Automatic Selection of Machine Learning Models for WCET-aware Compiler Heuristic Generation

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PREDATOR

Outline

- **Introduction**
  - Motivation for WCET-aware Compiler Optimizations
  - Compilers and Machine Learning
- **Current Workflow for MLB Heuristic Generation**
- **Automatic Model Selection**
  - Learning Algorithms
  - Performance Evaluation
  - Parameter Optimization
- **Case Study: Loop Invariant Code Motion**
- **Experimental Environment & Results**
- **Conclusions & Future Work**

Motivation

- **Embedded Systems used as Real-Time Systems**
- **Worst-case execution time (WCET) is a key parameter**
  - Crucial for safety-critical systems
  - Required for task scheduling
  - Helps to design hardware platforms
- **Estimated by static timing analyzers**

Meeting Real Time Constraints

☹ Trial-and-error approaches

☺ Automatic WCET reduction by compilers

- Integration of timing analyzer into compiler framework

Compiler Developers' Struggle

- **Development of compiler heuristics tedious**
  - Requires expertise and extensive trial-and-error tuning
  - Complicated by advent of complex architectures
    - Abstract models don't exploit target features
  - Optimizations performed in a sequence
    - Interference with possible conflicts

- Which choices do we have?
  - ☹ Use conservative assumptions missing optimization potential
  - ☹ Tune heuristic for a fixed optimization sequence

Machine Learning Based Compiler Heuristics

- **Finding relevant information in high dimensional space**
- **Help to understand and control complex systems**
- **ML approaches allow automatic heuristic generation**

<*static features*> → *heuristic parameters*

Benefits

- Learning results enhance flexibility of compiler
    - Automatic *re-learning* for new target / optimization sequence
- Reduce effort for compiler development

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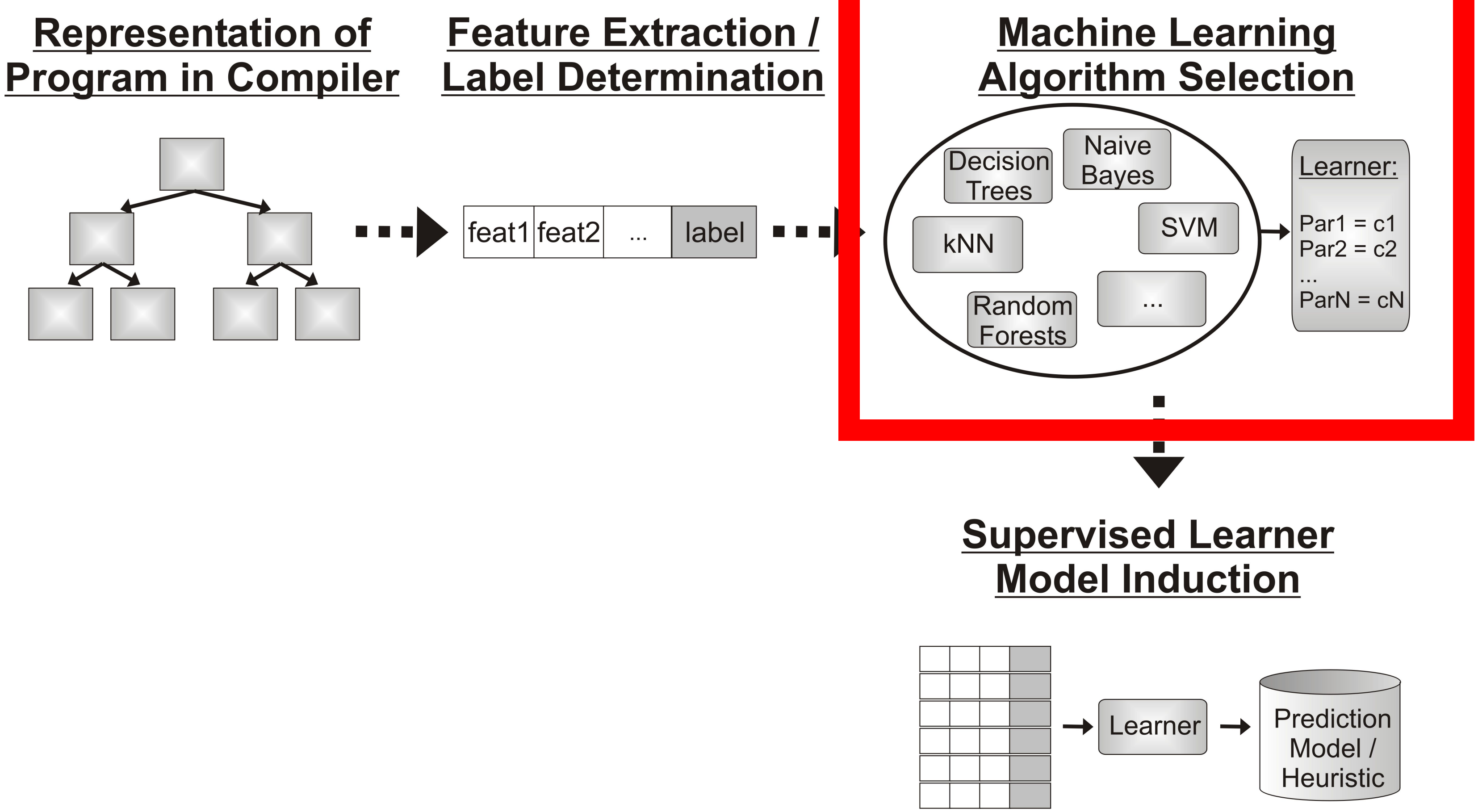
Current Workflow for Heuristic Generation



Problem Specification: Model Selection

- **Goal: Find induced model with best performance**
- **But**
  - Complex structure of learning algorithms
  - Non-trivial impact on prediction => performance
- ➢ **Prediction of performance of induced models infeasible**
- ➢ **Evaluate generated heuristics using cross-validation**

☹ Current approach: Trial-and-error

- Time-consuming, error-prone & benefits of further tuning?

- Few combinations of learner/parameters tested

Effort shifted from manual tuning to model selection

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Automatic Model Selection

Systematic evaluation of induced models by different learners and parameter settings

Learning Algorithms

- **Decision Trees: Split training set into sub-trees**
  - Splitting criterion, depth of trees, min. # examples in leaf …
- **Random Forests: Sets of decision trees + majority vote**
  - # of trees, # randomly chosen features for node split …
- **Linear SVM: Find hyperplane to separate examples**
  - Soft margin for misclassification
- **SVM with RBF kernel: separation based on Gaussian dist.**
  - Soft margin for misclassification, Gaussian's width
- **k-Nearest Neighbor: based on nearest neighbors classes**
  - Number of considered neighbors
- **Naïve Bayes: probabil. classifier based on Bayes' theorem**

Performance Evaluation (1)

- **Standard performance measurement: Accuracy**
  - Comparison of predicted and real class using *N*-fold cross validation

- **Goal for embedded RT systems: WCET minimization**

Accuracy the right measure?

Performance Evaluation (2)

Example

- 4 Optimization Decisions:

	YES	NO
A	-10	0
B	-10	0
C	-20	0
D	50	0

Scenario 1:

- *A, B, C* correct
  - **-10**
  - **-10**
  - **-20**
  - **50 => 10**
- WCET increase
- Accuracy: 75%

Scenario 2:

- *C, D* correct
  - **0**
  - **0**
  - **-20**
  - **0 => -20**
- WCET decrease
- Accuracy: 50%

➢ **Accuracy not suitable performance measure**

Performance Evaluation (3)

- Benchmark-wise cross-validation based on WCET

for all algorithm *alg*
  for all parameter settings *set*
    performance = 0
    for all benchmarks *b* in training set E {
      generateHeuristic$_{MLB}$(alg,s, E \ b)
      WCET$_{MLB}$ = computeWCET$_{MLB}$(b)
      performance += **(WCET$_{MLB}$ / WCET$_{ref}$)**
    }

    evaluation[*alg*][*s*] = **performance** / |E|

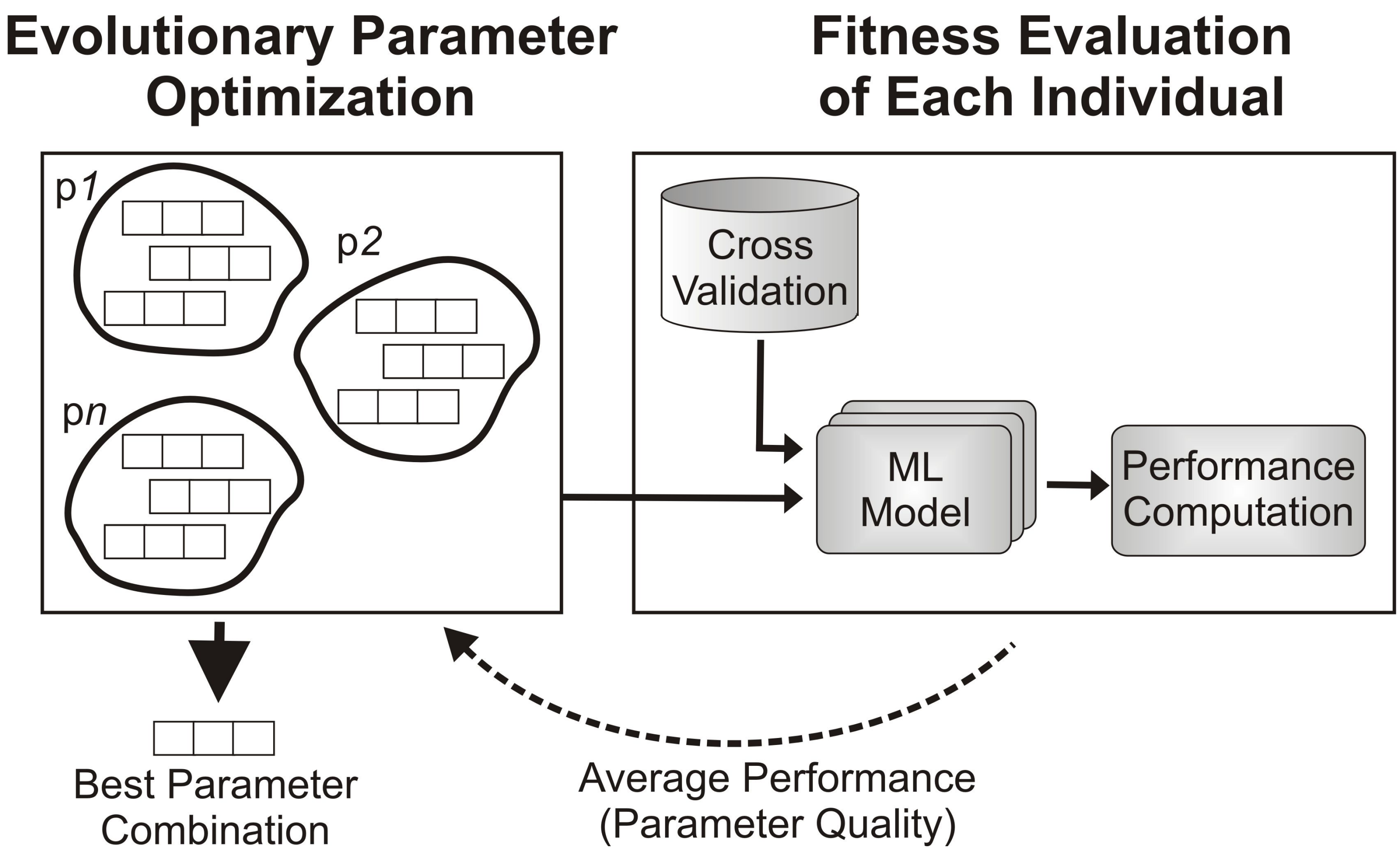
Parameter Optimization

- Exhaustive search over all combinations of user-defined learner parameters not feasible

Our solution: Evolutionary search

- Genetic algorithm
- Represent each parameter combination as individual
- Performance (fitness) calculation based on WCET
- Reproduction via one-point crossover & mutation

Workflow of Parameter Optimization



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Loop Invariant Code Motion (LICM)

- **Well-known ACET optimization**
- **Moves *loop invariant* computations outside the loop**
- **Can be applied at source code or <u>assembly level</u>**

Positive Effects

- Reduced execution frequencies of shifted invariants
- Positive effects on instruction cache
- Shortens variable live ranges ➔ decreased reg. pressure

Negative Effects

- Moved computations increase register pressure
- Lengthen other CFG paths (above zero-trip test, …)

Heuristics for LICM

- Heuristics for LICM not trivial
  - register pressure dilemma …
- No heuristics in compiler literature

😐 LICM performed whenever possible

Automatic Generation of LICM Heuristics using Supervised Machine Learning

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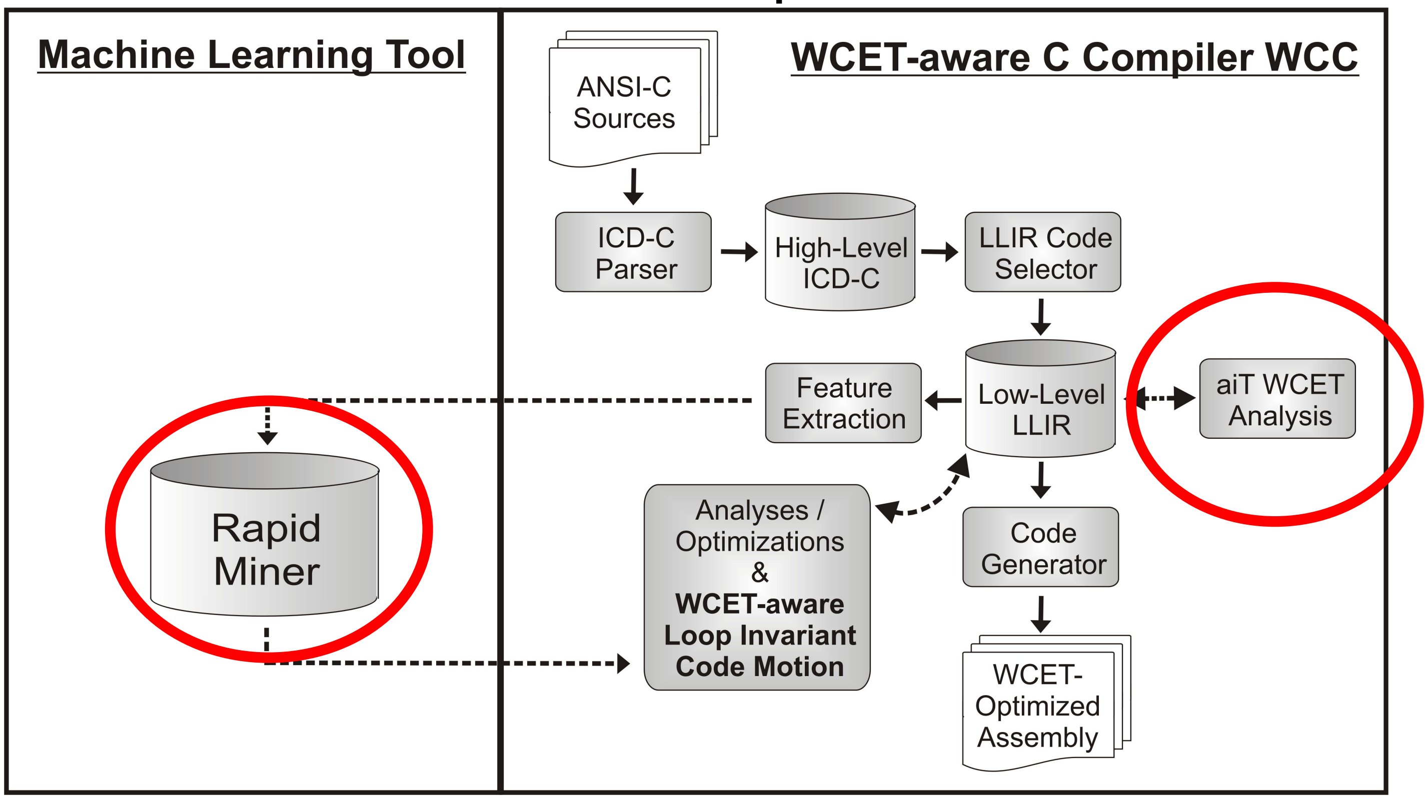
Compiler Framework

- WCC *– WCET-aware C compiler for Infineon TC1796



[*http://ls12-www.cs.tu-dortmund.de/research/activities/wcc/]

Experimental Setup

- **39 Benchmarks from DSPstone, MediaBench, UTDSP …**
- **3491 examples (LICM instructions)**
- **73 static features to characterize loop-invariant instruction or its environment**
  - Structural features, LTA-related, loop-related, reg. pressure, …
  - Large number of features to support generality of framework

Construction of Training Set

- Feature Extraction: for each instruction before LICM
- Label: Measure WCET before and after LICM (YES|NO)
- Training phase took 50 hours on 2.13 GHz 4-Core

Evolutionary Parameter Optimization

- **Parameter optimization performed for all 6 learners**
- ➢ **Finds MLB heuristic with highest reduction of the WCET**

- **Performance evaluation (fitness) based on benchmark-wise cross validation**
- **Highly optimized code (*O3*) w/o LICM used as reference**
- **Optimization time between 5h - 37h on 2.13 GHz 4-Core**

Final State

- Best model integrated into compiler framework
- Before LICM, prediction by ML tool

Results – Parameter Optimization (1)

Parameter	Range	Best
Decision Trees		
max. depth	[1;20]	16
min. split size	[4;100]	19
min. leaf size	[2;100]	31
min. gain	[0;0.03]	0.014
prepr. altern.	[3;10]	4
confidence	[0.1;0.5]	0.476
Random Forests		
no of trees	[1;100]	7
features	[1;73]	39

Parameter	Range	Best
SVM with RBF kernel		
C	[0;10,000]	2405.15
γ	[0;74]	30.08
Linear SVM		
C	[0;10,000]	616.11
kNN		
k	[3;100]	11
Naive Bayes		
no configurable parameters		

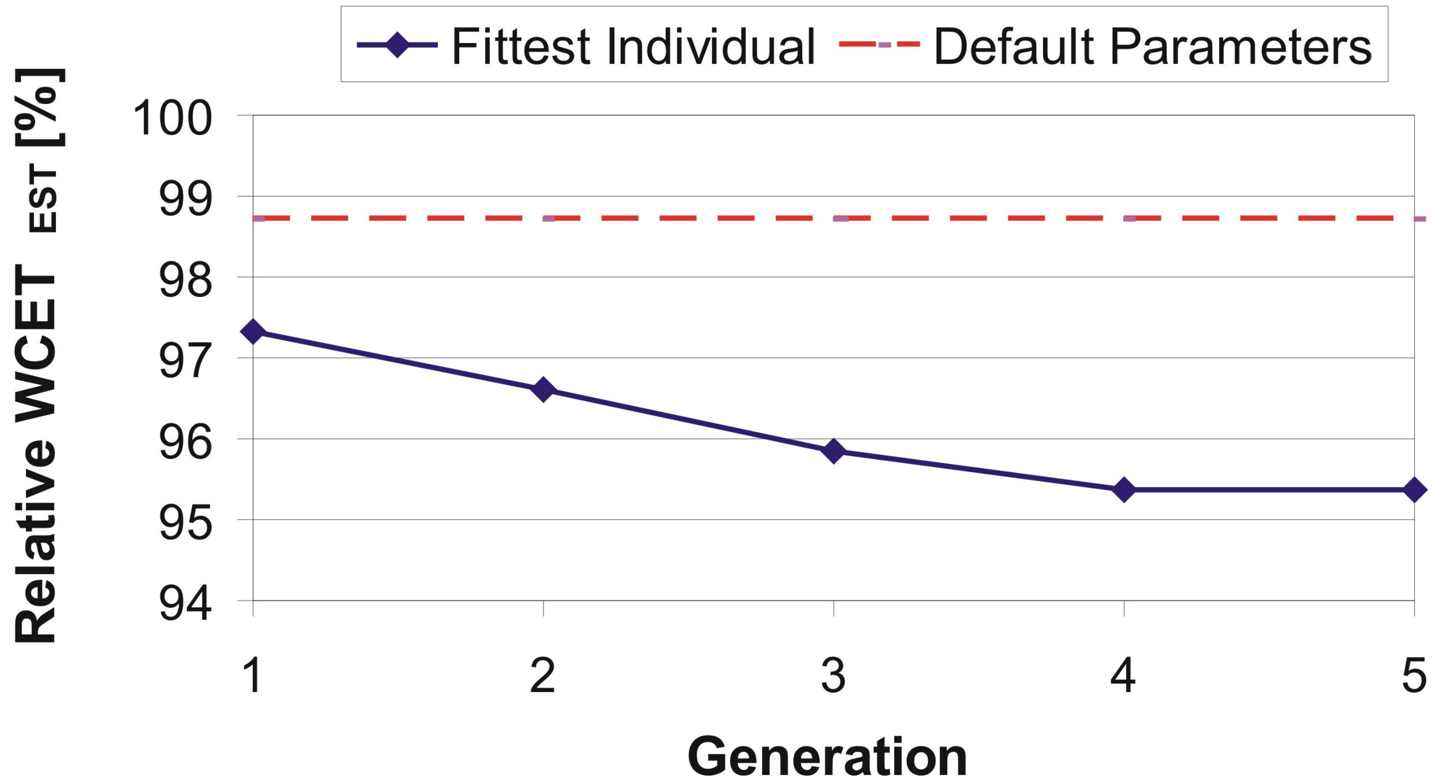
➢ **#parameter combinations too large for exhaustive search**

Results – Parameter Optimization (2)

Learner	Best	Worst	Average	Accuracy
Decision Tree	96.17%	99.78%	97.42%	63.16%
Random Forests	96.60%	98.96%	97.69%	60.43%
Linear SVM	98.24%	98.62%	98.34%	53.50%
SVM with RBF kernel	**95.36%**	98.80%	97.12%	57.78%
kNN	97.32%	98.94%	97.98%	**67.48%**
Naive Bayes	98.17%	98.17%	98.17%	54.31%

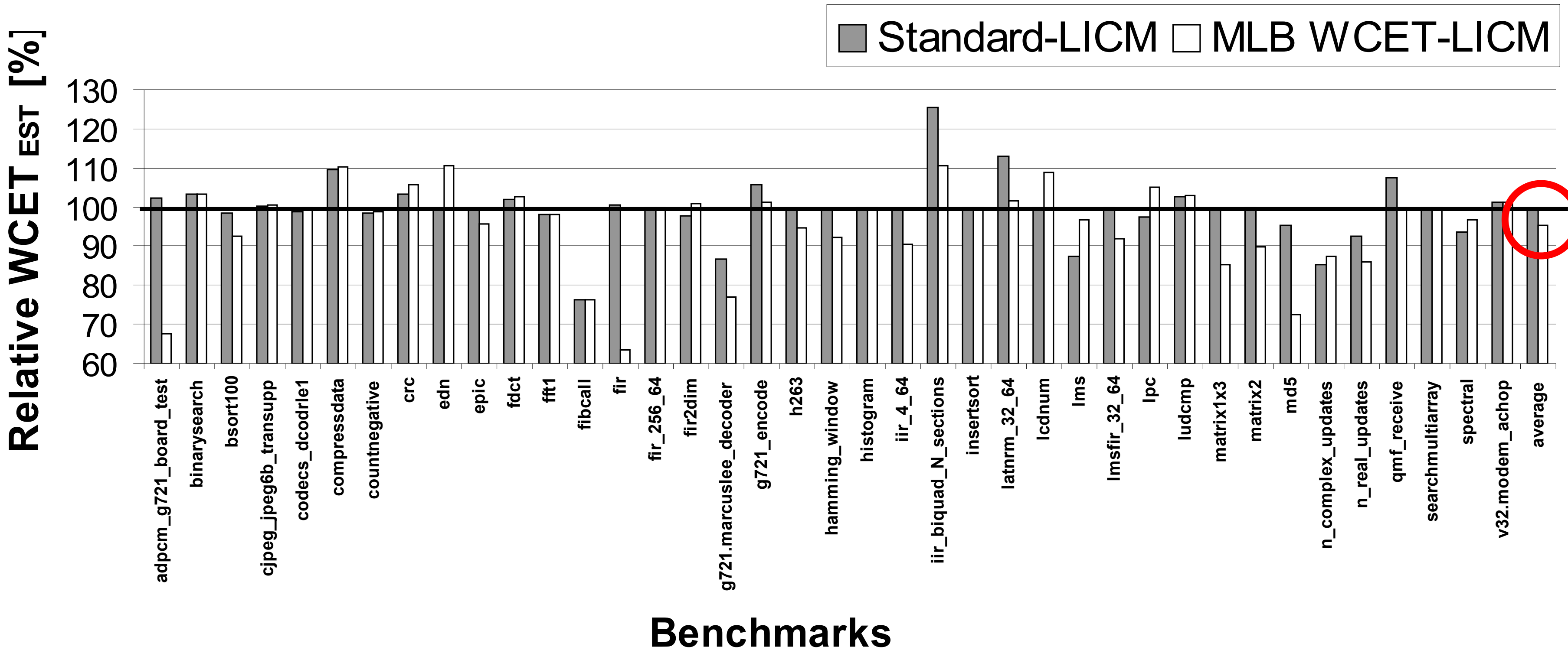
- **WCET reduction varies between 1.76% and 4.64%**
- **Compared to standard ACET LICM achieving a WCET reduction of 0.56%, significant improvement of 8.3x**
- **Parameters have strong impact on learner performance**
- **No correlation between WCET reduction and accuracy**

Progress of Evolutionary Parameter Optimization



- Convergence plot for best learner (SVM with RBF kernel)

Results – Relative WCET for Best Model



- 100% corresponds to –O3 without LICM
- Average: Standard 0.56% ; WCET-driven LICM 4.64%

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- Traditional Function Inlining
- WCET-driven Function Inlining
  - Supervised Learning (Random Forests)
  - Feature / Label Extraction
  - Heuristic Generation
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Conclusions & Future Work

- Central issue in MLB heuristic generation:
  Model Selection
- Choice of learner and its parameters has strong impact on performance of induced model (heuristic)
- Exhaustive search not feasible => Evolutionary search
- Case study on WCET-driven LICM
- Novel optimization outperforms std. LICM by 8.3x

Future Work

- Evaluation of further learning algorithms & optimizations
- Feature selection

Thank you for your attention.

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