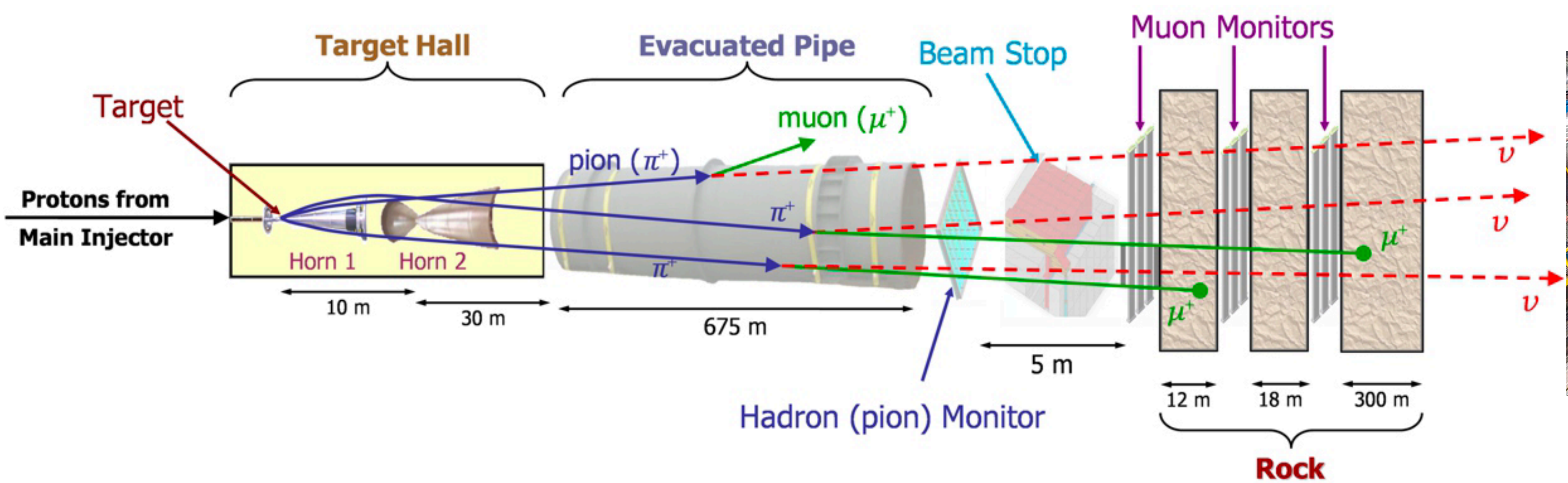
Fermilab U.S. DEPARTMENT OF ENERGY Office of Science

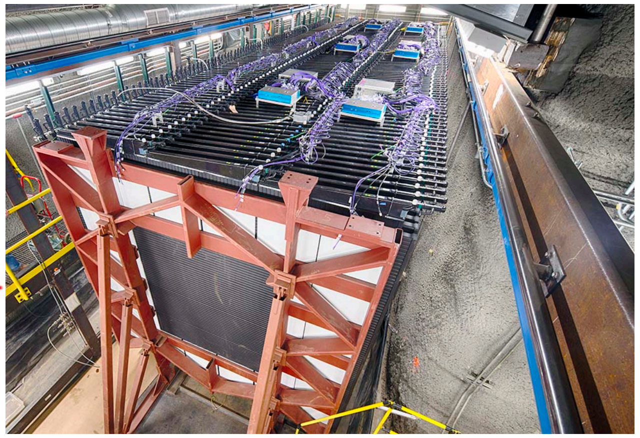
Machine Learning Applications with Muon Monitor Data

Athula Wickremasinghe
TSD Topical Meeting
21 June 2020

Importance of the Muon Monitors

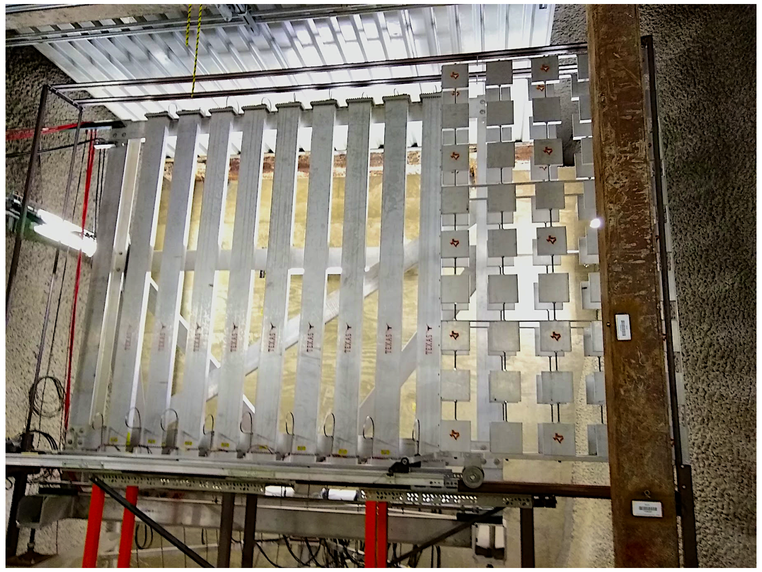


Neutrino Experiments



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

Helping to understand neutrino beam quality



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

Why Do We Need Muon Monitors?

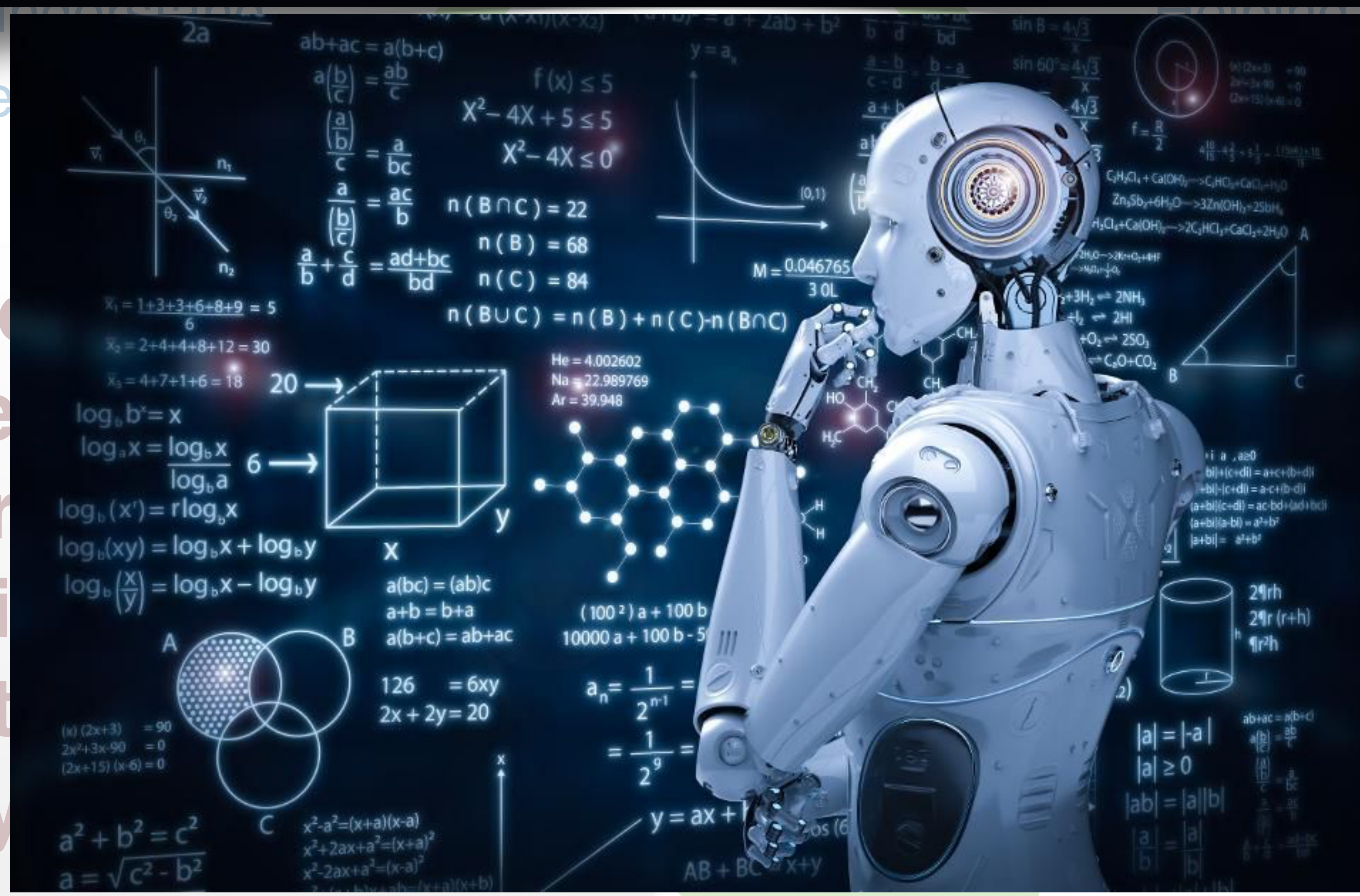
Recalling the neutrino production in the NuMI beam line

$$\text{proton} + \text{C} \rightarrow \text{Hadrons } (\pi^{\pm} \text{ or Kaon}) \rightarrow \nu + \mu^{\pm}$$

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

Helping to u... ...understand

beamline pe... ...beam



Getty Images. GETTY

Accelerat...
- **Beam pe...**
- **Horn cur...**
- **Beam ali...**
- **Target st...**
- **Probably... tune**

...eriments:
- **...eam stability**
- **...flux**
- **...errors**

Brief Introduction to ML

ML

Supervised Learning

Learning with a known output

Regression

- Forecasting
- Predicting
- New Insights
- Process Optimizing
- ....

Classification

- Categorizing
- Labeling
- Seperations
- ....

Unsupervised Learning

Learning without a known output

Clustering

- Finding hidden patterns
- Identifying data structure
- Grouping data
- ....

Dimensionality reduction

- Reduce dimensional space from a high dimensional space
- Reduce number of features to make it easy

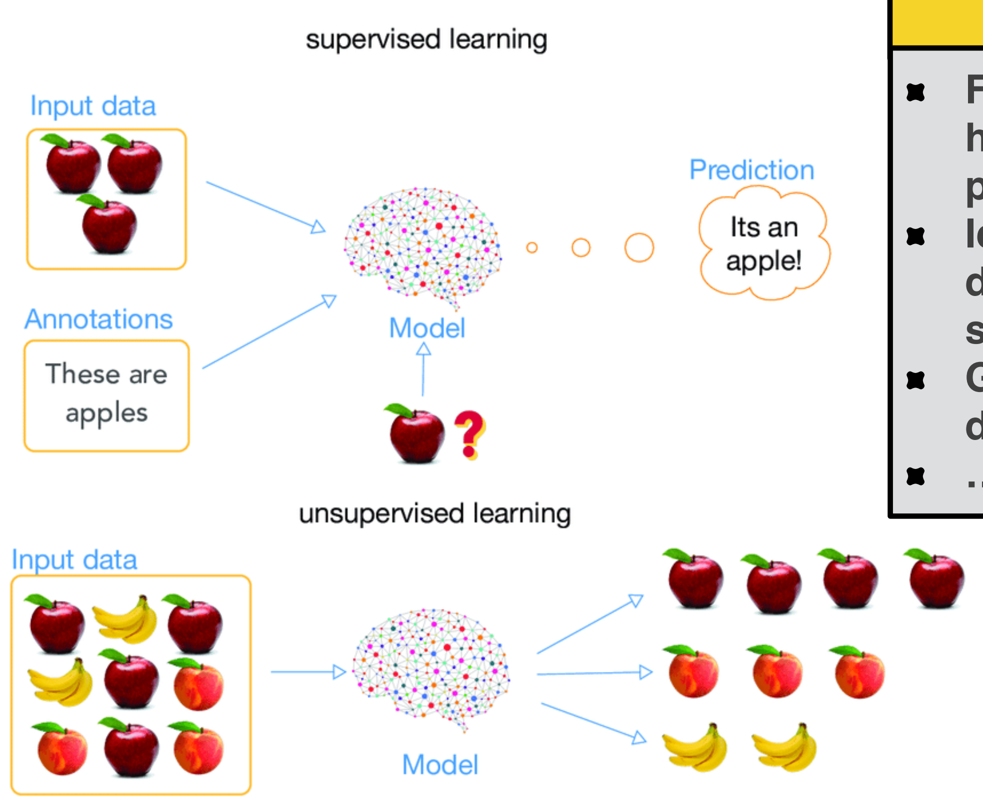
Semi supervised Learning

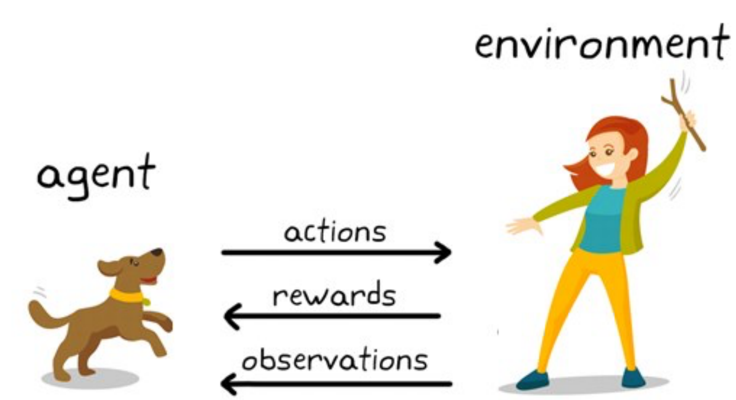
Learning from large data which has small set of data with known output

Reinforcement Learning

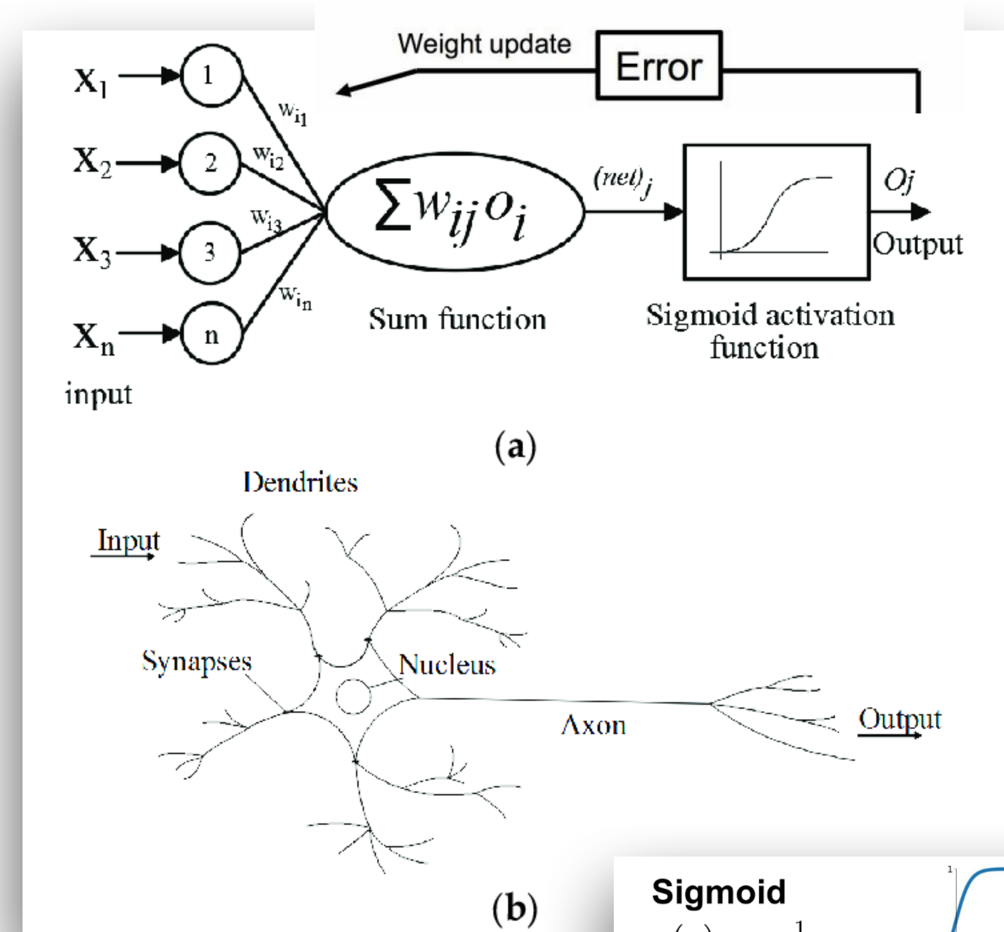
Self learning with some supervision

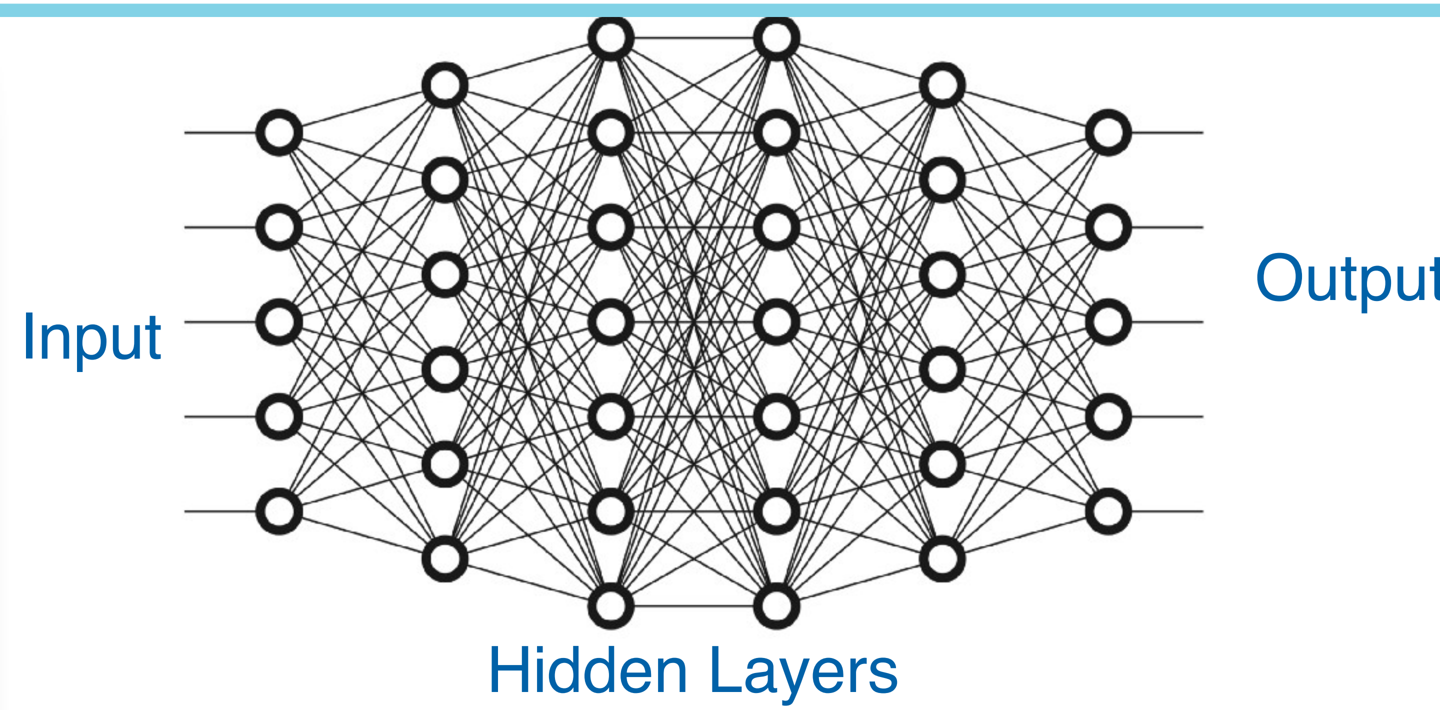
- Agent Learns itself by getting rewards
-
- ....





Brief Introduction to Neural Network

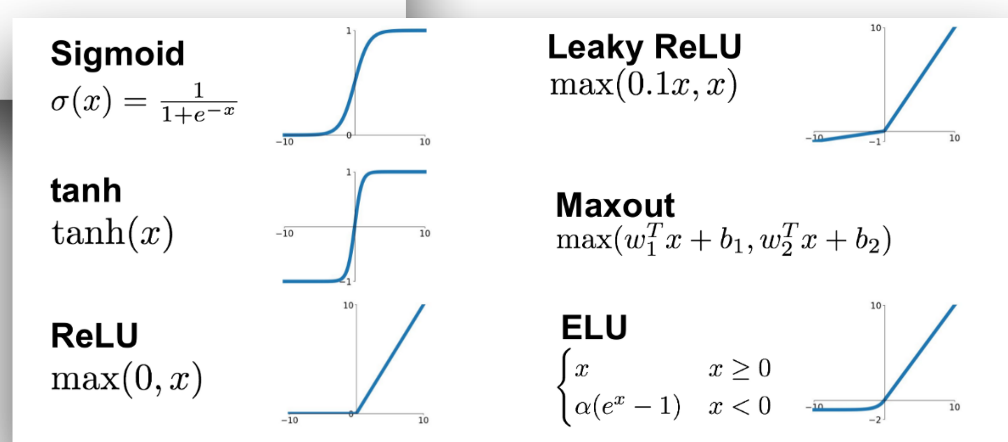




$$\boxed{w_{new} = w_{old} + \eta \cdot \nabla Error}$$

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!**

Linear Regression Model Applications

Variable Measurement

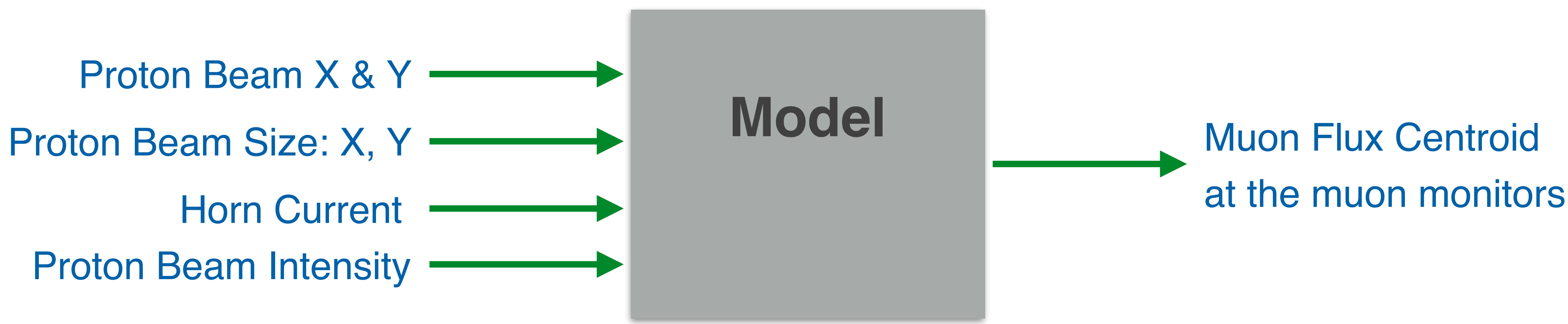
Residual coefficient

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

Regression coefficient

Predicting Muon Monitor Centroid from beam and horn parameters

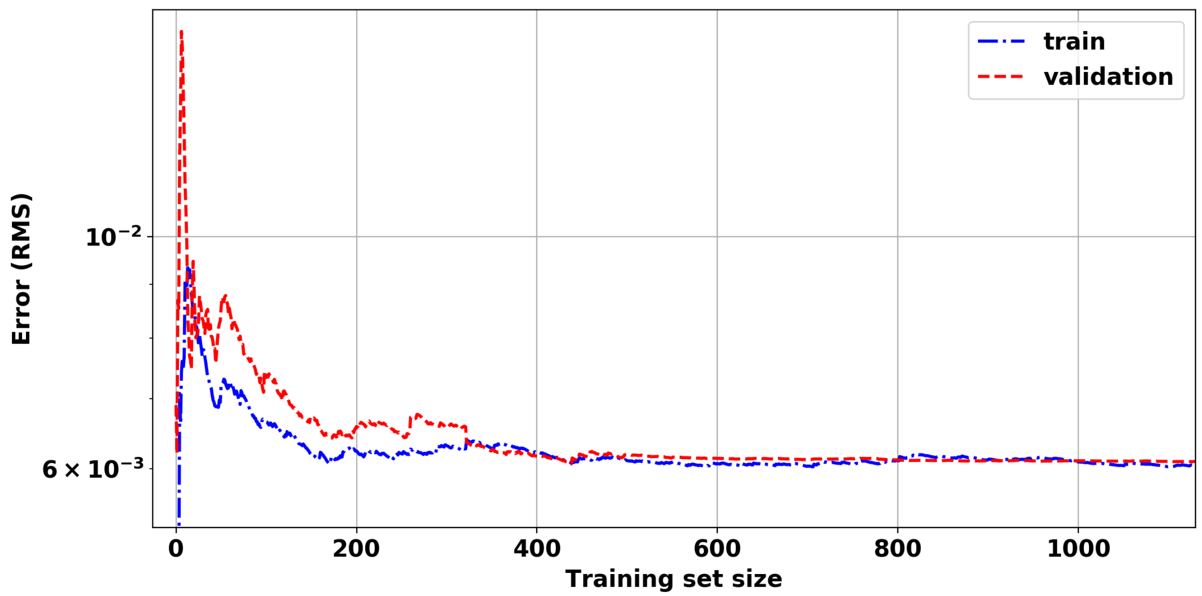
MOTIVATION: Developing a muon flux centroid prediction model by taking account upstream variables such as horn current and proton beam profile changes as inputs



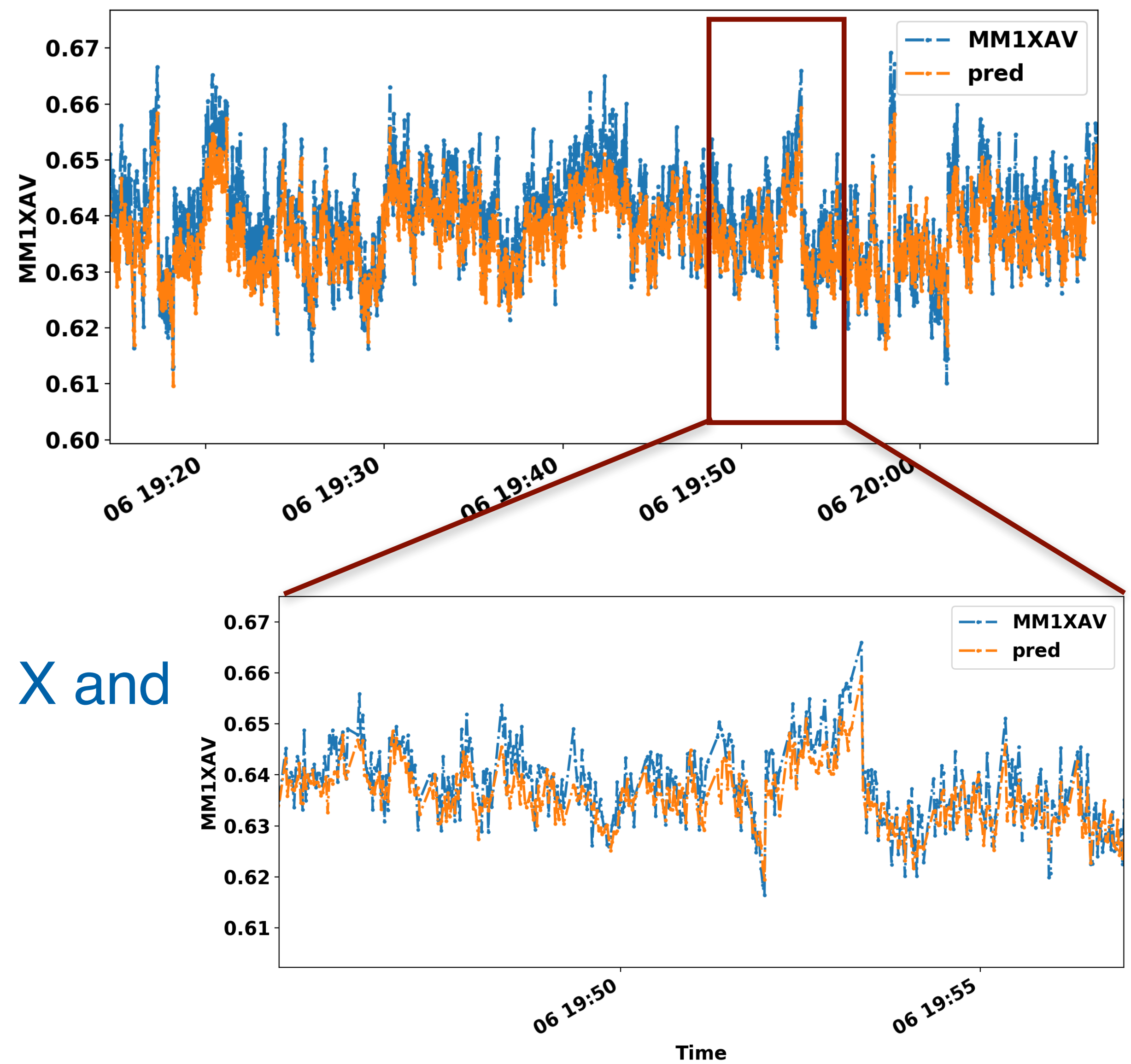
Muon Flux centroid prediction

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

Training performance for a random data set

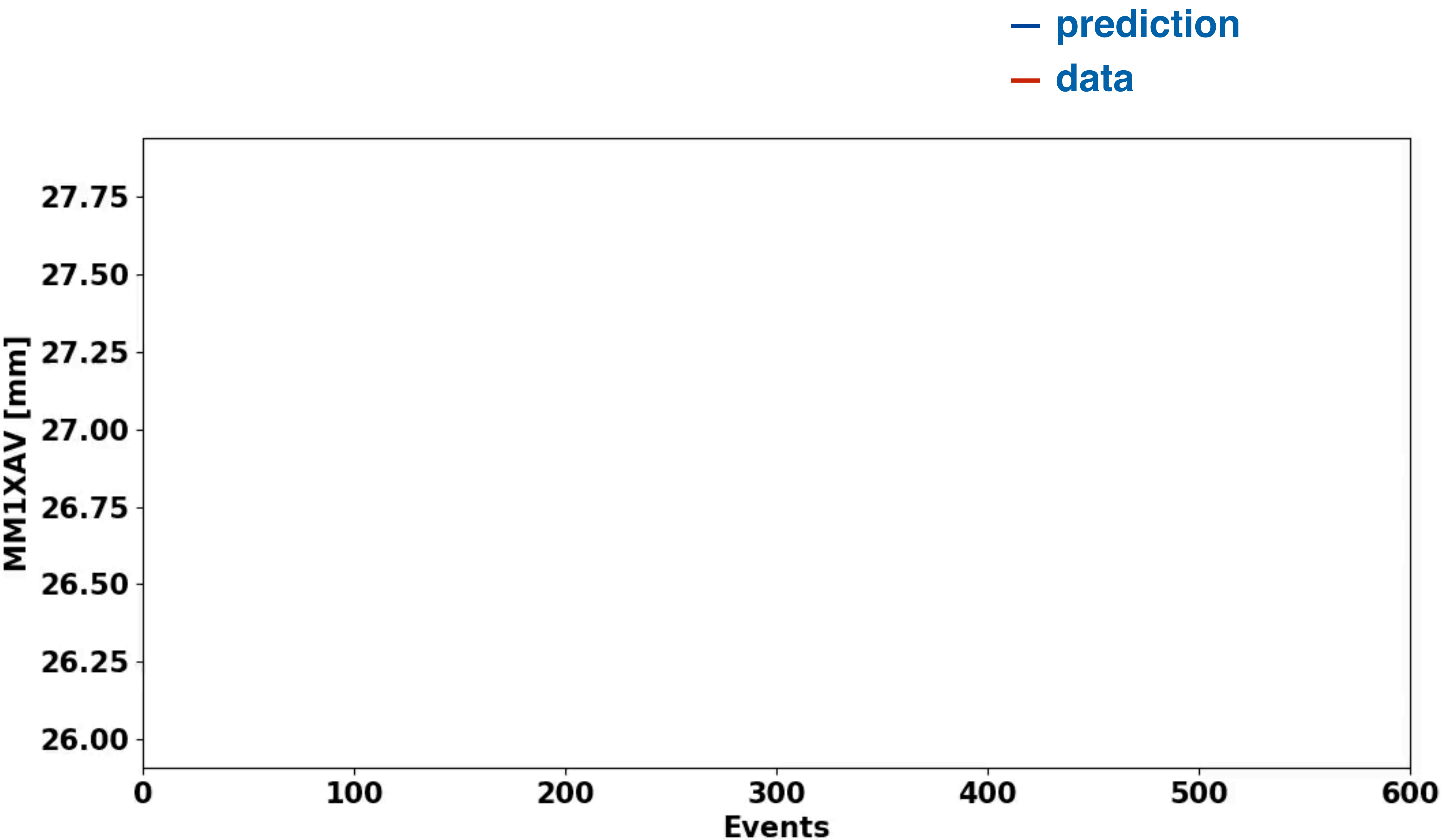


Prediction for muon monitor1 <X>



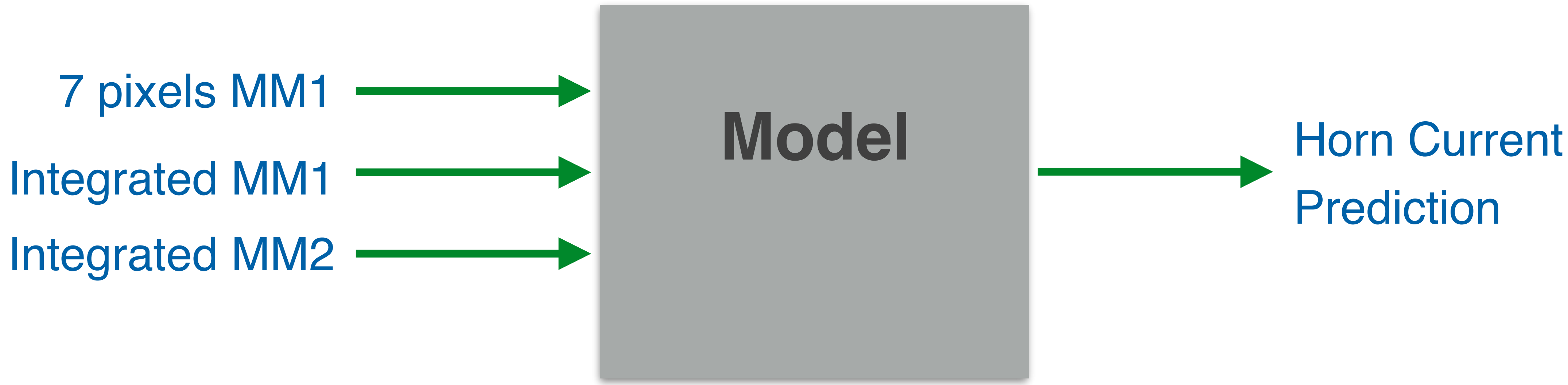
The predictions are accurate as +/- 0.1 mm in X and +/- 0.5 mm in Y

Muon Flux centroid prediction



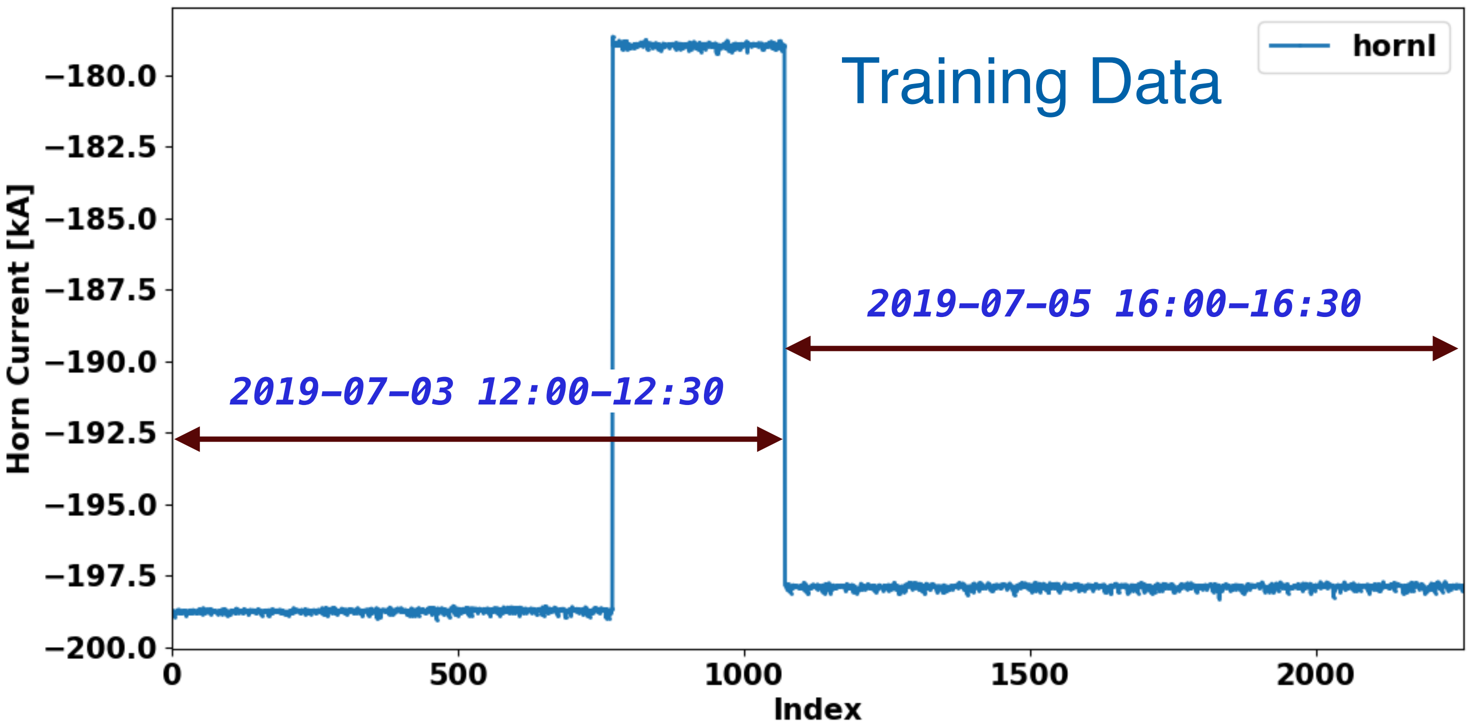
Predicting Horn Current from Muon Monitor Data

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

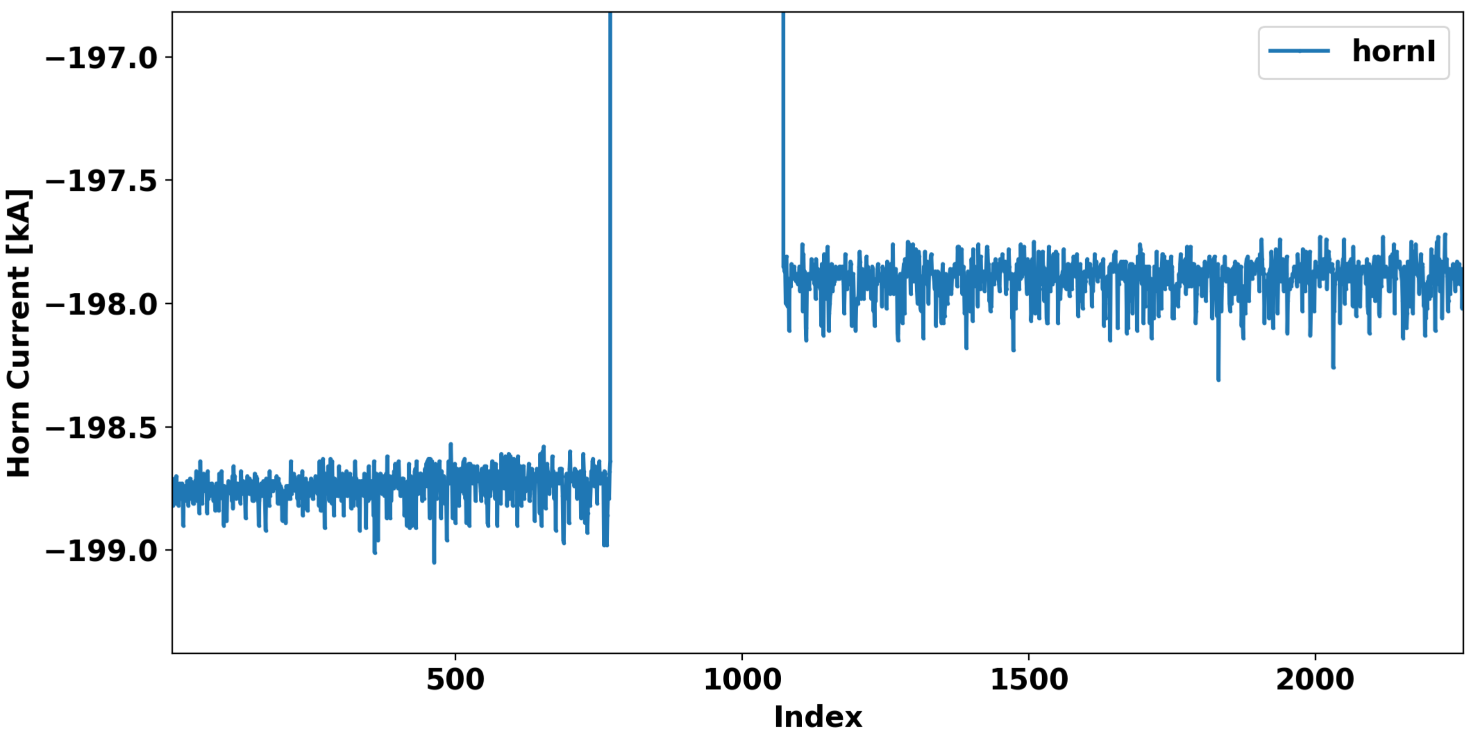


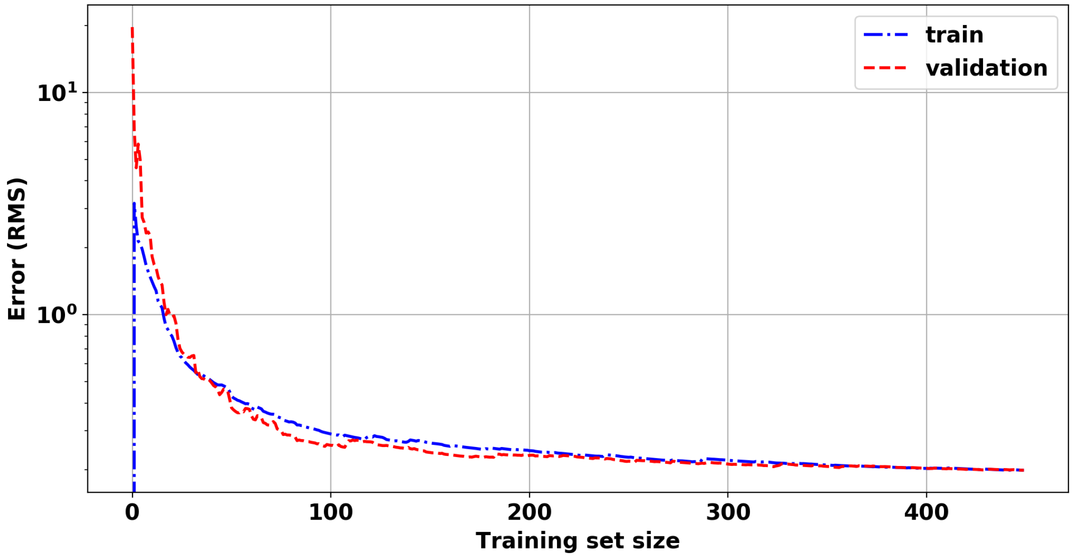
Training the Model

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

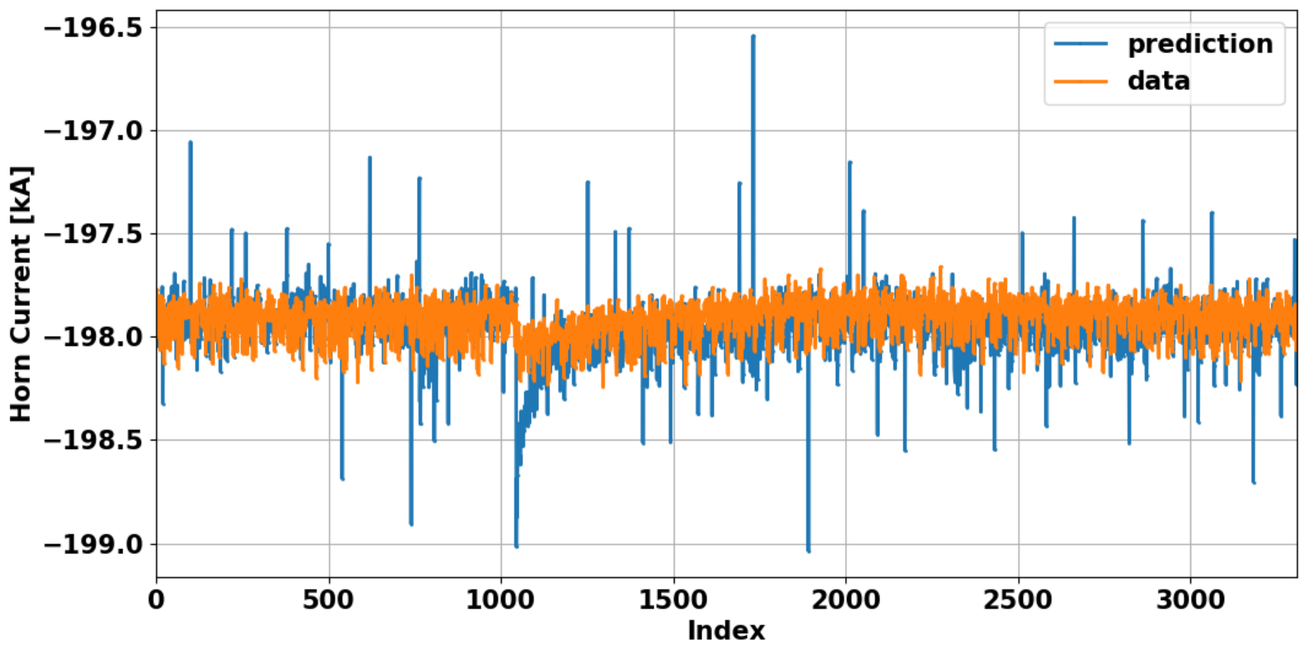


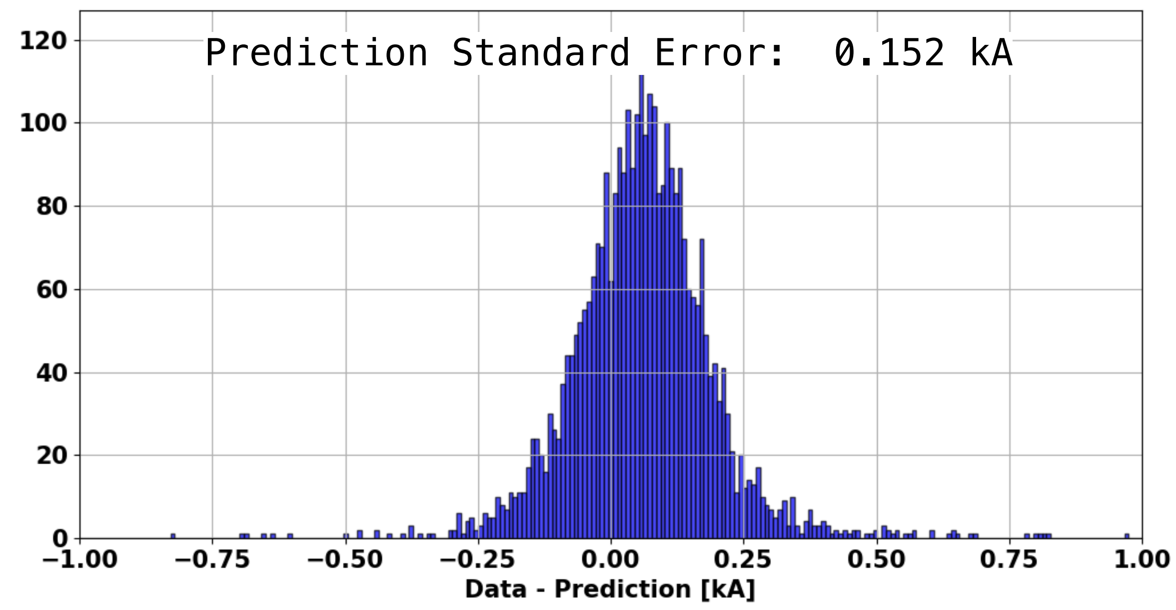
We use 10 input variable to train the model

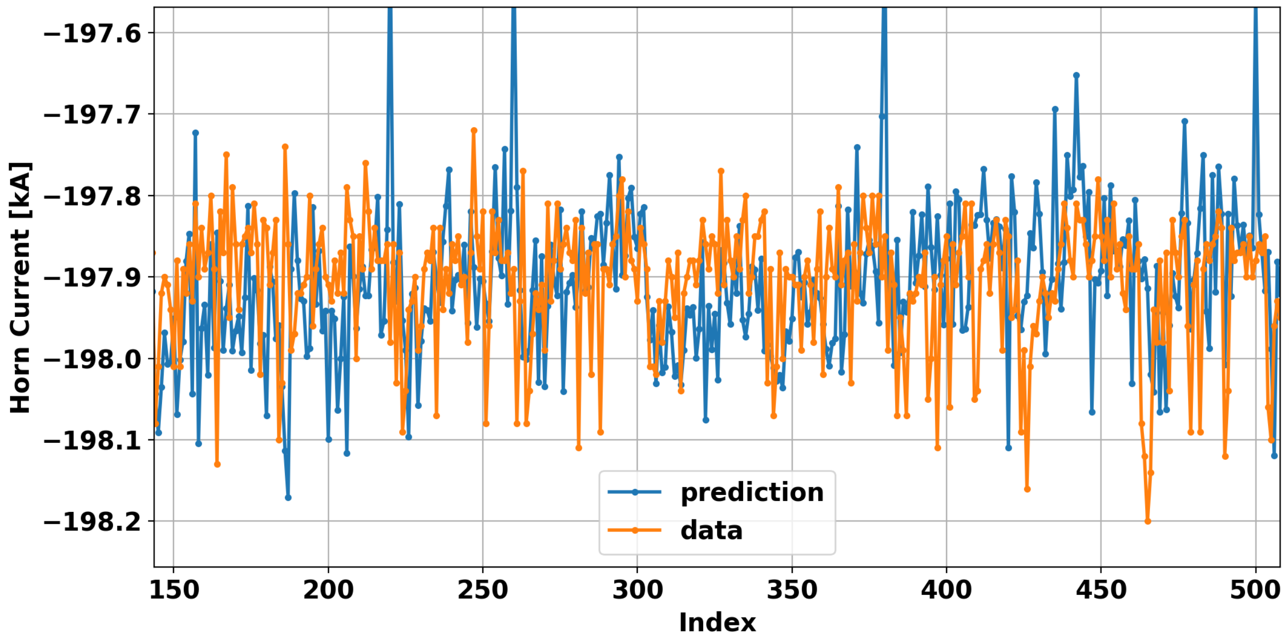




Horn Current Predictions

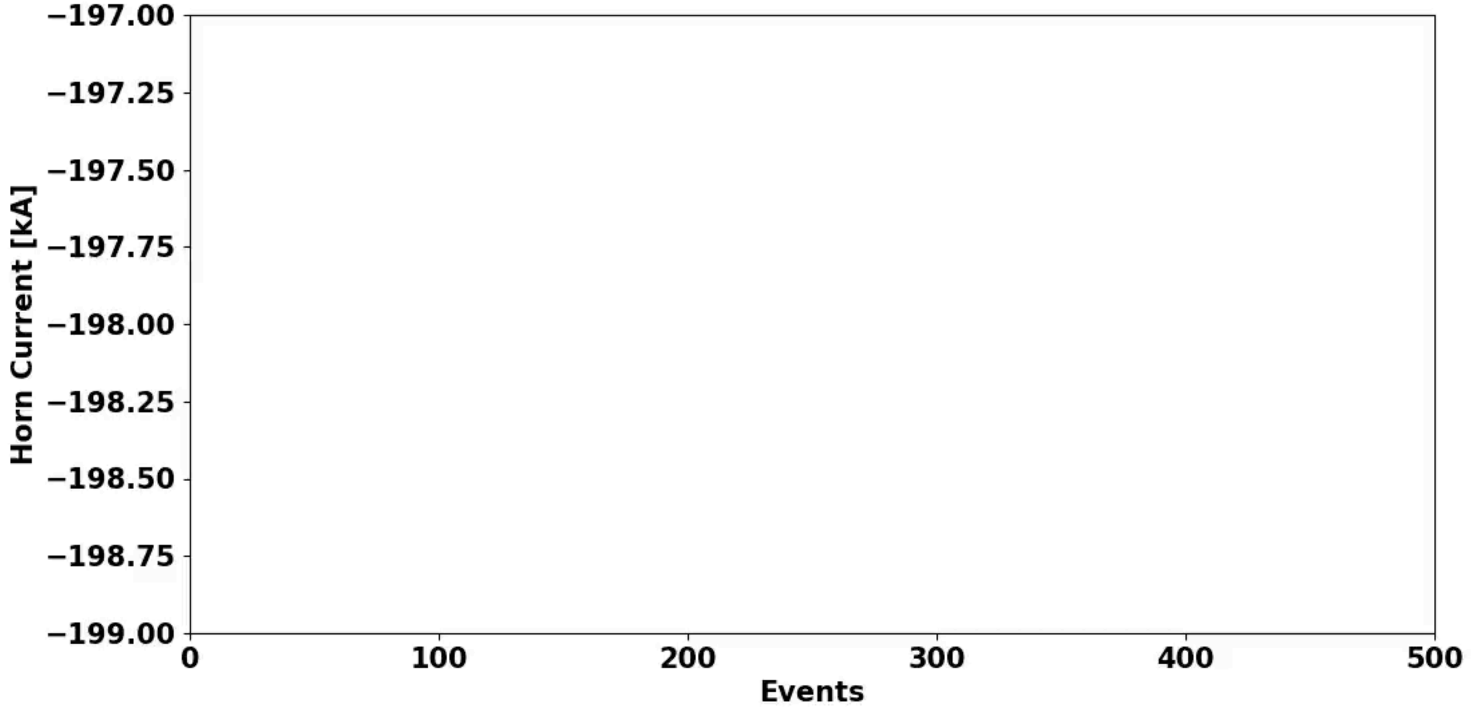


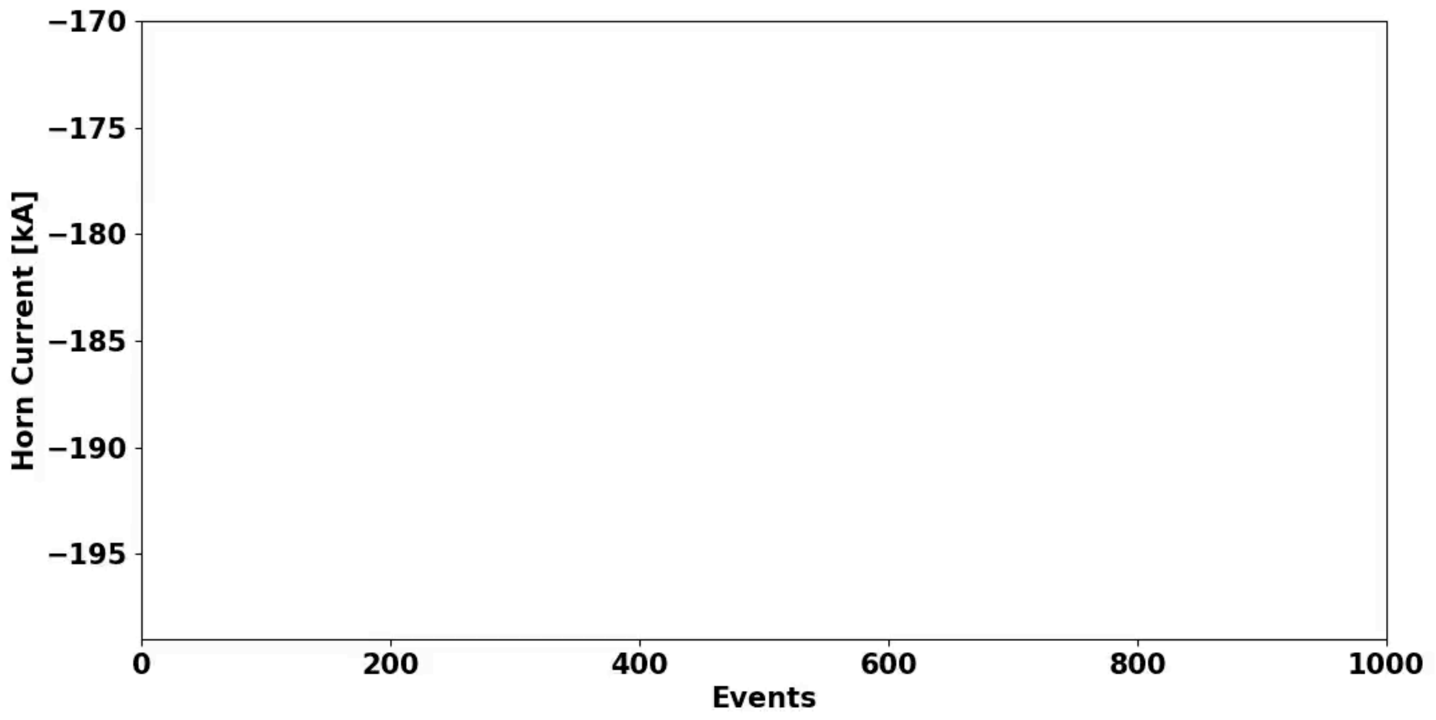




We have the capability to predict the horn current by taking account muon monitor signal data

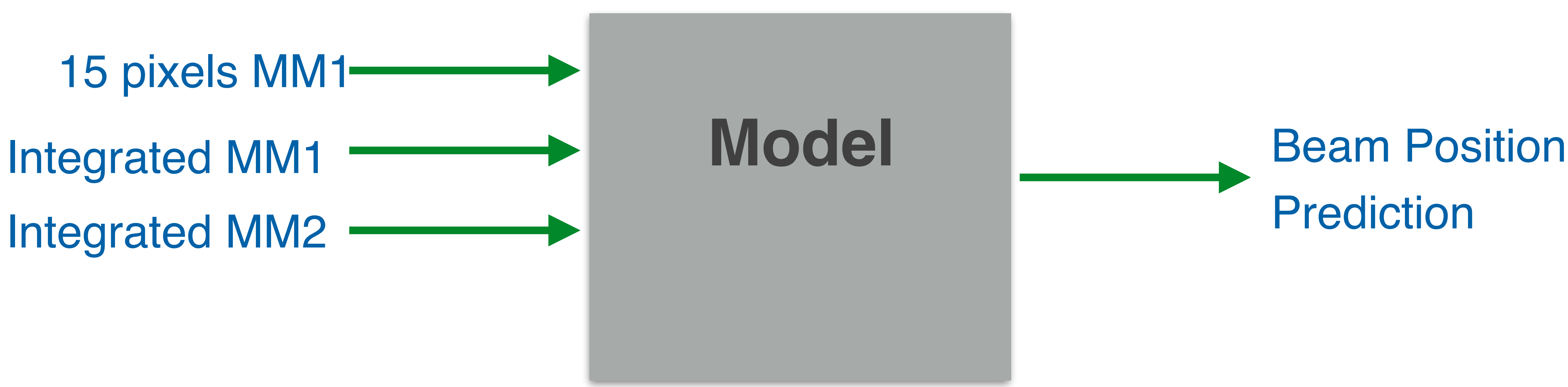
Horn Current Predictions





Predicting Beam Position from Muon Monitor Data

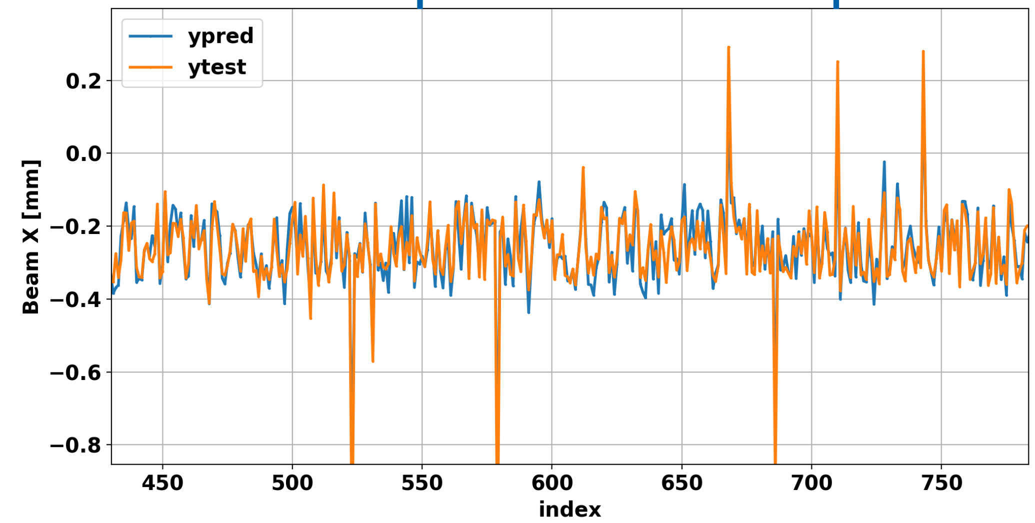
MOTIVATION: A tool to predict the proton beam position at the target by taking account muon monitor signals



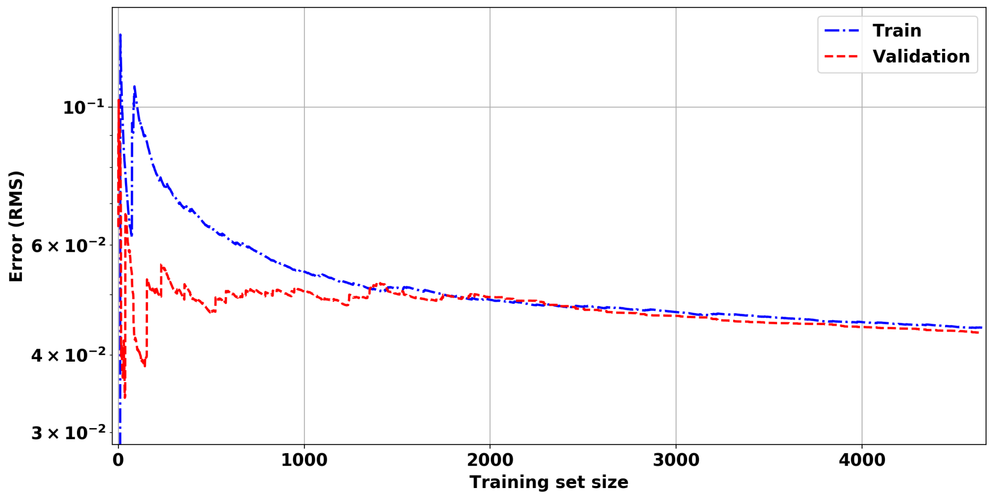
Beam centroid X prediction

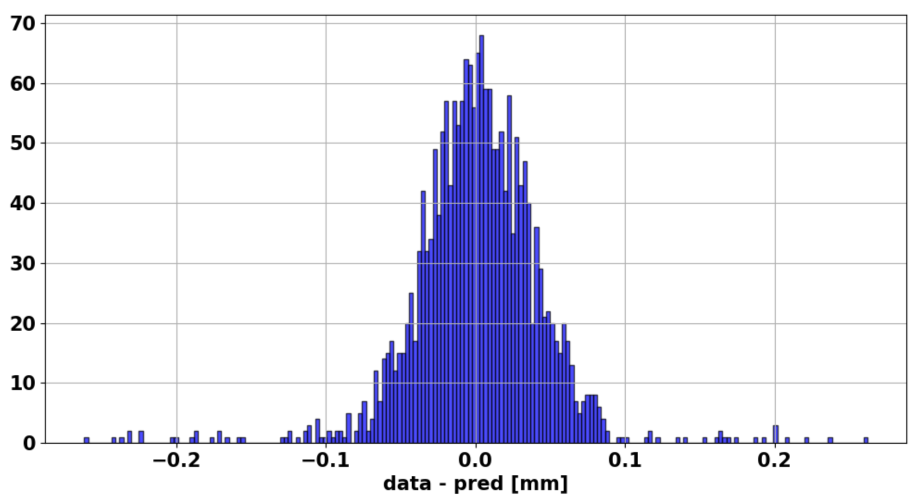
We have used selected muon monitor pixels as inputs for the model

Example of test sample

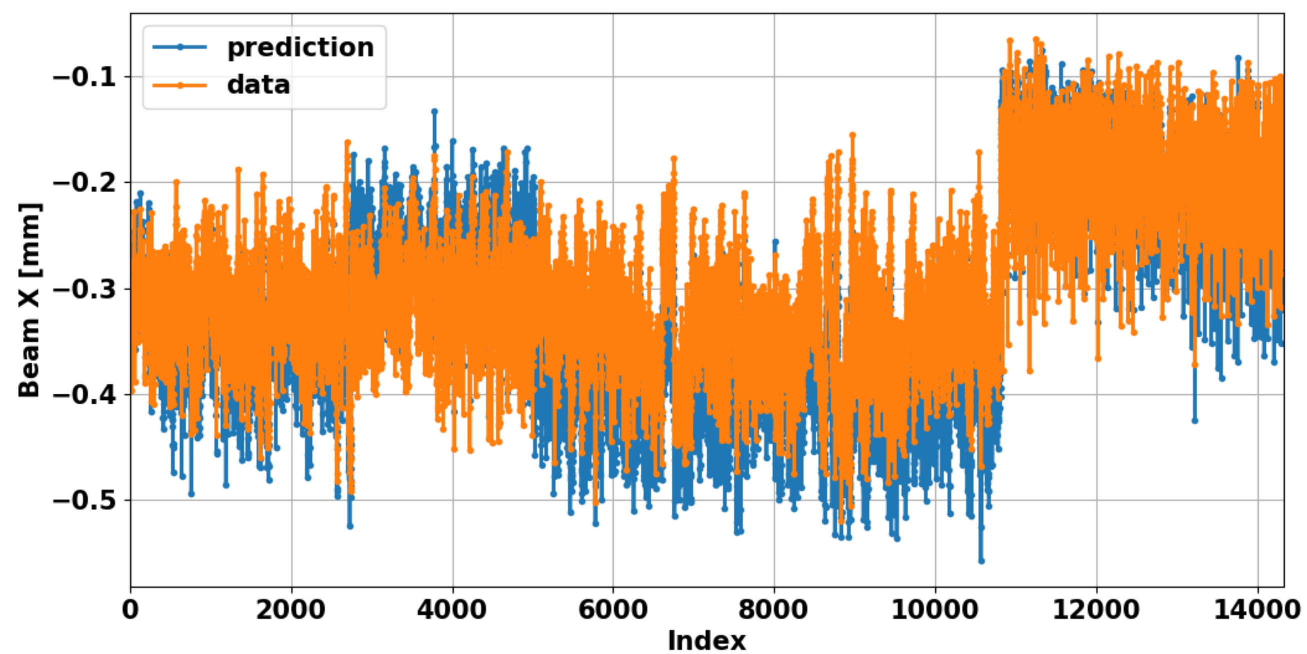


Training performance for a random data set

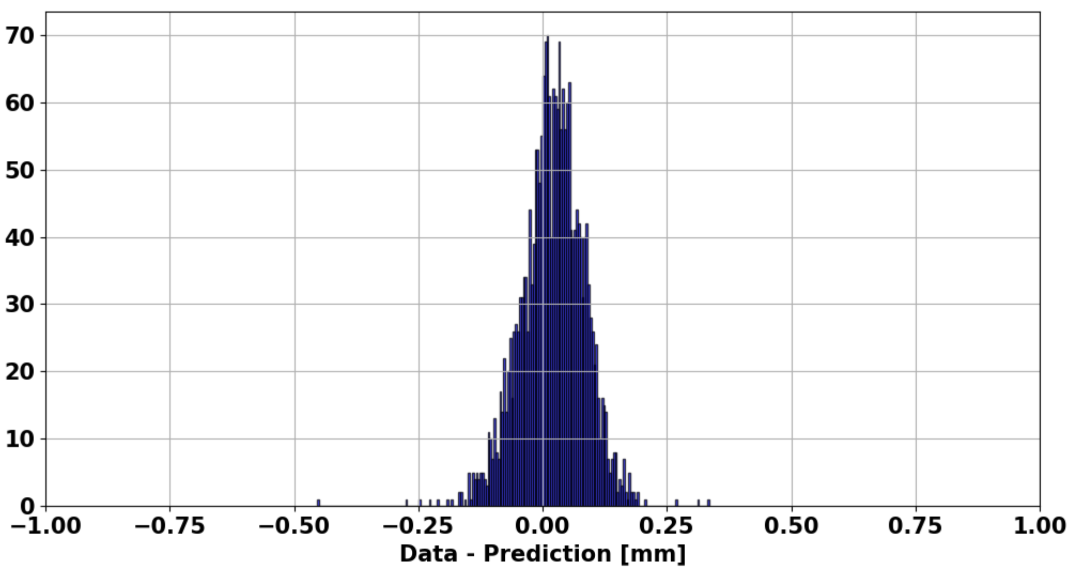


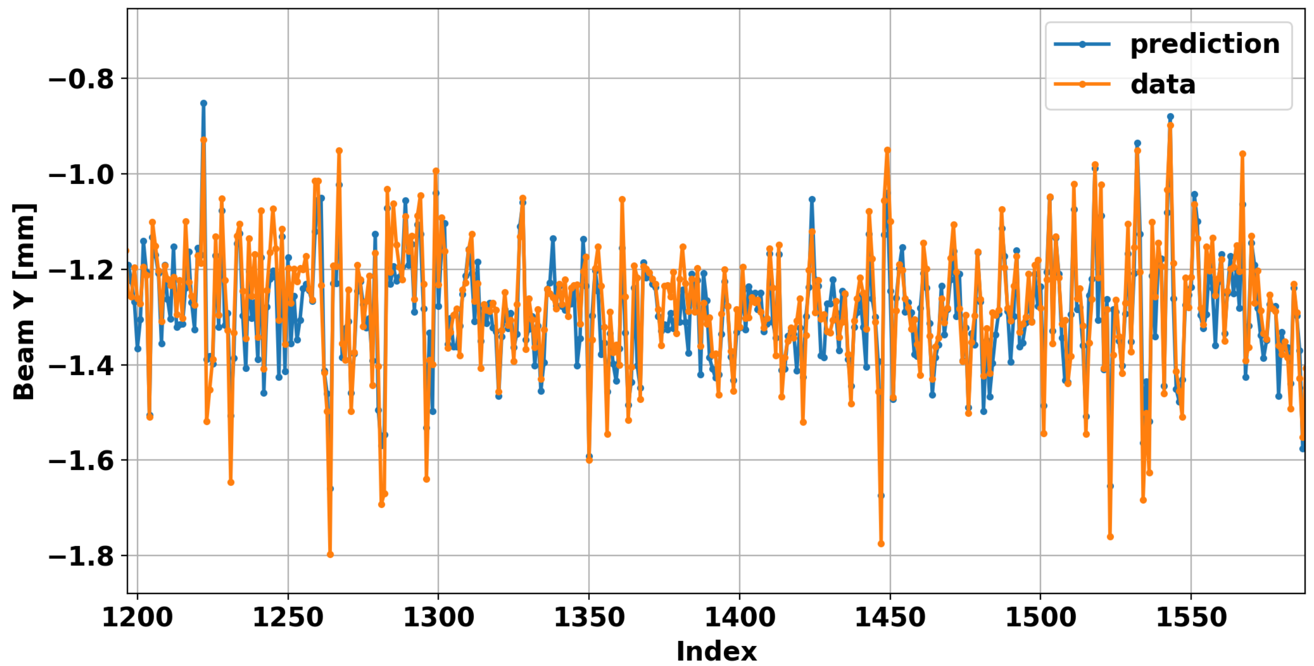


Testing for randomly selected large data set with different beam settings

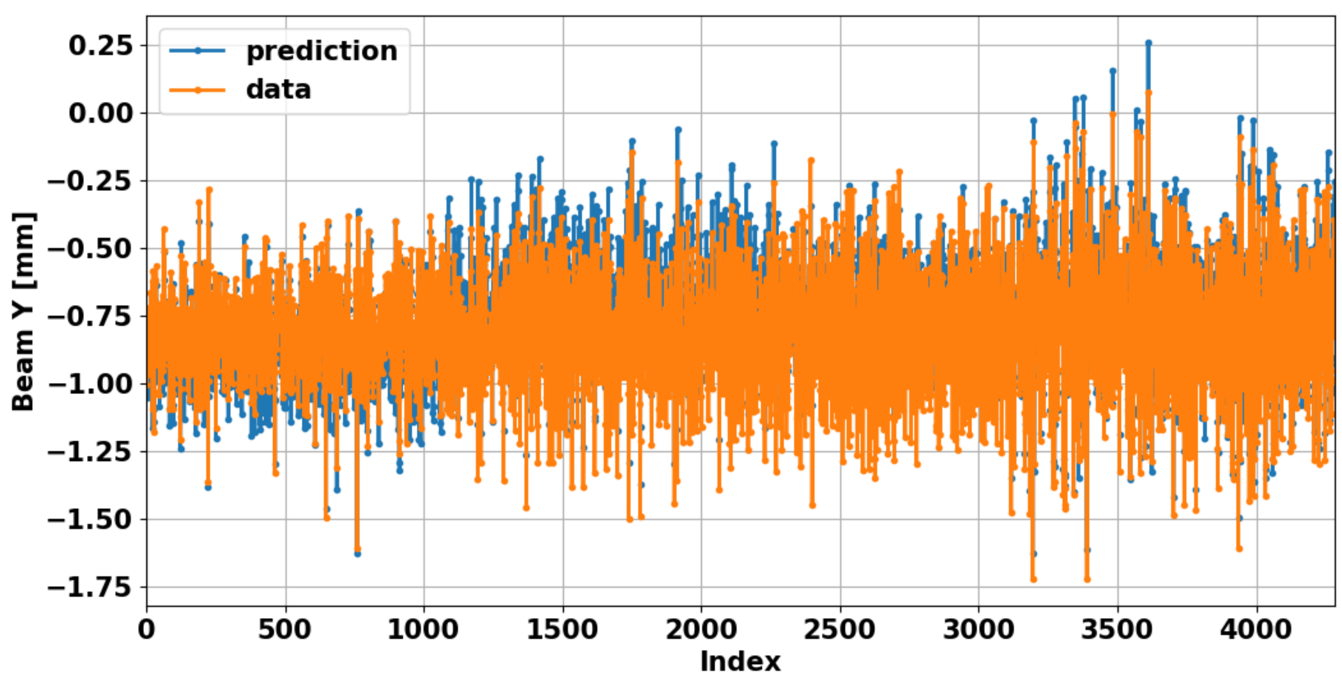


Beam centroid Y prediction

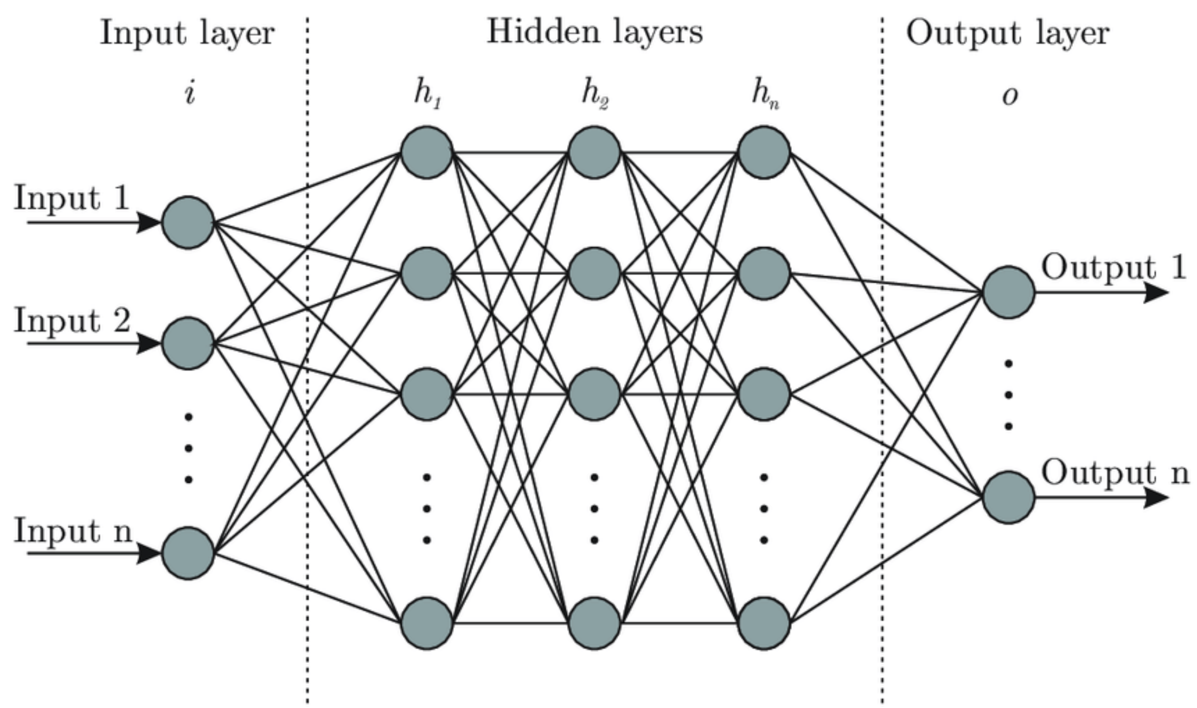




The predictions are accurate as +/- 0.05 mm in X and +/- 0.07 mm in Y



Neural Network Applications

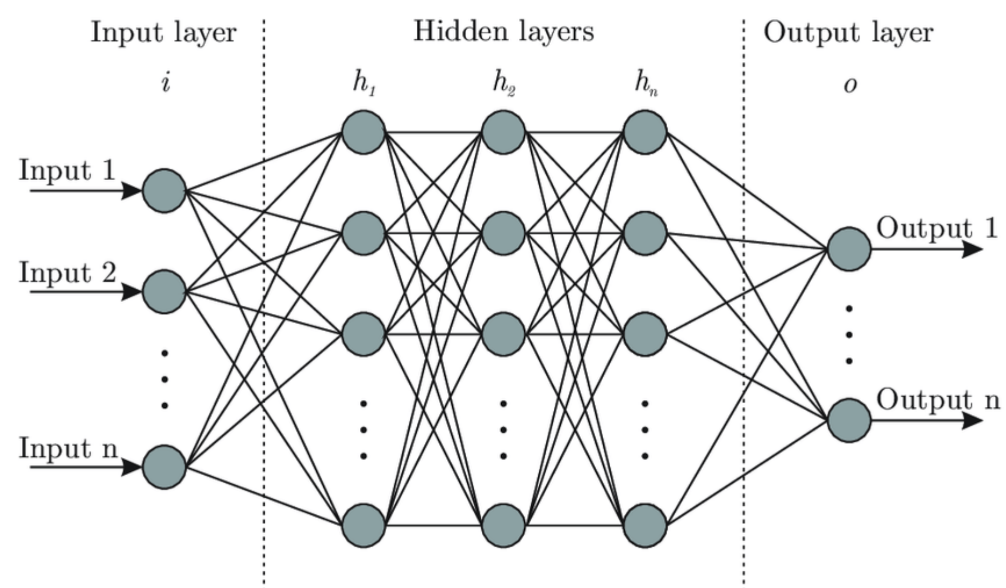


Identifying/predicting Incidents from Muon Monitor Data

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

Muon Monitor Signals

81x3 pixels



Status

243 Nodes

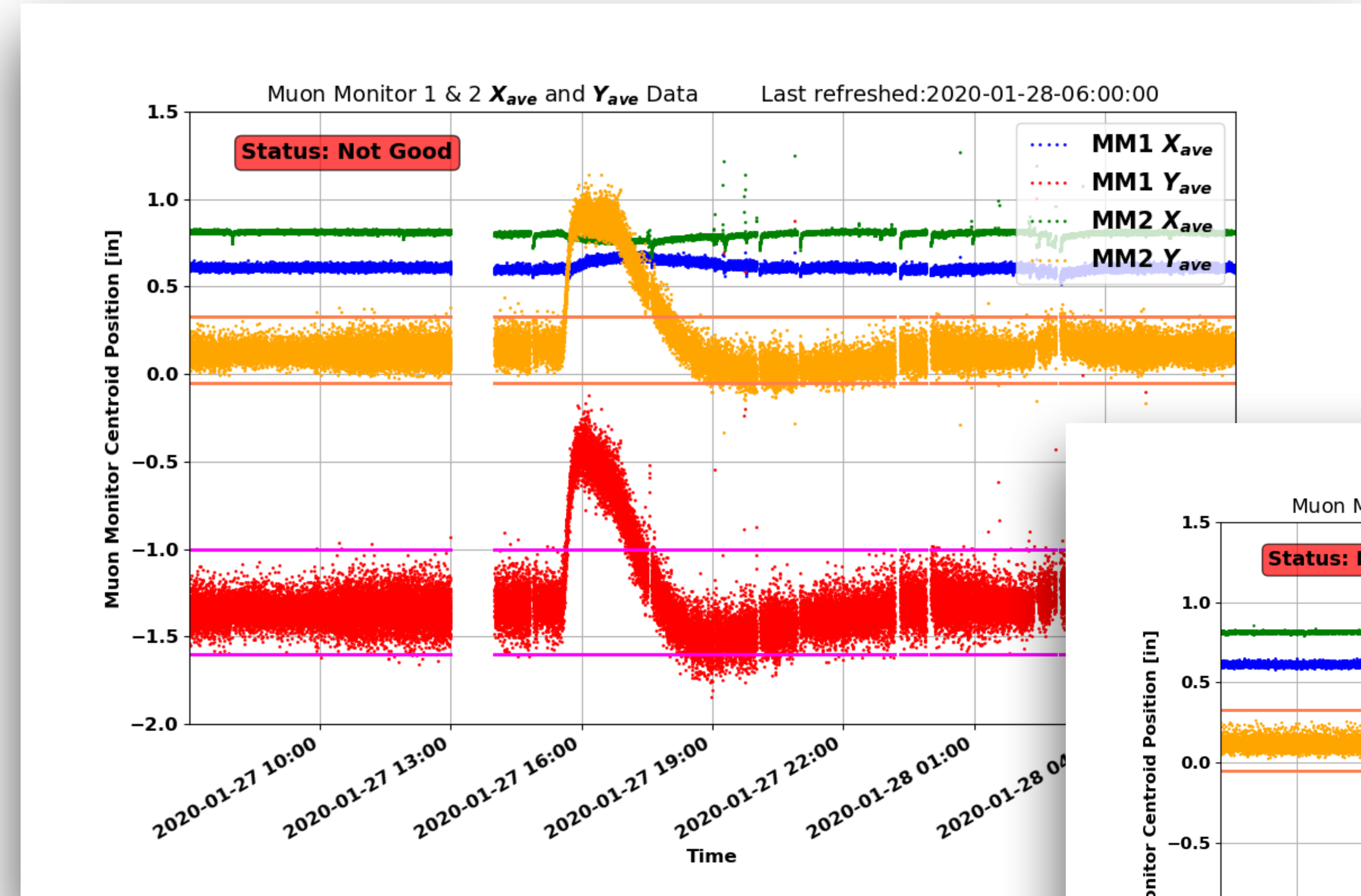
165 Nodes

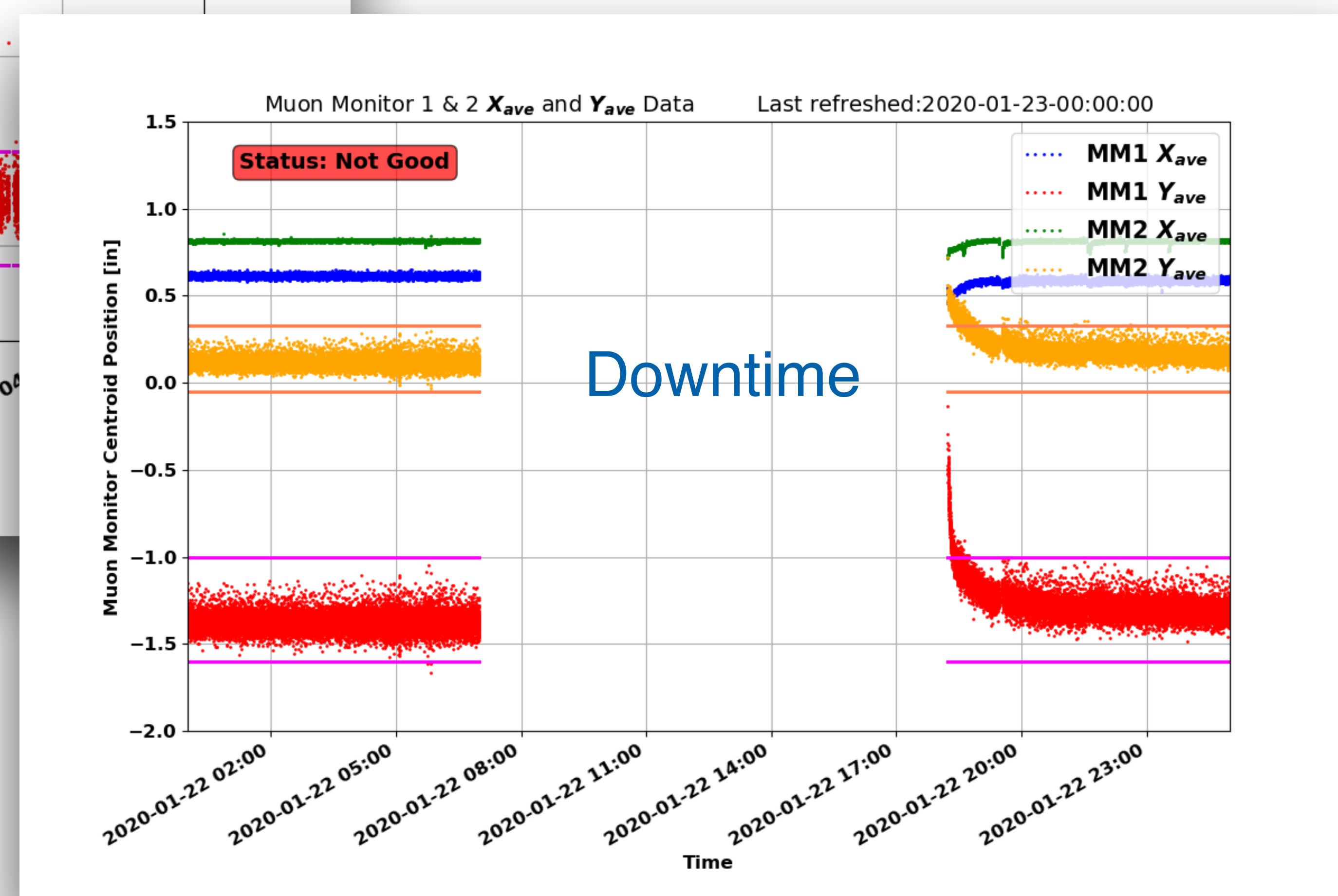
3 Nodes

Identifying/predicting Incidents

Identifying/predicting Gas Bottle Change or After Down Time Status

Muon Monitor Response After the Gas Bottle Changes





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: 0.6930 - 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

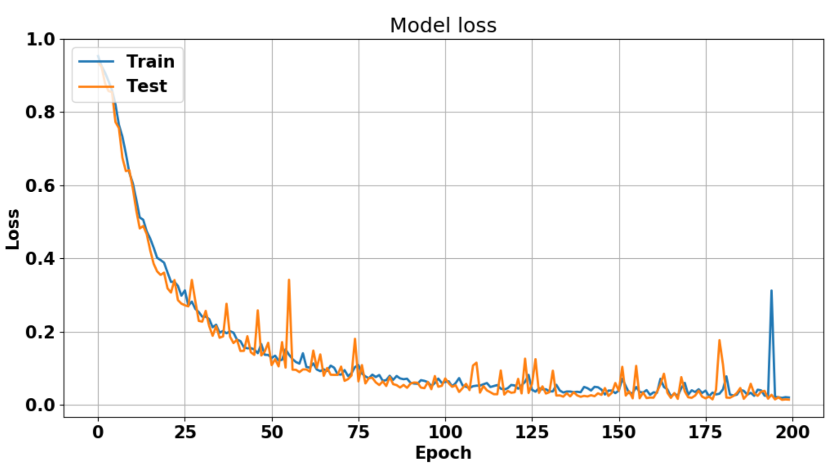
```
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0273 - accuracy: 0.9949 - val_loss: 0.0204 - val_accuracy: 0.9952
Epoch 183/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0292 - accuracy: 0.9937 - val_loss: 0.0480 - val_accuracy: 0.9923
Epoch 184/200
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: 0.0239 - accuracy: 0.9960 - val_loss: 0.0196 - val_accuracy: 0.9978
Epoch 190/200
7263/7263 [==============================] - 0s 20us/sample - loss: 0.0[illegible]85 - 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
```

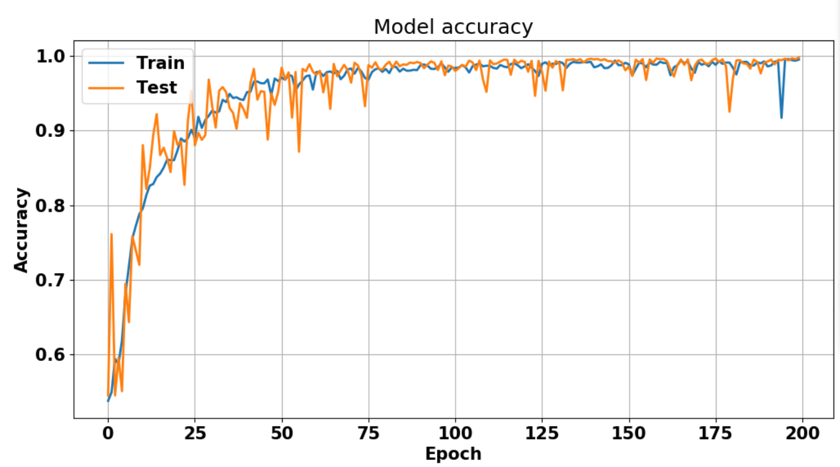
Training and validation in each epoch

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

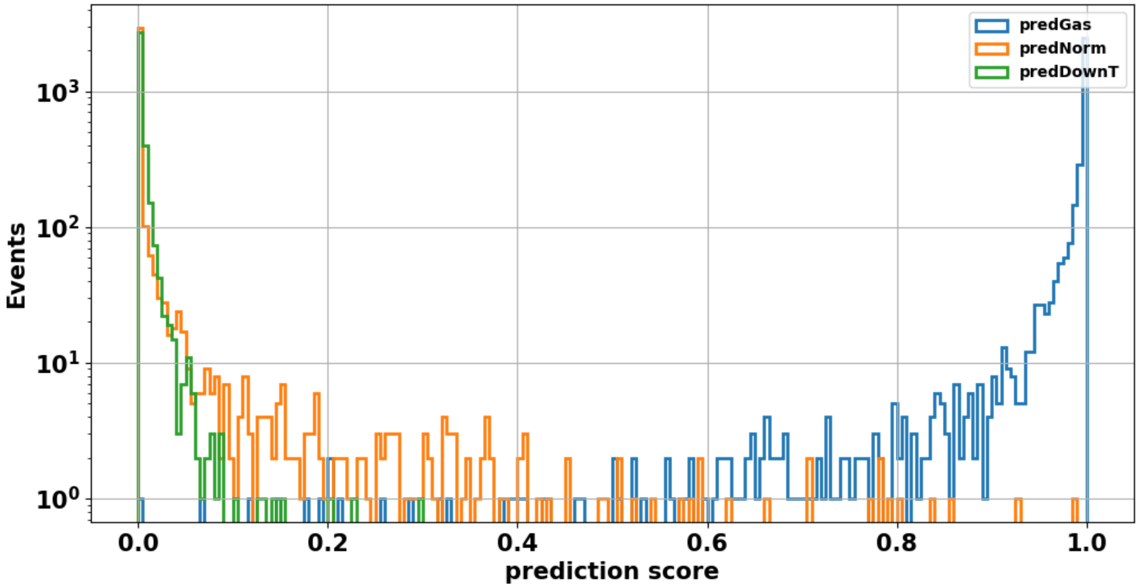




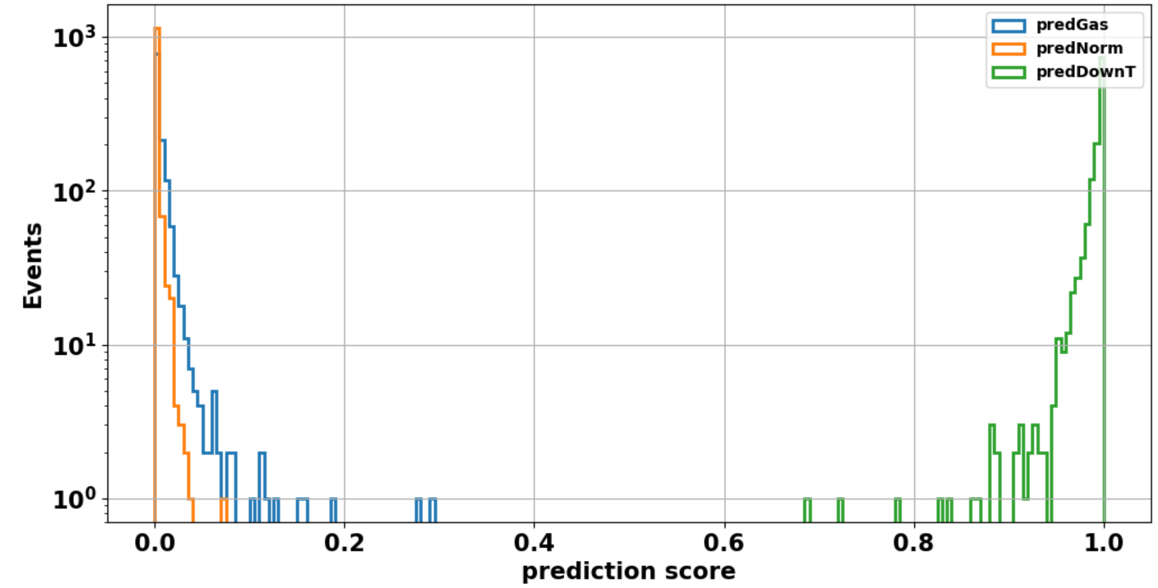
Results looks good and can predict incidents spill by spill

Identifying/predicting Incidents

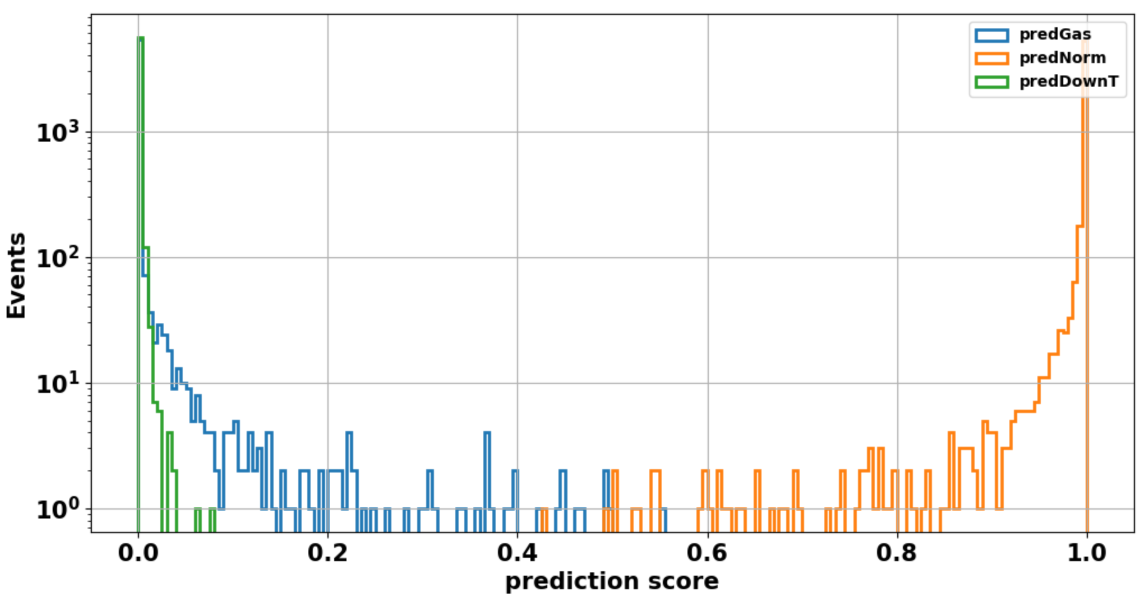
True Gas Bottle Events



True After Downtime Events



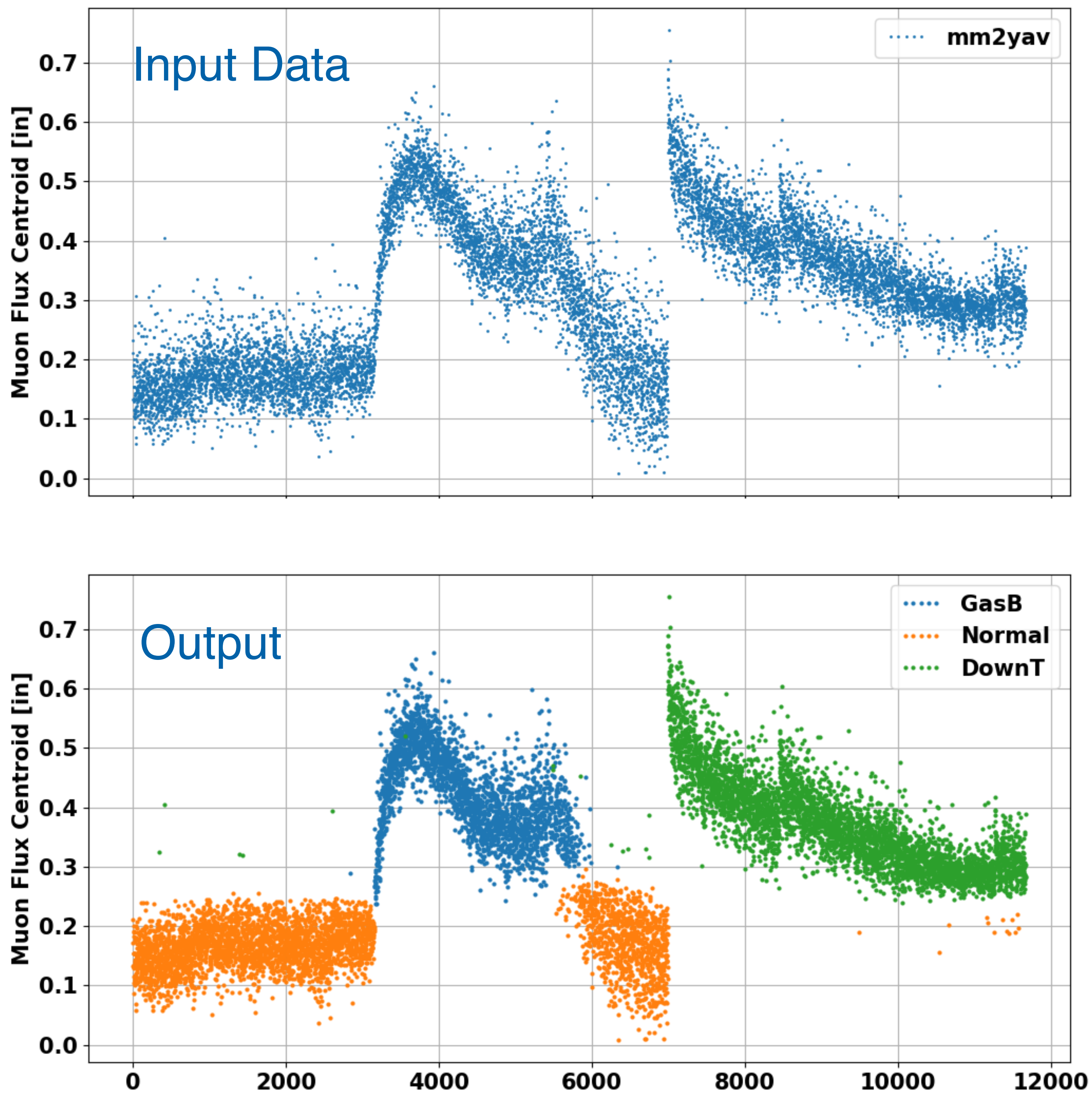
True Normal Events



- 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

Fermilab

Identifying/predicting Incidents



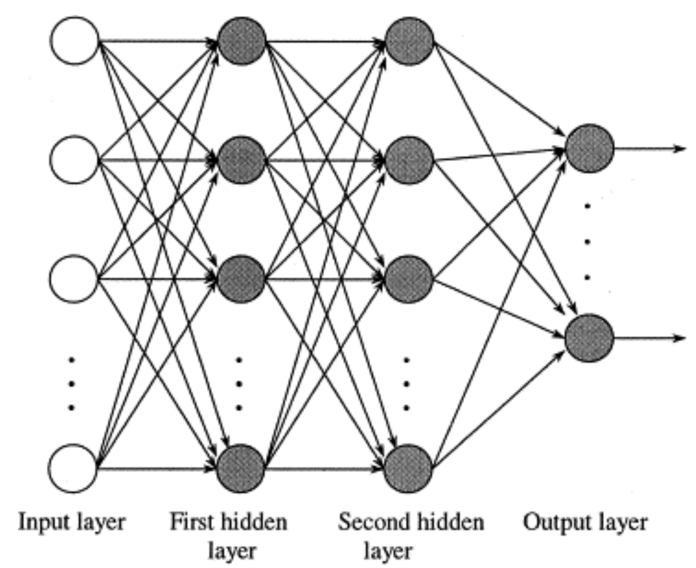
- Testing the model application with a combined data sets
- Model predictions has classified data as expected

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

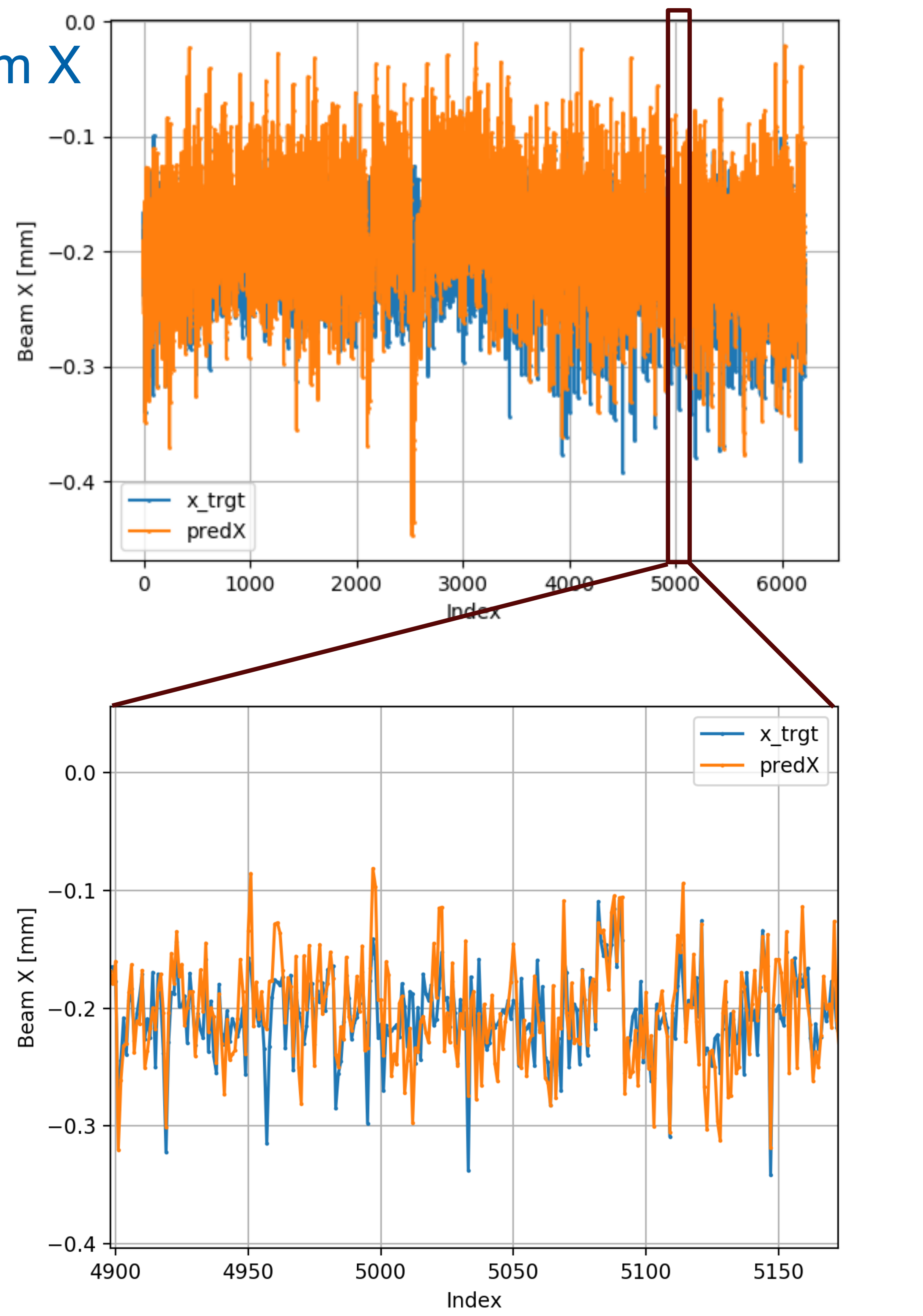


Output

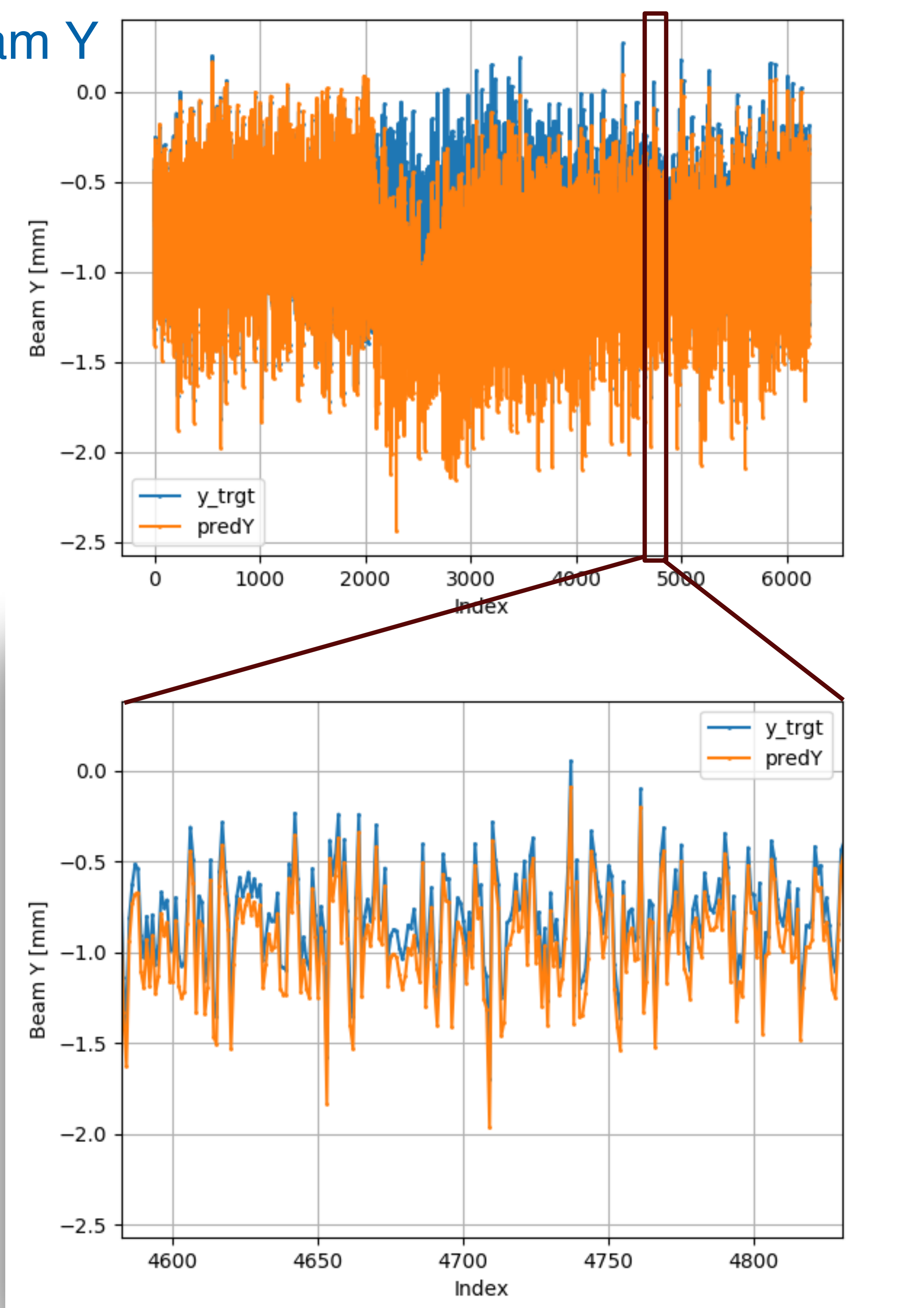
243 Nodes | 400 Nodes | 350 Nodes | 4 Nodes

Beam centroid X and Y prediction

Beam X

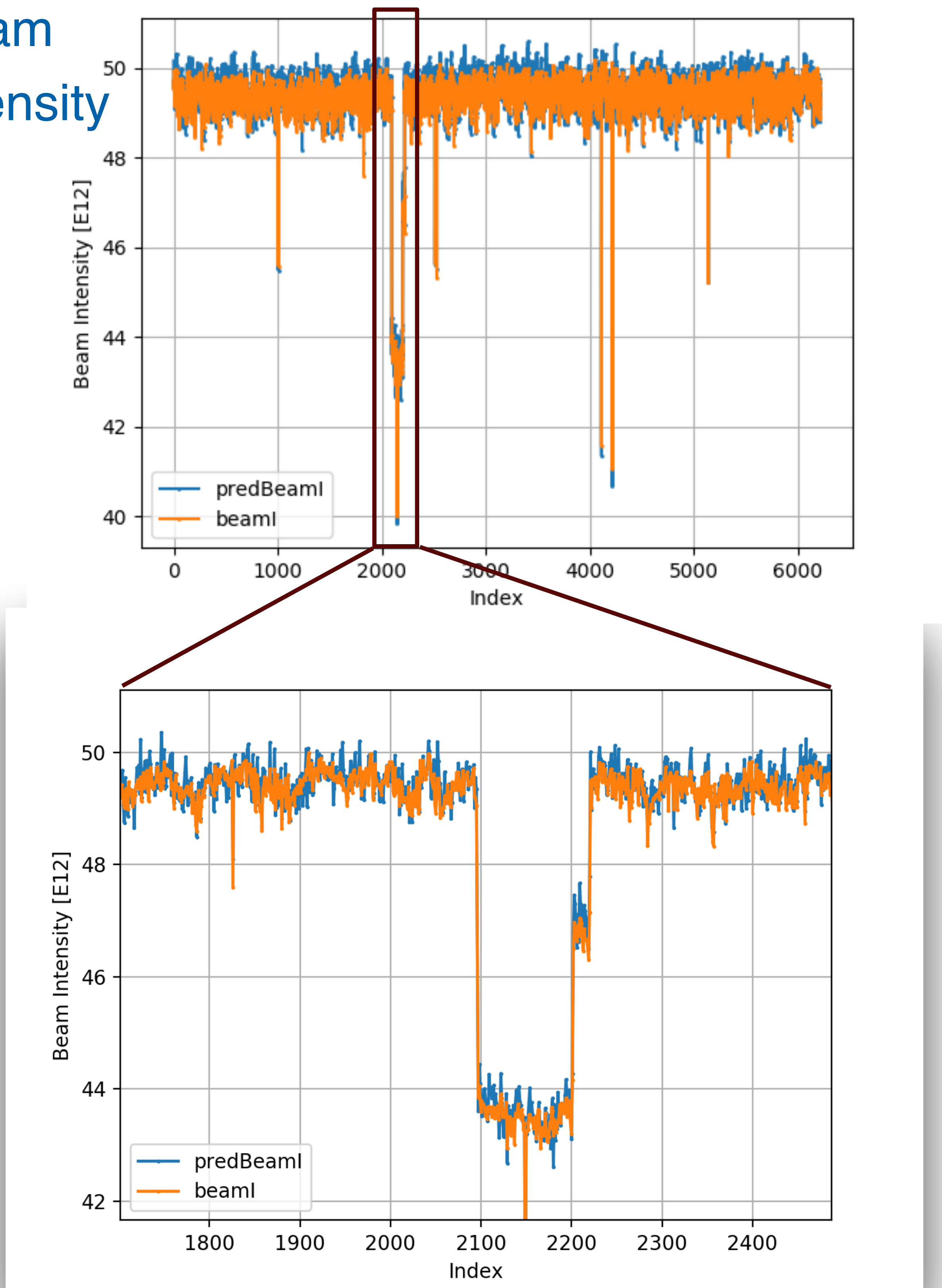


Beam Y

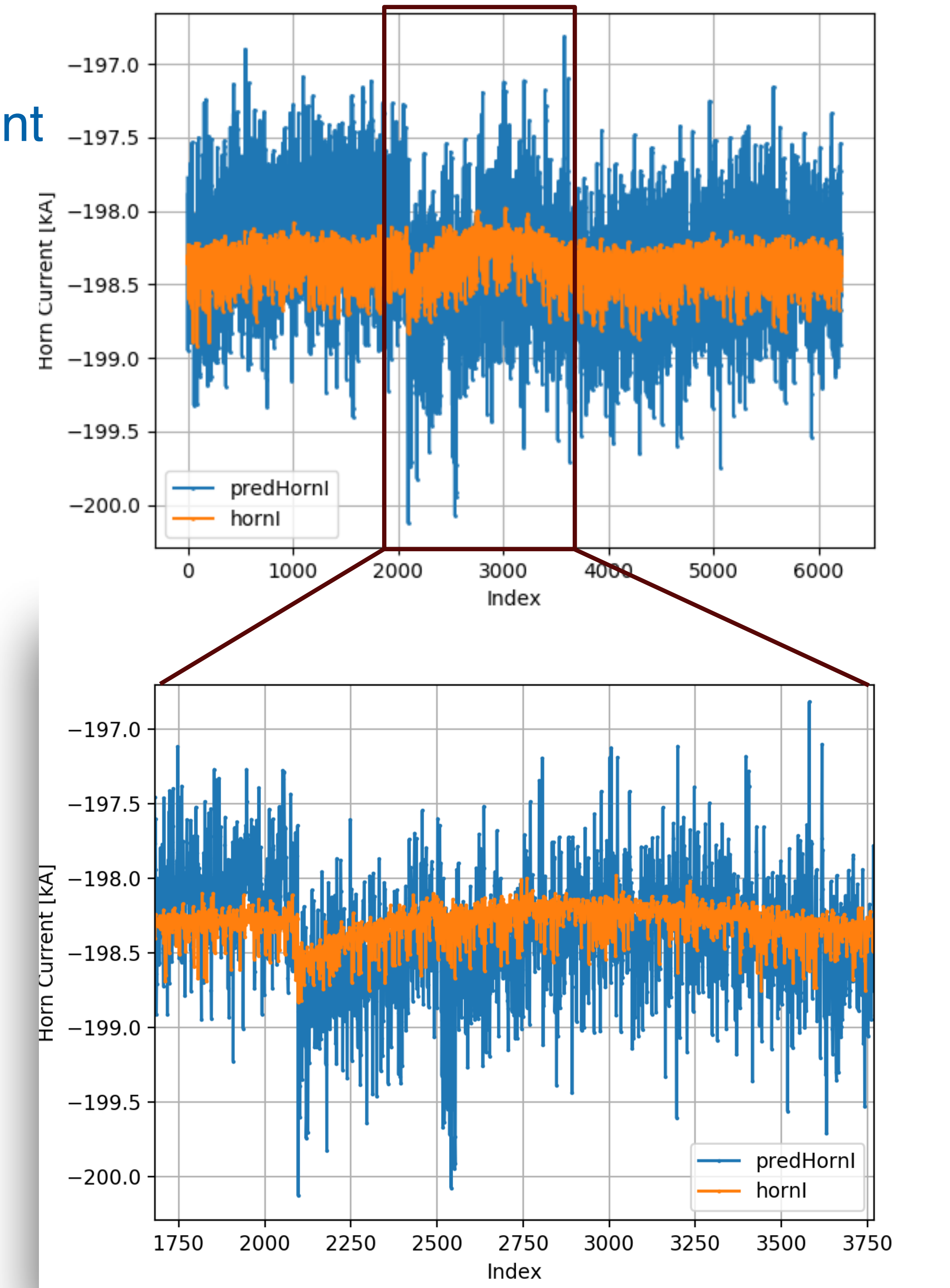


Beam Intensity and Horn Current

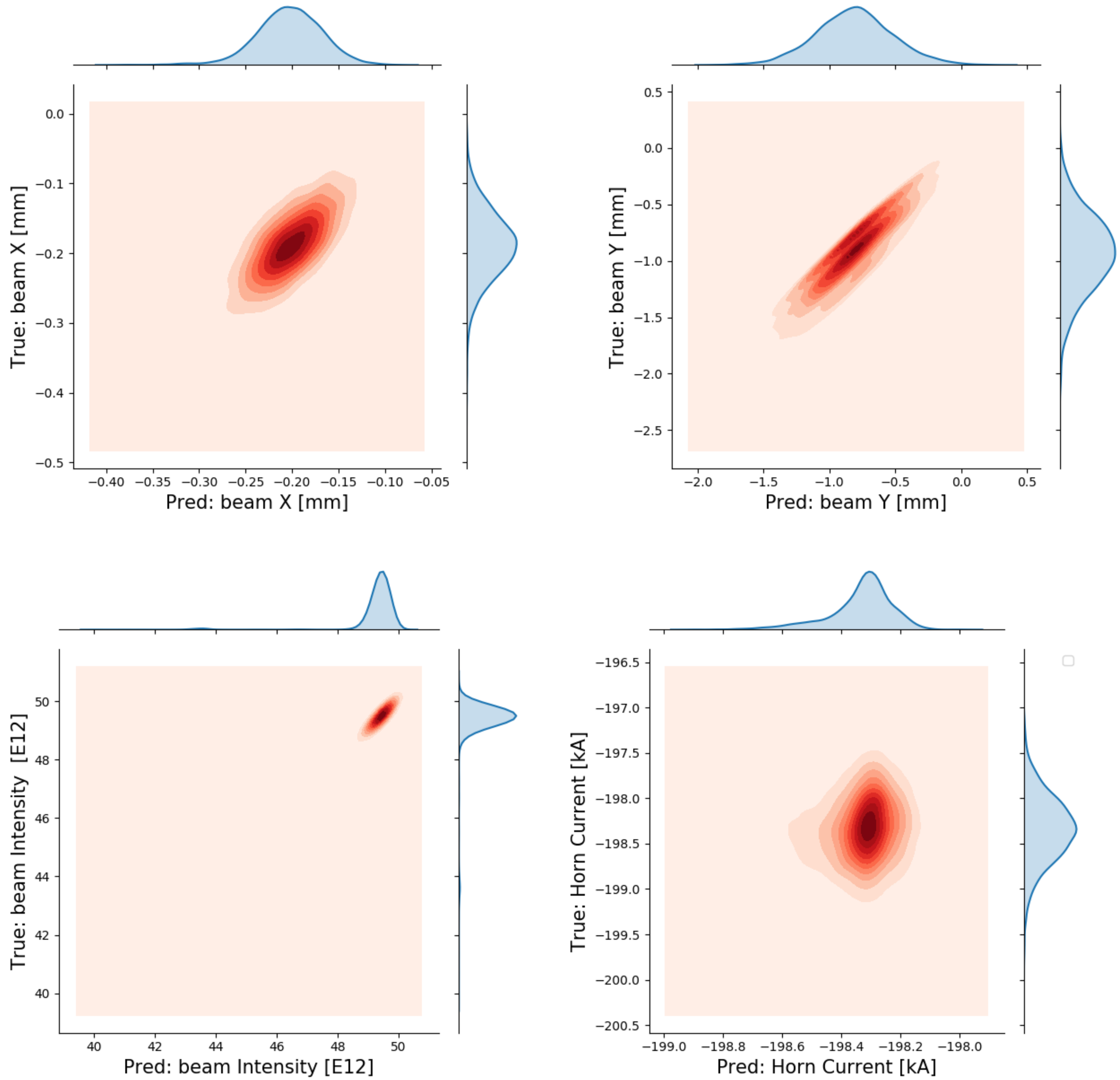
Beam Intensity



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

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

Thank you