NPFL099 - Statistical dialogue systems

User simulation

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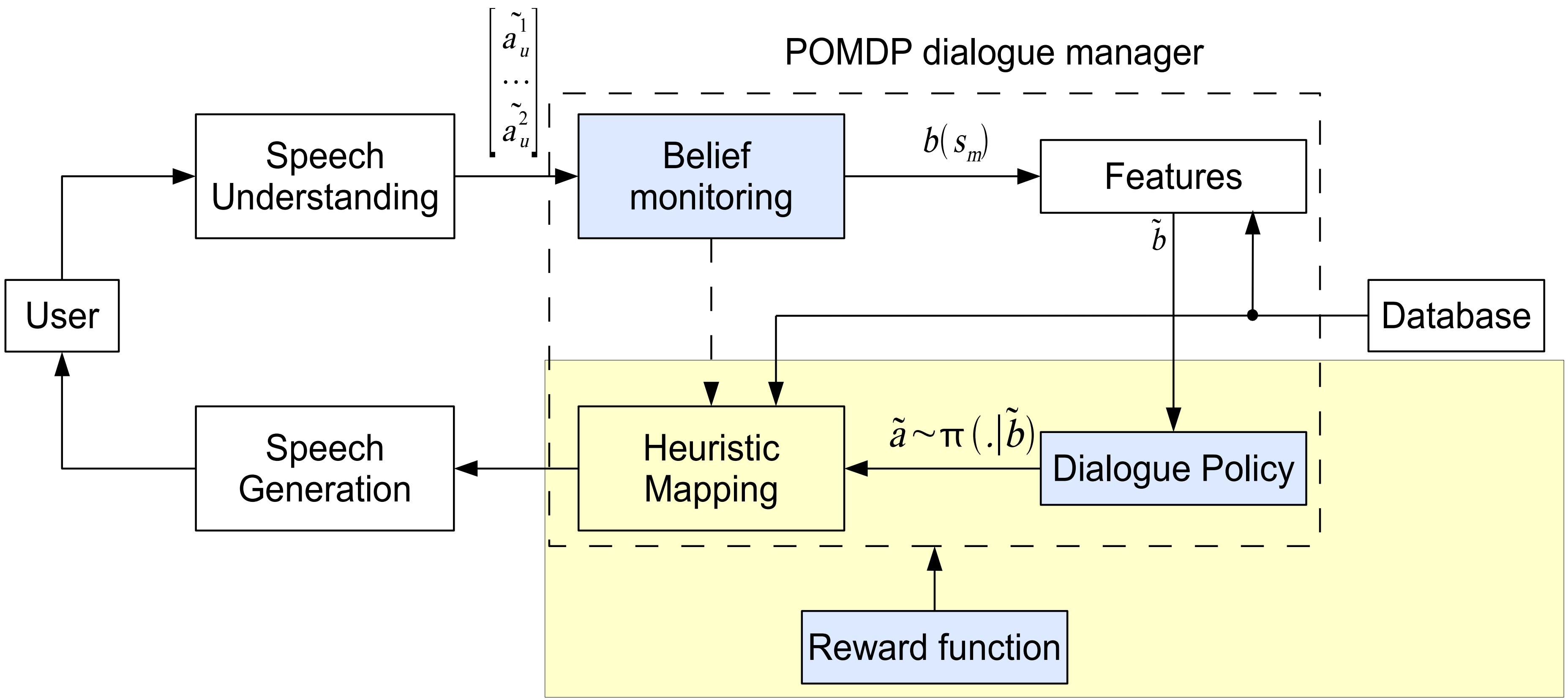
Outline

- User simulation
- Dialogue act level simulations
  - N-gram dialogue act model
  - Agenda based simulation
  - ISU based approach
  - Bayesian user simulation
- Word level simulation
- Speech level simulation

POMDP Dialogue systems



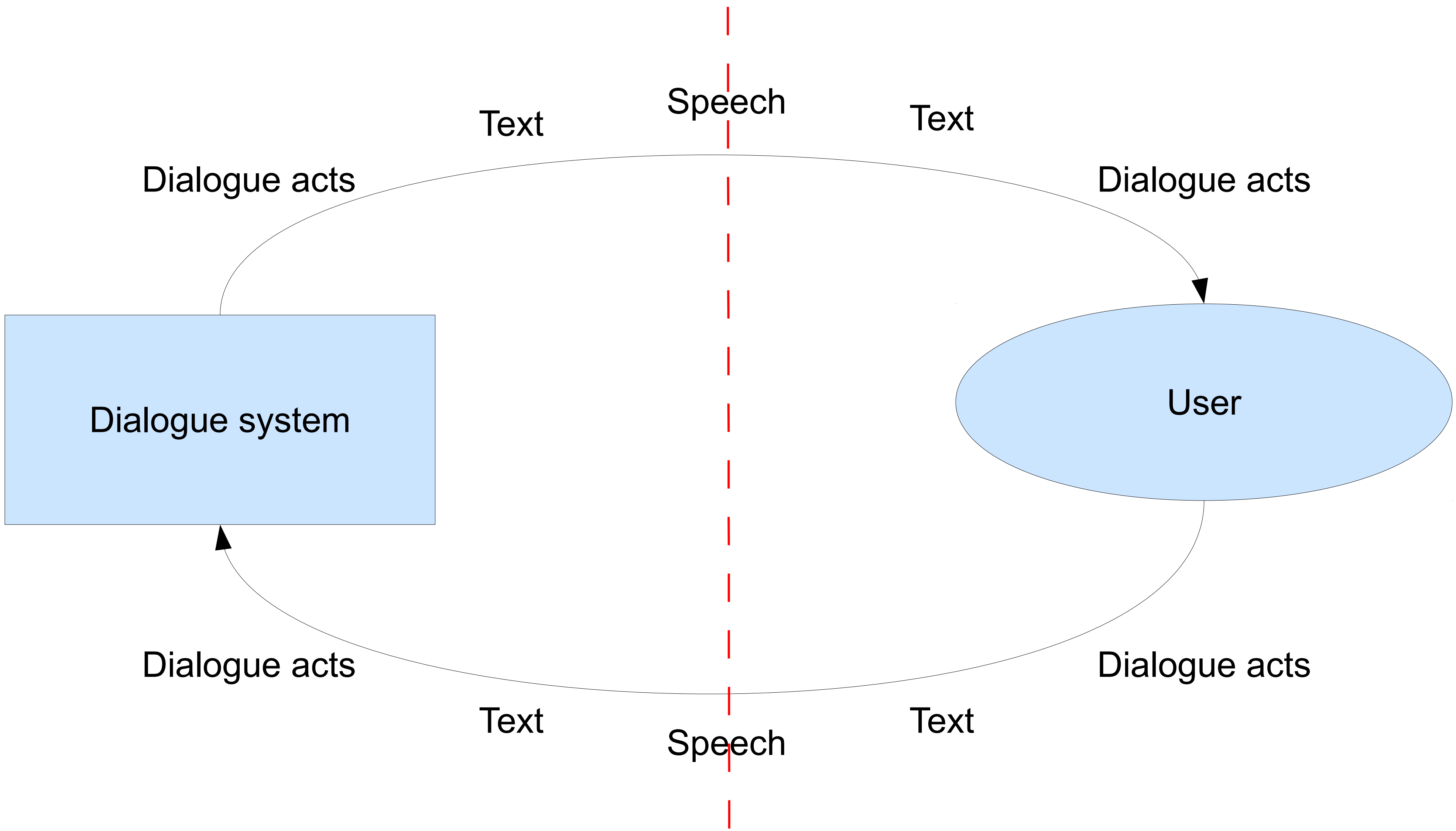
- Ideally the policy is optimized to maximize the reward function

User simulation

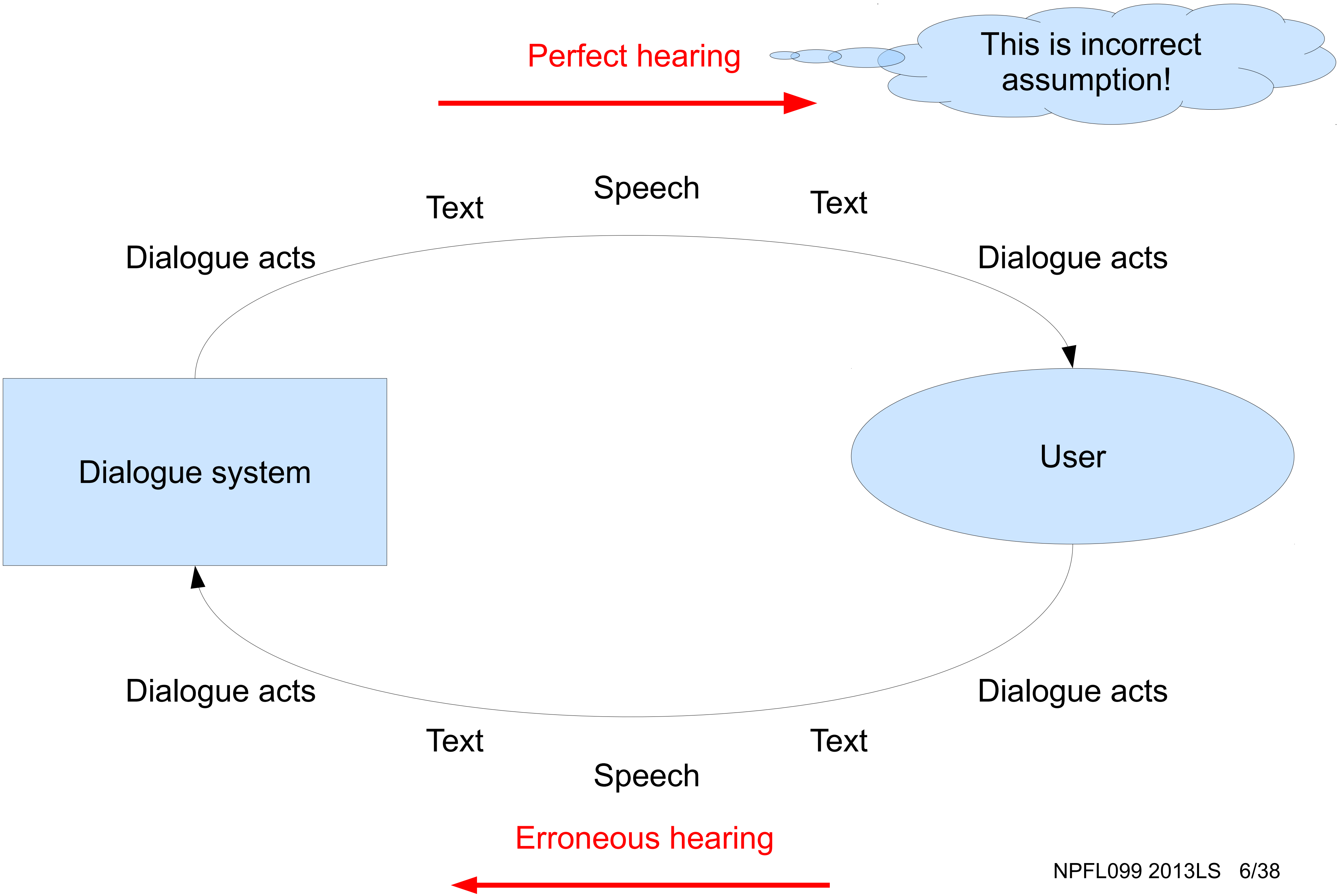
- Ideally, the POMDP dialogue systems would be optimised in interaction with real users
- The problem
  - state-of-the-art techniques still needs to more than 10000 dialogues
- User simulators are used to train and test POMDP techniques
- User simulators are mostly hand-crafted, though parametrised

User simulation

- It is like building another SDS

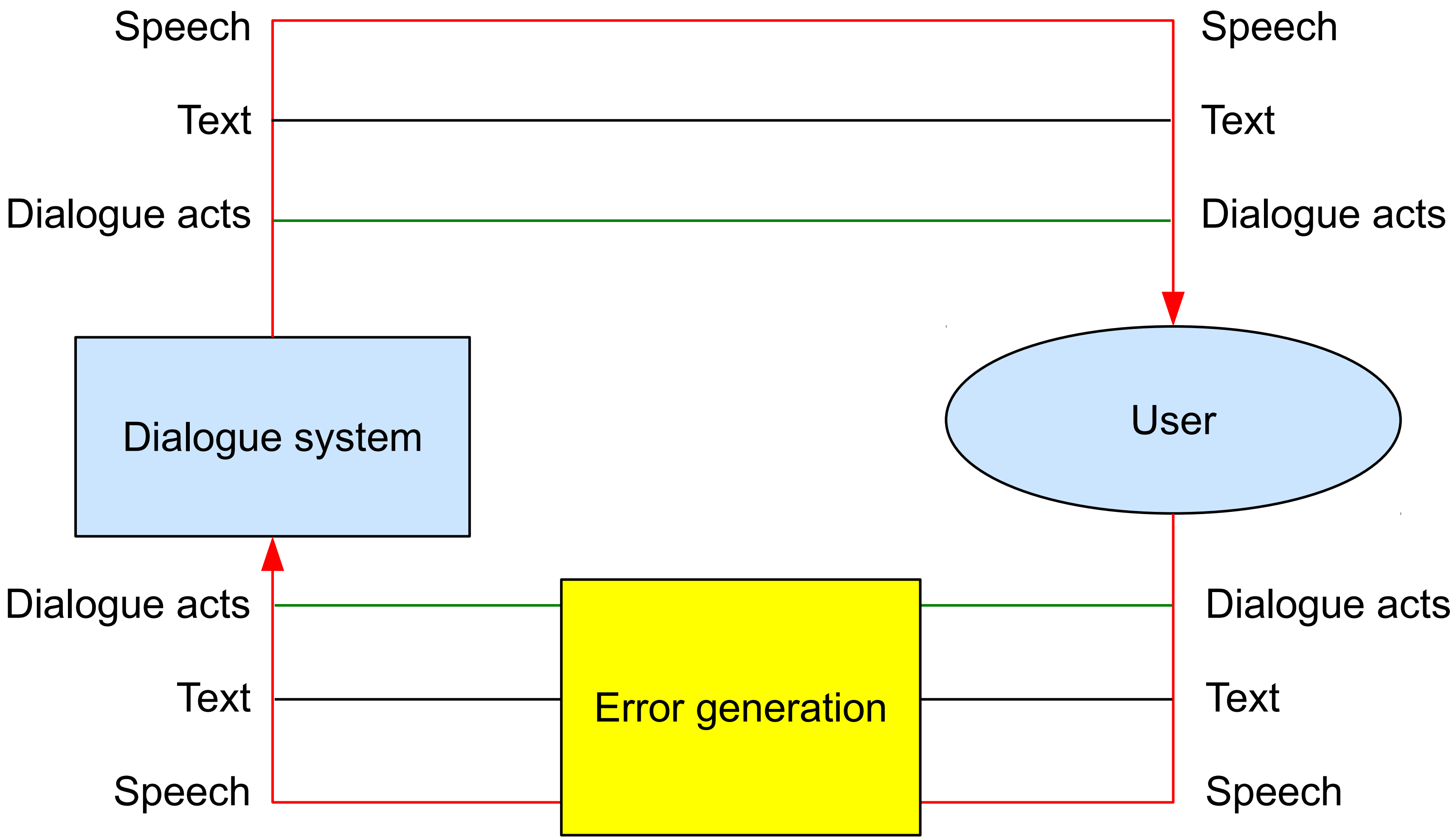


Error simulation



Types of user simulation

- Dialogue act level, Word level, Speech level

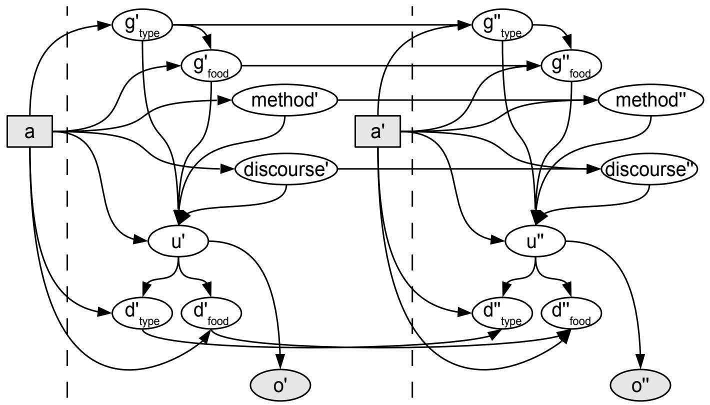


Dialogue act level simulation

- Dialogue act level
  - S: request(food_type)
  - U: inform(food_type=Chinese)

- Many different implementations
  - bigram model for dialogue act types and random sampling slots
  - agenda based simulator
  - using user model to sample user dialogue acts

- Output dialogue act confusion model



N-gram level user simulation

- Dialogue act level simulation
- Predict the next dialogue act given some context

$$P\left(d \middle| \ldots\right)$$

- Sample from a distribution
  - sampling insures variability in the output
- Typical context:
  - None – unigram models
  - Previous dialogue act – bigram models

N-gram dialogue act user simulation

- In general, $P(d|...)$ is too complex to model explicitly

- Model dialogue act type independently of the slots

$$P(dat|...) \approx P(dat_{t+1}|dat_t) \approx P(dat_{t+1})$$

request → inform
inform → inform
inform → deny
inform → confirm
….

- Slots names depends on DAT

$$P(sn_{t+1}|dat_{t+1})$$

  - or are drawn from a uniform distribution

N-gram dialogue act user simulation

- Can be easily learned from the collected data
- These users are not rational due to small context considered
- Values are very often randomly selected
  - there is not enough data to estimate probabilities for this
- Example:
  - S: request(pricerange)
  - U: inform(pricerange=cheap)
  - S: request(pricerange)
  - U: inform(pricerange=expensive)

The use did not changed its mind. **He did not had a clue about what he said before.**

Agenda based simulations

- Inspired by agenda based approach for SDS:
  - X Wei and AI Rudnicky. 1999. An agenda-based dialog man- agement architecture for spoken language systems. In Proc. of IEEE ASRU. Seattle,WA.
- In this case, the dialogue state is factored into
  - the goal – G
  - the agenda – A
- The goal ensures that the user behaves in a consistent, goal-directed manner.
- For example in tourist information domain, the goal can be further factored into
  - requirements - R
  - constraints - C

Agenda based simulations

- The user agenda is a stack-like structure containing the pending user dialogue acts
- Note: the agenda is a special way of representing a dialogue policy and the context history at the same time
- At the start of the dialogue the agenda contains
  - Inform acts about all constraints
  - Request act for all requirements
  - Bye dialogue act

Agenda update

- Based on the systems responses, update the agenda of the simulator, e.g. what to say next

$$P\left(a_{t+1} \middle| a_t, g_t, u_{a:t}\right)$$

- Although it can have probabilistic representation, it is mostly done deterministically, e.g.:
  - If system misunderstands then the user simulator puts on the agenda a correction

- Since agenda operates with a stack-like structure, the allowed operation are:
  - push and pop acts to and from agenda
  - the dialogue end when *bye()* act is popped of the stack

Example

$$C_0 = \begin{bmatrix} type = bar \\ drinks = beer \\ area = central \end{bmatrix}$$

$$R_0 = \begin{bmatrix} name = \\ addr = \\ phone = \end{bmatrix}$$

Sys 0 Hello, how may I help you?

$$A_1 = \begin{bmatrix} inform(type = bar) \\ inform(drinks = beer) \\ inform(area = central) \\ request(name) \\ request(addr) \\ request(phone) \\ bye() \end{bmatrix}$$

Usr 1 I'm looking for a nice bar serving beer.

Sys 1 Ok, a wine bar. What pricerange?

$$A_2 = \begin{bmatrix} \underline{negate(drinks = beer)} \\ inform(pricerange = cheap) \\ inform(area = central) \\ request(name) \\ request(addr) \\ request(phone) \\ bye() \end{bmatrix}$$

Usr 2 No, beer please!

Sys 2 A bar serving beer, correct?

$$A_3 = \begin{bmatrix} affirm() \\ inform(pricerange = cheap) \\ inform(area = central) \\ request(name) \\ request(addr) \\ request(phone) \\ bye() \end{bmatrix}$$

Usr 3 Yeah something cheap in the town centre.

Sys 3 Murphy's on Main Square serves cheap beer.

$$A_4 = \begin{bmatrix} request(phone) \\ bye() \end{bmatrix}$$

Usr 4 Ok, and what's the phone number?

Sys 4 The number is 796 69 94.

$$A_5 = \begin{bmatrix} bye() \end{bmatrix}$$

Usr 5 Thanks, goodbye!

Schatzmann, J., Thomson, B., Weilhammer, K., Ye, H., & Young, S. (2007). Agenda-based User Simulation for Bootstrapping a POMDP Dialogue System. Proceedings of HLT/NAACL. Rochester, NY.

Agenda update

- Agenda update tends to be complex
  - due to limited number of ways of updating the agenda
  - !!! the update is limited to make its use easier !!!
- Agenda update is unnecessary factored into to too small and specific operations
- Some trivial things are just too complex to be achieved with push and pop operations

ISU based approach

- ISU based approach would simply build a dialogue system behaving like a user:

- Such system:
  - would track what the dialogue systems said
  - compared that information with the goals of the user
  - then made it decisions using either:
    - a handcrafted policy
    - a stochastic policy

- To limit complexity of the dialogue policy
  - summary action can be used
  - they can be tuned to needs of a user simulator

ISU based approach

- It is like building a dialogue system without reinforcement learning
  - we can learn stochastic policy using maximum likelihood

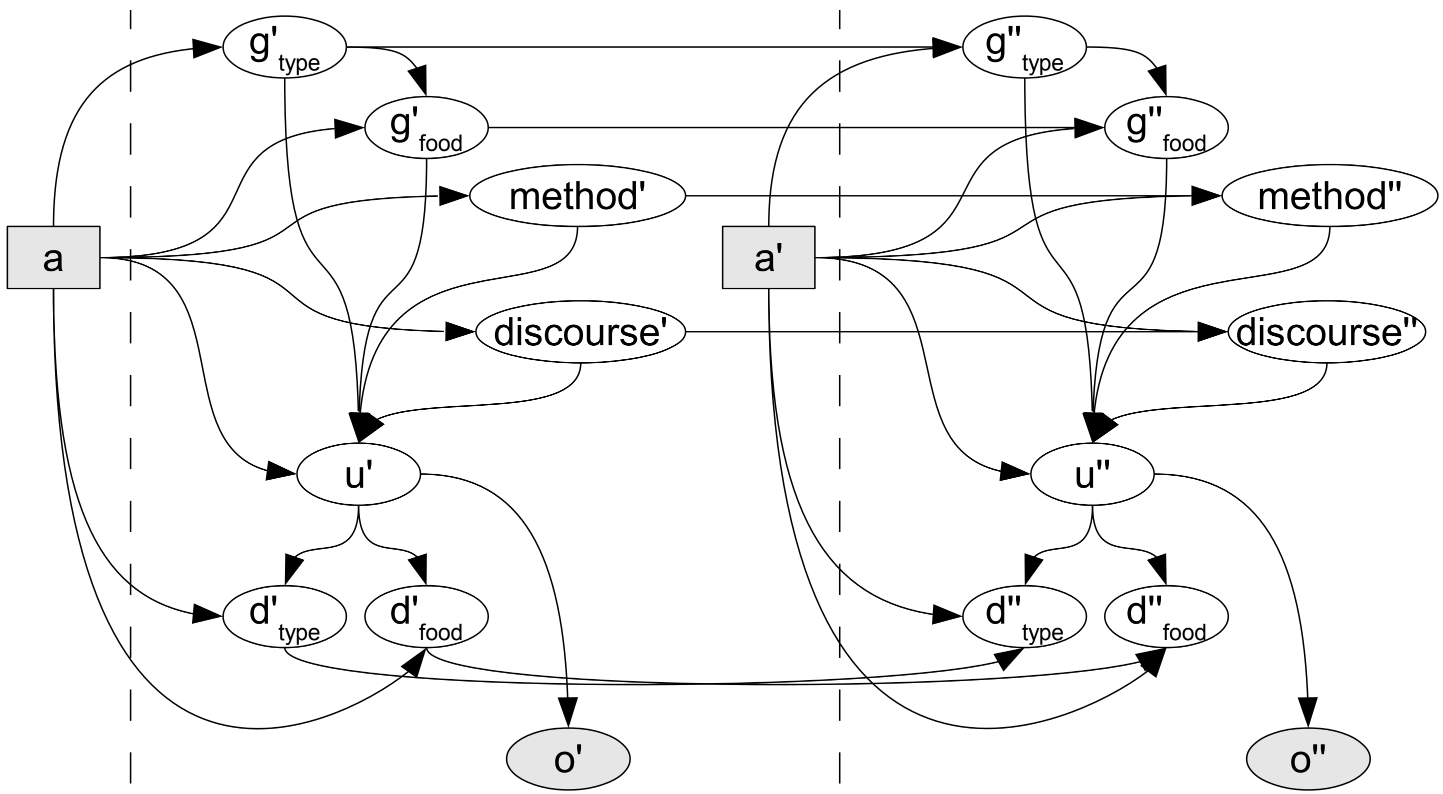
- We do not want to be better than a user

- We want to do exactly what a user is doing

- Though, we could use reward function to constrain our model to, for example, cooperative policies
  - e.g.: a user wants to succeed in a dialogue

Bayesian approach

- Use model similar to the dialogue model in a dialogue manager



Sample from the Bayesian model

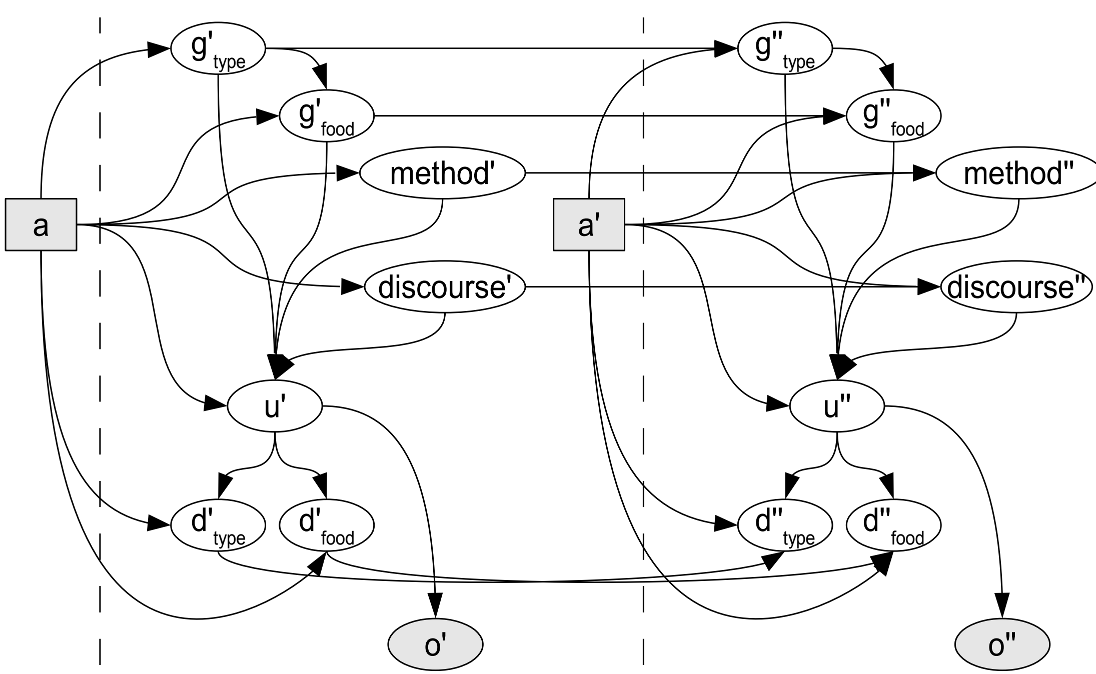
- Sample next dialogue state

$$s \sim P(s_{t+1} | s_t, a_t)$$

- Sample next user action

$$o_{t+1} \sim P(s_{t+1})$$

- Problem
  - it is not always rational
  - this is similar to the N-gram dialogue act level simulations



Bayesian approach

- Ideally the model for simulations and the dialogue system would be the same
- However, as typical for generative models:
  - generative models can be useful for classification
  - without being good for generation!
- The model for user simulations must be:
  - more constrained → more (probabilistic) handcrafting
  - it needs longer context
  - it turns out to be complex and hard to maintain
- However, it appears to be the principled way to do

Error generation

- So far, we wanted from the user simulator reasonable behaviour

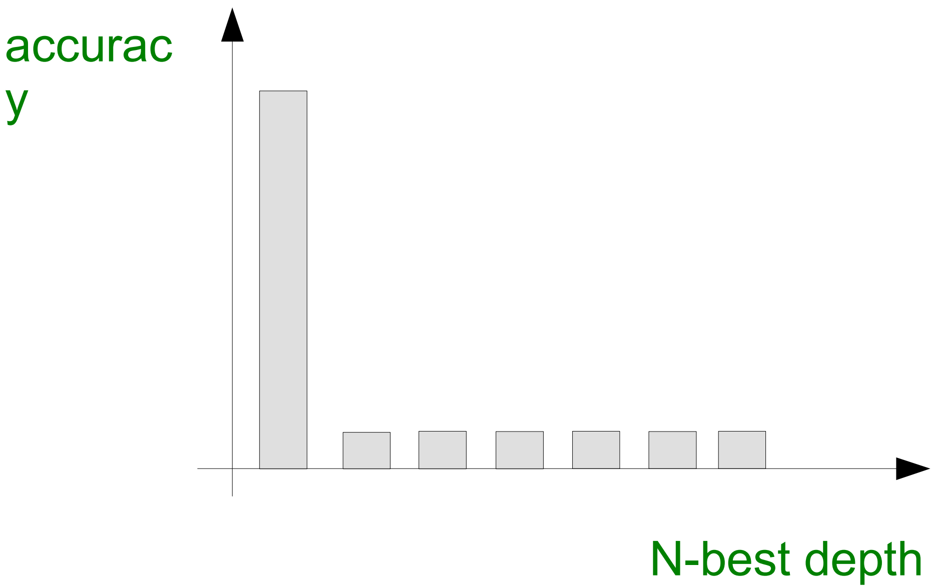
- However, for training a robust dialogue system we need a model of errors: ASR + SLU

inform(food=Italian)&request(price): 1.0	→	inform(food=Italian)	: 0.50
	→	inform(food=Italian)&request(price)	: 0.20
	→	request(price)	: 0.20
	→	confirm(food=Italian)	: 0.05
	→	null()	: 0.05

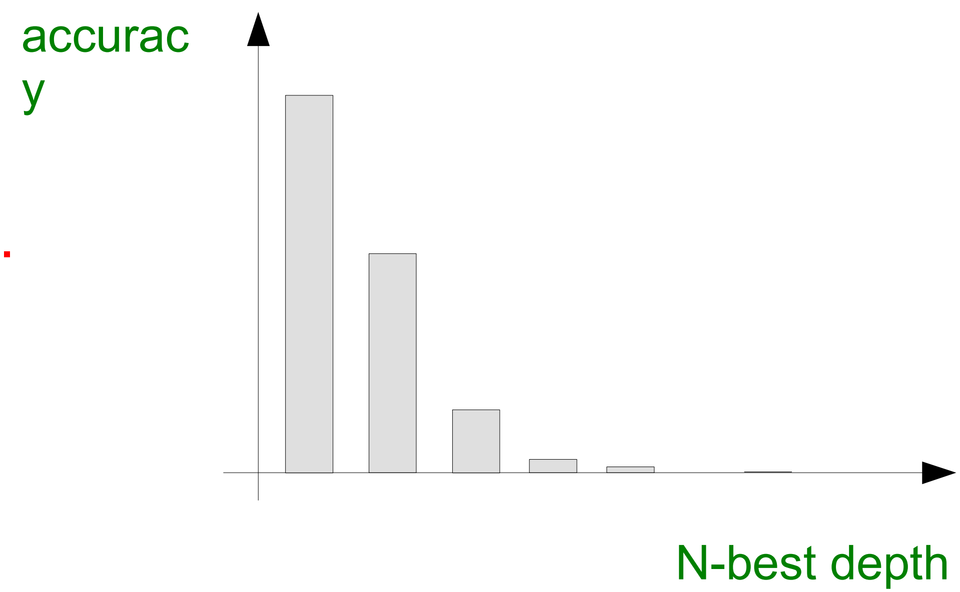
- Ideally, we can control this error model using a simple variable: error rate
  - measure of the number of errors in the N-best lists / top hypothesis

Error generation

- We want to control both the accuracy of the top hypothesis and the distribution of the accuracy at different positions in the N-best list

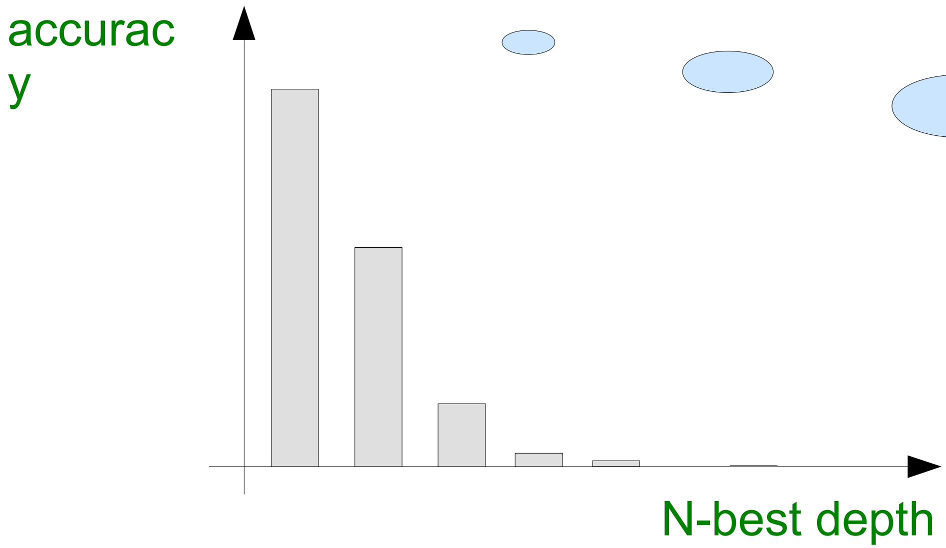


VS.



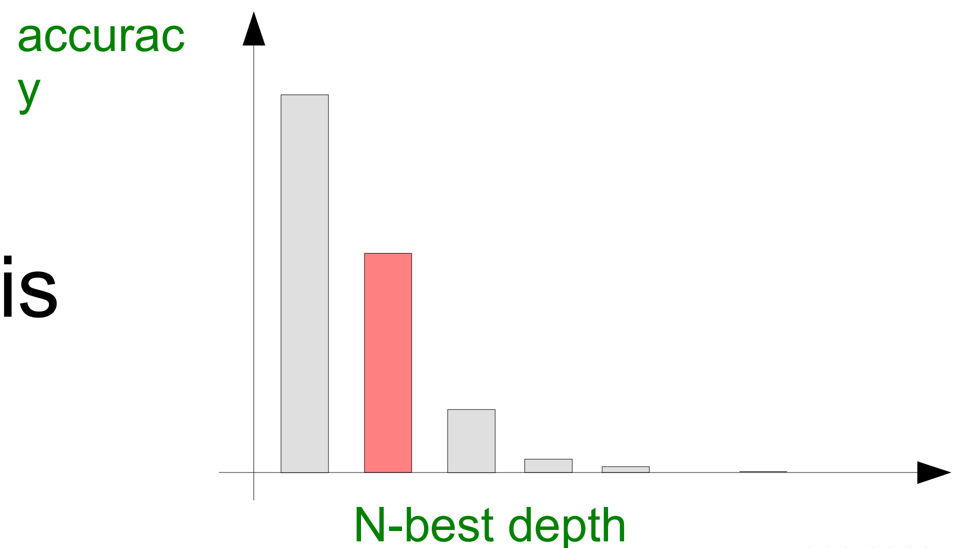
Model for error generation

- Error model : accuracy = P(position in the N-best list)



This is multinomial, possibly infinite, distribution.

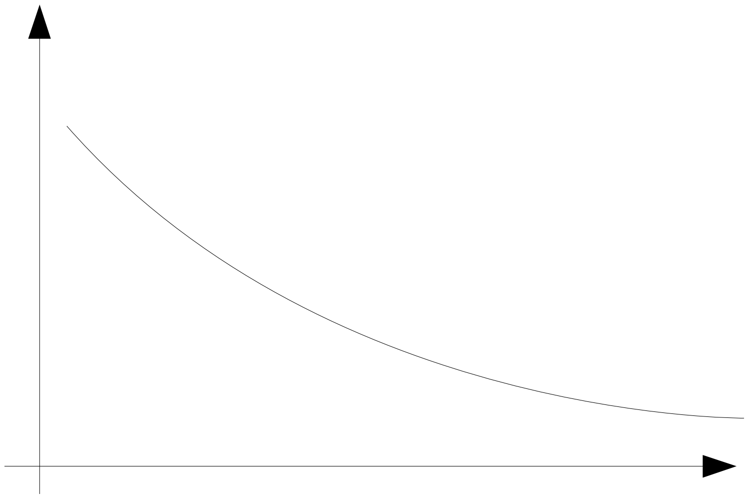
- Sample position of the correct hypothesis



Model for error generation

- Example implementation

$$P(n|err;\alpha) \approx e^{-\alpha \frac{n}{err}}$$



- Having a position of the correct hypothesis

inform(food=Italian)&request(price): 1.0	→	…	: 0.50
	→	inform(food=Italian)&request(price)	: 0.20
	→	…	: 0.20
	→	…	: 0.05
	→	…	: 0.05

- We have to fill in the missing hypotheses

Model for error generation

- Sample from a dialogue act confusion model

$$d \sim P\left(d_{err} \middle| d, err, n\right)$$

- This is usually factored into

$$d \sim \prod_i P\left(dact^i_{err} \middle| dact^i, err, n\right) P\left(sn^i_{err} \middle| dact^i_{err}, sn^i, err, n\right)$$
$$P\left(sv^i_{err} \middle| sn^i_{err}, err, n\right)$$

- And then the individual probabilities are usually handcrafted:
  - typically ignores **err** and **n**

Trained model for error generation

- Use logistic (multiclass) regression to train the model from errors generated by ASR, SLU

$$P\left(dact_{err} \middle| dact, err, n\right) \approx e^{\theta^T \Phi(dact_{err}, dact, err, n)}$$

$$P\left(sn^i_{err} \middle| act^i_{err}, sn^i, err, n\right) \approx e^{\theta^T \Phi(sn_{err}, act_{err}, sn, err, n)}$$

$$P\left(sv^i_{err} \middle| sn^i_{err}, err, n\right) \approx e^{\theta^T \Phi(sv^i_{err}, sn^i_{err}, err, n)}$$

- Every time you change ASR (AM, LM) or SLU, you have to re-train these models

Word level user simulation

- In addition to dialogue act level simulation
  - implements reasoning and goal oriented behaviour
- It include the generation of sentences
  - e.g. using a corpus of dialogue act annotated sentences
- The confusion model then operate on words
  - it learns mapping between correct word strings and confused words
  - it can use again pre-recorded and consequently recognised corpus
  - however, some generalisation is needed to obtain larger variability in the output

Word level user simulation

- Tries to solve the problem of similarity of
  - inform(type=bar) - “A bar please!”
  - inform(drinks=beer) - “Uh beer please!”
- and dissimilarity of
  - inform(type=restaurant) - “A restaurant please!”
- In general, semantically similar items does not have to be similar on the word/phone level

Word level simulation

- Phone level simulation would be ideal
- However, this is far too complex

- It is more efficient to learn how to confuse individual words or word sequences

- Note: this is still too computationally expensive anyway

Word level confusion model

$$P(\tilde{a_u}|a_u) = \sum_{\tilde{w_u}} \sum_{w_u} P(\tilde{a_u}, \tilde{w_u}, w_u|a_u)$$

$$= \sum_{\tilde{w_u}} \underbrace{P(\tilde{a_u}|\tilde{w_u})}_{\substack{\text{semantic}\\\text{decoder}}} \sum_{w_u} \underbrace{P(\tilde{w_u}|w_u)}_{\substack{\text{confusion}\\\text{model}}} \underbrace{P(w_u|a_u)}_{\substack{\text{utterance}\\\text{generation}}}$$

$$P(\tilde{w}_u|w_u) = \sum_{\lambda} P(\tilde{w}_u, \lambda | w_u)$$

Schatzmann, J., Thomson, B., & Young, S. (2007). Error Simulation for Training Statistical Dialogue Systems. ASRU (pp. 2-7). Kyoto, Japan.

Utterance generation model

- For error generation, a simple template generation model can be considered

Source:	inform(food=Chinese, pricerange=cheap) CHINESE FOOD IN THE CHEAP PRICERANGE
Template:	inform(food=$X, pricerange=$Y) $X FOOD IN THE $Y PRICERANGE
Unseen:	inform(food=French, pricerange=expensive) FRENCH FOOD IN THE EXPENSIVE PRICERANGE

- Templates can be easily derived from the corpus using a database of slot values
- P(template|dialogue act) can be also collected

Word confusion model

- At the word-level, ASR confusions can be viewed as translations of a source utterance w_s to a confused target utterance w_t

$$P(\tilde{w}_u | w_u) = \sum_{\lambda} P(\tilde{w}_u, \lambda | w_u)$$

```
I WANT AN EXPENSIVE HOTEL PLEASE
1 2    3  3         4     5
| |    | /          |     |
1 2    3            4     5
  ONE  INEXPENSIVE  HOTEL PLEASE
```

Word confusion model

- There are many ways how to define this confusion model

- Nevertheless, all depend on some alignment of between w_s and w_t

- The easiest is to use a Levenshtein distance
    - automatically generated alignment
    - word level with costs defined on the letter/phone level

- This is a bit different from machine translation since we work with the same language on both sides

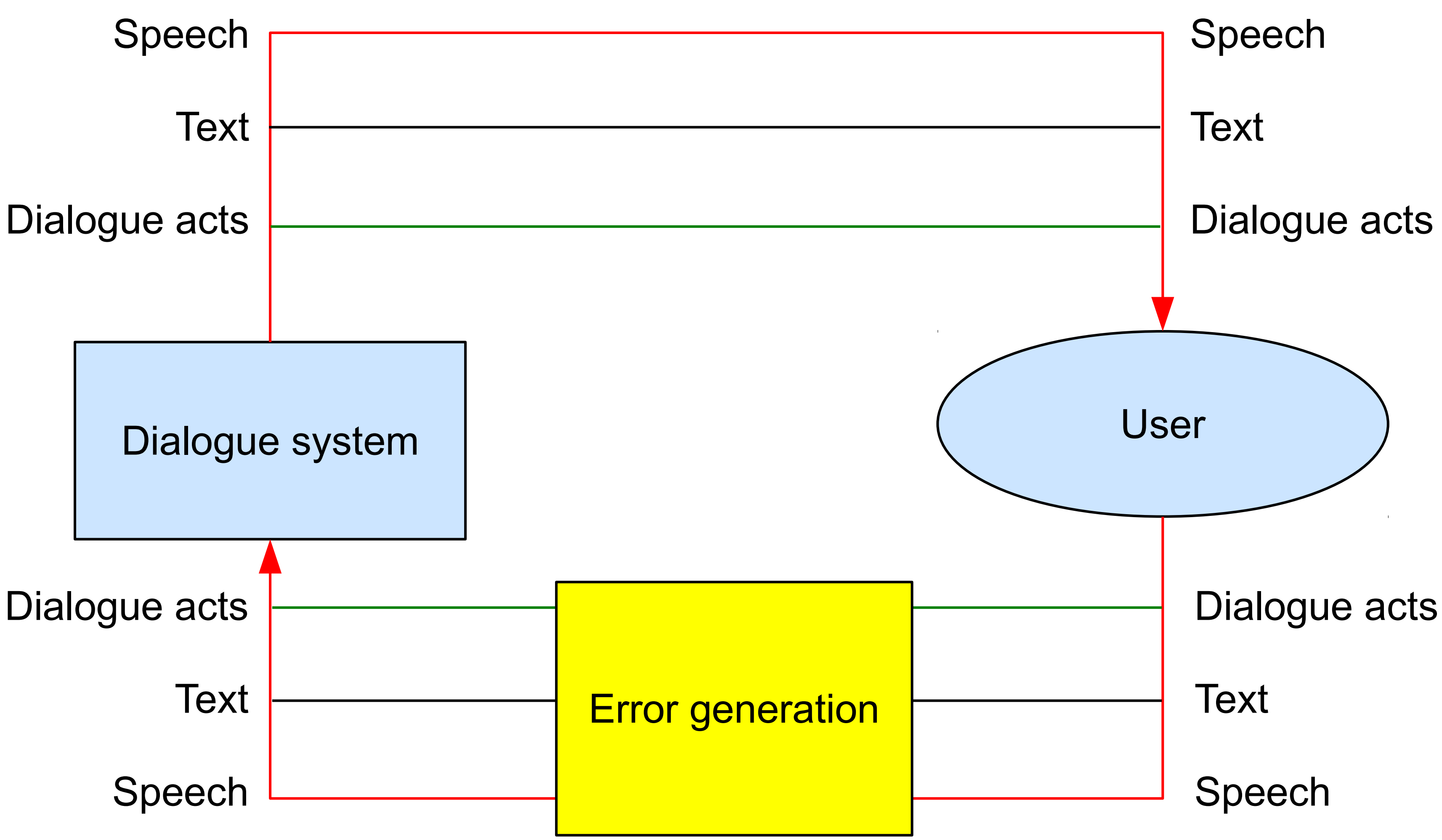
Word confusion model

- Once you get the alignments,
  - you can compute word / word sequence confusion model
  - e.g. "A BAR" maps to
    - "ALL", "ART", "A BAR", "A BAR", "A CAR", "BAR", "BAR", "BAR", "BAR", "CAR"
  - and corresponding probabilities
- Then the following can be used compute the probability of the alignment

$$P\left(\tilde{w}_u, \lambda \middle| w_u\right) \approx \prod_i P\left(\tilde{w}_{\lambda_i} \middle| w_{\lambda_i}, w_{\lambda_{i-1}}, \tilde{w}_{\lambda_{i-1}}\right)$$
$$\approx \prod_i P\left(\tilde{w}_{\lambda_i} \middle| w_{\lambda_i}\right)$$

Types of user simulation

- Dialogue act level, Word level, Speech level



Speech level user simulation

- In addition to word level simulation, it generate speech
- The generation of speech is done using TTS on correctly generated text
- The noise is added by simply mixing generated speech and some artificial noise
- The noise is controlled by its volume and type
- Problems:
  - The generated text has low variability and can be unnatural in some cases
  - The synthesised speech has low variability
  - Obviously, the acoustic noise is not responsible for all uncertainty in the SDS input

Thank you!

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