Learning Individual Adaptation in Dialogue Systems

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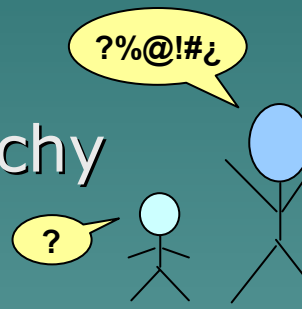
Outline

- Motivation
- Training a sentence generator
- Results of individual models
  - Model performances
  - Qualitative analysis of preferences
- Adaptation in a full dialogue system

Motivation

- People adapt to conversational partner
  - Based on individual differences
    - Age, social group, intelligence, hierarchy
  - Affects many aspects of language
    - Acoustic parameters (Coulston et al. 02)
    - Lexicon (Brennan 96)
    - Syntax (Niederhoffer & Pennebaker 02)



Motivation

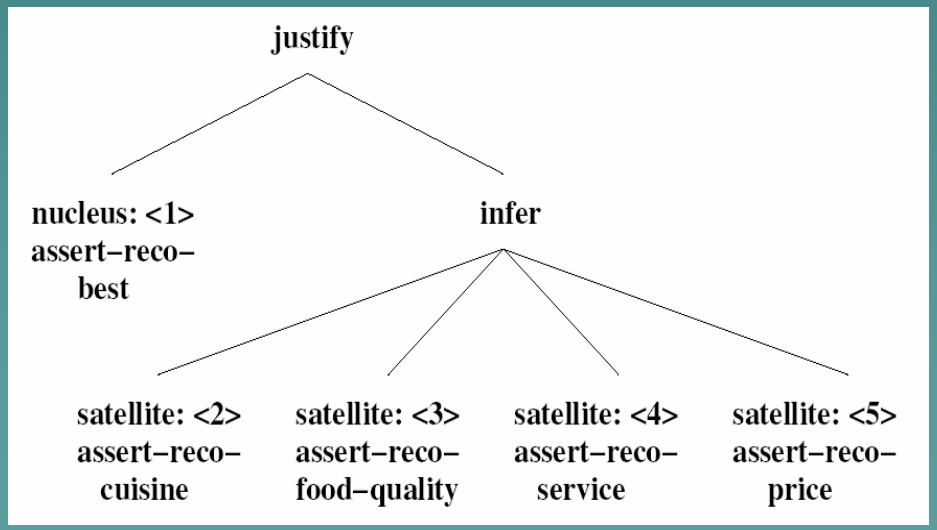
- User specific content selection (Rich 79)
- User prefer systems with same personality (Reeves and Nass 96)
  - Similarity-attraction effect

→ Individual adaptation is useful

- Hypothesis: individual linguistic preferences can be modeled and analyzed

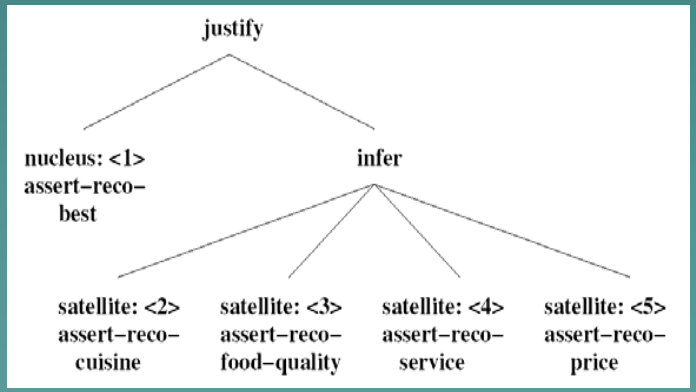
Trainable Sentence Generator

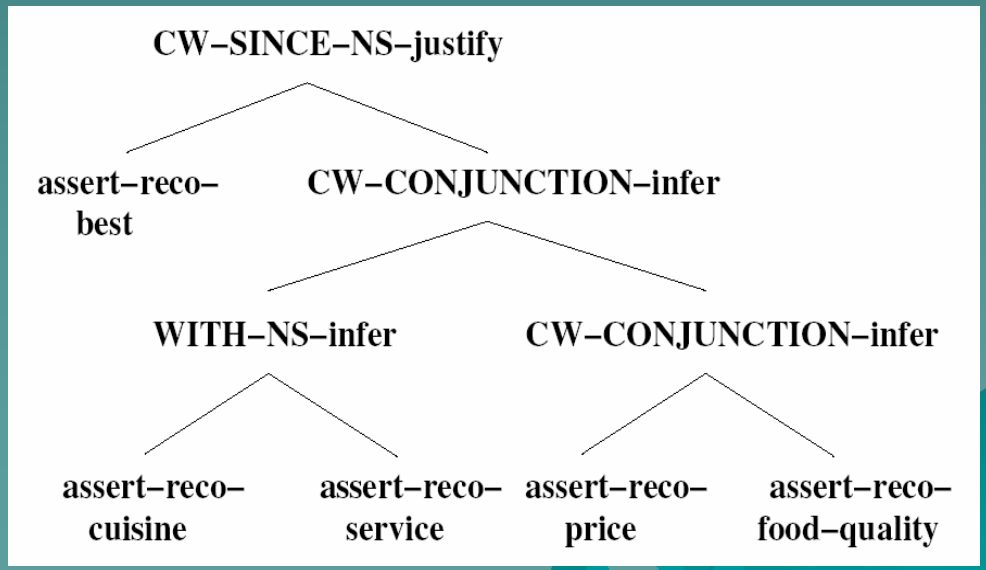
- SPoT (Walker et al. 02)
  - Stochastic sentence generation
  - Trainable sentence ranker
- Input is a content plan



Stochastic Sentence Generation

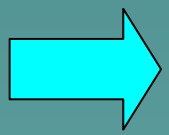
- Randomly generate sentence plan trees
  - Map rhetorical relations to clause combining operations
    E.g. justification → *since*, *because*
    inference → conjunction, period, merge
  - Nodes are ordered





Stochastic Sentence Generation

- Last step: realization of each alternative
  - Based on sentence plan tree and deep syntactic trees of each assertion
  - Add function words

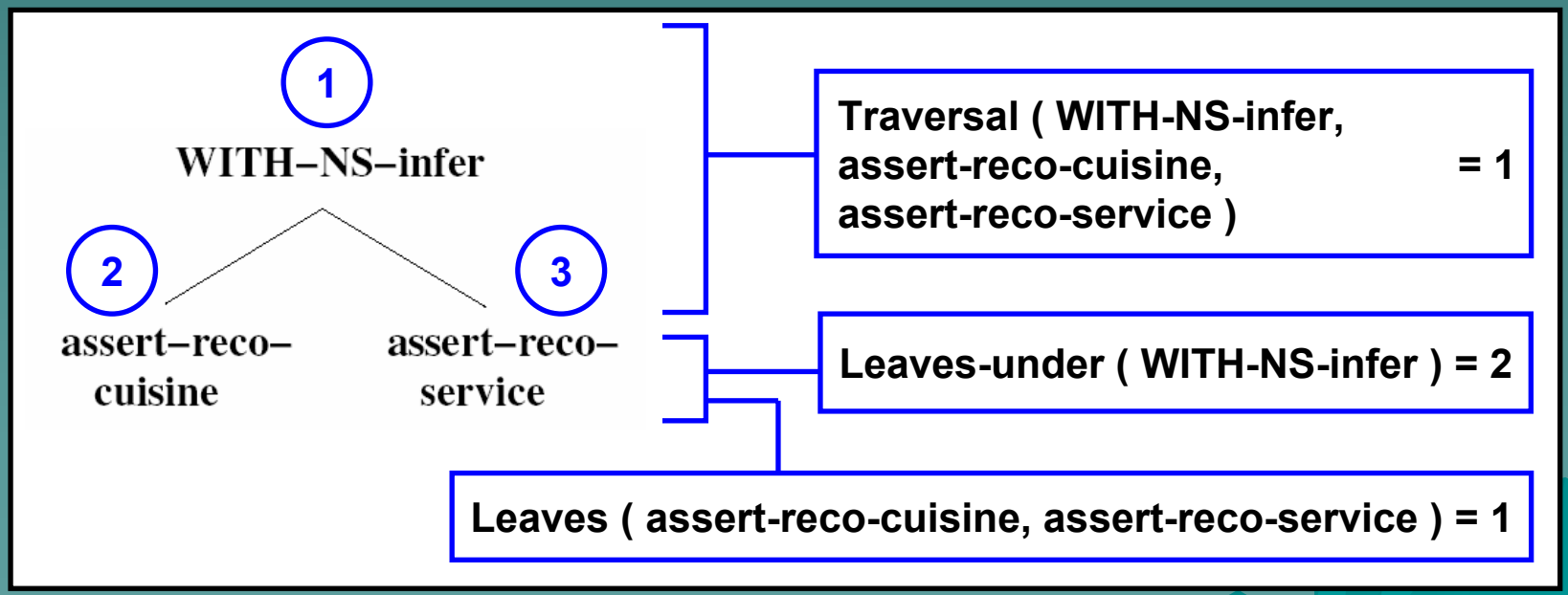


"Chanpen Thai has the best overall quality among the selected restaurants since it is a Thai restaurant, with good service, its price is 24 dollars, and it has good food quality."

"Chanpen Thai is a Thai restaurant, with good food quality. It has good service. Its price is 24 dollars. It has the best overall quality among the selected restaurants."

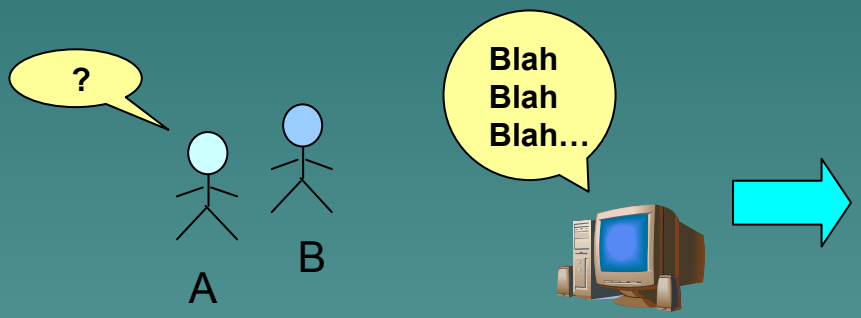
Trainable Sentence Ranking

- Learn user preferences
- Associate features to alternatives
  - Node counts of sentence plan tree



Trainable Sentence Ranking

- Training the ranker
  - Training data: user ratings of sentences



	User A	User B
Sentence 1	4/10	6/10
Sentence 2	8/10	9/10
Sentence 3	7/10	5/10
…		

  - Learning algorithm: RankBoost (Freund et al. 98)
  - Generalizes user ratings for any new sentence
    - Compute ranking score

User models

- RankBoost produces a set of rules

If feature ≥ threshold then modify ranking score by α

- Compute the ranking score

$$h(u) = \sum_{i \in R} \alpha_i$$

  - Given an utterance **u1** with **feature vector F = (2,1, …)** and rules:
    - if F(1) ≥ 1 increase score by 0.8
    - if F(2) ≥ 0.5 decrease score by 0.3

    →h(u1) = 0.8 - 0.3 = 0.5

  - If for another utterance h(u2) = 0.3, **u1 is preferred over u2**

Quantitative Results

- Testing the models
  - Compare correct ranking of 300 sentences with models
  - 2 fold cross validation

$$\text{Ranking Loss} = \frac{\text{Incorrectly ranked utterance pairs}}{\text{Total number of utterance pairs}}$$

Ranking Loss	A's test data	B's test data
A's model	**0.16**	0.51
B's model	0.51	**0.15**
AVG model	0.27	0.26

→ **Individual models perform better than averaged ones**

Qualitative Analysis

- Compare individual preferences

"Chanpen Thai has the best overall quality among the selected restaurants since it is a Thai restaurant, with good service, its price is 24 dollars, and it has good food quality."

User A: **2/10** – Model: **1.6/10**
User B: **8/10** – Model: **6.5/10**

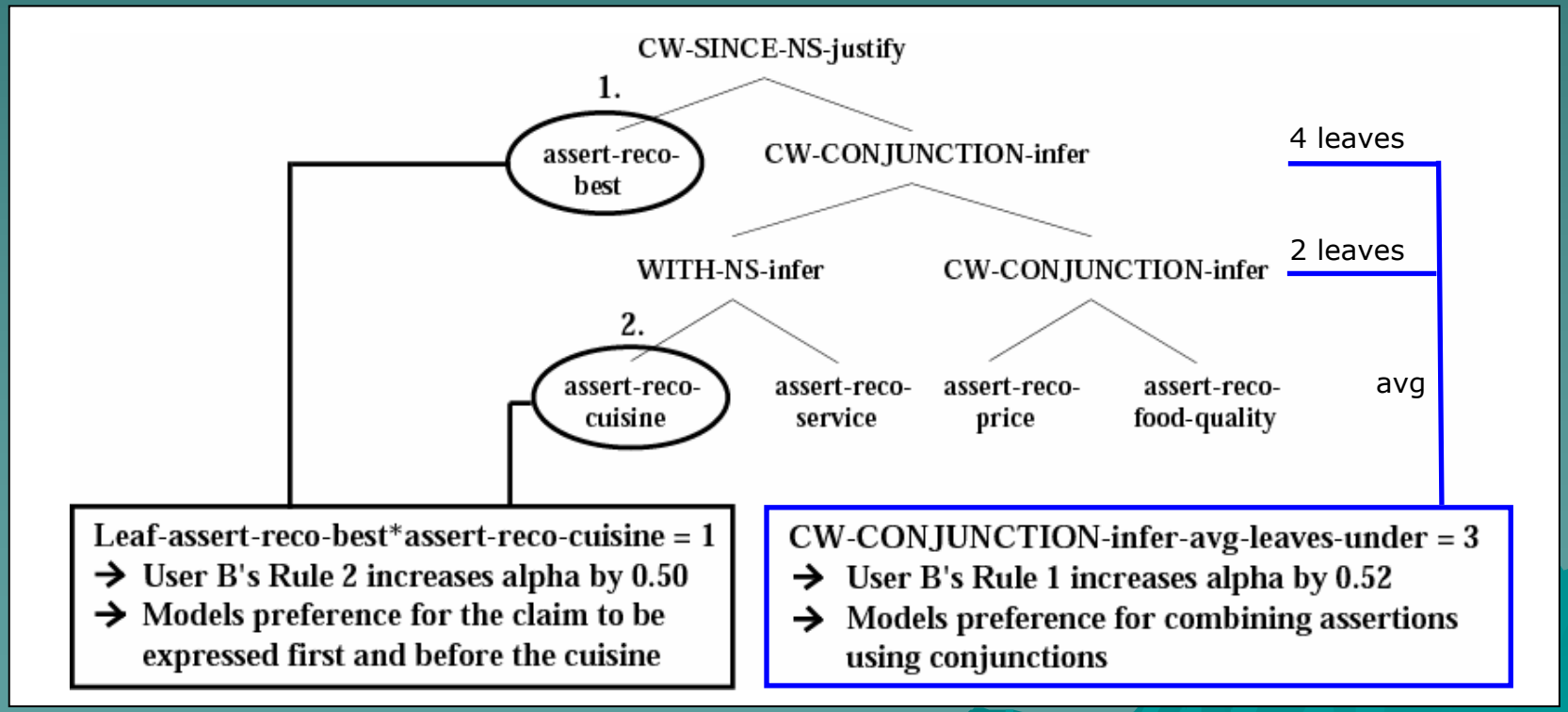
Conditions of some rules of User B's model	**α**
1. Average Leaves Under (CW-CONJUNCTION-infer) ≥ 2.8	0.52
2. Leaves (assert-reco-best, assert-reco-cuisine) ≥ 1	0.50
3. Ancestor (assert-reco, PERIOD-infer, PERIOD-infer) ≥ 1.5	-0.49
…	…

- Features associated with high α values tend to be preferred by the user

Qualitative Analysis: Example

Rule 1: Average Leaves Under (CW-CONJUNCTION-infer) ≥ 2.8
→ increase alpha by 0.52

Rule 2: Leaves (assert-reco-best, assert-reco-cuisine) ≥ 1
→ increase alpha by 0.50



Qualitative Analysis: More Examples

"Chanpen Thai is a Thai restaurant, with good food quality. It has good service. Its price is 24 dollars. It has the best overall quality among the selected restaurants."

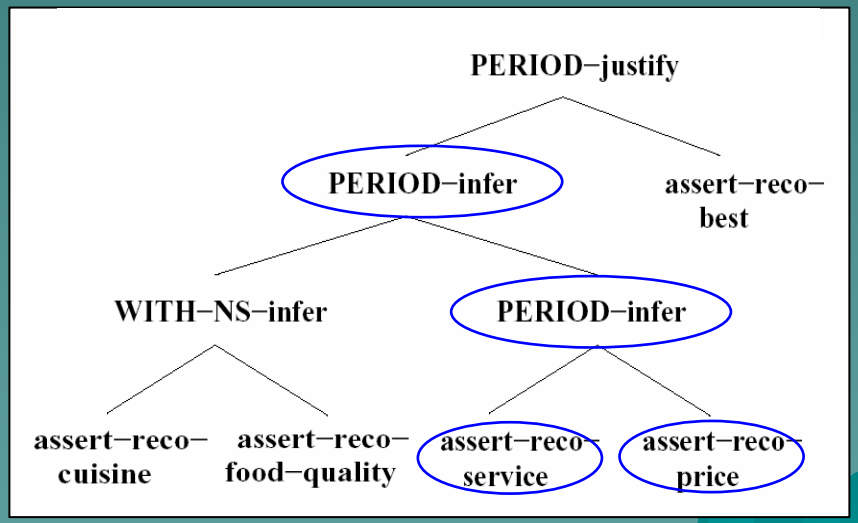
Other realization of the same content:

User A: **8/10** – Model: **8.1/10**
User B: **4/10** – Model: **2.9/10**

- Why doesn't User B like it?
  - Doesn't respect ordering
  - No conjunctions
  - Many periods

    Rule 3: Ancestor (assert-reco, PERIOD-infer, PERIOD-infer) ≥ 1.5

    → decrease alpha by 0.49

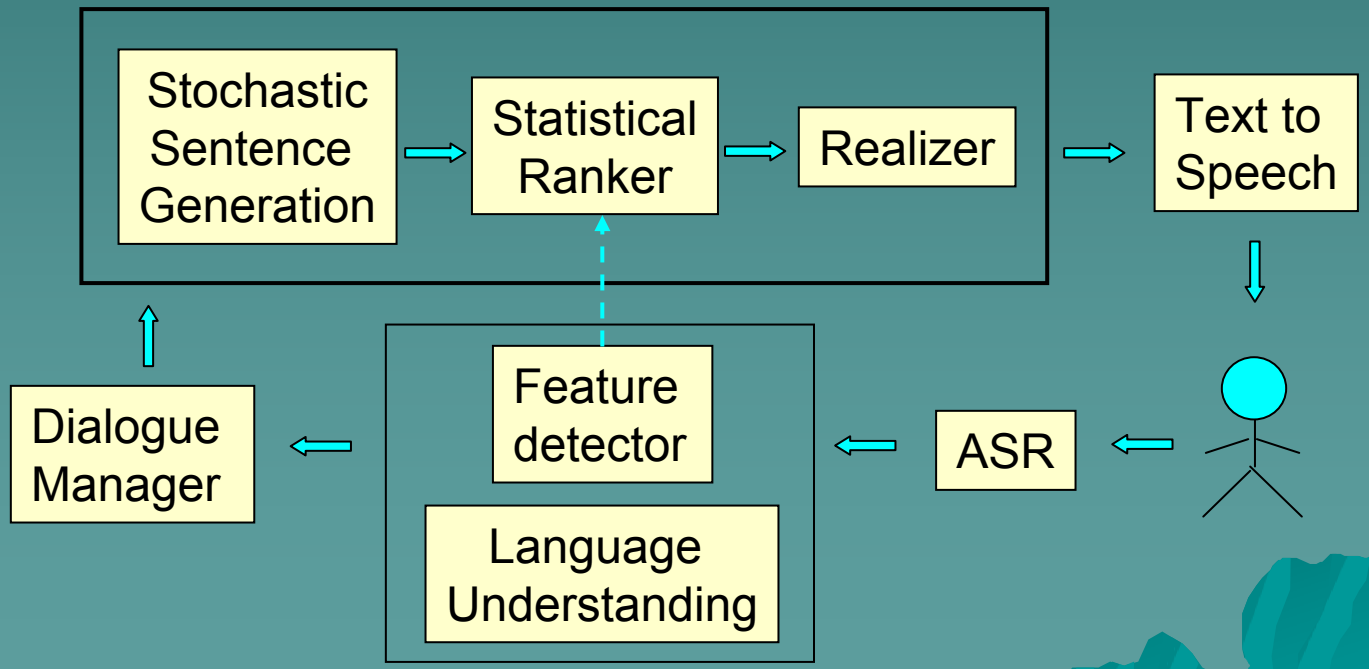


Future Work

- Problems
  - Time consuming to acquire feedback
    - 120 sentence ratings to get 0.2 ranking loss
- Integration in a full dialogue system
  - User utterances as direct feedback
  - Domain-independent features
  - Long term use

Future Work: Full System

- New modules
  - Feature detection
    - Communicate feature information to learning algorithm
  - Associate positive feedback on the fly



Conclusion

- Language generators can be trained for individual users
- Individual models perform better than averaged models
- User preferences can be analyzed
- Learn preferences in real-time?

References

- S. E. Brennan. Lexical entrainment in spontaneous dialog. In Proc. of 1996 International Symposium on Spoken Dialogue, p. 41-44, 1996.
- B. Reeves and C. Nass. The Media Equation. University of Chicago Press, 1996.
- M. Walker, R. Prasad and A. Stent. A trainable generator for recommendations in multimodal dialogue. In Proc. of Eurospeech 2003, p. 1697-1701, 2003.
- Y. Freund, R. Iyer, R. E. Schapire, and Y. Singer. An efficient boosting algorithm for combining preferences. In Proc. of 15th ICML, p. 170-178, 1998.
- O. Rambow, M. Rogati, M. Walker. Evaluating a trainable sentence planner for a spoken dialogue system. In Proc. of Annual Meetings of ACL, p. 426-433, 2001.
- B. Lavoie and O. Rambow. A fast and portable realizer for text generation systems. In Proc. of 3rd Conference on ANLP, p. 265-268, 1997.
- Niederhoffer, K.G. & Pennebaker, J.W.. Linguistic style matching in social interaction. Journal of Language and Social Psychology, 21, 337-360, 2002.
- Coulston, R., Oviatt, S.L, Darves, C. Amplitude Convergence in Children's Conversational Speech with Animated Personas, in Proceedings of the 7th ICSLP, vol.4, pages 2689-2692, 2002.
- Elaine Rich. User modeling via stereotypes. Cognitive Science, 3:329-354, 1979.

- Thank you! Questions?