On-line Active Reward Learning for Policy Optimisation in Spoken Dialogue Systems

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- Design a suitable learning objective (**reward**) to train an RL-based dialogue system online from real users

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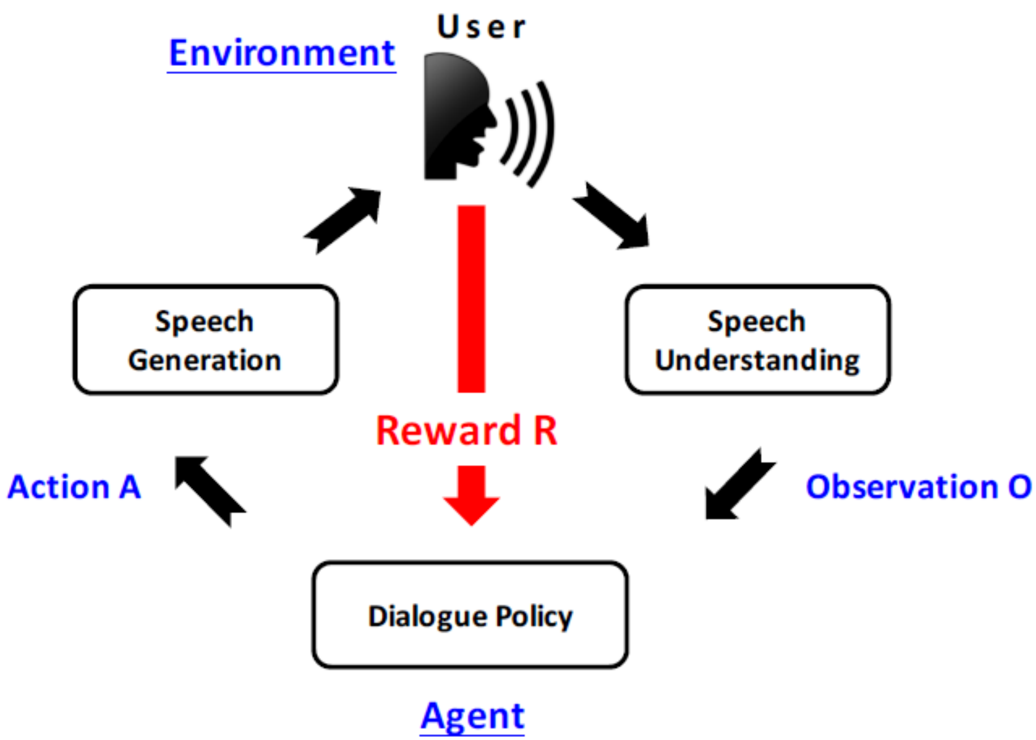

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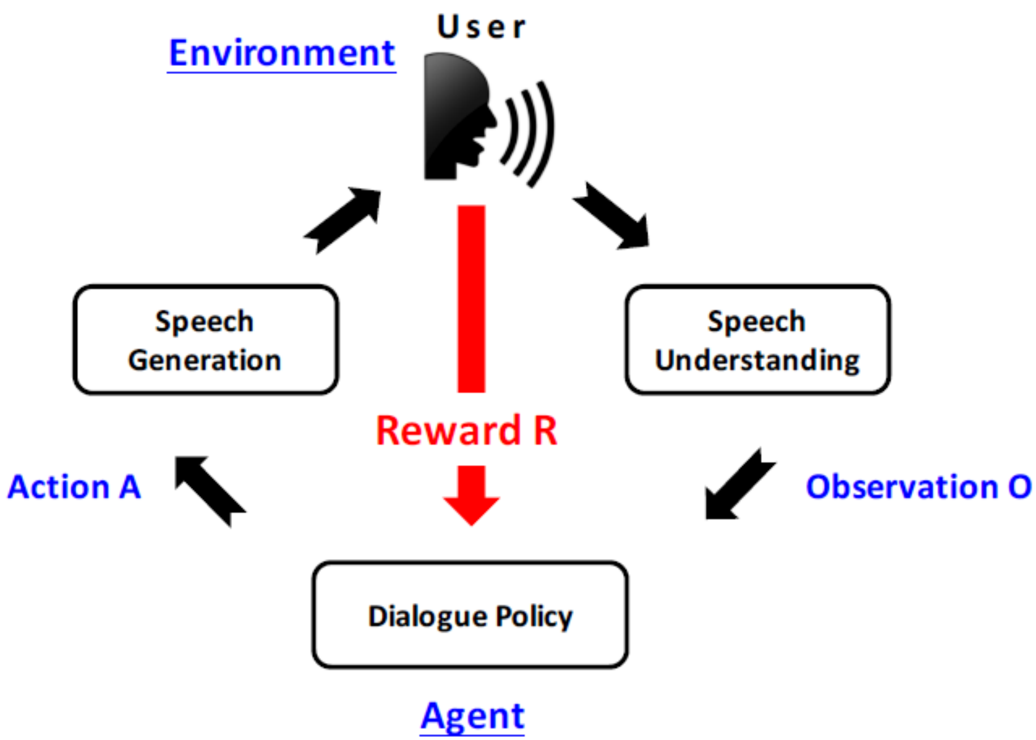

Correct rewards are critical in dialogue policy training

Reinforcement signals in dialogue systems

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  - Difficult/costly to obtain
  - Noisy

Reinforcement signals in dialogue systems

How to learn policy from real users?

- Infer success (reward) directly from dialogues
  - Train a reward estimator from data (Su et al. 2015)
- ~~User rating~~ Reward modeling on user rating
  - Difficult/costly to obtain → Active learning
  - Noisy → Gaussian process with uncertainty

Proposed method

Reward modeling on user binary success rating

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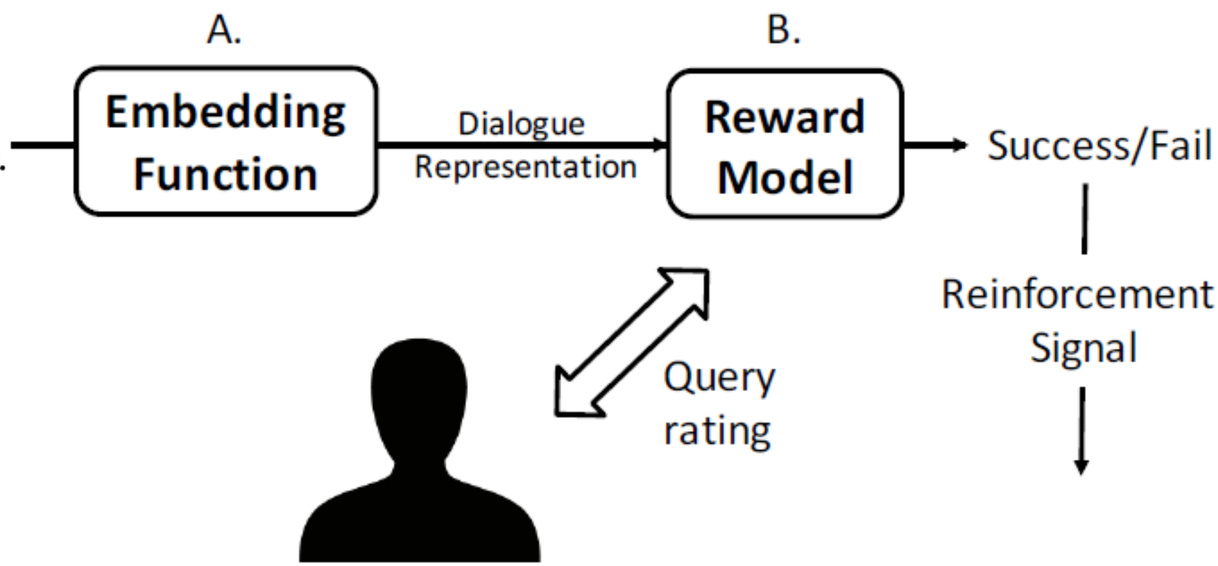
Dialogue (input)

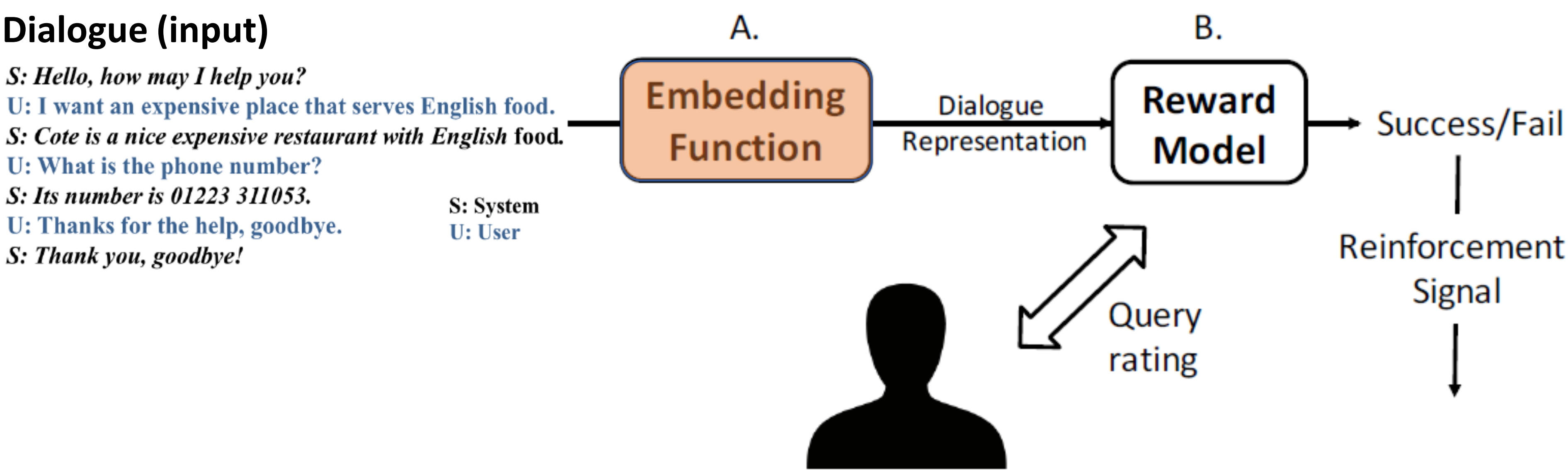
S: Hello, how may I help you?
U: I want an expensive place that serves English food.
S: Cote is a nice expensive restaurant with English food.
U: What is the phone number?
S: Its number is 01223 311053.
U: Thanks for the help, goodbye.
S: Thank you, goodbye!

S: System
U: User



Proposed method

Reward modeling on user binary success rating



A. Dialogue embedding

Mapping a dialogue sequence to a fixed-length vector

S: Hello, how may I help you?

Turn 1 f_1 U: I want an expensive place that serves English food.

S: Cote is a nice expensive restaurant with English food.

Turn 2 f_2 U: What is the phone number?

S: Its number is 01223 311053.

S: System
U: User

f_t : concatenated vector of

- user intention determined the semantic decoder
- distribution over each concept defined in the ontology
- one-hot encoding of the system's reply action
- turn number

(Vandyke et al., ASRU 2015)

A. Dialogue embedding

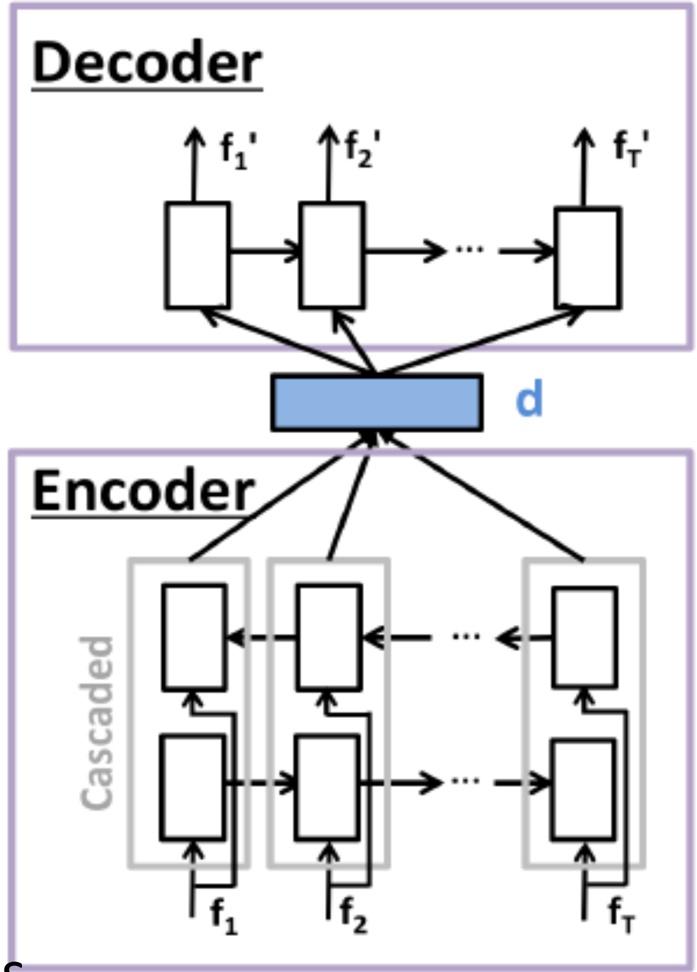
Bi-directional LSTM encoder-decoder

- Inputs are turn-level features
- $h_t = [\overrightarrow{h_t}; \overleftarrow{h_t}]$ captures forward and backward information
- Dialogue representation

$$\mathbf{d} = \frac{1}{T}\sum_{t=1}^{T}\mathbf{h}_t$$

- Mean squared error training:

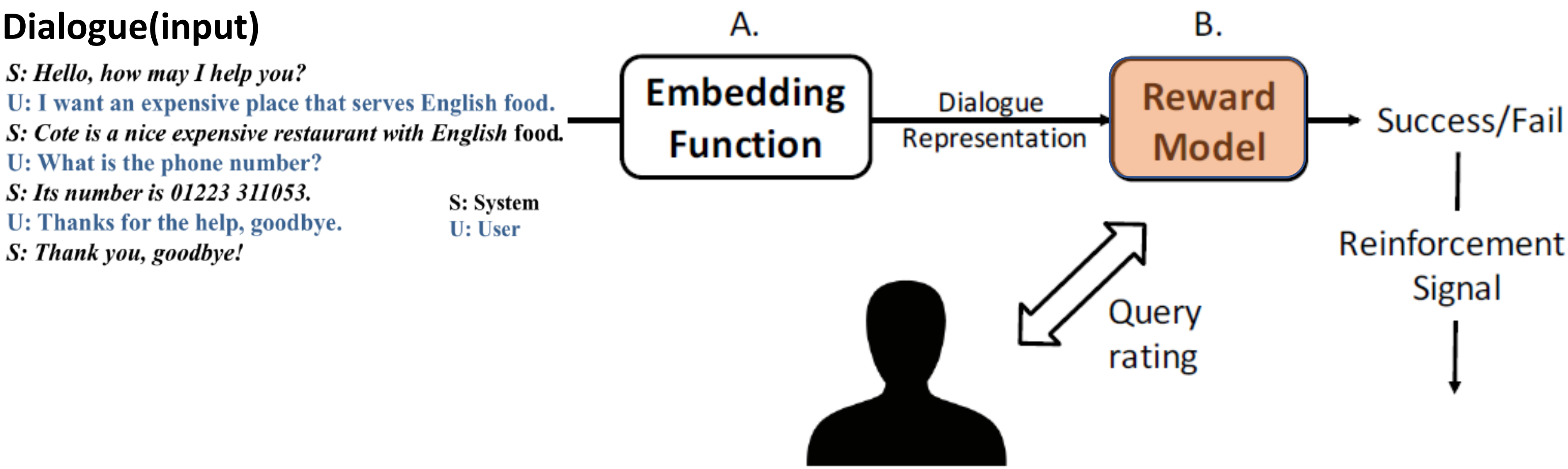
$$MSE = \frac{1}{N}\sum_{i=1}^{N}\sum_{t=1}^{T}||\mathbf{f}_t - \mathbf{f}'_t||^2$$



T: number of turns, N: number of all dialogues

Proposed method

Reward modeling on user binary success rating



B. Active reward learning model

Model dialogue success using Gaussian process regression

$$p(y = 1|\mathbf{d}, \mathcal{D}) = \phi(f(\mathbf{d}|\mathcal{D}))$$

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$$p(y = 1|\mathbf{d}, \mathcal{D}) = \underbrace{\phi}_{\text{cumulative Gaussian}}(\underbrace{f(\mathbf{d}|\mathcal{D})}_{\mathrm{GP}(m(\mathrm{d}),\, k(\mathrm{d},\mathrm{d}'))})$$

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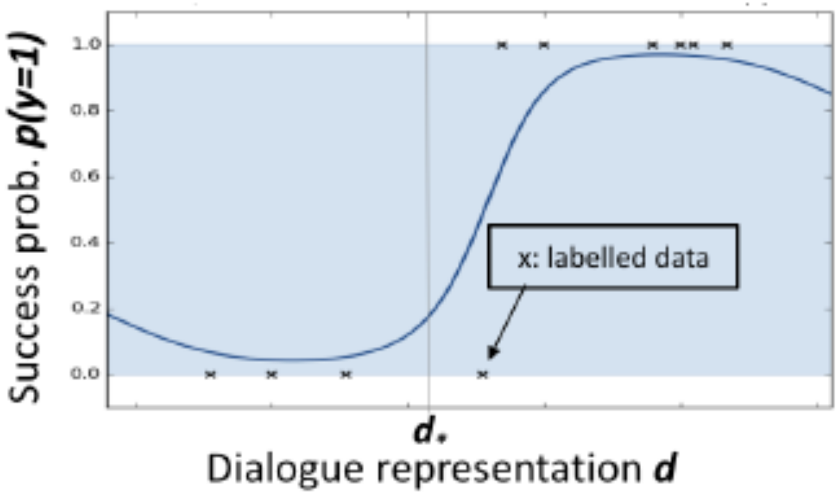
Model dialogue success using Gaussian process regression

$$p(y=1|\mathbf{d},\mathcal{D}) = \phi(f(\mathbf{d}|\mathcal{D}))$$

- **Noise term** in the RBF kernel affects uncertainty

$$k(\mathbf{d},\mathbf{d}') = \underbrace{p^2 \exp(-\frac{||\mathbf{d}-\mathbf{d}'||^2}{2l^2})}_{\text{Input correlation}} + \underbrace{\sigma_n^2}_{\text{User rating uncertainty}}$$



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- **Noise term** in the RBF kernel affects uncertainty
- **Active learning:** uncertainty + threshold
  - Model is uncertain → query user rating actively

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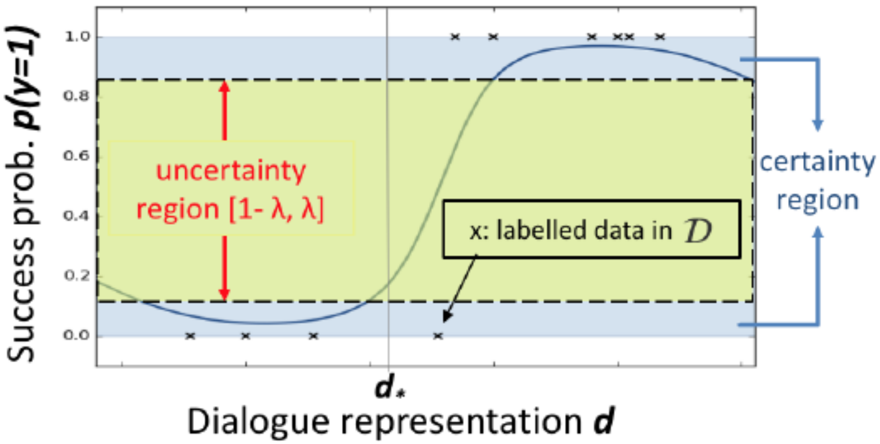


Experiments

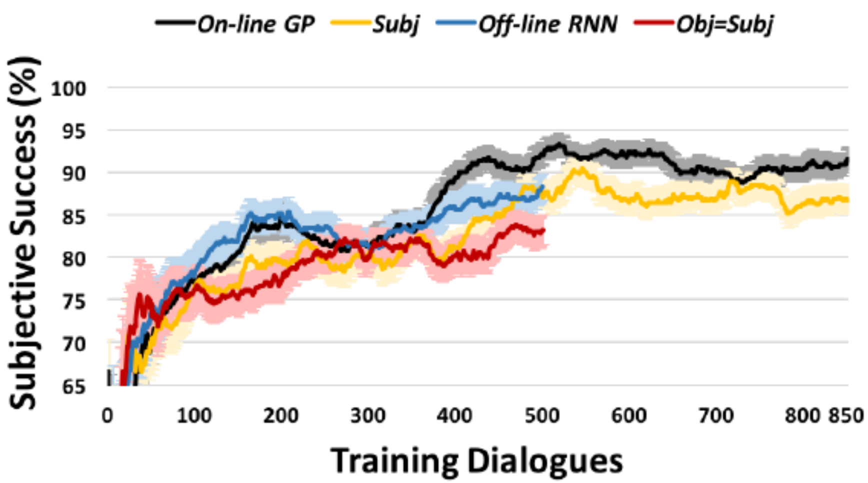
- Dataset: Cambridge restaurant domain

  - 150 venues
  - 3 information slots: area, price range, food
  - 3 request slots: address, phone, postcode

- Reward for success/failure

  - Per turn: -1
  - When dialogue ends, binary(0/1) * 20

Experiments



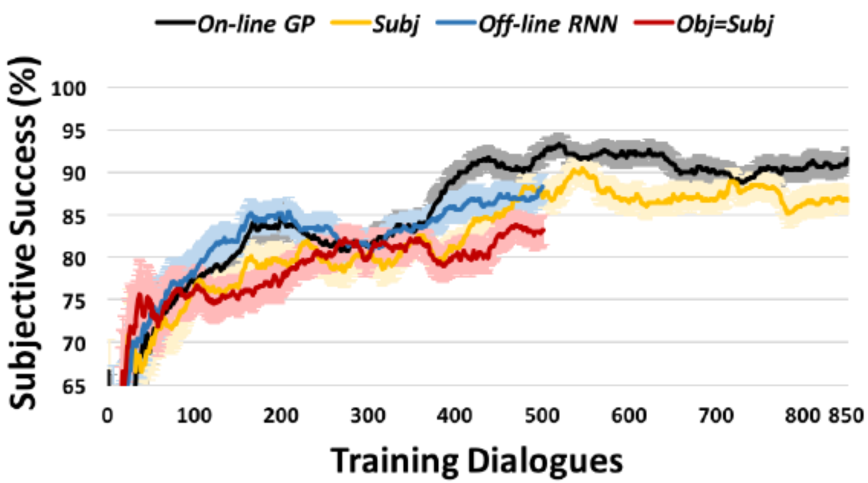
Dialogues	**Reward Model**	***Subjective*** (%)
400-500	*Obj=Subj*	85.0 ± 2.1
	off-line RNN	89.0 ± 1.8
	Subj	90.7 ± 1.7
	on-line GP	91.7 ± 1.6
500-850	*Subj*	87.1 ± 1.0
	on-line GP	$\mathbf{90.9 \pm 0.9}$*

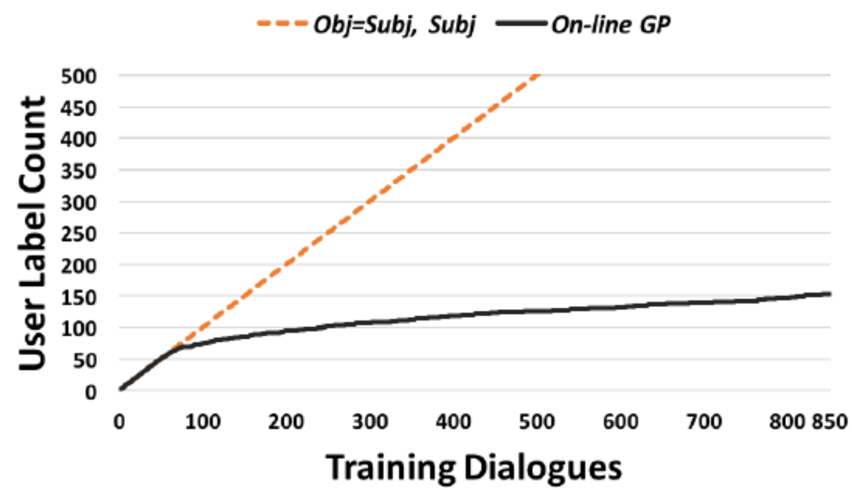
$* \, p < 0.05$

- All reached > 85% after 500 dialogues
- Proposed method is better than others in the longer run

On-line GP: proposed method
Subj: method that optimizes the policy using only user assessment
Off-line RNN: RNN with 1K simulated data
Obj=Subj: method using the dialogues that user's subjective assessment is consistent to the objective one

Experiments





- All reached > 85% after 500 dialogues
- Proposed method is better than others in the longer run
- Proposed method needs smaller queries from user rating

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Conclusion

- Propose method: on-line active reward learning
  - Dialogue embedding: Bi-LSTM Encoder and Decoder
  - Active reward model: GP regression with uncertainty threshold
  - Reduce data annotation costs and model noisy user rating

- Achieve online policy learning from real users w/o task information