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

MicroBooNE Collaboration

R. Acciarri[g] C. Adams[z] R. An[h] J. Asaadi[w] M. Auger[a] L. Bagby[g] B. Baller[g] G. Barr[q] M. Bass[q] F. Bay[x] M. Bishai[b] A. Blake[j] T. Bolton[i] L. Bugel[m] L. Camilleri[f] D. Caratelli[f] B. Carls[g] R. Castillo Fernandez[g] F. Cavanna[g] H. Chen[b] E. Church[r] D. Cianci[l,f] G. H. Collin[m] J. M. Conrad[m] M. Convery[u] J. I. Crespo-Anadón[f] M. Del Tutto[q] D. Devitt[j] S. Dytman[s] B. Eberly[u] A. Ereditato[a] L. Escudero Sanchez[c] J. Esquivel[v] B. T. Fleming[z] W. Foreman[d] A. P. Furmanski[l] G. T. Garvey[k] V. Genty[f] D. Goeldi[a] S. Gollapinni[i] N. Graf[s] E. Gramellini[z] H. Greenlee[g] R. Grosso[e] R. Guenette[q] A. Hackenburg[z] P. Hamilton[v] O. Hen[m] J. Hewes[l] C. Hill[l] J. Ho[d] G. Horton-Smith[i] C. James[g] J. Jan de Vries[c] C.-M. Jen[y] L. Jiang[s] R. A. Johnson[e] B. J. P. Jones[m] J. Joshi[b] H. Jostlein[g] D. Kaleko[f] G. Karagiorgi[l,f] W. Ketchum[g] B. Kirby[b] M. Kirby[g] T. Kobilarcik[g] I. Kreslo[a] A. Laube[q] Y. Li[b] A. Lister[j] B. R. Littlejohn[h] S. Lockwitz[g] D. Lorca[a] W. C. Louis[k] M. Luethi[a] B. Lundberg[g] X. Luo[z] A. Marchionni[g] C. Mariani[y] J. Marshall[c] D. A. Martinez Caicedo[h] V. Meddage[i] T. Miceli[o] G. B. Mills[k] J. Moon[m] M. Mooney[b] C. D. Moore[g] J. Mousseau[n] R. Murrells[l] D. Naples[s] P. Nienaber[t] J. Nowak[j] O. Palamara[g] V. Paolone[s] V. Papavassiliou[o] S.F. Pate[o] Z. Pavlovic[g] D. Porzio[l] G. Pulliam[v] X. Qian[b] J. L. Raaf[g] A. Rafique[i] L. Rochester[u] C. Rudolf von Rohr[a] B. Russell[z] D. W. Schmitz[d] A. Schukraft[g] W. Seligman[f] M. H. Shaevitz[f] J. Sinclair[a] E. L. Snider[g] M. Soderberg[v] S. Söldner-Rembold[l] S. R. Soleti[q] P. Spentzouris[g] J. Spitz[n] J. St. John[e] T. Strauss[g] A. M. Szelc[l] N. Tagg[p] K. Terao[f] M. Thomson[c] M. Toups[g] Y.-T. Tsai[u] S. Tufanli[z] T. Usher[u] R. G. Van de Water[k] B. Viren[b] M. Weber[a] J. Weston[c] D. A. Wickremasinghe[s] K. Wierman[r] S. Wolbers[g] T. Wongjirad[m] K. Woodruff[o] T. Yang[g] G. P. Zeller[g] J. Zennamo[d] C. Zhang[b]

[a] *Universität Bern, Bern CH-3012, Switzerland*
[b] *Brookhaven National Laboratory (BNL), Upton, NY, 11973, USA*
[c] *University of Cambridge, Cambridge CB3 0HE, United Kingdom*
[d] *University of Chicago, Chicago, IL, 60637, USA*
[e] *University of Cincinnati, Cincinnati, OH, 45221, USA*
[f] *Columbia University, New York, NY, 10027, USA*
[g] *Fermi National Accelerator Laboratory (FNAL), Batavia, IL 60510, USA*
[h] *Illinois Institute of Technology (IIT), Chicago, IL 60616, USA*
[i] *Kansas State University (KSU), Manhattan, KS, 66506, USA*
[j] *Lancaster University, Lancaster LA1 4YW, United Kingdom*
[k] *Los Alamos National Laboratory (LANL), Los Alamos, NM, 87545, USA*
[l] *The University of Manchester, Manchester M13 9PL, United Kingdom*

[m] Massachusetts Institute of Technology (MIT), Cambridge, MA, 02139, USA
[n] University of Michigan, Ann Arbor, MI, 48109, USA
[o] New Mexico State University (NMSU), Las Cruces, NM, 88003, USA
[p] Otterbein University, Westerville, OH, 43081, USA
[q] University of Oxford, Oxford OX1 3RH, United Kingdom
[r] Pacific Northwest National Laboratory (PNNL), Richland, WA, 99352, USA
[s] University of Pittsburgh, Pittsburgh, PA, 15260, USA
[t] Saint Mary's University of Minnesota, Winona, MN, 55987, USA
[u] SLAC National Accelerator Laboratory, Menlo Park, CA, 94025, USA
[v] Syracuse University, Syracuse, NY, 13244, USA
[w] University of Texas, Arlington, TX, 76019, USA
[x] TUBITAK Space Technologies Research Institute, METU Campus, TR-06800, Ankara, Turkey
[y] Center for Neutrino Physics, Virginia Tech, Blacksburg, VA, 24061, USA
[z] Yale University, New Haven, CT, 06520, USA

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 m^3. 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. The detector began observing interactions of neutrinos from the FNAL Booster Neutrino Beam (BNB) [22] in October, 2015.

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. Most of the roughly 9600x3000 pixels that constitute one of the three images for each event are at their pedestal value. A typical event is seen in Figure 1.

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.

Outline roughly from

`https://docs.google.com/https://docs.google.com/document/d/1HalATQK5RneLrzhL2Tk-n-c1jI-7h`

2 Particle Classification

In this paper we study the performance of five particle classification (e^-, γ, μ^-, π^-, proton) using a variety of Convolutional Neural Networks (CNNs). We simulate these particles in the momentum range of interest to MicroBooNE, namely over a flat 50-500 MeV/c, using the relevant Geant4-based LArSoft package [8]. The tracks are mostly all contained in the fiducial volume. We anticipate the networks to learn to classify according to hints such as dQ/ds differences at the end of tracks – the Bragg peak – and for overall Q deposition differences, per the Bethe-Bloch curve for different particle species. We expect learning to proceed from macroscopic track-shower features, as well. We note, however, that unlike in the traditional cat, dog, human-face image data catalogs, we are faced with some level of irreducible ambiguity. In particular, μs and πs are minimum-ionizing particles which will only be discernable in the cases that, say, the μ^- captures or the π^- scatters and produces a kink or inelastic interaction. There trajectories are frequently indistinguishable.

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.

Therefore, we will not be surprised by some level of confusion in our networks between particular species.

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 ...

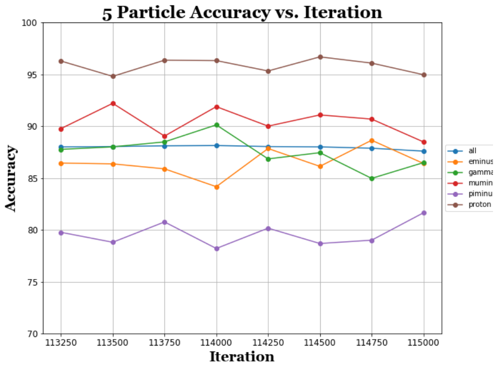
4 Training and Inference

A disciplined training and inference procedure is required in order to compare different networks to each other. We describe our procedure here. Our training sample consists of 2000 events of each particle type. The testing sample consists of 10000 more images. This is sample A. We let the training run in the normal iterative way, watching the testing sample A's Loss plot at each iteration. Our batch size is about 20 images, the complete forward/backward pass through each of which marks an iteration. When the Loss has achieved its minimum and begins to rise again, such that the global minimum is reached at 85% or less of the total number of iterations we stop the training and note the iteration value. The goal is to see that learning has plateaued before we stop training. We then run the inference stage on the Test sample A, using the weight file at the identified minimum plus/minus about 5 Epochs. We want to see that the learning is stable, and we can account for any epoch-to-epoch jitter.

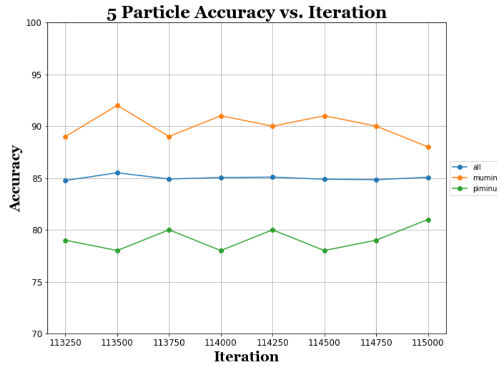
The best inference run on a given epoch in sample A is then identified as the weight file to be used in the final inference stage to be run on a new sample of simulated data, B.

5 The Architectures

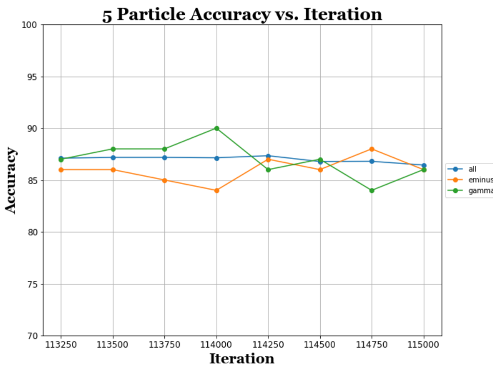
Broad descriptions here of ResNet and Vgg16 and whatever else we have results for. GoogleNet, AlexNet? Why we want to stick with flavors of ResNet and Vgg here. Perhaps we don't want each flovor of ResNet and Vgg16 to be its own subsection.



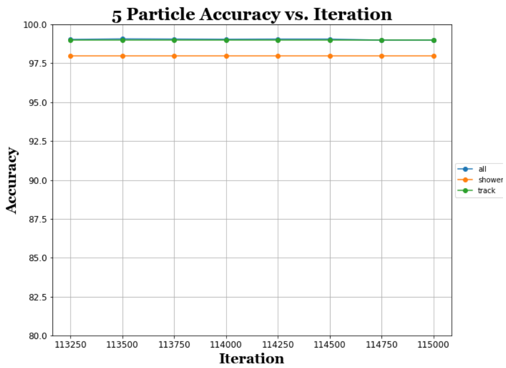
(a) The Accuracy for 5 species classification



(b) μ/π classification.



(c) e/γ classification



(d) e/γ versus μ, π, p classification

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.

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.

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