Dynamic Programming

Lecture 13
**Recursion types**

1. **Divide and Conquer**: Problem reduced to multiple **independent** sub-problems.
   
   Examples: Merge sort, quick sort, multiplication, median selection.
   
   Each sub-problem is a fraction smaller.

2. **Backtracking**: A sequence of decision problems. Recursion tries all possibilities at each step.
   
   Each subproblem is only a constant smaller, e.g. from $n$ to $n - 1$. 
Recursion types

1. **Divide and Conquer**: Problem reduced to multiple independent sub-problems.

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2. **Backtracking**: A sequence of decision problems. Recursion tries all possibilities at each step.

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3. **Dynamic Programming**: Smart recursion with memoization.
Part I

Fibonacci Numbers
Fibonacci Numbers

Fibonacci numbers defined by recurrence:

\[ F(n) = F(n - 1) + F(n - 2) \text{ and } F(0) = 0, F(1) = 1. \]

These numbers have many interesting and amazing properties. A journal *The Fibonacci Quarterly*!

1. \[ F(n) = \left( \phi^n - (1 - \phi)^n \right) / \sqrt{5} \] where \( \phi \) is the golden ratio \( (1 + \sqrt{5})/2 \approx 1.618. \)
2. \[ \lim_{n \to \infty} F(n + 1) / F(n) = \phi \]
Question: Given $n$, compute $F(n)$.

Fib($n$):
    if ($n = 0$)
        return 0
    else if ($n = 1$)
        return 1
    else
        return Fib($n - 1$) + Fib($n - 2$)
Recursive Algorithm for Fibonacci Numbers

Question: Given $n$, compute $F(n)$.

```
Fib(n):
    if (n = 0)
        return 0
    else if (n = 1)
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    else
        return Fib(n - 1) + Fib(n - 2)
```

Running time? Let $T(n)$ be the number of additions in Fib(n).
Recursive Algorithm for Fibonacci Numbers

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Running time? Let $T(n)$ be the number of additions in Fib(n).

$$T(n) = T(n - 1) + T(n - 2) + 1 \text{ and } T(0) = T(1) = 0$$
Question: Given $n$, compute $F(n)$.

```python
Fib(n):
    if (n = 0)
        return 0
    else if (n = 1)
        return 1
    else
        return Fib(n - 1) + Fib(n - 2)
```

Running time? Let $T(n)$ be the number of additions in Fib(n).

$$T(n) = T(n - 1) + T(n - 2) + 1 \text{ and } T(0) = T(1) = 0$$

Roughly same as $F(n)$

$$T(n) = \Theta(\phi^n)$$

The number of additions is exponential in $n$. Can we do better?
Memoization

- The recursive algorithm is slow because it computes the same Fibonacci numbers over and over.
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Memoization

1. Write down the results of recursive calls and look them up later
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2. An array $F(n)$, where $F(i)$ stores the result of $\text{Fib}(i)$
The recursive algorithm is slow because it computes the same Fibonacci numbers over and over.

Memoization

1. Write down the results of recursive calls and look them up later
2. An array $F(n)$, where $F(i)$ stores the result of $\text{Fib}(i)$
3. Evaluation order: From bottom up, $i = 2$ then $i = 3$ and so on
An iterative algorithm for Fibonacci numbers

\[ \text{FibIter}(n) : \]
\[ \text{if } (n = 0) \text{ then return } 0 \]
\[ \text{if } (n = 1) \text{ then return } 1 \]
\[ F[0] = 0 \]
\[ F[1] = 1 \]
\[ \text{for } i = 2 \text{ to } n \text{ do} \]
\[ \quad F[i] = F[i - 1] + F[i - 2] \]
\[ \text{return } F[n] \]

What is the running time of the algorithm? \( O(n) \) additions.
An iterative algorithm for Fibonacci numbers

\[ \text{FibIter}(n): \]
\[
\begin{align*}
\text{if } (n = 0) & \text{ then } \\
\quad & \text{return } 0 \\
\text{if } (n = 1) & \text{ then } \\
\quad & \text{return } 1 \\
F[0] & = 0 \\
F[1] & = 1 \\
\text{for } i = 2 \text{ to } n & \text{ do} \\
\quad & F[i] = F[i - 1] + F[i - 2] \\
\text{return } F[n]
\end{align*}
\]

What is the running time of the algorithm?
An iterative algorithm for Fibonacci numbers

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\begin{align*}
\text{if } (n = 0) & \text{ then} & \text{return } 0 \\
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F[0] & = 0 \\
F[1] & = 1 \\
\text{for } i = 2 \text{ to } n \text{ do} & \\
& \quad F[i] = F[i - 1] + F[i - 2] \\
\text{return } F[n]
\end{align*}
\]

What is the running time of the algorithm? \(O(n)\) additions.
DP prunes recursion tree
What is the difference?

Dynamic Programming:
Finding a recursion that can be *effectively/efficiently* memoized.

Leads to polynomial time algorithm if number of distinct sub-problems is polynomial in input size.
Do we need an array of \( n \) numbers? Not really.

\[
\text{FibIter}(n):
\]
\[
\begin{align*}
\text{if } (n = 0) & \text{ then } \quad \text{return } 0 \\
\text{if } (n = 1) & \text{ then } \quad \text{return } 1 \\
prev2 & = 0 \\
prev1 & = 1 \\
\text{for } i = 2 \text{ to } n & \text{ do } \\
& \quad temp = prev1 + prev2 \\
& \quad prev2 = prev1 \\
& \quad prev1 = temp \\
\text{return } prev1
\end{align*}
\]
Dynamic Programming: Smart recursion with memoization

Dynamic Programming is not about filling tables. It is about finding a smart recursion. First, find the correct recursion. Use memoization to avoid recomputation of common solutions, hence optimizing running time and space. First, allocate a data structure (usually an array or a multi-dimensional array that can hold values for each of the subproblems). Figure out a way to order the computation of the subproblems starting from the base case. Often an iterative algorithm with bottom up computation.
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- Use memoization to avoid recomputation of common solutions, hence optimizing running time and space.
Dynamic Programming

**Dynamic Programming**: Smart recursion with memoization

- Dynamic programming is not about filling tables. It is about finding a smart recursion. First, find the correct recursion.

- Use **memoization** to avoid recomputation of common solutions, hence optimizing running time and space.
  
  - First, allocate a data structure (usually an array or a multi-dimensional array that can hold values for each of the subproblems)
  
  - Figure out a way to order the computation of the sub-problems starting from the base case.

- Often an *iterative algorithm* with *bottom up* computation.
Part II

Text Segmentation
Problem

Input A string \( w \in \Sigma^* \) and access to a language \( L \subseteq \Sigma^* \) via function \( \text{IsStrInL}(\text{string } x) \) that decides whether \( x \) is in \( L \).

Goal Decide if \( w \in L^* \) using \( \text{IsStrInL}(\text{string } x) \) as a black box sub-routine.

Example

Suppose \( L \) is \textit{English} and we have a procedure to check whether a string/word is in the \textit{English} dictionary.

- Is the string “isthisanenglishsentence” in \textit{English}*?
- Is “stampstamp” in \textit{English}*?
- Is “zibzzzad” in \textit{English}*?
Backtracking

- Changes the problem into a sequence of decision problems
- Each tries all possibilities for the current decision
- Let the recursion fairy make all remaining decisions
Text Segmentation

Backtracking

- Changes the problem into a sequence of decision problems
- Each tries all possibilities for the current decision
- Let the recursion fairy make all remaining decisions

Only the suffix matters.

HEARTHANDSATURNSPIN
Text Segmentation

Backtracking

- Changes the problem into a sequence of decision problems
- Each tries all possibilities for the current decision
- Let the recursion fairy make all remaining decisions

Only the suffix matters.

Base case

- zero-length string
Recursive Solution

Assume \( w \) is stored in array \( A[1..n] \)

\[
\text{IsStringInLstar}(A[1..n]):
\]

- If \( n = 0 \) Output YES
- If \( \text{IsStrInL}(A[1..n]) \)
  - Output YES
- Else
  - For \( i = 1 \) to \( n - 1 \) do
    - If \( \text{IsStrInL}(A[1..i]) \) and \( \text{IsStrInLstar}(A[i + 1..n]) \)
      - Output YES
  - Output NO
Recursive Solution

Assume $w$ is stored in array $A[1..n]

\[
\text{IsStringinLstar}(A[1..n]) : \\
\quad \text{If } (n = 0) \text{ Output YES} \\
\quad \text{If (IsStrInL}(A[1..n])) \\
\quad \quad \text{Output YES} \\
\quad \text{Else} \\
\quad \quad \text{For } (i = 1 \text{ to } n - 1) \text{ do} \\
\quad \quad \quad \text{If (IsStrInL}(A[1..i]) \text{ and IsStrInLstar}(A[i + 1..n])) \\
\quad \quad \quad \quad \text{Output YES} \\
\text{Output NO}
\]

**Question:** How many distinct sub-problems does $\text{IsStrInLstar}(A[1..n])$ generate?
Recursive Solution

Assume \( w \) is stored in array \( A[1..n] \)

\[
\text{IsStringInLstar}(A[1..n]) : \\
\text{If (} n = 0 \text{) Output YES} \\
\text{If (} \text{IsStrInL}(A[1..n]) \text{) Output YES} \\
\text{Else} \\
\text{For (} i = 1 \text{ to } n - 1 \text{) do} \\
\text{If (} \text{IsStrInL}(A[1..i]) \text{ and } \text{IsStrInLstar}(A[i + 1..n]) \text{) Output YES} \\
\text{Output NO}
\]

**Question:** How many distinct sub-problems does \( \text{IsStrInLstar}(A[1..n]) \) generate? \( O(n) \)
Naming subproblems

After seeing that number of subproblems is $O(n)$ we name them to help us understand the structure better.

$\text{ISL}(i)$: a boolean which is 1 if $A[i..n]$ is in $L^*$, 0 otherwise

Base case: $\text{ISL}(n + 1) = 1$ interpreting $A[n + 1..n]$ as $\epsilon$
Evaluate subproblems

Recursive relation:

- \( ISL(i) = 1 \) if \( \exists i < j \leq n + 1 \) such that (\( ISL(j) = 1 \) and \( IsStrInL(A[i..(j - 1)]) = 1 \))
- \( ISL(i) = 0 \) otherwise

Alternatively: \( ISL(i) = \max_{i < j \leq n+1} ISL(j)IsStrInL(A[i..(j - 1)]) \)
Evaluate subproblems

Recursive relation:

- \( \text{ISL}(i) = 1 \) if \( \exists i < j \leq n + 1 \) such that (\( \text{ISL}(j) = 1 \) and \( \text{IsStrInL}(A[i..(j - 1)]) = 1 \))
- \( \text{ISL}(i) = 0 \) otherwise

Alternatively: \( \text{ISL}(i) = \max_{i < j \leq n+1} \text{ISL}(j)\text{IsStrInL}(A[i..(j - 1)]) \)

Output: \( \text{ISL}(1) \)
Iterative Algorithm

**IsStringinLstar-Iterative** \((A[1..n])\):

boolean \( \text{ISL}[1..(n + 1)] \)

\[
\text{ISL}[n + 1] = \text{TRUE}
\]

for \((i = n \text{ down to } 1)\)

\[
\text{ISL}[i] = \text{FALSE}
\]

for \((j = i + 1 \text{ to } n + 1)\)

If \((\text{ISL}[j] \text{ and } \text{IsStrInL}(A[i..j - 1]))\)

\[
\text{ISL}[i] = \text{TRUE}
\]

Break

If \((\text{ISL}[1] = 1)\) Output YES

Else Output NO

Running time: \(O(n^2)\) (assuming call to \(\text{IsStrInL}\) is \(O(1)\) time)

Space: \(O(n)\)
Iterative Algorithm

**IsStringInLstar-Iterative**($A[1..n]$):

```java
boolean ISL[1..(n + 1)]
ISL[n + 1] = TRUE
for (i = n down to 1)
    ISL[i] = FALSE
    for (j = i + 1 to n + 1)
        If (ISL[j] and IsStrInL($A[i..j - 1]$))
            ISL[i] = TRUE
            Break

If (ISL[1] = 1) Output YES
Else Output NO
```

- **Running time:** $O(n^2)$ (assuming call to `IsStrInL` is $O(1)$ time)
Iterative Algorithm

**IsStringInLstar-Iterative**($A[1..n]$):

```java
boolean ISL[1..(n + 1)]
ISL[n + 1] = TRUE
for (i = n down to 1)
    ISL[i] = FALSE
    for (j = i + 1 to n + 1)
        If (ISL[j] and IsStrInL($A[i..j - 1]$))
            ISL[i] = TRUE
            Break
If (ISL[1] = 1) Output YES
Else Output NO
```

- **Running time:** $O(n^2)$ (assuming call to `IsStrInL` is $O(1)$ time)

\[
1 + 2 + \cdots + (n-1) = O(n^2)
\]
Iterative Algorithm

\textbf{IsStringinLstar-Iterative}(A[1..n]):

\begin{align*}
\text{boolean } & \text{ ISL}[1..(n + 1)] \\
\text{ISL}[n + 1] & = \text{ TRUE} \\
\text{for } (i = n \text{ down to } 1) & \\
\text{ISL}[i] & = \text{ FALSE} \\
\text{for } (j = i + 1 \text{ to } n + 1) & \\
\text{If (ISL}[j] \text{ and IsStrInL}(A[i..j - 1])) & \\
\text{ISL}[i] & = \text{ TRUE} \\
\text{Break} & \\
\end{align*}

\text{If (ISL}[1] = 1) \text{ Output YES} \\
\text{Else Output NO}

- **Running time:** $O(n^2)$ (assuming call to IsStrInL is $O(1)$ time)
- **Space:**
Iterative Algorithm

\textbf{IsStringinLstar-Iterative}(A[1..n]):

\begin{itemize}
  \item boolean ISL[1..(n + 1)]
  \item ISL[n + 1] = TRUE
  \item for (i = n down to 1)
    \item ISL[i] = FALSE
    \item for (j = i + 1 to n + 1)
      \item If (ISL[j] and IsStrInL(A[i..j – 1]))
        \item ISL[i] = TRUE
        \item Break
  \end{itemize}

If (ISL[1] = 1) Output YES
Else Output NO

- \textbf{Running time: } \(O(n^2)\)  (assuming call to \texttt{IsStrInL} is \(O(1)\) time)
- \textbf{Space: } \(O(n)\)
Find a “smart” recursion (The hard part)

1. Formulate the sub-problem
2. so that the number of distinct subproblems is small; polynomial in the original problem size.
How to design DP algorithms

1. Find a "smart" recursion (The hard part)
   1. Formulate the sub-problem
   2. so that the number of distinct subproblems is small; polynomial in the original problem size.

2. Memoization
   1. Identify distinct subproblems
   2. Choose a memoization data structure
   3. Identify dependencies and find a good evaluation order
   4. An iterative algorithm replacing recursive calls with array lookups
Part III

Longest Increasing Subsequence
Longest Increasing Subsequence Problem

Input  A sequence of numbers $a_1, a_2, \ldots, a_n$

Goal  Find an increasing subsequence $a_{i_1}, a_{i_2}, \ldots, a_{i_k}$ of maximum length
Longest Increasing Subsequence Problem

Input  A sequence of numbers $a_1, a_2, \ldots, a_n$

Goal  Find an increasing subsequence $a_{i_1}, a_{i_2}, \ldots, a_{i_k}$ of maximum length

Example

1. Sequence: 6, 3, 5, 2, 7, 8, 1
2. Increasing subsequences: 6, 7, 8 and 3, 5, 7, 8 and 2, 7 etc
3. Longest increasing subsequence: 3, 5, 7, 8
Recursive Approach: Take 1

**LIS**: Longest increasing subsequence

Can we find a recursive algorithm for **LIS**?

\[
\text{LIS}(A[1..n]):
\]

1. **Case 1**: Does not contain \( A[n] \) in which case
   \[
   \text{LIS}(A[1..n]) = \text{LIS}(A[1..(n - 1)])
   \]

2. **Case 2**: contains \( A[n] \) in which case \( \text{LIS}(A[1..n]) \) is not so clear.

**Observation**

For second case we want to find a subsequence in \( A[1..(n - 1)] \) that is restricted to numbers less than \( A[n] \). This suggests that a more general problem is \( \text{LIS}(A[1..n], x) \) which gives the longest increasing subsequence in \( A \) where each number in the sequence is less than \( x \).
Can we find a recursive algorithm for \textbf{LIS}?

\textbf{LIS}(A[1..n]):

1. \underline{Case 1:} Does not contain \textcolor{red}{A[n]} in which case
   \[ \text{LIS}(A[1..n]) = \text{LIS}(A[1..(n - 1)]) \]

2. \underline{Case 2:} contains \textcolor{red}{A[n]} in which case \textbf{LIS}(A[1..n]) is not so clear.

\textbf{Observation}

\textit{For second case we want to find a subsequence in }\textcolor{red}{A[1..(n - 1)]} \textit{that is restricted to numbers less than }\textcolor{red}{A[n]}. \textit{This suggests that a more general problem is }\textbf{LIS}_\text{smaller}(A[1..n], x) \textit{which gives the longest increasing subsequence in }A \textit{where each number in the sequence is less than }x.
Recursive Approach

\textbf{LIS}(A[1..n]): the length of longest increasing subsequence in A

\textbf{LIS\_smaller}(A[1..n], x): length of longest increasing subsequence in A[1..n] with all numbers in subsequence less than x

\begin{verbatim}
LIS\_smaller(A[1..n], x):
    if (n = 0) then return 0
    m = LIS\_smaller(A[1..(n-1)], x)
    if (A[n] < x) then
        m = max(m, 1 + LIS\_smaller(A[1..(n-1)], A[n]))
    Output m
\end{verbatim}

\begin{verbatim}
LIS(A[1..n]):
    return LIS\_smaller(A[1..n], \infty)
\end{verbatim}
Recursive Approach

```
LIS_smaller(A[1..n], x):
    if (n = 0) then return 0
    m = LIS_smaller(A[1..(n - 1)], x)
    if (A[n] < x) then
        m = max(m, 1 + LIS_smaller(A[1..(n - 1)], A[n]))
    Output m

LIS(A[1..n]):
    return LIS_smaller(A[1..n], ∞)
```

- How many distinct sub-problems will `LIS_smaller(A[1..n], ∞)` generate?
Recursive Approach

\[
\text{LIS\_smaller}(A[1..n], x) :
\]
\[
\begin{align*}
\text{if } (n = 0) \text{ then return } 0 \\
 m &= \text{LIS\_smaller}(A[1..(n - 1)], x) \\
\text{if } (A[n] < x) \text{ then} \\
 & \quad m = \max(m, 1 + \text{LIS\_smaller}(A[1..(n - 1)], A[n])) \\
\text{Output } m
\end{align*}
\]

\[
\text{LIS}(A[1..n]) :
\]
\[
\text{return LIS\_smaller}(A[1..n], \infty)
\]

- How many distinct sub-problems will \text{LIS\_smaller}(A[1..n], \infty) generate? \(O(n^2)\)
Recursive Approach

\[
\text{LIS}_{\text{smaller}}(A[1..n], x):
\begin{align*}
\text{if } (n = 0) & \text{ then return 0} \\
m & = \text{LIS}_{\text{smaller}}(A[1..(n-1)], x) \\
\text{if } (A[n] < x) & \text{ then} \\
& \quad m = \max(m, 1 + \text{LIS}_{\text{smaller}}(A[1..(n-1)], A[n])) \\
\text{Output } m
\end{align*}
\]

\[
\text{LIS}(A[1..n]): \quad \text{return } \text{LIS}_{\text{smaller}}(A[1..n], \infty)
\]

- How many distinct sub-problems will \text{LIS}_{\text{smaller}}(A[1..n], \infty) generate? \(O(n^2)\)
- What is the running time if we memoize recursion?
Recursive Approach

$$\text{LIS\_smaller}(A[1..n], x):$$

if ($n = 0$) then return 0

$m = \text{LIS\_smaller}(A[1..(n - 1)], x)$

if ($A[n] < x$) then
  $m = \max(m, 1 + \text{LIS\_smaller}(A[1..(n - 1)], A[n]))$

Output $m$

$$\text{LIS}(A[1..n]):$$

return $\text{LIS\_smaller}(A[1..n], \infty)$

- How many distinct sub-problems will $\text{LIS\_smaller}(A[1..n], \infty)$ generate? $O(n^2)$
- What is the running time if we memoize recursion? $O(n^2)$ since each call takes $O(1)$ time to assemble the answers from two recursive calls and no other computation.
Recursive Approach

**LIS\_smaller**(*A[1..n], x*):

1. **if** (*n = 0*) **then** return 0
2. \(m = \text{LIS}\_\text{smaller}(A[1..(n - 1)], x)*
3. **if** (*A[n] < x*) **then**
   - \(m = \text{max}(m, 1 + \text{LIS}\_\text{smaller}(A[1..(n - 1)], A[n]))\)
4. Output \(m\)

**LIS**(*A[1..n]*):

- return **LIS\_smaller**(*A[1..n], \(\infty\))*

- How many distinct sub-problems will **LIS\_smaller**(*A[1..n], \(\infty\)) generate? \(O(n^2)\)

- What is the running time if we memoize recursion? \(O(n^2)\) since each call takes \(O(1)\) time to assemble the answers from two recursive calls and no other computation.

- How much space for memoization?
Recursive Approach

\[
\text{LIS}_{\text{smaller}}(A[1..n], x) : \\
\quad \text{if } (n = 0) \text{ then return } 0 \\
\quad m = \text{LIS}_{\text{smaller}}(A[1..(n-1)], x) \\
\quad \text{if } (A[n] < x) \text{ then} \\
\quad \quad m = \max (m, 1 + \text{LIS}_{\text{smaller}}(A[1..(n-1)], A[n])) \\
\text{Output } m
\]

\[
\text{LIS}(A[1..n]) : \\
\quad \text{return } \text{LIS}_{\text{smaller}}(A[1..n], \infty)
\]

- How many distinct sub-problems will \text{LIS}_{\text{smaller}}(A[1..n], \infty) generate? \(O(n^2)\)
- What is the running time if we memoize recursion? \(O(n^2)\) since each call takes \(O(1)\) time to assemble the answers from two recursive calls and no other computation.
- How much space for memoization? \(O(n^2)\)
Naming subproblems and recursive equation

After seeing that number of subproblems is $O(n^2)$ we name them to help us understand the structure better. For notational ease we add $\infty$ at end of array (in position $n+1$)

$LIS(i,j)$: length of longest increasing sequence in $A[1..i]$ among numbers less than $A[j]$ (defined only for $i < j$)
How to order bottom up computation?

Base case:

\[ \text{LIS}(0, j) = 0 \] for \( 1 \leq j \leq n + 1 \)

Recursive relation:

\[ \text{LIS}(i, j) = \begin{cases} \text{LIS}(i-1, j) & \text{if } A[i] > A[j] \\ \max\{\text{LIS}(i-1, j), 1 + \text{LIS}(i-1, i)\} & \text{if } A[i] \leq A[j] \end{cases} \]
How to order bottom up computation?

Base case: \( \text{LIS}(0, j) = 0 \) for \( 1 \leq j \leq n + 1 \)
How to order bottom up computation?

Base case:  \( \text{LIS}(0, j) = 0 \) for \( 1 \leq j \leq n + 1 \)

Recursive relation:

- \( \text{LIS}(i, j) = \text{LIS}(i - 1, j) \) if \( A[i] > A[j] \)
- \( \text{LIS}(i, j) = \max\{\text{LIS}(i - 1, j), 1 + \text{LIS}(i - 1, i)\} \) if \( A[i] \leq A[j] \)
How to order bottom up computation?

Sequence: $A[1..7] = 6, 3, 5, 2, 7, 8, 1$

\[ \begin{array}{cccccc}
  & 1 & 2 & 3 & 4 & n+1 \\
 0 & 0 & 0 & 0 & 0 & 0 \\
 1 & 0 & 0 & 0 & 1 & 1 \\
 2 & 0 & 1 & 1 & 1 & 1 \\
 3 & 0 & 2 & 2 & 2 & 2 \\
 6 & 0 & 3 & 3 & 3 & 4 \\
 3 & 0 & 4 & 4 & 4 & 4 \\
 5 & 0 & 4 & 4 & 4 & 4 \\
 2 & 0 & 4 & 4 & 4 & 4 \\
 7 & 0 & 4 & 4 & 4 & 4 \\
 8 & 0 & 4 & 4 & 4 & 4 \\
 n & 0 & 4 & 4 & 4 & 4 \\
\end{array} \]
Iterative algorithm

\textbf{LIS-Iterative}(A[1..n]):

\begin{align*}
A[n + 1] &= \infty \\
\text{int } LIS[0..n, 1..n + 1] \\
\text{for } (j = 1 \text{ to } n + 1) \text{ do} \\
\quad LIS[0, j] &= 0
\end{align*}

\begin{align*}
\text{for } (i = 1 \text{ to } n) \text{ do} \\
\quad \text{for } (j = i + 1 \text{ to } n) \\
\quad\quad \text{If } (A[i] > A[j]) \quad LIS[i, j] &= LIS[i - 1, j] \\
\quad\quad \text{Else } LIS[i, j] &= \max\{LIS[i - 1, j], 1 + LIS[i - 1, i]\}
\end{align*}

Return \( LIS[n, n + 1] \)

\textbf{Running time: } \( O(n^2) \)

\textbf{Space: } \( O(n^2) \)