

**CS 181:
NATURAL LANGUAGE
PROCESSING**

*Lecture 4: Dynamic Programming &
Minimum String Edit Distance*

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Disclaimer: Slide contents borrowed from many sources on web!

CATCHING TYPOS

- Recognizing misspellings easy - check dictionary
 - But lots of suffixes and prefixes: use fsa!
- What about making corrections to isolated words?
 - Look for spellings that are “close” to word
- Context-dependent errors detection/correction
 - Transpositions may accidentally create real words!

SPELLING CORRECTION

- Map words into equivalence classes that likely hold correct spelling.
 - CS 51 lab: canonize words by removing vowels and doubled consonants: canonize lab
 - Find all words w/same canonization as word.
- Alternatively, develop metric and find real world closest to word.
 - Use minimum edit distance

MINIMUM EDIT DISTANCE

- Can convert any word to another by series of additions, deletions, and substitutions.
 - Once specify cost of each operation then can measure distance between them
 - We'll use 1 for cost of addition/deletion, 2 for substitution.
 - Use same algorithm if choose different costs, but get different answer.

EXAMPLE

- Convert “INTENTION” to “EXECUTION”
- INTENTION

EXAMPLE

- Convert “INTENTION” to “EXECUTION”
- N TENTION *delete I*

cost = 1

EXAMPLE

- ⊛ Convert "INTENTION" to "EXECUTION"
- ⊛ *ETENTION* *subst E for N*

cost = 3

EXAMPLE

- ⊛ Convert "INTENTION" to "EXECUTION"
- ⊛ *EXENTION* *subst X for T*

cost = 5

EXAMPLE

- ⊛ Convert "INTENTION" to "EXECUTION"
- ⊛ *EXECTION* *subst C for N*

cost = 7

EXAMPLE

- ⊛ Convert "INTENTION" to "EXECUTION"
- ⊛ *EXECUTION* *insert U*

cost = 8

OPTIMALITY

- ⊛ How can we know if that is the minimal edit distance?
- ⊛ Check all possible conversions? Too many!

SOLVING PROBLEMS

- ⊛ Optimal substructure property: The optimal solutions to a problem contain optimal solutions to its subproblems.
- ⊛ Ex: Shortest distance from LA to NYC
 - ⊛ If shortest path goes through Chicago then portion of the path from LA to Chicago and from Chicago to NYC are also optimal.

DYNAMIC PROGRAMMING

- If problem has overlapping subproblems (solve same problem repeatedly) & optimal substructure property then can use dynamic programming.
- Key idea is to save solutions to subproblems so don't have to recalculate
 - Memoization!
- Can do top-down or bottom-up
 - We'll do bottom-up

MINIMUM EDIT DISTANCE

- What is minimal cost of transforming v to w ?
- Transform to problem with subproblems.
- Define $\text{distance}[i,j]$ to be min cost of transforming $v[1..j]$ to $w[1..i]$
- Does it satisfy optimal substructure property?
- Does it have overlapping subproblems?

MINIMUM EDIT DISTANCE

- Let $|v| = m, |w| = n$
- Consider last move in aligning. 3 choices:
 - Add move: Take moves changing v to $w[1:n-1]$ & insert $w[n]$
 - Delete move: Take moves changing $v[1:m-1]$ to w & delete $v[m]$
 - Replace move: Take moves changing $v[1:m-1]$ to $w[1:n-1]$ & change $v[m]$ to $w[n]$

MINIMUM EDIT DISTANCE

- Recursive solution:

$$\text{distance}[i,j] = \min \begin{cases} \text{distance}[i-1,j] + \text{ins_cost}(w_i) \\ \text{distance}[i-1,j-1] + \text{sub_cost}(w_i, v_j) \\ \text{distance}[i,j-1] + \text{del_cost}(v_j) \end{cases}$$

$\text{ins_cost} = 1$

$\text{del_cost} = 1$

$\text{sub_cost} = 0$ if $w_i = v_j$, 2 otherwise

DISTANCE[I,J]

	#	P	A	R	K
#	0	1	2	3	4
S	1	2	3	4	5
P	2	1	2	3	4
A	3	2	1	2	3
N	4	3	2	3	4
K	5	4	3	4	3

Recover edits from table

```
def minEditDist(target, source):
```

```
    n = len(target)
```

```
    m = len(source)
```

```
    # m+1 rows, n+1 cols
```

```
    distance = [[0 for i in range(n+1)] for j in range(m+1)]
```

```
    for col in range(1, n+1):
```

```
        distance[0][col] = distance[0][col-1] + 1
```

```
    for row in range(1, m+1):
```

```
        distance[row][0] = distance[row-1][0] + 1
```

```
    for col in range(1, n+1):
```

```
        for row in range(1, m+1):
```

```
            distance[row][col] = min(
```

```
                distance[row-1][col] + 1,
```

```
                distance[row][col-1] + 1,
```

```
                distance[row-1][col-1] + substCost(source[row-1], target[col-1]))
```

```
    return distance[m][n]
```

VARIANTS & IMPROVEMENTS

- ⊛ Needleman-Wunch distance: cost of substitution varies depending on characters
 - ⊛ E.g., distance btm characters nearby is less
- ⊛ Want to match names: Kim Barry Bruce, Kim B. Bruce, K. B. Bruce, Kim Bruce, K. Bruce.
 - ⊛ One idea: n character gap costs less than n gaps of length 1.

N-GRAMS

N-GRAMS

- ⊛ N-gram is sequence of N words that occur sequentially in text
- ⊛ Determine probabilities of N-grams
- ⊛ Use to predict which word is most likely to be correct in context.
- ⊛ Can help in spelling correction

USING CONTEXT

- ⊛ Spell-checking:
 - ⊛ They are leaving in about 15 minuets.
- ⊛ Part of speech tagging
 - ⊛ Which meaning of “dogs”
- ⊛ Machine translation
- ⊛ Speech & handwriting recognition
 - ⊛ Compare possible word decodings
- ⊛ Authorship identification

WHICH IS MOST PROBABLE?

- ⊛ First Example:
 - ⊛ ... I think they're OK ...
 - ⊛ ... I think there OK ...
 - ⊛ ... I think their OK ...
- ⊛ Second Example:
 - ⊛ ... by the way, are they're likely to ...
 - ⊛ ... by the way, are there likely to ...
 - ⊛ ... by the way, are their likely to ...

WHICH IS MOST PROBABLE?

- ⊛ Third Example:
 - ⊛ How do you wreck a nice beach?
 - ⊛ How do you recognize speech?
- ⊛ Fourth Example:
 - ⊛ Put the file in the folder
 - ⊛ Put the file and the folder

COUNTING WORDS

- * Types vs Tokens
 - * “They picnicked by the pool, then lay back on the grass and looked at the stars”
 - * 16 tokens, 14 types
 - * Shakespeare: 884,647 tokens, 29,006 types
 - * Also interested in number of lemmas
 - * Remove affixes

LANGUAGE MODELS

- * Develop a “language model” to help us predict the likelihood of strings.
- * In English:
 - * $P(\text{the big dog}) > P(\text{dog big the}) > P(\text{dog gib etb})$
- * How can the computer know this?
- * Each sentence is sequence w_1, \dots, w_n
- * How determine $P(w_1, \dots, w_n)$

N-GRAMS

- * Computes a probability for observed input
- * Probability is likelihood of observation being generated by same source as training data.
- * Different models arise from different training sets: English vs. French
- * Problems!

ANY QUESTIONS?