Why is my code slow?

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Outline

- Caching, Memoization, and Vectorization
- Parallel Computing
- Greedy and Exhaustive Algorithms
- Faster Implementations versus Faster Algorithms

Section 1

Caching, Memoization, and Vectorization

Caching

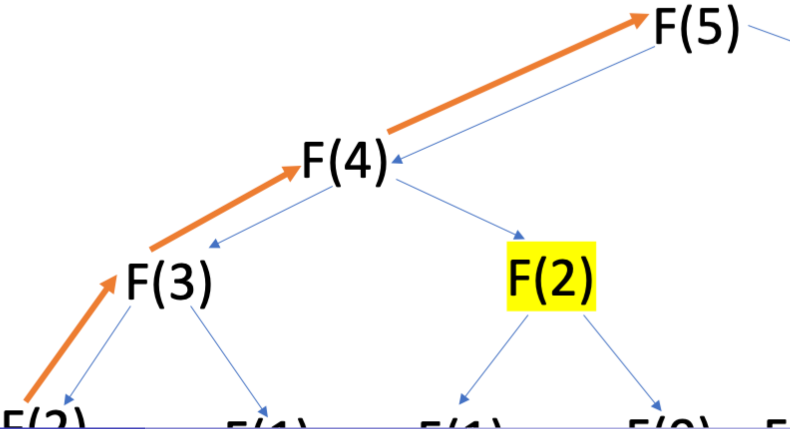
- *Caching* refers to storing things for later use
  - Your browser probably does by temporarily downloading page details on your local disk
  - Faster, reduces server load
  - Other examples include 3D rendering and saving common database queries
- However, caching usually takes space in exchange for faster run times
- The *space-time* trade off is a case where an algorithm trades increased space usage for faster runtimes

Memoization

- *Memoization* refers to storing results of function calls to use for later
  - Specific method of caching
- This is useful for methods with a lot of repeated computations
- For instance, in our recursive Fibonacci number function.
- `fib(12)` is called by `fib(13)`, `fib(14)` etc.
  - And `fib(3)` is called many many times
- $F(5) = F(4) + F(3) = F(3) + F(2) + F(2) + F(1)$ Which calculates repeated subproblems

How Memoization Works

- Since we store the results, each function call is only made once, making the time complexity $O(n)$, much better than $O(2^n)$ [1]
- Memoization can also avoid the maximum recursion depth error because the call stack is smaller



Memoization Python

```
cache = {0: 0, 1: 1}

def fib(n):
  if n in cache:
    return cache[n]
  else:
    cache[n] = fib(n - 1) + fib(n - 2)
    return cache[n]
```

For the base cases, we replace calling `fib(0)` and `fib(1)` by getting the values from the dictionary

Memoization Python

- We can use the `functools` library, which is included in the standard library (no pip install needed!)
  - `functools` does memoization for you!
- We can use the `@cache` decorator, but the cached dictionary can grow to massive sizes
- Instead, `@lru_cache(maxsize = n)` uses the LRU (least recently used) `n` computations
- Alternatively, we can use `joblib` to store the memoized results in a file

Memoization Python

```python
from functools import lru_cache

@lru_cache(maxsize=10)
def fib_rec(n):
  if n == 0 or n == 1:
    return n
  else:
    return fib_rec(n-1) + fib_rec(n-2)
```

Vectorized Operations

- *Vectorization* is a technique of implementing array operations without for loops
- We use functions defined by various modules that are highly optimized for the specific problem
- NumPy provides a lot of functions that vectorized and are faster than for loops
  - Array add/subtract/multiply/divide by scalar
  - Sum of array
  - Max/min of array
- Keep this in mind for some ML processes that are iterative, such as gradient descent

Why Vectorized Operations Work

- Python (and R) are interpreted languages. There is no compiler and the languages are dynamic
- C language, for instance, makes optimization at the compiler level (before execution) to speed up your code
- Thus, NumPy implements arrays in C, which speeds things up
- The other reason vectorization works in because of parallelization

Section 2

Parallel Computing

Parallelization

Compare the following codes. What are their run times?

```
def fib(n):
  if n <= 1:
    return n
  else:
    return fib(n - 1) + fib(n - 2)
```

Parallelization

```
import numpy

def add_one(n, x):
  y = np.zeros(n)
  for i in range(n):
    y[i] = x[i] + 1

  return y
```

Parallelization

- Both are $O(n)$, but the second code chunk can be done in *parallel* because the n computations are independent.
- Fibonacci depends on the previous two values
- The requirements for code to the parallelized and vectorized are similar, but not the same
- The Numba library can help will parallelizing your code
- Note parallel means the process takes place on one machine, but *distributed* means the computation is shared across many machines

Section 3

Greedy and Exhaustive Algorithms

Greedy Approach (literally)

- Let's revisit the knapsack problem, taking a different approach.
- The items are:
  - Stereo: \$3000, 4 kg
  - Laptop: \$2000, 3 kg
  - Guitar: \$1500, 1 kg
- If we follow the rule "get the most valuable item, then get second most valuable etc." we would make \$3000 by taking the stereo, which isn't the optimal \$3500
- A *greedy algorithm* picks the optimal move at each step, which hopefully leads to the overall optimal solution
  - But it finds the solution in $O(n)$ time

Greedy Apporach

- Let's say you could take fractions of an item and we tried the greedy approach
  - Peanuts: \$7/kg
  - Rice: \$5/kg
  - Tea: \$12/kg
- We would take tea until it runs out, followed by peanuts and rice. This is the optimal solution in $O(n)$ time!

Classroom Scheduling Problem

- Suppose we want to hold as many classes in a classroom as possible [2]

Class	Start	End
Yoga	9AM	10AM
Music Theory	9:30AM	11AM
Painting	10AM	11AM
Algorithms	10:30AM	11:30AM
Calculus	11AM	12PM

2 Minutes: write down a greedy algorithm to solve this problem

[2] From Bhargava chapter 8

Classroom Scheduling Problem

Algorithm

1. Pick the class that ends the soonest. This is the first class you'll hold in this classroom
2. Now, you have to pick a class that starts after the first class. Again, pick the class that ends the soonest. This is the second class you'll hold
3. Repeat the second step

This not only produces the correct solution but also does so in $O(n)$ time, for n classes!

Classroom Scheduling Problem

- An alternative algorithm is the *exhaustive approach*
  - We try every combination of classes. At the end, we see which solution fits the most classes
  - We try every combination of items to steal. At the end, we see which solution has the most value
- While brute forcing might sound always unnecessary, there are cases where it is needed to get the optimal solution
  - When performing subset selection for regression or decision tree, we can't guarantee the variables are uncorrelated. So forward/backward stepwise selection isn't guaranteed to produce the best outcome
  - More on this in a few slides
- 2 minutes: what is the time complexity of best subset selection?

Greedy Approximation Algorithms

- Problems involving finding the best subset of a variable to max/min an objective value are generalized as the problem of finding the best *power set*.
  - There are 2^n power sets, which becomes impossible to calculate past $n = 100$ (depending on the constants)
- *Approximation algorithms* are judged by how fast they are and how close they are to the optimal solution
  - Forward/backwards stepwise selection is an approximation algorithm to best subset selection

N-P Complete Problems

- In the power set problem, we need to brute force all combinations and test them. Such problems are called *N-P Complete*
  - A lot of smart people think it's not possible to solve these with efficient algorithms
- It's hard to tell if a problem is N-P complete
  - Finding the shortest path between two points is N-P complete (travelling salesman)
  - But the knapsack problem isn't N-P complete because we can solve it using dynamic programming

Section 4

Faster Implementations versus Faster Algorithms

Faster Implementations versus Faster Algorithms

- There are two ways we speed up our code
  - Use a faster algorithm, such as dynamic programming instead of brute force. Algorithms are concerned with the approach to the problem
  - Use a faster implementation, such as vectorization instead of loops
- It is useful to think about these separately when developing a programming, then combining them to create a super-fast approach!

Section 5

Recommended Problems and References

Recommended Problems and Readings

- Cormen: Chapter 34 on NP-Completeness (highly optional)
- Bhargava: Chapter 8 exercises
  - 8.1 - 8.8
- Vectorize the second code chunk in the Parallelization section
- Find the longest palindrome from a string Hint: use a greedy alogrithm
- Computing Pascal's triangle Hint: use dynamic programming

References

- Bhargava, A. Y. (2016). *Grokking algorithms: An illustrated guide for programmers and other curious people.* Manning. Chapter 1.
- Cormen, T. H. (Ed.). (2009). *Introduction to algorithms* (3rd ed). MIT Press. Chapter 1 and 3.
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