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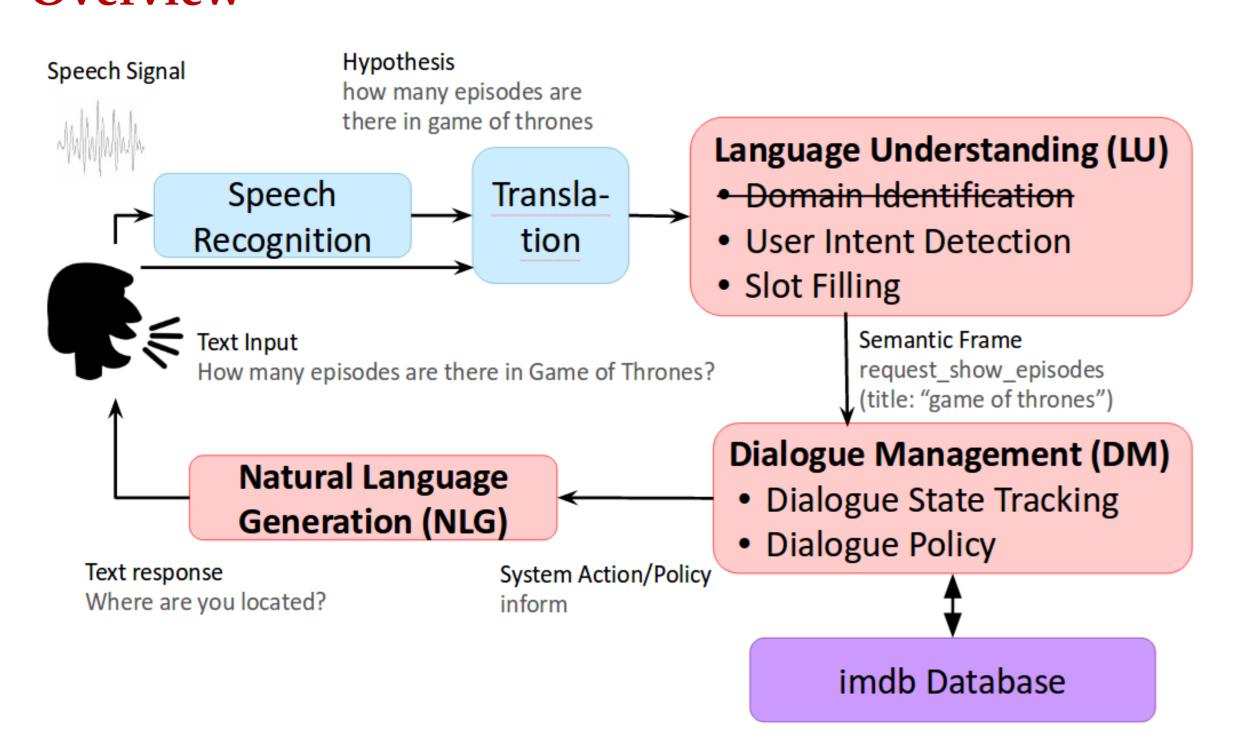
TVBot

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https://facebook.com/theTVBot



Overview



We are able to:

- find show info given other info.
- find character name given person's real name, or the opposite.
- find the person related to a show given her/his job.
- accept English and Chinese.
- do voice recognition.

Ontology and Database

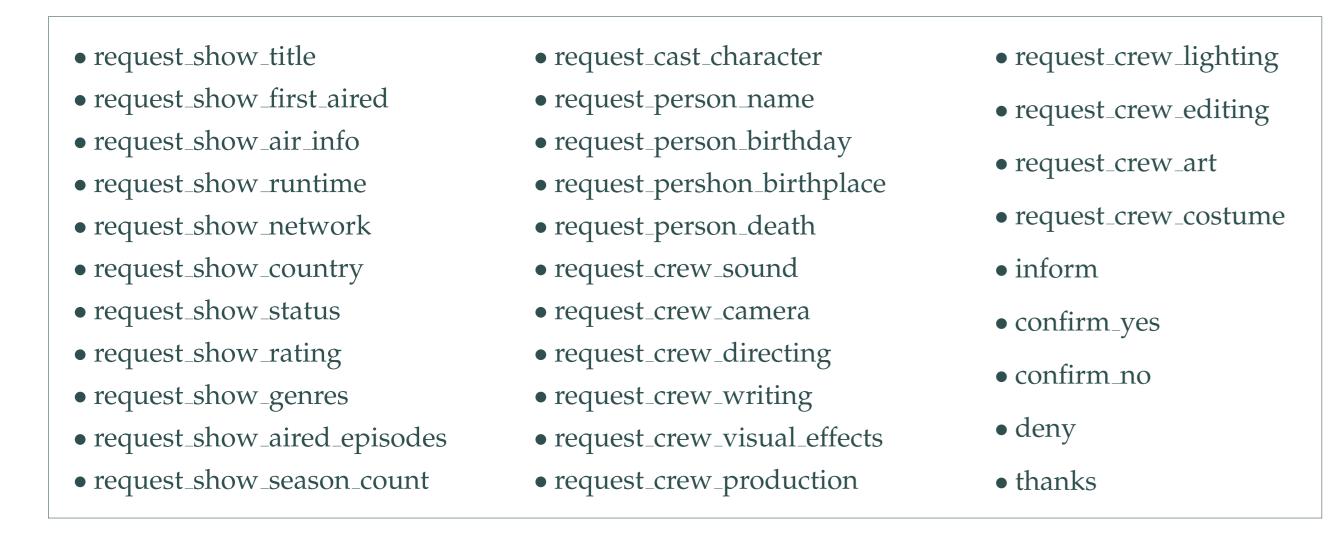
Source

Trakt.tv: it provides a unified interface to popular movie / tv show sources (IMdb, etc.).

Intent List

Fine-grained intents over vague intents. *Why?* Reduce possibility for wrong slot filling.

e.g. Who directed House of cards? v.s. How many episodes are there in Game of Thrones?



Value Mapping

The slot value from user NL might not match actual slot.

- country: Japan, Japanese → jp
- rating: nine, $9 \rightarrow 9.0$
- year: 1970, the $70s \to 1970$
- time: 16:00, 4p.m., 4 oclock \rightarrow 16:00

Language Understanding

RNN-NLU

RNN-NLU is able to classify intent and fill slots at the same time, *jointly optimized*.

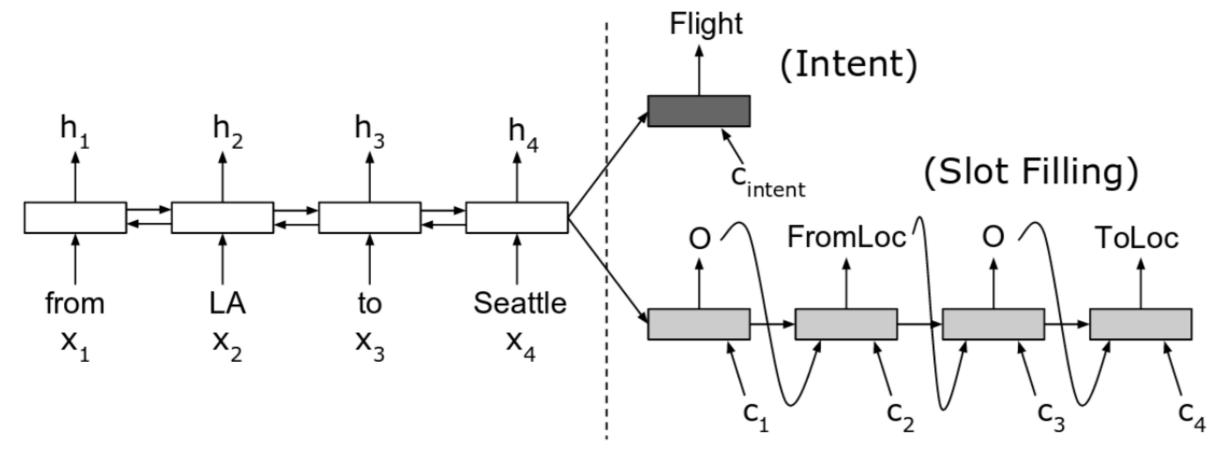


Figure 1: The framework of RNN-NLU [1]

Tend to *over-fill*. e.g. *I* would like to watch a show that airs <u>on</u> Friday. \rightarrow request_show_title(show.air_day: 'Friday', show.country:

api.ai

Provided by an external service. Model unknown.

Tend to under-fill. e.g. I would like to find a show produced by Jamie. \rightarrow request_show_title()

Comparison

	RNN-NLU	api.ai
Good	New model, powerful if fine tuned.	Online training.
Bad	Hard to train (days every time).	Black box, can't tune or apply tricks.

Table 1: NLU comparison

Accuracy 0.80 N/A F1 0.89 N/A		RNN-NLU	api.ai
F1 0.89 N/A	Accuracy	0.80	N/A
	F1	0.89	N/A

Data

Mostly generated by hands. We generate almost 1000 templates, and fill in the db values as the training sentences.

Table 2: Performance for NLU

Dialogue Management

State Tracker

For both user and agent, the state tracker tracks the following information in vector form $(a_1, a_2, ..., a_n), a_i \in \{0, 1\}, n = |Slots|$:

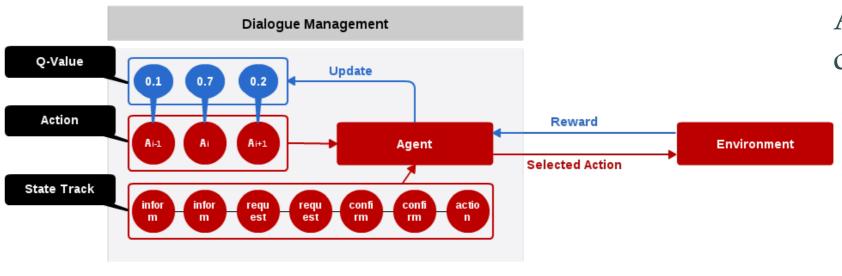
- (latest_)inform_slots
- (latest_)inform_values
- (latest_)request_slots

RL Agent (DQN[2])

- (latest_)confirm_slots
- (latest_)confirm_values
- latest_action

Ruled-based Agent

Ask user by a pre-defined sequence.



User Simulator

- Goal: contains *target slot* and *information* known by user.
- Success: after episode ends, check if agent reply correct slot.
- Error model: to simulate NLU error, a parameter controlls the possibility of wrong NLU.

	Ruled-based	DQN
w/ error	0.66	0.53
w/o error	1.0	0.93

Table 3: Performance for agent

Reward function

Our reward function definition is

when dialog fails $-1 \times max_turn$, when dialog success $2 \times max_turn$, otherwise

Performance

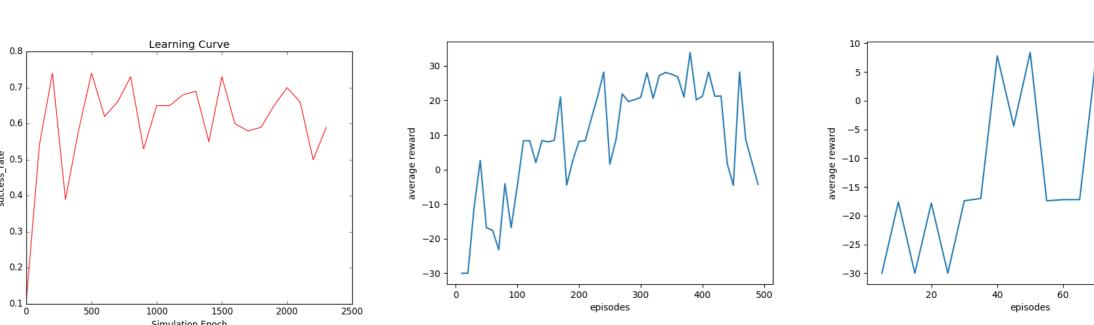


Table 4: Succ. rate of warmup

Table 5: Avg. reward against user-Table 6: Avg. reward against usersim w/o error sim w/error

Natural Language Generation

We separated the sentence into 7 categories:

• inform

request

thanks

- confirm_conflict
- confirm_no_conflict • multiple_choice
- **BLEU Training Testing** 0.4425

• confirm_again

Table 7: Performance for NN-NLG

Rule-based NLG

For each categories, we designed a template to fill the info.

NN-NLG

The model is a seq2seq. Trained on several templates for each categories.

Miscellaneous

Speech API

Integrated with Bing Speech-totext API. If audio gotten, call the api.

Translation API

The db is built in *English*. To support other language, sent to Bing Translation API if other language detected.

References

- [1] Bing Liu and Ian Lane. Attention-based recurrent neural network models for joint intent detection and slot filling. In *Interspeech* 2016, pages 685–689, 2016.
- [2] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. In NIPS Deep Learning Workshop. 2013.