# 19. Learning the social pragmatics of language

*Luca Maria Aiello*

## INTRODUCTION

Language is the prime source of sociocultural processes in human societies (Levinson, 1979; Schieffelin & Ochs, 1986). Through spoken and written language, we exteriorize our psychological processes and trigger psychological reactions in others, thus facilitating cooperation and a shared understanding of reality (Clark, 1996). The complex combination of social processes that are set off by language is the main determinant of crucial societal outcomes (Bond et al., 2012; Onnela & Reed-Tsochas, 2010), including the diffusion of innovation (Rogers, 2010), community prosperity (Putnam, 1993), economic opportunities (Granovetter, 2005), life expectancy (Holt-Lunstad et al., 2010), and happiness (Fowler & Christakis, 2008). Given its crucial role in the functioning and evolution of society, language has been an object of investigation throughout human history (O'Grady et al., 1997; Robins, 2013), and for at least a century scientists have been studying in depth the complex relationship between language, psyche, and social behavior (Leech, 2016; Levelt, 2013).

For long, language research conducted at the intersection of psychology and linguistics has been constrained by limited access to data about conversations taking place in real-world settings. The advent of the information era introduced three key innovations that expanded the scope of language research enormously: (a) the growing pervasiveness of the Participatory Web increased dramatically the availability of linguistic data generated in a wide variety of natural settings; (b) the computing power needed to analyze such extensive data became cheap and abundant; and (c) the development of increasingly effective machine learning methods made it possible to extract complex information from speech and text (Hirschberg & Manning, 2015). Thanks to these advances, in the last two decades computational scientists have furthered the computational understanding of text with a broad array of Natural Language Processing (NLP) tools.

Linguistic analysis is traditionally understood as composed of the three fundamental and interrelated dimensions of syntactics, semantics, and pragmatics (Oller, 1972); most NLP techniques developed so far have addressed mostly the first two of these three dimensions. At the syntactics level, methods trained to perform syntactic parsing of text achieve great performance despite the logical ambiguities of natural language (O'Horan et al., 2016). At the semantics level, a plethora of techniques have been developed to capture some of the key cognitive layers on which language operates (Dascal, 2003), including sentiment on diverging positive–negative scales (Medhat et al., 2014), emotion categories (Sailunaz et al., 2018), and discussion topics (Alghamdi & Alfalqi, 2015). The recent developments in deep neural networks trained on very large-scale data allowed for the creation of language models that contain rich information about words and their usage that can be used as a basis to solve potentially any task related to syntactic and semantic analysis of text (Qiu et al., 2020).

Unlike syntactics and semantics, the domain of pragmatics has been far less explored by computational linguists. Pragmatic analysis deals with the purpose of a sentence, which is



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often determined by the broad context in which it is uttered. From the angle of pragmatics, conversations can be seen as sequences of *communicative acts* that effectively change the perception of reality of the parties involved (Austin, 1975). To see how, consider the following stylized example. Imagine a researcher addressing a colleague by saying: *"You are a brilliant scientist."* When analyzed from the semantic perspective, this message might be seen as characterized by positive sentiment and categorized under topics such as "research" or "academic relationships." Pragmatics analysis would instead interpret such an utterance through the lens of the intent of the speaker: expressing admiration and esteem for the alter. This interpretation is the most interesting from a sociological standpoint: it captures elements of language that have the effective power of changing reality, because it contributes to shaping the relationship status of those two people, as they perceive it.

Pragmatics is at the heart of several influential theories that describe the mechanics of how social relationships, groups, and societies function (Blau, 1964; Habermas, 2014; Neale, 1992). However, measuring from language the key pragmatics aspects that constitute the foundations of these theories has proved challenging. There is an ongoing debate on whether the latest deep-learning language models trained to tackle tasks that are inherently related to semantics can also capture pragmatics, but recent experimental evidence indicates otherwise (Ettinger, 2020). Developing tools that could automatically identify elements of pragmatics from text is one of the biggest next frontiers in NLP (Li et al., 2021), and it could bring immense benefits to a number of disciplines. Social scientists could apply those tools to large-scale interaction data to gather strong quantitative evidence in support of long-standing theories (Conte et al., 2012). Computer scientists could build new services to enhance the quality of online conversations—especially in social media plagued by hate speech and polarization—and to build AI conversational agents that can better emulate genuine human conversations (Jacquet et al., 2018). Complex systems scientists could characterize the dynamics of social networks by modeling social ties beyond the mere concept of strength (Aiello, 2017).

In this chapter, we describe an attempt at using machine learning to capture key aspects of *social pragmatics* from conversational text, namely, communicative speech acts that contribute to the definition of the nature of the social relationship between pairs of individuals. We understand this process of language transforming the nature of social ties through the lens of social exchange theory (Blau, 1964), conceiving every conversation as a repeated series of transactions of different types of nonmaterial resources, such as social support, knowledge exchange, or manifestation of esteem (Foa & Foa, 1980).

Our contribution is articulated in four parts. First, we discover aspects of language pragmatics by aggregating topics of conversations using social information ("Inferring Pragmatics by Semantic Reciprocity"). Second, we identify social dimensions that embody fundamental elements of social pragmatics ("Fundamental Dimensions of Pragmatics In Relationships"). Last, we develop supervised machine learning algorithms to capture these social dimensions from conversational text, and apply them to real-world conversation data at different scales ("Conclusion").

## INFERRING PRAGMATICS BY SEMANTIC RECIPROCITY

The reciprocity principle is a corollary of the social exchange theory: a person expressing a given pragmatic intent toward an alter will likely trigger the reciprocation of that intent. For

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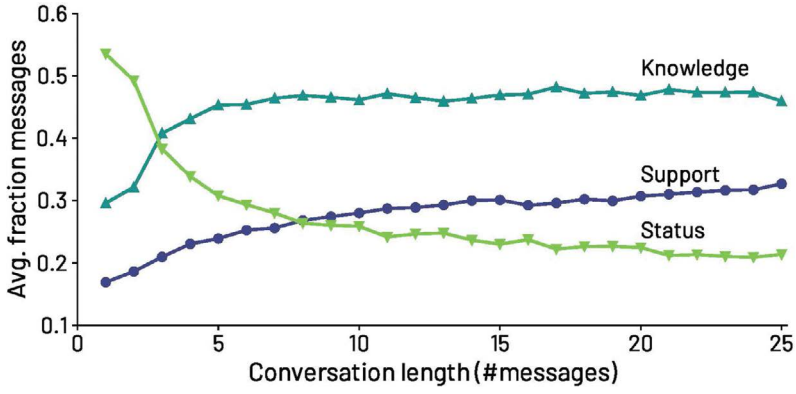
example, it is expected that a person who receives social support for the loss of a grieving relative ("I'm sorry for your loss") to respond with another utterance that signals or acknowledges social support ("Thank you for being a good friend"). By leveraging this concept, we proposed an unsupervised algorithm that analyzes reciprocity in conversations to learn classes of utterances that share similar pragmatic functions (Aiello et al., 2014).

The algorithm takes as input a set of messages $M$, where each message $m^t_{u,v} \in M$ is a textual communication between source $u$ and destination $v$ at time $t$. The algorithm works in three main steps. First, messages are grouped into topics using matrix decomposition techniques, such as non-negative matrix factorization (NMF). Second, a *Conversation Graph* is built; its nodes are the topics, and an edge between topics $A$ and $B$ is weighted by the number of times a conversation between two individuals transitions from $A$ to $B$. A topical transition is defined as a pair of two consecutive messages sent between user $u$ and $v$, where message $m_1 : u \rightarrow v$ belongs to $A$ (with the highest probability) and message $m_2 : u \rightarrow v$ belongs to $B$. The last step is aimed at extracting the pragmatics layer out of the semantics layer represented by the discussion topics. In light of the reciprocity principle, we hypothesized that highly clustered parts of the Conversation Graph aggregate topics that are often in a relationship of reciprocity, and therefore have a higher likelihood of performing similar pragmatic functions. To find "communities" of topics that are highly connected among each other but sparsely connected with the rest of the Conversation Graph, we used algorithms for community detection on graphs (Fortunato, 2010). This four-step procedure results in the assignment of a message to a topic, and the assignment of topics to a community (i.e., to a resource type).

When tested on conversational datasets from the bibliophile community aNobii (Aiello et al., 2010), we found three communities, corresponding to three types of pragmatic intents. Manual inspection of messages reveals that those reflect three pragmatic aspects of interactions that have been long studied in social science: *knowledge exchange* (knowledge about the specific platform domains, i.e., books), *status exchange* (appreciation, esteem, or admiration), and *social support* (aid, emotional caring, or concern).

We showed that knowledge about the pragmatic function of interactions can improve the descriptive power of social analytics. Assortativity analysis is one example. The aNobii communication network follows an assortative pattern, that is, people who communicate with each other receive a similar number of messages overall. However, when considering only the set of edges that convey status, the network becomes disassortative, meaning that status-giving follows a hierarchical pattern: People receive status from people who have less status than them. Another example is tie evolution. When computing the average ratio of messages belonging to each of the three resources for conversations of length $n$, the resulting trends match our commonsense expectation of how social relationships evolve (Figure 19.1). Status exchange is particularly present in the first conversational exchanges of a relationship but becomes far less likely as the conversation progresses, while the likelihood of knowledge exchange and social support increases. In short, status exchange sets the foundation for future relationships, fading to the background after the tie-formation stage. Such a nuanced description of the temporal evolution of a social relationship is only possible because of the ability to describe a social interaction according to its purpose rather than its topical theme or structural position.

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*Note:* As a conversation thread becomes longer, the exchange of knowledge and support grows, whereas status-giving messages become less frequent.
*Source:* Figure adapted from Aiello et al. (2014).

*Figure 19.1 Average proportion of messages carrying each of the three nonmaterial resources (support, knowledge, status) for pairs of users, versus conversation length*

## FUNDAMENTAL DIMENSIONS OF PRAGMATICS IN RELATIONSHIPS

Our unsupervised technique was able to discover groups of messages with similar pragmatic functions, yet it was limited in its applicability (it needs to reconstruct the whole conversation network) and scope (it was able to find only three different interaction types, which are not exhaustive of all types of human communication). In contrast, a supervised algorithm would be applicable to any message and could be trained to identify all the aspects of social pragmatics that are most present in everyday conversations.

Approaching this task in a supervised fashion requires knowing in advance all the possible classes of social pragmatics functions that language can have. To determine these classes, we relied both on previous literature and on a crowdsourcing experiment (Deri et al., 2018).

First, we reviewed the relevant literature in sociology and social psychology and obtained dimensions along which relationships could be classified (Fiske, 1992; Spencer & Pahl, 2006; Wellman & Wortley, 1990). Last, we asked 100 crowd-sourcing users to describe their relationships with words. We obtained 1352 terms and grouped them by similarity, thus obtaining 10 coherent groups representing 10 *social dimensions*: *similarity, social support, trust, romance, identity, respect, knowledge, power, fun,* and *conflict* (summarized in Table 19.1). Although these categories are not meant to exhaustively cover all possible social experiences, with our crowdsourcing study we provided empirical evidence that most people are able to characterize the nature of their relationships using these 10 concepts only. This categorization of social relationships is one of the most comprehensive to date.

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*Table 19.1 The 10 social dimensions of relationships studied by decades of research in the social sciences*

| Dimension | Description | Keywords | References |
|---|---|---|---|
| Knowledge | Exchange of ideas or information; learning, teaching | teaching, intelligence, competent, expertise, know-how, insight | (Fiske et al., 2007; Levin & Cross, 2004) |
| Power | Having power over the behavior and outcomes of another | command, control, dominance, authority, pretentious, decisions | (Blau, 1964; French, 1956; French et al., 1959) |
| Status | Conferring status, appreciation, gratitude, or admiration upon another | admiration, appreciation, praise, thankful, respect, honor | (Blau, 1964; Emerson, 1976) |
| Trust | Will of relying on the actions or judgments of another | trustworthy, honest, reliable, dependability, loyalty, faith | (Luhmann, 1982; Zaheer et al., 1998) |
| Support | Giving emotional or practical aid and companionship | friendly, caring, cordial, sympathy, companionship, encouragement | (Baumeister & Leary, 1995; Fiske et al., 2007; Vaux, 1988) |
| Romance | Intimacy among people with a sentimental or sexual relationship | love, sexual, intimacy, partnership, affection, emotional, couple | (Buss, 2003; Buss & Schmitt, 1993; Emlen & Oring, 1977) |
| Similarity | Shared interests, motivations or outlooks | alike, compatible, equal, congenial, affinity, agreement | (Jackson, 2010; McPherson et al., 2001) |
| Identity | Shared sense of belonging to the same community or group | community, united, identity, cohesive, integrated | (Cantor & Mischel, 1979; Oakes et al., 1994; Tajfel, 2010) |
| Fun | Experiencing leisure, laughter, and joy | funny, humor, playful, comedy, cheer, enjoy, entertaining | (Argyle, 2013; Billig, 2005; Radcliffe-Brown, 1940) |
| Conflict | Contrast or diverging views | hatred, mistrust, tense, disappointing, betrayal, hostile | (Berlyne, 1960; Tajfel et al., 1979) |

*Note:* The keywords are the most popular terms used by people to describe those dimensions, according to the study by Deri et al. (2018).

## MACHINE-LEARNING THE SOCIAL PRAGMATICS OF LANGUAGE

By combining the 10 social dimensions in opportune proportions, one can draw an accurate, explainable, and intuitive description of the pragmatic intent of most relationships as perceived by the people involved. However, although these dimensions provide a useful way to conceptualize relationships, it is unclear to what extent these concepts are expressed through language and what their role is in shaping observable dynamics of social interactions.

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To find out, we went back to crowdsourcing. We asked workers to label approximately 8000 Reddit comments according to the social dimensions they convey (Choi et al., 2020). Specifically, we collected a random set of comments, selected sentences containing at least one first- or second-person pronoun (to focus on phrases that are more likely to follow a conversational structure), and asked workers to pick the dimensions that they believed the selected sentence conveys among the 10 provided, or to pick the option *"other"* if none of the 10 applied.

Despite the selection of sentences being random, almost 60% of them were deemed to carry a pragmatic function that could be linked to the 10 social dimensions. Also, examples of all dimensions were found in the sample, albeit to varying extents—*conflict* being the most frequent one (approx. 1000 sentences) and *power* the least frequent one (approx. 100).

Using the collected labels as the training set, we trained multiple classifiers to predict the 10 social dimensions purely from the text (Choi et al., 2020). In particular, given a sentence $s$ and a social dimension $d \in D = \{d_1, \ldots, d_{10}\}$, our task was to determine whether $s$ conveys $d$. Rather than training one multiclass classifier, we treated each dimension independently and trained multiple binary classifiers. This choice was motivated by the nonexclusive nature of the social dimensions (Deri et al., 2018): a sentence may convey any pair (or subsets) of dimensions at once.

In each round of a 10-fold cross-validation, we randomly split each set into 80% for training, 10% for tuning, and 10% for testing. Since all dimensions have a higher number of negative examples than positive ones, we performed random oversampling (Ling & Li, 1998) to balance the classes. Specifically, within each training, tuning, and testing split, we added multiple copies of positive samples picked at random until the size of the two classes got balanced. We measured performance with the average "Area Under the ROC Curve" across all folds—AUC, in short. AUC measures the ability of the model to correctly rank positive and negative samples by confidence score, independent of any fixed decision threshold. Because the data are balanced, the expected value of AUC for a random classification is 0.5.

Using this setup, we trained three types of classifiers: (a) An XGBoost classifier Chen and Guestrin (2016) trained on a number of interpretable feature families that account for linguistic style, textual complexity, affect, sentiment, and word distribution; (b) an LSTM model that uses word and sentence embeddings (Hochreiter & Schmidhuber, 1997); and (c) a transformers-based BERT model pretrained on a 3.3B word corpus (Devlin et al., 2018).

Prediction results are summarized in Figure 19.2. LSTM and BERT reached comparable performances, yielding top scores on five dimensions each, with a tie on knowledge; their performance gap was minor in most dimensions, with peak performances ranging from 0.75 to 0.98. AUC generally dropped when using the XGBoost model.

To demonstrate the descriptive and predictive power of our social dimensions classifier, we applied it to three use cases that represent social dynamics at the level of dyads, groups, and the whole society. First, by analyzing dyadic conversations on Reddit, we found that among the various social dimensions, the ones that are most likely to produce an opinion change are knowledge, similarity, and trust, which resonates with existing sociological theories, and chiefly with Habermas's theory of communicative action (Monti et al., 2022). Second, at group scale, we found that social pragmatics dimensions measured from 85 corporate meeting conversations were more predictive of self-reported meeting success than semantics markers such as topics or sentiment (Zhou et al., 2021). Last, at the societal scale, we applied our classifier to 160 million Reddit messages written by residents in the US to find that some of the

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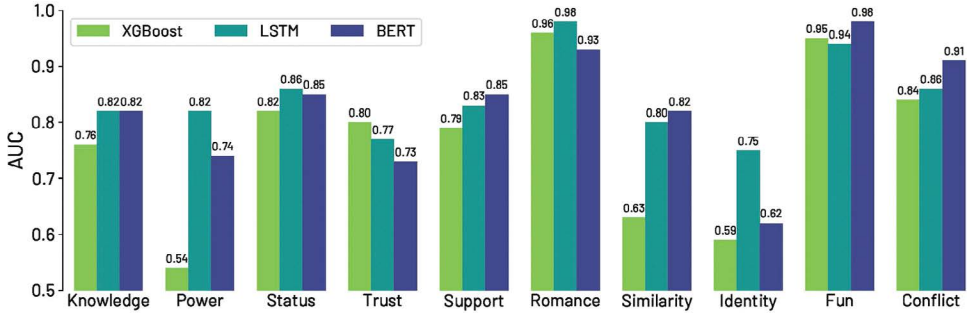



*Figure 19.2 Performance of different models on each dimension for the Reddit dataset (average AUC over 10-fold cross-validation)*

social dimensions are predictive of societal outcomes such as education, wealth, and suicide rates (Choi et al., 2020).

## CONCLUSION

There is a rising consensus on the key role of machine models that can capture language pragmatics in furthering the advancement of NLP research and its applications (Li et al., 2021). Our work demonstrated that some aspects of social pragmatics can be captured quite effectively with neural architectures and appropriate training data.

The main technical challenge for making such models more scalable, accurate, and applicable across domains resides in finding ways to use large-scale and *readily available* data to train language models to capture the pragmatics of discourse rather than its semantics. Large language models (LLMs) represent a very promising technology that can overcome this challenge, as their extensive training data might allow them to capture aspects of pragmatics with limited training data or in a zero-shot fashion (Møller et al., 2024a). LLMs have indeed shown promise also in generating synthetic data that can be later used to improve the performance of specialized classifiers, especially for low-resource tasks (Møller et al., 2024b).

Regardless of the underlying technologies, the ability to measure social pragmatics at scale is essential to add descriptive and predictive power when modeling the dynamics of social groups, at different scales. In the future, we envision our computational framework of social pragmatics as a fundamental tool for investigating dynamics of behavioral change and collective action (Pera et al., 2023).

## FURTHER READING

A detailed account of the work described in this chapter is provided by Deri et al. (2018) and Choi et al. (2020). Theoretical background on the pragmatics of language and social relationships is given by Blau (1964) and Neale (1992).

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