CSE 421
Algorithms

Richard Anderson

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Lecture 4

Announcements

- Reading
  - Chapter 2.1, 2.2
  - Chapter 3 (Mostly review)
  - Start on Chapter 4
- Homework Guidelines
  - Prove that your algorithm works
    - A proof is a “convincing argument”
  - Give the run time for you algorithm
    - Justify that the algorithm satisfies the runtime bound
  - You may lose points for style

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) $n \log^4 n$
b) $2n^2 + 10n$
c) $2^{n/100}$
d) $1000n + \log^8 n$
e) n^{100}
f) 3^n
g) $1000 \log^{10} n$
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 $\varepsilon > 0$ such that $T(n) > \varepsilon f(n)$ for all $n > n_0$
- Warning: definitions of Ω vary

- T(n) is $\Theta(f(n))$ if T(n) is $O(f(n))$ and T(n) is $\Omega(f(n))$

Useful Theorems

- If lim (f(n) / g(n)) = c for c > 0 then f(n) = Θ(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 $x > 0$
  - $\log^b n$ is $O(n^x)$

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

Graph Theory

- G = (V, E)
  - V – vertices
  - E – edges
- Undirected graphs
  - Edges sets of two vertices {u, v}
- Directed graphs
  - Edges ordered pairs (u, v)
- Many other flavors
  - Edge / vertices weights
  - Parallel edges
  - Self loops

Definitions

- Path: $v_1, v_2, \ldots, v_k$, with (v_i, v_{i+1}) in E
  - Simple Path
  - Cycle
  - Simple Cycle
- Distance
- Connectivity
  - Undirected
  - Directed (strong connectivity)
- Trees
  - Rooted
  - Unrooted

Graph search

- Find a path from s to t

S = {s}

While there exists (u, v) in E with u in S and v not in S

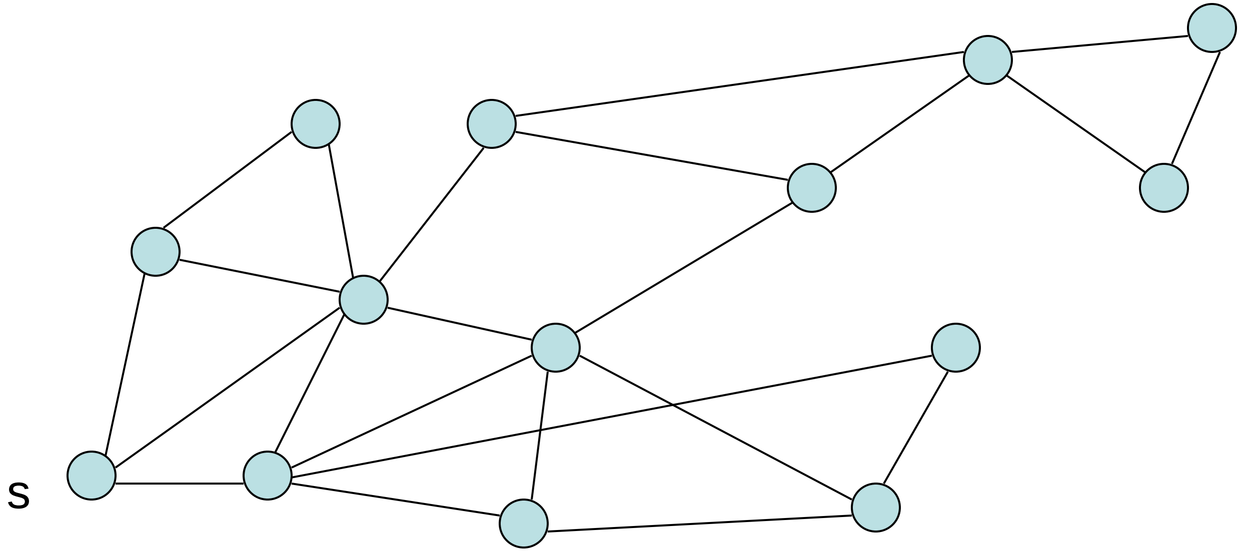
    Pred[v] = u

    Add v to S

    if (v = t) then path found

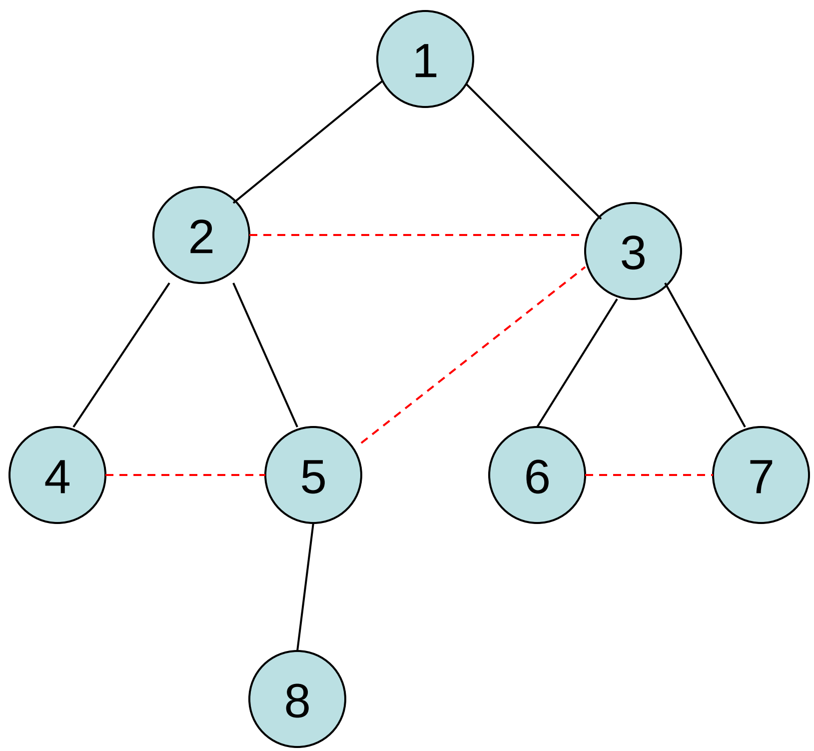
Breadth first search

- Explore vertices in layers
  - s in layer 1
  - Neighbors of s in layer 2
  - Neighbors of layer 2 in layer 3 . . .



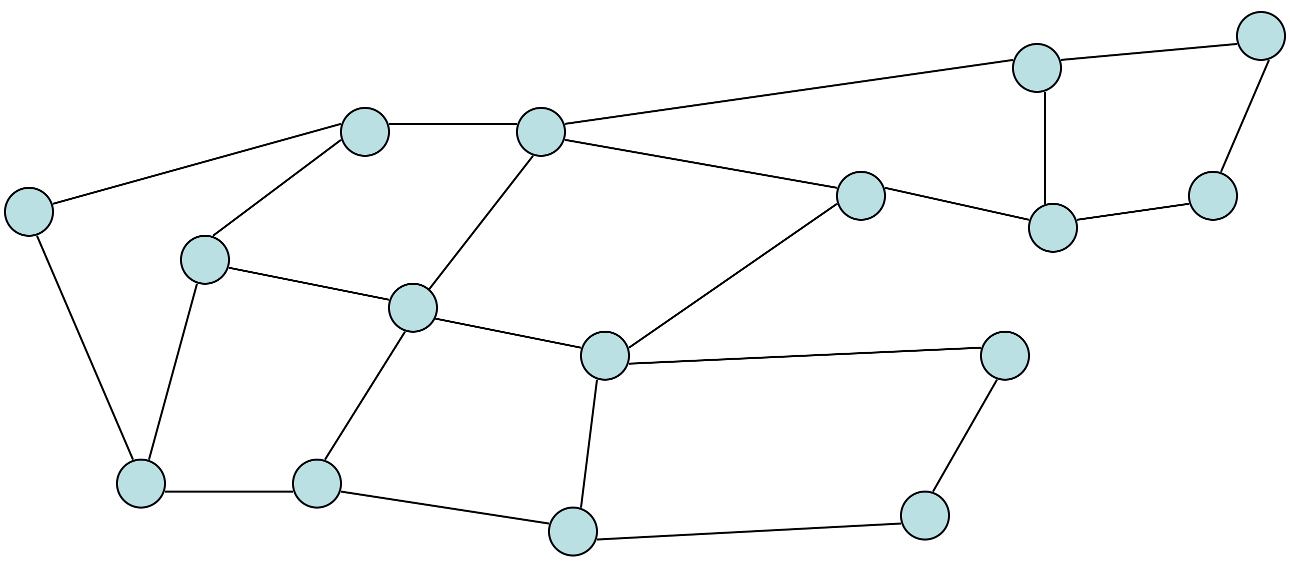
Key observation

- All edges go between vertices on the same layer or adjacent layers

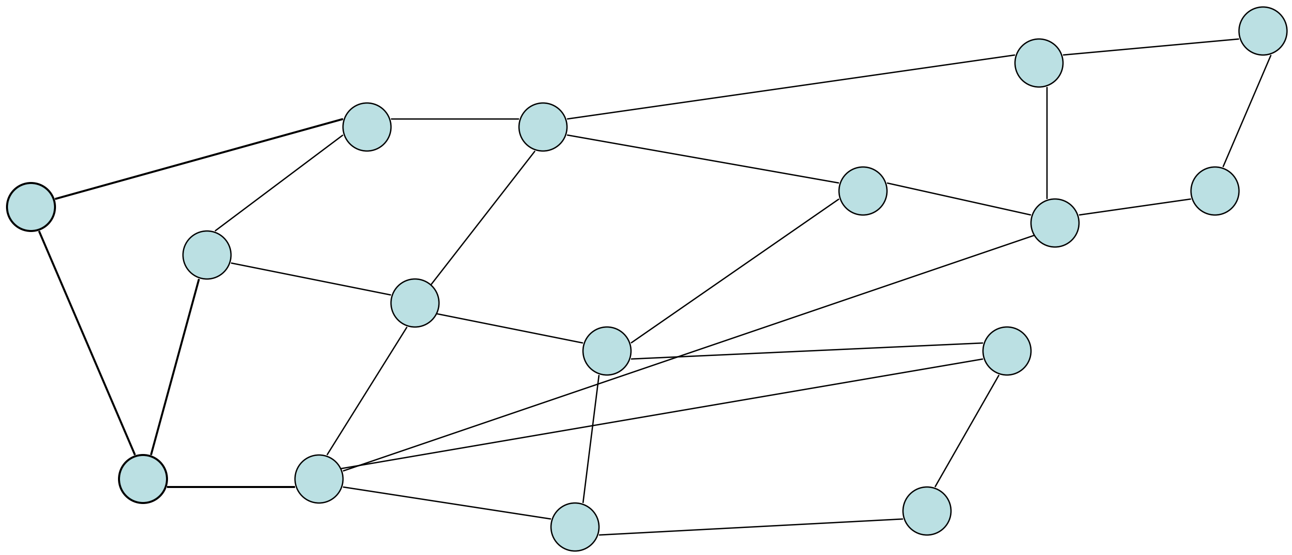


Bipartite Graphs

- A graph V is bipartite if V can be partitioned into V_1, V_2 such that all edges go between V_1 and V_2
- A graph is bipartite if it can be two colored



Can this graph be two colored?



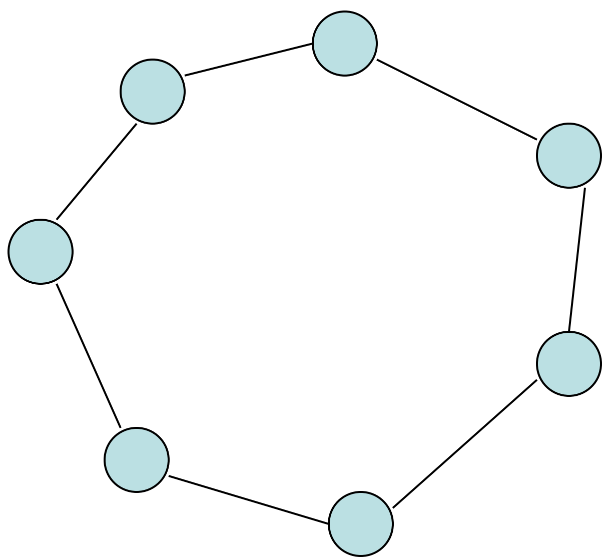
Algorithm

- Run BFS
- Color odd layers red, even layers blue
- If no edges between the same layer, the graph is bipartite
- If edge between two vertices of the same layer, then there is an odd cycle, and the graph is not bipartite

Theorem: A graph is bipartite if and only if it has no odd cycles

Lemma 1

- If a graph contains an odd cycle, it is not bipartite



Lemma 2

- If a BFS tree has an *intra-level edge*, then the graph has an odd length cycle

Intra-level edge: both end points are in the same level

Lemma 3

- If a graph has no odd length cycles, then it is bipartite