Many data sets in a domain (reviews, forums, news, etc.) exist in parallel languages. They all cover the same content, but the linguistic differences make it impossible to use traditional, bag-of-word-based topic models. Models have to be either single-language or suffer from a huge, but extremely sparse vocabulary. Both issues can be addressed by transfer learning. In this paper, we introduce a zero-shot cross-lingual topic model, i.e., our model learns topics on one language (here, English), and predicts them for documents in other languages. By using the text of the same document in different languages, we can evaluate the quality of the predictions. Our results show that topics are coherent and stable across languages, which suggests exciting future research directions.

Do Spanish customers value the same features of a smart speaker as German users? Do Brazilian Reddit users discuss immigration as much as their American counterparts? Many times, we have data from the same domain in different languages. Topic models (Blei, 2012; Terragni et al., 2020) allow us to find the main themes and overarching tropes. Methods that are based on neural variational inference are also popular (Miao et al., 2016; Srivastava and Sutton, 2017). However, traditional methods are language-specific. They rely on a fixed vocabulary specific to the training language. These models can not be applied to other languages, since the vocabulary would not match. Training on several languages, however, results in a vocabulary so vast that it creates problems with parameter size, search, and overfitting (Boyd-Graber et al., 2014).

However, a cross-lingual setup proves ideal for transfer learning: provided that the gist of topics is the same across languages, we can learn this gist on one language, and then apply it to others. This setup is zero-shot learning: we train a model on English and test it on several other languages that the model had no access to during training.

Zero-shot topic modeling requires the ability to leverage language-independent representations. Traditional topic modeling provides methods to extract meaningful word distributions from “unstructured” text, but requires language-specific bag-of-words (BoW) representations.

Recently, pre-trained representations, like the ones provided by BERT (Devlin et al., 2019), have enabled exciting new results in several different tasks like Named Entity Recognition, POS Tagging, and Natural Language Inference (Nozza et al., 2020; Rogers et al., 2020).

Previous work (Bianchi et al., 2020) has shown that neural variational frameworks allow us to use pre-trained document representations in addition to the bag of words to increase the topic coherence.

In this paper, we propose a novel neural topic modeling architecture in which we replace the input BoW with contextualized embeddings — here, we use SBERT (Reimers and Gurevych, 2019) embeddings. More precisely, a neural encoding layer for pre-trained document representations from the BERT language model is introduced before the sampling process of the topic model. This change allows us to infer topics on unseen documents in languages other than the one present in the training data. The inferred topics consists of tokens that refer to the training language.

While the BoW provides valuable symbolic information, the structure of this information is lost after the first hidden layer in any neural architecture. We, therefore, hypothesize that it can be replaced...
with contextual information. One limitation of our approach is that the BERT is limited to a fixed maximum input length. The resulting embeddings thus capture only the first 768 words.

We first show that results obtained with this architecture match those considering only the BoW (i.e., without the contextual information). We then show how to use our architecture for zero-shot cross-lingual topic modeling.

Contributions We propose a novel neural topic model that relies on language-independent representations to generate topic distributions. We show that this input can replace the standard input BoW without loss of quality. Indeed, we go on to show that the BERT representations enable zero-shot cross-lingual tasks. We make our model and evaluation metrics available as a Python package at https://github.com/MilaNLProc/contextualized-topic-models

1 A Fully Contextualized Neural Topic Model

We focus our work on Neural-ProdLDA (Srivastava and Sutton, 2017), a neural topic model that is based on the Variational AutoEncoder (VAE) (Kingma and Welling, 2014). The neural variational framework trains an inference network, i.e., a neural network that directly maps the BoW representation of a document onto a continuous latent representation. A decoder network is then used to reconstruct the BoW by generating its words using the latent document representation. The hidden document representation is sampled from a Gaussian distribution parameterized by \( \mu \) and \( \sigma^2 \) that are part of the variational inference framework (Kingma and Welling, 2014) — see (Srivastava and Sutton, 2017) for more details. The framework explicitly approximates a Dirichlet prior using Gaussian distributions.

We extend Neural-ProdLDA by replacing the input BoW with pre-trained representations from BERT. In Figure 1, we sketch the architecture of our contextual neural topic model. Let us note that the reconstructed BoW is still a component of the model. It is necessary during training to obtain the topic words but it becomes useless if we want to predict a document’s topics.

The proposed model, Contextual TM, can be trained with document representations that account for the input word-order and contextual information, overcoming one of the central limitations of BoW models. Moreover, using language-independent document representations permits us to do zero-shot topic modeling for unseen languages: this is important in settings in which there is little data available for the new languages. Because BERT exists for multiple languages, it also allows zero-shot modeling in a cross-lingual scenario. Indeed, Contextual TM is language independent: given any multilingual BERT contextual representation of an unseen language, it can predict the topic distribution of the document. The top-words of predicted topics will be in the same language as in the training. One current limitation is that the contextual representations of BERT are limited to a maximum input length of 768 words. The model can, therefore, capture small to mediums-sized documents, but only the beginning of long documents.

2 Experiments

Our experiments evaluate two main hypotheses: (i) we can create a topic model that does not rely on the BoW given in input, but use contextual information instead; (ii) the model can tackle zero-shot cross-lingual topic modeling.

Data Sets We use two data sets that we collected from English Wikipedia abstracts from DBpedia1. The first data set (W1) contains 20,000 randomly sampled abstracts with more than 300 characters. The second data set (W2) contains 100,000 English documents. We trained on 99,700 documents and

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1https://wiki.dbpedia.org/downloads-2016-10
consider the remaining 300 documents as test set. We collect their respective versions in Portuguese, Italian, French, and German. This collection, that also contains the English abstract, serves as a test set of comparable documents, i.e., documents that refer to the same entity in Wikipedia, but in different languages.

We pre-process both data sets to make a comparison as direct as possible: we take only the first 200 tokens of each abstract to reduce the effects of the length limit in BERT. We train SBERT (Reimers and Gurevych, 2019), using the multi-lingual model, on this unpreprocessed text. We then remove stopwords and use the most frequent remaining 2,000 words to create the BoW vocabulary for English.

2.1 To Contextualize or not To Contextualize

| Model        | $\tau$ (50) | $\tau$ (100) |
|--------------|-------------|--------------|
| Contextual TM | 0.1632      | 0.1381       |
| Combined TM  | 0.1644      | 0.1409       |
| Neural-ProdLDA | **0.1658** | 0.1285       |
| LDA          | -0.0246     | -0.0757      |

Table 1: NPMI Coherences on W1 data set.

We compare our fully-contextualized neural topic modeling (Contextual TM) on W1 with: (i) a version that combines both BoWs and BERT representations as inputs (Combined TM) (Bianchi et al., 2020), (ii) Neural-ProdLDA (Srivastava and Sutton, 2017), and (iii) LDA (Blei et al., 2003). We compute the topic coherence via NPMI ($\tau$) for 50 and 100 topics. For each of those conditions, we average model results over 30 runs, to minimize variation. Table 1 shows the results of this experiment. Contextual TM obtains a comparable topic coherence as the Combined TM and Neural-ProdLDA on this specific data set and settings. This result confirms our first hypothesis: contextual embeddings can replace BoWs input representations without loss of coherence. This result opens up interesting future applications.

2.2 Zero-shot Cross-Lingual Topic Modeling

With the previous results, we now show how to use our model for zero-shot cross-lingual topic modeling. Given a document in an unseen language, we predict its topic distribution with Contextual TM. We evaluate these predictions on the parallel multi-lingual abstracts in W2. We use both a quantitative and qualitative evaluation.

2.2.1 Quantitative Evaluation

Since the predicted document-topic distribution is subject to a stochastic sampling process, we average them over 100 samples. This process gives us a more reliable estimate of the correct distribution.

Metrics We expect the topic distributions over a set of comparable documents to be similar, even if they are written in different languages. We compare the topic distributions of each document in a test language (Portuguese, Italian, French, and German) with the topic distribution of the respective document in English, which is the language used to train the model. Note that the specific document in English is also unseen. We evaluate our model on three different metrics in this cross-lingual setting. The first metric is matches, i.e., the percentage of times the most likely topic predicted for the non-English test document is the same as for the same test document in English. Higher scores are better. The limitation of this metric is that it does not consider the fact that a topic model can create several similar topics: a wrong match does not necessarily mean that the predicted topic is wrong.

We use a second metric to account for this issue. We compute the centroid embeddings of the five words describing the predicted topic for both test document, and compute the cosine similarity between those two centroids (CD).

Finally, to capture the distributional similarity, we also compute the KL divergence between the predicted topic distribution on the test document and the same test document in English. Here, lower scores are better, indicating that the distributions do not differ by much.

Automatic Evaluation Our baseline is the uniform distribution over the topics. Therefore, we compute the matches with respect to English topic predictions, and the KL divergence between the uniform and the English predicted document-topic distributions. Table 2 shows the evaluation results of our model in the zero-shot context. Topic predictions are significantly better than the uniform baselines: more than 70% of the time, the predicted topic on the test set matches the topic of the same document in English. The CD similarity suggests that even when there is no match, the predicted
Table 2: Match, KL-divergence, and centroid similarity for 25 and 50 topics on various languages on W2.

| Lang | Mat25↑ | KL25↓ | CD25↑ | Mat50↑ | KL50↓ | CD50↑ |
|------|--------|-------|-------|--------|-------|-------|
| IT   | 75.67  | 0.16  | 0.84  | 62.00  | 0.21  | 0.75  |
| FR   | 79.00  | 0.14  | 0.86  | 63.33  | 0.19  | 0.77  |
| PT   | 78.00  | 0.14  | 0.85  | 68.00  | 0.19  | 0.79  |
| DE   | 79.33  | 0.15  | 0.85  | 64.33  | 0.20  | 0.77  |
| Uni  | 4.00   | 0.75  | —     | 2.00   | 0.85  | —     |

Table 3: Average topic quality (out of 3).

| Language | Average Topic Quality |
|----------|-----------------------|
| English  | 2.3478                |
| Italian  | 2.2900                |
| French   | 2.2244                |
| Portuguese | 2.2600            |
| German   | 2.1922                |
| Average  | 2.2629                |

Manual Evaluation Three of us independently rated the predicted topics for 300 test documents in five languages (including English) on an ordinal scale from 0-3. A score of 0 means that the predicted topic is wrong, a 1 means the topic is somewhat related, a 2 means the topic is probably correct and a 3 means the topic is correct. Each document and the associated predicted topic-words are given for each of the 5 different languages (English, Italian, French, Portuguese, and German). Table 3 shows the results per language.

We also evaluate the inter-rater reliability using Gwet AC1 (Gwet, 2014) an inter-rater reliability measure. We use ordinal weights, to account for the fact that our ratings are on an ordinal scale. A value of 0.88 indicates that our ratings are consistent.

2.2.2 Qualitative Evaluation

In Table 4 we show some examples of topic predictions on test languages. Our model effectively predicts the main topic for all languages, even though it had no access to them during training on the English corpus.

A more detailed analysis reveals that the predicted topic is generally consistent with the text. I.e., the topics are easily interpretable and give the user a correct impression of the text. In some cases, noise biases the results: dates in the abstract tend to make the model predict a topic about time (i.e., calendar, year, era). Another interesting case, for example, is the abstract of the artist Joan Brossa, who was both a poet and a graphic designer. In the English and Italian abstract, the model has discovered a topic related to writing, while in the Portuguese abstract the model has discovered another, related to art, which is still meaningful.

3 Related Work

Several researchers have studied multilingual and cross-lingual topic modeling (Ma and Nasukawa, 2017; Gutiérrez et al., 2016; Hao and Paul, 2018; Heyman et al., 2016; Liu et al., 2015; Krstovski et al., 2016). The first model proposed to process multilingual corpora with LDA is the Polylingual Topic Model (PLTM) by Mimno et al. (2009). It uses LDA to extract language-consistent topics from parallel multilingual corpora, under the assumption that translations share the same topic distributions. Models that transfer knowledge on the document level have many variants, including (Hao and Paul, 2018; Heyman et al., 2016; Liu et al., 2015; Krstovski et al., 2016). However, existing models require to be trained on multilingual corpora and are always language-dependent: they cannot predict the main topics of a document in an unseen language.

Another approach models the connection between languages through words, using multilingual dictionaries (Boyd-Graber and Blei, 2009; Jagarlamudi and III, 2010). However, all these approaches require supervised dictionaries to learn the mappings between languages.

To the best of our knowledge, there is no prior work on zero-shot cross-lingual topic modeling. In contrast, our model can be applied to new languages after training is complete, and does not
Table 4: Examples of zero-shot cross-lingual topic classification in various languages.

| Lang | Sentence                                                                 | Predicted Topic                                                                 |
|------|--------------------------------------------------------------------------|---------------------------------------------------------------------------------|
| EN   | Blackmore’s Night is a British/American traditional folk rock duo [...]   | rock, band, bass, formed                                                         |
| IT   | I Blackmore’s Night sono la band fondatrice del renaissance rock [...]    | rock, band, bass, formed                                                         |
| PT   | Blackmore’s Night uma banda de folk rock de estilo renascentista [...]    | rock, band, bass, formed                                                         |
| EN   | Langton’s ant is a two-dimensional Turing machine with [...]              | mathematics, theory, space, numbers                                              |
| FR   | On nomme fourmi de Langton un automate cellulaire [...]                  | mathematics, theory, space, numbers                                              |
| DE   | Die Ameise ist eine Turingmaschine mit einem zweidimensionalen [...]     | mathematics, theory, space, numbers                                              |
| EN   | The Journal of Organic Chemistry, colloquially known as JOC or [...]     | journal, published, articles, editor                                             |
| IT   | Journal of Organic Chemistry una rivista accademica [...]                | journal, published, articles, editor                                             |
| PT   | Journal of Organic Chemistry uma publicacao científica [...]              | journal, published, articles, editor                                             |
| EN   | The Pirate Party Germany (German: Piratenpartei Deutschland) [...]       | political, movement, party, alliance                                              |
| PT   | Piratenpartei Deutschland (Partido Pirata da Alemanha, [...].            | political, movement, party, alliance                                              |
| DE   | Die Piratenpartei Deutschland (Kurzbezeichnung Piraten, [...].           | political, movement, party, alliance                                              |
| EN   | Joan Brossa [...] was a Catalan poet, playwright, graphic designer [...]  | book, french, novel, written                                                     |
| IT   | Fu l’ispiratore e uno dei fondatori della rivista ”Dau al Se” [...]      | book, french, novel, written                                                     |
| PT   | Joan Brossa i Cuervo [...] foi um poeta, dramaturgo, artista plástico [...]| painting, art, painter, works                                                    |

4The reason we work with aligned documents here is only to guarantee comparability.

4 Conclusions

In this paper, we propose a novel neural architecture for cross-lingual topic modeling using contextualized document embeddings as input. Our results show that (i) BoW representations are not necessary as input to create coherent topics (ii) using contextualized document representations allows us to tackle zero-shot cross-lingual topic modeling. The resulting model can be trained on any one language and applied to any other language for which there are embeddings available. Both the content and the distribution over topics match across languages, enabling direct comparisons.

5 Acknowledgements

Federico Bianchi, Dirk Hovy, and Debora Nozza are members of the Boconi Institute for Data Science and Analytics (BIDSA) and the Data and Marketing Insights (DMI) unit.

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