Frame detection - a comprehensive overview of different frame detection methods

Elias Christian Anderlohr

Universität Mannheim, Schloss 68161 Mannheim, Germany
eanderlo@mail.uni-mannheim.de

Abstract. In this work, the evolution of frame detection in the field of natural language processing has been analyzed through a classical literature review. In addition, several problems with the current state-of-the-art approaches were identified and several works were proposed that attempt to solve these problems. These works are then summarized and critically evaluated based on further research and the author's own findings. Finally, the author proposes a new, untested approach to frame detection that combines the presented methods and attempts to overcome the existing weaknesses.

Keywords: Frame detection · Natural Language Processing · Literature Review.

1 Introduction

The concept of framing originates in the field of psychology and sociology [28]. Psychologists describe framing as changes in judgment caused by a change in the definition of decision or choice problems [31]. The framing definition of the sociological perspective focuses mainly on the use of stories, symbols, or stereotypes in public media and describes frames in terms of ideology or value perspective [28]. Current research describes framing as the "process of emphasizing a certain aspect of an issue over the others"[34], which results in changing the position of readers or listeners on an issue without making a biased argument [34].

Suppose two different news media publish articles on the topic of poverty. The first media outlet blames the individual, emphasizing that individuals fall into poverty because they are lazy. The second media outlet, on the other hand, blames the government, arguing that national policies have failed, making it impossible for individuals to escape or prevent poverty. Readers of the first newspaper will most likely blame the individual, but readers of the second newspaper's article will see it differently and will probably blame the government rather than the individual. Neither the first nor the second newspaper lied, but both tell only part of the overall problem, and this can lead the reader to a desired decision. [34]

2 Motivation

Framing is used in many different areas of our public life. For example, politicians use the powerful effects of framing [28], but it is also used in marketing, public health campaigns, and other areas [34]. Because framing is such a powerful and widespread tool, much research, including this paper, has examined how to identify and measure framing. Identifying and measuring framing could, for example, enable readers to obtain additional information about a news article, such as the direction in which the author wants to influence the reader. By providing this data, frames can be made visible and thus the risk of an unwanted change of opinion on a topic can be made more difficult or prevented [34].

3 Related Works

The first researches in the field of framing can be traced back to the scientific disciplines of psychology and sociology [45, 27]. The foundation of framing research from the psychological point of view was laid by Kahneman and Tversky [31] in the 1980s. Nearly 10 years earlier, in the 1970s, Goffman [21] conducted research on framing from a sociological perspective. In these early attempts, most research was conducted in the field of politics and was based on manual surveys or manual studies [27, 28, 38].

Thus, Iyengar [27] chose a psychological approach and introduced a cognitive method to measure the effect of news frames on the audience. The study examined the effect of episodic and thematic media frames on television news [27]. Results show that viewers exposed to episodic news frames tend to hold political actors less accountable for problems compared to thematic news frames [27].

Based on this research, Iyengar and Simon [28] analyzed news coverage of the Gulf crisis. Iyengar and Simon [28] attempted to measure episodic and thematic news frames by combining content data and survey data. The authors analyzed how various attributes such as *news exposure*, *gender*, *race*, or *party affiliation* influence the decision on the topic of military spending. The results show that white Republican males with higher education tend to support military spending. But notably, viewers who watch more television are also more likely to support military options. [28]

Another early approach to framing research was undertaken by Nelson et al. in 1997. Nelson et al. [43] analyzed how public opinion about a Ku Klux Klan rally changed based on two different types of articles. The results of the study indicate that individuals who read the article (which emphasizes free speech) were more likely to be tolerant of the Ku Klux Klan rally than individuals who read the second article (which discusses that the rally could end violently). [43]

The problem with these studies is that they rely on study data and manual classification of articles. Studies that use surveys suffer from various problems such as inaccurate responses or lack of understanding [14]. The problem with manual classification of articles is that they rely on the objectivity of the annotator, which proves to be quite difficult [58]. It is extremely challenging to remove a researcher's subjectivity during the framing research process [58].

In the years that followed, researchers moved away from conducting large-scale studies and turned more to using existing data. For example, some researchers used not only articles to identify framing, but also other related information such as comments, votes, or links between articles. Park et al. [46] attempted to identify the political bias of news articles by looking at the comments on those articles. Social media, in particular, is very useful in this research area because it forms a network of users and their posts and is therefore a frequently used data source for researchers [42]. Some proposed a language model to classify users' political orientation in social media [42], others use label propagation to disseminate users' vote on these articles [61], or use the Lion algorithm to analyze Italian tweets on immigration to generate related clusters of users with the same opinion [48].

Other research, such as Bamman and Smith [4], approached the problem from a different angle. Bamman and Smith [4] introduced an unsupervised approach to assessing the political significance of type-level claims. In other words, the paper seeks to answer questions such as: are liberals more likely to claim that global warming is a hoax [4]?

All of these studies have an explanatory flaw. While these papers identify whether a text is more inclined toward a particular political orientation, they do virtually nothing to explain how that orientation is determined.

To address this issue, further research has been conducted to identify not only partisanship but also different frames. For example, Ha and Shin [23] analyzed partisanship in Korean news articles about the Arab Spring. The authors identified different frames such as *Dictatorship and Oppression* or *Economic Insecurity*, which were then used to determine how prominently they are used in liberal or conservative news outlets. This approach allows the use of frames to be visible and transparent about which frames liberal or conservative media outlets use to influence public opinion. Others have used manually defined frames to identify political partisanship for U.S. parties [55] and users with anti-science or anti-vaccine attitudes on Twitter [49, 53]. Boydstun and Gross [9] sought to define a set of frames that could be used universally. The authors called it *The Policy Frames Codebook* and it consists of 15 clearly defined dimensions such as an *economic* frame or an *morality* frame. The authors used this codebook along with Sim et al. [56] to identify the framing used by presidential candidates in various speeches. Boydstun et al. [8], Kwak et al. [35] further used the codebook to analyze whether the frames used by the news media change over time and whether they are influenced by important events. The results showed that some frames such as the security frame increased after the September 11 attacks and the political frame increased around the 2006 midterm elections [8, 35]. Nguyen et al. [44] extends codebook research into how agenda setting is used along with framing by the two political parties in the United States. For example, Republicans view the agenda/framing issue *tax* more from the business perspective than Democrats, who focus more on the "benefits of taxation to society"[9, 44]. This approach allows to automatically discover predefined agenda/frameworks [9, 44]. Based on the Moral Foundation Theory (MFT) introduced by Haidt and

Graham [25], other authors used these different predefined moral foundations to classify texts in terms of these foundations [19, 30, 41, 17, 51, 47].

All these solutions are based on a set of predefined frameworks either adopted from MFT or developed exclusively for this task. Therefore, all presented solutions focus on a specific problem and their solution cannot be generalized or easily applied to other tasks [26]. Moreover, these approaches do not help to discover previously unknown frames that could have a great impact on the reader. Moreover, frame classification is a sensitive issue where solutions need to be transparent [34, 32]. To solve this problem, some authors have addressed not only how to make frames visible, but also how to discover new frames in a transparent and understandable way. In short, current research requires large amounts of annotated datasets, predefined topic-specific frames, and is not transparent. In this paper, we present four state-of-the-art approaches to address the aforementioned problems.

FrameAxis Kwak et al. published a paper in 2021 that developed an unsupervised framework called *FrameAxis* for characterizing texts towards a semantic axis. A semantic axis, also called *microframe*, is a combination of two antonyms (e.g., *good* and *bad*) that together form a semantic axis [2]. The authors formed the semantic axis by taking the difference between the word embedding vector of the positive and negative pole words [2]. Using a similarity measure such as cosine similarity, the angle between any word and the newly formed semantic axis vector can be calculated. This measurement is also called the word contribution. The higher the contribution of the word, the closer the word is to the positive pole and the smaller the value compared to *-1*, the more it is to the negative pole. In this way, it is possible to measure to which pole any word is leaning. To classify whole text corpora, the authors introduced two measurements: Microframe Bias and Microframe Intensity. Microframe bias measures how strongly the text is biased toward a particular microframe, and intensity measures how prominently a particular microframe is used. Microframe bias is the first moment of the word's contribution to the microframe for all words in the text corpus, and microframe intensity is the centered second moment of the word's contribution to the corpus bias for all words in the text corpus. To evaluate the statistical significance of the microframes, the null model approach is used to compare each microframe to a null model. A null model is created from a text corpus using bootstrap samples that are not used in the target dataset. A two-tailed test is then performed, and the best microframes with the largest distance between target bias and null model bias or target intensity and null model intensity (also called effect size) are considered. The authors also introduce auxiliary measurements to explain the bias or intensity of the microframes of the text corpus. The measurements calculate either the bias or intensity at the word level (shift) or at the document level (spectrum). These measurements can be used to examine how different words or whole documents shift bias toward a pole or how prominently they are used. The framework is than applied to a frequently used demo dataset for testing. To ensure the quality and capabilities of the framework, the authors validated the results by applying the framework to a dataset and having human coders validate the results. The human coders had to decide whether a random set of microframes (with highest bias/intensity) or a set of microframes identified by FrameAxis better matched sentences such as *positive ratings of ambiance.* [34]

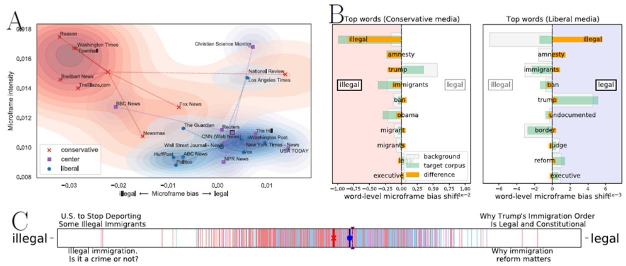

Fig. 1: FrameAxis on political news with topic "immigration" and microframe "illegal/legal" (Kwak et al. 2021)

The FrameAxis framework is then applied to a large number of real news articles with headlines on various political topics. Figure 1 shows the application of the framework to news articles on the topic of "immigration" with the microframe "illegal/legal". The heat-map in A shows that conservative media tend to use the microframe "illegal/legal" more frequently and negatively than liberal news outlets. Conservative media also use words such as *illegal* or *amnesty* to make the reader believe that something is *illegal*, while liberal media use the same words to make the user believe that something is *legal* (B). Finally, the microframe bias spectrum shows example sentences that lean more toward one of the two poles. For example, the sentence "Why Trump's immigration order is legal and constitutional" wants the reader to think that what Trump is doing is *legal*. [34]

The FrameAxis approach allows to successfully characterize texts towards predefined microframes using the two measurements. It also allows to use predefined microframes, explore new potential microframes, or automatically discover relevant microframes [34]. In short, FrameAxis is an unsupervised, transparent approach for automatic frame detection.

OpenFraming Bhatia et al. published a tool called OpenFraming for analyzing frames in multilingual text documents. The tool enables the exploration, classification, and prediction of frames in text corpora using a combination of supervised and unsupervised methods and the use of a modern multilingual language model. The authors have divided their analysis process into five steps. Step 1 focuses on an inductive approach to find topics in a text document. The tool uses the Mallet Latent Dirichlet Allocation (LDA) implementation [40] to identify different topics used in the text corpus. The LDA approach automatically discovers the topics that the text corpus contains [12]. LDA represents the text corpus as mixtures of topics that produce words with a certain probability [12]. In the second step, the inductively identified topics from the LDA method will be filtered and extended with deductive knowledge from previous research in this area. In step 3, a dataset needs to be annotated using manual coding to the identified frames from step 2. In Step 4, the tool uses Bidirectional Encoder Representations from Transformers (BERT) [15] to build a supervised machine learning model that can predict frames in unlabeled documents. Bhatia et al. [5] use the latest multilingual extension of BERT called XLM-Roberta (XLM-R) [13] trained on 100 different languages and an additional 2.5 TB of web data. To reduce the training time, the authors apply the transfer learning technique and do not compute the word embeddings from scratch, but use the pre-trained word embeddings from XLM-R and fine-tune them with the annotated dataset from step 3. The resulting embeddings from step 4 can be used in the fifth step to predict unseen data. [5]

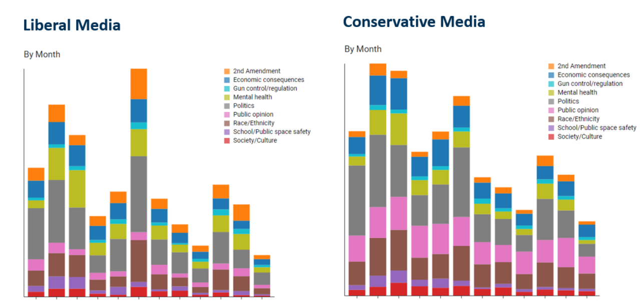

Fig. 2: OpenFraming predicted frames of liberal and conservative newspaper articles per month for 2016 (Bhatia et al. 2021)

The authors applied their tool to a set of media articles from various liberal, conservative, or mainstream news outlets on the topic of gun violence. Using the LDA approach, 10 distinct themes were discovered. These 10 themes were then labeled, filtered, and expanded using other related research on gun violence. This resulted in 9 frames ranging from *Gun/2nd Amendment rights*, to *Politics*, to *Mental health*, to *Economic consequences*. In the next step, the authors used two coders to assign about 3,000 samples to the 9 identified frames. The two coders achieved a Krippendorff's alpha intercoder reliability of α 0.90. The resulting annotated dataset is then used to predict the retained data. For example, the results show that conservative media use the frame *mental health* more frequently throughout the year than liberal media. Liberal media also used the *2nd Amendment* and *Mental health* frame much more frequently than conservative media after the Orlando shootings in June 2016 (see figure 2). [5]

The Bhatia et al. [5] approach and tool provides an option to automatically discover new frames for large datasets using inductive and deductive approaches. It also provides a state-of-the-art classification approach to classify unseen data based on these identified frames. Finally, the tool can be used through an easy-to-use website. [5]

Framing Unpacked Khanehzar et al. developed a semi-supervised model called "*Fr*ame classifier, which is *I*nterpretable and *S*emi-*s*upervised" (FRISS) that learns to incorporate local information about events and their actors using an automatic coding system to classify document-level frames. The authors use the 15 moral foundations developed by Boydstun and Gross [9] to analyze framing. *FRISS* consists of two components, an unsupervised automatic coding module and a supervised classification module. These two modules are trained together. The supervised model predicts frames based on an aggregate sentence representation, while the unsupervised module uses the aggregate fine-grained latent representations that capture local actors and events in the article. The supervised module combines the auto-encoding object with a multi-view dictionary learning system that allows the predicate and its associated arguments *ARG0* and *ARG1* to be captured as separate views. The predicate of a sentence describes what is happening, to whom or to what (ARG0) and by whom or by what (ARG1). [32]

The FRISS model takes documents with a frame label as input. Using a BERT-based semantic role labeling (SRL) model, the predicate, ARG0 and ARG1 are identified. The unsupervised module then uses the ARG0 and ARG1 predicates embeddings along with the sentence embedding to learn latent role-specific embedding matrices using an automatic coding frame. The document-level frames are then predicted using the document embeddings and the view-specific latent representation using the cross entropy as a loss function and the annotated true frame label. [32]

The FRISS framework is then applied to the Media Frames Corpus [9] to leverage the already annotated dataset of various articles from U.S. newspapers on immigration. Using the AllenNLP model [20] to create Semantic Role Labeling (SRL) [54], the authors can extract the predicates and their associated ARG0 and ARG1 for each sentence. As a sentence encoder, FRISS uses the RoBERTa model [37], which outperforms BERT and XLNet [59]. Each sentence is passed to RoBERTa to obtain the sentence embedding by averaging the token-level embeddings. The SRL span embeddings are extracted by taking the average of all words in a predicted span. Kahneman and Tversky [31] then applied various hyperparameter optimizations and compared the final model to other models from Card et al. [10], Field et al. [18] and to the supervised module based on RoBERTa with and without pre-training. FRISS outperforms all of these approaches. In Figure 3, two example articles on an SRL span are annotated with the FRISS model. [32]

The model developed by Khanehzar et al. provides an option for a transparent prediction of media frames based on MFC using an interpretable semi-supervised

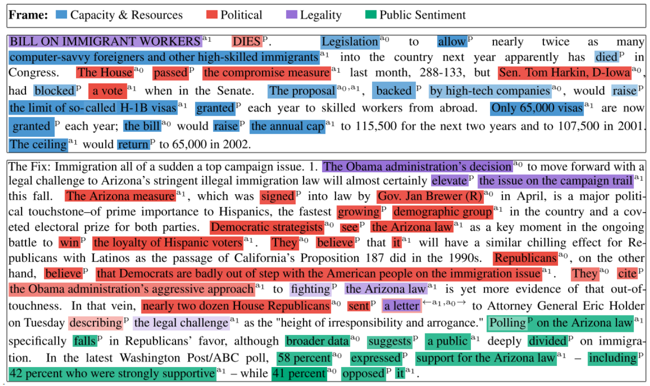

Fig. 3: Two example articles from the MFC dataset annotated with SRL-level frame prediction using the FRISS model (Khanehzar et al. 2021)

model. The approach predicts document frames and local frames using local predicates that allow to see how different sentences in a document affect the document frame. [32]

Frame Detection in German Political Discourses Yu and Fliethmann focused on how to detect frames without performing extensive manual corpus annotation. The authors compared an LDA-based topic modeling approach with a combination of word2vec and hand-crafted framing keywords.

First, the unsupervised LDA-based approach of Blei et al. [6] is analyzed. The authors use about 20,000 unannotated articles from three major German newspapers (BILD, FAZ and SZ) on the topic of immigration. In order to apply the LDA approach, the newspaper articles are first preprocessed using classical NLP preprocessing techniques. Further preprocessing was done by removing ambiguous words using topic knowledge and n-grams that were too frequent or not frequent enough. The number of topics k was calculated by trying different values to maximize the coherence value [52]. The coherence value reaches a low value for an optimized k, indicating that the keywords in the identified topics overlap. Moreover, the optimized k ranges from 78 to 90, which makes it extremely difficult to interpret the results for humans. The authors suggest that the homogeneity of words in the articles leads to these poor results.

In a second step, a knowledge-based natural language processing (NLP) approach using word2vec in combination with the hand-crafted framing keywords is analyzed. In this approach, a topic-specific framing scheme must first be deductively created to thematically classify and sort given frames. Furthermore, a framing vocabulary must be created for each category of the framing scheme. The authors also apply this method to the 20k German unannotated articles. Yu and Fliethmann developed the *Refugees and Migration Framing Schema* based on the general categorization of arguments [24] and based on the codebook developed by Boydstun and Gross [9]. The vocabulary list for the schema categories will be developed using the vocabulary proposed by domain experts, which will then be extended with synonyms from GermaNet [16]. The vocabulary is extended using the DEbateNet-mig15 corpus [36], which contains annotated text passages of news about refugees and migration from a German newspaper. This yields a list of keywords for each schema category. To validate the approach, the authors calculate how often each category is mentioned in the news articles by calculating the normalized weighted number of words in a category in the articles and testing for statistic significance. The results are statically significant and the different frames are used differently in each newspaper (see figure 4). For example, the frame *security* is used more frequently in the BILD newspaper than in the FAZ or SZ newspaper. The results are promising, but some subtle attitude differences still cannot be distinguished by the current frame. The authors tried to solve this problem by creating a word2vec model with 300 dimensions for each newspaper. Using cosine similarity, the angle between each word in a category and an average embedding vector of all refugee keywords is calculated to see which words are closer to the refugee topic. With this approach, it is possible to further match the associated keyword to the different categories. [60]

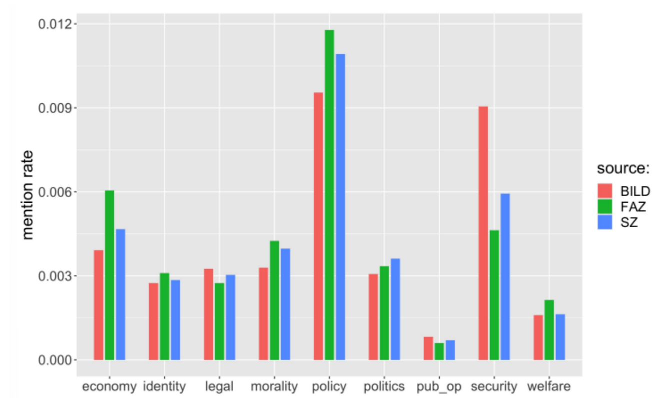

Fig. 4: Usage of frames in German news articles (Yu and Fliethmann 2021)

Research by Yu and Fliethmann has shown that the LDA approach for frame category discovery presents problems when applied to homogeneous data. The second approach, which used a knowledge-based NLP approach to first find frames and corresponding keywords, using expert knowledge and word2vec embeddings to further optimize the assigned keywords, enables the creation of useful frame categories and matching keywords [60]. This approach of Yu and Fliethmann [60] does not require a large annotated dataset and is therefore unsupervised and finds frames semi-automatically.

4 Discussion

The fours works summarized in the previous chapter all focus on a particular problem in current research. The OpenFraming approach of Bhatia et al. [5] attempts to automate frame detection, the FrameAxis approach of Kwak et al. [34] and the approach of Yu and Fliethmann [60] also attempt this, but use a unsupervised approach. Furthermore, Khanehzar et al. [32] contributes a model for identifying local frames in articles and an option for more transparent frame detection. The different contributions to the three identified shortcomings of previous research for each selected paper can be seen in table 1. The following chapter discusses the contributions and identified limitations for each of these approaches.

	Unsupervised approach	**Find frames automatically**	**Interpretable**
FrameAxis (Kwak et al. 2021)	Yes	Yes	Yes
OpenFraming (Bhatia et al. 2021)	No	Yes	No
Framing Unpacked (Khanehzar et al. 2021)	No	No	Yes
Frame Detection in German Political Discourses (Yu et al. 2021)	Yes/No	Yes	No
Authors approach	**No**	**No**	**Yes**

Table 1: Contributions to current research in the field of frame detection of the selected papers and the author's approach

The FrameAxis approach presented by Kwak et al. [34] is an easy-to-use, unsupervised approach for measuring framing bias. The framework can be applied to large corpus since it does not require manual annotation. Moreover, FrameAxis allows not only the use of predefined microframes, but also the search for relevant microframes that are useful in the context of the text corpus. The authors also introduce measurements that help explain the results, which makes the results transparent. Overall, the approach provides a simple approach to make framing visible, yet some authors have either improved or criticized the method.

Chambers and Evans [11] criticize the method for creating the semantic axis vector and instead proposes to extend the method from using simple word vectors to using the centroid from a cloud of points of similar words. Chambers and Evans [11] further propose to extend the semantic axis approach to implement low-dimensional subspaces with multiple concepts. By selecting a collection of archetypes defined by known and widely used meanings, new anchor points could be created in the embedding space [11]. This could yield more reliable results [11]. In addition, the authors suggest using transformer embeddings instead of the GloVe embeddings used in the FrameAxis approach to achieve better results and eliminate the problem of unintended bias in pre-trained word embeddings [7, 57, 11]. Kwak et al. [34] also found that the dictionary-based approach used creates problems and using a sentence-based approach solves them. The use of transformers to generated embeddings allows sentence embeddings to be created instead of word embeddings, which could solve this limitation [34, 50]. Mokhberian et al. [41] or Priniski et al. [47] use FrameAxis to create vector representations of sentences using microframe bias and intensity scoring. The authors first compute the word embeddings using BERT and then use FrameAxis to compute the microframe bias and intensity for the documents. In addition, Mokhberian et al. [41] use the microframe bias and intensity scores to represent text documents by 12 dimensions, each representing the microframe bias and microframe intensity score for each of the six dimensions of moral foundation. Mokhberian et al. [41] then uses these new documents to create a logistic regression classifier to predict moral basis for unseen data. This requires the use of an annotated dataset, but leads to better accuracy in classifying party affiliation [41]. Furthermore, the authors of FrameAxis point out that their approach cannot replace classical frame detection methods and that it is not possible to map microframes to classical frames [34]. Furthermore, the frame itself is not compared to other frame detection models [34].

The OpenFraming tool, developed during Bhatia et al. [5]'s research, like FrameAxis, allows users to find frames and classify articles according to those frames. The authors of OpenFraming and Yu and Fliethmann [60] use an LDA approach to find frames from unannotated documents. Yu and Fliethmann [60] criticizes the use of LDA for an automated framing identification approach. Yu and Fliethmann [60] found that keywords for different frames overlap when the dataset has a large word homogeneity between articles. In addition, Yu and Fliethmann [60] found that based on their dataset, a large number of frames are required to obtain a high coherence score, which makes it difficult for people to understand and unintentionally splits coherent frames. Instead, the authors suggest using a combination of word2vec and hand-crafted framing keywords to successfully create important frames. Again, the use of transformer-generated embeddings could be useful. The OpenFraming tool also requires a large amount of annotated data to successfully categorize the data towards the identified frames, which raises the issue of unintentional subjectivity of human coders [34, 58]. In addition, the results of the OpenFraming approach were not compared with those of other frame detection models.

The semi-supervised model FRISS presented by Khanehzar et al. [32] learns to incorporate local information about events and their actors by using an automated coding system to classify document-level frames. This model enables not only document-level frame identification, but also word-level frame identification by identifying predicates and their associated arguments [32]. However, the approach still relies on predefined frames, which limits this approach to a specific area of study [32]. Identifying framing at the word level allows the results to be interpretable, which is important in the field of framing measurement [32]. FRISS, like OpenFraming, requires large amounts of annotated data, which also introduces the problem of unintended subjectivity [34, 58].

None of the current research incorporates the concept of emotion into frame identification. Studies have shown that framing effects can also be triggered by emotions [33], so another approach Alhuzali and Ananiadou [1] focuses on measuring emotions in texts. Much research has been done in the field of emotion analysis [1, 3, 22], but none has attempted to combine frame identification with emotion.

5 Conclusion

Based on the findings in this work, a new approach combining the different approaches mentioned above could provide interesting and promising results. One proposed combination could be to first identify different frames using the approach presented by Yu and Fliethmann [60]. Each frame is assigned positive and negative keywords associated with that frame. For example, the frame *food quality* might consist of positive words such as *appetizing*, *delicate*, or *tasty* and negative words *stale*, *spoiled*, or *unappetizing*. Then a pre-trained transformer model has to be fine-tune on our own dataset to extract the word embeddings to compute a centroid for the positive words and a centroid for the negative words to create the semantic axis, as recommended in Chambers and Evans [11]. A sentence transformer (e.g., sBERT) is also applied to extract the sentence embeddings for each sentence in the document. Following the approach of Mokhberian et al. [41], the FrameAxis microframe intensity and bias are calculated for each of the identified frames to use as features. We then annotate a training dataset with the identified frames.

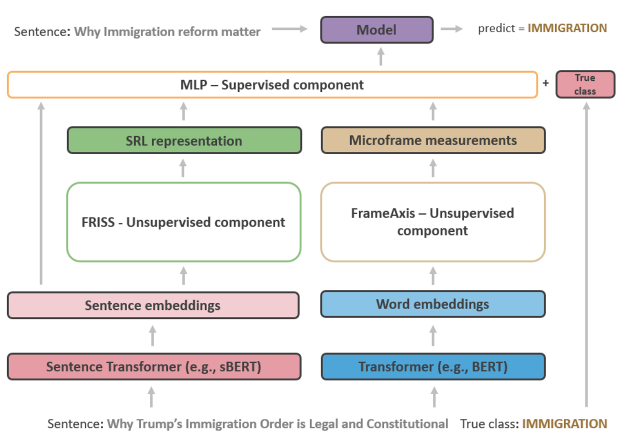

Fig. 5: A visual representation of the author's approach. BERT implementations are used to compute word and sentence embeddings. The sentence embeddings are used in the unsupervised FRISS module to identify the SRL representations. The word embeddings are used in the FrameAxis component to compute the microframe features. The two results are combined with the sentence embeddings and used as input for an MLP classifier. This model can be used to predict unseen data.

The proposed model (see figure 5) consists of two unsupervised components and one supervised component. The first component leverages the research results of Khanehzar et al. [32] by applying the FRISS model. The component takes sentence embeddings as input and returns the SRL embeddings. The second unsupervised component uses the FrameAxis approach from Kwak et al. [34] to compute new features based on the identified frames. The component takes the word embeddings as input and returns the bias and intensity for each frame, resulting in a new representation of each sentence. In the supervised component, the sentence embeddings, SRL embeddings, and frame vectors are combined and inserted into a multilayer perceptron model (MLP) to learn a classifier. The model can then be used to predict the frame of unseen data based on the input from a single sentence.

The newly developed approach offers a transparent method to detect frames while using predefined frames and an annotated dataset. Therefore, the approach is not unsupervised anymore and is not capable of finding frames automatically. But, the supervised approaches from Mokhberian et al. [41] and Khanehzar et al. [32] returns promising results which validate the usage of a supervised method for detecting frames. The only fully unsupervised approach by Kwak et al. [34] states that its model cannot replace the classical frame detection methods which are currently following a supervised approach.

5.1 Summary

This paper analyzed the evolution of frame detection in the field of natural language processing. It also highlighted several problems with the current state of the art, which rely on large annotated datasets, do not allow automatic detection of frames, and are not transparent. This paper proposes several works that attempt to address these issues. The FrameAxis framework by Kwak et al. [34] provides an unsupervised approach that is transparent and can automatically detect frames, the OpenFraming tool by Bhatia et al. [5] provides automatic frame discovery, Framing Unpacked by Khanehzar et al. [32] provides a transparent model for frame classification, and finally Yu and Fliethmann [60] proposes two methods for frame creation. These works are then summarized and critically evaluated based on further research and the author's own findings. Finally, the author proposes a new, untested approach to frame detection. The proposed approach incorporates the findings from the four different papers and the associated criticisms of these papers. This approach and work are then critically evaluated in the limitations section, and additional topics for further research are suggested.

5.2 Limitations

The new approach to frame detection proposed by the author is untested, which means that any conjectures about the capabilities of this approach are only speculations that would have to be proven in a separate work.

Furthermore requires the newly developed approach an annotated dataset and the frames have to be initially identified using an inductive and deductive approach.

Moreover, the approaches examined in this paper are all relatively new, so there is not yet much scientifically supported criticism of the approaches presented by the researchers.

5.3 Future work

The untested approach proposed by the author should be tested. In addition, it could also be interesting to include the emotion of a sentence or a document in the classification of frame recognition. The problem is that currently there is no pre-trained model that allows emotion classification [1, 3, 22, 39].

In addition, Jin et al. [29] investigated an unsupervised method for collecting starting words by giving only the topic as input. This approach is not useful for the proposed approach because it provides similar or associated words to a topic and not the positive and negative words required for FrameAxis. However, this approach to collect seed words could be improved to automatically find positive and negative words and create semantic axes based on the input topic words.

Bibliography

[1] Alhuzali, H., Ananiadou, S.: Spanemo: Casting multi-label emotion classification as span-prediction (2021), https://arxiv.org/pdf/2101.10038

[2] An, J., Kwak, H., Ahn, Y.Y.: Semaxis: A lightweight framework to characterize domain-specific word semantics beyond sentiment. Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) pp. 2450–2461 (2018), https://aclanthology.org/P18-1228/

[3] Arbieu, U., Helsper, K., Dadvar, M., Mueller, T., Niamir, A.: Natural language processing as a tool to evaluate emotions in conservation conflicts. Biological Conservation 256, 109030 (2021)

[4] Bamman, D., Smith, N.A.: Open extraction of fine-grained political statements. Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing pp. 76–85 (2015), https://aclanthology.org/D15-1008/

[5] Bhatia, V., Akavoor, V.P., Paik, S., Guo, L., Jalal, M., Smith, A., Tofu, D.A., Halim, E.E., Sun, Y., Betke, M., Ishwar, P., Wijaya, D.T.: Openframing: Open-sourced tool for computational framing analysis of multilingual data. Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing: System Demonstrations pp. 242–250 (2021), https://aclanthology.org/2021.emnlp-demo.28/

[6] Blei, D.M., Ng, A.Y., Jordan, M.I.: Latent dirichlet allocation. Advances in Neural Information Processing Systems 14 [Neural Information Processing Systems: Natural and Synthetic, NIPS 2001, December 3-8, 2001, Vancouver, British Columbia, Canada] 3(Jan), 601–608 (2001), https://www.researchgate.net/publication/221620547_Latent_Dirichlet_Allocation

[7] Bolukbasi, T., Chang, K.W., Zou, J.Y., Saligrama, V., Kalai, A.T.: Man is to computer programmer as woman is to homemaker? debiasing word embeddings. Advances in Neural Information Processing Systems 29 (2016)

[8] Boydstun, A., Card, D., Gross, J., Resnik, P., Smith, N.: Tracking the development of media frames within and across policy issues (2014)

[9] Boydstun, A.E., Gross, J.: Identifying media frames and frame dynamics within and across policy issues. undefined (2013), https://www.semanticscholar.org/paper/Identifying-Media-Frames-and-Frame-Dynamics-Within-Boydstun-Gross/e06095c181afe22f1dba486e21928b48d0f74764

[10] Card, D., Gross, J., Boydstun, A., Smith, N.A.: Analyzing framing through the casts of characters in the news. In: Su, J., Duh, K., Carreras, X. (eds.) Proceedings of the 2016 Conference on Empirical Methods in Natural Language Processing. pp. 1410–1420. Association for Computational Linguistics, Stroudsburg, PA, USA (2016)

[11] Chambers, B., Evans, J.: Semantic maps and metrics for science semantic maps and metrics for science using deep transformer encoders. undefined (2021), https://www.semanticscholar.org/paper/Semantic-maps-and-metrics-for-science-Semantic-maps-Chambers-Evans/8ecb08beba33df69eaa7a13f4dbed0390e47415e
[12] Chen, E.: Introduction to latent dirichlet allocation (2011), http://blog.echen.me/2011/08/22/introduction-to-latent-dirichlet-allocation/
[13] Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., Grave, E., Ott, M., Zettlemoyer, L., Stoyanov, V.: Unsupervised cross-lingual representation learning at scale (2019), https://arxiv.org/pdf/1911.02116
[14] Defranzo, S.E.: Advantages and disadvantages of surveys. Snap Surveys (16112012), https://www.snapsurveys.com/blog/advantages-disadvantages-surveys/
[15] Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: Bert: Pre-training of deep bidirectional transformers for language understanding (2018), https://arxiv.org/pdf/1810.04805
[16] Eberhard Karls Universität Tübingen: Germanet (2022), https://uni-tuebingen.de/fakultaeten/philosophische-fakultaet/fachbereiche/neuphilologie/seminar-fuer-sprachwissenschaft/arbeitsbereiche/allg-sprachwissenschaft-computerlinguistik/ressourcen/lexica/germanet-1/
[17] Ekici, H., Yücel, E., Cesur, S.: Deciding between moral priorities and covid-19 avoiding behaviors: A moral foundations vignette study. Current Psychology (New Brunswick, N.j.) pp. 1–17 (2021), https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8173317/
[18] Field, A., Kliger, D., Wintner, S., Pan, J., Jurafsky, D., Tsvetkov, Y.: Framing and agenda-setting in russian news: a computational analysis of intricate political strategies. In: Riloff, E., Chiang, D., Hockenmaier, J., Tsujii, J. (eds.) Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing. pp. 3570–3580. Association for Computational Linguistics, Stroudsburg, PA, USA (2018)
[19] Fulgoni, D., Carpenter, J., Ungar, L., Preoţiuc-Pietro, D.: An empirical exploration of moral foundations theory in partisan news sources. Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC'16) pp. 3730–3736 (2016), https://aclanthology.org/L16-1591/
[20] Gardner, M., Grus, J., Neumann, M., Tafjord, O., Dasigi, P., Liu, N., Peters, M., Schmitz, M., Zettlemoyer, L.: Allennlp: A deep semantic natural language processing platform (2018), https://arxiv.org/pdf/1803.07640
[21] Goffman, E.: Frame analysis: An essay on the organization of experience. Harvard Univ. Press, Cambridge, Mass., 3. print edn. (1976)
[22] Guo, S., Burghardt, K., Rao, A., Lerman, K.: Emotion regulation and dynamics of moral concerns during the early covid-19 pandemic (2022), https://arxiv.org/pdf/2203.03608

[23] Ha, J.S., Shin, D.: Framing the arab spring: Partisanship in the news stories of korean newspapers. International Communication Gazette 78(6), 536–556 (2016)

[24] Habermas, J.: Erläuterungen zur Diskursethik, Suhrkamp-Taschenbuch Wissenschaft, vol. 975. Suhrkamp, Frankfurt am Main, 6. aufl. edn. (2015)

[25] Haidt, J., Graham, J.: When morality opposes justice: Conservatives have moral intuitions that liberals may not recognize. Social Justice Research 20(1), 98–116 (2007), https://link.springer.com/article/10.1007/s11211-007-0034-z

[26] Hamborg, F., Heinser, K., Zhukova, A., Donnay, K., Gipp, B.: Newsalyze: Effective communication of person-targeting biases in news articles. undefined pp. 130–139 (2021), https://www.semanticscholar.org/reader/893fa2e6543173b41fa1fb8ba0a7c0fe2b3a3bbd

[27] Iyengar, S.: Is anyone responsible? How television frames political issues. American politics and political economy series, University of Chicago Press, Chicago (1991)

[28] Iyengar, S., Simon, A.: News coverage of the gulf crisis and public opinion. Communication Research 20(3), 365–383 (1993)

[29] Jin, Y., Bhatia, A., Wanvarie, D.: Seed word selection for weakly-supervised text classification with unsupervised error estimation (2021), https://arxiv.org/pdf/2104.09765

[30] Johnson, K., Goldwasser, D.: Classification of moral foundations in microblog political discourse. Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers) pp. 720–730 (2018), https://aclanthology.org/P18-1067/

[31] Kahneman, D., Tversky, A.: Choices, values, and frames. American Psychologist 39(4), 341–350 (1984)

[32] Khanehzar, S., Cohn, T., Mikolajczak, G., Turpin, A., Frermann, L.: Framing unpacked: A semi-supervised interpretable multi-view model of media frames (2021), https://arxiv.org/pdf/2104.11030

[33] Kühne, R., Sommer, K., Weber, P.: Kognitive und emotionale framingeffekte auf einstellungen. überlegungen zur relevanz der untersuchung von mediationsprozessen und eine empirische überprüfung. Medien & Kommunikationswissenschaft 63(1), 44–61 (2015)

[34] Kwak, H., An, J., Jing, E., Ahn, Y.Y.: Frameaxis: characterizing microframe bias and intensity with word embedding. PeerJ. Computer science 7, e644 (2021), https://arxiv.org/pdf/2002.08608

[35] Kwak, H., Jisun, Ahn, Y.Y.: A systematic media frame analysis of 1.5 million new york times articles from 2000 to 2017 (2020), https://arxiv.org/pdf/2005.01803

[36] Lapesa, G., Blessing, A., Blokker, N., Dayanık, E., Haunss, S., Kuhn, J., Padó, S.: Debatenet-mig15:tracing the 2015 immigration debate in germany over time. Proceedings of the Twelfth Language Resources and Evaluation Conference pp. 919–927 (2020), https://aclanthology.org/2020.lrec-1.115/

[37] Liu, Y., Ott, M., Goyal, N., Du Jingfei, Joshi, M., Chen, D., Levy, O., Lewis, M., Zettlemoyer, L., Stoyanov, V.: Roberta: A robustly optimized bert pretraining approach (2019), https://arxiv.org/pdf/1907.11692

[38] Lugalambi, G.: An assessment of democratic deliberation in uganda: A case study of the framing of key political issues in the press. undefined (2006), https://www.semanticscholar.org/paper/AN-ASSESSMENT-OF-DEMOCRATIC-DELIBERATION-IN-UGANDA%3A-Lugalambi/d286e918c1c1f23bfbeccb45377e85a7335e681d

[39] Majeed, A., Mujtaba, H., Beg, M.O.: Emotion detection in roman urdu text using machine learning. In: Grundy, J., Le Goues, C., Lo, D. (eds.) 2020 35th IEEE/ACM International Conference on Automated Software Engineering workshops. pp. 125–130. IEEE, Piscataway, NJ (2020)

[40] McCallum, M.K.: Mallet: Machine learning for language toolkit (2002), https://mimno.github.io/Mallet/

[41] Mokhberian, N., Abeliuk, A., Cummings, P., Lerman, K.: Moral framing and ideological bias of news (2020), https://arxiv.org/pdf/2009.12979

[42] Morales, P.R., Zolotoochin, G.M.: Measuring the accuracy of social network ideological embeddings using language models (2022), https://halshs.archives-ouvertes.fr/hal-03385061/

[43] Nelson, T.E., Clawson, R.A., Oxley, Z.M.: Media framing of a civil liberties conflict and its effect on tolerance. American Political Science Review 91(3), 567–583 (1997)

[44] Nguyen, V.A., Ying, J.L., Resnik, P.: Lexical and hierarchical topic regression. Advances in Neural Information Processing Systems 26 (2013)

[45] Pan, Z., Kosicki, G.: Framing analysis: An approach to news discourse. Political Communication 10(1), 55–75 (1993)

[46] Park, S., Ko, M., Kim, J., Liu, Y., Song, J.: The politics of comments: predicting political orientation of news stories with commenters' sentiment patterns. In: Hinds, P. (ed.) Proceedings of the ACM 2011 conference on Computer supported cooperative work. p. 113. ACM Conferences, ACM, New York, NY (2011)

[47] Priniski, J., Mokhberian, N., Harandizadeh, B., Morstatter, F., Lerman, K., Lu, H., Brantingham, P.: Mapping moral valence of tweets following the killing of george floyd. undefined (2021), https://www.semanticscholar.org/paper/Mapping-Moral-Valence-of-Tweets-Following-the-of-Priniski-Mokhberian/690a9413993c30acfd36735e4a2a5b017b385e61

[48] Radicioni, T., Squartini, T., Pavan, E., Saracco, F.: Networked partisanship and framing: A socio-semantic network analysis of the italian debate on migration. PloS one 16(8), e0256705 (2021)

[49] Rao, A., Morstatter, F., Hu, M., Chen, E., Burghardt, K., Ferrara, E., Lerman, K.: Political partisanship and antiscience attitudes in online discussions about covid-19: Twitter content analysis. Journal of medical Internet research 23(6), e26692 (2021), https://pubmed.ncbi.nlm.nih.gov/34014831/

[50] Reimers, N.: Sentencetransformers documentation — sentence-transformers documentation (2022), https://www.sbert.net/

[51] Reiter-Haas, M., Kopeinik, S., Lex, E.: Studying moral-based differences in the framing of political tweets. Proceedings of the International AAAI Conference on Web and Social Media Vol. 15 ((2021), https://arxiv.org/pdf/2103.11853

[52] Röder, M., Both, A., Hinneburg, A.: Exploring the space of topic coherence measures. In: Cheng, X. (ed.) Proceedings of the Eighth ACM International Conference on Web Search and Data Mining. pp. 399–408. ACM Digital Library, ACM, New York, NY (2015)

[53] Schmitz, M., Murić, G., Burghardt, K.: Detecing anti-vaccine users on twitter (2021), https://arxiv.org/pdf/2110.11333

[54] Shi, P., Lin, J.: Simple bert models for relation extraction and semantic role labeling (2019), https://arxiv.org/pdf/1904.05255

[55] Shurafa, C., Darwish, K., Zaghouani, W.: Political framing: Us covid19 blame game. In: Social Informatics 12th International Conference. pp. 333–351. Springer, Cham (2020), https://link.springer.com/chapter/10.1007/978-3-030-60975-7_25

[56] Sim, Y., Acree, B.D.L., Gross, J.H., Smith, N.A.: Measuring ideological proportions in political speeches. Proceedings of the 2013 Conference on Empirical Methods in Natural Language Processing pp. 91–101 (2013), https://aclanthology.org/D13-1010/

[57] Sweeney, C., Najafian, M.: A transparent framework for evaluating unintended demographic bias in word embeddings. In: Korhonen, A., Traum, D., Màrquez, L. (eds.) Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. pp. 1662–1667. Association for Computational Linguistics, Stroudsburg, PA, USA (2019)

[58] van Gorp, B.: Where is the frame? European Journal of Communication 20(4), 484–507 (2005)

[59] Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R., Le V, Q.: Xlnet: Generalized autoregressive pretraining for language understanding (2019), https://arxiv.org/pdf/1906.08237

[60] Yu, Q., Fliethmann, A.: Frame detection in german political discourses : How far can we go without large-scale manual corpus annotation? In: 1st Workshop on Computational Linguistics for Political and Social Sciences. pp. 13–24 (2021), http://kops.uni-konstanz.de/handle/123456789/56106

[61] Zhou, D.X., Resnick, P., Mei, Q.: Classifying the political leaning of news articles and users from user votes. Proceedings of the International AAAI Conference on Web and Social Media 5(1), 417–424 (2011), https://ojs.aaai.org/index.php/ICWSM/article/view/14108