Fault-Tolerant Collaborative Inference through the Edge-PRUNE Framework

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Abstract
Collaborative inference has received significant research interest in machine learning as a vehicle for distributing computation load, reducing latency, as well as addressing privacy preservation in communications. Recent collaborative inference frameworks have adopted dynamic inference methodologies such as early-exit and run-time partitioning of neural networks. However, as machine learning frameworks scale in the number of inference inputs, e.g., in surveillance applications, fault tolerance related to device failure needs to be considered. This paper presents the Edge-PRUNE distributed computing framework, built on a formally defined model of computation, which provides a flexible infrastructure for fault tolerant collaborative inference. The experimental section of this work shows results on achievable inference time savings by collaborative inference, presents fault tolerant system topologies and analyzes their cost in terms of execution time overhead.

1. Introduction
Since a few years already, the execution of machine learning workloads has been moving from servers and the cloud to less powerful platforms, such as embedded and mobile devices. A considerable hindrance to this progress has been the significant computation load of machine learning inference, especially related to deep neural network (DNN) architectures. In order to match neural network complexity with computation platform resources, several different approaches have been developed: lightweight architectures such as MobileNets (Howard et al., 2017) attempt to maintain high inference accuracy despite drastically reduced number of trainable parameters; post-hoc optimizations such as dense layer pruning (Zhu & Gupta, 2018), separable convolutions (Jaderberg et al., 2014) and weight quantization (Courbariaux et al., 2016) reduce inference time by approximating the original trained neural architecture, whereas neural accelerators (Skillman & Edsö, 2020; Han et al., 2016) leverage specialized hardware to speed up inference.

Orthogonal to the aforementioned techniques, distributed and collaborative inference have emerged as a notable branch of research. In these approaches, the neural network inference workload is distributed between low-resource endpoint devices and high performance edge servers (or the cloud); early milestone works of this direction are Neurosurgeon (Kang et al., 2017) and DDNN (Teerapittayanon et al., 2017). In conjunction with collaborative inference, several dynamic neural network techniques have been successfully adopted: for instance, early-exit (Teerapittayanon et al., 2017) can terminate inference at intermediate layers saving on communication bandwidth, whereas dynamic onloading (Almeida et al., 2021) decides at runtime the target execution platform of DNN layers.

Collaborative inference can be used to target a variety of optimization objectives: reducing endpoint device computation load, end-to-end latency optimization, energy reduction or server workload reduction. A less frequently mentioned by-product of collaborative inference is privacy preservation. This topic has been extensively studied in (He et al., 2019), where key observations point out that malicious model inversion attacks against collaborative inference are significantly
less effective if they cannot access the feature vectors produced by the early neural network layers – especially if inference has passed one or more dense layers of the DNN. In terms of collaborative inference this means that the endpoint device should perform the inference of as many early DNN layers as possible before transmitting the intermediate feature vectors over a network interface to server processing.

This paper addresses the topic of collaborative inference, especially from the point of multiple inference inputs and system fault tolerance. An example scenario for multi-input collaborative inference is a smart surveillance camera system (see Figure 1), where several smart cameras have been deployed across a site for performing object detection and/or tracking. For privacy preservation, the smart cameras perform the inference of early DNN layers, and transmit the intermediate feature vectors to a local edge server for completing the inference.

In safety critical areas, node (endpoint device or server) failures related to malicious actions or hardware faults needs to be taken in account. Concretely, the surveillance system should be able to continue its operation if one or more of the endpoint devices become disabled, or even in the more severe case of server failure. Figure 1 illustrates a highly redundant configuration, where a single failure of any kind of resource (endpoint device, server or connection) does not incapacitate the overall system. Such redundancy evidently comes with a price, which in this case is the redundant server and the related connectivity.

This study, related to fault tolerant collaborative inference, is realized around the open source Edge-PRUNE framework (Boutellier et al., 2022). Edge-PRUNE is based on a formally defined model of computation, and provides the necessary theoretical infrastructure for specifying and designing collaborative inference between one or more endpoint devices and servers. Besides the theoretical basis, the Edge-PRUNE framework includes a self-sustained runtime engine that is hardware and training framework agnostic, providing a software environment for both endpoint devices and servers. Although not detailed in this work, Edge-PRUNE also has inherent support for conditional computing.

2. Related Work

Significant early works on collaborative inference were DDNN (Teerapittayanon et al., 2017) and Neurosurgeon (Kang et al., 2017). DDNN proposed distributing inference across endpoint, edge and cloud resources, also introducing early exits for reducing communication. Neurosurgeon, on the other hand, presented a scheduler for intelligently distributing neural network layers across endpoint and server resources. Edgent (Li et al., 2018a) further developed Neurosurgeon’s concept by introducing DNN right-sizing, joint optimization of early exits and DNN partitioning. Edgent later evolved into Boomerang (Zeng et al., 2019) inspired by the early exit mechanism of BranchyNet (Teerapittayanon et al., 2016). IONN (Jeong et al., 2018) also continued in the vein of Neurosurgeon, however based on the offloading concept: the endpoint device can upload DNN partitions to an edge server for optimizing mobile device energy consumption, among other optimization goals. Similar to Neurosurgeon, also IONN is based on Caffe (Jia et al., 2014). Recently, SplitNets (Dong et al., 2022) combined neural architecture search with multi-input partition point search.

JointDNN (Eshratifar et al., 2019) introduced a directed acyclic graph (DAG) based model for DNN partitioning, optimizing for energy and latency. Besides partitioning, JointDNN also considers layer compression, similar to the preceding work JALAD (Li et al., 2018b), and the recent supervised compression work (Matsubara et al., 2022). A graph-based modeling approach is also adopted by DADS (Hu et al., 2019), the industrial effort Auto-Split (Banitalebi-Dehkordi et al., 2021) and D² (Zhang et al., 2021), enabling capturing of branched DNN topologies as opposed to simpler chain-like DNN structures. Finally, SPINN (Laskaridis et al., 2020) and DynO (Almeida et al., 2021) contribute to dynamic DNN partitioning, which is useful under, e.g., varying wireless network conditions.

An orthogonal approach to endpoint-server computation partitioning is taken by (Mao et al., 2017b;a; Zhao et al., 2018; Gao et al., 2021) that propose partitioning DNN inference across multiple endpoint devices.

3. The Edge-PRUNE Framework

The Edge-PRUNE framework used in this study significantly differs from the related works in the sense that it is based on a formal model of computation. The overall computation scheme of Edge-PRUNE is dataflow, similar to that of TensorFlow (Abadi et al., 2016). However, Edge-PRUNE goes further in computation modeling, by formalizing concepts such as data packaging, data rates, triggering of computations, and necessary conditions for deadlock-free conditional computations.

3.1. Model of Computation

The Edge-PRUNE framework relies on the VR-PRUNE model of computation (Boutellier et al., 2022). In VR-PRUNE, a neural network is described as a directed graph \( G = (A, F) \), where the actors \( A \) represent vertices that perform computation, such as inference of a DNN layer. The links \( F \) of graph \( G \) represent first-in-first-out (FIFO) buffers that carry data between actors. For each link \( f \in F \), data is quantized into fixed-size tokens that in the neural network

1\footnote{Available at https://gitlab.com/jboutell/vprf/-/tree/edge-prune}
context can be understood as feature vectors between layers. A FIFO $f \in F$ is connected to an actor $a \in A$ through a port $p_a$, such that $f_i f_o(p_a) = f$.

An actor $a \in A$ can fire (perform a computation) when it has a sufficient number of input tokens available. To specify the required number of tokens, for each input port $p_a$ of actor $a$, a non-negative integer-valued token rate $\text{atr}(p_a)$ is defined; once each input port of $a$ has at least $\text{atr}(p_a)$ number of tokens in the associated FIFO buffer $f_i f_o(p_a)$, actor $a$ becomes enabled, that is, ready to fire. The exact moment in time when an enabled actor fires can depend, for instance, on availability of compute resources. As dataflow models in general, also VR-PRUNE is inherently concurrent: individual actors can execute in parallel, independent of others (Lee & Messerschmitt, 1987).

The VR-PRUNE model of computation balances between expressiveness and analyzability: while being expressive enough for allowing conditional computations, the model simultaneously provides means for analyzing graph consistency. The following subsection illustrates how conditional computation is expressed using VR-PRUNE concepts.

### 3.2. Conditional Computation

In order to maintain analyzability against graph deadlock and/or buffer overflow, the VR-PRUNE model restricts conditional computation to take place within dynamic processing (sub)graphs. DPGs: within a DPG, conditional computation can be realized between two dynamic actors. Figure 2 shows a minimal case of a DPG: the dynamic actor $x$ provides a control signal (dashed connection) that at run time sets the input and output token rates of the dynamic actor $y$ and the dynamic processing actor $a$. The range of allowed token rates and associated actor ports is expressed in the control table $T$ of Figure 2: port $p_{ac}$ dynamically sets the token rate of ports $p_{x1}, p_{a1}, p_{a2}$ and $p_{b1}$ to either 0 or to 1. With token rates set to 1, $a$ becomes enabled, whereas token rate 0 disables execution of $a$. Actor $b$ does not receive such a control signal and thus maintains static token rates.

### 3.3. Distributed Computing and Fault Tolerance

The Edge-PRUNE framework enables concurrent execution of actors both within a computing platform, and between computing platforms using a mapping specification. Within a platform, each actor $a \in A$ is mapped for execution to a specific CPU core, or to the local GPU. The same mapping specification is also used to set the execution platform (endpoint device or server) of each actor. To this extent, Edge-PRUNE provides mapping exploration functionality, which auto-generates endpoint-server mapping alternatives for discovering the best DNN partition point for collaborative inference.

### 3.4. Inference Engine

The Edge-PRUNE computing functionalities have been implemented in the C language to a lightweight runtime library for Linux-based platforms, enabling deployment to embedded devices as well as to servers. This inference engine is independent of neural network training frameworks (e.g., TensorFlow), but allows leveraging DNN acceleration libraries such as Intel oneDNN or ARM CL. Edge-PRUNE has deeply built-in support for GPU leverage, but can equally well operate on GPU-less platforms. Distributed computing functionality has been implemented using Linux Sockets, such that the endpoint devices are expected to establish an ssh connection to the server(s), delegating data security issues to the level of ssh connections. Fault tolerance functionality is implemented on the actor port level: ports responsible for inter-platform communication monitor and adjust to remote platform liveness by Linux socket error conditions: broken pipe, connection reset, no data sent. Finally, Edge-PRUNE does not constrain the nature (wired or cable) or number (shared or point-to-point) of connections between endpoints and servers.

### 4. Experiments

#### 4.1. Collaborative Inference Partition Point Exploration

Figure 3 shows endpoint device inference time for the SSD-MobileNet v1 (Howard et al., 2017; Liu et al., 2016) ob-
Inference Time and Fault Tolerance

Both virtual and physically distributed system configurations were used to validate Edge-PRUNE collaborative inference and system behavior on computing node failures.

**Virtual environment.** Table 1 illustrates performance scaling of Edge-PRUNE collaborative inference for single and dual-server configurations with $1 \leq n \leq 6$ endpoint devices and complete bipartite graph $K_{m,n}$ interconnection topology. Per-frame processing time was measured in a virtual distributed environment: each endpoint process and each server process was assigned to a dedicated core on the 8-core Intel Core i7-8650U processor, and connections between endpoints and servers were handled over the Linux loopback network interface, which allowed using exactly the same server and endpoint software configurations as in a physically distributed system. Each endpoint performed the inference of 7 initial layers (Conv2D-ReLU-MaxPool-Conv2D-ReLU-MaxPool-Dense) of a vehicle classification CNN (Xie et al., 2016), whereas each server process performed the inference of the last 5 layers of the same CNN. The 7 CNN layers of each endpoint subgraph were realized by 100 Mbit Ethernet or 16 Mbit WiFi. The full-precision CNN (32 bit float) is implemented as an Edge-PRUNE application such that each Conv-BNorm-ReLU layer triplet is wrapped inside a dedicated actor, forming a graph of 53 actors and 69 links. Endpoint device inference time was explored by shifting the endpoint/server partition point actor-by-actor from inference input towards inference output, resulting in Figure 3. The graph shows that partition points 13 and 14 provide minimal endpoint inference time, 6.0× higher than endpoint-only inference. On the endpoint device, the CNN layers inside Edge-PRUNE actors were implemented using ARM Compute Library functions.

**4.2. Inference Time and Fault Tolerance**

In this work the topic of collaborative inference fault tolerance was studied for configurations consisting of one or more network-connected edge servers and one or more endpoint devices. The experimental study was done using the Edge-PRUNE framework, which was shown to scale successfully with an increasing number of endpoint devices and/or edge servers, and furthermore was shown to be capable of continuing operation after computing node failure.
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