NYTWIT: A Dataset of Novel Words in the New York Times

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Abstract

We present the New York Times Word Innovation Types dataset, or NYTWIT, a collection of over 2,500 novel English words published in the New York Times between November 2017 and March 2019, manually annotated for their class of novelty (such as lexical derivation, dialectal variation, blending, or compounding). We present baseline results for both uncontextual and contextual prediction of novelty class, showing that there is room for improvement even for state-of-the-art NLP systems. We hope this resource will prove useful for linguists and NLP practitioners by providing a real-world environment of novel word appearance.

1 Introduction

Novel words, or Out-Of-Vocabulary words (OOVs), are a pervasive problem in modern Natural Language Processing (Brill, 1995; Young et al., 2018). A common scenario in which this problem appears is that of a pre-trained model containing a word representation component such as an embedding table, encountering a previously-unseen word in a downstream task such as question answering or natural language inference. Multiple lines of work attempt to alleviate the downstream effect of OOV words (Müller and Schüttke, 2011; Pinter et al., 2017), but most tend to focus on individual categories of OOVs: typographical errors (Sakaguchi et al., 2017), domain-specific terminology (Du et al., 2016), stylistic variability (Eisenstein, 2013; van der Goot, 2019), morphological productivity (Bhatia et al., 2016), or novel named entities (Hoffart et al., 2014). In reality, unseen texts contain all these classes of novelty, and more. OOVs are typically presented as a significant challenge for generalization or understanding in noisy user-generated text (e.g. Twitter) and/or domain-specific content. Surprisingly, even large corpora that are narrow in domain (edited news stories) contain linguistic innovations, including but not limited to novel morphological processes, typographical errors, and loan words.

In this paper, we present a dataset of novel words in English relative to the corpus of articles published by the New York Times (NYT), as collected automatically in real time by a Twitter bot. We name it the New York Times Word Innovation Types corpus, or NYTWIT for short. We annotated each word for one of eighteen linguistically-informed categories of novelty within the context of the NYT corpus, as well as for its date of publication and a retrieval document identifier to enable context extraction. To our knowledge, this is the first resource to include novel words along with their contextual information in addition to linguistically-informed annotation, expanding beyond dictionary-based methods (Cook and Stevenson, 2010; Dhuliawala et al., 2016) and decontextualized neologisms (Kulkarni and Wang, 2018).

Next, we provide results for the task of classifying words into their categories based on word form and contextual information. We show that both character-level models and large pre-trained sentence encoders struggle on this task, illustrating the challenges of modeling language innovation.

We release the data under the GNU General Public License v3.0.

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1Context articles themselves cannot be published without licensing from the New York Times.

2The data is available at https://github.com/yuvalpinter/nytwit.
2 The New York Times Word Innovation Types Dataset

Our dataset relies on tweets by the NYT First Said bot, which operates by scraping new articles as they post on the NYT site and tweeting out novel words following a filtering process which we will describe at a high level. After tokenizing on white space and punctuation, the precision-oriented script rejects capitalized words in order to avoid proper nouns, at the cost of missing sentence-initial true OOVs; langid (Lui and Baldwin, 2012) is used to reject non-English sentences, while still allowing loanwords in English sentences. Words are queried against the historical NYT search API to detect unpublished words. For the time range of our collected corpus, November 7, 2017 to March 28, 2019, a bandwidth limit of five words per 30 minutes was imposed, but we confirmed that this did not have a substantial effect on OOV coverage, leaving our artifacts distributionally reliable for the news domain.

An associated context bot replies to the tweets with links to the original articles. We used the URLs from this bot’s posts as the main reference for the words’ contexts. For 17 words, the article URL had to be retrieved manually by searching for the target article directly.

2.1 Annotation

The extracted data was independently annotated and filtered by the first two authors. Initially, all 2,587 words were assigned one of 20+ tags inspired by the word formation literature (Kiparsky, 1982; Klymenko, 2019). Certain categories were filter categories intended to capture and exclude false positives from the final dataset: DUPLICATE for inflections of words already appearing in the dataset in a morphologically simpler form, e.g. batchcode and batchcodes; FOREIGN and PRP for foreign words and proper names (mostly all-lowercase Twitter usernames) which were not caught by the automatic filtering; SPACES and TYPO for unintended cases of space deletion and typographical errors which were not caught by NYT editors. Agreement between the annotators at this phase was 68% over all labels, and 0.6495 Cohen’s Kappa. Following removal of aforementioned categories, amounting to 40% of the original dataset, agreement over the remaining 1,553 words was calculated to be 65% at 0.6062 Kappa. The filtered items are provided in the dataset under the label FILTERED.

The annotators then examined each other’s annotations and agreed on some consolidation of rarely-occurring original labels, as well as introduction of new labels deemed useful post-hoc. We describe the eighteen categories in the finalized dataset, organized by a thematic grouping not explicitly annotated. Counts for each category are provided [in brackets].

Lexical OOVs. We deem certain categories to arise from the fact that the NYT, while being interested in many aspects of life, has not had the chance to delve into each and every one at depth over its 168 years of existence. These are the DOMAIN label for technical terms from uncommon domains (e.g. glossopoeia) [260]; the INNOVATION label for terms coined with no discernable prevailing linguistic process (e.g. swanicles, a term from a work of fiction) [11]; and the ONOMATOPEIA label for sound-based sequences (e.g. krtktk) [23], which includes cases of verbatim vocalization such as trololo.

Morphological OOVs. In this group we include categories of words composed of meaning-carrying units present in existing English words which have appeared in the NYT before, manifested in a new form. In increasing order of syntactic and semantic novelty, they are: INFL, unseen inflections of existing wordforms: same part-of-speech, different syntactic attributes (e.g. pennyloafers) [51]; DERIV, unseen derivations of existing words into new parts-of-speech which carry no semantic distancing beyond that implicit in the new part-of-speech itself (e.g. foamability) [211]; AFFIX, affixation of very distinct base words which are typically derivational in nature but include a semantic charge (e.g. extraphotographic, pizzless) [475]; AFFIX LIBFIX, affixation of distinct base words with particles extracted from another
word in a process known as libfixation (Zwicky, 2010) or splintering (Berman, 1961), where the liberated affix still elicits the originating word but can be freely attached to a growing selection of words (e.g. dripware) [15]; COMPOUND_COMP, a concatenation of two complete words each contributing essential semantics to the final form in a way we deem (subjectively, with help of context) to be compositional (e.g. smellwalks, strolls focusing on olfactory input) [123]; COMPOUND_NEW, a concatenation of base words resulting in a new semantic concept deemed remote from the bases (e.g. nothingbuffet, a play on nothingburger) [55]; and BLEND, a fusion of two or more base forms together where original characters are lost or shared, or new ones are added (e.g. chipster, a hipster of chips) [182].

**Syntactic OOVs.** This group consists solely of the SYNTH category of tokens which synthesize multiple syntactic words into one form, a rare formation process in English limited typically to auxiliary contractions (e.g. this'll) [6].

**Sociopragmatic OOVs.** Words in this group exhibit an orthographic diversion from standard English usually intended as a statement of register or status, or as a faithful representation of a certain linguistic style or sentiment. ARCHAIC, a register of older variants of English or an ironic semblance of such (e.g. shooketh, a mock-archaic form of shake using Middle English morphology) [13]; DIALECT, a geographically- or demographically-specific form of a word typically spelled differently in the NYT (e.g. skwarsh, an r-full squash) [46]; INFIX, a morphological tool reserved in English for expletive emphasis (McCawley, 1978) (e.g. unfreakingbelievable) [2]; PHONAESTHEME, a phonological duplication phenomenon used in contemporary English nearly only as derisive echo reduplication borrowed from Yiddish (Wales and Ramsaran, 1990) (e.g. schmarket) [6]; LENGTHENING, a written manifestation of the expressive elongation of phonetic segments (e.g. greaaaaat) [53]; VARIANT, spelling alternations or intentional typos which are not intended to be read differently from the standard form of the word, used for branding and jest (e.g. kyllyng) [16]; and SPACES_SIC, the removal of whitespace to simulate breathlessness (e.g. lineafterlineafterline) [5].

2.1.1 Difficult Distinctions
Naturally, some annotation cases are not clear-cut, as evidenced by the imperfect inter-annotator agreement. We found the most challenging cases to be within the morphological categories, where a sense of the nearest in-vocabulary word can signal the difference between INFL and DERIV; where an affix is either semantically null (DERIV) or not (AFFIX); where an AFFIX_LIBFIX has been “liberated” enough from the underlying word such that it is now simply an AFFIX (does cyber- still envoke the full word cybernetics? What about crypto-/cryptography?); if it has not been liberated yet, it should be a BLEND or a COMPOUND. In addition, the pre-processing phase required a demarcation between DOMAIN and FOREIGN which was not easy to make given the heavy foreign-word influence in certain knowledge domains. Adaptation into English morphology would usually suffice to rule in DOMAIN’s favor.

In many cases, we found the contexts in which the words were introduced to give sufficient disambiguation (cyberlibel is a blend, cybermalfeasance is a compound). In others, a consistent executive decision was made for a specific item (crypto- is still not a libfix)[10]

3 OOV Classification Task
To get a sense of the predictability of the various OOV classes in the dataset, we present several baselines for the immediate task of classifying the label of a novel word. The uniqueness of our dataset allows us to apply both type-level and context-dependent systems, the latter operating in the real-world scenario of encountering a word for the first time in the actual context of its introduction to the corpus.

For all following models we trained a ridge classifier with default regularization parameters in scikit-learn. Scores for all supervised models are reported via 10-fold cross-validation using the same folds for all systems. Due to the class imbalance, we chose to implement training in such a way that upsampled rare classes with replacement at each iteration to equal frequency as the most common class. We report accuracy (ACC) and macro F1 (F1) scores.

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[10]We invite readers to email errata to either of the first two authors, or submit a pull request in the data repository.
Table 1: Baseline results for OOV classification ($N = 1553$, $|C| = 18$).

| Contextless          | Acc | F1  | Contextual    | Acc | F1  |
|----------------------|-----|-----|---------------|-----|-----|
| Majority class       | .306| .026| Char RNN      | .135| .064|
| Char n-grams         | .490| .325| ELMo          | .305| .202|
| ELMo embeddings      | .305| .202| ELMo          | .334| .166|
| BERT no-context      | .410| .304| BERT          | .494| .338|

3.1 Contextless features

We compare and contrast several input features to our classifier that only have access to the form of the OOV, without consideration of the context: Char n-grams. We extract bag-of-character features ranging from one to three characters for each OOV. ELMo embeddings. We use the word-level embeddings from ELMo (Peters et al., 2018), obtained via a pre-trained character-level convolutional net. BERT no-context. We apply BERT-Base (Devlin et al., 2019) to the OOVs only preceded by the CLS token and appended by a SEP. From this we selected our classifier input to be the averaged top-layer embeddings associated with all word pieces of the OOV.

3.2 Context-aware features

Char RNNs. We train a 2-layer forward- (backward-) character-level GRU language model and run it through the beginning (end) of the sentence until the OOV, then use the concatenated final hidden states from each direction as features. ELMo. We obtain contextualized embeddings for all words in our sentences and select the top layer representation associated with each OOV. BERT. We apply BERT-Base to the entire sentence in which the OOV appears, and use the averaged top-layer embeddings at the indices of each OOV.

3.3 Results

The results, presented in Table I, show that while context is a useful signal to individual models, it is still difficult to beat the straightforward surface signal from character sequences without any further fine-tuning or auxiliary mechanisms. We intend to pursue such techniques in future work.

4 Conclusion

We have presented a novel dataset of OOVs along with their contexts and linguistic novelty class annotations. While we showed that contextual information in the form of other parts of the sentence provides some signal, simple models relying on character n-gram information alone achieve high performance.

The availability of broader document contexts in which these neologisms occur permits many linguistic and technical applications. From the perspective of the study of language growth and formation, the dataset may be of interest to those who wish to assess the morphological productivity of different affixes and roots, or the prevalence of the different word formation processes in a realistic setting, or perform in-depth analysis on any of the specific types of innovations for which we provide annotations. In addition, the in-vivo nature of the dataset provides a reference for neologisms which may or may not be later adopted into everyday use, allowing diachronic studies anchored in the time of word introduction. Analysis of the phonological, morphological, and discourse-level properties of these words may provide insight into lexical adoption dynamics.

For NLP researchers, an important component of text applications is proper normalization and segmentation of word forms. Our preliminary experiment shows that popular wordform encoders, such as the first layer of ELMo or the WordPiece encoder, still have a long way to go in terms of recognizing the origins of a novel form. Such errors might lead to inability to handle morphologically complex OOVs in downstream semantic applications, although a study of such effects is still necessary. Properly leveraging context for morphological decomposition of complex forms also remains an open problem.

11Using just the embedding of the final word piece produced similar results.
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