Package Development

The *warmthcompetence* package consists of two functions (*warmth* and *competence*) that use elastic net machine learning models to predict warmth and competence perceptions of self-presentational text. We took a five-step, bottom-up, exploratory approach to developing these models

Step 1: Feature Generation

First, we built a repository of 654 natural language processing (NLP) features and used supervised machine-learning models to determine which features are most predictive of warmth and competence perceptions in self-presentational text (see OSF for feature repository). Approximately half of these features were developed by the authors and the other half were aggregated through a comprehensive search of the NLP literature.

The features in the repository broadly fall under one of four categories. The first category is count-based dictionary features, or features that use counts of a collection of words to assess a construct in natural language. For example, a feature developed to assess greetings might count the number of instances of “hello” and “hey.” The second category is score-based word list features, or features that assign scores to words or phrases and use the average score of words in the text to assess a construct. For example, a feature developed to assess authenticity might assign words like “faithful” with a high authenticity score and words like “scam” with a low authenticity score. If a text contains more words similar to “faithful” compared to words similar to “scam,” then the average authenticity score of the text will be higher.

While the first two categories of features focus on the content of the text, the third and fourth categories focus on the construction of the text. The third category of features is text complexity features, or features that use word syllables, sentence length and other language characteristics to understand text diversity and readability. For example, a feature might look at the number of words with at least six syllables. The fourth category, structural features, focuses on the parts of speech used and how they relate to one another in a sentence. For example, a feature developed to understand the relationship between pronouns and verbs in a sentence could examine the number of pronouns present before a verb versus after a verb in a sentence. We developed the majority of features in this category ourselves, and to the best of our knowledge, no tools yet exist that use text structure to assess warmth and competence in natural language.

Step 2: Training and Validation Data Collection

To develop warmth and competence prediction models using the repository of features, we needed to train them on a dataset with warmth and competence perception scores. To generate this dataset, we ran a study on Prolific Academic where we asked participants to write an introduction about themselves. In order to increase the dataset's variation in warmth and competence and capture a wide range of signaling strategies, participants were randomly assigned to present themselves as particularly competent, particularly warm, or no additional instructions were given. Then, we recruited another set of participants on Prolific Academic to independently judge warmth and competence perceptions.

Method

Participants.

Text Writers. We recruited 1,193 participants located in the United States through Prolific Academic (M_{age} = 37.4 years; SD_{age} = 13.1; 49.7% male, 76.6% white).

Text Evaluators**.** To evaluate the introductions, we recruited anther 1,193 participants located in the United States through Prolific Academic (M_{age} = 36.3 years; SD_{age} = 13.0; 50.2% male, 70.3% white).

Design.

Text Writers. Writers were randomly assigned to one of three conditions (competence, warmth, and control) and asked to write an introduction about themselves that would be shown to other Prolific workers. Those in the competence and warmth conditions were also provided with the following additional instructions: "Your goal is to present yourself as a [competent/warm] person. In other words, you want to write an introduction so that others describe you as [competent/warm]. Participants were required to write at least 250 characters.

After all the introductions were collected, they were deidentified by the research team before they were shown to other Prolific participants to protect participant privacy. Deidentification included replacing all letters in people's names with underscores except for the first letter and replacing all Prolific IDs with underscores. For example, John Doe was deidentified as "J___ D__." This method maintained the word count and character count of the original introductions.

Evaluations Collection. Each evaluator was randomly presented with six of the 1,193 introductions. They used the following question to assess [competence/warmth]: "Compared to the average Prolific worker, how [COMPETENT/WARM] is the Prolific worker that wrote the introduction above?" (7-point scales; Competence: 1 = "Extremely incompetent" to 7 = "Extremely competent"; Warmth: 1= "Extremely cold" to 7 = "Extremely warm"). Under these questions, evaluators were provided with descriptions of [competence and warmth to aid their assessments: "Competence includes traits like cleverness, creativity, effectiveness, foresightedness, ingenuity, intelligence, and being knowledgeable" and "Warmth includes traits like fairness, generosity, helpfulness, honesty, sincerity, tolerance, and understanding".

Each introduction received six evaluations of competence and warmth and reliability was moderate ($ICC_{competence}$ = .52; ICC_{warmth} = .69).

Step 3: Feature Reduction

In preparation for model development, we randomly split the data into a training dataset (90%; n = 1073) and a validation dataset (10%; n = 120). Then, we replaced all NA and infinite values in our predictors (features) with zero and standardized all predictors. We also standardized average evaluator assessments of competence and warmth, our outcome variables.

We created the feature set for the competence perceptions model by running recursive LASSO (least absolute shrinkage and selection operator) regression models on the training dataset. We performed a 10-fold cross validation procedure to fit models using the caret R package (Kuhn, 2008). These models shrink the coefficients of the least predictive features to zero, reducing the pool of predictive features for each model (Tibshirani, 1996). After the features with zero coefficients were removed, we eliminated features with the smallest coefficients until model performance on the training dataset began declining significantly.
We began by using all 654 features to predict average evaluator assessments of competence; by the end of this process we had a set of 29 features to predict competence perceptions (Table 1)

We replicated this method to develop the feature set for the warmth perceptions model. By the end of the process, we also had a set of 29 features to predict warmth perceptions (Table 2).

Table 1

Competence Features Ordered By Coefficient

Feature	Enet Model Coefficient	Feature Source
Features Positively Related to Competence Perceptions		
First_Person_Singular_Pronouns	0.114	Politeness R Package
Power_Language	0.108	Stone et al. (1966)
Vague_Discourse_Markers	0.089	Alemany (2005)
Lexical_Diversity_Measure2	0.089	qdap R package
Infinitival_To	0.088	Author Developed
Competence_Language	0.086	Author Developed
Adverbs	0.069	Author Developed
Negative_Tone	0.069	Henry (2008)
Punctuation	0.063	Author Developed
Adpositions	0.063	Author Developed
Simple_Introductions	0.061	Author Developed
Word_Complexity	0.060	Kuperman et al. (2012)
Personal_Pronouns_as_Subjects	0.039	Author Developed
Features Negatively Related to Competence Perceptions		
Negated_Surprise	-0.057	Sentimentr R Package
Superlative_Adjectives_After_Subject	-0.058	Author Developed
Prevention_Words	-0.061	Gamache et al. (2014)
Adverbial_Modifiers	-0.067	Author Developed
Nouns_Before_Main_Verb	-0.069	Author Developed
Happiness_Emotion	-0.073	Dodds et al. (2011)
Future_Oriented_Language	-0.084	Matsumoto et al. (2011)
First_Person_as_Subject	-0.085	Author Developed
Orthographic_Neighborhood	-0.101	Buchanan et al. (2012)
Average_Sentiment	-0.103	Sentimentr R Package
Negative_Emotion	-0.105	Politeness R Package
Anger_Emotion	-0.115	Sentimentr R Package
Lexical_Diversity_Measure1	-0.151	Quanteda R Package
Readability_Measure1	-0.156	Quanteda R Package
Sentence_Length	-0.161	Author Developed
Readability_Measure2	-0.164	Quanteda R Package

Table 2

Warmth Features Ordered By Coefficient

Feature	Enet Model Coefficient	Feature Source
Features Positively Related to Warmth Perceptions		
Lexical_Diversity	0.223	qdap R package
Imagery	0.123	Paetzold & Specia (2016)
Warmth_Language	0.123	Author Developed
Joy_Emotion	0.116	Sentimentr R Package
Present_Participle_Verbs	0.115	Author Developed
Possession_Modifers	0.114	Author Developed
Concreteness	0.111	Bestgen & Vincze (2012)
Plural_Nouns_After_Subject	0.101	Author Developed
Hello	0.096	Politeness R Package
Mental_Verbs	0.089	Author Developed
Free_Association_Norms	0.087	Buchanan et al. (2012)
Adjectives_After_Main_Verb	0.085	Author Developed
Social_Orientation	0.073	Moss et al. (2016)
Base_Form_Verbs	0.071	Author Developed
Personal_Pronouns_After_Subject	0.059	Author Developed
Warmth_Orientation	0.052	Payne et al. (2011)
Features Negatively Related to Warmth Perceptions		
Competence_Adjectives	-0.047	Payne et al. (2011)
Readability	-0.049	Quanteda R Package
Exploration_Words	-0.050	Uotila et al. (2009)
Interjections_Before_Subject	-0.054	Author Developed
Happiness_Emotion	-0.064	Dodds et al. (2011)
Swearing	-0.066	Politeness R Package
Polysemic_Discourse_Markers	-0.071	Alemany (2005)
Employment_Language	-0.073	Author Developed
Finance_Words	-0.080	Matsumoto et al. (2011)
Strength_Language	-0.081	Stone et al. (1966)
Anger_Emotion	-0.082	Sentimentr R Package
Negated_Disgust	-0.123	Sentimentr R Package
Word_Complexity	-0.223	Paetzold & Specia (2016)

Step 4: Model Development

After feature reduction, we trained cross-validated elastic net models to predict the independent judges' average perceptions of warmth and competence using the reduced feature pool generated by the recursive LASSO regression models (see Tables 1 and 2 for model coefficients). We calculated performance metrics for each model across 10 resamples of the training dataset (competence model: $MAE_{mean} = 0.67$, $RMSE_{mean} = 0.85$, $R^2_{mean} = 0.29$; warmth model: $MAE_{mean} = 0.63$, $RMSE_{mean} = 0.80$, $R^2_{mean} = 0.36$).

Step 5: Validation

We used the validation dataset to assess the performance of the warmth and competence models. The warmth model predictions were moderately correlated with the independent judges' average warmth perceptions, $r = 0.56$, $p < 0.001$. The competence model predictions had a moderately strong correlation with the independent judges' average competence perceptions, $r = 0.53$, $p < .001$.

References

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Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, *58*(1), 267-288.