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

Pei-Hao Su, Milica Gasic, Nikola Mrksic, Lina Rojas-Barahona, Stefan Ultes, David Vandyke, Tsung-Hsien Wen and Steve Young
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Juho Kim
Goal

- Design a suitable learning objective (reward) to train an RL-based dialogue system online from real users.
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Correct rewards are critical in dialogue policy training.
Reinforcement signals in dialogue systems

How to learn policy from real users?
Reinforcement signals in dialogue systems

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• Infer success (reward) directly from dialogues
  - Train a reward estimator from data (Su et al. 2015)
Reinforcement signals in dialogue systems

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• User rating
Reinforcement signals in dialogue systems

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• User rating
  - 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
Proposed method

Reward modeling on user binary success rating

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!

A. Embedding Function → Dialogue Representation → B. Reward Model

Success/Fail → Reinforcement Signal

Query rating
Proposed method

Reward modeling on user binary success rating

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Embedding Function → Dialogue Representation → Reward Model → Success/Fail

Query rating → Reinforcement Signal

A. B.
A. Dialogue embedding

Mapping a dialogue sequence to a fixed-length vector

Turn 1 $f_1$:
- 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.
- S: Its number is 01223 311053.

Turn 2 $f_2$:
- S: What is the phone number?
- U: What is the phone number?
- S: System
- S: Its number is 01223 311053.
- 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

$$d = \frac{1}{T} \sum_{t=1}^{T} h_t$$

- Mean squared error training:

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

$T$: number of turns, $N$: number of all dialogues
Proposed method

Reward modeling on user binary success rating

Dialogue(input)
S: Hello, how may I help you?
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B. Active reward learning model

Model dialogue success using Gaussian process regression

\[ p(y = 1|d, \mathcal{D}) = \phi(f(d|\mathcal{D})) \]
B. Active reward learning model

Model dialogue success using Gaussian process regression

\[ p(y = 1|d, D) = \phi(f(d|D)) \]

cumulative Gaussian \quad GP(m(d), k(d, d'))
B. Active reward learning model

Model dialogue success using Gaussian process regression

\[ p(y = 1|d, D) = \phi(f(d|D)) \]

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

\[ k(d, d') = p^2 \exp\left(-\frac{||d - d'||^2}{2l^2}\right) + \sigma_n^2 \]

Input correlation  User rating uncertainty
B. Active reward learning model

Model dialogue success using Gaussian process regression

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

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

\[ k(\mathbf{d}, \mathbf{d}') = p^2 \exp\left(-\frac{||\mathbf{d} - \mathbf{d}'||^2}{2l^2}\right) + \sigma_n^2 \]

Input correlation

User rating uncertainty

![Diagram showing dialogue representation and user rating regions](image)
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

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

<table>
<thead>
<tr>
<th>Dialogues</th>
<th>Reward Model</th>
<th>Subjective (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>400-500</td>
<td>Obj=Subj</td>
<td>85.0 ± 2.1</td>
</tr>
<tr>
<td></td>
<td>off-line RNN</td>
<td>89.0 ± 1.8</td>
</tr>
<tr>
<td></td>
<td>Subj</td>
<td>90.7 ± 1.7</td>
</tr>
<tr>
<td></td>
<td>on-line GP</td>
<td>91.7 ± 1.6</td>
</tr>
<tr>
<td>500-850</td>
<td>Subj</td>
<td>87.1 ± 1.0</td>
</tr>
<tr>
<td></td>
<td>on-line GP</td>
<td>90.9 ± 0.9*</td>
</tr>
</tbody>
</table>

* p < 0.05

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