Turftopic: Topic Modelling with Contextual Embeddings

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Summary

Turftopic is a topic modelling library including a number of recent topic models that go beyond bag-of-words and can understand text in context, utilizing representations from transformers. The library focuses on ease-of-use, providing a unified, interface for a number of different modern topic models, and boasting both model-specific and model-agnostic interpretation and visualization utilities. The user is afforded great flexibility in model choice and customization, but the library comes with reasonable defaults, not to overwhelm first-time users with a plethora of choices. In addition, our library is capable of modeling topics over time, modeling topics in streams of texts, finding hierarchical themes, and multilingual usage. For ease of interpretation, users can utilize large language models to assign human-readable names to topics, and can model key phrases, lemmas or stems right out of the box.
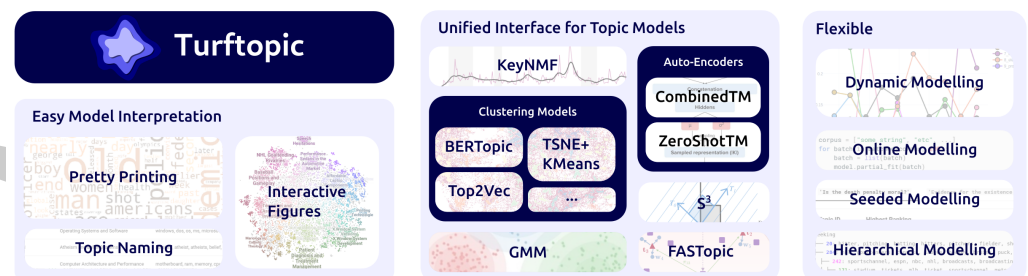
Figure 1: An Overview of Turftopic's Functionality

Statement of need

While a number of software packages have been developed for contextual topic modelling in recent years, including BERTopic (Grootendorst, 2022), Top2Vec (Angelov, 2020), CTM (Bianchi, Terragni, & Hovy, 2021), these packages include implementations of one or two topic models, and most of the utilities they provide are model-specific. This has resulted in the unfortunate situation that practitioners need to switch between different topic modelling libraries if they intend to try different models for their use case, and adapt to their particularities in both interface and functionality. Some attempts have been made at creating unified packages for modern topic models, including STREAM (Thielmann et al., 2024) and TopMost (Wu, Pan, et al., 2024). These packages, however have a focus on neural models and topic model evaluation, have abstract and highly specialized interfaces, and do not include all popular topic

30 models. Additionally, we considered the interpretation utilities included in these libraries fairly
31 limited.

32 Turftopic unifies state-of-the-art contextual topic models under a superset of the scikit-learn
33 (Pedregosa et al., 2011) API, which users are likely already familiar with, and can be readily
34 included in scikit-learn workflows and pipelines. We focused on making Turftopic first and
35 foremost an easy-to-use library, that does not necessitate expert knowledge or excessive amounts
36 of code to get started with, but gives great flexibility to power users. The library also includes
37 three topic models, which to our knowledge only have implementations in Turftopic, these are:
38 KeyNMF (Kristensen-McLachlan et al., 2024), S^3 (Kardos et al., 2024) and GMM.

Functionality

40 Turftopic includes a wide array of contextual topic models from the literature, these include:
41 FASTopic (Wu, Nguyen, et al., 2024), Clustering models, such as BERTopic (Grootendorst,
42 2022) and Top2Vec (Angelov, 2020), auto-encoding topic models, like CombinedTM (Bianchi,
43 Terragni, & Hovy, 2021) and ZeroShotTM (Bianchi, Terragni, Hovy, Nozza, et al., 2021),
44 KeyNMF (Kristensen-McLachlan et al., 2024), Semantic Signal Separation (Kardos et al.,
45 2024) and GMM. We believe these models to be representative of the state of the art in
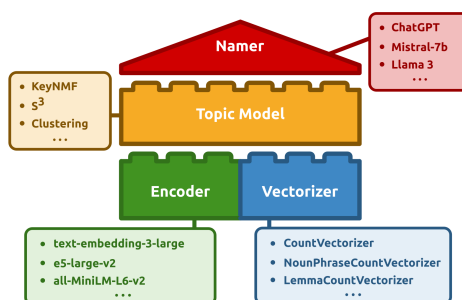46 contextual topic modelling and intend to expand on them in the future.

Figure 2: Components of a Topic Modelling Pipeline in Turftopic

47 Each model in Turftopic has an *encoder* component, which is used for producing continuous
48 document-representations, and a *vectorizer* component, which extracts term counts in each
49 documents, thereby dictating which terms will be considered in topics. The user has full
50 control over what components should be used at different stages of the topic modelling process,
51 thereby having fine-grained influence on the nature and quality of topics.

52 The library comes loaded with a lot of utilities to help users interpret their results, including
53 *pretty printing* utilities for exploring topics, *interactive visualizations* partially powered by the
54 `topicwizard` (Kardos, 2023) Python package, and *automated topic naming* with LLMs.

55 To accommodate a variety of use-cases, Turftopic can be used for dynamic topic modelling,
56 where we expect topics to change over time, can be used for uncovering hierarchical structure
57 in topics. Some models can also be fitted in an *online* fashion, where documents are accounted
58 for as they come in by batches. Turftopic also includes *seeded* topic modelling, where a seed
59 phrase can be used to retrieve topics relevant to the specific research question.

Target Audience

Topic models can be utilized in a number of research settings, including exploratory data analysis, discourse analysis of many domains, such as newspapers, social media or policy documents. Turftopic has already been utilized by Kristensen-McLachlan et al. (2024) for analyzing information dynamics in Chinese Diaspora Media, and is currently being used in multiple ongoing research projects, including one analyzing discourse on the HPV vaccine in Denmark. In addition, the library has already seen extensive use in student exam papers at Aarhus University. We expect that computational researchers, especially in digital humanities and in social sciences will benefit from an easy-to-use, unified contextual topic modelling package.

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