

# Recognizing Social Constructs from Textual Conversation

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## Abstract

In this paper we present our work on recognizing high level social constructs such as *Leadership* and *Status* from textual conversation using an approach that makes use of the background knowledge about social hierarchy and integrates statistical methods and symbolic logic based methods. We use a stratified approach in which we first detect lower level language constructs such as politeness, command and agreement that help us to infer intermediate constructs such as deference, closeness and authority that are observed between the parties engaged in conversation. These intermediate constructs in turn are used to determine the social constructs *Leadership* and *Status*. We have implemented this system successfully in both English and Korean languages and achieved considerable accuracy.

## 1 Introduction and Related Works

The traditional information extraction paradigm has seen success in extracting simplistic behaviors or emotions from text. However, to detect high-level social constructs such as leadership or status, we require robustly defined notions about language constructs that cannot always be directly inferred from text. Hence, in this paper we focus on extracting information from text that requires additional background knowledge and inference. There are a few works in this direction, such as (Tari et al., 2010), however our focus in this paper is to extract information pertaining to different social constructs from textual conversation. The earlier research in analyzing conversations includes developing annotated

chat corpuses (Shaikh et al., 2010), and developing a socio-cultural phenomena model from discourse with a small-scale implementation (Strzalkowski et al., 2010). Other researchers have focused on automatically annotating social behavior in conversation using statistical approaches (Mayfield et al., 2013). The discourse structure of a conversation is modeled as a Hidden Markov Model in (Stolcke, 2000) to determine dialogue acts such as Statement, Question and Agreement. In (Prabhakaran et al., 2012) annotated email threads are presented for facilitating detection of social relations.

Among recent works, (Gilbert, 2012) uses linguistic cues to discover workplace hierarchy from emails. The use of phrases to detect *language use* such as “commands” is motivating. However, due to the lack of logical explanation and robust definition, the effectiveness of this method decreases in the semi-formally moderated Wikipedia community, which has interplay of several different *LUs* such as command, politeness and informal language. In (Danescu-Niculescu-Mizil et al., 2012), the authors explain how reflection of linguistic styles can shed light on power differentials; though, a social community like Wikipedia might not always conform to the *linguistic style coordination assumption*. For example, two friends who are coordinating on writing an article may have the same status socially, but difference in their expertise will drive the conversation. Other works such as (Gupte et al., 2011) have concentrated more on other features of the persons involved in social network, than linguistic cues. Also, we feel that, the hierarchy depends on the task or the context. In other words, one person could as-

some different roles in different context. The above works do not seem to address this. (Prabhakaran et al., 2012) achieves a commendable accuracy in detecting overt display of “power”. However, by our definitions, this is a lower level attribute and is similar to *authoritative behavior* which is a lower level concept than Leadership or Status. Hence, their results are not directly comparable to ours.

In this paper, we use a mixture of logic-based and statistical approaches which better encodes the domain knowledge and infers higher-level constructs from indirect textual cues. The aim of this paper is to formalize the theory behind our work, highlight the advantages of integration of statistical and logic-based approaches and present results from an empirical study.

## 2 Motivation by a use-case

We start our discussion by presenting a use-case and explain how results of other traditional methods inspired us to come up with an integrated approach.

Consider the following conversation from Wikipedia where the participants discuss about a misleading animation that is used under the topic *Convolution*.

*D: Put a message on the talk page of the guy who made it. You're right;  $g(t)$  should be  $g(\tau - t)$ , and  $(f*g)(t)$  should be  $(f*g)(\tau)$ .*

*T: I don't think he has a talk page. He's provided the code so I can reproduce it. I think he's right with  $(f*g)(t)$ , though?*

*D: Actually, I think we're both wrong. You need a variable of integration running opposite directions ...*

*T: I've updated ... I guess it's not important, but would be kind of cool. Feel free to suggest improvements to the animations.*

As we understand, these conversations suggest that participant *D* is supposed to hold a higher rank/status than *T*. If we analyze manually, we understand that phrases like *Put a message*, *You're right*, *I think we're both wrong* together supports our conclusion. Considered separately, the above phrases might be misleading. To conclude the example, our system outputs :

*D has a higher status than T because D demonstrates more language uses associated with status than T. Confidence: high.*

The above example illustrates the degree of context-sensitivity of our problem. The current statistical literature suggests methods such as Decision Trees, Boosting methods comprising of a collection of Weak classi-

fiers (basically rules) and probabilistic generative models (Medhat et al., 2014), (Hutto and Gilbert, 2014), (Vanzo et al., 2014) and (Saif et al., 2012). While their accuracy on some datasets is quite satisfactory, it is not clear how well they do on completely unseen data.

From our experience on such classifiers, we believe that a higher level of accuracy with explainability can be achieved by imposing a structure that encodes background knowledge about the social hierarchy that is observed in nature. With this motivation, we built a system whose hierarchical architecture robustly defines the social constructs, the “hidden” concepts that induce them and their inter-connections. We define notions of intermediate *Language Use (LU)* and lower level *Language Indicator (LI)* categories<sup>1</sup>. With the help of these robust definitions, our system properly explains how different emotions and behaviors interact to express status and leadership among individuals.

## 3 Social Constructs

Our framework supports determination of various important *Social Constructs* such as *Leadership*, *Status*, *Group Cohesion* and *Sub-Group Formation*. However, due to the length constraints of the paper, we will only discuss **Leadership** and **Status**.

### 3.1 Definitions and Architecture

We begin by first formally defining the two Social Constructs and the different Language Use categories.

**Leadership:** A leader is someone who guides a group toward outcomes, controls the group actions, manages interactions between members and members usually recognize the leader.

**Status:** Status is defined as the social position of one person with respect to another in a group.

The principal *Language Use* categories that we detect are: Deference, Closeness, Authoritative Behavior and Motivational Behavior. The following intuitions are used to infer such *LUs* from text:

**Deference** is understood when one uses language that shows respect to another conversational participant or defers to another's expertise or knowledge or authority.

**Closeness** is understood when one uses language that shows familiarity with another conversationalist. It is also indicated by dialogues where conversationalists refer to similar events, experiences etc.

**Authoritative Behavior** is understood when one uses language that shows power, dominance and control over a situation.

**Motivational Behavior** is understood when one uses language that moves conversational participants toward

<sup>1</sup>These definitions were proposed as part of the IARPA Socio-Cultural Content In Language(SCIL) program.

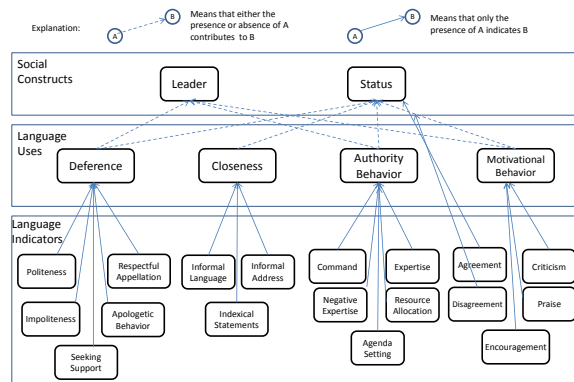


Figure 1: Social Construct-Language Use-Language Indicator hierarchy for English Language

sharing a common goal, collaboration, problem solving and solidarity.

In Figure 1, we present the entire hierarchy and how the categories are connected among each other. The arrows in the figure show which of the *LI* categories are used to infer a particular type of *LU*. It also demonstrates how each of the *LU* contributes to the Social Constructs.

#### 4 Behind the Curtain: Our Intuitions

One of the fundamental contributions in this paper is formally describing the hierarchy to determine the Social Constructs, as shown in Figure 1. To come up with these interconnections and each of the different *pieces of the puzzle*, we went through an iterative process of discussions with many social scientists and linguists to analyze a large number of example conversations. In this process, we came up with the aforementioned hierarchy, definitions of *SC*, *LU* and *LIs* and most importantly, the following understanding:

- The *Language Indicators* as shown in the Figure 1, suffice for the detection of *Leadership* and *Status*.
- Each detected *LI* is associated with an *Intensity Level* that helps us to encode the dissimilar effects of different words in inferring *LIs*.
- Each *LI* is associated with a **Signed Language Use**. For example, the *LI politeness* is associated with the signed *LU positive deference*.
- Indicators of an *LU* with a certain sign are **counter-indicators** of the same *LU* with the opposite sign.
- A signed *LU* may contribute either **favorably or unfavorably** towards its associated *SC*. For example, positive authoritative behavior contributes favorably towards higher status.

- The signed *LUs* that contribute towards the *SC Status* are **ordered** based on their importance. We assume the following ordering exists: authoritative behavior > motivational behavior > negative deference > positive deference in the opposite direction > closeness. However, we do not assume such an ordering for the *SC Leadership*.

Our extensive research and successful implementation of our system for different natural languages leads us to believe that these notions are universal in application.

### 5 Fundamentals of the implementation

After we parse each sentence using Stanford Dependency parser to get the POS tags and mutual dependencies, the detection of individual *LIs* and the mapping of *LIs*, *LUs* to *SCs* are achieved using a combination of statistical and logic based approach. Many of the ideas and insights about the detection of *LIs* and their relations with the *LUs* are motivated from (Simon, 1946), (Pennebaker et al., 2003), (Bernstein, 2010), (Brown and Levinson, 1988) and a few others. Some of our ideas for textual inference have been inspired by (Scherl et al., 2010).

#### 5.1 Determining the Language Indicators

The process of detection of language indicators from sentences uses a huge ensemble of complex rules. To create these rules, we borrowed ideas from the researchers of social science and psychology (Simon, 1946; Pennebaker et al., 2003).

With the help of POS tags, mutual dependencies and regular expressions, we create a framework where we detect individual events, verbs, other sentence constituents and their positive and negative sense. On top of this framework, we use two different methods to detect language indicators. The ideas are similar for all the *LIs*. We will only present a few examples for the *LI "Command"*.

##### 5.1.1 Using Regular Expressions Alone

We use regular expressions of the form `".*b[wW]hy don't (you|YOU) (start|read|submit|make|write|get)s.*b.*"` to detect *LIs* such as "Command". We employ a collection of such expressions to cover several different linguistic styles which indicates "Command" by an individual.

We achieved a very high recall (close to 1.0) for most indicators with these rules on test data. However, in few cases, the frequency of such indicators (such as politeness) were very low deeming the set of regular expressions as incomplete. This observation led us to refine the regular expressions with Logical rules so that we can incorporate our domain knowledge and remove such bias to the training set.

### 5.1.2 Using Logical rules on Regular Expression output and Sentence constituents

One example of the rules we use to detect “Command” is: *if the subject of the verb is second person and the verb is associated with a modal verb which indicates a question that suggests command, then the LI “Command” is detected.*

Examples of such verbs are “Would you” and “Could you” etc. It is to be noted that such a verb will denote both politeness and command depending on the rest of the sentence. This fascinating inter-dependency is one reason why we have to collect all such *Language Indicators* before we infer the higher level *Language Uses*.

## 5.2 Mapping of LIs to LUs and LUs to Social Constructs

**Input:** To encode one conversation we use a collection of facts of the form *participant(X)* and *addresses(X, Y, LI, Level)*.

These facts essentially encode the identity of the participants and the *Language Indicators* observed in the overall conversation among a pair of participants.

**Output:** The module outputs a collection of claim, evidence and confidence mappings.

For example one such mapping is: *claim\_mapping(X, "is the leader", "because", X, "demonstrates <language use>", "(Confidence: <confidence level>")*. Here <language use> is one of the language uses, <confidence level> is either low, medium, or high.

**Algorithm:** We employ statistical and logic-based procedure in parallel to get the above output. On the statistical side, we adopt a regression technique to learn a function that can map the scores associated with *LIs* to individual *LUs* based on annotated training data and this function is then applied to test data to get confidence score on *LUs*. The same procedure is adopted for mapping *LUs* to *SCs*.

In parallel to this procedure, we also employ a rule-based technique that uses quantized confidence scores and outputs confidence levels along with explanations. As we are able to get the explanation from logical reasoning, we use the output confidence scores as votes from statistical learning to output the final confidence level.

The rules for logical reasoning are explained as definitions and intuitions in the following paragraphs.

**Mapping LIs into LUs:** A signed *LU* is said to be exhibited by participant *X* towards participant *Y* with a certain degree of confidence based on the number of indicators(*LI*) and counter-indicators(*LI*) of the signed *LU* used by *X* when addressing *Y*. The **confidence** in *LU* is directly proportional to the difference between the number of indicators and counter-indicators.

We categorize *LUs* according to the number of indicators and apply slight variation to the above rules for each such category. Also, there are a few *LIs* that, when used, automatically **override** the computed **confidence level** for an *LU* and increase it to high. For example, “criticism” increases confidence level of positive “motivational behavior” to high.

**Mapping LUs to SCs:** The relative status of two participants is determined based on i) the number of relevant signed *LUs* exhibited by each participant towards the other, ii) the ordering of relevant signed *LUs* and iii) the confidence level in each exhibited signed *LU*.

The leader is determined based on the number of exhibited relevant *LUs* (both favorable and unfavorable).

**Mapping LIs to SCs:** As shown in Figure 1, we directly associate some of the *LIs* to Social Constructs. For such an association, we again adopt the regression technique mentioned previously. In this case, the confidence scores from *LIs* are directly mapped to the confidence scores of *SCs*. We combine this confidence with the above confidence levels using simplistic rules to output final social constructs.

It should be noted *that the constants used in the rules are obtained from statistics on annotated conversations.* The annotation process involves labels about *SCs*, *LUs* and *LIs* for each conversation data.

## 5.3 Brief Details and Results of the Regression Technique

In this sub-section, we provide few details of the Sparse Logistic Regression technique we have used alongside the logical formulation and present few results from our experiments with relevant statistical methods. We have used a similar formulations for mapping *LIs* to *LUs* and *LUs* to *SCs*. Here, we provide the example of formulating the entire problem of detection of Social Constructs directly in the Classification paradigm.

Status and Leadership can be formulated as a three-class and two-class problem respectively. For Status, we had 102 samples with the 38(*higher*), 26(*equal*) and 38(*lower*) samples each for three classes. For Leadership, we had 149 samples with 108(not-leader) and 41(leader) samples for the two classes. For both the tasks, we extracted 28 textual features. We used the one-vs-rest scheme for multi-class problem. For each task, we evaluated the framework as follows: i. First, we randomly separate the dataset into training set(*p*) and test set(*1-p*). ii. In the training set, we use 10-fold cross validation to select proper parameters. iii. We iterate the above procedure for 100 times, and accuracy is evaluated on the predictions in all iterations. iv. We select different *p* (from 0.25 to 0.9) and observe the change of accuracy.

We compared the accuracy achieved using Sparse Logistic Regression with SVM(with RBF Kernel) among

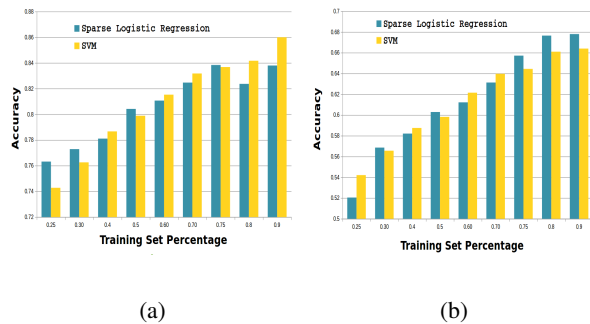


Figure 2: (a) Training set percentage vs Accuracy graph for Leadership problem, (b) Training set percentage vs Accuracy graph for Status classification problem.

others. The accuracy comparison of the SVM(with RBF kernel) and sparse Logistic Regression is provided in Figure 2. As we can observe, though the two methods are comparable, in most cases Sparse Logistic regression performs better.

#### 5.4 Advantages from the integrated approach

The primary advantages are the following:

In general, statistical approaches need a “lot of data” to attain a certain level of accuracy. As the rules we use are quite universal and compact, we can achieve a comparable(or higher) accuracy with much less training data.

Using the *evidence* and *claim* mappings, we give an “explanation” as to why we detected such a particular SC in the dialogue. Knowledge of such depth is very hard to achieve with only statistical approaches.

Explicit representation of “context” specific information via rules results in improved accuracy in detection of LIs such as criticism, praise, command etc.

Statistical modules complement the rule-based approach where our domain knowledge is “incomplete”.

We use ASP as the Logic Programming language of our choice as its ability to represent defaults and exceptions eases the implementation procedure.

## 6 Results

We have implemented this system using ASP(Gelfond and Lifschitz, 1988) and Java. The Wikipedia conversations are obtained by parsing the wiki dump from <http://dumps.wikimedia.org/>. We also evaluated on the NWTRB (US Nuclear Waste Technical Review Board) dataset. The accuracy and F1 measure are summarized in Table 1 for approximately two thousand English and one thousand Korean Wikipedia conversations. We evaluated two types of questions - i. *Yes-No* indicates questions like *Is John the leader?* and ii. *List* indicates questions such as *List all the leaders..* Our work

is perhaps unique in determining such social constructs and evaluating on familiar and unfamiliar datasets. Table

Table 1: Results

SC	Q-Type	Language	Accuracy	F1
Task Leader	Y-N	EN	0.8900	0.6700
Task Leader	List	EN	0.6700	0.9900
Status	Y-N	EN	0.4700	0.3457
Status	List	EN	0.6923	0.5200
Task Leader	Y-N	KO	0.5667	0.4338
Status	Y-N	KO	0.4074	0.3900

1 reports evaluations on wikipedia dump. These values are computed by comparing the results of our systems with annotated data. Note, in our experiments, we have performed strict evaluations. For example, the results are only marked positive if the complete list of leaders matches with a human-annotated list. Also, we consider the “explanation” too while performing the evaluation. The results are true positive only when the detected construct is correct alongwith the explanation provided by the reasoning module. In general, the previous research achieves an accuracy of 0.45 in comparable tasks such as dialog act tagging (Stolcke, 2000).

## 7 Conclusion

In this paper, we have proposed a novel approach for logically recognizing social constructs from textual conversations. We have used both statistical classification and logical reasoning to robustly detect status and leadership as observed in virtual social networks. From our experiments, we show empirically how our approach achieves a significant accuracy and provides logical explanation of construct detection.

This research shows the merits of using logical rules along with statistical techniques to determine Social Constructs. As per our understanding, this level of accuracy and explainability needs integration of both statistical and logic based methods. Our observations suggest that there is an increasing need for such integration in various domains. We believe that this work is one of the early steps in that direction.

## 8 Acknowledgement

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