Abstract

Clustering token-level contextualized word representations produces output that shares many similarities with topic models for English text collections. Unlike clusterings of vocabulary-level word embeddings, the resulting models more naturally capture polysemy and can be used as a way of organizing documents. We evaluate token clusterings trained from several different output layers of popular contextualized language models. We find that BERT and GPT-2 produce high quality clusterings, but RoBERTa does not. These cluster models are simple, reliable, and can perform as well as, if not better than, LDA topic models, maintaining high topic quality even when the number of topics is large relative to the size of the local collection.

1 Introduction

Contextualized word representations such as those produced by BERT (Devlin et al., 2019) have revolutionized natural language processing for a number of structured prediction problems. Recent work has shown that these contextualized representations can support type-level semantic clusters (Sia et al., 2020). In this work we show that token-level clustering provides contextualized semantic information equivalent to that recovered by statistical topic models (Blei et al., 2003). From the perspective of contextualized word representations, this result suggests new directions for semantic analysis using both existing models and new architectures more specifically suited for such analysis. From the perspective of topic modeling, this result implies that transfer learning through contextualized word representations can fill gaps in probabilistic modeling (especially for short documents and small collections) but also suggests new approaches for latent semantic analysis that are more closely tied to mainstream transformer architectures.

Topic modeling is often associated with probabilistic generative models in the machine learning literature, but from the perspective of most actual applications the core benefit of such models is that they provide an interpretable latent space that is grounded in the text of a specific collection. Standard topic modeling algorithms operate by estimating the assignment of individual tokens to topics, either through a Gibbs sampling state or through parameters of variational distributions. These token-level assignments can then provide disambiguation of tokens based on context, a broad overview of the themes of a corpus, and visualizations of the location of those themes within the corpus (Boyd-Graber et al., 2017).

A related but distinct objective is vocabulary clustering. These methods operate at the level of distinct word types, but have no inherent connection to words in context (e.g. Brown et al., 1992; Arora et al., 2013; Lancichinetti et al., 2015). Recently, there has also been considerable interest in continuous type-level embeddings such as GloVe (Pennington et al., 2014) and word2vec (Mikolov et al., 2013a,b), which can be clustered to form interpretable semantic groups. Although it has not been widely used, the original word2vec distribution includes code for $k$-means clustering of vectors. Sia et al. (2020) extends this behavior to contextualized embeddings, but does not take advantage of the contextual, token-based nature of such embeddings.

In this work, we demonstrate a new property of contextualized word representations: if you run a simple $k$-means algorithm on token-level embeddings, the resulting word clusters share similar properties to the output of an LDA model. Traditional topic modeling can be viewed as token clustering. Indeed, a clustering of tokens based on BERT vectors is functionally indistinguishable from a Gibbs sampling state for LDA, which as-
signs each token to exactly one topic. For topic modeling, clustering is based on local context (the current topic disposition of words in the same document) and on global information (the current topic disposition of other words of the same type). We find that contextualized representations offer similar local and global information, but at a richer and more representationally powerful level.

We argue that pretrained contextualized embeddings provide a simple, reliable method for users to build fine-grained, semantically rich representations of text collections, even with limited local training data. While for this study we restrict our attention to English text, we see no reason contextualized models trained on non-English data (e.g. Martin et al., 2020; Nguyen and Nguyen, 2020) would not have the same properties. It is important to note, however, that we make no claim that clustering contextualized word representations is the optimal approach in all or even many situations. Rather, our goal is to demonstrate the capabilities of contextualized embeddings for token-level semantic clustering and to offer an additional useful application in cases where models like BERT are already in use.

2 Related Work

We selected three contextualized language models based on their general performance and ease of accessibility to practitioners: BERT (Devlin et al., 2019), GPT-2 (Radford et al., 2019), and RoBERTa (Liu et al., 2019). All three use similar Transformer (Vaswani et al., 2017) based architectures, but their objective functions vary in significant ways. These models are known to encode substantial information about lexical semantics (Petroni et al., 2019; Vulić et al., 2020).

Clustering of vocabulary-level embeddings has been shown to produce semantically related word clusters (Sia et al., 2020). But such embeddings cannot easily account for polysemy or take advantage of local context to disambiguate word senses since each word type is modeled as a single vector. Since these embeddings are not grounded in specific documents, we cannot directly use them to track the presence of thematic clusters in a particular collection. In addition, Sia et al. (2020) find that reweighting their type-level clustering by corpus frequencies is helpful. In contrast, such frequencies are “automatically” accounted for when we operate on the token level. Similarly, clusterings of sentence-level embeddings have been shown to produce semantically related document clusters (Aharoni and Goldberg, 2020). But such models cannot represent topic mixtures or provide an interpretable word-based representation without additional mapping from clusters to documents to words. It is widely known that token-level representations of single word types provide contextual disambiguation. For example, Coenen et al. (2019) show an example distinguishing uses of die between the German article, a verb for “perish” and a game piece. We explore this property on the level of whole collections, looking at all word types simultaneously.

There are a number of models that solve the topic model objective directly using contemporary neural network methods (e.g. Srivastava and Sutton, 2016; Miao et al., 2017; Dieng et al., 2020). There are also a number of neural models that incorporate topic models to improve performance on a variety of tasks (e.g. Chen et al., 2016; Narayan et al., 2018; Wang et al., 2018; Peinelt et al., 2020). Additionally, BERT has been used for word sense disambiguation (Wiedemann et al., 2019). In contrast, our goal is not to create hybrid or special-purpose models but to show that simple contextualized embedding clusters support token-level topic analysis in themselves with no significant additional modeling. Since our goal is simply to demonstrate this property and not to declare overall “winners”, we focus on LDA in empirical comparisons because it is the most widely used and straightforward, highlighting the similarities and differences between contextualized embedding clusters and topics.

3 Data and Methods

We use three real-world corpora of varying size, content, and document length: Wikipedia articles (WIKIPEDIA), Supreme Court of the United States legal opinions (SCOTUS), and Amazon product reviews (REVIEWS). We select WIKIPEDIA for its affinity with the training data of the pretrained models. Because its texts are similar to ones the models have already seen, WIKIPEDIA is a “best-case” scenario for our clustering algorithms. If a clustering method performs poorly on WIKIPEDIA, we expect the method to perform poorly in general. In contrast, we select SCOTUS and REVIEWS for their content variability. Legal opinions tend to be long and contain many technical legal terms, while user-generated product reviews tend to be short and highly variable in content and vocabulary.
In this collection, documents are Wikipedia articles (excluding headings). We randomly selected 1,000 articles extracted from the raw/character-level training split of Wikitext-103 (Merity et al., 2017). We largely use the existing tokenization, but recombine internal splits on dot and comma characters but not hyphens so that “Amazon @.@ com” becomes “Amazon.com”, “1 @.@ 000” becomes “1,000”, and “best @.@ selling” becomes “best - selling”.

In this collection, documents are legal opinions from the Supreme Court of the United States filed from 1980 through 2019. These documents can be very long, but have a regular structure.

In this collection, documents are Amazon product reviews. For four product categories (Books, Electronics, Movies and TV, CDs and Vinyl), we select 25,000 reviews from category-level dense subsets of Amazon product reviews (He and McAuley, 2016; McAuley et al., 2015).

For SCOTUS and REVIEWS, we tokenize documents using the spaCy NLP toolkit. Tokens are case-sensitive non-whitespace character sequences. For consistency across models, we also delete all control, format, private-use, and surrogate Unicode codepoints since they are internally removed by BERT’s tokenizer. We extract contextualized word representations from BERT (cased version), GPT-2, and RoBERTa using pretrained models available through the huggingface transformers library (Wolf et al., 2019). All methods break low-frequency words into multiple subword tokens: BERT uses WordPiece (Wu et al., 2016), while GPT-2 and RoBERTa use a byte-level variant of byte pair encoding (BPE) (Sennrich et al., 2016). For example, the word disillusioned is represented by four subtokens “di -si -llus -ioned” in BERT and by two subtokens “disillusion -ed” in GPT-2 and RoBERTa. One key difference between these tokenizers is that byte-level BPE can encode all inputs, while WordPiece replaces all Unicode codepoints it has not seen in pretraining with the special token UNK. For simplicity, rather than using a sentence splitter we divide documents into the maximum length subtoken blocks. To make vocabularies comparable across models with different subword tokenization schemes, we reconstitute the original word tokens by averaging the vectors for subword units (Bommasani et al., 2020).

### Clustering

We cluster tokens using spherical $k$-means (Dhillon and Modha, 2001) with spkm++ initialization (Endo and Miyamoto, 2015) because of its simplicity and high-performance, and cosine similarities are commonly used in other embedding contexts. Although we extract contextualized features for all tokens, prior to clustering we remove frequent words occurring in more than 25% of documents and rare words occurring in fewer than five documents. Each clustering is run for 1000 iterations or until convergence. For LDA,
we train models using Mallet (McCallum, 2002) with hyperparameter optimization occurring every 20 intervals after the first 50. For each embedding model, we cluster the token vectors extracted from the final layer $L[-1]$, the penultimate layer $L[-2]$, and the antepenultimate layer $L[-3]$. Vušić et al. (2020) suggest combining multiple layers, but no combination we tried provided additional benefit for this specific task. We consider more than the final hidden layer of each model because of the variability in anisotropy across layers (Ethayarajh, 2019). In a space where any two words have near perfect cosine similarity, clustering will only capture the general word distribution of the corpus. Since Ethayarajh (2019) has shown GPT-2’s final layer to be extremely anisotropic, we do not expect to produce viable topics in this case. For each test case, we build ten models each of size $K \in \{50, 100, 500\}$.

4 Evaluation Metrics

We evaluate the quality of “topics” produced by clustering contextualized word representations with several quantitative measures. For all models we use hard topic assignments, so each word token has a word type $w_i$ and topic assignment $z$. Note that we use “topic” and “cluster” interchangeably.

Word Entropy. As a proxy for topic specificity, we measure a topic’s word diversity using the conditional entropy of word types given a topic: $- \sum_i \Pr(w_i|z) \log \Pr(w_i|z)$. Topics composed of tokens from a small set of types will have low entropy (minimum 0), while topics more evenly spread out across the whole vocabulary will have high entropy (maximum log of vocabulary size; approx. 10 for WIKIPEDIA). There is no best fit between quality and specificity, but extreme entropy scores indicate bad topics. Topics with extremely low entropy are overly specialized, while those with extremely high entropy are overly general.

Coherence. We measure the semantic quality of a topic using two word-cooccurrence-based coherence metrics. These coherence metrics measure whether a topic’s words actually occur together. Internal coherence uses word cooccurrences from the working collection, while external coherence relies on word cooccurrences from a held-out external collection. The former measures fit to a dataset, while the latter measures generalization. For internal coherence we use Mimno et al. (2011)’s topic coherence metric, $\sum_{i} \sum_{j<1} \log \frac{D(w_i, w_j) + \epsilon}{D(w_i)}$, where $D$ refers to the number of documents that contain a word or word-pair. For external coherence we use Newman et al. (2010)’s topic coherence metric: $\sum_{i} \sum_{j<1} \log \frac{\Pr(w_i, w_j) + \epsilon}{\Pr(w_i) \Pr(w_j)}$, where probabilities are estimated from the number of 25-word sliding windows that contain a word or word-pair in an external corpus. We use the New York Times Annotated Corpus (Sandhaus, 2008) as our external collection with documents corresponding to articles (headline, article text, and corrected text) tokenized with spaCy. For both metrics, we use the top 20 words of each topic and set the smoothing factor $\epsilon$ to $10^{-12}$ to reduce penalties for non-cooccurring words (Stevens et al., 2012). We ignore words that do not appear in the external corpus and do not consider topics that have fewer than 10 attested words. These “skipped” topics are often an indicator of model failure. Higher scores are better.

Exclusivity. A topic model can attain high coherence by repeating a single high-quality topic multiple times. To balance this effect, we measure topic diversity using Bischof and Airoldi (2012)’s word-level exclusivity metric to quantify how exclusive a word $w$ is to a specific topic $z$: $\frac{\Pr(w_i|z)}{\sum_j \Pr(w_i|z_j)}$. A word prevalent in many topics will have a low exclusivity score near 0, while a word occurring in few topics will have a score near 1. We lift this measure to topics by computing the average exclusivity of each topic’s top 20 words. While higher scores are not inherently better, low scores are indicative of topics with high levels of overlap.

5 Results

We evaluate whether contextualized word representation clusters can group together related words, distinguishing distinct uses of the same word based on local context. Compared to bag-of-words LDA, we expect contextualized embedding clusters to encode more syntactic information. As we are not doing any kind of fine-tuning, we expect performance to be best on text similar to the pretraining data. We also expect contextualized embedding clusters to be useful in describing differences between partitions of a working collection.

BERT produces meaningful topic models. BERT cluster models consistently form semantically meaningful topics, with the final layer performing marginally better for larger $K$. Figure 1
Figure 1: Contextualized embedding clusters produce mean internal and external coherence scores comparable to LDA (dashed line). BERT clusters (blue) have high mean external coherence, better than LDA for large numbers of topics. BERT clusters contain more unique words, while RoBERTa (red) and GPT-2 (green) \( L^{-1} \) clusters tend to repeat similar clusters. BERT clusters have the highest word concentrations.

This shows that BERT clusterings have the highest external coherence, matching LDA for \( K \in \{50, 100\} \) and beating LDA for \( K = 500 \). For internal coherence, the opposite is true, with BERT on par with LDA for smaller \( K \), while LDA “fits” better for \( K = 500 \). This distinction suggests that at very fine-grained topics, LDA may be overfitting to noise. BERT has relatively low word entropy, indicating more focused topics on average. Figure 2 shows the number of word types per cluster. BERT clusters are on average smaller than LDA topics (counted from an unsmoothed sampling state), but very few BERT clusters fall below our 10-valid-words threshold for coherence scoring. BERT clusters are not only semantically meaningful, but also unique. Figure 1 shows that BERT clusters have exclusivity scores as high if not higher than LDA topics on average. Since there is little difference between layers, we will only consider BERT \( L^{-1} \) for the remainder of this work.

**GPT-2 can produce meaningful topic models.** As expected, the final layer clusterings of GPT-2 form bad topics. These clusters tend to be homogeneous (low word entropy) and similar to each other (low exclusivity). They also highlight the differences between our two coherence scores. Since these clusters tend to repeatedly echo the background distribution of WIKIPEDIA, they perform relatively well for internal coherence, but poorly for external coherence. Since the final layer of GPT-2 has such high anisotropy, we cannot expect vector directionals to encode semantically meaningful information. In contrast, the penultimate and antepenultimate layer clusterings perform much better. We see a large improvement in external coherence surpassing LDA for \( K = 500 \). Topic word entropy and exclusivity are also improved.

For \( K = 500 \), GPT-2 \( L^{-3} \) has surprisingly low mean internal coherence—the worst scores in Figure 1 by a significant margin. The number of topics below the 10-valid-words threshold is similar to BERT, so this result is comparable. We posit that this layer is relying more on transferred knowledge from the pretrained GPT-2 model than the working collection. Because of this less explained behavior, we will only consider GPT-2 \( L^{-2} \) going forward.

**RoBERTa clusters are noticeably worse.** Given BERT’s success and GPT-2’s partial success, we were surprised to find that RoBERTa cluster models were consistently of poor quality, with very low exclusivity scores and high word entropies. Although RoBERTa scores fairly well in coherence, this is not indicative of collectively high quality topics because of the correspondingly low exclusivity scores. As shown in Figure 1, RoBERTa has the highest average number of distinct words per cluster, but also large numbers of clusters that contain very few distinct words. For \( K = 500 \), 25–50 clusters are skipped on average for different layer choices. For example, one topic consists entirely of the words game, games, Game, another just ago, and one simply the symbol. The remaining tokens are thus limited.
to a smaller number of more general topics that are closer to the corpus distribution.

While it is commonly accepted that RoBERTa outperforms BERT for a variety of natural language understanding tasks (Wang et al., 2019), we find the opposite to be true for semantic clustering. There are a number of differences between BERT and RoBERTa, but our experimental results do not mark a clear cause. The tokenization method is a very unlikely source since GPT-2 uses the same scheme.

Contextualized embedding clusters capture polysemy. A limitation of many methods that rely on vocabulary-level embeddings is that they cannot explicitly account for polysemy and contextual differences in meaning. In contrast, token-based topic models are able to distinguish differences in meaning between contexts. There has already been evidence that token-level contextualized embeddings are able to distinguish contextual meanings for specific examples (Wiedemann et al., 2019; Cönen et al., 2019), but can they also do this for entire collections?

Instead of manually selecting terms we expect to be polysemous, we choose terms that occur as top words for clusters with dissimilar word distributions (high Jensen-Shannon divergence). While dissimilarity is not indicative of polysemy—different topics can use a term in the same way—it narrows our focus to words that are more likely to be polysemous. In Table 1, we see topics for two such terms “land” and “metal”. All models are able to distinguish metal the material from metal the genre, but BERT and GPT-2 are also able to distinguish land the noun from land the verb.

Contextualized embedding clusters are more syntactically consistent than LDA topics. Contextualized word representations are known to represent a large amount of syntactic information that is not available to traditional bag-of-words topic models (Goldberg, 2019). We therefore expect that token-level clusterings of contextualized word representations will have more homogeneity of syntactic form, and indeed we find that they do.

As a simple proxy for syntactic similarity, we find the most likely part of speech (POS) for the top words in each cluster. We use this method because it is easily implemented; inaccuracies should be consistent across models. To quantitatively evaluate the homogeneity of POS within each topic, we count the distribution of POS tags for the top 20 words of a cluster and calculate the entropy of that distribution. If all 20 words are the same POS, this value will be 0, while if POS tags are more diffuse it will be larger. We find that BERT and GPT-2 clusters have consistently lower entropy. In Table 3, we see that the 25th percentile for LDA topics has entropy 0.97, higher than the median entropy for both BERT and GPT-2. We find that these results are consistent across model sizes. Although contextualized embedding clusters are more homogeneous in POS, LDA may appear more homogeneous because it is dominated by nouns. For LDA, nouns and proper nouns account for 43.7% and 33.4% respectively of all the words in the top 20 for all topics, while verbs make up 8.5% and adjectives 6.7%. These proportions are 39.0%, 25.3%, 14.9%, and 8.1% for BERT, and 37.0%, 23.4%, 16.9%, and 9.5% for GPT-2.

Compression improves efficiency while maintaining quality. We have established that we can effectively learn topic models by clustering token-level contextualized embeddings, and we have shown that there are advantages to clustering at the token rather than vocabulary level. But for token-level clustering to be more than a curiosity we need to address computational complexity. Vocabularies are typically on the order of tens of thousands of words, while collections often contain millions of words. Even storing full 768-dimensional vectors for millions of tokens, much less clustering them, can be beyond the capability of many potential users’ computing resources. Therefore, we investigate the effects of feature dimensionality reduction to reduce the memory footprint of our method.

The hidden layers of deep learning models are known to learn representations with dimensionalities much lower than the number of neurons (Raghu et al., 2017). We apply two methods for dimensionality reduction: principal component analysis (PCA) and sparse random projection (SRP) (Li et al., 2006; Achlioptas, 2001).3 We find that reducing our token vectors to as few as 100 dimensions can have little negative effect. Figure 3 shows that reduced PCA features produce improved internal coherence and little significant change in external coherence, but reduced SRP features are worse in both metrics, especially for BERT. We note that more clusters pass the 10-valid-words threshold for reduced PCA and SRP features. Instead of skipping 10 BERT clusters and 7 GPT-2

3All implementations from (Pedregosa et al., 2011).
clusters on average, no clusters are skipped for PCA reduced features and only 1 for 100-dimensional SRP features. For 300-dimensional SRP features there is only a significant drop for GPT-2 with 3 skipped on average. This decrease in skipped topics indicates that overly specific topics are being replaced with less specific ones. We hypothesize that dimensionality reduction is smoothing away “spikes” in the embeddings space that cause the algorithm to identify small clusters. Finally, larger dimensionality reductions decrease concentration and exclusivity, making clusters more general.

PCA is significantly better than SRP, especially for more aggressive dimensionality reductions. We find that mean-centering SRP features does not significantly improve results. An advantage of SRP, however, is that the projection matrix can be generated offline and immediately applied to embedding vectors as soon as they are generated. To overcome the memory limitations of PCA, we use a batch approximation, incremental PCA (Ross et al., 2008). Using 100 dimensions and scikit-learn’s default batch size of five times the number of features (3840), we find no significant difference in results between PCA and incremental PCA. For the remainder of experiments we use 100-dimensional vectors which correspond to the top 100 components produced by incremental PCA.

Table 3: Contextualized embedding clusters are more syntactically aware than LDA. Topics ranked by the entropy of POS distribution of the top 20 words (10 shown) with $K = 500$.

| Model   | Perc. | Entr. | Top Words (noun verb adj adv other)                                                                 |
|---------|-------|-------|-----------------------------------------------------------------------------------------------------|
| LDA     | 5%    | 0.69  | Valley Death valley Creek California mining Valley Nevada Desert                                    |
|         | 25%   | 0.97  | army forces soldiers campaign troops captured defeated Battle victory commander                     |
|         | 50%   | 1.11  | society News Week Good Spirit Fruit says Doug host free                                             |
|         | 75%   | 1.28  | Washington Delaware ceremony Grand Capitol building 156 Number laying Master                       |
|         | 95%   | 1.53  | reviews review positive mixed list Entertainment Times style something                              |
| BERT    | 5%    | 0.00  | 1997 1996 1995 1937 1895 1935 96 1896 1795 97                                                    |
|         | 25%   | 0.61  | Jewish Israel Jews Ottoman Arab Muslim Israeli Islamic Jerusalem Islam                             |
|         | 50%   | 0.86  | captured defeated attacked capture attack siege destroyed surrender defeat occupied                 |
|         | 75%   | 1.09  | separate combined co joint shared divided common combination distinct respective                    |
|         | 95%   | 1.48  | 2004 2003 2015 2000 2014 1998 2001 2013 2002 1997                                                 |
| GPT-2   | 5%    | 0.00  | Atlantic Pacific Gulf Mediterranean Caribbean Indian Baltic Bay Florida                           |
|         | 25%   | 0.42  | knew finds discovers learned reveals discovered know heard discover learns                        |
|         | 50%   | 0.73  | Olympic League FA Summer Premier Division UEFA European Winter Tour                               |
|         | 75%   | 1.02  | positive mixed critical negative garnered favorable mostly attracted commercial                   |
|         | 95%   | 1.42  |                                                                                                   |
Pretrained embeddings are effective for different collections. While BERT and GPT-2 cluster models produce useful topics for WIKIPEDIA, will this hold for collections less similar to the training data of these pretrained models? Does it work well for collections of much shorter and much longer texts than Wikipedia articles? We find that both BERT and GPT-2 produce semantically meaningful topics for SCOTUS and REVIEWS, but BERT continues to outperform GPT-2. As with WIKIPEDIA, we find that contextualized embedding clusters have the largest advantage over LDA for large \( K \). Figure 4 shows that for \( K = 500 \) BERT and GPT-2 clusters have significantly higher external coherence scores on average than LDA topics for SCOTUS and very similar scores for REVIEWS. For smaller \( K \), LDA has the highest external coherence scores followed by BERT. Internal coherence is more difficult to interpret because of the variability in exclusivity. With \( K = 500 \), BERT clusters have substantially worse internal coherence scores. In contrast, GPT-2 clusters tend to experience a smaller drop in scores, but this can be partially explained by their much lower average exclusivity. We find that BERT consistently produces the most unique topics for SCOTUS and REVIEWS. BERT consistently has significantly higher mean exclusivity scores for both SCOTUS and REVIEWS, while GPT-2 tends to have scores as good as LDA for \( K \in \{50, 100\} \), but significantly lower for \( K = 500 \).

Contextualized embedding clusters support collection analysis. Token-level clusterings of contextualized word representations support sophisticated corpus analysis with little additional complexity. In practice, topic models are often used as a way to “map” a specific collection, for example by identifying key documents or measuring the prevalence of topics over time (Boyd-Graber et al., 2017). A key disadvantage therefore of vocabulary-level semantic clustering is that it is not grounded in specific documents in a collection. Token-level clustering, in contrast, supports a wide range of analysis techniques for researchers interested in using a topic model as a means for studying a specific collection. We provide two case studies that both use additional metadata to organize token-level clusterings \textit{post hoc}. Given a partition of the working collection, we can count tokens assigned to each topic within a given partition to estimate locally prominent topics. Table 4 shows the three most prominent topics for the four product categories in REVIEWS from a BERT cluster model with \( K = 500 \). Many of these

| books       | book books author novel novels work Book fiction by authors Kindle published volume works literature read reading copy Read reads Reading readable reader reread across follow opened researched study hand problem children problems course power lives mystery questions issues words death example reality battle |
|-------------|-------------------------------------------------------------------------------------------------------------|
| electronics | use up than off used back over using there about work need down thing nice other full no easy small screen quality sound device power battery unit system software remote video player mode drive audio setup remote battery mode card set range input signal support setting manual stand menu GPS fan power |
| movies      | movie movies films flick theater Movie flicks game cinema film comedies Movies pictures westerns into up over through between off down about around during under found away along though film movie picture screen documentary films Film cinema feature work production filmmaker piece picture album albums record release Album LP releases records effort up label EP thing titled studio label titled songs tracks hits tunes singles material stuff Songs ballads cuts ones numbers sounds artists Hits versions lyrics guitar vocals voice bass singing solo vocal sound work music piano chorus style here live playing |

Table 4: Unlike vocabulary-level clusters, token-level clusters are grounded in specific documents and can be used to analyze collections. Here we show the most prominent BERT topics \((K = 500)\) for the four product categories in REVIEWS. This analysis is purely \textit{post hoc}, neither BERT nor its clustering have access to product labels.

Table 5: The ten BERT topics from REVIEWS with the most \textit{uniform} distribution over product categories.
Table 6: Grounded topics allow us to analyze trends in the organization of a corpus using a BERT topic model with $K = 500$. Here we measure the prevalence of topics from 1980 to 2019 in US Supreme Court opinions by counting token assignments. Topics related to unions and natural resources are more prevalent earlier in the collection, while topics related to firearms and intellectual property have become more prominent.

6 Conclusion

We have presented a simple, reliable method for extracting mixed-membership models from pre-trained contextualized word representations. This result is of interest in several ways. First, it provides insight into the affordances of contextualized representations. For example, our result suggests a way to rationalize seemingly ad hoc methods such as averaging token vectors to build a representation of a sentence. Second, it suggests directions for further analysis and development of contextualized representation models and algorithms. The significant differences we observe in superficially similar systems such as BERT and RoBERTa require explanations that could expand our theoretical understanding of what these models are doing. Why, for example, is RoBERTa more prone to very small, specific clusters, while BERT is not? Furthermore, if models like BERT are producing output similar to topic model algorithms, this connection may suggest new directions for simpler and more efficient language model algorithms, as well as more representationally powerful topic model algorithms. Third, there may be substantial practical benefits for researchers analyzing collections. Although running BERT on a large-scale corpus may for now be substantially more computationally inefficient than running highly-tuned LDA algorithms, passing a collection through such a system is likely to become an increasingly common analysis step. If such practices could be combined with online clustering algorithms that would not require storing large numbers of dense token-level vectors, data analysts who are already using BERT-based workflows could easily extract high-quality topic model output with essentially no additional work.
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References

Dimitris Achlioptas. 2001. Database-friendly random projections. In PODS ’01.

Roee Aharoni and Yoav Goldberg. 2020. Unsupervised domain clusters in pretrained language models. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7747–7763, Online. Association for Computational Linguistics.

Sanjeev Arora, Rong Ge, Yonatan Halpern, David Mimno, Ankur Moitra, David Sontag, Yichen Wu, and Michael Zhu. 2013. A practical algorithm for topic modeling with provable guarantees. In International Conference on Machine Learning, pages 280–288.

Jonathan Bischof and Edoardo M. Airoldi. 2012. Summarizing topical content with word frequency and exclusivity. In Proceedings of the 29th International Conference on Machine Learning (ICML-12), pages 201–208.

David M Blei, Andrew Y Ng, and Michael I Jordan. 2003. Latent dirichlet allocation. Journal of machine Learning research, 3(Jan):993–1022.

Rishi Bommasani, Kelly Davis, and Claire Cardie. 2020. Interpreting Pretrained Contextualized Representations via Reductions to Static Embeddings. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, Online. Association for Computational Linguistics.

Jordan Boyd-Graber, Yuening Hu, David Mimno, et al. 2017. Applications of topic models. Foundations and Trends in Information Retrieval, 11(2-3):143–296.

Peter F. Brown, Peter V. deSouza, Robert L. Mercer, Vincent J. Della Pietra, and Jennifer C. Lai. 1992. Class-based n-gram models of natural language. Computational Linguistics, 18(4).

Wenhu Chen, Evgeny Matusov, Shahram Khadivi, and Jan-Thorsten Peter. 2016. Guided alignment training for topic-aware neural machine translation. AMTA 2016, Vol., page 121.

Andy Coenen, Emily Reif, Ann Yuan, Been Kim, Adam Pearce, Fernanda B. Viégas, and Martin Wattenberg. 2019. Visualizing and measuring the geometry of BERT. In Advances in Neural Information Processing Systems 32, pages 8594–8603. Curran Associates, Inc.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Inderjit S Dhillon and DharMendra S Modha. 2001. Concept decompositions for large sparse text data using clustering. Machine learning, 42(1-2):143–175.

Adji B. Dieng, Francisco J. R. Ruiz, and David M. Blei. 2020. Topic modeling in embedding spaces. Transactions of the Association for Computational Linguistics, 8:439–453.

Yasunori Endo and Sadaaki Miyamoto. 2015. Spherical k-means++ clustering. In International Conference on Modeling Decisions for Artificial Intelligence, pages 103–114. Springer.

Kawin Ethayarajh. 2019. How contextual are contextualized word representations? comparing the geometry of BERT, ELMo, and GPT-2 embeddings. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 55–65, Hong Kong, China. Association for Computational Linguistics.

Yoav Goldberg. 2019. Assessing bert’s syntactic abili- ties. ArXiv, abs/1901.05287.

Ruining He and Julian McAuley. 2016. Ups and downs: Modeling the visual evolution of fashion trends with one-class collaborative filtering. In proceedings of the 25th international conference on world wide web, pages 507–517.

Andrea Lancichinetti, M Irmak Sirer, Jane X Wang, Daniel Acuna, Konrad Körding, and Luis A Nunes Amaral. 2015. High-reproducibility and high-accuracy method for automated topic classification. Physical Review X, 5(1):011007.

Ping Li, Trevor J. Hastie, and Kenneth Ward Church. 2006. Very sparse random projections. In KDD ’06.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. ArXiv, abs/1907.11692.

Louis Martin, Benjamin Muller, Pedro Javier Ortiz-Suárez, Yoann Dupont, Laurent Romary, Éric de la Clergerie, Djämen Seddah, and Benoît Sagot. 2020. CamemBERT: a tasty French language model. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7203–7219, Online. Association for Computational Linguistics.
Julian McAuley, Christopher Targett, Qinfeng Shi, and Anton Van Den Hengel. 2015. Image-based recommendations on styles and substitutes. In Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval, pages 43–52.

Andrew Kachites McCallum. 2002. Mallet: A machine learning for language toolkit.

Stephen Merity, Caiming Xiong, James Bradbury, and Richard Socher. 2017. Pointer sentinel mixture models. In 5th International Conference on Learning Representations, ICLR 2017.

Yishu Miao, Edward Grefenstette, and Phil Blunsom. 2017. Discovering discrete latent topics with neural variational inference. In PMLR.

Tomas Mikolov, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013a. Efficient estimation of word representations in vector space. In Proceedings of Workshop at ICLR.

Tomas Mikolov, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. 2013b. Distributed representations of words and phrases and their compositionality. In Advances in Neural Information Processing Systems 26, pages 3111–3119. Curran Associates, Inc.

David Mimno, Hanna Wallach, Edmund Talley, Miriam Leenders, and Andrew McCallum. 2011. Optimizing semantic coherence in topic models. In Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing, pages 262–272. Edinburgh, Scotland, UK. Association for Computational Linguistics.

Shashi Narayan, Shay B. Cohen, and Mirella Lapata. 2018. Don’t give me the details, just the summary! topic-aware convolutional neural networks for extreme summarization. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing, pages 1797–1807. Brussels, Belgium. Association for Computational Linguistics.

David Newman, Youn Noh, Edmund Talley, Sarvnaz Karimi, and Timothy Baldwin. 2010. Evaluating topic models for digital libraries. In Proceedings of the 10th annual joint conference on Digital libraries, pages 215–224.

Dat PhoBERT Nguyen and Anh Tuan Nguyen. 2020. PhoBERT: Pre-trained language models for Vietnamese. Findings of EMNLP.

F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay. 2011. Scikit-learn: Machine learning in Python. Journal of Machine Learning Research, 12:2825–2830.

Nicole Peinelt, Dong Nguyen, and Maria Liakata. 2020. tBERT: Topic models and BERT joining forces for semantic similarity detection. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7047–7055, Online. Association for Computational Linguistics.

Jeffrey Pennington, Richard Socher, and Christopher Manning. 2014. Glove: Global vectors for word representation. In Proceedings of the 2014 Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 1532–1543, Doha, Qatar. Association for Computational Linguistics.

Fabio Petroni, Tim Rocktäschel, Sebastian Riedel, Patrick Lewis, Anton Bakhktin, Yuxiang Wu, and Alexander Miller. 2019. Language models as knowledge bases? In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 2463–2473, Hong Kong, China. Association for Computational Linguistics.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. 2019. Language models are unsupervised multitask learners. OpenAI Blog, 1(8):9.

Maithra Raghu, Justin Gilmer, Jason Yosinski, and Jascha Sohl-Dickstein. 2017. Svécca: Singular vector canonical correlation analysis for deep learning dynamics and interpretability. In Advances in Neural Information Processing Systems 30, pages 6076–6085. Curran Associates, Inc.

David A Ross, Jongwoo Lim, Ruei-Sung Lin, and Ming-Hsuan Yang. 2008. Incremental learning for robust visual tracking. International journal of computer vision, 77(1-3):125–141.

Evan Sandhaus. 2008. The new york times annotated corpus. Linguistic Data Consortium, Philadelphia, 6(12):e26752.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725. Berlin, Germany. Association for Computational Linguistics.

Suzanna Sia, Ayush Dalmia, and Sabrina J. Mielke. 2020. Tired of topic models? clusters of pretrained word embeddings make for fast and good topics too! In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing.

Akash Srivastava and Charles Sutton. 2016. Neural variational inference for topic models. In NeurIPS Bayesian deep learning workshop.

Keith Stevens, Philip Kegelmeyer, David Andrzejewski, and David Buttlar. 2012. Exploring topic coherence over many models and many topics. In Proceedings of the 2012 Joint Conference on Empirical
