

## Question

Solve the following recurrence relation arising from the LUP decomposition solve procedure:

$$T(n) = \sum_{i=1}^n \left[ O(1) + \sum_{j=1}^{i-1} O(1) \right] + \sum_{i=1}^n \left[ O(1) + \sum_{j=i+1}^n O(1) \right].$$

## Answer

### Step 1: Interpret the Recurrence

The recurrence consists of two main summations, each iterating over  $i = 1$  to  $n$ .

Each part models the cost of:

- constant-time operations, and
- inner loops that perform a constant-time operation multiple times.

Our goal is to count the total number of constant-time operations and determine the overall asymptotic complexity.

### Step 2: Simplify the First Summation

Consider the first term:

$$\sum_{i=1}^n \left[ O(1) + \sum_{j=1}^{i-1} O(1) \right].$$

#### Inner Summation

The inner sum

$$\sum_{j=1}^{i-1} O(1)$$

executes  $i - 1$  times. Hence:

$$\sum_{j=1}^{i-1} O(1) = O(i).$$

## First Summation Becomes

$$\sum_{i=1}^n [O(1) + O(i)] = \sum_{i=1}^n O(i).$$

## Step 3: Evaluate the First Summation

We know that:

$$\sum_{i=1}^n i = \frac{n(n+1)}{2}.$$

Therefore:

$$\sum_{i=1}^n O(i) = O(n^2).$$

## Step 4: Simplify the Second Summation

Now consider the second term:

$$\sum_{i=1}^n \left[ O(1) + \sum_{j=i+1}^n O(1) \right].$$

## Inner Summation

The inner sum

$$\sum_{j=i+1}^n O(1)$$

executes  $n - i$  times. Hence:

$$\sum_{j=i+1}^n O(1) = O(n - i).$$

## Second Summation Becomes

$$\sum_{i=1}^n [O(1) + O(n - i)] = \sum_{i=1}^n O(n - i).$$

## Step 5: Evaluate the Second Summation

As  $i$  ranges from 1 to  $n$ , the quantity  $n - i$  ranges from  $n - 1$  down to 0. Thus:

$$\sum_{i=1}^n (n - i) = \sum_{k=0}^{n-1} k = \frac{n(n-1)}{2}.$$

Therefore:

$$\sum_{i=1}^n O(n-i) = O(n^2).$$

## Step 6: Combine Both Parts

From the above steps:

- The first summation contributes  $O(n^2)$ ,
- The second summation contributes  $O(n^2)$ .

Hence:

$$T(n) = O(n^2) + O(n^2) = O(n^2).$$

## Final Answer

$T(n) = O(n^2)$

**Comparison with LUP Decomposition Cost.** While the LUP decomposition itself requires  $O(n^3)$  time, the solve phase analyzed here runs in  $O(n^2)$  time, making it efficient when solving linear systems with multiple right-hand sides once the factorization has been computed.

## Relation to LUP Solve Algorithm (Pseudocode)

The recurrence corresponds to the solve phase of the LUP decomposition, which consists of forward and backward substitution.

### Forward Substitution (Solving $Ly = Pb$ )

```
for i = 1 to n:
    y[i] = b[i]
    for j = 1 to i-1:
        y[i] = y[i] - L[i][j] * y[j]
```

The outer loop runs  $n$  times, and the inner loop executes  $i - 1$  constant-time operations, giving rise to the summation

$$\sum_{i=1}^n \left[ O(1) + \sum_{j=1}^{i-1} O(1) \right].$$

## Backward Substitution (Solving $Ux = y$ )

```
for i = n down to 1:
    x[i] = y[i]
    for j = i+1 to n:
        x[i] = x[i] - U[i][j] * x[j]
```

Here, the inner loop executes  $n - i$  constant-time operations, producing the summation

$$\sum_{i=1}^n \left[ O(1) + \sum_{j=i+1}^n O(1) \right].$$

Together, these two procedures account for the full recurrence analyzed above.

## Relation to LUP Solve Algorithm (Pseudocode Interpretation)

The recurrence solved earlier corresponds to the *solve phase* after LUP decomposition, not to the decomposition itself. This solve phase consists of two steps:

- Forward substitution to solve  $Ly = Pb$ ,
- Backward substitution to solve  $Ux = y$ .

Below, we present the pseudocode-level interpretation and show how each loop maps directly to the recurrence relation.

## Forward Substitution (Lower Triangular Solve)

### Pseudocode

```
for i = 1 to n:
    y[i] = b[i]
    for j = 1 to i-1:
        y[i] = y[i] - L[i][j] * y[j]
```

### Cost Analysis

- The outer loop runs  $n$  times.
- The inner loop runs  $i - 1$  times for a given  $i$ .
- Each inner operation takes  $O(1)$  time.

Thus, the total cost of forward substitution is:

$$\sum_{i=1}^n \left[ O(1) + \sum_{j=1}^{i-1} O(1) \right],$$

which matches the first summation in the recurrence.

## Backward Substitution (Upper Triangular Solve)

### Pseudocode

```
for i = n down to 1:
    x[i] = y[i]
    for j = i+1 to n:
        x[i] = x[i] - U[i][j] * x[j]
```

### Cost Analysis

- The outer loop runs  $n$  times.
- The inner loop runs  $n - i$  times for a given  $i$ .
- Each inner operation takes  $O(1)$  time.

Thus, the total cost of backward substitution is:

$$\sum_{i=1}^n \left[ O(1) + \sum_{j=i+1}^n O(1) \right],$$

which matches the second summation in the recurrence.

## Combined Interpretation

Combining both phases, the total running time of the LUP solve procedure is:

$$T(n) = \sum_{i=1}^n \left[ O(1) + \sum_{j=1}^{i-1} O(1) \right] + \sum_{i=1}^n \left[ O(1) + \sum_{j=i+1}^n O(1) \right].$$

This recurrence therefore represents exactly the combined cost of:

- Forward substitution, and
- Backward substitution.

As shown earlier, this simplifies to:

$$T(n) = O(n^2).$$

## Result

The recurrence arises directly from the nested-loop structure of forward and backward substitution in the LUP solve procedure. This confirms that, while the LUP decomposition itself requires  $O(n^3)$  time, each subsequent solve step runs in quadratic time.

**Practical Efficiency.** Both forward and backward substitution access matrix entries in a largely sequential manner, which leads to good cache locality in practice. This memory access pattern further contributes to their efficiency beyond the quadratic asymptotic time complexity.

## Interpretation in the Context of LUP Decomposition

This recurrence corresponds to the forward substitution and backward substitution steps used when solving:

$$Ax = b \quad \text{using} \quad PA = LU.$$

The key insight is:

- LUP decomposition itself takes  $O(n^3)$  time,
- Once  $L$  and  $U$  are available, each solve step (forward and backward substitution) takes  $O(n^2)$  time.

This confirms that the solve phase is quadratic, not cubic.

## Conclusion

The given recurrence simplifies to a quadratic time complexity. This aligns with the theoretical expectation for forward and backward substitution in LUP-based linear system solvers, where nested loops execute a linear number of constant-time operations.