

Inference at the edge: tuning compression parameters for performance

Deliverable 1: Final year Dissertation

Bsc Computer Science: Artificial Intelligence

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DECLARATION

I, Sam Fay-Hunt confirm that this work submitted for assessment is my own and is expressed in my own words. Any uses made within it of the works of other authors in any form (e.g., ideas, equations, figures, text, tables, programs) are properly acknowledged at any point of their use. A list of the references employed is included.

Signed:Sam Fay-Hunt.....

Date:10/12/2020.....

Abstract: *Abstract here*

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1 Introduction

- *Introduce terminology - Inference, neural network model, pruning, layers, channels, filters*
- *Introduce models to be used - high level conceptual representation of the models*
- *Introduce hypothesis*
- *Describe research aims*
- *Define project objectives*
- *Describe how this work contributes to further research*

2 Background

- *Adapt from D1*
- *rewrite with more of a focus on the concrete channel and pruning methodology used*
- *Would be good to include wandb bayse hyperparam optimisation details*

3 Methodology

3.1 Overview

- *Questions to be addressed*
- *Metrics to be measured - why*

This section will discuss the methodology used to search for lower latency models by tweaking pruning parameters.

3.2 Conceptual Process

- *Sensitivity analysis - filter/channel selection and layer interdependencies*
- *Filter pruning implementation - Theory*
- *Channel pruning implementation - Theory*
- *Retraining pruned model*

3.3 Filter and channel selection

Link back to selected model - concrete examples of process described in previous section

- *Filter selection (visual representation of filters)*
- *Channel selection (visual representation of channels)*
- *Discussion of pruning consequences (and recovery) - \dot{e} top1/top5 before retraining and after*

3.4 Engineering/implementation details

- *High level overview of physical system - justify need for multiple training agents*
- *Pruning & retraining setup - Distiller (Pruning & training)*
- *Benchmarking setup - openvino + benchmark (getting latency/throughput)*
- *Data processing - wandb + data visualisation steps*

3.4.1 High level overview of system

Figure 1 shows how each system interacts in the workflow, pruning is handled by the agent/s marked ‘Producer’, benchmarking is handled by the ‘Consumer’ agent, and the wandb system serves the next set of sweep parameters to each of the ‘Producer’ agents.

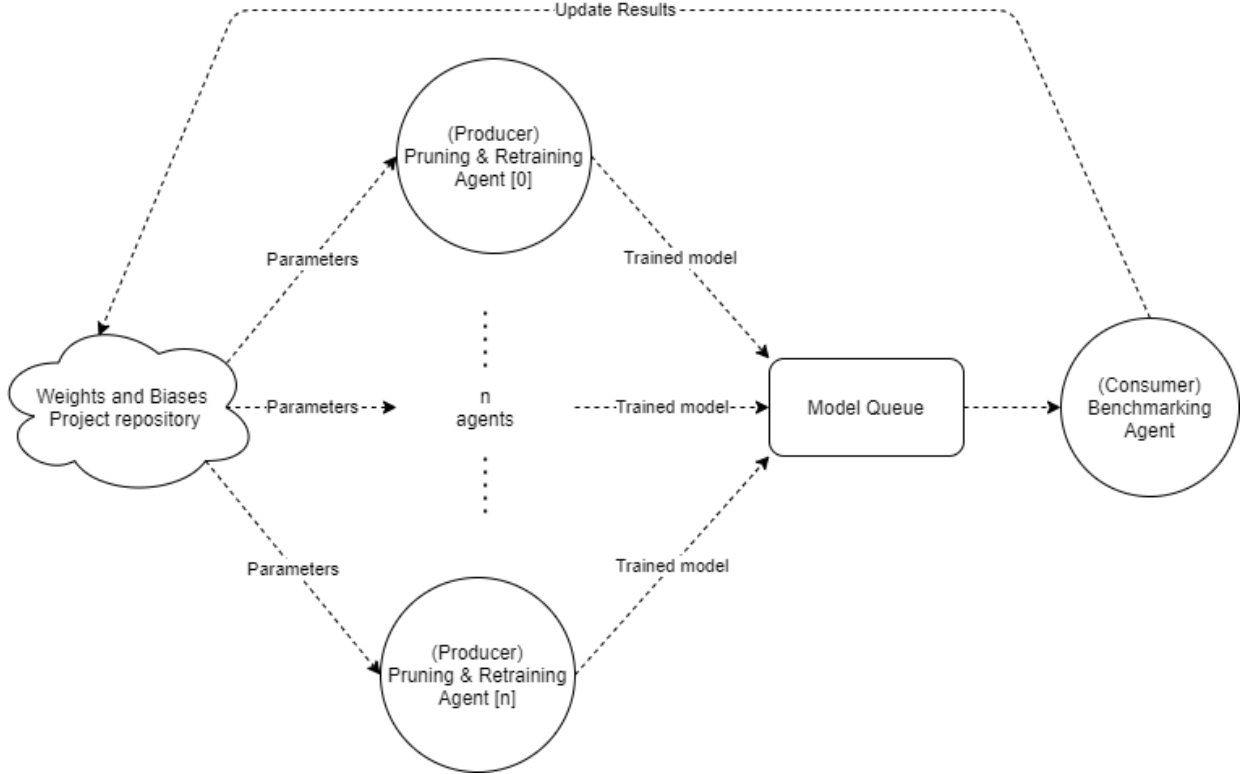


Figure 1: Diagram showing agent communication

When pruning begins, the producer agent requests the (initially random) pruning parameters from the Weights and Biases Project server, the producer then applies the pruning algorithm and begins retraining the model. Upon completion of retraining the model is exported into ONNX format and added to a queue for the consumer (the benchmarking agent) to benchmark and record the results, these results are then logged to weights and biases. As described in **(TBD)** the parameter importance and correlation with the target metric is re-computed each time results are logged this can help determine in what direction to tune the parameter settings to minimise (or maximise) the target metric.

The runtime of a full benchmark for one model on the NCS is usually at most 5 seconds, pruning and retraining the network however can take between 20 - 120 mins depending on the network size

and number of epochs. To improve the efficiency of the training we separated the benchmarking system (consumer) from the pruning and retraining systems (producer), this made it easy to add new pruning and benchmarking agents to a single experiment or run multiple experiments in parallel.

3.4.2 Defining parameters to prune

```

pruners:
  layer_1_conv_pruner:
    class: 'L1RankedStructureParameterPruner'
    group_type: Filters
    desired_sparsity: 0.9
    weights: [
      module.layer1.0.conv1.weight,
      module.layer1.1.conv1.weight
    ]
lr_schedulers:
  exp_finetuning_lr:
    class: ExponentialLR
    gamma: 0.95

policies:
  - pruner:
    instance_name: layer_1_conv_pruner
    epochs: [0]

  - lr_scheduler:
    instance_name: exp_finetuning_lr
    starting_epoch: 10
    ending_epoch: 300
    frequency: 1

```

Figure 2: Example distiller schedule file, showing the pruning algorithm selected, and that algorithms parameters

Figure 2 shows a example compression schedule document in .yaml format which will provide instructions to Distiller to use the ‘L1RankedStructureParameterPruner’ algorithm (section **TBD**) to prune the weights in each of the convolutions visible inside the ‘weights’ array, specifying filter pruning and a target sparsity.

The pruning schedule is composed of lists of sections that define Pruners, LR-schedulers, and

policies. A Pruner defines a pruning algorithm and the layers on which that pruning algorithm will be applied, LR-schedulers define the **learning-rate decay**(**Definition required**) algorithm. Finally each policy references the instance of the pruner or LR-scheduler it is managing (instance_name), and controls when the respective algorithm will be applied, such as the start and end epoch, and the frequency of application.

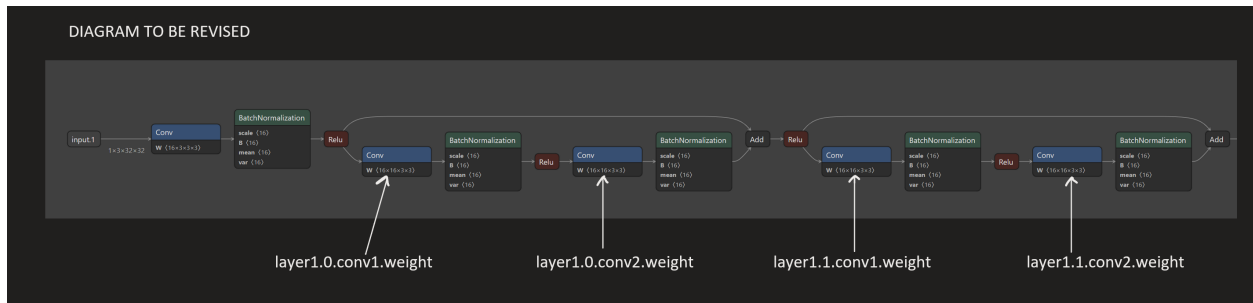


Figure 3: Resnet56 example showing wight labels. (**TODO: rescale and redraw to highlight pertinent information**)

Each layer in the network is labelled either manually or automatically (see figure 3), distiller uses these labels to identify which layers being referenced by the compression schedule.

3.4.3 WandB API

Key	Description	Value
program	Script to be run	Path to script
method	Search strategy	grid, random, or bayse
metric	The metric to optimise	Name and direction of metric to optimise
parameters	The parameter bounds to search	Name and min/max or array of fixed values

Table 1: Configuration setting keys, descriptions and values

To explore the space of possible models the hyperparameter optimisation tool within WandB called Sweeps was leveraged. This involves writing a python script that can run the entire workflow (pruning, training & benchmarking) and record the results, each sweep needs a configuration file (see Figure 4), table 1 shows a descption of each key in the wandb configuration file and their

appropriate arguments.

```
program: workflow.py
method: bayes
metric:
  goal: minimize
  name: Latency
parameters:
  layer_1_conv_pruner_sparsity:
    min: 0.01
    max: 0.99
  layer_1_conv_pruner_group_type:
    values: [Channels, Filters]
```

Figure 4: WandB sweep configuration file

3.4.4 Benchmarking

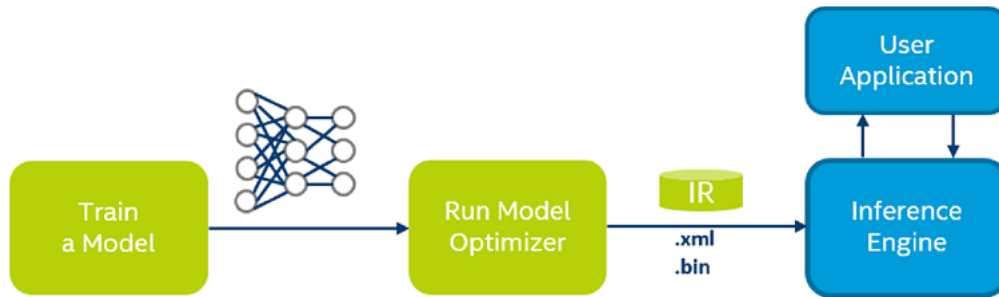


Figure 5: Workflow for deploying trained model onto NCS [1]

To pass the pruned and trained model to the Neural Compute stick OpenVino was used, it is a toolkit providing a high level **inference engine(Definition needed)** API, this facilitates the process of optimising the model for specialised hardware (in this case the NCS), and loading the optimised model into the NCS. OpenVino itself has a Benchmarking tool that we leverage to access to detailed latency and throughput metrics. A predefined set of images are selected and loaded into the NCS, the benchmarking application then runs 100 inference iterations network and returns the mean end-to-end latency (including loading images into the NCS memory), VPU processing latency (Inference latency), and throughput in FPS.

3.5 Experiment setup

- Wrapper on Distiller, reading schedule & parameterise elements
- WandB implementation, defining parameters to optimise
- communication between producer & consumer (redis - pub/sub)
- running benchmark and logging results

For the purpose of this experiment we chose to use the L1RankedStructureParameterPruner algorithm with both channel and filter pruning.

We conducted three experiments using the Resnet56 model trained on the CIFAR10 dataset. These three experiments each used a different target metric: Latency, Top1, and a hybrid metric (see section (TBD)).

3.5.1 Schedules

The following groups of weights were selected for pruning in the resnet56 model:

Lable	Weights
filter_pruner_70	module.layer1.0.conv1.weight,
module.layer1.1.conv1.weight,	
module.layer1.2.conv1.weight,	
module.layer1.3.conv1.weight,	
module.layer1.4.conv1.weight,	
module.layer1.5.conv1.weight,	
module.layer1.6.conv1.weight,	
module.layer1.7.conv1.weight,	
module.layer1.8.conv1.weight	

3.5.2 Latency Target Metric

This experiment targeted pure inference latency, no information regarding accuracy was encoded in the optimisation metric.

4 Evaluation

4.1 Evaluation of experimental design

- *Duration of training*
- *volume of data gathered*
- *(im)practicalities - power consumption?*
- *limitations - single optimisation metric*
- *Criticism of methodology*

4.2 Evaluation of results

- *Summary of results per model/dataset*
- *Deep dive into results, detailed visualisations of accuracy & latency tradeoffs (maybe example with poor quality sensitivity analysis vs higher quality layer selection)*
-

5 Conclusion

5.1 Further work

- *Suggested improvements for methodology*
- *Next steps*

5.2 Discussion

- *Discuss results*

A Back matter

A.1 References

References

- [1] (). “Model Optimizer Developer Guide - OpenVINO™ Toolkit,” [Online]. Available: https://docs.openvinotoolkit.org/latest/openvino_docs_MO_DG_Deep_Learning_Model_Optimizer_DevGuide.html (visited on 03/15/2021).