A Cost Model for Compilers Based on Transfer Learning

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The Seventeenth International Workshop on Automatic Performance Tuning (iWAPT2022)

Outline

- **Introduction**
- **Proposed Method**
- **Dataset and Evaluation Metrics**
- **Evaluation and Results**
- **Discussions and Conclusions**

Introduction

■HPC system architectures are getting more complicated

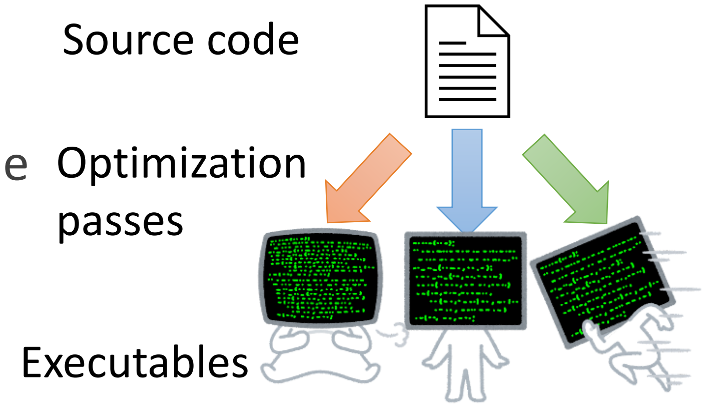
- Automatic optimization by compilers, ***compiler optimization***, is becoming more crucial

■Compilers perform code optimizations for high-performance

- Various optimization passes are implemented and can be applied automatically
- Sometime applying these passes might even decrease the performance depending on the target system and application

■Compiler needs to select which passes to apply to maximize the performance

- In what order to apply them? / What parameters to use?
- Need to evaluate the candidates of optimization passes
  - Execution a huge number of candidates results in long compilation time



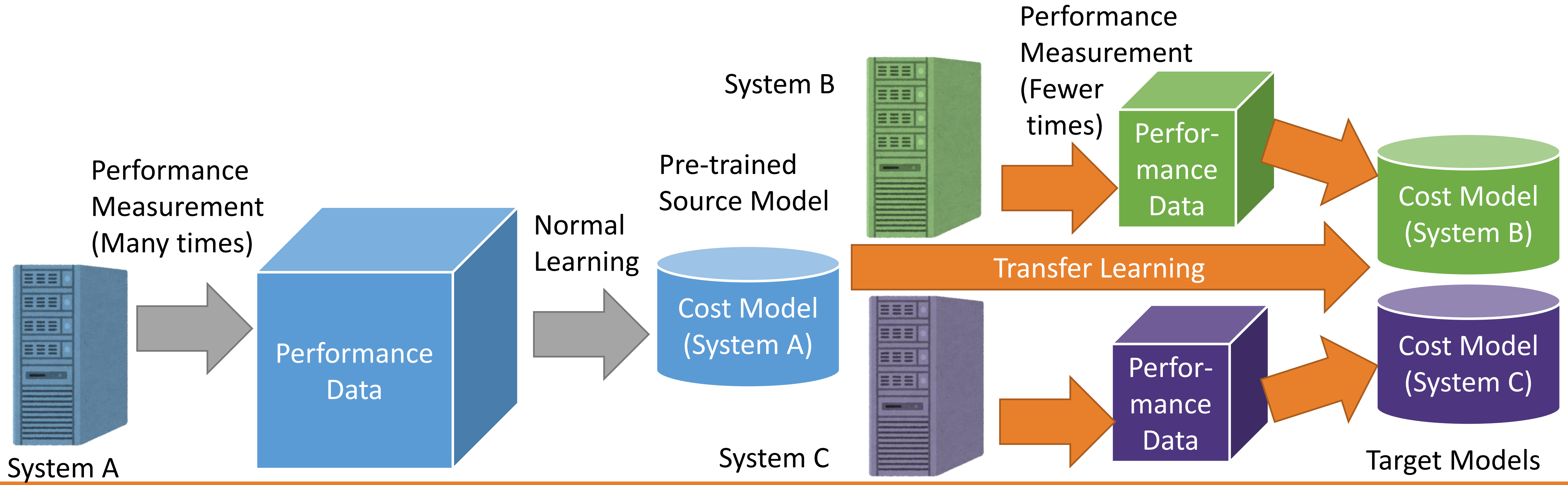
Cost Model for Compiler Optimization

- **Cost models are used to predict the performance improvement without running the program**
  - Machine learning is often used to empirically construct cost models in a data-driven way
  - Analytical modeling of a modern complex computing system is infeasible

- **Cost model based on machine learning**
  - Built from performance data, which are collected
    by running a huge number of programs on the target system
    - Time-consuming
  - Many cost models based on machine learning is specialized for training system
    - Users need to collect performance data in their systems to build their own models

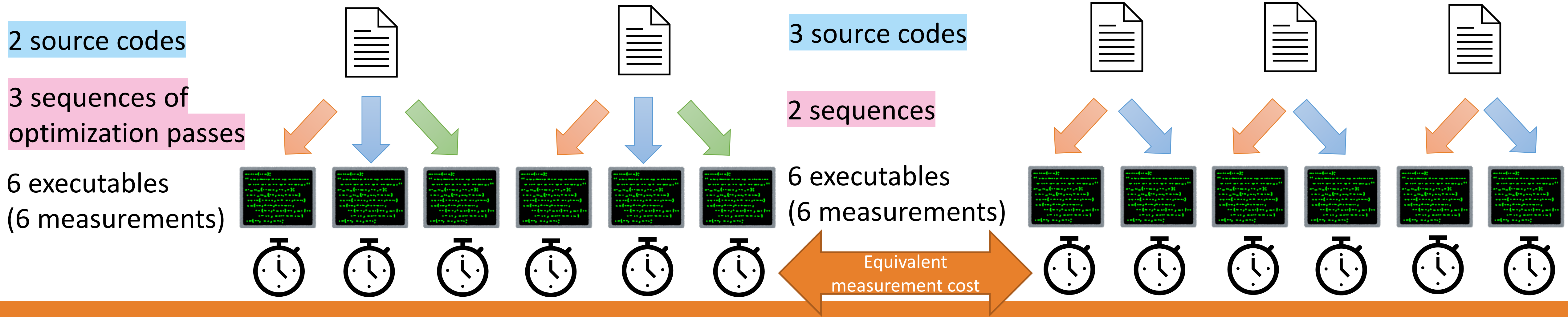
Overview of the Proposed Method

- **Building a cost model of a target system from as few data as possible**
  - Adopts transfer learning to build a cost model of the target system from a pre-trained cost model, ***a source model***, of another system
  - Can build build multiple models from a single source model with fewer data



The Cost of Building a Training Dataset

- A data-driven approach to build a cost model needs a large dataset
- The cost of building a training dataset is strongly correlated to the number of times to run programs on the target system
  - A program is defined by its source code and a sequence of optimization passes
    - Each sample in training data is a pair of a program and its performance on the target system
  - It is potentially possible to improve the prediction accuracy by carefully selecting training data with the same number of training data



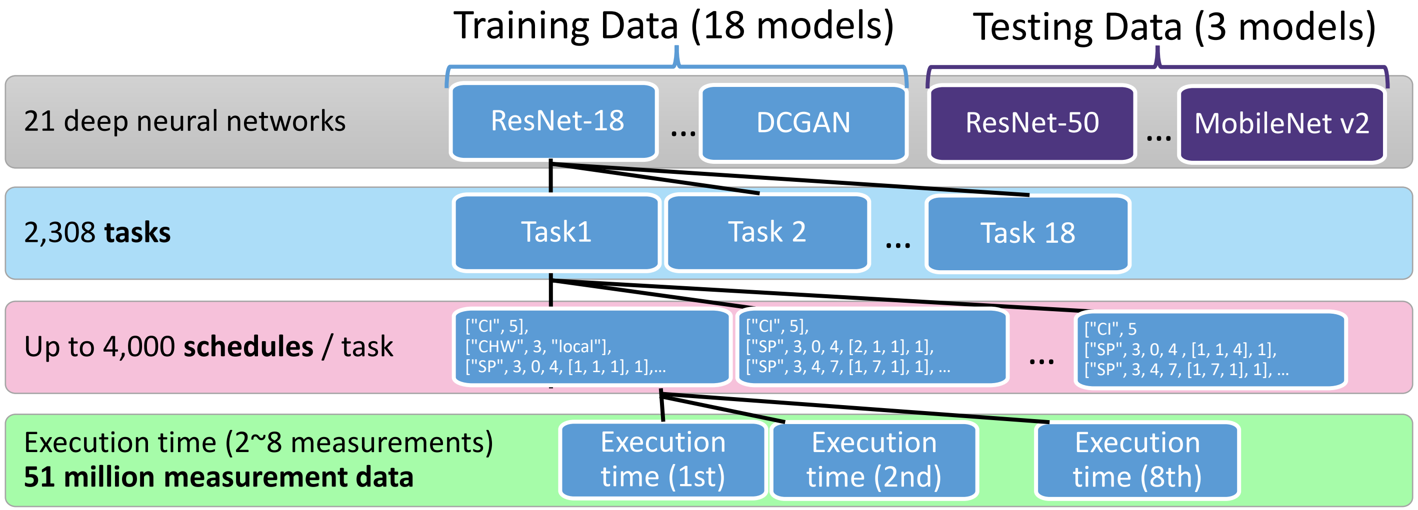
Dataset for the Evaluation

■TenSet [1] : A large-scale dataset to train the cost model for TVM

- Consists of trained deep neural networks and sequences of optimization passes
  - Neural networks are divided into subgraphs called *tasks*
  - TVM compiler optimizes the whole network by applying a sequence of optimization passes called a ***schedule*** to each task
- Annotated with performance labels on 4 CPU and 2 GPU systems
  - 4 CPU systems : Xeon E5-2673, Xeon Platinum 8272, AMD EPYC 7452 and ARM Graviton2
  - 2 GPU systems : NVIDIA Tesla T4 and NVIDIA Tesla K80

■We use DNNs in two ways

- To build a cost model
- A program to be optimized



Evaluation Metrics

■Learning efficiency of transfer learning

$$\frac{\text{\# of programs required to reach the baseline performance by transfer learning}}{\text{\# of programs used to train the baseline model}}$$

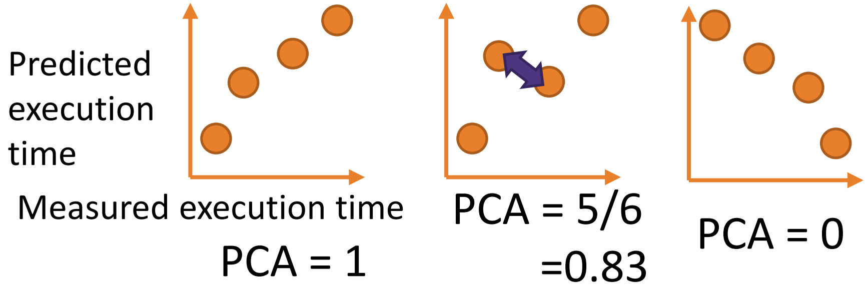
- Not include # of training data used to train the source model in the numerator

■Prediction accuracy (Pairwise Comparison Accuracy)

- Predicts performance of N programs
- M: # of pairs of which the predicted and measured performance values match

$$\mathrm{PCA} = \frac{M}{{}_N C_2} = \frac{M}{N \cdot (N-1)/2}$$

- The cost model with PCA close to 1 will be able to select a better optimization pass



Overview of the Evaluation

■ **To achieve higher prediction accuracy with less training data**

- Source model selection
- Transfer learning technique
- Training data selection

■ **Using the model trained on a small number of data, optimize the program and evaluate its performance**

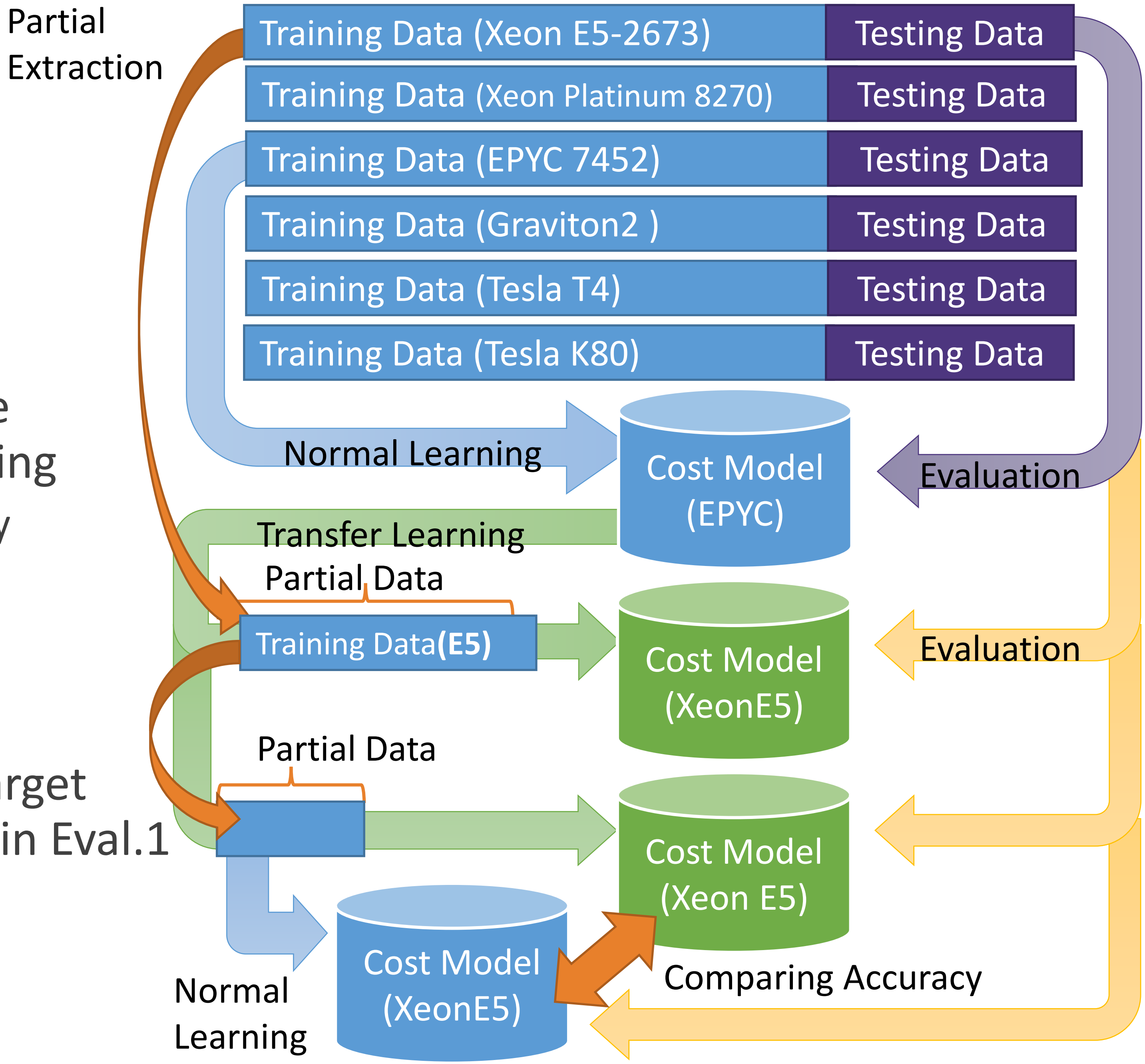
Evaluation Setup

■Eval.1: Build baseline models

- Train six cost models using all training data on the six systems.
- Test on the data obtained from the same/different systems from training
  - Baseline models : Targets of Accuracy
  - Source models : Initial state of TL

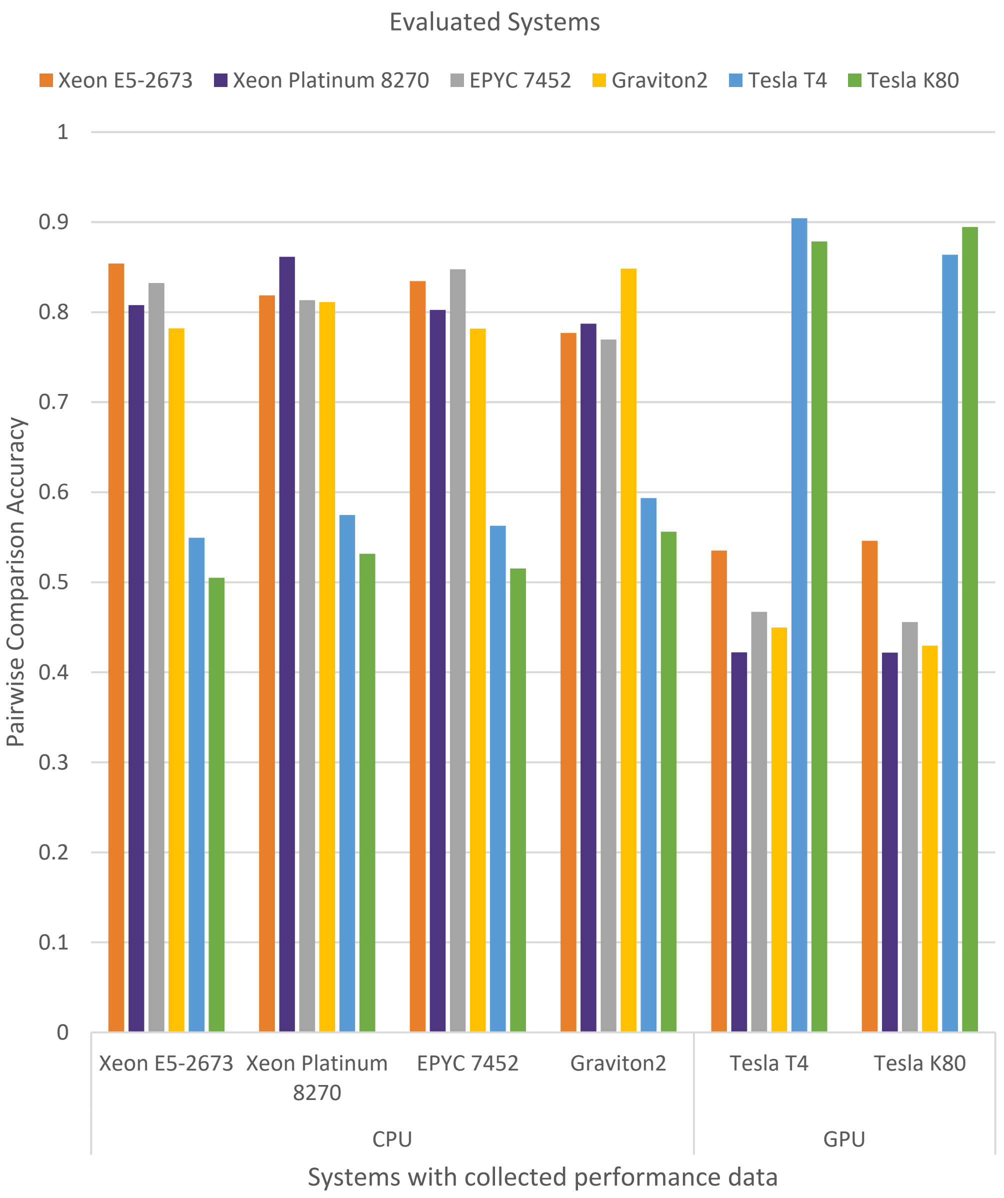
■Eval.2: Transfer learning

- From partial training data of the target system, re-train other five models in Eval.1
- Target systems
  - CPU system, Xeon E5-2673
  - GPU system, Tesla T4



Results of Eval.1

- **Baseline/Source model**
- **Testing data are obtained from the same/different systems from training data**
  - Cost models trained for each system
    - Highest PCA for each sysytem
  - Cost models trained for other CPU systems
    - Lower PCA, differences even between models
  - Cost models of different architecture systems
    - PCA is around 0.5, which is equivalent to random
- CPU performance prediction uses different features than GPU performance prediction
  - Different architectures could need different program features for prediction

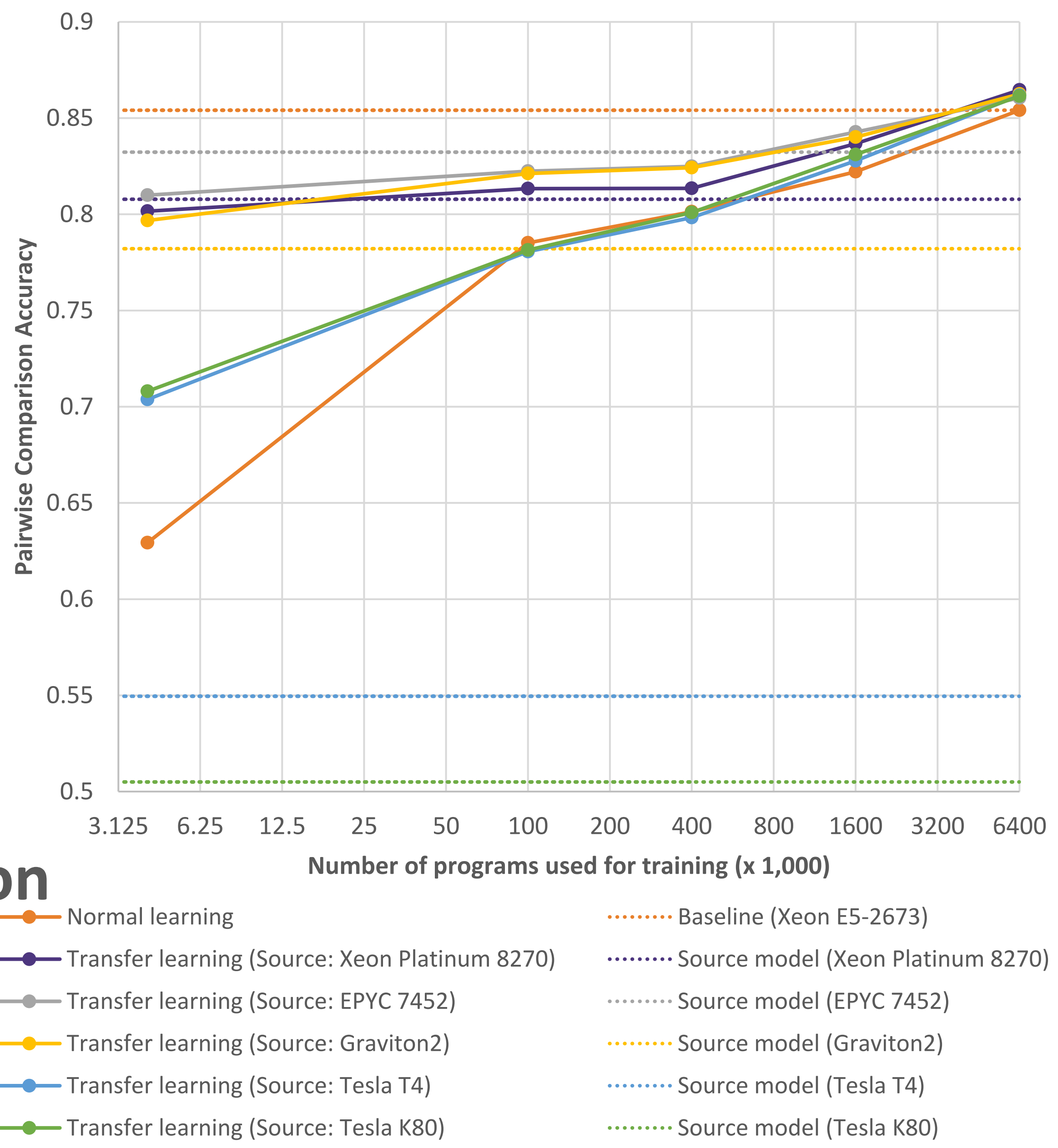


Results of Eval.2

■**Target system : Xeon E5-2673**
- Normal learning
- Transfer learning
- Baseline model
- Source models

■**Single task (4,000 programs)**
- Transfer learning shows a higher PCA

■**Selecting the most accurate source modelcan finally achieve high prediction accuracy with less training data in TL**



Transfer Learning Technique

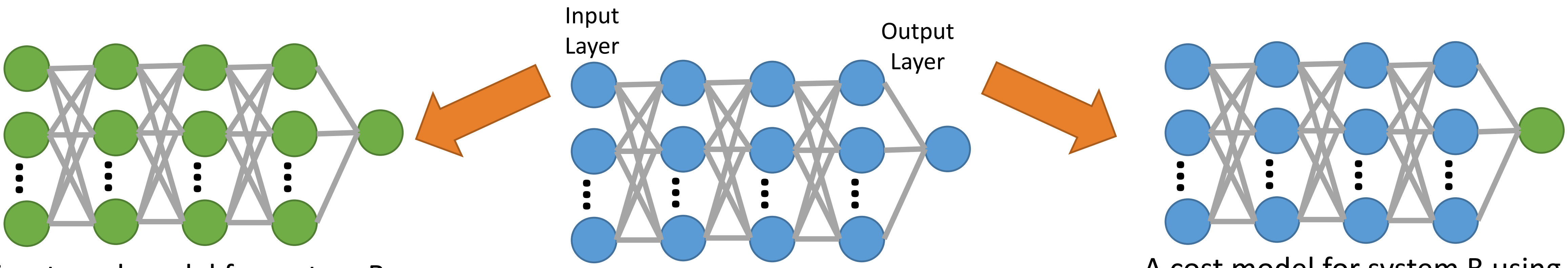
Use 5-layer perceptron

■Fine-tuning (Eval.2)

- Updates all layers in the same way as in normal model learning where network weights are initialized randomly
- The same accuracy can be expected if enough training data are available

■Feature Extractor (Eval.3)

- Retains the weights in some layers of the source model and update only other layers during training
- Reduces the degree of freedom of the network, faster convergence



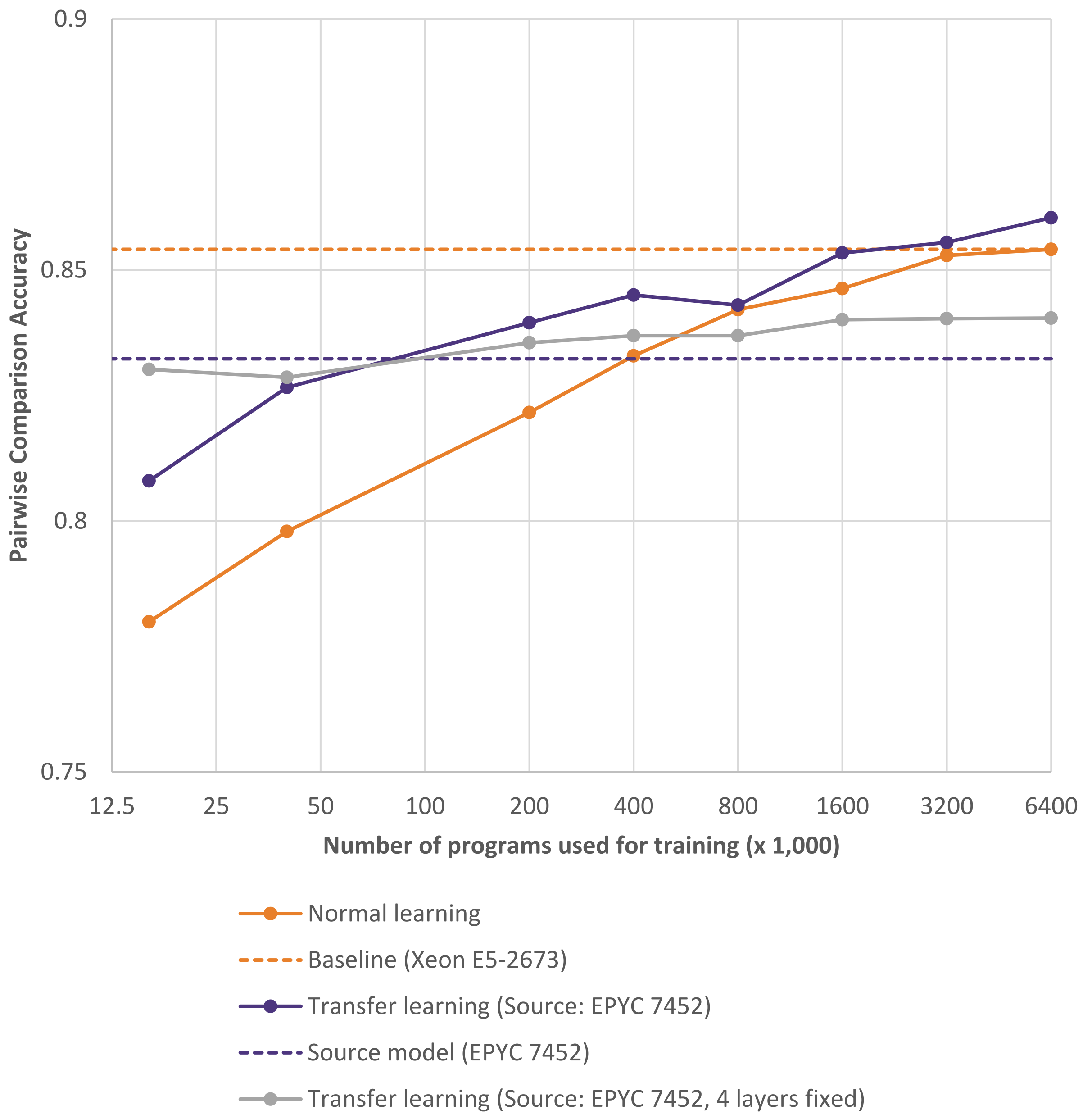
A fine-tuned model for system B

A pre-trained model for system A

A cost model for system B using the feature extractor of A

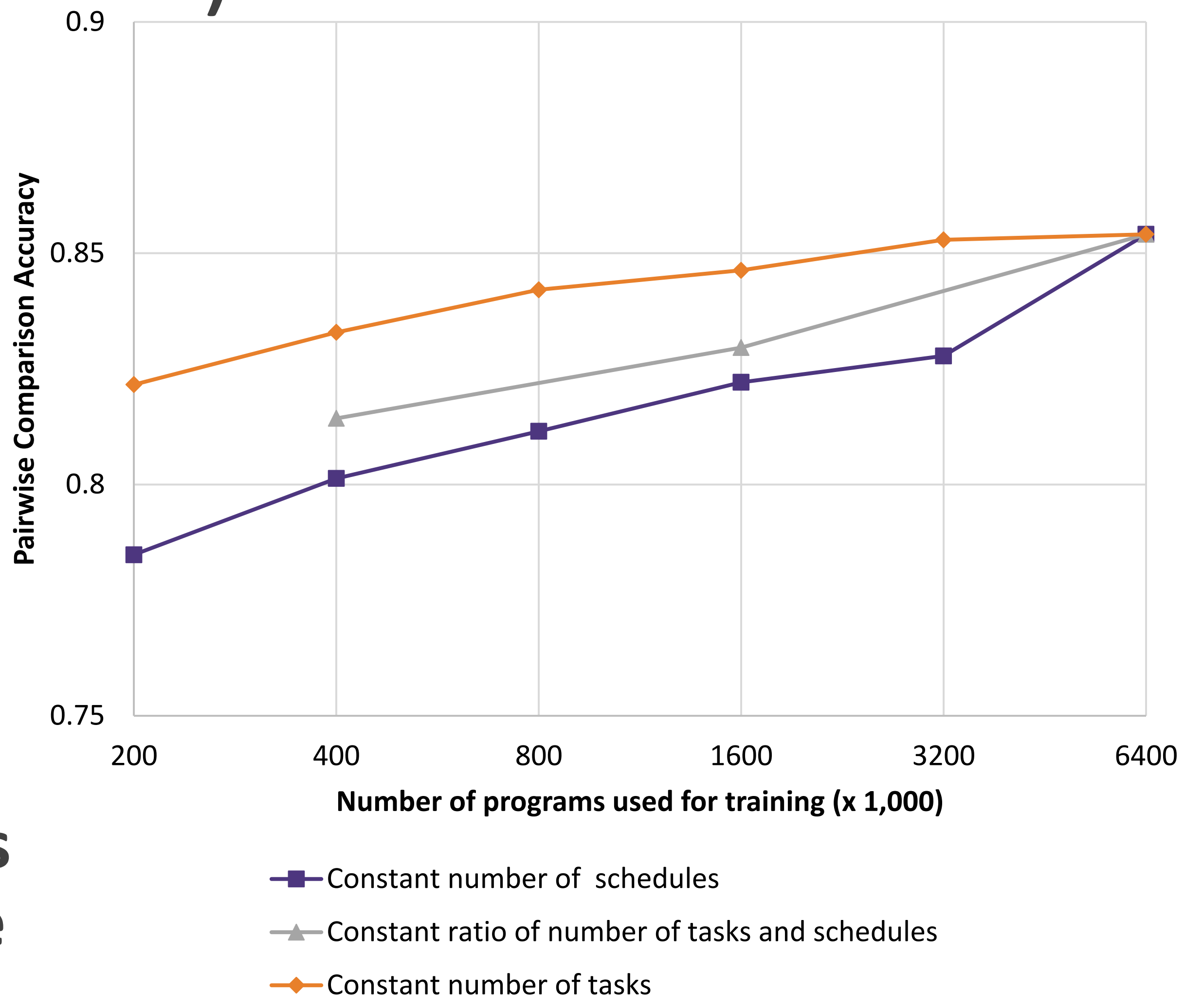
Results of Eval.3

- **Fixed four layers as feature extractor and updated only single output layer**
  - Source : EPYC 7452
  - Target : Xeon E5-2673
- **The accuracy saturates at a lower value**
  - Because the number of weights tuned for the target system is smaller
- **Fine tuning is better when a sufficient amount of data are available**
  - But the feature extractor approach could be one option when only few data are available



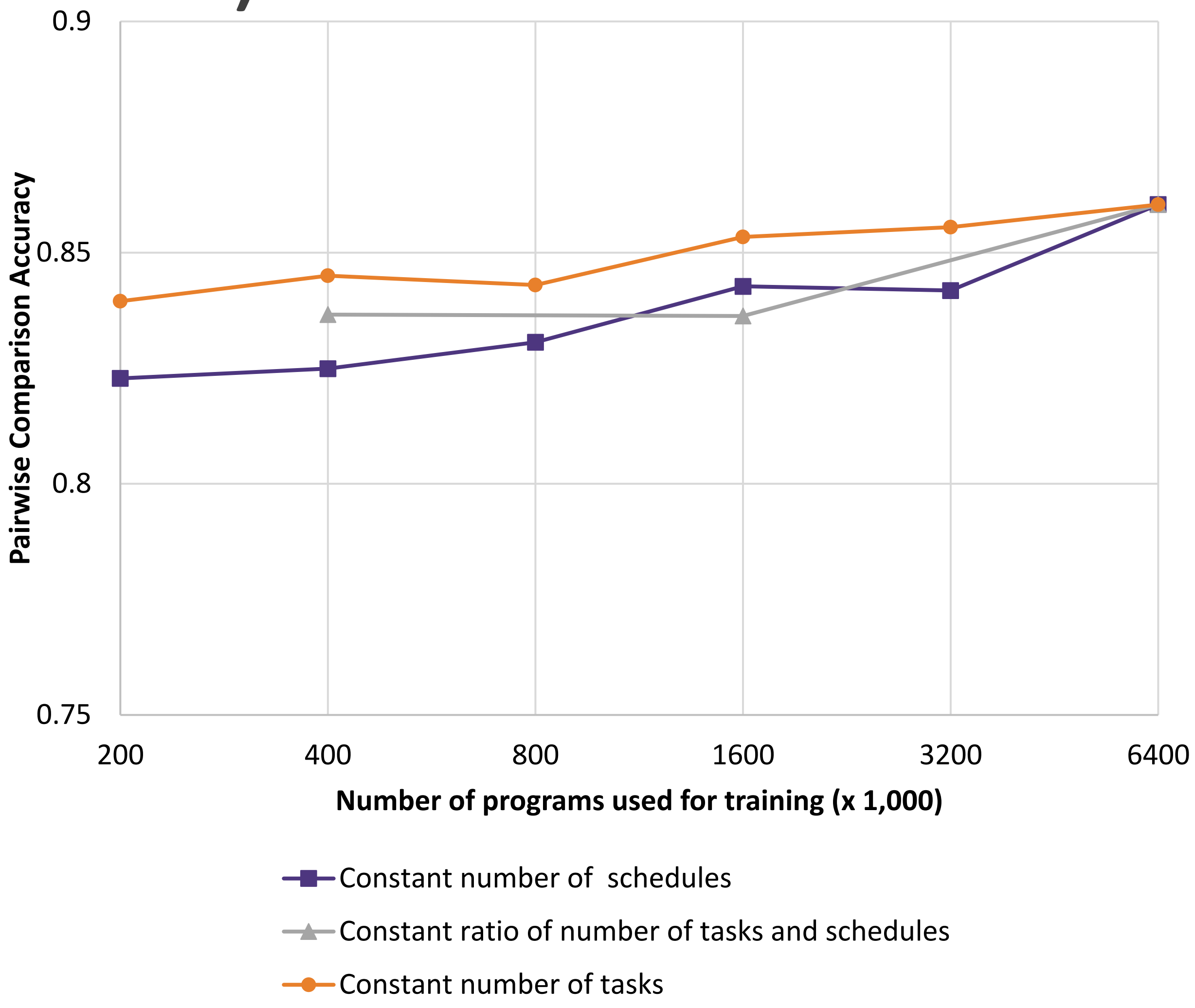
Training Data Selection (Eval.4)

- Compared three methods for reducing the training data in **normal learning**
  - (1) the number of schedules is fixed to 4,000 and the number of tasks is reduced by half
  - (2) the number of tasks is fixed to 1,600 and the number of schedules is reduced by half
  - (3) the number of programs and tasks is reduced by half respectively
- **A higher priority to getting more tasks achieve higher accuracy even with the same amount of performance data**



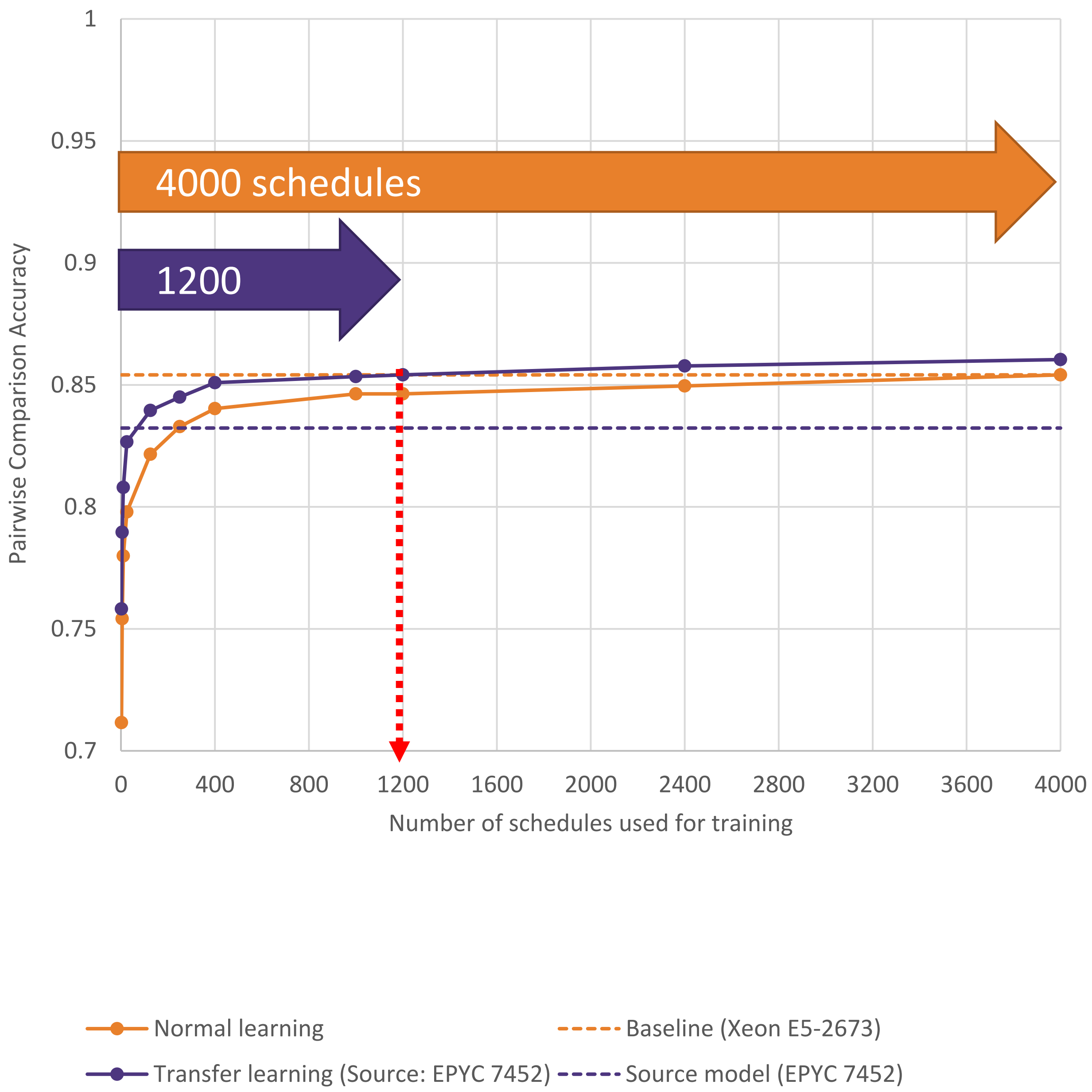
Training Data Selection (Eval.4)

- Compare three methods for reducing the training data in **transfer learning**
  - Source : EPYC 7452
  - Target : Xeon E5-2673
- Unlike normal learning, the decrease in accuracy is small when reducing data
  - Source model is trained with all the available data of EPYC
  - Learns program features useful for prediction very well
- **A higher priority to getting more tasks achieve higher accuracy**



Learning Efficiency

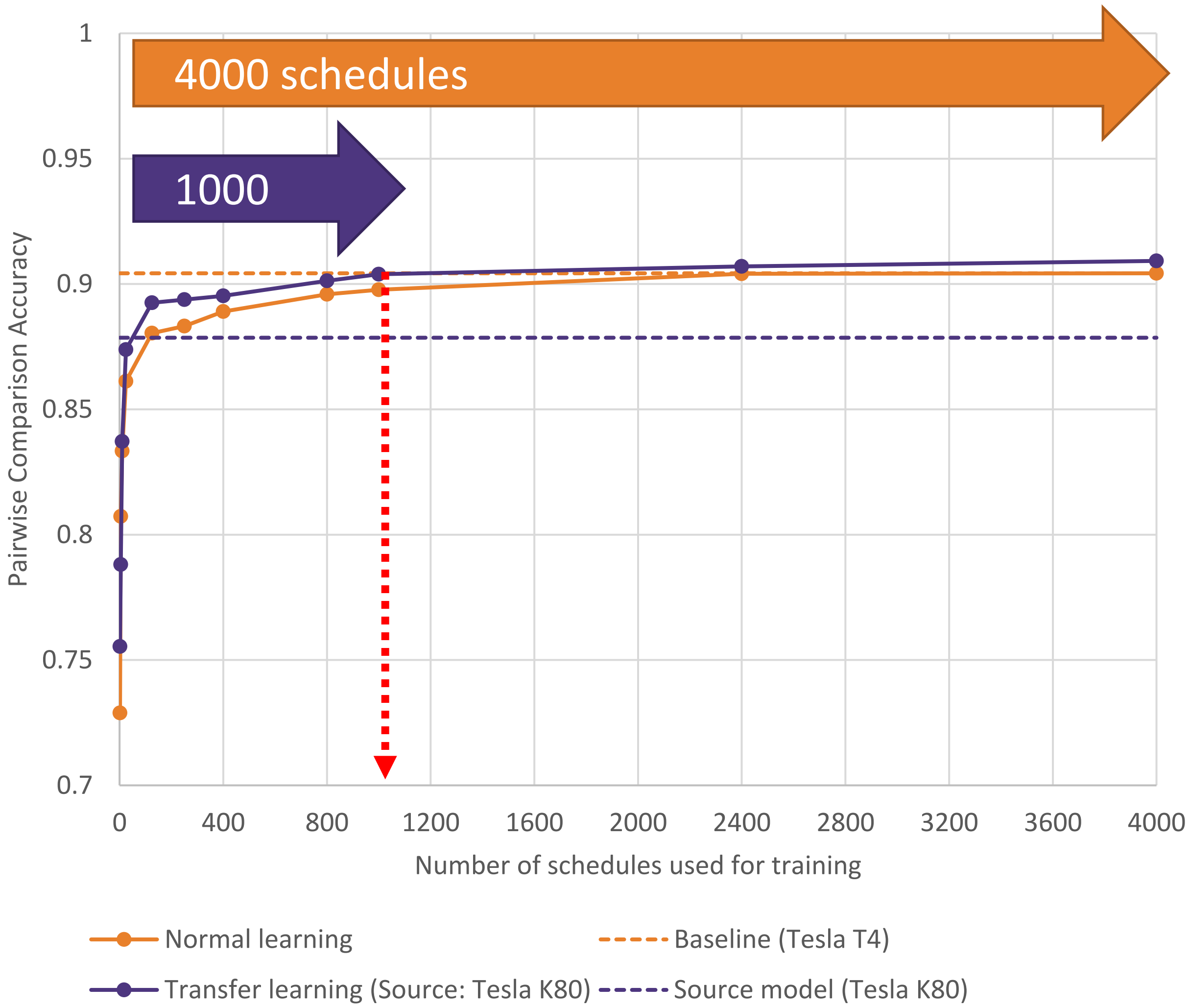
- Construct a cost model with the same prediction accuracy from a smaller number of training data
  - Source model with the highest PCA
  - Fine tuning is performed to update all layers
  - Fix the maximum number of tasks to 1,600, gradually increase the number of schedules
- TL requires only about 1200 to achieve the same accuracy as normal learning
  - which is 30% of the baseline model



Learning Efficiency

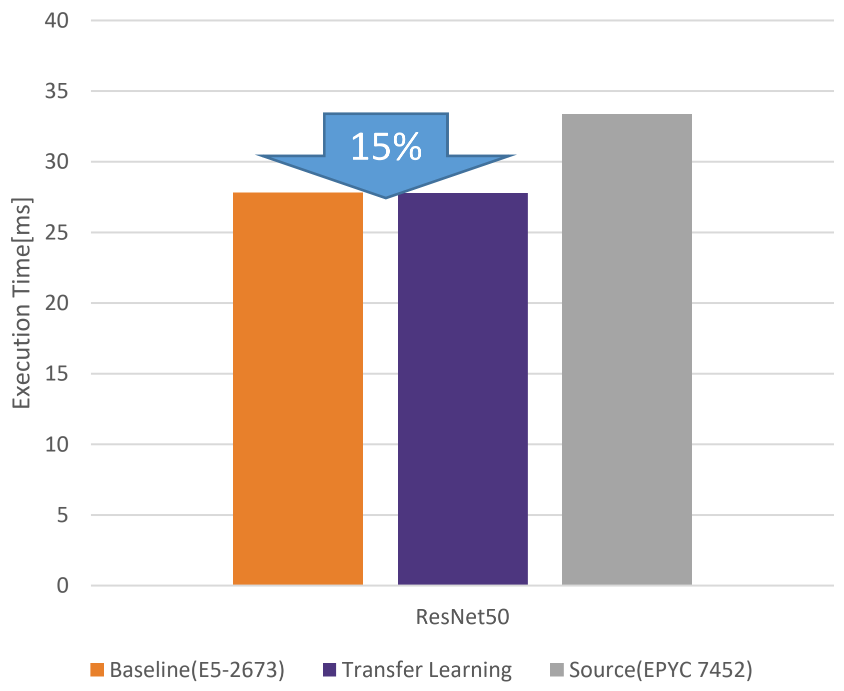
- TL model of Tesla T4
  - Achieves the same prediction accuracy using 1,000 schedules which is 25% of the baseline model

- The proposed method is effective in reducing not only the amount of data but also training time
  - TL can reduce the execution time by 78% to achieve the same accuracy



Program Performance

- Optimize a pre-trained inference model, ResNet-50 for Xeon E5-2673
  - Baseline model
  - Transfer learning trained with 30% data
  - Source Model
- The transfer learning model achieves the same reduction in inference time as the baseline model
  - The optimized inference models achieved a 16% reduction in execution time
- The model built from a small amount of performance data achieves program speedup as the model trained with a large amount of data



Conclusions

- We proposed a data-driven method to build cost models for compiler optimization
  - Focus on reducing the performance data of a target system, by using transfer learning
  - Proposed method can significantly reduce the training data
  - TL can make it more affordable to build a cost model for compiler optimization in a data-driven way

- Future work
  - Use this approach also to other applications while further improving the accuracy with less training data
  - Explore a way to provide even higher performance in a variety of combinations of systems and applications.

Acknowledgments

■ **This work is partially supported by**

- MEXT Next Generation High-Performance Computing Infrastructures and Applications R&D Program “R&D of A Quantum-Annealing-Assisted Next Generation HPC Infrastructure and its Applications”
- JSPS KAKENHI Grant Number JP20H00593