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Using Topic Modeling in Innovation Studies: The Case of a Small Innovation System under Conditions of Pandemic Related Change

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Abstract

It is a challenge to empirically investigate rapidly developing situations. An economic crisis is such a situation in which firms exit, enter, and create new business models. The current pandemic has caused a turbulent situation with hardship, but at the same time with creative potential of innovative change. It calls for empirical analyses, but firm level data based on surveys is hard to collect given the high speed of developments. An alternative data source are news articles reporting on innovation issues and assessed by text mining techniques. This is exemplified in this chapter. It shows how topic modeling can be used to scrutinize the shift of innovation topics since the beginning of the COVID-19 crisis. The results apply to a small innovation system in Germany and confirm that innovation priorities change during a crisis and that many different actors are involved.

Keywords

topic modeling, innovation, structural change, crisis

JEL Classifications

O30; R11; R58

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1. Introduction

The world nowadays is full of events, which require rapid responses and dynamic reactions to occurring challenges. The year 2020 is marked by a unique event – COVID-19 pandemic. This crisis poses social, health and economic challenges to people worldwide (World Bank 2020; OECD 2020). Particularly, in Germany a decline in the gross domestic product of 5.1% is expected in 2020 (Sachverständigenrat 2020), which nearly equals the economic downturn of the global financial and economic crisis of the year 2009. Small firms in certain service sectors and self-employed are especially threated by the recession, and many of them lost their business foundation (Kritikos et al. 2020). Despite these negative effects, such crises can also lead to the exploitation of innovation potentials to meet the impending challenges. This has been shown in quite a number of empirical analyses for the economic crisis of the year 2008/2009 (e.g. Archibugi et al. 2013a and 2013b; Brautzsch et al. 2015; Günther et al. 2019).

Schumpeter (1934) describes economic crises as conditions in which companies are in greater competition with each other and therefore try to increase their efficiency and innovation activity in order to survive in the market This leads to the increase of market dynamics, which means that on the one hand, new players enter the market, and on the other hand, players who are not in line with the new situation exit the market (Archibugi et al. 2013a; Malerba, Orsenigo 1995; Francois, Lloyd-Ellis 2003).

Due to these dynamic changes, which in times of crisis are present to greater extent, regions can develop differently than under normal conditions. As the result, already within a short time period a strong structural change can be observed. The structural change in a region can not only develop through changing actors and the emergence of innovations but also through long-term changes in the orientation of the regional economy (Cantner et al. 2019; Gifford, McKelvey 2019; Fritsch et al. 2019). Many researchers throughout the world are trying to assess the consequences of COVID-19 pandemic with regards to different aspects, including economic, psychological, social, healthcare aspects etc. Furthermore, for the research in the field of innovation economics the COVID-19 pandemics poses important research questions: How companies deal with a pandemic? What innovations do they introduce in order to continue manufacturing products or offer services? Which companies become more successful with respect to innovative performance and which had to close? How do regions adapt their innovation strategies in face of these challenges?

The typical ways of innovative performance measurement, such as official statistics, company surveys or patent data, cannot be applied when dealing with highly dynamic situations because of the lag within the data and time needed for its collection. In this case press releases can be used to observe changes in innovative activities, as they often contain news from science and technology, including for example corporate successes and failures, technological and disruptive innovations, mergers and acquisitions.

As news articles normally contain considerable amounts of texts, it is rather impossible to analyze them manually. In this case text mining and topic modeling methods present a useful approach for systematization and categorization of this textual data and thus presenting trends in innovative activities based on the highly updated data.

In this chapter we are applying the topic modeling approach in order to follow the news in the articles related to Bremen. This study uses the information source "Factiva", which is based on press releases before and during the first phase of COVID-19 pandemic. In this way, information on the structural and thematic changes caused by the crisis can be collected systematically. In particular, the pandemic-related change in relevant topics can be highlighted.

In Bremen, as in many other regions, the COVID-19 pandemic led to a collapse of economic performance. Furthermore, the massive slump in exports is placing a heavy burden on the State of Bremen, known for its maritime profile (Kruse, Wedemeier 2020). Thus, it serves as a good example of dynamic change, which needs to be addressed through an innovation strategy as a response to the pandemic.

In this chapter we are using a topic modeling approach on the example of Bremen to answer two questions:

(1) What innovation-related topics appeared in the news agenda during the first phase of the COVID-19 pandemic and how did these topics evolve over time?

(2) What actors were prominently present in the reporting about innovation activities during the first months of the pandemic?

To answer the first question, news texts, collected in “Factiva” are pre-processed and split into tokens, which allows later a definition of the limited number of topics occurring in the texts. Each of the documents thus is related to each of the topic with specific probability. Thus, this step allows us to define what was reported about the innovation related activities in Bremen before and during the pandemic. Importantly, it also allows us to follow how the relative importance of topics in media coverage changed over time.

To answer the second question, we manually identify actors from research, industry, and state institutions, related to each of the news texts. The assignment of the actor to a specific topic was done by looking at the probabilities of a document to be assigned to each of the topics[1] and choosing the highest of these probabilities. Then the actors, related to the specific topics were presented in the word clouds with the size of the name depending on the number of occurrences of an actor in the specific topic. Thus, main players in each of the classified topics were identified.

2. The regional innovation system of Bremen

In this chapter we provide the specific empirical example of the topic modeling application. We exemplarily use the structural topic modeling algorithms to follow the changes of the focus of innovative activities in the federal state of Bremen under conditions of the initial phase of the COVID-19 crisis.

Bremen is the smallest federal state in Germany with a population of around 680 thousand people[2], located close to the North Sea and consisting of two cities: Bremen and Bremerhaven. It is a small innovation system with all relevant science, technology, and innovation policy institutions (Koschatzky, Kroll 2007). Despite its small size, the federal state of Bremen, also known as Free Hanseatic City of Bremen, has a well-diversified but so far traditionally oriented industry structure. The industrial sector is characterized by several big players in aerospace, automotive, food processing and steel industry. However, the headquarters of these players with strategic R&D functions are mostly located elsewhere in Germany or abroad so that the industrial R&D and innovation intensity in Bremen is rather moderate as comparted to other federal states in Germany (Koch, Stahlecker 2006).

For centuries the Port of Bremen was in the center of the state´s economic activities, connecting the federal state to international worldwide trade. Its central position, however, was lately challenged as the shipbuilding and maritime industry had been shifted towards Southeast Asia (Kruse, Wedemeier 2020). However, the federal state of Bremen is still characterized by a service sector strongly related to logistics and transport businesses.

Apart from this, the science organizations and related research facilities of the smallest federal state are diverse. The federal state of Bremen has five higher education institutions (University of Bremen, Jacobs University, City University of Applied Sciences, University of the Arts, and Bremerhaven University of Applied Sciences) as well as the large number of non-university research institutions in marine and polar as well as in

[1] Reflecting the proportion of words in the document, which are assigned to the topic (Silge, Robinson 2017).
[2] As of 31.12.2019, according to the Federal Statistical Office of Germany: https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Bevoelkerung/Bevoelkerungsstand/Tabellen/bevoelkerung-nichtdeutsch-laender.html (accessed on November 24, 2020)

natural and technical sciences (e.g. The Alfred Wegener Institute, Helmholtz Centre for Polar and Marine Research, Fraunhofer Institute for Manufacturing Technology and Advanced Materials IFAM, Max Planck Institute for Marine Microbiology or Robotics Innovation Center). This combination of basic and applied research is an important prerequisite for the vivid research environment in the federal state. In this case strong networking between science, industry and state administration is an important factor, which may turn inventions and creative ideas into innovations. This is of a special importance in times of crisis, where the speed of communication and decision-making is crucial. Possessing a dynamic innovation system with short ways and all functions of a federal state, Bremen may serve as an example of such strategy.

Despite the diversified research and industry landscape, embedding high tech innovation potential, cannot be fully realized in the federal state of Bremen because of the lack of headquarters in the federal state. Due to this issue, the political decision-makers of the state facing the task to develop the innovation strategy of the federal state, e.g. including digitalization and artificial intelligence as focus areas. In this sense the COVID-19 shock can serve as a catalyst of changes into new technological directions.

3. Data base

This chapter applies the topic modeling approach to examining the innovation process in the federal state of Bremen and its developments in times of the COVID-19 pandemic with the help of news articles.

The standard data sources, which can be used to measure innovation performance or to follow innovative activities on different level, include for example patent, bibliographic or survey data (e.g. Community Innovation Survey). These sources of data have proven to be reliable for analyzing the innovative activities (e.g. Archibugi et al. 2013a; 2013b; Noori et al. 2017; Aggarwal, Hsu 2014). However, they have an important limitation in turbulent and dynamic times: they can be obtained only with a considerable time lag. With respect to survey data, the problem lies particularly in the strong speed of developments during the recession. Once a survey has been conducted, the data may be obsolete already short time after.

Yet, nowadays the dynamics of some industries and regions with respect to innovative activities requires the usage of the data available on short notice. This may be especially true in times of pandemic. Therefore, the daily press (press articles, web news and blog posts) can become such a source of scientific data. The advantages of daily press data include regular content updates, easy access, and the options for its usage not only for the public, but also in the political decision-making purposes (Arnaldi 2008). The information expressed by the press reflect the topics that possess high importance for a region at a specific point in time. Thus, by following the press coverage over a certain period of time, the frequency of certain topics and their relevance to society in general or to the region specifically can be revealed. Methodically such news texts, normally containing plain text, can be evaluated with the help of text mining and topic modeling techniques, presented in this chapter.

Despite many advantages, it is important to consider that messages of the news texts can have structural peculiarities, such as focus on specific topics, typical for media. This special feature of this data type is countered by the fact that not the absolute frequency of a topic, but its relative frequency over time is observed and interpreted.

One of the data sources, which allows consolidating the data from different publishing houses around the world, is “Factiva”. "Factiva" is operated as a digital information system by Dow Jones and is based on more than 30,000 different sources for press data collection. In addition, it allows searching for certain keywords, topics or specific regions. It is also applicable for the case of the Free Hanseatic City of Bremen, as “Factiva” is containing news sources relevant for this federal state. German language news sources are used here, whose seat is in the federal state of Bremen (e.g. Weser Kurier, Bremer Nachrichten) or outside the State of Bremen (e.g. Nordwest-Zeitung, Ostsee-Zeitung, Immobilien Zeitung), which report about Bremen.

The aim of the following example is to identify trends in innovation themes and their change before and during the COVID-19 pandemic, therefore a time filter was set. The first confirmed infection case with the novel coronavirus SARS-CoV-2 in Bremen was announced on February 29, 2020. Thereupon numerous measures to contain the spread of the virus have been initiated. With the first COVID-19-related ordinance of the federal state of Bremen on April 17, 2020, the closure of businesses with close customer contact as well as a prohibition of the contact in public space was arranged. On June 25, 2020, the relaxation of the contact prohibition was introduced, thus, from that date on "meetings between relatives of two households [...] or by a group of up to ten people from several households" (Legal act of the Free Hanseatic City of Bremen of June 25, 2020 No. 57) were allowed.

In the empirical analysis, the time 'during COVID-19' is defined as the period of six months, starting on February 29, 2020. For the period 'before COVID-19' an interval of the same duration (six months) until February 28, 2020 is defined. Since we are interested in topic trends in the area of "innovation” an additional filter has been set when collecting articles: the title or the first paragraph of the news item should contain the word stem "innov*"[3]. As a result, a total of 143 articles were identified: 91 belong to the period before COVID-19 and 52 to the period during COVID-19. This set of articles

[3] Adding the * to the abbreviation "innov" in the search strategy ensures that all conceivable word variants, such as innovation, innovation, innovator, innovator, innovative, innovation, etc. can be recorded.

thus presents the complete reporting about the innovation activities in Bremen and about Bremen during a one-year period, available in “Factiva”[4]. Unless hidden beyond the paywall, the full texts of these articles could be downloaded as a pdf document, collecting all texts from one of the time intervals.

The number of news texts per month is depicted in Figure 1. As can be seen, the active reporting about innovative activities before the pandemic start went sharply downturns in the first two months after the first COVID-19 case. This is most probably related to the shock situation and adaption as well as re-orientation phase of the actors to the new conditions. Afterwards, the number of innovation related articles rose starting from May 2020 and stayed relatively stable until July 2020, reflecting the wave of innovative activities as an answer to challenges caused by the pandemic. In August 2020 a second downturn was observed, showing the slowdown of the first phase of innovative activities.

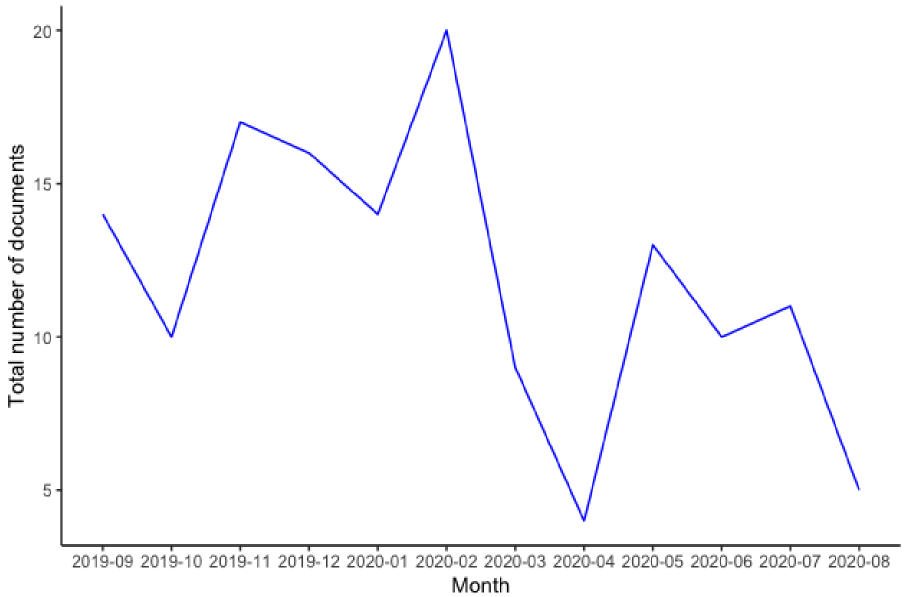


Figure 1: Number of articles per month

[4] Here can be discussed whether this number of documents in enough to perform the topic modeling analysis. To the best of our knowledge, up to now there exists no consensus in literature with regards to necessary total number of documents or words to perform the analysis, which would fit universally to each analytical situation. The validity and reliability of the model is the result of not only the number of documents, but also, for example, their length, topics separation and number of topics (e.g. Tang et al. 2014). In our case this dataset can present a reliable reference as it presents complete population available in the given source of data (“Factiva”) provided stated filters.

After this general statistical description, some more details about the documents should be provided to give an in depth insight into the data material used. The following descriptive statistics relate to the text material before pre-processing, i.e. with stop words and symbols. The length of the documents ranges from 56 to 2012 words with an average length of 402 and median of 324 words. The overall length of all texts is estimated at 57496 words. Figure 2 presents the monthly average number of words per document as well as the most frequent words, which appear in the whole corpus. As can be seen from the figure, even though during the first phase of COVID-19 the number of articles went down, articles themselves on average became longer and more detailed. As can be seen, the most frequent terms across all texts present words, that do not inhibit any meaning (for example, definite articles or prepositions). This already points out at the necessity to perform some “data cleaning” steps, which will be explained in the next section.

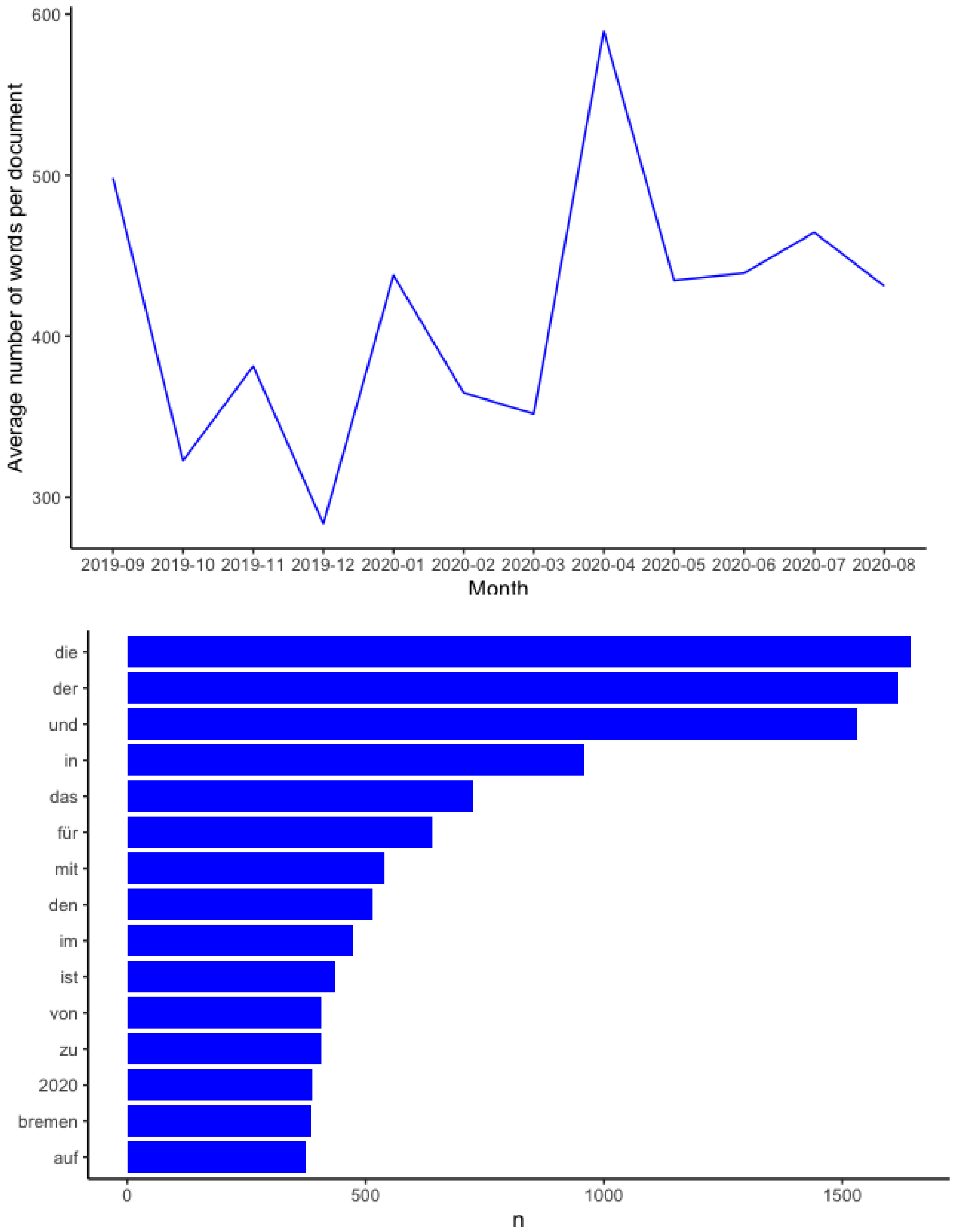


Figure 2: Corpus statistics

Apart from analyzing topics of news texts, this chapter focuses on the actors that engage in innovation related activities in the federal state of Bremen before and during the first COVID-19 phase. For that, the identification of the actors was done by a manual review of the news articles and matching of the names of actors to the articles. Thereby, different spellings were identified and harmonized. As the result, 343 actors from industry, politics, and research could be identified, with some articles including more than one actor and some actors appearing in more than one article. The top of most active actors includes University of Bremen, German Research Center for Artificial Intelligence (as Deutsche Forschungszentrum für Künstliche Intelligenz (DFKI)), German Aerospace Center (Deutsches Zentrum für Luft- und Raumfahrt (DLR)), European Regional Development Fund (Europäischer Fonds für regionale Entwicklung (efre)) and Justus Grosse (real estate firm). Table 1 presents all actors, having 3 and more occurrences in the dataset. As can be seen, the most frequently reported actors belong to the area of research or policy. Apart from Justus Grosse, the only frequently reported business enterprise is Vitakraft – a company of the pet care products industry, headquartered in Bremen.

Table 1: The main actors

Actor	Number of articles
University of Bremen	10
German Research Center for Artificial Intelligence	5
German Aerospace Center	3
European Regional Development Fund	3
Justus Grosse	3
Radio Bremen	3
Rot-Grün-Rot[5]	3
Senate	3
Senator for Economics, Labor and Europe	3
Theater of Bremen	3
Vitakraft	3

4. Topic Modeling

4.1. Overview of the method

Text data as a form of unstructured data and methods to collect and assess them is gaining more and more importance. Data science, especially advancements in unsupervised learning algorithms, are offering approaches to address this fact. Since unsupervised learning does not rely on predefined indicators, it allows the detection of hidden patterns. In innovation economics text documents inhibit room for analysis of topics and developments over time which cannot be covered by existing secondary data. Therefore, the technique of topic modeling seems to be especially beneficial related to explorative analyses. Furthermore, it allows the analysis of qualitative changes.

[5] This relates to the colloquial name of the government of the federal state of Bremen, composed of the colors, representing governing parties: Social Democratic Party of Germany (red) - Alliance 90/The Greens (green) – The Left party (red).

As part of the natural language processing (NLP), topic modeling techniques summarize various algorithms aiming at the extraction of topics out of a selection of text documents. Topics are groups of words which are co-occurring in documents more often than expected. Therefore, a topic is defined by a group of words like for example “study”, “university”, “student”, “learning”. A discussion of all topic modeling techniques is beyond the scope of this chapter, therefore, one of the most common algorithms called latent Dirichlet allocation (LDA) (Silge, Robinson 2017; Roberts et al. 2014) and structural topic modeling (STM) are focussed on here.

The latent Dirichlet allocation (LDA) algorithms are based upon two assumptions. Firstly, every document is understood as a mixture of topics and secondly, every topic is a mixture of words (Blei, Ng, Jordan 2003; Silge, Robinson 2017; Roberts et al. 2014). In order to perform the identification of latent topics in the text corpus, the document texts are tokenized. This means, that each document is now represented by a list of tokens without those being in a readable form any longer. A token can be a single word (unigram) or sequential words[6] (in case of two words those are called bigrams) or even a phrase or a sentence. In this chapter unigrams are used as unit of analysis. Since documents are not analysed in their original structure but as a list of tokens, the grammar structures and the order of the tokens become irrelevant for analysis. Therefore, the LDA is following a “Bag of words” procedure (Blei, Ng, Jordan 2003). Having the list of tokens per document, the LDA algorithm estimates the probability of tokens to be paired based upon text excerpts. This step reveals the token-topic probability which is further applied to estimate the prevalence of topics in the documents in the text corpus.

However, LDA does not allow an incorporation of meta-data of the analysed documents like for example the journal the text is coming from or the point in time it is published. Structural topic modeling (STM) as put forward by Roberts et al. (2014) further developed the analytical approach of LDA to fill this gap. By applying the STM approach, it becomes possible to consider covariates of interest in document-topic proportion distribution as well as in topic-word distributions (Roberts et al. 2014). This is especially beneficial whenever topics may be influenced by external effects or attitudes. In this chapter this approach is taken since it is suspected that publishing houses differentiate from each other in how often they are reporting about specific topics. For example, we expect to find different topical structures in a daily newspaper like “Weser Kurier” in contrast to a magazine specialised in one area like “Immobilien Zeitung”. The STM algorithm allows to control for this issue by adapting the estimation procedure. It may also be appropriate to assume covariates to influence the word-topic distribution by different ways of reporting (for example when having radio transcripts and written news texts in one text corpus). In such a case, STM also offers a way to counteract this bias

[6] There are also other methods to identify n-grams, for example, building n-grams from all possible combinations of words in a sentence.

in estimation. Since this chapter does not use news from different types of sources, this adaption is not needed.

Due to the rising importance of text data, topic modeling techniques can be considered as a tool with increasing use in economic analyses and beyond. For example, the LDA approach was taken by Ambrosino et al. (2018) to analyse the topics discussed in economic scientific literature. The authors were able to map the discipline over time. Besides the analysis of scientific articles, text information retrieved from websites can also be a subject of analysis. Arora et al. (2020) for example studied dynamic capabilities of new ventures by employing website data. Apart from being able to make use of data not analysable with standard approaches before, it may even give rise to new ways of data gathering (Roberts et al. 2014). Beyond the scope of economic literature, topic modeling techniques become more frequently employed in other disciplines as well. For example, Rhody (2012) discusses the usability of topic modeling for the analysis of poems. Moreover, Roberts et al. (2014) show the application of the STM approach to analyse open questions in questionnaires and analyse the interdependence of political attitudes and responses in open ended questions.

4.2. Text data preparation and empirical procedure

In order to perform a topic model analysis three steps are required. Firstly, text data needs to be pre-processed. This procedure requires different steps than for numerical data. Secondly, the number of appropriate topics needs to be chosen and settings of the topic model estimation needs to be determined. Thirdly, the topic model has to be interpreted.

Data pre-processing

In the phase of pre-processing the documents have to be split into words which need to be cleansed by applying three steps. This cleaning is important in order to prepare the text for the analysis by removing words and word parts, which are superfluous for our purpose and may bias the analysis.

At first, stop words, which are words not inhibiting a meaning and therefore irrelevant for the analysis (for example: and, or, however, …), are removed from the documents. In the following example a German dictionary of stop words was applied. Such dictionaries for every language are normally available online. One can also create or expand dictionaries by adding custom words, depending on the underlying texts. For example, when working with patent data such words can be “innovation”, “present(s)”, “relate(s)”, “activity”, “summary”. These words, even though not appearing in each patent document, present standard patent lexicon.

In a second step, the words are stemmed. Using the word stems as unit of analysis it is ensured, that all forms of a word are summarized. It helps, to account for singular and plural form of the same word or different word endings. For example, the words “culture”, “cultures” and “cultural” would be limited to the form “cultur”. Thus, the bias in counting the words with similar meaning could be minimized. However helpful, stemming may bring biased results by long queries and documents (Korenius et al. 2004) via bringing irrelevant texts in the analysis or combining irrelevant terms without accounting for their actual meaning. Apart from that, stemming procedure may not be appropriate for some languages, depending on their complexity. Thus, an alternative of the stemming can be introduced for the case of long documents, which is lemmatization. For the case of lemmatization, the basic (dictionary) form of each word is identified also referred to as lemma (Korenius et al. 2004). Although several studies have found the better results when retrieving or analysing texts using lemmatization than when using stemming (Balakrishnan, Lloyd-Yemoh 2014; Korenius et al. 2004), lemmas present the footprint of a lexicon at a static point of time, as available in the dictionary and not all words can be lemmatized (Zeroual, Lakhouaja 2017). Apart from that, it may lead to the loss of the precision, especially when not uni- but bigrams or further n-grams are used[7]. As this example makes use of news texts, which may contain neologisms not yet included in dictionaries we stuck to stemming.

Lastly, overly frequent words are removed from the data set to avoid bias in the topic model result. This step complements step one in deleting the standard lexicon of the corpus, which were not present in the dictionary or manually added. In the following example a threshold of 90 percent is used, meaning that if a word is appearing in more than 90 percent of the documents it is deleted entirely[8].

After applying these three steps within the cleansing procedure, a look at the descriptive statistics reveals the changes (as compared to the statistics presented in section 3 above). As the result of text cleansing, the average length of the document was reduced to 187 words and the median to 140 words. The document length now ranges from 18 to 1,053 words with the total number of words now being estimated at 26,804. Figure 3 below provides the insights into corpus statistics after the pre-processing. As can be seen, pre-processing has not changed the trend in the average number of words per document. However, when looking at the most frequent terms, the big difference in comparison to the unprocessed data can be observed: now the most frequent terms

[7] Alternatively, one may think about performing the analysis without applying stemming or lemmatization (e.g. Schofield. Mimno 2016).

[8] To the best of our knowledge, there exists no typically used percentage threshold in the literature. We would suggested to calculate the most frequent words with the number of their occurrences in the documents and their distribution in order to get an impression, which percentage can be used in the individual case. In our example the threshold number is relatively low because of the relative heterogeneity of the underlying documents. Therefore, only a small number of words appearing in >90% of the documents.

reflect directly the underlying topic (e.g. “innovative”, “unternehm” (relating to enterprise), “project”).[9]

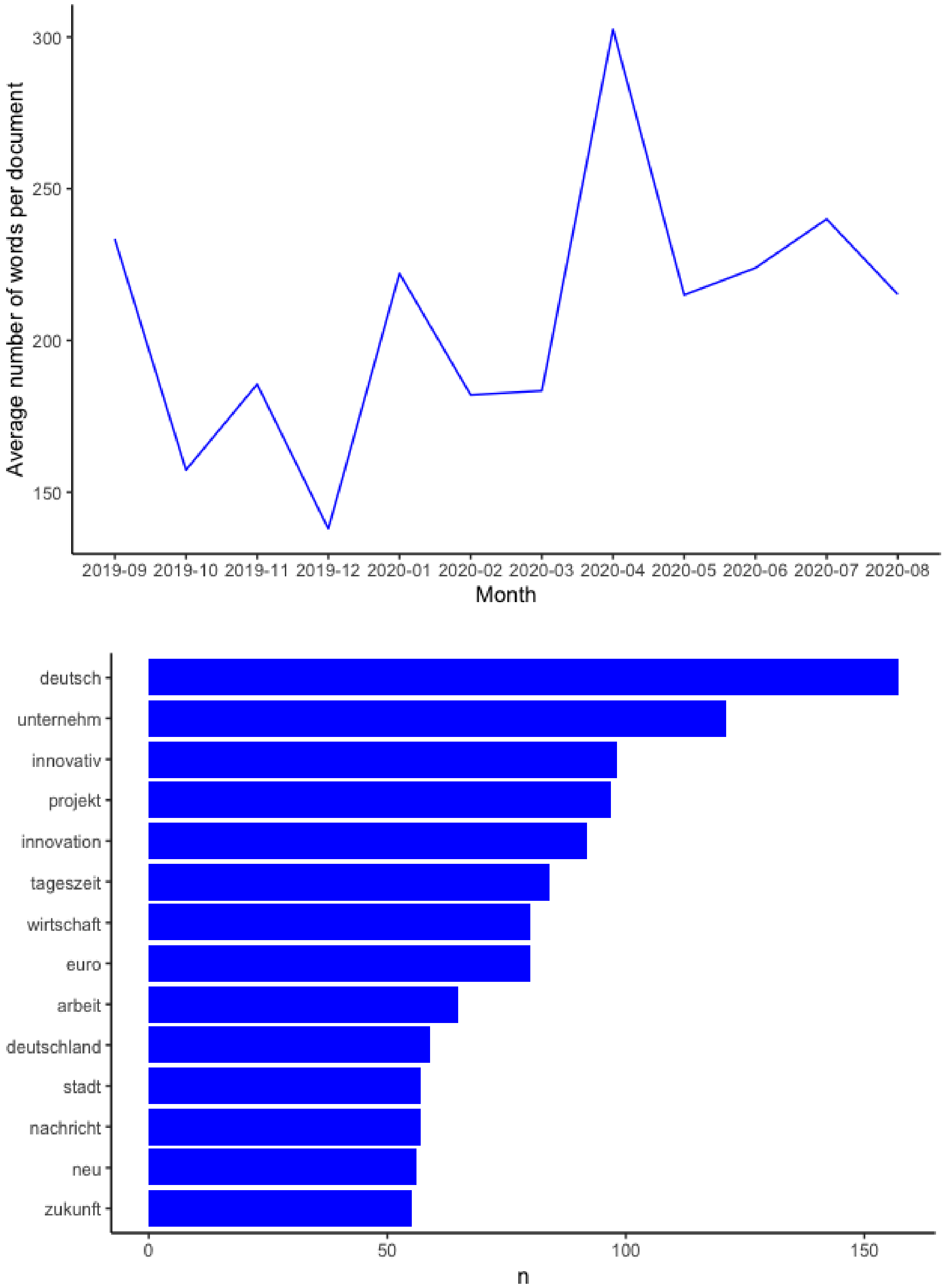


Figure 3: Corpus statistics, after pre-processing

[9] Here several words, related to innovation can be observed in the figure (“innovative” and “innovation”). This reflects the imperfection of stemming, especially for the languages other than English. However, this approach was taken by authors as it allows unification of the most of the terms.

Number of topics selection

After pre-processing, the actual data analysis can be done. Topic models can be estimated by applying the algorithm in a statistical software like R (LDA algorithm can be found in the package “topicmodels”, and STM algorithm is included in the package “stm”). By applying the STM approach, covariates can be included in the model estimation as described above. In order to determine an appropriate number of topics, several measures are available. Standard measures include implementing the Bayesian approach via log-likelihood calculation for all models within a span of number of topics using sampling, e.g. Gibbs sampling (Sbalchiero, Eder 2020) or predictive perplexity or its change (Zhao et al. 2015) with lower predictive perplexity presenting the best choice of number of topics.

Chang et al. (2009) found evidence for less reliability of standard model fit measures, stating that these measures “do not address (…) exploratory goals of topic modeling”. Thus, several authors propose other consideration criteria, namely semantic coherence, reflecting whether the topics would also be divided so by human beings, as well as exclusivity. Some words may occur along several topics. Therefore, exclusivity measures the uniqueness of words the topics consists of (Silge 2018; Chang et al. 2009). These measures are normally looked at together, in order to account for the situation when the topics are created by common words (Silge 2018). For the chosen number of topics both semantic coherence and exclusivity should be high.

Thus, even though the choice of the number of topics is defined in the literature through several measures, they sometimes deliver different recommendations. In this case it makes sense to check all the measures and depict the most common words, which are creating each of the topics for several number of topics. By viewing these words one can make the first guess on what each topics orientation may be as well as whether the proposed number of topics provide a good document classification. Such “educated guess” combined with quantitative measures goes at best in line with the explorative character of topic modeling outlined by Chang et al. (2009).

Presentation and interpretation

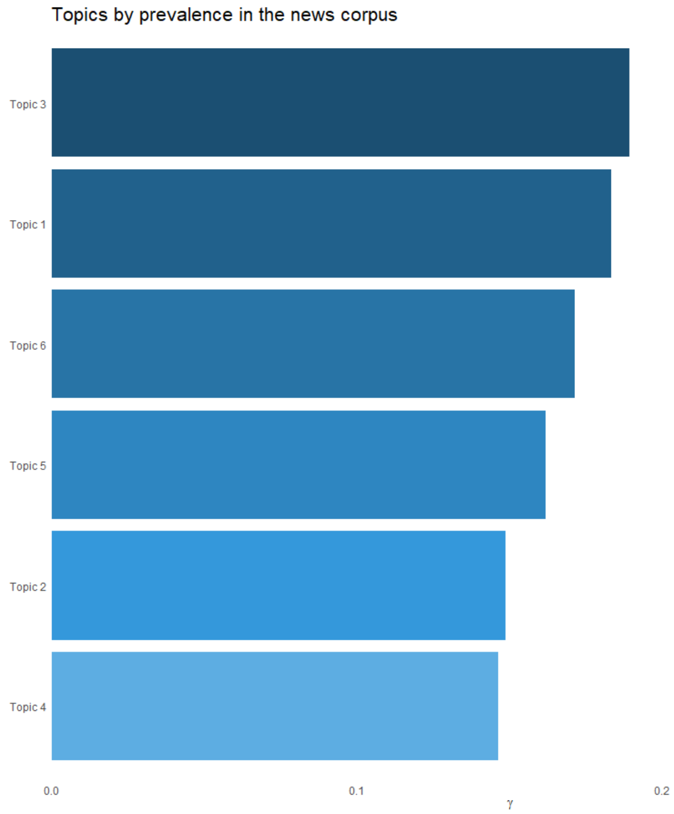
After the identification of the topics, the output of the topic model can be presented. It can be twofold. Firstly, word-topic probabilities β are retrieved. Each combination, the β indicates the probability to which a word is generated by a specific topic (Silge, Robinson 2017). Secondly, document-topic probabilities γ are generated. These values show the estimated proportion of a document containing a specific topic (Silge, Robinson 2017). Based on these outputs, the model is typically illustrated by displaying the estimated γ in the whole news corpus and the most frequently occurring words within this topic. The following section will provide a detailed presentation and interpretation of both the innovation topics and their emergence over time (research question 1) and the actors involved (research question 2).

5. Empirical findings

5.1. Innovation topics

The number of topics and their numbering is based on the defined evaluation indicators. These include maximizing exclusivity of the topics and their semantic coherence. The x-axis (γ) of Figure 4 reflects the expected share of each topic (Silge 2018). Each document has a certain probability to be assigned to each of the topics. The expected share of a topic in the entire news corpus corresponds to the mean value of these probabilities. So, in our case each topic has a share from 15 to 20 percent of all texts. The size of the bars corresponds to the frequency of the respective topic in the news corpus. Thereupon, topic three is the most prevalent topic in the text corpus. It is associated with more than 18 percent of the text corpus. Moreover, it can be seen, that topic four is the least frequently occurring topic in the text corpus, making up approximately 15 percent. The top words to the right of the bars are included in the underlying news texts particularly frequently. Some words (e.g. projects, Euro, company) occur in more than one topic, which makes these words highly relevant for several topics. In these cases, combinations of words were considered to allow the delimitation of topics. In addition, news texts that have a strong association to a topic field, are manually checked and used for the interpretation of the topic. Thus, the topic modeling method enables in comparison to clustering methods an overlap between topics, which is more in line with the natural language (Silge, Robinson 2017).

Figure 4 summarizes the result of the topic model, which was developed using the 143 innovation-related articles (news corpus). In total six subject areas can be identified in the messages.



Topic	Top 8 terms
Topic 3	projekt, inform, innov, märz, tageszeitungen, theater, euro, arbeit
Topic 1	euro, unternehmen, inform, niedersachsen, achim, projekt, wirtschaft, politik
Topic 6	unternehmen, innov, deutschland, zukunft, innovationen, produkt, wasserstoff, stahlwerk
Topic 5	smart, kunden, bremerhaven, oldenburg, team, digitalisierung, unternehmen, studi
Topic 2	überseekontor, unternehmen, rostock, innov, europa, modern, bietet, projekt
Topic 4	innov, music, inform, projekt, joint, tageszeitungen, septemb, theater

Figure 4: Expected frequency of topics in the news corpus

The result of this analysis allows an insight into essential thematic focal points of innovative activities documented in the media for the federal state of Bremen. Furthermore, these can be set in relation to each other. In the following the topics, which are all discussed in the context of the innovation activities in Bremen, will be described in more detail in terms of content and be correspondingly labelled.

Thus, among the words, which are most frequently related to topic 3 are project, Euro and work. This already points to a promotion of new and innovative projects. The examination of text sections on this topic also allows recognition of a connection to the entrepreneurship scene in the federal state of Bremen. Summarizing, this topic can be titled as follows: "New ideas with potential".

Topic 1 is the one with the second highest frequency of publication in the news about Bremen and Bremerhaven. The words economy, politics and business point to the political importance of local competitiveness, reflected by this topic. This impression is supported by the exemplary viewing of text sections, and it becomes clear that growth is relevant term for this topic. For this reason, topic 1 is entitled as "Political focus on economic growth".

In the third place, along the topic 6 future, hydrogen and companies appear as frequently occurring words. In addition, in news texts that are associated with this topic, especially forward-looking new projects and innovative technologies are present in the foreground. Additionally, the focus here is set on sustainability. Topic 6 is therefore referred to as "Future orientation of the regional environment".

Topic 5 is particularly characterized by the words smart, team and digitization. Excerpts from the news also show the focus on innovative and digital solutions. In addition, Bremerhaven together with Oldenburg is closely involved with to this topic. Overall, topic 5 can be labeled as "Digitization and smart technologies".

Based on the frequently used words overseas office, modern and project as well as viewing associated news texts, it becomes apparent that topic 2 is related to the spatial planning. In this complex of topics new concepts of real estate use and their significance for the region are discussed. Therefore, topic 2 can be titled "Space for innovations".

The last identified topic area is concerned with music, projects and theater. It is apparent that in the news on this topic, especially about social events are reported. For these reasons the topic 4 is named "Art and culture".

Figure 5 presents the distribution of the topics over the documents. The y-axis represents the number of documents in each box of the histogram. On the x-axis the probability of the topic to be associated with a document is illustrated. Looking at the histograms, it can be concluded, that the documents represent very heterogeneous topical structures. This is visible in the strong separation between documents being only weakly connected to a topic (having a value of 0.2 or lower) and those being almost completely associated with one topic (having a value of 0.8 and higher).

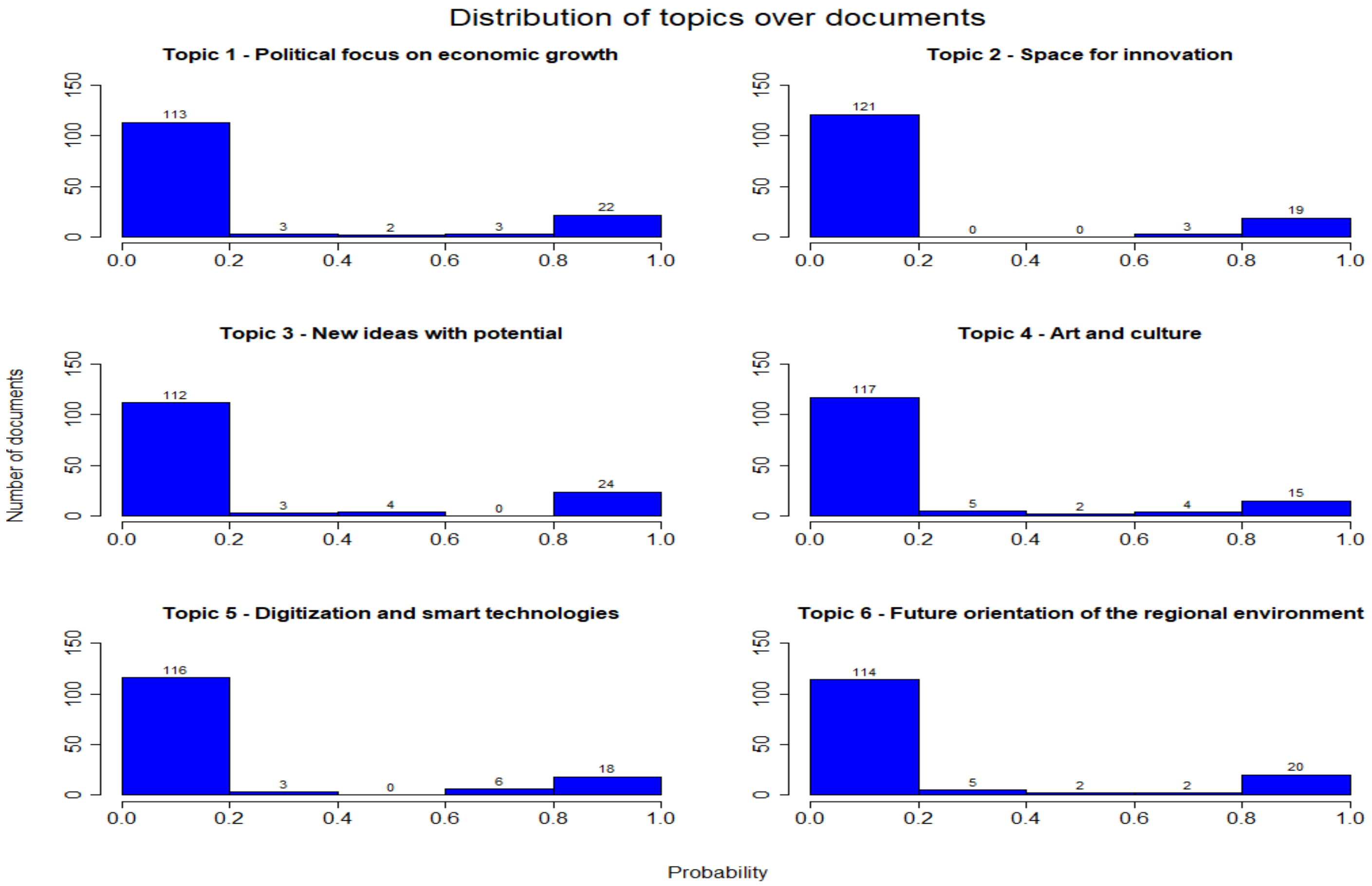


Figure 5: Distribution of topics over documents

In order to gain an even more detailed impression of the retrieved topical structure of the documents, the similarity between topics can be evaluated. In Table 2 the cosine index as an acknowledged similarity measure is applied (for example, Li, Han 2013; Muflikhah, Baharudin 2009). The cosine index ranges between 0 and 1. The nearer it is to 1, it indicates a stronger relation between two topics. However, the values confirm the former impression of the topics as being strongly separated from each other. It is surprising that the lowest value of the cosine index can be found between the topics 3 and 5. Thereupon, new ideas with potential differ from those being associated with digitization and smart technologies. Moreover, the strongest relation can be found between topic 1 and 6. This indicates, that economic growth and its political importance is most likely connected to future orientation of the regional environment, which is not a surprising result, because new technologies such as hydrogen or renewable energy technologies are typically discussed in relation to work place reduction and creation.

Table 2: Cosine index - Similarity of topics

	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic 6
Topic 1						
Topic 2	0.018					
Topic 3	0.028	0.022				
Topic 4	0.030	0.023	0.045			
Topic 5	0.025	0.008	0.010	0.046		
Topic 6	0.054	0.016	0.026	0.022	0.042	

5.2. Change of topics with the beginning of the pandemic

Figure 6 shows the relative frequency of the six previously identified subject areas over the observed time period. The blue, thin marking shows the subdivision of the time period before the first confirmed SARS-CoV-2 infection in the federal state of Bremen and afterwards. In addition, the lockdown (from the adoption of the first contact restriction until the relaxation of this) in the federal state of Bremen by the light blue colored surface recognizable. The relative frequency reflects the graphic representation of the prevalence of the topic.

The observation of the relative frequency of the topics makes it possible to estimate on how the importance of innovation themes changed after the outbreak of the corona pandemic and the lockdown in the federal state of Bremen. The investigation of the relative frequencies of the topics represents an explorative analysis that shows which innovative activities or topics have gained or lost relative importance during the crisis.

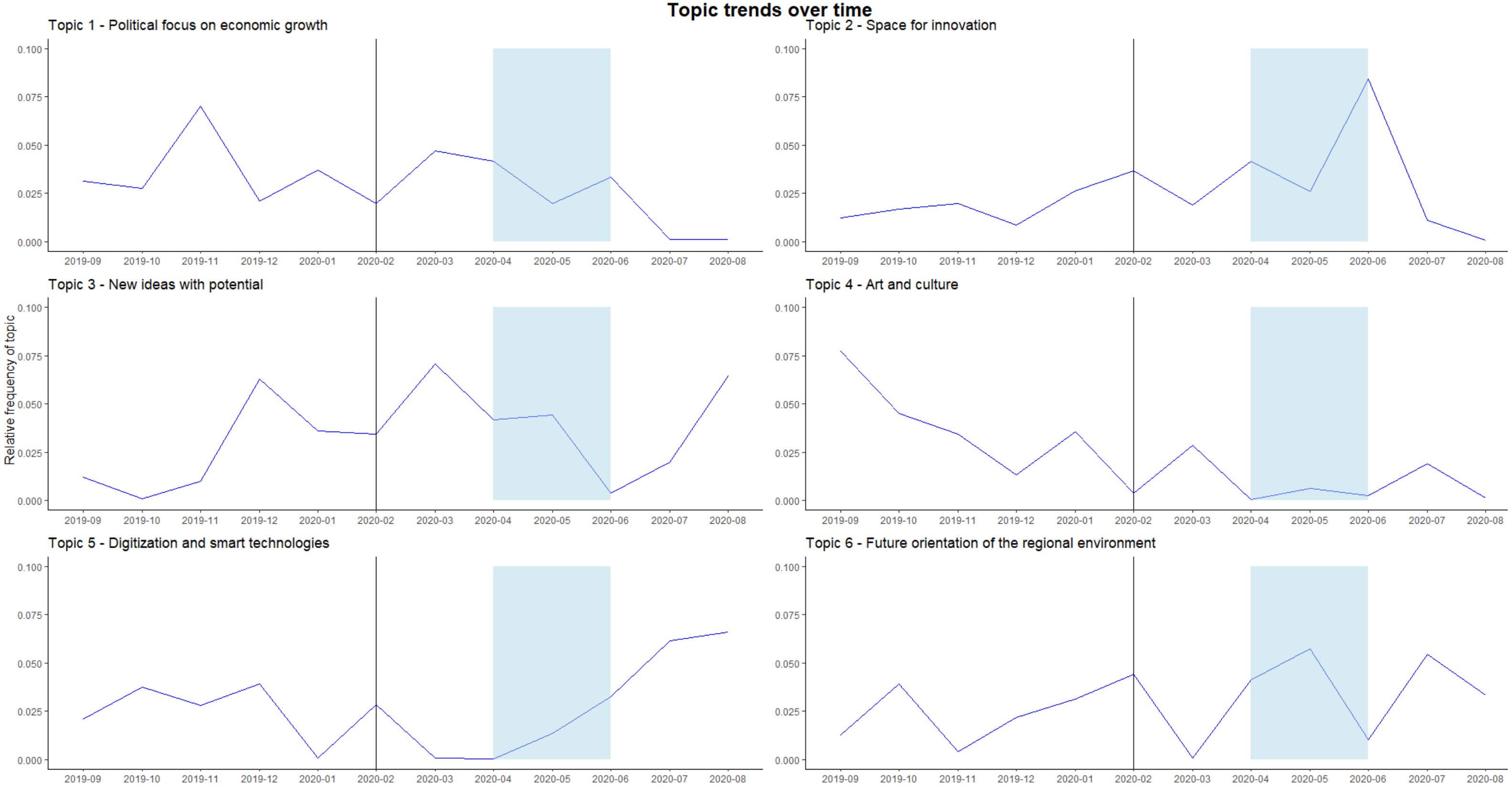


Figure 6: Topic trends over time

It becomes clear that in the context of innovation, the thematic fields of "Political focus on economic growth" and "Art and culture" have lost much of its relevance after the first SARSCoV-2 infection was confirmed in the federal state. During the pandemic, there were significant slumps in reporting on these two topics. As a result of the severe restrictions in people's everyday working lives and in of leisure activities caused by lockdown, this development is not surprising. Instead of setting economic impulses on the political level, measures aimed at achieving survival of companies and therefore the preservation of the economic structures were taken at the political level. Innovations give way to damage-limiting strategies, whereby expectations to the economic developments after the lockdown are shrinking. Beyond that the cultural life in the federal state of Bremen before the COVID-19 pandemic is relatively frequently mentioned and therefore integral part of the innovation events. This has collapsed and, even after the lockdown, has so far not regained the initial level. These observations allow the conclusion that the growth objective and cultural life in the context of innovation recede into the background due to the crisis.

"Space for innovations" as a topic shows a strong increase in relative frequency. It is obvious that this observation is consistent with the emergence of new work habits, such as working from home. However, the relevance of this topic seems to decrease after gradual relaxation of the measures. Based on this result, it does not seem to be a profound and medium-term change in the space for innovation.

"New ideas with potential" and "Future orientation of the regional environment” show a rather positive trend on average over the entire course of the year, although the reactions in the two areas during the lockdown are opposite. While Figure 6 shows a sharp drop in the frequency of "New ideas with potential", the "Future orientation of the regional environment" seems to benefit from the lockdown in the short term. These observations could be an indication that these topics are subject to strong fluctuations, but potentially could serve as origin of innovative solutions.

In contrast to the only short-term increase in the relevance of "Space for innovation” the relative importance of "Digitization and smart technologies” experience a strong increase in the second half of the observation period, which sustains after the lockdown. The importance of digitization and smart technologies will therefore be of great importance for innovation in the federal state of Bremen.

5.3. Actors related to the innovation topics

After the presentation of identified topics and trends, the following section will focus on actors in the innovation process who played a role before and during the first phase of COVID-19 pandemic in Bremen. The actors associated with each of the six identified topics are shown in Figure 7. The word clouds include all actors mentioned in the news texts. The names of the actors are displayed larger the more often they are mentioned in the respective topic.

Topic 1: Political focus on economic growth

Topic 2: Space for innovations

Topic 3: New ideas with potential

Topic 4: Art and Culture

Topic 5: Digitization and smart technologies

Topic 6: Future orientation of the regional environment

Figure 7: Actors in each topic

Both political decision-makers and actors from research and education can be observed across all topics. In addition to University of Bremen, Jacobs University and City University of Applied Sciences, other universities and universities of applied sciences in the federal state of Bremen and the neighboring federal state of Lower Saxony appear to play an important role in Bremen's innovative activities, which is supported by the presence of Jade University of Applied Sciences Wilhelmshaven in topic 1 and Bremerhaven University of Applied Sciences in topic 3.

In addition, theaters, museums and other actors from the cultural landscape are present in all topics. However, while before the COVID-19 pandemic these actors appear in articles in the light of new performances and different awards, during SARS-CoV-2 pandemic these institutions face new challenges. Thus, at the beginning of the COVID-19 pandemic, the appearance of these actors in the innovation-related news texts was connected to the search for ways to conquer the lockdown-related limitations and the uncertainty about the future. The importance of these issues is rising in anticipation of the new cultural season 2020/2021.

Large companies are also appearing as players in the innovation process, both before and during the COVID-19 pandemic. Some aspects, especially ones connected to the topics 3, 5 and 6, retained their importance for the region and were constantly appearing in the headlines. This trend reflected in the continuing discussion about the change in the automotive industry, connected with such aspects as digitalization and CO2 neutrality, resulting in the presence of the automotive companies BMW, Daimler and Volkswagen as well as the SWB (Bremen public utility company) in topics 3 and 5.

The same applies to hydrogen research and climate-neutral production in the Bremen steelworks. The discussion on this topic began before and continued during the COVID-19 pandemic. In addition, the topic of hydrogen transition and climate neutrality is becoming more and more important over time: later articles outline the importance of small and medium firms (SMEs) and North Sea ports in this task. In this case the COVID-19 pandemic is even seen by political actors as an opportunity to pursue a climate-neutral industrial policy.

As far as the importance of SMEs for the region is concerned, their role in providing intelligent and digital solutions is reflected in particular as a reaction to the crisis. This is reflected in the strongly increased importance of topic 5 during the COVID-19 pandemic. For example, the intelligent helmet of the Bremen-based start-up company Ubimax is intended to protect the bicycle couriers, who are affected by the changes in consumers experience resulted in increased workload (Nordwest Zeitung of July 22, 2020). Another example could be the innovative face mask, which a restaurant manager from Bremerhaven has developed (Nordwest Zeitung of May 27, 2020).

6. Conclusions

This chapter presents an insight into topic modeling, in particular structural topic modeling, as a method for identifying the trends of innovative activities in highly dynamic environments. Topic modeling thus presents a handy approach for systemization and summarizing of large amounts of data, in particular news texts. However, also the patent or research article texts can be analyzed using this approach. As a result of topic modeling application, unstructured quantity of data can be described along a limited number of topics and thus allows conclusions about the main directions of an industry’s or a region’s development as well as about changing trends of this development. Apart from that, topic modeling allows for a context-specific analysis, where words are not looked at in vacuum but in context, such as combinations of words are regarded as important (Savin et al. 2020).

Thus, the topic modeling approach may serve as a useful tool for analyzing large amount of data and identify the trends in the thematic direction of innovative activities. In this chapter, it was used as a single method because the crisis situation calls for quickly available and comprehensive data. However, there are also limitations of topic modeling. Apart from the already mentioned data selectivity problem, one of the limitations of topic modeling may be the sensitivity towards changing of specific criteria along the algorithm. Moreover, it needs to be considered that the stemming of words may be enhanced by using lemmatization which aims at the meaning of words rather than their word stems. Thus, in order to get a holistic picture, topic modeling toolkit may be combined with other indicators of thematic orientation among industry or region (e.g. IPC/CPC classes of patents or research areas of research papers).

In this chapter we have applied the topic modeling approach on the example of the change in innovative activities in the federal state of Bremen as the answer to challenges caused by COVID-19 pandemic. Our results show that in the course of the COVID-19 crisis six main topics play an important role in the context of Bremen's innovative activities. These range from cultural events and innovative construction projects to the future-oriented strategy of regional development and growth. The current COVID-19 pandemic has influenced the relative frequency with which these topics are covered in the news and thus the importance of these topics during the pandemic. As a result, the growth orientation of politics loses importance during the pandemic, and cultural institutions become visible in their particular problem situation with the beginning of the pandemic. The issues of digitization and intelligent solutions will gain considerably in relevance during the pandemic period. Apart from this, there are some issues that will retain their importance for the region even during the crisis. These include climate-neutral production and the future of the automotive and steel industries. The COVID-19 pandemic can serve as a springboard or accelerator for innovations in these areas. Beyond that, the commitment of various groups of actors is important: both the promotion of start-up hubs as well as the focus on the interaction between start-ups as well as large players, SMEs and research institutions can lead to fruitful synergy effects in the country. The results also show that various groups of players play an important role in the innovation process in the State of Bremen example. Thus, in particular SMEs seemed to be demonstrating innovative solutions during the pandemic. These solutions can also be applied by the major key players. In addition, scientific institutions are emerging as important players in almost all topics.

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