Power Dynamics in Spoken Interactions: A Case Study on 2012 Republican Primary Debates

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ABSTRACT

In this paper, we explore how the power differential between participants of an interaction affects the way they interact in the context of political debates. We analyze the 2012 Republican presidential primary debates where we model the power index of each candidate in terms of their poll standings. We find that the candidates' power indices affected the way they interacted with others in the debates as well as how others interacted with them.

Categories and Subject Descriptors

J.4 [**Computer Applications**]: Social and behavioral sciences

Keywords

power; relations; political science; social status; debates

1. INTRODUCTION

Recently, there has been a rapid increase in online social interactions and interactions from other media sources being stored in repositories such as YouTube. This has triggered great interest in computationally analyzing interactions to gain insights about people. In this area, there is work on finding how the power or status difference between participants is reflected in the various facets of interactions (e.g. [3, 4]). A computational system to analyze power differentials between participants in an interaction could have various practical applications. It could help improve effectiveness of advertisements within online communities, help in information retrieval systems in assessing relevance, and aid intelligence agencies to detect leaders and influencers in online communities. Most computational efforts to analyze power relations between participants of interactions have relied on static hierarchies as sources for the power differential [4]. However, many interactions (e.g. online forums, political debates) happen outside the context of a pre-defined static power structure or hierarchy and have dynamic forms of power; an area that is not well explored computationally. In this paper, we analyze political debates where the power differential is dynamic. Specifically, we analyze the 2012 Republican presidential primary debates, modeling power based on their poll standings. We analyze interactions in the structural, lexical, and topical dimensions and find various significant correlations. To our knowledge, our work is the first to do an in-depth computational analysis of the structure of interactions, modeling patterns of interruptions and mentions of participants, in relation to power as well as analyzing the linguistic, psychological, and topical dimensions of interactions. Also, the domain is interesting since the primary objective of the interactants is to pursue and maintain power over each other, as opposed to operating within a static power structure. Lastly, the findings are note-worthy as they relate to the domain of political debates, an area which has not been well-studied in this fashion before.

2. POWER IN POLITICAL DEBATES

We obtained transcripts of the 2012 Republican presidential primary debates held between May 2011 and February 2012.[1] These debates serve as a platform for candidates to discuss policy stances as well as to pursue and maintain power over other candidates. Interactions in these debates are fairly well structured and follow a pattern of the moderator asking questions and candidates responding, with some interruptions from other candidates. There were 20 debates, each 90-120 minutes (around 20K words spoken) long. There were 10 candidates, seven of whom were among the top 3 candidates for at least three debates. We model the power with which a candidate X comes into the debate (Power Index, $\mathcal{P}(X)$) based on their recent state or national poll standings.[2][3] Other factors (funds raised, endorsements etc.) can also be factored in. Debates from December 2011 onwards were held in states where the primaries were to be held in the near future. For those debates, we chose the respective state's poll scores as the reference, since we believe that state polls would be the focus at that time. For others, we chose the national polls. For each debate, we find the poll results released most recently and use the percentage of electorate supporting a candidate as his/her $\mathcal{P}(X)$. If multiple polls were released most recently, then we take the mean of all poll scores to find the $\mathcal{P}(X)$.

3. MANIFESTATIONS OF POWER

We analyze the manifestations of power in three dimensions of the debates: structural, lexical, and topical. Fig-

[1]http://www.presidency.ucsb.edu/debates.php
[2]http://en.wikipedia.org/wiki/Statewide_opinion_polling_for_the_Republican_Party_presidential_primaries,_2012
[3]http://en.wikipedia.org/wiki/Nationwide_opinion_polling_for_the_Republican_Party_2012_presidential_primaries

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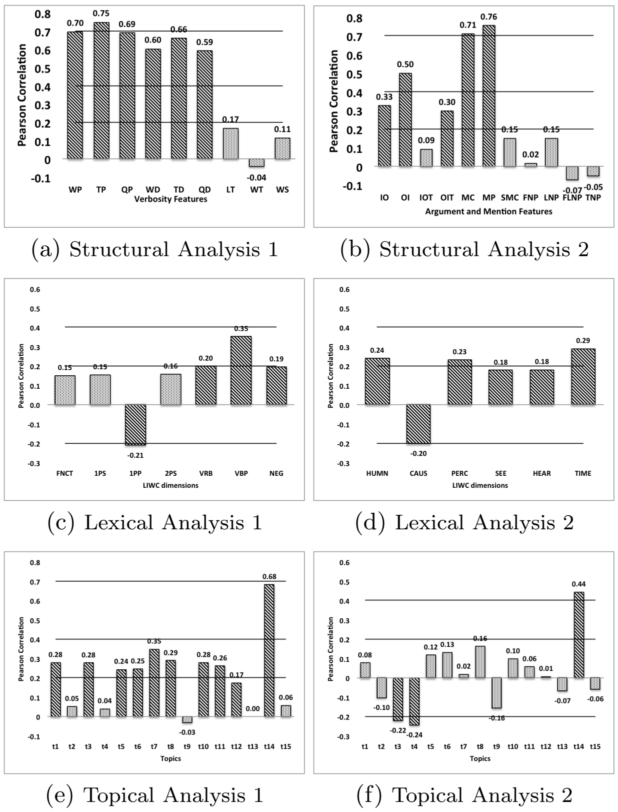
ure 1 shows the Pearson's product correlation of each feature with the candidate's power index $P(X)$.



(a) Structural Analysis 1 (b) Structural Analysis 2

(c) Lexical Analysis 1 (d) Lexical Analysis 2

(e) Topical Analysis 1 (f) Topical Analysis 2

Figure 1: Pearson Product Correlation. Dark bars denote statistically significant features ($p < 0.05$)

Structure: We analyze how much the candidates spoke, how they interrupted each other and how they were talked about. To capture how much they spoke, we use the % of turns, words, and questions asked to them (TP, WP, QP) and the deviations of these measures from an equal distribution (TD, WD, QD). We also use longest turn length (LT), words per turn (WT) and words per sentence (WS). To capture interruption patterns, we use how often they interrupted others (IO) and how often others interrupted them (OI) as well as their per-turn normalized values (IOT, OIT). To capture how often they were talked about, we use raw mention counts as well as a % of total mentions (MC, MP). We also use the distribution of each candidate's mentions in terms of the form of address: first name, last name, first & last name, title and name (FNP, LNP, FLNP, TNP). We obtained significant moderate to high positive correlation for the word and turn features with $P(X)$ (Fig. 1(a)). Questions posed to the candidate also obtained a moderate positive correlation which suggests that the candidates with higher $P(X)$ were asked significantly more questions by the moderators. We also find that the candidates with higher $P(X)$ were interrupted more (Fig. 1(b)). They were also mentioned more often by others, but the form of address did not matter.

Lexical: We use the Linguistic Inquiry and Word Count (LIWC) tool [2] to analyze the use of language in two dimensions: linguistic and psychological. In Fig. 1(c), we show that the candidates with higher $P(X)$ use significantly more verbs (VRB), especially in the past tense form (VBP), than others. Another interesting observation is the first person (1P) pronoun usage: individuals with more power used more singular 1Ps (*i*, *me*, *mine*), while those with less power used more plural 1Ps (*we*, *our* and *us*). In Fig. 1(d), we show 6 psychological dimensions which had significant correlations with $P(X)$. The correlations obtained in the lexical analysis are rather weak overall. However, the fact that many categories had statistically significant correlations with $P(X)$ suggests that these categories could help a system trying predict or rank candidates based on power indices.

Topical: We use a Latent Dirichlet Allocation based topic modeler [1] to find the topics in the turns (#topics: 15). The extracted manually labeled topics are: *Space, Afghanistan, US, Energy, Election, Immigration, Budget, Banks, Conservative, Judiciary, Healthcare, Middle East, Monetary policy, Economy and Education*. We calculated two sets of measures for each candidate: $TP_1(t)$ = % of candidate's turns on topic t; $TP_2(t)$ = % of turns on topic t by candidate across all turns on topic t (across all candidates). For the values of $TP_1(t)$, we obtain significant positive correlations for 10 topics (Fig. 1(e)). The numbers are biased by the fact that candidates with higher $P(X)$ talked more than others. For the values of $TP_2(t)$, we still find high to weak correlations for some topics (Fig. 1(f)); candidates with higher $P(X)$ talked significantly more about some topics (14:Economy) and less about some others (3:Energy and 4:Election). These correlations in topic distributions are artifacts of the dominant issues in the 2012 US presidential election.

4. CONCLUSION AND FUTURE WORK

In this paper, we studied the manifestations of power differentials between candidates in the 2012 Republican presidential primary debates, modeling the candidates' power after their recent poll scores. We analyzed the debates in structural, lexical and topical dimensions. We found that the candidates' power affected how they interacted in the debates — how much and what they spoke (topical), and how they spoke about it (linguistic). We also found that power affected the way others interacted with them — how many questions they were asked, how often they were interrupted and how often they were talked about. As future work, we plan to implement a power ranker system using these insights.

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