

Generating Language with Personality

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ART Module on Dialogue Systems



Outline

- A bit of personality psychology
- Why do we need language variation?
- Linguistic markers of personality
- Generating language with personality
- Evaluation
- Continuous variation: statistical modelling
- Conclusion



Personality Psychology



- Personality

The complex of all the attributes – behavioural, temperamental, emotional and mental – that characterize a unique individual.

- Do personality traits exist?
 - Created to maintain an illusion of consistency in the world?
- Find the most essential independent traits
- Lexical Hypothesis
 - Important traits are encoded in the language (Allport & Odbert, 1936)
 - Participants describe people using a pool of adjectives
 - Factor analysis

The Big Five Personality Traits



- Factor analysis → 5 dimensions (Norman, 1963)
 - Extraversion
 - Sociability, assertiveness vs. quietness
 - Emotional stability
 - Calmness vs. neuroticism, anxiety
 - Agreeableness
 - Kindness vs. unfriendliness
 - Conscientiousness
 - Need for achievement, organization vs. impulsiveness
 - Openness to experience
 - Imagination, insight vs. conventionality

Individual Differences in Language



- Example (Mehl et al. 2006)

Introvert 🗣️	Extravert 🗣️
<ul style="list-style-type: none">- I don't know man, it is fine I was just saying I don't know.- I was just giving you a hard time, so.- I don't know.- I will go check my e-mail.- I said I will try to check my e-mail, ok.	<ul style="list-style-type: none">- Oh, this has been happening to me a lot lately. Like my phone will ring. It won't say who it is. It just says call. And I answer and nobody will say anything. So I don't know who it is.- Okay. I don't really want any but a little salad.

- 96 participants recorded for 2 days
- Filled a personality questionnaire

Language and Personality



- Linguistic markers of extraversion (Furnham, 1990)
 - Talk more, faster, louder and more repetitively
 - Fewer pauses and hesitations
 - Lower type/token ratio
 - Less formal, more references to context (Heylighen & Dewaele, 2002)
 - More positive emotion words (Pennebaker & King, 1999)
 - E.g. happy, pretty, good
- Emotional instability (Pennebaker & King, 1999)
 - 1st person singular pronouns
 - Negative emotion words
- Conscientiousness (Pennebaker & King, 1999)
 - Fewer negations and negative emotion words
- Low but significant correlations

Motivation for Linguistic Variation



- Different tasks require different languages
 - Intelligent tutoring system
 - Extravert, agreeable, conscientious
 - Store
 - Agreeable and extravert (persuasive)
 - Critical information provider
 - Conscientious, not extravert, not agreeable (no politeness)
 - Video games
 - Psychotherapy
- Frustration with repetitiveness in dialogue systems
 - Assumption: preference for human-like behaviour
- Developer's implicit style unlikely to be optimal

Personality Generation at the University of Sheffield



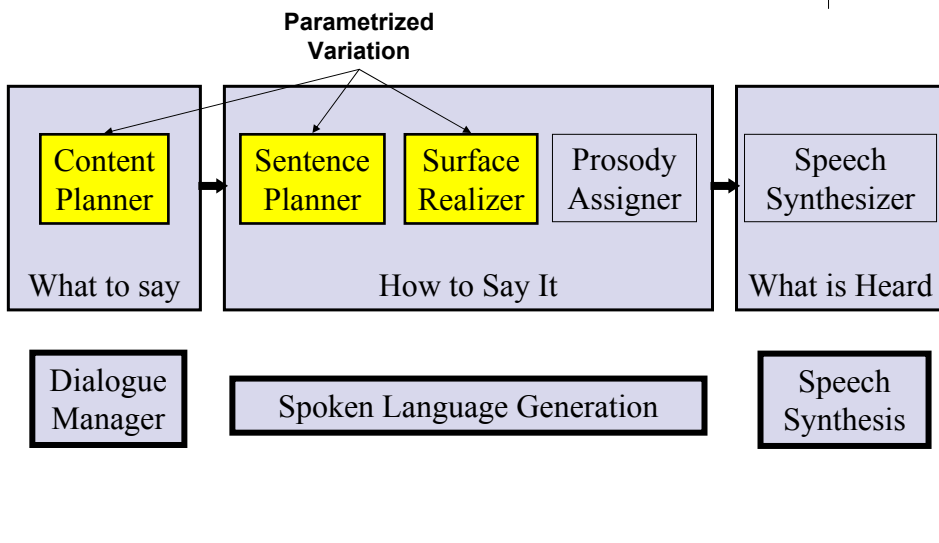
- PERSONAGE
 - Information presentation in the restaurant domain
 - Focus on extraversion
 - Most important dimension
 - Most visible dimension
 - Two goals
 - Generate extreme extravert and introvert personality
 - Generate personality on a continuous scale
- Can individual differences observed in general studies be recognised
 - In a very specific domain?
 - Within a single utterance?

Overview of PERSONAGE's Framework

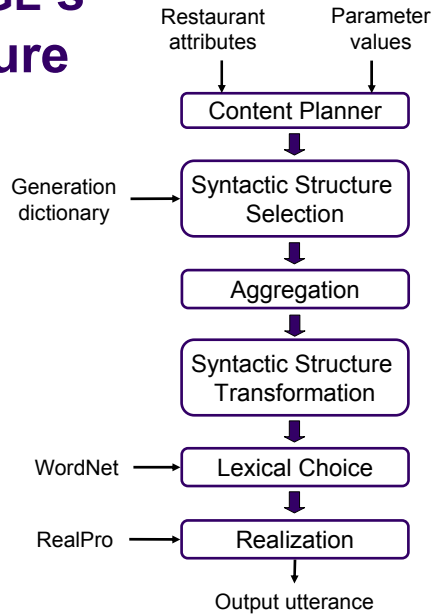


- Develop initial generator
 1. Identify personality markers from psychological studies
 2. Map those markers to NLG decisions
 3. Generate utterances covering the full parameter range
- Train the generator
 1. Judges rate the output with a standard personality test
 2. Compute feature values for each utterance
 - Based on the generator's actual decisions and the literature
 3. Train a statistical model to predict the judge's ratings from the features
- Generating language given personality parameters
 - **Direct generation:** interpolate between parameter values associated with both ends of the personality dimension
 - **Overgenerate and rank:** use the statistical model to rank randomly generated utterances

Variation in the NLG Pipeline Architecture

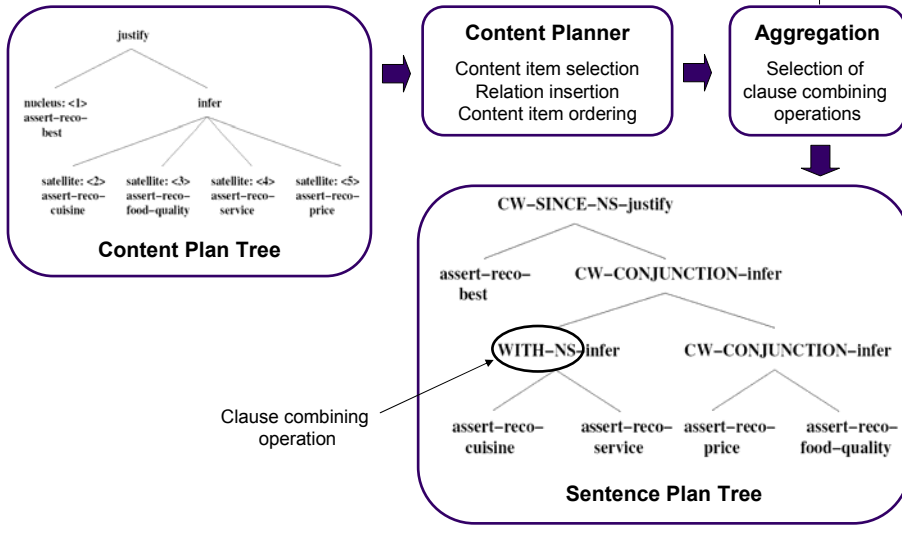


PERSONAGE'S Architecture



NLG modules	Introvert findings	Extravert findings	Parameter	Intro	Extra
Content selection and structure	Single topic Strict selection	Many topics Think out loud*	VERBOSITY RESTATEMENTS REPETITIONS	low low low	high high low
	Problem talk, dissatisfaction	Pleasure talk, agreement, compliment	CONTENT POLARITY REPETITIONS POLARITY CLAIM POLARITY CONCESSIONS CONCESSIONS POLARITY POLARISATION POSITIVE CONTENT FIRST	low low avg low low low low	high high high avg high high high
Syntactic templates selection	Few self-references Elaborated constructions Many articles	Many self-references Simple constructions* Few articles	SELF-REFERENCES CLAIM COMPLEXITY	low high	high low
Aggregation Operations	Many words per sentence/clause	Few words per sentence/clause	RELATIVE CLAUSES WITH CUE WORD CONJUNCTION PERIOD ...	high high low high	low low high low
	Many unfilled pauses	Few unfilled pauses			
Syntactic transformations	Many nouns, adjectives, prepositions (explicit) Many negations Many tentative words	Many verbs, adverbs, pronouns (implicit) Few negations Few tentative words	SUBJECT IMPLICITNESS NEGATION INSERTION DOWNTONER HEDGES: -SORT OF, SOMEWHAT, QUITE, RATHER, ERR, I THINK THAT, IT SEEMS THAT, IT SEEMS TO ME THAT, I MEAN -AROUND -KIND OF, LIKE ACKNOWLEDGMENTS: -YEAH -RIGHT, OK, I SEE, WELL EMPHASIZER HEDGES: -REALLY, BASICALLY, ACTUALLY, JUST HAVE, JUST IS, EXCLAMATION -YOU KNOW TAG QUESTION INSERTION HEDGE VARIATION HEDGE REPETITION	low high high avg low low high low low low low low low low	high low low high high low high high high high high high high high high
	Formal	Informal			
	Realism	Exaggeration*			
	No politeness form Lower word count	Positive face redressment* Higher word count			
Lexical choice	Rich Few positive emotion words Many negative emotion words	Poor Many positive emotion words Few negative emotion words	LEXICON FREQUENCY <i>see polarity parameters</i> <i>see polarity parameters</i>	low	high

Phase 1: Content Planning and Aggregation



Generation Decisions: Content Planning



- Verbosity
 - Content items selection, e.g. food quality, price, service, etc.
- Choice of content based on polarity
 - Zagat scalar ratings, e.g. food = 2/5, service = 5/5
- Insertion of restatements/repetitions
 - Small generation dictionary
 - WordNet based paraphrasing, e.g. *"the food is awful, terrible"*
- Concession of content items with different polarity
 - E.g. *"Even if Wok Mania has awful food, it's cheap"*
- Position of positive content

Generation Decisions: Aggregation operations

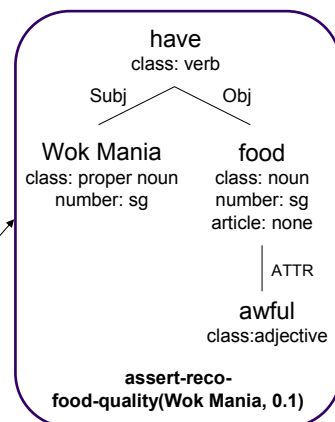
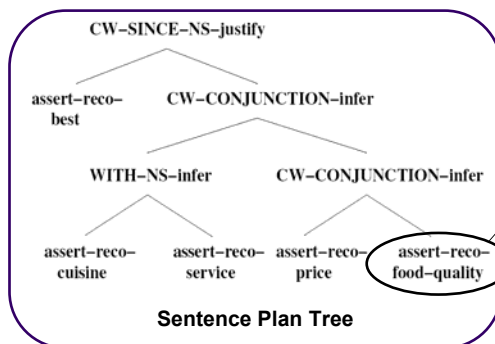


- Many ways to combine information
- Inferences
 - Relative clauses, e.g. "X, which has good food, is ..."
 - Conjunctions
 - Period, etc.
- Concessions
 - "Even if X has awful food, ..."
 - "Although X has awful food, ..."
- Restatements
 - Comma, e.g. "X has awful food, it has bad food"
 - Merge, e.g. "X has awful food, bad food"
- Generation parameter define probability of selection

Phase 2: Syntactic Template Selection



- Generation dictionary
 - Content item → Syntactic Structures



Phase 3: Syntactic Transformation

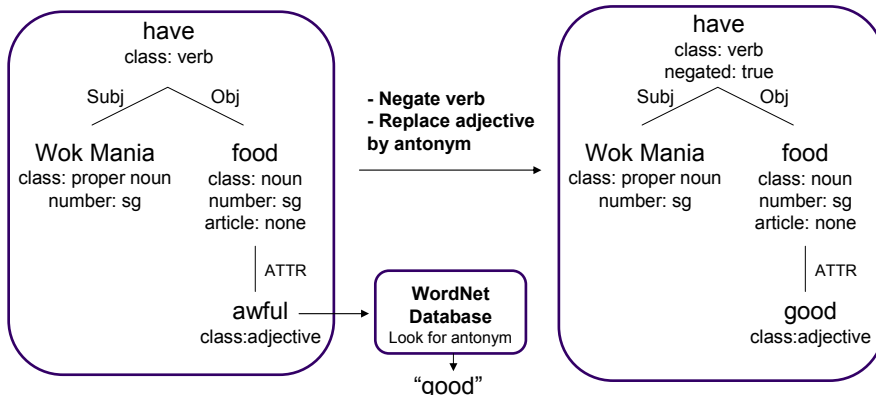


- Sequential modifications of the syntactic tree
 - Subject implicitness
 - “X has awful food” → “The food is awful”
 - Negation insertion
 - WordNet antonyms of adjectives
 - “X has good food” → “X doesn’t have bad food”
 - Hedge insertion
 - Downtoners: “kind of”, “quite”, “It seems that”, “around”, etc.
 - Fillers: “err...”, “I mean”, “like”
 - Acknowledgments: “right”, “I see”, “well”, “yeah”
 - Emphasizers: “really”, “basically”, “you know”, exclamation, etc.
 - Tag question insertion
 - “X has good food, doesn’t it?”

Example of Syntactic Transformation



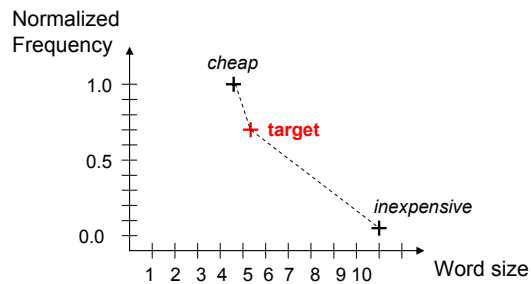
- Negation insertion
 - “X has awful food” → “X doesn’t have good food”



Phase 4: Lexical Choice



- Need to choose from WordNet synonyms
- Each word is associated to a point in a feature space
 - E.g. word frequency of use, word size, etc.
 - Machine-readable dictionary
- Select the closest synonym to the input target values



PERSONAGE Example Outputs



- Recommendation for John's Pizzeria
 - Extravert:
"I am sure you would like John's Pizzeria, it's one of my favourite places. It's cheap. Even if the atmosphere is just bad, it has really good food."
 - Introvert:
"Well, I mean, John's Pizzeria is the only restaurant that is any good."

Extreme Personality Generation

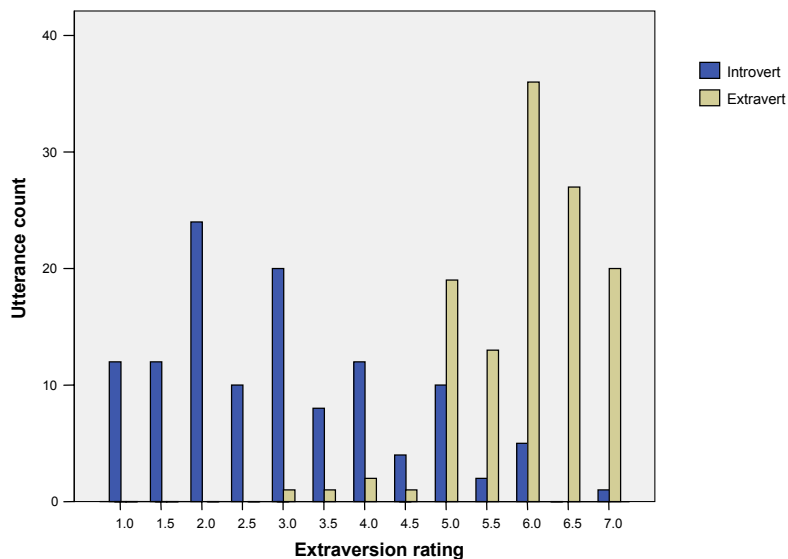


- Generate either extravert or introvert language
- Use parameter settings from the psychology literature
- Evaluation: can people recognise both types of language?
 - 3 human judges rated 80 outputs
 - Fill short personality questionnaire for every utterance
 - Extraversion score between 1 (introvert) and 7 (extravert)
 - 2 input parameter sets → 2 types of utterances
 - 40 introvert utterances vs. 40 extravert

Rating	Introvert	Extravert
Extraversion	2.96	5.98
Naturalness	4.93	5.78

- If binary classification of output: ~ 90% accuracy

Predefined Parameter Sets





Correlational Analysis

- What makes an utterance extraverted?
- Parameters can be refined based on correlation between generation decision and ratings
- Significant positive correlations ($p < .05$)

Feature	Correlation	Naturalness
Verbosity	0.30	0.09
Concessions	0.28	0.15
Aggregation: justify - <i>period</i>	0.27	0.16
Hedge: <i>exclamation</i>	0.21	-0.02
Lexicon: Maximum BNC Frequency	0.19	0.07
Aggregation: restate - <i>conjunction</i>	0.15	-0.13
Aggregation: infer - <i>merge</i>	0.15	0.09
Negative Content Items	0.14	-0.02
Use of First Person in Claim	0.13	0.14
Neutral Content	0.12	-0.08
Restatements	0.12	-0.01
Hedge: <i>it seems that</i>	0.12	0.02



Correlational Analysis

- Significant negative correlations ($p < .05$)

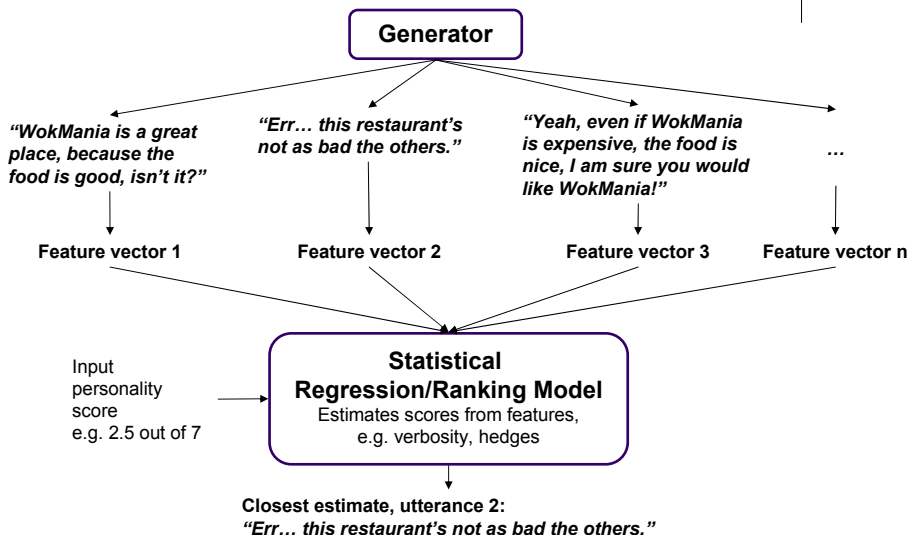
Feature	Correlation	Naturalness
Aggregation: Contrast - <i>period however</i>	-0.23	-0.09
Hedge: <i>err</i>	-0.22	0.02
Lexicon: Imageability	-0.22	0.18
Lexicon: Number of Syllables	-0.20	0.07
Lexicon: Number of Phonemes	-0.20	0.03
Positive Content	-0.19	0.07
Content Polarity	-0.18	0.06
Aggregation: Justify - <i>with</i>	-0.18	-0.17
Lexicon: Age of Acquisition	-0.18	0.80
Aggregation: Contrast - <i>period on the other hand</i>	-0.15	-0.03
Hedge: <i>sort of</i>	-0.13	-0.07
Hedge: <i>just have</i>	-0.13	0.02
Hedge: <i>right</i>	-0.12	-0.03
Hedge: <i>kind of</i>	-0.11	-0.03
Negation Insertion	-0.10	-0.14

Generate Variation on a Continuous Scale



- Goal: produce language close to an arbitrary input personality value
- Two approaches
 - Direct generation through parameter interpolation
 - Interpolation between extreme parameter settings
 - Pros: faster approach
 - Demo: [recommend-2.avi](#)
 - Trainable language generation
 - Overgenerate and rank

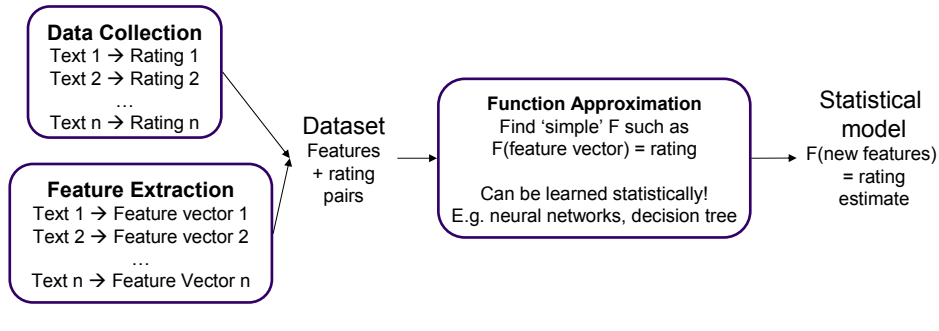
Overgenerate and Rank



Making NLG Trainable



- Where do we get the ranking model from?
 - Train the statistical model from a source of language
 - The ratings can reflect anything we want to control
 - Utterance quality
 - Perceived personality



What Features to Use?



- N-grams: HALogen (Langkilde, 2002)
 - Only takes consecutive surface words into account (bigrams, trigrams)
 - N gram will never model deep relations in a sentence, like information restatements or specific content structure
- Deeper linguistic features: SPoT (Walker et al. 02)
 - Syntactic configurations
 - Content organisation
 - Features reflecting generation decisions



Why Trainable NLG?

- Producing hand crafted rule is time consuming
- Requires less linguistic expertise
- Makes it less domain dependent
 - Different sources of data for different domain
- Can use other features than generation decisions
 - e.g. word count, dictionaries, syntactic features
- Regression models model a continuous function
 - Appropriate for linguistic variation!



Statistical Models of Personality Perception

- Source of data: 3 judges rate 120 random utterances
- Feature based on generation decisions
- Results for predicting extraversion
 - Best model: Support Vector Machines
 - Correlation between rating and prediction
 $r = 0.5$
 - Average prediction error on a scale from 1 to 7
absolute error = 0.9
- E.g. regression tree model

