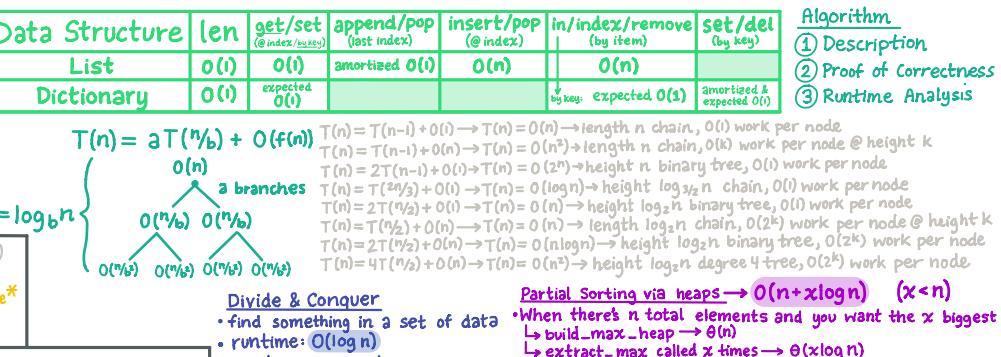


Algorithm							
① Description	② Proof of Correctness	③ Runtime Analysis					
$O(n) = O(f(n)) \text{ IFF } g(n) \leq c \cdot f(n)$	$\Omega(n) = \Omega(f(n)) \text{ IFF } g(n) \geq c \cdot f(n)$	$\log(xy) = \log x + \log y$	$\log(\log n) = O(\log n)$	$\log(1) = \text{zero}$			
$\Theta(n) = \Theta(f(n)) \text{ IFF } g(n) = O(f(n)) = \Omega(f(n))$		$a \log_b c = \log_b c^a$					
$(n) \rightarrow \frac{n!}{6006!(n-6006)!} = \frac{n(n-1)\dots(n-6005)}{6006!} = O(n^{6006})$		$\log_b b^n = b \log_b n = n$					
$2^{n+1} = \Theta(2^n) \text{ but } 2^{2^{n+1}} = \Omega(2^{2^n}) \text{ b/c } 2^{2^{n+1}} = (2^n)^2$		$(ab)^n = abc = (a^n)b$					
$(\log n)^a = O(n^b) \vee \text{positive } a \text{ & } b$	<u>Stirling's Approximation</u>	$(\log n)^c = O(n)$					
$(\log n) \log n = \Omega(n)$		$n! = \sqrt{2\pi n} \left(\frac{n}{e}\right)^n = O(n^{n+\frac{1}{2}})$					
$\Theta(1) \rightarrow \text{constant}$		$\log(n!) = \Theta(n \log n)$	$\log(n!) = O(\log(\log n))$				
$\Theta(\log n) \rightarrow \text{logarithmic}$		$(\log n)! = \Omega(n!)$	$\log((\log n)!) = \Theta(\log(n!))$				
$\Theta(n) \rightarrow \text{linear}$							
$\Theta(n^2) \rightarrow \text{quadratic}$	* Sometimes it's helpful to take log of functions						
$\Theta(n^3) \rightarrow \text{polynomial}$							
$\Theta(c^n) \rightarrow \text{exponential}$							
		$n^{\log n} \text{ vs. } (\log n)^n \rightarrow (\log n)^n = O(n \log n)$					

Master Theorem	$T(n) = aT(\frac{n}{b}) + f(n)$	Weak Master Theorem	$T(n) = aT(\frac{n}{b}) + \Theta(n^c)$
↳ case #1:	$\hookrightarrow f(n) = O(n^{\log_b a - \epsilon}) \text{ for } \epsilon > 0$	↳ case #1: leaf heavy recurrence tree	$\hookrightarrow c < \log_b a$
	$\hookrightarrow T(n) = \Theta(n^{\log_b a})$	$\hookrightarrow T(n) = \Theta(n^{\log_b a})$	
↳ case #2:	$\hookrightarrow f(n) = O(n^{\log_b a \log^{\epsilon} n}) \text{ for } \epsilon \geq 0$	↳ case #2: balanced recurrence tree	$\hookrightarrow c = \log_b a$
	$\hookrightarrow T(n) = \Theta(n^{\log_b a \log^{\epsilon+1} n})$		$\hookrightarrow T(n) = \Theta(n^c \log n)$
↳ case #3:	$\hookrightarrow f(n) = \Omega(n^{\log_b a + \epsilon}) \text{ for } \epsilon > 0$	↳ case #3: root heavy recurrence tree	$\hookrightarrow c > \log_b a$
	and $af(\frac{n}{b}) < c f(n)$ for $0 < c < 1$		$\hookrightarrow T(n) = \Theta(n^c)$
	$\hookrightarrow T(n) = \Theta(f(n))$		



Sort	Insertion Sort*	Selection Sort*	Mergesort*	Heapsort*	AVL Sort*	Counting Sort	Radix Sort
Description	maintain & grow subset of first i elements	maintain & grow i elements; swap min with i th element	recursively sort left and right halves individually and then merge them	BUILD_MAX_HEAP(A) EXTRACT_MAX(A) called n times	insert each item into tree; perform in-order traversal	elements must be $0 \times k \times k$ insert n elements into freq table with k bins, then scan thru freq table to get sorted array	better than counting sort if $n \ll k$
Example						data n elements freq table k bins ADD DATA TO FREQ TABLE freq table k bins cum freq table k bins GO THRU DATA, DECREMENT IN CFT ADD TO SORTED DATA ARRAY sorted data	$K = \max \text{ value in inputs}$ $d = \# \text{ digits for each input}$ $n = \# \text{ inputs}$ $b = \text{size of freq table}$ • Find $\# \text{ digits}(d)$ in K • Apply counting sort d times
Runtime	$O(n^2)$	$O(n^2)$	$O(n \log n)$	$O(n \log n)$	$O(n \log n)$	$O(n+k)$	$O(n)$ if $K = O(n^k)$ $O(d(d+n))$ otherwise
In place?	✓ at most $O(1)$ extra space	✓	✗	✓	✗	✗	✗
Stable	$[3, 2, 1, \dots]$ $[1, 2, 2, 3]$	✓	✗	✓	✗	✓	✓
Comments	$O(nk)$ if k far from sorted	$O(n)$ swaps	stable optimal comparison	low space optimal comparison	good if also need dynamic	k is size of domain of possible values	b^d is size of domain of possible values

Data Structure	Sorted Array	Array	Dynamic Array	Binary Heap	AVL Tree	Hash Table	BST
Insert	$O(n)$	$O(1)$	Amortized $O(1)$	$O(\log n)$	$O(\log n)$	Amortized & Expected $O(1)$	$O(h)$
Delete	$O(n)$	$O(n)$	$O(n)$	$O(n)$	$O(\log n)$	Amortized & Expected $O(1)$	$O(h)$
Min	$O(1)$	$O(n)$	$O(n)$	$O(1)$	$O(1)$ (augment)		$O(h)$
Find	$O(\log n)$	$O(n)$	$O(n)$	$O(n)$	$O(\log n)$	Expected $O(1)$	$O(h)$
Successor	$O(\log n)$	$O(n)$	$O(n)$	$O(n)$	$O(\log n)$		$O(h)$

• Max-Heap every node's key is \geq its children's • must be balanced & left justified to be a heap		fast for building heap in $O(n)$	• BST → every node contains $k \geq$ keys in left subtree & \leq keys in right subtree		self-balancing & fast insertion/deletion self-balancing & parent self-balances self-balancing & right child	Dynamic Arrays	Hashing
↳ Max_Heapify-Up(A, i) → $O(\log i)$			↳ Minimum(T) → $O(1)$			array something size newarray	$\ast = \text{comparison sort}$
↳ bubble up i th element until it is in correct spot $\leftarrow \text{left}(i) = 2i$			↳ go left until no left child			total memory	
↳ assume all other elements $\leftarrow \text{right}(i) = 2i+1$ in correct spot			↳ Find(T, k) → $O(h)$ complete = all levels filled bottom			allocate extra space for appending new elements	
↳ Max_Heapify-Down(A, i) → $O(\log n - \log i)$			↳ check if $k = \text{key of current node}$			$n = \# \text{ elements in data structure}$	
↳ bubble down i th element until it is in correct spot			↳ if $k < \text{current key}$, go left, else right			$m = \# \text{ slots}$	
↳ assume both subtrees are heaps			↳ if k not in T return None			initialize $m = 2n$	
↳ always swap with larger of two children			↳ Successor → $O(h)$			when run out of space, double size of array	
↳ Insert(x) → $O(\log n)$			↳ returns node w/ next largest key			if $n \leq \frac{1}{4}m$, half size of array	
↳ append x to end of array			↳ Predecessor → $O(h)$			list of all nodes ordered by key	
↳ call Max_Heapify-Up(A, n)			↳ returns node w/ next smallest key			Delete(T, k) → $O(h)$	
↳ Extract_Max(A) → $O(\log n)$			↳ Insert(T, k) → $O(h)$			↳ run find, if node is leaf, remove	
↳ swap first & last elements			↳ if 1 child, link child to node's parent			↳ if 2 children swap keys of node & its successor, then remove node	
↳ pop last element out of array			↳ In_Order_Traversal → $O(n)$			↳ problematic if $N \gg n$ or if $N=0$	
↳ call Max_Heapify-Down(A, 1)						1 3 4 5 2 8 7 3	
↳ return popped element						Rolling Hashes → $h(k) = \sum_{i=0}^{r-1} (k[i] \cdot \sigma^i) \bmod m$	
↳ Build_Max_Heap(A, i) → $O(n)$						Given str s & t is s in t?	
↳ Build_Max_Heap(A, left(i)) if exists						↳ Hash s	
↳ Build_Max_Heap(A, right(i)) if exists						↳ For each substring of t: $t[i:i+l]$ compare hashes	
↳ Max_Heapify-Down(A, i)						↳ if hashes match, check if $s = t[i:i+l]$	
↳ Max_Heapify-Down(A, i)						↳ b/c we assume $\Pr(\text{collision}) < \frac{1}{m}$ & $l \leq m$, runtime is:	
↳ Build_Max_Heap(A, i)						$O(s + t + l + \frac{l}{m}) = \text{expected } O(s + t + l)$	
↳ Extract_Max(A) called n times						hash query	
						hash(O)	
						Insert → keep checking until empty slot found	
						Delete → indicate variable has recently been deleted	

	BFS	DFS	TOPOSORT RELAXATION	DIJKSTRA	BELLMAN FORD
path length	shortest	any path	Shortest (or longest)	Shortest (or longest)	Shortest (or longest)
edge weights	equal weights	ignores weights	+ & -	+ only	+ & -
cycles	OK	OK	DAGs only	OK	OK
runtime	$O(V+E)$	$O(V+E)$	$O(V+E)$	$O(V \log V + E)$	$O(V \cdot E)$
example					
applications	<ul style="list-style-type: none"> • find all connected components • testing graph for bipartiteness • queue 	<ul style="list-style-type: none"> • topological sort order • find connected components • find articulation points • (single) cycle detection • back edges • stack 	<ul style="list-style-type: none"> • scheduling with prerequisites • shortest/longest DAG path* • AKA DAG-SP* 	<ul style="list-style-type: none"> • calculating by relaxing edges, getting confirmed SP to a node with SP using 1 edge, then edges, then weight cycle • travel time from point A to point B • identifying a new weight cycle excess 	

GRAPHS

- graph: $G = (V, E)$
- undirected edge: $\{u, v\} \in E$
- directed edge: $(u, v) \in E$
- degree (v) = # edges adjacent to vertex v
- $\sum_{v \in V} \text{degree}(v) = 2|E|$
- Connected: there is a path between every pair of vertices (treat as undirected)
- Strongly connected: there's a path between all distinct $u \& v$ (only for directed graphs)

- to compute level set L_{i+1} , include all neighbors of L_i that aren't already in a level
- can discover SP from s to all other nodes

Pseudocode

visited set/array/dictionary = { $S: \text{None}$ }
current_level = [s] dict can be used for parent pointers

while current_level is not empty:

for node in current_level:

```
    for neighbor in outgoing(node):
        if neighbor not in visited:
            next_level.append(neighbor)
            visited[neighbor] = node
```

current_level = next_level

• does not give SP, just finds any path to the given end node

Pseudocode # A is an adjacency list

```
def dfs(A, start, parent=None, order=[]):
    if parent is None:
        parent = {start: None}
    for neighbor in A[s]:
        if neighbor not in parent:
            parent[neighbor] = start
            dfs(A, neighbor, parent, order)
    order.append(start) # allows us to get topo order
    return parent, order
```

Edge Classification

• tree edge → edge used by DFS to discover a new node

↳ tree edges compose a tree

• back edge → edge from a descendant to an ancestor

• forward edge → edge from an ancestor to a descendant

• cross edge → neither are ancestors of the other

an undirected graph only has tree edges & back edges

a graph has a cycle IFF it has a back edge

if there is a cycle then there is no topological sort possible

RELAXATION

Definitions

$w(u,v)$ = weight of edge (u,v)

$\Pi = (v_1, \dots, v_k)$ = some path from v_1 to v_k

$\delta_s(v)$ = weight of the shortest path from s to v

$d_s[v]$ = length of SP from s to v found so far in our algorithm

↳ initially: $d_s[s] = 0$

↳ by end of algorithm: $d_s[v] = \delta_s(v)$

Relaxation

for an edge (u,v) :

if $d_s[v] > d_s[u] + w(u,v)$:

$d_s[v] = d_s[u] + w(u,v)$

return d_s , parent

if there is a shorter path possible we replace our current SP with this new shortest path

Path Relaxation Property: For a shortest path $\Pi = (s, \dots, v)$ from s to v , if we relax each edge in the path, in path order, $d_s[v] = \delta_s(v)$

• in a connected graph, $V = 0(E)$

• #tree edges = $V-1$

• BFS → queue

• DFS → stack

• Dijkstra → priority queue

DP Problem Solving Tips

	Adjacency List	Adjacency Matrix	Adjacency Set
insert edge	$O(1)$	✓	$O(1)$ ✓
delete edge	$O(\text{out-degree}(v))$	X	$O(1)$ ✓
find edge	$O(\text{out-degree}(v))$	X	$O(1)$ ✓
iterate through neighbors	$O(\text{out-degree}(v))$	✓	$O(\text{out-degree}(v))$ ✓
Example	 $\begin{array}{ c c c c c c } \hline & a & b & c & d & e & f \\ \hline a & 0 & 1 & 0 & 0 & 0 & 0 \\ \hline b & 1 & 0 & 1 & 0 & 0 & 0 \\ \hline c & 0 & 1 & 0 & 1 & 0 & 0 \\ \hline d & 0 & 0 & 1 & 0 & 1 & 0 \\ \hline e & 0 & 0 & 0 & 1 & 0 & 1 \\ \hline f & 0 & 0 & 0 & 0 & 1 & 0 \\ \hline \end{array}$	$\begin{array}{ c c c c c c } \hline & a & b & c & d & e & f \\ \hline a & 0 & 1 & 0 & 0 & 0 & 0 \\ \hline b & 0 & 0 & 1 & 0 & 0 & 0 \\ \hline c & 0 & 0 & 0 & 1 & 0 & 0 \\ \hline d & 0 & 0 & 0 & 0 & 1 & 0 \\ \hline e & 0 & 0 & 0 & 0 & 0 & 1 \\ \hline f & 0 & 0 & 0 & 0 & 0 & 0 \\ \hline \end{array}$	$\{0: \{1, 3\}, 1: \{2\}, 2: \{0, 1\}, 3: \{0\}\}$
Space	$\Theta(V+E)$	$\Theta(V^2)$	$\Theta(E)$

Path Relaxation Property

- If there are no negative weight cycles then no SP uses $\geq |V|$ edges
- If we relax every edge and repeat $|V|-1$ times all paths of length $\leq |V|-1$ will be relaxed in path order

Pseudocode

```
def Bellman_Ford(A, weights, start):
    d = [∞ for _ in A]
    d[s] = 0
    parent = {s: None}
    V = len(A) # V = # of vertices
    for i in range(V-1):
        for u in range(V):
            for v in A[u]:
                relax(A, weights, d, parent, u, v)
    return d, parent
```

```
def Dijkstra(A, weights, s):
    d = [float('inf') for _ in A]
    d[s] = 0
    parent = {s: None}
    Q = PriorityQueue()
    for node in A:
        Q.insert(node, d[node])
    for _ in range(V-1):
        node = Q.extract_min()
        for neighbor in neighbors(node):
            relax(A, weights, d, parent, node, neighbor)
            Q.decrease_key(neighbor, d[neighbor])
    return d, parent
```

General Technique for SP Algorithms
• specify which node to start at, identify nodes & edges
• sometimes it's helpful to add an auxiliary node
• to find longest path, negate edges
• phrase solution as a SP problem
• Shortest path from some start node(s) to some end node(s)
optimizing some quantity with some constraint/requirement

↳ modify edge weights or relaxation step
↳ graph copying: each copy of the graph represents a state & state transitions are connections between graph copies

sometimes it's possible to use a faster algorithm by modifying the graph

SP

Find SP s to t using ≤ 2 marked edges

Find SP from s to t using a multiple of 3 edges

Find SP from s to t using 2 mod 3 edges

Find SP from s to t using 1 mod 3 edges

Find SP from s to t using 0 mod 3 edges

Find SP from s to t using 3 mod 3 edges

Find SP from s to t using 2 mod 3 edges

Find SP from s to t using 1 mod 3 edges

Find SP from s to t using 0 mod 3 edges

Find SP from s to t using 3 mod 3 edges

Find SP from s to t using 2 mod 3 edges

Find SP from s to t using 1 mod 3 edges

Find SP from s to t using 0 mod 3 edges

Decidability

Since # possible problems > # possible programs, some problems don't have programs & thus are undecidable

- R → decidable problems
- EXP → problems decidable in exponential time → $2^{n^{O(1)}}$
- P → problems decidable in polynomial time → $n^{O(1)}$
- NP → set of decision problems that are verifiable
 - ↳ verifiable → there exists a certificate in which we can verify is valid if the solution to problem is true
 - ↳ Problem Certificate (aka a possible solution)
 - SP: A path with weight $\leq d$
 - Knapsack: A set of items with total value $\geq V$ and capacity C
 - P = NP? Non-satisfiability
 - NP → no certificate
- Are problems that are verifiable in polynomial time also solvable in polynomial time?
- P ⊂ EXP ⊂ R
- P ⊂ NP ⊂ EXP ⊂ R Reductions: To prove problem B is NP-hard, convert A to B. If A is NP-hard, then B is NP-hard.

NP-Hard → all other problems in NP can be reduced to this problem in polynomial time. The problem is at least as hard as the hardest problem for any problem in NP

How to show problem is NP-Hard:

- ① reduce every problem in NP to the given problem
- ② reduce an NP-hard problem into the given problem
- ③ reduce an NP-hard problem to a NP-hard A

↳ NP-Hard → A → NP-Hard → B

↳ Problem Difficulty

B = unknown

A = NP-Hard & B = NP-complete

NP Complete: 3SAT, Hamiltonian Path, Knapsack, Clique, 3 coloring

If B can be used to solve A, we reduced A to B. B is at least as hard as A

We convert a problem we know is hard into a problem you want to show is hard → want to show B is NP-hard if we can show how to solve A in poly-time using a black box to solve B in poly-time, then B is NP-hard (aka this blackbox can solve A & any other NP problem in poly-time)

• relax each node's outgoing edges in topological order

DAG_shortest_path (A,w,s):

topo_order = topo_order(A,s) $\xrightarrow{\text{DFS}} O(V+E)$

d = [0 for v in A]
parent = {s: None}
d[s] = 0
for u in topo_order:
 for v in A[u]:
 relax(u, v, w, parent, u, v)
return d, parent

SELECT AVL AUGMENTATION

Design an augmented AVL tree which supports the following operations in $O(\log n)$ time.

COUNT-GREATER-THAN(x): Return the number of values greater than x .

Solution: We augment the AVL tree such that $node_count$ stores the number of nodes in the subtree of x . For each node, $node_count = \text{node_left_count} + \text{node_right_count} + 1$. $node_parent$ contains the parent of x . Anytime a node is updated, we update its $node_count$. Finally, we convert a problem we know is hard into a problem you want to show is hard → want to show B is NP-hard if we can show how to solve A in poly-time using our black box to solve B in poly-time, then B is NP-hard.

COUNT-OUTLIERS: Use our augmented AVL tree from part (a). In addition, we keep track of n , the number of nodes in the tree (and update it accordingly during deletions and insertions).

Using the SELECT algorithm from the AVL recitation notes we may find $Q_1 = \text{SELECT}(n/4)$ and $Q_2 = \text{SELECT}(3n/4)$. Then, we return COUNT-LESS-THAN($Q_1 - 1.5(Q_2 - Q_1)$), which takes $O(\log n)$ time in total.

Example: Fibonacci

$F_0 = 0, F_1 = 1, F_n = F_{n-1} + F_{n-2}$

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

Ex: Bottom Up Approach:

def fib(n):
 sub = [None for i in range(n+1)]
 sub[0] = sub[1] = 1
 for i in range(2, n+1):
 sub[i] = sub[i-1] + sub[i-2]

return sub[n]

Ex: Top-Down Approach:

def fib(n, sub = None):
 if sub is None:
 sub = [None for i in range(n+1)]
 if sub[1] == None:
 return sub[0]
 if i > 1:
 sub[i] = sub[i-1] + sub[i-2]

sub[0] = fib(n-1, sub) + fib(n-2, sub)

return sub[n]

5) Analyze Runtime

↳ Runtime = # subproblems × work per subproblem

Ex: For above examples, runtime = $O(n) \times O(1) = O(n)$

1) Think about how the problem is making a sequence of choices/selections

2) Think about how your first selection reduces the overall search space (total sequence = first choice + remaining choices)

3) Think about what subproblem to use

↳ always start with the obvious one

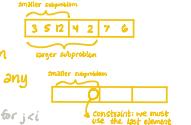
↳ larger subproblem must be able to utilize any solution to smaller subproblem

↳ constrain the smaller subproblem so you can decide whether you can use it for any solution to the smaller subproblem

ex: subproblem: $X[i] = \text{longest increasing subsequence ending @ element } i$; $X[i] \rightarrow X[j]$ for $j < i$

4) Think about base cases

↳ search space becomes constant size



	Subproblem	relation	DAG	base cases	solution *memoization*	runtime
Longest Increasing Subsequence (not necessarily contiguous)	$x[i] = \text{length of longest subsequence for subarray } a_0 \text{ to } a_i, \text{ ending in } a_i$	$x[i] = \max_{j \in [0, i-1], a_j < a_i} \{x[j]+1\} \cup \{1\}$	subproblems $x[i]$ only depend on strictly smaller i	$x[0] = 1$	$\max \{x[i]\}_{i=0}^n$ for $i \in [0, n-1]$ *store parent pointers* to reconstruct line breaks	$O(n)$ subproblems $O(n)$ work per subproblem $O(n^2)$ overall runtime
Text Justification	$x[i] = \text{minimum badness sum of formatting the words from } w_i \text{ to } w_{n-1}$	$x[i] = \min_{j \in [i, n-1]} (bl(i,j) + x[j+1])$	subproblems $x[i]$ only depend on strictly larger i	$x[n] = 0$ (badness of justifying zero words is zero)	$x[0]$ *store parent pointers* to reconstruct line breaks	$O(n)$ subproblems $O(n)$ work per subproblem $O(n^2)$ overall runtime
Alternating Coin Game	$x(i,j) = \text{maximum value winnable for player moving when # coins } j-i+1 \text{ is even, starting from the contiguous subsequence of coins from } i \text{ to } j$	$x(i,j) = \begin{cases} \text{player must choose coin } i \text{ or coin } j. \text{ Even player will seek to maximize } x(i,j), \text{ odd player will seek to minimize } x(i,j). \\ \text{value} = \max(v(i,j) + x(i+1,j), v(j) + x(i,j+1)) \\ x(i,j) = \min(x(i+1,j), x(j-1)) \end{cases}$	subproblems $x(i,j)$ only depend on strictly smaller $j-i$ ↳ solve in order of increasing $j-i$	$x(i,i) = 0$ (even player never gains value from last coin)	if $x(i,n) \geq \sum(\text{values})$ $\frac{n}{2}$ play on even turns, odd turns otherwise	$O(n^2)$ subproblems $O(1)$ work per subproblem $O(n^2)$ overall runtime
Edit Distance	$x(i,j) = \text{minimum number of edits to transform prefix up to } A(i) \text{ to prefix up to } B(i)$	$x(i,j) = \begin{cases} x(i-1,j-1) & \text{if } A(i)=B(i) \\ 1 + \min(x(i-1,j-1), x(i,j-1), x(i-1,j)) & \text{otherwise} \end{cases}$	subproblems $x(i,j)$ only depend on strictly smaller $i \& j$	$x(i,0) = i$ $x(0,j) = j$ (need all insertions or all deletions)	$x(A , B)$ *store parent pointers* to reconstruct all edits	$O(n^2)$ subproblems $O(1)$ work per subproblem $O(n^2)$ overall runtime
Box Separation	$x(i) = \text{minimum weight required to separate boxes } 1 \text{ to } i$	$x(i) = \min \left\{ \begin{array}{l} \text{weight}[i] + x(i-1) \\ \text{weight}[i-1] + x(i-2) \end{array} \right\}$ we must move either box i or the one before	subproblems $x(i)$ only depend on strictly smaller i	$x(0) = 0$ $x(1) = 0$	$x(n)$ where n is the total number of boxes	$O(n)$ subproblems $O(1)$ work per subproblem $O(n)$ overall runtime
Contiguous Subarray Sum (1D)	$x(i) = \text{sum of largest contiguous subarray from } 1 \text{ to } i, \text{ ending at } i$	$x(i) = \max(x(i-1), 0) + A[i]$	subproblems $x(i)$ only depend on strictly smaller i solve bottom up	$x(0) = 0$	$x(n)$ where n is the total length of the array	$O(n)$ subproblems $O(1)$ work per subproblem $O(n)$ overall runtime
Contiguous Subarray Sum (2D)	$x(i,j) = \text{sum of largest contiguous subarray with bottom left corner } A[i][j] \& \text{ top right corner } A[i][j]$	$x(i,j) = x(i-1,j) + x(i,j-1) - x(i-1,j-1) + A[i][j]$	subproblems $x(i,j)$ only depend on strictly smaller $i+j$	$x(i,0) = 0$ $x(0,j) = 0$	$x(n,m)$ for a $n \times m$ matrix	$O(nm)$ subproblems $O(1)$ work per subproblem $O(nm)$ overall runtime
Largest Black Square	$x(i,j) = \text{height of largest black square in subarray with corners } A[i][j] \& A[i][j]$	$x(i,j) = \begin{cases} 0 & \text{if } A[i][j] \text{ is 0} \\ \min(x(i-1,j), x(i,j-1), x(i-1,j-1)) + 1 & \text{otherwise} \end{cases}$	subproblems $x(i,j)$ only depend on strictly smaller $i+j$	$x(i,0) = 0$ $x(0,j) = 0$	$[\max(x(i,j))]^2$ for $i, j \in [1, n]$	$O(n^2)$ subproblems $O(1)$ work per subproblem $O(n^2)$ overall runtime
Choosing Prizes	$x(i) = \text{sum of best prize values from 1 to } i \text{ when you choose prize } i$	$x(i) = \max \left\{ \begin{array}{l} x(i-1) \\ A[i] + x(i-2) \end{array} \right\}$	subproblems $x(i)$ only depend on strictly smaller i	$x(k) = 0$ for $k \leq 0$ no values if no prizes	$x(n)$ store parent pointers	$O(n)$ subproblems $O(1)$ work per subproblem $O(n)$ overall runtime
Subset Sum	$x(i,j) = \text{True if can make sum } j \text{ using items 1 to } i, \text{ False otherwise}$	$x(i,j) = \text{OR } \{x(i-1,j-k) \text{ if } j \geq A[i]\} \text{ for } k \in [1, i]$	subproblems $x(i,j)$ only depend on strictly smaller i	$x(i,0) = T$ for $i \in [1, n]$ $x(0,j) = F$ for $j \in [1, s]$	$x(n,s)$ $n = \# \text{ integers}, s = \text{sum}$	$O(ns)$ subproblems $O(1)$ work per subproblem $O(ns)$ overall runtime
0-1 Knapsack	$x(i,j) = \text{maximum value by packing size } j \text{ knapsack with items 1 to } i$	$x(i,j) = \begin{cases} \max(x(i-1,j-S_i) + V_i, x(i-1,j)) & \text{if } S_i \leq j \\ x(i-1,j) & \text{otherwise} \end{cases}$ where $i \in [0, n]$ & $j \in [0, S]$	subproblems $x(i,j)$ only depend on strictly smaller i	$x(i,0) = 0$ for $i \in [1, n]$ $x(0,j) = 0$ for $j \in [1, s]$	$x(n,s)$ $n = \# \text{ items}, s = \text{size of bag}$ store parent pointers	$O(ns)$ subproblems $O(1)$ work per subproblem $O(ns)$ overall runtime
Unbounded Knapsack	$x(j) = \text{max value by packing knapsack of size } j \text{ using provided items}$	$x(j) = \max_{i \in [0, s]} \{x(i, \max\{v_i + x(j-S_i), 0\}_{i \in [1, n], S_i \leq j}\})\}$	subproblems $x(j)$ only depend on strictly smaller i	$x(0) = 0$ no space to pack	$x(s)$ $s = \text{space in knapsack}$	$O(s)$ subproblems $O(1)$ work per subproblem $O(ns)$ overall runtime
Professor Devkusha	$x(i,j) = \text{max coin value achievable if it's professors turn to divide c[i:c;j]}$	$x(i,j) = \min_{k \in [i,j]} \{ \max_{l \in [i,k]} \{x(l,k) + x(k+1,j)\} \}$ where $m(i,j) = \max(m(i,j-1), c_i)$	subproblems $x(i,j)$ & $m(i,j)$ only depend on strictly smaller $j-i$	$x(i,i) = 0$ $m(i,i) = c_i$	$x(i,n) \geq k$	$O(n^2)$ subproblems $O(1)$ work per subproblem $O(n^2)$ overall runtime
DNA Debacle	$x(i,j,k,l) = \text{True if can match } K \text{ seq. chars from } A[i:j] \text{ and } l \text{ from } B[i:j] \text{ to all chars in } C[i:k+l], \text{ False otherwise}$	$x(i,j,k,l) = \text{OR } \{x(i-1,j-k-1, l-1) \text{ if } A[i]=C[l] \& B[i]=C[k+l-1] \\ \{x(i-1,j-k-1, l) \text{ always} \& B[i]=C[k+l] \text{ always} \}$	subproblems $x(i,j,k,l)$ depend on strictly smaller $i+j+k+l$	$x(i,j,0,0) = \text{True}$ $x(i,j,k,l) = \text{False}$ for $i < \min(i, j) \& j < \min(k, l)$	$x(n,n,\frac{n}{2},\frac{n}{2})$	$O(n^4)$ subproblems $O(1)$ work per subproblem $O(n^4)$ overall runtime
Election Votes	$x(i,j) = \text{min population to win exactly } j \text{ electoral counts from districts } i \text{ to } i$	$x(i,j) = \begin{cases} \min(x(i-1,j), L_i) + x(i-1,j-1) & \text{if } j > c_i \\ x(i-1,j) & \text{otherwise} \end{cases}$ ↳ if $j > c_i$	subproblems $x(i,j)$ only depend on strictly smaller i	$x(i,0) = 0$ for $i \in [1, n]$ $x(0,j) = \infty$ for $j \in [1, s]$	$x(n,c)$ or none if $x(n,c) = \infty$	$O(nc)$ subproblems $O(1)$ work per subproblem $O(nc)$ overall runtime
Wire Wafer	$x(i,j) = \text{max # of matchings in the interval } p_i \text{ to } p_j \text{ where } 1 \leq i \leq j \leq n$	$x(i,j) = \max \left\{ \begin{array}{l} x(i+1,j) \\ \max \left\{ \begin{array}{l} x(i+1,t) + x(t+1,j) \\ x(i+1,t+1) \end{array} \right\} \end{array} \right\}_{t \in [i+1, j-1]}$	subproblems $x(i,j)$ only depend on strictly smaller $j-i$	$x(i,j) = 0$ for $j-i \in \{1, 0\}$	$\max(x(2,n), \max_{t \in [1, n-1]} \{x(2,t+1) + x(t+1,n)\})$	$O(n^2)$ subproblems $O(1)$ work per subproblem $O(n^2)$ overall runtime
Longest Common Subsequence	$x(i,j) = \text{length of longest common subsequence of prefixes } A[i:i], B[i:j]$	$x(i,j) = \begin{cases} x(i-1,j-1) + 1 & \text{if } A[i]=B[j] \\ \max(x(i-1,j), x(i,j-1)) & \text{else} \end{cases}$	subproblems $x(i,j)$ only depend on strictly smaller $i+j$	$x(i,0) = 0$ $x(0,j) = 0$	$x(A , B)$ where $A \& B$ are strings	$O(A B)$ subproblems $O(1)$ work per subproblem $O(A B)$ overall runtime
Rod Cutting	$x(i) = \text{max value obtainable by cutting rod of length } i$	$x(i) = \max \{x(i-j) + v(j) \mid j \in [1, i]\}$	subproblems $x(i)$ only depend on strictly smaller i	$x(0) = 0$	$x(n)$ where n is original length	$O(n)$ subproblems $O(1)$ work per subproblem $O(n^2)$ overall runtime
Arithmetic Parenthesization	$x(i,j,-i) = \text{min parenthesized evaluation of subsequence from integer } i \text{ to } j$	$x(i,j,-i) = \min_{k \in [i,j]} \{O_k(x(i,k,-i), x(k+1,j,-i))\}$ $x(i,j,-i) = \min_{k \in [i,j]} \{O_k(x(i,k,-i), x(i,k+1,-i))\}$	subproblems $x(i,j,-i)$ only depend on strictly smaller $j-i$	$x(i,i,-i) = a_i$	$x(i,n,+1)$ store 2 parent pointers	$O(n^2)$ subproblems $O(1)$ work per subproblem $O(n^3)$ overall runtime
Egg Drop	$x(f,e) = \text{min # of drops to check any sequence of } f \text{ floors using } e \text{ eggs}$	$x(f,e) = 1 + \min \{ \max \{x(i-1,e-1), x(f-i,e) \} \mid i \in [1, f]\}$	subproblems $x(f,e)$ only depend on strictly smaller f	$x(0,e) = 0$ $x(f,1) = f$	$x(n,k)$ $n = \# \text{ floors} \& k = \# \text{ eggs}$	$O(nk)$ subproblems $O(1)$ work per subproblem $O(n^2k)$ overall runtime

[15 points] Design an algorithm to determine whether Chad can make money on the exchange, and if so, provide a sequence of currencies from US dollars to US dollars for which the sequence of conversions makes money. Hint: Products can be transformed into sums using logarithms.

Solution: Let $r(i,j)$ represent the conversion rate from currency i to currency j . Our goal is to find a sequence of currency exchanges (v_0, \dots, v_k) such that $\prod r(v_{i-1}, v_i) > 1$. We can convert this optimization to finding a negative sum by taking a negative logarithm of both sides: $\sum_{i=1}^k -\log(r(v_{i-1}, v_i)) < 0$.

Construct a graph with a vertex for each of the n currencies on the exchange. Add a directed edge from vertex u to vertex v weighted by $-\log(r(u, v))$. Assuming there is an exchange rate between every pair of currencies, there will be $n(n-1)$ edges in the graph. Run Bellman-Ford from the vertex associates with US dollars to find a negative weight cycle of weight $-c$. If the vertex associated with US dollars is on the cycle, return the cycle. Otherwise, convert dollars to an arbitrary vertex v on the cycle and back to dollars. This single loop has weight d . Compute k such that $d - kc < 0$. Then return the single loop with k repetitions of the negative weight cycle in between, representing a conversion sequence that will make money. This algorithm takes $O(n \times n^2)$ time to find the negative weight cycle using Bellman-Ford, but the output sequence may be arbitrarily large depending on the value of k ; however an implicit representation of the sequence could be returned in $O(n^3)$ time.

[15 points] Longer Shortest Paths: Given a connected undirected graph $G = (V, E)$ with positive edge weights, describe algorithms to find a minimum weight path (if one exists) between two specified vertices that uses: (1) exactly k edges in $O(k|E|)$ time, and (2) at least k edges in $O(k|E| + |V| \log |V|)$ time.

Solution: Let s and t be the two specified vertices. For part (1), to find a shortest path from s to t using exactly k vertices, we construct a graph on $(k+1)|V|$ vertices: (v, i) for each $v \in V$ and $i \in [0, k]$. Connect a directed edge from vertex $(u, i-1)$ to (v, i) for each edge $(u, v) \in E$ and for every $i \in [1, k]$. Since traversing an edge adds one to the second index of any vertex, this graph is acyclic and a path from $(s, 0)$ to (t, k) will represent a (possibly non-simple) path traversing exactly k edges from s to t in the original graph. To find such a path of minimum weight, relax edges from vertices in a topological sort order in $O((k+1)|V| + k|E|) = O(k|E|)$ time, since $|V| = O(|E|)$ in a connected graph, resulting in shortest path weight $\delta_s(v)_k$ for a path from s to v using exactly k edges.

For part (2), we take the original graph and add an auxiliary node a , with a directed edge (a, v) to each vertex $v \in V$, weighted by $\delta_s(v)_k$, the shortest path weight from s to each vertex using exactly k edges. A minimum weight path π from s to t using at least k edges will have as a prefix a minimum weight path using exactly k edges ending at some vertex u . Further, the (possibly empty) subset of the path π from u to t cannot have cycles (as they would have positive weight and could be removed), so finding a shortest path from a to t in this new graph will correspond to a minimum weight path using at least k edges. This graph has only positive weights, so we can apply Dijkstra in $O(|V| \log |V| + |E|)$ time using a Fibonacci Heap to implement its queue. Constructing the graph takes $O(k|E|)$ time using the method from part (1), so this algorithm takes $O(k|E| + |V| \log |V|)$.

CLASSES

[10 points] Given a list of classes you've already taken, describe a linear time algorithm to determine the earliest semester you can take 19.006, assuming you can take as many classes as you want in any semester.

Solution: Construct a graph with a vertex for each of the n classes at MIT. Add a directed edge from class a to class b if class a is a prerequisite to class b and you have not yet taken class a . Let m be the number of such prerequisites. Then add auxiliary vertex s and connect it to every class. We assume that this graph is acyclic (that no cycle of prerequisite dependencies exists), or else no one would be allowed to take a class in that cycle. Then the length of the longest path from s to class 19.006 in this graph, will be the minimum number of semesters you need to take.

For each class/vertex v in the graph, we will compute the minimum number of semesters $m(v)$ needed to take that class starting from node s . Let $N(v)$ be the set of prerequisites to v . Since v cannot be taken before any prerequisite, then $m(v) = 1 + \max_{u \in N(v)} m(u)$. Compute $m(v)$ in topological sort order of the vertices from s , with $m(s) = 0$. All of these can be computed in $O(n + m)$ time as each edge appears in at most one prerequisite list $N(v)$.

Alternatively, one can assign each edge of the graph a weight of -1 and run topological sort relaxation to find a path with lowest weight from s to 19.006 in $O(n + m)$ time. The negative weight of this path will then be the number of semesters required. Note that we can negate weights to find longest paths because the graph is acyclic. This strategy would fail if the graph contained positive weight cycles.

[10 points] Unfortunately, being able to take as many classes as you want isn't realistic, and your adviser is upset at you for proposing such a schedule. You've been given a credit limit of only 1 class per semester. Since you don't want to pay tuition indefinitely, design an algorithm that returns a valid schedule for every semester that minimizes the number of semesters you're here.

Solution: First, we identify set of classes that must be taken prior to 19.006, and then we schedule those classes in a valid order. Begin with the same graph constructed for part (a), but remove any vertices from the graph not reachable from 19.006 following prerequisite edges in the opposite direct. We can identify such vertices by running breadth- or depth-first search from 19.006 in $O(n + m)$ time, traversing edges only in the backward direction. Then, compute a topological sort order on the classes using DFS, and then schedule classes in the order of the topological sort, also in $O(n + m)$ time.

[10 points] **Shortest Solve:** Given a board configuration, describe an $O((nm + 1)!)$ time algorithm to output a shortest sequence of moves that solves the board, if such a sequence of moves exists.

Solution: Perform a breadth-first search from a solved configuration of the board, producing parent pointers and expanding a frontier of configurations until the input configuration is found (can alternatively search from the input configuration until the solved configuration is found). When the target is found, follow parent pointers to produce a sequence of moves for return. If the search completes before finding the target configuration, the board is not solvable. Because breath-first search finds shortest paths in an unweighted graph, this algorithm will find a shortest sequence of moves. Breadth-first search runs in linear time with respect to graph size. By part (a), there are at most $(nm)!$ vertices in the graph. Each vertex has constant out-degree, so the number of edges is also $O((nm)!)$. By part (b), each configuration takes $O(nm)$ time to compute, so the breadth-first search takes $O((nm)!) \cdot nm = O((nm + 1)!)$ time.

[10 points] **Rover Scheduling:** NASA scientists need to plan a task schedule for the Mars rover. Each task requires a certain amount of time to complete. One task may be required to complete prior to another. For example, before transmitting soil sample data to Earth, the samples must have been collected, and the antennae battery must have been charged. Given a list of rover tasks including their durations and dependencies, describe an algorithm to compute the shortest time to complete all tasks.

Solution: Construct a graph with a vertex for each task, and a directed edge from task a to task b if a must be completed prior to b , weighted by the negation of the time required to complete task a . Further, add vertices s and t , with a directed edge from s to every other vertex in the graph and a directed edge from every vertex in the graph to t , each with weight 0. If there are n tasks and m dependencies, this graph has size $O(n + m)$. Use depth-first search to check whether this graph contains any cycles; if it does, then no task on the cycle can be first, so no plan can be constructed.

Otherwise, finding the shortest path from s to t will correspond to the longest time to complete any sequence of tasks, with all other tasks being performed in parallel. Since the graph is acyclic, relax edges in topological sort order to compute the path of minimum weight in $O(n + m)$ linear time, which is as faster than other methods.

$$\binom{n}{k} = \binom{n-1}{k-1} + \binom{n-1}{k} \text{ with } k=0 \text{ or } k=n. \text{ Help Pascal calculate his binomial}$$

The recursive definition of a binomial coefficient is a natural dynamic program:

1. Subproblems: $p(i, j)$ represents $\binom{i}{j}$.

2. Relation: $p(i, j) = p(i-1, j-1) + p(i-1, j)$

3. DAG: • Subproblems only depend on other subproblems with strictly smaller $n+k$, so acyclic

• Base case: $p(i, 0) = p(i, i) = 1$ for any $i \in [0, n]$

4. Solution: Calculating $\binom{n}{k}$ is simply evaluating $p(n, k)$

5. Algorithm: • Use notepad to memoize results of smaller subproblems, either top-down or bottom-up

• Running Time: At most $(n+1)(k+1)$ subproblem solutions written on notepad,

$O(1)$ work per subproblem using the calculator, so $O(nk)$ time

Ally wants to spend her gift certificate by purchasing the fewest possible items at the store, allowing items to be purchased more than once. Given a price list of items in the store, describe an efficient algorithm to return a shortest shopping list to Ally. Assume there are n items, and let $c(i)$ be the price of item i , where items are indexed in an arbitrary linear order

1. Subproblems: $p(j)$ is the smallest number of items that can be chosen whose respective prices sum to j (i.e. filling a j dollar gift certificate).

2. Relation: • Either a minimizing subset uses item i or it does not.

• Similar to Knapsack, where "size" is the cost to fill, and the 'price' to minimize is the same for all items (1 per item used).

$$p(j) = \min_{i \in [1, n]} p(j - c(i)) + 1$$

3. DAG:

• Subproblems only depend on other subproblems with strictly smaller j , so acyclic

• Base case: zero or negative gift certificate $p(0) = 0$, $p(j) = \infty$ for $j < 0$

4. Solution: • $p(d)$ represents filling a d dollar gift certificate using the fewest items

• Shopping list is constructable by storing parent pointers to minimizing subproblems

5. Algorithm: • Memoize subproblems in topological sort order, either top-down or bottom-up

• Running Time: $d + 1$ subproblems each taking $O(n)$ time, so $O(nd)$ time

Let A be the n characters of the person's DNA, and let B be the k characters of the disease substring

1. Subproblems: $p(i, j)$ is the minimum distance between any substring of $A[:i]$, and disease substring $B[:j]$.

2. Relation: Minimize over five local options

(a) If last characters match, match them and recurse on smaller problem. Otherwise:

(b) Replace $A[i]$ with $B[j]$ and match them at a cost of one modification

(c) Insert $B[j]$ to the end of $A[:i]$ and match them at a cost of one modification

(d) If we've already started matching, delete $A[i]$ and recurse at cost one

(e) If we haven't started matching, find best match in smaller substring

$$p(i, j) = \min(p(i-1, j-1) \text{ if } A[i] = B[j],$$

$$p(i-1, j) + 1, \quad (b)$$

$$p(i, j-1) + 1, \quad (c)$$

$$p(i-1, j) + 1 \text{ if } j < k, \quad (d)$$

$$p(i-1, j) \text{ if } j = k, \quad (e)$$

3. DAG:

• Subproblems only depend on other subproblems with strictly smaller $i+j$, so acyclic

• Base case: Done if no disease to match, $p(i, 0) = 0$

• Base case: Negative number of characters impossible, $p(i, j) = \infty$ for negative i or j

4. Solution:

• $p(n, k)$ represents the minimum distance match between B and any substring of A

5. Algorithm:

• Memoize subproblems in topological sort order, either top-down or bottom-up

• Running Time: $O(nk)$ subproblems each taking $O(1)$ time, so $O(nk)$ time

[5 points] An **articulation point** of a connected undirected graph is any vertex that, if removed from the graph would make the graph no longer connected. For example, if only one path of vertices connects vertices u and v in a graph, then every vertex in the path between u and v would be an articulation node. Given an undirected graph, describe a $O(|V||E|)$ time algorithm to output a list of articulation points in a graph.

Challenge: listing all articulation points of an undirected graph can be accomplished in $O(|V| + |E|)$ time.

Solution: For each vertex, check if removing it would disconnect the graph. The check can be done by running either BFS or DFS on any remaining vertex of the graph with the selected vertex removed. The running time is $O(|V|(|V| + |E|))$. Since the graph is connected, $|E| = \Omega(|V|)$, so the running time simplifies to $O(|V||E|)$.

The challenge finds articulation points in linear time. Run depth-first search from an arbitrary root vertex r . During the DFS, label each graph edge as a directed tree or back edge, and label each vertex v with its depth $d(v)$ in the DFS tree. Then for each vertex v , compute the lowest depth $D(v)$ of any vertex reachable from v via a (possibly empty) path of tree edges followed by at most one back edge. If $T(v)$ and $B(v)$ are the sets of outgoing tree and back edges from v respectively, then

$$D(v) = \min\{D(u) \mid u \in T(v)\} \cup \{d(u) \mid u \in B(v)\}.$$

Because each edge is labeled out-going from at most one vertex, these $D(v)$ values can be computed in $O(|E|)$ time by computing in reverse topological sort order of the vertices. Any vertex v that is not the root of the DFS tree, will be an articulation point if and only if none of its children in the DFS tree can reach a vertex with depth lower than $d(v)$ (a rigorous proof of this statement is omitted). So, for each non-root vertex v with DFS tree children $C(v)$, v is an articulation point if and only if $d(v) \geq \min_{u \in C(v)} D(u)$. Again, all such evaluations can be computed in $O(|E|)$ time since each vertex appears as a child of at most one vertex, and each such relation corresponds to an edge of the graph. As a special case, the root of the DFS tree will be an articulation point only when it has more than one child in the DFS tree. Since $|E| = \Omega(|V|)$, this algorithm runs in $O(|E|)$ time.

[10 points] **Ground Transportation:** Tim the Beaver needs to get from MIT to a recruiting event in San Francisco, but the airlines no longer allow beavers to fly. Tim cannot drive, so he decides to travel to his destination via bus and train. Tim vastly prefers trains over buses, and wants his trip to be **bus-spars**: the trip should not contain a transfer from a bus to another bus, only from a bus to a train, a train to a bus, or a train to a train. Given a map of bus and train routes across the country, describe a linear time algorithm to find a bus-spars itinerary containing the fewest vehicle transfers, or tell Tim that no bus-spars itinerary exists to his destination.

Solution: Construct a graph having two vertices per transit station v : vertex v_b representing arrival at the station by bus, and vertex v_t representing arrival at the station by train. For each train route from station u to station v , add directed edges (u_t, v_t) and (u_b, v_t) to the graph, and for each bus route from station u to station v , add directed edge (u_b, v_b) (not (u_b, v_b)) as such an edge would mean taking two buses in a row). Let s be the starting station and t be the ending station. Use breadth-first search to determine whether a path exists from s_b or s_t to t_b or t_t . If there is, return the itinerary associated with the path; otherwise return that no such itinerary exists. Let n be the number of stations and m be the number of routes. The graph has two vertices for each station and at most two edges for each route, so the size of the graph is $O(n + m)$. Running breadth first search twice (once from s_b and once from s_t) takes $O(n + m)$ time, so this algorithm will answer Tim's query in linear time. (Note that running 3FS once from s_t is sufficient, since s_t is connected to all vertices that s_b is connected

[10 points] **Purchasing Parts:** Faylee Krye is the mechanic on board a Sirefly-class spaceship named Ferentiy. While docked at a spaceport, she heads into town to purchase six parts for the ship: a power converter, a flux capacitor, a hyper drive, an ion shield generator, a binary motivator, and an air freshener. Faylee has downloaded a map of the town including the location of the parts distributors and time estimates to travel long any particular road in town (you may assume that the number of parts distributors is large). Looking down the list of distributors, Faylee observes that each store sells at most one of the parts, so she will need to visit six different stores to buy everything. Assume that the time spent in any store is negligible compared to transit time. Describe an algorithm to find a route for Faylee to travel from the spaceport and back, purchasing all the needed spaceship parts in the minimum amount of time.

Solution: Let n be the number of stores and road intersections, let m be the number of the roads between stores and intersection in the town, and let s be location of the spaceport. Construct a graph on $2^6 \times n$ vertices of the form $(b_1, b_2, b_3, b_4, b_5, b_6, u)$, denoting that Faylee arrives at store or intersection v while either possessing or not possessing item i , depending on whether boolean b_i is True (1) or False (0) respectively. For every directed road (u, v) between stores or intersections u and v , add many directed edges weighted by the time to traverse the road. Specifically add an edge from vertex $(b_1, b_2, b_3, b_4, b_5, b_6, u)$ to vertex $(b_1, b_2, b_3, b_4, b_5, b_6, v)$ (Faylee did not buy anything at u), one edge for every assignment of the b_i 's; and if u is a store selling a desired part, say part 1 without loss of generality, add a directed edge from vertex $(0, b_2, b_3, b_4, b_5, b_6, u)$ to vertex $(1, b_2, b_3, b_4, b_5, b_6, v)$, one edge for every assignment of the remaining b_i 's. This graph has $2^6 n$ vertices and $(2^6 + 2^5)^2 m$ edges, so the graph has size $O(n + m)$ if n and m are large compared to 2^6 . A route that corresponds to purchasing all six items and returning home will be a path from vertex $(0, 0, 0, 0, 0, 0, s)$ to vertex $(1, 1, 1, 1, 1, 1, s)$ in the graph. Under the assumption that it takes positive time to traverse any road, we can run Dijkstra to find the shortest such path in $O(n + m \log n)$ time (using a Fibonacci Heap). Dijkstra is faster than Bellman-Ford, and the graph may have cycles and many weights, so linear time methods do not apply.

[5 points] Prove that for any connected undirected graph G on n vertices and any positive integer $k < n$, either G has some path of length at least k , or G has fewer than $k \cdot n$ edges.

Solution: Note that this problem statement is ambiguous as to whether the desired path must be simple. If non-simple paths are allowed, the following argument holds. If there is a cycle in the graph, then there is a path of length n , and if there is not, the undirected graph is a tree, and has at most $n - 1$ edges.

If non-simple paths are disallowed, the following argument holds. Run depth-first search from some node in the graph and consider the longest path in the DFS tree. If it has length at least k , we are done. Otherwise, since G is undirected, there are no cross edges with respect to the DFS tree, so each edge of the graph connects an ancestor and a descendant in the DFS tree. This bounds the number of edges in the graph by counting the total number of ancestors of each descendant; but if the longest path is shorter than k , each descendant has at most $k - 1$ ancestors. So there can be at most $(k - 1)n$ edges.

[10 points] **Specific Improvement:** For many graphs, single source breadth-first search can be done faster by making the search **bidirectional**: perform a breadth-first search separately from s and t , alternating the exploration of level i from s , then level i from t , then level $i + 1$ from s , etc., until the frontier levels from the two searches intersect, returning the concatenation of the two shortest paths found¹. Consider the family of unweighted undirected graphs having bounded degree b , where a shortest path from vertices s to t is known to contain d edges. Describe a graph from this family for which breadth-first search from s takes at least $\Omega((b-1)^d)$ time, while bidirectional breadth-first search from s and t takes at most $O(b^{d/2})$ time.

Solution: Consider a tree rooted at s with lower branching factor $b-1$ and depth d . Let t be any leaf of the tree, so there is a unique path from s to t . Let the vertices on this path be labeled $s = v_0$ through $t = v_d$. Regular breadth-first search from s would explore the entire tree, which has size $\Omega((b-1)^d)$, so breadth-first search will take at least that long to touch all nodes. On the other hand, a bidirectional search would terminate a breadth-first search from s at vertex $v_{d/2}$, exploring a subtree of depth $d/2$ of size $\Omega((b-1)^{d/2})$. The search from t will also explore out $d/2$ levels before reaching node $v_{d/2}$. Each node at level $i > 0$ in the search from t has one parent and at most $b-1$ unexplored neighbors to add to level $i+1$, so the search from t also touches at most $O((b-1)^{d/2})$ nodes. Thus bidirectional search runs in at most $O((b-1)^{d/2}) = O(b^{d/2})$ time.

Assume there are n students, with $a(i)$ being the dodge ball ability of the i th student in the initial line up. 1. Subproblems: $p(i, j)$ and $q(i, j)$ are the maximum ability score you can achieve, when either you or your opponent choose next respectively, from among students remaining in a line up from student i to j , where $i \leq j$.

2. Relation:

• You will maximize ability sum, while your opponent will minimize.

$$\bullet p(i, j) = \max(q(i+1, j) + a(i), q(i, j-1) + a(j))$$

$$\bullet q(i, j) = \min(p(i+1, j), p(i, j-1))$$

3. DAG:

• Subproblems only depend on other subproblems with strictly smaller $j-i$, so acyclic

• Base case: Only one choice if only one student, $p(i, i) = a(i), q(i, i) = 0$

4. Solution:

• $p(1, n)$ represents a maximal score for you when choosing first

• Optimal choices are constructable by storing parent pointers to maximizing subproblems

5. Algorithm:

• Memoize subproblems in topological sort order, either top-down or bottom-up

• Running Time: $O(n^2)$ subproblems each taking $O(1)$ time, so $O(n^2)$ time

We will guess a pair of edges to bring together first and recurse on the remaining unmatched subsets. Let $c(i) \in \{\text{Blue}, \text{Red}\}$ be the color of edge i . 1. Subproblems: $p(i, j)$ is the maximum number of matchings from among any valid folding of the contiguous subset of edges from the i th to the j th, matching only within the subset.

2. Relation: • Guess the edge k that matches to edge i (could be any other edge from $i+1$ to j)

$$\bullet p(i, j) = \max_{k \in [i+1, j]} p(i+1, k-1) + p(k+1, j) + (1 \text{ if } c(i) = c(k), \text{ and } 0 \text{ otherwise})$$

3. DAG:

• Subproblems only depend on other subproblems with strictly smaller $j-i$, so acyclic

• Number of segments to match is given by $j-i+1$

• Base case: If odd or negative number of segments, valid folding impossible, so $p(i, j) = -\infty$ when $j-i+1$ is odd or less than zero.

• Base case: If exactly zero segments, no matchings, so $p(i, j) = 0$ when $j-i+1 = 0$

• Optimal matching is constructable by storing parent pointers to maximizing subproblems

5. Algorithm:

• Memoize subproblems in topological sort order, either top-down or bottom-up

• Running Time: $O(n^3)$ time

Describe an efficient algorithm to calculate an assignment of each day to either 'buy', 'sell', or 'none' would have maximized his revenue during those days. Let $c(i)$ be the price of FredEx stock on day i

1. Subproblems: $p(i, j)$ maximum revenue trading only in the first i days while holding j shares at the end of day i (j can be either 0 or s).

2. Relation:

• To maximize revenue in first i days, either Seorge sell shares on day i or not

• If sell on day i , must be holding s shares to sell, so $j = s$

• To buy on day i , must not be holding any shares, so $j = 0$

• $p(i, 0) = \max(p(i-1, 0), p(i-1, s) + sc(i))$

• $p(i, s) = \max(p(i-1, s), p(i-1, 0) - sc(i))$

3. DAG: • Subproblems only depend on other subproblems with strictly smaller i , so acyclic

4. Solution:

• $p(d, 0)$ represents the maximum return in d days (holding shares at end is suboptimal)

• Order of trades constructable by storing parent pointers to maximizing subproblems

5. Algorithm:

• Memoize subproblems in topological sort order, either top-down or bottom-up

• Running Time: $O(d)$ subproblems each taking $O(1)$ time, so $O(d)$ time

Describe an efficient algorithm to calculate an assignment of each day to either 'buy', 'sell', or 'none' would have maximized his revenue during those days. Let $c(i)$ be the price of FredEx stock on day i

1. Subproblems: $p(i, j)$ maximum revenue trading only in the first i days while holding j shares at the end of day i (j can be either 0 or s).

2. Relation:

• To maximize revenue in first i days, either Seorge sell shares on day i or not

• If sell on day i , must be holding s shares to sell, so $j = s$

• To buy on day i , must not be holding any shares, so $j = 0$

• $p(i, 0) = \max(p(i-1, 0), p(i-1, s) + sc(i))$

• $p(i, s) = \max(p(i-1, s), p(i-1, 0) - sc(i))$

3. DAG: • Subproblems only depend on other subproblems with strictly smaller i , so acyclic

4. Solution:

• $p(d,$