# Full Reconstruction VI Updated
## Correlations

Chiaki Yanagisawa

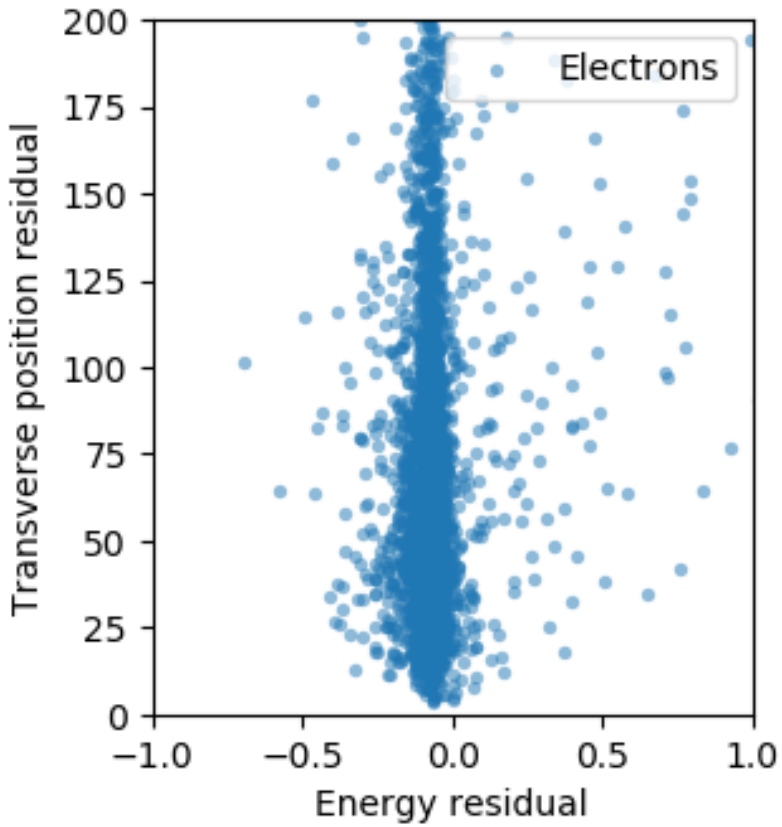
Generative Neural Network for Water Cherenkov Meeting

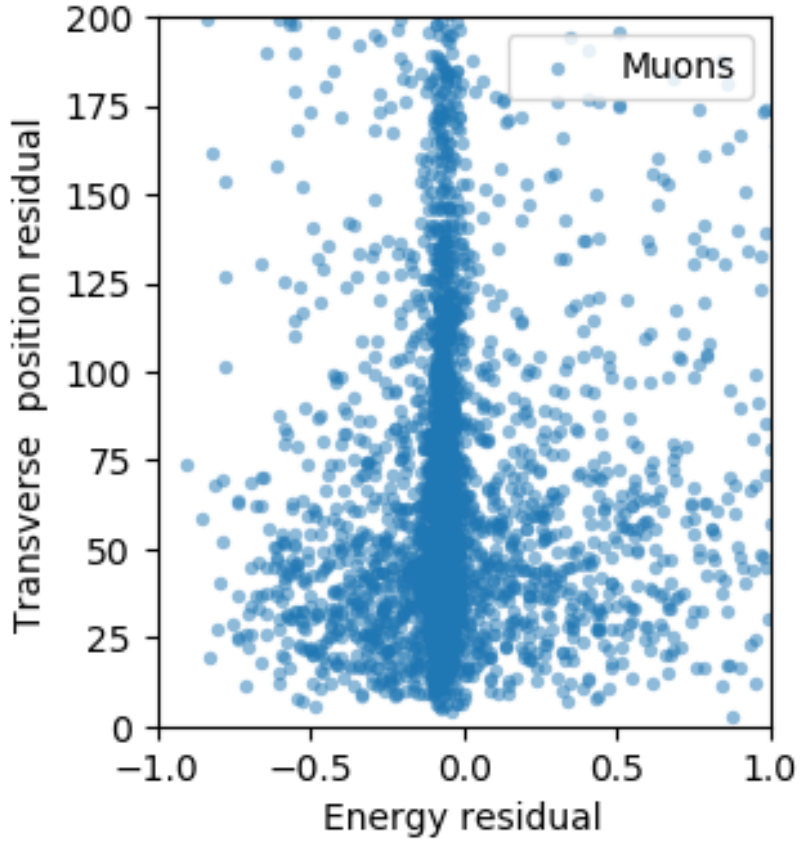
10/20/2022

# Correlations

- ΔTransverse vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  No E cut

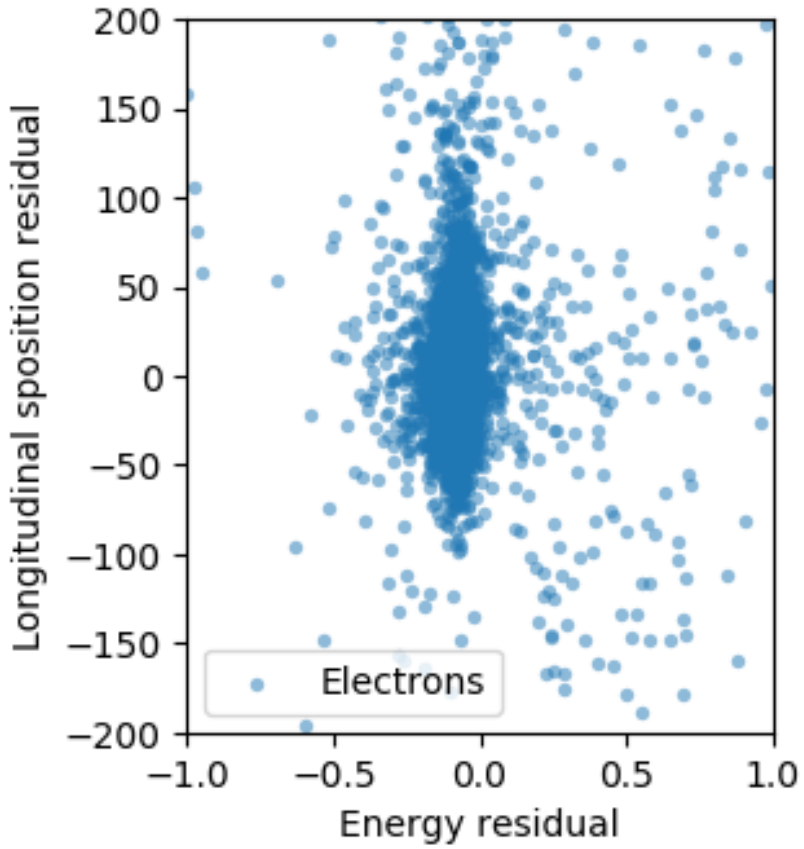


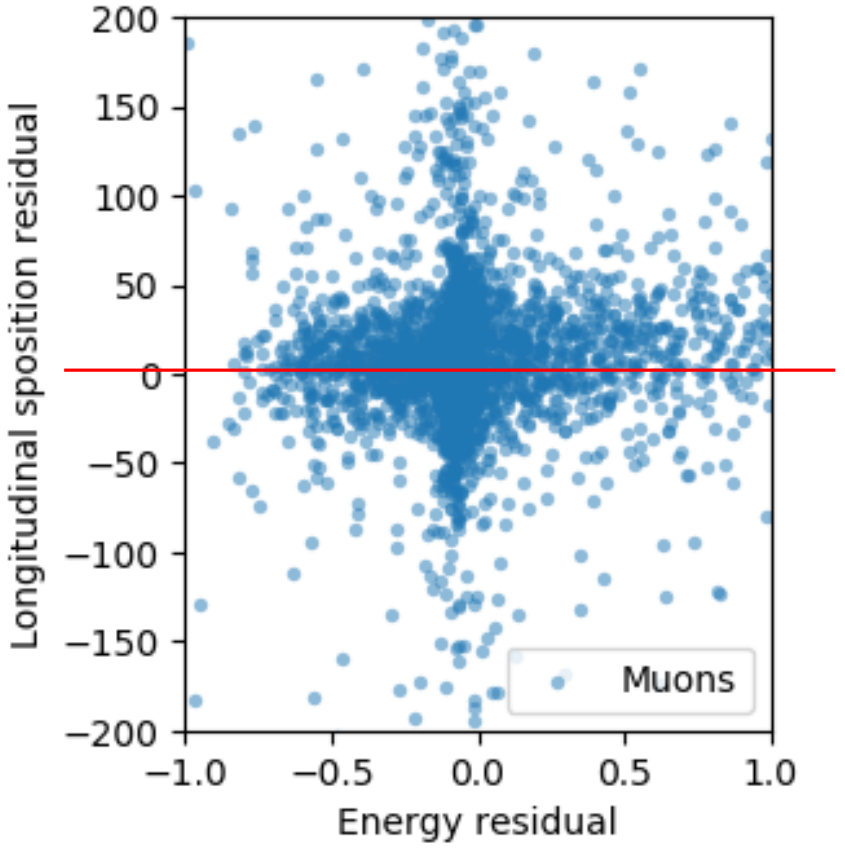



# Correlations

- ΔLongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  No E cut

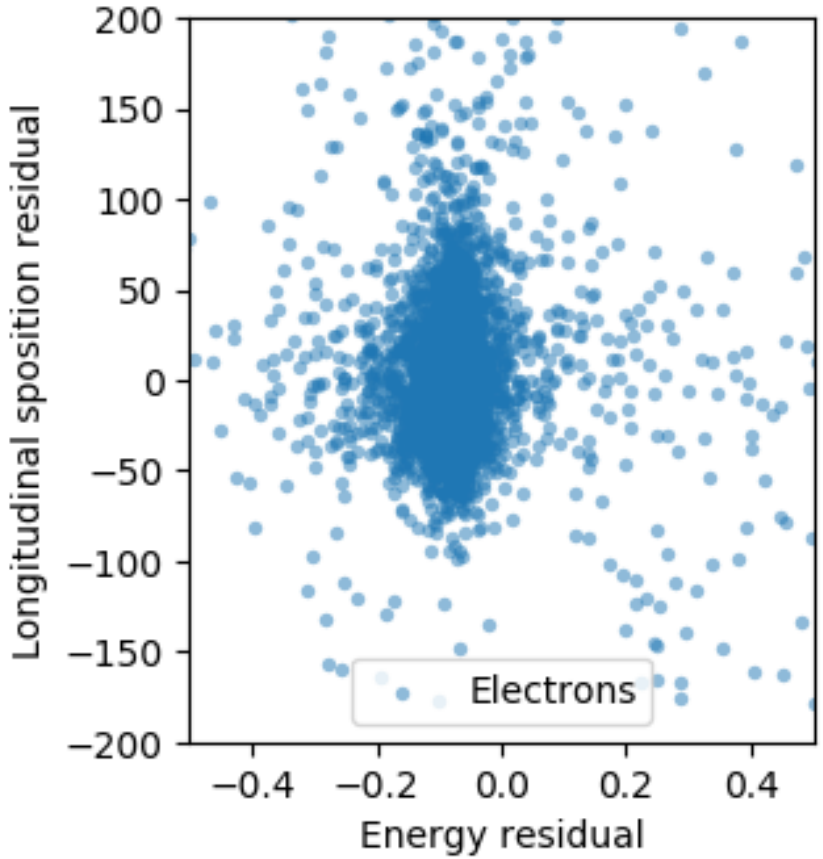


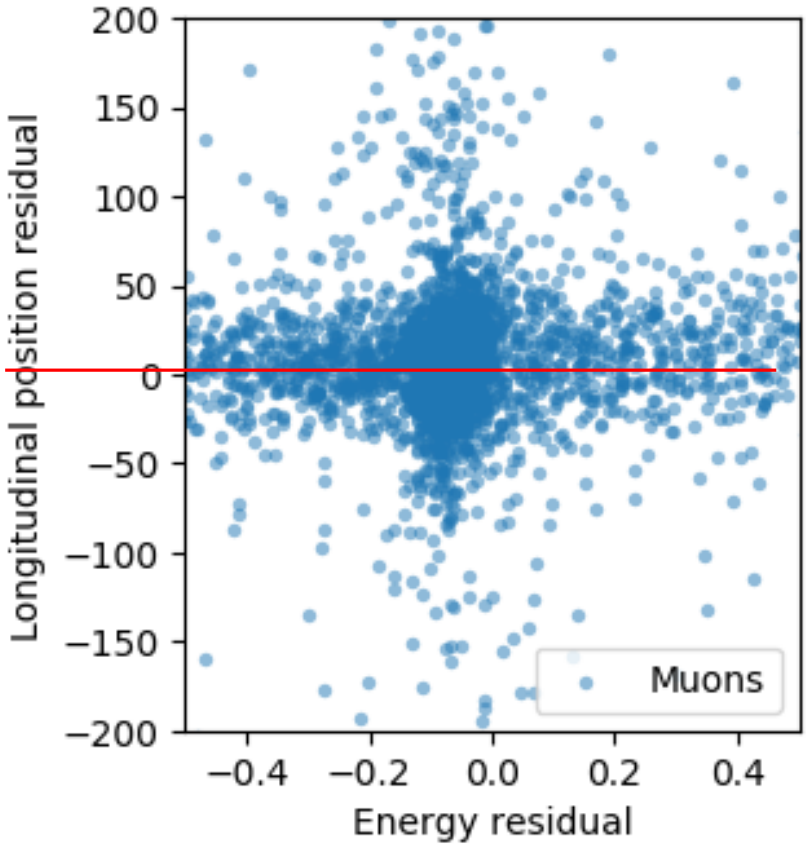



# Correlations

- ΔLongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  No E cut , Energy residual scale change

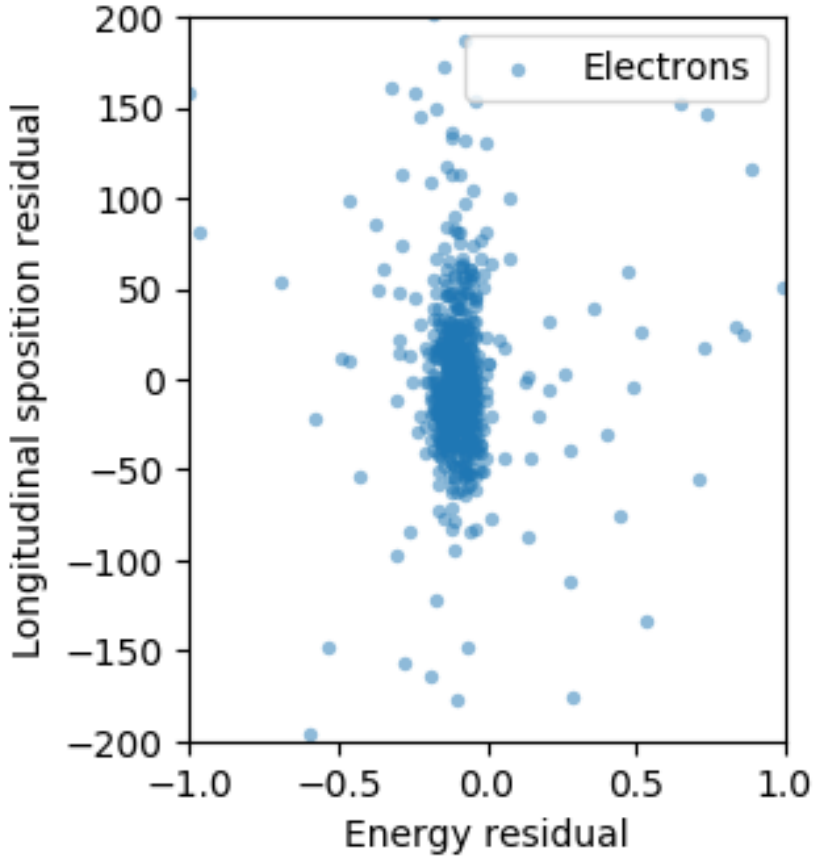


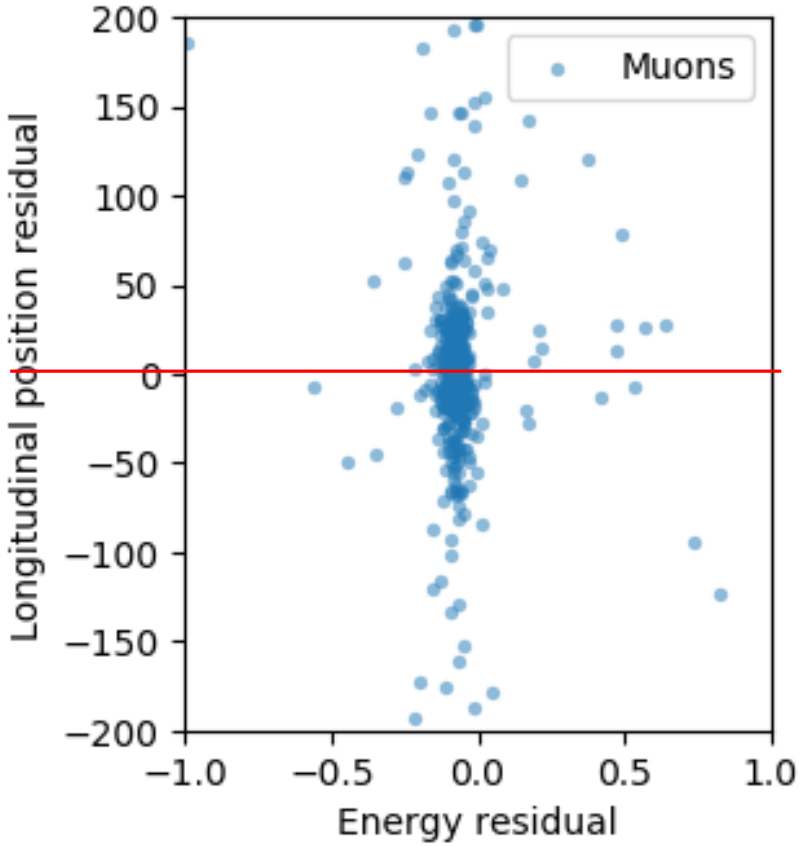



# Correlations

- ΔLongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  E < 1 GeV

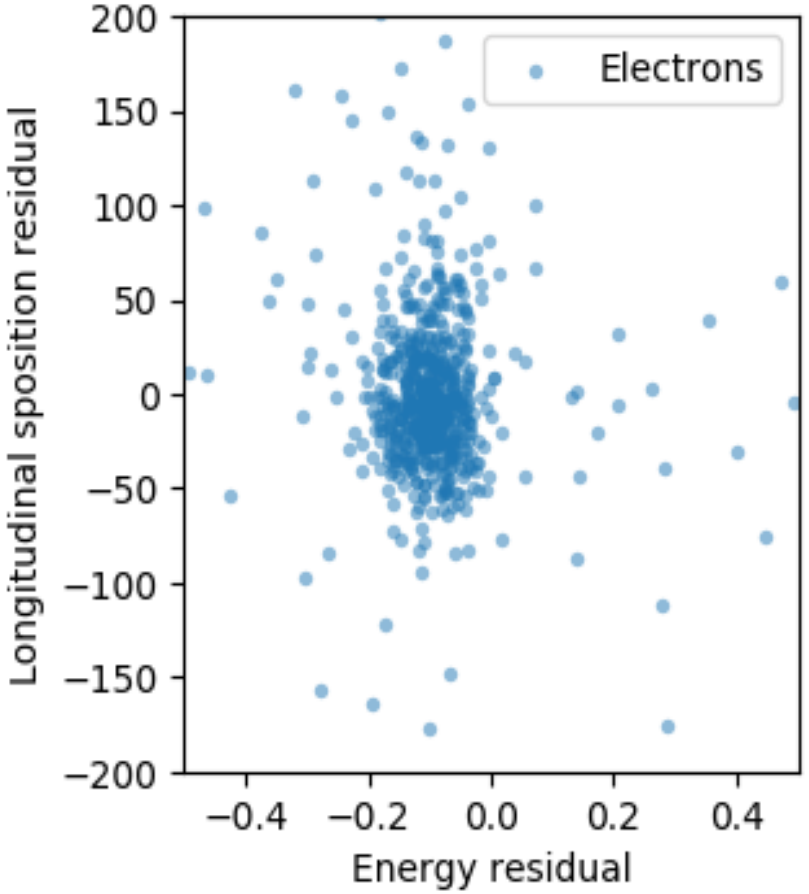


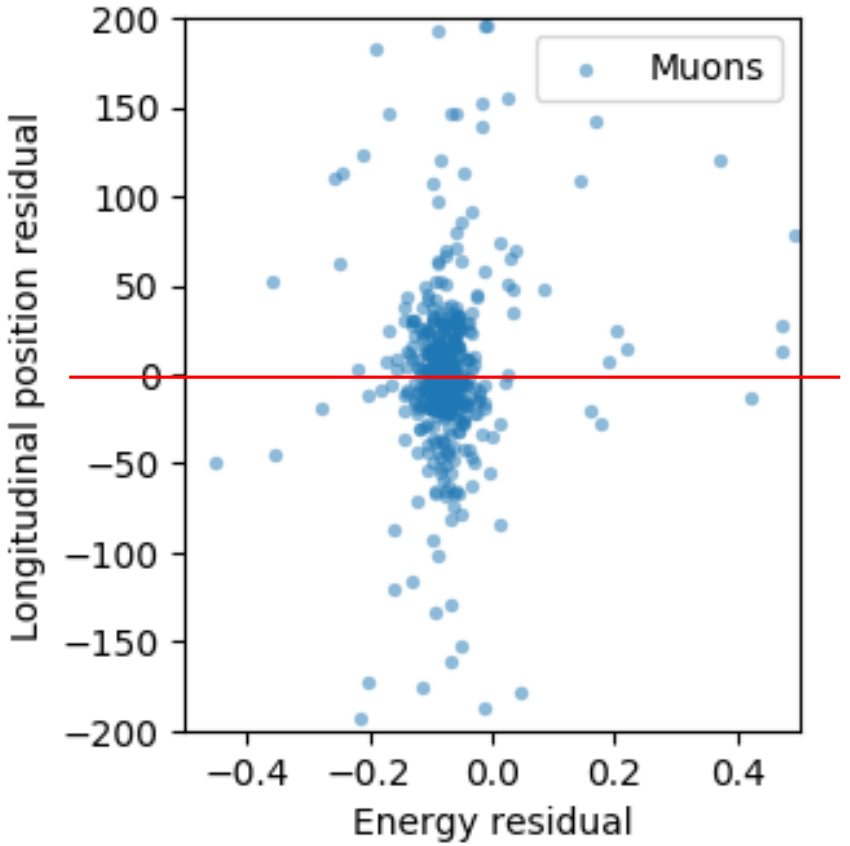



# Correlations

- ΔLongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  E < 1 GeV, Energy residual scale change New



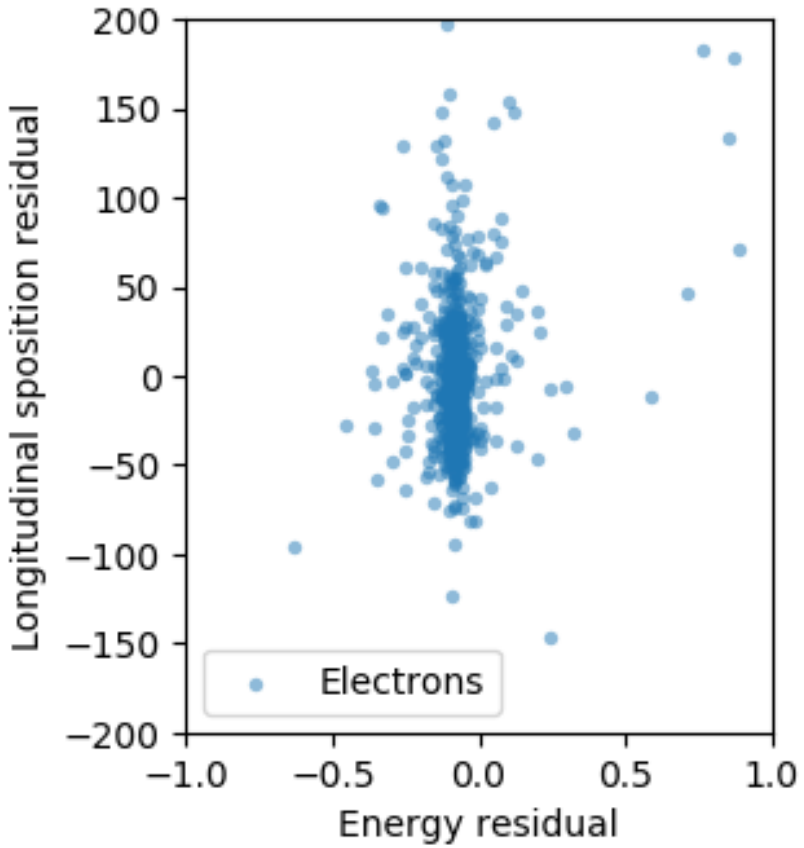



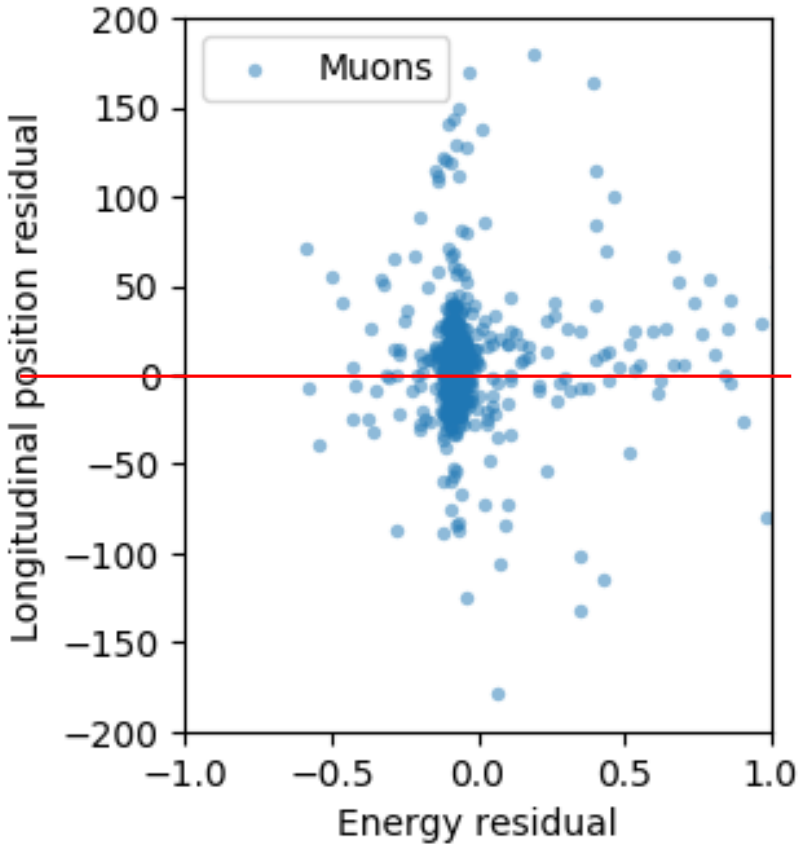
# Correlations

- ΔLongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  1 GeV < E < 2 GeV

New



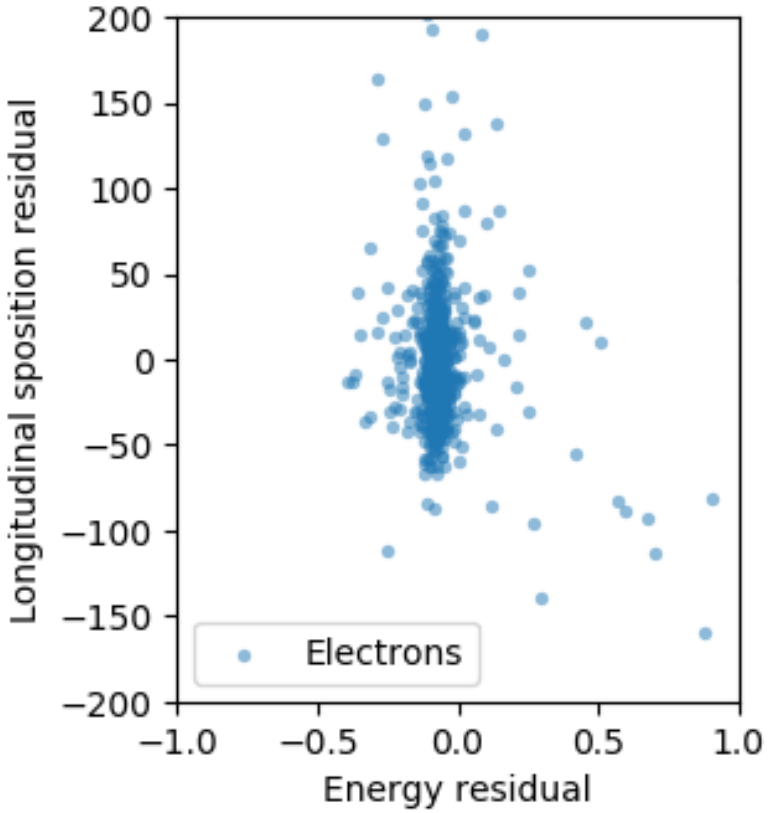



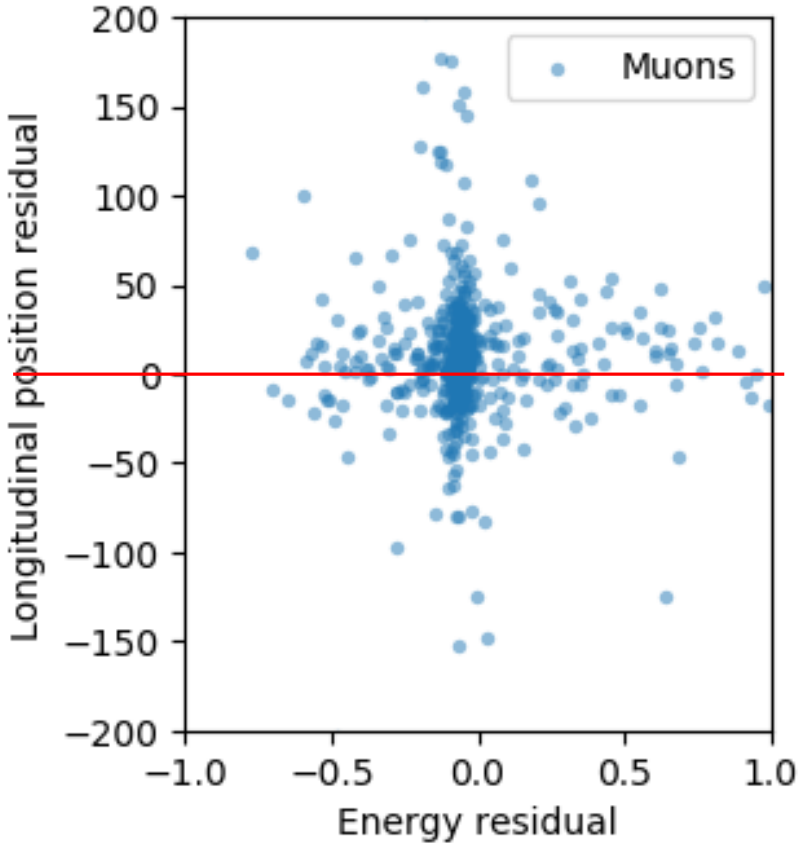
# Correlations

- ΔLongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  2 GeV < E < 3 GeV

New



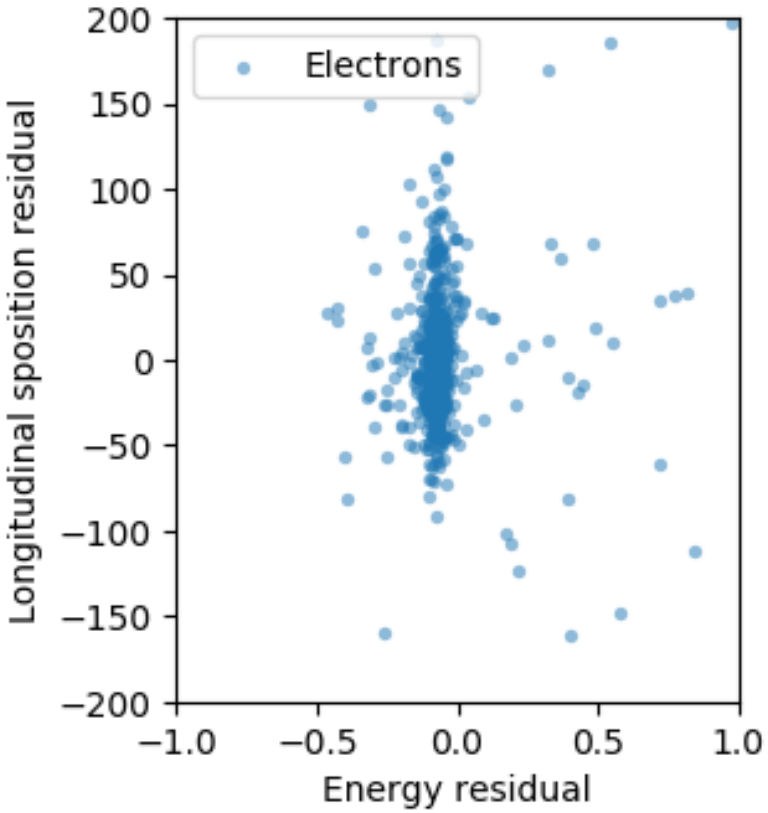



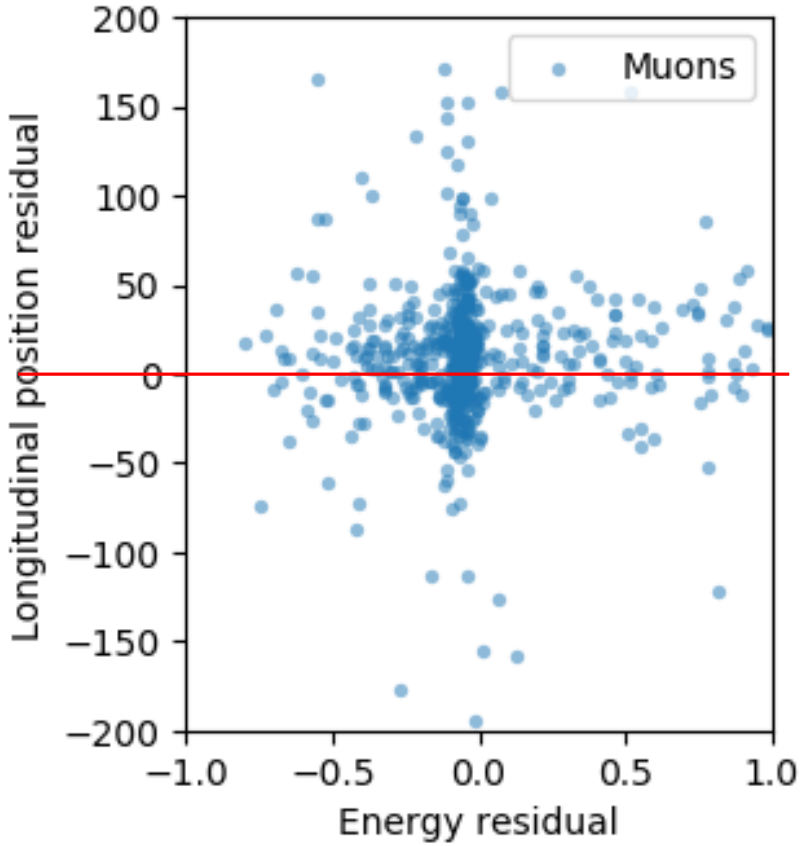
# Correlations

- ΔLongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  3 GeV < E < 4 GeV

New



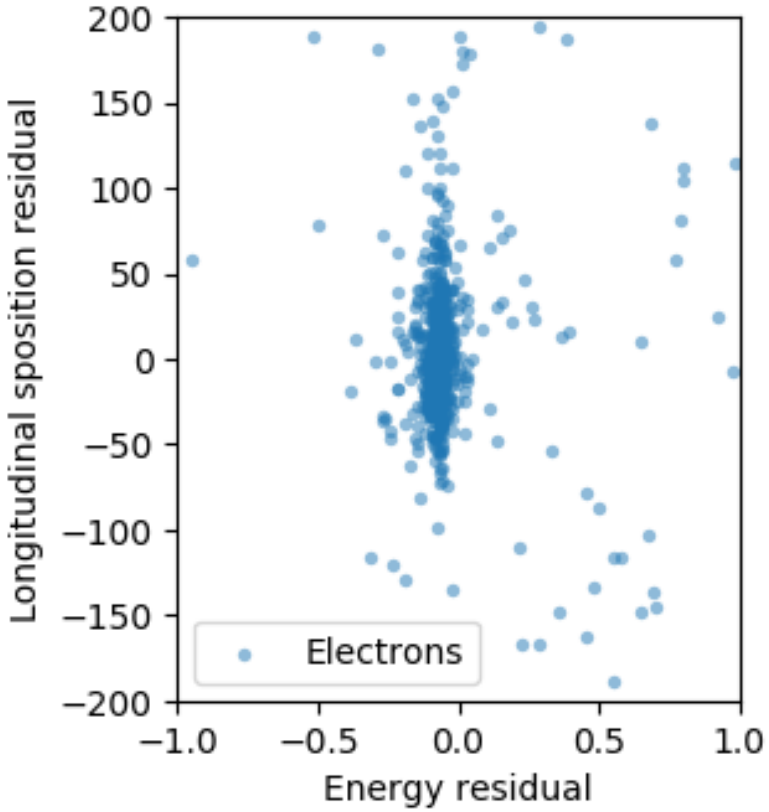



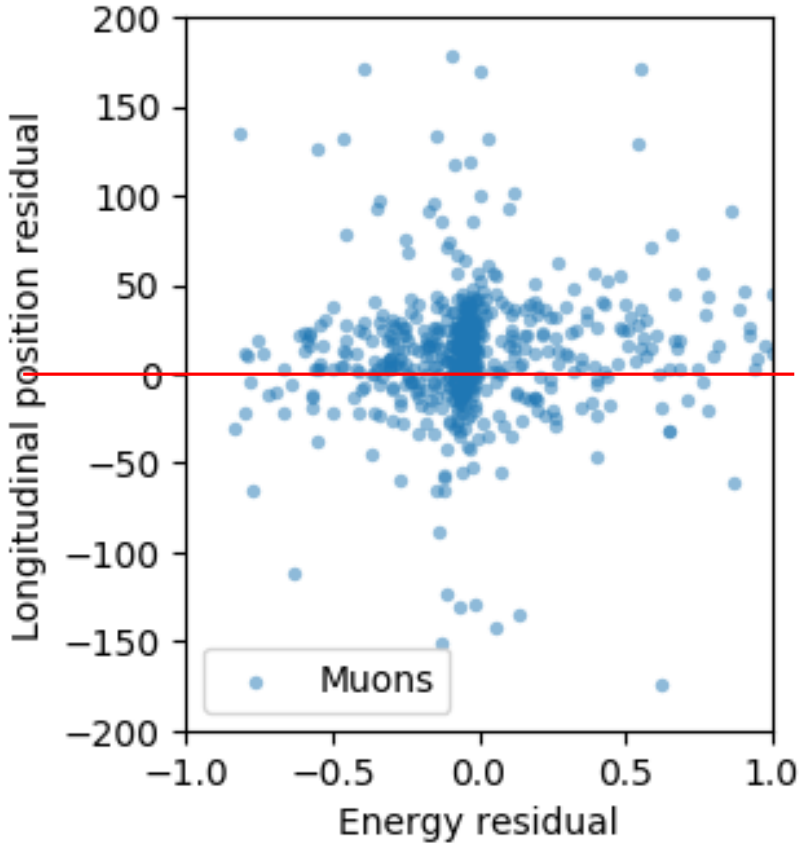
# Correlations

- ΔLongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  4 GeV < E < 5 GeV

New

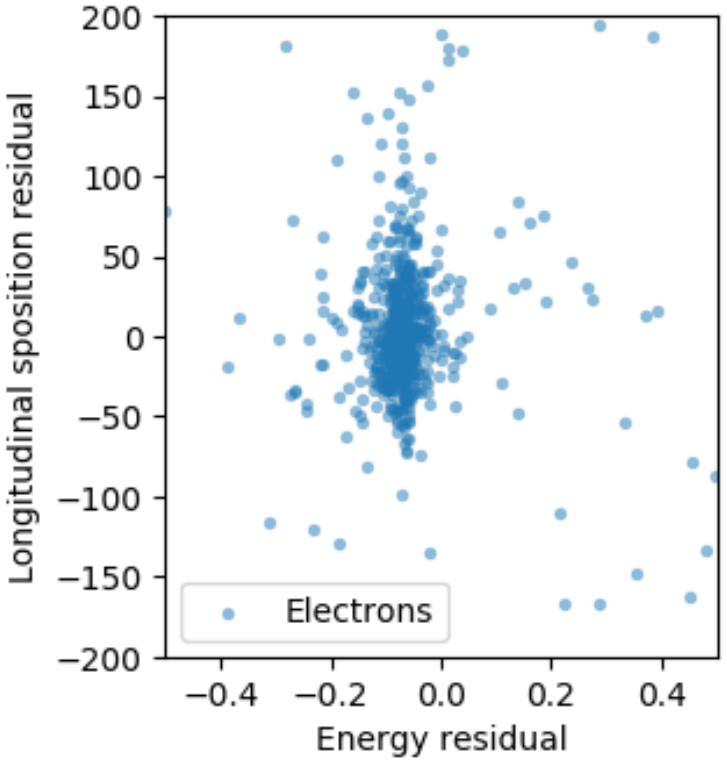


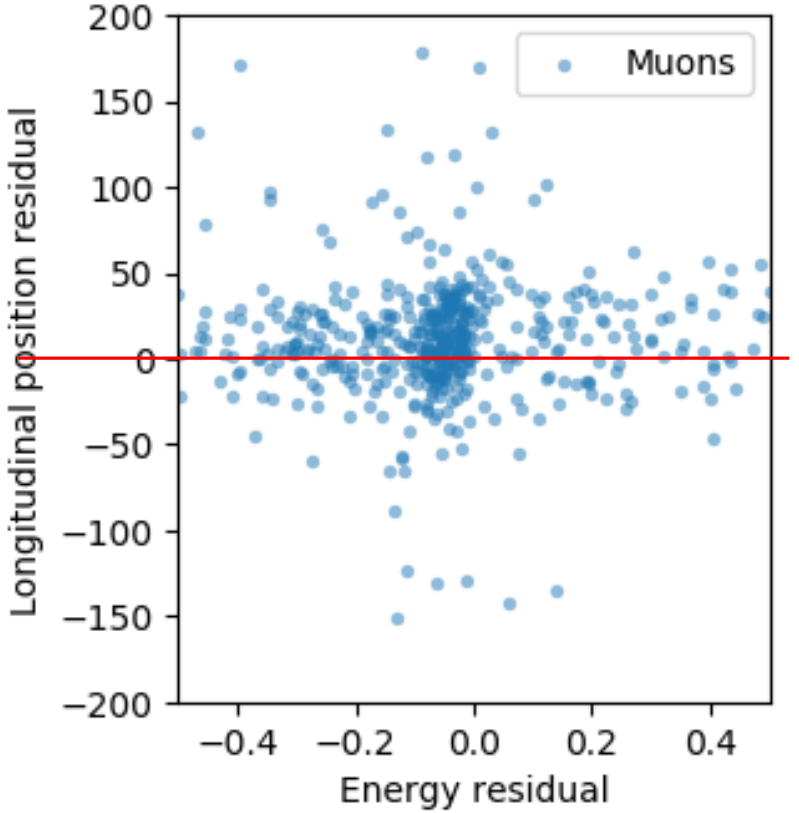
# Correlations

- Δlongitudinal vertex position vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  4 GeV < E < 5 GeV, Energy residual scale change



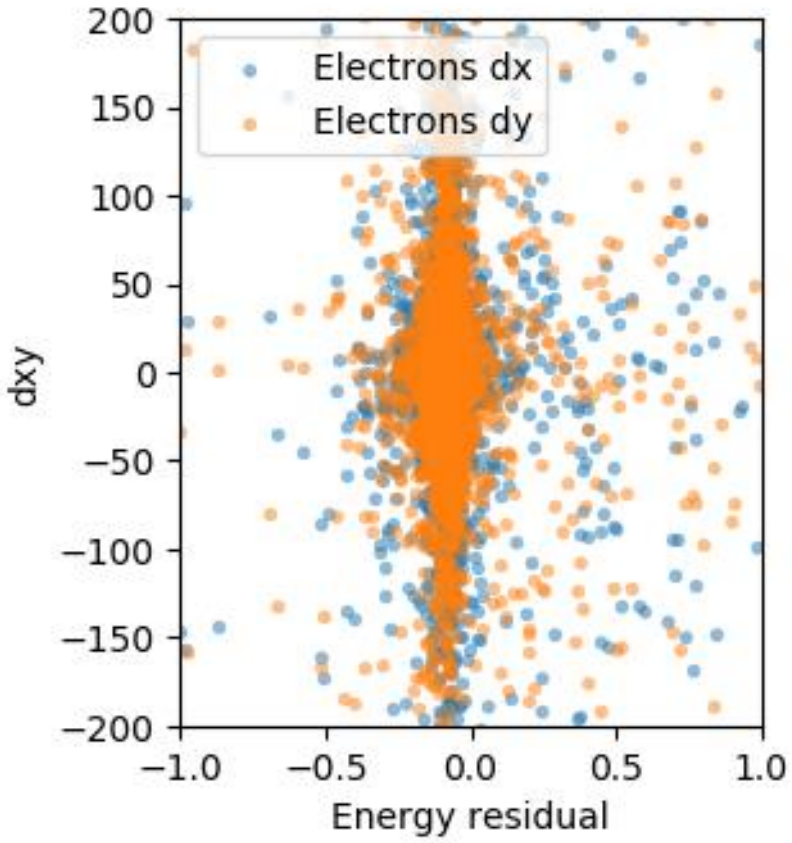

New

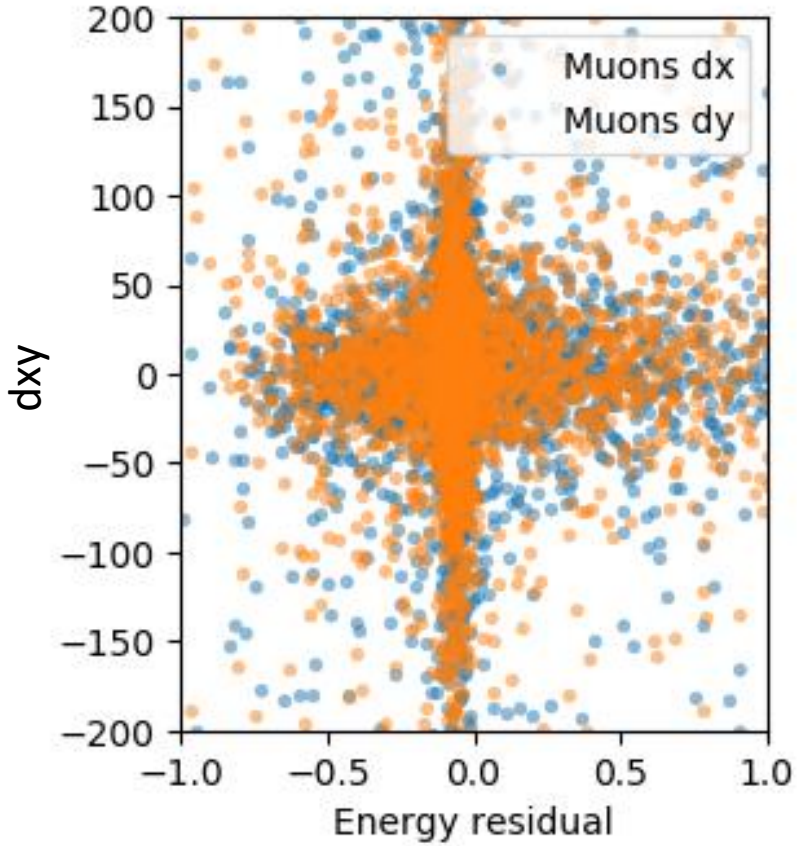


# Correlations

- ∆xy vs. ∆E/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

  No E cut

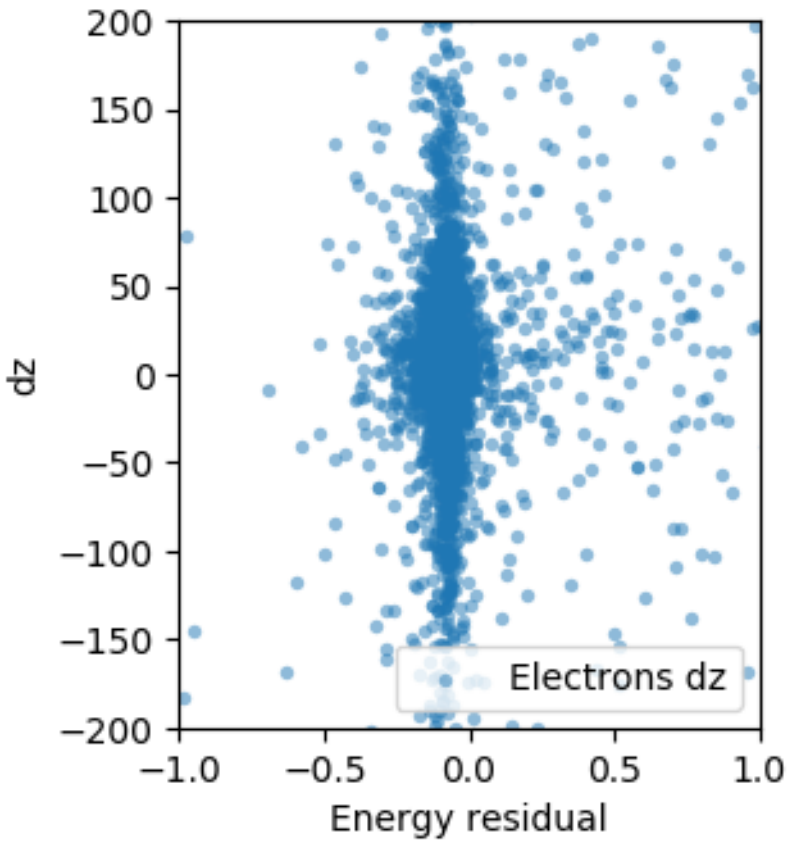


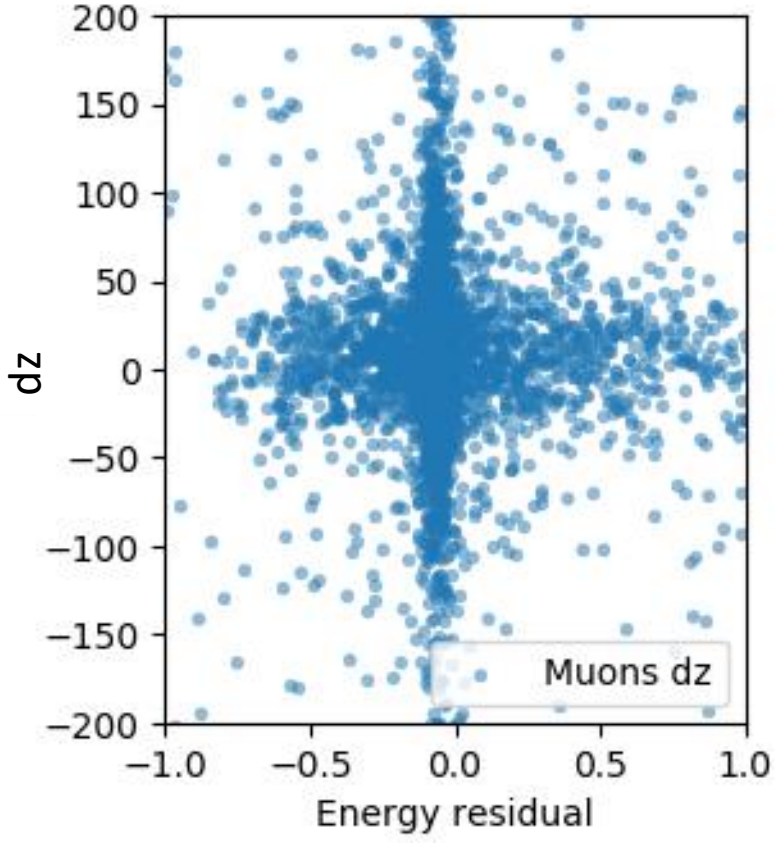



# Correlations

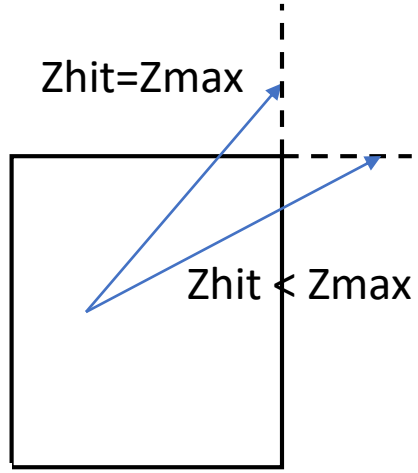
- $\Delta z$ vs. $\Delta E/E$ with10-Gaussian fit with $Towall_{true}$ > 200 cm

  No E cut



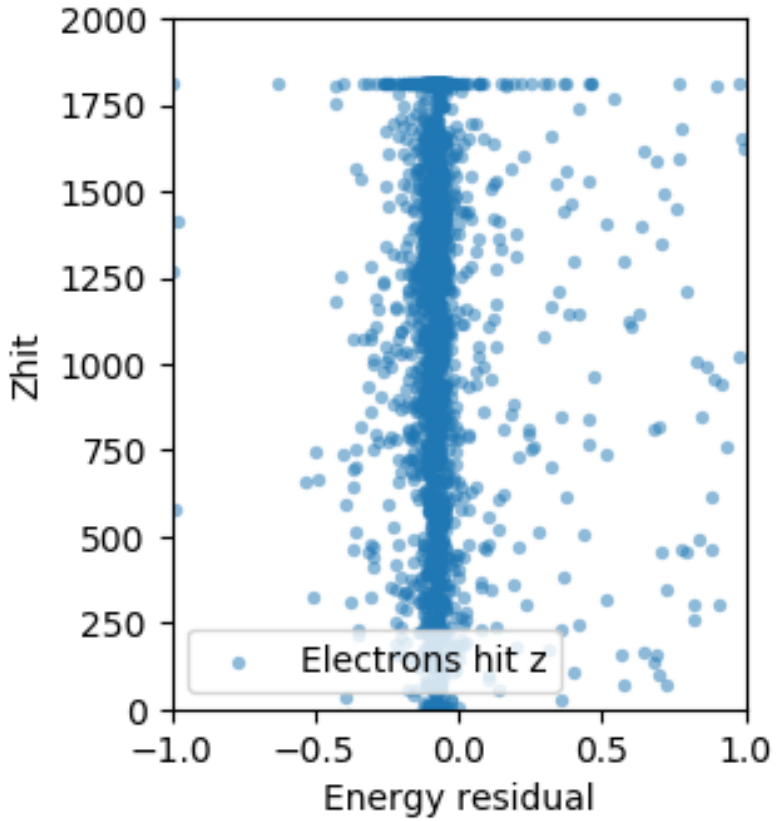
# Correlations (corrected)

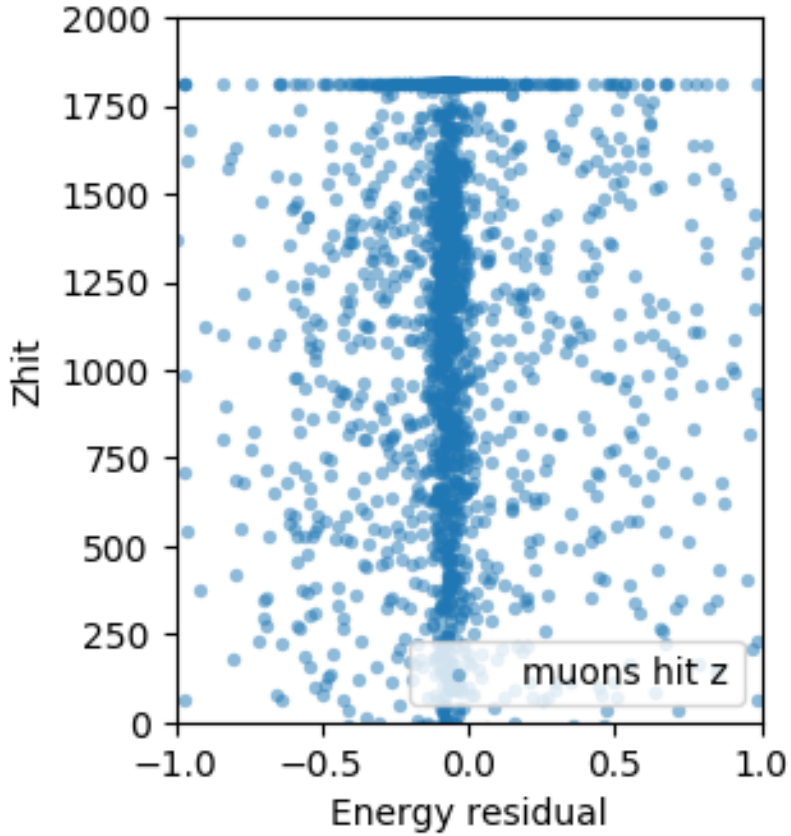



- Zhit vs. ΔE/E with10-Gaussian fit with $Towall_{true}$ > 200 cm

No E cut

Updated



# Conclusions

- Correlations between several variables and the energy residual were checked.
- A small effect may be in the correlation between the longitudinal vertex residual and the energy residual with muons with ?. But there are no other obvious correlations.
- This means a bad fit for a variable is not translated to bad fits for other variables. → the cause of the shift in the peak position of the energy residual distribution is not due to bad fit.
- As we saw the shifts of peak positions of various variables depend on the number of Gaussians for the charge distribution, probably we need to check the shifts as a function of the number of Gaussians.
  (Use the Cris' cnn files he posted).

# A Problem to Solve

- Tried to use Cris's 50-epoch training results and ran into a problem:

```
Loading model: CRinGe_SK_MultiGaus
With options:  {'N_GAUS': 10}
Traceback (most recent call last):
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 187, in nti
    n = int(s.strip() or "0", 8)
ValueError: invalid literal for int() with base 8: 'sor_v2\nq'

During handling of the above exception, another exception occurred:

Traceback (most recent call last):
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 2289, in next
    tarinfo = self.tarinfo.fromtarfile(self)
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 1095, in fromtarfile
    obj = cls.frombuf(buf, tarfile.encoding, tarfile.errors)
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 1037, in frombuf
    chksum = nti(buf[148:156])
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 189, in nti
    raise InvalidHeaderError("invalid header")
tarfile.InvalidHeaderError: invalid header
```

# A Problem to Solve

During handling of the above exception, another exception occurred:

```
Traceback (most recent call last):
  File "/home/chiaki/anaconda3/lib/python3.7/site-packages/torch/serialization.py", line 595, in _load
    return legacy_load(f)
  File "/home/chiaki/anaconda3/lib/python3.7/site-packages/torch/serialization.py", line 506, in legacy_load
    with closing(tarfile.open(fileobj=f, mode='r:', format=tarfile.PAX_FORMAT)) as tar, \
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 1591, in open
    return func(name, filemode, fileobj, **kwargs)
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 1621, in taropen
    return cls(name, mode, fileobj, **kwargs)
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 1484, in __init__
    self.firstmember = self.next()
  File "/home/chiaki/anaconda3/lib/python3.7/tarfile.py", line 2301, in next
    raise ReadError(str(e))
tarfile.ReadError: invalid header
```

# A Problem to Solve

During handling of the above exception, another exception occurred:

Traceback (most recent call last):
  File "fit_event_CY1.py", line 154, in <module>
    network = load_model(args)
  File "fit_event_CY1.py", line 135, in load_model
    network.load_state_dict(torch.load(args.model_weights_path, map_location=network.device))
  File "/home/chiaki/anaconda3/lib/python3.7/site-packages/torch/serialization.py", line 426, in load
    return _load(f, map_location, pickle_module, **pickle_load_args)
  File "/home/chiaki/anaconda3/lib/python3.7/site-packages/torch/serialization.py", line 599, in _load
    raise RuntimeError("{} is a zip archive (did you mean to use torch.jit.load()?)".format(f.name))
RuntimeError: /storage/shared/chiaki/WC/CRinGe_SK_MultiGaus_Q10G.cnn is a zip archive (did you mean to use torch.jit.load()?)

# The Draft for Proceedings

- If I include a short acknowledgements, I run out pages (4-page limit)

We acknowledge the support of the Water Cherenkov Machine Learning (WatChMaL) group4. Stony Brook Research Computing and Cyberinfrastructure, and the Institute for Advanced Computational Science, SeaWulf computing system, and WestGrid and Compute Canada with its high performance  heterogeneous cluster Cedar.

If we decide to keep the acknowledgements, one possible omission would be the corresponding figure and :

We trained the network using 75% of simulated events with the remaining 25% used for validation. Figure 4 show how the loss function descreases and becomes more stable with the number of epochs using charge information only, independent charge and timing information, and correlated charge and time information. In all cases 1-,3-,5- and 10-Gaussian fits were used for Figure 4.

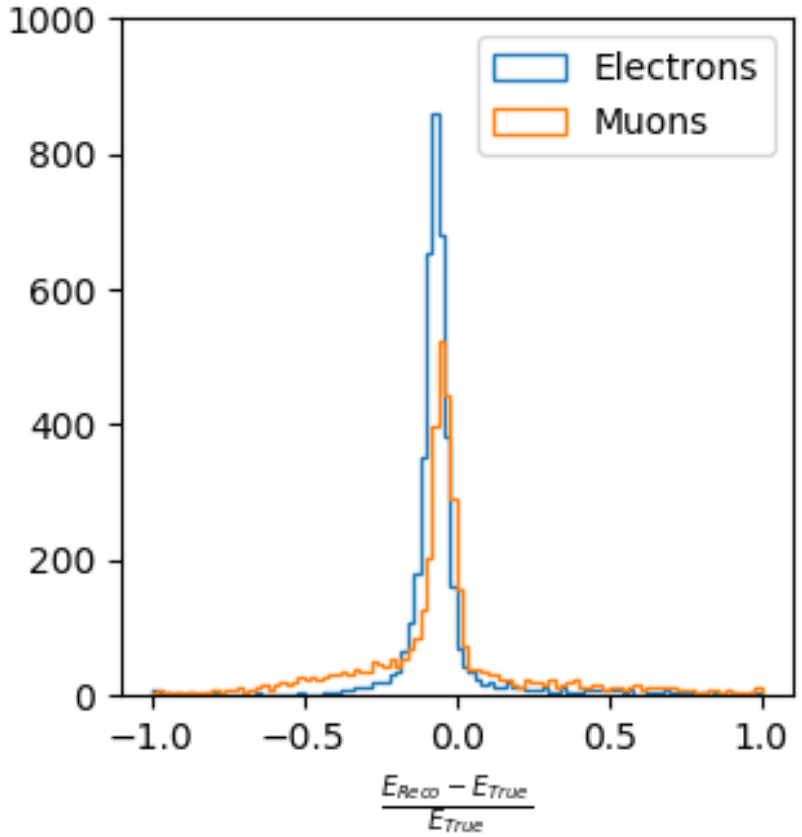
**Figure 4:** Changes in the loss function value as the tranning progresses for charge only fitting (left), independent fitting of charge and timing (middle), and fitting of correlated charge and timing (right)

# Backup Slides

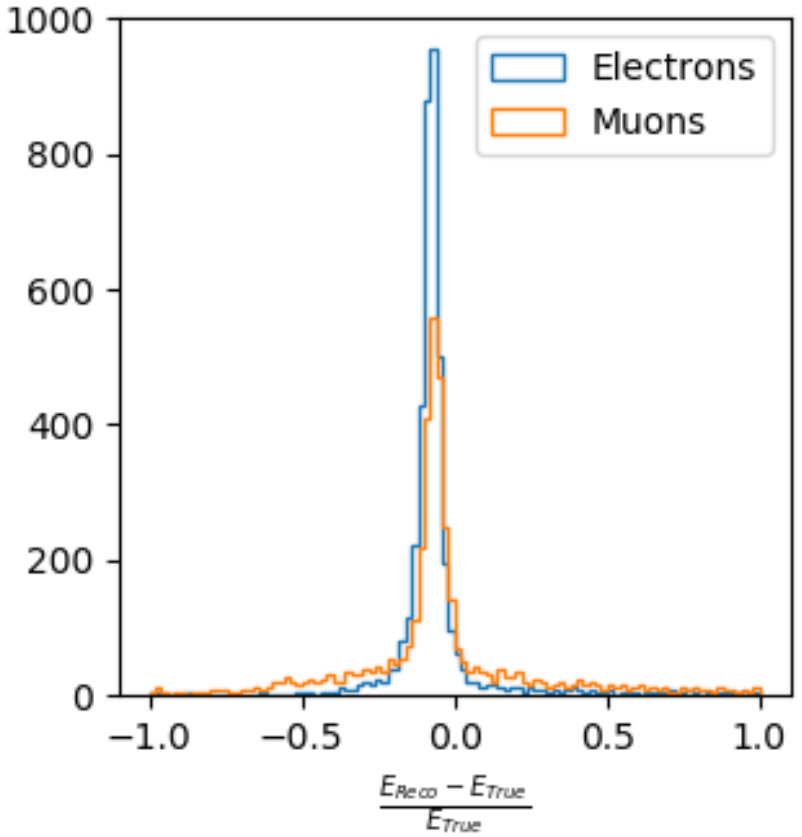
# What Causes the Shifts of the Peak

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Energy reconstruction residual of with a cut on $Dwall_{true}$ > 200 cm

6G



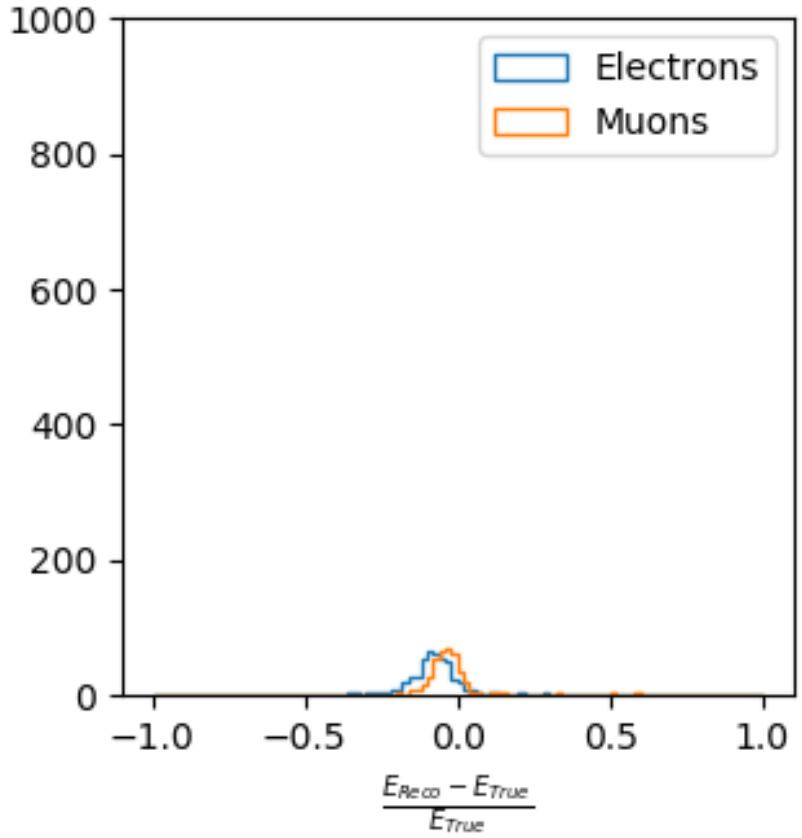

10G



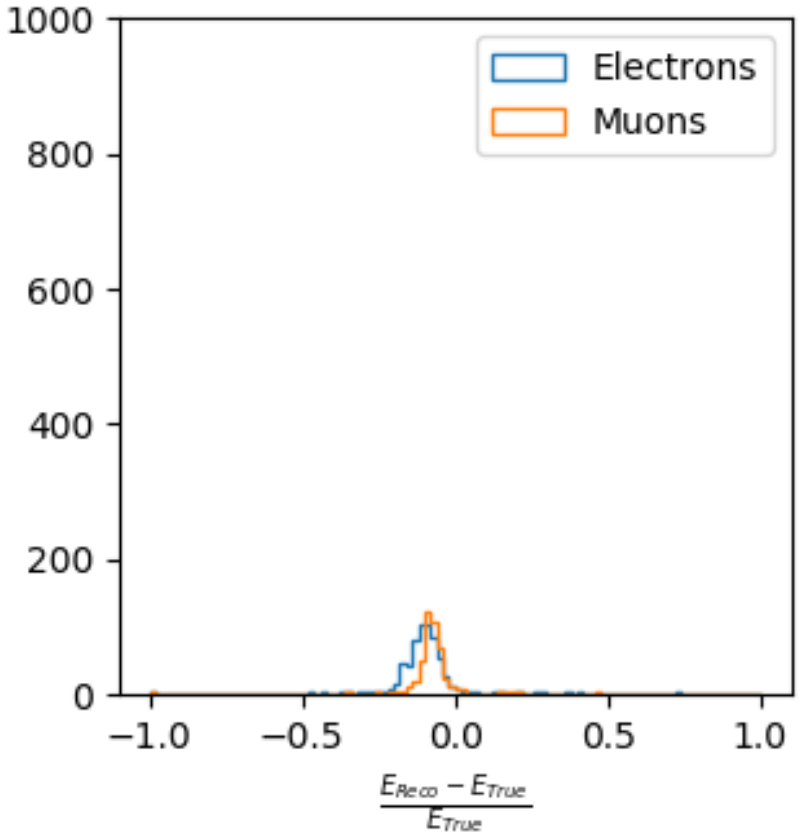
# What Causes the Shifts of the Peaks

- ❑ Performance difference between 6-Gaussian and 10-Gaussian fit with Ecut
  - Energy reconstruction residual of with a cut on Dwall > 200 cm and on $E_{true}$ (0 GeV - 1 GeV)

6G



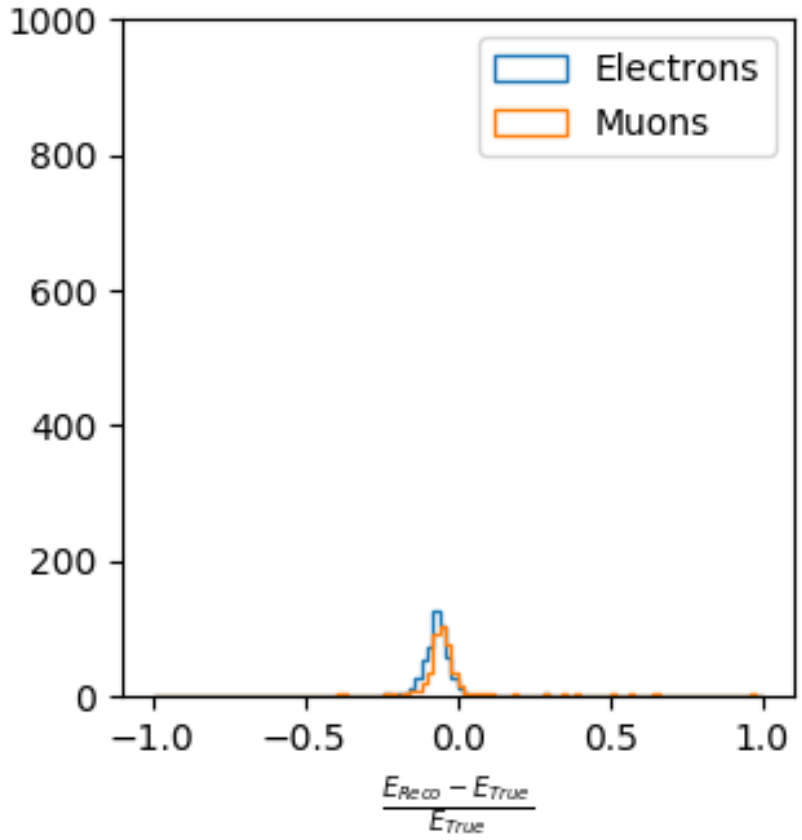

10G



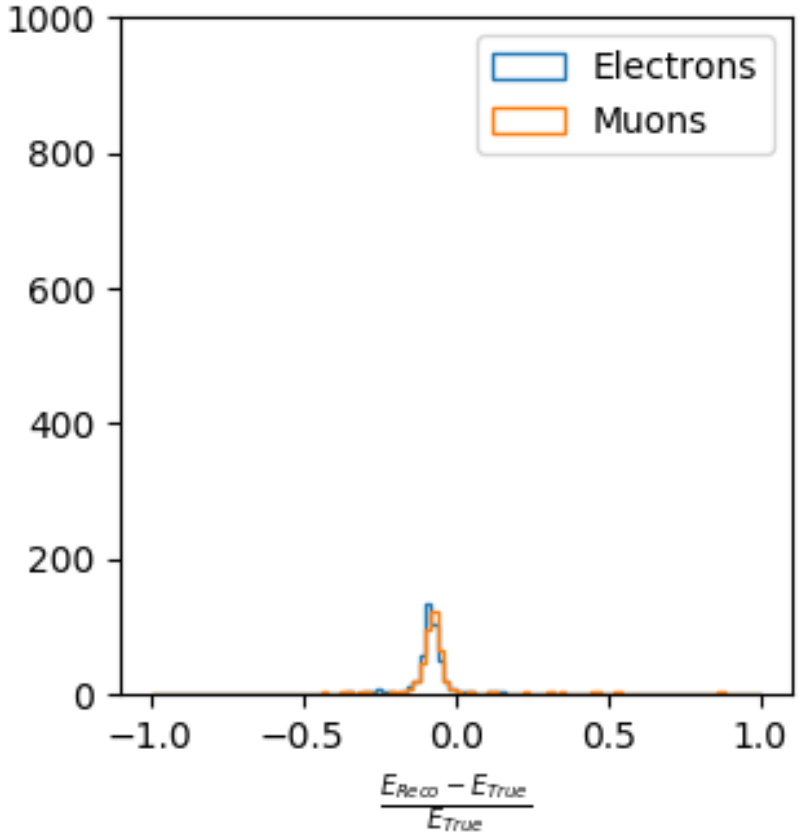
# What Causes the Shifts of the Peaks

- ❑ Performance difference between 6-Gaussian and 10-Gaussian fit with Ecut
  - Energy reconstruction residual of with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (1 GeV – 2 GeV)

6G



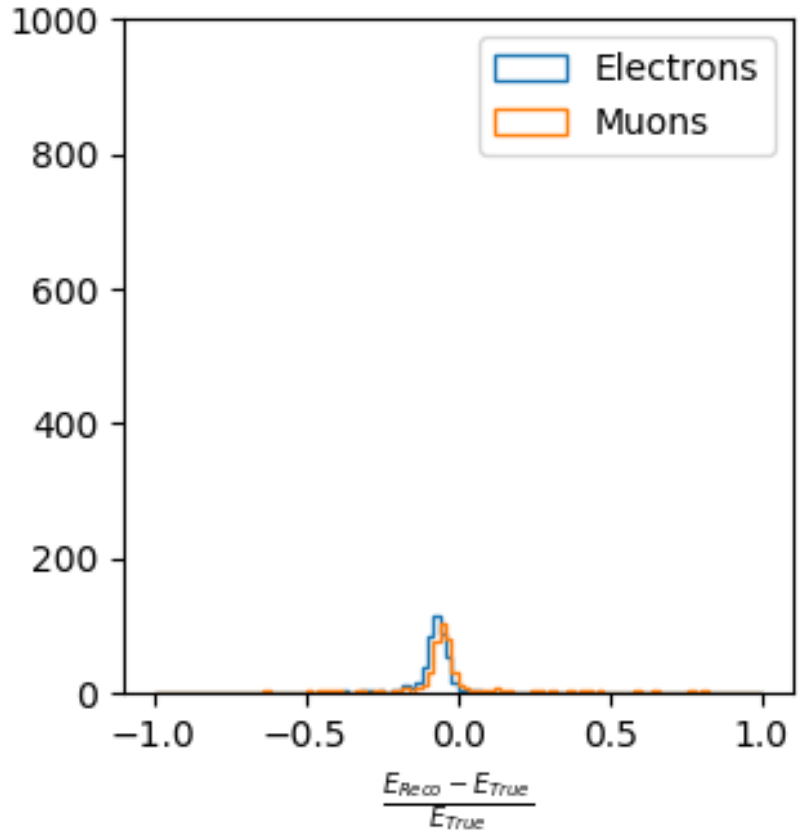

10G



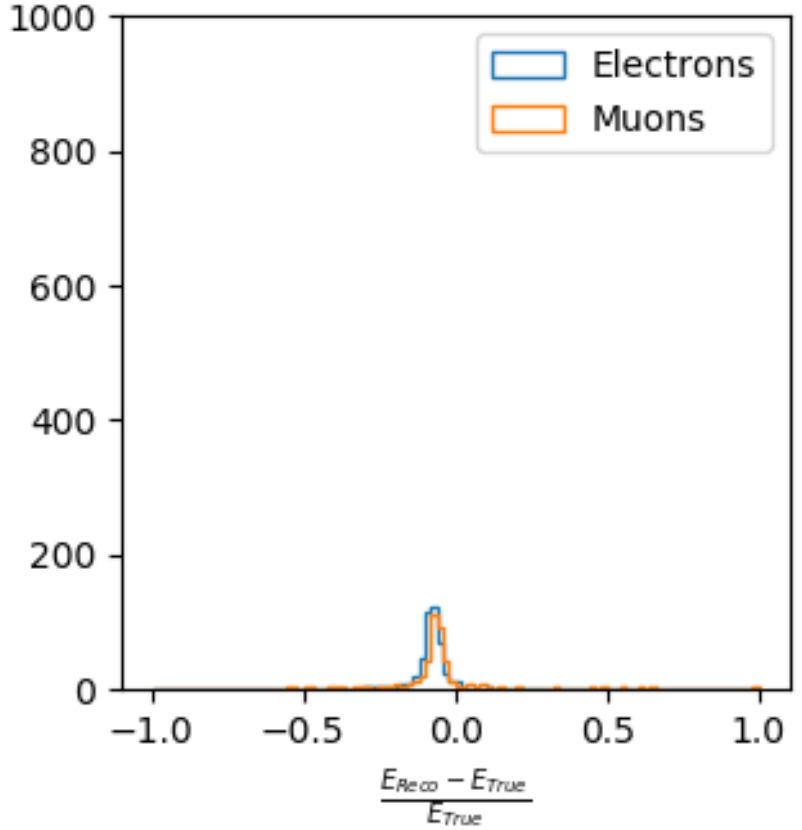
# What Causes the Shifts of the Peaks

- ❑ Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Energy reconstruction residual of with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (2 GeV – 3GeV)

6G



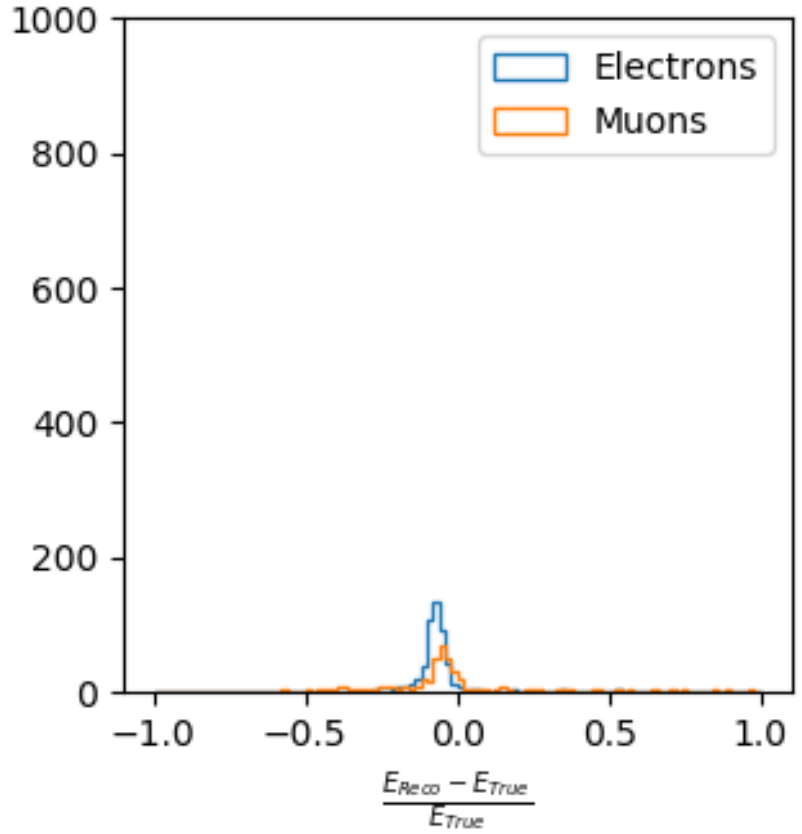

10G



# What Causes the Shifts of the Peaks

- ❑ Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Energy reconstruction residual of with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (3 GeV – 4 GeV)

6G

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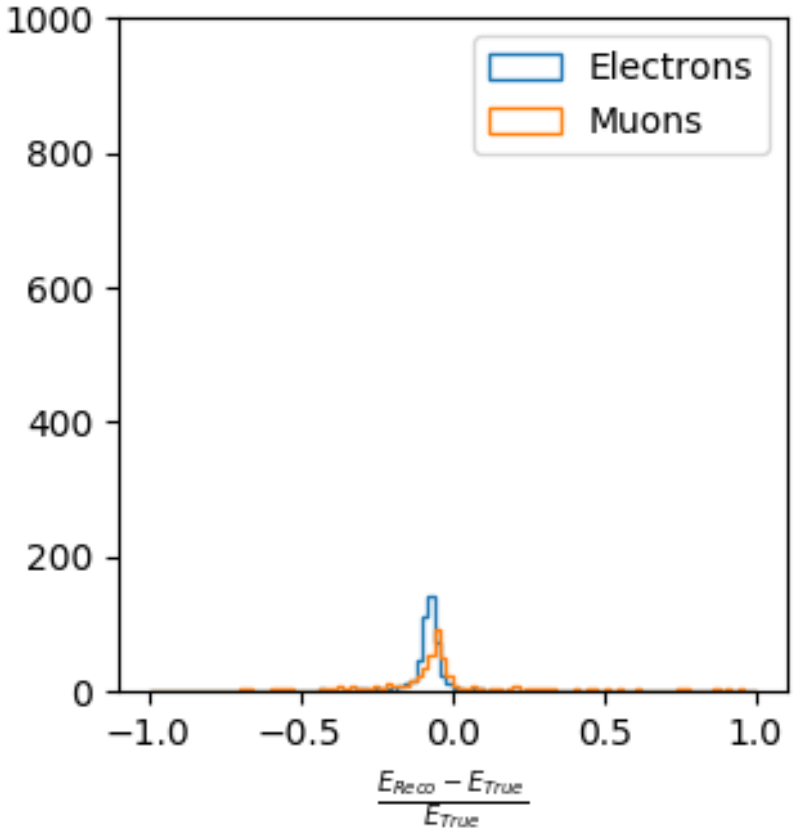
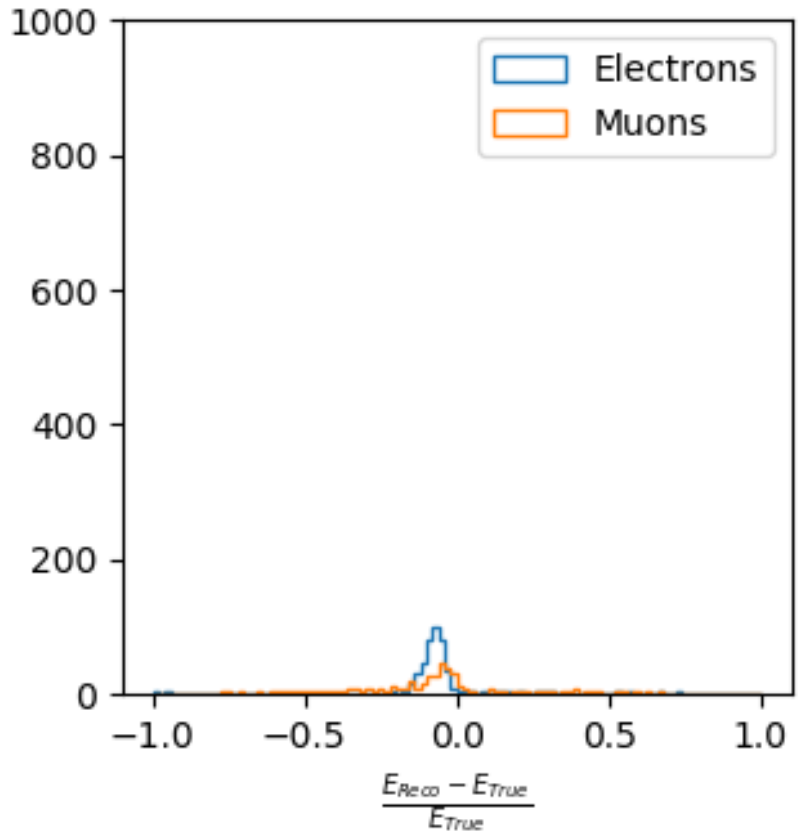


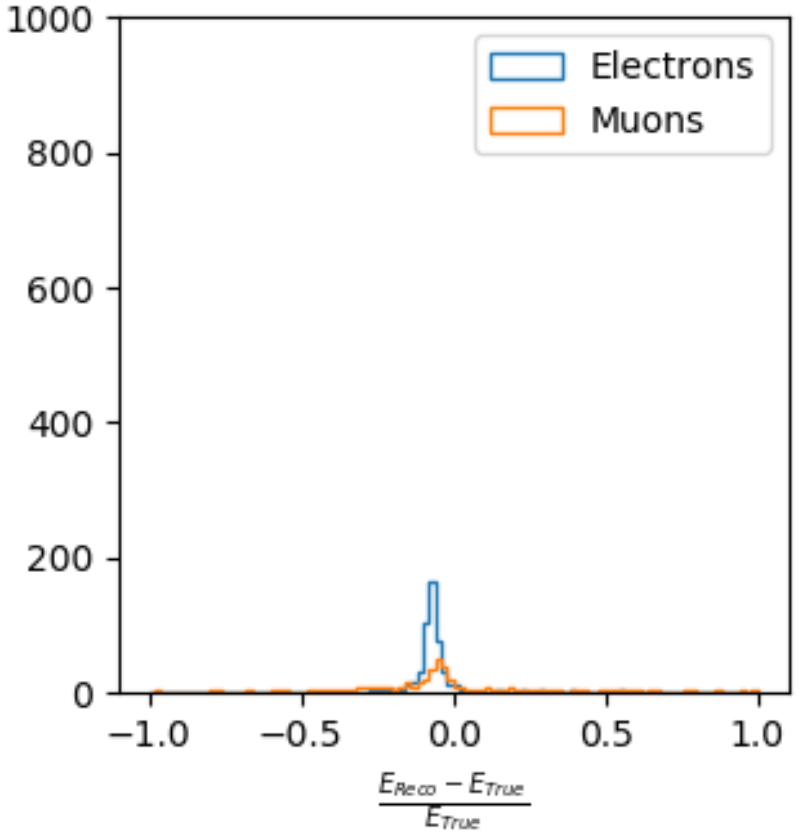
# What Causes the Shifts of the Peaks

- ❑ Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Energy reconstruction residual of with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (4 GeV – 5 GeV)

6G



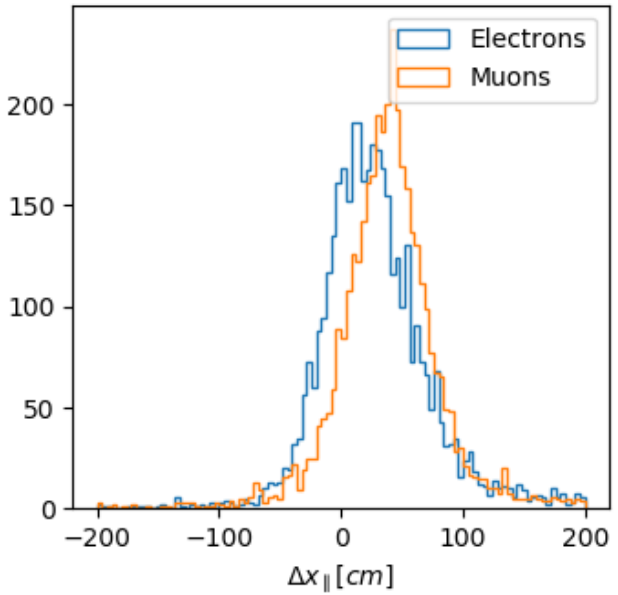

10G

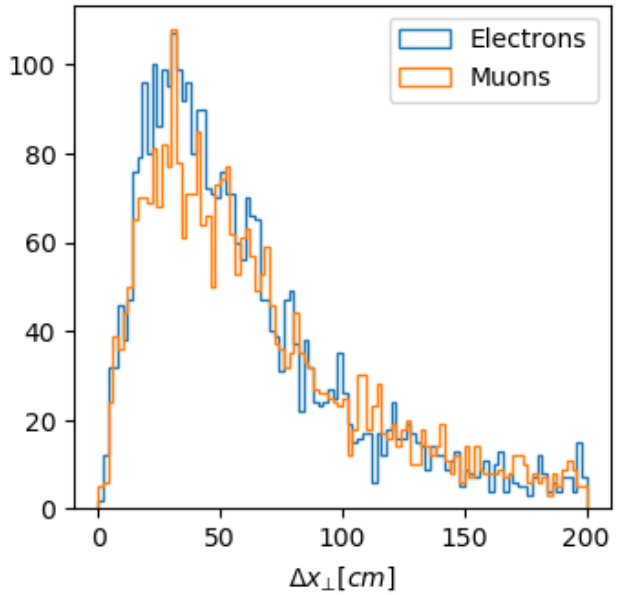


# What Causes the Shifts of the Peaks

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Position residuals with a cut on $Dwall_{true}$ > 200 cm

6G

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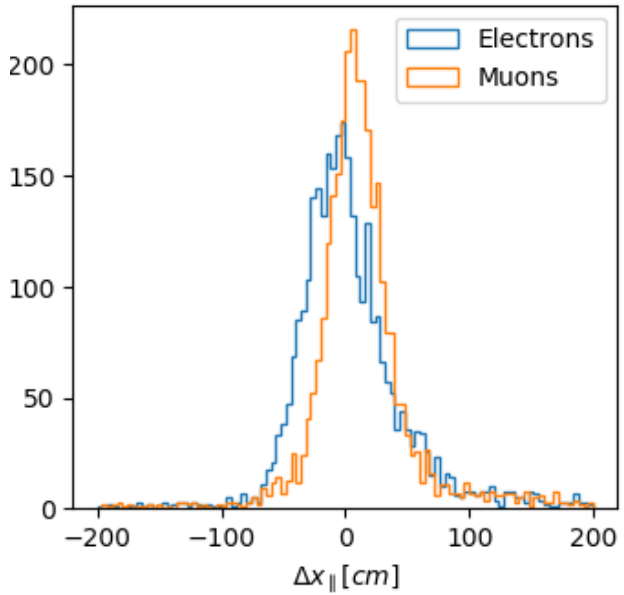
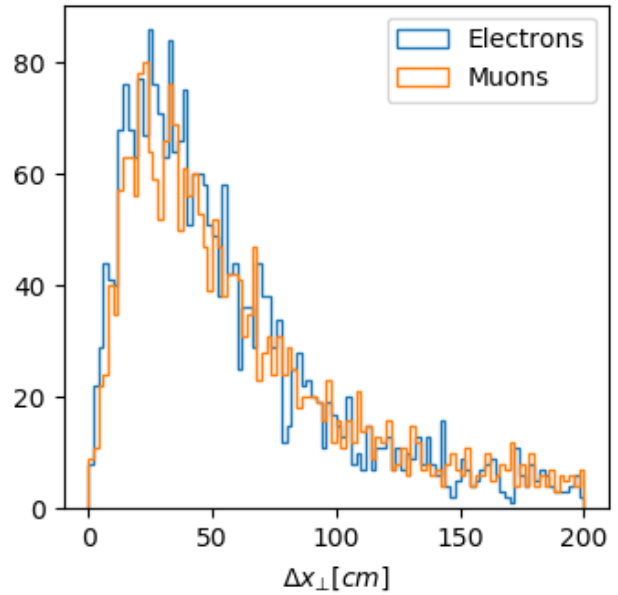
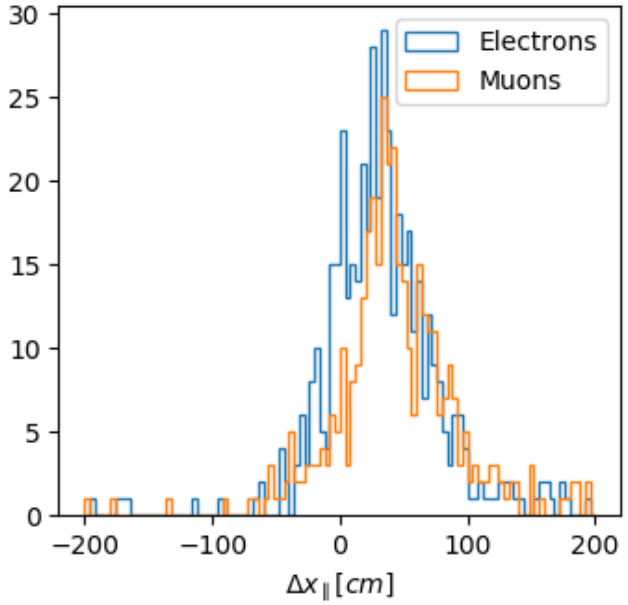


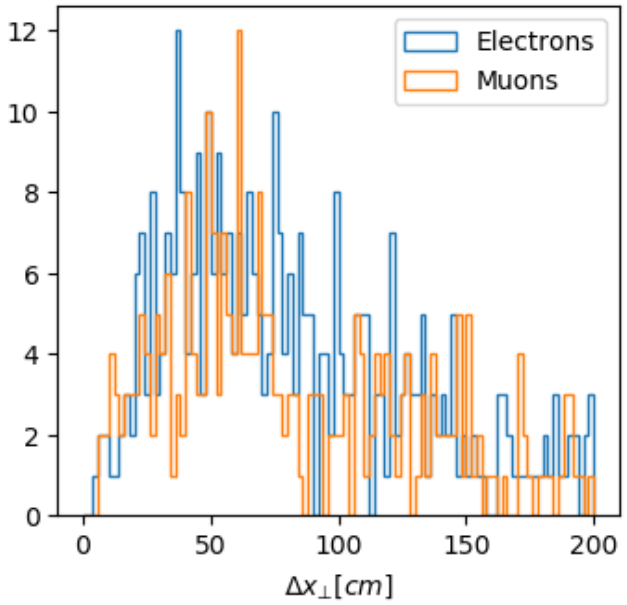



# What Causes the Shifts of the Peaks

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Position residuals with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (0 GeV – 1 GeV)

6G

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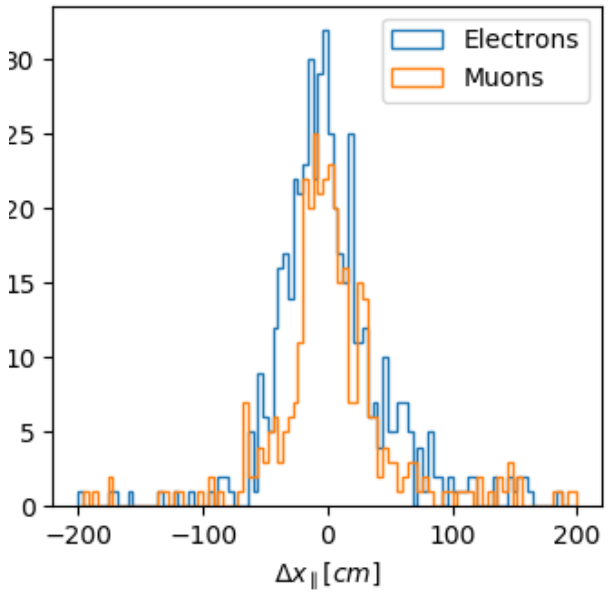
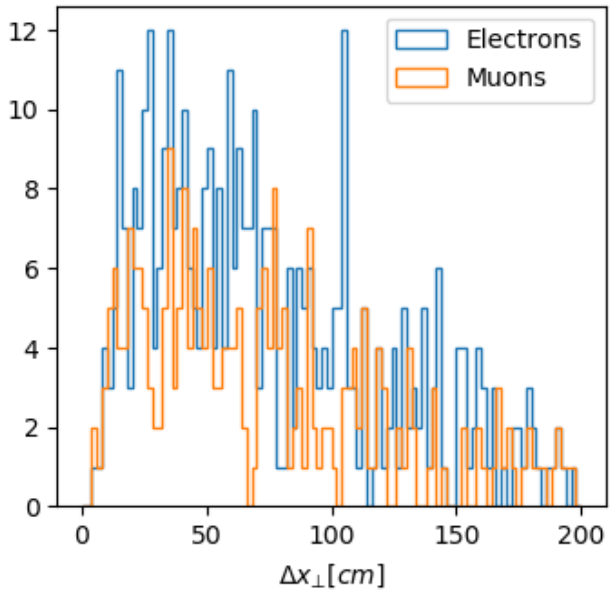
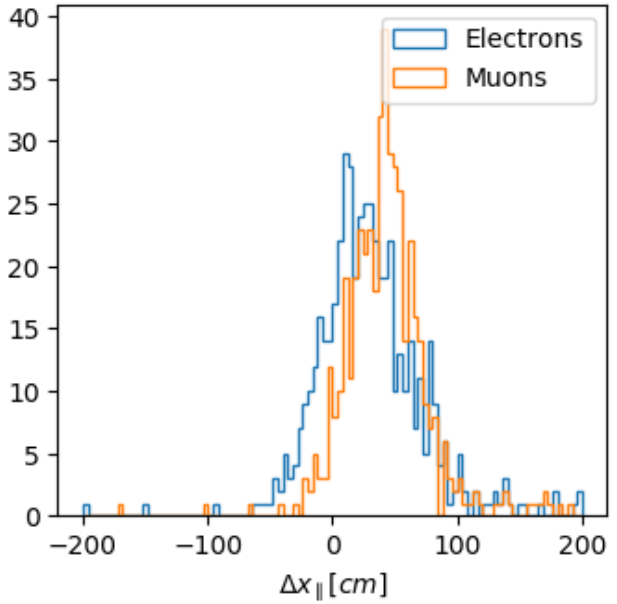


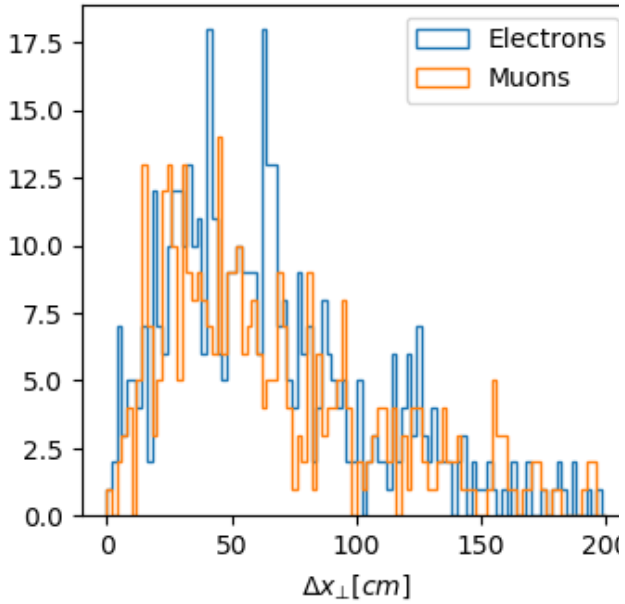



# What Causes the Shifts of the Peaks

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Position residuals with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (1 GeV – 2 GeV)

6G

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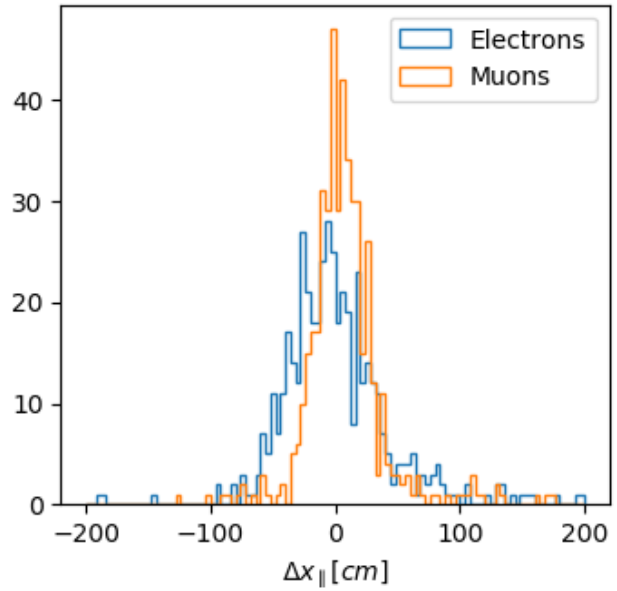
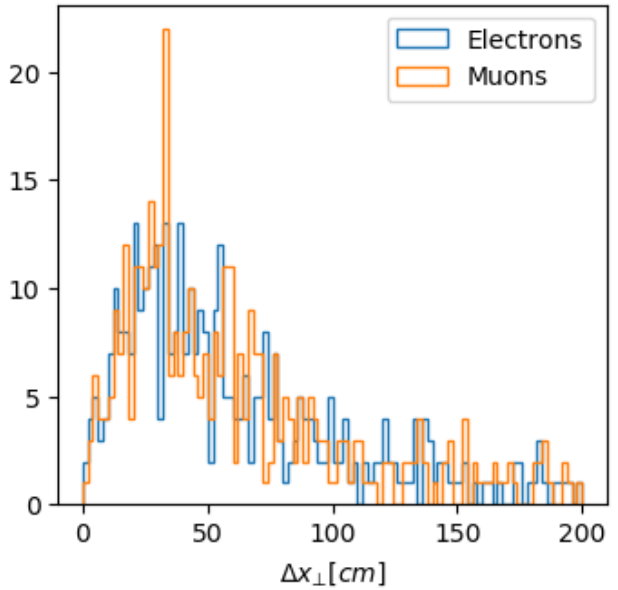
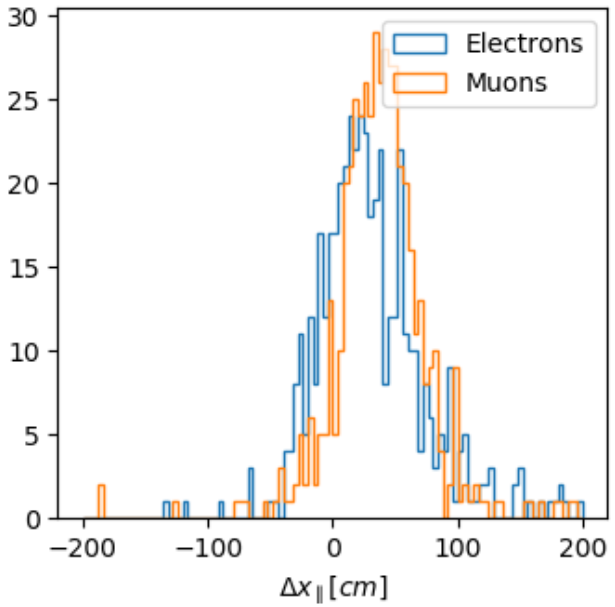


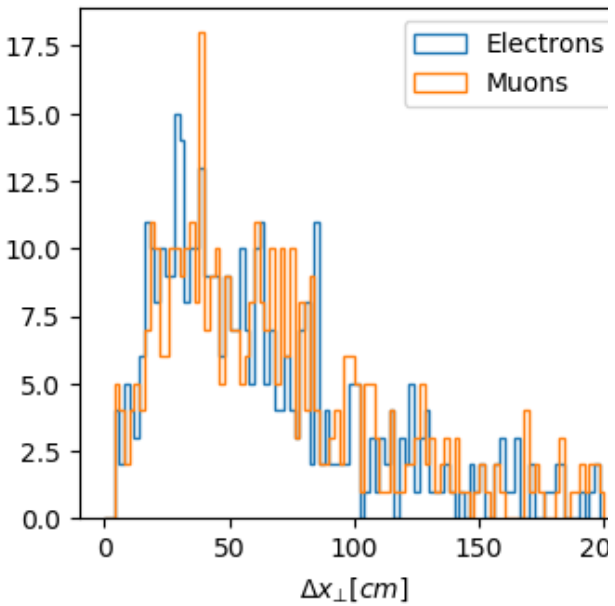



# What Causes the Shifts of the Peaks

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Position residuals with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (2 GeV – 3 GeV)

6G

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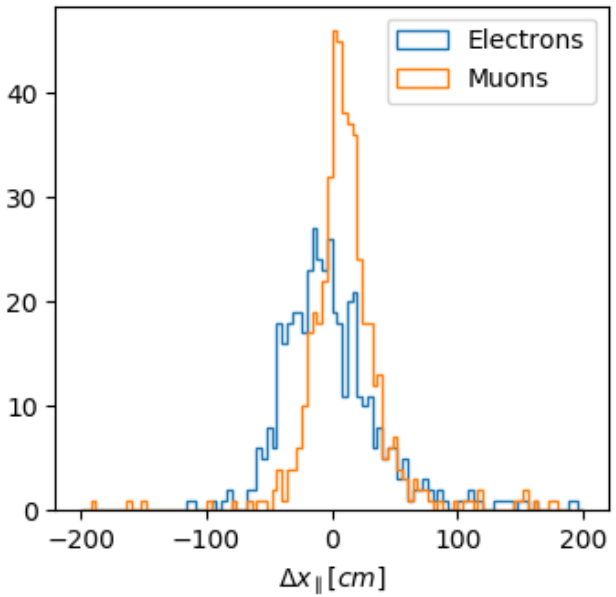
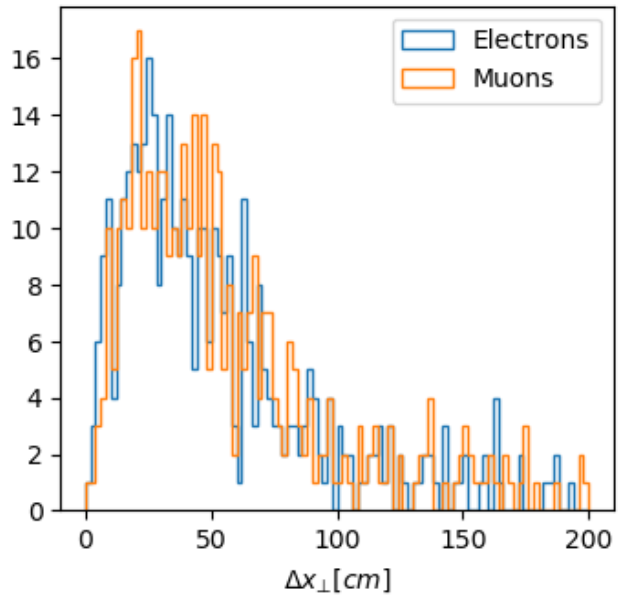
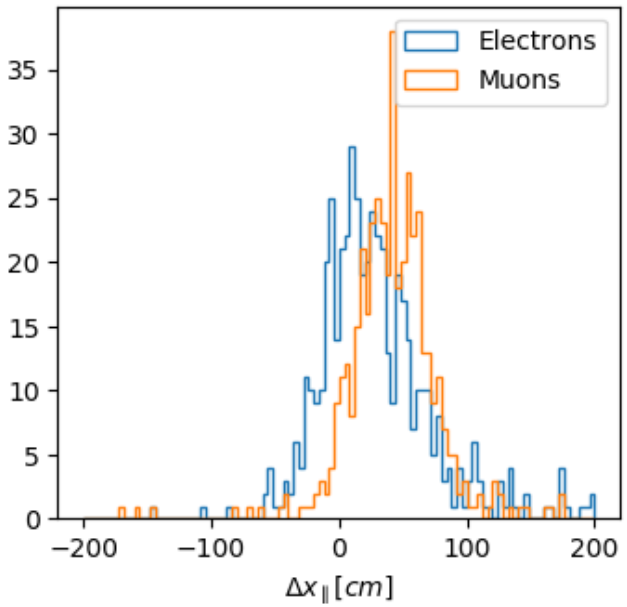


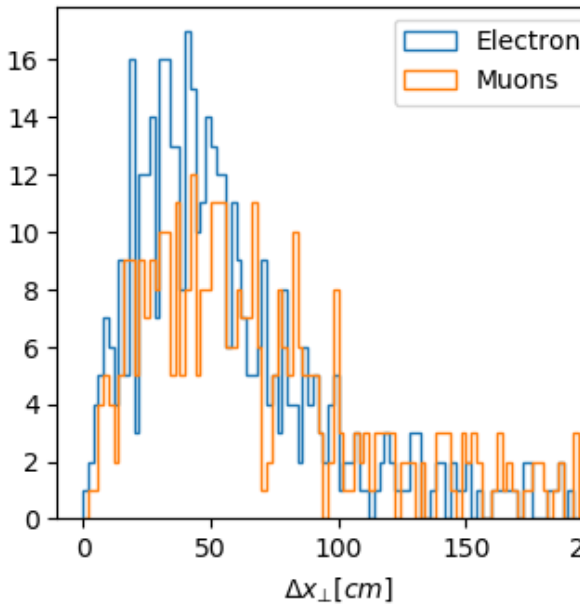



# What Causes the Shifts of the Peaks

- ❑ Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Position residuals with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (3 GeV – 4 GeV)

6G

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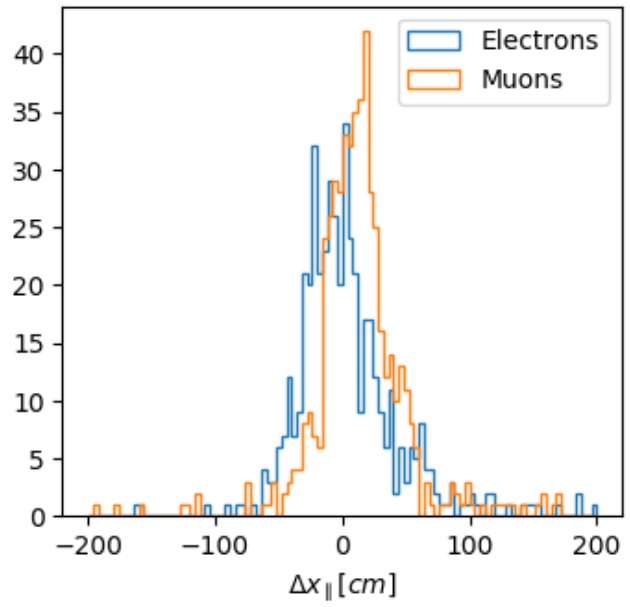
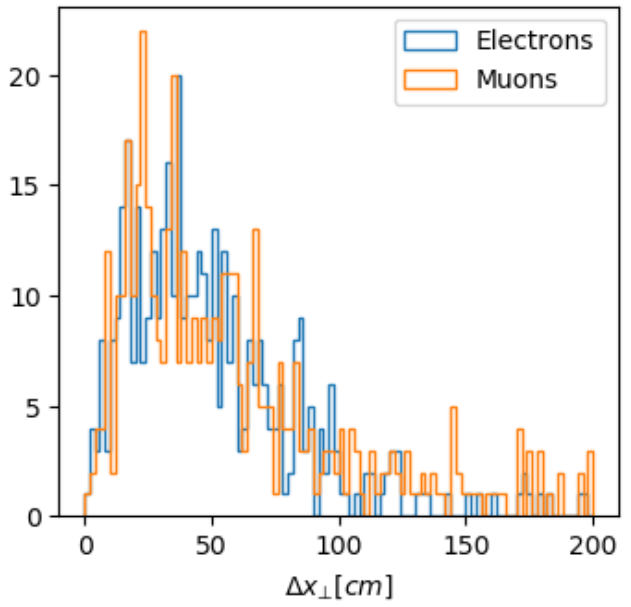
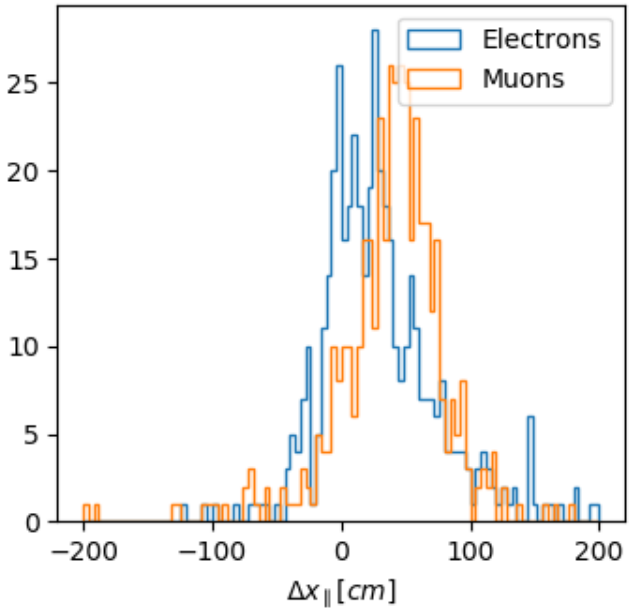


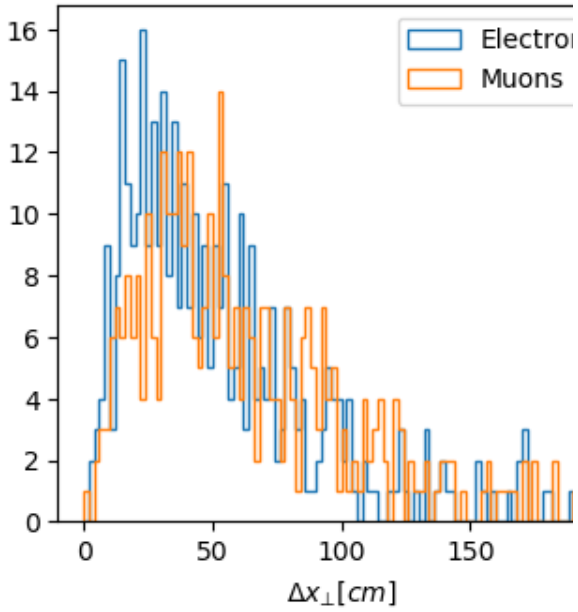



# What Causes the Shifts of the Peaks

- ❑ Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - Position residuals with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (4 GeV – 5 GeV)

6G

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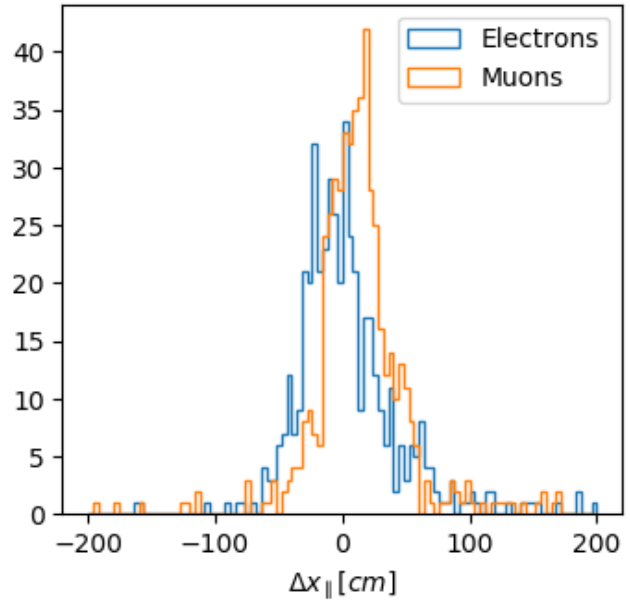
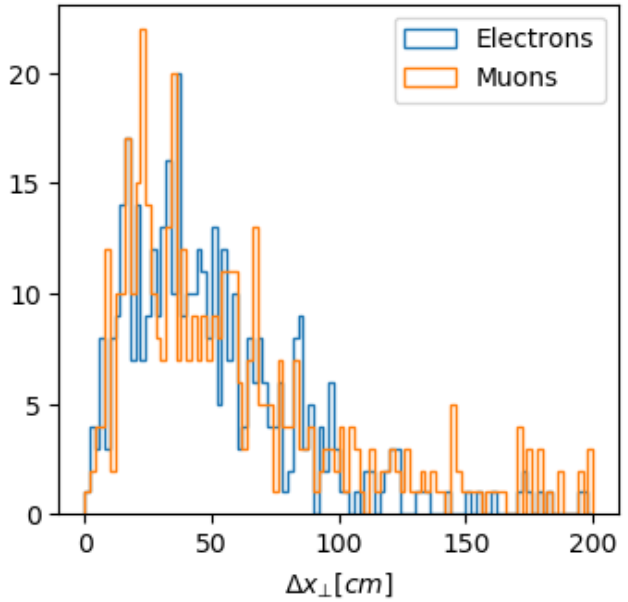


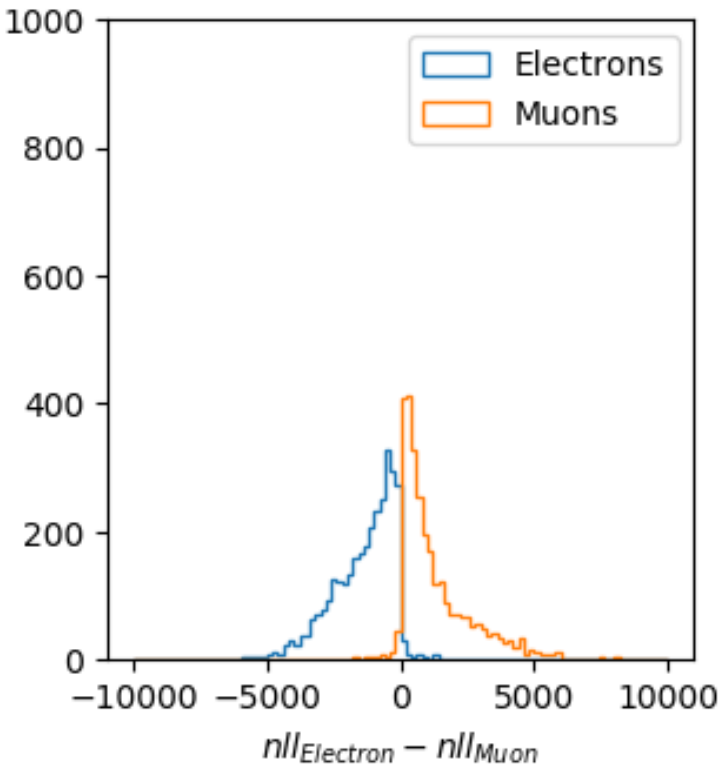



# What Causes the Shifts of the Peaks

❑ Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut

- PID with a cut on $Dwall_{true}$ > 200 cm; No cut on E

6G

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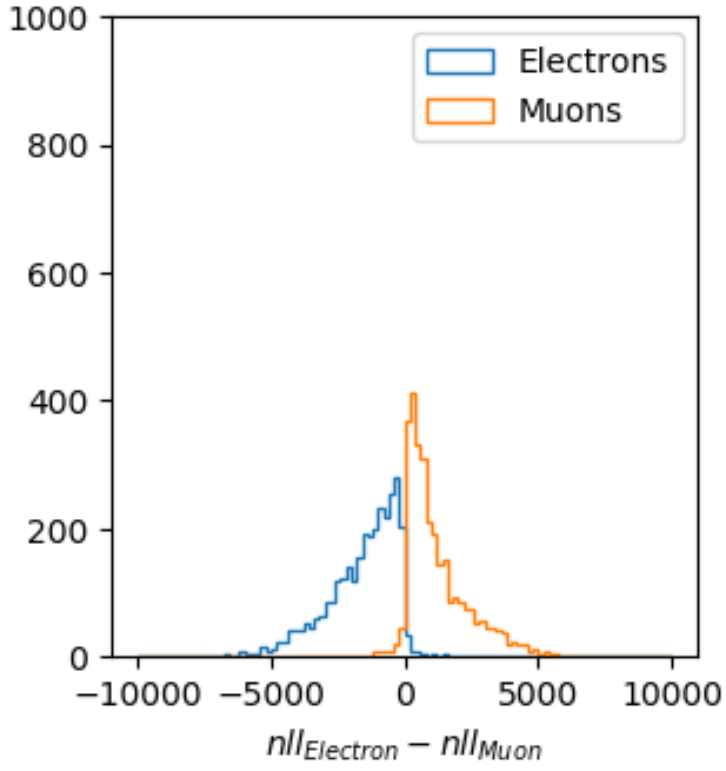
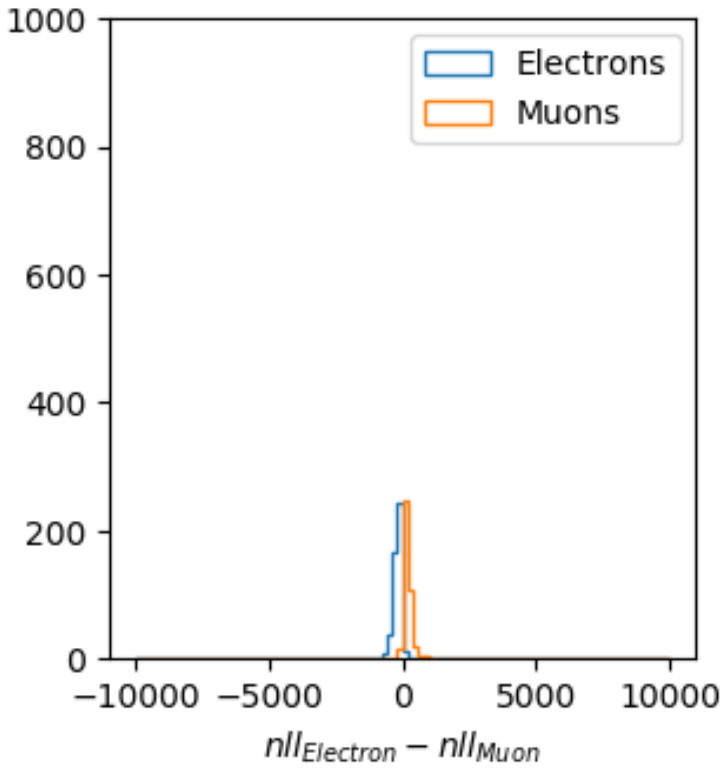


# What Causes the Shifts of the Peaks

- ❑ Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - PID with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (0 GeV – 1 GeV)

6G

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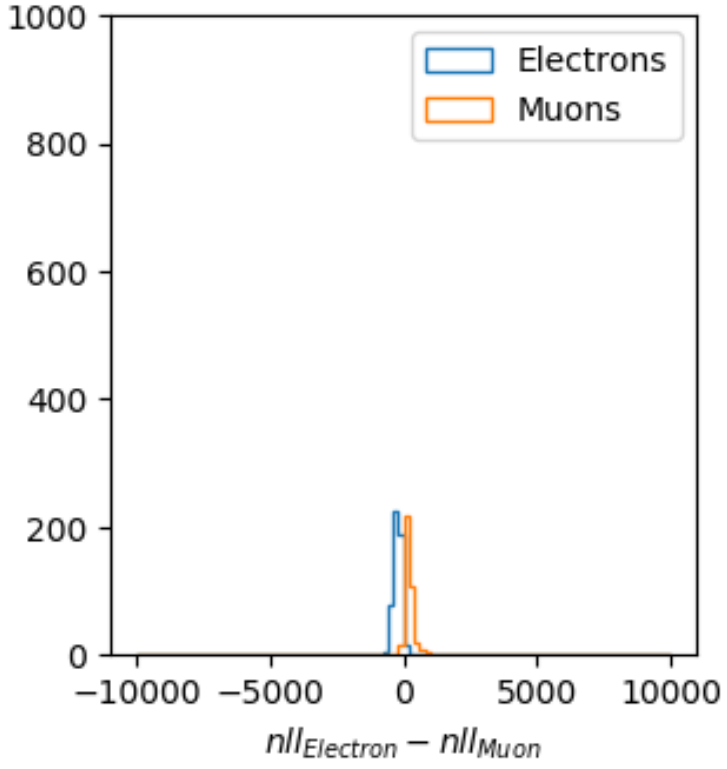
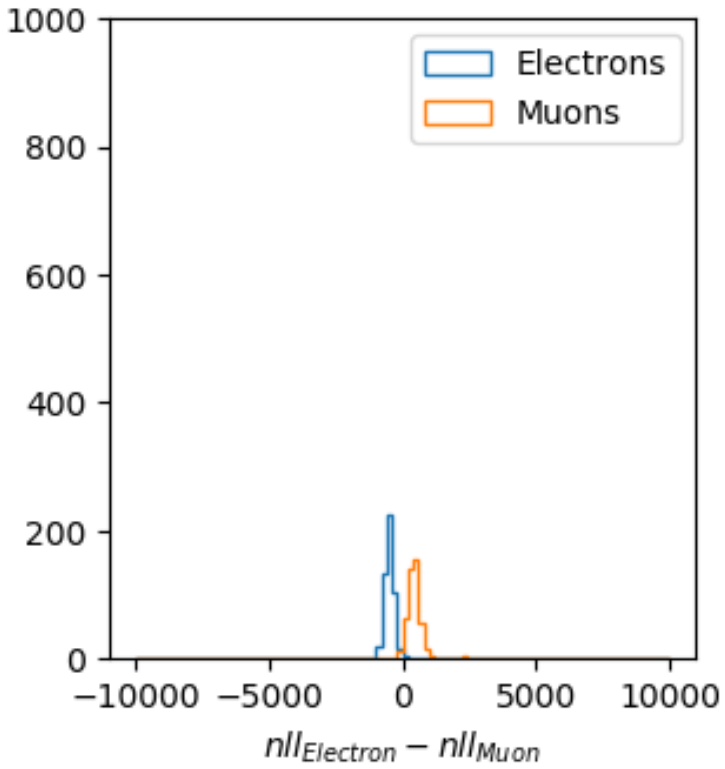


# What Causes the Shifts of the Peaks

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - PID with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (1 GeV – 2 GeV)

6G

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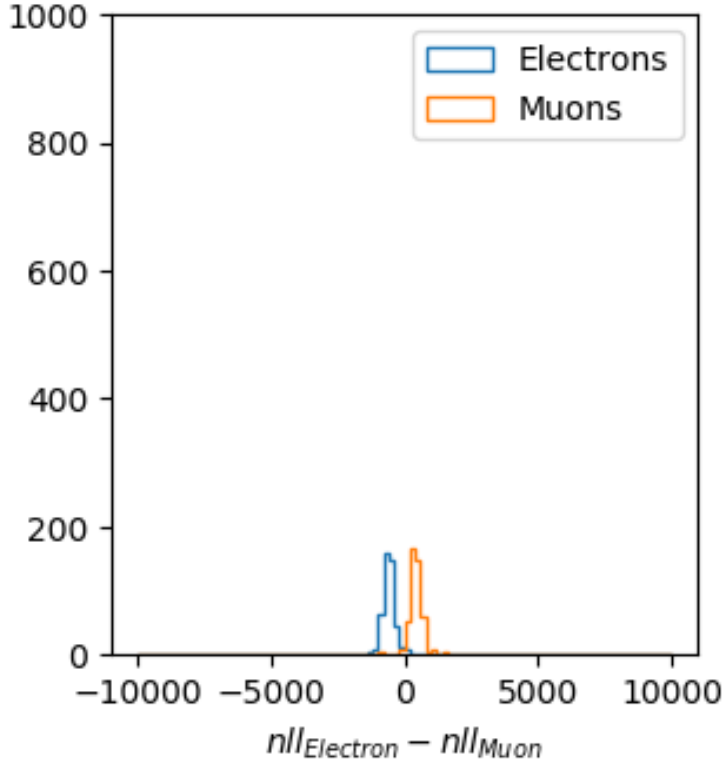
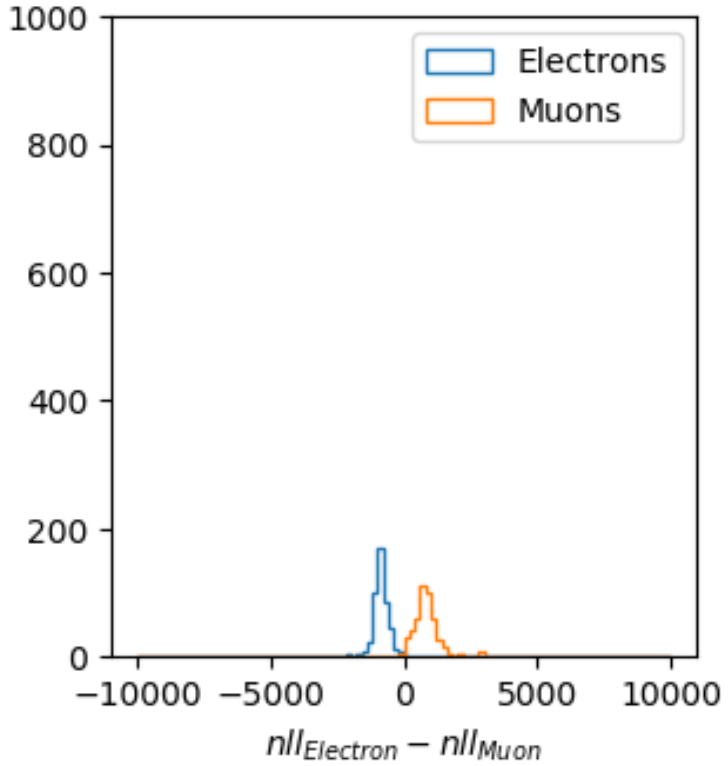


# What Causes the Shifts of the Peaks

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - PID with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (2 GeV – 3 GeV)

6G

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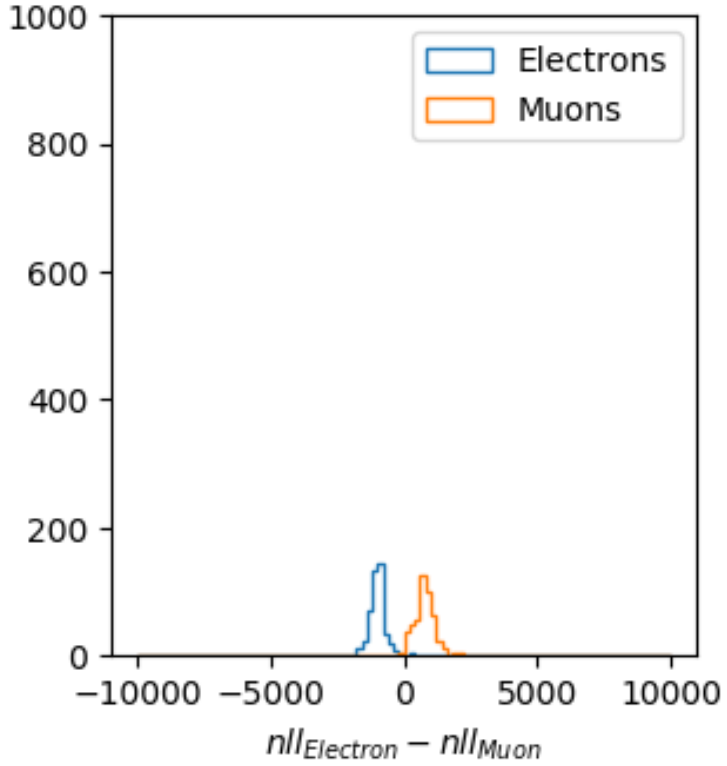
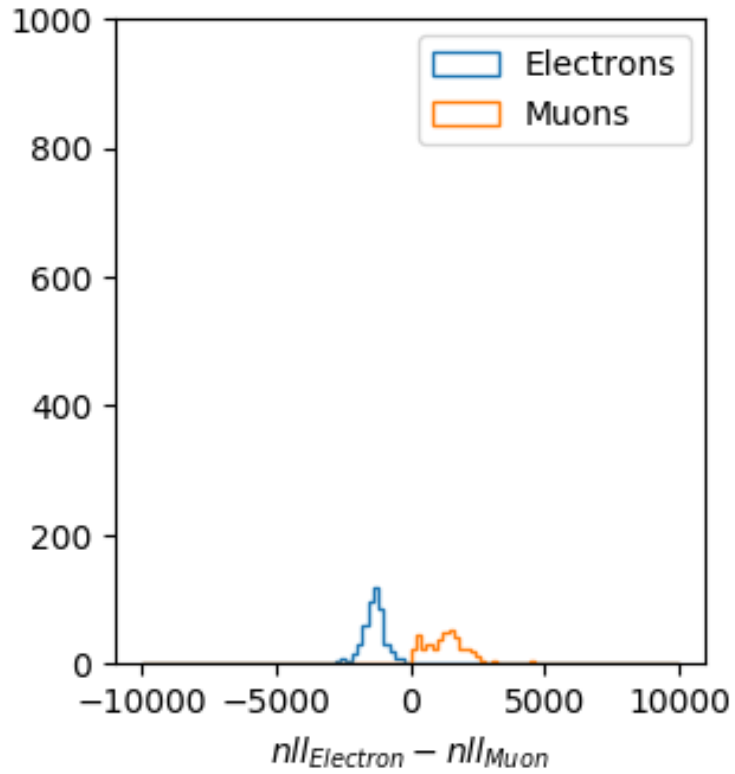


# What Causes the Shifts of the Peaks

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - PID with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (3 GeV – 4 GeV)

6G

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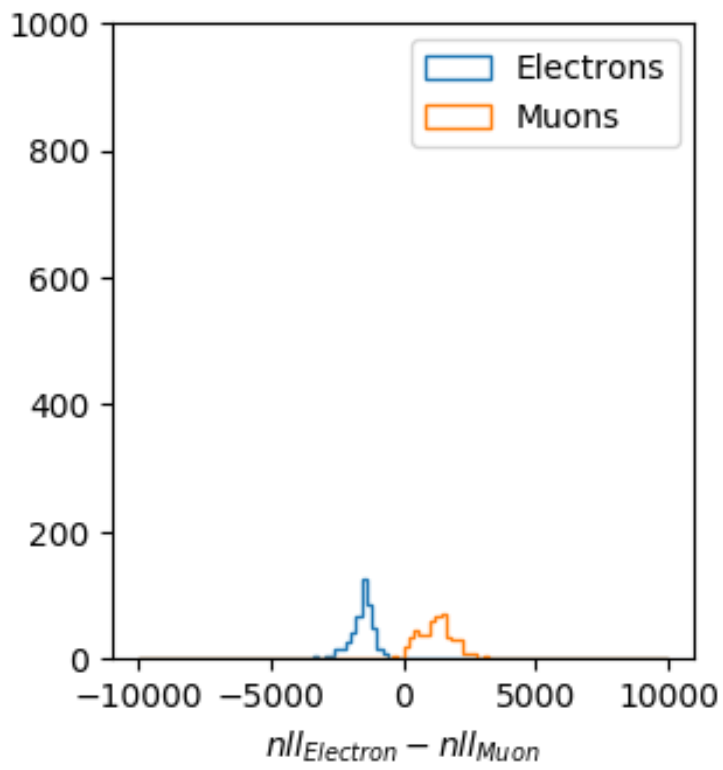
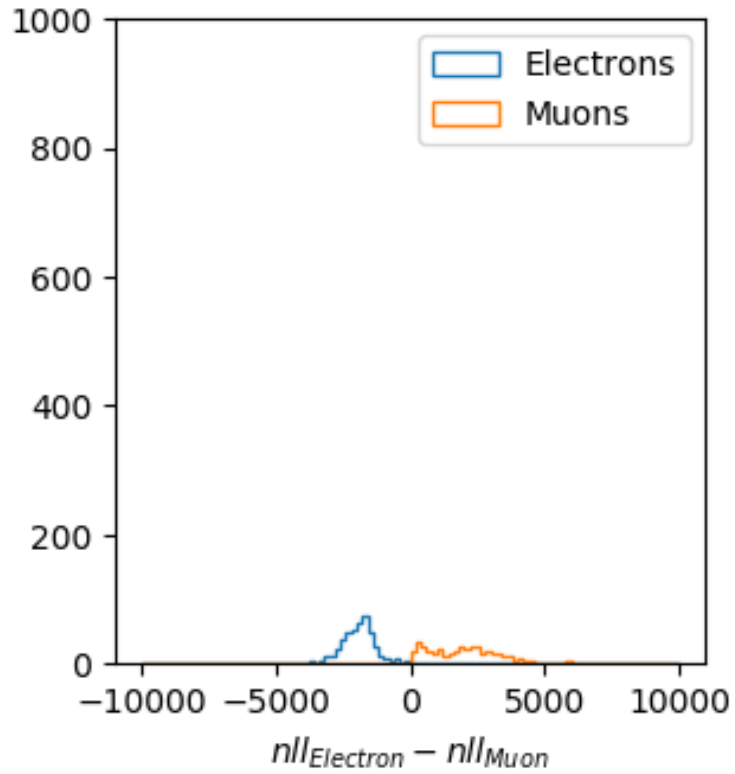


# What Causes the Shifts of the Peaks

- Performance difference between 6-Gaussian and 10-Gaussian fit with $E_{true}$ cut
  - PID with a cut on $Dwall_{true}$ > 200 cm and on $E_{true}$ (4 GeV – 5 GeV)

6G

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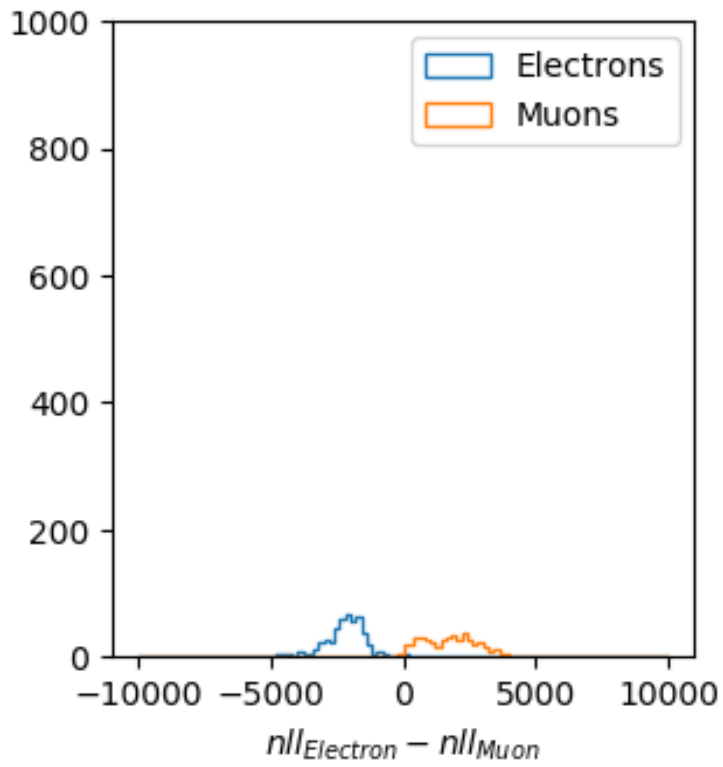


# Observations

- The peak positions of the energy residual shifts to the left for both electros (~5%) and muons (~3%) over all energy ranges.
  - Muons start to show a lower tail in higher energy ranges probably due to leak from the detector.
  - These shifts seem dependent on the number of Gaussians used for the charge distributions.
- The peak position of the longitudinal vertex residual shifts towards the direction of the particle.
  - This effect is more pronounced with muons especially with 6-Gaussians.
  - This effect for electrons is not visible with 10-Gaussians.
  - This effect for muons get worse with the muon energy probably due to leak from the detector.

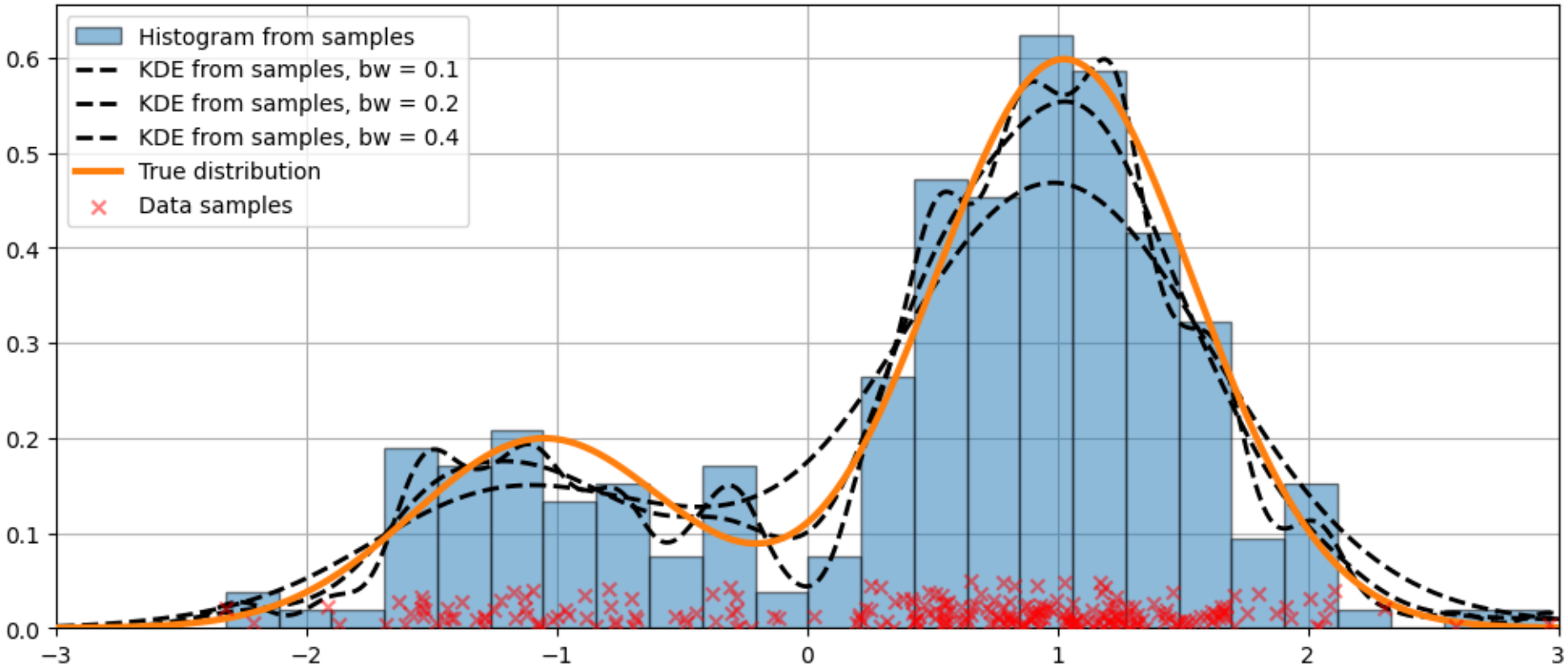
# Observations

- The distributions of the residual of transverse vertex position show similar shapes between for electrons and muons, and do not depend on the particle energy.
- The separation of PID distributions between for electron and muon becomes better with the particle energy.
  - The PID distribution for muon becomes flattened with the energy probably due to leak from the detector.
  - This effect doesn’t depend on the number of Gaussians used.

# What's Next

- As Cris suggested at the previous meeting, it is worth investigating the results with more number of epochs – wait until the loss function value settles.
- As Junjie's analysis with the correlated Q and T Gaussians showed that the peak position of the energy residual distribution is at zero, I should try the Q-T correlated Gaussians for fitting.
  - Fatter distribution could be a problem?
- A new fitting method?
  - Instead using multiple independent Gaussians, we may use Kernel Density Estimation which is based a non-parametric distribution using multiple Gaussians with the same parameters.

# KDE


Histogram from samples
KDE from samples, bw = 0.1
KDE from samples, bw = 0.2
KDE from samples, bw = 0.4
True distribution
Data samples
0.0
0.1
0.2
0.3
0.4
0.5
0.6
−3
−2
−1
0
1
2
3