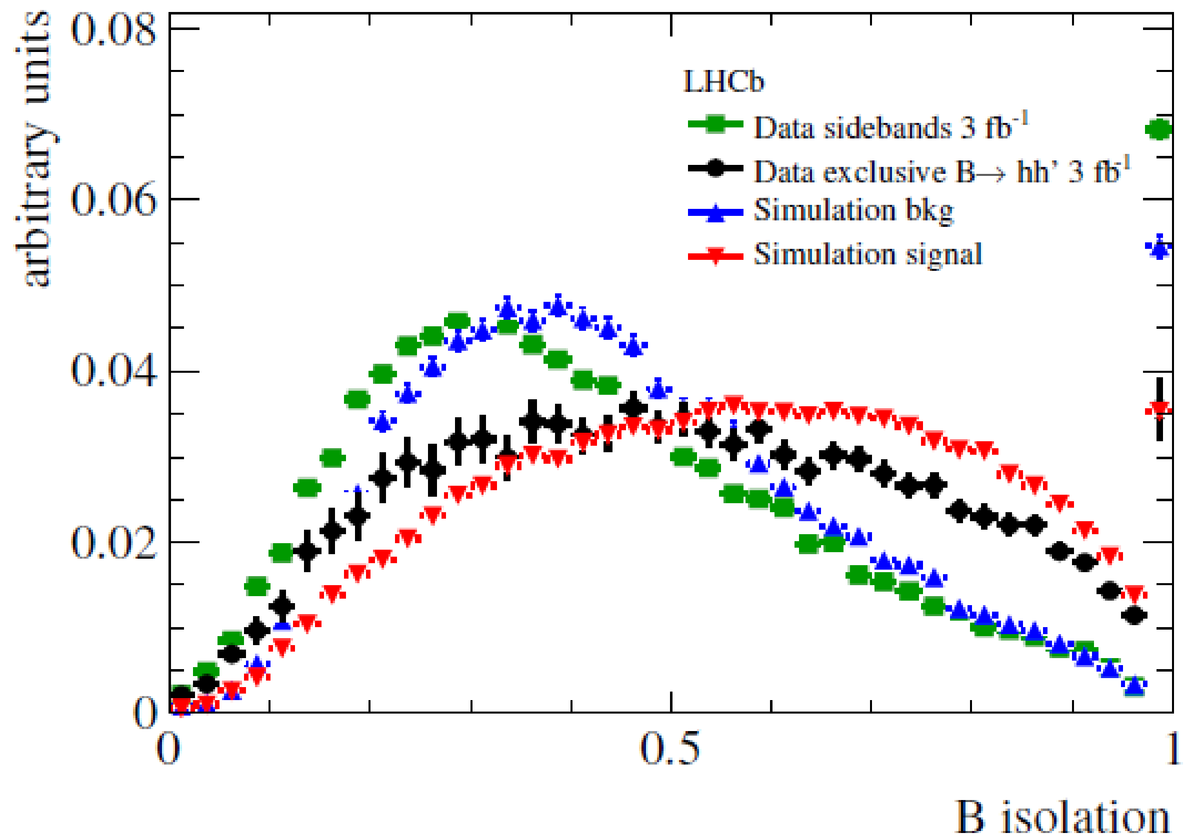

μ^+
DOCA
μ^-


arbitrary units
LHCb
Data sidebands 3 fb[-1]
Data exclusive B→ hh' 3 fb[-1]
Simulation bkg
Simulation signal
muons DOCA [mm]

Isolation

- Form cone around B direction, add pT of all other tracks around this cone.

$$I = \frac{p_T(B)}{p_T(B) + \Sigma_i^{tracks} p_T^i}$$

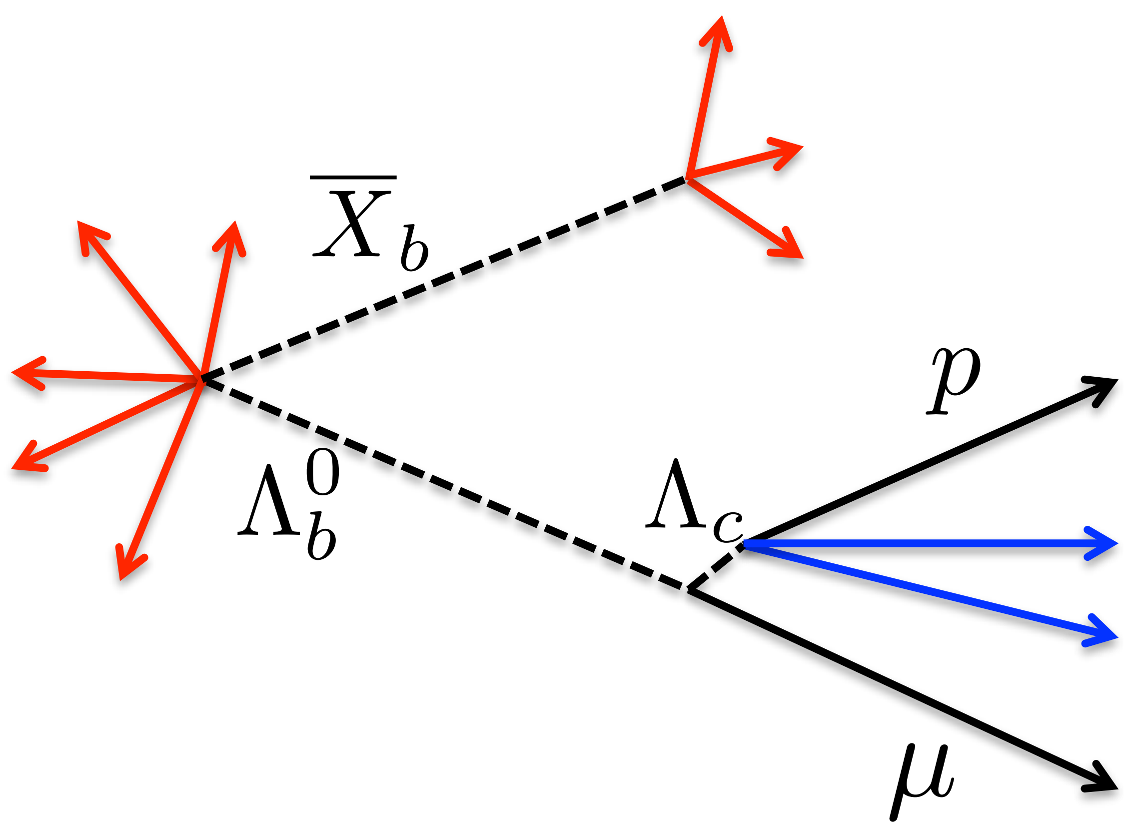


- Now we see some disagreement between calibration and training samples - is this OK?

  - Depends on situation, here removing background is much more important than anything else.

Multivariate isolation

- Many LHCb publications now use separate MVA to isolate signal from nearby particles.



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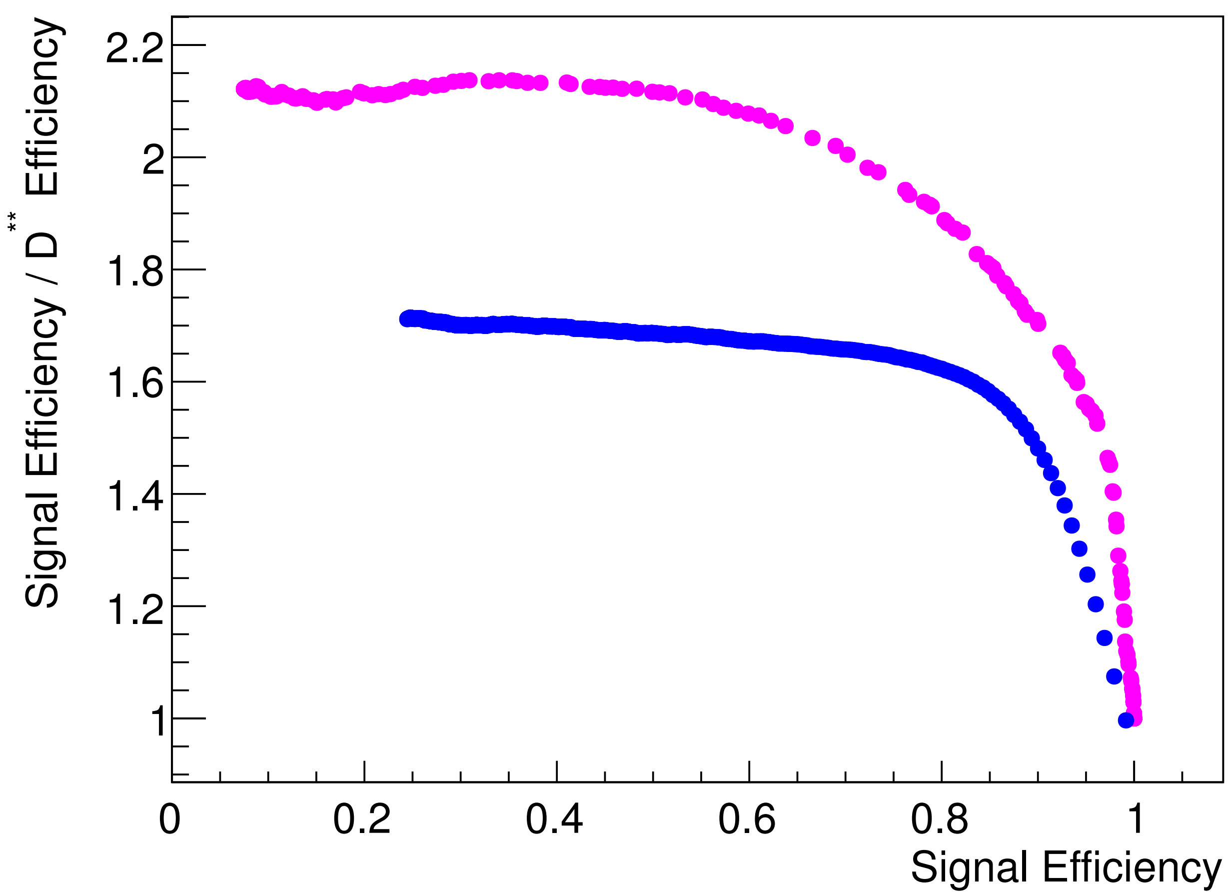


- Most important variable is the vertex quality difference when a track is added to signal vertex.

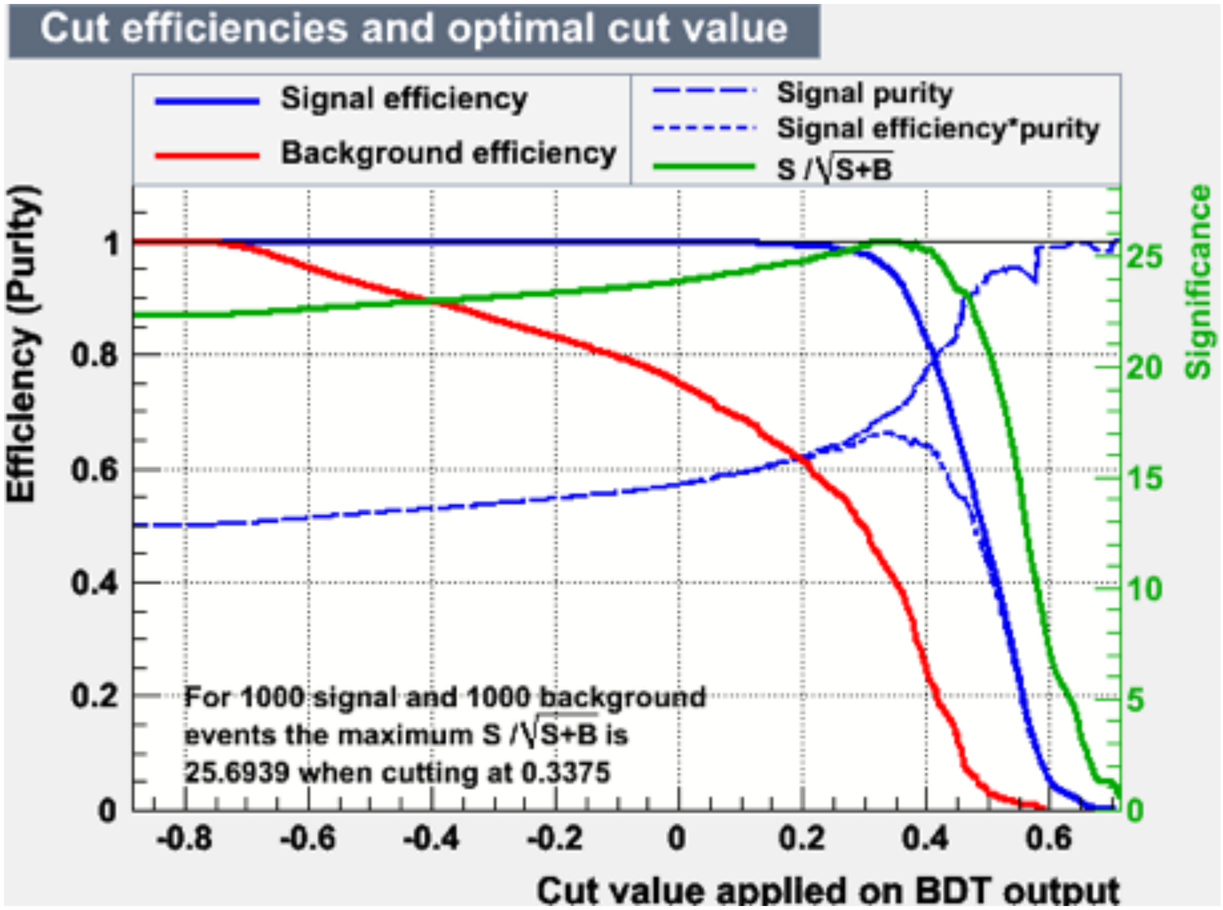
MVA application

- Simplest option is to place a cut on BDT response.
  - Most analyses in LHCb do this.
- Typically optimise requirement by maximising a figure of merit.

$$S/\sqrt{S+B}$$

$$\frac{\epsilon}{N_\sigma/2+\sqrt{B}}$$

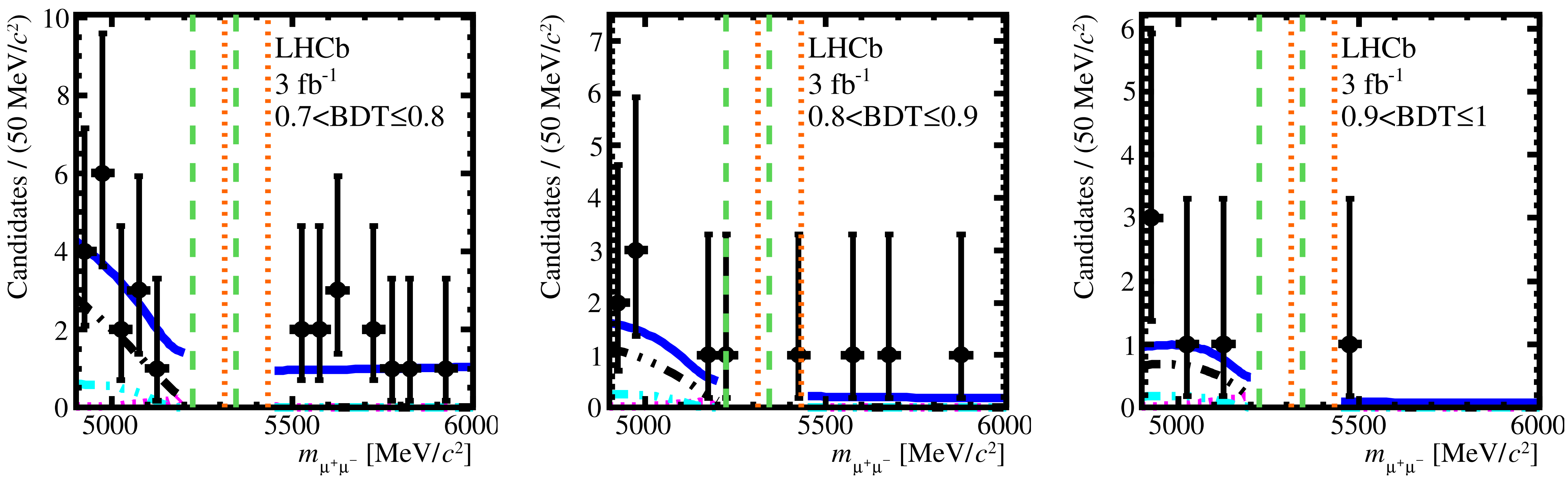
$$\mathcal{L}(\mathrm{sig}+\mathrm{bkg})/\mathcal{L}(\mathrm{bkg})$$



Binned response

- Will always get more sensitivity by binning the response instead of cutting on it.

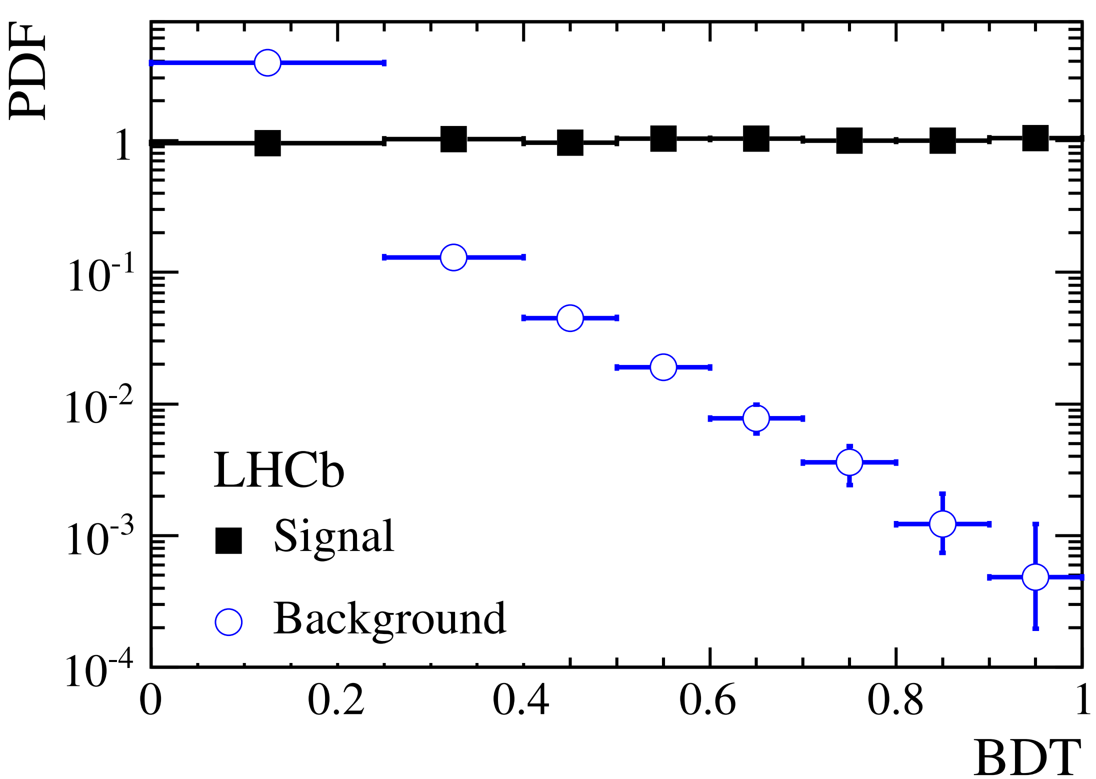
  - All events above BDT cut are treated equally, but this is of course not the case.

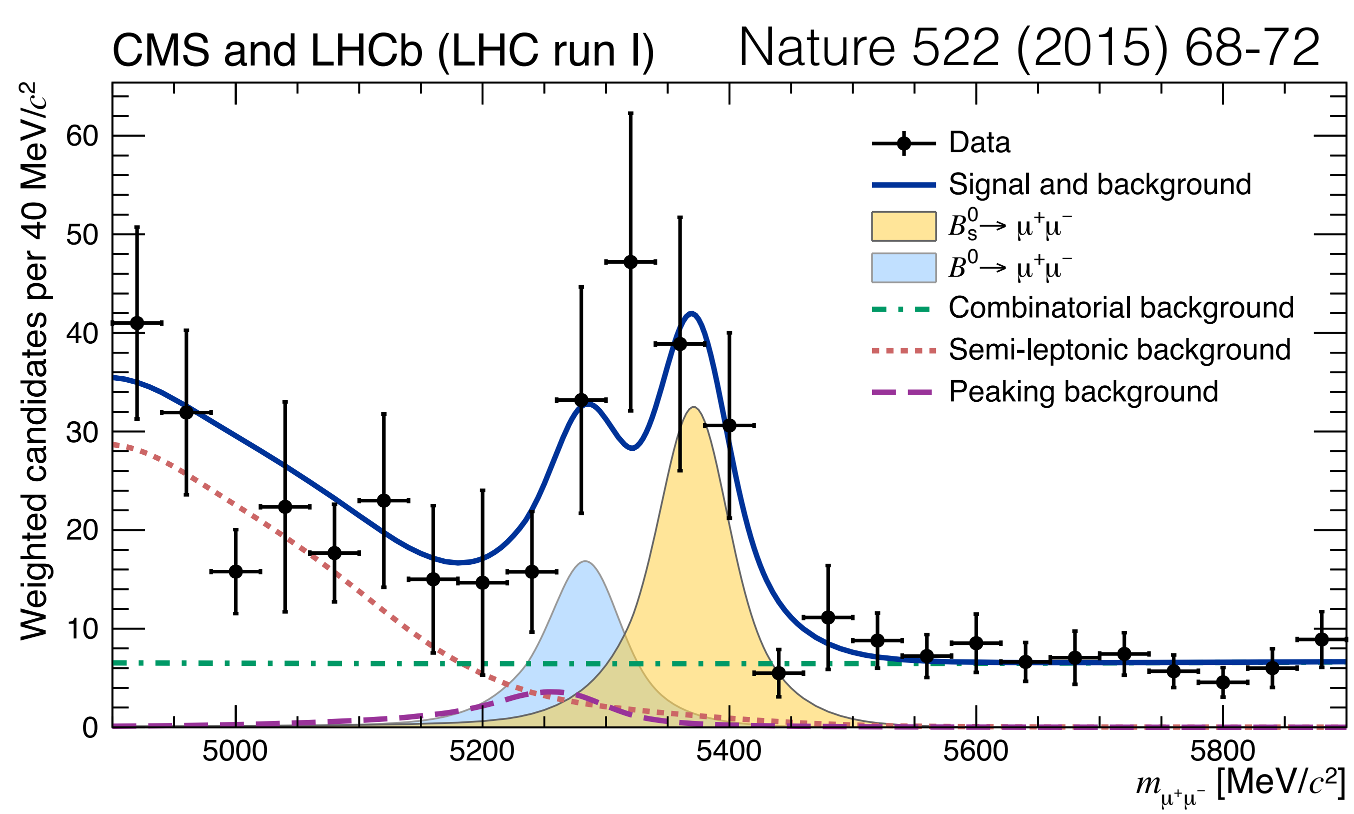


- There is no downside to doing this method, apart from the additional complexity.

Final performance

- Difficult to directly compare with cut-based approach (dropped it long ago), but clear that MVA made discovery possible.





- LHCb+CMS published observation of the decay in Nature earlier this year.

Choice of classifier

- Within LHCb, most common choice of classifier is BDT or Neutral Net.

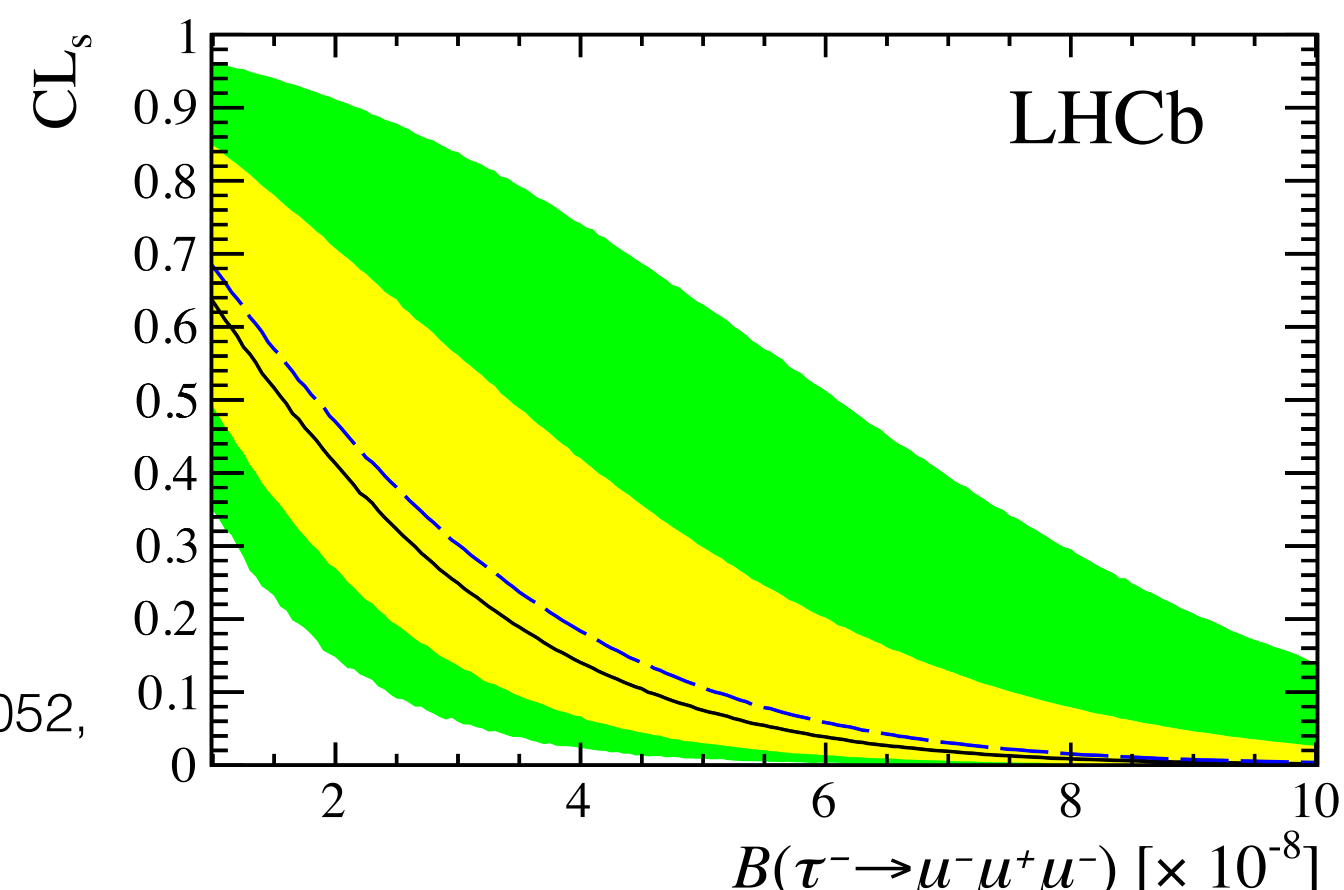
- For $B_s^0 \to \mu^+\mu^-$, there were many that were tried, performance based on separation power and bias to di-muon mass.

- Hot competition for the last round led to a very thorough optimisation, good improvement compared to previous papers.

- Proper tuning of configuration and experience tends to be more important than the actual choice.

Blending method

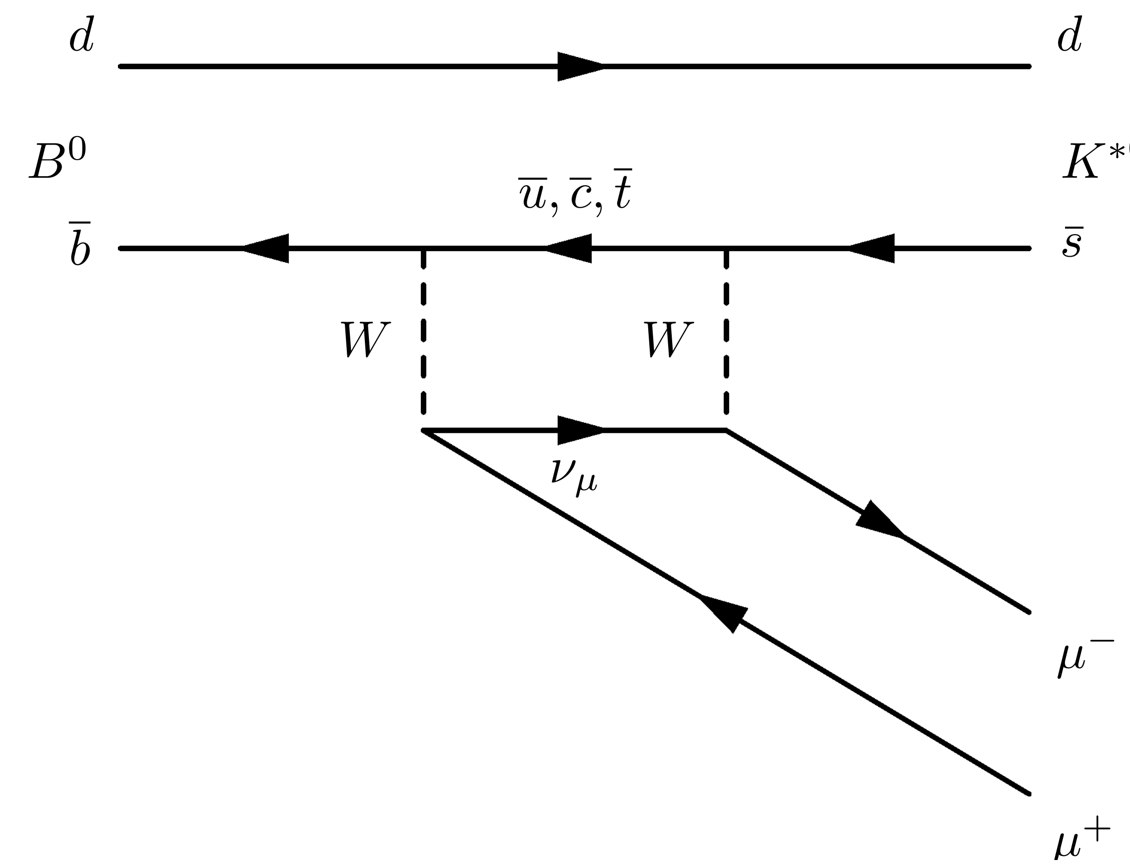
- Interesting approach used by $\tau^+ \to \mu^+\mu^-\mu^+$ analysis
  - Train 8 different classifiers with different configurations and combine responses into one BDT classifier.
    - 1 BDT, 2 Fisher discriminants, 4 neural networks, 1 one function-discriminant analysis, 1 linear discriminant.
- Improves sensitivity by 6% compared to using the best single classifier.



LHCb-PAPER-2014-052,
arXiv:1409.8548

Badly modelled variables

- Consider a slightly different decay, $B^0 \to K^{*0}\mu^+\mu^-$



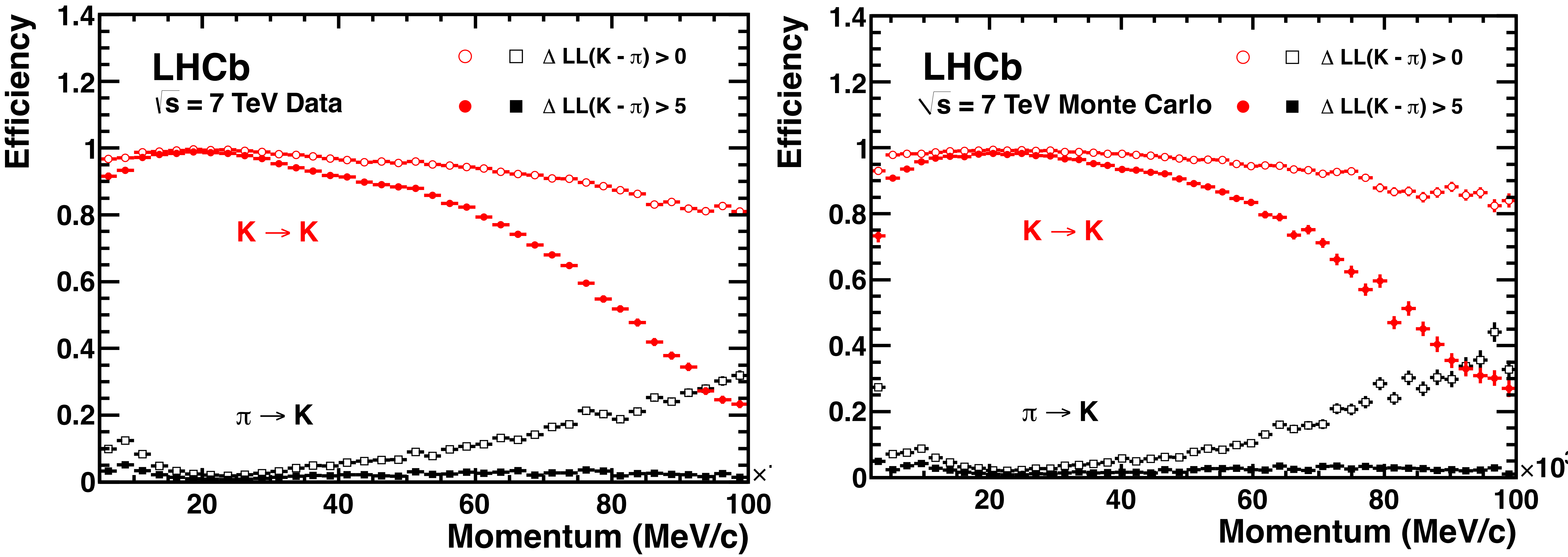
- Not as rare as $B_s^0 \to \mu^+\mu^-$, (no helicity suppression).

- Get an extra pion and kaon in the final state.

- Very important to use PID information in selection to remove background

Using Particle ID in an MVA

Particle identification criteria dependence strongly on momentum - perfect example of a variable that is useful in an MVA



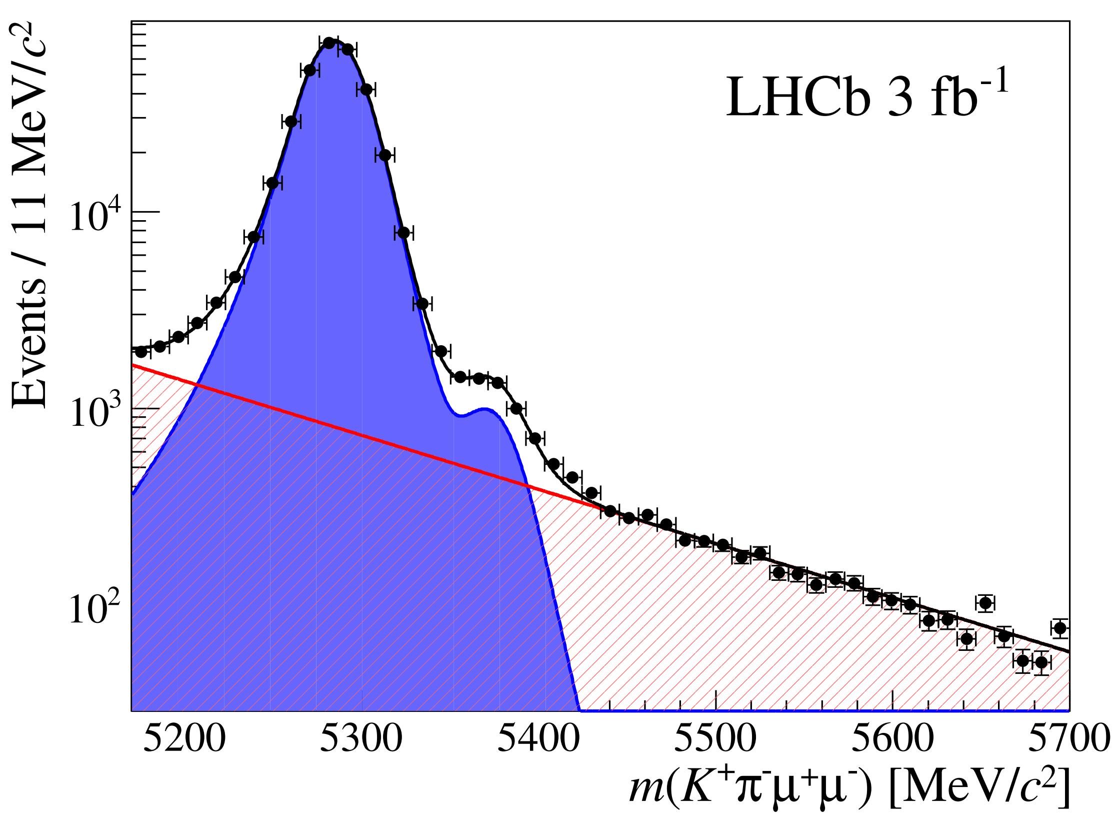
Unfortunately, it is not perfectly well modelled in the simulation.

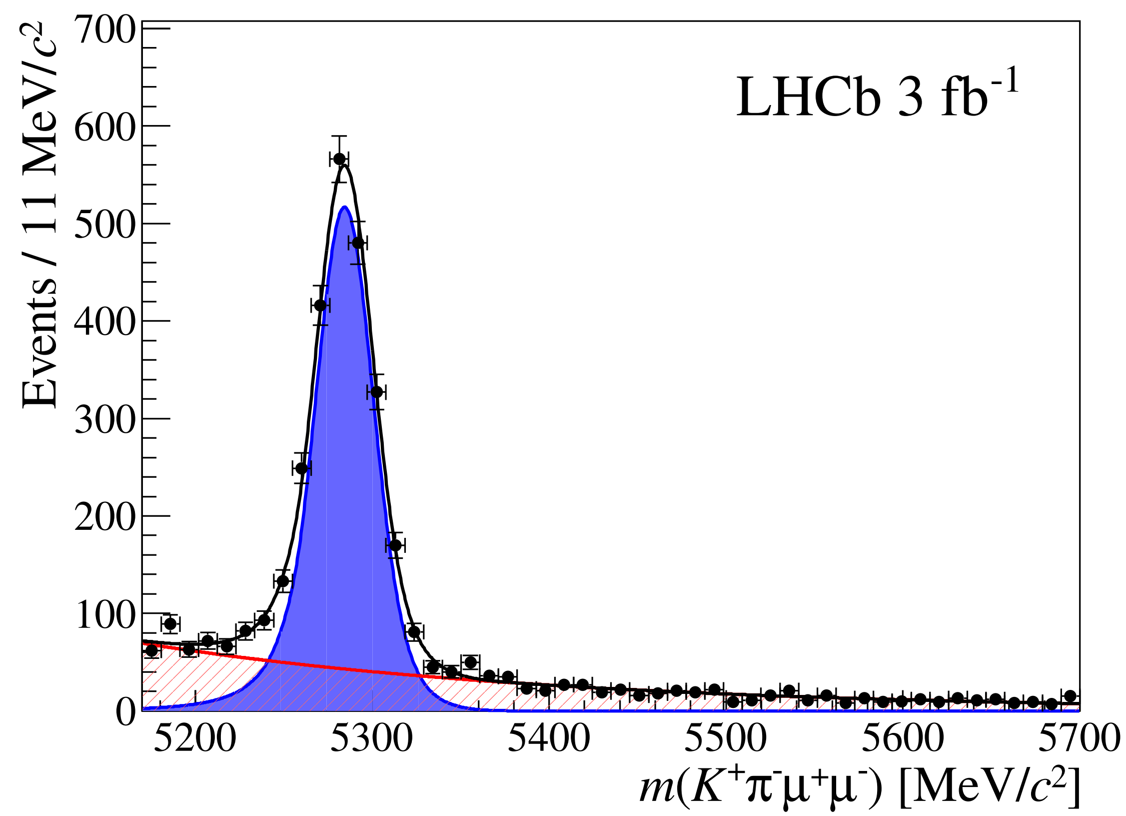
Cannot correct by simple 1D re-weighting - correlated to other observables.

Particle ID

- Use calibration samples in data to generate PID distributions as a function of momentum,eta and track multiplicity.
- Lose correlations between different PID observables

LHCb-CONF-2015-002

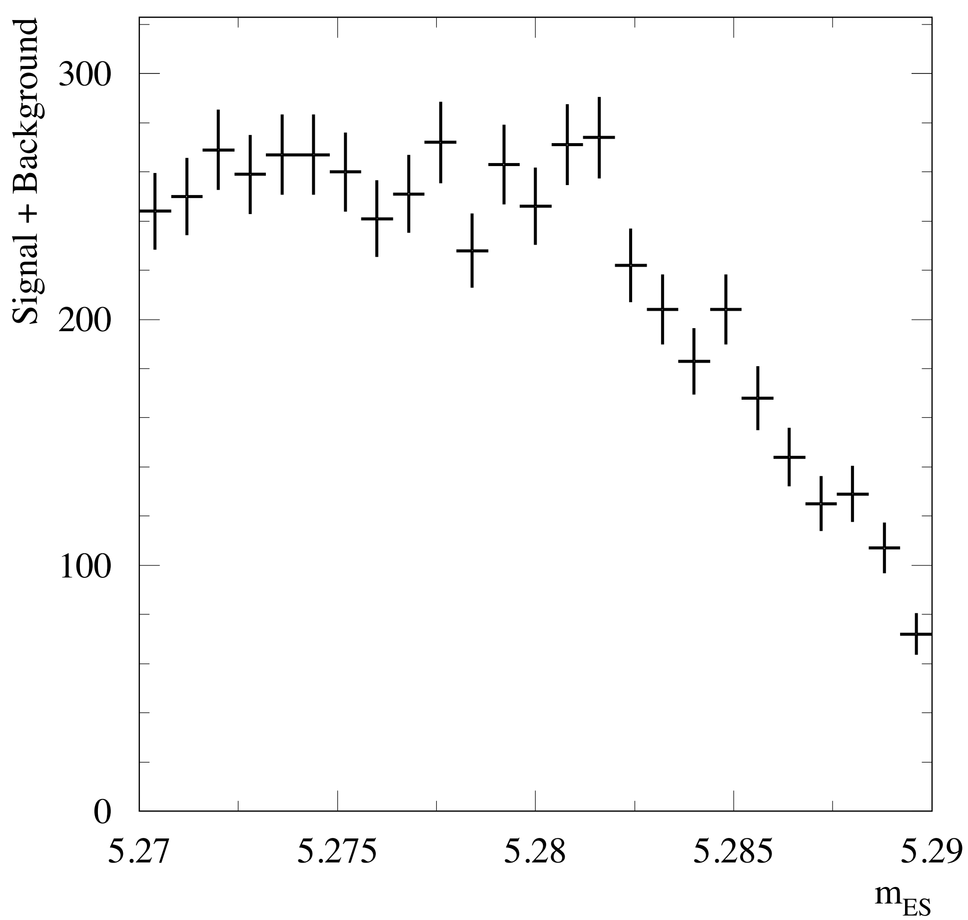




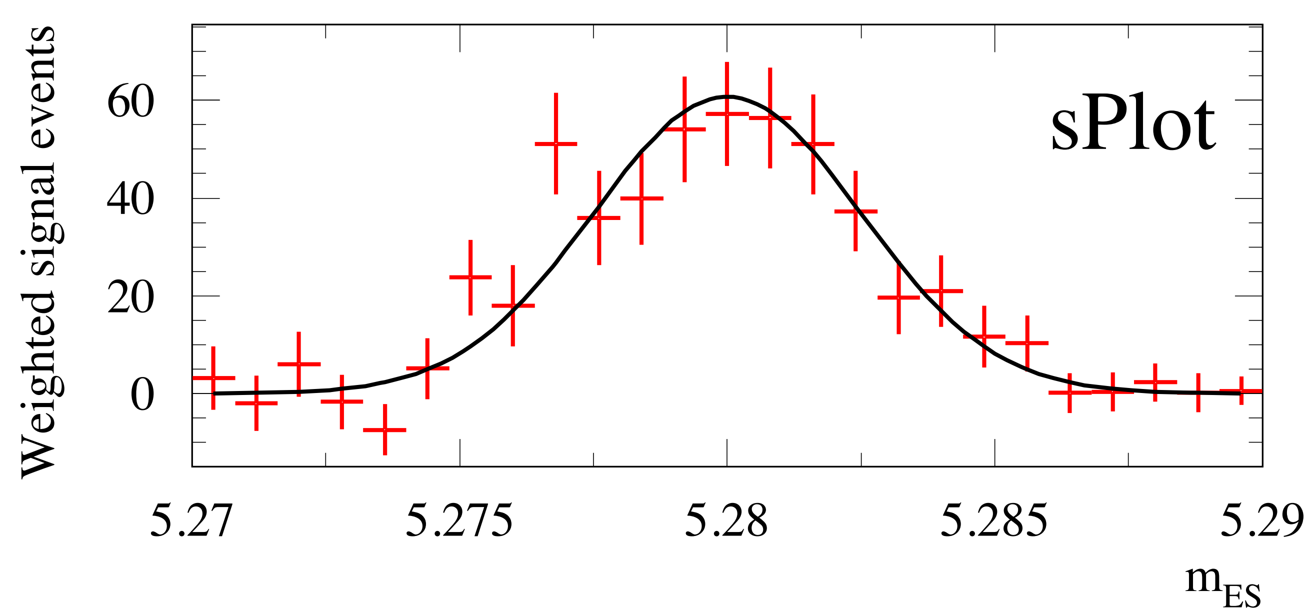
Answer: train on data!

Training on data

- Unfortunately unlike simulation, data is not purely signal.
- We use s-Plot technique to subtract background from signal region.



- Negatively weight the events in background rich regions to get purely.



Keeping data unbiased

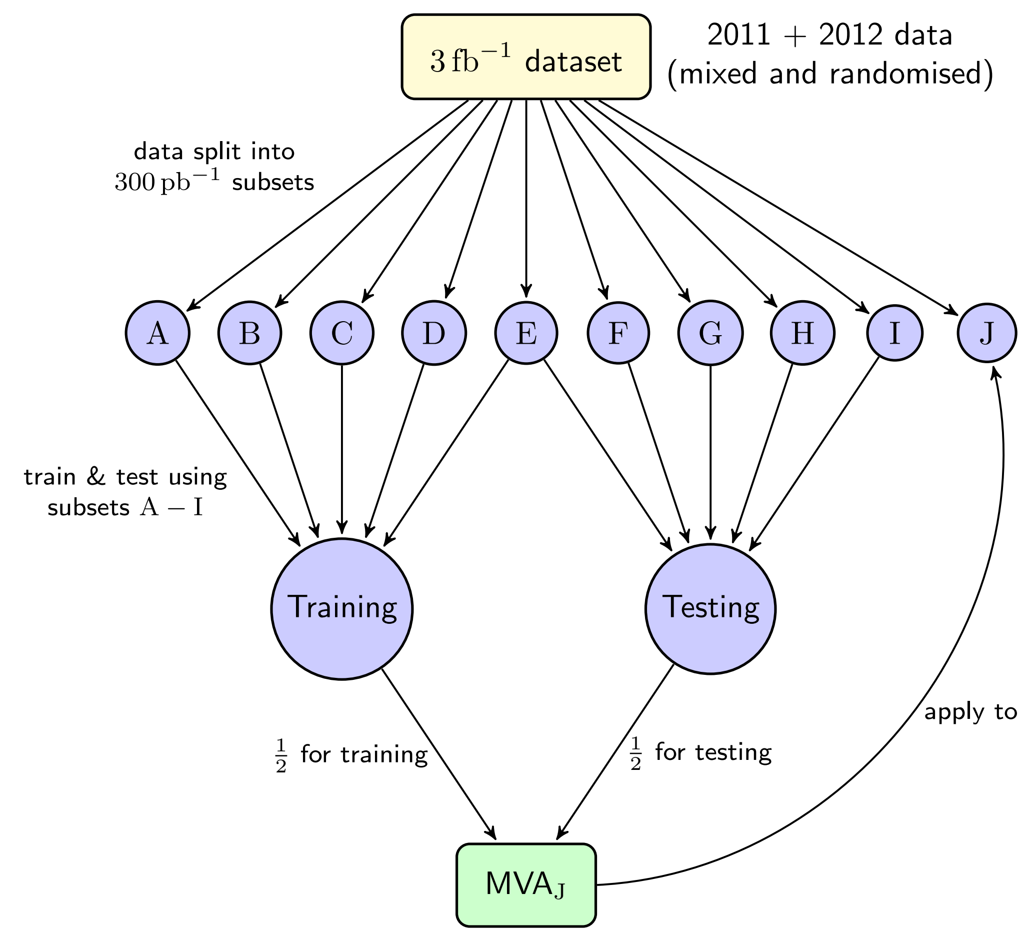
- Obviously can't train (or test) on data if you plan on using it later.

- Common solution in LHCb is to split data sample into subsets.

- Train/test on n-1 subsets, apply to final subset.

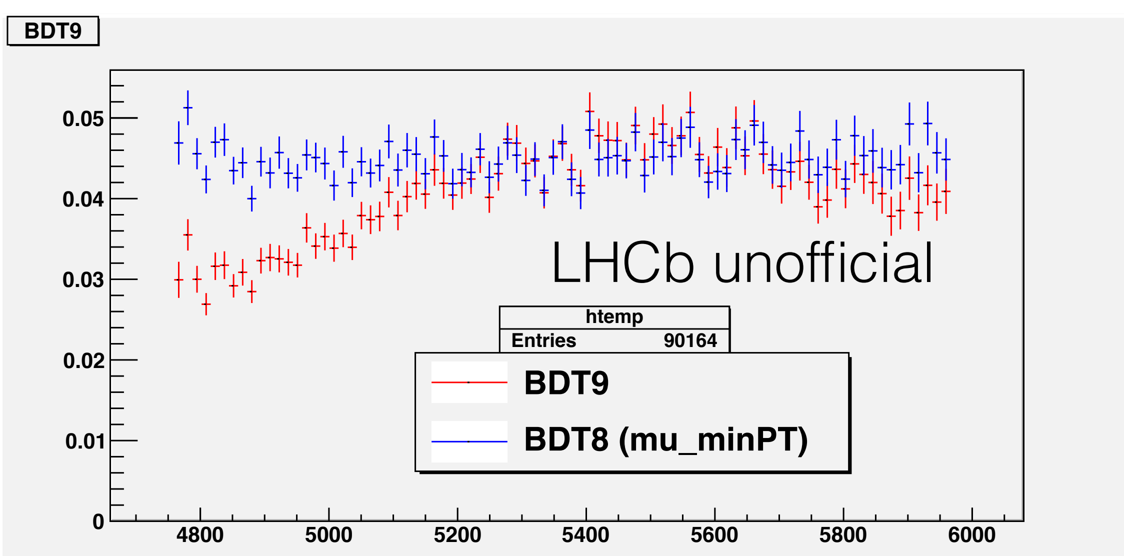
- Technique first used in LHCb for the $K_s^0 \to \mu^+\mu^-$ analysis.

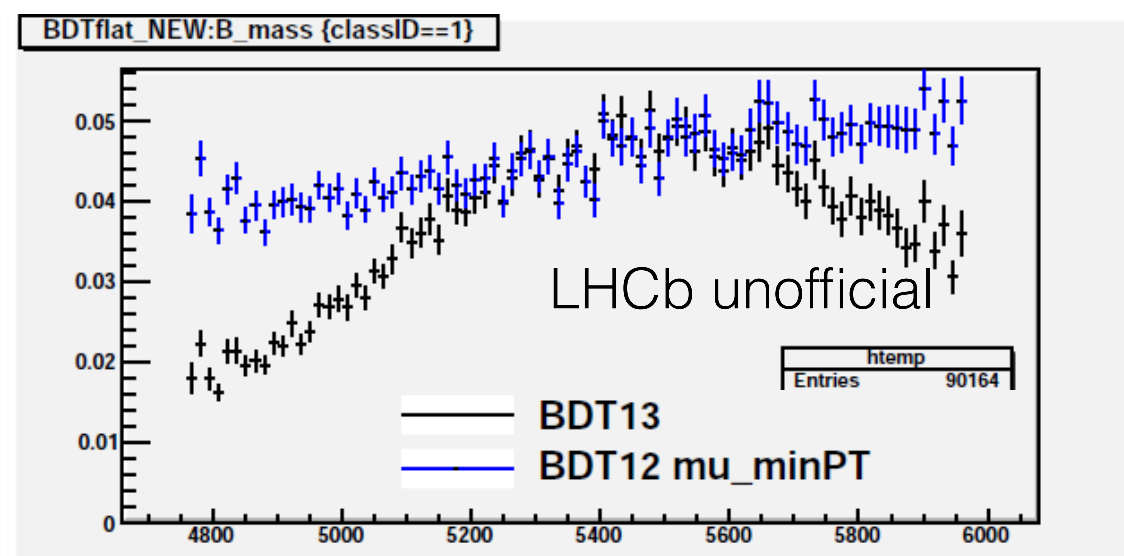
LHCb-PAPER-2012-023, arXiv:1209.4029



Correlation with mass

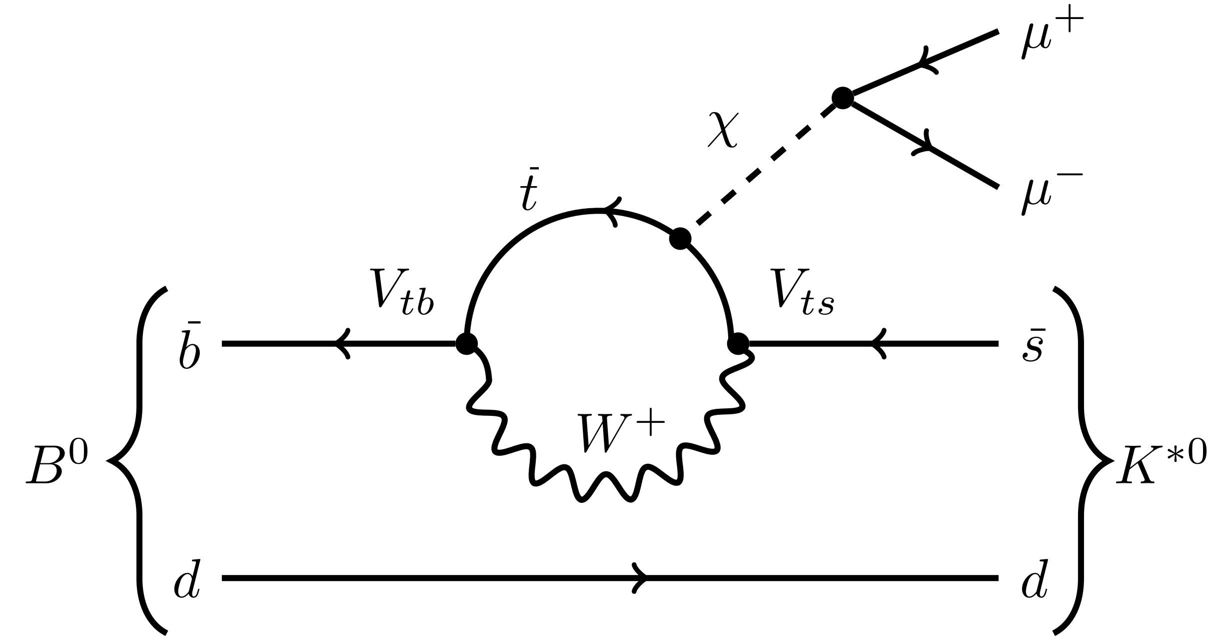
- Nearly always want to fit a mass distribution after MVA selection.
- Need to keep correlation between MVA and mass small, and smooth.
- Typically only an issue with two-body decays, as its easy to calculate the mass of the parent.





Slightly more complicated example

- LHCb good place to search for light, exotic particles, present in many extensions to the SM.



- Unknown lifetime and mass - want to train a selection which is unbiased in both of these.

- Problem: almost every useful variable is going to be correlated to at least of one these.

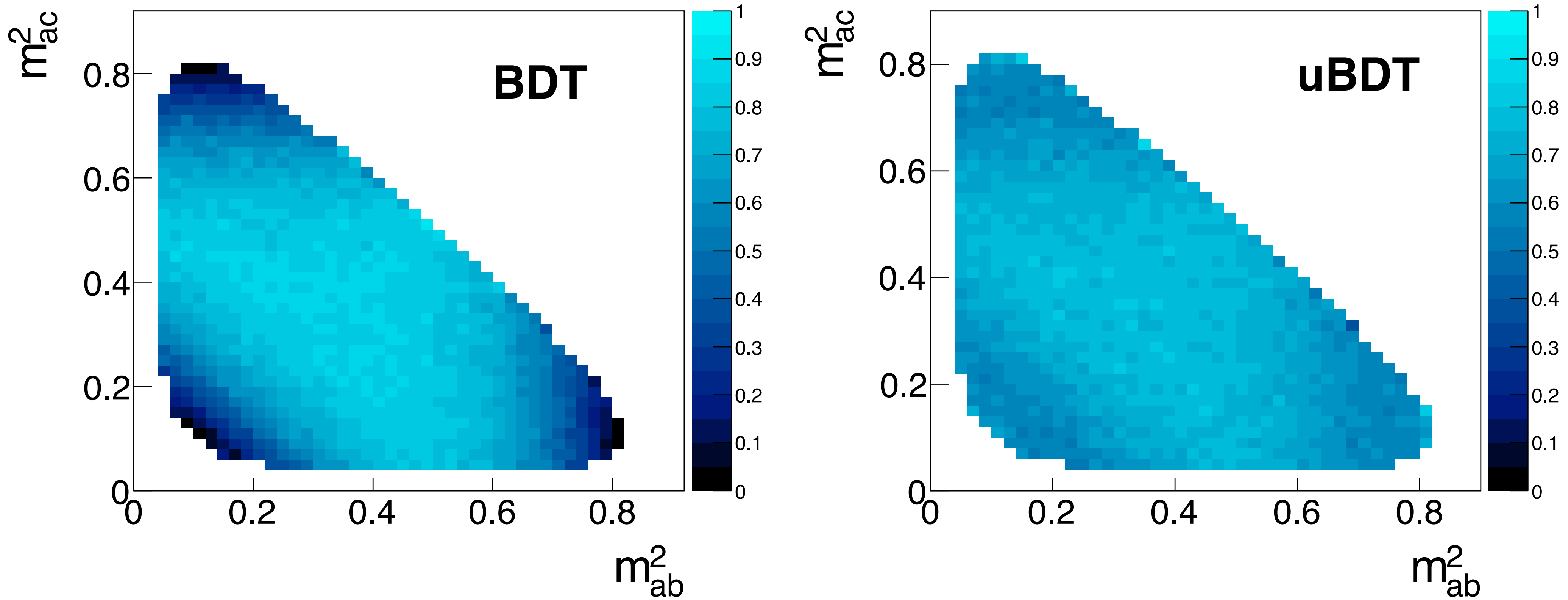
uBoost

- uBoost, is a method of boosting which preserves a uniform efficiency in variables of choice.

- Multiply boosting weights by the non-uniformity.

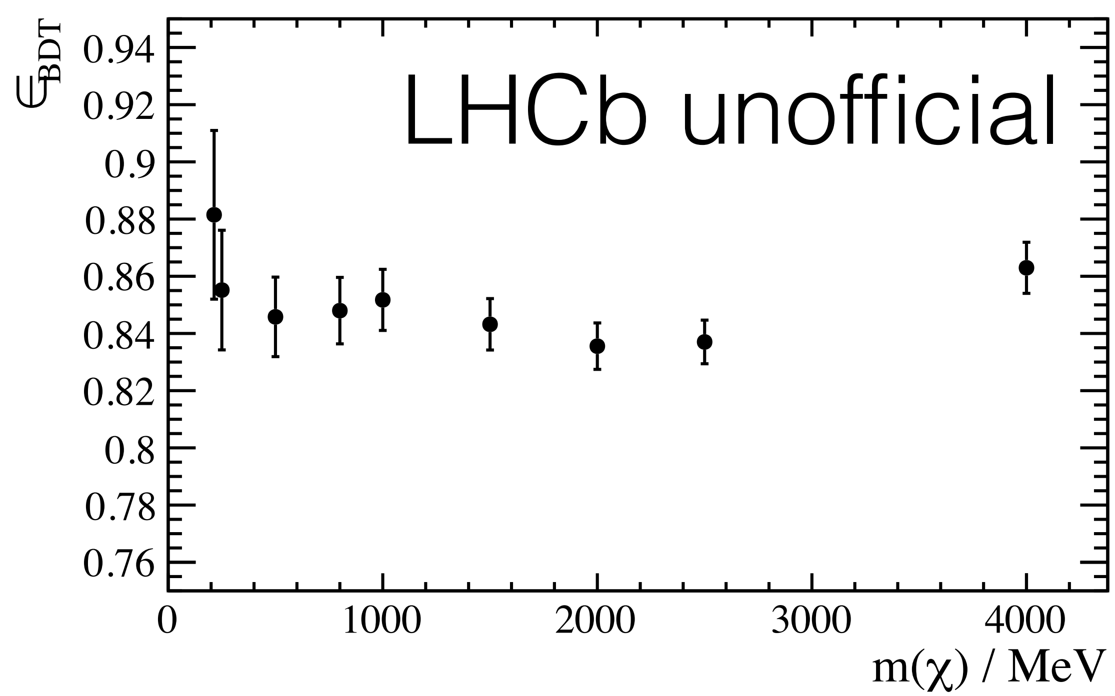
    - Approach improved recently, see: A. Rogozhnikov et al, arXiv:1410.4140

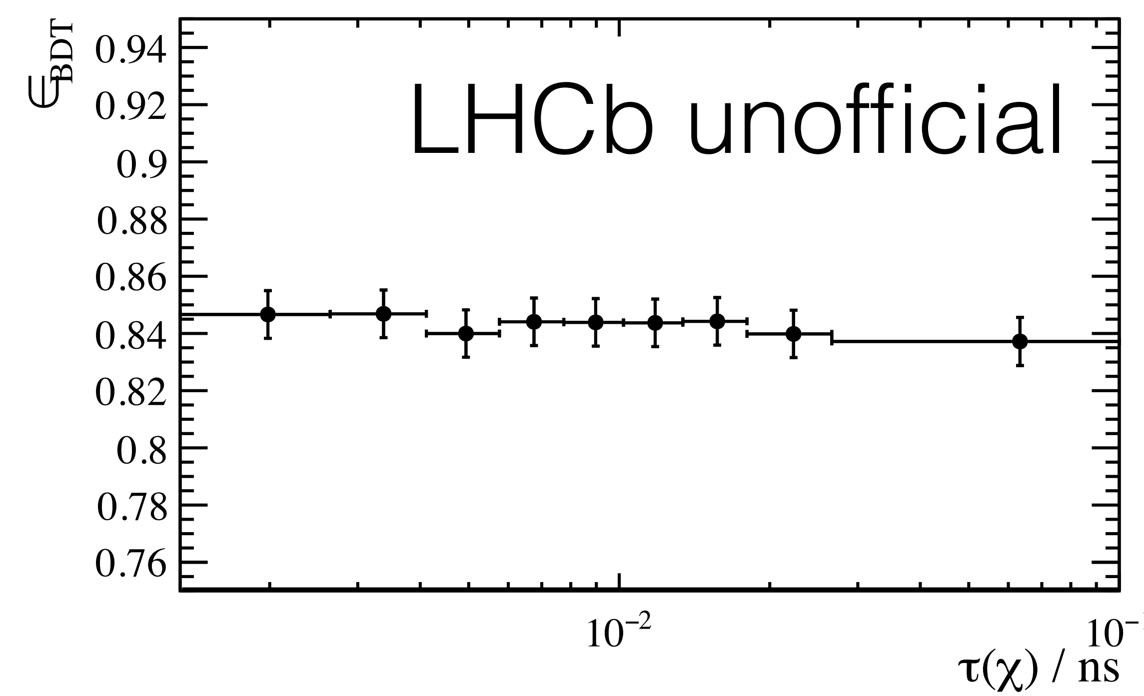
- Not only mis-classified events are boosted but also events which have low efficiency.



uBoost advantages

- To avoid bias normally one needs to remove variables
- Exploit maximal amount of information whilst keeping POIs flat in efficiency.

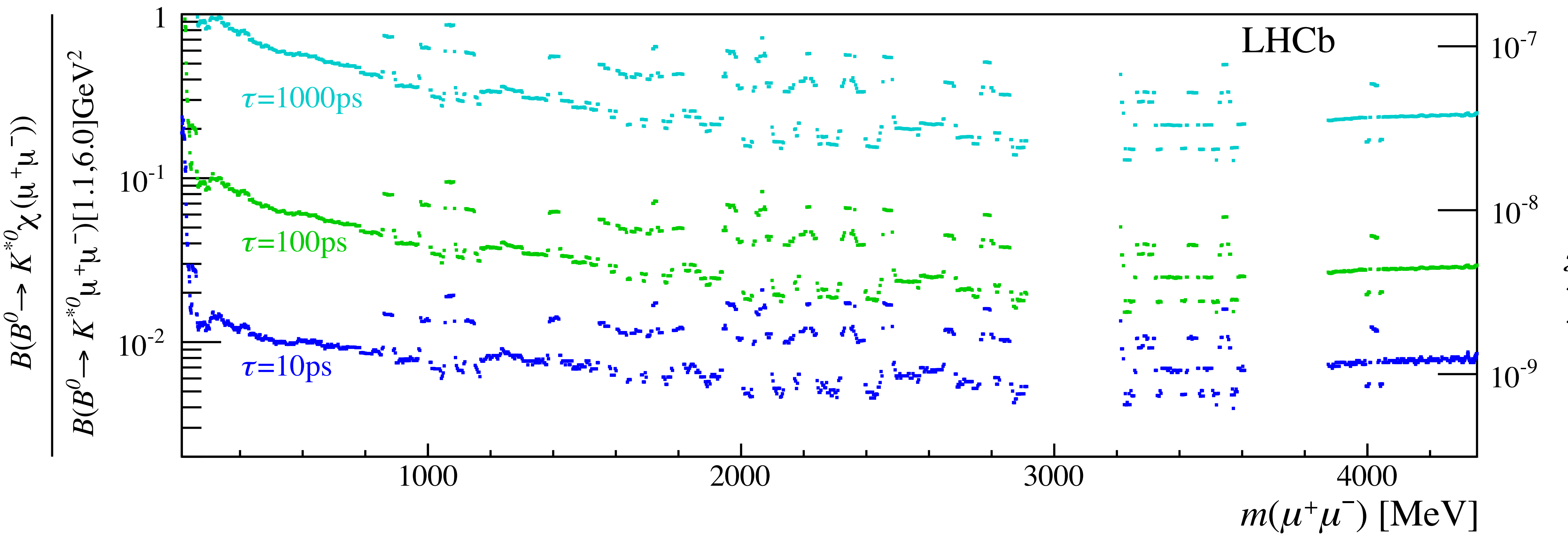




- uBoost BDT has flat efficiency in both mass and lifetime.

Results

- Set limits on decay mode.



- Efficiency as a function of lifetime inversely proportional to limit, but no issue regarding final selection.

Things for the future

conservatism

[k*uh* n-**sur**-v*uh*-tiz-*uh* m]

Spell Syllables

Examples Word Origin

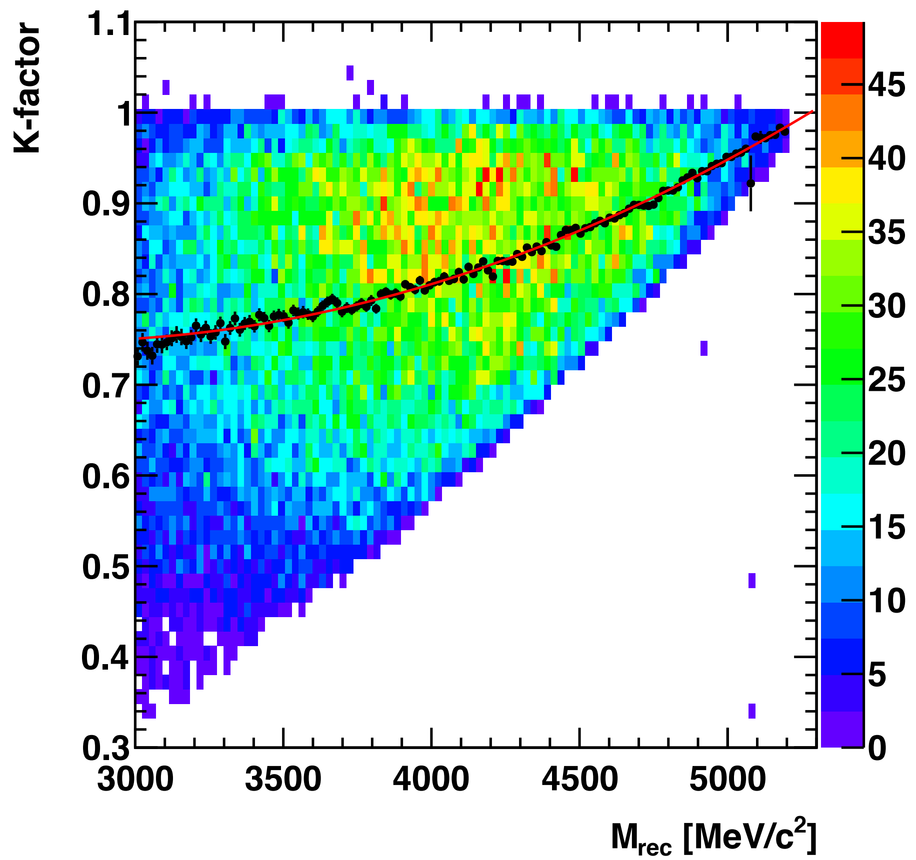
noun

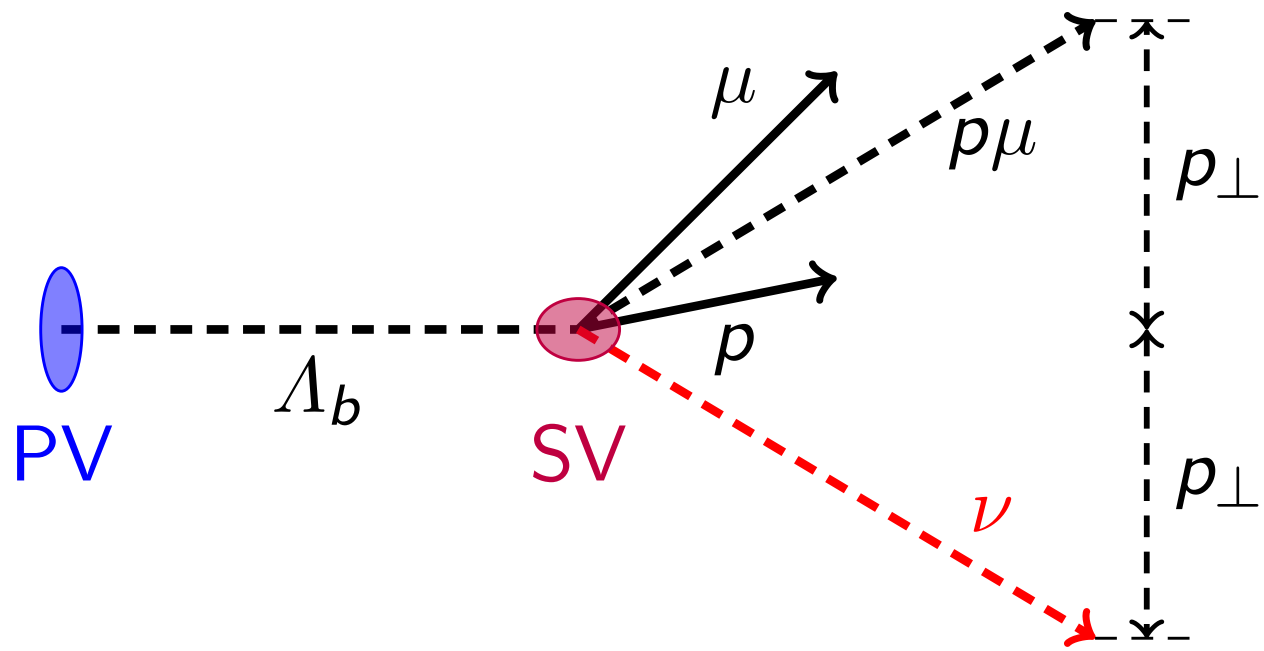
1. the disposition to preserve or restore what is established and traditional and to limit change.

Resolution and regression

- Many interesting B decays contain neutrinos in the final state, e.g. B—>Dmunu.

- Two methods commonly used: k-factor and ‘neutrino reconstruction’.



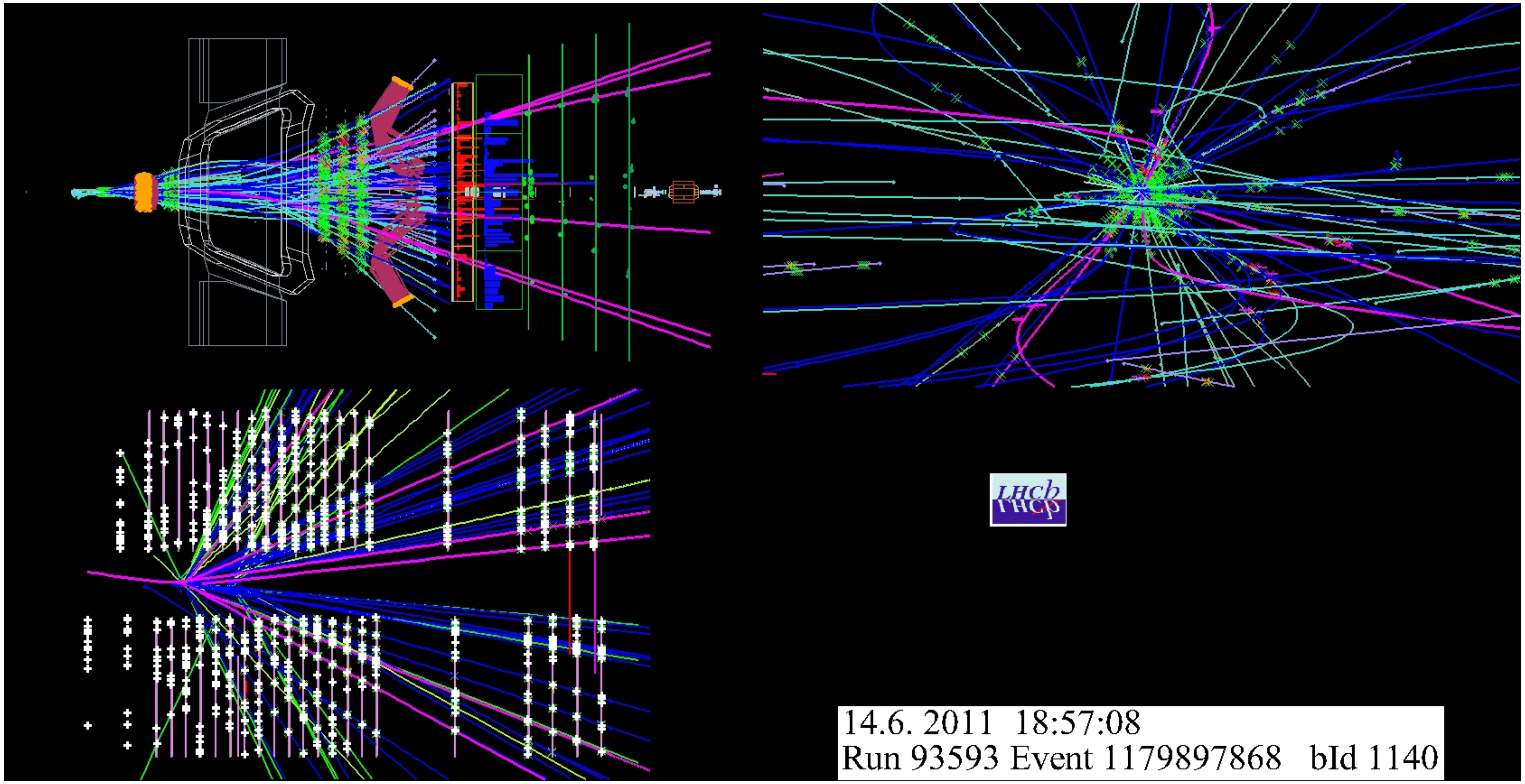


This does not utilise any information rest of event - could a regression algorithm improve things further?

Image recognition software

- Most of the ML tools we use are fairly old now.

- Can we make use of image recognition software? For isolation? For flavour tagging?



Conclusion and outlook

- LHCb is an LHC experiment dedicated to studying charm and beauty particles.
- Machine learning is used in many places in LHCb.
  - Its rare to see an analysis without an MVA.
- Mostly use ML for high level information (momentum, impact parameter ..).
- We are still using old MVA techniques, but are slowly moving towards more modern tools and techniques.