Spell Checker

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Spelling Correction

Spelling correction is an integral part of modern writing, ranging from **texting** and **emailing** to document creation and **web searches**. Despite their ubiquity, modern spell correctors aren't perfect, as evidenced by "autocorrect-gone-wrong" scenarios.

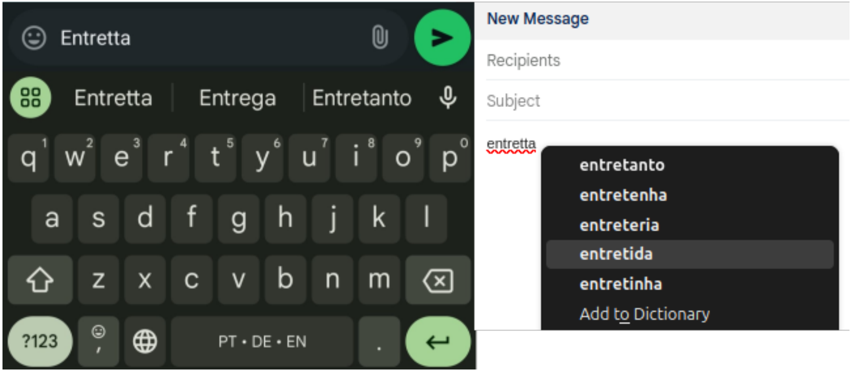

Figure 1: Spell checker.

Applications of Spell Checking

- Text Writing
- Automated and Information Systems
  - Data Entry Systems
  - Search and Information Retrieval
  - Optical Character Recognition (OCR)
  - Chatbots
  - Translation Systems

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Automatic Spelling Correction Task

1. detection of an error;
2. generation of correction candidates;
3. ranking of candidate corrections;
4. perform automatic correction.

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Perspectives in Spelling Correction

1. Non-Word Spelling Correction
   - Detects and corrects errors where the **word does not exist** in the dictionary. Example:
     - Input: `speling`
     - Correction: `spelling`
2. Real-Word Spelling Correction
   - Detects and corrects errors where the **word exists** but is contextually wrong. Example:
     - Input: `I no what to do.`
     - Correction: `I know what to do.`

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Error Sources in Spelling

1. Typographical Errors:
   - May change with input devices (physical or virtual keyboard, or OCR system) and environment conditions.
   - Insertion: `speeling` → `spelling`
   - Deletion: `spelng` → `spelling`
   - Substitution: `spolling` → `spelling`
   - Transposition: `spelilng` → `spelling`
   - Diacritical marking: `naive` → `naïve`
2. Homophone Errors:
   - Homophones: `their` / `there`
   - Near-homophones: `accept` / `except`
3. Grammatical Errors:
   - among / between
4. Cross Word Boundary Errors:
   - maybe / may be

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Notable Algorithms and Tools

- **Soundex** (1918): Phonetic algorithm that maps similar-sounding names.

```
Stephen → S315, Perez  → P620, Juice  → J200, Robert → R163
Steven  → S315, Powers → P620, Juicy  → J200, Rupert → R163
Stefan  → S315, Price  → P620, Juiced → J230, Rubin  → R150
```

function SOUNDEX(*name*) **returns** *soundex form*

1. Keep the first letter of *name*
2. Drop all occurrences of non-initial a, e, h, i, o, u, w, y.
3. Replace the remaining letters with the following numbers:

   b, f, p, v → 1
   c, g, j, k, q, s, x, z → 2
   d, t → 3
   l → 4
   m, n → 5
   r → 6

4. Replace any sequences of identical numbers, only if they derive from two or more letters that were *adjacent* in the original name, with a single number (e.g., 666 → 6).
5. Convert to the form `Letter Digit Digit Digit` by dropping digits past the third (if necessary) or padding with trailing zeros (if necessary).

Figure 2: Soundex algorithm.

- **Shannon (1948)**: A Mathematical Theory of Communication.

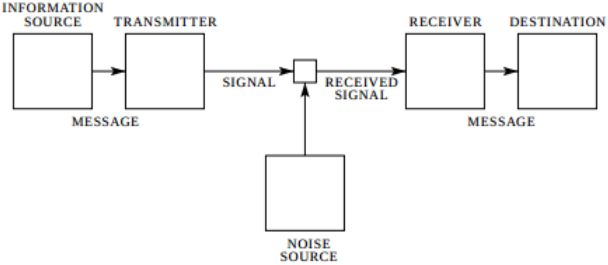

Fig. 1—Schematic diagram of a general communication system.

Figure 3: Noisy Channel.

- **Shannon (1950)**: Introduction of n-gram models in text analysis.

Figure 4: Word prediction is mean?

- **Blair (1960)**: Early algorithm for spelling error correction.
  - Blair introduced the concept of similarity keys to group words based on their likelihood of being confused with one another.
  - r-letter abbreviation of an n-letter word
    - Information theory assumes that the information conveyed is inversely proportional to its a priori probability of occurrence.
    - 1st proposal: eliminate $n - r$ letters in the order of their expected frequency
    - 2nd proposal: eliminate by their frequency of their occurrence as errors (best approach)
    - weight must also be given to the position of the letter in the word

EXAMPLE

A	B	S	O	R	B	E	N	T		A	B	S	O	R	B	A	N	T
5	1	5	4	4	1	7	3	3.	Letter score	5	1	5	4	4	1	5	3	3
0	2	4	5	5	5	4	3	1	Position score	0	2	4	5	5	5	4	3	1
5	3	9	9	9	6	11	6	4	Sum of scores	5	3	9	9	9	6	9	6	4
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TABLE I

THE LOGARITHM OF THE DESIRABILITY OF DELETING A LETTER AS A FUNCTION OF ITS NAME

Letter	Score	Letter	Score
A	5	N	3
B	1	O	4
C	5	P	3
D	0	Q	0
E	7	R	4
F	1	S	5
G	2	T	3
H	5	U	4
I	6	V	1
J	0	W	1
K	1	X	0
L	5	Y	2
M	1	Z	1

TABLE II

THE LOGARITHM OF THE DESIRABILITY OF DELETING A LETTER AS A FUNCTION OF ITS POSITION

Position	Score	Position	Score
1	0	9	5
2	1	10	5
3	2	11	6
4	3	12	6
5	4	13	6
6	4	14	6
7	5	15	6
8	5	16 up	7

- **Damerau–Levenshtein** distance (1964, 1966): A string metric for measuring the edit distance between two sequences.

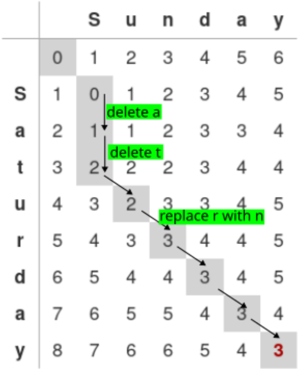

Figure 6: How many operations does it take to turn Saturday into Sunday?

Levenshtein Distance Calculator

https://phiresky.github.io/levenshtein-demo/

The Levenshtein distance between two strings a, b (of length $|a|$ and $|b|$ respectively) is given by

$$\operatorname{lev}(a,b) = \begin{cases} |a| & \text{if } |b| = 0, \\ |b| & \text{if } |a| = 0, \\ \operatorname{lev}\big(\operatorname{tail}(a), \operatorname{tail}(b)\big) & \text{if } \operatorname{head}(a) = \operatorname{head}(b), \\ 1 + \min \begin{cases} \operatorname{lev}\big(\operatorname{tail}(a), b\big) & \text{deletion} \\ \operatorname{lev}\big(a, \operatorname{tail}(b)\big) & \text{insertion} \\ \operatorname{lev}\big(\operatorname{tail}(a), \operatorname{tail}(b)\big) & \text{replacement} \end{cases} & \text{otherwise} \end{cases}$$

Damerau-Levenshtein distance: also allows transposition of adjacent symbols.

Operations are expensive and language dependent: e.g. as of version 16.0, Unicode defines a total of 98682 Chinese characters.

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- **BK-Trees** (1973): Efficient search for near matches using Levenshtein distance.
  - An arbitrary element a is selected as root node.
  - The k-th subtree is recursively built of all elements b such that $d(a, b) = k$.
  - Search idea: restrict the exploration of the tree to nodes that can only improve the best candidate found so far (use triangle inequality).

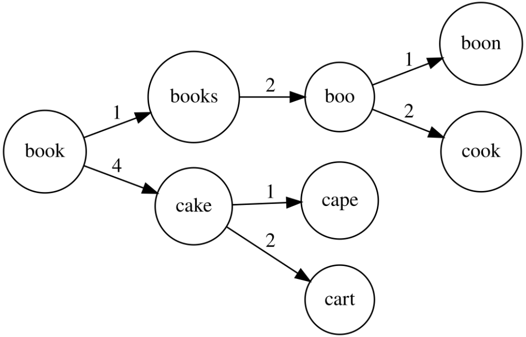
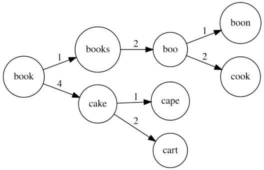
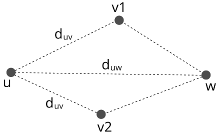


Figure 7: Burkhard-Keller Tree.

Search for w = 'cool'





1 $d_u = d(w,u) = d(\text{'cool'}, \text{'book'}) = 2$, set $d_{\text{best}} = 2$;

2 v = 'books', $|d_{uv} - d_u| = |1 - 2| = 1 < d_{\text{best}}$, then select v;

3 v = 'cake', $|d_{uv} - d_u| = |4 - 2| = 2 \not< d_{\text{best}}$, do not select v;

4 $d_u = d(w,u) = d(\text{'cool'}, \text{'books'}) = 3$, $d_u \not< d_{\text{best}}$;

5 $d_u = d(w,u) = d(\text{'cool'}, \text{'boo'}) = 2$, $d_u \not< d_{\text{best}}$;

6 v = 'boon', $|d_{uv} - d_u| = |2 - 1| = 1 < d_{\text{best}}$, then select v;

7 v = 'cook', $|d_{uv} - d_u| = |2 - 2| = 0 < d_{\text{best}}$, then select v;

8 $d_u = d(w,u) = d(\text{'cool'}, \text{'cook'}) = 1$, $d_u < d_{\text{best}}$, set $d_{\text{best}} = 1$;

9 $d_u = d(w,u) = d(\text{'cool'}, \text{'boon'}) = 2$, $d_u \not< d_{\text{best}}$;

10 'cook' is returned as the answer with $d_{\text{best}} = 1$.

- **SPELL** (Unix, 1975)
  - Error detection only.
  - Prefix and suffix removal (reduces the list below 1/3);
    - `buzzed` $\rightarrow$ `buzz`, `mapping` $\rightarrow$ `map`, `possibly` $\rightarrow$ `possible`, `antisocial` $\rightarrow$ `social`, `metaphysics` $\rightarrow$ `physics`.
  - Hashing (discarding 60% of the remaining bits);
    Examples of hashing functions:
    1. Shift-and-Add: $h = (h << 1) + \text{char}\%m$
    2. Multiplicative Hashing: $h = (a \cdot h + \text{char})\%m$ (with a typically 31 or 33)
    3. XOR-based Hashing: $h = h \oplus (\text{char} << k)$
  - Words were represented by 16-bit machine words;
  - Bloom filter;
  - False positives.

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- **Jaro similarity** (1989)

The Jaro similarity sim_j of two given strings s_1 and s_2 is

$$sim_j = \begin{cases} 0 & \text{if } m = 0 \\ \frac{1}{3}\left(\frac{m}{|s_1|} + \frac{m}{|s_2|} + \frac{m-t}{m}\right) & \text{otherwise} \end{cases}$$

where:

- $|s_i|$ is the length of the string s_i;
- m is the number of ''matching characters" (see below);
- t is the number of ''transpositions" (see below).

Jaro similarity score is 0 if the strings do not match at all, and 1 if they are an exact match. In the first step, each character of s_1 is compared with all its matching characters in s_2. Two characters from s_1 and s_2 respectively, are considered **matching** only if they are the same and not farther than $\left\lfloor \frac{\max(|s_1|,|s_2|)}{2} \right\rfloor - 1$ characters apart. **Transposition** is the number of matching characters that are not in the right order divided by two.

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- **Jaro-Winkler similarity** (1990)
  - Introduces Winkler modification.
  - Prefix length ℓ: if two strings share a common prefix, they are likely to be more similar.
  - Scale factor p: enhances the Jaro similarity score based on the length of the common prefix (usually set to 0.1 and should not exceed 0.25).

$$sim_w = sim_j + \ell p(1 - sim_j)$$

$1 - sim_j$: This component adjusts the contribution of the prefix similarity term relative to the base Jaro similarity score (sim_j). If sim_j already high, the impact of the prefix adjustment diminishes, but when sim_j lower, the prefix similarity can significantly boost the final similarity score.

- **Jaro-Winkler similarity** (1990)
  - Introduces Winkler modification.
  - Prefix length ℓ: if two strings share a common prefix, they are likely to be more similar.
  - Scale factor p: enhances the Jaro similarity score based on the length of the common prefix (usually set to 0.1 and should not exceed 0.25).

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- **Metaphone** (1990), Double Metaphone (2000), Metaphone 3 (2009): Extracts phonetic information for better matching.
  - Set of rules to improves on the Soundex algorithm.
  - `Smith → SM0, [SM0, XMT]`, `Schmidt → SXMTT, [XMT, SMT]`,
  - `Taylor → TLR, [TLR]`, `Taylor → EFNS, [AFNS]`,
  - `Roberts → RBRTS, [RPRTS]`
  - `spelling → SPLNK, [SPLNK]`, `speling → SPLNK, [SPLNK]`, `speeling → SPLNK, [SPLNK]`, `sprlling → SPRLNK, [SPRLNK]`

- **Noisy Channel Model (Kernighan et al., 1990 and Mays et al., 1991)**: Combined prior and likelihood models.

In the noisy channel model, we imagine that the surface form we see is actually a "distorted" form of an original word passed through a noisy channel. The decoder passes each hypothesis through a model of this channel and picks the word that best matches the surface noisy word. (Jurafsky and Martin, 2024)

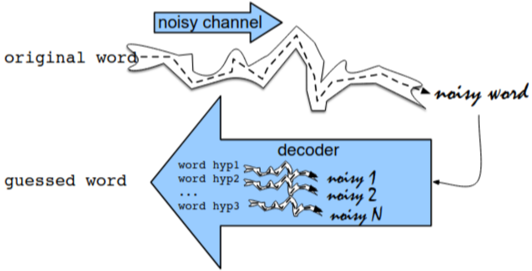

Figure 8: Noisy Channel Model

This noisy channel model is a kind of **Bayesian inference**.

Out of all possible words in the vocabulary V we want to find the word $\hat{w}$ such that $P(w|x)$ is highest for a given observed string x.

$$\hat{w} = \operatorname*{arg\,max}_{w \in V} P(w|x)$$

Using Bayes: $P(x, w) = P(w|x)P(x) = P(x|w)P(w)$,

$$\hat{w} = \operatorname*{arg\,max}_{w \in V} \frac{P(x|w)P(w)}{P(x)} = \operatorname*{arg\,max}_{w \in V} \underbrace{P(x \mid w)}_{\substack{\text{channel model} \\ \text{or likelihood}}} \underbrace{P(w)}_{\text{prior}}$$

$$\hat{w} = \operatorname*{arg\,max}_{w \in V} (\log P(x \mid w) + \log P(w))$$

function NOISY CHANNEL SPELLING(*word x*, *dict D*, lm, *editprob*) **returns** *correction*

  if $x \notin D$
    candidates, edits $\leftarrow$ All strings at edit distance 1 from x that are $\in D$, and their edit
    for each c, e in candidates, edits
      channel $\leftarrow$ editprob(e)
      prior $\leftarrow$ lm(c)
      score[c] = log *channel* + log *prior*
    return argmax_c *score*[c]

Figure 9: Noisy channel model for spelling correction for unknown words (Jurafsky and Martin, 2024).

Example

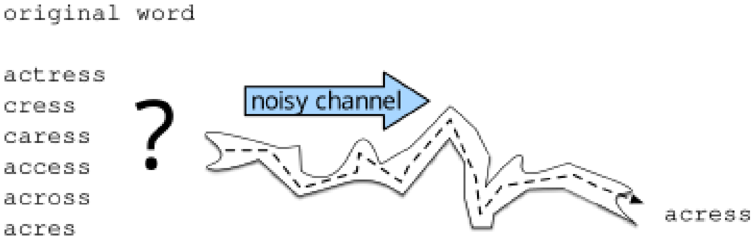

Figure 10: Example: misspelling `acress`.

		Transformation			
Error	Correction	Correct Letter	Error Letter	Position (Letter #)	Type
acress	actress	t	—	2	deletion
acress	cress	—	a	0	insertion
acress	caress	ca	ac	0	transposition
acress	access	c	r	2	substitution
acress	across	o	e	3	substitution
acress	acres	—	s	5	insertion
acress	acres	—	s	4	insertion

Figure 11: Candidate corrections for the misspelling acress and the transformations that would have produced the error (after Kernighan et al. (1990)). "—" represents a null letter. (Jurafsky and Martin, 2024)

w	count(w)	p(w)
actress	9,321	.0000231
cress	220	.000000544
caress	686	.00000170
access	37,038	.0000916
across	120,844	.000299
acres	12,874	.0000318

Figure 12: Language model from the 404,253,213 words in the Corpus of Contemporary English (COCA) (Jurafsky and Martin, 2024).

Error model

- A perfect model would need all sorts of factors: who the typist was, whether the typist was left-handed or right-handed, and so on.
- We can get a pretty reasonable estimate of $P(x|w)$ just by looking at **local context**: the identity of the correct letter itself, the misspelling, and the surrounding letters.
- Confusion Matrices:
  - `del[x, y]: count(xy typed as x)`
  - `ins[x, y]: count(x typed as xy)`
  - `sub[x, y]: count(x typed as y)`
  - `trans[x, y]: count(xy typed as yx)`

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sub[X, Y] = Substitution of X (incorrect) for Y (correct)

X \ Y (correct)	a	b	c	d	e	f	g	h	i	j	k	l	m	n	o	p	q	r	s	t	u	v	w	x	y	z
a	0	0	7	1	342	0	0	2	118	0	1	0	0	3	76	0	0	1	35	9	9	0	1	0	5	0
b	0	0	9	9	2	2	3	1	0	0	0	5	11	5	0	10	0	0	2	1	0	0	8	0	0	0
c	6	5	0	16	0	9	5	0	0	0	1	0	7	9	1	10	2	5	39	40	1	3	7	1	1	0
d	1	10	13	0	12	0	5	5	0	0	2	3	7	3	0	1	0	43	30	22	0	0	4	0	2	0
e	388	0	3	11	0	2	2	0	89	0	0	3	0	5	93	0	0	14	12	6	15	0	1	0	18	0
f	0	15	0	3	1	0	5	2	0	0	0	3	4	1	0	0	0	6	4	12	0	0	2	0	0	0
g	4	1	11	11	9	2	0	0	0	1	1	3	0	0	2	1	3	5	13	21	0	0	1	0	3	0
h	1	8	0	3	0	0	0	0	0	0	2	0	12	14	2	3	0	3	1	11	0	0	2	0	0	0
i	103	0	0	0	146	0	1	0	0	0	0	6	0	0	49	0	0	0	2	1	47	0	2	1	15	0
j	0	1	1	9	0	0	1	0	0	0	0	2	1	0	0	0	0	0	5	0	0	0	0	0	0	0
k	1	2	8	4	1	1	2	5	0	0	0	0	5	0	2	0	0	0	6	0	0	0	4	0	0	3
l	2	10	1	4	0	4	5	6	13	0	1	0	0	14	2	5	0	11	10	2	0	0	0	0	0	0
m	1	3	7	8	0	2	0	6	0	0	4	4	0	180	0	6	0	0	9	15	13	3	2	2	3	0
n	2	7	6	5	3	0	1	19	1	0	4	35	78	0	0	7	0	28	5	7	0	0	1	2	0	2
o	91	1	1	3	116	0	0	0	25	0	2	0	0	0	0	14	0	2	4	14	39	0	0	0	18	0
p	0	11	1	2	0	6	5	0	2	9	0	2	7	6	15	0	0	1	3	6	0	4	1	0	0	0
q	0	0	1	0	0	0	27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
r	0	14	0	30	12	2	2	8	2	0	5	8	4	20	1	14	0	0	12	22	4	0	0	1	0	0
s	11	8	27	33	35	4	0	1	0	1	0	27	0	6	1	7	0	14	0	15	0	0	5	3	20	1
t	3	4	9	42	7	5	19	5	0	1	0	14	9	5	5	6	0	11	37	0	0	2	19	0	7	6
u	20	0	0	0	44	0	0	0	64	0	0	0	0	2	43	0	0	4	0	0	0	0	2	0	8	0
v	0	0	7	0	0	3	0	0	0	0	0	1	0	0	1	0	0	0	8	3	0	0	0	0	0	0
w	2	2	1	0	1	0	0	2	0	0	1	0	0	0	0	7	0	6	3	3	1	0	0	0	0	0
x	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	9	0	0	0	0	0	0	0
y	0	0	2	0	15	0	1	7	15	0	0	0	2	0	6	1	0	7	36	8	5	0	0	1	0	0
z	0	0	0	7	0	0	0	0	0	0	0	7	5	0	0	0	0	2	21	3	0	0	0	0	3	0

Figure 13: Confusion matrix for spelling errors (Kernighan et al., 1990).

Estimating the channel model

$$P(x|w) = \begin{cases} \frac{\text{del}[x_{i-1}, w_i]}{\text{count}[x_{i-1} w_i]}, & \text{if deletion} \\ \frac{\text{ins}[x_{i-1}, w_i]}{\text{count}[w_{i-1}]}, & \text{if insertion} \\ \frac{\text{sub}[x_i, w_i]}{\text{count}[w_i]}, & \text{if substitution} \\ \frac{\text{trans}[w_i, w_{i+1}]}{\text{count}[w_i w_{i+1}]}, & \text{if transposition} \end{cases}$$

Candidate Correction	Correct Letter	Error Letter	x|w	P(x|w)
actress	t	-	c|ct	.000117
cress	-	a	a|#	.00000144
caress	ca	ac	ac|ca	.00000164
access	c	r	r|c	.000000209
across	o	e	e|o	.0000093
acres	-	s	es|e	.0000321
acres	-	s	ss|s	.0000342

Figure 14: Channel model for acress; the probabilities are taken from the `del[]`, `ins[]`, `sub[]`, and `trans[]` confusion matrices as shown in Kernighan et al. (1990).

Final probabilities for each of the potential corrections

Candidate Correction	Correct Letter	Error Letter	x|w	P(x|w)	P(w)	10^9*P(x|w)P(w)
actress	t	-	c|ct	.000117	.0000231	2.7
cress	-	a	a|#	.00000144	.000000544	0.00078
caress	ca	ac	ac|ca	.00000164	.00000170	0.0028
access	c	r	r|c	.000000209	.0000916	0.019
across	o	e	e|o	.0000093	.000299	2.8
acres	-	s	es|e	.0000321	.0000318	1.0
acres	-	s	ss|s	.0000342	.0000318	1.0

Figure 15: Computation of the ranking for each candidate correction, using the language model shown earlier and the error model. The final score is multiplied by 10^9 for readability (Jurafsky and Martin, 2024).

*Unfortunately, the algorithm was wrong here; the writer's intention becomes clear from the context: ... was called a "stellar and versatile **acress** whose combination of sass and glamour has defined her ...". The surrounding words make it clear that actress and not across was the intended word.* (Jurafsky and Martin, 2024)

Using the *Corpus of Contemporary American English* to compute **bigram** probabilities for the words *actress* and *across* in their context using add-one smoothing, we get the following probabilities:

$$P(\text{actress}|\text{versatile}) = .000021$$
$$P(\text{across}|\text{versatile}) = .000021$$
$$P(\text{whose}|\text{actress}) = .0010$$
$$P(\text{whose}|\text{across}) = .000006$$

Multiplying these out gives us the language model estimate for the two candidates in context:

$$P(\text{versatile actress whose}) = .000021 \times .0010 = 210 \times 10^{-10}$$
$$P(\text{versatile across whose}) = .000021 \times .000006 = 1 \times 10^{-10}$$

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Jurafsky, D., & Martin, J. H. (2024). *Speech and Language Processing*.

Kernighan, M. D. et al. (1990). *A spelling correction program based on a noisy channel model*.

Mays, E. et al. (1991). *Context based spelling correction*.

- Noisy Channel Model
  - Correct (Unix, 1990): Takes inputs from SPELL rejected words and provides candidates. Operations: Insertion, Deletion, Substitution, Reversal. Uses error probabilities.

- **Brill-Moore channel model** (2000): String to string edits.
  - Let Σ be an alphabet, the model allows all edit operations of the form $\alpha \to \beta$, where $\alpha, \beta \in \Sigma^*$.
  - $P(\alpha \to \beta)$ is the probability that when users intends to type α and they typed β instead.
  - $P(\alpha \to \beta | PNS)$ probability conditioned by the position on the string
    - P(e | a) does not vary greatly with position.
    - P(ent | ant) is highly dependent upon position.
    - People rarely mistype *antler* as *entler*, but often mistype *reluctant* as *reluctent*.

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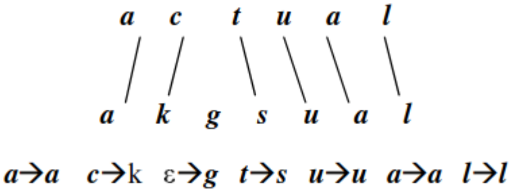

Figure 16: String alignment (Brill and Moore, 2000).

Brill, E. and Moore, R. C. (2000). *An Improved Error Model for Noisy Channel Spelling Correction.*

- **Aspell** (2000): Combines spelling and phonetic correction.
  - Hashing for Spell Checking: Efficient candidate lookup using hash tables.
  - Metaphone Algorithm: Handles phonetic corrections by matching words that sound similar.
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Example - Handling Homophones in Aspell

- Misspelled word: `ther`
- Candidates: `there`, `their`, `they're`

1. Metaphone
   - The Metaphone algorithm transforms words into phonetic codes based on pronunciation.
   - Phonetic codes for the candidate words:
     - `there` → `0R`
     - `their` → `0R`
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   - Homophones share the same code (`0R`).

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2 Workflow:

- Input: Misspelled word `ther`.
- Step 1: Generate candidates using **edit distance 2 or less**:
  - Candidates: `there`, `their`, `thee`, `thor`, `her`, `the`, `they're`.
- Step 2: Compute Metaphone codes for all candidates:
  - Candidates phonetically similar to `ther` (`0R`) rank higher: `there`, `their`, `thor`, `they're`.
- Step 3: Rank and suggest based on:
  - Word frequency, Edit distance, Phonetic Similarity, Error Likelihood.

3 Limitations:

- Metaphone matches words by sound but lacks **contextual understanding**.
- Example:
  - Input: *"I went to ther house."*
  - Suggestions: `thee`, `their`, `there`, `therm`, `the`, `her`, `Thar`, `Thea`, `Thor`, `Thur`.
  - Aspell cannot infer the correct word (`their`) without considering the sentence's context.

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GNU Aspell

- **Hunspell** (2002): Morphological analyzer with affix rules and phonetic matching.

Key Features:

- Morphological Analysis:
  - Supports complex languages with rich morphology (e.g., Hungarian, Turkish, Finnish).
  - Handles word roots, prefixes, and suffixes using affix rules.
- Dictionary System:
  - Two components:
    1. Dictionary File: Contains root forms of words.
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  - Uses *edit distance* to generate and rank candidate corrections.
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Applications:

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Hunspell at GitHub

- Multilingual Support:
  - Available for 98 languages with extensive dictionaries.

Applications:

- Integrated into tools like LibreOffice, Firefox, and Chrome for multilingual spell checking.
- Supports custom dictionaries for specialized fields (e.g., medical, legal).

Hunspell at GitHub

- **Norvig**'s Algorithm (2007): Uses Damerau-Levenshtein distance to generate candidates.

Key Features:

- Edit Distance:
  - Generates all possible words within a given edit distance (e.g., 1 or 2) from the misspelled word.
  - Handles insertion, deletion, substitution, and transposition.
- Dictionary Lookup:
  - Filters candidates by validating them against a word dictionary.
- Ranking:
  - Ranks valid candidates based on:
    - Word Frequency: More frequent words are prioritized.
    - Likelihood of Errors: Based on the Noisy Channel Model (optional).

How to Write a Spelling Corrector: https://norvig.com/spell-correct.html

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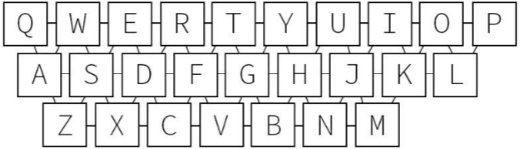
- **QWERTY Weighted Levenshtein Distance**: takes keyboard distance into account.



	a	s	d	...	l	p
a	0	1	2	...	8	9
s	1	0	1	...	7	8
d	2	1	0	...	6	7
...	...	...	...	0	...	...
l	8	7	6	...	0	1
p	9	8	7	...	1	0

Figure 17: QWERTY keyboard and keyboard distance matrix.

- Distance between keys are in [0,9] range. They are multiplied by 2/9.

- Deletion: weighted by the average of the distances to the adjacent characters in the string.
- Insertion: unchanged, weight 1.
- Substitution: weighted according to the distance between the character that is removed and the character that is inserted.
- Transposition: unchanged, weight 1.

Samuelsson, 2017

- **Neural-Based Models**: Leverage deep learning for advanced error detection and correction.
  - Utilize deep learning techniques to improve spellchecking:
    - Recurrent Neural Networks (RNNs)
    - Word Embeddings
    - Transformers
  - Contextual Awareness
  - Learning from Data
  - Handling Typos

Examples:

- Google's Smart Compose
- Grammarly
- Microsoft Editor
- LanguageTool

Lexical Similarity Metrics

1. **Levenshtein Distance** (Edit Distance):
   Minimal number of insertions, deletions, and replacements to transform one word into another.
2. **Jaro Similarity**:
   Measures similarity based on matching characters and transpositions.
3. **Keyboard Distance**:
   Considers physical proximity of keys.
4. **Phonetic Matching**:
   Algorithms like Soundex and Metaphone to identify similar-sounding words.

Domain-Specific Spell Checkers

1. Medical
   - MedSpell: a medical spelling and autocorrect application
   - OpenMedSpel (open-source)
2. Programming
   - CodeSpell: designed primarily for checking misspelled words in source code
3. Learning
   - Kidspell: A child-oriented, rule-based, phonetic spellchecker
4. Accessibility
   - Real Check: A Spellchecker for Dyslexia
5. Custom Dictionaries
   - Hunspell and Aspell: Add specialized vocabularies

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