# Unsupervised Models for Predicting Strategic Relations between Organizations

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***Abstract*—Microblogging sites like Twitter provide a platform for sharing ideas and expressing opinions. The widespread popularity of these platforms and the complex social structure that arises within these communities provides a unique opportunity to understand the interactions between users. The political domain, especially in a multi-party system, presents compelling challenges, as political parties have different levels of alignment based on their political strategies. We use Twitter to understand the nuanced relationships between differing political entities in Latin America. Our model incorporates diverse signals from the content of tweets and social context from retweets, mentions and hashtag usage. Since direct communications between entities are relatively rare, we explore models based on the posts of users who interact with multiple political organizations. We present a quantitative and qualitative analysis of the results of models using different features, and demonstrate that a model capable of using sentiment strength, social context, and issue alignment has superior performance to less sophisticated baselines.**

## I. Introduction

Social media platforms have the potential to revolutionize our understanding of the nuanced interactions and relationships between organizations. In many cases, social media services are the primary channel for both individuals and organizations to communicate ideas, share opinions, promote resources, and report on events. In addition to the content in social media posts, there is a similarly rich set of social relationships between the users of the service. Combining signals from the content and social connections of users promises to provide a deeper understanding of how users relate to each other and the views they hold.

In this paper, we focus on determining political relationships using microblogging data from Twitter. Microblogging data has a number of appealing characteristics that make it ideal for social network analysis. The accessibility of the platform from diverse devices results in frequent and open posting and provides copious data for analysis. Microblogging sites encourage terse posts, leading to direct statements that provide a clearer understanding of user intent. In addition to textual content, microblogging sites frequently include explicit social cues, including following other users, rebroadcasting user posts ('retweeting'), replies to user posts, and mentioning users associated with a topic.

Models that integrate both social network and user content using microblogging posts are an area of active research. Diverse approaches, including understanding information propagation/diffusion, measuring emotional contagion [1], analyzing sentiment using related tweets [2], and forecasting events [3] have shown the importance of both the social network and user content. In this paper, we present a novel framework for analyzing microblogging data focused on the political domain.

The political sphere emphasizes how social media has resulted in unprecedented changes in human behavior. Many political and religious organizations disseminate information via Twitter. Leaders including the Pope, the Ayatollah of Iran, and presidential candidate Donald Trump all have an active presence on Twitter. This social media presence often has a strong influence on political evolution. A key element of politics is cultivating large groups of followers and building coalitions among groups; politicians and political organizations reach this audience and consolidate power by communicating through this novel medium. For example, the rise of Donald Trump in the US politics is often attributed to his copious use of provocative Twitter posts [4], and he even officially announced his running mate via Twitter. As a result, our effort at understanding this complex process opens up a new perspective on the politics of mass communication.

The analysis of political discourse on Twitter shows great promise, but also presents novel modeling challenges. The magnitude of social media data deters manual analysis and labeling, encouraging computational approaches to network analysis. However, the relationships among political leaders and organizations are extremely nuanced. Organizations may support or oppose one another to varying degrees, adopt differing political strategies, or agree on some issues and disagree on others. We refer to this complex alignment between

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political entities as a *strategic relationship*. Determining these complex strategic relationships from social media data using computational models can be difficult.

We identify three key challenges facing models that infer strategic relationships. First, models must be able to capture the diversity of relationships between political entities. In particular, models should be able to determine the *type* of relationship and its *strength*. Second, models must be capable of understanding strategic relationships in terms of *issues* that each organization advocates or opposes. Third, models must incorporate *social context*, determining strategic relationships between two organizations by incorporating social connections with users and other organizations.

In this paper we propose a model that addresses all three challenges. Our model identifies two types of strategic relationships, allies and adversaries, and provides a strength for each relationship type. We capture organizational alignment towards issues both explicitly, through hashtag usage, and implicitly, using topic models, and incorporate these alignment features when determining strategic relationships. Finally, our model integrates social context (reciprocity/transitivity between organizations and user-organization associations) to collectively reason about strategic relationships between different organizations.

The task we describe requires a modeling approach that fulfills a number of criteria. First, the model must produce continuously-valued outputs to capture the strength of strategic relationships. Second, it should be able to incorporate a wide variety of features, including those from natural language processing. Finally, it should be capable of collective reasoning to capture the complex interactions of strategic relationships. To address all of these criteria, we use a probabilistic modeling tool, Probabilistic Soft Logic (PSL) [5]. PSL uses a first-order logic syntax that is translated into a joint probability distribution over possible worlds of strategic relationship strengths.

The remainder of the paper is organized as follows: Section 2 talks about the related work in this area, in Section 3, we describe the dataset in detail. A brief overview of PSL is given in Section 4, followed by a detailed description of our models in Section 5. Section 6 details the experimental setup and the results of our empirical evaluation.

## II. Related Work

Social media has become an integral part of our daily routines, and it has become very useful and increasingly important to analyse and understand them. There have been many efforts in mining, analysing and making sense of social media data, and specifically micro-blogging sites like twitter to understand opinions and sentiments of users. This paper mainly focuses on inferring relationships between organizations (individuals or groups), hence, given this vast field of research, we will only focus on the work closest to ours in this area.

### A. Sentiment Analysis

Sentiment analysis has been a huge area of research, especially in social media data. To point out a few, Jiang et al. [2] have worked on target dependent sentiment classification, where they classify the sentiment of a tweet towards a given query. They also use a graph based approach to build a graph of tweets related to input tweet collection, consisting of retweets, replies and those published by the same user. Xiang et al. [6] show that clustering tweets based on topic and analysing sentiment on these clusters can help improve sentiment predictions. Qadir et al. [7] present interesting work on learning hashtags and hashtag patterns associated with five nuanced emotions(anger, fear, affection, joy and disappointment), using bootstrapping methods. These works mostly focus on modeling the sentiment of the tweet, while in this work, we use sentiment to model strategic relationships.

### B. Topics, events and sentiment

There has also been extensive work analysing social media data, to identify, extract and forecast events. Ramakrishnan et al. [8] build a system to forecast civil unrest across ten Latin American countries, by using tweets, news sources, blogs and other data sources. Chierichetti et al. [9] analyze Twitter stream to automatically discover events and the behavior of users around the time of such events.

There is also a rich literature on identifying 'topics' of interest in tweets and also analyzing the attitudes of users towards different topics. Ferrara et al. [10] perform social media analysis based on sentiment, investigating the effect of sentiment on information diffusion, and observing that negative conversations spread faster than positive conversations, but positive messages reach a larger audience. Gao et. al [11] have studied inferring a user's attitude towards controversial topics in social media. They jointly model three aspects of users' attitude towards a topic or an issue, sentiment, opinion and action (retweet/posting a tweet) and provide explanation to user's actions and sentiments using opinions. Weng et al. [12] try to detect communities in the hashtag co-occurrence network to model user interests towards topics, that could be diverse or focused based on their hashtag usage.

However, most of these works look at attitudes of individual users, whereas we try to address the issue of finding relationships between different users by modeling their interests and opinions on topics and issues.

### C. Inferring relationships

O'Connor et al. [13] extracted and modeled events to detect and infer international relations.

The closest work to this paper is work by Chambers et al. [14] on identifying political sentiment between nation states. In this work, they focus on contextual sentiment analysis and try to model the sentiment of a tweet with respect to a specific nation mentioned in the tweet. Our work is more focused on using political issues and incorporating social context, in the form of posts by users, retweets, hashtags, mentions, etc. in the Twitter network to identify relationships.

### D. Probabilistic Soft Logic

PSL, a framework for collective, probabilistic reasoning [5] has been used in various relational domains. In the political domain, Huang et al. [15] model group affiliations of social media users by analysing hashtags, posts and sentiment in Twitter. Sridhar et al. [16] in their work, reason about author level or post level stance and disagreement in debate forums, jointly. Ramakrishnan et al. [8] also use PSL for location prediction to forecast events of civil unrest.

## III. Dataset

The dataset consists of a collection of tweets from May 2012 to December 2014. We focus on the political organizations of Latin America that include individual politicians and political groups, that could include media groups, activists, etc. Based on a collaboration with researchers at Virginia Tech and political scientists at UC San Diego and San Diego State University, we identified a set of 63 organizations mainly from Latin American countries including Venezuela, Columbia, Mexico, Argentina and Chile. The tweets were collected using the Twitter API, based on these organizations of interest, i.e., all tweets *mentioning* these organizations, and tweets that are *posted* by these organizations. Approximately 6.9 million tweets were collected, of these about 10,400 tweets by the organizations, with the remaining tweets containing mentions of these organizations by users.

The dataset has various fields such as time of tweet, whether the tweet is a retweet or an original post, language, mentions (a list of names and corresponding ids of users who are mentioned in the tweet) and geolocation of the tweet. The dataset also has details of users who posted/retweeted a tweet; user location, status count, number of followers, number of friends and klout score (representing a user's influence on Twitter as a score between 1-100). Every tweet is enriched with features extracted from the text using BASIS technology[1], including features like part of speech tags, lemmas, normalized date expressions, noun phrases, named entities and so on. Most of the tweets are also associated with a sentiment score, ranging between -24 to 24, computed by Datasift[2].

## IV. Probabilistic Soft Logic (PSL)

*Hinge-Loss Markov Random Fields (HL-MRFs)* [17] are a class of continuous, conditional graphical models that can be used to model complex interactions, in our case, between users and organizations. A hinge-loss Markov Random Field over random variables $\mathbf{Y}$ conditioned on $\mathbf{X}$ defines a probability density function of the form below:

$$P(\mathbf{Y}|\mathbf{X}) \propto \exp\Big(-\sum_{r=1}^{M} \lambda_r \phi_r(\mathbf{Y},\mathbf{X})\Big) \tag{1}$$

[1]http://www.basistech.com/
[2]http://datasift.com

where $\phi_r(\mathbf{Y},\mathbf{X})$ is a *hinge-loss potential* corresponding to an instantiation of a rule, defined by:

$$\phi_r(\mathbf{Y},\mathbf{X}) = (\max\{l_r(\mathbf{Y},\mathbf{X}),0\})^{\rho_r} \ , \tag{2}$$

and is specified by a linear function $l_r$ and optional exponent $\rho_r \in \{1,2\}$.

These models are highly scalable, and can be specified using *Probabilistic Soft Logic (PSL)* [5], a weighted first order logical templating language. An example of a PSL rule is

$$\lambda : P(a) \wedge Q(a,b) \rightarrow R(b),$$

where *P*, *Q*, and *R* are predicates, *a* and *b* are variables, and $\lambda$ is the weight associated with the rule.

Using the HL-MRF model, we can encode domain knowledge, network structure and dependencies among the predicates and is hence very suitable in modeling social networks. In addition, the continuous values help in representing the confidence of predictions.

Consider the following example of a positive tweet T. The associated predicates that are included in our models are described below. *"@EPN: Quiero ser el presidente que le de estabilidad economica a la poblacin. @EPN #ConPeaMexicoVaAcambiar"* (translated to: "*I want to be the president that gives economic stability to the population. @EPN #ConPeaMexicoVaAcambiar*". This can be encoded with the following predicates (these predicates are fully observed) with their associated *values* shown in Table I:

TABLE I
PSL PREDICATES

| **PSL Predicates** |
|---|
| 1.0 : USERPOSTED(*EPN*, T) |
| 1.0 : MENTIONS(T, *EPN*) |
| 1.0 : HAS_HASHTAG(T, *ConPeaMexicoVaAcambiar*) |
| 0.9 : POSITIVE(T) |
| 0.1 : NEGATIVE(T) |

## V. Strategic Relation Identification Models

In this section we describe three types of models for predicting strategic relationships between organizations. The first class of models uses only direct interactions between organizations, such as mentions and retweets. The second class of models incorporates social context, by adding collective rules for reciprocity and transitivity between organizations as well as extracting patterns of support from users that interact with the political organizations. The third class of models attempts to identify issues or topics where organizations have similar or opposing views.

### A. Direct Interaction Models

*1) Baseline Model:* We first constructed a simple baseline model, which we refer to as the *Aggregate model*, for predicting the strategic relationship between organizations. In this model, we aggregate all of the tweets between organizations,

TABLE II
MODEL 1: ORGANIZATION RETWEET MODEL

| PSL RULES FOR ORGANIZATION RETWEET MODEL |
|---|
| $\text{ORGPOSTS}(T, \text{ORGA}) \wedge \text{MENTIONS}(T, \text{ORGB}) \wedge \text{POSITIVE}(T) \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY})$ |
| $\text{ORGPOSTS}(T, \text{ORGA}) \wedge \text{MENTIONS}(T, \text{ORGB}) \wedge \text{NEGATIVE}(T) \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ADVERSARY})$ |
| $\text{RETWEETS}(\text{ORGA}, \text{ORGB}) \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY})$ |

TABLE III
MODEL 3: USER-ORGANIZATION MENTION MODEL

| PSL RULES FOR USER-ORGANIZATION MENTION MODEL |
|---|
| $\text{USERRETWEETSORG}(U, \text{ORGA}) \rightarrow \text{SUPPORTS}(U, \text{ORGA})$ |
| $\text{USERPOSTS}(T, U) \wedge \text{MENTIONS}(T, \text{ORGA}) \wedge \text{POSITIVE}(T) \rightarrow \text{SUPPORTS}(U, \text{ORGA})$ |
| $\text{USERPOSTS}(T, U) \wedge \text{MENTIONS}(T, \text{ORGA}) \wedge \text{NEGATIVE}(T) \rightarrow \text{NOTSUPPORTS}(U, \text{ORGA})$ |
| $\text{SUPPORTS}(U, \text{ORGA}) \wedge \text{SUPPORTS}(U, \text{ORGB}) \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY})$ |
| $\text{NOTSUPPORTS}(U, \text{ORGA}) \wedge \text{SUPPORTS}(U, \text{ORGB}) \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ADVERSARY})$ |

and analyze their overall sentiment. A tweet posted by an organization that mentions another organization is a powerful indicator of the type of interaction and relationship between the two. In this model, we aggregate all tweets where one organization mentions another. For each of the tweets in this set, we use the sentiment scores to determine its polarity. A simple frequency-based approach is used to determine the strategic relationship: if there are more tweets with positive sentiment than negative, then we label the posting organization as an ally of the mentioned organization. When the majority of tweets have negative sentiment, we infer the strategic relationship of adversaries. Note that our baseline model does not meet one of the important modeling goals, assessing the strength of strategic relationships, and instead outputs a single binary classification.

*2) Organization Mention Model (PSL_OrgMention):* To improve upon the baseline model, we introduce a simple model that uses PSL to infer the strength of strategic relationships. Like the baseline, it uses the sentiment of tweets where one organization mentions another. In contrast to the baseline, this model outputs a soft truth value for each strategic relationship, producing a real-valued output instead of a binary label.
The mention rule,

$$\text{ORGPOSTS}(T, \text{ORGA}) \wedge \text{MENTIONS}(T, \text{ORGB}) \wedge \text{POSITIVE}(T) \\ \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY})$$

states that if an organization A mentions an organization B in a tweet, and the tweet has positive sentiment, then the two organizations are more likely to be allies. Similarly if the tweet expresses a negative sentiment, then the organizations are more likely to be adversaries. While our original model used all mentions, a stronger signal of organizational alignment is the use of retweets. By rebroadcasting a post, an organization often indicates a deeper level of support. We introduce additional rules for retweeted posts, and treat them as a stronger form of evidence for strategic relationships.

*3) Organization Retweet Model (PSL_OrgRetweet) :* In addition to mentions, retweets provide valuable information to infer relationships between users. If a user retweets the post of another user, we assume a positive interaction between the two. These facts are used, along with the sentiment score of the tweet to determine the strategic relationship between two organizations. Table II lists the rules used in this model. The retweet rule,

$$\text{ORGRETWEETSORG}(\text{ORGA}, \text{ORGB}) \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY})$$

states that if an organization A retweets an organization B in a tweet, then the two organizations are more likely to be allies.

### *B. Social Context Models*

*1) Organization Retween Model With Social Context (PSL_OrgRetweet + Context):* One simple extension to our existing model of direct organization interactions is to introduce basic elements of social context. One such element is reciprocity, the idea that organizations are mutually allies or adversaries. We encode this idea with the rule:

$$\text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY}) \rightarrow \text{RELATION}(\text{ORGB}, \text{ORGA}, \text{ALLY})$$

*2) User-Organization Mention Model (PSL_UserMention):* So far, the previous model used the interaction between the organizations alone to determine their relationship. Twitter has a very rich network: an organization can have followers, users mentioning them, tweets can also have hashtags associated with the organizations. This model uses the information about the users possibly associated with the political organizations of interest, to determine the relation between the organizations.

The model tries to capture the latent association between the user and organization (we do not consider the direct interaction between the organizations). The model uses mentions (based on the organization mention model) to capture the latent support of the user towards the organization:

$$\text{USERPOSTS}(T, U) \wedge \text{MENTIONS}(T, \text{ORGA}) \\ \wedge \text{POSITIVE}(T) \rightarrow \text{SUPPORTS}(U, \text{ORGA})$$

TABLE IV
MODEL 3: USER-ORGANIZATION HASHTAG MODEL

| **PSL RULES FOR USER-ORGANIZATION HASHTAG MODEL** |
|---|
| $\text{USERRETWEETSORG}(U, \text{ORGA}) \rightarrow \text{SUPPORTS}(U, \text{ORGA})$ |
| $\text{USERPOSTS}(T, U) \wedge \text{MENTIONS}(T, \text{ORGA}) \wedge \text{POSITIVE}(T) \rightarrow \text{SUPPORTS}(U, \text{ORGA})$ |
| $\text{USERPOSTS}(T, U) \wedge \text{MENTIONS}(T, \text{ORGA}) \wedge \text{NEGATIVE}(T) \rightarrow \text{NOTSUPPORTS}(U, \text{ORGA})$ |
| $\text{USERPOSTS}(T, U) \wedge \text{HASHTAG}(T, H) \wedge \text{POSITIVE}(T) \wedge \text{SUPPORTS}(U, \text{ORGA}) \rightarrow \text{ORGLIKESHASHTAG}(\text{ORGA}, H)$ |
| $\text{USERPOSTS}(T, U) \wedge \text{HASHTAG}(T, H) \wedge \text{NEGATIVE}(T) \wedge \text{SUPPORTS}(U, \text{ORGA}) \rightarrow \text{ORGDISLIKESHASHTAG}(\text{ORGA}, H)$ |
| $\text{ORGLIKESHASHTAG}(\text{ORGA}, H) \wedge \text{ORGLIKESHASHTAG}(\text{ORGB}, H) \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY})$ |
| $\text{ORGLIKESHASHTAG}(\text{ORGA}, H) \wedge \text{ORGDISLIKESHASHTAG}(\text{ORGB}, H) \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ADVERSARY})$ |

i.e, if a person positively mentions an organization in his tweet, then he is more likely a supporter of the organization. Similarly, if he mentions the organization negatively, he is more likely a non-supporter. Another important factor as discussed previously are retweets, and we encode these as :

$$\text{USERRETWEETSORG}(U, \text{ORGA}) \rightarrow \text{SUPPORTS}(U, \text{ORGA})$$

Table III shows the PSL rules used in this model. The rule,

$$\text{SUPPORTS}(U, \text{ORGA}) \wedge \text{SUPPORTS}(U, \text{ORGB}) \\ \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}), \text{ALLY})$$

encodes the knowledge that if a user supports both organizations A and B, A and B are likely to be allies.

*3) User-Organization Hashtag Model (PSL_UserHashtag):* One of the approaches to defining a topic in case of twitter, is using hashtags. Since tweets are of very short length, hashtags form an important means of expressing opinions. Hashtags define a common theme or topic, that other users can use and provide valuable information about the current trending event and the emotion of a tweet. In this model, we extend the user-organization association model by capturing the latent 'likes' and 'dislikes' of the organization towards the hashtags, similar to the work by Huang et al. [15]. The rule below tries to model this association.

$$\text{USERPOSTS}(T, U) \wedge \text{HASHTAG}(T, H) \wedge \text{POSITIVE}(T) \\ \wedge \text{SUPPORTS}(U, \text{ORGA}) \rightarrow \text{ORGLIKESHASHTAG}(\text{ORGA}, H)$$

i.e., if the user posts a positive tweet containing a hashtag H, and the user is a supporter of A, then it is likely that A is positively associated with the hashtag H.
Further,

$$\text{ORGLIKESTAG}(\text{ORGA}, H) \wedge \text{ORGLIKESTAG}(\text{ORGB}, H) \\ \rightarrow \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY}),$$

if two organizations A and B, like the same hashtags, they are more likely to be allies, and adversaries otherwise. Table IV gives the PSL rules for this model.

### C. Issue-based Models

*1) Organization Topic Model (PSL_TopicSentiment):* Extracting strategic relationship type between political organizations becomes very interesting and hard, especially because political organizations tend to agree on some issues, but are against each other on other issues. In this model, we attempt to capture these 'topics' in the tweet, and based on the sentiment of the organizations towards these topics, they can be allies or adversaries. Commonly, topic models like Latent Dirichlet Allocation (LDA) [18] that identify latent themes from text documents, have been successfully used to discover topics in news documents, debate forums, to identify 'aspects' in product reviews, etc. On the other hand, tweets are very short texts and unlike other documents, a single tweet is more likely to talk about a single topic. Hence traditional topic models are not very applicable to tweets. We use Twitter LDA [19] developed specifically for tweets to extract topics.

Table V describes the Organization-Topic model. The model uses two latent variables - LikesTopic and DislikesTopic to encode an organization's affinity towards a topic, that can be used to derive the relationship between the organization pairs.

$$\text{LIKESTOPIC}(\text{ORGA}, P) \wedge \text{LIKESTOPIC}(\text{ORGB}, P) \rightarrow \\ \text{RELATION}(\text{ORGA}, \text{ORGB}, \text{ALLY})$$

## VI. EXPERIMENTAL SETUP

In this section, we describe the experimental set up and feature-extraction techniques for the models discussed above.

### A. Dataset and Labels

The dataset consisted of 6.95 million tweets posted by and mentioning 63 organizations. Based on a collaboration with political scientists, who are experts at Latin American politics, the organization pairs were labeled with 'ally' and 'adversary' labels. Twenty-two pairs of organizations, involving nineteen unique organizations were identified with the above labels. The remaining pairs, which were either unrelated or did not have a definitive relationship, were excluded from our experiments. Among the nineteen organizations, Diosdado Cabello R, Hugo Chavez, Henrique Capriles and Nicolas Maduro are from Venezuela, six from Mexico (Enrique Peña Nieto, José Angel Córdova, Patricia Espinosa, Elba Esther Gordillo, Andrés Manuel Lõpez Obrador and Jose Meade), two from Columbia (Alvaro Uribe Velez and Juan Manuel Santos), two from Argentina (Cristina Fernãndez de Kirchner

TABLE V
MODEL 4: ORGANIZATION TOPIC MODEL

| **PSL RULES FOR ORGANIZATION TOPIC MODEL** |
|---|
| RETWEETS(ORGA, ORGB) $\rightarrow$ RELATION(ORGA, ORGB, ALLY) |
| ORGPOSTS(T, ORGA) $\wedge$ TOPIC(T, P) $\wedge$ POSITIVE(T) $\rightarrow$ LIKESTOPIC(ORGA, P) |
| ORGPOSTS(T, ORGA) $\wedge$ TOPIC(T, P) $\wedge$ NEGATIVE(T) $\rightarrow$ DISLIKESTOPIC(ORGA, P) |
| DISLIKESTOPIC(ORGA, P) $\wedge$ LIKESTOPIC(ORGB, P) $\rightarrow$ RELATION(ORGA, ORGB, ADVERSARY) |

and Mauricio Macri) and two from Chile (Sebastian Piñera and Andres Chadwick P).

### B. Filtering tweets

Based on the labels involving 19 organizations, the dataset was filtered to remove the mentions and tweets of other organizations, this resulted in approximately 5 million tweets, which consisted of approximately 1.5 million users and 23,817 unique hashtags.

### C. Blocking for users

To reduce the number of users from 1.5M, we filtered the users based on popularity. The more popular the users are, the more they tweet. Hence, we only considered the users who had two thousand or more followers. In our models, we infer the strategic relationships based on users interaction with more than one organization. Therefore, among these popular users, we further filtered out the users that mentioned or interacted with only one organization. This filtering reduced the above set to approximately 18274 users.

### D. Hashtag filtering

We filtered the hashtags based on popularity, i.e, the number of times they have been used in the dataset. Based on this, we did our experiments with hashtags that were used at least 100 times. Also out of these, hashtags of length ten and less were filtered out leaving us with 225 hashtags.

### E. Mapping sentiment

For all our models, we consider tweets with either positive or negative sentiment. The dataset includes sentiment scores associated with the tweets, computed by Datasift. Though most of the tweets do have sentiment scores, many have a 0 score or no scores (denoted by "None"). We filter out such tweets with neutral sentiment or none, resulting in about 3.56 million tweets. The sentiment values range from -24 to 24. These are mapped to values between 0 and 1, with the highest score mapped to 1 and lowest to 0.

### F. Twitter LDA

We use TwitterLDA, topic model specifically for twitter data, implemented by (Qiming et al.)[3] based on [19]. We tokenize and filter out the stopwords using the Natural Language ToolKit (NLTK) [20]. We used default settings for the topic model Dirichlet hyperparameters, set to $\alpha$ = 0.5, $\beta$ = 0.01 and number of topics=100 in our experiments.

[3]https://github.com/minghui/Twitter-LDA

## VII. EMPIRICAL EVALUATION

In this section, we present and discuss the outcomes of the various models described above. All our models are unsupervised and do not need any labels for training. We use the labels for the twenty-two pairs of organizations for evaluation. We refer to Table VII for the discussion of the results in this section. The '✓' represents the correctly identified pairs; '✗', the wrongly identified ones, and the uninferred pairs are denoted by '-'.

### A. Aggregate Model for Strategic Relationships

The aggregate model column of Table VII shows the outcome of our baseline (frequency-based) model. The model is able to infer only 9 pairs out of the 22 pairs that we consider, and this is due to the lack of tweets between the organizations. This is further evident from the fact that, in the 5 million tweets collected over two years, only 9 of the 19 organizations directly mentioned other organizations. Of these, only one pair had more than fifteen tweets between them.

Though it accurately finds the relationship type for some of the pairs, for example, [Diosdado Cabello and Hugo Chavez], due to lack of direct conversational tweets, it inaccurately classifies many others, for example, the pair [Nicolas Maduro and Hugo Chavez] are labeled as adversaries. The inference in this model also depends on the directionality of tweets between the pairs. For example, analysing Nicolas Maduro's tweets mentioning Diosdado Cabello, the model regards them as adversaries, but analysing Cabello's tweets mentioning Maduro, the model classifies them as allies (this pair is marked as uninferred '-').

Table VI shows the root mean squared error (RMSE) scores for the baseline model and each of the models we will discuss below. The baseline model gives an RMSE score of 0.83. This model has two main issues; firstly, because it only considers the direct conversations of the tweets, it is unable to infer all the pairs (only 9 out of 22). Secondly, the model only considers the frequencies of the positive/negative tweets to infer the relationships, and does not look at the level of positivity or negativity.

### B. Probabilistic Models for Strategic Relationships using PSL

We now discuss the outcomes of the different probabilistic models. In these models, we are able to encode the extent of positivity/negativity in each tweet, rather than evaluating based on the frequencies of positive and negative tweets. We also model issues of interest to the organizations and encode social context in the form of interactions in Twitter to make

TABLE VI
RMSE SCORES FOR STRATEGIC RELATIONS

| Model Type | Model | RMSE |
|---|---|---|
| BASELINE | AggregateModel | 0.83 |
| BASE MODEL | PSL_OrgMention | 0.46 |
| | PSL_OrgRetweet Model | **0.46** |
| SOCIAL CONTEXT MODELS | PSL_OrgRetweet + Context | **0.44** |
| | PSL_UserMention Model | 0.48 |
| | PSL_UserHashtag Model | 0.47 |
| ISSUE BASED MODELS | PSL_TopicSentiment | 0.43 |
| | PSL_TopicSentimentAndMentions | **0.31** |
| COMBINED MODEL | PSL_Combined Model | **0.31** |

better predictions. These models output *the strength* of the relationship, rather than a binary value.

*1) Direct Interaction Models:* Our first probabilistic model, i.e., organization mention model (*PSL_OrgMention*), is very similar to the frequency based model, here we encode the level of polarity of the tweets. We show the outcomes of two variants of this model, one with retweet information and one without it. Table VI shows the RMSE scores of 0.46 for the model with and without retweet information. The table shows the outputs from *PSL_OrgMention*. We can see that these models are able to determine the strength of the relationship between the pairs. This can be attributed to the number of positive/negative tweet exchanges between them. A lower confidence score can be explained from the fact that the pairs exchange both positive and negative tweets.

The model with retweet information, *PSL_OrgRetweet*, shows similar performance. But including retweets does increase its confidence of relationships between some of the pairs. For example, the confidence of the ally relationships between [Jose Meade, Enrique Peña Nieto] increases from 0.76 to 0.79 and that between [Diosdado Cabello, Hugo Chavez] increases from 0.67 to 0.75 respectively. This is because of the additional information about retweets between these pairs.

*2) Social Context Models:* The above models suffer from the issue that they are unable to infer all pairs due to missing direct conversational tweets between the pairs. We include social context to address this issue in the form of user-organization interactions and collective reasoning of strategic relationships between organizations.

Collective reasoning of relationships by enforcing reciprocity to the *PSL_OrgRetweet* model, improves RMSE to 0.44. Adding social context in the form of user-organization mentions shows an RMSE of 0.48. This higher error rate compared to the previous models can be attributed to the fact that we do not use direct conversational tweets, and there is noise added due to inclusion of many users. Table VII shows some interesting *additional* predictions by this model, that the *PSL_OrgMention* is unable to infer.

The *PSL_UserMention* model is still unable to infer five pairs as shown in the table. The *PSL_UserHashtag* is able to infer all pairs. The hashtag model presents some interesting findings about the affinity of the organizations towards the

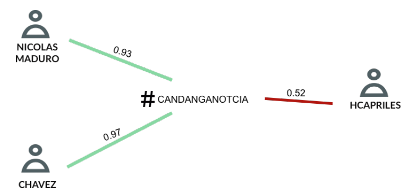


Fig. 1. Organization sentiment towards hashtags

hashtags, an example of which is shown in Fig. 1. The model infers that Nicolas Maduro and Hugo Chavez (allies) like the hashtag *#candanganoticia* with a 0.93 and 0.97 affinity score, and Henrique Capriles (who is an adversary to both), dislikes the hashtag with 0.52 value.

*3) Issue-based Models:* The Organization Topic Model (*PSL_TopicSentiment*) models organization sentiment towards latent topics in the tweets. This model gives RMSE score of 0.43 and makes better predictions with better confidence scores. Extracting abstract topics from tweets helps in identifying 'political topics' of interest, and modeling sentiment towards these topics helps to differentiate the organizations based on their ideologies towards the political issues. The *PSL_TopicSentimentMentions* is a combination of the *PSL_OrgRetweet* and *PSL_TopicSentiment*. Finally, *PSL_Combined* is a combination of the direct interaction models, social context based models and issue based models. These two models show the best performance with an RMSE of 0.31. These models get 19 of the 22 pairs right, with high confidence.

## VIII. CONCLUSION

In this work, we develop unsupervised probabilistic models to describe the strategic relationships between political organizations. We address three main challenges; expressing strength of relationships, incorporating social context and analyzing issues to infer relationships. To begin with, we use the direct interactions between organizations and further extend the models to incorporate social context to collectively infer strategic relationships. Lastly, we propose a model that analyzes issues of political interest and the sentiment towards them. We compare these to a simpler frequency-based model and show that our models are able to address these challenges and infer relationships far more accurately. These models are not limited to the political domain and can very easily be applied to other areas as well. An interesting extension would be to model the *change* in relationships over time, since this is common in a multi-party political system. In this work, we have explored representation of strategic relationships in terms of allies or adversaries and these are a step towards analyzing and representing more complex and nuanced relationships.

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TABLE VII
ALL RESULTS (THE NUMBERS IN BRACKETS REPRESENT THE STRENGTH OF THE RELATIONSHIP)

| | | Direct Interaction Models | | Social Context Models | | Issue Based Model | | | Combined |
|---|---|---|---|---|---|---|---|---|---|
| Org1, Org2 | Agg. Model | PSL_Org Mention | PSL_Org Retweet | PSL_User Mention | PSL_User Hashtag | PSL_Topic Sentiment | PSL_Topic Sentiment Reciprocity | PSL_Topic Sentiment Mention | PSL_All Combined |
| E. P. Nieto, SNTE | - | - (0.5) | - (0.5) | - (0.5) | ✓ (0.96) | ✓ (0.92) | ✓ (0.80) | ✓ (0.89) | ✓ (0.93) |
| D. Cabello, H. Capriles | - | - (0.5) | - (0.5) | ✓ (0.51) | ✓ (0.98) | ✓ (0.92) | ✓ (0.81) | ✓ (0.94) | ✓ (0.93) |
| D. Cabello, N. Maduro | - | ✓ (0.54) | ✓ (0.55) | ✓ (0.53) | ✗ (0.97) | ✓ (0.86) | ✓ (0.86) | ✓ (0.55) | ✓ (0.56) |
| H. Capriles, N. Maduro | ✓ | ✓ (1) | ✓ (1) | ✓ (0.53) | ✓ (0.99) | ✓ (0.92) | ✓ (0.81) | ✓ (1) | ✓ (1) |
| C. Kirchner, M. Macri | ✓ | - (0.5) | - (0.5) | ✗ (0.54) | ✗ (0.543) | ✓ (0.95) | ✓ (0.92) | ✓ (1) | ✓ (1) |
| H. Chavez, N. Maduro | ✗ | - (0.5) | - (0.5) | ✓ (0.53) | ✗ (0.98) | ✗ (0.81) | ✗ (0.78) | ✗ (0.57) | ✗ (0.57) |
| S. Piñera, A. Chadwick | - | - (0.5) | - (0.5) | ✗ (0.57) | ✓ (0.98) | ✗ (0.92) | ✗ (0.87) | ✗ (0.87) | ✗ (0.66) |
| EPN, A. M. Lopez | - | - (0.5) | - (0.5) | ✗ (0.51) | ✓ (0.76) | ✓ (0.99) | ✓ (0.96) | ✓ (0.97) | ✓ (0.93) |
| C. Kirchner, N. Maduro | ✓ | - (0.5) | - (0.5) | ✓ (0.51) | ✗ (0.89) | ✗ (0.92) | ✓ (0.75) | ✓ (0.61) | ✓ (0.62) |
| A. U. Velez, J. M. Santos | ✗ | ✓ (0.53) | ✗ (0.52) | ✓ (0.51) | ✓ (0.68) | ✗ (0.88) | ✗ (0.84) | ✗ (0.51) | ✗ (0.54) |
| SNTE, E. Gordillo | - | - (0.5) | - (0.5) | - (0.5) | ✓ (0.97) | ✓ (0.92) | ✓ (0.80) | ✓ (0.89) | ✓ (0.93) |
| J. M. Santos, N. Maduro | - | - (0.5) | - (0.5) | ✓ (0.52) | ✓ (0.82) | ✓ (0.93) | ✓ (0.83) | ✓ (0.97) | ✓ (0.93) |
| E. P. Nieto, sicilia_oficial | - | - (0.5) | - (0.5) | - (0.5) | ✓ (0.96) | ✓ (0.92) | ✓ (0.80) | ✓ (0.89) | ✓ (0.93) |
| J A Córdova, E. Gordillo | - | - (0.5) | - (0.5) | - (0.5) | ✓ (0.97) | ✓ (0.92) | ✓ (0.80) | ✓ (0.89) | ✓ (0.75) |
| C. Kirchner, J. M. Santos | - | - (0.5) | - (0.5) | ✓ (0.51) | ✓ (0.64) | ✓ (0.94) | ✓ (0.85) | ✓ (0.95) | ✓ (0.93) |
| P. Espinosa, J. A Córdova | - | - (0.5) | - (0.5) | - (0.5) | ✓ (0.98) | ✓ (0.92) | ✓ (0.80) | ✓ (0.89) | ✓ (0.50) |
| J. Meade, E. P. Nieto | ✓ | ✓ (0.76) | ✓ (0.79) | ✓ (0.53) | ✓ (0.52) | ✓ (0.86) | ✓ (0.855) | ✓ (0.78) | ✓ (0.80) |
| N. Maduro, A. U. Velez | - | - (0.5) | - (0.5) | ✓ (0.54) | ✓ (0.83) | ✓ (0.91) | ✓ (0.84) | ✓ (0.94) | ✓ (0.93) |
| D. Cabello, J. M. Santos | ✓ | ✓ (0.64) | ✓ (0.63) | ✓ (0.52) | ✓ (0.77) | ✓ (0.97) | ✓ (0.84) | ✓ (0.97) | ✓ (0.93) |
| D. Cabello,H. Chavez | ✓ | ✓ (0.67) | ✓ (0.75) | ✓ (0.70) | ✗ (0.98) | ✓ (0.97) | ✓ (0.93) | ✓ (0.73) | ✓ (0.63) |
| H Chavez, H. Capriles | - | - (0.5) | - (0.5) | - (0.50) | ✓ (0.99) | ✓ (0.96) | ✓ (0.86) | ✓ (0.89) | ✓ (0.93) |
| CNC_CEN, E. P. Nieto | ✓ | ✓ (0.54) | ✓ (0.54) | ✓ (0.58) | ✓ (0.54) | ✗ (0.98) | ✗ (0.91) | ✓ (0.54) | ✓ (0.54) |

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