"C'mon – You Should Read This": Automatic Identification of Tone from Language Text

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Abstract

Information extraction researchers have recently recognized that more subtle information beyond the basic semantic content of a message can be communicated via linguistic features in text, such as sentiments, emotions, perspectives, and intentions. One way to describe this information is that it represents something about the generator's mental state, which is often interpreted as the *tone* of the message. A current technical barrier to developing a general-purpose tone identification system is the lack of reliable training data, with messages annotated with the message tone. We first describe a method for creating the necessary annotated data using human-based computation, based on interactive games between humans trying to generate and interpret messages conveying different tones. This draws on the use of *game with a purpose* methods from computer science and *wisdom of the crowds* methods from cognitive science. We then demonstrate the utility of this kind of database and the advantage of human-based computation by examining the performance of two machine learning classifiers trained on the database, each of which uses only shallow linguistic features. Though we already find near-human levels of performance with one classifier, we also suggest more sophisticated linguistic features and alternate implementations for the database that may improve tone identification results further.

Keywords: language text, mental states, tone, game with a purpose, information extraction

1. INTRODUCTION

One focus of information extraction research has been identifying basic semantic content (e.g., identifying who did what to whom when). Recently, however, researchers have recognized that more subtle information can be communicated via linguistic features in text (see [1] for a review), and this has spurred research in sentiment analysis [2][3][4][5][6][7][8][9], emotion and speech act identification [10][11][12], perspective identification [13][14], and deception detection [15][16][17][18][19] in language text. All of these research areas have in common the basic idea that humans have a mental state that they express in the messages they create, in addition to the basic semantic content of those messages. This mental state can be an emotion like anger or embarrassment, an attitude like confidence or disbelief, or an intention like persuasion or deception (among other things), and it is often perceived as the *tone* of the message. For example, in "C'mon – you should read this", the basic semantic content is something like *read(you, this)* while the tone of the message is persuasive. A message's tone is instrumental in understanding the underlying mental state (and motives) of the person who generated the message, and for predicting how this message will be interpreted by humans reading it.

While most text software is equipped with a spell checker and a grammar checker, no programs currently offer a "tone checker" – though this would be a highly desirable feature to have. As one example, it could be used to check that an email will not be interpreted in a way the sender didn't intend, such as offensive, pushy, or stilted. One technical barrier to developing a general-purpose system dedicated to tone identification in text is a lack of reliable data on which to train it. Currently, there are no large-scale text databases annotated with tone information, and so it is difficult to know what linguistic features to use as cues. Specifically, there are few examples of the "ground truth" for tone, i.e., text annotated with human perceptions of the message's tone. Given the success of natural language processing methods in the other information extraction endeavors mentioned above, we believe tone could also be retrievable once the relevant linguistic cues are identified.

One way to create the necessary annotated data is to make use of human-based computation [20], since humans are used to transmitting messages with specific tones and interpreting the tone of messages. We first describe a methodology for creating this kind of database that we have implemented in the form of a *game with a purpose* (GWAP) [21][22][23], and discuss some salient properties of the resulting database. We then present results from two machine learning classifiers trained on data from the database, which demonstrate the utility of the database, the advantage of human-based computation, and the benefits and pitfalls of using shallow linguistic features for identifying tone. We conclude with suggestions for more sophisticated linguistic features based on the current results, as well as some discussion of what constitutes the "ground truth" for tone information.

2. A RELIABLE DATABASE FOR TONE

2.1 The need for databases

In general, reliable databases are required to develop reliable machine learning algorithms. Unfortunately, few databases annotated with mental state information exist, and these are generally small in size compared to corpora generally available for natural language processing (e.g., the English Gigaword corpus [24] contains approximately 1.75 million words; the Personal Story Subset of the Spinn3r Blog Dataset [25][26] contains approximately 5.3 million words). A few recent examples demonstrate this.

The Language Understanding Annotation Corpus (LUAC) [27] includes text annotated with committed belief, which "distinguishes between statements which assert belief or opinion, those which contain speculation, and statements which convey fact or otherwise do not convey belief." This database is meant to aid in determining which beliefs can be ascribed to a communicator and how strongly the communicator holds those beliefs. The LUAC contains only about 9000 words across two languages (6,949 English, 2,183 Arabic).

The Bitter Lemon corpus [14] is a compilation of essays on various Middle East issues, written from both Israeli and Palestinian perspectives. It is derived from a website (http://www.bitterlemons.net) that invites weekly discussions on a topic and publishes essays from two sets of authors each week. It has been used to investigate automatic classification of perspective [13][14], and contains 297 essays averaging 700-800 words each, for a total of approximately 22,000 words.

A corpus of blog posts annotated for persuasive tactics such as moral generalizations and redefinition was compiled by Anand and colleagues [11], for the purpose of training machine learning algorithms to recognize when persuasion is intended. This corpus contains 380 blog posts (as the rest of the approximately 25,000 examined did not contain easily identifiable persuasive acts). Based on estimates from the larger blog corpus from which these posts were taken [28], there were approximately 200 words per post, leading to a corpus size of approximately 76,000 words.

The last corpus demonstrates an additional issue that surfaces when trying to find realistic examples of language expressing different mental states: It may well be that most of the available data does not actually express any of the mental states of interest. One way around this is to look for open-source data that are highly likely to express the mental states of interest by happenstance, e.g., online gaming forums with games that happen to involve deception (e.g., Mafia game forums [19]). This can often lead to datasets that may be larger in size. However, another issue remains, even in these situations where larger quantities of open-source data are available: The breadth of coverage is limited. While it may be easy to find examples of some mental states in open-source data, it is not always easy to find all the ones of interest.

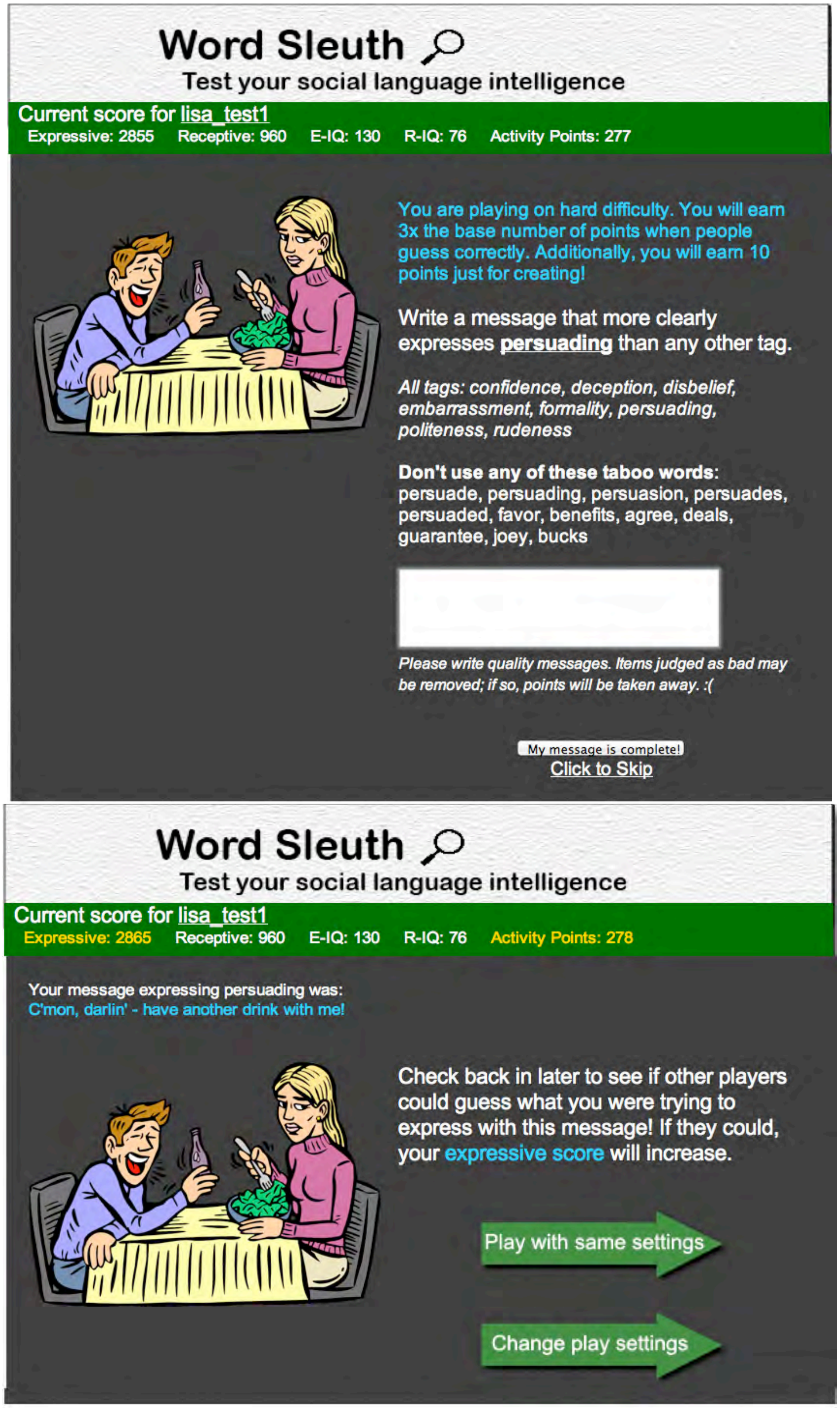
Moreover, real world data sets present the basic problem of ground truth, i.e., knowing for certain which mental states were intended to be conveyed by a particular message. Human annotators can attempt to recover this information, which is the approach taken by the annotated corpora mentioned above. However, this is often a time-intensive and human-resource-intensive process.

2.2 Using games with a purpose

Notably, the human annotation process used for previous corpora highlights that humans are in fact able to interpret the mental state behind a message. Human-based computation can leverage this ability from the population, and use it to construct a reliable database of messages expressing different mental states. Interestingly, groups of humans are sometimes capable of producing more precise and reliable results than any particular individual in the group. This kind of “wisdom of the crowds” phenomenon has been demonstrated in many knowledge domains, including human memory, problem solving, and prediction [29][30][31][32]. Snow and colleagues [33] have additionally demonstrated that a relatively small number of non-expert annotations in natural language tasks can achieve the same results as expert annotation. This suggests that this approach on a larger scale will likely be able to yield a reliable annotation of mental state information in language, as expressed by message tone.

One approach is to use a game with a purpose (GWAP) [21] that is designed to encourage people to provide both kinds of data needed in the database: the messages expressing a particular tone and the annotation of that tone for every message. GWAPs are currently used to accumulate information about many things that humans find easy to identify (see http://www.gwap.com/gwap/ for several examples), such as objects in images [22], common sense relationships between concepts [23], belief about others’ preferences [34], and the musical style of songs [35]. Using a GWAP for message tone, we can also take advantage of human-based computation and the potential wisdom of the crowds inherent in this setup. In particular, since the collected data come from and are vetted by a large number of participants, we can gauge which messages are reliable examples of particular mental states and which are confusing examples.

We have designed a GWAP called Word Sleuth (available at http://gwap.ss.uci.edu/) that takes the form of an online game played through a web browser interface. In the context of the game, Word Sleuth encourages participants to play two different roles, which participants can freely alternate between as they desire: the message generator (called the Expressor) and the message interpreter (called the WordSleuth). As the Expressor, participants generate messages expressing a particular tone; as the Word Sleuth, they label messages created by other participants as expressing a particular tone. Game play is asynchronous, so participants do not need a partner to play. Figures 1 and 2 show example game play for both the Expressor and Word Sleuth roles.



Word Sleuth

Test your social language intelligence

Current score for lisa_test1

Expressive: 2855 Receptive: 960 E-IQ: 130 R-IQ: 76 Activity Points: 277

You are playing on hard difficulty. You will earn 3x the base number of points when people guess correctly. Additionally, you will earn 10 points just for creating!

Write a message that more clearly expresses **persuading** than any other tag.

All tags: confidence, deception, disbelief, embarrassment, formality, persuading, politeness, rudeness

Don't use any of these taboo words: persuade, persuading, persuasion, persuades, persuaded, favor, benefits, agree, deals, guarantee, joey, bucks

Please write quality messages. Items judged as bad may be removed; if so, points will be taken away. :(

Word Sleuth

Test your social language intelligence

Current score for lisa_test1

Expressive: 2865 Receptive: 960 E-IQ: 130 R-IQ: 76 Activity Points: 278

Your message expressing persuading was:
C'mon, darlin' - have another drink with me!

Check back in later to see if other players could guess what you were trying to express with this message! If they could, your expressive score will increase.

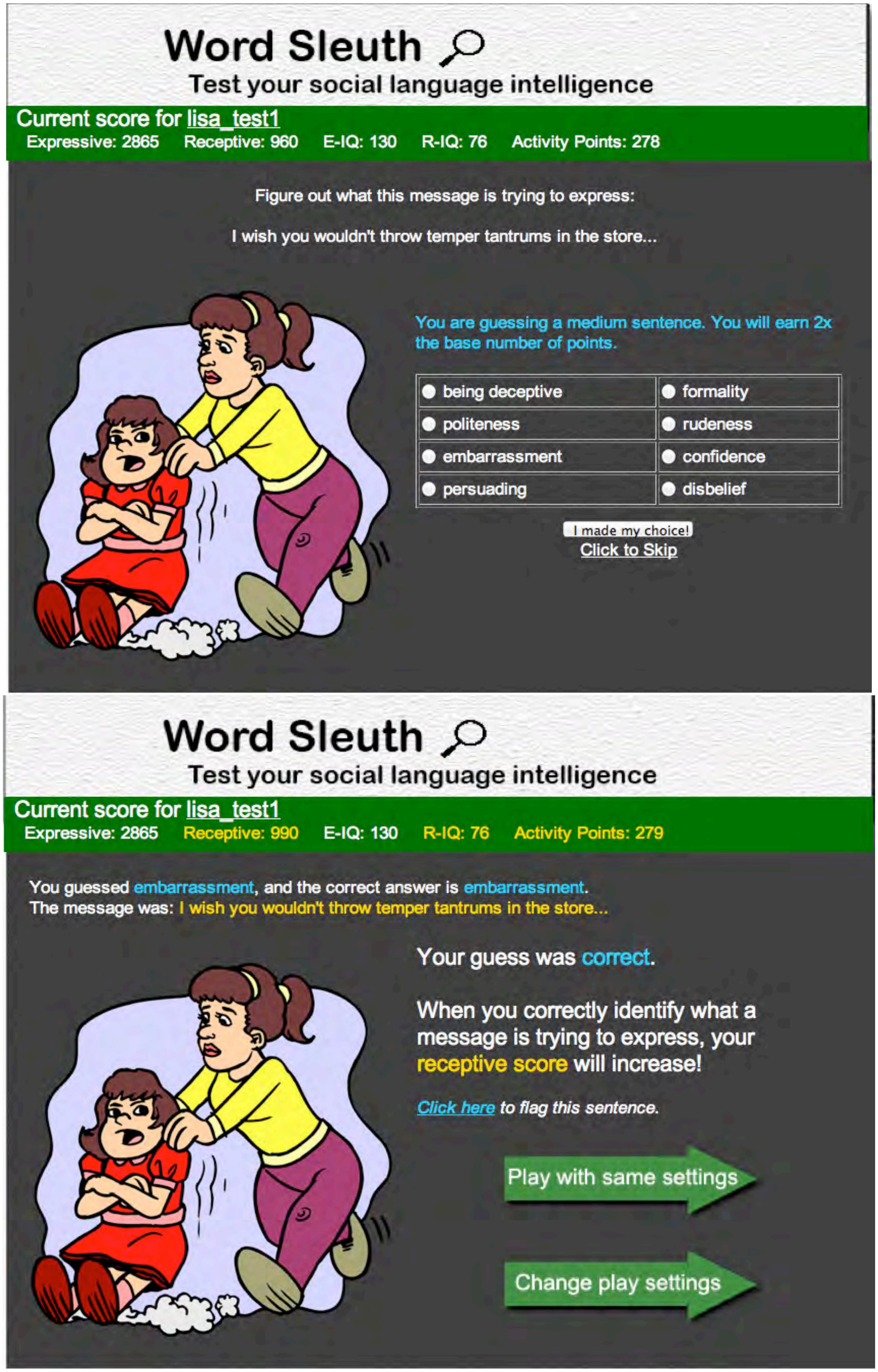
FIGURE 1: An example of Expressor game play.

The first panel of figure 1 shows a sample screen for generating a persuasive message. The participant is shown a random context picture to help them generate a message, and this context picture will be shown to any interpreter attempting to interpret the generated message. Participants can choose what difficulty level they want to play, with harder difficulty levels earning them more points. The difficulty level for Expressors determines how many "taboo" words there are – these are words that the participant cannot use in the message. For the easiest level, this includes only morphological variants of the intended tone (e.g., "persuading", "persuasion", "persuades", and "persuaded" for the "persuading" tone). Harder levels add additional words (3 for medium difficulty, 7 for hard difficulty) that are dynamically generated based on the messages that have previously been created for that tone – words that currently have the highest mutual information are included in the taboo list. The motivation behind taboo words is two-fold. First, the morphological variants discourage certain kinds of cheating (e.g., explicitly writing "This is a persuading message"). Second, the dynamically generated taboo words encourage participants to create more varied messages, rather than relying on a few key words.

Participants are additionally shown the other potential message tones that interpreters will have to choose from. This encourages them to make their messages unambiguously express the intended tone. Participants are also reminded that there is a mechanism for flagging poor messages – if a generator's message is flagged as poor by enough other participants, that message is removed from game play and the generator's expressive score is penalized. Because the intended tone type is randomly selected, it is possible to get the same type multiple times in a row when generating messages. Given this, we also give participants the option to skip creating a message – this is useful when they don't wish to generate a message for a particular tone (perhaps because they just generated a message of that kind).

The second panel of figure 1 displays a sample follow-up for message creation. The participants can see that their activity points have increased, and are encouraged to check in later to see if their expressive score has increased. They then have the option to continue the current game mode (e.g, Expressor, hard difficulty), or change either the role or difficulty or both.

The first panel of figure 2 shows a sample screen for interpreting a message's tone. The message, which was generated by another participant previously, is shown, along with the context picture that the generator used to create it. The difficulty level is shown, with higher difficulty levels gaining the participant more points if the message's tone is interpreted correctly. A message's difficulty is determined by how accurate other people have been so far at interpreting its intended tone – the third of the message set with the lowest accuracy is labeled "hard", the middle third is labeled "medium", and the top third is labeled "easy". The second panel of figure 2 shows a sample screen that would appear after a message's tone has been chosen from among the available options. The intended tone is displayed along with the interpreted tone. If they match, the receptive score is shown to increase and the receptive IQ may increase. If they do not match, the receptive score is shown to decrease and the receptive IQ may decrease. In either event, the activity points increase (with the aim of motivating continued game play). Participants also have an option at this point to flag a message if they believe it is a particularly poor example of a message expressing the intended tone. This helps to immediately weed out very poor examples from the database.



Word Sleuth

Test your social language intelligence

Current score for lisa_test1

Expressive: 2865 Receptive: 960 E-IQ: 130 R-IQ: 76 Activity Points: 278

Figure out what this message is trying to express:

I wish you wouldn't throw temper tantrums in the store...

You are guessing a medium sentence. You will earn 2x the base number of points.

○ being deceptive	○ formality
○ politeness	○ rudeness
○ embarrassment	○ confidence
○ persuading	○ disbelief

Word Sleuth

Test your social language intelligence

Current score for lisa_test1

Expressive: 2865 Receptive: 990 E-IQ: 130 R-IQ: 76 Activity Points: 279

You guessed embarrassment, and the correct answer is embarrassment.
The message was: I wish you wouldn't throw temper tantrums in the store...

Your guess was correct.

When you correctly identify what a message is trying to express, your receptive score will increase!

Click here to flag this sentence.

FIGURE 2: An example of Word Sleuth game play.

The scoring system within the game reflects the inherent connection between the generator's ability, the message, and the interpreter's ability. When a message's tone is correctly interpreted, both the generator of that message and the interpreter of that message get points added to their scores – the generator's expressive score increases while the interpreter's receptive score increases. In addition, the generator's "expressive IQ" increases and the interpreter's "receptive IQ" increases, based on z-scores of overall percent correct expressing or interpreting, respectively. When a message is not labeled correctly (whether due to the generator creating a poor message or the interpreter interpreting it poorly), no points are subtracted from the respective expressive and receptive scores – however, the expressive and receptive IQs are decreased (again, based on z-scores of percent correct expressing or interpreting). Because scores and IQs are updated only when messages are interpreted, we additionally have activity points which are increased whenever a participant either creates a message or guesses the label for a message. This is meant to particularly encourage participants to play the Expressor role, as activity points give them instant gratification for creating a message. To encourage game play in general, there are high score tables available, as well as individual achievement badges.

With enough game players, many messages expressing different tones can be created and interpreted. Given previous successes with human computation and wisdom of the crowds effects, we expect the cumulative knowledge to be quite reliable, even if a message is only labeled with a single tone (perhaps expressing that message's most obvious tone from the perspective of the interpreter). This is because the same text can be evaluated by many different people, which can reduce the effect of idiosyncratic responses from a few individuals.

One clear advantage of the GWAP approach is the ability to target which mental states we are interested in, and subsequently create messages with those tones that are also annotated with that tone information. In this way, we simultaneously address three issues that previous databases have encountered. First, we know that nearly all our data[1] will in fact contain at least one of the tones of interest, because the data have been generated to express those very tones. Second, we can infer tone annotations in a fairly inexpensive way – using the collective interpretations of the Word Sleuth game players. Third, we can be fairly sure of the accuracy of the annotation by using a wisdom of the crowds approach that aggregates data across multiple interpretations.

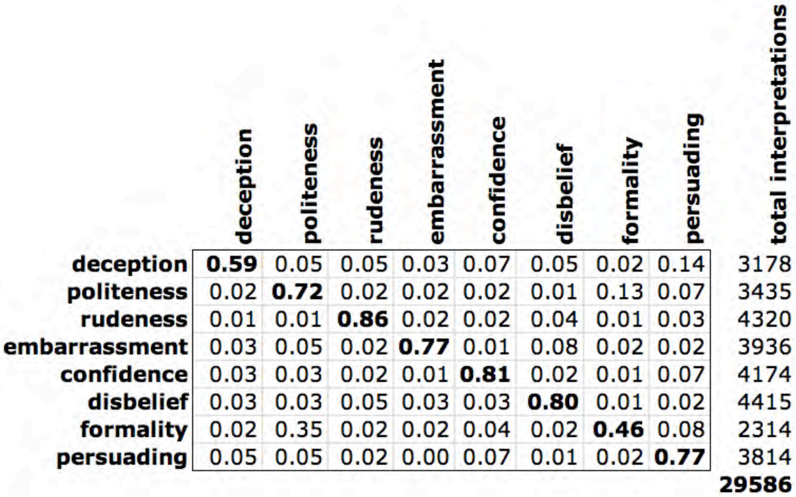
2.3 Creating a tone database with Word Sleuth

We decided to explore eight mental states that are indicators for different emotional states, attitudes, and intentions: deception, politeness, rudeness, embarrassment, confidence, disbelief, formality, and persuading. As of March 2012, Word Sleuth has attracted 877 online game players, with 4,157 messages generated (~48,500 words) and 29,586 interpretations of those messages (an average of about 7 interpretations per message). Participants generally played the Word Sleuth role more than the Expressor role, which has led to significantly more interpretations as compared to messages. There was no limit on message length, though more participants tended to keep messages fairly brief (approximately 11-12 words).

Averaged across messages and participants, humans were successful at mental state transmission (via message tone) approximately 74.4% of the time. That is, approximately 3 out of every 4 messages were interpreted as expressing the tone they were intended to express. This is significantly better than chance performance, which would be 1 out of 8 (12.5%), and demonstrates that humans are fairly good at transmitting message tone – though notably not

[1] The messages flagged during game play as being very poor are the only data that might not be useful.

perfect. Moreover, human accuracy is not evenly distributed across the different tone types, as shown in figure 3. Figure 3 is a confusion matrix that shows the likelihood that a message will be interpreted as a specific tone (in the columns), given that it has been generated with that specific tone in mind (in the rows), averaged over messages and participants. In other words, figure 3 shows the conditional probability distribution *p(interpreted | generated*). The diagonal probabilities indicate how often a message's tone was correctly interpreted for each tone type; this shows how often transmission of that particular mental state was successful. The total number of interpretations for each tone type is show in the rightmost column. While the messages are chosen randomly for interpretation when participants play the Word Sleuth role, participants do have the option to skip messages they find difficult – this is what causes certain tone types, such as deception and formality, to be less represented in the dataset. In essence, this is one indication of the inherent difficulty of those two tone types.



	deception	politeness	rudeness	embarrassment	confidence	disbelief	formality	persuading	total interpretations
deception	**0.59**	0.05	0.05	0.03	0.07	0.05	0.02	0.14	3178
politeness	0.02	**0.72**	0.02	0.02	0.02	0.01	0.13	0.07	3435
rudeness	0.01	0.01	**0.86**	0.02	0.02	0.04	0.01	0.03	4320
embarrassment	0.03	0.05	0.02	**0.77**	0.01	0.08	0.02	0.02	3936
confidence	0.03	0.03	0.02	0.01	**0.81**	0.02	0.01	0.07	4174
disbelief	0.03	0.03	0.05	0.03	0.03	**0.80**	0.01	0.02	4415
formality	0.02	0.35	0.02	0.02	0.04	0.02	**0.46**	0.08	2314
persuading	0.05	0.05	0.02	0.00	0.07	0.01	0.02	**0.77**	3814
									29586

FIGURE 3: Human confusion matrix for the eight tone types investigated. The rows represent the intended tone, while the columns represent the interpreted tones. The bolded diagonal indicates the percentage of correct interpretations for each tone type. The total number of interpretations for each tone type is shown in the rightmost column.

Another indication is the accuracy of transmission – deception (0.59) and formality (0.46) are much harder to transmit correctly than the other tone types. Table 1 shows some sample messages (with the participants' own spelling and punctuation), highlighting why some tone types may be easier than others.

Intended Tone	Interpreted Tone	Message
confidence	confidence	"here's the paper! i'm positive its really good this time"
rudeness	rudeness	"You are the stinkiest person I've ever met."
deception	persuading	"I recommend that you take one step forward. Don't worry, it's not dangerous."
formality	politeness	"may i take the road on the left please"

TABLE 1: Sample messages created in the Word Sleuth game. The top two message tones are correctly interpreted, while the bottom two message tones are not.

Confidence (0.81) and rudeness (0.86) have the highest rates of successful transmission, as shown in figure 3, and Table 1 shows how these messages may be very distinctive. For example, the confident message uses an indicator of certainty ('positive'), while the rude message uses the negative valence word 'stinkiest'. In contrast to these two tone types, deception is more difficult and often confused with persuading (0.14) and confidence (0.07). This is likely because the linguistic cues overlap – when attempting deception, it may often be while in the act of persuading, and the deceiver may be attempting to appear confident in order to be believed. This appears in the example message in Table 1 – the overall message is attempting to persuade the listener to move forward. Since it is intended as deception, the most likely part that is deceptive involves the speaker's assessment of how dangerous the situation is (presumably, it *is* in fact dangerous to take a step forward). This highlights one way in which deception may be a more complex intention – it effectively involves a semantic inversion, where the opposite of the semantic content is actually true, and the participant must detect that inversion. This in contrast to the other tone types, which can be viewed as an adjusted version of the underlying semantic content (e.g., a persuasive form of *read(you, this)* does not change this underlying semantic content). Interestingly, while participants have difficulty detecting all the deceptive messages (that is, having good recall), their precision is fairly good (0.59/Σ(deception column) = 0.76) – i.e., when they have decided something is deceptive, it usually is.

The confusion matrix in figure 3 also shows that formality is often confused with politeness (0.35) – that is, formal messages are mistaken as polite about one third of the time. The sample message in Table 1 shows how this might happen – while the 'may ' construction is often used to convey formality (as opposed to 'can I'), other linguistic cues may have conveyed politeness more strongly to the interpreter, such as the 'please' at the end of the utterance. Precision is somewhat better (0.46/Σ(formality column) = 0.68), again showing that the messages interpreted as formal often are indeed formal. Interestingly, figure 3 also shows us that politeness is more accurately transmitted overall (0.72) and not as often confused with formality (0.13). This suggests that, though these tones do overlap, formality may be viewed by the participants as a subset of politeness. In effect, it is easier to be polite without being formal, and it seems more difficult to be formal without also being polite. This has some intuitive appeal, as a formal tone may be viewed as polite, even if the content of the message is not very polite (e.g., a complaint).

From a natural language processing standpoint, these human confusion data are useful in two ways. First, they give us a goal to aim at – we would like to eventually do as well as humans (and perhaps even better, by avoiding the confusions humans stumble over). Second, these data suggest that two tones – deception and formality – are likely to be more difficult to automatically classify.

3. LEARNING TO IDENTIFY TONE AUTOMATICALLY

To demonstrate the utility of this kind of database for developing automatic systems for tone detection, we investigated the performance of two machine learning classifiers that were trained on portions of the current database. While we realize that there are many machine learning techniques that could be used, we decided to examine one very simple classifier and one more sophisticated classifier in order to demonstrate the utility of the kind of database we have constructed.

The goal of each classifier was the same as that of the humans playing the Word Sleuth role: select the intended tone from one of the eight choices. Though the database is still small when compared to the standard corpora used for developing natural language processing systems, we nonetheless find quite good performance when using the kind of linguistic features often used in previous studies of sentiment analysis, emotion identification, perspective identification, and deception detection. Performance is enhanced when we apply a simple wisdom of the crowds measure for selecting reliable messages to train on. These promising results suggests that larger databases constructed in a similar fashion may well lead to human-level classification performance and beyond.

More broadly, we are interested in the linguistic features that are useful for tone detection in text, and how machine learning algorithms compare to human performance. In particular, if we can identify the linguistic features humans are using, we may able to increase the performance of machines to human levels. This can also help us understand why humans make the mistakes they do (e.g., on deception and formality), so that software can be designed to recognize those mistakes. To this end, we use the classifier results to suggest more sophisticated linguistic features that may be more similar to the ones humans use.

3.1 Setting up the classification task

There are several considerations for any classifier approach: what data are used to train the classifier, what is a reasonable baseline to compare performance against, and what features does the classifier use to make its decision? We look at each of these in turn.

Given the relatively small size of the current database, there are two approaches regarding the data we use to train the classifiers. The first approach is to use a message regardless of how reliable it is, with the idea that the quantity of messages will make up for poor examples. An alternative approach is to only use a message if it is reliable, with the idea that better quality messages will make up for having fewer of them. The first approach will use all 4,157 messages currently available. For the second approach, we defined a simple measure that draws on the wisdom of the crowds: if a message has two or more interpretations and also has more than 50% agreement with the intended tone, it is included. This rules out messages with only one interpretation (since that doesn't represent a crowd's collective interpretation), and also messages where there was so much confusion that the intended tone was chosen 50% or less of the time. Applying this metric, we are left with a dataset of 1,862 messages (~21,750 words).

Turning now to reasonable assessments of baseline performance, we have two reasonable options. One is based on the task itself – given that there are 8 options, and the classifier must select one, there is a 1 in 8 chance of doing so correctly by chance (0.125). A slightly more informed baseline might be to always choose the tone type that is most frequent in the training data. For the complete dataset, this is the rudeness tone, which accounts for 570 of the 4,157 messages (0.137). For the filtered dataset, this is again the rudeness tone, which accounts for 321 of the 1,862 messages (0.172). Each dataset and its accompanying baselines are summarized in Table 2.

Dataset	Description	# Messages	baseline: 1 in 8	baseline: most frequent in training set
complete	all	4,157	0.125	0.137
filtered	2+ interpretations and >50% agreement	1,862	0.125	0.172

TABLE 2: Summary of two datasets that the classifiers are trained on, including the description of messages included in the dataset, the number of messages in the dataset, and two baseline performance measures.

The next question is which features the classifiers will use. As a first pass measure, we examined a number of fairly shallow linguistic features similar to what previous studies in sentiment analysis, emotion and speech act identification, perspective identification, and deception detection have used [7][8][11][13][14][15][16][17][18][19][36]. Table 3 shows the features the classifiers had access to. These include character-level features (number of punctuation marks; proportion of punctuation marks; proportion of characters; proportion of digits), word-level features (unigrams, bigrams, and trigrams appearing more than once in the database; number of word types; number of word tokens; lexical diversity; average word length; average word log frequency; proportion of first person pronouns), and sentence-level features (number of sentences per message; average sentence length). This led to approximately 11,600 features, most of which were the unigrams, bigrams, and trigrams (only 42 were features other than these, as shown in Table 3). Some of these shallow features are coarse measures of more complex properties. For example, first person pronouns index self-reference, which is thought to decrease during deception as the deceiver puts more psychological distance between herself and the message (e.g., see [15]).

Feature type	Description	#	Implementation	Sample calculation
punctuation marks	? ! . ; : ,	6	frequency of mark	'c'mon!' = 1 !
characters	Letters a, b, c…z, all digits, all punctuation marks	28	#/ # character tokens	(# digits)/(total # letters, digits, punctuation marks)
n-grams	unigrams, bigrams, & trigrams appearing more than once in the database	varies	frequency of n-gram	'BEGIN+please' appears once in 'please read this'
word types	number of word types	1	# word types	'the penguin ate the fish' = 4
word tokens	number of word tokens	1	# word tokens	'the penguin ate the fish' = 5
lexical diversity	word type to word token ratio	1	# word types / # word tokens	'the penguin ate the fish' ≈ 4/5
average word length	average number of characters per word	1	# characters/ # word tokens	'the penguin ate the fish' = 4
average word log frequency	average of the log of the normalized frequency for each word in the message that appears more than once in the database	1	$\frac{\sum_{w \in msg} \log(\frac{freq(w)}{\sum_{d \in database} freq(d)})}{\#\ \text{word tokens in msg}}$	same as implementation
1st person pronouns	*I, me, my, mine, we, us, our, ours, myself, ourselves*	1	# 1st person pro/ # word tokens	'we saw penguins' ≈ 1/3
sentences	number of sentences	1	# sentences	"what did you see? We saw penguins" = 2
average sentence length	average number of words per sentence	1	# word tokens in msg/ # sentences in msg	"what did you see? We saw penguins" ≈ 7/2

TABLE 3: Linguistic features used by classifiers. Note that for all proportion calculations, a smoothing constant (0.5) was added to the raw counts. Note also that lexical diversity values range between 0 and 1, with higher values indicating more diverse usage (each word appears around once). In addition, all bigrams and trigrams include begin-message (BEGIN) and end-message (END) markers.

3.2 Classifier performance

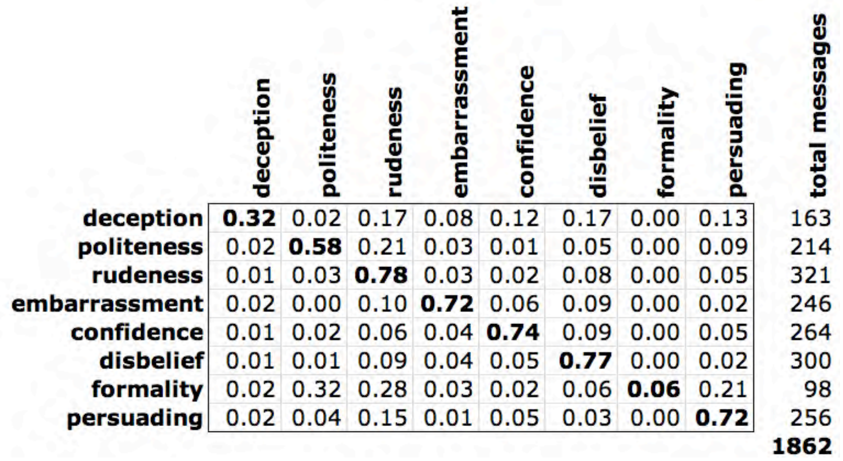
For each classifier we examined, we used 10-fold cross validation, such that the classifier was trained on the interpretations for 90% of the messages and tested on its predictions of the remaining 10% of the messages, with this process repeated 10 times (for each of the 10 folds). The results reported in table 4 represent the ability of each classifier to predict the correct interpretation for a message, averaged over all messages from the eight tone types. The first classifier selected was the Naïve Bayes classifier, which uses all available features when making its decision. This contrasts with the second classifier selected, the Sparse Multinomial Logistic Regression (SMLR) classifier [37], which uses regression analysis to identify classifier features that are particularly useful for detecting each tone type. In particular, not all features may be useful for each tone type, and this analysis allows us to downweight and possibly remove the features that are less discriminative. Two parameters in the SMLR classifier are λ, which determines how strongly the classifier prefers to rely on a small number of features (i.e., by giving those features non-zero weight), and r, the number of regression rounds. The results in table 4 are from the SMLR classifier that performed the best, using λ = 0.05 and r = 3.

	Complete	**Filtered**
# Messages	4,157	1,862
Baseline: 1 in 8	0.125	0.125
Baseline: most frequent in training set	0.137	0.172
Naïve Bayes	0.585	0.655
SMLR (λ = 0.05, r = 3)	0.586	0.704

TABLE 4: Summary of classifier performance across the complete and filtered datasets, including the number of messages in the dataset, two baseline performance measures, and classifier performance.

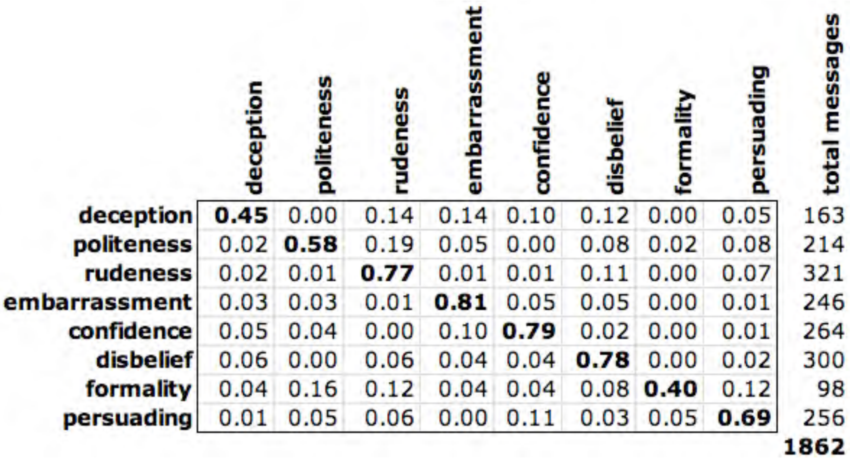
From these results, we can make several striking observations. First, both classifiers are doing quite well compared to the best baseline, no matter which dataset they use – they are 4.3 times better than the best baseline on the complete dataset (0.585 or 0.586 vs. 0.137) and 3.8 – 4.1 times better than the best baseline on the filtered dataset (0.655 or 0.704 vs. 0.172). This suggests that this kind of dataset is very useful for developing tone detection systems – even fairly small datasets can yield good performance. This relates to the second observation: The SMLR classifier trained on the filtered dataset is very close to human performance already (human: 0.744, SMLR: 0.704), even when using shallow linguistic features. If we want to understand how humans interpret message tone so that we can develop software that will automatically identify unintended tones, these data suggest that even very shallow features may be useful. Third, we can see the importance of using quality messages, even at the expense of the quantity of messages. In particular, while there is equivalent performance by both classifiers on the complete dataset, both improve when using the filtered dataset, with the SMLR improving the most (from 0.586 to 0.704). This is true despite the filtered dataset having approximately a third the number of messages that the complete dataset has.

We also note that the performance of both classifiers is similar to human performance, in that some tone types are more difficult than others. Figures 4 and 5 show confusion matrices for each classifier trained on the filtered dataset.



	deception	**politeness**	**rudeness**	**embarrassment**	**confidence**	**disbelief**	**formality**	**persuading**	**total messages**
deception	**0.32**	0.02	0.17	0.08	0.12	0.17	0.00	0.13	163
politeness	0.02	**0.58**	0.21	0.03	0.01	0.05	0.00	0.09	214
rudeness	0.01	0.03	**0.78**	0.03	0.02	0.08	0.00	0.05	321
embarrassment	0.02	0.00	0.10	**0.72**	0.06	0.09	0.00	0.02	246
confidence	0.01	0.02	0.06	0.04	**0.74**	0.09	0.00	0.05	264
disbelief	0.01	0.01	0.09	0.04	0.05	**0.77**	0.00	0.02	300
formality	0.02	0.32	0.28	0.03	0.02	0.06	**0.06**	0.21	98
persuading	0.02	0.04	0.15	0.01	0.05	0.03	0.00	**0.72**	256
									1862

FIGURE 4: Naïve Bayes confusion matrix for the eight tone types investigated. The rows represent the intended tone, while the columns represent the interpreted tones. The bolded diagonal indicates the percentage of correct predictions for each tone type. The total number of messages for each tone type is shown in the rightmost column.



	deception	politeness	rudeness	embarrassment	confidence	disbelief	formality	persuading	total messages
deception	**0.45**	0.00	0.14	0.14	0.10	0.12	0.00	0.05	163
politeness	0.02	**0.58**	0.19	0.05	0.00	0.08	0.02	0.08	214
rudeness	0.02	0.01	**0.77**	0.01	0.01	0.11	0.00	0.07	321
embarrassment	0.03	0.03	0.01	**0.81**	0.05	0.05	0.00	0.01	246
confidence	0.05	0.04	0.00	0.10	**0.79**	0.02	0.00	0.01	264
disbelief	0.06	0.00	0.06	0.04	0.04	**0.78**	0.00	0.02	300
formality	0.04	0.16	0.12	0.04	0.04	0.08	**0.40**	0.12	98
persuading	0.01	0.05	0.06	0.00	0.11	0.03	0.05	**0.69**	256
									1862

FIGURE 5: SMLR confusion matrix for the eight tone types investigated. The rows represent the intended tone, while the columns represent the interpreted tones. The bolded diagonal indicates the percentage of correct predictions for each tone type. The total number of messages for each tone type is shown in the rightmost column.

Similar to the human confusion matrix of figure 3, these figures show the likelihood that a message will be interpreted as a specific tone (in the columns), given that it has been generated with that specific tone in mind (in the rows), averaged over messages. In other words, these figures show the conditional probability distribution *p(predicted | generated*) for the Naïve Bayes classifier (figure 4) and the SMLR classifier (figure 5). The diagonal probabilities indicate how often a message's tone was correctly predicted for each tone type. The total number of messages for each tone type is show in the rightmost column.

We can observe some similarities in the performance of both classifiers. Similar to humans, both classifiers struggle with deception and formality. Also similar to humans, the precision of formality is very good (Naïve Bayes: .06/Σ(formality column) = 1.00, SMLR: .40//Σ(formality column) = 0.85), as is the precision of deception (Naïve Bayes: .32/Σ(deception column) = 0.74, SMLR: .45//Σ(deception column) = 0.66). However, we also see some non-human confusions in both classifiers. Unlike humans, who mostly confuse formality with politeness and persuading, we find that both classifiers are much more variable in their formality confusions – both often confuse formality with rudeness (Naïve Bayes: 0.28, SMLR: 0.12), for example. A similar non-human behavior occurs with politeness, which is often confused with rudeness (Naïve Bayes: 0.21, SMLR: 0.19), and rarely with formality (Naïve Bayes: 0.00, SMLR: 0.02). Deception is also more often confused with rudeness (Naïve Bayes: 0.17, SMLR: 0.14), unlike what humans do (Humans, figure 3: 0.05).

We can think of two potential reasons for this non-human behavior. First, it may be that there is some kind of default in both classifiers to the most frequent message in the training set when there is uncertainty (rudeness is the most frequent tone in the filtered dataset, at 17.2%). In fact, if we look at the confusions for both classifiers with rudeness in the complete dataset (where rudeness is still the most frequent tone, but now is only 13.7% of the dataset), it turns out there's considerably less confusion with rudeness (Naïve Bayes: deception with rudeness: .09, politeness with rudeness: .09, formality with rudeness: .05; SMLR: deception with rudeness: .09, politeness with rudeness: .09, formality with rudeness: .05). So, this could be a result of the small size of the filtered dataset – in particular, because there are more reliable rude messages in the filtered dataset, it becomes the default prediction, and this is not human-like.

Still, humans have even less confusion with rudeness for these tone types (Human: deception with rudeness: .05, politeness with rudeness: .02, formality with rudeness: .02), which suggests the bias in the training set is only part of the issue. A second cause of the non-human performance could be the particular linguistic features the classifiers are basing their decision on. While shallow linguistic features work fairly well, it may be that we can improve performance to human levels and beyond by tapping into more sophisticated linguistic features.

3.3 Linguistic features for tone

The SMLR classifier offers some insight into what features would be appropriate, as it learns to base its decision on a small number of features. Using λ = 0.05 and r= 3 on the filtered training set, between 497 and 1112 features of the approximately 11,600 available per tone type are given non-zero weight by the classifier. From these, we can see which are strongly weighted, and see if these can suggest useful linguistic features. Table 5 shows a selection of strongly weighted features for each tone type.

Tone	Sample features with strong non-zero weight
deception	i+would+never (3.2), you+have+such (3.1), nope (2.7), umm (2.5), i'm+not (2.0), promise (1.9), would+never (1.9), i'm+just (1.8), i+uh (1.5), i+promise (1.3)
politeness	lovely (4.3), fantastic (3.7), thanks (3.5), love+to (3.0), could+you+please (2.9), thank (2.9), if+you+would (2.4), prettiest (2.3), help+you (2.2), *may-i-take (-1.1)*
rudeness	screw (4.8), filthy (3.5), loser (3.5), annoying (3.5), stupid (3.2), ugly (2.8), fat (2.6), don't+like (2.5), *nice (-1.1), pretty (-1.3), beautiful (-1.7)*
embarrassment	ashamed (3.6), accidentally (3.4), forgot (3.4), awkward (2.7), whoops (2.5), should+have (2.1), oh+no (1.8), 1st person pronouns (1.6), didn't+mean (1.6)
confidence	certain (3.4), really+good (3.3), easy (3.0), i+could (2.8), definitely (2.8), positive (2.7), i'm+sure (2.5), i+look (2.3), i+can+tell (2.3), BEGIN+i+knew (2.2)
disbelief	can't+be (3.8), surprised (3.2), impossible (3.2), didn't+know (3.1), shock (3.0), unreal (2.8), no+way (2.6), outrageous (2.1), # question marks (1.4)
formality	honor (5.5), welcome (3.8), BEGIN+sir (3.5), mrs (3.2), may-i-take (2.5), majesty (2.7), highness (2.2), mr (2.2), may (2.1), madam (1.6), allow (1.6), pardon+me (1.4)
persuading	guarantee (4.8), lets (3.9), just+one (3.0), believe+me (2.8), you+have+to (2.8), fun (2.4), would+look (2.4), trust+me (2.4), think+you+should (2.2), try (1.9)

TABLE 5: A selection of features strongly weighted by the SMLR classifier (λ=0.05, r = 3) for each tone type. The weight given by the classifier is in parentheses after each feature, with negatively weighted features in *italics*.

We discuss some highlights of each tone's features in turn. For deception, instead of finding that first person pronouns are not used, we find that they are used in conjunction with negation words like 'not' and 'never'. We also find indicators of uncertainty ('umm', and 'uh'), and verbs indicating intention ('promise'). For politeness, we find that positive valence words and thanking expressions are positively weighted, in addition to turns of phrase involving some modal verbs ('could', 'would'). Interestingly, we find that the modal 'may' is negatively weighted, presumably because here the classifier is attempting to distinguish between politeness and formality – and 'may' is positively weighted for formality. For rudeness, we find a fairly straightforward pattern of negative valence words being positively weighted and positive valence words being negatively weighted. For embarrassment, we find several words expressing shame or the appearance of an accident ('ashamed', accidentally', awkward', 'whoops', 'oh no'). For confidence, we find many indicators of certainty ('certain', 'definitely', 'positive', 'i'm sure', 'i knew' 'i can tell'), some of which use first person pronouns in them. For disbelief, we find many indicators of surprise ('can't be', 'surprised', 'impossible', 'shock', 'unreal', 'outrageous', the number of question marks), including some that involve negation ('didn't know', 'no way'). For formality, in addition to some fixed formal expressions ('may i', 'pardon me'), we also find several titles ('honor', 'sir', 'mrs', 'majesty', 'highness', 'mr'). For persuading, we see indications of certainty ('guarantee', 'believe me', 'trust me'), positive valence words ('fun'), and coercive expressions ('just', 'you have to', 'think you should', 'try').

Perhaps most notably, the most useful features for these tone types typically are the n-grams, rather than stylometric indicators such as punctuation marks and message length. Given the particular n-grams identified by the SMLR classifier for each tone type, we now have some idea of the more sophisticated syntactic and semantic indicators for each tone. Syntactic classes could continue to include first person pronouns (deception, embarrassment, confidence) while also including negations (deception, embarrassment, disbelief) and modal verbs (politeness, embarrassment, formality, persuading). Semantic classes could include uncertainty (deception), intentions or promises (deception, persuading), social routines (politeness, formality), positive and negative valence (politeness, rudeness, embarrassment, confidence, persuading), shame (embarrassment), surprise (embarrassment, disbelief), accidents (embarrassment, disbelief), certainty (confidence, persuading), titles of address (formality), and coercion (persuading).

The suggested syntactic classes are straightforward enough to extract using defined lists, or perhaps a natural language parser such as the Stanford Parser [38]. The suggested semantic classes pose a more interesting challenge, as they may not be so straightforward to either list or extract. Fortunately, there are some existing tools that may help us make these classes more precise. If we are interested in explicit lists, the Linguistic Inquiry and Word Count database [39] was developed to examine emotional, cognitive, structural, and process components present in language. It includes lists of words that cover positive and negative valence (affective processes: positive and negative emotion), modal verbs (cognitive processes: discrepancy), uncertainty (cognitive processes: tentative), and certainty (cognitive processes: certainty). Similarly, WordNet-Affect [40] was developed to aid in emotion identification research, and includes WordNet classes that correspond to some positive valence words ('joy' class), some negative valence words ('anger', 'disgust', 'fear', and 'sadness' classes), and surprise ('surprise' class).

If we are instead interested in extracting the words and expressions of interest, we may be able to use a machine learning technique called *topic modeling* [41]. Topics are probability distributions over keywords that relate to a cohesive concept such as *food, commerce, casual expressions*, etc. These topics, and the keywords that comprise them, are identified in an unsupervised fashion from a collection of documents. Without any additional information beyond the documents themselves, topic models can use the words contained in the documents to identify both the topics expressed and which topic each word, sentence, or subsection of the document most likely belongs to. For our purposes, this is useful since we are interested in collections of words that correspond to cohesive concepts like *surprise, social routines,* and *coercion*, but which may not have explicit lists of words available. Given a topic model trained over a large enough collection of documents, we may find that a topic model can spontaneously create the list of words associated with some of the concepts of interest. For example, Pearl & Steyvers [36] trained a topic model on the Personal Story Subset of the Spinn3r Blog Dataset [25][26], and this topic model discovered a topic consisting of casual expressions, such as 'oh', 'lol', 'yeah', 'stuff', and 'gonna'. One can easily imagine that such words would not appear in messages with a formal tone. Given a large enough collection of documents, a topic model may thus discover other concepts that are useful for tone detection. Ideally, we would simply train a topic model on messages from the tone database itself, since these are exactly the kind of language text we wish to extract cohesive concepts from. However, we will need to collect significantly more data via Word Sleuth to make this possible, since topic models require large datasets to train on (e.g., the blog entry dataset above had 5.3 million words).

3.4 The ground truth of message tone

As a final note on the success of automatic tone classification, it is worth returning to the issue of the ground truth with respect to message tone. We have assumed so far that the ground truth of a message's tone is the generator's intended tone. While this seems a reasonable approach, we also encountered a situation where the majority of interpreters agree on a message's tone and it is *not* the generator's intended tone. Some examples of this are shown in Table 6, where it seems that majority opinion has converged a tone other than the intended tone. In this case, is the "true" tone the intended tone or the majority-perceived tone? It may be that it is more reasonable to assume that the generator made a mistake, and instead that the majority-perceived tone is the true message tone. We note that this would differ from our current implementation, where the ground truth for messages in the complete dataset was the intended tone, and only messages where there was majority agreement on the intended tone were included in the filtered dataset. Instead, we could let the true tone be the majority-perceived tone, whatever that tone may be.

Intended tone	Perceived tone	Message
formality	politeness (0.80)	"would you mind please pushing my swing ?"
embarrassment	disbelief (0.70)	"I can't believe John stood me up AGAIN, on our anniversary too."
deception	rudeness (0.67)	"What? I'm not wearing a purple shirt. Your eyes are broken."
confidence	persuading (0.63)	"You should go out there and be yourself in front of others!"

TABLE 6: Sample messages from the current tone database, where the majority of interpreters perceived one tone, even though the generator intended a different tone. The percentage of interpreters identifying the perceived tone are shown in parentheses after the perceived tone.

A related issue is that we have forced participants to choose a single tone to express and perceive, when in fact messages may be more naturally viewed as a mixture of tones, some more strongly expressed than others. This would account for the examples in Table 6, for instance – in each case, the perceived tone and the intended tone are both likely expressed in the message. It's simply that the perceivers disagree with the generator about which tone is expressed more strongly. A future implementation of the Word Sleuth game could allow perceivers to indicate if a message expresses multiple tones, as well as indicating which tones are more strongly expressed. This more nuanced information could then be used to train tone identification systems.

4. CONCLUSION

We have examined the problem of tone identification, viewing it as the expression of a mental state in language text. Aware that there are few existing reliable resources of language text annotated with tone data, we described a methodology for creating such a database using a game with a purpose. We subsequently demonstrated the utility of this database, even though it is currently a small-scale one, on the problem of tone identification. Using two machine learning classifiers that operate over shallow linguistic features, we were able to obtain near human-level identification performance once we applied a simple wisdom of the crowds filter on the dataset. We also discussed some future directions for linguistic features as well as other implementations of the database that may yield better natural language processing performance. Given these initial positive results, the future of the "tone checker" seems promising..

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