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Automated selection of build configuration based on machine learning

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Background

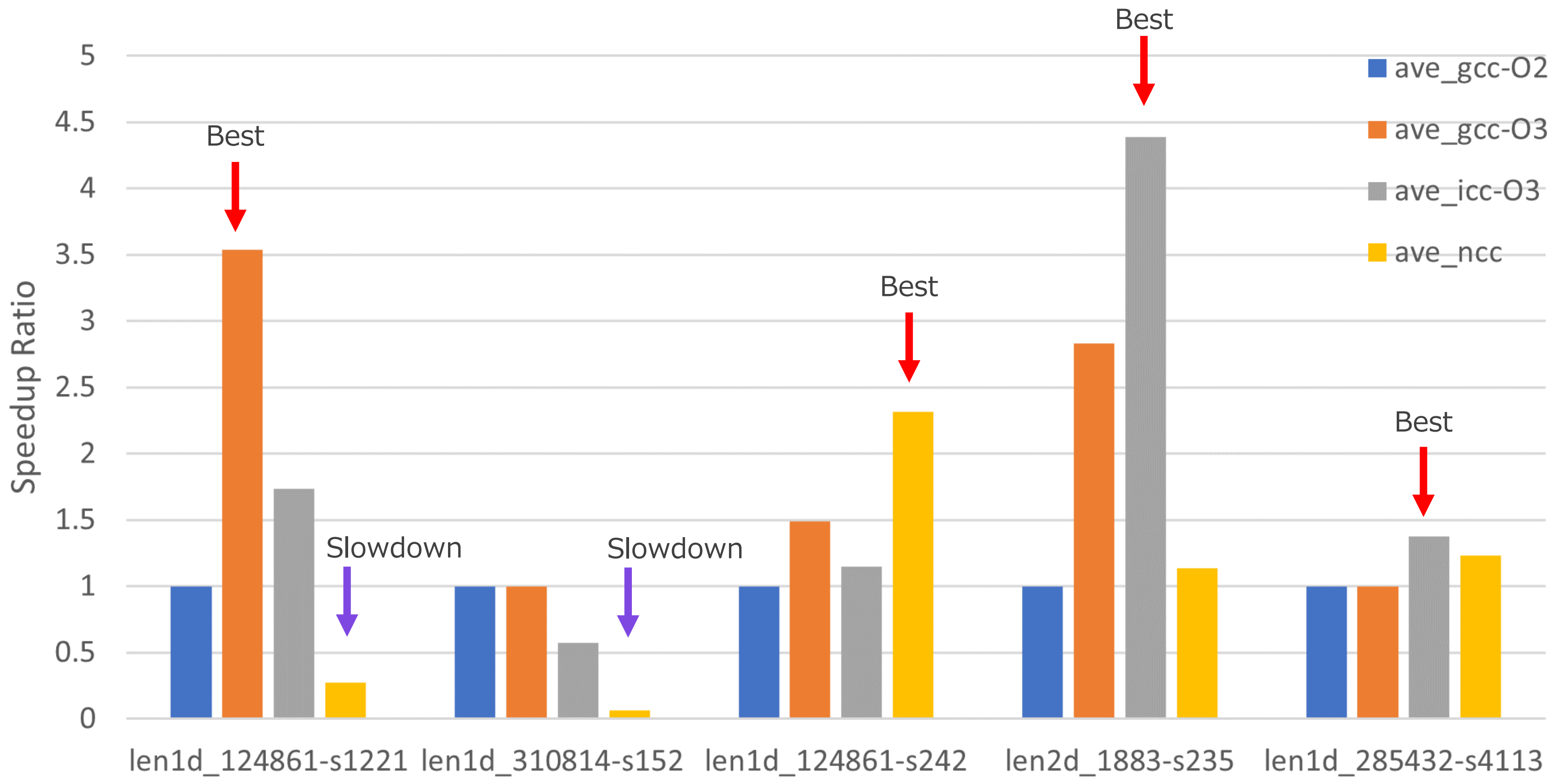
- Automatic Software Performance Tuning (Auto-Tuning, AT)
  - Automatically tuning **Performance Knobs** of a code for its target platform
    - Performance knob: parameter of a code affecting the performance
      e.g., selecting one of multiple code versions for a platform.

  - **Build Configuration** = a set of important performance knobs
    - There are many options to compile a code, e.g., **compiler** and its **option flags**.
    - Various kinds of code optimizations are incorporated into each compiler and enabled by compiler option flags.
    - Different compilers provide different optimizations and thus different option flags.

→ A compiler and its option flags must be selected properly.

Compilers and their flags

- Speedup from “gcc –O2” configuration



Motivation

- A code could potentially have a huge number of build configurations
  - There is no explicit algorithm to find an appropriate build configuration.
  - Full search for finding the best is time-consuming and could be infeasible.

- Research Questions
  - Is it technically **feasible** to automatically find the best build configuration?
  - **From what data**, can we predict the best configuration most accurately?

This Work

- Characterizing a code for identifying an appropriate build configuration.
  - **Performance Monitoring Counters (PMC)**

- What we have done in this work
  - Machine learning models are used for the **best build configuration prediction**.
    - Predicting the performance with each build configuration.
  - **Feature selection** to eliminate redundant PMC attributes for inference

Related Work

- Logistic Regression of PMC values (Cavazos et al, 2007)

Is it possible to improve the accuracy by using more advanced ML models?

  - The feasibility of automatically finding an appropriate set of compiler option flags is demonstrated.

Is it possible to select the compiler itself if multiple compilers are available?

  - All available PMC attributes are used for regression.

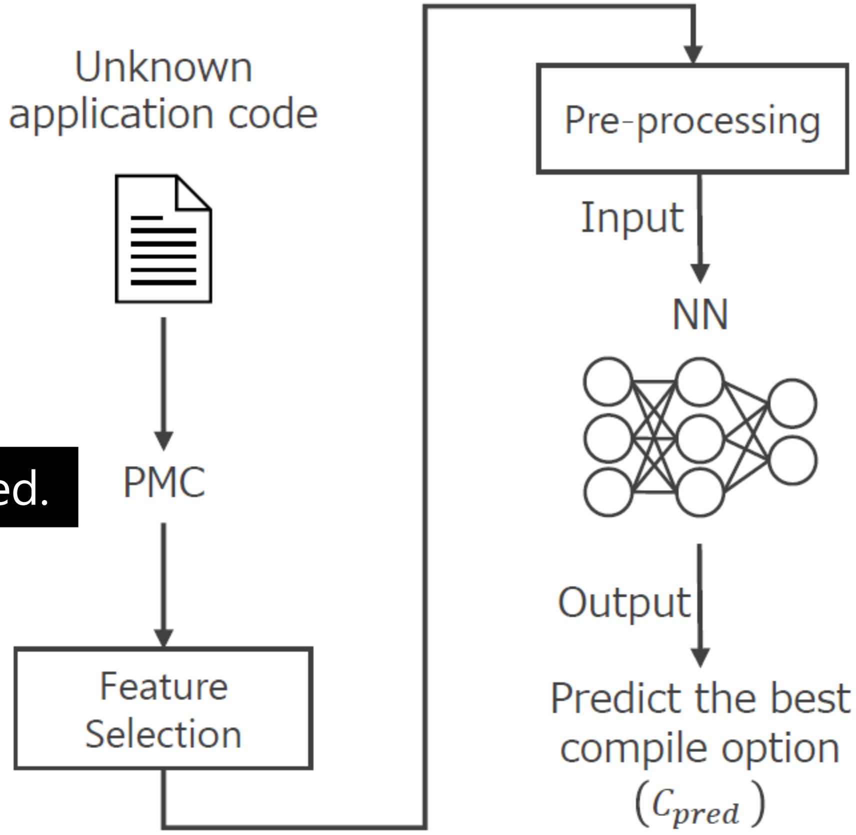
Are they all needed? Is it possible to select only necessary features?

Overview of Build Configuration Prediction

Z-score standardization

Compiled with gcc –O0 and executed.

Redundancy reduction



Performance Monitoring Counters

- There are a large number of PMCs available on modern processors.
  - Performance information obtained at runtime (=dynamic information)
  - Available PMC attributes are **microarchitecture-dependent** ☹
  - PMC values are **compiler-dependent** ☹

- In this work, PMC values are measured with gcc –O0 (no optimization)
  - Compiler optimization could change the statistics of PMC values.

Attribute	Description
TOT_INS	Total number of instructions
LST_INS	Number of load and store instructions
TOT_CYC	Total number of cycles
SP_OPS	Number of floating-point operations
L2_TCM	Number of L2 cache misses
BR_INS	Number of branch instructions

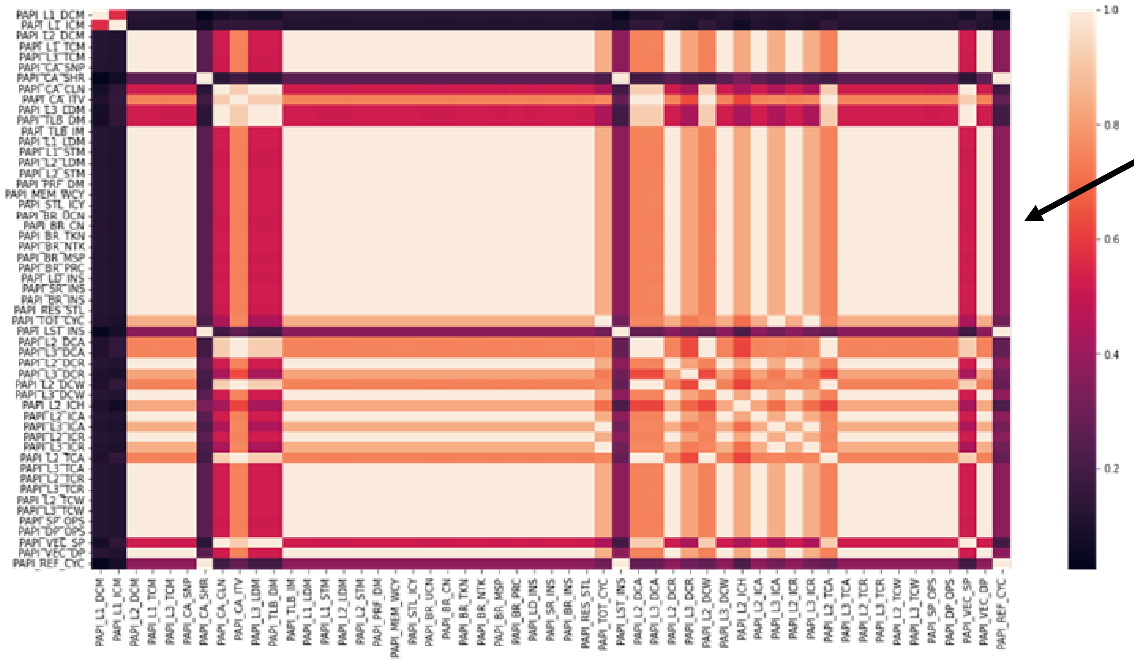
Feature Selection

- Use commonly available PMC attributes across various processors
- Exclude invalid or less useful attributes
  - E.g. some attributes are not affected by build configurations and always constant
- Filter out highly correlated attributes
  - Check if the correlation between two attributes exceeds a threshold.

Feature Selection (cont'd)

- Many PMC values are highly correlated (= multicollinearity)
  - thus expressing identical performance characteristics.
- ML model can learn better from weakly correlated inputs (Alin, 2010).

→ **If two PMC values are highly correlated, only one of them is used for ML**.



Correlation diagram between PMC attributes

A brighter color means a higher correlation, and many PMC attributes are highly correlated.

Are all PMCs important for characterizing a code? Probably not (experimentally discussed later).

Z-Score Standardization

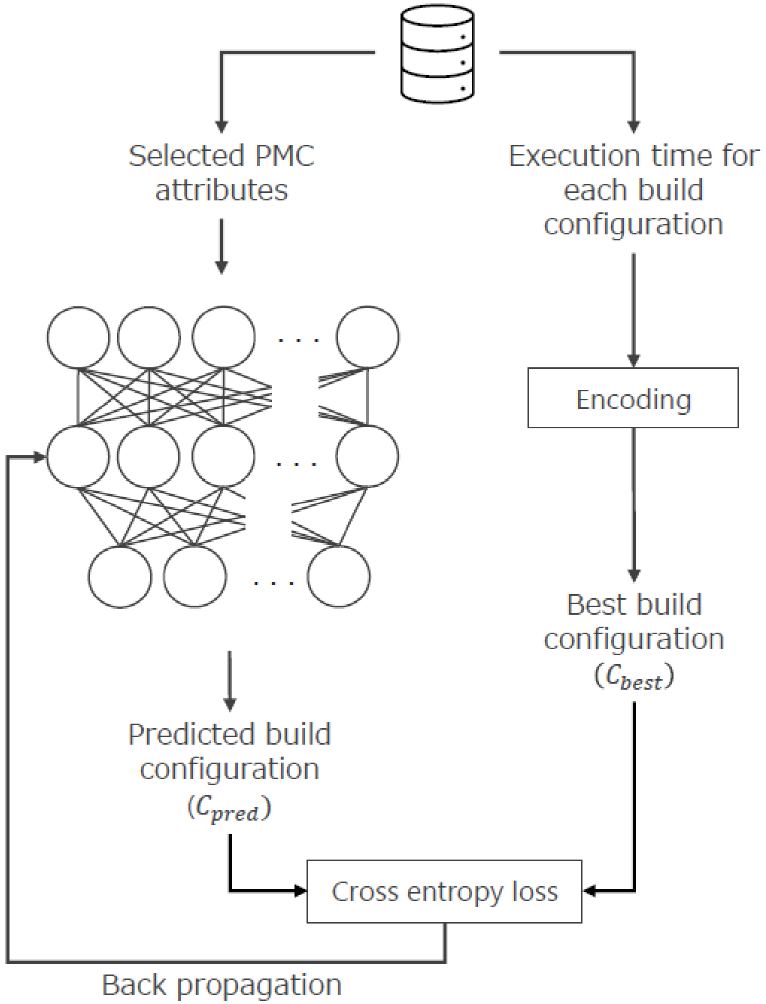
- PMC attributes have totally different statistics
  - The average values of data cache misses and instruction cache misses are in the orders of 10^9 and 10^5, respectively.
    → **Significant differences would lead to information loss at training**.
- In this work, we apply data-scaling and standardization to PMC values.
  - Each value is normalized by TOT_INS (total number of instructions), and then Z-score standardization is applied.

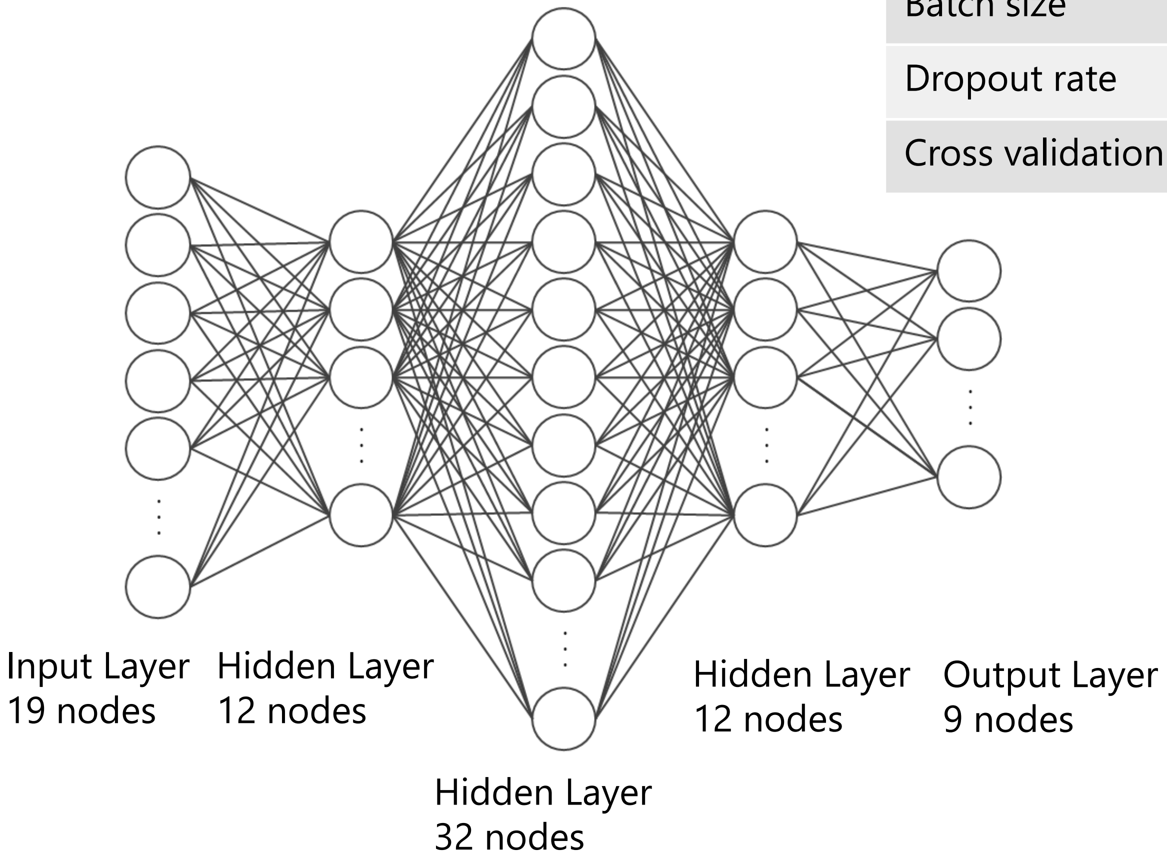
$$z_i = \frac{x_i - \bar{x}}{s}$$

where $\bar{x}$ and s are the average and standard deviation of x_i.

Machine Learning Model

Hyperparameter	Value
Optimization	Adam (rate: 0.0005)
Epoch count	60
Loss function	Cross entropy
Activation function	ReLU
Batch size	20
Dropout rate	0.3
Cross validation	4-fold





Evaluation Setup

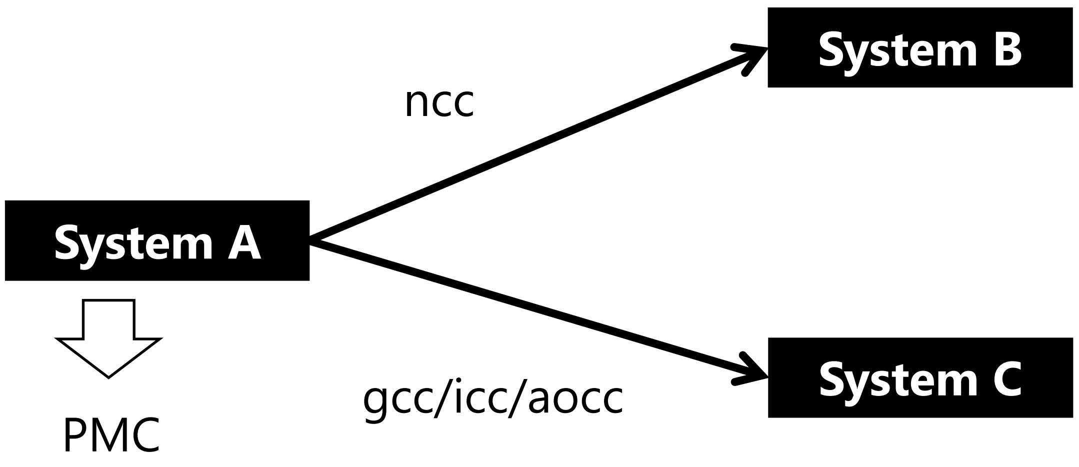
- Build Configurations
  - `gcc -O2, gcc -O3`
  - `icc -O2, icc -O3`
  - `clang -O2, clang -O3`
  - `ncc -O2, ncc -O3, ncc -O4`

Compilation for x86 processors with –march=native option

Compilation for NEC Vector Engine

- Benchmark
  - Test Suite for Vectorization Compilers 2 (TSVC 2)
    - 151 **vectorizable** loops are provided
    - 1,447 loops are generated by changing their loop lengths.
      - 1D loop length : 100 ~ 512,000
      - 2D loop length : 8 ~ 2,048 (nested)
- Performance Application Programming Interface (PAPI)
  - PMC values and execution time are obtained at different runs

Evaluation Setup



	System A	System B	System C
CPU	Intel Core i7 9700K	AMD EPYC 7402P	AMD EPYC 7702
VE		NEC VE Type 20B	
Memory	32 GB	256 GB	256 GB
Linux Kernel	5.11.0	4.18.0	4.18.0
Compiler	gcc-9.3.0	ncc-3.3.0	gcc-8.4.1 icc-2021.3.0 aocc clang-12.0

Evaluation Metric 1

- **PWGA (Penalty-Weighted Geometric Accuracy)**

$$PWGA = \left(\prod_{l=1}^{N} \frac{T_{best,l}}{T_{pred,l}}\right)^{\frac{1}{N}}$$

  - N: Number of data
  - $T_{best,l}$: Execution time of the l –th code with the best config.
  - $T_{pred,l}$: Execution time of the l –th code with the predicted config.

PWGA = 1 for perfect prediction.

PWGA becomes smaller if performance with the predicted config is lower than that with the best config.

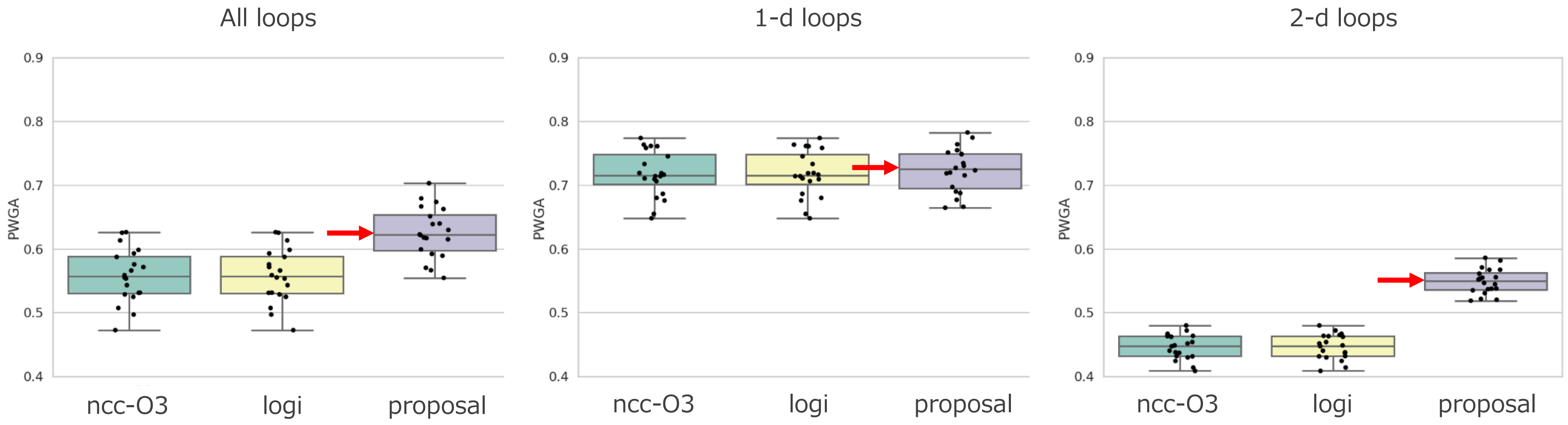
Evaluation Metric 2

- **Speedup Ratio**

$$\text{Speedup Ratio}(l) = \frac{T_{\text{baseline},l}}{T_{*,l}}$$

- $T_{*,l}$: Execution Time of the l-th code with a configuration
- $T_{baseline,l}$: Execution Time of the l-th code with gcc –O2. (baseline)

Evaluation Results in PWGA

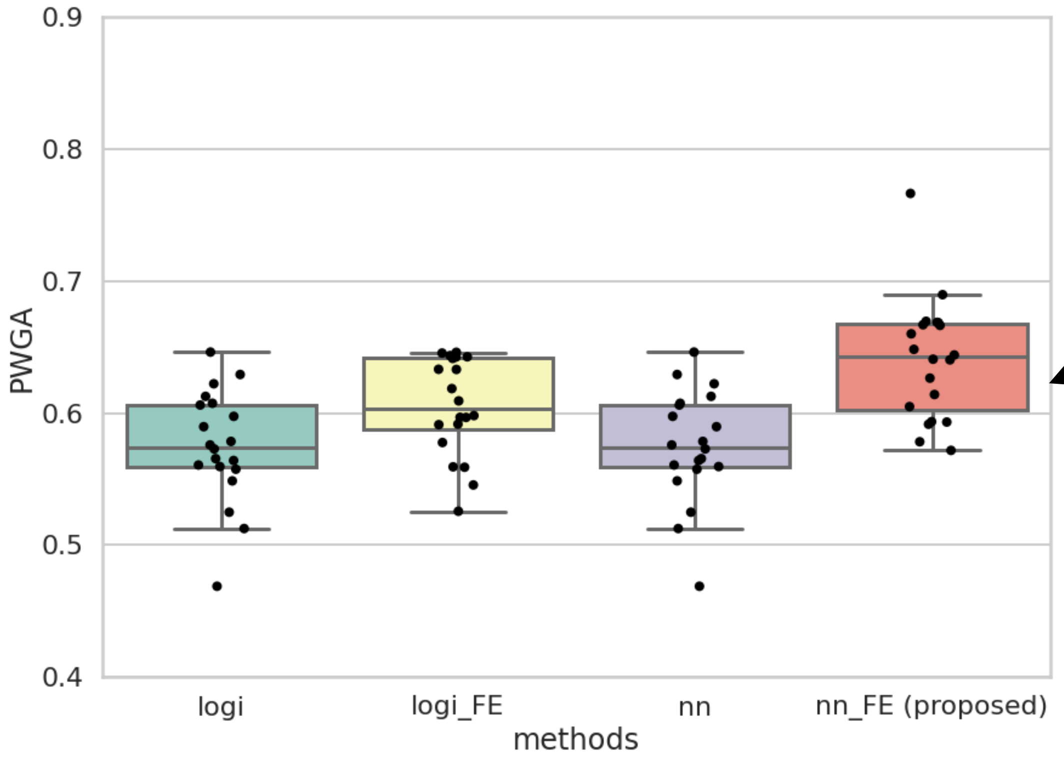


- ncc –O3: always use ncc –O3 for any loop
- logi : logistic regression (existing work)

1-D: ncc –O3 is almost always best for 1d loops (= long loops).
2-D: proposed approach can select better ones for more 2d loops.

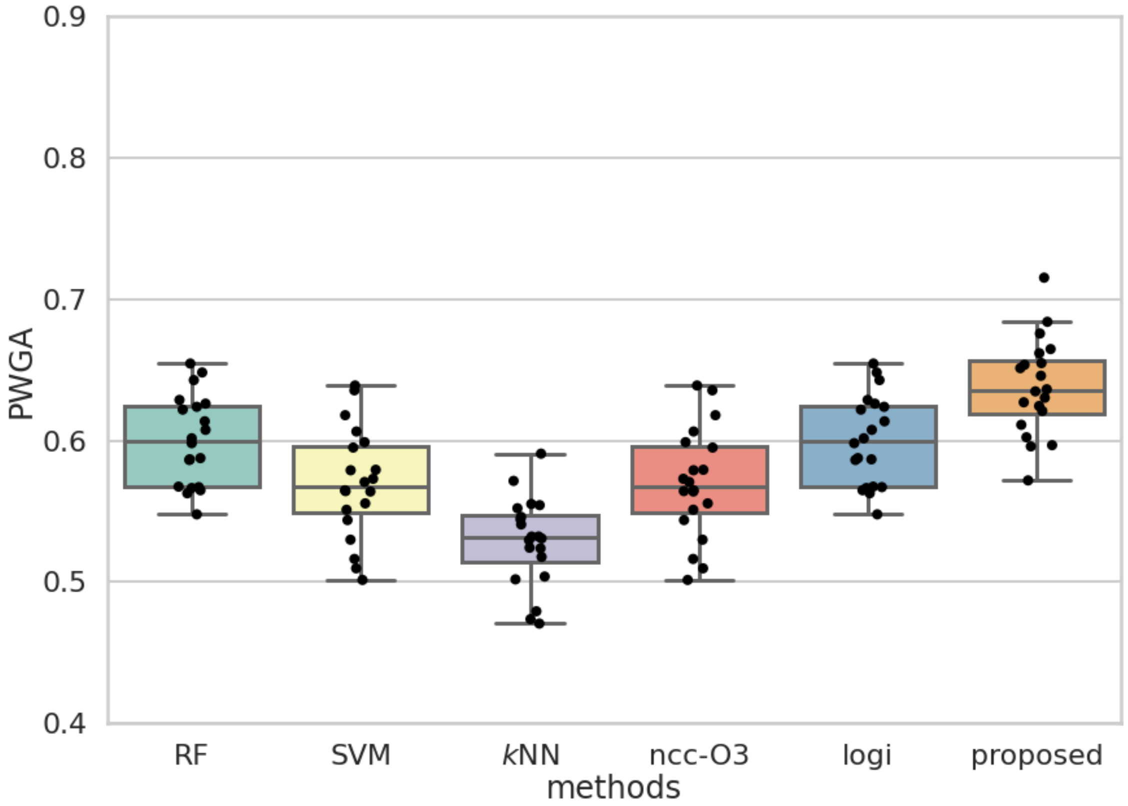
Effect of Feature Selection

- Feature selection improves the prediction accuracy (PWGA) of **not only NN but also logistic regression**.



Without feature selection, the prediction accuracy of NN is almost the same as that of logi. But **with feature selection, NN outperforms logi.**

Machine Learning Models



- RF: Random Forest
- SVM: Support Vector Machine
- kNN: k Nearest Neighbor
- ncc –O3: always use ncc –O3
- logi: Logistic Regression
- proposed:
  neural network+feature selection

Speedup by Changing Build Configuration

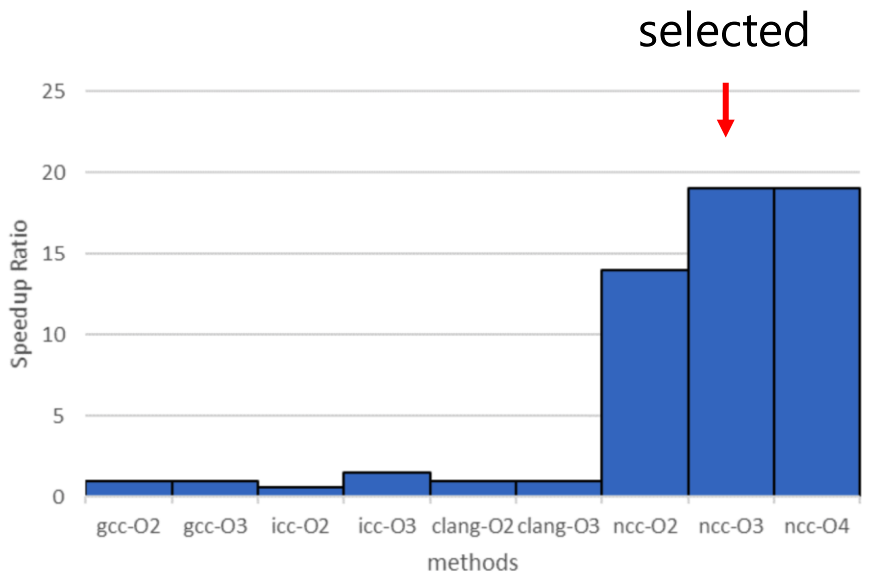


Figure 9: Speedup ratios of each build configuration on a len1d loop (s352 in TSVC 2 with the loop length of 31,039).

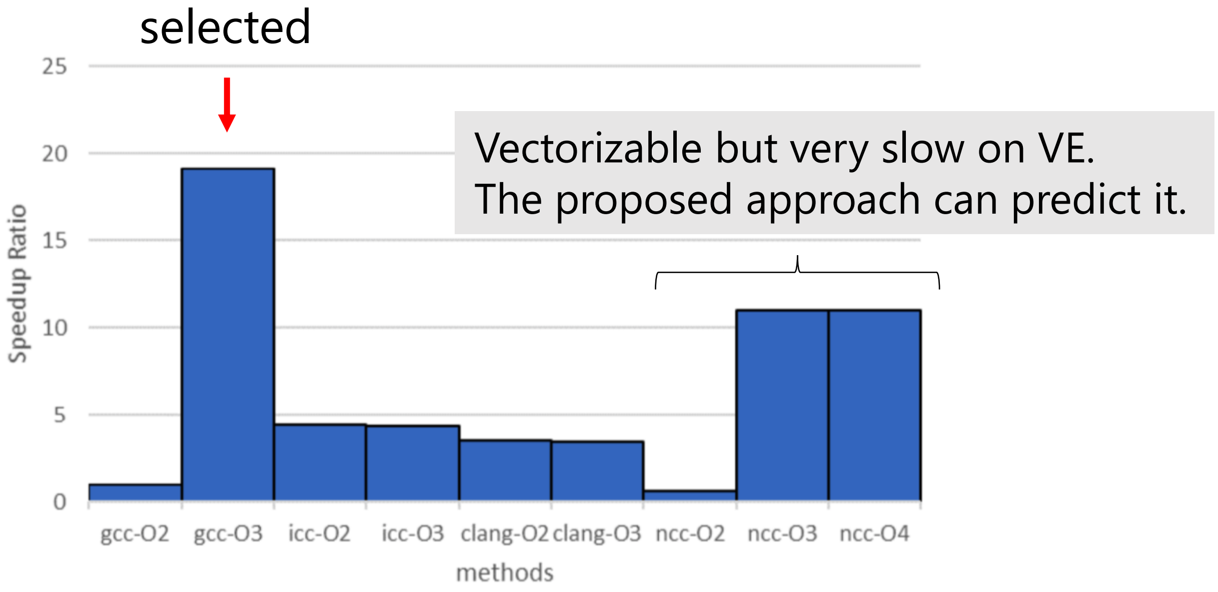


Figure 10: Speedup ratios of each build configuration on a len2d loop (s231 in TSVC 2 with the loop length of 87).

- (Left) ncc is selected and the speedup ratio is about **19**
- (Right) gcc is selected, and the speedup ratio is about **19**.

Conclusions

- Build configuration selection
  - Compiler and its option flags can significantly affect the performance
  - The best configuration for each code could be different
- PMC-based approach
  - **PMC values could be used to predict the best build configuration**
  - Many of PMC attributes are highly correlated and **feature selection to reduce the redundancy could improve the prediction accuracy**.
- Evaluation results with TSVC-2
  - 1-dimensional vectorizable long loops → "ncc –O3" works best
  - 2-dimensional nested loops → the proposed approach works better than others.

Acknowledgements

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