

## Dynamic Programming

### Edit distance and its variants

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Lecture 17

Some slides created by or adapted from Dr. Kevin Wayne. For more information see

<http://www.cs.princeton.edu/~wayne/kleinberg-tardos>. Some code reused from [Python Algorithms](#) by Magnus Lie Hetland.

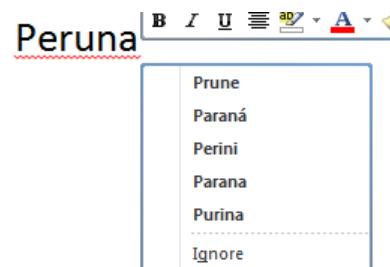
## Edit distance

- Misspellings make approximate pattern matching an important problem
- If we are to deal with inexact string matching, we must first define a cost function telling us how far apart two strings are, i.e., a distance measure between pairs of strings.
- The edit distance is the minimum number of changes required to convert one string into another

## String edit operations

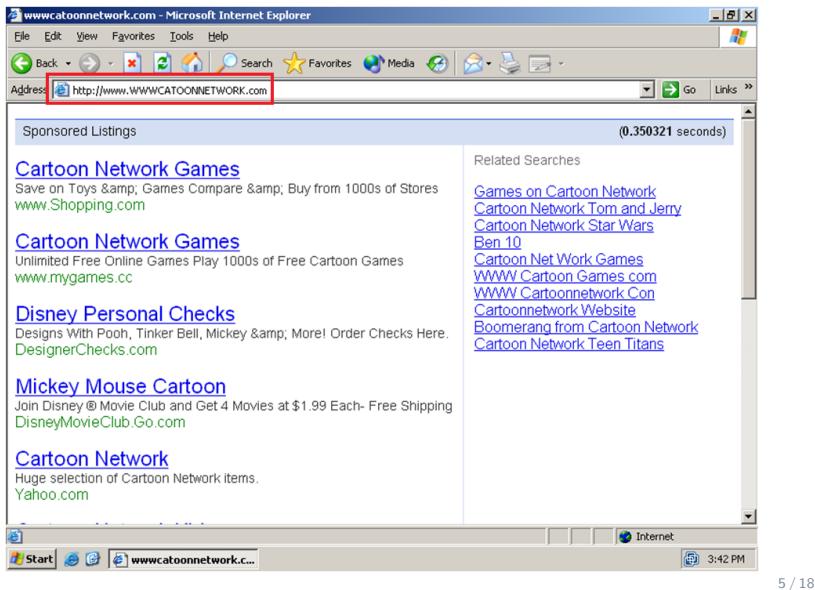
- We consider three types of changes to compute edit distance:
  - ① Substitution: Change a single character from pattern  $s$  to a different character in text  $t$ , such as changing “shot” to “spot”
  - ② Insertion: Insert a single character into pattern  $s$  to help it match text  $t$ , such as changing “ago” to “agog”.
  - ③ Deletion: Delete a single character from pattern  $s$  to help it match text  $t$ , such as changing “hour” to “our”
- This definition of edit distance is also called Levenshtein distance
- Can you think of any other natural changes that might capture a single misspelling?

## Edit distance application #1



- Spell checkers identify words in a dictionary with close edit distance to the misspelled word
- But how do they order the list of suggestions?

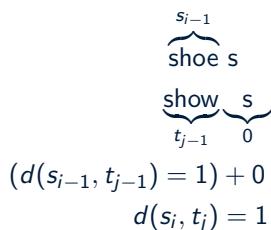
## Edit distance application #2



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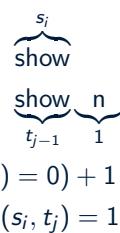
## Edit distance: recursive algorithm design

- Match: no substitutions



$$(d(s_{i-1}, t_{j-1}) = 1) + 0 \\ d(s_i, t_j) = 1$$

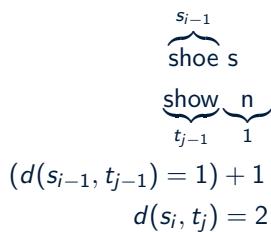
- Insertion



$$(d(s_i, t_{j-1}) = 0) + 1$$

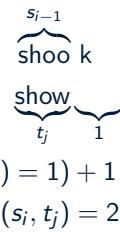
$$d(s_i, t_j) = 1$$

- Match: substitution



$$\begin{aligned} (d(s_{i-1}, t_{j-1}) = 1) + 1 \\ d(s_i, t_j) = 2 \end{aligned}$$

- Deletion



$$\begin{aligned} (d(s_{i-1}, t_j) = 1) + 1 \\ d(s_i, t_j) = 2 \end{aligned}$$

## Recursive edit distance code

```

def string_compare(s,t):
    #start by prepending empty character to check 1st char
    s = "_" + s
    t = "_" + t
    P = {}
    @memo
    def edit_dist(i,j):
        if i==0: return j
        if j==0: return i
        #case 1: check for match at i and j
        if s[i]==t[j]: c_match = edit_dist(i-1,j-1)
        else: c_match = edit_dist(i-1,j-1)+1
        #case 2: there is an extra character to insert
        c_ins = edit_dist(i,j-1)+1
        #case 3: there is an extra character to remove
        c_del = edit_dist(i-1,j)+1
        return min(c_match,c_ins,c_del)
    return edit_dist(len(s)-1,len(t)-1)

```

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## Towards a dynamic programming alternative

- We note that there are only  $|s|$  possible values for  $i$  and  $|t|$  possible values for  $j$  when invoking `edit_dist(i, j)` recursively
- This means there are at most  $|s| \cdot |t|$  recursive function calls to cache in an iterative version
- The table is a two-dimensional matrix  $C$  where each of the  $|s| \cdot |t|$  cells contains the cost of the optimal solution of this subproblem
- We just need a clever way to calculate the cost for each entry based on only a small subset of already-computed values.

## Evaluation order

- To determine the value of cell  $(i, j)$  we need three values to already be computed: the cells  $(i - 1, j - 1)$ ,  $(i, j - 1)$ , and  $(i - 1, j)$ .
- Any evaluation order with this property will do, including the row-major order used in the upcoming code
- But there are plenty of other valid orderings
- Think of the cells as vertices, where there is an edge  $(i, j)$  if cell  $i$  value is needed to compute cell  $j$ . Any topological sort of this DAG provides a proper evaluation order.

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## Edit distance: dynamic programming code

```
def iter_string_compare_lists(s, t):  
    C, s, t = [], "—" + s, "—" + t #prepend empty character for edge case  
    C.append(range(len(t) + 1)) #initialize cost data structure  
    for i in range(len(s)):  
        C.append([i + 1])  
    for i in range(1, len(s)): #go through all characters of s  
        for j in range(1, len(t)):  
            #case 1: check for match at i and j  
            if s[i] == t[j]: c_match = C[i - 1][j - 1]  
            else: c_match = C[i - 1][j - 1] + 1  
            #case 2: there is an extra character to insert  
            c_ins = C[i][j - 1] + 1  
            #case 3: there is an extra character to remove  
            c_del = C[i - 1][j] + 1  
            c_min = min(c_match, c_ins, c_del)  
            C[i].append(c_min)  
    return C[i][j]
```

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## Edit distance: DP with cost table as dictionary

```
def iter_string_compare(s, t):  
    C, s, t = {}, "—" + s, "—" + t #prepend empty character for edge case  
    for j in range(len(t)): #initialize cost data structure  
        C[0, j] = j  
    for i in range(1, len(s)):  
        C[i, 0] = i  
    for i in range(1, len(s)): #go through all chars of s  
        for j in range(1, len(t)):  
            #case 1: check for match at i and j  
            if s[i] == t[j]: c_match = C[i - 1, j - 1]  
            else: c_match = C[i - 1, j - 1] + 1  
            #case 2: there is an extra character to insert  
            c_ins = C[i, j - 1] + 1  
            #case 3: there is an extra character to remove  
            c_del = C[i - 1, j] + 1  
            c_min = min(c_match, c_ins, c_del)  
            C[i, j] = c_min  
    return C[i, j]
```

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## Building edit distance cache

s: run  
t: drain

C	-	d	r	a	i	n
-	0	← 1 ↙ 1	← 2	← 3	← 4	← 5
r	↑ 1	↖ 1	↖ 1 ↙ 1	↖ 2	↖ 3	↖ 4
u	↑ 2	↖ 2	↖ 2	↖ 2 ↙ 2	↖ 3 ↙ 3	↖ 4
n	↑ 3	↖ 3	↖ 3	↖ 3	↖ 3	↖ 3 ↙ 3

Steps to turn "run" into "drain"

- ① Insert d
- ② Keep r
- ③ Substitute a for u
- ④ Insert i
- ⑤ Keep n

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## Edit distance exercises

- Build cost table by hand following DP algorithm
  - ① s: bear, t: pea
  - ② s: farm, t: for
- Performance cost of DP edit distance
  - Operations:  $\Theta(|s| \cdot |t|)$
  - Storage:  $\Theta(|s| \cdot |t|)$

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## Variation of edit distance: approximate substring matching

- Suppose we want to find the best close match to a smaller word in a larger string (e.g., find the closest match to "Tulsa" in "SMU Tulda Rice")
- We need to modify our existing code in two ways
  - ① Cost table initialization: all starting costs  $C[0,j]$  should be set to 0
  - ② Return the finishing cell  $C[i,k]$  that minimizes the overall cost

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## Substring matching code

```
def iter_substring_match(s,t):
    C,s,t = {}," "+s," "+t #prepend empty character for edge case
    for j in range(len(t)): #initialize cost data structure
        C[0,j]=0 #changed: ignore cost of preceding unmatched text
    for i in range(1,len(s)):
        C[i,0]=i
    for i in range(1,len(s)): #go through all chars of s
        for j in range(1,len(t)):
            #case 1: check for match at i and j
            if s[i]==t[j]: c_match = C[i-1,j-1]
            else: c_match = C[i-1,j-1]+1
            #case 2: there is an extra character to insert
            c_ins = C[i,j-1]+1
            #case 3: there is an extra character to remove
            c_del = C[i-1,j]+1
            c_min=min(c_match,c_ins,c_del)
            C[i,j]=c_min
    finj = min([(C[i,k],k) for k in range(1,len(t)-1)])
    return "with edit dist %i, %s morphs into %s finishing at position %i" % (finj[0], s, t, finj[1])
```

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## Excercise: substring matching cache

s: Tulsa

t: SMU Tulta Rice

c	-	S	M	U	-	T	u	l	d	a	-	R	i	c	e
-	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
T	↑1	↑1	↑1	↑1	↑1	↑0	↑1	↑1	↑1	↑1	↑1	↑1	↑1	↑1	↑1
u	↑2	↑2	↑2	↑2	↑2	↑1	↖0	↖1	↑2	↑2	↑2	↑2	↑2	↑2	↑2
l	↑3	↑3	↑3	↑3	↑3	↑2	↑1	↖0	↖1	↖2	↖3	↑3	↑3	↑3	↑3
s	↑4	↑4	↑4	↑4	↑4	↑3	↑2	↑1	↖1	↖2	↖3	↑4	↑4	↑4	↑4
a	↑5	↑5	↑5	↑5	↑5	↑4	↑3	↑2	↖2	↖1	↖2	↖3	↖4	↑5	↑5

Substring ending at position 9 ("Tulda") is the closest substring to "Tulsa"

## Variation of edit distance: longest common subsequence

- We might want to find the longest scattered sequence of characters within both strings
- For example, the longest common subsequence of "republican" and "democrat" is "eca"
- To get the longest subsequence, we can still allow insertions and deletions, but substitutions are forbidden
- We can change the edit distance code to behave as before on matches where the last characters are the same, but never select a substitution