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Frame Detection in German Political Discourses: How Far Can We Go Without Large-Scale Manual Corpus Annotation?

Abstract

Automated detection of *frames* in political discourses has gained increasing attention in natural language processing (NLP). However, earlier studies in this area focus heavily on frame detection in *English* using *supervised* machine learning approaches. Addressing the difficulty of the lack of annotated data for training and evaluating supervised models for low-resource languages, we investigate the potential of two NLP approaches that do not require large-scale manual corpus annotation from scratch: 1) LDA-based topic modelling, and 2) a combination of word2vec embeddings and handcrafted framing keywords based on a novel, expert-curated framing schema. We test these approaches using an original corpus consisting of German-language news articles on the "European Refugee Crisis" between 2014-2018. We show that while topic modelling is insufficient in detecting frames in a dataset with highly homogeneous vocabulary, our second approach yields intriguing and more humanly interpretable results. This approach offers a promising opportunity to incorporate domain knowledge from political science and NLP techniques for exploratory political text analyses.

1 Introduction

Print media plays a substantial role in forming public opinion. *Framing*, defined by Entman (1993) as "select[ing] some aspects of a perceived reality and mak[ing] them more salient in a communicating text (...)", has been shown by political communication studies to have a consistent influence on citizens' political opinions (Druckman, 2004; Nelson & Oxley, 1999; Slothuus, 2008). In the field of NLP, recent years have witnessed growing attention on the automated detection of frames in political discourse (e.g., Baumer, Elovic, Qin, Polletta, & Gay, 2015, Card, Gross, Boydstun, & Smith, 2016, Field et al., 2018, Khanehzar, Turpin, & Mikolajczak, 2019, Cabot, Dankers, Abadi, Fischer, & Shutova, 2020).

Notwithstanding these developments, earlier studies comprise two major limitations. First, many of these studies apply supervised machine learning approaches and thus rely heavily on manually labeled data (a detailed review follows in Section 2). Second, as a consequence of this need of manually labeled data, the majority of the earlier studies utilize the English-language, human-annotated Media Frames Corpus (MFC; Card, Boydstun, Gross, Resnik, & Smith, 2015), thus neglecting framing in non-English language contexts, for which only few or no annotated data is available. Specifically, since the annotation of frames requires a deep understanding of both the text material itself and the background of the issue discussed in the text, creating large-scale annotated datasets in a high quality - such as the MFC - is time-consuming and labor intensive. This expensive enterprise would therefore be prohibitive for many low-resource languages.

To address these two limitations, this paper investigates the potential of unsupervised and knowledge-based NLP approaches for automated frame detection in cases where few to none labeled data is available. We use non-annotated German-language newspaper articles on the so-called "European Refugee Crisis" of 2014-2018 as data, and experiment with two approaches: 1) LDA-based topic modelling (Blei, Ng, & Jordan, 2003), and 2) a combination of word2vec (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013) and carefully selected framing keywords. Our contributions are three-fold:

1) We show that topic modelling is insufficient in detecting frames in a dataset with highly homogeneous vocabulary;

2) We propose a novel framing schema, the *Refugees and Migration Framing Schema*, which is specifically designed to analyze frames in the context of refugees and migration;

3) We show that the combination of word2vec and the handcrafted framing keywords based on our *Refugees and Migration Framing Schema* has a greater potential than topic modelling when conducting data-driven explorations of frame differences, as these results are more explainable. We release the resulting framing keywords as a publicly available lexical resource under: `https://github.com/qi-yu/refugees-and-migration-framing-vocabulary`

2 Related Work

Owing to the public availability of the large-scale MFC, which includes manual annotations of frames based on the codebook of Boydstun, Card, Gross, Resnik, and Smith (2014), a large amount of previous studies on frame detection have focused on the classification of the frame categories annotated in the MFC. The methods used vary from neural networks, such as Ji and Smith (2017) (RNN) and Naderi and Hirst (2016) (LSTM and GRU), to state-of-the-art language models as in Khanehzar et al. (2019) (XLNet, BERT and RoBERTa) and Cabot et al. (2020) (multi-task learning models combined with RoBERTa). Further studies using similarly supervised or weakly supervised settings, but based on other manually annotated datasets than the MFC, include Baumer et al. (2015); Johnson, Jin, and Goldwasser (2017); Liu, Guo, Mays, Betke, and Wijaya (2019); and Mendelsohn, Budak, and Jurgens (2021).

Frame detection in languages other than English remains greatly neglected so far. To the best of our knowledge, Field et al. (2018) and Akyürek et al. (2020) are the only two studies of this kind. Field et al. (2018) employ the annotations in MFC to extract a frame lexicon for each frame category. This English-language lexicon is then translated to Russian and used for identifying frames in Russian newspapers. Their work provides a transferable method for other languages lacking annotated data. Akyürek et al. (2020) use multilingual transfer learning to detect frames in low-resource languages by translating framing-keywords extracted from the MFC to the target language and then training classifiers on the code-switched texts. However, an application of this method on a low-resource target language still requires an available gold standard of that target language, in order to evaluate the performance of the trained model. In Akyürek et al. (2020), this is again achieved by manually annotating the texts of the target language.

3 Data Collection

In our work here, we investigate the effectiveness of NLP approaches in frame detection that do not require large-scale corpus annotation from scratch. For this purpose, we use a novel corpus of German newspaper articles on the "European Refugee Crisis" between 2014-2018 as data, for which no prior annotation of frames is available. In order to build a wide representation of different styles (broadsheet vs. tabloid) and political orientations of the German press, while at the same time assuring comparability between newspapers, we selected the newspapers *BILD*, *Frankfurter Allgemeine Zeitung* (FAZ) and *Süddeutsche Zeitung* (SZ) for our study. All three are nation-wide daily newspapers. With the slightly right-leaning FAZ and the center-left-leaning SZ (Pew Research Center, 2018), our sample is balanced and covers a range of the political spectrum within the media landscape in Germany. Moreover, by including BILD, we did not only incorporate a tabloid, but also brought together the three most highly-circulated printed newspapers in Germany (Deutschland.de, 2020).

From each newspaper, articles containing at least one match with the following quasi-synonyms of 'refugee' (including all their inflected forms) were selected: {*Flüchtling*, *Geflüchtete*, *Migrant*, *Asylant*, *Asylwerber*, *Asylbewerber*, *Asylsuchende*}. We refer to this set of keywords as *refugee-keywords* in later sections. In a post-hoc cleaning phase, articles with a ratio of *refugee-keywords* smaller than 0.01 and articles from non-political sections such as *Sport* were excluded. After the cleaning phase, we obtained the dataset reported in Table 1.[1]

newspaper	category	#articles	#tokens
BILD	R, T	12,287	3,554,105
FAZ	R, B	6,832	3,526,323
SZ	L, B	4,770	1,893,868

Table 1: Dataset overview. (R = right-leaning; L = left-leaning; T = tabloid; B = broadsheet)

[1] The newspaper articles were purchased from the respective publishers. Unfortunately, due to their copyright regulations, we cannot make the corpus publicly available.

4 Experiment 1: Detecting Frames Using Topic Modelling

As the task of detecting frames strongly resembles the detection of sub-aspects within the event under discussion, it is reasonable to give topic modelling a trial as a first bottom-up, data-driven method for exploring differences in frames between the newspapers. We therefore trained one LDA-based model per newspaper to explore frame differences between the publications.

4.1 Training

We used the Python library *Gensim* (Řehůřek & Sojka, 2010) to train the models. Monograms, bigrams and trigrams are used for training. The following preprocessing steps were done prior to the training:

1) All articles were tokenized and lemmatized using the *Stanza* NLP kit (Qi, Zhang, Zhang, Bolton, & Manning, 2020). All stop words, numbers, punctuation marks and URLs were removed;

2) For each newspaper, n-grams with a document frequency higher than 0.15 and n-grams occurring less than 5 times were excluded;[2]

3) Since the *refugee-keywords* appear in all articles, we masked them in order to eliminate their interference in the topic modelling algorithm. Note that not all of them can be excluded by step 2) since not all of them have a document frequency higher than 0.15.

Topic modelling requires the number of topics K to be pre-defined. As we do not have gold standard data available, we use the C_v coherence score as a measure to search for the optimal value of K, as well as to evaluate the model performance. The C_v coherence score is proposed by Röder, Both, and Hinneburg (2015) as the best performing coherence measure. C_v yields a value in the range of $[0, 1]$. The closer the value is to 1, the more coherent the resulting topics are.

4.2 Results and Discussion

Figure 1 shows the C_v coherence scores of the LDA models trained respectively on BILD, FAZ and SZ for $K \in [2, 200]$, using 50 iterations. As indicated in the figure, C_v stops growing significantly after $K = 80$, $K = 90$ and $K = 78$ for BILD, FAZ and SZ, respectively. Thus, we chose 80, 90 and 78 as the optimal topic numbers for the final training, again using 50 iterations.

Yet, the results of the topic modelling approach post two major problems for our aim of detecting and comparing frame differences between the newspapers: First, the

[2] The threshold of document frequency as 0.15 was defined experimentally. With the threshold set as 0.15, most of the high-frequency items with little discriminative power for the topic of refugees and migration, such as *Mensch* ('People') and *Jahr* ('year'), can be excluded.

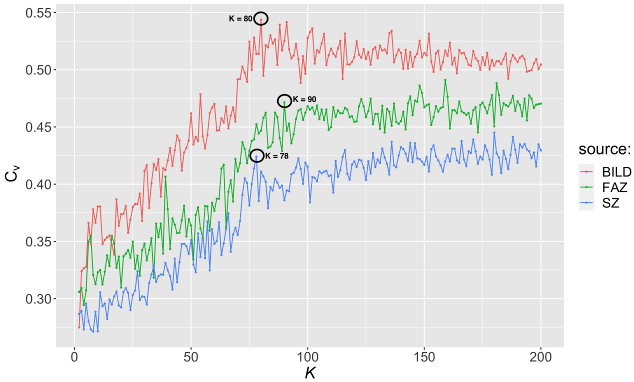

Figure 1: C_v coherence score of topic number $K \in [2, 200]$ in BILD, FAZ and SZ.

resulting C_v scores with the optimized K values are at a rather low level (BILD: $C_v = 0.544$, FAZ: $C_v = 0.471$, SZ: $C_v = 0.424$). A manual evaluation of the most dominant words in each resulting topic also suggests a high degree of overlap between topics, as illustrated in Table 2. Second, the high number of K considerably complicates human interpreting of the overall topic differences between newspapers. The results can therefore barely inform further analyses of framing differences between the publications.

A possible explanation for the poor performance of topic modelling is that the degree of vocabulary homogeneity among the articles in our dataset is fairly high, since all articles focus thematically on issues related to refugees and migration. This contrasts to other more vocabulary-heterogeneous datasets on which LDA-based topic modelling has been shown to achieve much clearer topic division, e.g., the 20 NewsGroups corpus used in Harrando, Lisena, and Troncy (2021), the Wikipedia corpora used in Markoski, Markoska, Ljubešić, Zdravevski, and Kocarev (2021), or the IMDB movie review dataset used in Kherwa and Bansal (2020). In a closer manual check of the dataset and the topic modelling results, we found that many words appear in different sub-topics due to their high relevance to the overall topic of refugees and migration, e.g., the keywords *Syrien* ('Syria'), *Land* ('country') and *Zahl* ('number') can either appear in discussions of refugee allocation policies or in reports about security on the Eastern Mediterranean Route. This "stop word-resembling" behavior of such words may confuse the topic modelling algorithm. However, eliminating such words would lead to a loss of information in the results since they, unlike real stop words, bear highly relevant information for the context of refugees and migration. We leave further theoretical and empirical investigation on the reason of the poor performance of topic modelling for future studies, as this is beyond the scope of the current paper.

source	topic modelling results	remark
BILD	**Topic 21:** Vergewaltigung (rape), DNA (DNA), Abschiebepraxis (deportation practice), Feuerwehrmann (firefighter), Komplize (accomplice), Altena (Altena), Benzin (gasoline), Baden_Württemberg (Baden Württemberg), wegen_versuchtem_Mord (because of attempted murder), N. (N.) **Topic 23:** Jugendliche (youths), Mitarbeiterin (employee), Landkreistag (county council), Angreifer (attacker), Sexualdelikt (sexual offense), Schuss (shot), schwer_verletzt (heavily injured), Organisation_pro_Asyl (organization 'Pro Asyl'), Messer (knife), Polizei (police)	Both topics are about criminality and violence. Ideally, they should be aggregated to one topic.
FAZ	**Topic 77:** Griechenland (Greece), EU (EU), mehr (more), Million_Euro (million Euro), Land (country), Band (band), Europa (Europe), Türkei (Turkey), Integration (integration), Kreis (district) **Topic 80:** Türkei (Turkey), EU (EU), Griechenland (Greece), Ankara (Ankara), Europa (Europe), Brüssel (Brussels), türkisch (Turkish), EU_Staat (EU country), Flüchtlingskrise (refugee crisis), Erdoğan (Erdoğan)	Both topics are about the "refugee crisis" in terms of the Eastern Mediterranean route of refugees and the EU.
SZ	**Topic 49:** Merkel (Merkel), Seehofer (Seehofer), Kanzlerin (chancellor), CDU (CDU), CSU (CSU), Flüchtlingspolitik (refugee policy), Partei (party), Union (union), AfD (AfD), Land (country) **Topic 61:** SPD (SPD), Bund (federation), Berlin (Berlin), Deutschland (Germany), Seehofer (Seehofer), Bundesregierung (federal parliament), Land (country), fordern (demand), mehr (more), neu (new)	Both topics are about domestic refugee policies and party competition.

Table 2: Overlapping topics in the results of topic modelling. The 10 most dominant items of each topic are listed.

5 Experiment 2: Detecting Frames Using *word2vec* and Framing Vocabulary

Facing the low-quality results of the bottom-up, data-driven topic modelling method, in our second experiment we investigate a top-down, theory-driven method. First, we deductively compiled a framing schema specifically tailored to the issue "refugees and migration" along which we can thematically classify and sort given frames in our data. Next, we created framing vocabulary lists for each category of our framing schema to further explore frame differences between newspapers that cannot be detected via topic modelling. This method is inspired by the observation and empirical verification in earlier studies that framing in news is to a large extent a keyword-driven phenomenon (Akyürek et al., 2020; Field et al., 2018; Johnson et al., 2017).

5.1 Creating the *Refugees and Migration Framing Schema*

Our Refugees and Migration Framing Schema is based on two theoretical works: 1) the general categorization of arguments by Habermas (1991), and 2) the extensive frame schema developed by Boydstun et al. (2014). We decided against creating a completely new framing schema in an inductive fashion (this is done by, amongst others, Helbling, 2014) for two reasons: First, the work of Habermas (1991), rooted in philosophical theory, generally distinguishes types of arguments that can justify actions (in our case these "actions" are attitudes towards refugees; see also Helbling, 2014 and Sjursen, 2002). He distinguishes between *identity-related*, *moral-universal* and *utilitarian* arguments. By applying his theory, we arrange for an *extremely broad* range of kinds of arguments. Second, building on Boydstun et al. (2014) allows us to benefit off an already well-established and empirically verified frame schema. This schema is – unlike other published framing schemata such as Baumgartner, de Boef, and Boydstun (2008) and Iyengar (1994) – designed to focus not only on a single issue, but includes very general, high-level issue dimensions of frames, beneath which more issue-specific categorizations can be specified. It therefore provides a comprehensive fit to parts of the general categorization by Habermas (1991). However, because the schema by Boydstun et al. (2014) is originally tailored towards coding and differentiating enacted *policies*, it predominantly provides detailed and meaningful differentiations of frames in the category of *utilitarian* arguments in Habermas (1991). For our final Refugees and Migration Framing Schema, we therefore innovatively compiled the two theoretical works to incorporate the issue-related, scientifically evaluated breadth of the work by Boydstun et al. (2014), while providing for additional relevant categories presented by Habermas (1991). The resulting schema is elaborated in Table 3 (see columns *category* and *description*).

5.2 Creating the *Refugees and Migration Framing Vocabulary*

For each of the frame categories in our *Refugees and Migration Framing Schema*, we created one vocabulary list containing informative keywords for that category. The following two sources are utilized for constructing our *Refugees and Migration Framing Vocabulary*:

1) **Seed vocabularies by domain experts + GermaNet**: With an exploratory reading of a sample of articles from our corpus, 5 domain experts (graduate students of political science) listed words and phrases that they found highly relevant to each frame category in our schema. These seed vocabulary lists were then expanded by synonyms of each item, found using GermaNet (Hamp & Feldweg, 1997; Henrich & Hinrichs, 2010).

2) ***DEbateNet-mig15* corpus**: The DEbateNet-mig15 corpus (Lapesa et al., 2020) is, to the best of our knowledge, the only annotated corpus of news on refugees and migration in German language. DEbateNet-mig15 contains 3,442 text passages from the German newspaper *Die Tageszeitung* (TAZ) in 2015 that are annotated as *claims* (i.e., statements made by political actors). The annotation was carried out using an ad-hoc annotation schema with eight high-level categories inductively developed by the authors.

We are aware that the *claims* annotated in DEbateNet-mig15 are by definition not equal to *frames*: While claims are strictly action-related, frames emphasize a certain aspect of an issue, whether action related or static. We also admit that a certain bias of word usage cannot be ruled out as DEbateNet-mig15 only contains data from the left-leaning TAZ. Nevertheless, DEbateNet-mig15 qualifies as an immediate base for the expansion of our *Refugees and Migration Framing Vocabulary* for two reasons: First, though claims per se differ from frames, the categorization of claims in DEbateNet-mig15 resembles frames to a large extent, i.e., claims are categorized based on the aspect(s) they emphasize. Second, the data of DEbateNet-mig15, as mentioned above, is in German language and arises from the same political issue as the one under investigation in our study. Considering these two reasons, we opted out of extracting vocabularies from corpora that are directly annotated with frames but are from different political

categories by Habermas (1991)	frame	description: frames...	exemplary keywords
utilitarian	economy*	... related to jobs, education, financial issues, etc., incl. *human resources frames*, *material resources frames*	Armutsflüchtling (poverty refugees), Arbeitskräftemangel (labor shortage), Ausbildung (training)
	legal	... related to legal questions, incl. *jurisprudence frames*, *law frames*	Rechtsanspruch (legal entitlement), Bleibeperspektive (perspective to stay), Asylrecht (asylum right)
	policy	... related to concrete policies enacted by government, incl. *national policy frames*, *international policy frames*	Visum (visa), Richtlinie (guideline), Flüchtlingsquote (refugee quota)
	politics*	... regarding political proceedings and party competition	Asylstreit (Asylum-dispute), GroKo (grand coalition), Opposition (opposition)
	public opinion*	... on public attitudes and moods	Demonstration (demonstration), Meinungsmache (propaganda), Öffentliches Interesse (public interest)
	security*	... on violence and safety related issues, incl. *national security frames*, *terrorism frames* and *crime frames*	Anschlag (assault), Verbrechensrate (crime rate), Schlepperbande (human trafficking ring)
	welfare	... on questions of benefit provision, incl. *health care frames*, *welfare benefit frames*	Sozialhilfe (social care), Hartz-IV (Hartz-IV), Versicherung (insurance)
moral-universal	morality*	... concerning ethics and moral concepts, incl. *humanitarianism frames*, *fairness and equality frames*	Menschenwürde (human dignity), Willkommenskultur (welcoming culture), solidarisch (showing solidarity)
identity-related	identity*	... regarding group membership and individual senses of belonging, incl. *nationalism frames*, *cultural identity frames*	Herkunftsland (country of origin), Muslim (Muslim), rechtsextrem (right-wing extreme)

Table 3: *Refugees and Migration Framing Schema* and corresponding example keywords to each category extracted with methods described in Section 5.2. *Category names following Boydstun et al. (2014).

backgrounds and/or in different languages, such as the MFC or the Gun Violence Frame Corpus (Liu et al., 2019).

For each of the eight high-level categories C in DEbateNet-mig15, we extracted the top 200 words w with the highest *pointwise mutual information* (PMI; Church & Hanks, 1990) to C:

$$PMI(C, w) \equiv log\frac{P(C, w)}{P(C)P(w)} = log\frac{P(w|C)}{P(w)} \tag{1}$$

Since the annotation schema of DEbateNet-mig15 diverges from our *Refugees and Migration Framing Schema* - although some of their categories are either identical to or are a subset of our categories - we re-sorted the extracted words into the suitable categories in our schema.

After merging the vocabulary lists obtained from the two sources above, a manual evaluation of the lists was conducted. In the evaluation, items that are too general and thus non-informative for detecting specific frame categories (e.g., *Einwanderung* 'migration', *wenigstens* 'at least') were omitted. Note that some items appear in more than one vocabulary list since they are highly relevant for multiple frame categories, e.g., *Fachkräfteeinwanderung* ('skilled employee migration') is a keyword for both economy frames and policy frames. Exemplary keywords for each frame category are given in Table 3.

5.3 Mention Rate of Frames

As a first exploratory analysis using our *Refugees and Migration Framing Vocabulary*, we computed the *mention rate* of each frame in different newspapers. We represent a frame F as the list of extracted keywords $\{w_1, w_2, ..., w_k\}$ (as described in Section 5.2) of F, and the mention rate of F in a certain newspaper N as the cumulative frequency of $\{w_1, w_2, ..., w_k\}$:

$$mention\_rate_N(F) = \frac{\sum_{i=1}^{k} count_N(w_i)}{count_N(allwords)} \tag{2}$$

Figure 2 shows the mention rates of the frames in articles from all years between 2014-2018 in BILD, FAZ and SZ. To examine whether the mention rate differences between the newspapers are statistically significant, we applied a Kruskal-Wallis test to each frame. The Kruskal-Wallis test is a non-parametric alternative of *analysis of variance* (ANOVA), and we chose it because the mention rate values in single articles of each newspaper do not follow a normal distribution. A post-hoc Wilcoxon rank sum test was also conducted to understand pairwise differences between the newspapers.

Test results given in Table 4 indicate that the mention rate differences of all frames are statistically significant, except for the pairwise differences of the *Legal Frame*, *Politics Frame* and *Public Opinion Frame* occurrences between FAZ and SZ. As shown in Figure

2, the *Security Frame* shows the most striking difference, with the mention rate in BILD being considerably higher as compared to FAZ and SZ. Moreover, a large difference can be observed in *Economy Frame* occurrences, with FAZ showing the highest mention rate. The *Policy Frame* shows a higher mention rate in FAZ and SZ, which is expected given the tabloid-nature of BILD: BILD tends to produce sensational and shorter articles (which can also be observed from the article numbers and token numbers in Table 1) instead of in-depth discussions about intricacies of concrete refugee policies. These are instead more easily found in broadsheet newspapers. Finally, the *Morality Frame*, which includes mentions of moral ideas and concepts that tend to be more associated with a liberal, refugee-friendly discourse, is found to be mentioned more in FAZ and SZ.

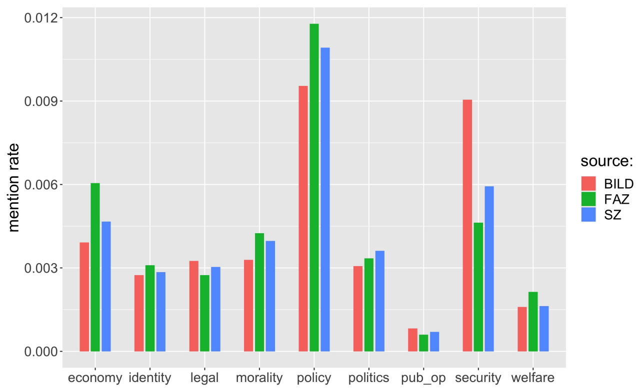

Figure 2: Mention rates of different frames in articles from 2014-2018 in BILD, FAZ and SZ.

	Kruskal-Wallis test		**Wilcoxon rank sum test (with Bonferroni-adjusted *p*-values)**		
frame category	χ^2	p	BILD vs. FAZ	BILD vs. SZ	FAZ vs. SZ
economy	782.09	<2.2e-16	<2e-16	0.00016	<2e-16
identity	359.29	<2.2e-16	<2e-16	<2e-16	9.5e-08
legal	43.816	3.058e-10	3.3e-07	1.1e-07	1^{ns}
morality	775.02	<2.2e-16	<2e-16	<2e-16	<5.2e-14
policy	600.83	<2.2e-16	<2e-16	<2e-16	6.2e-09
politics	627.47	<2.2e-16	<2e-16	<2e-16	1^{ns}
public opinion	21.838	1.811e-05	5.9e-05	0.0031	1^{ns}
security	442.61	<2.2e-16	<2e-16	<2e-16	<2e-16
welfare	560.77	<2.2e-16	<2e-16	<4.3e-07	2e-16

Table 4: Kruskal-Wallis test and post-hoc Wilcoxon rank sum test of mention rate differences of each frame category in BILD, FAZ and SZ. (ns = not significant)

5.4 Semantic Similarity

Though some first intriguing frame usage differences can be observed by measuring the mention rate, this metric is coarse and unable to distinguish the more subtle attitudinal differences associated to certain frames. For instance, the keywords *Fachkräftemangel* ('shortage of skilled employees') and *Wirtschaftsflüchtlinge* ('economic refugees') belong both to the *Economy Frame*. However, *Fachkräftemangel* in the context of refugees and migration conveys the migration-friendly attitude that skilled employees, and thus the migration of skilled employees, are sought after by the domestic economy. *Wirtschaftsflüchtlinge*, on the other hand, connotes a denunciation of refugees as exploiters of the social system and as (alleged) asylum abusers, because they did not flee for "real" political reasons (Bade, 2015; Wodak, 2015).

We apply word embedding to investigate such differences in greater depth. For each newspaper, we trained a 300-dimensional word2vec model. Before the training, all articles were tokenized and lemmatized using *Stanza*, and all stop words, numbers, punctuation marks and URLs were removed. To quantify how different newspapers portray refugees and the event "refugee crisis", we use a `refugee_centroid`, which is computed as the average embedding of all *refugee-keywords* mentioned in Section 3. For each frame-specific vocabulary list, we rank items in the list by their cosine similarity to the `refugee_centroid`. This measurement allows us to find out which frame-specific keywords are collocated closer to the *refugee-keywords* in which newspaper, and thus gain insight on the fine-grained semantic differences in the discourse of the "refugee crisis" in different newspapers.

We inspect the top ten words with the highest cosine similarities to the `refugee_centroid` in the four frames we mentioned above that show the largest differences in mention rate, i.e., the *Security*, *Economy*, *Policy* and *Morality Frame*. Table 5 depicts the top ten keywords per frame category in each newspaper. In all four frame categories interesting differences can be observed:

Security Frame The highest semantic contrast is found in the keywords of the *Security Frame*. Whereas the item *Minderjährige* ('underage persons') has a high rank in all three newspapers - indicating an increased salience of reporting on the security of underage refugees - seven out of the top ten most similar items to the `refugee_centroid` in BILD are either related to criminality (e.g., *Delikt* 'offense', *Straftäter* 'perpetrator') or religious extremism (*Dschihad* 'Jihad', *Islamist* 'Islamist'). This implies a strong semantic association of refugees to threats to domestic security in BILD. For SZ, seven out of the top ten items are related to the security of refugees on the migration route or in their country of origin (i.e., *Rettungsmission* 'rescue mission', *Schlepper* 'human trafficker', *Bürgerkrieg* 'civil war'), rendering refugees as particularly threatened and thus in need of humanitarian aid. FAZ, finally, covers a middle ground between BILD and SZ with items both on crime (e.g., *Straftat* 'crime', *Kriminalitätsrate* 'crime rate') and on refugee related security issues, such as on the migration route (*Küstenwache* 'coast guard') or in the country of origin (*Bürgerkrieg* 'civil war').

frame	BILD	FAZ	SZ
security	Minderjährige (underage persons)	Minderjährige (underage persons)	Rettungsmission (rescue mission)
	Delikt (offense)	illegal (illegal)	Minderjährige (underage persons)
	Straftäter (perpetrator)	Bürgerkrieg (civil war)	Krieg (war)
	Dschihad (Jihad)	Küstenwache (coast guard)	Bürgerkrieg (civil war)
	Gewaltkriminalität (violent crime)	Straftat (crime)	illegal (illegal)
	Islamist (Islamist)	Kriminalitätsrate (crime rate)	minderjährig (underage)
	Bürgerkrieg (civil war)	Schiffsunglück (shipwreck)	Schlepper (human trafficker)
	Tatverdächtiger (suspect)	Schlepper (human trafficker)	Straftat (crime)
	Schiffsunglück (shipwreck)	Gefängnis (prison)	Schutzstatus (protection status)
	inhaftieren (imprison)	Gefängnisstrafe (imprisonment)	Schiffsunglück (shipwreck)
economy	Kredit (credit)	Wirtschaftsflüchtling (economic refugee)	Kosten (costs)
	Arbeitsvertrag (working contract)	Fachkraft (skilled employee)	Wohnung (lodging)
	Bildungsniveau (level of education)	Studium (academic studies)	Berufsqualifikation (vocational qualification)
	Integrationskurs (integration course)	Schulausbildung (school education)	Ausbildung (training)
	Anstellung (employment)	Arbeitsstelle (workplace)	erwerbstätig (employed)
	Wirtschaftsflüchtling (economic refugee)	Arbeitsvertrag (working contract)	Arbeitslosenquote (unemployment rate)
	Studium (academic studies)	Berufsausbildung (vocational training)	zahlen (pay)
	Deutschkurs (German course)	erwerbslos (unemployed)	Bildungsniveau (level of education)
	Berufsausbildung (vocational training)	arbeitslos (unemployed)	Bleibeperspektive (prospect of staying)
	Hilfsmittel (aid)	Fachkräfteeinwanderung (skilled employee migration)	qualifiziert (qualified)
policy	Visum (visa)	Aufenthaltserlaubnis (residence permit)	Rettungsmission (rescue mission)
	Aufenthaltserlaubnis (residence permit)	Visum (visa)	Abschiebung (deportation)
	Ausreise (departure)	Asylverfahren (asylum procedure)	Asylverfahren (asylum procedure)
	Integrationskurs (integration course)	Abschiebung (deportation)	Herkunftsland (country of origin)
	Sozialhilfe (social care)	Balkanroute (Balkan route)	Wohnung (lodging)
	einstufen (classify)	Ausreise (departure)	Sozialleistung (social benefit)
	Studium (academic studies)	Studium (academic studies)	Ausreise (departure)
	Abschiebung (deportation)	Herkunftsland (country of origin)	Aufenthaltserlaubnis (residence permit)
	Deutschkurs (German course)	Schulausbildung (school education)	Balkanroute (Balkan route)
	Sozialleistung (social benefit)	Aufenthaltsrecht (right of residence)	Bleibeperspektive (prospect of staying)
morality	Integrationskurs (integration course)	Wirtschaftsflüchtling (economic refugee)	Rettungsmission (rescue mission)
	Wirtschaftsflüchtling (economic refugee)	Fachkräfteeinwanderung (skilled employee migration)	Flüchtlingsversorgung (provisioning for refugees)
	Hartz IV (Hartz IV)	Wirtschaftskrise (economic crisis)	Quote (quota)
	Hilfsmittel (aid)	Integrationskurs (integration course)	Armut (poverty)
	Flüchtlingsversorgung (provisioning for refugees)	Quote (quota)	Seenotrettungsprogramm (sea rescue program)
	Arbeitslosengeld (unemployment benefit)	Armut (poverty)	Leistung (merit)
	menschenwürdig (humane)	Wirtschaftsmigrant (economic migrant)	Kontingent (quota)
	Wirtschaftsmigrant (economic migrant)	Punktesystem (point system)	gemeinnützig (non-profit)
	Armut (poverty)	Hartz IV (Hartz IV)	Wirtschaftsflüchtling (economic refugee)
	Ungleichheit (inequality)	menschenwürdig (humane)	Versorgung (provisioning)

Table 5: Top ten most similar items to the `refugee_centroid` within the *Security*, *Economy*, *Policy* and *Morality Frames* in BILD, FAZ and SZ.

Economy Frame Among the keywords of the *Economy Frame*, *Wirtschaftsflüchtling* ('economic refugee') is among the top ten similar words to `refugee_centroid` in the two right-leaning newspapers BILD and FAZ. For the left-leaning SZ, however, it only ranks as the 25th of all keywords of the *Economy Frame* (not shown in the table). Although the different ranks of keywords cannot be compared in absolute terms between newspapers, the lower rank of *Wirtschaftsflüchtling* in SZ indicates a reluctance to reduce refugees to having fled for economic reasons. Indeed, among the top ten most similar items for SZ, focus appears to lie on measures to support refugees to find jobs (i.e., *Berufsqualifikation* 'vocational qualification', *Ausbildung* 'training'). Also, *Wohnung* ('lodging') is one of the top ten items in this frame category only in SZ. Regarding the other two newspapers, items for BILD are related to integration (i.e., *Integrationskurs* 'integration course', *Deutschkurs* 'German course') and education (i.e., *Bildungsniveau* 'level of education', *Studium* 'academic studies'), opening up additional subject dimensions of cultural diversity and (educational) merit. Important items in FAZ, finally, are even more focused on merit with top ten items including *Fachkraft* ('skilled employee') and *Fachkräfteeinwanderung* ('skilled employee migration'). This is not surprising because the FAZ is known for its economic focus.

Policy Frame Given that the mention rate of *Policy Frame* is the highest of all frames within each of the three newspapers, and given that within the top ten items of the *Policy Frame* in all three newspapers items related to the asylum procedure (i.e., *Aufenthaltserlaubnis* 'residence permit', *Asylverfahren* 'asylum procedure', *Abschiebung* 'deportation') feature prominently, this topic appears to play an outstanding role in the overall medial discourse on refugees and migration. Apart from this, however, some semantic nuances among the top *Policy Frame* items can be observed: While SZ, again, is the only newspaper focusing on the issue of accommodation (*Wohnung* 'lodging') and has a humanitarian policy item within its top ten items (*Rettungsmission* 'rescue mission'), top items for BILD, once more, include references to integration policies (i.e., *Deutschkurs* 'German course') and the controversial issue of welfare benefits (*Sozialhilfe* 'social care' and *Sozialleistung* 'social benefit'). For FAZ, items related to education (*Studium* 'academic studies', *Schulausbildung* 'school education') again add economically focused nuance.

Morality Frame For the top ten items of the *Morality Frame*, the trends and focuses of the previously discussed frame categories are continued: Top items for BILD include once more *Integrationskurs* ('integration course') and impacts on the economy and the welfare system (i.e., *Wirtschaftflüchtling* 'economic migrant', *Arbeitslosengeld* 'unemployment benefit'). For the FAZ, top ten items are again focused both on the economic impact of refugees (i.e., *Armut* 'poverty') and on their merit (i.e., *Fachkräfteeinwanderung* 'skilled employee migration' and *Punktesystem* 'point system', a system that aims to identify skilled migrants with better chances of receiving working permits). Though also partially featured in the top ten items for this frame category in BILD, SZ's focus on humanitarian issues (i.e., *Rettungsmission* 'rescue mission', *Flüchtlingsversorgung* 'provisioning for refugees' and *Seenotrettungsprogramm* 'sea rescue program') in the *Morality Frame* category is once more distinctive.

6 Conclusion and Outlook

In this article we addressed the difficulty that for many low-resource languages there are no large-scale annotated datasets available for training and/or evaluating models of automated frame detection. We did so by experimenting with two NLP approaches for the data-driven exploration of frame differences which do not require building large-scale annotated corpora from scratch. Our first experiment with LDA-based topic modelling illustrated the difficulty of this method for detecting topic preferences in a corpus where the vocabulary is highly homogeneous. Our second experiment with word2vec embeddings and the carefully selected *Refugees and Migration Framing Vocabulary* based on an expert-curated, comprehensive *Refugees and Migration Framing Schema*, however, yielded much more insightful and intelligible results.

Regarding the second experiment, it is worth mentioning that the quality of the handcrafted vocabulary lists has great impact on the quality of the results. Given the broadness of our corpus from which we took parts of our vocabulary lists, as well as the inclusion of additional vocabulary from an additional corpus, we are confident in having achieved unbiased word lists of acceptable quality. Nevertheless, achieving a reliable and objective evaluation of the quality of vocabulary lists is a generally inevitable difficulty for dictionary-based approaches. In future work we will therefor attempt to further strengthen the quality of our vocabulary lists by exploring the potential of more sophisticated keyword mining techniques, such as the method proposed by Jin, Bhatia, and Wanvarie (2021) which ranks PMI-mined keywords by training interim classifiers.

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