Facebook News Feed personalization filter: a case study during the Brazilian elections

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Abstract—The 2018 Brazilian presidential elections were marked by a massive use of social media. Promising to improve user's quality of experience, social media recommend, filter and reorder the posts that will be shown to users. These social media filtering and personalization algorithms determine the flow of posts on the network and shape users' information diets. In this paper, we report measurements and findings from Facebook in the 2018 Brazilian presidential elections. To this aim, a reproducible methodology encompassing a method to identify publishers and candidates alignment and measurements to evaluate the posts selection carried out by Facebook filtering algorithms. The obtained results leverage the understanding of social media influence on the Brazilian elections. This knowledge can be useful in future elections around the world to ensure that the population exercises their right to choose their representatives in a democratic way.

Index Terms—Social media, biases, algorithmic transparency.

I. INTRODUCTION

Social media plays a key role in our modern society. Economic and political decisions are influenced, in a daily basis, by social media. In particular, the role of social media in presidential elections has been increasing over the past few years, and has reached unprecedented levels during the most recent elections, e.g., in Brazil 2018 [1], [2].

Our goal is to assess the impact of social media filters in the flow of information received by users in the 2018 Brazilian presidential elections. Determining this influence is a challenging process. In contrast to traditional media, where information is broadcasted to the entire audience, social media creates personalized timelines where users get a particular view of reality.

Timelines are recommender systems that match posts created by sources to followers' timelines in a personalized fashion in which neither followers nor sources need to explicitly polarize themselves. Rather than counting with explicit feedback from users, social media developed private algorithms to learn preferences from implicit feedback provided by likes, shares and many unknowns features. Therefore, social media filtering algorithms create a new form of public sphere [3] affecting the public discourse reception, impacting democracy as well as society as a whole [4].

Black-box recommendation algorithms pose a number of challenges to determine the influence of social media in elections. In particular, they motivate questions related to the characterization and comparison of information received by different users:

- how to compare the information received by different users?
- how to quantify the similarities between followers and sources?
- how to determine political leaning of media outlets?

In this paper we report findings from data collected from Facebook during the 2018 Brazilian presidential elections. We created virtual users, referred to as bots, that follow a given set of sources (publishers). All bots access simultaneously Facebook, and follow the same sources. We developed methods to polarize the bots, to characterize the information they received and to compare the similarities between these flows of information.

Prior art. A utility-based modeling approach for social media filters, accounting for different fairness criteria to infer social media biases, was presented in [5]. In the mechanism proposed in [5], followers can explicitly map sources to classes and post impressions are granted according to that mapping. In this paper, we extend results presented in [5] by proposing a method to automatically classify the sources and to leverage Facebook advertising API to refine such alignment.

Contributions. Our key contributions are threefold:

- **Candidate clustering:** we use unsupervised learning methods to cluster presidential candidates based on information collected from candidates proposals (Section III);
- **An approach for leveraging Facebook advertising API to refine alignment:** we refine the alignment between sources and political candidates, leveraging information provided by Facebook advertising API (Section IV);
- **Empirical findings:** we report insights from our Facebook measurement campaign during the 2018 Brazilian presidential elections. In particular, we show that users impressions are subject to non-trivial filtering, whose effects are interpretable in light of the refined clustering of candidate alignments (Section V).

Outline. In the following section we report basic background on our measurement campaign. Then, Sections III and IV discuss the clustering of the candidates and the metrics of interest considered in our analysis. Section V reports our findings, and Section VI concludes.

II. FACEBOOK MEASUREMENT METHODOLOGY

A. Terminology

Next, we introduce some basic terminology. *Publishers* produce *posts* that are fed into users' timelines. Each user
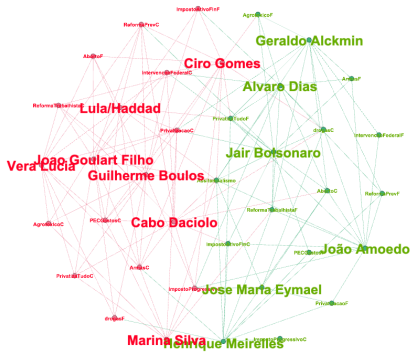
Fig. 1. Candidates divided into clusters

Fig. 2. Publisher alignment

consumes posts from his/her timeline. In Facebook a timeline is called *News Feed*. A timeline is an ordered list of posts presented to a given user. The *topmost* element in the timeline is usually assumed to be the most relevant post.

Users *follow* publishers that they are interested in. The timeline of a user is populated with posts from publishers that they follow. A user may follow a publisher to have posts from that publisher in the user's timeline. A user who *likes* a publisher automatically follows that publisher. A user likes a publisher to show general support for its posts. In our work, users orientations are established by letting them *like* a subset of the selected publishers *a priori*.

A post that appears in a timeline of user i is referred to as an *impression*. Although timelines might have infinite size, we consider that timelines have a finite size K. Therefore, posts are *evicted* from the timeline according to an eviction policy. Each timeline access is referred as a *snapshot*. Therefore, an access, or a snapshot, is a collection of K impressions. The terms access and snapshot will be used interchangeably throughout this paper.

A social media platform connects the users by populating the follower's timelines with posts generated by the leaders. The platform has a *filtering algorithm* which decides which posts will be stored at the timeline of i. Therefore, the filtering algorithm is a *recommender system* deciding which posts will be displayed to user i.

B. Data collection

Next, we present our measurement methodology. We applied the general methodology of [5] to the 2018 Brazilian presidential election, which constitutes the key case study considered in this paper. The Brazilian election had two rounds, where the first was held on October 7, 2018 and the second round was held on October 28, 2018. Our experiment was conducted between October 19, 2018 and October 28, 2018, encompassing the second round campaign.

We asked some Brazilian voters to select a set of representative public political Facebook pages. Our dataset comprises such pages, in addition to all the candidates official pages and the pages of their respective political parties. The publishers were classified in two orientations using the Facebook
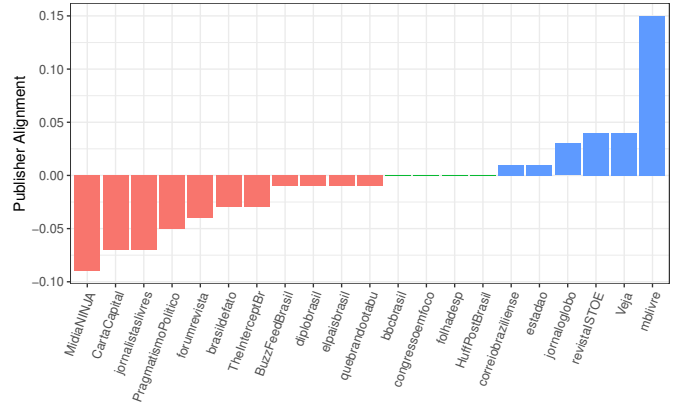
advertising interface according to the methodology described in Section III.

Then, we created 13 virtual Facebook users, henceforth also referred to as *bots*. Each bot followed *all* the selected *pages*. We created four bots with a left-wing political orientation and four bots with a right-wing political orientation. We polarized the bots by "allowing" each of them "like" pages from publishers belonging to corresponding orientation. The remaining 5 bots were keep undecided.

Each bot kept open an Internet browser window (Firefox or Chrome) accessing the Facebook page. The bots were prepared to collect the posts to which they were exposed using a browser extension named Facebook Tracking Exposed [6].[1]

Every auto-scroll produces a set of impressions which are stored at a local database. Each collection of posts is referred to as a *snapshot*.

1) Three *low* sampling bots collect posts once every day.

2) Nine *regular* bots collect posts every hour.

3) One bot was scheduled to collect snapshots every ten minutes. We refer to this user as a *high* sampling user.

Each bot is referred to by a number, indicating one of the above classes, followed by its polarization and nickname to distinguish among bots within the same class and polarization.

Each post appearing in a snapshot counts as a post *impression*. At each bot, Facebook Tracking Exposed collects all impressions and stores their corresponding publisher, publication time, impression time and impression order.

III. CANDIDATE CLASSIFICATION AND BOT PROFILING

A. Parties and candidates political views

We begin by assessing the positions of different candidates towards multiple political dimensions. To that aim, we analyzed the official plans of the candidates, and produced Table I. The table is admittedly oversimplified, but already captures some of the differences between the candidates perspectives towards contending questions. Table I describes the features that served as inputs to cluster candidates and sources using

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[1]All the collected data is available by contacting the authors.

TABLE I
PARTIES, CANDIDATES AND THEIR POLITICAL VIEWS

party	candidate	decriminalization drugs	flexible arms	legal abortion	flexible agrotoxics	privatization oil and gas	assistance programs	privatization other sectors	reforms pensions	reduce consumers taxes	increase taxes rich	reform workers laws	limit public expenses	militars in RJ
Podemos	Álvaro Dias	-1	+1	-1	+1	0	+1	+1	+1	+1	+1	+1	0	-1
Patriota	Cabo Daciolo	-1	-1	-1	0	-1	+1	-1	-1	+1	-1	-1	-1	-1
PDT	Ciro Gomes	-1	-1	+1	+1	-1	+1	+1	-1	+1	+1	-1	-1	-1
PSDB	Geraldo Alckmin	-1	+1	-1	+1	-1	+1	+1	+1	0	0	+1	0	+1
PSOL	Guilherme Boulos	+1	-1	+1	-1	-1	+1	-1	-1	+1	+1	-1	-1	-1
MDB	Henrique Meirelles	+1	-1	-1	0	+1	+1	+1	+1	-1	-1	+1	+1	0
PSL	Jair Bolsonaro	-1	+1	-1	+1	-1	+1	+1	-1	0	-1	+1	+1	-1
Novo	João Amoêdo	-1	+1	-1	0	+1	+1	+1	+1	+1	-1	+1	+1	+1
PPL	João Goulart Filho	+1	-1	+1	0	-1	+1	-1	-1	0	+1	-1	-1	-1
DC	José Maria Eymael	-1	0	-1	0	+1	+1	0	0	+1	0	0	0	0
PT	Lula/Haddad	0	-1	+1	-1	-1	+1	+1	-1	0	0	-1	-1	0
Rede	Marina Silva	0	-1	0	-1	-1	+1	-1	+1	+1	-1	+1	-1	0
PSTU	Vera Lúcia	+1	-1	+1	-1	-1	0	-1	-1	0	0	-1	-1	-1

k-means. We assign to each candidate c a vector v_c with 13 dimensions, $v_c \in \{+1, -1, 0\}^{13}$. Then, k-means partitions the candidates vectors into 2 groups through a mapping $\phi : v_c \rightarrow \{L, R\}$, in such a way that the Euclidean distance of the vectors to the corresponding centroids is minimized. The clusters provide a big picture overview of the political arena in Brazil, as seen from the lens of the candidates proposals.

Figure 1 illustrates Table I through a graph $G = (V, E)$ where vertices correspond to candidates or perspectives towards topics, i.e., $|V| = 2t + n$ where t is the number of topics and n is the number of candidates. Edges link candidates to topics. For instance, the presence of an edge between vertices 'Jair Bolsonaro' and '+ flexible arms race' captures the fact that the candidate has a '+1' in the corresponding column at Table I. The visualization in Figure 1, , showing candidates and topics colored based on k-means results, will be instrumental to assess the alignment of candidates and sources.

B. Candidates and sources alignment

Next, we describe our methodology to measure the alignment between media outlets and the two presidential candidates of the second round. We start from Facebook advertising interface to measure the Facebook audience interested in a given topic following the media bias monitor approach [7]. We assume that publishers with a larger audience in common are related [8]. To obtain media publishers political leaning, we assume that media sources with many subscribers in common with a given candidate are closely related to that candidate and have a political leaning towards the candidate.

Let A_x be the estimated audience returned by the advertising interface when selecting as criteria for target audience the candidate x alone, $x \in \{Bolsonaro, Haddad\}$. Similarly, let $A_{x,j}$ be the audience of the advertisement when both publisher j and candidate x were selected.

Combining the above terms, we obtain the closeness index to measure the alignment of publisher j and candidate x, $C(j|x) = A_{x,j}/A_x$. The political leaning of publisher j is:

$$L(j) = C(j|B) - C(j|H) \tag{1}$$

We choose closeness as alignment metric because it is used by Facebook in its advertising API and the same metric was also adopted in [8].

Figure 2 shows the alignments of publishers using (1). Publishers are ordered according to such alignments. Publishers aligned with Haddad are colored in red, and Publishers aligned with Bolsonaro are colored in blue.

C. Bot profiling

In the first round, the regular and high sampling bots follow all the publishers. The low sampling bots only follow the political candidates and their respective political parties. After the candidates profiling, as described in Section III-A, the bots were polarized by "liking" pages from the corresponding candidates orientations. Undecided bots also follow all the considered pages, but do not "like" any page.

IV. METRICS OF INTEREST

A. Timeline occupancy metrics

Let B be the number of bots (users), and let M be the total number of unique posts. We denote by S_i the number of snapshots collected by the i-th bot, where each snapshot contains K posts, with each of those posts being one of the M unique posts collected through our measurement campaign.

Each time a user views a post we count an additional *impression* towards that post. Let P_{ij} denote the number of impressions of publisher j at user i.

Occupancy is the average number of posts of publisher j in the News Feed of user i and is calculated as follows:

$$N_{ij} = P_{ij}/S_i. \tag{2}$$

The *normalized occupancy* is given by N_{ij}/K.

B. Bot closeness metrics

Let I be an impression matrix where each element $I(i, x)$ is indicator variable which characterizes posts viewed by users:

$$I(i, x) = \begin{cases} 1, & \text{if user } i \text{ viewed post } x \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

Then, I is an $B \times M$ matrix.

The similarity between the impressions of bot i and bot j is captured through the closeness metric. The closeness between bots i and j is given by element (i, j) of a $B \times B$ matrix C, defined as follows:

$$C = I \cdot I^T \oslash \text{diag}(I \cdot I^T) \tag{4}$$

where I^T is the transpose of matrix I, $diag(I \cdot I^T)$ is a vector of the diagonal elements of the matrix $I \cdot I^T$ and $\oslash$ is an element-wise division following the Hadamard notation.
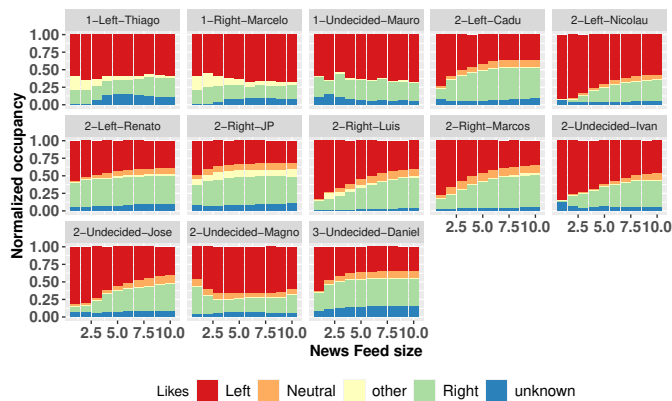
Fig. 3. Normalized occupancy as a function of K, given publisher orientations

Fig. 4. Heatmap of closeness matrix 1st round Facebook topmost position

Each element (i,j) of the matrix $I \cdot I^T$ is the number of posts viewed by both bots i and j. The i-th element of vector $diag(I \cdot I^T)$ contains the total impressions seen by bot i. Therefore, closeness captures the normalized number of impressions shared by two bots. Note that closeness is asymmetric: $C(i,j)$ may be different from $C(j,i)$ to capture the fact that if a bot B_1 sees more posts than B_2, but almost all posts seen by B_2 are also seen by B_1, B_2 may be "closer" to B_1 than B_1 to B_2.

V. EMPIRICAL FINDINGS

A. Timeline occupancies are more biased at the top

Figure 3 summarizes the normalized publisher occupancies, as a function of the News Feed size K, across all bots. The publishers are colored according to their political orientation obtained using equation (1). All figures show that the occupancy distribution over the orientations changes with the considered News Feed size. Figure 3 shows that the filtering process is stronger at the topmost position. It also shows that the undecided bots were typically exposed to more left-oriented content, when accounting for the topmost positions, but that such a bias is diluted when accounting for larger timeline sizes. In general, similarly parametrized bots tend to be exposed to a similar fraction of posts from each orientation, although important exceptions occur. The 1-Right-Marcelo bot, for instance, which was polarized as a right-wing bot, received mostly left-oriented content.

B. Filtering of posts is non-trivial and bots closeness is weak

As shown in Figure 4, closeness between bots is typically smaller than 0.5. Such result suggests that users are subject to non-trivial filtering effects, even when they do not "like" any page. Interestingly, the largest closeness value of 0.8 occurs between two undecided bots, which bodes well with our intuition that undecided bots should see a similar view of the world. Nonetheless, such an entry is a notable exception in the matrix, and typical values range between 0 and 0.5. Indeed, given that similarly parameterized users have a dissonant set of impressions, the clustering of posts and pages as indicated
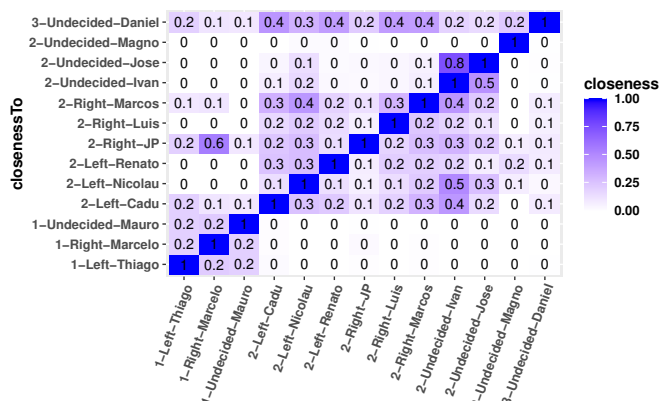
in the previous section is key to assess the biases to which users are exposed to.

VI. CONCLUSION

In many democratic countries, the months before presidential elections have classically been periods wherein the population is exposed to homogeneous sources of information. This occurs, for instance, through federally mandated broadcasts of candidates messages over the TV. In this paper, we have indicated that social media is shifting the scene to another extreme of the spectrum: users with similar interests are now typically exposed to posts whose contents have small overlap with those presented to their peers. This, in turn, suggests that the collective political discourse may now be based on a much more diverse set of posts, posing novel challenges to curate and filter those contents, e.g., against fake news. As a step towards addressing those challenges, we have indicated the feasibility of clustering sources based on their alignments with candidates. In particular, we found that the fraction of posts at each of the considered classes, e.g., left, neutral or right, typically follows an expected pattern aligned with the users orientations.

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