Chameleon: Adaptive Code Optimization for Expedited Deep Neural Network Compilation

(arXiv: 2001.08743)

Taehee Jeong

Chameleon is an animal that is capable of Adapting to their environments which helps them survive.

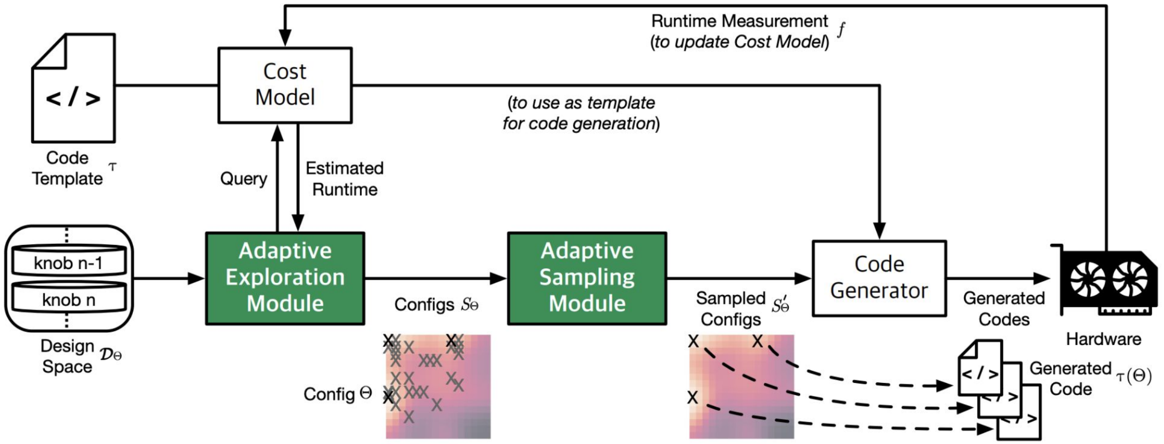

Figure 3: Overall design and compilation overview of the CHAMELEON.

Chameleon is an animal that is capable of Adapting to their environments which helps them survive. In our work, **CHAMELEON** is an entity that Adapts to the variations in the design space and the distribution of the candidate configurations, enabling expedited deep neural network compilation.

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Model Compilation Workflow

2.1 Compilation Workflow for Deep Neural Networks

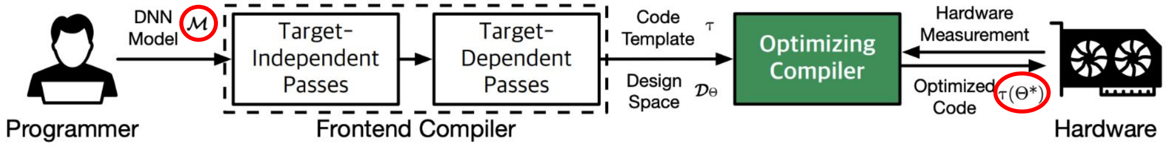

Figure 1: Overview of our model compilation workflow, and highlighted is the scope of this work.

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Model Compilation Workflow

2.1 COMPILATION WORKFLOW FOR DEEP NEURAL NETWORKS

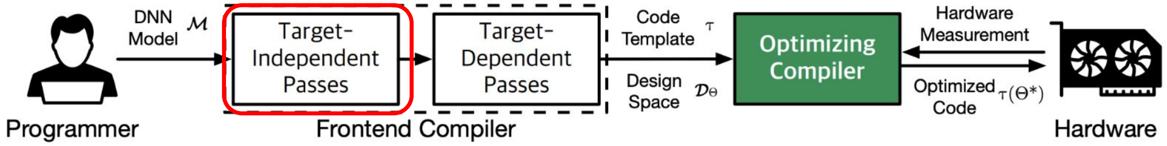
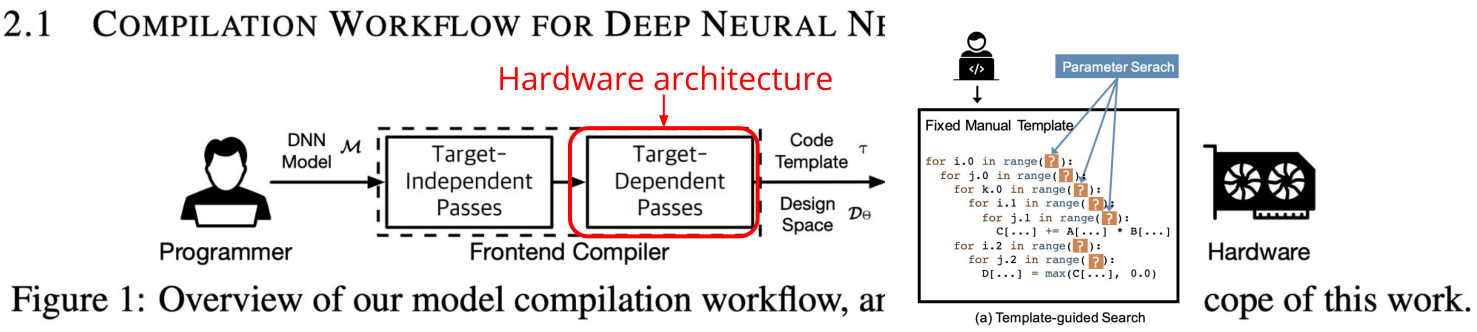


Figure 1: Overview of our model compilation workflow, and highlighted is the scope of this work.

- Target-independent pass
  - Optimizations in code model semantics + traditional compiler frontend optimizations
  - Operator fusion, data layout transformation
  - Dead code elimination, constant folding, ...

(arXiv: 2001.08743, 1805.08166)

Model Compilation Workflow



- Target-dependent pass
  - Template code(τ) generation based on target hardware architecture
  - Traditional compiler backend optimizations
  - Cost of execution time is not taken into account yet

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Model Compilation Workflow

2.1 COMPILATION WORKFLOW FOR DEEP NEURAL NETWORKS

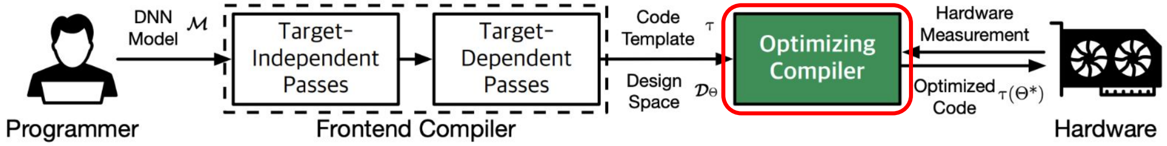

Figure 1: Overview of our model compilation workflow, and highlighted is the scope of this work.

- “Black-box” optimization pass: Optimizing Compiler
  - Generate optimal code, given design space D_Θ, find $\Theta^* \in D_\Theta$ that minimizes runtime.
  - $\tau(\Theta^*)$: optimal code given template and configurations
  - Leverages actual runtime measurements from HW to get data points

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Optimizing Compiler: **Components**

Configuration Exploration

- Configuration (“Knobs”): optimization parameters (tiling, loop unrolling)
- Search space should **diverse** enough. (10^{10}? design space)
- Algorithm should be **effective** at navigating large design space
- **Reduce** costly hardware measurements

Cost Estimation

- Estimate runtime (fitness) based on code. (Same as AutoTVM)
- Avoid overfitting to specific set of configurations

Optimizing Compiler: **Previous approaches**

Configuration Exploration

- Hand-optimized libraries, Compiler heuristics
- Genetic algorithm (TensorComprehension)
- Stochastic methods (Simulated annealing - AutoTVM)
- Diversity-aware exploration (AutoTVM)

Cost Estimation

- Actual HW measurements
- ML-based approach (AutoTVM, **Chameleon** - XGBoost)

Optimizing Compiler: **Existing problems**

Configuration Exploration

- Takes too much time
- Similar configurations -> redundant calculations -> waste of computing resource
- Invalid randomly sampled configuration -> Hardware failure -> reset time needed

Cost Estimation

- Greedy sampling based on cost model -> hard to explore untried configs

Chameleon: **Key contributions** in Configuration Exploration

Adaptive Exploration

- **RL** based approach - novel method in this domain
- Adapt to unseen design space

Adaptive Sampling

- **Clustering** of similar configurations: reduce redundant calculations
- Sample synthesis w/ **domain knowledge**: generate novel configurations that are **non-invalid**, by taking **"safe"** choices

Result:

- **4.45x** improvement in **optimizing compilation** time
- **5.56%** improvement in inference time (vs. AutoTVM)

Adaptive Exploration

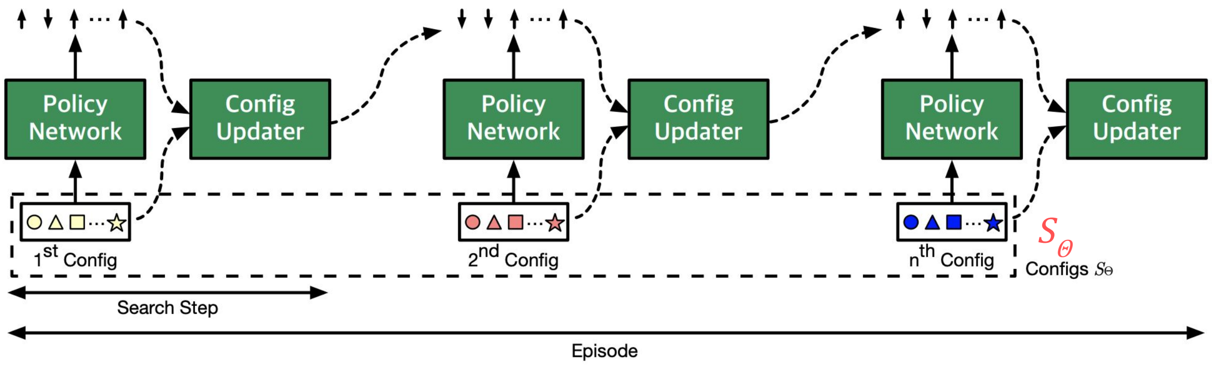
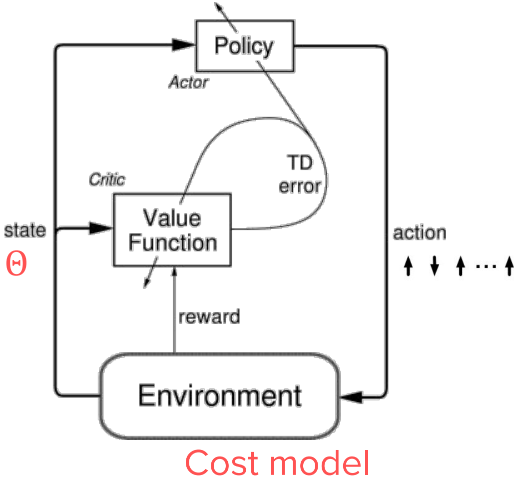


Figure 4: Adaptive Exploration Module of CHAMELEON in action.



Actor-critic style RL

- *“actor”* **proposes config updates** (turn each “knob” up/down/stay)
- *“critic”* gets **fitness** (predicted execution time) as **reward**, and then gives “actor” a feedback.
  - Critic **learns design space** while getting reward and giving feedback

(arXiv: 2001.08743), *Reinforcement Learning: An Introduction*

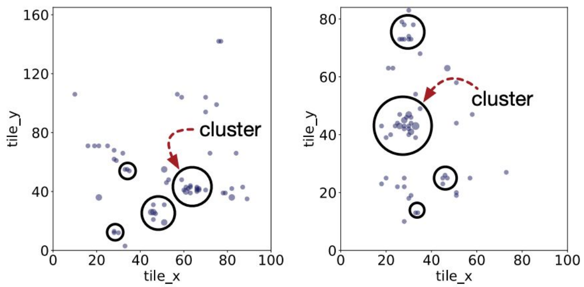
Adaptive Exploration

- **Policy networ**k suggests **good configurations** as the iteration goes
- **Value network** assists this by learning value function: *design space -> fitness*
- Used **PPO**(Proximal policy optimization) algorithm
- Performed **architecture search** to find tradeoff between performance vs network latency

Output

- S_{θ}: set of **all configurations** emitted from policy network each step.

Adaptive Sampling



(a) VGG-16 4th layer (b) ResNet-18 11th layer

Figure 5: Clusters of candidate configurations.

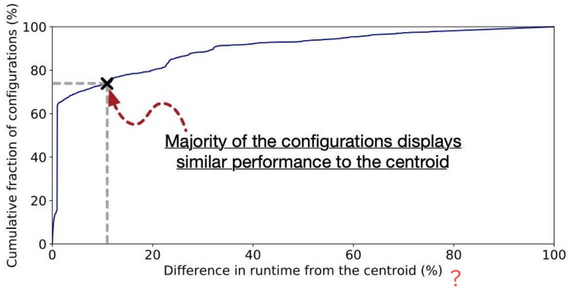


Figure 6: Cumulative Distribution Function (CDF) of the difference in runtime among the configurations in the cluster.

1. Explored configurations are **clustered**
2. For each cluster, most of configurations has **runtime really close to the centroid** configuration (80% of configs has 20% diff - Pareto?!)

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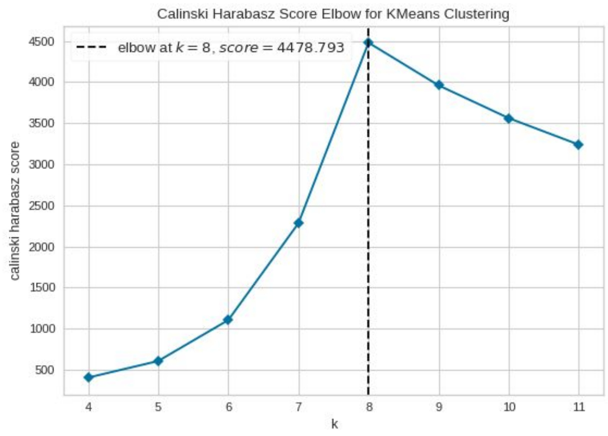
Adaptive Sampling: **K-means clustering**

- *Threshold-based Swift Meta-Search*
  - `L2_loss * threshold > prev_loss? break`
- Determine optimal K by getting **“elbow point”** from L2 loss.
  - Choose “just enough” amount of hardware measurements



(https://www.scikit-yb.org/en/latest/api/cluster/elbow.html)

Adaptive Sampling: **Sample Synthesis**

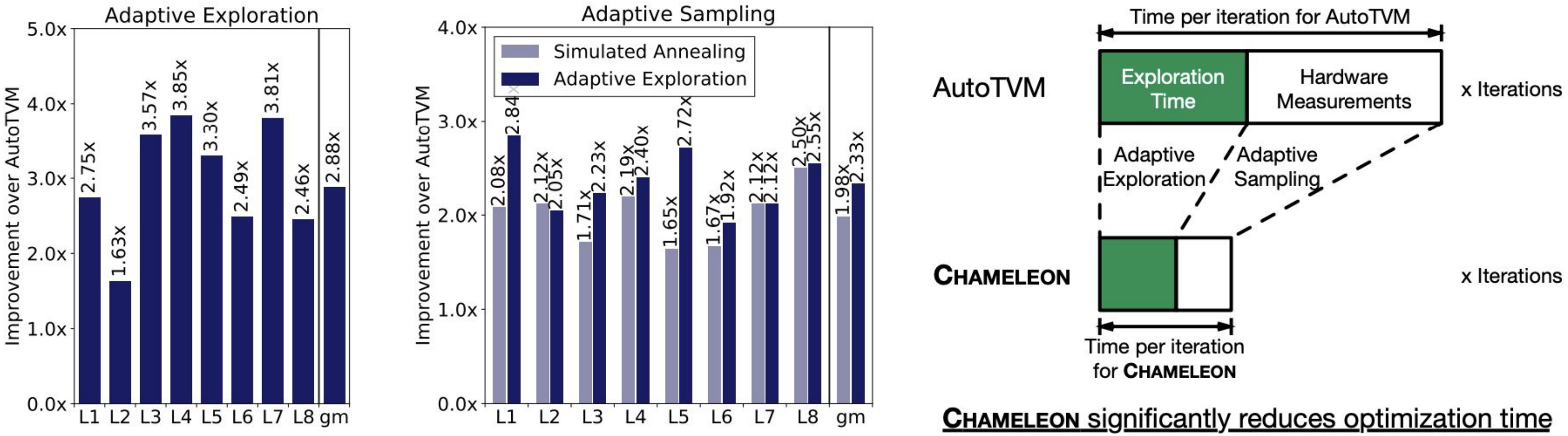
- K-means remove redundancy **within iteration**
- Overfit cost model preferes already seen configurations -> redundancy **among iterations** when greedily sampling best configurations.
    - Unvisited regions will usually have lower fitness, and thus ignored
- Randomly generated new samples would be often **invalid**. ex) too large tile -> memory error. -> **H/W reset** required
- When a config is **already explored** - replace with **mode(최빈값)** of proposed configurations(S_Θ)

Sample Synthesis

Algorithm 1 Adaptive Sampling and Sample Synthesis

procedure ADAPTIVESAMPLING(s_Θ, v_Θ) ▷ s_Θ: candidate configs, v_Θ: visited configs
    new_candidates $\leftarrow \emptyset$, previous_loss $\leftarrow \infty$
    for k **in** range(8, 64) **do**
        new_candidates, clusters, L2_loss $\leftarrow$ K-means.run(s_Θ, k)
        if Threshold $\times$ L2_loss $\geq$ previous_loss **then** break ▷ Exit loop at *knee* of loss curve
        previous_loss $\leftarrow$ L2_loss
    end for
    for candidate **in** new_candidates **do** ▷ Replace visited config with new config
        if candidate **in** v_Θ **then** new_candidates.replace(candidate, mode(s_Θ))
    end for
    return new_candidates ▷ Feed to *Code Generator* to make measurements on hardware
end procedure

Results



(a) Reduction in number of steps for convergence.

(b) Reduction in number of hardware measurements.

(c) Illustration of how the each component of CHAMELEON reduces the optimization time.

Figure 7: Component evaluation of CHAMELEON.

=> Adaptive sampling (obviously) reduces H/W measurements. (better w/ RL)

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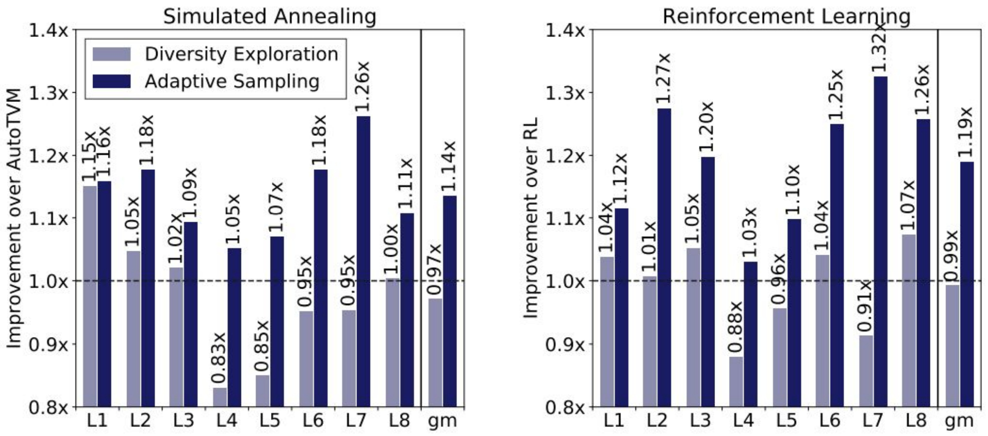
Results



(a) Simulated Annealing. (b) Reinforcement Learning.

Figure 8: Comparison to AutoTVM's diversity exploration.

Compared with **AutoTVM's diversity exploration**.

Adaptive sampling works better in all cases, possibly due to domain knowledge(S_{Θ})

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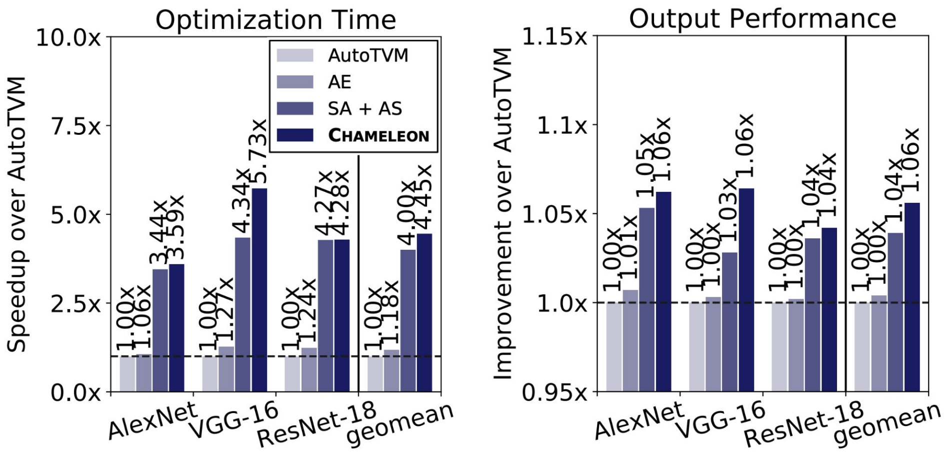
Results



(b) End-to-end evaluation.

Adaptive sampling is the more effective improvement

RL also have notable impact, but less impressive than adaptive sampling.

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Limitations (My opinion)

- RL seems noble, but not so much improvement (1.18x) despite significant reduction in number of steps (2.88x)
- Runtime performance improvement is also not impressive with RL only. Value network can't generalize its value function beyond what it has seen.
- Limited result in pretty simple convolution models. Not sure if it can be generalized to more complex models (e.g. NASNet, Inception)
- Only convolution performance is considered - maybe MauMul is already highly optimized?

THANKS!