DETECTING BIASES IN THE NEWS REPORTING ACROSS COUNTRIES AND THEIR IMPLICATIONS FOR BUSINESSES

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Abstract
This study provides a methodology to reveal a biased news reporting in the media of a country. The study reveals topics that have a continuously benevolent or bad media reporting without any objective reason. The analysis is done in an empirical and quantitative way.
The picture of certain topics in the news is measured by the sentiment in the media in the UK and Germany. The study measures the sentiment with the help of a Long Short Term Memory (LSTM) artificial neural network that analyses the sentiment in publicly available news streams in the UK and Germany. The approach targets topics that have a similar (high) media coverage in both countries but different sentiments.
The results show that there are indeed topics that have a continuously biased reporting. Interestingly these findings often refer to topics that are well known to be controversial. Due to the fact that these biases exists in the whole news universe of a country we can well think of an alternative truth per country.
These findings show that the fake news and post-truth debate is also important on a country level, as the news might be tendentious based on stereotypes, prejudices or special economic interests that obfuscate the universal truth for everyone and not just for people in a filter bubble.
Businesses, News providers, social media networks, political actors, and policymakers can consider the provided information to analyse the source of the information gaps and the impact on their operations and policies.

Keywords
Online media; fake news; biased news; news coverage; sentiment analysis; machine learning;

JEL Classification
L82, C45, M10

Introduction

Today many people in the society believe that news are manipulated, biased, tendentious or that the media is not reporting about the most important topics if they should not be disclosed to the public. This phenomenon is global. The American president Donald Trump complains about fake news if the news do not reflect his worldview on climate change. The presidential campaign of Donald Trump is investigated for their use of a very narrow social media targeting with the help of Cambridge Analytica, a British social media analysis company. Many Germans suspect that the media reporting in Germany regarding the refugee crisis is biased and benevolent to the government and that many crimes committed by asylum seekers are not reported in the news. In the UK many Brexiteers and Remainers accuse each other of lying regarding several topics. One problem of this is that very important political and social discussions are not arising anymore at all, since the parties simply accuse each other of lying and arguments are not heard and accepted anymore. In many countries this culminates in the strengthening of the populist parties and the end of reasoning.

This study focuses on the analysis of online news articles. While there are many more news sources like TV or social media, online news articles are still one of the most important news source for many internet users. Many news articles are also spread through social media and the users do not even need to visit only newspapers.

The online news transport all the sentiments and emotions – either wrong or right – that are discussed in the public. Therefore, those articles are an interesting source to analyze how biased or tendentious the news reports are and what a reader can expect to take home when reading the news.

While there are many fact-checking websites and organizations that focus on the analysis of single news reports or social media posts in a fundamental way of reasoning, this study tries to detect biased and tendentious news in an automated and quantitative way with the help of machine learning. We expect to detect the biasedness of news regarding a certain topic when we compare the sentiments and emotions transported regarding this topic in different news sources. Ideally, the different news sources cover a broad range with many news and include many viewpoints

Many news sources are often slightly biased by definition and intentionally due to the (political) target group and the targeted readership. This is in general not a problem, of course will a newspaper that targets conservatives focuses on different topics and take different viewpoints than a newspaper focusing on democrats. For the mentioned study, this fact still does matter because we want to take a broader focus on the biasedness and the tendentiousness of the whole news available.

To overcome these issues we compared the news across different countries – in our case the UK and Germany – to have broadly based news streams with the news of many viewpoints and target groups included.

With these broadly based news Streams with more than four million news in total we were able to analyze the similarities and the differences between the sentiments in the German and British news regarding several topics. Germany and the UK very often proclaim that they – despite political differences and the Brexit – are a community values. Further the German as well as the British media state that it is objective, no news are deliberately kept secret and that the most important news are delivered in a timely manner.

These working hypotheses – the UK and Germany are a community of values and the media on both countries is in general neutral and objective – lead to the assumption that the online media in both countries should transport similar sentiments for each topic under consideration. If this is not the case, it could be a good indication that the news in one of the countries is biased and tendentious. Further, the media coverage for each of the analyzed topics can be an indication on how prominent the topic was in the media. Big differences in the media coverage can again be a good indication that the news in one of the countries is biased and tendentious.

In this study we analyze the sentiment in the German and British media towards the most important topics in the UK and Germany in the period between Jan. 2010 and March 2019.

Our objective and quantitative approach can help to identify which topics probably have biased and tendentious news. Businesses, news providers, social media networks, political actors, and policymakers can consider the provided information to analyse the source of the information gaps and the impact on their operations and policies.

Theoretical Foundations

The theoretical foundations of this study are from different disciplines. Computer science provides this study with the foundations of sentiment analysis and information retrieval. Media analysis research gives the foundations for the current state of research of fake news, biased news and tendentious news. The fields of finance and economics contribute several interesting studies regarding the macroeconomic effects of sentiment in the mass media on stock markets or economic indicators.

While the strong current interest about biased and fake news started in 2016 with the election of Donald Trump as the president of the United States, the debate in general started already a long time ago. The following three studies give a good overview on the impact of biased news. The most recent study on the impact of biased news on the presidential election is from Allcott and Gentzkow who present detailed figures on how fake news affected the 2016 election in the United States (Allcott and Gentzkow 2017). An earlier study of Bernhardt et al. demonstrated how the targeting of specific audiences of newspapers lead to polarized and biased news, even if the median ideology is centrist and therefore the median target audience is centrist (Bernhardt et al. 2008). A more similar study to this study shows how the mass media collective coverage of all news significantly influences political outcomes (Luo 2017).

To detect and analyze biased or fake news it is important to define what are actually the characteristics of biased and fake news. This study considers two dimensions as biases: One dimension is the agenda setting of the newspapers, and one dimension the accurateness. This is in line with many other studies regarding validity of media reports. While the media reports might be inaccurate and biased, also the problems that arise from a biased agenda setting – an over or underreporting of events compared to their objective relevance – can have a similar impact than inaccurate, wrong, or fake news. Several studies report the impact and the detection of both dimensions.

The first comprehensive study on the agenda-setting dimension came from McCombs and Shaw who could show that the importance of each event or issue is determined by the presence in the media and probably not by its “objective” relevance (McCombs and Shaw 1972). Snyder and Kelly analyzed the agenda setting problem comprehensively in the context of racial conflicts in the USA. Their model just analyses the probability that events will be reported in newspapers (Snyder and Kelly 1977). While the issue of the agenda setting is known for long, it still is increasingly important today especially in the context of the internet and the filter-bubbles. Maurer released a comprehensive study on the theoretical foundations, methodological approaches, empirical findings and social repercussions of the mass media engaging in agenda setting today (Maurer 2017).

Besides the dimension of the agenda setting which leads to biased news, the second dimension contains the truly wrong, tendentious and fake news. Often those news are hard to grasp as there is a thin line between telling different opinions and the untruth. According to Google Scholar only in 2017 and 2018 more than 13500 studies contain the term fake news. One of the most recognized study is the one Allcott and Gentzkow who present detailed figures on how fake news affected the 2016 election in the United States (Allcott and Gentzkow 2017).

To analyze the news computer-based in an empirical and quantitative way computer science research provides the fundamentals for this study. Since the 2000s computational sentiment analysis is a research area that has grown rapidly; Pang and Lee created one of the first comprehensive studies (Pang and Lee 2008). Sentiment analysis is done today with many machine-learning algorithms, such as Naïve Bayes, artificial neural networks, Support

Vector Machines, Logistic Regression, Conditional Random Fields, etc. Moreover, there are less generic approaches that detect the sentiment with the help of wordlists, n-gram lists, and similar techniques. The most recent comprehensive study on sentiment analysis with machine learning is by Liu (Liu 2015). While there is a vast volume of research in the field of machine learning and sentiment analysis, this study focuses on production-ready and tested algorithms. Several studies show that even simple algorithms perform well enough for this kind of study, with more than 85% correct sentiment predictions (Endres 2003, Domingos and Pazzani 1997, Potts 2011). There have been various efforts in the applied computer science domain to analyze the impact of the sentiment on economic indicators, stocks and financial markets. Zhang et al. report relations between the emotional words Hope, Happy, Fear, Worry, and others and the indices of NASDAQ, S&P500, Dow Jones Industrial and VIX (Zhang et al. 2010). When much hope or fear is uttered on Twitter, the indices tends to plunge the next day. Bollen et al. attempts to forecast the Dow Jones Industrial Index with the help of Twitter (Bollen et al. 2011). Feldman et al. analyze economic news with an algorithm that provides a better and deeper textual understanding (Feldman et al. 2011). Si et al. try to analyze the sentiment on specific topics and aspects, similar to Ren and Hong (Si et al. 2013, Ren and Hong. 2017). This study follows the approach of Starosta et al. and uses a Long Short Term Memory artificial neural network to analyze the sentiment in the media (Starosta et al. 2018a).
Moreover did the finding of Starosta et al. – that some differences in the perceptions could be explained neither by the differences in the coverage nor by a weak coverage in general – provide the impulse to this study (Starosta et al. 2019). If there is in general a broad consensus in the media reporting between the UK and Germany but there are significant outliers there must be some reason for this information gap. The reason for this information gap might be a distorted reporting. This study explicitly targets these information gaps and tries to reveal topic that suffer from distorted media reporting.

Research Question

In contrast to Starosta et al. 2019 this study does not try to explain all differences in the media reporting between the UK and Germany by differences in the coverage of a topic, but by specifically searching for topics with a distorted media reporting.

H1: A similar high presence of a topic in the German and the English media should lead to a similar perception of that topic in the sentiment indices.

H2: If a topic has a similarly high presence in the German and English media, but the sentiment regarding that topic differ greatly, it is due to distorted reporting.

Even though it is difficult to determine whether deviations at the end are actually biased news or only dissenting opinions, this study can give a good indication on where fake news and a distorted reporting lurks. In some cases fundamental reasoning can do the judgement if there are really fake news and in other cases the judgement is up to the reader.

Methodology

For the analysis, a corpus of news between 2010-01-01 and 2019-03-28 with a total number of 469’211 UK news and 1’637’502 German news was retrieved.

The methodology splits up into the four steps:

1. Analyze the most important topics in the observation period
2. Analyze the coverage of these topics in the UK and German media
3. If there is a similar (high) coverage analyze compare the sentiments regarding the identified topics over time

4. If there is high correlation between the sentiment indices hypothesis H1 is validated, if the correlation is weak we are very likely to see a distorted news reporting in one or the other country and hypothesis H2 can be analyzed.

Analysis of Important Topics

The most important terms in the period of observation are determined as proposed in Starosta et al. 2018c. Formula 1 shows how the rank of the terms are generated. The formula assumes that the most important words of the current text are used often in in that text but rarely in all other texts of our corpus.

$$Rank = \tanh\left(\frac{Occurences\ in\ Text}{Number\ of\ words\ in\ Text}\right) - 5 * \tanh\left(\frac{Occurences\ in\ Corpus - Occurences\ in\ Text}{Number\ of\ Words\ in\ Corpus - Number\ of\ Words\ in\ Text} * 200\right) \quad (4)$$

After the identification of the 2000 most important words we analyzed which of these words have the highest number of occurrences in the corpus. The 500 words with the most occurrences where considered for this study.

Analysis of the Coverage

We compare the coverage of the chosen topics between the UK and Germany by simply comparing the share of news mentioning the topic under observation in comparison to the total number of news. We define that a topic has a high coverage in both countries if the topic is mentioned in more than 0.3% of the news.

Creation of Sentiment Indices

The sentiment indices are created based on the methodology of Starosta et al. 2019. The indices are created with a LSTM neural network that analysis the sentiment of each news in the news corpus. These sentiments were then aggregated to sentiment indices that reflect the sentiment over time in the German and British media.

Hypotheses Testing

To verify or falsify the hypothesis, we conducted a correlation analysis between the sentiment indices of the UK and Germany for each topic.
To carry out this analysis, we used the ordinary least squares estimator [OLS], as displayed in Equation (8).

$$y = \beta_0 + Idx_t \beta_1 + \varepsilon \quad (8)$$

where Idx_t is the index data of Equation (7). However, as there are heteroscedasticity and autocorrelations in our time series, and it is not a reasonable approach to create different models for different topics, we used Newey-West standard errors to address the problems that arise with OLS estimators because of the existence of these properties.
To measure the goodness of fit between the British and German sentiment indices for each topic, we used the coefficient of determination adjusted by the degrees of freedom [$Adj\ R^2$].
To verify the H1 hypothesis, the indices should correlate strongly, and we reject the hypotheses H1 if the r < 0.7. If the correlation is weaker (news coverage is high for the topic under observation) we have an indication for a distorted media reporting in one or the other country (H2).

Results

Table 1 shows the results of the analysis. Topics marked with a "^" show which topics have a high media coverage (more than 0.3% of all news report on the topic) in both countries. Topics that are highlighted gray are topics that have a high media coverage in both countries but a lower correlation between the sentiment indices in each country (r < 0.7). In these topics hypothesis H1 is rejected and H2 can be analyzed. All other topics that are marked with a "^" and not highlighted in gray verify H1.

Table no. 1 Results

Topic	# of UK News	# of German News	% of UK news	% of German news	r
Apple ^	4658	10345	0.99	0.63	0.99
Bayer	211	7322	0.04	0.45	0.65
Bonds	9354	4481	1.99	0.27	0.99
Brexit ^	12634	6136	2.69	0.37	0.87
Britain ^	10991	6287	2.34	0.38	-0.88
China ^	30512	42643	6.5	2.6	0.97
Debt	22115	6688	4.71	0.41	0.99
Diesel	805	6239	0.17	0.38	0.91
Dollar ^	11291	111856	2.41	6.83	0.88
Draghi	1266	3593	0.27	0.22	0.96
ECB ^	4651	29943	0.99	1.83	0.96
Economy ^	19865	42947	4.23	2.62	0.99
EU ^	23359	72132	4.98	4.41	-0.78
Euro ^	19640	332220	4.19	20.29	0.98
Europe ^	40022	41462	8.53	2.53	0.81
Facebook ^	4057	7126	0.86	0.44	0.94
Fed ^	9404	15439	2	0.94	0.96
France ^	6999	7104	1.49	0.43	0.62
Germany ^	7674	96717	1.64	5.91	-0.89
Glyphosate	30	469	0.01	0.03	0.94
Gold ^	4862	39886	1.04	2.44	0.84
Google ^	4013	19019	0.86	1.16	0.97
Greece ^	5383	19016	1.15	1.16	0.93
IMF ^	2772	5453	0.59	0.33	0.91
Inflation ^	9969	9755	2.12	0.6	0.99
Israel ^	2937	3075	0.63	0.38	-0.98
Italy ^	5291	11214	1.13	0.68	0.63
May (Theresa) ^	71692	67012	15.28	4.09	0.42
Merkel ^	2595	14211	0.55	0.87	0.93
Obama	6842	3025	1.46	0.18	0.13
Oil ^	21121	23199	4.5	1.42	0.44
Refugees ^	1106	455	0.48	0.6	0.81
Russia ^	11391	10778	2.43	0.66	0.19

Snowden	279	358	0.06	0.02	0.3
Spain ^	4285	5933	0.91	0.36	0.39
Trade Balance	56	2002	0.01	0.12	0.94
Trump ^	12183	12343	2.6	0.75	0.63
Ukraine ^	2696	5817	0.57	0.36	0.79
US ^	89503	227187	19.08	13.87	0.93
VW	1020	12862	0.22	0.79	0.88
Washington	4910	4580	1.05	0.28	-0.98

Discussion

The analysis shows that indeed the UK and Germany share the same values on many topics and that in most cases hypothesis H1 is satisfied, if there is a high or moderate media presence in both countries. The topics where H1 is violated but where still a high media presence is and thus H2 is satisfied are indeed controversial. In these cases the media in one country seems to report on an "alternative" truth. It is not possible to evaluate who is right or who is wrong in these cases even if a benchmark indicator might give an indication as discussed in Starosta et al. 2019. The only way to identify the distorted reporting is a substantial analysis of the evaluation topic. Three interesting cases are Israel, Russia and Trump that we found in this study might truly be a biased reporting. The history of WWII could lead Germany to report on Israel in a rather benevolent manner compared to the UK. In addition, the "too" good relationship between Germany and Russia (that is currently criticized by the US) might be reflected in the media. Further, the cases France, Italy, Spain, Germany and EU could probably be explained by the ongoing British aversion to the EU. However, this study cannot and should not provide any further substantial analysis at this point, but it is clear that the news are biased in one or the other of the analyzed countries.

Conclusions

We could show that our approach can consistently find topics with biased and distorted news. These biases have a clear business impact – sometimes on a larger and sometimes on a smaller scale. A billion dollar project like the new natural gas pipeline "North Stream II" between Russia and Germany would probably politically not be possible with a less benevolent media reporting of Russia in the German media. Further, the Brexit might never have been an issue if the media reporting on the EU countries and the EU itself would have been more "German" and friendlier in the UK. Even if this does not explain which media reports are right or wrong, it shows that the economy and all businesses are affected by the media perceptions regardless of whether they are right or wrong. While these are two prominent examples, where a biased media reporting played its part, biased and distorted media reporting also has a big impact on all small and medium size enterprises. In addition to the results of this study, the new approach to find biased media reporting will help to analyze the impact of it on all kinds of businesses and for all topics further.

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