An Analysis of the Australian Political Discourse in Sponsored Social Media Content

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ABSTRACT

Disinformation is deliberately designed to spread false information over internet. Recent concerns about the use of disinformation to manipulate political voting campaigns have attracted researchers' attention. In this paper, we conduct our first study towards the understanding of how sponsored social media content is used in Australian voting campaigns. To this end, we collect the ad posts sponsored by Australian organizations on Facebook from 1 Feb, 2020 to 17 May, 2021. We also retain the screenshot of each collected ad that originally appeared on Facebook and download the images and videos that were presented in these ad posts. To obtain annotations of these ads, we generate labels that describe general objects, locations, activities presented in the images or videos by algorithms, as well as human created annotations over crowdsourcing platforms. Based on the collected human annotations, we then design a second-round crowdsourcing task to ask workers to provide more detailed annotations for the collected ads, ranging from truthfulness evaluation of the content to various political aspects (e.g., topics and sentiment). The multi-modal dataset created in our work enables future research, for example, to train supervised learning algorithms for further analysis on the use of disinformation on social media that may affect political campaigns.

CCS CONCEPTS

• **Information systems** → **Data analytics**; **Data mining**; Web crawling; *Social tagging*; *Social advertising*; **Crowdsourcing**; *Content analysis and feature selection*; Information extraction; Sentiment analysis; • **Human-centered computing** → Social tagging.

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KEYWORDS

Social Media, Political Campaign, Disinformation, Crowdsourcing

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1 INTRODUCTION

Disinformation, which can be defined as the deliberate attempt to spread false and misleading information [2, 14], is not new but the contemporary version is 'different, and dangerous' (according to [8]). There appears widespread agreement that citizens are increasingly exposed to online information intentionally designed to mislead and influence them [2, 6]. While there is little evidence to suggest disinformation influences voting behaviour [7, 11], the concern that many democratic theorists, policymakers and commentators hold is campaigns can use disinformation tactics to increase polarisation, fragment the public sphere and increase dissatisfaction with democracy and key institutions such as media and political parties.

Aiming at understanding how sponsored social media content is used in such campaigns, we focus on Australian politics. To this end, we will perform a data-driven analysis of Facebook political advertising using data already collected from the Facebook ad Library. As the first step to perform such data-driven analysis, in this paper we present our first work to create an Australian dataset[1] that contains sponsored media content published on Facebook as well as human annotations of that. To achieve this, we use data analytics methods at scale (e.g., Apache Spark) to deal with the size of available data and AI methods (e.g., computer vision) to process media content at scale. Specifically, we continuously crawl the sponsored ads posted on Facebook every 12 hours from 1 Feb, 2020 to 17 May, 2021. The textual content of the ads such as 'body content',

[1]To enable follow up research, the datasets we have created in this work can be downloaded at https://github.com/tomhanlei/21adcs-facebook-ads.

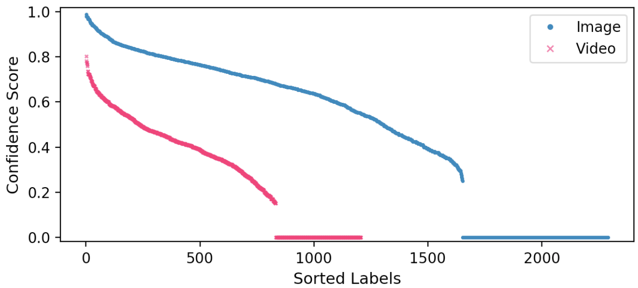

Figure 1: Average confidence score of each generated label.

'ad title' and 'funding entity', as well as metadata like 'ad posting date', distribution of 'demographic target', and 'money spent' are then stored in Pandas DataFrame. For the ads containing images or videos, we additionally download the multimedia files through Facebook API. We also generate labels using Google Cloud API for these images and videos, to describe general objects, locations, activities, animal species, and products that are presented in these multimedia files. To allow human annotators to read the original ad posting page, we also take a screenshot of each original ad appearing on Facebook. This enables generating crowdsourcing tasks to label, for example, truthfulness and political sentiment, and using the collected sample labels to train supervised machine learning models to then classify the entire dataset for further analysis on the use of disinformation on social media.

To generate annotations of the collected ads, we run a crowdsourcing labelling task via Amazon MTurk in a two-stage manner. At the first stage, we ask crowd workers to label (i) whether a given ad is an election ad, and (ii) if there exists a subject (e.g., a person or organization) that the ad refers to. Having obtained the binary labels for the two questions, at the second stage, we select the ads which are both election ads and having a subject to generate the tasks asking workers to provide more detailed annotations, including (i) party or non-party organizations, (ii) Australian state or territory that the posting entity is from, (iii) the attitude or sentiment towards the subject of the ad, (iv) the topic of the ad, and (v) truthfulness evaluation of the ad. As an ongoing work, we leave the second stage of the crowdsourcing task as our future work, and focus on the first stage in this paper.

In summary, this paper makes the following contributions.

- We create an Australian dataset containing 35K distinct ad posts that are sponsored media content published on Facebook. We also download the multimedia content (e.g., images and videos) that appears in these ad posts along with the created dataset.
- For each ad post, we retain a screenshot of the original post that appears on Facebook page, which enables future research to present these ads to human annotators.
- We generate labels for each downloaded image and video through Google Cloud API. The labels describe general objects, locations, activities, animal species, and products that are presented in these multimedia files.
- Through a crowdsourcing task over Amazon MTurk, we collected human annotations indicating whether a given ad is an election post and contains a subject. Sampling based on the collected annotations, we have designed another task to ask workers to provide more detailed annotations for future research.

The rest of this paper is structured as follows. In Section 2, we provide a detailed description of our dataset, created by crawling the Australian sponsored ad posts on Facebook. We then describe the creation of manual annotations for these ad posts through crowdsourcing tasks (in Sec. 3), followed by the discussion of our future work on understanding the Australian political discourse in sponsored social media content (Sec. 4). Finally, in Section 5 we conclude the paper with a brief summary of our contributions.

2 DATASET OF AUSTRALIAN SPONSORED AD POSTS

To create the dataset of sponsored Australian social media content, we continuously crawl the sponsored ads every 12 hours from 1 Feb, 2020 to 17 May, 2021 through Python code from Facebook Ad Library API[2]. Table 1 shows the examples of our dataset created by the crawled data. This dataset includes: the ad body text, the language of the body text, the creative link title and caption, creation date and delivery date, the page name and funding entity, the money spent (in terms of lower and upper bound), the target impressions (with lower and upper bound) which indicate the number of times the posting entity wants the ad to be displayed before the campaign ends, and region and demographic distribution. To allow future research where the original Facebook ad page is able to be presented to human annotators, we also take a screenshot of the ad page by opening the URLs of each ad post using Selenium WebDriver[3]. We also check whether a given ad post contains an image or video in the body by checking if the source of ad had a particular '`img`' or '`video`' element found in HTML, respectively. For those containing an image or video, we have downloaded and stored the corresponding multimedia files through Facebook API. Having obtained the images and videos that are extracted from ad posts, we use the Google Cloud Vision API (and Video Intelligence API) to (i) generate labels that describe general objects, locations, activities, animal species, and products appearing in the images (and videos), and (ii) to detect if any text is present in the images (and videos).

Overall, we have crawled 35 105 distinct ad posts from Facebook, among which 26 113 (74.4%) ads were posted with images and 8041 (22.9%) ads were with videos. The total number of unique labels that we have generated from ad images and videos are 2290 and 1206, respectively. The Google Cloud API also provides a confidence score for each generated label. Figure 1 shows the distribution of the average confidence for each generated label. Because one label may be assigned to multiple images (or videos), we observe that the confidence score for the labels of images is higher than that for videos on average. Table 2 shows the top-10 most frequent labels and their confidence scores. We can see that most videos are related to speech (94.2%), public speaking (89.7%) and presentation (88.9%), while the images have some diversity across different ads, such as font, event and plant. Figure 2 shows the distribution of the duration of the videos presented in sponsored ads. While generating the labels for these videos, 1564 (19.5%) out of 8041 videos were failed. Thus, we distinguish these videos (in Fig. 2) with respect to

[2]https://www.facebook.com/ads/library/api/
[3]https://www.selenium.dev/documentation/webdriver/

Table 1: Examples of the DataFrame created by Australian sponsored social media content crawled from Facebook.

id	ad body language	creation time	creative body	creative link caption	creative link title	delivery start date	page name	funding entity	spend (in AUD)		impressions		region distribution	demographic distribution
									lower	upper	lower	upper		
276	English	24/03/2020	While Covid-19 dominates the news, it's clear some politicians ...	getup.org.au	JOIN: Hold them accountable	24/03/2020	GetUp!	GetUp!	200	299	60 000	69 999	NSW: 32.7%, QLD: 18.3% ...	age: 65+ (female): 15.1%, age: 55–64 (male): 10.5% ...
760	English	09/03/2021	For an experienced Government to keep WA safe & strong vote ...	votewa.com.au	Vote now	10/03/2021	Mark McGowan	Team McGowan	300	399	15 000	19 999	WA: 100%	age: 45–54 (female): 11.1%, age: 45–54 (male): 8.4% ...
2946	Italian	08/11/2020	Sapevi che gli aborigeni non sono riconosciuti nella Costituzione ...	sbs.com.au	Italian: The Uluru tatement from ...	08/11/2020	SBS Italian	SBS Italian	0	99	3000	3999	VIC: 38.1%, NSW: 27.8% ...	age: 65+ (female): 17.4%, age: 25–34 (male): 16.2% ...

Table 2: Top-10 most frequent labels and their popularity (by means of percentage) among all images and videos.

Image				Video			
Label	**Frequency**	**%**	**Confidence**	**Label**	**Frequency**	**%**	**Confidence**
font	13 946	53.4	0.814	speech	1136	94.2	0.672
smile	9091	34.8	0.934	public speaking	1082	89.7	0.681
event	6388	24.5	0.709	presentation	1072	88.9	0.640
happy	5385	20.6	0.805	vehicle	864	71.6	0.716
plant	4926	18.9	0.905	official	851	70.6	0.473
sky	4907	18.8	0.917	facial expression	782	64.8	0.492
sleeve	4773	18.3	0.860	tree	743	61.6	0.469
gesture	4326	16.6	0.849	conversation	711	59.0	0.563
advertising	4209	16.1	0.679	text	631	52.3	0.561
tree	4203	16.1	0.842	professional	617	51.2	0.573

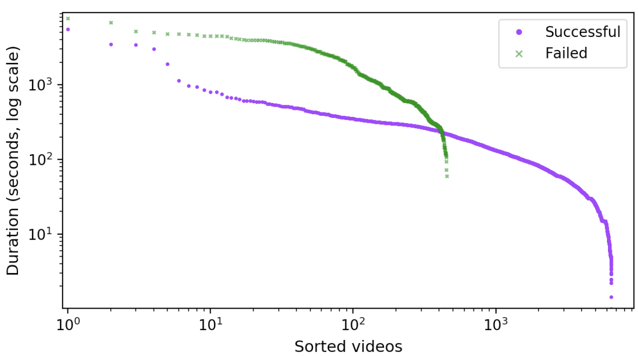

Figure 2: Duration of the videos that are presented in Australian sponsored ad posts on Facebook.

their label creation status. We can make the following observations: (i) Among all videos, 6436 (80.0%) videos are less than 2 minutes, while the duration of 33 (0.4%) videos are as long as 1 hour or more; and (ii) The videos failed in label creation are longer than those for which labels are successfully generated. Therefore, we suspect this failure occurs due to long video duration, which requires further investigation in our future work.

3 CROWDSOURCED ANNOTATIONS

To label the ads displayed on Facebook, we run a crowdsourcing task (or HIT) over Amazon MTurk[4], where we recruit crowd workers to judge (i) whether a given ad is an election ad, and (ii) if the ad has a subject. Figure 3 shows the task interface, in which we present the snapshot of the ad that are captured from original Facebook page. We also show (in task instructions) the date when the ad was shown to the public. If the ad was available for multiple days, we use the first day as the date of the ad being displayed. Based on this information, the participating workers are asked to make a binary judgment by clicking the radio button for each of the two questions. They are also allowed to search the web (e.g., Google) for relevant information. Each worker are asked to judge ten ads that appear one after another, and they are rewarded at the rate US$0.03 per ad[5]. Among the ten ads, two of them are gold standard [1, 5] that have already been judged by experts (e.g., doctoral candidates in political science). We check if the worker produces the same judgments as those given by experts.

Overall, we have collected 34K unique Australian ads with images or videos presented and dated from 1 Feb, 2020 to 17 May, 2021. Considering that the number of newly posted ads may vary from one day another, we sample these ads for our labelling tasks according to the frequency of new ads on a daily basis. Figure 4 shows the frequency of new ads posted over time. We can see that the posted ads (with either images or videos) are significantly more in September and October than any other months in 2020, and similarly more in March and April in 2021. Thus, we randomly sample ads from each day and keep two ratios in our samples: (i) the proportionality of the ads posted on a specific date to the total number of ads in our database, and (ii) the ratio of ads with images to those with videos. By this sampling strategy, we select in total 2440 ads that are distributed in 305 crowdsourcing tasks (each task containing 8 ads plus 2 gold standard). All ads are randomized in each task to eliminate ordering effect [4]. To control the quality of the crowdsourced judgments, we randomly assign the same ad to three different workers, which enables to aggregate the created labels. Each worker is allowed to participate in our tasks only once. Therefore, we target 915 (= 305 × 3) workers to be recruited to contribute to our labels.

[4]https://www.mturk.com

[5]Based on our pilot experiment, this rate is equivalent to US$13.5 per hour on average.

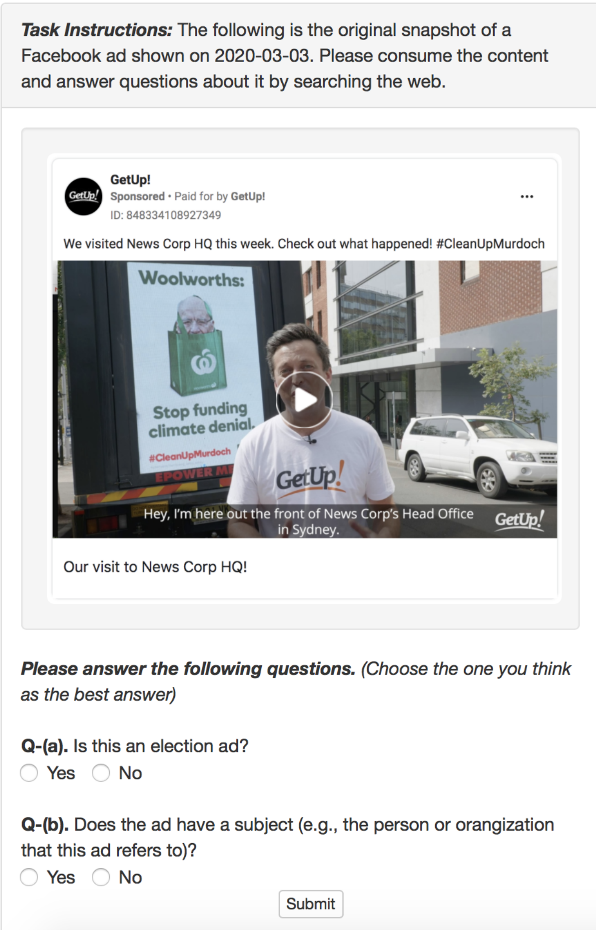

Figure 3: The interface of the task.

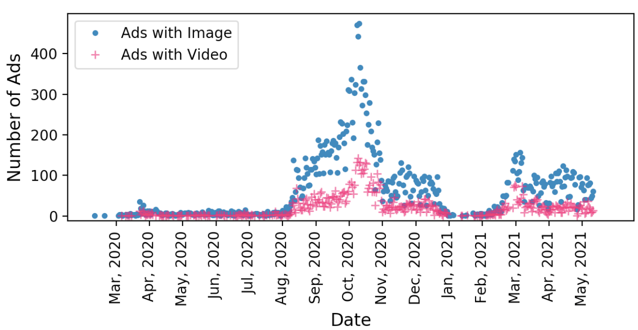

Figure 4: Frequency of new ads posted on Facebook.

Because we have embedded two ads as gold standard to check the worker quality and we ask two questions for each ad (see Fig. 3), there are in total four gold questions in each HIT. Table 3 shows the number of workers who pass the gold questions. Overall, 15.5% of the workers have provided the same judgments on gold standard as those given by experts. Another 55.2% of the workers have agreed on two or three (out of four) gold questions with the experts. We

Table 3: Number and percentage of workers passing the gold standard.

#Gold Questions Passed per HIT	4	3	2	1	0	Total[6]
#Workers	141	225	276	185	81	908
Percentage	15.5%	24.8%	30.4%	20.4%	8.9%	100%

Table 4: Number of ads that all qualified workers agreed on.

Judgment Question		#Ads that all workers agreed on				
(a) Election ad	(b) Having a subject	$\tau = 4$	$\tau = 3$	$\tau = 2$	$\tau = 1$	($\tau = 0$)
Yes	Yes	290	452	401	260	208
Yes	No	53	72	32	9	4
No	Yes	413	723	561	356	264
No	No	126	161	115	39	20
Total		882	1408	1109	664	496

also observe that 8.9% of the workers totally disagree with the experts on the four gold questions, indicating that their answers may either be biased or are in low quality.

Given the worker performance on gold standard, we discard the judgments made by the worker whose agreement with the experts on the gold questions is below a threshold $\tau(\tau = 1, 2, 3, 4)$[7]. As a quality control method, we only consider the ad for which all qualified workers have made the same judgments and use these judgments to create our annotation dataset. Table 4 shows the number of ads included in our annotation dataset with different values of τ. We find that when $\tau = 3$ we can obtain the maximum number of labeled ads. By contrast, $\tau = 4$ may be too rigorous for crowd workers to agree with experts on gold questions, which makes a lot of workers be unqualified for annotation (see Tab. 3). On the other hand, setting a lower threshold (e.g., $\tau = 1$) would allow more crowd judgments to be available for the creation of our annotation dataset. The number of ads included in the created dataset, however, decreases (see Tab. 4) because we required each ad being agreed by all qualified workers. Including low-quality workers (i.e., those who do not agree with the experts on gold questions) would make it difficult to achieve a consensus among other workers. Therefore, the best threshold based on our experiment is to be set as $\tau = 3$. Having obtained 452 election ads with a subject (see Tab. 4 with $\tau = 3$), we decide to run a second round of labelling task to get detailed annotations[8].

4 DISCUSSION AND FUTURE WORK

While questions in regard to how data is being used in political campaigning have been the focus of significant scholarly attention (e.g., [9]), our approach focuses on how truthfulness in social media advertising is related to various political aspects. The unique collection of complementary data we have created in this work

[6]We have received 908 (99.2% of 915) successfully submitted HITs from workers.
[7]Note that we still pay the worker even if one failed in our quality check by the gold questions.
[8]In the future, we will analyze in detail the impact of failing in each gold standard question (see Tab. 3 and 4), as well as consider the ads that are not election ads or do not have a subject for the second round of labelling task.

enables to develop a large-scale analysis of all political sponsored content published on Facebook with a specific focus on election events such as Australian federal elections. As an ongoing work, in our detailed labelling task design, we will ask crowd workers to provide answers to the following questions.

- The entity posting this ad is a member of ______ (which party or non-party organization). Please also indicate the name of the organization.
- Which Australian state or territory is the posting entity from? Is the posting entity from metropolitan or regional rural area?
- What person or organization does this ad refer to?
- Which party or non-party organization is the ad primarily about?
- Which state of Australia is the subject of the ad from? Is the subject of the ad from a metropolitan or regional rural area?
- What is the attitude (sentiment) towards the subject of the ad? Select one from 'positive', 'neutral', and 'negative', and provide a justification for the answer given.
- What is the topic of this ad?
- Please evaluate the truthfulness of the body of this ad. Select one from (i) 'true', where the body of the ad is accurate and there is nothing significant missing; (ii) 'half true', where the body of the ad is partially accurate but leaves out important details or takes things out of context, (iii) 'false', where the body od the ad is not accurate, and (iv) 'do not know', and provide the motivation for the provided answer (e.g., why you give this score).

Based on verified methodologies [10, 13], these crowdsourced annotations of truthfulness and various political aspects for a sample of sponsored ad posts in the collection allow to train supervised machine learning models and to then classify the entire dataset for further analysis on the use of disinformation on social media. As a strategy for quality control of the collected annotations, we adopt the following methods in our work: (i) embedding the questions that we already asked in the first-round labelling tasks (see Fig. 3) and checking if the provided answers match what other qualified workers agreed on (see Tab. 4), (ii) introducing inter-question dependencies in the task design by which only certain combinations of the answers make sense (e.g., the selection of partisan actors and non-party organizations for the same entity are mutually exclusive), and (iii) assigning the same task to multiple workers to aggregate their answers. The created annotations also enable to classify future posts that may or may not be triggered by political campaigns.

On the other hand, our work will generate an understanding of the challenges and opportunities of this type of personalised campaigning with a human-in-the-loop approach [3]. The significance of our study relates to the contemporary media environment and the widespread perception that disinformation poses a threat to the integrity of democratic elections. In fact, 48% of Australians rely on online media as their main source of news and as one example of the spread of disinformation, 66% say they have encountered disinformation online related to Covid-19 [12]. Therefore, the work presented in this paper moves one step further in understanding how disinformation has led to the formation of parliamentary committees in many advanced democracies in Australia. Our work will produce an authoritative set of findings that can inform the work of electoral regulators, and our elected representatives who are working to maintain the integrity of democratic elections.

5 CONCLUSIONS

Online disinformation has been shown to be influential in deliberately spread misleading information. To understand how disinformation can affect voting behaviour, we study the usage of sponsored social media content in political campaigns. In this work, we create a multi-modal dataset including (i) 35K sponsored Australian ad posts crawled from Facebook, (ii) 26K images and 8K videos that were presented in these posts, (iii) 3K unique labels describing general objects, locations, activities, animal species, and products that are presented in the images or videos. Through a crowdsourcing task deployed on Amazon MTurk, we have collected binary annotations for (i) whether a given ad is an election ad post and (ii) if the ad has a subject. Based on these collections, we have designed a more detailed annotation task using the ads sampled from our dataset to ask workers to provide various political related information (e.g., partisan organization and political attitude) as well as the truthfulness evaluation of the ad. Our future work extends from this paper, and includes collecting the above mentioned detailed annotations, using these annotations to train learning models to classify all ad posts in our dataset, as well as performing detailed analysis from various political perspectives.

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