Universität Hamburg
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DESY.

Neural Network based pulse shape analysis with the Belle II electromagnetic calorimeter

5th of November 2020

Women Physicists' Conference

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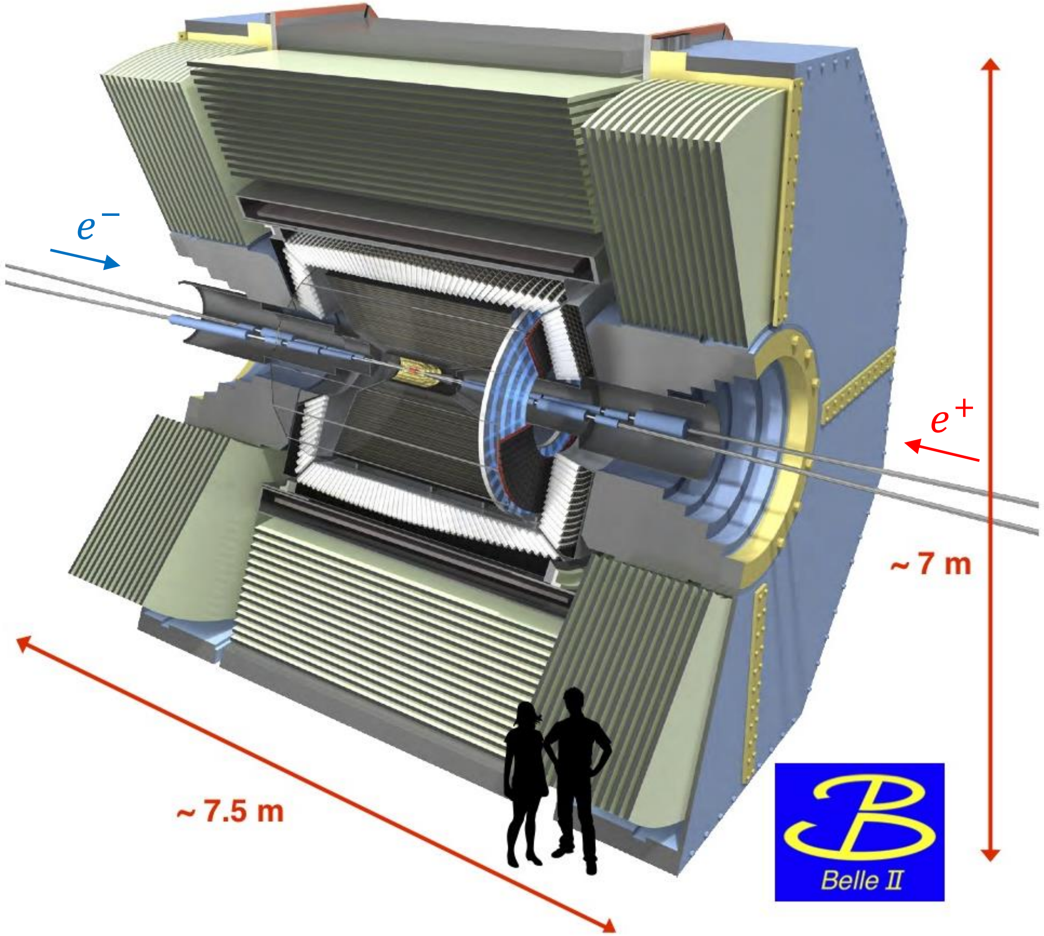
Belle II overview

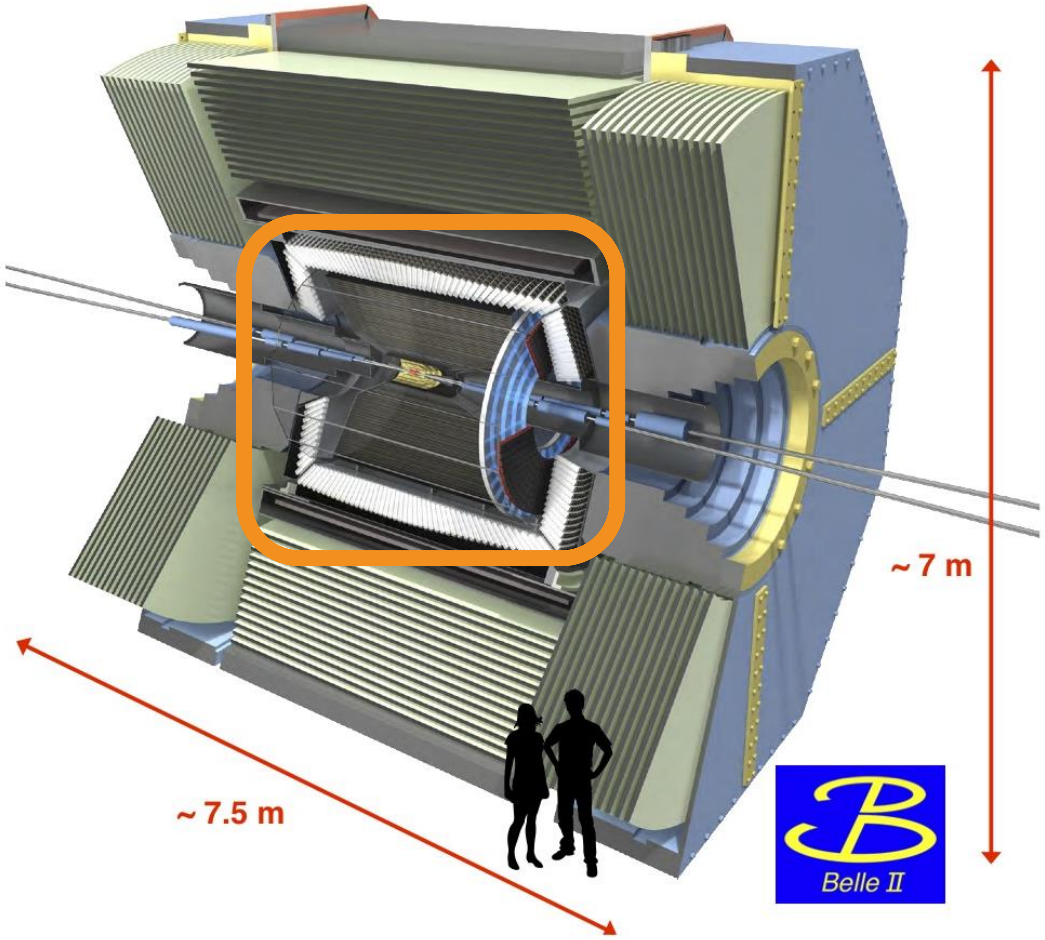
- SuperKEKB e^+e^- collider in Japan
- Collision energy: 10.58 GeV

- Main goals of Belle II:
  - Precision measurements
  - Rare/forbidden processes
  - Beyond Standard Model search



https://www.belle2.org/project/super_kekb_and_belle_ii

Electromagnetic Calorimeter (ECL)

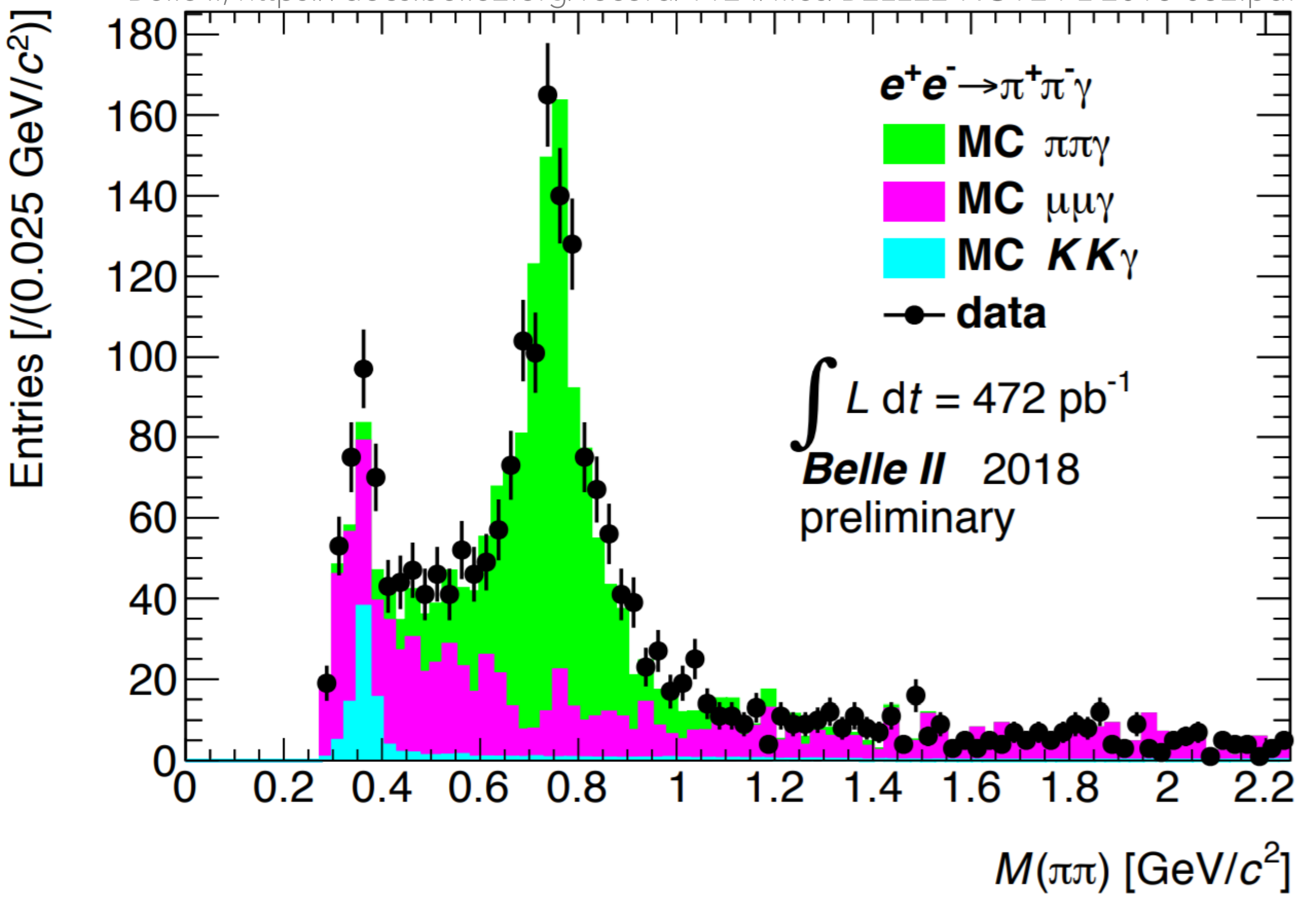


https://www.belle2.org/project/super_kekb_and_belle_ii

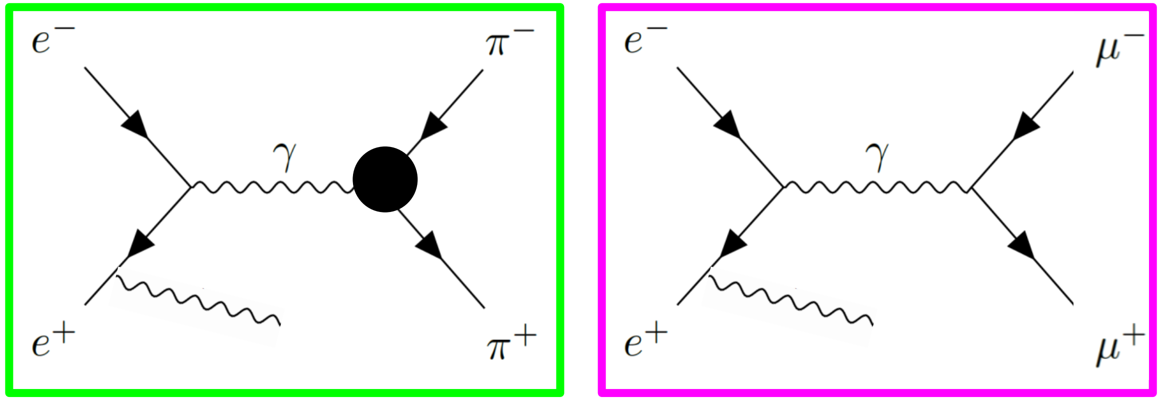
- ~9000 scintillator crystals CsI(Tl)
- Main task:
  - Measuring electromagnetic energy
  - Reconstructing neutral particles
  - Particle identification using shower shapes

Analysis: $e^+e^- \to \pi^+\pi^-\gamma$

Belle II, https://docs.belle2.org/record/1124/files/BELLE2-NOTE-PL-2018-032.pdf

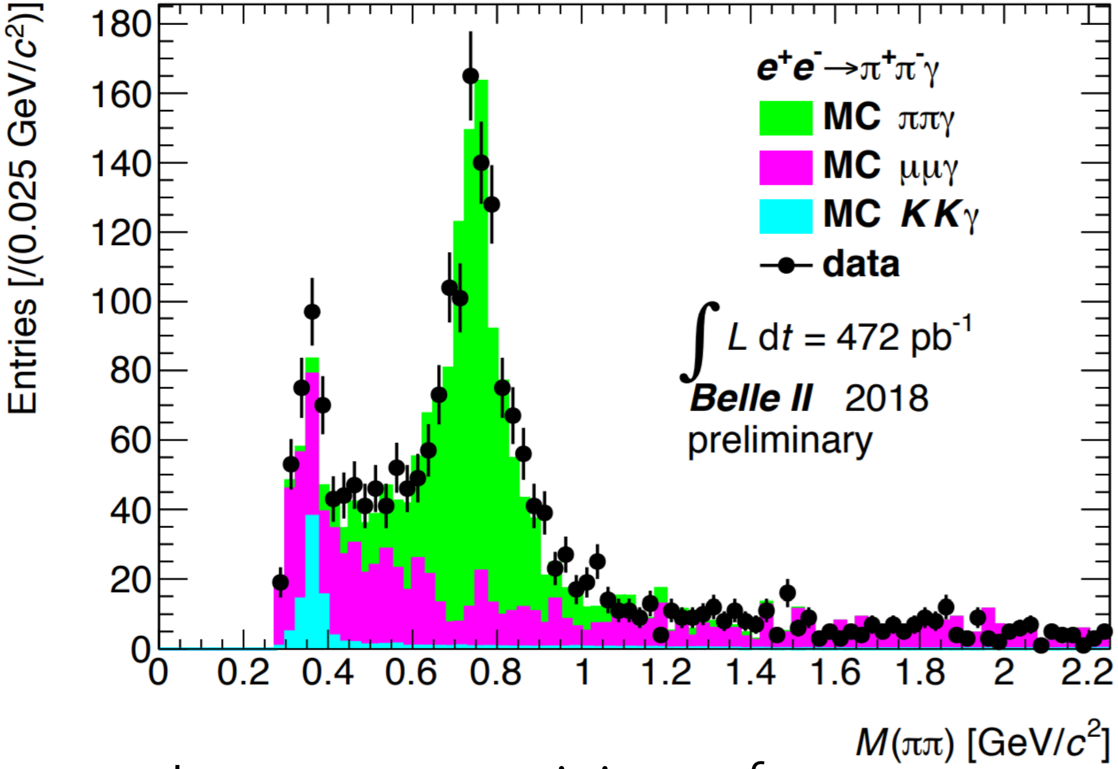


Need good particle identification!



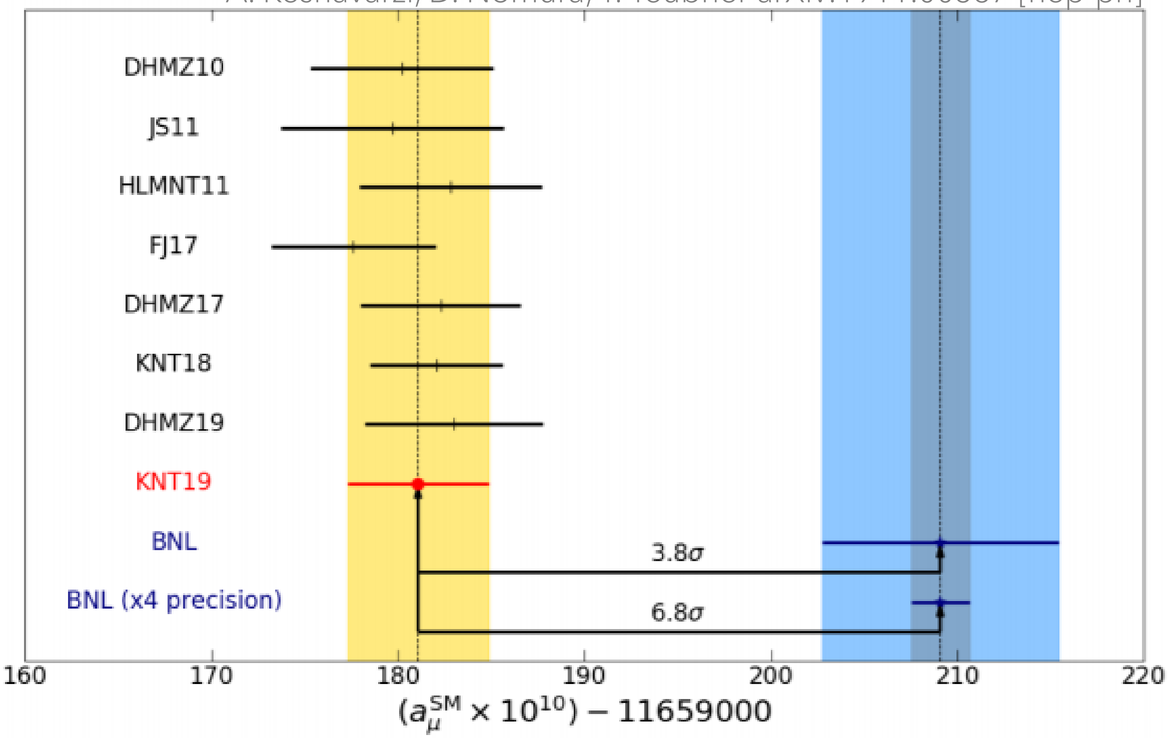
Analysis: $e^+e^- \to \pi^+\pi^-\gamma$

Belle II, https://docs.belle2.org/record/1124/files/BELLE2-NOTE-PL-2018-032.pdf



Theory Experiment

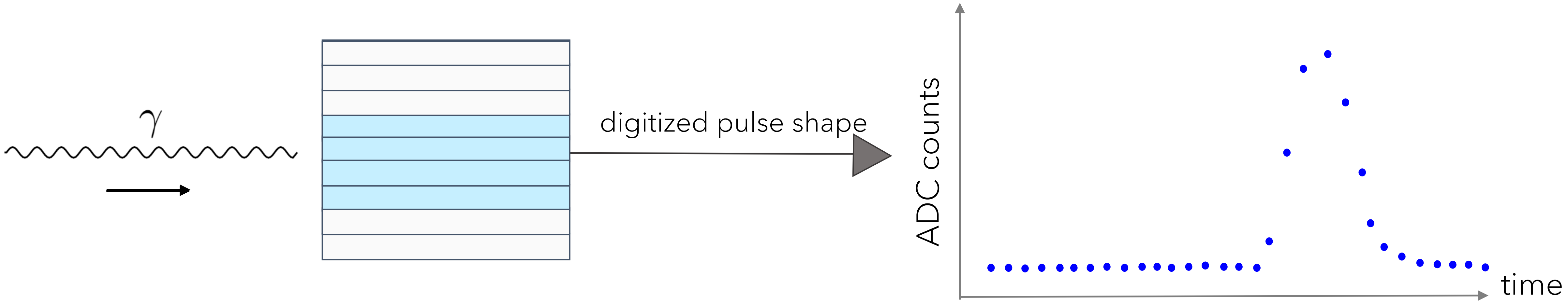
A. Keshavarzi, D. Nomura, T. Teubner arXiv:1911.00367 [hep-ph]



Improve precision of $e^+e^- \to \pi^+\pi^-$ measurement

Reduce uncertainty of SM-calculation of the anomalous magnetic momentum of the muon

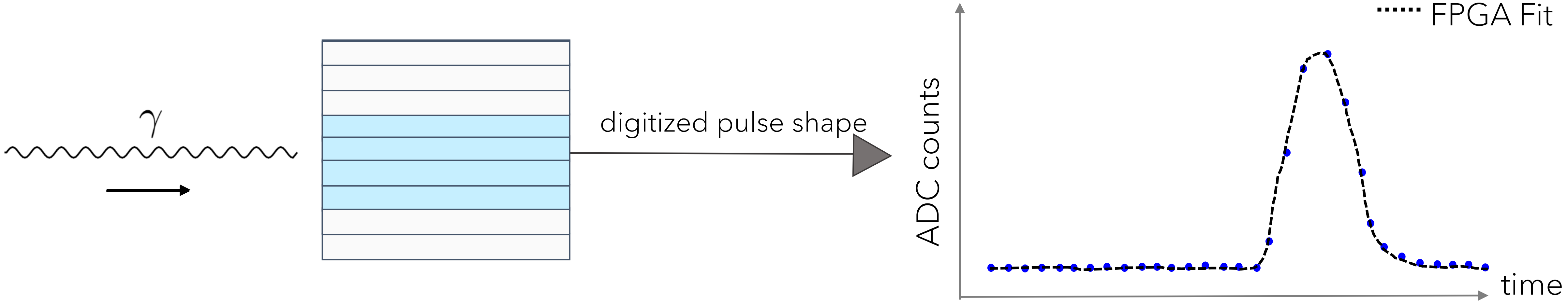
What happens in the ECL?



= ECL crystal

= ECL crystal where energy is deposited

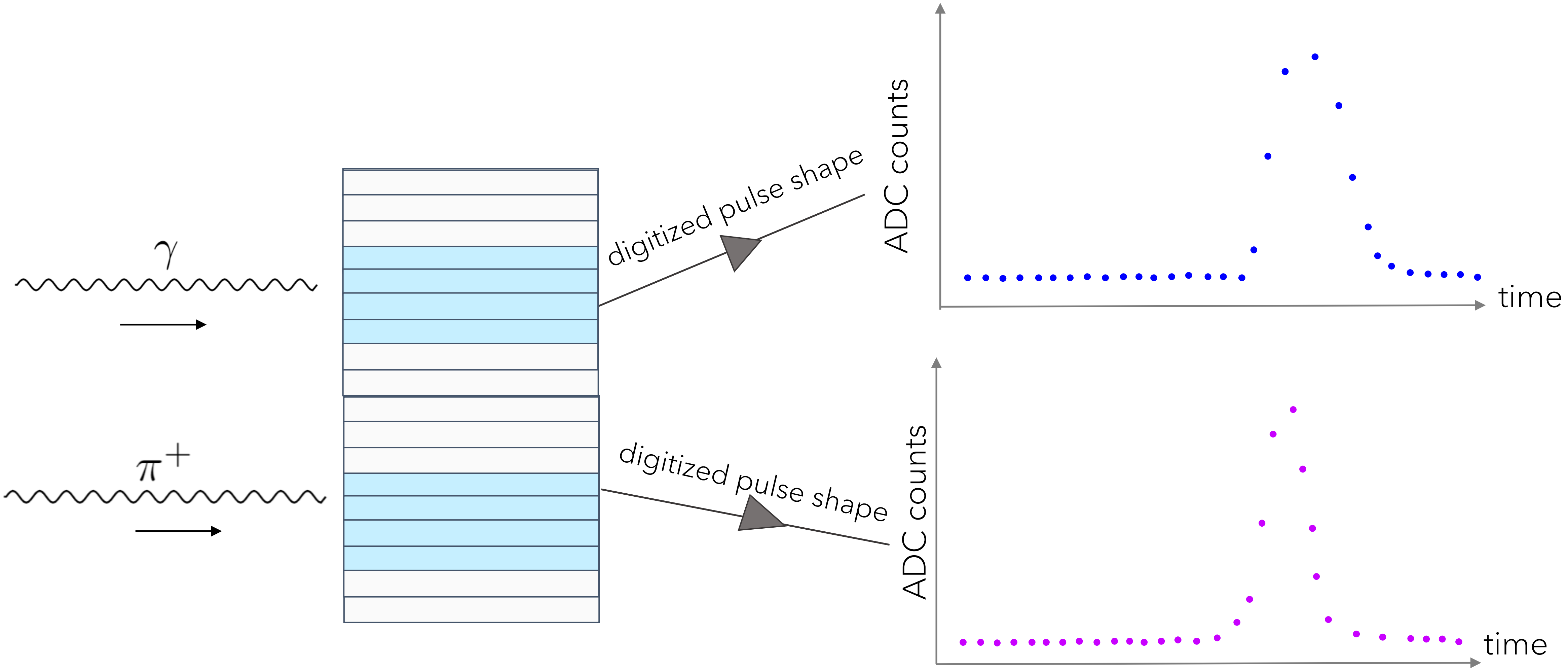
What happens in the ECL?



FPGA

- Fit pulse shape
- Reconstruct E_{total}
- Optimized for photons

Particle Identification with the ECL

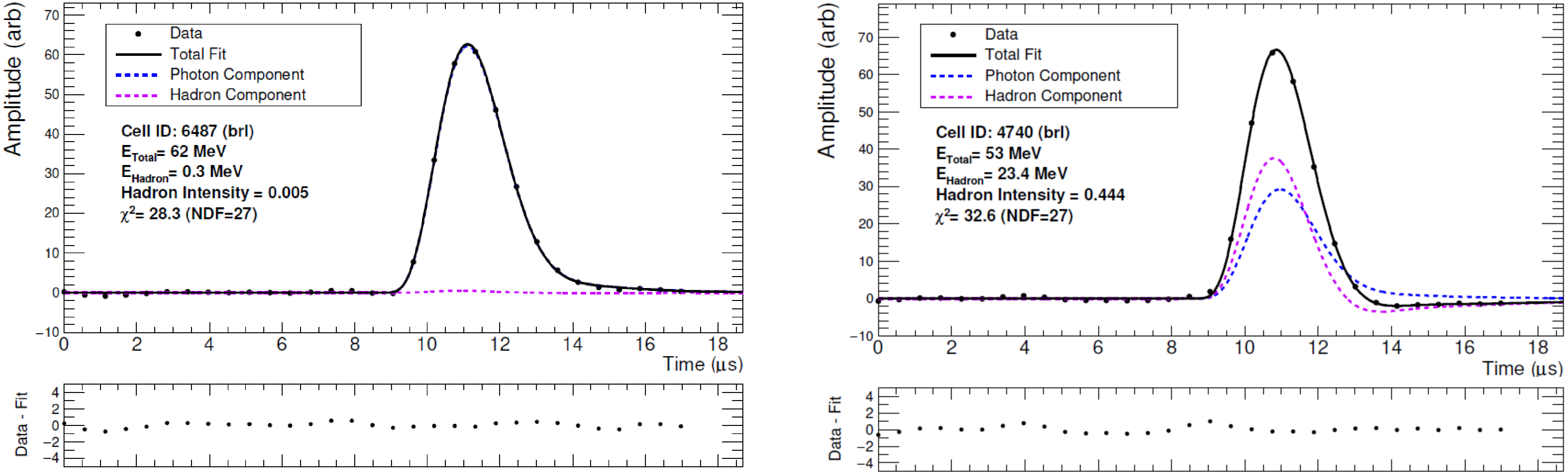


fast „hadron“ scintillation component

Pulse Shape Discrimination

- Multi-template fit (photon and hadron template)
- Offline
- Reconstruct E_{total}, E_{hadron}

$$\text{Hadron Intensity} = \frac{E_{had}}{E_{tot}}$$



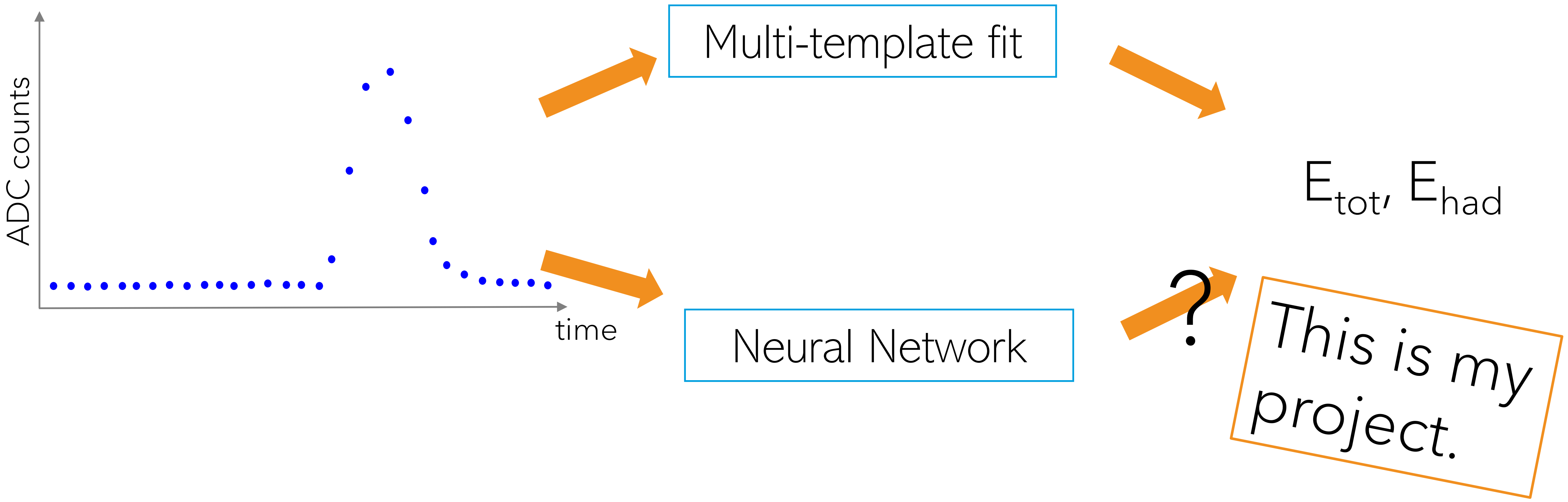
Savino Longo, https://dspace.library.uvic.ca/handle/1828/11301

Keywords to remember:

- Pulse shape:
  - 31 ADC points
  - Difference between photon-like and hadron-like pulse shapes
- Default methods:
  - FPGA: E_{total}, optimized for photons (online)
  - Multi-template: E_{total}, E_{hadron} (offline)
- Hadron Intensity $= \frac{E_{had}}{E_{tot}}$

Neural Network approach

What can we gain by using a Neural Network instead of a multi-template fit? (speed, precision, robustness)



Neural Network structure

- Fully connected NN
- 2 hidden layers (256 neurons each)
- 31 inputs (normalized ADC counts)
- 2 outputs (E_{tot}, E_{had})

Neural Network input

Particle:

Photons as proxy for EM interactions	Pions as proxy for hadronic interactions

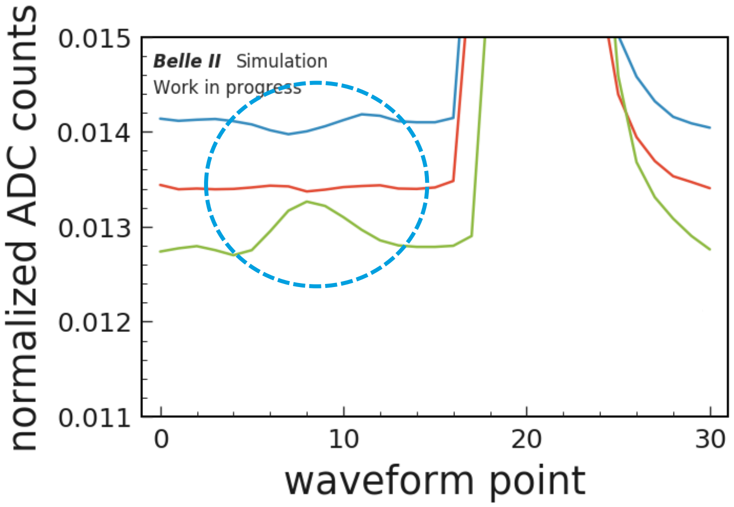
Neural Network input

Particle:

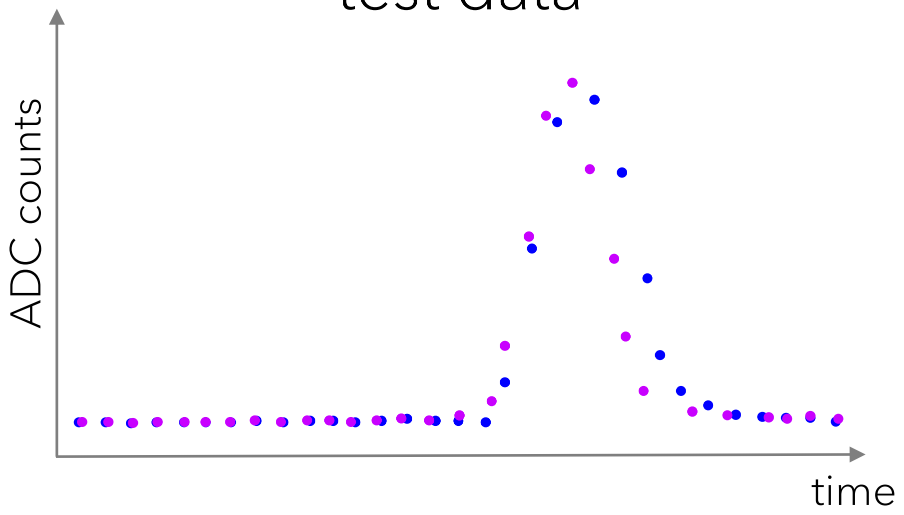
Photons as proxy for EM interactions	Pions as proxy for hadronic interactions

Stability tests:

Baseline fluctuations



Different particle test data



Neural Network input

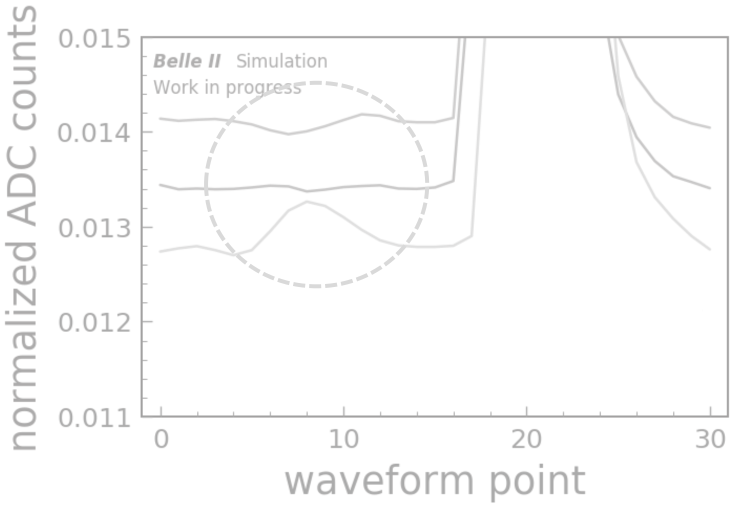
Particle:

Photons
as proxy for EM interactions

Pions
as proxy for hadronic interactions

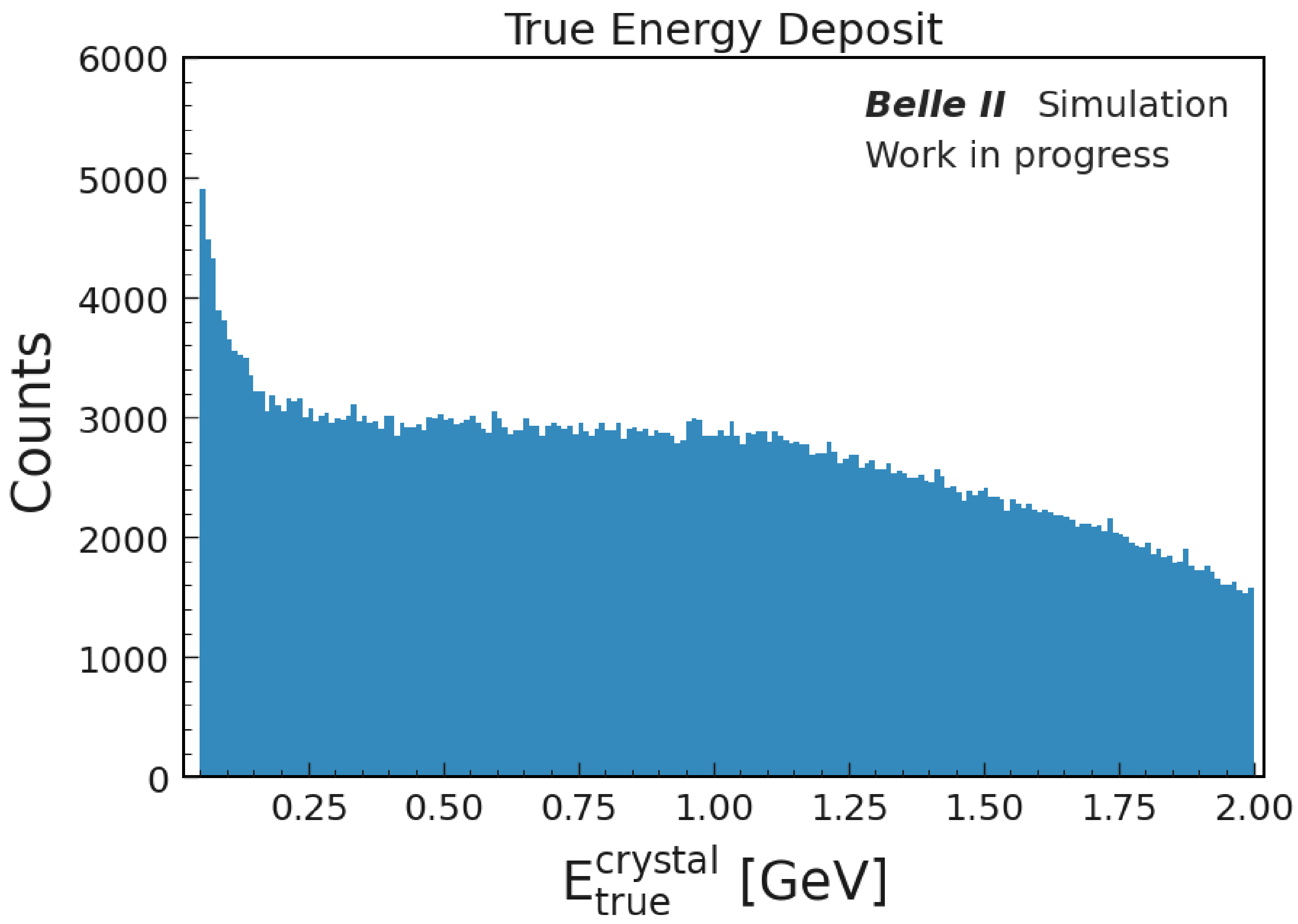
Stability tests:

Baseline fluctuations



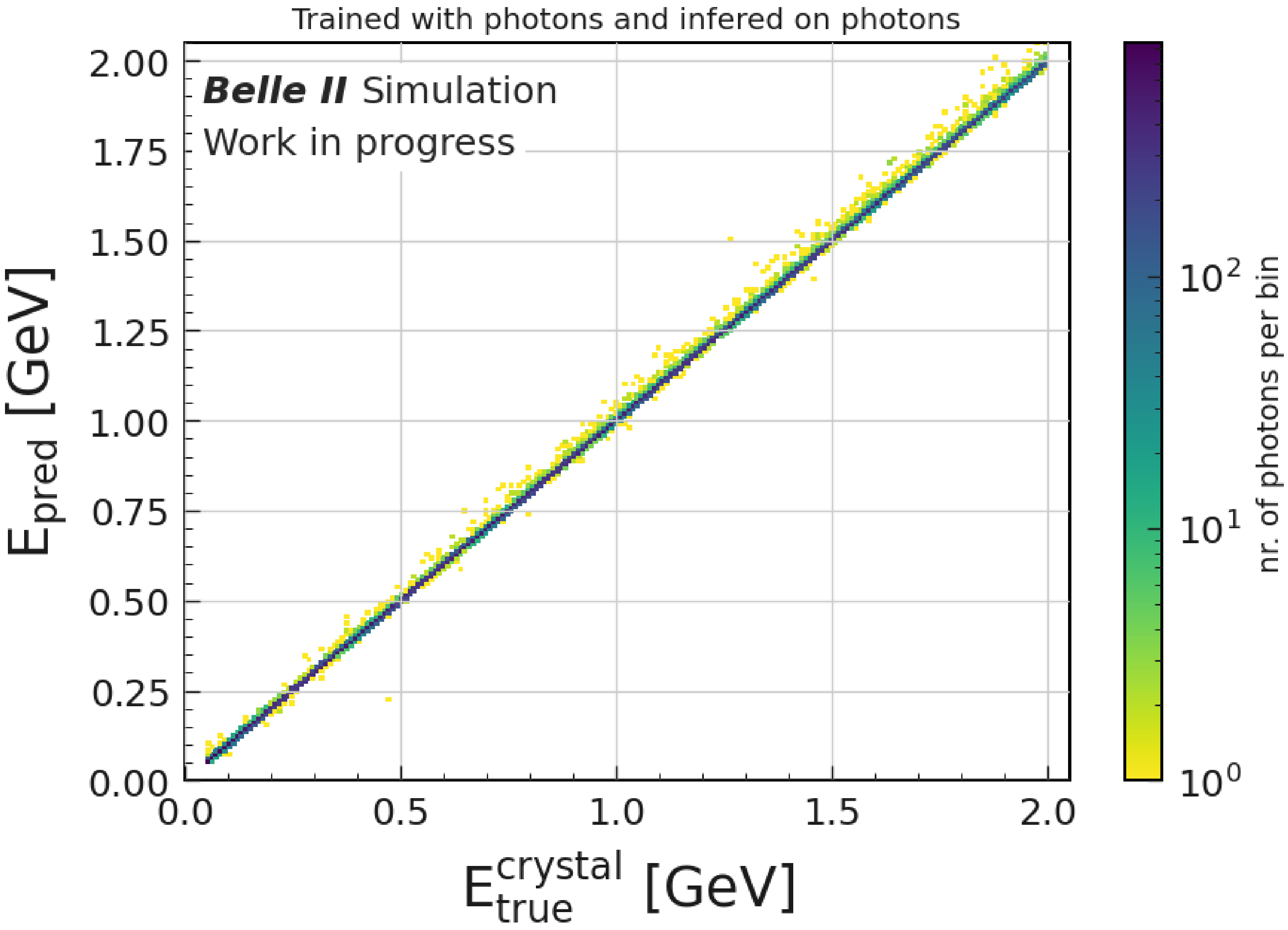
Different particle test data

Neural Network input photons



- Trained with ~400 000 pulse shapes
- Tested with ~80 000 pulse shapes

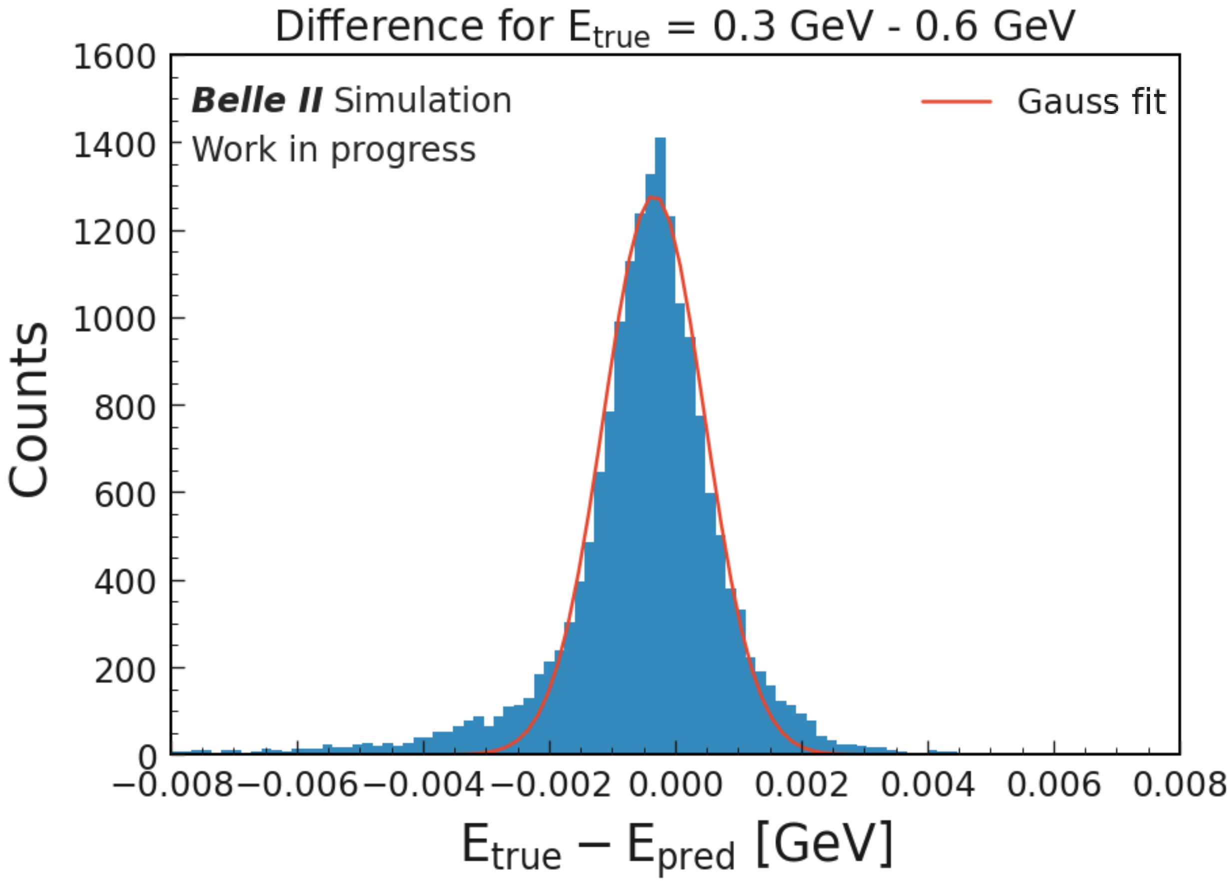
Neural Network E_{total} prediction



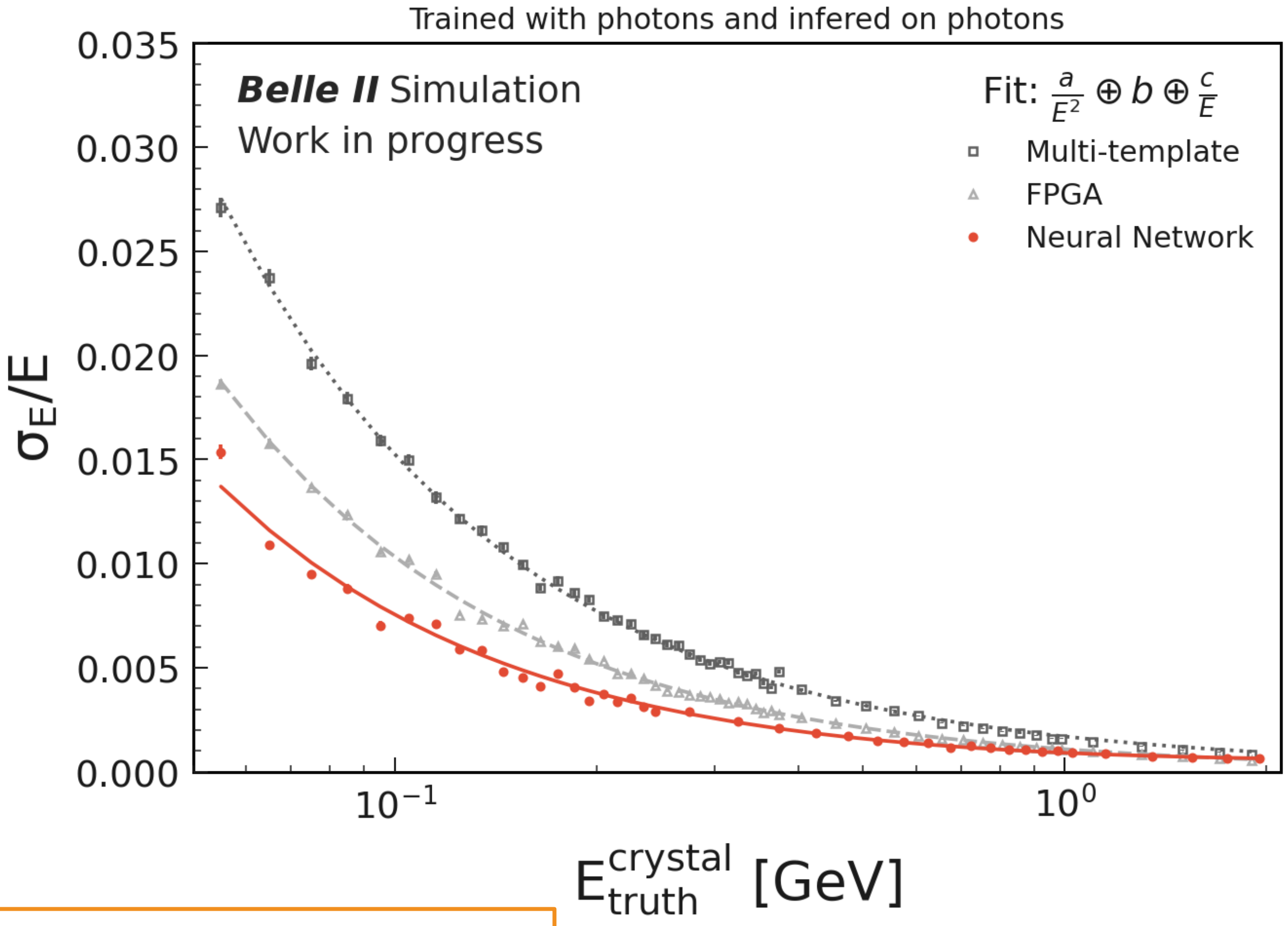
linear response

Neural Network E_{total} resolution

difference of true value and prediction



E_{tot} resolution



energy resolution improved

Neural Network input

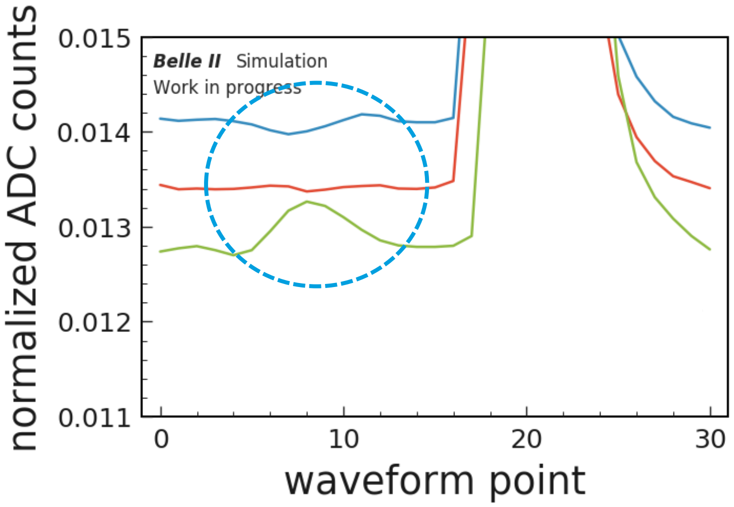
Particle:

Photons
as proxy for EM interactions

Pions
as proxy for hadronic interactions

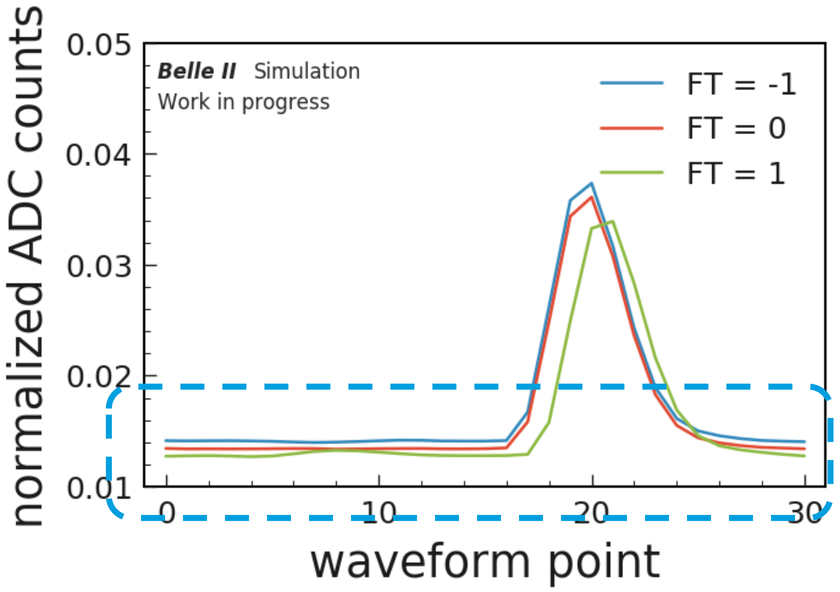
Stability tests:

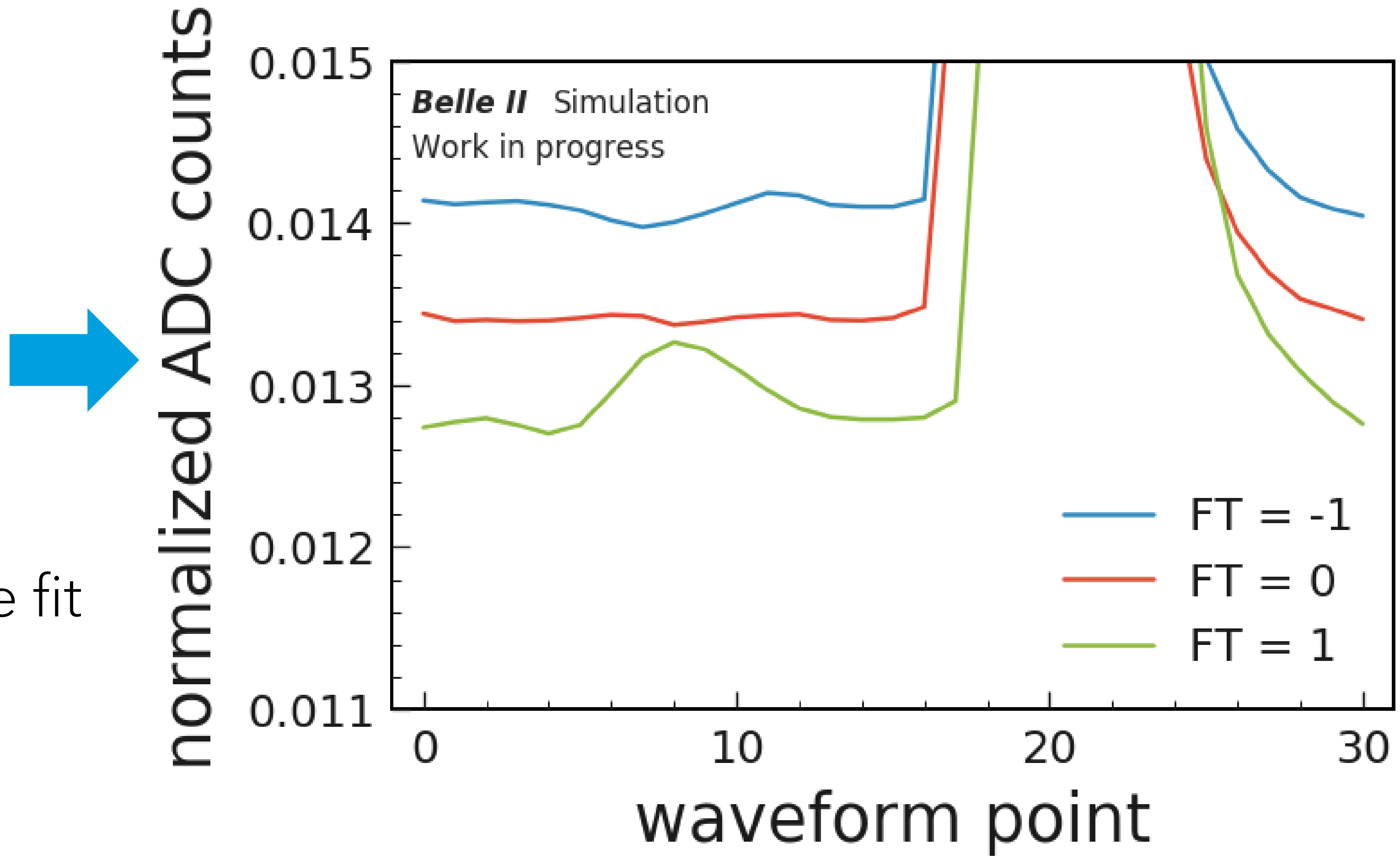
Baseline fluctuations



Different particle test data

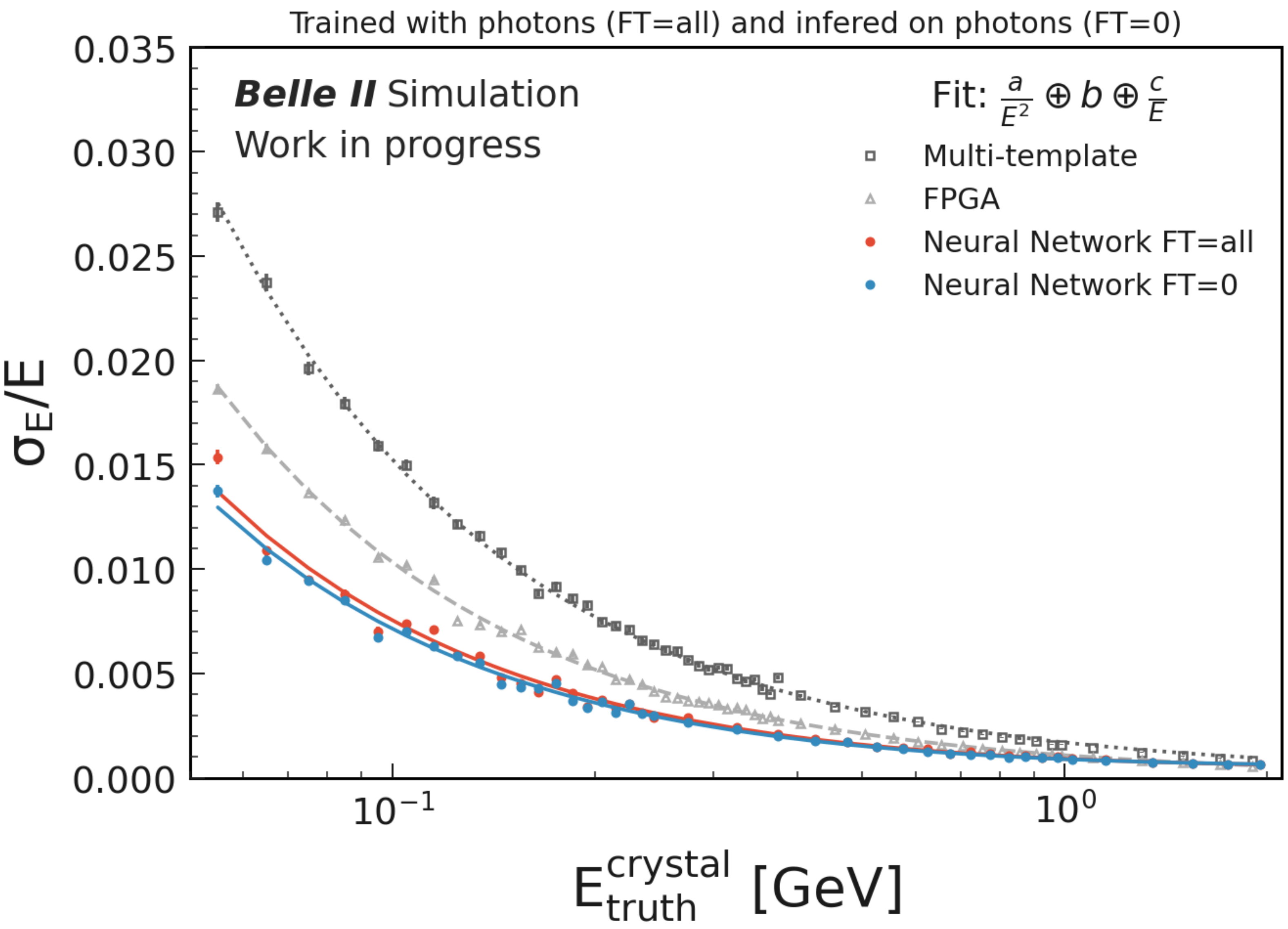
Baseline fluctuations: fittype (FT)





- Assigned by multi-template fit
- Fittype = 0 good
- Fittype = 1 additional peak
- Fittype = -1 bad

Baseline fluctuations: fittype (FT)



Neural Network input

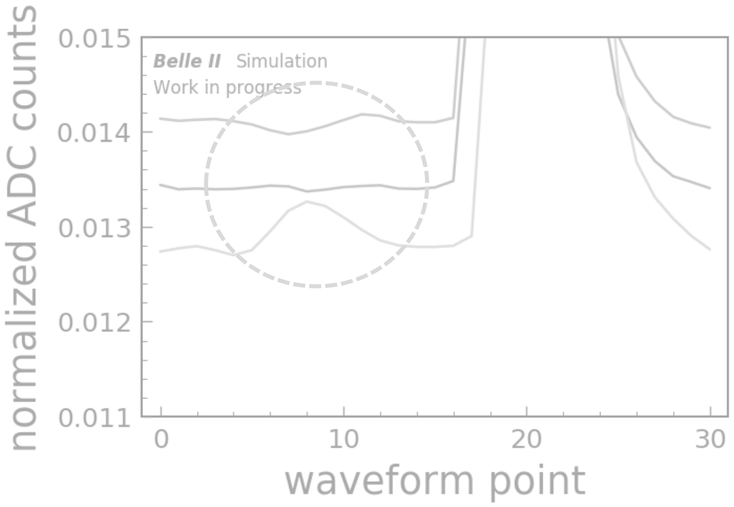
Particle:

Photons
as proxy for EM interactions

Pions
as proxy for hadronic interactions

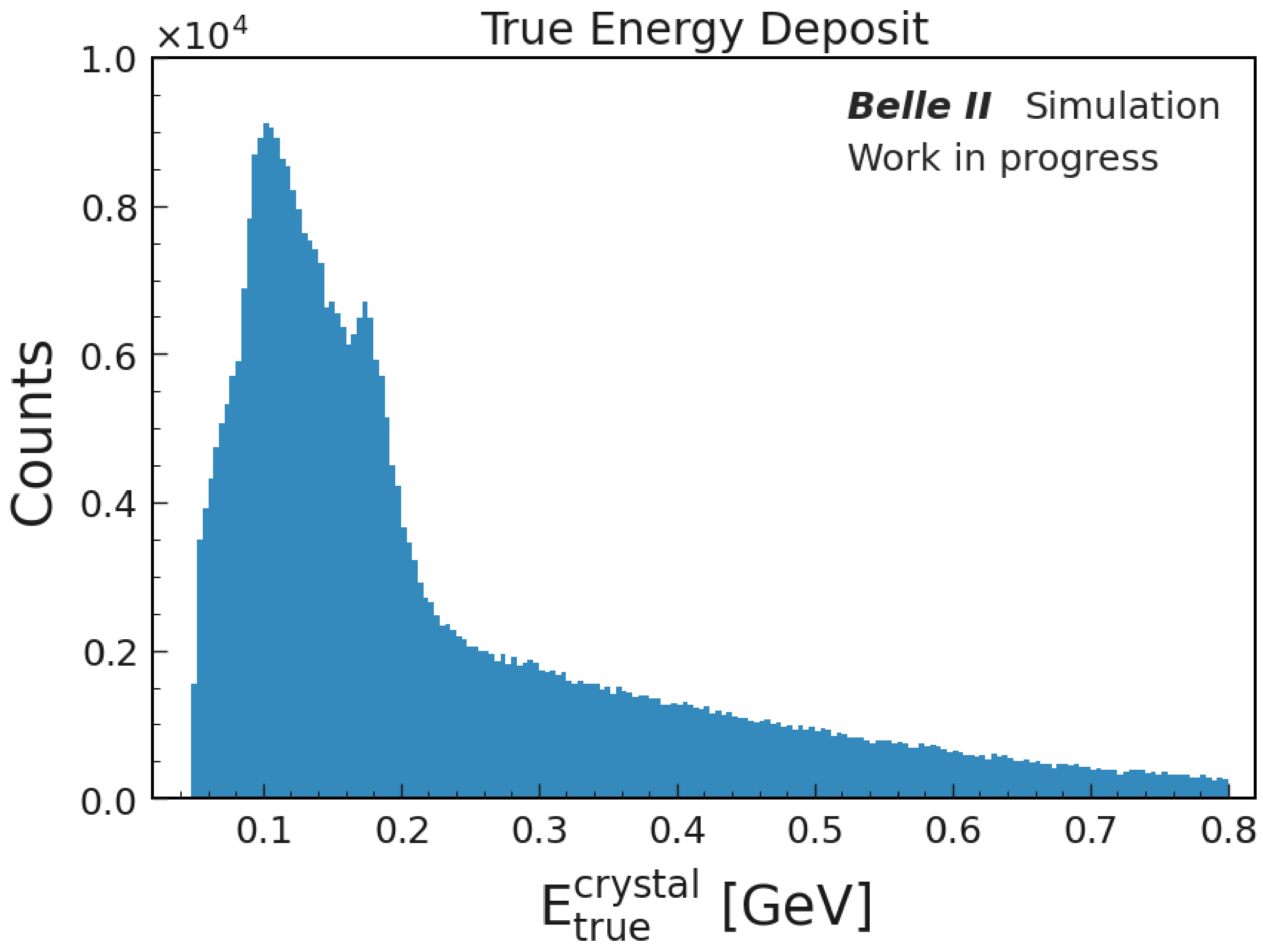
Stability tests:

Baseline
fluctuations



Different particle
test data

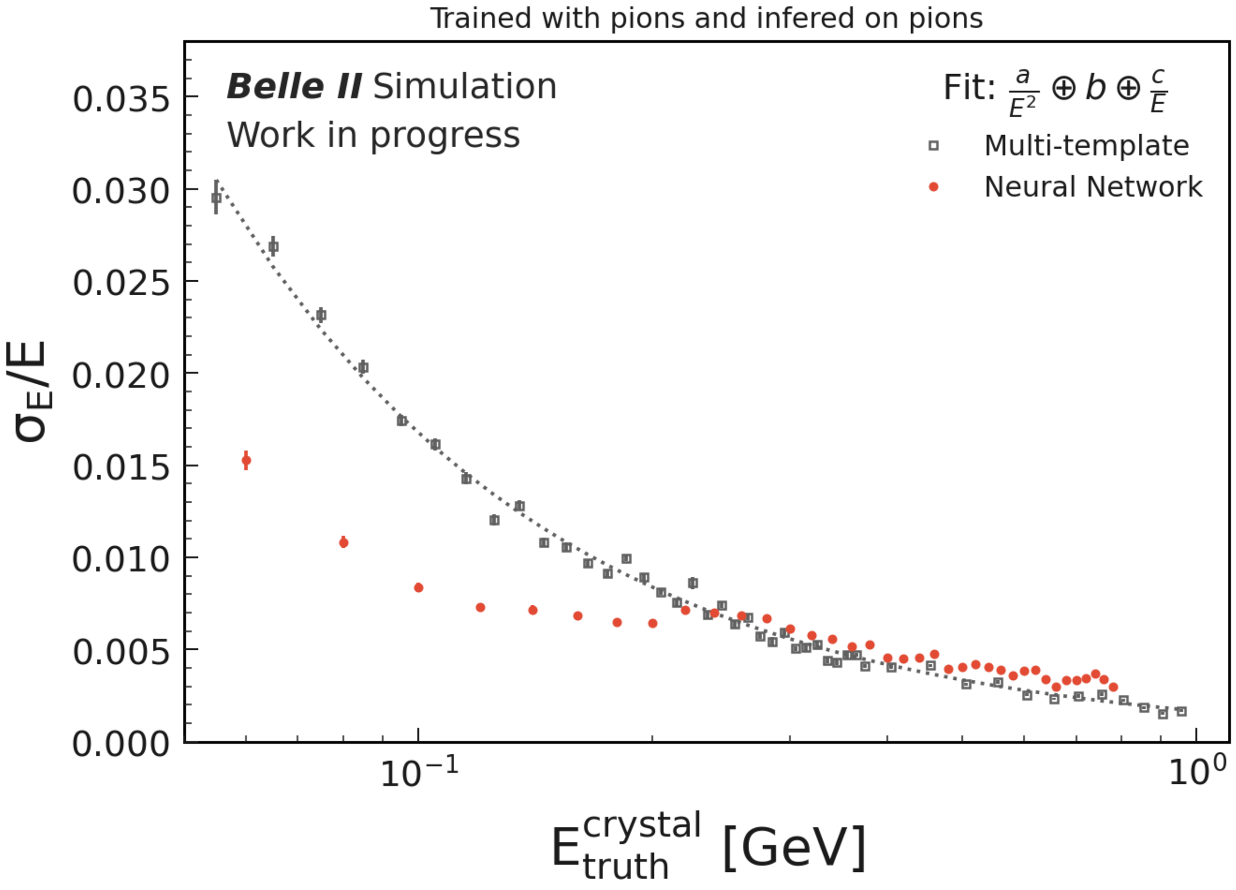
Neural Network input pions



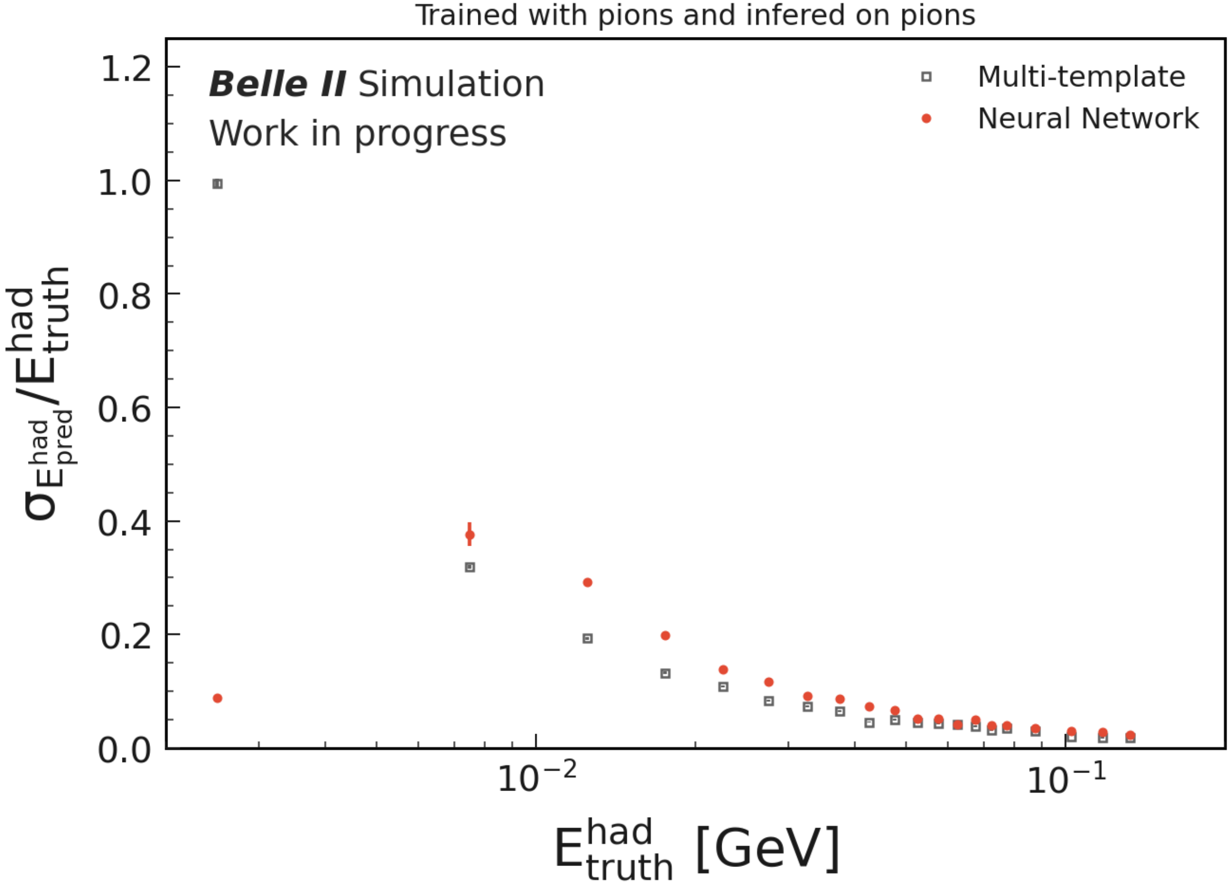
- Trained with ~328 000 pulse shapes
- Tested with ~82 000 pulse shapes

Neural Network E_{tot} & E_{had} resolution

E_{tot} resolution



E_{had} resolution



hadron resolution improved for photon-like pulse-shapes

Neural Network input

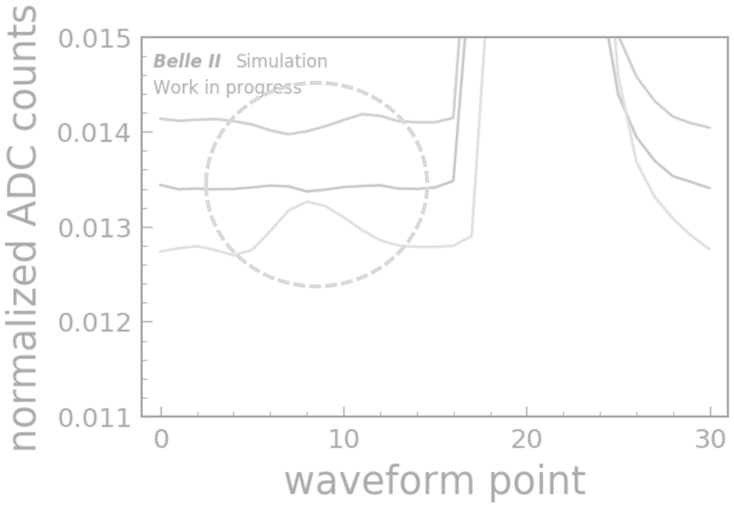
Particle:

Photons
as proxy for EM interactions

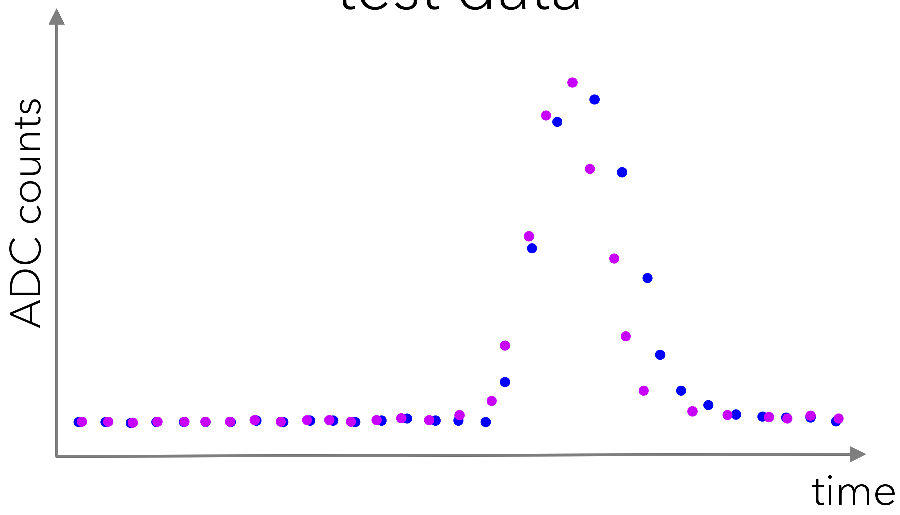
Pions
as proxy for hadronic interactions

Stability tests:

Baseline fluctuations

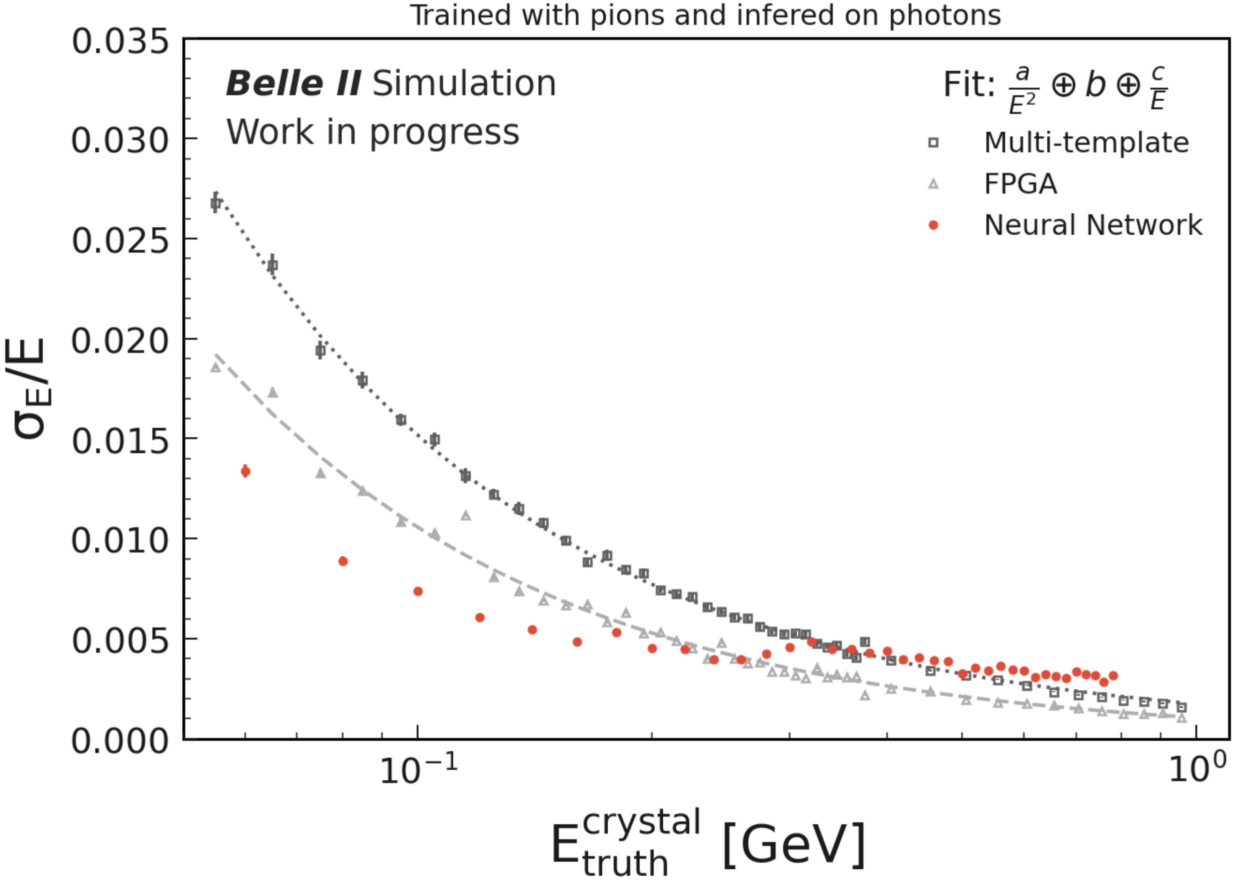


Different particle test data

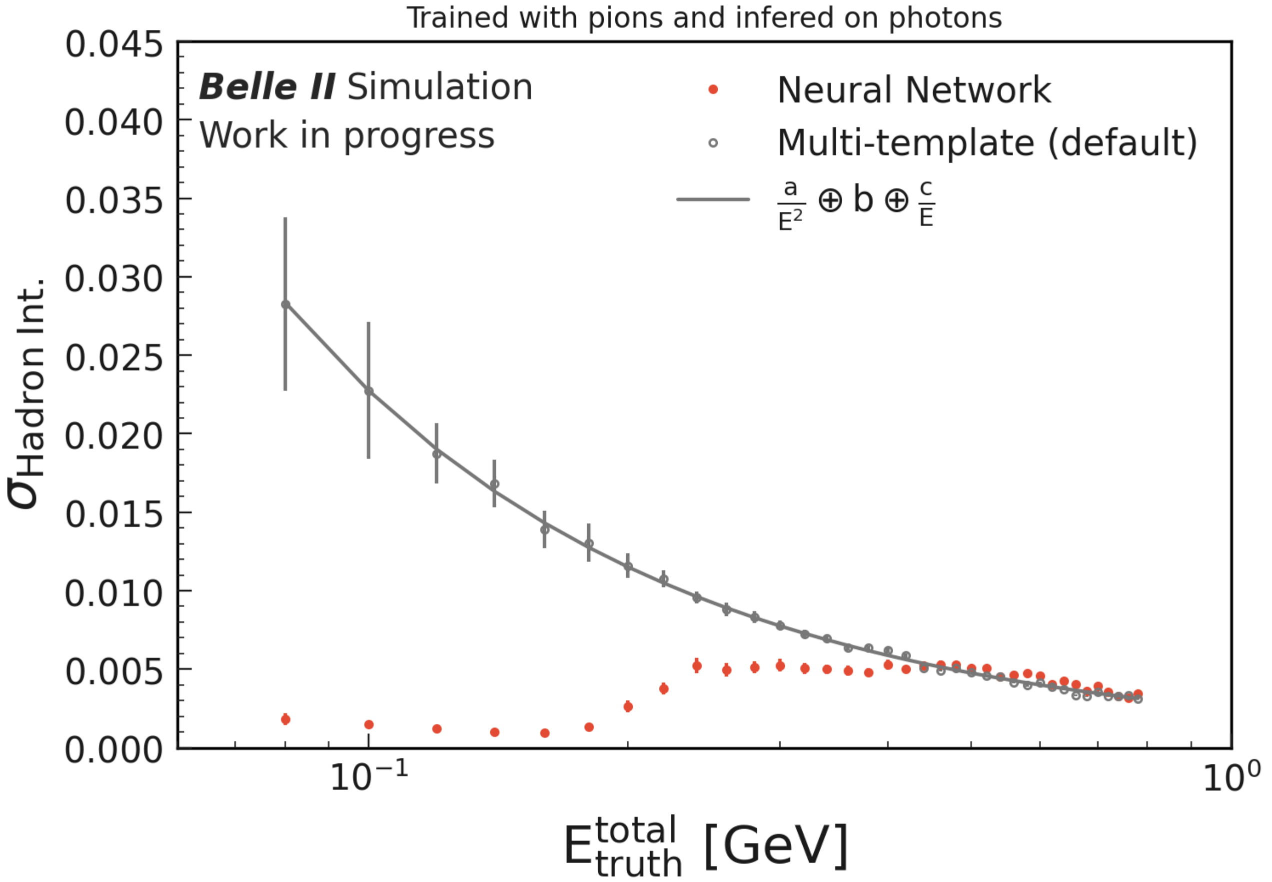


Train with pions, infer on photons

E_{tot} resolution



E_{had} resolution



total and hadron energy resolution improved up to 200 MeV

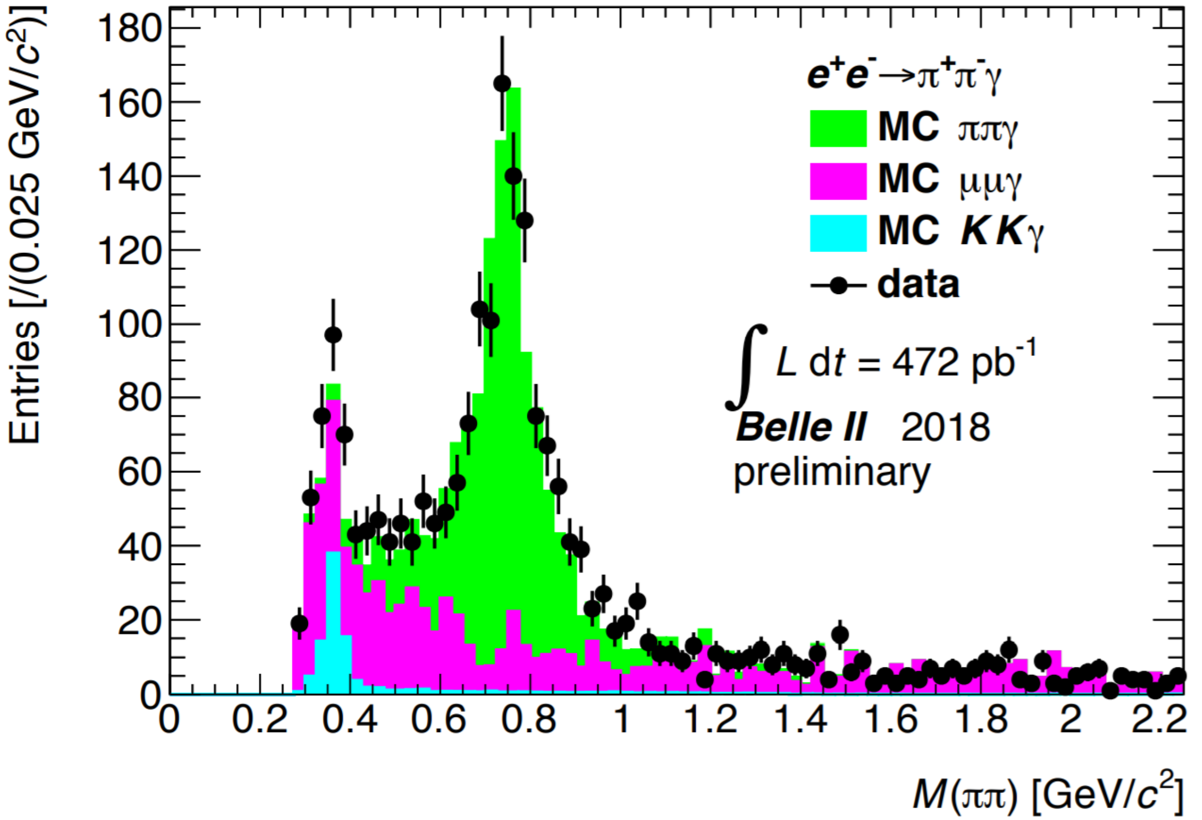
What is next?

Running Neural Network

Data & Analysis

- Move towards data
- Look at $\pi\pi\gamma$ analysis
- See if NN can improve π/μ-separation
- Reduce μ-background
- Reduce systematic uncertainty

Belle II, https://docs.belle2.org/record/1124/files/BELLE2-NOTE-PL-2018-032.pdf



Summary

- Running Neural Network for pulse shape analysis
- Performance compared with multi-template and FPGA fit

- Results:
  - Improved E_{tot} and E_{had}-resolution (for pions up to 200 MeV)
  - Stable with respect towards fittype

- Interesting application: $e^+e^- \to \pi^+\pi^-\gamma$
- Implement ML on FPGA (new PhD project starting soon)

Back Up.

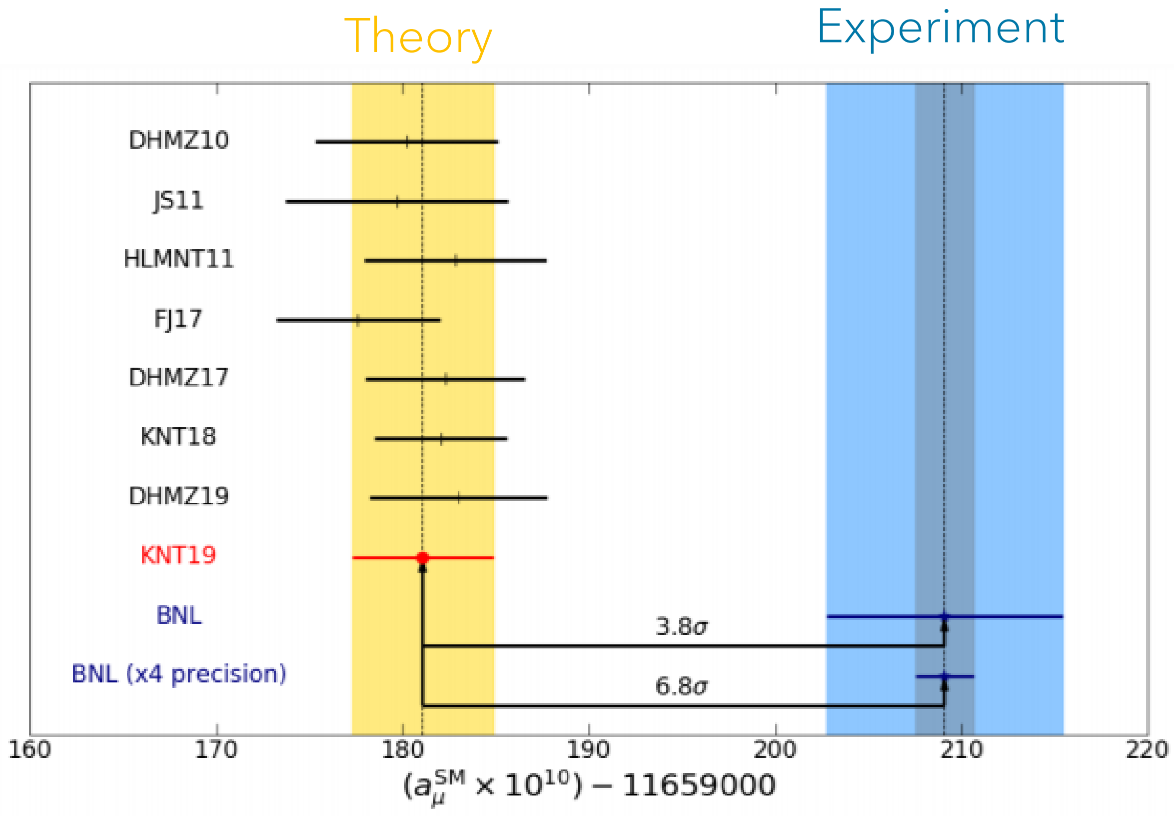
Traditional Particle Identification

- Measure track → momentum (CDC)
- Measure velocity (TOP)
- Combine information for mass

- π/μ-separation hard, tracks too close

Excursion: g-2 muon

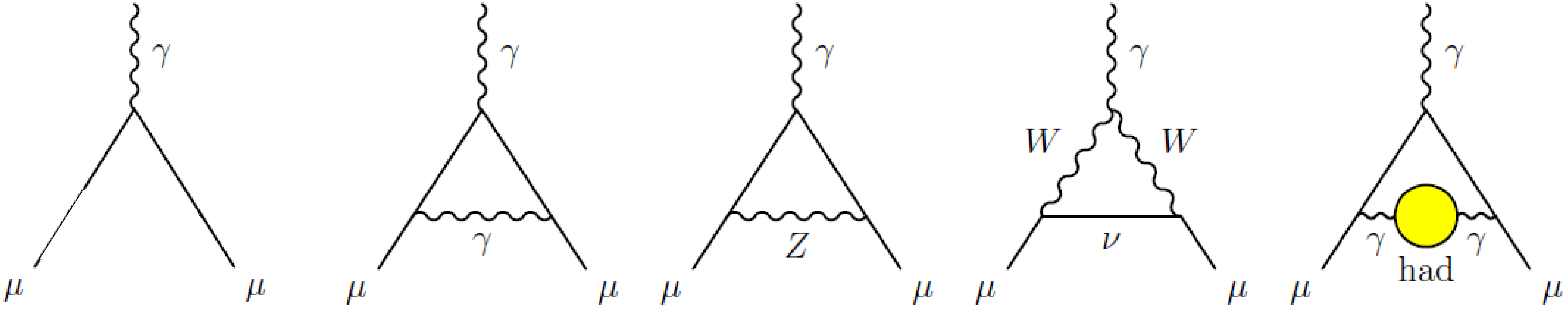
- High precision measurement of the anomalous magnetic momentum of the muon
- 3.7σ discrepancy (arXiv:2006.04822, 2020 paper)
- Theory limited by $e^+e^- \to \pi^+\pi^-$



A. Keshavarzi, D. Nomura, T. Teubner arXiv:1911.00367 [hep-ph]

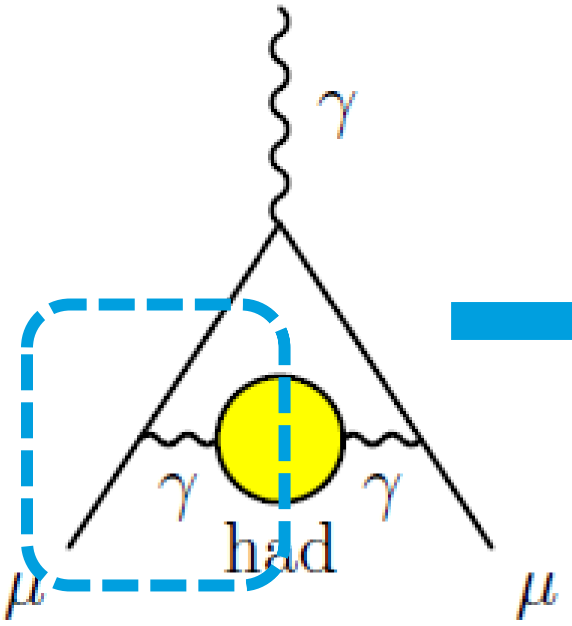
Excursion: theory of g-2

A. Hoecker and W. J. Marciano, 2013 „The Muon Anomalous Magnetic Moment"

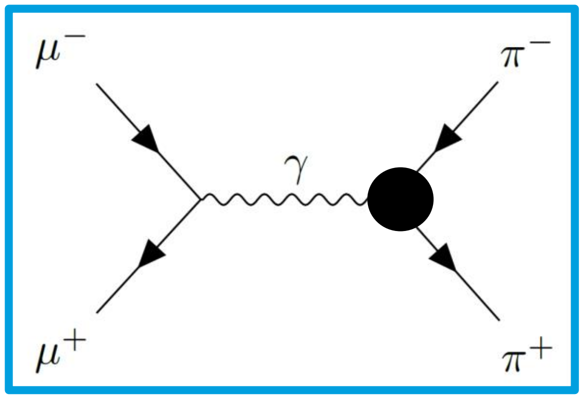


QCD:
Needs to be
measured

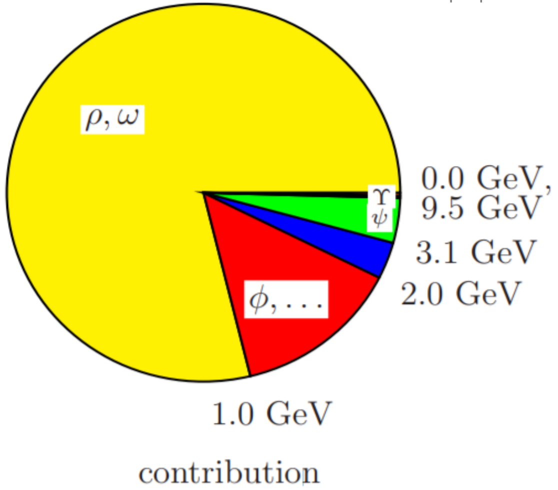
Excursion: theory of g-2



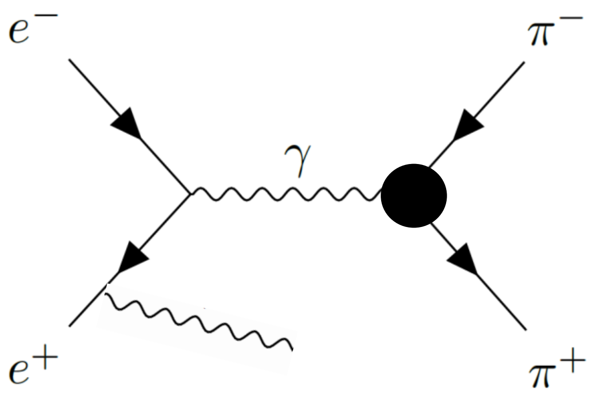
A. Hoecker and W. J. Marciano, 2013
„The Muon Anomalous Magnetic Moment"



T. Aoyama et al. arXiv:2006.04822 [hep-ph]

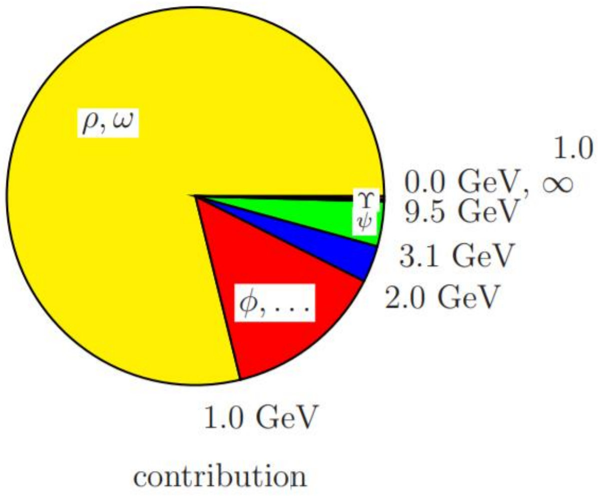


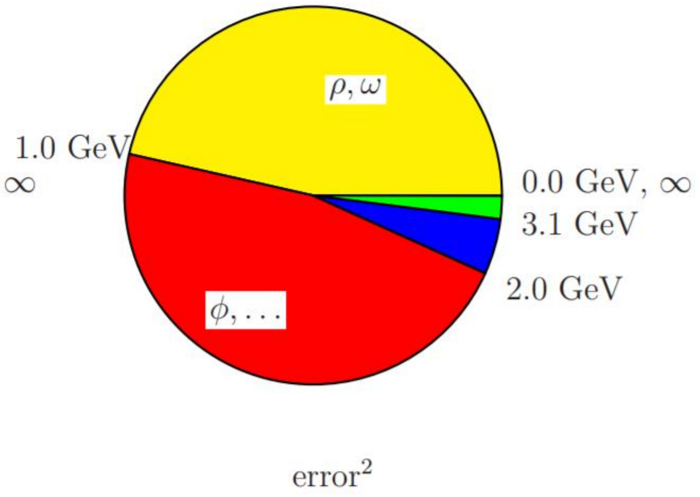
QED Universality



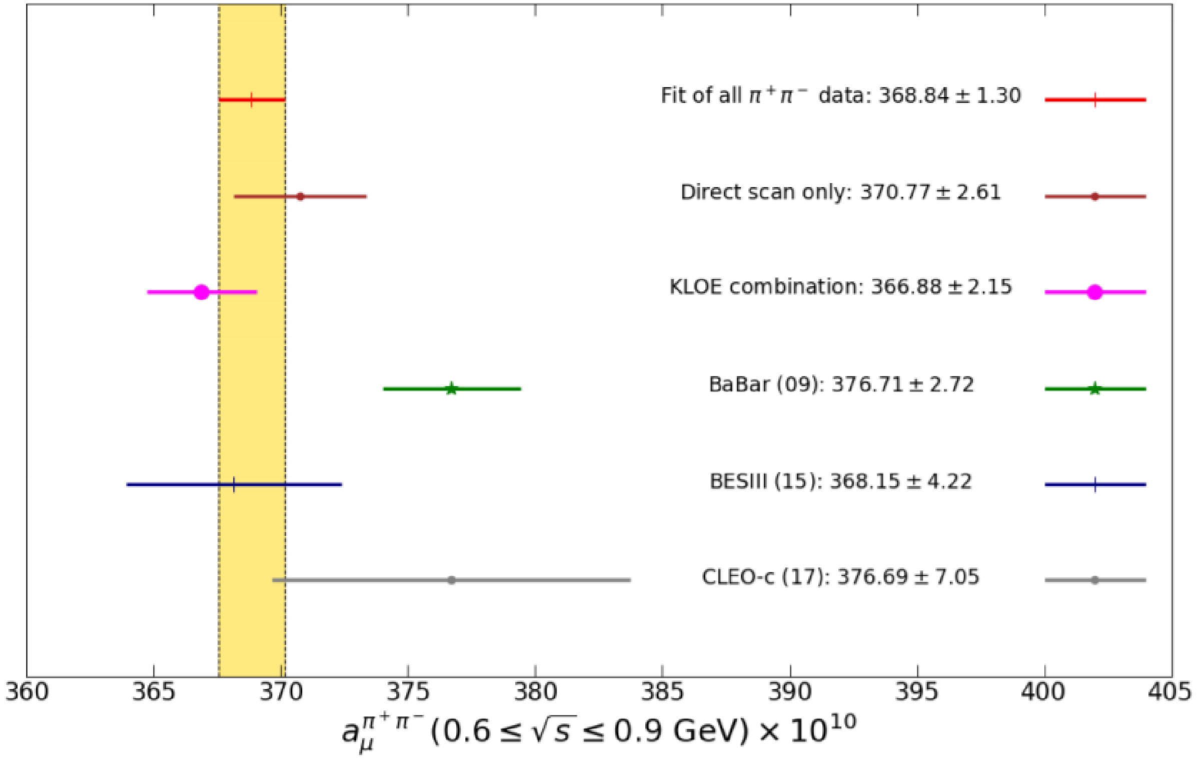
Improve precision of g-2 theory by improving precision of the measurement of this process

Analysis: $e^+e^- \to \pi^+\pi^-\gamma$



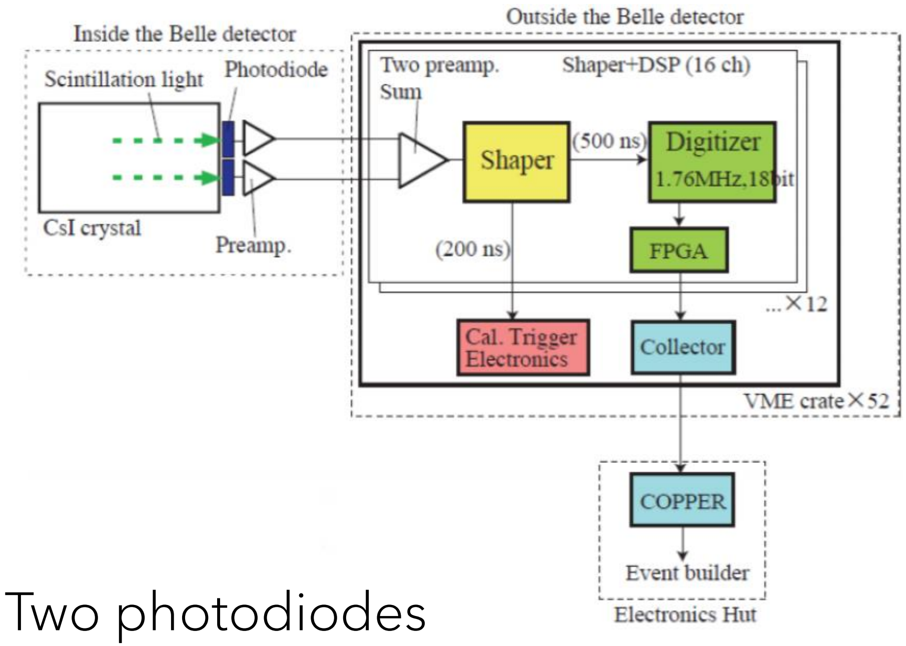


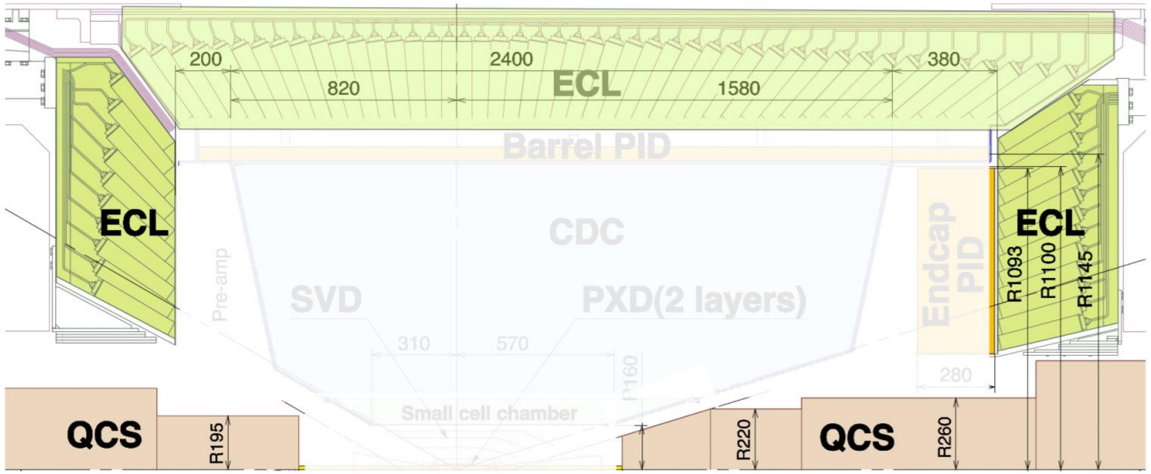
arXiv:2006.04822 [hep-ph]



FPGA Fit within the ECL

A. Sibidanov, https://docs.belle2.org/record/800/files/BELLE2-TALK-CONF-2018-019.pdf





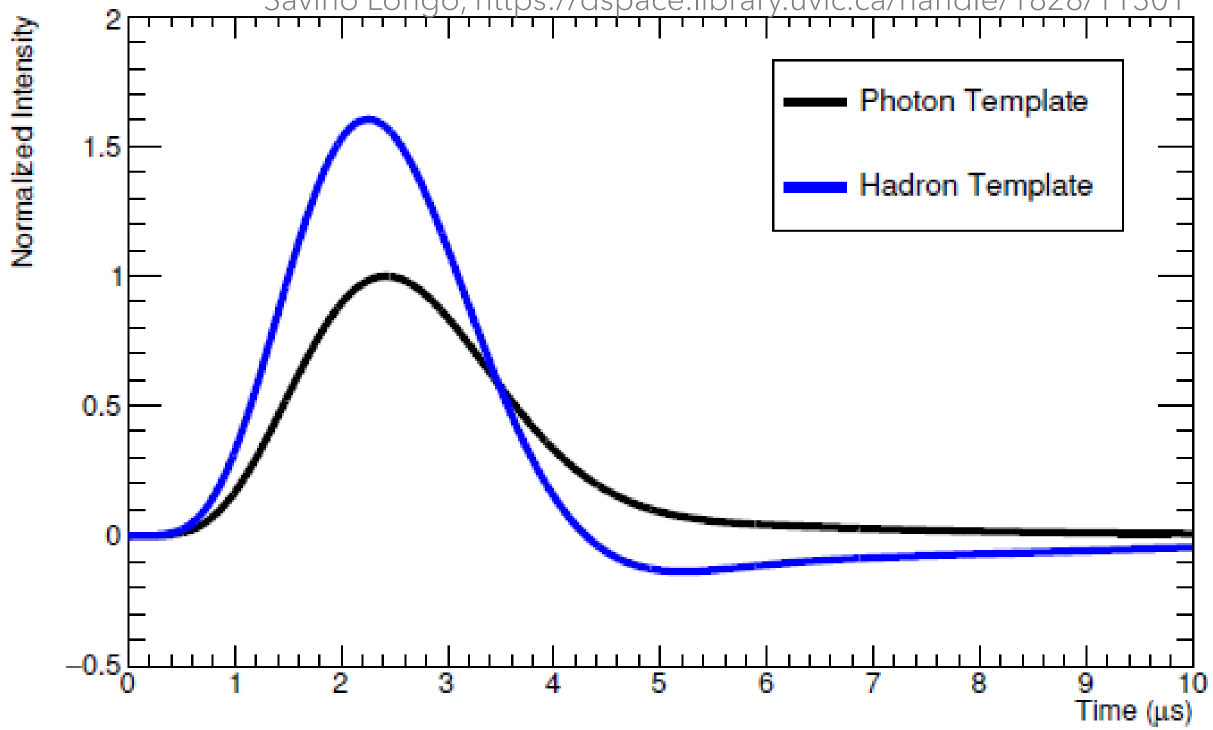
- Two photodiodes
- Pre-amplifier (integrate and shape the signal)
- Sum
- ShaperDSP (shaping amplifier, tail subtraction)
- Digitizer (into 31 ADC points)
- FPGA (template fit, photon)

Savino Longo, https://dspace.library.uvic.ca/handle/1828/11301 - Chapter 6.1

Multi-template fit

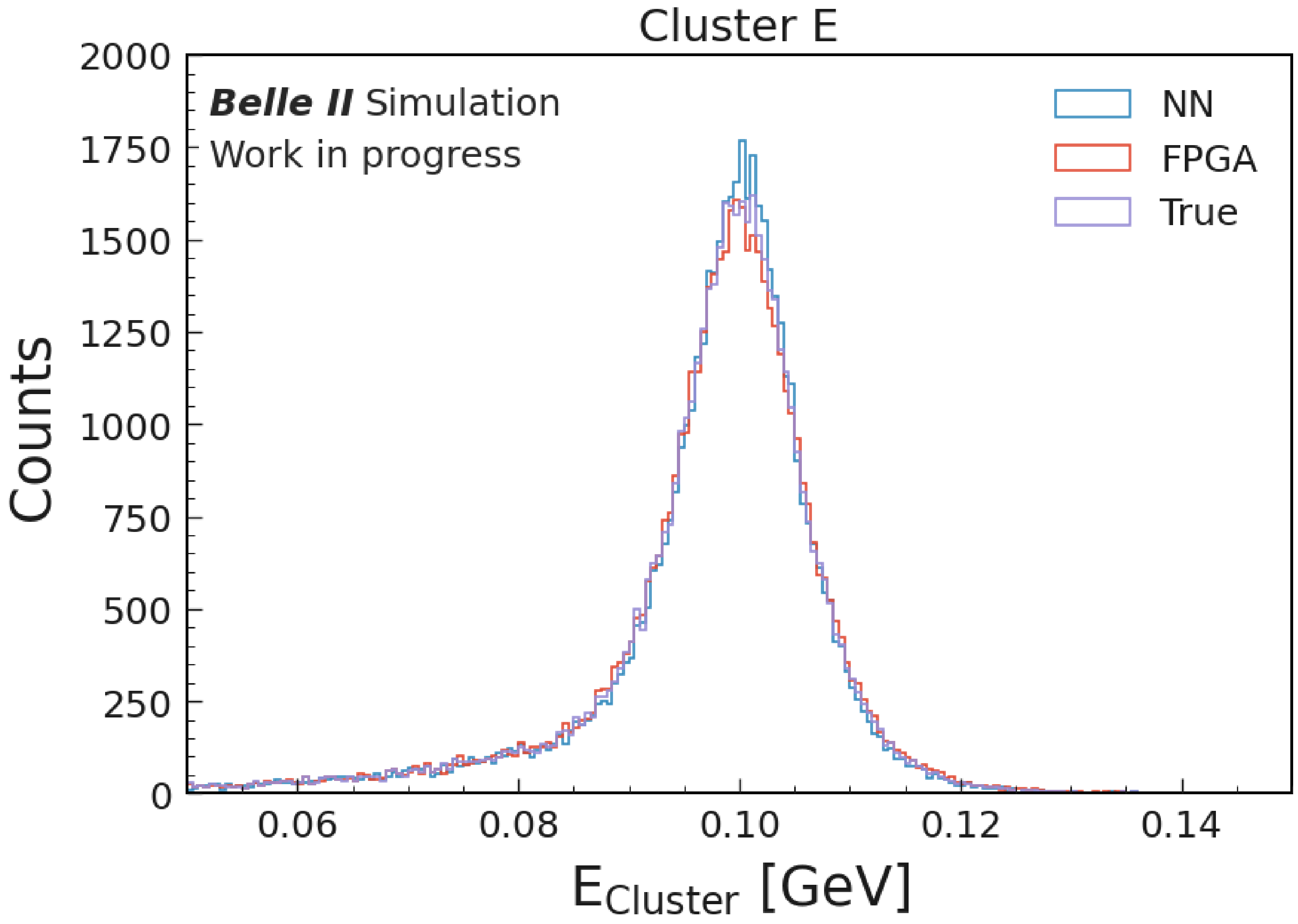
- All pulse shapes with energy above 50 MeV are stored for offline analysis
- Photon template:
  - pure photon scintillation component emission
  - Use Bhabha scattering events for computing the templates
- Hadron template
  - pure hadron scintillation component emission
  - Compute with input from signal chain response and testbeam study
- Need to compute signal chain output for calibration (11 parameters for template for each crystal)

Savino Longo, https://dspace.library.uvic.ca/handle/1828/11301

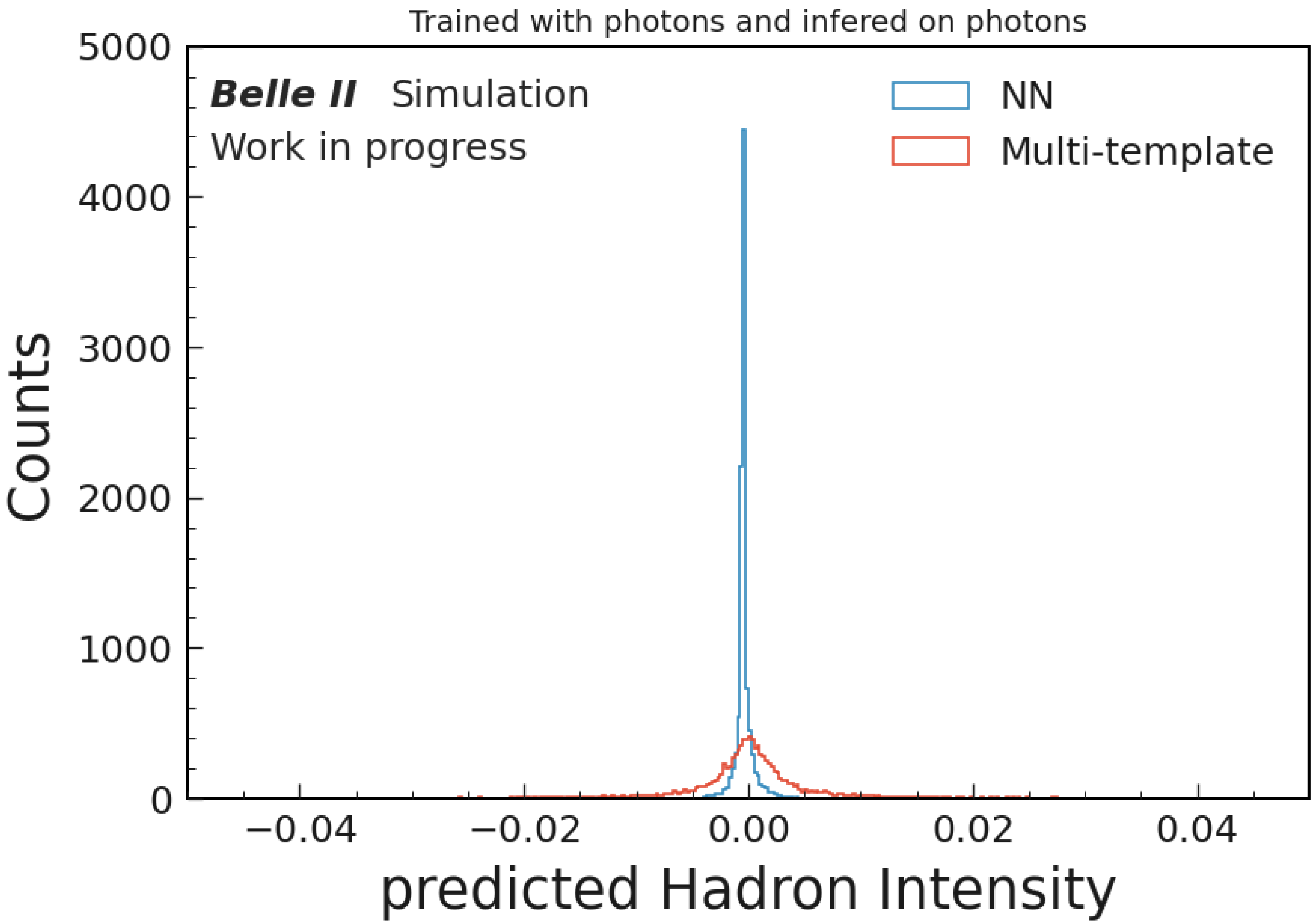


Savino Longo, https://dspace.library.uvic.ca/handle/1828/11301 - Chapter 6.3

Cluster resolution



Neural Network hadron intensity



Beam background

Trained with run 3363, infered on run 3363 and 5649 separatly