ORACLE

Necessar(il)y Evil
dealing with benchmarks, ugh

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MAKE THE FUTURE JAVA

Java

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Intro

Intro: Speaker's Credentials

- ex-«Intel, Apache Harmony performance guy»
- ex-«SPEC Techrep for Oracle»
- in-«Oracle JDK performance guy»
- Guilty for:
  1. *cough*aurora*cough*
  2. SPECjbb2013
  3. Concurrency improvements (e.g. @Contended)
  4. Java Microbenchmark Harness (jmh)
  5. Java Concurrency Stress Tests (jcstress)

Basics

Basics: Naive question

What is benchmark?

Basics: Getting the units right

*Benchmarks:

- micro:

Basics: Getting the units right

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- micro: 1...1000 us, single webapp request

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- `milli`: 1...1000 ms, SPECjvm98, SPECjbb2005
- `micro`: 1...1000 us, single webapp request
- `nano`: 1...1000 ns, single operations

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- nano: 1...1000 ns, single operations
- pico: 1...1000 ps, pipelining

Basics: Benchmarks are experiments

- Computer Science → Software Engineering
  - Way to construct software to meet functional requirements
  - Mostly don't care about HW and data specifics
  - Abstract and composable, «formal science»

- Software Performance Engineering
  - «Real world strikes back!»
  - Exploring complex interactions between hardware, software, and data
  - Based on empirical evidence, i.e. «natural science»

Basics: Experimental Control

Any experiment requires the control

- Sometimes, just a few baseline measurements
- Sometimes, vast web of support experiments

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Benchmarking assumes
the performance model

Basics: Common Wisdom

Microbenchmarks are bad

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~~Microbenchmarks are bad~~

Basics: The Root Cause

«Premature optimization
is the root of all evil»
(Khuth, 1974)

Basics: The Root Cause

«~~Premature~~ Optimization
is the root of all evil»
(Shipilev, 2013)

Basics: Evil Optimizations

Optimizations distort the performance models!

- Applied in «common» (= special) cases
- Unclear inter-dependencies
- «Black box» abstraction fails big time

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Examples:

- interpreter vs. compiler: which is simpler to benchmark?

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- Unclear inter-dependencies
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Examples:

- interpreter vs. compiler: which is simpler to benchmark?
- `new MyObject()`: allocated in TLAB? allocated in LOB? scalarized? eliminated?

Basics: Benchmarks vs. Optimization

Rule #1

Benchmarking is the fight against the optimizations

Level out the performance model:

- collapse the search space
- get predictable benchmarks
- contrast the optimizations we are after

Basics: Know Thy Optimizations

Understanding the performance model is the road to awe

- This is the endgame result for benchmarking
- Benchmarking is for exploring the performance models (which also helps to get better at benchmarking)
- Every new optimization ⇒ new hassle for everyone

Basics: JMH

Java Microbenchmark Harness:
`http://openjdk.java.net/projects/code-tools/jmh/`

- Works around many pitfalls tailored to HotSpot/OpenJDK specifics
- Bug fixes as VM evolves, or we discover more
- We (performance team) validate micros by rewriting them with JMH
- Facilitates peer review

Basics: JMH API Sneak Peek

Let users declare the benchmark body:

```
@GenerateMicroBenchmark
public void helloWorld() {
    // do something here
}
```

...then generate lots of supporting synthetic code around that body.

(At this point, simply generating the auxiliary subclass works fine, but it is limiting for some cases)

Basics: ...increaseth sorrow

Benchmarks amplify all the effects visible at the same scale.

- Millibenchmarks are not really hard
- Microbenchmarks are challenging, but OK
- Nanobenchmarks are the damned beasts!
- Picobenchmarks...

Basics: Warmup

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- Every online optimization requires warmup

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- JIT compilation is **NOT** the only online optimization

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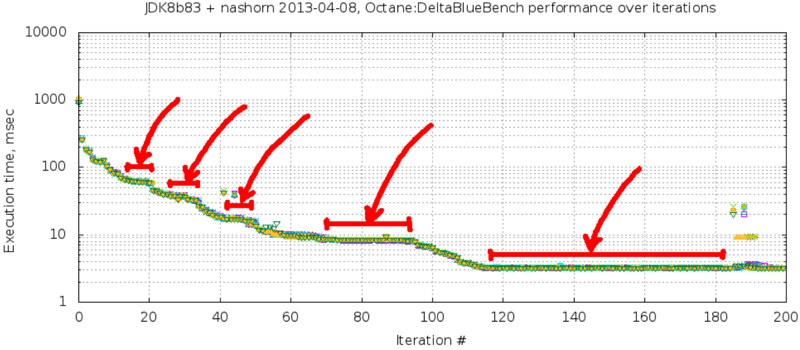
Definition

«Warmup» = waiting for the transient responses to settle down

- Every online optimization requires warmup
- JIT compilation is **NOT** the only online optimization
- Ok, «Watch -XX:+PrintCompilation»?

Basics: Warmup plateaus



Major pitfalls

System: Optimization Quiz (A)

Let us run the empty benchmark.
System reports 4 online CPUs.

Threads	Ops/nsec	Scale
1	3.06 ± 0.10	
2	5.72 ± 0.10	1.87 ± 0.03
4	5.87 ± 0.02	1.91 ± 0.03

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- Why no change for $2 \rightarrow 4$ threads?
- Why 1.87x change for $1 \rightarrow 2$ threads?

System: Power management

Running dummy benchmark,
+ Down-clocking to 2.0 GHz
(effectively disable TurboBoost)

Threads	Ops/nsec	Scale
1	1.97 ± 0.02	
2	3.94 ± 0.05	2.00 ± 0.02
4	4.03 ± 0.04	2.04 ± 0.02

System: Power management

Many subsystems balance power vs. performance. (cpufreq, SpeedStep, Cool&Quiet, TurboBoost ...)

- **Downside**: breaks the homogeneity of time
- **Remedy**: disable power management, fix CPU clock frequency
- **JMH Remedy**: run longer, do not park threads

System: OS Schedulers

OS schedulers balance the load vs. power

- **Downside**: breaks the processing symmetry
- **Remedy**: tight up scheduling policies
- **JMH Remedy**: run longer, do not park threads

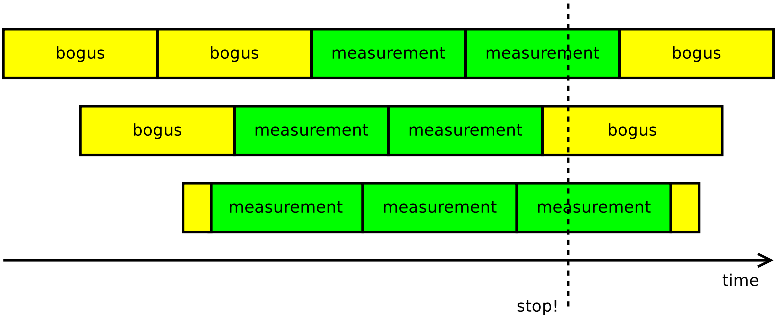
System: Time Sharing

Time sharing systems balance utilization.

- **Downside**: thread start/stop is not instantaneous, thread run time is non-deterministic, the load is non-uniform
- **Remedy**: make sure everything runs before measuring
- **JMH Remedy**: «synchronize iterations»

System: Time Sharing, #2

JMH provides the remedy – bogus iterations:



VM: Optimization Quiz (B)

```
@GenerateMicroBenchmark
public void baseline() {
}
```

0.5 ± 0.1 ns

```
@GenerateMicroBenchmark
public void measureWrong() {
    Math.log(x);
}
```

0.5 ± 0.1 ns

```
@GenerateMicroBenchmark
public double measureRight() {
    return Math.log(x);
}
```

34 ± 1 ns

VM: Dead-code elimination

Compilers are good at eliminating the redundant code.

- **Downside**: can remove (parts of) the benchmarked code
- **Remedy**: consume the results, depend on the results, provide the side effect
- **JMH Remedy**: API support

VM: DCE, Avoiding

DCE is somewhat easy to avoid for primitives:

- Primitives have binary combinators!
- Caveat #1: combinator cost
- Caveat #2: low-range primitives enable speculation (`boolean`)

```
int sum = 0;
for (int i = 0; i < 100; i++) {
    sum += op(i);
}
return sum; // consume in caller
```


VM: DCE, Avoiding

DCE is hard to avoid for references:

- Caveat #1: fast object combinator?
- Caveat #2: need to escape object to limit thread-local opto
- Caveat #3: publishing ⇒ heap write ⇒ store barrier

VM: DCE, Blackholes

JMH provides «Blackholes».
Blackhole consumes the value.

```
class Blackhole {
  void consume(int v) { doMagic(v); }
  void consume(Object o) { doMagic(o); }
}
```

- Returns are implicitly fed into the blackhole
- User can request additional blackhole ⇒ pushes us for heap writes?

VM: DCE, Blackholes

Relatively easy for primitives:

```
class Blackhole {
  static volatile Wrapper NULL;
  volatile int g1 = 1, g2 = 2;

  void consume(int v) {
    if (v == g1 & v == g2) {
      NULL.field = 0; // implicit NPE
    }
  }
}
```


VM: DCE, Blackholes

Harder for references:

```
class Blackhole {
  Object sink;
  int prngState;
  int prngMask;

  void consume(Object v) {
    if ((next(prngState) & prngMask) == 0) {
      sink = v; // store barrier
      prngMask = (prngMask << 1) + 1;
    }
  }
}
```


VM: Optimization Quiz (C)

```
@GenerateMicroBenchmark
public void baseline() {
}
```

0.5 ± 0.1 ns

```
@GenerateMicroBenchmark
public double measureWrong() {
    return Math.log(42);
}
```

1.0 ± 0.1 ns

```
private double x = 42;
@GenerateMicroBenchmark
public double measureRight() {
    return Math.log(x);
}
```

34 ± 1 ns

VM: Constant folding, etc.

Compilers are good at partial evaluation[1]

- **Downside**: can remove (parts of) the benchmarked code
- **Remedy**: make the sources unpredictable, avoid partially evaluated coffee
- **JMH Remedy**: API support

[1] All right, @w7cook! It is not really *the* PE.

VM: CSE

JMH prevents load commoning across @GMB calls

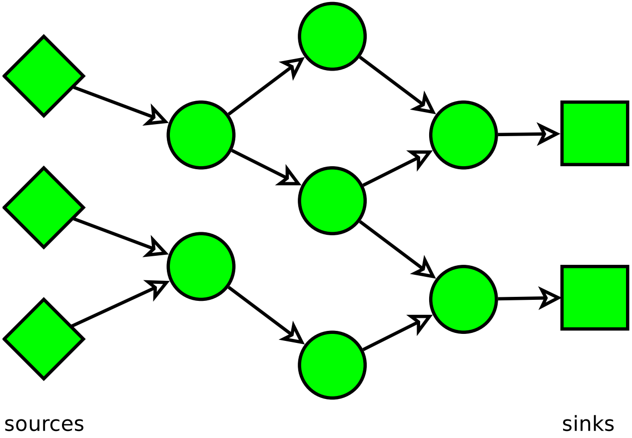
```
double x;

@GMB
double doWork() {
  doStuff(x);
}
```

```
volatile boolean done;
void doMeasure() {
  while (!done) {
    doWork();
  }
}
```

(i.e. read everything from heap ⇒ you are good!)

VM: DCE and CSE are brothers



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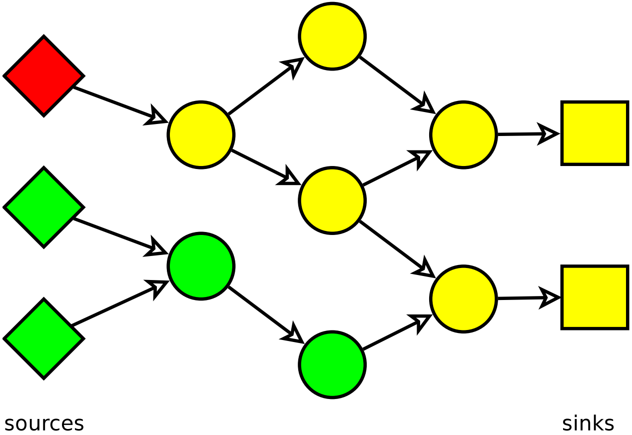

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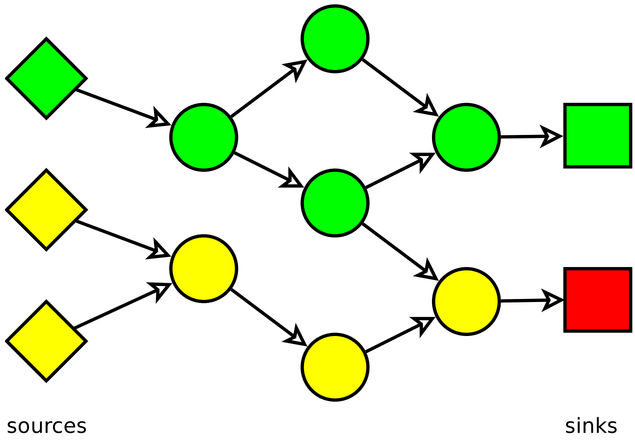

VM: Optimization Quiz (D)

```
int x = 1, y = 2;

private int reps(int reps) {
    int s = 0;
    for (int i = 0; i < reps; i++) {
        s += (x + y);
    }
    return s;
}

@GenerateMicroBenchmark
public int test() { // Q: performance vs. N?
    return reps(N);
}
```


VM: Optimization Quiz (D), #2

N	ns/call		ns/add	
(jmh)	1.5	± 0.1	1.5	± 0.1
1	1.5	± 0.1	1.5	± 0.1
10	2.0	± 0.1	0.1	± 0.01
100	2.7	± 0.2	0.05	± 0.02
1000	68.8	± 0.9	0.07	± 0.01
10000	410.3	± 2.1	0.04	± 0.01
100000	3836.1	± 40.6	0.04	± 0.01

VM: Optimization Quiz (D), #2

N	ns/call		ns/add	
(jmh)	1.5	± 0.1	1.5	± 0.1
1	1.5	± 0.1	1.5	± 0.1
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10000	410.3	± 2.1	0.04	± 0.01
100000	3836.1	± 40.6	0.04	± 0.01

0.04 ns/add ⇒ 25 adds/ns ⇒ GTFO!

VM: Loop unrolling

Loop unrolling greatly expands
the scope of optimizations

- **Downside**: assume the single loop iteration is M ns. After unrolling the effective cost is αM ns, where $\alpha \in [0; +\infty]$
- **Remedy**: avoid unrollable loops, limit the effect of unrolling
- **JMH Remedy**: proper handling for CSE/DCE nils loop unrolling effects

VM: Optimization Quiz (E)

```java
interface Counter {
  void inc();
}

abstract class AC implements Counter {
  int c;
  void inc() {
    c++;
  }
}

class M1 extends AC {}
class M2 extends AC {}
```


VM: Optimization Quiz (E), #2

```
Counter m1 = new M1();
Counter m2 = new M2();

@GenerateMicroBenchmark
public void testM1() { test(m1); }

@GenerateMicroBenchmark
public void testM2() { test(m2); }

void test(Counter c) {
    for (int i = 0; i < 100; i++)
        c.inc();
}
```


VM: Optimization Quiz (E), #3

test	ns/op
testM1	4.6 ± 0.1
testM2	36.0 ± 0.4

VM: Optimization Quiz (E), #3

test	ns/op
testM1	4.6 ± 0.1
testM2	36.0 ± 0.4
repeat testM1	

VM: Optimization Quiz (E), #3

test	ns/op
testM1	4.6 ± 0.1
testM2	36.0 ± 0.4
repeat testM1	35.8 ± 0.4

VM: Optimization Quiz (E), #3

test	ns/op
testM1	4.6 ± 0.1
testM2	36.0 ± 0.4
repeat testM1	35.8 ± 0.4
forked testM1	4.5 ± 0.1
forked testM2	4.5 ± 0.1

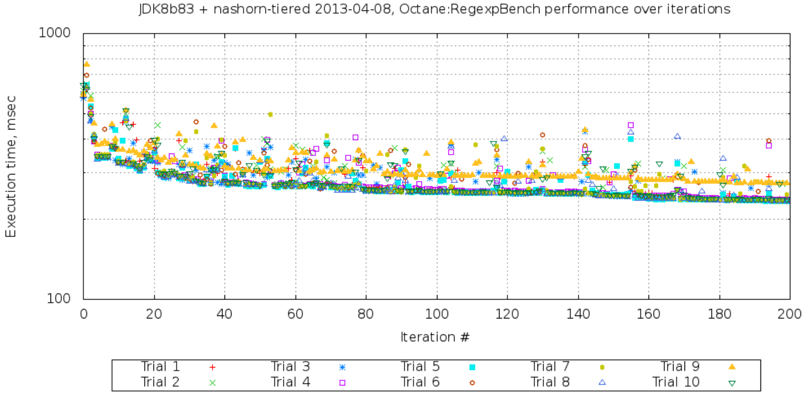
VM: Profile feedback

Dynamic optimizations

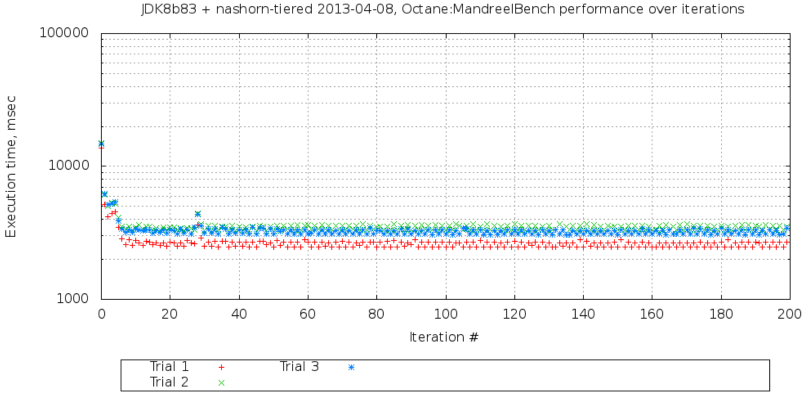
can use runtime information
(E.g. call/type profile)

- **Downside**: Big difference in running multiple benchmarks, or a single benchmark in the VM
- **Remedy**: Warmup everything together; fork JVMs
- **JMH Remedy**: Bulk warmup support; fork JVMs

VM: Optimization Quiz (F)



VM: Optimization Quiz (F), #2



VM: Run-to-run variance

Many scalable algos are inherently non-deterministic! (E.g. memory allocators, profiler counters, schedulers)

- **Downside**: (Potentially) large run to run variance
- **Remedy**: Replays withing every subsystem, multiple JVM runs
- **JMH Remedy**: multiple JVM runs

VM: Inlining budgets

Inlining is the uber-optimization

- **Downside**: You can't inline everything ⇒ subtle inlining budget considerations
- **Remedy**: Smaller methods, smaller loops, examining -XX:+PrintInlining, forcing inlining
- **JMH Remedy**: Generated code peels potentially hot loops, @CompileControl

VM: Inlining example

Small hot method: inlining budget starts here.

```
public RawResultPair testLong_loop
   (Loop loop, MyBenchmark bench) {
  long ops = 0;
  long start = System.nanoTime();
  do {
    bench.testLong(); // @GMB
    ops++;
  } while(!loop.isDone);
  long end = System.nanoTime();
  return new RawResultPair(ops, end - start);
}
```


CPU: Optimization Quiz (G)

```
@State
public class TreeMapBench {
  Map<String, String> map = new TreeMap<>();

  @Setup
  public void setup() { populate(map); }

  @GenerateMicroBenchmark
  public void test(BlackHole bh) {
    for(String key : map.keySet()) {
      String value = map.get(key);
      bh.consume(value);
    }
  }
}
```


CPU: Optimization Quiz (G), #2

```
@GenerateMicroBenchmark
public void test(BlackHole bh) {
  for(String key : map.keySet()) {
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```

	Exclusive	Shared
Throughput, op/sec	615 ± 12	828 ± 21

CPU: Optimization Quiz (G), #2

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Threads	4	4

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Threads	4	4
Maps	4	1

CPU: Optimization Quiz (G), #2

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@GenerateMicroBenchmark
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	Exclusive	**Shared**
Throughput, op/sec	615 ± 12	828 ± 21
Threads	4	4
Maps	4	1
Footprint, Kb	$\sim$1024	$\sim$256

CPU: Cache capacity

DRAM memory is too far and too slow. Let's cache a lot of stuff near the CPUs in SRAMs!

- **Downside**: Severely different performance profiles for memory accesses
- **Remedy**: Track the memory footprint; multiple experiments with different problem sizes; shared/distinct data for the worker threads
- **JMH Remedy**: @State scopes

CPU: Optimization Quiz (G)

Scalability for this code?

```
public class QuizG {
  @State(Scope.Benchmark) class Shared {
    int[] c = new int[64];
  }
  @State(Scope.Thread) class Local {
    static final AtomicInteger COUNTER = ...;
    int index = COUNTER.incrementAndGet();
  }
  @GenerateMicroBenchmark
  void work(Shared s, Local l) {
    s.c[l.index]++;
  }
}
```


CPU: Optimization Quiz (G), #2

Thread	average ns/call	Hit
1	2.0 ± 0.1	
2	18.5 ± 2.4	9x
4	32.9 ± 6.2	16x
8	85.4 ± 13.4	42x
16	208.9 ± 52.1	104x
32	464.2 ± 46.1	232x

Why?

CPU: Bulk method transfers

Memory subsystem is mostly dealing with high locality data. Cache lines are 32, 64, 128 bytes long.

- **Downside**: the dense inter-thread accesses are very hard (false sharing)
- **Remedy**: padding, subclass juggling, @Contended
- **JMH Remedy**: control structures are heavily padded, auto-padding for @State

CPU: Optimization Quiz (H)

Exhibit B.	Exhibit P.

<pre>int sum = 0;
for (int x : a) {
  if (x < 0) {
    sum -= x;
  } else {
    sum += x;
  }
}
return sum;</pre>
	<pre>int sum = 0;
	for (int x : a) {
	  sum += Math.abs(x);
	}
	return sum;</pre>

Which one is faster?

CPU: Optimization Quiz (H)

E. Branched	E. Predicated

<pre>L0: mov 0xc(%ecx,%ebp,4),%ebx
    test %ebx,%ebx
    jl   L1
    add %ebx,%eax
    jmp L2
L1: sub %ebx,%eax
L2: inc %ebp
    cmp %edx,%ebp
    jl   L0</pre>
	<pre>L0: mov 0xc(%ecx,%ebp,4),%ebx
	    mov %ebx,%esi
	    neg %esi
	    test %ebx,%ebx
	    cmovl %esi,%ebx
	    add %ebx,%eax
	    inc %ebp
	    cmp %edx,%ebp
	    jl Loop</pre>

Which one is faster?

CPU: Optimization Quiz (H)

Regular Pattern = $(+, -)^*$

	NHM	Bldzr	C-A9[2]	SNB
branch_regular	0.9	0.8	5.0	0.5
branch_shuffled	6.2	2.8	9.4	1.0
branch_sorted	0.9	1.0	5.0	0.6
predicated_regular	2.0	1.0	5.3	0.8
predicated_shuffled	2.0	1.0	9.3	0.8
predicated_sorted	2.0	1.0	5.7	0.8

time, nsec/op

[2] actually, not C2, but C1

CPU: Optimization Quiz (H)

Regular Pattern = $(+, +, -, +, -, -, +, -, -, +)^*$

	NHM	Bldzr	C-A9[3]	SNB
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time, nsec/op

[3] actually, not C2, but C1

CPU: Branch Prediction

OoO engines speculate a lot.
Most of the time (99%+) correct!

- **Downside**: vastly different performance on mispredicts
- **Remedy**: realistic data!

Conclusion

Conclusion: Benchmarking is serious

- Control the hardware optimizations
- Control the OS optimizations
- Control the JVM optimizations
- Control the language runtime optimizations
- Control the data
- Control the results

Conclusion: Things on list to do

JMH does one thing, and does it right

Other things to improve usability:

- `@Param`-eters
- Java API
- Bindings to the other JVM languages
- Bindings to more reporters

Thanks!

