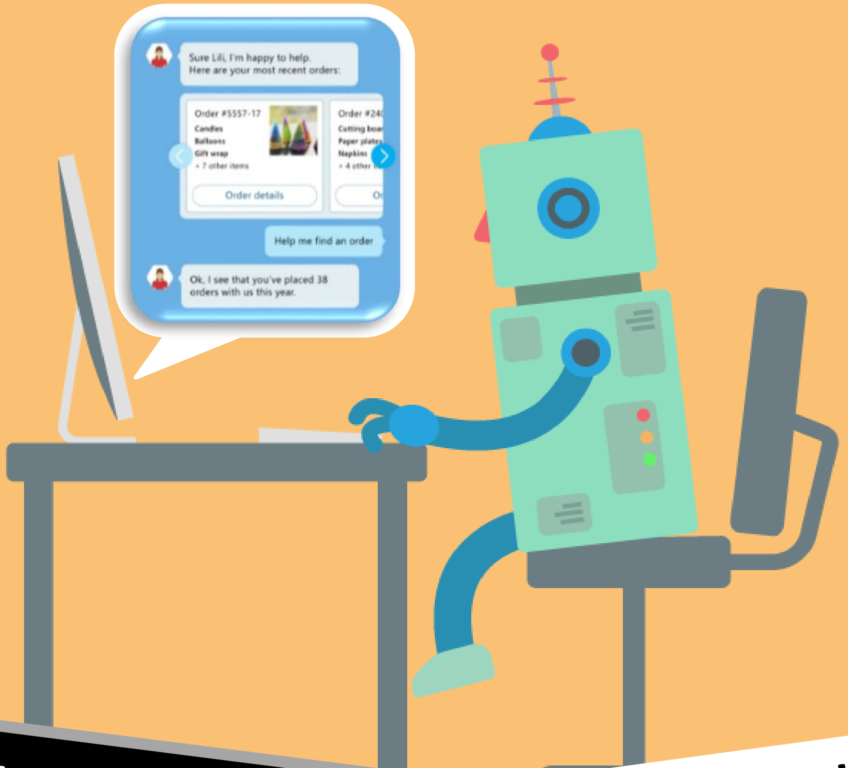

Intelligent Conversational Bot

Introduction

Feb 21st, 2017

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Course Logistics

Outline

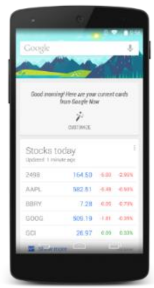
- Introduction and Background
- Modular Dialogue System
  - Spoken/Natural Language Understanding (SLU/NLU)
  - Dialogue State Tracking (DST)
  - Dialogue Policy
  - Natural Language Generation (NLG)
- End-to-End Learning for Dialogue Systems
- Conclusion

Part I

Introduction & Background

Language Empowering Intelligent Assistants

Apple Siri (2011)



Google Now (2012)

Microsoft Cortana (2014)

Amazon Alexa/Echo (2014)

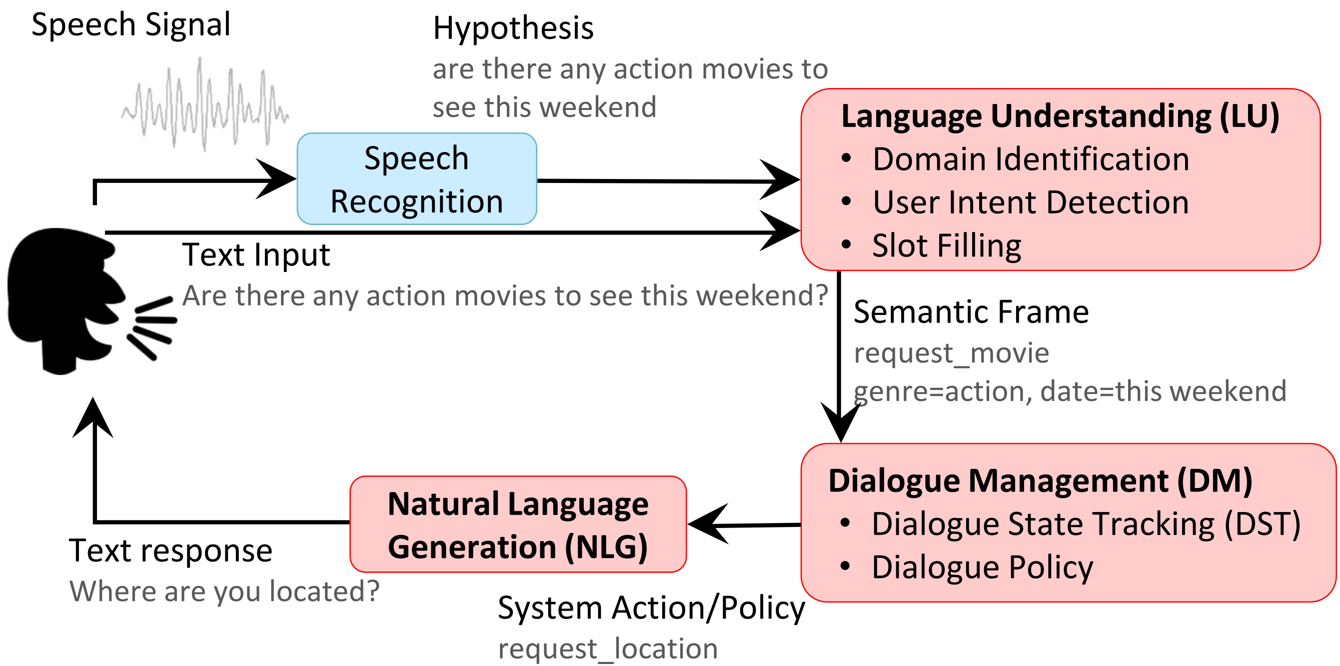
Facebook M & Bot (2015)

Google Home (2016)

Dialogue System

- Task-Oriented
  - Personal assistant, achieve a certain task
  - Combination of rules and statistical components
    - POMDP for spoken dialog systems (Williams and Young, 2007)
    - Learning End-to-End Goal-oriented Dialog (Antoni and Weston, 2016)
    - An End-to-End Trainable Task-oriented Dialogue System (Wen el al., 2016)
- Chit-Chat
  - No specific goal, focus on conversation flow
  - Work using variants of seq2seq model
    - A Neural Conversation Model (Vinyals and Le, 2015)
    - Deep Reinforcement Learning for Dialogue Generation (Li et al., 2016)
    - Conversational Contextual Cues: The Case of Personalization & History for Response Ranking (Al-Rfou et al., 2016)

Pipelined Task-Oriented Dialogue System



Part II

Modular Dialogue System

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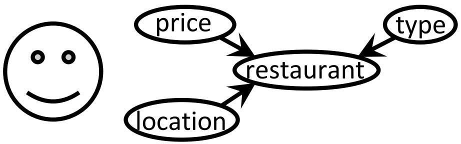
Semantic Frame Representation

- Requires a domain ontology
- Contains **core content (intent, a set of slots with fillers)**

Restaurant Domain

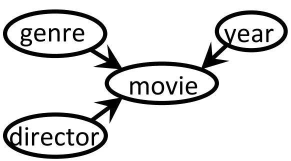
find a cheap taiwanese restaurant in oakland



find_restaurant (price="cheap", type="taiwanese", location="oakland")

Movie Domain

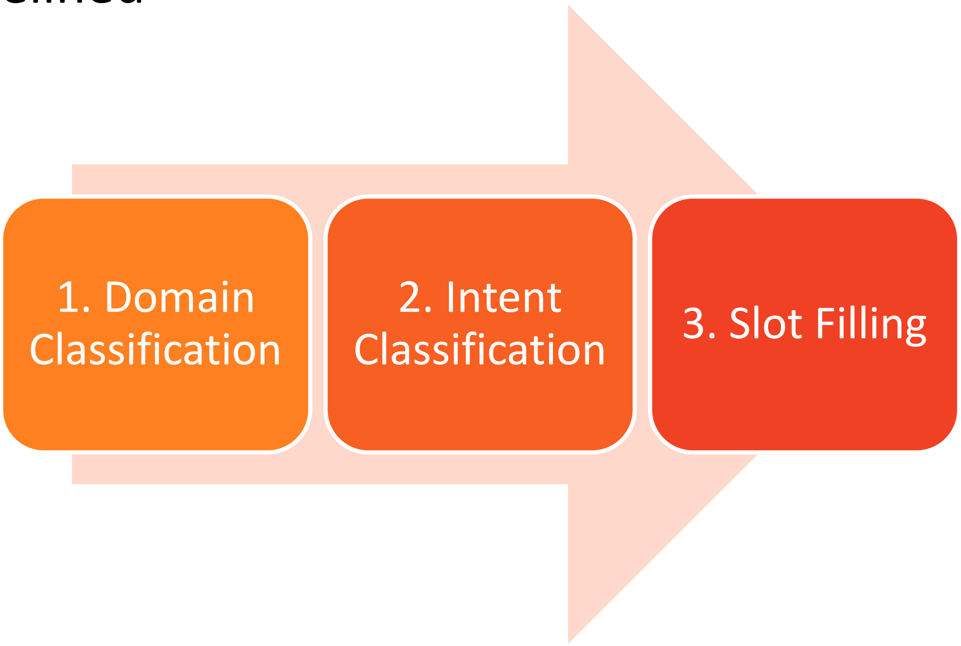
show me action movies directed by james cameron



find_movie (genre="action", director="james cameron")

Language Understanding (LU)

- Pipelined



LU – Domain/Intent Classification

Mainly viewed as an utterance classification task

- Given a collection of utterances u_i with labels c_i, D= $\{(u_1,c_1),\ldots,(u_n,c_n)\}$ where $c_i \in C$, train a model to estimate labels for new utterances u_k.

find me a cheap taiwanese restaurant in oakland

Movies	Find_movie
Restaurants	Buy_tickets
Sports	Find_restaurant
Weather	Book_table
Music	Find_lyrics
…	…

Language Understanding - Slot Filling

Is there um a cheap place in the centre of town please?

As a sequence tagging task

- CRF for tagging each utterance

As a classification task

- SVM for each slot value pair

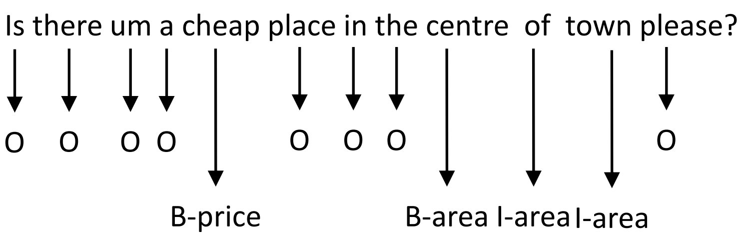
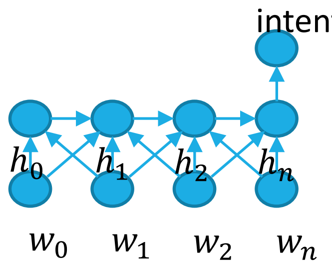


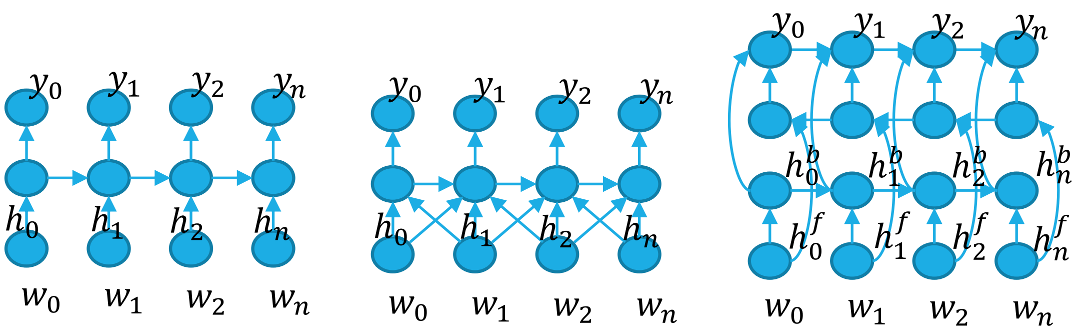
Figure credited by Milica Gašić

Language Understanding

- Intent Classification (Ravuri and Stolcke, 2015)



- IOB Sequence Labeling for Slot Filling (Hakkani-Tur et al., 2016)



(a) LSTM (b) LSTM-LA (c) bLSTM-LA

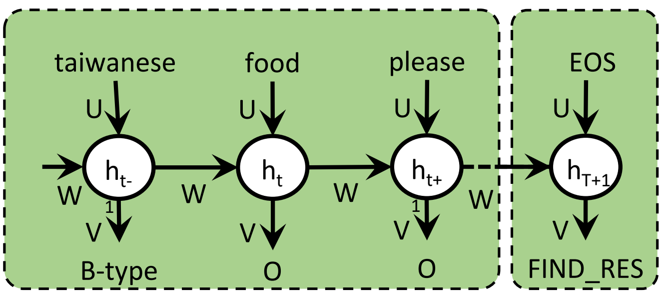
Joint Semantic Frame Parsing

Sequence-based (Hakkani-Tur et al., 2016)

- Slot filling and intent prediction in the same output sequence

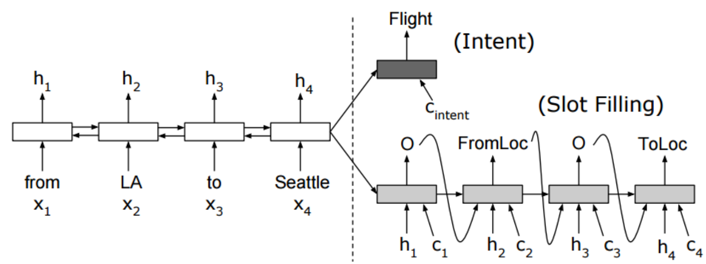
Parallel (Liu and Lane, 2016)

- Intent prediction and slot filling are performed in two branches



Slot Filling

Intent Prediction



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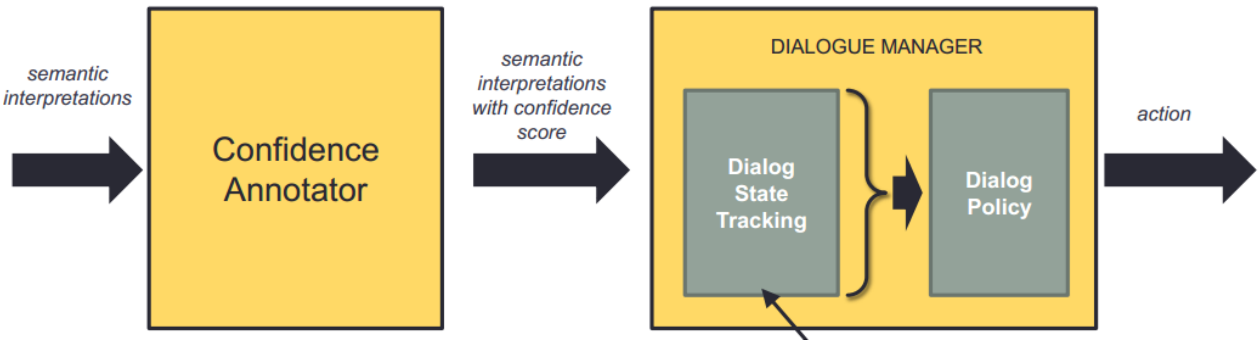
Dialogue State Tracking (DST)

sample problem

S: where would you like to fly from?
U: [Boston/0.45]; [Austin/0.30]
S: sorry, did you say you wanted to fly from Boston?
U: [No/0.37] + [Aspen / 0.7]

Updated belief = ?
[Boston/?; Austin/?; Aspen/?]



Slide credited by Sungjin Lee

Dialogue State Tracking (DST)

- Maintain a probabilistic distribution instead of a 1-best prediction for better robustness

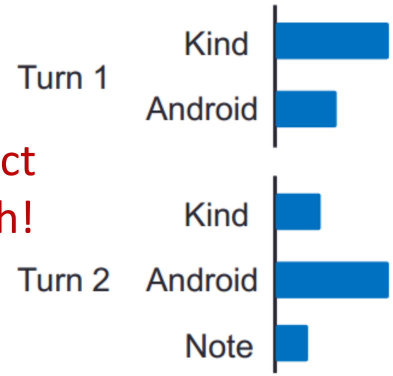
Turn 1
Kind
Android

Turn 2
Note
Android

Turn 1	
Kind	0.5
Android	0.3

Turn 2	
Note	0.4
Android	0.3

Incorrect for both!



Dialogue State Tracking (DST)

- Maintain a probabilistic distribution instead of a 1-best prediction for <u>better robustness to SLU errors or ambiguous input</u>

Slot	Value
# people	5 (0.5)
time	5 (0.5)

Slot	Value
# people	3 (0.8)
time	5 (0.8)

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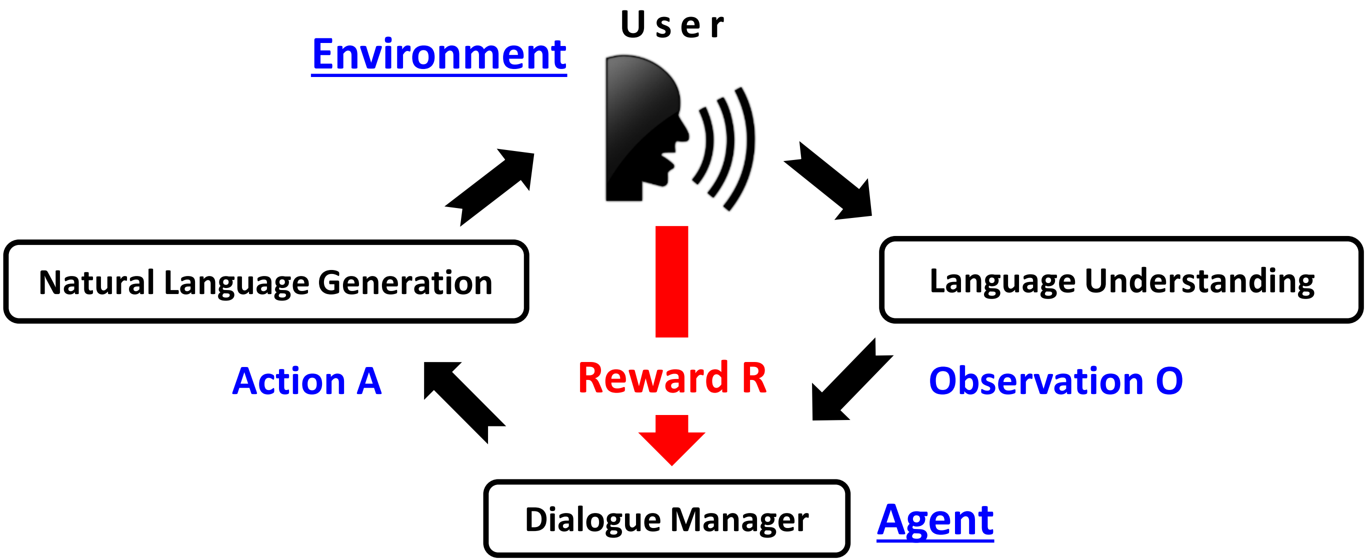
Dialogue Policy Optimization

- Dialogue management in a RL framework



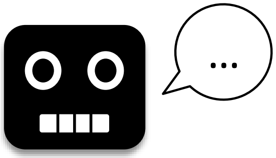
Optimized dialogue policy selects the best action that can maximize the future reward.
Correct rewards are a crucial factor in dialogue policy training

Reward for RL $\cong$ Evaluation for SDS

- Dialogue is a special RL task
  - Human involves in **interaction** and **rating (evaluation)** of a dialogue
  - Fully human-in-the-loop framework
- Rating: correctness, appropriateness, and adequacy

- Expert rating	high quality, high cost
- User rating	unreliable quality, medium cost
- Objective rating	Check desired aspects, low cost

Dialogue Reinforcement Signal



Typical Reward Function

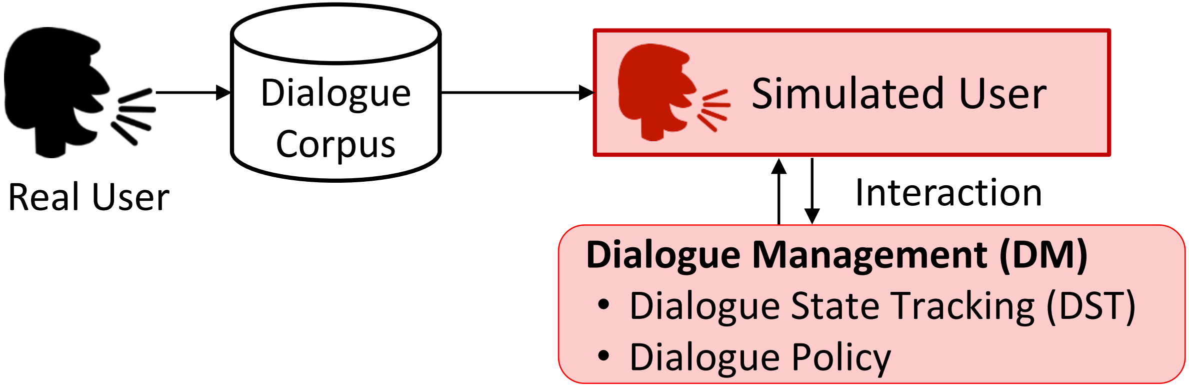
- per turn penalty -1
- Large reward at completion if successful

Typically requires domain knowledge

- ✔ Simulated user
- ✘ Paid users (Amazon Mechanical Turk)
- ✖ Real users

User Simulation

- User Simulation
  - Goal: generate natural and reasonable conversations to enable reinforcement learning for exploring the policy space
  - Approach
    - Rule-based crafted by experts (Li et al., 2016)
    - Learning-based (Schatzmann et al., 2006)



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Natural Language Generation (NLG)

- Mapping semantic frame into natural language

inform(name=Seven_Days, foodtype=Chinese)

↓

Seven Days is a nice Chinese restaurant

Template-Based NLG

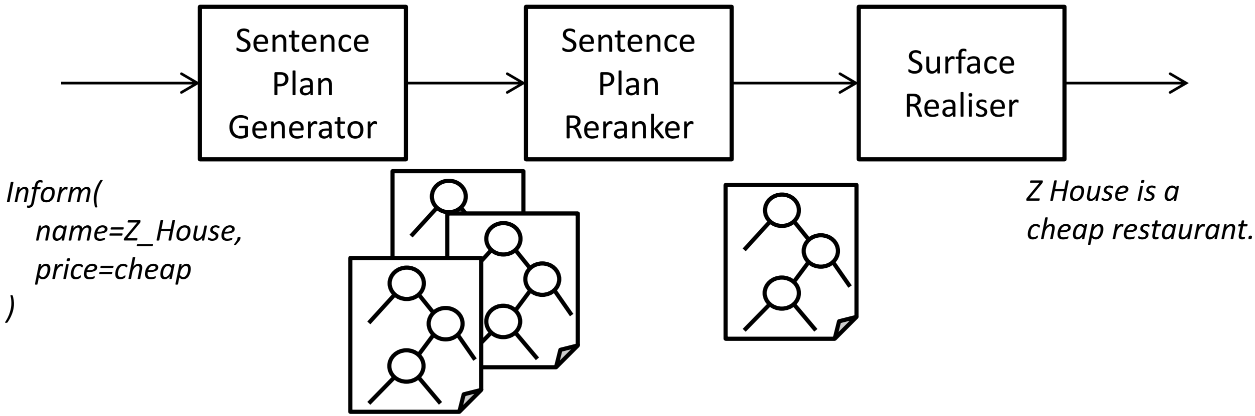
- Define a set of rules to map frames to NL

Semantic Frame	Natural Language
confirm()	“Please tell me more about the product your are looking for.”
confirm(area=$V)	“Do you want somewhere in the $V?”
confirm(food=$V)	“Do you want a $V restaurant?”
confirm(food=$V,area=$W)	“Do you want a $V restaurant in the $W.”

Pros: simple, error-free, easy to control
Cons: time-consuming, poor scalability

Trainable Generator (Walker et al., 2002)

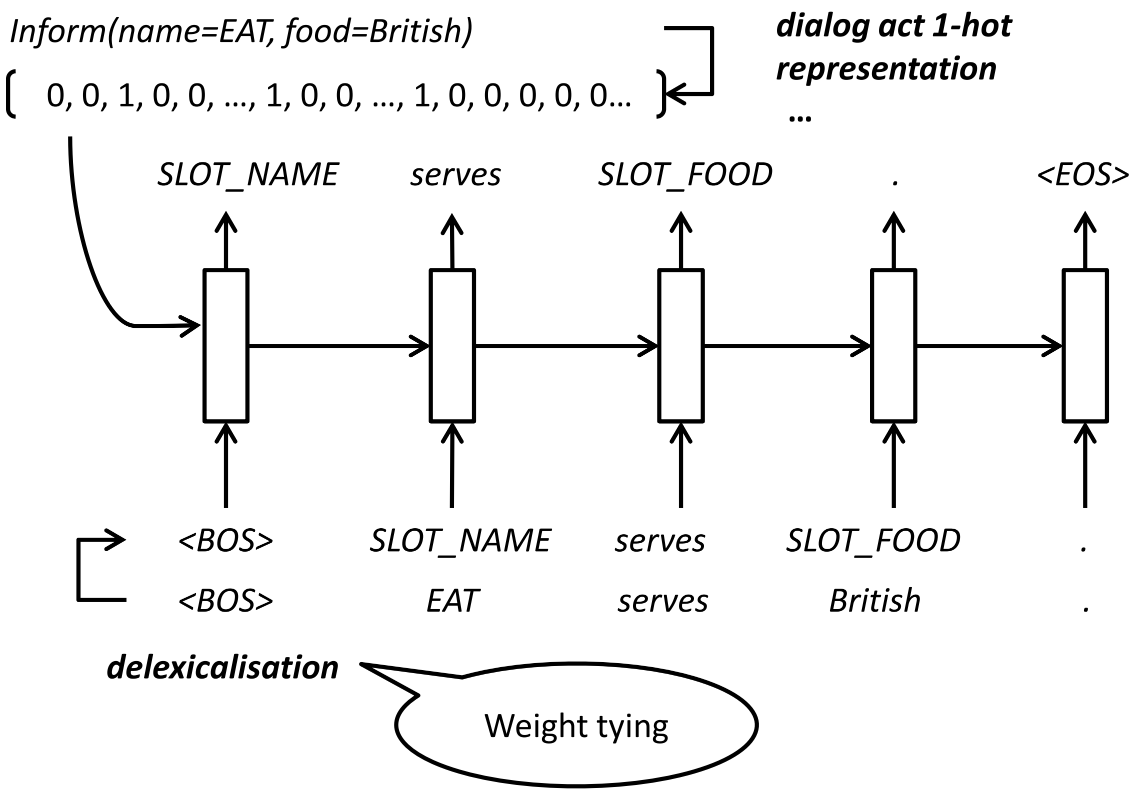
- Divide the problem into pipeline



  - Statistical sentence plan generator (Stent et al., 2009)
  - Statistical surface realization (Dethlefs et al., 2013; Cuayáhuitl et al., 2014; …)

Pros: can model complex linguistic structures
Cons: heavily engineered, require domain knowledge

RNN Language Generator (Wen et al., 2015)



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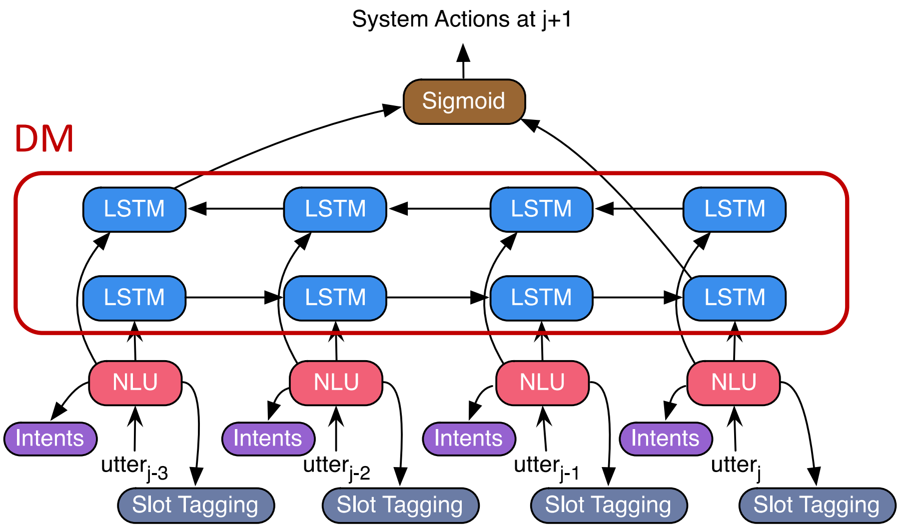
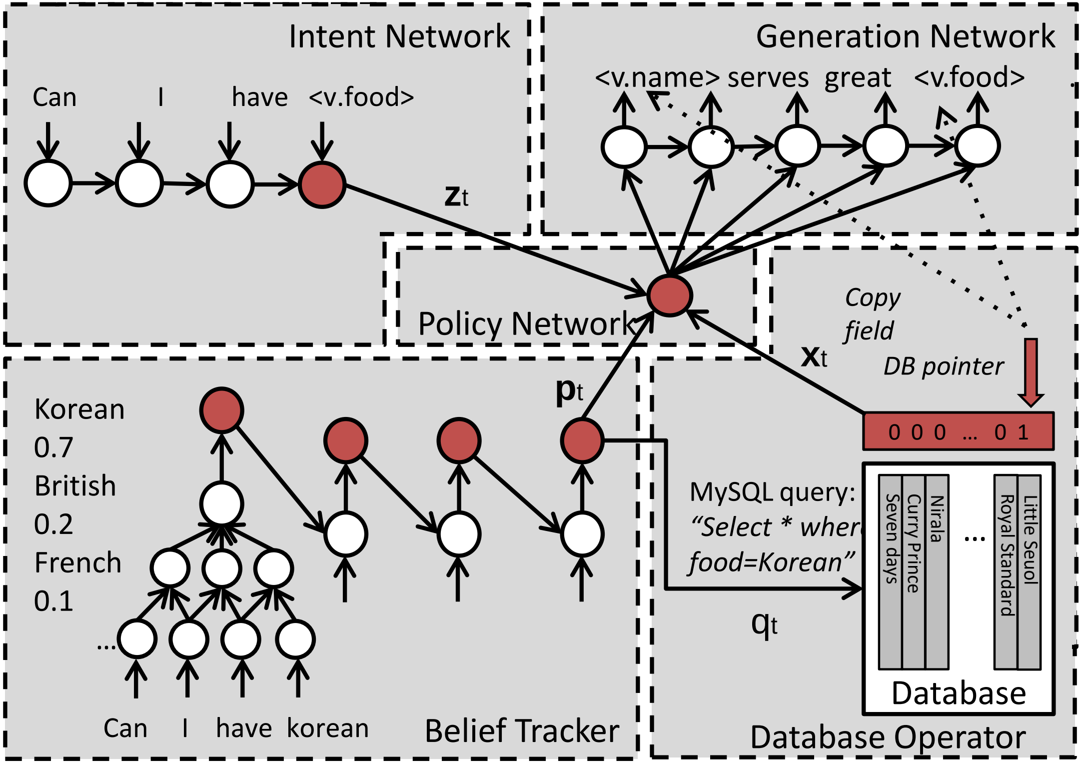
E2E Joint NLU and DM (Yang et al., 2017)

- Errors from DM can be propagated to NLU for better robustness

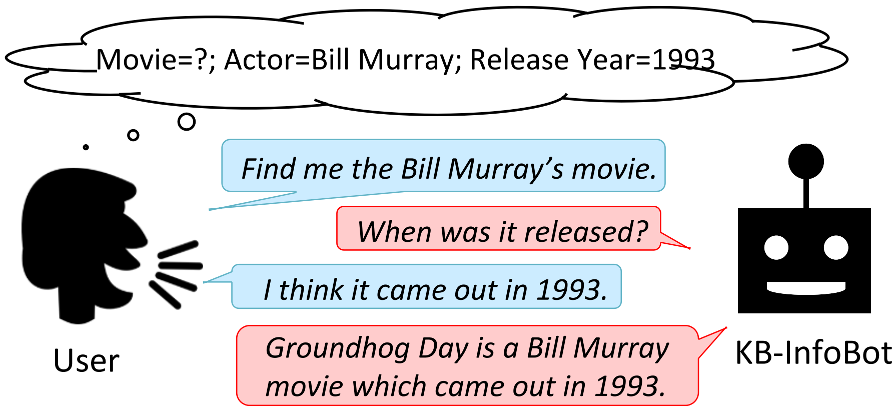


E2E Supervised Dialogue System (Wen et al., 2016)



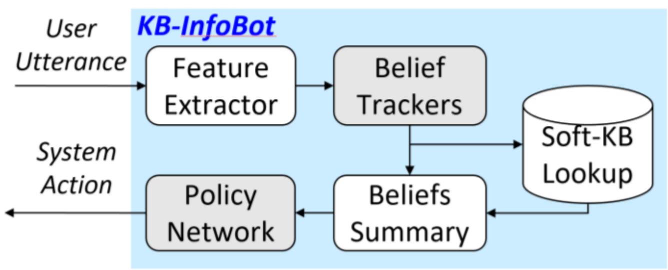
Wen, et al., "A Network-based End-to-End Trainable Task-Oriented Dialogue System," arXiv.:1604.04562v2.

Info Access Bot (Info-Bot) (Dhingra et al., 2016)



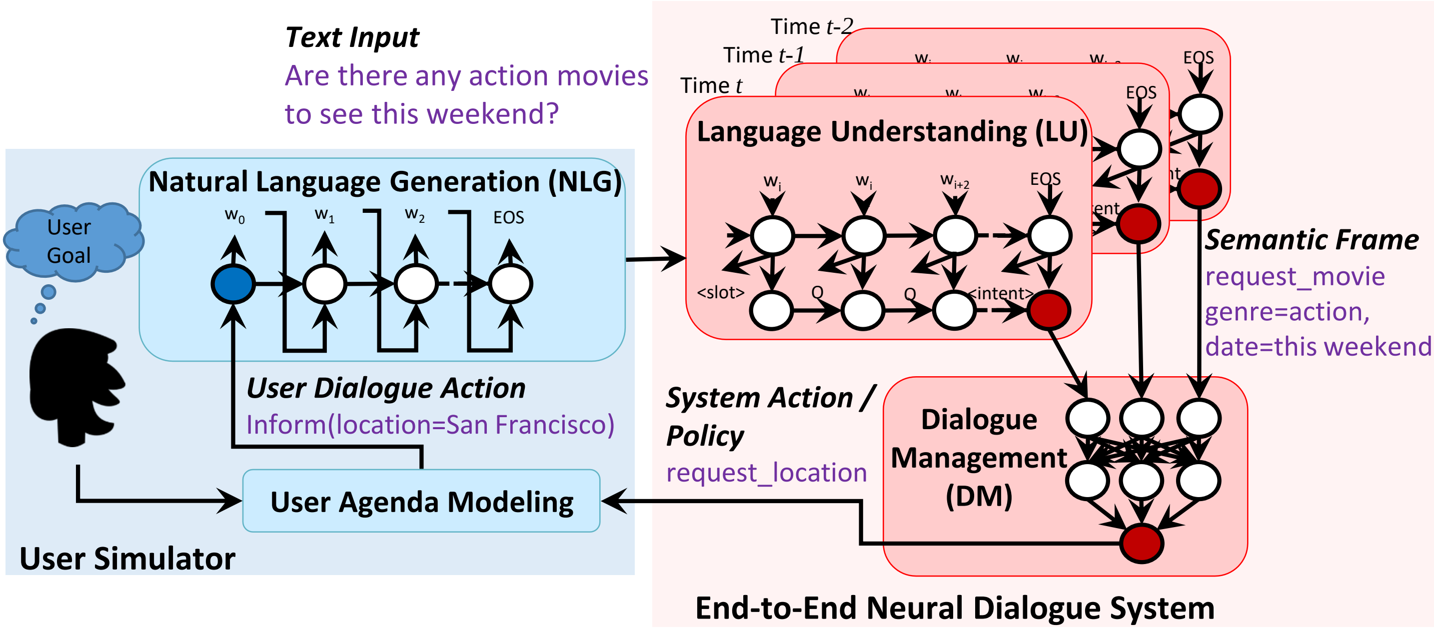
Knowledge Base *(head, relation, tail)*

(Groundhog Day, actor, Bill Murray)
(Groundhog Day, release year, 1993)
(Australia, actor, Nicole Kidman)
(Mad Max: Fury Road, release year, 2015)



Dhingra et al., "End-to-End Reinforcement Learning of Dialogue Agents for Information Access," arXiv.:1609.00777v2.

E2E Task-Completion Bot (TC-Bot) (Li et al., 2017)



Idea: supervised learning for each component and reinforcement learning for end-to-end training the neural dialogue system

E2E Task-Completion Bot (TC-Bot) (Li et al., 2017)

- User goal: ***Two tickets for "the witch" tomorrow 9:30 PM at regal meridian 16, Seattle.***

RULE BASED SYSTEM
User: Can I get 2 tickets for the witch?
Agent: Which theater do you want?
User: Regal meridian 16
Agent: What time would you like to see it?
User: 9:30 pm
Agent: What date would you like to see it?
User: Tomorrow!
Agent: How many people are you?
User: Just two adults.
Agent: What is your location?
User: Seattle!
Agent: What kind of video format do you like?
User: Oh, any kind is okay.
Agent: Do you have any price constraint?
User: No, I don't care.
Agent: Great - I was able to purchase 2 tickets for you to see the witch tomorrow at regal meridian 16 theater in Seattle at 9:30 pm.
User: Thank you.
Agent: Thank you!

REINFORCEMENT LEARNING SYSTEM
User: Can I get 2 tickets for the witch?
Agent: What date would you like to see it?
User: Tomorrow
Agent: Which theater do you prefer?
User: Regal meridian 16
Agent: What is your location?
User: Seattle
Agent: What time would you like to see it?
User: 9:30 pm.
Agent: Great - I was able to purchase 2 tickets for you to see the witch tomorrow at regal meridian 16 theater in Seattle at 9:30 pm.
User: Thanks.
Agent: Thanks!

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Concluding Remarks

- Modular dialogue system