

MACHINE LEARNING FOR BACKGROUND HIT REJECTION IN THE MU2E STRAW TRACKER

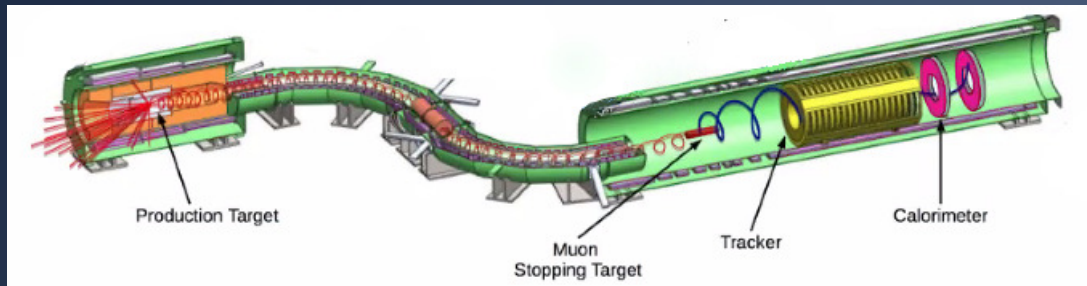
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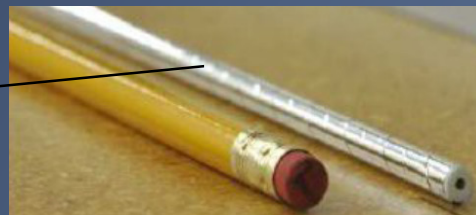
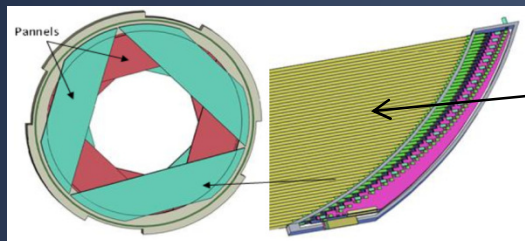
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Mu2e setup and objectives



Mu2e will search for Charged Lepton Flavor Violation, using a cylindrical straw tracker for detecting particles.



- This talk is about developing a cut based on information from single straw hits to select only the signal hits, i.e. enhance the signal reconstruction by maximizing cut efficiency and signal acceptance.

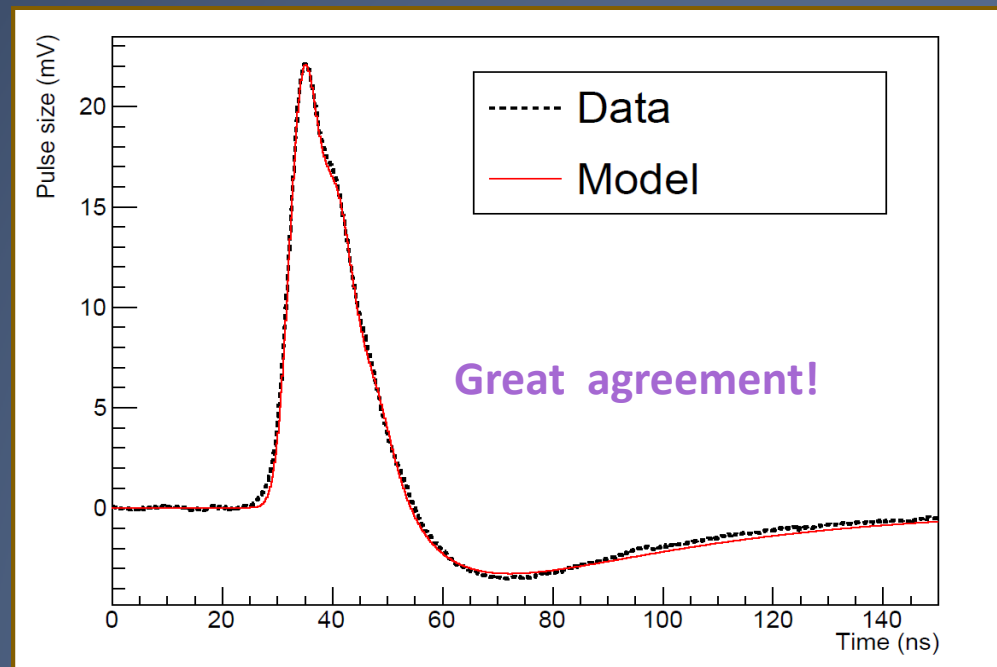
- Signal is a 105 MeV/c electron from CLFV conversion of muons. (we accept a window

centered at 105 MeV/c, i.e. $80 \text{ MeV/c} < \text{MC truth momentum} < 110 \text{ MeV/c}$)

- We want to reject highly-ionizing tracker hits from other sources, like protons from nuclear capture.

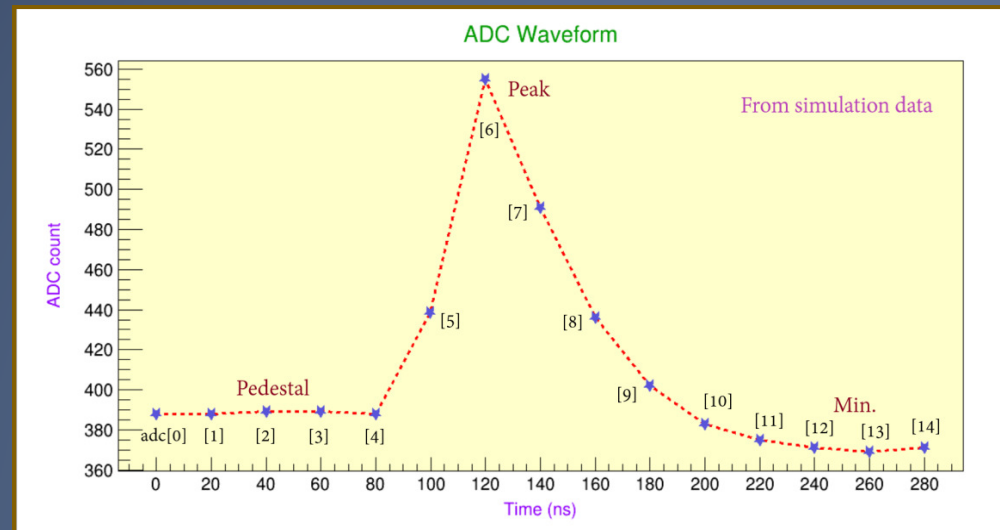
Simulation of the physical processes

- We analyze **simulation data** that includes expected tracker measurements from **conversion electron** signals as well as from backgrounds (like **protons**).
- **Geant4 simulation** uses a detailed model of the Mu2e **geometry**, with customized simulation of ionization **cluster** creation, **drifting & electronics** response (including nonlinear contributions and **channel to channel gain differences**).
- **Comparison** of a measured pulse from the straw and the simulation output, for an **Fe55 source** event → →



After each straw hit ...

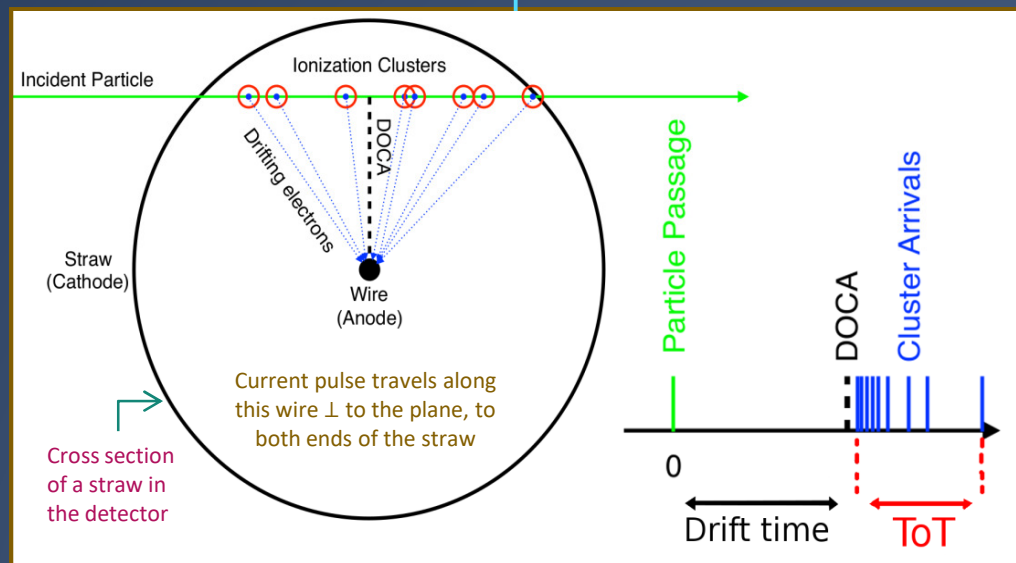
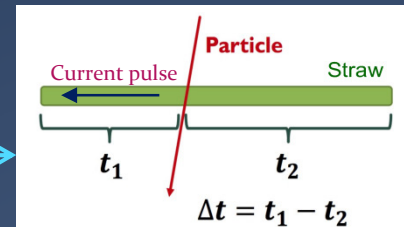
- The hit produces **ionization clusters** → **drift** to anode wire → **current pulse** travels as a **time signal** to the two ends (**cal** and **HV**) of the straw → two-sided readout determines **position of the hit** along the straw by comparing the two arrival times
- Record **duration** for which time signal is over a pre-set **threshold** on each side
- **Shaped waveform** is digitized by ADCs every 20ns, over a period of ~300ns, thus giving an array : **adc[15]**
- Energy deposited in straw (**edep**) is estimated as **peak minus pedestal** of this waveform, converted into keV



ToT : Time over Threshold

- **Time** for which the signal in straw stays above a threshold value
- Ranges from from **0 to 80ns**, with a binning of 5ns.
- **Correlated to path length** of the particle through the straw (longer path \rightarrow more distance b/w the clusters which are nearest and farthest from anode \rightarrow larger ToT)

Longitudinal view



- So from simulations, numerically compute the path length (**dx**) from **ToT** and then get a measure of specific ionization (**dE/dx**) of each incident particle as **edep \div dx**.

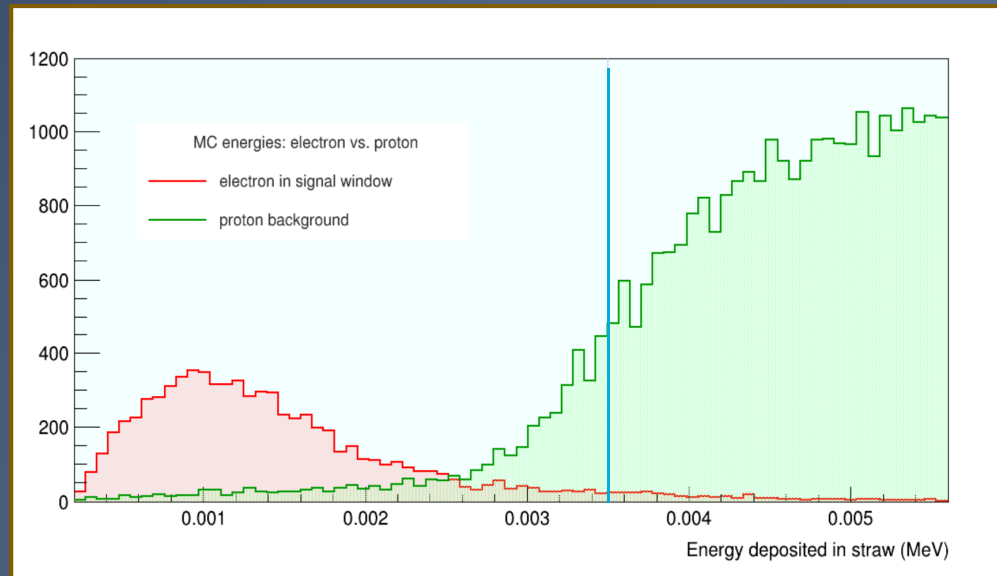
Current Performance

- A cut on the reconstructed energy deposited in each straw (edep) has been used so far to separate electrons and protons:
edep < 3.5 KeV → conversion electron

- Works because electrons at this energy are "minimum ionizing particles" while protons deposit a lot of energy. A part of the energy deposition distribution → →

- Testing on a simulation ...
Signal acceptance : 94.49 %
& Proton rejection : 84.57 %

Can be improved



TMVA

- Train a type of artificial neural network called **Multi-Layer Perceptron (MLP)** that outputs a **value between 0 and 1**. In our case an output of **0 = proton hit**, and **1 = conversion electron hit** with $80 < \text{MC truth momentum} < 110$
- Want to separate high-quality measurement from low-quality measurements, so want output to **strongly peak at 0 and 1**.
- Specify desired cuts on input to tell TMVA what “signal” & “background” are. Define the **input variables** (in our case, edep, dE/dx, adc[15], total, tothv and/or calibration) for which **weights** are determined via the MLP method.
- TMVA automatically splits the input tree into a training and a testing sample.

Using alternative parameters to define the cut value

Some promising candidates to start with:

- **MODEL 1** : Combination of **edep** and **dE/dx** (reconstructed energy loss per distance, which is correlated to edep and ToT)
- **MODEL 2** : Combination of full **ADC** waveform and **ToT**
- **MODEL 3** : **Simplify the adc** information to **lessen the no. of input** variables in Model 2 from 17 to 5 → make the classification sequence **run faster** when used in the trigger, and also make the model **less sensitive to small differences** between simulation and real data . (Time drops by 70.5% when Model 3 is used instead of Model 2, while classifying 646215 simulated events)

The simplified variables are **Max(adc)**, **Min(adc)** and **pedestal** = $0.25 * (\text{adc}[0] + \text{adc}[1] + \text{adc}[2] + \text{adc}[3])$. **Tothv** and **totcal** are kept intact.

Continued on next slide ...

Including ADC channel calibrations

- Calibration used to convert the peak minus pedestal into units of KeV.
 - Gain of each ADC channel has been varied by 20% to simulate a smearing effect that is observed in the real readout system.
 - Model 4 assumes perfect calibration (i.e. the calibration factor exactly accounts for differences in gain across channels).
- **MODEL 4** : Try adding calibrations for each ADC channel, combined with simplified adc-tot variables in 2 different ways :-
- ❖ **Model 4a** : Divide peak and min(adc) by the normalized (i.e. value per mean) calibration
 - ❖ **Model 4b** : Include calibration as extra input variable in addition to max(adc), min(adc), pedestal and ToT

Time taken is 27.7% (4a) and 28.4% (4b) of that for Model 2, when tested on the same set of 646215 events mentioned earlier.

TMVA Training Results

for the case when input variables are `adc[15]`, `totcal` and `tothv` only

- At the end, the training and testing efficiencies are almost identical

| cut 0.01: 0.936, 0.938 |

| cut 0.10: 0.987, 0.987 |

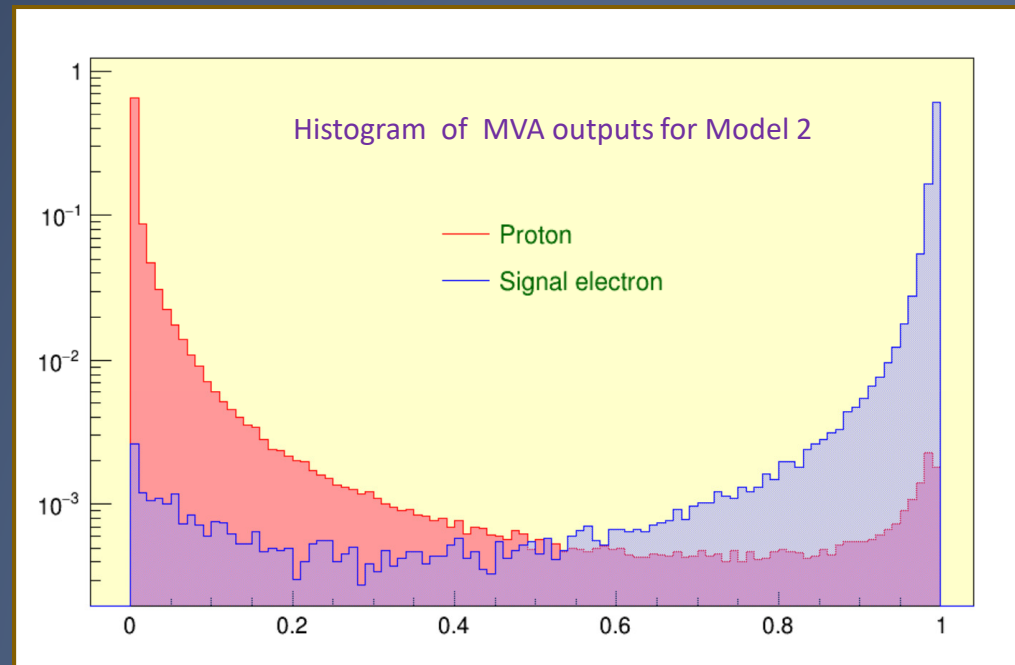
| cut 0.30: 0.999, 0.999 |

- Looks like there has been **no over-fitting**

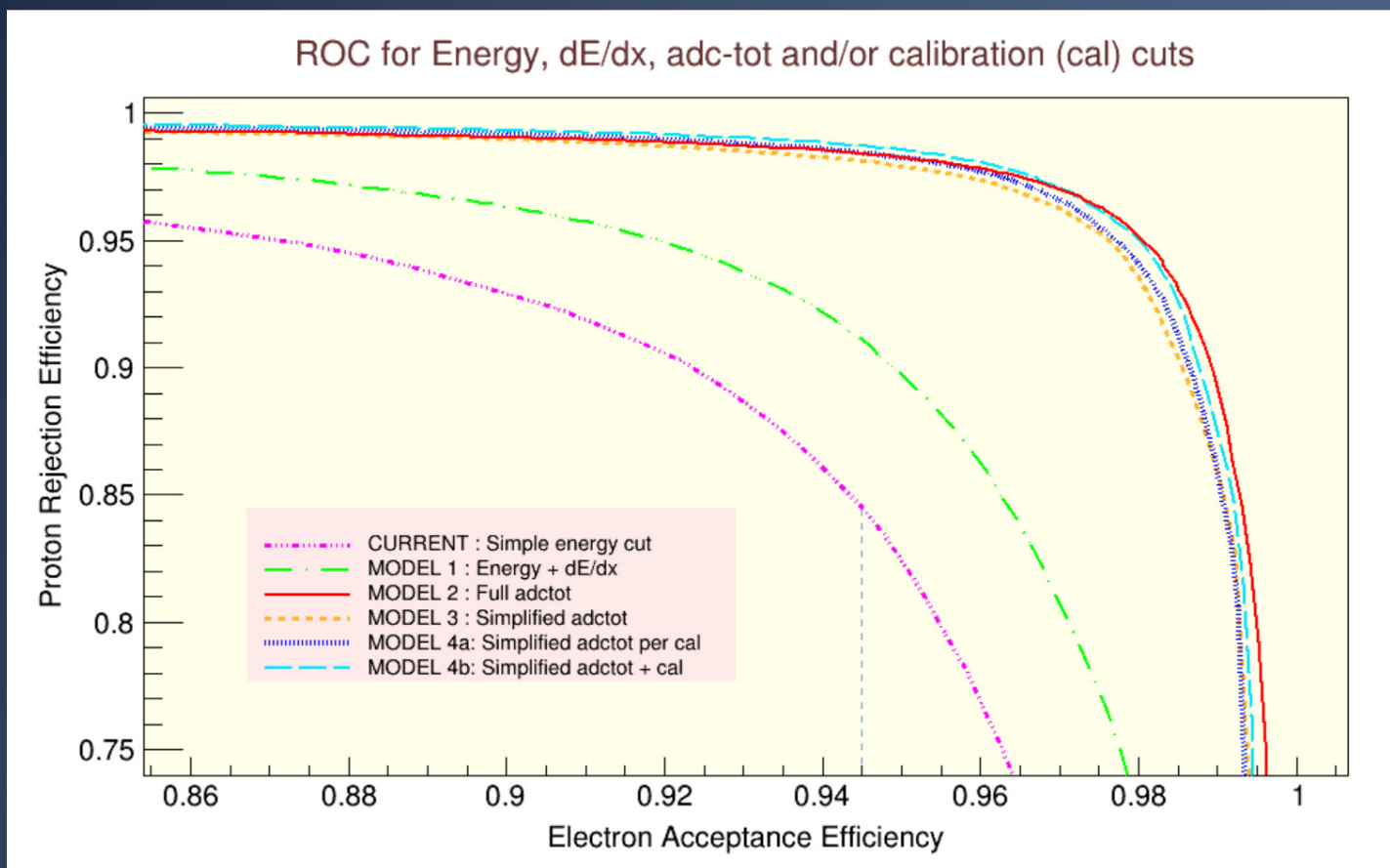
Rank	Variable	Importance
1	<code>adc_12</code>	10.95
2	<code>adc_14</code>	10.27
3	<code>adc_11</code>	9.433
4	<code>adc_10</code>	9.308
5	<code>adc_6</code>	8.256
6	<code>adc_13</code>	8.215
7	<code>adc_7</code>	6.541
8	<code>adc_9</code>	4.888
9	<code>adc_8</code>	3.939
10	<code>tot_cal</code>	3.704
11	<code>tot_hv</code>	2.858
12	<code>adc_5</code>	1.725
13	<code>adc_2</code>	1.664
14	<code>adc_3</code>	1.519
15	<code>adc_0</code>	1.484
16	<code>adc_4</code>	1.100
17	<code>adc_1</code>	0.985

Apply TMVA Classification

- Set up script to **compute MVA outputs** (0-1) of all events in a test file, using the weights; the distribution of these outputs form a **histogram**
- For each position of cut, area to left gives p+ rejection and area to right gives signal e- acceptance; we printed these to identify the most **optimum cuts**
- **ROC** plotted & overlaid in slide 13 for all the tested models.



Efficiency/acceptance curves (ROCs)



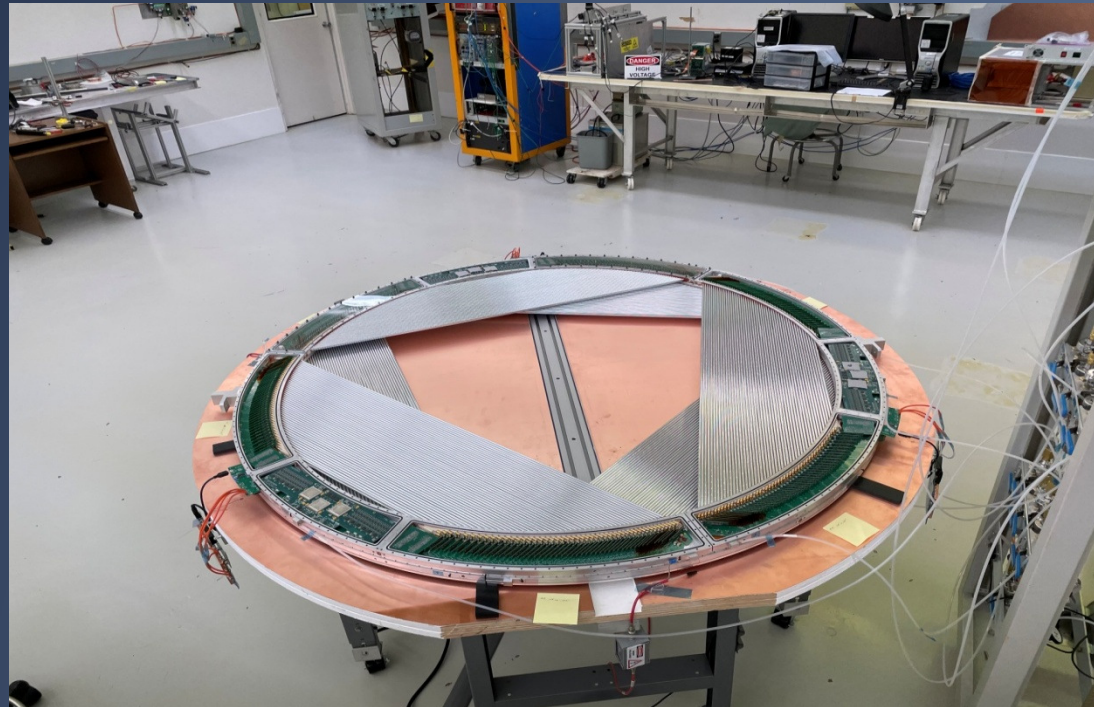
Conclusions

- Best performance when the full ADC waveform is combined with ToT readings (Model 2)

** Tested on a random ** simulation dataset	Current Model edep cut = 3.5 keV	Model 2 Full adc-tot cut = 0.55
Signal Acceptance	94.49 %	96.99 %
Proton Rejection	84.57 %	97.95 %

- The improvement is significant , so for now we have implemented this MVA in the official Mu2e Straw Hit Reconstruction module (had been using energy cuts so far)
- Good news : Simplifying adc inputs in TMVA does not depreciate the performance by much, and inclusion of calibrations improves those models. In fact, adding channel calibrations as a separate TMVA input variable along with the simplified adc waveform and tot (Model 4b) does almost as good as Model 2

Future work: “Real data” from Vertical Slice Test --- 6 production quality panels (~600 channels) operated together. We will use this extensive setup to perform a more detailed comparison between cosmic ray signals and our simulations.





Thank You