Neurosurgeon: Collaborative Intelligence Between the Cloud and Mobile Edge

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# Abstract

The computation for today’s intelligent personal assistants such as Apple Siri, Google Now, and Microsoft Cortana, is performed in the cloud. This cloud-only approach requires significant amounts of data to be sent to the cloud over the wireless network and puts significant computational pressure on the datacenter. However, as the computational resources in mobile devices become more powerful and energy efficient, questions arise as to whether this cloud-only processing is desirable moving forward, and what are the implications of pushing some or all of this compute to the mobile devices on the edge.

In this paper, we examine the status quo approach of cloud-only processing and investigate computation partitioning strategies that effectively leverage both the cycles in the cloud and on the mobile device to achieve low latency, low energy consumption, and high datacenter throughput for this class of intelligent applications. Our study uses 8 intelligent applications spanning computer vision, speech, and natural language domains, all employing state-of-the-art Deep Neural Networks (DNNs) as the core machine learning technique. We find that given the characteristics of DNN algorithms, a fine-grained, layer-level computation partitioning strategy based on the data and computation variations of each layer within a DNN has significant latency and energy advantages over the status quo approach.

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Using this insight, we design Neurosurgeon, a lightweight scheduler to automatically partition DNN computation between mobile devices and datacenters at the granularity of neural network layers. Neurosurgeon does not require per-application profiling. It adapts to various DNN architectures, hardware platforms, wireless networks, and server load levels, intelligently partitioning computation for

best latency or best mobile energy. We evaluate Neurosurgeon on a state-of-the-art mobile development platform and show that it improves end-to-end latency by 3.1× on average and up to 40.7×, reduces mobile energy consumption by 59.5% on average and up to 94.7%, and improves datacenter throughput by 1.5× on average and up to 6.7×.

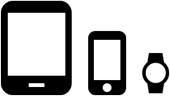
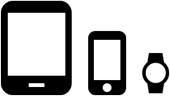
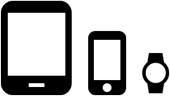
*Keywords* mobile computing; cloud computing; deep neural networks; intelligent applications

# Introduction

The way we interact with today’s mobile devices is rapidly changing as these devices are increasingly personal and knowledgeable. Intelligent Personal Assistants (IPAs), such as Apple Siri, Google Now, and Microsoft Cortana, are integrated by default on mobile devices and are expected to grow in popularity as wearables and smart home devices continue to gain traction [1, 2]. The primary interface with these intelligent mobile applications is using speech or images to navigate the device and ask questions. Demand for this mode of interaction is expected to replace the traditional text based inputs [3–5].

Processing speech and image inputs for IPA applications requires accurate and highly sophisticated machine learning techniques, the most common of which are Deep Neural Networks (DNNs). DNNs have become increasingly popular as the core machine learning technique in these applications due to their ability to achieve high accuracy for tasks such as speech recognition, image classification and natural language understanding. Many companies, including Google, Microsoft, Facebook, and Baidu, are using DNNs as the machine learning component for numerous applications in their production systems [6–8].

Prior work has shown that speech or image queries for DNN-based intelligent applications require orders of magnitude more processing than text based inputs [9]. The common wisdom has been that traditional mobile devices cannot support this large amount of computation with reasonable latency and energy consumption. Thus, the status quo approach used by web service providers for intelligent applications has been to host all the computation on high-end cloud servers [10–13]. Queries generated from a user’s mo-



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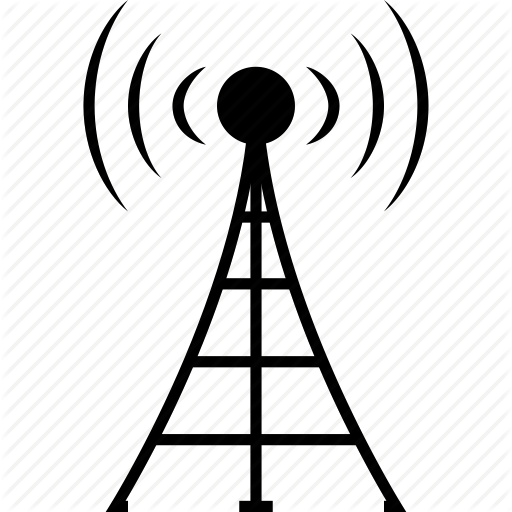
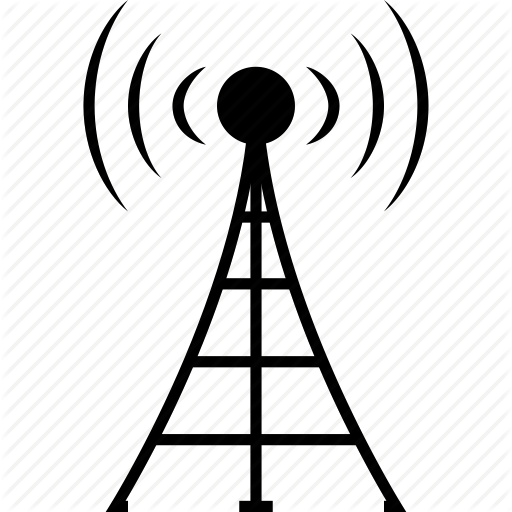
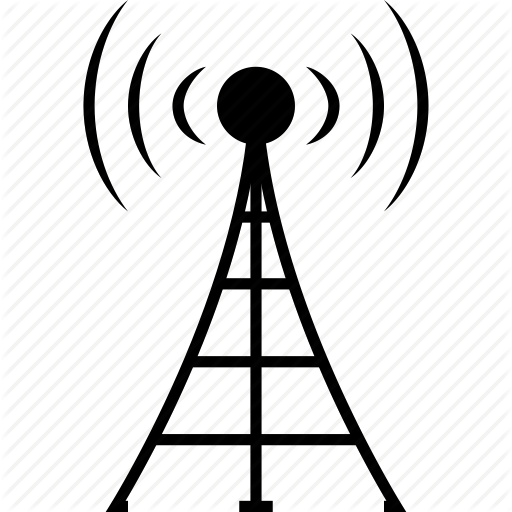
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,92,

[7



**a. Status quo b. Mobile-only c. Neurosurgeon Approach Approach Approach**

Figure 1: Status quo, mobile-only and the **Neurosurgeon** approach. Status quo approach performs all computation remotely in the cloud, the mobile-only approach performs all computation locally on the mobile device, and the **Neurosurgeon** approach partitions computation between the cloud and mobile device.

bile device are sent to the cloud for processing, as shown in Figure 1a. However, with this approach, large amounts of data (e.g., images, video and audio) are uploaded to the server via the wireless network, resulting in high latency and energy costs.

While data transfer becomes the latency and energy bottleneck, performance and energy efficiency of modern mobile hardware have continued to improve through powerful mobile SoC integration [14, 15]. Motivated by this observation, this work re-examines the computation breakdown for intelligent applications between mobile and cloud. In particular, we investigate how computation can be pushed out of the cloud and onto the mobile devices on the edge to execute all or parts of these conventionally cloud-only applications. Key questions we address in this work include:

1. How feasible it is to execute large-scale intelligent workloads on today’s mobile platforms?
2. At what point is the cost of transferring speech and image data over the wireless network too high to justify cloud processing?
3. What role should the mobile edge play in providing processing support for intelligent applications requiring heavy computation?

Based on our investigation using 8 DNN-based intelligent applications spanning the domains of vision, speech, and natural language, we discover that, for some applications, due to the high data transfer overhead, locally executing on the mobile device (비전, 자연어 등의DNN 기반의 8가지 어플리케이션에서 높은 양의 데이터 전송 과부하를 디바이스에서 발생한 다는 것을 발견) (Figurethe cloud-only approach (Figure1b) can be up to1a). Furthermore, we find11× faster than that instead of limiting the computation to be either executed entirely in the cloud or entirely on the mobile, a fine-grained layer-level partitioning strategy based on a DNN’s topology and constituent layers can achieve far superior end-to-end latency performance and mobile energy efficiency. By pushing compute out of the cloud and onto the mobile devices, we also improve datacenter throughput, allowing a given datacenter to support many more user queries, and creating a win-win situation for both the mobile and cloud systems.

Given the observation that ideal fine-grained DNN partition points depend on the layer compositions of the DNN, the particular mobile platform used, the wireless network configuration and the server load, we design a lightweight dynamic scheduler, Neurosurgeon. (이상적인 세밀한 DNN 파티션 포인트는 DNN의 계층 구성, 사용 된 특정 모바일 플랫폼, 무선 네트워크 구성 및 서버로드에 따라 달라진다는 점을 감안하여 경량 동적 스케줄러 인 Neurosurgeon을 설계한다.) Neurosurgeon is a runtime system spanning cloud and mobile platforms that automatically identifies the ideal partition points in DNNs and orchestrates the distribution of computation between the mobile device and the datacenter.( Neurosurgeon은 DNN에서 이상적인 파티션 포인트를 자동으로 식별하고 모바일 장치와 데이터 센터 간의 계산 분산을 오케스트레이션하는 클라우드 및 모바일 플랫폼에 걸친 런타임 시스템입니다.) As Figure 1c shows, Neurosurgeon partitions the DNN computation and takes advantage of the processing power of both the mobile and the cloud while reducing data transfer overhead. The detailed contributions of this paper are as follows:

* In-depth examination of the status quo – We show the latency and energy consumption of executing stateof-the-art DNNs in the cloud and on the mobile device. We observe that uploading via the wireless network is the bottleneck of the status quo approach, and mobile execution often provides better latency and energy consumption than the status quo approach. (Section 3)
* DNN compute and data size characteristics study – We provide an in-depth layer-level characterization of the compute and data size of 8 DNNs spanning across computer vision, speech and natural language processing. Our investigation reveals that DNN layers have significantly different compute and data size characteristics depending on their type and configurations. (Section 4)
* DNN computation partitioning across the cloud and mobile edge – Based on the compute and data characterization of DNN layers, we show that partitioning DNN at layer granularity offers significant performance benefits. We then design a systematic approach to identify the optimal points to partition computation for reduced latency and mobile energy consumption across a suite of applications. (Section 4)
* **Neurosurgeon** runtime system and layer performance prediction models – We develop a set of models to predict the latency and power consumption of a DNN layer based on its type and configuration, and create Neurosurgeon, a system to intelligently partition DNN computation between the mobile and cloud. We demonstrate that Neurosurgeon significantly improves end-to-end latency, reduces mobile energy consumption, and improves datacenter throughput. (Sections 5 and 6)

Our evaluation on a suite of 8 DNN applications shows that using Neurosurgeon on average improves end-toend latency by 3.1×, reduces mobile energy consumption. by 59.5%, and improves datacenter throughput by 1.5×

# Background

In this section, we provide an overview of Deep Neural Network (DNN) and describe how computer vision, speech, and natural language processing applications leverage DNNs as their core machine learning algorithm.

DNNs are organized in a directed graph where each node is a processing element (a neuron) that applies a function to its input and generates an output. Figure 2 depicts a 5 layer

Inference (Classify Image)

Neurons

Layer

“Tree”

Figure 2: A 5-layer Deep Neural Network (DNN) classifies input image into one of the pre-defined classes.

DNN for image classification where computation flows from left to right. The edges of the graph are the connections between each neuron defining the flow of data. Multiple neurons applying the same function to different parts of the input define a layer. For a forward pass through a DNN, the output of a layer is the input to the next layer. The depth of a DNN is determined by the number of layers. Computer Vision (CV) applications use DNNs to extract features from an input image and classify the image into one of the predefined classes. Automatic Speech Recognition (ASR) applications use DNNs to generate predictions for speech feature vectors, which will then be post-processed to produce the most-likely text transcript. Natural Language Processing (NLP) applications use DNNs to analyze and extract semantic and syntactic information from word embedding vectors generated from input text.

# Cloud-only Processing: The Status Quo

Currently, the status quo approach used by cloud providers for intelligent applications is to perform all DNN processing in the cloud [10–13]. A large overhead of this approach is in sending data over the wireless network. In this section, we investigate the feasibility of executing large DNNs entirely on a state-of-the-art mobile device, and compare with the status quo.

3.1 Experimental setup

We use a real hardware platform, representative of today’s state-of-the-art mobile devices, the Jetson TK1 mobile platform developed by NVIDIA [16] and used in the Nexus 9 tablet [17]. The Jetson TK1 is equipped with one of

NVIDIA’s latest mobile SoC, Tegra K1: a quad-core ARM A15 and a Kepler mobile GPU with a single streaming multiprocessor (Table 1).

Table 1: Mobile Platform Specifications

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| --- | --- |
| Hardware | Specifications |
| System | Tegra K1 SoC |
| CPU | 4-Plus-1 quad-core ARM Cortex A15 CPU |
| Memory | 2 GB DDR3L 933MHz |
| GPU | NVIDIA Kepler with 192 CUDA Cores |

Table 2: Server Platform Specifications

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| --- | --- |
| Hardware | Specifications |
| System | 4U Intel Dual CPU Chassis, 8×PCIe 3.0×16 slots |
| CPU | 2× Intel Xeon E5-2620 V2, 6C, 2.10 GHz |
| HDD | 1TB 2.5” HDD |
| Memory | 16× 16GB DDR3 1866MHz ECC/Server Memory |
| GPU | NVIDIA Tesla K40 M-Class 12 GB PCIe |

Our server platform is equipped with an NVIDIA Tesla K40 GPU, one of NVIDIA’s latest offering in server class GPUs (Table 2).

We use Caffe [18], an actively developed open-source deep learning library, for the mobile and server platform. For the mobile CPU, we use OpenBLAS [19], a NEONvectorized matrix multiplication library and use the 4 cores available. For both GPUs, we use cuDNN [20], an optimized NVIDIA library that accelerates key layers in Caffe, and use Caffe’s CUDA implementations for rest of the layers.

3.2 Examining the Mobile Edge

We investigate the capability of the mobile platform to execute a traditionally cloud-only DNN workload. We use AlexNet [21] as our application, a state-of-the-art Convolutional Neural Network for image classification. Prior work has noted that AlexNet is representative of today’s DNNs deployed in server environments [22].

In Figure 3, we break down the latency of an AlexNet query, a single inference on a 152KB image. For wireless communication, we measure the bandwidth of 3G, LTE, and Wi-Fi on several mobile devices using TestMyNet [23].

Communication Latency(통신지연) – Figure 3a shows the latency to upload the input image via 3G, LTE, and Wi-Fi. The slowest is 3G connection taking over 870ms. LTE and Wi-Fi connection require 180ms and 95ms to upload, respectively, showing that the network type is critical for achieving low latency for the status quo approach.

Computation Latency(계산지연) – Figure 3b shows the computation latency on mobile CPU, GPU and cloud GPU. The slowest platform is the mobile CPU taking 382ms to process while the mobile GPU and cloud GPU take 81ms and 6ms, respectively. Note that the mobile CPU’s time to process the image is still 2.3× faster than uploading input via 3G. (모바일 자체 출력이 3g보다 2.3배 좋다. LTE보단 그닥..?)

End-to-end Latency – Figure 3c shows the total latency required by the status quo and the mobile-only approach. Annotated on top of each bar is the fraction of the end-to-end latency spent on computation. The status quo approach spends less than 6% of the time computing on the server and over 94% of the time transferring data. The mobile GPU achieves a lower end-to-end latency than the status quo approach using LTE and 3G, while the status quo approach using LTE and Wi-Fi performs better than mobile CPU execution.( 모바일 GPU는 LTE 및 3G를 사용하는 상태 유지 접근 방식보다 낮은 엔드 투 엔드 지연 시간을 달성하는 반면, LTE 및 Wi-Fi를 사용하는 상태 유지 접근 방식은 모바일 CPU 실행보다 성능이 우수합니다.)

Energy Consumption – We measure the energy consumption of the mobile device using a Watts Up? meter [24] and

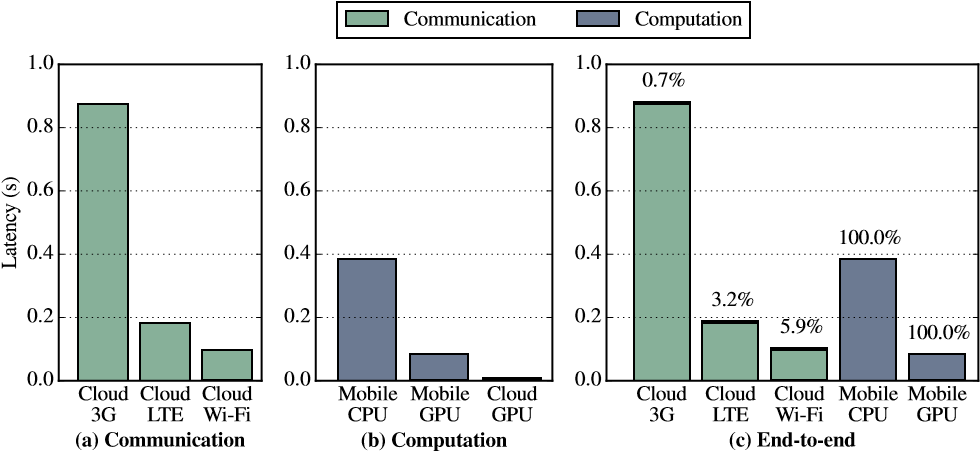


Figure 3: Latency breakdown for AlexNet (image classification). The cloud-only approach is often slower than mobile execution due to the high data transfer overhead.

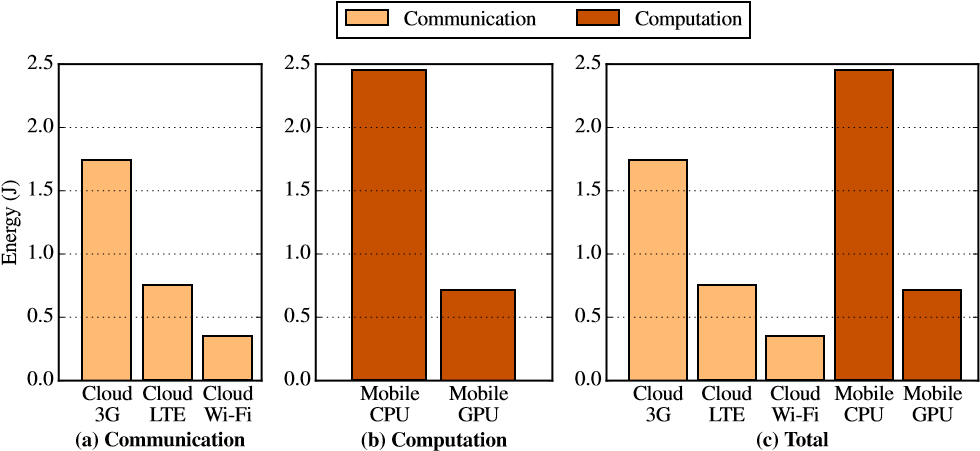


Figure 4: Mobile energy breakdown for AlexNet (image classification). Mobile device consumes more energy transferring data via LTE and 3G than computing locally on the GPU.

techniques described by Huang et al. [25]. Similar to the trends shown in Figure 3a, Figure 4a shows that the communication energy is heavily dependent on the type of wireless network used. In Figure 4b, the mobile device’s energy consumption is higher on the CPU than the GPU (while the GPU needs more power, the device is used for a shorter burst thus it consumes less total energy)( 모바일 장치의 에너지 소비는 GPU보다 CPU에서 더 높습니다 (GPU는 더 많은 전력을 필요로하지만 장치는 더 짧은 버스트에 사용되므로 총 에너지를 덜 소비 함)). Figure 4c shows the total mobile energy consumption for the cloud-only approach and mobile execution where the energy in the cloud-only approach is dominated by communication. The mobile GPU consumes less energy than transferring input via LTE or 3G for cloud processing, while cloud processing via Wi-Fi consumes less energy than mobile execution.( 모바일 GPU는 클라우드 처리를 위해 LTE 또는 3G를 통해 입력을 전송하는 것보다 적은 에너지를 소비하는 반면 Wi-Fi를 통한 클라우드 처리는 모바일 실행보다 적은 에너지를 소비합니다.)

*Key Observations* – 1) The data transfer latency is often higher than mobile computation latency, especially on 3G and LTE. 2) Cloud processing has a significant computational advantage over mobile processing, but it does not always translate to end-to-end latency/energy advantage due to the dominating data transfer overhead. 3) Local mobile execution often leads to lower latency and energy consumption than the cloud-only approach, while the cloud-only approach achieves better performance if using fast Wi-Fi connection. (1)데이터 전송 대기 시간은 종종 3G 및 LTE에서 모바일 계산 대기 시간보다 높습니다. 2) 클라우드 프로세싱은 모바일 프로세싱에 비해 계산상의 이점이 크지 만, 데이터 전송 오버 헤드가 지배적이므로 엔드-투-엔드 대기 시간 / 에너지 이점으로 항상 전환되는 것은 아닙니다. 3) 로컬 모바일 실행은 종종 클라우드 전용 접근 방식보다 대기 시간과 에너지 소비를 낮추는 반면 빠른 Wi-Fi 연결을 사용하는 경우 클라우드 전용 접근 방식이 더 나은 성능을 달성합니다.)

# Fine-grained Computation Partitioning

Based on the findings in Section 3, the question arises as to whether it is advantageous to partition DNN computation between the mobile device and cloud. Based on the observation that DNN layers provide an abstraction suitable for partitioning computation, we begin with an analysis of the data and computation characteristics of state-of-the-art DNN architectures at the layer granularity.

4.1 Layer Taxonomy(레이어 분류)

Before the layer-level analysis, it is important to understand the various types of layers present in today’s DNNs.

Fully-connected Layer (**fc**) – All the neurons in a fullyconnected layer are exhaustively connected to all the neurons in the previous layer. The layer computes the weighted sum of the inputs using a set of learned weights.

Convolution & Local Layer (**conv**, **local**) – Convolution and local layers convolve the image with a set of learned filters to produce a set of feature maps. These layers mainly differ in the dimensions of their input feature maps, the number and size of their filters, and the stride with which the filters are being applied.

Pooling Layer (**pool**) – Pooling layers apply a pre-defined function (e.g., max or average) over regions of input feature maps to group features together. These layers mainly differ in the dimension of their input, size of the pooling region, and the stride with which the pooling is applied.

Activation Layer – Activation layers apply a non-linear function to each of its input data individually, producing the same amount of data as output. Activation layers present in the neural networks studied in this work include sigmoid layer (sig), rectified-linear layer (relu), and hard Tanh layer (htanh).

Other layers studied in this work include: normalization layer (**norm**) normalizes features across spatially grouped feature maps; softmax layer (**softmax**) produces a probability distribution over the number of possible classes for classification; argmax layer (**argmax**) chooses the class with the highest probability; and dropout layer (**dropout**) randomly ignores neurons during training to avoid model over-fitting and are passed through during prediction.(이러이런걸 사용했다)

4.2 Characterizing Layers in AlexNet

We first investigate the data and computation characteristics of each layer in AlexNet. These characteristics provide insights to identify a better computation partitioning between mobile and cloud at the layer level. In the remainder of this and subsequent sections, we use the GPU in both mobile and server platforms.

Per-layer Latency – The left bars (light-colored) in Figure 5 show the latency of each layer on the mobile platform, arranged from left to right in their sequential execution order. The convolution (conv) and fully-connected layers (fc) are the most time-consuming layers, representing over 90% of the total execution time. Convolution layers in the middle

(conv3 and conv4) takes longer to execute than the early convolution layers (conv1 and conv2). Larger number of filters are applied by the convolution layers later in the DNN to progressively extract more robust and representative fea

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| Figure 5: The per layer execution time (the light-colored left bar) and size of data (the dark-colored right bar) after each layer’s execution (input for next layer) in AlexNet. Data size sharply increases then decreases while computation generally increases through the network’s execution.    Figure 6: End-to-end latency and mobile energy consumption when choosing different partition points. After the execution of every layer is considered a partition point. Each bar represents the total latency (a) or mobile energy (b) if the DNN is partitioned after the layer marked on the X-axis. The left-most bar represents cloud-only processing and the right-most bar represents mobile-only processing. The partition points for best latency and mobile energy are annotated. |

tures, increasing the amount of computation. On the other hand, fully-connected layers are up to one magnitude slower than the convolution layers in the network. The most timeconsuming layer is the layer fc6, a fully-connected layer deep in the DNN, taking 45% of the total execution time.( 중간에 컨볼 루션 레이어

(conv3 및 conv4)는 초기 회선 레이어 (conv1 및 conv2)보다 실행 시간이 더 오래 걸립니다. DNN에서 나중에 컨볼 루션 레이어에 의해 더 많은 수의 필터가 적용되어 더욱 강력하고 대표적인 기능을 점진적으로 추출하여 계산량을 증가시킵니다. 반면, 완전히 연결된 레이어는 네트워크의 컨볼 루션 레이어보다 최대 1 배 느립니다. 가장 시간이 많이 걸리는 계층은 DNN에 완전히 연결된 계층 fc6이며 총 실행 시간의 45 %를 차지합니다.)

Data Size Variations – The right bars (dark-colored) in Figure 5 shows the size of each layer’s output data, which is also the input to the next layer. The first three convolution layers (conv1, conv2 and conv3) generate large amounts of output data (shown as the largest dark bars) as they apply hundreds of filters over their input feature maps to extract interesting features. The data size stays constant through the activation layers (relu1 - relu5). The pooling layers regions of neighboring features by taking the maximum.sharply reduce the data size by up to 4.7× as they summarize

The fully-connected layers deeper in the network (fc6 fc8) gradually reduce the data size until the softmax layer

(softmax) and argmax layer (argmax) at the end reduce the data to be one classification label.

*Key Observations* – 1) Depending on its type and location in the network, each layer has a different computation and data profile. 2) The latency of convolution and pooling layers on the mobile GPU are relatively small, while fully-connected layers incur high latency. 3) Convolution and pooling layers are mostly at the front-end of the network, while fullyconnected layers are at the back-end. 4) With convolution layers increasing data and then pooling layers reducing data, the front-end layers altogether reduce the size of data gradually. Data size in the last few layers are smaller than the original input. 5) The findings that data size is generally decreasing at the front-end, and per-layer mobile latency is generally higher at the back-end, indicates the unique opportunity for computation partitioning in the middle of the DNN between the mobile and cloud. (주요 관찰 – 1) 네트워크의 유형과 위치에 따라 각 계층마다 다른 계산 및 데이터 프로파일이 있습니다. 2) 모바일 GPU에서 컨볼 루션 및 풀링 계층의 대기 시간은 비교적 작지만 완전히 연결된 계층은 대기 시간이 길어집니다. 3) 컨볼 루션 및 풀링 계층은 대부분 네트워크의 프런트 엔드에 있고 완전히 연결된 계층은 백엔드에 있습니다. 4) 컨볼 루션 레이어는 데이터를 증가시키고 풀링 레이어는 데이터를 감소시키면서 데이터의 크기를 점차적으로 줄입니다. 마지막 몇 층의 데이터 크기는 원래 입력보다 작습니다. 5) 데이터 크기가 일반적으로 프론트 엔드에서 감소하고 있으며 계층 당 모바일 대기 시간이 일반적으로 백엔드에서 높다는 결과는 모바일과 클라우드 사이의 DNN 중간에 계산 분할의 고유 한 기회를 나타냅니다.)

4.3 Layer-granularity Computation Partitioning

The analysis in Section 4.2 indicates that there exist interesting points within a neural network to partition computation. In this section, we explore partitioning AlexNet at each layer between the mobile and cloud. In this section, we use Wi-Fi as the wireless network configuration.

Each bar in Figure 6a represents the end-to-end latency of AlexNet, partitioned after each layer. Similarly, each bar in Figure 6b represents the mobile energy consumption of Alexnet, partitioned after each layer. Partitioning computation after a specific layer means executing the DNN on the mobile up to that layer, transferring the output of that layer to the cloud via wireless network, and executing the remaining layers in the cloud. The leftmost bar represents sending the original input for cloud-only processing. As partition point moves from left to right, more layers are executed on the mobile device thus there is an increasingly larger mobile processing component. The rightmost bar is the latency of executing the entire DNN locally on the mobile device.( 그림 6a의 각 막대는 각 계층마다 분할 된 AlexNet의 전체 지연 시간을 나타냅니다. 유사하게,도 6b의 각 막대는 각 층마다 분할 된 Alexnet의 모바일 에너지 소비를 나타낸다. 특정 계층 이후의 분할 계산은 해당 계층까지 모바일에서 DNN을 실행하고 무선 네트워크를 통해 해당 계층의 출력을 클라우드로 전송하고 클라우드에서 나머지 계층을 실행하는 것을 의미합니다. 가장 왼쪽 막대는 클라우드 전용 처리를 위해 원래 입력을 보내는 것을 나타냅니다. 파티션 포인트가 왼쪽에서 오른쪽으로 이동함에 따라 더 많은 레이어가 모바일 장치에서 실행되므로 점점 더 큰 모바일 처리 구성 요소가 있습니다. 가장 오른쪽 막대는 전체 DNN을 모바일 장치에서 로컬로 실행하는 대기 시간입니다.)

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| Figure 7: The per layer latency on the mobile GPU (left light-color bar) and size of data (right dark-color bar) after each layer’s execution. |

Partition for Latency – If partitioning at the front-end, the data transfer dominates the end-to-end latency, which is consistent with our observation in Section 4.2 that the data size is the largest at the early stage of the DNN.(섹션의 데이터 크기가 DNN의 초기 단계에서 가장 크다는 관찰 결과와 일치합니다.) Partitioning at the back-end provides better performance since the application can minimize the data transfer overhead, while taking advantage of the powerful server to execute the more computeheavy layers at the back-end. In the case of AlexNet using the mobile GPU and Wi-Fi, partitioning between the last pooling layer (pool5) and the first fully-connected layer (fc6) achieves the lowest latency, as marked in Figure 6a, improving 2.0× over cloud-only processing. (백엔드에서의 파티셔닝은 애플리케이션이 데이터 전송 오버 헤드를 최소화 할 수있는 반면, 강력한 서버를 활용하여 백엔드에서 더 많은 계산량의 계층을 실행할 수 있으므로 성능이 향상됩니다.)

Partition for Energy – Similar to latency, due to the high energy cost of wireless data transfer, transferring the input for cloud-only processing is not the most energy-efficiency approach. As marked in Figure 6b, partitioning in the middle of the DNN achieves the best mobile energy consumption, 18% more energy efficient than the cloud-only approach.

*Key Observations* – Partitioning at the layer granularity can provide significant latency and energy efficiency improvements. For AlexNet using the GPU and Wi-Fi, the best partition points are between the intermediate layers of the DNN. (주요 관찰 – 레이어 단위로 파티셔닝하면 대기 시간과 에너지 효율성이 크게 향상 될 수 있습니다. GPU와 Wi-Fi를 사용하는 AlexNet의 경우 가장 좋은 파티션 지점은 DNN의 중간 계층 사이에 있습니다.)

4.4 Generalizing to More DNNs

We expand our investigation to 7 more intelligent applications to study their data and computation characteristics and their impact on computation partitioning opportunity. We use the DNNs provided in the Tonic suite [9], as well as VGG, a state-of-the-art image classification DNN, and LTE as the wireless network configuration. Details about the benchmarks are listed in Table 3. We count the number of layers of each DNN starting from the first non-input layer to the last layer, including argmax if present.

CV Applications – The three remaining computer vision DNNs (VGG, FACE and DIG) have similar characteristics as AlexNet (Figure 5), as shown in Figures 7a –7c. The frontend layers are convolution layers increasing data, and pooling layers reducing data. The data size in the back-end layers are similar or smaller than the original input data. The latency for the back-end layers are higher than most of the

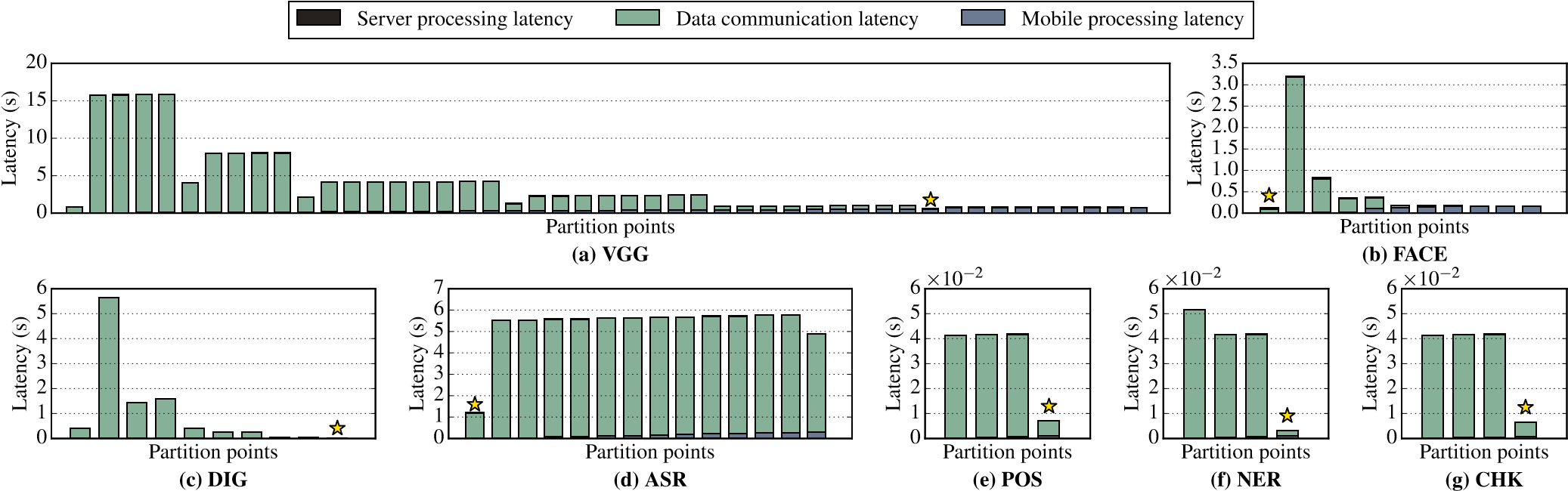
Table 3: Benchmark Specifications

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| App | Abbr. | Network | Input | Layers |
| Image classification | IMC VGG | AlexNet [21] VGG [26] | Image  Image | 24  46 |
| Facial recognition | FACE | DeepFace [27] | Image | 10 |
| Digit recognition | DIG | MNIST [28] | Image | 9 |
| Speech recognition | ASR | Kaldi [29] | Speech features | 13 |
| Part-of-speech tagging | POS | SENNA [30] | Word vectors | 3 |
| Named entity recognition | NER | SENNA [30] | Word vectors | 3 |
| Word chunking | CHK | SENNA [30] | Word vectors | 3 |

front-end layers (e.g., fc6 is the most time-consuming layer in VGG), except for DIG where convolution layers are most time-consuming. Similar to AlexNet, these characteristics indicate partitioning opportunities in the middle of the DNN. Figure 8a shows that the partition point for best latency for VGG is in the intermediate layers. In addition, Figures 8a 8c show that different CV applications have different partition points for best latency, and Figures 9a - 9c show the different partition points for best energy for these DNNs.( VGG는 중간 계층에 있습니다. 또한, 그림 8a 8c는 각기 다른 CV 애플리케이션이 최상의 대기 시간을 위해 서로 다른 파티션 포인트를 가지고 있음을 보여 주며, 그림 9a-9c는 이러한 DNN을위한 최상의 에너지를위한 다른 파티션 포인트를 보여줍니다.)

ASR and NLP Applications – The remaining four DNNs in the suite (ASR, POS, NER and CHK) only consist of fullyconnected layers and activation layers. The layer breakdowns are shown in Figures 7d - 7g, where, throughout the execution, layers of the same type incur similar latency and the data size stay relatively constant except for the very first and last layer of each DNN. These DNNs do not have dataincreasing layers (i.e., convolution layers) or data-reducing layers (i.e., pooling layers). As a result, there only exist opportunities for partitioning the computation at the extremities of these networks. Figures 8d - 8g and Figures 9d 9g show the different partition points for best latency and energy for these DNNs, respectively. There are data communication components in the right-most bars (mobile-only processing) for these applications because the output of the DNN is sent to the cloud for post-processing steps required by these applications.

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| Figure 8: End-to-end latency when choosing different partition points. Each bar represents the end-to-end latency if the DNN is partitioned after each layer, where the left-most bar represents cloud-only processing (i.e., partitioning at the beginning) while the right-most bar represents mobile-only execution (i.e., partitioning at the end). The wireless network configuration is LTE. The partition points for best latency are each marked by F.    Figure 9: Mobile energy consumption when choosing different partition points. Each bar represents the mobile energy consumption if the DNN is partitioned after each layer, where the left-most bar represents cloud-only processing (i.e., partitioning at the beginning) while the right-most bar represents mobile-only execution (i.e., partitioning at the end). The wireless network configuration is LTE. The partition points for best energy are |

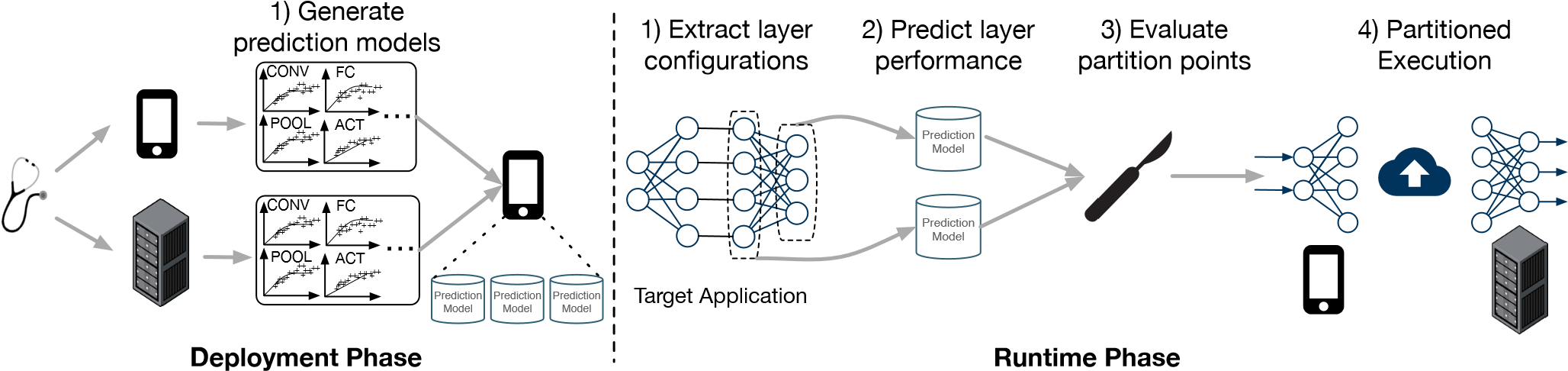
each marked by F.

*Key Observations* – 1) In DNNs with convolution and pooling layers (e.g. Computer Vision applications), the data size increases after convolution layers and decreases after pooling layers, while the per-layer computation generally increases through the execution. 2) DNNs with only fullyconnected layers of similar size and activation layers see small variations in per-layer latency and data size (e.g., ASR and NLP DNNs). 3) The best way to partition a DNN depends on its topology and constituent layers. Computer vision DNNs sometimes have better partition points in the middle of the DNN, while it is more beneficial to partition at the beginning or the end for ASR and NLP DNNs. The strong variations in the best partition point suggest there is a need for a system to partition DNN computation between the mobile and cloud based on the neural network architecture.

*1)컨볼 루션 및 풀링 계층 (예 : Computer Vision 애플리케이션)이있는 DNN의 경우 컨볼 루션 계층 이후 데이터 크기가 증가하고 계층 풀링 후 감소하는 반면 계층 당 계산은 일반적으로 실행을 통해 증가합니다. 2) 비슷한 크기 및 활성화 계층의 완전히 연결된 계층 만있는 DNN은 계층 별 대기 시간 및 데이터 크기 (예 : ASR 및 NLP DNN)에서 약간의 변화를 볼 수 있습니다. 3) DNN을 분할하는 가장 좋은 방법은 토폴로지와 구성 계층에 따라 다릅니다. 컴퓨터 비전 DNN은 때때로 DNN 중간에 더 나은 파티션 포인트를 가지지 만 ASR 및 NLP DNN의 시작 또는 끝에서 파티션하는 것이 더 유리합니다. 최상의 파티션 포인트의 강력한 변형은 신경망 아키텍처에 기초하여 모바일과 클라우드간에 DNN 계산을 파티션 할 시스템이 필요하다는 것을 시사합니다.)*

# Neurosurgeon(partition point)

The best partition point for a DNN architecture depends on the DNN’s topology, which manifests itself in the computation and data size variations of each layer. In addition, dynamic factors such as state of the wireless network and datacenter load affect the best partition point even for the same DNN architecture. For example, mobile devices’ wireless connections often experience high variances [31], directly affecting the data transfer latency. Datacenters typically experience diurnal load patterns [32], leading to high variance in its DNN query service time. Due to these dynamic factors, there is a need for an automatic system to intelligently select the best point to partition the DNN to optimize for end-to-end latency or mobile device energy consumption. To address this need, we present the design of Neurosurgeon, an intelligent DNN partitioning engine.( 이러한 역동적 인 요인으로 인해 DNN을 분할하기위한 최적의 지점을 지능적으로 자동 선택하여 엔드 투 엔드 대기 시간 또는 모바일 장치 에너지 소비를 최적화해야하는 자동 시스템이 필요합니다.) Neurosurgeon consists of a deployment phase and a runtime system that manages the partitioned execution of an intelligent application. Figure 10 shows the design of Neurosurgeon, which has two stages: deployment and runtime.

At Deployment – Neurosurgeon profiles the mobile device and the server to generate performance prediction models for the spectrum of DNN layer types (enumerated in Section 4.1). Note that Neurosurgeon’s profiling is application

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| Figure 10: Overview of **Neurosurgeon**. At deployment, **Neurosurgeon** generates prediction models for each layer type. During runtime, **Neurosurgeon** predicts each layer’s latency/energy cost based on the layer’s type and configuration, and selects the best partition point based on various |

dynamic factors.

agnostic and only needs to be done once for a given set of mobile and server platforms; per-application profiling is not needed. This set of prediction models are stored on the mobile device and later used to predict the latency and energy cost of each layer (Section 5.1).

During Runtime – During the execution of an DNN-based intelligent application on the mobile device, Neurosurgeon dynamically decides the best partition point for the DNN. As illustrated in Figure 10, the steps are as follows:

1) Neurosurgeon analyzes and extracts the DNN architecture’s layer types and configurations; 2) the system uses the stored layer performance prediction models to estimate the latency and energy consumption for executing each layer on the mobile and cloud; 3) with these predictions, combined with the current wireless connection bandwidth and datacenter load level, Neurosurgeon selects the best partition point, optimizing for best end-to-end latency or best mobile energy consumption; 4) Neurosurgeon executes the DNN, partitioning work between the mobile and cloud. 5.1 Performance Prediction Model

Neurosurgeon models the per-layer latency and the energy consumption of arbitrary neural network architecture.( This approach allows Neurosurgeon to estimate the latency and energy consumption of a DNN’s constituent layers without executing the DNN.( 4) Neurosurgeon은 DNN을 실행하여 모바일과 클라우드 간 분할 작업을 수행합니다. 5.1 성능 예측 모델

Neurosurgeon은 임의의 신경망 아키텍처의 레이어 당 대기 시간과 에너지 소비를 모델링합니다. 이 접근 방식을 통해 Neurosurgeon은 DNN을 실행하지 않고도 DNN 구성 요소 계층의 대기 시간 및 에너지 소비를 추정 할 수 있습니다.)

We observe that for each layer type, there is a large latency variation across layer configurations. Thus, to construct the prediction model for each layer type, we vary the configurable parameters of the layer and measure the latency and power consumption for each configuration. Using these profiles, we establish a regression model for each layer type to predict the latency and power of the layer based on its configuration. We describe each layer’s regression model variables later in this section. We use GFLOPS (Giga Floating Point Operations per Second) as our performance metric. Based on the layer type, we use either a logarithmic or linear function as the regression function. The logarithmic-based regression is used to model the performance plateau as the computation requirement of the layer approaches the limit of the available hardware resources.

Convolution, local and pooling layers’ configurable parameters include the input feature map dimension, number, size and stride of the filters. The regression model for convolution layer is based on two variables: the number of features in the input feature maps, and(# *of filters*), which represents the amount of computa-(*filter size/stride*)2× tion applied to each pixel in the input feature maps. For local and pooling layers, we use the size of the input and output feature maps as the regression model variables.

In a fully-connected layer, the input data is multiplied by the learned weight matrix to generate the output vector. We use the number of input neurons and number of output neurons as the regression model variables. Softmax and argmax layers are handled similarly.

Activation layers have fewer configurable parameters compared to other layers because activation layers have a one-to-one mapping between their input data and output. We use the number of neurons as the regression model variable. We apply the same approach to normalization layers.

As previously mentioned, it is a one-time profiling step required for each mobile and server hardware platform to generate a set of prediction models. The models enable Neurosurgeon to estimate the latency and energy cost of each layer based its configuration, which allows Neurosurgeon to support future neural network architectures without additional profiling overhead.

5.2 Dynamic DNN Partitioning

Utilizing the layer performance prediction models, Neurosurgeon dynamically selects the best DNN partition points, as described in Algorithm 1. The algorithm has two-steps: analysis of the target DNN and partition point selection.

Analysis of the Target DNN – Neurosurgeon analyzes the target DNN’s constituent layers, and uses the prediction models to estimate, for each layer, the latency on mobile and cloud, and power consumption on the mobile. Specifically, at lines 11 and 12 of Algorithm 1, Neurosurgeon extracts each layer’s type and configuration (*Li*) and uses the regression models to predict the latency of executing layer *Li* on (대상 DNN 분석 – Neurosurgeon은 대상 DNN의 구성 계층을 분석하고 예측 모델을 사용하여 각 계층, 모바일 및 클라우드의 대기 시간 및 모바일의 전력 소비를 추정합니다. 특히 알고리즘 1의 11 번과 12 번 라인에서 Neurosurgeon은 각 계층의 유형 및 구성 (Li)을 추출하고 회귀 모델을 사용하여 계층 Li 실행의 대기 시간을 예측합니다.)

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| Table 4: **Neurosurgeon**’s partition point selections for best end-to-end latency. Green block indicates **Neurosurgeon** makes the optimal partition choice and white block means a suboptimal partition point is picked. On average, **Neurosurgeon** achieves within 98.5% of the optimal performance.   |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | Mobile | | Wireless network | |  |  |  | | Benchmarks | | |  |  | |  | | | IMC | VGG | FACE | | DIG | | ASR | POS | NER | | CHK | | | CPU | | Wi-Fi | | input | input | input | | input | | input |  | fc3 | |  | | | LTE | | input | input | input | | argmax | | input |  | fc3 | |  | | | 3G | | argmax | input | input | | argmax | | input |  | fc3 | |  | | | GPU | | Wi-Fi | | pool5 | input | input | | argmax | | input |  | fc3 | |  | | | LTE | | argmax | argmax | input | | argmax | | input |  | fc3 | |  | | | 3G | | argmax | argmax | argmax | | argmax | | input |  | fc3 | |  | | |  | | Neurosurgeon Wi-Fi | | | | Neurosurgeon LTE | | Neurosurgeon 3G | | | | Neurosurgeon avg. | | | Status quo | |     Figure 11: Latency speedup achieved by **Neurosurgeon** normalized to status quo approach (executing entire DNN in the cloud). Results for three wireless networks (Wi-Fi, LTE and 3G) and mobile CPU and GPU are shown here. **Neurosurgeon** improves the end-to-end DNN |

inference latency by 3.1× on average (geometric mean) and up to 40.7×.

mobile (*TMi*) and cloud (*TCi*), while taking into consideration of current datacenter load level (*K*). Line 13 estimates the power of executing layer *Li* on the mobile device (*PMi*) and line 14 calculates the wireless data transfer latency (*TUi*) based on the latest wireless network bandwidth. Partition Point Selection – Neurosurgeon then selects the best partition point. The candidate points are after each layer. Lines 16 and 18 evaluate the performance when partitioning at each candidate point and select the point for either best end-to-end latency or best mobile energy consumption. Because of the simplicity of the regression models, this evaluation is lightweight and efficient.

Algorithm 1 Neurosurgeon DNN partitioning algorithm

1: Input:

2: *N*: number of layers in the DNN

3: {*Li*|*i* = 1···*N*}: layers in the DNN

4: {*Di*|*i* = 1···*N*}: data size at each layer

5: *f,g*(*Li*): regression models predicting the latency and power of executing *Li*

6: *K*: current datacenter load level

7: *B*: current wireless network uplink bandwidth

8: *PU*: wireless network uplink power consumption 9: procedure PARTITIONDECISION

|  |  |  |
| --- | --- | --- |
| 10: | for each *i in* 1···*N* do |  |
| 11: | *TMi* ← *fmobile*(*Li*) |  |
| 12: | *TCi* ← *fcloud*(*Li,K*) |  |
| 13: | *PMi* ← *gmobile*(*Li*) |  |
| 14: | *TUi* ← *Di/B* |  |
| 15: | if *OptTarget* == *latency* then |  |
|  | *j* | *N* |

16: return argmin

*j*=1··· =1 *k*=*j*+1

17: else if *OptTarget* == *energy* then

18: return *j*

5.3 Partitioned Execution

We prototype Neurosurgeon by creating modified instances of Caffe [18] to serve as our mobile-side (NSmobile) and server-side (NSserver) infrastructures. Through these two variations of Caffe, we implement our client-server interface using Thrift [33], an open source flexible RPC interface for inter-process communication. To allow for flexibility in the dynamic selection of partition points, both NSmobile and NSserver host complete DNN models, and partition points are enforced by NSmobile and NSserver runtime. Given a partition decision by NSmobile, execution begins on the mobile device and cascades through the layers of the DNN leading up to that partition point. Upon completion of that layer, NSmobile sends the output of that layer from the mobile device to NSserver residing on the server side. NSserver then executes the remaining DNN layers. Upon the completion of the DNN execution, the final result is sent back to NSmobile on the mobile device from NSserver. Note that there is exactly one partition point within the DNN for which information is sent from the mobile device to the cloud.(장치를 만들어 보았다 뭐 그런)

# Evaluation

We evaluate Neurosurgeon using 8 DNNs (Table 3) as our benchmarks across Wi-Fi, LTE and 3G wireless connections with both CPU-only and GPU mobile platforms. We demonstrate Neurosurgeon achieves significant end-toend latency and mobile energy improvements over the status quo cloud-only approach (Sections 6.1 and 6.2). We then compare Neurosurgeon against MAUI [34], a well-known

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| Table 5: **Neurosurgeon** partition point selections for best mobile energy consumption. Green block indicates **Neurosurgeon** makes the optimal partition choice and white block means a suboptimal partition point is picked. On average, **Neurosurgeon** achieves a mobile energy reduction within 98.8% of the optimal reduction.   |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | | Mobile | | Wireless network | |  |  | | Benchmarks | | | |  |  | |  | | IMC | VGG | | FACE | DIG | | ASR | POS | NER | | CHK | | CPU | | Wi-Fi | | input | input | | input | input | | input |  | fc3 | |  | | LTE | | input | input | | input | input | | input |  | fc3 | |  | | 3G | | input | input | | input | argmax | | input |  | fc3 | |  | | GPU | | Wi-Fi | | input | input | | input | argmax | | input |  | fc3 | |  | | LTE | | pool5 | input | | input | argmax | | input |  | fc3 | |  | | 3G | | argmax | argmax | | input | argmax | | input |  | fc3 | |  | |  | | Neurosurgeon Wi-Fi | | | Neurosurgeon LTE | | | Neurosurgeon 3G | | | | Neurosurgeon avg. | | | | Status quo | |     Figure 12: Mobile energy consumption achieved by **Neurosurgeon** normalized to status quo approach (executing entire DNN in the cloud). Results for three wireless networks (Wi-Fi, LTE and 3G) and mobile CPU and GPU are shown here. **Neurosurgeon** reduces the mobile energy consumption by 59.5% on average (geometric mean) and up to 94.7%. |

computation offloading framework (Section 6.3). We also evaluate Neurosurgeon’s robustness to variations in wireless network connections (Section 6.4) and server load (Section 6.5), demonstrating the need for such a dynamic runtime system. Finally, we evaluate the datacenter throughput improvement Neurosurgeon achieves by pushing compute out of the cloud to the mobile device (Section 6.6).

6.1 Latency Improvement

Partition Point Selection – Table 4 summarizes the partition points selected by Neurosurgeon optimizing for latency across the 48 configurations (i.e., 8 benchmarks, 3 wireless network types, mobile CPU and GPU). The green cells indicate when Neurosurgeon selects the optimal partition point and achieves the best speedup while the white cells indicate Neurosurgeon selects a suboptimal point. Neurosurgeon selects the best partition point for 44 out of the 48 configurations. The mispredictions occur because the partition points and its associated performance are very close to one another and thus a small difference in Neurosurgeon’s latency prediction shifts the selection. Across all benchmarks and configurations, Neurosurgeon achieves latency speedup within 98.5% of optimal speedup.

Latency Improvement – Figure 11 shows Neurosurgeon’s latency improvement over the status quo approach, across the 8 benchmarks on Wi-Fi, LTE, and 3G. Figure 11a shows the latency improvement when applying Neurosurgeon to a mobile platform equipped with a CPU, and Figure 11b shows that of a mobile platform with a GPU. For CV applications, Neurosurgeon identifies the best partition points for 20 out of 24 cases and achieves significant latency speedups, especially when the mobile GPU is available. For the NLP applications, Neurosurgeon achieves significant latency speedups even when Wi-Fi is available. For ASR, Neurosurgeon successfully identifies that it is best to execute the DNN entirely on the server and, therefore Neurosurgeon performs similar to the status quo for that particular benchmark. Across all benchmarks and configurations,on average and up to 40.7Neurosurgeon achieves a latency speedup of 3.1× over the status quo approach. ×

6.2 Energy Improvement

Partition Point Selection – Table 5 summarizes the partition points identified by Neurosurgeon for best mobile energy. Neurosurgeon selects the best partition point for 44 out of the 48 configurations. For the suboptimal choices, Neurosurgeon consumes 24.2% less energy on average than the status quo approach.

Energy Improvement – Figure 12 shows the mobile energy consumption achieved by Neurosurgeon, normalized to the status quo approach. Figure 12a and 12b present results for CPU-only mobile platform and GPU-equipped mobile platform, respectively. When optimizing for best energy consumption, Neurosurgeon achieves on average a 59.5% reduction in mobile energy and up to 94.7% reduction over the status quo. Similar to the improvement for latency, the energy reduction is also higher for most benchmarks when the mobile platform is equipped with a GPU.

6.3 Comparing Neurosurgeon to MAUI

In this section, we compare Neurosurgeon to MAUI [34], a general offloading framework. Note that MAUI is control-

IMC

VGG

FACE

DIG

ASR

POS

NER

CHK

(

)

a

using the mobile CPU

1

X

3

X

X

5

7

X

Latencyspeedup

IMC

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DIG

ASR

POS

NER

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(

b

)

using the mobile GPU

X

1

3

X

5

X

7

X

x

32

MAUI

Neurosurgeon

Figure 13: Latency speedup achieved by **Neurosurgeon** vs. MAUI [34]. For MAUI, we assume the optimal programmer annotation that achieves minimal program state transfer. **Neurosurgeon** outperforms MAUI by up to 32× and 1.9× on average.

centric, reasoning and making decisions about regions of code (functions), whereas Neurosurgeon is data-centric, making partition decisions based on the structure of the data topology that can differ even if the same code region (function) is called.

Figure 13 presents the latency speedup achieved by Neurosurgeon normalized to MAUI when executing the 8 DNN benchmarks, averaged across three wireless network types. Figure 13a presents the result when applying MAUI and Neurosurgeon on a CPU-only mobile platform and Figure 13b presents the result on a mobile platform equipped with a GPU. In this experiment, we assume that for MAUI, programmers have optimally annotated the minimal program states that need to be transferred.

Figure 13 shows that Neurosurgeon significantly outperforms MAUI on the computer vision applications. For the NLP applications, both Neurosurgeon and MAUI correctly decide that local computation on the mobile device is optimal. However, MAUI makes incorrect offloading choices for more complicated scenarios (e.g., VGG, FACE, DIG and ASR). This is because MAUI relies on past invocation of a certain DNN layer type to predict the latency and data size of the future invocations of that layer type, leading to mispredictions. This control-centric prediction mechanism is not suitable for DNN layers because the latency and data size of layers of the same type can be drastically different within one DNN, and Neurosurgeon’s DNN analysis step and prediction model correctly captures this variation. For instance, in VGG, the input data size for the first and second convolution layers are significantly different: 0.57MB for conv1.1, and 12.25MB for conv1.2. For the mobile CPU and LTE, MAUI decides to offload the DNN before conv1.2 due to its misprediction, uploading large amount of data and resulting in a 20.5× slowdown over the status quo approach.successfully identifies that for

Meanwhile, Neurosurgeon this case it is best to execute the DNN entirely in the cloud, and thus achieves similar performance as the status quo and a 20.5× speedup over MAUI.

|  |
| --- |
| LTE bandwidth |

|  |
| --- |
| Status quo Neurosurgeon |

Figure 14: The top graph shows bandwidth variance using a LTE network. The bottom graph shows the latency of AlexNet (IMC) of the status quo and **Neurosurgeon**. **Neurosurgeon**’s decisions are annotated on the bottom graph. **Neurosurgeon** provides consistent latency by adjusting its partitioned execution based on the available bandwidth.

0

1

2

3

4

5

Mbps

Time

0

*.*

0

0

*.*

5

1

*.*

0

1

*.*

5

2

*.*

0

Latency(s)

partitioned

local

partitioned

remote

Status quo

Neurosurgeon

%

10

%

20

%

30

%

40

%

50

60

%

%

70

%

80

%

90

Server load level

0

0.2

0.4

0.6

0.8

Latency(s)

remote

partitioned

local

Figure 15: **Neurosurgeon** adjusts its partitioned execution as the result of varying datacenter load.

6.4 Network Variation

In this section, we evaluate Neurosurgeon’s resilience to real-world measured wireless network variations. In Figure 14, the top graph shows measured wireless bandwidth of T-Mobile LTE network over a period of time. The bottom graph shows the end-to-end latency of the status quo approach and Neurosurgeon executing AlexNet (IMC) on the mobile CPU platform. Annotated on the bottom graph is Neurosurgeon’s dynamic execution choice, categorized as either local, remote or partitioned. The status quo approach is highly susceptible to network variations and consequently the application suffers significant latency increases during the low bandwidth phase. Conversely, Neurosurgeon successfully mitigates the effects of large variations and provides consistent low latency by shifting partition choice to adjust the amount of data transfer based on the available bandwidth.

6.5 Server Load Variation

In this section, we evaluate how Neurosurgeon makes dynamic decision as the server load varies. Datacenters typically experience diurnal load patterns and high server utilization leads to increased service time for DNN queries. Neurosurgeon determines the best partition point based on the current server load level obtained by periodically pinging

Wi-Fi

LTE

3

G

1

X

2

X

X

3

X

4

X

5

X

6

7

X

Normaliedthroughput

Baseline (Status quo)

Neurosurgeon (0% mobile GPU users)

Neurosurgeon (30% mobile GPU users)

Neurosurgeon (70% mobile GPU users)

Neurosurgeon (100% mobile GPU users)

Figure 16: Datacenter throughput improvement achieved by **Neurosurgeon** over the status quo approach. Higher throughput improvement is achieved by **Neurosurgeon** for cellular networks (LTE and 3G) and as more mobile devices are equipped with GPUs.

the server during idle period, and thus avoids long latency caused by high user demand and the resulting high load.

Figure 15 presents the end-to-end latency of AlexNet (IMC) achieved by the status quo approach and Neurosurgeon as the server load increases. The mobile device is equipped with a CPU and transfers data via Wi-Fi. As shown in the figure, the status quo approach does not dynamically adapt to varying server load and thus suffers from significant performance degradation when the server load is high. The end-to-end latency of the status quo approach increases from 105ms to 753ms as the server approaches its peak load level. On the other hand, by taking server load into consideration, Neurosurgeon dynamically adapts the partition point. In Figure 15, two vertical dashed lines represent the points where Neurosurgeon changes its selection: from complete cloud execution at low load, to partitioning the DNN between mobile and cloud at medium load, and eventually completely onloading to mobile at peak load. Regardless of the server load, Neurosurgeon keeps the end-toend latency of executing image classification below 380ms. By considering server load and its impact on the server performance, Neurosurgeon consistently delivers the best latency regardless of the variation in server load.

6.6 Datacenter Throughput Improvement

Neurosurgeon onloads part or all of the computation from the cloud to mobile devices to improve end-to-end latency and reduce mobile energy consumption. This new compute paradigm reduces the computation required on the datacenter, leading to shorter query service time and higher query throughput. In this section, we evaluate Neurosurgeon’s effectiveness in this aspect. We use BigHouse [38] to compare the achieved datacenter throughput between status quo and Neurosurgeon. The incoming DNN queries are composed evenly of the 8 DNNs in the benchmark suite. We use the measured mean service time of DNN queries combined with Google web search query distribution for the query inter-arrival rate.

Figure 16 presents the datacenter throughput improvement achieved by Neurosurgeon, normalized to the baseline status quo approach of executing the entire computation on the server. Each cluster presents results for a given wireless network type. Within each cluster, the first bar represents the status quo cloud-only approach, while the other four bars represent Neurosurgeon with different compositions of the mobile hardware. For example, “30% Mobile GPU users” indicates 30% of the incoming requests are from mobile devices equipped with a GPU while the remaining 70% are from devices equipped only with a CPU.

When the mobile clients are connected to the server via fast Wi-Fi network, Neurosurgeon achieves on average

1.04tion changes to LTE and 3G, the throughput improvement× throughput improvement. As the wireless connecbecomes more significant: 1.43× for LTE and 2.36× for 3G. Neurosurgeon adapts its partition choice and pushes larger portions of the DNN computation to the mobile devices as the wireless connection quality becomes less ideal. Therefore the average request query service time is reduced and a higher throughput is achieved in the datacenter. We also observe that as the percentage of mobile devices with GPU increases, Neurosurgeon increases the computation onloading from the cloud to mobile, leading to higher datacenter throughput improvement.

# Related Work

Previous research efforts focus on offloading computation from the mobile to cloud. In Table 6, we compare Neurosurgeon with the most relevant techniques on properties including whether there is heavy data transfer overhead, datacentric or control-centric partitioning, low run-time overhead, whether application-specific profiling is required, and whether programmer’s annotation is needed.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Table 6: Comparing **Neurosurgeon** to popular computation offloading/partition frameworks   |  |  |  |  |  |  | | --- | --- | --- | --- | --- | --- | |  | MAUI [34] | Comet [35] | Odessa [36] | CloneCloud [37] | Neurosurgeon | | No need to transfer program state |  |  | 3 |  | 3 | | Data-centric compute partitioning |  |  |  |  | 3 | | Low/no runtime overhead  Requires no application-specific profiling | 3 |  | 3 | 3 | 3  3 | |  | 3 |  |  | | No programmer annotation needed Server load sensitive |  | 3 | 3 | 3 | 3  3 | |  | 3 |  | |

In addition to these key differences, computation partition frameworks have to make predictions as to when to offload computation and the correctness of the prediction dictates the final performance improvements for the application. COMET [35] offloads a thread when its execution time exceeds a pre-defined threshold, ignoring any other information (amount of data to transfer, wireless network available, etc.). Odessa [36] makes computation partition decisions only considering the execution time and data requirements of part of the function, without taking the entire application into consideration. CloneCloud [37] makes the same offloading decisions for all invocations of the same function. MAUI’s [34] offloading decision mechanism is better in that it makes predictions for each function invocation separately and considers the entire application when choosing which function to offload. However, MAUI is not applicable for the computation partition performed by Neurosurgeon for a number of reasons: 1) MAUI requires a profiling step for each individual application, whereas predictions are required to perform DNN partitioning. Neurosurgeon makes decisions based on the DNN topology without any runtime profiling. 2) MAUI is control-centric, making decisions about regions of code (functions), whereas Neurosurgeon makes partition decisions based on the structure of the data topology that can differ even if the same code region (function) is executed. Layers of a given type (even if mapped to the same function) within one DNN can have significantly different compute and data characteristics. 3) Neurosurgeon transfers only the data that is being processed in contrast to transferring all program state. 4) MAUI requires the programmer to annotate their programs to identify which methods are

“offload-able”.

In addition to prior work investigating the utilization and efficiency of datacenter systems [39–52], there has been growing interest in building large scale datacenter systems for Deep Neural Network workloads. Various accelerators, such as GPUs, ASICs, and FPGAs, have been proposed for datacenters to better handle DNN computation [9, 53–55]. There has also been effort in designing compact DNNs suitable for the mobile edge. Microsoft and Google explore small-scale DNNs for speech recognition on mobile platforms [56, 57]. MCDNN [58] proposes generating alternative DNN models to trade-off accuracy for performance/energy and choosing to execute either in the cloud or on the mobile. This work investigates intelligent collaboration between the mobile device and cloud for executing traditionally cloud-only large-scale DNNs for reduced latency and energy consumption without sacrificing the DNNs’ high prediction accuracy.

# Conclusion

As an essential component of today’s intelligent applications, Deep Neural Networks have been traditionally executed in the cloud. In this work, we examine the efficacy of this status quo approach of cloud-only processing and show that it is not always optimal to transfer the input data to the server and remotely execute the DNN. We investigate the compute and data characteristics of 8 DNN architectures spanning computer vision, speech, and natural language processing applications and show the trade-off of partitioning computation at different points within the neural network. With these insights, we develop Neurosurgeon, a system that can automatically partition DNN between the mobile device and cloud at the granularity of neural network layers. Neurosurgeon adapts to various DNN architectures, hardware platforms, wireless connections, and server load levels, and chooses the partition point for best latency and best mobile energy consumption. Across 8 benchmarks, when compared to cloud-only processing, Neurosurgeon achieves on average 3.1× and up to 40.7× latency speedup, reduces mobile energy consumption by on average 59.5% and up to 94.7%, and improves datacenter throughput by on average 1.5× and up to 6.7×.

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