Towards Automated Personality Identification using Speech Acts

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Abstract

The way people communicate– be it verbally, visually, or via text– is indicative of personality traits. In social media the concept of the status update is used for individuals to communicate to their social networks in an always-on fashion. In doing so individuals utilize various kinds of speech acts that, while primarily communicating their content, also leave traces of their personality dimensions behind. We human-coded a set of Facebook status updates from the myPersonality dataset in terms of speech acts label and then experimented with surface level linguistic features including lexical, syntactic, and simple sentiment detection to automatically label status updates as their appropriate speech act. We apply supervised learning to the dataset and using our features are able to classify with high accuracy two dominant kinds of acts that have been found to occur in social media. At the same time we used the coded data to perform a regression analysis to determine which speech acts are significant of certain personality dimensions. The implications of our work allow for automatic large-scale personality identification through social media status updates.

Introduction

A link between individuals' personality traits and their communications has been previously investigated (e.g., Chung & Pennebaker, 2008; Tausczik & Pennebaker, 2010), but determining the correlation between communication patterns and personality dimensions automatically and at large scales (without human-coding) is a remaining challenge. Being able to recognize personality from traces left in social media would be advantageous for social computing, advertising, and other work in informational influence.

Here we present work-in-progress towards identifying new lexical and syntactic features of text that can be used to automatically classify speech acts from social media in a content-free fashion, and finally used to determine posters' personality traits. First, using a set of Facebook statuses from the myPersonality dataset (Celli et. al., 2013), we perform supervised learning experiments using SVM to select relevant features and then conduct cross validation to measure mean accuracy and report the precision and recall of classifying the speech acts associated with each status update.

Our second objective is to automatically determine personality traits through the use of our speech act coded Facebook status updates with the corresponding speech acts. We perform regression analysis to identify significant correlations between personality dimensions on the Big 5 Personality inventory (Costa & McRae, 1992) and speech act labeling. Using our subset of human annotated speech act labels paired with status updates (the same associated with individuals and their personality dimensions), we make significant finding about the links between speech acts as predictors of personality dimensions. The implications of our work are that we can do automatic large-scale personality identification through social media status updates using speech acts labeling.

The rest of the paper is organized as follows: first we briefly review literature on: 1) speech acts, 2) unsupervised modeling of speech acts in conversations using social media corpora, and 3) the link between natural language use and personality traits. Next, we discuss the features we used for feature selection and supervised classification experiments, explain our approach, and review results. In the fourth section we use our hand-coded subset of Facebook status updates along with personality dimensions to perform a regression analysis and discuss results. We conclude with discussion on our automated approach and future work.

Background

Speech Acts

To briefly review, speech acts (Austin, 1963; Searle 1965; Searle, 1976) are a "basic unit of human linguistic communication" (Searle, 1976) and can be used for categorizing human conversational utterances. There have been five basic types of speech acts proposed: assertives, commissives, declaratives, directives, and expressives. With regard to speech acts occurring in social media, Carr, Schrock, and Dauterman (2012) did a content analysis of 204 status messages over 14 consecutive days and found that most status messages were expressives, followed by assertives. This also agrees with the distribution of the coding that we have done with the myPersonality shared task dataset (discussed later).

Speech Act	Description	Examples
Assertive	commits a speaker to the truth of the expressed proposition	*"is watching movies."; "bought new jeans ."*
Commissive	commits a speaker to some future action	*"will post some Halloween pictures... eventually."*
Declarative	change the reality in accord with the proposition of the declaration	*"It is so true - your hair always looks great the day before you have a hair appointment…"*
Directive	cause the hearer to take a particular action	*"Has anyone figured out how to filter the Facebook feeds, using the new Facebook page?..."*
Expressive	express the speaker's attitudes and emotions towards the proposition	*"is a happy human being :D"; "yay for chocolate ice cream!!!!!"*

Table 1. Presents descriptions of human-coding guidelines (Vanderveken & MacQueen, 1990) and examples of identified speech acts from the Facebook status personality dataset for the shared task. [1]

Classifying Speech Acts in Conversations

Recent work (Ritter, Cherry, and Dolan, 2010; Paul, 2012) has concentrated on the topic of classifying speech acts from social media corpora with a focus on modeling conversational structure. Our classification approach though, focused on individual acts, not conversation reconstruction, most closely aligns with the previous work done by Qadir and Riloff (2011) performing classification experiments using lexical and syntactic, and word list features. We focus here on content-free features rather than domain-specific features. We use unsupervised clustering to achieve results, which can be compared to expert labelings and visualized through principle components analysis. Other important differences in our work are based on the different nature of social media phenomena we classify i.e. status updates instead of message board posts; this is important to the number of speech acts we cluster and use in automatic personality identification.

Classifying Speech Acts in Social Media

While large-scale linguistic analysis of social media data using deep parsing may be an attractive solution to understanding the most descriptive properties that represent and distinctly separate speech act phenomena, we find it to currently be an intractable solution and instead propose an approach using lexical, syntactic, and strongly-typed speech act verb lists as features. To understand which features are the most useful we do feature selection, then using the most informative features we apply unsupervised learning to cluster status updates into speech act clusters. We evaluate our results both quantitatively using precision, recall, and F-1 score and visually through inspection of principal components analysis based on our selected features.

Features

For the shared task we came up with a set of features that we thought to be highly discriminating between the various kind of speech acts encountered in Facebook status updates. Previous unsupervised approaches to categorizing speech act phenomena, summarized earlier, have focused on automatically inducing features (including content) from the corpora. Instead, we hypothesize that a good portion of speech acts that constitute social media can be quickly identified based on simple features like: lexical, syntactic, sentiment (Nielsen, 2011), and emoticon usage.

These features are as follows:

Ends with Period?	Has a question word?
Has a Copula Verb?	Has an exclamation mark?
Begins with Copula Verb?	Has sentiment-laden words?
Has a Question Mark?	Contains emoticons?

Table 2. Content-free features used during supervised learning of speech acts for social media-style status updates.

Before doing feature extraction we apply corpus pre-processing to properly segment the tokens in the same style as TweetMotif (O'Connor, Krieger, and Ahn, 2010) and remove contractions. We also filter out status updates that contain less than 3 tokens.

Then, with our coded data we did 10-fold stratified cross validation feature ranking (Guyon et. al., 2002) using support vector machines to understand which features were most useful for describing the data. We found that all features excluding *emoticon* and *question word*, and *begins with period* were determined to be useful.

[1] We also observe sequences of speech acts in status updates but save this for future work. E.g. *"is taking suggestions for blog post for the new Planet Jules website. What do y'all want to see//hear?"*

Fold	Assertives	Commissives	Declaratives	Directives	Expressives	Accuracy
1	57% / 36%	0% / 0%	NA	33% / 21%	83% / 95%	79%
2	**70% / 56%**	0% / 0%	NA	27% / 15%	87% / 95%	**83%**
3	61% / 47%	0% / 0%	NA	0% / 0%	85% / 95%	81%
4	60% / 53%	0% / 0%	NA	100% / 5%	87% / 95%	82%
5	54% / 39%	0% / 0%	NA	**45% / 25%**	84% / 93%	79%
6	59% / 52%	NA	0% / 0%	33% / 15%	86% / 92%	80%
7	70% / 50%	0% /0%	NA	0% / 0%	85% / 95%	80%
8	55% / 44%	0%/ 0%	NA	NA	**95% / 85%**	80%
9	61% / 46%	NA	NA	NA	84% / 95%	80%
10	65% / 57%	NA	NA	0% / 0%	88% / 95%	82%

Table 3. Precision and recall values for 10-fold stratified cross validation of supervised classification. NA values represent folds that did not include that category of acts. Accuracy scores represent overall classifier success on each fold. In contrast, baseline system mean accuracy was 60%.

Evaluation

The human-coded set of 5,849 Facebook status updates 5849 (roughly 59%) from 250 users had a distribution as follows: 19% assertives, 76% expressives, 3% directives, 1.3% commissives, and 0.007% declaratives. Inter-annotator reliability of human coding was measured via the Kappa statistic with 0.672 indicating a strong agreement. Using selected features we performed 10-fold stratified cross validation using support vector machines and saw 81% mean classification accuracy compared to 60% mean accuracy for our baseline system (stratified random sampling w.r.t distribution of training set). Table 3 lists precision and recall for each act type for the folds. The classifier does nicely on expressives and decently on assertives given the distribution of the status updates. There is some small success with classifying directive speech acts phenomena but we see empirically that they are difficult to disambiguate with our current features. For example rehetorical question is a form of an expressive speech act but shares similar properties of real questions (a kind of directive). In some cases, the number of question punctuation marks can be discriminative of the two but is not always reliable. An example from the corpus: "what kind of school does not have free printing for [students] and libraries that close at five ?", this statement is considered a rhetorical question given the implied usage context of Facebook status updates. In order to capture these cases and disambiguate from real questions posted in status such as "do i want another grilled cheese ?", we need more descriptive features, this could be based on considering the relationship between the function and negation words and the presence of question words.

Personality and Speech Act Patterns in Social Media

Using the rough approximations of speech act classifications from earlier we analyze the specific patterns of speech acts exhibited by individuals in the shared task dataset in order to understand the relationships between status updates and personality dimensions. To use automatic speech act classification for personality dimension prediction, we sought to understand any significant patterns between them.

Methodology

Using the same human-annotated Facebook status updates described earlier, we performed a multiple regression analysis in which each personality trait (Conscientiousness, Neuroticism, Agreeableness, Extraversion, and Openness) was individually regressed onto all speech acts at once. Thus, the association of speech acts and personality is the main focus of the current method and analysis.

Results

When Conscientiousness was regressed onto the speech acts, the only significant finding was that it negatively predicted Assertives (β=-.026; p<.05). Neuroticism was negatively associated with Commissives (β=-.028; p<.05). Agreeableness was negatively associated with Assertives (β=-.091; p<.01). Extraversion predicted Assertives (β=-.053; p<.01). Openness did not significantly predict any speech act. Thus, Assertives was the most prevalent speech act across most personality traits.

Discussion

Thorne (1987) studied the link between personality and speech acts where human subject experimentation took place that revealed specific patterns of speech acts associated with different configurations of individuals who exhibited primarily extroverted or introverted personality traits. Thorne found that, “Extraverts showed more pleasure talk, reaches for similarity, compliments, and agreements with extraverts than with introverts.” Thorne describes several sub-classifications of acts, which fall underneath the basic categories described earlier. We note that specifically, these kinds of speech acts (e.g. pleasure talk) exhibited between extraverts fall underneath the category of expressives.

Previous work on identifying personality from natural language falls under two major categories: content and meta-level approaches. Content approaches make use of the particular topics and the description of those topics through words associated with specific psychological phenomena. LIWC (Tausczik & Pennebaker, 2010) is an example of a text analysis tool composed of several dictionaries encoding degrees of strength to which accessed words predict certain psychological phenomena including personality dimensions. For example, specific words associated with social and emotional language were found to be significant w.r.t. extraversion. Content-based approaches though require human judges to rate whether or not content should be included in a particular dictionary. This process, though producing high quality association lists, requires continual maintenance and versioning from human experts as language use changes over time and new words and expressions come into and out of use. Our approach however makes use of meta-level indicators of speech act phenomena to predict personality dimensions.

Conclusions

The current study found that speech acts indeed predict personality, and that certain speech acts are associated with certain traits. However, assertiveness was associated with three of the five traits, thus demonstrating some independence of speech acts from personality on social media sites. Thus, the current results contribute to the growing literature on personality profiling on social media sites. The implications of our work are that we can achieve high accuracy for automatically labeling certain speech act phenomena and can begin to automatically estimate personality dimensions of individuals based from that without the need for direct personality testing.

References

Austin. J. 2005. *How to Do Things With Words.* Cambridge (Mass.) Harvard University Press, 2nd edition, ISBN 0-674-41152-8.

Carr, C. T., Schrock, D. B., & Dauterman, P. 2012. Speech acts within Facebook status messages. In *Journal of Language and Social Psychology, 31*: 176–196.

Celli, F., Pianesi, F., Stillwell, D.S., Kosinski, M. 2013. Workshop on Computational Personality Recognition (Shared Task). In proceedings of WCPR13, in conjuction with ICWSM13. Boston, MA.

Costa, P.T.,Jr. & McCrae, R.R. 1992. *Revised NEO Personality Inventory (NEO-PI-R) and NEO Five-Factor Inventory (NEO-FFI) manual.* Odessa, FL: Psychological Assessment Resources.

Chung, C. K., & Pennebaker, J. W. 2007. The psychological function of function words. In K. Fiedler (Ed.), *Social Communication: Frontiers of Social Psychology*: 343-359. New York: Psychology Press.

Guyon, I., Weston, J., Barnhill, S., & Vapnik, V., 2002. “Gene selection for cancer classification using support vector machines”, In *Machine Learning*, 46(1-3): 389–422.

Kosinskia, M., Stillwell, D., and Graepel, T. 2013. Private traits and attributes are predictable from digital records of human behavior. In PNAS’13, Early Edition. March 11, 2013.

Nielsen, F. Å.. 2011. "A new ANEW: Evaluation of a word list for sentiment analysis in microblogs", Proceedings of the ESWC2011 Workshop on 'Making Sense of Microposts': Big things come in small packages 718 in CEUR Workshop Proceedings, 93-98.

O'Connor, B., Krieger, M., and Ahn, D. 2010. TweetMotif: Exploratory Search and Topic Summarization for Twitter. In the *Proceedings of the International AAAI Conference on Weblogs and Social Media,* Washington, DC, May 2010.

Paul, M. 2012. Mixed Membership Markov Models for Unsupervised Conversation Modeling. *Proceedings of the 2012 Joint Conference on Empirical Methods in Natural Language Processing and Computational Natural Language Learning*, 94–104, Jeju Island, Korea, 12–14 July 2012.

Qadir, A. and Riloff, E. 2011. Classifying sentences as speech acts in message board posts. In *Proceedings of the 2011 Conference on Empirical Methods in Natural Language Processing*, 748–758. Edinburgh, Scotland, UK.

Ritter, A., Cherry, C., and Dolan, B. 2010. Unsupervised modeling of twitter conversations. In *Human Language Technologies: The 2010 Annual Conference of the North American Chapter of the Association for Computational Linguistics*, HLT ’10, 172–180.

Searle, J. 1975. Indirect Speech Acts. In *Syntax and Semantics 3: Speech Acts*: 59–82.

Searle, J. 1976. The classification of illocutionary acts. In Lang. Soc. 5:1-23.

Tausczik, Y.R., & Pennebaker, J.W. 2010. The psychological meaning of words: LIWC and computerized text analysis methods. *Journal of Language and Social Psychology*, *29*: 24–54.

Thorne, A. (1987). The press of personality: A study of conversations between introverts and extraverts. Journal of Personality and Social Psychology, 53: 718-726.

Vanderveken, Daniel and MacQueen, Kenneth. 1990. *Meaning and Speech Acts: Volume 1, Principles of Language Use:* Chapter 6– Semantic Analysis of Performative Verbs. Cambridge: Cambridge University Press.