Architecture-aware design and implementation of CNN algorithms for embedded inference: the ALOHA project


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Abstract—The use of Deep Learning (DL) algorithms is increasingly evolving in many application domains. Despite the rapid growing of algorithm size and complexity, performing DL inference at the edge is becoming a clear trend to cope with low latency, privacy and bandwidth constraints. Nevertheless, traditional implementation on low-energy computing nodes often requires experience-based manual intervention and trial-and-error iterations to get to a functional and effective solution. This work presents a computer-aided design (CAD) support for effective implementation of DL algorithms on embedded systems, aiming at automating different design steps and reducing cost. The proposed tool flow comprises capabilities to consider architecture- and hardware-related variables at very early stages of the development process, from pre-training hyperparameter optimization and algorithm configuration to deployment, and to adequately address security, power efficiency and adaptivity requirements. This paper also presents some preliminary results obtained by the first implementation of the optimization techniques supported by the tool flow.

I. INTRODUCTION

In recent years, Deep Learning (DL) algorithms have become an extremely promising instrument in the machine learning and artificial intelligence landscape, empowering innovation in a wide variety of application domains from computer vision to speech recognition and automotive systems [1].

Recent trends push towards deployment of DL algorithms on edge nodes as close as possible to the data sources. This approach helps overcoming limitations of cloud-based computing, when it comes to latency, communication bandwidth, privacy, security and reliability. However, performing highly accurate and reliable inference tasks at the edge without compromising performance and energy consumption is still a challenge [2]. A wide landscape of novel very power- and performance-efficient parallel processing architectures are emerging on the market and in literature to meet this need. They are often endowed with accelerators and specialized hardware for speeding-up the most computation-intensive tasks and reducing power consumption, such as convolution layers in Convolutional Neural Networks (CNNs). Two successful examples are the Google Tensor Processing Unit [3] and the NVIDIA Deep Learning Accelerator [4]. Other approaches rely on embedded heterogeneous system-on-chips (SoCs) integrating multi-core processor and using field-programmable gate arrays (FPGAs) optimized for low power operation, such as Xilinx Zynq [5] and Intel Arria 10 [6].

Unfortunately, programming these embedded computing architectures to perform inference task on the edge is highly time-consuming and requires expert developers. In traditional design flows, DL algorithms are in fact designed and trained to improve accuracy without considering the specific features of the processing platform in charge of executing the inference process. This determines the need for multiple design iterations, potentially leading to long tuning phases. The designer skills and the deep knowledge of the target platform features determine the degree of success of the inference process. This limits the adoption of DL mainly to very big actors in the
market that can afford the required development costs.

Thus, a computer-aided design tool capable of assisting software developers in implementing DL algorithms on heterogeneous low-energy processing platforms represents a considerable advancement with respect to the state of the art.

In this paper, we propose a software framework capable of automating the selection of an optimal algorithm configuration and the optimization of its implementation according to the given hardware and architectural constraints. This work is part of the activities of the H2020 ALOHA European project, started in January 2018. The goal is to relieve designers from the burden related to implementing inference on embedded systems, as well as open the access to DL also to small-medium enterprises and mid-range software development companies, that may focus on the use-case-related problem at the application level rather than on tedious implementation and porting details. The rest of the paper is organized as follows. Section II presents an overview of the tool flow, providing a description of its main components and tools. Section III describes the preliminary experiments performed.

II. THE ALOHA TOOL FLOW

The ALOHA tool flow is specifically aimed to help software developers when facing the implementation of DL algorithms on modern heterogeneous platforms. It automates different time-consuming developments steps, including the selection of an optimal algorithm configuration, the optimization of its partitioning and mapping on a target processing platform, and the optimization of power and energy savings during its deployment.

The key inputs and outputs of the tool flow are shown in Figure 1. The tool flow receives a configuration file, application-related constraints involving accuracy, security, performance and power, initial DNN(s), a dataset and hardware architecture/specification files as inputs. It generates as output a partitioned and mapped DNN configuration addressing architecture-awareness, ready to be ported on the target computing platform. The three main steps of the proposed tool flow are described in the following sections. Each step is composed of interacting components that influence each other by exchanging HTTP/REST APIs. The overall tool flow exploits a RESTful Microservice architecture and will be integrated considering all requirements posed by Agile development methodologies.

A. Tailoring the algorithm to the architecture

Automation of the algorithm design process is the first step of the tool flow. This is done by exploiting a Design Space Exploration (DSE) engine and a set of evaluation and refinement tools, capable of generating the optimal algorithm configuration considering the target task, the constraints, and the target embedded system that will execute the inference task. The DSE engine requests evaluation and refinement of an initial DNN to the tools shown on the right-hand side of Figure 1, with respect to different metrics (i.e. accuracy, security, power and performance). If no initial DNN is provided, by default, the DSE engine generates a population of design points using random or minimum topologies. To reduce the number of evaluations to be performed, the DSE engine uses design-space pruning techniques. However exploration can require several iterations. At each iteration, the DSE creates a Pareto graph populated with design points corresponding to candidate algorithm configurations. When the exploration is finished, the DSE engine triggers the next step of the tool flow.

a) Accuracy evaluation tool: This tool evaluates the accuracy of a candidate algorithm configuration. It is based on a training engine able to support training from scratch or to apply transfer learning to reuse pre-trained networks in a different use-case. The output of the training engine comprises numerical values for the network parameters (weights and bias; hyper parameters) and some meta-information describing accuracy results.

b) Algorithm refinement tool: This tool tries to reduce the computing effort and the energetic cost of the execution of inference of a candidate design point. It applies quantization and pruning methods to the DNN model provided by the DSE. Quantization reduces data precision, using different numerical representation formats in activations and weights. This is needed to lower the data representation from the one used for the original floating-point training to one which allows for parsimonious inference on the target embedded device. Pruning removes low-impact connections between network layers. It includes both iterative method [8] and INQ pruning [9]. The output of this tool is a modified algorithm description that gives the needed accuracy results while reducing the computational workloads.

c) Security evaluation tool: This tool receives as inputs the design point proposed by the DSE engine and the dataset. It
then generates an adversarial perturbation that, when applied to
the data point, maximizes its probability of being misclassified
by the DNN model under evaluation [15]. The output of this
tool is a measure of the DNN robustness to adversarial input
perturbations, expressed as a security level which can be low,
medium or high.

d) Performance/Power evaluation tool: This tool evalu­
ates the performance and the power consumption associated
with the execution of the inference of a candidate design
point on the target architecture. As shown in Figure 1, it
receives as inputs one or several DNN models coming from the
DSE engine, and the target architecture description. For every
DNN model, the tool generates as output the DNN inference
execution time in seconds (Performance), the DNN infer­
ence energy consumption in joules (Energy), the number of
processing elements prospectively usable for DNN inference
(Processors), and the memory required for DNN inference in
bytes (Memory).

B. Identifying partitioning and mapping

The second step of the tool flow aims at automating a
system-level design process, optimizing the partitioning and
the mapping of the algorithm configuration generated by
step 1 on the target processing platform. Similarly to the
previous step, the design process is driven by a System-level
DSE engine. This component controls the exploration of the
design space exposed by different partitioning and mappings
of the different inference software tasks, and creates a Pareto
graph populated with design points corresponding to candidate
system-level configurations. To populate the mentioned Pareto
graph, the system-level DSE engine requests evaluation of
the design points to two evaluation tools: Sesame [10] and
Architecture Optimization Workbench (AOW) [11]. To find
more efficient mappings of DNN actors to the underlying
platform architecture and to optimize the usage of the avail­
ables resources in the target architecture, the system-level
DSE engine may also deploy transformations on the DNN
algorithm graph by, for example, merging or splitting actors
(i.e., increasing or decreasing the concurrency in the DNN
algorithm). Alternatively, it may also invoke the post-training
algorithm refinement for parsimonious inference to achieve
a workload reduction by considering specific features of the
target architecture.

a) Sesame and AOW evaluation tools: In Step 2, the
synergy between Sesame and AOW is exploited. AOW ex­
ploros the whole design space, subject to system requirements
and resource constraints (e.g., serializing processing cores and
communication buses) using coarse-grain models for computa­
tion and communication, while Sesame performs more precise
simulation of both computation and communication over a
more limited search space for better mapping.

b) Post-training algorithm refinement tool: This tool
reduces the computation burden needed for implementing
inference by performing a post-selection refinement of the
candidate DNN. It is able to apply both a sophisticated
on-line data-dependent kernel/component pruning mechanism
[14] and a conversion from static to dynamic computing graph
to the underlying DNN model. If the process can converge to a
solution that delivers a more parsimonious inference, retaining
at the same time the accuracy of the initial model within
specified margins, the post-training refinement tool generates
as output a modified model, otherwise notifies the system-level
DSE engine to proceed with the initial trained model.

C. Porting on the target architecture

The last step of the tool flow aims at automating the porting
of the target inference application on the target architecture,
translating mapping information in adequate calls to comput­
ing and communication primitives exposed by the architecture.
This step exploits also the power- and performance-related
knobs exposed by the platform (VFS, power and clock gating
etc.).

III. PRELIMINARY EXPERIMENTAL RESULTS

A first set of preliminary experiments has been performed
to illustrate the potential of the optimization techniques im­
plemented in the ALOHA components.

A. Selection of algorithm parameters

As a first glimpse on ALOHA capabilities, we assessed the
possibility of improving computing efficiency of an inference
process by considering the specific features of a target archi­
tecture when selecting the algorithm-level parameters. To this
aim we compare here the performance achievable when exe­
cuting the well known VGG-16 algorithm on the NEURAghe
platform [7] with a custom VGG-like algorithm, modified
increasing the number of convolution kernels executed in each
layer to match the size of the multiply-and-accumulate (MAC)
matrix inside the accelerator. As may me noticed in Table I the
architecture-aware configuration better exploits the accelerator,
allowing for accuracy improvement.

| TABLE I |
|------------------|--------|----------|
| Benchmark | Performance (GOPS/s) | Accuracy (Top-1) |
| VGG16 | 172.67 | 88.4% |
| NEURAghe-aware VGG16 | 182.43 | 89.6% |

Moreover, we report in Table II performance levels achiev­
able on the same architecture using iterative quantization/re­
training to change the data format used to represent activation
weights. A first optimization can be achieved considering
the possibility of NEURAghe to operate on 16 and 8 bits
data formats. The accelerator uses the same MAC hardware
actor executing 16 bits operation to execute two different 8
bits operation. Thus this bring to a significant speed-up that
can be captured by the toolflow and exploited when allowed
by the specific use case (see third row). Quantization can be
used when needed as a compression method, to reduce
pressure on memory bandwidth, often stressed when weights
are loaded from DDR to on-chip memory, as may be noticed
when comparing the two configurations with 16-bit activations. The iterative re-training procedure after quantization was capable of reconstructing accuracy even for reduced precisions, stabilizing cumulative loss without significant degradation.

### Table II

<table>
<thead>
<tr>
<th>Quantization</th>
<th>Performance</th>
</tr>
</thead>
<tbody>
<tr>
<td>16-bit activations 16-bit weights</td>
<td>172 GOPs/s</td>
</tr>
<tr>
<td>16-bit activations 8-bit weights</td>
<td>175 GOPs/s</td>
</tr>
<tr>
<td>8-bit activations 8-bit weights</td>
<td>335 GOPs/s</td>
</tr>
</tbody>
</table>

### Table III

<table>
<thead>
<tr>
<th>$\varepsilon$</th>
<th>Classification accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>max</td>
<td>Without adversarial training</td>
</tr>
<tr>
<td>0</td>
<td>80%</td>
</tr>
<tr>
<td>0.4</td>
<td>20%</td>
</tr>
<tr>
<td>0.8</td>
<td>10%</td>
</tr>
<tr>
<td>1</td>
<td>9%</td>
</tr>
</tbody>
</table>

### B. Evaluation of security against adversarial attacks

In this section we present an experiment related with evaluation and improvement of the security level of a deep network, taking into account handwritten digit classification as a use-case. For this experiment we used a task-specific CNN model of Keras library [12]. We trained the underlying model on the MNIST dataset, after normalizing all images in $[0,1]$ by dividing the pixel values by 255, and manipulated 10,000 test samples using the Fast Gradient Sign Method (FGSM) attack algorithm [13]. This attack bounds the max-norm distance between a (legitimate) input $x$ and its adversarial counterpart $x'$ as $||x - x'||_\infty \leq \varepsilon$. Thus, every pixel $p$ in the image $x'$ is manipulated independently in the interval $[p - \varepsilon, p + \varepsilon]$. An example of manipulated MNIST handwritten digit is shown in Figure 2. Note that, within this setting, the adversarial perturbation is almost imperceptible to the human eye, though still effective to mislead recognition.

We then applied a defense mechanisms, called adversarial training [13], by augmenting the training dataset with adversarial examples and by re-training the neural network and repeating the FGSM attack for $\varepsilon \in \{0, 0.4, 0.8, 1\}$ against the robust network. The effect of the adversarial training is analyzed by gradually changing perturbation $\varepsilon$. In both cases, as expected, classification accuracy degrades under attacks characterized by an increasing perturbation. However, when using adversarial training it was possible to significantly increase resilience to attacks, as reported in Table III for different noise levels.

### CONCLUSIONS

In this paper, we have introduced a CAD tool flow to overcome the limits of traditional practices currently used to deploy deep learning algorithms at the edge. In contrast to previous approaches, we have focused on the possibility of automating the selection of an optimal algorithm configuration and the optimization of its implementation, considering the specific features of the processing platform executing the inference task during the whole development process. We have evaluated the potential of the optimization techniques implemented in the proposed tool flow and presented first results.

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### REFERENCES