"This is a parallel parrot!" (CPA 2011 fringe edition)

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Python

- Dynamically typed
- Multiparadigm
- Indentation-structured
- Designed to support teaching
- Widely deployed and used
- Lots of good-quality libraries
- Really slow bytecode interpreter



```
import sys, re
space re = re.compile(r'[ t\r\n\f\v]+')
punctuation_re = re.compile(r'[!"#%&\'()*,-./:;?@\[\\\]_{}]+')
max words = int(sys.argv[1])
f = open(sys.argv[2])
data = f.read()
f.close()
words = [re.sub(punctuation re, '', word).lower()
         for word in re.split(space_re, data)]
words = [word for word in words if word != ""]
found = \{\}
for i in range(len(words)):
    max phrase = min(max words, len(words) - i)
    for phrase_len in range(1, max_phrase + 1):
        phrase = " ".join(words[i:i + phrase len])
        uses = found.setdefault(phrase, [])
        uses.append(i)
for (phrase, uses) in found.items():
    if len(uses) > 1:
        print ('<"%s":(%d,[%s])>'
               % (phrase, len(uses), ",".join(map(str, uses))))
print
```

Benchmarking

- Machine:
 - 2x 2.27GHz Intel E5520 8 cores, 16 HTs
 - 12GB RAM; files in cache for benchmarks
 - Debian etch x86_64 with Python 2.6.6
- Using WEB.txt, 3 words, output to /dev/null
- Concordance.hs: (still waiting)
- ConcordanceTH.hs: 22.7s
- mini-concordance.py: 13.5s



Parallel Python

- Python's had threading support for a long time
- ... but the bytecode engine is single-threaded

- The "Global Interpreter Lock"

- Useful for IO-bound programs, or where you're mostly calling into native code
- No good for parallelising pure-Python code



Multiprocessing

- The **multiprocessing** module provides the same API as the **threading** module...
- ... but it uses operating system processes
- Synchronisation becomes more expensive, but you can execute in parallel



So let's parallelise...

- This is a **trivially-parallelisable** problem
 - You can break it down into separate jobs that don't need to interact with each other
- Split up input file into C chunks
- Do concordance on each in parallel
- Merge results from different chunks together
- Print them out





- Pick C points in the file
- Seek to each point
- Read forward until you find a word boundary
- Read a few words more forward to handle overlap between chunks
- Don't have to read the whole file
- Cheap $O(\mathbf{C})$ not worth parallelising



Concordance

 Read appropriate chunk of file and do concordance just as before

- IO has been parallelised

- Return dict (hashed map) of phrases to uses, and number of words read in total
- Parallelise using multiprocessing.Pool

```
pool = Pool(processes=C) # num to run at once
jobs = []
for i in range(C):
    jobs.append(pool.apply_async(concordance, (args ...)))
results = [job.get() for job in jobs]
```



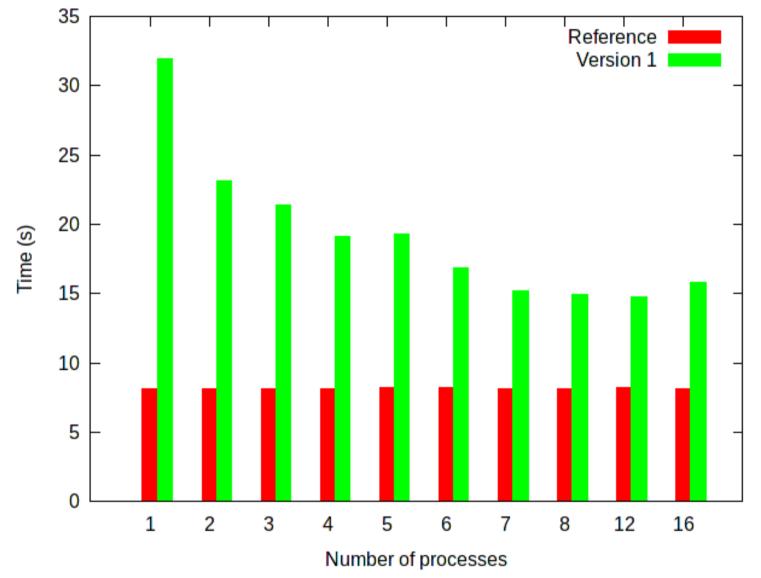


• Iterate through all the results, and add to a dict, adjusting word numbers based on the totals

```
merged = {}
first_word = 0
for (found, num_words) in results:
    for (phrase, uses) in found.items():
        all_uses = merged.setdefault(phrase, [])
        all_uses += [use + first_word for use in uses]
    first_word += num_words
```

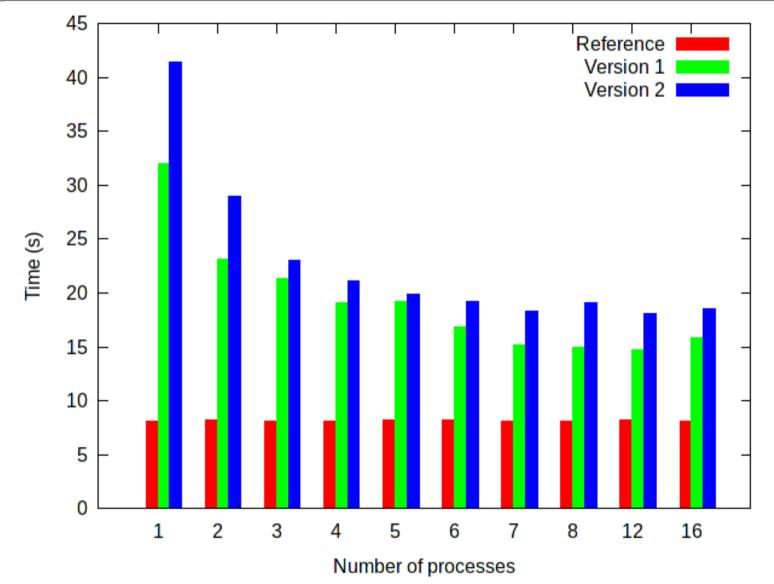
return merged





Hmm...

- Some scalability, but there's a massive constant overhead
- At this point, I forget Rule 3 of optimisation...
 - 1. Don't
 - 2. Don't yet
 - 3. Profile first
- The merge must be the slow part, right?
- Rewrite to sort in each concordance, and use heapq.imerge to merge sorted lists...



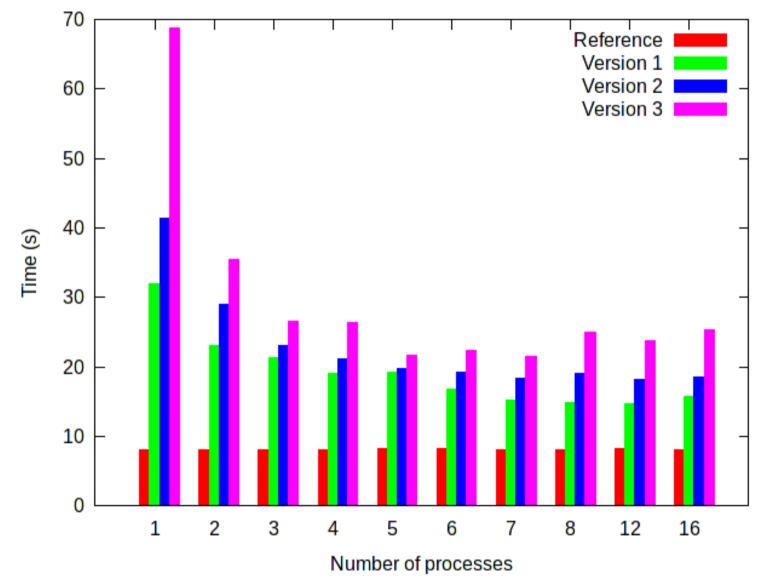
Well, that didn't work...

- Complicated Python is often slower...
 - ... because the runtime system and libraries are well-optimised for the common cases
- Stick with the obvious approach!
- Parallelise the merge instead



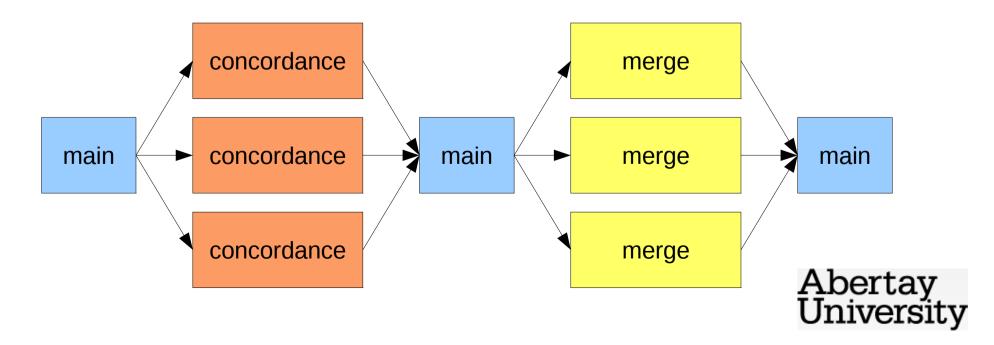
Parallel merge

- Compute hash of each phrase (Python hash), and group phrases by hash % C
- Each concordance returns several dicts
- Each merge takes all the dicts with the same hash % C, merges as before, and returns its merged dict
- Output iterates through merged dicts
 - It's useful that the output doesn't have to be sorted (although sorting the strings would be cheap)



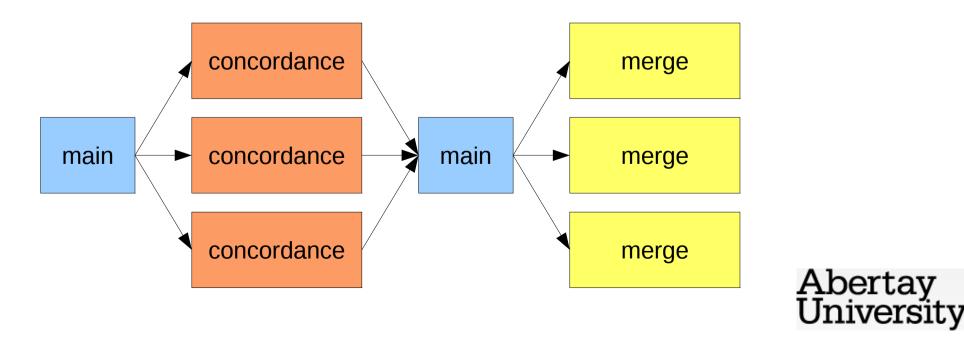
Applying Rule 3

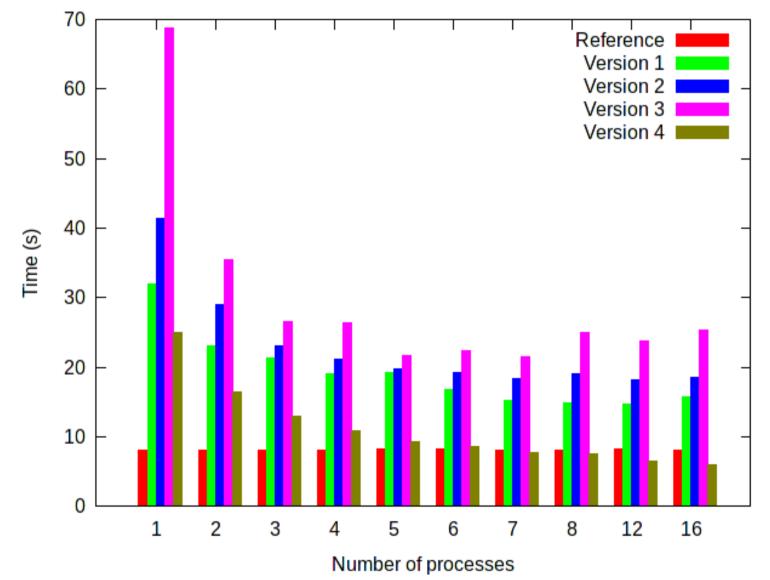
- That's even slower, although at least it scales...
- Break out the profiler: it's now spending most of its time communicating between processes
 - in **pickle**, Python's serialiser



Arrow removal, stage 1

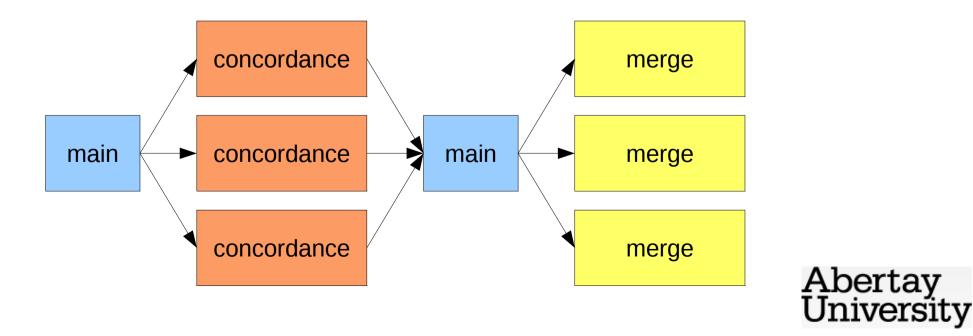
- Parallelise the output
- Each merge writes its own output, serialised using a Lock
- No less work to do but less communication







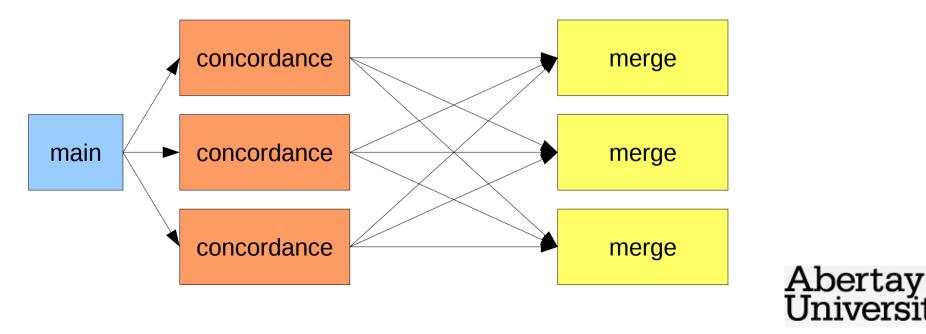
- We're beating the original version now!
- Let's keep going along those lines...

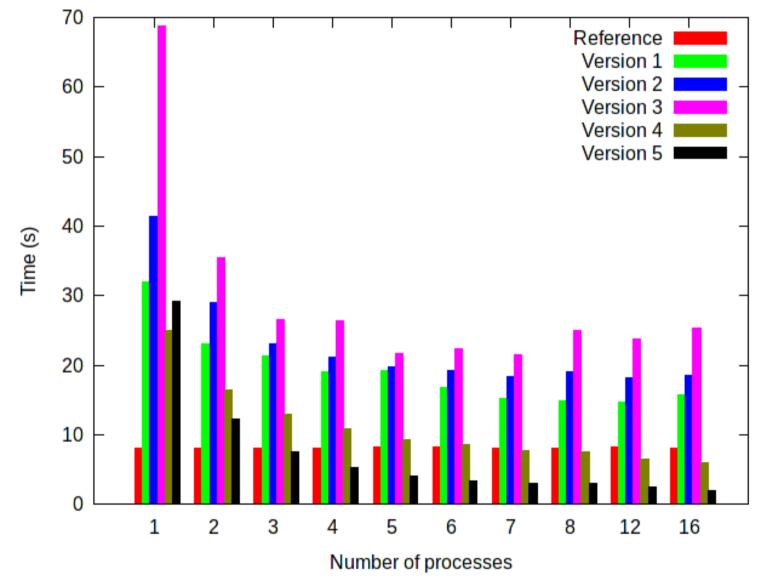


Arrow removal, stage 2

- Give each merge an incoming Queue
- Connect concordances directly to merges
- Each phrase only communicated once...

– \ldots and the communication is parallelised too





Success

- We beat the original version at 3 cores, and it hasn't hit a bottleneck by 16
- Even better: it's scaling linearly!
 - Using **N** cores requires **1/N** time
- This is a concurrent solution giving the kernel more freedom to schedule efficiently
 - ... and how I would have built it in the first place using a process-oriented approach



Summing up

- "Do the simplest thing that can possibly work"
- Profile first
- All the improvement has come from changing the **structure** of the program
- **No shared memory** this is a messagepassing solution, amenable to distribution
- Could optimise the sequential bits but this is probably fast enough now; CPUs are cheap...



Any questions?

- Thanks for listening!
- Get the code: git clone http://offog.org/git/sicsa-mcc.git
- Contact me or get this presentation: http://offog.org/

