End-to-end LSTM-based dialog control optimized with supervised and reinforcement learning

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Outline

- Introduction
- Model description
- Optimizing with supervised learning
- Optimizing with reinforcement learning
- Conclusion

Task-oriented dialogue systems

A dialog system for:

Initiating phone calls to a contact in an address book

How can I help you?

Call Jason

Which type of phone: mobile or work?

Oh, actually call Mike on his office phone

Calling Michael Seltzer, work.

PlaceCall

- Ordering a taxi
- Reserving a table at a restaurant

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Reinforcement learning Setting

- - -

State = (user's goal, dialogue history)

Reward = 1 for successfully completing the task, and 0 otherwise

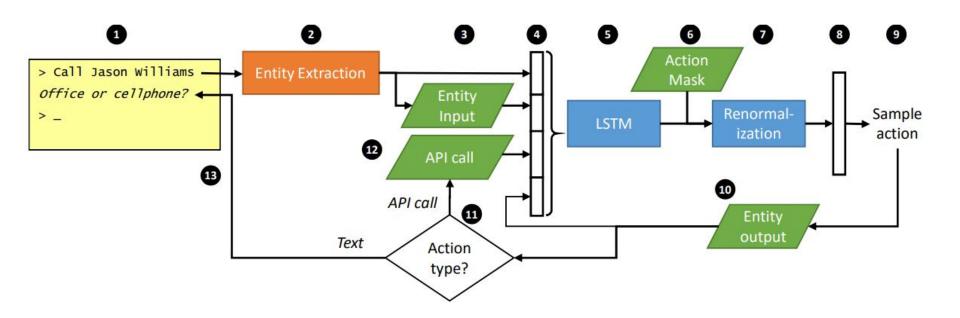
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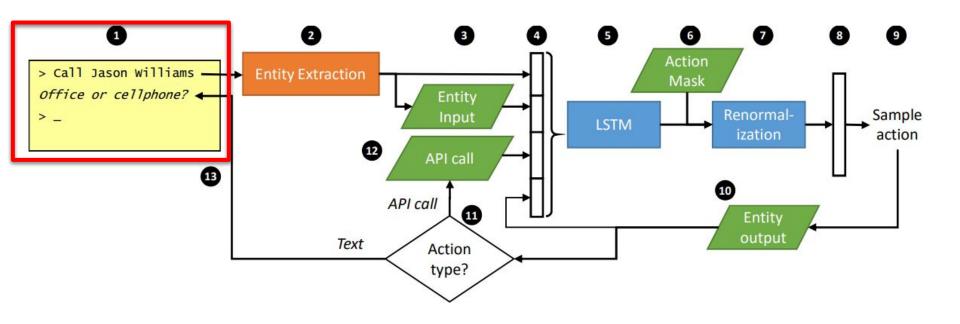
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Model description

Model

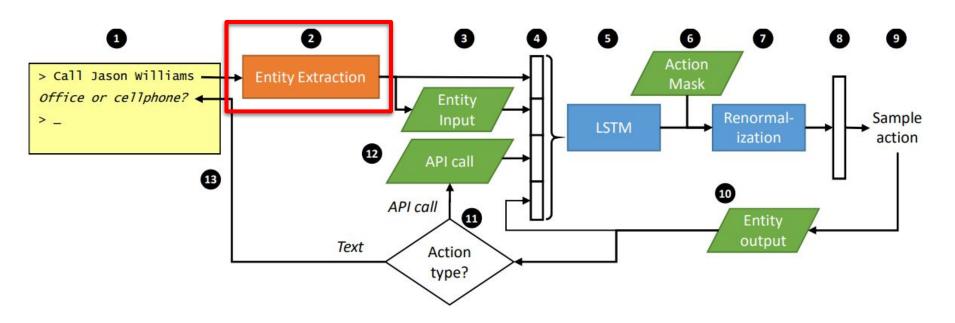


User Input



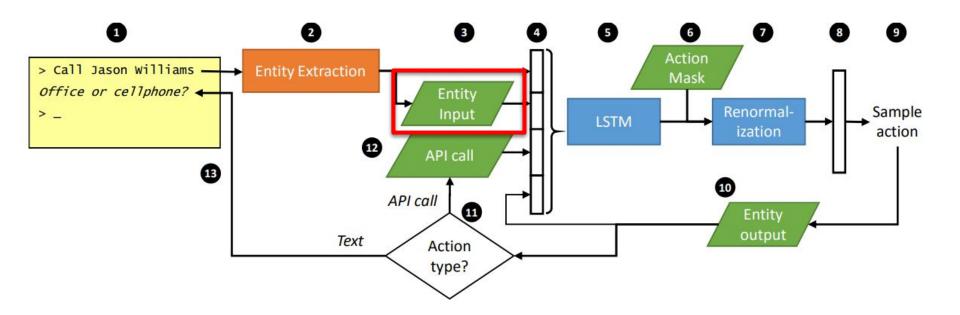
Entity Extraction

For example: identifying "Jason Williams" as a <name> entity

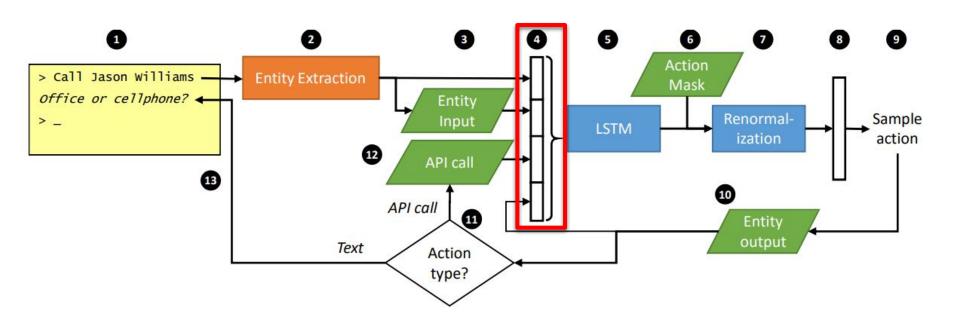


Entity Input

For example: Maps from the text "Jason Williams" to a specific row in a database

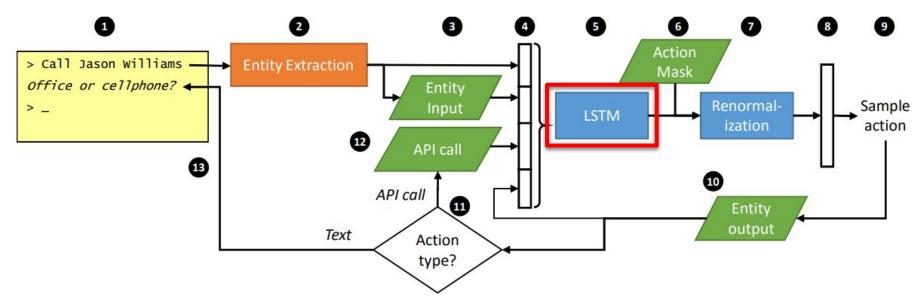


Feature Vector



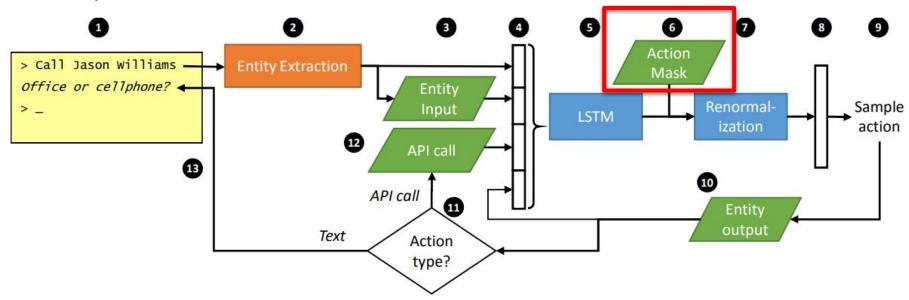
Recurrent Neural Network

LSTM neural network is used because it has the ability to remember past observations arbitrarily long.



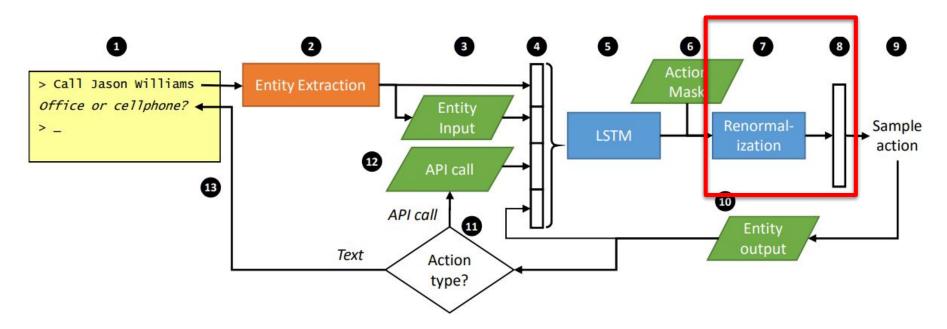
Action Mask

If a target phone number has not yet been identified, the API action to place a phone call may be masked.



Re-normalization

Pr{masked actions} = 0 → Re-normalize into a probability distribution

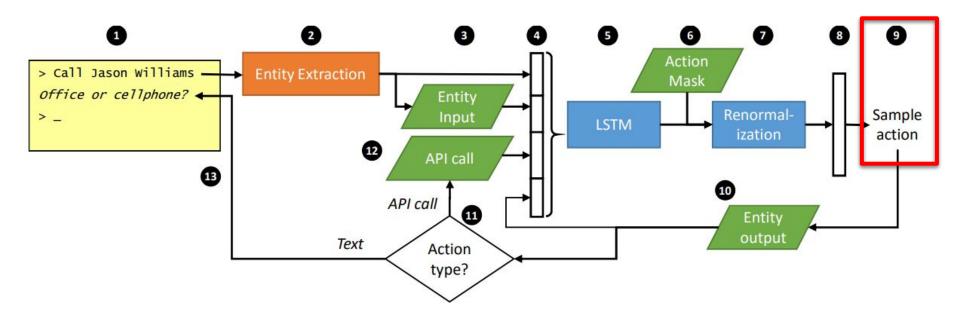


Sample Action

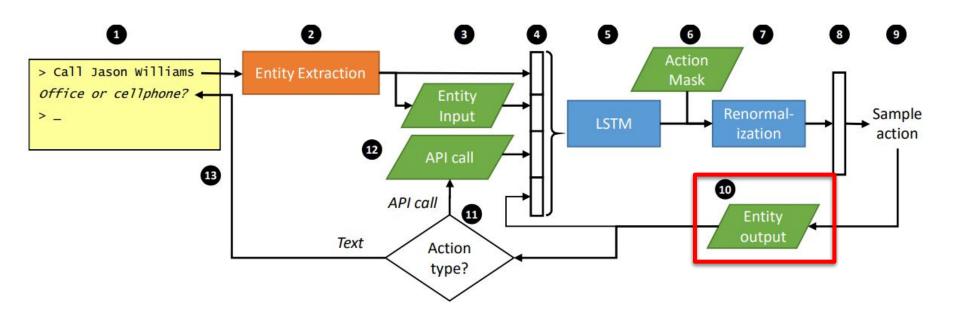
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RL: sample from the distribution

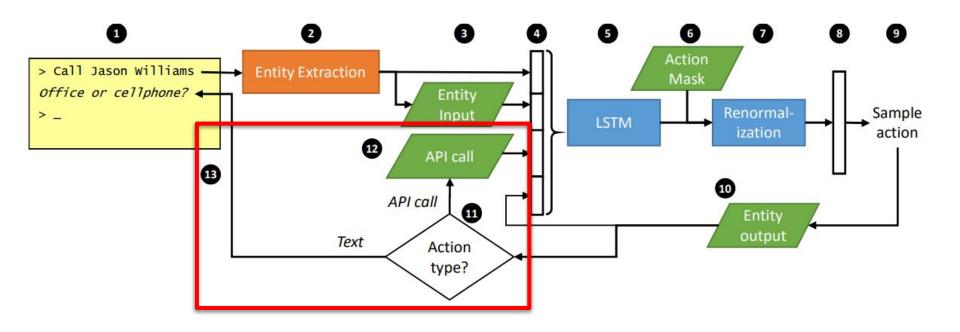
SL: select action with highest probability



Entity Output



Taking Action



Training the Model

1. Hit or exceed the 15-day minimum initial

- 2. Introduce the team to your business
- 3. Stress the significance of schedule adherence
- 4. Emphasize the importance of etiquette and customer relationships

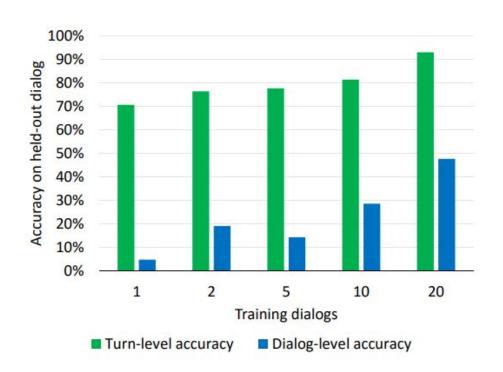


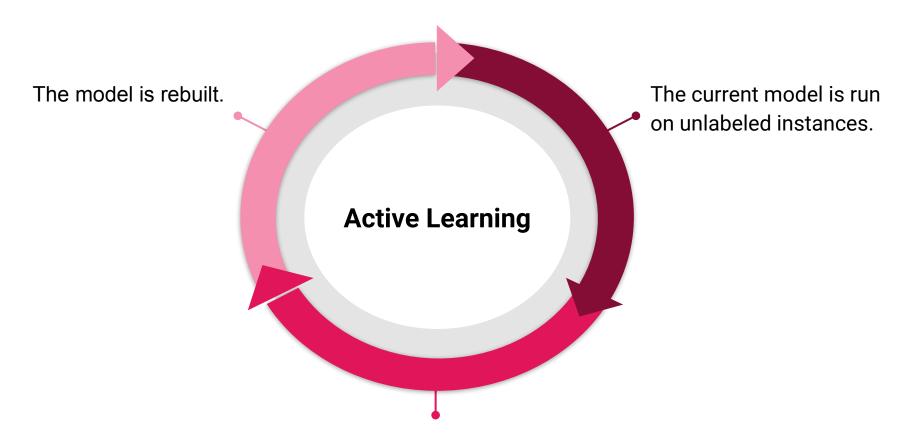


Optimizing with supervised learning

Prediction accuracy

- Loss = categorical cross entropy
- Training sets = 1, 2, 5, 10, and 20 dialogues
- Test set = one held out dialogue





The unlabeled instances for which the model is most uncertain are labeled.

Active learning

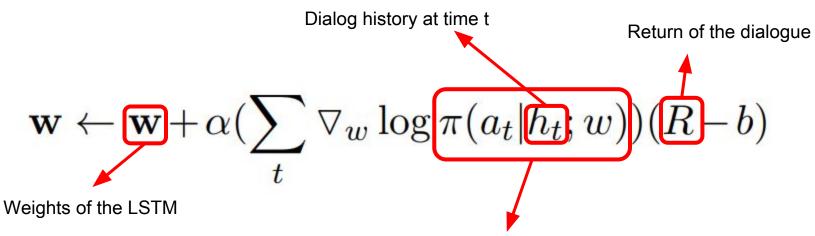
- For active learning to be effective, the scores output by the model must be a good indicator of correctness.
- 80% of the actions with the lowest scores are incorrect.
- Re-training the LSTM is fast



Labeling low scoring actions will rapidly improve the performance.

Optimizing with reinforcement learning

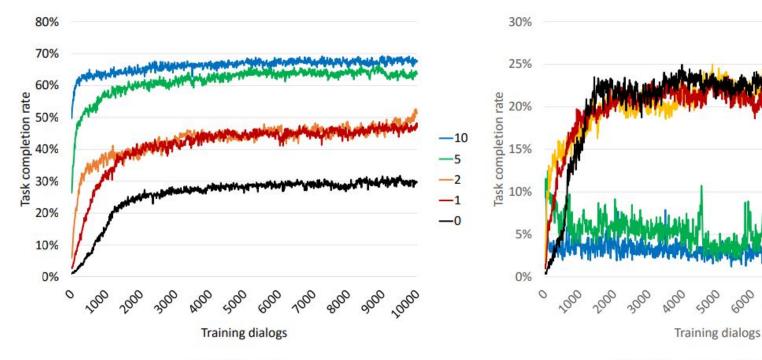
Policy gradient



The LSTM which outputs a distribution over actions

RL Evaluation

(a) TCR mean.



(b) TCR standard deviation.

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Conclusion

- This paper has taken a first step toward an end-to-end learning for task-oriented dialog systems.
- 2. The LSTM automatically extracts a representation of the dialogue state (no hand-crafting).
- 3. Code provided by the developer can enforce business rules on the policy.
- 4. The model is trained using both SL & RL.

Thank you