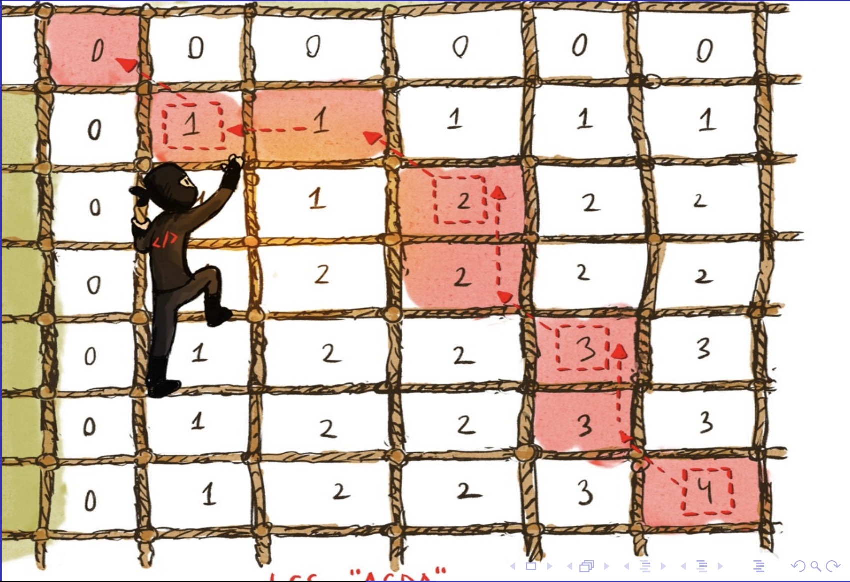
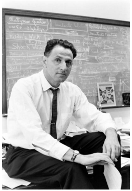
Dynamic Programming



Dynamic Programming

For a gentle introduction to DP see Chapter 6 in DPV, KT and CLRS also have a chapter devoted to DP.

Richard Bellman: *An introduction to the theory of dynamic programming* RAND, 1953



Dynamic programming is a powerful technique for efficiently implement *recursive algorithms* by storing partial results and re-using them when needed.

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- Repeated subproblems: The recursive algorithm solves a small number of distinct subproblems, but they are repeatedly solved many times.

This last property allows us to take advantage of memoization, store intermediate values, using the appropriate dictionary data structure, and reuse when needed.

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- I.e. In DP we solve all possible subproblems, while in greedy we are bound for the initial choice

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- D & C breaks a problems into a small number of subproblems each of them with size a fraction of the original size (size/b).
- In DP, we break into many subproblems with smaller size, but often, their sizes are not a fraction of the initial size.

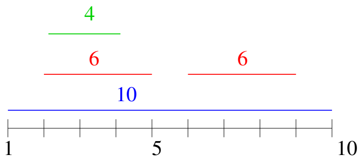
Guideline to implement Dynamic Programming

1. *Characterize the structure of subproblems:* make sure space of subproblems is not exponential. Define variables.
2. Define recursively the value of an optimal solution: Find the correct recurrence, with solution to larger problem as a function of solutions of sub-problems.
3. *Compute, memoization/bottom-up, the cost of a solution:* using the recursive formula, tabulate solutions to smaller problems, until arriving to the value for the whole problem.
4. *Construct an optimal solution:* compute additional information to trace-back an optimal solution from optimal value.

WEIGHTED ACTIVITY SELECTION problem

WEIGHTED ACTIVITY SELECTION problem: Given a set $S = \{1, 2, \dots, n\}$ of activities to be processed by a single resource. Each activity i has a start time s_i and a finish time f_i, with $f_i > s_i$, and a weight w_i. Find the set of mutually compatible activities such that it maximizes $\sum_{i \in S} w_i$

Recall: We saw that some greedy strategies did not provide always a solution to this problem.



W Activity Selection: looking for a recursive solution

- Let us think of a backtracking algorithm for the problem.
- The solution is a selection of activities, i.e., a subset $S \subseteq \{1, \ldots, n\}$.
- We can adapt the backtracking algorithm to compute all subsets.
- When processing element i, we branch
  - i is in the solution S, then all activities that overlap with i cannot be in S.
  - i is not in S.

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Each backtracking call receives a partial solution (S) and a candidate set (C), those activities that are compatible with the ones in S. It returns the weight of the best solution enlarging S.

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WAS-1 (S, C)
if $C = \emptyset$ **then**
  return $(W(S))$
Let i be an element in C; $C = C - \{i\}$;
Let A be the set of activities in C that overlap with i
return $(\max\{\textbf{WAS-1}(S \cup \{i\}, C - A), \textbf{WAS-1}(S, C)\})$

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How many subproblems appear here? hard to count better than $O(2^n)$.

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For the unweighted case, the greedy algorithm made use of a particular ordering that helped to discard overlapping tasks. Assume that the activities are sorted by finish time, i.e., $f_1 \leq f_2 \leq \cdots \leq f_n$.

- We can look to the incompatible activities that appear before activity i (finishing before t_i) when dealing with activity i.
- An incompatibility with a task j with $f_j \geq t_i$ will be discovered when dealing with task j.
- Note that activity i is not compatible with activity $j < i$ when $f_j \geq s_i$.
- Then i can be incompatible with a contiguous set of activities $i-1, i-2, \ldots, j$.

This suggest the following backtracking algorithm.

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WAS-2 (S, i)
if $i == 1$ **then**
  return $(W(S) + w_1)$
if $i == 0$ **then**
  return $(W(S))$
Let j be the largest integer $j < i$ such that $f_j \leq s_i$, 0 if none is compatible.
return $(\max\{\textbf{WAS-2}(S \cup \{i\}, j), \textbf{WAS-2}(S, i-1)\})$

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WAS-2 $(\emptyset, n)$ will return the cost of an optimal solution, as we are considering adding or not i to the solution and discarding all incompatible tasks when choosing i.

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Inside the code, we are not using S, only $W(S)$.

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WAS-3 (W, i)
if $i == 1$ **then**
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if $i == 0$ **then**
  return (W)
Let j be the largest integer $j < i$ such that $f_j \leq s_i$, 0 if none is compatible.
return $(\max\{\textbf{WAS-2}(W + w_i, j), \textbf{WAS-2}(W, i-1)\})$

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WAS-3 $(\emptyset, n)$ will return the cost of an optimal solution. Still, the algorithm has cost $O(2^n)$.

DP from WAS-3: a recurrence

- We have n activities with $f_1 \leq f_2 \leq \cdots \leq f_n$ and weights w_i, $1 \leq i \leq n$.

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- Supproblems calls WAS-3(W, i)
  - i defines the subproblem: Maximize the weight of the activity selection for activities $\{1, \ldots, i\}$, for $0 \leq i \leq n$.
  - A recursive call returns this maximum.
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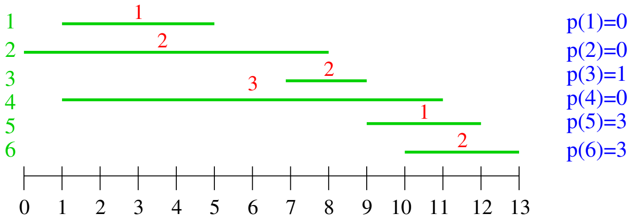
  - A recursive call returns this maximum.
  - There are only $O(n)$ subproblems!
- Let Opt(j) be the value of an optimal solution O_j to the sub problem consisting of activities in the range 1 to j.

DP from WAS-3: a recurrence

Define $p(i)$ to be the largest integer $j < i$ such that i and j are disjoints ($p(i) = 0$ if no disjoint $j < i$ exists).



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$$\mathrm{Opt}(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max\{(\mathrm{Opt}(p[j]) + w_j), \mathrm{Opt}[j-1]\} & \text{if } j \geq 1 \end{cases}$$

We add activity 0 for compatibility with p.

DP from WAS-2: a recurrence

$$\text{Opt}(j) = \begin{cases} 0 & \text{if } j = 0 \\ \max\{(\text{Opt}(p[j]) + w_j), \text{Opt}[j-1]\} & \text{if } j \geq 1 \end{cases}$$

Correctness: The base case is correct. From the previous discussion, we have two cases:

1.- $j \in O_j$:

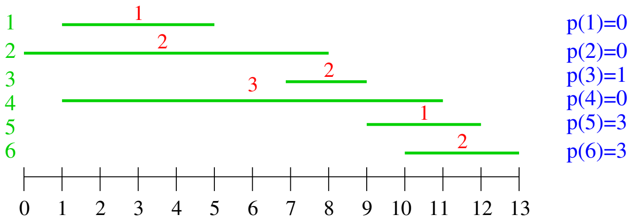
- As j is part of the solution, no jobs $\{p(j)+1, \dots, j-1\}$ are in O_j,
- $O_j - \{j\}$ must be an optimal solution for $\{1, \dots, p[j])\}$, otherwise then $O'_j = O_{p[j]} \cup \{j\}$ will be better (optimal substructure)

2.- If $j \notin O_j$: then O_j is an optimal solution to $\{1, \dots, j-1)\}$.

DP from WAS-3: Computing p values

- We need to compute efficiently $p(i)$
  - sort the activities by increasing values of start time.
  - merge the sorted list of finishing times an the sorted list of start times, in case of tie put before the finish times.
  - $p[j]$ is the last activity whose finish time precedes s_j in the combined order, activity 0, if no finish time precedes s_j
- We can thus compute the p values in $O(n \lg n + n) = O(n \lg n)$ time.

DP from WAS-3: omputing p values



Sorted finish times: 1:5, 2:8, 3:9, 4:11, 5:12, 6:13

Sorted start times: 2:0, 1:1, 4:1, 3:7, 5:9, 6:10

Merged sequence:

2:0, 1:1, 4:1,1:5,3:7,2:8,3:9,5:9,6:10, 4:11,5:12, 6:13

DP from WAS-3: Preprocessing

Considering the set of activities S, we start by a pre-processing phase:

- Sort the activities by increasing values of finish times.
- Compute the values of $p[i]$,
- This can be done in $O(n \lg n)$

DP from WAS-2: Memoization

Assuming that tasks are sorted and all $p(j)$ are computed and tabulated in $P[1 \cdots n]$

We keep a table $W[n+1]$, at the end $W[i]$ will hold the weight of an optimal solution for subproblem $\{1, \ldots, i\}$. Initially, set all entries to -1 and $W[0] = 0$.

R-Opt (j)
if $W[j]! = -1$ **then**
  return $(W[j])$
else
  $W[j] = \max(w_j + \textbf{R-Opt}(P[j])), \textbf{R-Opt}(j-1))$
  return $W[j]$

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No subproblem is solved more than once, so cost is $O(n \log + n) = O(n \log n)$

DP from WAS-3: Iterative

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Opt-Val (n)
$W[0] = 0$
for $j = 1$ to n **do**
  $W[j] = \max(W[P[j]] + w_j, W[j-1])$
return $W[n]$

Time complexity: $O(n \lg n + n)$.
Notice: Both algorithms gave only the numerical max. weight
We have to keep more info to recover a solution form $W[n]$.

DP from WAS-2: Returning an optimal solution

To get also the list of activities in an optimal solution, we use W to recover the decision taken in computing $W[n]$.

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Find-Opt (j)
if $j = 0$ **then**
  return $\emptyset$
else if $W[p[j]] + w_j > W[j-1]$ **then**
  return $(\{j\} \cup \text{Find-Opt}(p[j]))$
else
  return $(\text{Find-Opt}(j-1))$

Time complexity: $O(n)$

DP for Weighted Activity Selection

- We started from a suitable recursive algorithm, which runs $O(2^n)$ but solves only $O(n)$ different subproblemes.
- Perform some preprocesing.
- Compute the weight of an optimal solution to each of the $O(n)$ subproblems.
- Guided by optimal value, obtain an optimal solution .

0-1 Knapsack

(This example is from Section 6.4 in Dasgupta,Papadimritriou,Vazirani's book.)

0-1 KNAPSACK: Given as input a set of n items that can NOT be fractioned, item i has weight w_i and value v_i, and a maximum permissible weight W.

QUESTION: select a set of items S that maximize the profit.

Recall that we can NOT take fractions of items.

Subproblems and recurrence

Input: $(w_1, \ldots, w_n)$, $(v_1, \ldots, v_n)$, W.

- Let $S \subseteq \{1, \ldots, n\}$ be an optimal solution to the problem
  The optimal benefit is $\sum_{i \in S} v_i$

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- Let $S \subseteq \{1, \ldots, n\}$ be an optimal solution to the problem
  The optimal benefit is $\sum_{i \in S} v_i$
- With respect to the last item we have two cases:
  - $n \notin S$, then S is an optimal solution to the problem $(w_1, \ldots, w_{n-1})$, $(v_1, \ldots, v_{n-1})$, W
  - $n \in S$, then $S - \{n\}$ is an optimal solution to the problem $(w_1, \ldots, w_{n-1})$, $(v_1, \ldots, v_{n-1})$, $W - w_n$

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- in both cases we get an optimal solution of a subproblem in which the last item is removed and in which the maximum weight can be W or a value smaller than W.

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- in both cases we get an optimal solution of a subproblem in which the last item is removed and in which the maximum weight can be W or a value smaller than W.
- This identifies subproblems of the form $[i, x]$ that are knapsack instances in which the set of items is $\{1, \ldots, i\}$ and the maximum weight that can hold the knapsack is x.

Subproblems and recurrence

Let $v[i, x]$ be the maximum value (optimum) we can get from objects $\{1, 2, \ldots, i\}$ within total weight $\leq x$.

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To compute $v[i, x]$, the two possibilities we have considered give raise to the recurrence:

$$v[i, x] = \begin{cases} 0 & \text{if } i = 0 \text{ or } w = 0 \\ v[i-1, x] & \text{if } w_i > x \\ \max v[i-1, x - w_i] + v_i, v[i-1, x] & \text{otherwise} \end{cases}$$

DP algorithm: tabulating

Define a table $P[n+1, W+1]$ to hold optimal values for the corresponding subproblem.

Knapsack(i, x)
for $i = 0$ **to** n **do**
  $P[i, 0] = 0$
for $x = 1$ **to** W **do**
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for $i = 1$ **to** n **do**
  for $x = 1$ **to** W **do**
    $P[i, x] = \max\{P[i-1, x], P[i-1, x-w[i]] + v[i]\}$
return $P[n, W]$

The number of steps is $O(nW)$

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The number of steps is $O(nW)$ which is pseudopolynomial.

An example

i	1	2	3	4	5
w_i	1	2	5	6	7
v_i	1	6	18	22	28

$W = 11.$

		w											
		0	1	2	3	4	5	6	7	8	9	10	11
	0	0	0	0	0	0	0	0	0	0	0	0	0
	1	0	1	1	1	1	1	1	1	1	1	1	1
	2	0	1	6	7	7	7	7	7	7	7	7	7
I	3	0	1	6	7	7	18	19	24	25	25	25	25
	4	0	1	6	7	7	18	22	23	28	29	29	40
	5	0	1	6	7	7	18	22	28	29	34	35	40

For instance, $v[4, 10] = \max\{v[3, 10], v[3, 10 - 6] + 22\} = \max\{25, 7 + 22\} = 29.$

$v[5, 11] = \max\{v[4, 11], v[4, 11 - 7] + 28\} = \max\{40, 4 + 28\} = 40.$

Recovering the solution

To compute the actual subset $S \subseteq I$ that is the solution, we modify the algorithm to compute also a Boolean table $K[n+1, W+1]$, so that $K[i, x]$ is 1 when the max is attained in the second alternative ($i \in S$), 0 otherwise.

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Knapsack(i,x)
for $i = 0$ **to** n **do**
  $P[i,0] = 0;\ K[i,0] = 0$
for $x = 1$ **to** W **do**
  $P[0,x] = 0;\ K[0,x] = 0$
for $i = 1$ **to** n **do**
  for $x = 1$ **to** W **do**
    if $P[i-1,x] \geq P[i-1,x-w[i]] + v[i]$ **then**
      $P[i,x] = P[i-1,x]$;
      $K[i,x] = 0$
    else
      $P[i,x] = P[i-1,x-w[i]] + v[i]$;
      $K[i,x] = 1$
return $P[n,W]$

Complexity: $O(nW)$

An example

	0	1	2	3	4	5	6	7	8	9	10	11
0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
1	0 0	1 1	1 1	1 1	1 1	1 1	1 1	1 1	1 1	1 1	1 1	1 1
2	0 0	1 0	6 1	7 1	7 1	7 1	7 1	7 1	7 1	7 1	7 1	7 1
3	0 0	1 0	6 0	7 0	7 0	18 1	19 1	24 1	25 1	25 1	25 1	25 1
4	0 0	1 0	6 0	7 0	7 0	18 1	22 1	23 1	28 1	29 1	29 1	40 1
5	0 0	1 0	6 0	7 0	7 0	18 0	22 0	28 1	29 1	34 1	35 1	40 0

Recovering the solution

- To compute an optimal solution $S \subseteq I$, we use K to trace backwards the elements in the solution.
- $K[i, x]$ is 1 when the max is attained in the second alternative: $i \in S$.

Recovering the solution

- To compute an optimal solution $S \subseteq I$, we use K to trace backwards the elements in the solution.
- $K[i, x]$ is 1 when the max is attained in the second alternative: $i \in S$.

$x = W$, $S = \emptyset$
for $i = n$ **downto** 1 **do**
  if $K[i, x] = 1$ **then**
    $S = S \cup \{i\}$
    $x = x - w_i$
Output S

Complexity: $O(nW)$

An example

i	1	2	3	4	5
w_i	1	2	5	6	7
v_i	1	6	18	22	28

$W = 11.$

An example

i	1	2	3	4	5
w_i	1	2	5	6	7
v_i	1	6	18	22	28

$W = 11$.

	0	1	2	3	4	5	6	7	8	9	10	11
0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0	0 0
1	0 0	1 1	1 1	1 1	1 1	1 1	1 1	1 1	1 1	1 1	1 1	1 1
2	0 0	1 0	6 1	7 1	7 1	7 1	7 1	7 1	7 1	7 1	7 1	7 1
3	0 0	1 0	6 0	7 0	7 0	18 1	19 1	24 1	25 1	25 1	25 1	25 1
4	0 0	1 0	6 0	7 0	7 0	18 1	22 1	23 1	28 1	29 1	29 1	40 1
5	0 0	1 0	6 0	7 0	7 0	18 0	22 0	28 1	29 1	34 1	35 1	40 0

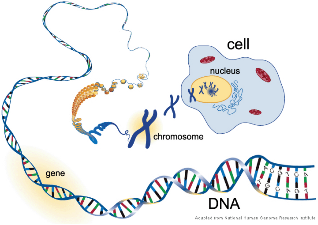
$K[5, 11] \to K[4, 11] \to K[3, 5] \to K[2, 0]$. So $S = \{4, 3\}$

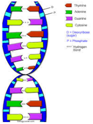
Complexity

The 0-1 KNAPSACK is NP-complete.

- 0-1 KNAPSACK, has complexity $O(nW)$, and its length is $O(n \lg M)$ taking $M = \max\{W, \max_i w_i, \max_i v_i\}$.
- If W requires k bits, the cost and space of the algorithm is $n2^k$, exponential in the length W. However the DP algorithm works fine when $W = \Theta(n)$, here $k = O(\log n)$.
- Consider the unary knapsack problem, where all integers are coded in unary (7=1111111). In this case, the complexity of the DP algorithm is polynomial on the size, i.e., UNARY KNAPSACK $\in$P.

Matching DNA sequences



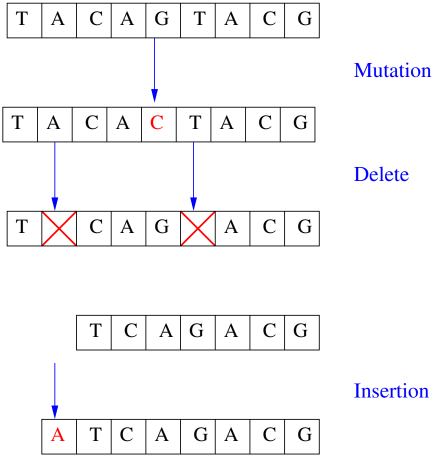


- DNA, is the hereditary material in almost all living organisms. They can reproduce by themselves.
- Its function is like a program unique to each individual organism that rules the working and evolution of the organism.
- Model as a string of 3×10^9 characters over $\{A, T, G, C\}$.

Computational genomics: Some questions

- When a new gene is discovered, one way to gain insight into its working, is to find well known genes (not necessarily in the same species) which match it closely. Biologists suggest a generalization of edit distance as a definition of approximately match.
- GenBank (`https://www.ncbi.nlm.nih.gov/genbank/`) has a collection of $> 10^{10}$ well studied genes, BLAST is a software to do fast searching for similarities between a gene an those in a DB of genes.
- Sequencing DNA: consists in the determination of the order of DNA bases, in a short sequence of 500-700 characters of DNA. To get the global picture of the whole DNA chain, we generate a large amount of DNA sequences and try to assembled them into a coherent DNA sequence. This last part is usually a difficult one, as the position of each sequence is the global DNA chain is not know before hand.

Evolution DNA



How to compare sequences?

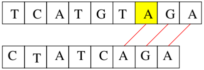
A	C	C	G	G	T	C	G	A	G	T	···

?

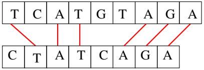
G	T	C	G	T	T	C	G	G	A	A	···

Three problems

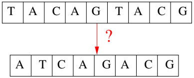
Longest common substring: Substring = consecutive characters in the string.



Longest common subsequence: Subsequence = ordered chain of characters (might have gaps).

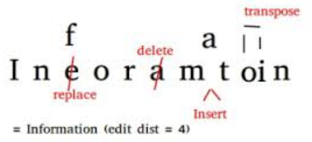


Edit distance: Convert one string into another one using a given set of operations.



The EDIT DISTANCE problem

(Section 6.3 in Dasgupta, Papadimritriou, Vazirani's book.)



The edit distance between strings $X = x_1 \cdots x_n$ and $Y = y_1 \cdots y_m$ is defined to be the minimum number of *edit operations* needed to transform X into Y.

All the operations are done on X

Edit distance: Applications

- Computational genomics: evolution between generations, i.e. between strings on $\{A, T, G, C, -\}$.
- Natural Language Processing: distance, between strings on the alphabet.
- Text processor, suggested corrections

EDIT DISTANCE: Levenshtein distance

In the Levenshtein distance the set of operations are

- insert$(X, i, a) = x_1 \cdots x_i a x_{i+1} \cdots x_n$.
- delete$(X, i) = x_1 \cdots x_{i-1} x_{i+1} \cdots x_n$
- modify$(X, i, a) = x_1 \cdots x_{i-1} a x_{i+1} \cdots x_n$.

the cost of modify is 2, and the cost of insert/delete is 1.

To simplify, in the following we assume that *the cost of each operation is 1.*

For other operations and costs the structure of the DP will be similar.

Exemple-1

$X = aabab$ and $Y = babb$

$aabab = X$

$X' = \text{insert}(X, 0, b)$ $baabab$

$X'' = \text{delete}(X', 2)$ $babab$

$X'' = \text{delete}(X'', 4)$ $babb$

$X = aabab \rightarrow Y = babb$

Exemple-1

$X = aabab$ and $Y = babb$
$aabab = X$
$X' =$insert$(X, 0, b)$ $\color{red}{b}aabab$
$X'' =$delete$(X', 2)$ $babab$
$X'' =$delete$(X'', 4)$ $babb$
$X = aabab \rightarrow Y = babb$

A shortest edit distance

$aabab = X$
$X' =$modify$(X, 1, b)$ $babab$
$Y =$delete$(X', 4)$ $babb$

Use dynamic programming.

The structure of an optimal solution

- In a solution O with minimum edit distance from $X = x_1 \cdots x_n$ to $Y = y_1 \cdots y_m$, we have three possible alignments for the last terms

(1)	(2)	(3)
x_n	$-$	x_n
$-$	y_m	y_m

- In (1), O performs delete x_n, and it transforms optimally, $x_1 \cdots x_{n-1}$ into $y_1 \cdots y_m$.
- In (2), O performs insert y_m at the end of x, and it transforms optimally, $x_1 \cdots x_n$ into $y_1 \cdots y_{m-1}$.
- In (3), if $x_n \neq y_m$, O performs modify x_n by y_m, otherwise O, aligns them without cost. Furthermore O transforms optimally $x_1 \cdots x_{n-1}$ into $y_1 \cdots y_{m-1}$.

The recurrence

Let $X[i] = x_1 \cdots x_i$, $Y[j] = y_1 \cdots y_j$.
$E[i,j] =$ edit distance from $X[i]$ to $Y[j]$ is the maximum of

- I *put y_j at the end of x*: $E[i, j-1] + 1$
- D *delete x_i*: $E[i-1, j] + 1$
- if $x_i \neq y_j$, M *change x_i into y_j*: $E[i-1, j-1] + 1$, otherwise $E[i-1, j-1]$

Edit distance: Recurrence

Adding the base cases, we have the recurrence

$$E[i,j] = \begin{cases} j & \text{if } i = 0 \text{ (converting } \lambda \to Y[j]) \\ i & \text{if } j = 0 \text{ (converting } X[i] \to \lambda) \\ \min \begin{cases} E[i-1,j]+1 & \text{if D} \\ E[i,j-1]+1, & \text{if I} \\ E[i-1,j-1]+\delta(x_i,y_j) & \text{otherwise} \end{cases} \end{cases}$$

where

$$\delta(x_i,y_j) = \begin{cases} 0 & \text{if } x_i = y_j \\ 1 & \text{otherwise} \end{cases}$$

Computing the optimal costs and pointers

Edit(X, Y)
for $i = 0$ **to** n **do**
    $E[i, 0] = i$
for $j = 0$ **to** m **do**
    $E[0, j] = j$
for $i = 1$ **to** n **do**
    for $j = 1$ **to** m **do**
        $\delta = 0$
        if $x_i \neq y_j$ **then**
            $\delta = 1$
        $E[i,j] = E[i,j-1] + 1$ $b[i,j] = \uparrow$
        if $E[i-1, j-1] + \delta < E[i,j]$ **then**
            $E[i,j] = E[i-1,j-1] + \delta,\ b[i,j] := \nwarrow$
        if $E[i-1,j] + 1 < E[i,j]$ **then**
            $E[i,j] = E[i-1,j] + 1,\ b[i,j] := \leftarrow$

Space and time complexity: $O(nm)$.

$\leftarrow$ is a I operation, $\uparrow$ is a D operation, and $\nwarrow$ is either a M or a no-operation.

Computing the optimal costs: Example

X=aabab; Y=babb. Therefore, $n = 5, m = 4$

		0	1	2	3	4
		λ	b	a	b	b
0	λ	0	$\leftarrow$ 1	$\leftarrow$ 2	$\leftarrow$ 3	$\leftarrow$ 4
1	a	$\uparrow$ 1	$\nwarrow$ 1	$\nwarrow$ 1	$\leftarrow$ 2	$\leftarrow$ 3
2	a	$\uparrow$ 2	$\nwarrow$ 2	$\nwarrow$ 1	$\leftarrow$ 2	$\leftarrow$ 3
3	b	$\uparrow$ 3	$\nwarrow$ 2	$\uparrow$ 2	$\nwarrow$ 1	$\nwarrow$ 2
4	a	$\uparrow$ 4	$\uparrow$ 3	$\nwarrow$ 2	$\uparrow$ 2	$\nwarrow$ 2
5	b	$\uparrow$ 5	$\nwarrow$ 4	$\uparrow$ 3	$\uparrow$ 2	$\nwarrow$ 2

$\leftarrow$ is a I operation, $\uparrow$ is a D operation, and
$\nwarrow$ is either a M or a no-operation.

Obtain Y in edit distance from X

Uses as input the arrays E and b.

The first call to the algorithm is **con-Edit** (n, m)

con-Edit(i, j)
if $i = 0$ or $j = 0$ **then**
  return
  if $b[i, j] = \nwarrow$ and $x_i = y_j$ **then**
    change$(X, i, y_j))$; **con-Edit**$(i-1, j-1)$
  if $b[i, j] = \uparrow$ **then**
    delete(X, i); **con-Edit**$(i-1, j)$
  if $b[i, j] = \leftarrow$ **then**
    insert(X, i, y_j), **con-Edit**$(i, j-1)$

This algorithm has time complexity $O(nm)$.

The Longest Common Subsequence

(Section 15.4 in CormenLRS' book.)

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- $Z = z_1 \cdots z_k$ is a subsequence of X if there is a subsequence of integers $1 \leq i_1 < i_2 < \ldots < i_k \leq n$ such that $z_j = x_{i_j}$.

  TTT is a subsequence of $ATATAT$.

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LCS Given sequences $X = x_1 \cdots x_n$ and $Y = y_1 \cdots y_m$, compute the longest common subsequence Z.

DP approach: Characterization of optimal solution

Let $X = x_1 \cdots x_n$ and $Y = y_1 \cdots y_m$ and let Z be a longest common subsequence (lcs). Then,

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- There are no i, j, with $i > i_k$ and $j > j_k$, s.t. $x_i = y_j$. Otherwise, Z will not be optimal.

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- There are no i, j, with $i > i_k$ and $j > j_k$, s.t. $x_i = y_j$. Otherwise, Z will not be optimal.
- $a = x_{i_k}$ might appear after i_k in X, but not after j_k in Y, or viceversa.
- There is an optimal solution in which i_k and j_k are the last occurrence of a in X and Y respectively.

DP approach: Characterization of optimal solution

Let $X = x_1 \cdots x_n$ and $Y = y_1 \cdots y_m$ and let $Z = x_{i_1} \ldots x_{i_k} = y_{j_1} \ldots y_{j_k}$ a lcs s.t. the index of the final common symbol in Z is its last occurrence in both X and Y.

DP approach: Characterization of optimal solution

Let $X = x_1 \cdots x_n$ and $Y = y_1 \cdots y_m$ and let $Z = x_{i_1} \ldots x_{i_k} = y_{j_1} \ldots y_{j_k}$ a lcs s.t. the index of the final common symbol in Z is its last occurrence in both X and Y.

Let $X^- = x_1 \cdots x_{n-1}$ and $Y^- = y_1 \cdots y_{m-1}$

DP approach: Characterization of optimal solution

Let $X = x_1 \cdots x_n$ and $Y = y_1 \cdots y_m$ and let $Z = x_{i_1} \ldots x_{i_k} = y_{j_1} \ldots y_{j_k}$ a lcs s.t. the index of the final common symbol in Z is its last occurrence in both X and Y.

Let $X^- = x_1 \cdots x_{n-1}$ and $Y^- = y_1 \cdots y_{m-1}$

- Let us look at x_n and y_m.
- If $x_n = y_m$, $i_k = n$ and $j_k = m$ so, $x_{i_1} \ldots x_{i_{k-1}}$ is a lcs of X^- and Y^-.

DP approach: Characterization of optimal solution

Let $X = x_1 \cdots x_n$ and $Y = y_1 \cdots y_m$ and let $Z = x_{i_1} \ldots x_{i_k} = y_{j_1} \ldots y_{j_k}$ a lcs s.t. the index of the final common symbol in Z is its last occurrence in X and Y.

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Let $X^- = x_1 \cdots x_{n-1}$ and $Y^- = y_1 \cdots y_{m-1}$

- Let us look at x_n and y_m.
- If $x_n \neq y_m$,
  - If $i_k < n$ and $j_k < m$, Z is a lcs of X^- and Y^-.
  - If $i_k = n$ and $j_k < m$, Z is a lcs of X and Y^-.
  - If $i_k <$ and $j_k = m$, Z is a lcs of X^- and Y.
  - The last two include the first one!

DP approach: Supproblems

Subproblems = lcs of pairs of prefixes of the initial strings.

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Notation:

- $X[i] = x_1 \dots x_i$, for $0 \leq i \leq n$
- $Y[j] = y_1 \dots y_j$, for $0 \leq j \leq m$
- $c[i, j]$ = length of the LCS of $X[i]$ and $Y[j]$.
- Want $c[n, m]$ i.e. length of the LCS for X and Y.

DP approach: Recursion

Therefore, given X and Y

$$c[i,j] = \begin{cases} 0 & \text{if } i = 0 \text{ or } j = 0 \\ c[i-1,j-1]+1 & \text{if } x_i = y_j \\ \max(c[i,j-1], c[i-1,j]) & \text{otherwise} \end{cases}$$

The recursive algorithm

LCS(X, Y)
$n = X.size(); \; m = Y.size()$
if $n = 0$ or $m = 0$ **then**
  return 0
else if $x_n = y_m$ **then**
  return $1+$**LCS**(X^-, Y^-)
else
  return $\max\{$**LCS**(X, Y^-), **LCS**$(X^-, Y)\}$

The recursive algorithm

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$n = X.size();\; m = Y.size()$
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  return 0
else if $x_n = y_m$ **then**
  return $1+$**LCS**(X^-, Y^-)
else
  return $\max\{$**LCS**(X, Y^-), **LCS**$(X^-, Y)\}$

The algorithm makes 1 or 2 recursive calls and explores a tree of depth $O(n+m)$, therefore the time complexity is $2^{O(n+m)}$.

DP: tabulating

We need to find the correct traversal of the table holding the $c[i, j]$ values.

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We need to find the correct traversal of the table holding the $c[i,j]$ values.

- Base case is $c[0,j]=0$, for $0 \leq j \leq m$, and $c[i,0]=0$, for $0 \leq i \leq n$.
- To compute $c[i,j]$, we have to access

$c[i-1,j-1]$	$c[i-1,j]$
$c[i,j-1]$	$c[i,j]$

  A row traversal provides a correct ordering.
- To being able to recover a solution we use a table b, to indicate which one of the three options provided the value $c[i,j]$.

Tabulating

LCS(X, Y)
for $i = 0$ **to** n **do**
  $c[i, 0] = 0$
for $j = 1$ **to** m **do**
  $c[0, j] = 0$
for $i = 1$ **to** n **do**
  for $j = 1$ **to** m **do**
    if $x_i = y_j$ **then**
      $c[i, j] = c[i-1, j-1] + 1,\ b[i.j] = \nwarrow$
    else if $c[i-1, j] \geq c[i, j-1]$ **then**
      $c[i, j] = c[i-1, j],\ b[i, j] = \leftarrow$
    else
      $c[i, j] = c[i, j-1],\ b[i, j] = \uparrow$.

complexity:
$T = O(nm)$.

Example.

X=(ATCTGAT); Y=(TGCATA). Therefore, $m = 6, n = 7$

		0	1 T	2 G	3 C	4 A	5 T	6 A
0		0	0	0	0	0	0	0
1	A	0	↑0	↑0	↑0	↖1	←1	↖1
2	T	0	↖1	←1	←1	↑1	↖2	←2
3	C	0	↑1	↑1	↖2	←2	↑2	↑2
4	T	0	↖1	↑1	↑2	↑2	↖3	←3
5	G	0	↑1	↖2	↑2	↑2	↑3	↑3
6	A	0	↑1	↑2	↑2	↖3	↑3	↖4
7	T	0	↖1	↑2	↑2	↑3	↖4	↑4

Following the arrows: TCTA

Construct the solution

Access the tables c and d.
The first call to the algorithm is **sol-LCS**(n, m)

sol-LCS(i, j)
if $i = 0$ or $j = 0$ **then**
  STOP.
else if $b[i, j] = \nwarrow$ **then**
  sol-LCS$(i - 1, j - 1)$
  return x_i
else if $b[i, j] = \uparrow$ **then**
  sol-LCS$(i - 1, j)$
else
  sol-LCS$(i, j - 1)$

The algorithm has time complexity $O(n + m)$.

Longest common substring

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- LCSt: Given two strings $X = x_1 \ldots x_n$ and $Y = y_1 \ldots y_m$, compute their longest common substring Z, i.e., the largest k for which there are indices i and j with $x_i x_{i+1} \ldots x_{i+k} = y_j y_{j+1} \ldots y_{j+k}$.

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- For example:
  X : DEADBEEF
  Y : EATBEEF
  Z :

Longest common substring

- A slightly different problem with a similar solution
- LCSt Given two strings $X = x_1 \ldots x_n$ and $Y = y_1 \ldots y_m$, compute their longest common substring Z, i.e., corresponding to the largest k for which there are indices i and j with $x_i x_{i+1} \ldots x_{i+k} = y_j y_{j+1} \ldots y_{j+k}$.
- For example:
  X : DEADBBEEF
  Y : EATBEEF
  Z :

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- For example:
  X : DEADBBEEF
  Y : EATBEEF
  Z : BEEF pick the longest substring

Characterization of optimal solution

- Let $X = x_1 \cdots x_n$ and $Y = y_1 \cdots y_m$ and let Z be a longest common substring.
  - $Z = x_i \ldots x_{i+k} = y_j \ldots y_{j+k}$

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- We can consider the subproblems $LCStf(i,j)$: compute the longest common suffix of $X(i)$ and $Y(j)$.
- The $LCSf(X, Y)$ is the longest of such common suffixes.

Computing the LC Suffixes

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- Can we do it faster? Let us use DP!

A recursive solution for LC Suffixes

Notation:

- $X[i] = x_1 \dots x_i$, for $0 \leq i \leq n$
- $Y[j] = y_1 \dots y_j$, for $0 \leq j \leq m$
- $s[i, j]$ = the length of the LC Suffix of $X[i]$ and $Y[j]$.
- Want $\max_{i,j} s[i, j]$ i.e., the length of the LCSt of X, Y.

DP approach: Recursion

Therefore, given X and Y

$$s[i,j] = \begin{cases} 0 & \text{if } i = 0 \text{ or } j = 0 \\ 0 & \text{if } x_i \neq y_j \\ s[i-1, j-1] + 1 & \text{if } x_i = y_j \end{cases}$$

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Using the recurrence the cost per recursive call (or per element in the table) is constant

Tabulating

LCSf(X, Y)
for $i = 0$ **to** n **do**
    $s[i, 0] = 0$
for $j = 1$ **to** m **do**
    $s[0, j] = 0$
for $i = 1$ **to** n **do**
    for $j = 1$ **to** m **do**
        s[i,j]=0
        if $x_i = y_j$ **then**
            $s[i, j] = s[i-1, j-1] + 1$

complexity: $O(nm)$.

Which gives an algorithm with cost $O(nm)$ for LCSt