CS 4248 Natural Language Processing

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Spelling Errors

- Three increasingly broader problems:
 - Non-word error detection
 - E.g., detecting graffe (misspelling of giraffe)
 - Isolated-word error correction
 - Consider a word in isolation
 - E.g., correcting *graffe* to *giraffe*
 - Context-sensitive error detection and correction
 - Use of context to detect and correct spelling errors
 - Real-word errors
 - there for three, dessert for desert, piece for peace

Spelling Error Patterns

- Most misspelled words in human typewritten text are single-error misspellings
- Single-error misspellings:
 - Insertion: mistyping the as ther
 - Deletion: mistyping the as th
 - Substitution: mistyping the as thw
 - Transposition: mistyping the as hte

Assume:

- Detect and correct non-word spelling errors
- No use of context

• Two steps:

- Propose candidates of correctly spelled words
- Score the candidates

- Proposing candidates of correctly spelled words:
 - Need a large dictionary of words (correctly spelled)
 - Assume single-error misspellings (one insertion, deletion, substitution, or transposition)

Example:

Error	Correction	Type (w.r.t. correction)
acress	actress	deletion
acress	cress	insertion
acress	caress	transposition
acress	access	substitution
acress	across	substitution
acress	acres	insertion
acress	acres	insertion

Example:

- Given a mis-spelled word acress (observation o)
- Determine whether the correct word is *actress*, *cress*, or *acres* (class c_1 , c_2 , c_3)
- Use Bayesian classification

Bayesian Classification

- Problem: Given an observation o and a set of classes C, infer the class c ∈ C that o belongs to
- Choose the class c which is the most probable given the observation o

$$\hat{c} = \arg\max_{c \in C} P(c \mid o)$$

Bayesian Classification

$$\hat{c} = \underset{c \in C}{\operatorname{arg\,max}} P(c \mid o)$$

$$= \underset{c \in C}{\operatorname{arg\,max}} \left\{ \frac{P(o \mid c) \cdot P(c)}{P(o)} \right\}$$
 Bayes' Theorem
$$= \underset{c \in C}{\operatorname{arg\,max}} \left\{ P(o \mid c) \cdot P(c) \right\}$$

$$= \underset{c \in C}{\operatorname{arg\,max}} \left\{ P(o \mid c) \cdot P(c) \right\}$$

$$\text{likelihood prior}$$

Noisy Channel Model



- Scoring the candidates:
 - Need a corpus of annotated text where the misspelled words are identified and labeled with the correctly spelled words
 - Supervised machine learning
 - Gather the probability estimates from the annotated corpus

$$\hat{c} = \arg\max_{c \in C} \{ P(o \mid c) \cdot P(c) \}$$

Estimating the Prior P(c)

$$P(c) = \frac{C(c)}{N}$$

Maximum Likelihood Estimate (MLE)

С	C(c)
actress	1343
cress	0
caress	4
access	2280
across	8436
acres	2879

Smoothing

С	C(c)	C(c) + 1
actress	1343	1344
cress	0	1
caress	4	5
access	2280	2281
across	8436	8437
acres	2879	2880

Smoothing

$$P(c) = \frac{C(c) + \lambda}{N + B \cdot \lambda}$$

λ: small positive number

C(c): Frequency of c in training corpus

N: Total num of c's

B: Num of bins the c's are divided into (i.e., num of distinct c's)

$$N = C(c_1) + C(c_2) + \dots + C(c_B)$$

$$N + B \cdot \lambda = \{C(c_1) + \lambda\} + \{C(c_2) + \lambda\} + \dots + \{C(c_B) + \lambda\}$$

$$1 = \frac{C(c_1) + \lambda}{N + B \cdot \lambda} + \frac{C(c_2) + \lambda}{N + B \cdot \lambda} + \dots + \frac{C(c_B) + \lambda}{N + B \cdot \lambda}$$

Smoothing

$$\lambda$$
 = 1 Laplace's law (add-one smoothing)

$$P(c) = \frac{C(c)+1}{N+B}$$

$$\lambda$$
 = 0.5 Jeffreys-Perks law

$$P(c) = \frac{C(c) + 0.5}{N + B \cdot 0.5}$$

Estimating the Likelihood P(o|c)

- Use letter frequencies in annotated training corpus to approximate P(o|c)
- sub[m, l]: # times the correct letter I was typed as m
- trans[k, l]: # times the correct letter sequence kl was typed as lk
- ins[l, m]: # times the extraneous letter m was inserted after l
- del[k, l]: # times the letter I was deleted from the correct letter sequence kl

Estimating the Likelihood P(o|c)

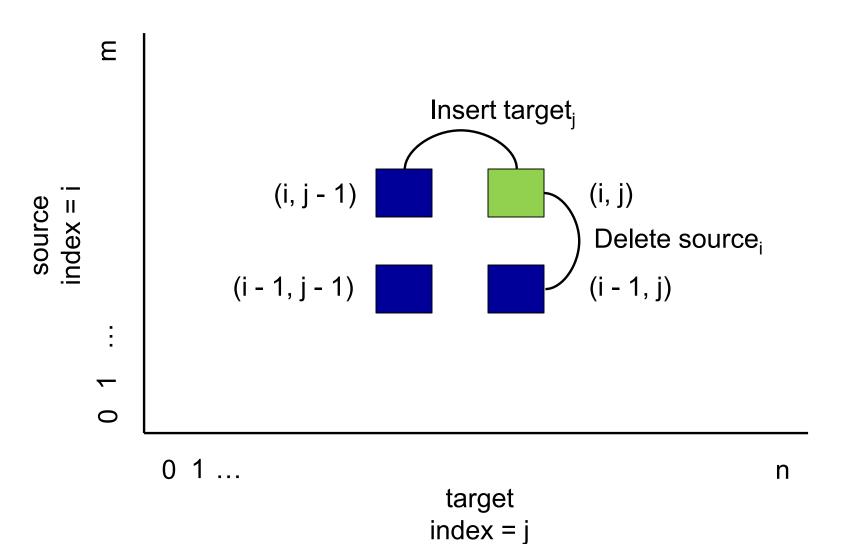
$$P(o \mid c) = \begin{cases} \frac{sub[m,l]}{C(l)} & \text{if substitution} \\ \frac{trans[k,l]}{C(kl)} & \text{if transposition} \\ \frac{ins[l,m]}{C(l)} & \text{if insertion} \\ \frac{del[k,l]}{C(kl)} & \text{if deletion} \end{cases}$$

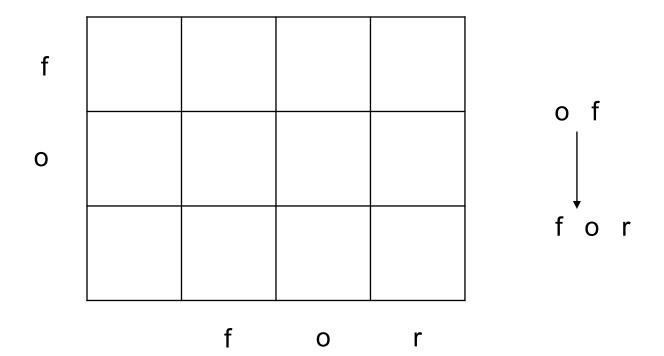
- Multiple-error misspellings
- Minimum edit distance between 2 strings:
 The minimum number of editing operations (insertion, deletion, substitution) needed to transform one string into another

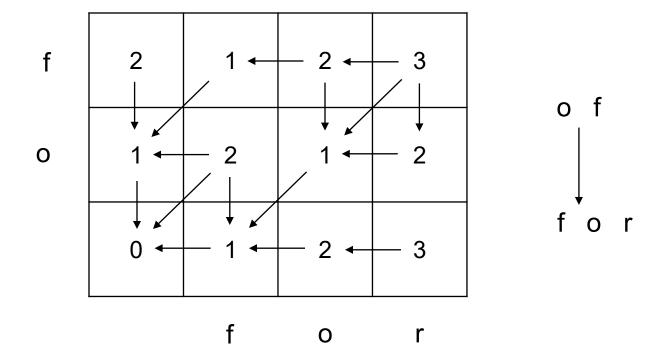
```
Alignment of \epsilon \epsilon
                  εfor
Operations
               delete o → f
                keep f →
                insert o \rightarrow f
                insert r \rightarrow f \circ r
```

- Cost of operation:
 - Insertion: 1
 - Deletion: 1
 - Substitution: 2 if the two characters are different;
 else 0
- Compute minimum edit distance by dynamic programming

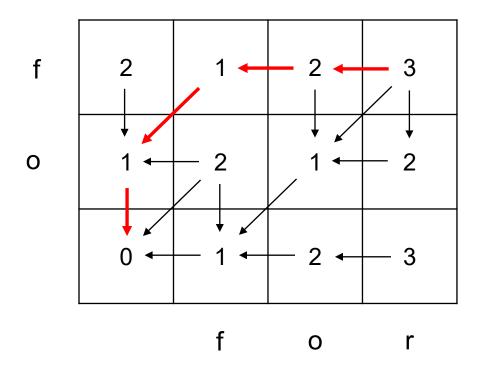
```
function min-edit-distance(source, target) returns min-distance
m \leftarrow length(source)
n ← length(target)
create a matrix d[m + 1, n + 1]
d[0, 0] \leftarrow 0
for each row i from 1 to m do
   d[i, 0] \leftarrow d[i - 1, 0] + del-cost(source_i)
for each column j from 1 to n do
   d[0, j] \leftarrow d[0, j - 1] + ins-cost(target_i)
for each row i from 1 to m do
   for each column j from 1 to n do
         d[i, j] \leftarrow min(d[i-1, j] + del-cost(source_i),
                       d[i, j-1] + ins-cost(target_i),
                       d[i - 1, j - 1] + subst-cost(source_i, target_i))
return d[m, n]
```







Time complexity: O(mn)



f o r

delete o
keep f
insert o
insert r

