

# Spell-checking, query correction, wildcards

Stanislav Protasov

# Agenda

- Wildcards and regexp support
  - Wildcard types
  - Permuterm
  - Regexp support
- Spell-checking
  - Isolated words
  - Context-dependent approach
  - Soundex

# Wildcards

# Why do we need wildcards?

- uncertain of the spelling of a query term
- aware of multiple variants of spelling (colou?r)
- unsure about part of speech and stemming
- foreign words and spelling (**University** street vs **Universitetskaya** ulitsa)

# Syntax of wildcards

- \*? - wildcards with joker symbols
  - *Trailing* wildcard query (**Mos\***) — handled with **search trees**
  - *Leading* wildcard queries (**\*sity**) — handled with **reversed search trees** (**ytis...**)
  - Can we handle **Mos\*ow** query? **M\*S\*K?**
- SQL
  - column LIKE “%ab\_d”
- Regexp
  - [a-zA-Z][a-zA-Z0-9]{0-30}

# How they do it in databases

*“The SQL LIKE operator very often causes unexpected performance”*

Only the part before the first wild card serves as an access predicate. The remaining characters do not narrow the scanned index range—non-matching entries are just left out of the result.

PostgreSQL: The optimizer can also use a **B-tree index** for queries involving the pattern matching operators LIKE and ~ if the pattern is a constant and is anchored to the beginning of the string — for example, col LIKE 'foo%' or col ~ '^foo', but not ~~col LIKE '%bar'~~

LIKE 'WI%ND'	LIKE 'WIN%D'	LIKE 'WINA%'
WIAW	WIAW	WIAW
WIBLQQNPUA	WIBLQQNPUA	WIBLQQNPUA
WIBYHSNZ	WIBYHSNZ	WIBYHSNZ
WIFMDWUQMB	WIFMDWUQMB	WIFMDWUQMB
WIGLZX	WIGLZX	WIGLZX
WIH	WIH	WIH
WIHTFVZNLC	WIHTFVZNLC	WIHTFVZNLC
WIJYAXPP	WIJYAXPP	WIJYAXPP
WINAND	WINAND	WINAND
WINBKYDSKW	WINBKYDSKW	WINBKYDSKW
WIPOJ	WIPOJ	WIPOJ
WICBOK	WICBOK	WICBOK

# Permuterm index

1. Add \$ to the end of the word: hello → hello\$
2. Compose all rotations of this word
  - a. hello\$, ello\$h, llo\$he, lo\$hel, o\$hell, \$hello
3. Build a search tree (B-tree, trie) on this extended vocabulary
4. For a particular query run the following search algorithm (star \* means *exhaustive search* of a subtree, with filtering maybe):
  - a. X lookup on X\$
  - b. X\* lookup on \$X\*
  - c. \*X lookup on X\$\*
  - d. \*X\* lookup on X\*
  - e. X\*Y lookup on Y\$X\*
  - f. X\*Y\*Z – ?

**hel\*o?**

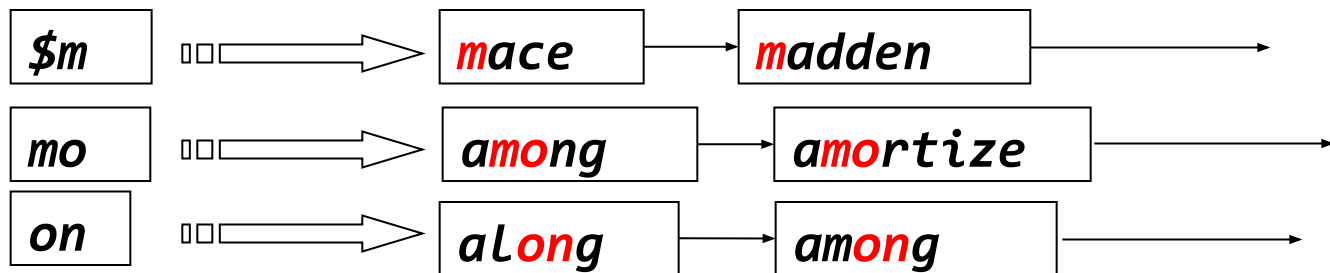
## What's wrong with permuterm?

- Not handling **multiple** joker symbols
- **4-10-times increases** vocabulary size



## K-gram index (q-grams)

1. Mark word start/end with \$
2. 3-grams of `castle` are: \$ca, cas, ast, stl, tle, le\$.
3. Maintain a second inverted index from k-grams to dictionary terms that match each k-gram (here k=2)



4. Convert wildcards into **boolean queries**  
 $re^*ve \rightarrow \$re \ \& \ ve\$$ .
5. *Comment:* as words, **not all k-grams of fixed k are equally useful** (zzz vs the). 9

## Multigrams (V-grams)

Each  $k$ -gram can have specific  $k$ : “<a href” and “.mp3”

**Selectivity of  $x$ -gram** is the fraction of data units which contain at least one occurrence of the gram. **Filter factor.**

$$FF = 1 - \text{selectivity}(x)$$

Take only grams with high FF.

Order query parts by  
filter factor.

*Comment: hard to maintain **online***

### Algorithm 3.1 Multigram index

**Input:** database

**Output:** index: multigram index

#### Procedure

```
[1]  $k = 1$ ,  $\text{expand} = \{\cdot\}$  //  $\cdot$  is a zero-length string
[2] While ( $\text{expand}$  is not empty)
[3]    $k\text{-grams} :=$  all  $k$ -grams in database
      whose  $(k-1)$ -prefix  $\in \text{expand}$ 
[4]    $\text{expand} := \{\}$ 
[5]   For each gram  $x$  in  $k$ -grams
[6]     If  $\text{sel}(x) \leq c$  Then // check selectivity
[7]        $\text{insert}(x, \text{index})$  // the gram is useful
[8]     Else
[9]        $\text{expand} := \text{expand} \cup \{x\}$ 
[10]   $k := k + 1$ 
```

# Regex support

## Index support for regular expression search

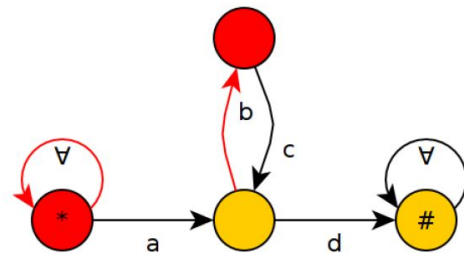
expressing same class of “languages” as finite automata.

General idea is similar:

`/a(bc)*d/`

xyzabc**b**cdxyz

`/[ab]cde/ => (acd OR bcd) AND cde`

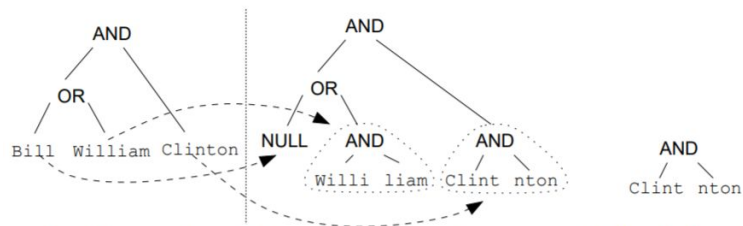
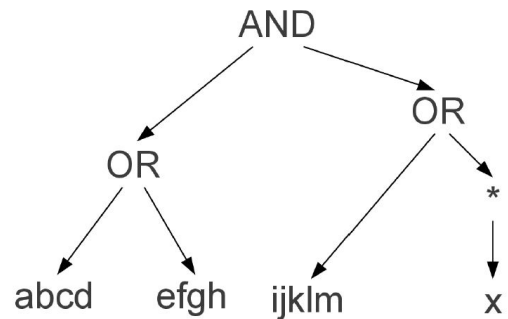


# Regex support methods: FREE

FREE (2002):

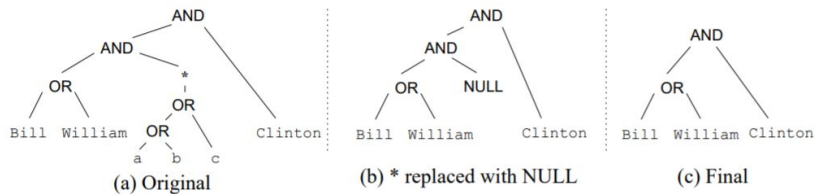
1. Extract tree of continuous string fraction from regex.
  - \* = NULL, NULL “eats” parent OR
  - AND eats child NULL
2. Transform those continuous fractions to **multigrams**
3. Use inverted index on multigrams for query evaluation

`/((abcd|efgh)(ijklm|x*))`



(a) Generation of physical access plan

(b) Final physical access plan



# Regex support methods: GCS

## [Regular Expression Matching with a Trigram Index](#) (Google Code Search, 2006)

- Get 5 characteristics about each part of regex: *emptyable*, *exact*, *prefix*, *suffix*, *match*.
- Recursively union them (with possible simplification)
- Use inverted index of trigrams for query evaluation (similar to pg\_trgm)

Original regex: `/a(bc)+d/`

a: {exact: a}

bc: {exact: bc}

d: {exact: d}

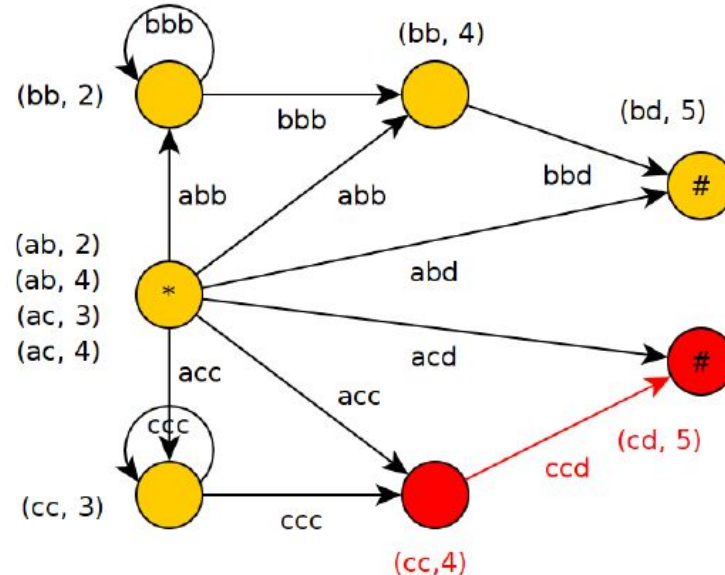
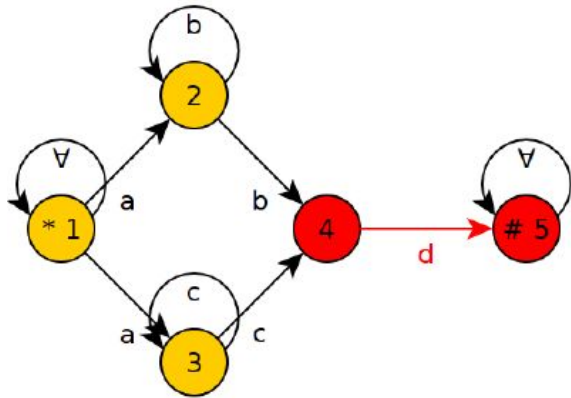
(bc)+: {prefix:bc, suffix: bc}

a(bc)+: {prefix:abc, suffix:bc}

a(bc)+d: {prefix:abc, suffix:bcd} == abc AND bcd

# Regex support methods: automaton transformation (2012)

1. Procedure for automaton transformation into corresponding graph
2. Procedure to simplify a graph
3. Collect path matrix and convert to binary query



# Query correction

# Spell correction

- Two principal uses
  - Correcting **document**(s) being indexed
  - Correcting user **queries** to retrieve “right” answers
- Two principles:
  - proximity-base (take closest)
  - probability-base (take most frequent)



# Spell correction

- Two main flavors:
  - Isolated word
    - Check each word on its own for misspelling
    - Will not catch typos resulting in correctly spelled words  
e.g., *from* → *form*
  - Context-sensitive
    - Look at surrounding words,
    - e.g., *I flew form Heathrow to Narita.*
- Two approaches
  - Fix the query and retrieve documents
  - Suggest corrected query option[s]

# Document correction

Especially needed for OCR'ed documents

- Correction algorithms are tuned for this: **rn/m**
- Can use domain-specific knowledge
  - E.g., OCR can confuse O and D more often ...
  - ... than it would confuse O and I (adjacent on the QWERTY keyboard, so more likely interchanged in typing).

But also: web pages and even printed material have typos

Goal: the dictionary contains fewer misspellings

# Isolated words correction

# Isolated word correction

Fundamental premise – **there is a lexicon** from which the correct spellings come

Two basic choices for this

A **standard** lexicon such as

- Webster's English Dictionary
- An “industry-specific” lexicon – hand-maintained

The lexicon of the **indexed corpus**

- E.g., all words on the web
- All names, acronyms etc.
- (Including the mis-spellings)

# Isolated word correction

Given a lexicon and a character sequence  $Q$ , return the words in the lexicon closest to  $Q$

What's “closest”?

- Edit distance (Levenshtein distance) and LCS (longest common subsequence)
- Weighted edit distance
- $n$ -gram overlap

# Edit distance

Given two strings  $S_1$  and  $S_2$ , the minimum number of operations to convert one to the other

Operations are typically character-level

- Insert, Delete, Replace, (Transposition)

E.g., the edit distance from **dof** to **dog** is 1

- From **cat** to **act** is 2 (Just 1 with transpose.)
- from **cat** to **dog** is 3.

Generally found by dynamic programming.

$$D(i, j) = \begin{cases} 0, & i = 0, j = 0 \\ i, & j = 0, i > 0 \\ j, & i = 0, j > 0 \\ \min\{ & \\ D(i, j - 1) + 1, & \\ D(i - 1, j) + 1, & \\ D(i - 1, j - 1) + m(S_1[i], S_2[j]) & j > 0, i > 0 \\ \} & 22 \end{cases}$$

# Weighted edit distance

As above, but the weight of an operation depends on the character(s) involved

1. Meant to capture OCR or **keyboard errors**  
Example: ***m*** more likely to be mis-typed as ***n*** than as ***q***
2. Therefore, replacing ***m*** by ***n*** is a smaller edit distance than by ***q***
3. This may be formulated as a probability model

Requires weight matrix as input

# Edit distance to all dictionary terms?!

Given a (mis-spelled) query – do we compute its edit distance to every dictionary term?

- Expensive and slow
- Alternative?

How do we cut the set of candidate dictionary terms?

One possibility is to use  $n$ -gram overlap for this.

This can also be used by itself for spelling correction.



# $n$ -gram overlap

Enumerate all the  $n$ -grams in the query string as well as in the lexicon

Use the  $n$ -gram index to retrieve all lexicon terms matching any of the query  $n$ -grams

**Threshold by number of matching  $n$ -grams**

- Variants – weight by keyboard layout, etc.

# Jaccard coefficient (IoU)

A commonly-used measure of overlap

Let  $X$  and  $Y$  be two sets; then IoU is  $|X \cap Y| / |X \cup Y|$

Equals 1 when  $X$  and  $Y$  have the same elements and zero when they are disjoint

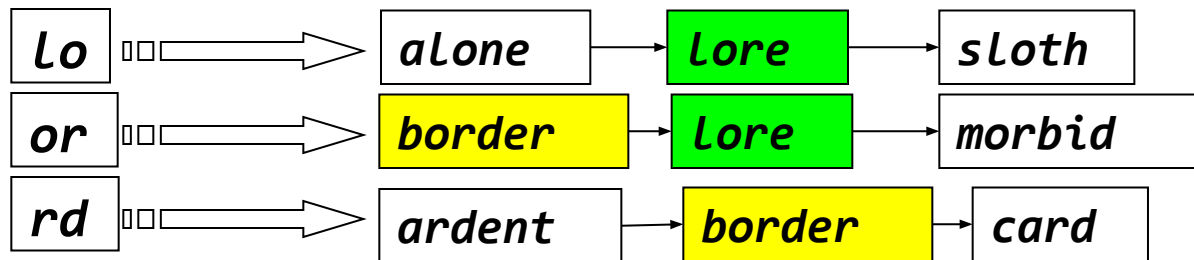
$X$  and  $Y$  don't have to be of the same size

Always assigns a number between 0 and 1

- Now threshold to decide if you have a match
- E.g., if  $\text{IoU} > 0.8$ , declare a match

# Matching trigrams

Consider the query *lord* – we wish to identify words matching 2 of its 3 bigrams (*lo*, *or*, *rd*)



Standard postings “merge” will enumerate ...

Adapt this to using Jaccard (or another) measure.

# Context sensitive correction

# Context-sensitive spell correction

Text: *I flew from Heathrow to Narita.*

Consider the phrase query “*flew form Heathrow*”

We’d like to respond:

Did you mean “*flew from Heathrow*”?

because no docs matched the query phrase.

# Context-sensitive correction

1. Retrieve **dictionary terms close** (in weighted edit distance) **to** each **query term**

Now try all possible resulting phrases with **one word “fixed” at a time**

- *flew from heathrow*
- *fled form heathrow*
- *flea form heathrow*

**Hit-based spelling correction:** Suggest the alternative that has lots of hits.

## 2. Biword statistical approach

Break phrase query into a **conjunction of biwords**.

Look for **biwords** that need **only one term corrected**.

**Enumerate** only phrases containing “common” biwords.

# General issues in spell correction

We enumerate multiple alternatives for “Did you mean?”

Need to figure out which to present to the user

- The alternative hitting most docs
- Query log analysis

More generally, rank alternatives probabilistically

$$\operatorname{argmax}_{corr} P(corr \mid query)$$

- From Bayes rule, this is equivalent to

$$\operatorname{argmax}_{corr} P(query \mid corr) * P(corr)$$

Noisy channel



Language model



Soundex: phonetic correction



# Soundex motivation

Class of heuristics to expand a query into **phonetic** equivalents

- Language specific – mainly for names
- E.g., *chebyshev* → *tchebycheff*

Invented for the U.S. census ... in 1918

# Soundex – typical algorithm

1. Turn every token to be indexed into a **4-character reduced form**
2. Do the same with **all query terms**
3. Build and **search** an **index** on the reduced forms (when the query calls for a soundex match)

# Soundex — part 1

1. Retain the first letter of the word.
2. Change all occurrences of the following letters to 0:  
'A', 'E', 'I', 'O', 'U', 'H', 'W', 'Y'.
3. Change (similar) letters to digits as follows:  
B, F, P, V  $\rightarrow$  1  
C, G, J, K, Q, S, X, Z  $\rightarrow$  2  
D, T  $\rightarrow$  3  
L  $\rightarrow$  4  
M, N  $\rightarrow$  5  
R  $\rightarrow$  6

# Soundex — part 2

4. Remove all pairs of **consecutive digits**.
5. Remove all **zeros** from the resulting string.
6. **Pad** the resulting string with **trailing zeros** and return the first four positions, which will be of the form  
**<uppercase letter> <digit> <digit> <digit>.**

E.g., *Herman* becomes H655.

*H e r m a n n ?*

# Soundex and improvements

Even used by all databases, it is not very efficient in typo fixing. High recall, but very low precision.

Other phonometric algorithms exist:

Phonetic string matching (1996) =  
= editorial distance + phoneme representation

Senc iu fo itenshn!