

Measuring Context Change to Detect Statements Violating the Overton Window

Christian Kahmann and Gerhard Heyer

Department for Natural Language Processing, Leipzig University, Augustusplatz 10, Leipzig, Germany

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Abstract: The so-called Overton window describes the phenomenon that political discourse takes place in a narrow window of terms that reflect the public consensus of acceptable opinions on some topic. In this paper we present a novel NLP approach to identify statements in a collection of newspaper articles that shift the borders of the Overton window at some period of time, and apply it on German newspaper texts detecting extreme statements about the refugee crisis in Germany.

1 MOTIVATION

A central task in the Digital Humanities is to transform a humanities or social science research question into a format where digital data and computational analyses become key components of the research. In what follows we shall consider the very notion of *Overton window* in political science, and discuss how this notion can be applied in the context of media analyses using suitable text mining methods. The Overton window is a theory which aims to explain why at some time the consensus of socially accepted opinions and statements changes, and what is behind the dynamics of political discourse (Lehman, 2018). In detail, it describes the phenomenon that political discourse takes place in a narrow window of terms that reflect the public consensus of acceptable opinions on some topic. The Overton window has recently attracted public attention in connection with the growth of populism in the USA and Europe noticing that populists have shifted the Overton window of acceptable public discourse rightwards (Bugarcic and Kuhelj, 2018). In this paper we will introduce an approach of how to automatically identify newspaper articles and with that, statements of politicians, which displace the Overton window for a predefined topic (set of words describing a political issue). In order to solve this complex task, we will use several steps using different techniques of Natural Language Processing.

2 REALIZATION

The basic idea of our approach is to identify, for a set of words and period of time (reference), the *standard context* of words. Using this as a reference, we evaluate new documents with respect to their co-occurrence behaviour in relation to the learned reference context. If they contain a high proportion of words that have never been used, or used differently, in the reference, it is more likely that they reflect a new (and possibly extreme) opinion, thus serving as an indicator of an extreme opinion or statement shifting the Overton window.

2.1 Data Set

The basis for our approach are newspaper texts from the German daily newspaper taz¹. We use articles published in the time between 2010 and 2018 producing a set of 339367 documents. The discourse of interest in this paper is the refugee crisis in Germany. Hence we limit the set of documents to those that deal with refugees in any manner, resulting in a set of 37966 documents.

2.2 Identify Target Words

At first we need to define a set of words which represent our target topic. To achieve that, we calculate co-occurrence statistics based on a sentence term matrix

¹<http://www.taz.de/>

of the reduced corpus. Afterwards we extract synonyms for the word "flüchtling" (refugee) using the cosine similarity based on the co-occurrence vectors. We are using Dice significance.

Table 1: Extracted synonyms (target words) for source word "flüchtling" and the corresponding cosine similarity.

word	cosine similarity
flüchtling	1
syrer	0.279
geflüchtete	0.2626
asylbewerber	0.275
migrant	0.239
asylsuchender	0.228
ausländer	0.196

2.3 Learn Reference

Having done this, we set a reference range of time which will serve as our test set. In more detail, we used 8067 documents in the time between 2013-01-01 to 2014-12-31 concerning refugees. This resulted in 386632 sentences. We then applied pre-processing (tolower, stopword-, number-, hyphenation removal). We used uni- and bi grams for our analysis. A sentence term matrix stm was created based on the finished pre-processing. This resulted in a set of 106285 features. In order to model the standard context of multiple words with one variable, we created a synthetic column representing the set of target words. In this column an entry is either 0 or 1. The calculation is shown in formula 1.

$$stm_{i,syn} = \begin{cases} 1 & \text{if } \sum_{k=1}^m stm_{(i,k)} \geq 1 \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

m = number of words in the target set

Next we calculated the co-occurrence significance for the synthetic word that represents our target set of words. The result is a vector with a length equal to the vocabulary size, whereby each entry corresponds to the significance value for the particular word and our target set of words. The most likely words to occur together in the same context with refugees are shown in table 2. The calculated dice significance values were normalized to improve the functionality of the distance measure.

Table 2: Top co-occurrences of target word set with their dice significance and the normalized reference weight.

word	dice significance	weight ²
deutschland	0.061	1
oraniensplatz	0.059	0.976
berlin	0.043	0.711
leben	0.043	0.704
schule	0.041	0.669
senat	0.037	0.61
unterbringung	0.034	0.563
hamburg	0.033	0.549
zahl	0.033	0.542
italien	0.032	0.524
syrien	0.031	0.513
land	0.031	0.51
migration	0.027	0.451
millionen	0.026	0.432
untergebracht	0.026	0.43
migration_flüchtlinge	0.025	0.413
europa	0.025	0.405
derzeit	0.024	0.4
stadt	0.024	0.397
gruppe	0.024	0.394
aufnahme	0.024	0.391
aufnehmen	0.023	0.383
lampedusa	0.023	0.377
syrische	0.023	0.37
taz	0.022	0.363
polizei	0.022	0.361
bremen	0.021	0.353
flüchtlinge_oraniensplatz	0.021	0.353
spd	0.021	0.35
syrische_flüchtlinge	0.021	0.343
bezirk	0.021	0.341
bleiben	0.021	0.34
bundesamt	0.021	0.338
unterkunft	0.02	0.33
unterbringung_flüchtlingen	0.02	0.325
wohnungen	0.019	0.316
bundesamt_migration	0.019	0.315

2.4 Apply Distance Measure

We define distance as the amount of unpredictability for a given sentence. A measure is used, which is close to Context Volatility (Kahmann et al., 2017), to calculate a score for every sentence in the test set quantifying how much this sentence differs from

²normalized weights, reflecting the relative likelihood of a word appearing together with the target words inside a sentence

what was seen in the reference corpus. In contrast to Context Volatility (CV) we are measuring the context change for a set of words for a single sentence whereby CV works on a single word on a set of documents over time. The distance for the i 'th sentence s is calculated by using the combination of sum ϕ and mean τ of word distances per sentence:

$$\tau_{s_i} = \frac{\sum_{j=1}^n (1 - ref(w_j))}{n} \quad (2)$$

$$\phi_{s_i} = \sum_{j=1}^n (1 - ref(w_j)) \quad (3)$$

with j words w in s_i and $ref(w_j)$ representing the normalized reference significance weight for the j 'th word in sentence s_i . Using the mean solely, sentences consisting of only one unknown word would be ranked highest. Taking the sum of words distances only, would lead to a preference for very long sentences. Therefore, we combine both values using a factor λ . To make the combination work, we need to set the range for the sum of word distances per sentence to same interval as the mean values $[0, 1]$.

$$\phi_s^{norm} = \frac{\phi_s}{max(\phi_s)} \quad (4)$$

Our results are created with $\lambda = 0.90$. We use a big λ , because the calculated values for $mean_{s_i}$ are very dense ($\mu = 0.923$, $\sigma = 0.059$). Whereas the sums reveal a much higher variation ($\mu = 0.186$, $\sigma = 0.105$).

$$d_{s_i} = \lambda * \tau_{s_i} + (1 - \lambda) * \phi_{s_i}^{norm} \quad (5)$$

The range of the results is located between 0 and 1. We see a maximal distance of 1, when a sentence with the maximum number of words (in the test set) only contains words that have never co-occurred with any one of the target words in the reference corpus. The distance for a sentence that only uses the word "Deutschland" together with one of the target words (reference weight 1) is 0.

Table 3: Example sentence: "Sie sind Flüchtlinge vom Oranienplatz." The missing words are reduced during the pre-processing in the step of stopword removal. Calculated distance for this sentence is 0.3325, and with that it has the shortest distance relating to the learned reference.

word	oraniplatz	flüchtlinge_oraniplatz
distance	0.024	0.647

2.5 Indicators for Statements

Applying the algorithm enables the discovery of sentences that deviate from the "standard" as defined for

a certain topic. In this paper we are especially interested in statements from politicians or other prominent agents. We therefore limit our analysis to sentences that have an indicator for including a statement. The presence of words like "sagte"(said), "behauptet"(asserted) and also quotations marks are applied as a filter. This reduced our analysis base from overall 14894 sentences containing at least one of the target words, to 3126 sentences containing both, target word(s) and statement indicator during the defined test period of time.

3 RESULTS

We apply the shown mechanism on articles in the time from 2015-01-01 to 2015-12-31.

Table 4: Result excerpt of sentences with highest and lowest distance.

sentence s	distance d_s
Das Online-Magazin Vice titelt "Warnschüsse gegen Flüchtlinge :	0.9909
Flüchtlinge wollen vom Tellerwäscher zum Millionär werden, da ist keine Zeit für irgendein Ministeramt.	0.9909
"Oft ging es um Flüchtlinge, die von Schleuserbanden ausgeraubt oder zusammengeschlagen wurden.	0.9907
Als Motiv gab der Feuerwehrmann an, keine Flüchtlinge in seinem Wohnumfeld haben zu wollen.	0.9907
Clowns quälen Flüchtlinge.	0.9904
Es gibt immer mehr davon, Bildungserfolg von Migranten ist doch nichts Exotisches mehr.	0.9904
Jetzt wollen diese Schreckensgestalten auch noch bedauernswerte Flüchtlinge quälen.	0.9903
"Er hat mit dem Tötungsdelikt an dem Asylbewerber aber nichts zu tun.	0.9902
...	...
Syrer sollen nicht alle nach Deutschland kommen.	0.4812
"Jeder dritte Syrer und jeder fünfte Afrikaner will nach Deutschland", sagt er.	0.4762
Wie viele Flüchtlinge sind in Deutschland?	0.3966
Sie sind Flüchtlinge vom Oranienplatz.	0.3325

We are able to find sentences with words, that reveal new contexts. With this basic approach we can't guarantee that every found sentence is extreme

in the sense of a statement outside the Overton window (see table 4: "Bildungserfolg von Migranten" - *Educational success of immigrants*). Nevertheless we find a high amount of sentences and especially statements, that seem to exceed the boundaries of the Overton window in extreme manner (see table 5: "Warnschüsse gegen Flüchtlinge" - *Warningshots versus refugees*).

3.1 Reduction on Statements

The same can be said for the found statements. The filtering for finding statements works. The found sentences reflect opinions and statements of different agents. Many of them tend to be interesting in the concern of finding extreme assertions.

Table 5: Result excerpt after filtering for statements of sentences with highest and lowest distances.

sentence s	distance d_s
Das Online-Magazin Vice titelt "Warnschüsse gegen Flüchtlinge :	0.9909
"Oft ging es um Flüchtlinge, die von Schleuserbanden ausgeraubt oder zusammengeschlagen wurden.	0.9907
"Er hat mit dem Tötungsdelikt an dem Asylbewerber aber nichts zu tun.	0.9902
Auf Ausländer schmeißt man Steine "Wir sollten gar nicht hier sein", sagt Philipp.	0.9901
Diese Migranten sind wie Kakerlaken", steht schon in der Unterzeile."	0.9901
"Ich nehm die Asylbewerber mit", sagt ein Passant.	0.9892
"Wir können Ausländer klatschen!	0.9891
Premierminister David Cameron bezeichnete die Migranten als "Menschenschwärme".	0.9889
...	...
"Aber ich habe in den Nachrichten gehört,dass jeder dritte Afrikaner und jeder fünfte Syrer nach Deutschland will".	0.7512
" Immer mehr Flüchtlinge leben deshalb illegal im Land", sagt Beuze.	0.7258
" Deutschland, Deutschland", skandieren die Flüchtlinge.	0.6533
"Jeder dritte Syrer und jeder fünfte Afrikaner will nach Deutschland", sagt er.	0.4765

4 LIMITATIONS

A big problem that must be dealt with in further work is the fact that the use of new words does not always necessarily reflect an opinion outside the Overton window. Often co-occurrences are given a high distance value simply because this combination was not used in the previous period. The non-use, however, cannot be attributed to the fact that it was politically incorrect to make a corresponding statement during the reference period, but rather to random effects. This effect increases as the amount of text decreases.

In the efforts so far, only the changes from a reference period to a test period have been considered. According to the theory of the Overton window, however, statements outside the window should also shift the future public opinion in the direction, which the statement indicates. Therefore, the next step would be to estimate this shift. A possible approach might be looking at a time window after a statement, which shows a large distance to the reference. If a similar behavior is found in the following documents, the statement may have a high impact on public opinion and was able to shift the Overton window and hence is an even more interesting statement to extract.

The 2-dimensional orientation of the Overton window, which models political extremes (left vs. right, pro-refugee vs. contra-refugee...) has not yet been considered. So far, changes from the reference have not been classified into political extremes. Only the deviation itself has been used for further analysis. The categorization of statements into political positions would require a better semantic understanding of statements. Here various approaches might be conceivable (e.g. SVM-classification, semantic embeddings...).

Another exciting approach is the diachronic view of the Overton window. To specify exactly what seems to be socially accepted according to data at what time and what is not, are thrilling questions. Also to know at what time the window changes very strongly and at what times it remains stable, is exciting.

In addition it is imperative to develop an evaluation possibility for the described measurements of the Overton window. As there is no gold standard yet which places political statements in the dimensions of the Overton window. In order to check the validity of the calculations, a synthetic data set could be used which adequately models the underlying dynamics of the Overton window. However, the final evaluation will always require the cooperation and judgment of an domain expert (e.g. political scientist).

In summary, it can be said that the work on text data with the basic assumption of the Overton window provides many exciting analyses. However, these have to be processed in future work. Nevertheless, the first results already show promising results.

5 FURTHER WORK

One of the next changes to be made is the shift from co-occurrence statistics to the use of embeddings. At the moment we are dependent on the mere presence and identical use of a number of "learned" terms from the reference period. By using embeddings in general and sentence embeddings (Wieting et al., 2016) in particular, we hope to be able to solve some of the mentioned limitations. So hopefully it would be possible to assign political statements to different camps using embeddings. The use of sentence embeddings would also assist with the previous problems of different sentence lengths during the distance calculation by being able to use a distance measure for vectors with the same dimensions (no matter the length of the sentence).

6 CONCLUSION

The mechanism uses basic co-occurrence statistics and nonetheless enables the detection of unusual contexts around a set of target words. With that, we enable locating statements, that may exceed the limits of the Overton window and as a consequence shift the political discourse in the society. More advanced approaches like sentence embeddings (Mikolov et al., 2013), might be able to generate even more reasonable results. The segmentation of the resulted sentences towards one of the two basic attitudes about a political discourse is an issue which needs to be addressed in future work.

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