CS 161: Design and Analysis of Algorithms

Dynamic Programming I: Weighted Interval Scheduling

- Example: Fibonacci Numbers
- Recurrence Trees
- Dynamic Programming Dags
- Weighted Interval Scheduling

Example: Fibonacci Numbers

```
    F(n) = {

            O if n = 0
            1 if n = 1
            F(n-1) + F(n-2) if n > 1
```

```
    Fib1(n) = {

            If n < 2, return n</li>
            Fib1(n-1) + Fib1(n-2) otherwise
```

- Running Time?
 - Claim: For n>0, number of additions is F(n)-1
 - True for n = 1, 2
 - Inductively assume true for k < n
 - Fib1(n) uses 1 addition, plus the additions of
 Fib1(n-1) and Fib1(n-2)
 - Number of additions: 1 + (F(n-1)-1) + (F(n-2)+1)

- Running Time?
 - $-\Omega(F(n))$
 - How fast does F(n) grow?

Fibonacci Growth Rate

- Let φ and ψ be solutions to $x^2 = x + 1$
 - $\phi \approx 1.62$, the golden ratio
 - $-\Psi \approx -0.62$
- Claim: $F(n) = \theta(\varphi^n)$
- Stronger Claim: $F(n) = (\phi^n \Psi^n)/(\phi \Psi)$
- Proof: True for n = 0, 1
 - Assume true for k < n
 - -F(n) = F(n-1) + F(n-2)

Fibonacci Growth Rate

- $F(n) = (\varphi^n \Psi^n)/(\varphi \Psi)$
- Proof: True for n = 0, 1
 - Assume true for k < n

$$F(n) = F(n-1) + F(n-2) = \frac{\varphi^{n-1} - \psi^{n-1}}{\varphi - \psi} + \frac{\varphi^{n-2} - \psi^{n-2}}{\varphi - \psi}$$
$$= \frac{\varphi^{n-2} (1 + \varphi) + \psi^{n-2} (1 + \psi)}{\varphi - \psi} = \frac{\varphi^{n} - \psi^{n}}{\varphi - \psi}$$

- Running Time?
 - $-\Omega(F(n)) \approx \Omega(1.62^n)$
 - Grows extremely rapidly
 - Example: My computer
 - Running time $\approx 1.7 \text{ x } (1.62)^n \text{ nanoseconds}$
 - n = 30: 4 milliseconds
 - n = 40: 0.42 seconds
 - n = 50: 51 seconds
 - n = 60: 1.8 hours (projection)
 - n = 70: 9.1 days (projection)
 - n = 130: 93 billion years (projection)

Problem

- To compute F(n):
 - Compute F(n-1) and F(n-2)
 - Computing F(n-1) requires computing F(n-2) and F(n-3)
 - Computing F(n-2) requires computing F(n-3) and F(n-4)

— ...

Problem

- To compute F(n):
 - Call F(n-k) a total of F(k-1) times
 - Way too much repeated work

Solution: Memoization

- Remember answers to F(k) for future calls
- Keep track of (k,F(k)) mappings
 - Hash table
 - Array
- Fib2(n) = $\{$
 - If(n < 2) return n
 - Check if Fib2(n) has been computed already, if so, output it
 - Otherwise, return Fib2(n-1) + Fib2(n-2)

Alternative Approach

- We are going from top down
- How about going bottom up:
 - Keep array A, where A[k] = F(k)
 - Iteratively build array
 - First, set A[0] = 0, A[1] = 1
 - Then, for k = 2,...,n, set A[k] = A[k-1] + A[k-2]

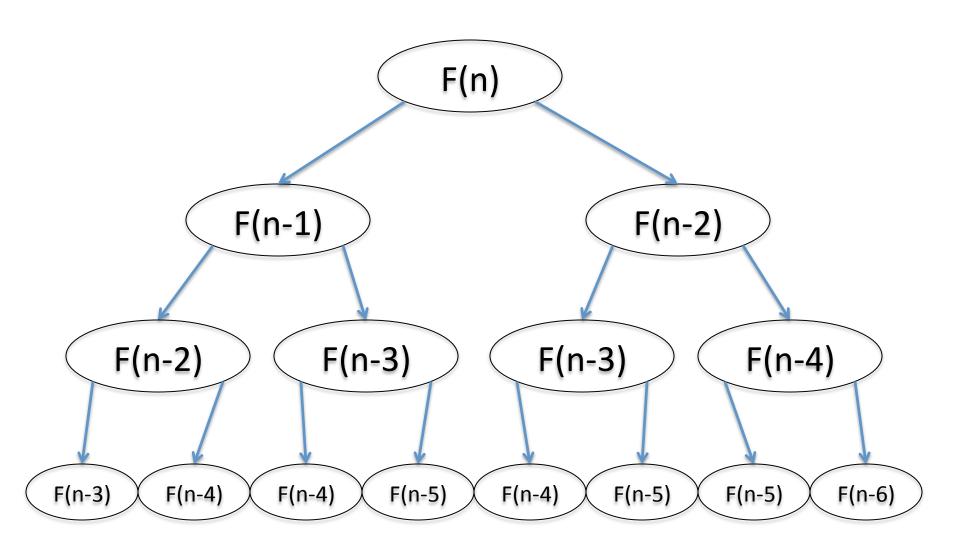
Iterative Algorithm

- Fib3(n) = $\{$
 - Construct array A of length n+1
 - Set A[0] = 0, A[1] = 1
 - For k = 2, ..., n
 - A[k] = A[k-1] + A[k-2]
 - Return A[n]

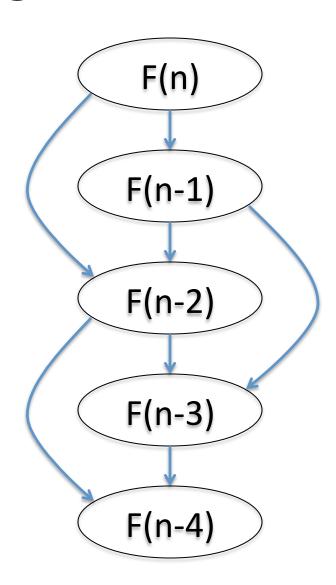
Iterative Algorithm

- Running Time:
 - n-1 iterations
 - Each step has a 1 addition (pretend all additions are constant time)
 - -O(n) time
 - Much more tractable now

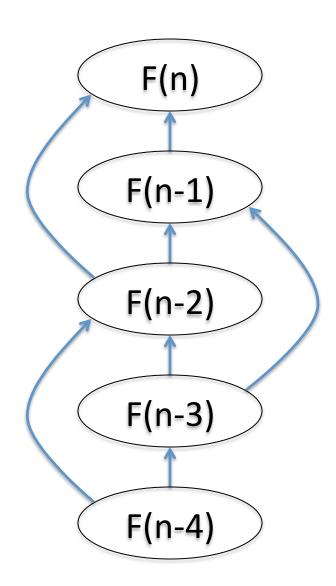
Recursion Tree



Merge Identical Nodes



Process Bottom Up

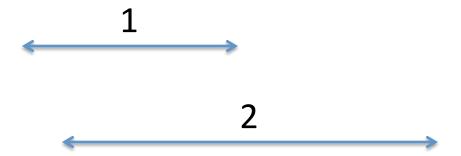


Dynamic Programming

- Subproblems have dag structure
 - Edge represents prerequisite
- Solve subproblems in topological order
 - Whenever we solve a subproblem, we have already solved all of the other subproblems we need
- Very general, flexible tool

- Given set of n intervals (s(i),f(i)), each with a weight w(i)
- Goal: pick set of overlapping intervals with largest possible weight
- If w(i) = 1, we have the unweighted scheduling problem, which can be solved by greedy
- Does greedy work here?

Recall greedy: pick interval that ends earliest



This greedy approach does not work

- Say we have optimal schedule S
- Two possibilities:
 - Interval n (the last one) is in S
 - Interval n is not in S

- Suppose interval n is not in S
 - Then S is actually optimal for first n-1 intervals
 - Otherwise, any optimal solution for first n-1 intervals is solution for n intervals with higher weight

- Suppose interval n is in S
 - Then no interval that overlaps n can be in S
 - S {n} must be optimal over intervals that don't overlap interval n

- Suggest the following approach:
 - Subproblems will consist of subsets of intervals
 - If subset has single interval, the optimal solution for that subproblem is just that interval
 - Otherwise, let T be some subset, and let t be the last interval
 - The optimal for a subset T is either:
 - The optimal for T {t}
 - (The optimal for T {s intersecting t}) + {t}

Problem

- There are 2ⁿ subsets, so solving for all subsets will take exponential time
- Instead, we will be clever:
 - Order intervals by finish time (i.e. if i < j, f(i) < f(j))
 - Let p(i) be the last interval that ends before i starts,
 or 0 if no such interval
 - Now, we only need to solve problems on sets{1, 2, ..., k}

- Optimal on {1, 2, ..., k}:
 - If interval k is not in optimal, then optimal is just optimal on {1, 2, ...,k-1}
 - If k is in optimal, then optimal is the optimal on $\{1, 2, ..., p(k)\}$, plus the interval k
 - Only need to check two cases

- WeightedIntervalSchedule:
 - Create solution array S of length n+1
 - Create weight array W of length n+1
 - Sort intervals by f(i)
 - $-S[0] = {}, W[0] = 0, S[1] = {1}, W[1] = w(1)$
 - For k = 2, ..., n:
 - If W[k-1] < W[p(k)] + w(k), then:
 - -W[k] = W[p(k)] + w(k)
 - $S[k] = S[p(k)] + \{k\}$
 - Else W[k] = W[k-1], S[k] = S[k-1]
 - Output S[n]

Running Time

- Say we have p(i) values, and list already sorted.
- Then, each iteration takes only O(1), so O(n) overall
- Computing p(j)?
 - Obvious algorithm: O(n²)

Underlying Dag

- Nodes represent sets {1,...,k}
- Pointer from set {1,...,k-1} to {1,...,k} for all k
- Pointer form set {1,...,p(k)} to {1,...,k} for all k

Dynamic Programming Outline

- Find good subproblems
- Express solution to suproblem k in terms of solutions to other subproblems
 - Solution to subproblem k needs to be efficiently computable given solutions to other subproblems
- Solve subproblems in topological order

- Dynamic solution isn't necessarily best
- Once we've computed F(k-1) and F(k-2), we no longer need F(k-3), F(k-4), ..., F(0)
- Save space: only keep around last two computed values

- Keep around F(k) and F(k-1)
- To update:

$$F(k) = F(k-1) + F(k-2)$$

$$F(k-1) = F(k-1)$$

- Keep around F(k) and F(k-1)
- To update:

$$\begin{pmatrix} F(k) \\ F(k-1) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix} \begin{pmatrix} F(k-1) \\ F(k-2) \end{pmatrix}$$

Can we do better than O(n) additions?

$$\begin{pmatrix} F(n) \\ F(n-1) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}^{n-1} \begin{pmatrix} F(1) \\ F(0) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}^{n-1} \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

- Say we have a set X where we can multiply elements together
- How do we compute $x^n = x * x * x * ... * x$?
 - Obvious solution: compute xⁿ⁻¹ recursively, and multiply by x
 - Requires n-1 multiplications in the set

- What if we are computing x^4 ?
 - First compute $y = x^2$, then compute y^2
 - Only 2 multiplications
- What about x⁸?
 - Compute $y = x^4$ as above, then compute y^2
 - Only 3 multiplications

- In general, can compute x^{2ⁿ} using n multiplications
- What about exponents that are not powers of 2?

```
    Pow(x, n) = {

            If n = 1, return x
            If n is even, return Pow(x * x, n/2)
            If n is odd, return x * Pow(x * x, (n-1)/2)
```

- Number of multiplications?
 - At most 2 per call to Pow
 - Exponent is at least divided by 2
 - O(log n) multiplications

Can we do better than O(n) additions?

$$\begin{pmatrix} F(n) \\ F(n-1) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}^{n-1} \begin{pmatrix} F(1) \\ F(0) \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 1 & 0 \end{pmatrix}^{n-1} \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

- Can compute using O(log n) 2x2 matrix multiplications
- O(log n) additions and multiplications

The Catch

- The integers we are adding and multiplying are large (exponential, in fact)
- Number of digits: O(n)
- Even though O(log n) additions and multiplications, each addition and multiplication takes time up to O(M(n)), where M(n) is the time to multiply 2 n-digit integers

Actual Running Time

- T(n) = T(n/2) + O(M(n))
- M(n) is at least n, so running time dominated by O(M(n)) term
- Therefore, T(n) = O(M(n))