Cooperative User Models in Statistical Dialog Simulators

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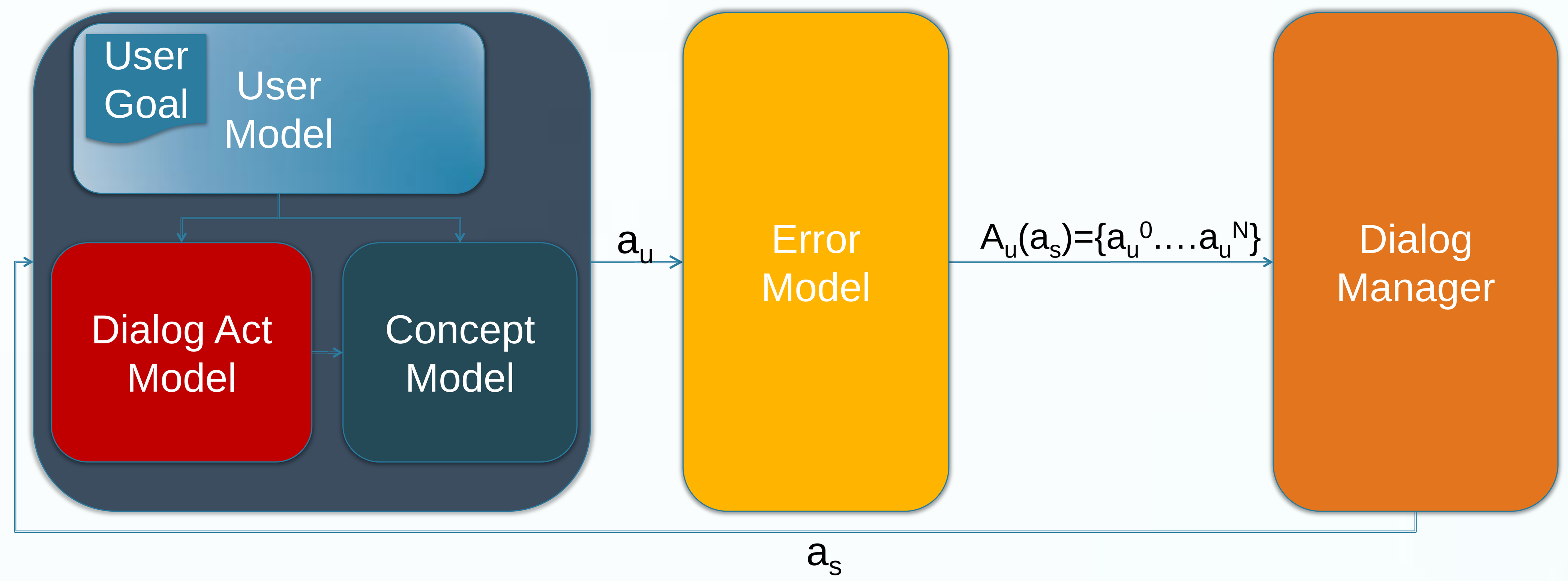
Abstract

- Train a dialog simulator that combines traits of human behavior with domain-related aspects.
- A modular architecture for data-driven dialog simulation where the intentional component of user simulator includes a **User Model**.
- Combine the models for different features via the Expectation-Maximization algorithm.

Architecture



- Dialog Manager action: $a_s=\{da_0,\ldots,da_n\}$
- The User Simulator generates a N-best list of actions: $A_u(a_s)=\{a_u^0 \ldots a_u^N\}$
  - The *User Model* simulates a user behavior.
  - The *Dialog Act Model* generates a distribution of M actions. Each action has a probability based on the context as seen in the corpus.
  - The *Concept Model* generates concepts values according to the *User Goal.*
  - The *Error Model* distorts $\hat{a}_u$ to simulate the ASR-SLU noise.
- An action $\hat{a}_u$ is chosen following a random sampling according to the distributions as seen in the corpus.

User Model

- Transient features:
  - User Goal: task name and list of concepts and values
- Persistent features:
  - Patience = 1 - the tendency to abandon the conversation. *pat = 1 - P(HangUp | a_s)*
  - "noinput" probability accounts (also) for noisy environments. *noi = P(NoInput | a_s)*
  - Cooperativeness is the ratio of concepts mentioned in a_s that also appear in $\hat{a}_s$.

Cooperativeness Model and the context

- Cooperativeness feature:
  - *$coop_t$* is the rate of system and user DAs sharing the same concepts *within a turn*.

$$coop_t(a_u,a_s)=\frac{|a_u \cap a_s|}{|a_s|}$$

  - Feature *coop* is the dialog average of *$coop_t$.*

$$coop=\frac{\sum_{t=0}^{T} coop_t(a_u^i,a_s)}{\sum_{v=0}^{T}|a_s^v|}$$

- Cooperativeness model:
  1. Discretize *coop* into a binary variable: ***k*** **= high vs. low** cooperativeness.
     - *coop threshold in ADASearch is 0.28*
  2. Train a bigram model for high/low *coop.*

$A_u(a_s,k) = \{(a_u^0,P(a_u^0|a_s,k)),\ldots,(a_u^M,P(a_u^M|a_s,k))\}$

- Combining different models
  - **$A_u(a_s,k)$** is the cooperativeness model
  - **$A_u(a_s,\varphi)$** represents the context. It is the distribution of actions as obtained from the Dialog Act Model

$Au(a_s, \varphi) = \{(a_u^0,P(a_u^0|a_s, \varphi)),\ldots,(a_u^M,P(a_u^M|a_s, \varphi))\}$

- The cooperativeness and context model are linearly interpolated.

$A_u(a_s) = \lambda_k \cdot A_u(a_s,k) + \lambda_\varphi \cdot A_u(a_s, \varphi)$; $\lambda_\varphi + \lambda_k = 1$

- The weight of the cooperative model for a given bigram $[a_s,a_u^i]$ is calculated as follows:

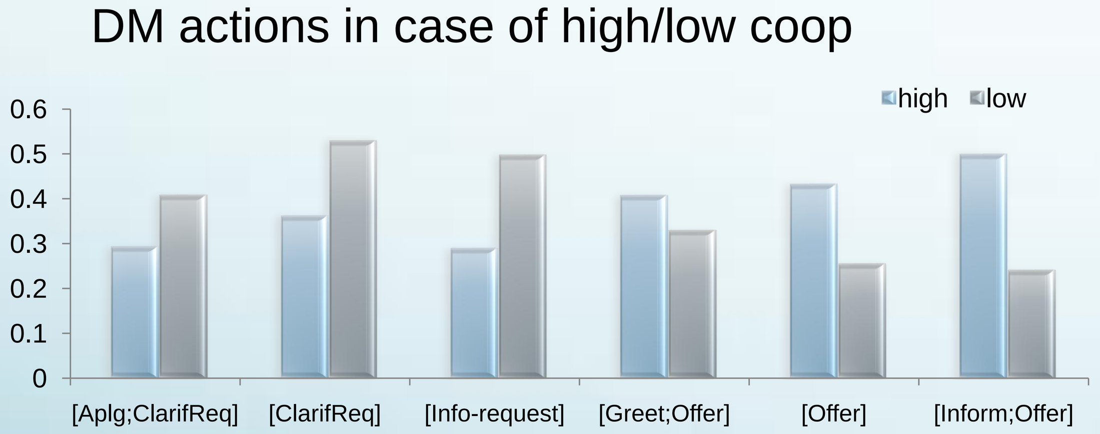
$$\lambda_k=\frac{\sum_{j=0}^{M} P(k|a_s,a_u^j)}{M}.$$

- And the global weight of the cooperative models is:

$$P(k|a_s,a_u^i)=\frac{P(a_u^i|a_s,k)}{P(a_u^i|a_s,k)+P(a_u^i|a_s,\varphi)}\ \forall_{i=0}^{M} a_u^i$$

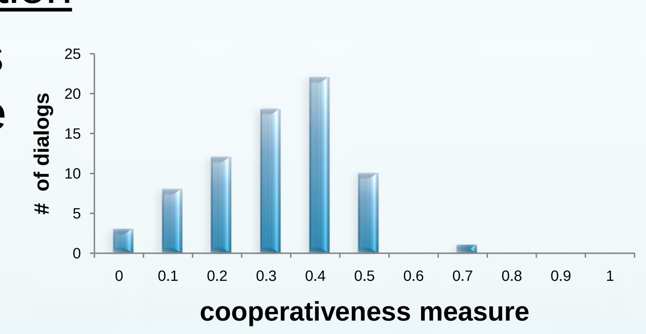
Experiments

- Effect of Cooperativeness
  - Estimated λ_k weights in response to selected DM actions in case of high/low coop



- λ_k achieves high values in case of uncooperative users in response to DM dialog acts as [ClarificationRequest] and [Info-request].
- In contrast, forward-looking actions, such as the ones including [Offer], seem to discard the contribution of the low coop model, but to favor the contribution provided by high coop.

- Cooperativeness distribution
  - The majority of dialogs is clustered around the [0.1..0.4] range.



- Dialog Act Precision & Recall wrt real calls
  - A simulated dialog act is correct when it appears in the real action a_u.

$$P_{DA}=\frac{|correct\ DA|}{|DA \in \hat{a}_u|}, R_{DA}=\frac{|correct\ DA|}{|DA \in \hat{a}_u|}$$

DA Model	Simulation (a^*_u)		Most Frequent (a^*_u)	
	P_{DA}	R_{DA}	P_{DA}	R_{DA}
OB	33.8	33.4	33.9	33.5
BI(+*coop*)	35.6 **(35.7)**	33.5 **(35.8)**	**49.3** (47.9)	**48.8** (47.4)
TP(+*coop*)	38.2 **(39.7)**	38.1 **(39.4)**	**51.1** (50.6)	**50.6** (50.2)

- Task Duration and Completion rates
  - We ran 60 simulated dialogs between the DM and each combination of the Task-based and Bigram models and high and low values of *coop*.
  - Under *high-coop* regime the number of turns taken to complete tasks is lower than under *low-coop*.
  - TCR is higher when cooperativeness is higher, indicating that *cooperative* users make dialogs not only shorter but also more efficient.

$$TCR=\frac{number\ of\ times\ a\ task\ has\ been\ completed}{total\ number\ of\ task\ requests}$$

	Lodging Enquiry		Lodging Reserv		Event Enquiry		All TCR
	#turns	TCR	#turns	TCR	#turns	TCR	TCR
OB	9.2±0.0	78%	9.7±1.4	82%	8.1±2.9	67%	77%
BI+low	15.1±4.1	71%	14.2±3.9	69%	9.3±1.8	52%	67%
BI+high	**12.1±2.5**	**75%**	**12.9±3.1**	**82%**	**7.8±1.8**	**75%**	**77%**
TB+low	13.6±4.1	76%	13.4±3.7	83%	8.4±3.3	65%	77%
TB+high	**11.6±2.8**	**80%**	**12.6±3.6**	**84%**	**6.5±1.9**	**57%**	**78%**
Real Dialogs	11.1±3.0	71%	12.7±4.7	70%	9.3±4.0	85%	73%

Conclusions

- Modular combination of user features with different models of dialog act, concept-value and ASR/SLU error simulation.
- Joint model of user intentions with a model of individual user traits.
- User's cooperativeness as a real-valued feature of the User Model .
- Improved accuracy of dialog act estimation when evaluated on a training set of real conversations.
- In future work, we will refine our simulators by studying more fine-grained and realistic User Model representations.

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