- **Introduce Dark Matter and XENON Collaboration & Experiment**
  - Give details regarding the physics, historical observations of dark matter, and what it means if we successfully make a direct detection
    - Effects of dark matter were observed through gravitational lensing, cosmic microwave background, and galaxy formation
    - Dark matter is difficult to detect outside of its large scale gravitational effects
    - Requires keV sensitivity if we hope to make a direct detection of it
    - Making a direct detection allows us to learn the mass and match this to theory
  - Give details on what the XENON collab. and experiment are.
    - Detector is a dual phase TPC using 1 ton of xenon
    - Located at LNGS
    - 2 science runs (caused by earthquake)
    - 258 photomultiplier tubes
    - 1 meter diameter
    - Most sensitive dark matter direct detection experiment (soon to be overcome by its successor XENONnT)
    - What is the fiducial volume
      - Cover where it is (plot)
      - Cover how big it is (exact volume)
      - Cover why it is there (volume of most radio-purity and therefore the most confident)
- **Introduce observations from XENON1T and project idea**
  - Example hit pattern from simulation and/or experiment
    - Simulation can show the true position of an event
    - Experiment can show noise/background that is difficult to overcome
  - What is position reconstruction, why is it important
    - Based on the signal seen by the photomultiplier tubes, we're trying to figure out where an event originated from
    - Allows for quick removal of data that is outside the fiducial volume of the detector
  - What are the old position reconstruction algorithms

    * Multilayer Perceptron
    * Weighted Sum Position
    * Max PMT Position
    * Problems with these were accuracy and reconstructing positions outside the detector
  - Why is it difficult to achieve accurate reconstructions
    * Difficult for the machine to learn that there is a wall to the detector
    * There is less information given the to PMTs that are near the wall of the detector
    * PMTs will break at some point during the science run, so we'll start to receive less information
    * Each event is not perfect and contains background events that are not easy to filter out

- **What is a Neural Network, a Convolutional Neural Network, and a Graph Convolutional Neural Network**
  - Explain the idea of what a neural network is
    * How it came about as an analogy to animal brains and the neurons in them
    * How it can be useful to our problem as shown by the Multi-Layer Perceptron
  - Explain what a convolutional neural network is and why we can't use it
    * Convolutional neural networks have generally been applied to images
    * For input, they require data in a rectangular format, such as an image matrix where each pixel is a value in a matrix
    * They are able to preserve locality of pixels when trying to learn about the image
    * Our data cannot easily be made into a rectangular format; there is no analogous image matrix for out data
    * How can be preserve locality of PMTs like a convolutional neural network does?
  - Explain what a graph convolutional neural network is
    * Makes use of a graph data structure instead of rectangular data structures, which is a format any dataset can use

    * Give a simple example (4-5 nodes) of how a graph convolutional neural network works
    * They have mainly been used for classification, but we will be using it for regression
    * Our PMTs are the nodes in the graph
    * These nodes take the amount of light seen by each PMT for an event as a feature
    * The edges between nodes preserve the locality if we do it correctly
  - Explain how our approach to a graph convolutional neural network is
    * Show the graph structures we considered and chose
    * Show the network structure that we chose
    * Came to this network structure based on the successful convolutional neural networks

- **Simulation Data**
  - Optical Simulation
    * 989,875 events: 791,900 training, 197,975 validation
    * 0.8:0.2 :: training:validation
    * 1,000 photons were events
    * True position of events are a random, uniform distribution within the detector
    * All PMTs are working
    * There are no background events, only the main signal is present

- **Results**
  - Many plots of the results of our network on the optical simulation
    * Resolution histograms for x, y, and R
    * True positions of events that were reconstructed greater than 1 cm away
    * 2D resolution histogram
    * Histogram of poorly reconstructed radius and the true radius
  - Identify where it succeeded and where it failed
    * Success: All events within the detector
    * Success: Did not normalize the simulation data before inputting

    * Success: Outperforms a Multi-Layer Perceptron with similar count of trainable parameters
    * Failure: Still produced positions that were greater than 1 cm away from the true position
    * Failure: These poor position reconstructions are primarily along the wall and is the same as problem as the Multi-Layer Perceptron

- **Conclusions & Future Work**
  - Can we address these failures?
    * We think that a graph convolutional neural network is not the best answer
    * A graph neural network in the broader sense could still perform better
  - Should graph neural networks see use in other experiments
    * This is one of the earliest applications of a graph convolutional neural network for regression in particle physics, and it did well
    * Graph Neural Networks have a place in particle physics for detectors with awkward data structures
    * The broader graph neural networks can and still should be researched for their applicability
    * Still possible to research what the most optimal graph structure is for a given detector