Introduction to Information Retrieval
http://informationretrieval.org

IIR 3: Dictionaries and tolerant retrieval

Hinrich Schütze

Institute for Natural Language Processing, Universität Stuttgart

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Overview

1. Recap
2. Dictionaries
3. Wildcard queries
4. Spelling correction
5. Soundex
Outline

1 Recap
2 Dictionaries
3 Wildcard queries
4 Spelling correction
5 Soundex
Type/token distinction

- **Token** – An instance of a word or term occurring in a document.
Type/token distinction

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- **Type** – An equivalence class of tokens.
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How many tokens? How many types?
Type/token distinction

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- **Type** – An equivalence class of tokens.

> *In June, the dog likes to chase the cat in the barn.*

- How many tokens? How many types?
- 12 tokens, 9 types
Problems in tokenization

- What are the delimiters? Space? Apostrophe? Hyphen?
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- For each of these: sometimes they delimit, sometimes they don’t.
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- No whitespace in Dutch, German, Swedish compounds (Lebensversicherungsgesellschaftsangestellter)
- No whitespace in English: database, whitespace
Problems in “equivalence classing”

- A term is an equivalence class of tokens.
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- How do we define equivalence classes?
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  - Accents, umlauts
Skip pointers

Recap

Dictionaries
Wildcard queries
Spelling correction
Soundex

Schütze: Dictionaries and tolerant retrieval
Positional indexes

- Postings lists in a **positional index**: each posting is a docID and a list of positions
- Example: *to₁ be₂ or₃ not₄ to₅ be₆*

**TO**, 993427:

- 1, 6: ⟨7, 18, 33, 72, 86, 231⟩;
- 2, 5: ⟨1, 17, 74, 222, 255⟩;
- 4, 5: ⟨8, 16, 190, 429, 433⟩;
- 5, 2: ⟨363, 367⟩;
- 7, 3: ⟨13, 23, 191⟩; ...

**BE**, 178239:

- 1, 2: ⟨17, 25⟩;
- 4, 5: ⟨17, 191, 291, 430, 434⟩;
- 5, 3: ⟨14, 19, 101⟩; ...

Document 4 is a match.
Positional indexes

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- Example: $to_1 \ be_2 \ or_3 \ not_4 \ to_5 \ be_6$

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$\langle 1, 6: \langle 7, 18, 33, 72, 86, 231 \rangle; 2, 5: \langle 1, 17, 74, 222, 255 \rangle; 4, 5: \langle 8, 16, 190, 429, 433 \rangle; 5, 2: \langle 363, 367 \rangle; 7, 3: \langle 13, 23, 191 \rangle; \ldots \rangle$

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**Document 4 is a match.**
Positional indexes

- With a positional index, we can answer phrase queries.
Positional indexes

- With a positional index, we can answer **phrase queries**.
- With a positional index, we can answer **proximity queries**.
Outline

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3 Wildcard queries

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Inverted index

For each term $t$, we store a list of all documents that contain $t$.

<table>
<thead>
<tr>
<th>Term</th>
<th>Postings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brutus</td>
<td>1 2 4 11 31 45 173 174</td>
</tr>
<tr>
<td>Caesar</td>
<td>1 2 4 5 6 16 57 132 ...</td>
</tr>
<tr>
<td>Calpurnia</td>
<td>2 31 54 101</td>
</tr>
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</table>

dictionary

postings
Inverted index

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...
The dictionary is the data structure for storing the term vocabulary.
Dictionaries

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- Term vocabulary: the data
Dictionaries

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- Term vocabulary: the data
- Dictionary: the data structure for storing the term vocabulary
Dictionary as array of fixed-width entries

- For each term, we need to store a couple of items:
Dictionary as array of fixed-width entries

- For each term, we need to store a couple of items:
  - document frequency
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For each term, we need to store a couple of items:
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- pointer to postings list
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- Assume that we store these entries in an array.
### Dictionary as array of fixed-width entries

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<tr>
<td>a</td>
<td>656,265</td>
<td>➡️</td>
</tr>
<tr>
<td>aachen</td>
<td>65</td>
<td>➡️</td>
</tr>
<tr>
<td>…</td>
<td>…</td>
<td>…</td>
</tr>
<tr>
<td>zulu</td>
<td>221</td>
<td>➡️</td>
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</tbody>
</table>

Space needed: 20 bytes 4 bytes 4 bytes

How do we look up an element in this array at query time?
Data structures for looking up term

- Two main classes of data structures: hashes and trees
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- Criteria for when to use hashes vs. trees:
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  - What are the relative frequencies with which various keys will be accessed?
  - How many terms are we likely to have?
Hashes

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  - need to rehash everything periodically if vocabulary keeps growing
Trees

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- \textbf{B-tree} definition: every internal node has a number of children in the interval \([a, b]\) where \(a, b\) are appropriate positive integers, e.g., \([2, 4]\).
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- Note that we need a standard ordering for characters in order to be able to use trees.
Binary tree
B-tree
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Wildcard queries

- mon*: find all docs containing any term beginning with mon
Wildcard queries

- $\text{mon}^*$: find all docs containing any term beginning with $\text{mon}$
- Easy with B-tree dictionary: retrieve all terms $t$ in the range: $\text{mon} \leq t < \text{moo}$
Wildcard queries

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- *mon: find all docs containing any term ending with mon
Wildcard queries

- **mon**: find all docs containing any term beginning with *mon*
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  - Maintain an additional tree for terms *backwards*
**Wildcard queries**

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- *mon: find all docs containing any term ending with *mon*
  - Maintain an additional tree for terms *backwards*
  - Then retrieve all terms $t$ in the range: $\text{nom} \leq t < \text{non}$
Query processing

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- E.g., consider the query: gen* AND universit*
- This may result in the execution of many Boolean AND queries.
How to handle * in the middle of a term

Example: m*nchen
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- We could look up m* and *nchen in the B-tree and intersect the two term sets.
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How to handle * in the middle of a term

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- Expensive
- Alternative: `permuterm` index
- Basic idea: Rotate every wildcard query, so that the * occurs at the end.
Permuterm index

- For term HELLO: add hello$, ello$h, llo$he, lo$hel, and o$hell to the B-tree where $ is a special symbol
Permuterm index

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- Queries
Permuterm \rightarrow \text{term mapping}
Permuterm index

- For **HELLO**, we’ve stored: *hello*, *elloh*, *llosh*, *lohel*, and *ohell*
Permuterm index

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  - For X, look up X$
Permuterm index

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  - For X*, look up X*$
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  - For X, look up X$
  - For X*, look up X*$
  - For *X, look up X$*
Permuterm index

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- Queries
  - For `X`, look up `X$`
  - For `X*`, look up `X*$`
  - For `*X`, look up `X$*`
  - For `*X*`, look up `X*`
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  - For $X$, look up $X$
  - For $X*$, look up $X*$
  - For $*X$, look up $X*$
  - For $*X*$, look up $X$
  - For $X*Y$, look up $Y*$
  - For $X*Y$, look up $Y*$
  - For $X*Y$, look up $Y*$
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  - For X, look up X$
  - For X*, look up X*$
  - For *X, look up X$
  - For *X*, look up X*
  - For X*Y, look up Y$X*$
  - Example: For hel*o, look up o$hel*
Permuterm index

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    - For *X*, look up X
    - For X*Y, look up Y$X$
    - Example: For hel*X*, look up o$hel*
    - How do we handle X*Y*Z?
Permuterm index

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  - For $X*$, look up $X*$
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  - For $X*Y$, look up $Y*$
  - Example: For hel*$o$, look up o*$hel*
  - **How do we handle $X*$Y*Z?**

- It’s really a tree and should be called permuterm tree.
Permuterm index

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  - For $X*Y$, look up $Y*$
  - Example: For hel*$o$, look up o*$hel*$
  - How do we handle $X*$

- It’s really a tree and should be called permuterm tree.

- But permuterm index is more common name.
Processing a lookup in the permuterm index

- Rotate query wildcard to the right
Processing a lookup in the permuterm index

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- Use B-tree lookup as before
Processing a lookup in the permuterm index

- Rotate query wildcard to the right
- Use B-tree lookup as before
- Problem: Permuterm *quadruples* the size of the dictionary compared to a regular B-tree. (empirical number)
$k$-gram indexes

- More space-efficient than permuterm index
**k-gram indexes**

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- Enumerate all character $k$-grams (sequence of $k$ characters) occurring in a term
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- 2-grams are called **bigrams**.
k-gram indexes

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- 2-grams are called bigrams.
- Example: from *April is the cruelest month* we get the bigrams:

  $a \, ap \, pr \, ri \, il \, l$ $i \, is \, s$ $t \, th \, he \, e$ $c \, cr \, ru \, ue \, el \, le \, es \, st \, t$ $m \, mo \, on \, nt \, h$
**k-gram indexes**

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  - $a$ $ap$ $pr$ $ri$ $il$ $i$ $is$ $s$ $t$ $th$ $he$ $e$ $c$ $cr$ $ru$ $ue$ $el$ $le$ $es$ $st$ $t$ $m$ $mo$ $on$ $nt$ $h$
- $\$ is a special word boundary symbol.
**k-gram indexes**

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- Enumerate all character $k$-grams (sequence of $k$ characters) occurring in a term
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- Example: from *April is the cruelest month* we get the bigrams: $a$ $a$ $p$ $a$ $p$ $r$ $i$ $i$ $l$ $l$ $i$ $s$ $s$ $t$ $t$ $h$ $h$ $e$ $e$ $c$ $c$ $r$ $r$ $u$ $u$ $e$ $e$ $l$ $l$ $e$ $e$ $s$ $s$ $t$ $t$ $m$ $m$ $m$ $o$ $o$ $n$ $n$ $t$ $t$ $h$ $h$
- $\$ is a special word boundary symbol.
- Maintain an inverted index from bigrams to the terms that contain the bigram
Postings list in a 3-gram index

et
→ BEETROOT → METRIC → PETRIFY → RETRIEVAL
Bigram indexes

- Note that we now have two different types of inverted indexes
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- The term-document inverted index for finding documents based on a query consisting of terms
Bigram indexes

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- The term-document inverted index for finding documents based on a query consisting of terms
- The $k$-gram index for finding terms based on a query consisting of $k$-grams
Query mon* can now be run as:
$m$ AND mo AND on
Processing wildcarded terms in a bigram index

- Query mon* can now be run as:
  \$m \text{ AND } mo \text{ AND } on

- Gets us all terms with the prefix *mon* ...
Processing wildcarded terms in a bigram index

- Query mon* can now be run as:
  $m \text{ AND mo AND on}$
- Gets us all terms with the prefix mon ...
- ... but also many “false positives” like MOON.
Query mon* can now be run as:
   $m \text{ AND } mo \text{ AND } on$

Gets us all terms with the prefix mon . . .

. . . but also many “false positives” like MOON.

We must postfilter these terms against query.
Query mon* can now be run as:
$\text{m AND mo AND on}$

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- . . . but also many “false positives” like $\text{MOON}$. We must postfilter these terms against query.
- Surviving terms are then looked up in the term-document inverted index.
Recap Dictionaries  Wildcard queries  Spelling correction  Soundex

Processing wildcarded terms in a bigram index

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  $m \text{ AND } mo \text{ AND } on$
- Gets us all terms with the prefix \textit{mon} \ldots
- \ldots but also many “false positives” like \textit{MOON}.
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- \textit{k}-gram indexes are fast and space efficient (compared to permuterm indexes).
Processing wildcard queries in the term-document index

- As before, we must potentially execute a large number of Boolean queries for each enumerated, filtered term.
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Recall the query: gen* AND universit*
Processing wildcard queries in the term-document index

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- . . . a lot
Outline

1. Recap
2. Dictionaries
3. Wildcard queries
4. Spelling correction
5. Soundex
Spelling correction

- Two principal uses
Spelling correction

- Two principal uses
  - Correcting documents being indexed
Spelling correction

- Two principal uses
  - Correcting documents being indexed
  - Correcting user queries
Spelling correction

- Two principal uses
  - Correcting documents being indexed
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- Two different methods for spelling correction
Spelling correction

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  - Isolated word spelling correction
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    - Check each word on its own for misspelling
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    - Will not catch typos resulting in correctly spelled words, e.g.,
      an asteroid that fell *form* the sky
  - **Context-sensitive** spelling correction
    - Look at surrounding words
    - Can correct *form/from* error above
Correcting documents

- We’re not interested in interactive spelling correction of documents (e.g., MS Word) in this class.
Correcting documents

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- In IR, we use document correction primarily for OCR’ed documents.
Correcting documents

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- In IR, we use document correction primarily for OCR’ed documents.
- The general philosophy in IR is: don’t change the documents.
Correcting queries

- First: isolated word spelling correction
Correcting queries

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- Fundamental premise 1: There is a list of “correct words” from which the correct spellings come.
Correcting queries

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- Simple spelling correction algorithm: return the “correct” word that has the smallest distance to the misspelled word.
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- Example: *informaton* → *information*
- We can use the term vocabulary of the inverted index as the list of correct words.
Correcting queries

- **First:** isolated word spelling correction

- **Fundamental premise 1:** There is a list of “correct words” from which the correct spellings come.

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- **Example:** *informaton* → *information*

- **We can use the term vocabulary of the inverted index as the list of correct words.**

- **Why is this problematic?**
Alternatives to using the term vocabulary

- A standard dictionary (Webster’s, OED etc.)
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- An industry-specific dictionary (for specialized IR systems)
Alternatives to using the term vocabulary

- A standard dictionary (Webster’s, OED etc.)
- An industry-specific dictionary (for specialized IR systems)
- The term vocabulary of the collection, appropriately weighted
Distance between misspelled word and “correct” word

- We will study several alternatives.
Distance between misspelled word and "correct" word

- We will study several alternatives.
- Edit distance
Distance between misspelled word and “correct” word

- We will study several alternatives.
- Edit distance
- Levenshtein distance
Distance between misspelled word and “correct” word

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- Weighted edit distance
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- Edit distance
- Levenshtein distance
- Weighted edit distance
- $k$-gram overlap
Edit distance

- The edit distance between string $s_1$ and string $s_2$ is the minimum number of basic operations to convert $s_1$ to $s_2$. 
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Damerau-Levenshtein distance $\text{cat}-\text{act}$: 1

Damerau-Levenshtein includes transposition as a fourth possible operation.
Levenshtein distance: Computation

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Levenshtein distance: algorithm

\[
\text{LEVENSHTEINDISTANCE}(s_1, s_2)
\]

1. for \( i \leftarrow 0 \) to \( |s_1| \) 
2. do \( m[i, 0] = i \) 
3. for \( j \leftarrow 0 \) to \( |s_2| \) 
4. do \( m[0, j] = j \) 
5. for \( i \leftarrow 1 \) to \( |s_1| \) 
6. do for \( j \leftarrow 1 \) to \( |s_2| \) 
7. do if \( s_1[i] = s_2[j] \) 
8. then \( m[i, j] = \min\{m[i - 1, j] + 1, m[i, j - 1] + 1, m[i - 1, j - 1]\} \) 
9. else \( m[i, j] = \min\{m[i - 1, j] + 1, m[i, j - 1] + 1, m[i - 1, j - 1] + 1\} \) 
10. return \( m[|s_1|, |s_2|] \)

Operations: insert, delete, replace, copy
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Operations: insert, delete, replace, copy
Levenshtein distance: algorithm

```
LEVENSHTEINDISTANCE(s₁, s₂)
1   for i ← 0 to |s₁|
2       do m[i, 0] = i
3   for j ← 0 to |s₂|
4       do m[0, j] = j
5   for i ← 1 to |s₁|
6       do for j ← 1 to |s₂|
7           do if s₁[i] = s₂[j]
8               then m[i, j] = min{m[i - 1, j] + 1, m[i, j - 1] + 1, m[i - 1, j - 1]}
9           else m[i, j] = min{m[i - 1, j] + 1, m[i, j - 1] + 1, m[i - 1, j - 1] + 1}
10   return m[|s₁|, |s₂|]
```

Operations: insert, delete, replace, copy
Levenshtein distance: algorithm

\[
\text{LEVENSHTEINDISTANCE}(s_1, s_2)
\]

1. for \( i \leftarrow 0 \) to \( |s_1| \)
2. \hspace{1em} do \( m[i, 0] = i \)
3. for \( j \leftarrow 0 \) to \( |s_2| \)
4. \hspace{1em} do \( m[0, j] = j \)
5. for \( i \leftarrow 1 \) to \( |s_1| \)
6. \hspace{1em} do for \( j \leftarrow 1 \) to \( |s_2| \)
7. \hspace{2em} if \( s_1[i] = s_2[j] \)
8. \hspace{3em} then \( m[i, j] = \min\{m[i - 1, j] + 1, m[i, j - 1] + 1, m[i - 1, j - 1]\} \)
9. \hspace{3em} else \( m[i, j] = \min\{m[i - 1, j] + 1, m[i, j - 1] + 1, m[i - 1, j - 1] + 1\} \)
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10 \quad \textbf{return} \: m[|s_1|, |s_2|]

Operations: insert, delete, replace, copy
Levenshtein distance: Example

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</table>
## Each cell of Levenshtein matrix

<table>
<thead>
<tr>
<th>Cost of getting here from my upper left neighbor (copy or replace)</th>
<th>Cost of getting here from my upper neighbor (delete)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cost of getting here from my left neighbor (insert)</td>
<td>The minimum of the three possible “movements”; the cheapest way of getting here</td>
</tr>
</tbody>
</table>
Dynamic programming (Cormen et al.)

- Optimal substructure: The optimal solution to the problem contains within it optimal solutions to subproblems.
Dynamic programming (Cormen et al.)

- **Optimal substructure**: The optimal solution to the problem contains within it optimal solutions to subproblems.

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- **Optimal substructure**: We compute minimum distance of substrings in order to compute the minimum distance of the entire string.

- **Overlapping subproblems**: Need most distances of substrings 3 times (moving right, diagonally, down)
Exercise

- Given: *cat* and *catcat*
Exercise

- Given: *cat* and *catcat*
- Compute the matrix of Levenshtein distances
Exercise

- Given: *cat* and *catcat*
- Compute the matrix of Levenshtein distances
- Read out the editing operations that transform *cat* into *catcat*
Weighted edit distance

- As above, but weight of an operation depends on the characters involved.
Weighted edit distance

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- Meant to capture keyboard errors, e.g., $m$ more likely to be mistyped as $n$ than as $q$. 
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- As above, but weight of an operation depends on the characters involved.
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- Meant to capture keyboard errors, e.g., $m$ more likely to be mistyped as $n$ than as $q$.
- Therefore, replacing $m$ by $n$ is a smaller edit distance than by $q$.
- We now require a weight matrix as input.
- Modify dynamic programming to handle weights.
Using edit distance

- Given query, first enumerate all character sequences within a preset (possibly weighted) edit distance
Using edit distance

- Given query, first enumerate all character sequences within a preset (possibly weighted) edit distance
- Intersect this set with list of "correct" words
Using edit distance

- Given query, first enumerate all character sequences within a preset (possibly weighted) edit distance
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- Then suggest terms you found to the user.
Using edit distance

- Given query, first enumerate all character sequences within a preset (possibly weighted) edit distance
- Intersect this set with list of "correct" words
- Then suggest terms you found to the user.
- Or do automatic correction – but this is potentially expensive and disempowers the user.
*k*-gram indexes for spelling correction

- Enumerate all *k*-grams in the query term
**k-gram indexes for spelling correction**

- Enumerate all $k$-grams in the query term
- Use the $k$-gram index to retrieve “correct” words that match query term $k$-grams
$k$-gram indexes for spelling correction

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- Example: bigram index, misspelled word *bordroom*
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- Example: bigram index, misspelled word bordroom
- Bigrams: $bo$, $or$, $rd$, $dr$, $ro$, $oo$, $om$
**k-gram indexes for spelling correction: bordroom**

```
BO  ->  aboard  ->  about  ->  boardroom  ->  border
```
```
OR  ->  border  ->  lord    ->  morbid   ->  sordid
```
```
RD  ->  aboard   ->  ardent  ->  boardroom  ->  border
```
Example with trigrams

- **Issue**: Fixed number of $k$-grams that differ does not work for words of differing length.
Example with trigrams

- Issue: Fixed number of $k$-grams that differ does not work for words of differing length.
- Suppose the correct word is **NOVEMBER**
Example with trigrams

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- Suppose the correct word is **NOVEMBER**
- Trigrams: *nov, ove, vem, emb, mbe, ber*
Example with trigrams

- **Issue**: Fixed number of $k$-grams that differ does not work for words of differing length.
- Suppose the correct word is **NOVEMBER**
- Trigrams: $nov, ove, vem, emb, mbe, ber$
- And the query term is **DECEMBER**
Example with trigrams

- Issue: Fixed number of $k$-grams that differ does not work for words of differing length.
- Suppose the correct word is NOVEMBER
- Trigrams: nov, ove, vem, $emb$, mbe, ber
- And the query term is DECEMBER
- Trigrams: dec, ece, cem, $emb$, mbe, ber
Example with trigrams

- Issue: Fixed number of $k$-grams that differ does not work for words of differing length.
- Suppose the correct word is NOVEMBER
- Trigrams: $nov$, $ove$, $vem$, $emb$, $mbe$, $ber$
- And the query term is DECEMBER
- Trigrams: $dec$, $ece$, $cem$, $emb$, $mbe$, $ber$
- So 3 trigrams overlap (out of 6 in each term)
Example with trigrams

- Issue: Fixed number of $k$-grams that differ does not work for words of differing length.
- Suppose the correct word is \textsc{November}
- Trigrams: \textit{nov, ove, vem, emb, mbe, ber}
- And the query term is \textsc{December}
- Trigrams: \textit{dec, ece, cem, emb, mbe, ber}
- So 3 trigrams overlap (out of 6 in each term)
- How can we turn this into a normalized measure of overlap?
Jaccard coefficient

- A commonly used measure of overlap of two sets
Jaccard coefficient

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- Let $A$ and $B$ be two sets
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**Jaccard coefficient**

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- december/november example: Jaccard coefficient?
- Application to spelling correction: declare a match if the coefficient is, say, $> 0.8$. 
Context-sensitive spelling correction

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Context-sensitive spelling correction

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Context-sensitive spelling correction

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- One idea: **hit-based** spelling correction
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  - Retrieve “correct” terms close to each query term
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  - for *flew form munich*: *flea* for *flew*, *from* for *form*, *munch* for *munich*
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  - Now try all possible resulting phrases as queries with one word “fixed” at a time
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  - Try query “flew from munich”
Our example was: *an asteroid that fell form the sky*

How can we correct *form* here?

Idea?

One idea: **hit-based** spelling correction

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- Now try all possible resulting phrases as queries with one word “fixed” at a time
  - Try query “*flea form munich*”
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  - Try query “*flew form munch*”
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  - The correct query “*flew from munich*” has the most hits.
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    - Try query “**flew from munich**”
    - Try query “**flew form munch**”
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Suppose we have 7 alternatives for **flew**, 19 for **form** and 3 for **munich**, how many “corrected” phrases will we enumerate?
Context-sensitive spelling correction

- The “hit-based” algorithm we just outlined is not very efficient.
Context-sensitive spelling correction

- The “hit-based” algorithm we just outlined is not very efficient.
- More efficient alternative: look at “collection” of queries, not documents
General issues in spelling correction

- User interface
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- User interface
  - automatic vs. suggested correction
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  - *Did you mean* only works for one suggestion.
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- Cost
General issues in spelling correction

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- Cost
  - Spelling correction is potentially expensive.
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  - Maybe just on queries that match few documents.
General issues in spelling correction

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- **Cost**
  - Spelling correction is potentially expensive.
  - Avoid running on every query?
  - Maybe just on queries that match few documents.
  - Guess: Spelling correction of major search engines is efficient enough to be run on every query.
Peter Norvig’s complete spelling corrector in only 21 lines of code!
Outline

1 Recap
2 Dictionaries
3 Wildcard queries
4 Spelling correction
5 Soundex
Soundex

- Soundex is the basis for finding **phonetic** (as opposed to orthographic) alternatives.
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Example: *chebyshev / tchebyscheff*
Soundex

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- Algorithm:
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  - Turn every token to be indexed into a 4-character reduced form
Soundex

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- Algorithm:
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- Example: chebyshev / tchebyscheff
- Algorithm:
  - Turn every token to be indexed into a 4-character reduced form
  - Do the same with query terms
  - Build and search an index on the reduced forms
Soundex algorithm

- Retain the first letter of the term.
Soundex algorithm

1. Retain the first letter of the term.
2. Change all occurrences of the following letters to '0' (zero): 'A', 'E', 'I', 'O', 'U', 'H', 'W', 'Y'
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   - D, T to 3
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   - L to 4
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   - D, T to 3
   - L to 4
   - M, N to 5
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   - C, G, J, K, Q, S, X, Z to 2
   - D, T to 3
   - L to 4
   - M, N to 5
   - R to 6
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4. Repeatedly remove one out of each pair of consecutive identical digits
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   - D, T to 3
   - L to 4
   - M, N to 5
   - R to 6
4. Repeatedly remove one out of each pair of consecutive identical digits
5. Remove all zeros from the resulting string; pad the resulting string with trailing zeros and return the first four positions, which will consist of a letter followed by three digits
Example: Soundex of HERMAN

- Retain H
Example: Soundex of HERMAN

- Retain H
- $ERMAN \rightarrow ORM0N$
Example: Soundex of *HERMAN*

- Retain H
- *ERMAN* $\rightarrow$ *ORM0N*
- *ORM0N* $\rightarrow$ *06505*
Example: Soundex of HERMAN

- Retain H
- \textit{ERMAN} \rightarrow 0\textit{RM0N}
- 0\textit{RM0N} \rightarrow 06505
- 06505 \rightarrow 06505
Example: Soundex of HERMAN

- Retain H
- ERMAN → ORM0N
- ORM0N → 06505
- 06505 → 06505
- 06505 → 655
Example: Soundex of HERMAN

- Retain H
- ERMAN → ORM0N
- ORM0N → 06505
- 06505 → 06505
- 06505 → 655
- Return H655
Example: Soundex of HERMAN

- Retain H
- ERMAN $\rightarrow$ ORM0N
- ORM0N $\rightarrow$ 06505
- 06505 $\rightarrow$ 06505
- 06505 $\rightarrow$ 655
- Return H655

Will HERMANN generate the same code?
Compute soundex code of your last name.
How useful is Soundex?

- Not very – for information retrieval
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- Ok for “high recall” tasks in other applications (e.g., Interpol)
How useful is Soundex?

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- Ok for “high recall” tasks in other applications (e.g., Interpol)
- Zobel and Dart (1996) suggest better alternatives for phonetic matching in IR.
The complete search system
Resources

- Chapter 3 of IIR
Resources

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- Resources at http://ifnlp.org/ir
Resources

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- Resources at http://ifnlp.org/ir
- Soundex demo
Resources

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- Levenshtein distance demo
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- Levenshtein distance demo
- Levenshtein distance slides
- Peter Norvig’s spelling corrector