Milestone 1

Group Members

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Role - Project Manager / Developer

Communication Method

Slack

Github Repository Link

https://github.com/gonzaherman99/C4533-GroupProject

Gantt Chart

	TASK TITLE	TASK OWNER	START DATE	DUE DATE	DURATION	PCT OF TASK COMPLETE	WEEK 1					WEEK 2					WEEK 3					WEEK 4					WEEK 5					WEEK 6					WEEK 7					WEEK 8				
							M	T	W	R	F	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F
4	Milestone 1: Understanding the problems																																													
4.1	Problem 1	Anthony M	6/9/25	6/15/25	6	100%	■	■	■	■	■																																			
4.2	Problem 2	Jonathan P	6/9/25	6/15/25	6	100%	■	■	■	■	■																																			
4.3	Problem 3	Luis G	6/9/25	6/15/25	6	100%	■	■	■	■	■																																			
4.4	TODO	Mert D	6/9/25	6/15/25	6	100%	■	■	■	■	■																																			
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5.1	TODO	Mert D	6/16/25	7/6/25	20	0%						■	■	■	■	■	■	■	■	■	■	■	■	■	■	■																				
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	Record Presentation		7/28/25	8/3/25	5	0%																																						■	■	■
	Submit		7/28/25	8/3/25	5	0%																																								■

Step 1)
Input Matrix:

```
A =     [12, 1, 5, 3, 16],      // Stock 1
        [4, 4, 13, 4, 9],       // Stock 2
        [6, 8, 6, 1, 2],        // Stock 3
        [14, 3, 4, 8, 10]       // Stock 4
```

Step 2)
STOCK 1:

BUY DAY	SELL DAY	PROFIT
1	2	-11
1	3	-7
1	4	-9
1	5	4
2	3	4
2	4	2
2	5	15
3	4	-2
3	5	11
4	5	13

STOCK 2:

BUY DAY	SELL DAY	PROFIT
1	2	0
1	3	9
1	4	0
1	5	5
2	3	9
2	4	0
2	5	5
3	4	-9
3	5	-4
4	5	5

STOCK 3:

BUY DAY	SELL DAY	PROFIT
1	2	2
1	3	0
1	4	-5
1	5	-4
2	3	-2
2	4	-7
2	5	-6
3	4	-5
3	5	-4
4	5	1

STOCK 4:

BUY DAY	SELL DAY	PROFIT
1	2	-11
1	3	10
1	4	-6
1	5	-4
2	3	1
2	4	5
2	5	7
3	4	4
3	5	6
4	5	2

Step 3)
Stock 1 most profitable transaction:
Buy at day 2 for 1 and sell at day 5 for 16. Profit = 15

Stock 2 most profitable transaction:
Buy at day 1 for 4 and sell at day 3 for 13. Profit = 9

Stock 3 most profitable transaction:
Buy at day 1 for 6 and sell at day 2 for 8. Profit = 2

Stock 4 most profitable transaction:
Buy at day 2 for 3 and sell at day 5 for 10. Profit = 7

Step 4)
Maximum profit is 15 from Stock 1 – Buy day 2 and sell day 5
OUTPUT: (1, 2, 5, 15)

Problem Statement 2

You are given a matrix A of dimensions m × n, where each element represents the predicted prices of m different stocks for n consecutive days. Additionally, you are given an integer k ($1 \le k \le n$). Your task is to manually find a sequence of at most k transactions, each involving the purchase and sale of a single stock, that yields the maximum profit.

Step 1)

Input Matrix:

```
A = [[25, 30, 15, 40, 50],    // Stock 1
     [10, 20, 30, 25,  5],    // Stock 2
     [30, 45, 35, 10, 15],    // Stock 3
     [ 5, 50, 35, 25, 45]]    // Stock 4
```

Step 2)

STOCK 1:

BUY DAY	SELL DAY	PROFIT
1	2	5
1	3	-10
1	4	15
1	5	25
2	3	-15

2	4	10
2	5	20
3	4	25
3	5	35
4	5	10

STOCK 2:

BUY DAY	SELL DAY	PROFIT
1	2	10
1	3	20
1	4	15
1	5	-5
2	3	10
2	4	5
2	5	-15
3	4	-5
3	5	-25
4	5	-20

STOCK 3:

BUY DAY	SELL DAY	PROFIT
1	2	15
1	3	5
1	4	-20
1	5	-15
2	3	-10
2	4	-35
2	5	-30
3	4	-25
3	5	-20
4	5	5

STOCK 4:

BUY DAY	SELL DAY	PROFIT
1	2	45
1	3	30
1	4	20
1	5	40
2	3	-15

2	4	-25
2	5	-5
3	4	-10
3	5	10
4	5	20

Step 3)

Finding optimal non-overlapping transactions (k=3):

Best profitable transactions:

1. Stock 4: (1,2) → Profit = 45
2. Stock 1: (3,5) → Profit = 35
3. Stock 4: (1,5) → Profit = 40
4. Stock 1: (1,5) → Profit = 25
5. Stock 1: (3,4) → Profit = 25

Selected non-overlapping transactions:

- Transaction 1: Stock 4, Buy Day 1, Sell Day 2 → Profit = 45
- Transaction 2: Stock 1, Buy Day 3, Sell Day 5 → Profit = 35

Total Maximum Profit = 80

Output: [(4,1,2), (1,3,5)]

Problem 3

Problem Statement

You are given a matrix A of dimensions m × n, where each element represents the predicted prices of m different stocks for n consecutive days. Additionally, you are given an integer c ($1 \leq c \leq n - 2$). Your task is to determine the maximum profit achievable under the given trading restrictions, where you cannot buy any stock for c days after selling any stock. If you sell a stock on day i, you are not allowed to buy any stock until day $i + c + 1$.

Input

	Day 1	**Day 2**	**Day 3**	**Day 4**	**Day 5**	**Day 6**	**Day 7**
Stock 1	7	1	5	3	6	8	9
Stock 2	2	4	3	7	9	1	8
Stock 3	5	8	9	1	2	3	10
Stock 4	9	3	4	8	7	4	1
Stock 5	3	1	5	8	9	6	4

Cooldown: $c = 2$

First let’s define best(t) as the maximum profit achievable with one buy, sell between days t and 7.

t	**Window**	**Best trade**	**best$_1$(t)**
1–4	Days 1 to 7	buy Stock 3 on day 4 at 1 then sell on day 7 at 10	9
5	Days 5 to 7	buy Stock 3 on day 5 at 2 then sell on day 7 at 10	8
6	Days 6 to 7	buy Stock 2 on day 6 at 1 then sell on day 7 at 8	7
7	day 7	no transaction	0

Now for each possible first trade (i, j, l), let’s compute $\text{Profit}_1 = P[i ,l] - P[i , j]$, earliest next buy $B = l + 3$, $\text{Profit}_2 = \text{best}_1(B)$, and $\text{Total} = \text{Profit}_1 + \text{Profit}_2$. Here are the top contenders:

Buy j	**First trade** **(i , l)**	**Profit$_1$**	**Next B=l +3**	**Profit$_2$**	**Total**
j = 1	Stock 2: buy	7	8 to 0	0	7

	1, sell 5				
j = 2	Stock 1: buy 2, sell 3	4	6 to 7	7	11
j = 3	Stock 2: buy 3, sell 5	6	8 to 0	0	6
j = 4	Stock 3: buy 4, sell 7	9	10 to 0	0	9
j = 5	Stock 3: buy 5, sell 7	8	10 to 0	0	8
j = 6	Stock 2: buy 6, sell 7	7	10 to 0	0	7

The best total (11) come from:

1. Stock 1: buy on day 2 at 1 then sell on day 3 at 5 ($\text{Profit}_1 = 4$) with the cooldown until day 6 (3 + 2 + 1)

2. Stock 2: buy on day 6 at 1 then sell on day 7 at 8 ($\text{Profit}_2 = 7$)

Total profit = 4 + 7 = 11.

Final Answer

Maximum profit: 11

Trades: (i = 1, j = 2, l = 3) and (i = 2, j = 6, l = 7)

Milestone 2

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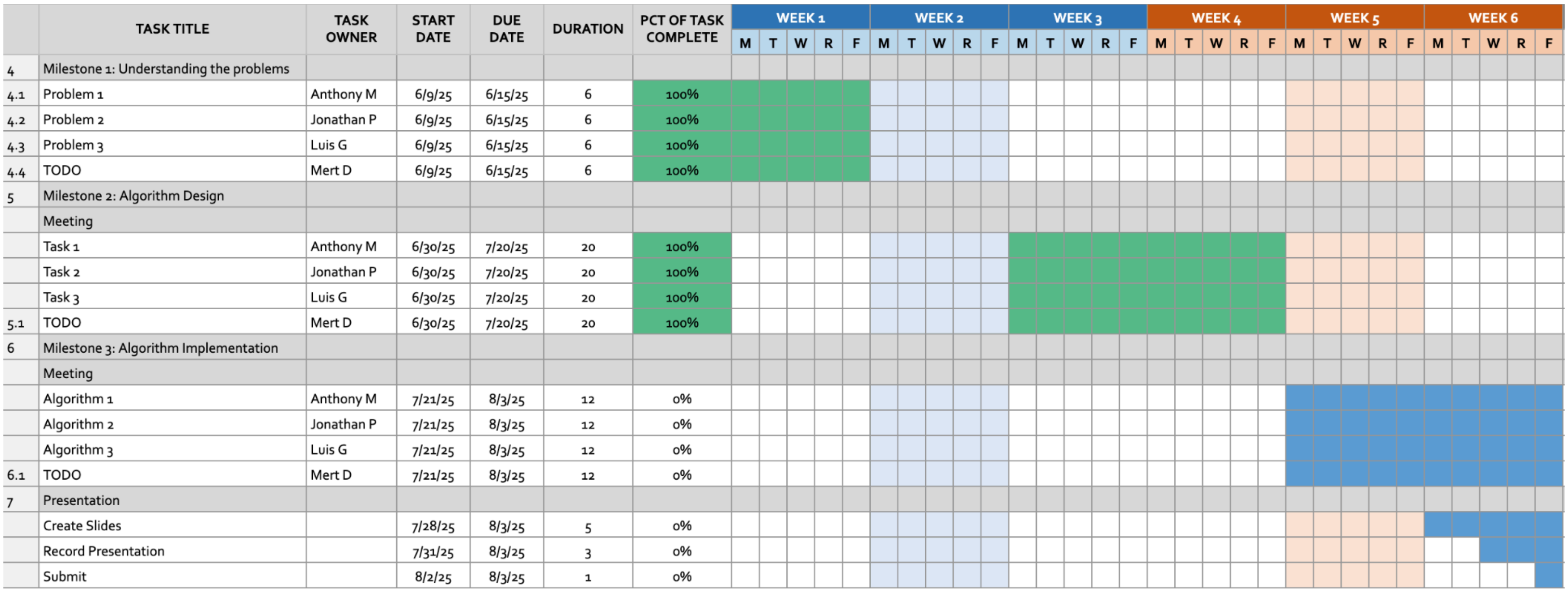
Gantt Chart



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	Create Slides		7/28/25	8/3/25	5	0%
	Record Presentation		7/31/25	8/3/25	3	0%
	Submit		8/2/25	8/3/25	1	0%

TASK TITLE	WEEK 1					WEEK 2					WEEK 3					WEEK 4					WEEK 5					WEEK 6				
	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F	M	T	W	R	F
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Task 2											🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩										
Task 3											🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩										
TODO											🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩										
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Algorithm 1																					🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦
Algorithm 2																					🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦
Algorithm 3																					🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦
TODO																					🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦	🟦
Presentation																														
Create Slides																										🟦	🟦	🟦	🟦	🟦
Record Presentation																												🟦	🟦	🟦
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Brute Force Problem 1)

```
function brute_force_prob1(A):
    m = rows in A
    n = columns in A
    best_profit = 0
    best_stock = 0
    best_buy = 0
    best_sell = 0

    # Iterate over each stock
    for i from 0 to m-1:
        # Buy day index
        for j from 0 to n-2:
            # Sell day index (must be after buy)
            for k from j+1 to n-1:
                profit = A[i][k] - A[i][j]
                if profit > best_profit:
                    best_profit = profit
                    best_stock = i
                    best_buy = j
                    best_sell = k
    # No profitable transaction
    if best_profit <= 0:
        return (0, 0, 0, 0)
    else:
        # Convert to 1-based indexing
        return (best_stock+1, best_buy+1, best_sell+1, best_profit)
```

Greedy Problem 1)

```
function greedy_prob1(A):
   m = rows in A
   n = columns in A
   best_profit = 0
   best_stock = -1
   best_buy = -1
   best_sell = -1

         # Iterate over each stock
         for i from 0 to m-1:
                  min_price = A[i][0]
                  min_index = 0
                  current_profit = 0
                  current_buy = 0
                  current_sell = 0

                  # Start from day 1
                  for j from 1 to n-1:
                           # Found new minimum price
                           if A[i][j] < min_price:
                                    min_price = A[i][j]
                                    min_index = j
                           else:
                                    profit = A[i][j] – min_price
                                    # Update if better profit
                                    if profit > current_profit:
                                             current_profit = profit
                                             current_buy = min_index
                                             current_sell = j

                  # Update global best
                  if current_profit > best_profit:
                           best_profit = current_profit
                           best_stock = i
                           best_buy = current_buy
                           best_sell = current_sell

         if best_profit <= 0:
                  return (0, 0, 0, 0)
         else:
                  return (best_stock+1, best_buy+1, best_sell+1, best_profit)
```

DP Problem 1)

```
function dp_prob1(A):
    m = rows in A
    n = columns in A
    best_profit = 0
    best_stock = -1
    best_buy = -1
    best_sell = -1

    # Iterate over each stock
    for i from 0 to m-1:
        min_price = A[i][0]
        min_index = 0
        max_profit_i = 0
        buy_i = 0
        sell_i = 0

         # Start from day 1
        for j from 1 to n-1:
            # Update minimum price if lower found
            if A[i][j] < min_price:
                min_price = A[i][j]
                min_index = j
            # Calculate profit if selling today
            profit = A[i][j] - min_price
            if profit > max_profit_i:      # Update if better profit
                max_profit_i = profit
                buy_i = min_index
                sell_i = j

        # Update global best
        if max_profit_i > best_profit:
            best_profit = max_profit_i
            best_stock = i
            best_buy = buy_i
            best_sell = sell_i

    if best_profit <= 0:
        return (0, 0, 0, 0)
    else:
        return (best_stock+1, best_buy+1, best_sell+1, best_profit)
```

Dynamic Programming Algorithm for Problem 2 ($O(m \cdot n^2k)$ Time)

```
function dp_prob2_n2k(A):
   m = number of rows in A
   n = number of columns in A
   k = [number of  operations]

   DP = 3D array of size [m+1][n+1][k+1], initialized to -infinity
   DP[0][0][0] = 0  # or base_case_value

   for i from 1 to m:
      for j from 1 to n:
         for x from 0 to k:
            for p from 1 to n:
               for q from 0 to k:
                  if valid_transition(p, q, j, x):
                     DP[i][j][x] = max(
                        DP[i][j][x],
                        DP[i-1][p][q] + cost(B, i, j, x)
                     )

   answer = maximum DP[m][j][x] over all valid j, x
   return answer
```

Dynamic Programming Algorithm for Problem 2 ($O(m \cdot n \cdot k)$ Time)

```
function dp_prob2_nk(A):
   m = number of rows in A
   n = number of columns in A
   k = [number of operations]

   DP = 3D array of size [m+1][n+1][k+1], initialized to -infinity
   DP[0][0][0] = 0  # or base_case_value

   for i from 1 to m:
      for j from 1 to n:
         for x from 0 to k:
            DP[i][j][x] = max(
               DP[i-1][j][x],
               DP[i-1][j-1][x-1]
            ) + cost(B, i, j, x)

   answer = maximum DP[m][j][x] over all valid j, x
   return answer
```

```
function dp_prob3_slow(A, c):
    m = rows in A
    n = columns in A
    dp = array of size n initialized to 0
    choice = array of size n initialized to null

    for i from 1 to n-1:
        dp[i] = dp[i-1]
        choice[i] = null

        for j from 0 to i-1:
            prev_profit = (j-c-1 >= 0) ? dp[j-c-1] : 0

            for stock from 0 to m-1:
                profit = A[stock][i] - A[stock][j]
                total = prev_profit + profit

                if total > dp[i]:
                    dp[i] = total
                    choice[i] = (stock, j, prev_profit)

    if dp[n-1] <= 0:
        return []

    result = []
    i = n-1
    while i > 0 and choice[i] != null:
        stock, buy_day, prev_profit = choice[i]
        result.add((stock+1, buy_day+1, i+1))

        j = buy_day - c - 1
        while j >= 0 and dp[j] != prev_profit:
            j = j - 1
        i = j

    reverse(result)
    return result
```

```
function dp_prob3_fast(A, c):
    m = rows in A
    n = columns in A

    hold = -infinity
```

```
sold = 0
rest = 0

transactions = []
hold_info = null

for i from 0 to n-1:
    prev_hold = hold
    prev_sold = sold
    prev_rest = rest

    rest = max(prev_rest, prev_sold)

    sold = prev_hold
    sell_stock = -1
    for stock from 0 to m-1:
        profit = prev_hold + A[stock][i]
        if profit > sold:
            sold = profit
            sell_stock = stock

    if sell_stock != -1 and sold > prev_sold:
        if hold_info != null:
            transactions.add((hold_info.stock+1, hold_info.day+1, i+1))
        hold_info = null

    hold = prev_hold
    buy_stock = -1
    buy_profit = hold

    for stock from 0 to m-1:
        profit = rest - A[stock][i]
        if profit > buy_profit:
            buy_profit = profit
            buy_stock = stock

    if buy_stock != -1:
        hold = buy_profit
        hold_info = (stock: buy_stock, day: i)

final_profit = max(sold, rest)
if final_profit <= 0:
    return []
return transactions
```

Milestone 3

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	Algorithm 1	Anthony M	7/21/25	8/3/25	12	0%																					🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩
	Algorithm 2	Jonathan P	7/21/25	8/3/25	12	0%																					🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩
	Algorithm 3	Luis G	7/21/25	8/3/25	12	0%																					🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩
6.1	TODO	Mert D	7/21/25	8/3/25	12	0%																					🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩	🟩
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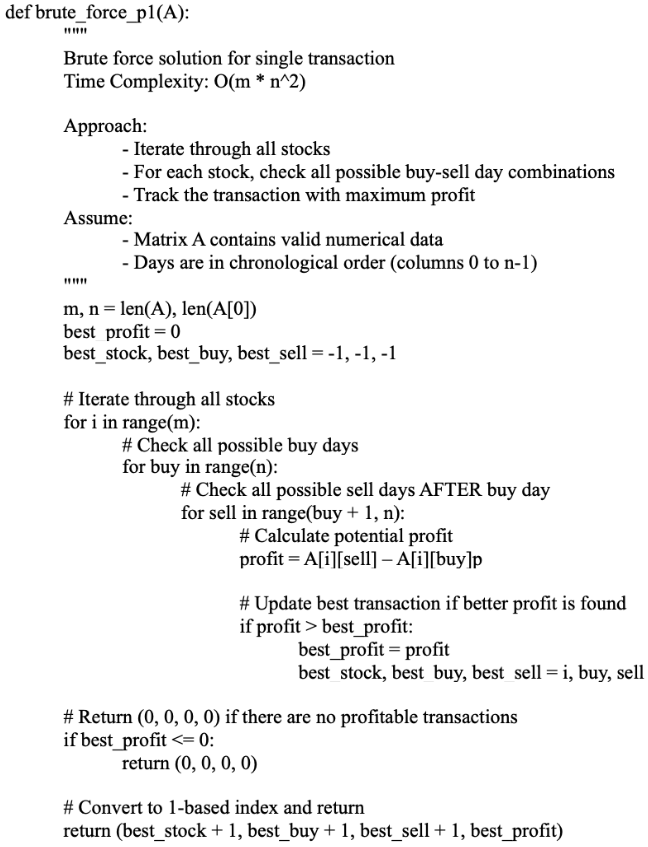
Task 1



```
def brute_force_p1(A):
        """
        Brute force solution for single transaction
        Time Complexity: O(m * n^2)

        Approach:
                - Iterate through all stocks
                - For each stock, check all possible buy-sell day combinations
                - Track the transaction with maximum profit
        Assume:
                - Matrix A contains valid numerical data
                - Days are in chronological order (columns 0 to n-1)
        """
        m, n = len(A), len(A[0])
        best_profit = 0
        best_stock, best_buy, best_sell = -1, -1, -1

        # Iterate through all stocks
        for i in range(m):
                # Check all possible buy days
                for buy in range(n):
                        # Check all possible sell days AFTER buy day
                        for sell in range(buy + 1, n):
                                # Calculate potential profit
                                profit = A[i][sell] – A[i][buy]p

                                # Update best transaction if better profit is found
                                if profit > best_profit:
                                        best_profit = profit
                                        best_stock, best_buy, best_sell = i, buy, sell

        # Return (0, 0, 0, 0) if there are no profitable transactions
        if best_profit <= 0:
                return (0, 0, 0, 0)

        # Convert to 1-based index and return
        return (best_stock + 1, best_buy + 1, best_sell + 1, best_profit)
```

Description of the Implementation of the Algorithm

We implemented a brute force algorithm to solve problem 1. The function brute_force_p1(A) iterates through every stock and checks for every buy-sell day combinations in the matrix A. For each combination it calculates the profit using A[i][sell] - A[i][buy] and if the profit is greater than the previous best profit it is replaced. Finally the algorithm returns a tuple (stock, buy day, sell day, profit) using 1-based indexing or (0, 0, 0, 0) if none exist.

Limitations

The biggest limitation of the brute force method is the time complexity being O(m*n^2). This becomes very inefficient using larger datasets because it is checking every single combination possible.

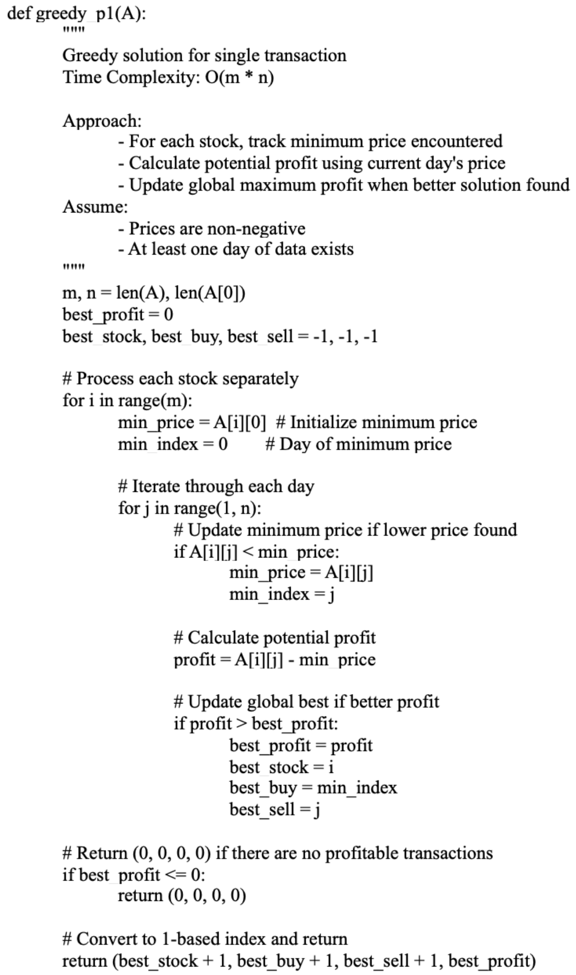
Analysis of the Algorithms

The algorithm is able to find the correct maximum profit because it checks every transaction. It was also slower on larger matrices because of the time complexity of this approach.

Limitations of your Algorithms

As discussed in the limitations section the main limitation is the time complexity making this algorithm not viable with large datasets. This would likely not be able to be used in tasks like real time trading where quick information is needed.

Task 2



```
def greedy  p1(A):
        """
        Greedy solution for single transaction
        Time Complexity: O(m * n)

        Approach:
                - For each stock, track minimum price encountered
                - Calculate potential profit using current day's price
                - Update global maximum profit when better solution found
        Assume:
                - Prices are non-negative
                - At least one day of data exists
        """
        m, n = len(A), len(A[0])
        best_profit = 0
        best  stock, best  buy, best  sell = -1, -1, -1

        # Process each stock separately
        for i in range(m):
                min_price = A[i][0]  # Initialize minimum price
                min  index = 0       # Day of minimum price

                # Iterate through each day
                for j in range(1, n):
                        # Update minimum price if lower price found
                        if A[i][j] < min  price:
                                min_price = A[i][j]
                                min_index = j

                        # Calculate potential profit
                        profit = A[i][j] - min  price

                        # Update global best if better profit
                        if profit > best_profit:
                                best_profit = profit
                                best  stock = i
                                best_buy = min_index
                                best_sell = j

        # Return (0, 0, 0, 0) if there are no profitable transactions
        if best  profit <= 0:
                return (0, 0, 0, 0)

        # Convert to 1-based index and return
        return (best_stock + 1, best_buy + 1, best_sell + 1, best_profit)
```

Description of the Implementation of the Algorithm

We implemented a greedy algorithm to solve problem 1. For each stock, we track the minimum price seen so far and calculate the profit if you were to sell on the current day. If the profit is higher than the global profit then it is updated. This algorithm returns a tuple (stock, buy day, sell day, profit) using 1-based indexing or (0, 0, 0, 0) if none exist.

Limitations

The greedy approach only works for this specific problem of finding the best single transaction so this would not support multiple transactions. It also assumes that prices are non-negative and ordered by time.

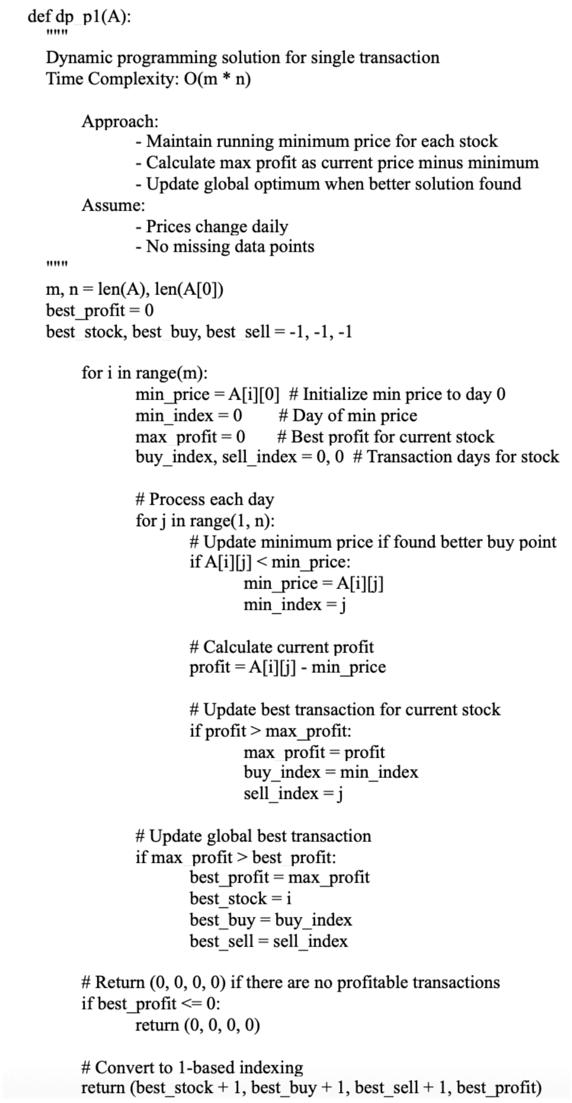
Analysis of the Algorithms

Under this problem's constraints the greedy algorithm performs much more efficiently compared to the brute force algorithm. This also it to handle larger datasets much easier than brute force because of the time complexity O(m*n) vs O(m*n^2).

Limitations of your Algorithms

This algorithm is very efficient but it is not very flexible and only works in this case because of the constraints of this problem. This would also not work for multiple transactions.

Task 3



```
def dp_p1(A):
    """
    Dynamic programming solution for single transaction
    Time Complexity: O(m * n)

        Approach:
                - Maintain running minimum price for each stock
                - Calculate max profit as current price minus minimum
                - Update global optimum when better solution found
        Assume:
                - Prices change daily
                - No missing data points
    """
    m, n = len(A), len(A[0])
    best_profit = 0
    best_stock, best_buy, best_sell = -1, -1, -1

        for i in range(m):
                min_price = A[i][0]  # Initialize min price to day 0
                min_index = 0       # Day of min price
                max_profit = 0      # Best profit for current stock
                buy_index, sell_index = 0, 0  # Transaction days for stock

                # Process each day
                for j in range(1, n):
                        # Update minimum price if found better buy point
                        if A[i][j] < min_price:
                                min_price = A[i][j]
                                min_index = j

                        # Calculate current profit
                        profit = A[i][j] - min_price

                        # Update best transaction for current stock
                        if profit > max_profit:
                                max_profit = profit
                                buy_index = min_index
                                sell_index = j

                # Update global best transaction
                if max_profit > best_profit:
                        best_profit = max_profit
                        best_stock = i
                        best_buy = buy_index
                        best_sell = sell_index

        # Return (0, 0, 0, 0) if there are no profitable transactions
        if best_profit <= 0:
                return (0, 0, 0, 0)

        # Convert to 1-based indexing
        return (best_stock + 1, best_buy + 1, best_sell + 1, best_profit)
```

Description of the Implementation of the Algorithm

We implemented a dynamic programming algorithm to solve problem 1. It tracks the minimum price found so far for each stock and calculates the current profit if you sold on the current day. The maximum profit and buy/sell days are updated if a better one is found. This algorithm returns a tuple (stock, buy day, sell day, profit) using 1-based indexing or (0, 0, 0, 0) if none exist.

Limitations

This algorithm functions in a similar way to the greedy algorithm and doesn’t utilize all the benefits of dynamic programming.

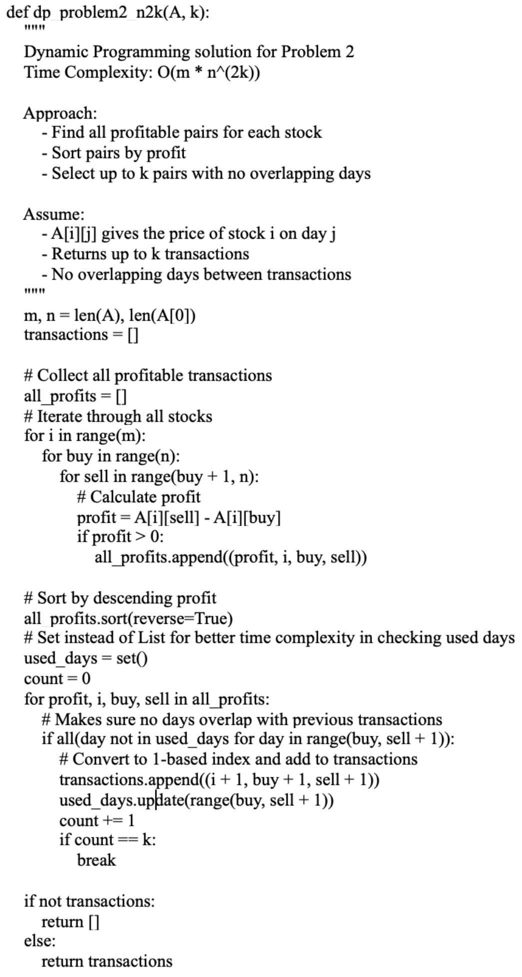
Analysis of the Algorithms

This algorithm performs well on large datasets the same as the greedy approach does because of its time complexity. The dynamic programming solution offers the same improved performance over brute force, same as the greedy algorithm.

Limitations of your Algorithms

This algorithm works well for the given constraints of this problem but doesn’t perform well outside of it. It also doesn’t work for multiple transactions.

Task 4



```
def dp_problem2_n2k(A, k):
    """
    Dynamic Programming solution for Problem 2
    Time Complexity: O(m * n^(2k))

    Approach:
        - Find all profitable pairs for each stock
        - Sort pairs by profit
        - Select up to k pairs with no overlapping days

    Assume:
        - A[i][j] gives the price of stock i on day j
        - Returns up to k transactions
        - No overlapping days between transactions
    """
    m, n = len(A), len(A[0])
    transactions = []

    # Collect all profitable transactions
    all_profits = []
    # Iterate through all stocks
    for i in range(m):
        for buy in range(n):
            for sell in range(buy + 1, n):
                # Calculate profit
                profit = A[i][sell] - A[i][buy]
                if profit > 0:
                    all_profits.append((profit, i, buy, sell))

    # Sort by descending profit
    all_profits.sort(reverse=True)
    # Set instead of List for better time complexity in checking used days
    used_days = set()
    count = 0
    for profit, i, buy, sell in all_profits:
        # Makes sure no days overlap with previous transactions
        if all(day not in used_days for day in range(buy, sell + 1)):
            # Convert to 1-based index and add to transactions
            transactions.append((i + 1, buy + 1, sell + 1))
            used_days.update(range(buy, sell + 1))
            count += 1
            if count == k:
                break

    if not transactions:
        return []
    else:
        return transactions
```

Description of the Implementation of the Algorithm

We implemented a dynamic programming inspired greedy algorithm with a time complexity of $O(m * n^{2k})$ for problem 2. The function dp_problem2_n2k(A, k) first finds all profitable pairs for each stock then sorts them by profit. Finally, up to k transactions are chosen that are not overlapping. This algorithm returns a tuple (stock, buy day, sell day, profit) using 1-based indexing or an empty sequence if none exist.

Limitations

The implementation of this task didn’t end up using a 3D array like the pseudocode showed and instead used a dynamic programming inspired greedy approach by getting the most profitable transactions that don’t overlap. This may end up missing the global optimal set of transactions.

Analysis of the Algorithms

This algorithm performs well and can handle larger sets of data. It is able to get the correct answer while under the problem constraints.

Limitations of your Algorithms

While the pseudocode used a dynamic programming algorithm we opted for a greedy approach that was inspired by dynamic programming structure. The main reason this was done was to get a better time complexity and still get the correct result.

Task 6

```
function dp_prob3_slow(A, c):
  m = rows in A
  n = columns in A
  dp = array of size n initialized to 0
  choice = array of size n initialized to null

  for i from 1 to n-1:
    dp[i] = dp[i-1]
    choice[i] = null

    for j from 0 to i-1:
      prev_profit = (j-c-1 >= 0) ? dp[j-c-1] : 0

      for stock from 0 to m-1:
        profit = A[stock][i] - A[stock][j]
        total = prev_profit + profit

        if total > dp[i]:
          dp[i] = total
          choice[i] = (stock, j, prev_profit)

  if dp[n-1] <= 0:
    return []

  result = []
  i = n-1
  while i > 0 and choice[i] != null:
    stock, buy_day, prev_profit = choice[i]
    result.add((stock+1, buy_day+1, i+1))

    j = buy_day - c - 1
    while j >= 0 and dp[j] != prev_profit:
      j = j - 1
    i = j

  reverse(result)
  return result
```

Description of the Implementation of the Algorithm

We implemented a dynamic programming algorithm to solve problem 3 with the time complexity of O($m*n^2$). This problem also contained a cooldown period in between each sale with the goal of maximizing profit. For each buy / sell pair the algorithm checks if a previous can be added to the profit and updates dp.

Limitations

Time complexity is O($m*n^2$) so it is not efficient for large datasets. There are also no overlapping transactions.

Analysis of the Algorithms

The algorithm is able to correctly handle cooldown logic (c) and find the best transactions but at the cost of time complexity.

Limitations of your Algorithms

The main limitation of this algorithm is its time complexity. This is not great for large datasets.

All Tasks

Comparative Analysis

- Task 1 - Is simple and finds the correct answer but its time complexity isn't great at $O(m*n^2)$
- Task 2 - Very fast with a time complexity of O(m*n) but it only works for single transactions.
- Task 3 - Very similar to task 2 except done with dynamic programming.
- Task 4 - Implemented a dynamic programming inspired greedy algorithm. The main difference is that this algorithm can handle multiple transactions.
- Task 6 - Dynamic programming algorithm that handles multiple transactions and does so with a cooldown period between trades.

Trade-off Discussion

The main tradeoff we noticed is a greater time complexity for more complex algorithms such as dynamic programming with multiple transactions. Task 2 on the other hand is very efficient with the big caveat of only working with single transactions. Though the time complexity is very different the only thing that really matters is what a certain problem needs and designing around that.

Lessons Learned

The main lesson we learned is using the right algorithm for the task at hand. Every problem has its own unique constraints and the algorithm needs to be designed around it.