# Microbenchmarks in Java and C#

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**Abstract:** Sometimes one wants to measure the speed of software, for instance, to measure whether a new way to solve a problem is faster than the old one. Making such time measurements and microbenchmarks requires considerable care, especially on managed platforms like the Java Virtual Machine and Microsoft's Common Language Infrastructure (.NET), or else the results may be arbitrary and misleading.

Here we give some advice on running microbenchmarks, in particular for managed platforms. Most examples are in Java but the advice applies to any language executed on a managed platform, including Scala, C# and F#. This version uses Java functional interfaces and requires Java 8.

## 1 The challenge of managed platforms

Measuring the execution time of a piece of software is an experimental activity, involving the software and a computer system, itself consisting of much (systems) software and some hardware. Whereas biological experiments, such as measuring bacterial growth, are influenced by natural variation and many unknown circumstances, software performance measurements may seem straightforward: in principle, everything is man-made and under the experimenter's control. However, in practice, software performance measurements are influenced by so many factors, and modern computer systems are growing so complex, that software experiments increasingly resemble biological experiments.

One source of complications is the widespread use of managed execution platforms, such as the Java Virtual Machine (JVM), Microsoft's Common Language Infrastructure (.NET), and high-performance Javascript implementations such as Google's v8 engine. These managed execution platforms typically accept software in intermediate form (bytecode or even source code) and compile that intermediate form to real machine code at runtime, by so-called just-in-time compilation. This seriously affects the execution time, for several reasons.

First, the just-in-time compilation process itself takes some time, contributing start-up overhead. Second, just-in-time compilation typically involves adaptive optimizations, based on the execution counts actually observed at runtime. If the code is executed only a few times, the just-in-time compiler may quickly generate slow code; if it is executed many times, the just-in-time compiler may spend more time generating faster code. Hence the speed of a piece of code is likely to depend on input parameters in complex ways, making it dubious to extrapolate from measurements with short execution times. Third, the just-in-time compiler, or its designers, will try to avoid time-consuming code analyses. This means that code that gets optimized well in a simple context may not be optimized at all in a more complex context that is harder to analyse. Fourth, managed platforms typically have automatic memory management, which in practice means that the garbage collector may decide to run at any time, affecting the code execution measurements in unpredictable ways.

In addition, all this software typically runs on top of complex operating systems (MacOS, Linux, Windows 7), complex processors (Intel i5, AMD), and complex memory management systems (caches, memory management hardware), adding further uncontrollable parameters.

## 2 Measuring execution time

The time spent executing some software may be measured in many different ways: wall-clock time or elapsed time (that is, the total amount of real time that has passed), CPU time spent by the client code only (measured by the operating system), CPU time spent by the client code and any system calls it made, CPU time plus time spent doing input and output, and more.

Here we shall measure simply wall-clock time, because this simplifies comparison between platforms (Java, C#, Linux, MacOS, Windows). Measuring wall-clock time, not just CPU time (or even CPU cycles), means that the measurements are easily affected by other processes running on the same machine, so one should terminate as many of those processes as possible. See warnings in section 7.

### 2.1 A simple timer class for Java

This Java class Timer measures wall-clock time and is portable over most Java execution platforms (in particular Linux, MacOS and Windows):

```
public class Timer {
  private long start, spent = 0;
  public Timer() { play(); }
  public double check() { return (System.nanoTime()-start+spent)/1e9; }
  public void pause() { spent += System.nanoTime()-start; }
  public void play() { start = System.nanoTime(); }
}
```

The timer is started when the Timer object is created. The elapsed time (in seconds) is returned whenever `check()` is called. The methods `pause` and `play` may be used to suspend and resume the timer; see section 5.

### 2.2 A simple timer class for C#

A similar Timer class for C# can be defined like this:

```
public class Timer {
  private readonly System.Diagnostics.Stopwatch stopwatch
    = new System.Diagnostics.Stopwatch();
  public Timer() { Play(); }
  public double Check() { return stopwatch.ElapsedMilliseconds/1000.0; }
  public void Pause() { stopwatch.Stop(); }
  public void Play() { stopwatch.Start(); }
}
```

Like the Java Timer class it measures wall-clock time in seconds.

## 3 Developing basic microbenchmark code

Our microbenchmark code is intended to measure CPU time, memory access time and any associated systems overhead. This may be used to compare different data structures or algorithms, to compare different implementations of methods, or to compare speed of access to different levels of the memory hierarchy.

The microbenchmark code here is not suitable for measuring end-to-end performance of systems that involve disk accesses or network accesses, in particular when these involve asynchronous operations such as non-blocking input-output operations.

Let us assume that you want to measure the time to call and execute this little method:

```
private static double multiply(int i) {
  double x = 1.1 * (double)(i & 0xFF);
  return x * x * x * x * x * x * x * x * x * x
       * x * x * x * x * x * x * x * x * x * x;
}
```

Each call to the method performs 20 floating-point multiplications, as well as an integer bitwise "and" (`&`) and a conversion of a 32-bit `int` to a 64-bit `double`. Performing these operations should take 20–50 CPU cycles, or 8–20 nanoseconds (ns), on a contemporary laptop or desktop Intel i7 CPU with a clock frequency of 2.4 GHz, since 20 / 2.4 GHz equals 8.3 ns.

The purpose of the `(double)(i & 0xFF)` part is to make the computation dependent on the unknown argument `i` instead of a constant. The `(i & 0xFF)` part just makes sure that `x` is between 0 and 255, in other words, it does not grow very large. The dependency on the argument `i` prevents the compiler from simply performing the multiplications once and for all (before the method is called), either when the program is compiled to bytecode by `javac`, or when the bytecode is compiled to native machine code by the `java` just-in-time compiler.

We shall now consider a sequence of increasingly meaningful ways to measure the time it takes to perform a call of method `multiply`.

## 3.1 Mark0: measure one operation (useless)

The simplest attempt is to start the timer, call the function, and measure and print the elapsed time in nanoseconds (ns):

```
public static void Mark0() {          // USELESS
  Timer t = new Timer();
  double dummy = multiply(10);
  double time = t.check() * 1e9;
  System.out.printf("%6.1f ns%n", time);
}
```

However, this is useless for many reasons. Running a Java program that calls Mark0 from the command line a couple of times may produce output like this:

```
5249.0 ns
4992.0 ns
5098.0 ns
```

First, this is far too slow for 20 multiplications, and secondly, the numbers may vary widely. Possibly we are measuring the time it takes to compile the `multiply` method (and maybe the Timer's `check` method) from bytecode to native x86 code; it is hard to know, but the results are certainly wrong. Moreover, on some platforms the timer resolution is so low that the result is always 0.0 ns, which is equally wrong. From this measurement you can conclude nothing at all.

## 3.2 Mark1: measure many operations

A much better approach is to start the timer, execute the function many times, here 1 million times, and print the elapsed time divided by 1 million:

```
public static void Mark1() {          // NEARLY USELESS
  Timer t = new Timer();
  Integer count = 1_000_000;
  for (int i=0; i<count; i++) {
    double dummy = multiply(i);
  }
  double time = t.check() * 1e9 / count;
  System.out.printf("%6.1f ns%n", time);
}
```

The CPU now also has to perform the test on loop counter `i`, the increment `i++` and so on, which affects the time spent. On a modern CPU such as Intel Core 2 or i5 or i7, instruction-level parallelism means that these operations are likely to be executed in parallel with the multiplication. In fact, the results of a couple of runs seem somewhat reasonable:

```
      5.0 ns
      5.5 ns
      5.0 ns
```

However, the variation from run to run still appears unpleasantly high, and the times themselves implausibly low. Worse, if you increase `count` to 100 million in an attempt to reduce variation between runs, then the execution time drops to 0.0 ns or 0.1 ns, highly implausible:

```
      0.1 ns
      0.1 ns
      0.0 ns
```

## 3.3 Mark2: avoid dead code elimination

What happened in Mark1 probably was that the JIT compiler realized that the result of `multiply` was never used, and so the loop has no effect at all — it is dead code — and therefore the loop was removed completely. Hence the implausibly low execution times.

To avoid this, we change the benchmark loop to pretend that the result is used, by adding it to a dummy variable whose value is returned by the method:

```
  public static double Mark2() {
    Timer t = new Timer();
    int count = 100_000_000;
    double dummy = 0.0;
    for (int i=0; i<count; i++)
      dummy += multiply(i);
    double time = t.check() * 1e9 / count;
    System.out.printf("%6.1f ns%n", time);
    return dummy;
  }
```

Running this program multiple times we now get more consistent and plausible results, like these:

```
  30.5 ns
  30.4 ns
  30.3 ns
```

These execution times are somewhat reasonable for a method call, 20 floating-point multiplications, one floating-point addition, and a few integer operations, although somewhat slow compared to our 8–20 ns estimate made above. And in fact, with another virtual machine or slightly different hardware, one might get reproducible execution times such as 16.6 ns.

## 3.4 Mark3: automate multiple runs

Our next step is a simple convenience to automate the execution of multiple runs, instead of having to run the entire program multiple times:

```
public static double Mark3() {
  int n = 10;
  int count = 100_000_000;
  double dummy = 0.0;
  for (int j=0; j<n; j++) {
    Timer t = new Timer();
    for (int i=0; i<count; i++)
      dummy += multiply(i);
    double time = t.check() * 1e9 / count;
    System.out.printf("%6.1f ns%n", time);
  }
  return dummy;
}
```

The output gives a good idea of the variation, which in this particular case is very small:

```
30.7 ns
30.3 ns
30.1 ns
30.7 ns
30.5 ns
30.4 ns
30.9 ns
30.3 ns
30.5 ns
30.8 ns
```

This is much more satisfactory. All the iterations take nearly the same amount of time, and the results are consistent with the Mark2 measurements.

## 3.5 Mark4: compute standard deviation

Instead of printing all the measurements we could compute and print the empirical mean and standard deviation of the measurements:

```
public static double Mark4() {
  int n = 10;
  int count = 100_000_000;
  double dummy = 0.0;
  double st = 0.0, sst = 0.0;
  for (int j=0; j<n; j++) {
    Timer t = new Timer();
    for (int i=0; i<count; i++)
      dummy += multiply(i);
    double time = t.check() * 1e9 / count;
    st += time;
    sst += time * time;
  }
  double mean = st/n, sdev = Math.sqrt((sst - mean*mean*n)/(n-1));
  System.out.printf("%6.1f ns +/- %6.3f %n", mean, sdev);
  return dummy;
}
```

This executes the same benchmark runs but reduces the amount of output:

```
30.3 ns +/-  0.137
```

This result is pleasantly consistent with those obtained from Mark3 above.

In general, one should not expect such consistency for very short methods. For instance, if one simplifies `multiply` to just return the `x` computed in the first line, then it is possible that all iterations of Mark3 reports 1.7 ns/call, yet Mark4 would find that the mean is 2.2 ns. The exact cause for this observation is unknown, but probably it just indicates that one cannot reliably measure the execution time of very small methods.

The standard deviation is a kind of summary of the variation between the 10 measurements, removing the need to inspect them all manually. More precisely, the central limit theorem from statistics tells us that the average of $n$ independent identically distributed observations $t_1, \dots, t_n$ tends to follow the normal distribution $N(\mu, \sigma^2)$, also known as the Gaussian distribution, when $n$ tends to infinity, where $\mu$ and $\sigma$ may be estimated like this:

$$\mu = \frac{1}{n}\sum_{j=1}^{n} t_j$$

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{j=1}^{n}(t_j - \mu)^2}$$

Moreover, from the distribution function of the normal distribution $N(\mu, \sigma^2)$ we know that 68.3% of the observations should fall within the interval $[\mu - \sigma, \mu + \sigma]$ and 95.4% of the observations should fall within the wider interval $[\mu - 2\sigma, \mu + 2\sigma]$, see figure 1.

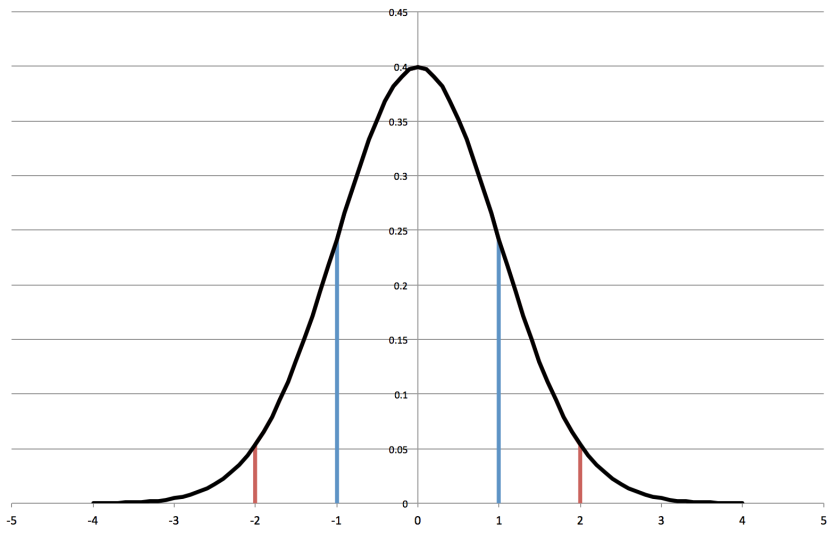


Figure 1: The density function of the normal distribution $N(0, 1)$. The area under the curve between the blue lines at $-1$ and $+1$ is 68.3% of the total area under the curve. Hence 68.3% of the observations should fall between $-1$ and $+1$, that is, at most one standard deviation from the mean. Similarly, 95.4% of the observations fall between $-2$ and $+2$, that is, at most two standard deviations from the mean.

Applying this theory to the `Mark4` measurement above, we conclude that there is 68.3% chance that the actual execution time for `multiply` is between 30.163 ns and 30.437 ns, and 95.4% chance that it is between 30.026 and 30.574 ns. Now this theory is based on the number $n$ of observations being very large, as $n$ tends to infinity, but our $n$ is a modest 10, namely the number of repeated measurements. For a more trustworthy application of the theory, you may choose a larger value of `n`, but then your benchmarks take that much longer to run.

### 3.6 Mark5: choosing the iteration count automatically

The number of iterations (`count` equals 100 million) used above was rather arbitrarily chosen. While it probably is sensible for the small `multiply` function, it may be far too large when measuring a more time-consuming function. To "automate" the choice of `count`, and to see how the mean and standard deviation are affected by the number of iterations, we add an outer loop. In this outer loop we double the `count` until the execution time is at least 0.25 seconds:

```
public static double Mark5() {
  int n = 10, count = 1, totalCount = 0;
  double dummy = 0.0, runningTime = 0.0;
  do {
    count *= 2;
    double st = 0.0, sst = 0.0;
    for (int j=0; j<n; j++) {
      Timer t = new Timer();
      for (int i=0; i<count; i++)
        dummy += multiply(i);
      runningTime = t.check();
      double time = runningTime * 1e9 / count;
      st += time;
      sst += time * time;
      totalCount += count;
    }
    double mean = st/n, sdev = Math.sqrt((sst - mean*mean*n)/(n-1));
    System.out.printf("%6.1f ns +/- %8.2f %10d%n", mean, sdev, count);
  } while (runningTime < 0.25 && count < Integer.MAX_VALUE/2);
  return dummy / totalCount;
}
```

This might produce output like this:

```
100.0 ns +/-   200.00          2
100.0 ns +/-   122.47          4
 62.5 ns +/-    62.50          8
 50.0 ns +/-    37.50         16
 46.9 ns +/-    15.63         32
 40.6 ns +/-    10.36         64
 39.8 ns +/-     2.34        128
 36.3 ns +/-     1.79        256
 36.5 ns +/-     1.25        512
 35.6 ns +/-     0.49       1024
111.1 ns +/-   232.18       2048
 36.1 ns +/-     1.75       4096
 33.7 ns +/-     0.84       8192
 32.5 ns +/-     1.07      16384
 35.6 ns +/-     4.84      32768
 30.4 ns +/-     0.26      65536
 33.1 ns +/-     5.06     131072
 30.3 ns +/-     0.49     262144
 30.0 ns +/-     0.20     524288
 30.6 ns +/-     1.34    1048576
 30.2 ns +/-     0.24    2097152
 30.5 ns +/-     0.35    4194304
 30.3 ns +/-     0.20    8388608
```

As one might hope, the mean (first column) converges towards 30.3 ns, and the standard deviation (second column) becomes smaller, as `count` (third column) grows. The end result is also consistent with that of Mark4. The exception is the sudden increase to 111.1 ns for iteration count 2048, but we also see that the standard deviation is very large in that case, which tells us we can have no confidence in that result. This outlier measurement may be caused by the garbage collector accidentally performing some work at that time, or the just-in-time compiler, or some other external disturbance.

A side remark: The second half of the `do-while` loop condition prevents `count` from overflowing the `int` range. This effectively limits the iteration count to 1 billion ($10^9$), but that is sufficient for methods with execution time 2.5 ns or more, and it would be meaningless to benchmark functions that are faster than that. Alternatively, to avoid overflow one might declare `count` as a 64-bit `long`, but on some architectures the overhead of `long` arithmetics and comparisons might distort the actual measurement results.

## 3.7 Summary of benchmarking functions

Let us summarize the steps that led to the design of our benchmarking function `Mark5`:

- `Mark0` measured a single function call, but that included some unknown virtual machine start up costs, and also ran for too short a time to be measured accurately, and hence was useless.
- `Mark1` improved on `Mark0` by measuring a large number of function calls, hence distribution the start up costs on these. Unfortunately, the just-in-time compiler might optimize away all the function calls because their results were not used.
- `Mark2` improved on `Mark1` by accumulating the function results in the `dummy` variable and returning its value, thereby preventing the just-in-time compiler from optimizing away the calls. Unfortunately, it made just one timing measurement (of `count` function calls), thus not allowing us to estimate the reliability of the reported average.
- `Mark3` improved on `Mark2` by making a set of ten measurements, so one can inspect the variation in the averages. Unfortunately, visual inspection of the variation is cumbersome when making many sets of measurements, for instance of many different functions.
- `Mark4` improved on `Mark3` by additionally computing the standard deviation and printing only the average and the standard deviation for each set of 10 measurements. Unfortunately, the number `count` of function calls in each set of measurements was fixed but chosen arbitrarily, and might be far too large for some functions we want to benchmark.
- `Mark5` improved on `Mark4` by choosing `count` to be 2 initially, and doubling it until the running time of the last measurement (in a set) was at least a quarter second, long enough to avoid problems with virtual machine startup and clock resolution.

Hence we have arrived at a somewhat reliable and usable benchmarking function, `Mark5`.

## 4 General microbenchmark code

Now that we are happy with the basic benchmarking code, we generalize it so that we can measure many different functions (not just `multiply`) more easily, for instance to compare alternative algorithms or implementations.

### 4.1 Mark6: generalize to any function

The functional interface java.util.function.IntToDoubleFunction in Java 8 has method `applyAsDouble`:

```
public interface IntToDoubleFunction {
  double applyAsDouble(int i);
}
```

Any function from `int` to `double` can be represented by this interface. A general benchmarking function Mark6 would simply take an IntToDoubleFunction as argument and hence work for any such function, not just `multiply`:

```
public static double Mark6(String msg, IntToDoubleFunction f) {
  int n = 10, count = 1, totalCount = 0;
  double dummy = 0.0, runningTime = 0.0, st = 0.0, sst = 0.0;
  do {
    count *= 2;
    st = sst = 0.0;
    for (int j=0; j<n; j++) {
      Timer t = new Timer();
      for (int i=0; i<count; i++)
        dummy += f.applyAsDouble(i);
      runningTime = t.check();
      double time = runningTime * 1e9 / count;
      st += time;
      sst += time * time;
      totalCount += count;
    }
    double mean = st/n, sdev = Math.sqrt((sst - mean*mean*n)/(n-1));
    System.out.printf("%-25s %15.1f %10.2f %10d%n", msg, mean, sdev, count);
  } while (runningTime < 0.25 && count < Integer.MAX_VALUE/2);
  return dummy / totalCount;
}
```

In addition to the method to be benchmarked, the benchmarking function takes as argument a string `msg` that describes that function. Also, the printed output has been simplified so that it is easier to further process with other software, for instance to make charts with gnuplot (section 9) or MS Excel (section 10).

We can now apply the general benchmarking method Mark6 to `Benchmark::multiply`, which is a method reference denoting the `multiply` method:

```
Mark6("multiply", Benchmark::multiply);
```

The result may look like this, which says that function `multiply` used on average 30.3 ns per call when called 8 million times, and that the standard deviation between 10 such runs was 0.20:

```
multiply                                  750.0    1289.38          2
multiply                                  200.0     100.00          4
multiply                                  212.5      80.04          8
multiply                                  206.3      40.02         16
multiply                                  209.4      93.80         32
multiply                                  100.0      62.58         64
multiply                                   48.4       5.85        128
multiply                                   48.0       1.79        256
multiply                                   48.2       6.18        512
multiply                                   42.6       0.65       1024
multiply                                   42.3       1.69       2048
multiply                                   41.7       2.43       4096
multiply                                   34.0       1.73       8192
multiply                                   33.2       0.57      16384
multiply                                   31.2       1.74      32768
multiply                                   35.8       6.24      65536
multiply                                   30.8       0.90     131072
multiply                                   30.9       0.60     262144
multiply                                   30.8       0.69     524288
multiply                                   31.2       1.20    1048576
multiply                                   30.2       0.15    2097152
multiply                                   30.3       0.24    4194304
multiply                                   30.3       0.20    8388608
```

This is neat, and consistent with all the previous measurements. In any case, it seems that the extra call through the functional interface IntToDoubleFunction does not in itself slow down the program, presumably because the just-in-time (JIT) compiler optimizes it away.

## 4.2 Mark7: print only the final measurement

When the mean converges and the standard deviation decreases, as in the `multiply` example just shown, it would suffice to print the results for the final value of `count`, which can be achieved simply by moving the computation and printing of `mean` and `sdev` out of the `do-while` loop in Mark6. This is the only difference between Mark6 and the new Mark7:

```
public static double Mark7(String msg, IntToDoubleFunction f) {
  ...
  do {
    ...
  } while (runningTime < 0.25 && count < Integer.MAX_VALUE/2);
  double mean = st/n, sdev = Math.sqrt((sst - mean*mean*n)/(n-1));
  System.out.printf("%-25s %15.1f %10.2f %10d%n", msg, mean, sdev, count);
  return dummy / totalCount;
}
```

Printing just the final value makes sense if one assumes that the optimizations performed by the just-in-time compiler and runtime system stabilize eventually, but not if the just-in-time compiler indefinitely tries and retries new optimizations and generates new machine code.

Using Mark7 on `multiply` is easy:

```
Mark7("multiply", Benchmark::multiply);
```

and produce a result consistent with the final result of Mark6:

```
multiply                                   30.1       0.16    8388608
```

When benchmarking many different functions, the Mark7 simplification of the output considerably improves the overview, and we can now benchmark many functions in one go. Here we pass a lambda expression (of type IntToDoubleFunction) in each call:

```
Mark7("pow", i -> Math.pow(10.0, 0.1 * (i & 0xFF)));
Mark7("exp", i -> Math.exp(0.1 * (i & 0xFF)));
Mark7("log", i -> Math.log(0.1 + 0.1 * (i & 0xFF)));
Mark7("sin", i -> Math.sin(0.1 * (i & 0xFF)));
Mark7("cos", i -> Math.cos(0.1 * (i & 0xFF)));
Mark7("tan", i -> Math.tan(0.1 * (i & 0xFF)));
Mark7("asin", i -> Math.asin(1.0/256.0 * (i & 0xFF)));
Mark7("acos", i -> Math.acos(1.0/256.0 * (i & 0xFF)));
Mark7("atan", i -> Math.atan(1.0/256.0 * (i & 0xFF)));
```

This may produce results such as the following:

```
pow                                          76.0       0.57    4194304
exp                                          55.0       0.41    8388608
log                                          31.9       0.55    8388608
sin                                         116.1       0.61    4194304
cos                                         116.1       0.49    4194304
tan                                         143.4       1.40    2097152
asin                                        232.1       2.70    2097152
acos                                        216.4       2.30    2097152
atan                                         54.1       0.27    8388608
```

A word of warning: Whereas these results are quite reliable for more complicated functions such as `pow`, `exp` and trigonometry, the result for method `multiply` or even simpler ones may not be. What is measured in that case is really the just-in-time compiler's ability to inline function calls and schedule instructions in a particular context. For instance, on other hardware and with a different Java implementation, we have found the execution time for `multiply` to be 18.4 ns, 13.8 ns, and 16.5 ns, all apparently with low standard deviation. Those results were heavily influenced, in mysterious ways, by other code executed before and after (!) the code being benchmarked.

## 4.3 Mark8: problem size parameters

Often, the execution time of a method depends on the problem size. For instance, we may want to measure the execution time of a binary array search method:

```
static int binarySearch(int x, int[] arr) { ... }
```

The method returns the index of item `x` in sorted array `arr`, or returns $-1$ if `x` is not in the array. Clearly the execution time depends on the size of the array, so we would want to measure it for a range of such array sizes. Moreover, we would like the array size to be printed along with the measured mean execution time and the standard deviation.

As a further generalization, we want to make the rather arbitrarily chosen `repeat` count (10) and minimal execution time (0.25 s) into user-controllable parameters.

Thus we define yet another benchmarking method that simply takes several additional parameters:

```
public static double Mark8(String msg, String info, IntToDoubleFunction f,
                           int n, double minTime) {
  int count = 1, totalCount = 0;
  double dummy = 0.0, runningTime = 0.0, st = 0.0, sst = 0.0;
```

```
    do {
      count *= 2;
      st = sst = 0.0;
      for (int j=0; j<n; j++) {
        Timer t = new Timer();
        for (int i=0; i<count; i++)
          dummy += f.applyAsDouble(i);
        runningTime = t.check();
        double time = runningTime * 1e9 / count;
        st += time;
        sst += time * time;
        totalCount += count;
      }
    } while (runningTime < minTime && count < Integer.MAX_VALUE/2);
    double mean = st/n, sdev = Math.sqrt((sst - mean*mean*n)/(n-1));
    System.out.printf("%-25s %s%15.1f %10.2f %10d%n", msg, info, mean, sdev, count);
    return dummy / totalCount;
  }
```

A couple of convenient overloads with useful parameter values include these, where the first one is equivalent to the old `Mark7`:

```
  public static double Mark8(String msg, IntToDoubleFunction f) {
    return Mark8(msg, "", f, 10, 0.25);
  }
  public static double Mark8(String msg, String info, IntToDoubleFunction f) {
    return Mark8(msg, info, f, 10, 0.25);
  }
```

To measure the binary search execution time for a range of array sizes, we run this benchmark:

```
  for (int size = 100; size <= 10_000_000; size *= 2) {
    final int[] intArray = SearchAndSort.fillIntArray(size);  // sorted [0,1,...]
    final int successItem = (int)(0.49 * size);
    Mark8("binary_search_success",
          String.format("%8d", size),
          i -> SearchAndSort.binarySearch(successItem, intArray));
  }
```

Notice the use of `String.format` to make sure that the `info` string always has the same length, so that the ASCII output continues to line up in columns. Indeed, a possible result from running this benchmark may be:

```
  binary_search_success          100             4.4       0.05   67108864
  binary_search_success          200            15.9       0.10   16777216
  binary_search_success          400            17.3       0.17   16777216
  binary_search_success          800            14.1       0.18   33554432
  binary_search_success         1600            19.2       0.19   16777216
  binary_search_success         3200            20.8       0.08   16777216
  binary_search_success         6400            17.5       0.36   16777216
  binary_search_success        12800            25.4       0.19   16777216
  binary_search_success        25600            29.2       0.33   16777216
  binary_search_success        51200            30.8       0.23    8388608
  binary_search_success       102400            33.3       0.34    8388608
  binary_search_success       204800            31.3       0.38    8388608
```

```
binary_search_success        409600             37.1        0.19    8388608
binary_search_success        819200             35.3        0.45    8388608
binary_search_success       1638400             41.5        0.28    8388608
binary_search_success       3276800             46.1        0.17    8388608
binary_search_success       6553600             44.1        0.13    8388608
```

This looks neat, but it turns out that these results probably seriously underestimate realistic execution times, not because we measure in the wrong way, but because we measure the wrong thing: it is not realistic to search for the same item again and again. See section 11.1 for a discussion and more realistic results.

### 4.4 Collecting and further processing benchmark results

The output of a benchmark run, as shown for instance at the end of section 4.3, can be piped into a file for further processing by other software (see also section 9):

```
$ java Benchmark > binary-search.out
```

## 5 Benchmarks that require setup

Sometimes a method that we want to benchmark will modify or destroy the data it works on, so the data must be restored before each execution of the code. For instance, an array sort procedure will leave the argument array sorted, and since there is little point in measuring how long it takes to sort an already-sorted array, the array disorder must be reestablished before the next benchmark run, for instance by randomly shuffling the array.

A general method for this purpose can be defined by declaring an abstract class Benchmarkable that implements the functional interface IntToDoubleFunction and in addition has a `setup` method that sets up data before performing the measurement:

```
public abstract class Benchmarkable implements IntToDoubleFunction {
  public void setup() { }
  public abstract double applyAsDouble(int i);
}
```

We define new variant of method `Mark8` that takes a Benchmarkable argument, and avoids measuring the setup time by suspending the timer (section 2.1) before the call to `setup` and resuming the timer after it:

```
public static double Mark8Setup(String msg, String info, Benchmarkable f,
                                int n, double minTime) {
  int count = 1, totalCount = 0;
  double dummy = 0.0, runningTime = 0.0, st = 0.0, sst = 0.0;
  do {
    count *= 2;
    st = sst = 0.0;
    for (int j=0; j<n; j++) {
      Timer t = new Timer();
      for (int i=0; i<count; i++) {
        t.pause();
        f.setup();
        t.play();
        dummy += f.applyAsDouble(i);
      }
```

```
        runningTime = t.check();
        double time = runningTime * 1e9 / count;
        st += time;
        sst += time * time;
        totalCount += count;
      }
    } while (runningTime < minTime && count < Integer.MAX_VALUE/2);
    double mean = st/n, sdev = Math.sqrt((sst - mean*mean*n)/(n-1));
    System.out.printf("%-25s %s%15.1f %10.2f %10d%n", msg, info, mean, sdev, count);
    return dummy;
  }
```

This method should be used only to benchmark functions that take some substantial amount of time (say, at least 100 ns/call) to execute, otherwise the benchmark will mostly measure the amount of time it takes to suspend and resume the timer.

To compare three algorithms for array sort: selection sort, quicksort, and heap sort, we may use a random permutation (shuffle) of an array of 10,000 integers, like this:

```
final int[] intArray = SearchAndSort.fillIntArray(10_000);
Mark8Setup("selection_sort",
   new Benchmarkable() {
     public void setup() { SearchAndSort.shuffle(intArray); }
     public double applyAsDouble(int i)
     { SearchAndSort.selsort(intArray); return 0.0; } });
Mark8Setup("quicksort",
   new Benchmarkable() {
     public void setup() { SearchAndSort.shuffle(intArray); }
     public double applyAsDouble(int i)
     { SearchAndSort.quicksort(intArray); return 0.0; } });
Mark8Setup("heapsort",
   new Benchmarkable() {
     public void setup() { SearchAndSort.shuffle(intArray); }
     public double applyAsDouble(int i)
     { SearchAndSort.heapsort(intArray); return 0.0; } });
```

Here are the results from one execution. They show that selection sort is more than 120 times slower than quicksort, and that heap sort is 1.18 times slower than quicksort, on arrays with 10000 elements:

```
selection_sort                38147737.5  221026.39          8
quicksort                       767679.5    2299.36        512
heapsort                        829134.2    8257.46        512
```

## 6 Execution time as a function of problem size

We can further use `Mark8Setup` to measure the time to sort arrays of size 100, 200, 400, and so on:

```
for (int size = 100; size <= 2_000_000; size *= 2) {
  final int[] intArray = SearchAndSort.fillIntArray(size);
  Mark8Setup("quicksort",
             String.format("%8d", size),
             new Benchmarkable() {
               public void setup() { SearchAndSort.shuffle(intArray); }
               public double applyAsDouble(int i)
               { SearchAndSort.quicksort(intArray); return 0.0; } });
}
System.out.printf("%n%n"); // data set divider
... and similarly for other sorting algorithms ...
```

The result may look like this:

```
quicksort                      100         4486.7       60.39      65536
quicksort                      200         9882.7       23.95      32768
quicksort                      400        21778.9       81.49      16384
quicksort                      800        47738.3      246.73       8192
quicksort                     1600       102736.4      328.70       4096
quicksort                     3200       222186.8     1601.44       2048
quicksort                     6400       480137.4     7955.89       1024
quicksort                    12800      1005463.7     1390.13        256
quicksort                    25600      2147215.6    11412.37        128
quicksort                    51200      4547435.9    44073.21         64
quicksort                   102400      9539396.9    40881.14         32
quicksort                   204800     20100187.5   247344.67         16
quicksort                   409600     41916537.5   238098.67          8
quicksort                   819200     87614550.0   701559.32          4
quicksort                  1638400    182791750.0  1547216.20          2
```

Note that the standard deviation is now much larger than previously, though never more than 3 percent of the mean. For the low iteration counts (16, 8, 4, 2) near the bottom of the table it is natural that the standard deviation is high. For the problem size 6400, where the iteration count is still rather high (1024), the large standard deviation may be caused by some external computer activity during one or more of the measurements.

## 7 Hints and warnings

Above we have already described many pitfalls of performance measurements; here are some more:

- To minimize interference from other software during benchmark runs, you should shut down as many external programs as possible, and in particular web browsers, Skype, Microsoft Office, OpenOffice, mail clients, virus checkers, iTunes, virtual machines (such as Virtual PC, Parallels, VMware), web servers and database servers running on the same machine. The Windows Update mechanism seems particularly prone to seriously slow down the machine at inopportune times. Although this probably affects the disk subsystem more than CPU times and memory accesses, it appears to have some effect on that too.
- Remove or disable all logging and debugging messages in the code being benchmarked. Generating such messages can easily spend more than 90 per cent of the execution time, completely distorting the measurements, and hiding even major speed-ups to the actual data processing.
- Never measure performance from inside an integrated development environment (IDE) such as Eclipse or Visual Studio; use the command line. Even in "release builds" and similar, the software may be slower due to injected debugging code, some form of execution supervision, or just because the IDE itself consumes a lot of CPU time.
- Turn off power savings schemes in your operating system and BIOS, to prevent them from reducing CPU speed in the middle of the benchmark run. In particular, some laptops by default reduce CPU speed when running on battery instead of mains power, and a desktop computer might similarly slow down when there is no user interface activity.

- Compile code with relevant optimizations options, such as `csc /o MyProg.cs` for Microsoft's C# compiler. Without the `/o` option, the generated bytecode may include extraneous no-op instructions and similar (to better accommodate debugging).

- Be aware that different implementations of the Java Virtual Machine (from Oracle or from IBM, say), and different implementations of CLI/.NET (from Microsoft or from Mono, say) may have very different performance characteristics. Hence statements about "the speed of Java" or "the speed of C#" should be taken with large grains of salt.

- Be aware that the Java or .NET virtual machines incorporate several different garbage collectors, which may have very different performance characteristics.

- Be aware that different C compilers (`gcc`, `clang`, Microsoft `cl`, Intel's C compiler) generate code of very different quality, and that the same compiler will generate very different code depending on the optimization level (`-O`, `-O1`, and so on). Also, most of these compilers take a large number of other optimization-related options, allowing detailed control over code generation. Hence statements about "the speed of C" should be taken with large grains of salt.

- Be aware that different CPU brands (Intel, AMD) and different CPU microarchitectures (Netburst, Core, Nehalem) and different versions of these (desktop, mobile) and different generations of these, may have different performance characteristics, even when they implement the same native code instruction set, such as x86. Confusingly, different microarchitectures (eg Intel P5, P6, Netburst, Core) may be marketed under the same name (eg Pentium), and the same microarchitecture may be marketed under different names (Intel Pentium, i3, i5, i7). Hence, if this matters to you, take note of the processor model number. Also, the rest of the system around the CPU matters: the speed of RAM, the latency and bandwidth of the memory bus, the size of caches, and so on.

- If you measure the time to execute threads, input-output, GPU calls or other asynchronous activities, make sure that you wait for these activities to actually compute and terminate, for instance by calling `thread.join()`, before `timer.check()` is called.

- Reflect on your results. If they are unreasonably fast or unreasonably slow, you may have overlooked something important, and there may be an opportunity to learn something.

  For example, once I found that array read access in C code on an AMD processor was unreasonably fast. It turned out that the array was never actually allocated in RAM; the memory pages were just entered into a CPU memory management table and assumed to contain all zeroes. By first writing to the array elements, actual allocation of the memory pages to RAM was forced, and this increased the subsequent read access time to a realistic amount.

  For another example, once I found that some early Scala code was unreasonably slow. It turned out that because the code was written in a Scala Application trait, it was compiled to Java Virtual Machine (JVM) bytecode inside a constructor, which apparently the JVM did not bother to optimize. Putting the Scala code into an ordinary Scala function made it 12 times faster.

## 8 Platform identification

Sometimes the purpose of a performance test is to compare the speed of several different platforms (virtual machines, processors, and operating systems) or several different versions of such platforms. Then it is useful to let each platform identify itself as part of the test output.

Printing this information before any benchmarking is performed has the beneficial side effect of forcing the virtual machine to load (and possibly compile) library classes involved in console input-output, string manipulation, and string formatting, so that this does not happen in the middle of the benchmark runs.

## 8.1 Platform identification in Java

In Java, the following method can be used to print relevant system information:

```
public static void SystemInfo() {
  System.out.printf("# OS:   %s; %s; %s%n",
                    System.getProperty("os.name"),
                    System.getProperty("os.version"),
                    System.getProperty("os.arch"));
  System.out.printf("# JVM:  %s; %s%n",
                    System.getProperty("java.vendor"),
                    System.getProperty("java.version"));
  // The processor identifier works only on MS Windows:
  System.out.printf("# CPU:  %s; %d \"procs\"%n",
                    System.getenv("PROCESSOR_IDENTIFIER"),
                    Runtime.getRuntime().availableProcessors());
  java.util.Date now = new java.util.Date();
  System.out.printf("# Date: %s%n",
    new java.text.SimpleDateFormat("yyyy-MM-dd'T'HH:mm:ssZ").format(now));
}
```

The hash mark (#) at the beginning of each line marks it as a non-data line in input to eg. `gnuplot`. The output may look like this on a Windows 7 machine:

```
# OS:   Windows 7; 6.1; amd64
# JVM:  Oracle Corporation; 1.8.0_25
# CPU:  Intel64 Family 6 Model 58 Stepping 9, GenuineIntel; 4 "procs"
# Date: 2015-02-04T14:21:35+0100
```

and like this on Mac OS X:

```
# OS:   Mac OS X; 10.9.5; x86_64
# JVM:  Oracle Corporation; 1.8.0_51
# CPU:  null; 8 "cores"
# Date: 2015-09-15T14:36:48+0200
```

and like this on Linux:

```
# OS:   Linux; 3.2.0-72-generic; amd64
# JVM:  Oracle Corporation; 1.8.0_20
# CPU:  null; 32 "procs"
# Date: 2015-02-04T14:25:02+0100
```

The Date stamp in the very last line says 4 February 2015 at 14:25:02 UTC plus 1 hour, that is, east of Greenwich. There seems to be no portable way, across operating systems, to obtain more detailed CPU data, such as brand, family, version, speed (in GHz), cache sizes, and so on. The processor count `"procs"` is as reported by the Java library, and sometimes includes hyperthreading, sometimes not.

### 8.2 Platform identification in C#

This C# method can be used to print basic system information, just as the above Java method:

```
private static void SystemInfo() {
  Console.WriteLine("# OS          {0}",
    Environment.OSVersion.VersionString);
  Console.WriteLine("# .NET vers.  {0}",
    Environment.Version);
  Console.WriteLine("# 64-bit OS   {0}",
    Environment.Is64BitOperatingSystem);
  Console.WriteLine("# 64-bit proc {0}",
    Environment.Is64BitProcess);
  Console.WriteLine("# CPU         {0}; {1} \"procs\"",
    Environment.GetEnvironmentVariable("PROCESSOR_IDENTIFIER"),
    Environment.ProcessorCount);
  Console.WriteLine("# Date        {0:s}",
    DateTime.Now);
}
```

## 9 Simple charting with gnuplot

Using `gnuplot` one can plot the binary search data produced in section 4.3:

```
set term postscript
set output "binary-search-plot.ps"
plot 'binary-search.out' using 2:3:4 with errorlines
```

This says that the data $(x, y, dy)$ are in columns 2, 3 and 4 (thus ignoring the descriptive text in column 1) of text file `binary-search.out`, and that $dy$ should be used for plotting $y$-value error bars at each data point $(x, y)$. The resulting plot is shown in figure 2.

Similarly, we can plot the running times of the three sorting algorithms benchmarked in section 6, using logarithmic axes because selection sort is so much slower than quicksort and heap sort:

```
set term postscript
set output "sorting-plot.ps"
set logscale xy
plot 'sort-scalability.out' using 2:3:4 with errorlines
```

The resulting plot is shown in figure 3. Gnuplot has many options and features, see its manual.

## 10 Simple charting with Excel

In MS Excel 2010 or 2013 for Windows, choose `File > Open > All Files` and select a text output file such as that created in section 4.3. A Text Import Wizard dialog appears, where you should choose `Fixed width`, and may choose `Start import at row 5` (to ignore the system information at the top of the file), then click `Next`. The wizard will usually guess the columns correctly, in which case just click `Next` again, then `Finish`. In Excel 2011 for Mac, choose `File > Import > Text file > Import > All files` and select the appropriate text file, to get a similar Text Import Wizard. Hint: If Excel uses decimal comma and the text file uses decimal point, or vice versa, then open the Advanced subdialog and change Excel's expectations; otherwise the import goes wrong.

The data appears in an Excel sheet, as shown in figure 4.

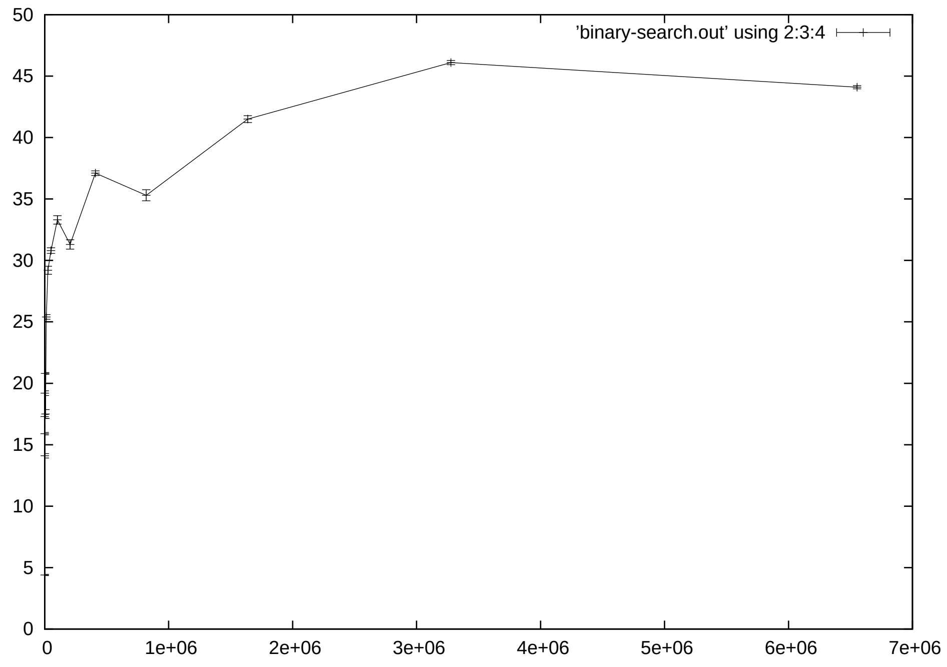


Figure 2: Binary search execution time as a function of array size. Graph produced by `gnuplot`. It displays the suspicious results from section 4.3, not the more correct ones from section 11.2.

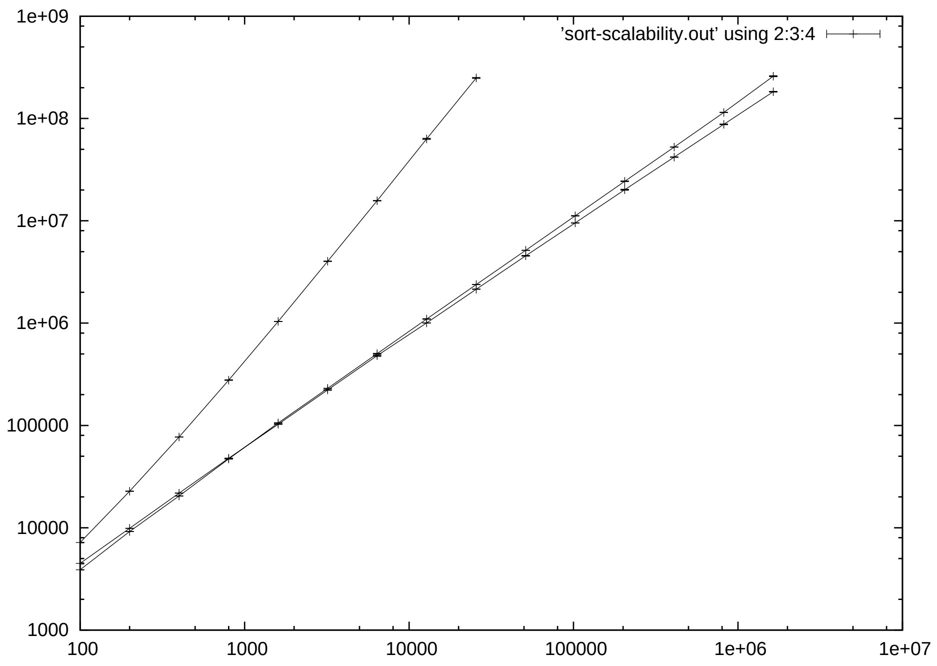
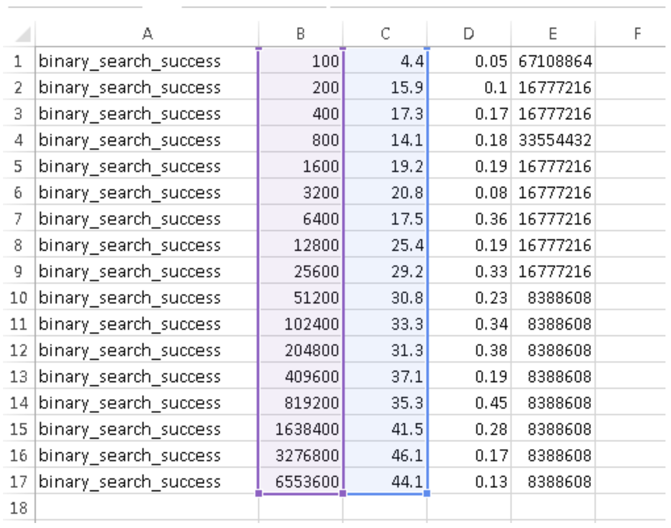


Figure 3: Three sorting algorithms, execution time as a function of array size; `gnuplot` graph. Note the logarithmic scale on both axes.



| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | binary_search_success | 100 | 4.4 | 0.05 | 67108864 | |
| 2 | binary_search_success | 200 | 15.9 | 0.1 | 16777216 | |
| 3 | binary_search_success | 400 | 17.3 | 0.17 | 16777216 | |
| 4 | binary_search_success | 800 | 14.1 | 0.18 | 33554432 | |
| 5 | binary_search_success | 1600 | 19.2 | 0.19 | 16777216 | |
| 6 | binary_search_success | 3200 | 20.8 | 0.08 | 16777216 | |
| 7 | binary_search_success | 6400 | 17.5 | 0.36 | 16777216 | |
| 8 | binary_search_success | 12800 | 25.4 | 0.19 | 16777216 | |
| 9 | binary_search_success | 25600 | 29.2 | 0.33 | 16777216 | |
| 10 | binary_search_success | 51200 | 30.8 | 0.23 | 8388608 | |
| 11 | binary_search_success | 102400 | 33.3 | 0.34 | 8388608 | |
| 12 | binary_search_success | 204800 | 31.3 | 0.38 | 8388608 | |
| 13 | binary_search_success | 409600 | 37.1 | 0.19 | 8388608 | |
| 14 | binary_search_success | 819200 | 35.3 | 0.45 | 8388608 | |
| 15 | binary_search_success | 1638400 | 41.5 | 0.28 | 8388608 | |
| 16 | binary_search_success | 3276800 | 46.1 | 0.17 | 8388608 | |
| 17 | binary_search_success | 6553600 | 44.1 | 0.13 | 8388608 | |
| 18 | | | | | | |

Figure 4: Binary search execution time data imported into Excel 2013.

To display this kind of data, one should almost always use a scatter plot (xy-plot), not any of the other fancy but more business-oriented chart types. Select the data in columns B and C, that is, range B1:C17, as shown in the figure, choose `Insert > Charts > Scatter`, and choose the chart subtype with straight lines and markers. Smooth lines may look neater, but they distort the data. The result will be a chart as shown in figure 5. The appearance of such charts can be improved interactively by right-clicking on relevant chart elements, such as the axes, the plot lines, the data point markers, chart background, and so on.

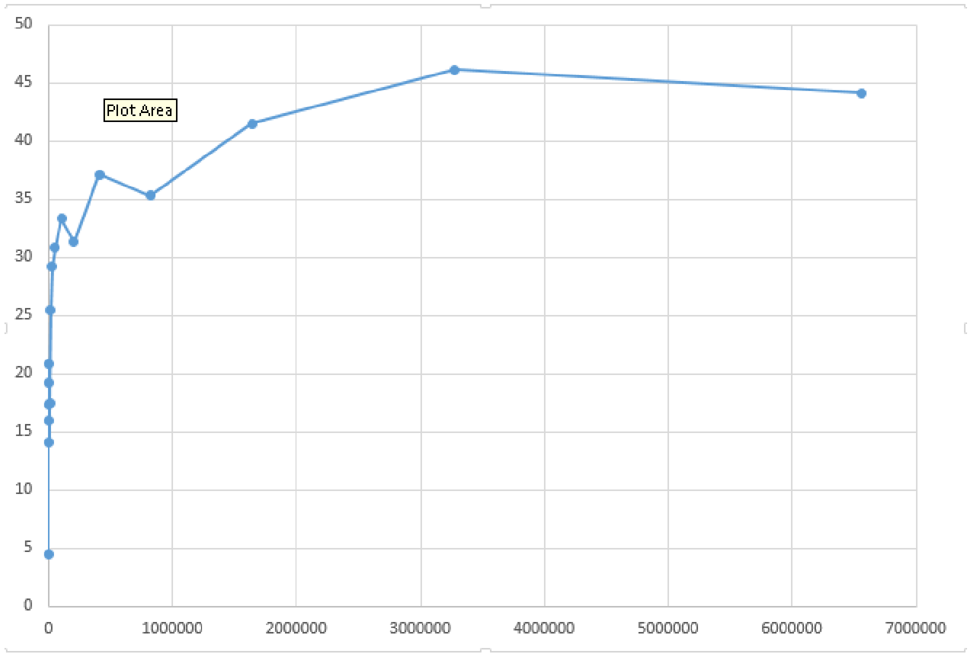


Figure 5: Excel scatter chart showing the binary search data from figure 4.

# 11 Benchmark design considerations

Until now we have mostly been concerned with *how* to measure execution time. We also need to think about *what* to measure: on which inputs should we run the code when measuring execution time? The answer of course is highly problem dependent, but for inspiration, let us consider again the binary search benchmark.

## 11.1 Benchmark design for binary search

The binary search routine in section 4.3 has two input parameters whose values we need to choose: the item `x` to search for, and the sorted array `arr` of items to search in.

- Let us consider first the array `arr`. It is clear that the execution time depends on the *size* of the array, so we want to call the method on a range of such sizes. Indeed we did that, by virtue of the outer for loop, in section 4.3.

  The array should be sorted in non-decreasing order (or else the method does not work at all), but still there are many possible choices of array contents: all items are equal, some items are equal, or no items are equal (that is, all items are distinct). For binary search, the latter choice forces the worst case execution time, so that is what we choose. Moreover, when all items are distinct, they may be dense as in $0, 1, 2, 3, \ldots$ or have gaps as in $1, 17, 18, 23, \ldots$. For the execution time of binary search in a sorted array, this makes no difference, but for other representations of sets or bags it may. We choose a dense set of items.

- Next, what items `x` should we search for? The most basic decision is whether we want successful search (for an item that is in the array) or an unsuccessful search (for an item not in the array). The latter forces the highest execution time, and therefore might be a reasonable choice, but precisely for binary search it does not make much of a difference. In general one should choose a representative mix of successful and unsuccessful searches.

  In the example from section 4.3, we ran only successful searches, and always for the same item `successItem`, at a position just before the middle of the array. In retrospect, this was a dubious choice, because the same search is performed repeatedly and each one will hit the same array positions, which are therefore almost guaranteed to be in all levels of CPU caches. This unrealistic scenario may severely underestimate the typical execution time for a successful binary search.

  There are several ways to remedy this situation. For an $n$-element array, we could either search for the items $0, 1, ..., n-1$ in order, or we could repeatedly generate a pseudorandom number in the range $[0, n-1]$ and search for that. However, the first approach is "too predictable", likely to use the caches well, and hence report unrealistically low execution times. The second approach suffers from another problem: the cost of generating a pseudorandom item to search for is high, comparable to that of the search itself. We will investigate this and a possible solution in the next section.

## 11.2 Binary search for pseudorandom items

We can generate a pseudorandom item in the range $[0, n-1]$ by `rnd.nextInt(n)`. Using the machinery already developed we can measure the cost of this operation:

```
final java.util.Random rnd = new java.util.Random();
final int n = 1638400;
Mark8("random_index", i -> rnd.nextInt(n));
```

Running this code tells us that the cost of generating a pseudorandom item is a whopping 12.0 ns, which is comparable to be cost of the binary search itself as measured in section 4.3. Even when searching an array with millions of items, this is nearly a quarter of the cost of the search itself, and thus would seriously distort the measurements.

What can be done? One possibility is to pre-generate a large enough array `items` of pseudorandom items *before* performing the benchmark, and sequentially retrieve and search for these items in the benchmark itself. Then the time measurements will include the time to access the `items` array, but this access will be sequential and cache-friendly, and hence hopefully not contribute too much to the execution time:

```
for (int size = 100; size <= 10_000_000; size *= 2) {
  final int[] intArray = SearchAndSort.fillIntArray(size);  // sorted [0,1,...]
  final int[] items = SearchAndSort.fillIntArray(size);
  final int n = size;
  SearchAndSort.shuffle(items);
  Mark8("binary_search_success",
        String.format("%8d", size),
        i -> SearchAndSort.binarySearch(items[i % n], intArray));
}
```

Now the results are as follows:

```
binary_search_success        100          17.3      0.22   16777216
binary_search_success        200          18.8      0.20   16777216
binary_search_success        400          34.0      0.24    8388608
binary_search_success        800          53.9      0.08    8388608
binary_search_success       1600          64.5      0.44    4194304
binary_search_success       3200          71.1      0.39    4194304
binary_search_success       6400          76.9      0.49    4194304
binary_search_success      12800          84.0      0.39    4194304
binary_search_success      25600          91.7      0.70    4194304
binary_search_success      51200          98.5      0.74    4194304
binary_search_success     102400         110.9      0.85    4194304
binary_search_success     204800         125.0      0.73    2097152
binary_search_success     409600         139.0      0.33    2097152
binary_search_success     819200         166.6      2.99    2097152
binary_search_success    1638400         203.2      2.35    2097152
binary_search_success    3276800         271.3      5.55    1048576
binary_search_success    6553600         320.4      2.62    1048576
```

These execution times are up to 7 times higher than those measured in section 4.3! Whether they are more correct is a question of which usage scenario is more likely in practice: repeatedly searching for the same item, or repeatedly searching for an item that is completely unrelated to the one previously searched for. Certainly the latter gives a more conservative execution time estimate, and one that fits the textbook complexity $O(\log n)$ for binary search better.

Note that we still perform only successful searches, which may be unrealistic. To improve on this situation we could make the `intArray` contain only odd numbers $1, 3, 5, \ldots$ and have both even and odd numbers in the array of `items` to search for. It is left as an exercise to see what results this would give.

Another possible concern is that the new higher execution times include the time to compute the remainder operator (`%`) and retrieve the pre-generated pseudorandom items from the array. If we suspect that this overhead is significant, we can measure it:

```
for (int size = 100; size <= 10_000_000; size *= 2) {
  final int[] items = SearchAndSort.fillIntArray(size);
  final int n = size;
  SearchAndSort.shuffle(items);
  Mark8("get_pseudorandom_items",
        String.format("%8d", size),
        i -> items[i % n]);
}
```

The results below show that the time to access the pseudorandom items is quite negligible, and completely constant over very different `items` array sizes, confirming that the sequential retrieval of items is cache-friendly:

```
get_pseudorandom_items         100            6.9       0.07   67108864
get_pseudorandom_items         200            6.9       0.05   67108864
get_pseudorandom_items         400            6.9       0.03   67108864
get_pseudorandom_items         800            6.9       0.04   67108864
get_pseudorandom_items        1600            6.9       0.08   67108864
get_pseudorandom_items        3200            6.9       0.04   67108864
get_pseudorandom_items        6400            6.9       0.05   67108864
get_pseudorandom_items       12800            6.9       0.03   67108864
get_pseudorandom_items       25600            6.9       0.06   67108864
get_pseudorandom_items       51200            6.9       0.07   67108864
get_pseudorandom_items      102400            6.9       0.04   67108864
get_pseudorandom_items      204800            6.9       0.04   67108864
get_pseudorandom_items      409600            6.9       0.04   67108864
get_pseudorandom_items      819200            6.9       0.04   67108864
get_pseudorandom_items     1638400            6.9       0.03   67108864
get_pseudorandom_items     3276800            6.9       0.03   67108864
get_pseudorandom_items     6553600            6.9       0.05   67108864
```

## 12 Source code for examples

The complete source code presented here, including the examples, can be found (in Java and C#) at:

```
http://www.itu.dk/people/sestoft/javaprecisely/benchmarks-java.zip
http://www.itu.dk/people/sestoft/csharpprecisely/benchmarks-csharp.zip
```

The hope is that the reader can adapt and further develop the benchmarking code to any particular use context.

## 13 Other online resources

- Brent Boyer: Robust Java benchmarking, Part 1: Issues and Part 2: Statistics and solutions [1].
- Cliff Click: How NOT to write a microbenchmark [2].
- Brian Goetz: Java theory and practice: Dynamic compilation and performance measurement [3].
- Brian Goetz: Java theory and practice: Anatomy of a flawed microbenchmark [4].
- TODO: ... more

## 14 Acknowledgements

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## 15 Exercises

**Exercise 1:** Run the `Mark1` through `Mark6` measurements yourself. Use the `SystemInfo` method to record basic system identification, and supplement with whatever other information you can find about the execution platform; see section 8.

**Exercise 2:** Use `Mark7` to measure the execution time for the mathematical functions `pow`, `exp`, and so on, as in section 4.2. Record the results along with appropriate system identification. Preferably do this on at least two different platforms, eg. your own computer and a fellow student's or a computer at the university.

**Exercise 3:** Run the measurements of sorting algorithm performance as in section 6. Record the results along with appropriate system identification. Use Excel or gnuplot or some other charting package to make graphs of the execution time as function of the problem size, as in figure 3. Preferably do this on at least two different platforms, eg. your own computer and a fellow student's or a computer at the university.

## Appendix: Tips from the creators of the Hotspot JVM

Below are some tips about writing micro benchmarks for the Sun/Oracle HotSpot Java Virtual Machine, reproduced from [5]. While the advice is of general interest, the runtime options of type `-X` and `-XX` discussed below are non-standard. They are subject to change at any time and not guaranteed to work on, say, IBM or Apple implementations of the Java Virtual Machine.

- Rule 0: Read a reputable paper on JVMs and micro-benchmarking. A good one is Brian Goetz, 2005 [4]. Do not expect too much from micro-benchmarks; they measure only a limited range of JVM performance characteristics.

- Rule 1: Always include a warmup phase which runs your test kernel all the way through, enough to trigger all initializations and compilations before timing phase(s). (Fewer iterations is OK on the warmup phase. The rule of thumb is several tens of thousands of inner loop iterations.)

- Rule 2: Always run with -XX:+PrintCompilation, -verbose:gc, etc., so you can verify that the compiler and other parts of the JVM are not doing unexpected work during your timing phase.

- Rule 2.1: Print messages at the beginning and end of timing and warmup phases, so you can verify that there is no output from Rule 2 during the timing phase.

- Rule 3: Be aware of the difference between -client and -server, and OSR [On-Stack Replacement] and regular compilations. The -XX:+PrintCompilation flag reports OSR compilations with an at-sign to denote the non-initial entry point, for example: Trouble$1::run @ 2 (41 bytes). Prefer server to client, and regular to OSR, if you are after best performance.

- Rule 4: Be aware of initialization effects. Do not print for the first time during your timing phase, since printing loads and initializes classes. Do not load new classes outside of the warmup phase (or final reporting phase), unless you are testing class loading specifically (and in that case load only the test classes). Rule 2 is your first line of defense against such effects.

- Rule 5: Be aware of deoptimization and recompilation effects. Do not take any code path for the first time in the timing phase, because the compiler may junk and recompile the code, based on an earlier optimistic assumption that the path was not going to be used at all. Rule 2 is your first line of defense against such effects.
- Rule 6: Use appropriate tools to read the compiler's mind, and expect to be surprised by the code it produces. Inspect the code yourself before forming theories about what makes something faster or slower.
- Rule 7: Reduce noise in your measurements. Run your benchmark on a quiet machine, and run it several times, discarding outliers. Use -Xbatch to serialize the compiler with the application, and consider setting -XX:CICompilerCount=1 to prevent the compiler from running in parallel with itself.

Similar tips would apply to the Common Language Infrastructure (.NET) platform, but the Microsoft .NET implementation does not seem to have (publicly available) means for controlling just-in-time compilation and so on. Only the choice of garbage collector can be controlled, using the runtime settings schema of the so-called application configuration files, named `MyApp.exe.config` or similar. I have no experience with this. The Mono implementation has a range of runtime configuration options, displayed by `mono -help` and `mono -list-opt`.

## References

[1] Brent Boyer: Robust Java benchmarking, Part 1: Issues and Part 2: Statistics and solutions. IBM developerWorks, 24 June 2008, at
http://www.ibm.com/developerworks/java/library/j-benchmark1/ and
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[2] Cliff Click: How NOT to write a microbenchmark. JavaOne 2002 talk, at
http://www.azulsystems.com/events/javaone_2002/microbenchmarks.pdf

[3] Brian Goetz: Java theory and practice: Dynamic compilation and performance measurement. IBM developerWorks, 21 December 2004, at
http://www.ibm.com/developerworks/library/j-jtp12214/

[4] Brian Goetz: Java theory and practice: Anatomy of a flawed microbenchmark. IBM developerWorks, 22 February 2005, at
http://www.ibm.com/developerworks/java/library/j-jtp02225/index.html

[5] John Rose: Microbenchmarks: So You Want to Write a Micro-Benchmark HotSpot Internals wiki, at https://wikis.oracle.com/display/HotSpotInternals/MicroBenchmarks

[6] Scala documentation: Parallel Collections: Measuring Performance Scala documentation page, at
http://docs.scala-lang.org/overviews/parallel-collections/performance.html