

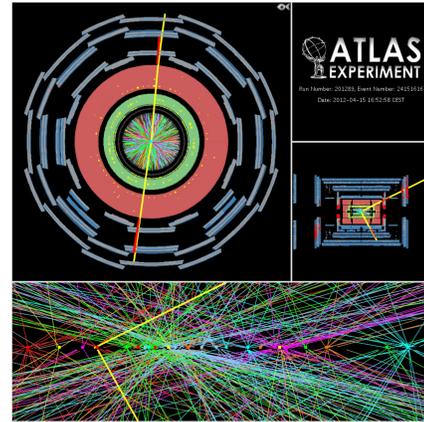


# NEURAL NETWORKS FOR CALIBRATING ATLAS JETS

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## MOTIVATION

- ATLAS is a particle detector analyzing proton-proton collisions from the LHC.
- Jets are collimated sprays of particles in the detector.
- Other low energy collisions in a beam crossing can add extra energy to the jet degrading our accuracy in reconstructing the jet's transverse momentum,  $p_T$ .
- Goal: Take energy depositions in the detector and use regression and neural networks to improve the  $p_T$  reconstruction that is uniform over a range of  $p_T$  values.

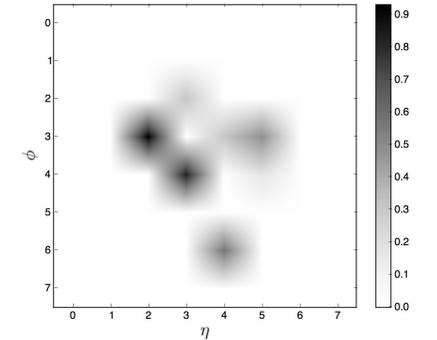


## DATASET

Our dataset consists of  $\sim 6$  million jets of detector level jets which contain:

- The true jet  $p_T$
- The  $(\eta, \phi)$  coordinates with the corresponding  $p_T$  for the clusters in a jet.
- Jet's transverse area:  $A_T$
- Number of primary vertices in event,  $N_{PV}$
- The event weights.

We divided our data into three samples: 80% as training set, 10% as CV set, and 10% as test set. Since we had vastly more low  $p_T$  events, we revised the event weights by flattening the truth  $p_T$  distribution in 4 GeV bins.



Pixel image of a jet in a  $8 \times 8$  matrix binned in the  $(\eta, \phi)$  coordinates relative to the jet's center with the bin's greyness set by the  $p_T$ .

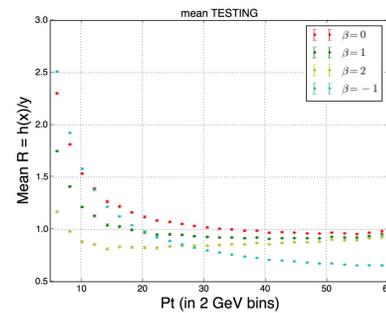
## FEATURES

- $p_T(j \text{ no area sub}) = \sum_{clusters} p_T(cluster)$
- $p_T(j0) = \sum_{clusters} p_T(cluster) - \rho A_T$
- Rings of  $p_T$  summed in annuli of  $\Delta R = 0.5$  (Jet radius:  $R = \sqrt{\eta^2 + \phi^2} = 0.4$ )

Currently ATLAS accounts for pile-up using  $p_T^{reco} = p_T^{deposited} - \rho A_T - \alpha(N_{PV} - 1)$ . Then numerical inversion accounts for the non-uniformities of the detector.

## COST FUNCTION

In initial linear regression studies we tried cost functions:  $J_\alpha(\theta) = \sum_i w_i \frac{(y-h(x))^2}{y^\beta}$ ,  $\beta = 2, 1, 0, -1$ .

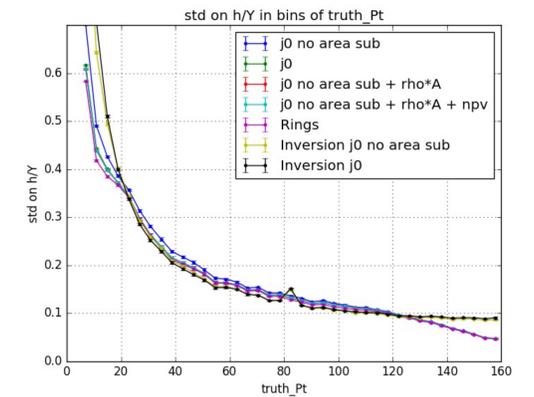
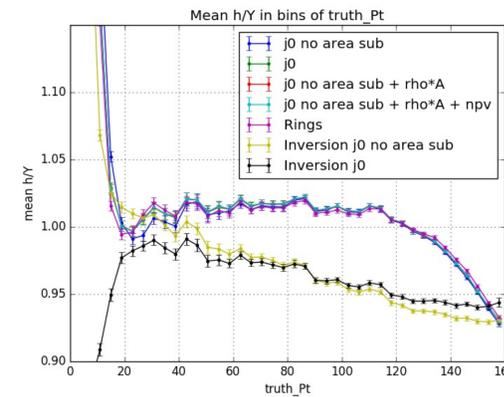


Optimize performance over entire  $p_T$  range by combining  $\beta = 0$  and  $\beta = 2$  cost functions:

$J(\theta) = \sum_i w_i (y - h(x))^2 \left(1 + \frac{\lambda}{y^2}\right)$ , where  $\lambda = 100$  to appropriately scale  $J_2$  to  $J_0$ .

## RESULTS I

To ensure uniform performance over the entire  $p_T$  range, we looked at the closure  $h_\theta(x)/y$  in 4 GeV bins and calculated the mean and standard deviation.



## RESULTS II

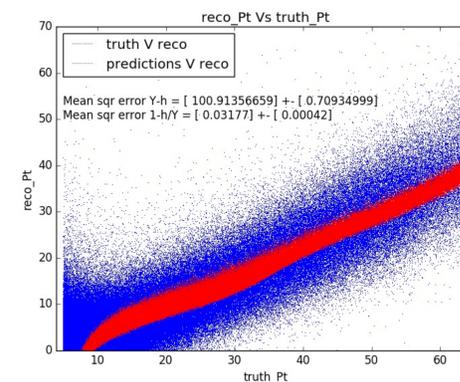
Since the neural networks aren't expected to do well at the high and low  $p_T$  limits, evaluate models using the error in  $p_T$  range [45,120] GeV.

Models	CV error
Inversion on $j0$	$0.0327 \pm 0.0006$
Inversion on $j \text{ no area sub}$	$0.0311 \pm 0.0006$
NN with $j0$ input	$0.0151 \pm 0.0007$
NN with $jj \text{ no area sub}$	$0.0138 \pm 0.0007$
NN: $j \text{ no area sub}, \rho A_T$	$0.0153 \pm 0.0007$
NN: $j \text{ no area sub}, \rho A_T, N_{PV}$	$0.0141 \pm 0.0007$
NN with 8 annuli and $j0$	$0.0129 \pm 0.0007$

All the neural networks are sequential and have 1 hidden layer with 5 input nodes. We prototyped a CNN on 50,000 jets with  $(2 \times 8 \times 8) + (5 \times 5 \times 5) + (2 \times 2) + 5 + 1$  architecture, with a CV err over  $p_T \in [20, 140]$  GeV of  $0.076 \pm 0.005$

## DISCUSSION

- Every NN that we derived performs better than the current ATLAS standard, numerical inversion.
- The NN with annuli info does best, showing that jet substructure helps.
- All other NNs perform comparably.
  - The  $j \text{ no area sub}$  with  $\rho A_T$  contains the same info as  $j0$ .
  - No new info appears to be gained by including the  $N_{PV}$  variable.



## FUTURE STEPS

- Use a series of classifiers to predict which truth  $p_T$  bin a given jet is in, then train a regression model on the combined outputs.
- Improve and understand CNN architecture to better adapt to ATLAS jet reconstruction.

## REFERENCES

[1] The ATLAS Collaboration. Performance of pile-up mitigation techniques for jets in pp collisions at  $\sqrt{s} = 8$  tev using the atlas detector. *arXiv 1510.03823*, 2015.

[2] Aviv Cukierman and Benjamin Nachman. Mathematical properties of numerical inversion for jet calibrations. *arXiv 1609.05195v1*, 2016.