Muon Monitor Data with Machine Learning Applications to Maintain the Quality of the NuMI Neutrino Beam

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Accelerator Physics and Technology Seminar

30 June 2020

Outline

1. **Introduction to the muon monitors**
2. Responses of Muon Monitors to the beam and the horn current
   - Beam Scan
   - Horn current scan
3. Machine Learning Applications
   - Linear Regression Models
   - Neural Networks

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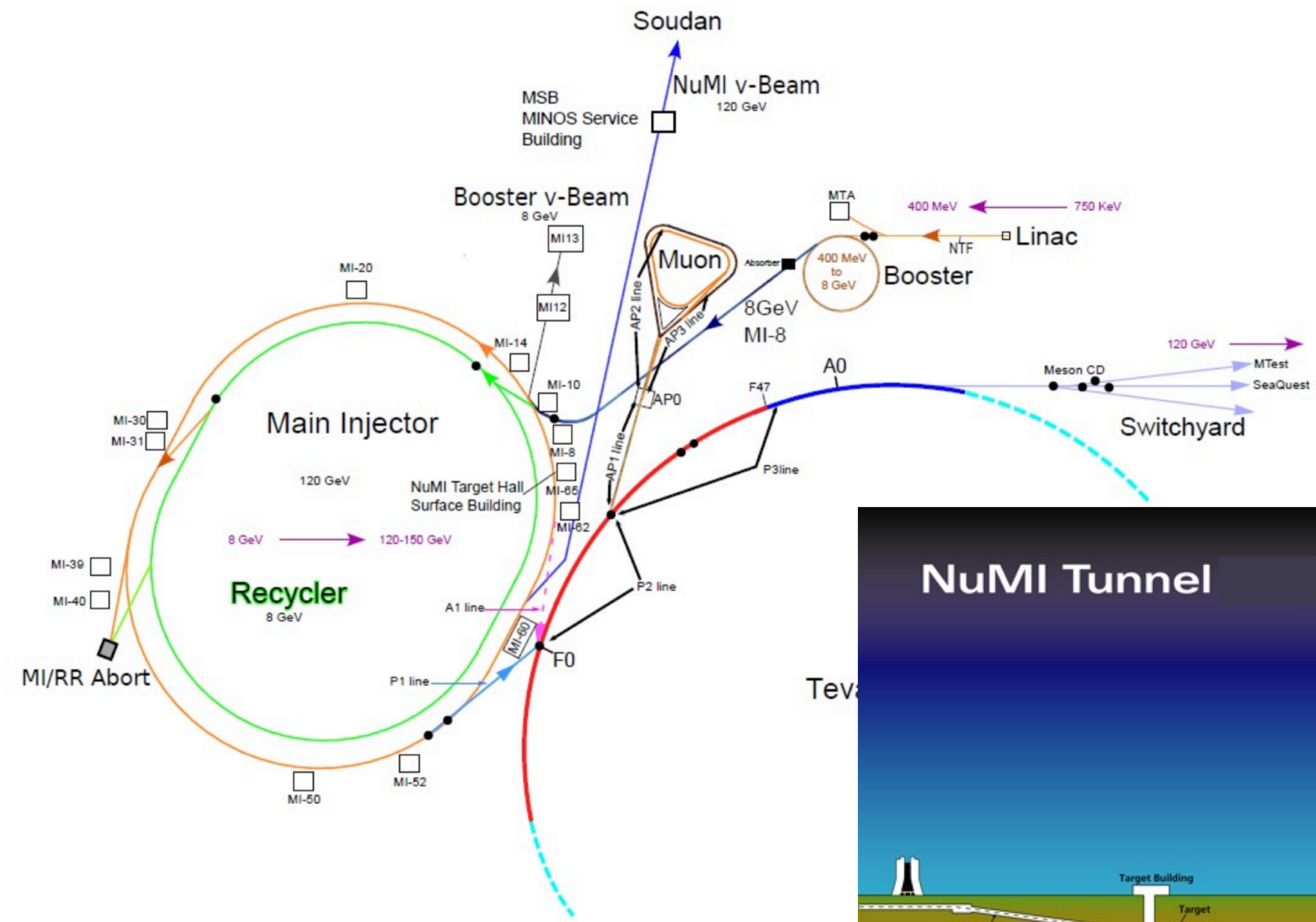
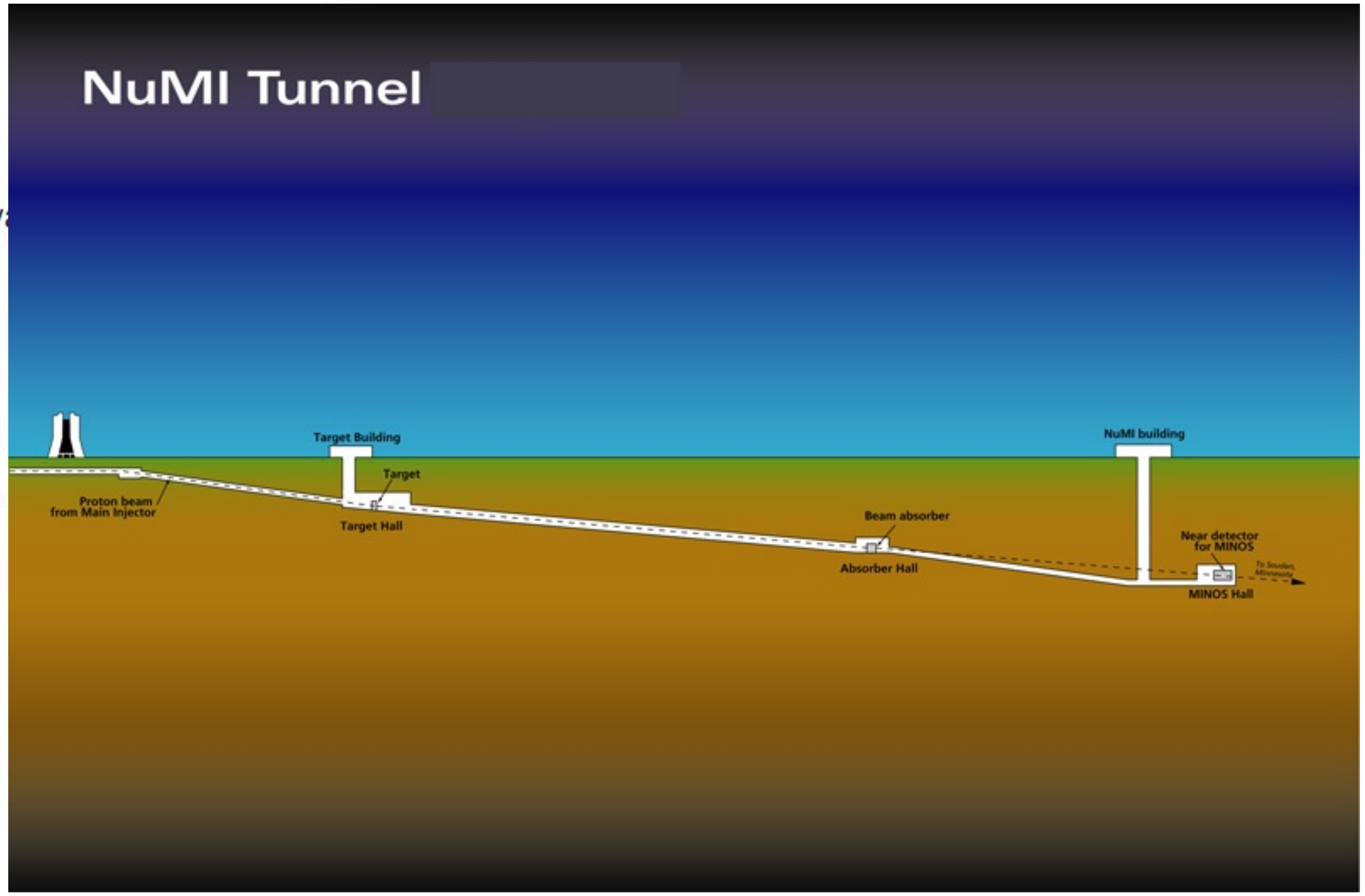
NuMI beamline





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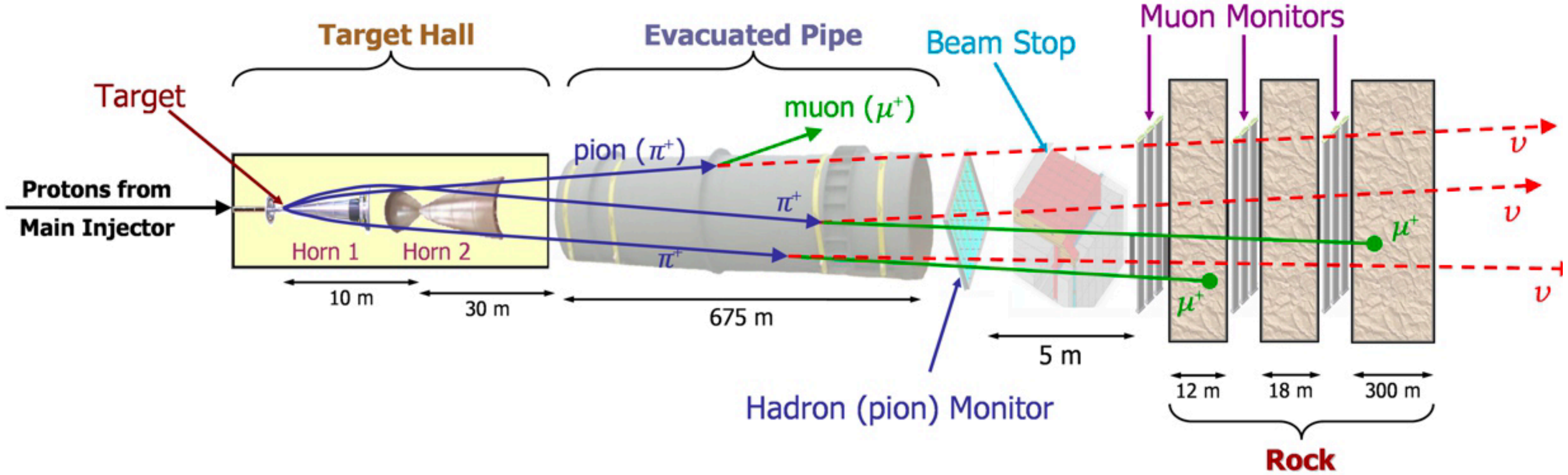
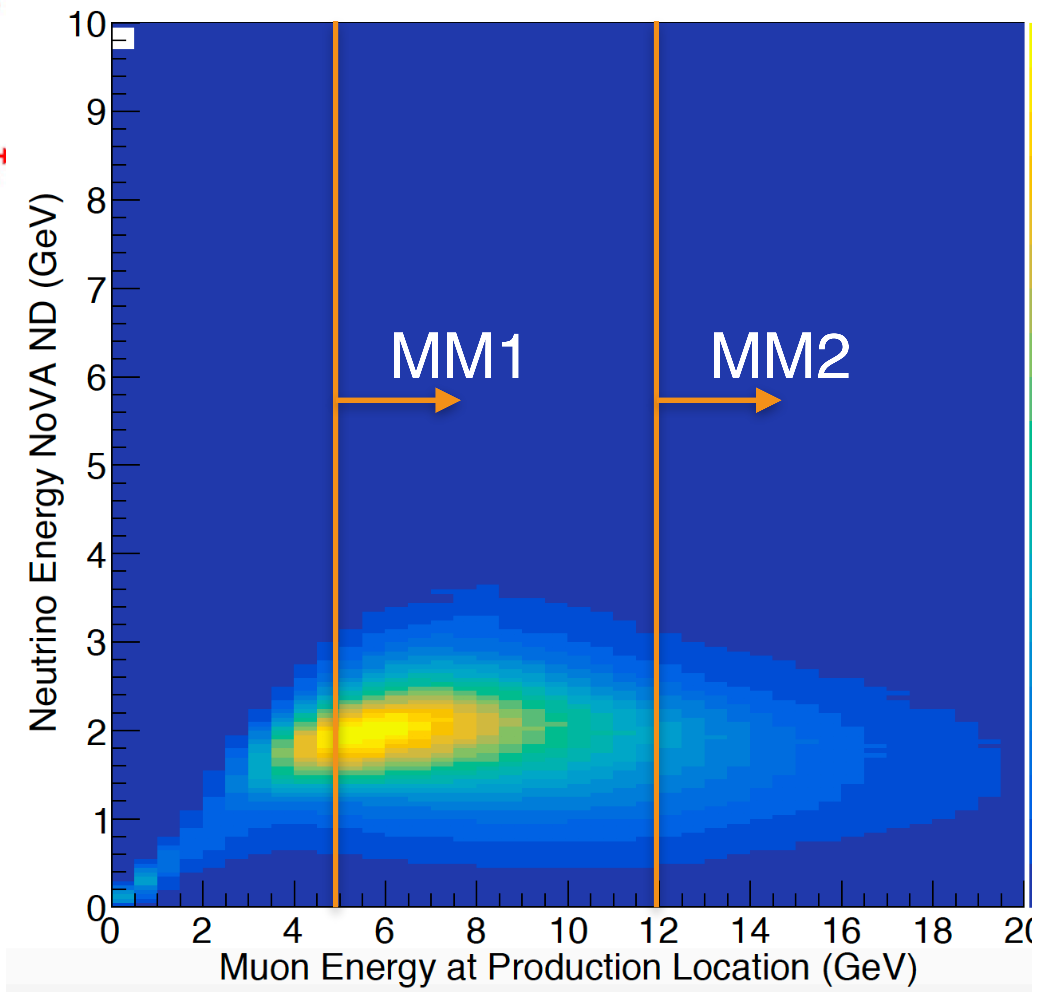
Introduction to Muon Monitors



- Three muon monitors are located in the downstream of the hadron absorber
- Each muon monitor consist of 9x9 arrays of ionization chambers
- Each ionization chamber consists of two ceramic parallel plates with the separation of 3 mm gap
- The chambers are filled with He gas



Muon monitor array

- According to the MC studies, MM1 has a good sensitivity to see the correlation of neutrino beam to muons

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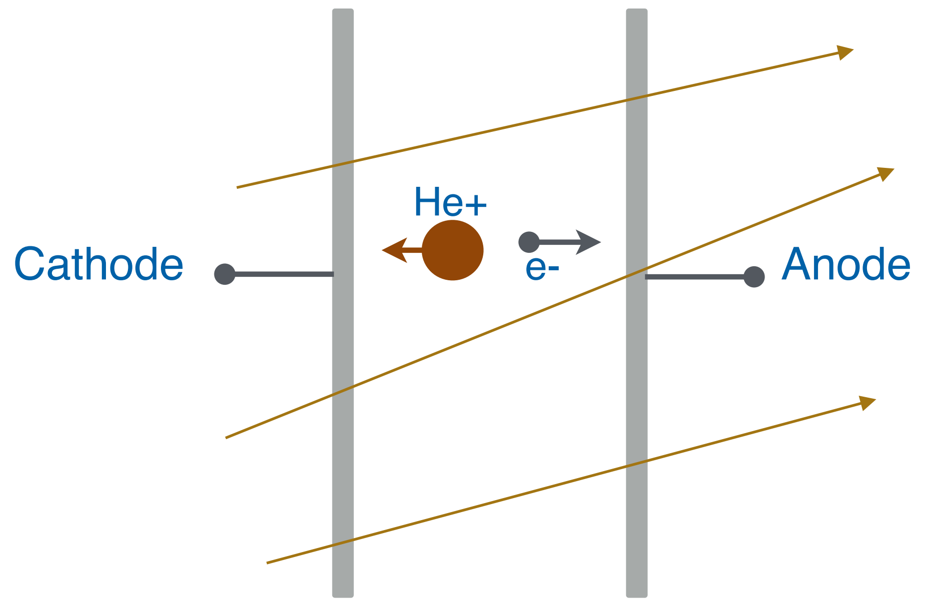
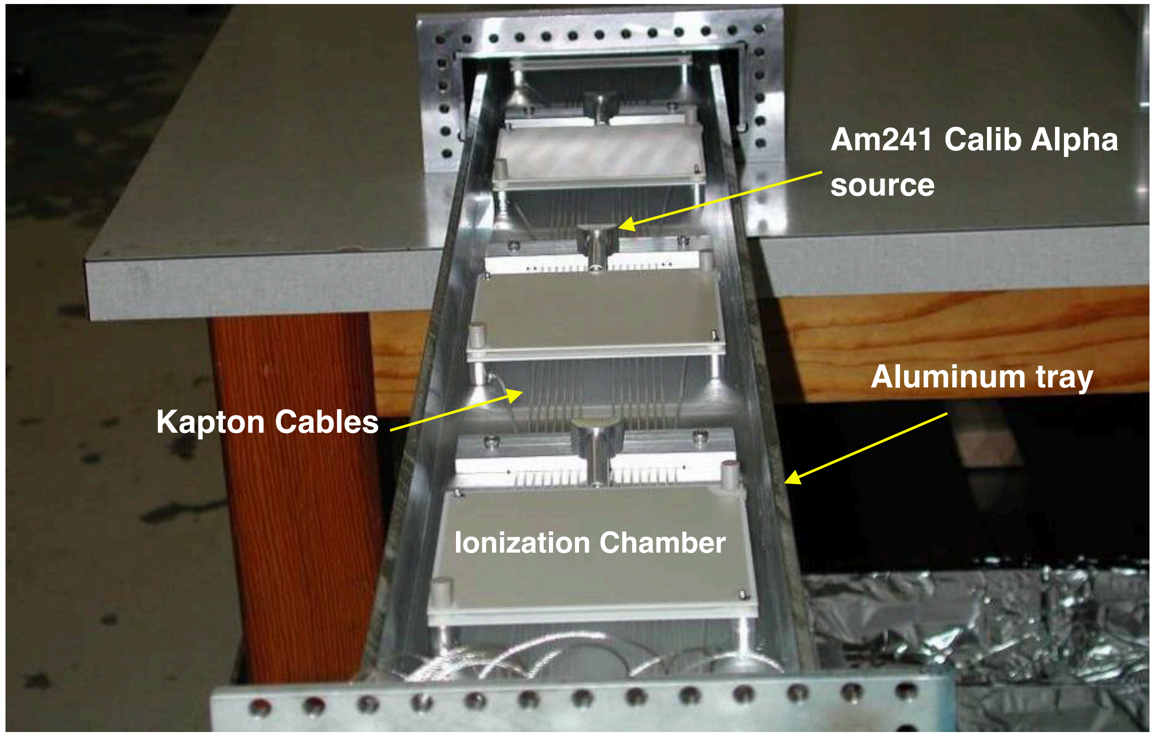
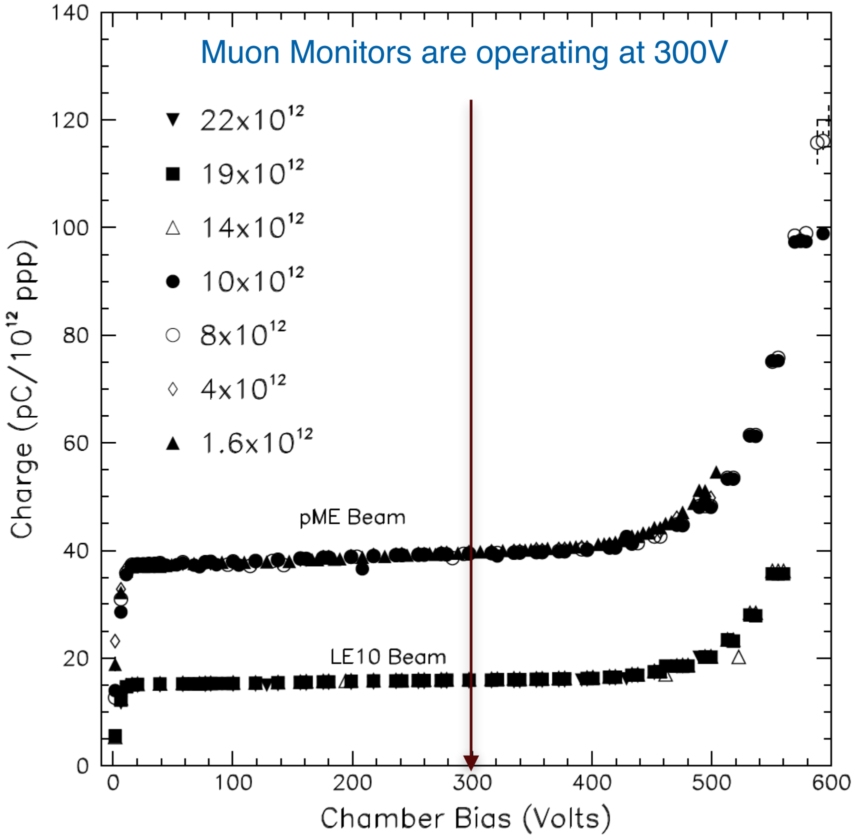
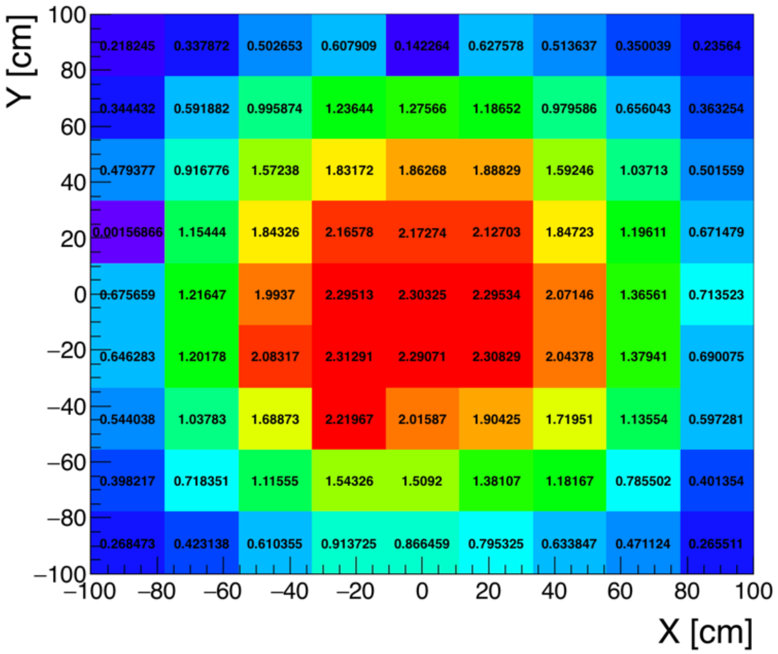
Introduction to Muon Monitors



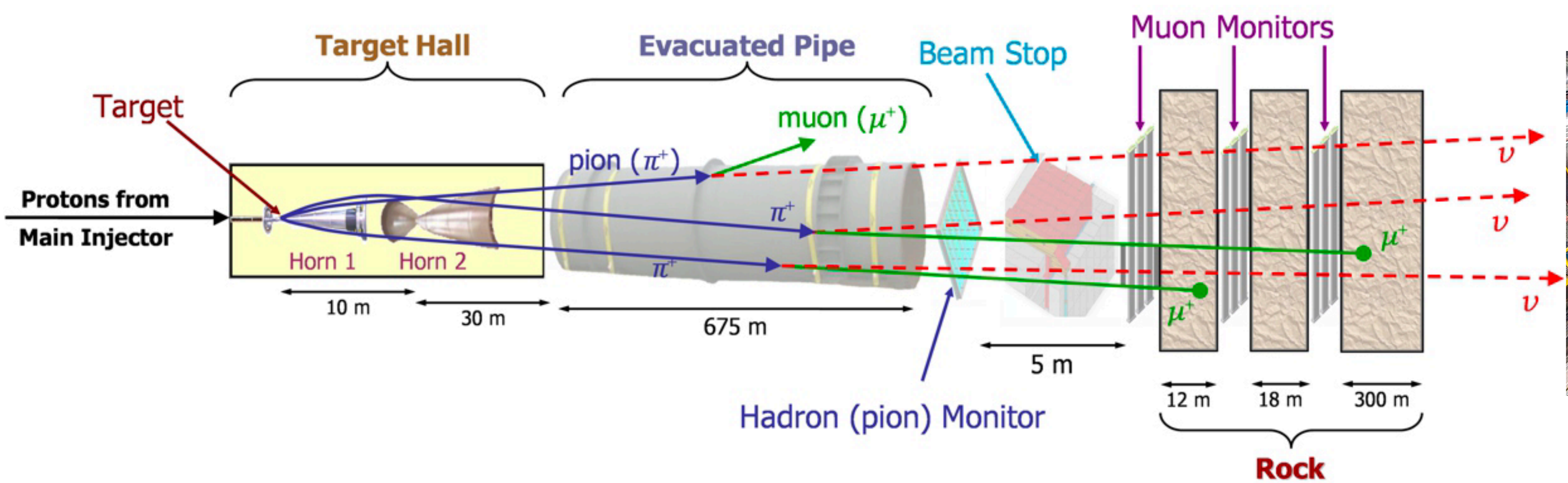




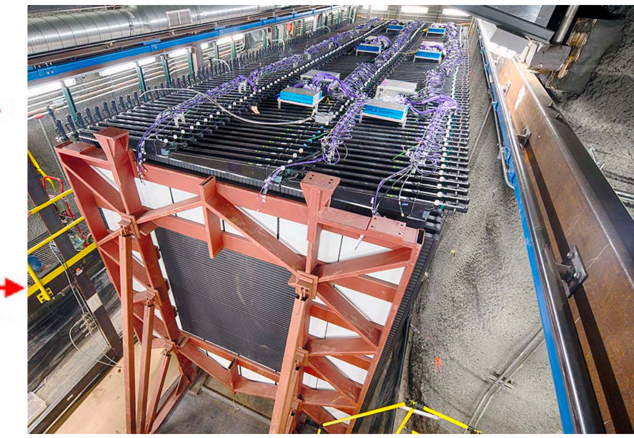


- Operational voltage has been selected to minimize the recombination effects and to avoid the signal issues with the proportional region

Importance of the Muon Monitors



Neutrino Experiments



Muon Monitors Data

Helping to understand beamline performance

Helping to understand neutrino beam

Accelerator Division:

- **Beam performance**
- **Horn current stability**
- **Beam alignment**
- **Target status**
- **Probably for beam Auto-tune**

Neutrino Experiments:

- **Neutrino beam stability**
- **To Reduce flux systematic errors**

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   - Linear Regression Models
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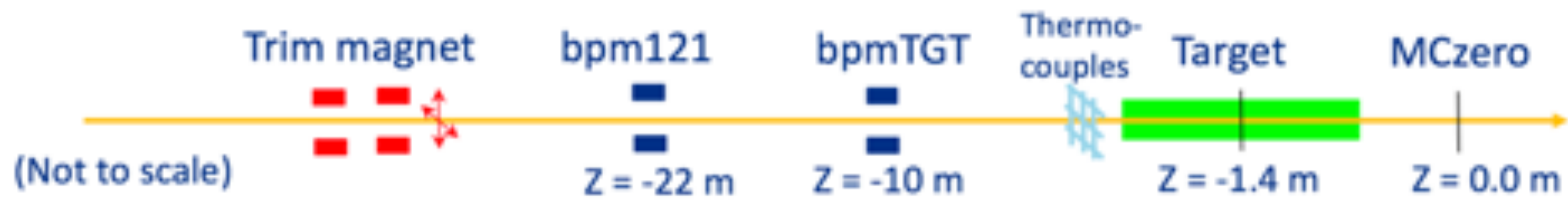
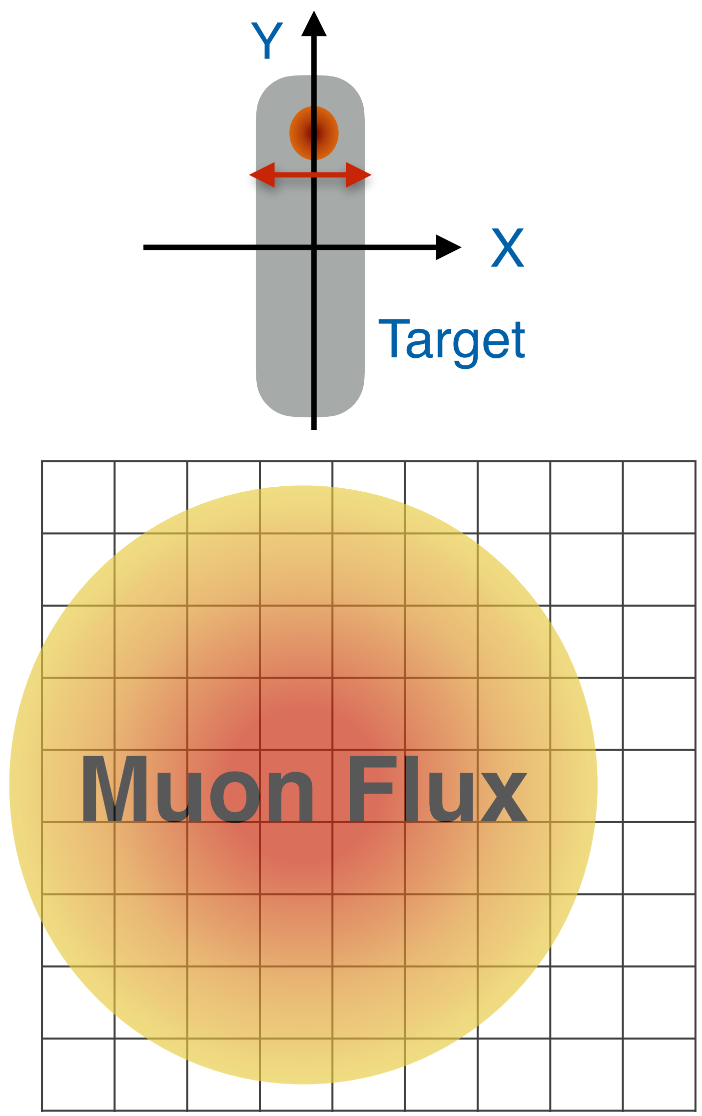
Beam and Horn Current Scans

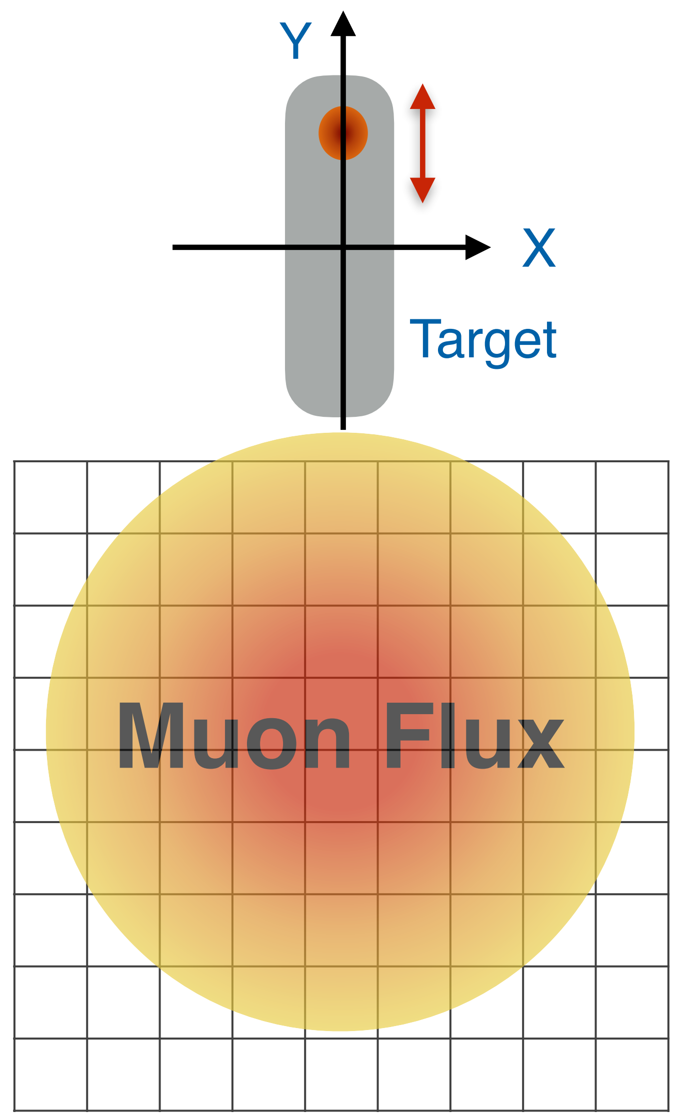


We have used two BPMs to extrapolated the beam on to the target

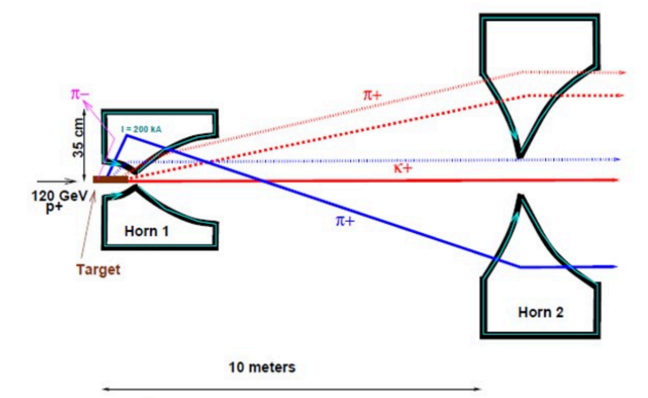
Horizontal Scan

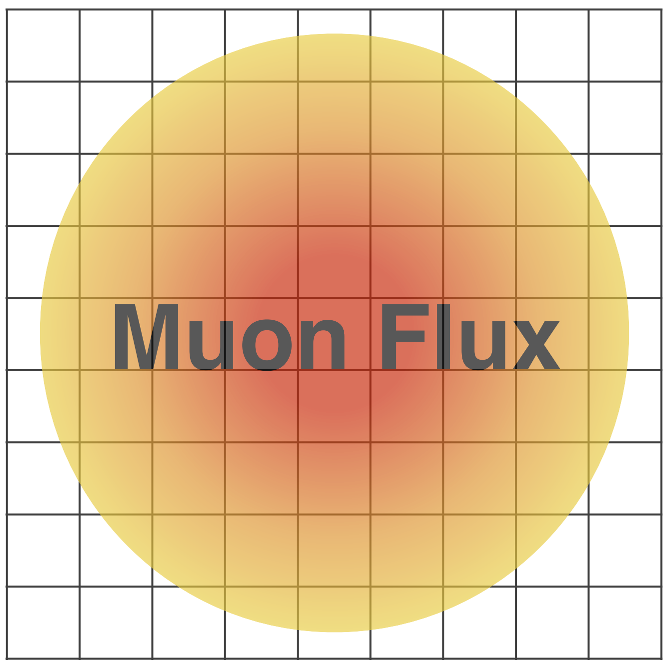


Vertical Scan

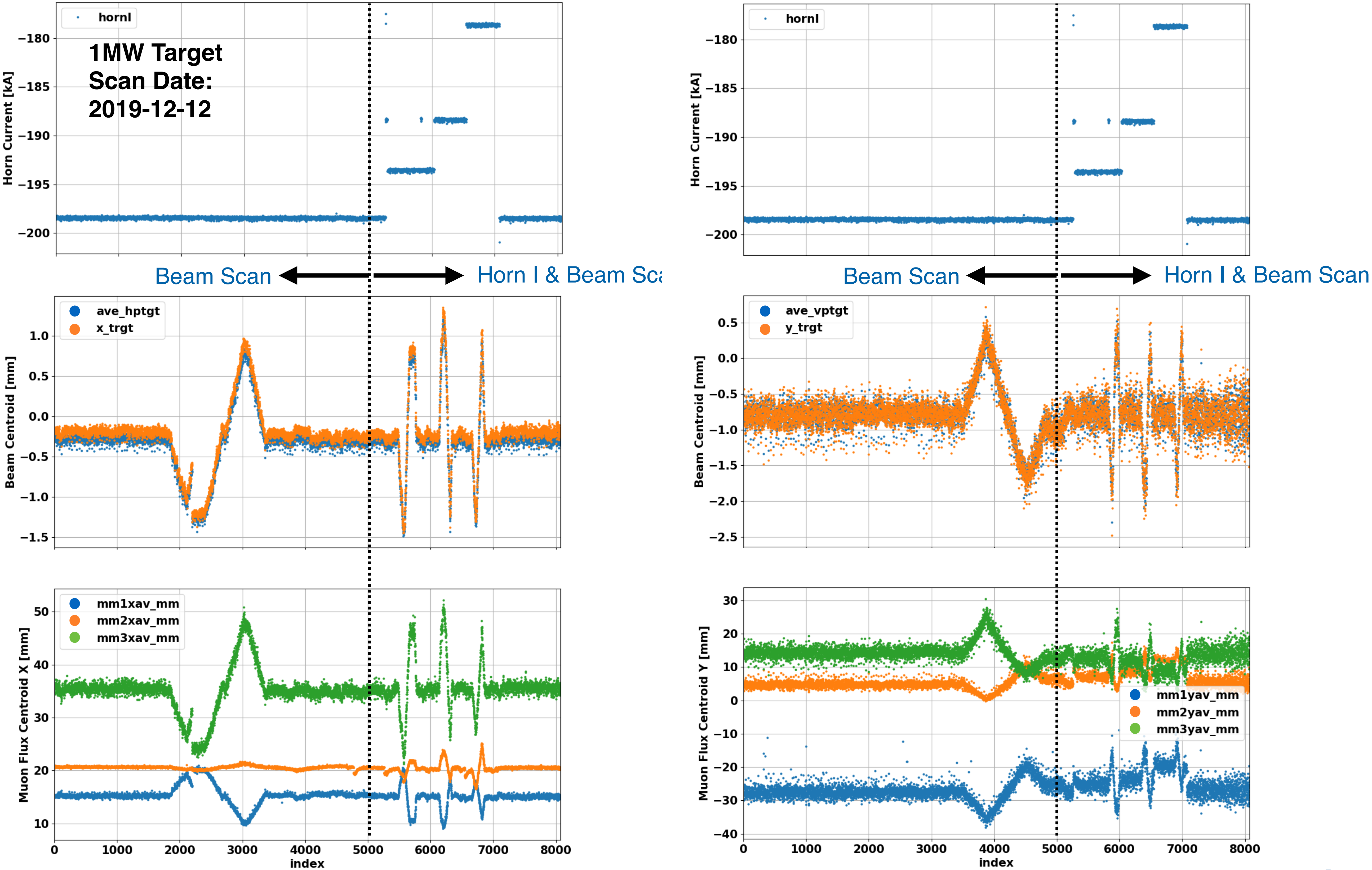


Horn Current Scan





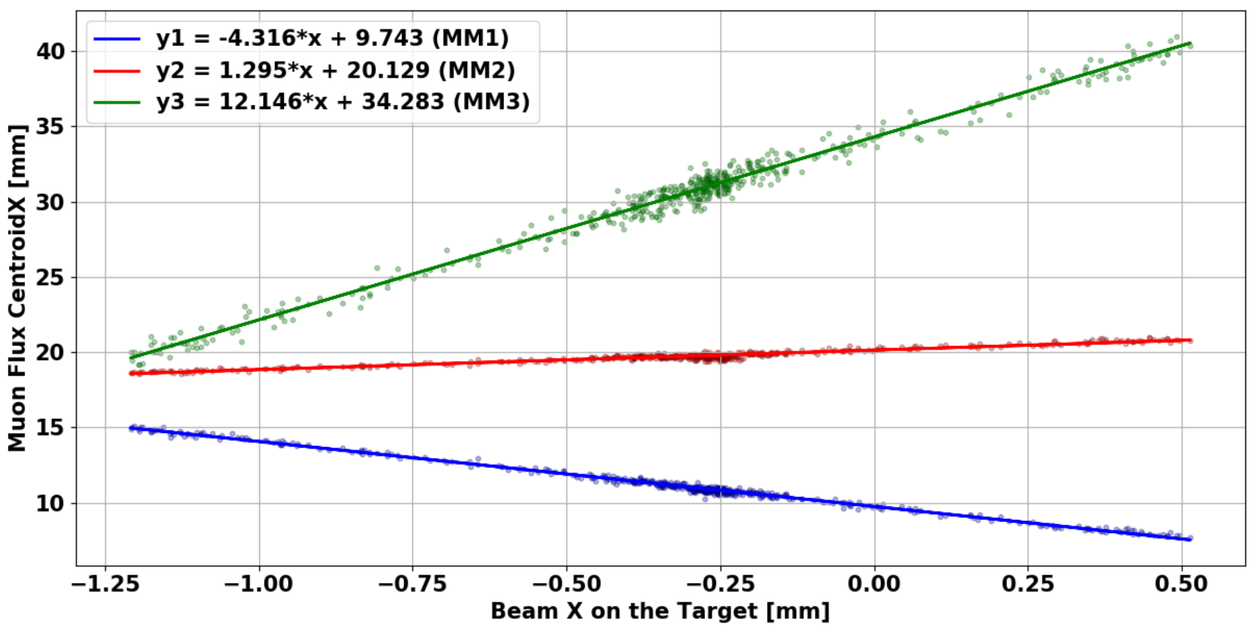
Horizontal and Vertical Scan

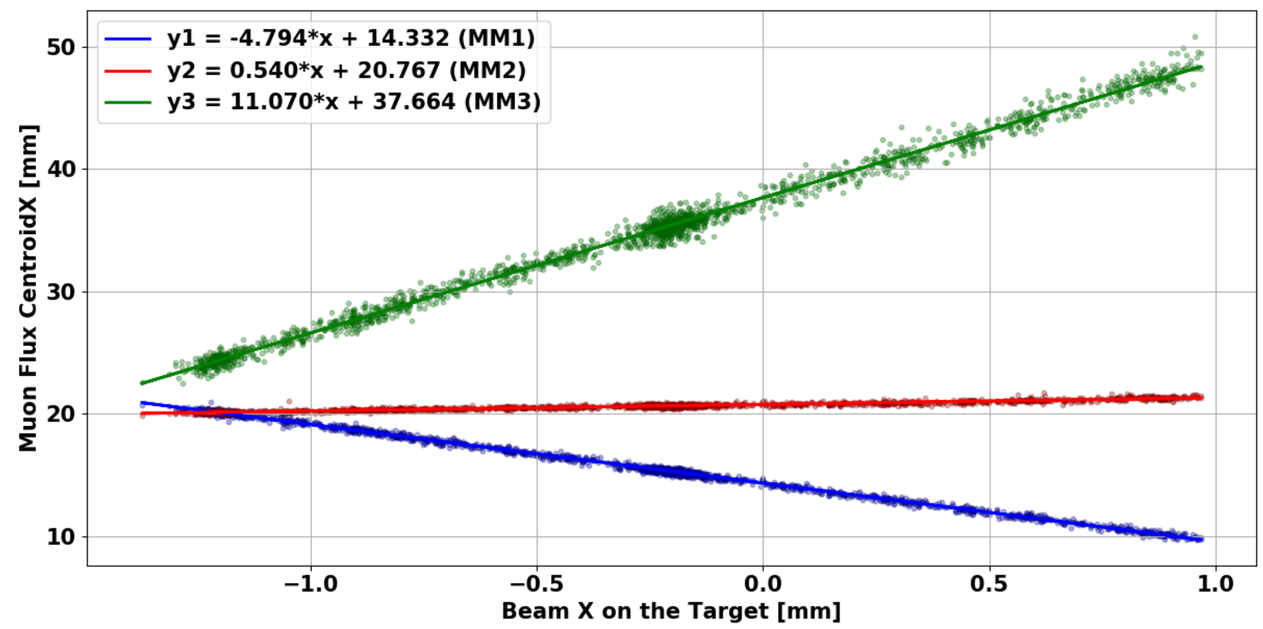


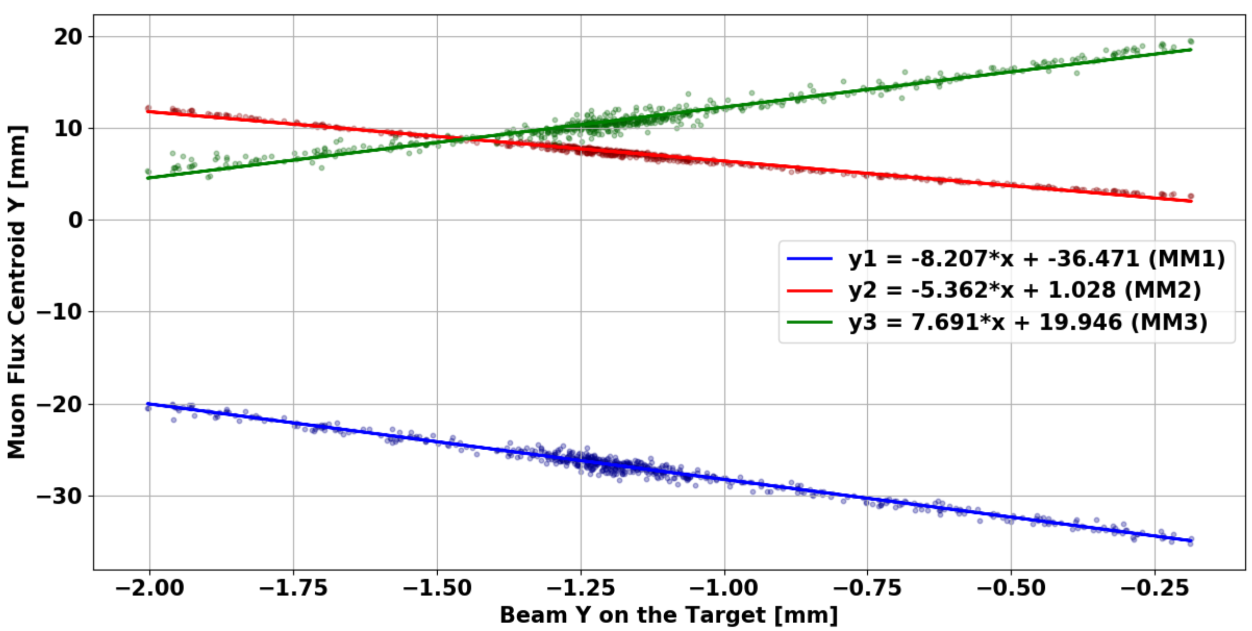
Correlations from beam scans

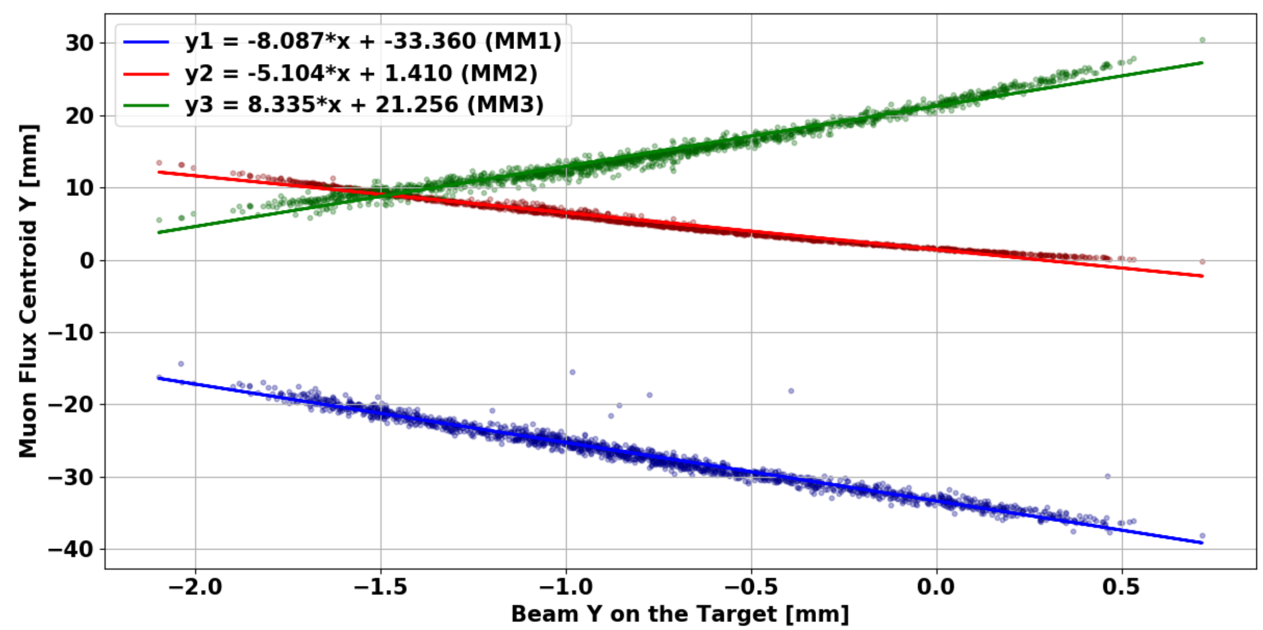
Scan data: 2019-07-03

Scan data: 2019-12-12



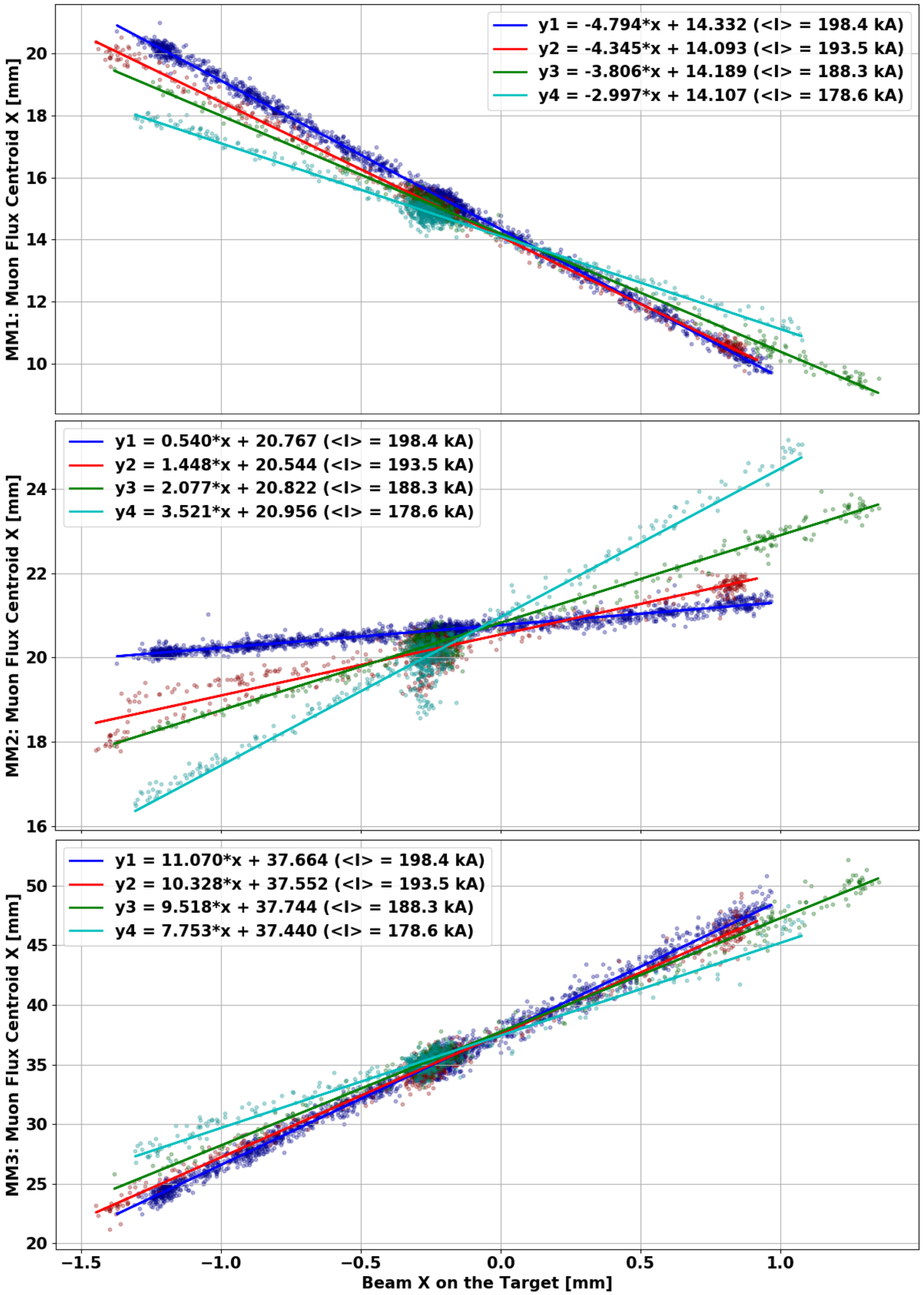




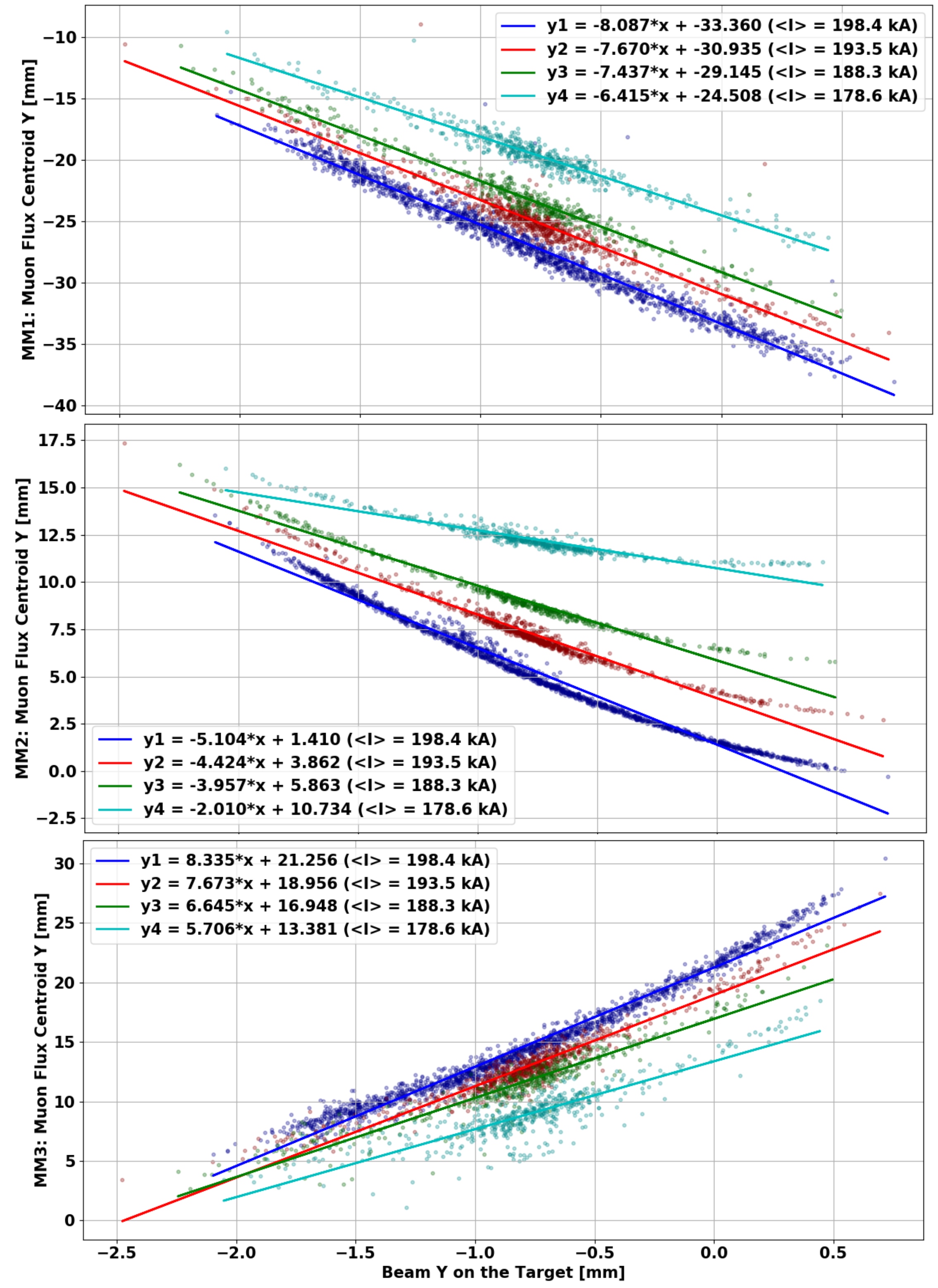


Beam scans with horn current settings

Horizontal Scan



Vertical Scan



Normalized Integrated Signal

$$\text{Noramlized Integrated Signal} = \frac{MM\#COR}{POT}$$

$MM\#COR$ = Muon Monitor integarted signal with pedetal subtractioins and calibrations

$MM\#$ = Muon Monitor (1,2 or 3)

POT = Beam Intensity

Measurement indicates:

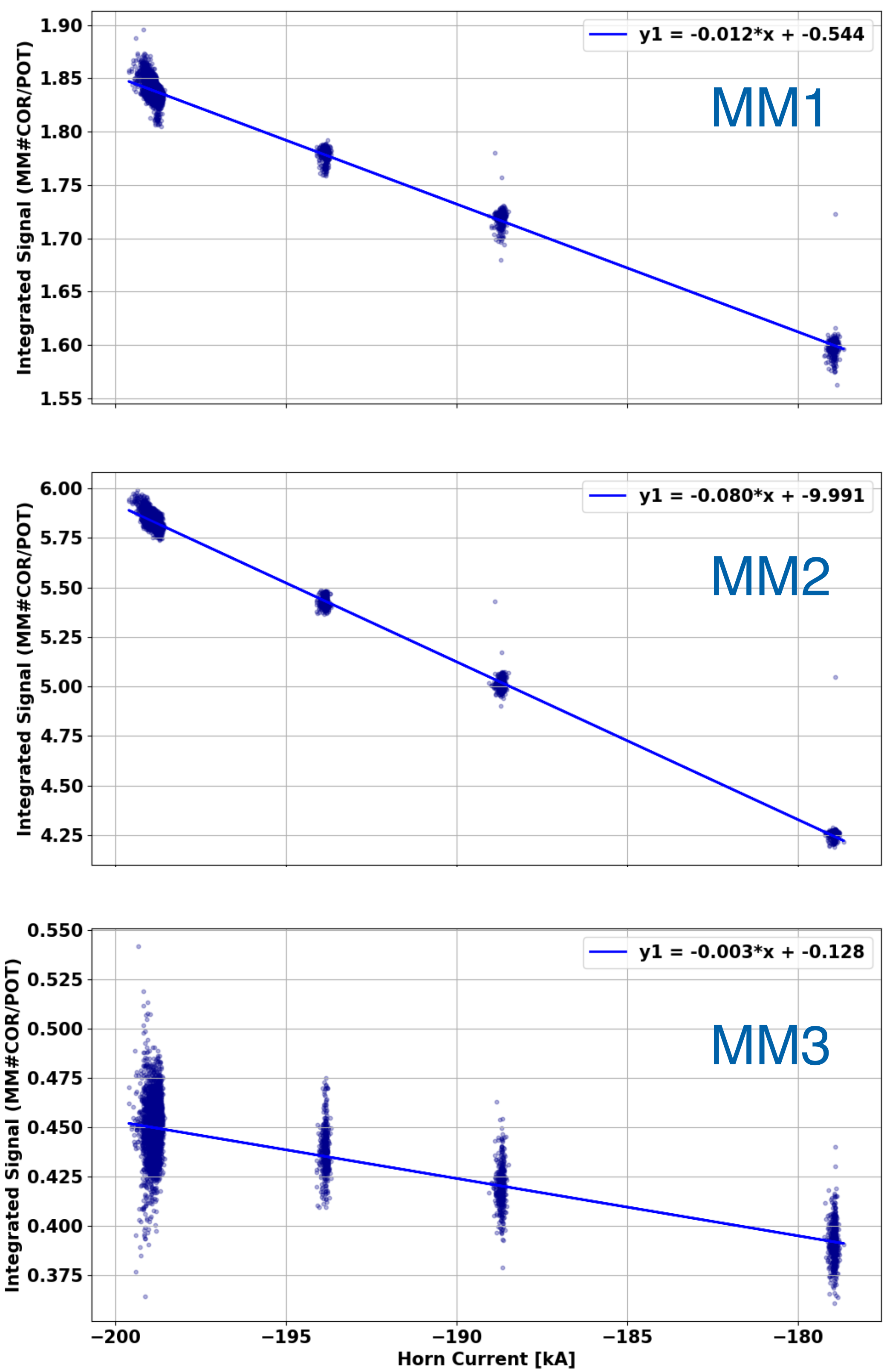
- **Proportional to the total muon flux passing through the detector per proton**
- **Proportional to the total muon energy lost in the detector**

Importance of the measurement:

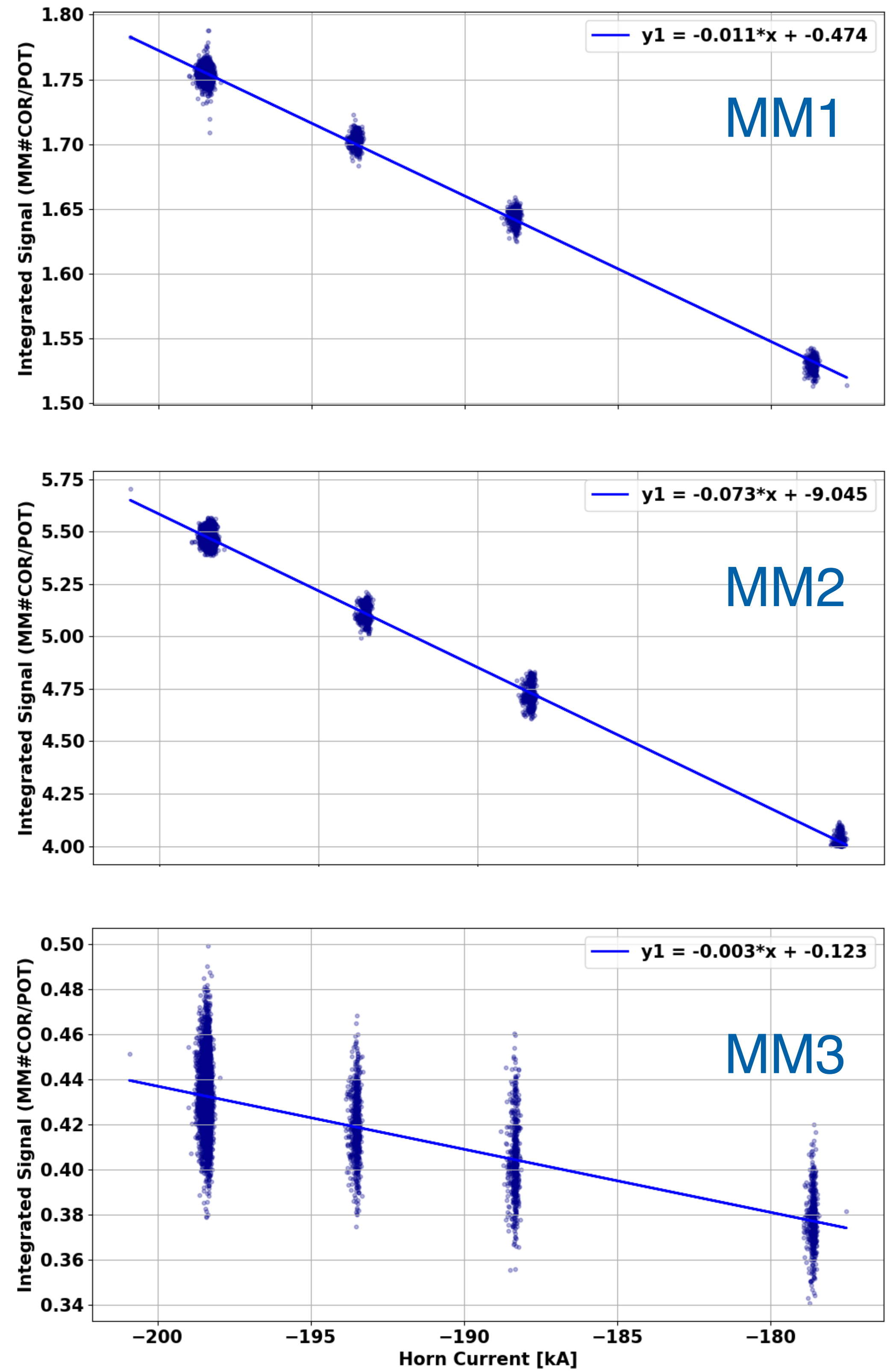
- **Indicates the hadron production related to the target profile**
- **Sensitive to the horn current variations**

Integrated Muon Signal vs Horn Current

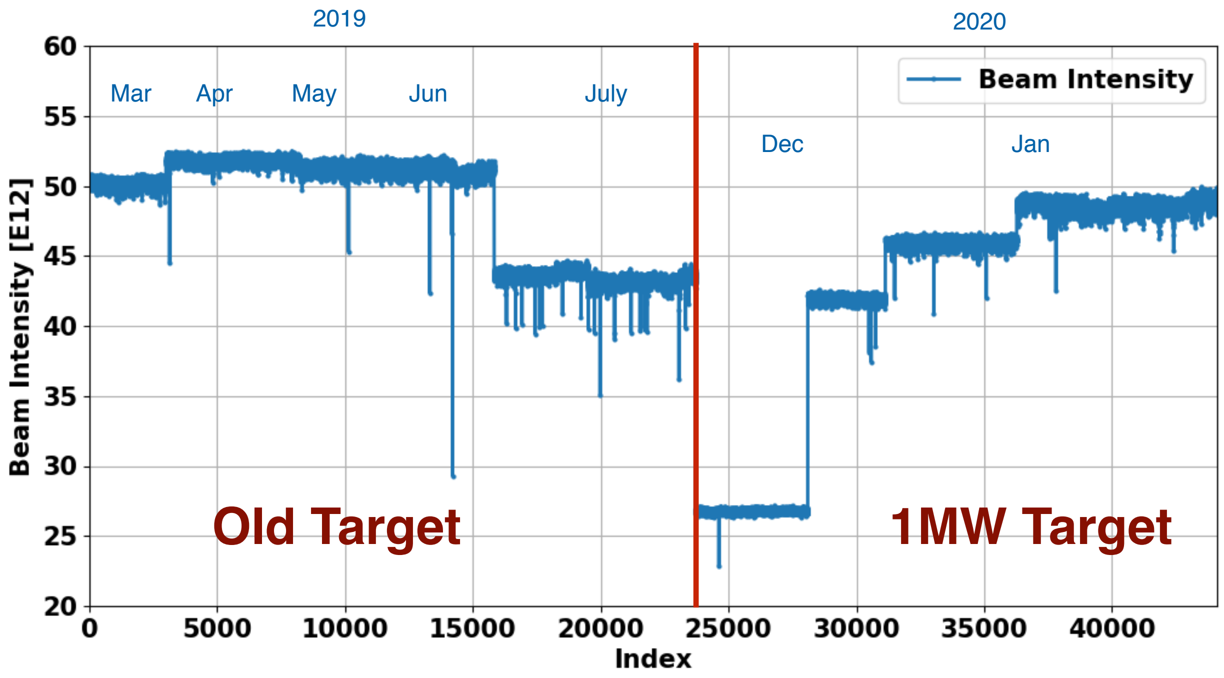
Scan data: 2019-07-03

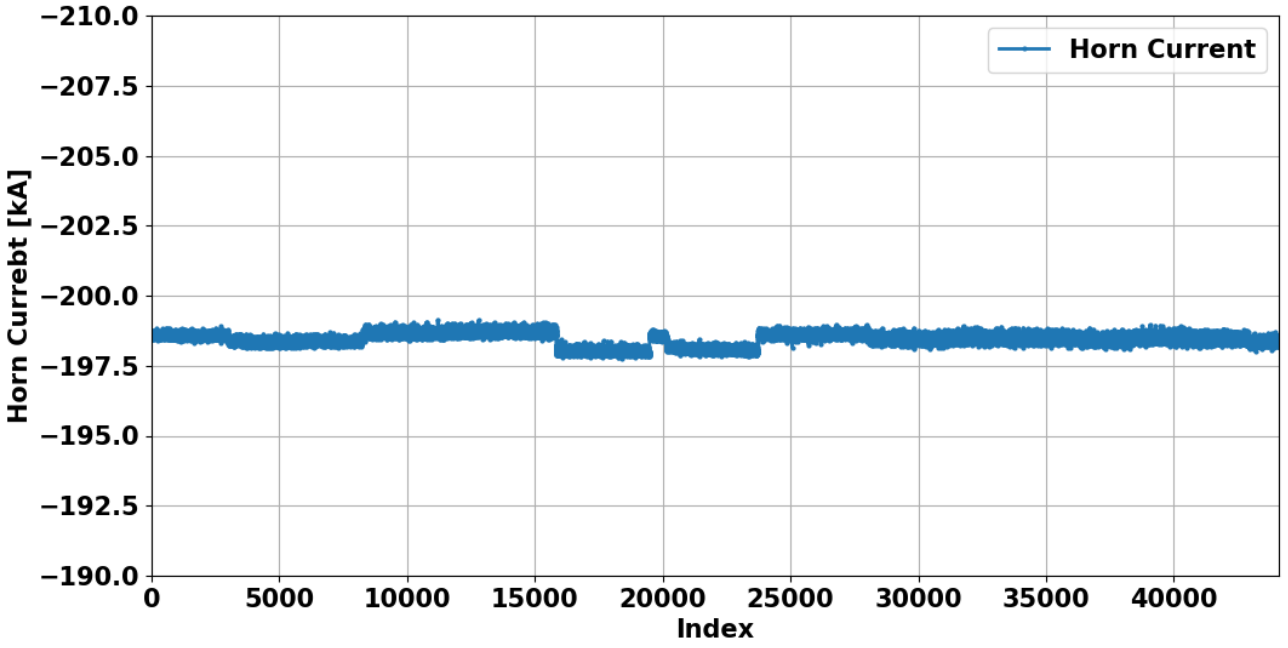


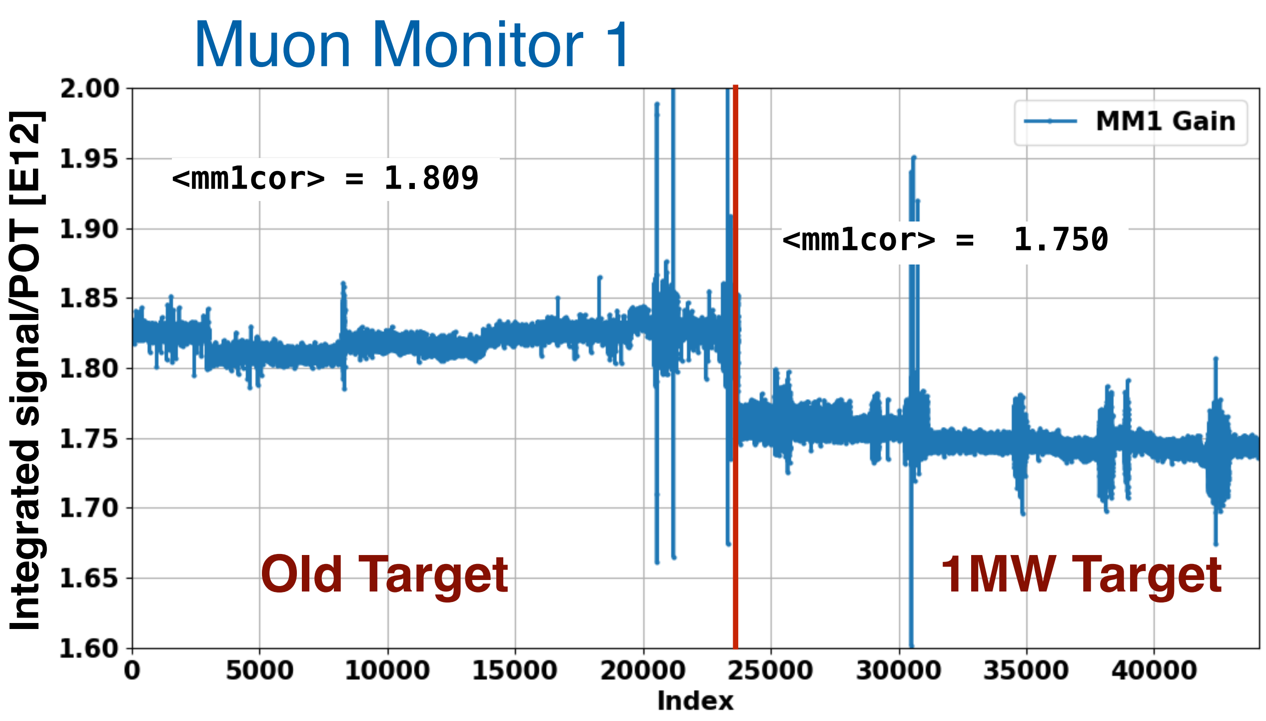
Scan data: 2019-12-12



Integrated signal responses to the new target







» This is a good example of how that muon monitor observations are responding to the target geometry changes

» There is a ~5% difference from the old target to the new target

Remarks from the beam and horn scans

- Usually, beam scans are used for the beam alignments with the help of the hadron monitor measurements
- Muon flux centroid behaves linearly with the incident beam position for different horn current settings
- Each muon monitor has a unique behavior to the beam parameters
- Helping to understand the horn focusing effects
- Integrated signal is a key measurement to understand the target related issues
- Studies are helpful to test or validate the beamline Monte Carlo predictions
- Beam scan data are useful for data modeling or Machine Learning applications

Why Do We Need Muon Monitors?

Recalling the neutrino production in the NuMI beam line

Next…

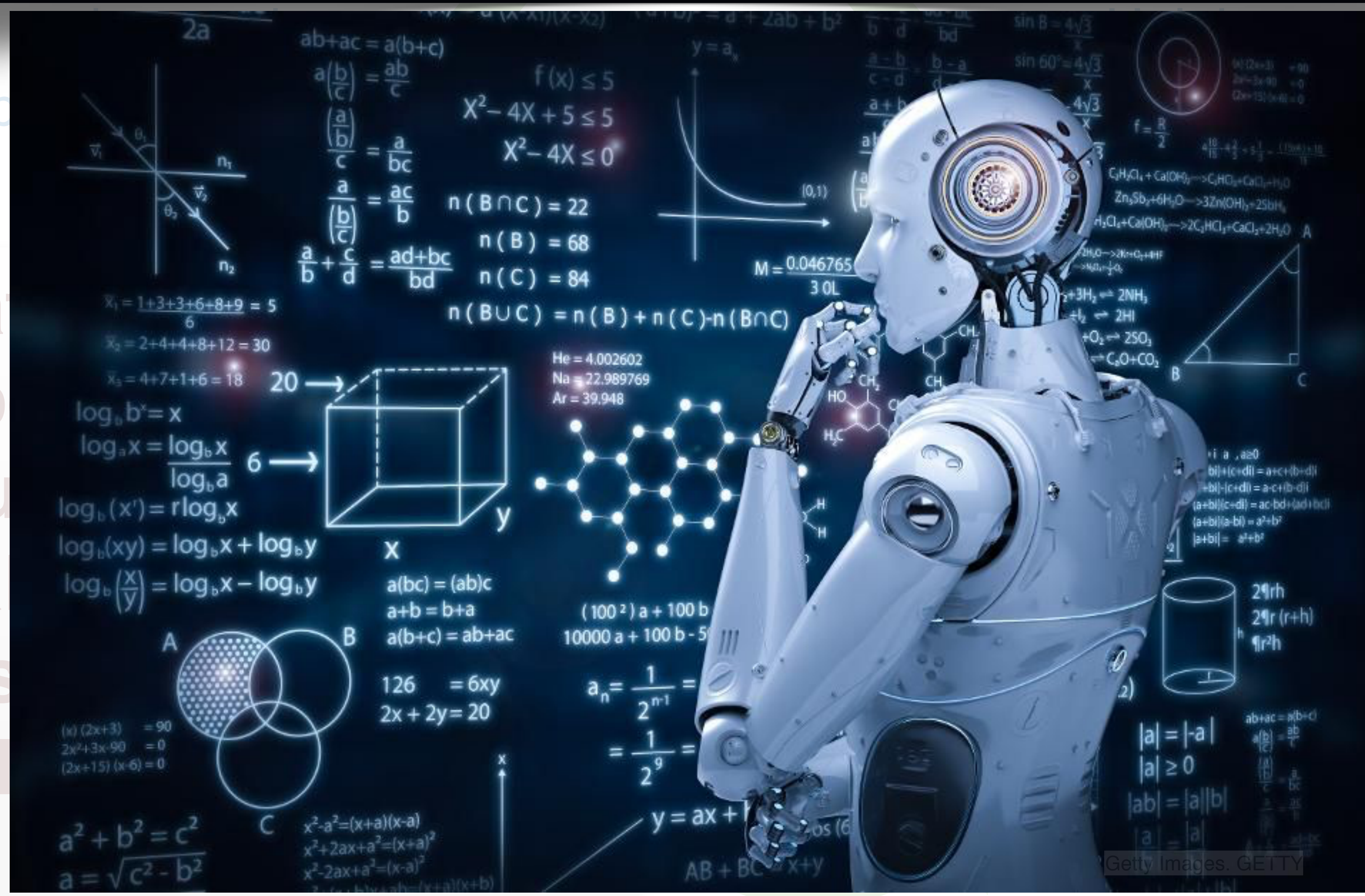
Can we make intelligent predictions for experiments with the help of Machine Learning ?

Helping to … understand

beamline p… am

Accelera… ments:

- Beam p… m stability
- Horn cu… ux
- Beam a… rrors
- Target s…
- Probabl… tune



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   - **Linear Regression Models**
   - **Neural Networks**

Linear Regression Model Applications

Variable
Measurement

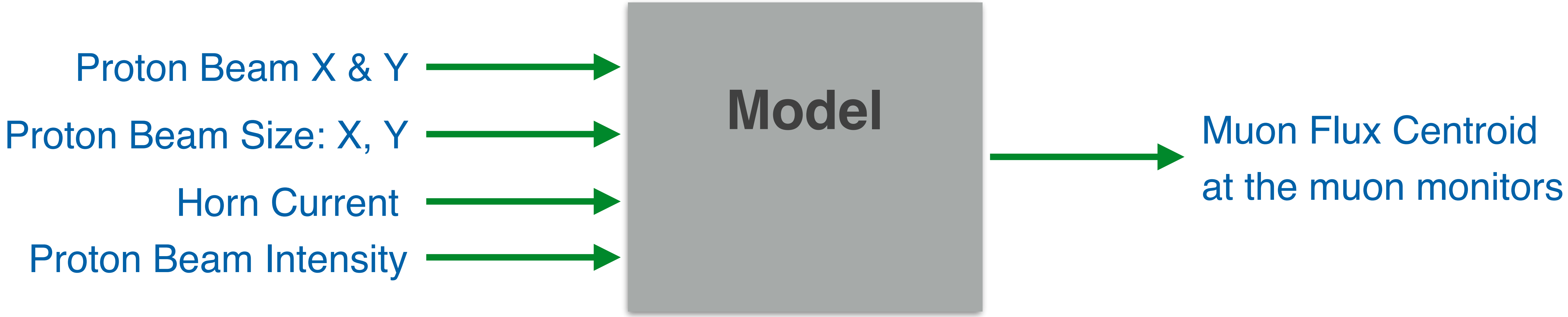
Residual
coefficient

$$prediction = \sum_{i=0}^{N} \alpha_i \cdot X_i + \beta_i$$

Regression
coefficient

Predicting Muon Monitor Centroid from beam and horn parameters

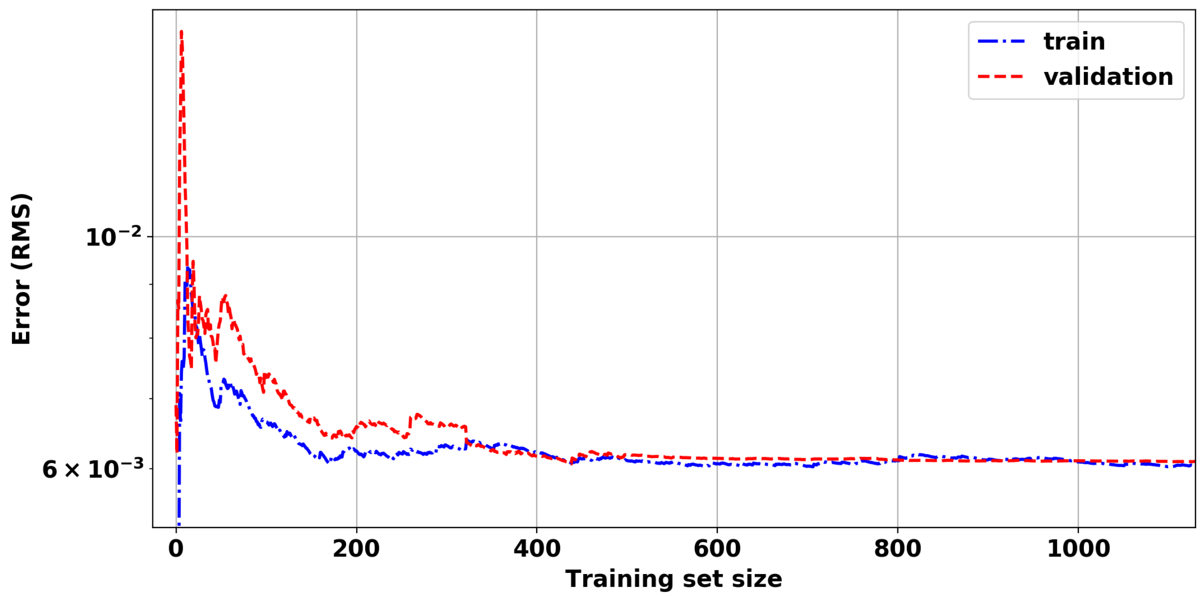
MOTIVATION: Developing a muon flux centroid prediction model by taking account upstream variables such as horn current and proton beam profile changes as inputs



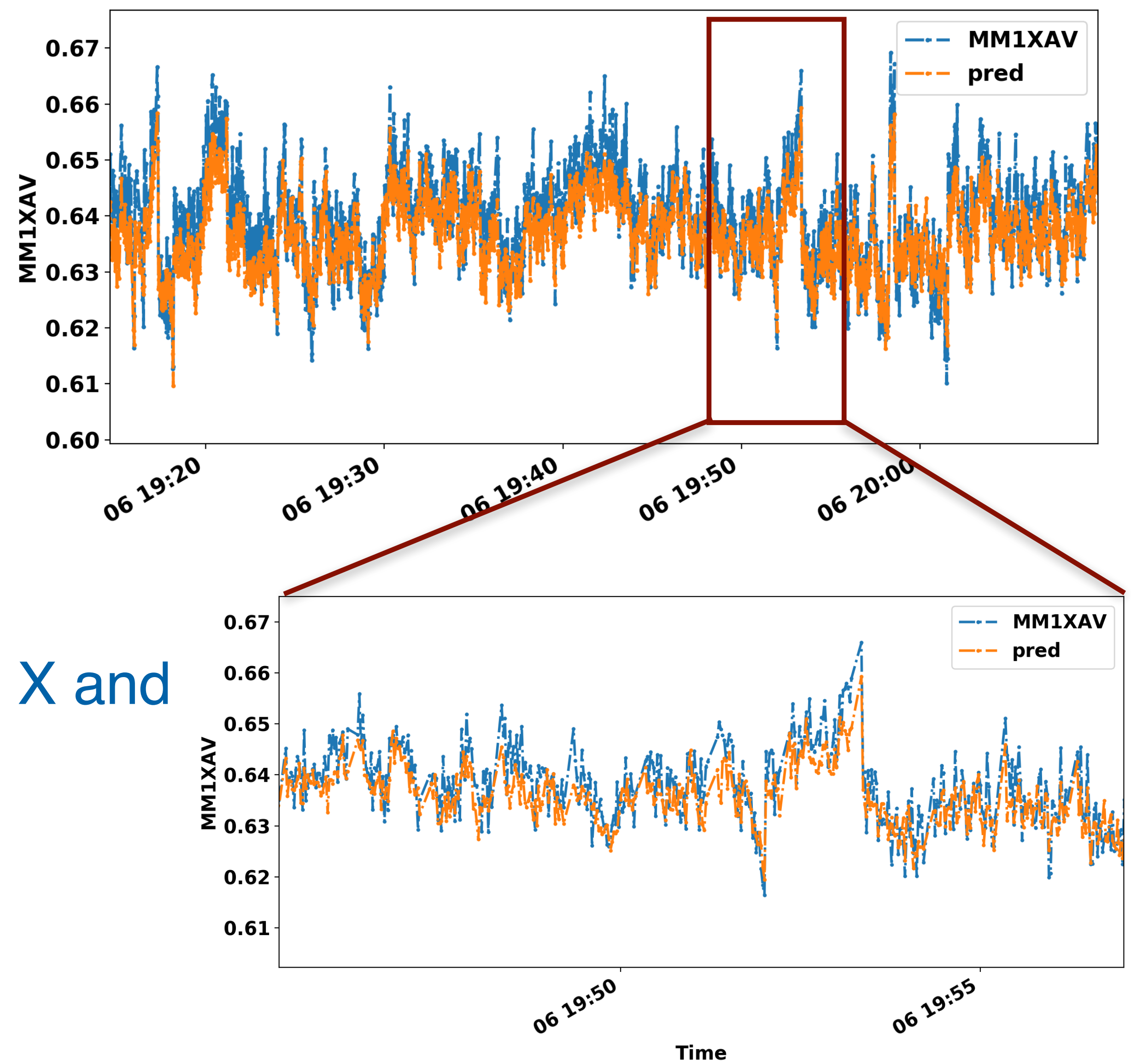
Muon Flux centroid prediction

$$prediction = f(X_b, Y_b, \sigma_X, \sigma_Y, Intensity_{beam}, I_{horn})$$

Training performance for a random data set

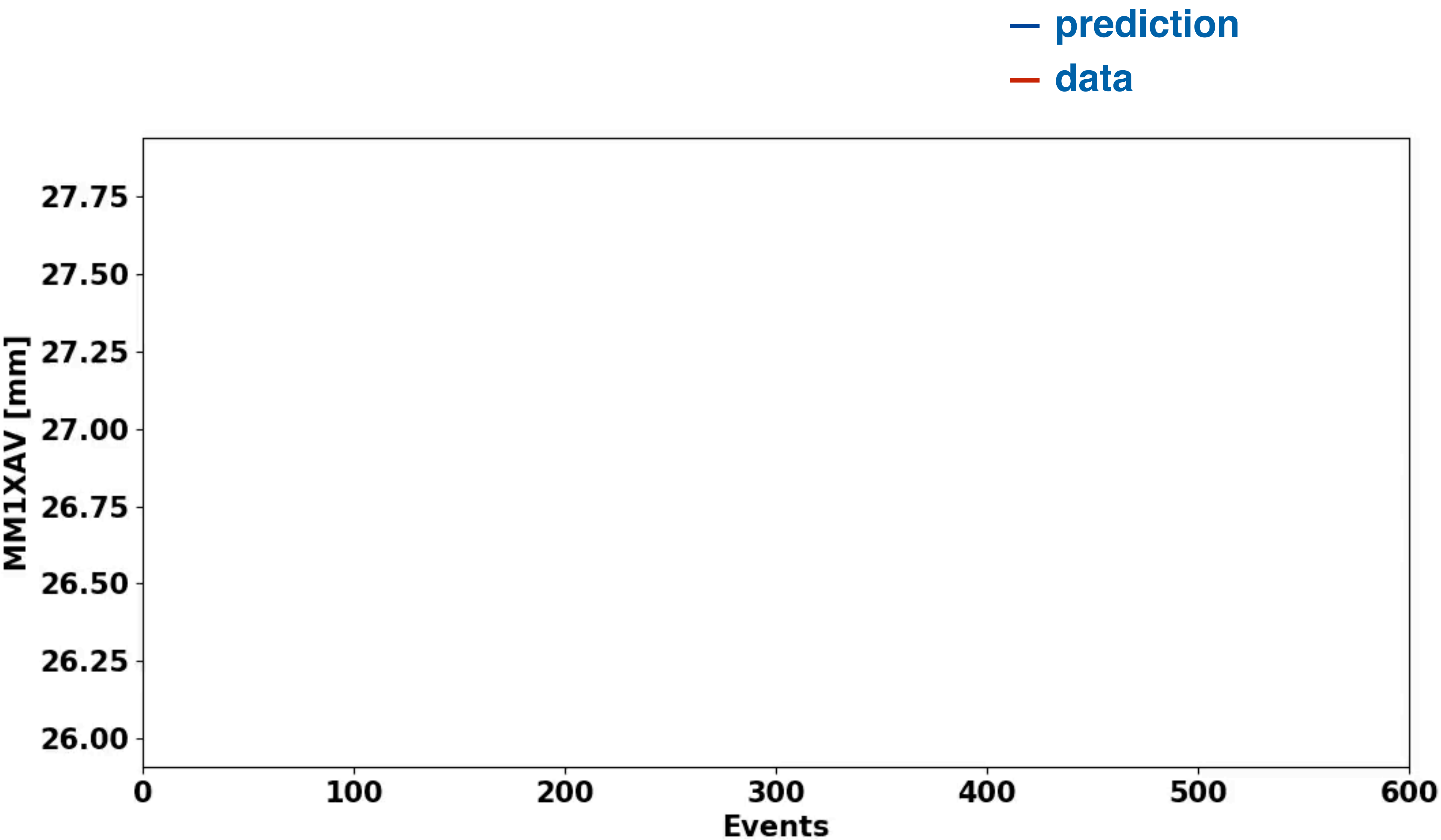


Prediction for muon monitor1 <X>



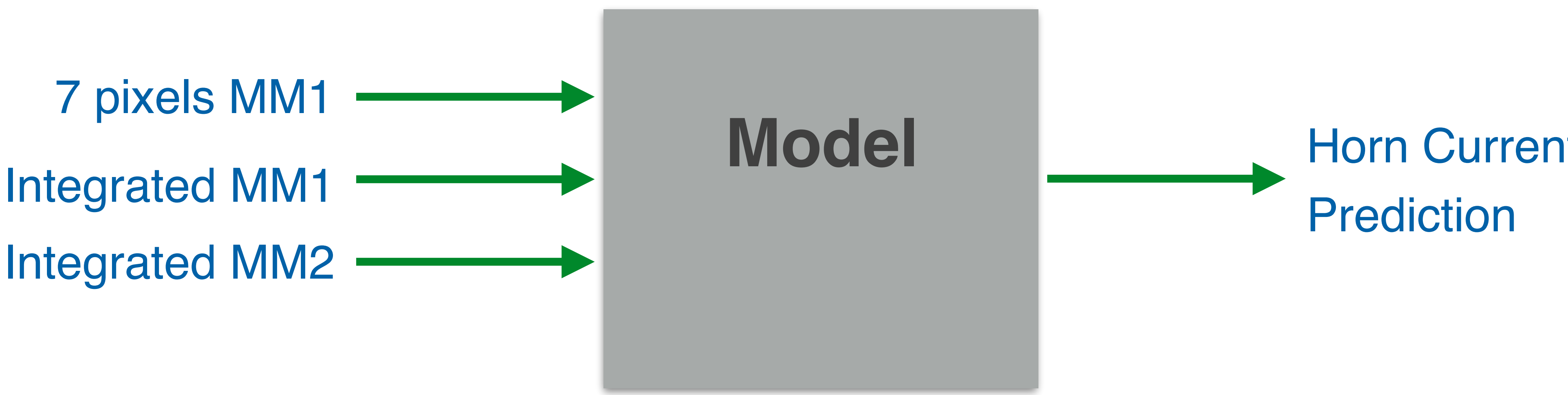
The predictions are accurate as +/- 0.1 mm in X and +/- 0.5 mm in Y

Muon Flux centroid prediction



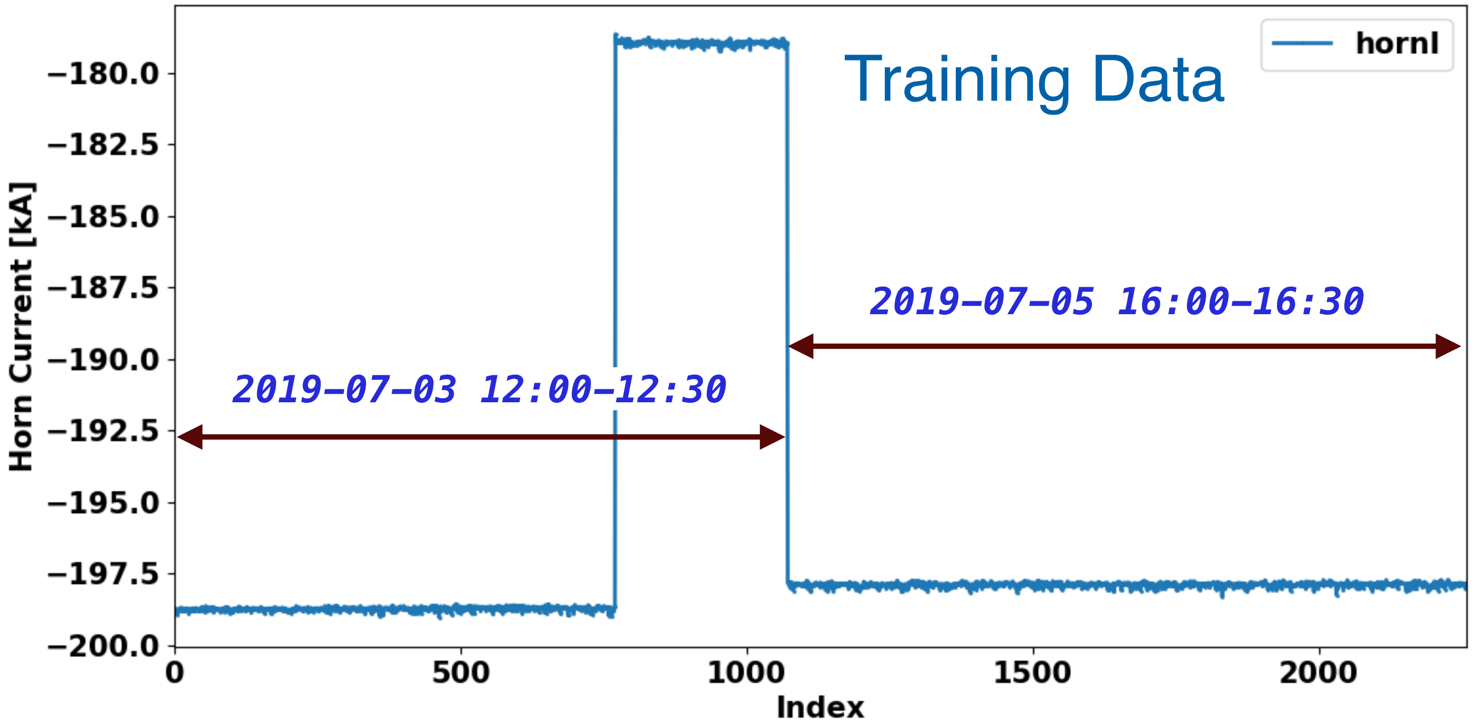
Predicting Horn Current from Muon Monitor Data

MOTIVATION: That would be a very useful tool if we have a model to predict the horn current behaviors by taking account muon monitor signals

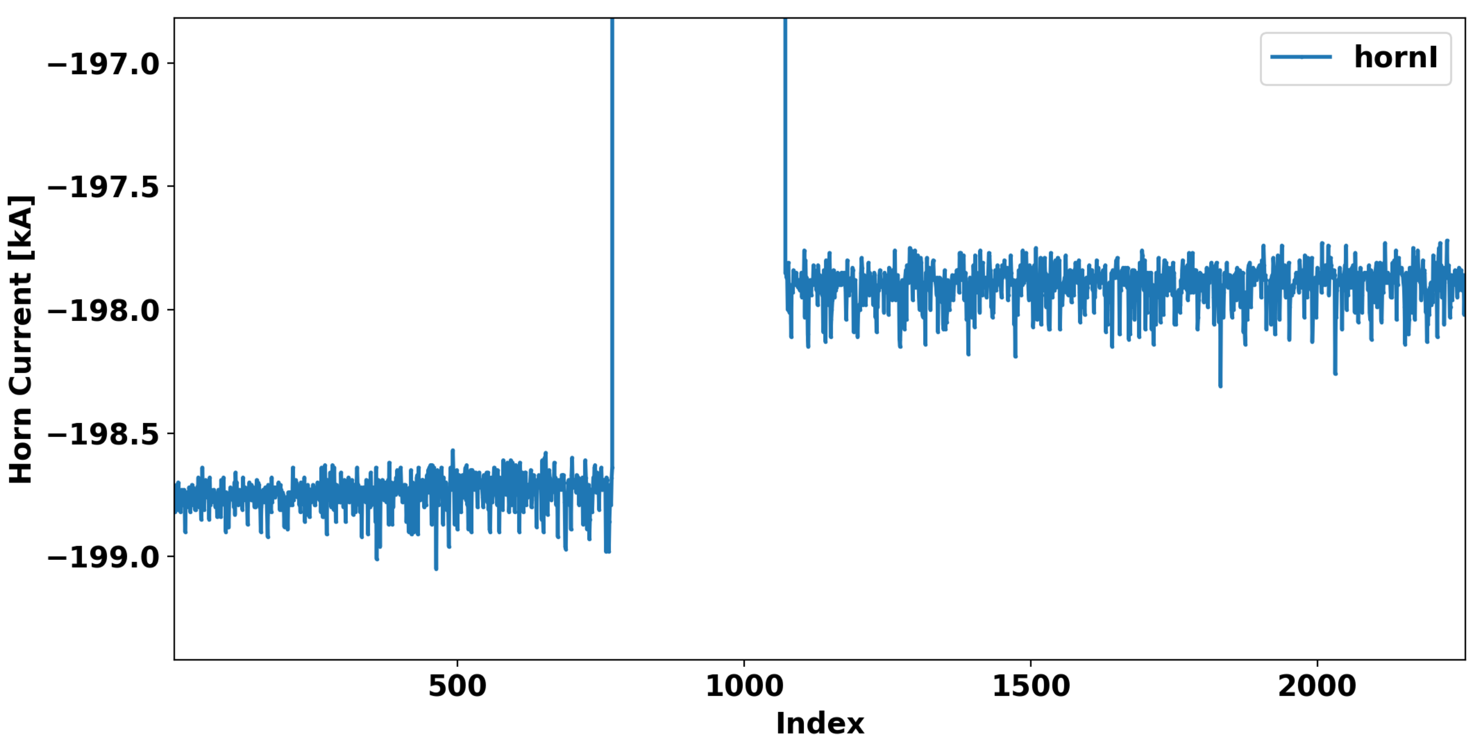


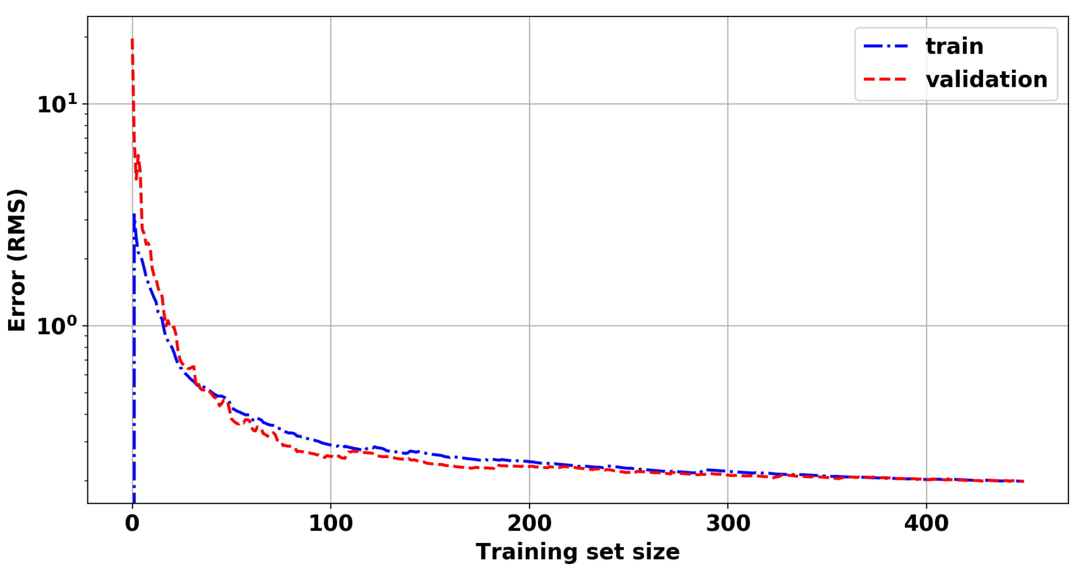
Training the Model

Pred Horn I = f(MM1PIXELs, MM1COR and MM2COR, beam Intensity)



We use 10 input variable to train the model





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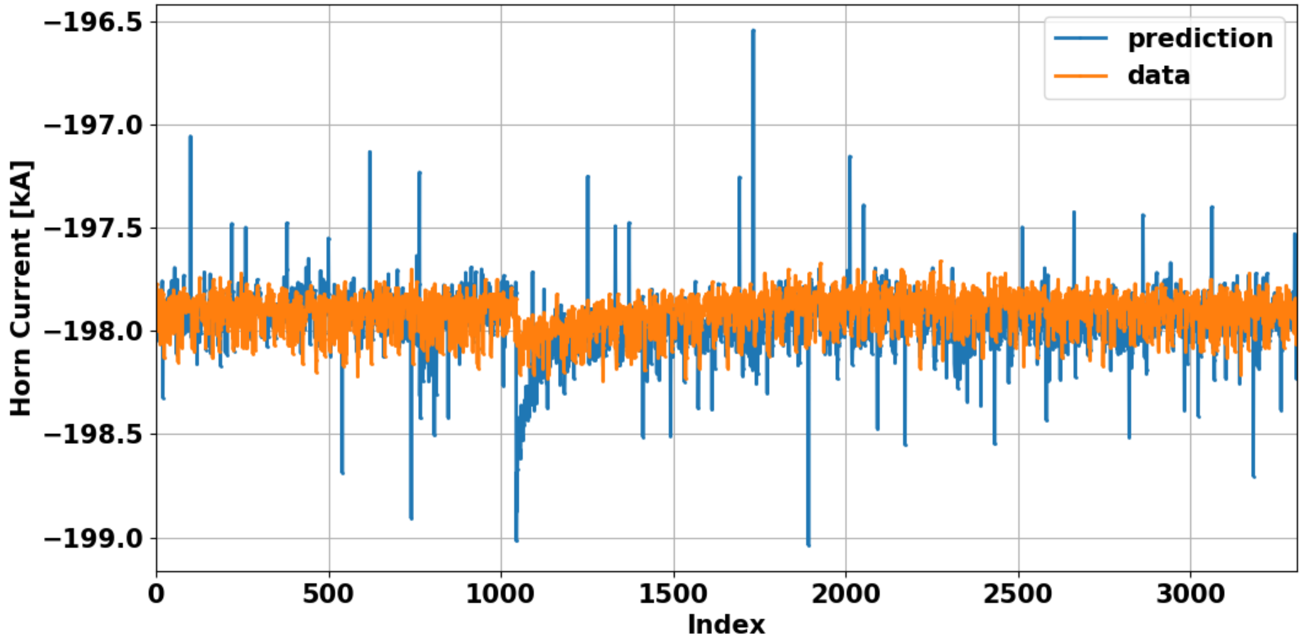
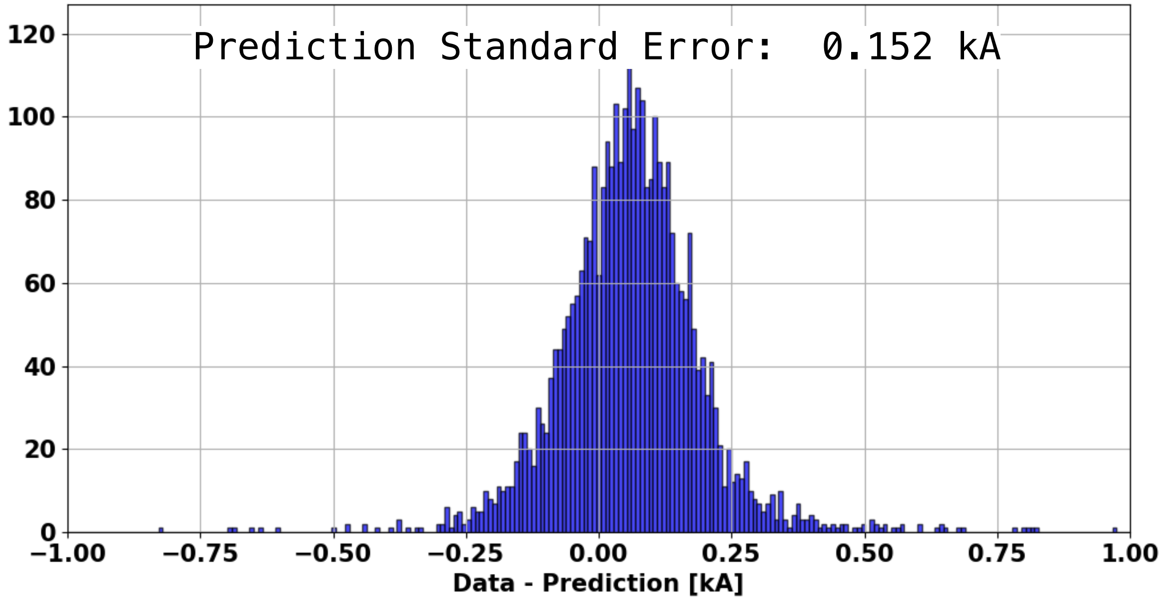
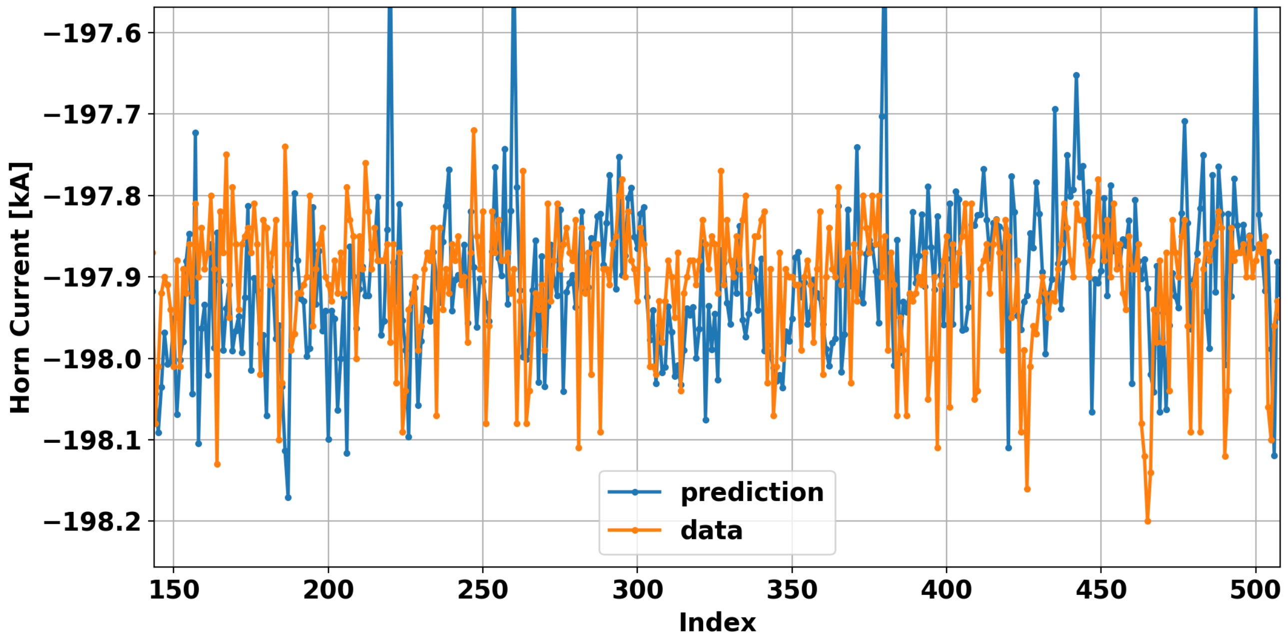
Horn Current Predictions

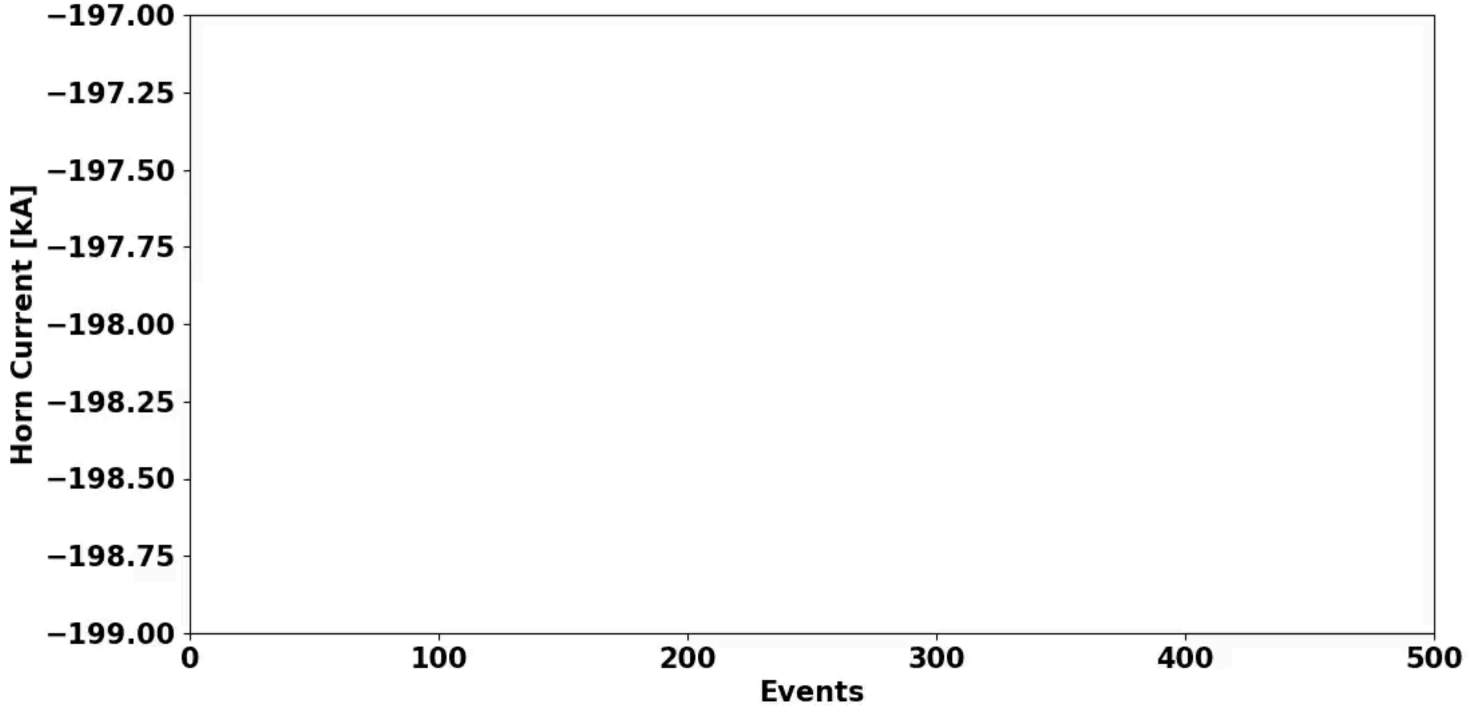


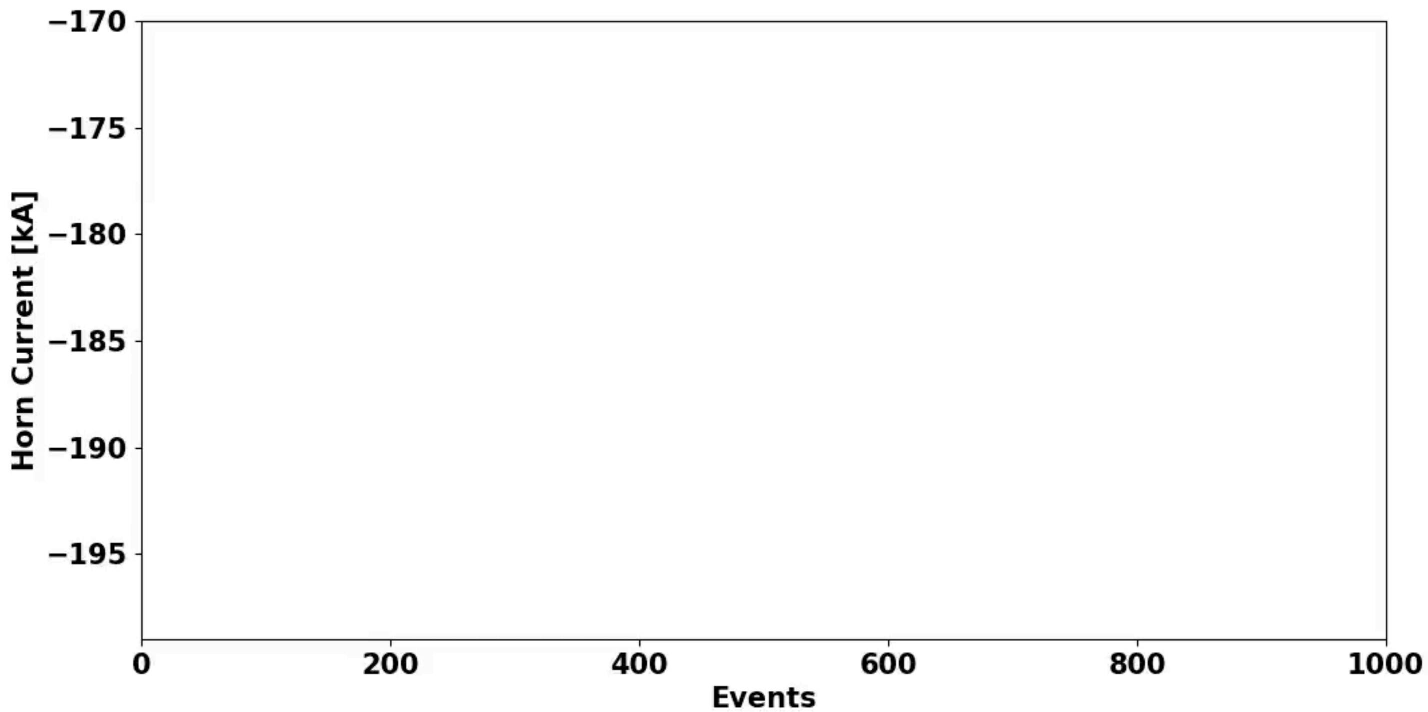




We have the capability to predict the horn current by taking account muon monitor signal data

Horn Current Predictions





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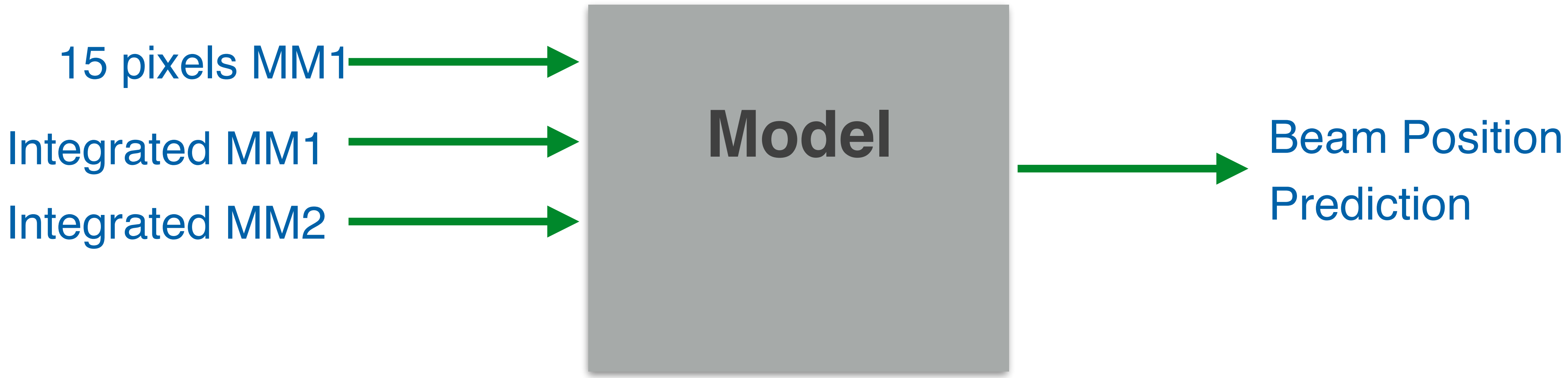
Predicting Beam Position from Muon Monitor Data

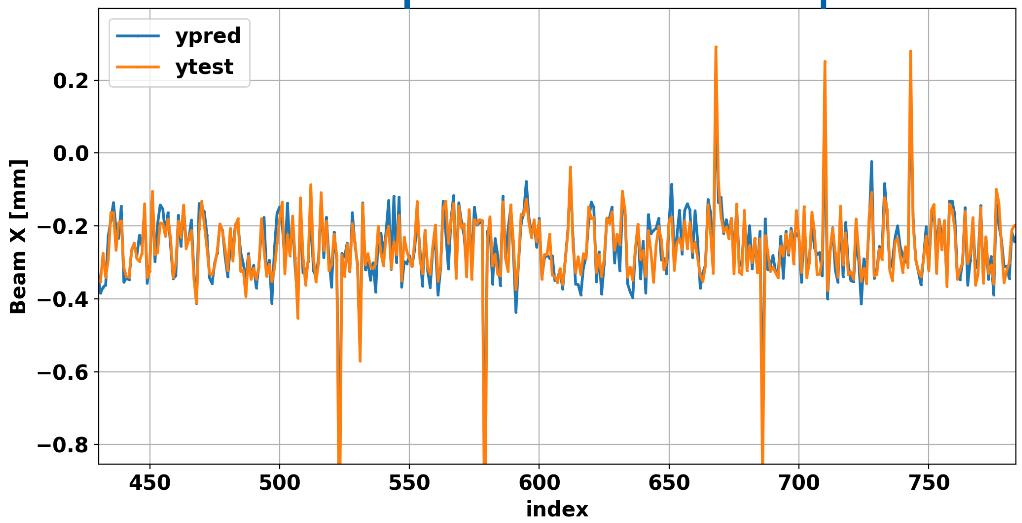
MOTIVATION: A tool to predict the proton beam position at the target by taking account muon monitor signals



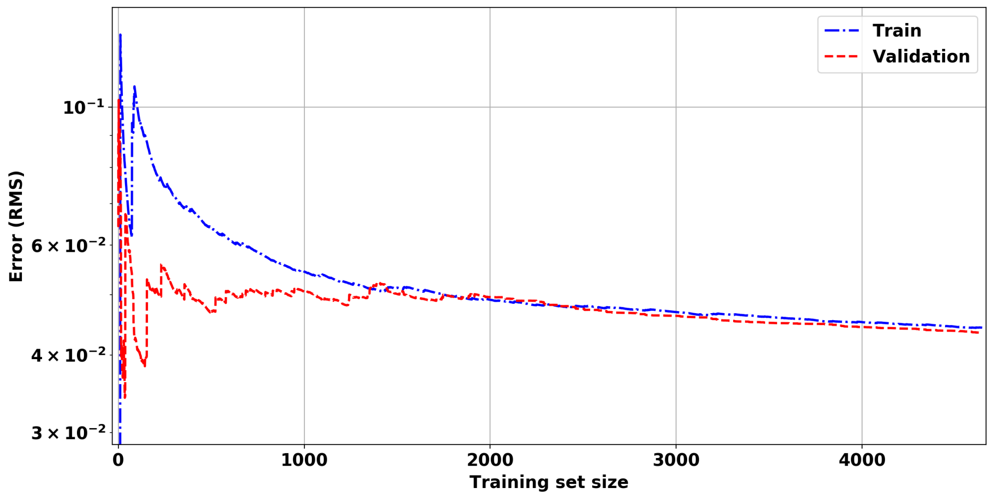
Beam centroid X prediction

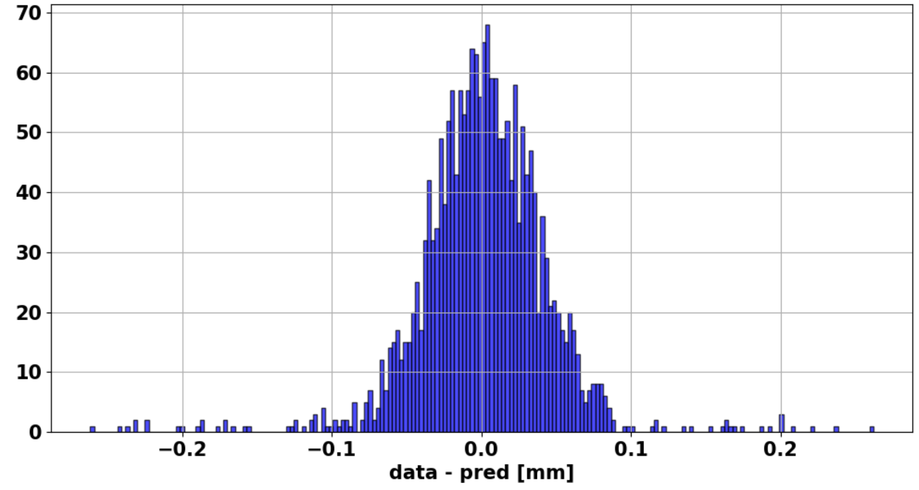
We have used selected muon monitor pixels as inputs for the model

Example of test sample

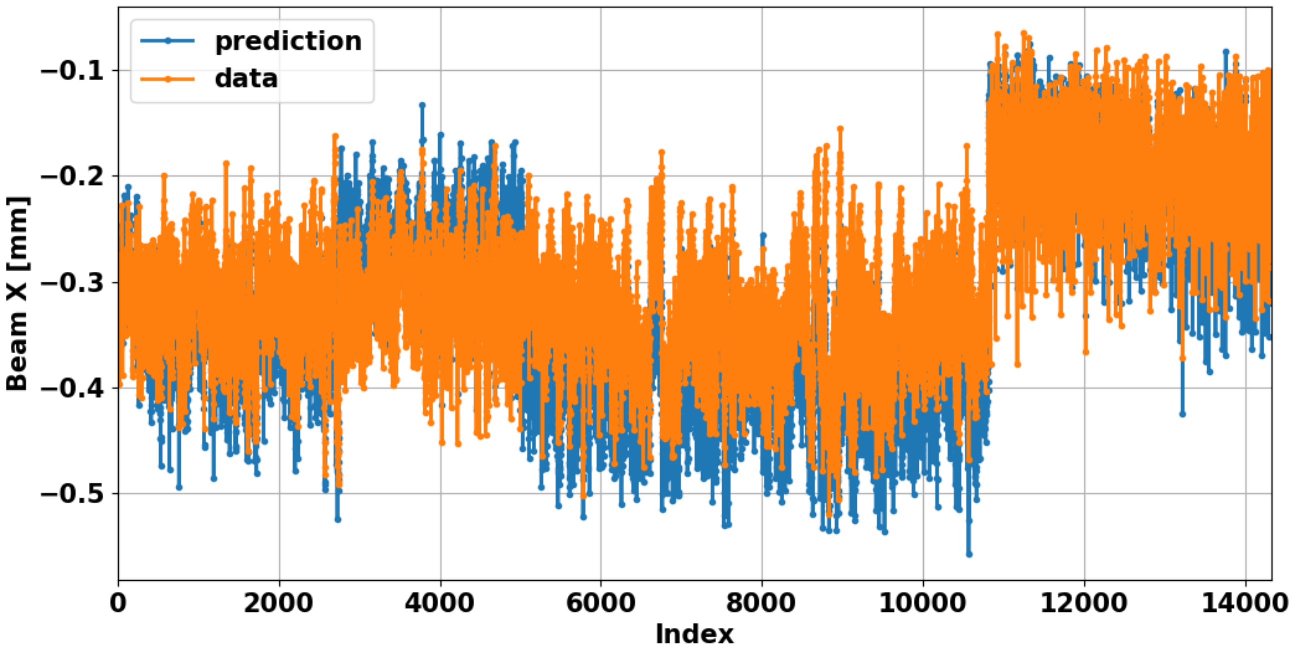


Training performance for a random data set

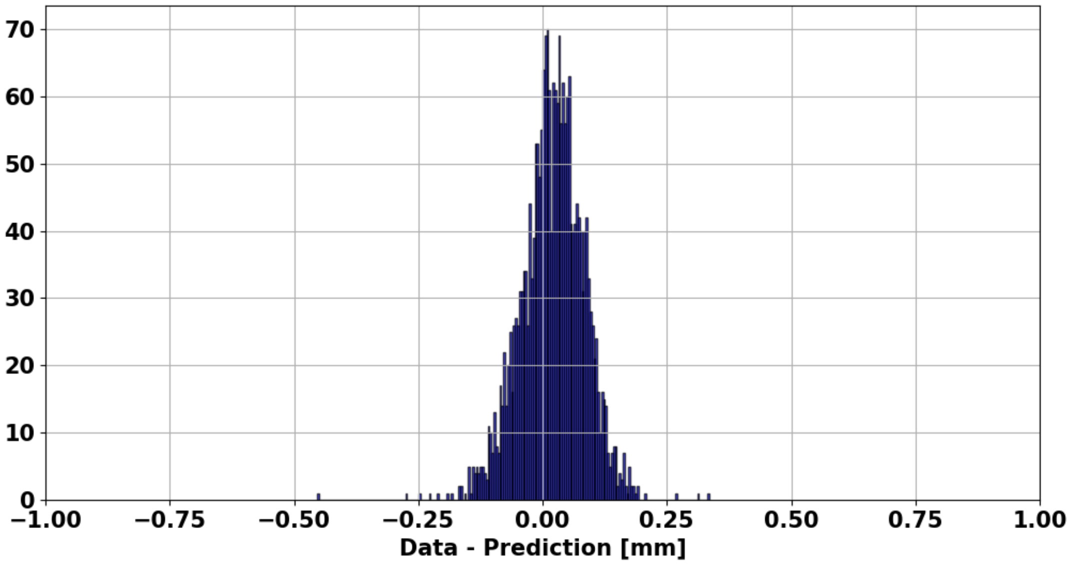


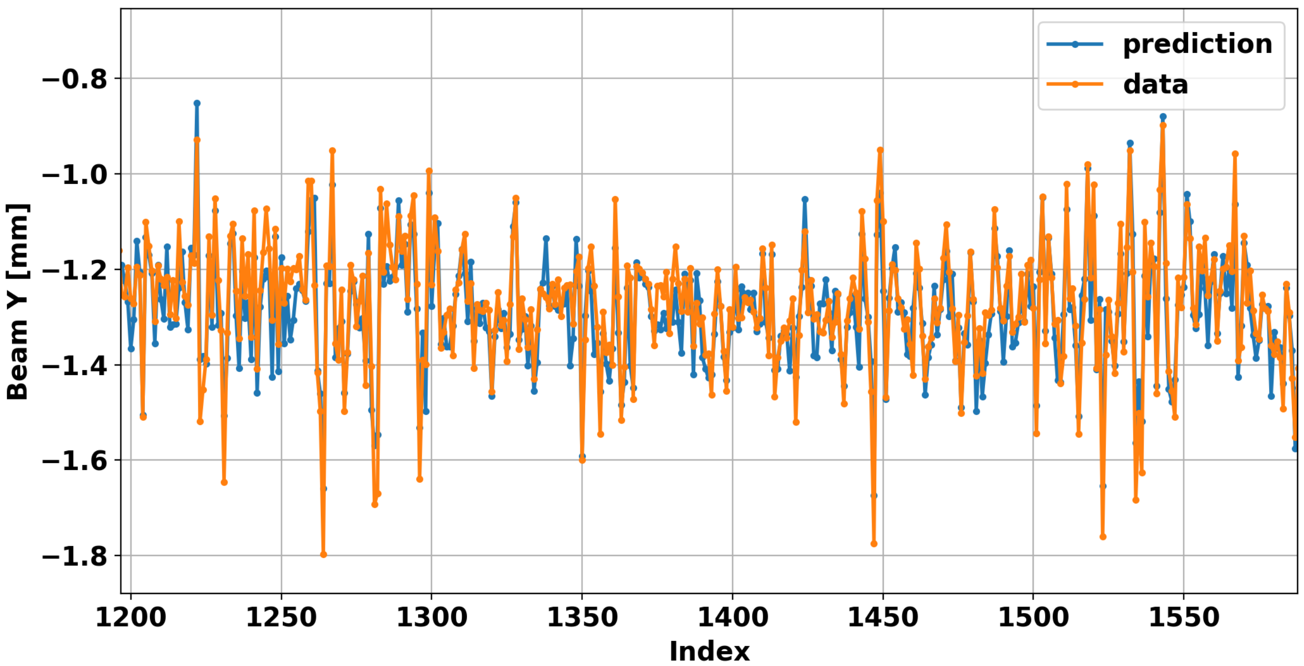


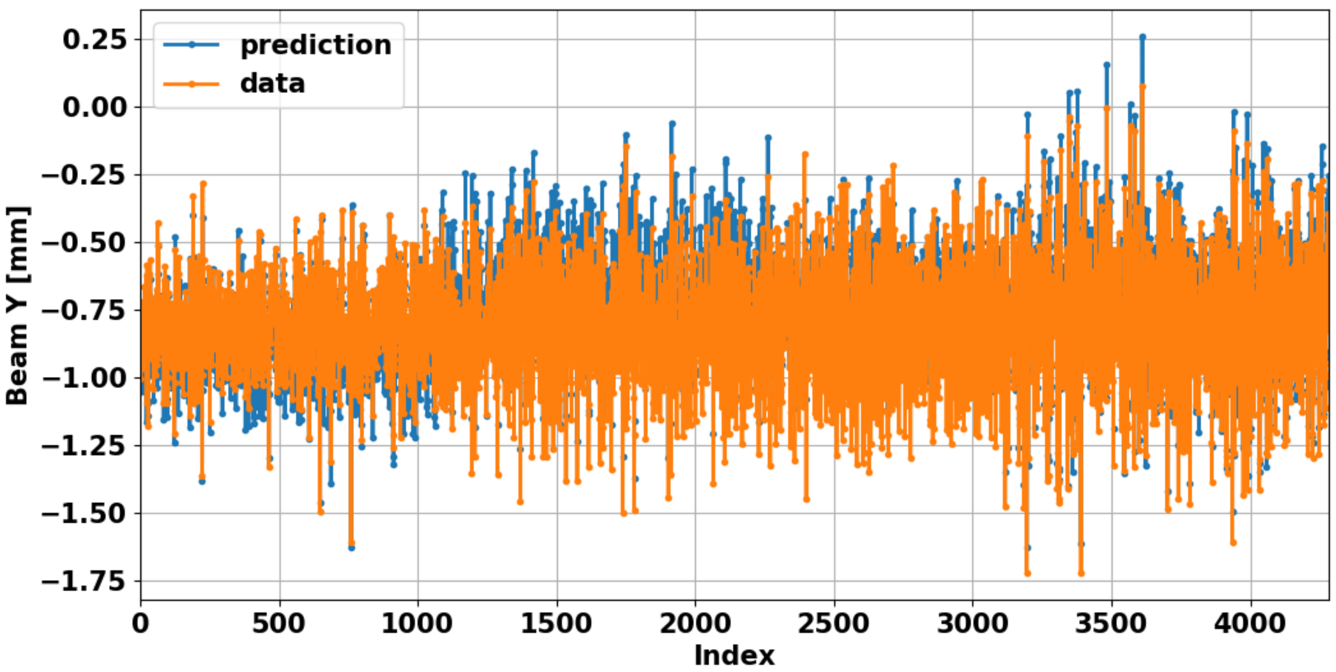
Testing for randomly selected large data set with different beam settings



Beam centroid Y prediction

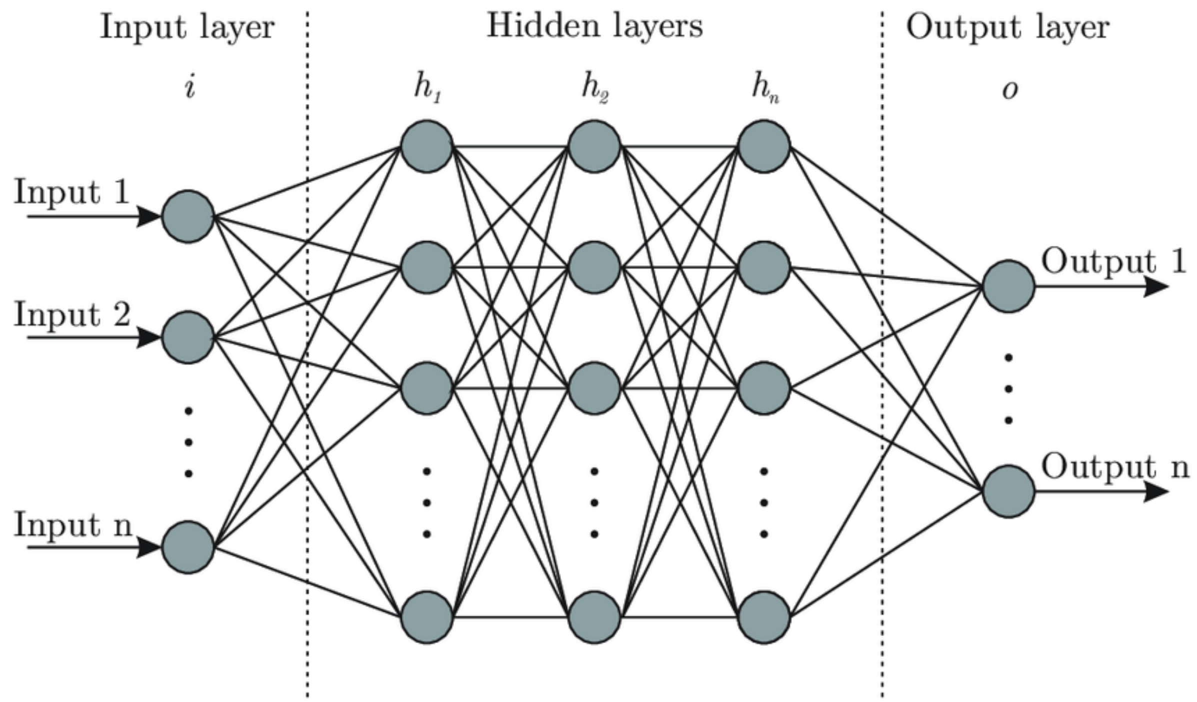




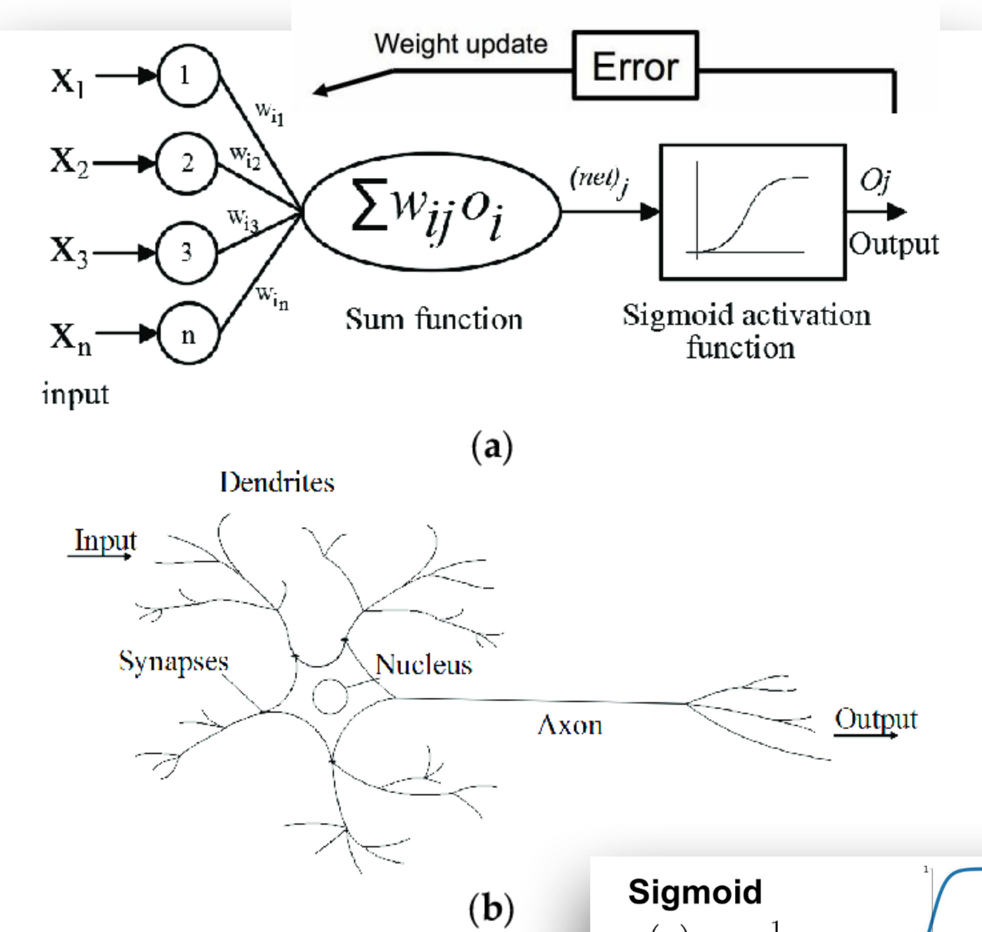


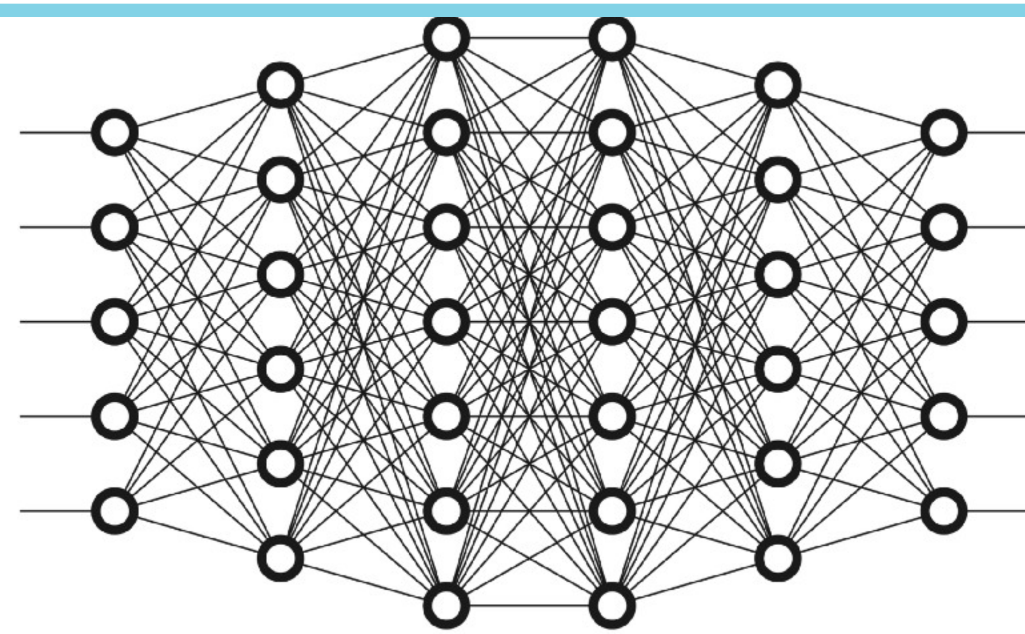
The predictions are accurate as +/- 0.05 mm in X and +/- 0.07 mm in Y

Neural Network Applications



Brief Introduction to Neural Network





Input

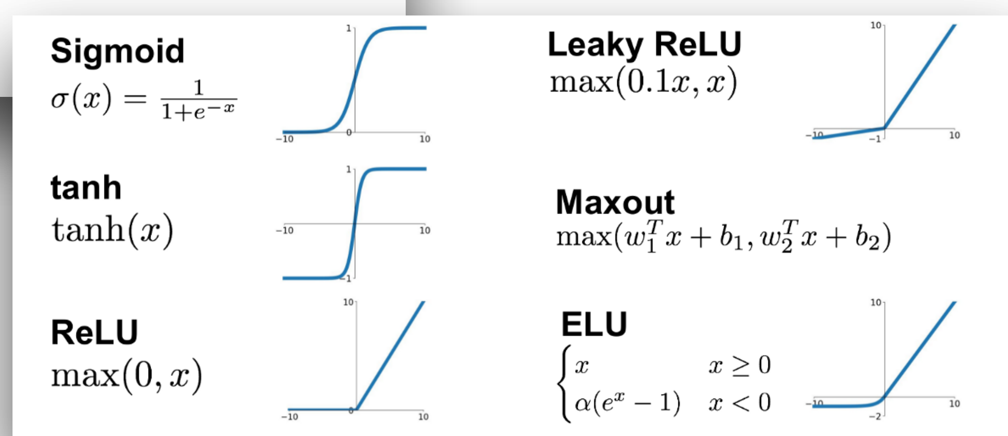
Output

Hidden Layers

$$\boxed{w_{new} = w_{old} + \eta \cdot \nabla Error}$$

Weights are updated according to the backpropagation algorithm

Activation function



Example of an activation function

$$\frac{1}{1 + \exp\left(-\sum_j w_j x_j - b\right)}.$$

Network tuning

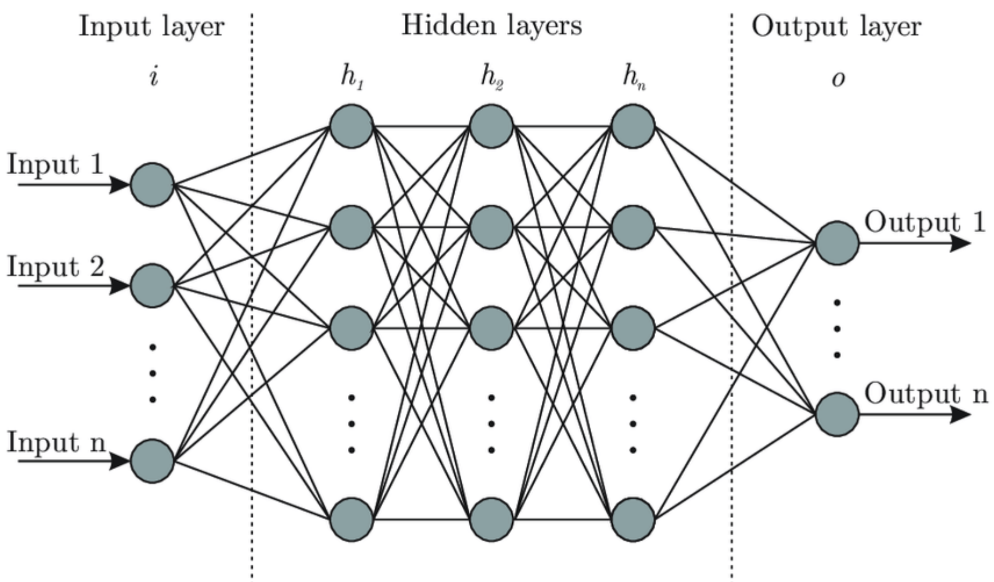
- » **Learning rate**
- » **Number of nodes**
- » **Number of hidden layers**
- » **Bias**
- » **Batch size**
- » **Patient and Luck!**

Identifying/predicting Incidents from the Muon Monitor Data

MOTIVATION: A tool to predict and identify incidents or anomalies by taking account muon monitor signals

Muon Monitor Signals

81x3 pixels



Status

243 Nodes

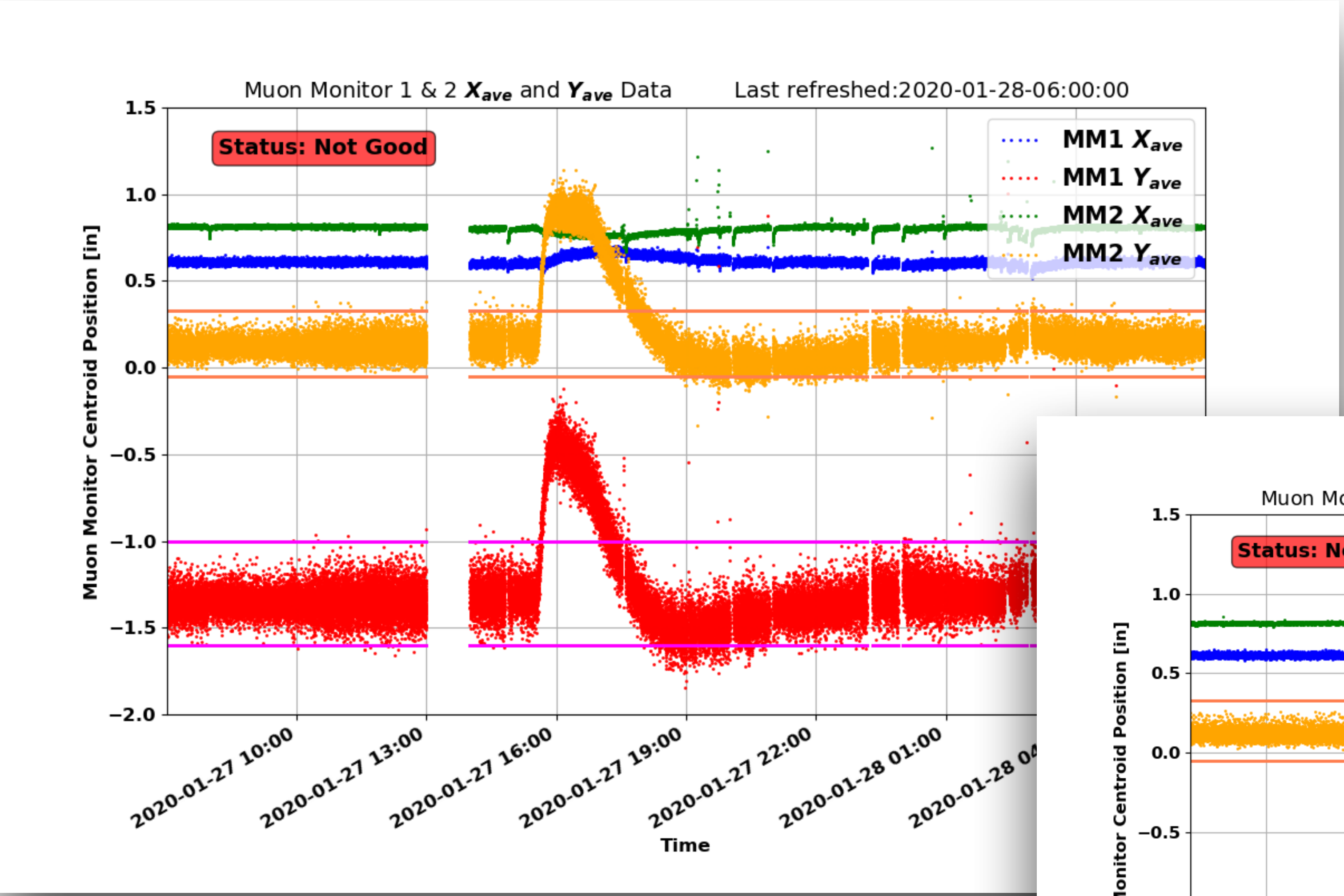
165 Nodes

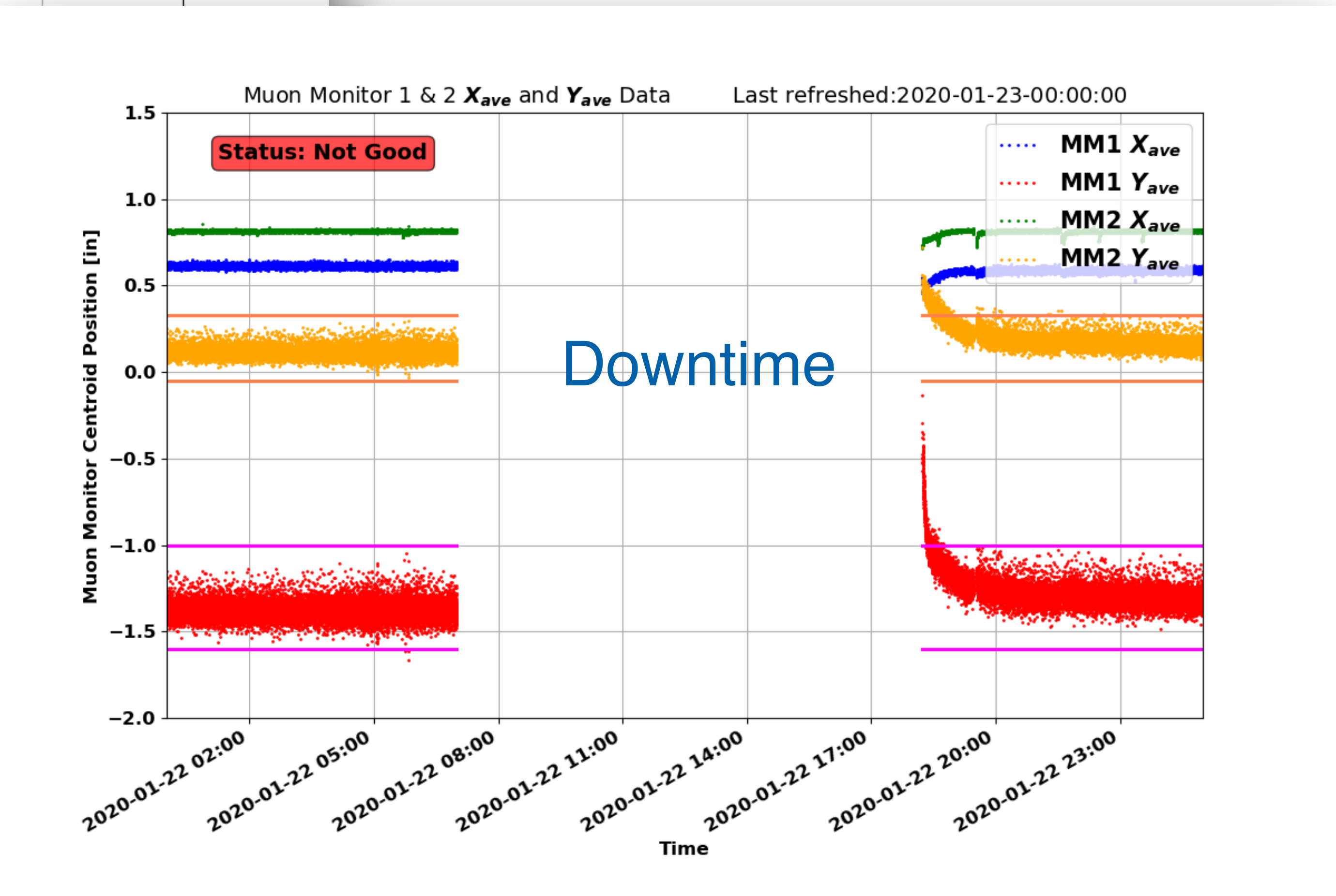
3 Nodes

Identifying/predicting Incidents

Identifying/predicting Gas Bottle Change or After Down Time Status

Muon Monitor Response After the Gas Bottle Changes





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Identifying/predicting Incidents

Muon Monitor Data

	mm1pix0	mm1pix1	mm1pix2	mm1pix3	mm1pix4	mm1pix5	mm1pix6	mm1pix7	mm1pix8	mm1pix9	mm1pix10	mm1pix11	...	mm2pix69	mm2pix70	mm2pix71	mm2pix72	mm2pix73	mm2pix74	mm2pix75	mm2pix76	mm2pix77	mm2pix78	mm2pix79	mm2pix80
4549	-2.12950	-2.29101	-2.29508	-1.88962	-1.36845	-0.787263	-0.513025	-0.981087	-1.59398	-1.84693	-2.06724	-2.03526	...	-2.76439	-4.30909	-5.65307	-6.47068	-7.05677	-7.08356	-5.89329	-4.15643	-2.66779	-2.71071	-4.38492	-5.74972
3571	-2.12950	-2.29782	-2.31198	-1.90902	-1.38508	-0.796875	-0.513331	-0.980186	-1.59276	-1.84753	-2.07357	-2.04804	...	-2.78029	-4.33801	-5.69269	-6.51591	-7.11847	-7.15474	-5.95995	-4.21189	-2.70817	-2.72249	-4.41288	-5.79243
7082	-2.15853	-2.32322	-2.32796	-1.91529	-1.38631	-0.797185	-0.521289	-0.997003	-1.61962	-1.87459	-2.09619	-2.06386	...	-2.80200	-4.37022	-5.73203	-6.56385	-7.16178	-7.19002	-5.97952	-4.21726	-2.70632	-2.74350	-4.45202	-5.84009
3019	-2.21444	-2.37929	-2.37621	-1.94543	-1.39986	-0.802146	-0.528636	-1.016220	-1.66509	-1.93501	-2.16916	-2.12867	...	-2.84757	-4.45251	-5.85475	-6.68928	-7.26649	-7.25742	-6.00368	-4.21845	-2.69831	-2.78965	-4.53715	-5.95489
215	-2.13691	-2.29751	-2.30061	-1.89350	-1.36968	-0.788813	-0.597508	-1.031240	-1.60710	-1.85264	-2.07116	-2.03739	...	-3.08364	-4.45102	-5.69062	-6.49088	-7.07694	-7.10467	-5.90552	-4.16567	-2.67642	-3.02297	-4.51664	-5.79243
5155	-2.20301	-2.37402	-2.37713	-1.94872	-1.40417	-0.804006	-0.522820	-1.006310	-1.64617	-1.91968	-2.15498	-2.12411	...	-2.82616	-4.42329	-5.82400	-6.66546	-7.25819	-7.26025	-6.01561	-4.22889	-2.70262	-2.76737	-4.50235	-5.92024
999	-2.19405	-2.31517	-2.30368	-1.89231	-1.36968	-0.788193	-0.555267	-1.067570	-1.70629	-1.91878	-2.09800	-2.04317	...	-2.94022	-4.55538	-5.87989	-6.60064	-7.11698	-7.11033	-5.90583	-4.16567	-2.67396	-2.88769	-4.64899	-5.98120
1039	-2.20424	-2.32663	-2.31567	-1.90275	-1.37707	-0.793154	-0.556185	-1.068780	-1.71331	-1.92930	-2.11036	-2.05595	...	-2.94573	[illegible]	-5.90650	-6.63471	-7.14932	-7.14214	-5.93518	-4.18655	-2.69214	-2.89406	-4.65614	-6.00224
6905	-2.12734	-2.28915	-2.29569	-1.88932	-1.36814	-0.787573	-0.514249	-0.980486	-1.59459	-1.84723	-2.06573	-2.03343	...	[illegible]	[illegible]	-5.64922	-6.46676	-7.05617	-7.08451	-5.89482	-4.15822	-2.67056	-2.70403	-4.38274	-5.75282
9594	-2.11252	-2.28357	-2.30030	-1.90216	-1.38107	-0.794704	-0.510270	-0.974480	-1.58391	-1.83641	-2.06332	-2.03830	...	[illegible]	-4.30194	-5.64922	-6.47068	-7.06893	-7.11254	-5.92815	-4.19102	-2.69492	-2.69925	-4.37963	-5.75127
6565	-2.17058	-2.32105	-2.31198	-1.89141	-1.36599	-0.784782	-0.524044	-1.003610	-1.63152	-1.88030	-2.09197	-2.04560	...	[illegible]	-4.41941	-5.78821	-6.60787	-7.17839	-7.17773	-5.94558	-4.18327	-2.67981	-2.78074	-4.50577	-5.88867
7641	-2.12981	-2.29503	-2.30491	-1.90007	-1.37645	-0.793464	-0.513331	-0.982889	-1.59673	-1.84934	-2.07176	-2.04134	...	-2.76592	-4.31655	-5.66549	-6.48606	-7.08228	-7.11569	-5.92418	-4.18356	-2.68998	-2.71039	-4.39082	-5.76705
7878	-2.12487	-2.29225	-2.30553	-1.90365	-1.38138	-0.794704	-0.511494	-0.979285	-1.59185	-1.84543	-2.06754	[illegible]	...	-2.76042	-4.31506	-5.66608	-6.48968	-7.08465	-7.12325	-5.93396	-4.19072	-2.69245	-2.70562	-4.39206	-5.76613
2373	-2.22247	-2.37712	-2.36392	-1.93170	-1.39000	-0.797185	-0.532309	-1.026730	-1.68065	-1.94733	-2.16916	[illegible]	...	-2.86683	-4.48322	-5.88432	-6.70195	-7.25848	-7.23694	-5.98656	-4.21100	-2.69861	-2.81161	-4.55734	-5.97965
3269	-2.12827	-2.29255	-2.30184	-1.89619	-1.37430	-0.790674	-0.512719	-0.979586	-1.59276	-1.84693	-2.06875	[illegible]	...	-2.76623	-4.31476	-5.66194	-6.48003	-7.07308	-7.10655	-5.91317	-4.17343	-2.68043	-2.70976	-4.39051	-5.76396
5042	-2.13661	-2.30154	-2.31136	-1.90365	-1.37892	-0.792844	-0.524350	-0.985592	-1.60039	-1.85445	[illegible]	-2.04804	...	-2.81393	-4.33891	-5.68678	-6.50626	-7.10215	-7.13648	-5.93824	-4.19012	-2.69183	-2.74764	-4.41381	-5.79119
4469	-2.12363	-2.28667	-2.29508	-1.89081	-1.36845	-0.787883	-0.512106	-0.978384	-1.58971	-1.84212	[illegible]	-2.03252	...	-2.76653	-4.31088	-5.65455	-6.47219	-7.06567	-7.09585	-5.90491	-4.16836	-2.68135	-2.71007	-4.37870	-5.75096
4173	-2.11282	-2.27924	-2.29446	-1.89440	-1.37522	-0.791604	-0.509658	-0.972679	-1.58055	-1.83340	[illegible]	-2.03222	...	-2.74604	-4.29210	-5.63858	-6.45651	-7.05083	-7.08923	-5.90246	-4.16806	-2.67889	-2.68875	-4.37031	-5.73982
9318	-2.12641	-2.29225	-2.30184	-1.89857	-1.37645	-0.792534	-0.512719	-0.981087	-1.59307	[illegible]	-2.06784	-2.03830	...	-2.76133	-4.31207	-5.65691	-6.47792	-7.07249	-7.10718	-5.91714	-4.17969	-2.68536	-2.70721	-4.39020	-5.76241
3610	-2.12888	-2.29379	-2.30460	-1.89917	-1.37676	-0.792224	-0.513637	-0.980787	-1.59368	[illegible]	-2.06935	-2.04104	...	-2.76470	-4.31804	-5.67022	-6.48938	-7.08198	-7.11443	-5.92051	-4.17760	-2.68351	-2.70848	-4.39455	-5.77015
9156	-2.11252	-2.27521	-2.28893	-1.88574	-1.36537	-0.785402	-0.509045	-0.974781	[illegible]	[illegible]	-2.05458	-2.02644	...	-2.74146	-4.28077	-5.61669	-6.43028	-7.02265	-7.05837	-5.87494	-4.14868	-2.66779	-2.68716	-4.35758	-5.71940
7885	-2.14587	-2.31114	-2.32089	-1.91350	-1.38569	-0.797185	-0.517004	-0.988294	[illegible]	-1.86166	-2.08443	-2.05473	...	-2.78824	-4.34696	-5.70482	-6.53340	-7.13478	-7.16892	-5.96852	-4.21487	-2.70879	-2.73045	-4.42717	-5.81007
4855	-2.11097	-2.27459	-2.28493	-1.88484	-1.36660	-0.786333	-0.510270	-0.972378	[illegible]	-1.83190	-2.05307	-2.02522	...	-2.75002	-4.28494	-5.62172	-6.43540	-7.02621	-7.06026	-5.87769	-4.15077	-2.66348	-2.69416	-4.35882	-5.71847
49	-2.11591	-2.27800	-2.28832	-1.88664	-1.36568	-0.786953	-0.555879	-0.984390	-1.58544	-1.83581	-2.05789	-2.02796	...	-2.92952	-4.32907	-5.64153	-6.45108	-7.03541	-7.06656	-5.88350	-4.15345	-2.66902	-2.84695	-4.39299	-5.73270
235	-2.12888	-2.29286	-2.29999	-1.89619	-1.37184	-0.790363	-0.597815	-1.033940	-1.60558	-1.84843	-2.06905	-2.03921	...	-3.07814	-4.45967	-5.69624	-6.49118	-7.07961	-7.10939	-5.91347	-4.17581	-2.68289	-3.02456	-4.52690	-5.78810
1063	-2.19776	-2.32229	-2.31167	-1.89977	-1.37492	-0.792224	-0.553124	-1.063970	-1.70690	-1.92479	-2.10523	-2.05139	...	-2.92921	-4.54703	-5.88048	-6.61119	-7.12707	-7.12325	-5.91684	-4.17522	-2.68197	-2.87559	-4.63439	-5.97934
747	-2.15761	-2.28977	-2.28924	-1.88425	-1.36383	-0.786023	-0.563531	-1.070280	-1.68462	-1.88150	-2.06905	-2.02856	...	-2.95551	-4.54285	-5.81246	-6.51802	-7.05024	-7.06593	-5.87586	-4.14629	-2.66348	-2.90552	-4.62880	-5.90043
4470	-2.09615	-2.26158	-2.27479	-1.87768	-1.36137	-0.783232	-0.504760	-0.964570	-1.56865	-1.81897	-2.04191	-2.01579	...	-2.73228	-4.26318	-5.59836	-6.41219	-7.00219	-7.04073	-5.86546	-4.14212	-2.66008	-2.67474	-4.33893	-5.69773
7227	-2.11468	-2.27738	-2.28678	-1.88514	-1.36599	-0.785712	-0.510270	-0.975982	-1.58544	-1.83701	-2.05608	-2.02491	...	-2.74237	-4.28196	-5.61935	-6.43450	-7.02473	-7.05711	-5.87678	-4.14838	-2.66348	-2.68811	-4.35633	-5.71909
4034	-2.14834	-2.31145	-2.31782	-1.90872	-1.38200	-0.795945	-0.517922	-0.989195	-1.60741	-1.86316	-2.08533	-2.05443	...	-2.78702	-4.34696	-5.70452	-6.52918	-7.12114	-7.14907	-5.94803	-4.19698	-2.69461	-2.73299	-4.42468	-5.80543
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...

Start of the training

```
Train on 7263 samples, validate on 3114 samples
Epoch 1/200
7263/7263 [==============================] - 0s 45us/sample - loss: 0.9334 - accuracy: 0.5773 - val_loss: 0.8918 - val_accuracy: 0.5867
Epoch 2/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.8963 - accuracy: 0.5729 - val_loss: 0.9349 - val_accuracy: 0.5867
Epoch 3/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.8871 - accuracy: 0.6175 - val_loss: 0.8358 - val_accuracy: 0.5867
Epoch 4/200
7263/7263 [==============================] - 0s 22us/sample - loss: 0.8607 - accuracy: [illegible] - val_loss: 0.7989 - val_accuracy: 0.5867
Epoch 5/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.8025 - accuracy: 0.6590 - val_loss: 0.8591 - val_accuracy: 0.7046
Epoch 6/200
7263/7263 [==============================] - 0s 21us/sample - loss: [illegible] - accuracy: 0.7307 - val_loss: 0.7179 - val_accuracy: 0.8388
Epoch 7/200
7263/7263 [==============================] - 0s 21us/sample - loss: [illegible] - accuracy: 0.7597 - val_loss: 0.6434 - val_accuracy: 0.7193
Epoch 8/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.6340 - accuracy: 0.7871 - val_loss: 0.5990 - val_accuracy: 0.8035
Epoch 9/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.6172 - accuracy: 0.7931 - val_loss: 0.6287 - val_accuracy: 0.7036
Epoch 10/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.5382 - accuracy: 0.8207 - val_loss: 0.4923 - val_accuracy: 0.8529
Epoch 11/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.5097 - accuracy: 0.8258 - val_loss: 0.5284 - val_accuracy: 0.8751
Epoch 12/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.4859 - accuracy: 0.8305 - val_loss: 0.4518 - val_accuracy: 0.8757
Epoch 13/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.4524 - accuracy: 0.8448 - val_loss: 0.4100 - val_accuracy: 0.8215
Epoch 14/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.4260 - accuracy: 0.8524 - val_loss: 0.3921 - val_accuracy: 0.8722
Epoch 15/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.4088 - accuracy: 0.8582 - val_loss: 0.3742 - val_accuracy: 0.8818
Epoch 16/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.3929 - accuracy: 0.8582 - val_loss: 0.3578 - val_accuracy: 0.8426
```

Identifying/predicting Incidents

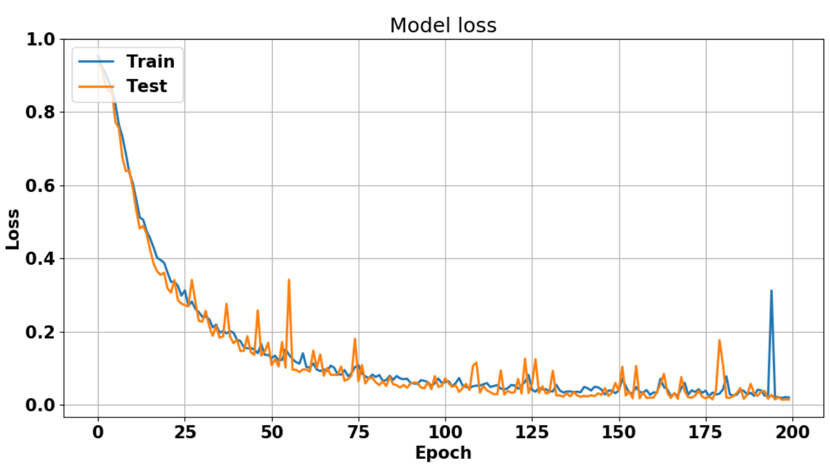
```
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0273 - accuracy: 0.9949 - val_loss: 0.0204 - val_accuracy: 0.9952
Epoch 183/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0292 - accuracy: 0.9937 - val_loss: 0.0480 - val_accuracy: 0.9923
Epoch 184/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.2947 - accuracy: 0.9368 - val_loss: 0.0201 - val_accuracy: 0.9978
Epoch 185/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0282 - accuracy: 0.9953 - val_loss: 0.0186 - val_accuracy: 0.9984
Epoch 186/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0243 - accuracy: 0.9956 - val_loss: 0.0271 - val_accuracy: 0.9981
Epoch 187/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0264 - accuracy: 0.99[illegible] - val_loss: 0.0181 - val_accuracy: 0.9968
Epoch 188/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0271 - accuracy: 0.9946 - val_loss: 0.0215 - val_accuracy: 0.9974
Epoch 189/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0230 - accuracy: 0.9960 - val_loss: 0.0196 - val_accuracy: 0.9978
Epoch 190/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0285 - accuracy: 0.9946 - val_loss: 0.0195 - val_accuracy: 0.9984
Epoch 191/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0243 - accuracy: 0.9960 - val_loss: 0.0299 - val_accuracy: 0.9968
Epoch 192/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.0304 - accuracy: 0.9934 - val_loss: 0.0347 - val_accuracy: 0.9952
Epoch 193/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0296 - accuracy: 0.9939 - val_loss: 0.0647 - val_accuracy: 0.9868
Epoch 194/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0342 - accuracy: 0.9928 - val_loss: 0.0161 - val_accuracy: 0.9984
Epoch 195/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0241 - accuracy: 0.9960 - val_loss: 0.0172 - val_accuracy: 0.9978
Epoch 196/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0300 - accuracy: 0.9927 - val_loss: 0.0490 - val_accuracy: 0.9894
Epoch 197/200
7263/7263 [==============================] - 0s 21us/sample - loss: 0.0570 - accuracy: 0.9807 - val_loss: 0.0798 - val_accuracy: 0.9753
Epoch 198/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.2692 - accuracy: 0.9336 - val_loss: 0.2183 - val_accuracy: 0.9056
Epoch 199/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0473 - accuracy: 0.9886 - val_loss: 0.0292 - val_accuracy: 0.9936
Epoch 200/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0296 - accuracy: 0.9942 - val_loss: 0.0168 - val_accuracy: 0.9987
```

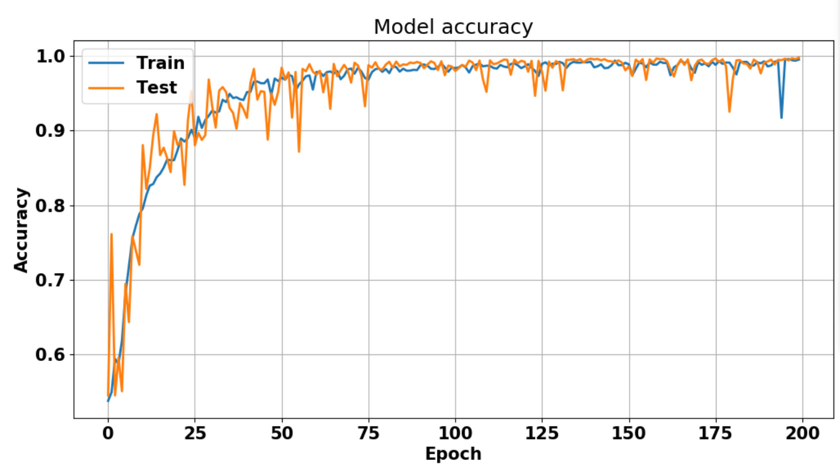
Training and validation in each epoch

Output

	gasB	normal	downT	predGasB	predNor	predDownT
4248	0.0	1.0	0.0	5.560883e-04	9.955161e-01	0.003928
6580	0.0	0.0	1.0	4.115437e-02	2.184273e-03	0.956661
5960	0.0	0.0	1.0	2.112069e-02	4.677800e-05	0.978833
4063	0.0	1.0	0.0	2.706660e-05	9.996575e-01	0.000315
4170	0.0	1.0	0.0	4.744743e-05	9.996727e-01	0.000280
6695	0.0	0.0	1.0	2.560753e-02	5.432077e-03	0.968960
4167	0.0	1.0	0.0	1.516400e-05	9.997737e-01	0.000211
5240	0.0	1.0	0.0	2.084184e-02	9.697281e-01	0.009430
3586	0.0	1.0	0.0	3.156578e-04	9.978682e-01	0.001816
1670	1.0	0.0	0.0	9.965866e-01	4.277346e-09	0.003413
2636	1.0	0.0	0.0	9.834563e-01	1.773778e-04	0.016366
9283	0.0	1.0	0.0	2.363441e-05	9.996248e-01	0.000352
5693	0.0	0.0	1.0	5.510638e-03	4.629294e-07	0.994489
7697	0.0	1.0	0.0	4.813714e-05	9.994815e-01	0.000470
6848	0.0	1.0	0.0	1.726739e-08	9.938573e-01	0.006143
4885	0.0	1.0	0.0	3.647148e-05	9.994612e-01	0.000502
6987	0.0	1.0	0.0	6.409470e-05	9.995772e-01	0.000359
1905	1.0	0.0	0.0	9.924038e-01	5.684391e-09	0.007596
361	1.0	0.0	0.0	9.997049e-01	5.836613e-12	0.000295
6981	0.0	1.0	0.0	1.021493e-05	9.998505e-01	0.000139
4921	0.0	1.0	0.0	1.316497e-04	9.987055e-01	0.001163
2064	1.0	0.0	0.0	9.937924e-01	1.132411e-06	0.006207
10054	0.0	1.0	0.0	1.057661e-04	9.994668e-01	0.000427
8536	0.0	1.0	0.0	1.509197e-05	9.997284e-01	0.000256
3183	0.0	1.0	0.0	8.964246e-04	9.907430e-01	0.008361
9365	0.0	1.0	0.0	1.410647e-04	9.984589e-01	0.001400
1580	1.0	0.0	0.0	9.947845e-01	6.307261e-09	0.005215
9504	0.0	1.0	0.0	9.882946e-05	9.987740e-01	0.001127
190	1.0	0.0	0.0	9.994029e-01	7.396588e-10	0.000597
447	1.0	0.0	0.0	9.997837e-01	5.109794e-13	0.000216
...	...	...	...	...	...	...
5349	0.0	1.0	0.0	5.329467e-03	9.933785e-01	0.001292
5723	0.0	0.0	1.0	2.808570e-02	1.404456e-07	0.971914
137	1.0	0.0	0.0	9.959538e-01	4.153644e-06	0.004042
5335	0.0	1.0	0.0	1.230800e-03	9.983526e-01	0.000416
4221	0.0	1.0	0.0	2.105590e-05	9.993468e-01	0.000632
296	1.0	0.0	0.0	9.997254e-01	1.119302e-11	0.000275
10159	0.0	1.0	0.0	5.361607e-05	9.994683e-01	0.000478
8740	0.0	1.0	0.0	1.718472e-05	9.996898e-01	0.000293
5691	0.0	0.0	1.0	5.813967e-03	5.042001e-08	0.994186
8769	0.0	1.0	0.0	1.697518e-04	9.978683e-01	0.001962
5872	0.0	0.0	1.0	2.539637e-02	1.043655e-05	0.974593
6722	0.0	0.0	1.0	8.047541e-02	3.865379e-03	0.915659
5713	0.0	0.0	1.0	3.560955e-03	3.006403e-06	0.996436
5982	0.0	0.0	1.0	8.350230e-02	3.244622e-06	0.916494
1360	1.0	0.0	0.0	9.962084e-01	9.642172e-11	0.003792
6028	0.0	0.0	1.0	2.985809e-02	5.376980e-05	0.970088
5596	0.0	0.0	1.0	3.091521e-05	2.821582e-04	0.999687

Training performance



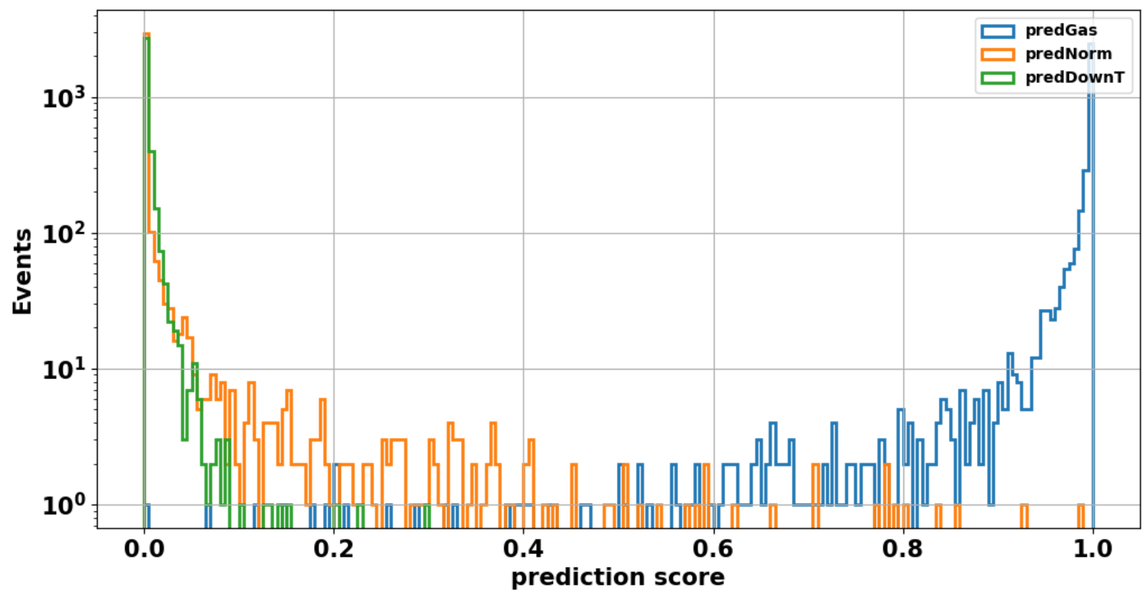


Results looks good and can predict incidents spill by spill

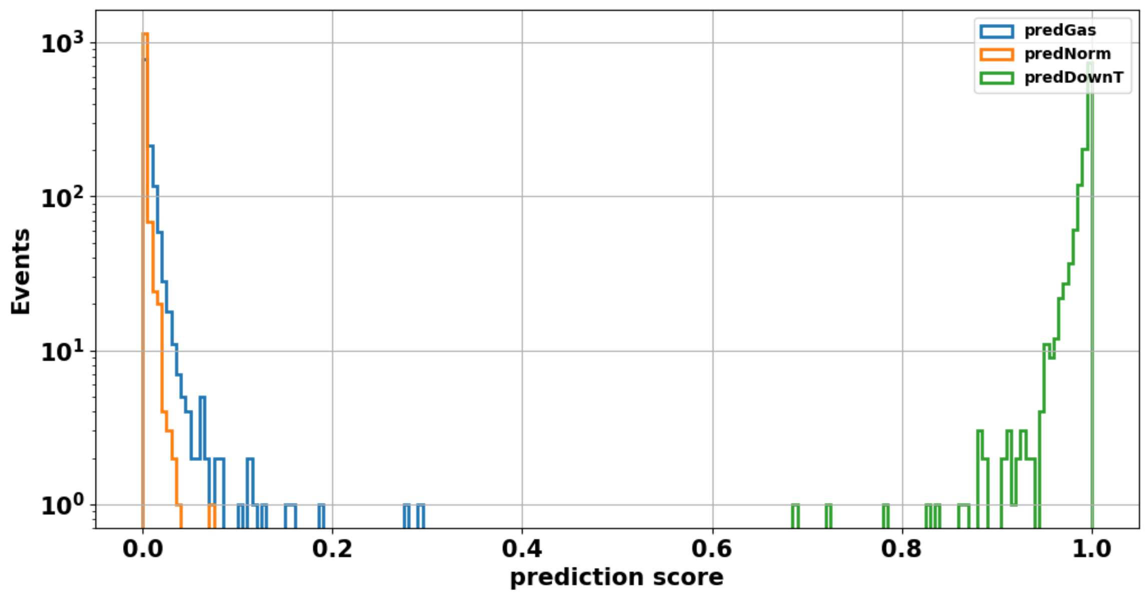
Fermilab

Identifying/predicting Incidents

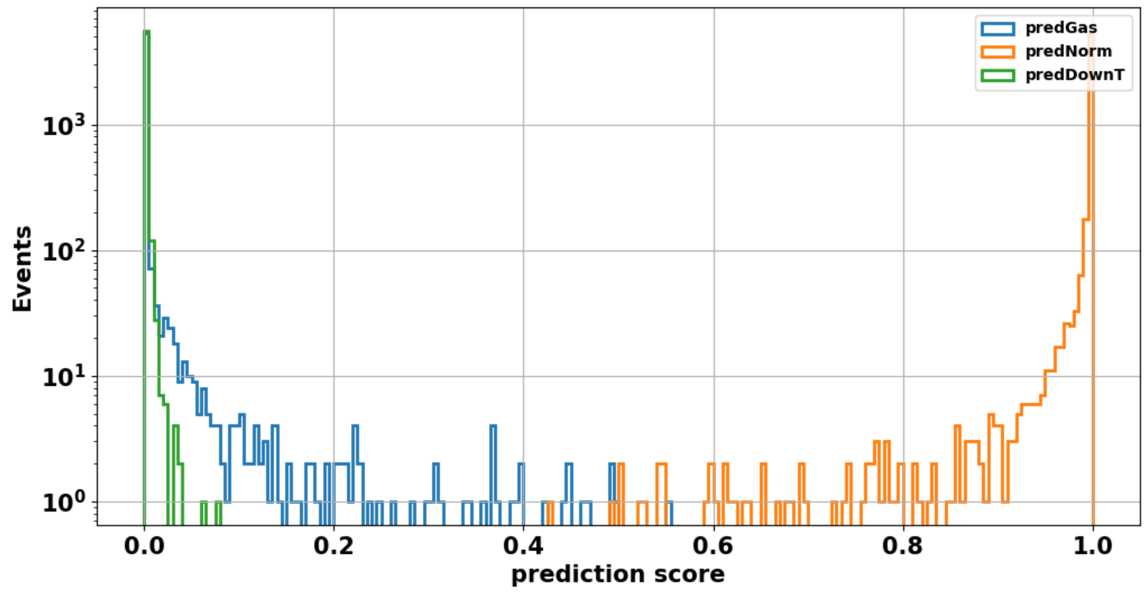
True Gas Bottle Events



True After Downtime Events

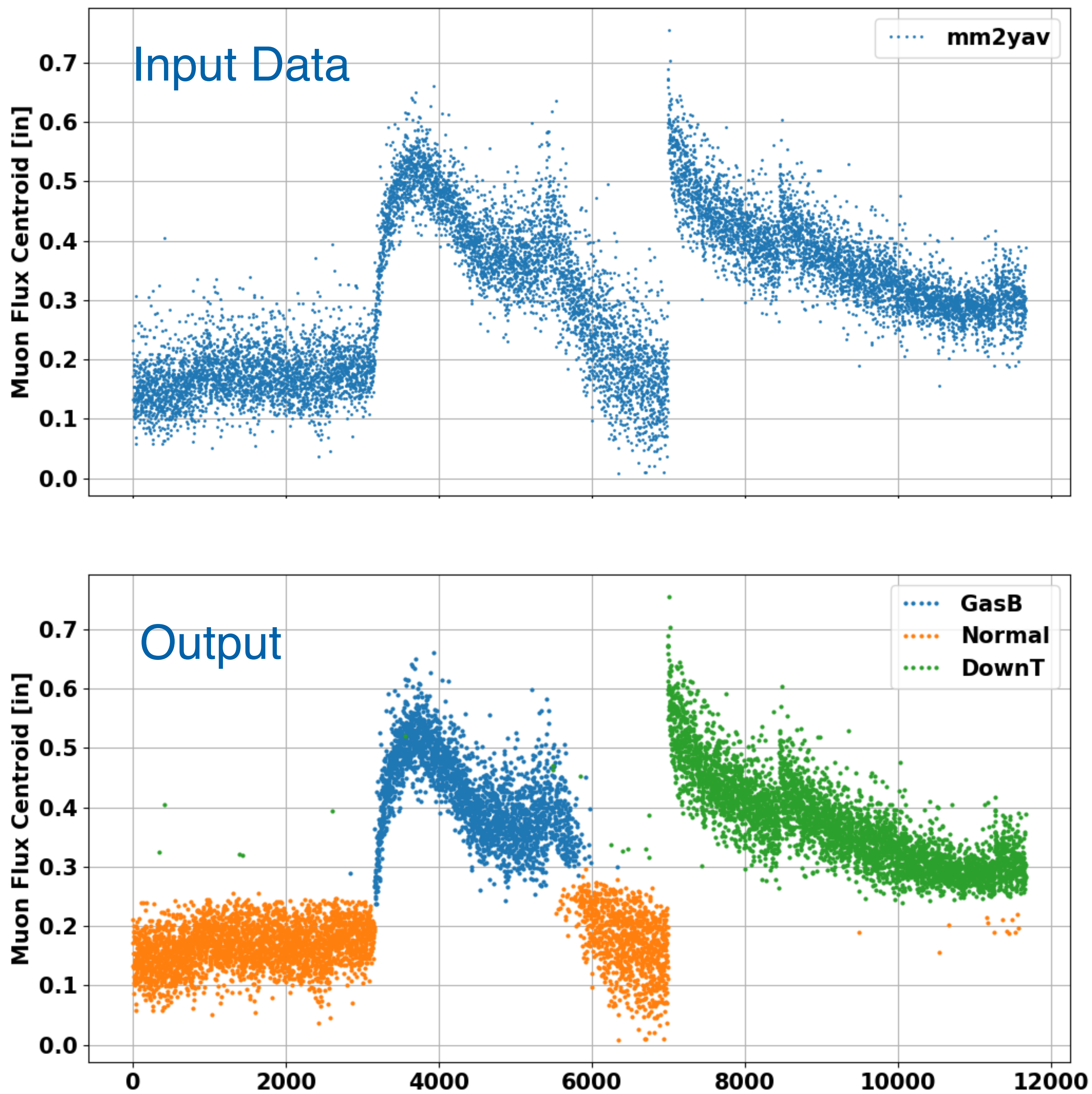


True Normal Events



- The separation looks good
- Can setup cutoff limits to categorize incidents to predict spill to spill
- Searching for more incidents as training data
- Looking for different incident categories from the past experiences

Identifying/predicting Incidents



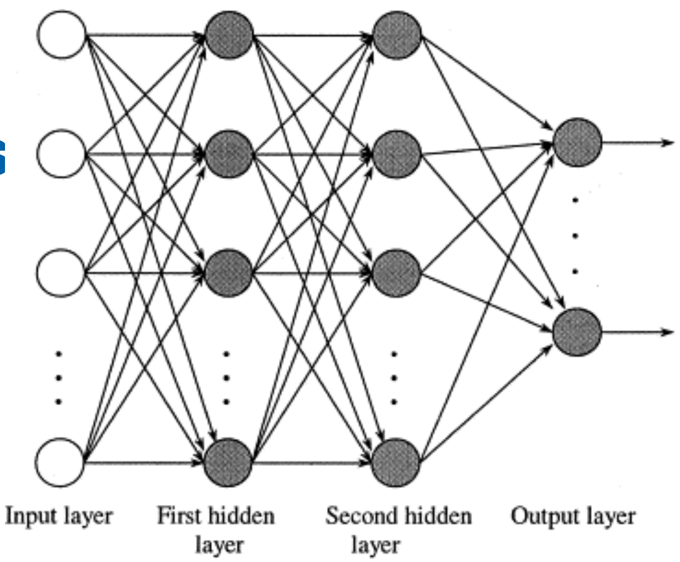
- Testing the model application with a combined data sets
- Model predictions has classified data as expected

Predicting Beam Parameters and Horn Current from Muon Monitor Data

MOTIVATION: A tool to predict beam parameters and horn current by taking account muon monitor signals

Muon Monitor Signals

81x3 pixels



243 Nodes | **400 Nodes** | **350 Nodes** | **4 Nodes**

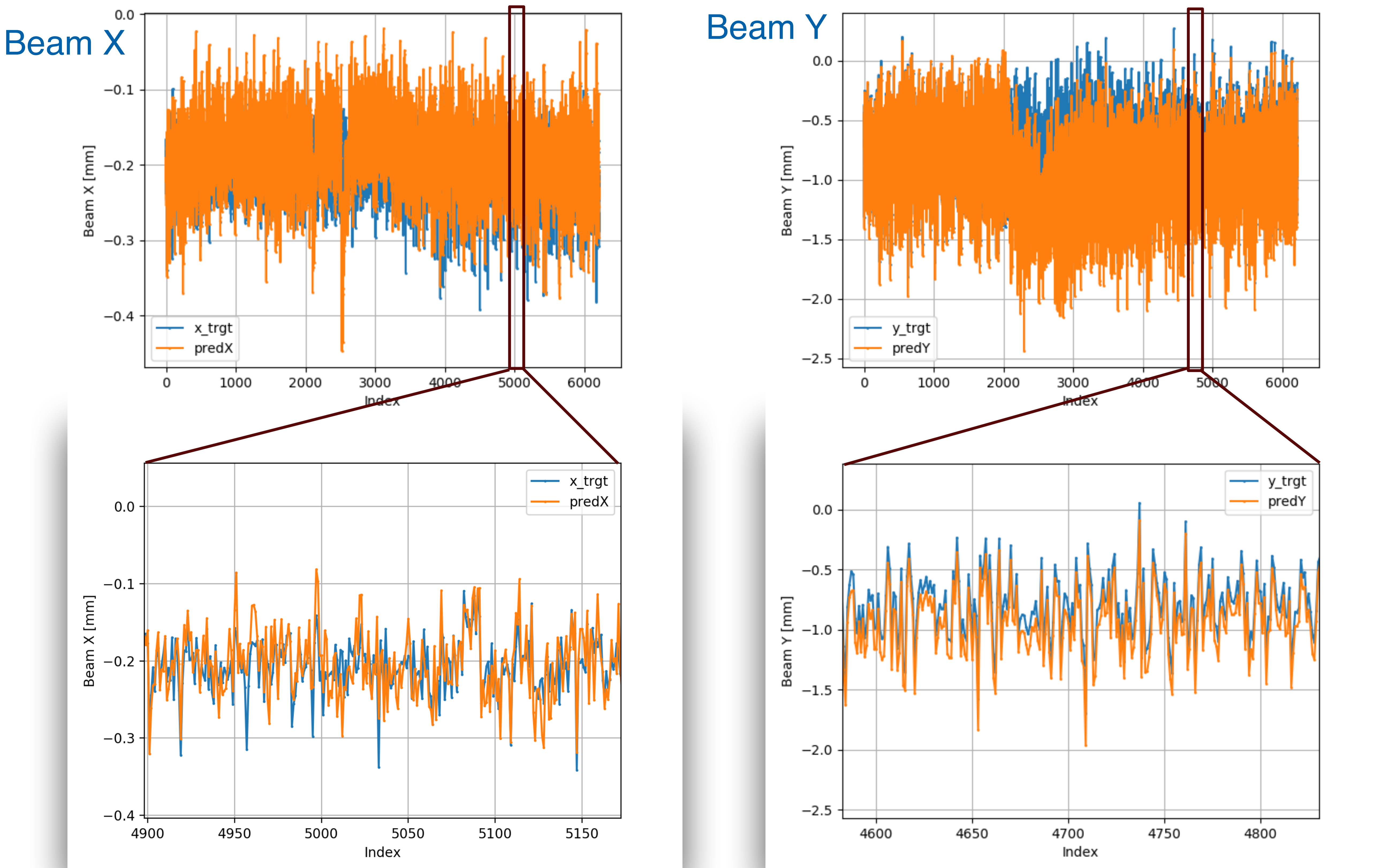
Output

Beam X and Y

Beam Intensity

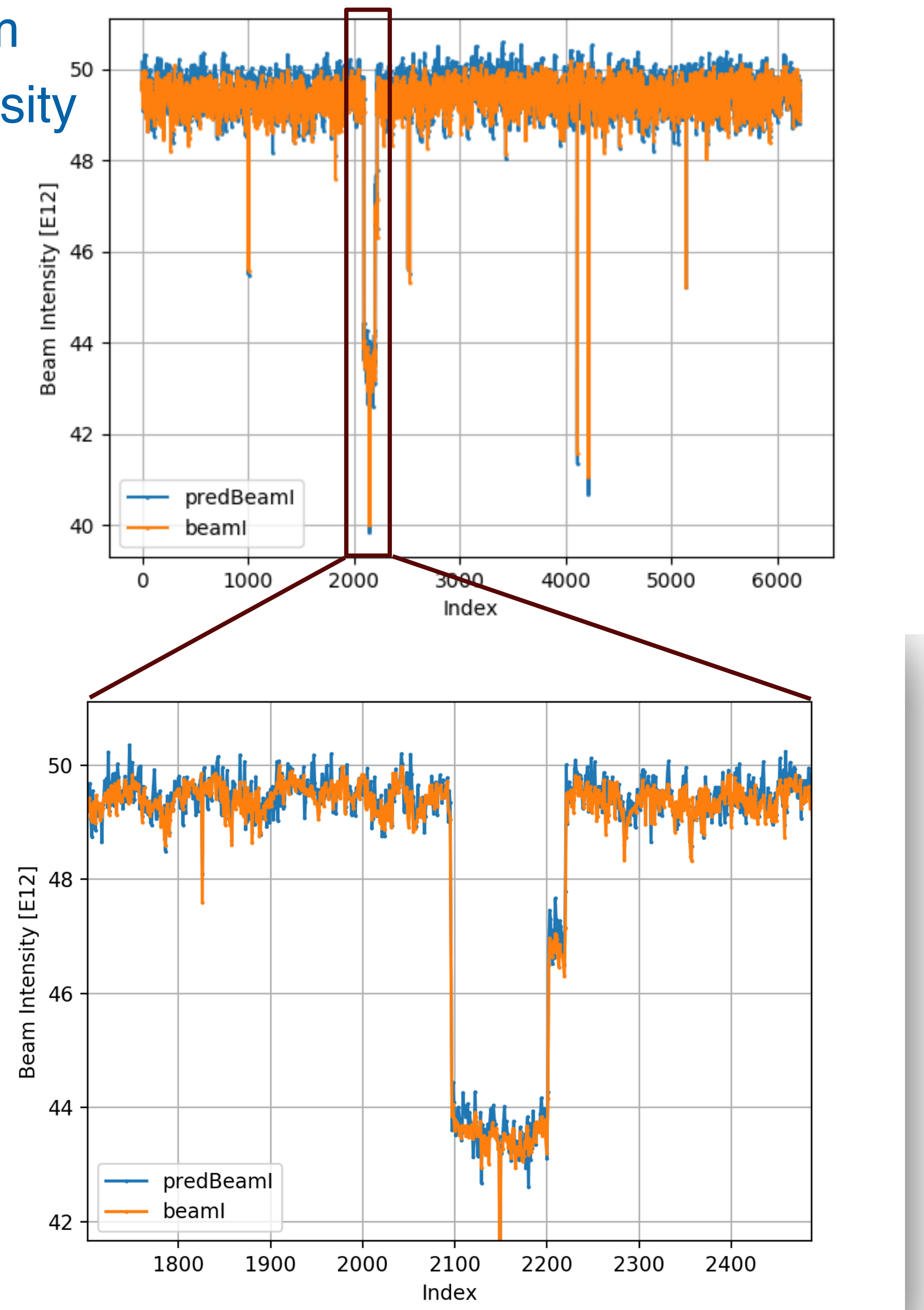
Horn Current

Beam centroid X and Y prediction

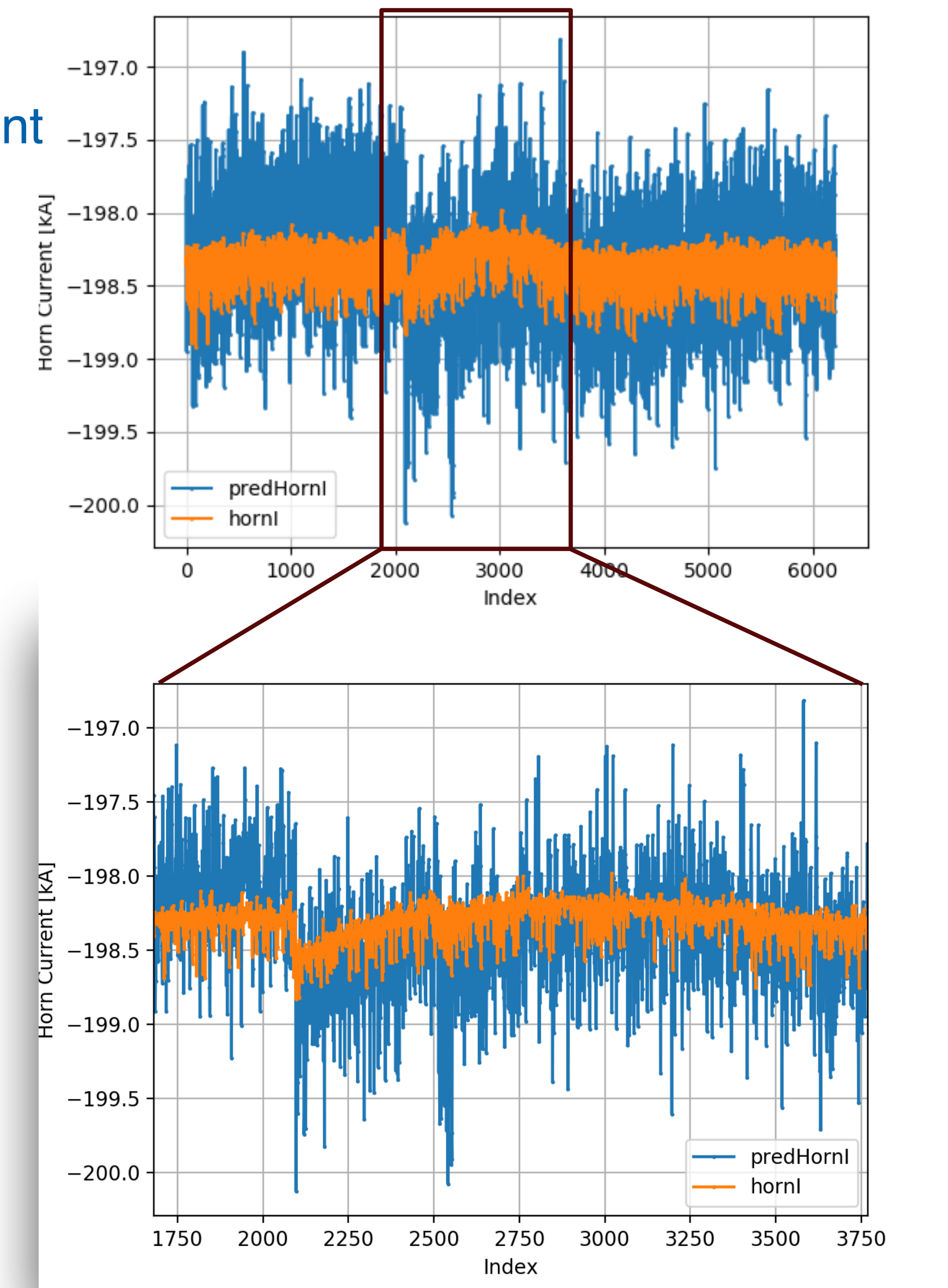


Beam Intensity and Horn Current

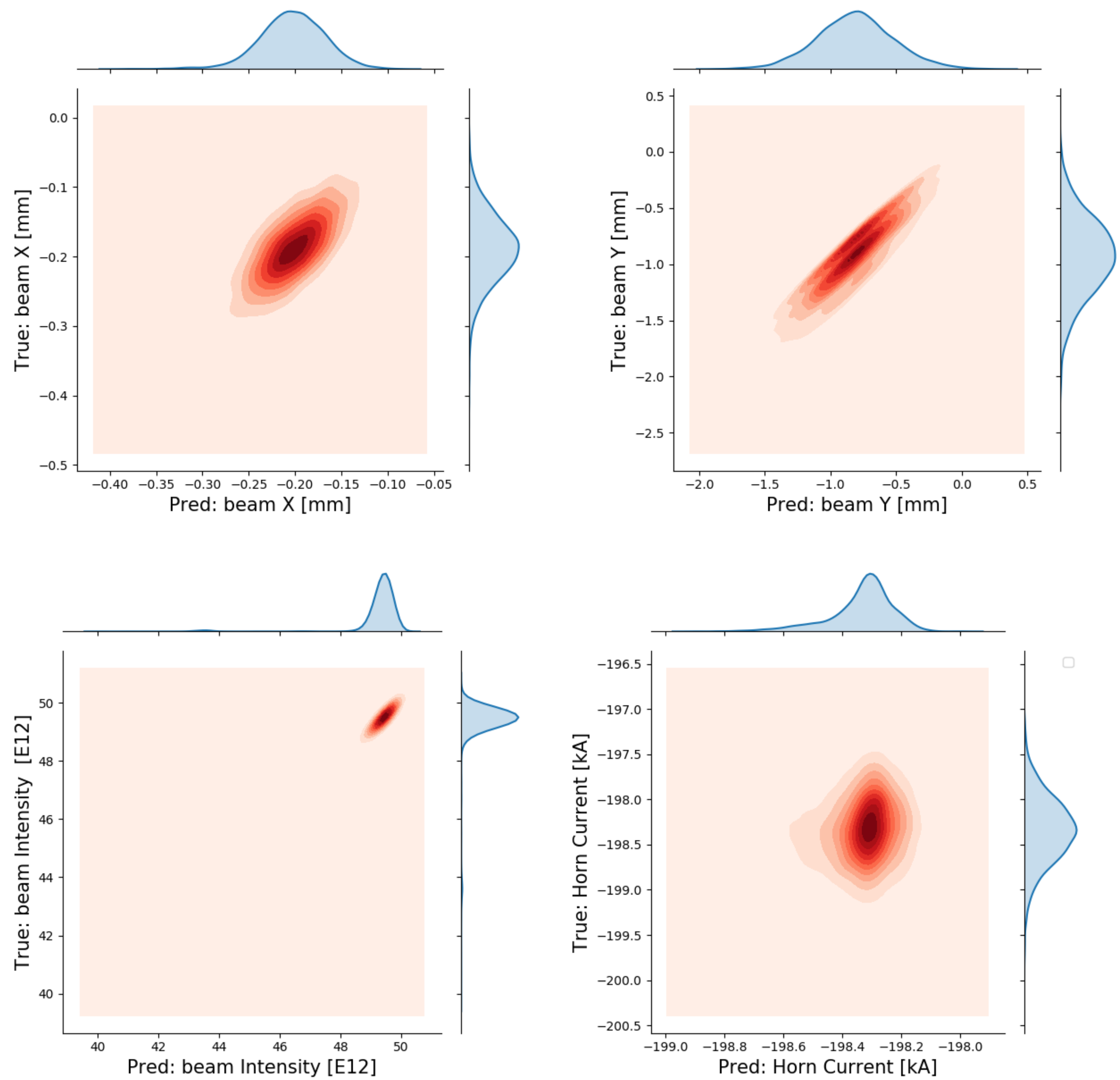
Beam Intensity



Horn Current



True vs Prediction



- We have a good predictions for beam position and beam intensity
- We have to optimize the models to achieve the best horn current predictions

Remarks on ML studies

- ML model prediction techniques are useful to monitor beam profile changes, beam quality and horn current related issues.
- Possible to recover missing data
- We have a capability to identify and predict incidents spill-by-spill
- ML tools are useful for the beam auto-tune and horn current tuning

Ongoing Projects and Plans

1. **Predicting beam quality cuts for NOvA by modeling muon monitor data**
   - **Application:** NOvA use limits of beam parameters to select NOvA good and bad runs/sub runs
   - **Advantage:** ML can be used to apply better selection rules, fast results, percentage confidence of the prediction. We are able to optimize selection rules to achieve the best selections
   - **Data:** 3xMM data + Gas Pressure + HV + ?

2. **Neutrino flux predictions from the muon signals**
   - **Application:** Flux predictions are depending on the beam parameters. Beam and horn current related systematics are independent from the real status
   - **Advantage:** ML will be able to predict the flux spill by spill and thats helpful to address the flux systematics
   - **Data:** inputs: 3xMM data + Gas Pressure + HV + Beam Intensity + ?
   - **MC:** Need to have simulation data to link MM data with flux

Muon Monitor is a very useful tool to make a communication bridge between accelerator physics and neutrino experiments

Thank you