Deep Learning in Liquid argon time projection chambers: Optimizing the Architecture for Particle Classification

MicroBooNE Collaboration

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ABSTRACT: Liquid argon time projection chambers (LArTPCs) produce image-like data that may be analyzed with deep neural networks (Deep Learning, or DL). This approach to data analysis is becoming more common in LArTPCs, as well as other high channel-count segmented detectors where the events leave imprints on the detector that may be interpreted as images. In particular, MicroBooNE is an 8256 wire detector viewing 89 tons fiducial liquid argon where DL studies have been performed [2] and show great promise. That study showed progress in single particle classification as well as progress toward neutrino identification, using networks that were not necessarily chosen to be optimal. This paper reports results on single particle classification using DL network architectures in which the literature or experience suggest further progress can be made on images such as ours. We answer key questions about performance on this problem as a function of network architectures and show that networks __, __ and __ give functionally equivalent high performance, with gains in network __ in resource consumption that suggest its use.

Contents

1 Introduction

MicroBooNE is the first large-scale LArTPC detector to collect data in a neutrino beam in the United States. The experiment has a total liquid argon mass of 170 tons and a rectangular active volume of 2.3×2.6×10.4 m³. The system consists of two subdetectors: a time projection chamber (TPC) for tracking and calorimetry along with a light collection system for the detection of scintillation light. We consider here only the TPC information. In October 2015, the detector began observing interactions of neutrinos from the FNAL Booster Neutrino Beam (BNB) [22].

In this paper We will survey the relevant networks for image detection that are typical for LArTPCs and compare performance metrics. A particular characteristic of our images that makes them unique compared to other efforts on image classification is that our images are sparse. Tracks and showers and isolated electromagnetic activity produce a relatively small fraction of pixels that are activated in LArTPCs. This is true even for MicroBooNE's particular case in which the detector sits on the surface and sees a ≈ 5 kHz of through-going cosmic rays and associated activity.

We want to survey networks that are well-used in the image recognition literature and explore the (hyper) parameters of those networks. This means we will explore the depth and width of networks, the existence of fully connected layers, stride sizes, as well as input sparsification and existence of things like "bottlenecks," which is .... We will use variants of ResNet [], Vgg16 [] and ... One motivation of this exploration, in addition to seeking the best classification performance, is to see if networks that are less computationally expensive might in fact retain all performance of their more computationally expensive counterpart networks, and thus might be used in their place.

The organization of this paper consists of a description of our single particle metrics, the preparation of the images, the training and inference protocol used here, and finally a description of the various architectures with results, followed by conclusions.

2 Particle Classification

We study the performance of five particle classification (e^-, γ, μ^-, π^-, proton) using Convolutional Neural Networks (CNNs).

3 Image Preparation

Throughout all studies in this work, we use one of the most popular open-source CNN software frameworks, CAFFE [11], for CNN training and analysis. Input data is in a ROOT file format [16] created by the LArCV software framework [10], which we developed to act as the interface between LArSOFT and CAFFE. LArCV is also an image data processing framework and is used to further process and analyze images as described in the following sections. One can find our custom version of CAFFE that utilizes the LArCV framework in [10]. The computing hardware used in this study consists of multiple servers at various institutions. We have two dual-GPU 12 GByte memory, NVIDEA GPU servers of similar specifications at the Massachusetts Institute of Technology, Columbia University, University of Michigan, Yale University. We also emply a DGX-1 10-GPU 18 GB/GPU server at Pacific Northwest National Laboratories.

... representative image picture here, as from the original CNN paper ...

Figure 1: Example neutrino candidate observed in the MicroBooNE detector. The same interaction is shown in all three wire plane views. The top image is from wire plane U; the middle from wire plane V; and the bottom from wire plane Y. The image is at full resolution and is only from a portion of the full event view.

4 Training and Inference

A disciplined training and inference procedure is required in order to make the comparisons we wish to make.

5 The Architectures

Broad descriptions here of ResNet and Vgg16 and whatever else we have results for. GoogleNet, AlexNet? Why we want to stick with flavors of ResNet and Vgg here.

Not to be included, but for convenience, all results areshould-be referenced at

https://docs.google.com/presentation/d/1Rvo2Yt9KqRQk2eDyO1WeA5GwaWamLvZR2CR3txfYbBE/edit#s

5.1 Original CNN paper architectures

5.2 ResNet14b

5.3 ResNet14b_w2

5.4 vgg16a

5.5 vgg16b

5.6 vgg16c

6 Conclusions

We have surveyed a variety of CNNs for the sake of classifying five charged particles as they appear in LArTPCs. Some interesting conclusions are that while Ref. [2] achieved formidable performance, a few other networks do as well or better, and it is seen now that RestNetXYZ and VGG16XYZ are better choices.

We plan to start with these networks for future physics-identification tasks in MicroBooNE; we believe similar guidance for general TPCs applies there, as well. We advocate, per this study, that the full and infinite (hyper) parameter space for CNNs need not be explored in those future analyses in favor of the identified best-performing networks here.
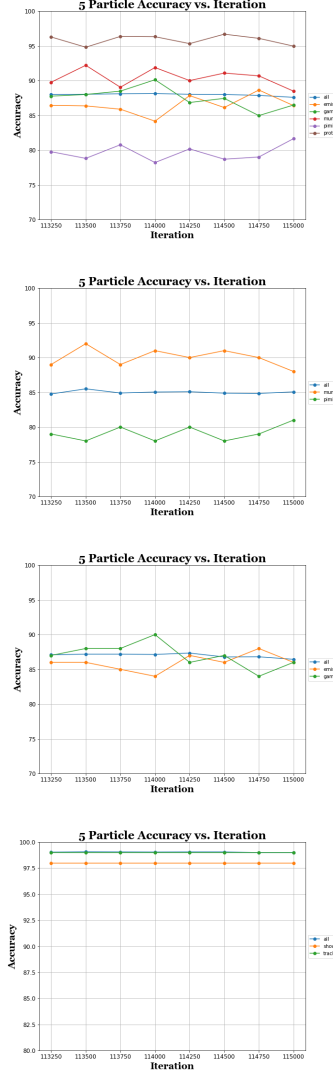
Figure 2: This is the (a) five particle classification, and (b) μ^-, π^-, (c) e, γ, and (d) shower-track separations for the vgg16b network.

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