# Frame-oriented Summarization of Argumentative Discussions

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## Abstract

Online discussions on controversial topics with many participants frequently include hundreds of arguments that cover different framings of the topic. But these arguments and frames are often spread across the various branches of the discussion tree structure. This makes it difficult for interested participants to follow the discussion in its entirety as well as to introduce new arguments. In this paper, we present a new ranking-based approach to the extractive summarization of online discussions, centered around argumentation frames that capture the different aspects of a discussion. Our approach includes three retrieval tasks to find arguments in a discussion that are (1) relevant to a frame of interest, (2) relevant to the topic under discussion, and (3) informative to the reader. Based on a joint ranking by these three criteria for a set of user-selected frames, our approach allows readers to quickly access an ongoing discussion. We evaluate our approach using a test set of 100 controversial Reddit ChangeMyView discussions, for which the relevance of a total of 1871 arguments was manually annotated.

## 1 Introduction

Web-based forums like Reddit facilitate discussions on all kinds of topics. Given the size and scope of some communities (known as "subreddits"), multiple individuals regularly participate in the discussions of timely controversial topics, such as on ChangeMyView [1]. Notably, the volume of arguments tends to grow substantially in a tree-like response structure wherein each branch forms a concurrent discussion thread. These threads develop in parallel as different perspectives are introduced by the participants. After a discussion subsides, the resulting collection of threads and their arguments often represents a comprehensive overview of the most pertinent perspectives (henceforth, referred to as *frames*) put forth by the participants.

[1](CMV)https://www.reddit.com/r/changemyview/

Frames help shape one's understanding of the topic and deliberating one's own stance (Entman, 1993; Chong and Druckman, 2007). However, in large discussions, prominent arguments as well as the various frames covered may be distributed in arbitrary (and often implicit) ways across the various threads. This makes it challenging for participants to easily identify and contribute arguments to the discussion. Large online forums like Reddit typically provide features that enable the reorganization of posts, for example, based on their popularity, time of creation, or in a question–answer format. A popularity-based ranking may seem beneficial, but Kano et al. (2018) discovered that an argument's popularity is not well correlated with its informativeness. Furthermore, a popularity-based ranking does not cover the breadth of frames of a discussion, as we will show in this paper.

In this paper, we cast discussion summarization as a ranking task with an emphasis on frame diversity, thereby introducing a new paradigm to discussion summarization in the form of *multiple* summaries per discussion (one per frame). Previous research has focused on creating a single summary per discussion instead (Section 2). As illustrated in Figure 1, we first assign arguments to one or more frames. Next, we re-rank arguments in a frame according to their topic relevance. Additionally, we also rank them based on their informativeness via post-processing. Finally, we fuse these rankings to create the final ranking from which the top-$k$ candidates can be used as an *extractive* summary of the discussion centered around a specific frame.

In our experiments, we explore various state-of-the-art methods to realize the three steps of our approach. Our results suggest that: (1) Utilizing retrieval models together with query variants is an effective method for frame assignment, reducing the reliance on large labeled datasets. Here, our approach outperforms a state-of-the-art supervised baseline. (2) Re-ranking arguments of a frame
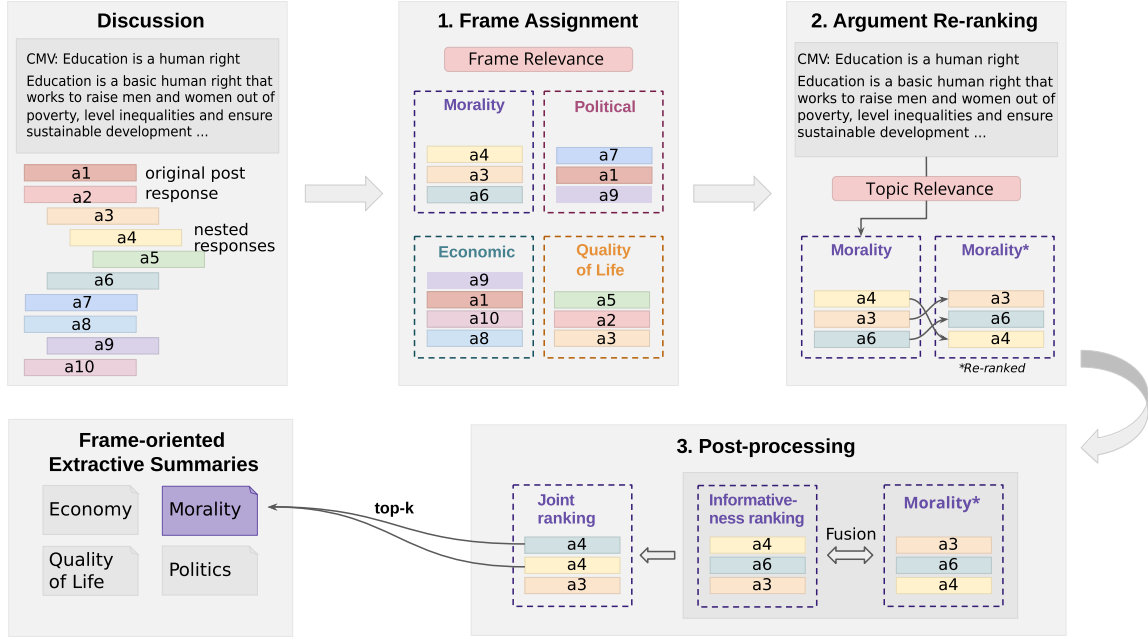
Figure 1: The proposed modular approach to frame-oriented discussion summarization: *1. Frame assignment* assigns arguments to frames ensuring frame relevance. *2. Argument re-ranking* ensures topic relevance of a frame's arguments (here, the *morality* frame is exemplified). *3. Post-processing* fuses the re-ranked arguments with an informativeness ranking. The top-$k$ arguments are then taken as an extractive summary of the discussion.

based on content overlap with the discussion topic is more effective than retrieval-based approaches for ensuring the relevance of the frame's arguments to the topic. (3) Post-processing the argument rankings based solely on content features is insufficient to signal informativeness.

In summary, our contributions include: (1) A fully unsupervised frame assignment approach that assigns one or more frame labels to every argument within a discussion (Section 3.1). (2) An argument retrieval approach that ranks frame-specific arguments based on their topic relevance and informativeness (Section 3.2). (3) A dataset consisting of 1871 arguments sourced from 100 ChangeMyView discussions, where each argument has been judged in terms of frame relevance, topic relevance, and informativeness (Section 4) which forms the basis for an extensive comparative evaluation (Section 5).[2]

## 2 Related Work

Previous approaches to summarizing discussions can be broadly classified into two categories: *discussion unit extraction* and *discussion unit grouping*. We survey the literature on discussion summarization according to these two categories, followed by the literature on *argument framing*.

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[2]All code and data will be made publicly available.

### 2.1 Discussion Unit Extraction

Extraction-based approaches use either heuristics or supervised learning to identify important units, such as key phrases, sentences, or arguments, within a discussion, which are then presented as the summary.

Tigelaar et al. (2010) identified several features for identifying key sentences from the discussion, such as the use of explicit author names to detect the response-tree structure, quoted sentences from the preceding arguments, and author-specific features such as participation and talkativity. They found that, while these features can be helpful, summarizing discussions primarily involves balancing coherence and coverage in the summaries. Ren et al. (2011) developed a hierarchical Bayesian model trained on labeled data to track the various topics within a discussion and a random walk algorithm to greedily select the most representative sentences for the summary. Ranade et al. (2013) extracted relevant and sentiment-rich sentences from debates, using lexical features to create indicative summaries. Bhatia et al. (2014) leveraged manually annotated dialogue acts to extract key posts as a concise summary of discussions on question-answering forums (Ubuntu, TripAdvisor). This dataset was further extended with more annota-

tions by Tarnpradab et al. (2017) who proposed a hierarchical attention network for extractive summarization of forum discussions. Egan et al. (2016) extracted key content from discussions via "point" extraction derived from a dependency parse graph structure, where a point is a verb together with its syntactic arguments.

Closely related to the domain we consider, Kano et al. (2018, 2020) studied the summarization of non-argumentative discussions on Reddit. They found that using the karma scores of posts was not correlated with their informativeness and that combining both local and global context features for comments was the most effective way to identify informative ones. Therefore, we do not rely on karma scores in our post-processing module (Section 4.2) and instead extract several content features for computing informativeness.

The outlined approaches all create a single summary for the entire discussion via end-to-end models. In contrast, we model the extraction of informative arguments organized by frames, thus enabling diverse summaries for a discussion. Furthermore, our experiments with unsupervised retrieval models for frame assignment (Section 4.2) enable us to assess the need to create labeled datasets beforehand to develop strong frame-oriented summarization models tailored to discussions.

## 2.2 Discussion Unit Grouping

Grouping-based approaches first categorize a discussion's units into explicit (or implicit) classes, such as queries, aspects, topics, dialogue acts, argument facets, or expert-labeled keypoints, and generate individual summaries for each class. They rely on specific reference points to organize a discussion's units, providing flexibility to the readers by allowing them to choose from diverse summaries that best fit their information needs.

Qiu and Jiang (2013) modeled the discovery of latent viewpoints to group arguments based on two user characteristics: *user identity*, as arguments from the same user are likely to contain the same viewpoint; and *user interaction*, as users with different viewpoints may express disagreement or attack each other, while those with similar viewpoints may support each other. Misra et al. (2015) used summarization to discover repeating arguments and grouped them into facets. Reimers et al. (2019) proposed agglomerative clustering via contextual embeddings to identify similar arguments on a sen-

tence level based on their aspects.

Nguyen et al. (2021) proposed an unsupervised approach to class-specific abstractive summarization of customer reviews with the goal of reducing generic and uninformative content in summaries. They model reviews in the context of topical classes of interest, which are treated as latent variables. These approaches represent their reference points as latent variables to be discovered through supervised or reinforcement learning. In contrast, our frame inventory provides a more controlled–and thus more interpretable–set of reference points for discussion summarization. More recently Shapira et al. (2022) proposed a query-assisted, sentence-level interactive summarization approach for news reports using reinforcement learning. Their approach consists of two subtasks of query-based sentence selection and suggested-queries list generation to enable an interactive setting. In our scenario, we enable this interaction via the predefined set of frames.

Summarizing public debates, Bar-Haim et al. (2020a,b) investigated mapping similar arguments to expert-written key points. Bražinskas et al. (2021) summarized product reviews by selecting subsets of informative reviews, treating the choice of review subset as a latent variable that is learned by a model trained on a dataset compiled from professional product review forums. Amplayo et al. (2021) proposed aspect-controlled opinion summarization via employing multi-instance learning on a labeled dataset to identify aspects in reviews for grouping followed by summarization. The reference points of these approaches are defined either through manual annotations or distant supervision. Some of these reference points are highly topic-specific, requiring them to be created manually for each topic, for instance, the key points from Bar-Haim et al. (2020a). In contrast, we use a fixed and topic-independent set of reference points, namely media frames (Boydstun et al., 2014), grounded in framing theory (Chong and Druckman, 2007).

## 2.3 Argument Framing

Framing theory was initially utilized to categorize (political) newspaper articles in order to manifest the specifically reported perspective (Neuman et al., 1992; Semetko and Valkenburg, 2006; Boydstun et al., 2014). It was first introduced to the field of argumentation by Naderi and Hirst (2017). Later, Ajjour et al. (2019) modeled framing in argumenta-

tion more systematically, introducing automatically extracted, fine-grained, issue-specific frame labels. Heinisch and Cimiano (2021) successfully combined computational argumentation with framing theory by showing a latent connection between the different frame granularities for the media frames defined by Boydstun et al. (2014). Hartmann et al. (2019) also used frame-labeled data from newswire corpus to successfully train frame classifiers for political discussions via multi-task and adversarial learning. Following literature, we chose the media frames due to their wide adoption in categorizing arguments (Card et al., 2015; Chen et al., 2021).

## 3 Ranking-based Summarization

This section describes our ranking-based approach to the extractive summarization of online discussions, centered around argumentation frames (Figure 1). First we describe our novel unsupervised approach for frame assignment, followed by methods for re-ranking arguments of a frame based on their relevance to the discussion topic and informativeness. The top-$k$ arguments from the joint ranking are taken as the frame's summary.

### 3.1 Frame Assignment

Our approach to frame assignment IRFRAME is completely unsupervised in that it employs information retrieval models to rank arguments in a discussion by their *frame relevance*. Here, we consider arguments as documents and frames as queries. This offers a simple and interpretable alternative to frame assignment that does not require labeled data to train supervised models. We investigated both lexical and dense retrieval models.

We used an existing inventory of media frames to organize the arguments in a discussion. This originates from Boydstun et al. (2014) and consists of 15 classes (frames) listed in Table 1. This inventory aims to support an issue-generic frame categorization of political communication. In the context of discussions on Reddit CMV, these issue-generic frames ideally cover a wide variety of controversial topics. The *other* frame is a catch-all category for frames that do not fit into any of the other categories. We excluded it from our experiments as it is not well defined, thus difficult to evaluate. For full frame descriptions see Table 4 in the appendix.

Employing query variants–semantically related queries derived from the primary query–has been shown to improve the retrieval performance (Ben-

| Frame Inventory | |
|---|---|
| Capacity & Resources | Morality |
| Constitutionality & Jurisprudence | Policy Prescription & Evaluation |
| Crime & Punishment | Political |
| Cultural Identity | Public Opinion |
| Economic | Quality of Life |
| External Regulation & Reputation | Security & Defense |
| Fairness & Equality | Other |
| Health & Safety | |

Table 1: Inventory of frames proposed by Boydstun et al. (2014) to track the media framing on policy issues.

ham et al., 2019). Thus, we manually created ten query variants for each frame to retrieve and rank all arguments in the discussion based on their frame relevance. Each variant is a high-quality sentence describing the various *aspects* of a frame. We manually curated these sentences from the Wikipedia pages of the frame labels as well as those of the various aspects mentioned in their descriptions (in Table 4). For example, a query variant for the frame *cultural identity* is: "Cultural identity is defined as the identity of a group or culture or of an individual as far as one is influenced by one's belonging to a group or culture and is similar to, and overlaps, with identity politics". The complete list of query variants for all frames is provided in the supplementary material. The output of this module is a ranked list of arguments for each frame, which is then used for extractive summarization (Section 3.2).

We first obtained ten rankings of the arguments (one for each query variant) and then combined these via reciprocal rank fusion (Cormack et al., 2009) to obtain the final list of ranked arguments for a frame. We also compare our approach with a supervised baseline, SUPERFRAME, a classifier finetuned on a set of labeled arguments (details in Section 4.2).

### 3.2 Extractive Summarization

Building upon the frame assignment component described above that ensures frame relevance, we now perform an *extractive* summarization of the discussion by re-ranking the frame-relevant arguments based on their relevance to the discussion topic and informativeness. This modular approach to summarizing discussions does not require expensive ground-truth summaries, and is thus more scalable than supervised approaches. We first de-

scribe the argument re-ranking module followed by the post-processing module.

**Argument Re-ranking**   Besides being relevant to a frame, arguments in the summary must also be relevant to the discussion topic. Thus, we re-rank the frame's arguments according to their *topic relevance*. In our scenario, a "topic" is the combination of the title and the reasoning of the original post on CMV. We propose two approaches for computing topic relevance. The first approach computes content overlap (lexical and semantic) between each argument and the topic. We used Jaccard similarity for lexical overlap, and for semantic overlap, we used the cosine similarity between the contextual sentence embeddings of an argument and the topic. Arguments within a frame are then re-ranked by their overlap scores. The second approach employs retrieval models and (re-)ranks the frame's arguments using the entire topic as the query (details in Section 4).

**Post-processing**   Parallel to the aforementioned re-ranking by topic relevance, we derive a separate re-ranking of the frame's arguments based on their *informativeness*. Our goal is to prioritize content-rich and argumentative texts in the top-$k$ arguments of our approach. We operationalize this through *content scoring* and *argumentativeness scoring*. For content scoring we employed a set of content-specific features such as named entities, noun phrases, the number of discourse markers, and the number of children an argument has in the discussion. Next, for argumentativeness scoring, we trained a topic-based argumentativeness scoring model (details in Section 4). The informativeness score of an argument is the sum of its content score and the argumentativeness score. We then re-rank the frame's arguments by this score.

**Frame-oriented Extractive Summaries**   Given the list of arguments first ranked by frame relevance, then re-ranked by topic relevance, we fuse this ranking with the standalone informativeness ranking from the post-processing module (via reciprocal rank fusion) to derive the final ranking. The top-$k$ arguments from this ranking are taken as the *extractive* summary of the discussion. A key benefit of our ranking-based extractive summarization approach is the flexibility to determine the summary length (i.e., $k$) by the user according to the discussion's length and their information need. Thus we refrain from setting a specific length budget for the summary.

## 4   Data and Experiments

This section describes the dataset on which our approach was evaluated, the various retrieval models with their respective parameters, and the content features that we used in our experiments. Also described is the supervised baseline for frame classification SUPERFRAME that we implemented to assign multiple frames to each argument.

### 4.1   Data

We constructed a dataset of 100 long discussions from CMV, dated January 2020, using the Pushshift Reddit dataset (Baumgartner et al., 2020). For the purpose of this study, we defined a long discussion as a post with at least 100 comments. As preprocessing, we filtered out comments that were deleted by their authors, removed by moderators due to violating community rules, or posted by bots (e.g., DeltaBot, RemindMeBot). The average length of the posts in our dataset is 304 words, with a minimum of 83 words and a maximum of 1611 words. These posts have a total of 25,385 comments, with an average of 253 comments per discussion. The shortest discussion has 105 comments, while the longest has 1066 comments. The average length of a comment is 90 words, with a minimum of 2 words and a maximum of 1589 words excluding the quoted text from either the post or the parent comments they responded to.[3]

**Popularity Ranking**   We investigated to what extent does ranking the arguments only by their popularity (via karma scores) covers all the top-$k$ arguments of the frames in the discussion (as assigned by our approach). Confirming the findings of Kano et al. (2018), we found that simply sorting arguments by popularity is not enough to cover a sufficient number of arguments that belong to *some* frame. This encourages the need for tailored summarization approaches for long discussions. More details can be found in Appendix B.

### 4.2   Experiments

We first describe the models and parameters for our approaches to frame assignment and extractive

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[3]The strict community guidelines of CMV (https://www.reddit.com/r/changemyview/wiki/rules) ensure that comments are primarily argumentative. Therefore, in this paper, we consider each comment to be an argument and do not perform any argument mining.

summarization. We then describe the supervised baseline for frame assignment.

**Frame Assignment** We experimented with three retrieval models for IRFRAME to retrieve frame-relevant arguments: BM25 (Robertson et al., 1994), SBERT (Reimers and Gurevych, 2019), and Col-BERT (Khattab and Zaharia, 2020). The latter two are dense retrieval models based on contextual embeddings to match arguments to frames, addressing the limitation of BM25 not finding arguments with exact lexical matches to our query variants. We used the Okapi BM25 model with default settings ($k$=1.5, $b$=0.75) [4] , initialized SBERT with the `all-mpnet-base-v2` model, and used ColBERT-v2 (Santhanam et al., 2022).[5]

**Argument Re-ranking** We experimented with two approaches to re-rank the arguments retrieved by IRFRAME: content overlap and retrieval-based re-ranking. Content overlap considers both lexical and semantic overlap between the topic and the argument. For lexical overlap, we used Jaccard similarity and for semantic overlap, we used SBERT (`all-mpnet-base-v2` model). For the retrieval-based re-ranking, we experimented with BM25 and ColBERT, with the topic as the query, to (re-)rank the frame's arguments. We excluded using SBERT as an additional retrieval model since it is already integrated in the content overlap approach.

**Post-processing** Informativeness is computed based on the content richness and the argumentativeness of the arguments. Content is scored as the sum of the ratios of named entities, discourse markers, and noun phrases found in the argument and the number of children for an argument in the discussion. We used spaCy (Honnibal et al., 2020) for text tokenization and extraction of the named entities and noun phrases.[6] For discourse markers, we used a lexicon of claim-related words constructed by Levy et al. (2017) for identifying claim-containing sentences. The ratios of named entities and noun phrases were on the token level, while the ratio of discourse markers was on the word level, all normalized by the arguments' lengths. For argumentativeness, we developed *ArgDetector* [7] , a RoBERTa model (Liu et al., 2019) fine-tuned on

the dataset by Schiller et al. (2022), containing 150 controversial topics with 144 sentences labeled for their argumentativeness, given the topic. Training details are provided in Appendix C.

**SUPERFRAME** This is the supervised baseline for frame assignment. Extending the state-of-the-art frame classification model of Heinisch and Cimiano (2021), we developed a new classifier trained on an external frame-labeled dataset. The existing classifier of Heinisch and Cimiano (2021), utilizes a recurrent neural network to assign a *single* frame to an argument, and combines it with a model that predicts a cluster of frame labels from the inventory of Ajjour et al. (2019) in a multi-task setting. Particularly longer arguments, however, often contain multiple frames. Thus, assigning a single frame to an argument may not be sufficient (Reimers et al., 2019). We therefore extend the model to predict *multiple* frames for an argument. Given the probability distribution of the classification model $P = (p_{f_1}, \cdots, p_{f_k})$ over a set of frames $\mathcal{F} = \{f_1, \ldots, f_k\}$, $k \geq 2$, we apply nucleus sampling (Holtzman et al., 2020) to predict multiple frames for an argument. Specifically, given a cumulative probability mass threshold $\tau$, we assign the minimal subset of frames $F \subseteq \mathcal{F}$ such that:

$$\sum_{f \in F} p_f \geq \tau$$

When the model is very confident in predicting one frame, it is hence likely that an argument is tailored to that specific frame. In cases where the model has lower confidence in its prediction, the argument may consist of multiple frames. This overcomes the limitation of clustering-based approaches and classifiers which strictly assign a single frame to arguments that may often contain multiple ones (Reimers et al., 2019; Heinisch and Cimiano, 2021).

To train SUPERFRAME, we used the Media Frames Corpus by Card et al. (2015) consisting of 14,515 news articles with text spans manually annotated for the frame classes in Table 1. Following Heinisch and Cimiano (2021), we trained two variants of the classifier, *single-task* and *multi-task* which additionally used the framing dataset by Ajjour et al. (2019) with 12,326 labeled arguments. Both models were based on BiLSTMs, used GloVe embeddings [8], and trained up to 12 epochs

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[4] We used the Rank BM25 toolkit (Brown, 2020)

[5] We used PyTerrier (Macdonald and Tonellotto, 2020) for the ColBERT pipeline

[6] We used the `en_core_web_md` model.

[7] https://huggingface.co/roberta-base

[8] https://nlp.stanford.edu/data/glove.840B.300d.zip

using early stopping. We truncated the input to 75 words with a batch size of 64. We used a cumulative probability distribution with a threshold of $\tau = 0.9$. On average, SUPERFRAME assigned 2.6 frames to each argument, with a minimum of 1 and a maximum of 8.2 frames, respectively. The frequency counts of all frames in both posts and arguments are shown in Table 5. We evaluated it via precision scores on manually-annotated frame labels for 150 arguments. The best variant of this classifier (*single-task*) has precision of 60.5% and 55.4% micro- and macro-average respectively (see Table 3, Appendix A for more details). Thus, we combined this model with our argument re-ranking and post-processing modules for a comprehensive evaluation against our IRFRAME approach.

## 5 Evaluation

Given that our entire approach is based on retrieval models, we evaluated it manually via relevance judgments. We followed the evaluation style of TREC (Harman, 1993) as best practice. Our evaluation was comprised of judging the *frame relevance*, the *topic relevance*, and the *importance* (in the discussion's context) of arguments retrieved by our models. Following the TREC protocol, we created first 50 evaluation topics, each comprising a post's title, the post itself, and a frame of interest (see supplementary material). To obtain a sufficiently large set of arguments to pool from, we then selected only those discussions for which all models assigned at least 20 arguments to each of the five most frequent frames identified in the comments: *cultural identity*, *economic*, *quality of life*, *public opinion*, and *political* (see Table 5 in the appendix for the full list). We retrieved arguments for each evaluation topic and performed pooling at depth 5 using TrecTools (Palotti et al., 2019), resulting in 1871 unique arguments to be judged.

### 5.1 Pilot Study

Multi-annotator relevance judgments can often result in low agreement due to the subjective nature of defining *relevance* and the varying perspectives of annotators (Voorhees, 1998; Bailey et al., 2008; McDonnell et al., 2016; Thomas et al., 2022). Additionally, judges may experience inconsistencies in their decisions as the task progresses (Scholer et al., 2011). To mitigate these issues, we conducted a pilot study with 100 arguments (not included in the main evaluation) to train three annotators and

gather feedback for improving the main evaluation interface. The annotators were Computer Science graduates with backgrounds in NLP and IR.

**Task Design** Following McDonnell et al. (2016), we used a four-point scale for assessing the frame and topic relevance, and the importance of an argument with these options: *definitely not*, *probably not*, *probably*, and *definitely* relevant/important.[9] In assessing importance, we asked annotators to indicate the relevance of an argument to a discussion by answering this question: "How important it is to be included in a *summary* of the discussion?". We also experimented with an automatic summary (Nathan, 2016) for long arguments to reduce the cognitive load of the annotators. They were instructed to use the summary if they found it helpful, otherwise to read the entire argument (for details, see Appendix D, Figure 3).

**Pilot Agreement and Feedback** We measured the inter-annotator agreement (IAA) for the three evaluated criteria using Krippendorff's $\alpha$, similar to Card et al. (2015). The resulting $\alpha$ values were 0.22 for frame relevance, 0.33 for topic relevance, and 0.22 for importance, respectively. While the agreement is thus limited, the values are consistent with the findings of Card et al. (2015) in their annotation of frame-relevant text spans for the Media Frames Corpus, particularly the frame relevance $\alpha$ value. From feedback, we improved the task design for the main evaluation. Firstly, we removed the automatic summary for each argument since it did not provide significant help. Secondly, we rephrased the importance question to "how important is the argument to be included in the *discussion* of the given topic" to make it more straightforward, since we did not have ground-truth summaries of the discussions at hand. Annotators also reported that assessing the relevance of an argument for a *single* frame was too restrictive, since an argument may belong to multiple frames, which aligns with the observations of Card et al. (2015). Therefore, we allowed them to assign multiple frames to an argument if the currently-assigned one was not relevant. Accordingly, we proceeded with the main evaluation by assigning each annotator an independent set of arguments to judge. This allowed us to collect more relevance judgments while ensuring a certain level of *shared* understanding of the task.

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[9]We mapped these labels to numerical values ranging from 0 (*definitely not* relevant/important) to 3 (*definitely* relevant/important) for computing nDCG scores.

| | nDCG@5 | | |
|---|---|---|---|
| Model | Frame | Topic | Imp. |
| **Our Approach** | | | |
| IRFr_BM25 | **0.573**[1] | 0.708 | 0.375[2] |
| IRFr_SBERT | 0.480 | 0.525 | 0.303 |
| IRFr_ColBERT | 0.522 | 0.659 | 0.361[3] |
| IRFr_BM25_rr_BM25 | 0.516 | 0.781[3] | 0.349 |
| IRFr_BM25_rr_overlap | 0.560[2] | **0.847**[1] | 0.350[5] |
| IRFr_BM25_rr_ColBERT | 0.540[4] | 0.761 | 0.358[4] |
| IRFr_BM25_rr_BM25_post | 0.489 | 0.735 | 0.297 |
| IRFr_BM25_rr_overlap_post | 0.522 | 0.755 | 0.339 |
| IRFr_BM25_rr_ColBERT_post | 0.526 | 0.719 | 0.325 |
| **Supervised Baseline** | | | |
| SupFr_rr_BM25 | 0.545[3] | 0.765[4] | **0.381**[1] |
| SupFr_rr_overlap | 0.536[5] | 0.785[2] | 0.334 |
| SupFr_rr_ColBERT | 0.529 | 0.764[5] | 0.348 |
| SupFr_rr_BM25_post | 0.493 | 0.714 | 0.322 |
| SupFr_rr_overlap_post | 0.493 | 0.734 | 0.348 |
| SupFr_rr_ColBERT_post | 0.487 | 0.709 | 0.329 |

Table 2: nDCG@5 for the manual relevance judgments for frame relevance, topic relevance, and importance. The best results for each evaluated criterion are highlighted in bold, alongside the rankings for the five best models. We evaluated our frame assignment approach (*IRFr*) against the supervised baseline (*SupFr*), combined with our argument re-ranking (*_rr*) and post-processing components (*_post*). We see that our approach to frame assignment results in the best models for frame and topic relevance and is also competitive for argument importance.

## 5.2 Main Evaluation Results

Evaluated models are shown in Table 2 [10]. We obtained relevance judgments for a total of 1871 arguments and calculated nDCG@5 (Järvelin and Kekäläinen, 2002) as the performance measure (mean over all topics). Described below are the key findings for each module of our ranking-based extractive summarization framework.

**Frame Relevance** Our frame assignment approach (*IRFr* with BM25) outperforms other models for identifying frame-relevant arguments in a discussion with an nDCG@5 of 0.573. Among the retrieval models, BM25 performs better than SBERT and ColBERT, also for re-ranking by topic relevance. Upon further inspection, we found that

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[10]Model names in Table 2 shortened for brevity. SUPER-FRAME → *SupFr* denotes the baseline, IRFRAME → *IRFr* denotes our frame assignment approach, Argument Re-ranking → *_rr* (via overlap and retrieval models), and Post-processing → *_post*

BM25 often retrieves longer arguments compared to the embedding-based SBERT and ColBERT models. This may provide annotators with more context for informed judgments compared to the shorter arguments. Given the computational costs of running dense retrieval models in real-time, it is promising that a relatively simple and explainable model performs well on our query variants. For the baseline (*SupFr*), combinations with argument re-ranking (via BM25 and topic overlap) also perform reasonably well. However, as various query variants can be easily designed, our *IRFr* approach is more flexible and can be adapted to other domains and topics without the need for labeled data.

**Topic Relevance** Argument re-ranking by overlap (*_rr_overlap*) outperforms retrieval models for ensuring topic relevance of a frame's arguments. This benefits both *IRFr* and *SupFr* frame assignment approaches with nDCG@5 scores of 0.847 and 0.785 for the top two models, respectively. Among the retrieval models, BM25 slightly outperforms ColBERT. Given the intuitive nature of content overlap, we conclude that it is favorable to use for re-ranking arguments in a frame.

**Importance** None of the post-processed models (using informativeness) appear in the top-5 for ranking arguments by importance in the context of the discussion. Instead, argument re-ranking by topic relevance performs best, with nDCG@5 of 0.381 combined with *SupFr* for frame assignment. This contradicts our intuition of post-processing to promote important arguments in the final ranking. As future work, we plan to investigate using context features of the arguments (Kano et al., 2018), as well as pairwise judgments for importance (Zopf, 2018; Luo et al., 2022).

## 6 Conclusion and Future Work

We proposed an intuitive ranking-based approach for extractive summarization of online discussions via argumentation frames which considers relevance to a chosen frame and the discussion topic. Evaluation shows that our approach effectively ensures frame and topic relevance of arguments, while informativeness requires further investigation. Furthermore, our frame assignment outperforms a state-of-the-art supervised baseline. We plan to develop practical applications based on our approach for scalable exploration of online discussions guided by argumentation frames.

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## A  Single-Task vs. Multi-Task Classifier

To choose between the `single-task` and `multi-task` variants of `SuperFrame`, three of the authors first manually assigned frame(s) for 150 arguments. We then predicted the frames for these arguments using both variants.[11] We opted

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[11]We also experimented with multiple preprocessing methods (e.g. generating a conclusion or ranking the sentences) before automatically predicting the frames. However, these methods negatively impacted the frame prediction.

| Model | Minority | Majority | Full |
|-------|----------|----------|------|
| single-task | 59.6 / 49.6 | **41.7 / 34.1** | **38.8 / 28.8** |
| single-$\tau = .8$ | 55.0 / 45.5 | 32.6 / 27.6 | 34.8 / 27.6 |
| single-$\tau = .9$ | **60.5 / 55.4** | 27.8 / 24.5 | 30.4 / 23.7 |
| multi-task | 52.4 / 50.1 | 27.9 / 22.7 | 38.4 / 29.5 |
| multi-$\tau = .8$ | 56.4 / 55.0 | 33.0 / 26.6 | 27.4 / 20.1 |
| multi-$\tau = .9$ | 51.0 / 46.9 | 26.7 / 21.7 | 25.4 / 17.9 |

Table 3: Precision scores (% – micro / macro) of the `SuperFrame` model variants at different annotator agreements and using different thresholds $\tau$ for predicting multiple frames.

for higher precision as our goal is to minimize mislabeling arguments with an unrelated frame that can negatively impact the resulting frame-oriented summaries. Since frame assignment is a subjective task (Card et al., 2015) and the boundaries of the frame classes are fuzzy (Reimers et al., 2019; Budzynska et al., 2022), we observed some diversity in our manual annotations. Specifically, we observed that 92% of all the annotated arguments have at least one frame, which was assigned by only a single annotator (minority), indicating different perceptions of observing specific frames in texts. On average, an argument was assigned 3.8 frame classes (or 1.3 and 0.4 considering the majority and full agreements, respectively).

Table 3 presents the precision scores of both variants using the cumulative probability threshold $\tau$ as described in Section 4.2. Assigning only the most probable frame as predicted by the `single-task` model results in a precision of 59.6% (micro-average) and 49.6% (macro-average), respectively. The `multi-task` model is slightly better at predicting rare frame classes (+0.5% macro-average) but worse at predicting the frequent ones (-7.2% micro-average). Assigning multiple frames per argument increases the performance of the `single-task` model by +0.9% for micro-average, and especially at predicting rare frame classes, increasing the macro-precision by +5.8% (at $\tau = 0.9$). Considering only the majority labeled frame classes as ground truth restricts the set of manually assigned frame classes, and hence, reduces the precision scores. On this restricted subset of frame labels, the `single-task` model performs best in nearly all cases, by predicting only the most probable frame class due to the sparsity of the manually assigned frame classes. This variant of `single-task` model which predicts only a single frame for an argument

has a micro-precision of 41.7% and 38.8% in the majority and full agreement scenarios, respectively. Despite this, we extended the `single-task` variant to predict multiple frames per argument, resulting in a high overlap with ground truth frame labels from at least one annotator as well as benefiting from a higher recall. This also avoids having sparse sets of arguments assigned under rare frames. In conclusion, our internal evaluation supports using the `single-task` model, as opposed to the findings of Heinisch and Cimiano (2021) due to our emphasis on precision while the `multi-task` variant primarily encourages the model in its recall-generalization ability.

## B Insufficient of Popularity Rank for Frame Argument Coverage
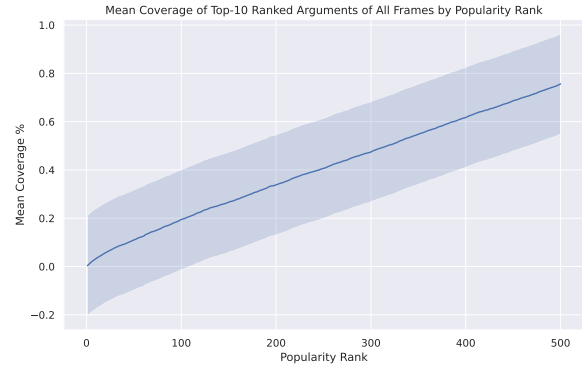


Figure 2: Mean coverage percentage by popularity rank of the top 10 (unique) frame arguments as assigned by our approaches.

Similar to Kano et al. (2018), we find that sorting comments by popularity is ineffective to cover a sufficient number of frame relevant arguments within a reasonable summary length budget. To quantify this, we computed the mean coverage of the top 10 arguments across all frames and models by their popularity ranking. We considered discussions with at least 500 arguments and ranked them by their popularity scores provided by the Reddit API. Then, at each rank, we computed the percentage of top 10 arguments from all frames that have been covered by the popular arguments. Figure 2 shows that in order to completely cover the top 10 arguments from all frames, a user must read through hundreds of arguments. This encourages us to investigate novel approaches to group arguments in a discussion via frames instead of solely relying on their popularity.

| Frame | Description |
|---|---|
| Capacity & Resources | The lack of or availability of physical, geographical, spatial, human, and financial resources, or the capacity of existing systems and resources to implement or carry out policy goals. |
| Constitutionality & Jurisprudence | The constraints imposed on or freedoms granted to individuals, government, and corporations via the Constitution, Bill of Rights and other amendments, or judicial interpretation. This deals specifically with the authority of government to regulate, and the authority of individuals/corporations to act independently of government. |
| Crime & Punishment | Specific policies in practice and their enforcement, incentives, and implications. Includes stories about enforcement and interpretation of laws by individuals and law enforcement, breaking laws, loopholes, fines, sentencing and punishment. Increases or reductions in crime. |
| Cultural Identity | The social norms, trends, values and customs constituting culture(s), as they relate to a specific policy issue. |
| Economic | The costs, benefits, or monetary/financial implications of the issue (to an individual, family, community or to the economy as a whole). |
| External Regulation & Reputation | A country's external relations with another nation; the external relations of one state with another; or relations between groups. This includes trade agreements and outcomes, comparisons of policy outcomes or desired policy outcomes. |
| Fairness & Equality | Equality or inequality with which laws, punishment, rewards, and resources are applied or distributed among individuals or groups. Also the balance between the rights or interests of one individual or group compared to another individual or group. |
| Health & Safety | Healthcare access and effectiveness, illness, disease, sanitation, obesity, mental health effects, prevention of or perpetuation of gun violence, infrastructure and building safety. |
| Morality | Any perspective—or policy objective or action (including proposed action)— that is compelled by religious doctrine or interpretation, duty, honor, righteousness or any other sense of ethics or social responsibility. |
| Policy Prescription & Evaluation | Particular policies proposed for addressing an identified problem, and figuring out if certain policies will work, or if existing policies are effective. |
| Political | Any political considerations surrounding an issue. Issue actions or efforts or stances that are political, such as partisan filibusters, lobbyist involvement, bipartisan efforts, deal-making and vote trading, appealing to one's base, mentions of political maneuvering. Explicit statements that a policy issue is good or bad for a particular political party. |
| Public Opinion | References to general social attitudes, polling and demographic information, as well as implied or actual consequences of diverging from or getting ahead of public opinion or polls. |
| Quality of Life | The effects of a policy, an individual's actions or decisions, on individuals' wealth, mobility, access to resources, happiness, social structures, ease of day-to-day routines, quality of community life, etc. |
| Security & Defense | Security, threats to security, and protection of one's person, family, in-group, nation, etc. Generally an action or a call to action that can be taken to protect the welfare of a person, group, nation sometimes from a not yet manifested threat. |
| Other | Any frames that do not fit into the above categories. |

Table 4: Descriptions of frames as per Boydstun et al. (2014). We substituted the term "policy" with the phrase "actions/decisions" to align the frame definitions with the individualistic style of arguments in CMV. Similarly, in *External Regulation & Reputation*, we substituted "United States" with "country" to generalize it.

## C   Argumentativeness Scoring Model

The dataset of Schiller et al. (2022) consists of topics formulated as phrases as opposed to the topic titles in CMV, which are often formulated as claims. To unify this, we manually transformed their topics by appending them with stance-indicative phrases (e.g., "Abortion" → "Abortion should be banned"). We trained the RoBERTa model for the binary classification task with default training parameters: a learning rate of 5e-5, 5% of the training data for warmup, early stopping, and a batch size of 32.

| Posts | | Comments | |
|---|---|---|---|
| **Frame** | **Count** | **Frame** | **Count** |
| Cultural Identity | 53 | Cultural Identity | 13,540 |
| Quality of Life | 37 | Economic | 8931 |
| Economic | 33 | Quality of Life | 8559 |
| Public Opinion | 26 | Public Opinion | 7257 |
| Health & Safety | 22 | Political | 5177 |
| Political | 19 | Health & Safety | 4927 |
| Morality | 12 | Morality | 4237 |
| Policy Prescription & Evaluation | 10 | Policy Prescription & Evaluation | 4108 |
| Fairness And Equality | 10 | Constitutionality & Jurisprudence | 3226 |
| Constitutionality & Jurisprudence | 9 | Fairness & Equality | 2457 |
| Security & Defense | 1 | Crime & Punishment | 898 |
| Crime & Punishment | 1 | Security & Defense | 515 |
| | | External Regulation & Reputation | 216 |
| | | Capacity & Resources | 169 |

Table 5: Counts of frames in posts and comments in our dataset of 100 discussions as predicted by `SuperFrame`. Since each text can be assigned multiple frames, the counts include duplicates. Here, we observe that there are two additional frames found in the comments: *External Reputation & Regulation*, *Capacity & Resources* that are not found in the posts.

On the test split provided by Schiller et al. (2022), our fine-tuned model performs with a macro-F1 of 67%, which is comparable with the results from the best model reported in Schiller et al. (2022).[12] To label a given text (along with the topic) as argumentative for our post-processing as described in Section 4.2, we take the mean argumentativeness scores of its constituent sentences.

## D Annotation Interface

Annotation interfaces for the pilot study and the main evaluation are shown in Figure 3 and Figure 4, respectively. We improved the interface for our main evaluation based on annotator feedback from the pilot study with the following changes: (1) We substituted "probably" with "rather" in our scales to indicate a clearer relevance judgment. (2) For non-argumentative texts or meta-arguments (e.g. "I agree.", "I don't understand what you mean." etc., ) we allowed annotators to mark the text as *noisy* and skip it. (3) We asked annotators to select at least one relevant frame if the current frame was (definitely/rather) not relevant, with the possibility of selecting multiple frames if required.

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[12]A text is labeled as argumentative if the predicted probability is higher than 50%.

Figure 3: Annotation interface for the **pilot study**. Annotators were provided a summary of the argument alongside the entire argument. There was no option to mark a text as noisy/non-argumentative. Furthermore, the importance of an argument was assessed based on how likely it was to be included in a frame-oriented *summary* of the discussion.

Figure 4: Annotation interface for the **main evaluation**. First, we removed the summary of the argument and always showed the complete argument. Next, we allowed marking a text as "noisy" and skip answering the remaining questions. Finally, as it was difficult to decide if an argument was important enough to be included in a summary of the discussion before reading the entire discussion, we rephrased the important question as the likelihood of including an argument in the *discussion* of the topic.