Analysis of Climate Campaigns on Facebook using Weakly Supervised Model Soup Approach

Anonymous ACL submission

Abstract

Climate change is the defining issue of our time, and we are at a defining moment. Various interest groups, social movement organizations, and individuals engage in collective action on this issue on social media. In addition, issue advocacy campaigns in social media often arise in response to ongoing societal concerns, especially those faced by energy industries. Our goal in this paper is to analyze how those industries, their advocacy group, and climate advocacy group use social media to influence the narrative on climate change. In this work, we propose a weakly supervised model soup approach combined with messaging themes to identify the stances of climate ads on Facebook. Finally, we release our stance dataset, model, and set of themes related to climate campaigns for future work on opinion mining and the automatic detection of climate change stances. Our data, code, and model are anonymously available here.

1 Introduction

We are approaching a decisive moment for international efforts to tackle the climate crisis, and International Energy Agency (IEA) report sets out a pathway for achieving this goal by reducing global carbon dioxide (CO2) emissions to *net zero by 2050*. IEA emphasizes policy interventions by governments worldwide to drive the energy transition and lower greenhouse gas emissions. Towards a net-zero future, the United Nations campaign for individual action on climate change and sustainability called ActNow* so that by making choices that have less harmful effects on the environment, we can be part of the solution and influence change. Despite the urgency to avoid catastrophic climate change (Moritz and Agudo, 2013), scientific explanation (Dessler and Theater, 1995), the policy plans of the world's governments (Adger et al., 2003), digital activism (Hestres and Hopke, 2017) we are still lagging from climate goals. The reason behind this lag is the negative influence of fossil fuel companies working to undermine and weaken much-needed climate action (Nosek, 2020).

Over the last decade, online advertising has significantly increased to disseminate agendas and sponsored content has been used to reach more people on social media (Goldberg et al., 2021; Krupenkin et al., 2021; Capozzi et al., 2021; Burki, 2020). Advertising plays a pivotal role in climate change because some advertising defends the destructive oil and gas industry, greenwashes brands and drives consumption. At a congressional hearing in April 2021, Facebook chief Mark Zuckerberg admitted that climate misinformation was a "big issue"†. A Bloomberg analysis pointed out that millions of climate change-denial ads continue to be approved on the platform despite increasing pressure from climate groups to more effectively regulate content‡. Oil and gas industries have been using paid-for social media advertising on Facebook to capture the narrative on climate change. However, climate scientists have reached a consensus that climate change is real and is caused by human activity on the planet, which has and will have adverse effects on humanity and the biosphere around the planet (Cook et al., 2016). Stakeholders supporting climate change also use Facebook advertising platform to influence targeted audience focusing on transitioning to renewable energy. Though transition to a renewable energy economy may be exciting to renewable energy advocates and scholars, many industries and community has different perspectives on it (Morris et al., 2019; Richardson and Anderson, 2021). For example, Fig. 1 presents two sponsored ads on Facebook having two different stances on climate change. The *stance* of the top ad (inside the brown box in Fig. 1)

*https://www.un.org/en/actnow

†www.theguardian.com

‡www.campaignasia.com

The oil and gas industry supports millions of local jobs. Unnecessary regulations can stand in the way. Support local jobs by taking action today!

Fossil fuels threaten our health and climate. Join us in calling for a just global transition away from fossil fuels. #COP26

Figure 1: Example of sponsored ads in Facebook where the advertisers have different stances on climate change focusing on a specific theme.

is (`pro-energy`) as the sponsor is against 'unnecessary regulations on oil and gas industry' and the ad *theme* is (`economy_pro`) mentioning 'oil and gas industry supports local jobs'. The *stance* of the bottom ad (inside the green box in Fig. 1) is (`clean-energy`) as the sponsor supports 'transition away from fossil fuels' and the reason for this is the 'threatening effect of fossil fuels on our health'. So the ad *theme* is (`HumanHealth`).

In this work, we aim to understand how climate advocates and fossil fuel corporations are using advertising to control the narrative on climate change and climate policy. Our goal is twofold: first to characterize the themes of the ads, and second to build on this characterization to identify the stances of the ads i.e., **pro-energy**, **clean-energy**, **neutral**.

In recent years, research has shown that models pre-trained on large and diverse datasets learn representations which transfer well to a variety of tasks (Jiao et al., 2020; Edunov et al., 2019; Chronopoulou et al., 2019; Howard and Ruder, 2018). The fine-tuning process has two steps: (1) fine-tune models with a variety of hyperparameter configurations, and (2) select the model which achieves the highest accuracy on the held-out validation set and discard remaining models. (Wortsman et al., 2022) recently showed that selecting a single model and discarding the rest has several downsides and they proposed *model soup* which averages the weights of fine-tuned models independently. While (Wortsman et al., 2022) showed model soup perfomance on four text classification datasets from the GLUE benchmark (Wang et al., 2018), we develop a weakly supervised model soup approach leveraging messaging theme to detect stance for analyzing climate campaigns on Facebook. Our theme assignment process is motivated by a thematic analysis approach (Braun and Clarke, 2012). We begin by defining a seed set of relevant arguments based on recent studies (Miller and Lellis, 2016; Cha et al., 2021), where each pro-energy theme is defined by multiple sentences. Since the initial set of themes contains only pro-energy arguments, we add clean-energy themes and phrases. We fine-tune a pre-trained textual inference model using a contrastive learning approach to identify paraphrases in a large collection of climate related ads. We focus on the following research questions (RQ) to analyze climate campaigns on social media:

- **RQ1.** Can a model that has been weakly trained be leveraged to predict the presence of stances in facebook ads that relate to climate change?
- **RQ2.** What are the intersecting themes of the messaging?
- **RQ3.** What demographics and geographic are targeted by the advertisers?
- **RQ4.** Do the messages differ based on entity type?

Our contributions are summarized as follows:

1. We formulate a novel problem of exploiting weak supervision and Bayesian model averaging to analyze the landscape of climate advertising on social media.
2. We propose a weakly supervised model soup approach to identify stance combining themes of the content of climate campaigns. We show that our model outperforms the baselines.
3. We conduct quantitative and qualitative analysis on real-world dataset to demonstrate the effectiveness of our proposed model.

2 Related Work

Recent studies have shown climate change activism in social media and news media (Bloomfield and Tillery, 2019; Walter et al., 2018; Stoddart et al., 2016). Sponsored content on social media – especially Facebook, is the main channel to reach the targeted audience on a specific event such as: US Presidential election (Islam et al., 2022), or specific issues, i.e., covid (Islam and Goldwasser, 2022b; Silva and Benevenuto, 2021; Mejova and Kalimeri, 2020), immigration(Capozzi et al., 2020; Ribeiro et al., 2019).

Several studies have analyzed the discourse around climate change. (Luo et al., 2020) proposed an opinion framing task on the global warming debate on media. (Koenecke and Feliu-Faba, 2019)

studied whether climate change related sentiment in tweets changed in response to five natural disasters occurring in the US in 2018. To understand the narratives of climate change skepticism, (Bhatia et al., 2021) studied automatic classification of neutralization techniques. (Diggelmann et al., 2020) introduced a veracity prediction task in a fact-checking setting on climate claims. Our work differs from these in that we use a probabilistic approach to detect stance incorporating theme information of climate related ads in social media. Our work falls in the broad scope of weak supervision (Islam and Goldwasser, 2022a; Mekala et al., 2020; Ratner et al., 2018; Belkin et al., 2006), contrastive learning (Wang et al., 2021; Gao et al., 2021; Giorgi et al., 2020; Wu et al., 2020) and Bayesian model averaging (Madigan et al., 1996; Madigan and Raftery, 1994) where averaging the weights of multiple models fine-tuned with different hyperparameter configurations improves accuracy and robustness (Wortsman et al., 2022).

3 Data

We collect $88,022$ climate related English ads focusing on United States from January 2021 - January 2022 using Facebook Ad Library API[§] with the search term 'climate change', 'energy', 'fracking', 'coal'. To create the list of keywords for collecting ads about climate and oil & gas industries, we read multiple articles about climate policy, environmental justice, climate change mentioning green/clean energy, transition from fossil fuel to renewable energy, coal dependent US states, protection of fossil-fuel workers and communities, and other climate debates, and made a list of repeating statements. Then, we consult two researchers in Computational Social Science, and construct a list of relevant keywords. The full list of keywords are in Table 1. Our collected ads are written in English. For each ad, the API provides the ad ID, title, ad description, ad body, funding entity, spend, impressions, distribution over impressions broken down by gender (male, female, unknown), age (7 groups), location down to states in the USA. So far, we have 408 unique funding entities whose stances are known based on their affiliation from their websites and Facebook pages. These funding entities are the weak sources in our model. As we don't know the stance of the ads, we assign the same stance for all ads sponsored by the same funding entity. This way, we have $25,232$ ads whose stances are known. We have duplicate content among those collected ads because the same ad has been targeted to different regions and demographics with unique ad id. Therefore, we have 5414 unique ads.

[§] https://www.facebook.com/ads/library/api

climate change, climate, fossil fuel, fracking, energy, oil, coal, mining, gas, carbon, power, footprint, solar, drilling, tri-city, petroleum, renewable, global warming, emission, ecosystem, environment, greenhouse, ozone, radiation, bioenergy, biomass, green energy, methane, pollution, forest, planet, earth, ocean, nuclear, ultraviolet, hydropower, hydroelectricity, geothermal, sustainable, clean energy

Table 1: List of the keywords for data collection.

4 Problem Formulation

We formulate our stance prediction problem as a weakly supervised model soup approach. We know the stance of the funding entity but we don't know the stance of the ads. We assign the same stance for all ads sponsored by the same funding entity. We want to predict the stance of the ad using model soup approach in the following way:

$$\text{Point estimation: } P(y_s|X_a, \theta, y_t) \quad (1)$$

$$\text{Bayesian posterior:}$$
$$P(\theta|y_s, X_a, y_t) \propto P(\theta)P(y_s|X_a, \theta, y_t) \quad (2)$$

where, X_a is the ad, y_s is the predicted stance, y_t is the assigned themes, θ is the model parameter. For the point estimation in Equation 1, we fine-tuned the pre-trained BERT model (Devlin et al., 2019) by concatenating theme information. For Bayesian model averaging (Equation 2), we implement both the uniform and greedy soup approaches provided by (Wortsman et al., 2022) including messaging theme, which can be regarded as cheap Bayesian posterior approximations. We get the theme y_t, using the contrastive learning approach following (Reimers and Gurevych, 2019).

5 Methodology

In this section, we describe how to obtain sentence embedding using contrastive learning, generate themes and phrases, assign themes for the ad content, and implement model soup in our problem.

5.1 Sentence Embeddings with Contrastive Learning

We use $88k$ unlabeled ads for finetuning Sentence BERT (SBERT) (Reimers and Gurevych, 2019). Our training approach uses a siamese-BERT architecture during fine-tuning (Fig. 2). During

each step, we process a sentence S (anchor) into BERT, followed by sentence T (positive example). In our case, the anchor is the ad text and positive example is the ad description or ad summary. Some ads do not have ad descriptions. In that case, we generate ad summary using BART summarizer (Lewis et al., 2020). BERT generates token embeddings. Finally, those token embeddings are converted into averaged sentence embeddings using mean-pooling. Using the siamese approach, we produce two of these per step — one for the anchor A and another for the positive called P. We use multiple negatives ranking loss.

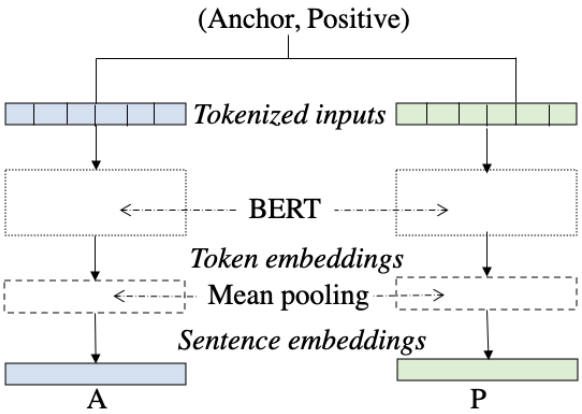


Figure 2: Siamese-BERT network for contrastive learning to generate sentence embeddings.

5.2 Themes and Phrases Generation

To analyze climate campaigns, we model the climate related stance expressed in each ad (i.e., pro-energy, clean-energy) and the underlying reason behind such stance. For example, in the top ad (brown box) of Fig. 1 expresses a pro-energy stance, and mentions their support for local jobs as the reason to take this stance.

Three main challenges are involved in this analysis: 1) constructing the space of possible themes, 2) mapping ads to the relevant themes, 3) predicting the stance leveraging the themes. We combine computational and qualitative techniques to uncover the most frequent themes cited for pro-energy and clean-energy stances. We build on previous studies that characterized the arguments supporting the oil and gas industries (Miller and Lellis, 2016). In this work, researchers develop four broad categories of pro-energy themes by looking at audience responses to ads from fossil fuel companies. As energy is an economic, social, security, and environmental concern, we go through relevant research

PRO-ENERGY	Economy_pro, Identity, Climate solution, Pragmatism, Patriotism, Against climate policy, Give away
CLEAN-ENERGY	Economy_clean, Future generation, Environmental, Human health, Animals, Support climate policy, Alternative energy, Political affliation

Table 2: Resulting themes.

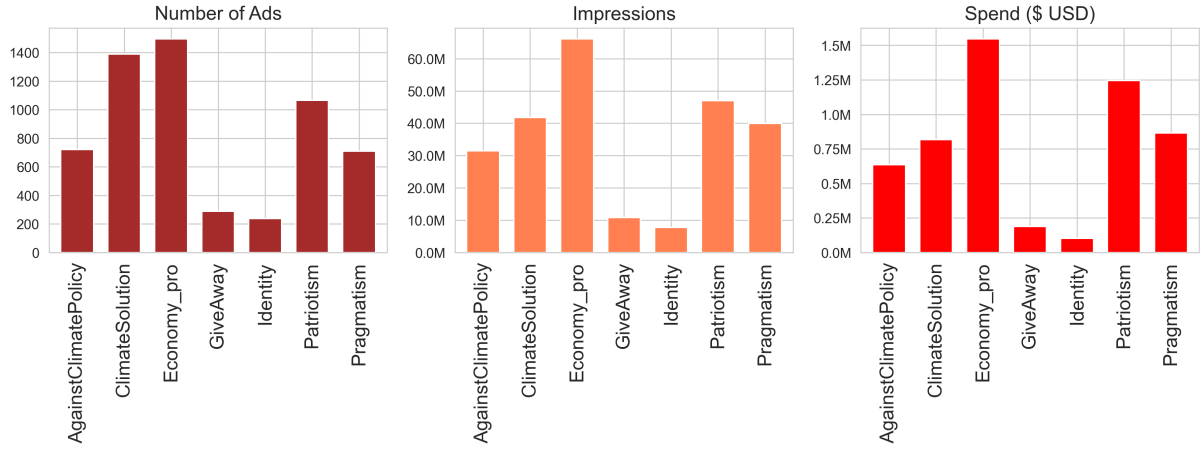
conducted by United Nations, influencemap.org and pewresearch.org to construct a list of potential themes and phrases for each theme. We add new relevant pro-energy themes and corresponding phrases that were not covered by previous work, such as *"Green New Deal would take America back to the dark ages"* which falls under a new theme called '**Against Climate Policy**'. As the initial set of themes contains mostly pro-energy arguments, we add reasons for supporting climate actions which are clean-energy themes, e.g., "*Climate change is a grave threat to children's survival*" $\Rightarrow$ **Future Generation**. Then, we consult with two researchers in Computational Social Science and finalize the relevant themes with corresponding phrases. The final set of themes can be observed in Table 2. The full list of phrases for each theme can be observed in Table 6 at Appendix A.1.

5.3 Assign Themes

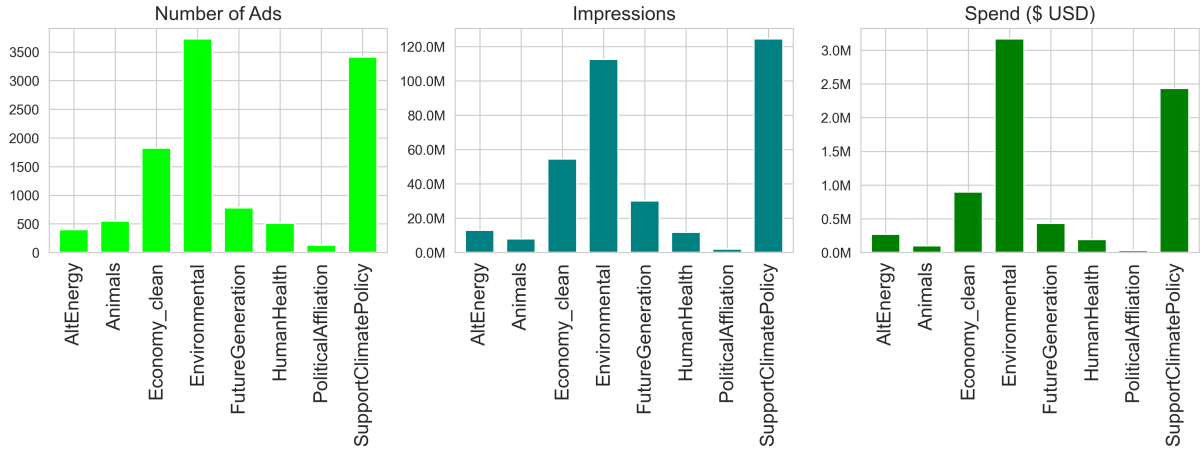
Our main goal is to ground these themes in a set of approximately $25k$ weakly labeled (stance) ads. To map ads to themes, we use the similarity between their fine-tuned sentence BERT embeddings (details of fine-tuning provided in subsection 5.1). To check the quality of theme label, we annotated around 300 ads with corresponding themes and we notice an accuracy of 38.4% and macro-avg F1 score of 40.2%, which is better than random (6.6%).

5.4 Bayesian Model Averaging

In this work, we develop a weakly supervised model soup approach by incorporating messaging themes to identify the stances of climate ads on Facebook. We used two approaches for model soup. The first one is uniform soup (Wortsman et al., 2022). We consider a neural network $f(x, \theta)$ with input data x and parameters θ. For uniform soup, we take the average of the finetuned model parameters ($f(x, \frac{1}{k}\sum_{i=1}^{k}\theta_i)$) where θ_i can be considered as samples from the Bayesian posterior and the average can be viewed as a cheap approximation to Bayesian model average. The second one

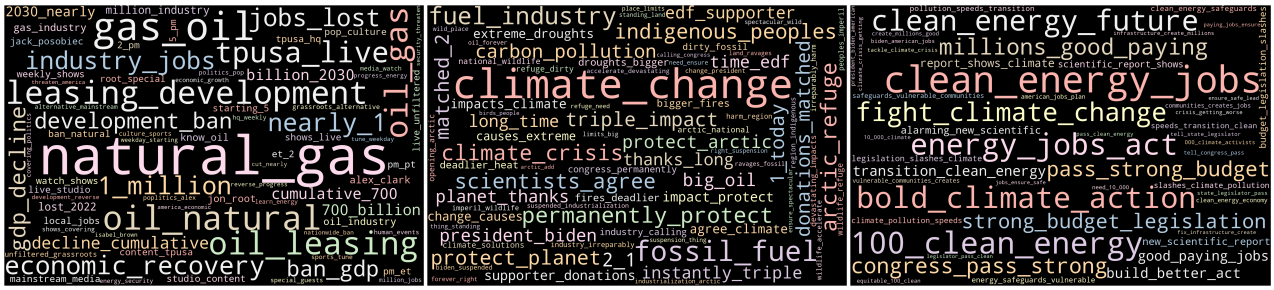


(a) Pro-energy ads



(b) Clean-energy ads

Figure 3: Distribution of ad themes by Number of Ads, Impressions, and Spend.



(a) Economy_pro (b) Environmental (c) SupportClimatePolicy

Figure 4: Wordcloud for three messaging themes based on the popularity of ad impressions, expenditure, and number of sponsored ads for both pro-energy and clean-energy ads.

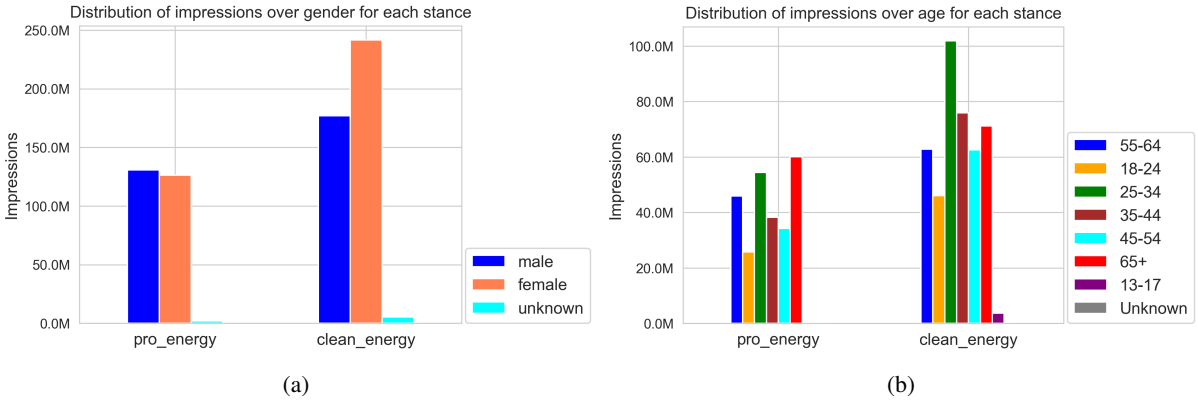


Figure 5: Distribution of impressions over demographic **(a) gender**, **(b) age** both for pro-energy and clean-energy ads.

Data split	Number of Funding entities	Number of Ads
Training	261	8874
Validation	65	2219
Testing	82	2773

Table 3: Data details.

Model	Accuracy	Macro-avg F1	Learning rate	Weight decay
FBERT_Hyper1 (text)	0.897	0.833	2.00E-05	0.01
FBERT_Hyper2 (text)	0.909	0.866	1.00E-05	0.01
FBERT_Hyper3 (text)	0.899	0.687	1.00E-04	0.001
FBERT_Hyper4 (text)	0.895	0.774	1.00E-04	0.01
FBERT_Hyper5 (text)	0.905	0.856	1.00E-05	0.001
FBERT_Hyper6 (text)	0.898	0.813	3.00E-05	0.001
FBERT_Hyper7 (text)	0.896	0.825	3.00E-05	0.01
FBERT_Hyper8 (text)	0.892	0.833	2.00E-05	0.1
FBERT_Hyper9 (text)	0.885	0.813	1.00E-04	0.0001
FBERT_Hyper10 (text)	0.906	0.861	1.00E-05	0.1
Uniform Model soup (text)	*0.943*	*0.880*	-	-
Greedy Model soup (text)	*0.933*	*0.872*	-	-
Point_est_Hyper1 (text + thm)	0.921	0.854	2.00E-05	0.01
Point_est_Hyper2 (text + thm)	0.883	0.835	1.00E-05	0.01
Point_est_Hyper3 (text + thm)	0.916	0.695	1.00E-04	0.001
Point_est_Hyper4 (text + thm)	0.874	0.845	1.00E-04	0.01
Point_est_Hyper5 (text + thm)	0.897	0.826	1.00E-05	0.001
Point_est_Hyper6 (text + thm)	0.902	0.825	3.00E-05	0.001
Point_est_Hyper7 (text + thm)	0.894	0.830	3.00E-05	0.01
Point_est_Hyper8 (text + thm)	0.894	0.829	2.00E-05	0.1
Point_est_Hyper9 (text + thm)	0.888	0.781	1.00E-04	0.0001
Point_est_Hyper10 (text + thm)	0.879	0.822	1.00E-05	0.1
Uniform Model soup (text + thm)	0.944	**0.888**	-	-
Greedy Model soup (text + thm)	**0.945**	0.884	-	-

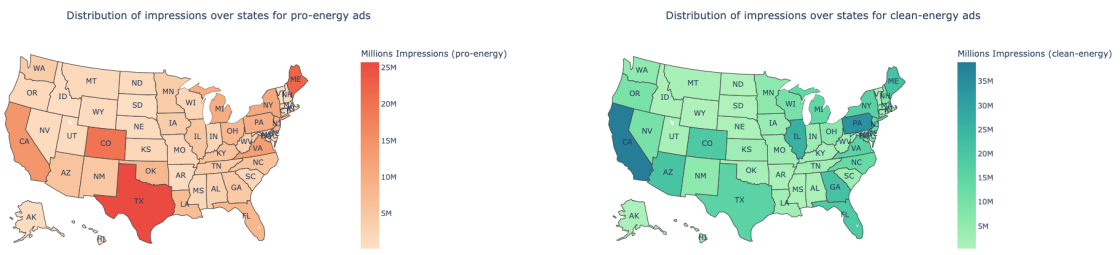
Table 4: Model performance for stance prediction using weakly supervised model soup approach. FBERT: Fine-tuned of pre-trained BERT model, Point_est: Point estimation, thm: Theme, Hyper: Hyperparameter.

is greedy soup approach (Wortsman et al., 2022). For the greedy soup, at first, we sort the models in decreasing order of validation set accuracy. The soup is constructed by sequentially adding each model as a potential ingredient in the soup, and only keeping the model in the soup if performance on the validation set improves.

6 Results and Analysis

This section presents the experimental results of the stance prediction task on climate change-related ads. We randomly split our data based on the funding entity so that the same ads do not appear in the other splits. At first, we randomly split 20% of the funding entities and keep them as a testing set. Then we randomly split the rest of the data and keep 20% of that as a validation set and the rest as the training set. Details number of funding entities and ads for each split are shown in Table 3. We fine-tune the pre-trained BERT-base-uncased model (Devlin et al., 2019) and run for 10 epochs for each hyperparameter setting, i.e., learning rate and weight decay. We set the maximum text sequence length to 110, batch size 32, and use Adam optimizer (Kingma and Ba, 2015). We concatenate the assigned theme with ad text so that our model can leverage the theme information. We use pre-trained weights from the Huggingface Transformers library (Wolf et al., 2020). Evaluation is conducted once at the end of the training, without early stopping. We use a single GPU GeForce GTX 1080 Ti GPU, with 6 Intel Core i5-8400 CPU @ 2.80 GHz processors to run each model, and it takes around 15 minutes to run each model. But averaging several of these models to form a model soup requires no additional training and adds no cost at inference time. We provide experimental results in Table 4. For the evaluation metrics, we use accuracy and macro-average F1 score. We notice that the uniform model soup using ad text + theme (88.8% macro-avg F1 score) outperforms the greedy model soup for text + theme and the best single models (Table 4) (Answer to **RQ1**).

For the ablation study, we run the experiments using only ad text (we **do not** provide any theme information). We notice that uniform model soup (text + theme) still gives better performance than the uniform model soup (text), greedy model soup



(a) pro-energy

(b) clean-energy

Figure 6: Distribution of impressions over geographic.

(text), and the best single text only models (Table 4).

6.1 Narrative Analysis

We consider only ads with correct stance prediction and corresponding themes for narrative analysis. To answer **RQ2**, we analyze the messaging strategies used by the advertisers (Fig. 3). By impressions and expenditures, the most popular ***pro-energy*** messaging theme is '**Economy_pro**', accounting for approximately 27% of total impressions and 28.7% of total expenditure (Fig. 3a). Under this theme narratives promote how *'natural gas and oil industry will drive economic recovery', 'GDP would decline by a cumulative* 700 *billion through 2030 and* 1 *million industry jobs would be lost by 2022 under natural gas and oil leasing and development ban'*(Fig. 4a).

Based on impression, the most popular ***clean-energy*** messaging category is '**SupportClimatePolicy**' (Fig. 3b)(approximately 35%), which features narratives supporting Build Back Better Act[¶] to *fight climate change, create clean energy jobs, equitable clean energy future, take bold climate action*(Fig. 4c). Based on spend, the most popular (42%) ***clean-energy*** messaging theme is '**Environmental**' (Fig. 3b). This theme focuses on narratives about *'how dirty fossil fuel industries would harm the indigenous peoples and wildlife', 'why climate scientists agree that climate change causes more extreme droughts, bigger fires and deadlier heat', 'effects of carbon pollution on climate crisis'* etc (Fig. 4b).

6.2 Demographic and Geographics Distribution by Impressions

As Facebook enables its customers to target ads using demographics and geographic information,

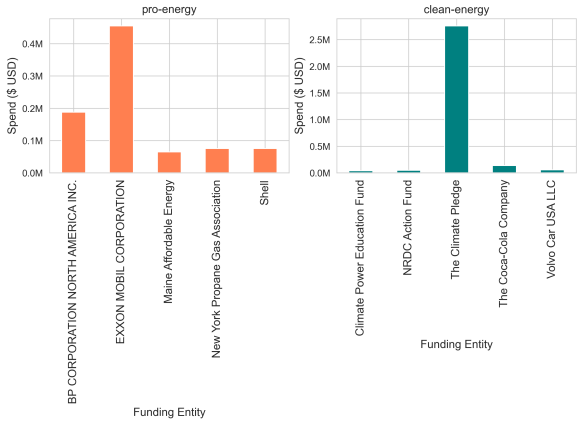


Figure 7: Top 5 funding entities based on expenditure. Orange plot represents pro-energy. Green plot represents clean-energy.

we further analyze the distribution of the messaging categories to answer **RQ3**. Fig. 5a shows that *more males than females* see the ***pre-energy*** ads, and *more females than males* watch ***clean-energy*** ads. However, ***pro-energy*** ads are mostly viewed by the *older population* (65+) (Fig. 5b). On the other hand, *young people from the age range of* $25-34$ view ***clean-energy*** ads (Fig. 5b).

In Fig. 6, we show the distribution of impressions over US states for both stances. To plot the distribution, we use the Choropleth map in Python. Pro-energy ads receive the most views from Texas which is the energy capital of the world[‖] (Fig. 6a). Fig. 6b shows that clean-energy ads are mostly viewed from California because recently, CA has become one of the loudest voices in the fight against climate change[**].

[¶] https://www.whitehouse.gov/build-back-better/

[‖] www.eia.gov/

[**] www.pewtrusts.org

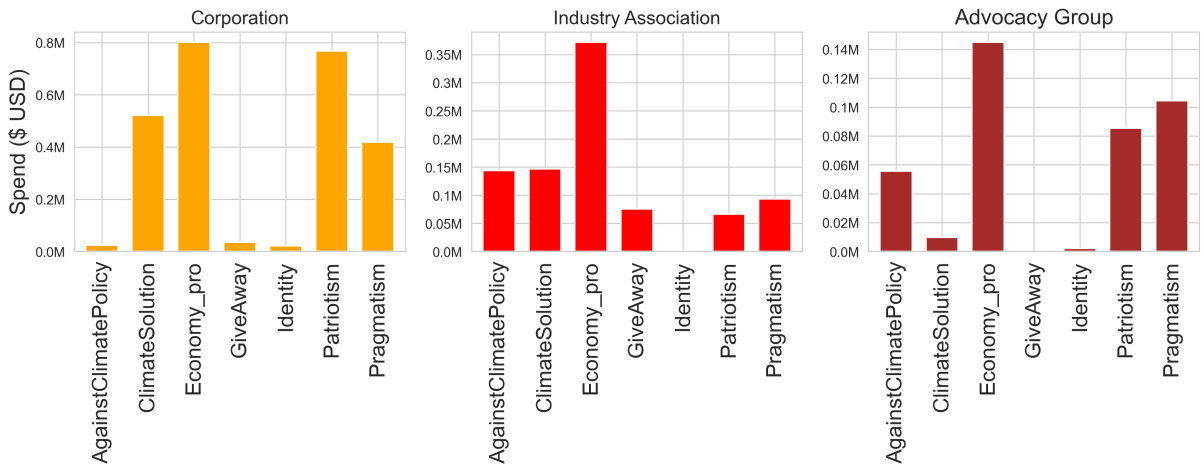


Figure 8: Pro-energy ad themes by funding entity type.

Type	Entity
Corporation	EXXON MOBIL CORPORATION
Corporation	Shell
Corporation	BP CORPORATION NORTH AMERICA INC.
Corporation	Twin Metals Minnesota
Corporation	Wink to Webster Pipeline LLC
Industry Association	AMERICAN PETROLEUM INSTITUTE
Industry Association	New York Propane Gas Association
Industry Association	Texas Oil & Gas Association
Industry Association	New Mexico Oil and Gas Association
Industry Association	National Propane Gas Association
Advocacy Group	Coloradans for Responsible Energy Development
Advocacy Group	Grow Louisiana Coalition
Advocacy Group	Voices for Cooperative Power
Advocacy Group	Consumer Energy Alliance
Advocacy Group	Maine Affordable Energy

Table 5: List of entities from pro-energy ads.

6.3 Distribution of Messaging by Entity Type

Fig. 7 shows the top 5 funding entities based on expenditure in pro-energy and clean-energy ads. We notice that **Exxon Mobil Corporation**, which is one of the world's largest publicly traded international oil and gas companies[††], spends the most on sponsoring pro-energy ads on Facebook. Clean-energy ads are mostly sponsored by **The Climate Pledge**, which is powered by 378 companies in 34 countries around the globe[‡‡].

To understand how fossil fuel industries and their support groups influence public opinion, we categorize pro-energy funding entities into three types, i.e., Corporation, Industry Association, and Advocacy Group. Finally, we select the top 5 pro-energy funding entities based on their expenditure for each category. Table 5 shows the list of pro-energy entities included in our analysis.

The highest spending on '**Economy_pro**' narratives comes from all three entity types (Fig. 8). Corporation entities spend on '**Patriotism**' narratives as their second target. Furthermore, advocacy groups focus on '**Pragmatism**' narratives as their second target. Moreover, industry associations spend almost equally on '**ClimateSolution**' and '**AgainstClimatePolicy**' narratives. Analyzing the messaging themes for different funding entities indicates different groups are fulfilling different messaging roles (Answer to **RQ4**).

7 Limitations

In this work, we predict the stances of ads using the theme information. We can further explore other potential tasks, such as moral foundation analysis (Haidt and Joseph, 2004; Haidt and Graham, 2007) which will help model the dependencies between the different level of analysis. Moreover, our analysis might have an unknown bias as it is based on English written ads focusing on the United States only. Another limitation is transparency – some particular aspects of the advertising campaigns are not available to the public through the Facebook Ads Library API, thus limiting our findings.

8 Conclusion

We propose a weakly supervised model soup approach leveraging messaging themes to identify stances of climate related ads on social media. To the best of our knowledge, our work is the first work that uses a probabilistic machine learning approach to analyze climate campaigns. We hope our approach of stance detection and theme analysis will help policymakers to navigate the complex world of energy.

[††] https://corporate.exxonmobil.com/
[‡‡] https://www.theclimatepledge.com/

9 Ethics Statement

The data collected in this work was made publicly available by Facebook Ads API. The data does not contain any personally identifying information and reports engagement patterns at an aggregate level.

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A Appendix

A.1 Themes and Phrases

Table 6 shows the full list of phrases for pro-energy and clean-energy themes.

Themes	Phrases
Economy_pro	"Oil and gas will create more jobs", "Without oil and gas there is no job", "Fracking supports thousands of jobs", "Without fracking we will be jobless", "Oil and gas help local business", "Without oil and gas our economy would be in risk", "Oil and gas industries pay high wages", "Jobs would be lower paid without oil and gas", "Local business would suffer without oil and gas industry", "Don't take jobs away from the coal miners", "Coal is powering economic progress", "Protect our jobs", "Banning fossil fuels will lead to job losses", "Fracking jobs will bring new opportunities to rural areas", "Local communities would suffer due to the loss of tax revenue", "Natural gas ban would kill local jobs", "Oil and gas industires help community through philanthropic efforts", "Energy industry gives back to communities", "Without oil and gas industry, there would be less philanthropy"
Identity	"Shifting away from fossil fuels is the loss of our culture", "Destruction of fossil fuel industry feels like the destruction of our identity", "Fossil fuel workers struggle with a loss of identity due to factory shut down", "We should protect our community identity", "Our identities are at stake", "Support the miners", "Coal is not just a Job, it's a way of Life", "Remember the pride that coal mining gave us", "We are fighting for our identity", "Support our families and communities through supporting oil and gas industries"
ClimateSolution	"We support reducing green house gas emissions", "We develop technologies to reduce carbon emission", "We are comimitting to net-zero emissions", "We are transitioning energy mix away from fossil fuels", "We are moving towards renewables", "Natural gas is the future for clean energy", "Fossil gas is a low carbon energy source", "Natural gas is the perfect partner to renewables", "Natural gas is part of the solution on climate change", "Thanks to natural gas, emissions have reduced", "The oil and gas industry has to be a partner, not a problem", "Renewable natural gas will help us get to net zero carbon emissions as fast as we can"
Pragmatism	"Oil and gas are affordable energy sources", "Without oiland gas energy would be expensive", "Oil and gas are reliable energy sources", "Oil and gas will keep the lights on no matter what", "Banning fossil fuel would make energy unreliable", "Without oil and gas energy would be unreliable", "Oil and gas are safe", "Oil and gas powers our lives", "Oil and gas is efficient", "Oil and gas meets our essential energy needs", "Oil and gas is resilient", "Oil and gas is abundant", "Oil and gas is secure"
Patriotism	"Shutting down local oil and gas production would force us to increase reliance on unstable foreign oil", "We achieved record-high oil and gas production", "US is leading in oil and gas production", "US is an energy leader", "Without US oil and gas the world would be forced to use dirtier emissions intensive oil and gas", "Stand up for American energy", "Keep Alaska competitive", "It's not patriotic to shut off American energy", "We don't have to necessarily be reliant on the Middle East", "We are loaded with coal. It's here and it's ours"
AgainstClimatePolicy	"The Build Back Better Act will ruin our economy", "Green New Deal would take America back to the dark ages", "Biden and Democrats own this energy crisis", "Biden's pipeline closure increases gas price", "Government's climate agenda is harmful for our economy", "Democrats' impractical energy policies won't stop climate change", "Government's climate policy is outrageous", "D.C. Socialists are attacking the oil and gas industry", "Biden's climate policy would make energy unaffordable"
GiveAway	"We are giving away free gas", "Collect free coupon for gas"
Economy_clean	"Compared with fossil fuel technologies, which are typically mechanized and capital intensive, the renewable energy industry is more labor intensive", "Fast-growing renewable energy jobs offer higher wages", "Fossil fuels are expensive", "Renewable energy opens up job opportunities", "Clean energy will create jobs boom", "Clean energy can rebuild our economy", "Nuclear energy can bring new clean energy jobs", "Losing nuclear power plants meaning losing jobs", "Make polluters pay to clean up their messes", "Energy companies put profit over people", "Big oil and gas companies are forcing American families to pay more"
HumanHealth	"Climate change is the single biggest health threat facing humanity", "Changing weather patterns are expanding diseases, and extreme weather events increase deaths and make it difficult for health care systems to keep up", "Our communities are facing increased risk of illness, disease, and even death from our changing climate", "Climate impacts are already harming health, through air pollution, disease, extreme weather events, forced displacement, pressures on mental health, and increased hunger and poor nutrition in places where people cannot grow or find sufficient food", "Climate crisis is impacting our communities", "Fossil fuesls threaten our health", "We need breathable air", "Toxic pollution kills people"
FutureGeneration	"Protect our children, family and future generations", "Climate change is a grave threat to children's survival", "Clean air for healthier kids", "Children's immune systems are still developing, leaving their rapidly growing bodies more sensitive to disease and pollution", "Save the children" "Hotter temperatures, air pollution and violent storms are leading to immediate, life-threatening dangers for children, including difficulty breathing, malnutrition and higher risk of infectious diseases",
Environmental	"Carbon dioxide and additional greenhouse gas emissions are leading contributors to climate change and global warming", "By slowing the effects of climate change and eventually reversing them, we can expect to see a reduction in extreme weather like droughts, floods, and storms caused by global warming", "Protect our planet", "Changes in the climate and increases in extreme weather events are among the reasons behind a global rise in hunger and poor nutrition", "Changes in snow and ice cover in many Arctic regions have disrupted food supplies from herding, hunting, and fishing", "Destructive storms have become more intense and more frequent in many regions due to climate change", "Climate change is changing water availability, making it scarcer in more regions", "Global warming exacerbates water shortages in already water-stressed regions and is leading to an increased risk of agricultural droughts affecting crops, and ecological droughts increasing the vulnerability of ecosystems", "The rate at which the ocean is warming strongly increased over the past two decades, across all depths of the ocean", "Melting ice sheets cause sea levels to rise, threatening coastal and island communities", "More carbon dioxide makes the ocean more acidic, which endangers marine life and coral reefs", "As greenhouse gas concentrations rise, so does the global surface temperature", "Wildfires start more easily and spread more rapidly when conditions are hotter", "Protect our air", "Protect our ocean", "Climate crisis affects the environment", "The top cause contributing to carbon dioxide emissions is electricity generation from fossil fuel power plants"
Animals	"Climate change poses risks to the survival of species on land and in the ocean", "One million species are at risk of becoming extinct within the next few decades", "Toxic pollution kills animals", "Wildlife is severely affected by reduction of rainfall and a lack of water", "In the U.S. and Canada, moose are struggling due to an increase in ticks and parasites that are surviving the shorter, milder winters"
AltEnergy	"Transitioning to renewable energy is not only necessary to fight the climate crisis, it is also the only way we can quickly and effectively meet rising energy demands", "Alternative energy sources have a much lower carbon footprint than natural gas, coal, and other fossil fuels", "We can diversify our energy supply by implementing the widespread use of large-scale renewable energy technologies and minimizing our imported fuel dependency", "Renewable energy is cheap", "Sustainable energy is the future"
SupportClimatePolicy	"The Build Back Better Act would put $555 billion toward building a clean energy economy in the United States, the largest single investment in combating climate change in American history", "Green New Deal is a crucial framework for meeting the climate challenges we face", "Support the Energy Jobs & Justice Act", "Stop corporate polluters", "Big oil and gas industries should be held accountable for climate change", "Join Regional Greenhouse Gas Initiative today", "Support climate policy", "Support clean energy", "Biden should honor his climate and justice commitments", "We need climate leader", "We need to hold our leaders accountable for climate crisis"
PoliticalAffiliation	"Owners of oil and gas companies are the top donors to a political action committee", "Big oil and gas industries spend millions to fight climate bills"

Table 6: Pro-energy (red) and clean-energy (green) themes and phrases to show how the sponsors use social media to influence the narrative on climate change.