Simple Profile Rectifications Go A Long Way

—Statistically Exploring and Alleviating

the Effects of Sampling Errors for Program Optimizations

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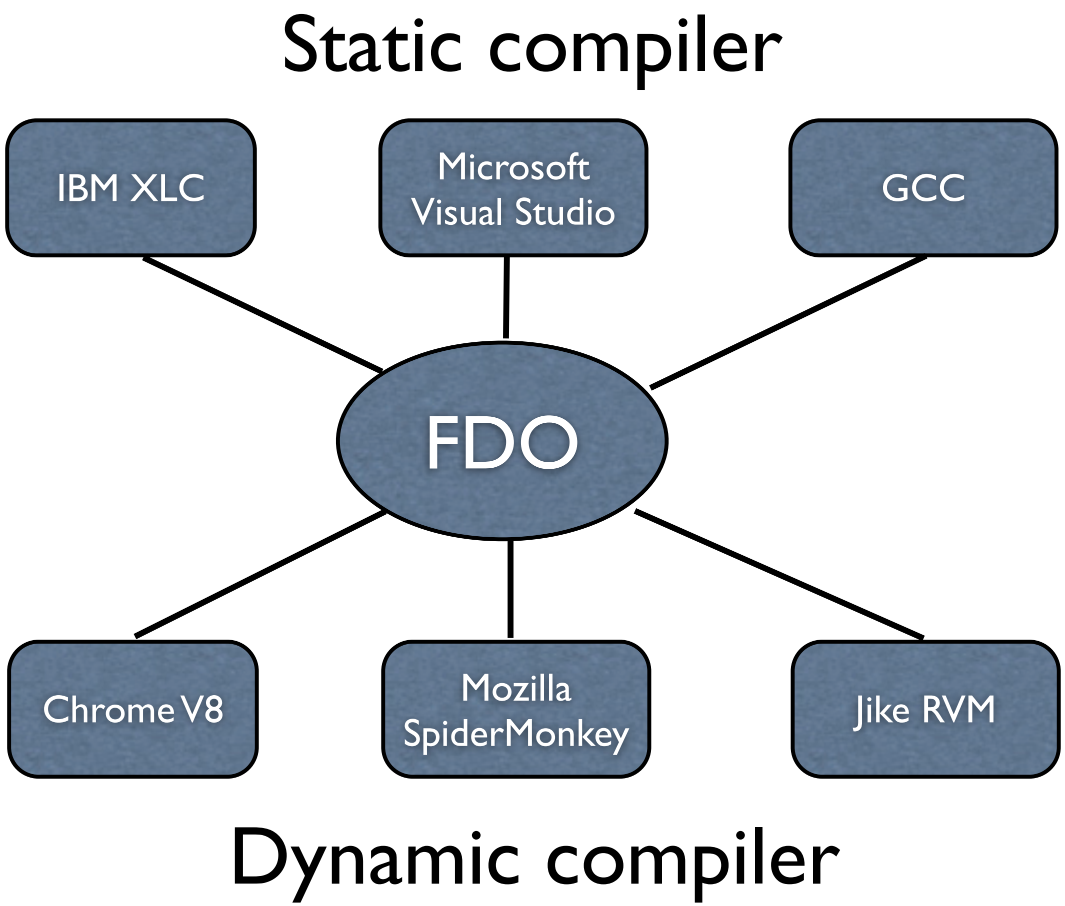
FDO (feedback-driven optimizations)



Guiding Opt:

- Code layout enhancement
- Function inlining
- Loop unrolling
- Type specialization

… …

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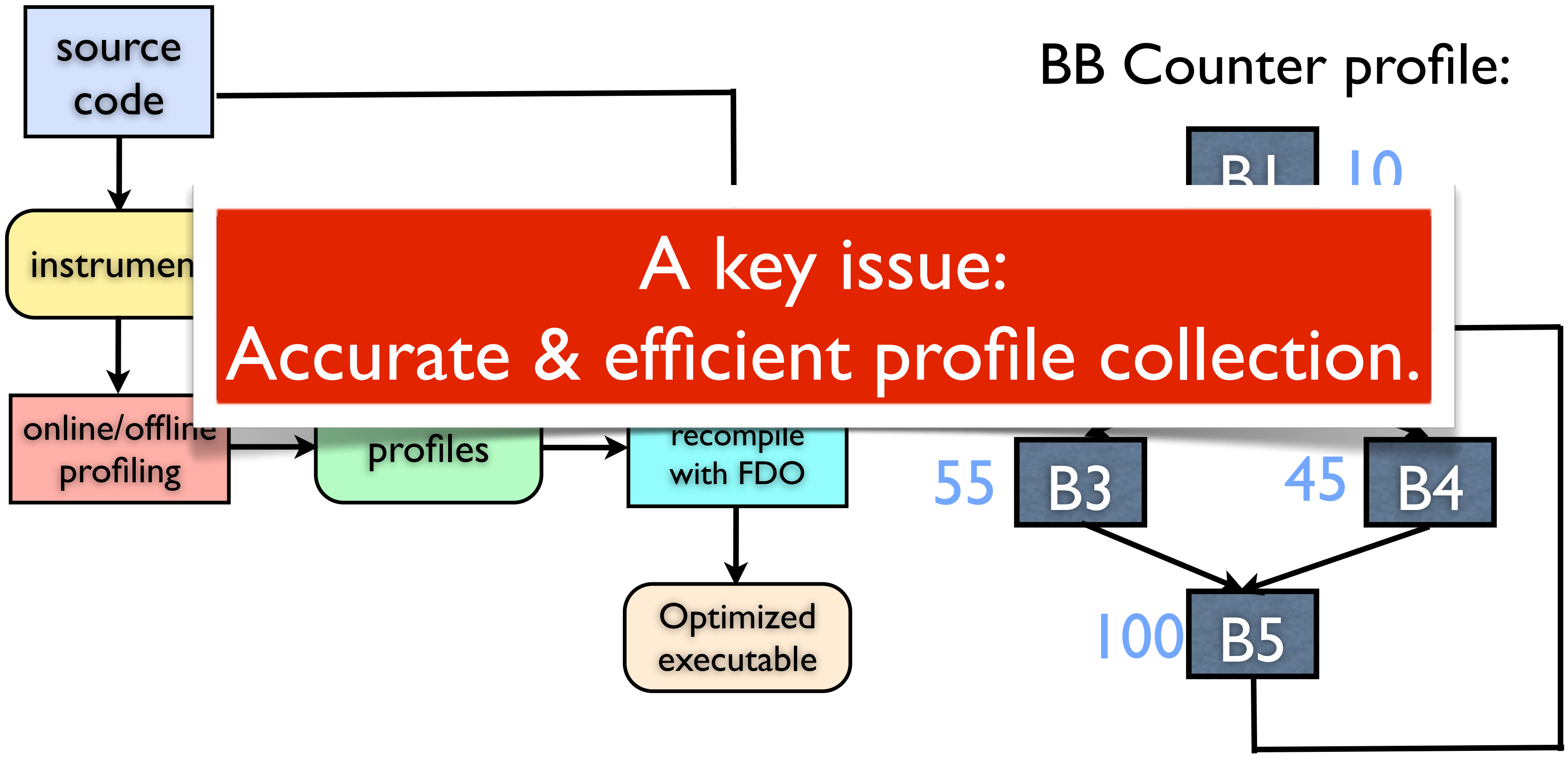
Workflow of FDO



A key issue:
Accurate & efficient profile collection.

Sampling for FDO

- Take samples rather than profile the whole execution
  - A common approach to efficiency
    - Jikes RVM, J9, V8, Google cluster app. sampling, etc.

- Many efforts for efficient profiling with good accuracy
    - [Arnold and Ryder, PLDI'01], [Bond and McKinley, MICRO'05], [Arnold and Grove, CGO'05], ...

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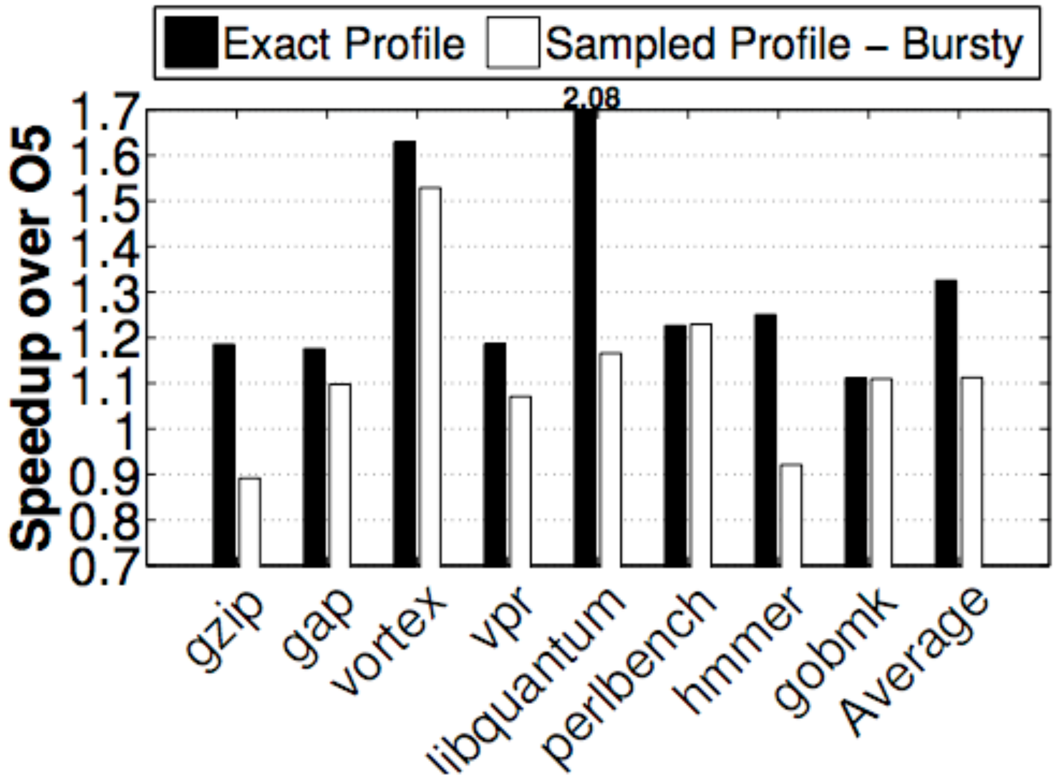
FDO speedups



5% sampling rate

1/3 benefits

Substantial gap from what exact profiles provide

Goal of This Work

A new angle to attack the problem:
Rectify sampling errors for FDO.

- Questions to answer
  - ❖ Do higher sampling rates really give more useful profiles?
  - ❖ What types of errors in a sampled profile are essential?
  - ❖ Can they be easily fixed?

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Outline

- Measuring the relations between sampling and FDO
- Analyzing critical sampling errors
- Statistical profile rectification

Impact of sampling on FDO

Common Perception

Sampling rate ↑ ⇨ Profile accuracy ↑ ⇨ Usefulness for FDO ↑

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A systematic measurement

(4 levels, 8 dimensions, 7680 runs)

Levels	Dimensions	Variations	Description
sampling	methods	2	Bursty, Uniform
	frequencies	12	6 for Bursty, 6 for Uniform
system	compilers	2	XLC, GCC
	platforms	2	Intel Xeon & IBM POWER7
workload	benchmarks	8	SPEC CPU2000 & CPU2006
	inputs	4	1 train input, 3 ref inputs
noise avoidance	repetitions	10	number of repetitive runs per setting

- BB counter profile for XLC, edge profile for GCC
  - **Bursty sampling**: Sample *m* BBs for every *n* BB executions
  - **Uniform sampling**: Sample 1 instruction every *n* dynamic instructions
- Using C/C++ compilers
  - Sophisticated FDO optimizers
  - Better noise control that JIT
- 8 SPEC benchmarks most sensitive to FDO

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- Sampling frequencies
  - 1/1000, 10/1000, 50/1000, 100/1000, 200/1000, 400/1000

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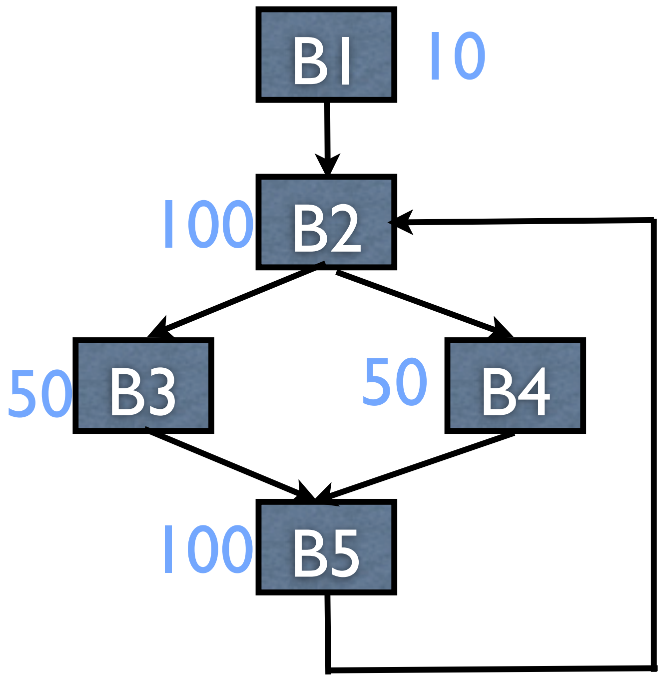
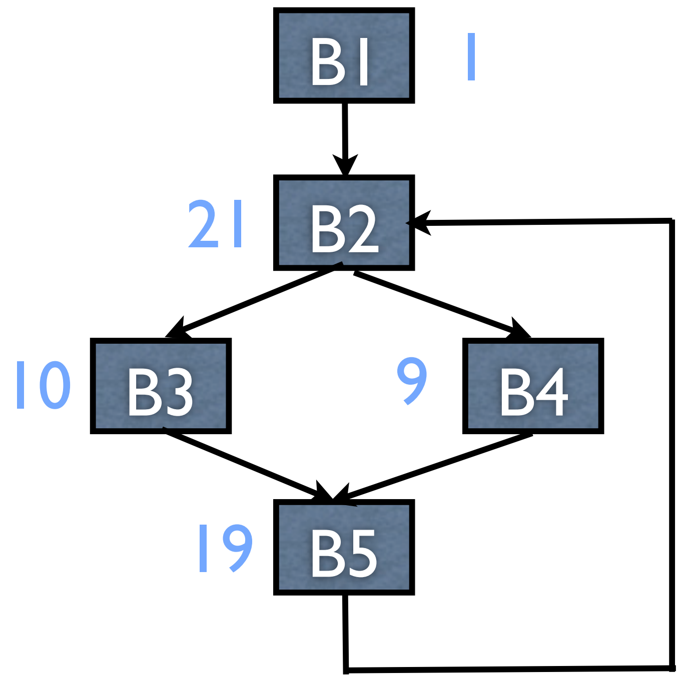
Profile accuracy definition

Exact BB counter profile:



Sample BB counter profile:



(e.g., sampling rate: 1/5)

Profile accuracy definition

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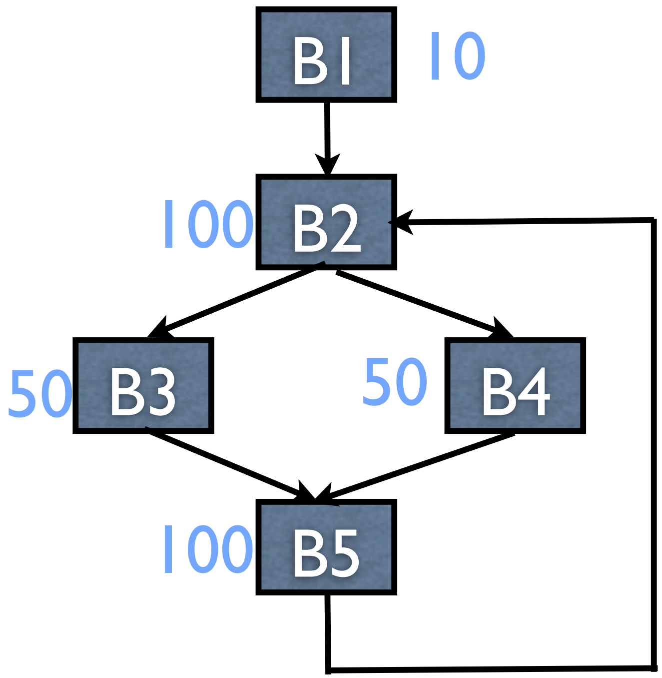
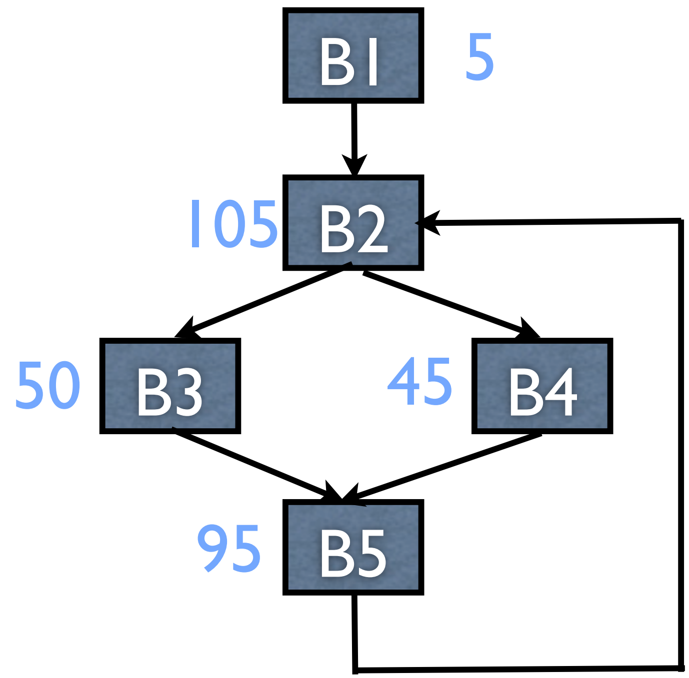


Scaled sample BB counter profile:



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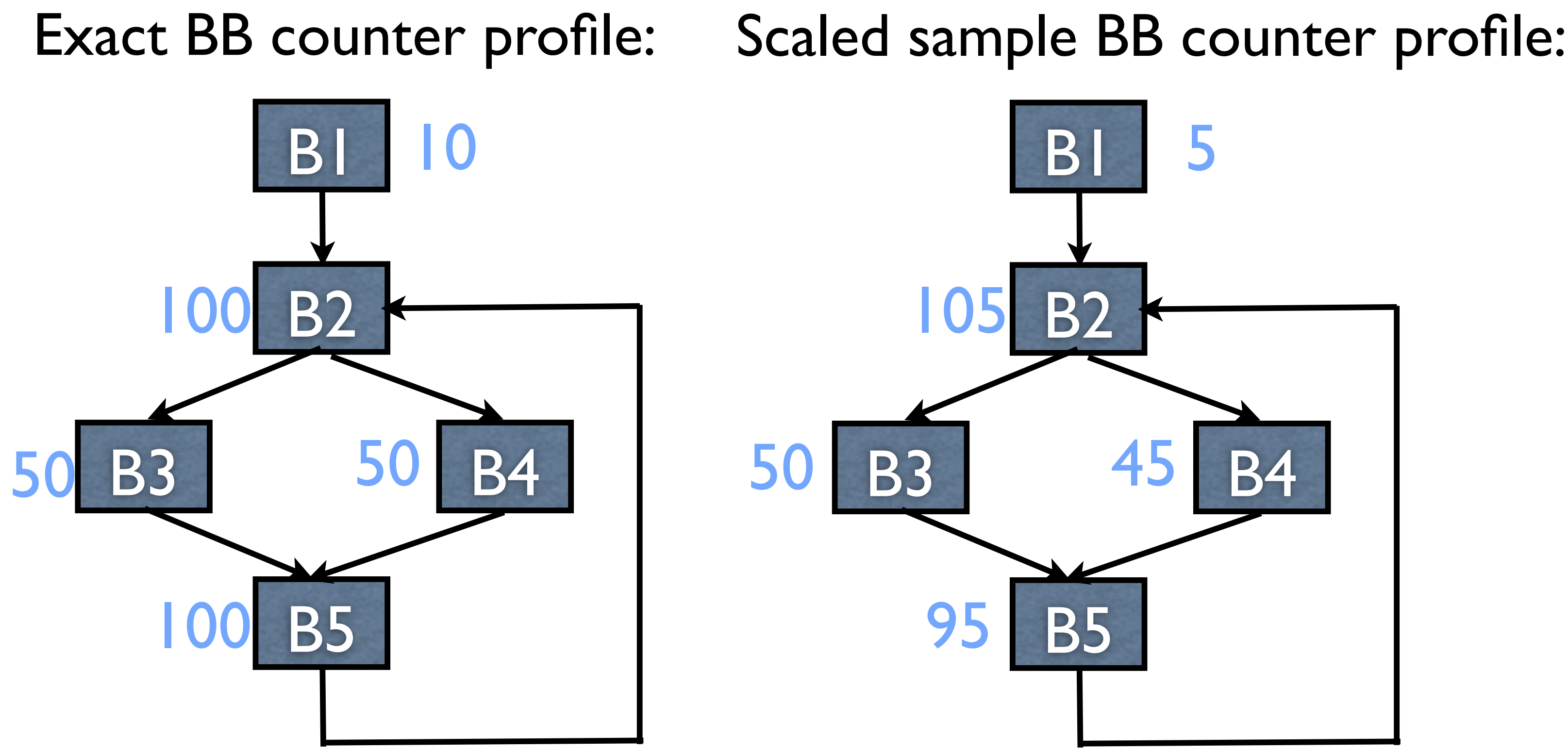
Profile accuracy definition



Accuracy of B1: 1 - |10-5| /10 = 0.5

Unweighted accuracy: avg of all BB's accuracy

Weighted accuracy: weighted with the exact counter values

Metric for correlations

- Spearman's rank correlation coefficient
  - ❖ Quantifying the monotonic relationship

(sample rate 1, accuracy 1)
(sample rate 2, accuracy 2)
(sample rate 3, accuracy 3)
... ...

x_i: rank of sample rate i
y_i: rank of accuracy i

$$r = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_i (x_i - \bar{x})^2 \sum_i (y_i - \bar{y})^2}}$$

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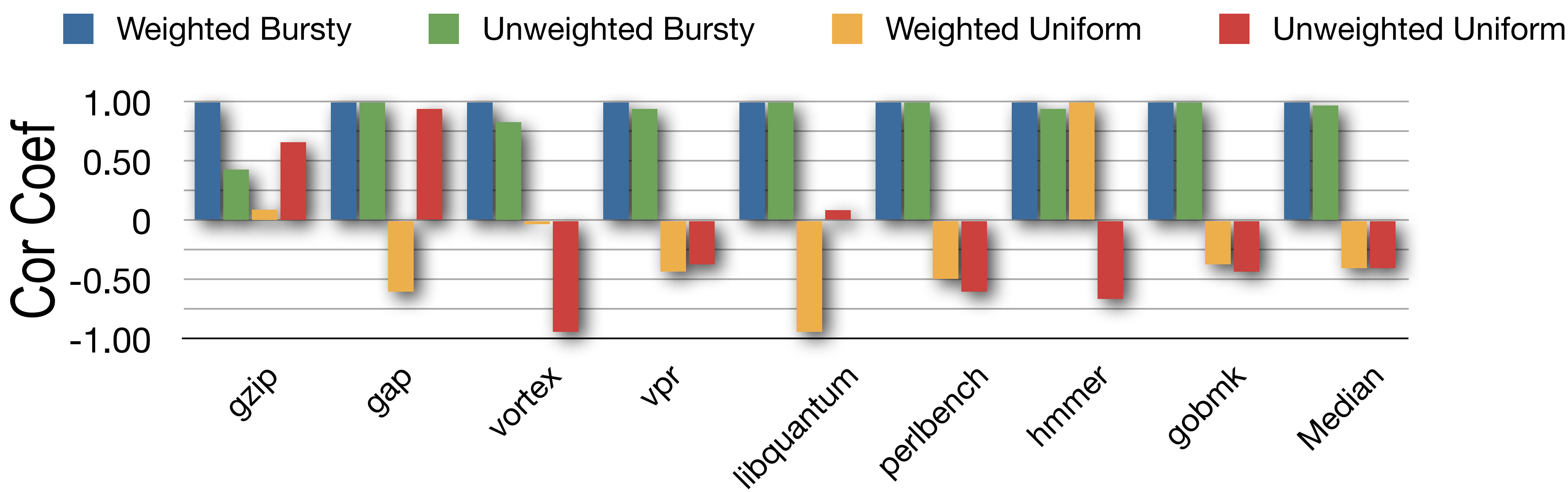
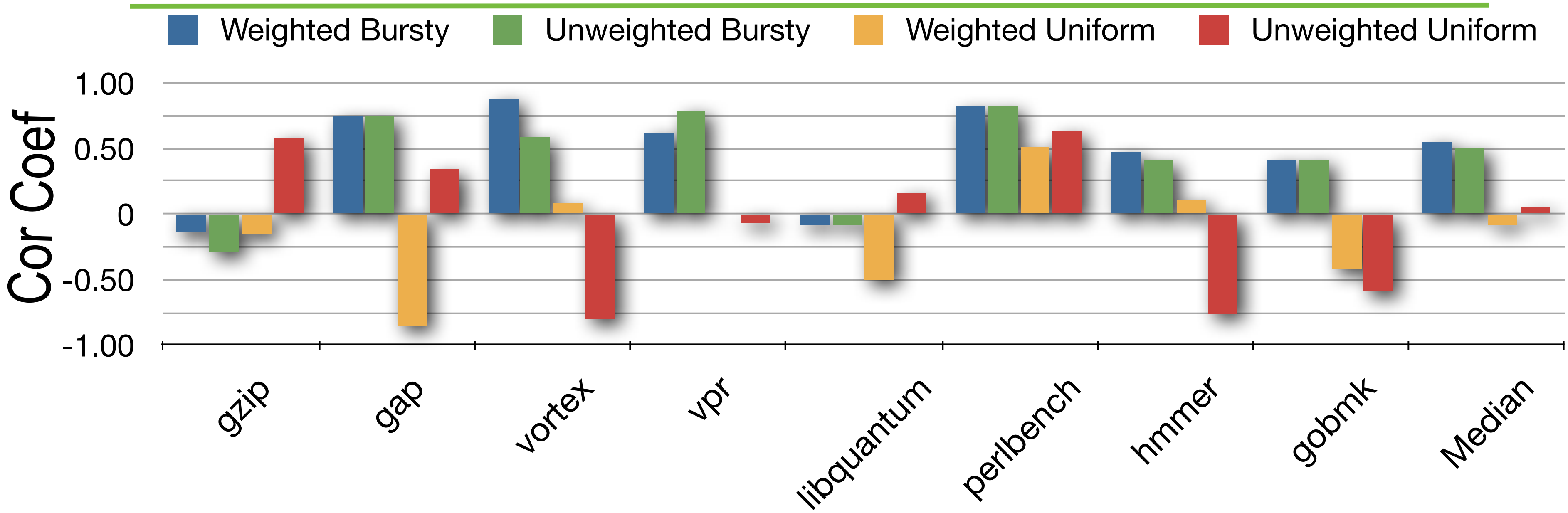
Sampling rates vs. Profile accuracy



- Bursty sampling: Higher rates => Better accuracy
- Uniform sampling: not the case.

Profile accuracy v.s. FDO speedup



- Profile accuracy weakly correlates with speedup.
  - ❖ Hypothesis 1: the FDO fails to exploit profiles effectively
    - ✤ Unlikely as it gives best performance on exact profiles.
  - ❖ Hypothesis 2: Some errors hurt speedups but not accuracies much.

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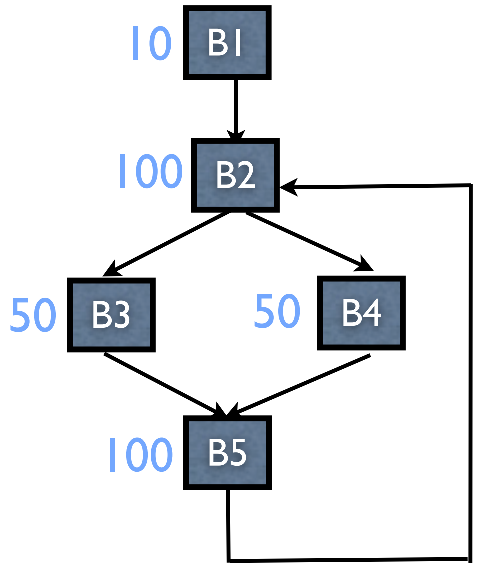
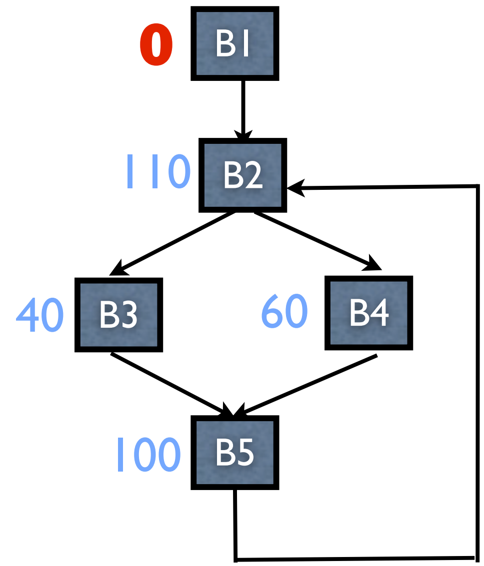
- Analyzing critical sampling errors
  - Zero-counter error
  - Inconsistency error
- Statistical profile rectification

Zero-counter error

Exact profile:

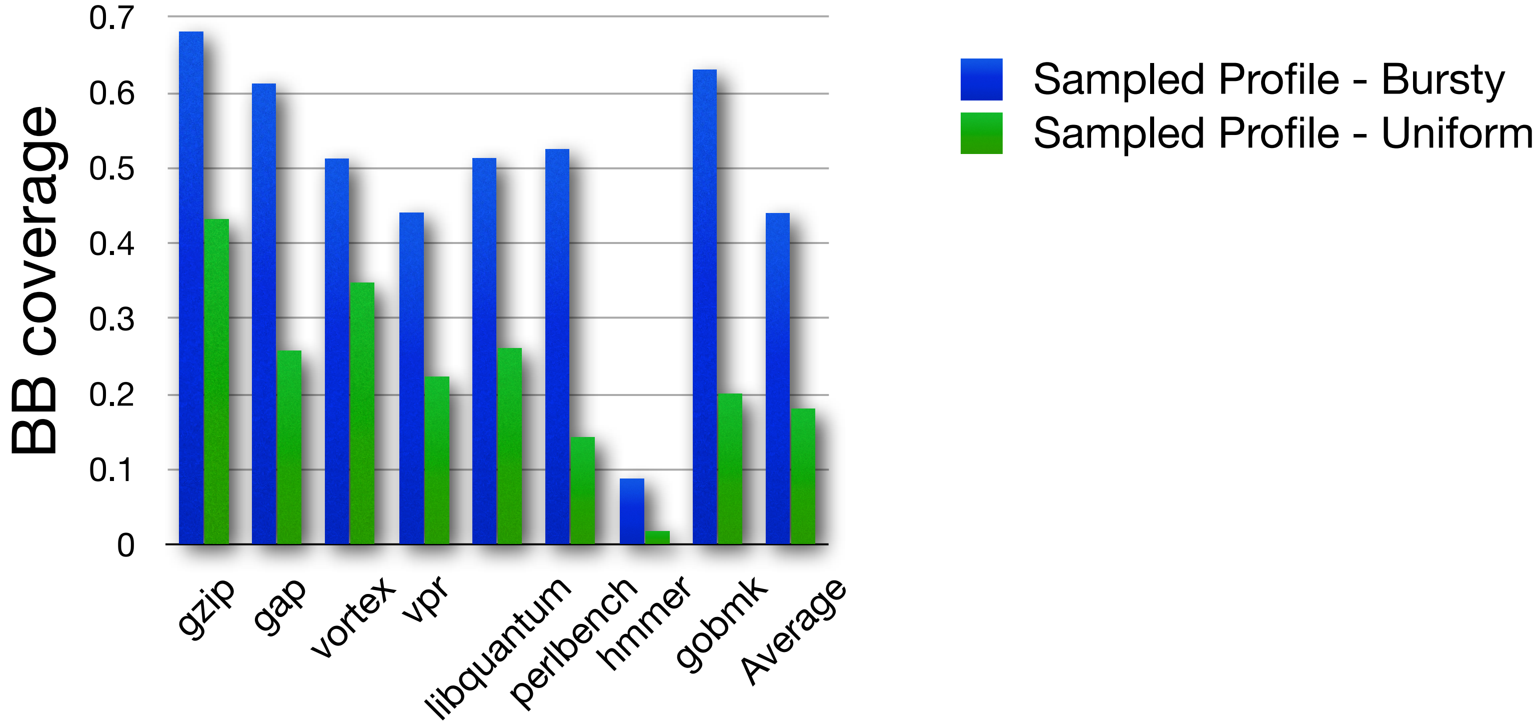


Scaled sampled profile:



Def: zero in the sampled profile, but not in the exact profile.
Shows the difference in coverage.

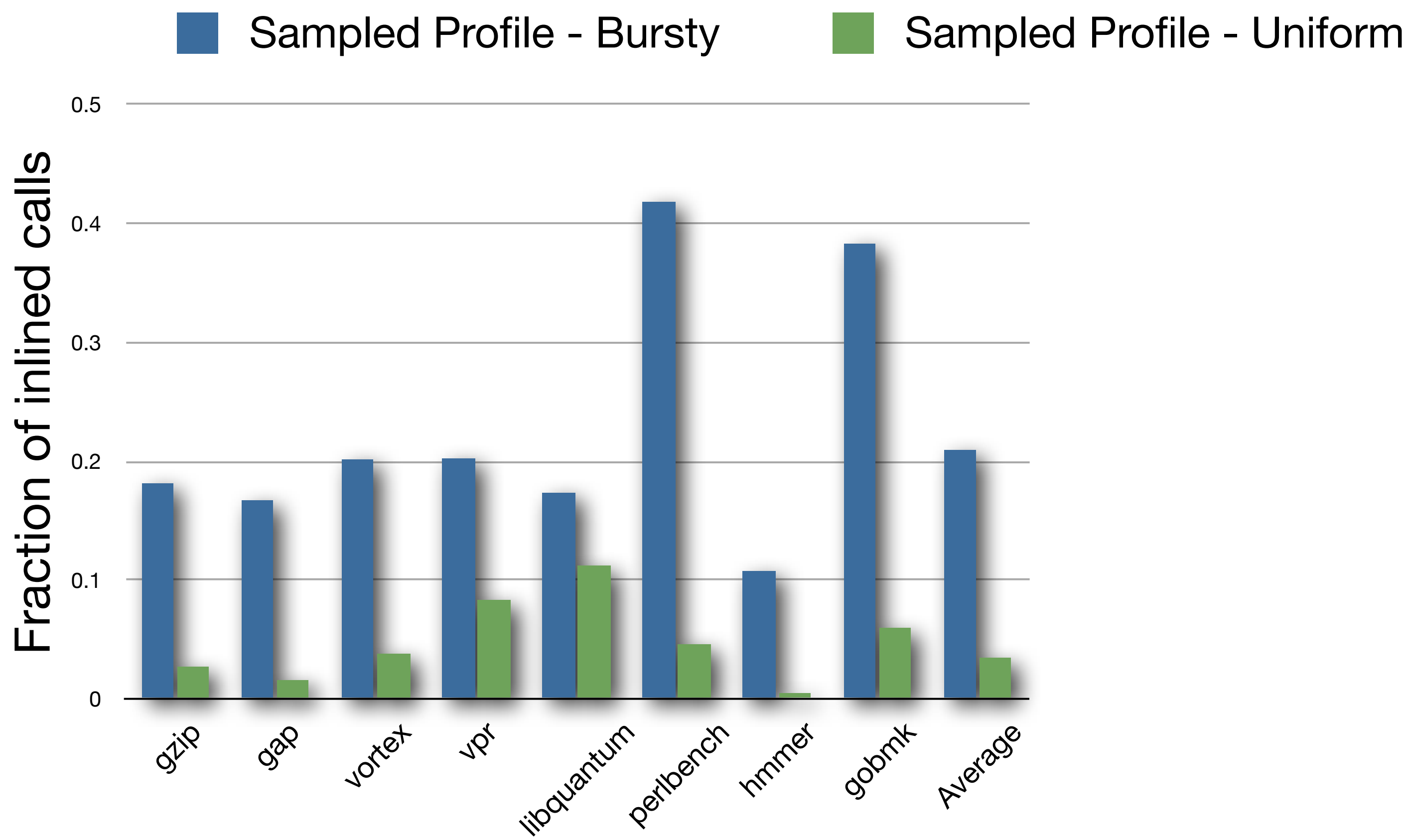
Zero-counter errors



- Many BBs are missed in a sampled profiles.

Influence on function inlining

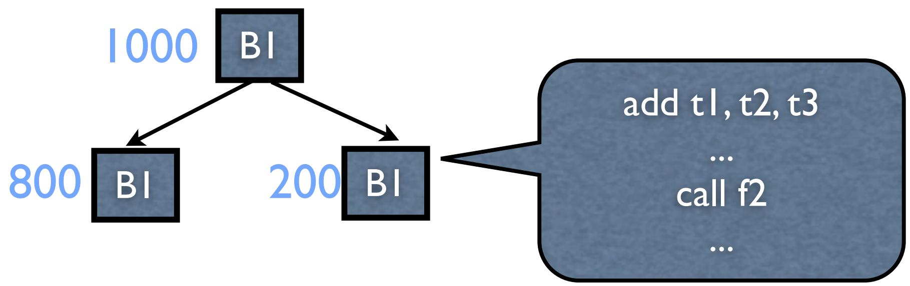
FDO on sampled profiles inlines much fewer calls.



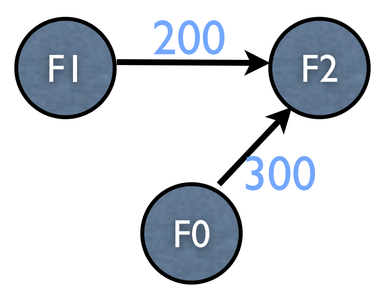
Influence on function inlining

- Different BB coverage ⇒ different dynamic call graphs

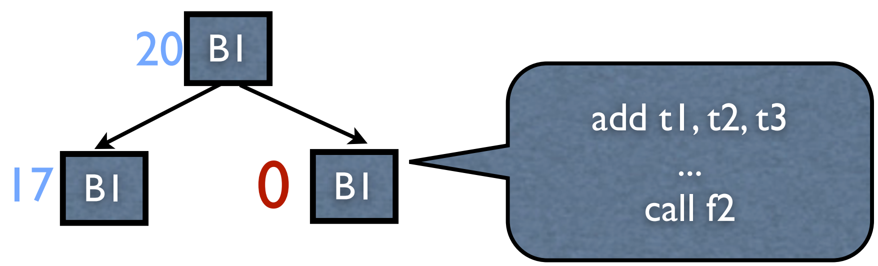
CFG in F1 (exact)



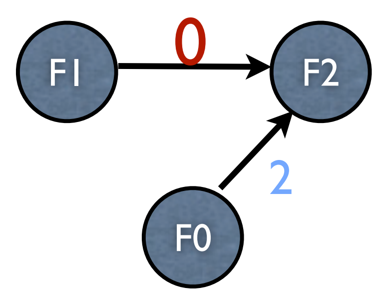
Dynamic call graph (exact)



CFG in F1 (sampled)

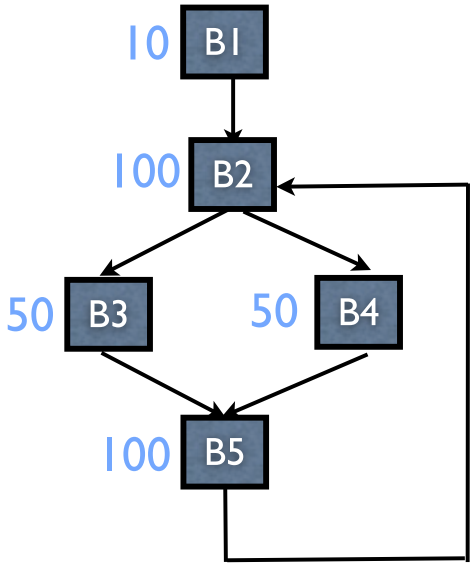


Dynamic call graph (sampled)

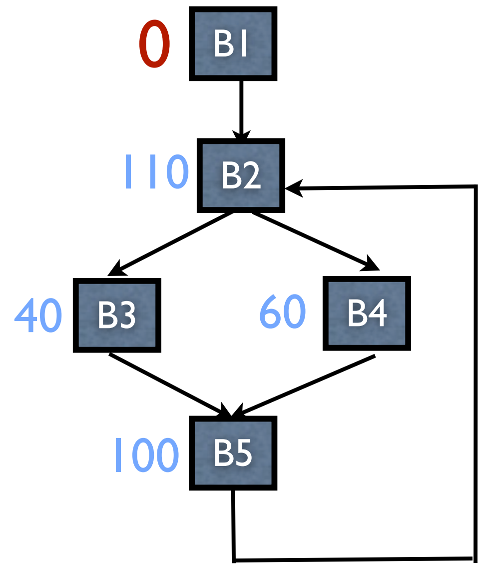


Influence on Loop Optimization

- Small counters are important for loop optimizations



Loop iteration: 100/10 = 10



Loop iteration: ?

- Influence on unrolling, specialization and many other transformations

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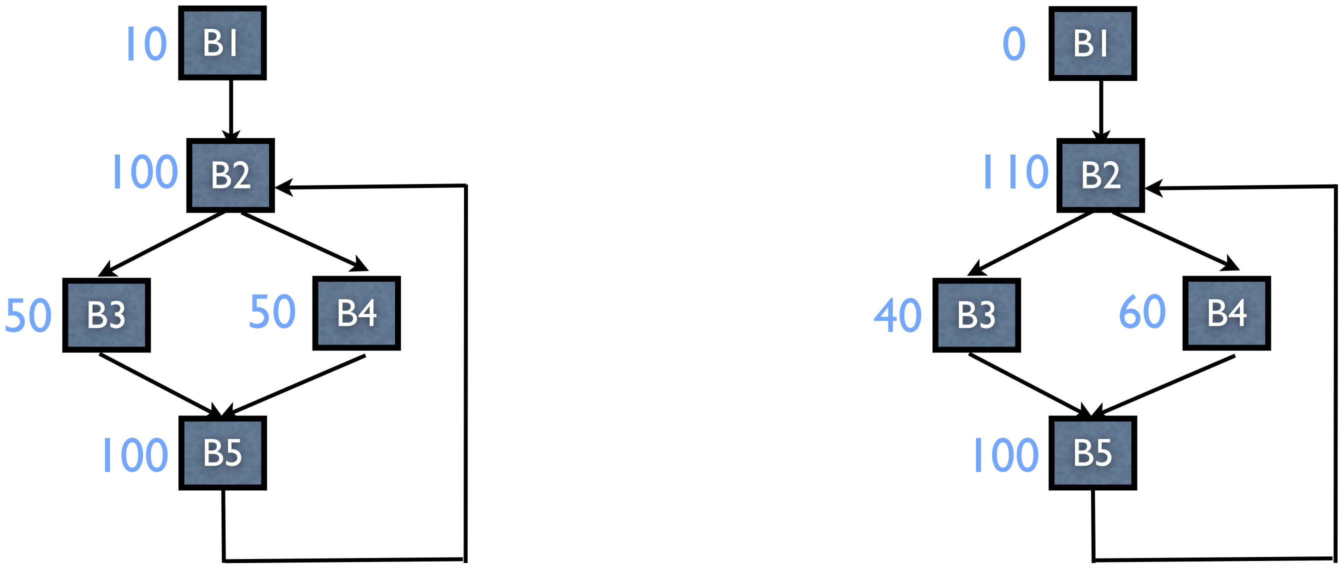
Inconsistency errors

1/10 sampling rate

Exact BB counter profile: Scaled sample BB counter profile:



Inconsistency errors

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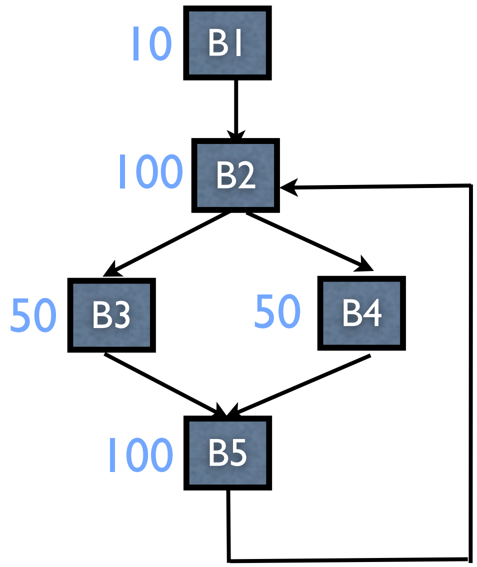

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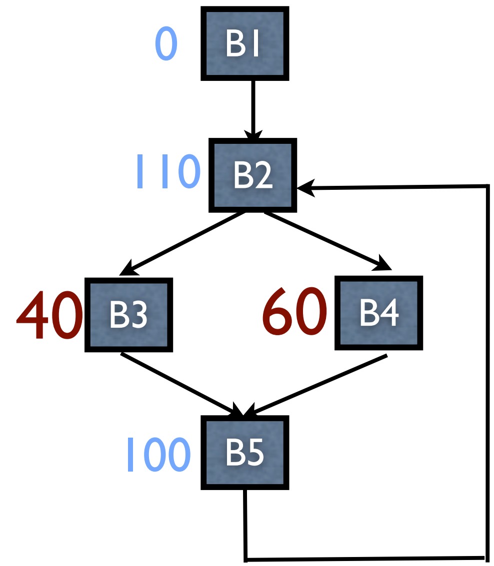

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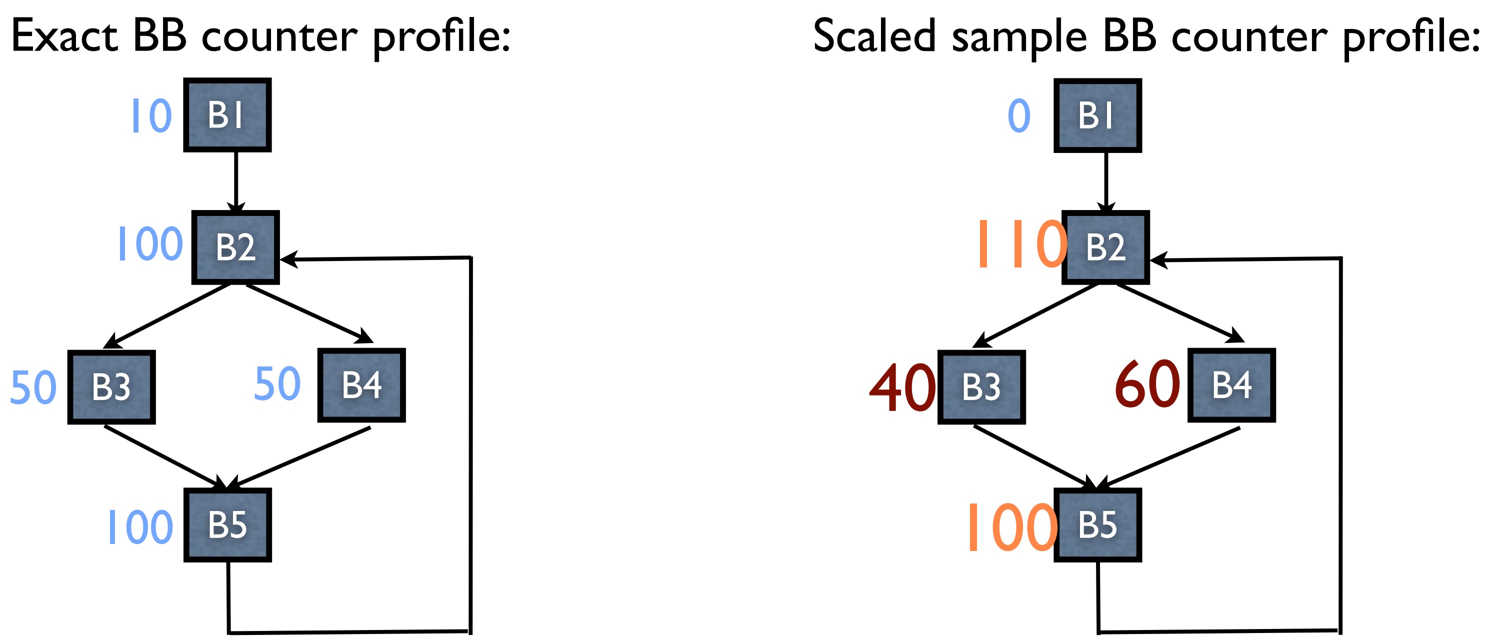
Inconsistency errors

1/10 sampling rate

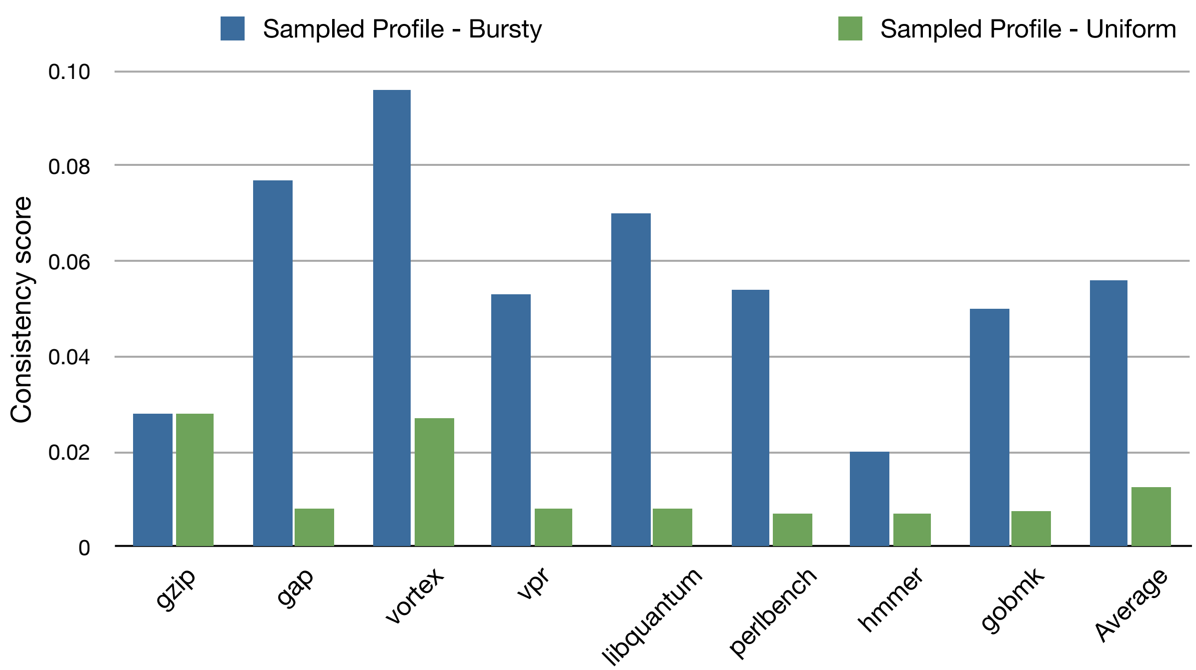


- Inconsistency between B2 and B5 fixable
- Hard to fix B3 and B4

Quantify the degree of inconsistency

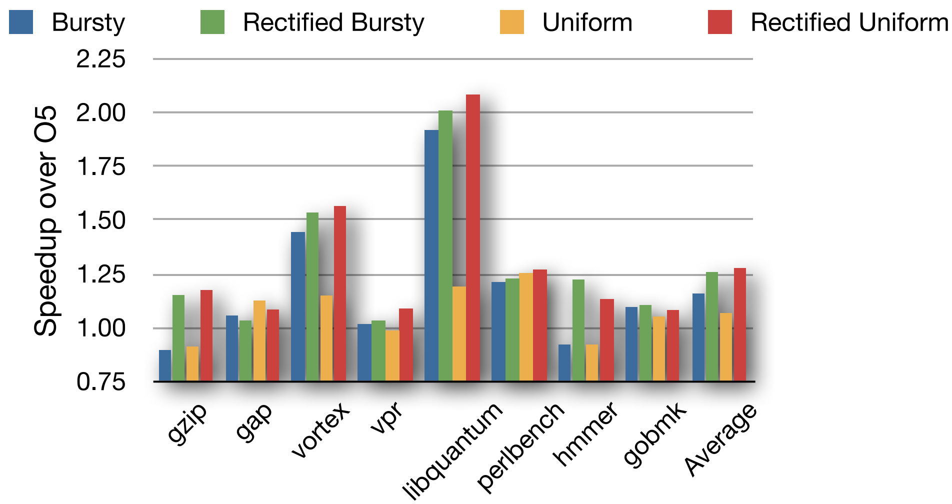
- G: a group of BBs having the same counter value
- G': the largest subset of G having the same counter value in the sample profile

Consistency Score(G) = |G'|/|G|

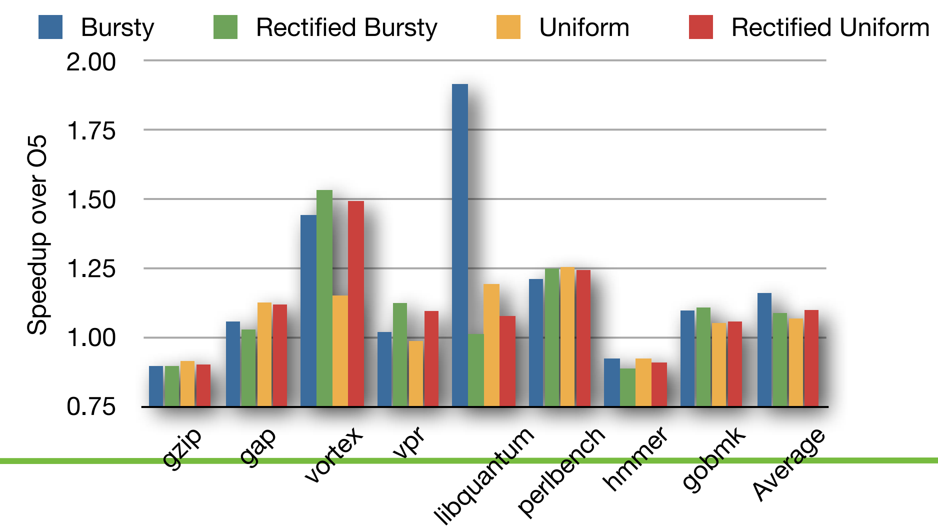


Potential of rectifying errors with exact profiles

Replace 0-counters with corresponding values in exact profiles



Replace inconsistent counters with their average



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Concept and options

- Profile rectification: Correct errors in a profile
- Option methods
  - Through static analysis
    - Conservative, subject to compile-time unknown
  - Through statistical patterns
    - Learn from training profiles

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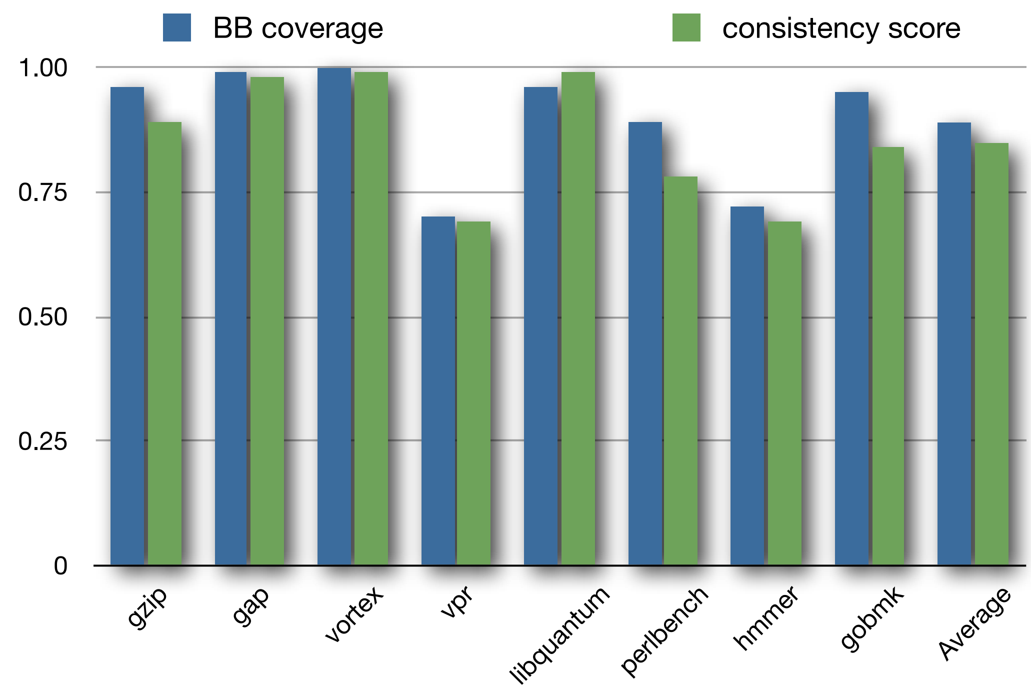
Cross-input stableness of patterns



- 3 ref inputs for each benchmark
- Average of pairwise comparison
- Suggest to use a training profiles to provide the pattern
- Note: pattern is stable, not the exact profile values

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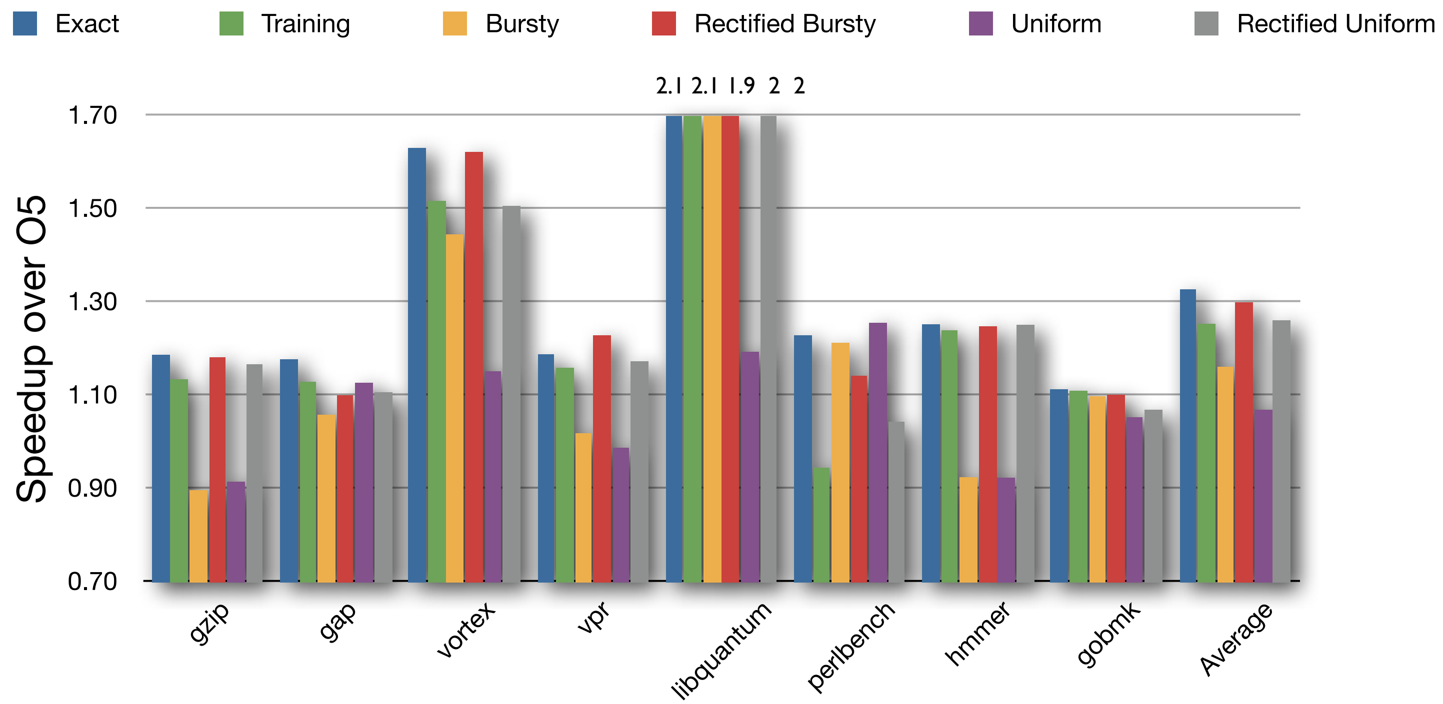
Rectification using a training profile



- Both kinds of errors rectified
- Rectified profiles achieved around 90% benefit of FDO
- Rectified bursty profiles outperform training profiles

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Related Work

- Sample profile guided optimization in static compilers
  - ❖ Chen and others: Taming hardware samples [CGO'10]
- Profile errors
  - ❖ Mytkowicz and others: Java profile inconsistency [PLDI'10]
- Correlation between profile accuracy and usefulness
  - ❖ Langdale and Gross [DDD'03]

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Conclusion

- Counter-intuitive findings on sampling for FDO
  - ❖ intuition: higher sampling rates -> more accurate profiles
    - ❖ reality: strong correlations for bursty sampling, but not for uniform sampling
  - ❖ intuition: more accurate profiles -> better performance
    - ❖ reality: weak correlations
- Two types of critical errors in sampled profiles
  - ❖ 0-counter errors & inconsistency errors
- Effectiveness of simple statistical profile rectification
  - ❖ 92% of the speedups that exact profiles provide

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