Topic Modeling/Clustering

Clustering and extracting topics from a set of documents

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1 Introduction

Machine learning models require more and more data to be trained, particularly in the field of natural language processing (NLP). Manually labeling data takes up a considerable amount of time that could be devoted to a more useful task. One way of solving this problem is to use topic modeling/clustering to help us divide the data into clusters, and then label the data using these clusters as classes [1]. Topic modeling is defined as a statistical and probabilistic technique used to automatically identify topics or themes in a collection of documents. Whereas Topic Clustering is defined as a text analysis technique used to group similar documents or textual data according to their content. This document will be used to answer the following two questions:

- How can we correctly group a dataset of documents (i.e. a corpus of text) by topic?
- How can this help us to label a given dataset?

It will be divided into two parts, as shown in Figure 1. First, we will focus on the scenario in which the input data are documents and topics (represented by keywords) into which we want to classify the documents, i.e. Topic Clustering. The second scenario is one in which the input data are documents only. We need to extract topics for each group of documents, i.e. Topic Clustering. It should be noted that, in Topic Modeling, there is a version of the models, called the Guided Version, which also takes as input keywords for several topics to guide the extraction. Nevertheless, this is still topic modeling, as it simply helps the model to extract topics, but its aim is not to classify documents into these topics.

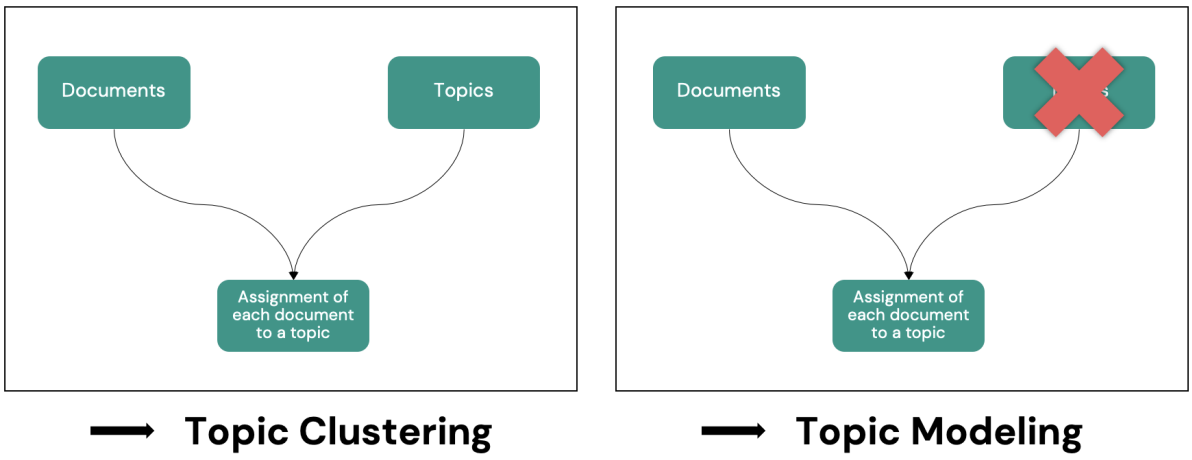


Figure 1: Difference between topic clustering and topic modeling.

[1] Code for this document is available at the following url. Each section of this report is represented by a separate folder.

2 Datasets

Before researching and applying models in an attempt to solve data labeling problems, we need data. Table 1 shows the following reference datasets that will be used in the project. These datasets were extracted using the OCTIS library and pre-processed by manually rewriting each ambiguous class name with an easier-to-interpret name. The manually extracted keywords are presented in the next section.

Name	# Docs	# Train/Test Docs	# Classes
BBC_News	2225	1780/445	5
20NewsGroup	16309	13047/3262	20
DBLP	54595	43676/10919	4
M10	8355	6684/1671	10

Table 1: Datasets extracted from OCTIS and used throughout the project.

2.1 Keywords

The keywords used for each class in each dataset are shown in tables 2 and 3. The reason behind replacing the original heading name with something more legible is that some models use these keywords to find other similar words. Word abbreviations distort these similarity measures. For example, ”sci.space” is not perfectly similar to ”space”. A more easily interpretable name was therefore needed for these models to work properly.

Topic	Topic Index	Keywords
soc.religion.christian	0	religion christianism
rec.sport.hockey	1	sport hockey
sci.space	2	science space
comp.os.ms-windows.misc	3	computer operating systems microsoft windows
comp.graphics	4	computer graphics
comp.sys.mac.hardware	5	computer systems mac hardware
rec.motorcycles	6	motorcycles
comp.sys.ibm.pc.hardware	7	computer systems ibm pc hardware
talk.politics.guns	8	politics guns
sci.electronics	9	science electronics
talk.politics.misc	10	politics miscellaneous
rec.sport.baseball	11	sport baseball
talk.religion.misc	12	religion miscellaneous
sci.crypt	13	science cryptography
alt.atheism	14	atheism
talk.politics.mideast	15	politics middle east
sci.med	16	science medicine
rec.autos	17	automobiles
comp.windows.x	18	computer windows x
misc.forsale	19	miscellaneous for sale

Topic	Topic Index	Keywords
2	0	archaeology
3	1	computer science
4	2	financial economics
0	3	agriculture
7	4	petroleum chemistry
9	5	social science
1	6	biology
8	7	physics
6	8	material science
5	9	industrial engineering

Table 2: Keywords for the 20NewsGroup dataset (left) and the M10 dataset (right).

Topic	Topic Index	Keywords
business	0	business
sport	1	sport
entertainment	2	entertainment
tech	3	technology
politics	4	politics

Topic	Topic Index	Keywords
2	0	computer vision
0	1	database
3	2	data mining
1	3	artificial intelligence

Table 3: Keywords for the BBC News dataset (left) and the DBLP dataset (right).

2.2 Straightforward data analysis

Figure 2.2 shows the class distributions for the datasets. It can be seen that the DBLP and M10 datasets have more consistent document lengths than the 20NewsGroup and BBC News datasets. In addition, the BBC News and DBLP datasets may be more suitable for testing, as they have fewer classes. As the BBC News dataset has many advantages, we will focus mainly on it for our primary experiments and then compare results on the other datasets.

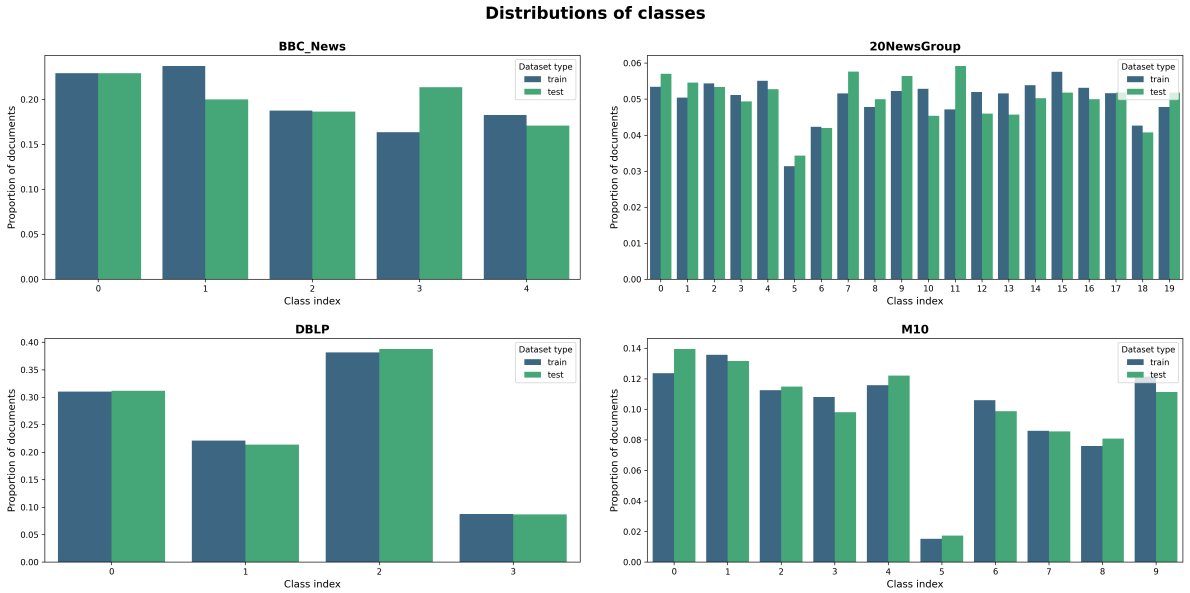


Figure 2: Class distribution for all datasets.

Figure 2.2 shows the document length distribution for the datasets. The DBLP and M10 datasets contain shorter documents, which raises a question. Is it better to have a large number of shorter documents, or a few larger ones? After some research, the choice depends on a number of factors, and there is no single answer. Both approaches have their advantages and limitations.

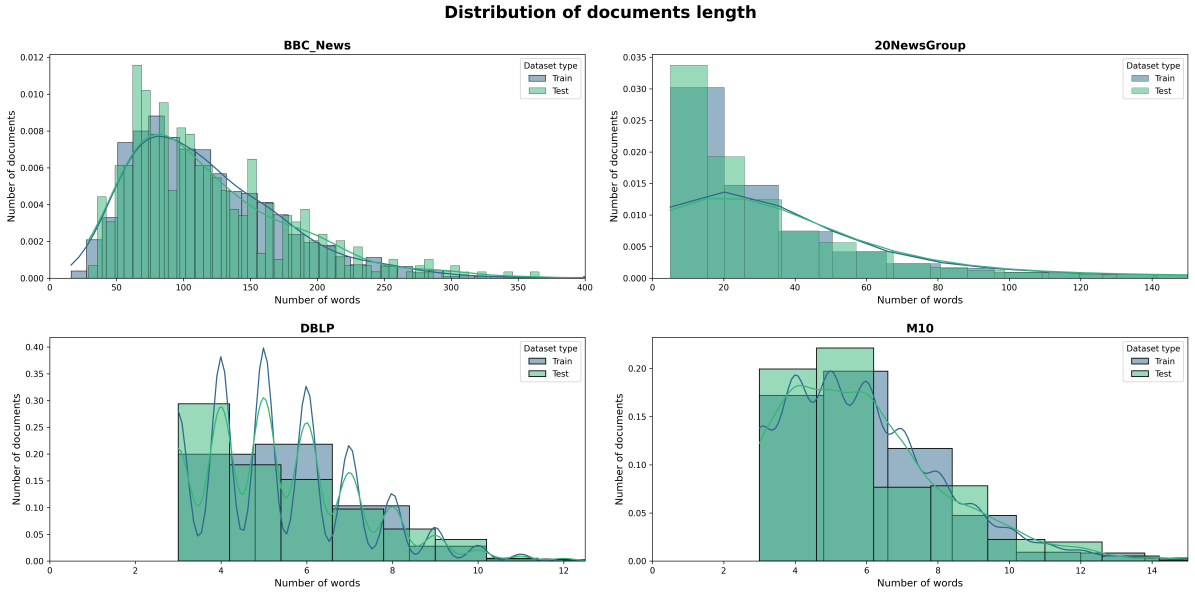


Figure 3: Document length distribution for all datasets.

The 10 most frequent words for each dataset are shown in Figure 2.2. This could be even more useful if we had a visualization of the most frequent words directly by class. This will be done as part of some experiments.

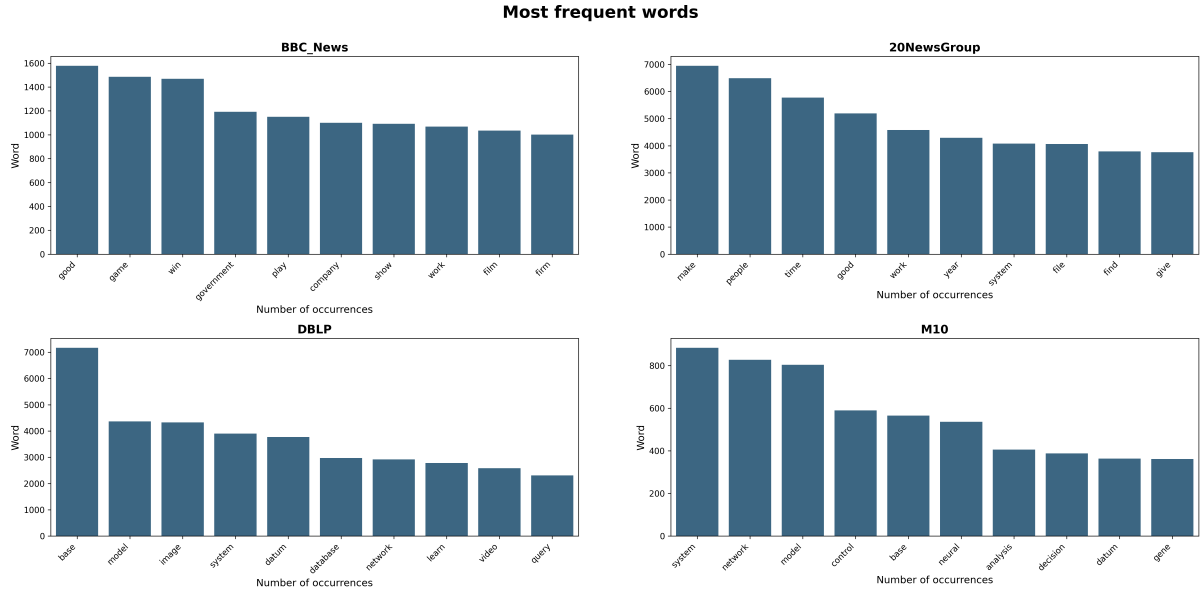


Figure 4: Most frequent words used in each dataset.

The distribution of word occurrences for the datasets is shown in Figure 2.2. The general rule is that most words rarely occur. Furthermore, with the exception of dataset M10, no dataset contains words that only appear 2 or 3 times. This can be explained in part by the fact that the dataset has already been processed and therefore contains no empty words or punctuation. It may also be explained by the fact that pre-processing has removed words that appear only a few times because they contain only a small amount of information.

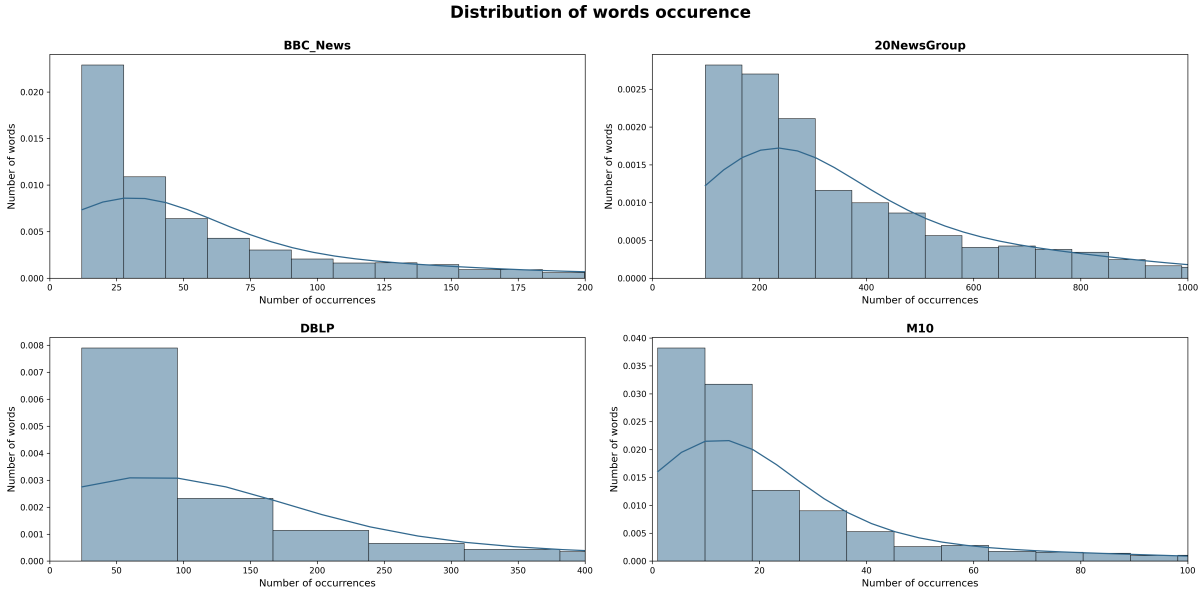


Figure 5: Distribution of word occurrences for each dataset.

3 Topic Clustering

This section deals with the scenario in which we receive not only input documents, but also the classes into which we want to classify the documents. Each class is represented by the keywords defined in section 2.1 but, depending on the situation, these can be modified and adapted for analysis. In this section, we will look at the Lbl2Vec model and its transformer-based variants.

3.1 Lbl2Vec and Lbl2TransformerVec

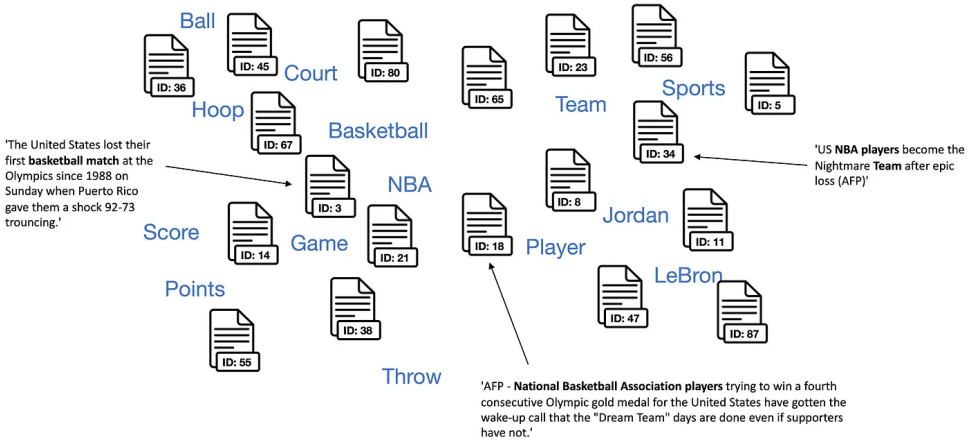
3.1.1 Theory

Lbl2Vec [6] is an unsupervised algorithm that classifies documents into classes defined on the basis of predefined knowledge, namely the keywords associated with each class. At a high level, this algorithm performs the following tasks:

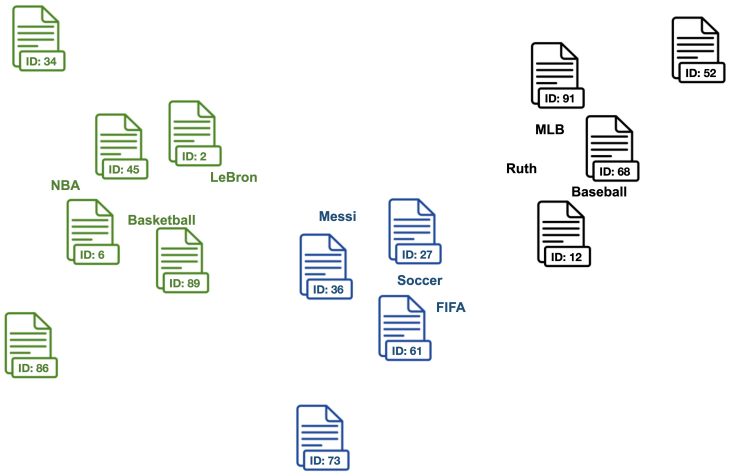
1. Use manually defined keywords for each category of interest.

Basketball	Soccer	Baseball
NBA	FIFA	MLB
Basketball	Soccer	Baseball
LeBron	Messi	Ruth
...	...	...

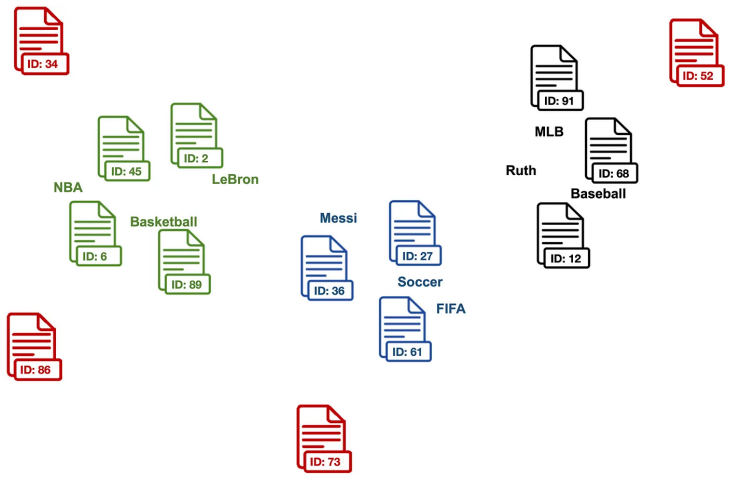
2. Create jointly embedded word and document vectors. The idea behind embedding vectors is that similar words or text documents will have similar vectors. Therefore, after creating jointly embedded vectors, documents are located close to other similar documents and close to the most distinctive words.



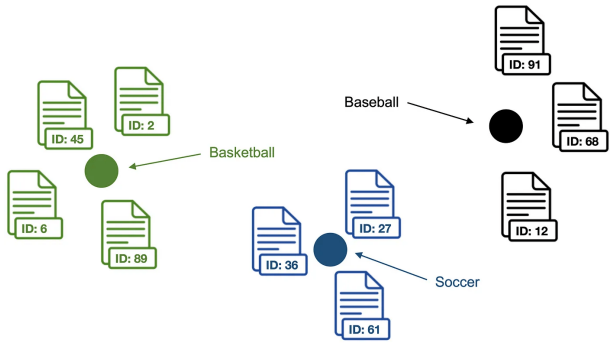
3. Find the document vectors that are similar to the keyword vectors for each classification category. We calculate cosine similarities between documents and manually defined keywords for each category. Documents that are similar to the category keywords are assigned to a dataset of candidate documents in the respective category.



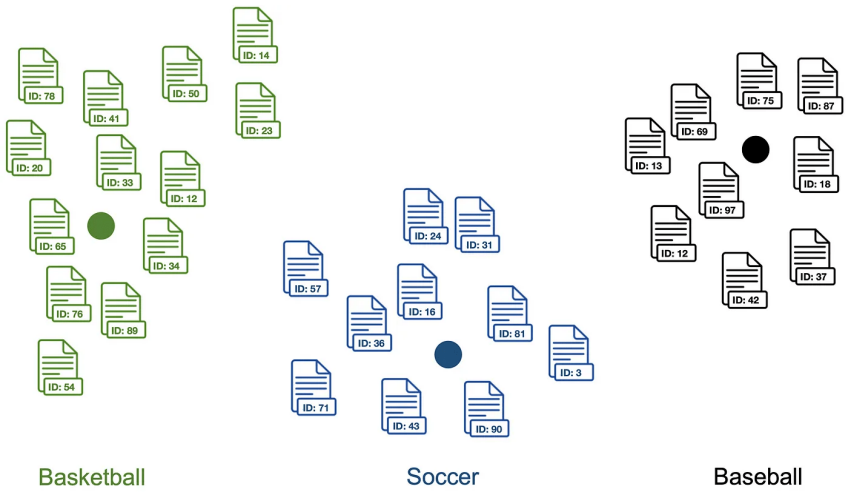
4. Clean outliers for each classification category using an algorithm called Local Outlier Factor (LOF).



5. Calculate the centroid of outlier vectors cleaned as a label vector for each classification category.



6. The algorithm computes label vector ⇔ document vector similarities for each label vector and document vector in the dataset. Finally, text documents are classified into the category with the highest label vector ⇔ document vector similarity.



This algorithm raised a number of questions:

- How do you choose the defined keywords?
- How do you create embeddings?
- Is LOF really useful for model performance? (Future work)

Note: the original article provides a library for the efficient use of models. But there are two problems. Firstly, we have no freedom over the internal model. We cannot define a random state for the internal model, and it's impossible to extract the embeddings created during inference. Secondly, it sometimes produces strange results. For example, it has a high F1 score on the BBC News dataset with Doc2Vec as embeddings, while it has a very poor F1 score with a transformer embedding. To solve these problems, we decided to rewrite the model from scratch (you can find it on the Github repository under the name DaCluDeK (Data Clustering with Defined Keywords)).

3.1.2 Embeddings models

Two types of embedding model can be used. One uses Doc2Vec and the other a transformer-based model. The advantages and disadvantages of these two architectures are presented in Table 4. Both models have been used and compared in this section, generally in a 2D framework for visualization purposes. Doc2Vec can directly generate 2D embeddings, which is not the case with transformer-based models. To solve this problem, we use a dimensionality reduction method called *Principal Component Analysis (PCA)*. The transformer-based model used is *all-MiniLM-L6-v2*.

Doc2Vec		**Transformer-based**	
Advantages	**Disadvantages**	**Advantages**	**Disadvantages**
Fast to calculate	Can only use keywords seen during training Poor performance Random	Can use any keywords Better embeddings leading to better performance	Costly in terms of computing

Table 4: Advantages and disadvantages of Doc2Vec architecture compared with transformer-based models.

3.1.3 Doc2Vec: Unknown keywords problem

A major problem with using Doc2Vec-based models is that they can only use keywords seen during training. This problem can be solved in an unsupervised way by using the similarity between two words. Knowing that, when using Doc2Vec-based models, instead of using the keywords from the datasets, we will calculate the similarity between the keywords and all the words contained in each document. The keywords used will be those that are most similar to the predefined keywords. To do this, the *spaCy* package will be used. Here's how similarity is calculated in spaCy:

1. Word vectors: Each word in the input text is represented by a high-dimensional vector in a continuous vector space.
2. Sentence or document vectors: spaCy combines the individual word vectors in the sentence or document to create a vector representation of the entire sentence or document dataset. This is usually done by taking the average or weighted average of the word vectors.
3. Cosine similarity: Once the sentence or document vectors have been obtained, spaCy calculates the similarity between them using cosine similarity. Cosine similarity measures the cosine of the angle between two vectors and provides a value between -1 (completely dissimilar) and 1 (perfectly similar).

A perplexed user may ask, "What is the point of using Doc2Vec if you always have to use a transformer as does spaCy to find keywords?". It should be noted that spaCy is only used as a pre-processor to retrieve the keywords most similar to the predefined keywords and is not used directly in the model. This step could be avoided by directly selecting predefined keywords as words contained in documents.

3.1.4 Embeddings

Figure 3.1.4 shows an example of 2D embeddings created for Doc2Vec and a transformer-based model. We can see that the transformer-based model has a better ability to find embeddings because they are more clustered. All the clusters found by Doc2Vec overlap. But we must bear in mind that we are in a 2D configuration and it is possible that Doc2Vec also creates good embeddings in a higher dimension. One might ask: are Doc2Vec's embeddings really relevant, since they do not respect the property that similar words will have closer embeddings? See the next section for a partial answer.

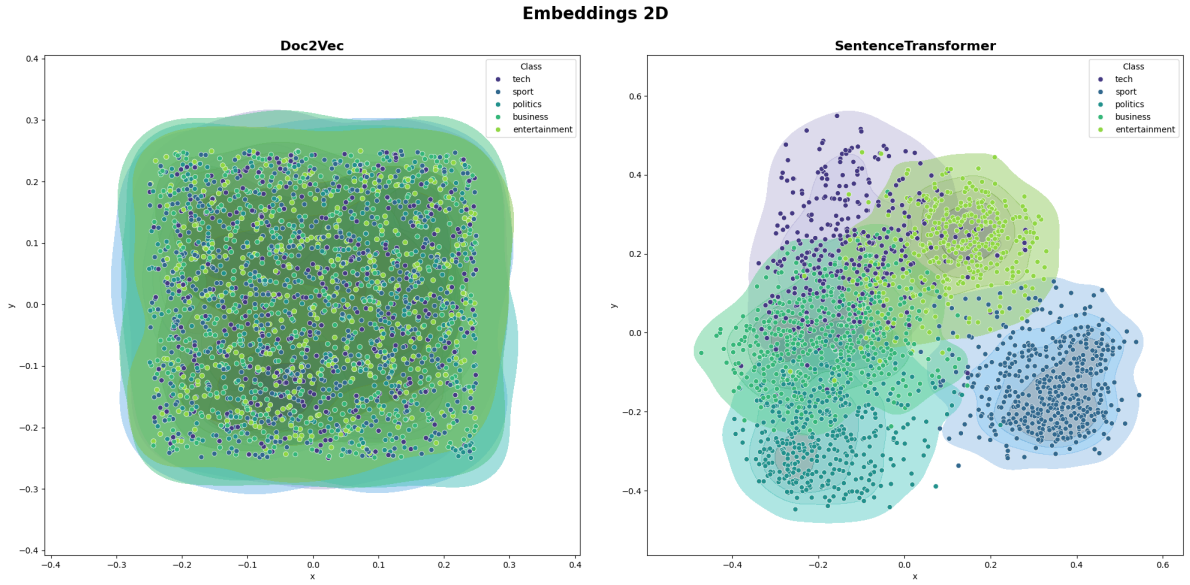


Figure 6: 2D embeddings generated by Doc2Vec and a transformer-based model on the BBC News dataset.

3.1.5 Performances

This section will attempt to answer the following question: How does model performance vary according to the keywords used? We will extract three types of keywords: the most frequent (supervised), the most similar (unsupervised) and the most important (supervised).

3.1.5.1 Performance using the most frequent words

The keywords used in this section are the 5 most frequent words per class, and have been extracted in a supervised way. They are listed in Table 5.

business	**entertainment**	**politics**	**sport**	**tech**
company	film	government	win	game
firm	good	election	game	technology
market	award	party	play	phone
rise	music	labour	player	mobile
sale	show	plan	good	service

Table 5: The 5 most frequent keywords by class for the BBC News dataset.

Figure 3.1.5.1 shows the performance of the two models on the BBC News dataset using these keywords. The measure used is the F1 score. We can see that the transformer-based model performs better than Doc2Vec, but is still very unbalanced. The score obtained for the ”tech” class is much lower than that obtained for the ”politics” class.

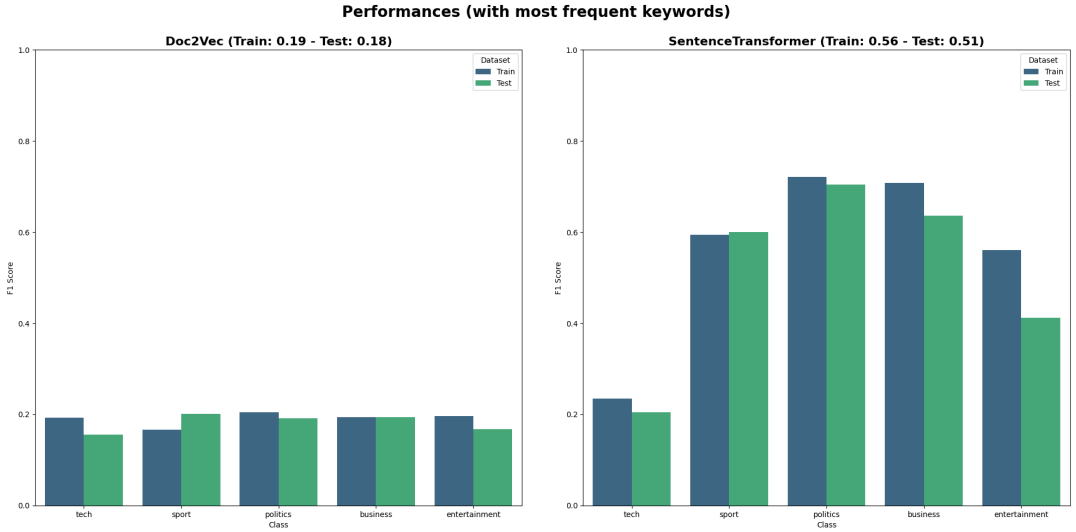


Figure 7: F1 scores obtained after applying Doc2Vec and a transformer-based model to the BBC News dataset using the most frequent words in each class.

3.1.5.2 Performance using the most similar words

The main problem with the previous result is that we retrieve the most frequent words per class in a supervised way. However, our problem is related to unsupervised learning and we need to use another method. One solution is to use the keywords defined in section 2.1 and use the spaCy algorithm as explained in section 3.1.3. We use the 5 keywords most similar to the predefined keywords, which are listed in Table 6.

business	entertainment	politics	sport	tech
business	entertainment	political	sport	technology
corporate	television	democracy	tennis	technological
company	theatre	democratic	rugby	innovation
marketing	gaming	debate	athletic	innovative
industry	multimedia	liberal	football	engineering

Table 6: The 5 most similar keywords by class for the BBC News dataset.

The results are shown in Figure 3.1.5.2. The question remains: Why is the F1 score so low in the ”tech” class, and how can this problem be solved? To solve this problem, we will return to a supervised solution to see what the results are with the ”best” method.

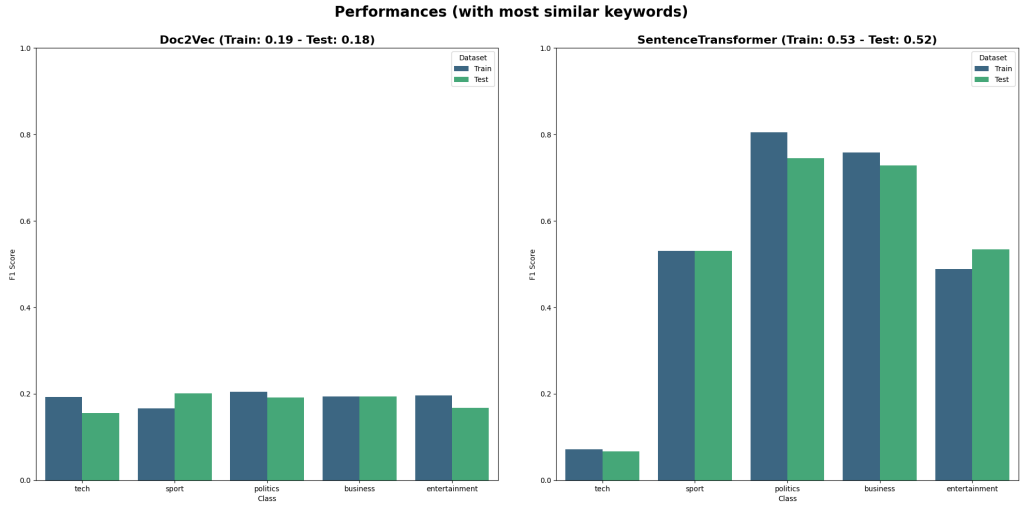


Figure 8: F1 score obtained after applying Doc2Vec and a transformer-based model to the BBC News dataset using the most similar words in each class.

3.1.5.3 Performance using the most important words

To determine which might be the best keywords to use to improve the score, we use a supervised algorithm to extract the most important words. We applied a *TfidfVectorizer* to the documents before running a *Logistic Regression* model. The model predicts the classes with an F1 score of 0.99, meaning that the model will be able to extract the important words accurately. We extract the 100 most important keywords and then use them to predict classes using our model. The choice of 100 is due to the fact that other numbers were tried and nothing was as good as 100. The results can be seen in Figure 3.1.5.3. We can see that the scores are more balanced (the ”tech” class is not as bad as with the other methods), but that the average score remains the same. Doc2Vec scores have not improved. This may mean that our unsupervised method of finding keywords is as good as a supervised method.

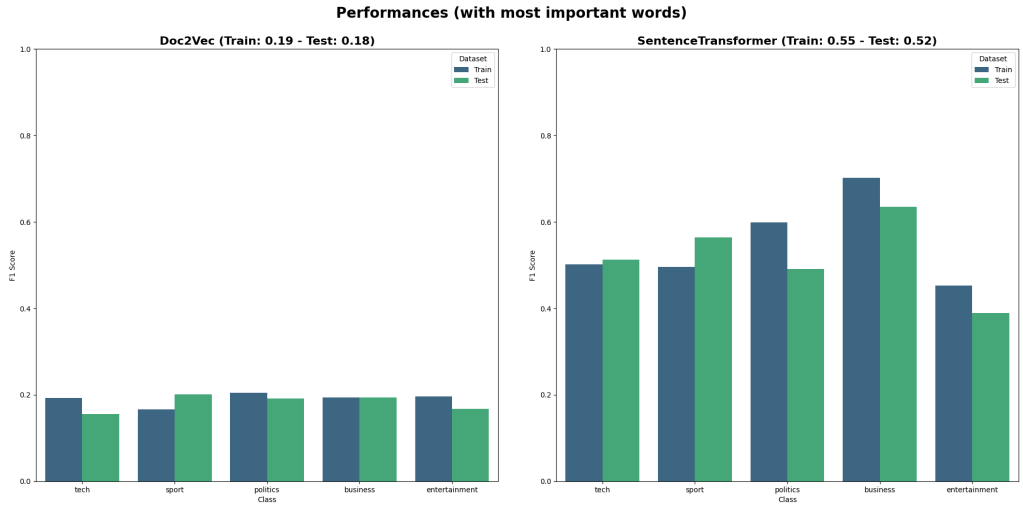


Figure 9: F1 scores obtained after applying Doc2Vec and a transformer-based model to the BBC News dataset, using the 100 most important words in each class.

3.1.6 General performances

As the previous observation suggests, i.e. that our unsupervised method provided as good an average score as a supervised method, we will see how the models perform on each dataset using the most similar keywords method, and the number of most similar keywords will be set to 10. The results can be seen in figure 3.1.6. We have also plotted the F1 score obtained using a random method, i.e. by selecting a class at random. We can see that Doc2Vec is often worse than this random classifier, which may be explained by its poor integration performance. Interestingly, the transformer-based model outperforms the random classifier. We can say that the results are quite good, since we are in an unsupervised framework and the number of classes is quite high. But compared with a supervised method, the results are still pretty poor. The results are just as bad when we use the paper library, with the exception of the BBC News dataset where the F1 score obtained with Doc2Vec is strangely good. What could be different in the paper library that could cause this behavior?

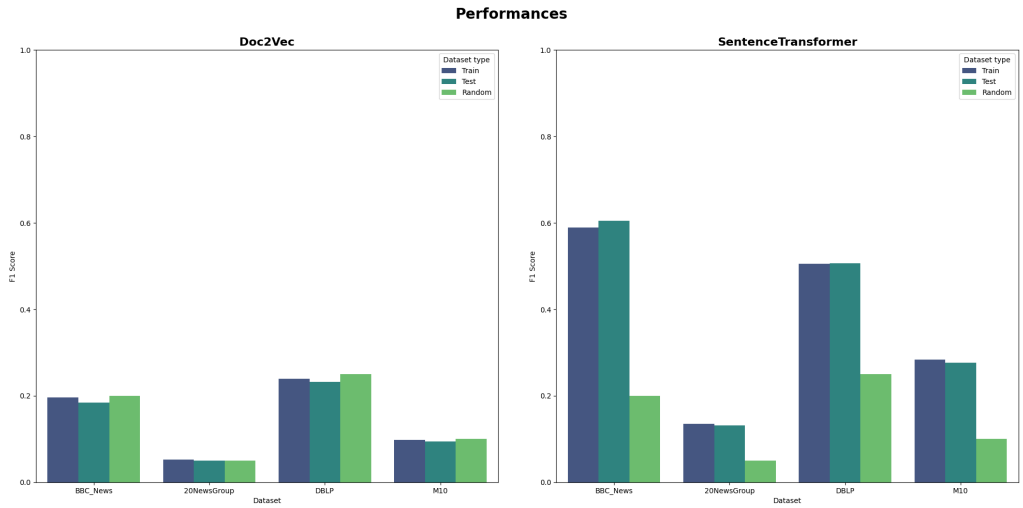


Figure 10: F1 scores obtained after applying Doc2Vec and a transformer-based model to all datasets, using the 10 most similar words in each class.

3.1.7 Assignment confidence

In the previous section, we observed that the results are not very good. But we wanted to relate this to assignment confidence. How confident is the model in the event of a bad prediction? Can we detect the data points that will cause problems? To answer these questions, we began by plotting the confidence score of the two models applied to the BBC News dataset. This can be seen in Figure 3.1.7. We can see that Doc2Vec is not at all confident. It is as if he is making random guesses. Fortunately, the transformer-based model gives better results.

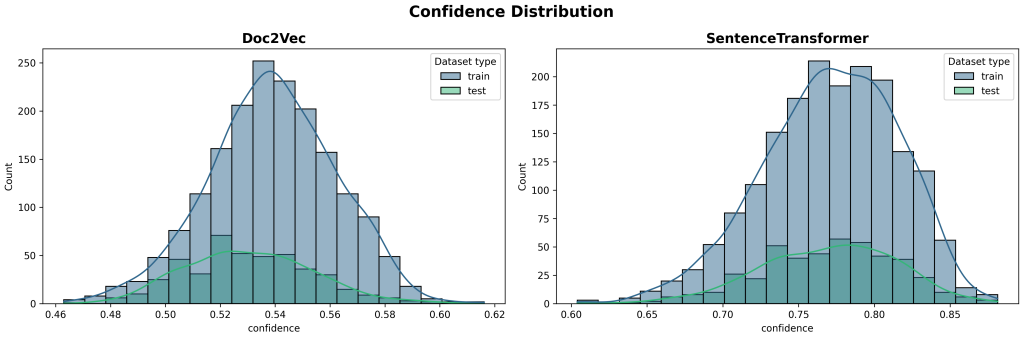


Figure 11: Confidence distributions obtained by applying the models to the BBC News dataset.

In order to differentiate between correct and incorrect predictions on the basis of a threshold applied to the confidence probability scores, we plotted these distributions when the models made both correct and incorrect predictions. This is shown in Figure 3.1.7. Unfortunately, the distributions are almost equal. This means we can't apply a threshold to differentiate between correct and incorrect predictions.

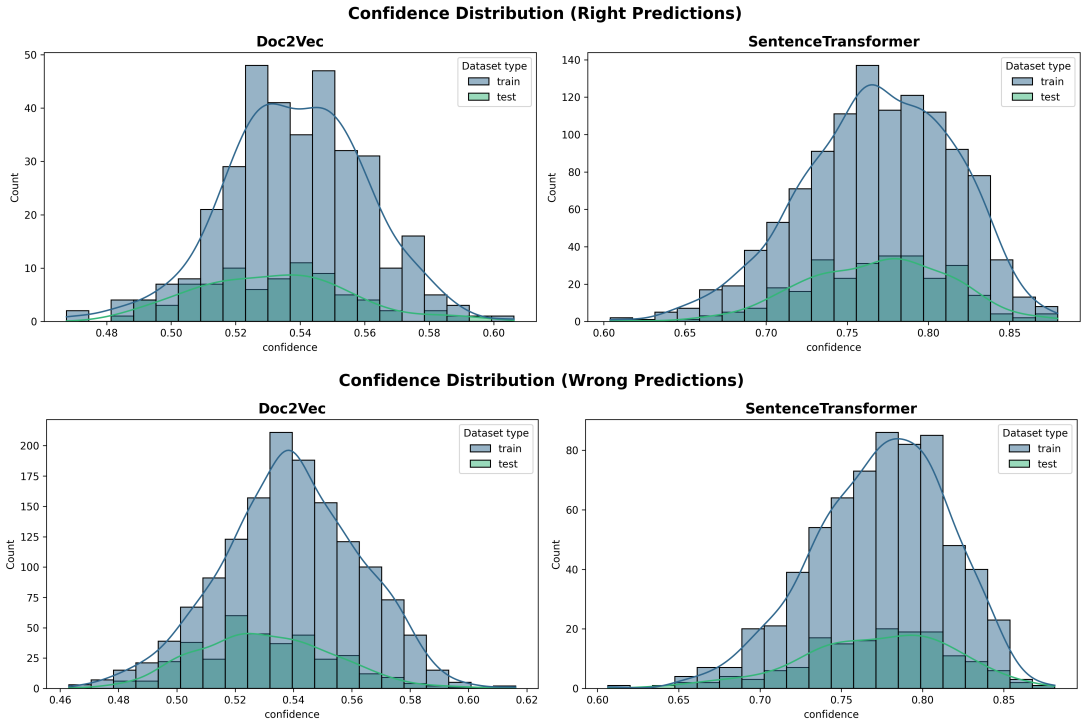


Figure 12: Confidence distributions on correct and incorrect predictions obtained by applying the models to the BBC News dataset.

To ensure that no threshold could be found, we applied the transformer-based model to all four datasets and plotted the distributions of correct and incorrect predictions. The result is shown in Figure 3.1.7. Indeed, we can see that the distributions overlap on each dataset, so there is no way to detect right and wrong predictions based on the confidence score.

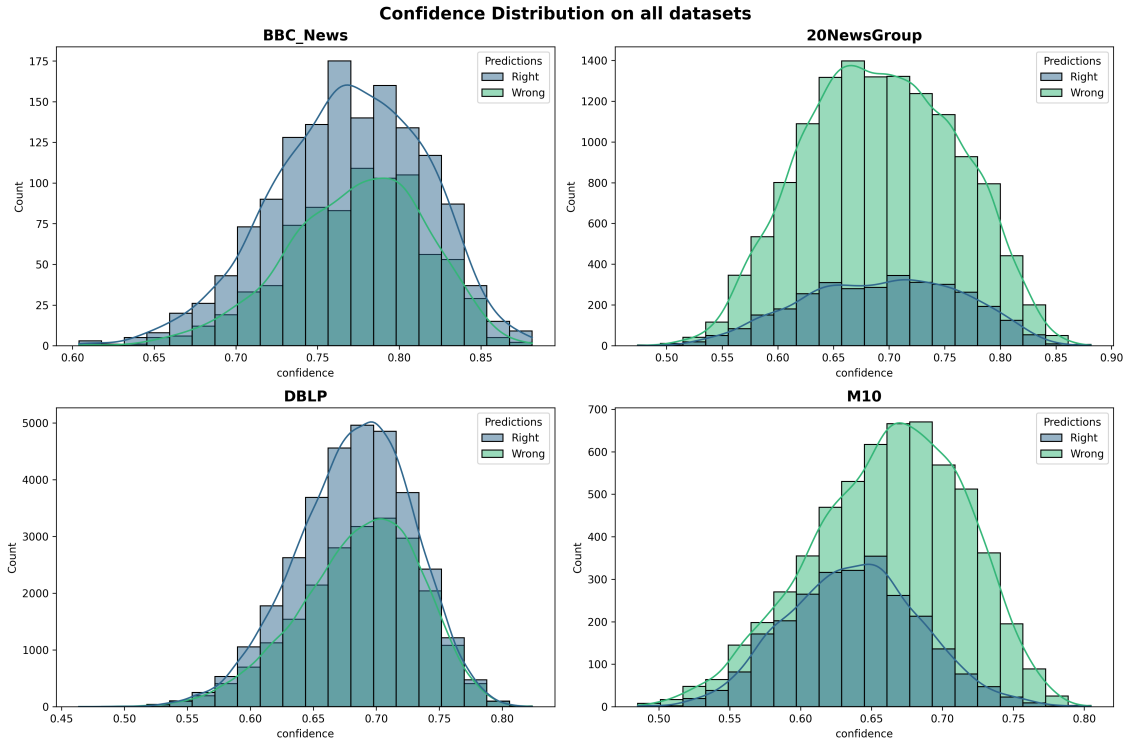


Figure 13: Confidence distributions obtained by applying the transformer-based model to all datasets.

4 Topic Modeling

This section deals with the scenario in which we only receive input documents, and not the classes as we saw earlier. This means that we also have to extract the various topics.

4.1 Evaluation

Before we start gathering information on the main method used in this scenario, we need to know how to evaluate these models. Since we are not doing classification, we cannot use basic measures such as F1 score, accuracy, etc. Evaluation measures must be linked to the topics extracted by the model and/or their correlation with the real labels in the dataset. Without using these true labels, we can define two general metrics, namely *Topic Coherence* and *Topic Diversity*, and we created a specific supervised metric to assess the correlation between topics found by the models and the actual labels in the dataset.

4.1.1 Topic Coherence (TC)

This measure assesses the extent to which a topic is "supported" by a text set (called a reference corpus) [5]. Four types of coherence metrics were compared, namely C_v (Cohesion Coherence), C_{uci} (Exclusive Coherence), C_{npmi} (Normalized Pointwise Mutual Information) and U_{mass} (Unsupervised Mass Coherence). Before briefly explaining each type, let's define a few quantities:

- $P(w_i)$: probability assigned to a word w_i.
- $P(w_i, w_j)$: probability of words w_i and w_j occurring together.
- Pointwise Mutual Information defined as PMI $= \frac{P(w_i,w_j)}{P(w_i)P(w_j)}$.

4.1.1.1 Cohesion Coherence (C_v)

This metric emphasizes the coherence of words within the topic by calculating the average pairwise PMI for all word pairs within the topic. It is defined as:

$$C_v = \frac{2}{n(n-1)} \sum_{i=2}^{n} \sum_{j=1}^{i-1} \text{PMI}(w_i, w_j) \tag{1}$$

4.1.1.2 Exclusive Coherence (C_{uci})

The formula is the same as for C_v, but C_{uci} focuses more on the exclusivity of words within the topic, emphasizing the uniqueness of co-occurrences within the topic relative to the corpus. In practical terms, the difference may lie in the way probabilities are estimated and the specific context in which these measures are applied.

4.1.1.3 Normalized Pointwise Mutual Information (C_{npmi})

C_{npmi} calculates the normalized PMI, which is the PMI divided by the negative log probability of the word pair. This normalization helps to bring the value within a specific range and emphasize the strength of association between words.

$$C_{npmi} = \frac{2}{n(n-1)} \sum_{i=2}^{n} \sum_{j=1}^{i-1} \frac{\text{PMI}(w_i, w_j)}{-\log(P(w_i, w_j))} \tag{2}$$

4.1.1.4 Unsupervised Mass Coherence (U_{mass})

U_{mass} computes the coherence of a topic by comparing the co-occurrences of words within the topic against a background of all the words in the corpus. The addition of the smoothing term ϵ ensures that the logarithm is defined even for very small probabilities.

$$U_{mass} = \frac{2}{n(n-1)} \sum_{i=2}^{n} \sum_{j=1}^{i-1} \log \frac{P(w_i, w_j) + \epsilon}{P(w_j)} \tag{3}$$

4.1.2 Topic Diversity (TD)

This metric is defined as the percentage of unique words for all topics. The measure ranges from $[0, 1]$ where 0 indicates redundant topics and 1 indicates more varied topics. It is calculated by taking the first k words of each subject and calculating how many words are identical in different sets.

4.1.3 Supervised Correlation

Now, to compare the correlation between the extracted topics and the actual labels in the datasets, we can use the first N words for each topic/label and define a metric that counts the number of similar words and provides a value between 0 (totally different topic) and 1 (same topic). This metric will be weighted by the number of each main word to take into account the number of words contained in the documents. Figure 4.1.3 shows a simple example of this metric. This process will be carried out for each real label and for each extracted topic. The result will be a $N \times N$ matrix of similarity scores. To avoid each extracted topic being associated with the same class, we will not perform this task iteratively. We could perform it iteratively to reduce computation time, since computing the assignment of an $N \times N$ matrix is an NP-hard problem. Instead, we decided to use the Hungarian algorithm, which can solve this problem in $O(n^3)$. This algorithm will be able to maximize the global similarity of the assignment.

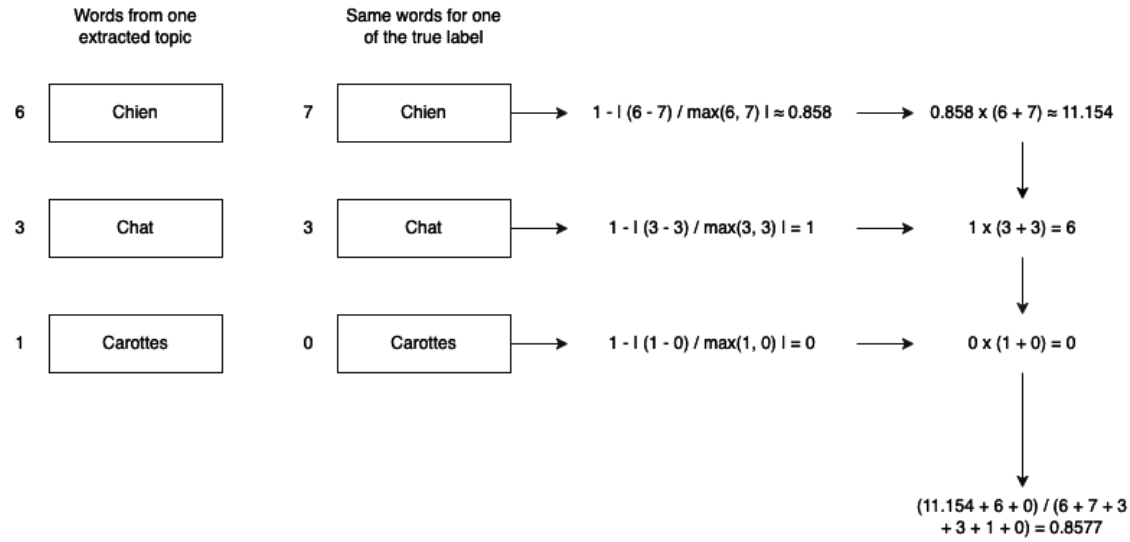


Figure 14: Example of the application of this weighted metric for one given topic and one given true labels.

In the following sections, we explain and discuss the results of the various topic modeling models. It should be noted that no hyperparameters were used that would improve the results. Firstly, because it takes a long time to find the best hyperparameters for a model. Secondly, this is not the aim of this report. We want to compare several methods in general, even if they can be improved for a given problem.

4.2 Latent Dirichlet Allocation (LDA)

4.2.1 Theory

For this model to work, multiple assumptions are done [3, 1]:

- Each document is simply a collection of words or a ”bag of words” (BOW). Thus, word order and the grammatical role of words (subject, object, verbs, etc.) are not taken into account in the model.
- Documents with similar topics use similar word groups.
- Words that appear in at least 80%-90% of documents can be eliminated, without losing any information.
- The number of topics we want is specified in advance. This number is represented by the K parameter.
- Documents are probability distributions over latent topics, meaning that a given document will contain more words on a specific topic. The topics themselves are probability distributions over words. See figure 4.2.1 for a visual explanation of these two assumptions.

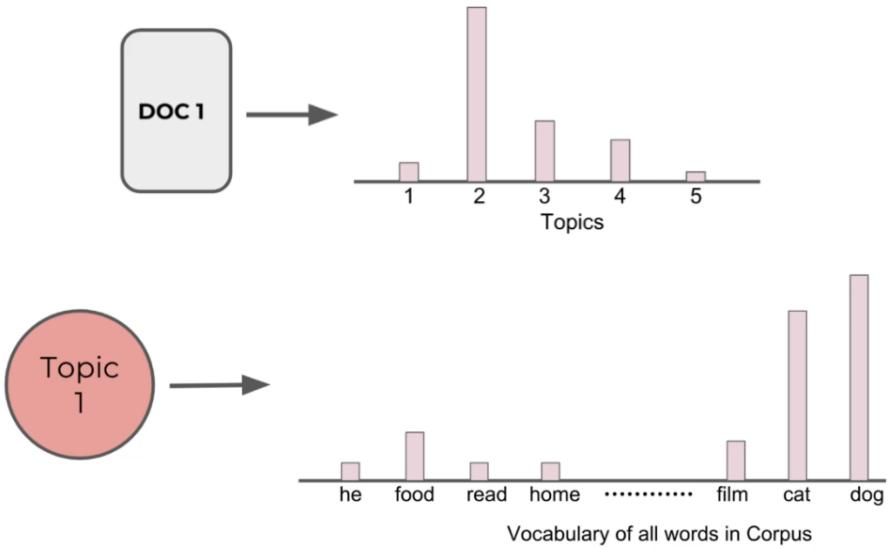


Figure 15: Visual explanation of the assumptions that documents and topics are probability distributions over latent topics and words respectively.

Once these assumptions have been made, the LDA algorithm works as follows:

1. For each document, randomly assign each word in the document to one of the K subjects.
2. For each document d and for each word w in the document, calculate:
   - $\mathbb{P}$(topic t | document d): the proportion of words in document d that are assigned to topic t.
   - $\mathbb{P}$(word w | topic t): the proportion of assignments to topic t over all documents that come from this word w. This tries to determine how many documents are in subject t because of the word w.
3. Update the probability of the word w belonging to the subject t, as

$$\mathbb{P}(\text{word } w \text{ with topic } t) = \mathbb{P}(\text{topic } t \mid \text{document } d) * \mathbb{P}(\text{word } w \mid \text{topic } t) \tag{4}$$

4. Repeat steps 1 to 3 until it converges.

4.2.2 Words in extracted topics

The results in this section are the results of applying the LDA model to the BBC News dataset. The first thing we wanted to show is the list of the most important words by topic and their level of importance. This is shown in Figure 16. As LDA is random, we set a random state in the model for these results. We can see that some topics are clearly linked to the real label. Topic 0 can be associated with ”politics”, topic 1 with ”sport”, topic 2 with ”entertainment”, topic 4 with ”business” and topic 3, although more subtle than the others, can be associated with ”technology”. The question is: How can we get this ”automatic” detection when we are in the full input scenario, i.e. when we have the documents and the topics in which to classify them? This will be answered in Section 4.6.2.

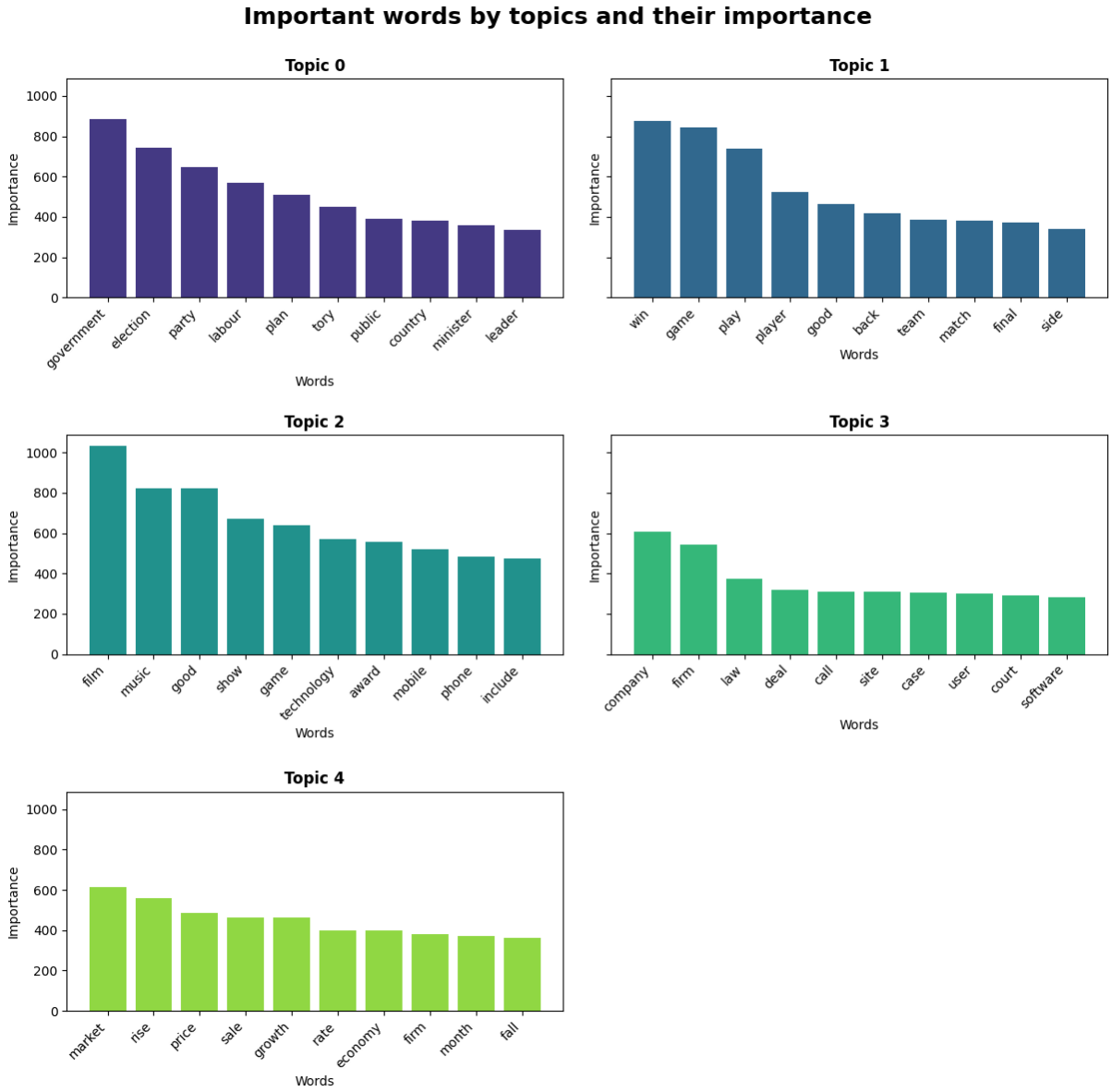


Figure 16: Important words by topic by applying the LDA method to the BBC News dataset.

The second result we can observe is the assignment of a topic directly to the words of a document. This is shown in Figure 17. Note that these are only the first 10 words of each document. This means that even if no words from the assigned topic appear, it does not mean that there is a problem with the model. This may be because all the

other invisible words come from that topic.

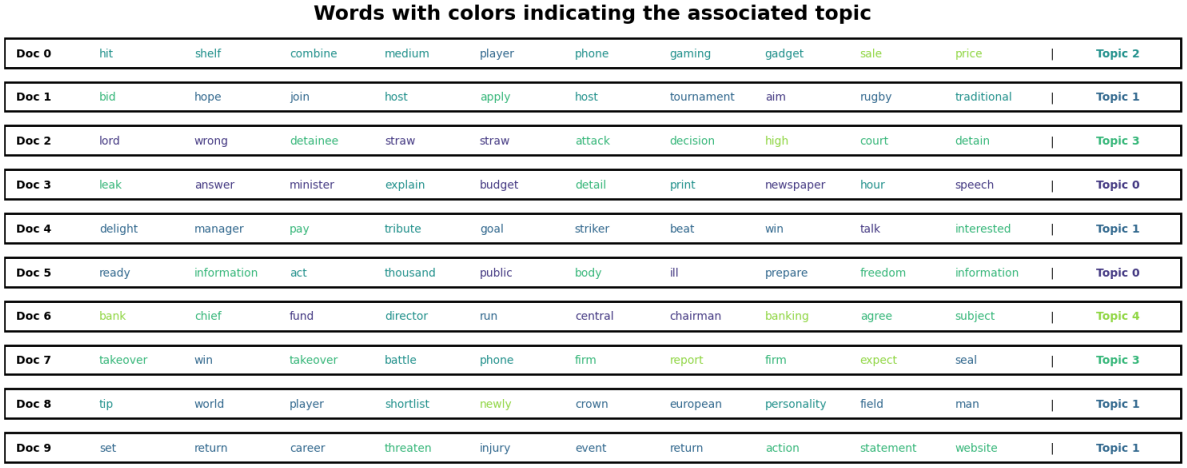


Figure 17: The first 10 words of the first 10 documents with their associated topics.

4.2.3 Randomness

As LDA is random, one way of evaluating the model is to calculate several iterations of the model and average all the scores. We wanted to know if the scores were always close to the mean, or if the variance was high. This is shown in Figure 18. The number of iterations used is fixed at 10. It can be seen that all metrics remain close to the mean, which means that this solution can be used. The fact that some box plots are larger than others (e.g. for u_{mass} and u_{uci}) can simply be explained by the fact that, unlike the other metrics, they are not bounded between 0 and 1.

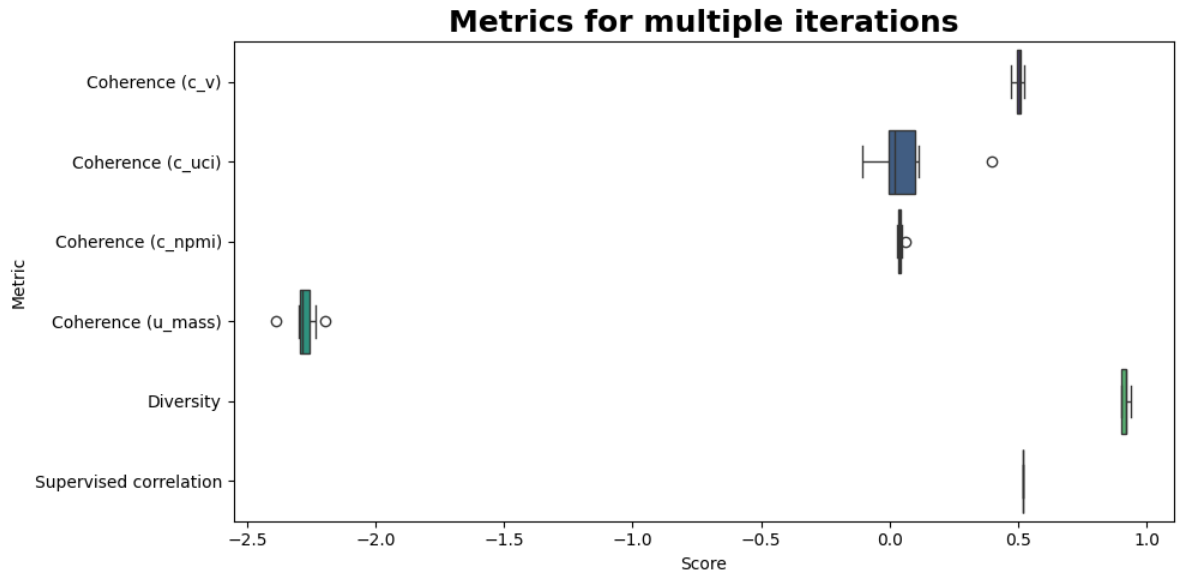


Figure 18: Box plots for all scores obtained by running the LDA model for 10 iterations.

4.3 BERTopic

4.3.1 Theory

BERTopic is another topic modeling model that uses SBERT to extract topics. It works as follows [4, 2]:

1. Convert documents into embeddings using any sentence transformer. The default transformer is *Sentence-BERT*.
2. Reduce the dimensionality of the embeddings using the *Uniform Manifold Approximation and Projection (UMAP)* algorithm. The main problem is that UMAP is random, which makes BERTopic random.
3. Group the reduced embeddings into clusters using an algorithm called *HDBSCAN (Hierarchical DBSCAN)*.
4. Extract topics from each cluster using their *c-TF-IDF scores*.

    - *Term Frequency (TF)*: how frequently a term/word appears in a document, calculated as:

$$TF = \frac{\text{Number of times term appears in a document}}{\text{Total number of terms in the document}} \tag{5}$$

    - *(Class-Based Term Frequency (CTF)*: for a term within a specific class or category is the number of times that term appears in documents belonging to that class. It measures how frequent a term is within documents of a particular class.)
    - *Inverse Document Frequency (IDF)*: Inverse document frequency measures how unique or rare a term is across the entire corpus. The purpose of IDF is to give more weight to terms that are relatively rare in the corpus, as they are likely to carry more meaningful information. It is calculated as:

$$IDF = \log \frac{\text{Total number of documents in the corpus}}{\text{Number of documents containing the term}} \tag{6}$$

    - *TF-IDF Score*: It quantifies how important a term is within a specific document while considering its rarity across the entire corpus. It is calculated as:

$$\text{TF-IDF} = TF * IDF \tag{7}$$

4.3.2 Words in extracted topics

As in the LDA section, the results come from applying the model to the BBC News dataset, also by setting a random state in the model. First of all, we wanted to show the most important words per topic and their level of importance. This is shown in figure 19. We can see that some topics are also linked to the actual label. Topic -1 contains all documents that cannot be classified in any other topic. We can clearly make the following assignments: topic 0 with the class ”entertainment”, topic 1 with ”politics”, topic 2 with ”business” and topic 3 with ”sport”. Topic 4, however, cannot be assigned to ”tech”.

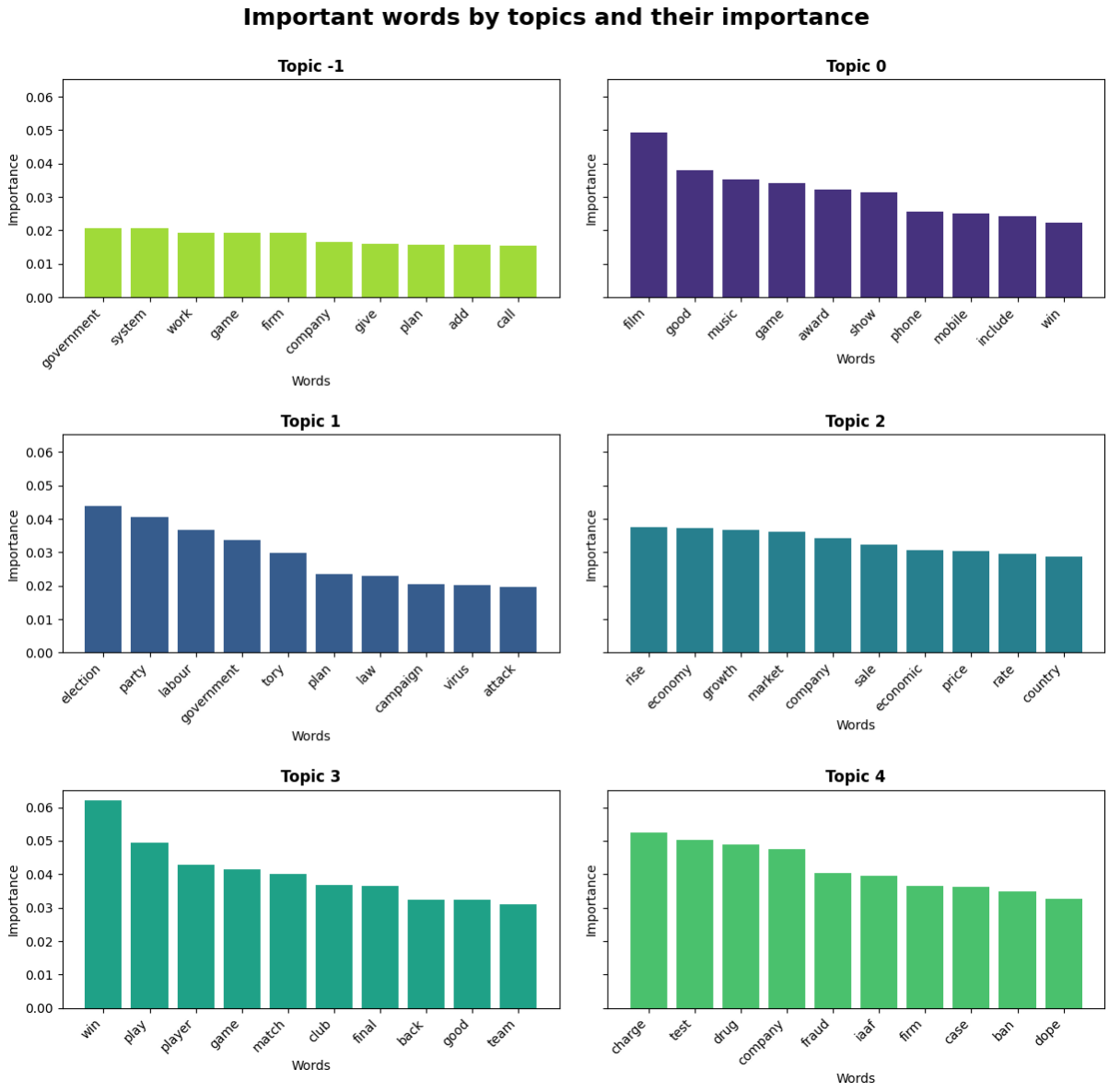


Figure 19: Important words by topic by applying BERTopic to the BBC News dataset.

4.3.3 Similarity matrix

Another thing we wanted to see is related to the diversity score. We wanted to see how similar the subjects were to each other. This is shown in Figure 20. We can see that the topics are somewhat similar, which can be explained by the fact that there are few topics. But in general, they are different.

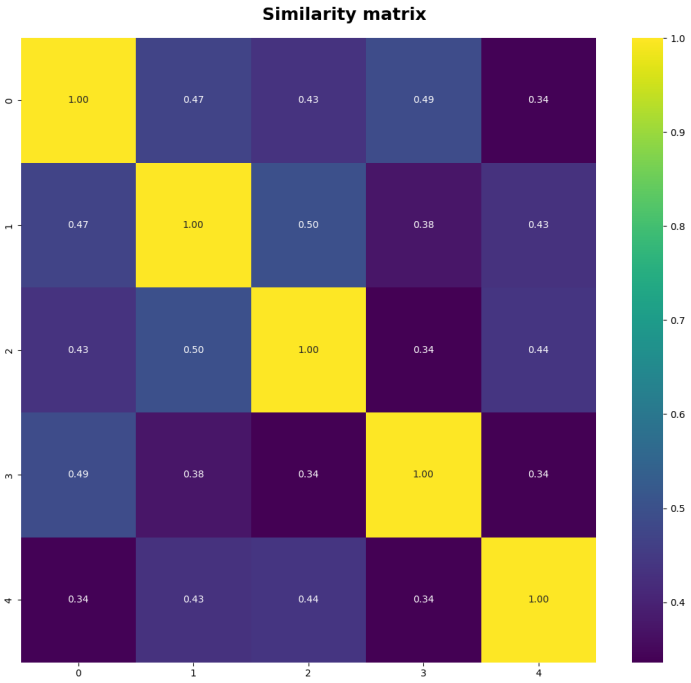


Figure 20: Similarity matrix between topics obtained by applying BERTopic to the BBC News dataset.

4.3.3.1 Randomness

As with LDA, we wanted to see if the method of taking the mean of the scores from several iterations could handle the randomness of the model. This is shown in Figure 21. The number of iterations is also fixed at 10. It can be seen that, similarly to LDA, this method can be used to counteract the randomness of the model. Indeed, all iterations produce values closer to the mean, i.e. the variance is not high. This method will therefore be used for the remainder of the report.

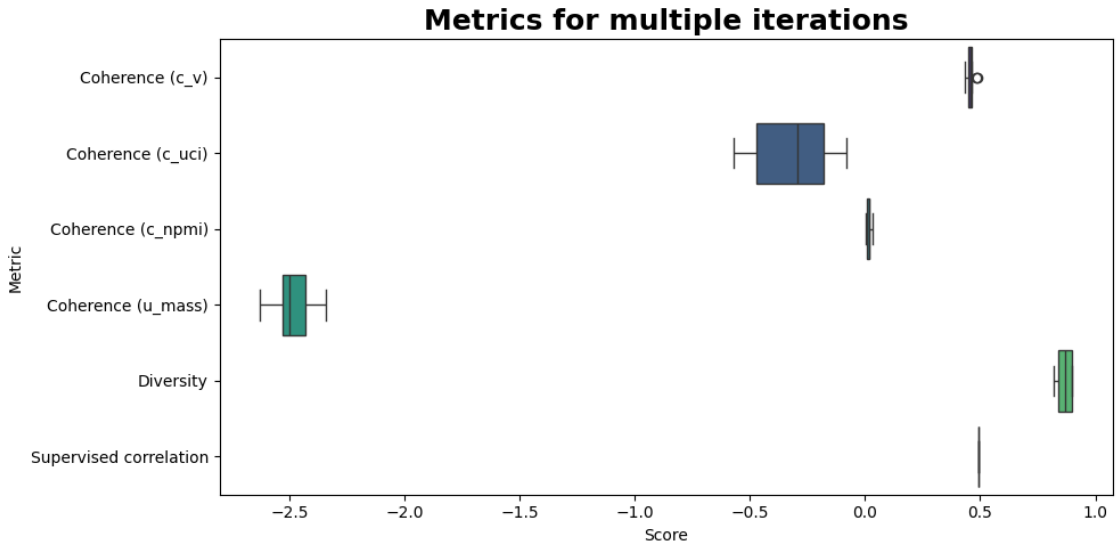


Figure 21: Box plots for all scores obtained by running the BERTopic model for 10 iterations.

4.4 Guided Topic Modeling

Guided Topic Modeling is a method of discovering specific topics or themes within a dataset of documents. Unlike traditional techniques, it allows users to provide clues or hints to guide the model towards particular areas of interest. Users can enter relevant words or phrases, which act as cues for the model to prioritize certain topics during analysis. By incorporating these hints, the resulting topics are more focused and aligned with the user's expectations, making them easier to interpret.

The aim of this section is to compare the models with and without the guided version and see how it can be useful. For this section, we have set a random state in the different models so that we can visualize the result. We will assume that, in general, the result will be quite similar for other random states. The keywords used are those defined in section 2.1.

4.4.1 Guided LDA

What we wanted to see in this section was to compare the different topics obtained with the LDA models with and without the guided version. To do this, we calculate the most important words for both models on the BBC News dataset and plot them to see if there is any visual similarity. In addition, we use the supervised correlation metric to see if it improves. As expected, the guided version is better than the basic version, and we can clearly see the assignment of the topic to the 5 real classes. In addition, we can see that the supervised correlation metric improves, from 0.52 to 0.59.

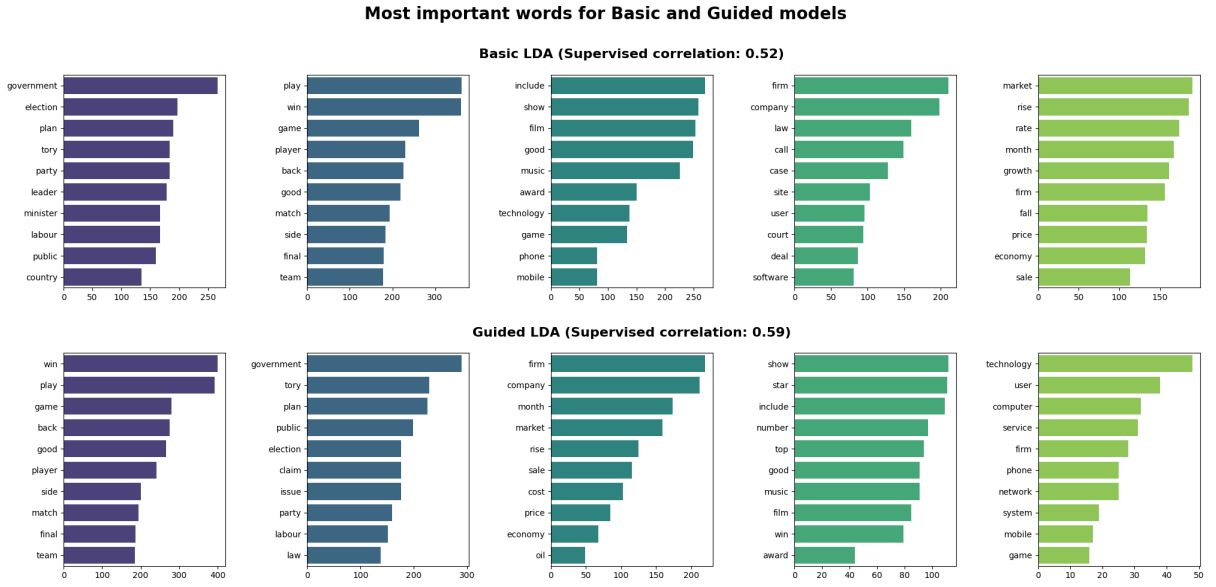


Figure 22: The most important words found by the basic model compared with those found with the guided version.

4.4.2 Guided BERTopic

As with the guided LDA, we wanted to see how close the clusters found by the guided version of the BERTopic model were to the true clusters, i.e. those manually labeled in the dataset. We applied the same methodology as before. The result can be seen in Figure 23. We only take into account clusters other than -1, i.e. those containing possible outliers. This result is interesting because, as with LDA, we can see that the clusters seem more similar to the true clusters found. In addition, the supervised correlation metric improves considerably. One hypothesis that follows from these observations is that these guided topic modeling method could be used for clustering as in the first section. This point will be detailed in Section 4.6.2.

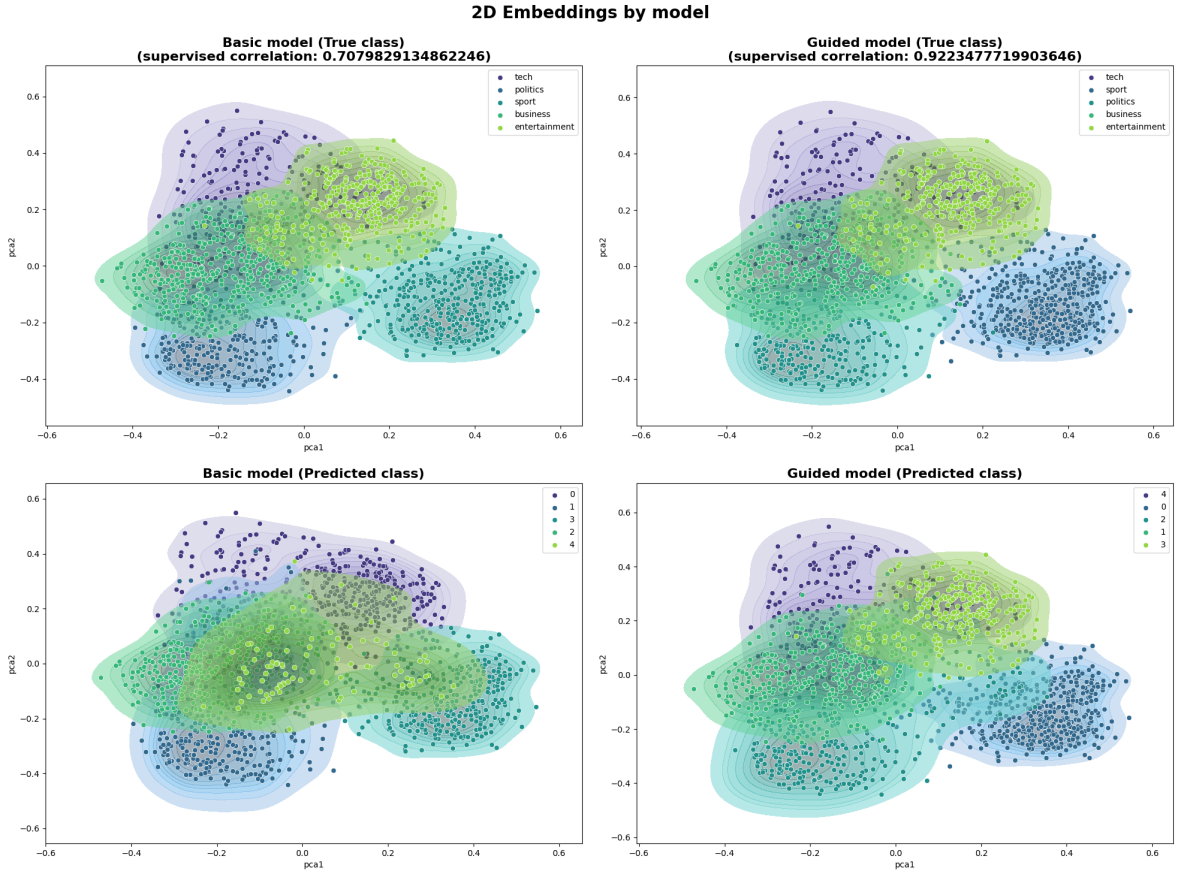


Figure 23: Clusters found by the basic model versus those found with the guided version.

4.5 vONTSS

This section has been added to provide a brief overview of a recent model created in July 2023. This model is a combination of the two scenarios. Indeed, vONTSS is a semi-supervised topic modeling method that takes a few keywords as input and, instead of classifying documents into topics defined by these keywords as in the first scenario, it generates topics based on these keywords as in the second scenario. As this method generates topics and therefore meets the definition of topic modeling, it is added to this section rather than the first.

4.5.1 Theory

The architecture of this model is shown in Figure 24. In this section, we will explain how it works, but not why. We leave that for future work. First, the encoder network ϕ transforms the document representation X_d into a latent vector generated by the von Mises-Fisher distribution and generates a sample η_d. A temperature function τ is applied to this sample with a softmax function to obtain a probabilistic distribution of topics z_d. Finally, the decoder uses a modified topic-word matrix E to reconstruct the BoW representation of the document Xd.

In this architecture, L_{recon} represents the reconstruction loss, L_{KL} represents the KL divergence and L_{OT} represents the optimal transport loss. Explanations of the different losses and how this architecture is trained given a set of keywords S associated with topics T can be found in the article. Compared with other architectures, they have introduced a temperature function to modify the radius of the vMF distribution.

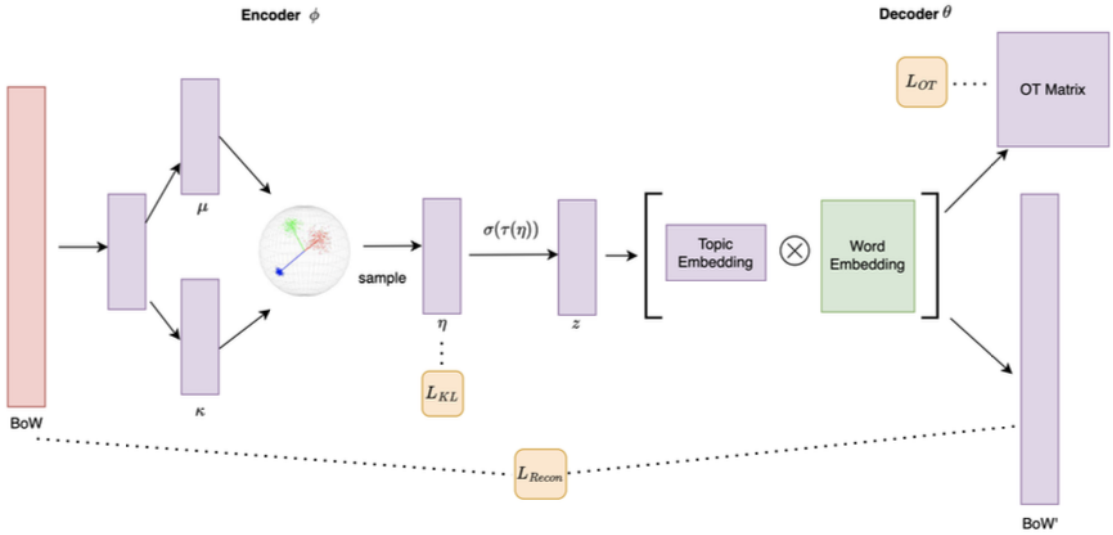


Figure 24: Architecture of the vONTSS model.

4.5.2 Words in extracted topics

As with the other sections on topic modeling, we simply wanted to see the most important words in each topic extracted by vONTSS. This is shown in Figure 25. One of the major problems with this model is that it sometimes fails to assign any documents to a given topic. This problem is due to the fact that the topics extracted by vONTSS are sometimes very different from the real topics, as shown in the graph below. As a result, some documents cannot be classified in the extracted topics. To solve this problem, a naive method is to run the model several times until all topics are assigned at least one document. Future work should try to use a more practical method, or to understand why this problem occurs with vONTSS. We can see that, compared with other topic modeling models, topics are really different from ”real” topics. Topics 0 and 4 may be associated with ”sport” and ”technology”, but the others are totally different from ”business”, ”politics” and ”entertainment”. In the next section, we will see whether this has an impact on the model’s performance, or whether it is simply due to the random state chosen.

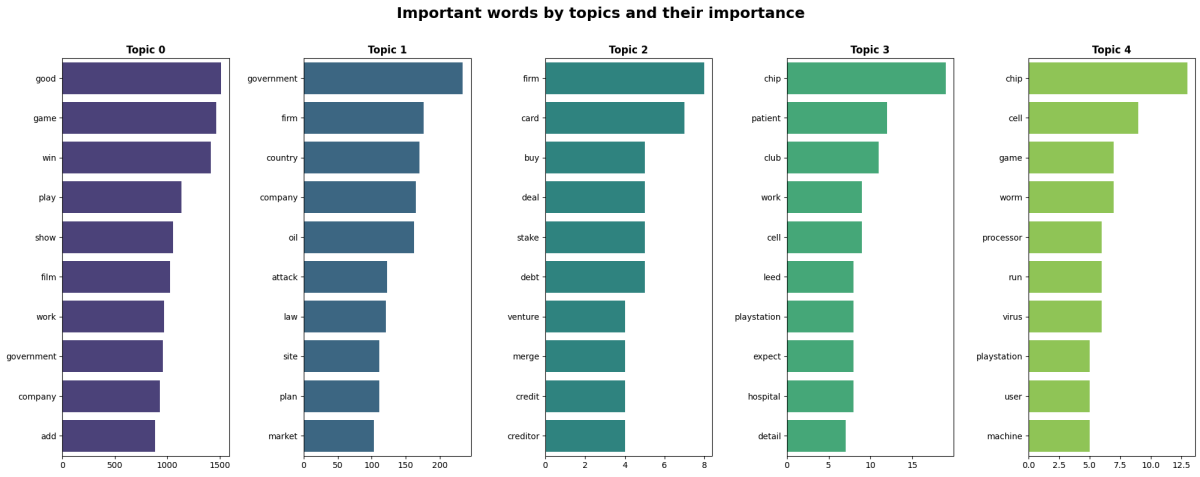


Figure 25: Important words by topic by applying vONTSS to the BBC News dataset.

As far as randomness is concerned, we would like to see whether the methodology of taking the mean is always

close to the mean, as we did in the LDA and BERTopic sections. We could have assumed that this is the case and used this methodology for the rest of this report, but the randomness issue explained above is important for checking whether this method can be used or not. The randomness of topic modeling models remains an important issue and should be one of the main questions to be addressed in future work. The result can be seen in Figure 26. As we can see, the metric seems to be as variant as with the other models, which means that this method can also be used to manage the randomness of the model.

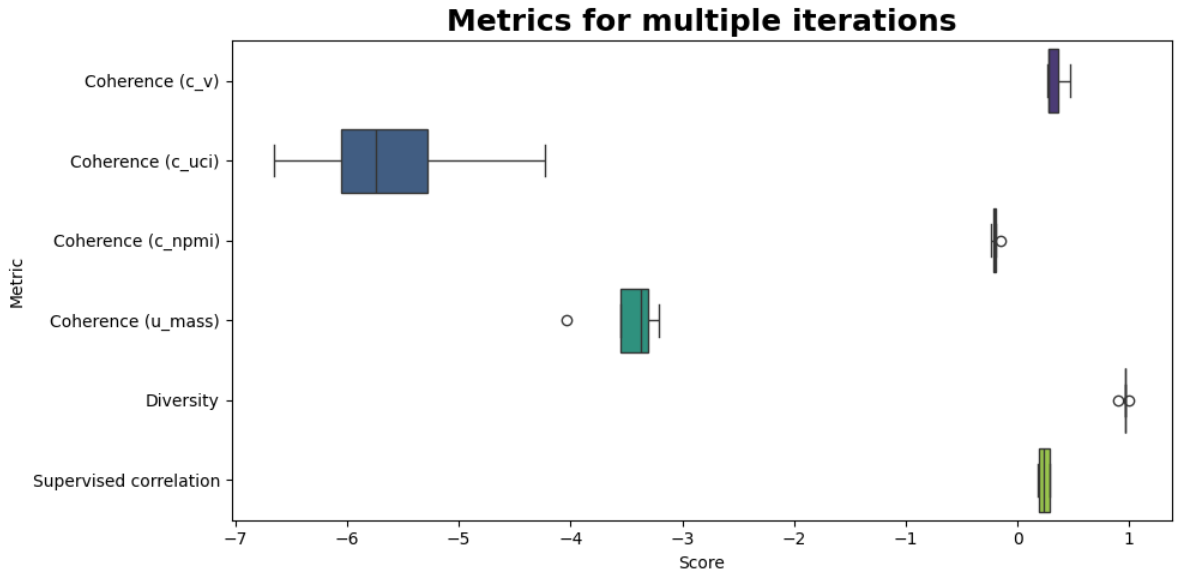


Figure 26: Box plots for all scores obtained by running the BERTopic model for 10 iterations.

This model is still in an experimental state, and is really difficult to use due to its highly random nature and lack of proper documentation. Its randomness means that we have to perform many iterations to find a model that assigns each topic to at least one document, and for each of these iterations we also have to run it for several iterations to average the results. The computation time is therefore enormous. Because of these problems, we decided not to use this model in the comparison. Future work should attempt to readapt this model when it is in a more advanced state. Nevertheless, as this section has shown, this model looks promising due to the use of a new architecture, and should be explored in more detail.

4.6 Comparison

4.6.1 Performances

Comparison using the same number of classes than in the true labels can be seen in Table 7.

Dataset	Models	Coherence (C_v) ↗	Coherence (c_uci) ↗	Coherence (c_npmi) ↗	Coherence (u_mass) ↘	Diversity ↗	Supervised correlation ↗
BBC News	LDA	**0.507245**	-0.224381	**0.026653**	**-2.237404**	**0.920000**	**0.824987**
	BERTopic	0.480479	**-0.194804**	0.021948	-2.220241	0.856667	0.701449
	GuidedLDA	0.480479	**-0.194804**	0.021948	-2.220241	0.856667	0.701449
	GuidedBERTopic	0.480479	-0.194804	0.021948	-2.220241	0.856667	0.701449
20NewsGroup	LDA	**0.600076**	**0.660461**	**0.091718**	-1.767074	0.743000	**0.611222**
	BERTopic	0.510362	0.175887	0.067621	**-2.255179**	**0.827619**	0.382447
	GuidedLDA	0.480479	**-0.194804**	0.021948	-2.220241	0.856667	0.701449
	GuidedBERTopic	0.480479	**-0.194804**	0.021948	-2.220241	0.856667	0.701449
DBLP	LDA	**0.566795**	**0.094171**	**0.038986**	-1.931211	**0.830000**	**0.612566**
	BERTopic	0.555418	-0.304531	0.022946	**-2.246640**	0.760000	0.299963
	GuidedLDA	0.480479	**-0.194804**	0.021948	-2.220241	0.856667	0.701449
	GuidedBERTopic	0.480479	**-0.194804**	0.021948	-2.220241	0.856667	0.701449
M10	LDA	0.457851	**-0.061817**	**0.016673**	-2.270753	0.838000	0.520814
	BERTopic	**0.515526**	-2.204118	-0.050275	**-2.546092**	**0.914545**	**0.626878**
	GuidedLDA	0.480479	**-0.194804**	0.021948	-2.220241	0.856667	0.701449
	GuidedBERTopic	0.480479	**-0.194804**	0.021948	-2.220241	0.856667	0.701449

Table 7: Advantages and disadvantages of the Doc2Vec architecture compared to transformer-based models using the same number of classes than in the true labels

Comparison using a different number of classes than in the true labels can be seen in Table 8. The models therefore extracted themselves the ”right” number. Here we don't compared the supervised correlation metric since it make no sence because this is two different number of classes. Also the Guided version have not be shown for the same reason. The vONTSS model has not been shown either, since there is no way to add a random number of topics to be extracted.

Dataset	Models	Coherence (C_v) ↗	Coherence (c_uci) ↗	Coherence (c_npmi) ↗	Coherence (u_mass) ↘	Diversity ↗
BBC News	LDA	**0.507245**	-0.224381	**0.026653**	**-2.237404**	**0.920000**
	BERTopic	0.480479	**-0.194804**	0.021948	-2.220241	0.856667
20NewsGroup	LDA	**0.600076**	**0.660461**	**0.091718**	-1.767074	0.743000
	BERTopic	0.510362	0.175887	0.067621	**-2.255179**	**0.827619**
DBLP	LDA	**0.566795**	**0.094171**	**0.038986**	-1.931211	**0.830000**
	BERTopic	0.555418	-0.304531	0.022946	**-2.246640**	0.760000
M10	LDA	0.457851	**-0.061817**	**0.016673**	-2.270753	0.838000
	BERTopic	**0.515526**	-2.204118	-0.050275	**-2.546092**	**0.914545**

Table 8: Advantages and disadvantages of the Doc2Vec architecture compared to transformer-based models using a different number of classes than in the true labels.

4.6.2 Topic modeling with defined classes

As we saw in the previous comparison, some models perform well when it comes to finding topics similar to the ”real” topics, i.e. those that have been manually labeled in the dataset. Hence the idea of using topic modeling to perform topic clustering as in the first section. To assign each extracted topic to a true topic, we will calculate

the similarity between the keywords defining each topic (extracted and true) and assign the most similar together exactly as we did for the supervised correlation metric, with the Hungarian algorithm, which can solve the $O(n^3)$ assignment problem. This algorithm will be able to maximize the overall similarity of the assignment.

Figure 27 and Figure 28 shows a topic assignment using LDA and BERTopic on the BBC News dataset. We use principal component analysis to plot the embeddings in two dimensions. For BERTopic, we have considered topic -1 as a topic and not as outliers, since we have yet to make predictions for these documents. One thing that could be done is to take these potential outliers into account when calculating F1 scores, but we will leave that for future work. We can see that the assignment algorithm is capable of finding similar clusters, which is very promising. It can also be seen that BERTopic extracts topics as similar as with LDA, but the -1 class is obviously less precise. Nevertheless, this cluster still seems to cover most of the true class.

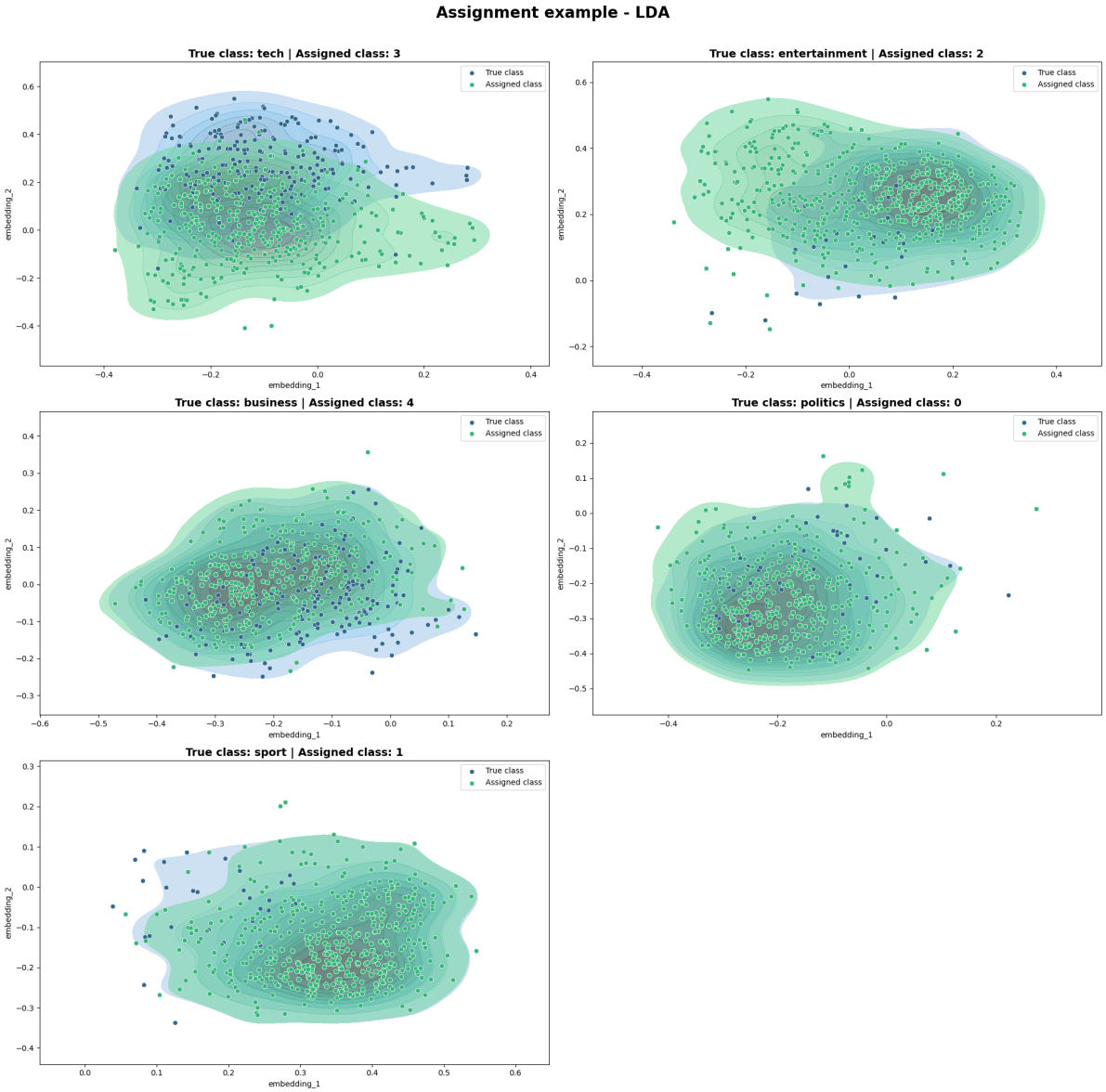


Figure 27: Example of assignment of topics using LDA on the BBC News dataset using the Hungarian algorithm.

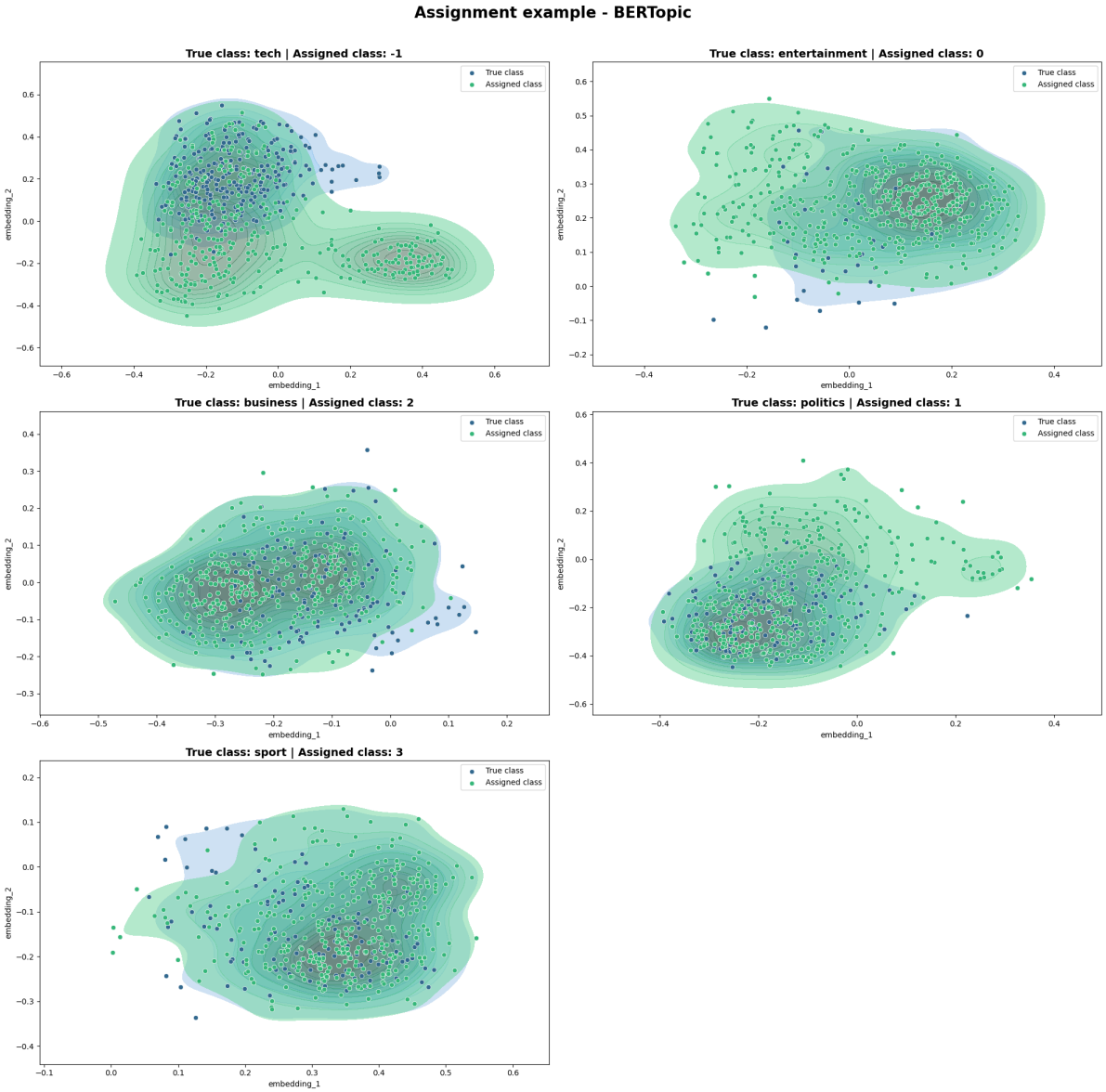


Figure 28: Example of assignment of topics using BERTopic on the BBC News dataset using the Hungarian algorithm.

Using this assignment strategy, we compare the F1 score obtained using multiple models on the datasets and we put that in comparison with the randomized predictor and Lbl2Vec. As a reminder, the randomized predictor just assign a class at random. Therefore the F1 score for this predictor is set as 1 divided by the number of classes. As we can see on Figure **??**, ... TODO

5 Future work

About Lbl2Vec:

- Is LOF really useful for model performance?

About the scenario in which we have documents and classes in which we want to classify the documents:

- Only *all-minilm-l6-v2* was used for Lbl2Vec, could we use other LLMs?
- Are there any models other than Lbl2Vec that use LLMs in a different way to classify documents?
- Is there a way to fine-tune LLMs to fit to the problem instead of using the pre-trained version?

About BERTopic:

- Is there other transformer more relevant for this problem ?
- Can other dimensionality reduction methods be used ?
- Can other clustering methods be used ?
- How to handle the extracted topic about irrelevant words (-1) ?

About vONTSS:

- How to solve the big issue that some document are never assigned to any topics?
- The decoder seems to generate different topics than the true ones, even when given predefined keywords. How to guide the decoder into generating more similar results?

6 Conclusion

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