Deployment of unsupervised learning in the search for new physics at the LHC with the ATLAS detector

by

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Abstract

Acknowledgments

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Introduction

Outline of the Thesis

Chapter 1

Machine learning phenomenology

Anomaly detection

Anomaly detection is a tool with a wide range of uses, from time series data, fraud detection or anomalous sensor data. Its main purpose is to detect data which does not conform to some predetermined standard for normal behavior. The predetermined standard varies from situation to situation, both from the context it self and what is expected as an anomaly. Anomalies are typically classified in three categories [1]:

1. Point anomalies
2. Contextual anomalies
3. Collective anomalies

Point anomalies are singular or few outliers from a larger contect or group.

Neural Networks

There are several categories of statistical algorithms for data analysis within machine learning. Amongst them are neural networks, which have for the last decade exponentially been used within industry and academia for a number of usecases. From image analysis to weather prediction, these models are used extensively.

Neural networks, or feed forward neural networks (FFNN), are based on a few principles. First, the data is feeded forward through the network. The end output is evaluated in some fashion, and corrections are then back propagated through the network, updating the weights and biases. This ”training” is done until a sufficient threshold is met. A general layout of a neural network is displayed in figure 1.1.

The input layer has the same shape of the dataset one uses to train or predict on, with one node for each feature in the dataset. The next layer is the hidden layers. For a given network, the amount of hidden layers can be tuned, as well as the number of nodes per layer. Finally, the last hidden layer is connected to the ouput layer, which is determined by the aim of the problem. In the case of figure 1.1, this neural netork would represent a binary classification problem. The nodes in the network interacts through so called weights w and biases b.

Autoencoders

Autoencoders are a subset of neural networks. Whereas a general neural network in principle can take any shape, autoencoders are more restrictive. This restrictiveness can in its most general sence we condensed into the following points:

- Same number of output categories as input categories
- A latent space with smaller dimensionality than the input/output layer

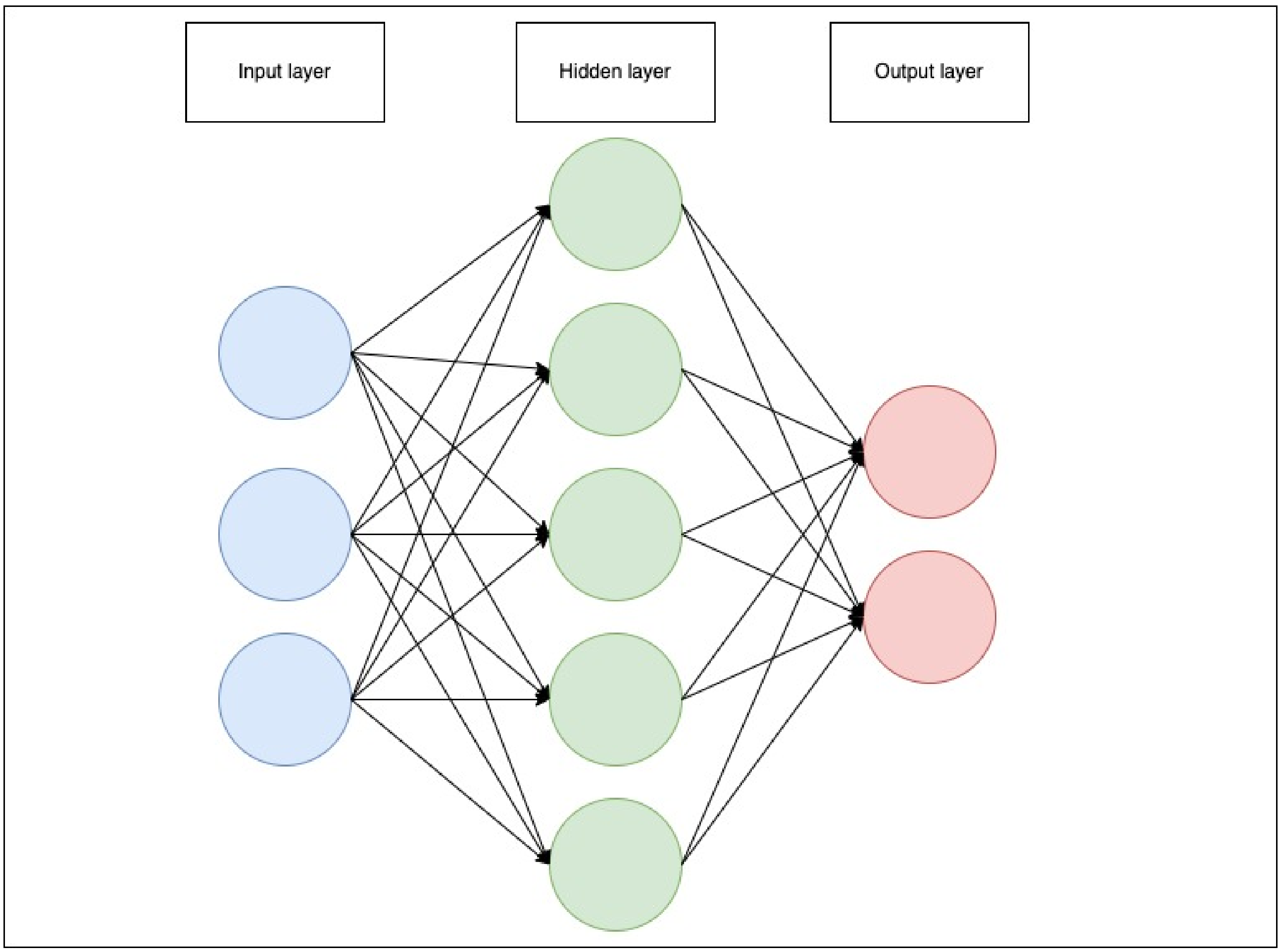

Figure 1.1: Simple neural network diagram.

What we end up with two funnel shaped parts linked together. The two funnels are called the encoder (left funnel) and decoder (right funnel) respectively. This architecture is not accidental, but rather designed with a very specific solution of ploblems in mind, reconstruction. A good example to illustrate this is image denoising. Suppose you have a noised image, and want to denoise it. By feeding the encoder a noised image, and comparing the decoder output to the actual image, the autoencoder can tune itself to denoise images.

Chapter 2

The Standard model

Why the Standard Model

Structure and composition of the Standard Model

Limitations

All though the standard model have had great success comparing with experiments, there are still several problems not addressed by it. First and foremost, the standard model as described above, does not and cannot explain gravity in a quantized way. There are models that try to address this problem, but they supplement the standard model, and does not derrive it from it.

Proposal model

Chapter 3

Implementation

Chapter 4

Results

Chapter 5

Discussion

Conclusion

Future work, more work

Appendices

Appendix A

Appendix B

Appendix C

Appendix D

Bibliography

[1] V. Chandola, A. Banerjee and V. Kumar, *Anomaly detection: A survey*, *ACM Comput. Surv.* **41** (07, 2009) .