Use of Code Structural Features for Machine Learning to Predict Effective Optimizations

International Workshop on Automatic Performance Tuning

May 25, 2018@Vancouver, Canada

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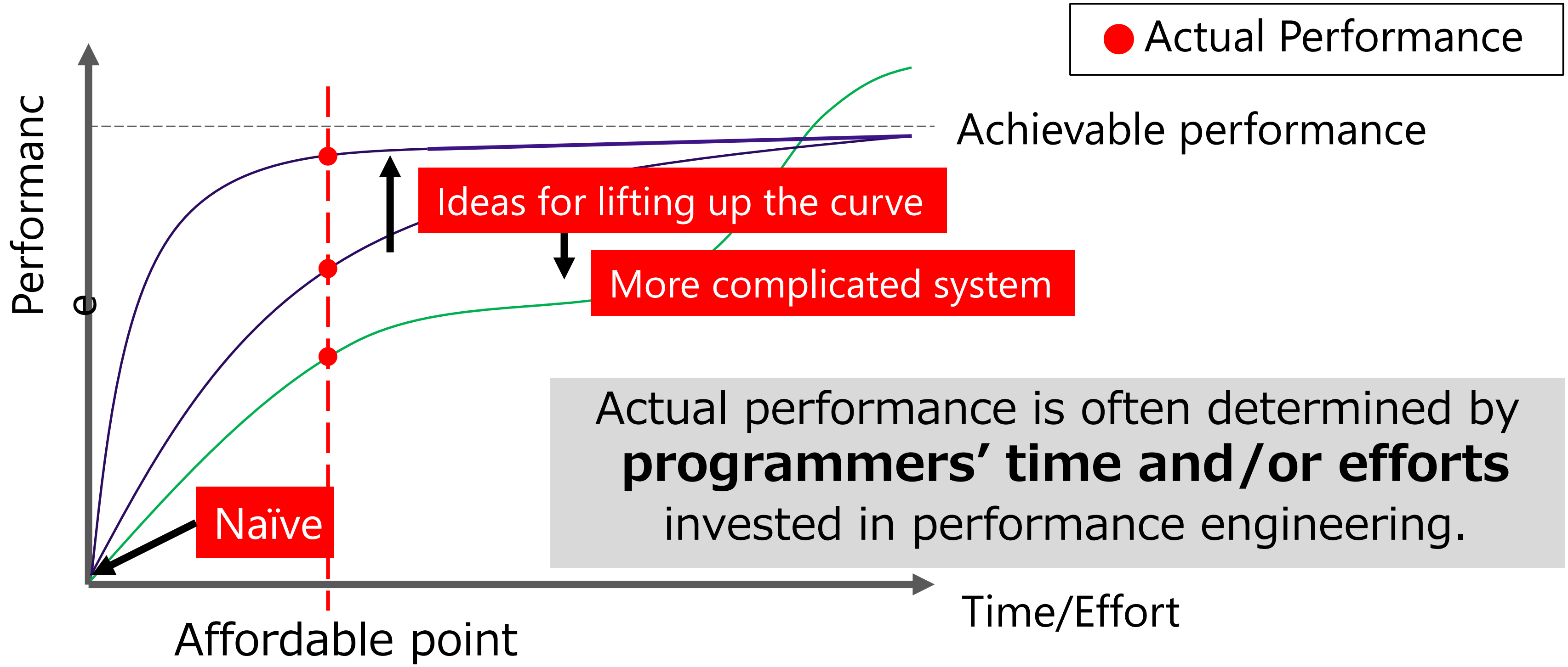
Outline

- Introduction
- Use of code structures for machine learning
- Preliminary evaluation results
- Conclusion and future work

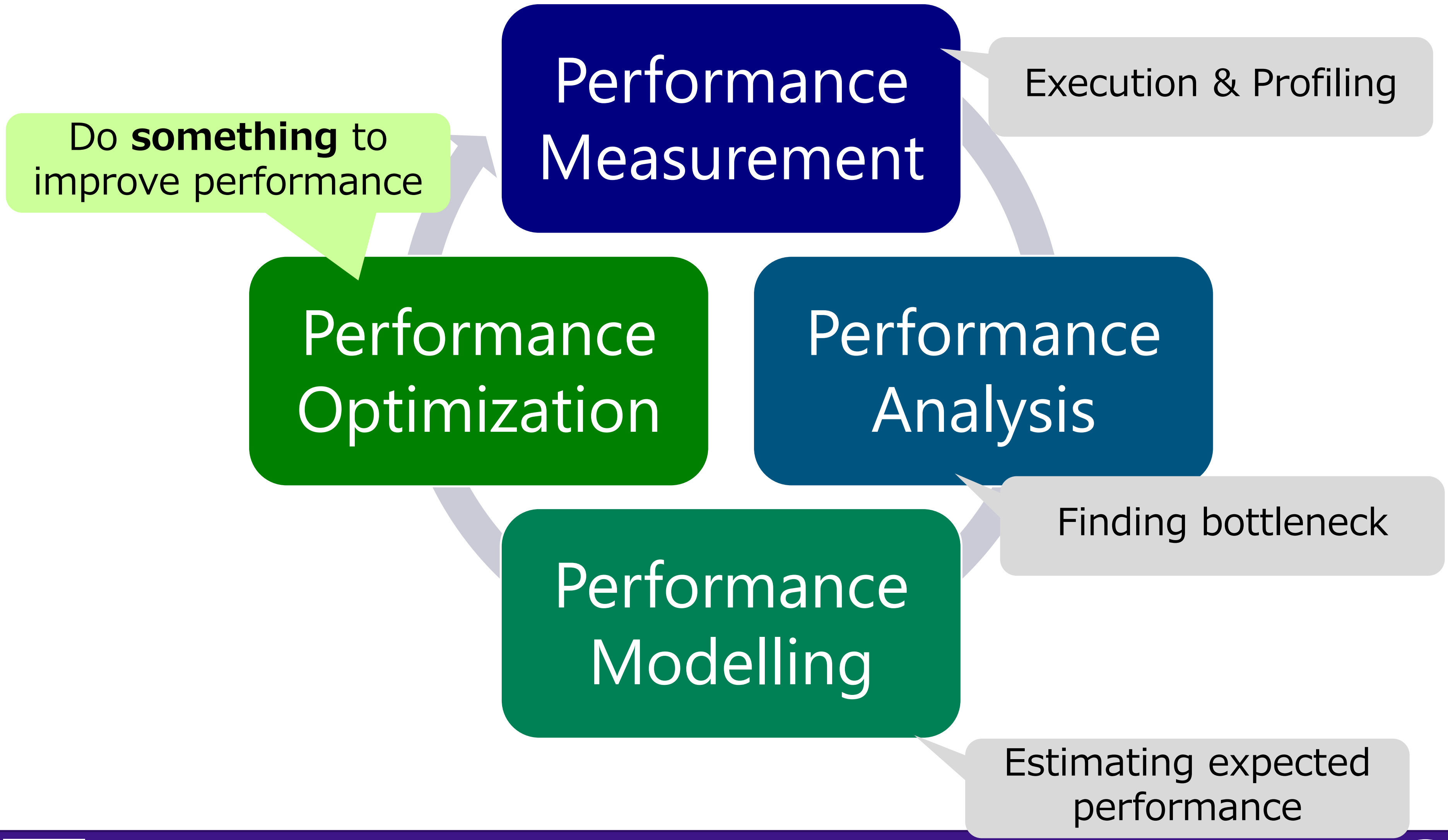
Background

- What is the dominant factor of actual simulation performance? Peak flop/s rate?



Actual performance is often determined by **programmers' time and/or efforts** invested in performance engineering.

Performance-aware Programming



Motivation

- **Can we write an explicit algorithm to predict effective optimizations for a given code? → Yes and No.**
  - **Yes.** Compilers automatically apply various optimizations to a given code.
  - **No.** Expert programmers still have to select various options in practice.
    - Algorithms, data structures, loop transformations, …
- **Since there is no clear algorithm of the prediction, human experts have to predict effective optimizations on a case-by-case basis.**

The final goal is to automate the prediction to reduce burdens of performance optimization on programmers.

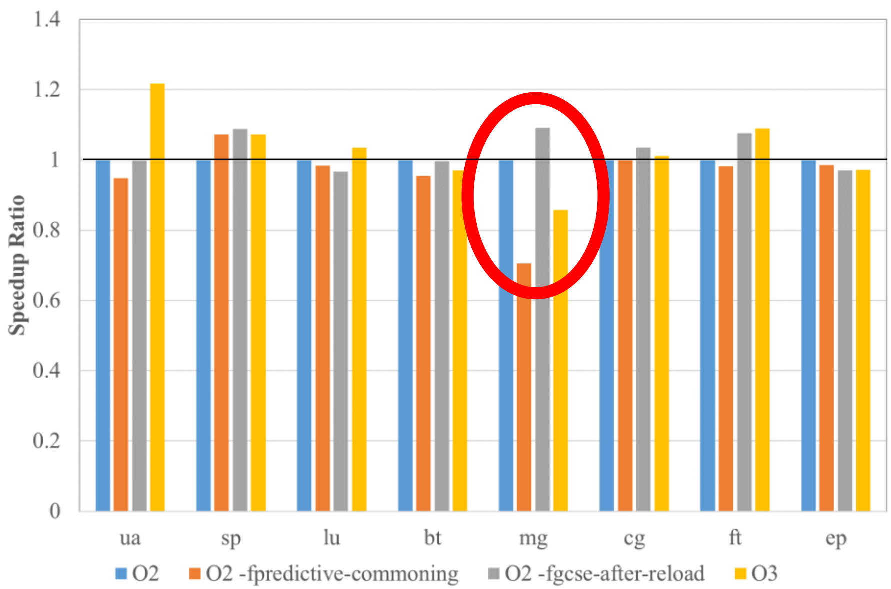
This paper

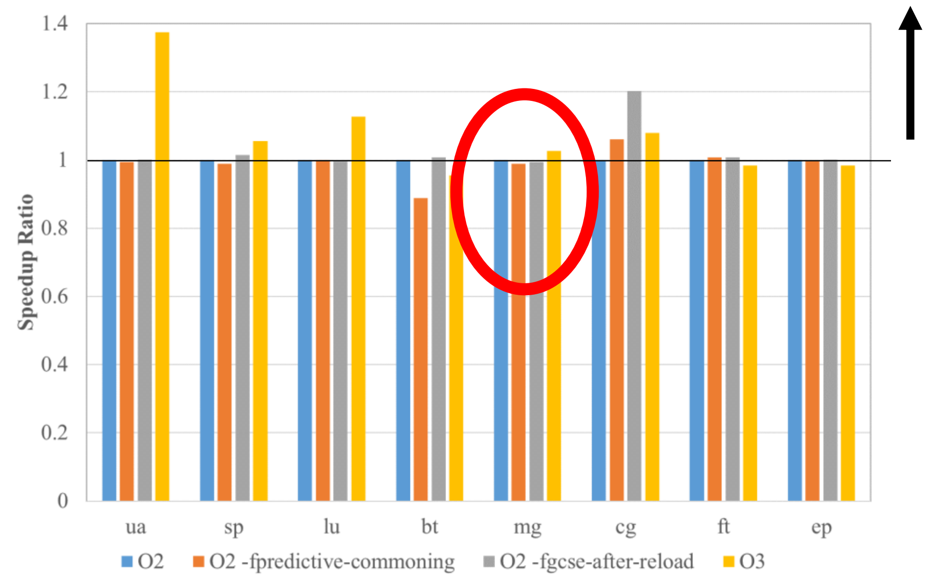
■ Effective Compiler Option Prediction

Compiler option selection = Performance optimization selection

- **O2 option flag** = almost all supported optimizations that do not involve a space-speed tradeoff.
- **O3 option flag** = more optimizations are turned on.

Higher is better





Size S **NAS Parallel Benchmark** **Size A**

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Penalty Weighted Geometric Accuracy

Definition of Average Prediction Accuracy

- Misprediction of compiler option flags **sometimes** leads to drastic performance degradation, but **other times not.**

  → Need to consider not only the misprediction count but also the **performance penalty** of each misprediction.

- Arithmetic mean of ratios such as normalized values can be misleading.

  → Use **Geometric Mean**, instead.

Penalty Weighted Geometric Accuracy (PWGA)

- Prediction accuracy with considering the performance penalty of misprediction.

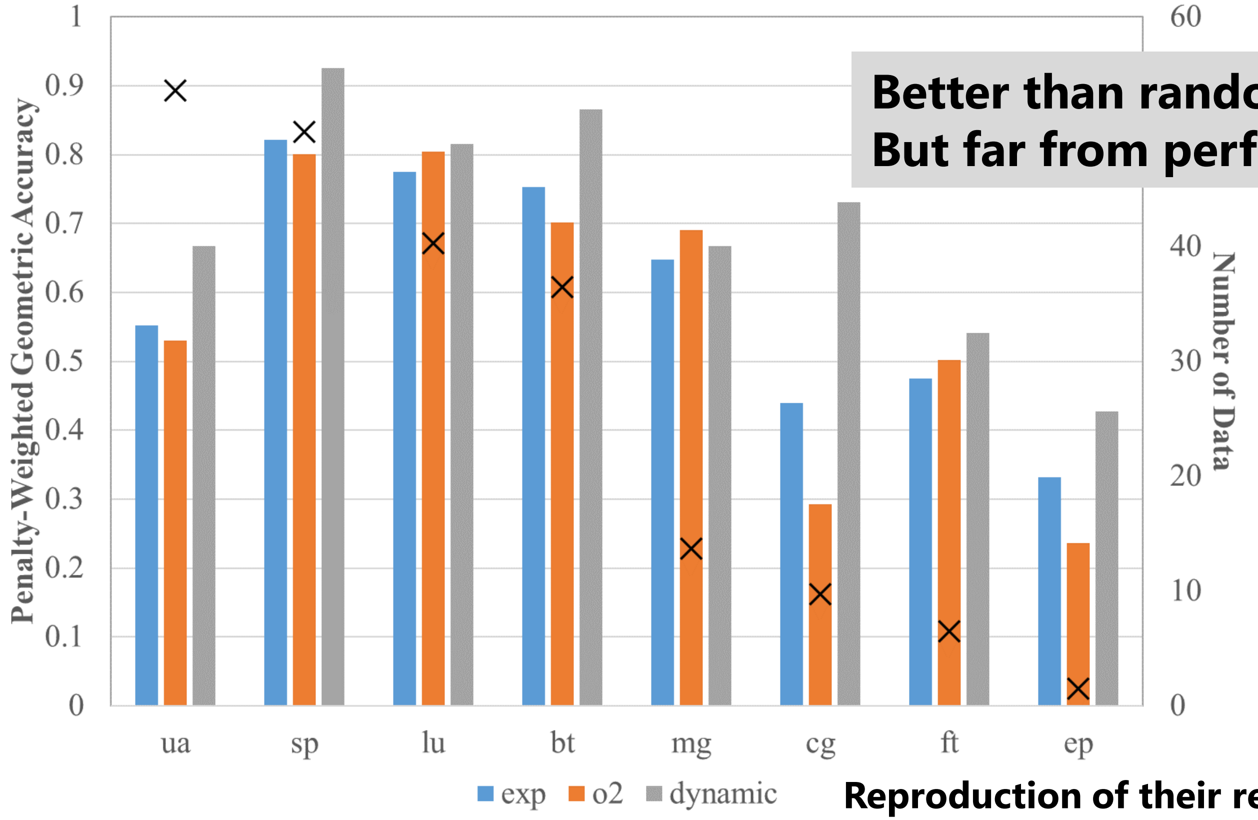
$$PWGA = \sqrt[N]{\prod_{i=1}^{N} \frac{T_{\mathrm{best},i}}{T_{\mathrm{pred},i}}}$$

Execution time with **best** compiler options

Execution time with **predicted** compiler options

Related Work

- **Prediction by machine learning with performance profiling information** (Cavazos+ 2007)



Better than random selection.
But far from perfect.

Reproduction of their results on our environment

How can we improve it?

■ Why not perfect?

- The number of training data is too small.
  - Only **263** loops are used for our experiment.
- The information about the code itself is not available.
  - Human experts also see the code to find the performance bottleneck to consider effective optimizations.

What happens **if the code information is available** for machine learning to predict effective compiler options?

Not so easy…

How can we express code structures as a vector?

- It's not easy to appropriately quantify the features

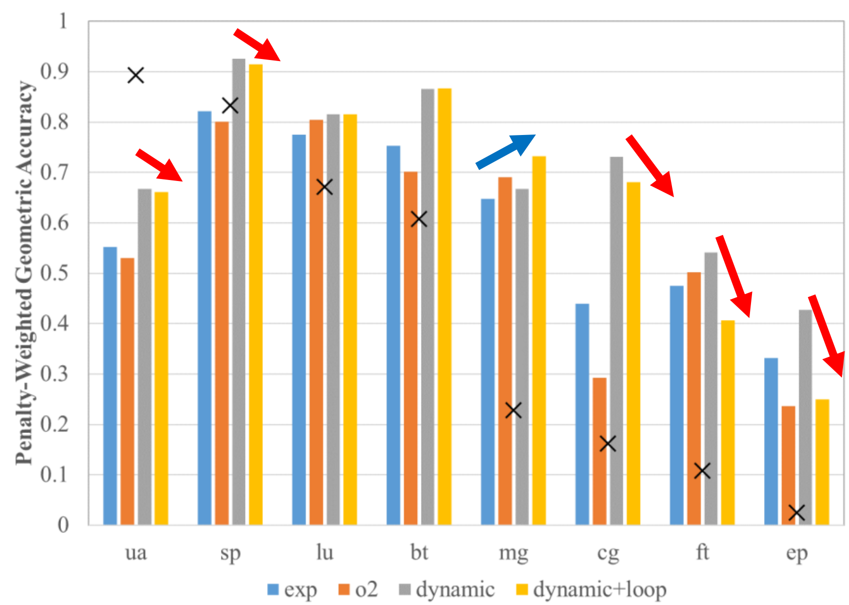
```
do k = 1, nk
  do j = 1, nj1
    do i = 1, ni1
      Y(j-g1+1+g2*(i-1)) = x(i,j,k)
    end do
  end do
  do j = 1, nj2
    z(i,k) = Y(g1+1+g2*(i-1))
  end do
end do
```

(a) A loop nest

Depth of a loop nest	3
The number of loop bodies	2
The number of arithmetic operations	9
The number of AST nodes	52
The number of array access operations	4
The number of `if` statements	0

(b) Predefined loop parameters

The accuracy is **degraded** by using the additional features.



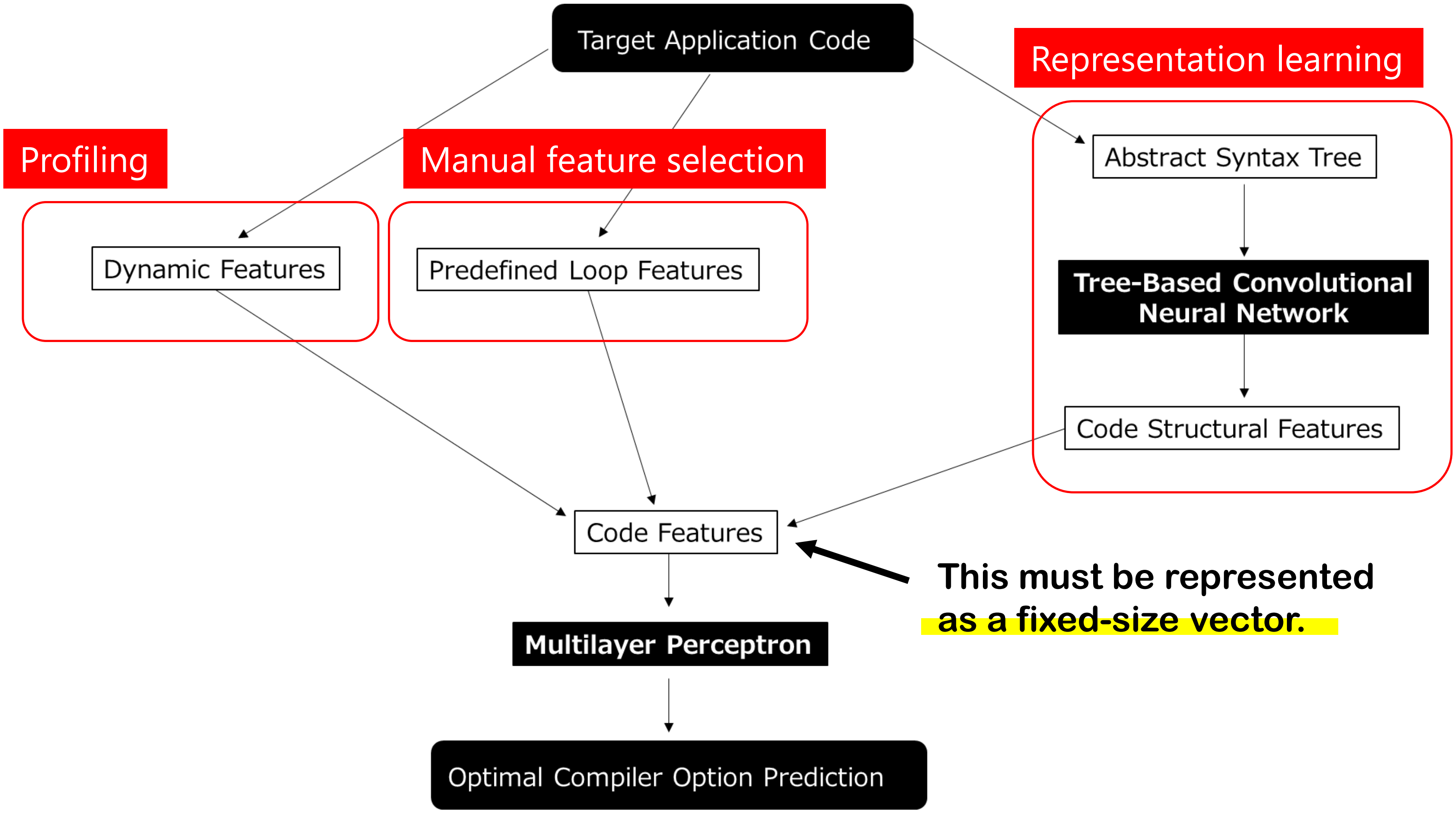
Manually-defined code features

Discovering Useful Features

■ Success in image recognition/classification

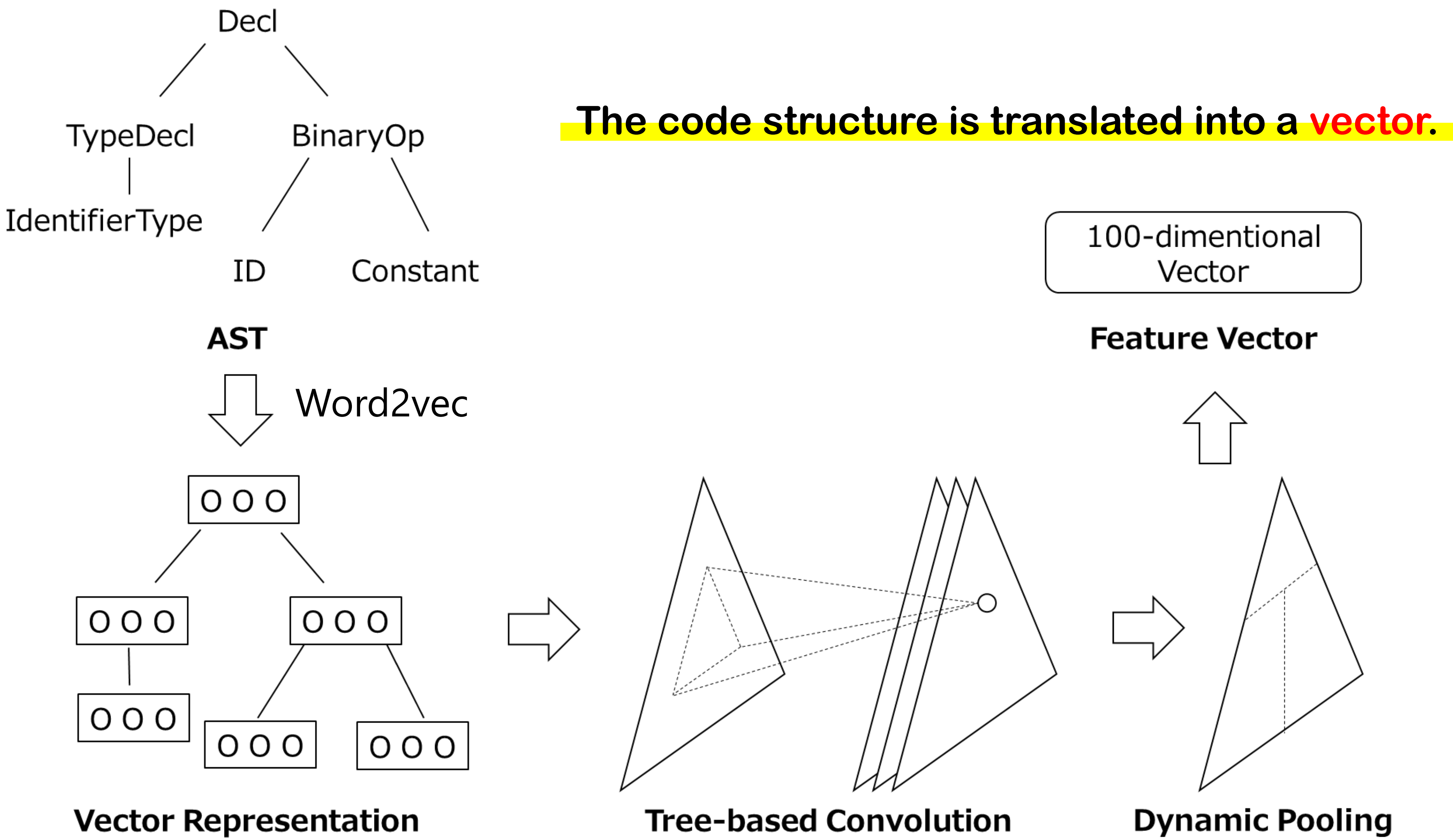
- Conventional approaches
  - Features of images are predefined.
  - **Feature selection** is the key to success.
- Deep learning (LeCun+ 2015)
  - **Feature learning/representation learning**
    - Machine learning can find not only underlying classification rules but also useful features for the classification.
    - Big data with high computing power are the key to success.


Use of code structural features



Tree-Based Convolutional Neural Network

The code structure is translated into a vector.



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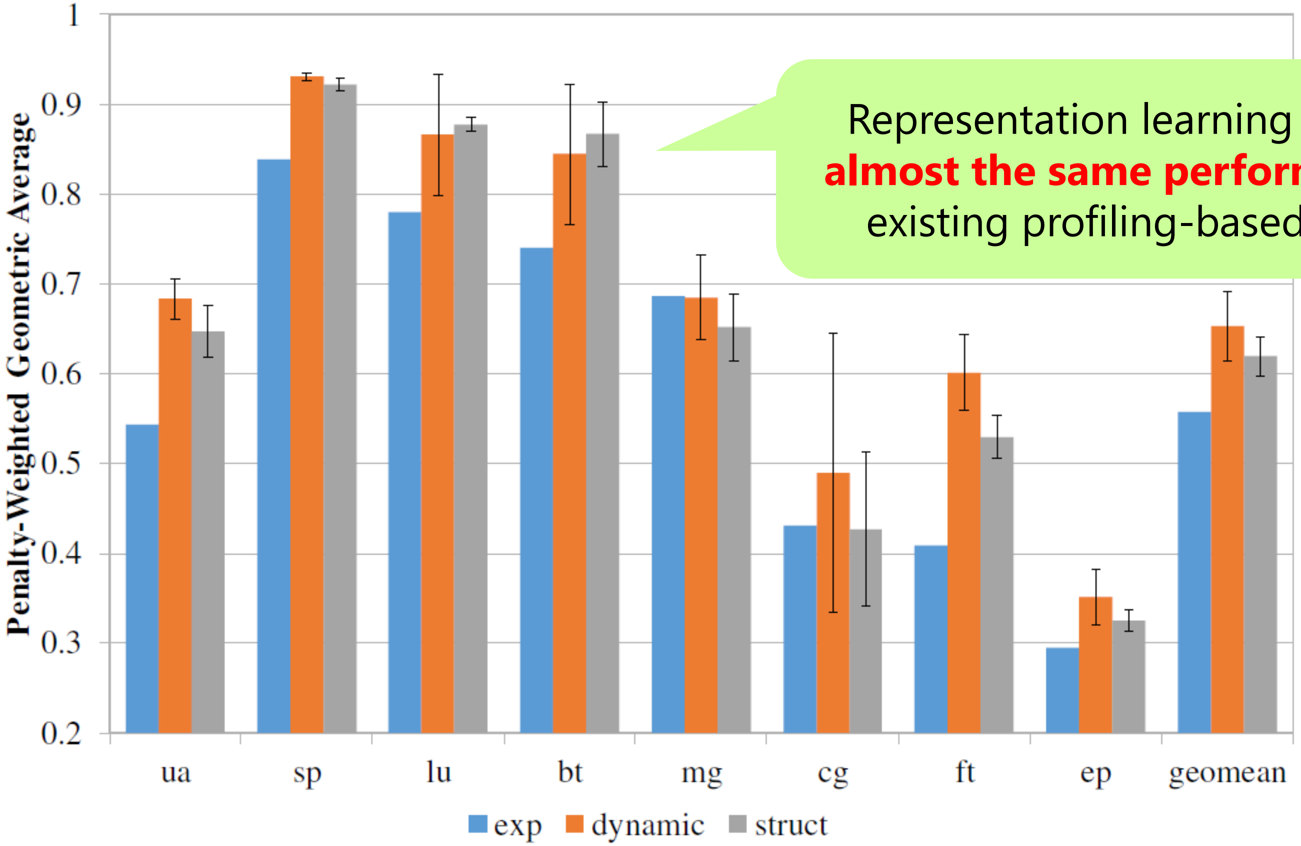
Experimental Setup

	Intel Xeon E5-2695v2
Peak Performance [Gflop/s]	230.4/socket, 19.2/core
Number of cores	12
Vector length/ SIMD width (double)	4
Cache size	L2:256KB/core, L3:30MB/socket
Memory bandwidth [GB/s]	59.7
Compiler	GNU Fortran Compiler 4.4.7
Performance Counter	PAPI 5.3.2

Cross-validation is performed for the evaluation.
Some of data are used for training and the others are for testing.

Randomly selected

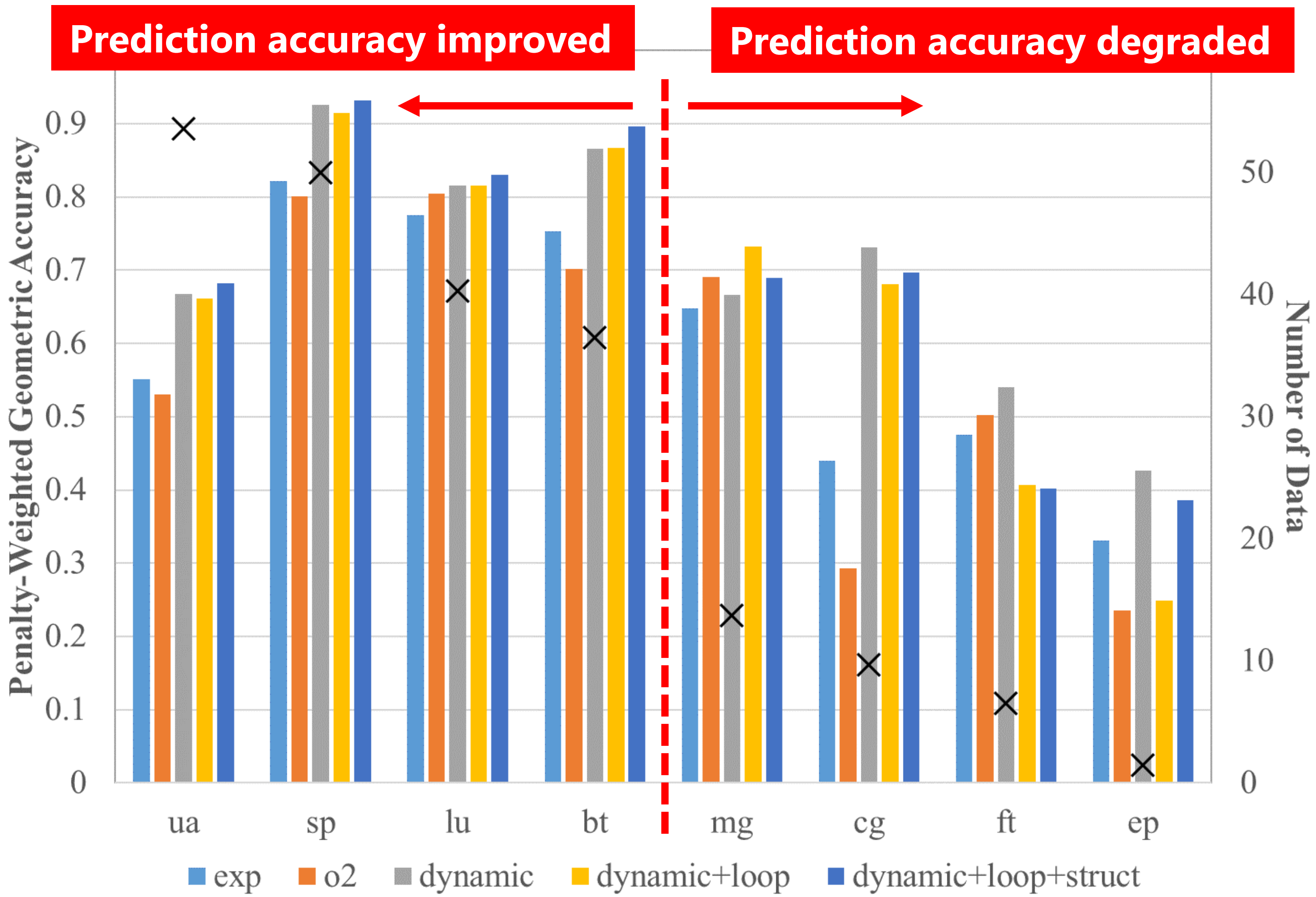
Prediction Using **Only** Code Structural Features



Representation learning can achieve **almost the same performance** as the existing profiling-based approach.

Representation learning can extract useful features from code structures.
→ A higher performance is achieved for some cases.

Using All the Features



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Conclusions

This work is still ongoing.

- Code structural features are used to predict effective performance optimizations
  - TBCNN is used to convert a code structure to a fixed-size vector so that it can discover useful features from training data.
- The prediction accuracy **improves** if the number of training data is **not too small**, but **degrades** if it is **too small**.
  - It is unclear why use of the code structural features differently affects the accuracy, depending on the number of training data.

Conclusion

- Use of code structural features discovered by representation learning is promising to improve the accuracy if an enough number of data are available.
  → Artificial training data generation (future work)

Acknowledgments

- **This work was partially supported by**
  - JST CREST Xevolver Project
  - DFG SPPEXA ExaFSA project
  - Grant-in-Aid for Scientific Research(B) 16H02822
  - Grant-in-Aid for Challenging Exploratory Research 15K12033

  - The performance evaluation results were obtained using supercomputing resources of the **Cyberscience Center, Tohoku University.**