ACAT Track 2 Summary

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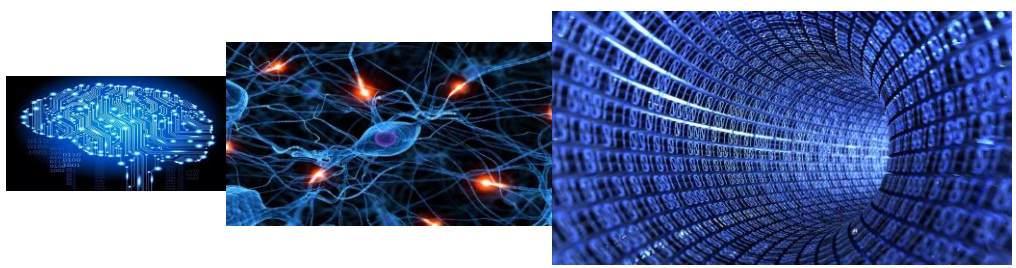
University of Florida



August 25, 2017

Statistics

- **33 talks**
- **26 posters**
- **13 collaborations represented**
  - ALPHA, ATLAS, Belle II, BESIII, CMS, Dune, DZero, IceCube, JUNO, LHCb, MicroBooNE, Opera, PANDA

Topics

- **Algorithms and applications**
  - Physics, object id, reconstruction, tracking, trigger, simulation
- **Analysis Tools**
  - General, Simulation, Fitting, ML, Visualization, Preservation

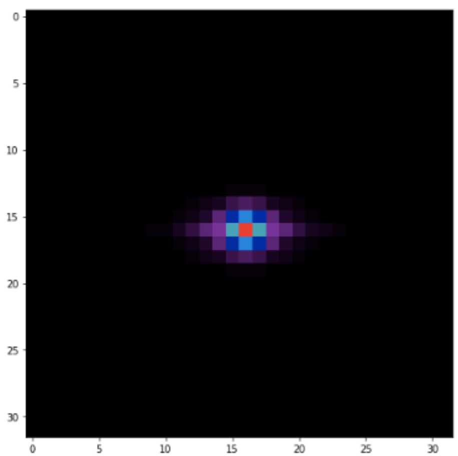
Machine Learning

“End-to-End” Learning

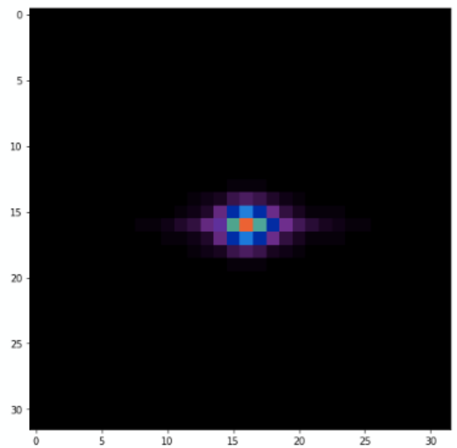
Convolutional Neural Networks

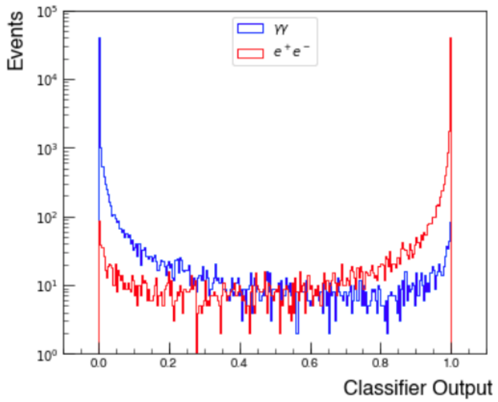
- By-passing traditional reconstruction

Photon-Induced EM Shower
mean energy distribution over 10k events



Electron-Induced EM Shower
mean energy distribution over 10k events



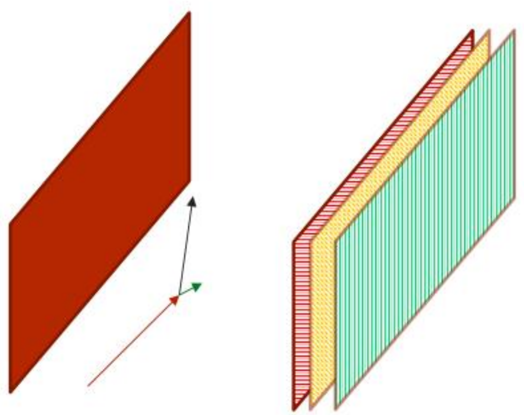


	ResNet-23
Test Set ROC AUC	0.997

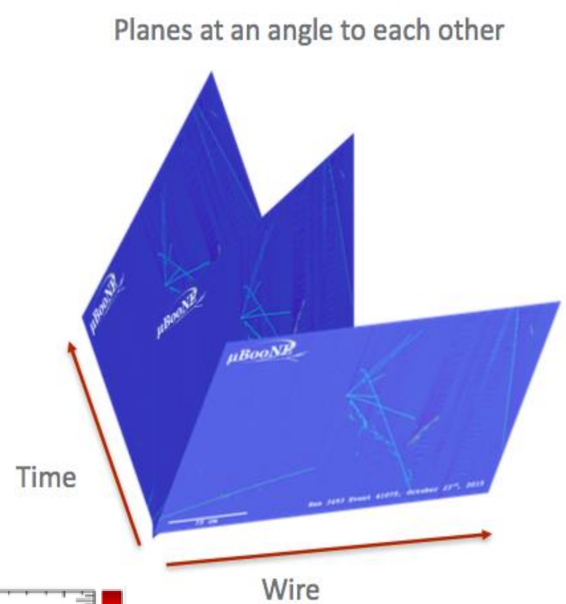
Talk by M. Andrews

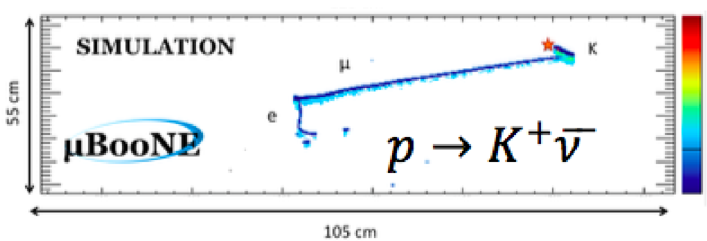
Neutrinos

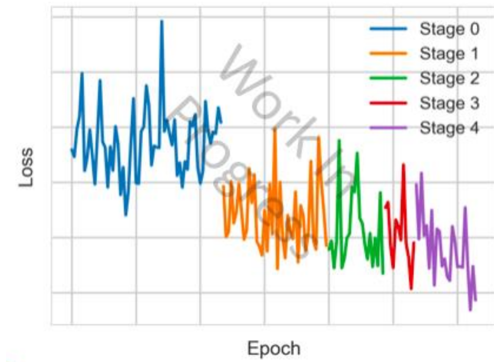
Convolutional NNs in μBooNE

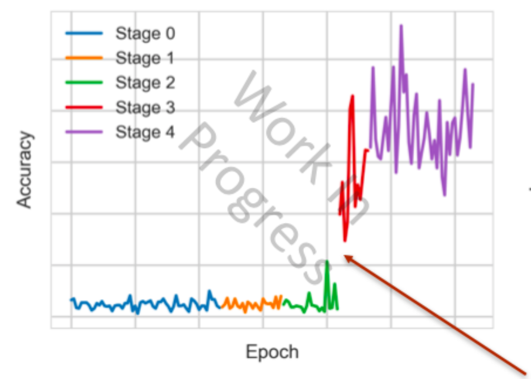


Particle tracks project onto wire planes



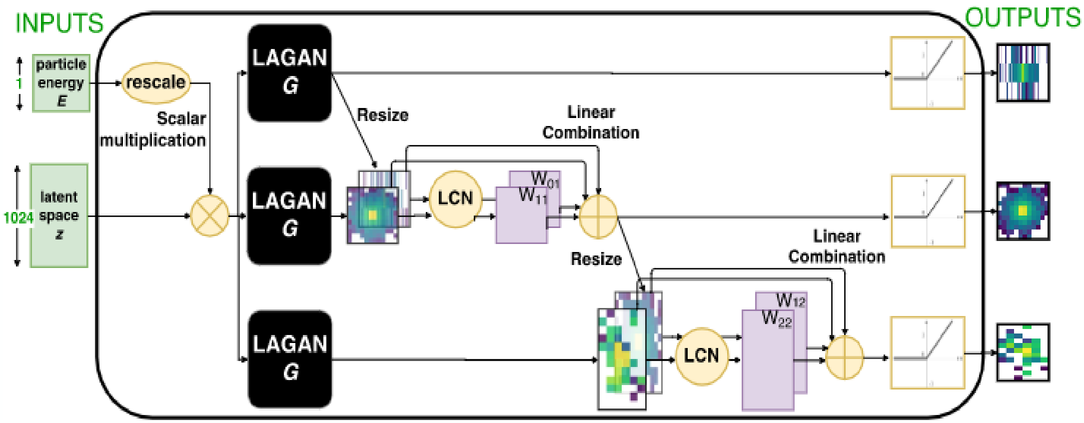




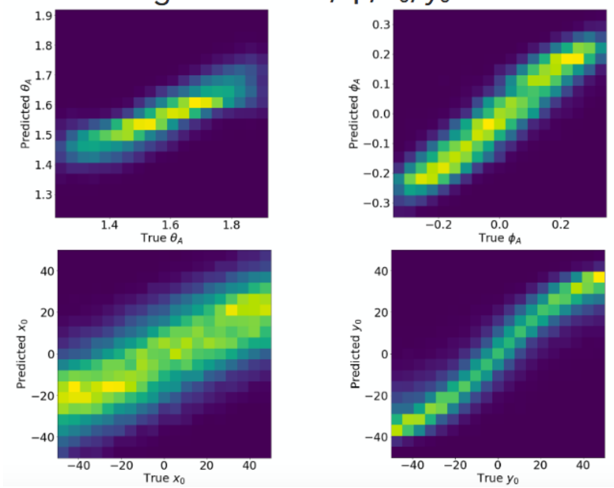


Talk by K. Wierman

Simulation GANs

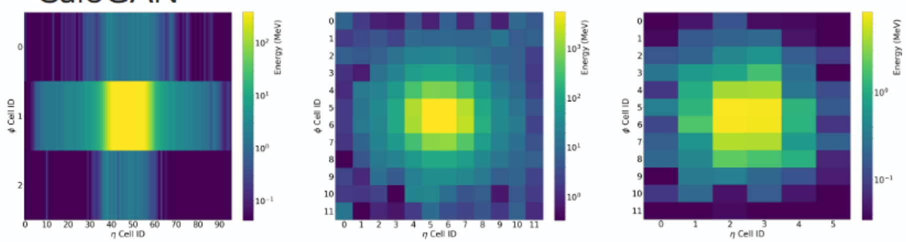


- Regression on θ, φ, x_0, y_0

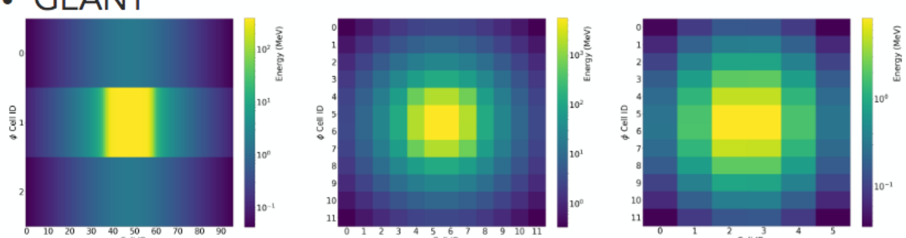


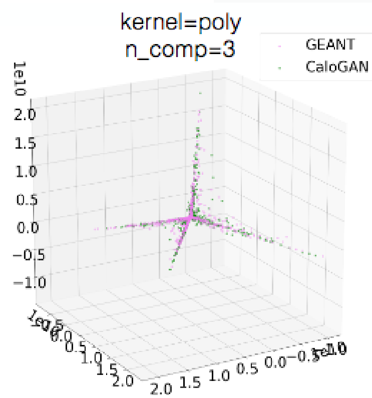
Dataset: 5˚; Net: soft sparsity, multiplied E, Conv. attn. and layers

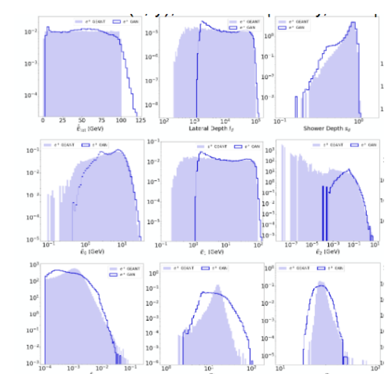
- CaloGAN



- GEANT



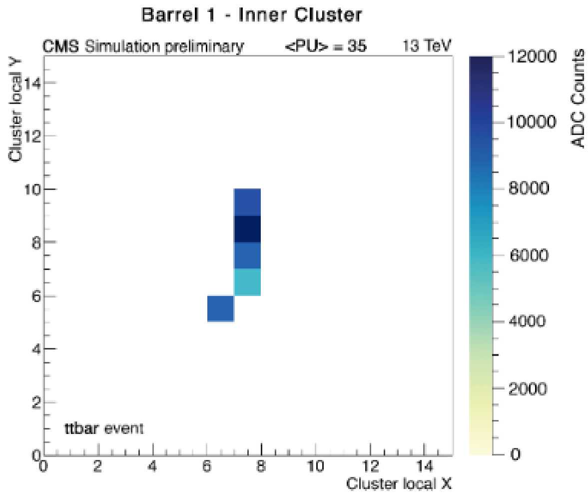


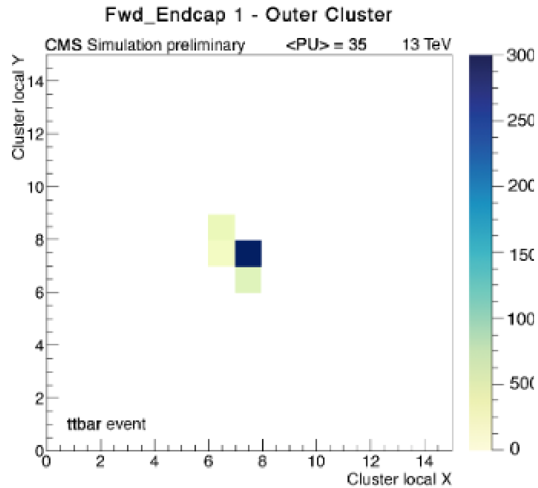


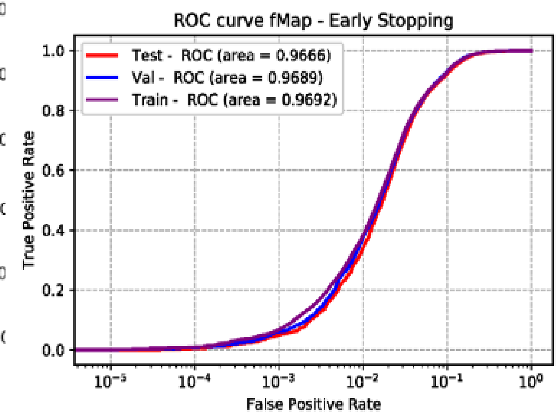
Talk by L. de Oliveira

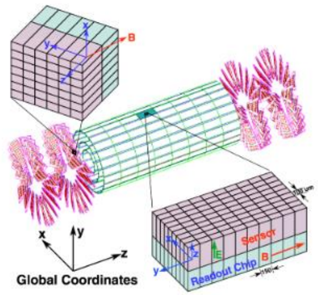
Tracking

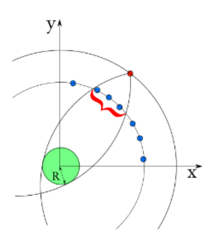
CNNs for track seeding at CMS HLT

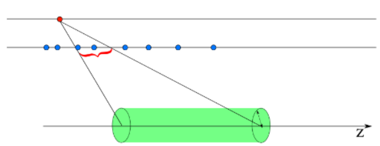










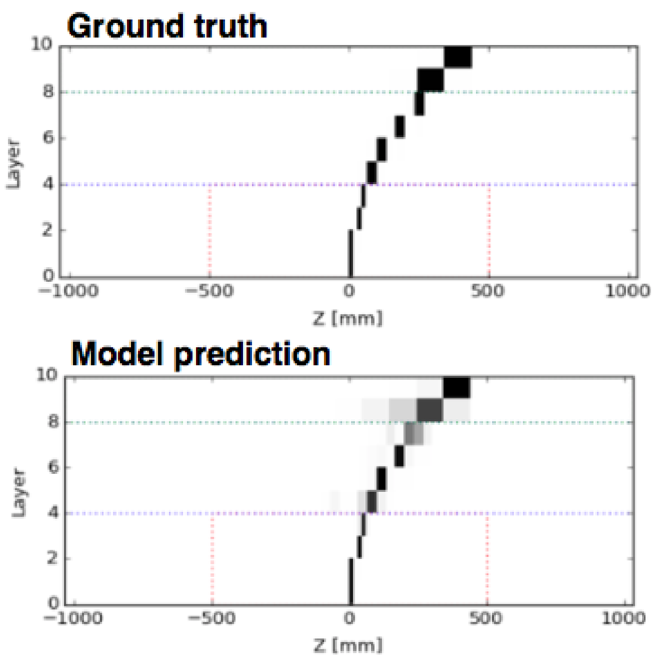


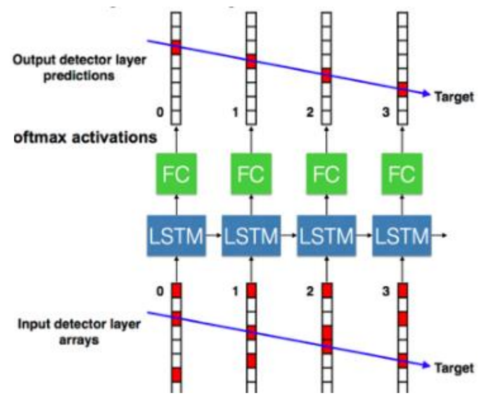
Efficiency (tpr) @ fake rejection

```
tpr @ rej 50%: 0.99767728149
tpr @ rej 75%: 0.986272733607
tpr @ rej 90%: 0.896151255429
tpr @ rej 99%: 0.285555013588
```

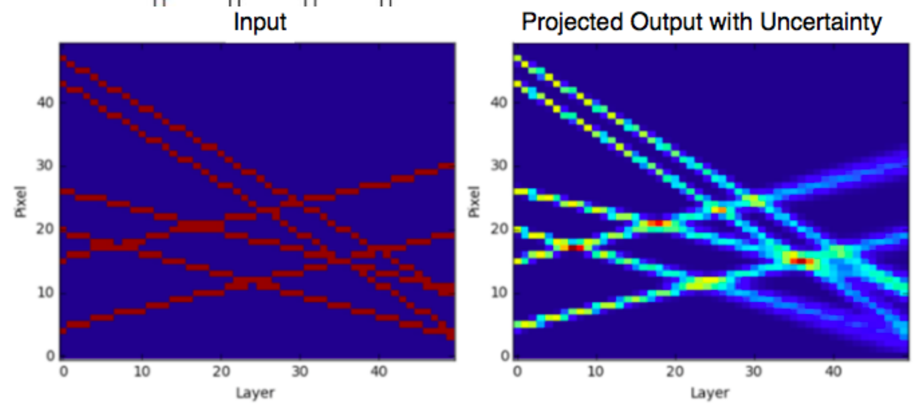
Talk by F. Pantaleo

Recurrent networks for tracking





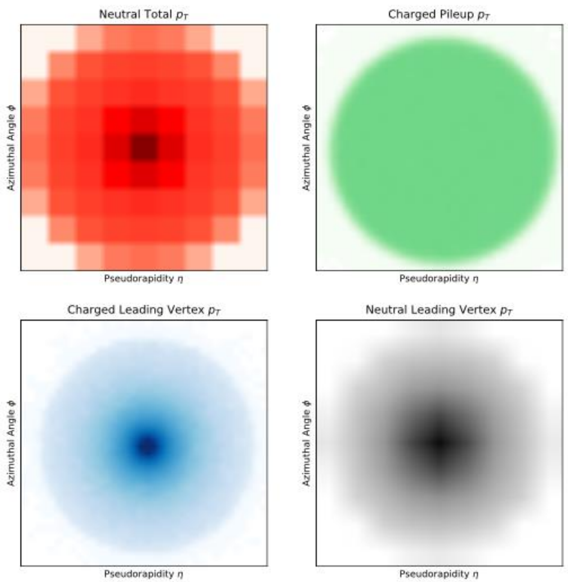
Time dimension (state memory)

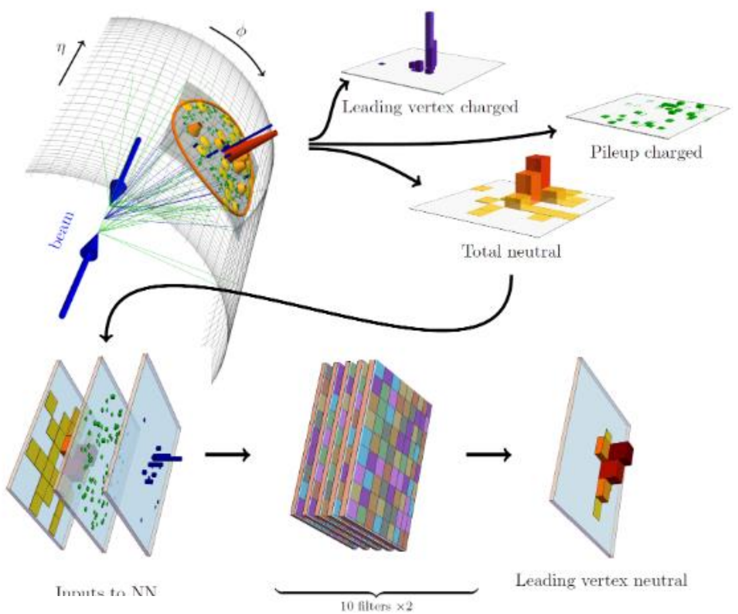


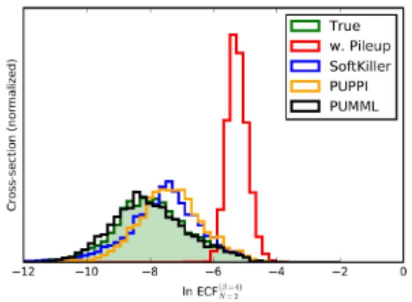
Talk by A. Tsaris

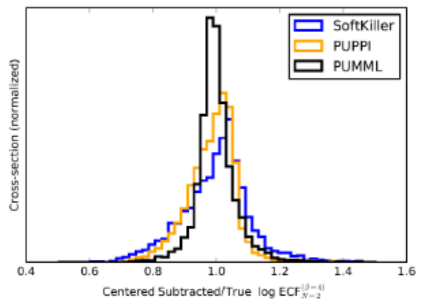
Pileup Removal

Convolutional NNs with images



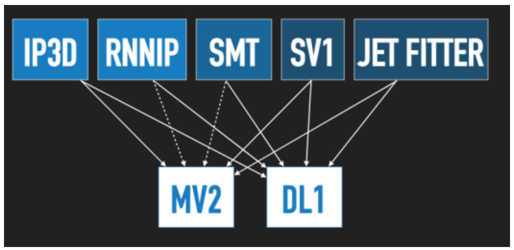


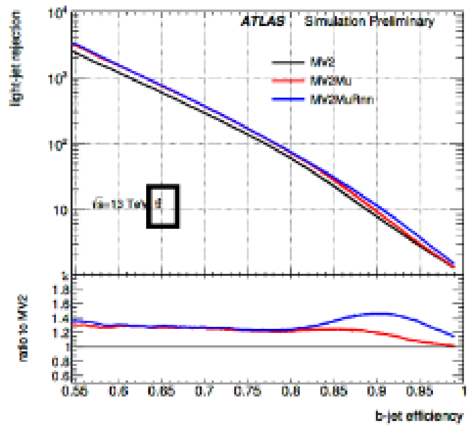


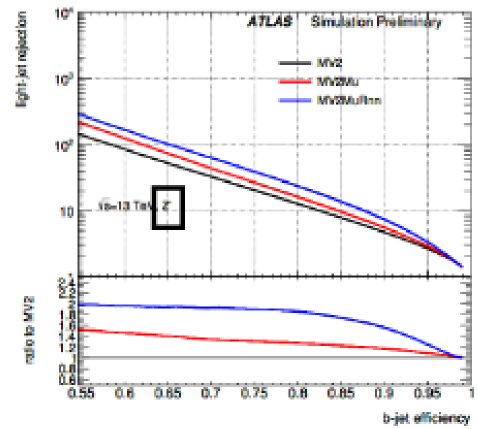


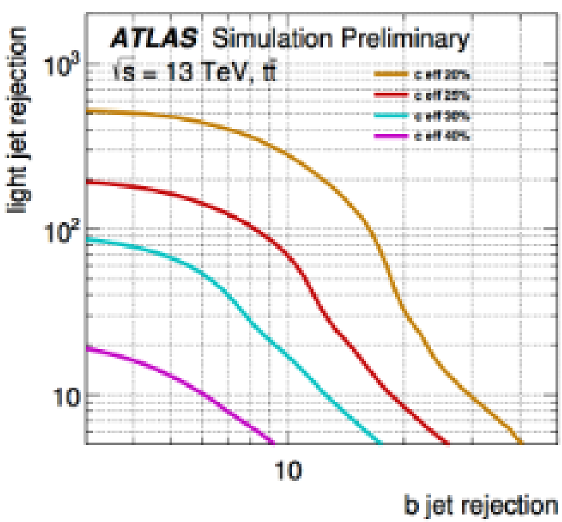
Talk by E. Metodiev

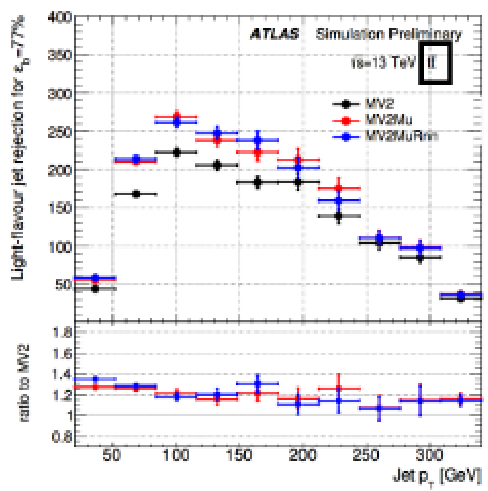
ATLAS B Tagging

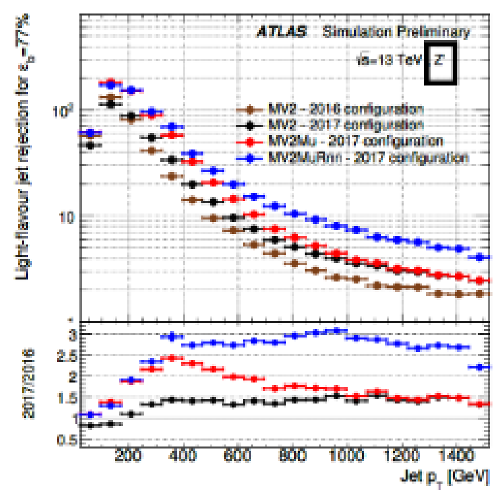






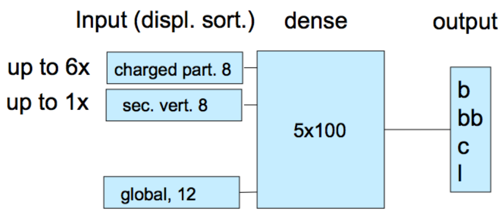


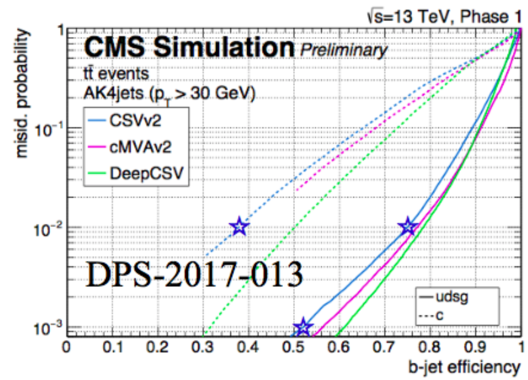


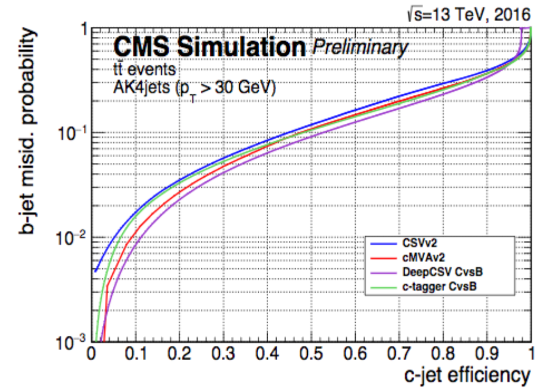


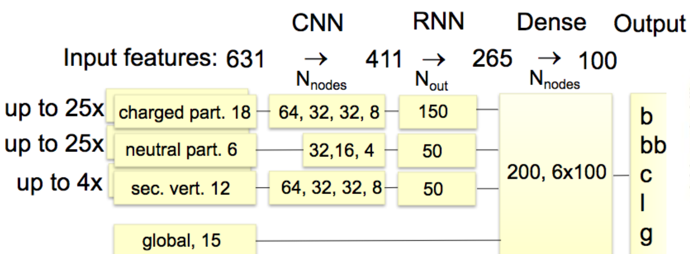
Talk by M. Paganini

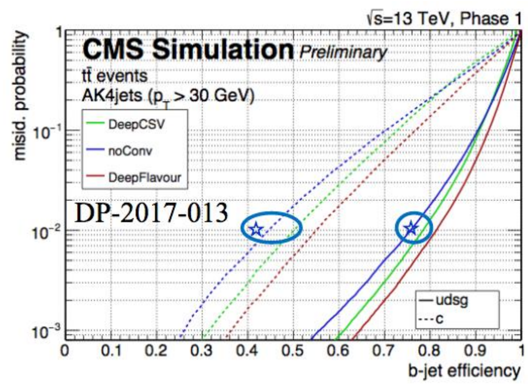
CMS Flavor Tagging

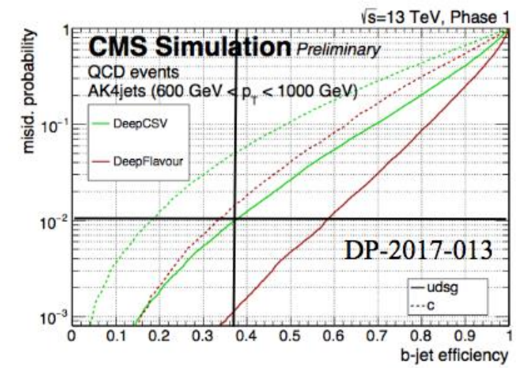


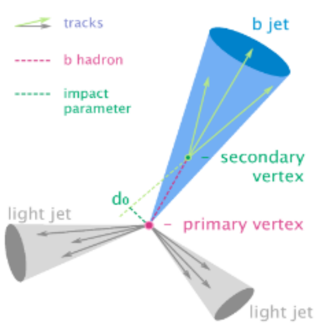


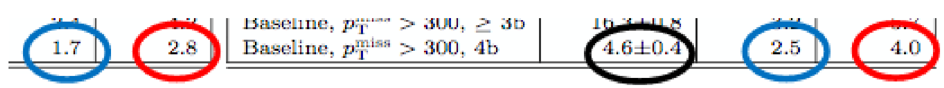








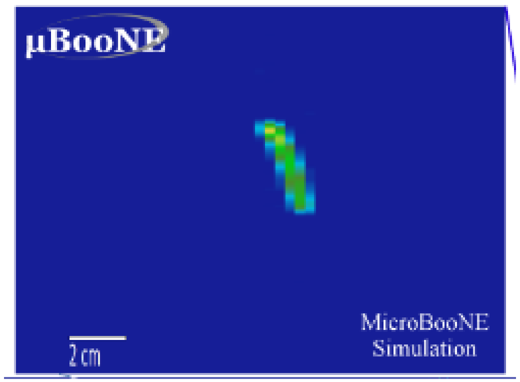




e.g. up to ~50% more signal for 15% more bkg

Talk by M. Stoye

MicroBooNE XGBoost



$$
\begin{aligned}
P(\mathrm{p}) &= \mathbf{0.9789}\\
P(\mu^{\pm}) &= 0.0012\\
P(\pi^{\pm}) &= 0.0067\\
P(e^{\pm}/\gamma) &= 0.0075\\
P(\mathrm{cosmic}) &= 0.0058
\end{aligned}
$$

Boosting and the XGBoost[3] algorithm

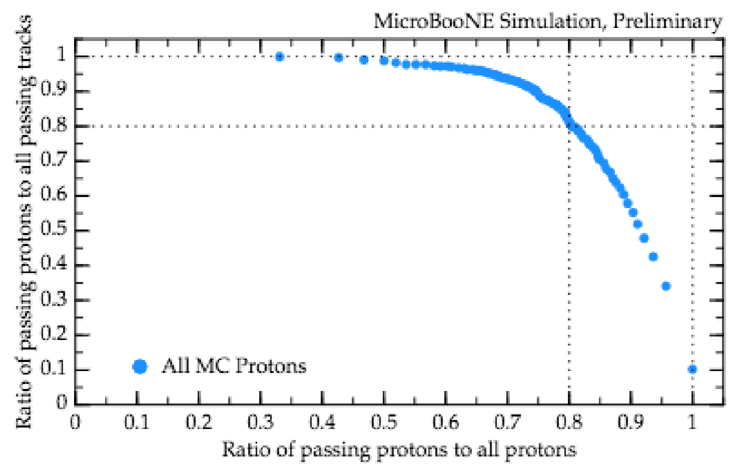
Gradient-Boosting:

- The loss function, l at tree t is

$$l(y_i, \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i))$$

- the difference between the true label (y_i) and the prediction of the existing ensemble $(\hat{y}_i^{(t-1)})$ plus the output of the new tree $(f_t(\mathbf{x}_i))$
- To simplify the computation, use the second-order approximation:

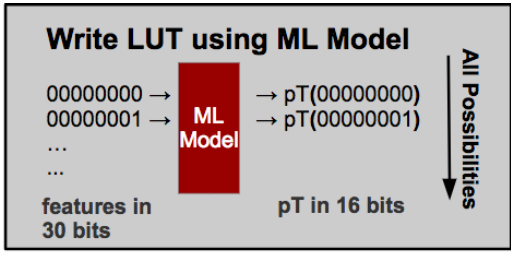
$$l(y_i, \hat{y}_i^{(t-1)} + f_t(\mathbf{x}_i)) \approx l(y_i, \hat{y}_i^{(t-1)}) + \frac{\partial\, l(y_i, \hat{y}_i^{(t-1)})}{\partial\, \hat{y}^{(t-1)}} f_t(\mathbf{x}_i) + \frac{1}{2}\frac{\partial^2\, l(y_i, \hat{y}_i^{(t-1)})}{\partial^2\, \hat{y}^{(t-1)}} f_t^2(\mathbf{x}_i)$$

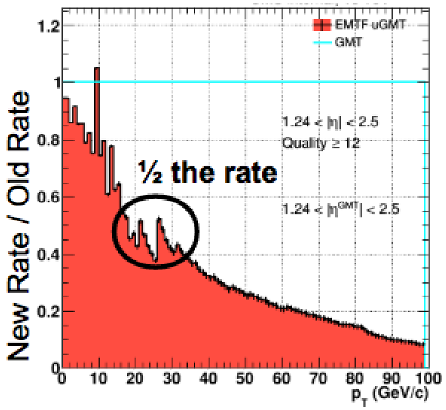


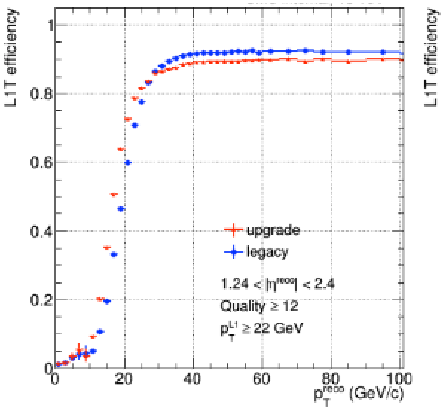
Talk by K. Woodruff

Trigger Applications

CMS L1

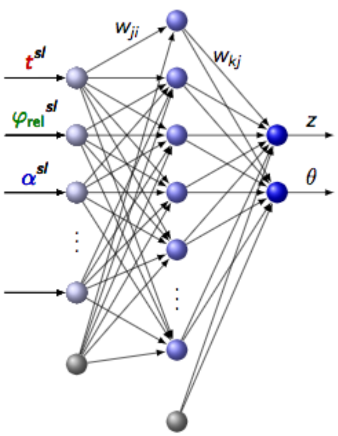


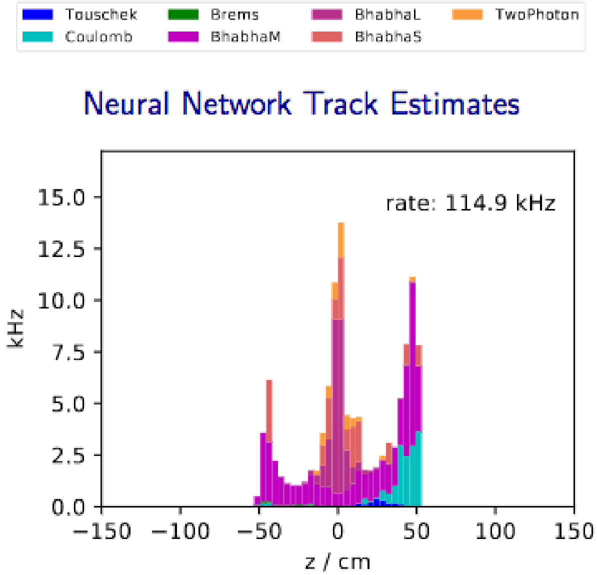


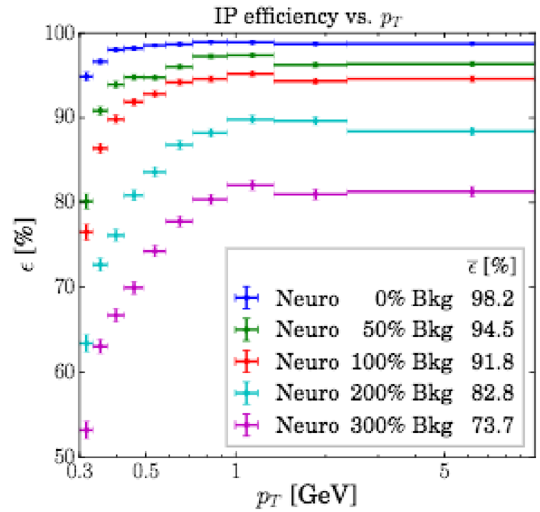


Talk by A. Carnes

Belle II





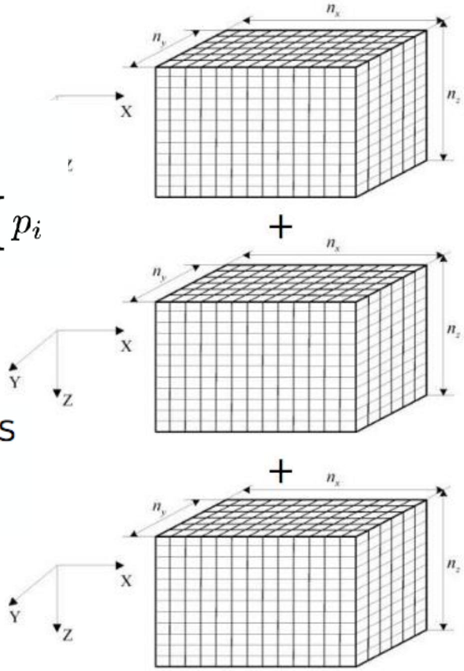


Talk by S. Skambraks

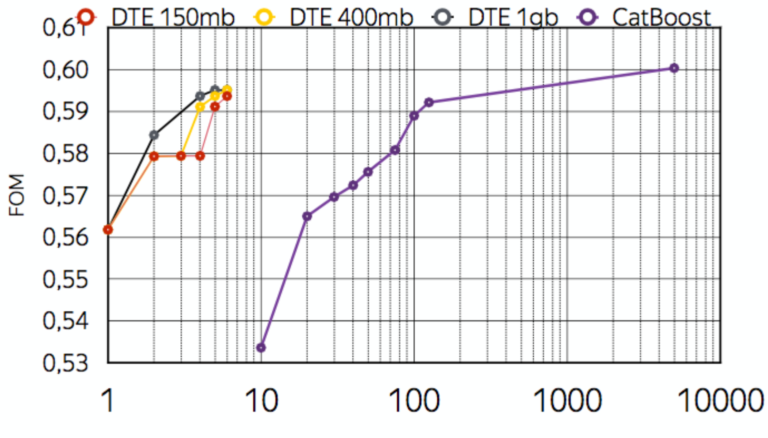
Trigger Applications

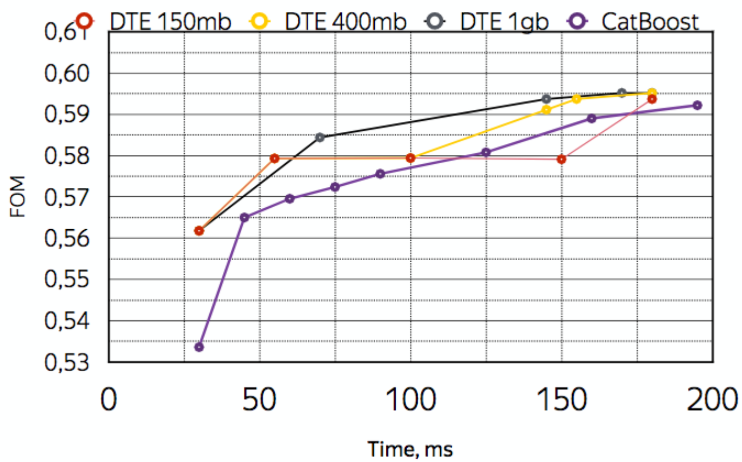
LHCb

- $D = (f_1, \ldots, f_n)$
  $f_i = \{b_{i1}, \ldots, b_{ip_i}\}$
  $S(D) \propto \prod |f_i| = \prod p_i$



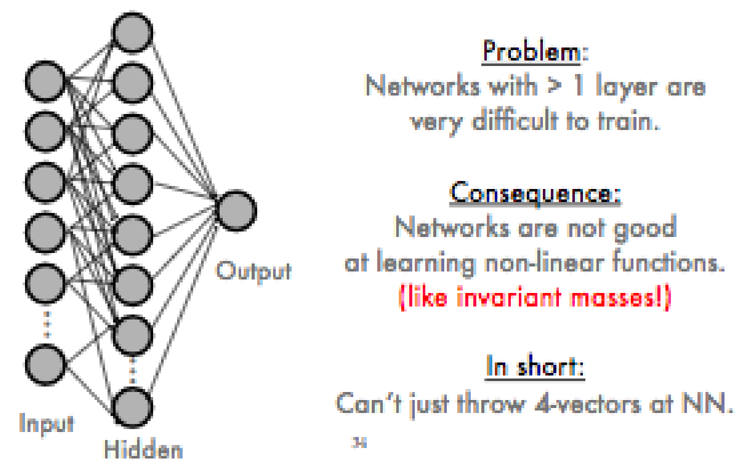
- CatBoost
- Uses oblivious trees
- Discretize features

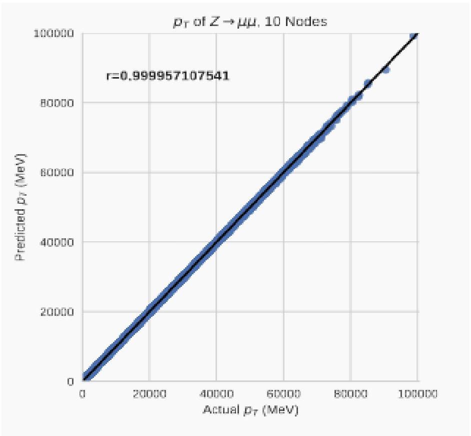


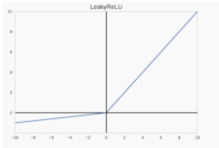


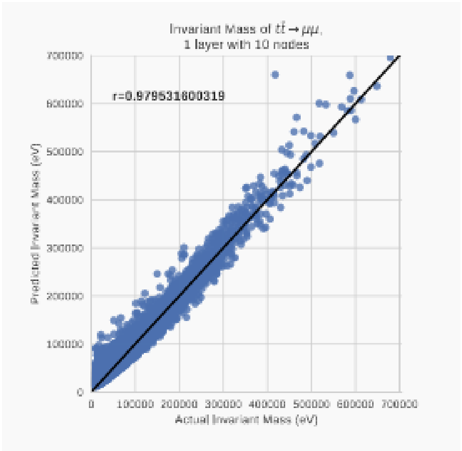
Talk by A. Ustyuzhanin

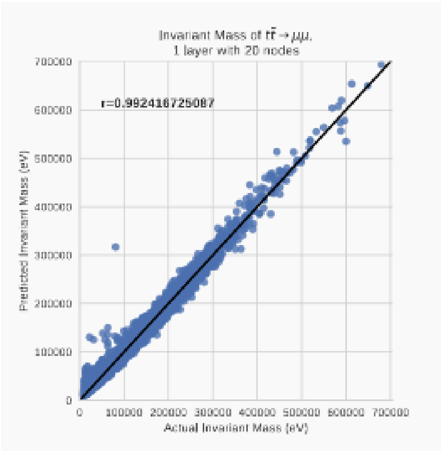
Learning Features

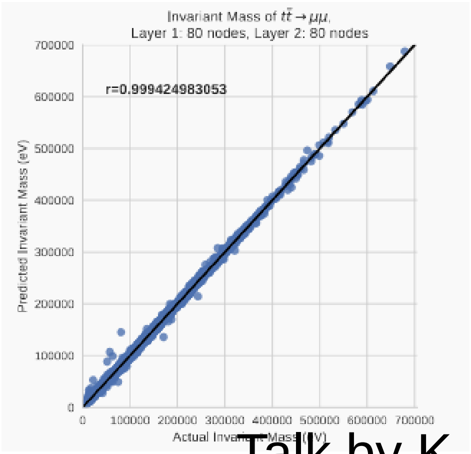












Talk by K. Chitturi

Analysis Tools

ROOT

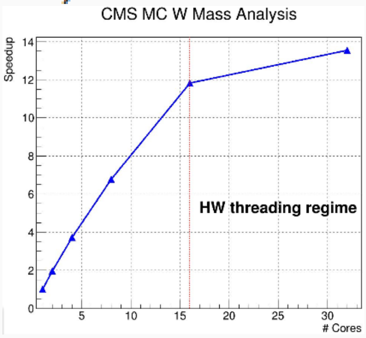
Conclusion - Main Evolution Items

- I/O: LZ4, vectorized zlib; TTree merging
- Parallelization: math, I/O, analysis
- Vectorization: math, user interfaces
- Math: see above, plus RooFit, TMVA with GNN, RNN
- Graphics: using web technology

Talk by A. Naumann

TDataFrame: Declarative Analysis

- New way to interact with ROOT columnar data format
  - Inspiration from Pandas, Spark, and others
  - Similar ideas proposed in the past (e.g. LINQToROOT by G. Watts)
- Analysis is a graph of:
  - **Transformations**: filter, add a column, …
  - **Actions**: Fill an histogram, a profile, count events, …
- Specify **what** you want and let ROOT choose **how**
  - Computation triggered lazily
  - Several optimisations (e.g. partitioning, caching, reordering, parallelisation)



Talk by G. Amadio

Spark and Histogrammar

DIANA: Histogrammar

- Spark manages concurrency (no event loop)
- Histogrammar designed for map-reduce environment
  - Functional interface
    - Fill histograms by passing lambda functions
    - Same as transformations in Spark
  - Histogrammar fills histogram data structures ➜ afterwards convert into favorite plotting tool

histo·*grammar*
/histō,'gɹæm.ər/

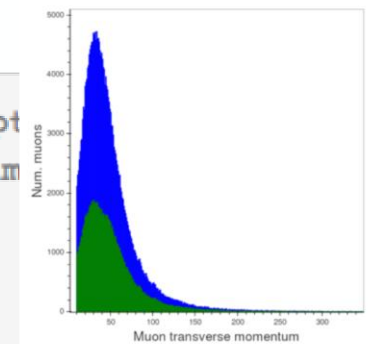
MAKING HISTOGRAMS FUNCTIONAL

ROOT:

```
histogram = ROOT.TH1F("name", "title", 100, 0, 10)
for muon in muons:
    if muon.pt > 10:
        histogram.fill(muon.mass)
```

Histogrammar:

```
histogram = Select(lambda mu: mu.pt
                Bin(100, 0, 10, lam
                    Count()))
for muon in muons:
    histogram.fill(muon)
```



Talk by O. Gutsche
http://histogrammar.org

More Tools

GooFit 2.0	Fitting
Matex	Deep learning
Vispa	Deep learning
CatBoost	Gradient Descent
Rift	VR
RECAST	Re-interpretation

Summary

- **Excellent sessions**
- **State of ML in HEP**
- **Thanks to all the presenters and attendees**