Understanding Gender Stereotypes and Electoral Success from Visual Self-presentations of Politicians in Social Media

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ABSTRACT

Social media have been widely used as a platform for political communication, promoting firsthand dialogue between politicians and the public. This paper studies the role of visual self-presentation in social media in political campaigns with a primary focus on gender stereotypical cues exhibited in Facebook timeline posts of 562 candidates in the 2018 U.S. general elections. We train a convolutional neural network (CNN) that infers gender stereotypes from the photographs based on crowdsourced annotations. Using regression analysis, we find that masculine traits are predictive factors for winning elections for both gender and parties. In contrast, feminine traits are not correlated with electoral success. Prediction experiments show that the visual traits on gender stereotypes can predict the election outcomes with an accuracy of 0.739, which was better than the performance (0.724) of making a direct prediction from the raw photographs. Our study demonstrates that the automated visual content analysis can reliably measure subtle, emotional, and subjective personal trait dimensions from political images, thereby enabling systematic investigations on multi-modal political communication via social media.

CCS CONCEPTS

• **Information systems** → **Social networks**; • **Human-centered computing** → *Collaborative and social computing*; • **Computing methodologies** → **Computer vision**; • **Applied computing** → *Law, social and behavioral sciences.*

KEYWORDS

Social Media based Election Prediction; Visual Communication; Gender Stereotypes; Computer Vision

1 INTRODUCTION

In the past decade, social media have become a powerful platform for political discourses, civic engagement, and electoral campaigning [5, 12]. The new technology has helped achieve decentralized and personalized public communication by enabling self-presentation and direct exchanges of ideas between politicians and citizens [7, 23, 24], unlike the mass media where professional journalists act as gatekeepers who decide what and how politicians are presented [28]. More citizens are attending social media as their primary news sources, and consequently, politicians are also quickly shifting to social media to reach out to their supporters.

A considerable body of literature has examined the effects of gender stereotypical representations of politicians in media on voter preference and electoral success. Many studies have reported that compared to male politicians, female politicians are often discussed in terms of their role as mothers on news coverage and, therefore, possibly lose viability as competent candidates [4]. In social media, however, the gender stereotype may be alleviated because candidates themselves can choose what to post on their accounts. This implies that social media may be an effective platform for the self-presentation of politicians underrepresented or portrayed stereotypically in the mass media.

The main objective of our paper is to understand how politicians attempt to establish themselves as competent leaders on social media. In particular, we mainly investigate the role of the visual dimension of political messages, i.e., photographs that politicians post on their accounts. Previous studies have explored the effects of candidates' visual appearance on voter perception in TV, print media, and social media [10, 21]. Nevertheless, it has rarely been attempted to analyze a large amount of visual data due to the difficulty in processing large-scale visual data. We use a computer vision approach to automatically analyze visual content on the dimensions related to gender stereotypes, from which we examine the role of visual self-presentation of candidates in election campaigning. Incorporated with image and text categories identified from the politicians' Facebook posts, we will discuss the importance of visual gender stereotypes through regression analysis and prediction experiments.

2 RELATED WORK

Social media and election. Many scholars have actively studied the role of social media in political communication and campaigning. In particular, these platforms provide a substantial amount of visual data on political campaigns, making the dataset readily available for quantitative analysis [3, 9, 19, 27, 29, 31]. The following section will discuss how some key traits have been identified from the existing literature and are incorporated into our study.

Visual presentation of politicians and gender stereotypes. A large volume of research has examined the gender stereotypes of both male and female politicians and their effects on public perception and candidate evaluation. It is generally accepted that voters interpret masculinity as a sign of competency and may penalize female politicians who lack typical masculine features [15, 20, 26]. For example, a study reported that female candidates benefited from presenting themselves explicitly as caregivers [2]. On the other hand, a backlash effect was also reported for Democratic female candidates expressing masculine visuals, whereas Republican female candidates are not disadvantaged by such incongruities due to Republican Party stereotypes [2].

Automated visual content analysis. Computational social scientists have recently used computer vision and deep learning for the large-scale visual content analysis of massive data from media. Such methods can significantly improve the efficiency of coding and provide new insights on human behaviors and social events such as election [18, 32, 33, 36, 38], collective actions and protest [34, 37], and political traits and ideology inference [14, 17, 35]. Furthermore, since a substantial portion of online communication is in the form of visual data, image data offers unprecedented potential for social science research on the web and media [30].

3 DATA AND METHODOLOGY

3.1 Data Collection

Using Facebook Graph API and selenium, we collected a novel Facebook dataset of 800 politicians who ran for the 2018 U.S. House, Senate, or Governor election. The candidates and the election outcomes (voting shares) were obtained from Ballotpedia, and their Facebook accounts were manually confirmed. We collected photographs, captions, number of comments, and posting time. Along with Facebook photographs, posting time was examined to filter the photographs by the year 2018 (January 1, 2018 – November 5, 2018). Facebook was chosen as our target domain of analysis because it has been widely used as a platform for political discussions in recent elections in the U.S.

Some images display only large text or big logos without much photographic content without depicting the visual traits of candidates. We excluded these images by training a classifier from a small annotation set we created. Among the politicians who had a Facebook account and posted at least five images, we only considered the complete pairs for this study's analyses. In other words, politicians without opponents in this dataset are discarded. The final dataset used for analysis is composed of 80,131 images shared by 562 politicians, which is well balanced across gender and party.

3.2 Data Annotation on Personal Traits

Personal traits are a critical basis to understand how voters perceive candidates and predict their competence. However, quantifying the personal traits can be challenging because there exist several potential trait dimensions one can consider. This study aims to provide a method that automatically quantifies scores for the selected traits by training a deep neural network with crowdsourced annotations. To the end, we first construct a list of traits by borrowing from research on personal traits of politicians [1, 6, 11, 17, 18, 22, 25]. Along with *Masculinity* and *Femininity*, we target the following

22 trait dimensions that could affect perception of electorates and election outcomes: *Ordinary, Elitist, Qualified, Ambitious, Attractive, Threatening, Communal, Formal, Patriotic, Professional, Energetic, Trustworthy, Agreeable, Reassuring, Friendly, Caring, Maternal, Credible, Competent* and *Confident*.

We employed Amazon Mechanical Turk to collect human judgment ratings on each of the 22 trait dimensions. Note that the aim of the annotation task was not to identify the truth but to collect subjective opinions of people on the politicians' personal traits; the perceived traits indeed affect the voting decision of electorates. We randomly sampled at least five images per candidate and collected 8,954 images while ensuring the balance between gender and political affiliation. We assigned ten annotators in the U.S. to each image and ask to rate to which extent the given image exhibits each trait on a five-point scale (1 to 5). The results were aggregated by averaging the responses to each image. We excluded ratings from the annotators who indicated that they recognize the politicians in the given photographs as their evaluations might be biased.

As we ask for subjective opinions, instead of conventional measures such as Cronbach's alpha, we adopted a method suggested in a study in a similar setting [16]. In particular, the method split the annotations into two groups and then evaluate the correlation of average scores between the two via Pearson's r. This measure intuitively tells us how well the first half of the annotations predict the ratings made by the second half of the annotators. The results show that the crowdsourced trait scores achieved an acceptable level of inter-annotator agreements for each trait dimension (>.2), which suggests the reliability of the annotations.

Table 1: Prediction accuracy for the personal traits measured on the test set by Pearson's Correlation.

Trait	Accuracy	Trait	Accuracy
Feminine	0.870	Trustworthy	0.819
Formal	0.867	Energetic	0.816
Professional	0.859	Maternal	0.810
Agreeable	0.853	Masculine	0.802
Reassuring	0.853	Communal	0.797
Friendly	0.851	Ambitious	0.797
Caring	0.852	Patriotic	0.797
Credible	0.844	Attractive	0.752
Competent	0.838	Elitist	0.650
Qualified	0.827	Ordinary	0.610
Confident	0.823	Threatening	0.339

3.3 Automatic Trait Inference from Images

We trained a CNN model to quantify the 22 trait values from each photograph automatically. In particular, we employed ResNet-34 [13]. From the model pretrained on the ImageNet data, we replaced the last layer with the 22-dimensional output and added a sigmoid layer to ensure the computed personal traits ranging from 0 to 1. We fine-tuned the network by minimizing the sum of the 22 different mean square errors. During training, we employed the Stochastic Gradient Descent (SGD) optimizer with a learning rate of 0.03 and a momentum value of 0.9. Out of 8,954 labeled images, 500 were randomly selected for testing the trait inference model.

High Masculinity   **High Femininity**

Figure 1: Examples of image clusters of high Masculine(left) and high Feminine scores (right) identified by k-means (k=300).

Table 1 presents the accuracy of our trait inference model, measured on a separate test set with the average rating per image. The CNN model trained on the annotated scores could predict the trait values with high accuracy scores similar to or higher than 0.8, except for Attractive, Elitist, Ordinary, and Threatening. Considering the low prediction accuracy, we did not utilize the four dimensions in the following analyses.

4 RESULTS

4.1 Understanding Visual Gender Stereotypes

An essential question in our study is to understand what constitutes femininity and masculinity. To illustrate how they are displayed differently, we conducted a clustering analysis using the trait prediction model. In particular, we utilized the vector of the penultimate layer by feeding each image into the trait model as input. Then we took the top 10,000 images with the highest femininity score and the top 10,000 with the highest masculinity score and clustered them using the k-means algorithm with k=300. Figure 1 displays samples of the image clusters with a high masculinity and femininity score, respectively. Images from the same cluster are bounded by a border. In the figure, we can clearly see that femininity (red) is formed around the candidates and highlights their friendly, attractive, and maternal personality along with visual cues such as smile and family whereas masculinity (blue) is conveyed through strong and authoritative activities, such as military, handshaking and construction sites.

To better understand the context of the politicians' posts on social media and how they are associated with gender stereotypes (and in turn election outcomes), we further analyzed topics that appear in image and text.

Using the Google Vision API, we investigated the top-10 concepts in images of high masculinity and high femininity by calculating the expected frequency for each gender based on the frequency of images shared by each gender; then, we computed the chi-square value based on the difference from the actual frequency and the expected. Results show that male-dominated occupations (Military, Engineering) appeared more frequently in images shared by the male politicians; on the contrary, emotion-related concepts (Friendship, Happy, Laugh, Hug) were highly associated with images shared by the female politicians. Note that the identified image

categories also appeared in the masculine and feminine clusters in Figure 1: for example, images of politicians in a military event or those doing handshakes are observed in the masculine clusters while politicians with smiling or laughing faces appeared in the feminine clusters. The two different analyses' common trend suggests that masculinity and femininity could be visually represented by certain image concepts, such as context and type of persons.

Similarly, we analyzed texts using Empath [8]. Similar to Google Vision API, the library returns the list of text categories for a given text. We fed the caption of a Facebook post as the input of Empath. In this analysis, we found that while work- and achievement-related text categories were prominently used by the male politicians (Office, Achievement), the female politicians tend to use emotion- and family-related text (Affection, Children). In addition to the image analysis, the text analysis suggests that male and female politicians cover different topics, and hence masculinity and femininity may be captured by distinct concepts.

4.2 Identifying Important Traits for Election

To investigate the predictive roles of each of the stereotype dimensions with ruling out the effects of the other factors, we utilized two regression models for predicting voting shares (continuous) and whether a given politician win the election (binary). In particular, ordinary least square (OLS) and logistic regression were fitted using the three categories of features: the political traits estimated by CNN (Personal trait), the image categories identified via Google Vision API (Image category), and the text categories found by Empath (Text category). To reduce the number of independent variables in the regression models, we first fitted a model for each set of features (e.g., Personal trait) and only considered the significant variables for the model using all the categories. Dummy variables on gender (Female=1) and party (Democrats=1) were included as control variables; therefore, the predictive power of significant variables from each model is also independent of the effects of gender and party.

Table 2 presents the regression results. Here we make three sets of observations. First, the models can predict the election outcomes with the Adjusted R-squared of 0.282 and the Pseudo R-squared of 0.2726; that is, how the politicians present themselves on social media, including the gender stereotypical traits, were important for explaining election outcomes. Second, among the personal traits

Table 2: Fitted regression results. Bold text indicates statistically significant variables.

(a) OLS regression for voting shares

Category	Feature	Coefficient	Std. Error	P-value
	(Intercept)	-0.2329	0.128	0.069
Control	Gender	0.0079	0.017	0.639
	Party	0.0339	0.012	0.004
Personal trait	**Masculine**	0.7675	0.346	0.027
	Feminine	0.3801	0.316	0.229
	Professional	0.2096	0.243	0.388
	Patriotic	0.0481	0.229	0.834
	Energetic	0.1174	0.378	0.757
Image category	**T-shirt**	-0.3655	0.103	<0.001
	Smile	-0.2548	0.076	0.001
	Vehicle	-0.1122	0.084	0.183
	Employment	0.1369	0.082	0.098
	Social group	0.2729	0.088	0.005
Text category	**Tourism**	3.7182	1.606	0.021
	Journalism	-5.8585	2.281	0.010
	Business	2.0814	0.776	0.008
	Achievement	1.6222	0.800	0.043
Adjusted R-squared				0.282

(b) Logistic regression for win/lose

Category	Feature	Coefficient	Std. Error	P-value
	(Intercept)	-7.8704	3.063	0.010
Control	Gender	0.2393	0.361	0.507
	Party	0.1997	0.254	0.432
Personal trait	**Masculine**	23.6045	8.056	0.003
	Feminine	12.5612	7.453	0.092
	Professional	-4.4074	5.588	0.430
	Patriotic	3.2534	5.493	0.554
	Energetic	-12.7146	9.201	0.167
Image category	**T-shirt**	-6.8475	2.595	0.008
	Smile	-4.7920	1.989	0.016
	Vehicle	-5.1648	1.821	0.005
	Employment	4.3472	1.914	0.023
	Social group	4.7296	3.029	0.118
	Team	1.6945	1.733	0.328
Text category	Home	-49.9361	26.695	0.061
	Military	84.8846	43.551	0.051
	Business	51.2308	18.325	0.005
	Achievement	41.5964	17.431	0.017
Pseudo R-squared				0.2726

estimated by CNN, masculinity was the only significant feature for predicting election outcomes. This finding is congruent with the finding of the previous studies which discusses the importance of masculinity through manual analysis [20, 26]. Third, there were significant variables from image and text categories identified from the Facebook posts. Among the Google Vision categories identified from the photographs, both regression models exhibited a statistical significance on T-shirt and Smile, which was more used in the images of female politicians. By contrast, among the text categories of Empath, Business and Achievement were the significant variables with a positive association with the election outcome. Those two text categories were more frequently used by male politicians. Together, the image and text categories captured from politician's Facebook posts support the advantage of exploiting masculine traits for winning the election.

4.3 Election Outcome Prediction from Images

The last step of the analysis was to test the predictive power of visual self-presentation for the election outcome. To this end, we mimic the election setting using 5-fold cross-validation. In particular, we split the list of positions (e.g., Governor in California) into five, and therefore it ensures every politician having the opponent in the same fold. We decided a winner when a politician achieves a higher score than its counterpart.

In particular, we utilized the two different models to evaluate the relative importance of the stereotyped traits for predicting election outcomes: (i) *Direct model* and (ii) *Trait-based model*. The direct model takes an image as input and returns a probability of winning the election. We fine-tuned ResNet-34 pretrained on ImageNet by replacing the last layer with a sigmoid layer. We used up to 300 images for each politician for training to prevent overfitting. For inference, we took the average of the model outputs of all images a candidate posted. The trait-based model is a logistic regression

classifier that predicts whether a candidate wins from the inferred visual traits for the politician. To have a vector for each politician, we took an average of each of the trait dimensions for all images shared by the politician.

From the evaluation experiments, we made two key findings. First, the image-based direct model achieved a fair accuracy of 0.724 with a significance level of 0.001 by McNemar's test. This performance suggests that the visual self-presentation of politicians contains predictive cues for election outcomes. Second, the trait-based model achieved an accuracy of 0.739 with a significance level of 0.001, which was slightly better than the image-based direct model's performance. This suggests the gender-stereotyped visual traits are essential features for classifying winners and losers, as we also identified masculinity as a significant factor in Table 2.

5 CONCLUSION

In this paper, we investigated the role of visual self-presentation of political candidates in social media in campaigning using 80,131 photographs shared by the 562 political candidates in the 2018 U.S. general election. While the previous research in political science has discussed the importance of visual information [10], the main challenge in the visual data analysis in political science was on how to conduct a systematic analysis on a large-scale data. This study employed an advanced computer vision method that allows an automated prediction of political traits displayed in photographs to fill the gap. For computer scientists, we believe this study also provides a promising view for future studies investigating gender stereotypes and bias through online multimedia.

ACKNOWLEDGMENTS

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