A SEARCH FOR SUPERSYMMETRY IN EVENTS WITH A Z BOSON, JETS, AND MISSING TRANSVERSE ENERGY WITH THE ATLAS DETECTOR

TOVA RAY HOLMES

Physics Department
University of California, Berkeley

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ABSTRACT

PUBLICATIONS

Some ideas and figures have appeared previously in the following publications:

Put your publications from the thesis here. The packages `multibib` or `bibtopic` etc. can be used to handle multiple different bibliographies in your document.

ACKNOWLEDGEMENTS

Put your acknowledgements here.

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LISTINGS

ACRONYMS

LHC Large Hadron Collider

IBL Insertable B-Layer

NN Neural Network

CCA Connected Component Analysis

ToT Time Over Threshold

MC Monte Carlo simulation

Part I

INTRODUCTION

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1 INTRODUCTION

The pages that follow detail the author's work on the ATLAS experiment from 2011 through 2016, focusing on an analysis of 13TeV proton-proton collisions at the Large Hadron Collider (LHC) looking for Supersymmetry with the ATLAS Detector.

CHAPTER 2 outlines the Standard Model of Particle Physics and the benefits of extending it to include Supersymmetry, then continues to describe the motivation behind searching for this particular model.

CHAPTER 3 describes the LHC and its operation.

CHAPTER 4 contains descriptions of the many pieces of the ATLAS detector, and how they serve to detect particles coming from LHC collisions.

CHAPTER 5 presents a neural network designed to improve tracking in the ATLAS Pixel Detector, and describes the benefits of its implementation.

Part II

THEORY AND MOTIVATION

You can put some informational part preamble text here.

2 THEORY AND MOTIVATION

Some kind of preamble here I guess.

2.1 THE STANDARD MODEL

2.1.1 *How do you explain the standard model?*

I will put this off for now.

2.1.2 *Problems in the Standard Model*

2.2 SUPERSYMMETRY

Part III

WHERE DATA COME FROM

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3 THE LARGE HADRON COLLIDER

The LHC is unique in the world, producing particle collisions at energies an order of magnitude higher than any accelerator before. It provides unique environments in its proton-proton collisions where massive, unstable particles can exist for an instant, then decay to the ordinary material of the universe.

3.1 OPERATION OF THE LARGE HADRON COLLIDER

4 THE ATLAS DETECTOR

The ATLAS detector circumscribes the LHC ring, enclosing the collision point with a series of particle detecting subsystems, aimed at making as many measurements of the particles leaving the interaction as possible. Its goal is to get a precise measurement of all the stable particles flying from proton-proton collisions at its center, allowing analyzers to fully reconstruct the kinematics of the underlying event.

4.1 SUBDETECTORS OF ATLAS

The ATLAS Detector consists of many layers of detectors, each of which contributes to the measurements of the position and energy of particles in different ways. This section will describe each of these detetors, in the order in which they are traversed by a particle coming from the collision point.

4.1.1 *The Pixel Detector*

The Pixel detector lies closest to the beam pipe of the LHC, and has four layers comprising 92 million read-out channels. There are three standard layers, referred to as L1-L3, and an additional layer added for the 2015 datataking, called the Insertable B-Layer (IBL).

4.1.1.1 *The Original Pixel Detector*

4.1.1.2 *Addition of the IBL*

In 2015, the IBL was lowered into the ATLAS cavern and added to the Pixel Detector. As its name suggests, it was added to improve detection of B mesons, whose non-trivial lifetimes create secondary vertices in ATLAS events, which allow them to be distinguished from other particles with precise track measurement. The IBL is closer to the interaction point and has a smaller spacing between sensors, giving it a better chance to see these slightly displaced vertices.

5

APPLICATION OF A NEURAL NETWORK TO PIXEL CLUSTERING

5.1 CLUSTERING IN THE PIXEL DETECTOR

Creating tracks from individual hits in the Inner Detector is one of most computationally challenging parts of the reconstruction of ATLAS events. Each event typically contains thousands of hits in the pixel detector alone, which must be combined into one coherent picture of which particles traversed the detector, and how they moved and lost energy as they traveled. A typical particle deposits charge in several pixels per layer, forming a series of clusters which can be connected together to form a track. This track can in turn be used to measure the charge, momentum, and trajectory of the particle, and in many cases, provides ATLAS's most precise measurement of a charged particle.

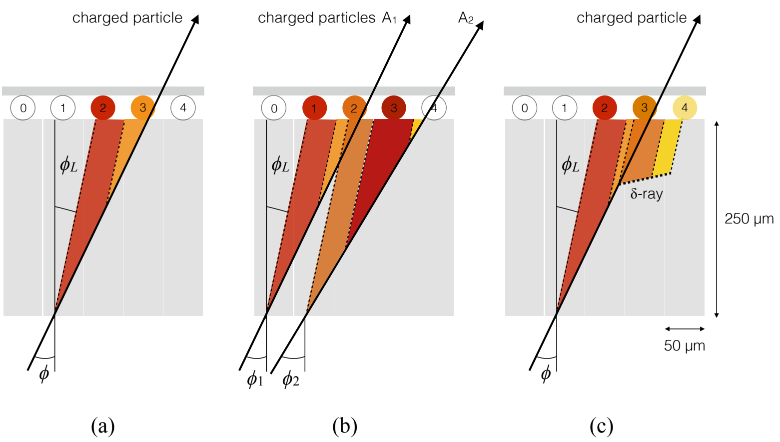

Figure 1: A few possible types of clusters in the Pixel Detector. (a) shows a single particle passing through a layer of the detector, (b) shows two particles passing through the detector, creating a single merged cluster, and (b) shows a single particle emitting a δ-ray as it passes through the detector.

The process of going from clusters to track is relatively simple in an isolated environment in which one particle travels cleanly through all the layers, but can be complicated by multiple close-by tracks and by a single particle's emission of low energy particles, called δ-rays. In these cases, it can be hard to tell how many particles were involved in creating a cluster, and where exactly each of those particles passed through the layer. A few examples of these cases can be seen in Figure 1 . The process of determining this is called Clustering, and it has recently been updated from a charge interpolation method to a method using a NN.

5.1.1 *Charge Interpolation Method*

A typical cluster contains a few pixel hits spanning in the x and y directions, each with its own measurement of charge deposition, or Time Over Threshold (ToT). The extent of the cluster is defined by grouping together any pixels with a shared edge or corner. In the charge interpolation method, also called the CCA clustering algorithm, these individual hits are combined to make one estimation of the position a single particle which passed through them, using the following equation:

$$x_{cluster} = x_{center} + \Delta_x(\phi, N_{row}) \cdot \left[\Omega_x - \frac{1}{2}\right] \tag{1}$$

$$x_{cluster} = x_{center} + \Delta_x(\phi, N_{row}) \cdot \left[\Omega_x - \frac{1}{2}\right] \tag{2}$$

where $\Omega_{x(y)}$ is defined by

$$\Omega_{x(y)} = \frac{q_{last\ row(col)}}{q_{first\ row(col)} + q_{last\ row(col)}} \tag{3}$$

and q represents the ToT of a given pixel, and $\Delta_{x(y)}$ is a function derived from either data or Monte Carlo simulation (MC) and produces an output related to the projected length of the particles track on the pixel sensor and is measured as a function of ϕ, the incident angle of a particle on the sensor, and $N_{row(col)}$, the number of pixels in the x and y direction.

In a simple case, such as (a) of Figure 1 , this method works quite effectively. However, in cases like (b), it has no ability distinguish two-particle from one-particle clusters, and can only assign a cluster center between the two particles' locations, despite that intermediate pixel having the lowest ToT. Furthermore, because this method can't differentiate two-particle clusters, the tracking software can't use that information to preferentially allow multiple tracks to be fit to the cluster. In cases like (c), the δ-ray will bias the measurement of the particle's position in whichever direction it is emitted.

5.1.2 *Improving Measurement with Neural Networks*

To address these problems, a series of NNs were created [1]. The first determines the number of particles in a given cluster, the second predicts their positions with the cluster, and the third assesses the resolution of the position measurement.

These NNs are all trained with:

- a 7×7 grid of cluster ToT information[1]
- a seven-element vector containing the y-size of the pixels in the grid
- the layer number of the cluster
- a variable indicating whether the cluster located in the barrel or endcap
- θ and ϕ variables projecting the incident angles of the particle on the sensor, assuming it comes from the interaction point
- the η index of the pixel module

After the Number NN predicts a number of particles associated with the cluster, required to be between 1 and 3, the same inputs are fed to one of three Position NNs based on the determined number of particles, which then outputs the x and y positions of each of the particles. Then, the same inputs combined with the output of the Position NN are fed into one of three Error NNs (also distinguished by number of particles), which outputs a resolution for each of the position predictions made. An example of the output of this process can be seen in Figure 2, where the improved position resolution from the ability to identify a multi-particle cluster is evident. The particle location predictions from the NNs are then handed to the tracking software, which is able to independently consider multiple locations from a given cluster to find the best fit.

5.2 IMPACT OF THE NEURAL NETWORK

The NN was first applied to 7TeV data, where it improved position resolution for particles in small and large clusters. Figure 3 shows the improvement from the addition of the NN in x resolution in different cluster sizes. The improvement from CCA clustering is particularly evident in the 4-pixel case, where the double peaked structure of the interpolation method has been completely removed with the NN.

5.2.1 *The Neural Network in 13 TeV Data*

In Run 2, tracking algorithm is first run on the CCA clusters, where it constructs loose tracks that allow shared clusters, clusters to which multiple tracks are fit. The NN is then used to identify which clusters are likely to have had multiple particles pass through them, and to identify the positions of those particles. In the case that the cluster is

1 Clusters spanning more than seven pixels in either direction are split into multiple clusters.

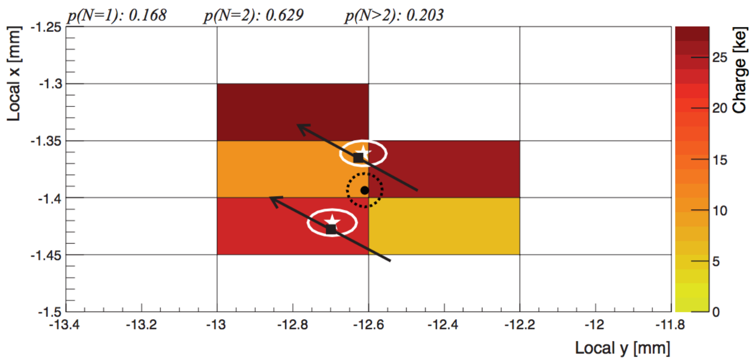

Figure 2: One example of a two-particle cluster and its truth information compared with the output of the NNs. At top, the $p(N = i)$ values give the output of the Number NN, the probabilities that the cluster contains 1, 2, and 3 particles. Given the highest probability is for $N = 2$, the other NNs predict the postion and errors of the two particles (in white). The black arrows and squares represent the truth information from the cluster, and the black dot and dotted line show the position measurement for the un-split cluster.

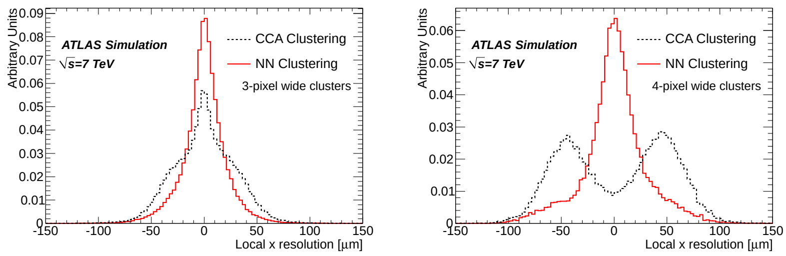

Figure 3: x resolutions for clusters with 3 (left) and 4 (right) pixels in the x direction in 7TeV data for CCA and NN clustering.

determined to have resulted only from one particle, tracks that share that cluster are penalized.

Performance in 13 TeV [2].

Robustness [3]

Part IV

SEARCHING FOR SUSY

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Part V

CONCLUSIONS

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Part VI

APPENDIX

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