

1)

- Algorithm: // **Assuming n and H could be equal to 0**
 - Initialize a 2-D array of size $(n + 1) \times (H + 1)$, opt
 - Initialize an iterator i
 - For all values of i from 0 to n :
 - Set $opt[i][0]$ to $f_i(0)$
 - For all values of i from 0 to H :
 - Set $opt[0][i]$ to 0
 - Initialize an iterator j to 1
 - Reset i to 1
 - While i is less than or equal to n and j is less than or equal to H :
 - Set $opt[i][j]$ to -1
 - Initialize an iterator k
 - For all values of k from 0 to j :
 - Set $opt[i][j]$ to the maximum of its current value and $f_i(k) + opt[i - 1][j - k]$
 - If the maximum changes, pair the current value of k with the entry
 - If j is equal to H :
 - Increment i by 1
 - Reset j to 1
 - Else:
 - Increment j by 1
 - Set i to n and j to H
 - Initialize a list res of size n
 - While i is greater than 0:
 - Insert the paired value of k of $opt[i][j]$ into res
 - Decrement i by 1
 - Decrement j by the paired value of k
 - Reverse res
 - Return res // **res contains the # of hours spent on each class in order**
- Proof:
 - Mathematically, maximizing average grade means you must maximize the total grade you earn between all courses
 - Base Case:
 - $n = 1$
 - Regardless of how many hours are given in H , the optimal solution will always be to spend all of those hours in course 1

- Since all functions $f_i(h)$ are guaranteed to be non-decreasing, whenever we make the comparison to find the optimal solution, we will always pick the highest value of k to pair with the entry
 - At the end, we will simply place this highest value of k into res
 - Based on our logic above, this must be the correct answer
 - Base case passed
- Inductive Step:
 - Assume: We have found the optimal solutions for all entries, scanned in row-major order, up until some arbitrary entry (i, j)
 - Prove: We can now find the optimal solution for entry (i, j)
 - When we process this entry, we are looking for the optimal solution (highest grade) for the subproblem where we're given i courses and j hours of studying
 - Our algorithm processes all possible time allocations to course i , by using an iterator k to find the optimal solution when k hours are spent on course i
 - This can be done by using the function $f_i(k)$ to calculate the current course's contribution to the total grade
 - Once this contribution is found, it is added to the optimal solution of $i - 1$ courses and $j - k$ hours
 - This is because we have used k hours to study for the current course i , so we must reference back to a the previously memoized solution for $i - 1$ courses, given $j - k$ time
 - Since we exhaustively search all of these possible allocations, we are guaranteed to find the optimal solution, as we consider all possible solutions
 - We will have the optimal solution for entry (i, j) by the end of the iteration of the loop
 - We can extend this logic until we have entry (n, H) , which represents the optimal solution given access to all n courses and H hours of studying
 - Inductive step passed
- Proof by induction complete
- Time Complexity: $O(H^2n)$
- Time Complexity Proof:
 - We initialize and process all elements of an $n \times H$ array
 - This results in a time complexity of $O(Hn)$
 - Each time we calculate the entry into the array, we must iterate through a maximum of H elements to process all possible times
 - Since all Hn elements take $O(H)$ time to finalize, the main loop structure takes $O(H^2n)$ time to execute

- The final loop that gathers the final time distributions for each course is guaranteed to run n times, as each iteration processes a single row of the 2-D array, resulting in an $O(n)$ time complexity
- The reversal of the *res* array takes $O(n)$ time
- The overall time complexity of the algorithm is $O(H^2n)$

2)

- Algorithm:
 - Initialize an array of size $(k + 1) \times (n + 1)$, opt
 - Initialize iterators i and j
 - For all values of i from 0 to k :
 - Set $opt[i][0]$ to 0 and pair it with a null pair
 - For all values of j from 0 to n :
 - Set $opt[0][j]$ to 0 and pair it with a null pair
 - For all values of i from 1 to k
 - Set a variable $pMax$ to some value representing negative infinity
 - For all values of j from 1 to $n - 1$:
 - Set $pMax$ to the maximum of its current value and $opt[i - 1][j - 1] - p(j - 1)$
 - If it was set to $opt[i - 1][j - 1] - p(j - 1)$, pair it with $j - 1$
 - Set $opt[i][j]$ to the maximum of $pMax + p(j)$ and $opt[i][j - 1]$
 - If it was set to $pMax + p(j)$, pair it with $pMax$'s paired value and j
 - Else, pair it with $opt[i][j - 1]$'s pairing
 - Set i to k and j to $n - 1$
 - Initialize a list res
 - While i is greater than 0:
 - If $opt[i][j]$'s paired pair is not null:
 - Place $opt[i][j]$'s paired pair into res
 - Set j equal to the first value in $opt[i][j]$'s paired pair
 - Decrement i by 1
 - Reverse res
 - Return res
- Proof:
 - Each array entry (i, j) represents the optimal solution given i transactions and j days
 - Base Case:
 - There is 1 day:
 - No transactions can be made
 - The main loop won't process anything
 - No pairs are created, so the backtracking will simply output nothing
 - This is the correct behavior
 - There are 2 days:
 - There are 2 possibilities:
 - Buying on day 1 and selling on day 2 makes a profit
 - Buying on day 1 and selling on day 2 makes no profit
 - Both possibilities are checked when we compare maximums within the nested for loop
 - If a profit does exist, a pair will be created

- The backtracking will therefore either output the only possible pairing or a null pairing, based on if the profit was correct
 - This is the correct behavior
 - Base case passed
- Inductive Step:
 - Assume: We have found the optimal solutions for all entries, scanned in row-major order, up until some arbitrary entry (i, j)
 - Prove: We can find the optimal solution for entry (i, j)
 - When we come across the entry, there are 2 possibilities:
 - We sell on day j :
 - This means we gain profit equal to the maximum possible profit gained from selling on day j
 - We exhaustively check all possible options for this profit by maintaining the variable $pMax$, and comparing it to the profit gained from buying on day $j - 1$
 - This comparison allows us to find the maximum possible profit when selling on day j , by exhaustively searching all possible buy days
 - This is covered in both max-comparisons
 - We don't sell on day j :
 - This means we gain no extra profit, so the optimal solution for (i, j) is the same as the optimal solution for $(i, j - 1)$
 - This is covered in the second max-comparison
 - The maximum profit of both entries will be placed into $opt[i][j]$
 - By definition, this maximum profit will be the optimal solution, so this is the correct behavior
 - Inductive step passed
- Proof by induction complete
- Time Complexity: $O(kn)$
- Time Complexity Proof:
 - We initialize a $k \times n$ (ish) array
 - For each element of the array, we perform a constant number of comparisons and array accesses
 - Based on this, we know that filling this array using dynamic programming costs $O(kn)$ time
 - After we finish filling the array, we backtrack through our solution in order to get the actual k -shot strategy
 - Since each iteration is guaranteed to process one row of the opt array, and there are k rows, there are guaranteed to be k iterations, each performing constant time operations, so this backtracking takes $O(k)$ time

- The list is then reversed, resulting in another $O(k)$ time operation
- The overall algorithm is therefore $O(kn)$ time

3)

- Algorithm: // Assumes n will be an even number, party votes are stored in an array where $P[i][0]$ is the number of votes for party A in precinct i and $P[i][1]$ is the number of votes for party B in precinct i
 - Initialize variables v and $party$ to 0
 - For all precincts:
 - Add the number of votes for party A to v
 - If v is less than $m / 2$: // Get majority party's total votes into v
 - Set v to $m - v$
 - Set $party$ to 1
 - Initialize a 3-D array of size $n \times (n / 2) \times (v - nm / 4 - 1)$, dp
 - For all values of x from 0 to n : // Base case
 - Set $dp[x][0][0]$ to true
 - For all values of i from 1 to n :
 - For all values of j from 1 to $n / 2$:
 - For all values of k from 1 to $v - nm / 4 - 1$:
 - If i and j are equal to 1 and k is equal to $P[1][party]$:
 - Set $dp[i][j][k]$ to true
 - Else if $dp[i - 1][j - 1][k - P[i][party]]$ is true:
 - Set $dp[i][j][k]$ to true
 - Else if $dp[i - 1][j][k]$ is true:
 - Set $dp[i][j][k]$ to true
 - Else:
 - Set $dp[i][j][k]$ to false
 - For all values of x from $nm / 4 + 1$ to $v - nm / 4 - 1$:
 - If $dp[n][n / 2][x]$ is true
 - Return true
 - Return false
- Proof:
 - Each array entry (i, j, k) represents if it is possible to gerrymander using j out of the first i precincts with exactly k majority party votes
 - We know that for a party to win a district, it must be true that the number of votes for that party in that district is greater than or equal to $nm / 4 + 1$
 - In order to win both districts, it must also hold that this is true for the other district as well
 - If we say that the total number of votes for this majority party is v , we can conclude that gerrymandering is possible for some number of votes x , where $nm / 4 + 1 \leq x \leq v - nm / 4 - 1$
 - Base Case:
 - n is 0:
 - This is true by vacuous truth
 - There are 0 possible majority party votes, and 0 precincts to access
 - This is represented by an entry $(0, 0, 0)$

- This entry is set to true in the for loop that handles this base case
 - This is the correct behavior
- n is 1:
 - This is true, as long as there is a majority party in the single district
 - The bounds for this condition are checked by the inequality presented above
 - The entry $(1, 1, k)$, where k is equal to the number of majority votes in the single precinct will be set to true by the first check in the nested for loop
 - If k satisfies the above inequality, it will cause the algorithm to return true from within the backtracking for loop
 - This is the expected behavior by the logic above
- Base cases passed
- Inductive Step:
 - Assume: we've filled our array such that we know all values up until $dp[i - 1][j - 1][k - 1]$
 - Prove: we can determine the value of $dp[i][j][k]$
 - When we come across this value, we have 2 options:
 - Include P_i in the majority district:
 - If we choose to do this, we must trace back to see if gerrymandering is possible in the entry $dp[i - 1][j - 1][k - P[i][party]]$
 - This is because we've included P_i , which means there is $j - 1$ precincts left to use for this entry, and we must account for the majority votes in the current precinct
 - We are guaranteed access to the referenced value by our assumption
 - If the referenced value is true, that means we could add the current precinct to the district, and gerrymandering would be possible, so the current value is true
 - Don't:
 - If we choose to do this, we must trace back to see if gerrymandering is possible in the entry $dp[i - 1][j][k]$
 - This is because we didn't include P_i , so we still have j precincts left to use and, since no majority votes were taken from P_i , we still have k votes left to use
 - We are guaranteed access to the referenced value by our assumption
 - If the referenced value is true, that means we could skip the current precinct and gerrymandering would be possible, so the

current value is true

- Both of these conditions are checked, alongside conditions that represent the base cases described above
- All possibilities are counted for exhaustively
- (i, j, k) is guaranteed to hold the correct value, given our assumption
- We can repeat this logic until our array is completely filled
- By the inequality we originally described, we must see if it is possible to gerrymander with n precincts available, using $n / 2$ precincts, with x votes, where $nm / 4 + 1 \leq x \leq v - nm / 4 - 1$
 - This is checked by brute force in our final for loop
- Inductive step passed
- Proof by induction complete
- Time Complexity: $O(n^3m)$
- Time Complexity Proof:
 - Getting the majority vote count requires an array access and arithmetic operation for all n precincts, resulting in an $O(n)$ runtime
 - We initialize an array of size $n \times (n / 2) \times (v - nm / 4 - 1)$ and iterate through each element of it once, performing a set of comparisons (constant time) on each
 - This results in $n^2v / 2 - n^3m / 8 - n^2 / 2$ sets of comparisons
 - v is at most m , so this can be rewritten as $n^2m / 2 - n^3m / 8 - n^2 / 2$
 - The n^3m dominates, so the loop processing is $O(n^3m)$ time
 - The final backtrack through a row of our dp array takes at most $O(nm)$ time
 - The overall complexity of our algorithm takes $O(n^3m)$

4a)

- Algorithm:
 - Create a source node S and target node T
 - Create nodes $x_O, x_A, x_B,$ and x_{AB} to represent the supply of each blood type
 - Create nodes $y_O, y_A, y_B,$ and y_{AB} to represent the demand of each blood type
 - Create directed edges from S to each of the x nodes and assign each of them their corresponding supply as a capacity (edge (S, x_O) has capacity s_O , etc.)
 - Create directed edges from each of the y nodes to T and assign each of them their corresponding demand as a capacity (edge (y_O, T) has capacity d_O , etc.)
 - Create a directed edge of infinite capacity from x_i to y_j if people of blood type j can receive blood of type i
 - The edges $(x_O, y_A), (x_O, y_B), (x_O, y_{AB}), (x_O, y_O), (x_A, y_A), (x_A, y_{AB}), (x_B, y_B), (x_B, y_{AB}),$ and (x_{AB}, y_{AB}) will be created
 - Run Ford and Fulkerson on the resultant network
 - For each edge leading into T :
 - If the edge's capacity is non-zero:
 - Return false
 - Return true
- Proof: (?)
 - Based on our algorithm design, each edge leading from S to x_i will carry a flow equal to the amount of blood of type i
 - Since we assign capacity based on our supply, this flow can never exceed the supply of that type of blood
 - Likewise, each edge leading from y_i to T will carry a flow equal to the amount of blood of type i
 - Since we assign capacity based on our demand, this flow can never exceed the supply of that type of blood
 - The edges connecting our x nodes and y nodes have a limitless capacity, so there's no worry about an arbitrary limit being set on how much blood can be transferred, other than the supply given to us
 - There are only edges between valid suppliers and demanders, so no blood can be assigned to an invalid recipient
 - Based on this, the flow from each x_i to y_j will correctly represent the amount of blood taken from blood type i and given to recipient's blood type j
- Time Complexity: $O(f)$
- Time Complexity Proof:
 - The initialization of the algorithm creates a constant number of nodes and edges and assigns the edges weights
 - We then run Ford and Fulkerson, which has an $O(|f| (n + e))$ runtime
 - However, since the number of nodes and edges are constant, this simplifies down to an $O(|f|)$ runtime
 - We will then search a constant number of edges in the final loop
 - The algorithm's overall runtime is $O(f)$

4b) // **Assuming there's a typo in the table and B should have a demand of 10**

- Network Explanation:
 - A possible optimal solution is to send 3 units of AB to AB patients, 10 units of B to B patients, 36 units of A to A patients, 45 units of O to O patients, and 5 units of O to A patients
 - We know that the max flow must be equal to the capacity of the min-cut
 - This means that, given a cut, the maximum flow must be less than or equal to the capacity of that cut
 - Based on our network's setup, the cut consisting of S and the vertices corresponding to types B and AB in one cut and the rest of the vertices in the other cut has a capacity of 99
 - This means that the maximum total flow in the network is capped at 99, which immediately tells us that we cannot meet a demand of 100
- Simple Explanation:
 - If we look at the total demand for blood types O and A, we find that the total demand is 87
 - The only blood types that can donate to O and A are O and A, respectively
 - That means the total supply for these recipients is the supply of O and A
 - The total supply of O and A is only 86, so there isn't enough supply to cover the demand

5)

- Algorithm:
 - Initialize lists *res* and *cut*
 - Initialize an iterator *i*
 - Run Ford and Fulkerson to arrive at a residual network G'
 - Use BFS starting from *s*, where “reachable” edges have a capacity in the residual network that is greater than 0
 - During execution, if an edge that has capacity 0 is found, insert it into *cut* and do not follow it
 - For all values of *i* from 0 to $k - 1$:
 - If *i* is equal to the size of *cut*: **// There were less than k edges in the min-cut**
 - Exit the loop
 - Else:
 - Insert *cut*[*i*] into *res*
 - While the size of *res* is less than k :
 - Insert an arbitrary edge that is not already in *res* into *res*
 - Return *cut*
- Proof:
 - The termination condition for Ford and Fulkerson is that there is no augmented path from *s* to *t* in the residual network
 - The fact that there is no augmented path tells us that there exists some cut of G' such that the flow of the graph is equal to the capacity of the cut
 - This is because we can remove all saturated paths from G'
 - This guarantees that *t* will be unreachable from *s*, since we know for a fact that there are no augmented paths in the graph
 - If *t* was reachable after this modification, then there would have to exist some augmented path
 - We place all vertices reachable from *s* into one cut and the rest into another
 - By conservation of flow, the capacity of this cut must be the flow of the network, since anything that comes out of *s* must eventually reach *t*
 - If there exists some cut of G' such that the flow of the graph is equal to the capacity of the cut, then that flow must be the max flow
 - By definition, the max flow of a network must be less than or equal to the minimum capacity of any cut in the network
 - Since we have found a cut that has a capacity equal to the flow, we know that no flow that is greater than this capacity can exist
 - Based on this, the flow we found must be the maximum possible flow
 - We can combine these 2 facts to say that the result of Ford and Fulkerson guarantees that we have found a max flow, and that forming cuts based on vertices that are reachable from *s* allows us to generate a min-cut
 - The removal of an edge that travels between the cuts of the min-cut decreases the capacity of the cut

- Since the max flow must be less than or equal to the minimum capacity of the cut, decreasing the min-cut's capacity decreases the max flow
- Based on this, we can decrease the max flow by at most k by removing k edges from the min-cut
 - This is exactly what we do using BFS and the following traversal
- If there are less than k edges in the min-cut, then we can remove all the edges in the min-cut and the max flow will drop to 0 since the network will be disconnected
 - This is also covered by our BFS and following traversals
- Proof complete
- Time Complexity: $O(ne)$
- Time Complexity Proof:
 - The Ford and Fulkerson algorithm has a runtime of $O(|f| (n + e))$
 - Since each edge has a capacity of 1, f is at most e
 - This means we can simplify our runtime to $O(ne + e^2)$
 - Using the relationship between n and e , we can say that ne will be greater than or equal to e^2 , allowing us to simplify this even further to $O(ne)$
 - The modified BFS simply adds an extra constant time check for each iteration, so it still has a runtime of $O(n + e)$
 - The final loops can run through k times, which will be at most e , so we have a runtime of $O(e)$ for these loops
 - The overall runtime of this algorithm is therefore $O(ne)$

6)

- Algorithm: // Assume input array is *seq* and its size is *n*
 - Initialize arrays *inc* and *dec* of length *n* with values of 1
 - Initialize an array *res*
 - Initialize iterators *i* and *j*
 - Initialize variables *maxLen* and *maxIndex* to -1 and *flag* to true
 - For all values of *i* from 1 to *n* - 1: // Get maximum length of inc/dec subarrays
 - For all values of *j* from 0 to *i* - 1:
 - If *seq[i]* is greater than *seq[j]*:
 - Set *inc[i]* equal to the maximum of *inc[j]* and (*dec[j]* + 1)
 - Else if *seq[i]* is less than *seq[j]*:
 - Set *dec[i]* equal to the maximum of *dec[j]* and (*inc[j]* + 1)
 - For all values of *i* from 0 to *n* - 1: // Find the max length subarray and its index
 - If the maximum of *inc[i]* and *dec[i]* is greater than *maxLen*:
 - Set *maxLen* to the maximum of *inc[i]* and *dec[i]*
 - Set *maxIndex* to *i*
 - If *maxLen* is equal to *dec[maxIndex]*: // Set flag appropriately
 - Set *flag* to false
 - Append *seq[maxIndex]* to *res*
 - For all values of *i* from *maxIndex* - 1 to 0: // Rebuild subsequence, using *flag* to alternate
 - If *maxLen* equals 1:
 - Exit the loop
 - If *flag*:
 - If *dec[i]* + 1 is equal to *maxLen*:
 - Append *seq[i]* to *res*
 - Decrement *maxLen* by 1
 - Invert *flag*
 - Else:
 - If *inc[i]* + 1 is equal to *maxLen*:
 - Append *seq[i]* to *res*
 - Decrement *maxLen* by 1
 - Invert *flag*
 - Reverse *res*
 - Return *res*
- Proof:
 - Base Case:
 - *n* = 1
 - The only subsequence possible is simply the input
 - The *inc* and *dec* arrays will both be initialized with a single 1
 - The first set of nested for loops will not run
 - The next for loop will run, allowing us to find the correct maximum index and length (0 and 1)
 - The only value in *seq* will be placed into the result

- The result will be returned
- Base case passed
- Inductive Step:
 - $inc[i]$ represents the maximum length of an increasing subsequence built from the first i elements of seq
 - $dec[i]$ represents the maximum length of an decreasing subsequence built from the first i elements of seq
 - Assume: We have the correct values of $inc[i - 1]$ and $dec[i - 1]$
 - Prove: We can get the correct values of $inc[i]$ and $dec[i]$
 - There are 2 options for each array:
 - We account for $seq[i]$ in the maximum length:
 - If we account for it in $inc[i]$, then $seq[i]$ must have increased from previous elements
 - If we account for it in $dec[i]$, then $seq[i]$ must have decreased from previous elements
 - Both options are checked exhaustively for each iteration by iterating through each previous element and maintaining the maximum length found thus far
 - This accounts for the correct behavior if $seq[i]$ is to be considered in either array
 - We don't:
 - If we skip it in $inc[i]$, then $seq[i]$ must have decreased from or been equal to previous elements
 - If we skip it in $dec[i]$, then $seq[i]$ must have increased from or been equal to previous elements
 - Both options are checked exhaustively for each iteration by iterating through each previous element and maintaining the maximum length found thus far
 - This accounts for the correct behavior if $seq[i]$ is to be skipped in either array
 - Both options will exhibit the correct behavior
 - We can get the correct values of $inc[i]$ and $dec[i]$ for any value of i from 0 to $n - 1$
 - All we need to prove now is that we can reconstruct the subsequence afterwards
 - We do this by maintaining a flag that tells us which array to look in next
 - We reference this flag to determine if we want a decreasing value or an increasing value, then combine this information with an access to the seq array to retrieve the appropriate value
 - This can be proved with common sense
 - Since we iterate backwards, we reverse and return the value
- Inductive step passed

- Proof by induction complete
- Time Complexity: $O(n^2)$
- Time Complexity Proof:
 - The initialization of 2 length- n arrays with the value 1 takes $O(n)$ time
 - The first for loop iterates through n elements
 - It contains a nested for loop which, in the worst-case, iterates through n - elements, performing constant time operations on each
 - This loop therefore takes $O(n^2)$ time
 - The for loop that finds the maximum length and index iterates through n values and performs constant time operations on each, resulting in an $O(n)$ runtime
 - The for loop that builds the subsequence runs a maximum of n times, performing constant time operations with each iteration, resulting in an $O(n)$ runtime
 - The reversal of the resulting array can take $O(n)$ time
 - The overall algorithm's runtime is $O(n^2)$