Multivariate Jet Calibration Using Neural Networks

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Large-Radius Jets

Why do we care?
  • Provides simplified event reconstruction
  • Jet energy → mass scale of the process
  • Jet mass → identity of particle
  • Understanding scale and resolution is important!
Energy Calibration

- Calibration from MC, $R \approx \frac{\text{True energy}}{\text{Reconstructed energy}}$

- $true \ pT \approx R(\text{Jet } pT, \eta) \times \text{reconstructed } pT$

- Does more information give more precision?

- Limitations
  - not very practical

- Use Neural Networks!
Neural Networks

Why Neural Nets?
• Accommodates many variables
• Easily updatable

Network Training
• Input: simulated data
• Output: calibration factor $R$
• loss function: $L^2 = \left( \frac{true p_T}{reco p_T} - R \right)^2$

Simulated data sample:
• simulated di-jet events
• $p_T > 200$ GeV, $|\eta| < 2.0$
• matched geometrically to true jet
Network Configuration

Many options!
- Number of layers
- Number of nodes (neurons)
- Activation functions
- Propagation algorithms

Does it matter?
- Yes!
- Effects on runtime and convergence

Epoch: one forward pass and one backward pass of all training examples
Impact of Structure: Layers

- Multiple layers may improve convergence
- Runtime increased by factor of 2.5/epoch
- Still effective to use a single layer
Impact of Structure: Nodes

- Performance not correlated with nodal number
- More input variables requires more nodes
Impact of Structure: Activation Function

- Relu (rectified linear unit)
- Sigmoid and tanh are more comparable

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Final Network Structure

Network Parameters

• Number of layers: 1

• Number of nodes per layer: 20-50

• Activation function: Tanh

• Propagation algorithm: Adam
Preliminary Results

So, how are we doing?

- Successfully calibrated!

- Convergence occurs within 10,000 epochs and takes roughly 2 hours.
Preliminary Results

How do we compare?

• NN looks very similar to by-hand JES calibration

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Future Directions

• Formalize optimization strategy and find optimal $p_T$ calibration

• Repeat studies with new (jet substructure) input variables and less generic jets

• Expand strategy to calibrate other observables
  • particularly jet mass!
Backup Slides
## Back up Slides: Layers

<table>
<thead>
<tr>
<th>Layers</th>
<th>Final Training MSE</th>
<th>Final Validation MSE</th>
<th>Training time</th>
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<tbody>
<tr>
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<td>378.272</td>
<td>67.8496</td>
<td>107 sec</td>
</tr>
<tr>
<td>2</td>
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<td>4</td>
<td>360.221</td>
<td>85.7614</td>
<td>290 sec</td>
</tr>
</tbody>
</table>

One data file (JZW7) and 20 nodes

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Backup Slides: Layers

- Convergence is comparable among the different layers
- Only see difference when lower numbers of nodes are used
Backup Slides: Propagation algorithm

- although there are strong early fluctuations away from best calibration, Adam converges fastest

- Other algorithms are smoother, but may be susceptible to getting stuck in a local minimum.

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Backup Slides: Calibration Comparison

Comparison of Final Response Functions (Normalized)

Legend
- No Calibration
- New Calibration
- Old Calibration
- Target at 1

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