Edit distance String edit distance nal Linguistics III . In many applications, we want to know how similar (or different) two string Data Structures and Algorithms for Com- Comparing two files (e.g., source code)
 Comparing two DNA sequences
 Spell checking Çağrı Çöltekin ccoltekin@sfs.uni-tuebingen.de Spell checking Approximate string ma Determining similarity matching rity of two languages - Machine translation * The solution is typically formulated as the (inverse) cost of obtaining one of the strings from the other through a number of edit operation. Winter Semester 2023/24 Once we obtain the optimal edit operations, we may (depending on the edit operations) also be able to determine the optimal alignment between the A family of edit distance problems Hamming distance The same overall idea applies to a number of well-knothat differ in the type of operations allowed The Hamming distance measures number of different symbols in the corresponding positions nate causer in site types or operations amounted.

Hamming distance only replacements

Langust common subsequence. (LCS) insortions and deletions

Leronsteiral distance insertions, deletions and substitutions

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Leronsteiral binneran distance insertions, deletions and substitutions and transpositions (ewap) of allocatent symbols h y g i e n e h y g i e n e h i y g e i n · Naive solutions to all (except Hamming distance) have exponential time complexity But cannot handle sequences of different lengths (consider lugger) . Polynomial-time solution can be obtained using durantic reservanting Longest common subsequence (LCS) LCS: a naive solution A subsequence is an order-preserving (but not necessarily contiguous) sequence of symbols from a string (a version of the sequence where zero or · A simple solution is Enumerate all subsequences of the first string
 Check if it is also a subsequence of the second str more elements are removed)

- hyg, gn, yenr, hen, gene are subsequences of hygiene

Note that a subsequence does not have to be a substring (substrings are There are exponential number of subsequences of a string - the string alc has 8 subsequences: contiguous)

- hyg, gime, one are substrings of hygime - tim string are tase o stateoqueroos:

- shr. rothing removed

- sh., s. freelevidual elements are removed

- For sh. s., s. freelevidual elements are removed

- For sh. s., s. freelevidual elements are decided to the second and second are second as the second are The LCS of two strings is the longest string that is a subsequence of both strings
- LDS(hygiane, hiygian) - hygian
- LDS(hygiane, hygian) - hygiae / hygene
- LDS is exactly the problem solved by the UNIX diff utility . For strings of size n and m, the complexity of the brute-force algorithm is O(2ⁿm) It has wide-ranging applications from s bioinformatics (e.g., DNA sequencing) LCS: recursive definition LCS: divide-and-conquer * Consider two strings Xx, Yy and their LCS Zz (X, Y, Z are possibly empty _ab-ab b a-a c-c strings, x, y, z are characters) If x = y, then this character has to be part of the LCS, x = y = z, and Z must be the LCS of X and Y cde-abec = abcd-abec = aboa aboe $= abca = abca = a \cdot a \xrightarrow{a} c \cdot c$ $= abcd \cdot c$ $= abcd \cdot c$ If x ≠ y, there are three case. $-x \neq y \neq z$ Zz is also the LCS of X and Y -x = z Zz is also the LCS of Xx and Y -y = z Zz is also the LCS of X and Yy · This leads to following recursive definition $LCS(Xx,Yy) = \begin{cases} LCS(X,Y)x & \text{if } x = y \\ longer of LCS(Xx,Y) \text{ and } LCS(X,Yy) & \text{otherwise} \end{cases}$. Note the repeated computat LCS: dynamic programming LCS with dynamic programming + To calculate LCS($X_{:i},Y_{:j}$), the LCS of string X up to index i, and the LCS of string Y up to index j, we (may) need
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 - $LCS(X_{i-1}, Y_{i-1})$ - LCS(X_{i-1}, Y_{ij}) - LCS(X_i, Y_{i-1}) * If we store the above three values, we need only $i\times j$ operations In the standard dynamic programming algorithm, we store the length of the LCS, in a matrix ℓ, where ℓ_{i,j} is the length of the LCS(X_i, Y_{ij}) + Once we fill in the matrix, the $\ell_{n,m}$ is the length of the LCS 6 n 0 1 2 2 3 4 4 5 5 7 e 0 1 2 2 3 4 4 5 6 . We can trace back and recover the LCS using the dynamic progra matrix Recovering the LCS from the matrix Complexity of filling the LCS matrix 0 1 2 2 5 c h i y g e i n e 0 [1 h 0 1+-1, 1 1 1 1 2 y 0 1 1 2 2 2 2 2 2 3 8 0 1 1 2 3 ÷ -3 3 3 3 3 else: l[i, j] = max(l[i-1, j], l[i, j-1]) 4 1 0 1 2 2 3 3 4 4 4 5 e 0 1 2 2 3 4 4 4 5 * Two loops up to $\mathfrak n$ and $\mathfrak m$, the time complexity is $O(\mathfrak n\mathfrak m)$ + Similarly, the space complexity is also $O(\pi m)$ n 0 1 2 2 3 4 4 5 5 7 e 0 1 2 2 3 4 4 5 6

Transforming one string to another LCS alignments 0 1 2 3 4 5 6 c h i y g e i n e The table (back arrows) also gives a set of edit operations to transtring to another 0 6 0 0 0 0 0 0 0 . For LCS, operations are h 0 14-1, 1 1 1 1 1 1 - cory (diagonal arrows in the de-2 2 2 2 2 2 2 2 3 3 3 3 2 y 0 1 2 insert (left arrows in the demo – assuming original string is the vertical one)
 delete (up arrows in the demo) hiygei-ne g 0 3 1 1 3 4 3 These also form an alignment between two strings 4 Different set of edit operations recovered will yield the same LCS, but e 0 1 2 2 3 4 4 4 hiyg-eine different alignments 5 n 0 1 2 2 3 4 4 5 e 0 1 2 2 3 4 4 5 6 Levenshtein distance LCS - some remarks . Levenshtein difference between two strings is the total cost of insertion + We formulated the algorithm as maximizing the LCS deletions and substitut Alternatively, we can minimize the costs associated with each operation: · With cost of 1 for all operations - copy = 0 - delete = [len(X) if len(Yy) = 0 if len(Xx) = 0. The cost settings above are the typical, e.g., as in diff $lev(Xx, Yy) = \begin{cases} lev(X, Y) \end{cases}$ if x = y In some applications we may want to have different costs for delete and in (e.g., mapping lemmas to inflected forms of words) Similarly, we may want to assign different costs for differ higher cost to delete consonants in historical linguistics) · Naive recursion (as defined above), again, is intractable . But, the same dynamic programming method works Levenshtein distance Louonehtoin dietanco 2 c h i y g e i n e c 0 1 2 3 4 5 6 7 8 h 1 0 1 2 3 4 5 6 7 y 2 1 1 1 2 3 4 5 6 y 2 1 1 1 2 g 3 2 2 2 1 i 4 3 2 3 e 5 4 3 3 3 2 3 3 n 6 5 4 4 4 3 3 3 3 Summary Edit distance: extensions and variations * Edit distance is an important problem in many fields including computational linguistics . Another possible operation we did not cover is some (or transpose), which is A number of related problems can be efficiently solved by dyn useful for applications like spell checking programming . In some applications (e.g., machine translation, OCR correction) we may Edit distance is also important for approximate string matching and aligns want to have one-to-many or many-to-one alignments Reading suggestion: Goodrich, Tamassia, and Goldwasser (2013, chapter 13), Jurafsky and Martin (2009, section 3.11, or 2.5 in online draft) · Additional requirements often introduce additional complexity It is sometimes useful to learn costs from data Next · Algorithms on strings: tries * Reading: Goodrich, Tamassia, and Goldwasser (2013, chapter 13), Acknowledgments, credits, references Goodrich, Michael T., Roberto Tamassia, and Michael H. Goldwasser (2013). Data Structures and Algorithms in Pathon. John Wiley & Sons, Incorporated. ss

