Interim report: Using machine learning in identifying background signals at LZ

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Abstract

The aim of this project is to implement a neural net approach using Keras to discriminate between different decay sources in the outer detector of the LUX-ZEPLIN Dark matter detector (LZ). This approach will be compared to using a pedestrian 'cut' approach and a more robust statistical method. This project has room for expansion depending on the neural net model that is implemented as well as other statistical approaches. In this literature review, the reasons for discovering dark matter, using direct detection and different machine learning approaches will be discussed, thereby explaining the motivation and direction for the project. Finally, the progress made towards these goals will discussed.

1 Literature review

1.1 Dark matter

Dark matter is a theoretical form of matter which is thought to account for 85% of the total mass found in the universe [1]. Dark matter is itself 'dark' as it has not been observed directly, as if dark matter exists, it barely interacts with baryonic matter and radiation, with its only interaction being with gravity. Nevertheless, the theory of dark matter is a well motivated one, as a variety of gravitational effects cannot be explained without the addition of more mass within current theories of gravity.

The first primary evidence of dark matter comes from a study on the Coma cluster in 1933 by Fritz Zwicky [2]. By comparing the mass from the virial theorem and the mass inferred from the bright, luminous matter in the galaxies, he found that the mass predicted from the virial theorem is 500 times greater than expected, this lead him to determine that a large amount of non-luminous matter must be present [3]. Similar surveys show us that this is the case for most galaxies and clusters. Typically, there is 6 times more mass present in the universe than can be visually accounted for [4].

Another piece of evidence is from the Galactic rotation curves. From newtons law of universal gravitation:

$$\frac{mv^2}{r} = \frac{GMm}{r^2} \tag{1}$$

Where G is the gravitational constant. From Equation 1, it's expected that the velocity of stars to decrease as the star's distance from the centre of the galaxy increases. In 1970, Rubin and Ford measured the rotation curve of M31 using optical spectroscopy and found that the velocities stay approximately constant over the radius [5] which can be seen in figure 1.

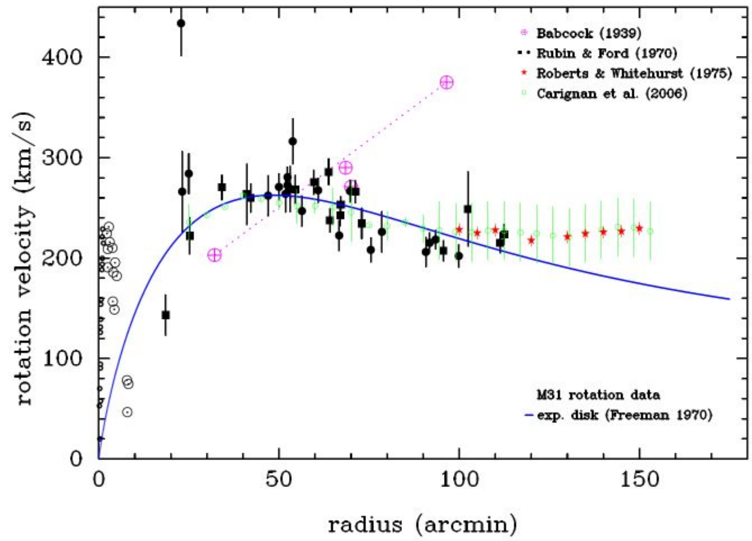

Figure 1: The rotation curve data for M31. The data points are supplemented by an exponential disk curve.

This again shows the existence of a form of matter that cannot be directly observed which rather than be concentrated in the centre of the galaxy, the dark matter is diffused in a 'halo' that extended well beyond the edges of the luminous galaxy.

Another piece of evidence for dark matter lies in the bullet cluster, which is actually composed of two colliding galaxy clusters. The hot gas clouds contain most of the baryonic mass, which after colliding, decelerate in the collision shock. Gravitational lensing effects show that the centre of total mass has been spacial displaced from the centre of baryonic mass, as seen in figure 2:

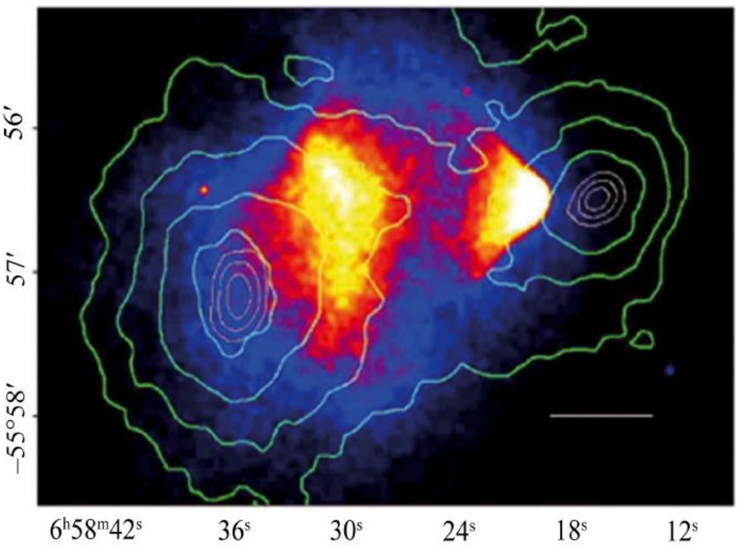

Figure 2: An x-ray image of the Bullet Cluster obtained by the Chandra x-ray observatory [6]. The Brighter regions represent greater x-ray intensity. The green contours represent the mass density constructed by gravitational lensing signal. The white bar represents a 200kpc distance.

Again, like the other examples, this implies the existence of a type of matter which cannot be directly observed and does not interact with baryonic matter. The evidence of dark matter in this example is even more compelling, as it is the first system where the dark and baryonic matter components have been separated.

At the time of writing, dark matter is the most compelling theory to the observations discussed. There are other theories such as Modified Newtonian dynamics (MOND) which have had successes in describing galactic rotation curves, but have not provided a full set of explanations for the bullet cluster and Zwicky's observation of the galaxy clusters. There are many candidates to explain what dark matter is, however the one of particular interest is Weakly Interacting Massive Particles or WIMPS.

1.2 WIMPS

Weakly Interacting Massive Particles (WIMPS) is a broad term describing any massive particle that does not interact through any forces stronger than the weak force [7] with masses in a range of 1 GeV to 10 TeV. Most models for WIMPS assume that they were produced in the thermal equilibrium of the early universe and gradually decrease in number through self-annihilations. From this, its possible to model the expected contributions of WIMPS to energy density of the universe using equation 2:

$$\Omega_x h^2 \ (3 \times 10^{-26} cm^3/sec)/(\sigma v)_{ann} \tag{2}$$

Where $\Omega_x h^2$ is the energy density of the universe. By substituting the observed dark matter density obtained by WMAP [8], the dark matter interaction strength turns out very close to the strength of the weak nuclear force, in what has been dubbed 'The Wimp Miracle'. The method of WIMP production that most closely matches with observed cosmological observations is known as the 'Freeze-out' model. The model assumes that at the very beginning of the universe, baryonic matter and dark matter were in a thermal plasma. The thermal plasma is in a state of thermal equilibrium where the rates of production and annihilation are equal. The annihilation rate stayed constant for both types of matter because the density and temperature at the beginning of the universe was so high that the matter could not travel any substantial distance before being annihilated. However, as the universe expanded, the temperature and density of the universe decreased, allowing dark matter particles to travel further distances without annihilating and decouple from the thermal plasma. These dark matter particles would go on to form galaxies and galaxy clusters.

Out of all the possible WIMPS, the lightest super symmetric particle (LSP) from supersymmetry (SUSY) is the most likely candidate for dark matter. Supersymmetry is a theory that poses a symmetry between the two classes of particles, fermions and bosons. SUSY proposes that every particle in the standard model has a supersymmetric partner whose spin differs by 1/2. SUSY models focus on a conserved quality known as R-parity, which replaces baryon and lepton number conservation. R parity calculated through equation 3:

$$P_R = (-1)^{3(B-L)+2s} \tag{3}$$

Where B and L are the baryon and lepton numbers respectively, and s is the spin. The value of R-Parity for the standard model particles is +1 and for the supersymmetric pairs is -1. This means that SUSY particles can't decay into standard model particles. Since the LSP is the lightest SUSY particle, it cannot decay into other SUSY particles and cannot decay into the standard model particles. This makes it an ideal candidate for dark matter. As of the time of writing this, no SUSY particles of any type have been detected [9].

Despite the fact that SUSY has not been proven, the model is well motivated. Not only could WIMPS be a viable candidate for dark matter, SUSY could also be a solution to the hierarchy problem as well as modifying the coupling constants for the weak, strong and EM forces, leading to a unified theory of physics [10]. There are a number of different methods for detecting WIMPS, however for the purpose of this review, the method of interest is direct detection.

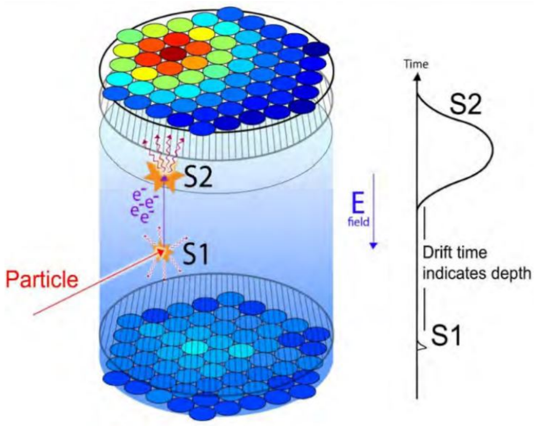

Figure 3: This diagram of shows the operating principle of a dual-phase xenon detector [13]. A particle interaction with the Liquid xenon creates 2 signals, one from the scintillation of the xenon (S1) and a second, delayed signal coming from the ionization (S2). These are detected via a photomultiplier tubes on the top and bottom layer

1.3 Direct Detection

Direct detection experiments are experiments that search for signals created by dark matter WIMPS from the galactic dark matter halo using terrestrial detectors. The signals direct detectors observe are generated by the elastic scattering of WIMP's off a target nucleus [11]. The momentum transfer between the WIMP and nucleus will give rise to a nuclear recoil, which could be detectable. The WIMP-matter interaction is very feeble, therefore the background levels for the experiment need to be extremely low.

A common form of detector for direct detection of WIMP's is a noble gas detector. Noble gas detectors work by having the WIMP particle recoil against the xenon or argon in the tank. Xenon and Argon are used due to their extremely low reactivity and have very long half-lives, but their most important characteristic is that they are excellent scintillators. However, Liquid Xenon is what it used for the most precise WIMP detectors because Xenon has a higher nuclear charge which implies it is very good as a shield against radioactivity, which is very important given the nature of the Xenon-WIMP interaction [12].

The two major detectors that have been built this way are the Large Underground Xenon experiment (LUX) and the LUX-Zeplin experiment (LZ) which is a merger of the LUX and Zeplin experiments. Both of these detectors are Dual-phase liquid xenon detectors, which means that the detector takes two different signals from an interaction, which can be seen in figure 3. Both detectors use a top layer and bottom layer of photomultiplier tubes. A Photomultiplier tube (PMT) is a class of vacuum tube that is sensitive to the near-infrared, visible and ultraviolet ranges of electromagnetic radiation.

Photo multiplier tubes consist of a photosensitive cathode, which converts the photons from the radiation to electrons via the photoelectric effect, several dynodes which multiply the numbers of electrons and an anode for collection. This can be seen in figure 4. The sensitivity of the photomultiplier tube is important as it acts as the eyes of the detector, with S2 (as seen on figure 3) giving the position of the interaction and the time difference between S1 and S2 being used to find the depth of the interaction.

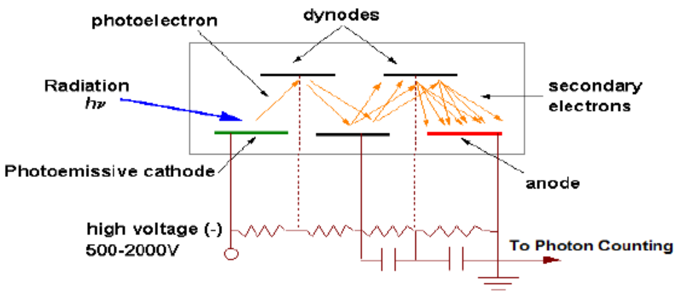

Figure 4: A Diagram of a photomultiplier tube

LUX was an experiment that ran from 2013 to 2016 which housed 370 kg of liquid xenon and searched for interactions between WIMPS and Xenon. Over its lifespan, it ruled out interaction cross-sections of $1.1 \times 10^{-11} cm^2$ for a 50 GeV/c^2 with 90% C.L [14]. At the time, LUX was the most sensitive direct dark matter detector in the world and disproved potential WIMP signals from both CoGeNT and CDMS-II. The results from LUX presented a lot of evidence against SUSY models, with some scientists abandoning SUSY altogether [15]. However, the LZ experiment proposes to be nearly 100 times more sensitive than the LUX experiment. LZ will contain more than 10 tonnes of liquid xenon and 494 photomultiplier tubes compared to the LUX experiments 61 [16].

Despite the evidence against the SUSY model, searching for WIMPS remains important as a dark matter candidate as it appears as a solution to multiple problems in physics, which gives more credibility to its existence. However, in order to find dark matter at LZ, the interactions must be distinguished from the background radiation. There are a number of ways to distinguish between the background sources, one of which is to use a machine learning algorithm.

1.4 Machine learning

Machine learning is the field of study that looks at using computational algorithms to generate usable models from empirical data [17]. Humans learn from experiences whereas computers have to be coded exactly how to function, machine learning allows computers to learn without being explicitly programmed. Machine learning does not consist of a single one-size fits all algorithm, as it depends on the problem itself.

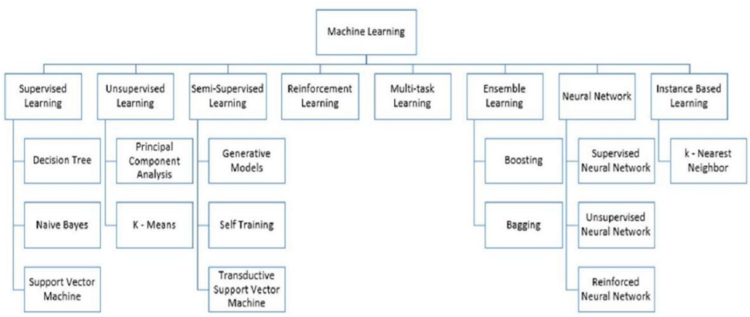

Figure 5: A flow diagram showing the different forms of machine learning.

There are too many algorithms to cover for the purposes of this review, so instead of covering each one in detail, this review will look mainly at deep learning models or neural networks.

A neural network is a series of algorithms that aim to imitate how the human brain operates. Similar to biological neural network, a neural network refers to a collection of nodes called appropriately neurons [18]. The artificial neuron itself is a function that accepts one or more inputs, weights them and passes them into a non-linear function know as an activation function to produce an output. This gets more interesting when neurons get grouped together to form the neural network.

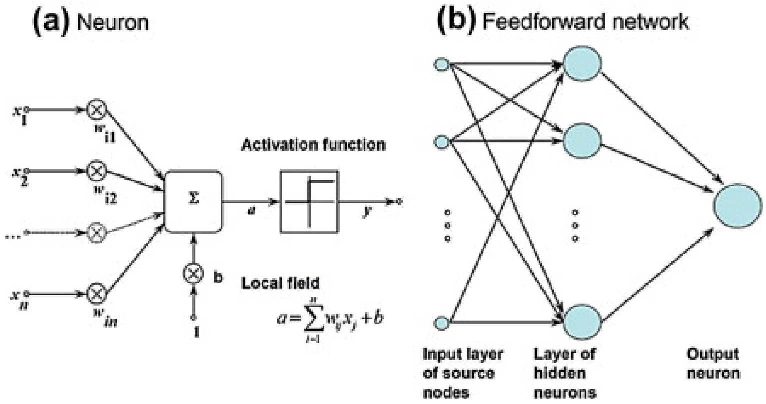

Figure 6: A diagram showing an artificial neuron and a basic neural network, with each grey circle indicating a neuron.

A neural network can be broken down into three parts. The input layer takes in the information that the neural network intends to learn from, the output layer outputs the final end product of the neural network and the hidden layers that perform the majority of the calculation of the neural network. All the neurons are fully connected, which means each neuron can influence the neurons they are connected to. Each connection in a neural network is 'weighted', which indicates how much they can affect the other neurons they are connected to. Neural networks can be separated into supervised and unsupervised networks [19].

With a supervised neural network, the neural network is 'trained' against a set of test data. The neural net predicts an output and its error is compared with the actual output from the test data. The weights of the neural net are modified, and the data is fed again in order to reduce the error further using a gradient descent algorithm [20]. An unsupervised neural network has no prior idea about what function it needs to perform. The role of the neural network in this instance is to categorize the data in terms of its similarities. The two main types of unsupervised learning is clustering, which involves grouping up data points and dimensionality reduction, which is the process of reducing the dimension of your feature set which aims to summarize the data into a reduced number of variables.

Machine learning and deep learning are more important than ever in both science and every aspect of modern life. Without machine learning algorithms, using huge data sets would become increasingly unwieldy and impossible to work with in a time efficient manner. As well as this, machine learning allows scientists to make programs for more abstract problems that are simple for humans but very daunting for computers. It's important to note that machine learning is not the only way to distinguish background sources in the LZ experiment, but a machine learning approach could improve the accuracy of techniques.

Appendices

A Relevant skills

The important skills relevant to this project are all coded related. The most important of which is Python 3 which is the main programming which the data analysis is coded in. The relevant libraries used for this project are NumPy, SciPy, Matplotlib and Pandas. The NumPy library is used for its arrays, SciPy is used for its scientific functions like scipy.stats.zscore which is used to remove erroneous data points from data sets and Matplotlib is used to plot and display the data sets. The Pandas library is important as the amount of data needed to process is very large, so keeping the data organized in data frames is important for both organization and manipulation. All of this coding is done using a Jupyter notebooks.

The Keras library for Python is used to implement the machine learning aspects of the code. Keras acts as a human friendly user interface for TensorFlow. This makes it easy to experiment with deep neural networks, which will be important as the project progresses. As well as using python, the project required learning how to use Unix to remotely use the node for the project.

B Current Progress

The Background signals that are being distinguished between are caused from the decay of radioactive elements that surround the LZ detector. The decays that are being distinguished between are $^{214}_{83}$Bi, $^{214}_{84}$Po, $^{252}_{98}$Cf and $^{22}_{11}$Na.

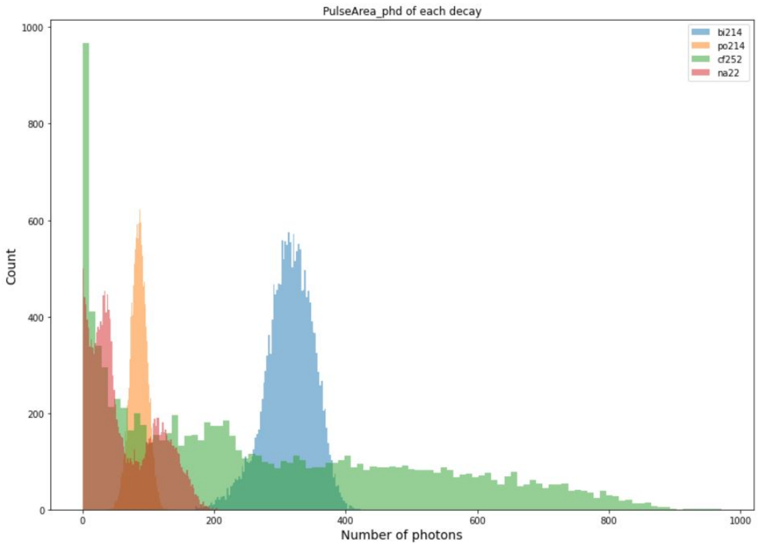

Figure 7: A graph that displays the pulseArea which Indicates the number of photons detected in that pulse as a histogram for each of the 4 decays. This data set uses 400 files of data for each decay.

For example, by looking at figure 7 and using the cut method for the decay of $^{214}_{83}$Bi you could say that if the pulseArea is between 200 and 400, then the decay is from $^{214}_{83}$Bi. However $^{252}_{98}$Cf also has decays that appear between this boundary as well, so the cut isn't completely clean. This can be improved upon by plotting multiple variables against each other, which can separate the data further. This can be seen in figure 8.

Using figure 8, $^{214}_{83}$Bi can be seen to have slightly different coincidence values to $^{252}_{98}$Cf, therefore there is opportunity to further separate these decays. As more progress is made on the project, a more advanced likelihood method will be implemented and then finally a machine learning algorithm.

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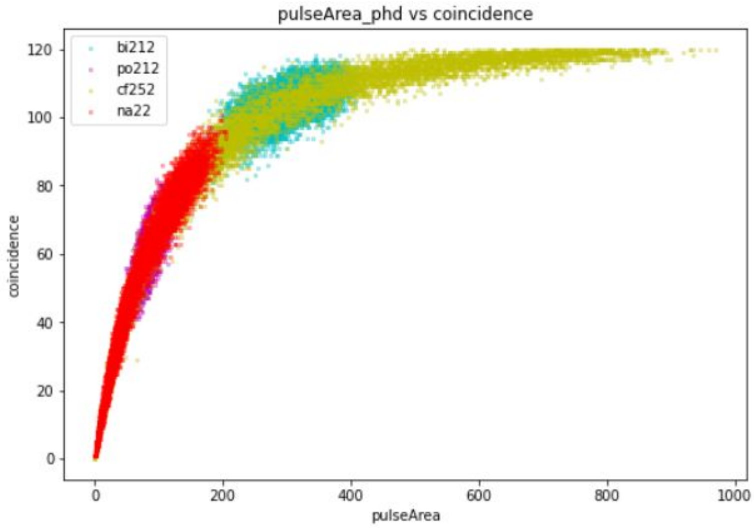

Figure 8: A Graph that plots the pulseArea of each of the 4 decays against the respective coincidence of these decays

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