Analyzing Online Political Advertisements

Danae Sánchez Villegas\(^\alpha\) Saeid Mokaram\(^\beta\) Nikolaos Aletras\(^\alpha\)
\(^\alpha\) Computer Science Department, University of Sheffield, UK
\(^\beta\) Emotech
\{dsanchezvillegas1, n.aletras\}@sheffield.ac.uk
saeid.mokaram@gmail.com

Abstract

Online political advertising is a central aspect of modern election campaigning for influencing public opinion. Computational analysis of political ads is of utmost importance in political science to understand the characteristics of digital campaigning. It is also important in computational linguistics to study features of political discourse and communication on a large scale. In this work, we present the first computational study on online political ads with the aim to (1) infer the political ideology of an ad sponsor; and (2) identify whether the sponsor is an official political party or a third-party organization. We develop two new large datasets for the two tasks consisting of ads from the U.S. Evaluation results show that our approach that combines textual and visual information from pre-trained neural models outperforms a state-of-the-art method for generic commercial ad classification. Finally, we provide an in-depth analysis of the limitations of our best-performing models and linguistic analysis to study the characteristics of political ads discourse.

1 Introduction

Online advertising is an integral part of modern digital election campaigning (Fulgoni et al., 2016; Fowler et al., 2020a). The increased spending on online political ads (e.g. the 2020 U.S. election campaign spending hit an all-time record\(^2\)) poses a significant challenge to the democratic oversight of digital campaigning,\(^3\) with serious implications about transparency and accountability, for example how voters are targeted and by whom (Kriess and Barrett, 2020).

Political advertising is defined as ‘any controlled message communicated through any channel designed to promote the political interests of individuals, parties, groups, government, or other organizations’ (Kaid and Holtz-Bacha, 2006). It is guided by ideology and morals (Scammell and Langer, 2006; Kumar and Pathak, 2012), and often expresses more negativity (Haselmayer, 2019; Iyengar and Prior, 1999; Lau et al., 1999) compared to the aesthetic nature of commercial advertising. Table 1 shows examples of online political ads across different political parties and sponsor types.

While the closely related online commercial advertising domain has recently been explored in natural language processing (NLP) for predicting the category (e.g. politics, cars, electronics) and sentiment of an ad (Hussain et al., 2017; Kalra et al., 2020), online political advertising has yet to be explored. Large-scale studies of online political advertising have so far focused on understanding targeting strategies rather than developing predictive models for analyzing its content (Edelson et al., 2019; Medina Serrano et al., 2020).

Automatically analyzing political ads is important in political science for researching the characteristics of online campaigns (e.g. voter targeting, sponsors, non-party campaigns, privacy, and misinformation) on a large scale (Scammell and Langer, 2006; Johansson and Holtz-Bacha, 2019). Moreover, identifying ads sponsored by third-party organizations is critical to ensuring transparency and accountability in elections (Liu et al., 2013; Speicher et al., 2018; Fowler et al., 2020b; Edelson et al., 2019). For example, third-party advertising had an increased presence in the U.S. House and Senate races in 2018 considerably more than in 2012 where almost half of the third-
| Political Ideology | Ad Sponsor Type | Sample Ad |
|--------------------|----------------|-----------|
| Liberal            | Political Party| ![Sample Ad](image1) |
| Conservative       | Political Party| ![Sample Ad](image2) |
| N/A                | Third-Party    | ![Sample Ad](image3) |

Table 1: Examples of online political ads by sponsor political ideology and type.

party sponsored ads were funded by dark-money sources (Fowler et al., 2020b). Finally, computational methods for political ads analysis can help linguists to study features of political discourse and communication (Kenzhekanova, 2015; Skorupa and Dubovičienė, 2015).

In this paper, we present a systematic study of online political ads (consisting of text and images) in the U.S. to uncover linguistic and visual cues across political ideologies and sponsor types using computational methods for the first time. Our contributions are as follows:

1. A new classification task for predicting the political ideology (conservative or liberal) of an ad (§3). We collect 5,548 distinct political ads in English from 242 different advertisers in the U.S., and label them according to the dominant political ideology of the respective sponsor’s party affiliation (Liberal or Conservative);

2. A new classification task to automatically classify ads that were sponsored by official political parties and third-party organizations, such as businesses and non-profit organizations (§3). For this task, we extract 15,116 advertisements in English from 665 distinct advertisers in the U.S., and label them as Political Party (i.e. officially registered) and Third-Party (i.e. other organizations) following Fowler et al. (2020b);

3. Experiments with text-based and multimodal (text and images) models (§4) for political ideology prediction and sponsor type classification reaching up to 75.76 and 87.36 macro F1 in each task respectively (§6);

4. Analysis of textual and visual features of online political ads (§7) and error analysis to understand model limitations.

2 Related Work

2.1 Political Communication and Advertising

Previous work on analyzing political advertising has covered television and online ads (Kaid and Postelnicu, 2005; Reschke and Anand, 2012; West, 2017; Fowler et al., 2020b). Ridout et al. (2010) analyze a series of YouTube videos posted during the 2008 presidential campaign to understand its influence on election results as well as the actors and formats compared to traditional television ads. Anstead et al. (2018) study how online platforms such as Facebook are being used for political communication and identify challenges for understanding the role of these platforms in political elections, highlighting the lack of transparency (Caplan and Boyd, 2016). Fowler et al. (2020b) explore differences between television and online ads, and demonstrate that there is a greater number of candidates advertising online than on television.

2.2 Political Ideology Prediction

Inferring the political ideology of various types of text including news articles, political speeches and social media has been vastly studied in NLP (Lin et al., 2008; Gerrish and Blei, 2011; Sim et al., 2013; Iyyer et al., 2014; Preoțiuc-Pietro et al., 2017; Kulkarni et al., 2018; Stefanov et al., 2020). Bhata and P (2018) exploit topic-specific sentiment analysis for ideology detection (i.e. conservative, liberal) in speeches from the U.S. Congress. Kulkarni et al. (2018) propose a multi-view model that incorporates textual and network information to predict the ideology of news articles. Johnson and Goldwasser
(2018) investigate the relationship between political ideology and language to represent morality by analyzing political slogans in tweets posted by politicians. Maronikolakis et al. (2020) present a study of political parody on Twitter focusing on the linguistic differences between tweets shared by real and parody accounts. Baly et al. (2019) estimate the trustworthiness and political ideology (left/right bias) of news sources as a multi-task problem. Stefanov et al. (2020) develop methods to predict the overall political leaning (left, center or right) of online media and popular Twitter users.

Political ideology and communicative intents have also been studied in computer vision. Political images have been analyzed to infer the persuasive intents using various features such as facial display types, body poses, and scene context (Joo et al., 2014; Huang and Kovashka, 2016; Joo and Steinert-Threlkeld, 2018; Bai et al., 2020; Chen et al., 2020). Joo et al. (2015) introduce a method that infers the perceived characteristics of politicians using face images and show that those characteristics can be used in elections forecasting. Xi et al. (2020) analyze the political ideology of Facebook photographs shared by members of the U.S. Congress. Chen et al. (2020) examine the role of gender stereotypical cues from photographs posted in social media by political candidates and their relationship to voter support.

2.3 Computational Analysis of Online Ads

Hussain et al. (2017) propose the task of ad understanding using vision and language. The aim is to predict the topical category, sentiment and rhetoric of an ad (i.e. what the message is about). The latter task has been approached as a visual question-answering task by ranking human generated statements that explain the intent of the ad in computer vision (Ye and Kovashka, 2018; Ahuja et al., 2018). More recently in NLP, Kalra et al. (2020) propose a BERT-based (Devlin et al., 2019) model for this task using the text and visual descriptions of the ad (Johnson et al., 2016). Thomas and Kovashka (2018) study the persuasive cues of faces across ad categories (e.g. beauty, clothing). Zhang et al. (2018) explore the relationship between the text of an ad and the visual content to analyze the semantics across modalities. Ye et al. (2018) integrates audio and visual modalities to predict the climax of an advertisement (i.e. stress levels) using sentiment annotations.

3 Tasks & Data

We aim to analyze the political ideology of ads consisting of image and text, and the type of the ad sponsor for the first time. To this end, we present two new binary classification tasks motivated by related studies in political communication (Grigsby, 2008; Fowler et al., 2020b):

- **Task 1: Conservative/Liberal** The aim is to label an ad according to the political party that sponsored the ad either as Conservative (i.e. assuming that the dominant ideology of the Republican Party is conservatism), or Liberal (i.e. assuming that the dominant ideology of the Democratic Party is social liberalism) (Grigsby, 2008);

- **Task 2: Political Party/Third-Party** The goal is to classify an ad according to the type of the organization that sponsored the ad. We distinguish between ads sponsored by official political parties and non-political organizations, such as businesses and non-profit groups, following Fowler et al. (2020b).

To the best of our knowledge, no datasets are available for modeling these two tasks. Therefore, we develop two new publicly available datasets consisting of political ads and ideology/sponsor type labels from the U.S. We opted to use data only from the U.S. because its Federal Election Commission (FEC) provides publicly available information of political ads sponsors such as official political parties (e.g. Democratic, Republican) via their FEC ID; and third-party organizations can be identified via their Employer Identification Number (EIN) suitable for our study.

3.1 Collecting Online Political Ads

We use the public Google transparency report platform to collect political ads. This platform contains information on verified political advertisers (i.e. sponsors) and provides links to actual political ads from Google Ad Services.

We collect all U.S. available data from the Google platform consisting of ads published from May 31, 2018 up to October 11, 2020 (note that...

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4 https://www.fec.gov/
5 https://www.irs.gov/businesses/small-businesses-self-employed/do-you-need-an-ein
6 https://transparencyreport.google.com/political-ads/region/US
3.3 Labeling Ads with Political Ideology

Our aim is to label political ads as Conservative or Liberal (see Task 1 description). First, we retrieve all the ad sponsors and their corresponding ads that are available in the Google Ads database. Official political committees associated with the Democratic or Republican parties are identified by their FEC ID (included in the sponsor’s information in the Google database). However, the name of the political party associated with a sponsor is not available in the Google database. Thus, we query the FEC database to obtain the affiliation for all committees of the Democratic and Republican parties (e.g. Donald J. Trump for President, Inc.). Then, we compare this information with the Google database (FEC ID and exact name), to assign the corresponding affiliation to the sponsors. For example an ad sponsored by the ‘Donald J. Trump for President, Inc.’ official committee is labeled as Republican and subsequently as Conservative (in a similar way we label ads for the Liberal class).

In total, we collect 242 unique sponsors corresponding to 5,548 ads. Liberal ads represent the 39% of the total ads and the rest are Conservative (61%).

3.4 Labeling Ads with Sponsor Type

We first label all ads from sponsors that have an associated FEC ID in the Google database as Political Party. These sponsors correspond to official political committees affiliated with the Democratic or Republican parties (e.g. Biden for President).

Third-party sponsors of political ads consist of groups not officially associated to any political party such as not-for-profit organizations (e.g. NRDC Action Fund) and businesses (Fowler et al., 2020b). This type of sponsors are identified with their EIN ID (included in the Google database). Thus, we label all ads linked to an EIN ID as Third-Party. We collected a total of 15,116 ads where 37% corresponds to Political Party and 63% corresponds to Third-Party.
|       | T1: Liberal/Conservative |       | T2: Political Party/Third-Party |
|-------|-------------------------|-------|-------------------------------|
|       | Train   | Dev    | Test   | Total     | Train   | Dev    | Test   | Total     |
| C     | 2,576 (58%) | 369 (69%) | 453 (75%) | 3,398 (61%) | 4,663 (39%) | 324 (21%) | 561 (37%) | 5,548 (37%) |
| L     | 1,835 (42%) | 165 (31%) | 250 (25%) | 2,150 (39%) | 5,427 (61%) | 1,188 (79%) | 953 (63%) | 9,568 (63%) |
| All   | 4,411 (79.5%) | 534 (9.6%) | 603 (10.9%) | 5,548 (100%) | 12,090 (80%) | 1,512 (10%) | 1,514 (10%) | 15,116 (100%) |

Table 3: Data set statistics for Task 1: Conservative (C) / Liberal (L), and Task 2: Political Party (PP) / Third-Party (TP).

|       | Task | Avg. Tokens (Train/Dev/Test) |
|-------|------|-------------------------------|
|       | IT   | D                             | IT+D                            |
| T1    | 17.1/16.5/17.1 | 38.3/39.9/36.9 | 55.4/56.4/54.0 |
| T2    | 16.2/17.6/19.2 | 36.7/38.9/37.2 | 52.9/56.5/56.4 |

Table 4: Average number of tokens in image text (IT), densecaps (D) and both (IT+D) for sponsor ad ideology (T1) and type (T2) prediction.

3.5 Data Splits

We split both datasets chronologically into train (80%), development (10%), and test (10%) sets. Table 3 shows the dataset statistics and splits for each task.

3.6 Data Preprocessing

**Text** We normalize the text from the image (IT) and the densecap (D) by lower-casing, and replacing all URLs and person names with a placeholder token. To identify the person names we use the Stanford NER Tagger (Finkel et al., 2005). Also, we replace tokens that appear in less than five ads with an ‘unknown’ token. We tokenize the text using the NLTK tokenizer (Bird et al., 2009). Table 4 shows the average number of tokens in IT and D for each data split.

**Image** Each image is resized to (300 x 300) pixels represented by red, green and blue color values. Each color channel is an integer in the range [0, 255]. The pixel values of all images are dived by 255 to normalize them in the range [0, 1].

4 Predictive Models

We experiment with textual, visual and multimodal models for political ad classification.

4.1 Linear Baselines

As baseline models, we use logistic regression with bag of n-grams and L2 regularization using (1) the image text (LR_{IT}); (2) densecap (LR_D); and (3) their concatenation (LR_{IT+D}) for representing each ad.

4.2 BERT

We also test three models proposed by Kalra et al. (2020) for generic ad classification demonstrating state-of-the-art performance. The models are based on Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2019) using a combination of the image text and the densecap. We follow a similar approach and fine-tune BERT for predicting the corresponding class in each task by adding an output dense layer for binary classification that receives the ‘classification’ [CLS] token as input. We use three types of inputs for each ad: (1) image text (BERT_{IT}); (2) densecap (BERT_D); and (3) their concatenation (BERT_{IT+D}).

4.3 EfficientNet

EfficientNet (Tan and Le, 2019) is a family of Convolutional Neural Network (CNN) (LeCun et al., 1995) models which has achieved state-of-the-art accuracy on ImageNet (Deng et al., 2009). In particular, we use EfficientNet-B3 and fine-tune it on political ad classification by adding an output dense layer for each binary classification task.

4.4 BERT+EffN

We finally test two multimodal models by combining: (1) BERT_{IT} and EfficientNet (BERT_{IT+EffN}); and (2) BERT_{IT+D} and EfficientNet (BERT_{IT+D+EffN}). We concatenate the text representation obtained by BERT and the visual information from EfficientNet into a $768 + 1536$ dimensional vector from BERT and EfficientNet respectively. This vector is then passed to an output layer for binary classification. We fine-tune the entire architecture for each task.

5 Experimental Setup

We select the hyperparameters for all neural models using early stopping by monitoring the validation binary cross-entropy loss, and we estimate the...
Table 5: Macro Precision (P), Macro Recall (R), and Macro F1-Score (F1) for political ideology prediction (± std. dev. for 3 runs). Best results are in bold.

| Model          | T1: Conservative/Liberal | T2: Political Party/Third-Party |
|----------------|--------------------------|---------------------------------|
|                | P          | R       | F1          | P          | R       | F1          |
| Majority       | 50.00 (0.00) | 37.56 (0.00) | 42.90 (0.00) | 50.00 (0.00) | 31.47 (0.00) | 38.62 (0.00) |
| LR_D           | 55.76 (0.85) | 54.91 (0.89) | 54.85 (1.12) | 53.60 (0.72) | 53.40 (0.65) | 53.11 (0.58) |
| LR_IT          | 78.38 (0.70) | 71.99 (0.56) | 72.65 (0.73) | 84.02 (0.14) | 85.04 (0.31) | 84.47 (0.18) |
| LR_IT+D        | 72.57 (1.03) | 71.32 (0.62) | 71.99 (0.79) | 86.46 (0.13) | 86.63 (0.09) | 86.54 (0.05) |
| Kalra et al. (2020) BERT_D | 59.40 (0.78) | 57.77 (0.98) | 57.64 (1.52) | 55.60 (0.89) | 56.31 (0.78) | 53.45 (1.26) |
| BERT_IT        | 72.88 (0.24) | 73.46 (0.16) | 73.16 (0.20) | 85.57 (0.86) | 86.42 (2.01) | 85.86 (1.23) |
| BERT_IT+D      | 78.62 (3.14) | 74.08 (2.81) | 75.49 (3.01) | 87.00 (0.89) | 86.81 (0.83) | 86.90 (0.86) |
| EfficientNet   | 69.02 (3.48) | 67.87 (1.23) | 68.15 (1.89) | 53.27 (2.86) | 53.93 (2.40) | 51.53 (5.46) |
| Ours BERT_IT+EffN | 74.99 (1.23) | 72.01 (2.27) | 72.02 (2.07) | 87.02 (2.74) | 85.81 (0.20) | 86.29 (1.11) |
| BERT_IT+D+EffN | 80.24 (0.06) | 74.59 (1.70) | 75.76 (2.19) | 86.78 (0.03) | 88.18 (1.10) | 87.36 (0.39) |

Table 6: Macro Precision (P), Macro Recall (R), and Macro F1-Score (F1) for sponsor type prediction (± std. dev. for 3 runs). Best results are in bold.

EfficientNet layers frozen. Unfreezing the base model did not result into lower validation loss. We use dropout rate of 0.2 before passing the output of EfficientNet to the classification layer. The average training time is 37.8 minutes.

BERT+EffN For ideology prediction, we freeze all the layers of the pre-trained models (BERT and EfficientNet) apart from the classification layer and train for 27 epochs with $\eta = 1e^{-3}$. We then fine-tune BERT for 30 epochs with $\eta = 1e^{-5}$. For sponsor type prediction, we freeze all EfficientNet layers and fine-tune BERT for 30 epochs with $\eta = 2e^{-6}$. We train in stages to ensure that the parameters of each part of the model (textual and visual) are properly updated (Kiela et al., 2019). The average training time is 56.65 minutes.

6 Results

This section presents the experimental results for the two predictive tasks, political ideology and sponsor type prediction (§3) using the methods described in §4. We evaluate our models using macro precision, recall and F1 score since the data in both tasks is imbalanced. Note that for all models we report the average and standard deviation over three runs using different random seeds. We also report the majority class baseline for each task.

6.1 Predictive Performance

Task 1: Conservative/Liberal Table 5 shows the results for the political ideology prediction. We first observe that BERT_IT (73.16%) which uses as input information the image text outperforms BERT_D (57.64%) and EfficientNet (68.15%) in...
macro F1. This suggests that the text shown on a
political ad is the dominant medium for conveying
its main message, corroborating findings in related
research on commercial ads (Dey et al., 2019; Kalra
et al., 2020).

Moreover, combining image text and densecap
(BERT\textsubscript{IT+D}), leads to higher performance, than
using only image text (BERT\textsubscript{IT}), i.e. 75.49% and
73.16% F1 respectively. This indicates that the
combination of textual with visual information (in
the form of image descriptions) improves the model
performance.

Finally, using all visual information sources, i.e.
densecaps and image representation from Efficient-
Net (BERT\textsubscript{IT+D+EfN}), further improves perfor-
ance achieving the highest macro F1 (75.76%)
across models, followed by BERT\textsubscript{IT+D} (75.49%).

**Task 2: Political-Party/Third-Party**  Table 6
shows the results for the sponsor type predic-
tion. The best overall performance is obtained
by BERT\textsubscript{IT+D+EfN} (87.36%) which combines
both image and textual information. BERT\textsubscript{IT+D}
(86.90%) and LR\textsubscript{IT+D} (86.54%) follow very
closely. By inspecting our data, we identified the
presence of noise in image text, particularly sen-
tences are interrupted by logos and other aesthetic
elements. This negatively affects the performance
of BERT because such models are usually pre-
trained on ‘cleaner’ generic corpora (Kumar et al.,
2020). On the other hand, LR models trained from
scratch can adapt to the noisy text (see § 6.2 for
error analysis).

Overall, our results in both tasks suggest that text
is a stronger modality for inferring the political ide-
ology and sponsor type of political ads compared to
visual information extracted from the images. How-
ever, integrating visual information in the form of
text descriptions (densecaps) or representations ob-
tained by pre-trained image classification models,

**6.2 Error Analysis**

We further perform an error analysis to exam-
mine the behavior of our best performing models
(BERT\textsubscript{IT+D+EfN} and BERT\textsubscript{IT+D}) and identify
potential limitations.

The ad shown in Fig. 1 (a) was mis-
classified as Conservative by BERT\textsubscript{IT+D}
and BERT\textsubscript{IT+D+EfN}. This particular ad requires
common knowledge of social issues (e.g. inadequate
health support) that are often discussed in political
campaigns to inform voters about a party’s views
on the issue (Scammell and Langer, 2006). This
makes the classification task difficult for the models
since it requires contextual knowledge. Incorporat-
ing external relevant knowledge to the models (e.g.
political speeches, interviews or public meetings)
might improve performance (Lin et al., 2018).

The ad depicted in Fig. 1 (b) was misclassified
by BERT\textsubscript{IT+D} and BERT\textsubscript{IT+D+EfN} as Conser-
vative. After analyzing the densecap descriptions,
we found that this information tends to be noisy.
For this particular example, it contains descriptions
such as ‘a man is holding a horse’, ‘the sign is blue’,
‘a blue and white stripe shirt’, and ‘a man wearing
a hat’. In fact, BERT\textsubscript{IT}, which only takes the
image text into account, classified this ad correctly as
Conservative. Improving the quality of the image
descriptions (e.g. pre-training on advertising or po-
litical images, capturing specific attributes such as
‘military hat’) might be beneficial for these models.

Fig. 1 (c) shows an example of a Political Party
ad misclassified by BERT\textsubscript{IT+D+EfN} as Third-
Party. The ad contains the following text:

\begin{quote}
WE CAN’T LET <person> WIN!
VOTE EARLY
\end{quote}

The message has a confrontational and divisive
tone that is common in Third Party ads (Edelson
Table 7: Feature correlations with Conservative/Liberal Ads, sorted by Pearson correlation (r). All correlations are significant at $p < .01$, two-tailed $t$-test.

| Liberal | Conservative |
|---------|--------------|
| Feature | $r$ | Feature | $r$ |
| necessary | 0.197 | senate | 0.271 |
| end | 0.196 | republican | 0.196 |
| prohibited | 0.190 | ! | 0.176 |
| approx | 0.186 | conservative | 0.127 |
| contrib | 0.181 | national | 0.116 |
| void | 0.177 | committee | 0.112 |
| values | 0.173 | petition | 0.109 |
| prz | 0.161 | border | 0.102 |
| subj | 0.156 | taxes | 0.099 |
| make | 0.156 | radical | 0.098 |
| win | 0.144 | sign | 0.096 |
| place | 0.140 | stop | 0.094 |
| beer | 0.139 | states | 0.093 |

Table 8: Feature correlations with Political Party/Third-Party Ads, sorted by Pearson correlation (r). All correlations are significant at $p < .01$, two-tailed $t$-test.

| Political Party | Third-Party |
|-----------------|-------------|
| Feature | $r$ | Feature | $r$ |
| congress | 0.365 | state | 0.193 |
| vote | 0.308 | learn | 0.181 |
| senate | 0.292 | champion | 0.175 |
| ! | 0.269 | senator | 0.166 |
| president | 0.248 | thank | 0.153 |
| committee | 0.236 | action | 0.147 |
| candidate | 0.223 | congressman | 0.130 |
| republican | 0.208 | urge | 0.129 |
| authorized | 0.208 | protect | 0.128 |
| donate | 0.202 | access | 0.119 |
| join | 0.199 | award | 0.117 |
| $<url>$ | 0.187 | american | 0.116 |
| $|$ | 0.180 | ? | 0.113 |

using univariate Pearson correlation. Features are normalized to sum up to unit for each ad. For each feature, we compute correlations independently between its distribution across ads and its label (Conservative/Liberal, or Political Party/Third Party).

7.1 Conservative vs. Liberal

Table 7 presents the top unigrams correlated with Liberal and Conservative ads. We first notice that the top words in the Conservative category are closely related to its ideology such as ‘conservative’ and ‘republican’. Other prominent terms in these categories are words related to current political issues, such as immigration (e.g. ‘border’) and taxation (e.g. ‘taxes’). In fact, these are examples of emotionally evocative terms (e.g. anger about taxes) that are frequently used in political campaigns to influence voters (Brader, 2005).

Top terms of Liberal ads include ‘necessary’, ‘end’, ‘values’, and ‘win’. For example, the following ads belong to the Liberal class:

$I’m$ supporting $<person>$ because he has the same values that I do and he’s an honest person.

$<person>$ FOR CONGRESS

To End Gun Violence

These are examples of ads containing a combination of moral and controversial topics (e.g. gun regulation) which are typical characteristics of political advertising (Kumar and Pathak, 2012).

7.2 Political Party vs. Third-Party

Table 8 shows the top unigram features correlated with the sponsor type of an ad (Political
Party/Third-Party). We observe that some top terms in the Political Party class also belong to the top terms of the political ideology task (see Table 7) such as ‘committee’, ‘republican’ and ‘senate’. Messages calling for vote and donation support (‘vote’, ‘donate’, ‘$’) are also prevalent in Political Party ads (Fulgoni et al., 2016), as in the next example (See Fig. 1 (b)):

Making sure our veterans get the care they’ve earned

VOTE FOR <person>

On the other hand, top features from the Third-Party category (e.g. ‘action’, ‘protect’) share common characteristics with the rhetoric used by media outlets focused on promoting specific political messaging (Edelson et al., 2019; Dommett and Temple, 2018). Many of these ads direct people to websites to read about a particular topic. For example:

Is <person> HIDING ANTI-GUN VIEWS?

Learn More

This ad belongs to the Third-Party class and points the viewer to an external website for reading further details.

8 Conclusion

We have presented the first study in NLP for analyzing the language of political ads motivated by prior studies in political communication. We have introduced two new publicly available datasets containing political ads from the U.S. in English labeled by (1) the ideology of the sponsor (Conservative/Liberal); and (2) the sponsor type (Political Party/Third Party). We have defined both tasks as advertisement-level binary classification and evaluated a variety of approaches, including textual, visual and multimodal models reaching up to 75.76 and 87.36 macro F1 in each task respectively.

In the future, we aim to incorporate other modalities such as speech, and video, and explore other methods of acquiring and integrating multimodal information. In addition, we aim to extend our work for analyzing political advertising discourse across different regions, languages and platforms.

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Ethics Statement

Our work complies with the Terms of Service of the Google Political Ads Dataset.11 We provide, for reproducibility purposes, the list of ad IDs and corresponding labels used for each task, as well as the data splits (train, development, test). All data used in this paper is in English. The ads information can be retrieved from Google according to their policy.

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