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Predicting Vectorization Profitability Using Binary Classification

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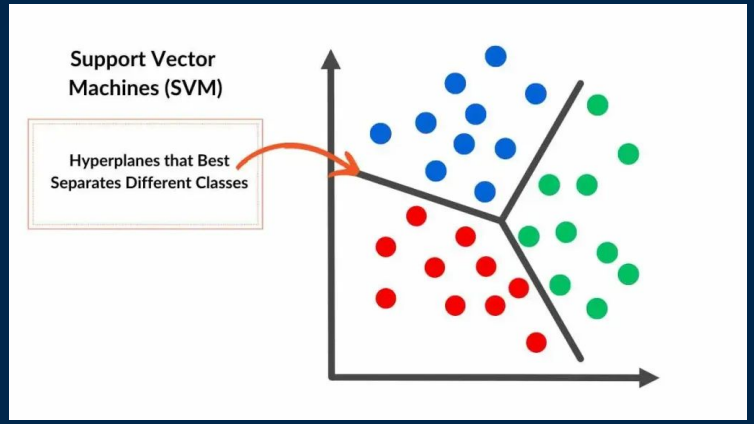

The paper discusses…

- Profitability of vectorization
- Machine learning techniques for classification
- Performance improvements
- Distinction between other ML-compiler research

Scalar

```
a[0] = b[0] + c[0]
a[1] = b[1] + c[1]
a[2] = b[2] + c[2]
a[3] = b[3] + c[3]
```

- Independent but seemingly similar instructions…
- Repeated work to load, add, then store

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Vectorization

One SIMD Instruction

```
a[0..3] = b[0..3] + c[0..3]
```

- Parallelization depends on…
  - Dependencies?
  - Memory alignment?
- Performance improvement depends on vector width
- Automatic vectorization by compiler
- Automatic Basic-Block Vectorization (ABBV)
- Overhead work:
  - Packing/unpacking vectors
  - Register pressure
  - Misalignment

Related Work

- Machine Learning for compiler optimizations
- Reduce execution time or compilation time
- Originality:
  - Classification problem instead of regression
  - Focus on vectorization profitability
  - Complementary to other traditional optimizations
  - Stock et al. did ML for automatic vectorization but for perfectly nested, independent loops

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Feature Inputs

Identifier	Level	Range	Description
AST1	AST	$\mathbb{N}$	The increment of the innermost `for` loop
AST2	AST	$\{0, 1\}$	Will the address of the first access to the array be always aligned with the machine's vector size ?
AST3	AST	$\{0, 1\}$	In array accesses, is the induction variables involved in the last dimension the one of the innermost loop ?
AST4	AST	$\mathbb{N}$	Number of array accesses in the body of the loop
AST5	AST	$\mathbb{N}$	The number of arrays accessed inside the loop
AST6	AST	$\{0, 1\}$	Does the benchmark involve any restrict keyword ?
IR1	IR	$\mathbb{N}$	The size of the dataset
IR2	IR	$\mathbb{N}$	Estimation of the dynamic instruction count
IR3	IR	$\mathbb{N}$	The depth of the innermost loop
IR4	IR	$\mathbb{N}$	The estimated trip-count of the innermost loop
IR5	IR	$\mathbb{N}$	Number of IR statements in the innermost loop
IR6	IR	$\mathbb{N}$	The number of variables used in the innermost loop, for the code in single static assignment (SSA) representation

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AST Features (Source Structure)

ID	Feature	Effect on Profitability
AST1	Loop increment (stride)	Contiguous = good
AST2	Memory alignment	Aligned = good
AST3	Induction variable on last array dim	Improves locality
AST4	# array accesses	Too many = alias risk
AST5	# arrays accessed	↑ → register pressure
AST6	`restrict` keyword	Helps vectorize

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IR Features (Compiler Level)

ID	Feature	Effect
IR1	Dataset size	Large loops amortize overhead
IR2	Dynamic instruction count	Too small → not worth SIMD
IR3	Loop depth	Shallow = less benefit
IR4	Trip count	Low trip count = bad
IR5	# IR statements	More ops = higher gain
IR6	# SSA variables	Too many = spills

TSVC Dataset

- 151 base loops × unroll factors (1–20) → ≈ 3020 programs
- Compilers: icc 12.1.5, gcc 4.6.3, LLVM 3.3
- CPU: Intel Core2 Duo 2.66 GHz
- Each program compiled with ABBV ON/OFF
- Speedup = scalar runtime / vectorized runtime
- Labeling:
  - ≥ 1.05 → Profitable
  - ≤ 0.95 → Non-profitable
  - 0.95–1.05 → Ignored

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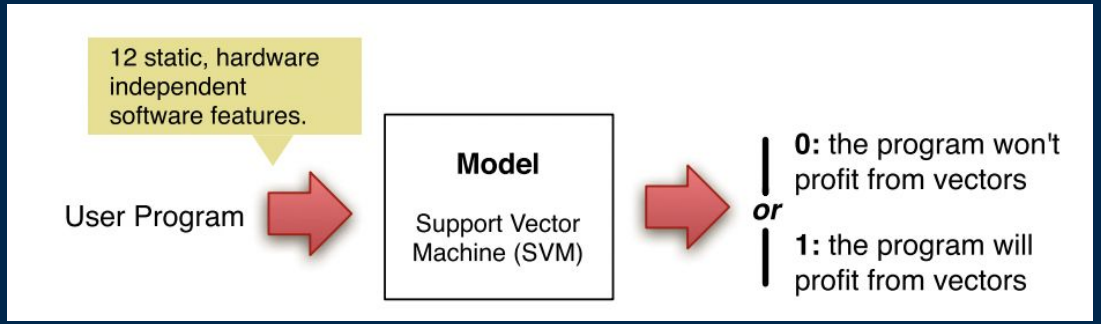
High-Level Model



- Validation: LOOCV (Leave-One-Out Cross-Validation)
- Train on N – 1 samples, test on 1; repeat N times. Maximizes use of small dataset (≈3 k samples)

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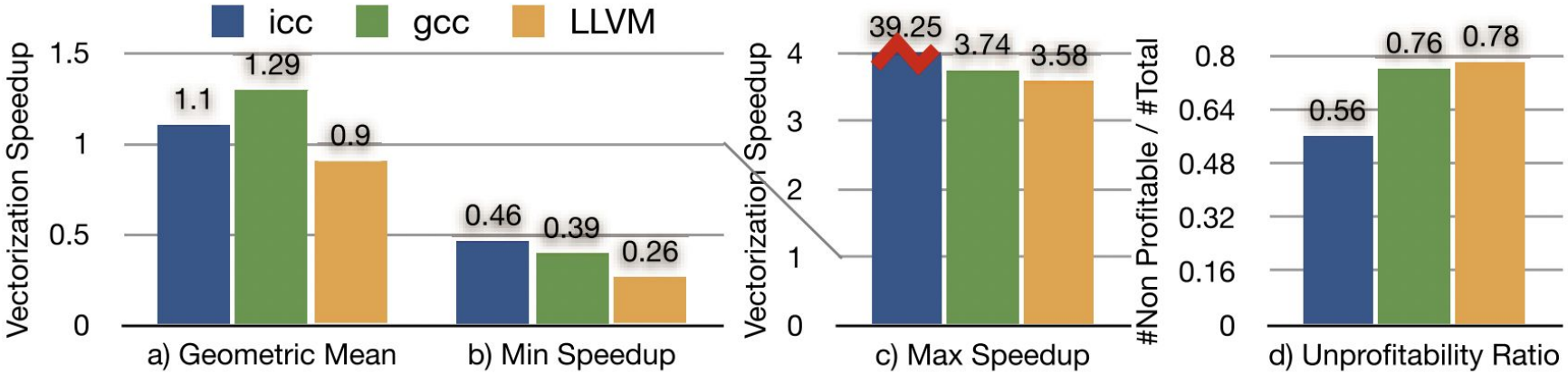
Early Results



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Improvements

- Imbalance of data (73% in class 1)
  - Train another SVM on balanced data
  - Compound Predictor
- Model Evaluation:
  - Add Class 2 - within 5% margin, ABBV has minimal effect
  - Model still predicts 0 or 1, but disregard class 2 as part of accuracy
- Comparison to other feature sets
  - GCC compared to random numbers had no difference
  - Keep select 12, more applicable

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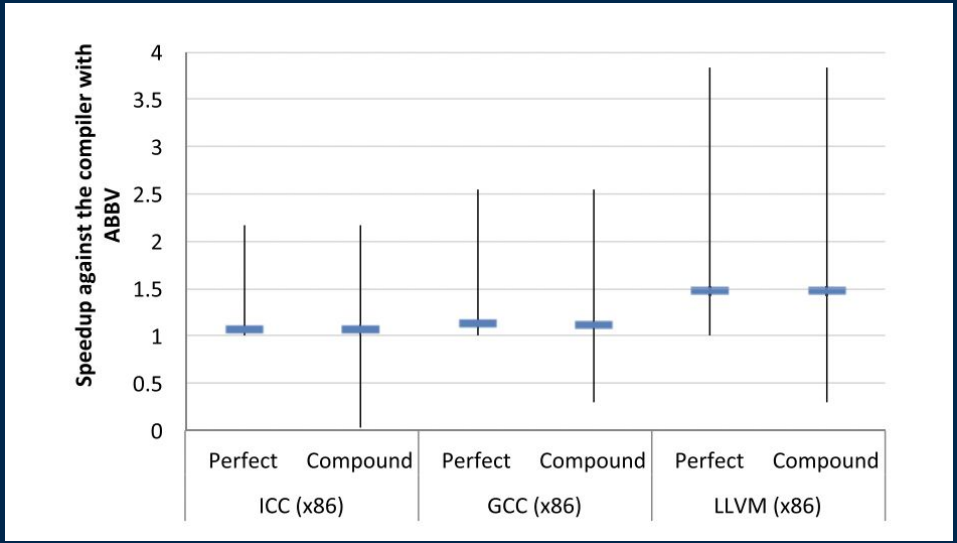
Final Results



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Final Results

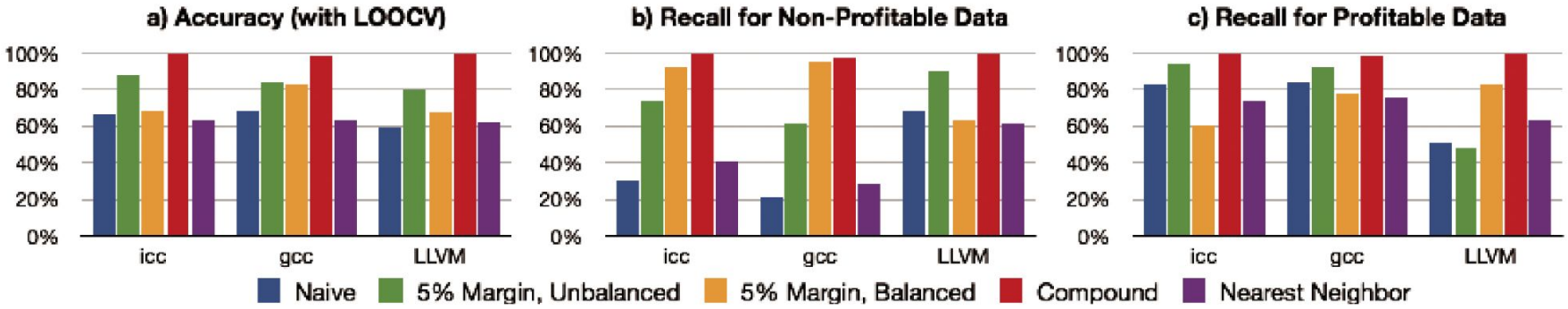

Fig. 3 Prediction accuracies for all methods and compilers: (a) the LOOCV total accuracies (b) the LOOCV accuracies per class.

Final Results

- Unprofitability ratio drops down to <1% for all compilers
- Mispredicts only 2 programs
- Up to 3.8 times speedup
- On average, 47.3% faster in LLVM
- Low compilation overhead (<1 second)
- One time training on user machine (several hours)

Future Challenges

- 2 Cases of Misprediction
  - Loop unroll factor of 12
  - 12 is a multiple of the SIMD datapath width
  - Singularity, edge case
- Non-linear expressions
  - Hard to measure software characteristics in these cases
  - These better express control flow-graph of programs

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Thank You!

Questions?