Application of Machine Learning in the Simulation of the Fermilab Muon g-2 Experiment

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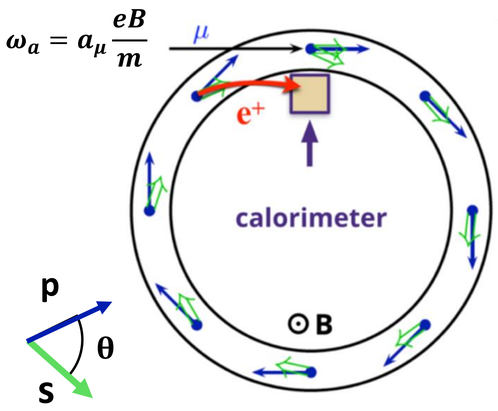
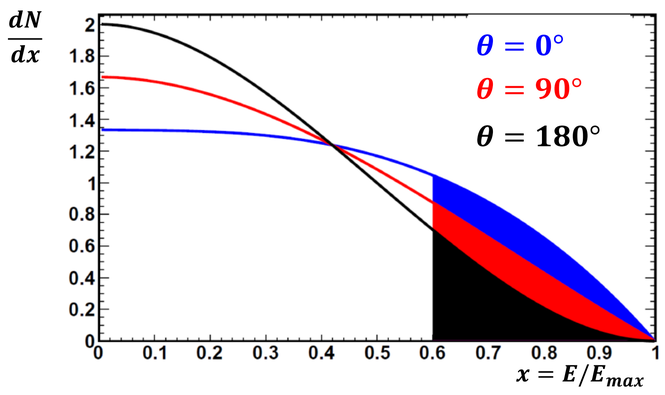
Muon's Magnetic Anomaly

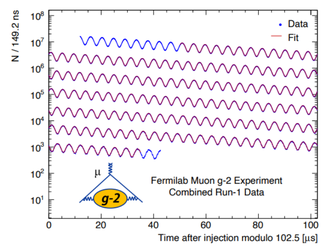
Anomalous Spin Precession

$\omega_a = a_\mu \frac{eB}{m}$



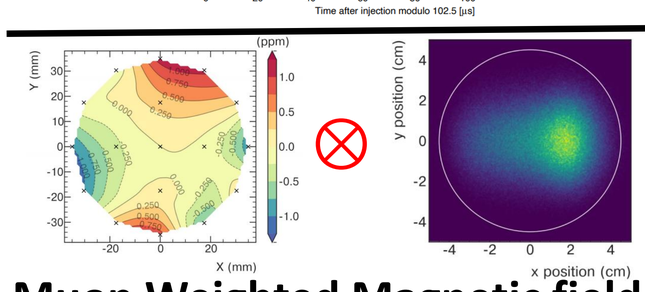
e^+ Spectrum Modulation





ω_a Analysis

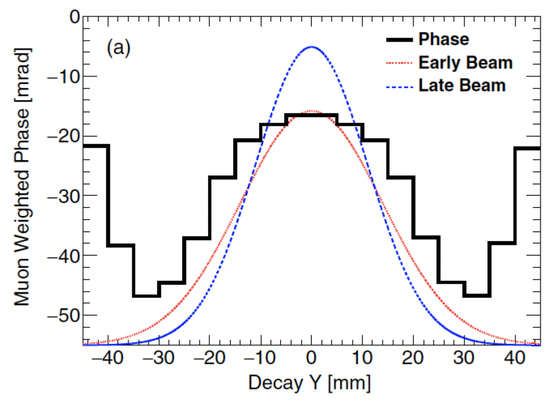
$a_\mu \propto$



Muon Weighted Magnetic field

Phase-Acceptance Systematic Correction

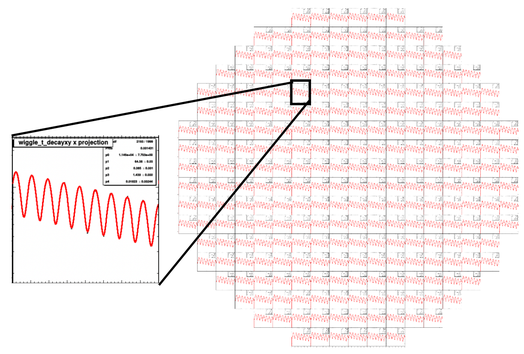
Time Dependent Shift in Fitted ω_a Phase



$$\frac{d\phi}{dt} = \frac{dY_{RMS}}{dt} \cdot \frac{d\phi}{dY_{RMS}}$$

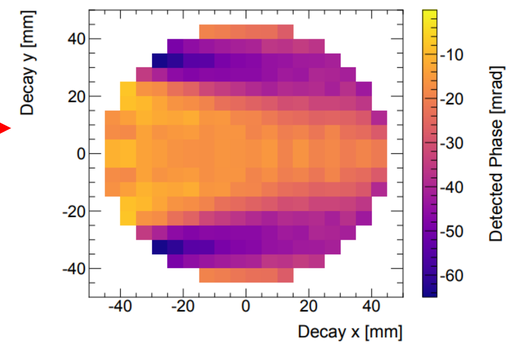
1. Time dependent beam effect
2. Dependent of phase on decay position (Phase-acceptance)

Phase Map Construction



$N(t) = N_0\, e^{-t/\tau}\,[1 + A\cos(\omega_a t + \phi_a)]$

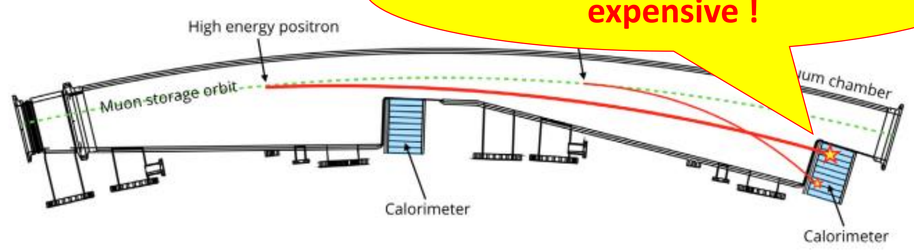
$\Delta\phi \sim 2$ mrad
Limited by Geant4 simulation !



Fast Simulation of the Muon Storage Ring

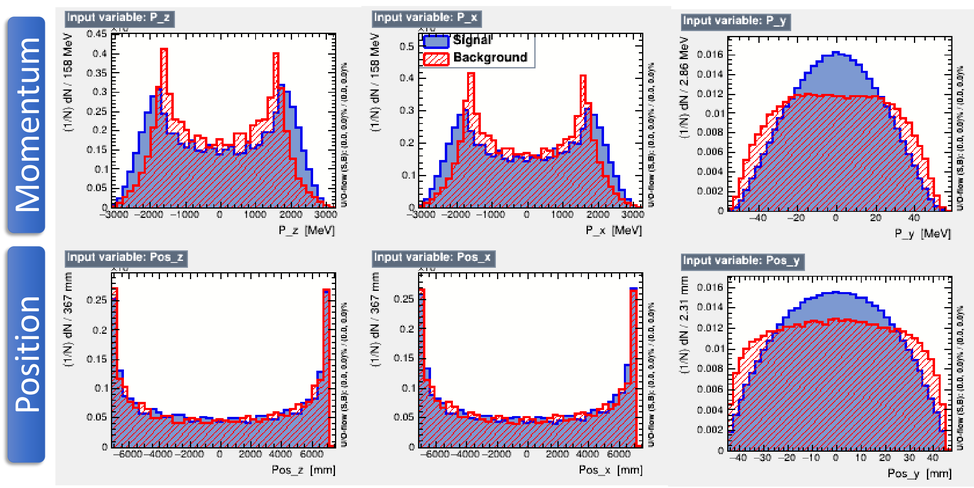
1. Muon beam & spin dynamics → Analytical calculation or Beam Optics Simulations (eg: BMAD, COSY)
2. Muon decay to positrons → Geant4 MuonDecayWithSpin Class
3. Positron transportation and EM Shower Development → Model with Machine Learning (this work)

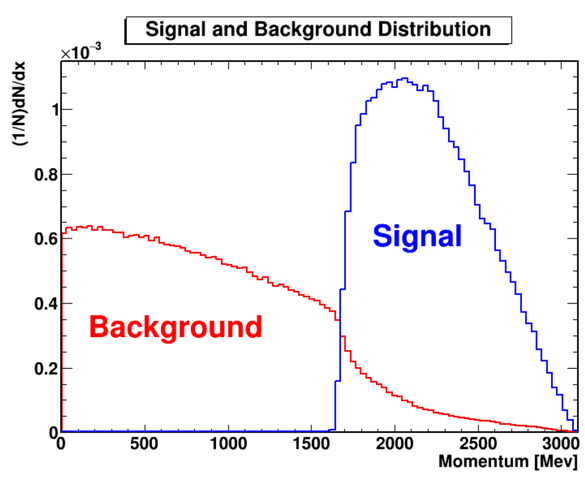
Geant4-based simulation is expensive !

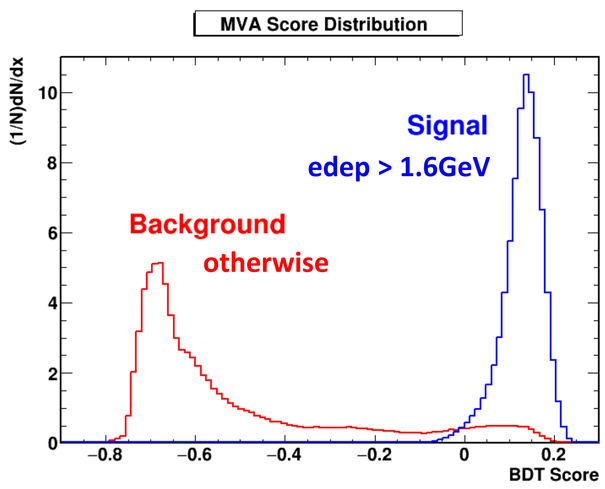


Machine Learning Models for Positron Acceptance at Calorimeters

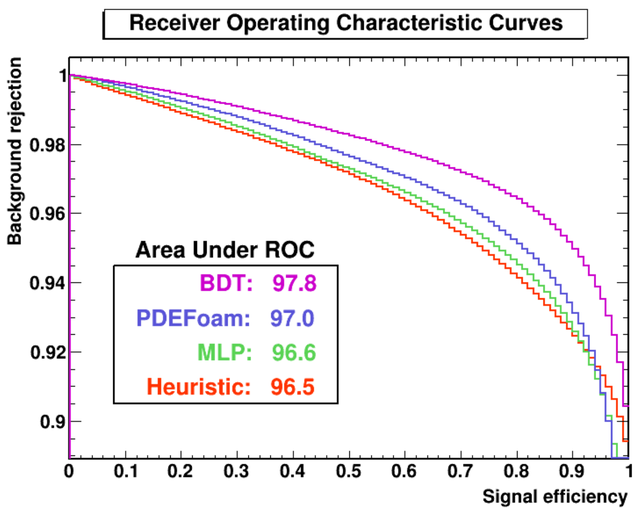
Training Variables



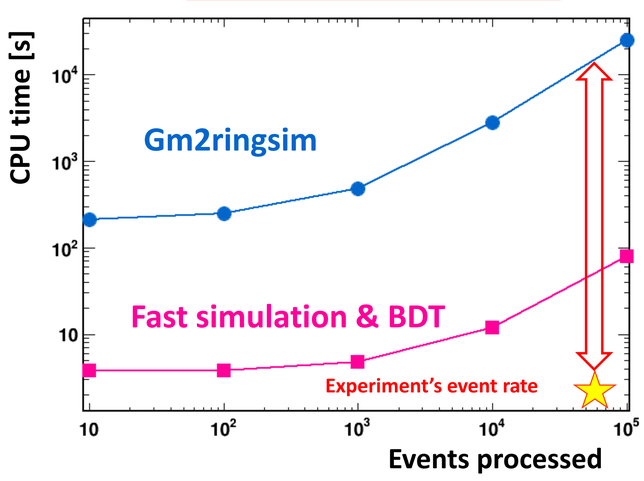




Comparison of Machine Learning Models Performances



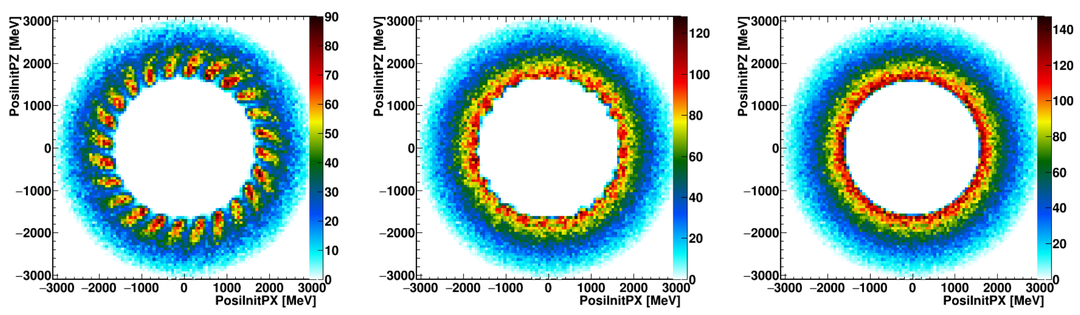
~10^2 more efficient



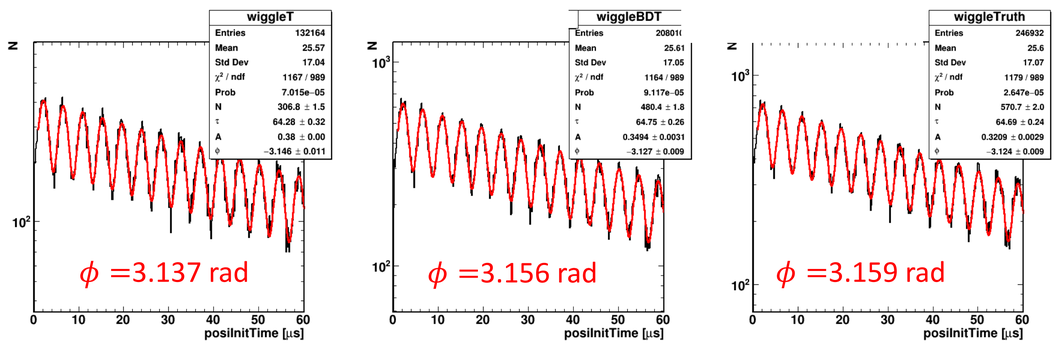
BDT Application

Predicted PZ:PX has MC truth's main features

Monte-Carlo Truth | BDT Prediction | Preselection Cut



Comparison of the predicted ω_a phase



References

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