A Narrative Framework for Analyzing Partisan Perspectives in Event Discourse

Anonymous ACL submission

Abstract

Experts from several domains, especially political science, are interested in analyzing political discourse associated with real-world news events. This process would typically require researchers to manually analyze a large collection of news articles on a given event, in order to characterize the underlying partisan perspectives from each side of the political map. Instead, in this work, we propose a systematic approach to summarize partisan perspectives, in an automated manner. Our framework allows us to represent each news article with a predefined structure, comprising of *talking points*, which we then cluster to identify the repeating themes that collectively shape the narrative of an event. Then, we utilize the resulting clusters to generate a summary for each ideology, *left* and *right*, that indicates how each side discusses the event. We show the effectiveness of our framework in capturing partisan perspectives across automated proxy tasks, and human evaluation over a set of events. We release the dataset derived from our narrative framework to the research community.

1 Introduction

One of the signs of the growing social and political polarization is the formation of insulated information bubbles (Gentzkow and Shapiro, 2011; Quattrociocchi et al., 2016; Dubois and Blank, 2018; Garimella et al., 2018), in which news media discourse is shaped around ideological lines, often intended to shape the readers' views. Understanding this phenomenon better, to the extent we can examine the degree to which members of the two communities hold opposite accounts of reality, requires computational methods that can compare the narratives of both sides and identify the points in which their accounts converge and diverge.

Past work analyzing political discourse typically focused on discrete aspects, such as stance and bias detection works (Liu et al., 2022; Luo et al., 2020; Kiesel et al., 2019; Li and Goldwasser, 2019), political news framing (Mendelsohn et al., 2021; Field et al., 2018; Card et al., 2015b), sentiment toward relevant entities (Park et al., 2021; Rashkin et al., 2016), which while relevant, fall short of providing the comprehensive view needed.

The rise of Large Language Models (LLM) has a transformative potential for enabling complex narrative analysis connecting these dimensions and explaining their relationship. However, realizing it is not straightforward, as demonstrated by several recent works analyzing political texts, either as a straightforward stance prediction task (Ziems et al., 2024), or mapping political positions to specific stances on policy issues (Santurkar et al., 2023).

To address these challenges, we suggest a structured approach, modeling the interactions between different narrative elements. We center our analysis around the notion of a *talking point*, a narrative frame structure, capturing a specific aspect of news event, through a short summary, and a set of properties – the lens through which it is discussed, using media-frames (Boydstun et al., 2014), relevant entities, their roles and attitudes towards them (Khanehzar et al., 2021; Roy et al., 2021). We analyze political discourse by creating a unified vocabulary of repeating talking points, and comparing their differences across the political sides, using these properties. This analysis allows us to identify *agenda-setting* attempts (McCombs and Shaw, 1972; Scheufele and Tewksbury, 2007) by looking at frequent talking points overwhelmingly discussed by one side, as well as *areas of consensus and polarization*, based on talking points frequently discussed by both sides, in a similar or contrasting way. Fig. 3 exemplifies this analysis for Covid-19.

To accomplish that, we suggest a pipeline approach (described in Fig. 1). First, we use an LLM for extracting information from each article using a structured schema. Second, we create a talking point vocabulary by clustering the extracted schema information, and using an LLM to improve the clusters by removing inconsistent and redundant clusters. The goal of this process is to identify repeating topics, which can potentially be shared by both sides of the political map. Finally, we use an LLM to reason about the partisan view of each point, capturing the differences in framing and attitudes towards entities expressed by each side.

This process provides several resources, validated through human and automatic validation, that can be used by other researchers. First, we provide a collection of narratives extracted from news articles, organized according to a structured schema. Our dataset consists of $6,141$ articles discussing 24 events related to 4 contested political issues. These articles are drawn from 126 sources, coded for bias[1]. Second, we identify the prominent talking points characterizing political discourse about a specific event, our data consists of the right- and left-winged perspectives of 389 higher-level talking points, relevant for 24 news events.

Note that unlike manual annotation based approach that are costly and as a result focus on specific topics, we suggest an automated method, broadly applicable across a very wide range of event topics, and show that it results in high quality information, through careful validation steps. First, we validate the framework's ability to characterize the space of possible talking points through a *topic classification task*. Then, we evaluate its ability to generate partisan perspectives, both automatically using a *partisan classification task*, and through a human evaluation. These results support our final finding, in which we use the extracted representation for stance classification. We show that our approach, extracting abstract partisan talking points, can be used for stance classification over a previously unseen set of documents.

More generally, we show that our narrative representation and methodology for extracting it using LLM with minimal human effort, can help LLMs deal with political text effectively. This has many real world applications. Similar to our stance classification task, our framework can be used for quickly adapting to emerging news events, identifying the key political actors, polarizing points, and so on.

To summarize our main contributions are: **(1)** We propose a new way to conceptualize partisan narrative extraction for news event coverage, which captures nuanced talking points, media frames and entity role analysis. **(2)** We suggest an LLM-based pipeline, along with automated validation mechanism, for extracting such partisan narratives. **(3)** we conduct automated and human validation of our pipeline, resulting in a novel dataset capturing partisan perspective over multiple topics, which can be used to drive future research.

[1] https://www.allsides.com/media-bias

2 Related Work

Prior work on studying partisan perspectives in NLP has primarily focused on *frames*. While a contested concept, framing is commonly conceived of as a communicative structure in which the speaker highlights specific aspects of an issue to promote a political viewpoint (Goffman, 1974; Entman, 1993; Kinder, 1998; Chong and Druckman, 2007). Card et al. (2015b) proposes the Media Frame Corpus that has 15 generic media frames defined by Boydstun et al. (2014), such as economics or public opinion. In a polarized media environment, frames serve as instrumental mechanisms to promote political agendas through the selective coverage of events (informational bias) and the manipulation of their presentation (lexical bias) (Gentzkow and Shapiro, 2006; Jamieson et al., 2007; Fan et al., 2019). Prior work has also explored approaches to automatically detect and mitigate framing biases. Liu et al. (2019); Akyürek et al. (2020) identify frames through news headlines, Ji and Smith (2017); Khanehzar et al. (2021) detect frames at a document level, and Lee et al. (2022); Liu et al. (2023) mitigate framing biases using multi-domain summarization and graphs. However, the formalization of frames oversimplifies the intricacies of partisan perspectives and falls short in capturing the nuance of how political agendas are deliberately conveyed in news articles. In this work, we look closer at news articles, and represent them with a predefined structure of *talking points*, carefully crafted statements that push the political messages, and cluster them to identify repeating themes, to collectively shape the different partisan perspectives. Identifying nuanced *talking points* can be thought of similar to using LLMs to generate explicit representations that helps in assessing arguments Hoyle et al. (2023). Recent work has also explored finer analysis in news articles/political biases. Lawlor and Tolley (2017) presents an entity-focused study of media news framing. Spinde et al. (2021) detects media biases at the word and sentence level, and Fremann et al. (2023) identifies and uses multi-label frames. Our work complements these by introducing a framework that allows us to establish repeating themes of talking points to unveil the partisan perspectives within an event.

3 Narrative Framework

When discussing real-world events, political parties and elites with a relatively large influence typically employ various mechanisms to advance their perspectives. In political communication, such carefully crafted messages, statements, or concepts are referred to as *talking points*. These points capture relevant topics with regards to the event, and often advance an underlying perspective, frequently from a specific ideological side.

Identifying and understanding these talking points is critical to analyze political discourse surrounding news events. This is because, the prominent talking points for a given event repeat several times across news articles related to that event, and thus shape the narrative of it. For instance, a right-leaning repeating talking point with respect to the issue `Climate Change` is *Highlighting skepticism towards global climate cooperation, favoring protection of US fossil fuel industries.* It clearly captures the right-wing's stance on the issue, and is cardinal in shaping the right narrative.

In this work, we aim to exploit this repeating nature of prominent talking points, in order to summarize the partisan perspectives around an event. To do this, we propose a narrative schema (Fig. 2), that enables us to obtain a structured representation of each news article, that is relevant to the event (Sec. 3.1). We then make use of this structured representation, to analyze the political discourse for the event, and characterize partisan viewpoints indicating how each political ideology discusses the event. Specifically, we use our structured representation to first group the talking points (TP) into clusters, which captures their topic similarity. Then, we generate partisan perspectives for each cluster, capturing *left* and *right* political ideologies with respect to the event and a specific topic in it (Sec. 3.2).

3.1 Narrative Schema

We start by identifying the prominent talking points for an event. For this, we propose a schema that analyzes each news article from the event by defining and building a structure that enables us to summarize the partisan perspectives for that event. Fig. 2 shows an overview. We start with a set of n news articles $\{d_z\}_{z=1}^{n}$, that are relevant to an event $\mathcal{E}$. Our schema reduces every news article d_z to a set of at most four key talking points, i.e. $\{t_i\}_{i=1}^{m}$, where $m \leq 4$. Each point t_i consists of a title and a brief description, explaining the talking point.

Next, we capture additional contextual information around each talking point t_i, by extracting relevant metadata information for it, that could be useful in analyzing partisan differences. To build this metadata, for each point t_i, we first identify the set of entities associated with it. We then capture the relationship between these entities, and how they influence one another, by identifying the set of activities linked to each point t_i. These activities are similar to the form *who did what to whom*. Specifically, each activity consists of a sentence-long activity description, an *actor* who is the entity propelling the activity, a *target* that is impacted by the actor, and the sentiment on the target entity, indicating whether the target is positively or negatively impacted by the actor. Finally, we also identify the media frame associated with every activity. The identified media frame follows Boydstun et al.'s nomenclature (Card et al., 2015a).

In order to obtain the structured representations defined by our schema above, we prompt an LLM to identify the key talking points, and the related metadata information, using the prompt template shown in Table 14.

3.2 Characterize Partisan Perspectives

Our overall goal is to analyze political discourse for an event $\mathcal{E}$ by summarizing how each political ideology, say {*left*, *right*}, is talking about the event $\mathcal{E}$. To achieve this, we rely on the schema described in Sec. 3.1, to better characterize the partisan viewpoints for the two political ideologies, rather than directly operating over the news articles.

Specifically, we organize each news article $\{d_z\}_{z=1}^{n} \in \mathcal{E}$ according to the schema, representing every article d_z as a set of at most four talking points, say $\{t_i\}_{i=1}^{m}$, where $m \leq 4$. These talking points are associated only with their respective news article, but we actually want to analyze the partisan discourse for the entire event $\mathcal{E}$. Therefore, we build a talking point set $\mathcal{T} = \{t_s\}_{s=1}^{p}$ for an event $\mathcal{E}$, by aggregating all the talking points from each article in the event. Then, to capture the topics of this event, we cluster this set $\mathcal{T}$ to identify topically relevant *prominent talking points* (PTP). We utilize the result from the clustering process to generate a left-summary and a right-summary for each

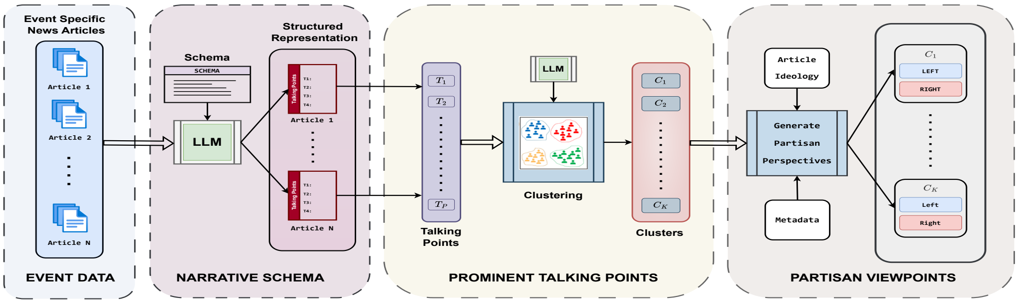

Figure 1: Provides an overview of our narrative framework.

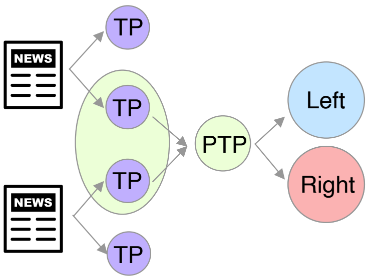

Figure 2: Our Narrative Schema: Given news articles, we extract talking points (TP), which we then cluster (green background), capturing topic relevance. Each cluster is represented by prominent talking point (PTP). Each PTP cluster captures partisan viewpoints for Left/Right political ideologies.

cluster, which each indicate the partisan viewpoints for the two political ideologies $\{left, right\}$, as it relates to the topics of this cluster. The following describes the prior two steps in more detail.

3.2.1 Clustering the Talking Points

In this first step, we aim to identify a set of *prominent talking points* that are topically relevant to the event, and are sufficient to represent the entire the talking point set $\mathcal{T}$. We do this by grouping topically similar talking points together such that the label associated with each group denotes a *prominent talking point*. Note that the talking points that are clustered together are likely to be topically related, while the cardinality of the cluster indicates the repeating characteristic of the talking point.

Alg. 1 describes the clustering process we use to obtain the *prominent talking points*. First, we embed each point in $\mathcal{T}$ using a dense retriever (Ni et al., 2021) model f, to obtain the corresponding embeddings $\mathcal{Z}$, which we then cluster using the HDBSCAN algorithm, to identify the candidate *clusters*. For each candidate cluster c, we prompt the LLM to characterize the candidate, by generating a cluster label. The cluster label consists of two components, an aspect and a short description about the cluster. The aspect indicates a high-level concept that is discussed in the top-5 talking points, while the description provides a brief summary of the top-5 points. In the prompt, we use the top-5 points closest to the cluster centroid, which we obtain by comparing cosine similarity scores between their respective embeddings.

We note that the output from the clustering process is not entirely perfect, as it is based on traditional distance measures. Therefore, we perform an additional step of updating the cluster label set by merging redundant clusters, and removing inconsistent ones. To remove redundancy, we compare every pair of cluster labels in a greedy manner, and merge the clusters that discuss the same aspect in their cluster labels. The updated label set we obtain after removing redundancy characterizes the space of possible talking points. More details of the merge/remove process and hyperparameters are provided in App. G. The prompt template used to characterize the candidate clusters, and remove redundancy is shown in Tables 24, 25, respectively. Note that the prompts are primarily designed to capture topically relevant talking points.

We then assign each talking point in $\mathcal{T}$ to one of these cluster labels, based on considering the cosine similarity between their corresponding embeddings. This results in a clustering $\{\mathcal{C}_j\}_{j=1}^{k}$ of the talking points along with their associated cluster labels $\{\mathcal{L}_j\}_{j=1}^{k}$, which are termed as the *prominent talking points*. App. G.3 provides further details.

3.2.2 Generate Partisan Perspective

Through the clustering process, we have obtained a set of *prominent talking points* that hold topically relevant information. However, these points still do not capture ideology-specific information that is crucial in characterizing partisan perspectives. Therefore, in this step, we provide an ideology label to each talking point in the cluster, and use the metadata associated with the talking point to generate ideology-specific viewpoints for *left*, and *right* political ideologies. These ideology-specific

Algorithm 1 Identify prominent talking points

Input: Talking points $\mathcal{T} = \{t_s\}_{s=1}^{p}$
Initialize: embeddings $\mathcal{Z} = \{z_s = f(t_s)\}_{s=1}^{p}\}$, n $\leftarrow$ no. of news articles, $\mathcal{C} \leftarrow \{\}$;
while $|\mathcal{Z}| > 0.1*$ n **do**
  clusters $\leftarrow$ *Clustering*($\mathcal{Z}$);
  labelSet $\leftarrow$ [];
  for c in clusters **do**
    Compute centroid μ_c by averaging;
    $Z' \leftarrow$ *getTopKPoints*(c, μ_c);
    cLabel $\leftarrow$ *getClusterLabel*(Z');
    Append cLabel to labelSet;
  end for
  updatedLabels $\leftarrow$ *updateLabelSet*(labelSet);
  $\mathcal{S} \leftarrow$ *TalkingPtMembership*($\mathcal{T}$, updatedLabels)
  $T' \leftarrow$ *getClusteredDocs*($\mathcal{S}$)
  $\mathcal{T} \leftarrow \mathcal{T} \setminus T'$;
  $\mathcal{Z} \leftarrow \mathcal{Z} \setminus$ {embeddings of T'};
  Append clusters in $\mathcal{S}$ to $\mathcal{C}$
end while
Output: k clusters $\mathcal{C} = \{\mathcal{C}_j\}_{j=1}^{k}$ with cluster labels $\{\mathcal{L}_j\}_{j=1}^{k}$

viewpoints indicate how the respective political ideology is discussing the event.

We assign an ideology label {*left, right, center*}, to each talking point in every cluster $\mathcal{C}_j$. We note that every news article gets an ideology label based on its media source. Since each talking point is derived from a news article, it gets the same ideology label as that of the news article.

Next, we describe the process of constructing the partisan perspective of the cluster in detail by explaining the generation of the left summary (the right summary is generated in a similar manner). Our goal is to generate a summary that it clearly depicts left specific viewpoints, and differs from the right perspective. Therefore, after labeling the talking points in each cluster, we prompt the LLM to generate the left summary in a contrastive manner. For this, we provide the LLM representative talking points from each ideology (left and right), so it can contrast the differences to identify what defines the left perspective. Specifically, for a cluster $\mathcal{C}_j$, the prompt consists of top-K left-leaning talking points along with top-M[2] right-leaning talking points for contrast. These representative points for each ideology are obtained by considering the cosine similarity between the talking point embeddings and the cluster label embedding.

We observe that context associated with the top-K left-leaning talking points is limited, and does not capture the potential ideological bias exhibited by the article as a whole, which is required to generate a partisan summary. Ideally, the news articles associated with the top-K points should be used to contextualize the prompt. Due to the issue of context length, we resort to working with the news article summaries instead.

We include the news article summaries corresponding to each of the top-K left-leaning points in the prompt. To ensure these article summaries capture the potential ideological bias and topically relevant information in the talking points, we prompt the LLM to generate the article summaries by conditioning on the ideology label of the article, and the aspect associated with the cluster $\mathcal{C}_j$.

Further, we also want to ensure that the generated left partisan summary captures the relationship between the associated entities in the top-K left-leaning talking points. Therefore, we also include the metadata information consisting of actors, targets, sentiment on the targets, and the relevant media frame as part of the prompt. The prompt template to generate partisan summary is in Table 15.

4 Dataset

To illustrate the effectiveness of our proposed framework, we use the `keyevents` dataset (Nakshatri et al., 2023). This dataset is constructed by segmenting the archive of news articles from NELA-2021 (Horne et al., 2022) into a set of temporally motivated news events. To construct these events, Nakshatri et al. (2023) dynamically analyzed the temporal trend of news articles published for a given issue, and identified the temporal landmarks that could signify the presence of an important news event. Then, the news articles published in and around the temporal landmarks were clustered to identify all the documents relevant to the news event. In this manner, Nakshatri et al. (2023) proposed a dataset comprising of $40k$ news articles with 611 key news events from 11 issues.

As our goal is to analyze political discourse and characterize partisan perspectives at an event-level granularity, this dataset can be directly applicable to test the efficacy of our narrative framework. Thus, we manually sample a set of six issues and a set of events which have the highest number of news articles per event from this dataset. Table 1 shows the detailed statistics of our final dataset.

5 Experiments & Results

We evaluate the ability of our framework to generate partisan perspectives using 3 automated tasks,

[2]M & K are hyperparameters ($M = K$ if context len permits).

Issue	No. of Articles	No. of Events
Climate Change	579	8
Capitol Insurrection	1,609	4
Immigration	1,137	4
Coronavirus	2,816	8
Total Count	6,141	24

Table 1: The dataset we use for testing our proposed framework. It is sampled from Nakshatri et al. (2023).

and a human evaluation. We use ChatGPT [3] as the LLM to analyze each news article, as described in our proposed schema (Sec. 3). Through this, we obtain structured representations for articles from every event in our dataset, and release these, along with the original dataset, to the community.

5.1 Evaluate the prominent talking points

First, we evaluate our framework's ability to effectively cluster the talking points using two metrics - *coverage*, and *topic diversity*. To broadly represent all the talking points, in Sec. 3.2.1, we had built a set of *prominent talking points* by clustering the set of all points $\mathcal{T}$ associated with the event $\mathcal{E}$. These *prominent talking points* capture topically relevant information, for each cluster of points, and as a whole characterize the space of possible talking points for that event.

Coverage. If the *prominent talking points* are actually representative of the cluster, then we expect that each talking point in $\mathcal{T}$ should be able to be mapped back to one of the *prominent talking points*. To evaluate this, we propose a metric called *coverage* that measures the extent to which the *prominent talking points* collectively capture all points in $\mathcal{T}$ for the event $\mathcal{E}$. Tab. 2 shows the average coverage for each issue. We observe that identified *prominent talking points* cover at least 80% of the talking point set $\mathcal{T}$, indicating they are a good representation of the set $\mathcal{T}$.

Issue	Avg. Coverage per event	Avg. # clusters
Climate Change	83.17	10
Capitol Insurrection	86.70	24
Immigration	90.55	21
Coronavirus	78.18	16

Table 2: Averaged results for coverage.

Topic Diversity. We also validate if the *prominent talking points* capture diverse topics.

Task formulation. To this end, we formulate the following ***topic classification task*** : Given a talking point and a set of K' cluster labels, assign the talking point to the most topically relevant cluster label k^*, where $k^* \in K'$. Note that the talking point is associated with only one of the K' labels, and the rest of the labels are randomly sampled negative examples (other clusters that don't have the talking point). The negative examples help assess the degree of cluster separation. Precisely, k^* helps assess how well the talking point assignments to map to their respective clusters, whereas the remaining negative labels, $K' \setminus \{k^*\}$, help measure the degree of separation between the clusters.

Experimental Setup. We first split the data in each cluster into 4 quartiles, where the 1st quartile refers to the top 25% closest talking points (TP) to the corresponding cluster label in the embedding space, the 2nd the top 50%, etc. We randomly sample half the TPs from each quartile for this experiment, with 3 neg. labels for each TP ($|K'| = 4$). We prompt ChatGPT to assign the TP to its most topically relevant label (prompt: Tab. 16).

Table 3 shows the performance of the topic classification task. We see all quartiles perform well, and documents closer to the cluster label (lower quartile) show strongest topical relevance to the cluster label. This shows that our cluster labels do clearly capture the diverse topics of our talking points, and each cluster captures a unique aspect, when compared to other clusters.

Issue	Q1	Q2	Q3	Q4
Climate Change	91.19	87.47	83.66	80.00
Capitol Insurrection	91.78	89.34	84.56	80.27
Immigration	91.96	88.69	85.01	80.34
Coronavirus	94.07	89.11	84.10	79.94
Avg. Accuracy	**92.74**	**88.90**	**84.37**	**80.12**

Table 3: Averaged results for each quartile for the *topic classification task* indicates that our prominent talking points capture diverse information.

Topic Classification Task + Coverage. Topic classification results indicate that topics associated with *prominent talking points* are diverse ($\approx$ 80% accuracy) when compared with one another, while the coverage indicate that the prominent points span at least 80% of the set $\mathcal{T}$. On combining both these dimensions, we observe that our approach forms reasonable set of *prominent talking points*.

5.2 Evaluate partisan perspectives

Here, we evaluate the ability of our framework in generating the partisan perspectives.

Partisan. In Sec. 3.2.2, we obtainined ideology-specific viewpoints (summaries) for each cluster $\mathcal{C}_j \in \mathcal{C}$. We now measure the "goodness" of these

[3] gpt-3.5-turbo-0125 (OpenAI, 2022)

viewpoints in capturing ideology-specific information. We expect left viewpoints will indicate how *left* political ideology discusses the issue with respect to that cluster, and vice-versa. Thus, ideally, left-leaning viewpoints should be entailed by left-sourced news articles and should not be entailed by right-sourced news articles (similar for right).

Task formulation. To test if the generated ideology-specific viewpoints for each cluster indicate such a partisan behavior, we formulate the following ***partisan classification task*** at the cluster-level granularity. To do it, we use the news article corresponding to each talking point in the cluster.

Given a news article biased towards a particular ideology, say left-biased, and the corresponding left-summary and right-summary for that cluster, the task is to assign the news article to the summary with which it more closely aligns with. In this task, a correct assignment of the news article to its respective summary would indicate that summary exhibits such a partisan behavior.

Experimental Setup. We compare 3 settings, by changing how summaries are constructed. In the first - *Topically Relevant Points (TPs)*, we construct the summary for a cluster to be the set of 3 topically relevant TPs from the same ideology which are closest to it's corresponding partisan summary for that cluster. In the next - *Partisan View*, we construct the summaries using our framework 3.2.2. In the last setting - *Partisan View + Metadata*, in addition to the *partisan view*, we also consider the metadata associated with the entire cluster. Details are in appendix D.2. In each case, we prompt the LLM to classify the news article using the prompt template shown in 17 We mask left/right summary terms so the LLM doesn't use it's prior bias.

Results. Table 4 shows the overall performance for the partisan classification task (each issue is shown App. A.1). We observe that topically relevant points (TPs) do not clearly distinguish between left and right viewpoints. On the contrary, our partisan view consistently performs better in discriminating between the left and right viewpoints. We also notice that including metadata in the prompt helps improve the performance further.

Approach	Prec.	Recall	F1
TPs	73.44	73.33	73.37
Partisan View	85.03	84.61	84.76
Partisan View + Metadata	**85.93**	**86.14**	**85.98**

Table 4: Averaged results for *partisan classification task* across all issues shows the efficacy of partisan perspectives in capturing ideology-specific information. Tab. 8 shows the breakdown by issue, TPs means Topically Relevant Points.

5.3 Evaluate validity of partisan viewpoints

Now, we use ***article ideology classification***, to test the correctness of the partisan perspectives from our framework. We hypothesize that if the generated partisan viewpoints correctly capture ideology-specific points, then they must be widely applicable to any news article that is relevant to the event. We hypothesize summaries must be valid if they can be utilized to perform ideology classification over *unseen* news articles that are related to the event.

Task Formulation. We evaluate ***ideology classification*** at the event-level granularity: Given an *unseen* news article (related to the event), the task is to predict the ideology of the article. We do this primarily under two settings - by using the partisan perspectives obtained from our framework, and directly prompting the LLM to predict ideology.

Experimental Setup. We construct a set of 481 *unseen* news articles (details in App. D.3) that were not part of the initial clustering process, but are related to the events under consideration for each issue. As we only know that the article is relevant to the event, to predict the ideology of the news article, we need a partisan summary for the entire event, rather than just each cluster, as our framework builds. Thus, to obtain an event-level partisan summary for an ideology, we concatenate all the summaries from every cluster for that ideology. We then compare the news article embedding with every viewpoint in the concatenated summary set for that ideology, and obtain top-3 closest viewpoints. We call this as *Event Partisan View*.

In addition, for an ideology and for each of the top-3 viewpoints, we also consider the corresponding cluster metadata obtained from 5.2, as it may be able to better distinguish the two political ideologies. We call this as *Event Partisan View + Metadata*. We follow a similar prompting strategy as 5.2 (masking the terms - *left/right*), but do not include the ground-truth label for the article ideology as part of the prompt. As a baseline, we directly prompt the LLM to predict the ideology of the given news article. App. 18 shows our prompts. Further, we also use few-shot experiments, where we consider the baseline under two settings - baseline with randomly selected few-shot examples (*baseline w/ random eg.*), and a baseline where few-shot examples are selected from the articles that were used in constructing the respective partisan summary (*baseline w/ selected eg.*). Note that for the latter, we are able to obtain *selected* few-shot examples based on the clustering process from our framework. We compare this performance against few-shot partisan view (*partisan view w/ selected eg.*), and few-shot partisan view along with its metadata (*partisan view + metadata w/ selected eg.*). To better generalize our results, we also benchmark against an open-sourced LLAMA-3 model[4].

Results. On both zero-shot and two-shot experiments, across multiple LLMs (ChatGPT and LLAMA), results show that performance with partisan view is either on par or better than competing baselines, indicating the validity of the generated viewpoints. More detailed results in App A.2.

Backbone	Method	Prec.	Recall	F1
ChatGPT (0-shot)	ChatGPT	81.38	74.66	73.52
	Event Partisan View	77.12	76.64	76.61
	+ Metadata	81.20	79.78	**79.69**
ChatGPT (2-shot)	Baseline w/ random eg.	80.47	78.23	78.09
	Baseline w/ selected eg.	83.48	81.38	81.34
	Event Partisan view w/ selected eg.	83.02	82.61	**82.65**
	+ metadata w/ selected eg.	83.79	82.50	82.52
LLAMA (2-shot)	Baseline w/ random eg.	78.01	75.26	74.94
	Baseline w/ selected eg.	79.57	78.80	**78.81**
	Event Partisan view w/ selected eg.	79.92	78.52	78.47
	+ metadata w/ selected eg.	80.87	76.43	75.92

Table 5: Zero-shot and two-shot ideology classification on unseen news articles averaged across all issues (see Tab. 9, 10 for each issue). Partisan viewpoints achieve superior 0-shot performance over baseline. Performance improves with in-context examples derived from our framework, across both LLMs. Performance with partisan viewpoints is on par (LLAMA) or better than baselines (ChatGPT).

5.4 Analyzing Event-Level Narratives

Using Fig. 3, we show a simple applicability of how our framework can be used for analyzing different aspects of political discourse for an event related to the Coronavirus - *Biden's COVID-19 Relief Bill*. Each TP (circle) is placed on the X-axis based on how one sided it is (prop. of instances associated with each side of the political map, an equal split landing that TP at the center). A high degree of frequent TPs with high positive or negative x-axis values, is evidence for "different realities", i.e., focusing on very different aspects of each topic. This allows us to analyze TPs by categorizing them into different types such as *agreement, disagreement, one-sided etc*. Tab. 11 another ex. Details: A.3.

5.5 Human Evaluation

In our framework, we generated the partisan perspective for each ideology by leveraging the top-K prominent talking points for that ideology and their respective news article summaries (3.2). We now use humans to evaluate them. We manually annotated data for 3 randomly sampled events from 3 different issues (shown in 12). App. A.4 describes the annotation procedure, results below.

[4]LLAMA-3-8B-Instruct-GGUF-v2

Metrics. We validate partisan summaries for coherence and mapping quality. *Summary coherence* is the proportion of partisan summaries that well represent the top-K prominent points that were used to construct the summary. *Mapping Quality* (MQ) is the prop. of articles where the partisan views are actually expressed in their respective news articles.

Evaluating MQ is a hard for humans, as they must read long news article excerpts. To mitigate this, we design a different variant of mapping quality - MQ_LLM, where we prompt GPT-4o, with a series of questions related to the partisan topic, entities etc. to obtain relevant evidence from the news article (see A.4). This evidence is validated against the talking point summaries by humans.

Tab. 6, 7 shows the results. We observe high coherence and MQ scores in both the settings, indicating good quality of the generated talking point perspectives. More detailed discussion in A.4.1.

Issue	L-Coherence	R-Coherence	L-MQ	R-MQ
Climate Change	85.71	100	75.00	76.92
Coronavirus	100	90.90	90.90	70.00
Immigration	93.33	100	84.62	94.44

Table 6: Results from 84 annotations indicate that partisan perspectives are indeed expressed in the original news articles. **L** refers to left political ideology. **R** refers to right political ideology.

6 Conclusion

In this paper, we proposed an LLM-based framework to analyze partisan narratives at an event-level granularity. We demonstrated the quality of partisan perspectives generated from our framework using several automated, and human validation tasks. We also performed multiple qualitative analysis on the general applicability of our framework. Our future work is identifying more details, like key political actors and detailed polarizing points.

Agreement between TP & Article	Score
Topic	97.82
Entities viewed negatively	80.43
Entities viewed positively	92.39
Angle of discussion	98.91

Table 7: Shows the GPT4o-Human agreement score for 92 article-talking point pairs (for *Climate Change* related event).

7 Limitations and Ethics

To the best of our knowledge, we did not violate any widely held ethical precepts when producing this paper. All results are from a Machine Learning model, and should be interpreted as such. We attempted to provide details about our work, both in the main paper and the Appendix, and explain everything thoroughly. In our dataset release, we take care to not release articles that are no longer public.

Our framework itself also has some limitations. As a first, our framework is based on a LLM model, ChatGPT, which is closed source, and the details of its construction unclear (Spirling, 2023). Our framework lets the LLM decide the key talking points from the news article, although it is possible that it could overlook a prominent talking point. While this is a potential limitation, we believe that if a talking point is really prominent, then it will repeat in many articles, to shape the narrative. Thus, there is a high chance that the LLM would identify that talking point in other articles, even if the model failed to recognize the prominent point in the given article. Further, we assume that all the talking points from a left-leaning news source are actually *left-biased*, and vice-versa. However, in reality, it need not be the case (Kim et al., 2022). Our approach performs fairly well, even with this assumption primarily because we are only interested in identifying salient talking points from each ideology, and less frequent talking points are rejected.

Our system has many real-world applications, but we caution against the safe usage of our framework. Though our approach can be used to identify ideologies, it can also be used in harmful ways, such as users using it to target specific people based on the beliefs that they spread or ideology they align to. For this and meany other reasons, users deploying our work should carefully consider all possible benefits and downsides.

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A Extended Results

A.1 Partisan Classification

Tab. 8 provides the results for partisan classification from Sec. 5.2, across all issues, and the overall performance.

A.2 Evaluating the validity of partisan viewpoints

Tab. 5 shows the results for zero-shot and two-shot LLM ideology classification task. Based on the zero-shot performance on *unseen* articles, we observe that the partisan view outperforms the LLM baseline, and metadata improves performance further. It indicates that generated partisan points are valid and not hallucinated by the LLM. Further, we observe that there is a general increase in the performance with ChatGPT when prompted in a two-shot manner (across all methods). Particularly, we observe that the performance improves when we utilize the in-context examples derived from our framework instead of randomly choosing in-context examples. This indicates that our clustering process has a reasonable performance as it is able to provide good in-context examples, resulting in better performance at this task. Overall, our event partisan view still performs better, indicating the validity of our partisan viewpoints. We also benchmark the two-shot experiment with LLAMA, and observe a similar trend with respect to the selection of in-context examples as that of ChatGPT. In this case, the performance from our partisan viewpoints are comparable to *baseline w/ selected eg.*, which reinforces the validity of partisan points produced by our method. Note that the overall performance reduced with the usage of metadata in the case of two-shot prompts (for both ChatGPT and LLAMA). We suspect that this could potentially be due to a large amount of information in the prompt, which does not help in guiding the model to focus on differentiating factors such as entities and their relationships.

Tab. 9, 10 provides the results for zero-shot and two-shot ideology classification resp. from Sec. 5.3, across all issues, and the overall performance.

A.3 Constructing Visualization for Partisan Narrative

To visualize the partisan narrative for an event, we would need to obtain agreement/disagreement between the talking point perspectives - *left/right*. To obtain this, we define a scale, where we prompt

Issue	Approach	Avg. Precision	Avg. Recall	Avg. F1-score
Climate Change	Topically Relevant Points	84.11	84.23	84.17
	Partisan View	91.73	89.46	90.29
	Partisan View + Metadata	92.43	90.86	**91.49**
Capitol Insurrection	Topically Relevant Points	69.50	71.62	69.18
	Partisan View	79.33	80.93	**79.93**
	Partisan View + Metadata	81.04	78.08	79.12
Immigration	Topically Relevant Points	69.14	74.64	69.92
	Partisan View	85.38	86.36	85.85
	Partisan View + Metadata	88.27	86.17	**87.15**
Coronavirus	Topically Relevant Points	73.11	72.60	72.77
	Partisan View	83.34	81.76	82.21
	Partisan View + Metadata	83.78	84.20	**83.92**
Overall Performance	Topically Relevant Points	73.44	73.33	73.37
	Partisan View	85.03	84.61	84.76
	Partisan View + Metadata	85.93	86.14	**85.98**

Table 8: Averaged results for *partisan classification task* shows the efficacy of partisan perspectives in capturing ideology-specific information.

Issue	Method	Avg. Precision	Avg. Recall	Avg. F1-score
Climate Change	Zero-shot chatGPT	82.47	71.29	70.83
	Event Partisan View	76.21	75.36	75.60
	Event Partisan View + Metadata	80.55	76.55	**77.01**
Capitol Insurrection	Zero-shot chatGPT	80.24	72.14	74.19
	Event Partisan View	80.00	83.75	80.91
	Event Partisan View + Metadata	83.82	84.91	**84.32**
Immigration	Zero-shot chatGPT	76.81	76.54	70.94
	Event Partisan View	80.14	82.13	78.47
	Event Partisan View + Metadata	81.73	83.56	**82.21**
Coronavirus	Zero-shot chatGPT	84.81	82.05	**81.19**
	Event Partisan View	69.16	68.96	68.96
	Event Partisan View + Metadata	77.29	76.83	76.48

Table 9: Compares the performance of zero-shot ideology classification on unseen news articles. On average, partisan viewpoints are able to achieve good zero-shot performance compared to baseline.

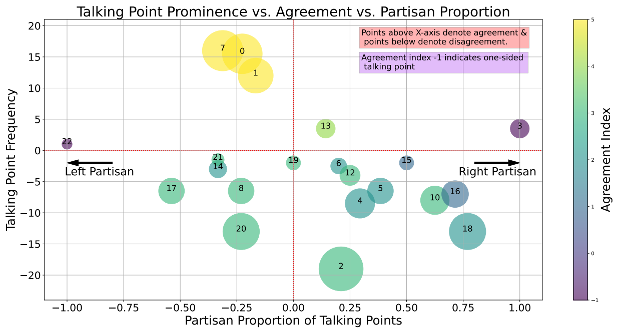


Figure 3: Shows talking point prominence vs. points agreed/disagreed vs. partisan proportion (for an event related to Coronavirus).

a better-performing model, GPT-4o, to assign a binary label - 0/1, for each of the following questions.

1. Do both summaries have at least one common aspect of discussion?
2. Are the summaries discussing about similar entities?
3. Are the entities in common viewed in the same manner? For example, is the entity viewed positively or negatively in both the summaries?
4. Do both the summaries talk about the event from the same perspective?

Issue	Backbone	Method	Avg. Precision	Avg. Recall	Avg. F1-score (macro)
Climate Change	ChatGPT	Baseline w/ random eg.	78.32	75.49	75.89
		Baseline w/ selected eg.	83.20	79.27	79.86
		Partisan view w/ selected eg.	82.87	81.27	**81.69**
		Partisan view + metadata w/ selected eg.	82.88	79.97	80.52
	LLAMA	Baseline w/ random eg.	78.59	75.39	75.79
		Baseline w/ selected eg.	82.14	80.29	80.74
		Partisan view w/ selected eg.	83.83	80.25	**80.85**
		Partisan view + metadata w/ selected eg.	84.10	77.38	77.89
Capitol Insurrection	ChatGPT	Baseline w/ random eg.	83.82	84.91	84.32
		Baseline w/ selected eg.	90.15	92.58	**91.17**
		Partisan view w/ selected eg.	90.89	90.89	90.89
		Partisan view + metadata w/ selected eg.	89.16	87.76	88.41
	LLAMA	Baseline w/ random eg.	90.89	86.07	**87.95**
		Baseline w/ selected eg.	83.82	84.91	84.32
		Partisan view w/ selected eg.	79.41	80.35	79.84
		Partisan view + metadata w/ selected eg.	82.52	80.08	81.11
Immigration	ChatGPT	Baseline w/ random eg.	80.83	82.62	78.53
		Baseline w/ selected eg.	79.53	81.64	78.40
		Partisan view w/ selected eg.	82.93	85.21	**83.27**
		Partisan view + metadata w/ selected eg.	81.94	84.34	81.70
	LLAMA	Baseline w/ random eg.	74.09	75.07	70.88
		Baseline w/ selected eg.	78.99	81.15	**78.32**
		Partisan view w/ selected eg.	77.81	79.80	76.67
		Partisan view + metadata w/ selected eg.	76.02	75.18	69.21
Coronavirus	ChatGPT	Baseline w/ random eg.	80.29	78.29	77.50
		Baseline w/ selected eg.	82.95	81.86	81.37
		Partisan view w/ selected eg.	76.93	76.28	76.31
		Partisan view + metadata w/ selected eg.	82.74	82.78	**82.71**
	LLAMA	Baseline w/ random eg.	71.38	69.68	68.65
		Baseline w/ selected eg.	67.85	67.85	67.85
		Partisan view w/ selected eg.	70.39	70.42	70.36
		Partisan view + metadata w/ selected eg.	76.88	75.73	**75.12**
Avg. across all issues	ChatGPT	Baseline w/ random eg.	80.47	78.23	78.09
		Baseline w/ selected eg.	83.48	81.38	81.34
		Partisan view w/ selected eg.	83.02	82.61	**82.65**
		Partisan view + metadata w/ selected eg.	83.79	82.50	82.52
	LLAMA	Baseline w/ random eg.	78.01	75.26	74.94
		Baseline w/ selected eg.	79.57	78.80	**78.81**
		Partisan view w/ selected eg.	79.92	78.52	78.47
		Partisan view + metadata w/ selected eg.	80.87	76.43	75.92

Table 10: Results for two-shot evaluation with ChatGPT and LLAMA. We consider an additional model to demonstrate the generalization capability of the partisan summaries generated by our method.

TP Type	TP ID	Left View (only titles)	Right View (only titles)
Agreement	1	Rejection of splitting COVID relief bill into separate components	Resistance to breaking down relief package into separate bills
Disagreement	10	Emphasis on Transparency and Improved Vaccine Distribution	Questioning Biden's Vaccine Distribution Transparency
Agenda Setting	16	Biden's Travel Restrictions and Bans for Public Health	Criticism of Biden's Executive Order on Pandemic Language (for banning term - 'China Virus')
Partisan Battle	2	Biden administration's emphasis on equitable vaccine distribution and healthcare reform	Criticism of Biden administration's vaccine distribution decisions
Right Only	3	-	Economic Impact of $15 Minimum Wage

Table 11: Overview of the talking points (TPs) based on its potential type.

5. If the summaries are viewing the event from different angles, do the summaries have atleast some agreement with each other?

We obtained 2 talking points with a cumulative score of 1; 5 points with a score of 2; 8 points with a score of 3; 4 points with a score of 1; and 3 talking points with a cumulative score of 5. We note that higher scores indicate that talking points are closer to being in agreement with each other, whereas lower scores imply that talking points are mostly disagreeing with each other. For a score of 3, we manually inspected the outputs from the model and deduced that the two summaries shared a common aspect, discussed similar entities and had some agreements with each other. However, the entities were not viewed in the same manner due to which we assigned these talking points to disagree with each other.

A.4 Human Evaluation

We conduct human evaluation over a set of three events for three different issues. In this section, we describe the annotation procedure for each task. Note that the annotations were conducted for a total of 84 talking points across three issues for the metrics - *Summary Coherence*, and *Mapping Quality*.

Summary Coherence We explain the procedure for *left* political ideology, and the same process is repeated for the *right* ideology as well. First, we explain the task to the annotators with an example. The annotators are provided a left-summary along with three-to-five left talking points and news article article summaries. We ask the annotators to validate if the left-summary can be derived from the news article summaries or the talking points. If it can be derived, then the response is 1, otherwise it is 0. In the cases where annotators are not sure, the response is -1.

Mapping Quality We explain the procedure for *left* political ideology, and the same process is repeated for the *right* ideology as well. In this case, we provide the annotators with a left summary, and a corresponding news article that is most relevant to the left summary (measured based on cosine similarity distance in the embedding space). We segment the news article into sentences of 7, and we only provide the most relevant 7 sentences from the news article to the annotators. First, we let the annotators know that there are at most three points in the left-summary, then ask them to compare the left summary with the left news article content to validate if at least one of the points in the summary is expressed in the article. If it is, then the response is 1, otherwise it is 0. In cases where annotators are not sure, the response is -1.

Mapping Quality-GPT To setup this experiment, we randomly sampled upto 5 news articles for each talking point (from *left/right*), and collected a set of 92 article-talking point pairs (with 48 *left* pairs, and 44 *right* pairs). For each article-talking point pair, we prompt GPT-4o to provide evidence by quoting the relevant sentences from the news article for the following questions -

1. Is the summary discussing the same topic as that of the news article?
2. In the summary and the news article, are there any entities in common that are viewed negatively from the same perspective?
3. In the summary and the news article, are there any entities in common that are viewed positively from the same perspective?
4. Does the news article cover the views presented in the summary from the same angle?

For each article-talking point pair, we present the talking point and the evidence from the article (provided by GPT-4o) to a human. Human is expected to validate each answer by verifying if the retrieved evidence aligns with the talking point summary.

Note that our annotators were graduate STEM-students who were not the authors of the paper and were under the age of 30.

A.4.1 Human Eval Results

From Tab 6, we notice a high coherence score for the generated partisan summaries for both political ideologies, implying that the summaries are in agreement with the talking points and the article summaries that were used to construct them. In addition, the high mapping quality scores for each ideology indicate that the generated summaries are actually expressed in the news articles.

We manually inspected annotated data, and observed that the generated partisan perspectives are incorrect at times, for example when the LLM fails to produce good news article summaries which are used to generate partisan perspectives. Table 23 shows an example of this. We also notice that the LLM fails at times to take into account the cited information found in the news articles, which forces the model to generate an incorrect summary.

Tab. 7 shows GPT-4o-human agreement score for MP_LLM. A manual inspection of annotated data reveals that GPT-4o fails at times to retrieve relevant evidence from the news article, especially when the entities are viewed in a negative manner (example shown in Tab. 13).

B Temporal Analysis - Case Study

Here, we provide a simple case study to show how the data obtained from our framework could be utilized to study the *left* and *right* ideology viewpoints for an entire issue. To do this, we consider 7 events related to the issue *Coronavirus* at various points in time, and at every point, analyze the most frequently repeating prominent talking point from each political ideology.

Fig. 4(a) shows a dynamic evolution of prominent talking point of each political party for the issue - *Coronavirus*. We observe that frequently discussed prominent point of each political party is different from one another in 3 out of the 7 events under consideration. However, both political parties predominantly discuss the same prominent point in the remaining cases. Note that Fig. 4(a) shows only the *aspect* associated with each prominent point for data visualization clarity.

In the cases where both political parties discuss the same prominent point, we can further investigate the manner in which they talk about the prominent point by observing its corresponding partisan summary. For instance, let us consider the prominent point with the aspect - *Evolving mask guidelines post-CDC update*, that is commonly discussed by both political parties. While both the parties criticize the ambiguity in CDC's mask guidance, the *left*-leaning articles emphasizes more on pointing out the discrepancies with state and local mandates, and how it is impacting businesses. However, *right*-leaning sources focus on delayed response by CDC in updating mask mandates for vaccinated individuals and raises concern about the leadership.

We can further analyze this prominent point discussed by both parties through its associated metadata. The entity viewed as a *target* by an ideology, its corresponding *actor*, and the associated *media frame* can help analyze the differences in the viewpoints across political parties. For the same prominent point with the aspect *Evolving mask guidelines post-CDC update*, we observed that *left*-leaning news sources viewed the entity *Centers for Disease Control and Prevention (CDC)* to have negatively impacted the target entity *Retailers*. Further investigation revealed that it was due to the criticism associated with changing mask guidelines, where *CDC* removed mask mandates for the vaccinated individuals, and left-leaning sources criticized *CDC* for creating ambiguity amongst the *retailers* regarding the mask guidelines. We note that *left*-leaning news sources commonly used *Policy* as the media frame of discussion in the context of this actor-target pair. In this way, the metadata associated with the prominent point of interest can further help distinguish left and right perspectives. To obtain an overall global view of variation in metadata for the entire issue, Fig. 4(b) shows a dynamic analysis over the actor/target entities for each prominent point across the two political parties over time.

C Schema

D Experiments Related

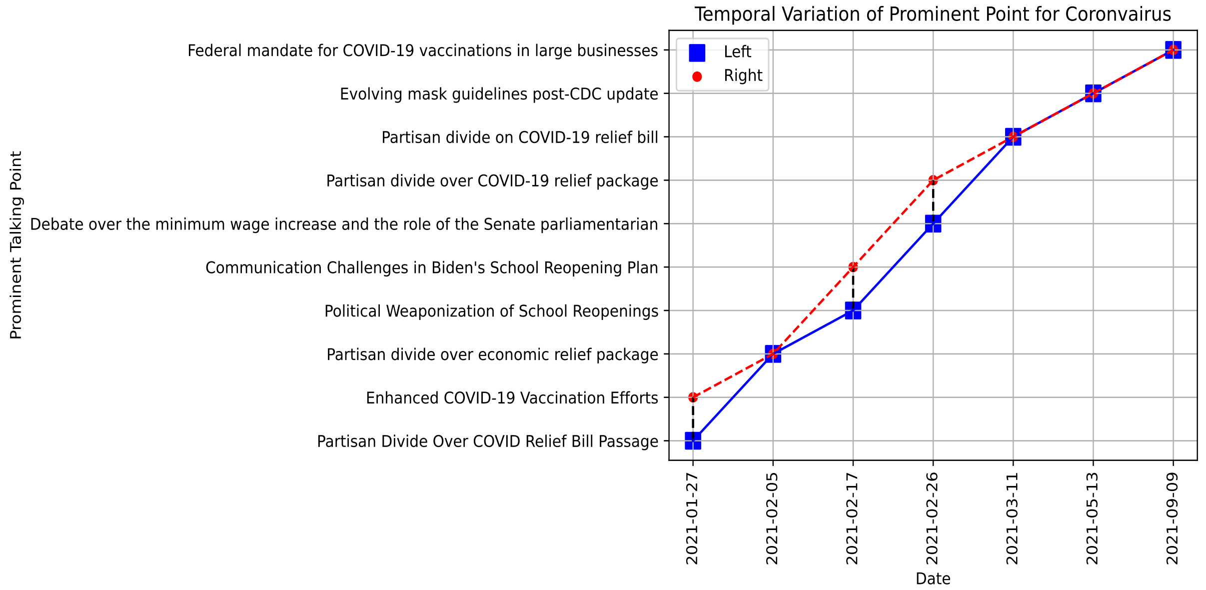
D.1 Prompt Templates for experiment section

D.2 Metadata generation

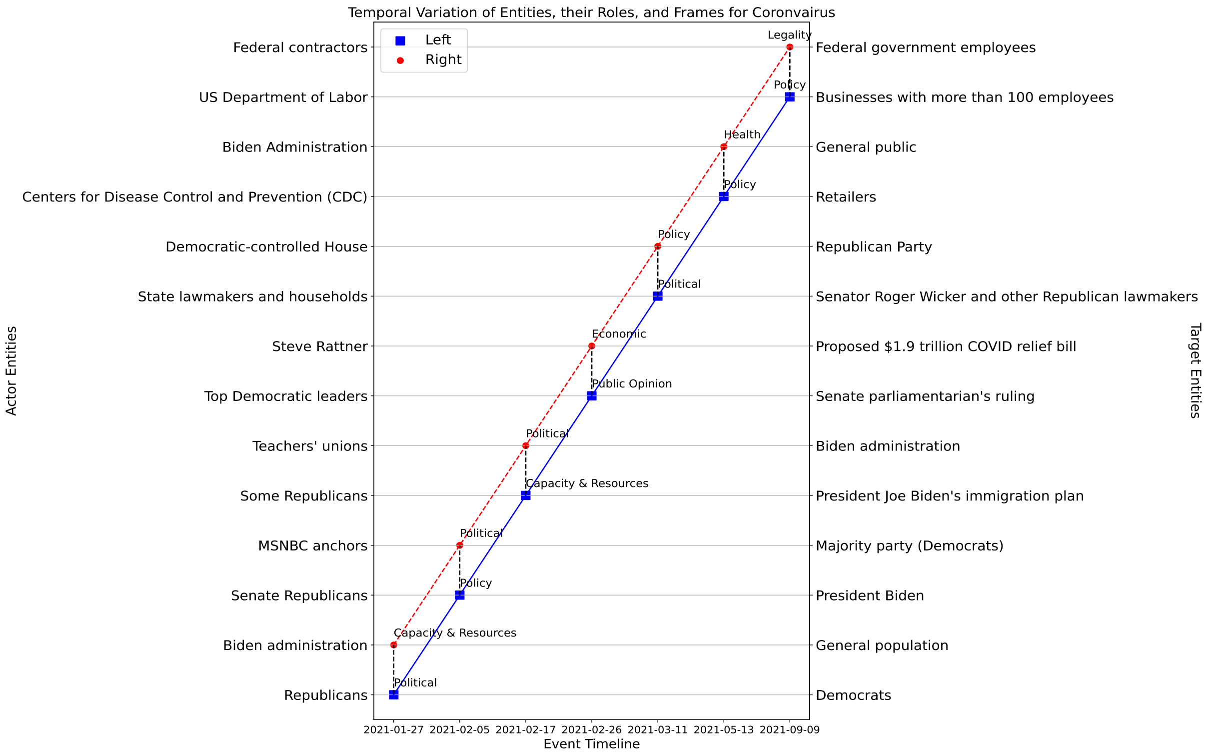
The goal from this step is to identify the most frequent and discriminative pair of entities along with their sentiments that can help distinguish between the two political ideologies. Note that for an ideology, we use only the top-K documents and its associated metadata for generating the partisan perspective. To account for the metadata from the rest of the members in the cluster and obtain a global cluster-view, we aggregate this information from the top-50% of the members in the cluster. Specifically, we obtain the top-3 target entities that have positive sentiment, and top-3 target entities that have negative sentiment. In each case, we obtain the most common actor associated with the respective target. We also obtain the most common mediaframe associated with the corresponding actor-target context. This information can be plugged into the prompt in addition to the partisan viewpoints to help better distinguish between the political ideologies.

D.3 Dataset extraction

Here, we describe the process used for extracting the set of *unseen* news articles. We note that (Nakshatri et al., 2023) used NELA-2021 dataset for segmenting the news articles into a set of temporally motivated news events. In this process, (Nakshatri et al., 2023) used a temporal window of



(a) Compares the temporal variation of most frequent prominent point for each political ideology, and across 7 events related to the issue - *Coronavirus*. Frequently discussed prominent points across the two ideologies intersect in 4 out of 7 cases.



(b) Temporal variation of the metadata with frequently repeating target entity with a negative sentiment for each ideology, and across 7 events for the issue - *Coronavirus*. For each target entity, its corresponding actor entity, and the associated media frame is also shown.

Figure 4: Temporal analysis of prominent points along with its respective metadata for the issue - *Coronavirus*.

Issue	News Event
Climate Change	**Event Title:** Biden Announces Ambitious Greenhouse Gas Emissions Cut **Event Description:** This is about President Joe Biden's announcement of an ambitious cut in greenhouse gas emissions as he looks to put the US back at the center of the global effort to address the climate crisis and curb carbon emissions.
Coronavirus	**Event Title:** Biden's COVID-19 Vaccination Mandate **Event Description:** This is about President Joe Biden's announcement of new COVID-19 vaccination requirements for federal government employees, healthcare workers, and companies with 100 or more employees, and his criticism of politicians who are undermining trust in COVID vaccines.
Immigration	**Event Title:** Biden's Refugee Cap Decision **Event Description:** This is about the criticism faced by President Biden for his decision to not raise the cap on refugees allowed to enter the US this year, which he had promised to do during his campaign.

Table 12: Events considered for human evaluation.

Talking Point Summary	Evidence From Article
Uncertainty in global cooperation and skepticism towards US leadership.Concerns persist over the uncertainty of international support, especially from major carbon emitters like China, India, and Russia, towards America's climate initiatives. Differing views on the urgency of climate action and skepticism towards US leadership may hinder effective global collaboration on climate change.,	Evidence: Both the summary and the news article mention skepticism towards US leadership and the challenges in global cooperation. The summary states, "Concerns persist over the uncertainty of international support, especially from major carbon emitters like China, India, and Russia, towards America's climate initiatives." The news article similarly notes, "Russian President Vladimir Putin and Chinese President Xi Jinping are two notable leaders who have both confirmed their attendance at the summit, underscoring the wide range of leaders attending," indicating the importance of their participation and potential skepticism.

Table 13: GPT-4o fails to correctly identify the evidence from the news article.

Schema	Schema Prompt Template (incremental)
Talking Point	You are tasked with discerning the key talking points from the following 'NEWS ARTICLE'. Your objective is to condense the contents of the 'NEWS ARTICLE' into a succinct list of up to four primary talking points, each accompanied by a brief description. \n 'NEWS ARTICLE': {article}
Entities	For each 'Talking Point', identify up to three pivotal entities associated with it, and assess whether the author of the 'NEWS ARTICLE' exhibits a bias either against or in favor of the mentioned entities. In instances where no discernible bias is evident, categorize the entity as neutral. The goal is to compile a list of entities along with their entity types, categorizing them as either against, in favor, or neutral, and accompany each categorization with a brief explanation.
Activity	For each 'Talking Point' and its associated 'Entities', identify the primary activities linked to it. For every identified 'Activity', pinpoint the entity assuming the role of 'Actor', driving the said 'Activity', and the entity acting as the 'Target', which is influenced by the 'Actor'. Assess whether the impact on the 'Target' is positive, negative, or neutral, providing a rationale for the impact. Focus only on pivotal 'Activities' closely related to the 'Talking Point'.
Media Frame	For each 'Talking Point' and its corresponding 'Activity', predict its media frame, and categorize it into one of 15 labels: Economic, Capacity & Resources, Morality, Fairness & Equality, Legality, Policy, Crime, Security, Health, Quality of Life, Cultural, Public Opinion, Political, External Regulation, or Other. With respect to the predicted 'Frame', provide a short explanation on how it is related to the main 'Activity'.

Table 14: Prompt template used to obtain the structured representation of the article along with the relevant metadata.

Generate Partisan Summary
You are provided with an aspect of discussion related to a news event, along with biased talking points from left and right political ideologies discussing the same aspect. Each talking point is associated with its respective news article summary, and metadata that includes actions, actors, targets, impacts, and framing. On comparing and analyzing the talking points from both ideologies, the objective is to refine and condense left-biased talking points into at most three unique points, such that the new points clearly capture the political bias towards left ideology. Redundant points and those not aligning well with left political ideology should be excluded. #### Input #### Aspect of discussion: {aspect} Left-biased talking points: {left-biased points} ## includes metadata for each point Left-biased news article summaries: {left-biased summaries} Right-biased talking points: {right-biased points}

Table 15: Prompt template used to obtain the partisan summary for left political ideology. Similar prompt is used for the obtaining partisan summary for the right political ideology as well.

3 in order to obtain coherent news events.

In order to obtain *unseen* news articles, yet relevant to the events under consideration, we extend this temporal window to 7 days, and retrieve all the

Topic Classification Task
You are given a 'document' and four labels, all derived from the same news event. The task is to determine the most topically relevant label to the document.
Your goal is to assign the document to only one of the four labels. If the document is topically relevant to 'label1', please respond 'label1'.
If the document is topically relevant to 'label2', please respond 'label2'. If the document is topically relevant to 'label3', please respond 'label3'.
If the document is topically relevant to 'label4', please respond 'label4'. Strictly refrain from providing additional information.
Input to analyze
'Document': {doc}
'Label1': {lab1}
'Label2': {lab2}
'Label3': {lab3}
'Label4': {lab4}

Table 16: Prompt template used for the topic classification task.

Partisan Classification Task
Given a segment of a 'news article' from a {ideology}-biased media source and two summaries derived from the same news event, your task is to perform binary classification by assigning the news article to one of the two summaries. Each summary has a set of talking points about the event. Each summary is also accompanied by metadata that includes frequently occurring actors, targets, sentiment on the target entities, and media frame associated with the context of the talking points. Your goal is to use the associated metadata to better determine if the provided news article segment has a viewpoint that is more similar to 'summary1' or 'summary2'.
The response should strictly be 'summary1' when the 'news article' segment has a consistent viewpoint with 'summary1'; otherwise, it should be 'summary2' indicating the 'news article' has consistent viewpoint with 'summary2'.
Refrain from providing any additional information.
Input to analyze
'News article': {article}
'Summary1':{summ1}
'Summary1 Metadata':{summMetadata1}
'Summary2':{summ2}
'Summary2 Metadata':{summMetadata2}

Table 17: Prompt template used for the partisan classification task.

Ideology Classification Task (Baseline Prompt)
The task is to perform a binary classification to determine whether the ideology of the given 'news article' leans more towards the 'left' or the 'right'. You are to output one of the two labels. Strictly adhere to the following output format, and refrain from providing additional information.
'News Article': {articleContent}

Table 18: Prompt template used for the zero-shot ideology classification task (baseline).

news articles for that time period from NELA-2021 dataset. We filter out all the news articles that part of our clustering process. Then, we consider the all the unseen articles that are closest to the event centroid in the embedding space (threshold ≥ 0.86). Note that we obtain event centroid by averaging the embedding of all news articles relevant to the event. In this way, we extracted 481 relevant news articles for the events under consideration, of which 234 news articles are from right-leaning news sources, and the rest are from the left-leaning news sources.

E Human Evaluation

F Examples

G Clustering the talking points

As described in 3.2.1, we cluster the initial talking point set to identify the prominent talking points. In this process, we merge redundant clusters and remove incoherent clusters. The details of this process is outlined in this section.

G.1 Merge Redundant Clusters

In order to merge redundant clusters, we devise a simple greedy algorithm. We consider pairwise combinations of cluster labels, and prompt the LLM to verify if the clusters can be merged based on the prompt template shown in 25.

We start by constructing a set of pairwise cluster labels $\mathcal{S} = \{(s_1, s_2), \cdots, (s_{n-1}, s_n)\}$. Precisely, for every cluster, we consider all possible pairwise combinations for the top-7 closest labels to that cluster in the embedding space. For each element in $\mathcal{S}$, we prompt LLM to infer if the pair of labels are discussing about the same aspect. If the aspects, say (s_1, s_2), are equivalent, then we merge these aspects, and update the set $\mathcal{S}$ by removing every element in the set that contains s_1 or s_2. In the second iteration, we construct a new set, $\mathcal{S}'$, that holds every combination of updated cluster labels, and repeat the previous step. We run the algorithm for two iterations or halt if there are no merges after the first iteration. Considering the cost constraints

Structured Representation from article	
News Article	(CNN) A White House riding high on a wave of ambition is setting up a series of inevitable tests of whether Joe Biden is promising more than he can deliver . The President 's aggressive pledge to cut US carbon emissions unveiled at his global online summit Thursday is the latest audacious bet in a presidency that is notable for a moderate tone but an increasingly expansive progressive agenda .\nThe scale of Biden 's plans that he will try to sell to the nation in an address to Congress marking his first 100 days next week shows @ @ @ @ @ @ @ his power to forge a legacy as a generational reformer .\nSome admirers have already put him in the company of great Democratic Presidents like Franklin Roosevelt and Lyndon Johnson .\nBut for such praise to be accurate , he will have to pass an agenda that aims to overhaul much of the economy to benefit American workers – and he 's about to hit a wall of Republican opposition in divided Washington .\nSo while the President has enjoyed a fast start , remarkable success in accelerating vaccines to fight the pandemic @ @ @ @ @ @ @ stirring , real questions are mounting over his capacity to follow through .\nA treacherous road lies ahead that will require Biden to convince the public to embrace all of his programs and to make his opponents pay a price for opposing them .\nThat 's one reason why Biden 's remarks opening a climate summit that included leaders like China 's Xi Jinping and Russia 's Vladimir Putin sounded more like a speech in a Pittsburgh union hall than the blueprint of a leader bent on a costly crusade to save the @ @ @ @ @ @ @ climate , I think jobs , " Biden said , billing the fight against global warming as an extraordinary economic opportunity that will put Americans to work capping abandoned oil wells and assembling electric cars . ...
Talking Point 1	Title: Biden's ambitious climate pledge Description: Biden unveiled an aggressive plan to cut US carbon emissions at a global online summit. The scale of his plans shows his power to forge a legacy as a generational reformer, but questions are mounting over his capacity to follow through.
Talking Point 2	Title: Republican opposition and challenges ahead Description: Biden is likely to face significant Republican opposition in his efforts to pass his agenda, including his plans to overhaul the economy and address climate change. He will need to convince the public to embrace his programs and make his opponents pay a price for opposing them.
Talking Point 3	Title: Biden's broader policy agenda Description: In addition to climate change, Biden has voiced support for sweeping election reform and infrastructure plans. Passing these bills is seen as necessary to preserve the party's hopes in future federal elections and to address American ideals about equal access to the franchise.
Talking Point 4	Title: The difficulty of compromise and the need for Democratic unity Description: Biden's aspirations may face challenges due to the lack of compromise in modern politics and the potential for Republican obstruction. Biden's unwillingness to pare down his aspirations and accept compromises may make it difficult to achieve his goals.

Table 19: Shows the reduction of the news article to its respective talking points.

Prominent Talking Point Generation	
Prominent Point	Key aspect: Opposition and Challenges to Biden's Climate Change Agenda Summary Description: The articles collectively highlight the significant opposition and challenges President Biden faces in pushing forward his ambitious climate change agenda. Republican resistance, concerns about economic impact on traditional energy sectors, difficulties in securing funding and political support, and obstacles in translating rhetoric into action are key themes discussed in relation to Biden's climate initiatives.
Talking Point 1	Title: Obstacles and opposition to Biden's climate change agenda Description: Republicans have vowed to fight against Biden's proposals to shift the U.S. energy sector away from fossil fuels, indicating potential challenges at home.
Talking Point 2	Title: Political challenges and opposition Description: The article mentions the challenges Biden faces in keeping political support and securing funding for his ambitious climate goals. It also highlights Republican opposition, arguing that transitioning to clean energy would harm American oil, natural gas, and coal workers.
Talking Point 3	Title: Republican opposition and challenges ahead Description: Biden is likely to face significant Republican opposition in his efforts to pass his agenda, including his plans to overhaul the economy and address climate change. He will need to convince the public to embrace his programs and make his opponents pay a price for opposing them.
Talking Point 4	Title: Challenges and opposition Description: The article highlights the difficulties Biden and his team may face in converting their bold rhetoric into action. It mentions potential obstacles such as the fate of Biden's infrastructure plan, Republican opposition to climate initiatives, and the power of the Supreme Court to strike down laws limiting carbon pollution.
Talking Point 5	Title: Challenges in passing Biden's agenda Description: The article mentions that Biden will face opposition from Republicans in Washington, which could pose a challenge to passing his agenda. Questions are raised about Biden's capacity to follow through on his plans, particularly in overhauling the economy to benefit American workers.

Table 20: An example showing a topically relevant prominent talking point that is constructed using top-5 talking points shown.

associated with chatGPT, we consider top-7 closest cluster labels,

G.2 Remove Incoherent Clusters

We note that HDBSCAN algorithm provides us with an initial set of candidate clusters. For each candidate, we use the aspect associated with the cluster label to validate if the top-3 members that are closest to the cluster label in the embedding space are discussing the same high-level concept. We prompt the LLM using the prompt shown in 26 to remove incoherent clusters.

G.3 Talking Point Membership

After obtaining the cluster labels, which characterize the space of possible talking points. We consider each talking point from the set of all the talking points and assign the closest cluster label based on cosine similarity score. If this score is beyond a threshold value of 0.85, we assign the talking point to that cluster label. Otherwise, the it is discarded but retained in the unclustered pool of talking points.

G.4 Hyperparameters

Note that we are interested in identifying the dense regions in the embedding space associated with talking points, as these are the potential candidate topic indicators. Due to this, we choose HDBSCAN method as our clustering algorithm, which does not require any prior number of clusters. However, we are still required to tune a few

Partisan Viewpoints	
Prominent Point	Key aspect: Opposition and Challenges to Biden's Climate Change Agenda Summary Description: The articles collectively highlight the significant opposition and challenges President Biden faces in pushing forward his ambitious climate change agenda. Republican resistance, concerns about economic impact on traditional energy sectors, difficulties in securing funding and political support, and obstacles in translating rhetoric into action are key themes discussed in relation to Biden's climate initiatives.
Left Talking Points	1. Title: Republican opposition and challenges ahead Description: Biden is likely to face significant Republican opposition in his efforts to pass his agenda, including his plans to overhaul the economy and address climate change. He will need to convince the public to embrace his programs and make his opponents pay a price for opposing them. 2. Title: Challenges in passing Biden's agenda Description: The article mentions that Biden will face opposition from Republicans in Washington, which could pose a challenge to passing his agenda. Questions are raised about Biden's capacity to follow through on his plans, particularly in overhauling the economy to benefit American workers. 3. Title: Climate change has become a centerpiece of President Biden's economic agenda Description: Over the past few years, addressing climate change has shifted from a backburner issue to a crucial part of President Biden's domestic agenda and economic policy. 4. Title: Republican opposition and challenges ahead Description: Biden is about to face a wall of Republican opposition in divided Washington. He will need to convince the public to embrace his programs and make his opponents pay a price for opposing them. 5. Title: Climate as a centerpiece of Biden's economic agenda Description: Biden has made climate a central focus of his economic agenda, seeing it as an opportunity for job creation and economic growth. His plans include transitioning to clean energy, promoting electric vehicles, and investing in infrastructure.
Right Talking Points	1. Title: Economic Concerns and Job Losses in Fossil Fuel Industries Description: Right-leaning critics express worries about job losses and economic impacts on industries like oil, natural gas, and coal due to Biden's climate agenda, contrasting it with the potential benefits of transitioning to cleaner energy sources. 2. Title: Opposition to Biden's Climate Policies Description: Republicans and conservative voices, including the Wall Street Journal Editorial Board, criticize Biden's climate policies as detrimental, labeling them as a disguised 'Green New Deal' that could lead to job destruction in fossil fuel and carbon-intensive sectors. 3. Title: Concerns Over Funding and Tax Increases Description: Right-leaning perspectives highlight concerns about the funding sources for Biden's climate initiatives, particularly criticizing potential tax increases on corporations and the economic challenges associated with financing the climate agenda.
Left Perspective	L1: Title: Republican Opposition to Biden's Climate Agenda Description: Biden's climate change agenda faces significant challenges from Republican opposition, highlighting the partisan divide on environmental policies and the struggle for bipartisan support in a politically divided landscape. L2: Title: Biden's Climate Agenda as Economic Focus Description: Climate change has become a central component of President Biden's economic agenda, emphasizing the integration of environmental goals with job creation and economic growth, reflecting a progressive approach to tackling climate issues. L3: Title: Challenges in Passing Progressive Climate Legislation Description: Biden's plans to overhaul the economy and address climate change are met with skepticism regarding their feasibility and potential impact on American workers, underscoring the need for navigating opposition and ensuring successful implementation of progressive climate policies.
Right Perspective	R1: Title: Economic Concerns and Job Losses in Fossil Fuel Industries Description: Right-leaning critics express worries about job losses and economic impacts on industries like oil, natural gas, and coal due to Biden's climate agenda, contrasting it with the potential benefits of transitioning to cleaner energy sources. R2: Title: Opposition to Biden's Climate Policies Description: Republicans and conservative voices, including the Wall Street Journal Editorial Board, criticize Biden's climate policies as detrimental, labeling them as a disguised 'Green New Deal' that could lead to job destruction in fossil fuel and carbon-intensive sectors. R3: Title: Concerns Over Funding and Tax Increases Description: Right-leaning perspectives highlight concerns about the funding sources for Biden's climate initiatives, particularly criticizing potential tax increases on corporations and the economic challenges associated with financing the climate agenda.

Table 21: Shows an example of partisan summaries obtained for a cluster.

hyperparameters in order to obtain a decent performance. We use a data-driven approach to estimate the best number of topics by maximizing the DBCV score(Moulavi et al. (2014)). We retain the default settings for *cluster_selection_method*, and *metric_parameters*, while we change the

Coherent Example
Right Partisan Summary: R1: Title: Opposition to Biden's Climate Goals Description: Right-leaning sources criticize Biden's emission reduction targets, highlighting concerns over economic costs, job losses, and potential negative impacts on industries like American oil and automobile sectors. R2: Title: Skepticism Towards Clean Energy Investment Description: Republicans express skepticism towards Biden's plans for massive investment in clean energy technologies, raising concerns about the associated costs, tax increases, and economic impact on American workers. R3: Title: Critique of Lack of Implementation Details Description: Right-leaning articles criticize the lack of specific details provided about how emission cuts will be achieved, highlighting concerns about economic damage, job losses, and the transparency of the implementation plans.
Topically relevant right talking points: 1. Title: Far-reaching changes required to meet emission reduction goals Description: Achieving a 50% reduction in emissions by 2030 would require significant changes, such as increasing renewable energy sources, transitioning to electric vehicles, shutting down coal plants, and adopting new energy efficiency targets in industries. 2. Title: Investment in clean energy Description: The summit highlighted the case for massive investment in clean energy technologies and infrastructure, both in the US and around the world. This investment is seen as crucial for creating prosperous and cleaner economies in the long run. 3. Title: Funding for carbon capture technology and critical minerals Description: The Department of Energy will begin accepting applications for a 75 million fund for carbon capture and storage technology. Additionally, 19.5 million in awards will be available for extracting critical minerals used in developing batteries and components for electric vehicles. 4. Title: Lack of details and economic cost Description: The article criticizes the lack of details provided about how the emissions cuts will be achieved and the potential cost to industries and American consumers. It suggests that the economic damage caused by the plans is conveniently ignored by the media.
Corresponding news article summaries: 1. President Biden's ambitious pledge to cut emissions by 2030, including substantial financial support for developing countries, is portrayed as a challenging and costly endeavor by a right-leaning source. The article emphasizes the significant economic changes required to achieve these emission reduction goals, highlighting the potential need for government subsidies and carbon taxes. It also underscores the limited global impact of U.S. emissions reductions compared to major emitters like China and India, suggesting that the efforts may not be effective in combating climate change on a global scale. 2. Biden closes global climate summit emphasizing collective action and massive investments in clean energy, contrasting with Republican skepticism and focus on economic impact on American workers. The article highlights Biden's push for clean-energy technology and infrastructure funding, facing opposition from Republicans who criticize the cost and potential tax increases, while emphasizing the economic benefits and job creation potential of transitioning to clean energy. 3. President Biden's administration targets job creation in fossil fuel communities through federal investments in renewable energy, aiming to reduce coal and petroleum emissions. The report outlines funding for carbon capture technology, critical minerals extraction, rural broadband expansion, and infrastructure projects. While some Republican leaders in coal-dependent states like West Virginia oppose Biden's climate agenda, others, including the nation's largest coal miners' union, support transitioning away from fossil fuels for a cleaner energy future. 4. Right-leaning news article criticizes left-wing media's praise of President Biden's climate plan as 'ambitious' and 'visionary', highlighting concerns about economic damage and lack of details on implementation and costs, while emphasizing the partisan bias in media coverage of climate policies.

Table 22: Shows a coherent example. The generated partisan summary is correct.

Incoherent Example
Right Partisan Summary: R1: Title: Criticism of Biden's vaccine mandate as dictatorial Description: Dr. Fauci's characterization of President Biden's vaccine mandate as 'moderate' is challenged by right-leaning perspectives, labeling the mandate as dictatorial and overly lenient, emphasizing concerns about individual liberty being compromised. R2: Title: Opposition to perceived leniency in vaccine mandate Description: Right-leaning voices critique Dr. Fauci and President Biden for what they view as a lenient approach in the vaccine mandate, suggesting a need for stricter measures to ensure compliance and public health protection. R3: Title: Advocating for a stricter vaccination-only policy Description: Right-leaning perspectives highlight a preference for a stricter vaccination-only policy over the compromise of allowing testing as an alternative in President Biden's vaccine mandate, emphasizing the importance of prioritizing vaccination for public health benefits.
Topically relevant right talking points: 1. Title: President Biden's vaccine mandate is considered somewhat 'moderate' by Dr. Anthony Fauci Description: Dr. Fauci believes that President Biden's vaccine mandate strikes a balance between the need for vaccination and the concerns of those who do not want to get vaccinated but also do not want to lose their jobs. 2. Title: Dr. Fauci's stance on the vaccine mandate Description: Dr. Fauci is quoted as saying that the President's approach is somewhat moderate and a compromise, but the article disagrees, stating that Fauci's true stance on vaccine mandates is even less moderate. 3. Title: President Biden's vaccine mandates Description: Dr. Fauci describes President Biden's vaccine mandates as a moderate approach, allowing for testing as an alternative to vaccination for those who are unwilling to get vaccinated.
Corresponding news article summaries: 1. Dr. Fauci describes Biden's vaccine mandate as 'moderate' on CNN, emphasizing the need for options for those hesitant to get vaccinated. Republican governors criticize the mandate as an infringement on individual liberty and plan to challenge it in court. The mandate's impact on those previously infected with COVID sparks debate, with Fauci acknowledging the complexity of the issue. 2. A right-leaning article criticizes Dr. Fauci for supporting what they view as President Biden's overly lenient vaccine mandate approach, highlighting Fauci's perceived lack of stringency and labeling Biden's actions as dictatorial, while emphasizing the need to expose the true intentions of political figures like Fauci and Biden. 3. Dr. Fauci characterizes President Biden's vaccine mandate as moderate, emphasizing the option for testing as a compromise for those hesitant to get vaccinated, reflecting a right-leaning perspective on the level of stringency in vaccine mandates.

Table 23: Shows a negative example. The generated partisan summary is incorrect. This is primarily attributed to inconsistent news article summaries (2 and 3), and LLM's failure to identify cited information in the news article.

Prompt to characterize a cluster
Given a set of news article excerpts taken from the same news event, the task is to analyze the articles with the intent to identify a high-level concept that captures the key aspect of discussion related to that event. The concept should be indicative of one of the main discussion angles related to the event, and not very specific to entities mentioned in the articles. The concept should be accompanied by a summary, which should not be a mere concatenation of articles.

Table 24: Prompt to characterize cluster candidate. We prompt the LLM in a two-shot setting.

Prompt to merge two clusters
Given two aspects from the same news event, you need to analyze them with the intent to understand if they are focusing on the same aspects of that event. You should compare the key emphasis of the aspects and their implications to decide if they are the 'same', or 'different'. Refrain from providing any additional explanations other than the label.

Table 25: Prompt to merge two clusters. We merge two clusters if their aspects are identical.

Prompt to remove inconsistent clusters
You are provided with a few news article excerpts and a key aspect of discussion, all of which are from the same news event. The task is to analyze if all of the provided news article excerpts are discussing the given key aspect. Respond with 'yes' if the central theme of discussion in each excerpt align in meaning with the key aspect, and 'no' if there is any variance, refraining from offering any additional explanation.

Table 26: Prompt to remove inconsistent clusters.

min_cluster_size and *min_samples* to get more sensible topics. This number is selected based on a grid search whose values are sensitive to the number of input talking points. Suppose |X| denote the number of talking points, then the grid parameters for HDBSCAN used in our method include $5, 7, 9, 0.01 * |X|, 0.02 * |X|, \cdots 0.04 * |X|$.

For our algorithm's talking point membership module, we choose a similarity threshold of 0.76 based on manually inspecting the prominent talking points, outputs for the cluster redundancy and removal of cluster incoherence operations for 3 events related to the issue - *Climate Change*.