JESEME: A Website for Exploring Diachronic Changes in Word Meaning and Emotion

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Abstract

We here introduce a substantially extended version of JESEME, a website for visually exploring computationally derived time-variant information on word meaning and lexical emotion assembled from five large diachronic text corpora. JESEME is intended as an interactive tool for scholars in the (digital) humanities who are mostly limited to consulting manually compiled dictionaries for such information, if available at all. JESEME uniquely combines state-of-the-art distributional semantics with a nuanced model of human emotions, two information streams we deem beneficial for a data-driven interpretation of texts in the humanities.

1 Introduction

Historical, manually compiled dictionaries are central to many kinds of studies in the humanities, since they provide scholars with information about the lexical meaning of terms in former time periods. Yet, this traditional approach is heavily limited in many ways, coverage being perhaps the most pressing issue: Is a dictionary for the specific time period a scholar is investigating really available and, if so, does it cover all of the lexical items of interest?

Word embeddings have been proposed to increase coverage (Kim et al., 2014). However, they depend on locally installed software and time-consuming calculations thus being ill-suited for mostly non-technical users in the humanities. As an alternative, we here present an extended version of JESEME, a user-friendly open source website\textsuperscript{1} for accessing embedding-derived diachronic information on lexical meaning and emotion. The first release of JESEME (Hellrich and Hahn, 2017b) mainly provides time-variant diachronic lexical semantic information. In contrast, the second version, presented in this paper, excels with the unique capability to also track the diachronic \textit{emotional} meaning of words in parallel with their lexical semantics. We and others deem such a capability beneficial for the data-driven interpretation of literary text genres (Kim et al., 2017).

As for related work, measuring affective information on the lexical level is an active field of research in computational linguistics (Liu, 2015). Yet, most contributions focus on contemporary language and are limited to shallow representations of human emotions, only distinguishing between \textit{positive} and \textit{negative} feelings. Current research in sentiment analysis either starts to include historical trends in word polarity (Hamilton et al., 2016a) or incorporates more nuanced models of emotions, such as Valence-Arousal-Dominance (Buechel and Hahn, 2018). Conversely, this contribution integrates \textit{both} lines of work thus continuing our prior research activities (Buechel et al., 2016; Buechel et al., 2017).

To the best of our knowledge, the few other websites for tracking diachronic word meaning offer a far less diverse collection of corpora compared to JESEME and neither of them covers emotional meaning facets. For example Arendt and Volkova (2017) provide only short term trends in word similarity in two social media corpora with their ESTEEM system.\textsuperscript{2} The system\textsuperscript{3} by Heimerl and Gleicher (2018) is

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\textsuperscript{1}jeseme.org \\
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\textsuperscript{3}embvis.flovis.net/s/neighborhoods.html
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intended as a mere showcase for a novel visualization technique and re-uses SGNS embeddings trained on the English Google Books corpus by Hamilton et al. (2016b). And finally, the DIACHRONIC EXPLORER,⁴ which uses sparse vector representations instead of word embeddings to calculate similarity, is limited to the Spanish Google Books corpus (Gamallo et al., 2018).

2 Architecture and Website

JESEMÉ uses five diachronic corpora, i.e., the Google Books N-Gram Corpus for German and its English fiction register (Michel et al., 2011), the Corpus of Historical American English (Davies, 2012), the Deutsches Textarchiv ‘German Text Archive’ (Geyken, 2013) and the Royal Society Corpus (Kermes et al., 2016). To ensure high embedding quality, these corpora are divided into temporal slices of roughly similar size, thus covering between 10 and 50 years each.

JESEMÉ’s processing pipeline is illustrated in Figure 1. It starts with orthographically normalizing these corpus slices, i.e., lower casing only for English and a slightly more complex, historical-spelling-aware lemmatization for German (Jurisch, 2013). We then use a modified version of hyperwords to calculate slice-specific embedding models with SVDPPMI (Levy et al., 2015). This algorithm was chosen for its superior reliability, which is essential for interpreting local neighborhoods in embeddings spaces as is done in remainder of this paper (Hellrich and Hahn, 2016; Hellrich and Hahn, 2017a). Apart from word vectors, we also calculate word-based co-occurrence statistics, frequency information and emotion values for each slice (see Section 3). All this information is stored in a relational database. Compared to Hellrich and Hahn (2017b), our current version also reduces the database size from approximately 120GB to 40GB. This is achieved by storing word vectors instead of pre-computed similarity scores. Similarity between most words will thus be computed on the fly, only the most similar ones for each word (automatically picked as references) being cached for fast retrieval.

⁴tec.citius.usc.es/explorador-diacronico
JESEMÉ’s website prompts users a search form for selecting the word under scrutiny as well as one of the five corpora we employ. Its result page then provides graphs for the development of similarity to automatically chosen reference words over time as an indicator for semantic change, as well as information on diachronic affective meaning (see Figure 2). These two main sources of information are complemented with information on word co-occurrence and relative frequency, thus providing scholars with additional information to increase interpretability and rule out measurement artifacts. Users may also add further reference words to the analysis on demand. Besides this graphical interface JESEMÉ also offers a REST API.  

3 Representing and Computing Emotions

We represent emotions following the Valence-Arousal-Dominance (VAD) scheme (Bradley and Lang, 1994), one of the major models of emotion in psychology, which is illustrated in Figure 3. The VAD model describes affective states relative to three dimensions, namely, Valence (degree of displeasure vs. pleasure), Arousal (degree of calmness vs. excitement) and Dominance (degree of perceived control in a social situation).

We used a modified version of the emotion induction algorithm by Turney and Littman (2003) which we found to outperform other methods for historical emotion lexicon creation in previous work (Buechel et al., 2017; Hellrich et al., 2018). It calculates each word’s predicted emotion value \( \hat{e}(w) \) by averaging the emotion values \( e(s) \) for each member \( s \) of a seed set \( S \), with \( \text{sim}(w, s) \), the similarity between \( w \) and \( s \), serving as a weight:

\[
\hat{e}(w) := \frac{\sum_{s \in S} \text{sim}(w, s) \times e(s)}{\sum_{s \in S} \text{sim}(w, s)}
\]

For the emotion scores stored in JESEMÉ, we used the emotion lexicons by Warriner et al. (2013) and Schmidtke et al. (2014) as seed sets for English and German corpora, respectively. Word emotions were induced independently for each temporal corpus slice, using the respective embedding model to retrieve similarity scores. Hence, the similarity between the seed words and the target word reflects word usage at a given language stage, thereby infusing historical emotion information into the resulting emotion ratings (Buechel et al., 2017).

4 Examples

The new insights provided by diachronic emotion models can be demonstrated by re-visiting the example of “heart” we used in Hellrich and Hahn (2017b) and shown in Figure 2. This lexeme is often used metaphorically or metonymically, despite the fact that the heart’s anatomical function was already known for a long time. Results for our novel emotion tracking functionality match a move from metaphorical to anatomical usage we previously observed in the genre-balanced COHA. Around 1900, the similarity of “heart” to lexemes such as “stroke” increases, while Dominance and Valence ratings drop sharply in tandem (see Figure 2; y-axis values are centered and scaled). This simultaneous drop seems plausible,

\[\text{See online documentation: jeseme.org/help.html#api}\]
since we can “change our heart” in a metaphorical sense, yet have little control over our anatomical heart. Also, with the increasing anatomical usage of “heart”, the lexeme becomes less positive, since we are under mortal threat by cardiovascular diseases such as a “stroke”.

Changes in emotion can also be traced for items with a more constant meaning, e.g., for “woman” shown in Figure 4. Here similarity scores for the most similar words—“man” and “girl”—remain rather static. Yet, emotion values are highly dynamic and seem to match turning points in women’s rights movement, e.g., women’s suffrage in the US is connected with an increase in all VAD dimensions for the 1920s.

5 Conclusion

We introduced a substantially extended version of JeSEME, an interactive website for tracking diachronic changes in word meaning and, as a unique feature, word emotion. To the best of our knowledge, no other website combines these two traits. JeSEME allows users with a limited technical background to interactively explore semantic evolution based on five large diachronic corpora for two languages, German and English. We believe that JeSEME will be most useful for diachronic linguists and scholars within the digital humanities. We see two major applications: First, it can be used to generate hypotheses by querying words of interest to get a first impression of their semantic evolution. Second, scholars can first shape a hypothesis using traditional means and then query JeSEME for testing its plausibility based on diachronic statistical evidence.

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