How Representative is an Abortion Debate on Twitter?

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ABSTRACT

Today, more than ever, social networks and micro-blogging platforms are used as tools for political exchange. However, these platforms are biased in several aspects, from their algorithms to the population participating in them. With respect to the latter, we analyze the discussion on Twitter about an abortion bill in Chile, proposed in January 2015, and approved as law in September 2017. We find that Twitter has strong biases in population representation. Still, when carefully paired with demographic attributes, Twitter-based insights on the characteristics of political discussion match those from national-level surveys.

CCS CONCEPTS

• **Human-centered computing → Social network analysis**;

1 INTRODUCTION

A prominent usage of the social platforms on the Web is the exchange of points of view. These platforms are biased in several aspects, from their algorithms to the population that participates in them [1]. Experiments have shown that, when controlling for demographic factors, social media users do not show different political behavior than non-social media ones [6]. However, it remains unclear to which extent insights from social-media discussion reflect those from the general population. In this work, we address the longitudinal discussion on a specific controversial issue, *abortion*. Its discussion on micro-blogging platforms has been studied before, delivering insights on how the different stances on the issue relate [3, 7]. In this context, we analyze a discussion about abortion in Chile, where we measure the *representativeness* of insights derived from the discussion. We processed more than one million tweets published during the entire life cycle of an abortion bill (2015—2017). The analysis included inference of political stance of users, estimation of population bias, and comparison between platform-insights with those from nationally representative opinion surveys.

As result, we confirm that Twitter is demographically biased; however, when incorporating demographic factors in the analysis, it provides insights comparable to traditional sources.

2 DATA SETS

We used three data sources, a data set of Twitter Discussion during 2015–2017, a census from 2017, and a survey of political opinions:

- A Twitter dataset, collected between Jan. 1, 2015, and Dec. 31, 2017, using the Streaming API. Query keywords included abortion vocabulary, mentions, hashtags, and contextual keywords (*e.g.*, #marchaabortolegal –protest for legal abortion–). This resulted in 1,443,865 tweets from 104,938 users.
- The Chilean government held a population census on April 2017 [4]. Chile has 17.5M inhabitants, with 14.5M aged 13 years old or greater (13 years old is the minimum Twitter user age according to the Terms of Service). The census is available as open-data.
- The Centro de Estudios Públicos (CEP) think-tank holds public opinion surveys every three months. In April 2017, they held one survey about abortion [2], in the context of the last year of the life cycle of the abortion bill.

With these three data sets we aim to measure the representativeness of insights obtained from the Twitter discussion.

3 ATTRIBUTE INFERENCE AND WEIGHTING

For each user in the data set we inferred demographic attributes, an stance with respect to abortion, and a weight with respect to the general population.

Demographic Attributes of Users. We are interested in age and gender. Since both attributes are not usually reported, we inferred them. First, we used heuristics to find users with self-reported attributes. For age, we matched common phrases in biographies that disclosed age or date of birth. For gender, in addition to such types of phrases, we analyzed the self-reported first name of the account. As result, we had a labeled set of users with gender (binary male/female) and age (in cohorts, *e.g.*, 18–24, 25–34, *etc.*). We built a feature matrix for all users with a biography (TF-IDF weighted document-term matrix of biography content), and objective arrays with the preliminary labels. We propagated the labels to the unlabeled users using LinearSVC for age (0.94 mean accuracy, 10-fold c.v.), and SGD with log-loss for gender (0.83 mean accuracy, 10-fold c.v.). In total, 89.21% of users were labelled with both age and gender (males 56.28%, females 43.72%).

Stance with respect to Abortion. We treated stance inference as a binary classification problem. Given a user profile (*e.g.*, the concatenation of her/his tweets), the task is to infer the corresponding stance: in *opposition*, or in *defense*. To do so, we built a list of seed keywords associated with each stance, based on previous work analyzing abortion in Chile [3]. Seed keywords for the *defense* stance include #abortolibre (unrestricted abortion), the NGO @miles_chile, and the hashtag #obligadasaparir (forced to give birth). Seed keywords for the *opposition* stance include #sialavida (yes to life), #salvemoslas2vidas (let's save the two lives), and the conservative site hazteoir.org. The seed keywords were used to fit a

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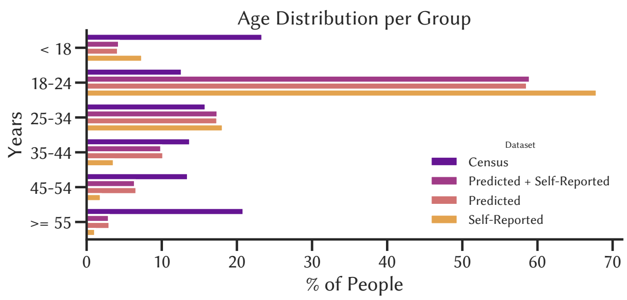

Figure 1: Distribution of age cohorts in the Census [4], and in our data set, including self-reported and inferred ages.

Table 1: Gender distribution in the data sets under study.

	Self-Reported	Inferred	S.R. + Inferred	Census
Males	57.42%	50.91%	55.70%	48.59%
Females	42.58%	45.22%	43.28%	51.41%
F/M Ratio	0.7414	0.8882	0.7769	1.0580

topic model, SeededLDA [5]. Seeded LDA is a semi-supervised variation of Latent Dirichlet Allocation, where the *a priori* information of words guide the topic inference. As input, we used a user-term matrix built using the tweets in the discussion. After fitting, the model provides $P(s \mid u)$, the probability of user u being associated with stance s. To label a user u with a stance s, we calibrated the threshold for $P(s \mid u)$ using profiles with self-reported abortion stances in their biographies. The accuracy of the model was 0.84.

Profile Weighting. For each user in the Twitter data set, we established a profile weight based on the representativeness of her/his demographic attributes according to the census.

4 REPRESENTATIVENESS AND CONCLUSION

To understand representativeness, we first analyzed how the Twitter demographic distributions differ from those in the census. Figure 1 shows the age cohort distribution. For each cohort, the figure contains bar charts of population distributions: census, all inferred Twitter profiles, and profiles with self-reported ages. We observe that younger people are more likely to report their age in their profile, and that the 25–34 range is the most similar in terms of census representation. Note that after predicting age for the rest of the data set, this bias is less pronounced. However, Chilean Twitter users still have an over-representation of 18–24 year old people.

Regarding gender, Table 1 shows the gender distribution in the data set, considering self-reported and inferred users. As result, females are severely under-represented in Twitter, as the female/male ratio is 0.78, in contrast with the census ratio of 1.06.

Representativeness of Insights. Next, we analyzed whether the insights that could be inferred from Twitter could be compared with those from a national level survey. A common way of analyzing survey data is through regression. We therefore decided to perform the same type of analysis in our data sets. In our case, the analysis would be representative (or not) according to the similarities in the coefficients of each model. If all Twitter coefficients have the same magnitude and sign than the survey coefficients,

Table 2: Regression results (N = 93,614 in Twitter models, N = 1,481 in CEP Survey). Positive coefficients show association to the *defense* stance; negative ones, to *opposition*. Significance: *** : $p < 0.001$ (Bonferroni corrected).

Coefficient	Twitter	Weighted	CEP Survey
Intercept (female, 18–24)	1.33^{***}	1.33^{***}	1.30^{***}
male	-0.28^{***}	-0.29^{***}	-0.22
< 18	-0.24^{***}	-0.24^{***}	—
25–34	-0.18^{***}	-0.18^{***}	-0.06
35–44	-0.27^{***}	-0.27^{***}	-0.31
45–54	-0.37^{***}	-0.37^{***}	-0.50
≥ 55	-0.48^{***}	-0.47^{***}	-0.58

then the inference is representative of the general public opinion. We constructed three logistic regression models of the form: $P_{\text{pop}}(Y = \text{stance} \mid X = \text{gender, age cohort})$, where *pop* was one of: the Twitter population, the weighted Twitter population, and the population from the CEP opinion survey. All models considered being female with age 18–24 as reference, thus, each β coefficient represents the influence of a change in the respective attribute, all else being equal. A positive value is associated with *defense* (a negative with *opposition*)

Table 2 shows the model results. All models have coefficients with the same signs and similar magnitudes. Here, insights of interest for social scientists would include, for instance, that males are more likely to be in *opposition* ($\beta_{\text{male}} < 0$), which is arguably expected, due to males not risking their lives through abortion. Other insight is that older adults are also more likely to be in *opposition*, in comparison with the 18–24 age cohort ($\beta_{\geq 55} < \beta_{45-54} < \beta_{35-44} < \beta_{25-34}$) — as people grow, they could be more likely to have a family, which could be a relevant factor in catholic countries like Chile. Thus, our procedure matched the tools (regression) and insights (interpretation of coefficients) that would be made by domain experts when analyzing social issues, implying that the analysis is equivalent to those from representative sources.

Conclusion. Regarding abortion in Chile, Twitter models augmented with demographic information have equivalent outcomes from those of surveys. Biased sources can deliver valuable insights, if taking proper care of who and what is being analyzed.

REFERENCES

[1] Ricardo Baeza-Yates. 2018. Bias on the Web. *Commun. ACM* 61, 6 (May 2018), 54–61.
[2] CEP. 2017. National Survey of Public Opinion, April–May 2017. https://www.cepchile.cl/cep/site/artic/20170601/asocfile/20170601155007/encuestacep_abr_may2017.pdf. [Online; accessed November 2th, 2018].
[3] Eduardo Graells-Garrido, Mounia Lalmas, and Ricardo Baeza-Yates. 2015. Finding intermediary topics between people of opposing views: a case study. In *Social Personalisation & Search*, Christoph Trattner, Denis Parra, Peter Brusilovsky, and Leandro Balby Marinho (Eds.). CEUR, Santiago, Chile.
[4] Instituto Nacional de Estadísticas. 2018. Censo 2017. http://www.censo2017.cl/microdatos/. [Online; accessed February 18th, 2019].
[5] Jagadeesh Jagarlamudi, Hal Daumé III, and Raghavendra Udupa. 2012. Incorporating lexical priors into topic models. In *Proceedings of the 13th Conference of the European Chapter of the Association for Computational Linguistics*. Association for Computational Linguistics, Avignon, France, 204–213.
[6] Jonathan Mellon and Christopher Prosser. 2017. Twitter and Facebook are not representative of the general population: Political attitudes and demographics of British social media users. *Research & Politics* 4, 3 (2017), 2053168017720008.
[7] Amy X Zhang and Scott Counts. 2016. Gender and Ideology in the Spread of Anti-Abortion Policy. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*. ACM, San Jose, CA, USA, 3378–3389.