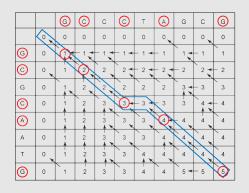
CSE 417 Algorithms

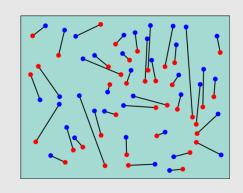
Richard Anderson Autumn 2024 Lecture 4

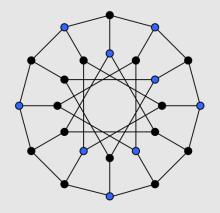
Announcements

- Reading
 - Chapter 2.1, 2.2
 - Chapter 3 (Mostly review)
 - Start on Chapter 4
- Homework Guidelines
 - Submit homework with Gradescope
 - Describing an algorithm
 - Clarity is most important
 - Pseudocode generally preferable to just English
 - But sometimes both methods combined work best
 - Prove that your algorithm works
 - A proof is a "convincing argument"
 - Give the run time for your algorithm
 - Justify that the algorithm satisfies the runtime bound
 - You may lose points for style
 - Homework assignments will (probably) be worth the same amount



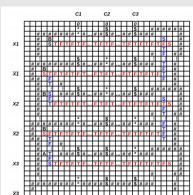






Five Problems

Scheduling
Weighted Scheduling
Bipartite Matching
Maximum Independent Set
Competitive Facility Location



Summary – Five Problems

- Scheduling
- Weighted Scheduling
- Combinatorial Optimization
- Maximum Independent Set
- Competitive Scheduling

What does it mean for an algorithm to be efficient?

Definitions of efficiency

Fast in practice

 Qualitatively better worst case performance than a brute force algorithm

Polynomial time efficiency

- An algorithm is efficient if it has a polynomial run time
- Run time as a function of problem size
 - Run time: count number of instructions executed on an underlying model of computation
 - T(n): maximum run time for all problems of size at most n

Polynomial Time

 Algorithms with polynomial run time have the property that increasing the problem size by a constant factor increases the run time by at most a constant factor (depending on the algorithm)

Why Polynomial Time?

 Generally, polynomial time seems to capture the algorithms which are efficient in practice

 The class of polynomial time algorithms has many good, mathematical properties

Polynomial vs. Exponential Complexity

- Suppose you have an algorithm which takes n! steps on a problem of size n
- If the algorithm takes one second for a problem of size 10, estimate the run time for the following problems sizes:

12 14 16 18 20

Ignoring constant factors

- Express run time as O(f(n))
- Emphasize algorithms with slower growth rates
- Fundamental idea in the study of algorithms
- Basis of Tarjan/Hopcroft Turing Award

Why ignore constant factors?

- Constant factors are arbitrary
 - Depend on the implementation
 - Depend on the details of the model

 Determining the constant factors is tedious and provides little insight

Why emphasize growth rates?

- The algorithm with the lower growth rate will be faster for all but a finite number of cases
- Performance is most important for larger problem size
- As memory prices continue to fall, bigger problem sizes become feasible
- Improving growth rate often requires new techniques

Formalizing growth rates

- T(n) is O(f(n)) $[T:Z^+ \rightarrow R^+]$
 - If n is sufficiently large, T(n) is bounded by a constant multiple of f(n)
 - Exist c, n_0 , such that for $n > n_0$, T(n) < c f(n)

- T(n) is O(f(n)) will be written as:
 T(n) = O(f(n))
 - Be careful with this notation

Prove $3n^2 + 5n + 20$ is $O(n^2)$

Let c =

Let $n_0 =$

T(n) is O(f(n)) if there exist c, n_0 , such that for $n > n_0$, T(n) < c f(n)

Order the following functions in increasing order by their growth rate

- a) n log⁴n
- b) $2n^2 + 10n$
- c) $2^{n/100}$
- d) $1000n + log^8 n$
- e) n^{100}
- f) 3ⁿ
- g) 1000 log¹⁰n
- h) $n^{1/2}$

Lower bounds

- T(n) is $\Omega(f(n))$
 - T(n) is at least a constant multiple of f(n)
 - There exists an n_0 , and $\epsilon > 0$ such that $T(n) > \epsilon f(n)$ for all $n > n_0$
- Warning: definitions of Ω vary

T(n) is Θ(f(n)) if T(n) is O(f(n)) and
 T(n) is Ω(f(n))

Useful Theorems

• If $\lim_{n\to\infty} \frac{f(n)}{g(n)} = c$ for c > 0 then $f(n) = \Theta(g(n))$

 If f(n) is O(g(n)) and g(n) is O(h(n)) then f(n) is O(h(n))

If f(n) is O(h(n)) and g(n) is O(h(n)) then
 f(n) + g(n) is O(h(n))

Ordering growth rates

- For b > 1 and x > 0
 - log^bn is O(n^x)

- For r > 1 and d > 0
 - $-n^d$ is $O(r^n)$