# Concurrency

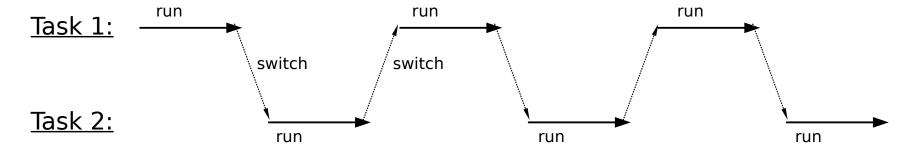


### Concurreny

- Basic principles
- The Global Interpreter Lock
- Async and asyncio
- Threading
- Multiprocessing
- The future

# Multitasking

Multitasking with a single CPU means task switching



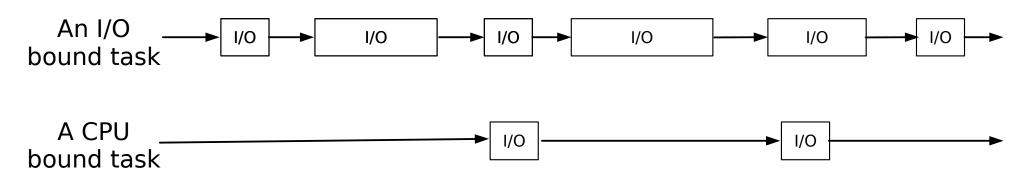
 The cost of task switching means running tasks concurrently is slower than running them consecutively

### True Concurrency

With multiple cores and multiple CPUs, modern computers can do "parallel processing" and run multiple tasks simultaneously without the overhead of task switching.

#### Task Execution

- Tasks tend to be "I/O bound" (Input/Output) or "CPU bound"
- I/O means a network request, or accessing a file or a database which is much slower than the CPU, so the task spends a lot of time waiting
- CPU bound tasks do a lot of processing and will use as much processing power as you can give them



#### Task Execution

- A web crawler is an example of an I/O bound task
- Image processing is an example of a CPU bound task
- A single processor can run many I/O bound tasks concurrently as they spend most of their time waiting
- The basic unit for concurrent task execution is the "thread", an OS level unit of execution
- Multiple threads can run within a process
- Threads in Python are real system threads, the OS does the scheduling/thread switching
  - POSIX threads (pthreads) for Linux/Mac
  - Windows threads
- An alternative model for running multiple tasks concurrently is to use multiple processes

#### **Processes**

- Every program runs as a separate process
- Processes have "memory isolation"
- A process inherits an environment from the OS
- With multiple CPUs multiple processes can run concurrently
- Programs may launch "sub-processes", which inherit the same (or a modified) environment
- Sharing information between processes means "interprocess communication" of some kind (or shared memory)
- Both the subprocess and multiprocessing modules enable you to work with processes
- "Use processes not threads" is a common Python mantra

## The Global Interpreter Lock

- Python has a Global Interpreter Lock, the GIL
- Only one thread of Python code executes at a time
- The GIL simplifies the interpreter and means fewer locks internally (faster single threaded code, the common case)
- The GIL makes threads suitable for I/O bound tasks only
- CPU bound tasks will run slower!
- C extensions may release the GIL and run concurrently
- For parallel processing use processes
- For I/O bound tasks, event loops and coroutines (green threading) are another alternative (asyncio)

### **Async**

- Not true concurrency, tasks are run sequentially with an "event loop", asyncio by default
- Tasks are non-blocking coroutines
- Defined with async, called with await
- await adds a new task to the loop
- Any blocking calls block the whole event loop
- Under the hood there are special non-blocking system calls used by the event loop (see methods on loops)
- Also called green threading
- Suitable for I/O bound concurrency
- Async generators use "async for"

### Async Demo

```
>>> loop = asyncio.new_event_loop()
>>> async def first():
... print("one")
... print(await other())
... print("three")
...
>>> async def other():
... return "two"
...
>>> loop.run_until_complete(first())
one
two
three
```

### Async Demo

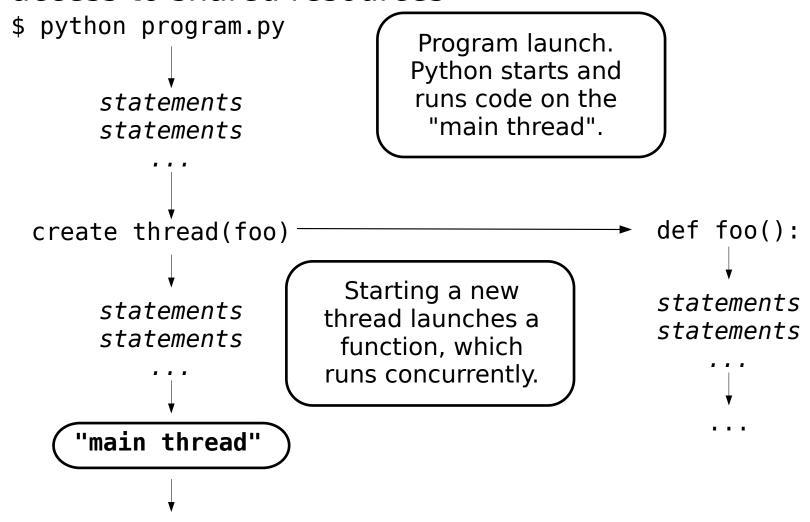
```
import asyncio
async def count():
    print("One")
    await asyncio.sleep(1)
    print("Two")
async def main():
    await asyncio.gather(count(), count(), count())
if __name__ == "__main__":
    import time
    s = time.perf counter()
    asyncio.run(main())
    elapsed = time.perf counter() - s
    print(f"Executed in {elapsed:0.2f} seconds.")
```

### **Async Generators**

```
>>> async def thing():
        return "thing"
>>> async def asyncgen():
        yield await thing() # await allowed!
        yield "two"
>>> async def function():
        async for value in asyncgen():
            print(value)
>>> import asyncio
>>> asyncio.run(function())
thing
two
```

### **Threads**

 With threads we have multiple tasks running together within a program, each thread is independent but with access to shared resources



#### **Threads**

- Threads run independently until they terminate on return or program exit
- Many "thread primitives" (locks, events, queues, etc) allow them to communicate and synchronise
- No shared resources (the "actor model"/CSP) is a way to minimise locking and maximise sanity
- The GIL ensures only one thread is actually running Python code at any time
- The GIL is released/acquired every hundred interpreter "ticks" or so (around bytecode boundaries)
- We use the threading module to access threads

#### Functions as Threads

How to launch a function in a thread

```
import threading
import time
def countdown(count):
    while count > 0:
        print("Counting down", count)
        count -= 1
        time.sleep(5)
>>> t1 = threading.Thread(target=countdown, args=(10,))
>>> t1.start()
Counting down 10
>>> Counting down 9
Counting down 8
Counting down 7
```

 countdown runs in a thread. We can still execute code in the interactive interpreter ("main thread") whilst it runs

## Joining a Thread

- Once you start a thread it runs independently until it returns or the program exits
- Threads don't return a value, use a queue
- Use t.join() to wait for a thread to exit

```
t.start()  # Launch a thread
...
# Do other work
...
# Wait for thread to finish
t.join()  # blocks until t exits
```

- This only works from another thread
- A thread can't join itself!

#### **Thread Termination**

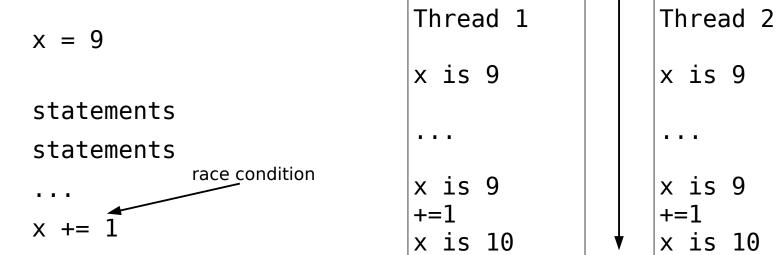
- Python has no built in support for thread cancellation
- Sometimes programs with threads can only be force killed! (kill -9)
- The normal solution is periodic polling and a terminate flag
- You can cancel threads at the OS level using the ctypes library and this solution (but it isn't recommended):

https://stackoverflow.com/questions/323972/is-there-any-way-to-kill-a-thread-in-python

### **Race Conditions**

- Threads can introduce great complexity
- Race conditions deadlocks, livelocks, resource contention, etc...
- You will need locks to access shared resources to avoid race conditions

  Executing concurrently



 If two threads read x as 9 at the same time and both add 1 then x will be 10 when it should be 11

#### **Mutex Locks**

Thread safe concurrent access to resources with locks

- Only one thread can acquire the lock at a time
- Others will block waiting for it to be released
- with automatically acquires and releases the lock
- All access to shared resources must be protected with locks

# **Coordinating Threads**

- Synchronising threads or communicating between them can be done with an **Event**
  - Events have an internal flag that can be set/clear and other threads can wait on it being set
- Other useful thread specific primitives:
  - Re-entrant locks
  - Queues (useful for implementing the actor model)
  - Conditions
  - Semaphores
  - Thread local variables

**See also:** concurrent futures ThreadPoolExecutor is a high level interface to push tasks to a background thread.

#### **Processes**

- For concurrent task execution with processes we use the multiprocessing module
- Provides a similar API and primitives to threading
- Uses fork on Linux
- On Windows tasks and their environment are pickled and sent to the new process (so higher startup cost)
- Using processes bypasses the problem of the GIL (one GIL per process)
- Can send (copy) objects between processes using queues, but use the actor model (CSP)
- New (Python 3.11) shared memory constructs (low level – bytes and numpy arrays)

## Multiprocessing

- Creating a process and sending it a task is easy
- The task must be "importable" by the new process
- Processes have useful methods like join/kill/is\_alive, etc

```
import multiprocessing
def worker(i):
    print(f'Worker {i}')
if name == ' main ':
    for \overline{i} in range(3):
        p = multiprocessing.Process(target=worker, args=(i,))
        p.start()
$ python workerprocesses.py
Worker 0
Worker 1
Worker 2
```

### Higher Level API: ProcessPool

A process based worker pool

```
p = multiprocessing.Pool([num_processes])
```

- It executes functions in a subprocess
- It maintains a pool of workers to divide tasks between
- A high level API, no need to worry about the details
- Core pool operations:

```
p.apply(func [, args [, kwargs]])
p.apply_async(func [, args [, kwargs [,callback]]])
```

- apply blocks and waits for a result
- apply\_async returns a result object you can poll for the result or wait on

### Pool: apply()

Running a function in another process

```
import multiprocessing

def add(x, y):
    return x + y

if __name__ == '__main__':
    p = multiprocessing.Pool()
    r = p.apply(add, (3, 4))
    print(r)

$ python processingpool.py
7
```

 apply() runs the function in one of the subprocesses and waits for the result

### Pool: apply\_async()

- Running a function in another process without blocking
- Provides a handle (an ApplyResult) to fetch the result

```
import multiprocessing
import time
def add(x, y):
    return x + y
if name == ' main ':
   p = multiprocessing.Pool()
    r = p.apply_async(add, (3, 4)) # r is an ApplyResult object
   # We could call r.wait([timeout])
   while not r.ready():
        time.sleep(0.1)
   print(r.ready())
   print(r.successful())
    print(r.get()) # get has an optional timeout param
```

### The Future: PEP 703

- Python 3.13: The GIL is optional.
- It's a compile time choice, extensions must be compiled against this version --disable-gil
- 5-8% slower for single threaded code
- Uses deferred reference counting (etc)



### The Future: Subinterpreters

- Python 3.12: Subinterpeters in C (PEP 684)
- Python 3.13: Subinterpreters in Python (PEP 554)
- A new interpreters module
- One GIL per subinterpreter
- Inspired by the PythonEngine from IronPython
- Adds an InterpreterPoolExecutor and an Interpreter class
- Objects copied between interpreters not shared
- Some limits on extension modules for sharing between interpreters (requires a "multi-phase init")