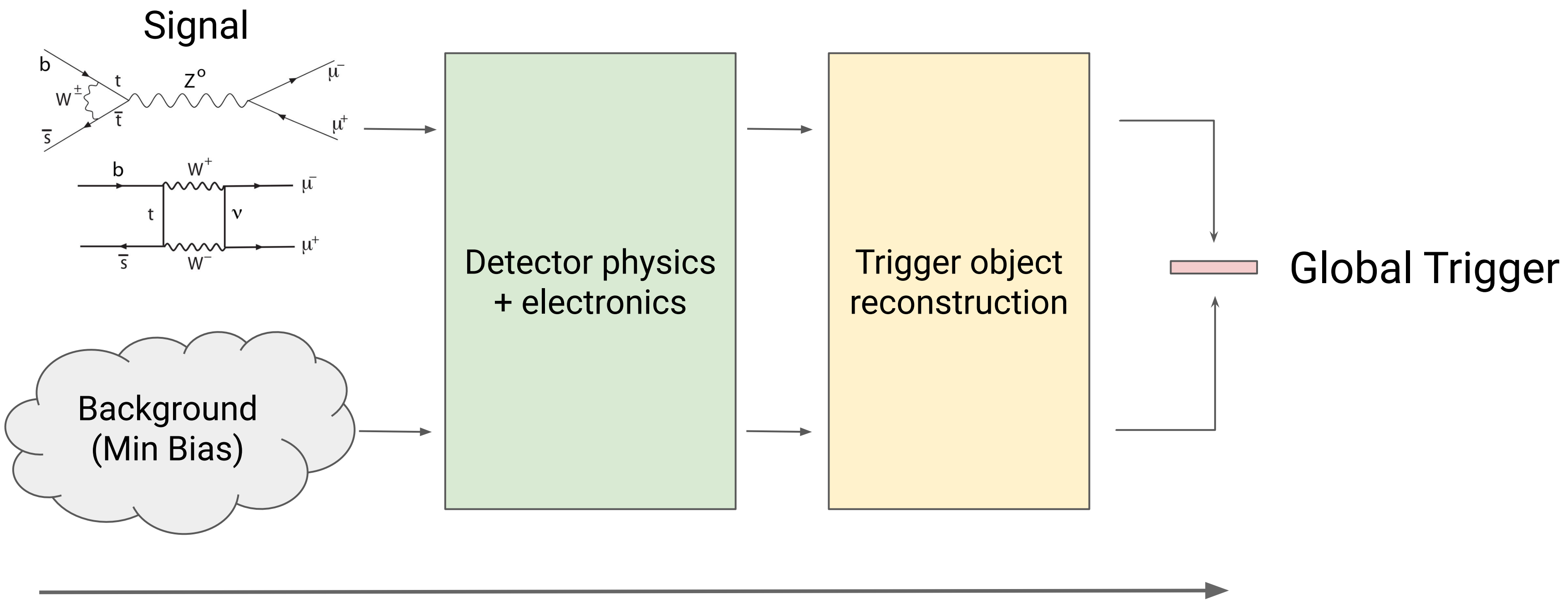
Optimizing cut-based algorithms to specific physics acceptance regions

Gabriele Bortolato[1,2], **Benjamin Huber**[1,3], Elias Leutgeb[1,3,4], Dinyar Rabady[1], Hannes Sakulin[1] on behalf of the CMS Collaboration

[1] CERN, [2] Universit´a degli Studi di Padova , [3] Technische Universität Wien, [4] Imperial College London

Introduction



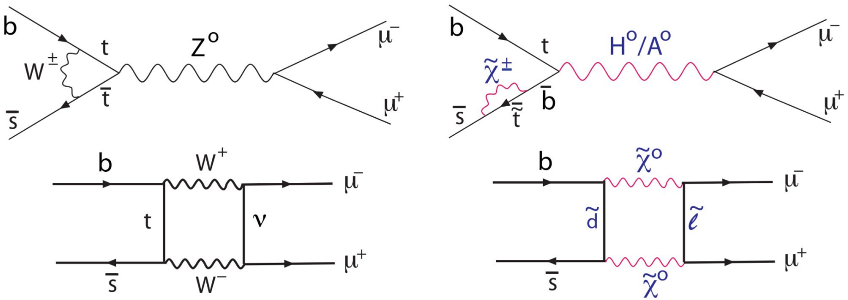
Difficult to model distributions and covariances of involved variables

Introduction

Idea: Automatize the building of a CMS Level-1 trigger selection for various physics signatures using cut-based algorithms

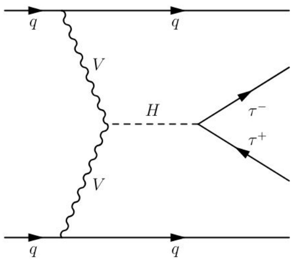
Two "toy" examples for demonstration

Bs ➞ μμ



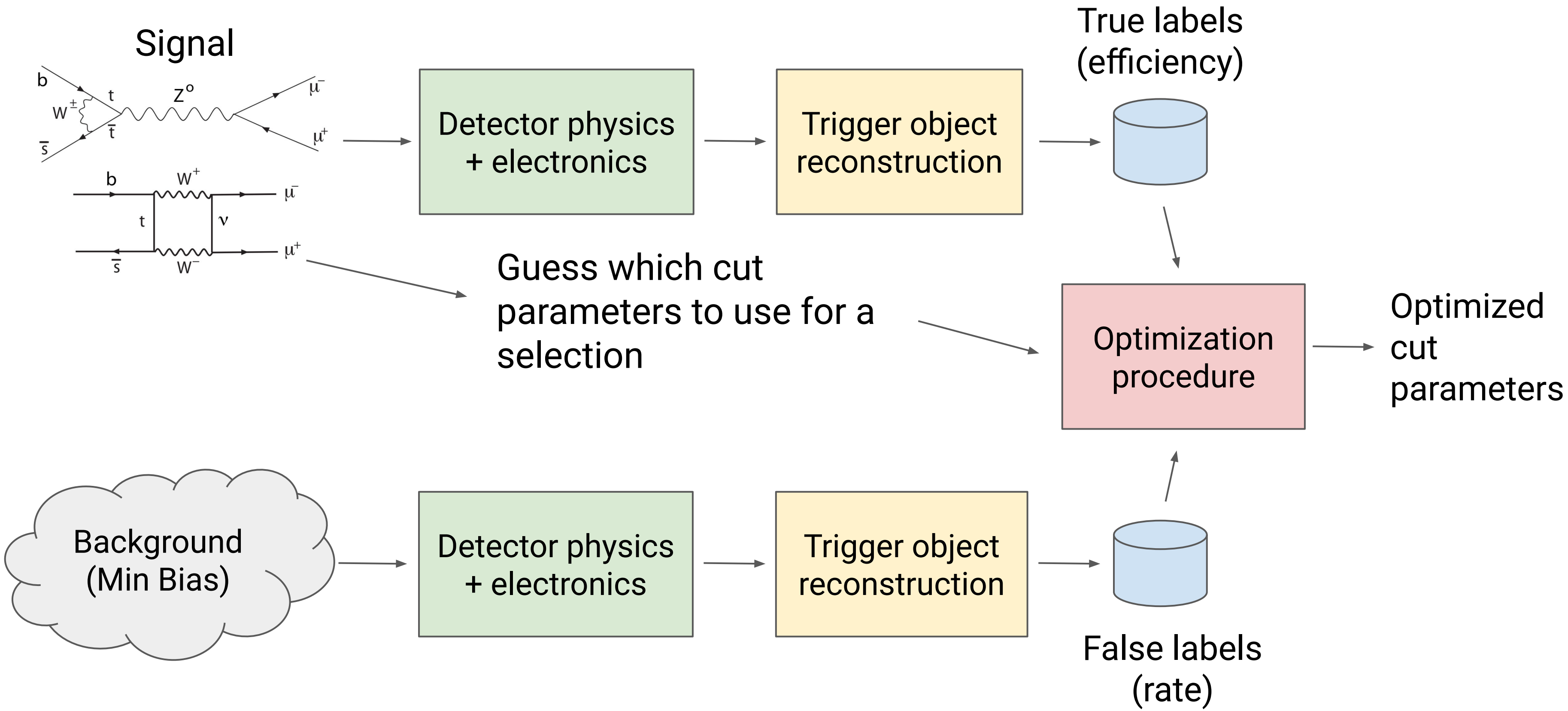
[1] **Left**: SM Bs ➞ μμ decay channels
Right: BSM Bs ➞ μμ decay channels

VBF H ➞ ττ

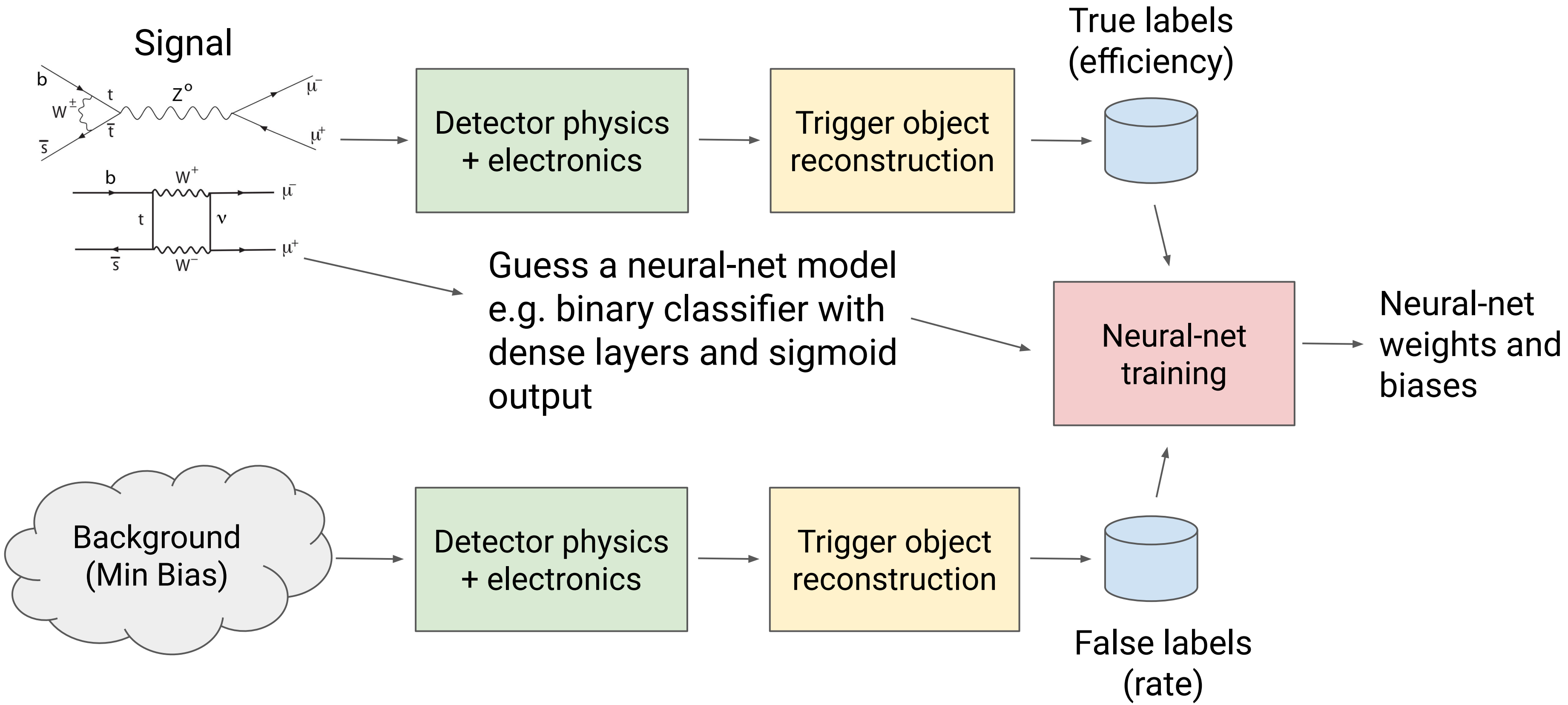


Goal: Determine the optimal cut parameters through an automated procedure to maximize signal efficiency, while maintaining the rate near a budgeted rate according to a specified trade-off preference

Introduction



Introduction: Similarity with neural-nets



Theoretical background

- Optimizing cut-based trigger algorithms (seeds) is a 2-objective optimization problem (maximize efficiency and minimize rate)
- One can leverage achievement scalarization = scalarize the problem by using a reference point
- Wierzbicki: $$s(f(x)) = \max_{i=1,\dots,k} \left[\omega_i \left(f_i(x) - g_i\right)\right] + \rho \sum_{i=1}^{k} \omega_i f_i(x)$$ [5, 6]

f_i … component of function to optimize

g_i … component of reference point

ω_i … scale factor

ρ … augmentation coefficient

k … number of objectives

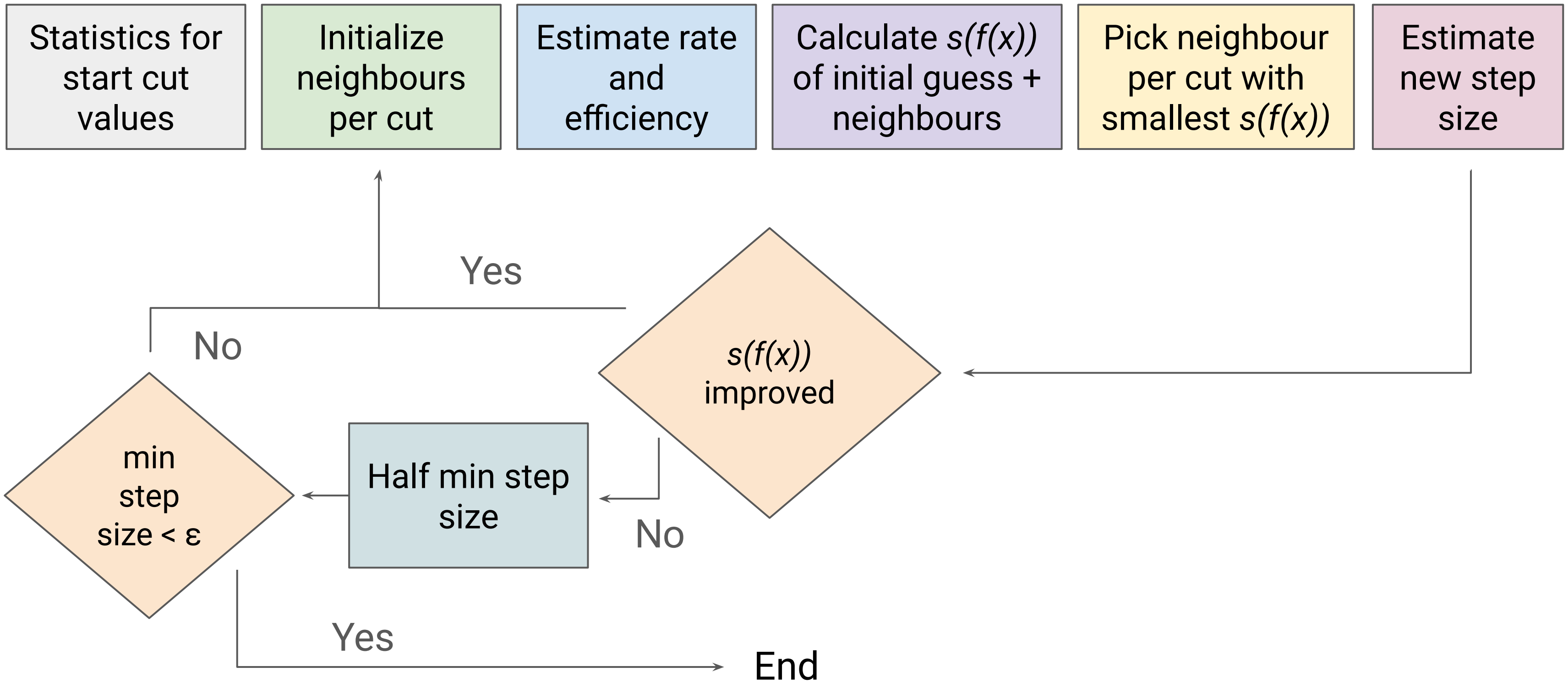
- In our case this loss function can be written as:

$$f_1 = \text{rate}, \quad \omega_1 = \frac{1}{\text{desired rate}}, \quad g_1 = \text{desired rate}$$

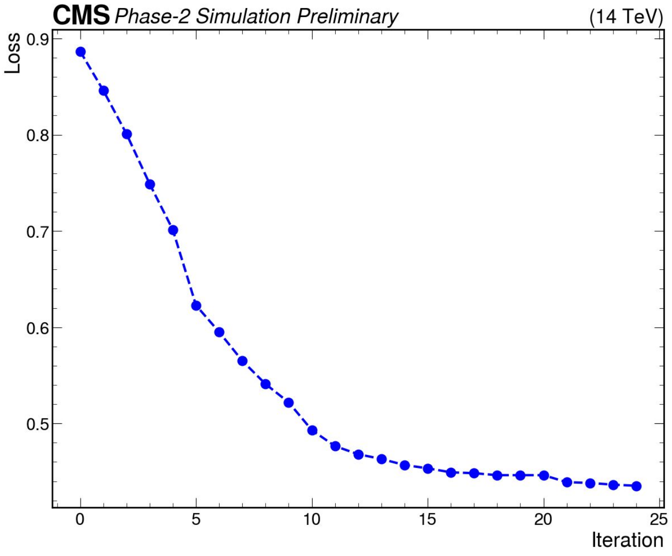
$$f_2 = 1 - \text{efficiency}, \quad \omega_2 = 1, \quad g_2 = 1 - \text{desired efficiency}$$

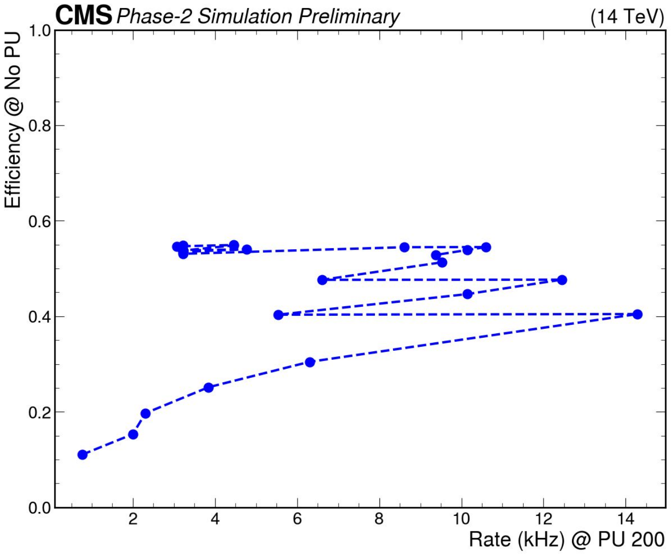
$$s = \max\left[\frac{\text{rate}}{\text{desired rate}} - 1, \text{desired efficiency} - \text{efficiency}\right] + 0.05\left(\frac{\text{rate}}{\text{desired rate}} - \text{efficiency}\right) + \text{Const}$$

Optimization procedure



Bs ⟶ μμ (optimization iterations)





Optimization of double track matched muon [4] seed with cuts on: p_T, η, quality, invariant mass, ΔR, Δz_0, charge correlation using the reference point: desired efficiency = 1, desired rate = 15 kHz.

Left: Evolution of loss vs. iteration, showing that the loss decreases with each iteration (dashed line for visual guidance).
Right: Evolution in the efficiency vs. rate phase space, starting with iteration 0 in the bottom left (dashed line for visual guidance).

Bs ⟶ μμ (solution plausibility)

Converged to 55 % efficiency (No Pile-Up) and 3.2 kHz rate ➞ 51 % efficiency with Pile-Up 200

Optimized cuts:

Muon1:
$p_T > 3.551$ GeV
~~$\eta > X$~~ pruned
$\eta < 2.431$
qualityFlags = loose

Muon2:
$p_T > 3.481$ GeV
~~$\eta > X$~~ pruned
$\eta < 2.431$
qualityFlags = very loose

Max measurable $\eta \sim 2.4$ ➞ both pruned

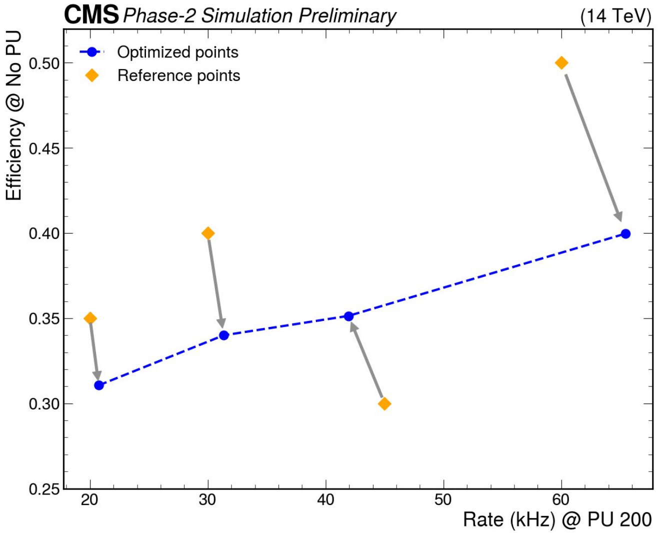
Correlations (Muon1 + Muon2):
Invariant Mass > 4.859 GeV
Invariant Mass < 6.522 GeV
$\Delta R > 0.0$
$\Delta R < 1.64$
$\Delta q = 2$ e ($q_1 \neq q_2$)
$\Delta z_0 < 1.317$ cm

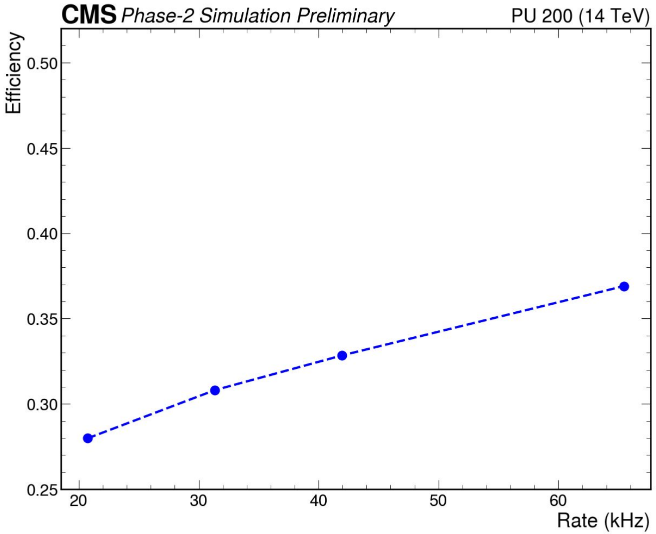
Invariant mass of Bs meson: 5.37 GeV

Bs meson q = 0 e

Close together ➞ from same mother particle ($c\tau \sim 0.5$ mm)

VBF H ⟶ ττ (moving the reference point)



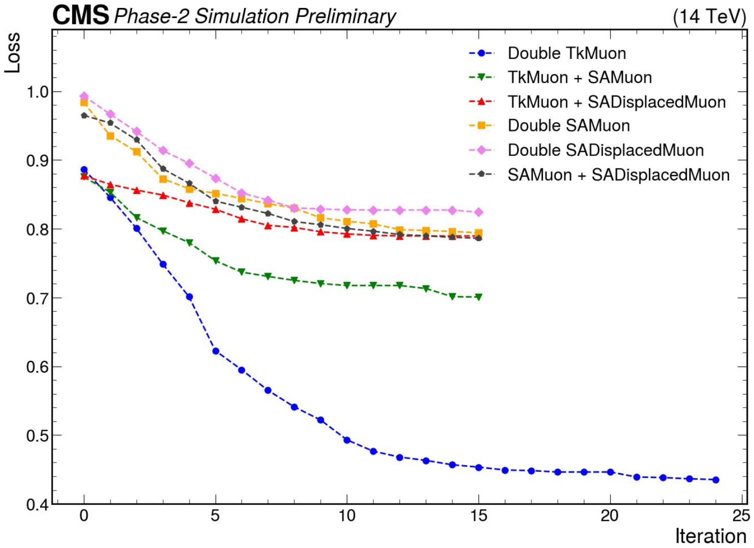


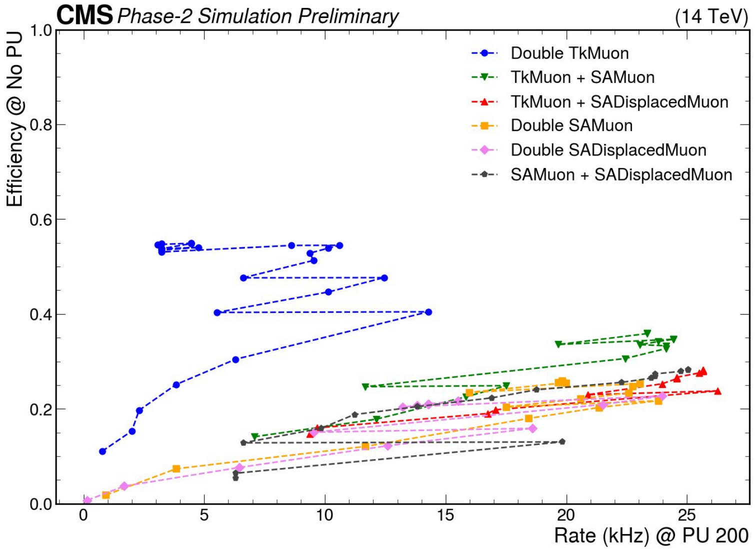
Optimization of VBF H ➞ ττ for various reference points using a double Puppi NN tau [5] algorithm. The plots exhibit that moving the reference point (desired rate + desired efficiency) allows finding different solutions on the Pareto front.

Left: Various reference points converging to points on the approximated Pareto front (Efficiency without PU, dashed line for visual guidance).

Right: The points form an approximated Pareto front (Efficiency with PU 200, dashed line for visual guidance).

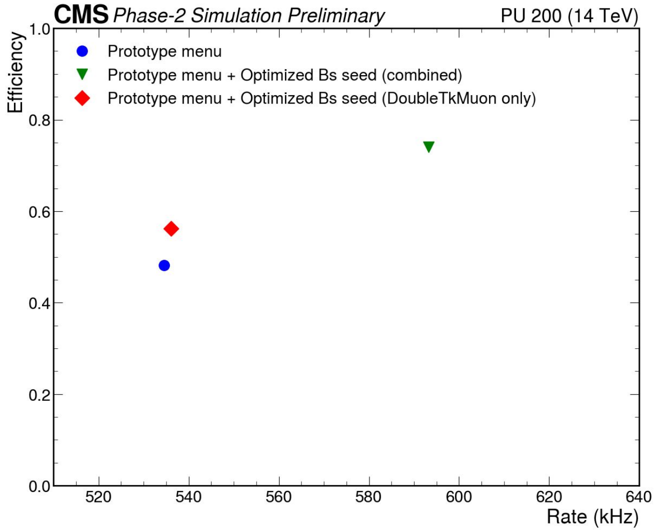
Bs ⟶ μμ (creating an algorithm)

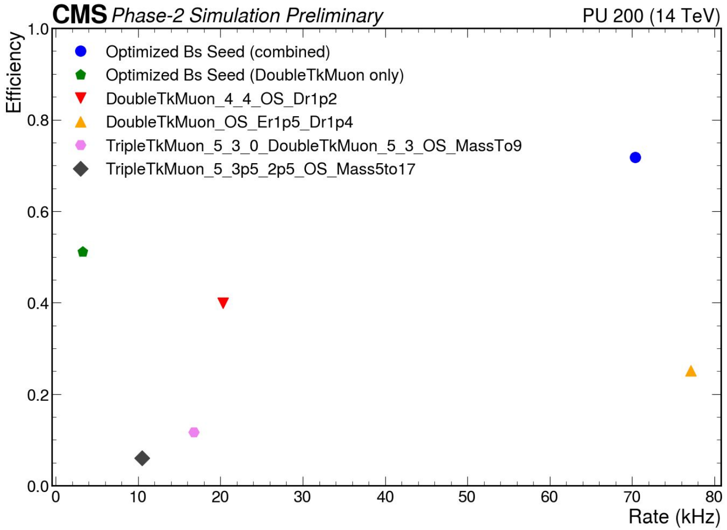




Optimization of all muon collection correlations (TkMuon = track matched muon, SAMuon= standalone muon, SADisplacedMuon = standalone displaced muon) separately with reference point: desired efficiency = 1, desired rate = 15 kHz.
This was done for a later combination via a logical “OR” into an algorithm.
Left: Evolution of loss vs. iteration, showing that the loss decreases with each iteration (dashed lines for visual guidance).
Right: Evolution in the efficiency vs. rate phase space, starting with iteration 0 in the bottom left (dashed lines for visual guidance).

Bs ⟶ μμ (creating an algorithm)





Adding the optimized combined algorithm (logical "OR" of all muon collection correlations of previous slide) to the prototype menu for Phase-2 (defined without using this optimization technique) and a comparison with other seeds of this menu.
Left: Efficiency (of Bs to μμ) vs. rate of the prototype menu with and without the optimized algorithm.
Right: Efficiency (of Bs to μμ) vs. rate of the "best" prototype menu seeds to compare with the optimized algorithm.

- Lowest rate and better efficiency than the prototype menu is achieved with the optimized DoubleTkMuon seed.
- Best overall efficiency is achieved with the optimized combined seed.

Summary

- Optimizing cut-based algorithms is a 2-objective optimization problem
  - Maximize trigger efficiency
  - Minimize trigger rate
- It follows that there is an infinite set of “optimal” solutions
- Problem can be scalarized using a **reference point**, defining a preference for a solution
- A slightly more “fancy” hill climb algorithm was used to find a minimum
- Converges to a single point in the efficiency, rate phase space
- Converges well for the two “toy” examples $B_s \rightarrow \mu\mu$ and VBF $H \rightarrow \tau\tau$
  - Moving the reference point allows finding different solutions
- The solutions **can** be checked for plausibility

References

Detailed study: CMS Collaboration, “Optimizing cut-based algorithms to specific physics acceptance regions at the CMS Level-1 Trigger”, 2024, https://cds.cern.ch/record/2916192

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[3] K. Miettinen, M. Mäkelä, “On scalarizing functions in multiobjective optimization”, OR Spectrum 24, 2002, pp. 193–213, doi: 0.1007/s00291-001-0092-9

[4] J. Konigsberg, “The Upgrade of the Level-1 Muon Trigger at the CMS experiment for the High-Luminosity LHC era”, Conference Technology & Instrumentation in Particle Physics, 2023, https://indico.tlabs.ac.za/event/112/contributions/3237/attachments/1079/1463/JKonigsberg-TIPP-2023-final.pdf

[5] CMS Collaboration, “NNPuppiTaus: PUPPI tau reconstruction in the Level-1 trigger with real-time machine learning”, 2024, CMS-DP-2024-018