Optimization: Introduction

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Definition

Optimization

- ***Optimization*** is the process of modifying a program to improve its efficiency
  - Increase its speed
  - Reduce its size (memory usage)

- **Optimization can often be seen as de-factoring**
  - **Program gets faster but…**
  - **Harder to understand, upkeep, read**

Efficiency

- Efficiency can be viewed in terms of:
  1. Program requirements
     - Does the program really need to run at a certain speed? Is it worth the extra effort
  2. Program design
     - If performance is important, design a performance-oriented architecture
       - Set resource goals for individual subsystems and classes
  3. Class and routine design
     - Choose efficient algorithms and datatypes
       - E.g. Quicksort vs. bubble sort
       - E.g. Binary search vs. linear search

Efficiency (cont'd)

4. Operating system interactions
   - Working with files, dynamic memory, or I/O devices means using system calls
     - May be slow or fast

5. Code compilation
   - Good compilers produce optimized machine code
     - May have options for different optimization levels

Efficiency (cont'd)

6. Hardware
   - A hardware upgrade may be the cheapest way to improve a program's performance
     - Not always possible

7. Code tuning
   - Small-scale changes made to code to make it run more efficiently
     - At the level of a single routine, or a few lines of code
   - Tends to produce hard-to-understand code
     - Obscures design

Guide to the galaxy of optimization

General Guidelines

- **Don't** optimize as you go
  - Focusing on optimization during initial development detracts from achieving correctness, readability, and design quality

General Guidelines (cont'd)

- Jackson's Rules of Optimization:
  - Rule 1. **Don't do it.**
  - Rule 2 (for experts only). **Don't do it yet**—that is, not until you have a perfectly clear and unoptimized solution.

- Code tuning should be done only as a last step
  - Knuth: **Pre-mature optimization is the root of all evil**

General Guidelines (cont’d)

- Optimize bottlenecks
  - **The 80/20 rule:** 20% of program’s routines consume 80% of its execution time
    - Knuth found 4% of a FORTRAN program accounted for over 50% of its run time
  - Spend your time fixing these ‘bottlenecks’
    - **Don’t waste effort on the other parts**

General Guidelines (cont'd)

- Measure performance when optimizing
  - Use a profiler to find bottlenecks
  - Use timers to measure CPU time
    - Make sure a change actually improves speed
      - May actually make things worse when using a different compiler, OS, or processor

- Run regression tests after each optimization
  - Make sure your program is still correct

Swipe right

Profiling

- **Profiling**
  - Is used to find how much time is spent in each function of a program
    - Helps find bottlenecks
    - Helps you compare the performance of algorithms or programs

Profiling (cont'd)

- Works by sampling the program counter (PC register)
  - Periodically queries the program, recording the function in which it is running
- Is statistical in nature
  - i.e. is somewhat inexact, and will vary from run to run
- Also the act of enabling profiling will generally slow down operation of code, this slowdown can be different for varying classes

C++ profiling

Profilers – gcc

- Available UNIX profilers for programs compiled with gcc:
  - prof (most commonly used)
  - gprof
  - pixie

Profilers – gcc (cont'd)

- Using prof:
  - Compile the program with the -p option
  - E.g.

    gcc -c myprog.c

    gcc -o myprog -p myprog.o
  - Run the program
  - E.g.

    ./myprog
    - Produces the file mon.out
  - Print the profile report to stdout
  - E.g. **prof myprog mon.out**

Profilers – gcc (cont’d)

- Example output:

```
Each sample covers 8.00 byte(s) for 0.17% of 0.5742 seconds

%time   seconds   cum %   cum sec   procedure (file)
 38.1   0.2188    38.1     0.22     mycompare (<myprog>)
 36.1   0.2070    74.1     0.43     unique (<myprog>)
 22.1   0.1270    96.3     0.55     bubble_sort (<myprog>)
  3.6   0.0205    99.8     0.57     extract (<myprog>)
  0.2   0.0010   100.0     0.57     main (<mysort>)
```

Timestamp profiling

Profilers - Timing

- Timing measurements
  - In UNIX, can use the time command to time an entire program
    - E.g.

      time java Test

      1.09u   0.12s   0:01.27   95.2%

      <user CPU time> <system CPU time> <real_time>

Profilers – C/C++ clock()

- In C and C++, use the clock() function to measure the CPU time used by a function or section of code
  - E.g.

```
#include <time.h>
#include <stdio.h>
. . .
   clock_t before;
   double elapsed;

   before = clock();
   long_running_function();
   elapsed = clock() - before;
   printf("function used %.3f seconds\n",
          elapsed/CLOCKS_PER_SEC);
```

Profilers – C/C++ clock() (cont'd)

- If the function takes a fraction of a second, run it in a loop to get a more accurate measurement

  - E.g.

```
before = clock();
for (i = 0; i < 1000; i++)
        short_running_function();
elapsed = (clock() - before) / (double) i;
```

Profilers – Java nanoTime()

- In Java, use the nanoTime() method

  - E.g.
    ```
    long startTime = System.nanoTime();
    longRunningMethod();
    long elapsedTime = System.nanoTime() - startTime;
    ```

  - Note: result is in nanoseconds (10^{-9} s)

  - Similar timing methods available for Python

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Profilers – IPython timeit

%timeit for one line (%time run once)

%%timeit for multiple lines (%%time run multiple lines once)

```
%timeit x = [n ** 2 for n in range(1000)]

1000 loops, best of 5: 264 µs per loop
```

```
In [2]: %timeit x = [n ** 2 for n in range(1000)]
230 µs ± 9.36 µs per loop (mean ± std. dev. of 7 runs,
 1,000 loops each)
```

Profilers – IPython prun

Be wary of stored results in **timeit** (could use time to only run once, or make sure we are sorting random each time)

```
import random
L = [random.random() for i in range(100000)]
%timeit L.sort()
```

```
The slowest run took 30.01 times longer than the fastest. This could mean that an intermediate result is being cached.
1000 loops, best of 5: 691 µs per loop
```

You can also profile something using **prun**

```
import random
L = [random.random() for i in range(100000)]
%prun %timeit L.sort()
```

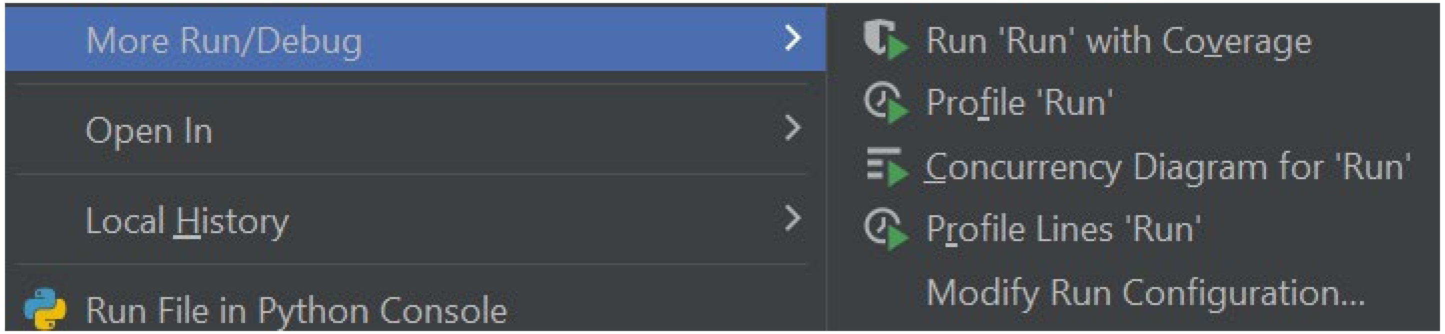
```
         7412 function calls (7312 primitive calls) in 4.308 seconds

   Ordered by: internal time

   ncalls  tottime  percall  cumtime  percall filename:lineno(function)
     6111    4.269    0.001    4.269    0.001 {method 'sort' of 'list' objects}
        9    0.036    0.004    4.305    0.478 <magic-timeit>:1(inner)
        5    0.002    0.000    0.002    0.000 socket.py:543(send)
       12    0.000    0.000    0.000    0.000 {built-in method builtins.compile}
        1    0.000    0.000    4.308    4.308 execution.py:909(timeit)
        9    0.000    0.000    4.305    0.478 execution.py:125(timeit)
     27/1    0.000    0.000    0.000    0.000 ast.py:320(generic_visit)
       71    0.000    0.000    0.000    0.000 ast.py:193(iter_child_nodes)
      138    0.000    0.000    0.000    0.000 {built-in method builtins.getattr}
        1    0.000    0.000    3.472    3.472 timeit.py:183(repeat)
     36/1    0.000    0.000    0.000    0.000 ast.py:153(_fix)
```

I profiled the ***timeit*** *sort command*

It ran 6111 samples

Profilers – Python cProfile

In Pycharm this is as simple as a run option



Name	Call Count	Time (ms)	Own Time (ms)
<listcomp>	1	381 93.2%	286 69.9%
<method 'random' of '_random.Random' o	1000000	95 23.2%	95 23.2%
wrapper	1	392 95.8%	11 2.7%
<built-in method nt.stat>	62	4 1.0%	4 1.0%
_path_join	203	2 0.5%	1 0.2%
_new_module	6	0 0.0%	0 0.0%

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Profilers – Python line_profiler

Also a run option but will need plugin installed for line_profiler

```
import random
from line_profiler_pycharm import profile
Time in function:                                          2195567 0.000000 s
Colormap '%Time':                                          0%            100%
                                                           % Time        Hits      Time []     Time / Hit []

@profile
def foo():
    L = [random.random() for i in range(1000000)]            100.0         1       2195254     2195254.0
    x = 5                                                      0.0         1            25          25.0
    y = 100                                                    0.0         1             5           5.0
    print("sdsd")                                              0.0         1           283         283.0

foo()
```

Java profiling

Profilers – Java

- Standard JVM Profilers
  - VisualVM, JProfiler, YourKit and Java Mission Control
  - method calls and memory usage
  - **Pros:**
    - Great for tracking down memory leaks, standard profilers detail out all memory usage by the JVM and which classes/objects are responsible.
    - Good for tracking CPU usage and zero in on hot spots.

Profilers – Java

- Standard JVM Profilers
  - VisualVM, JProfiler, YourKit and Java Mission Control
  - method calls and memory usage
  - **Cons:**
    - Requires a direct connection to the monitored JVM; this ends up limiting usage to development environments in most cases.
    - They slow down your application; a good deal of processing power is required for the high level of detail provided.

Profilers – Java

- Lightweight Java Transaction Profilers
  - XRebel and Stackify Prefix
  - Aspect Profilers
    - use aspect-oriented programming (AOP) to inject code into the start and end of specified methods.
  - Java Agent profilers (ex. Netbeans built-in)
    - use the Java Instrumentation API to inject code into your application. This method has greater access to your application since the code is being rewritten at the bytecode level.

Profilers – Java

- Lightweight Java Transaction Profilers
  - Aspect profilers are pretty easy to setup but are limited in what they can monitor and are encumbered by detailing out everything you want to be tracked.
  - Java Agents have a big advantage in their tracking depth but are much more complicated to write.

Profilers – Java

- Low Overhead, Java JVM Profiling in Production (APM – APplication Monitoring)
  - New Relic, AppDynamics, Stackify Retrace, Dynatrace
  - how your system performs in production is critical
  - Java APM tools typically use the Java Agent profiler method
    - different instrumentation rules to allow them to run without affecting performance in productions.

Algorithm Based Optimization

Algorithm-Based Optimization

- Choosing a more efficient algorithm or data structure is often the best way to improve program efficiency
  - Look for algorithms that reduce the order of complexity
    - E.g. Binary search $O(\log n)$ vs. linear search $O(n)$
    - E.g. Merge sort $O(n\log n)$ vs. bubble sort $O(n^2)$

Algorithm-Based Optimization

- Do this first before attempting other optimizations
  - Hand tuning an $O(n^2)$ algorithm won't yield near the same gains as using an $O(n \log n)$ algorithm

- **Beware of worst-case performance**
  - Some algorithms may not achieve their average Big-O performance under certain conditions
  - E.g. The quicksort degenerates to $O(n^2)$ with nearly-sorted inputs

Algorithm-Based Optimization

- Sometimes an inefficient algorithm is fine for small inputs

  - The overhead of a complicated algorithm may make it slower than a simple one
    - And harder to debug and maintain!

  - Measure performance to make sure you've made the right choice

Algorithm-Based Optimization

- Sometimes an inefficient algorithm is fine for small inputs
  - **Java's own internal Quick Sort uses an Insertion Sort below a specific array size**

Compiler Based Optimization

Compiler-Level Optimization

- Enabling compiler optimization can improve speed by as much as 2 times
- Most compilers turn off optimization by default
  - Optimized code tends to confuse debuggers
- Works best with straightforward code
  - Hand tuned code may actually be harder for the compiler to optimize

Compiler-Level Optimization

- Some compilers optimize better than others
- E.g.

Compiler (C++)	Time without optimization	Time with optimization	Savings
1	2.21	1.05	52%
2	2.78	1.15	59%
3	2.43	1.25	49%

Compiler-Level Optimization

- Aggressive optimizers may introduce bugs
  - Rerun regression tests to ensure correctness

- gcc optimization flags:
  - Optimize: **-O** or **-O1**
  - Optimize even more: **-O2**
  - Optimize yet more: **-O3**
  - Don’t optimize (default): **-O0**

Compiler-Level Optimization

- E.g. **gcc -O2 -o myprog myfile.c**

Onward to …
logic optimization.

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