Employing distributional semantics to organize task-focused vocabulary learning

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Abstract
How can a learner systematically prepare for reading a book they are interested in? In this paper, we explore how computational linguistic methods such as distributional semantics, morphological clustering, and exercise generation can be combined with graph-based learner models to answer this question both conceptually and in practice. Based on the highly structured learner model and concepts from network analysis, the learner is guided to efficiently explore the targeted lexical space. They practice using multi-gap learning activities generated from the book focused on words that are central to the targeted lexical space. As such the approach offers a unique combination of computational linguistic methods with concepts from network analysis and the tutoring system domain to support learners in achieving their individual, reading task-based learning goals.

1 Introduction
Learning vocabulary is a major component of foreign language learning. In the school context, initially vocabulary learning is typically organized around the words introduced by the text book. In addition to the incrementally growing vocabulary lists, some textbooks also provide thematically organized word banks. When other texts are read, the publisher or the teacher often provides annotations for new vocabulary items that appear in the text. A wide range of digital tools have been developed to support such vocabulary learning, from digital versions of file cards to digital text editions offering annotations.

While such applications serve the needs of the formal learning setting in the initial foreign language learning phase, where the texts that are read are primarily chosen to systematically introduce the language, later the selection of texts to be read can in principle follow the individual interests of the student or adult, which boosts the motivation to engage with the book. Linking language learning to a functional goal that someone actually wants to achieve using language is in line with the idea of Task-Based Language Teaching (TBLT) as a prominent strand of foreign language education (Willis and Willis, 2013).

Naturally, not all authentic texts are accessible to every learner, but linguistically-aware search engines, such as FLAIR (Chinkina and Meurers, 2016), make it possible to identify authentic texts that are at the right reading level and are rich in the language constructions next on the curriculum. Where the unknown vocabulary that the reader encounters in such a setting goes beyond the around 2% of unknown words in a text that can be present without substantial loss of comprehension (Schmitt et al., 2011), many digital reading environments provide the option to look up a word in a dictionary. Yet, frequently looking up words in such a context is cumbersome and distracts the reader from the world of the book they are trying to engage with. Relatedly, one of the key criteria of TBLT is that learners should rely on their own resources to complete a task (Ellis, 2009). But this naturally can require pre-task activities preparing the learner to be able to successfully tackle the task (Willis and Willis, 2013). But how can a learner systematically prepare for reading a text or book they are interested in reading?

In this paper, we explore how computational linguistic methods such as distributional semantics, morphological clustering, and exercise generation can be combined with graph-based learner models to answer this question both conceptually and in practice. On the practical side, we developed an application that supports vocabulary learning as a pre-task activity for reading a self-selected book. The conceptual
goal is to automatically organize the lexical semantic space of any given English book in the form of a
graph that makes it possible to sequence the vocabulary learning in a way efficiently exploring the space
and to visualize this graph for the users as an open learner model (Bull and Kay, 2010) showing their
growing mastery of the book’s lexical space. Lexical learning is fostered and monitored through auto-
matically generated multi-gap activities (Zesch and Melamud, 2014) that support learning and revision
of words in the contexts in which they occur in the book.

In section 2 we discuss how a book or other text chosen by the learner is turned into a graph encoding
the lexical space that the learner needs to engage with to read the book, and how words that are morpho-
logically related as word families (Bauer and Nation, 1993) are automatically identified and compactly
represented in the graph (2.1.1). In section 3 we then turn to the use of the graph representation of the
lexical semantic space of the book to determine the reader’s learning path and represent their growing
lexical knowledge as spreading activation in the graph. In section 4 the conceptual ideas are realized
in an application. We discuss how the new learner cold-start problem is avoided using a very quick
word recognition task we implemented, before discussing the content selection and activity generation
for practice and testing activities. Section 5 then provides a conceptual evaluation of the approach and
compares it with related work, before wrapping up with a conclusion in section 6.

2 Constructing a graph for the lexical space of a book: a structured domain model

Going beyond the benefits of interactivity and adaptivity of individualized digital learning tools, sup-
porting learner autonomy is known to be important for boosting motivation and self-regulation skills
(Godwin-Jones, 2019). This includes the choice of reading material a learner wants to engage with,
where the texts prepared by a teacher or publisher cannot reflect the interests of individual students, the
topics and genres they want to explore in the foreign language. The freedom of choosing a text that the
learner wants to engage with also identifying a clear functional goal for learning vocabulary – learning
new words to enable us to read a text of interest, so that the interest in the content coincides with the
interest in further developing the language skills. In that sense learning vocabulary becomes a pre-task
activity in the spirit of task-based language learning. Organizing vocabulary learning in this way also
helps turn the otherwise open-ended challenge of learning the lexical space of a new language to the
clearly delineated task of mastering a sub-space. This functionally guided approach contrasts with the
approach of other vocabulary learning tools selecting random infrequent lexical items from the language
to be learned, which given their rare and often highly specialized nature are likely to only be useful for
impressing friends when playing foreign language scrabble.

To make text-driven vocabulary learning work, we need to map the text selected by the learner into a
structured domain to support systematic and efficient learning of the lexical space as used in the book.
We distinguish the process of structuring the vocabulary used in the book, independent of the learner’s
background, from the representation of the individual learner’s knowledge. The former is tackled in this
section and can be regarded as our domain model, while the latter is a learner model that essentially is
an overlay over the domain model, and will be discussed in section 3.

Since vocabulary learning is about establishing form-meaning connections, in principle the basic unit
best suited for this would be word senses. At the same time, full automatic word sense disambiguation is
complex, error prone, and often domain specific – and in the context of a given book, a given word will
often occur with the same meaning. We therefore limit ourselves to only disambiguating homographs
in terms of their part-of-speech, following Wilks and Stevenson (1998). Throughout our approach, we
therefore use <word, POS> pairs as basic units. To POS annotate the book selected by the user, we
use the Spacy NLP tools (http://spacy.io). Given our focus on learning the characteristic vocabulary of
the book, we eliminate stop words as well as word-POS pairs appearing less than five times in the given
book.

2.1 Semantic and thematic relations

To structure the lexical space in terms of meaning, there are two related options. Words can be sem-
antically related, for example, tiger, lion, elephant, and crocodile all have the property of being wild
animals, on from the perspective of a WordNet, they are hyponyms of wild animal. On the other hand, words can also be thematically related, such as blackboard, teacher, and chalk all belonging to a school theme. Gholami and Khezrlou (2014) highlights the benefits of the semantic approach over the thematic approach from the perspective of a tutor. As we are building a system that acts like a tutor tracking and fostering the learner’s vocabulary knowledge, we decided to focus on semantic relatedness.

2.1.1 Word families

Complementing the lexical semantic relationships, words are also related to each other through derivational and inflectional morphology. Many of these morphological processes are semantically transparent. Bauer and Nation (1993) proposed the idea of grouping words into so-called word families stating that “once the base word or even a derived word is known, the recognition of other members of the family requires little or no extra effort”. The creation of word families is based on criteria involving frequency, regularity, productivity and predictability of all the English affixes. Bauer and Nation (1993) arranged the inflectional affixes and common derivational affixes into the graded levels, as exemplified on the left-hand side of Figure 1.

Figure 1: A word family example (Bauer and Nation, 1993) and an expanded family node in our graph

We adopt the idea of word families to compactly represent morphologically related words. The graph on the right side of Figure 1 exemplifies the word family that becomes visible when selecting the lemma dream in our graph representation (where word families normally are shown in collapsed form and represented by their underlying lemma). We currently collapse words belonging to any of the levels into one word family, though in the future one could chose to collapse only those levels that are semantically most transparently connected.

2.2 Generating a lexical graph of word families and their semantic relations

To structure the lexical space of the user selected book in terms of a semantically related word graph, we start with a distributional semantic vector representation of each word, which we obtain from the pre-trained model of GloVe (Pennington et al., 2014) based on the co-occurrence statistics of the the words form a large Common Crawl data-set (http://commoncrawl.org).

On this basis, the relationship score between the families are computed to be the maximum of pairwise cosine similarity score of all its members. Let \( F_1 \) be a family with \( m \) members and \( F_2 \) be a family with \( n \) members. The relationship score between the two family \( F_1 \) and \( F_2 \) is the maximum of cosine similarity score of all \( m \times n \) pairs, as spelled out in Figure 2. In this way, we create a fully connected network of word families, as exemplified in the figure. The families with members that are closer in the semantic vector space are connected with higher weights.

Following D’Angelo and West (1997), the number of edges in the graph can be computed as \( e = \frac{n \times (n-1)}{2} \), where \( e \) is the total number of edges and \( n \) is the number of nodes or families in the
\[ w_{12} = \max_{i \in F_1, j \in F_2} \frac{V_i \cdot V_j}{\|V_i\| \|V_j\|} \]

where, \( w_{12} \) is the cosine similarity between the families \( F_1 \) and \( F_2 \).

Figure 2: Formula for computing relationship between families and a resulting example

When inspecting graphs derived for sample texts, we observe the majority of the connections are weak. To obtain a graph of semantic relationships that meaningfully structure the vocabulary used in a book, we focus on stronger relationships and eliminate edges with weights less than 0.3.

We also observed that the node families of very frequently occurring verbs tend to be very densely connected, and this impact of frequency on distributional semantic measures has been discussed in the literature (Patel et al., 1998; Weeds et al., 2004). In order to control for this kind of over-sensitivity of distributional semantic measures for highly frequent words, we restrict the node degree to a maximum threshold, which based on experiments with sample data we set to five. So for each node, only the five edges with the highest weight are retained.

As a result of the method described in this section, we obtain a lexical graph for the user-provided text that structures and compactly represents the lexical space of the text in a graph-based domain model. This is the lexical space that the user wants to explore and master enough to be able to read the book. In terms of computational linguistic methods, on the one hand, distributional semantics creates the overall structure of a meaning-connected lexical space, on the hand, word families organize and collapse forms that are related by morphological processes in the linguistic system.

### 2.3 Example generation of graphs for books

To test the graph construction, we chose three books as a sample to study the characteristics of the vocabulary space created by our application: (a) Twenty Thousand Leagues Under the Sea by Jules Verne, (b) Harry Potter and the Sorcerer’s Stone by J. K. Rowling and (c) A Game of Thrones: A Song of Ice and Fire by George R. R. Martin. Table 1 indicates the size of the text and the graph created for each book.

| Book title                                 | Unique words | Learning targets | Graph nodes | Graph edges | Graph size |
|--------------------------------------------|--------------|------------------|-------------|-------------|------------|
| Twenty Thousand Leagues Under the Sea      | 10k          | 1.7k             | 1.3k        | 3.3k        | 18 MB      |
| Harry Potter and the Sorcerer’s Stone      | 6.5k         | 1.2k             | 1k          | 2.4k        | 13 MB      |
| A Game of Thrones: A Song of Ice and Fire  | 14k          | 3.7k             | 2.5k        | 5.6k        | 35 MB      |

Table 1: Characteristics of the graphs derived for vocabulary space for three books

for each book. We see that 15–25% of the words from the text qualifies as the lexical learning targets. 20–30% of those collapse into a family encoded by a graph node. The average connections a family has with other families is around 2.5. The algorithm thus seems to work as expected for these sample books. Some example word family clusters formed for these books at a threshold of similarity scores greater than 0.7 are shown in Figure 3 with only the root nodes of each family being displayed here.
3 Representing the lexical knowledge of a learner: an open learner model

With a structured domain model established for the vocabulary space to be explored by the user, we want to make use of it to efficiently guide the learner to cover the space and track learning in a learner model. The learner model is an overlay on the domain model that helps us track the learner’s vocabulary knowledge in terms of a mastery score associated with each word family. On the basis of the learner model, we then can propose the next set of words to be practiced in a way that reduces the number of interaction required to cover the vocabulary space. It also serves as an open learner model (Bull and Kay, 2010) by allowing the user to view and explore the lexical space of the book as a graph, with each node being colored according to the current mastery score. In this section we discuss how this is achieved.

3.1 Central node selection for efficient exploration of the vocabulary graph

Identifying the nodes that are more central than others is one of the vital task in network analysis (Freeman, 1978; Bonacich, 1987; Borgatti, 2005; Borgatti and Everett, 2006). Freeman (1978) formulated three major centrality measures for a node in a network: (a) degree centrality: Measure of strength of ties of each nodes in the network, (b) closeness centrality: Measure of closeness of a node to all other nodes in the network, and (c) betweenness centrality: Measure of cardinality (number of elements) of a set $S$, the set of shortest paths of other node pairs in the network that passes through a node.

The degree centrality measure is a greedy approach looking only at the immediate neighbours to decide the central node, whereas the closeness centrality measure accounts for the bigger picture of the entire network. So closeness centrality seems best suited for our goal of efficient coverage of the network, in our case: the graph representing the vocabulary of the given book. However, closeness centrality cannot as such be applied to networks with disconnected components – which is problematic since we may well obtain networks with many disconnected components due to the pruning of weak links discussed in the previous section. Fortunately, Wasserman et al. (1994) proposes an improved formula that also works for such graphs. Based on this metric, we choose the top 20 words for a learning session.

Selecting the next words to be learned based on closeness centrality brings up the problem that neighbors that are tightly bound to the central node are likely have a similar closeness centrality score. So when selecting the words to be practiced only based on closeness centrality, we would risk practicing closely related lexical items rather than systematically introducing the learner to the broader lexical space. In order to avoid this issue, we exclude the immediate neighbours of a word that was selected from that learning session. The resulting approach supports a more distributed selection of words, as illustrated by Figure 4 showing an example with highlighted central nodes selected for the next learning session.
3.2 Mastery scores and updating them in the graph to capture learning

Each node in the graph is associated with a mastery score ranging from 0 to 1, with 1 indicating that the learner masters the word. We initialize the master score of each node with 0.5 and interpret this as a middle ground, where the model is uncertain about the learner’s knowledge about that word.

The mastery score is updated based on the learner responses in the learning activities. To address this bottleneck that the system is tied to such a thin stream of evidence about the learner’s lexical knowledge, we make use of the fact that the learner model is based on a network of semantically related word families. We use this to spread some activation from a word where the learner has shown mastery to semantically closely related words to indicate that this word is more likely to also be known.

Let $r$ be the learner response for a learning activity involving a word from the family $F_i$. Then the update to its mastery score $m_i$ is updated using $\Delta m_i = m_i * \alpha * r$. The update to the mastery score of its immediate neighbours is weighted based on the similarity score between the families $\Delta m_j = m_j * (\beta * r * w_{ij})$ where $m_j$ is the mastery score of $F_j$, a neighbouring family of $F_i$ attached with a edge weight of $w_{ij}$. $\alpha$ and $\beta$ are tune-able parameters for the magnitude of an update. $r \in \{-1, +1\}$ indicate the polarity of the learner’s response, $+1$ for the learner responding correctly and $-1$ an incorrect response.

Figure 5 provides a close-up view of the graph with enlarged nodes highlighting the nodes selected for a learning activities. The figure also illustrates the color representation of the mastery level and the spreading activation to neighboring nodes. Initially all nodes are grey, corresponding to mastery level of 0.5 that has not yet been touched during learning. The closer the level gets to 1, the more green the node appears, and the closer to 0, the more red. A node the user has sometimes shown mastery for and sometimes not so that it returns to the 0.5 level is shown in yellow.

While the colored visualization of the lexical space serves as an open learner model allowing learners to inspect the current state of their knowledge in relation to the lexical demands of the book, the mastery level also plays a role in the selection of the next words to be practiced. Words with a mastery level over 0.8 are no longer selected. In the future, we plan to add a component that takes into account memory decay and the so-called spacing effect (Sense et al., 2016) to optimize when a word is selected again.
4 Putting it all together in an application

4.1 A warm start for the learner model

Given that we are targeting learners beyond the beginner stage, it is important to determine their vocabulary knowledge to avoid a cold start of the learner model. We do not want to start from a blank slate since that requires many interactions with the system until the learner model reflects the learner’s lexical competence – a time during which the system cannot optimally select the words to be learned next.

To avoid this cold start problem, we implemented a short web-based vocabulary Yes/No test, which has long been used for vocabulary estimation (Sims, 1929; Tilley, 1936; Goulden et al., 1990). The participants are provided with a checklist of words and the user has to select whether they know the word or not. While there is a rich literature on the test and various adjustments have been proposed to counter its weaknesses as a competence diagnostic (Meara and Buxton, 1987; Beeckmans et al., 2001; Huibregtse et al., 2002; Mochida and Harrington, 2006), for our goal of allowing learners to quickly initialize their learner model, it is very well suited.

The words included in the test are selected from the graph using the same central node selection approach we introduced in section 3.1, and the mechanism spreading activation to related nodes discussed in section 3.2 allows the system to make additional use of the information from the fast initial test.

4.2 Activity generation: practicing and testing in the target context

Content creation for vocabulary learning activities typically is a task requiring human effort so that adapting the material to individual learners’ language competence and interests is beyond the reach of traditional methods. To overcome this limitation, we generate activities based on the target text for which the user wants to acquire the vocabulary. While there are multiple activity types one could consider, we implemented multi-gap activities (Zesch and Melamud, 2014), given that they make it possible for the learner to engage with a word using several sentence contexts drawn from the targeted book. Given the frequency threshold used in constructing the domain model graph, there are at least five sentences for each word in the book. We rank sentences to determine which sentences are best out of context. Fortunately this issue has been addressed in lexicography, where authentic sentences are used in dictionaries to illustrate word usage. Kilgarriff et al. (2008) developed GDEX, a method to identify sentences that are well-suited to illustrate word meaning within a single sentence context. GDEX considers factors such as the sentence length, use of rare words and anaphora, target word occurrence in main clauses, sentence completeness, and target word collocations towards the end of sentences. Sentence length and rare word usage are the highly weighted features. We adapted GDEX for our purpose of ranking sentences for
vocabulary learning activities and customized the rare word feature to reflect the individual learner’s vocabulary knowledge as recorded in the learner model.

Learning and testing in the system is conducted in sessions. Each session consists of the top 20 central nodes from the learner model that are below the mastery score threshold. Multi-gap activities consisting of three to four sentences in which the target word chosen from the central node word family occurs are used for both learning and testing. The sentences are initially shown with the occurrences replaced by a blank. For each activity four lexical options are provided, the target word and three distractors chosen from the vocabulary space of the book as discussed below. Figure 6 shows an example activity targeting the word family *scowl* in a learning session for the book "A Game of Thrones: A Song of Ice and Fire", after the correct word was selected by the learner.

![Choose a word which satisfies all the blanks](image)

**Figure 6: An example activity**

In the learning mode, the learners are provided with learning aid such as dictionary look-up, translations, and word usage examples from within and outside the targeted book. The mastery scores in the learner model are not updated during training mode. In the testing mode, no such support is provided and the master score for the target family and its neighbours are updated based on the user responses.

Distractor generation is a critical part of multi-gap learning activities. If the distractors are randomly selected or heterogeneous in linguistic characteristics such as POS, this can make it easy to choose the right option for the given sentence contexts. We instead are interested in distractors that require more cognitive effort to discriminate, actively engaging the learner with the different sentence contexts. We base the distractor selection on the learner model. As this graph is built to encode semantically-related words near each other, many of the immediate neighbours are (near) synonyms so that there is a substantial danger of them fitting the gaps. By experimenting with different node distances, we found that choosing second neighbours as distractors that have the same POS as the target word works best. We are also considering combining the distractor generation based on the learner model with other distractor generation strategies discussed by Zesch and Melamud (2014).

### 5 Conceptual Evaluation and Related Work

Given the nature of the approach we presented, the evaluation and comparison with related work has to evaluate conceptual advances and put them into context. Our approach can be characterized by the following aspects: First, the user can select what they want to learn the vocabulary for; they pick the text of the book they want to be able to read, i.e., the functional task goal. Second, the system automatically creates a domain model graph representing the lexical semantic space to be learned. Third, a learner model is created as an overlay of the domain model graph and records the mastery of the concepts by the learner, with updates to the learner model spreading activation through the graph to indirectly activate related concepts as a way to avoid explicit interaction for every word. Fourth, it determines in which order the words can be learned in such a way that the lexical space is efficiently explored, prioritizing the words that are central nodes. Fifth, the system compactly represents word families to allow the visualization and open learner model to be concise and usable with minimal number of interactions.
Sixth, the system supports learning of the words using multi-gap activities using sentences drawn from the authentic context of the book to be learned.

Putting this approach into context of the related work on vocabulary learning, there is a large number of applications designed to support vocabulary learning – though, as we will see, the above characteristics clearly seem to set our approach apart from what is offered in this domain.

Foreign language textbooks systematically provide a list of vocabulary items per chapter and there are many specialized or general file card applications for memorizing these sentences including Phase-6.de, Quizlet.com, or Ankiweb.net. Other applications offer more language-related functionality.

Lexutor (https://lextutor.ca) is a website offering a collection of tools to learn vocabulary using lexical resources such as frequency-based vocabulary lists and corpus data. List learn supports learners in choosing words from frequency-based word lists and work with corpus concordances. Groupplex lets the learner select from a 2k crowd-sourced word list and practice them in fill-in-the-blank activities, with hints based on dictionary definition and POS tags. Flash employs cards showing words on one side and lexical support on the other. Apart from word meaning and usage, MorphoLex supports learning regular inflectional and derivational affixes based on the word family levels of Bauer and Nation (1993). Other lextutor tools target reading texts with support from concordances and dictionaries. Resource assisted reading lets the user choose a pre-processed book, but Hyper text allows the learner to upload their own text. While lextutor offers a variety of tools and corpus resources, none of them offer personalized learning, performance tracking, or structured vocabulary spaces.

Memrise.com is a flashcard based de-contextualized commercial vocabulary learning application focused on beginners, with learning units grouped by theme with little freedom for the learner to choose contents of interest. Duolingo.com is a strictly guided application supporting the users to learn foreign language using various learning activities offering some gamification elements but no personalized vocabulary learning for texts or domains of personal interest. Vocabulary.com is a gamified free vocabulary list learning application that lets learners choose from collections and the literature to practice the words in multiple choice questions activities to choose the correct meaning phrase for the given word usage. The literature only is a source of vocabulary though, it is not used as testing context or learning goal, and the vocabulary domain is not semantically structured or to construct a structured learner model. Cabuu.app supports learning of vocabulary lists scanned from books by associating each item with gestures.

Overall, while there is a rich landscape of applications supporting vocabulary learning, the six characteristics of the method presented in this paper set our approach apart – especially the use of distributional semantic methods to create a graph representation for any book or text the user wants to read, to efficiently organize and individually support and track the learning in this lexical space.

6 Conclusion

In this paper, we discussed the methodological basis and realization of a tool allowing the learner to systematically learn the lexical material needed to be able to read a book they are interested in. Automatically structuring the lexical space and sequencing the learning is achieved through distributional semantic methods, the automatic identification of word families, and concepts from network analysis. The graph-based domain model that is automatically derived from the given book serves as the foundation of a learner model supporting the selection of an efficient learning path through the lexical space to be acquired. Multi-gap activities are automatically generated from the targeted book and used for practice and testing activities.

In addition to self-guided learning for people interested in reading specific books, which may be particularly useful in the context of so-called intensive reading programs, the approach is particularly well-suited for the English for Specific Purposes context, where both the language and the particular content domain are of direct importance. Given this kind of integration of language and content learning, a similar affinity exists to so-called Content and Language Integrated Learning (Coyle et al., 2010).
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