Pan-American Parading: A Comparative Analysis of Self Promotion in US and Brazilian Congressional Tweets

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Abstract

We recall Yu et al.'s "Self Promotion in US Congressional Tweets", which uses BERT and members of Congress's tweets to analyze instances of self-promotion. We intend to replicate the paper's analysis in a different context to examine this research method's validity. Tweets from congresspeople in Brazil - a country with a highly similar political structure to the US, but with objectively and markedly worse gender parity levels - are annotated and used to train a BERT model, which then classifies historical tweets. After controlling for the same factors as Yu et al.'s paper, we observe similar results: In an apparent reversal of gender norms and related literature, women politicians self-promote more often than men**.** We further offer explainability and reproducibility perspectives and offer next steps for analysis.

Introduction

The advent of BERT has led to a series of papers exploring sequence classification for continuously more nuanced and specific events. The canonical issue of "spam or not spam" has given way to detecting filigreed events such as the kind of disaster being tweeted (Hamada et al., 2019) or near-subjective, complicated emotional states such as depression (Martínez-Castañoet al, 2020). These papers' analytical thrust is similar: Leveraging a fit-for-purpose (and often freshly annotated) dataset, researchers fine-tune some Transformer model (usually BERT or a variant thereof) for their predictions and conclusions.

Impressive prediction scores aside, one is always left wondering how much the takeaways from these highly bespoke tasks is subject to highly bespoke, scarce data[1]. This observation is not meant to disqualify anything that is not Big Data: Specialized datasets are (as the author learned) laborious to assemble, and the resulting models largely accomplish what they set out to do. Instead, we aim to validate (or challenge) this route of enquiry by replicating the analysis, dataset annotation method*,* and model usage as faithfully as possible while carrying out our analysis *in a markedly different* (but still comparable) population.

Background

Good Salesmen, Nasty Women: Gender and Self-Promotion

Our focus is on the human behavior of self-promotion, which is classically defined as the act of presenting oneself as competent (Jones Pittman, 1982). Social and workplace psychology literature confirms what any professional can probably intuit: When used in conjunction with other "impression management" techniques, self-promotion can improve job interview success (Proost et

[1] To illustrate the point: The aforementioned disaster and depression detection papers used corpora (train + test) of ~25,000 tweets and 354 Reddit users, respectively

al, 2010) and manager evaluations (Hartog et al., 2020).

Unfortunately that same literature shows that the benefit of self-promotion depends largely on the gender who practices it. Women who self-promote face reprisals for being immodest and selling themselves too hard; a seminal paper on the issue is aptly titled "Self-promotion as a risk factor for women" (Rudman, 1988). This dynamic has been further crystallized into the Backlash Avoidance Model, which posits that "...fear of backlash for stereotype violation inhibits women's performance because it serves as a catalyst for self-regulatory processes that interrupt their ability to freely sell themselves" - in other words, women undersell themselves in order to avoid reproach (Moss-Racusin et al, 2010).

Far from an academic model, this "feminine modesty effect" has been captured by numerous empirical findings. Women graduates in a top-ranked MBA program were statistically less likely to tout their accomplishments in the Summary or Job Description fields of their LinkedIn profiles (Altenburger et al., 2017). Germane to this medium, an analysis of 1.5 million JSTOR papers find that men self-cite at significantly higher rates than women across most academic fields (King et al., 2017).

Two Countries, One Government, One Stereotype?

Unsurprisingly, the feminine modesty effect is more prevalent in traditionally male-dominated trades such as politics. Experiments have shown that by violating power-seeking women violate communal gender expectations, resulting in lower perceived competence and moral animosity towards women candidates (Okimoto & Brescoll, 2010).

It is from this angle that Jun et al.'s "Self Promotion in US Congressional Tweets" comes in to test the gender gap in self-promotion[2]. The authors establish Twitter's storied use as a medium for self-promotion among politicians in countries as diverse as the UK, Belgium, and Spain (Coesemans and de Cock, 2017; Jackson & Lilleker, 2011). Using pre-existing archives of Congress tweets, the authors annotate a subset of tweets and use it to fine-tune a BERT model, which then classifies 2 million Congressional tweets as self-promoting or not. They then run a regression model on self-promoting tweets, controlling for party, chamber, other covariates, (and most crucially) gender.

In a reversal of gender norms and most published literature, the authors find that women self-promote *more often* than men. This paper seeks to shed further light on this unusual finding by replicating Jun et al.'s analysis, but in a markedly different context.

The Federative Republic of Brazil - or, as it was called until 1969, the United States of Brazil - is an excellent candidate for a replication and comparative analysis. First, Brazil's institutional architecture closely mirrors that of the United States. The US's position as regional hegemon after the Cold

[2] This paper is the author's effective source of inspiration for the upcoming analysis; a skim is not required but highly recommended.

War meant that Brazil was clearly shaped in the U.S.'s image during the democratization of 1988. American constitutional law has direct influences on the Brazilian legal system (Dollinger, 1990); A powerful president is checked by a bicameral legislature, with senators ("senadores") and congresspeople ("deputados") vying for their states with much the same rules as their American legislative counterparts (Ufiem et al., 2014). Secondly, Brazil has high rates of *social media and Internet usage* despite its relative poverty versus the US. It is the fifth country with the most Twitter users (Statista 2021) and 70% of its population uses the Internet, the same rate as Mexico or Puerto Rico (World Bank 2018).

At the same time, Brazil has *substantially* lower (higher) gender parity(inequality) indicators across most if not all observable outcomes. The Council of Foreign Relation's Women's Workplace Equality Index, which embeds several dozen data points across dimensions from violence protection to equal job opportunities and cultural norms, ranks the US globally at 20, right before Sweden; Brazil is ranked 51st. (Brazil scores lower in nearly every disaggregated measure, too.)

Hypothesis

We intend to reproduce Jun et al.'s paper in the Brazilian context, with the working hypothesis that *a worse gender parity will lead to a negative coefficient on the "female" regressor*, which would in turn suggest that Jun et al.'s finding is likely driven by comparatively high gender parity in the US. Conversely, finding results similar to Jun et al. should lead us to question the validity of our analysis methods given the insensibility of self-promotion frequency to markedly worse gender norms.

Methods

Annotated Corpus

Unlike the US, there is no regularly maintained archive of Congressional tweets. As such, we used the Brazilian legislature' website to gather key Congressperson data points - gender, age, number of terms served - and merged them with a think-tank's list of Congressional social media handles. Then, we used Twitter's Dev API to scrape a corpus of 4,698 tweets (no retweets) tweeted by Brazilian members of Congress over the period of July 12, 2021 - July 24, 2021 (bounds inclusive)[3]. To ensure a diversified sample, at most 20 tweets per congressperson (verus Jun et al.'s limit of 10) were scraped. Fig. 1 details some high-level statistics.

[3] This recency bias was due to Twitter API limitations; this and other qualifiers will be discussed later.

Fig. 1: Corpus Descriptive Statistics		
	Reps	**Senators**
Population	513	81
of which tweeted at least once on Jul 12-24	**466**	**79**
Avg. # of Followers	54,267	141,317
Avg. # Tweets Scraped	8.8	10.8
Total # of Tweets (% total)	4,115 (83%)	853 (17%)
of which men	**397**	**68**
Avg. # of Followers	44,929	153,128
Avg. # Tweets Scraped	8.7	11
Total # of Tweets (% total)	3,440 (69%)	749 (15%)
of which women	**69**	**11**
Avg. # of Followers	107,995	68,306
Avg. # Tweets Scraped	9.8	9.5
Total # of Tweets (% total)	675 (14%)	104 (2%)

While women are unfortunately underrepresented in the Congress overall, women reps boast a relatively high follower count and tweet frequency versus their peers; about 1 in 6 of the corpus's tweets are by women.

The author, a native Portuguese speaker, was responsible for classifying each tweet as an instance of self-promotion or not. Jun et. al's rubric self-promotion typology was used as guidance; Jun et al's (and the author's) most common types of self-promotion are reproduced together with a freely translated example in the Appendix Section.

To measure inter-annotator agreement, a (bilingual) native Brazilian Portuguese speaking volunteer read Jun et al's typology and annotated a random subset of the corpus (97 tweets, of which 49 were self-promoting). To avoid bias, the volunteer was not told about the purpose of the study nor the proportion of labels in the subsample. The resulting Cohen's Kappa score was 0.61

Our 4,968 observations in our corpus, 1,038 of observations were annotated as self-promotion instances, of which roughly 14% are tweeted by women - in line with their overall corpus representation. Compared to Jun et al., we are slightly more conservative in identifying self promotion (22.8% vs. 20.8% in our corpus). Our corpus also has 24% more observations, mostly due to the scraper returning slightly more tweets than anticipated.

Implementation - BERT

We tokenize and fine-tune our corpus on BERTimbau-Base (Souza et al., 2020). BERTimbau is a BERT model trained on a large Web corpus of Brazilian Portuguese using whole-word masking. BERTimbau was chosen over multilingual BERT models as it outperformed mBERT and indeed achieved SOTA results in NER and other tasks at time of model release.

Before tokenizing the data, we make two brief preprocessing steps. First, we remove emojis (which the tokenizer doesn't recognize and thus defaults to [UNK]) into the word "emoji", which the tokenizer recognizes. We do a similar process with all links, which we change into the word "link" due to tokenizer recognition. These steps were done ex-post, and increased per-class F1 by 0.2-0.5% depending on the model run.

Token max length was kept at BERTimbau base's max of 512, as several inputs were at or exceeding this level and ad-hoc reductions were met with marginally lower accuracy/F-1 metrics. The model was trained for a total of 5 epochs, as losses began to plateau (and then increase) after that which suggested overfitting. Through trial and error, the learning rate was set at 1e-05. Batch size, weight decay, and other hyperparameters were experimented with to negligible and/or negative results; the standard HuggingFace training arguments were used for those.

A summary of the model's performance can be seen below.

Fig. 2 Model Performance Metrics

Metric	*Jun et Al.*	*Author*	*(Author - Jun et Al.)*
Majority Class Guess Accuracy	77.2%	79.2%	**2.0%**
Model Macro Accuracy	92.3%	90.7%	**-1.6%**
Model Accuracy Gain vs. Maj. Class Guess	19.6%	14.5%	**-5.0%**
Model Macro Precision	89.1%	90.9%	**1.8%**
Model Self-Promotion Precision	83.4%	80.5%	**-3.0%**
Model Macro F-1	89.0%	91.0%	**2.0%**

As an "easy" baseline, simply guessing our majority class would yield an accuracy of 77.2%, which we beat in absolute terms but not relative to the model's accuracy improvement vis-a-vis original baselines. Our model is competitive in global overall precision and F-1, although for the positive class's precision (most relevant for this study) we are a few percentage points behind. While we are overall satisfied with our model's performance, we will later adjust for this last fact given the positive class's importance in subsequent analysis.

Results & Discussion

We now let our model predict on an exhaustive "archive" of 430,450 tweets which were scraped and preprocessed in the same manner as the corpus. These tweets encompass the period of February 1, 2019 (when the current members of Congress were sworn in) to June 30, 2021. Due to computing constraints, we randomly sample only 20% of this archive (86,000 tweets). To compensate for our comparatively low precision on self-promoting tweets, we raise the threshold on positive class prediction to a 0.6 probability.

In order to better inform our findings, we apply the LIME library's submodular pick algorithm to our data and predictions (). LIME is a model-agnostic explainability tool which randomly perturbs select features to derive linear (albeit local and thus non-generalizable) explanations; its submodular pick technique (a.k.a. SP-LIME) optimizes for a number of local explanations that best generalize into a given sample. Using SP-LIME to analyze tweets marked as self-promoting, we find that words such as *meu* (mine) and *artigo* (article), *projeto* (project), or *proposta* (proposal) are particularly prevalent, which highlight the selfishness and accomplishment-broadcasting components of self-promotion respectively. At the same time we see verbs conjugated in the "we" *-os* suffix, such as *obtermos* (we obtain) or *estamos* (we are). These show that even when (or perhaps because of) self-promotion, politicians are especially keen on embedding their accomplishments within a team effort. Finally, the preprocessed 'link' term's recurring presence confirms the usefulness of our preprocessing and illustrates contexts where a politician uses Twitter to provide/advertise further evidence of their accomplishments. Sample SP-LIME outputs are included in the Appendix.

Finally, we use Python statsmodels' mixed-effects model to control for a number of variables, most notably gender, all while (nearly perfectly) replicating Jun et Al.'s variable space. These variables and our findings can be seen on the following table:

Model:	MixedLM	Dependent Variable:	self_prom
No. Observations:	86811	Method:	REML
No. Groups:	407	Scale:	0.1618
Min. group size:	1	Likelihood:	-44857.9180
Max. group size:	1582	Converged:	Yes
Mean group size:	213.3		

	Coef.	Std.Err.	z	P>|z|	[0.025	0.975]
Intercept	0.753	0.042	17.990	0.000	0.671	0.835
female[T.1]	0.023	0.011	2.005	0.045	0.001	0.045
senator[T.1]	0.037	0.022	1.671	0.095	-0.006	0.080
num_terms	-0.006	0.003	-1.673	0.094	-0.013	0.001
age_yrs	0.000	0.000	0.799	0.424	-0.001	0.001
log_followers	-0.024	0.003	-8.221	0.000	-0.030	-0.018

Note that party-level and year-month dummies, while present, were omitted from the above table due to persimmony. Authors were used as the random effects component of the mixed-effects models. Jun et al.'s version of this table is presented immediately below in the Appendix for comparison convenience. We see that, as in their case, gender is significant and positive, albeit markedly smaller.

Though omitted in our case due to sheer number of parties in Brazil (around 25 and counting), the political party dummies were almost all significant and of large magnitude[4]. The impact of political parties perhaps subtracted from the importance of a politician's house, as our senate coefficient is the same sign as Jun et al. but weaker.

Unlike Jun et al. we capture a negative (but small) effect of a politician's number of terms in the frequency of their self-promotion, which suggests veteran politicians need not self-promote as vigorously. Age has a vanishingly small positive and significant effect, which contrasts with the negative and moderate effect seen in Jun et al. Finally, we are in agreement with regards to the number of followers: As with the number of terms, it seems like more popular politicians feel the need to tout accomplishments less often.

	Coef	Std Err	P-value
gender [F]	**0.110**	0.044	0.013 *
party [R]	0.071	0.039	0.065 ·
chamber [senate]	**0.224**	0.057	0.000 ***
age	**−0.006**	0.002	0.003 **
num_terms	0.008	0.005	0.108
daily_tweets	**−0.019**	0.000	0.000 ***
followers_log	**−0.136**	0.015	0.000 ***
AIC	1695986		
Num. obs.	1981428		

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\cdot}p < 0.1$

Conclusion

Reproducibility & Capacity Constraints

Before a conclusion of any sort, the author recognizes that certain constraints may influence the degree of conviction in these

[4] As an example, the dummy for the PT (Workers Party), the largest party in Congress currently, was -0.261 with a z-score of -10.5.

findings. They are listed here in approximate order of importance.

-Computing power: Due to GPU constraints, BERTimbau base was used in place of BERTimbau large. While this does mirror Jun et al.'s choice of BERTbase, we have little doubt that our model would've performed better otherwise. Computing constraints also prevented an exhaustive analysis of the tweets scraped for regression, which leaves my final regression subject to sampling bias despite my randomization.

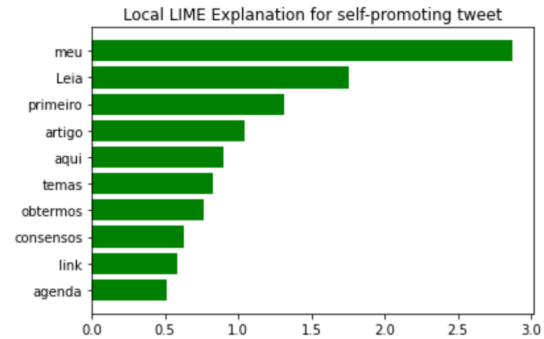
-Data scraping: Jun et al.'s usage of a think tank's cleaned and staged dataset allowed them a more robust cross-section of tweets to build their annotated corpus, while the author only used a recent cross-section of tweets due to time constraints (namely a long time for Twitter to give me a full-archive permission).A full, third-party-validated, historical dataset and an annotation regime as per Jun et al. would bolster the corpus and by extension the model.

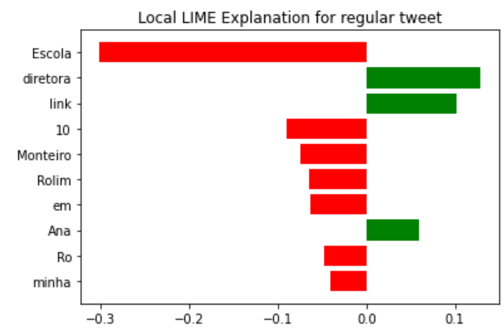
-Covariates and software: The author was unable to reproduce one regressor used by Jun et al., that of a congressperson's number of daily tweets. While their regression showed daily tweets to be significant, the coefficient associated with it was small in both relative and absolute terms. Secondly, differences between R and Python statistical packages[5] mean that only one variable could be used as a random effect in our mixed-effects model - Jun et al. use an R script to incorporate both the tweet author ID and time. We make author ID a fixed effect and make time fixed effects (at the year-month level).

Concluding Remarks

Considering the radically different context in which we sought to replicate Jun et al.'s framework, it is very interesting to observe that their key finding - a controversial one at that - has held. Women politicians seem to self-promote more often than men, rather in the US or in Brazil. A knee-jerk conclusion is to think that political office is perhaps a more high-minded arena than we thought, but this observed reversal of gender norms does not imply their elimination. It may well be that we are simply suffering from survivorship bias, and the female politicians who have made it into office are especially skilled at dribbling gender-norm reprisals when promoting themselves. It may also be that we are using binary classification tools for a measure that may be continuous. Women may advertise as often or more but simply with less intensity: Calculating sentiment scores on female vs. male self-promoting tweets and observing the subsequent distributions could help elucidate that particular question. Most importantly, perhaps, this paper has hopefully added to the gender-norms conversation by attempting to replicate (and ultimately bolstering) an interesting finding halfway across the globe.

[5] While the author did verify that the statsmodels.mixedlm class reproduced the glmer() package used by Jun et al., this particular feature was found to be missing fairly close to the deadline.





Appendix

Examples of Self-Promotion

Fig. 2: Illustrative

Common types of self-promotion (from Jun et al.)	**Examples (freely translated by autho**
(1) Sharing information about or soliciting participation in events	"In an interview with @luislacomberea the moves by Minister Barros and oth https://t.co/SlH5CybMFC"
(2) Talking about own work progress and accomplishments, such as introducing or passing bills, demonstrating authority, or acting in leadership positions	"We managed to pass a motion that v sector wage ceiling loopholes! Great \ https://t.co/OdbDHpaYoL" / "Drilling a budget earmark, for the people of Res https://t.co/ZqHnvSVJlD"
(3) Mentioning received recognitions, such as endorsements and awards	"Honored with an homage from Uberl recommended me for the Augusto Ce: parliamentary inquiry on the genocide

Sample SP-LIME Output - Predicted Self-Promotion/Regular Tweets

Free Translation (in order of SP-LIME explanation display):
-mine
-Read
-First
-article
-here
-topics
-We obtain
-consensus
-link [viz. preprocessing steps]
-agenda

-School
-director [gendered to feminine]
-link [viz. preprocessing steps]
-10
-Monteiro [proper noun]
-Rolim [proper noun]
-in
-Ana [proper noun]
-Ro [proper noun, potential fragment]
-mine [gendered to feminine]

Works Cited

Altenburger, K., De, R., Frazier, K., Avteniev, N., & Hamilton, J. (2017). Are There Gender Differences in Professional Self-Promotion? An Empirical Case Study of LinkedIn Profiles Among Recent MBA Graduates. *Proceedings of the International AAAI Conference on Web and Social Media*, *11*(1), 460-463. Retrieved from https://ojs.aaai.org/index.php/ICWSM/article/view/14929

Den Hartog, Deanne N., Annebel HB De Hoogh, and Frank D. Belschak. "Toot your own horn? Leader narcissism and the effectiveness of employee self-promotion." *Journal of Management* 46.2 (2020): 261-286.

Dolinger, Jacob. “The Influence of American Constitutional Law on the Brazilian Legal System.” *The American Journal of Comparative Law*, vol. 38, no. 4, 1990, pp. 803–837. *JSTOR*, www.jstor.org/stable/840613. Accessed 30 July 2021.

Edward E Jones and Thane S Pittman. 1982. Toward a general theory of strategic self-presentation, volume 1, chapter 9. Lawrence Erlbaum Associates.

“Individuals Using the Internet (% of Population) - Brazil.” *Data*, World Bank, 2018, data.worldbank.org/indicator/IT.NET.USER.ZS?locations=BR&most_recent_value_desc=true.

K. Proost, B. Schreurs, K. D. Witte, and Eva Derous. 2010. Ingratiation and self-promotion in the selection interview: The effects of using single tactics or a combination of tactics on interviewer judgments. Journal of Applied Social Psychology, 40:2155–2169.

Martínez-Castaño, Rodrigo, et al. "Early Risk Detection of Self-Harm and Depression Severity using BERT-based Transformers." *CLEF (Working Notes)*. 2020.

Maurice, Ogbonnaya Ufiem, Ogujiuba Kanayo, and Stiegler Nancy. "A Comparative Analysis of the Interplay of Administrative and Political Structures of the Legislature in the Legislative Procedures of Selected Federal Systems." *Journal of Social Sciences* 41.1 (2014): 27-35.

Molly M King, Carl T Bergstrom, Shelley J Correll, Jennifer Jacquet, and Jevin D West. 2017. Men set their own cites high: Gender and self-citation across fields and over time. Socius, 3.

Moss-Racusin, Corinne A., and Laurie A. Rudman. "Disruptions in women's self-promotion: The backlash avoidance model." *Psychology of women quarterly* 34.2 (2010): 186-202.

Nigel Jackson and Darren G. Lilleker. 2011. Microblogging, Constituency Service and Impression Management: UK MPs and the Use of Twitter. The Journal of Legislative Studies, 17:86–105

Okimoto, Tyler G., and Victoria L. Brescoll. "The price of power: Power seeking and backlash against female politicians." *Personality and Social Psychology Bulletin* 36.7 (2010): 923-936.

Roel Coesemans and Barbara de Cock. 2017. Selfreference by politicians on twitter: Strategies to adapt to 140 characters. Journal of Pragmatics, 116:37–50

Rudman, L. A. (1998). Self-promotion as a risk factor for women: The costs and benefits of counterstereotypical impression management. *Journal of Personality and Social*

Psychology, 74(3), 629–645.
https://doi.org/10.1037/0022-3514.74.3.629

Statista Research Department, and Jun 29. “Twitter: Most Users by Country.” *Statista*, Statista, 29 June 2021, www.statista.com/statistics/242606/number-of-active-twitte r-users-in-selected-countries/.

Souza, Fábio, Rodrigo Nogueira, and Roberto Lotufo. "BERTimbau: pretrained BERT models for Brazilian Portuguese." *Brazilian Conference on Intelligent Systems*. Springer, Cham, 2020.

“Top and Bottom Countries in Women's Workplace Equality.” *Council on Foreign Relations*, Council on Foreign Relations, 2018, www.cfr.org/legal-barriers/country-rankings/.

Wang, Jun, Kelly Cui, and Bei Yu. "Self Promotion in US Congressional Tweets." *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*. 2021.

Zahera, Hamada M., et al. "Fine-tuned BERT Model for Multi-Label Tweets Classification." *TREC*. 2019