"Real-Time" Identification of MWE Candidates in Databases from the BNC and the Web

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Objectives of Presentation

Describe background and biases Define key terms elastically Outline my software applications Sketch range of uses and target audiences envisioned Show and compare MRR and MI Encourage feedback and suggestions for further development

- Multimedia in CALL user (interface)
 KWiCFinder to...
 - Identify useful texts
 - Find examples of actual use for teaching and writing
 - Clarify linguistic questions
 - Explore emerging semantic fields
 - build web-based ad-hoc corpora
 - download free from KWiCFinder.com

 kfNgram *n-grams, phrase-frames* free, flexible, GUI; fast even on large datasets (20MW)
 "<u>Phrases in English</u>" website

*− n-*grams (*n* = 1 − 8)

- phrase-frames: set of *n*-gram variants identical in all but one word
- PoS-grams: set of n-gram variants with the same sequence of PoS tags
- chargrams
- now BNC; sub-corpora, MICASE and ANS to follow

Web as Corpus Search Engine Consortium

- Initiative of Silvia Bernardini and Marco Baroni, University of Bologna, Forlì
- Other WAC enthusiasts: Mr. Collocations Stefan Evert, Sebastian Hoffmann, Adam Kilgarriff and myself
- Initial goal: gigaword Web corpus (800M English, 100M each German and Italian)

Emphasis on the practical: reasonable speed, acceptable precision and recall Motivations – on-the-fly subcorpora for PIE – kfNgramDB overcome kfNgram limitations: static lists, straight frequency managing KWiCFinder ad-hoc Web corpora better integration all three tools

Objective

Evaluate and compare statistical techniques to identify MWE candidates for... corpus database gueries for MWEs with specific lexical items subsequent screening, either manually or with processing-intensive metrics deemed more effective than those used here

Terms

MWE cover-term for multi-word units, salient collocations, formulaic expressions Real-time / on-the-fly with "tolerable" delay Scalable from kilo- to mega- and gigacorpora In practice "real time" for (sub)corpora $\leq 25 MW$

Target Audience kfNgramDB

(Corpus) linguists

- compare subcorpora in large linguistic databases
- identify content domain and text-type for Web as corpus
- learn database principles by example on PC
- Language professionals
 - teachers, advanced language learners: readings, instructional materials, examples; identify (MW)Es
 - writers (L2 / L1): organize / maintain exemplars for imitatio, personal corpus and reference materials
 - translators: domain-specific parallel / comparable corpora, possibly compiled ad-hoc from Web sources

Relational databases (RDMS) – Why?

- organize linguistic data, "rapid" retrieval
- sophisticated queries *relating* the content of one field or table to others
- filter / focus results by relevant criteria
- dynamic interactive datasets, not static list
- standard query language SQL: skills transfer to other RDMS
- several powerful RDMS systems are
 - free
 - multi-platform (develop on PC, deploy on *nix)

Relational databases – Which?

Microsoft Access

 + "wizards" - easy to learn
 + produces SQL queries adaptable to other RDMS
 + excellent front-end to other RDMSs (e.g.

- MySQL)
- Windows only (MS Office Pro Suite)

Relational databases – Which?

MySQL +free, fast, scalable +tight integration with PHP for Web interface ±powerful non-standard SQL extensions +active development, large, helpful user base +user-defined C functions callable in gueries (e.g. to calculate lexical association metrics) +embeddable in other applications + multiple platform

Which Lexical Association Metric?

"Gravity Counts for the boundaries of collocations"*

Compares Mutual Information, T-score, Dice, Gravity Counts

Gravity Counts take larger context into account
 most useful for identifying collocation boundaries
 but data processing intensive

* Daudaravičius, Vidas and Rūta Marcinkevičienė, *International Journal of Corpus Linguistics*, 9:2 (2004), 321-348.

Mutual Rank Ratio

Paul Deane, Educational Testing Service, "<u>A</u> <u>Nonparametric Method for Extraction of Candidate Phrasal terms</u>", Association for Computational Linguistics 2005.

"lexical association metric for knowledge-free extraction of phrasal terms", identification of MWUs in untagged text

Based on ratio of "global" to "local" shared ranks

Performance similar or superior to other metrics identifying 2- and 3-grams in WordNet...

...when n-grams including the top 160 ranked types are excluded

1 of 4

Mutual Rank Ratio

shared rank: "tied" items assigned same rank e.g. - items 10-15 all have frequency 512 - shared rank is (10 + 15) / 2 = 12.5- next item ranked 16 (higher if shared) global and local rank United Kingdom - *local rank* of a specific n-gram (LR) united kingdom - global rank of phrase-frames of which n-gram is a variant (GR) * kingdom (the k., animal k., his k. ... united k.) united * (u. kingdom, u. states, u. nations, u. distillers...)

Mutual Rank Ratio

Formula $MRR = (GR_{united} * \cdot GR *_{kingdom})^{1/2}$



*n*th root of product of all Global (*phrase-frame*) Ranks divided by Local (*n-gram*) Rank

Mutual Rank Ratio Pros & Cons

+ Easy to calculate, especially if *n*-grams and phrase-frames are already known (*PIE, kfNgram*)

+ Finds MWUs in untagged text >= others*
+ Weighting reflects Zipfian distribution

- Excludes MWUs...

- with top types (state of the art, matter of principle)
- not in phrase-frames ("singletons")

* if most frequent types excluded

Mutual Information

Popular metric for finding rare word pairs Formula (after D & M) $MI(x,y) = \log_2 \left(N \cdot f(x,y) / f(x) \cdot f(y) \right)$ corpus size N f(x,y) frequency of co-occurrence f(x), f(y) total frequency in corpus Calculated for pairs of words with frequency rank > 150, span 2-4 words; *n*-grams with these pairs retrieved (could include state of the art, matter of principle)

Mutual Information Pros & Cons^{2 of 2}

+ Straightforward calculation with parameters needed for some other metrics
+ Finds "elusive" items, including singletons
+ Complements MRR

- Strong bias toward the infrequent:

Two co-occurring rare words will show a high score, but two co-occurring frequent words will show a low score. (D & M 325)

MRR and MI Compared

- Minimal overlap in MWEs (top 500 items < 20% shared; ranking very different)</p>
- Complementary: both identify different sets of "interesting" MWE candidates
- Both
 - calculation on-the-fly in series of SQL queries alone impractical / intractable on PC for corpora > 5MW
 - hybrid approach with programmatic math faster, more scalable

MRR and MI Compared

Top-ranked 500 *n*-grams by MRR but not by MI by MI but not by MRR by both (<20% of total)</p> in Michigan Corpus of Academic Spoken English, 1.8 MW) European Parliament transcripts, 500 KW) **Click for word lists**

MRR and "Singletons"

- In a large tagged corpus (BNC), Mutual Rank Ratio strands many MWE "singletons", n-grams lacking a phrase-frame for at least one wildword position
- Frequent singletons should be reviewed for potential MWEs
- Singletons less problematic for smaller untagged corpora

Click for word lists

Toward Gigacorpora

Today's RDMSs excel at locating and relating millions of records, but do not scale well into the billions

Search engine technology points the way

- Doug Cutting's Lucene open source text indexer (Java) handles large plain-text collections
- Hybrid approach
 - Lucene to locate documents / passages
 - RDMS to manage text metadata, markup

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Reactions and suggestions encouraged.

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