Scission: Context-aware and Performance-driven Edge-based Distributed Deep Neural Networks

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Abstract—Partitioning and distributing deep neural networks (DNNs) across end-devices, edge resources and the cloud has a potential twofold advantage: preserving privacy of the input data, and reducing the ingress bandwidth demand beyond the edge. However, for a given DNN, identifying the optimal partition configuration for distributing the DNN that maximizes performance is a significant challenge since: (i) the combination of potential target hardware resources that maximizes performance and (ii) the sequence of layers of the DNN that should be distributed across the target resources needs to be determined, while accounting for (iii) user-defined objectives/constraints for partitioning. This paper presents Scission, a tool for automated benchmarking of DNNs on a given set of target device, edge and cloud resources for determining optimal partitions that maximize DNN performance. The decision-making approach is context-aware by capitalizing on hardware capabilities of the target resources, their locality, the characteristics of DNN layers, and the network condition. Experimental studies are carried out on 18 DNNs. The decisions made by Scission cannot be manually made by a human given the complexity and the number of dimensions affecting the search space. The results obtained validate that Scission is a valuable tool for achieving performance-driven and context-aware distributed DNNs that leverage the edge. Scission is available for public download.

I. INTRODUCTION

Deep Neural Networks (DNNs) form an integral part of applications that rely on image, video or speech recognition and analytics [1], [2]. A DNN is a sequence of multiple layer types, such as convolution, activation or pooling, that have varying computational requirements. The output size of each layer depends on the layer type and configuration.

Typically, DNNs are trained and executed on the cloud. Data from end devices is sent to the cloud across wide area networks (WANs) for processing. Using the cloud-native (or cloud-only) approach [3] (Figure 1) is computationally scalable as more resources for complex analytics would be readily available, but is principally disadvantaged in the following three ways. Firstly, raw data (image, video or speech) needs to be transferred and processed in the cloud, which may not be privacy-sensitive. Secondly, the response time obtained from processing on geographically distant clouds may not be sufficient to meet real-time requirements of latency-critical applications. Thirdly, transferring the entire data to the centralized cloud increases the ingress bandwidth demand on the backhaul network.

Another approach is to execute the DNNs on end devices to mitigate the above disadvantages [3] (Figure 1). However, this would require that computationally intensive (and large) DNNs to be executed on relatively weaker devices that have a small form factor or are battery powered, for example drones or mobile phones. Approaches that reduce the battery life of end devices will limit their usefulness for ‘in the wild’ scenarios. There is however research that explores the compression of DNN models for executing DNNs on weak devices, but there are trade-offs against accuracy [3]. While running the entire DNN using compressed models on devices may be practical for certain use-cases, it may not be suitable for applications that require aggregation of data originating from multiple input streams of various devices. For example, centralized coordination of a fleet of drones. Thus, both cloud-native and device-native execution approaches of DNNs although straightforward are disadvantaged.

Another viable approach would be distributing the execution of the DNNs by leveraging compute resources at the edge of the network [3], [4], within the edge computing paradigm [5]–[7]. Such an execution approach could either execute the entire DNN on the edge if there is sufficient compute resources available or act as a pre-filter (partially processed) for the input data before it is sent in the WAN to the cloud. The edge can also be an aggregation point in use-cases, for example, a network of drones or cameras that are linked to an edge resource. It has also been demonstrated that for data streams, the frame drop rate can be reduced at the edge when compared to the cloud [8]. Additionally, resources at the edge may be powered to the main lines and may have relatively more compute capabilities than the end device, thereby providing opportunities for executing large DNNs while being sufficiently accurate.

Leveraging the edge provides numerous possibilities for distributing a DNN in addition to those when only using the device and the cloud [3], [4]. These possibilities as shown in Figure 1 are: (i) edge-native execution of the DNN, (ii) distributed execution across the edge and the device, or (iii) distributed execution across the cloud, edge and device. In edge-native execution, all the layers of the DNN will run on the edge and in distributed execution, a specific sequence of layers will run on each resource. However, for any given DNN, identifying the execution approach that maximizes its performance is not a trivial challenge. This is because the
following three associated questions need to be addressed:

(Q1) **Which combination of potential target hardware resources maximizes performance?** This question requires the identification of whether native or distributed execution approaches are best suited for a given DNN on a set of resources, comprising the device, edge, and cloud. Also, if there are multiple device, edge or cloud choices, which target resource(s) should be selected for deploying the DNN.

(Q2) **Which sequence of layers should be distributed across the target resource(s) for maximizing DNN performance?** DNNs can have a large number of layers with varying computational requirements and output sizes. For distributed execution, the layers at which a DNN is partitioned for optimal performance needs to be identified. This cannot be done manually because there are DNNs that could have a large number of layers. For example, DNNs such as the NASNetLarge has 1041 layers and the InceptionResNetv2 has 782 layers. In addition, DNNs cannot be partitioned at all layers (will be discussed in the next section). An ad hoc distribution of a DNN that arbitrarily selects the sequence of layers would result in under-performing DNNs.

(Q3) **How can the performance of DNNs be optimized given user-defined objectives or constraints?** Although addressing Q1 and Q2 will provide an ideal partition of a DNN for a given set of hardware resources, they may not be optimal when user-defined objectives or constraints are taken into account. For example, although a cloud native execution approach may be ideal for maximizing the performance of a DNN, an application owner may want to run a specific sequence of layers on the edge for enhancing data privacy or reducing the volume of output data sent to the cloud. If an edge resource has to undergo maintenance, then an administrator may require the DNN to be redistributed across the cloud and the device, which would have a different partition configuration.

To address the above the challenge and the associated questions, this paper proposes Scission, a tool for automated benchmarking of DNNs on a given set of target device, edge and cloud resources for determining the optimal partition for maximizing DNN performance. Scission is underpinned by a benchmarking approach that collects benchmark data by executing the DNNs on all target resources and subsequently identifies whether a native or distributed execution approach is most suited for the DNN (addresses Q1). For distributed execution, it identifies the optimal resource pipeline and partitions measured by the lowest end-to-end latency (compute time on resources and the communication time between resources) of the DNN by: (i) pairing the most computationally intensive layers with capable resources to minimize compute latencies, and at the same time (ii) selecting layers with the least amount of output data as potential end layers of a partition to minimize communication latencies (addresses Q2). Thus the decision-making approach in Scission is context-aware by capitalizing on the hardware capabilities of the target resources, their locality, the characteristics of DNN layers, and network condition. Scission relies on empirical data and does not estimate performance by making assumptions of the target hardware as alternate approaches presented in the literature (refer Section [V]). Additionally, it provides a querying engine to ensure that user-define constraints or objectives can be taken into account for determining optimal partitions that maximize the performance of distributed DNNs (addresses Q3).

Experimental studies are carried out to demonstrate that Scission can facilitate: 1) DNN partitioning under different network conditions, 2) DNN partitioning under different input data sizes, 3) DNN partitioning under user-defined constraints, 4) DNN partitioning for comparing different target resource pipelines, and 5) the identification of the top $N$ DNN partitions that maximize performance. The key observation is that ideal DNN partitioning needs to be context and data-driven, thereby making it impossible to determine optimal partitions manually. Scission achieves this and is a valuable tool for deploying context-aware and distributed DNNs in an edge environment.

The remainder of this paper is organized as follows. Section [I] provides a background to the DNN models considered in this paper. Section [III] presents Scission and provides an overview of the underpinning methodology for benchmarking, decision-making and querying. Section [IV] presents the results obtained from an experimental study on Scission. Section [V]
TABLE I: Pre-trained DNN models from Keras used in this paper; Type: L - linear, B - branching

| DNN Model       | Size (MB) | Layers | Partition points | Type |
|-----------------|-----------|--------|------------------|------|
| Xception [9]    | 88        | 134    | 13               | B    |
| VGG16 [10]      | 528       | 23     | 21               | L    |
| VGG19 [10]      | 549       | 26     | 24               | L    |
| ResNet50 [11]   | 98        | 177    | 23               | B    |
| ResNet101 [11]  | 171       | 347    | 40               | B    |
| ResNet152 [11]  | 232       | 517    | 57               | B    |
| ResNet50V2 [11] | 98        | 192    | 15               | B    |
| ResNet101V2 [11]| 171       | 379    | 15               | B    |
| ResNet152V2 [11]| 232       | 556    | 15               | B    |
| InceptionV3 [12]| 92        | 313    | 18               | B    |
| InceptionResNetV2 [13]| 215 | 782 | 60 | B |
| MobileNet [14]  | 16        | 93     | 91               | L    |
| MobileNetV2 [15]| 14        | 157    | 65               | B    |
| DenseNet121 [10]| 33        | 429    | 21               | B    |
| DenseNet169 [16]| 57        | 597    | 21               | B    |
| DenseNet201 [16]| 80        | 709    | 21               | B    |
| NASNetMobile [17]| 23       | 771    | 4                | B    |
| NASNetLarge [17]| 343       | 1041   | 4                | B    |

presents related work. Section VI concludes this paper by presenting avenues for future research.

II. BACKGROUND

A DNN is a sequence of layers and is a general term that covers all neural networks with multiple hidden layers (that is multiple layers between the input and output layers) [1], [2]. A DNN may consist of different layers and the most common types are as follows: 1) Fully-connected layers connect every neuron to all neurons in the previous layer with the aim of preforming high-leveled reasoning. 2) Convolution layers convolve the input to produce feature maps of inputs with the aim of learning features. 3) Pooling layers apply a pre-defined function (maximum or average) to down sample the input. 4) Activation layers apply non-linear functions and the most commonly used is the rectified linear unit (ReLu). 5) A Softmax layer is generally used for classification with the aim of generating a probability distribution over the possible classes.

In this paper, 18 DNNs as shown in Table I are considered. The table presents the size of a trained model and its corresponding weights, the total number of layers in the DNN (including input and output layers), the number of valid points for partitioning, and the type of the DNN. These models are explored in the context of Keras, an open source neural network library that runs on TensorFlow. These models are trained on the ImageNet database [18].

Two categories of DNNs are considered, namely linear and branching. In a linear DNN, the neural network is sequential - the input of one layer is connected to the next. This results in a singular path between the first and last layers as seen in Figure 2a. Figure 3 shows the execution time and the output data size of the 23 different layers of VGG16, an example linear model (executed on the ‘Cloud’ resource shown in Fig. 3).

If a linear DNN that has \( N \) layers needs to be distributed across two resources, then a partitioning approach would need to create two partitions of the DNN. The first partition would consist of a sequence of the first \( x \) layers and the second partition would consist of \( N - x \) layers. The output of the \( x \)th layer would need to be provided as an input layer for the second partition. DNNs naturally lend themselves to distributed execution as their segmented structure provides rational points to partition. There are \( N - 2 \) potential partitioning points (rather than \( N - 1 \)) since the partition configuration in which one partition comprises only the first layer and the second partition the remaining layers would duplicate the input layer. Figure 2a provides an example of a linear DNN that is distributed across a resource pipeline comprising the device, edge, and cloud. The red connectors show the valid partitioning points in the linear model.

On the other hand, in a branching DNN, a layer may be connected to more than two layers which results in parallel paths between the first and last layers. Partitioning a model in a parallel region can lead to synchronization issues and may
an automated approach for DNN partitioning would be ideal. Therefore, an automated approach would make DNN partitioning practical due to organizational or geo-political reasons. DNN partitioning must be context-aware across multiple dimensions. Identifying performance efficient partitions is not only dependent on DNN layer characteristics and output data. Performance is also affected by the hardware capabilities of the target platform, resource locality, load and failures, and network condition between resources. These dimensions need to be taken into account while partitioning.

(ii) DNN partitioning must be able to identify a set of performance efficient partitions. This is important because the most efficient DNN partitions may only have a negligible improvement over the other partitions, which may be more practical due to organizational or geo-political reasons.

(iii) DNN partitioning must be able to account for operational conditions, but also user-defined objectives/constraints. A performance efficient partition obtained by optimizing against the dimensions described above may not always be ideal. A human must be able to specify constraints as input to the partitioning process. For example, an application administrator may want a particular sequence of layers to be executed on an end device for retaining intermediate data of a few layers on the device although it affects the overall end-to-end latency.

(iv) DNN partitioning must be based on empirical data obtained from the underlying hardware rather than based on estimates. A large body of existing research estimate the optimal partitions by relying on predicted performance on a given resource by making assumptions of the target hardware platform. However, modern hardware is known to have complex processor and memory architectures that sometimes results in a non-linear relationship between performance and the amount of resource [19]. Therefore, partitioning based on empirical data is likely to be more reliable and reproducible than alternate approaches.

(i) DNN partitioning must account for multiple resource tiers in cloud-edge continuum. Many options for distributing large DNNs become available as more resource tiers between the cloud-edge continuum become accessible for computing. The approach used for identifying optimal partitions of DNNs should scale across the resource tiers. In this paper, the device, edge and cloud tiers are considered.

Step 1: Parse the DNN to find valid partitioning points. As presented in Section III the DNN is parsed to identify valid partitioning points. For a linear DNN this is straightforward, where as for a branching DNN, the parallel paths need to be determined efficiently.

This section firstly presents the observations that led to the development of Scission, followed by the architecture, the underlying benchmarking approach, the context-aware decision-making process, and finally the querying capability. The first version of Scission is available for download [20].

The above highlights that DNNs may have a large number of layers and may take the form of linear or branching models. The execution time of individual layers and the output size vary for each layer. If the DNN needs to be distributed across multiple resources, it would be impossible to manually determine efficient partition configurations. This is due to the potentially complex structure of a DNN and a large search space arising from the combination of partitioning points, target hardware resources, and optimization criteria. Therefore, an automated approach for DNN partitioning would be ideal.

III. SCISSION

This section firstly presents the observations that led to the development of Scission, followed by the architecture, the underlying benchmarking approach, the context-aware decision-making process, and finally the querying capability. The first version of Scission is available for download [20].

A. Motivation

Scission proposed in this paper is designed on the following six practical observations to make it widely applicable for maximizing the performance of DNNs:

(i) DNN partitioning must account for multiple resource tiers in cloud-edge continuum. Many options for distributing

https://github.com/qub-blesson/Scission.
identified. Layers within the parallel path are considered as a single entity, referred to as block. As shown in Figure 5, the red connectors show the valid partitioning points.

**Step 2: Partition into individual layers/blocks.** This step ensures that the DNN is partitioned into distinct sub-models with individual layers or blocks for the purposes of benchmarking. It should be noted that each sub-model requires an input layer to facilitate the processing of the output from the previous layer.

**Step 3: Benchmark each layer/block on target hardware resources.** In this step, given a set of target hardware resources, such as the device, edge, or cloud, each layer/block is benchmarked five times. The average execution time along with the size of the output data is recorded. In this article, the 18 DNNs shown in Table I are considered.

**Step 4: Create partition configuration from benchmark data.** The benchmark data comprises the average execution time of each layer/block. The communication overhead to transfer output data across different resources is calculated from user-provided data, such as the average bandwidth available between the link. This data is used to exhaustively develop partition configurations such that the end-to-end latency (compute and communication overheads) of all combinations of layers/blocks paired to different resources are known.

Two types of partition configurations are considered by Scission, namely native and distributed as shown in Figure 1. Native partition configurations are those in which all layers/blocks execute on a single resource (for example, device-native, edge-native, or cloud-native). Distributed partition configuration are those in which the DNN collaborates across multiple resources by executing the layers/blocks on multiple resources (for example, distributed execution across device-edge, device-cloud, and device-edge-cloud).

**Step 5: Rank partition configurations.** Once all partition configurations have been generated, they are ranked. The ranking may be generated by optimizing against end-to-end latency (additional objectives, such as minimum data transfer across resources, or a combination of these can be provided in Step 6). The Top N partition configurations are presented to the user.

**Step 6: Query Scission for partition configurations given user-defined constraints.** Scission interacts with the user by not only providing the default rankings produced in Step 5, but also accepting user-defined constraints provided as queries. The example shown in Figure 5 is the result of executing the query for the fastest DNN partition configuration that collaborates between all (device, edge, and cloud) resources. Queries are not limited to only minimizing for execution latency or lowest bandwidth, they may be constructed, for example, as follows to:

- Apply bandwidth constraints (for example, the edge resource must not transfer more than 1MB to the cloud).
- Apply execution time constraints (for example, the execution time on the device must not exceed 1 second, or 30% of the overall execution time must be on the edge).
- Include or exclude resources (for example, distribution must not include the cloud, or execution must be edge-native).
- Specify layer/block execution locations (for example, Layer 7 must execute on the edge).

The Top N partition configurations are presented to the user. More complex queries can be provided to Scission. Examples include: (i) Find the partition configuration that results in the lowest execution latency, but the device and edge must not transfer more than 1MB. (ii) Find partition configuration that has the lowest inter-resource data transfer, but n layers are executed on the edge. (iii) Find partition configuration with lowest end-to-end latency and does not use the cloud and at least half of the layers/blocks must be executed on the device.
IV. EXPERIMENTAL STUDIES

This section presents the experimental test bed and software set up and is followed by the results obtained from Scission.

A. Setup

Experiments are carried out on hardware resources shown in Table I to reflect a range of resources typically used. Two edge resources are employed with different hardware characteristics. Two cloud resources are used with and without a GPU.

To emulate real world network performance, Scission uses the average network latency and bandwidth for: (i) 3G (1.6 Mbps upload and 67ms network latency) \[20\], (ii) 4G (12.4Mbps upload and 55ms network latency) \[20\], and (iii) wired home fibre broadband (20Mbps upload and 20ms network latency) \[21\]. A network latency of 25ms and a bandwidth of 50Mbps is assumed for all edge-cloud connections. All results reported are averages from five experimental runs.

The Scission tool is implemented in Python and requires Tensorflow 2.0+ to be installed. Tensorflow is an end-to-end open source machine learning platform, which is used as the back end to run the pre-trained DNNs provided by Keras. NumPy is used for processing multi-dimensional arrays that are produced as layer outputs.

Scission makes two assumptions. Firstly, the communication overheads can be calculated as network latency + data size ÷ bandwidth. The second assumption is that the total inference time of a model can be calculated by adding the execution times of individual layers or blocks. This assumption has been validated in previous research \[22\], \[23\].

B. Results

The experimental results obtained from Scission are exhaustive and discussing them entirely is outside the scope of this paper. However, the experiments and results to demonstrate the following five capabilities of Scission are considered in this paper: 1) DNN partitioning under different network conditions, 2) DNN partitioning under different input data sizes, 3) DNN partitioning under user-defined constraints, 4) DNN partitioning for comparing different target hardware resource pipeline, and 5) the top \(N\) DNN partitions. Sample results for executions on VGG19, ResNet50, MobileNetV2, InceptionV3 and DenseNet169 are presented.

The results obtained from the above capabilities can address Q1: ‘Which combination of potential target hardware resources maximizes performance?’ that was posed in Section I but is specifically considered by the fourth capability. Similarly, all five capabilities will determine the best sequence of layers (or partition configuration) to address Q2: ‘Which sequence of layers should be distributed across the target platform for maximizing the DNN performance?’ The third capability specifically addresses Q3: ‘How can the performance of DNNs be optimized given user-defined objectives or constraints?’

Table II shows the execution time of five sample DNNs (from Table I) when natively executed on the device, edge and cloud for a single input image of size 150KB. All experiments in this paper use a 150KB size input image unless otherwise stated. DNNs executing on the device have a higher execution time than on the edge and cloud. MobileNetV2 is the DNN that executes fastest on the device. Of both the edge resources available, it is determined via benchmarking that Edge (1) produces marginally better execution times. The cloud resource with the GPU executes the fastest.

1) DNN partitioning under different network conditions: The results obtained from Scission highlight that DNN partitioning is affected by different network conditions (the optimal partitions for the same DNN may be different under different network conditions).

Figure 5 and Figure 7 show that the lowest end-to-end latency execution of VGG19 and ResNet50, respectively, under 3G and 4G conditions would be obtained if the DNN is cloud-native. This is because the cloud resource in terms of its execution performance is much faster than the device and edge resource utilized in this experiment. The communication overhead of 800ms of sending the image from the device to the cloud does not offset the compute performance obtained on the resource.

However, Figure 8 demonstrates the end-to-end latency of MobileNetV2 (that has sub-second execution performance when it is device-native) under 3G and 4G conditions. In the 3G context, the DNN has the least inference time when the DNN is device-native. However, in the 4G context, given a lower latency network, the DNN is performance efficient when it is cloud-native. The above highlights the capability of Scission to identify optimal DNN partitions under different network conditions.

2) DNN partitioning under different input data sizes: If the input image size were increased from 150KB to 170KB, then for ResNet50 under 3G conditions, a device-native execution is determined by Scission to be performance efficient as shown in Figure 9. This is in contrast to a cloud-native execution that Scission identifies as performance efficient for a 150KB input image size (Figure 7a).

3) DNN partitioning under user-defined constraints: Figure 10a and Figure 11 are exemplars of performance efficient distributed execution of the DNN when the constraint imposed is that the entire resource pipeline must be employed. The results are shown for 3G and 4G network conditions for VGG19 and ResNet50. The difference in the optimal DNN partition is immediately evident. For example, the optimal partition configuration for VGG19 in a 3G network is: device executes Layers 0-23, edge executes Layer 24 and cloud executes Layer 25 (refer Figure 10a). However, in a 4G network, the optimal partition configuration is: device executes Layers 0-6, edge executes Layers 7-22, and cloud executes Layers 23-25 (refer Figure 10b).

4) DNN partitioning for comparing different target hardware resource pipelines: Two examples from InceptionV3 and DenseNet169 highlight that Scission can compare target hardware resource pipelines specified by a user for identifying which resource pipeline is performance efficient.
TABLE II: Specification of the target hardware resources used

| Resource       | CPU Arch | CPU Freq (GHz) | CPU cores | RAM (GB) | GPU        | OS             |
|----------------|----------|----------------|-----------|----------|------------|----------------|
| Device         | ARMv8    | 1.5            | 4         | 4        | N/A        | Raspbian Buster|
| Edge (1)       | AMD64    | 4.5            | 4         | 8        | N/A        | Ubuntu 18.04 LTS|
| Edge (2)       | AMD64    | 3.7            | 8         | 32       | N/A        | Ubuntu 18.04 LTS|
| Cloud          | AMD64    | 4.5            | 8         | 32       | Nvidia GTX 1070 | Ubuntu 18.04 LTS|
| Cloud (with GPU)| AMD64    | 4.5            | 8         | 32       | Nvidia GTX 1070 | Ubuntu 18.04 LTS|

Fig. 6: DNN partition of VGG19 with lowest end-to-end latency for different network conditions

Fig. 7: DNN partition of ResNet50 with lowest end-to-end latency for different network conditions

Figure 12 considers the execution of InceptionV3 when the edge resource must be used in a pipeline and the device is connected to the edge resource via a wired connection for two different edge resources. Although the edge-native execution of InceptionV3 on Edge (1) and Edge (2) only differs by 0.07 seconds (refer Table III), the DNN partition configuration when the resource pipeline has Edge (1) and Edge (2) is different. The DNN partition is sensitive to the hardware capabilities of different resources in the pipeline. Since these are subtle, it would not be evident to a human, and therefore demonstrates the value of a tool, such as Scission.

Figure 13 and Figure 14 considers the distributed execution of InceptionV3 and DenseNet169, respectively, for the entire resource pipeline (device, edge and cloud) when a device is connected to the edge through a wired connection for two different edge resources. For both DNNs the partition configurations are different for the edge resources although there is limited performance difference when executed natively on the different edge resources.

5) Top N performance-efficient DNN partitions: Scission provides a list of potential candidate DNN partitions. Table IV shows the top three partitions with lowest end-to-end latency of ResNet50 for four different distributed pipelines that use a wired network between the device and the edge.

Figure 15 shows the DNN partitions with the first and second lowest end-to-end latencies for ResNet50 when Edge(1) must be used in the resource pipeline. The fastest partition requires offloading most layers to the cloud resulting in an end-to-end latency of 0.237 seconds transferring a total of...
TABLE III: Native execution times of different DNNs for sample models in seconds for single input image of 150KB

| Platform         | VGG19 | ResNet50 | MobileNetV2 | InceptionV3 | DenseNet169 |
|------------------|-------|----------|-------------|-------------|-------------|
| Device           | 2.71  | 1.04     | 0.40        | 1.26        | 1.52        |
| Edge (1)         | 0.45  | 0.18     | 0.11        | 0.21        | 0.28        |
| Edge (2)         | 0.47  | 0.22     | 0.11        | 0.28        | 0.36        |
| Cloud            | 0.13  | 0.08     | 0.06        | 0.11        | 0.16        |
| Cloud (with GPU) | 0.01  | 0.03     | 0.03        | 0.05        | 0.10        |

TABLE IV: Top 3 DNN partitions with the lowest end-to-end latency for ResNet50 across different distributed resource pipelines

| Layers          | End-to-end latency (s) | Total data transfer (MB) |
|-----------------|------------------------|--------------------------|
| Device-Edge     |                        |                          |
| 0-1 2-176       | 0.446                  | 0.634                    |
| 0-91 92-176     | 0.944                  | 0.831                    |
| 0-175 176       | 0.979                  | 0.008                    |
| Device-Cloud    |                        |                          |
| 0-1 - 2-176     | 0.339                  | 0.635                    |
| 0-91 - 92-176   | 0.920                  | 0.803                    |
| 0-101 - 102-176 | 0.996                  | 0.803                    |
| Cloud-Edge      |                        |                          |
| - 0-1 2-176     | 0.237                  | 0.785                    |
| - 0-175 176     | 0.269                  | 0.159                    |
| - 0-153 154-176 | 0.319                  | 0.552                    |
| Device-Edge-Cloud |                      |                          |
| 0-1 2-175 176   | 0.468                  | 0.643                    |
| 0-1 2-153 154-176 | 0.517                  | 1.036                    |
| 0-1 2-163 164-176 | 0.523                  | 1.036                    |

Fig. 8: DNN partition of MobileNetV2 with lowest end-to-end latency for different network conditions

Fig. 9: DNN partition of ResNet50 with lowest end-to-end latency in a 3G network when input data size is 170KB (instead of 150KB)

0.785MB across the resources. On the other hand, the second DNN partition is an edge-only execution that has an end-to-end latency of 0.248 seconds, and only requires the input 150KB to be transferred to the edge. The benefit of the second partition is that it uses a much lower bandwidth than the first partition. Scission, thus provides a user with a list of potential DNN configurations each of which might benefit in different scenarios.

C. Summary

The following are observations from the results:

1) DNN partitioning is affected by different network conditions. Although a cloud-native execution of the DNN was beneficial for some of the examples presented in this paper (VGG19 and ResNet50), it was noted that MobileNetV2 presented the possibility of both a device-native and cloud-native execution for 3G and 4G networks respectively.

2) A slightly larger input data of 170KB over 150KB changed the DNN partition of ResNet50. This highlights the potential sensitivity of DNN partitioning to data sizes. These are subtle and not quickly evident to manual inspection.

3) User constraints, such as the requirement of using the entire resource pipeline, affects DNN partitions. The sequence of layers on the device, edge and cloud change for different networks, such as VGG19 and ResNet50. It is noted that these cannot manually be identified.

4) Variation in the edge hardware characteristics affects DNN partitioning. For InceptionV3 and DenseNet169 it was noted that using two different edge resources for distributed execution resulted in different partition configurations.

5) Obtaining a set of ranked configurations can help maximize performance in different scenarios. For example, the fastest partition with the lowest end-to-end latency for ResNet50 when a certain edge resource had to be utilized had more layers running on the cloud. The second fastest partition was edge-native, potentially suitable for enhanced privacy.

The results that can be observed on Scission are exhaustive. The above is only a subset of those observations that can be made. Once again the need for such a tool in which more complex DNNs are appearing is required to optimally leverage
Fig. 10: DNN partition of VGG19 with lowest end-to-end latency when the constraint imposed is that the device, edge and cloud must be used in different networks

Fig. 11: DNN partition of ResNet50 with lowest end-to-end latency when the constraint imposed is that the device, edge and cloud must be used in different networks

the edge and maximize the performance of distributed DNNs.

V. RELATED WORK

DNNs can be executed natively on a single resource, such as a end user device, or on the edge or cloud, or in a distributed manner across multiple resources [3]. DNN partitioning is one approach that is essential for the distributed execution of DNNs [3], [4]. This has gained prominence with the upcoming paradigms in distributed systems, such as edge computing [5]–[7], because by using an edge resource a series of layers of the DNN can be executed closer to the input data source, thereby reducing the ingress bandwidth demands and end-to-end latency in a resource rich environment.

There are two main methodologies that have been considered in DNN partitioning for inference (DNN partitioning for training is not considered in this paper). The first is DNN layer distribution and the second is DNN sub-model distribution. **DNN layer distribution** refers to the distribution of a sequence of layers on to a resource by assuming that the resource has access to the entire pre-trained model and weights [24]–[26] (this methodology will be further considered).

**DNN sub-model distribution** on the other hand refers to slicing the DNN model for different resources and does not require the entire model, rather only requires the metadata relevant to the slice of the model being executed [27], [28]. IONN introduces the concept of incremental offloading in which a DNN is partitioned and incrementally uploaded on to an edge server so as to enable partial execution of the DNN even before the entire DNN is available on the edge server [27]. DeepX partitions the DNN model into several sub-models, which are then distributed to the edge [28].

However, DNN layer distribution is a less intrusive method than DNN sub-model distribution as it does not require the DNN to be modified. Regardless, both methodologies require the identification of valid and optimal partitioning points for deploying optimal DNN partitions across resources given the numerous combinations that may be possible. Scission is positioned as a tool to be used by system and network administrators for maximizing distributed DNN performance using the edge. Therefore, the design decision is one that is less intrusive and can be broadly applied.
Approaches adopted for determining optimal DNN partitions are: (i) Profiling and estimation-based, (ii) integer linear programming-based (ILP), (iii) structural modification-based, and (iv) benchmarking-based approaches.

Profiling and estimation-based approaches are popular and aim to estimate the performance against metrics, such as end-to-end latency, energy or a combination, for each layer type in the DNN. Four examples of this approach are presented. Neurosurgeon is one example in which a regression-based method is used for estimating optimal partitions between a device and the cloud [24]. This is achieved by building models on the performance of individual types of layers and their configuration. DeepWear similarly uses a similar approach to train prediction models to estimate latency and energy consumption of four popular layer types and their parameter combinations across a wearable and its paired device [29]. The models are also trained with device-specific latencies and energy prediction models. Musical Chair is another profiling and estimation-based approach that develops behavioral models that are trained to estimate the latency and memory usage of specific layer configurations [30]. Couper is another such approach [8]. The end-to-end latency of each potential is verified on a set of resources and then assumed as a direct correlation to hardware capability for other resource configuration. These approaches generally work well within the space they are trained for. For example, if a new layer type/configuration or a new hardware resources emerges, then the estimation models will not be accurate. In addition, many of these approaches make assumptions regarding the execution behavior of different layers on the underlying hardware. It is not entirely possible to accurately model the execution profiles on complex hardware architectures.

ILP-based approaches have also been considered for DNN partitioning. Within the context, the partitioning problem is formulated as an ILP problem with the aim to find an optimal partition that minimizes the inference latency and maximizes accuracy [25], [31]. ILP techniques can be time consuming.

Structural modification-based approaches can efficiently partition DNNs, but in an intrusive manner. It can be achieved realistically only by modifying underlying libraries of existing frameworks or by writing bespoke code for DNNs. However, these approaches provide a fine-grained control over DNN partitioning. Examples include DeepThings [32] and MoDNN [33]. DeepThings utilizes fuse tile partitioning, in
which a DNN is not partitioned horizontally (based on layers), rather they are partitioned vertically to reduce resource footprint [32]. MoDNN is developed for distributing DNNs across different nodes of the same cluster [33]. Three approaches are presented: (i) for partitioning the convolutional layers, biased one-dimensional partitioning, (ii) for partitioning the weights, modified spectral co-clustering (the fully connected layers are dependent on weights), and (iii) for partitioning sparse fully connected layers, fine-grain cross partition are proposed.

Benchmarking-based approaches are proposed so that actual measurements or observations are made on the target hardware resource. No assumptions are made of the underlying hardware or performance of the layers on the hardware and therefore are more reliable. In these approaches, benchmarking data of the DNN on the hardware is first obtained. Then during deployment, a snapshot of the operational environment (for example, load on the network and compute resource) is taken and the optimal partition is calculated. This approach is minimally intrusive, requires no modification to the code, and is a pragmatic solution in the complex space of DNNs with many layers (and layer types and configurations) and the availability of diverse hardware resources. Scission proposed in this paper is therefore positioned as a benchmarking-based approach. Alternate systems that consider this approach is LA VEA employed for distributed video analytics [34].

VI. CONCLUSIONS

This paper presented Scission, a tool for automated benchmarking of DNNs on a given set of target device, edge and cloud resources for determining the optimal partition for maximizing DNN performance. Scission is underpinned by a benchmarking approach that aims to determine the combination of potential target hardware resources and the sequence of layers that should be distributed for maximizing distributed DNN performance while accounting for user-defined objectives/constraints. Experimental studies are carried out on 18 different DNNs to demonstrate that Scission is a valuable tool for obtaining context-aware and performance efficient distributed DNNs and can make decisions that cannot
be manually made by a human given the complexity and the number of dimensions affecting the search space.

**Limitations and Future Work:** Scission relies on exhaustive search that cannot account for rapid changes (failures or variance). Meta-heuristic optimization will be considered to rapidly respond to network congestion or resource failure. Other metrics, such as monetary costs and performance improvement as well as trade-offs that exist among performance gain and costs, and optimal partitioning and responsiveness of the approach will be considered. The offering of Scission as a service will be integrated within a standard orchestration framework to monitor and partition DNNs. The current work assumes that partitioning a given DNN is beneficial and does not account for whether the performance gain may be relatively low. Scission can be further extended to determine whether an alternate DNN can be selected to improve performance instead of partitioning a given DNN.

**ACKNOWLEDGMENT**

Dr Blesson Varghese is supported by a Royal Society Short Industry Fellowship to British Telecommunications plc, UK and by funds from Rakuten Mobile, Japan.

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