Addressing the Memory Bottleneck in AI Model-Training for Healthcare

Executive Summary

Intel, Dell, and researchers at the University of Florida have collaborated to help data scientists optimize the analysis of healthcare data sets using artificial intelligence (AI). Healthcare workloads, particularly in medical imaging, require more memory usage than other AI workloads because they often use higher resolution 3D images.

In this white paper, we demonstrate how Intel-optimized TensorFlow* on a Dell EMC PowerEdge server equipped with 2nd Generation Intel Xeon Scalable Processors with large system memory allows for the training of memory-intensive AI/deep-learning models in a scale-up server configuration. We believe our work represents the first training of a deep neural network having large memory footprint (~ 1 TB) on a single-node server. We recommend this configuration to users who wish to develop large, state-of-the-art AI models but are currently limited by memory.

Key Takeaways

- Near-terabyte memory footprint in 3D model training
- 3.4x speedup with Deep Neural Network Library optimizations
Revisions

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This paper was produced by the following:

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Motivation

Healthcare data sets often consist of large, multi-dimensional modalities. Deep learning (DL) models developed from these data sets require both high accuracy and high confidence levels to be useful in clinical practice. Researchers employ advanced hardware and software to speed up this data- and computation-intensive process.

Medical image analytics, such as semantic segmentation, are particularly challenging because the model is trained to automatically classify individual voxels from large volumetric images [1]. The 3D (and sometimes 4D) nature of this data type demands increased memory capacity and processing power when training the model. Consequently, researchers resort to tricks, such as downsizing and tiling images, to cope with available system memory or adopting shallower neural network topologies to address the high processing requirement. Ultimately, most researchers choose a model based on the memory limitations of the hardware rather than based on the best possible model design.

A high-memory CPU-based server solution, such as the 2nd Generation Intel Xeon Scalable Processor, presents an attractive architecture for addressing the compute and memory requirement of 3D semantic segmentation algorithms, such as 3D U-Net model. With more than 1 TB of system memory available, the 2nd Generation Intel Xeon Scalable Processor allows researchers to develop large DL models that can be several orders of magnitude larger than those available on DL accelerators.

Multimodal Brain Tumor Analysis

Multimodal brain tumor analysis is an important diagnosis process in the healthcare industry. A brain tumor occurs when abnormal cells form within the brain. Gliomas are the most frequent primary brain tumors in adults, presumably originating from glial cells and infiltrating the surrounding tissues [2]. Current imaging techniques used in clinical studies are limited to basic assessments, indicating for example, the presence of gliomas, or limited to non-wholistic coverage of the scan as a result of the reliance on rudimentary measurement techniques [3]. By

“These models were only moderate size, and we require more GPU or CPU memory to be able to train larger models...”

“Our estimations are based on our current GPU hardware specifications. We hope that switching to a CPU based model (and using Intel-optimized TensorFlow) will make training large model more feasible.”

- NEUROMOD / University de Montreal.
replacing current assessments with highly accurate and reproducible measurements, AI and DL techniques can automatically analyze brain tumor scans, providing an enormous potential for improved diagnosis, treatment planning and patient follow-ups.

A typical MRI scans of the brain may contain 4D volumes with multimodal, multisite MRI data (FLAIR, T1w, T1gd, T2w). With appropriate training data sets, an AI-based brain tumor analysis solution should perform segmentation on the images, annotating regions of interest as necrotic/active tumor, oedema or benign.

![Figure 1. AI-based Gliomas segmentation.](image)

**Computing Challenges**

While the high *processing* requirement of medical data analysis may be addressed with hardware accelerators, such as GPUs, addressing the *memory* requirement is not straightforward. As an example, a GPU accelerator has between 8 GB to 32 GB of memory. Although convolutional neural networks may only have several million trainable parameters, the actual memory footprint of these models is not due to solely those parameters. Instead, most of the memory footprint of these models comes from the activation (feature) maps in the model (Figure 2, green boxes). These activation maps—essentially copies of the original images—are a function of the size of the input to the network. Therefore, models that use large batch, high resolution, high dimensional image inputs often require more memory than the accelerator card can accommodate. As a simple example, a ResNet-50 topology that can train successfully on a 224x224x3 RGB input image may report an out of memory (OOM) error when training on 4096x2160x3 input images common to 4k video streams.

To compensate for the memory constraints of accelerator cards, researchers use the following “tricks”:  

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5 Addressing the Memory Bottleneck in AI Model – Training for Healthcare
• Image size: Images are often down sampled to a lower resolution
• Batch size: Batch sizes are often reduced to one or two images
• Tiling/Patching: Images are often subsampled into overlapping tiles/patches
• Model Complexity: Reductions in the number of feature maps and/or layers are often necessary
• Model Parallelism: Models may be distributed across several compute nodes in a parallel fashion

Although these tricks have been used to produce clinically-relevant models, we believe that researchers would not choose to use them if it were not for the memory limitations in hardware. In other words, these tricks were not created to obtain better models—they are instead necessary workarounds for hardware limitations. We believe that researchers would prefer to use the full resolution image without having to account for hyperparameters such as batch size, model complexity, or subsampling (tiling/patching). The large memory capacity of the 2nd Generation Intel Xeon Scalable Processor allows researchers this ability.

**Experimental Data**

The medical decathlon dataset [4] is a 3D semantic segmentation challenge with a broad range of medical imaging tasks including tumor and cancer diagnoses for various parts of the human body, including the liver, brain, lung, colon, and prostate. The images were generated either through a CT or an MRI scan at various universities and research centers from across the globe. Given this variety of data, the images present the opportunity for data scientists and machine learning practitioners to optimize AI algorithms for generalizability in medical imaging tasks with a primary focus on semantic segmentation. Thus, the most commonly used metric in segmentation tasks, Dice Similarity Coefficient (DSC) [5], along with Normalized Surface Distance (NSD) (distance between reconstructed surfaces) are used to assess different aspects of the performance of each task and region of interest. In this paper, we focus on the DSC (or simply, “dice coefficient”) of the Brain Tumor task from the BraTS dataset, which contains 750 4D MRI volumes: 484 for training and 266 for testing.
3D U-Net Model

Convolutional neural networks (CNNs) such as U-Net have been widely successfully in 2D segmentation in computer vision problems [6]. However, most medical data used in clinical practice consists of 3D volumes. Since only 2D slices can be displayed on a computer screen, annotating these large volumes with segmentation labels in a slice-by-slice manner is cumbersome and inefficient. 3D U-Net [7], based on U-Net architecture, performs volumetric segmentation by taking 3D volumes as input and processing them with corresponding 3D operations: 3D convolutions, 3D max-pooling, 3D up-sampling, etc. The resulting output is a trained model that reasonably generalizes well since the image slices contain mostly repetitive structures with corresponding variation. In general, the 3D U-Net model is both computation- and memory-intensive.

Memory Profiling

Memory footprint is as important to deep-learning training as is raw processing throughput or Floating-Point Operations per Second (FLOPs), especially when dealing with volumetric data and large models such as 3D U-Net. Table 1. shows the breakdown of the memory requirement of the 3D U-Net model at the largest available image size (240x240x144 in the case of the BraTS dataset) using a kernel size of 3x3x3. As indicated, the estimated system memory requirement is a little less than 1 TB for a batch size of 16 MRI scans. On our development server equipped with only 192 GB of system memory (Table 2), it took only a couple of minutes after starting model training before the system ran out of memory and the whole experiment came to a stall.
Table 1. Memory requirement for training 3D U-Net.

Table 2. Provisioning training infrastructure for 3D U-Net. We used random pixel values as input tensors. Our development server failed when executing just the 3D convolution-kernel part of the full 3D U-Net architecture.
We overcame this memory bottleneck on our development server by reducing the training batch size from 16 down to 2, while reducing the image size to reasonably smaller sized dimensions instead of the full-scale image feature map (240x240x144). Of course, this has an impact on the model accuracy and convergence time. Next, we upgraded our server’s system memory to its maximum supported memory capacity (384 GB), increased the image size of the dataset to about one-half, but reduced the batch size by half. In this scenario, the training job completed successfully. In the next section, we will go over the details of the training infrastructure — with a “memory-rich” server—using the full-scale BraTS images.

Figure 3. Benchmarking the memory usage of 3D U-Net model-training over various input tensors sizes on an Intel Xeon Scalable Processor-based server with 1.5 TB system
Training 3D U-Net on a Large-Memory System

A single-node server with large memory has the potential to reduce organization’s total cost of ownership (TCO), while addressing the memory bottleneck involved with training large models with complex datasets. Using a 4-socket 2nd Generation Intel Xeon Scalable Processor system on a Dell EMC PowerEdge server equipped with 1.5 TB of system memory (Figure 4), we trained the 3D U-Net model with the BraTS dataset (using only the “FLAIR” channel) without the need for scaling down the data nor tiling images to fit in memory. We used Intel-optimized TensorFlow - available as an Anaconda library [9] - and Conda as the Python virtual execution environment. The Intel-optimized TensorFlow distribution incorporates Deep Neural Network Library (DNNL) [10] (formerly MKL-DNN), allowing us to leverage the processors’ underlying hardware features, including high CPU core count (80 cores), AVX-512 for floating-point operations, and integrated memory controllers supporting 1TB-per-socket system memory, to speed up the training process.

Using this system configuration, we achieved, within 25 training iterations (epochs), close to state-of-the-art performance: 0.997 accuracy, 0.125 loss and 0.82 dice coefficient. We also profiled the memory footprint of the training task, comparing the results (Figure 5) with our theoretical calculations from Table 1 and found our estimations to be accurate for our chosen hyperparameters (batch, feature-map, and image sizes). Meanwhile, the training speed (TS) for a single step (involving forward pass and backward pass of a single 3D scan) per training epoch

Figure 4. Training infrastructure for 3D U-Net model with a 4-socket 2nd Generation Intel Xeon Scalable Processor system on a 2U Dell EMC PowerEdge R840 server.
was 30 seconds per image, a 3.4x speedup (Figure 6) compared to stock TensorFlow (without DNNL) at the same training batch size of 16.

Figure 7 depicts the prediction performance of the trained model. As observed, the segmentation mask from the model predictions closely match the ground truth mask. Using Table 1 as a reference, along with the TS and epoch count, machine learning practitioners can “plug in” their specific training data and hyperparameters to estimate both the required system memory and task completion time when training their own deep learning models on Intel architecture.

**Figure 5.** 3D U-Net memory footprint shows correlation with our theoretical calculations from Table 1.

**Figure 6.** TensorFlow with Deep Neural Network Library (DNNL) enabled achieves increased performance versus stock TensorFlow (without DNNL).

**Figure 7.** Prediction performance of the trained model, showing a slice of the brain from different views. The red overlay is the prediction from the model and the blue overlay is the ground truth mask. Any purple voxels are true positives.
Conclusions

In this white paper, we presented the multimodal brain tumor analysis for medical diagnosis, highlighted the computing challenges, and presented the 3D U-Net model for the task of volumetric image segmentation. We pre-calculated the memory requirement of the model and analyzed 3 different server configurations with varying memory capacity: from a “dev server” with 192 GB of memory to a “memory-rich” server with over 1 TB of memory. With the memory-rich server, we trained the 3D U-Net model using the BraTS dataset (a medical segmentation benchmark) and achieved close to state-of-the-art accuracy of 0.997 and dice coefficient of 0.83. The maximum memory utilization of the model during training also corresponds to our pre-calculated memory requirement, suggesting the generalizability of our approach to other memory-bound deep learning algorithms.

To the best of our knowledge, the results presented in this paper represent the first milestone in training a deep neural network having large memory footprint (close to 1 TB) on a single-node server without hardware accelerators like GPUs. Further, by enabling Deep Neural Network Library (DNNL) optimizations, we achieved a speedup of 3.4x per training step compared to stock TensorFlow. By replicating the single-node, memory-rich configuration described in this paper into a multi-node CPU cluster setup, we can expect to see greatly enhanced training performance of the 3D U-Net model as well as that of other complex 3D models and data sets, potentially reducing organizations TCO [13].

Acknowledgments

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University de Montreal
NEUROMOD
Dell EMC
Intel
References


## Appendix: Reproducibility

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<tr>
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<td>Code repository: <a href="https://github.com/IntelAI/unet">https://github.com/IntelAI/unet</a></td>
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<td>Ubuntu 16.04</td>
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### Hardware

- **Architecture**: x86_64
- **CPU op-mode(s)**: 32-bit, 64-bit
- **Byte Order**: Little Endian
- **CPU(s)**: 80
- **On-line CPU(s) list**: 0-79
- **Thread(s) per core**: 1
- **Core(s) per socket**: 20
- **Socket(s)**: 4
- **NUMA node(s)**: 4
- **Vendor ID**: GenuineIntel
- **CPU family**: 6
- **Model**: 85
- **Model name**: Intel(R) Xeon(R) Gold 6248 CPU @ 2.50GHz
- **Stepping**: 6
- **CPU MHz**: 2494.155
- **BogoMIPS**: 4989.86
- **Virtualization**: VT-x
- **L1d cache**: 32K
- **L1i cache**: 32K
- **L2 cache**: 1024K
- **L3 cache**: 28160K
- **NUMA node0 CPU(s)**: 0,4,8,12,16,20,24,28,32,36,40,44,48,52,56,60,64,68,72,76
- **NUMA node1 CPU(s)**: 1,5,9,13,17,21,25,29,33,37,41,45,49,53,57,61,65,69,73,77
- **NUMA node2 CPU(s)**: 2,6,10,14,18,22,26,30,34,38,42,46,50,54,58,62,66,70,74,78
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