

Identifying Social Deliberative Behavior from Online Communication — A Cross-Domain Study

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Abstract

In this paper we describe automatic systems for identifying whether participants demonstrate social deliberative behavior within their online conversations. We test 3 corpora containing 2617 annotated segments. With machine learning models using linguistic features, we identify social deliberative behavior with up to 68.09% in-domain accuracy (compared to 50% baseline), 62.17% in-domain precision, and 84% in-domain recall. In cross-domain identification tasks, we achieve up to 55.56% cross-domain accuracy, 59.84% cross-domain precision, and 86.58% cross-domain recall. We also discover linguistic characteristics of social deliberative behavior. In the context of identifying social deliberative behavior, we offer insights into why certain machine learning models generalize well across domains and why certain domains pose great challenges to machine learning models.

Introduction

This research focuses on creating computational models to predict high-order communication skills by analyzing online conversations. The high-order communication skills we study are encapsulated by a celebrated human capacity. It is the ability to communicate productively in situations that involve heterogeneous opinions driven by different assumptions, beliefs, and goals. This research is also about developing robust systems that can be applied in a cross-domain manner.

The need for this important capacity is seen in all realms of human activities from international politics, to family squabbles, to civic deliberation, and to organizational decision making. This capacity is pressingly called for in online communication because participants exposed to one-shot interactions online are often challenged to understand each other's perspectives and opinions. To productively communicate in this situation, participants need to exercise the ability to perceive and respond to the feelings of others, reflect on their own bias, and respect others' perspectives. These behaviors are part of what we call *social deliberative behavior*. They are the horsepower to desirable end states in communication, such as mutually acceptable plans of action, creative win-win solutions, or simply greater clarity, understanding and trust.

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Creating computational models for assessing social deliberative behavior has profound implication on several fronts: it (1) supports more efficient analysis for research purposes into communication and deliberation; (2) provides assessment measures for evaluating quality and properties of group dialogue and deliberation; and (3) provides tools for informing facilitators to adjust support and intervention efforts.

Intensive prior work on text classification has been done fruitfully on creating automated systems to measure dialogue quality and communication skills through the constructs of basic speech acts, such as agreement/disagreement, assertions, questions, and sentiment polarity (Marineau, Wiemer-Hastings, and others 2000; Liu 2010). These speech act constructs are far less complex, interconnected, and subtle than the social deliberative behavior we study. Therefore, measuring perspective taking is undoubtedly much more challenging than measuring agreement/disagreement. To the best of our knowledge, we are the first to create automated systems that implement the state-of-the-art conceptual framework of deliberation in communication studies. In this paper, we make the initial attempt at addressing the following key challenges: (1) build models that can automatically identify social deliberative behavior in online conversations; (2) create a *robust* model of identifying social deliberative behavior serving a variety of online contexts and domain topics; and (3) discover linguistic characteristics of social deliberative behavior. We hope our endeavors will bring forward the field that lies in the intersection of machine learning, education, computational social science, and communication studies.

The organization of this paper is as follows. In Section 2 we introduce the concept of social deliberative behavior. In Section 3 we describe three experimental domains. Section 4 introduces experimental design and methodology, including machine learning features and models. We discuss experimental results in Section 5 and conclude with future plans in Section 6.

Social Deliberative Behavior

One popular school of thought in communication studies is that communication can be best understood through the lens of *deliberative democratic theory* (Gastil 2005), or the concept that democratic practice and policy making should rely on “open and informed” communication on the part of cit-

izenry. “Openness” refers to the ability to allow a voice for multiple perspectives in a discussion, and “informed” refers to the capacity of making rational arguments in the discussion. In the literature, an impressive body of research has focused in depth on the *analytic* aspect (i.e., “informed”) of deliberation, including rational argument and consensus (Cohen 1997), problem solving and inquiry (Schommer-Aikins and Hutter 2002), and metacognition (Mayer 1998). A burgeoning body of research has examined the *social* aspect (i.e., “openness”) of deliberation in group interactions, such as respect, conflict management (Littlejohn and Pearce 1997), and establishing trust (Rico et al. 2009).

Our social deliberative skills scheme (Murray et al. 2012) is among the first few conceptual frameworks that combine the dual dimensions (i.e., analytic and social aspects) of deliberation. Social deliberative skills include skills that are essential for effective communication that involves a disequilibrium of diverse perspectives. These component skills include social perspective seeking (i.e., social inquiry), social perspective monitoring (i.e., self-reflection, weighting opinions, meta-dialogue, meta-topic, and referencing sources for supporting claims), as well as cognitive empathy and reciprocal role-taking (i.e., appreciation, apology, intersubjectivity, and perspective taking). For example, the following statement is considered doing “perspective taking”: *From both of you I have now a little insight into how you view this problem and what the problem solution could be.*

Social deliberative skills can also be seen as a composite skill, which, though less precise can serve as a general marker of deliberative quality, for use in evaluation and real-time feedback in deliberative processes (Murray et al. 2013). This research focuses on creating computational models to assess whether participants in online communication demonstrate the use of *composite* social deliberative skill, or **social deliberative behavior**.

Corpora

We examined three corpora of online conversations: (1) postings from a civic online discussion forum; (2) email exchanges from a professional community listserv; and (3) postings from college classroom computer-mediated discussions. The first and third corpora involve individuals participating in open dialogue and opinion sharing, while the second corpus involves participants in negotiation. The third corpus is from classroom trials of online dialogues among college students.

In order to provide training data for machine learning models to automatically assess whether or not participants perform social deliberation, two independent trained human judges annotated the 3 corpora based on the social deliberative skill scheme (Murray et al. 2012). According to (Landis and Koch 1977), we achieved good inter-rater reliability scores ranging from 64.34% (college classrooms domain) to 73.49% (civic deliberation domain)¹, as measured using Cohen’s Kappa statistics. Below we describe the participant characteristics in each domain.

¹The inter-rater reliability for the professional community discussion domain was 68.36%.

Domains	Social deliberative behavior	Other speech acts	Total segment counts	Participant counts
Civic deliberation	225 (57%)	171 (43%)	396	32
Professional community negotiation	231 (53%)	207 (47%)	438	16
College classrooms	565(32%)	1218(68%)	1783	90
Civic deliberation + Professional community negotiation	456(55%)	378(45%)	834	47
All domains	1021(39%)	1596(61%)	2617	138

Table 1: Data statistics with various domains

In the **civic deliberation** domain, 32 participants were each self-initiated with the goal, in part, to improve community relations. Participants were mostly level-headed and demonstrated social deliberative behavior (SDB) repeatedly. SDB occupied 57% of the total 396 annotated segments, see Table 1. In the **professional community negotiation** domain, sixteen geographically dispersed faculty members from two academic communities negotiated about conference relocation. Participants were highly educated academic professionals, most of whom encouraged democratic decision making about relocating a conference, which partly led to a somewhat more deliberative dialogue. SDB occupied 53% of the total 438 annotated segments. In the **college classrooms dialogues** domain, 90 college students from a variety of disciplines discussed pros and cons of numerous topics. Participants were a part of experimental trails, whose goal was to assess educational software tools that support SDB. In contrast to participants from other two groups who were self-motivated to be deliberative, participants in this group were encouraged to be deliberative (participations were given class credits). SDB only occupied 32% of the total 1783 annotated segments.

Experimental Design and Methodology

To effectively address the key challenges listed in Section 1 and to shed light on future directions, we designed four experimental scenarios by exploring the use of different features sets and various machine learning models to build robust systems for identifying social deliberative behavior.

- **Scenario 1: In-domain analysis for each domain**
- **Scenario 2: Cross-domain analysis for each pair of domains**
- **Scenario 3: Combining a subset of domains and performing in-domain & cross-domain analysis accordingly**
- **Scenario 4: Combining all domains & performing appropriate analysis**

The first scenario allows feature comparison and model comparison and provides the basis for evaluating cross-domain performance. The second scenario offers a systematic view of how machine learning models perform at change of domains – we will evaluate all 6 combinations of domain pairs. The third scenario is designed to account for domain characteristics (i.e., pre-existing conversations vs. dialogues from experimental trials), characteristics of participants (i.e., motivated to be deliberative vs. asked to be), and data characteristics (i.e., class distributions). This design can provide

insights into the performance gain or loss of models created from one data source compared to models built from aggregated data sources. The last scenario is a more general case of the third one – it naively assumes data homogeneity and thereby disregards factors that characterize each domain. Aggregating data altogether from multiple sources is sometimes tempting due to data sparsity. We will show whether this is advisable.

With respect to performance measures, we use accuracy (% of correct identification of social deliberative behavior (SDB)), precision (% correct of identified as SDB), recall (% labeled as “SDB” that were predicted to be “SDB”), and F_2 measure (the harmonic mean of precision and recall that weights recall twice as high as precision). Recall is more valued than precision for this task for three reasons. First, our social deliberative skills scheme is expanding, so the SDB considered in this research is by no means extensive. The second reason is related to our pedagogical strategy. We believe that a false flag about not performing social deliberative behaviors not only confuses and overburdens participants, but also is inconsistent with our thinking of reinforcing *correct* skills until they become second nature. The third reason is related to our planned applications. Our first planned application to real-time deliberation is through a Facilitators Dashboard. The Dashboard will alert facilitators to potentially important patterns and metrics in the dialogues they are monitoring, in order to help them decide when and how to perform interventions. Because facilitators can intelligently filter out dubious analysis, our algorithms should err on the side of identifying all important patterns, at the risk of including some false positives.

Linguistic Features

In the seminal work of Blitzer (Blitzer et al. 2007), generalizability of the learning algorithms was shown to be improved by using features that are robust against the change of domains. We use two independent sources of linguistic features, **LIWC** (Linguistic Inquiry Word Count) (Pennebaker, Francis, and Booth 2001) and **Coh-Metrix** (Graesser and McNamara 2010) (Figure 1). LIWC features are derived across topic domains and from people from all walks of life; Coh-Metrix features are generated across genres and from a wide spectrum of disciplines. As a result, these features are domain-independent and ideal for this study, where the discourse data comes from multiple online participants and across different topic domains and online contexts. Both LIWC and Coh-Metrix features have been shown to be valid and reliable markers of a variety of psycholinguistic phenomena. For example, in (Wang, Kraut, and Levine 2011), LIWC features helped find the roles emotional and informational support play in participants’ commitment in online health support groups, and Coh-Metrix features helped predict complex phenomena, such as deception (Hancock et al. 2007).

Machine Learning Models

Understanding social deliberative behavior is a new research area and in choosing machine learning models, and therefore reliable predictive features of social deliberative behav-

ior are lacking in the literature. Additionally, filter-based approaches to feature selection (e.g., correlations) are often suboptimal². Based on these reasons, we did not pre-select features for our models. We chose machine learning models based on immediate factors (e.g., data characteristics, such as ratio of data to features and model transparency) as well as long-term factors (e.g., how easily the created model can be updated when more data arrives later, or, how robust is the model). We describe the three models that we tested: Naive Bayes (Rish 2001), l_1 regularized logistic regression (Tibshirani 1996), and support vector machines (Cortes and Vapnik 1995).

The **Naive Bayes** classifier (NB) is a generative probabilistic model. Although naively assuming feature independence, NB often performs surprisingly well on real-world problems. NB is fast to train and evaluate because it only computes relative frequencies of features and involves no optimization. With a relatively small in-domain data, we chose NB for the reason that as a high bias/low variance model, NB tends not to overfit the data, which is valued in creating a robust system. **l_1 Regularized Logistic Regression** (l_1 RRL) is a discriminative model. l_1 RRL selects features while performing learning and it formulates the learning problem as a trade-off between minimizing loss (i.e., achieving good accuracy on training data) and choosing a sparse model (i.e., improving generalization in prediction on unseen data, high interpretability, and computational savings). Regularization is an effective way to induce model sparsity and is often achieved by using norms. Here, we consider l_1 norm (Tibshirani 1996) and use the l_1 regularized dual averaging algorithm (Xiao 2010). Note that, when an online algorithm is appropriately used, l_1 RRL can be easily updated to take in new data for real time analysis. **Support Vector Machines** (SVM) is a discriminative model. It is the state-of-the-art supervised model for text classification. The basic idea of SVM is that input vectors, if linearly inseparable, are non-linearly transformed to a high-dimension feature space where a linear decision surface can be constructed. Feature space transformation is achieved by kernel functions. Previous research (Liu et al. 2005) has observed that SVM has performance loss in face of imbalanced class distribution (i.e., skewed label frequencies).

For the results reported in Table 2, we trained NB and l_1 RRL (i.e., $\lambda=0.1$, $\gamma=2$) with linguistic features, and we trained SVM (i.e., linear kernel, cost parameter $c=1$) with bag-of-word features. The results of training SVM with linguistic features are not reported – the performance of SVM was not as good as that of l_1 RRL, which may be partly because that the parameters were not tuned to their optimal values. For all in-domain experiments (i.e., a single domain, a subset of domains, or all domains combined), we report average performance over 10-fold stratified cross-validation within the same domain. For cross-domain experiments, we report results following the training-validating-testing protocol. We trained and validated on the training corpus (i.e., a

²The feature selection process is often independent of the learning phase, and therefore, the chosen subset of features may not be optimal for learning purposes.

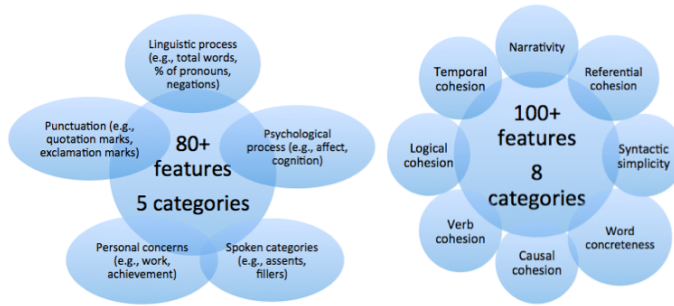


Figure 1: A snapshot view of LIWC (left) and Coh-Metrix (right) features

Table 2: Predictive accuracy, precision, recall, and F2 measure in % for various scenarios.

The highlights denote the best performance for corresponding scenario;

“*” denotes results, whose model class weights were adjusted to counterbalance class skewness.

We use “Deliberation”, “Negotiation”, and “Dialogue” to denote the civic deliberation, the professional community negotiation, and the college classrooms dialogues domain, respectively.

In-domain					Cross-domain						Subset of domains		All domains	
Training corpus		Deliberation	Negotiation	Dialogue	Deliberation	Deliberation	Negotiation	Negotiation	Dialogue	Dialogue	Deliberation + Negotiation	Deliberation + Negotiation	Combined	
Testing corpus		Deliberation	Negotiation	Dialogue	Negotiation	Dialogue	Deliberation	Dialogue	Deliberation	Negotiation	Deliberation Negotiation	Dialogue	Combined	
LIWC + Coh-metrix features	Naïve bayes	Accuracy	58.6	51.6	63.49	54.57	42.51	50.76	42.12	44.95	45.89	55.15	43.13	59.08
		Precision	61.25	53.7	40.14	55.63	31.09	57.65	31.15	53.04	45.71	58.13	31.55	45.86
		Recall	73.78	59.74	30.97	68.4	66.9	51.46	68.32	27.11	13.85	64.25	67.96	27.13
		F ₂ -measure	70.88	58.43	32.45	65.40	54.37	52.59	55.16	30.05	16.09	62.93	55.22	29.54
	L1 regularized logistic regression	Accuracy	61.84	55.94	68.09	54.11	38.19	55.56	39.2	41.41	46.58	57.44	34.77	60.41
		Precision	62.17	56.05	46.15	54.05	30.64	59.84	30.27	37.04	38.46	57.08	30.96	44.76
		Recall	84.00	76.19	4.25	86.58	75.22	66.22	70.44	4.44	2.16	89.25	86.02	6.27
		F ₂ -measure	78.49	71.08	5.19	77.28	58.27	64.84	55.67	5.39	2.66	80.21	63.45	7.57
Bag-of-words features (unigram)	Support vector machines	Accuracy	62.4	58.66	70.67*	53.65	51.43	50.76	51.71	51.77*	50*	60.2	51.26	63.55*
		Precision	62.67	60.25	53.89*	54.76	35.51	57.01	34.71	58.42*	52.61*	61.15	34.8	52.02*
		Recall	83.56	63.64	51.5*	69.7	65.31	54.22	59.47	52.44*	52.38*	74.56	61.59	84.33*
		F ₂ -measure	78.34	62.93	51.96*	66.09	55.92	54.76	52.04	53.54*	52.43*	71.43	53.37	75.01*

single domain or a subset of domains) and tested on the testing corpus. For SVM, we preprocessed the textual data by filtering standard English stopwords and performing stemming with the Porter2 algorithm. We used unigram features and created feature vectors based on TF-IDF. We also adjusted class weights of SVM³ to counterbalance skewed class distribution in the domain of college classrooms dialogues.

Results and Discussions

Experimental results (Table 2) reveal a number of interesting patterns. We show a subset of important observations below. Note that, we use “performance” and “recall” loosely in this discussion because recall is the most valued among all the performance measures in this application, as explained earlier. We use “C”, “N”, and “E” to denote the civic deliberation, the professional community negotiation, and the college classrooms dialogues domain, respectively.

Observation 1: l_1 regularized logistic regression

³The weight ratio was the inverse of the ratio of their class distributions.

(l_1 RLR) with domain independent features generalizes the best across domains. As shown in the 2nd column (cross-domain) of Table 2, l_1 RLR (using domain-independent features) built from N, when applied to C, achieves the best accuracy (55.56%) and precision (59.84%). l_1 RLR built from C, when applied to N, achieves the best recall (86.58%) and F₂ measure (77.28%). Moreover, l_1 RLR built from C achieves 86.58% cross-domain recall on N, whose in-domain recall is only 76.19%. Even more interestingly, the model built from C achieves 75.22% cross-domain recall on E, whose in-domain recall is as low as 4.25%. As can be seen from this observation, regularized machine learning models are useful for creating robust systems that can be applied in a cross-domain manner. In addition, domain-independent features seem to be more helpful than bag-of-word features for the purpose of developing such robust systems.

Observation 2: Imbalanced class distribution hurts predictive performance – more on recall than precision.

One important characteristic of domain E is skewed class distribution. This imbalanced data hurts predictive performance, regardless of feature types and models. For exam-

ple, as shown in the 3rd sub-column of the 1st column (in-domain) of Table 2, in-domain model recall is only 4.25% and cross-domain recall can be as low as 2.16% (the last two sub-columns of the 2nd column (cross-domain)). Therefore, before creating a model, it is important to strategically solve the imbalanced data problem, either from the algorithm level (e.g., adjusting class weights, cost, priors) or from the data level (e.g., upsampling, downsampling).

Observation 3: Coh-Metrix helps more than LIWC features for identifying social deliberative behavior. As can be seen from earlier analysis (observation 1), l_1 RLR built from C, when applied to N and E, has the best generalized performance. This implies model generalizability *across contexts* (i.e., open-end dialogue context vs. negotiation context) and *across participants*. In Table 3, we show the top 20 features outputted from that model – 17 out of which are from Coh-Metrix. For example, the results reveal that SDB is positively correlated with the use of negative additive connectives (e.g., conversely, instead), negation words (e.g., could not, will not), second person pronoun, meaningful words, verbs, and age of acquisition for words. SDB is also found to be negatively correlated with narrativity, lexical diversity, reading ease, concrete words, number of words, and nouns. This discovery increases our understanding of the composite social deliberative skill and provides the basis for our in-depth analysis of component SDB, such as perspective taking and inter-subjectivity.

Observation 4: Aggregating data from domains that have highly imbalanced class distribution degrades predictive performance. Excluding data from the domain that has imbalanced class distributions, we tested whether or not aggregating data from different sources would boost predictive performance. The results show that aggregating data can help boost performance. As shown in the 3rd column (subset of domains) in Table 2, the l_1 RLR model built from C and N combined has in-domain performance (89.25%). This is better than in-domain performance of models built from each domain alone (84% and 76.19%, respectively). Similarly, l_1 RLR built from C and N combined, when applied to E, has cross-domain performance (86.02%), which is better than cross-domain performance of models built from each domain alone on E (75.22% and 70.44%, respectively). However, when combining all domains together by adding data from E, who has a highly imbalanced class distribution, the performance 6.27% (the column about all domains) is far worse than averaging in-domain performance from each single domain (the three sub-columns of (in-domain)) 54.81%. Therefore, we suggest be cautious about combining data across domains.

Conclusion and Future Work

In this paper we built machine learning models to identify social deliberative behavior from online dialogues and designed four sets of experiments to better examine model generalizabilities across domains. The performance of the machine learning models is promising, which implies that (1) it is feasible to automatically analyze conversations in online communication to study high-order communication skills, and (2) it is possible to develop robust systems that

Table 3: Learnt features of l_1 regularized logistic regression built from the civic deliberation domain

	Feature code	Interpretation	Source	Feature weight
1	CONLOGi	negative additive connectives	coh-metrix	11.24
2	DENNEGi	negation density	coh-metrix	10.49
3	Pnar	narrativity	coh-metrix	-9.61
4	LEXDIVVD	lexical diversity	coh-metrix	-8.01
5	DENPRPi	pronoun	coh-metrix	6.48
6	PRO2i	second person pronoun	coh-metrix	5.58
7	READFRE	reading ease	coh-metrix	-5.32
8	CONi	all connectives	coh-metrix	-5.24
9	WRDCacwm	word concreteness	coh-metrix	-4.95
10	WRDMacwm	word meaningfulness	coh-metrix	4.58
11	WC	word count	LIWC	-4.48
12	AllPct	common punctuations	LIWC	4.09
13	SPATlpi	spatial location words	coh-metrix	-3.32
14	CAUSVP	causal verb and particles	coh-metrix	-3.27
15	WRDAcwm	age of acquisition for words	coh-metrix	3.1
16	SPATmpi	spatial motion words	coh-metrix	-2.89
17	NOUNi	noun	coh-metrix	-2.73
18	READNW	total number of words from Charniak parser	coh-metrix	-2.5
19	OtherP	uncommon punctuation	LIWC	1.57
20	VERBi	verbs	coh-metrix	1.41

can be applied in a cross-domain manner. In the future, we will consider more challenging domains, such as online dispute resolution, more sophisticated features, such as semantic features, interactions between participants, the effect of preceding segments, and demographic information. We also intend to create multi-task machine learning models (Caruana 1997) to simultaneously identify each component social deliberative skill from online messages.

As we move forward, we will be closer to our long-term goal of supporting socially literate citizens in a technology-advanced society capable of respecting differences and working together toward common interests and mutual welfare.

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