Overview

- Performance
- Benchmarking
- Profiling
- Performance analysis

Purpose of Performance Evaluation

Research:

- Establish performance advantages/drawbacks of an approach
  - may investigate performance limits
  - should investigate tradeoffs

Development:

- Ensure product meets performance objectives
  - new features must not unduly impact performance of existing features
  - quality assurance

Purchasing:

- Ensure proposed solution meets requirements
  - avoid buying snake oil
- Identify best of several competing products

Different objectives may require different approaches

- Unclear objectives will lead to unclear results
What Performance?

- Cold cache vs hot cache
  - hot-cache figures are easy to produce and reproduce
    o but are they meaningful?
- Best case vs average case vs worst case
  - best-case figures are nice — but are they useful?
  - average case — what defines the “average”?
  - expected case — what defines it?
  - worst case — is it really “worst” or just bad? Does it matter?
- What does “performance” mean?
  - is there an absolute measure?
  - can it be compared? With what?
  - Benchmarking

Note: Always analyse performance before optimising!

- Ensure that you focus on the bottlenecks, they may be non-obvious!

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Benchmarking in Research

- Generally one of two objectives:
  - Show new approach improves performance:
    o Progressive criterion: significant improvements of important aspect
  - Show otherwise attractive approach does not undermine performance
    o Conservative criterion: no significant degradation elsewhere
- Requirement: objectivity/fairness
  - Selection of baseline
  - Inclusion of relevant alternatives
  - Fair evaluation of alternatives
- Requirement: analysis/explanation of results
  - Model of system, incorporating relevant parameters
  - Hypothesis of behaviour
  - Results must support hypothesis

Lies, Damned Lies, Benchmarks

- Micro- vs macro-benchmarks
- Synthetic vs “real-world”
- Benchmark suites, use of subsets
- Completeness of results
- Significance of results
- Baseline for comparison
- Benchmarking ethics
- What is good? — Analysing the results
**Micro- vs Macro-Benchmarks**

- **Macro-benchmarks**
  - Use realistic workloads
  - Measure real-life system performance (hopefully)
- **Micro-benchmarks**
  - Exercise particular operation, e.g. single system call
  - *Good for analysing performance / narrowing down bottlenecks*
    - critical operation is slower than expected
    - critical operation performed more frequently than expected
    - operation is unexpectedly critical (because it’s too slow)
  - **Micro-benchmarks are an analytical tool**

**Benchmarking Crime: Micro-benchmarks only**

- Pretend micro-benchmarks represent overall system performance
- Real performance can generally not be assessed with micro-benchmarks
  - **Exceptions:**
    - Focus is on improving particular operation known to be critical
    - There is an established base line

**Note:** My macro-benchmark is your micro-benchmark

- Depends on the level on which you are operating
  - Eg: lmbench
    - … is a Linux micro-benchmark suite
    - … may be a hypervisor macro-benchmark

**Synthetic vs “Real-world” Benchmarks**

- Real-world benchmarks:
  - real code taken from real problems
    - Livermore loops, SPEC, EEMBC, …
  - execution traces taken from real problems
  - distributions taken from real use
    - file sizes, network packet arrivals and sizes
  - Caution: representative for one scenario doesn’t mean for every scenario!
    - may not provide complete coverage of relevant data space
    - may be biased
- Synthetic benchmarks
  - created to simulate certain scenarios
  - tend to use random data, or extreme data
  - may represent unrealistic workloads
  - may stress or omit pathological cases

**Standard vs Ad-Hoc Benchmarks**

**Why use ad-hoc benchmarks?**

- There may not be a suitable standard
  - Eg: lack of standardised multi-tasking workloads
- Cannot run standard benchmarks
  - Limitations of experimental system
  - Resource-constrained embedded system

**Why not use ad-hoc benchmarks?**

- Not comparable to other work
- Poor reproducibility

**Facit:** Use ad-hoc BMs only if you have no choice!

- Justify your approach carefully
- Document your benchmarks well (for reproducibility!)
Benchmark Suites

- Widely used (and abused!)
- Collection of individual benchmarks, aiming to cover all of relevant data space
- Examples: SPEC CPU{92|95|2000|2006}
  - Originally aimed at evaluating processor performance
  - Heavily used by computer architects
  - Widely (ab)used for other purposes
  - Integer and floating-point suite
  - Some short, some long-running
  - Range of behaviours from memory-intensive to CPU-intensive
    - behaviour changes over time, as memory systems change
    - need to grow working sets to ensure significant memory loads

Obtaining an Overall Score for a BM Suite

- How can we get a single figure of merit for the whole suite?
- Example: comparing 3 systems on suite of 2 BMs

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>System X</th>
<th>System Y</th>
<th>System Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>20</td>
<td>10</td>
<td>40</td>
</tr>
<tr>
<td>2</td>
<td>40</td>
<td>80</td>
<td>20</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>90</td>
<td>60</td>
</tr>
<tr>
<td>Mean</td>
<td>30</td>
<td>45</td>
<td>30</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>System X</th>
<th>System Y</th>
<th>System Z</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abs</td>
<td>Rel</td>
<td>Abs</td>
<td>Rel</td>
</tr>
<tr>
<td>1</td>
<td>20</td>
<td>1.00</td>
<td>10</td>
</tr>
<tr>
<td>2</td>
<td>40</td>
<td>1.00</td>
<td>80</td>
</tr>
<tr>
<td>Total</td>
<td>60</td>
<td>90</td>
<td>60</td>
</tr>
<tr>
<td>Geom. mean</td>
<td>1.00</td>
<td>1.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Rule: arithmetic mean for raw numbers, geometric mean for normalised! [Fleming & Wallace, ‘86]

Partial Data

- Frequently seen in I/O benchmarks:
  - Throughput is degraded by 10%
    - "Our super-reliable stack only adds 10% overhead"
  - Why is throughput degraded?
    - latency too high
    - CPU saturated?
  - Also, changes to drivers or I/O subsystem may affect scheduling
    - interrupt coalescence: do more with fewer interrupts
  - Throughput on its own is useless!

Benchmark Suite Abuse

**Benchmarking Crime: Select subset of suite**

- Introduces bias
  - Point of suite is to cover a range of behaviour
  - Be wary of "typical results", "representative subset"
- Sometimes unavoidable
  - some don’t build on non-standard system or fail at run time
  - some may be too big for a particular system
    - eg, don’t have file system and run from RAM disk...
- Treat with extreme care!
  - can only draw limited conclusion from results
  - cannot compare with (complete) published results
  - need to provide convincing explanation why only subset
- Other SPEC crimes include use for multiprocessor scalability
  - run multiple SPECS on different CPUs
  - what does this prove?
Throughput Degradation

Scenario: Network driver or protocol stack
- New driver reduces throughput by 10% — why?
- Compare:
  - 100 Mb/s, 100% CPU vs 90 Mb/s, 100% CPU
  - 100 Mb/s, 20% CPU vs 90 Mb/s, 40% CPU
- Correct figure of merit is processing cost per unit of data
  - Proportional to CPU load divided by throughput
- Correct overhead calculation:
  - 10 µs/kb vs 11 µs/kb: 10% overhead
  - 2 µs/kb vs 4.4 µs/kb: 120% overhead

Benchmarking crime: Show throughput degradation only
... and pretend this represents total overhead

Overview
- Performance
- Benchmarking
- Profiling
- Performance analysis

Profiling
- Run-time collection of execution statistics
  - invasive (requires some degree of instrumentation)
    - unless use hardware debugging tools or cycle-accurate simulators
  - therefore affects the execution it's trying to analyse
  - good profiling approaches minimise this interference
- Identify parts of system where optimisation provides most benefit
- Complementary to microbenchmarks
- Example: gprof
  - compiles tracing into code, to record call graph
  - uses statistical sampling:
    - on each timer tick record program counter
    - post execution translate this into execution-time share

Gprof example output

<table>
<thead>
<tr>
<th>% cumulative</th>
<th>self</th>
<th>self</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>time</td>
<td>seconds</td>
<td>seconds</td>
<td>calls</td>
</tr>
<tr>
<td>33.34</td>
<td>0.02</td>
<td>0.02</td>
<td>7208</td>
</tr>
<tr>
<td>16.67</td>
<td>0.03</td>
<td>0.01</td>
<td>244</td>
</tr>
<tr>
<td>16.67</td>
<td>0.04</td>
<td>0.01</td>
<td>8</td>
</tr>
<tr>
<td>16.67</td>
<td>0.05</td>
<td>0.01</td>
<td>7</td>
</tr>
<tr>
<td>16.67</td>
<td>0.06</td>
<td>0.01</td>
<td></td>
</tr>
<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>236</td>
</tr>
<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>192</td>
</tr>
<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>47</td>
</tr>
<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>45</td>
</tr>
<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>1</td>
</tr>
<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>1</td>
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<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>1</td>
</tr>
<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>1</td>
</tr>
<tr>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>1</td>
</tr>
</tbody>
</table>

Source: http://sourceware.org/binutils/docs-2.19/gprof
Gprof example output (2)

Granularity: each sample hit covers 2 byte(s) for 20.00% of 0.05 seconds

Index % time self children called name

1 100.0 0.00 0.05 spontaneous
0.00 0.00 1/1 main [1]
0.00 0.00 1/2 on_exit [28]
0.00 0.00 1/1 exit [50]

2 100.0 0.00 0.05 main [1]
0.00 0.05 1/1 report [3]

[3] 100.0 0.00 0.05
0.00 0.05 1/1 main [2]
0.00 0.01 1/1 print [9]
0.00 0.01 9/9 fgets [12]

Index % time self children called name

Source: http://sourceware.org/binutils/docs-2.19/gprof

Profiling

- Run-time collection of execution statistics
  - invasive (requires some degree of instrumentation)
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- Identify parts of system where optimisation provides most benefit
- Complementary to microbenchmarks
- Example: gprof
  - compiles tracing into code, to record call graph
  - uses statistical sampling:
    - on each timer tick record program counter
    - post execution translate this into execution-time share
- Example: oprof
  - collects hardware performance-counter readings
  - works for kernel and apps
  - minimal overhead

oprof example output

```
$ oreport --exclude-dependent
CPU: PIII, speed 863.195 MHz (estimated)
Counted CPU_CLK_UNHALTED events (clocks processor is not halted) with a ...

506605 54.0125 cc1plus
450385 88.9026 cc1plus
28201 5.5667 libc-2.3.2.so
27194 5.3679 vmlinux
677 0.1336 uhci_hcd
...
```

Drilldown of top consumers

```
60213 10.1156 lyx
29313 4.9245 XFree86
...
```

Source: http://oprofile.sourceforge.net/examples/
Performance Monitoring Unit (PMU)

- Collects certain events at run time
- Typically supports many events, small number of event counters
  - Events refer to hardware (micro-architectural) features
    - Typically relating to instruction pipeline or memory hierarchy
    - Dozens or hundreds
  - Counter can be bound to a particular event
    - Via some configuration register
    - Typically 2–4
    - OS can sample counters
    - Counters can trigger exception on exceeding threshold

Event Examples (ARM11)

<table>
<thead>
<tr>
<th>Ev #</th>
<th>Definition</th>
<th>Ev #</th>
<th>Definition</th>
<th>Ev #</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>0x00</td>
<td>I-cache miss</td>
<td>0x0b</td>
<td>D-cache miss</td>
<td>0x22</td>
<td>...</td>
</tr>
<tr>
<td>0x01</td>
<td>Instr. buffer stall</td>
<td>0x0c</td>
<td>D-cache writeback</td>
<td>0x23</td>
<td>Funct. call</td>
</tr>
<tr>
<td>0x02</td>
<td>Data depend. stall</td>
<td>0x0d</td>
<td>PC changed by SW</td>
<td>0x24</td>
<td>Funct. return</td>
</tr>
<tr>
<td>0x03</td>
<td>Instr. micro-TLB miss</td>
<td>0x0f</td>
<td>Main TLB miss</td>
<td>0x25</td>
<td>Funct. ret. predict</td>
</tr>
<tr>
<td>0x04</td>
<td>Data micro-TLB miss</td>
<td>0x10</td>
<td>Ext data access</td>
<td>0x26</td>
<td>Funct. ret. mispred</td>
</tr>
<tr>
<td>0x05</td>
<td>Branch executed</td>
<td>0x11</td>
<td>Load-store unit stall</td>
<td>0x30</td>
<td>...</td>
</tr>
<tr>
<td>0x06</td>
<td>Branch mispredicted</td>
<td>0x12</td>
<td>Write-buffer drained</td>
<td>0x38</td>
<td>...</td>
</tr>
<tr>
<td>0x07</td>
<td>Instr executed</td>
<td>0x13</td>
<td>Cycles FIRQ disabled</td>
<td>0xff</td>
<td>Cycle counter</td>
</tr>
<tr>
<td>0x09</td>
<td>D-cache acc cachable</td>
<td>0x14</td>
<td>Cycles IRQ disabled</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0x0a</td>
<td>D-cache access any</td>
<td>0x20</td>
<td>...</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

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Significance of Measurements

All measurements are subject to random errors
- Standard scientific approach: Many iterations, collect statistics
- Rarely done in systems work — why?
- Computer systems tend to be highly deterministic
  - Repeated measurements often give identical results
  - Main exception are experiments involving WANs
- However, it is dangerous to rely on this without checking!
  - Sometimes "random" fluctuations indicate hidden parameters

Benchmarking crime: Results with no indication of significance

Non-criminal approach:
- Show at least standard deviation of your measurements
- ... or state explicitly it was below a certain value throughout
- Admit results are insignificant unless well-separated std deviations
How to Measure and Compare Performance

Bare-minimum statistics:
- At minimum report the mean (µ) and standard deviation (σ)
  - Don’t believe any effect that is less than a standard deviation
    - 10.2±1.5 is not significantly different from 11.5
    - Be highly suspicious if it is less than two standard deviations
      - 10.2±0.8 may not be different from 11.5
- Be very suspicious if reproducibility is poor (i.e. σ is not small)
  - Exception: non-local networks
- Distrust standard deviations of small iteration counts
  - standard deviations are meaningless for small number of runs
  - ... but ok if effect > σ
  - The proper way to check significance of differences is Student’s t-test!

How to Measure and Compare Performance

Bare-minimum stats are sometimes insufficient
- Eg: Old: µ = 3.1 sec, New: µ = 3 sec

Example: gzip from SPEC CPU2000

Obtaining meaningful execution times:
- Make sure execution times are long enough
  - What is the granularity of your time measurements?
  - make sure the effect you’re looking for is much bigger
  - many repetitions won’t help if your effect is dominated by clock resolution
  - do many repetitions in a tight loop if necessary

Observations?
- First iteration is special
  - 20 Hz clock
    - will not be able to observe any effects that account for less than 0.1 sec

Lesson?
- Need a mental model of the system!
  - Here: repeated runs should give the same result
  - Find reason (hidden parameters) if results do not comply!
How to Measure and Compare Performance

Noisy data:
- Sometimes it isn't feasible to get a "clean" system
  - e.g. running apps on a "standard configuration"
  - this can lead to very noisy results, large standard deviations

Possible ways out:
- Ignoring lowest and highest result
- Taking the floor of results
  - makes only sense if you're looking for minimum
  - but beware of difference-taking!

Both of these are dangerous, use with great care!
- Only if you know what you are doing
  - need to give a convincing explanation of why this is justified
- Only if you explicitly state what you've done in your paper/report

Check outputs!
- Benchmarks must check results are correct!
  - Sometimes things are very fast because no work is done!
  - Beware of compiler optimisations, implementation bugs
- Sometimes checking all results is infeasible
  - eg takes too long, checking dominates effect you're looking for
  - check at least some runs
  - run same setup with checks en/disabled

Ensure runs are comparably reproducible:
- Avoid true randomness!
  - tends to lead to different execution paths or data access patterns
  - makes results non-reproducible
  - makes impossible to fairly compare results across implementations!
  - exceptions exist
    - crypto algorithms are designed for input-independent execution paths
- Pseudo-random is good for benchmarking
  - reproducible sequence of "random" inputs
    - capture sequence and replay for each run
    - use pseudo-random generator with same seed

Vary inputs!
- Easy to produce low standard deviations by using identical runs
  - but this is often not representative
  - can lead to unrealistic caching effects
    - especially in benchmarks involving I/O
    - disks are notorious for this
      - controllers do caching, pre-fetching etc out of control of OS
- Good ways to achieve variations:
  - time stamps for randomising inputs (but see below!)
  - varying order:
    - forward vs backward
    - sequential with increasing strides
    - random access
  - best is to use combinations of the above, to ensure that results are sane
How to Measure and Compare Performance

Environment

- Ensure system is quiescent
  - to the degree possible, turn off any unneeded functionality
    - run Unix systems in single-user mode
    - turn off wireless, disconnect networks, put disk to sleep, etc
  - Be aware of self-interference
    - e.g. logging benchmark results may wake up disk...

- Start different runs from the same system state (where possible)
  - back-to-back processes may not find the system in the same state

Real-World Example

Benchmark:

- 300.twolf from SPEC CPU2000 suite

Platform:

- Dell Latitude D600
  - Pentium M @ 1.8GHz
  - 32KiB L1 cache, 8-way
  - 1MiB L2 cache, 8-way
  - DDR memory @ effective 266MHz
- Linux kernel version 2.6.24

Methodology:

- Multiple identical runs for statistics...

**twolf on Linux: What's going on?**

Performance counters are your friends!

20% performance difference between "identical" runs!

Subtract 221 cycles (123ns) for each cache miss

**twolf on Linux: Lessons?**

- Pointer to problem was standard deviation
  - $\sigma$ for "twolf" was much higher than normal for SPEC programs
- Standard deviation did not conform to mental model
  - Shows the value of verifying that model holds
  - Correcting model improved results dramatically
- Shows danger of assuming reproducibility without checking!

Conclusion:

- Always collect and analyse standard deviations!
- Always check results against your (mental) system model!
How to Measure and Compare Performance

Vary only one thing at a time!

• Typical example: used a combination of techniques to improve system
  – what can you learn from a 20% overall improvement?
• Need to run sequence of evaluations, looking at individual changes
  – identify contribution and relevance
  – understand how they combine to an overall effect
  – they may enhance or counter-balance each other
  – make sure you understand what’s going on!!!!

Record all configurations and data!

• May have overlooked something at first
• May develop better model later
  – could be much faster to re-analyse existing data than re-run all benchmarks

How to Measure and Compare Performance

Measure as directly as possible:

• Eg, when looking at effects of pinning TLB entries
  – don’t just look at overall execution time (combination of many things)
  – use performance counter to compare
    o TLB misses
    o cache misses (from page table reloads)
    o ...
  – Cannot always measure directly
    o eg, actual TLB-miss cost not known
      o extrapolate by artificially reducing TLB size
      o eg by pinning useless entries

Avoid incorrect conclusions from pathological cases

• Typical cases:
  – sequential access optimised by underlying hardware/disk controller...
  – potentially massive differences between sequentially up/down
    o pre-fetching by processor, disk cache
  – random access may be an unrealistic scenario that destroys performance
    o for file systems
  – powers of two may be particularly good or particularly bad for strides
    o often good for cache utilisation
      • minimise number of cache lines used
    o often bad for cache utilisation
      • maximise cache conflicts
  – similarly just-off powers \((2^{n-1}, 2^{n+1})\)
• What is “pathological” depends a lot on what you’re measuring
  – e.g. caching in underlying hardware

Use a model

• You need a (mental or explicit) model of the behaviour of your system
  – benchmarking should aim to support or disprove that model
  – need to think about this in selecting data, evaluating results
  – eg: I/O performance dependent on FS layout, caching in controller...
  – cache sizes (HW & SW caches)
  – buffer sizes vs cache size
• Model should tell you roughly what to expect
  – you should understand that a 2ns cache miss penalty can’t be right
Example: Memory Copy

Loop and Timing Overhead

Ensure that measuring overhead does not affect results:
• Cost of accessing clock may be significant
• Loop overhead may be significant
• Stub overhead may be significant

Approaches:
• May iterations in tight loop
• Measure and eliminate timer overhead
• Measure and eliminate loop overhead
• Eliminate effect of any instrumentation code

How to Measure and Compare Performance

Understand your results!
• Results you don't understand will almost certainly hide a problem
  – Never publish results you don't understand
    o chances are the reviewers understand them, and will reject the paper
    o maybe worse: someone at the conference does it
      • this will make you look like an idiot

Of course, if this happens you are an idiot!

Eliminating Overhead

t0 = time();
for (i=0; i<MAX; i++) {
    asm(nop);
}
t1 = time();
for (i=0; i<MAX; i++) {
    asm(syscall);
}
t2 = time();
printf("Cost is %dus", (t2-2*t1+t0)*1000000/MAX);

Beware of compiler optimizations!
Relative vs Absolute Data

From a real paper (IEEE CCNC’09):
• No data other than this figure
• No figure caption
• Only explanation in text:
  – “The L4 overhead compared to VLX ranges from a 2x to 20x factor depending on the Linux system call benchmark”
• No definition of “overhead factor”
• No native Linux data

**Benchmarking crime: Relative numbers only**
• Makes it impossible to check whether results make sense
• How hard did they try to get the competitor system to perform?
  – Eg, did they run it with default build parameters (debugging enabled)?

Data Range

**Example: Scaling database load**

Looking a bit further:

Scales well, right?

**Benchmarking crime: Selective data set hiding deficiencies**

Benchmarking Ethics

• Do compare with published competitor data, but...
  – Ensure comparable setup
    o Same hardware (or convincing argument why it doesn’t matter)
    o You may be looking at an aspect the competitor didn’t focus on
      o Eg: they designed for large NUMA, you optimise for embedded
  – Be ultra-careful when benchmarking competitor’s system yourself
    – Are you sure you’re running the competitor system optimally?
      o You could have the system mis-configuration (eg debugging enabled)
      o Do your results match their (published or else) data?
    – Make sure you understand exactly what is going on!
      o Eg use profiling/tracing to understand source of difference
      o Explain it!

**Benchmarking crime: Unethical benchmarking of competitor**
• Lack of care is unethical too!

Other Ways to Lie With Benchmarks

• Benchmark-specific optimisations
  – Recognise particular benchmark, insert BM-specific hand-optimised code
  – Popular with compiler-writers, rarely an issue in OS area
  – Pioneered for smartphone performance by Samsung
    [http://bgr.com/2014/03/05/samsung-benchmark-cheating-ends/](http://bgr.com/2014/03/05/samsung-benchmark-cheating-ends/)
• Benchmarking simulated system
  – … with simulation simplifications matching model assumptions
  – GIGO
• Uniprocessor benchmarks to “measure” multicore scalability
  – … by running multiple copies of benchmark on different cores
• CPU-intensive benchmark to “measure” networking performance

I’ve seen all of these BM crimes!
What Is “Good”?  

• Easy if there are established and published benchmarks  
  – Eg your improved algorithm beats best published Linux data by x%  
  – But are you sure that it doesn’t lead to worse performance elsewhere?  
    o important to run complete benchmark suites  
    o think of everything that could be adversely effected, and measure!  

• Tricky if no published standard  
  – Can run competitor/incumbent  
    o eg run lmbench, kernel compile etc on your modified Linux and standard Linux  
    o but be very careful to avoid running the competitor sub-optimally!  
  – Establish performance limits  
    o ie compare against optimal scenario  
    o establish hardware limits on performance  
    o micro-benchmarks or profiling can be highly valuable here!

Real-World Example: Virtualization Overhead  

• Symbian null-syscall microbenchmark:  
  – native: 0.24µs, virtualized (on OKL4): 0.79µs  
    – 230% overhead  
• ARM11 processor runs at 368 MHz:  
  – Native: 0.24µs = 93 cy  
  – Virtualized: 0.79µs = 292 cy  
  – Overhead: 0.55µs = 199 cy  
  – Cache-miss penalty = 20 cy  
• Model:  
  – native: 2 mode switches, 0 context switches, 1 × save+restore state  
  – virtualized: 4 mode switches, 2 context switches, 3 × save+restore state

Performance Counters are Your Friends!  

<table>
<thead>
<tr>
<th>Counter</th>
<th>Native</th>
<th>Virtualized</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Branch miss-pred</td>
<td>1</td>
<td>1</td>
<td>0</td>
</tr>
<tr>
<td>D-cache miss</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>I-cache miss</td>
<td>0</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>D-pTLB miss</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>I-pTLB miss</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Main-TLB miss</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Instructions</td>
<td>30</td>
<td>125</td>
<td>95</td>
</tr>
<tr>
<td>D-stall cycles</td>
<td>0</td>
<td>27</td>
<td>27</td>
</tr>
<tr>
<td>I-stall cycles</td>
<td>0</td>
<td>45</td>
<td>45</td>
</tr>
<tr>
<td>Total Cycles</td>
<td>93</td>
<td>292</td>
<td>199</td>
</tr>
</tbody>
</table>
Yet Another One...

<table>
<thead>
<tr>
<th>Benchmark</th>
<th>Native [µs]</th>
<th>Virt. [µs]</th>
<th>Overhead</th>
<th>Per tick</th>
</tr>
</thead>
<tbody>
<tr>
<td>TDes16_Num0</td>
<td>1.2900</td>
<td>1.2936</td>
<td>0.28%</td>
<td>2.8 µs</td>
</tr>
<tr>
<td>TDes16_RadixHex1</td>
<td>0.7110</td>
<td>0.7129</td>
<td>0.27%</td>
<td>2.7 µs</td>
</tr>
<tr>
<td>TDes16_RadixDecimal2</td>
<td>1.2338</td>
<td>1.2373</td>
<td>0.28%</td>
<td>2.8 µs</td>
</tr>
<tr>
<td>TDes16_Num_RadixOctal3</td>
<td>0.6306</td>
<td>0.6324</td>
<td>0.28%</td>
<td>2.8 µs</td>
</tr>
<tr>
<td>TDes16_Num_RadixBinary4</td>
<td>1.0088</td>
<td>1.0116</td>
<td>0.27%</td>
<td>2.7 µs</td>
</tr>
<tr>
<td>TDesC16_Compare5</td>
<td>0.9621</td>
<td>0.9647</td>
<td>0.27%</td>
<td>2.7 µs</td>
</tr>
<tr>
<td>TDesC16_CompareF7</td>
<td>1.9392</td>
<td>1.9444</td>
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</tr>
<tr>
<td>TdesC16_MatchF9</td>
<td>1.1060</td>
<td>1.1090</td>
<td>0.27%</td>
<td>2.7 µs</td>
</tr>
</tbody>
</table>

Note: these are purely user-level operations!
• What's going on?

Lessons Learned
• Ensure stable results
  – repeat for good statistics
  – investigate source of apparent randomness
• Have a model of what you expect
  – investigate if behaviour is different
  – unexplained effects are likely to indicate problems — don’t ignore them!
• Tools are your friends
  – performance counters
  – simulators
  – traces
  – spreadsheets

Annotated list of benchmarking crimes: [http://www.gernot-heiser.org/benchmarking-crimes.html](http://www.gernot-heiser.org/benchmarking-crimes.html)