

## Profiling and Optimizing Java Streams

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# INTRODUCTION





- Stream API (package java.util.stream)
  - Data processing
    - MapReduce-style transformations
  - Two key abstractions:
    - Stream
    - Stream pipeline

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Stream

#### transactionList.stream()

```
.parallel()
.filter(t -> t.getStatus() == Transaction.VALID)
.map(Transaction::getID)
.collect(Collectors.toSet());
```

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Stream

#### transactionList.stream()

.parallel()
.filter(t -> t.getStatus() == Transaction.VALID)
.map(Transaction::getID)
.collect(Collectors.toSet());



A *stream* represents a sequence of data elements coming from a *data source* 



Pipeline

# transactionList.stream() .parallel() Data source .filter(t -> t.getStatus() == Transaction.VALID) .map(Transaction::getID) .collect(Collectors.toSet());





Pipeline

#### 



• A *pipeline* is associated with the stream

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**Operations** 

#### transactionList.stream()

.parallel()
.filter(t -> t.getStatus() == Transaction.VALID)
.map(Transaction::getID)
.collect(Collectors.toSet());



The pipeline can contain operations







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Tasks

parallel

#### **Execution Mode** transactionList.stream() sequential .parallel() .filter(t -> t.getStatus() == Transaction.VALID) .map(Transaction::getID) .collect(Collectors.toSet());



- Parallel streams may spawn *tasks*
- Tasks are executed in a *fork/join pool* by threads called *workers*





- Stream code suffers from important performance penalties when compared to imperative code [1, 2, 3]
- These penalties are mainly caused by:
  - Abstraction overheads
    - Due to extra object allocations and reclamations
  - Abundant virtual method calls
    - Can prevent *Just-In-Time* (JIT) compiler optimizations

[1] Biboudis et al. Clash of the Lambdas. ICOOOLPS'14.
[2] Kiselyov et al. Stream Fusion, to Completeness. ACM SIGPLAN Notices, 2017.
[3] Møller et al. Eliminating Abstraction Overhead of Java Stream Pipelines Using Ahead-of-Time Program Optimization. OOPSLA'20.



To mitigate stream-related overheads and optimize streams *developers need means* to study the **runtime behavior** of streams





Current approaches to stream optimization:

PMainly rely on static analysis techniques

Overlook runtime information key to spot stream-related performance issues

Suffer from important limitations to detect all streams used by a Java application



#### Research gap:

There is a lack of dedicated tools able to dynamically analyze stream processing on the JVM to help developers locate streams that impair good performance





Contributions

- Propose a technique enabling cycle-accurate stream profiling
  - Accurately measure the computations performed by a stream in terms of reference cycles (cycles for short)
- Analyze stream processing in *Renaissance* [4]
- Optimize stream-related performance issues in *Renaissance*
- Conduct an evaluation on accuracy and overhead

[4] Prokopec et al. Renaissance: Benchmarking Suite for Parallel Applications on the JVM. PLDI'19.



# PROFILING AND OPTIMIZING JAVA STREAMS



- Our technique to profile stream executions is implemented in *StreamProf*, the first dedicated stream profiler for the JVM
- Features:
  - Detects every form of stream execution
  - Shows the impact of stream processing on application performance
  - Generates accurate profiles that help developers detect problematic streams



StreamProf targets stream executions:

- Sequential stream executions:
  - Carried out by the current thread

#### Parallel stream executions:

- Typically involve the execution of tasks
  - Tasks can be executed by multiple workers





**Profiling Model** 

Nested stream: A stream whose execution is triggered by (and occurs during the execution of) another outer stream



Multiple nesting levels are possible



Location: Fully qualified name of the caller of the method executing the stream

ExampleClass.exampleMethod	
1290	transactionList.stream()
1291	.parallel()
1292	.filter(t -> t.getStatus() == Transaction.VALID)
1293	.map(Transaction::getID)
1294	.collect(Collectors.toSet());



**Profiling Model** 

#### We model stream execution around the concept of *span*

**Span:** The interval in which a stream is executed by a thread





















#### *measured cycles* = cycles<sub>end</sub> – cycles<sub>begin</sub>



For each span we compute the corresponding cycles and location







Profiling: Profile every span and associate it with the respective measured cycles and location



Difference when profiling sequential and parallel streams:

- Sequential stream execution:
  - Carried out by a single thread
  - Execution represented by a single span



- The measured cycles in the span can be <u>directly</u> attributed to the sequential stream execution
  - No stream ID required to identify a sequential stream
- Anonymous span:
  - Represents a sequential stream execution



#### Parallel stream execution:

- Typically carried out by multiple tasks multiple spans
  - To aggregate the measured cycles of all spans
    - A stream ID required to identify the parallel stream execution
- Named spans: All spans associated with the same parallel stream execution



### **Profiling Methodology**



- Primordial span: Represents the primordial task
  - Associated with a new unique stream ID
- Support span: Any named span other than the primordial span
  - Retrieves the already generated stream ID



The instrumentation relies on a *tracer*:

Reads cycle counters and stores the values in the form of 2 events:





- The tracer maintains thread-local buffers
  - Stores span information associated to a thread in memory
    - No synchronization (only when allocating new buffers)



- The tracer dumps data upon application completion:
  - Dumps one trace per thread participating in stream processing



Traces are post-processed offline



Span reconstruction: each stream profile is reconstructed from the span-begin and span-end events stored in the dumped traces




#### **Measured cycles computation:**

#### Sequential streams:

Computed from the single anonymous span



#### Parallel streams:

Computed from the respective multiple named spans





- The inserted instrumentation code introduces extra cycles that are included in the measured cycles of each span
  - Decreasing profile accuracy
- To remove these extra cycles they need to be estimated, which is the aim of the calibration phase



- Calibration: Produces estimated costs, i.e., estimations of the extra cycles required to profile spans
  - The estimated costs are approximated by constants



- Compensation: Produce compensated cycles, i.e., the measured cycles for a span after the removal of both:
  - Estimated costs (the output of the calibration)
  - *Nested cycles*, i.e., cycles elapsed due to nested spans



## **Profiling Methodology**







Using **StreamProf** to optimize stream processing:

- Target applications:
  - Stream-based workloads from *Renaissance* [8]
    - mnemonics
    - par-mnemonics
- Analysis targets steady state
- Testbed:
  - M<sub>1</sub>: 8 core, 128 GB RAM
  - M<sub>2</sub>: 18 cores, 256 GB RAM

[8] Prokopec et al. *Renaissance: Benchmarking Suite for Parallel Applications on the JVM*. PLDI'19.



## OPTIMIZATION 1: REMOVING UNNEEDED STREAMS



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Customized heatmap of stream executions in *mnemonics* 



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x-axis: streams are grouped by their compensated cycles



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#### y-axis: streams are grouped by their nesting level



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**Cell**: reports the number of stream executions for a given range of *nesting levels* and *cycles* 





Heat: the color of a cell indicates the total cycles of all the stream executions in the group



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Darker regions: good targets for stream code optimizations



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Hot locations: locations in application code responsible for most of the stream processing



### Optimization I:

- Target: mnemonics and par-mnemonics
- MnemonicsCoderWithStream.wordForNum:
  - Recursive method
  - Many stream executions
    - ▲ Finding: These streams always produce the same result
      - The result does not depend on any input of the current recursion level
- Optimization: Move the streams out the recursive code





- MnemonicsCoderWithStream.lambda\$encode\$9:
  - Many stream executions
    - Finding: These streams are always created from an empty set
      - The empty set never changes
      - The streams do not contribute in any form to the workload output
- **Optimization:** Remove the unneeded streams
  - Benefit: Reduce overheads due to unneeded stream executions

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#### Profiling and Optimizing Streams – Optimization I



Heatmaps of the original (*left*) and optimized (*right*) mnemonics

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#### Profiling and Optimizing Streams – Optimization I



Heatmaps of the original (*left*) and optimized (*right*) mnemonics



## OPTIMIZATION 2: IMPROVING LOAD IMBALANCE



#### Optimization II:

- Target: par-mnemonics
- StreamProf reports the distribution of cycles per worker

<u>Finding</u>: Only 2 workers execute more than 99.99% of the total cycles (on both machines)

Optimization: Tune task granularity to improve load balance
Benefit: Improve parallel stream execution performance





Benchmark			Time	Speedup	
	Version	Machine	[ms]	Factor	95% CI
		M <sub>1</sub>	4,944.72		
mnemonics	orig	$M_2$	3,303.64		
	opt 1	$M_1$	1,200.70	4.09	(3.99, 4.19)
		$M_2$	981.97	3.36	(3.32, 3.40)
	orig	M <sub>1</sub>	4,419.53		
		$M_2$	2,977.83		
par-mnemonics	opt 1	$M_1$	1,106.22	3.98	(3.89, 4.04)
		$M_2$	905.19	3.27	(3.20, 3.33)
	ont 2	$M_1$	880.09	5.00	(4.91, 5.10)
	opt 2	$M_2$	764.63	3.88	(3.80, 3.96)



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	orig	M <sub>1</sub>	4,419.53		
		$M_2$	2,977.83		
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	ορι 1	$M_2$	981.97	3.36	(3.32, 3.40)
	orig	<b>M</b> <sub>1</sub>	4,419.53		
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		$M_2$	981.97	3.36	(3.32, 3.40)	
	orig	$M_1$	4,419.53			
		$M_2$	2,977.83			
par-mnemonics	opt 1	$M_1$	1,106.22	3.98	(3.89, 4.04)	
		$M_2$	905.19	3.27	(3.20, 3.33)	
	opt 2	$M_1$	880.09	5.00	(4.91, 5.10)	
		$M_2$	764.63	3.88	(3.80, 3.96)	

speedup = exec time original workload exec time optimized workload



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Speedups

Benchmark		Time	Speedup		
	Version	Machine	[ms]	Factor	95% CI
		<b>M</b> <sub>1</sub>	4,944.72		
mnemonics	orig	$M_2$	3,303.64		
	opt 1	$M_1$	1,200.70	4.09	(3.99, 4.19)
		$M_2$	981.97	3.36	(3.32, 3.40)
	orig	$M_1$	4,419.53		
		$M_2$	2,977.83		
par-mnemonics	opt 1	$M_1$	1,106.22	3.98	(3.89, 4.04)
		$M_2$	905.19	3.27	(3.20, 3.33)
	ont 2	$M_1$	880.09	5.00	(4.91, 5.10)
	opt 2	$M_2$	764.63	3.88	(3.80, 3.96)

• 95% confidence intervals (CI)



Benchmark			Time	Speedup	
	Version	Machine	[ms]	Factor	95% CI
		$M_1$	4,944.72		
	orig	$M_2$	3,303.64		
mnemonics	opt 1	M <sub>1</sub>	1,200.70	4.09	(3.99, 4.19)
		$M_2$	981.97	3.36	(3.32, 3.40)
par-mnemonics	orig	$M_1$	4,419.53		
		$M_2$	2,977.83		
	opt 1	$M_1$	1,106.22	3.98	(3.89, 4.04)
		$M_2$	905.19	3.27	(3.20, 3.33)
	ont 2	$M_1$	880.09	5.00	(4.91, 5.10)
	opt 2	$M_2$	764.63	3.88	(3.80, 3.96)

Removing unneeded stream processing (*opt1*) improves the performance of both *mnemonics* and *par-mnemonics* ✓ Only 6 lines of code changed



Benchmark			. Time	Speedup	
	Version	Machine	[ms]	Factor	95% CI
		$M_1$	4,944.72		
mnemonics	orig	$M_2$	3,303.64		
	opt 1	$M_1$	1,200.70	4.09	(3.99, 4.19)
		$M_2$	981.97	3.36	(3.32, 3.40)
par-mnemonics	orig	$M_1$	4,419.53		
		$M_2$	2,977.83		
	opt 1	$M_1$	1,106.22	3.98	(3.89, 4.04)
		$M_2$	905.19	3.27	(3.20, 3.33)
	ont 3	$M_1$	880.09	5.00	(4.91, 5.10)
	opt 2	$M_2$	764.63	3.88	(3.80, 3.96)

- Improving load balance (*opt2*) results in performance gains in *par-mnemonics* 
  - 2 lines of code changed



Benchmark		Time	Speedup		
	Version	Machine	[ms]	Factor	95% CI
mnemonics		M <sub>1</sub>	4,944.72		
	orig	M <sub>2</sub>	3,303.64		
	opt 1	M <sub>1</sub>	1,200.70	4.09	(3.99, 4.19)
		$M_2$	981.97	3.36	(3.32, 3.40)
	orig	M <sub>1</sub>	4,419.53		
		$M_2$	2,977.83		
par-mnemonics	opt 1	$M_1$	1,106.22	3.98	(3.89, 4.04)
		$M_2$	905.19	3.27	(3.20, 3.33)
	opt 2	M <sub>1</sub>	880.09	5.00	(4.91, 5.10)
		M <sub>2</sub>	764.63	3.88	(3.80, 3.96)

Average speedup is **3.94x** considering all workloads on both machines



# ACCURACY AND OVERHEAD EVALUATION



- Average Cycles Per Span (CPS)
  - Expectation:
    - For workloads with a low CPS
      - the relative cost of the inserted instrumentation code
        - is higher than for workloads with a higher CPS





#### Baseline computation:

- To compute CPS and accuracy, we need a baseline
- All evaluated workloads take place only within stream executions
- Baseline: total cycles elapsed by all threads involved in stream processing



 $baseline = cycles_1 - cycles_0$ 



#### CPS computation:

CPS = baseline / total\_spans

Accuracy computation:

.

Accuracy = 1 - RE



- Testbed:
  - All stream-based workloads from *Renaissance* 
    - mnemonics
    - par-mnemonics
    - scrabble
  - OpenJDK [5]
    - Collection of stream-based workloads released by the developers of OpenJDK
  - JEDI [6]
    - Benchmark suite consisting of TPCH-queries recast to Java Streams

[5] <u>https://github.com/usi-dag/jdk20u/tree/master/test/micro/org/openjdk/bench/java/util/stream</u>
[6] <u>https://github.com/usi-dag/JEDI</u>



# ACCURACY EVALUATION


Benchmark	Version	Machine	CPS	Accuracy [%]
	oria	$M_1$	915	87.99
mnomonics	ong	$M_2$	679	95.18
milemonics	opt 1	$M_1$	2,972	98.99
	ορι τ	$M_2$	2,699	99.54
	orig	$M_1$	1,027	88.27
	ong	$ \begin{array}{ccccccccccccccccccccccccccccccccc$	95.83	
nar mnomonics	opt 1	$M_1$	3,290	99.68
pur-miemonics		$M_2$	2,989	99.66
	ont 2	$M_1$	3,241	99.42
	ορι 2	$M_2$	3,436	94.98
corabbla	orig	M <sub>1</sub>	1,481	89.97
SCIUDDIE	Ong	$M_2$	2,151	97.13



Benchmark	Version	Machine	CPS	Accuracy [%]
	oria	$M_1$	915	87.99
mnomonics	ong	$M_2$	679	95.18
milemonics	ont 1	M <sub>1</sub> 2,97		98.99
	οριι	$M_2$	2,699	99.54
	oria	$M_1$	1,027	88.27
	ong	$M_2$	Image: black	95.83
nar mnomonics	ont 1	$M_1$		99.68
pur-miemonics		$M_2$	2,989	99.66
	ont J	$M_1$	3,241	99.42
	ορι 2	$M_2$	3,436	94.98
ccrabbla	oria	M <sub>1</sub>	1,481	89.97
SCIUDDIE	Ong	$M_2$	2,151	97.13



Benchmark	Version	Machine	CPS	Accuracy [%]
	orig	$M_1$	915	87.99
mananics	ong	$M_2$	679	95.18
milemonics	opt 1	$M_1$	2,972	98.99
	ορι τ	$M_2$	2,699	99.54
	oria	$M_1$	1,027	88.27
	ong	$M_2$	761	95.83
nar mnomonics	opt 1	$M_1$	3,290	99.68
pur-innernomics		$M_2$	2,989	99.66
	opt 2	$M_1$	3,241	99.42
	ορι 2	$M_2$	3,436	94.98
carabbla	orig	M <sub>1</sub>	1,481	89.97
SCIUDDIE	orig	$M_2$	2,151	97.13

Accuracy shown as percentage



Benchmark	Version	Machine	CPS	Accuracy [%]
	oria	$M_1$	915	87.99
mananics	ong	$M_2$	679	95.18
milemonics	ont 1	$M_1$	2,972	98.99
	υρι 1	$M_2$	2,699	99.54
	orig	$M_1$	2,699 1,027 761 3,290	88.27
		M1     1,027       M2     761       M1     3,290	95.83	
nar mnomonics	opt 1	$M_1$	3,290	99.68
pur-innernomics		$M_2$	2,989	99.66
	ont 2	$M_1$	3,241	99.42
	ορι 2	$M_2$	3,436	94.98
carabbla	orig	M <sub>1</sub>	1,481	89.97
	ong	$M_2$	2,151	97.13

- Positive correlation between CPS and accuracy
  - PCC: 0.71, considering all workloads on M<sub>1</sub> and M<sub>2</sub>



Benchmark	Version	Machine	CPS	Accuracy [%]
	oria	M <sub>1</sub>	915	87.99
	orig	$M_2$	679	95.18
mnemonics	ont 1	$M_1$	CPS 915 679 2,972 2,699 1,027 761 3,290 2,989 3,241 3,436 1,481 2,151	98.99
	ορι Ι	$M_2$		99.54
	oria	$M_1$	1,027	88.27
	ong	$M_2$	nine CPS A   1 915   2 679   1 2,972   1 2,699   1 1,027   2 761   1 3,290   1 3,241   2 3,436   1 1,481   2 2,151   1 2   1 2   1 2   1 2	95.83
nar mnananias	opt 1	$M_1$		99.68
par-mnemonics	οριι	$M_2$	2,989	99.66
	ont 2	$M_1$	915     679     2,972     2,699     1,027     761     3,290     3,241     3,436     1,481     2,151	99.42
	ορι Ζ	$M_2$	3 <i>,</i> 436	94.98
aarabbla	oria	$M_1$	1,481	89.97
scrubble	orig	$M_2$	CPS 915 679 2,972 2,699 1,027 761 3,290 2,989 3,241 3,436 1,481 2,151	97.13
		M <sub>1</sub>		91.55
JEDI (mea	in)	$M_2$		90.34
OnenIDK /		M <sub>1</sub>		94.82
OpenJDK (m	ieanj	$M_2$		96.73



# OVERHEAD EVALUATION



### **Overhead Evaluation**

Bonchmark	Vorsion	Machina	Time CDS	Overhead		
Denchinark	version	Wachine	[ms]	CPS	Factor	95% CI
		$M_1$	4,944.72	915	1.55	(1.51, 1.60)
mananics		$M_2$	3,303.64	679	1.46	(1.44, 1.49)
miemonics	ont 1	$M_1$	1,200.70	2,972	1.16	(1.15, 1.16)
	υρι 1	$M_2$	981.97	2,699	1.12	(1.12, 1.13)
	oria	M <sub>1</sub>	4,419.53	1,027	1.51	(1.47, 1.54)
		$M_2$	2,977.83	4,944.729151.353,303.646791.463,303.646791.461,200.702,9721.16981.972,6991.124,419.531,0271.512,977.837611.411,106.223,2901.13905.192,9891.11880.093,2411.10764.633,4361.09	(1.38, 1.45)	
nar mnomonics	opt 1	$M_1$	1,106.22		(1.13, 1.14)	
pui-miemonics	υριι	$M_2$	905.19	2,989	1.11	(1.11, 1.12)
	opt 2	M <sub>1</sub>	880.09	3,241	1.10	(1.10, 1.11)
		$M_2$	764.63	3,436	1.09	(1.08, 1.09)
scrabble	orig	M <sub>1</sub>	310.84	1,481	1.43	(1.42, 1.44)
	UIR	$M_2$	187.09	2,151	1.23	(1.22, 1.23)

#### **Overhead**:

slowdown factor = exec time workload with profiling

exec time workload without profiling



### **Overhead Evaluation**

Bonchmark	Varsian	Machina	Time CPS	Overhead		
Denchinark	version	Wachine	[ms]	CPS 915 679 2,972 2,699 1,027 761 3,290 2,989 3,241 3,436 1,481	Factor	95% CI
	oria	$M_1$	4,944.72	915	1.55	(1.51, 1.60)
mamanics		$M_2$	3,303.64	679	1.46	(1.44, 1.49)
milemonics	opt 1	$M_1$	1,200.70	2,972	1.16	(1.15, 1.16)
	ορι 1	$M_2$	981.97	2,699	1.12	(1.12, 1.13)
	oria	M <sub>1</sub>	4,419.53	1,027	1.12	(1.47, 1.54)
		$M_2$	2,977.83	761	1.41	(1.38, 1.45)
nar mnomonics	ont 1	$M_1$	1,106.22	3,290	1.13	(1.13, 1.14)
pur-milemonics		$M_2$	905.19	2,989	1.11	(1.11, 1.12)
		M <sub>1</sub>	880.09	3,241	1.10	(1.10, 1.11)
	ορι Ζ	$M_2$	764.63	3,436	1.09	(1.08, 1.09)
ccrabbla	orig	M <sub>1</sub>	310.84	1,481	1.43	(1.42, 1.44)
	ong	$M_2$	187.09	2,151	1.23	(1.22, 1.23)

Negative correlation between CPS and overhead

PCC: -0.96, considering all workloads on M<sub>1</sub> and M<sub>2</sub>



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#### **Overhead Evaluation**

Bonchmark	Varcian	Machina	Time	CDS	Overhead		
Denchmark	version	wachine	[ms]	CP3	Factor	95% CI	
	oria	$M_1$	4,944.72	915	1.55	(1.51, 1.60)	
mananics	ong	$M_2$	3,303.64	679	1.46	(1.44, 1.49)	
milemonics	opt 1	$M_1$	1,200.70	2,972	1.16	(1.15, 1.16)	
	ορι 1	$M_2$	981.97	2,699	Factor 1.55 1.46 1.16 1.12 1.12 1.51 1.41 1.13 1.11 1.10 1.09 1.43 1.23 1.13 1.13 1.15 1.07 1.06	(1.12, 1.13)	
	oria	$M_1$	4,419.53	1,027	1.51	(1.47, 1.54)	
	orig opt 1	$M_2$	2,977.83	761	1.41	(1.38, 1.45)	
nar mnomonics	ont 1	$M_1$	1,106.22	3,290	1.13	(1.13, 1.14)	
pur-milemonics	οριι	$M_2$	905.19	CPS     Over Factor       915     1.55       679     1.46       2,972     1.16       2,699     1.12       1,027     1.51       761     1.41       3,290     1.13       2,989     1.11       3,241     1.10       3,436     1.09       1,481     1.43       2,151     1.23       1,131     1.13       1,151     1.13       1,481     1.13       1,151     1.13       1,481     1.13       1,155     1.13       1,481     1.13       1,155     1.15	(1.11, 1.12)		
	ont 2	$M_1$	880.09	3,241	1.10	(1.10, 1.11)	
	ορι 2	$M_2$	764.63	3,436	1.09	(1.08, 1.09)	
ccrabbla	• <i>*</i> : =	$M_1$	310.84	1,481	1.43	(1.42, 1.44)	
	Ung	$M_2$	187.09	2,151	1.23	(1.22, 1.23)	
		$M_1$			1.13		
	arr <i>)</i>	$M_2$		1.15			
		M <sub>1</sub>			1.07		
Obeinov (ii	icallj	$M_2$			1.06		



Limitations

#### Limitations of the technique:

- Additional sources of perturbation (e.g., prevention of JIT compiler optimizations) are not compensated
- The profiles produced using our technique are platform dependent and require the availability of per-thread virtualized reference-cycle counters



- New technique enabling cycle-accurate profiling of stream executions
  - Implemented in StreamProf, a novel stream profiler for the JVM
    - Uses a perturbation-compensation technique
- Analysis of *Renaissance*, revealing previously unknown streamrelated performance issues
- Optimization of two stream-based workloads from *Renaissance*
  - Average speedup: 3.94x
- Evaluation results show that our profiling technique is efficient and yields accurate profiles



# Thanks a lot for your attention!

