# 27.4. The Python Profilers

Source code: Lib/profile.py and Lib/pstats.py

# 27.4.1. Introduction to the profilers

cProfile and profile provide *deterministic profiling* of Python programs. A *profile* is a set of statistics that describes how often and for how long various parts of the program executed. These statistics can be formatted into reports via the pstats module.

The Python standard library provides two different implementations of the same profiling interface:

- 1. cProfile is recommended for most users; it's a C extension with reasonable overhead that makes it suitable for profiling long-running programs. Based on lsprof, contributed by Brett Rosen and Ted Czotter.
- 2. profile, a pure Python module whose interface is imitated by cProfile, but which adds significant overhead to profiled programs. If you're trying to extend the profiler in some way, the task might be easier with this module. Originally designed and written by Jim Roskind.

**Note:** The profiler modules are designed to provide an execution profile for a given program, not for benchmarking purposes (for that, there is timeit for reasonably accurate results). This particularly applies to benchmarking Python code against C code: the profilers introduce overhead for Python code, but not for C-level functions, and so the C code would seem faster than any Python one.

## 27.4.2. Instant User's Manual

This section is provided for users that "don't want to read the manual." It provides a very brief overview, and allows a user to rapidly perform profiling on an existing application.

To profile a function that takes a single argument, you can do:

```
import cProfile
import re
cProfile.run('re.compile("foo|bar")')
```

(Use profile instead of cProfile if the latter is not available on your system.)

The above action would run re.compile() and print profile results like the following:

```
197 function calls (192 primitive calls) in 0.002 seconds
Ordered by: standard name
                                   percall filename:lineno(function)
ncalls tottime
                          cumtime
                 percall
                            0.001
                                     0.001 <string>:1(<module>)
     1
          0.000
                   0.000
                                     0.001 re.py:212(compile)
     1
          0.000
                   0.000
                            0.001
     1
                                     0.001 re.py:268( compile)
          0.000
                   0.000
                            0.001
                                     0.000 sre compile.py:172( compile
     1
                   0.000
                            0.000
          0.000
                                     0.000 sre_compile.py:201( optimiz
     1
          0.000
                   0.000
                            0.000
                                     0.000 sre compile.py:25( identity
     4
          0.000
                   0.000
                            0.000
                                     0.000 sre compile.py:33( compile)
          0.000
                   0.000
                            0.000
   3/1
```

The first line indicates that 197 calls were monitored. Of those calls, 192 were *primitive*, meaning that the call was not induced via recursion. The next line: Ordered by: standard name, indicates that the text string in the far right column was used to sort the output. The column headings include:

#### ncalls

for the number of calls.

#### tottime

for the total time spent in the given function (and excluding time made in calls to sub-functions)

#### percall

is the quotient of tottime divided by ncalls

#### cumtime

is the cumulative time spent in this and all subfunctions (from invocation till exit). This figure is accurate *even* for recursive functions.

#### percall

is the quotient of cumtime divided by primitive calls

### filename:lineno(function)

provides the respective data of each function

When there are two numbers in the first column (for example 3/1), it means that the function recursed. The second value is the number of primitive calls and the former is the total number of calls. Note that when the function does not recurse, these two values are the same, and only the single figure is printed.

Instead of printing the output at the end of the profile run, you can save the results to a file by specifying a filename to the run() function:

```
import cProfile
import re
cProfile.run('re.compile("foo|bar")', 'restats')
```

The pstats. Stats class reads profile results from a file and formats them in various ways.

The file cProfile can also be invoked as a script to profile another script. For example:

```
python -m cProfile [-o output_file] [-s sort_order] myscript.py
```

- -o writes the profile results to a file instead of to stdout
- -s specifies one of the sort\_stats() sort values to sort the output by. This only applies when -o is not supplied.

The pstats module's Stats class has a variety of methods for manipulating and printing the data saved into a profile results file:

```
import pstats
p = pstats.Stats('restats')
p.strip_dirs().sort_stats(-1).print_stats()
```

The strip\_dirs() method removed the extraneous path from all the module names. The sort\_stats() method sorted all the entries according to the standard module/line/name string that is printed. The print\_stats() method printed out all the statistics. You might try the following sort calls:

```
p.sort_stats('name')
p.print_stats()
```

The first call will actually sort the list by function name, and the second call will print out the statistics. The following are some interesting calls to experiment with:

```
p.sort_stats('cumulative').print_stats(10)
```

This sorts the profile by cumulative time in a function, and then only prints the ten most significant lines. If you want to understand what algorithms are taking time, the above line is what you would use.

If you were looking to see what functions were looping a lot, and taking a lot of time, you would do:

```
p.sort_stats('time').print_stats(10)
```

to sort according to time spent within each function, and then print the statistics for the top ten functions.

You might also try:

```
p.sort_stats('file').print_stats('__init__')
```

This will sort all the statistics by file name, and then print out statistics for only the class init methods (since they are spelled with \_\_init\_\_ in them). As one final example, you could try:

```
p.sort_stats('time', 'cumulative').print_stats(.5, 'init')
```

This line sorts statistics with a primary key of time, and a secondary key of cumulative time, and then prints out some of the statistics. To be specific, the list is first culled down to 50% (re: .5) of its original size, then only lines containing init are maintained, and that sub-sub-list is printed.

If you wondered what functions called the above functions, you could now (p is still sorted according to the last criteria) do:

```
p.print_callers(.5, 'init')
```

and you would get a list of callers for each of the listed functions.

If you want more functionality, you're going to have to read the manual, or guess what the following functions do:

```
p.print_callees()
p.add('restats')
```

Invoked as a script, the pstats module is a statistics browser for reading and examining profile dumps. It has a simple line-oriented interface (implemented using cmd) and interactive help.

## 27.4.3. profile and cProfile Module Reference

Both the profile and cProfile modules provide the following functions:

```
profile. run(command, filename=None, sort=-1)
```

This function takes a single argument that can be passed to the exec() function, and an optional file name. In all cases this routine executes:

```
exec(command, __main__.__dict__, __main__.__dict__)
```

and gathers profiling statistics from the execution. If no file name is present, then this function automatically creates a Stats instance and prints a simple profiling report. If the sort value is specified, it is passed to this Stats instance to control how the results are sorted.

```
profile. runctx(command, globals, locals, filename=None, sort=-1)
```

This function is similar to run(), with added arguments to supply the globals and locals dictionaries for the *command* string. This routine executes:

```
exec(command, globals, locals)
```

and gathers profiling statistics as in the run() function above.

```
class profile. Profile(timer=None, timeunit=0.0, subcalls=True, builtins=True)
```

This class is normally only used if more precise control over profiling is needed than what the cProfile.run() function provides.

A custom timer can be supplied for measuring how long code takes to run via the *timer* argument. This must be a function that returns a single number representing the current time. If the number is an integer, the *timeunit* specifies a multiplier that specifies the duration of each unit of time. For example, if the timer returns times measured in thousands of seconds, the time unit would be .001.

Directly using the Profile class allows formatting profile results without writing the profile data to a file:

```
import cProfile, pstats, io
pr = cProfile.Profile()
pr.enable()
# ... do something ...
pr.disable()
s = io.StringIO()
sortby = 'cumulative'
ps = pstats.Stats(pr, stream=s).sort_stats(sortby)
ps.print_stats()
print(s.getvalue())
```

### enable()

Start collecting profiling data.

### disable()

Stop collecting profiling data.

```
create_stats()
```

Stop collecting profiling data and record the results internally as the current profile.

```
print stats(sort=-1)
```

Create a Stats object based on the current profile and print the results to stdout.

```
dump_stats(filename)
```

Write the results of the current profile to *filename*.

```
run(cmd)
```

Profile the cmd via exec().

```
runctx(cmd, globals, locals)
```

Profile the cmd via exec() with the specified global and local environment.

```
runcall(func, *args, **kwargs)
Profile func(*args, **kwargs)
```

## 27.4.4. The Stats Class

Analysis of the profiler data is done using the Stats class.

```
class pstats. Stats(*filenames or profile, stream=sys.stdout)
```

This class constructor creates an instance of a "statistics object" from a *filename* (or list of filenames) or from a Profile instance. Output will be printed to the stream specified by *stream*.

The file selected by the above constructor must have been created by the corresponding version of profile or cProfile. To be specific, there is no file compatibility guaranteed with future versions of this profiler, and there is no compatibility with files produced by other profilers, or the same profiler run on a different operating system. If several files are provided, all the statistics for identical functions will be coalesced, so that an overall view of several processes can be considered in a single report. If additional files need to be combined with data in an existing Stats object, the add() method can be used.

Instead of reading the profile data from a file, a cProfile.Profile or profile.Profile object can be used as the profile data source.

Stats objects have the following methods:

```
strip_dirs()
```

This method for the Stats class removes all leading path information from file names. It is very useful in reducing the size of the printout to fit within (close to) 80 columns. This method modifies the object, and the stripped information is lost. After performing a strip operation, the object is considered to have its entries in a "random" order, as it was just after object initialization and loading. If strip\_dirs() causes two function names to be indistinguishable (they are on the same line of the same filename, and have the same function name), then the statistics for these two entries are accumulated into a single entry.

### add(\*filenames)

This method of the Stats class accumulates additional profiling information into the current profiling object. Its arguments should refer to filenames created by the corresponding version of profile.run() or cProfile.run(). Statistics for identically named (re: file, line, name) functions are automatically accumulated into single function statistics.

### dump stats(filename)

Save the data loaded into the Stats object to a file named *filename*. The file is created if it does not exist, and is overwritten if it already exists. This is equivalent to the method of the same name on the profile.Profile and cProfile.Profile classes.

### sort\_stats(\*keys)

This method modifies the Stats object by sorting it according to the supplied criteria. The argument is typically a string identifying the basis of a sort (example: 'time' or 'name').

When more than one key is provided, then additional keys are used as secondary criteria when there is equality in all keys selected before them. For example, sort\_stats('name', 'file') will sort all the entries according to their function name, and resolve all ties (identical function names) by sorting by file name.

Abbreviations can be used for any key names, as long as the abbreviation is unambiguous. The following are the keys currently defined:

Valid Arg	Meaning
'calls'	call count
'cumulative'	cumulative time
'cumtime'	cumulative time
'file'	file name

Valid Arg	Meaning
'filename'	file name
'module'	file name
'ncalls'	call count
'pcalls'	primitive call count
'line'	line number
'name'	function name
'nfl'	name/file/line
'stdname'	standard name
'time'	internal time
'tottime'	internal time

Note that all sorts on statistics are in descending order (placing most time consuming items first), where as name, file, and line number searches are in ascending order (alphabetical). The subtle distinction between 'nf1' and 'stdname' is that the standard name is a sort of the name as printed, which means that the embedded line numbers get compared in an odd way. For example, lines 3, 20, and 40 would (if the file names were the same) appear in the string order 20, 3 and 40. In contrast, 'nf1' does a numeric compare of the line numbers. In fact, sort\_stats('nf1') is the same as sort\_stats('name', 'file', 'line').

For backward-compatibility reasons, the numeric arguments -1, 0, 1, and 2 are permitted. They are interpreted as 'stdname', 'calls', 'time', and 'cumulative' respectively. If this old style format (numeric) is used, only one sort key (the numeric key) will be used, and additional arguments will be silently ignored.

## reverse\_order()

This method for the Stats class reverses the ordering of the basic list within the object. Note that by default ascending vs descending order is properly selected based on the sort key of choice.

## print\_stats(\*restrictions)

This method for the Stats class prints out a report as described in the profile.run() definition.

The order of the printing is based on the last sort\_stats() operation done on the object (subject to caveats in add() and strip\_dirs()).

The arguments provided (if any) can be used to limit the list down to the significant entries. Initially, the list is taken to be the complete set of profiled functions. Each restriction is either an integer (to select a count of lines), or a decimal fraction between 0.0 and 1.0 inclusive (to select a percentage of lines), or a string that will interpreted as a regular expression (to pattern match the standard name that is printed). If several restrictions are provided, then they are applied sequentially. For example:

```
print_stats(.1, 'foo:')
```

would first limit the printing to first 10% of list, and then only print functions that were part of filename .\*foo:. In contrast, the command:

```
print_stats('foo:', .1)
```

would limit the list to all functions having file names .\*foo:, and then proceed to only print the first 10% of them.

## print\_callers(\*restrictions)

This method for the Stats class prints a list of all functions that called each function in the profiled database. The ordering is identical to that provided by print\_stats(), and the definition of the restricting argument is also identical. Each caller is reported on its own line. The format differs slightly depending on the profiler that produced the stats:

- With profile, a number is shown in parentheses after each caller to show how many times this specific call was made. For convenience, a second non-parenthesized number repeats the cumulative time spent in the function at the right.
- With cProfile, each caller is preceded by three numbers: the number of times this specific call was made, and the total and cumulative times spent in the current function while it was invoked by this specific caller.

## print\_callees(\*restrictions)

This method for the Stats class prints a list of all function that were called by the indicated function. Aside from this reversal of direction of calls (re: called vs was called by), the arguments and ordering are identical to the print\_callers() method.

# 27.4.5. What Is Deterministic Profiling?

Deterministic profiling is meant to reflect the fact that all function call, function return, and exception events are monitored, and precise timings are made for the intervals

between these events (during which time the user's code is executing). In contrast, statistical profiling (which is not done by this module) randomly samples the effective instruction pointer, and deduces where time is being spent. The latter technique traditionally involves less overhead (as the code does not need to be instrumented), but provides only relative indications of where time is being spent.

In Python, since there is an interpreter active during execution, the presence of instrumented code is not required to do deterministic profiling. Python automatically provides a *hook* (optional callback) for each event. In addition, the interpreted nature of Python tends to add so much overhead to execution, that deterministic profiling tends to only add small processing overhead in typical applications. The result is that deterministic profiling is not that expensive, yet provides extensive run time statistics about the execution of a Python program.

Call count statistics can be used to identify bugs in code (surprising counts), and to identify possible inline-expansion points (high call counts). Internal time statistics can be used to identify "hot loops" that should be carefully optimized. Cumulative time statistics should be used to identify high level errors in the selection of algorithms. Note that the unusual handling of cumulative times in this profiler allows statistics for recursive implementations of algorithms to be directly compared to iterative implementations.

## 27.4.6. Limitations

One limitation has to do with accuracy of timing information. There is a fundamental problem with deterministic profilers involving accuracy. The most obvious restriction is that the underlying "clock" is only ticking at a rate (typically) of about .001 seconds. Hence no measurements will be more accurate than the underlying clock. If enough measurements are taken, then the "error" will tend to average out. Unfortunately, removing this first error induces a second source of error.

The second problem is that it "takes a while" from when an event is dispatched until the profiler's call to get the time actually *gets* the state of the clock. Similarly, there is a certain lag when exiting the profiler event handler from the time that the clock's value was obtained (and then squirreled away), until the user's code is once again executing. As a result, functions that are called many times, or call many functions, will typically accumulate this error. The error that accumulates in this fashion is typically less than the accuracy of the clock (less than one clock tick), but it *can* accumulate and become very significant.

The problem is more important with profile than with the lower-overhead cProfile. For this reason, profile provides a means of calibrating itself for a given platform so that this error can be probabilistically (on the average) removed. After

the profiler is calibrated, it will be more accurate (in a least square sense), but it will sometimes produce negative numbers (when call counts are exceptionally low, and the gods of probability work against you :-). ) Do *not* be alarmed by negative numbers in the profile. They should *only* appear if you have calibrated your profiler, and the results are actually better than without calibration.

## 27.4.7. Calibration

The profiler of the profile module subtracts a constant from each event handling time to compensate for the overhead of calling the time function, and socking away the results. By default, the constant is 0. The following procedure can be used to obtain a better constant for a given platform (see Limitations).

```
import profile
pr = profile.Profile()
for i in range(5):
    print(pr.calibrate(10000))
```

The method executes the number of Python calls given by the argument, directly and again under the profiler, measuring the time for both. It then computes the hidden overhead per profiler event, and returns that as a float. For example, on a 1.8Ghz Intel Core i5 running Mac OS X, and using Python's time.clock() as the timer, the magical number is about 4.04e-6.

The object of this exercise is to get a fairly consistent result. If your computer is *very* fast, or your timer function has poor resolution, you might have to pass 100000, or even 1000000, to get consistent results.

When you have a consistent answer, there are three ways you can use it:

```
import profile

# 1. Apply computed bias to all Profile instances created hereafter.
profile.Profile.bias = your_computed_bias

# 2. Apply computed bias to a specific Profile instance.
pr = profile.Profile()
pr.bias = your_computed_bias

# 3. Specify computed bias in instance constructor.
pr = profile.Profile(bias=your_computed_bias)
```

If you have a choice, you are better off choosing a smaller constant, and then your results will "less often" show up as negative in profile statistics.

# 27.4.8. Using a custom timer

If you want to change how current time is determined (for example, to force use of wall-clock time or elapsed process time), pass the timing function you want to the Profile class constructor:

```
pr = profile.Profile(your_time_func)
```

The resulting profiler will then call your\_time\_func. Depending on whether you are using profile.Profile or cProfile.Profile, your\_time\_func's return value will be interpreted differently:

### profile.Profile

your\_time\_func should return a single number, or a list of numbers whose sum is the current time (like what os.times() returns). If the function returns a single time number, or the list of returned numbers has length 2, then you will get an especially fast version of the dispatch routine.

Be warned that you should calibrate the profiler class for the timer function that you choose (see Calibration). For most machines, a timer that returns a lone integer value will provide the best results in terms of low overhead during profiling. (os.times() is pretty bad, as it returns a tuple of floating point values). If you want to substitute a better timer in the cleanest fashion, derive a class and hardwire a replacement dispatch method that best handles your timer call, along with the appropriate calibration constant.

### cProfile.Profile

your\_time\_func should return a single number. If it returns integers, you can also invoke the class constructor with a second argument specifying the real duration of one unit of time. For example, if your\_integer\_time\_func returns times measured in thousands of seconds, you would construct the Profile instance as follows:

```
pr = cProfile.Profile(your_integer_time_func, 0.001)
```

As the cProfile.Profile class cannot be calibrated, custom timer functions should be used with care and should be as fast as possible. For the best results with a custom timer, it might be necessary to hard-code it in the C source of the internal lsprof module.

Python 3.3 adds several new functions in time that can be used to make precise measurements of process or wall-clock time. For example, see time.perf\_counter().