ML²Tuner: Efficient Code Tuning via Multi-Level Machine Learning Models



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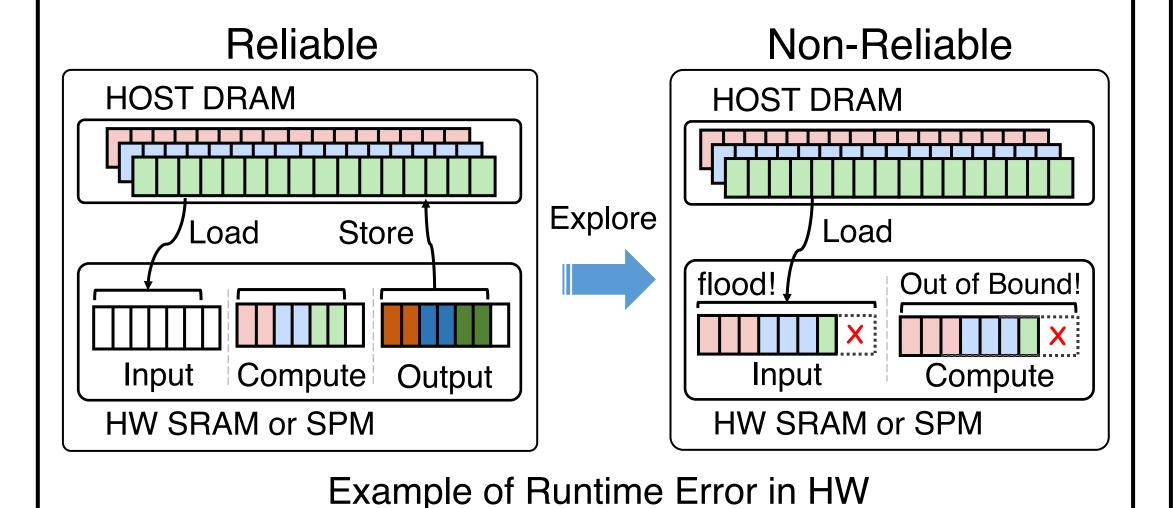
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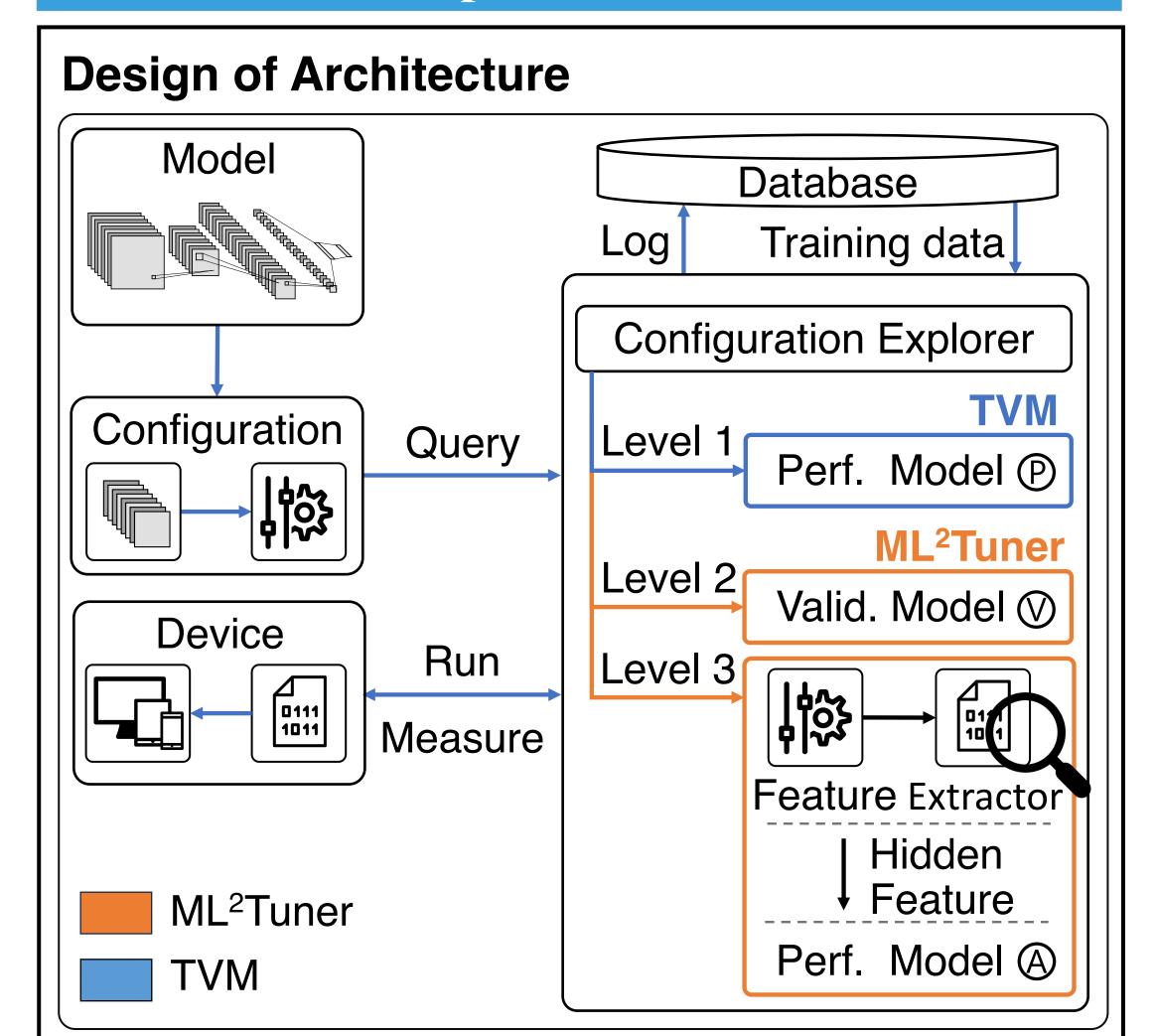
Motivation

Challenges in ML Code Auto-tuning

- Need to explore a vast search space
- Aggressive optimization increases the chance of runtime errors.



Proposed Method



P: Performance prediction

: Validity prediction

(A): Advanced performance prediction

Level 1 : Model ®

- Predict the Highest Performance from Configurations (such as Kernel, Layer Information)

Level 2 : Model ♥

- Validate Configuration from Configurations (Based on Configuration used in Model P)

Level 3: Model (A)

- Predict the Highest Performance from Configurations (Kernel, Layer Information and w/ Hidden Feature)

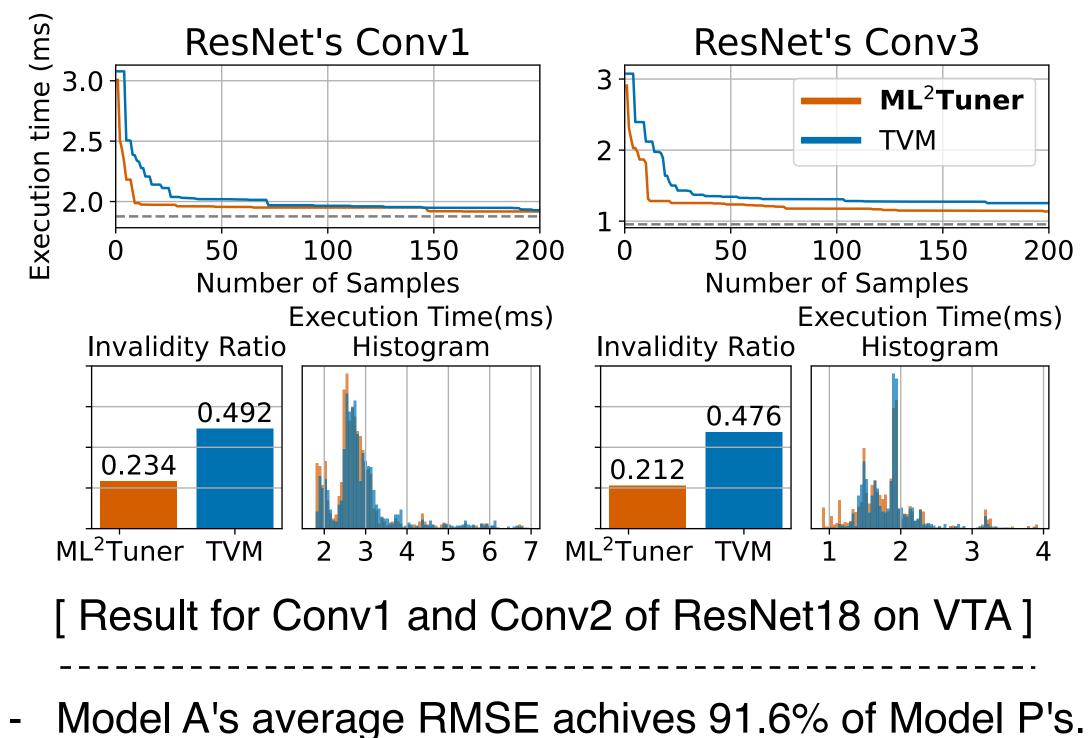
Feature Extractor:

- Find and Collect Hidden Feature in "Compiler" (such as decisions, loop sizes and tiling strategy)

Experimental

Experimental Setup

- Hardware Platform : VTA on **XILINX** ZCU102
- Compiler: MEST-C (based on C) G L O W)
- Optimizer: CBOOST (v2.1.1)
- Equivalent performance with 12.3% fewer Samples
- Reducing the invalidity ratio to 60.8%
- Provide increased opportunities for exploration



| No. | 1.0 | 0.945 | 0.948 | 0.929 | 0.881 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 | 0.842 |

Conclusion and Discussion

Our Contribution:

Error-Aware Search Refinement

Future Research

1. Validate Evaluation on Diverse Environment

- Testing Diverse hardware to assess generalizability.
- Testing Algorithm to further refine the tuning process.

2. Auto-identifying features from binaries

- Study on improved accuracy and probabilistic error detection systems.

References

