Comparative Evaluation of Collocation Extraction Metrics

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Abstract
Corpus-based automatic extraction of collocations is typically carried out employing some statistic indicating concurrency in order to identify words that co-occur more often than expected by chance. In this paper we are concerned with some typical measures such as the t-score, Pearson’s χ²-test, log-likelihood ratio, pointwise mutual information and a novel information theoretic measure, namely mutual dependency. Apart from some theoretical discussion about their correlation, we perform comparative evaluation experiments judging performance by their ability to identify lexically associated bigrams. We use two different gold standards: WordNet and lists of named-entities. Besides discovering that a frequency-biased version of mutual dependency performs the best, followed close by likelihood ratio, we point out some implications that usage of available electronic dictionaries such as the WordNet for evaluation of collocation extraction encompasses.

1. Introduction
Collocational information is important not only for second language learning but also for many natural language processing tasks. Specifically, in natural language generation and machine translation it is necessary to ensure generation of lexically correct expressions; for example, “strong”, unlike “powerful”, modifies “coffee” but not “computers”. From the other hand, in automatic construction of thesauri and ontologies, identification of multiwords representing characteristic entities and concepts of the domain, such as “General Motors” or “general relativity”, is an obvious necessity. These two types of collocations are quite different in terms of both compositionality and offset (signed distance between constituents in text). In this paper we are concerned with the latter type of collocations; that is multiwords the meaning of which is not compositionally derivable.

Collocations are abundant in language and vary significantly in terms of length, syntactic patterns and offset. They are also domain-dependent and language-dependent; therefore their automatic extraction from domain specific corpora is of high importance, as far as portability of NLP systems is concerned. Therefore, in this paper we will focus on purely corpus-based automatic extraction of collocations, assuming that other available knowledge sources, such as in (Justeson and Katz, 1995) or in (Pearce, 2001), can be employed additionally.

2. Corpus-based Collocation Extraction
Collocations are recurrent in texts and express lexical selectivity. Therefore two or more words that co-occur in text corpora (much) more often than expected by chance (most) possibly constitute a collocation. In order to test this hypothesis of dependence, several metrics have been adopted by the corpus linguistics community. Typical statistics are the t-score (TSC), Pearson’s χ²-test (χ²), log-likelihood ratio (LLR) and pointwise mutual information (PMI). However, usually no systematic comparative evaluation is accomplished. For example, Kita et al. (1993) accomplish partial and intuitive comparisons between metrics, while Smadja (1993) resorts to lexicographic evaluation of his approach. However, it is obvious that an objective and automated evaluation process offers repeatability, allowing for comparison among different collocation extraction measures and techniques.

The aforementioned metrics estimate lexical selectivity on bigrams. Smadja (1993) proposes an algorithm for joining significant bigrams together to construct significant n-grams. However, since his target task is NLG and therefore he is interested in collocations not necessarily non-compositional, he keeps the larger produced n-grams, while conceptually-oriented tasks such as automatic construction of ontologies and thesauri, require identification of the minimal semantic constituents. For example, “the president of United States” is a collocation but it can be decomposed in two minimal lexico-semantic units of which the straightforward combination produces its meaning: “president” and “United States”. However, extraction of significant bigrams is an important task for both applications. In order to eliminate the factor of offset and exploit available recourses for evaluation we focus on sequential collocations (multi-words).

An objective set of multi-words is necessary, as “gold standard”, for the comparative experiments. Unfortunately, complete machine-readable databases of collocations are not widely available, even for English. On-line lexical resources, such as WordNet (Miller, 1990), contain such information, although
incomplete (Roark and Charniak, 1998) and not pure, as we will note. Obvious, easily obtained and explicitly non-compositional multi-words are also entity names, such as location and organisation names. Terminology lists can also be used in the case of restricted domain corpora.

3. Pairwise significance measures

Since multiwords can be quite long (e.g. “Default Proof Credit Card System Inc”), applying straightforwardly statistics on n-gram counts are computationally prohibitive. The only feasible strategy for extraction of multiwords from large corpora is to initially extract a set of significant bigrams (according to a measure of pairwise dependence) and then, connecting significant bigrams together, to calculate the statistical significance of the larger strings (Smadja, 1993). In order to simplify the task of comparison among measures of significance, the present study is confined to the first stage, i.e. the extraction of significant bigrams.

The most simplistic approach to collocation extraction is to exploit the property of recurrency and therefore to extract the most frequent word co-occurrences. However this has the obvious drawback that the a priori word frequencies are not taken into account; therefore such collocations are often fully compositional and thus of no lexical interest (e.g. “analyst said”, “three years”, etc.). Therefore, measures of dependence taking into account word probabilities (using maximum likelihood estimators) have been widely employed for collocation extraction. In the following sub-sections we define some of the most prominent measures (see (Manning and Schütze, 1999) for more details), we discuss some of their prominent characteristics and we propose a few more measures.

3.1. Information theoretic measures

In one of the premier studies in automatic corpus-based collocation extraction, Church and Hanks (1990) proposed the association ratio, a metric based on the information theoretic concept of mutual information, and specifically to the pointwise mutual information (PMI), which is defined as:

$$I(w_1, w_2) = \log_2 \frac{P(w_1, w_2)}{P(w_1) \cdot P(w_2)}$$

However, PMI is actually a measure of independence rather than of dependence (Manning and Schütze, 1999). Considering perfectly dependent bigrams, i.e. $P(w_1) = P(w_2) = P(w_1, w_2)$, we obtain: $I(w_1, w_2) = -\log(P(w_1))$, which shows that PMI exhibits preference to rare events, because they a priori contain higher amount of information, in comparison to frequent events. This suggests that dependence can actually be identified subtracting from PMI the information that the whole event bears, which is its self-information (Gallager, 1968): $I(x) = -\log(P(x))$. We call the proposed measure Mutual Dependency (MD):

$$D(w_1, w_2) = I(w_1, w_2) - I(w_1), w_2) =\log_2 \frac{P^2(w_1, w_2)}{P(w_1) \cdot P(w_2)}$$

which is obviously maximized for perfectly dependent bigrams, without dependence to their frequency. However, intuition suggests that a slight bias towards frequency can be beneficial reflecting statistical confidence; that is among similarly dependent bigrams the most frequent ones should be favored. Therefore we also tested a few such measures (for example combining MD with the t-score), of which Log-Frequency biased MD (LFMD) proved experimentally the most satisfactory:

$$D_{LFMD}(w_1, w_2) = D(w_1, w_2) + \log_2 P(w_1, w_2)$$

3.2. Hypothesis testing

From a statistical point of view, our problem can be expressed as to determine if the word co-occurrence indicates lexical correlation or it is due to chance. The latter case, which constitutes the null hypothesis, is that the considered words $w_1$ and $w_2$ are generated independently in the corpus and thus their co-occurrence probability can be estimated as: $P(w_1, w_2) = P(w_1) \cdot P(w_2)$. Word probabilities are calculated using maximum likelihood estimators (MLE).

The most widely used statistical tests employed to estimate the divergence of the observed co-occurrence frequency from the one according to the null hypothesis are the t-score (TSC), the Pearson’s $\chi^2$-square test (XSQ) and the log-likehood ratio (LLR). The null hypothesis can be rejected with a certain confidence when the used statistic surpasses a certain threshold.

3.2.1. T-score

The t statistic is defined as:

$$t = \frac{\bar{x} - \mu}{\sqrt{s^2/N}}$$

where $\bar{x}$ is the sample mean, $s^2$ is the sample variance, $N$ is the sample size and $\mu$ is the mean of the distribution which generation of words follows. If the t statistic is large enough the null hypothesis can be rejected. The t-test is typically calculated supposing a normal distribution. That is, for a bigram $uv$ we have: $\bar{x} = P(uv), \mu = P(u) \cdot P(v)$ and $s^2 = P(uv) \cdot (1-P(uv)) \approx P(uv)$. In terms of frequency counts, we have:

$$t(u,v) = 1 - \frac{f_u \cdot f_v}{f_{uv}}$$
Then the relation between the t-score and mutual information can be easily derived:
\[ t = \sqrt{\sum_{uv} \left(1 - 2^{-I(u,v)}\right)} \]

This formula reveals that even loosely related bigrams (e.g. PMI ≈ 3) are ranked roughly according to their frequency; which indicates that the t-score is rather frequency biased.

### 3.2.2. Pearson’s $\chi$-square test

Pearson’s $\chi$-square test, bypasses the arbitrary assumption of normality employed for the calculation of the t-test. It sums the squared differences between the expected and observed frequencies scaled by the expected frequencies in all combinations of co-occurrence or not of the words under consideration:

\[ \chi^2 = \frac{(f_{uv} - f_u f_v)^2}{f_u f_v} + \frac{(f_{uv} - f_u f_v)^2}{f_u f_v} + \frac{(f_{uv} - f_u f_v)^2}{f_u f_v} + \frac{(f_{uv} - f_u f_v)^2}{f_u f_v} \]

where $uv$ represents the sequence of events $u$ and $v$ and $\bar{u}$ the event (word or bigram) $not(u)$.

In the case of statistical data from large corpora, frequency of occurrence is always many orders of magnitude higher than frequency of non-occurrence, and therefore the 3 latter additives are insignificant, compared to the former, which is actually a different formulation of the MD measure. Indeed, the ranking lists of the two measures are quite similar.

### 3.2.3. Likelihood ratio

A widely accepted measure of statistical significance is the logarithm of the ratio between the likelihoods of the hypotheses of dependence and independence (LLR):

\[ -2 \log \lambda = 2 \cdot \log \frac{L(H_1)}{L(H_0)} \]

where $L(H)$ is the likelihood of hypothesis $H$ based on observed data assuming that occurrence of words follows binomial distribution (Dunning, 1993), which is a more plausible assumption than the normality assumption.

### 4. Experimental evaluation

We conducted comparative evaluation experiments of the discussed measures using English language for the obvious reason of availability of both training text corpora and, mainly, lexical resources for automatic evaluation. Since the involved linguistic analysis is minimal we deem that our results and conclusions are valid for any language.

Statistical data were acquired from the Wall Street Journal corpus (WSJC) of 1988, comprised of about 11 million content words. Since Sentence Boundary Detection is, although not trivial, a rather solved NLP task and in WSJC sentence boundaries are annotated, we considered only intra-sentential co-occurrences. Moreover, we eliminate bigrams containing functional words or numbers and bigrams appearing less than 3 times in the corpus. Therefore our statistical data consist of roughly 4.4 million bigrams, that is 80000 distinct bigrams were considered.

The 30-best scoring bigrams for each measure are shown in Table 1. We can see that the t-score produces exactly the same hits (ranked slightly different) as plain frequency, some of which are compositional and uninteresting (e.g. “company said”, “says mr”), while LFMD and LLR produce some interesting and important collocations (e.g. merrill lynch, los angeles, dow jones). MI and MD (or $\chi^2$) 30-best lists contain exclusively named-entity bigrams (for all, it is $f_u = f_v = f_{uv}$); the former, unlike the latter, ranks higher the low frequency bigrams.

For the automatic evaluation we employed two completely unrelated gold standards. The one is WordNet (Miller, 1990); one of the most copious lexical resources in electronic form for English. WordNet contains semantic relations between lexical entities representing entities and concepts and therefore this set of lexical entities was used as a “gold standard”. Since we study bigram dependency measures, we kept only lexical entities comprised of two words. We didn’t extract bigrams from WordNet n-gram entities with n>2, because in many cases they are analytical descriptions of synsets or semantic categories (e.g. “capital_of_the_United_Kingdom”, “ABO_blood_group_system”) rather than lexical collocations.

The second source is comprised of named entities which appear in abundance in American newswire texts and were gathered mainly from the Internet for this specific purpose. Namely they are 5700 US cities (2000 of them periphrastic), 11000 US companies and 11000 person names which recurrently occur in newswire texts in the domains of politics, business, sports, arts, etc. In this case we maintained all extracted bigrams, excluding only words which are designators of the respective category (e.g. city, corp, company, ltd, sir, etc.) and therefore their contribution to the meaning of the phrase is compositional. In total there were 23000 distinct bigrams the 5400 of which occur in our corpus.
| R | FREQUENCY | T-score | LLR | LFMD | MD, $\chi^2$ | PMI |
|---|-----------|---------|-----|------|-------------|-----|
| 1 | vice president | vice president | vice president | vice president | bala cynwyd | leonie rysanek |
| 2 | stock exchange | stock exchange | stock exchange | wall street | zoete wedd | lineas aereas |
| 3 | chief executive | chief executive | chief executive | chief executive | ralston purina | yand renjun |
| 4 | year earlier | year earlier | cents-share | cents-share | bateman eichler | yue-kong pao |
| 5 | cents-share | cents-share | year-earlier | stock exchange | corpus christi | fayez sarofim |
| 6 | york stock | york stock | executive officer | executive officer | gallium arsenide | steer-mom pop's |
| 7 | million shares | executive officer | wall street | year-earlier | kaposi's sarcoma | tech-ops landauer |
| 8 | company said | composite trading | composite trading | dow jones | rotan mosle | sunder rajan |
| 9 | executive officer | million shares | york stock | los angeles | cahora bassa | tiang siew |
| 10 | composite trading | company said | net income | composite trading | mager dietz | tercel ez |
| 11 | spokesman said | spokesman said | exchange composite | real estate | vazquez rana | toa nenryo |
| 12 | wall street | wall street | interest rates | shearson lehman | ku klux | rabi blancos |
| 13 | interest rates | net income | real estate | hong kong | kwik kopy | rodrigo borja |
| 14 | net income | interest rates | dow jones | merrill lynch | nisho iwai | rubik's cube |
| 15 | exchange composite | exchange composite | shares outstanding | net income | deja vu | rossel uclaf |
| 16 | trading yesterday | trading yesterday | tender offer | exchange composite | fii fyffes | schiapparelli farmaceutici |
| 17 | common shares | common shares | years ago | interest rates | epeda bertrand | tu bishvat |
| 18 | shares outstanding | shares outstanding | los angeles | tender offer | revolucionario institucional | usinor sacilor |
| 19 | years ago | years ago | shearson lehman | burnham lambert | minas gerais | its sount |
| 20 | inc said | inc said | million shares | shares outstanding | ds bancor | immanuel kant |
| 21 | corp said | tender offer | trading yesterday | years ago | yom kippur | jebel kusha |
| 22 | says mr | real estate | common shares | york stock | munoz ledo | jovito salonga |
| 23 | stock market | says mr | merrill lynch | leveraged buy-out | kumagai gumi | koninklijke nedlloyd |
| 24 | tender offer | stock market | hong kong | lehman hutton | aerolineas argentinas | josip broz |
| 25 | real estate | corp said | years old | morgan stanley | mats wilander | lanthanum gallate |
| 26 | holding company | holding company | spokesman said | san francisco | aer lingus | katsuya takanashi |
| 27 | shares-closed | shares-closed | fourth quarter | years old | khalifa al-sabah | soti partis |
| 28 | million year | dow jones | white house | white house | modus operandi | sotto voce |
| 29 | dow jones | years old | holding company | drexel burnham | dextran sulfate | hau pei-tsun |
| 30 | said mr | exchange commission | west german | seasonally adjusted | twyla tharp | harve benard |

Table 1: The 30-best bigrams for all tested measures of bigram association. Bigrams lacking interesting (i.e. lexical) association are marked with a diagonal line, while lexically associated bigrams appearing in any of the gold standards are indicated with grey fill. Note that some named entity fragments (e.g. “ku klux” from “Ku Klux Klan” and “york stock” from “New York Stock Exchange”) have not matched WordNet entities due to the exclusion of n-grams with n>2.
Figure 1: Comparative evaluation against WordNet entities.

Figure 2: Comparative evaluation against Named Entities
Since for a certain level of confidence different statistics may provide different numbers of suggestions, resulting in different levels of coverage and precision, we follow a simple but objective evaluation scheme: We rank bigrams according to every measure and we depict the percentage of pairs retrieved correctly among the N-best candidates, with N ranging from 200 to 100000. As we noted in Section 3, the performance of Pearson’s χ²-square test is almost identical to that of Mutual Dependency. Baseline is drawn supposing random selection of bigrams.

The evaluation results show that LFMD and LLR outperform the other measures in both gold standard evaluations. It is interesting however that evaluation against WordNet favours not only the t-score but plain frequency as well, at the expense of information theoretic metrics. We argue that this demonstrates that employing straightforwardly WordNet as a “gold standard” multiword repository is not quite infallible for two reasons:

1. Many WordNet entities are rather analytical descriptions of lexical entities and therefore by no means non-compositional multiwords of interest. For example both “Japanese_capital” and “capital_of_Japan” are included in WordNet as well as many phrases of the same pattern. A preprocessing filter should probably be applied to exclude compositional expressions using the WordNet hypernym relations. Indeed, compositionality of “capital_of_Japan” can be easily identified as since there are numerous “capital_of_X” entities where X has the same hypernym as “Japan”. Moreover, the specific level of the hierarchy the entity occurs can be of assistance towards the same end. That is, the lower the level, the more possible the WordNet word sequence to be a non-compositional lexical entity rather than a synset description.

2. No systematic attempt to include (or omit) all named entities in WordNet (as probably in most dictionaries) have been done. Therefore only the most frequent named entities are included; introducing a preference to frequency-biased measures of association.

5. Conclusion

We have studied certain pairwise word association measures, typically applied for collocation extraction. We have discussed some associations among them, both analytically and experimentally. Although length and offset of collocations varies significantly, our study was restricted on bigrams in order to eliminate other intervening factors and to exploit available lexical resources for evaluation.

In specific, the strong bias of the t-score towards frequency, makes it incapable to identify rare collocations, which comprise a large portion of terminology, as Zipf’s law suggests. From the other hand, the inverse-frequency bias of pointwise mutual information can be corrected taking into consideration the self-information of the co-occurrence. Introducing a slight bias towards frequency results in a top-performing measure, surpassing even likelihood ratio.

The evaluation procedure needs also special attention. Available lexical resources such as WordNet are both impure and incomplete regarding non-compositional collocations. Therefore, enrichment with terminological information and elaborated preprocessing for the exclusion of descriptive expressions seem necessary prior to evaluation experiments.

6. References

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