"Km3NNeT"
A neural network for triggering, classifying and reconstructing KM3NeT events

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UNIVERSITY OF AMSTERDAM

Abstract

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For softness is great and strength is worthless. When a man is born, he is soft and pliable. When he dies, he is strong and hard. When a tree grows, it is soft and pliable. But when it's dry and hard, it dies. Hardness and strength are death's companions. Flexibility and softness are the embodiment of life. That which has become hard shall not triumph.

Tarkovsky's Stalker

Contents

Introduction

It are exciting time's for physics and astronomy which might gaining new 'senses' to look into the Universe. Where classical astronomy is only looking at the light coming from space a lot efforts is made to look at all the particles (and gravitational waves) coming our way. Even at the almost invisible neutrino. The KM3NET project is doing exactly that. With a whole network of spheres below the surface of the Mediterranean sea it hope's to answer some of the big questions in astronomy but also in particle physics.

In this thesis a research is committed to see how the use of machine learning techniques can be used to benefit the KM3NET Arca detector. It's core questions can be summed as following:

- How can the data coming from the Arca detector be represented to a machine learning algorithm.
- Can an AI differentiate between different neutrino types, atmospheric muon and optical background.
- Can an AI reconstructed the Energy, position and direction of an neutrino event.

First a introduction in the KM3NET project will be given. Here its goals and technical details will be discussed as well as a motivation for this research. Then a short overview of the theory of neural networks is given in chapter 2. The neural network used for this researched will be introduced in chapter 3. The results of these network will be given and discussed in chapter 4 and 5.

1
Km3NET

The research described in this paper is an effort to improve the KM3NeT project. In this chapter a overview will be given what this project includes. First the underlying physical questions that the KM3NeT will try to answer will be introduced. In the second part of this chapter the technical details of this project will be described.

1.1 Neutrino astroparticle physics

Neutrino's are weakly interacting fermions that are present in great abundance in the universe. Neutrinos are electrical neutral and are the lightest particles of the standard model, only upper bounds on there masses are known. They only interact with other particles through the weak force. In theory they do interact also through gravity but this interaction is negligible on subatomic scale.

It is challenging to measure a neutrino since the chance of interaction with (detector) material is low. A typical neutrino flies through the earth without any interaction. Neutrino detectors typically involve a large volume where the interaction that do happen can be measured.

Only neutrinos with left handed chirality exists in nature and the three neutrino flavour eigen states form a doublet with the corresponding leptons: the electron, muon and tauon. Neutrinos that are a mass eigen state can change flavour. This is called neutrino oscillation and is a topic that is being researched extensively for it can put upper limits on the neutrino masses and determine the mass hierarchy.

Cosmic rays

On earth high energy particles from outer space at observed to follow a energy spectrum that follows a power law with index 2.7. The spectrum also shows a a increase and decrease around 10^6 and 10^{10} GeV known as "the knee" and "ankle". The source of these particles or cosmic rays and there spectrum are unknown. Source candidate include but are not limited to super nova remnants, active galactic nuclei and gamma-ray bursts. [3] [4]

Neutrinos can be a messenger particle for astro physical and cosmological processes like the sources of

(a) CC interaction of (anti)neutrino. (b) NC interaction of either neutrino or anti neutrino.

Figure 1.1: Fundamental neutrino interactions.[12]

cosmic rays. If the direction of a neutrino can be determent the assumption can be made that the neutrino has travelled directly from it source to the point of interaction and detection. This is not the case with photons, the most studied messenger particle from space. Photons can diffuse and scatter of the interstellar material or interact with the CMB photons. Thereby deflecting there initial direction. Charged particles are deflected by the galactic magnetic field so they can also not be traced back to there origin.

Different cosmic rays sources predict a different ratio between electron-, muon- and tauon neutrino reaching earth. The standard scenario, where neutrino's are generated from the decay of charged pions, kaons and muons, predict a flavour production ratio of $\nu_e : \nu_\mu : \nu_\tau = 1 : 2 : 0$ this leads to a different observed ratio duo to flavour oscillations, namely $\nu_e : \nu_\mu : \nu_\tau = 0.93 : 1.05 : 1.02$. Note that there are no tau neutrinos produces but due to oscillations are expected to be seen at earth. Other neutrino creation models like the muon-damped and neutron-beam scenarios give rise to different flavour ratios. To study neutrino creation models and relate them to the origin of the cosmic ray spectrum as accurate as possible it is key to identify the flavour of neutrinos reaching earth. [3]

1.2 Detection principle

It is not possible to detect a neutrino directly but it decay products can be studied. Typical neutrino detectors consist of grid of detector units in a large volume of material e.g. water, ice, argon. The secondary particles from a interaction are measured and the energy and direction of the neutrino are reconstructed from the timing and positions of the interaction of the particles with the detector units. For this section a detector placed in water is assumed.

Event signatures

Neutrino interactions can be divided in two categories: charged current (CC) and neutral current (NC). In a charged current interaction the neutrino emits a charged W boson and decays into a charged lepton. In the other category the neutrino emits a neutral Z boson and doesn't decay into a lepton. The Feynman diagrams for these processes are shown in figure 1.1. The event signatures caused by these interactions are discussed below since they can be used to determine the flavour of the neutrino.

The decay products are also not directly detectable since they live only for a short amount of time. The decay products of a neutrino interaction decay them self in distinct ways. They can form a track like event, a shower like event or a combination. A track like event is coming from a long living particle i.e. muon. Originating from a muon neutrino that decays through the CC channel and thus produces a muon. The muon can travel meters up to kilo meters depending on the energy of the particle.

Shower like events consist of electromagnetic- and hadronic showers. In electromagnetic showers a cascade of electron, positrons and photons interact with each other through Bremstralung, annihilation and pair production. When a neutrino has enough energy to destroy the core of a atom the quarks make a hadronic shower where a cascade of mostly pions decay though muons to electrons. This is a deep

Figure 1.2: Deep inelastic scattering through charged current (left) and neutral current (right). X represents a hadronic shower. [12]

inelastic scattering process shown in figure 1.2. [12]

In a neutral current event there is no lepton to make a shower or track. The neutrino flies away undetected but the destroyed core makes a hadronic shower if the incoming neutrino has high enough energy. If neutrino energy is too low there is no detectable signature in the detector. The process NC does not discriminate between lepton flavours so a single hadronic shower can not identify neutrino flavour.

The same process happens in a charged current event. But next to the hadronic shower caused by the destroyed atom core a lepton arises. Here the event signature can help identify the neutrino flavour. An electron has a short mean free path and it decays into a electromagnetic shower that overlaps with the hadronic shower. Being much heavier the muon can travel up to several kilometres through the detector giving rise to a distinct Cherenkov cone (see section 1.2). If the muon energy is high enough small electromagnetic showers can occur along the path of the muon. [3]

There are two different signatures that a tau neutrino can make due the two decay modes of the tauon. It either decays into a muon that makes a track or into a shower. If the tauon decays into a shower the hadronic shower from the atom core does not have to overlap with it. This creates a way to distinguish between an electron- and a tau- neutrino CC event.

Cherenkov light

To measure the product particles of a neutrino interaction detectors rely on the detection of Cherenkov light. This light is created by the relativistic charged particles in the shower or track of the neutrino event. These particles move through a transparent medium, i.e. water, faster than the speed of light in that medium. The refractive index of the medium governs the properties of the Cherenkov radiation. The angle with respect to the charged particle in which the Cherenkov photons are emitted in sea-water is around 42.2 degrees. For a track like event this gives rise to a conical light-front. [3] [4]

1.3 Detector design

KM3NET is a neutrino telescope placed underwater at the bottom of the sea. It consists of a grid of light sensitive detector units capable of seeing the Cherenkov light coming from neutrino interactions (section 1.2). From the timing, position and energy of this light the position, direction and energy of the interacting neutrino can be estimated.

The KM3NET detector consists of two substructures called ARCA and ORCA that are being build at the moment of writing (2018) in the Mediterranean sea near Sicily, Italy and Toulon French respectively. ARCA and ORCA are similar in all but size. The research described in this thesis will cover only ARCA but it will become clear in chapter 3 that the techniques used easily extent to ORCA as well. [7]

The objective of ARCA is to study the cosmic neutrino flux and its sources. The ARCA detector is

(a) A PMT used in the KM3NET detector the gold material is the .....

(b) A DOM with 31 PMT facing all directions

Figure 1.3

bigger so it can contain the kilo meter scale signals coming from high energy (PeV) neutrino interactions [7]. ORCA will study neutrino mass hierarchy and neutrino oscillations. It is optimised for lower energies (GeV) and thus need be smaller and denser.

PMT's

Photo multiplier tubes (PMT) are the sensitive light detector units in KM3NET shown in figure 1.3 (a). They are able to detect single photons. The principle of a PMT is based on the photo-electric effect where a photon hits a material (photo cathode) and frees one electron. Inside a PMT is a high voltage and the freed electron will accelerate. The electron will hit the next material (dynode) where if frees more electrons. This step is repeated several time until there is a significant charge/voltage to charge to be registered by the anode. [13]

Due to thermal noise there is a constant voltage measured. To distinguish this noise from a photon hit, the voltage is discarded if the voltage does not exceed a certain threshold. In the KM3NET detector if a PMT voltage exceeds this threshold the time of this moment and the time duration of the voltage exceeding the threshold is saved. This is the time (t) and time over threshold (TOT) information of a event and is send from the detector to the main land for further processing. [7]

DOMs

The PMTs of KM3NET are arranged into several DOMs (Digital Optical Module) that each have 31 PMTs. The DOMs are spheres and the PMTs are facing all directions but upwards, shown in figure 1.3 (b). The DOMs are arranged in vertical lines or DUs.These each have 18 DOMS and are anchored onto the sea-floor. The 115 lines are placed in a triangular/hexagonal grid into a circle with a roughly 500 meter radius, see figure 1.4. This is called one building block and the final ARCA detector might consist of multiple. In this writing only one building block is taken into consideration and will be referred to as the whole (ARCA) detector. [8] [1]

Arca and Orca share this hexagonal grid with 115 lines and 18 DOMs per line but the dimensions are different. The horizontal spacing between DOMs is 90 meter for Arca and only 20 meter for Orca. The vertical spacing is 36 meter and 9 meter for Arca and Orca respectively.

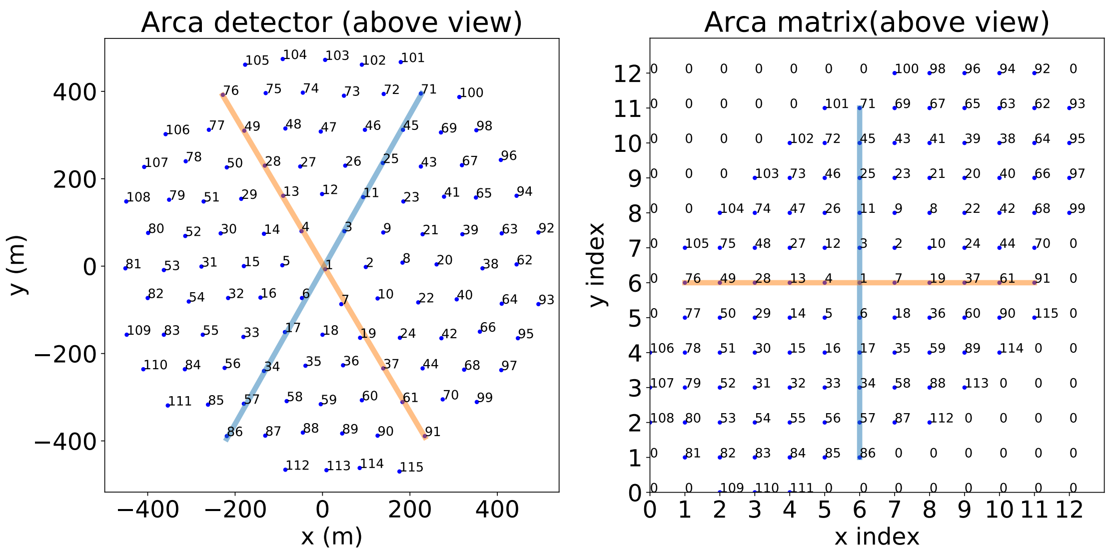

Figure 1.4: Above view of the Arca detector. Each point represents a DU with it corresponding ID. In the right plot the Arca matrix is given

1.4 Background sources

Next to the Cherenkov light coming from neutrino events there are other sources that produce photons that are detected by KM3NETs PMTs. This section will discuss the four background sources: bio luminescence, atmospheric muon, thermal noise and potassium 40 decay.

Some lifeforms in the sea water, like bacteria, algae, and fish, can emit light. These typical give rise to a increased count-rate of the PMTs for several seconds. This is a distinct signal and the KM3NET DAQ (Data acquisition system) is able to filter out the data from bio luminescence. This background wont further be taken into consideration in this thesis. [7] [3]

Muons originating from cosmic showers are a major background contribution in KM3NET. When high energy particles from space interact with the earths atmosphere they create a so called cosmic ray air shower. The large volume of water above the detector is a effective muon shield but it is possible for muons to reach the detector. To distinguish the signals from each other all muon going in a downward direction are disregarded. [7] [3]

As mentioned in section 1.3, the voltage of a PMT can pass the threshold without a photon hitting it. The rate a which this happens is called the dark count and is caused by thermal noise. The dark count can differ greatly between PMTs. Typically they are below 1 kHz. [3]

The sea water contains the isotope potassium 40. The potassium decays naturally to Argon and mostly to Calcium. In the decay to argon a 1.46 MeV photon is emitted, that typically frees two electrons above the 0.56 MeV Cherenkov threshold for electron in water. If the potassium decays to Calcium a electron electron is created with a maximum energy of 1.3 MeV, also above the Cherenkov threshold. KM3NET PMTs register the Cherenkov photons created by these electrons around 6000 times per second. [7]

1.5 Data acquisition

For each hit produces on a PMT the time and TOT are registered as well as the id of the PMT. The id of the PMT is used for the position and direction of the PMT. Since the majority of hits is produces by background sources it is not practical to save all data generated. roughly 25 GB of data per second is produced by the Arca detector and this is all send to shore for processing. There a reduction is performed in real-time by a designated trigger algorithm. Time intervals deemed interesting by this algorithm are then saved for further analysis. The rest of the data is disregarded and is expected to be from background sources. The infrastructure and software responsible for the data transportation and triggering is called the data acquisition system of DAQ. [3]

The trigger algorithm search for events corresponding the signatures of tracks or showers. The trigger only takes hits into account that coincide with another hit on the same DOM. These hits are then triggered as a shower, a track or both. For an event to be triggered as a shower there need to be 5 hits within 250 meter that are causally related. For a track trigger there need to be 5 causally related hits in cylinder in a certain direction. All directions are considered in $10°$ steps. [3]

The triggered events can be studied in more detail and all the hits are saved to disk. Specialised algorithm determine if the detector response corresponds to a neutrino interaction or not and determine its flavour. The energy of the neutrino is reconstructed as well as the interaction position and the direction of the neutrino.

1.6 Detector simulation

In order to determine the capability of the detector and DAQ to detect, classify and reconstruct neutrinos, a complete simulation is made. In the simulated data the true flavour, energy, position and direction of the interacting neutrino are known. With Monte Carlo techniques the interaction products are determined and the propagation through water simulated as well. The detector response is the second part of the simulation. Here the PMT response i.e. TOT is determined. Now the DAQ processes the data further and produces a flavour, energy, position and direction for the neutrino. This can be compared with the true values. This provides a feedback loop for improving the detector and DAQ software.[1]

2

Neural network functions

ReLU Sigmoid Softmax Dropout CONV CONV3D Flatten and reshape LSTM ADAM Crossentropy RGB [11] [2] [9] [5] [10] [6] [10]

2.1 Multi-layer perceptron

2.2 Convolutional network

2.3 LSTM network

2.4 Backpropegation

3

KM3NNET

In this chapter a description is given of the neural network used to classify and reconstructed km3net events. This network is called KM3-neural-net or "KM3NNET" and can be used for both the Arca as Orca detector since they have the same detector shape. The results of this network for the are discussed in chapter 4 and 5 for the Arca detector. The Orca detector is left outside scoop of this thesis.

A Km3net event, whether coming from a neutrino signal or from K40 background, is in it's core a list of the hits made by secondary photons on the PMT's. This list contains for each hit the hit time, the time of threshold, the id of the DOM on which the PMT is hit and the id of this PMT. Each DOM has a position and a attached to a certain DU with a line id. In this chapter first a description is given to process this event list of data into a format that can be handled by a Neural Network then several neural network models used to process this information are given.

3.1 Spacial data representation

As mentioned in section 1.3 the DOMs are ordered into lines of 18 doms with equal spacing. These lines are placed into a hexagonal grid as can be seen in figure 1.4. To distinguish neutrino events from background one has to take the spacial relations of hits into account. Coming from the same source hits from signal are expected to be close together i.e. on the same DOM or DOMS close to each other. K40 background is expected to be spatially unrelated and randomly distributed over the detector although a K40 decay can produces more hits on the same DOM it is unlikely to hits two nearby DOMS.

Since the spacial relations between the hits is a important factor that can distinguish a signal- from a background event a convolutional neural network is used to process the data since these kinds of networks are optimised for finding spacial patterns and exploiting the spacial symmetries (see 2.2). If the data i.e. list of hits is to be represented to a CNN the spacial relations should be conserved. CNN are able process data represented in a square or cubical grid thus the KM3NET hexagonal grid first has to be transformed. The CNNs described in section 2.2 are capable of $n \times m$ or $n \times m \times z$ matrices. This convenient for image processing where a image is represented a $n \times m$ where each matrix element is the grey value of a pixel. To represent the KM3NET hexagonal grid in a matrix where each matrix element represents a DOM transformation first has to determent.

The hexagonal grid can also bee seen as a triangular grid where two adjacent triangles make a rhombus.

Function	Filter size	Number of	Shape of data
Input			13, 13, 18, 3
Relu Conv3D	4, 4, 4, 3	filters = 25	13, 13, 18, 25
Relu Conv3D	3, 3, 3	filters = 35	13, 13, 18, 35
MaxPool			7, 7, 9, 35
Relu Conv3D	3, 3, 3	filters = 80	7, 7, 9, 80
Reshape			35280
Sigmoid fully connected		nodes = 40	40
Sigmoid fully connected		nodes = 20	20
Softmax output		nodes = 3 or 7	3 or 7

Table 3.1: Convolutional model

This rhombus is transformed into a square to get a square grid. This way the x and y position of the DOM grid can be transformed to a matrix element of a 13 by 13 matrix, see figure 1.4. If all 115 DU are represented in this matrix this leaves $13 \times 13 - 115 = 54$ unused matrix element. The z direction of the DOM grid does not need a transformation since it is evenly spaced. Each DU contains 18 DOMs so the final matrix has dimensions of 13 by 13 by 18.

3.2 Time over threshold, number of hits and weighted direction

The above section (3.1) provides a way to represent the km3net detector DOM grid as a matrix where each matrix element either represents a DOM or is left empty. This section will discuss the value of those matrix elements.

In this model several choices for these values are used. For a given time period all hits on a DOM are added together. This means a summation of either the TOT of the hits or the number of hits. When multiple photons hit a PMT at the same time it is recorded as one hit but the TOT is usually higher than the TOT of one photon. To use the TOT instead of the number of hits gives the advantage that this information stays to some extend conserved. The value of the TOT is related to the energy and number of photons but can greatly fluctuate. This is not the case for the number of hits so this can also be chosen.

These summation terms can be weighted with the direction vector of the PMT that is hit. This might give extra information to distinguish signal from background since it is expected that background hits are evenly distributed over a DOM while signal hits are expected to hit the DOM on one side. Note that the matrix value becomes a vector when the weighted sum is used. The matrix elements that do not represent a DOM have value zero and can be referred to as padding, note that they have the same value as a dom that has no hits.

As described in section 2.1, neural networks best with data that is normalised to be in the range between -1 and 1. This means that the matrix values need to be normalised depending on the time interval over which they are integrated.

3.3 Time integrated network

If a event is triggered by the km3net trigger algorithm it takes a piece of time slice and stores it. These so called snapshots consist of the hits in the time interval what the algorithm determines as the event time and also some time before and after that just to be sure. The snapshot usually span a time range of around 12000 ns going up to 18000 ns for high energy events. In this section a neural network is described that can process timeslices of 20000 ns and label it as a shower, track or K40 event.

Function	Filter size	Number of	Shape of data
Input			400, 13, 13, 18, 3
Relu Conv3D	4, 4, 4, 3	filters = 25	400, 13, 13, 18, 25
Relu Conv3D	3, 3, 3	filters = 35	400, 13, 13, 18, 35
MaxPool			400, 7, 7, 9, 35
Reshape			400, 15435
Sigmoid fully connected		nodes = 80	400, 80
Sigmoid fully connected		nodes = 40	400, 40
LSTM		nodes = 20	20
Softmax output		nodes = 3 or 7	3 or 7

Table 3.2: RNN model

The network has input a 13 by 13 by 18 by 3 matrix and as output a 3 (or 7) vector. This one-hot-encoded output vector represents the likeliness of an event to be class 1, 2 or 3 what in this case are shower like event coming from a (anti)electron neutrino CC or NC event, a (anti)muon neutrino CC track like event or K40 background. This output should be normalised so the values add up to 1.

The output of the neural network can also represent the energy, position and direction of the neutrino. In this case the output vector is of shape 7 since the position and direction are both 3 vectors and energy is a scalar. Note that the output vector does not have to be normalised so the output can take any real value.

The spacial dimensions of the matrix are the input of a 3D convolutional layer. The TOT 3 vector is the input for the RGB channel of this layer. The network consist of 3 convolutional layers and 2 fully connected layers. The non-linear function used in the convolutional layer is the ReLu function and the sigmoid function is used for the fully connected layer. A softmax function applied to the last layer results in the correct normalised output of the network. The final predicted class is obtained by taking the class with the highest output. The network is described in full detail in table 3.1

3.4 Time split network

The above model takes a time interval that is roughly the same of the whole event time and add all the hits together. This has the disadvantage that the information that can be extracted from the time correlations between hits is lost. For example a sequence of hits that hit the DOMs on one line from above to below has the same data as a sequence that hits the DOMs from below to above. This means the network can never distinguish an atmospheric muon from a neutrino muon on the simple feature that is comes from above the detector.

To take the time relations of hits into account the time interval is greatly reduced. For every 50 ns of data the hits are added together. This number is chosen because light travels $\tilde{3}0$ ns between doms. As mentioned before a typical neutrino event has a duration of about 12000 - 20000 ns. This means that in one mini timeslice of 50 ns only a fraction of the hits is added. To extract all the information needed the mini timeslices are chained as a time ordered sequence.

In each mini timeslice of 50ns the hits are added in the same way as described above. A CNN network similar to the one above is used on each mini timeslice. This results in a time ordered sequence of CNN outputs. These outputs are passed through a recursive neural network for reaching the final output. The details of this network is described in table 3.2. Note that one Conv3D layer is replaced with a LSTM layer.

3.5 Training

All models described above are trained on a simulated data set using the backpropagation method as described in section 2.4. This data set contains data as if coming from the detector. This means that for every event the corresponding label is known. The models are either trained as classifier- or as reconstruction algorithm each require a different cost function. For the classifier a cross entropy is calculated between the label and the (normalised) output of the network. The cost function for the reconstruction is the sum of the difference squared between the truth values (of energy, position and direction) and the output.

The parameters in the model are optimised with a Adam algorithm. The training procedure occurs with batches of randomly shuffled data. Batches contain 20 to 100 events depending on computing power available. The events used for training should at least have 5 monte carlo hits on PMTs since the classifying and reconstruction power of all algorithms reduces greatly with the number of hits. The details of the data set used are shown in table 3.3. From this table it becomes clear that the data set contains 129801 shower like events, 93532 track like events and 102930 K40 background events. 80 percent of events is used for training of the models and 20 percent for testing.

	Type						
	$\bar{\nu}_e$ CC	ν_e CC	$\bar{\nu}_e$ NC	ν_e NC	$\bar{\nu}_\mu$ CC	ν_μ CC	K_{40}
Train	30970	30856	20050	22074	38461	36638	82344
Test	7623	7578	5595	5055	8893	9540	206586

Table 3.3: Number of events in the dataset used to train and evaluate the models

4
Trigger en Classifier Results

5

Energy and direction reconstruction results

6
Outlook and Conclusion

A

Sammenvatting in het Nederlands

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