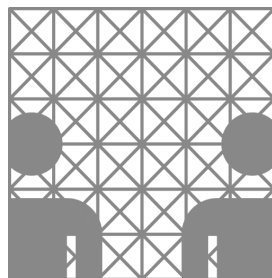


Natural Language Generation

Generating Referring Expressions

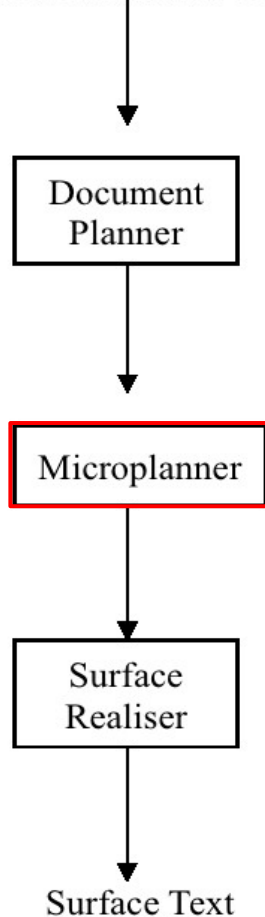
Katinka Böhm

SPEECH TECHNOLOGY
UNIVERSITÄT HAMBURG, DEPARTMENT OF INFORMATICS



Microplanning

Communicative Goal



[Reiter and Dale, 2000]

Two-stage model of a NLG system

- **Document Planner** - *what to say*
text content and structure
- **Surface Realizer** - *how to say it*
sentence-level syntax and morphology

Microplanner: fine-grained decisions

- **Lexicalisation** – particular words, syntactic constructs
- **Aggregation** – distribution of messages across sentences (order, length, number of sentences)
- **Referring Expression Generation (REG/GRE)** – phrases to use to identify particular domain entities

REG/GRE Problem

(Dale, Reiter 1995)

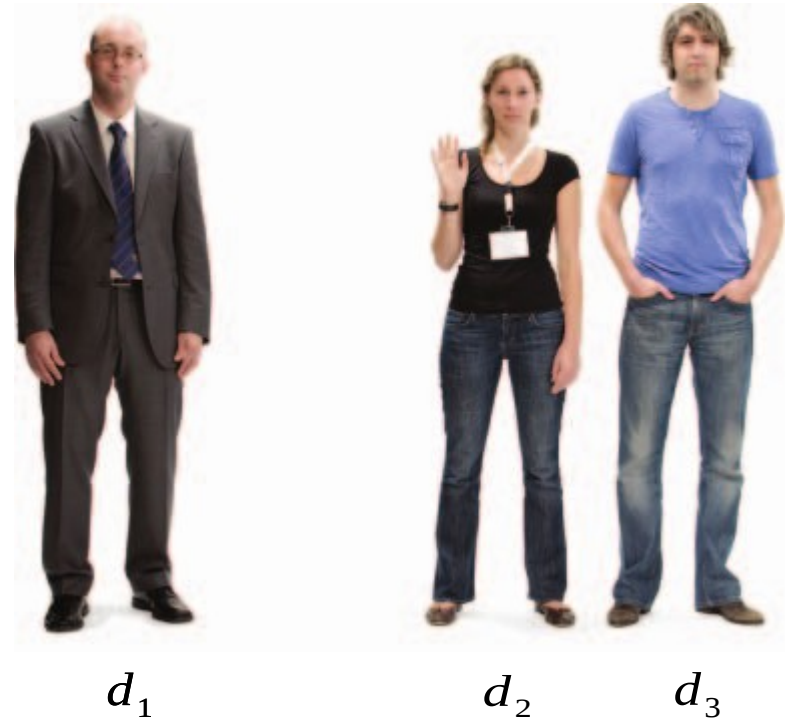
Domain of objects

$D = \{ d_1, d_2, d_3 \}$

Attributes

$A = \{ \text{type, gender, shape, clothing, position, ...} \}$

Goal: find attribute-value pairs (**property**), so that the conjunction is true of the target but not of any of the other domain objects



Can you describe d_1 ?

As a normal sentence? As a set of attribute-value pairs?

REG/GRE Problem

(Dale, Reiter 1995)

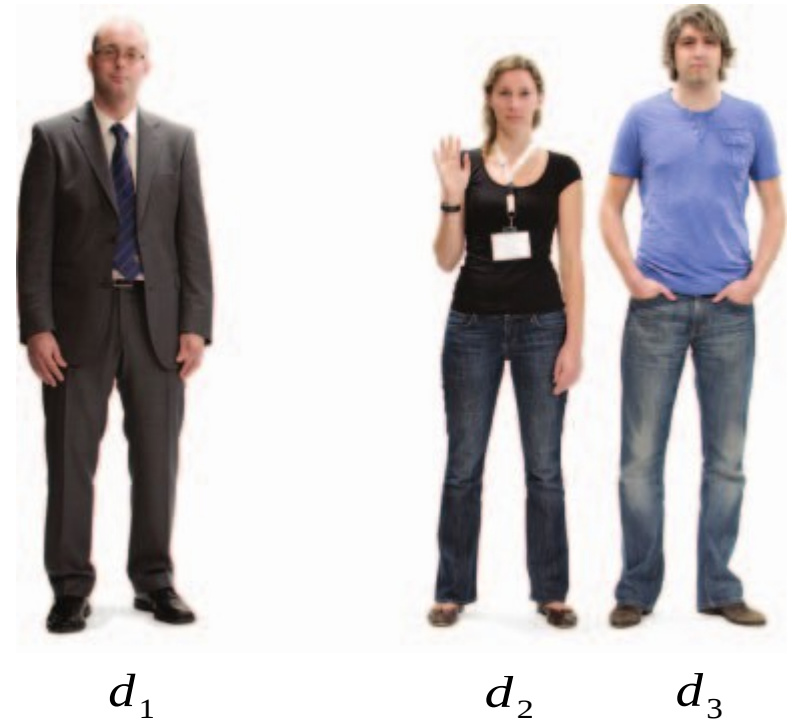
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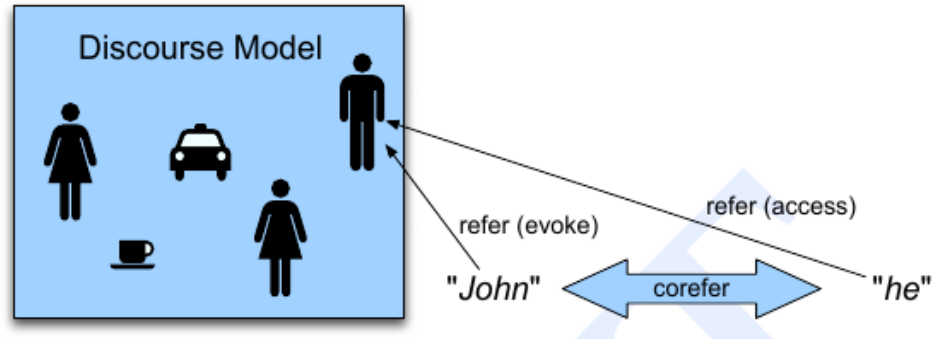
1. $\{ \langle \text{gender, man} \rangle, \langle \text{clothing, wearing suit} \rangle \}$
2. $\{ \langle \text{gender, man} \rangle, \langle \text{position, left} \rangle \}$
3. $\{ \langle \text{gender, man} \rangle, \langle \text{clothing, wearing suit} \rangle, \langle \text{position, left} \rangle \}$

Reference Resolution

- What entity is being referred to?

- one **referent**
- multiple **distractors**

- referring expression



- paradigm: distinguishing description = „definite description whose primary purpose it is to identify the referent and rule out distractors“
- **Coreference resolution** - linking expressions that refer to the same entity

{Victoria Chen, Chief Financial Officer of Megabucks Banking Corp since 1994, her, the 37-year-old, the Denver-based financial-services company's president, She}

- **Pronominal anaphora resolution** - finding the antecedent for a pronoun

It has been ten years since *she* came to Megabucks.

Incremental Algorithm

- most influential basic algorithm (1995)
- „preference“ for attributes (fixed order) → based on experimental data
- polynomial complexity

```
1. IncrementalAlgorithm ( $\{r\}, D, Pref$ ) {
2.    $L \leftarrow \emptyset$ 
3.    $C \leftarrow D - \{r\}$ 
4.   for each  $A_i$  in list  $Pref$  do
5.      $V = \text{Value}(r, A_i)$ 
6.     if  $C \cap \text{RulesOut}(\langle A_i, V \rangle) \neq \emptyset$ 
7.       then  $L \leftarrow L \cup \{ \langle A_i, V \rangle \}$ 
8.          $C \leftarrow C - \text{RulesOut}(\langle A_i, V \rangle)$ 
9.     endif
10.    if  $C = \emptyset$ 
11.      then return  $L$ 
12.    endif
13.  return failure }
```

r referent
 D domain
 $Pref$ list of ordered attributes

referring expression

list of open distractors

$\text{RulesOut}(\langle ., . \rangle)$ returns the set of objects which have a different value for that attribute than the referent

Too simple?

Which simplifications are made to the REG task?

What limitations does the IA have? Why is the IA not suitable for interactive tasks and dialogue systems?

- produces reference to a single referent (no sets of objects)
- predefined simple attributes
- no backtracking if a better description is found, includes redundant properties (is this a problem?)
- Closed World Assumption
- no vague property descriptions (height = large vs. height = 180cm)
- no relations between objects „*The girl left to the woman in the dress.*“
- objects are assumed to be equally salient
- no multimodal reference (intonation, gaze, gestures)

Dialogue Systems

Produce **human-like** referring expressions

- Simplicity is not everything
 - negations, relations, quantifiers
- Complex content does not require a complex form
 - break down information into smaller chunks over dialogue turns
- Overspecification
 - humans tend to overspecify
- Favorize fixed attributes (colour) over relative attributes (size)
- Include different modalities
 - spatial visual context, movement

Taking the addressee into account (**addressee modelling**)

- Lexical Entrainment (Alignment)
 - adapt to the dialogue partners' preferences and to the domain setting
 - frequency gives information about preference → requires data
 - dialogue history
- Account for differing domain views

Referability

1. Form of reference (deictic pronoun “*that one*” or full description “*the chair with the armrests*”)
2. Attribute Selection
3. Surface Realization

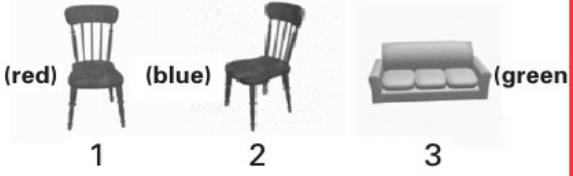
Experiments: How do people refer to objects?

- TUNA Corpus
 - Furniture Domain colour
 - People Domain wearing glasses
- Experiments on Adaption and Interaction in Interactive Setting
 - Inherent preferences for certain properties in a given domain
 - Tendency to adapt to references produced by the dialogue partner

Experiment I

how adaption influences attribute selection
preferred vs. dispreferred

Task I (prime)
Indicate which picture is being described




(red) 1 (blue) 2 (green) 3

Preferred description (color) Dispreferred description (orientation)

"The red chair" "The front facing chair"


Task II (filler)
Describe the picture in the middle



The man with the beard

find referent


Task III (filler)
Indicate which picture is being described



1 2 3

"The man with the beard"

Task IV (target)
Describe the picture in the middle



(red) 1 (blue) 2 (grey) 3

alignment with preferred property alignment with dispreferred property

The blue fan The left facing fan

create referring expression

Results: preferred attributes used more often, dispreferred attributes used significantly more if primed, more alignment in the furniture domain

Experiment II

priming of overspecification

- overspecified referring expressions in the prime turn
 - two attributes in addition to the type attribute
 - one preferred and one dispreferred
 - both sufficient to uniquely describe the referent

The sofa facing right (well-specified/minimal)
The red sofa facing right (overspecified)



Task I (prime)

Indicate which picture is being described



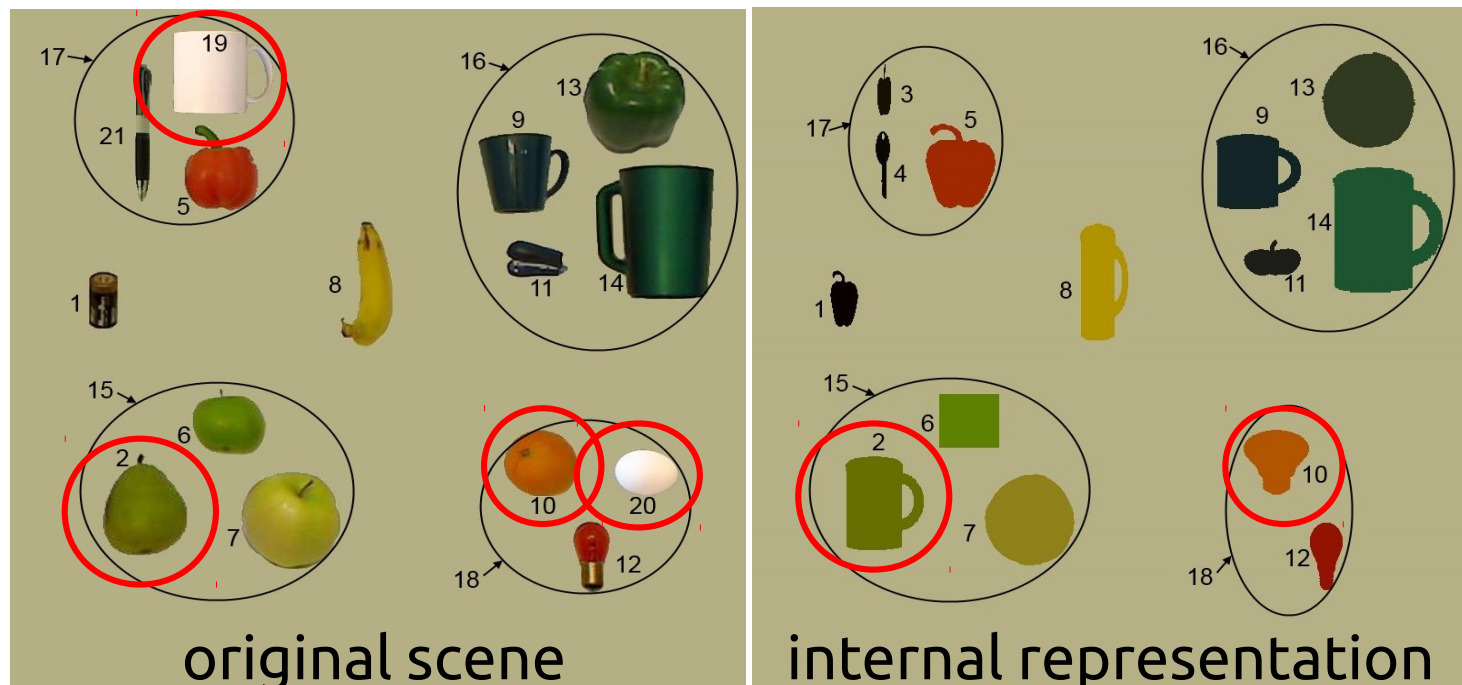
„The red chair seen from the front.“

Results: over 50% chose overspecification after being primed
(compared to 10% of overspecifications in Experiment I)

Collaborative Models in Situated Dialogue

[Fang et al., 2014]

- assumption: **perceptual basis** between human and agent (dialogue system) differs
- generate **multiple small expressions** that gradually lead to the target object
- reinforcement learning through human feedback



Collaborative Models in Situated Dialogue

[Fang et al., 2014]

- **Episodic description**

- sequence of smaller noun phrases that lead to the target

A: below the orange, next to the apple, it's the red bulb.

- **Installment description**

- waits for explicit feedback from the partner
- iterative process

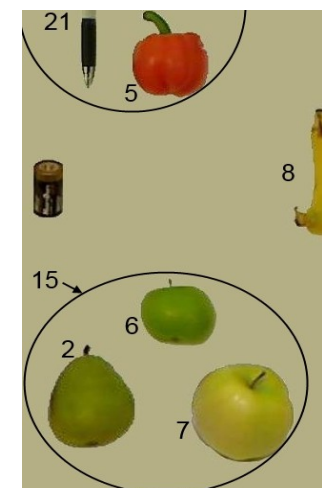
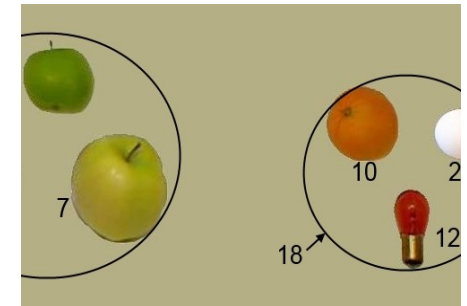
A: under the pepper we just talked about.

B: yes.

A: there is a group of three objects.

B: OK.

A: there is a yellow object on the right within the group.



Collaborative Models in Situated Dialogue

[Fang et al., 2014]

- **Episodic model**

- Branch-and-Bound & Graph Search → find path to the target with the lowest cost
- nodes = objects + concatenation of describing attributes (type, color, type with color, etc.) and their preference cost

- **Installment model**

- landmark object („current“ object confirmed by user)

Action: Object + RE + SP

RE = generation strategy (describes type, color, size, group)

SP = spacial location wrt. the landmark

Transition Function: updates landmark

Reward: 100 is target is reached and identified, 10 for correct intermediate steps, -1 else

Adapting to User Knowledge in Spoken Dialogue Systems

[Janarthanam, Lemon, 2010]

- reinforcement learning framework (hierarchical SARSA)
- technical support dialogue → set up home broadband connection
- learn to choose the **appropriate referring expressions based on user's domain expertise**

Jargon: Please plug one end of the broadband cable into the broadband filter.

Descriptive: Please plug one end of the thin white cable with grey ends into the small white box.

Adapting to User Knowledge in Spoken Dialogue Systems

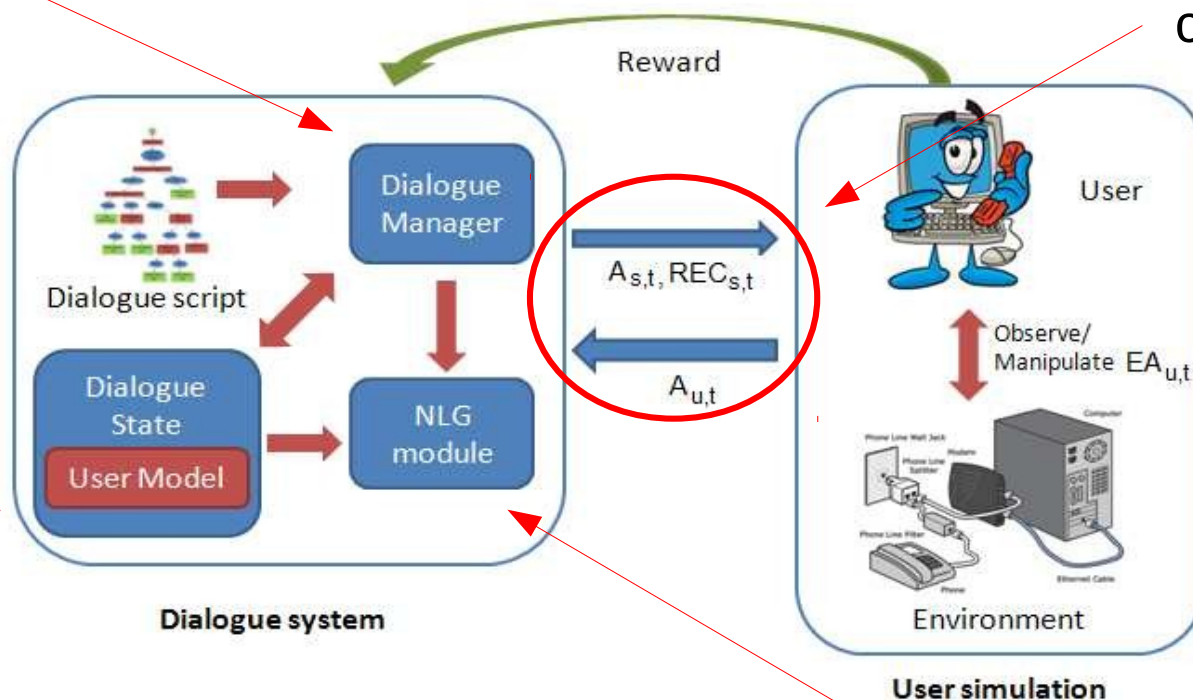
[Janarthanam, Lemon, 2010]

instruction based on dialogue management policy

observation

manipulation

action and referring expression choices (REC)



initial domain knowledge

jargon referring expression x

$user_knows_x = yes/no/not_sure$

REG module

Jargon

Descriptive

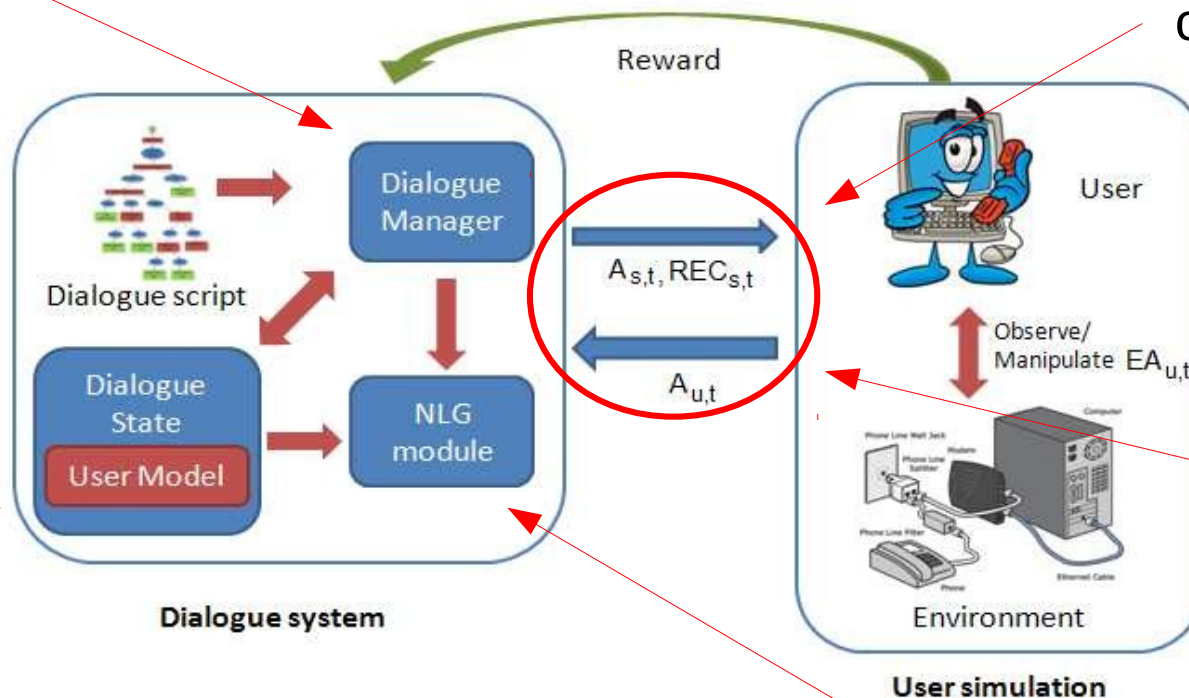
Adapting to User Knowledge in Spoken Dialogue Systems

[Janarthanam, Lemon, 2010]

instruction based on dialogue management policy

$$AA = \frac{1}{r} \sum_r \frac{|appropriate\ expr(r)|}{|instances(r)|}$$

action and referring expression choices (REC)



clarification request instruction response

initial domain knowledge
users' domain knowledge
updated dynamically



REG module

REG policy: User Model → REC

Conclusion

- generate a **referring expression**
- Incremental Algorithm is too restricted
- **attributes** and **overspecification** can be primed
- Dialogue Systems need to produce
 - **human-like** referring expressions
 - a **model of the dialogue partner**
- Applications:
 - collaborative models
 - adapt to user-knowledge

References

Books

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General

[Krahmer and van Deemter, 2012] Krahmer, E. and van Deemter, K. (2012). Computational Generation of Referring Expressions: A Survey. Computational Linguistics, 38(1):173–218.

[Gatt et al., 2011] Gatt, A., Goudbeek, M., and Krahmer, E. (2011b). Attribute preference and priming in reference production: Experimental evidence and computational modeling. In Proceedings of the 33th Annual Meeting of the Cognitive Science Society, CogSci 2011, Boston, Massachusetts, USA, July 20-23, 2011.

Application

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[Janarthanam and Lemon, 2010] Janarthanam, S. and Lemon, O. (2010). Learning to Adapt to Unknown Users: Referring Expression Generation in Spoken Dialogue Systems. In ACL 2010, Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics, July 11-16, 2010, Uppsala, Sweden, pages 69–78.