Data and text mining

**LexExp: a system for automatically expanding concept lexicons for noisy biomedical texts**

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Associate Editor: Jonathan Wren

Received on May 31, 2020; revised on October 4, 2020; editorial decision on November 13, 2020; accepted on November 17, 2020

**Abstract**

**Summary:** LexExp is an open-source, data-centric lexicon expansion system that generates spelling variants of lexical expressions in a lexicon using a phrase embedding model, lexical similarity-based natural language processing methods and a set of tunable threshold decay functions. The system is customizable, can be optimized for recall or precision and can generate variants for multi-word expressions.

**Availability and implementation:** Code available at: https://bitbucket.org/asarker/lexexp; data and resources available at: https://sarkerlab.org/lexexp.

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**Supplementary information:** Supplementary data are available at Bioinformatics online.

1 Introduction

Lexicon- or dictionary-based biomedical concept detection approaches require the manual curation of relevant lexical expressions, generally by domain experts (Demner-Fushman and Elhadad, 2016; Ghiassi and Lee, 2018; Rebolhoz-Schuhmann et al., 2013; Shivade et al., 2014). To aid the tedious process of lexicon creation, automated lexicon expansion methods have received considerable research attention, leading to resources such as the UMLS SPECIALIST system (McCray et al., 1993), which is utilized in MetaMap (Aronson and Lang, 2010) and cTAKES (Savova et al., 2010). Such systems perform well for formal biomedical texts, but not noisy texts from sources such as social media and electronic health records. Due to the presence of non-standard expressions, misspellings and abbreviations, it is not possible to capture all possible concept variants in noisy texts using manual or traditional lexicon expansion approaches. The number of lexical variants of a given concept that may occur, although finite, cannot be predetermined. Biomedical concepts, such as symptoms and medications, are specifically likely to be misspelled compared to non-biomedical concepts (Soualmia et al., 2012; Zhou et al., 2015). Despite advances in machine learning based sequence labeling approaches, which typically outperform lexicon-based approaches and can detect inexact concept expressions, the latter are frequently used in biomedical research. This is non-exclusively because machine learning methods require manually annotated datasets, which may be time-consuming and expensive to create, and training and executing state-of-the-art machine learning approaches may require technical expertise and high-performance computers, which may not be available. In this article, we describe an unsupervised lexicon expansion system (LexExp), which automatically generates many lexical variants of expressions encoded in a lexicon.

2 Materials and Methods

LexExp builds on recent studies, including our own, which utilize the semantic similarities captured by word2vec-type dense-vector models (Mikolov et al., 2013) to automatically identify similar terms and variants (Percha et al., 2018; Sarker and Gonzalez-Hernandez, 2018; Viani et al., 2019). LexExp employs customizable threshold decay functions (constant, linear, cosine, exponential), combined with dense-vector and lexical similarities, to generate many variants of lexicon entries. Similarity thresholding for determining lexical matches is popular (Fischer, 1982); most approaches apply static thresholding while some recent studies have attempted to employ dynamic thresholding for misspelling correction or generation (Sarker and Gonzalez-Hernandez, 2018; Savary, 2002). However, there is no existing tool that enables the use of customizable thresholding options for these tasks. The objective of LexExp is to generate lexical variants of multi-word expressions using customized thresholding, not lexically dissimilar semantic variants (e.g. synonyms).

Given a lexicon entry, LexExp first generates word n-grams (n = 1 and 2) from the entry (for one-word expressions, only unigrams are generated). For each n-gram within the entry, a dense embedding model is used to retrieve n most semantically similar words/phrases using cosine similarity, if the n-gram is present in the model. Next, all the words/phrases whose semantic similarities with the n-grams are higher than a threshold are included as candidate variations. For each candidate, its Levenshtein ratio is computed against the original n-gram and a separate threshold for lexical similarity (θ) is applied. All candidates below the threshold are removed from the list of possible variants. The same process is applied recursively on each remaining candidate until no new variants with
similarity above \( t \) are found. While we used an embedding model described in our past work (Sarker and Gonzalez, 2017), any can be used for identifying semantically similar terms in LexExp.

### 2.1 Lexical similarity thresholding functions

LexExp provides the user with four functions that can be used to vary \( t \) based on the character lengths of the input \( n \)-grams. Typically, longer terms/phrases have true variants that are lexically more distant from the original entry. So, adjusting \( t \) based on the length of an expression may lead to better precision and/or recall.

Note that recall and precision are both ill-defined in this context; recall—because there is no known bound for the total number of variants; precision—because the set of true variants depends on the research task. Given an expression, \( p \), the four functions are:

- **Static**: \( t = t_i \)

- **Linear decay**:

\[
t = \max \left( t_i - \frac{m \times (\text{len}(p) - n)}{100.0}, t_j \right)
\]

- **Cosine decay**:

\[
t = \min \left( \frac{\cos \left( \frac{\text{max(len}(p) - n, 0)}{m \times 2\pi} \right)}{t_i}, t_j \right)
\]

- **Exponential decay**:

\[
t = \min \left( \left( \frac{\text{len}(p) \times 2 \times m \times e^{(0.5 \times \text{len}(p))} + n}{10} \right), t_j \right)
\]

where \( m \) and \( n \) are constants, \( t_i \) is the initial threshold and \( t_j \) is the lower bound for \( t \). Figure 1 illustrates how these thresholding methods vary for expressions of length 1–30 characters. These thresholding functions are carefully designed to provide the user with flexibility to vary them as per the needs of a task.

### 2.2 Multi-word variants

A key functionality of LexExp is its ability to generate variants for multi-word expressions. Capturing variants of multi-word expressions comprehensively is particularly challenging via manual annotation since the number of possible word combinations can be very high. Also, phrase embedding models cannot capture the semantics of long multi-word expressions due to the sparsity of their occurrences.

LexExp uses two functions for generating multi-word variants. The first is a unigram variant generation function that generates variants for each word based on a specific value of \( t \) and then generates all combinations of the original expression based on the variants identified, keeping the ordering of the variants unchanged. Examples of variants generated by this function are shown below:

- **Original expression**: eyes were excruciatingly sensitive and sore.
- **Sample variants**:
  1. eyes were excruciatingly sensitive and sore;
  2. eyes were excruciatingly sensitive and sore;
  3. eyes were excruciatingly sensitive and sore;
  4. eyes were excruciatingly sensitive and sore.

The second is a bigram generation function, which first tokenizes the expressions into bigrams, then generates variants of the bigrams. These variants maybe uni- or multi-grams (e.g. stomach ache: stomachache, mild stomach ache). After the variants are generated, they are tokenized to unigrams and then all combinations of all unigrams are generated as described before. Recombining the bigrams following the generation of the variants can be complicated in some cases, as a term and its partial variant may both be present in a combination (see Figure 1 caption). LexExp attempts to resolve these using a simple forward and backward pass through the list of words, removing all words identical to or substrings of the next/previous one.

### 3 Conclusion

We ran LexExp on multiple lexicons, including lexicons for COVID-19 symptoms from Twitter (Sarker et al., 2020), adverse drug reactions (Sarker and Gonzalez, 2015), a subset of the consumer health vocabulary (Zeng and Tse, 2006) and psychosis symptoms from electronic health records (Viani et al., 2019). We also compared tweet retrieval numbers for COVID-19 symptom-mentioning tweets using the abovementioned lexicon with and without variants, and observed an increase of 16.6%. Further details about these experiments are provided in Supplementary Material. As a lexicon expansion system, the purpose of LexExp is not to obtain perfect accuracy—in fact, accuracy is not well-defined for this
generation task. The objective, instead, is to automatically generate large sets of possible variants that can be readily used by human experts for information retrieval and extraction.

**Funding**

Research reported in this publication was supported by the National Institute on Drug Abuse (NIDA) of the National Institutes of Health (NIH) under award No. R01DA046619. The content is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.

**Conflict of Interest**

None declared.

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