Understanding and Identifying Advocates for Political Campaigns on Social Media

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ABSTRACT
Social media is increasingly being used to access and disseminate information on sociopolitical issues like gun rights and general elections. The popularity and openness of social media makes it conducive for some individuals, known as advocates, who use social media to push their agendas on these issues strategically. Identifying these advocates will caution social media users before reading their information and also enable campaign managers to identify advocates for their digital political campaigns. A significant challenge in identifying advocates is that they employ nuanced strategies to shape user opinion and increase the spread of their messages, making it difficult to distinguish them from random users posting on the campaign. In this paper, we draw from social movement theories and design a quantitative framework to study the nuanced message strategies, propagation strategies, and community structure adopted by advocates for political campaigns in social media. Based on observations of their social media activities manifesting from these strategies, we investigate how to model these strategies for identifying them. We evaluate the framework using two datasets from Twitter, and our experiments demonstrate its effectiveness in identifying advocates for political campaigns with ramifications of this work directed towards assisting users as they navigate through social media spaces.

Keywords
Advocacy; Political Campaigns; User Interactions

1. INTRODUCTION
Social media is emerging to be a popular information channel for sociopolitical issues of broad importance for e.g. elections and gun rights. It provides access to a wide range of perspectives on these issues, enabling users to form independent opinions. Owing to this, millions of people are using social media to seek information, gather perspectives, and participate in discussions on these important issues. The popularity of social media as an information channel for important issues has given rise to individuals who use it to try and push their agenda for political campaigns [17]. Media advocacy is defined in the the literature as “the strategic use of mass media to advance a social or public initiative” [19]. We are motivated by this to define advocates for political campaigns on social media as individuals who use social media to advance strategically their agenda for a given political campaign. During the 2014 Indian elections, for example, a set of individuals formed an organization called NaMo Brigade with the motto of “Mission: Narendra Modi as PM” and used social media platforms to advocate for the election of Narendra Modi as Prime Minister [8].

Although these campaigns have considerable social media presence [37], it is difficult to identify individual accounts of advocates. Designing algorithms to identify accounts of individual advocates can better inform users as they navigate through social media spaces. People accessing information about an issue, for e.g. an election, through social media can be notified whether a given account is an advocate before reading their messages. On the other hand, understanding and modeling the characteristics of social media advocates can help campaign managers in recruiting new advocates for their digital political campaigns.

This task faces several challenges. First, advocates employ nuanced message construction and propagation strategies to shape user opinion and increase the spread of their messages, making it difficult to distinguish them from random users posting on issues related to the campaign. Second, these strategies are very diverse, manifesting both in the activity patterns restricted to individual advocates like constructing persuasive messages, and multiple relational patterns like shared language and interactions, making it a challenge to study collectively them in a unified model.

Theoretical constructs of strategies for message construction, propagation, and community formation by advocates have been extensively studied in social sciences. Social movement theory records persuasive language and high degrees of emotion in the messages of advocates in their attempts to shape the opinion of people [28]. The literature on campaign communications [13] studies the widespread use of focused messaging for effective communication during political campaigns. Also, distinctive language patterns shared among people with similar affiliations foster easier communication of messages between them [32]. To increase the reach of messages during political campaigns, the utility of popular users for widespread propagation has been studied in [15]. Formation of social and interaction networks between advocates for
possibly present in the status messages of advocates: persuasive language, a high degree of emotion, topical focus and shared language patterns. We construct the user word matrix $S \in \mathbb{R}^{N \times 1}$ from the status messages with tf-idf weighting, where $l$ is the total number of words. Shared language patterns between two users in $u$ are modeled taking hashtags as instances of language patterns. For each user $u_i \in u$, we construct a vector of hashtags $h_{ui}$ from his status messages. We define matrices capturing shared hashtag information as $Z^i$, where $Z^i_{ij} = \text{jac}_\text{sim}(h_{ui}, h_{uj})$. $\text{jac}_\text{sim}(x, y)$ indicates the Jaccard similarity between $x$ and $y$.

Propagation strategies comprise of the strategies employed by advocates to increase the spread of their messages. We model the propagation strategies of advocates from their targeting and co-propagation behavior. For each user in $u_i \in u$, let $t_{ui}$ denote the set of people targeted by the user. We define the targeting matrix $T \in \mathbb{R}^{N \times K}$ where $T_{ij}$ is equal to the number of times $u_i$ has targeted $r_j$ where $r = \bigcup_{i \in u} t_{ai}$ and $R$ is the total number of users in $r$. We next define the co-propagation network as $P \in \mathbb{R}^{N \times N}$, where $P_{ij}$ is the number of times $u_j$ has propagated a message of $u_i$.

Community structure deals with the patterns arising from the networks formed by advocates to facilitate easier communication and coordination. We model the community structures arising from social connections and interactions between advocates. The social connection matrix is defined as $Z^s \in \mathbb{R}^{N \times N}$. The value of $Z^s_{ij}$ is 1 if $u_i$ connects to $u_j$ and 0 otherwise. We also capture the interactions between the users in $Z^i \in \mathbb{R}^{N \times N}$, where $Z^i_{ij}$ is equal to the number of times $u_i$ interacts with $u_j$. In addition, we define the tensor $Z$ to hold the information contained in the relational matrices $Z^i$, $Z^s$ and $Z^j$, where $Z_{ij} = Z^i_{ij}$.

We model the message strategies, propagation strategies, and community structure and study them in a unified supervised learning framework to identify advocates for political campaigns on social media. The problem statement can then be stated as follows: “Given a set of advocates for a given political campaign on social media $a$ and a set of random users posting on the campaign $v$, their status message matrix $S$, the targeting matrix $T$, the propagation network $P$, and the relational tensor $Z$, determine if a new user $x$ is an advocate of the political campaign.”

3. QUANTIFYING STRATEGIES

In this section, we study the different nuanced strategies employed by advocates for political campaigns on social media drawing from theoretical constructs present in sociological literature and present ways to model them. We first study the employed strategies in terms of their message strategies, propagation strategies, and community structure. We explore each of them in detail, and then present ways to model them to derive characteristics possibly capable of distinguishing between advocates for political campaigns and random users posting on the campaign.

3.1 Quantifying Message Strategies

Message strategies deal with patterns from the construction of the status messages of advocates. Advocates can employ persuasive language in their status messages and attempt to sway opinions of other users. Parallels can be seen in the sociological literature which documents the high use of persuasive language during social movements [28]. The status messages of advocates can also contain a high degree...
of emotions both positive; when they try to generate positive feelings about their campaign, or negative; when they try to generate feelings of anger, fear, and anxiety [28].

Message strategies of advocates can also manifest across a set of status messages. For instance, advocates can concentrate their status messages around a small number of topics in their attempts at effective communication, resulting in high topical focus. Parallels can be seen in studies of campaign communications [13], which shows a widespread use of focused messaging. An advocate can also share distinctive language patterns with other advocates to support common issues and facilitate easier communication. Shared language patterns among people with similar affiliations have been shown in speech codes theory to foster easier communication [32]. Next, we present ways to model characteristics arising from persuasive language, emotions, focused messaging, and shared language patterns.

The use of persuasive language can be quantified by modeling theoretical principles of persuasion [11]. We consider two principles of reason and affinity [11] and model their occurrence. People employ reason as a rational justification for their views while persuading others. The number of words related to reason [14] in the status messages of a user is used to quantify reason. Expressions of affinity can also be used as a tool for persuasion by using words conveying liking, compliments, and association. We use social words in the LIWC corpus [31] to model expressions of affinity and count their occurrence in the messages of each user. We postulate that advocates in a use a higher number of words denoting persuasion than random users v posting on the campaign.

The emotional content in the posts of the users in u can be modeled using the positive and negative emotional words from the LIWC corpus [31]. We postulate that advocates in social media use a higher number of emotional words, both positive and negative than random users posting on an issue. A higher use of emotion can be an indication that advocates have a strong belief in their cause, which separates them from paid workers posting promotional comments for a campaign, who display fewer emotions in their posts [24].

To model the topical focus of a user in u, we first compute the topic distribution using LDA [6] on the user word matrix S. The topic model results in the user topic matrix $DT \in \mathbb{R}^{n \times t}$, where $DT_{ij}$ is the number of times a word of user $u_i$ has been assigned to topic $t_j$ and $t$ is the number of topics. To obtain the topic probability distribution, the document-topic matrix can be normalized $DT$ to obtain $DT^*$, where each row of $DT^*$ contains the probability distribution over topics of a user. The entropy of the topic distribution from the corresponding row of $DT^*$ for each user i to construct a vector $e_i$ where $e_i = \sum_{j=1}^{t} -DT^*_{ij} \log(DT^*_{ij})$. It is evident that a lower value of entropy for a user implies greater concentration on fewer topics in his messages and a higher value implies distribution over a larger number of topics. Therefore, the higher the topical focus in the status messages of a user, the lower the value of its entropy. We postulate that advocates have a higher topical focus in their messages than random users posting on the campaign.

We next model the shared language patterns among users in u and use hashtags as instances of language patterns. For each advocate $a \in a$, let $Z_{a}^{u}$ denote the amount of hashtags he shares with any other advocate $b \neq a \in a$ measured by Jaccard similarity. Similarly, let $Z_{av}$, where $v \in v$ is a random user posting on issues related to the campaign. We postulate that an advocate for a political campaign shares a higher amount of hashtags with other advocates than with random users in v posting on the campaign. We evaluate these characteristics using the datasets in Section 4.2.1.

Until now, we characterized and modeled message strategies capable of distinguishing advocates for political campaigns from random users posting on the issue like persuasive language, emotion, topical focus and shared language patterns with other advocates. We next examine characteristics of propagation strategies employed by advocates to increase the reach of these messages.

### 3.2 Quantifying Propagation Strategies

We examine the propagation strategies of advocates for political campaigns on social media, focusing on their targeting and co-propagation behavior. Social media enables advocates to target specific users for propagating information. We propose that advocates target popular users more frequently than random users posting on the campaign as popular users help to get messages across to a wider audience [15]. We then investigate how advocates assist each other in spreading their messages.

We first model the targeting behavior of the users in u. Let $r$ is the set of people targeted by all users in u as defined in Section 2. Taking the number of users connecting to a user as a measure of his popularity, we construct the vector $c$ where $c_i$ is the number of people connecting to $r_i$. We postulate that the attention of advocates is more skewed towards users with higher popularity than the attention of random users posting on the campaign. To model this postulate, we compute the vector $sta = Tc$, where $sta_i$ is the sum of number of times a user $k$ targets an user $r_i$ weighted by $c_i$, the number of users connecting to $r_i$. The value of $sta_i$ is higher if the user $k$ targets popular users a higher number of times. Therefore, our postulate is satisfied when advocates for a political campaign have a higher value of $sta$ than random users posting on the campaign.

We next model the co-propagation behavior of users in u. Advocates will be more interested in propagating messages of other advocates, and also, their messages will be more likely to be propagated by other advocates than random users posting on the campaign. Based on this, we characterize advocates by their hubs and authority scores [22] in the information propagation network $P$. We compute hubs and authority scores of users in u using the information propagation network $P$ and postulate that advocates have higher hub and authority scores than random users posting on the campaign. We evaluate these characteristics using the datasets in Section 4.2.2.

Until now, we proposed characteristics of advocates for political campaigns on social media from their message strategies and propagation strategies along with methods for modeling them. We next propose characteristics related to the community structure arising from their relationships with other advocates for the campaign.

### 3.3 Quantifying Community Structure

Community structure deals with the patterns arising from the networks formed by advocates to facilitate easier communication and coordination. Social media provides opportunities for advocates to connect to each other through many different types of relationships. Advocates can form social connections, interact with each other for coordination, and
carry out conversations. The formation of networks of social connections and interactions between advocates for commu-
nication and coordination have been studied in theoretical
studies of social movements [28]. Social connections and in-
teractions between advocates can give rise to the similarity
in community memberships. We now postulate a few under-
lying hypothesis to establish the similarity in community
memberships between advocates in social media

We first present postulates underlying community struc-
ture arising from social connections and interactions of ad-
voocates. For each advocate \( a \in A \), let \( Z^2_{ab} \) be 1 if a con-
nects to b and 0 otherwise, where b is another advocate
\( b \neq a \in A \) and \( Z^2 \) is defined in Section 2. Similarly, let
\( Z^3_{abv} \) be 1 if a connects to b and 0 otherwise, where \( v \in V \)
is a random user posting on issues related to the campaign
We then postulate that advocates are more likely to form
social connections with other advocates than with random
users posting on the campaign. We follow a similar proce-
dure using \( Z^3 \) to postulate that advocates are more likely
to interact with each other than with random users posting
on the campaign. These postulates underly that advocates
have similar community memberships for different types of
relationships. Are these community memberships of advo-
cates are similar when measured across relationship types?

To model this, we first select the users with whom the
advocates have at least one type of relation with. For each
advocate, we construct a vector \( \mathbf{co}_{ab} \), \( b \neq a \in A \), where
each element is the number of types a pair of advocates
have relations in. Similarly, we construct the vector \( \mathbf{co}_{av} \),
\( v \in V \), where each element is the number of types of rela-
tions between a pair of advocate and a random user posting
on the campaign. We postulate that given an advocate has
established one type of relation with a user, he has a sig-
nificantly higher propensity to form more types of relation
if the user is another advocate than if he is a random user
posting on the campaign. The postulate, if verified, under-
lies that community memberships of advocates are shared
across different relationship types, and hence, they can be
jointly inferred by combining different relationship types in
an efficient manner.

In this section, we draw from theoretical constructs in so-
ciological literature to propose different characterizations of
the nuanced message strategies, propagation strategies, and
community structure of advocates for political campaigns
on social media. Next, we are going to use two real-world
data sets from Twitter to evaluate these characteristics in
their ability to distinguish between advocates and random
users posting on the issue.

4. EVALUATING STRATEGIES

In this section, we describe the datasets used to evaluate
our characterizations of advocates of political campaigns in
social media. We have two datasets from Twitter, each re-
lated to a political campaign carried out using Twitter. We
then use these datasets to evaluate the ability of the pro-
posed characterizations of strategies to distinguish between
advocates for a given political campaign and random users
posting on issues related to the campaign.

4.1 Datasets

We have two datasets related each related to a political
campaign. The first dataset is focused on advocates for the
Indian election campaign. The rise of around 200 million

Table 1: Statistics of the datasets of advocates.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Elections</th>
<th>Gun Rights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total # of Users</td>
<td>9390</td>
<td>7695</td>
</tr>
<tr>
<td># of Tweets</td>
<td>20,362,442</td>
<td>19,275,481</td>
</tr>
<tr>
<td># of Links</td>
<td>514,501</td>
<td>899,535</td>
</tr>
<tr>
<td>Users posting on the campaign</td>
<td>8500</td>
<td>7000</td>
</tr>
<tr>
<td># of Advocates</td>
<td>890</td>
<td>695</td>
</tr>
</tbody>
</table>

users of social media in India has made it an important
platform for political discourse during elections [20]. Inde-
pendent groups like NaMo Brigade [8] were formed to ad-
voice for the political campaign of Narendra Modi. The
second dataset is related to the issue of gun rights in the
United States. This campaign is focused on preserving gun
rights, which is being questioned in the wake of increasing
gun-related violence. Organizations advocating to preserve
-gun rights as the National Rifles Association (NRA) have
considerable social media presence [30].

Although these organizations have a considerable media
presence, it is a challenge to obtain labels for individual users
involved in advocacy. Previous literature proposes the use of
publicly compiled lists as an effective alternative for inferring
affiliations of social media users [21]. The authors in [5] have
utilized lists in Twitter to characterize topical-identity based
groups. Informed by this literature, we identified two public
Twitter lists, titled “NaMo Brigade” [4], for advocates for
the election campaign of Narendra Modi and “NRA” [35],
for the advocates for gun rights.

To validate the datasets, we apply the mark and recapture
technique, drawing from population estimation methodolo-
dies [9]. For each of the two lists, we draw two random
samples and estimate the total number of errors in the list
as follows. Let the probability of finding errors in the ran-
don samples \( r_1 \) and \( r_2 \) be \( p_{r_1} \) and \( p_{r_2} \). The number of errors
in both the samples will then be given by \( e_{r_1} = p_{r_1}N_e \) and
\( e_{r_2} = p_{r_2}N_e \), where \( N_e \) is the total number of errors to be
estimated. The number of errors in the intersection of the
two samples is then \( e_{r1r2} = p_{r_1}p_{r_2}N_e \). The number of errors
in the dataset \( N_s \) can then be estimated as \( N_s = e_{r1} + e_{r2} - 2e_{r1r2} \).
This is shown to overestimate the population, and hence we
use a variation to estimate the number of errors as

\[
N_e = \frac{(e_{r1} + 1) \times (e_{r2} + 1)}{e_{r1r2} + 1} - 1
\]

A measure of uncertainty is given by the standard error,
which estimates of the variability of \( N \) if the above exper-
iment is conducted repeatedly. This is computed as follows

\[
SE = \sqrt{\frac{(e_{r1} + 1) \times (e_{r2} + 1) \times (e_{r2} - e_{r1r2}) \times (e_{r1} - e_{r1r2})}{(e_{r1r2} + 1)^2 \times (e_{r1r2} + 2)}}
\]

From the standard error, we then calculate the 95% con-
fidence interval i.e. the range within which the number of
errors lies with 95% certainty as \( L = N_e \pm 1.96 \times SE \), where
\( L \) is the 95% confidence interval of the error estimate.

We draw random samples of 10% of the size of the list
and use external evaluators to verify them. The evalu-
ators are asked to assess whether a user is an advocate of a
political campaign or not. The evaluators mark 1 if they think
the user is an advo-
advocates in Twitter. We collect the friends, followers, profile, and statuses of both advocates and random users posting on the campaign. From Table 2, we can see a strong evidence of the use of persuasive language by advocates in both the datasets, indicative of the attempts of advocates to sway the opinions of others. A significantly higher use of words denoting reason and affinity by advocates can be observed, demonstrating that the proposed model of persuasive language is effective. High positive and negative emotional content, which can be used to generate strong feelings about the campaign, is a strong characteristic in the tweets of advocates. This indicates that unlike workers who are paid to comment or post on a particular issue leading to a lack of emotion in their posts [24], advocates show a higher level of emotion in their messages.

A negative coefficient in the topical focus of advocates with high significance demonstrates that they concentrate their posts around fewer topics for effective messaging compared to random users posting on the campaign. In our experiments, we assign the number of topics t=20. The speech code theory states that users with common affiliations develop a common lingo to foster easier communication [32]. This is borne out by a significantly high coefficient of common hashtags, showing that advocates share higher amount of hashtags with other advocates than with random users posting on the campaign.

These observations indicate that the characterizations of message strategies drawn from theoretical constructs from sociological literature and the proposed approaches to modeling them are effective in distinguishing between advocates and random users posting on the campaign. We next evaluate the ability of the characterizations of the propagation strategies of advocates to distinguish between advocates and random users posting on the campaign.

### 4.2.2 Propagation Strategies

We first focus on the patterns arising from advocates targeting specific users, which can be performed in Twitter through the mention feature. The number of people who connect to the set of people targeted by the users in \( u \) given by \( c \) in Section 3.2 can be measured by their follower count in Twitter. We first examine if the targeting patterns of advocates differ from those of normal users posting on the issue. We plot the targeting patterns of users in Fig 2 with

#### Table 2: Evaluating strategies using logistic regression coefficients with p-value from t test ( *- p < 0.05, **- p < 0.01, ***- p < 0.0001)

<table>
<thead>
<tr>
<th>Factors</th>
<th>Features</th>
<th>Elections</th>
<th>Gun Rights</th>
</tr>
</thead>
<tbody>
<tr>
<td>Message Strategy</td>
<td>Persuasion</td>
<td>3.52*</td>
<td>6.52**</td>
</tr>
<tr>
<td></td>
<td>Liking</td>
<td>1.717***</td>
<td>1.04***</td>
</tr>
<tr>
<td></td>
<td>Entropy</td>
<td>-3.63***</td>
<td>-0.21**</td>
</tr>
<tr>
<td></td>
<td>Emotion</td>
<td>+ve 0.5731**</td>
<td>0.3669**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-ve 0.7782***</td>
<td>0.2621**</td>
</tr>
<tr>
<td>Shared Language</td>
<td>Targeting</td>
<td>3.857***</td>
<td>10.57***</td>
</tr>
<tr>
<td>Propagation Strategy</td>
<td>Hubs</td>
<td>2.91***</td>
<td>-3.185</td>
</tr>
<tr>
<td></td>
<td>Authorities</td>
<td>6.39***</td>
<td>0.51*</td>
</tr>
<tr>
<td>Community Structure</td>
<td>Following</td>
<td>1.5625***</td>
<td>0.9086***</td>
</tr>
<tr>
<td></td>
<td>Followers</td>
<td>2.045*</td>
<td>0.9554***</td>
</tr>
<tr>
<td></td>
<td>Interactions</td>
<td>1.441***</td>
<td>0.0112**</td>
</tr>
<tr>
<td></td>
<td>Multiple</td>
<td>.468***</td>
<td>4.08***</td>
</tr>
</tbody>
</table>

Figure 2: Interacting with Influencers (a) random users posting on the election campaign (\( \rho = 0.08 \)) (b) advocates for election campaign (\( \rho = 0.15 \)) (c) random users posting on gun rights (\( \rho = 0.15 \)) (d) advocates for gun rights (\( \rho = 0.20 \))

4.2 Evaluation

We now evaluate the characterizations of advocates to distinguish between advocates and random users posting on the issue using the datasets. Characterizations restricted to individual advocates such as persuasion, focus, emotion and propagation strategies are evaluated using logistic regression. The positive class is given by the advocates from the set \( a \) and the negative class consists of the random users posting on the campaign from \( v \). The regression coefficients for all the characterizations along with the significance values derived from the t-test are shown in Table 2.

Characterizations of pairwise relational patterns such as shared language and community structure are evaluated using paired t-test. We present the coefficients of the t-test along with its significance values in Table 2. We next evaluate the characterizations grouping them into message strategies, propagation strategies, and community structure.

#### 4.2.1 Message Strategies

We first evaluate the ability of characterizations of message strategies to distinguish between advocates and random users posting on the campaign. From Table 2, we can see a strong evidence of the use of persuasive language by advocates.
the log of the number of mentions on the y-axis and the log of the number of followers on the x-axis. For each plot, we fit a line to the data that minimizes the least square error in the data and its slope, $\rho$, given in the caption. A higher value of $\rho$ indicates that people with a higher number of followers are targeted more frequently.

We can see that mentioning patterns of advocates from Fig 2 that Fig 2(b) and 2(d) have a greater slope than that of random users posting on the campaign Fig 2(a) and 2(c). Advocates might target popular users as they have the potential to increase the reach of information. We model this notion in Section 3.2 and present the results in Table 2. We can say from a significantly high coefficient value of the targeting characteristic that the targeting patterns of advocates are more significantly skewed towards popular users than those of random users posting on the campaign.

We next evaluate the characterizations of co-propagation behavior of users in $u$. Fig 3 (a), (b), (c), and (d) illustrates the number of times each user has been retweeted. The logarithm of the times the user is retweeted is shown in the x-axis and the fraction of users who have been retweeted the corresponding number of times, choosing users with more than 100 tweets, on the y-axis. A larger fraction of advocates is retweeted than random users posting on the campaign.

For each user in $u$, we next compute the ratio of a number of their retweets to his total number of tweets. The retweet ratio is plotted on the x-axis and the fraction of users with the retweet ratio on the y-axis, choosing users with more than 100 tweets, in Fig 3 (e), (f), (g), and (h). A similar pattern can be observed, where the retweet ratio of random users posting on the campaign follows a power law distribution and those of advocates have a skewed distribution with a higher fraction of users actively involved in information propagation. These observations are reflected in Table 2, in the effectiveness of hubs and authority scores for distinguishing advocates and random users posting on the campaign.

These observations indicate that the proposed characterizations of propagation strategies drawn from sociological theories and approaches for modeling them can effectively distinguish between advocates and random users posting on the campaign. We next evaluate the ability of the characterizations of the community structure in their ability to distinguish between advocates for political campaigns and random users posting on the campaign.

### 4.2.3 Community Structure

We first evaluate the characteristics of social relationships of advocates. From Table 2, we can see that advocates tend to connect with each other significantly more than with random users posting on the topic. This indicates advocates are utilizing social media to build a strong network of connections with each other. Advocates interact significantly more with other advocates for the campaign than with random users posting on it, indicating that they maintain a high level of interactions with each other. These provide evidence of a community structure between advocates.

We next examine if advocates tend to establish multiple types of relationships with each other. From Table 2, we see that given an advocate has established one type of relation with a user, he has a significantly higher propensity to form multiple types of relation if the user is another advocate than if he is a normal user posting on the campaign. These results indicate a strong network of social connections and interactions between advocates, verifying our postulates. This also provides a basis to infer jointly community membership of users across different relationship types.

Until now, we proposed a set of characteristics capable of effectively distinguishing between advocates and random users posting on the issue. The set of characterizations include both individual characteristics from their messages and propagation strategies and multiple relational patterns like social connections, shared content patterns, and interactions, forming a heterogeneous feature space. We next design a mathematical formulation to combine individual and multiple pairwise characteristics in a unified framework to identify advocates for a political campaign.

### 5. A UNIFIED MODEL

Integration of individual and relational characteristics in a unified homogenous space for classification can be performed by deriving latent variables from the relational matrix [36].
A difference here is that we have multiple types of pairwise relations between users, and we need to derive latent dimension memberships by jointly exploiting pairwise connections across multiple types of relations. Individual characteristics can be then be combined with the latent variables derived from the relational characteristics to construct features for classification.

Let the proposed individual characteristics be denoted as $I$ and the relational characteristics be arranged in a tensor $Z$ as defined in Section 2. Tensors have been used in literature to analyze jointly multi-modal relationships in applications such as community detection [26] and link prediction [12]. We first factorize the tensor $Z$ to derive latent dimension memberships from the relational characteristics. Different types of connections between two users can be captured by their similarity in their memberships of latent dimensions. Two users who have pairwise relationships with each other across different types will have higher similarity in their latent dimension memberships than two users who do not have pairwise relationships with each other.

We factorize the tensor $Z$ to obtain the user matrices $U \in \mathbb{R}^{N \times K}$ and $V \in \mathbb{R}^{N \times K}$, and the relationship type dimension matrix $T \in \mathbb{R}^{T \times K}$, where $K$ is the number of latent dimensions, by solving the following optimization problem

$$\min_{U,V,T} ||Z - [U,V,T]||_F^2,$$  

(3) where $[U,V,T] \in \mathbb{R}^{N \times N \times T}$ is given by

$$[U,V,T] = \sum_{k=1}^{K} u_k \circ v_k \circ t_k.$$  

Here $u_k$, $v_k$, $t_k$ are the $k^{th}$ column vectors of $U$, $V$ and $T$ respectively. The symbol $\circ$ represents the vector outer product such that if the tensor $Y = u_k \circ v_k \circ t_k$ then $Y_{efg} = (u_k)_e(v_k)_f(t_k)_g$. Substituting this in Eqn 3, we get

$$f = \min_{U,V,T} ||Z - \sum_{k=1}^{K} u_k \circ v_k \circ t_k||_F^2.$$  

(4) We optimize this function motivated by the conjugate linear optimization method [1]. We first arrange the vectors $u,v$ and $t$ in a single vector $x = [u,v,t]$ and calculate the gradient of $f(x)$ with respect to each $x_k^m$ where $x^1 = u, x^2 = v, x^3 = t$. $f$ can be rewritten as

$$f = \frac{1}{2} ||Z||^2 - (\sum_{k=1}^{K} ||u_k \circ v_k \circ t_k||^2) + \frac{1}{2} ||\sum_{k=1}^{K} \sum_{m=1}^{m} u_k^m \circ v_k^m \circ x_k^m||^2$$

(5) The gradient of $f$ is obtained by computing its partial derivative with respect to each element in $x$ denoted by $x_k^m$. So

$$\frac{\partial f_1}{\partial x_k} = 0,$$  

(6) as $Z$ is a constant with respect to $x_k^m$. The partial derivative of $f_2$ with respect to each element in $x$ denoted by $x_k^m$ can then be computed as follows.

$$\frac{\partial f_2}{\partial x_k^m} = Z \times u_k^m \times v_k^m,$$  

(7) where $\times_m$ is the n-mode multiplication operator as defined as Section 2. The partial derivative of $f_3$ with respect to each term in $x$ denoted by $x_k^m$ can be computed as

$$\frac{\partial f_3}{\partial x_k^m} = \sum_{j=1}^{K} \prod_{r=1}^{r} x_j^r x_k^m,$$  

(8) The overall gradient can then be computed as

$$\frac{\partial f}{\partial x_k^m} = \frac{\partial f_1}{\partial x_k^m} + \frac{\partial f_2}{\partial x_k^m} + \frac{\partial f_3}{\partial x_k^m}$$  

(9) where $\frac{\partial f_1}{\partial x_k^m}$, $\frac{\partial f_2}{\partial x_k^m}$, $\frac{\partial f_3}{\partial x_k^m}$ are as described in Eqn 6, Eqn 7 and Eqn 8 respectively. The gradient descent step repeated for all values of $m$ and $k$ is continued until convergence. As the objective function in Eqn 4 is convex, the optimization is guaranteed to converge. The computational complexity of the iterations is low due to the high sparsity of $Z$.

To give an intuitive understanding of the optimization term in Eqn 4, we rewrite it as follows

$$\min_{U,V,T} \sum_{t=0}^{T} ||Z_t - UD_t V_t^T||_F^2,$$  

(10) where $Z_t$ represents the user relations of type $t$ and $D_t \in \mathbb{R}^{K \times K}$ is a diagonal matrix whose diagonal elements are the $t^{th}$ row of $T$. The matrices $U$ and $V$ contains the latent dimension memberships of users jointly inferred across different relationship types. If $Z_t/t$ is symmetric then $U = V$. The matrix $T$ contains the contribution of each relation type to different dimensions. For example, a high value of $T_2$ signifies that high-scoring users in $u_2$ form connections with high-scoring users in $v_2$ through relationship type 2. The latent features representing different kinds of pairwise relationships between users can be obtained from any linear combination of $U$ and $V$. For our experiments, we use $L = U + V$ after column normalization as latent features. We combine the individual characteristics $I$ and the latent features $L$ to construct a feature set $F = \{I, L\}$ for identifying advocates for political campaigns in social media.

### 6. IDENTIFYING ADVOCATES

In this section, we evaluate the performance of our framework by answering the following questions. How effective is our framework for identifying advocates for political campaigns on social media? How good are the characteristics group in identifying advocates? How robust is the proposed framework for variation in training sizes?

#### 6.1 Performance Evaluation

We classify the feature set derived in Section 5 using Linear Discriminant Analysis and perform 10-fold cross validation to evaluate the performance of the framework in identifying advocates. We measure the performance using two metrics, AUC, and F1-measure and present the results in

<table>
<thead>
<tr>
<th>Method</th>
<th>Elections AUC</th>
<th>Elections F1</th>
<th>Gun Rights AUC</th>
<th>Gun Rights F1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>0.4983</td>
<td>0.1607</td>
<td>0.5053</td>
<td>0.1536</td>
</tr>
<tr>
<td>Retweet Ratio</td>
<td>0.5804</td>
<td>0.1797</td>
<td>0.5078</td>
<td>0.1118</td>
</tr>
<tr>
<td>Volume</td>
<td>0.6830</td>
<td>0.2406</td>
<td>0.6519</td>
<td>0.2332</td>
</tr>
<tr>
<td>Bag of Words</td>
<td>0.7379</td>
<td>0.3515</td>
<td>0.7305</td>
<td>0.2919</td>
</tr>
<tr>
<td>Combine</td>
<td>0.7599</td>
<td>0.3604</td>
<td>0.7480</td>
<td>0.3065</td>
</tr>
<tr>
<td>Our Method</td>
<td>0.9301</td>
<td>0.6341</td>
<td>0.9431</td>
<td>0.6046</td>
</tr>
</tbody>
</table>
We compare the performance of the baselines and the proposed framework and illustrate the results in Table 3. Random assignment gives an AUC value of around 0.5 and the F1 measure is low for both the datasets indicating the difficulty of the problem. The retweet ratio is used to characterize the propagating behavior of biased users in [27]. We model a wider range of propagation strategies advocates employ in social media, and as we can see from Table 4, where our characterizations of propagation strategies outperform the retweet ratio. From Table 3, we see that advocates are more active than random users posting on the campaign. We model specific patterns in the messages based on the strategies of advocates and hence outperform this baseline that considers only the total number of messages.

The “Bag of Words” performs better than the other baselines, but the number of features here is high. We model specific strategies of advocates related to the message, propagation and community structure instead of using all the posted words, enabling us to outperform this baseline. Combining all the baselines gives a slight improvement in the performance, indicating the potential benefits of integrating heterogeneous information. The proposed framework outperforms the baselines demonstrating that it effectively models and integrates characteristics useful for identifying advocates for political campaigns. This signifies the ability of the framework in understanding the strategies and model them to effectively to identify advocates. We perform the t-test between the results of our framework and the baselines and find that the difference is significant.

In summary, we can say that our framework outperforms the baselines demonstrating that it effectively models and integrates strategies useful for identifying advocates for political campaigns. We next analyze the contributions of different characteristic groups in identifying advocates.

### 6.2 Contributions of Characteristic Groups

We separately select characteristics related to message strategies, propagation strategies, and community structure and present them to the classifier. We compare the performance of different characteristic groups in identifying advocates using AUC and F1 measure with 10-fold cross validation and illustrate the results in Table 4.

We first examine the performance of message strategies by combining individual characteristics and the latent features from shared content. From Table 4, we can see that the characterizations of message strategies like persuasion, emotion, focus, and shared linguistic patterns outperform random characteristics by a significant margin. This demonstrates that proposed characterizations of messages strategies contribute significantly in identifying advocates.
their content [24], predominant use of URLs [25] and lack of

25]. Paid workers are detected by less use of emotion in

for a product, has generated considerable interest [24, 10, 

paid crowdsourced workers are used to post advertisements

on identifying individual advocates. Crowdturfing, where

been studied in [23] and the authors here do not concentrate

ing campaigns from social media using textual similarity has

ceived considerable attention in literature [18, 23]. Extract-

identify individual advocates.

ganizations in social media, but do not propose models to

a qualitative understanding of the activities of advocacy or-

groups were studied in [7], and they link behaviors such as

ming user communities and call for action were found to be

their principal objectives. The behavior of advocacy groups

during crises was investigated in [38], and the role of social

media in organizing and distributing work related to rescue

operations was discussed. The Facebook pages of advocacy

groups were studied in [7], and they link behaviors such as

network activity and query responses by advocacy groups to

the extent and growth of their network. These works provide

a qualitative understanding of the activities of advocacy or-

ganizations in social media, but do not propose models to

identify individual advocates.

The use of social media to carry out campaigns has re-

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25]. Paid workers are detected by less use of emotion in

their content [24], predominant use of URLs [25] and lack of

interaction with other users [10]. We find that advocates

in social media have high emotional and textual content in

their messages and show strong communication among

themselves. Substantial work has been done on the behav-

ior of opinion leaders [3] in social media. Any social media

user can try to advance an agenda on an issue without nec-

essarily being an opinion leader.

Researchers have studied the spread of political misin-

formation [33] by identifying malicious links that spread

through social networks. We are interested in individual

users who are advocating for an issue, and they need not

necessarily spread misinformation. The behavior of social

media users with bias on a given political issue have been

studied in [27]. The paper identifies users who consistently

retweet messages from users with a particular viewpoint. We

aim to identify users who actively try to advance an agenda

that manifests in their distinct strategies.

Substantial efforts have been made to identify attributes

of social media users to give an additional context to their

posts. The properties of social relationships is shown to be

beneficial in identifying user attributes across social media

sites [40]. Researchers have worked on identifying political

orientations of users from their retweets [39] and network

connections [2]. The architecture of a web-based system to

aggregate profile attributes of a user drawn from diverse so-

cial media platforms is described in [16]. These works focus

on inferring different personality attributes of social media

users but do not determine whether a user is an advocate

for a political campaign on social media.

7. RELATED WORK

We present the related work in three categories: the study

of advocacy groups in social media, the use of social media
to carry out campaigns and identification of attributes of

social media users. We next survey each of them in detail.

Advocacy in social media has received considerable atten-
tion in the recent sociological literature. Obar et.al [29] sur-
veyed advocacy organizations to analyze their social media

use and stated that the ability of social media to facilitate
civic engagement and foster collective action is the primary

motivations. The Twitter use of nonprofit organizations was

studied in [17]; communicating relevant information, build-
ing user communities and call for action were found to be

their principal objectives. The behavior of advocacy groups

during crises was investigated in [38], and the role of social

media in organizing and distributing work related to rescue

operations was discussed. The Facebook pages of advocacy

groups were studied in [7], and they link behaviors such as

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for a political campaign on social media.

8. CONCLUSIONS

In this paper, we present a framework to identify advo-
cates for political campaigns on social media. We character-
ize advocates through their message strategies, propagation

strategies, and community structure and propose different

characterizations based on them. We integrate heteroge-

neous information derived from these diverse characteriza-
tions and demonstrate that the framework can identify ef-
f ectively advocates for political campaigns on social media.

We analyze contributions of individual characteristic groups

like message strategies, propagation strategies, and commu-
nity structure in identifying advocates. Finally, we evaluate

the performance of the framework for different proportions

of training sizes and demonstrate that the framework is ro-
bust to variation in training data size. This research is in a

step towards informing users before they imbibe information

from these accounts and also enabling campaign managers
to identify advocates to assist in digital political campaigns.

Future work can consider the detection of groups of peo-
lple involved in advocacy in social media drawing from com-

munity detection methods. Advocates might use strategies

other than those studied here, and investigation into the

strategies will increase the understanding of their behavior.

The impact of advocates on meme popularity in social media

is an interesting area of future research and can give insight

on the impact of their activities. Studying information seek-
ing patterns among social media advocates of a particular

political campaign can give interesting insights into interac-
tions among members of social communities. Finally, study-
ing the evolution of the behavior and interaction networks

of advocates can provide information about the process of

community formation in online social media.
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10. REFERENCES