

Unsupervised Acquisition of Comprehensive Multiword Lexicons using Competition in an n -gram Lattice

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Abstract

We present a new model for acquiring comprehensive multiword lexicons from large corpora based on competition among n -gram candidates. In contrast to the standard approach of simple ranking by association measure, in our model n -grams are arranged in a lattice structure based on subsumption and overlap relationships, with nodes inhibiting other nodes in their vicinity when they are selected as a lexical item. We show how the configuration of such a lattice can be optimized tractably, and demonstrate using annotations of sampled n -grams that our method consistently outperforms alternatives by at least 0.05 F-score across several corpora and languages.

1 Introduction

Despite over 25 years of research in computational linguistics aimed at acquiring multiword lexicons using corpora statistics, and growing evidence that speakers process language primarily in terms of memorized sequences (Wray, 2008), the individual word nonetheless stubbornly remains the *de facto* standard processing unit for most research in modern NLP. The potential of multiword knowledge to improve both the automatic processing of language as well as offer new understanding of human acquisition and usage of language is the primary motivator of this work. Here, we present an effective, expandable, and above all tractable new approach to comprehensive multiword lexicon acquisition. Our aim is to find a middle ground between standard MWE acquisition approaches based on association

measures (Ramisch, 2014), and more sophisticated statistical models (Newman et al., 2012) which do not scale to the large corpora, the main source of the distributional information in modern NLP systems.

A central challenge in building comprehensive multiword lexicons is paring down the huge space of possibilities without imposing restrictions which disregard a major portion of the multiword vocabulary of a language: allowing for diversity creates significant redundancy among statistically promising candidates. The lattice model proposed here addresses this primarily by having the candidates—contiguous and non-contiguous n -gram types—compete with each other based on subsumption and overlap relations to be selected as the best (i.e., most parsimonious) explanation for statistical irregularities due to lexical affinity. We test this approach across four large corpora in three languages, including two relatively free-word-order languages (Croatian and Japanese), and find that this approach consistency outperforms alternatives, offering scalability and many avenues for future enhancement.

2 Background and Related Work

In this paper we will refer to the targets of our lexicon creation efforts as **formulaic sequences**, following the terminology of Wray (2002; 2008), wherein a formulaic sequence (FS) is defined as “a sequence, continuous or discontinuous, of words or other elements, which is, or appears to be, prefabricated: that is, stored and retrieved whole from memory at the time of use, rather than being subject to generation or analysis by the language grammar.” That is, a FS

shows signs of being part of a mental lexicon.¹ As noted by Wray (2008), formulaic sequence theory is compatible with other highly multiword, lexicalized approaches to language structure, in particular Pattern Grammar (Hunston and Francis, 2000) and Construction Grammar (Goldberg, 1995); an important distinction, though, is that these sorts of theories often posit entirely abstract grammatical constructions/patterns/frames which do not fit well into the FS framework. Nevertheless, since many such constructions *are* composed of sequences of specific words, the FS of a language includes many flexible constructions (e.g., *ask * for*) along with entirely fixed combinations (e.g., *rhetorical question*) not typically of interest to grammarians. Note that the FS framework allows for individual morphemes be part of a formulaic sequence, but for practical reasons we focus primarily on lemmatized words as the unit out of which FS are built.

In computational linguistics, the most common term used to describe multiword lexical units is *multiword expression* (“MWE”: Sag et al. (2002), Baldwin and Kim (2010)), but here we wish to make a principled distinction between at least somewhat non-compositional, strongly lexicalized MWEs and FS, a near superset which includes many MWEs but also compositional linguistic formulas. This distinction is not a new one; it exists, for example, in the original paper of Sag et al. (2002) in the distinction between lexicalized and institutionalized phrases, and also to some extent in the MWE annotation of Schneider et al. (2014b), who distinguish between weak (collocational)² and strong (non-compositional) MWEs. It is our contention, however, that separate, precise terminology is useful for research targeted at either class: we need not strain the concept of MWE to include items which do not require special semantics, nor are we inclined to disregard the larger formulaticity of language simply because it is not the dominant focus of MWE

¹Though by this definition individuals or small groups may have their own FS, here we are only interested in FS that are shared by a recognizable language community.

²Here we avoid the term *collocation* entirely due to confusion with respect to its interpretation. Though some define it similarly to our definition of FS, it can be applied to any words that show a statistical tendency to appear in the vicinity of one another for any reason: for instance, the pair of words *doctor/nurse* might be considered a collocation (Ramisch, 2014).

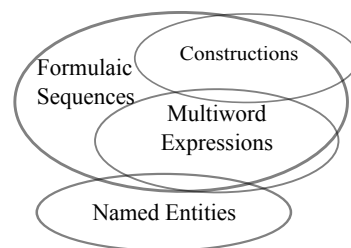


Figure 1: Multiword Terminology

research. Many MWE researchers might defensibly balk at including in their MWE lexicons and corpus annotations (English) FS such as *there is something going on*, *it is more important than ever to ...*, *...do not know what it is like to ...*, *there is no shortage of...*, *the rise and fall of...*, *now is not the time to...*, etc. as well as tens of thousands of other such phrases which, along with less compositional MWEs like *be worth ...'s weight in gold*, fall under the FS umbrella. Another reason to introduce a different terminology is that there are classes of phrases which are typically considered MWEs that do not fit well into an FS framework, for instance novel compound nouns whose semantics are accessible by analogy (e.g., *glass limb*, analogous to *wooden leg*). Also, we exclude from the definition of both FS and MWE those named entities which refer to people or places which are little-known and/or whose surface form appears derived (e.g., *Mrs. Barbara W. Smith* or *Smith Garden Supplies Ltd*). Figure 1 shows the conception of the relationship between FS, (multiword) constructions, MWE, and (multiword) named entities that we assume for this paper.

Regardless of the terminology used to describe them, the starting point for multiword lexicon creation has typically been lexical association measures (Church and Hanks, 1990; Dunning, 1993; Schone and Jurafsky, 2001; Evert, 2004; Pecina, 2010; Araujo et al., 2011; Kulkarni and Finlayson, 2011; Ramisch, 2014). When these methods are used to build a lexicon, particular binary syntactic patterns are typically chosen. Only some of these measures generalize tractably beyond two words, for example PMI (Church and Hanks, 1990), i.e., the log ratio of the joint probability to the product of the marginal probabilities of the individual words. Another measure which addresses sequences of longer

than two words is the *c*-value (Frantzi et al., 2000) which weights term frequency by the log length of the *n*-gram while penalizing *n*-grams that appear in frequent larger ones. Mutual expectation (Dias et al., 1999) involves deriving a normalized statistic that reflects the extent to which a phrase resists the omission of any constituent word. Similarly, the lexical predictability ratio (LPR) of Brooke et al. (2015) is an association measure intended for any possible syntactic pattern which is calculated by discounting syntactic predictability from the overall conditional probability for each word given the other words in the phrase. Though most association measures involve only usage statistics of the phrase and its subparts, the DRUID measure is an exception which uses distributional semantics around the phrase to identify how easily an *n*-gram could be replaced by a single word (Riedl and Biemann, 2015).

Typically multiword lexicons are created by ranking *n*-grams according to an association measure and applying a threshold. The algorithm of da Silva and Lopes (1999) is somewhat more sophisticated, in that it identifies the local maxima of association measures across subsuming *n*-grams within a sentence to identify MWEs of unrestricted length and syntactic composition; its effectiveness beyond noun phrases, however, seems relatively limited (Ramisch et al., 2012). Brooke et al. (2014; 2015) developed a heuristic method intended for general FS extraction in larger corpora, first using conditional probability statistics to do an initial (single pass) coarse-grained segmentation of the corpus, followed by a pass through the resulting vocabulary, breaking larger units into smaller ones based on a tradeoff between marginal and conditional statistics. An example of an unsupervised approach which does not use association measures, Newman et al. (2012) extends the Bayesian word segmentation approach of Sharon Goldwater and Johnson (2009) to multiword, applying a generative Dirichlet Process model which jointly constructs a segmentation of the corpus and a corresponding multiword vocabulary.

Other research in MWEs has tended to be rather focused on particular syntactic patterns such as verb-noun combinations (Fazly et al., 2009). The system of Schneider et al. (2014a) distinguishes a full range of MWE sequences in the English Web Treebank, including gapped expressions, using a supervised se-

quence tagging model. Though in theory automatic lexical resources could be a useful addition to the Schneider et al. model, which uses only manual lexical resources, attempts to do so have achieved mixed success (Riedl and Biemann, 2016).

The motivation for building lexicons of FS naturally overlaps with those for MWE: models of distributional semantics, in particular, can benefit from sensitivity to multiword units (Cohen and Widdows, 2009), as can parsing (Constant and Nivre, 2016) and topic models (Lau et al., 2013). One major motivation for looking beyond MWEs is the ability to carry out broader linguistic analyses. Within corpus linguistics, multiword sequences have been studied in the form of *lexical bundles* (Biber et al., 2004), which are simply *n*-grams that occur above a certain frequency threshold. Like FS, Lexical bundles generally involve larger phrasal chunks that would be missed by traditional MWE extraction, and so research in this area has tended to focus on how particular formulaic phrases (e.g., *if you look at*) are indicative of particular genres (e.g., university lectures). Lexical bundles have been applied, in particular, to learner language: for example, Chen and Baker (2010) show that non-native student writers use a severely restricted range of lexical bundle types, and tend to overuse those types, while Granger and Bestgen (2014) investigate the role of proficiency, demonstrating that intermediate learners underuse lower-frequency bigrams and overuse high-frequency bigrams relative to advanced learners. Sakaguchi et al. (2016) demonstrate that improving fluency (closely linked to the use of linguistic formulas) is more important than improving strict grammaticality with respect to native speaker judgments of non-native productions; Brooke et al. (2015) explicitly argue for FS lexicons as a way to identify, track, and improve learner proficiency.

3 Method

Our approach to FS identification involves optimization of the total explanatory power of a lattice, where each node corresponds to an *n*-gram type. The explanatory power of the whole lattice is defined simply as a product of the **explainedness** of the individual nodes. Each node can be considered either “on” (is an FS) or “off” (is not an FS). The basis of the

calculation of explainedness is the syntax-sensitive LPR association measure of Brooke et al. (2015), but it is calculated differently depending on the on/off status of the node as well as the status of the nodes in the vicinity: nodes are linked based on n -gram subsumption and corpus overlap relationships (see Figure 2), with “on” nodes typically explaining other nodes. Given these relationships, we iterate over the nodes and greedily optimize the on/off choice relative to explainedness in the local neighborhood of each node, until convergence.

3.1 Collecting statistics

The first step in the process is to derive a set of n -grams and related statistics from a large, unlabeled corpus of text. Since our primary association measure is an adaption of LPR, our approach in this section mostly follows Brooke et al. (2015) up until the last stage. An initial requirement of any such method is an n -gram frequency threshold, which we set to 1 instance per 10 million words, following Brooke et al. (2015).³

We include gapped or non-contiguous n -grams in our analysis, in acknowledgment of the fact that many languages have MWEs where the components can be “separated”, including verb particle constructions in English (Dehé, 2002), and noun-verb idioms in Japanese (Hashimoto and Kawahara, 2008). Having said this, there are generally strong syntactic and length (Wasow, 2002) restrictions on what can constitute a gap, which we capture in the form of a language-specific POS-based regular expression (see Section 4 for details). This greatly lowers the number of potentially gapped n -gram types, increasing precision and efficiency for negligible loss of recall. We also exclude punctuation and lemmatize the corpus, and enforce an n -gram count threshold. As long as the count threshold is substantially above 1, efficient extraction of all n -grams can be done iteratively: in iteration i , i -grams are filtered by the frequency threshold, and then pairs of instances of these i -grams with $(i - 1)$ words of overlap are found, which derives a set of $(i + 1)$ -grams

³Based on manual analysis using the MWE corpus of Schneider et al. (2014b), this achieves very good (over 90%) type-level MWE coverage using the frequency filtered n -gram statistics from the ICWSM blog corpus (see Section 4) after filtering out proper names.

which necessarily includes all those over the frequency threshold.

Once a set of relevant n -grams is identified and counted, other statistics required to calculate the **Lexical Predictability Ratio** (“LPR”) for each word in the n -gram are collected. LPR is a measure of how predictable a word is in a lexical context, as compared to how predictable it is given only syntactic context (over the same span of words). Formally, the LPR for word w_i in the context of a word sequence $w_1, \dots, w_i, \dots, w_n$ with POS tag sequence t_1, \dots, t_n , is given by:

$$\text{LPR}(w_i, w_{1,n}) = \max_{1 \leq j < k \leq n} \frac{p(w_i | w_{j,k})}{p(w_i | t_{j,k})}$$

where $w_{j,k}$ denotes the word sequence $w_j, \dots, w_{i-1}, w_{i+1}, \dots, w_k$ excluding w_i (similarly for $t_{j,k}$). Note that the lower bound of LPR is 1, since the ratio for a word with no context is trivially 1. We use the same equation for gapped n -grams, with the caveat that quantities involving sequences which include the location where the gap occurs are derived from special gapped n -gram statistics. Note that the identification of the best ratio across all possible choices of context, not just the largest, is important for longer FS, where the entire POS context alone might uniquely identify the phrase, resulting in the minimum LPR of 1 even for entirely formulaic sequences, an undesirable result.

In the segmentation approach of Brooke et al. (2015), LPR for an entire span is calculated as a product of the individual LPRs, but here we will use the minimum LPR across the words in the sequence:

$$\text{minLPR}(w_{1,n}) = \min_{1 \leq i \leq n} \text{LPR}(w_i, w_{1,n})$$

Here, minLPR for a particular n -gram does not reflect the *overall* degree to which it holds together, but rather focuses on the word which is its weakest link. For example, in the case of *be keep * under wraps*, a general statistical metric might assign it a high score due to the strong association between *keep* and *under* or *under* and *wraps*, but minLPR is focused on the weaker relationship between *be* and the rest of the phrase. This makes it particularly appropriate measure for use in a lattice model of completing n -grams, where the choice of *be keep*

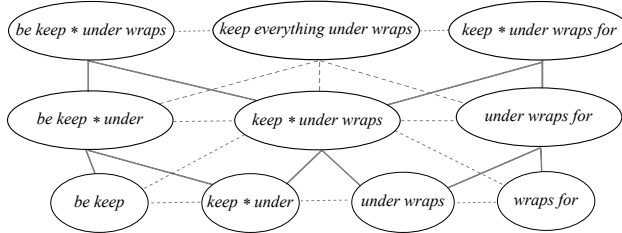


Figure 2: A portion of an n -gram lattice. Solid lines indicate subsumption, dotted lines overlaps

** under wraps* versus *keep * under wraps* should be based exactly on the extent to which *be* is an essential part of the phrase; the other affinities are, in effect, irrelevant, because they occur in the smaller n -gram as well.

3.2 Node interactions

The n -gram nodes in the lattice are directionally connected to nodes consisting of $(n + 1)$ -grams which subsume them and $(n - 1)$ -grams which they subsume. For example, as detailed in Figure 2, the (gapped) n -gram *keep * under wraps* would be connected “upwards” to the node *keep everything under wraps* and connected “downwards” to *under wraps*. These directional relationships allow for two basic interactions between nodes in the lattice when a node is turned on: **covering**, which inhibits nodes below (subsumed by) a turned-on node (e.g., if *keep * under wraps* is on, the model will tend not to choose *under wraps* as an FS); and **clearing**, which inhibits nodes above a turned-on node (e.g., if *keep * under wraps* is on, the model would avoid selecting *keep everything under wraps* as an FS). A third, undirected mechanism is **overlapping**, where nodes inhibit each other due to overlaps in the corpus (e.g., having both *keep * under wraps* and *be keep * under* as FS will be avoided).

3.2.1 Covering

The most important node interaction is **covering**, which corresponds to discounting or entirely excluding a node due to a node higher in the lattice. Our model includes two types of covering: hard and soft.

Hard covering is based on the idea that, due to very similar counts, we can reasonably conclude that the presence of an n -gram in our statistics is a direct result of the other. In Figure 2, e.g., if we

have 143 counts of *keep * under wraps* and 152 counts of *under wraps*, the presence of *keep * under wraps* almost completely explains *under wraps*, and we should consider these two n -grams as one. We do this by permanently disabling any hard covered node, and setting the minLPR of the covering node to the maximum minLPR among all the nodes it covers (including itself); this means that longer n -grams with function words (which often have lower minLPR) can benefit from the strong statistical relationships between open-class lexical features in n -grams that they cover. This is done as a preprocessing step, and greatly improves the tractability of the iterative optimization of the lattice. Of course, a threshold for hard covering must be chosen: during development we found that a ratio of 2/3 (corresponding to a significant majority of the counts of a lower node corresponding to the higher node) worked well. We also use the concept of hard covering to address the issue of pronouns, based on the observation that specific pronouns often have high LPR values due to pragmatic biases (Brooke et al., 2015); for instance, private state verbs like *feel* tend to have first person singular subjects. In the lattice, n -grams with pronouns are considered covered (inactive) unless they cover at least one other node which does not have a pronoun, which allows us to limit FS with pronouns without excluding them entirely: they are included only in cases where they are definitively formulaic.

Soft covering is used in cases when a single n -gram does not entirely account for another, but a turned-on n -gram to some extent may explain some of the statistical irregularity of one lower in the lattice. For instance, in Figure 2 *keep * under* is not hard-covered by *keep * under wraps* (since there are FS such as *keep * under surveillance*, *keep it under your hat*, etc.), but if *keep * under wraps* is tagged as an FS, we nevertheless want to discount the portion of the *keep * under* counts that correspond to occurrences of *keep * under wraps*, with the idea that these occurrences have already been explained by the longer n -gram. If enough subsuming n -grams are on, then the shorter n -gram will be discounted to the extent that it will be turned off, preventing redundancy. This effect is accomplished by increasing the turned-off explainedness of *keep * under* (and thus making turning on less desirable) in the following

manner: let $c(\cdot)$ be the count function, and $s_1 \dots s_m$ be any turned-on nodes which are above t in the lattice (covering nodes). Then, the $\text{cover}(t)$ score for a covered node t is:

$$\text{cover}(t) = \max \left(0, \frac{c(t) - \sum_{i=1}^m c(s_i)}{c(t)} \right)$$

This is intended as a simple, quick-to-calculate approximation of the result of recalculating minLPR with the counts corresponding to the covering nodes actually removed. cover takes on values in the range 0 to 1, with 1 being the default when no covering is occurring.

3.2.2 Clearing

In general, covering prefers turning on longer, covering n -grams since doing so explains nodes lower in the lattice. Not surprisingly, it is generally desirable to have a mechanism working in opposition, i.e., one which views shorter FS as helping to explain the presence of longer n -grams which contain them, beyond the FS-neutral syntactic explanation provided by minLPR. **Clearing** does this by changing the increasing the explainedness of nodes higher in the lattice when a lower node is turned-on. The basic mechanism is similar to covering, except that counts cannot be made use of in the same way—whereas it makes sense to explain covered nodes in proportion to the counts of their covering nodes (since the counts of the covered n -grams are from the covering n -gram), in the reverse direction this logic fails.

A simple but effective solution which avoids introducing extra hyperparameters is to make use of the minLPR values of the relevant nodes. In the most common two-node situation, we increase the explainedness of the cleared node based on the ratio of the minLPR of two nodes, though only if the minLPR of the lower node is higher. Generalized to the (rare) case of multiple clearing nodes, we define $\text{clear}(t)$ as:

$$\text{clear}(t) = \prod_{i=1}^m \min \left(1, \frac{\text{minLPR}(t)}{\text{minLPR}(u_i)} \right)$$

where u_i is the i th clearing node of t , i.e., turned-on nodes below t in the lattice. We refer to this mechanism as “clearing” because it tends to clear

away a variety of trivial uses of common FS which may have higher LPR due to the lexical and syntactic specificity of the FS. For instance, in Figure 2 if the node *keep * under wraps* is turned on and has a minLPR of 8, then, if the minLPR of a node such as *keep * under wraps for* is 4, $\text{clear}(t)$ will be 0.5. Like cover , clear takes on values in the range 0 to 1, with 1 being the default when no clearing occurs.

3.2.3 Overlap

The third mechanism of node interaction involves n -grams which overlap in the corpus. In general, independent FS do not consistently overlap. For example, given that *be keep * under* and *keep * under wraps* often appear together (overlapping on the tokens *keep * under*), we do not want both being selected as an FS, even in the case that both have high minLPR. To address this problem, we use a mechanism somewhat different than above: rather than increasing the explainedness of turned-off nodes, we decrease the explainedness of the overlapping turned-on nodes—a penalty rather than an incentive which expresses the model’s confusion at having overlapping FS. Let $oc(x, y)$ refer to number of times the n -grams corresponding to nodes x and y overlapped in the corpus, and o_1, \dots, o_m refer to overlapping nodes, i.e., turned-on nodes which overlap with our target node t in the corpus. We define $\text{overlap}(t)$ as:

$$\text{overlap}(t) = \frac{c(t)}{c(t) - \sum_{i=1}^m oc(t, o_i)}$$

Overlap takes on values in the range 1 to $+\infty$, also defaulting to 1 when no overlaps exist. The effect of overlap is hyperbolic: small amounts of overlap have little effect, but nodes with significant overlap will effectively be forced to turn off.

3.3 Explainedness

In order to capture the current state of the model and provide an overall explainedness score, we introduce two indicator functions: $I_{on}(t)$ is 1 if t is on and 0 if t is off; $I_{off}(t)$ is the reverse. The objective function maximized by the model is then the explainedness (*expl*) across all the nodes of the lattice, which can be defined in terms of minLPR and the node interaction functions:

$$expl(t_1, \dots, t_N) = \prod_{i=1}^N I_{on}(t_i) C^{-\text{overlap}(t_1)} + I_{off}(t_i) \text{minLPR}(t_i)^{-\text{cover}(t_i) \cdot \text{clear}(t_i)} \quad (1)$$

When a node is off, its explainedness is the inverse of its minLPR, except if there are covering or clearing nodes which explain it by pushing the exponent of minLPR towards zero. When the node is on, its explainedness is the inverse of a fixed cost hyperparameter C , though this cost is increased if it overlaps with other active nodes. All else being equal, when $\text{minLPR}(t) > C$, a node will be selected as an FS, and so, independent of the node interactions, C can be viewed as the threshold for the minLPR association measure under a traditional approach to MWE identification. There is no upper bound on C , but empirically, we have found values in the range [3, 6] give reasonable results for the languages presented in this paper.

3.4 Optimization

The dependence of the explainedness of nodes on their neighbors effectively prohibits a global optimization of the lattice. Fortunately, though most of the nodes in the lattice are part of a single main connected component, most of the effects of nodes on each other are relatively local, and effective local optimizations can be made tractable by applying some simple restrictions. The main optimization loop consists of iterations over the lattice until complete convergence (no changes in the final iteration). For each iteration over the main loop, each potentially active node is examined in order to evaluate whether its current status is optimal given the current state of the lattice. The order that we perform this has an effect on the result: among the obvious options, good results are obtained through ordering nodes by frequency, which gives an implicit advantage to relatively common n -grams.

Given the relationships between nodes, it is obviously not sufficient to consider switching only the present node. If, for instance, one or more of *be keep* * *under wraps*, *under wraps*, or *be keep* * *under* has been turned on, the covering, clearing, or overlapping effects of these other nodes will likely prevent

Algorithm 1 Optimization algorithm. N is an ordered list of the nodes in the lattice. Nodes (designated by n) contain pointers to the nodes immediately linked to them the lattice. States (designated by s) indicate whether each node is *ON* or *OFF*. Explainedness values are indicated by e .

function LOCALOPT($s_{start}, n, N_{rev}, N_{aff}$)

```

 $s_{start} \leftarrow \text{SETNODE}(s, n, \text{ON})$ 
 $Q \leftarrow \text{EMPTYQUEUE}()$ 
 $e_{best} \leftarrow 0$ 
 $s_{best} \leftarrow \text{NULL}$ 
PUSH( $Q, s_{start}$ )
repeat
   $s_{curr} \leftarrow \text{POP}(Q)$ 
   $e_{curr} \leftarrow \text{CALCEXPL}(s_{curr}, N_{aff})$ 
  for  $n_{rev}$  in  $N_{rev}$  do
     $s_{new} \leftarrow \text{SETNODE}(s_{curr}, \text{OFF})$ 
     $e_{new} \leftarrow \text{CALCEXPL}(s_{new}, N_{aff})$ 
    if  $e_{new} > e_{curr}$  then
      PUSH( $Q, s_{new}$ )
    if  $e_{new} > e_{best}$  then:
       $e_{best} \leftarrow e_{new}$ 
       $s_{best} \leftarrow s_{new}$ 
until ISEMPY( $Q$ )
return  $s_{best}$ 

```

FREQUENCYSORTREVERSE(N)

$s \leftarrow \text{INITIALIZEALLOFF}(N)$

repeat

$Changed \leftarrow \text{FALSE}$

for n in N **do**

$N_{rev} \leftarrow \text{GETRELEVANT}(n, N)$

$N_{aff} \leftarrow \text{GETAFFECTED}(N_{rev}, N)$

$s_{new} \leftarrow \text{LOCALOPT}(s, n, N_{rev}, N_{aff})$

if $s_{new} \neq s$ **then**

$s \leftarrow s_{new}$

$Changed \leftarrow \text{TRUE}$

until ! $Changed$

return s

a competing node like *keep * under wraps* from being correctly activated. Instead, the algorithm identifies a small set of “relevant” nodes which are the most important to the status of the node under consideration. Since turned-off nodes have no direct effect on each other, only turned-on nodes above, below, or overlapping with the current node in the Lattice need be considered. Once the relevant nodes have been identified, all nodes (including turned-off nodes) whose explainedness is affected by one or more of the relevant nodes are identified. Next, a search is carried out for the optimal configuration of the relevant nodes, starting from an ‘all-on’ state and then iteratively considering new states with one relevant node turned off; the search continues as long as there is an improvement in explainedness. Since the node interactions are roughly cumulative in their effects, this approach will generally identify the optimal state without the need for an exhaustive search. The details of the algorithm are given as Algorithm 1.

Omitted from Algorithm 1 for clarity are various low-level efficiencies which prevent the algorithm from reconsidering states already checked or from recalculating the explainedness of nodes when unnecessary. We also apply the following efficiency restrictions, which significantly reduce the runtime of the algorithm. In each case, more extreme (less efficient) values were individually tested using a development set and found to provide no benefit in terms of the quality of the output lexicon:

- We limit the total number of relevant nodes to 5. When there are more than 5 nodes turned on in the vicinity of the target node, the most relevant nodes are selected by ranking candidates by the absolute difference in explainedness across possible configurations of the target and candidate node considered in isolation;
- To avoid having to deal with storing and processing trivial overlaps, we exclude overlaps with a count of less than 5 from our lattice;
- Many nodes have a minLPR which is slightly larger than 1 (the lowest possible value). There is very little chance these nodes will be activated by the algorithm, and so after applying hard covering, we do not consider activating nodes with $\text{minLPR} < 2$.

4 Evaluation

We evaluate our approach across three different languages including evaluation sets derived from four different corpora. In English, we follow Brooke et al. (2015) in using a 890M token filtered portion of the ICWSM blog corpus (Burton et al., 2009) tagged with the Tree Tagger (Schmid, 1995). To facilitate a comparison with Newman et al. (2012), which does not scale up to a corpus as large as the ICWSM, we also build a lexicon using the 100M token British National Corpus (Burnard, 2000), using the standard CLAWS-derived POS tags for the corpus. Lemmatization included removing all inflectional marking from both words and POS tags. For English, gaps are identified using the same POS regex used in Brooke et al. (2015), which includes simple nouns and portions thereof, up to a maximum of 4 words.

The other two languages we include in our evaluation are Croatian and Japanese. Relative to English, both languages have freer word order: we were interested in probing the challenges associated with using an n -gram approach to FS identification in such languages. For Croatian, we used the *hrWaC* corpus (Šnajder et al., 2013), a filtered version of the Croatian web corpus *hrWaC* (Ljubešić and Klubička, 2014), which is POS-tagged and lemmatized using the tools of Agić et al. (2013). Similar to English, the POS regex for Croatian includes simple nouns, adjectives and pronouns, but also other elements that regularly appear inside FS, including both adverbs and copulas. For Japanese, we used a subset of the 100M-page web corpus of Shinzato et al. (2008), which was roughly the same size (in terms of token count) as the English corpus. We segmented and POS-tagged the corpus with MeCab (Kudo, 2008) using the UNIDIC morphological dictionary (Den et al., 2007). The POS regex for Japanese covers the same basic nominal structures as English, but also includes case markers and adverbials. Though our processing of Japanese includes basic lemmatization related to superficial elements like the choice of writing script and politeness markers, many elements (such as case marking) which are removed by lemmatization in Croatian are segmented into independent morphological units in the MeCab output, making the task somewhat different for the two languages.

	Contiguous		Gapped		κ	
	FS	non-FS	FS	non-FS	Pre	Post
ICWSM	169	702	29	916	0.52	0.84
BNC	49	403	8	475	0.51	0.84
Croatian	64	382	11	456	0.58	0.87
Japanese	102	337	9	438	0.49	0.82

Table 1: Statistics for test sets

Brooke et al. (2015) introduced a method for evaluating FS extraction without a reference lexicon or direct annotation of the output of a model. Instead, n -grams are sampled after applying the frequency threshold and then annotated as being either an FS or not. Benefits to this as compared to competing evaluation include replicability, the diversity of FS, and the ability to calculate a true F-score. We use the annotation of 2000 n -grams in the ICWSM corpus from that earlier work, and applied the same annotation methodology to the other corpora discussed above: after training and based on written guidelines derived from the definitions of Wray (2008), three native-speaker, educated annotators judged 500 contiguous n -grams and another 500 gapped n -grams for each of the new corpora.

Other than the inclusion of new languages, our test sets differ from Brooke et al. (2015) in two ways. One advantage of a type-based annotation approach (as compared to a corpus annotation), particularly with regards to annotation with a known subjective component, is that it is quite sensible to simply discard borderline cases, improving reliability at the cost of some representativeness. To this end, we entirely excluded from our test set n -grams which just one annotator marked as FS. Table 1 contains the counts for the four test sets after this filtering step as well as Cohen’s Kappa scores before (Pre) and after (Post). The second change is that for the main evaluation we collapsed gapped and contiguous n -grams into a single test set. The rationale is that the number of positive gapped examples is too low to provide a reliable independent F-score (see further discussion in Section 6).

Our primary comparison is with the heuristic LPR model from Brooke et al. (2015), which is scalable to large corpora and includes gapped n -grams.

For the BNC, we also compare, separately, the DP-seg model from Newman et al. (2012) with recommended settings, and the LocalMaxs algorithm of da Silva and Lopes (1999) using SCP; neither of these methods scale to the larger corpora.⁴ Because these other approaches only generate sequential multiword units, we use only the sequential part of the BNC test set for this evaluation. All comparison approaches have themselves been previously compared against a wide range of association measures. As such, we do not repeat all these comparisons here, but we do consider a lexicon built from ranking n -grams according to the measure used in our lattice (minLPR) as well as PMI and raw frequency. For each of these association measures we rank all n -grams above the frequency threshold and build a lexicon equal to the size of the lexicon produced by our model.

We created small development sets for each corpus and used them to do a thorough testing of parameter settings. Although it is generally possible to increase precision by increasing C , we found that across corpora we were always obtained near-optimal results using a C of 4, so to demonstrate the usefulness of the lattice technique as an entirely off-the-shelf tool, we present the results using identical settings for all four corpora. We treat covering as a fundamental part of the Lattice model, but to investigate the efficacy of other node interactions within the model we present results with each of overlap and clearing node interactions turned off.

5 Results

The main results for FS acquisition across all four corpora are shown in Table 2. As noted in previous work, simple statistical association measures like PMI do fairly poorly when faced with syntactically-unrestricted n -grams of variable length: minLPR is clearly a much better statistic for this purpose. The LPRseg method of Brooke et al. (2015) consistently outperforms simple ranking, and the lattice method proposed here does better still, with a margin that is fairly consistent across languages. Generally, clearing and overlap node interactions provide

⁴DP-seg is far too slow, and LocalMaxs, though faster, calculates counts for all n -grams in the corpus, which would require terabytes of RAM for the large corpora.

Source	English											
	ICWSM			BNC			Croatian			Japanese		
	P	R	F	P	R	F	P	R	F	P	R	F
Countrank	0.13	0.09	0.10	0.08	0.14	0.10	0.10	0.16	0.12	0.11	0.06	0.08
PMIrank	0.24	0.15	0.18	0.12	0.25	0.16	0.21	0.32	0.26	0.18	0.08	0.11
minLPRrank	0.49	0.31	0.39	0.25	0.44	0.32	0.36	0.45	0.40	0.47	0.21	0.29
LPR-seg	0.53	0.42	0.47	0.37	0.44	0.40	0.41	0.47	0.43	0.69	0.43	0.53
Lattice <i>-cl-ovr</i>	0.47	0.53	0.50	0.31	0.60	0.41	0.32	0.66	0.43	0.49	0.61	0.54
Lattice <i>-cl</i>	0.57	0.42	0.49	0.33	0.58	0.42	0.39	0.56	0.46	0.63	0.49	0.55
Lattice <i>-ovr</i>	0.52	0.51	0.51	0.34	0.60	0.44	0.36	0.67	0.47	0.53	0.62	0.58
Lattice	0.67	0.43	0.52	0.40	0.60	0.48	0.44	0.56	0.49	0.76	0.49	0.59

Table 2: Results of FS identification in various test sets; Countrank= lexicon created by ranking with frequency PMIrank = lexicon created with ranking pointwise mutual information, minLPRrank = lexicon created by ranking with minLPR, LPRseg = lexicon created by method of Brooke et al. (2015), -cl = no clearing, -ovr = no penalization of overlaps, P = Precision, R = Recall, F = F-score. Bold is best in column.

	P	R	F
PMIrank	0.20	0.29	0.23
minLPRrank	0.34	0.45	0.39
LPR-seg	0.42	0.45	0.43
LocalMaxs	0.56	0.39	0.46
DP-seg	0.35	0.71	0.47
Lattice	0.47	0.63	0.54

Table 3: Results of FS identification in contiguous BNC test set; LocalMaxs = method of da Silva and Lopes (1999); DP-seg = method of Newman et al. (2012)

a relatively large increase in precision at the cost of a smaller drop in recall, though the change is fairly symmetrical in Croatian. The Japanese and ICWSM corpus had relatively high precision and low recall, whereas both the BNC and Croatian corpus have low precision and high recall.

In the contiguous FS test set for the BNC (Table 3), we found that both the LocalMaxs algorithm and the DP-seg method of Newman (Newman et al., 2012) were able to beat our other baseline methods with roughly similar F-scores, though both are well below our Lattice method. Some of the difference seems attributable to fairly severe precision/recall imbalance, though we were unable to improve the F-score by changing the parameters from recom-

mended settings for either model.

6 Discussion

Though the results across the four corpora are reasonably similar with respect to overall F-score, there are significant discrepancies. By using the UNIDIC morpheme representation as the base unit for Japanese, the model is doing an extra layer of FS identification, one which is provided by word boundaries in the other languages. The result is that there are many more FS for Japanese: precision is high, and recall is relatively low. Importantly, the initial n -gram statistics derived from corpus reflect that Japanese is different: the number of n -gram types over length 4 is almost twice the number in the ICWSM corpus. One idea for future work is to automatically adapt to the input language/corpus in order to ensure a good balance between precision and recall.

At the opposite extreme, the low precision of the BNC is almost certainly at least somewhat a reflection of its relatively small size: whereas the n -gram threshold we have used here results in minimum counts of roughly 100 for the other three corpora used here, the BNC statistics includes n -grams with counts less than 10. This might be resolved by increasing the n -gram threshold, or simply avoiding small corpora, but for some applications it may be

useful to build comprehensive FS lexicons even in relatively low resource situations. One idea we are pursuing is modifying the calculation of the LPR metric to integrate uncertainty due to low counts.

There is one other more general explanation for the precision/recall imbalances we see across the four corpora: both the BNC and the Croatian corpus are composed primarily of published texts written by professional writers, particularly news. The ICWSM corpus and the Japanese corpus, on the other hand, are mostly blogs and web pages. Though all genres have FS, it is our observation that there is much more diversity in less controlled genres: many English gapped expressions, in particular, appear almost exclusively in relatively informal genres.

We were interested in addressing Croatian and Japanese in part because of their relatively free word order, and whether the handling of gaps would help with identifying FS in these languages. We discovered, however, that free word order actually results in *more* of a tendency towards contiguous FS, not less, a fact that is reflected in our test sets (the ratio between gapped and ungapped FS) as well as the content of the lexicon. Strikingly rare in Croatian, in particular, are expressions where the content of a gap is an argument which must be filled to syntactically complete an expression: it is English whose fixed-word-order constraints often keep elements of an FS distant from each other. The gaps that do happen in Croatian are mostly prosody-driven insertions of other elements into already complete FS. This phenomena highlights a problem with the current model, in that gapped and contiguous versions of the same n -gram sequence (e.g., *take away* and *take * away*) are, at present, considered entirely independently. Alternatives for dealing with this include collapsing statistics to create a single node in the lattice, creating a promoting link between contiguous and gapped versions of the same n -grams sequence in the lattice model, or switching to a dependency representation (which, we note, requires very little change to the basic model presented here, but would narrow its applicability).

As it stands, connections in the lattice are based entirely on explicit n -gram subsumption and overlap relations. One of the major benefits of this model as compared to alternatives is the relative ease with which additional kinds of interactions be-

tween nodes could be implemented. Another connection we have considered is based on identical or similar syntactic patterns (e.g., POS sequences), which could serve to encourage the model to make generalizations: in English, e.g., learning that verb-particle combinations are generally likely to be FS, whereas verb-determiner combinations are not. Our initial investigations suggest, however, it may be difficult to apply this idea without merely amplifying existing undesirable biases in the LPR measure. Bringing in other information such as simple distributional statistics might help the model identify non-compositional semantics, and could, in combination with the existing lattice competition, focus the model on detecting MWEs, which could in turn serve as a reliable basis for generalization when the raw LPR statistics alone are an unreliable indicator of formulaticity.

With respect to speed, although the optimization of the lattice is several orders of magnitude more time consuming than the decomposition heuristics of Brooke et al. (2015), the time needed to build and optimize the lattice was still only a fraction of the time required to collect the statistics necessary to calculate LPR, a necessary first step for both methods: therefore, the overall effect of adding the lattice optimization is fairly minimal. We note that for all four corpora, the lattice optimization algorithm converged within 10 iterations.

Finally, though in general using the sampling methodology to build test sets has significant benefits in terms of providing a robust, replicable evaluation, F-scores become unreliable when there are very few positive examples, such as with most of our gapped n -gram test sets. To do a reliable, focused evaluation of FS with gaps, we would need many more examples than can be produced with straightforward sampling. One option we might consider is adding additional filtering to the sampling processes, for instance using the LPR metric to exclude large numbers of unpromising n -grams.

Though the model presented here was designed specifically for FS extraction, we note that it could be useful for similar tasks such as unsupervised creation of morphological lexicons for agglutinative languages. In particular, character or phoneme n -grams could compete in an identically structured lattice (though without gapped n -grams) to be cho-

sen as the best morphemes for the language, and we could straightforwardly adapt LPR to use, as the denominator of the ratio, phonological predictably (i.e., based on vowel/consonant “tags”) instead of syntactic predictability. It is likely, though, that further modifications would be necessary to target morphological phenomena, and we leave this for future work.

7 Conclusion

We have presented here a new methodology for acquiring comprehensive multiword lexicons from large corpora, using competition in an n -gram lattice. Our evaluation using annotations of sampled n -grams shows that it is consistently outperforms alternatives across several corpora and languages. A tool which implements the method, as well as the acquired lexicons and test sets, are available at: <http://ANON.YMO.US>.⁵

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