CMPT 413 Computational Linguistics

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Minimum Cost Edit Distance

- String edit distance: what is the minimum number of changes (char insertions or deletions) to transform the string *intention* into *execution*?
- Assume cost of insertion is 1 and cost of deletion is 1
- Note that we assume that we can only change one character at a time

Levenshtein Distance

- Cost is fixed across characters
 - Insertion cost is 1
 - Deletion cost is 1
- Two different costs for substitutions
 - Substitution cost is 1 (transformation)
 - Substitution cost is 2 (one deletion + one insertion)

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Minimum Cost Edit Distance

• Think of it as an alignment between target and source

$$t_1, t_2, \dots, t_n$$
 Find $D(n,m)$ recursively s_1, s_2, \dots, s_m

$$D(i,j) = min \begin{cases} D(i-1,j) & + \mathrm{cost}(t_i,\emptyset) \text{ insertion into target} \\ D(i-1,j-1) + \mathrm{cost}(t_i,s_j) \text{ substitution/identity} \\ D(i,j-1) & + \mathrm{cost}(\emptyset,s_j) \text{ deletion from source} \end{cases}$$

$$D(0,0) = 0 \qquad D(i,0) = D(i-1,0) + \operatorname{cost}(t_i,\emptyset)$$

$$D(0,j) = D(0,j-1) + \operatorname{cost}(\emptyset,s_j)$$

Function MinEditDistance (target, source) n = length(target) m = length(source) Create matrix D of size (n+1,m+1) D[0,0] = 0for i = 1 to nD[i,0] = D[i-1,0] + insert-costfor j = 1 to m D[0,j] = D[0,j-1] + delete-costfor i = 1 to n for j = 1 to m D[i,j] = MIN(D[i-1,j] + insert-cost,D[i-1,j-1] + subst/eq-cost,D[i,j-1] + delete-cost) return D[n,m] 3/19/12

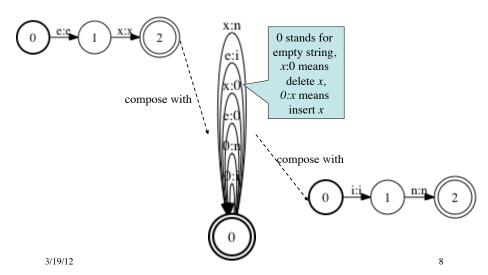
	target							
			g	a	m	b	1	e
source		0	1	2	3	4	5	6
	gg	1	0	1	2	3	4	5
	u	2	1	2s	3	4	5	6
	m	3	2	3	2_{e}	3	4	5
	b	4	3	4	3	2_e	3_i	4
	O	5	4	5	4	3	4	$\overline{\mathfrak{S}}_{s}$

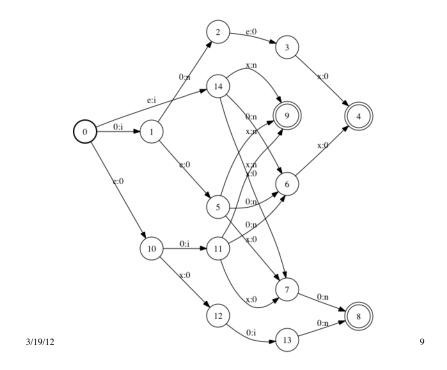
Edit Distance and FSTs

- Algorithm using a Finite-state transducer:
 - construct a finite-state transducer with all possible ways to transduce intention (source = input) into execution (target = output)
 - We do this transduction one char at a time
 - A transition x:x gets zero cost and a transition on ε:x
 (insertion) or x:ε (deletion) for any char x gets cost 1
 - Finding minimum cost edit distance == Finding the shortest path from start state to final state

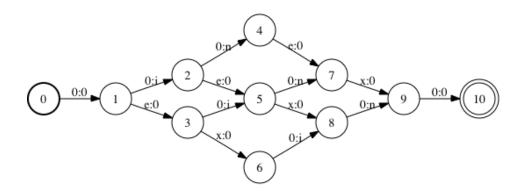
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Edit distance and FSTs





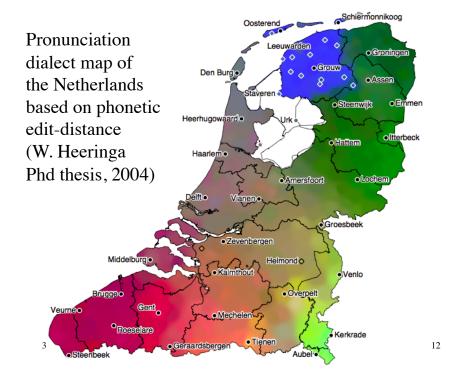
Edit distance and FSTs



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Edit distance

- Useful in many NLP applications
- In some cases, we need edits with multiple characters, e.g. 2 chars deleted for one cost
- Comparing system output with human output, e.g. <u>input:</u> ibm <u>output:</u> IBM vs. Ibm (TrueCasing of speech recognition output)
- Error correction
- Defined over character edits or word edits, e.g. MT evaluation:
 - Foreign investment in Jiangsu 's agriculture on the increase
- Foreign investment in Jiangsu agricultural investment increased 3/19/12



Variable Cost Edit Distance

- So far, we have seen edit distance with uniform insert/ delete cost
- In different applications, we might want different insert/ delete costs for different items
- For example, consider the simple application of spelling correction
- Users typing on a qwerty keyboard will make certain errors more frequently than others
- So we can consider insert/delete costs in terms of a probability that a certain alignment occurs between the *correct* word and the *typo* word

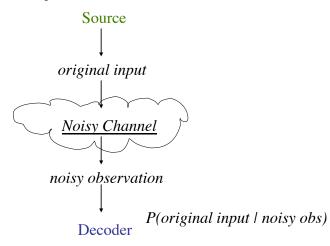
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Spelling Correction

- Types of spelling correction
 - non-word error detection
 - e.g. hte for the
 - isolated word error detection
 - e.g. *acres* vs. *access* (cannot decide if it is the right word for the context)
 - context-dependent error detection (real world errors)
 - e.g. she is a talented acres vs. she is a talented actress
- For simplicity, we will consider the case with exactly 1 error 3/19/12

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Noisy Channel Model



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Bayes Rule: computing P(orig | noisy)

• let x = original input, y = noisy observation

$$p(x \mid y) = \frac{p(x,y)}{p(y)} \qquad p(y \mid x) = \frac{p(y,x)}{p(x)}$$

$$p(x,y) = p(y,x)$$

$$p(x \mid y) \times p(y) = p(y \mid x) \times p(x)$$

$$p(x \mid y) = \frac{p(y \mid x) \times p(x)}{p(y)} \qquad \underline{\text{Bayes Rule}}$$

Chain Rule

$$p(a,b,c \mid d) = p(a \mid b,c,d) \times$$

$$p(b \mid c,d) \times$$

$$p(c \mid d)$$

Approximations: Bias vs. Variance

$$p(a \mid b, c, d) \approx p(a \mid b, c)$$
 less bias $p(a \mid b)$ $p(a)$ less variance

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Single Error Spelling Correction

- Insertion (addition)
 - acress vs. cress
- Deletion
 - acress vs. actress
- Substitution
 - acress vs. access
- Transposition (reversal)
 - acress vs. caress

Noisy Channel Model for Spelling Correction (Kernighan, Church and Gale, 1990)

• *t* is the word with a single typo and *c* is the correct word

$$P(c \mid t) = p(t \mid c) \times p(c)$$
 Bayes Rule

• Find the best candidate for the correct word

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

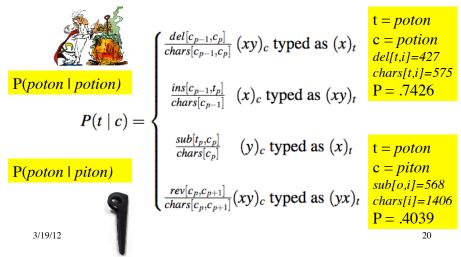
$$P(t \mid c) = ?? \qquad P(c) = \frac{f(c)}{N}$$

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C is all the words in the vocabulary; |C| = N

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Noisy Channel Model for Spelling Correction (Kernighan, Church and Gale, 1990) single error, condition on previous letter



Noisy Channel model for Spelling Correction

- The *del*, *ins*, *sub*, *rev* matrix values need data in which contain known errors (training data)
 - e.g. Birbeck spelling error corpus (from 1984!)
- Accuracy on single errors on unseen data (test data)

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Noisy Channel model for Spelling Correction

- Easily extended to multiple spelling errors in a word using edit distance algorithm (however, using learned costs for ins, del, replace)
- Experiments: 87% accuracy for machine vs. 98% average human accuracy
- What are the limitations of this model?

... was called a "stellar and versatile **acress** whose combination of sass and glamour has defined her

KCG model best guess is acres