Personality Modeling in Dialogue Systems

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Individual Differences in Dialogue

- Many dimensions of linguistic style
  - Formality (Labov 84)
  - Politeness (Brown & Levinson 87)
  - Dialects and sociolects
  - Personality
    - Most fundamental variation dimensions
    - Well defined in psychology studies
    - Many studies identify linguistic markers of personality
    - Can be evaluated using standard validated questionnaires

Personality Psychology

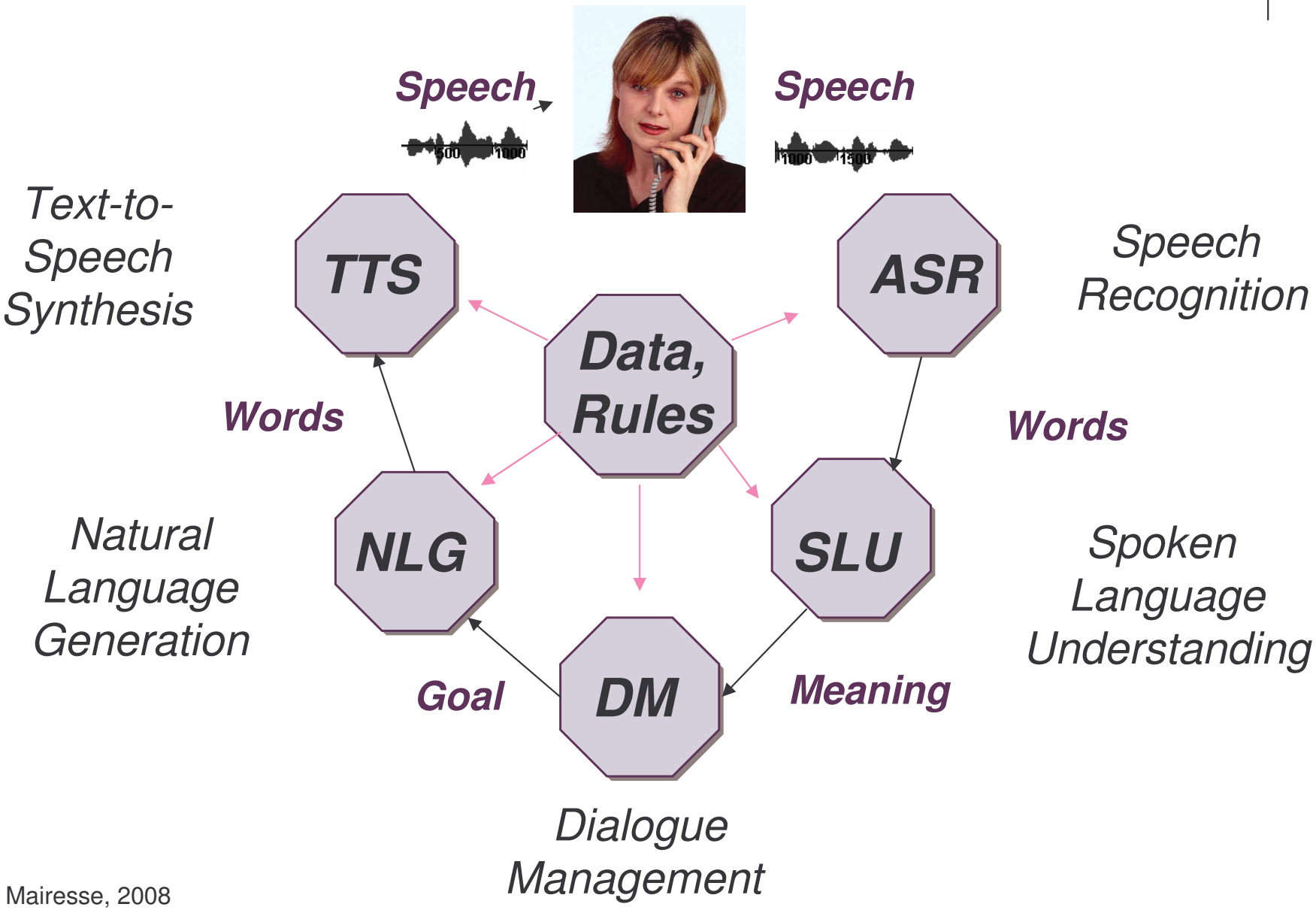
- Trait theories are widely accepted

- What are the main personality traits?
  - ‘Lexical Hypothesis’
    - Important traits are encoded in language (Allport & Odbert, 1936)
  - Participants describe people using a pool of adjectives
  - Factor analysis

The Big Five Personality Traits

- Factor analysis of trait-descriptive adjectives
  → 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

Modeling Individual Differences in Dialogue Systems



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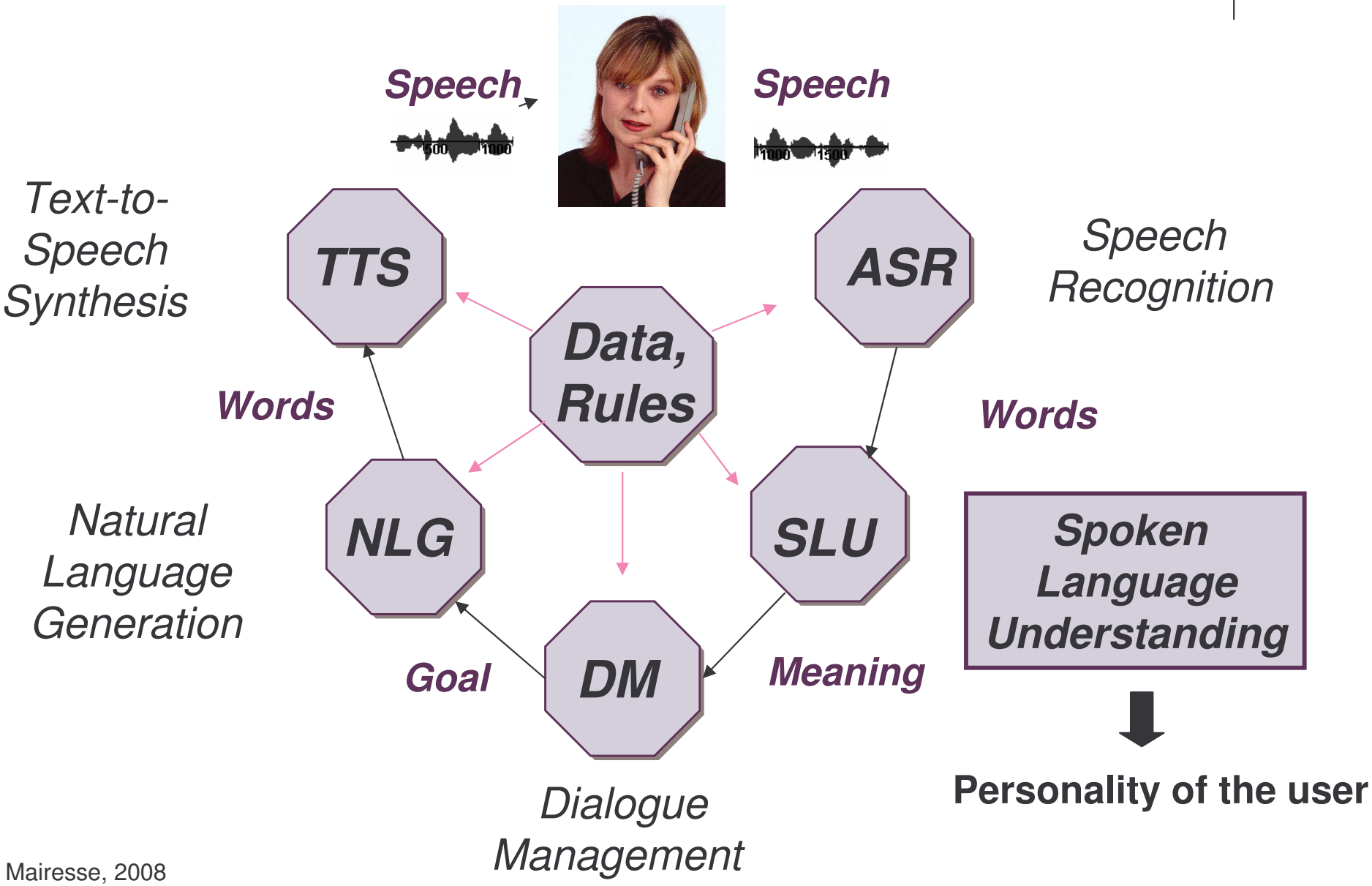
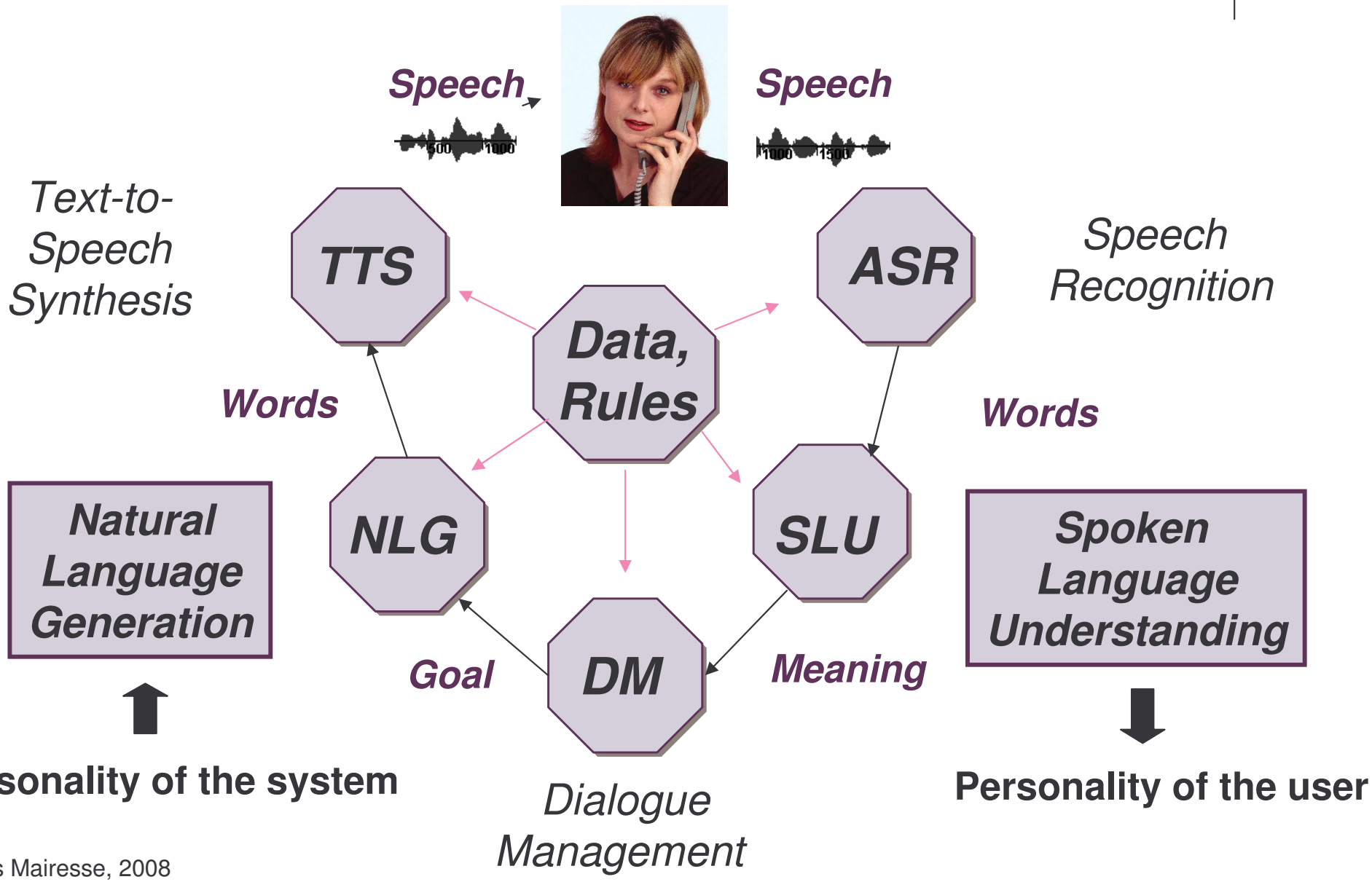


Modeling Individual Differences in Dialogue Systems



Part 1: Why Recognize the User's Personality?

- **Personality affects individual behavior**

- Attitude toward machines (Sigurdsson, 1991)
  - E.g. neurotics have problems using computers

- Leadership (Hogan et al., 1994)
  - High on extraversion, stability, conscientiousness and openness
  - ➢ Leader identification in meetings
  - ➢ Human resource management

- Academic motivation
  (Rushton et al., 1987, Komarraju & Karau, 2005)
  - Extravert and open students are more engaged in learning, conscientious achieve more
  - ➢ Intelligent tutoring systems

Part 2: Why Control the System's Personality?

- Cognitive science: can a machine convey a recognizable personality in different dialogue domains?

- The system's personality affects task performance
  - Similarity attraction effect (Nass & Lee 2001)
  - Extraverts prefer an ECA with social chitchat (Bickmore & Cassell 2002)
  - Politeness improves learning outcomes in intelligent tutoring (Poraysta-Pomsta & Mellish 2004; Wang et al 2004)
- Authoring bottleneck for interactive narratives (gaming) (Lester et al 1999, Mateas 2002)
- Any system that generates textual or spoken output has a personality whether you design it in or not

Some Linguistic Reflexes of Personality

- Extraversion (Furnham, 1990; Scherer, 1979; Gill & Oberlander, 2002)
  - Talk more, faster, louder and more repetitively
  - Lower type/token ratio
  - Less formal, more references to context (Heylighen & Dewaele, 2002)
- Neuroticism (Pennebaker & King, 1999, Gill & Oberlander, 2003)
  - 1st person singular pronouns
  - Negative emotion words
    - E.g. ‘hate’, ‘enemy’, ‘worthless’
- Conscientiousness (Pennebaker & King, 1999)
  - Fewer negations and negative emotion words

Personality in Language: Daily Conversations

- Example (Mehl et al., 2006)

Introvert	Extravert
- 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.	- 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

Personality in Language: Stream of Consciousness

- Stream of consciousness essays snippets (Pennebaker & King, 1999)

Introvert	Extravert
I've been waking up on time so far. What has it been, 5 days? Dear me, I'll never keep it up, being such not a morning person and all. But maybe I'll adjust, or not. I want internet access in my room, I don't have it yet, but I will on Wed??? I think. But that ain't soon enough, cause I got calculus homework [...]	I have some really random thoughts. I want the best things out of life. But I fear that I want too much! What if I fall flat on my face and don't amount to anything. But I feel like I was born to do BIG things on this earth. But who knows... There is this Persian party today.

Recognizing the Personality of the User

Personality Recognition Models

- Recognize personality
  - From written language (Pennebaker & King, 1999)
  - From conversations (Mehl et al., 2006)

- Personality assessment
  - From observer reports
  - From self-reports

Personality Recognition from Conversational Data

- Mairesse, Walker, Mehl & Moore (2006, 2007)

  E.g. can we predict if someone is extravert or introvert from conversations?

- Binary classification and regression from observer reports
  - Personality averaged over 7 judges
  - Features
    - Utterance type
      - E.g. question
    - Content analysis word categories (e.g. LIWC)
      - E.g. positive emotion words
    - Acoustic features
  - Train statistical models on feature/personality mappings
    - Algorithms: decisions trees, Naïve Bayes, SVM, etc.

Classification Results based on Observer Ratings

- Evaluation: percentage of correct classifications over a 10 fold cross-validation
  - Model trained on 90% of the data, tested on the rest
- Naïve Bayes learning algorithm performs best

	Accuracy (%)
Extraversion	**73.00●**
Emotional stability	**73.89●**
Agreeableness	**61.33●**
Conscientiousness	**67.67●**
Openness	57.00

● significantly better than the baseline (two-tailed, $p < 0.05$)

Regression Results based on Observer Ratings

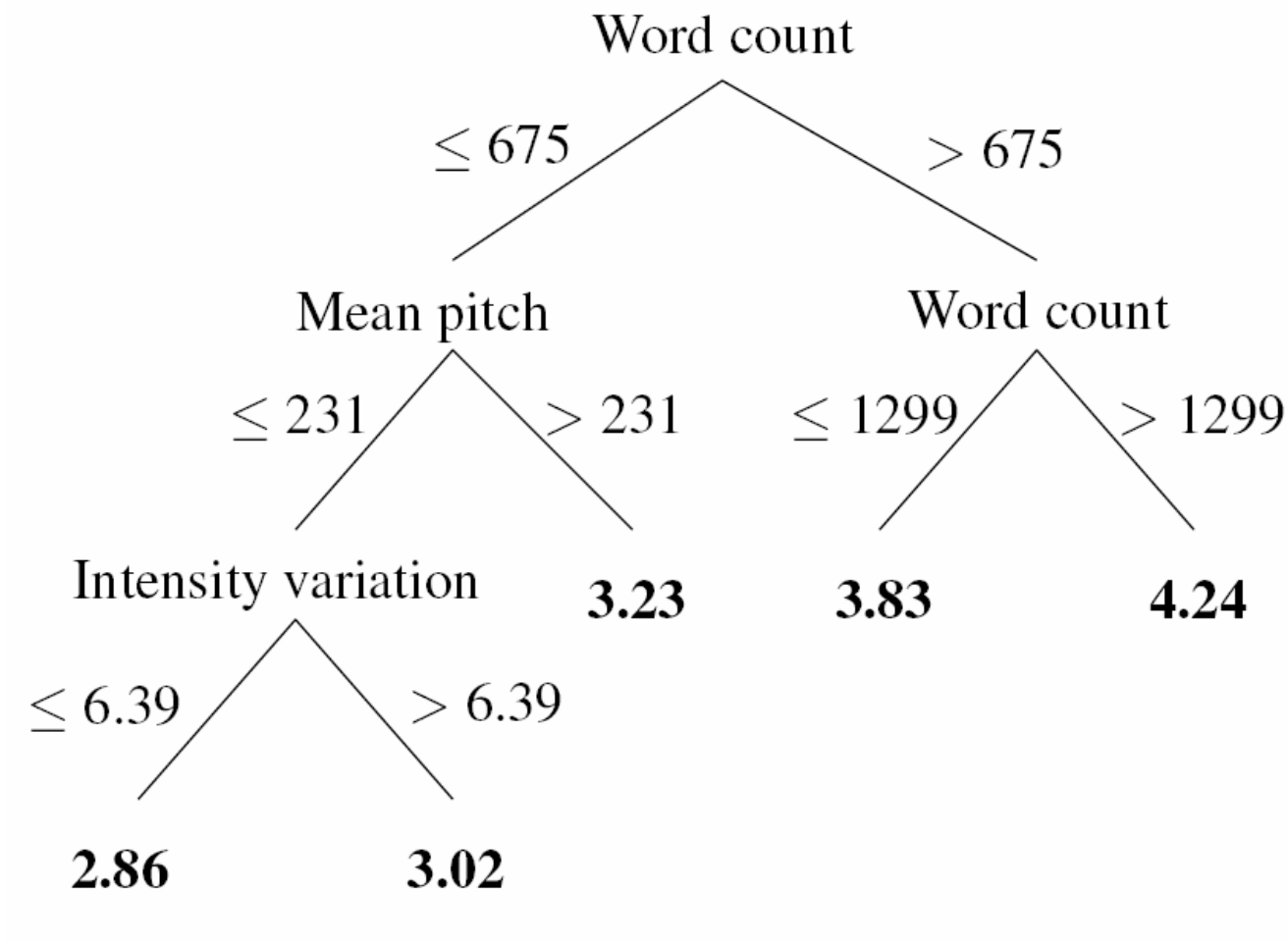
- Predict continuous personality scores
- Regression and model trees performs best

	Correlation	Model
Extraversion	**.54•**	REP tree
Emotional stability	**.47•**	M5' model tree
Agreeableness	**.44•**	M5' model tree
Conscientiousness	**.54•**	M5' tree
Openness	**.20**	M5' model tree

• significantly better than the mean value baseline (two-tailed, $p < 0.05$)

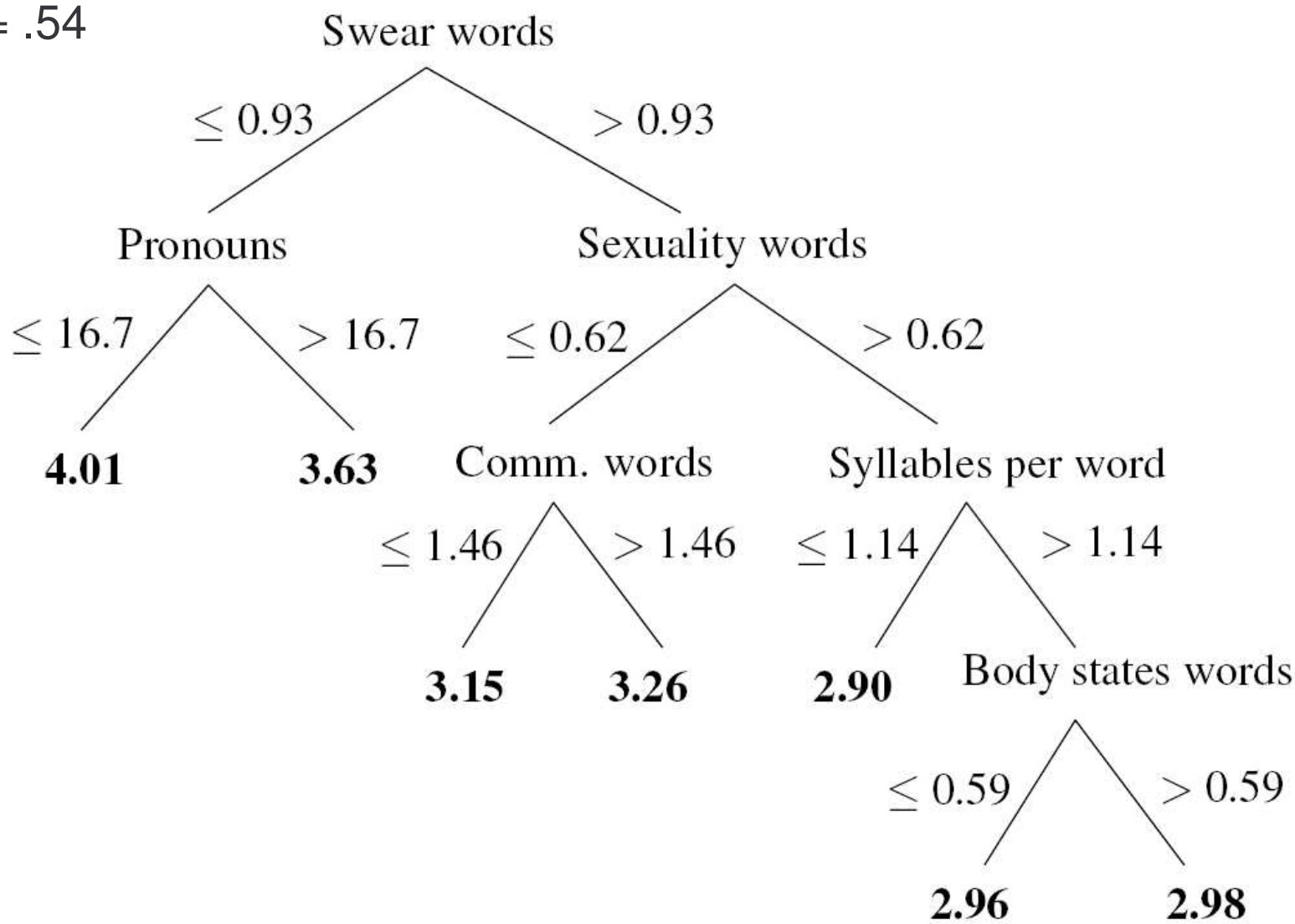
Regression Tree for Observed Extraversion

- Correlation = .47
- Better than constant baseline ($p < 0.05$)



Regression Tree for Observed Conscientiousness

- Correlation = .54
- Better than constant baseline ($p < 0.05$)



Personality Recognition

- Observer reports easier to model than self-reports
  - Less bias due to desirability of traits
  - Does the system needs to know
    - How the user is perceived?
    - How the user perceives him/herself?
- Models improve on baseline
  - User modeling is possible, but can it make a difference in dialogue?
  - Can the system *project* personality matching the user's?

How can we control the personality of the system?

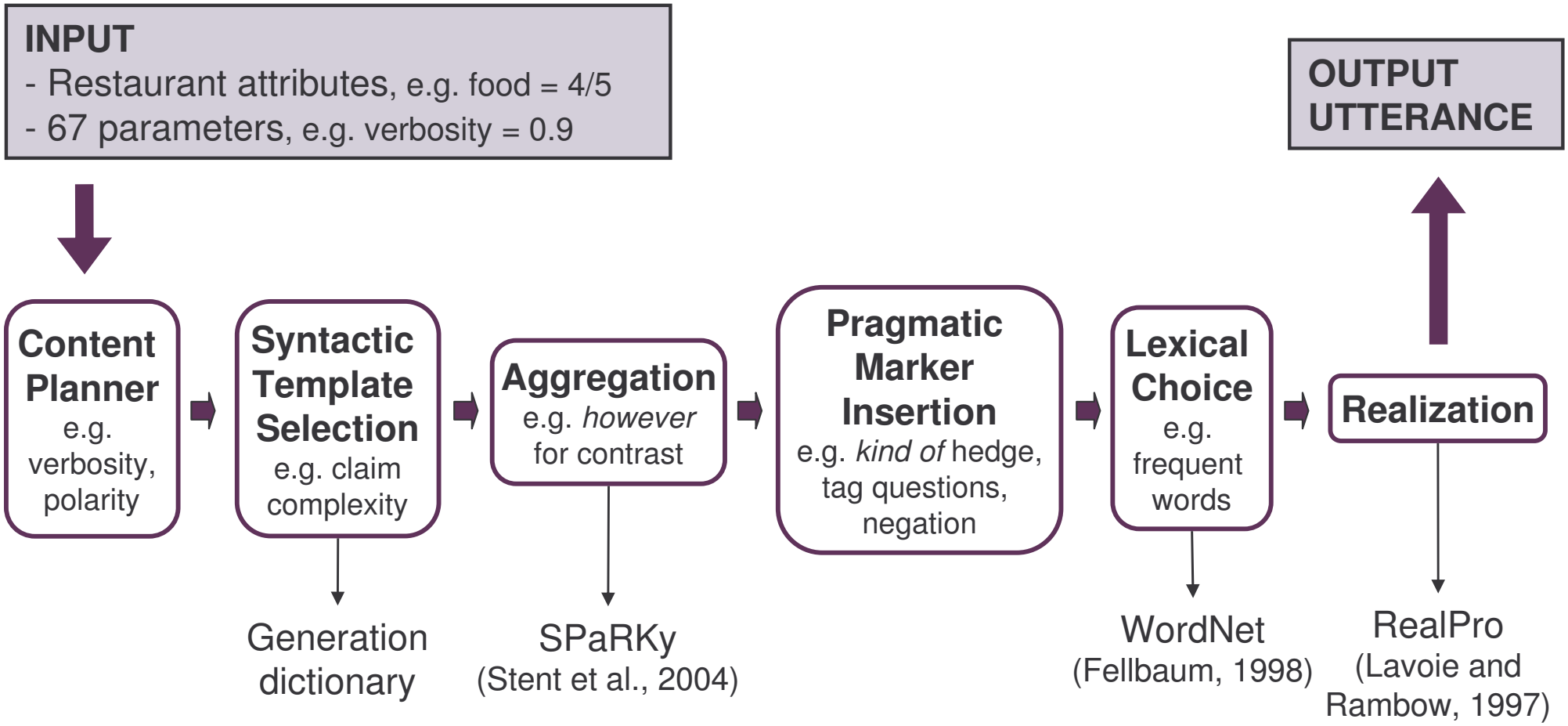
Research Challenges for Personality Generation

- Can personality markers observed in conversations, essays and emails be mapped to parameters in a spoken language generator?
- Can recognizable personality be produced
  - In a very specific domain?
  - Within a single utterance?
- Can we produce continuous variation using data-driven methods?
- Can language manifesting all Big Five personality traits be generated?
- What types of speech acts in particular domains manifest personality?

Research Challenges (2)

- **PERSONAGE generator**
  - Recommendations and comparison in the restaurant domain
    - Hypothesis: evaluative utterances suitable for expressing personality

PERSONAGE's Architecture



Methodology: First Steps

- For each level of NLG
  - Identify personality markers in the literature
  - Map markers to generation parameters

  - ➢ Organize the vast amount of psychology findings

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

Mapping Findings to Parameters

NLG modules	Introvert findings	Extravert findings	Generation parameters	Intro	Extra
Content planning	Single topic	Many topics	VERBOSITY	low	high
	Strict selection	Think out loud	RESTATEMENTS	low	high
	Problem talk	Pleasure talk	CONTENT POLARITY	low	high
			CONCESSION POLARITY	low	high
			REPETITION POLARITY	low	high
…	…	…	…	…	…

Mapping Findings to Parameters

Vague, genre specific findings

NLG modules	Introvert findings	Extravert findings	Generation parameters	Intro	Extra
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			CONCESSION POLARITY	low	high
			REPETITION POLARITY	low	high
…	…	…	…	…	…

Mapping Findings to Parameters

Vague, genre specific findings → 67 generation parameter hypotheses

NLG modules	Introvert findings	Extravert findings	Generation parameters	Intro	Extra
Content planning	Single topic	Many topics	VERBOSITY	low	high
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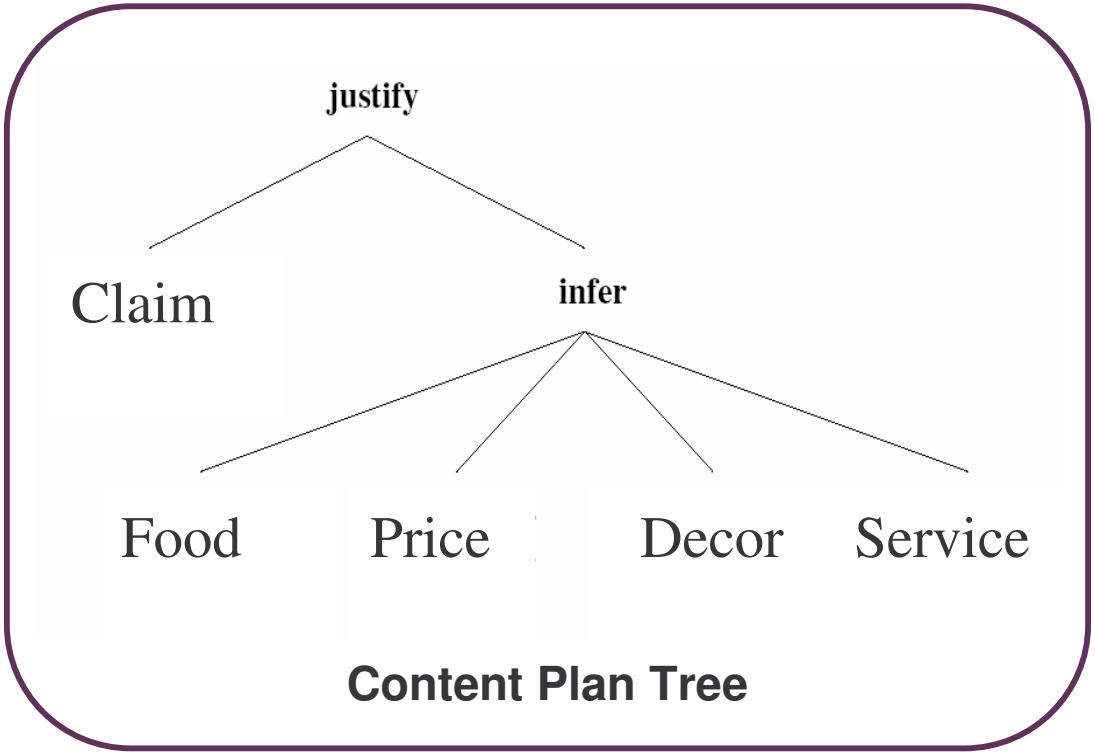
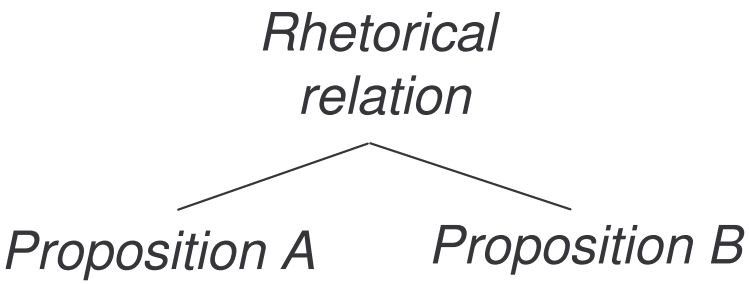
			REPETITION POLARITY	low	high
…	…	…	…	…	…

PERSONAGE Outputs: Recommend *Le Marais*

Alt	Realization	Extraversion
5	Err... it seems to me that Le Marais isn't as bad as the others.	**1.83**
4	Right, I mean, Le Marais is the only restaurant that is any good.	**2.83**
8	Ok, I mean, Le Marais is a quite french, kosher and steak house place, you know and the atmosphere isn't nasty, it has nice atmosphere. It has friendly service. It seems to me that the service is nice. It isn't as bad as the others, is it?	**5.17**
1	Le Marais has the best overall quality among the selected restaurants. It has decent decor, it has decent service, and its price is 44 dollars. This French, Kosher, Steak House restaurant has very good food quality.	**5.67**
9	Well, it seems to me that I am sure you would like Le Marais. It has good food, the food is sort of rather tasty, the ambience is nice, the atmosphere isn't sort of nasty, it features rather friendly servers and its price is around 44 dollars.	**5.83**
3	I am sure you would like Le Marais, you know. The atmosphere is acceptable, the servers are nice and it's a french, kosher and steak house place. Actually, the food is good, even if its price is 44 dollars.	**6.00**
10	It seems to me that Le Marais isn't as bad as the others. It's a french, kosher and steak house place. It has friendly servers, you know but it's somewhat expensive, you know!	**6.17**
2	Basically, actually, I am sure you would like Le Marais. It features friendly service and acceptable atmosphere and it's a french, kosher and steak house place. Even if its price is 44 dollars, it just has really good food, nice food.	**6.17** **out of 7**

Phase 1: Content Planning and Aggregation





Content Planner

Content item selection
Relation insertion
Content item ordering

Aggregation

Selection of clause combining operations

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
  - 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*"

Generation Decisions: Aggregation operations

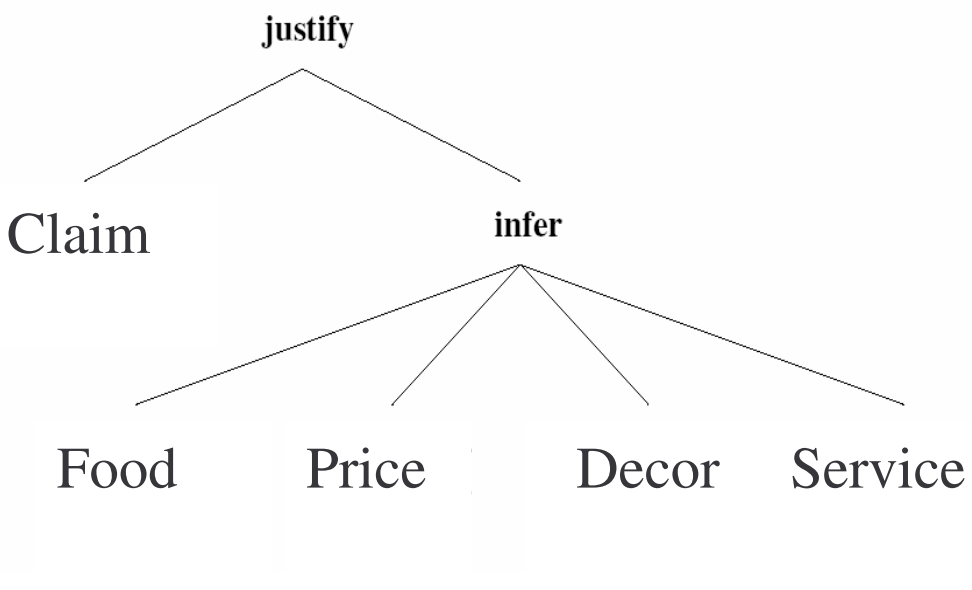
- Many ways to combine information with rhetorical relations (Scott and de Souza, 1990; Wang and Hovy, 1992; Stent et al., 2004)

- Justification
  - *"since"*, *"because"*, *"so"*, etc.
- Contrast
  - *"but"*, *"however"*, *"on the other hand"*, etc.
- Inference
  - Relative clause, e.g. *"X, which has good food, is …"*
  - Merge, e.g. *"X has good food and decent service"*
  - Conjunction, period, etc.
- Concession
  - *"Even if X has awful food, …"*
  - *"Although X has awful food, …"*

…

Phase 2: Syntactic Template Selection

- Generation dictionary
  - Propositions → Syntactic templates



Content Plan Tree

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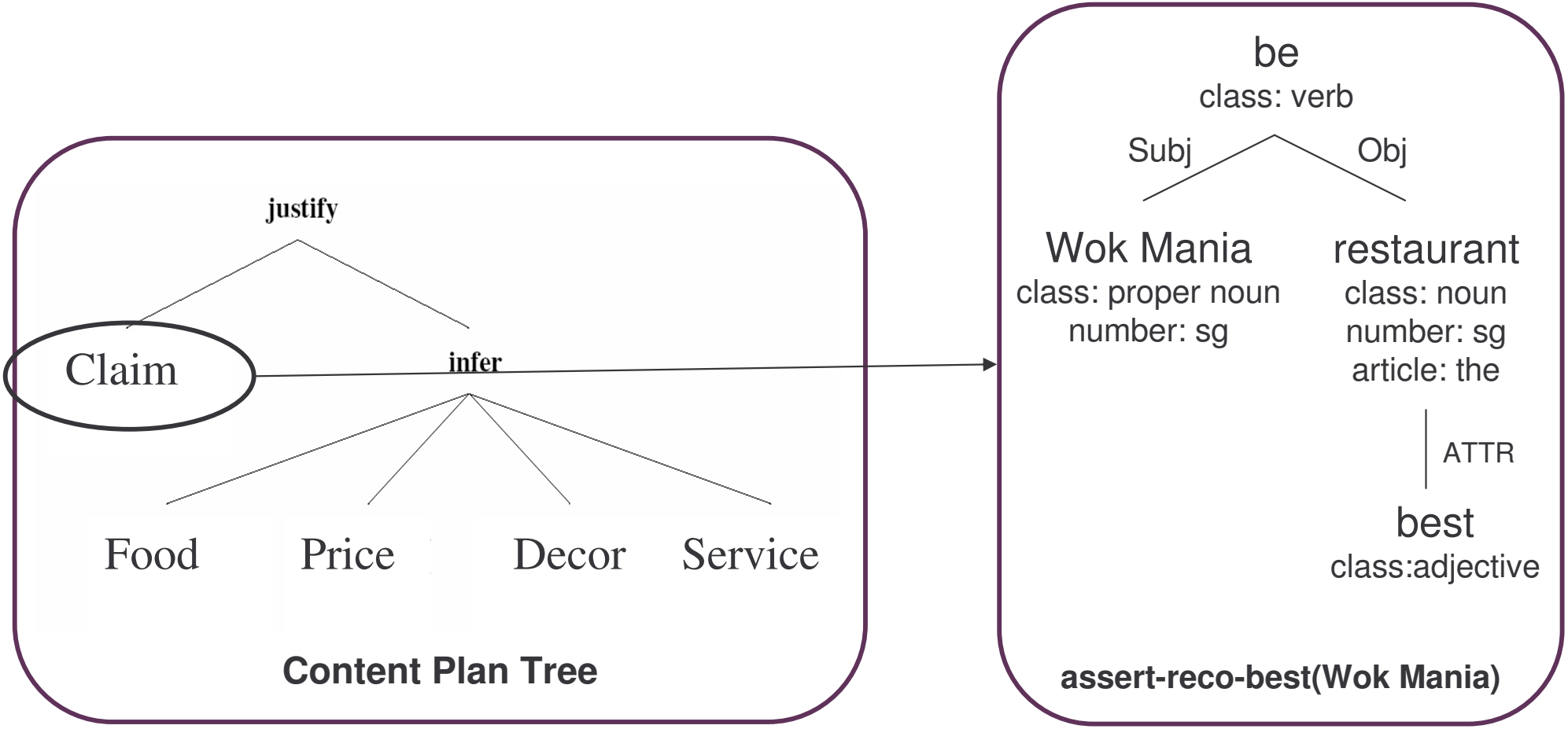
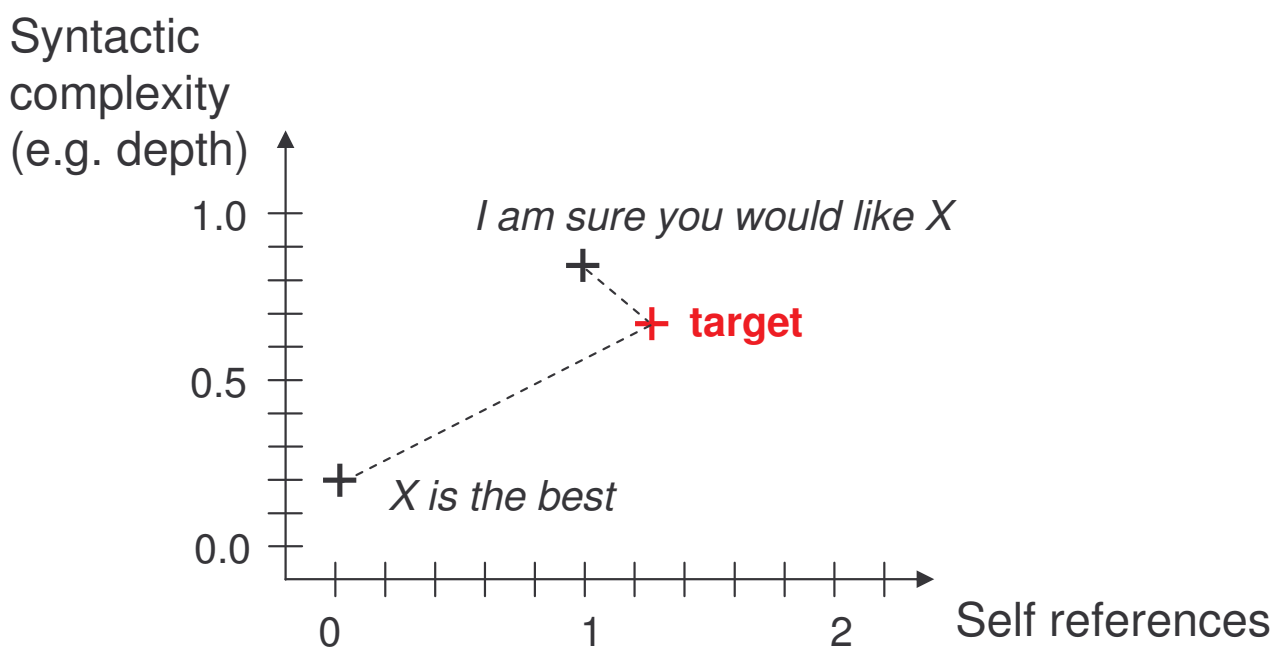


Phase 2: Syntactic Template Selection

- Need to choose from different syntactic templates
- Each template is associated to a point in a feature space
  - E.g. syntactic complexity, self-reference, positive connotation

- Select the closest claim template to the input target values



Phase 3: Pragmatic Transformations

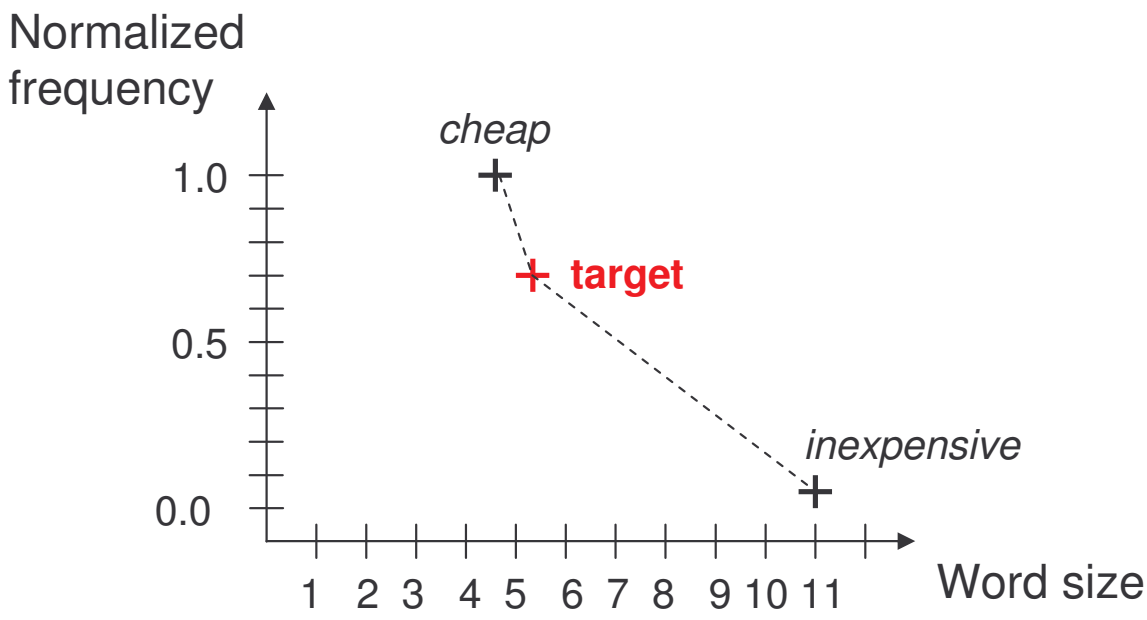
- Sequential modifications of the syntactic tree
  - Negation insertion:
    "*X has good food*" → *"X doesn't have bad food*"
  - Softeners: *"kind of", "quite", "It seems that", "around",* etc.
  - Emphasizers: *"really", "basically", "you know",* exclamation, etc.
  - Fillers: *"err…", "I mean", "like"*
  - Stuttering: *"Cha-Chanpen Thai has good food"*
  - In-group markers: *"mate", "pal", "buddy"*
  - Expletives/swearing: *"bloody", "damn", "darn"*
  - Mitigate competence: *"come on", "everybody knows that …"*
  - Tag question insertion: *"X has good food, doesn't it?"*

  …

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



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Can **PERSONAGE** produce utterances with recognizable personality ?

Generation Methods

- Rule-based
  1. Use parameters suggested by psycholinguistic findings;
  2. Collect judges' ratings on all dimensions;
  3. Evaluate if judges perceive each trait as predicted.

- Data-driven
  - Overgenerate and select
  - Parameter estimation models

Evaluation Experiment

- 3 judges: anthropologist, historian, psychologist
- Training: examine adjectives associated with Big Five traits (Goldberg, 1990)

- **Personality questionnaire**
  - Ten Item Personality Inventory (Gosling et al., 2003)
  - Extraversion score between 1 (introvert) and 7 (extravert)

- **Naturalness**: could have been said by human (1...7)

- 10 utterances for 20 content plans (200 total)
  - 2 generated with low trait parameters (e.g. introversion)
  - 2 generated with high trait parameters (e.g. extraversion)
  - 8 generated with random parameters

Restaurant Description Survey - Mozilla Firefox

File Edit View History Bookmarks Tools Help

http://www.dcs.shef.ac.uk/~francois/experiment-all/survey-temp.html

tipi questionnaire

Section 1 - you ask your friend to compare Japonica and Dojo and this is what your friend says:

Utterance 1:

"Obviously, oh gosh Dojo, which has bad waiters, is a japanese and vegetarian place, a japanese and vegetarian place, with poor atmosphere. Actually, I mean, Japonica is a japanese and sushi place and the atmosphere is nice, also this restaurant has rather nice waiters, you know."

I see the concierge as...

1. Extraverted, enthusiastic	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
2. Reserved, quiet	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
3. Critical, quarrelsome	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
4. Dependable, self-disciplined	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
5. Anxious, easily upset	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
6. Open to new experiences, complex	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
7. Sympathetic, warm	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
8. Disorganized, careless	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
9. Calm, emotionally stable	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
10. Conventional, uncreative	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly
The utterance sounds natural	Disagree strongly	1 ○	2 ○	3 ○	4 ○	5 ○	6 ○	7 ○	Agree strongly

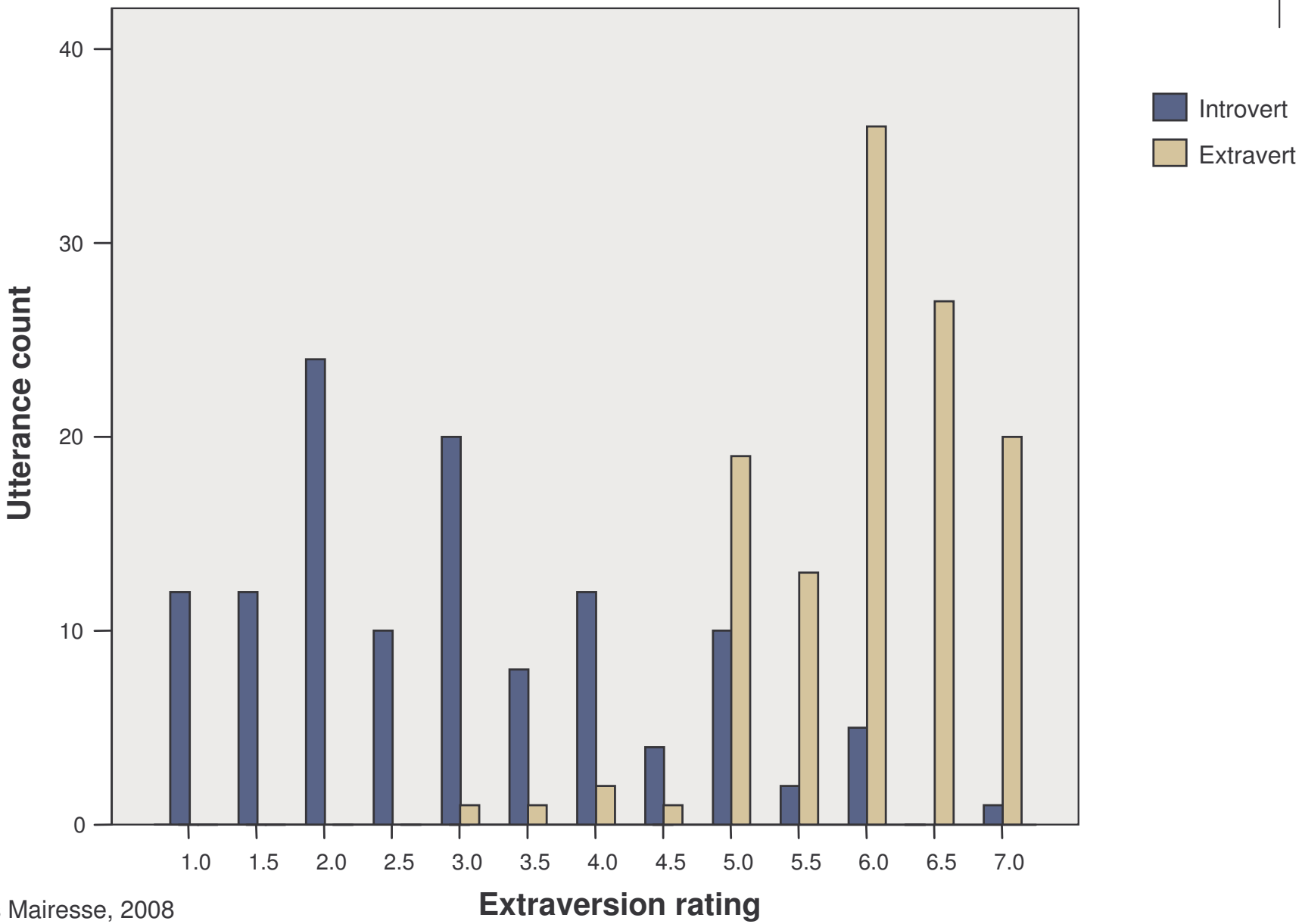
Done

First Method: Rule-Based Personality Generation

- Evaluation
  - Can judges recognize the system's personality?
  - Discriminate between two extreme utterance sets
    - Inter-rater correlations: 0.70, 0.74, and 0.76
    - **Significant at p < .01**

Parameter set	Low	High
Extraversion	2.96	5.98
Emotional stability	3.29	5.96
Agreeableness	3.41	5.66
Conscientiousness	3.71	5.53
Openness to experience	2.89	4.21

Distribution of Extraversion Ratings



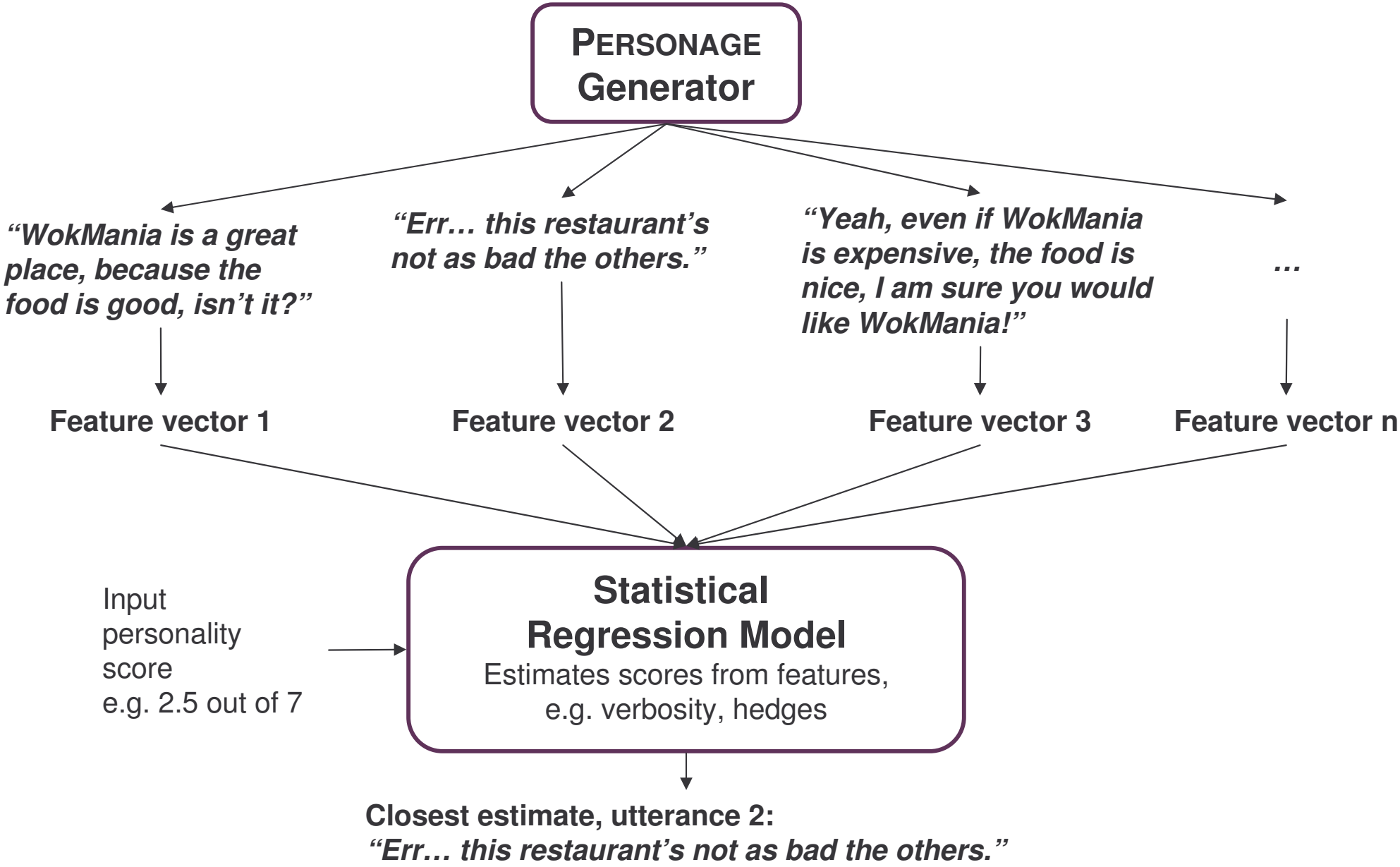
So Where Are We?

- Can produce recognizable variation at extreme ends of extraversion scale using findings from psycholinguistics
- Hypothesized mapping appears to be fairly successful

- We can generate language with extreme personality

- What if we want to produce language close to an arbitrary input personality value ?

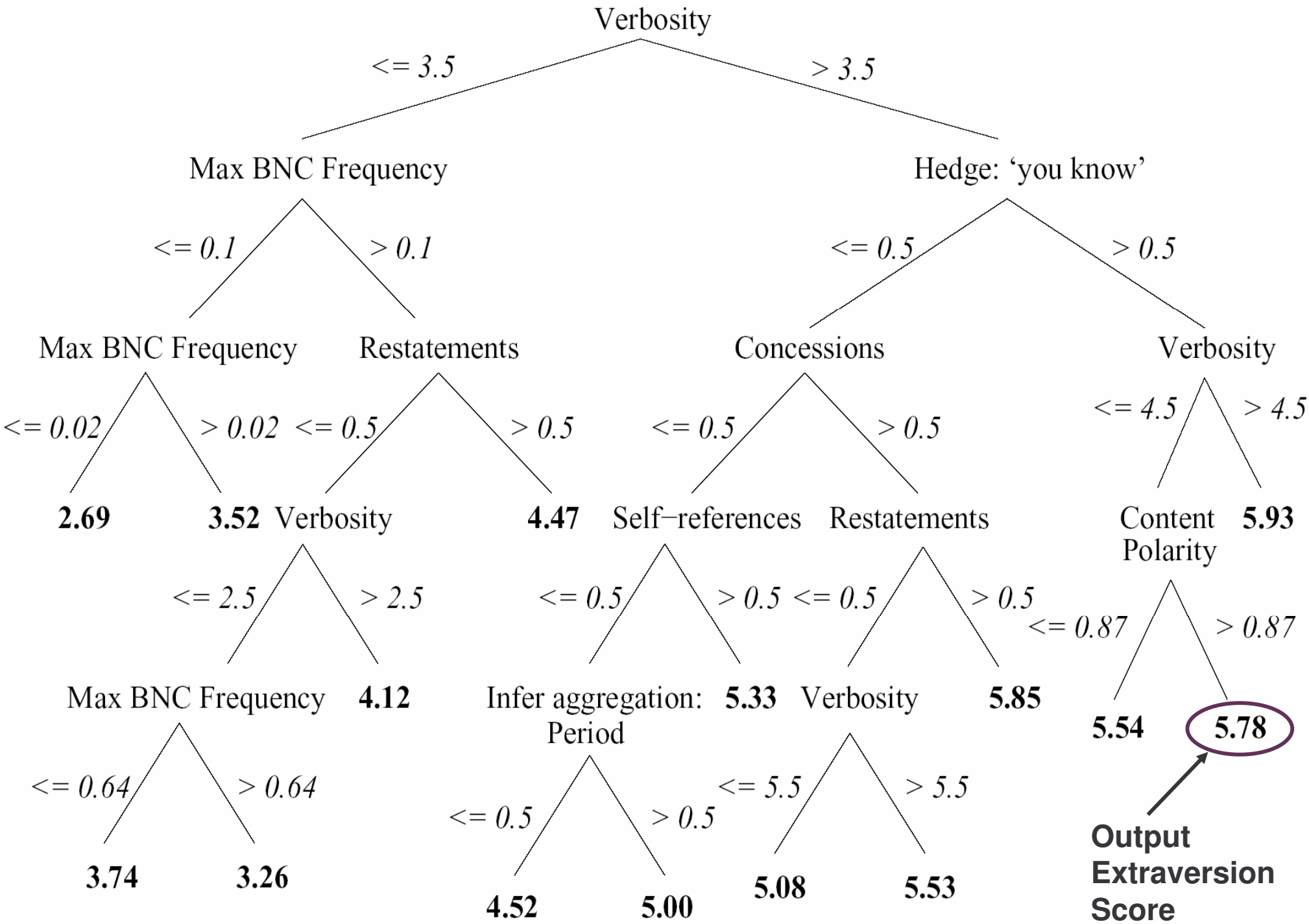
Second Method: Overgenerate and Rank



Statistical Models of Personality Perception

- Data: 160 random utterances rated by 2 judges
- Features based on generation decisions, content-analysis categories and n-grams
- Correlation between model and judges ratings

	Correlation	Model	Features
Extraversion	**.45●**	Linear Regression	LIWC
Emotional stability	**.32●**	SVM	Generation
Agreeableness	**.54●**	M5' regression tree	Generation
Conscientiousness	**.25●**	M5' model tree	Generation + LIWC
Openness	**.19●**	Linear regression	LIWC


Verbosity
<= 3.5
> 3.5
Max BNC Frequency
Hedge: 'you know'
<= 0.1
> 0.1
<= 0.5
> 0.5
Max BNC Frequency
Restatements
Concessions
Verbosity
<= 0.02
> 0.02
<= 0.5
> 0.5
<= 0.5
> 0.5
<= 4.5
> 4.5
2.69
3.52
Verbosity
4.47
Self−references
Restatements
Content Polarity
5.93
<= 2.5
> 2.5
<= 0.5
> 0.5
<= 0.5
> 0.5
<= 0.87
> 0.87
Max BNC Frequency
4.12
Infer aggregation: Period
5.33
Verbosity
5.85
5.54
5.78
<= 0.64
> 0.64
<= 0.5
> 0.5
<= 5.5
> 5.5
3.74
3.26
4.52
5.00
5.08
5.53
Output Extraversion Score

Linear regression model for agreeableness

Agreeableness score =

1.9614 +
0.919 * Content Planning: Content Polarity +
0.692 * Content Planning: Polarisation +
0.593 * Pragmatic Markers: *it seems to me that* +
0.432 * Pragmatic Markers: In-group Marker +
0.414 * Pragmatic Markers: *err*=0 +
0.326 * Tag Question=0 +
0.314 * Pragmatic Markers: *somewhat*=0 +
0.305 * Pragmatic Markers: Expletives=0 +
…

-0.0878 * Demonstrative Referring Expressions +
-0.0915 * Content Planning: Repetition Polarity +
-0.1942 * Content Planning: Concessions +
-0.2004 * Positive Content First +
-0.2099 * Aggregation Operation Probabilities: Contrast - PERIOD +
-0.3284 * Pragmatic Markers: *it seems that* +
-0.6367 * Pragmatic Markers: Competence Mitigation - *come on*

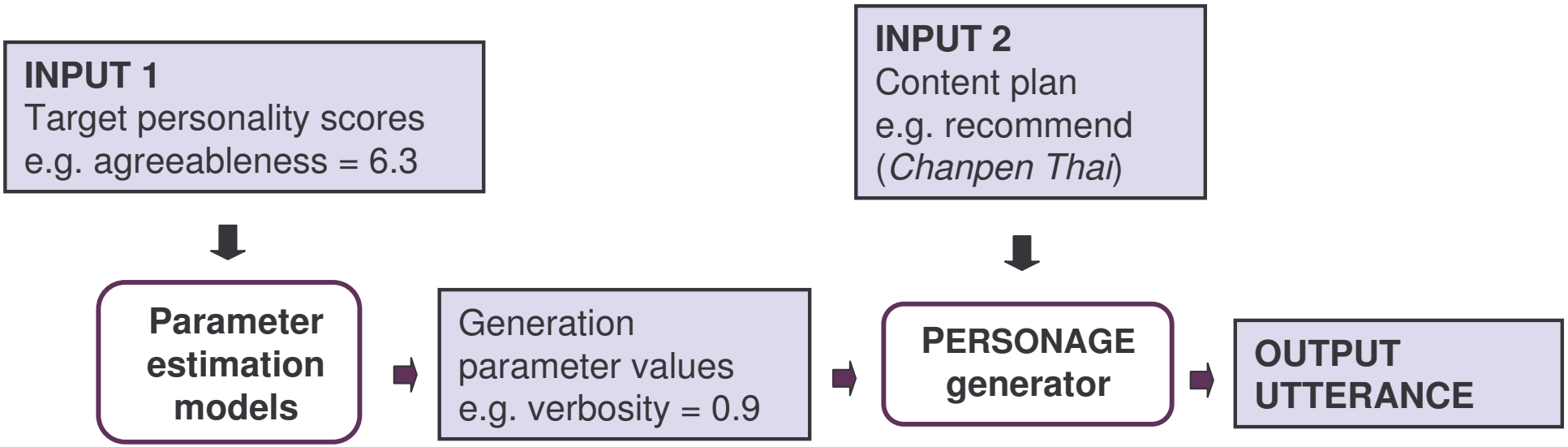
Out-of-domain Personality Recognition Models

- What if we use the recognition models we trained on general data?
  - Re-usable, but generalization issues
  - Interesting domain adaptation problem

	Correlation	Model	Features
Extraversion	**.25•**	M5' model tree	LIWC
Emotional stability	.05	M5' model tree	N-gram
Agreeableness	**.33•**	SVM	LIWC
Conscientiousness	**.20•**	SVM	LIWC
Openness	.11	M5' model tree	N-gram

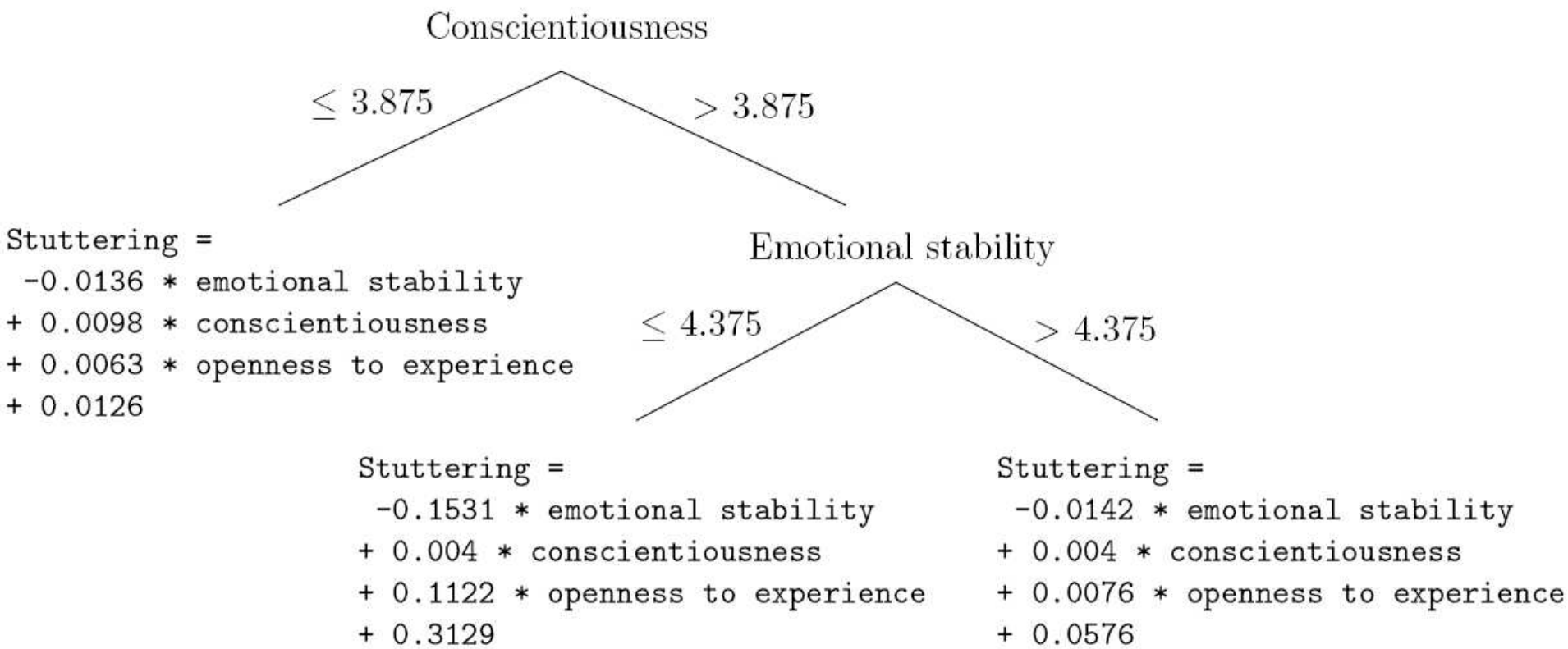
Third Method: Parameter Estimation Models

- Learn models that predict parameter settings *directly* from personality scores (ACL'08)
  - No overgeneration
- Trained on the 160 random utterances
- One model predicting each parameter
  - Selected through cross-validation



Example Parameter Estimation Model

- Model tree predicting the STUTTERING parameter value
  - Combination of multiple traits



Example Binary Parameter Estimation Model

- AdaBoost binary classifier predicting the exclamation parameter

```
Condition                        Class                          Weight
---------                        -----                          ------
if extraversion  >  6.42         then enabled else disabled     1.81
if extraversion  >  4.42         then enabled else disabled     0.38
if extraversion  <= 6.58         then enabled else disabled     0.22
if extraversion  >  4.71         then enabled else disabled     0.28
if agreeableness >  5.13         then enabled else disabled     0.42
if extraversion  <= 6.58         then enabled else disabled     0.14
if extraversion  >  4.79         then enabled else disabled     0.19
if extraversion  <= 6.58         then enabled else disabled     0.17
```

Large-scale Evaluation Experiment

- 24 judges rated 50 utterances
- Correlation between the target scores and the ratings
- The system's outputs correlate very highly with the average ratings

Trait	r	r_{avg}
Extraversion	.45 •	.80 •
Emotional stability	.39 •	.64 •
Agreeableness	.36 •	.68 •
Conscientiousness	-.01	-.02
Openness to experience	.17 •	.41 •

• statistically significant correlation

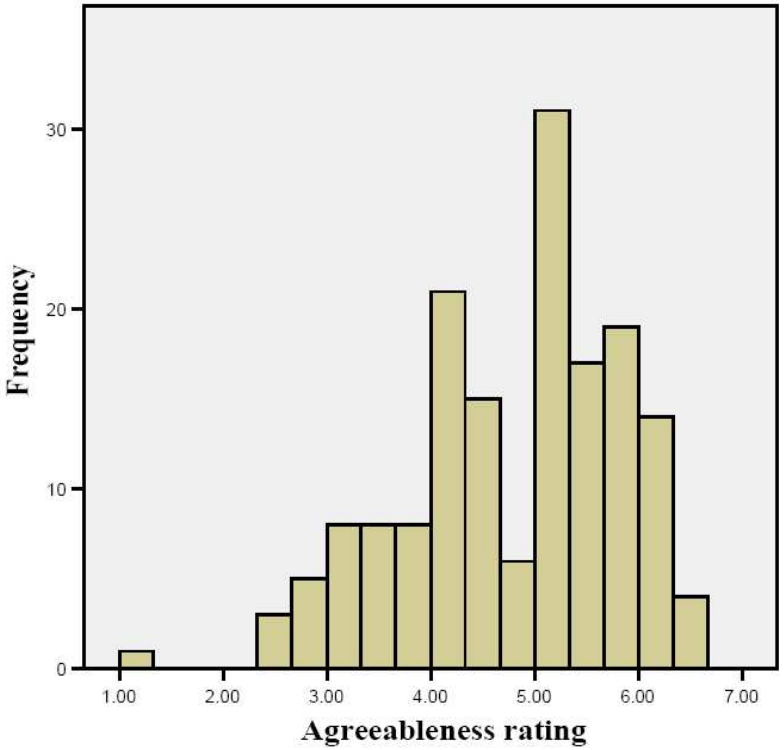
$p < .05$, • $p = .07$ (two-tailed)

Data-driven vs. Rule-based Methods

- Rule-based approach generally produces utterances perceived as more extreme
  - Stochastic exploration does not generate enough extreme data
  - Hybrid methods?
- Data-driven models produce continuous variation

Method	Rule-based		Param models	
Trait	Low	High	Low	High
Extraversion	2.96	5.98	3.69 ○	5.06 ○
Emotional stability	3.29	5.96	3.75	4.75 ○
Agreeableness	3.41	5.66	3.42	4.33 ○
Conscientiousness	3.71	5.53	4.16	4.15 ○
Openness to experience	2.89	4.21	3.71 ○	4.06

•,○ significant increase or decrease of the variation range over the average rule-based ratings ($p < .05$, two-tailed)



Research Challenges

- Can personality markers observed in conversations, essays and emails be mapped to parameters in a spoken language generator?
- Can recognisable personality be produced
  - In a very specific domain?
  - Within a single utterance?
- Can language manifesting all Big Five personality traits be generated?
- Can we produce continuous variation using data-driven methods?
- What types of speech acts in particular domains manifest personality?

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Application to Interactive Narrative Systems

- Does PERSONAGE generalize to a more general domain?
  - Different speech acts

- The Façade interactive narrative system (Mateas & Stern 2003)
  - 3D interaction with Trip and Grace, a dysfunctional couple
    - The storyline evolves dynamically based on the user input
  - *Authoring bottleneck* – all possible utterances are currently handcrafted

  ➢ **Can the personality conveyed by the characters be controlled automatically?**

A Façade Dialogue - Revisited

Speaker	Original dialogue	TRIP: extravert GRACE: introvert	TRIP: emotionally stable GRACE: neurotic
USER	· Do you like this place?	· Do you like this place?	· Do you like this place?
TRIP	· Yeah, you know, Grace's decorating has been such a great outlet for her.	· Yeah, Grace's decorating has been such like, a really great outlet for her, you know!	· Basically, Grace's decorating has been such a kind of outstanding outlet for her.
GRACE	· Outlet? What do you mean outlet?	· Outlet? Err... mmhm... what do you mean by an outlet?	· I mean, actually, I am not really sure. Outlet? Err... what do you mean by an ou-outlet?

A Façade Dialogue - Revisited

Speaker	TRIP: agreeable GRACE: disagreeable	TRIP: conscientious GRACE: unconscient.	TRIP: open GRACE: not open
USER	· Do you like this place?	· Do you like this place?	· Do you like this place?
TRIP	· Well, yeah, Grace's decorating has been such a sort of outstanding outlet for her mate, you know, alright?	· I see, ok, I suppose Grace's decorating has been such a rather outstanding outlet for her.	· I see, I suppose Grace's decorating has been such a sort of outstanding outlet for her, you know, you see?
GRACE	· Outlet? What I mean, do you mean by an outlet?	· I don't know mate! Outlet? Mmhm... err... what do you mean by an outlet?	· I mean, basically, I am not sure. Outlet? Err... mmhm... what do you mean by an outlet?

Application to Interactive Narrative Systems

- Exploratory work
  - Transformations only at the syntactic level
  - Content level parameters also important

- In the future
  - System designers produce the content
  - Off-the-shelf generators take care of the linguistic style

Future Work

- Prosodic parameters?
  - Introvert (Alt 5)

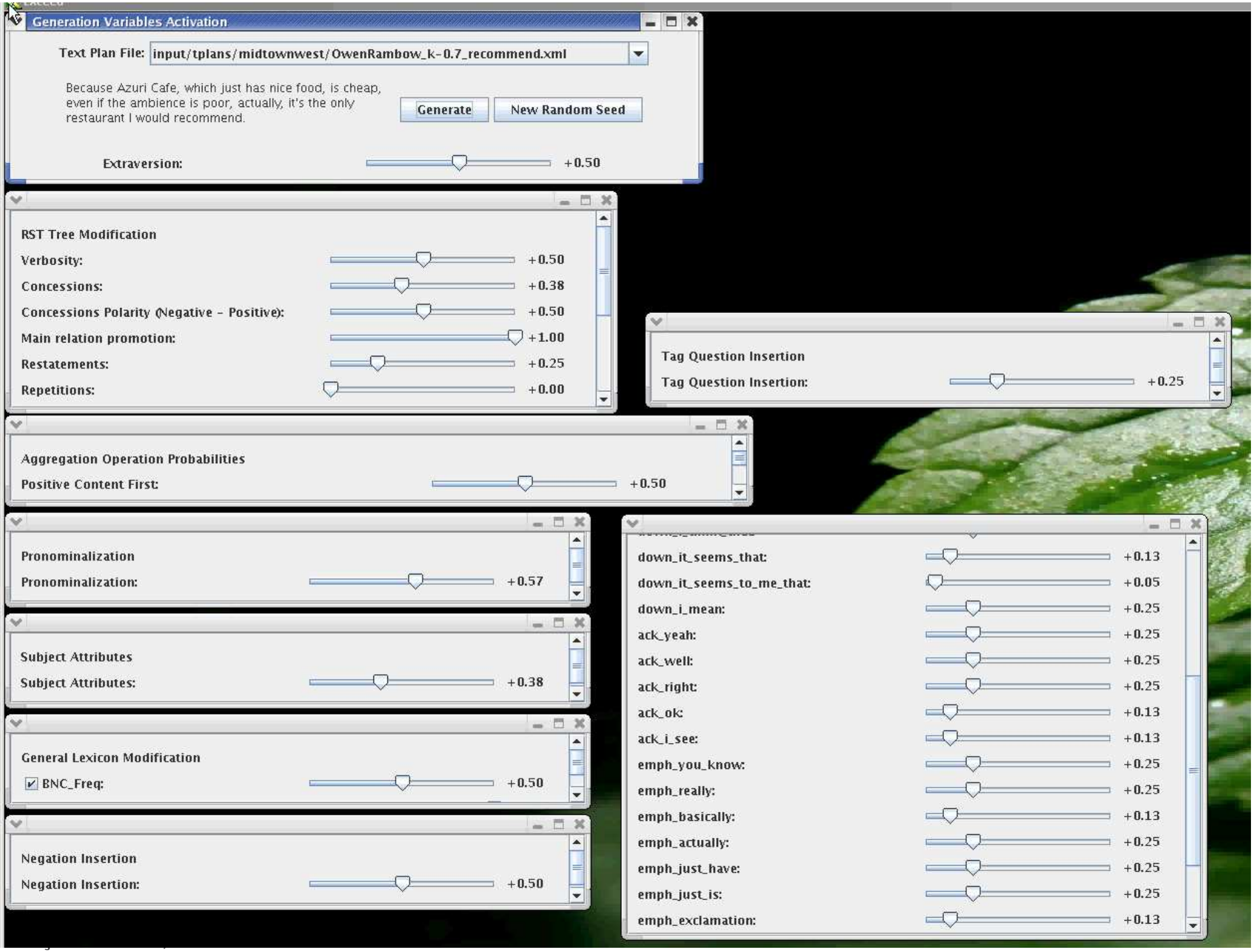
    "***Err... it seems to me that Le Marais isn't as bad as the others.***"
  - Extravert (Alt 2)

    "***Basically, actually, I am sure you would like Le Marais. It features friendly service and acceptable atmosphere and it's a French, kosher and steak house place. Even if its price is 44 dollars, it just has really good food, nice food.***"

- Hybrid data-driven methods combining rule-based utterances with data-driven generation

- Testing hypotheses regarding personality-based alignment (e.g. similarity-attraction effect?)

- Applications in dialogue system tasks, computer gaming and intelligent tutoring systems


Generation Variables Activation
Text Plan File: input/tplans/midtownwest/OwenRambow_k-0.7_recommend.xml
Because Azuri Cafe, which just has nice food, is cheap, even if the ambience is poor, actually, it's the only restaurant I would recommend.
Generate
New Random Seed
Extraversion: +0.50
RST Tree Modification
Verbosity: +0.50
Concessions: +0.38
Concessions Polarity (Negative - Positive): +0.50
Main relation promotion: +1.00
Restatements: +0.25
Repetitions: +0.00
Tag Question Insertion
Tag Question Insertion: +0.25
Aggregation Operation Probabilities
Positive Content First: +0.50
Pronominalization
Pronominalization: +0.57
Subject Attributes
Subject Attributes: +0.38
General Lexicon Modification
BNC_Freq: +0.50
Negation Insertion
Negation Insertion: +0.50
down_it_seems_that: +0.13
down_it_seems_to_me_that: +0.05
down_i_mean: +0.25
ack_yeah: +0.25
ack_well: +0.25
ack_right: +0.25
ack_ok: +0.13
ack_i_see: +0.13
emph_you_know: +0.25
emph_really: +0.25
emph_basically: +0.13
emph_actually: +0.25
emph_just_have: +0.25
emph_just_is: +0.25
emph_exclamation: +0.13

Thank you

- Java demo of PERSONAGE available
  http://www.dcs.shef.ac.uk/cogsys/personage.html

- Personality recognition demo
  http://www.dcs.shef.ac.uk/~francois/personality/demo.html

- Related papers

François Mairesse and Marilyn Walker. Trainable Generation of Big-Five Personality Styles through Data-driven Parameter Estimation. In *Proceedings of the 46th Annual Meeting of the ACL,* Columbus, June 2008.

François Mairesse and Marilyn Walker. PERSONAGE: Personality Generation for Dialogue. In *Proceedings of the 45th Annual Meeting of the ACL,* Prague, June 2007.

François Mairesse, Marilyn Walker, Matthias Mehl and Roger Moore. Using Linguistic Cues for the Automatic Recognition of Personality in Conversation and Text. Journal of Artificial Intelligence Research (JAIR), 30, 2007.