Unsupervised Neologism Normalization Using Embedding Space Mapping

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Abstract
This paper presents an approach for detecting and normalizing neologisms in social media content. Neologisms refer to recent expressions that are specific to certain entities or events and are being increasingly used by the public, but have not yet been accepted in mainstream language. Automated methods for handling neologisms are important for natural language understanding and normalization, especially for informal genres with user generated content. We present an unsupervised approach for detecting neologisms and then normalizing them to canonical words without relying on parallel training data. Our approach builds on the text normalization literature and introduces adaptations to fit the specificities of this task, including phonetic and etymological considerations. We evaluate the proposed techniques on a dataset of Reddit comments, with detected neologisms and corresponding normalizations.

1 Introduction
Linguistic evolution and word coinage are naturally occurring phenomena in languages. However, the proliferation of social media in recent years may expedite these processes by enabling the rapid spread of informal textual content. One aspect of this change is the increasing use of neologisms. Neologisms are relatively recent terms that are used widely and may be in the process of entering common use, but have not yet been fully accepted into mainstream language. Neologisms are rarely found in traditional dictionaries or language lexica, and they usually have lexical, phonetic or semantic connections to some relevant canonical words. They are also often, but not necessarily, generated by combining two different words into a single blend word. Examples include the word burkini, which is coined from the words burka and bikini. The burkini has its own individual meaning that cannot be entailed by a burka or bikini alone.

The goal of neologism normalization is not to generate a perfect replacement for the original text but rather to assist both humans and automated systems in understanding informal text. Inexact normalizations may nevertheless be useful hints to human readers who are unfamiliar with the new words. Normalizations can also substitute for out-of-vocabulary words in downstream NLP applications in order to compensate for data sparsity.

In this paper, we present an unsupervised approach for normalization, based on the hypothesis that neologisms—and non-standard words (NSWs) in general—are likely to share contexts with related canonical words. For instance, NSWs may be expected to lie near their canonical forms in a suitable embedding space. We develop measures to relate words more accurately using both orthography and distributed representations. We also enhance the embedding space with multi-word phrases and subword units, which induces a clustering of compound words with shared etymology, phrases with overlapping words, and entities with common names, thereby capturing novel puns, nicknames, etc.

2 Related Work
Prior work on automatic neologism handling, whether for detection or normalization, is relatively scarce. Most existing neologism detection approaches rely on exclusions lists of canonical or accepted words to filter plausible neologisms (de Yzaguirre, Lluis, 1995; Renouf, 1993). Other contributions based on the same architecture utilize additional filters like eliminating words with spelling errors or named entities to further reduce the set of detected plausible neologisms (Kerremans et al., 2012; Gérard et al., 2014; Cartier, 2016, 2017). There are also several machine learning based approaches, but with limited performance (Falk et al., 2014; Stenetorp, 2010).

In the broader text normalization literature, several supervised approaches have been proposed.
(Mays et al., 1991; Church and Gale, 1991; Brill and Moore, 2000; Aw et al., 2006; Sproat and Jaitly, 2016), all of which require relatively large datasets. Several unsupervised normalization models have also been presented. Li and Liu (2014); Rangarajan Sridhar (2015) use distributed word embeddings, where the embeddings are used to capture the notion of contextual similarity between canonical and noisy words, along with other measures. Rangarajan Sridhar (2015) further builds on this approach with phrase-based modeling using existing phrase corpora. Hassan and Menezes (2013) use a random-walk based algorithm to calculate contextual similarity, along with edit distance metrics, to obtain normalization candidates. In this paper, we extend the distributed word representation approach (Rangarajan Sridhar, 2015) for unsupervised neologism normalization through several adaptations.

3 Neologism Detection

We first present our neologism and NSW detection approach for Reddit comments. The resulting list of plausible neologisms is then used to analyze neologism etymology and coinage patterns, and later to produce normalization candidates in the normalization model.

Owing to the noisy domain of user-generated text and to the fact that neologisms must exclude names, domain jargon and typos, corpus frequency alone is not reliable for identifying neologisms. Exclusion lists prove effective at recovering a high-precision set of neologisms for this task when combined with frequency-based filters and adaptations to increase coverage. Our pipeline for neologism detection includes the following steps:

- Tokenization: We split on whitespace and handle many Reddit-specific issues, including URLs and specific punctuation patterns.
- Named entity removal: We use the SpaCy NLP toolkit\(^1\) to identify named entities in context and eliminate them from the plausible neologisms list.
- English exclusion lists: We use several corpora of English content as exclusion lists.
- Non-English content removal: We use the Langdetect library\(^2\) to identify and eliminate non-English content.
- Social media jargon removal: We use the social media word clusters from the work by Owoputi et al. (2013) along with the Reddit glossary\(^3\) as additional exclusion lists.

We apply exclusion list filtering on the stem level to further reduce the sparsity of the analysis and reduce the vocabulary. We use NLTK’s Snowball stemmer.\(^4\)

4 Neologism Normalization

Our approach is based on the hypothesis that neologisms and NSWs are likely to have similar contexts as their plausible canonical equivalents. We model this using distributed word representations derived from word2vec (Mikolov et al., 2013) via Gensim (Řehůřek and Sojka, 2010). We use these embeddings to learn normalization lexicons and use these lexicons to obtain plausible candidates for normalizing each neologism. We then select among these candidates using a language model and lattice-based Viterbi decoding.

4.1 Lexicon and Lattice Decoding

We use a list of canonical word forms as normalization candidates. This list of canonical forms can be obtained from traditional English language lexica like the Gigaword corpus. For each canonical candidate, we get the \(N\) nearest neighbors from the embedding space. This effectively functions as a reversed normalization lexicon, where the canonical candidates are mapped to the potential neologisms. We score the canonical forms using several similarity metrics. We then reverse this mapping to get the list of scored canonical candidates for each neologism.

Neologisms are expected to share semantic, lexical, and phonetic similarity with their canonical counterparts. We capture these different aspects using multiple measures of similarity:

**Semantic similarity** using the cosine distance over embeddings \(R_i\) corresponding to strings \(S_i\).

\[
\text{Cos}(S_1, S_2) = \frac{R_1 \cdot R_2}{||R_1|| \times ||R_2||} \tag{1}
\]

**Lexical similarity** based on the formula presented by Hassan and Menezes (2013) and used by Rangarajan Sridhar (2015)

\[
\text{LEX}(S_1, S_2) = \frac{LCSR(S_1, S_2)}{ED(S_1, S_2)} \tag{2}
\]

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\(^1\)Version 2.0.0: https://spacy.io

\(^2\)Version 1.0.7: https://pypi.python.org/pypi/langdetect

\(^3\)https://www.reddit.com/r/TheoryOfReddit/wiki/glossary

\(^4\)Version 3.2.4: http://www.nltk.org/api/nltk.stem.html
where ED is the edit distance and LCSR refers to the longest common subsequence ratio

\[
\text{LCSR}(S_1, S_2) = \frac{\text{LCS}(S_1, S_2)}{\max(|S_1|, |S_2|)}
\]

where LCS is the longest common subsequence in the two strings of length \(|S_1|\) and \(|S_2|\).

**Phonetic similarity** through the Metaphone phonetic representation algorithm (Philips, 1990), which is used for indexing words by their English pronunciation. We calculate the normalized edit distance for the Metaphone representation of \(S_1\) and \(S_2\) and use this score to reflect the phonetic similarity between the strings.

\[
\text{PHON}(S_1, S_2) = 1 - \frac{\text{ED}(mP(S_1), mP(S_2))}{\max(|S_1|, |S_2|)}
\]

where \(mP(S_i)\) is a Metaphone representation.

Next, a language model is used to further control the fluency of the normalized output in context. We use SRILM (Stolcke, 2002) to build the model. To decode the optimal path given the similarity scores and the language model probabilities, we encode the sentence, along with the various normalization candidates, in the HTK format. We then use SRILM’s lattice-tool toolkit to decode the space of potential paths using Viterbi decoding.

### 4.2 Phrases and Subword Units

The system so far is primarily targeted to word-level normalization, without explicitly handling multi-word phrases in the canonical form or recognizing shared etymology in the embeddings for plausible neologisms. This limits the normalization space for neologisms as the blending of two plausible neologisms. This limits the normalization candidates, in the HTK format. We then use SRILM’s lattice-tool toolkit to decode the space of potential paths using Viterbi decoding.

### 4.3 Combining Word Representations

An important aspect to consider when combining word, phrase and subword representations is to maintain the distributional properties of the text. We combine these representations by having the choice to switch to a certain representation for each word dictated through a uniformly distributed random variable. That is, for a given sentence \(T\) in a corpus, and for each word \(w_i \in T\), the resulting representation \(w'_i\) based on the distribution \(q(w'_i|w_i)\) is managed by the control variable \(c = \text{randl}(\alpha)\), where \(\alpha \in \{0, 1, 2\}\) indicates the choice of word/phrase/subword representations. We repeat this process for all the words of each sentence \(k\) different times, so we end up with \(k\) different copies of the sentence, each having a randomly selected representation for all of its words. \(k\) is tunable and we set \(k = 5\) for our experiments. A somewhat similar approach is used by Wick et al. (2016) to learn multilingual word embeddings.

### 5 Experimental Setup and Results

#### 5.1 Dataset

We use a dataset of Reddit comments from June 2016 to June 2017 for the normalization experiments in this paper, collected with the Reddit BigQuery API.\(^5\) We focus on five popular subreddit groups: worldnews, news, politics, sports, and movies. This dataset contains about 51M comments, 2B tokens (words), and 6M unique words.

A dataset of 2034 comments annotated with neologisms and their normalizations was used for tuning\(^6\) and evaluating the normalization model. These comments were selected from comments identified as containing unique plausible neologisms using the neologism detection pipeline described in Section 3. Normalization annotations were obtained using Amazon Mechanical Turk using three judgments per comment. Annotators were asked to provide up to five normalization candidates for each neologism; candidates that at

\(^5\)https://bigquery.cloud.google.com/dataset/fh-bigquery:reddit_comments

\(^6\)Parameters were tuned using a held-out validation set drawn from the manual neologism annotations. This also applies to the tuning of weights for the linear combination of the different similarity metrics.
of the normalization on the word level (the pound words. ologisms including phrases, nicknames and com-
tends these ideas to normalize a wide variety of ne-
ally. Based on our observations, 5% of the com-
ations contained neologisms, and 82% of these ne-
isms are present in our list of plausible neol-
isms, which suggests the recall of the proposed neol-
isms/canonical-equivalents level) along
with using BLEU score (Papineni et al., 2002).
BLEU is an algorithm for evaluating text quality
based on human references and is commonly
used in the machine translation literature. Using
BLEU is relevant here due to the potentially
multi-word output of the system with phrases and
subwords. Evaluation scores are calculated with
some relaxed matching, namely considering the
occurrences of plurals, lower/upper case, hyphen-
ation and punctuation, among others. So we treat
terms like trump and Trumps as equivalent, same
for posting and postings.

Table 2 shows the results. The system with
phrases and subwords clearly outperforms the
baseline, for both accuracy and BLEU scores.
BLEU scores are relatively high for both systems
since most of the sentences are preserved with
only modifications for the plausible neologisms.
The rest of the sentence should be an exact match
to the reference.

Table 3 presents three normalization examples,
with the raw, gold reference, and the output of our
system. The examples show a promising behavior,
but as can be seen at the third example, there is still
a room for improvement in normalizing the indi-
vidual phrase components. A potential future di-
rection here would be to improve embedding space
mappings for the subword entities.

6 Conclusion

We presented an approach to detect and normalize
neologisms in social media content. We leveraged
the fact that the neologisms and their canonical
equivalents are likely to share the same contexts
and hence have relatively close distributional rep-
resentations. We also presented some techniques
for handling phrases and subwords in the plausi-
ble neologisms, which is important given the et-
ymology behind most neologisms. Our approach
also makes use of the phonetic representation of
the words, to capture coinage patterns that involve
phonetic-based modification. Our results show
that the model is effective in both detection and

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Table 1: Subreddit-level detected neologisms

| Sample of detected neologisms                  | politics | news | world news | sports | movies | gaming |
|-----------------------------------------------|---------|------|------------|--------|--------|--------|
| pizzagate, drumpf, trumpster, shillary, hillary |          |      |            |        |        |        |
| antifa, brexit, drumpf, Liburis, redpilling, neonazi |          |      |            |        |        |        |
| burkin, brexit, pizzagate, edgeford, petrodollar |          |      |            |        |        |        |
| deflategate, handegg, ballboy, skurfing, playstyle |          |      |            |        |        |        |
| plothole, stuckumannized, jumpscare, MetaHuman |          |      |            |        |        |        |
| playerbase, pokestop, jumpscare, hitscan      |          |      |            |        |        |        |

Table 2: Evaluation of the normalization systems

| Accurancy | BLEU   |
|-----------|--------|
| Baseline  | 55.3   |
| This work | 64.2   |

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Table 3: Normalization examples

The rest of the sentence should be an exact match
to the reference.

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7We started with a dataset of 5000 unique neologisms and
eliminated those that did not have a consensus of two or that
the annotators indicated they were not sure about.
normalization. Future work includes more explicit generation models, utilizing natural language generation techniques, along with expanding and enhancing the coverage of the annotated data.

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