

Tutorial on ConversationalAI



Ivan

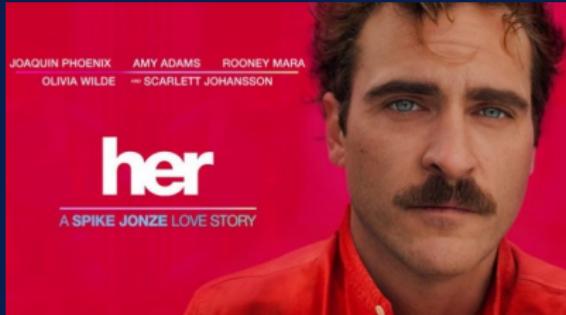
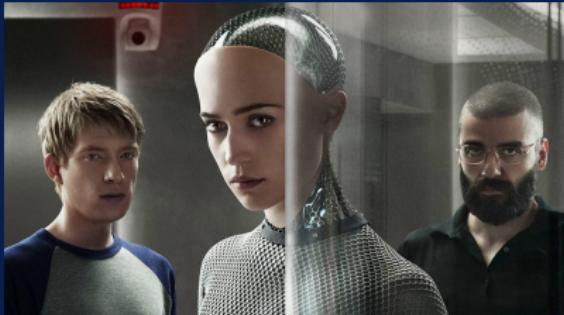


Inigo



Paweł

Conversational AI in Fiction



Virtual Assistants are the Next Platform



March, 1876.
Alexander Graham Bell
invented the telephone.



March, 1989.
Tim Berners-Lee
invented the World
Wide Web.



January, 2007
Apple released the 1st
iPhone, giving birth to
the smartphone era.



2011 - now
The era of virtual
personal assistants.

Virtual Assistants are the Next Platform

Voice and Language as the Command



Virtual Assistants are the Next Platform

The Amazon Echo is the top selling item on Amazon

20% of US homes *already own a smart speaker*

- ...and this number will quadruple in the next two years
- 53% of smart speaker owners bought their device last Christmas

Virtual assistants are becoming the main entry point for all actions and services available across all smart devices

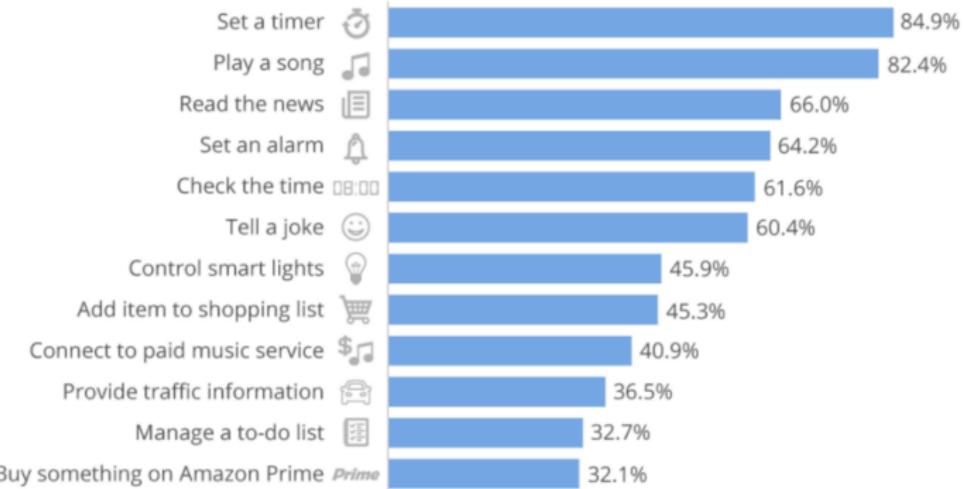
- Instead of different interfaces for smartphones, watches and homes, virtual assistants allow users to access them in the same way – using their voice

Conversational AI in 2018

Tech  Chart of the Day

How People Use Amazon's Virtual Assistant

% of Amazon Echo users who have asked the device to do the following at least once



Based on a survey of 180 Amazon Echo users conducted in 2016

BUSINESS INSIDER

Sources: Experian, Creative Strategies



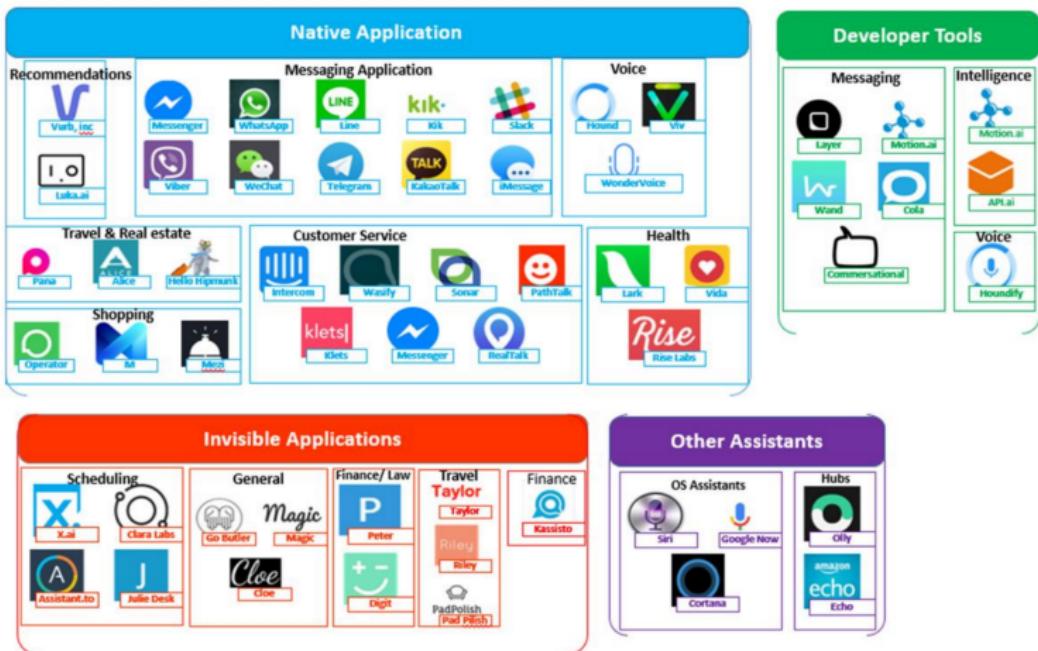
statista

Conversational AI = Conversational UI?

Searching with a specific goal (less information but relevant information)

- Information Precision: High
- Display: Non-structured
- Interface: (Human) language
- Navigation: Using text and speech
- Complexity of use: Extremely easy, no need to learn
- Availability: Integrated into message-based interfaces
- Flexibility: High

Conversational AI = Conversational UI?



Conversational AI = Conversational UI?

- Global Digital Statistics (2017 January)



Total Population
7.48B



Internet Users
3.77B



Active Social
Media Users
2.79B



Unique Mobile
Users
4.92B



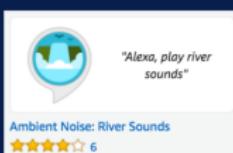
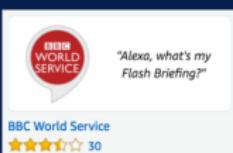
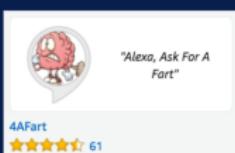
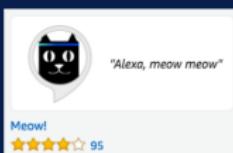
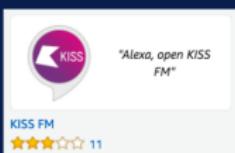
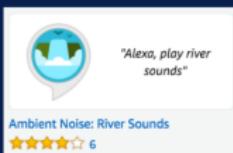
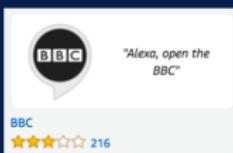
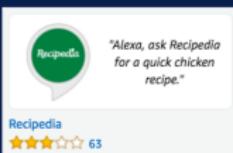
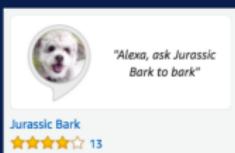
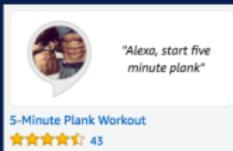
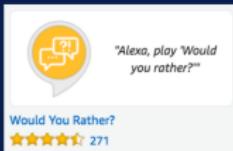
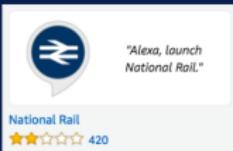
Active Mobile Social
Users
2.55B

The more **natural** and **convenient** input of devices evolves towards **speech**.

Conversational AI in 2018

Are we there yet?

- Top Alexa skills are still simple single-turn commands



Conversational AI in 1966

Joseph Weizenbaum's **ELIZA** (1966)

ELIZA: What is bothering you?

User: I feel sad all the time

ELIZA: Why do you feel sad all the time?

User: I don't get along with my parents.

ELIZA: Tell me about your parents.

Conversational AI in 2018

Applications

- Bookings: restaurants, hotels, flights, train tickets, ...
- E-commerce: from search to payment
- Accounting and Finance: from organising records to cryptocurrency trade
- Healthcare: from updating the EMRs to psychotherapy
- Marketing: e-mail marketing, social media search, ...
- Daily life: setting your alarm clock, reminding about meetings, ...

Are we there yet?

Tutorial Goals

Give an overview of recent research trends in deep learning for conversational AI

Provide a detailed overview of (importance of) task-based dialogue systems

Analyse most promising research avenues and stress their current limitations

Discuss the importance of data requirements vs. algorithm choices

Present an industry-based perspective on current deep conversational AI

Detect current “make it or break it” challenges in conversational AI

Conversational AI in 2018

Google Duplex: demo released in May 2018

"The technology is directed towards **completing specific tasks**, such as scheduling certain types of appointments. For such tasks, the system makes the conversational experience as natural as possible, allowing people to speak normally, like they would to another person, without having to adapt to a machine..."

"One of the key research insights was to constrain Duplex to **closed domains**, which are **narrow enough** to explore extensively. Duplex can only carry out natural conversations after being deeply **trained in such domains**. It **cannot carry out general conversations**."

Source: [ai.googleblog.com \[play demo\]](https://ai.googleblog.com/2018/05/introducing-duplex.html)

Challenges and Problems

- How to deal with **variability** and **flexibility** of language?
- What about other languages: **multilinguality**?
- How to build **robust** and **multi-domain** systems?
- How to get **high-quality in-domain data**?
- How to build **meaning representation**?
- How to integrate **commonsense** and **world knowledge**?
- Do we want **very specialised** or more **adaptable** systems?

Targeted Problem Types?

“I am smart”

Turing Test

“I have a question”

Information consumption

“I need to get this done”

Task completion

“What should I do?”

Decision support

- *What is the employee review schedule?*
- *What room is the project review meeting in?*
- *When is the ACL 2018 conference?*
- *What does DNN stand for?*

Targeted Problem Types?

“I am smart”

Turing Test

“I have a question”

Information consumption

“I need to get this done”

Task completion

“What should I do?”

Decision support

- *Book me the biz trip to San Francisco*
- *Reserve a table at Kisaku for 5 people, 7PM tonight*
- *Brief me on people in my Thursday 9:00 am meeting*
- *Schedule a meeting with Bill at 10:00 tomorrow.*

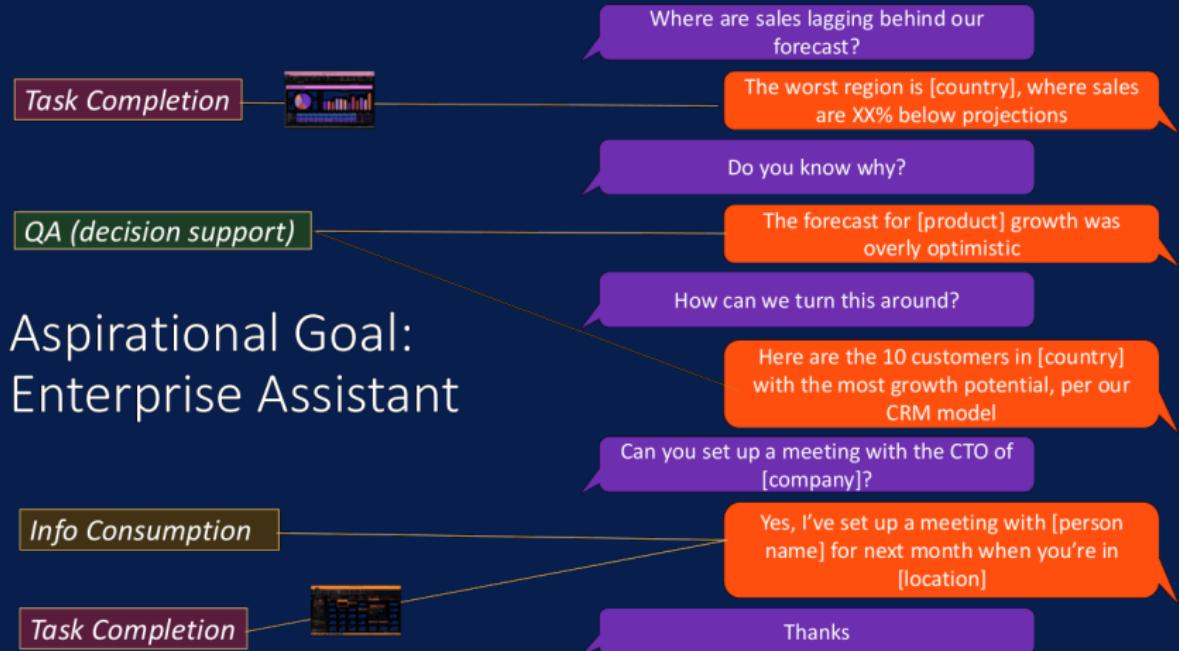
Targeted Problem Types?

“I am smart”	Turing Test
“I have a question”	Information consumption
“I need to get this done”	Task completion
“What should I do?”	Decision support



- *Why are sales in China so far behind forecast?*

Targeted Problem Types?



The Two Paradigms: Task-Oriented vs Chatbots

M: Hello, welcome to the Cambridge dialogue system, What kind of food would you like?
H: Yeah I want to find a restaurant that serves European food.
M: Hotel du Vin and Bistro is a nice place. It serves European food.
H: Uh what is the address and phone number?
M: Hotel du Vin and Bistro is a nice place. Their address is XXX and their phone is YYY.
H: Thank you goodbye.
M: Thank you for using this system.

[Su et al, 2016]

A: How old are you ?
B: I'm 16. Why are you asking ?
A: I thought you were 12.
B: What made you think so ?
A: I don't know what you are talking about.
B: You don't know what you are saying.

[Li et al, 2016]

The Two Paradigms

1. Task-Oriented Dialogue Systems

- Goal-oriented
- Require precise understanding, it is hard to collect data
- Modular, highly hand-crafted, restricted ability, but meaningful/useful systems

2. Chat-Based Conversational Agents

- Chit-chat (no goal)
- Large amounts of data (but probably not helpful so much)
- End-to-end, highly data-driven, but meaningless/inappropriate responses, unreliable systems

The Two Paradigms

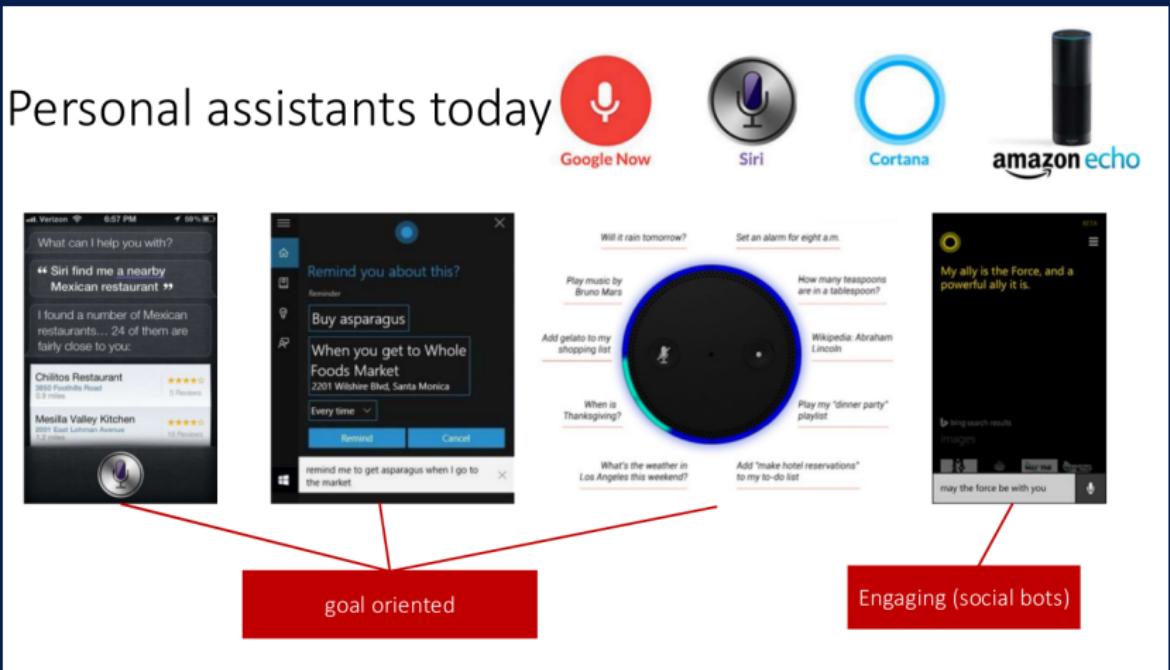
What kinds of problems?

"I am smart"	Turing Test ("I" talk like a human)
"I have a question"	Information consumption
"I need to get this done"	Task completion
"What should I do?"	Decision support

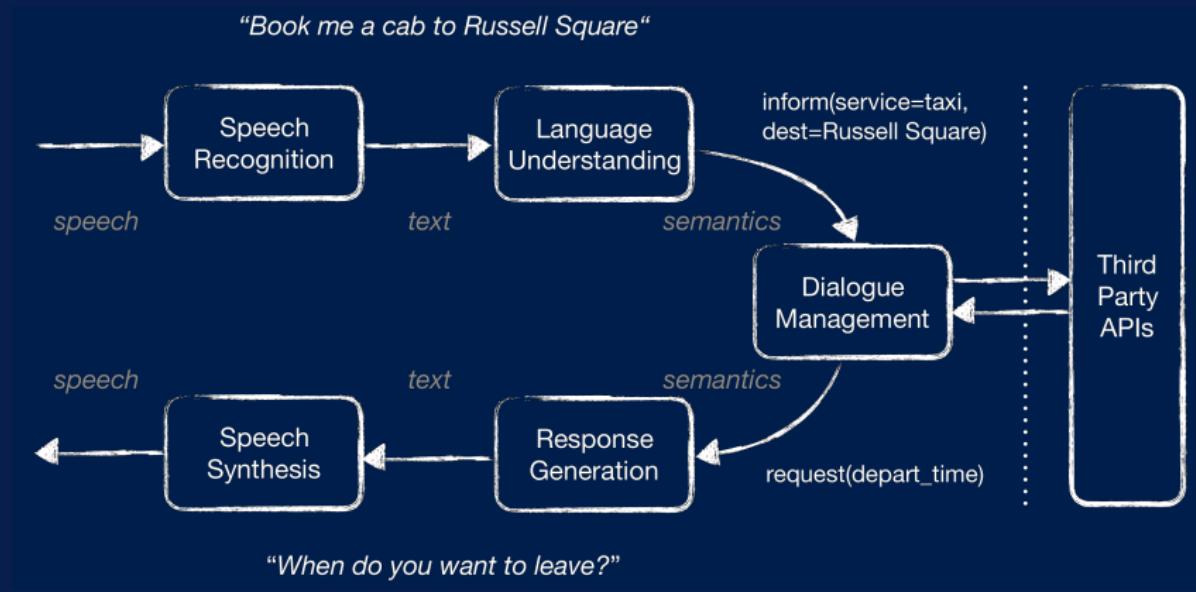
Chitchat (social bot)

Goal-oriented dialogues

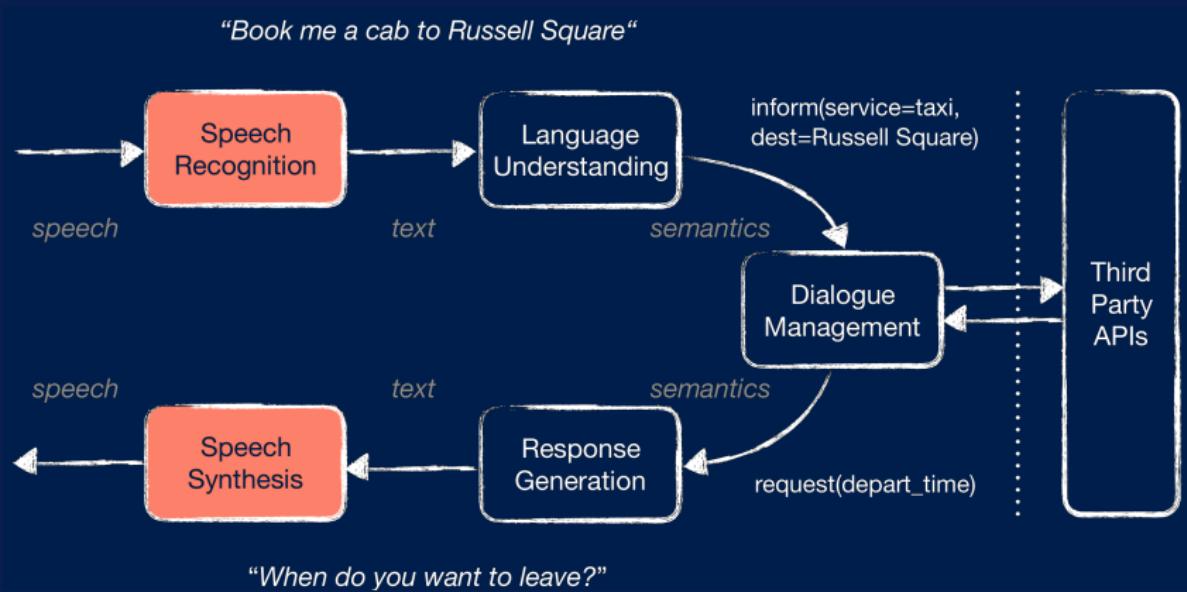
The Two Paradigms



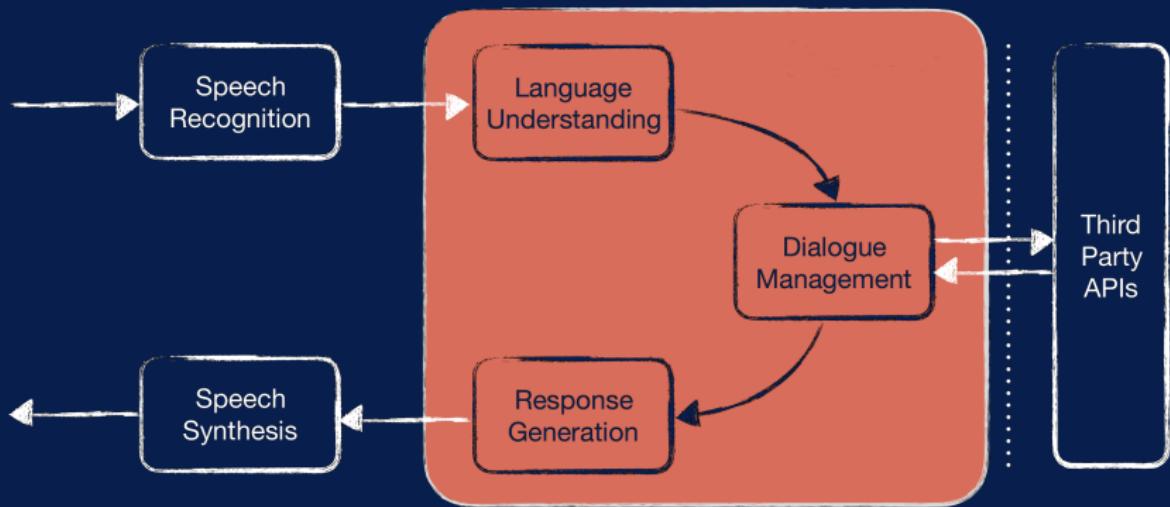
Task-Oriented Dialogue Systems



Task-Oriented Dialogue Systems



Task-Oriented Dialogue Systems



Dialogue as a Partially Observable Markov Decision Process (POMDP)

[Williams and Young, 2007; Young, 2010; Young et al., 2013]

Data

- Noisy observations
- Propagating uncertainty and modelling the *belief state*

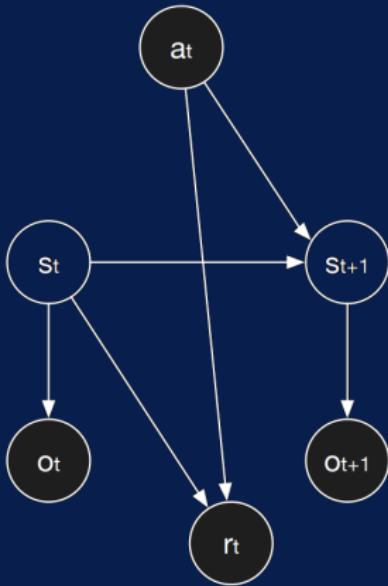
Model

- Partially observable Markov decision process

Predictions

- Optimal system actions in noisy environments

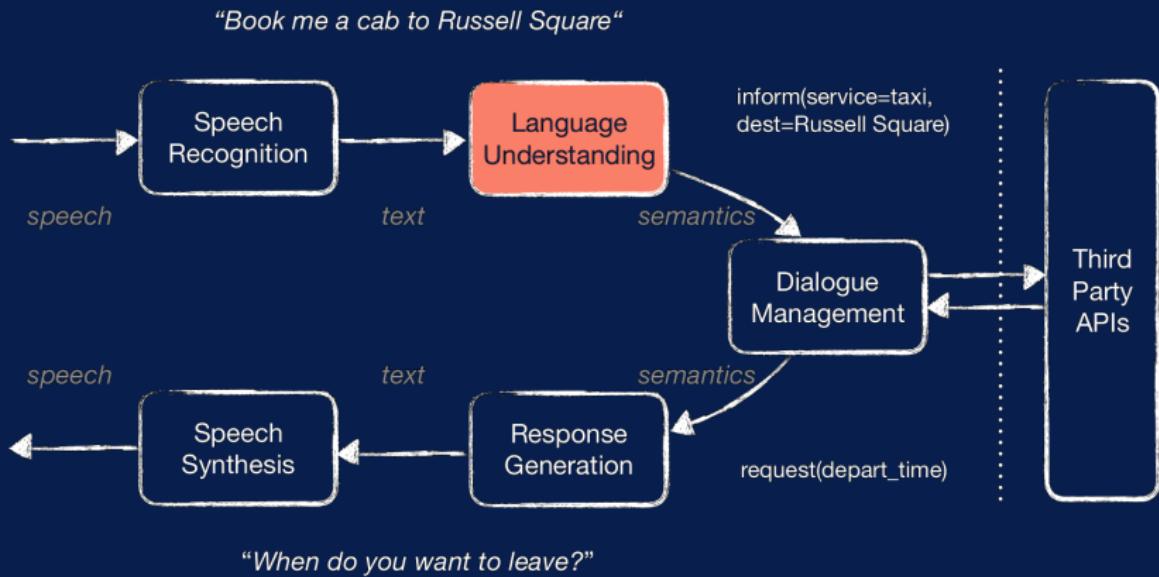
POMDP-Based Dialogue Systems



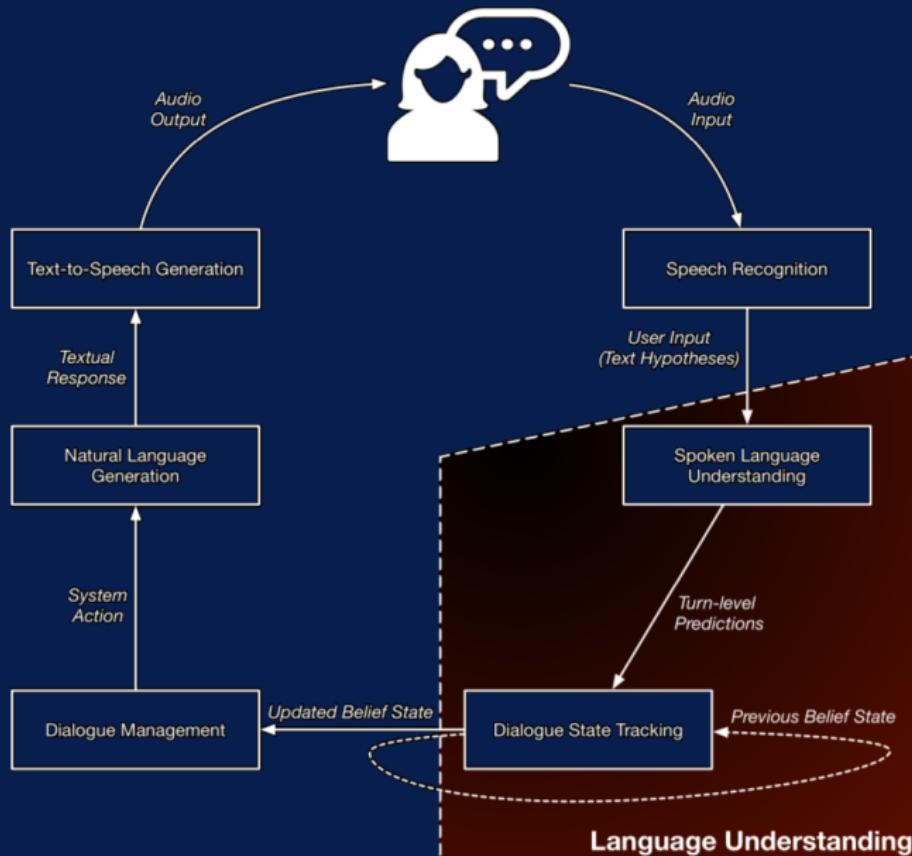
- $s_t \rightarrow$ dialogue states
- $o_t \rightarrow$ noisy observations
- $a_t \rightarrow$ system actions
- $r_t \rightarrow$ rewards
- $p(s_{t+1}|s_t, a_t) \rightarrow$ transition probability
- $p(o_{t+1}|s_{t+1}) \rightarrow$ observation probability
- $b(s_t) \rightarrow$ distribution over possible states

POMDP → the agent cannot directly observe the underlying state. Instead, it must maintain a prob distribution over the set of possible states, based on a set of observations and observation probabilities, and the underlying MDP

Natural Language Understanding



Language Understanding



Semantic Ambiguity and Variability

Challenge of NLP: the diversity of natural language

Many-to-many mapping btw *symbolic* language and *semantic* meaning

Ambiguity

Example: I made her duck.

- I cooked waterfowl for her.
- I cooked waterfowl belonging to her.
- I created the plaster duck she owns.
- I caused her to quickly lower her head or body.
- I waved my magic wand and turned her into undifferentiated waterfowl.

Paraphrase

Example: How long is the X river?

- The Mississippi River *is* 3,734 km (2,320 mi) *long*.
- ...*is a short river, some 4.5 miles (7.2 km) in length*
- *The total length of the river is 2,145 kilometers.*
- ... *at the estimated length of 5,464 km (3,395 mi)...*
- ... *has a meander length of 444 miles (715 km)...*
- ... *Bali's longest river, measuring approximately 75 kilometers from source to mouth.*
- *The ... mainstem is 2.75 miles (4.43 km) long although total distance from headwater source tributaries to the sea is 14 miles (23 km).*

Spoken Language Understanding

A lot of “deep work” recently:

- RNNs (encoder-decoder architectures) for slot tagging [Yao et al., 2013; Mesnil et al., 2015; Simmonet et al., 2015; Kurata et al., 2016, Tafforeau et al., 2016]: bidirectional LSTMs, attention-based, multi-task learning
- Joint semantic frame parsing [Hakkani-Tur et al., 2016; Liu and Lane, 2016]: slot filling and intent prediction jointly

but (besides **demanding data/resource requirements**)...

A recent trend has been to combine the two modules into a single *end-to-end learnable* component. Indeed, the top-performing approaches in DSTC2 use both SLU features and n-gram features extracted directly from ASR.

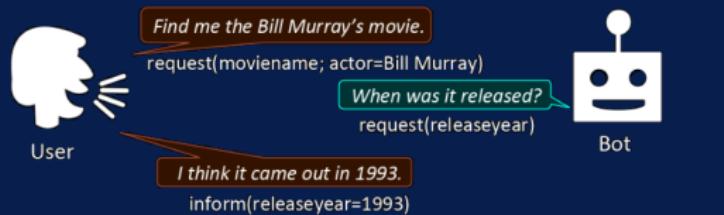
What is a Dialogue Act?

Dialogue Act

- inform, request, confirm (system only)
- Task-specific action (e.g. book_ticket)
- Others (e.g. thanks)

User Intent
= Dialogue Act + Slot

System Action
= Dialogue Act + Slot



Spoken Language Understanding

Requires a domain ontology: early connection to **backend**

Contains **core concept (intent, a set of slots with fillers)**

Restaurant
Domain

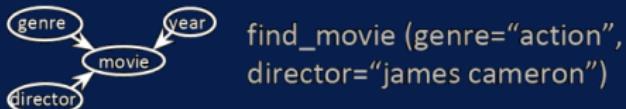


find me a cheap taiwanese restaurant in oakland



Movie
Domain

show me action movies directed by james cameron



Spoken Language Understanding



Three main components in the pipelined fashion

Spoken Language Understanding

Slot-Filling Dialogues

- **Domain:** movie, restaurant, flight, ...
- **Slot:** information to be filled in before completing a task
 - For Movie-Bot: movie-name, theater, number-of-tickets, price, ...
- **Intent (dialogue act):**
 - Inspired by speech act theory (communication as action)
request, confirm, inform, thank-you, ...
 - Some may take parameters:
thank-you(), request(price), inform(price=\$10)

"Is Kungfu Panda the movie you are looking for?"



confirm(moviename="kungfu panda")

Dialogue Act Classification...

...also known as **intent classification**

Label each dialogue utterance with intent

find me a cheap taiwanese restaurant in oakland

Movies	Find_movie
Restaurants	Buy_tickets
Sports	Find_restaurant
Weather	Book_table
Music	Find_lyrics

Deep neural networks can be directly applied to this standard classification problem

[Sarikaya et al., 2011; Tur et al., 2012; Ravuri and Stolcke, 2015; Lee and Dernoncourt, 2016; Khanpour et al., 2016]

Language Understanding as Slot Filling

Sequence/Slot Tagging

ATIS UTTERANCE EXAMPLE IOB REPRESENTATION

Sentence	<i>show</i>	<i>flights</i>	<i>from</i>	<i>Boston</i>	<i>To</i>	<i>New</i>	<i>York</i>	<i>today</i>
Slots/Concepts	O	O	O	B-dept	O	B-arr	I-arr	B-date
Named Entity	O	O	O	B-city	O	B-city	I-city	O
Intent	<i>Find Flight</i>							
Domain	<i>Airline Travel</i>							

- Variations of RNN architectures have been used: LSTM-based models, BiLSTMs, other variations... [Mesnil et al., 2015]
- More recently: (attention-based) encoder-decoder architectures instead of basic RNNs [Simmonet et al., 2015; Kurata et al., 2016]
- Multi-task learning formulation: sharing across domains to increase robustness [Jaech et al., 2016; Tafforeau et al., 2016]

A Note on Semantic Parsing

SLU and DST resemble the task of **semantic parsing**

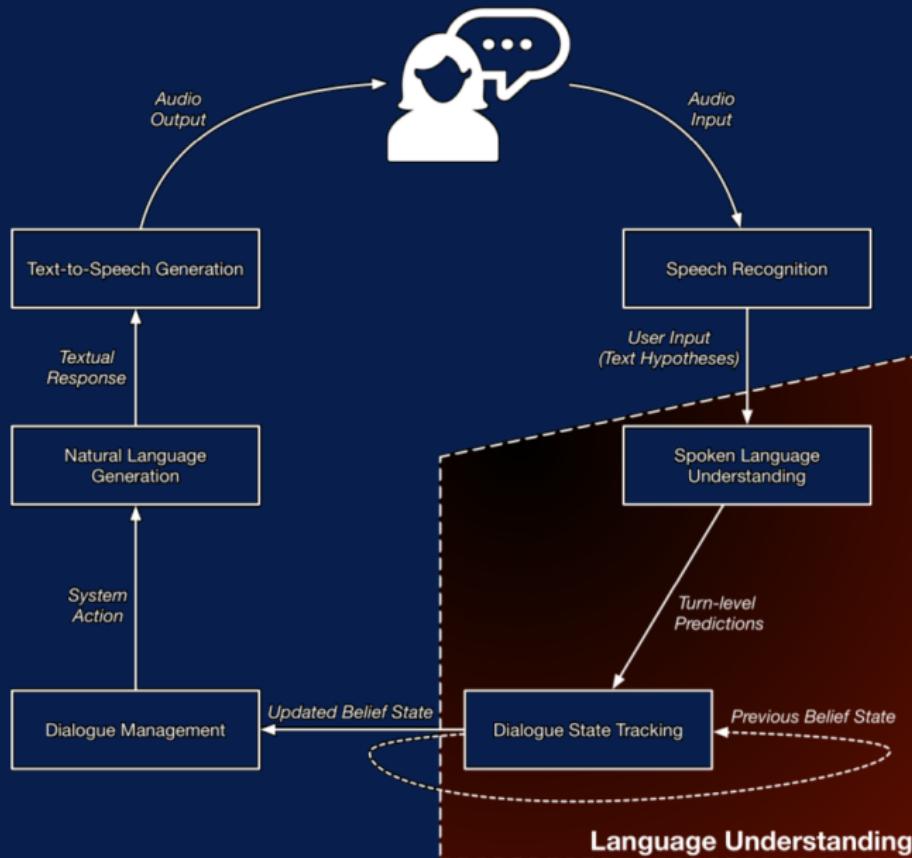
Converting natural language into computer-executable formal **meaning representations** for domain-specific applications

- The dialogue act formalism is considerably simpler
- Do we really need a full meaning representation of each sentence?

Dataset	Example
GEO	how many states border the state with the largest population? answer(A,count(B,(state(B),next_to(B,C),largest(D,(state(C),population(C,D))))),A))
JOBS	what jobs desire a degree but don't use c++? answer(A, (job(A), des_deg(A),+((language(A,C),const(C,'c++')))))
ATIS	what flights from tacoma to orlando on saturday (_lambda 0e(_and(_flight0) (_from 0tacoma :c i)(to0 orlando:_ci) (_day \$0 saturday:_da)))

[Kate et al., 2010; Liu and Lane, 2016; Hakkani-Tur et al., 2016, Padmakumar

Language Understanding



Dialogue State Tracking Challenge (DSTC)

Challenge	Type	Domain	Data Provider	Main Theme
DSTC1	Human-Machine	Bus Route	CMU	Evaluation Metrics
DSTC2	Human-Machine	Restaurant	Cambridge	User Goal Changes
DSTC3	Human-Machine	Tourist Info	Cambridge	Domain Adaptation
DSTC4	Human-Human	Tourist Info	I2R	Human Conversation
DSTC5	Human-Human	Tourist Info	I2R	Language Adaptation
DSTC6	Human-Human	Restaurant, Twitter	Various	End-to-End Modeling

It is now Dialogue System Technology Challenge!

Domain Ontology

Domain Ontologies for Task-Oriented Dialogue

Task-oriented systems' ontologies consist of a collection of slots $s \in S$ (i.e. *food*, *price*, etc.) and their slot values V_s (*cheap*, *expensive*, etc.).

Good morning, how can I help?

Hi. I'm looking for a Chinese restaurant.

inform (food = Chinese)

What area would you like?

How about something near Regent Street.

inform (area = Regent Street)
inform (food = Chinese)

Szechuan is the only restaurant which serves Chinese food near Regent Street.

What's the address please?

inform (area = Regent Street)
inform (food = Chinese)
request (address)

Szechuan can be found at 15 - 21 Ganton Street.

Awesome, thanks for your help, bye!

simple-act (goodbye)

Thank you, goodbye!

Domain Ontology

Dialogue State Tracking Challenge 2

The **belief state** is a probability distribution over the possible dialogue states defined by the **domain ontology**. The downstream **dialogue manager** component uses the distribution to decide on the next system action.

DSTC2 Ontology: three *Informable* slots...

Area: North, East, South, West, Centre + *dontcare*

Price: Cheap, Moderate, Expensive + *dontcare*

Food: Indian, Chinese, Thai, Japanese, Greek, French + 84 others

...and seven (turn-level) *Requestable* slots...

Food, Area, Price, Address, Phone Number, Postcode

Domain Ontology

A sample from the Cambridge Restaurants domain

INFORMABLE SLOTS: {

PRICE RANGE: [

- cheap,
- moderate,
- expensive

],

AREA: [

- centre,
- north,
- west,
- south,
- east

],

FOOD: [

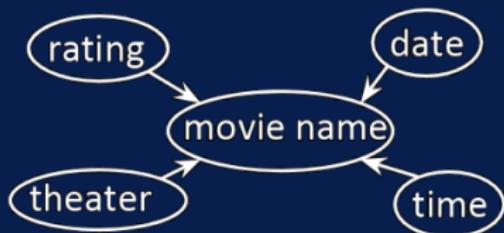
- Afghan, African, Afternoon Tea, Asian, Australian,
- Austrian, Barbeque, Basque, Belgian, Bistro, Brazilian,
- British, Cantonese, Caribbean, Catalan, Chinese,
- Christmas, Corsican, Creative, Crossover, Cuban,
- Danish, Dutch, English, Eritrean, French, Fusion ...

],

Domain Ontology and Knowledge Bases

Domain-specific table

- Target and attributes



Movie Name	Theater	Rating	Date	Time
Beauty and Beast	Taipei A1	8.5	2017/03/21	09:00
Beauty and Beast	Taipei A1	8.5	2017/03/21	09:25
Beauty and Beast	Taipei A1	8.5	2017/03/21	10:15
Beauty and Beast	Taipei A1	8.5	2017/03/21	10:40
Beauty and Beast	Taipei A1	8.5	2017/03/21	11:05

Dialogue State Tracking Challenge 2: Evaluation

We focus on two key evaluation metrics [Henderson et al., 2014]:

- **Goals** (joint goal accuracy): the proportion of dialogue turns where all the user's search goal constraints were correctly identified;
- **Requests**: similarly, the proportion of dialogue turns where user's requests for information were identified correctly.

Web-Style Ranking and SLU Combination

[Williams, 2014] uses web-style ranking (lambdaMART algorithm) to rank dialogue states, based on features from three different SLU engines. This was the top entry in the original DSTC2 challenge.

model	Goal		Method		Requested		Requested*	
	Acc.	L2	Acc.	L2	Acc.	L2	Acc.	L2
Best baseline	0.719	0.464	0.897	0.158	0.884	0.196	0.884	0.196
Best DSTC2 result from another team	0.768	0.346	0.940	0.095	0.978	0.035	0.978	0.035
SLU0+1, AB, model comb. (entry0)	0.775	0.758	0.944	0.092	0.954	0.073	0.977	0.037
SLU0+2, AB, model comb. (entry1)	0.784	0.735	0.947	0.087	0.957	0.068	0.980	0.034
SLU0+2, AB, maxent (entry3)	0.771	0.354	0.947	0.093	0.941	0.090	0.979	0.040

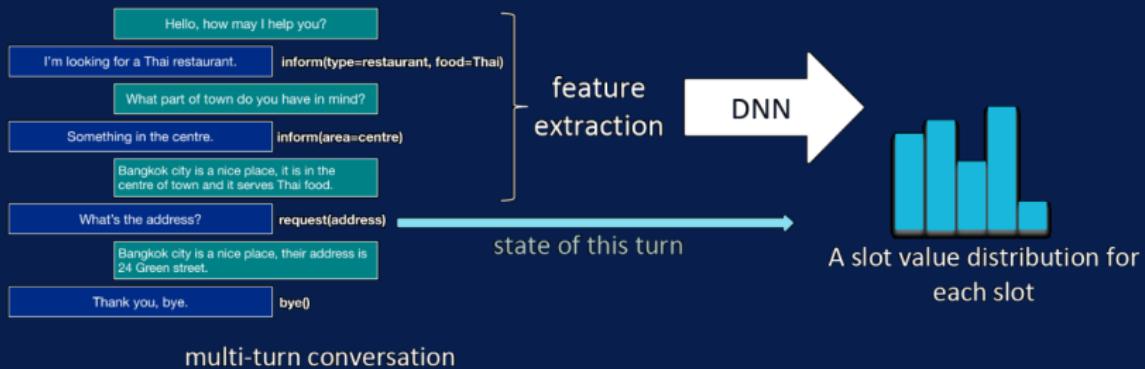
Language Understanding

Joint vs. Separate SLU?

Entry	Features		Joint Goals		Search Method		Requested		
	ASR	SLU	Acc.	L2	Acc.	L2	Acc.	L2	
1-best baseline ¹		✓	0.619	0.738	0.879	0.209	0.884	0.196	
focus baseline ¹		✓	0.719	0.464	0.867	0.210	0.879	0.206	
HWU baseline ²		✓	0.711	0.466	0.897	0.158	0.884	0.201	
team1 entry0		✓	0.601	0.648	0.904	0.155	0.960	0.073	
team3 entry0		✓	0.729	0.452	0.878	0.210	0.889	0.188	
team4 entry2		✓	0.742	0.387	0.922	0.124	0.957	0.069	
team6 entry2		✓	0.718	0.437	0.871	0.210	0.951	0.085	
team7 entry4		✓	0.735	0.433	0.910	0.140	0.946	0.089	
team8 entry1		✓	0.699	0.498	0.899	0.153	0.939	0.101	
team9 entry0		✓	0.499	0.760	0.857	0.229	0.905	0.149	
team2 entry2		✓	0.668	0.505	0.944	0.095	0.972	0.043	
team4 entry0		✓	0.768	0.346	0.940	0.095	0.978	0.035	
team7 entry0		✓	0.750	0.416	0.936	0.105	0.970	0.056	
team2 entry1		✓	✓	0.784	0.735	0.947	0.087	0.957	0.068
team2 entry3		✓	✓	0.771	0.354	0.947	0.087	0.941	0.090
team5 entry4		✓	✓	0.695	0.610	0.927	0.147	0.974	0.053

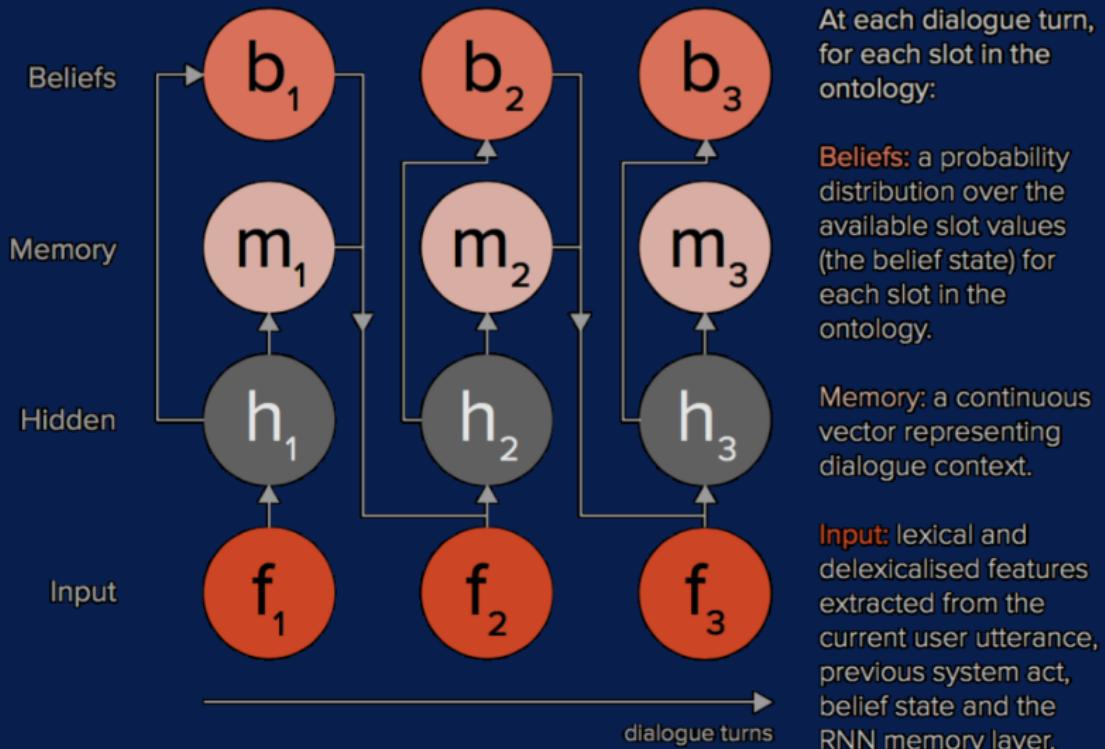
Language Understanding

Joint vs. Separate SLU?



Word-Based DST Using RNNs

[Henderson et al., 2014]



Delexicalisation-Based DST

Delexicalised Features

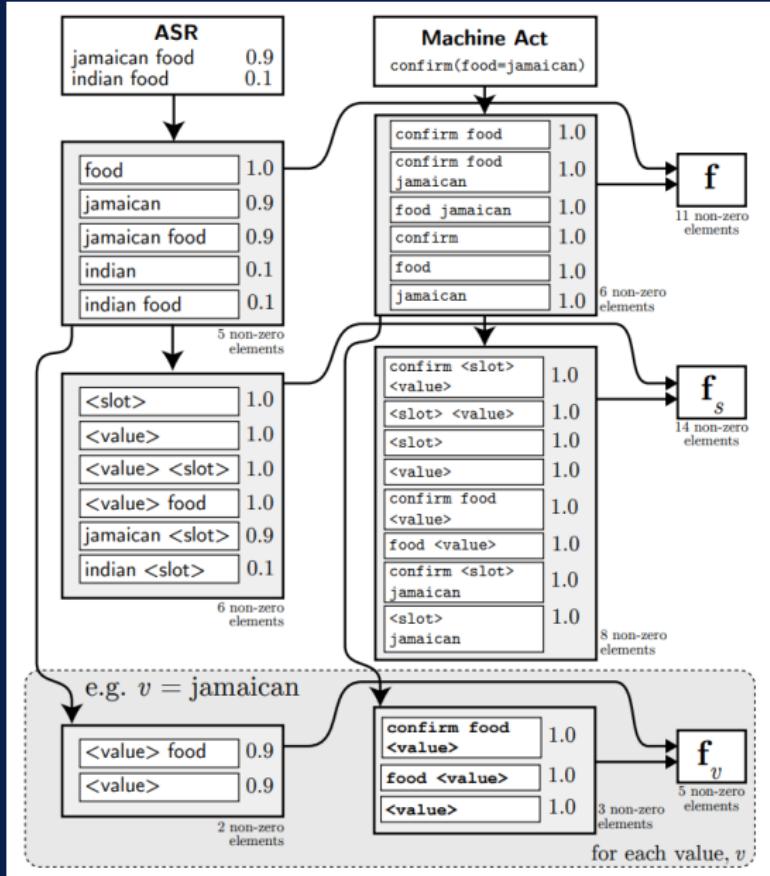
Delexicalised features: all occurrences of slot names and/or slot values in an utterance are replaced with **generic tags**

I want Chinese food
I want cheap price range] I want VALUE SLOT

The use of delexicalised n -gram features facilitates:

- Faster learning by facilitating transfer learning across slot values
- Generalisation to unseen slot values (or even entirely new slots)
- Bootstrapping dialogue systems to new domains with limited data

Delexicalisation-Based DST



Delexicalisation-Based DST

Towards Multi-Domain DST

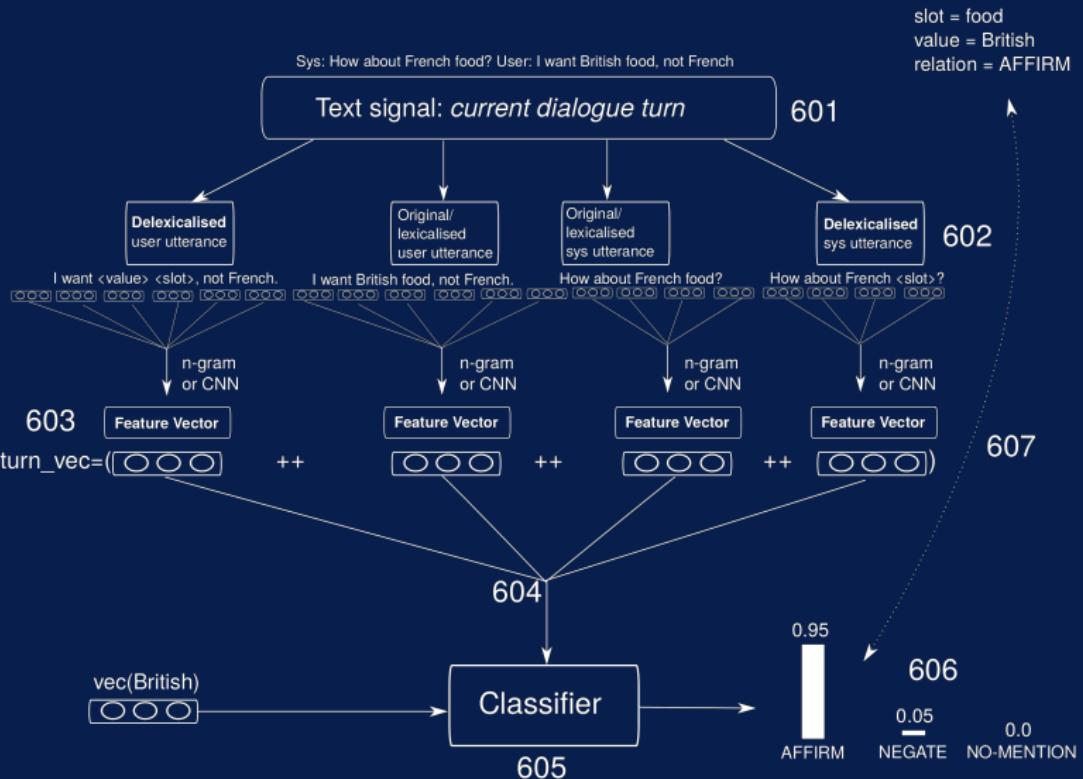
Delexicalised features allow transfer learning between slots

Delexicalisation facilitates multi-domain training

- RNN-based DST with shared initialisation + slot-specialised training [Mrkšić et al., 2015]



Delexicalisation-Based DST



Delexicalisation-Based Models

Shortcomings

Delexicalised Features = Exact Matching

Given an arbitrary domain ontology, delexicalisation-based models provide data-efficient language understanding - as long as users use only the actual ontology values to express their search constraints!

User: I'm looking for an affordable restaurant
inform(price=cheap)

System: How about Thai food?

User: Yes please, in central Cambridge
inform(price=cheap, food=Thai, area=centre)

System: The House serves cheap Thai food

User: Where is it?

inform(price=cheap, food=Thai, area=centre);
request(address)

System: The House is at 106 Regent Street

Traditional ‘Solution’: Semantic Dictionaries

Delexicalised Features = Exact Matching

Delexicalisation-based models allow fast deployment to new dialogue domains, but introduce a complete dependency on **semantic dictionaries**.

Food=Cheap: [affordable, budget, low-cost, low-priced, inexpensive, cheaper, economic, ...]

Rating=High: [best, high-rated, highly rated, top-rated, cool, chic, popular, trendy, ...]

Area=Centre: [center, downtown, central, city centre, midtown, town centre, ...]

The Neural Belief Tracker (NBT)

Semantic Dictionaries Re-Introduce the SLU module

Semantic dictionaries can be hand-crafted or learned - but only for simple toy domains such as DSTC2. Moreover, the Amazon Mechanical Turk data collection framework forces the users to use very simple (and unnatural) language, understating the challenge of dealing with linguistic variation.

The Neural Belief Tracker (NBT)

Semantic Dictionaries Re-Introduce the SLU module

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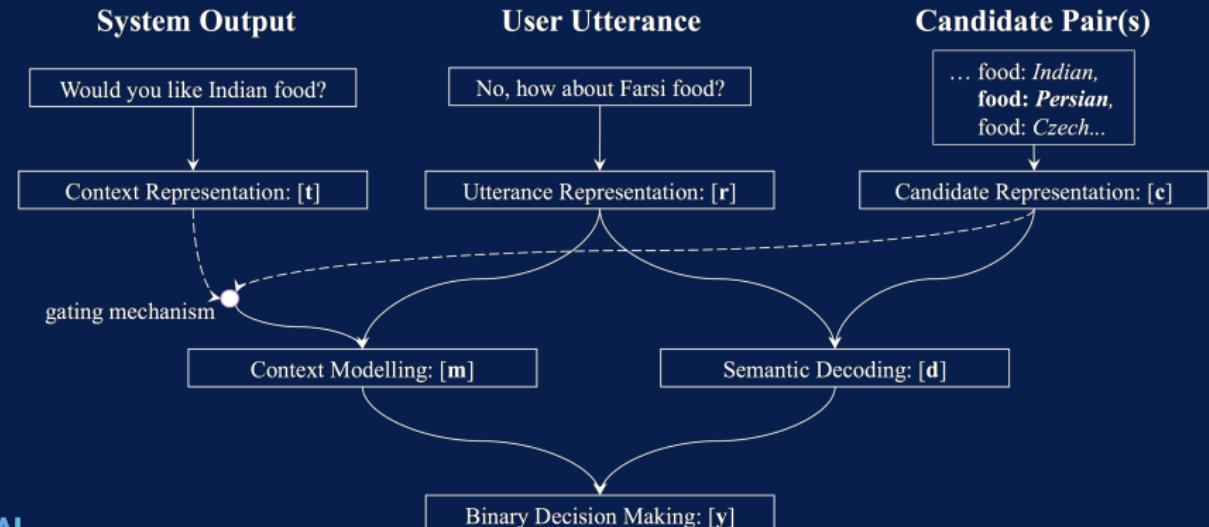
The **Neural Belief Tracker** is a statistical DST model/framework which aims to satisfy the following design goals:

- End-to-end learnable (no SLU modules or semantic dictionaries).
- Generalisation to unseen slot values.
- Capability of leveraging the semantic content of pre-trained word vector spaces without human supervision.

The Neural Belief Tracker (NBT)

Representation Learning + Label Embedding + Separate Binary Decisions

To overcome data sparsity, NBT models use *label embedding* to decompose multi-class classification into many binary ones.

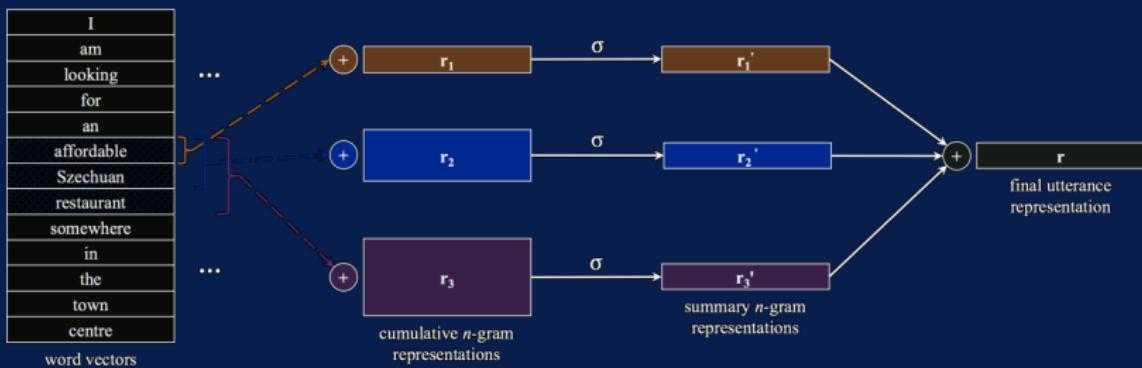


Representation Learning: NBT-DNN

Let u represent a user utterance consisting of k_u words u_1, u_2, \dots, u_{k_u} .

Each word has an associated **fixed** word vector u_1, \dots, u_{k_u}

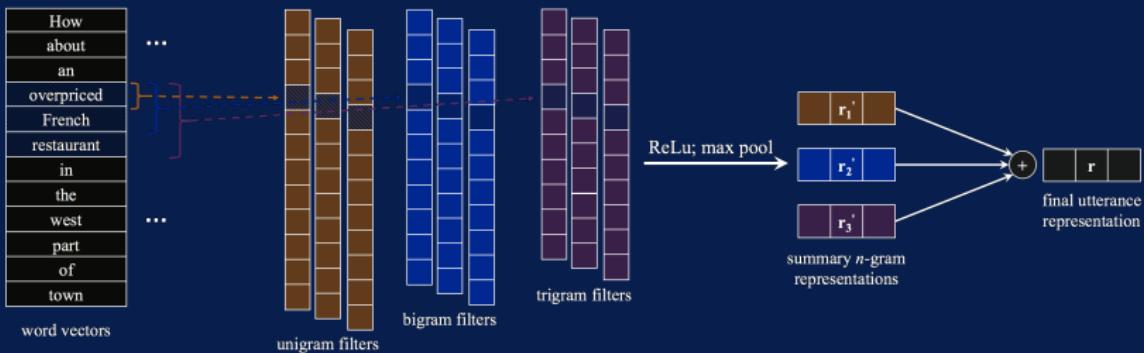
$$\mathbf{v}_i^n = \mathbf{u}_i \oplus \dots \oplus \mathbf{u}_{i+n-1}$$



$$\mathbf{r}_n = \sum_{i=1}^{k_u-n+1} \mathbf{v}_i^n; \quad \mathbf{r}'_n = \sigma(W_n^s \mathbf{r}_n + b_n^s); \quad \mathbf{r} = \mathbf{r}'_1 + \mathbf{r}'_2 + \mathbf{r}'_3$$

Representation Learning: NBT-CNN

Let $F_n^s \in R^{L \times nD}$ denote the collection of filters for each value of n , where $D = 300$ is the word vector dimensionality. If \mathbf{v}_i^n denotes the concatenation of n **fixed** word vectors starting at index i , let $\mathbf{m}_n = [\mathbf{v}_1^n; \mathbf{v}_2^n; \dots; \mathbf{v}_{k_u-n+1}^n]$ be the list of n -grams that convolutional filters of length n run over.

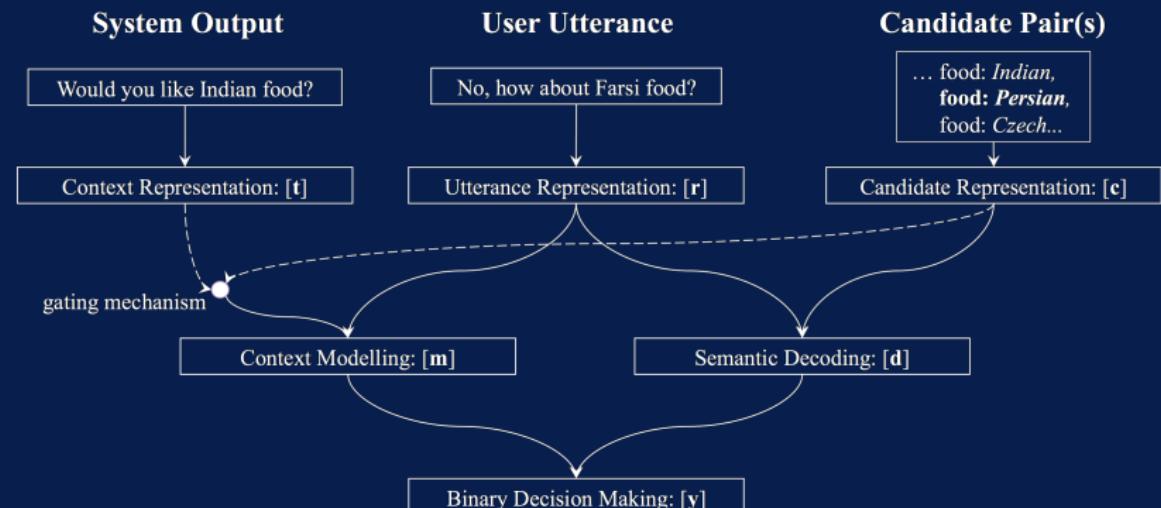


$$R_n = F_n^s \mathbf{m}_n \quad \mathbf{r}'_n = \text{maxpool}(\text{ReLU}(R_n + b_n^s)) \quad \mathbf{r} = \mathbf{r}'_1 + \mathbf{r}'_2 + \mathbf{r}'_3$$

How do we use the utterance representation?

Multi-class classification problem as many binary ones

We iterate over all slot-value pairs for the given slot, deciding whether each of them has been expressed in the given utterance.



Semantic Decoding

Let the vector space representations of a candidate pair's slot name and value be given by \mathbf{c}_s and \mathbf{c}_v . The NBT framework learns to map these into a *candidate pair* representation \mathbf{c} (of the same dimensionality as \mathbf{r}):

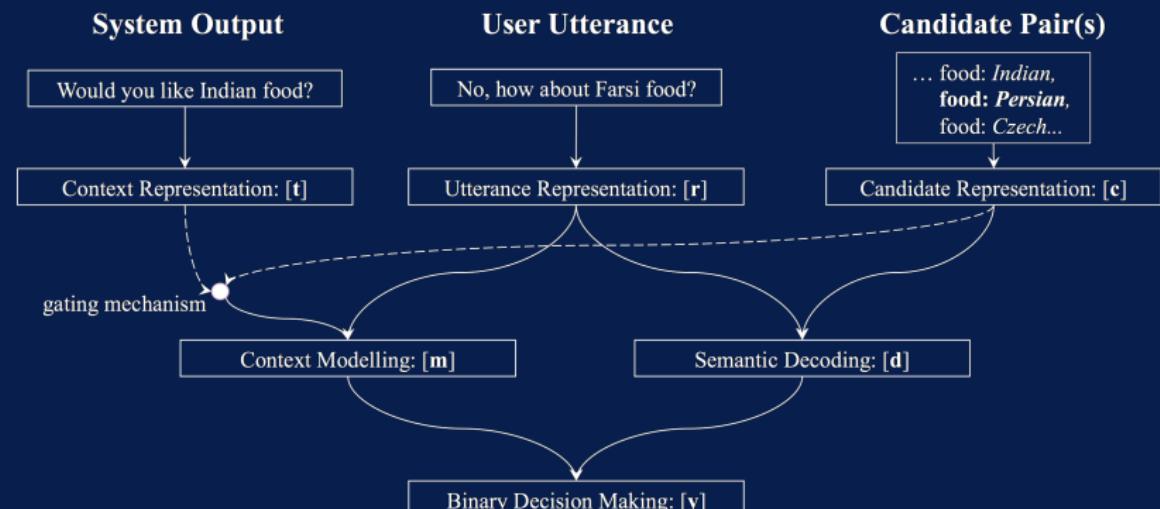
$$\begin{aligned}\mathbf{c} &= \sigma(W_c^s(\mathbf{c}_s + \mathbf{c}_v) + b_c^s) \\ \mathbf{d} &= \mathbf{r} \otimes \mathbf{c}\end{aligned}$$

where \otimes denotes *element-wise* vector multiplication. This vector is then passed to the downstream network, which combines it with the surrounding dialogue context to make a decision regarding the current candidate pair.

How do we take the system acts into account?

Gating Mechanisms for Modelling Context

Gating mechanisms activate the part of the network architecture which models context (limited to previous system acts).



Context Modelling

All previous system/user utterances are important, but the most relevant one is the last system utterance, in which the dialogue system could have performed (among others) one of the following two *system acts*:

- System Request: '*What price range would you like?*'
- System Confirm: '*How about Turkish food?*'

Context Modelling

Let t_q and (t_s, t_v) be the word vector representations of the arguments for the system request and confirm acts (zero vectors if none). The model computes the following measures of similarity between the system acts, candidate pair (c_s, c_v) and utterance representation r :

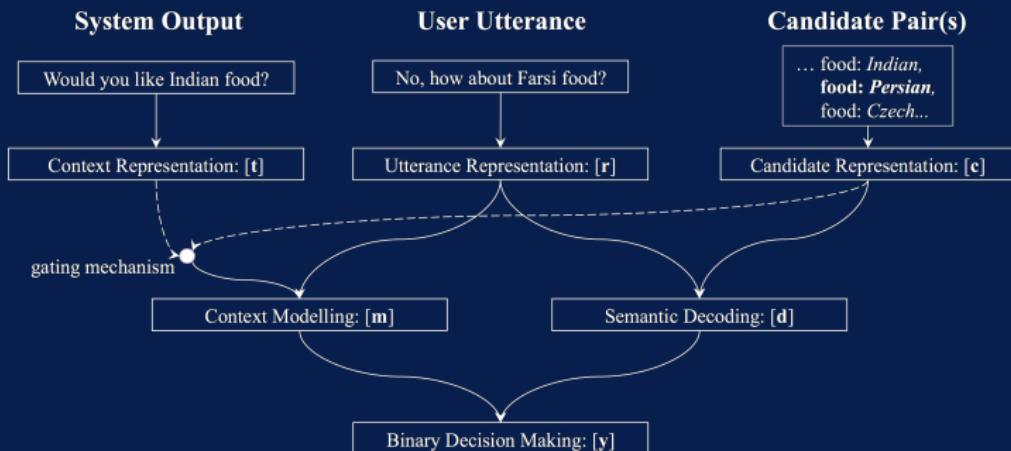
$$\begin{aligned} d_r &= (c_s \cdot t_q)r \\ d_c &= (c_s \cdot t_s)(c_v \cdot t_v)r \\ m &= d_r \oplus d_c \end{aligned}$$

where \cdot denotes dot product and \oplus denotes vector concatenation. The computed similarity terms act as gating mechanisms which only pass the utterance representation through if the system asked about the current candidate slot or slot-value pair.

What is the (final) NBT model output?

The NBT makes binary predictions for each slot value

Given a slot s with a set of values $v \in V_s$, the NBT models estimate $\mathbb{P}(s, v | u, sys)$, i.e. the probability that the utterance u which follows the system acts sys expresses each of the slot values.



Belief State Updates

Turn-level belief state estimate is then combined with the (cumulative) belief state up to time $(t - 1)$ to get the updated belief state estimate:

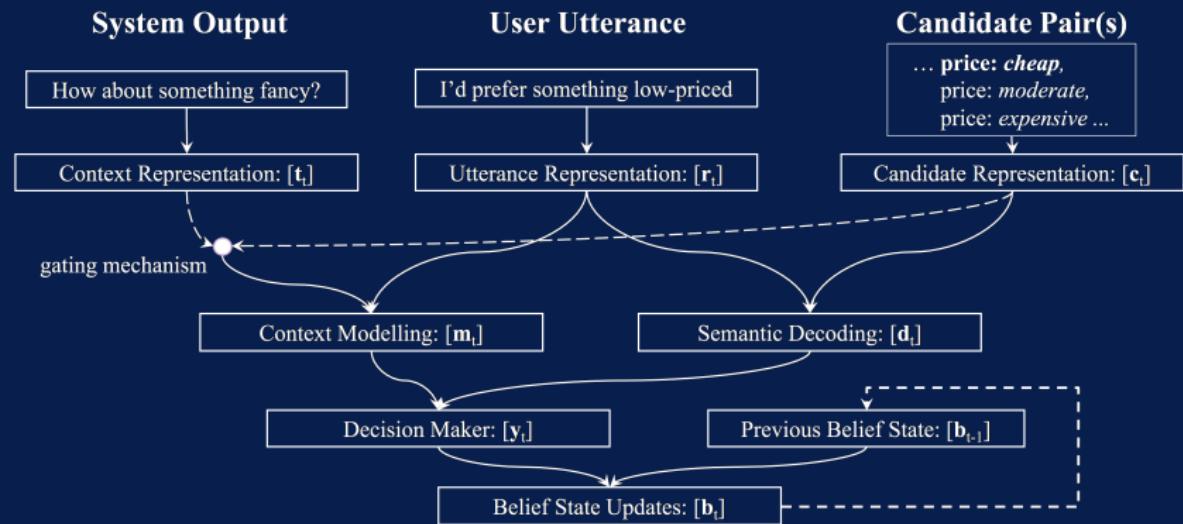
$$\begin{aligned}\mathbb{P}(s, v \mid h^{1:t}, sys^{1:t-1}) &= \lambda \mathbb{P}(s, v \mid h^t, sys^{t-1}) \\ &+ (1 - \lambda) \mathbb{P}(s, v \mid h^{1:t-1}, sys^{1:t-2})\end{aligned}$$

where λ is the coefficient which determines the relative weight of the turn-level and previous turns' belief state estimates. $\lambda = 0.55$ achieved the best performance on the DSTC 2 development set.

The Neural Belief Tracker (NBT) v2

Fully Statistical Belief State Update

Removing the last rule-based component of the NBT framework



NBTv2: Learned Belief State Update Mechanisms

$$\mathbf{b}_s^t = \phi(\mathbf{y}_s^t, \mathbf{b}_s^{t-1})$$

1. One-Step Markovian Update

$$\mathbf{b}_s^t = \text{softmax} \left(W_{curr} \mathbf{y}_s^t + W_{past} \mathbf{b}_s^{t-1} \right) \quad (1)$$

This variant violates the NBT design paradigm: each row of the two matrices learns to operate over *specific* slot values. This means the model will not learn to predict or maintain slot values as part of the belief state if it has not encountered these values during training.

NBTv2: Learned Belief State Update Mechanisms

$$\mathbf{b}_s^t = \phi(\mathbf{y}_s^t, \mathbf{b}_s^{t-1})$$

2. Constrained Markovian Update

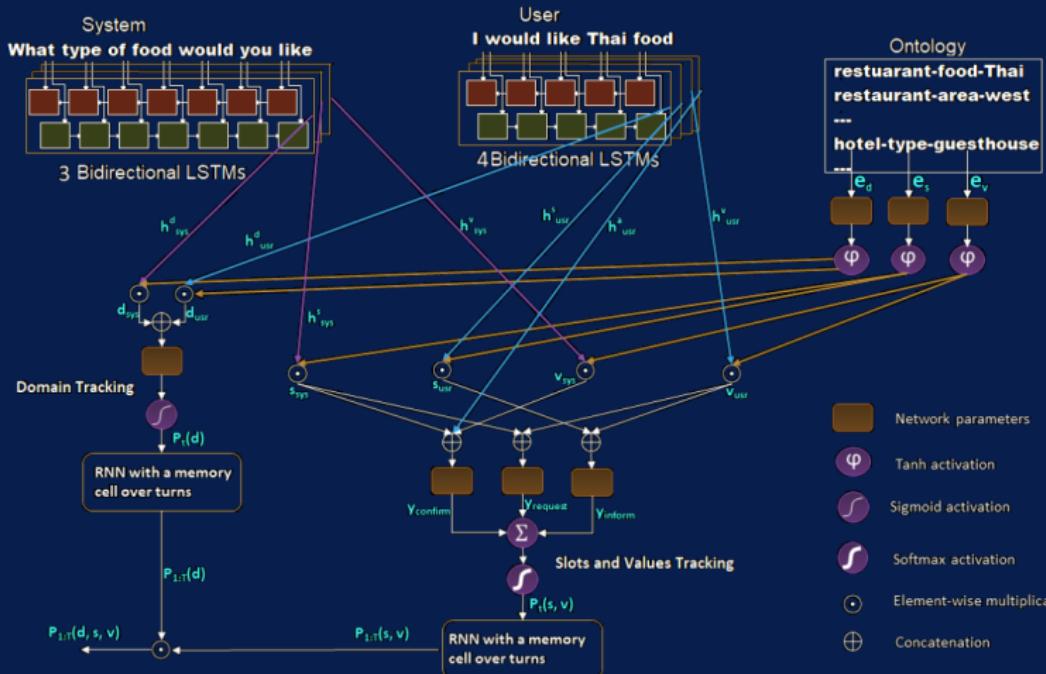
$$W_{curr,i,j} = \begin{cases} a_{curr}, & \text{if } i = j \\ b_{curr}, & \text{otherwise} \end{cases}$$

$$W_{past,i,j} = \begin{cases} a_{past}, & \text{if } i = j \\ b_{past}, & \text{otherwise} \end{cases}$$

This variant constrains the two matrices so that each of them contains only two different scalar values. The parameters acting over all slot values are in this way tied, ensuring that the model can deal with slot values unseen in training.

Belief Tracking across Multiple Domains

[Ramadan et al., ACL 2018]

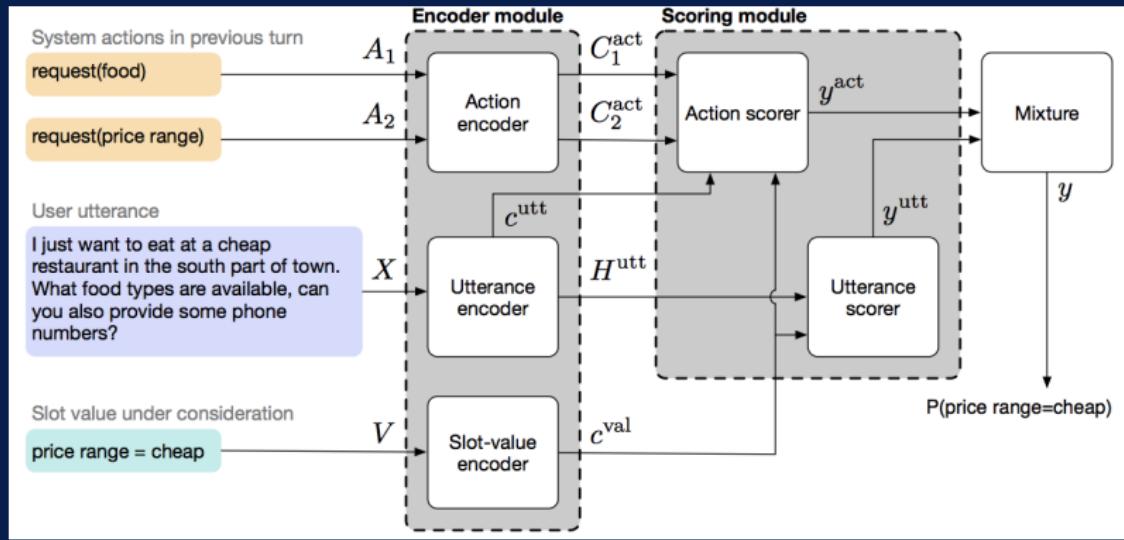


Based on semantic similarity between dialogue utterances and ontology terms;

Global-Locally Self-Attentive DST (GLAD)

[Zhong et al., ACL 2018]

The same idea as NBT, but a more advanced encoder



Global modules to share parameters between estimators for each slot and **local** modules to learn slot-specific feature representations.

Other Improvements to the Basic NBT Framework

Yet another improved encoder; works with dynamic values

[Ren et al., EMNLP 2018]

Cross-lingual extension of the NBT framework (transfer settings)

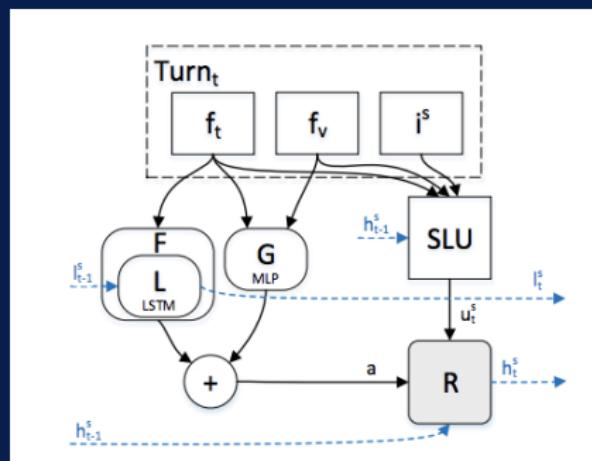
[Chen et al., EMNLP 2018]

DST as Machine Reading / Reasoning

[Perez and Liu, 2017] use Memory Networks and pose DST as a machine reading / multi-hop reasoning problem.

Locutor	Utterance	Hop 1	Hop 2	Hop 3	Hop 4	Hop 5
Cust	Im looking for a cheap restaurant that serves chinese food	0.00	0.18	0.11	0.04	0.00
Agent	What part of town do you have in mind	0.33	0.30	0.00	0.00	0.00
Cust	I dont care	0.00	0.00	0.17	0.37	1.00
Agent	Rice house serves chinese food in the cheap price range	0.01	0.00	0.00	0.00	0.00
Cust	What is the address and telephone number	0.58	0.09	0.01	0.00	0.00
Agent	Sure rice house is on mill road city centre	0.03	0.00	0.00	0.00	0.00
Cust	Phone number	0.00	0.00	0.00	0.00	0.00
Agent	The phone number of rice house is 765-239-09	0.02	0.01	0.00	0.00	0.00
Cust	Thank you good bye	0.02	0.42	0.71	0.59	0.00
What is the area ? Answer: dontcare						

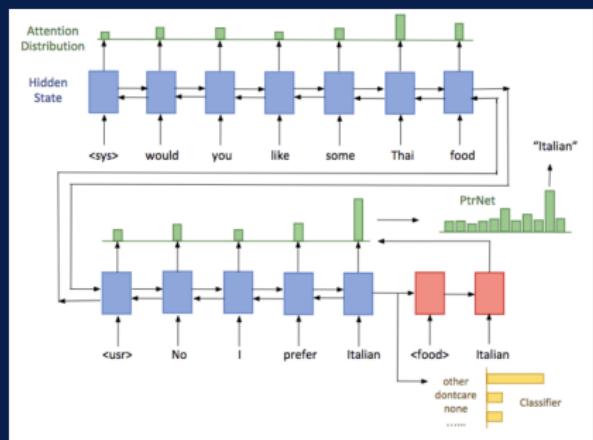
Hybrid Dialog State Tracker with ASR Features



[Vodolán et al., 2017] propose a *Hybrid Dialog State Tracker*, achieving strong performance for DSTC2 (0.796).

Their model uses a separate (learned) SLU decoder coupled with a rule-based system to achieve the best DSTC2 performance to date.

An End-to-end Approach for Handling Unknown Slot Values in Dialogue State Tracking



[Xu and Hu, 2017] use *Pointer Networks* to address the problem of dealing with *unknown*, rather than *unseen* values.

This is an important direction for future work, as most presented models rely on a canonical representation of the domain ontology that is *predefined* by the dialogue system designers.

Are Word Embeddings Useful for NLU?

Input Word Vectors Matter

Semantic Specialisation

It is essential that deployed word vectors are specialized for true semantic similarity [Mrkšić et al.; NAACL 2016, TACL 2017]

User: I'm looking for a cheaper restaurant
inform(price=expensive)

System: What kind of food?

User: English, in eastern Cambridge
inform(price=expensive, food=Spanish, area=east)

System: The Green Man is the best choice

User: Where is it?

inform(price=expensive, food=Spanish, area=east);
request(address)

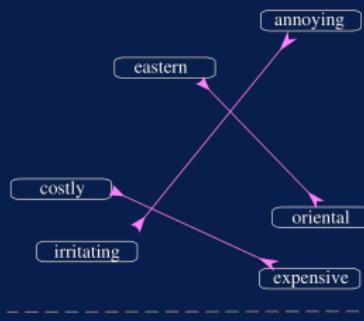
System: The Green Man is at 59 High St, Grantchester

Input Word Vectors Matter

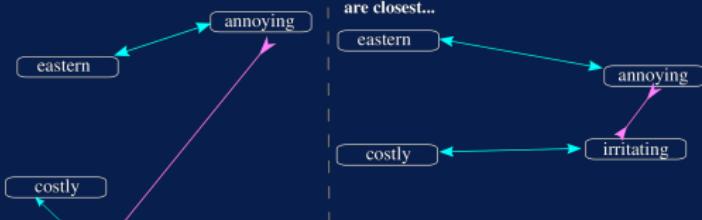
Semantic Specialisation

Take a mini-batch of ATTRACT and REPEL pairs...

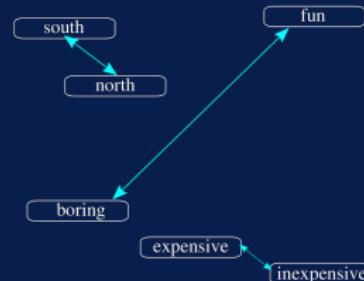
ATTRACT



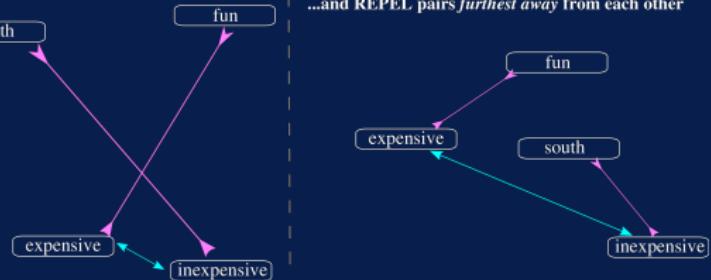
For each pair, find two *pseudo-negative examples*... ...and fine-tune the vectors so that ATTRACT pairs are closest...



REPEL



...and REPEL pairs furthest away from each other



Semantic Specialisation

Semantically-Specialising Word Vector Spaces

Injecting semantic constraints (such as synonymy and antonymy) into pre-trained word vectors can mitigate some of the negative aspects of **the distributional hypothesis**.

Word	east	expensive	British
Before	west	pricey	American
	north	cheaper	Australian
	south	costly	Britain
	southeast	overpriced	European
	northeast	inexpensive	England
After	eastward	costly	Brits
	eastern	pricy	London
	easterly	overpriced	BBC
	-	pricey	UK
	-	afford	Britain

Table : Nearest neighbours before and after semantic specialisation

The Importance of Semantic Specialisation

Three different word vector collections: **1)** 'random' word vectors initialised using the XAVIER initialisation; **2)** distributional GloVe vectors; and **3)** *semantically specialised* Paragraph-SL999 vectors.

Word Vectors	DSTC2		WOZ 2.0	
	Goals	Requests	Goals	Requests
xavier	64.2	81.2	81.2	90.7
GloVe	69.0*	96.4*	80.1	91.4
Paragraph-SL999	73.4*	96.5*	84.2*	91.6

(Full Vocabulary) Post-Specialisation

Post-processors such as Attract-Repel fine-tune only **seen** words

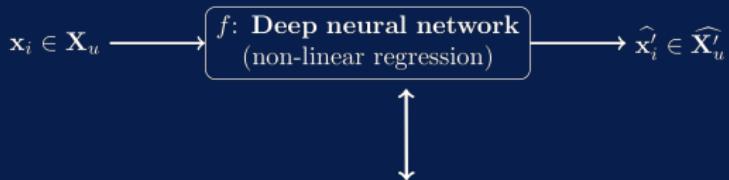
We want to leverage useful external knowledge also for **unseen** words

The main goal: **specialising the full vocabulary** from a distributional space

Post-Specialisation

Proof-of-concept model: (Vulić et al., NAACL 2018)

A more sophisticated model based on adversarial training: (Ponti, Vulić et al., EMNLP 2018)



Linguistic Constraints

- $(x_1 \in X_s, y_1 \in X_s)$
 - $(x_1 \in X_s, y_2 \in X_s)$
 - $(x_2 \in X_s, y_3 \in X_s)$
- ...

Training Pairs: Seen

- $(x_1 \in X_s, x'_1 \in X'_s)$
 - $(x_2 \in X_s, x'_2 \in X'_s)$
 - $(x_3 \in X_s, x'_3 \in X'_s)$
- ...

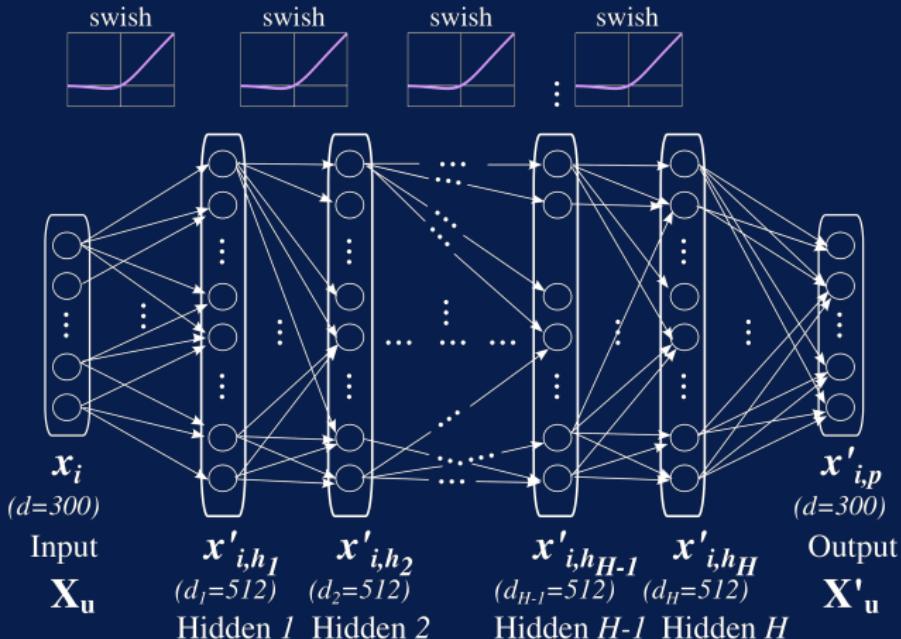
$X_d = X_s \cup X_u$ ATTRACT-REPEL
(distributional)

$X'_s \cup X_u$ (specialised: seen)

$X_f = X'_s \cup \widehat{X}'_u$ (specialised final: all)

(Post-)Specialisation

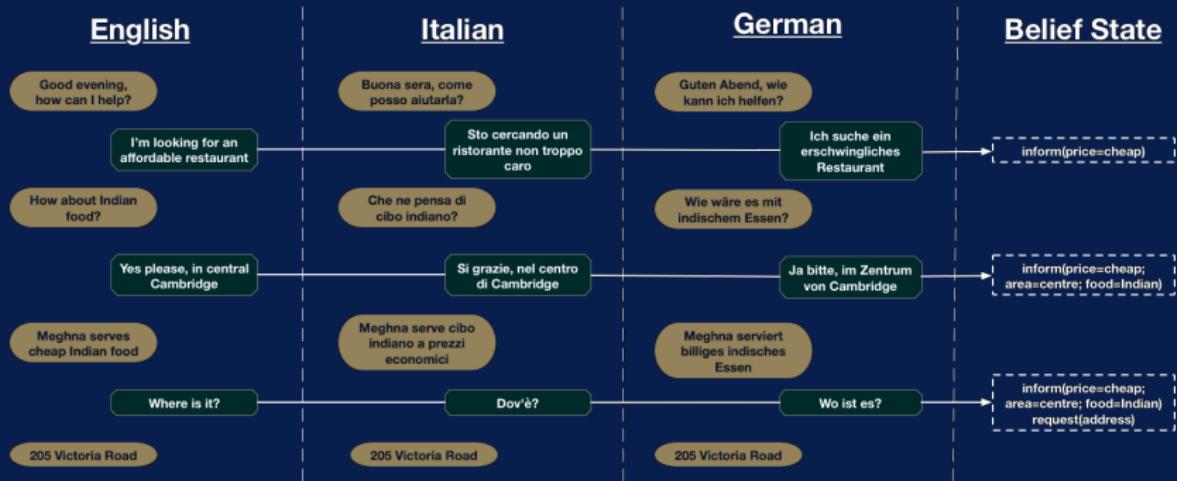
Proof-of-concept work: (Vulić et al., NAACL 2018)



Specialising **the full vocabulary** yields additional gains

Towards Multilingual DST

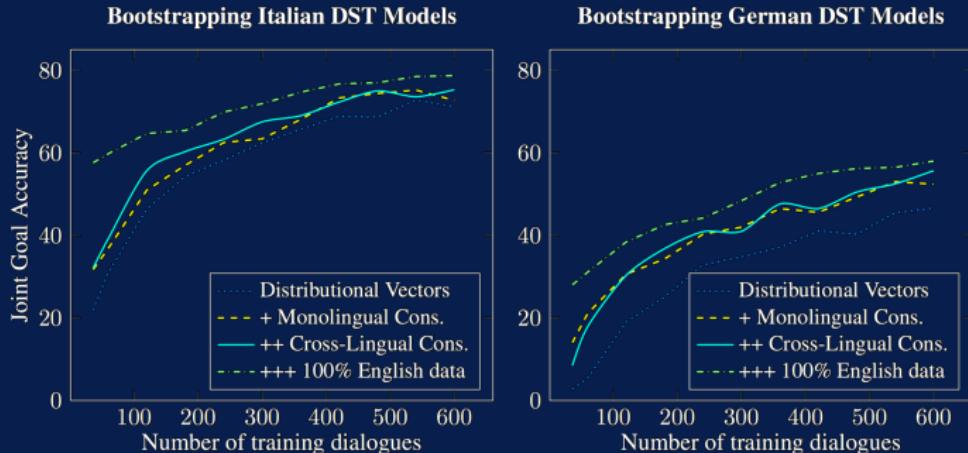
We're still (too) obsessed with English!



Bootstrapping DST for Resource-Poor Languages

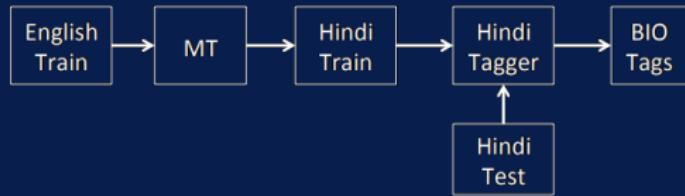
Ontology Grounding: Multilingual DST Models

The concepts expressed in the dialogue domain ontology are language-agnostic: 'labels' persist across languages. Given training data for two (or more) languages, and a cross-lingual vector space of high quality, we can train a multilingual DST model. [Mrkšić, Vulić et al., 2017]

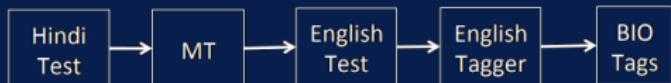


Bootstrapping SLU for Resource-Poor Languages

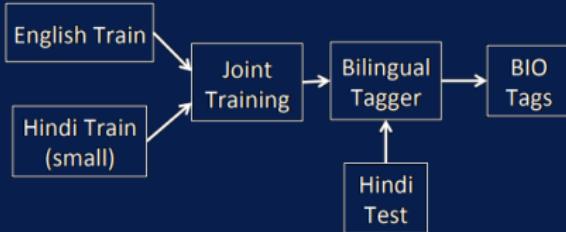
One example: [Upadhyay et al., ASRU 2018]



(a) Test on Source



(b) Train on Target



(c) Our Approach

Bootstrapping SLU for Resource-Poor Languages

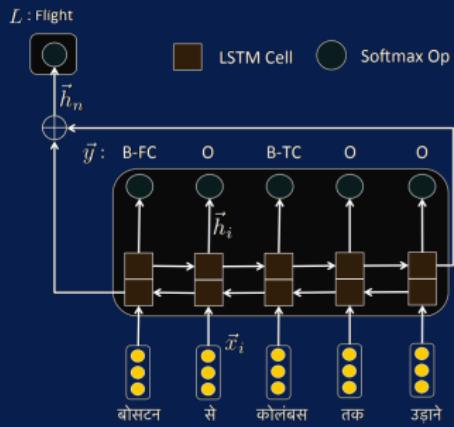


Fig. 3: Naive Model: Only target language examples are used during training. **Zero-Shot SLU:** The naive model is pre-trained on English, with fixed word embeddings from the shared vector space, and then tested directly on Hindi. Parameters enclosed in the grey box are pre-trained on English.

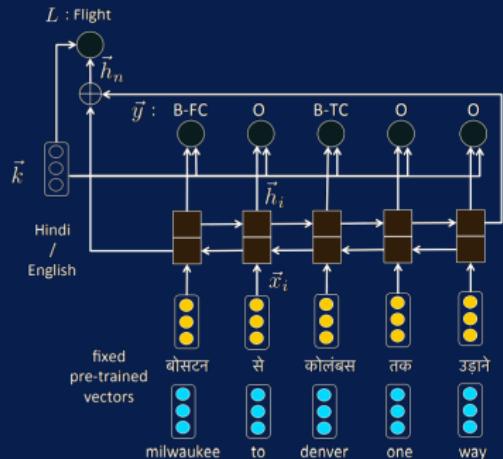
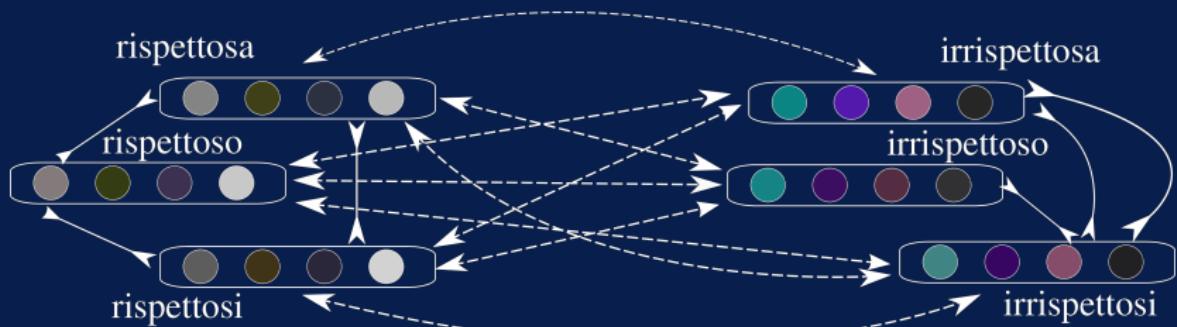


Fig. 4: The Bilingual Training Setup.

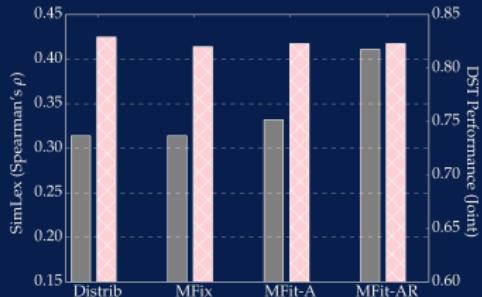
DST Beyond English: Additional Challenges

Using Different Sources of Supervision

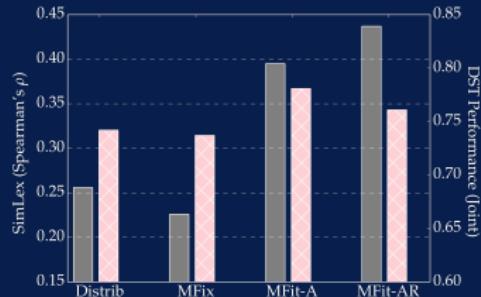
Morphological phenomena provide an inexpensive source of supervision. Consider both *inflectional* and *derivational* forms.



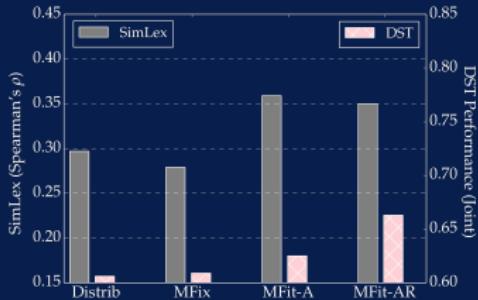
DST Beyond English with Morph-fitting



(a) English



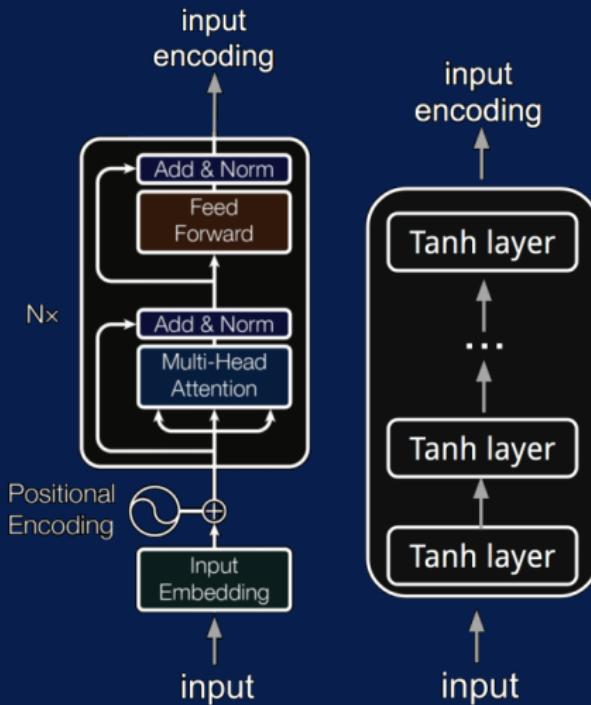
(b) Italian



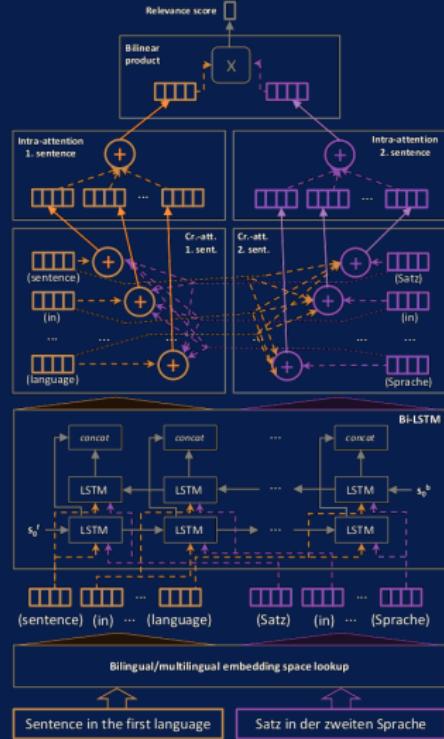
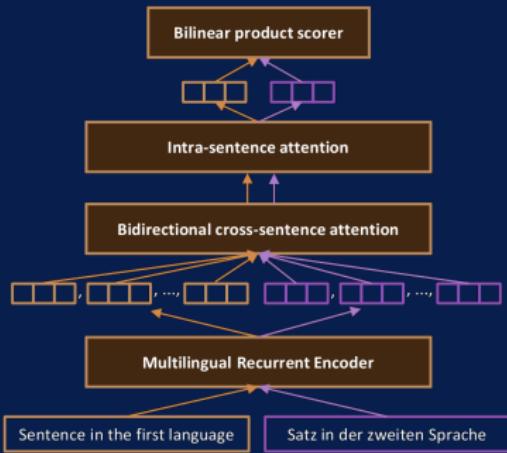
(c) German

NLU and Representation Learning

Plenty of very recent NLU research revolves around representations of our sentences/utterances → summary n -grams vs. more sophisticated architectures?



NLU and Representation Learning

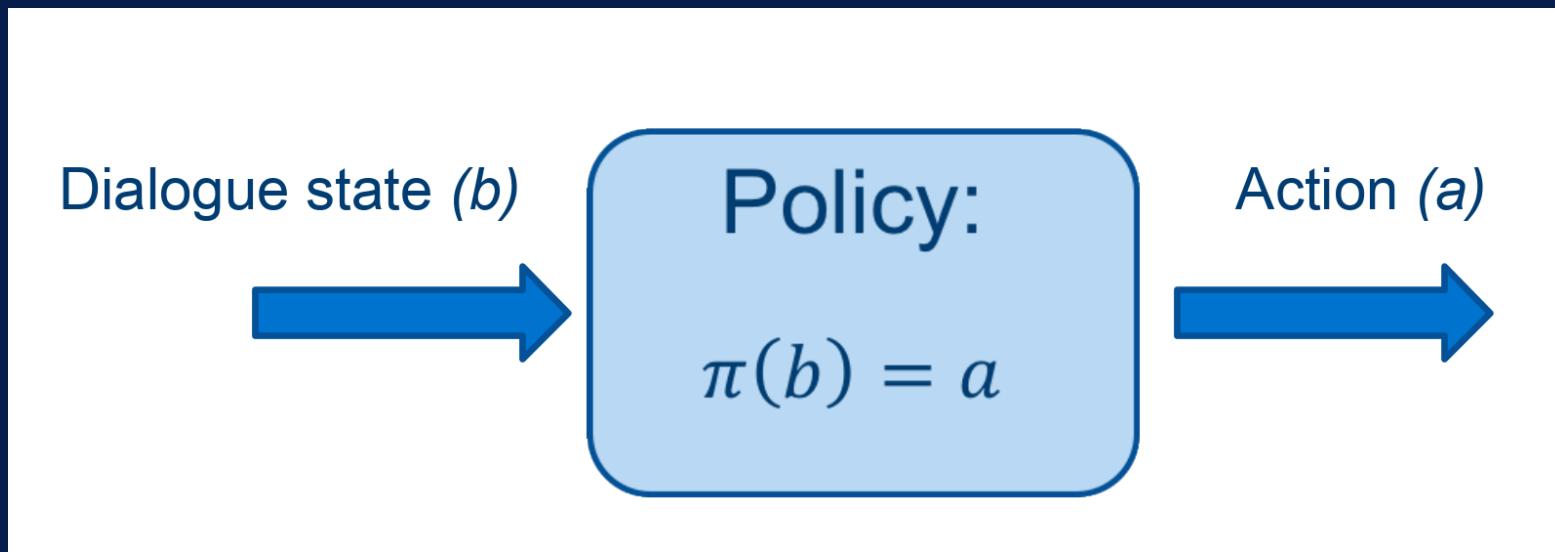


Linking sentences
cross-lingually?

Dialogue Management (DM)

What is dialogue management?

Control/Planning problem



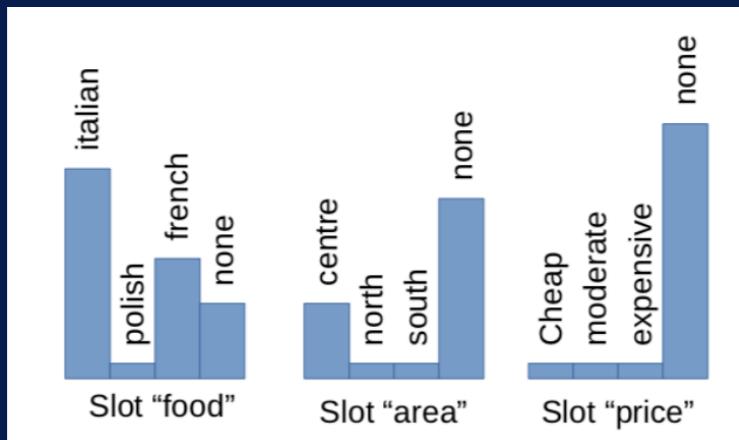
Decision making: Given a dialogue state b ,
take an (optimal) action a

dialogue state (input space)

- Dialogue state: set of features that capture all the dialogue history up to the current point in the dialogue.
- Dialogue state space: Set of all dialogue states (Set of states that model every possible different dialogue situation)
- Hand designed, different for each dialogue task
- Discrete / continuous
- Tradeoff between expressivity / learning complexity

Dialogue state example

Partially observable state



Fully observable state

- System actions taken by the DM
- Number of matching restaurants in your DB
- Booking availability for those restaurants

Usually a very heterogeneous input space

System actions (output space)

- Set of actions (outputs) the dialogue manager can take each turn in order to guide the dialogue towards its goal
- NLG (intractable for large systems)
 - Dialogue acts (high level representation of natural language)
 - API calls / third party actions

System Action example

- Request(Date, Time) -> *What date and time would you like to book?*
- Book(Date, Time, People) -> *API call to the restaurant booking server to book the table requested by the user*

Evaluation metrics

- **Chose optimal action with respect to what?**
- Theoretical answer: The (long term) user satisfaction
 - Task oriented dialogue systems: Fulfil the user goal in the less possible time
- Reality: We will come back to that later...

Dialogue Management Approaches

Rule-Based:

- Huge hand-crafting effort
- Non-adaptable and non-scalable
- But this is what works right now

Supervised:

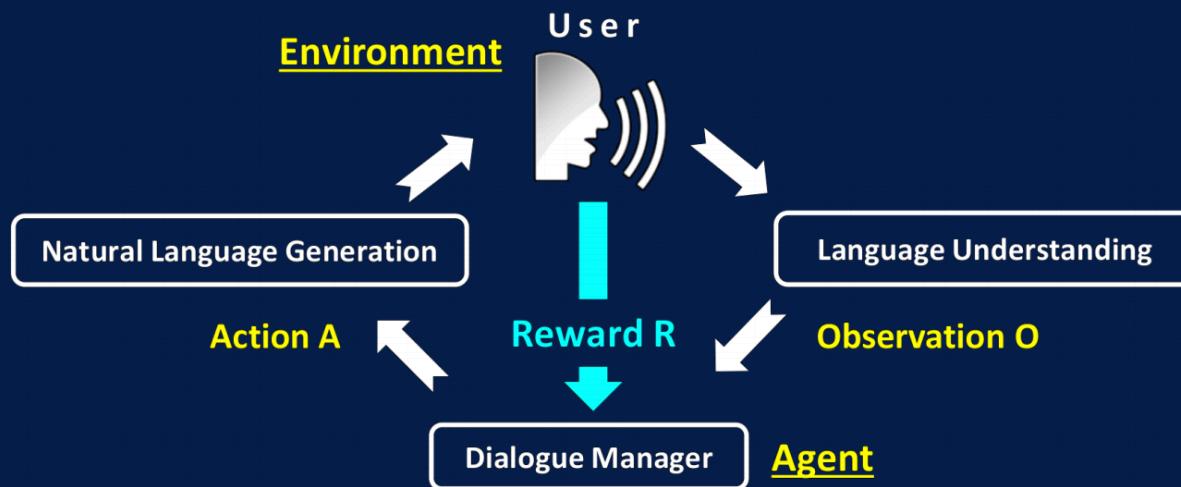
- Learn to “mimic” the answers of a corpus
- Assumes optimal human behaviour
- Does not do long-term planning

Reinforcement Learning (RL)

Reinforcement Learning

RL is a general-purpose framework for **decision making**

- RL concerns an **agent** with the capacity to **act**
- Each **action** a_0 influences the observations obtained from the **environment**
- The agent updates its internal **state** s_0 based on these **observations**
- Success is measured by a **reward** signal
- Goal: select actions to maximize total reward $R(s_0) + \gamma R(s_1) + \dots$



Reinforcement vs Supervised Learning

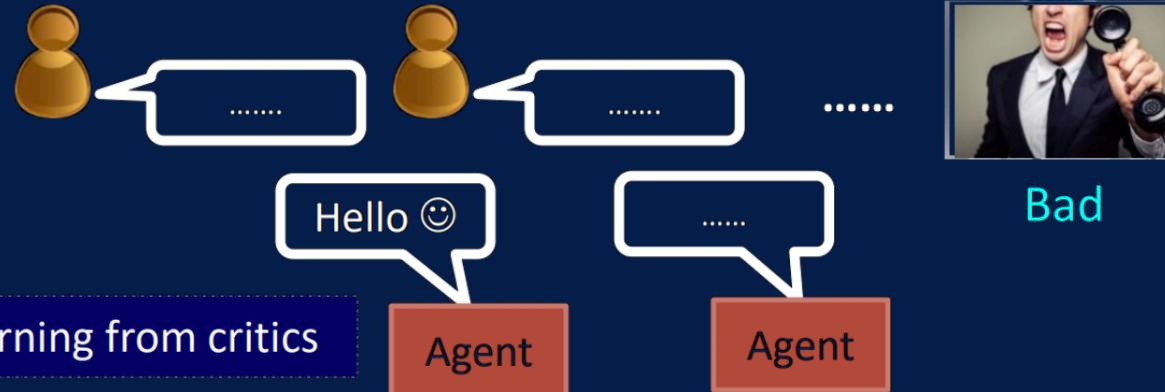
Supervised

Learning from teacher



Reinforcement

Learning from critics



RL-based dialogue manager

- Markov Decision Process (MDP) composed by
 - A set of dialogue states B
 - A set of system actions A
 - A reward function $R(b, a)$ where $b \in B$ and $a \in A$

So what is the reward?

In theory: **user satisfaction**

In reality: how do we **measure the satisfaction?**

- Ask the user for feedback after each dialogue → Very inefficient/annoying
- Hand-craft a “user satisfaction” estimator (e.g. success/length trade-off)
→ We usually need to know the user goal to succeed
- Train a “user satisfaction” estimator using user feedback → We ask for user feedback only when we are uncertain about it [Su et al., 2016]

In sum: reward modeling is still an **open question**

Typical Reward function

- Small per turn penalty (-1)
- Large reward at the end of the dialogue if successful (+20)

Value based RL

- Model Q-Value function:
 - $Q^\pi(b, a) = \mathbb{E}\{R_t | b_t = b, a_t = a, \pi\}$
 - $R_t = \sum_{\tau=t}^{T-1} \gamma^{(\tau-t)} r_\tau$, where t is the current timestep
- The optimal policy can be obtained by greedily taking the action which maximises Q
 - $\pi(b) = \arg \max_{a \in A} Q^\pi(b, a)$
- Example: Deep-Q Networks (Mnih et al. 2015)

Policy based RL

- Directly parametrise a policy: $\pi_\theta(b, a) = [0,1]$
- Adjust the policy parameters to maximise the expected reward (policy gradient theorem):
 - $\Delta\theta_t = \alpha \nabla_\theta \log \pi_\theta(b_t, a_t) R_t^\sim$
 - R_t^\sim can be any estimate of the return (actual return, TD-estimate...)
- Example: A2C (Silver et al. 2016)

RL based dialogue management: Pros and cons

- Learns through interaction in order to maximise a future reward
- Learns in the actual dialogue environment
- Adapts to new environments/users/situations
- Requires less annotation
- Slow and expensive learning
- Difficult to reuse data

Practical issues in RL based DM

- Data inefficiency!

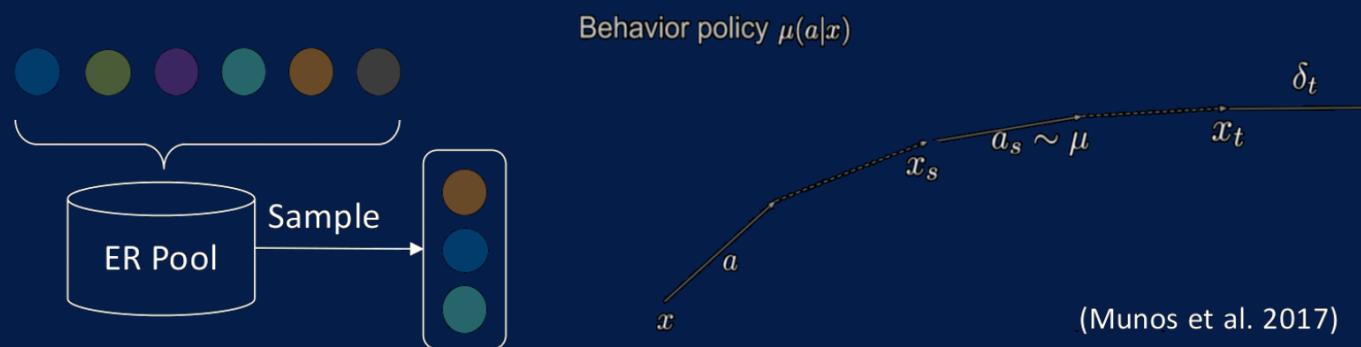
Sample efficient RL

Experience Replay (ACER, TRACER, eNACER)

Make efficient use of past data

[Su et al., 2017; Wang et al., 2017; Weisz et al., 2018]

- On-policy learning



(Munos et al. 2017)

- Off-policy learning with Experience Replay (ER)
- Correct sampling bias via Importance sampling ratio $\frac{\pi(a_s|x_s)}{\mu(a_s|x_s)}$

Hybrid SL+RL training

Supervised Learning (SL)

- Wizard-of-Oz (WoZ) methods to collect (high-quality?) data
- Easy to get to reasonable performance
- No planning, not optimal in deploying environments
- Low coverage

Reinforcement Learning (RL)

- Learn policy online with real or simulated users
- Poor performance in early training stages

Combine the best of both worlds using one single model

[Rieser and Lemon, 2016; Henderson, 2008; Fatemi, 2016; Zhao, 2016;

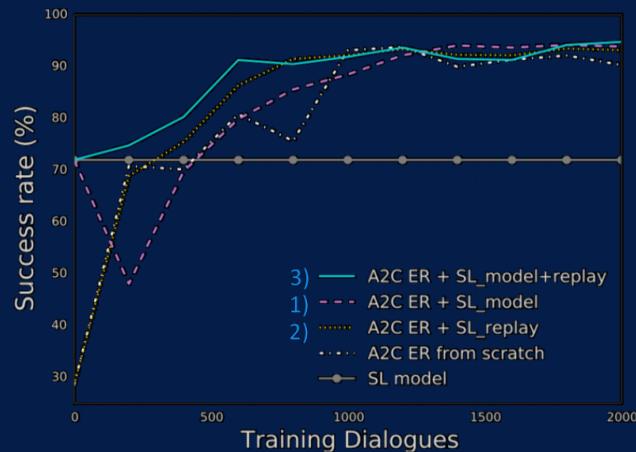
Williams, 2017]

Hybrid SL+RL training

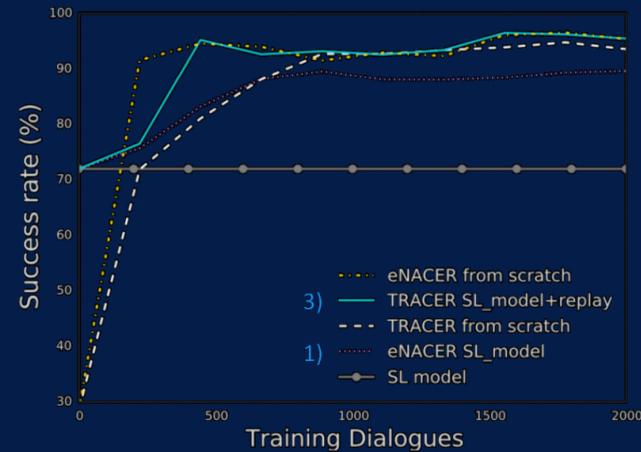
Sample-Efficient RL + Supervised Data

Some Empirical Results

[Su et al., 2017]



(a) Learning for A2C ER with demonstration data.



(b) Learning for TRACER and eNACER with demonstration data.

- 1) SL model: Pre-training with SL data
- 2) SL replay: Supervised replay pool P_{sup} for RL
- 3) SL model+replay: a + b

Agenda-Based user simulation

[Schatzman et al., 2007; Keizer et al., 2010]

First, generate a user goal.

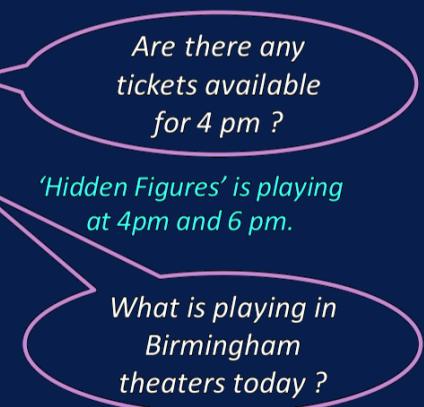
The user goal contains:

Dialog act

Inform slots

Request slots

start-time="4 pm"
date="today"
city="Birmingham"



```
{  
  "request_slots": {  
    "ticket": "UNK",  
    "theater": "UNK"  
  },  
  "diaact": "request",  
  "inform_slots": {  
    "city": "birmingham",  
    "numberofpeople": "2",  
    "state": "al",  
    "starttime": "4 pm",  
    "date": "today",  
    "moviename": "deadpool"  
  }  
}
```

User Simulation (Model/Learning-Based)

Transform a static corpus of dialogues into a dynamic tool

Previously:

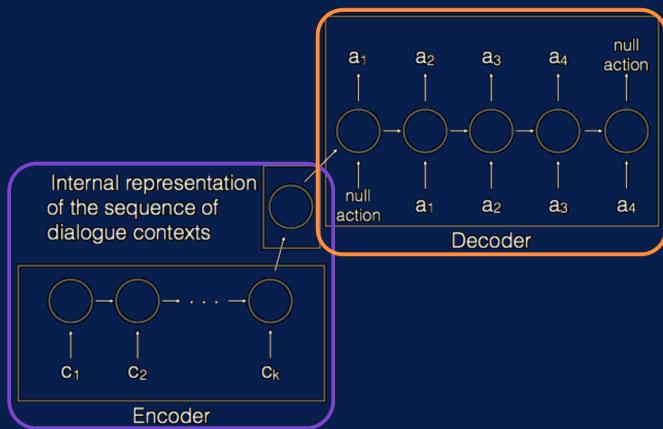
- bigram models [Eckert et al., 1997; Levin et al., 2000]
- graph-based [Scheffler and Young, 2000]
- HMMs [Georgila et al., 2005; Cuayahuitl et al., 2005]
- ...

Today: **neural models**

- Seq2Seq user simulation [El Asri et al., 2016; Crook and Marin, 2017; Kreyssig et al. 2018]

Seq2Seq User Simulation

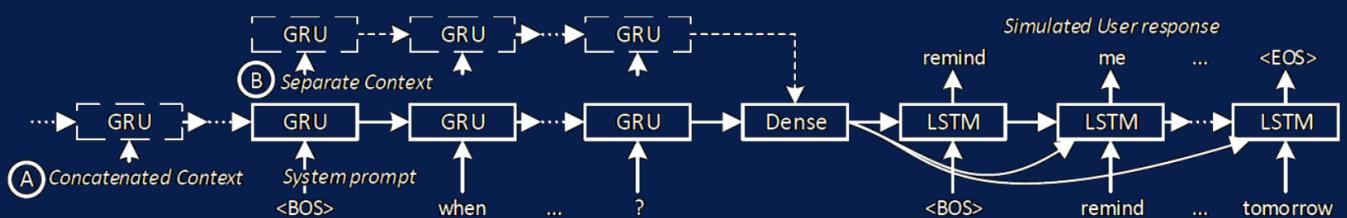
[El Asri et al., 2016]



- **Input:** c_i encodes contextual features (e.g., previous system action, consistency between user goals and system-provided values)
- **Output:** a dialogue act sequence from the user

Seq2Seq User Simulation

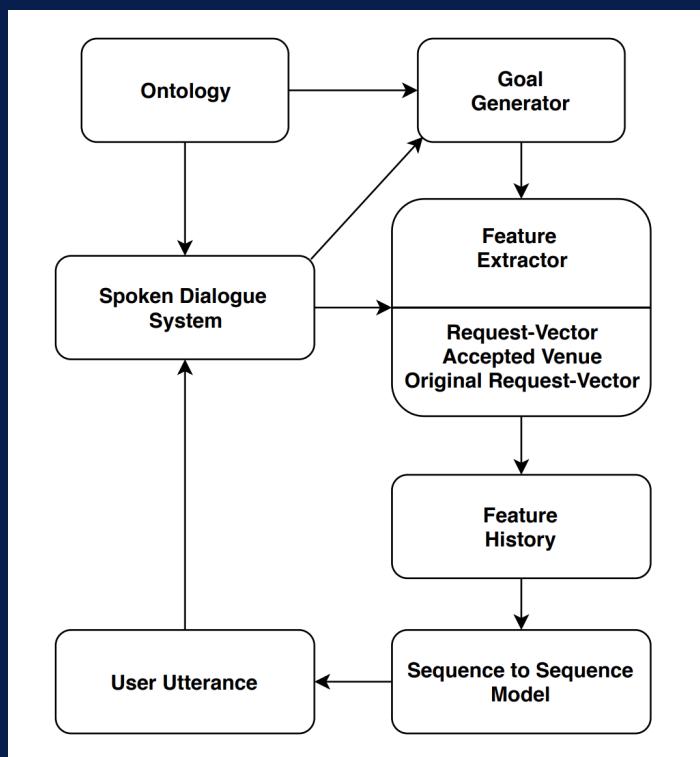
[Crook and Marin, 2017]



- Text based simulation
- No labeled data
- Trained on human-to-machine conversations

Seq2Seq User Simulation

[Kreyssig et al. 2018]



- **Input:** Contextual features
- **Output:** Natural language
- User goal and goal changes explicitly modelled → Can be used to train a RL-based policy

Evaluating User Simulation

Direct methods

- Measure the similarity between the outputs of the simulator and a real user in a test set
- Simulators trained on the same or similar metrics
- Variability is penalised, even if its consistent

Indirect methods

- Cross-model evaluation
- Training with simulated user / evaluating with real users

Indirect evaluation

[Kreyssig et al. 2018]

Training Simulator	Human Evaluation	
	Rew.	Suc.
NUS - \mathcal{N}_1	13.4	91.8
NUS - \mathcal{N}_2	13.8	93.4
ABUS - \mathcal{A}_1	13.3	90.0
ABUS - \mathcal{A}_2	13.1	88.5

- RL policy trained with simulated user and tested with real users
- Systems trained with a (good) simulated user perform well with real users
- System performance evaluation using simulated users correlates with performance evaluation with real users

Reusing data (transfer learning)

Domain transfer

- Use data collected in one domain to train / bootstrap a dialogue manager in another domain
- [Gašić et al., 2013, 2015; Wang et al., 2015; Papangelis et al., 2017]

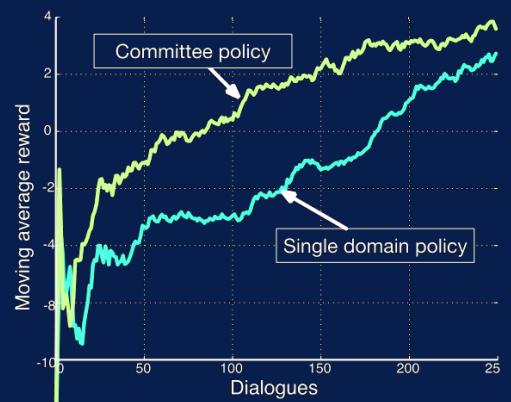
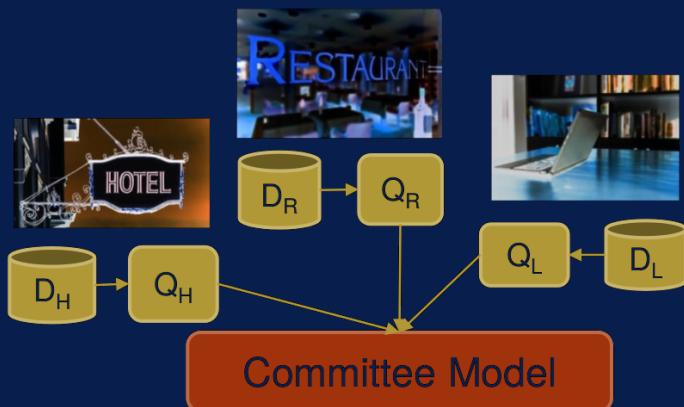
User adaptation

- Use data collected from a specific user to build an adapted dialogue manager for another user
- [Casanueva et al., 2015; Genevay et al., 2016; Laroche et al., 2017]

Domain Adaptation

[Gašić et al., 2015]

Bayesian committee machine (BCM) enables estimated Q-function to share knowledge across domains

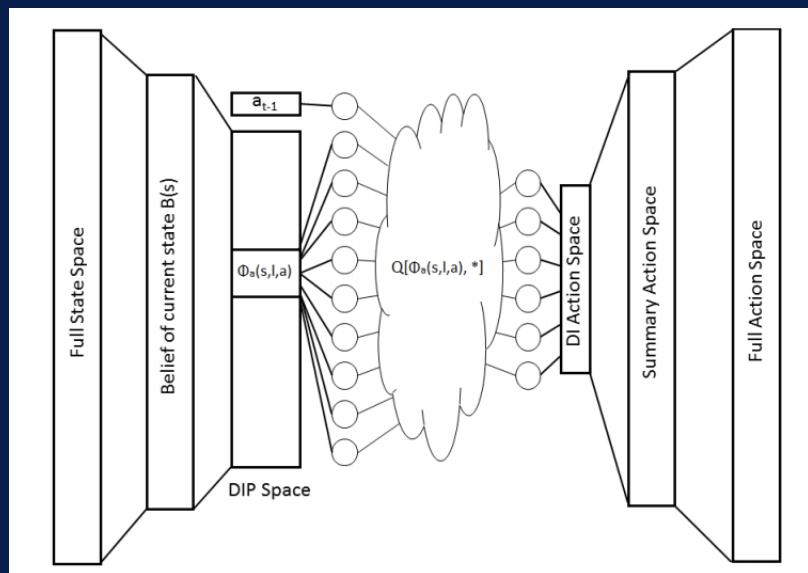


The policy for a new domain can be boosted by the committee policy

Domain Adaptation

Domain independent parametrisation (DIP)

[Wang et al., 2015; Papangelis et al., 2017]



- Map the domain specific dialogue state space into a domain independent space

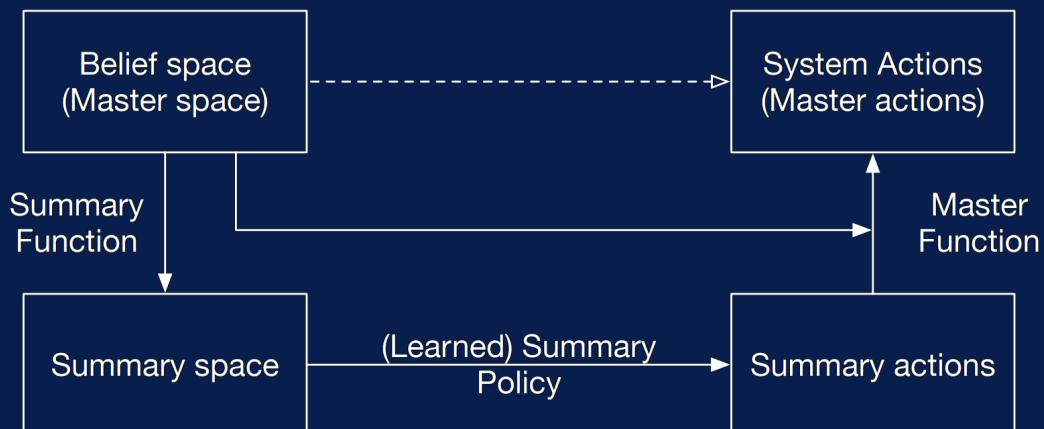
Battling Data Inefficiency

More structure → Less data needed

- Summary actions
- Action masks
- Hierarchical structures

Summary Actions

Action clustering to reduce the action set A



Summary mapping function: $a_m = sm(a, b)$

Summary action: `confirm(food)` → Master action: `confirm(food=Asian)`

Belief state can also be summarised

Action Masks

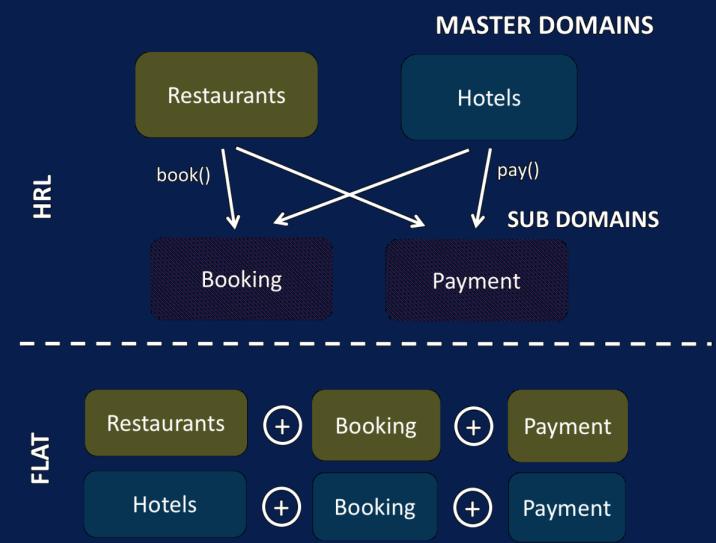
heuristics to reduce the action set A in each turn

- Mask `confirm()` actions if there is no belief assigned to particular slots
- Mask `inform()` actions if there is not enough evidence of user's goal

Action masks improve efficiency

[Thomson 2010; Williams et al., 2017; Weisz, 2017]

Dialogue Management Based on Hierarchical RL

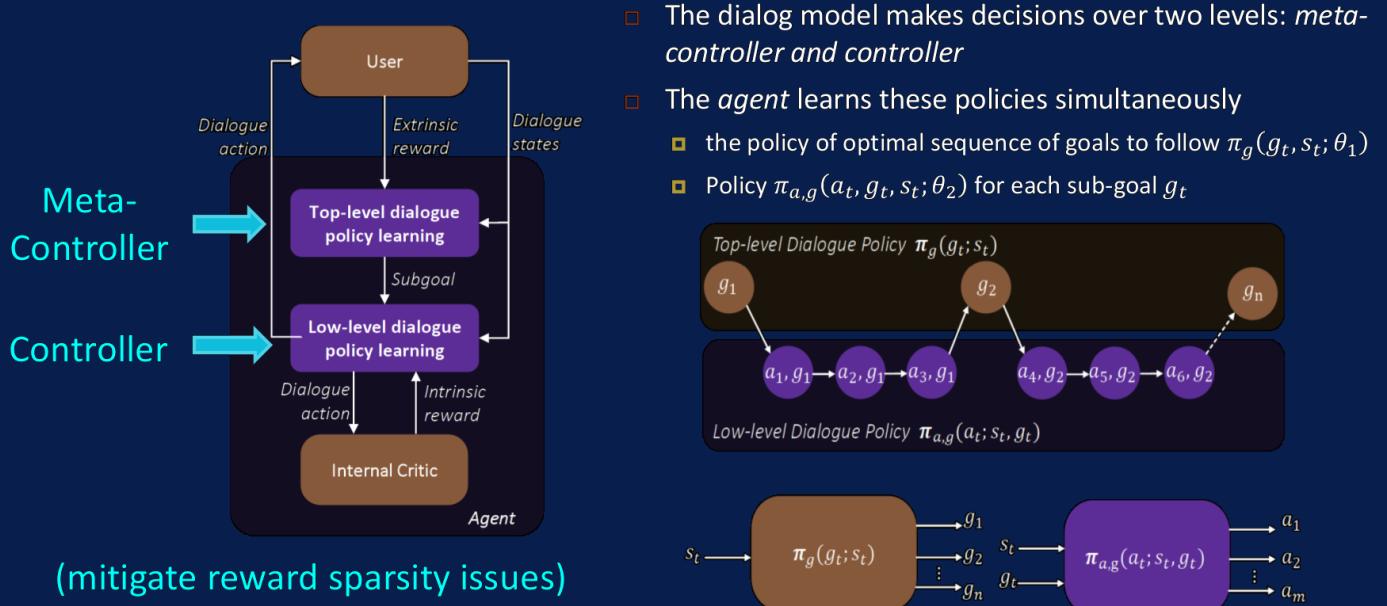


Hierarchical Policy

Control architectures and learning algorithms specifying a hierarchy of tasks and reusing parts of the space across sub-tasks

Dialogue Management Based on Hierarchical RL

[[Cuayáhuitl, 2009; Peng et al., 2017; Budzaniowski et al., 2017]]



Temporal abstraction

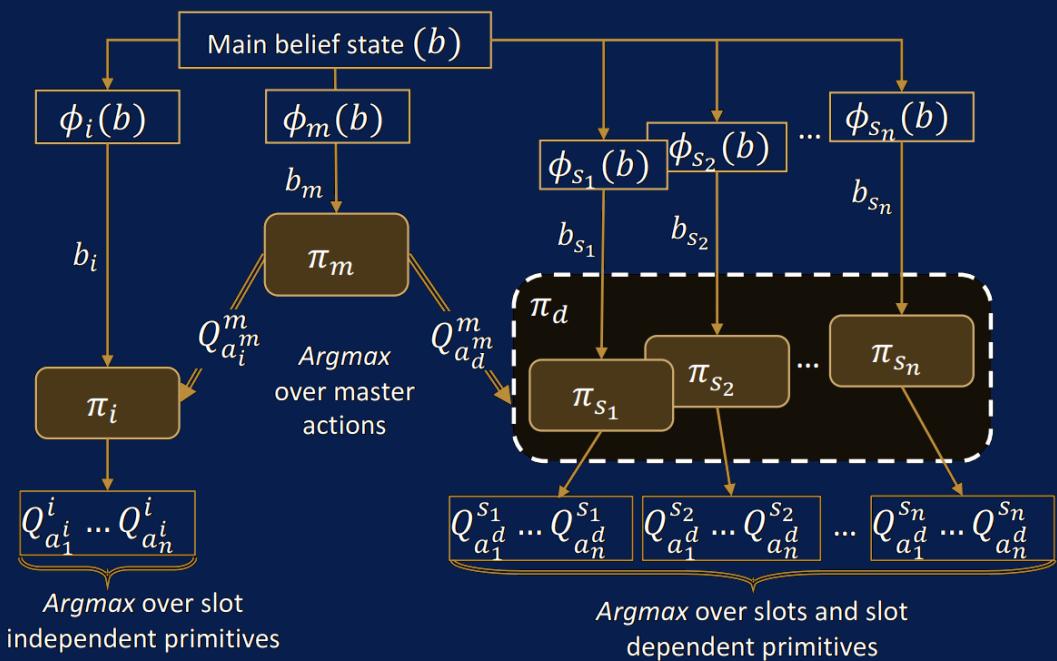
Decisions at the given level are not required at each step but can call temporally extended sub-tasks with their own policies

Dialogue Management Based on Feudal RL

Space abstraction

Decisions in each turn are divided into several steps, each step using a subset of the dialogue state space

[Casanueva et al., 2018]



Revisiting Problems of RL-Based DM

Training from scratch with real users is very expensive and slow

- **Simulated users:** necessary evil
- Pretraining with supervised learning (but we need the data!)

Domain transfer: data from one domain is often not reusable in another

Structure: Handcrafted structures are often necessary to make learning reliable

Reproducibility problems and recent improvements

- bAbI Dialogue tasks [Bordes et al., 2017] (ParlAI [Miller et al., 2018])
- PyDial (benchmarking) environment [Ultes et al., 2017]

Revisiting Problems of RL-Based DM

PyDial: Open-source task-oriented statistical DM toolkit

- **Benchmarking environment:** Simulated environments in 3 domains and 6 different environments (different SER, user behaviour, masks...)
- New domains and environments easily implementable

A recent benchmarking study of different DM approaches
[Casanueva et al., 2017]

- Domain complexity plays a crucial role, but...
- Data-driven models still fall way short of hand-crafted policies...
- Even in very constrained environments compared to real-world tasks

Revisiting Problems of RL-Based DM

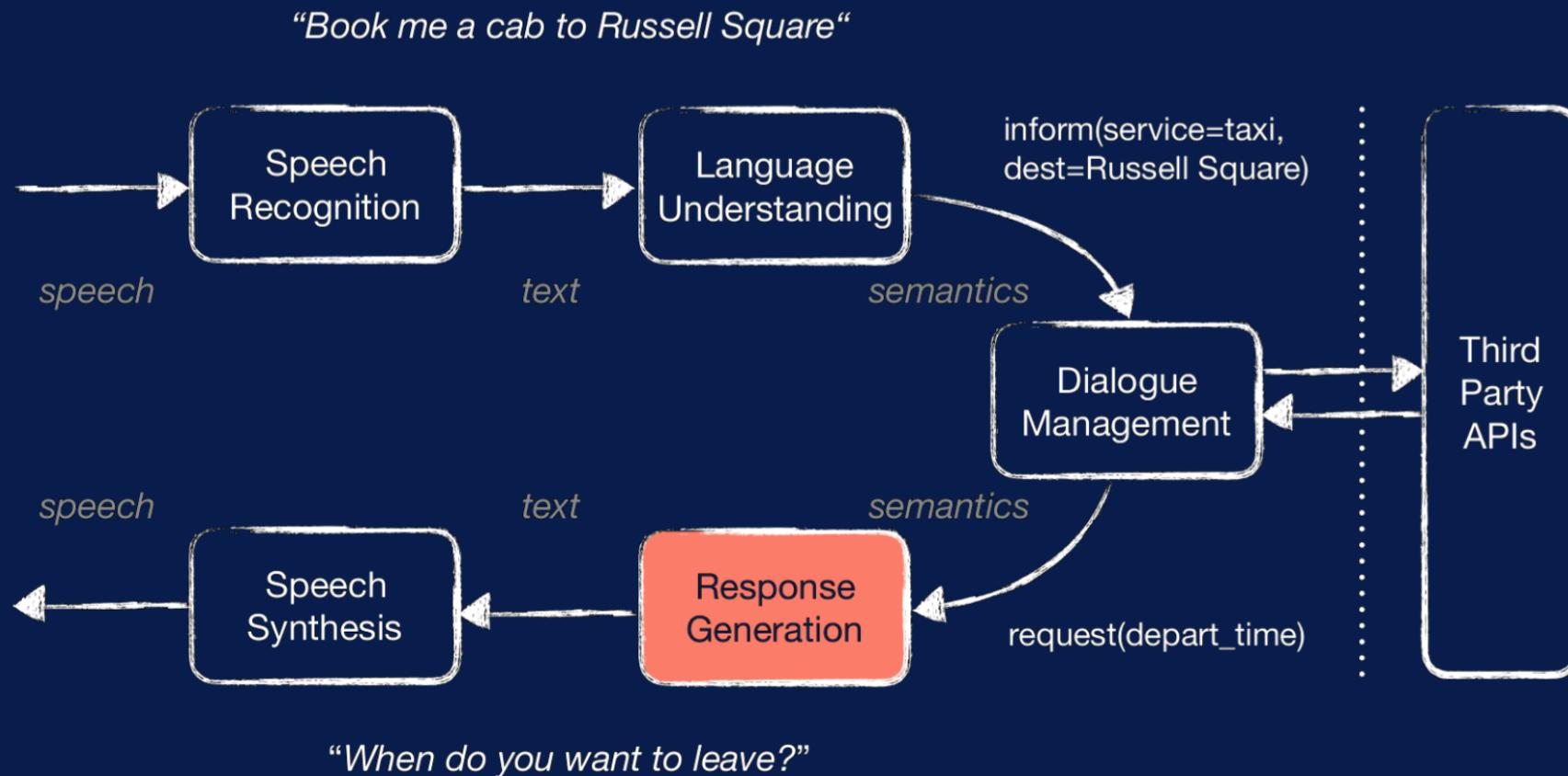
Some Quantitative Evidence

Task	GP-Sarsa		DQN		A2C		eNAC		Handcrafted	
	Suc.	Rew.	Suc.	Rew.	Suc.	Rew.	Suc.	Rew.	Suc.	Rew.
Env. 1	CR	99.4%	13.5	93.9%	12.7	89.3%	11.6	94.8%	12.4	100.0%
	SFR	96.1%	11.4	65.0%	5.9	58.3%	4.0	94.0%	11.7	98.2%
	LAP	89.1%	9.4	70.1%	6.9	57.1%	3.5	91.4%	10.5	97.0%
Env. 2	CR	96.8%	12.2	91.9%	12.0	75.5%	7.0	83.6%	9.0	100.0%
	SFR	91.9%	9.6	84.3%	9.2	45.5%	-0.3	65.6%	3.7	98.2%
	LAP	82.3%	7.3	74.5%	6.6	26.8%	-5.0	55.1%	1.5	97.0%
Env. 3	CR	95.1%	11.0	93.4%	11.9	74.6%	7.3	90.8%	11.2	96.7%
	SFR	81.6%	6.9	60.9%	4.0	39.1%	-2.0	84.6%	8.6	90.9%
	LAP	68.3%	4.5	61.1%	4.3	37.0%	-1.9	76.6%	6.7	89.6%
Env. 4	CR	91.5%	9.9	90.0%	10.7	64.7%	3.7	85.3%	9.0	96.7%
	SFR	81.6%	7.2	77.8%	7.7	38.8%	-3.1	61.7%	2.0	90.9%
	LAP	72.7%	5.3	68.7%	5.5	27.3%	-6.0	52.8%	-0.8	89.6%
Env. 5	CR	93.8%	9.8	90.7%	10.3	70.1%	5.0	91.6%	10.5	95.9%
	SFR	74.7%	3.6	62.8%	2.9	20.2%	-5.9	74.4%	4.5	87.7%
	LAP	39.5%	-1.6	45.5%	0.0	28.9%	-4.7	75.8%	4.1	85.1%
Env. 6	CR	89.6%	8.8	87.8%	10.0	62.3%	3.5	79.6%	8.0	89.6%
	SFR	64.2%	2.7	47.2%	0.4	27.5%	-5.1	66.7%	3.9	79.0%
	LAP	44.9%	-0.2	46.1%	1.0	32.1%	-3.8	64.6%	3.6	76.1%
Mean	CR	94.4%	10.9	91.3%	11.3	72.8%	6.4	87.6%	10.0	96.5%
	SFR	81.7%	6.9	66.3%	5.0	38.2%	-2.1	74.5%	5.7	90.8%
	LAP	66.1%	4.1	61.0%	4.1	34.9%	-3.0	69.4%	4.3	89.1%
	ALL	80.7%	7.3	72.9%	6.8	48.6%	0.4	77.2%	6.7	92.1%

Table 4: Reward and success rates after 4000 training dialogues for the five policy models considered in this benchmark. Each row represents one of the 18 different tasks. The highest reward obtained by a data driven model in each row is highlighted.

Dialogue generation

Natural Language Generation



Natural Language Generation

Problem Definition

“NLG is the process of deliberately constructing a natural language text in order to meet specified communicate goals.”

[McDonald, 1992]

Input: a communicative goal. E.g. non-linguistic representation of information

Output: natural language utterance (combined with graphics, tables, etc)

Knowledge Required: intended communication scope, domain knowledge, the actual language

Natural Language Generation

Problem Definition

- Meaning representation → natural language utterances

Dialogue Act

Inform(restaurant=Seven_days, food=Chinese)

Realisations

Seven days is a restaurant serving Chinese.

Seven days is a Chinese restaurant.

- What do we care about? - naturalness and variation
- Other applications - summarisation, short-text report

NLG Evaluation

Subjective: human judgement [Stent et al., 2005]

- **Adequacy:** correct meaning
- **Fluency:** linguistic fluency/naturalness
- **Readability:** fluency in the dialogue context
- **Variation:** multiple realisations of the same meaning

Objective: automatic evaluation measures

- Word overlap: BLEU, METEOR, ROUGE
- Embedding-based: greedy matching, embedding average
- Task-oriented: item error rate

Big gap and anti-correlation between human judgements and automatic measures

Template-Based NLG

- Define a set of rules to map meaning representation (i.e., frames) to natural language

```
confirm()          "Please tell me more about the product you 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, repetitive

Pipeline approach to NLG

What to say?

- Content planning: pick contents and order them
- Dialogue policy handles this in SDS

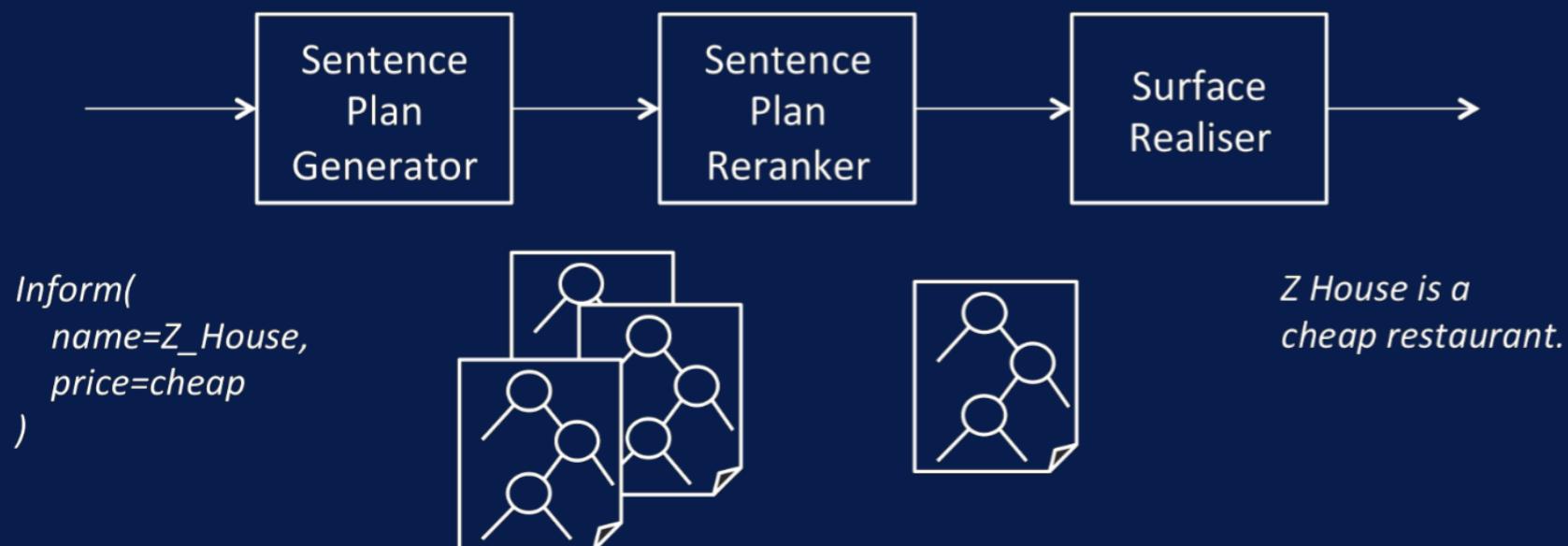
How to say it?

- Sentence planning: get sentence (tree), put content in right places, lexicalisation, etc
- Surface realisation: creates linear text and ensures its grammar

The "how to say it" Pipeline in NLG

[Walker et al., 2002]

■ Sentence planning + Surface realisation



Statistical approaches to pipelined NLG

- Statistical sentence plan generator
[Stent et al., 2009]
 - Statistical surface realizer
[Dethlefs et al., 2013; Cuayahuitl et al., 2014]
 - Learning from unaligned data
[Dušek and Jurčíček, 2015]
-
- Pros: can model complex linguistic structures
 - Cons: heavily engineered, require extensive domain knowledge

Sequential approaches to NLG

Class-Based NLG [Oh and Rudnicky, 2000]

Classes

inform_area, inform_address, ..., request_area, request_address, ...

Class-based Language Modeling

- $P(X|c) = \sum_t \log p(x_t|x_0, x_1, \dots, x_{t-1}, c)$
 - $X^* = \arg \max P(X|c)$
-
- **Pros:** easy to implement/understand, simple rules
 - **Cons:** computationally inefficient

Further work

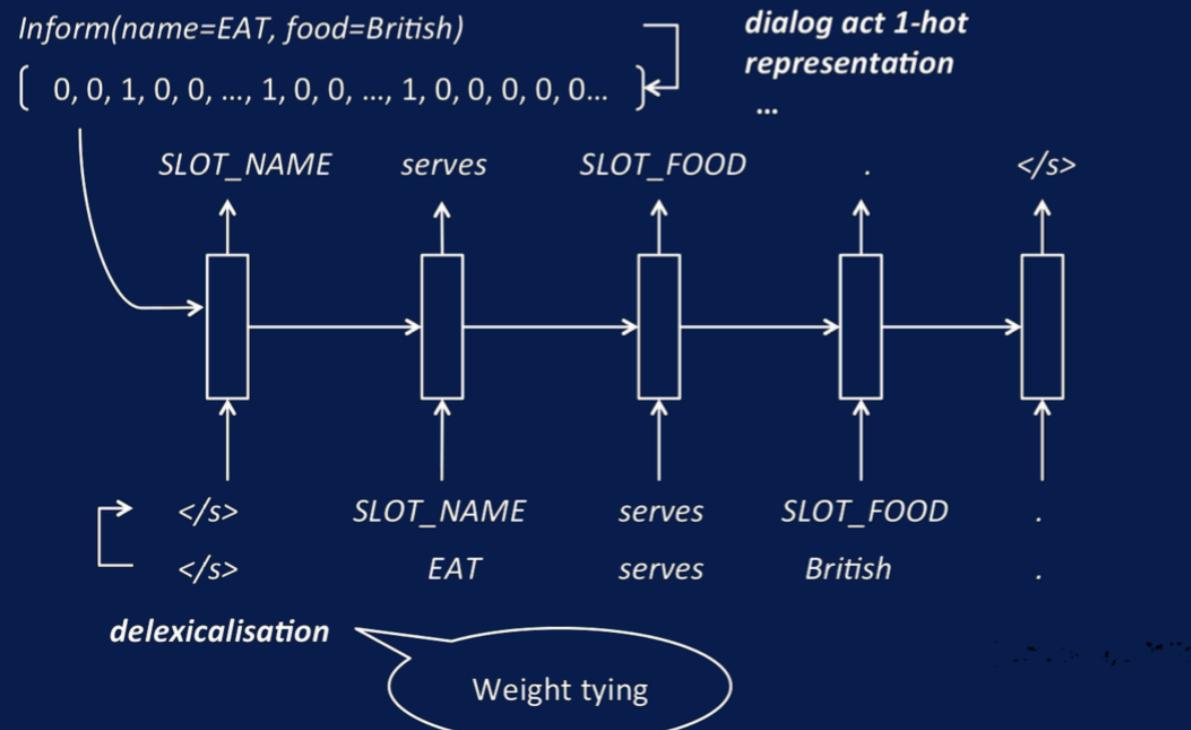
- ▶ Phrase-based NLG [Mairesse et al., 2010]

RNN-Based LM NLG

[Wen et al., 2015]

“Deep” revolution has also transformed NLG

- **Distributed representations:** Generalisation
- **Recurrent connections:** Long-term dependencies
- **Conditional RNNs:** Flexibility and creativity
- **Attention mechanism:** Focus on relevant and meaningful parts



RNN-Based LM NLG

Handling Semantic Repetition/Missing

Empirically, **semantic repetition** is observed

- “EAT is a great British restaurant that serves British food.”
- “EAT is a pet-friendly place in the cheap price range. It is affordable and also allows pets.

How to mitigate this problem?

- Post-processing rules [Oh and Rudnicky, 2000]
- Gating mechanism [Wen et al., 2015]
- Attention [Mei et al., 2016; Wen et al., 2016; Tran and Nguyen, 2017]

RNN-Based NLG

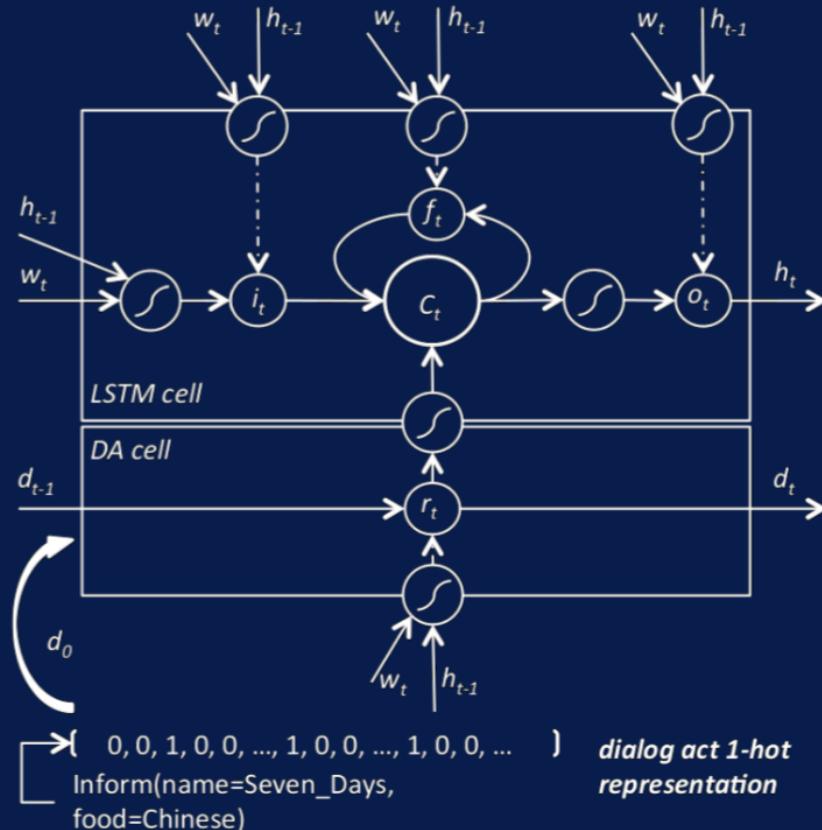
Learning to Control Gates

Learn to open/close the LSTM gates based on **generation history** [Wen et al., 2015]

- Cost function

$$\begin{aligned}\mathcal{L}(\theta) = & - \sum_t \mathbf{y}_t^T \log \mathbf{p}_t \\ & + \|\mathbf{d}_T\| \\ & + \sum_{t=0}^{T-1} \eta \xi \|\mathbf{d}_{t+1} - \mathbf{d}_t\|\end{aligned}$$

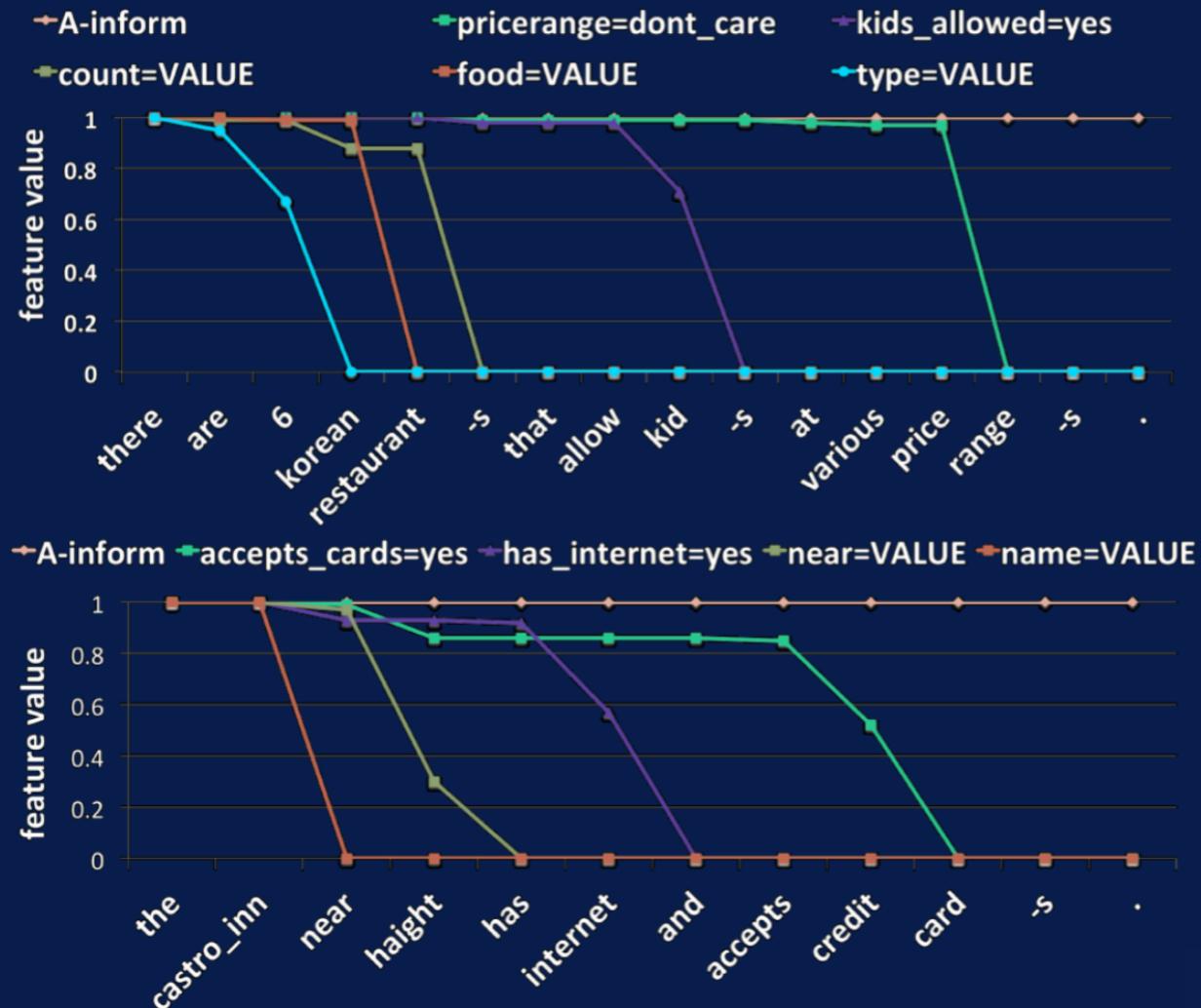
- 1st term : Log-likelihood
- 2nd term: make sure rendering all the information needed
- 3rd term: close only one gate at each time step.



Method	SF Restaurant		SF Hotel	
	BLEU	ERR(%)	BLEU	ERR(%)
hdc	0.451	0.0	0.560	0.0
kNN	0.602	0.87	0.676	1.87
classlm	0.627	8.70	0.734	5.35
rnn w/o	0.706	4.15	0.813	3.14
lstm w/o	0.714	1.79	0.817	1.93
rnn w/	0.710	1.52	0.815	1.74
lstm w/	0.717	0.63	0.818	1.53
sc-lstm	0.711	0.62	0.802	0.78
+deep	0.731	0.46	0.832	0.41

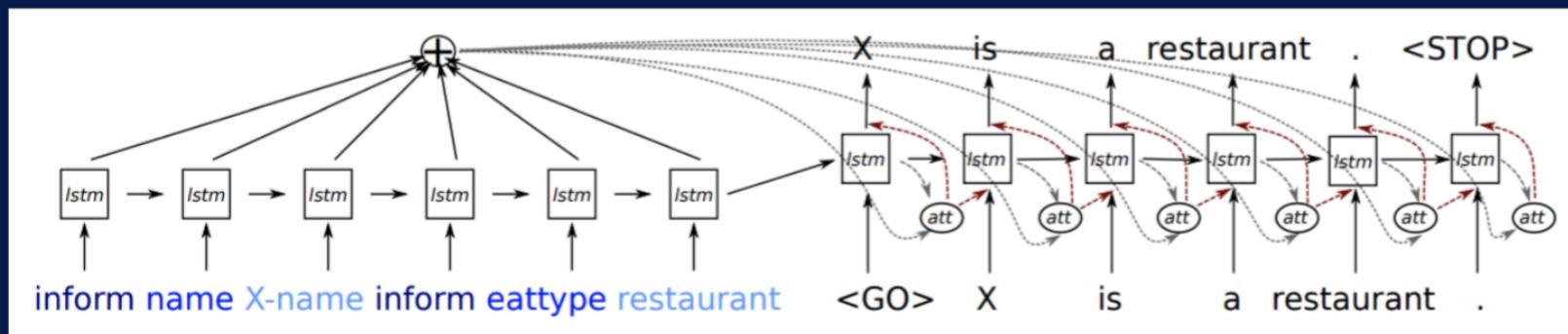
RNN-Based NLG

Feature Visualisation



(Attentive) Seq2Seq for NLG

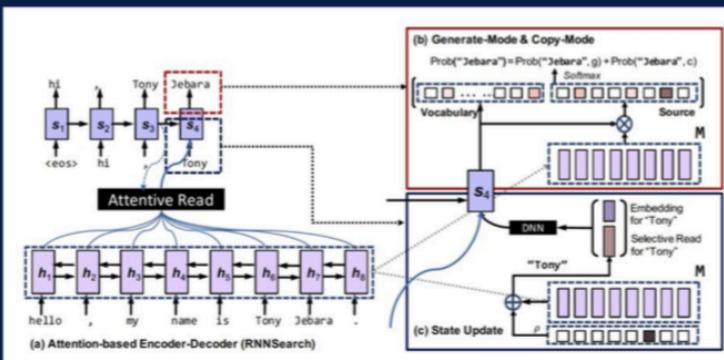
Encode Dialogue Act, Seq2Seq for generation [**Dušek and Jurčíček, 2016**, Wen et al., 2015; ...]



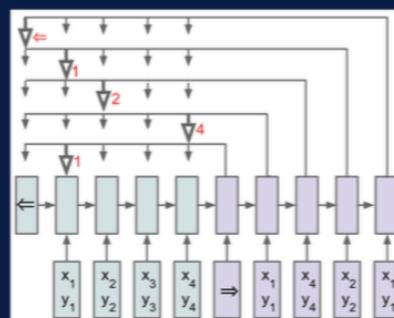
Recent Work in Neural NLG

Re-using info from the input directly: CopyNet and PointerNet [Gu et al., 2016; Gulcehre et al., 2016; Cao et al., 2016; He et al., 2016; Miao et al., 2016; Ling et al., 2017 ...]

Copy Network

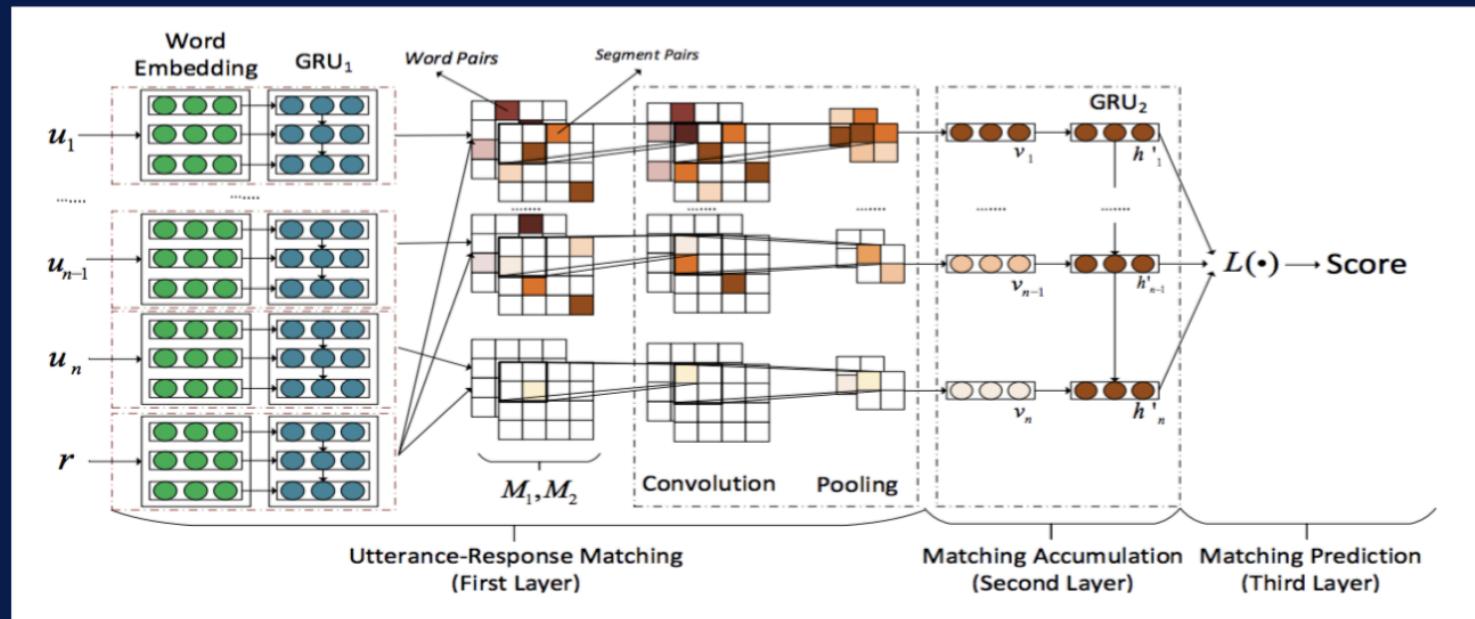


Pointer Network



Recent Work in Neural NLG

Retrieval-based NLG: select from a set of predefined responses
[Lowe et al., 2015; Yan et al., 2016; **Wu et al., 2017**]



Learning Objective for NLG

Closely related to the NLG evaluation

- Maximising the log-likelihood only optimises the perplexity.

$$\ell(\theta) = - \sum_{t=1}^T \log p(y_t|X, y_{<t}; \theta)$$

Other approaches

- Discriminative Training [Wen et al., 2016]
 - ▶ Separating correct examples from competing incorrect ones
- Reinforcement Learning [Li et al., 2016]
 - ▶ Additional info as reward: Mutual Information, Semantic Coherence, Information Flow...
- ...

Corpus and Data for NLG

Statistical models are reflecting what's in the data

- Data quality decides the quality of the NLG system
- Do not learn from templates or synthetic data - you are just reverse engineering the design
- Collect your own real user data! [Wen et al., 2016; Shah et al., 2018; ...]

Short Summary on NLG

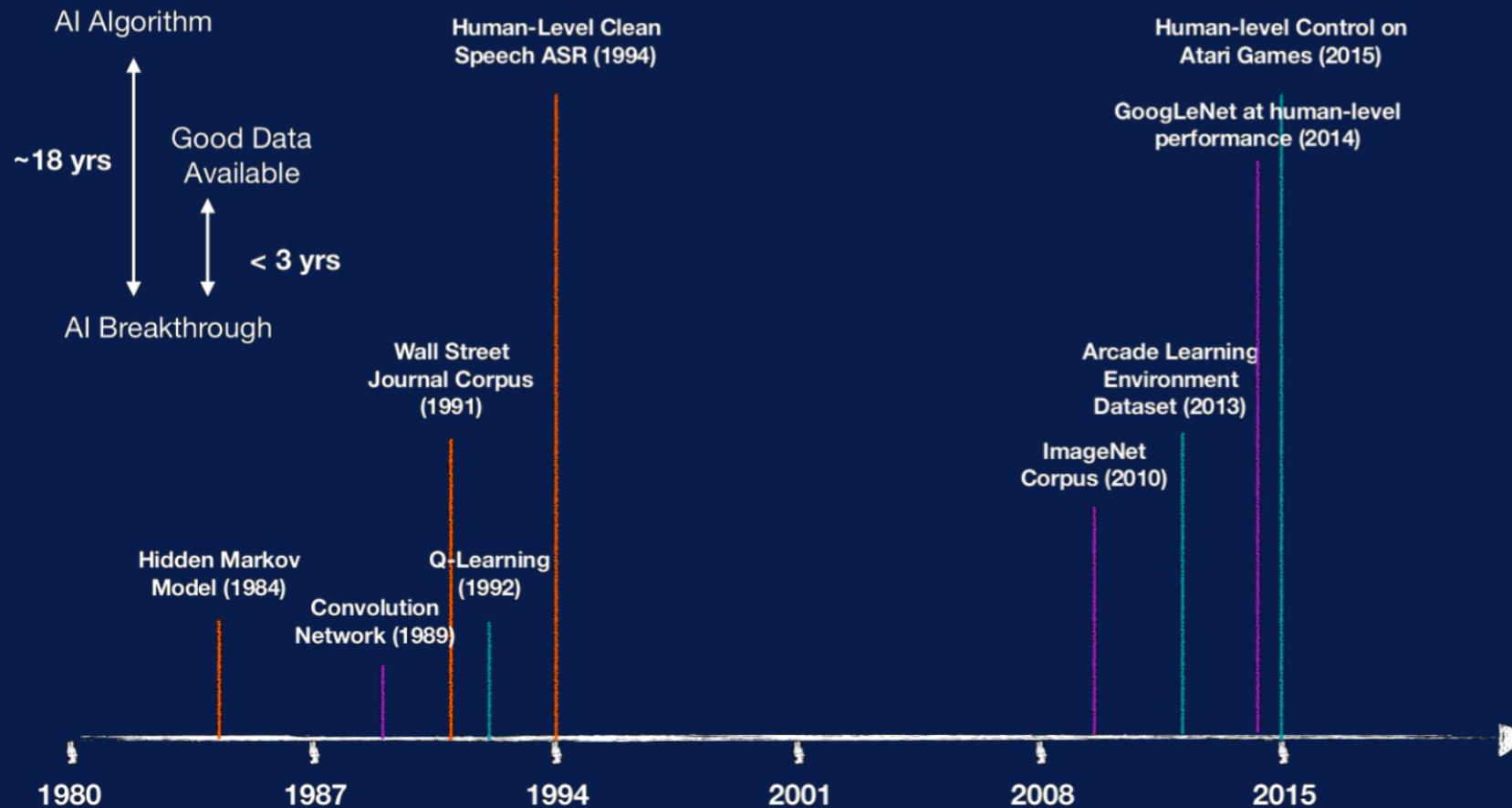
- Evaluating NLG is hard. The best way is *human evaluation*
- In product, template-based NLG is still most common
- Learning-based NLG (+ linguistic knowledge) are promising, but be careful of the objective and data
- NN-based NLG is a conditional neural LM that learns *realisation* and *semantic alignments* jointly
- Recent trends: adversarial modeling, E2E learning

Data collection

The Importance of Data

Data is the core of ML algorithms

<http://www.spacemachine.net/views/2016/3/datasets-over-algorithms>



Available corpora

- Human-to-Machine
 - Let's Go Bus Information System - Raux et al. 2005
 - Dialogue State Tracking Challenge - Williams et al. 2013
- Machine-to-Machine
 - Bordes et al. 2017
 - Shah et al. 2018
- Human-to-Human
 - Wen et al. 2017
 - El Asri et al. 2017
 - Eric et al. 2017

Available corpora

Metric	DSTC2	SFX	WOZ2.0	FRAMES	KVRET	M2M
# Dialogues	1,612	1,006	600	1,369	2,425	1,500
Total # turns	23,354	12,396	4,472	19,986	12,732	14,796
Total # tokens	199,431	108,975	50,264	251,867	102,077	121,977
Avg. turns per dialogue	14.49	12.32	7.45	14.60	5.25	9.86
Avg. tokens per turn	8.54	8.79	11.24	12.60	8.02	8.24
Total unique tokens	986	1,473	2,142	12,043	2,842	1,008
# Slots	8	14	4	61	13	14
# Values	212	1847	99	3871	1363	138

Getting Data for Training Dialogue Systems

Conversational data is hard to get

Reddit has a large volume of conversational data...

- ...Well, for chit-chat dialogue development

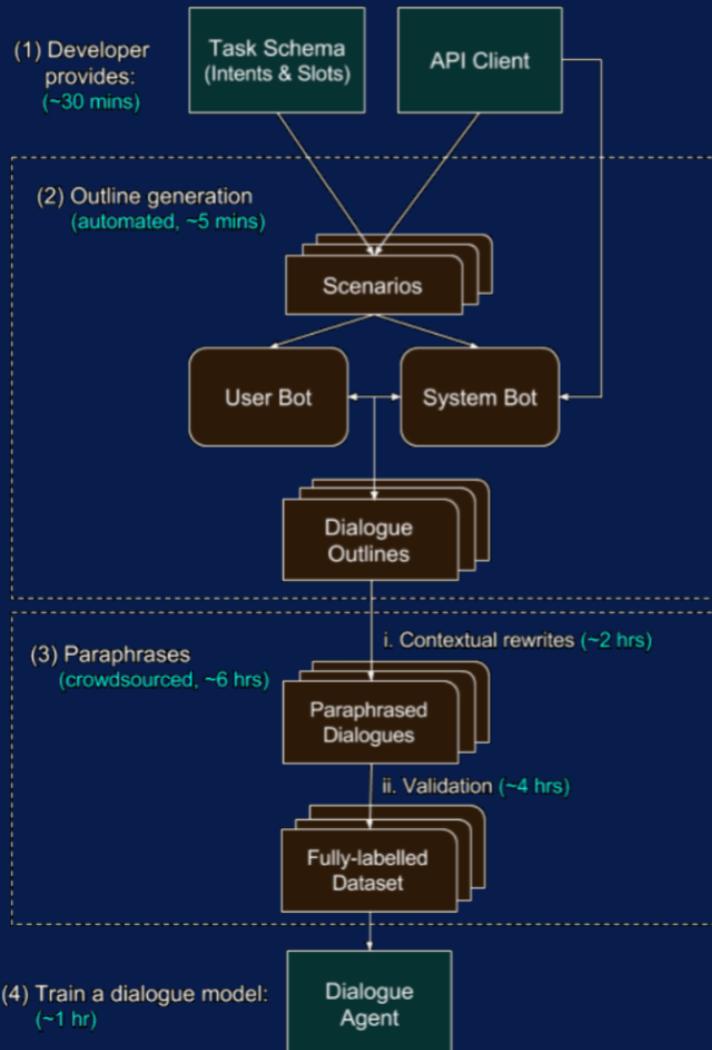


But how do we get **high-quality domain-specific** data sets?

- A pizza delivery agent?
- A taxi booking service?
- A flight booking agent?

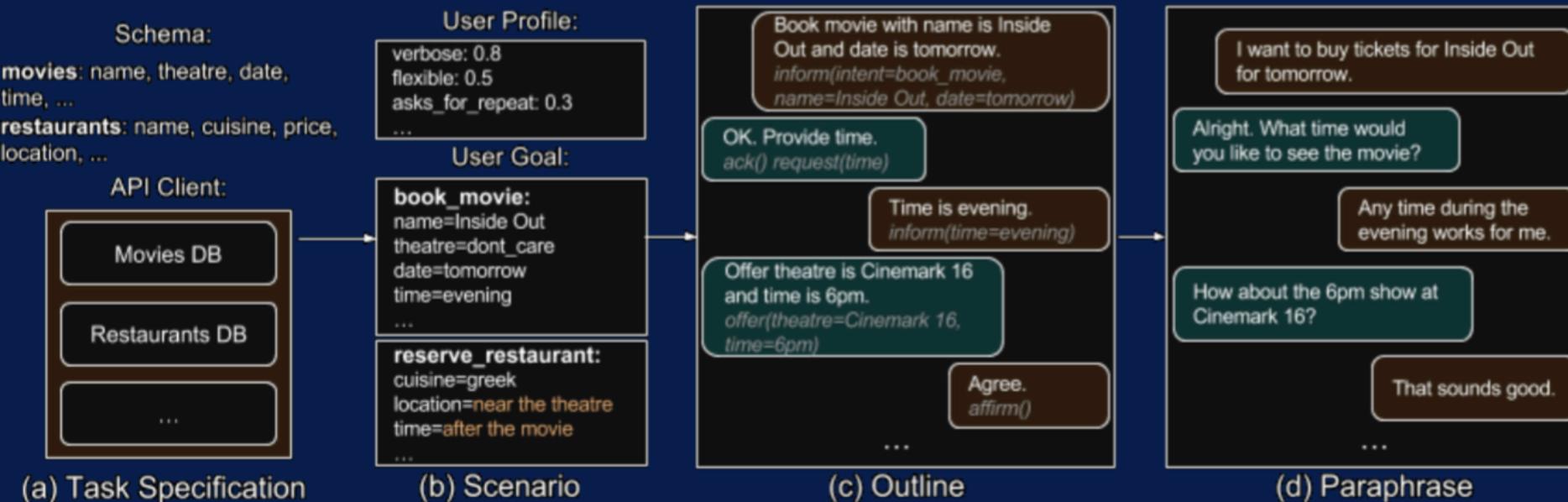
Getting Data for Training Dialogue Systems

Machines Talking to Machines (M2M) [Shah et al.; NAACL 2018]



Getting Data for Training Dialogue Systems

Machines Talking to Machines (M2M) [Shah et al.; NAACL 2018]



Getting Data for Training Dialogue Systems

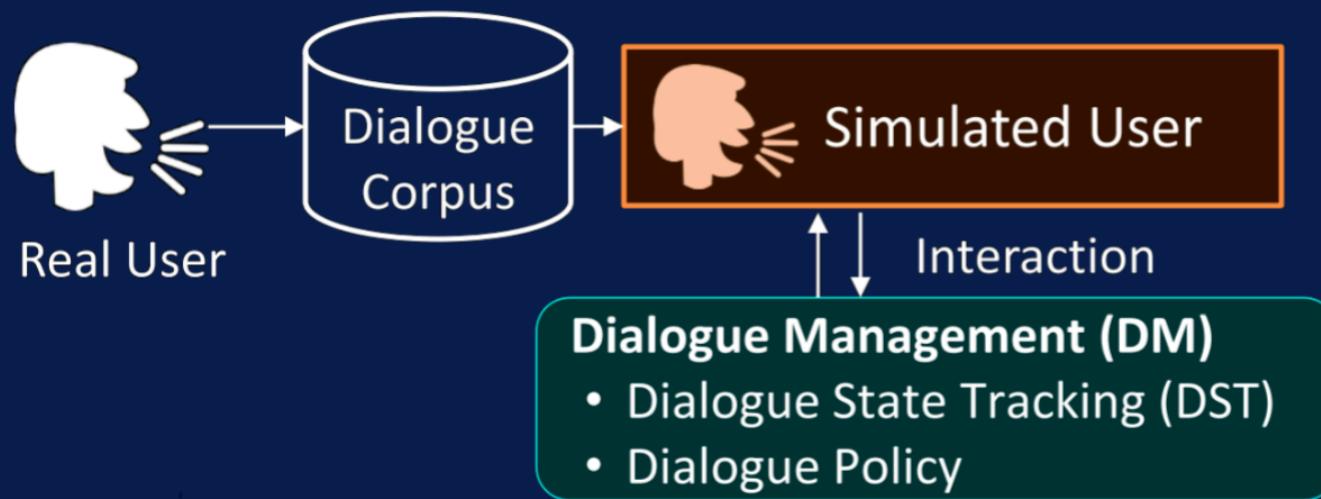
M2M: Reduced annotation complexity

Crowdsourcing simply as a paraphrasing task

<u>Original conversation</u>	<u>Paraphrased conversation</u>
Assistant: greetings	Hello
User: greetings AND buy movie tickets AND date is Wednesday	I would like to buy movie tickets for Wednesday.
Assistant: provide preference for: theatre name and time and number of tickets and movie	What theatre, movie, time, and number of tickets would you like?
User: unable to understand, must re-phrase your message	Sorry, I didn't understand. Could you repeat that?
Assistant: provide preference for: theatre name and time and number of tickets and movie	How many tickets would you like and what is the theatre, movie, and showtime?
User: movie is The Magnificent Seven and time is 4:00 pm and theatre name is Century 20 Great Mall and number of tickets is 6	I need 6 tickets for the 4:00 pm showing of The Magnificent Seven at the Century 20 Great Mall
Assistant: confirm the following: time is 4:00 pm	That was for 4:00 pm, right?
User: accept time is 4:00 pm	Yes, 4:00 pm.
Assistant: purchase confirmed with given details movie is The Magnificent Seven and number of tickets is 6 and time is 4:00 pm and date is March 08 and theatre name is Century 20 Great Mall	I have purchased 6 tickets for the Magnificent Seven at 4:00 o'clock on March 8 at the Century 20 Great Mall.
User: thank you AND goodbye	Thanks, bye.

Data Simulation

Goal: generate natural and reasonable conversations to enable reinforcement learning for exploring the policy space



Approaches:

- Rule-based (hand-crafted by experts) [Li et al., 2016]
- Learning-based [Schatzmann et al., 2006; El Asri et al., 2016; Shah et al., 2018]

Data Simulation

Specifying the dialogue flow before collecting the actual data

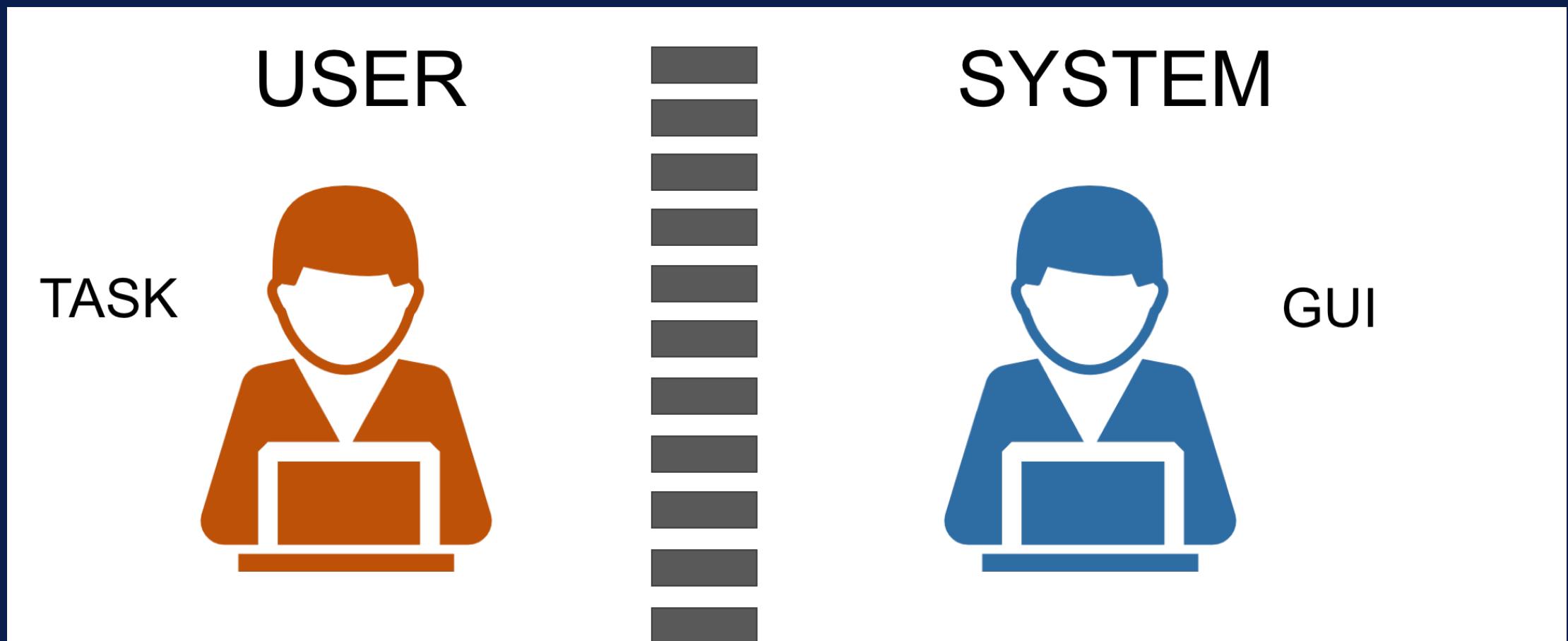
- How to cover all possible use cases?
- How to maximise coverage of different flows and slot-value pairs?
- How to quickly build simulators for new domains?

```
Turn 0.  
===== current_user_template: "I want price range is cheap\n AND price range is NOT moderate."  
last_system_template: "Greetings!"  
user_concept_highlights: [(price range="cheap") [-1:-1], (price range!="moderate") [-1:-1]]  
system_concept_highlights:[]  
dialogue_turn {  
    dialogue_id: "2e091838-6d2a-4ed5-bf06-caac5cde4d0e"  
    last_system_act: GREETING()  
    user_action: INFORM  
    slu_labels: (price range="cheap", price range!="moderate")  
    state_labels: (price range="cheap", price range!="moderate")  
}  
  
Turn 1.  
===== current_user_template: "I want has_wheelchair_access is True\n AND cuisine is Hot Dogs."  
last_system_template: "How about name is Boyce Da Roca\n AND price range is cheap?\n Anything else?  
user_concept_highlights: [(accessible_wheelchair=True) [-1:-1], (cuisine="Hot Dogs") [-1:-1]]  
system_concept_highlights:[(name="Boyce Da Roca") [-1:-1], (price range="cheap") [-1:-1]]  
dialogue_turn {  
    dialogue_id: "2e091838-6d2a-4ed5-bf06-caac5cde4d0e"  
    turn_index: 1
```

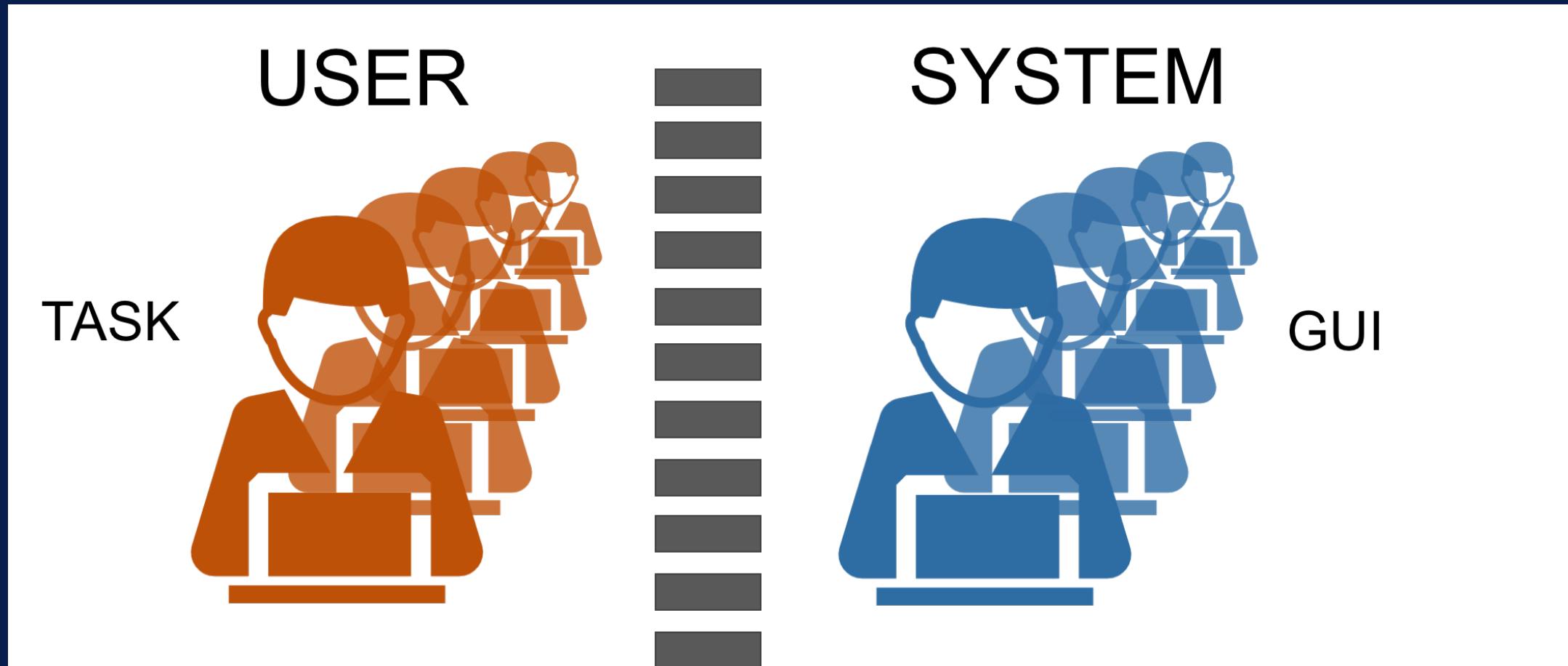
Wizard-of-Oz

- Using the Wizard-of-Oz set-up (Kelley, 1984), corpora of annotated dialogues can be gathered at relatively low costs and with a small time effort.
- Cam676 (Wen et al. 2017),
- MultiWOZ (Budzianowski et al. 2018)
- AirDialogue (Wei et al. 2018)

Wizard of Oz Setup



Wizard of Oz Setup



Data Collection Set-up

Such WOZ set-up has been successfully validated by Wen et al. (2017)

But more complex, longer and multi-domain dialogues can be gathered at large-scale (Wei et al., 2018; Budzianowski et al. 2018)

User side

Help Desk: Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you ?
Customer : I want a place to stay in the east.
Help Desk : I have 6 guesthouses and 1 hotel on the east side. What's your price range?
Customer : Doesn't matter too much. I'd like a 4 star property, though, and would prefer one of the guesthouses.
Help Desk : I'd recommend 517a coldham lane. Would you like me to book a room?
Customer : Could you give me their phone number? I would like to verify that they have free parking.
Help Desk : Allenbell does have parking and the phone is 01223210353. Can I help with anything else?

Next turn

Customer : (Your response)

you need to go through the dialogue first by clicking the 'next turn' button

30

What topics were mentioned in this turn:

General: Booking: Restaurant: Hotels: Attraction:

Hospital: Police: Train: Taxi: Bus:

Submit the HIT

Please try to chat about the following topic:

Task MUL0002:

- You are traveling to and looking forward to try local restaurants.
- You are looking for a **place to stay**. The hotel should be in the **east** and should **include free parking**.
- The hotel should have **a star of 4** and should be in the type of **guesthouse**.
- Make sure you get **address** and **phone number**.
- You are also looking for a **place to dine**. The restaurant should be in the **moderate** price range and should serve **australian** food.
- If there is no such restaurant, how about one that serves **turkish** food.
- Once you find the **restaurant** you want to book a table for **4 people** at **17:45 on friday**.
- Make sure you get the **reference number**

--- The End ---

Help Desk: Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you ?

Customer : I want a place to stay in the east.

Help Desk : I have 6 guesthouses and 1 hotel on the east side. What's your price range?

Customer : Doesn't matter too much. I'd like a 4 star property, though, and would prefer one of the guesthouses.

Help Desk : I'd recommend 517a coldham lane. Would you like me to book a room?

Customer : Could you give me their phone number? I would like to verify that they have free parking.

Help Desk : Allenbell does have parking and the phone is 01223210353. Can I help with anything else?

Next turn

Customer : (Your response)

you need to go through the dialogue first by clicking the 'next turn' button

30

What topics were mentioned in this turn:

General: Booking: Restaurant: Hotels: Attraction:

Hospital: Police: Train: Taxi: Bus:

Submit the HIT

Please try to chat about the following topic:

Task MUL0002:

- You are traveling to _____ and looking forward to try local restaurants.
- You are looking for a **place to stay**. The hotel should be in the **east** and should **include free parking**.
- The hotel should **guesthouse**.
- Make sure you get **moderate** price range.
- You are also looking for **moderate** price range.
- If there is no such place, then book **17:45 on friday**.
- Once you find the place, make sure you get **reference number**.

User Task

--- The End ---

Task

- You are traveling to Cambridge and looking forward to try local restaurants.
- You are looking for a **place to stay**. The hotel should be in the type of **hotel** and should be in the **centre**.
- The hotel should **include free wifi** and should have **a star of 4**.
- Once you find the **hotel** you want to book it for **3 people** and **5 nights** starting from **monday**.
- Make sure you get the **reference number**.
- You are also looking for a **restaurant**. The restaurant should serve **australasian** food and should be in the **moderate** price range.
- The restaurant should be **in the same area as the hotel**.
- If there is no such restaurant, how about one that serves **british** food.
- Once you find the **restaurant** you want to book a table for **the same group of people** at **18:30** on **the same day**.
- Make sure you get the **reference number**

- You are traveling to Cambridge and looking forward to try local restaurants.
- You are looking for a **hotel**, hotel should be in the type of **hotel** and should be in the **centre**.
- The hotel should **include free wifi** and should have a **star of 4**.
- Once you find the **hotel** you want to book it for **3 people** and **5 nights** starting from **monday**.
- Make sure you get the **reference number**.
- You are also looking for a **restaurant**. The restaurant should serve **australasian** food and should be in the **moderate** price range.
- The restaurant should be **in the same area as the hotel**.
- If there is no such restaurant, how about one that serves **british** food.
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- Make sure you get the **reference number**

- You are traveling to Cambridge and looking forward to try local restaurants.
- You are looking for a **hotel**, hotel should be in the type of **hotel** and should be in the **centre**.
- The hotel should **include free wifi** and should have a **star of 4**.
- Once you find the **hotel** you want to book it for **3 people** and **5 nights** starting from **monday**
- Make sure **First Domain**
- You are also looking for a **restaurant**. The restaurant should serve **australasian** food and should be in the **moderate** price range.
- The restaurant should be **in the same area as the hotel**.
- If there is no such restaurant, how about one that serves **british** food?
- Once **Second Domain** a table for **the same group of people** at **18:30** on **the same day**.
- Make sure you get the **reference number**

Help Desk: Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you ?

Customer : I want a place to stay in the east.

Help Desk : I have 6 guesthouses. What's your price range?

Customer : Doesn't matter too much though, and would prefer one of the guesthouses.

Help Desk : I'd recommend Allenbell. Would you like me to book a room?

Customer : Could you give me the address and phone number to verify that they have free parking.

Help Desk : Allenbell does have parking and the phone is 01223210353. Can I help with anything else?

Next turn

Customer : (Your response)

you need to go through the dialogue first by clicking the 'next turn' button

30

What topics were mentioned in this turn?

General: Booking: Restaurant: Hotels:

Hospital: Police: Train: Taxi: Bus:

User
answer

Submit the HIT

Please try to chat about the following topic:

Task MUL0002:

- You are traveling to _____ and looking forward to try local restaurants.
- You are looking for a **place to stay**. The hotel should be in the **east** and should **include free parking**.
- The hotel should be a **guesthouse**.
- Make sure you get the **reference number**.
- You are also looking for a **moderate** price range.
- If there is no such place, then book a **17:45 on friday**.
- Once you find the place, make sure you get the **reference number**.
- Make sure you get the **reference number**.

--- The End ---

User
Task

System side

Task MUL0002

Help Desk: Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you ?
Customer : I want a place to stay in the east.
Help Desk : I have 6 guesthouses and 1 hotel on the east side. What's your price range?
Customer : Doesn't matter too much. I'd like a 4 star property, though, and would prefer one of the guesthouses.
Help Desk : I'd recommend 517a coldham lane. Would you like me to book a room?
Customer : Could you give me their phone number? I would like to verify that they have free parking.

Next turn

Restaurant	Hotel	Attraction	Hospital	Police	Train	Taxi	Bus
------------	-------	------------	----------	--------	-------	------	-----

Please **modify** the following answers based on the latest customer response:

- What does the user want?

Is the user looking for a specific hotel by name ?	not mentioned
What is the hotel type the user wants?	guesthouse
What is the area the user wants?	east
What is the price range the user wants?	not mentioned
What is the star of the hotel the user wants?	4
Does the user need internet ?	not mentioned
Does the user need parking ?	not mentioned

Lookup

Help Desk : (Your response)

you need to fill in the questionnaires above first.

end-of-dialogue?

Submit the HIT

Task MUL0002

Help Desk: Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you ?
Customer : I want a place to stay in the east.
Help Desk : I have 6 guesthouses and 1 hotel
Customer : Doesn't matter too much. I'd like
Help Desk : I'd recommend 517a
Customer : Could you give me their phone number? I would like to verify that they have free parking.

Dialogue context

Next turn

Restaurant	Hotel	Attraction	Hospital	Police	Train	Taxi	Bus
------------	-------	------------	----------	--------	-------	------	-----

Please **modify** the following answers based on the latest customer response:

- What does the user want?

Is the user looking for a specific hotel by name ?	not mentioned
What is the hotel type the user wants?	guesthouse
What is the area the user wants?	east
What is the price range the user wants?	not mentioned
What is the star of the hotel the user wants?	4
Does the user need internet ?	not mentioned
Does the user need parking ?	not mentioned

Lookup**Help Desk : (Your response)**

you need to fill in the questionnaires above first.

 end-of-dialogue?**Submit the HIT**

Task MUL0002

Help Desk: Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you ?
Customer : I want a place to stay in the east.
Help Desk : I have 6 guesthouses and 1 hotel
Customer : Doesn't matter too much. I'd like
Help Desk : I'd recommend 517a
Customer : Could you give me their phone number? I would like to verify that they have free parking.

Next turn

Restaurant Hotel Attraction Hospital Police Train Taxi Bus

Please **modify** the following answers based on the latest customer response:

- What does the user want?

Is the user looking for a specific hotel **by name**? not mentioned

What is the **hotel type** the user wants? guesthouse

What is the **area** the user wants? east

What is the **price range** the user wants? not mentioned

What is the **star of the hotel** the user wants? 4

Does the user need **internet** ? not mentioned

Does the user need **parking** ? not mentioned

Lookup

Help Desk : (Your response)

you need to fill in the questionnaires above first.

end-of-dialogue?

Submit the HIT

Dialogue context

Database GUI

Task MUL0002

Help Desk: Hello, welcome to the TownInfo centre. I can help you find a restaurant or hotel, look for tourist information, book a train or taxi. How may I help you ?
Customer : I want a place to stay in the east.
Help Desk : I have 6 guesthouses and 1 hotel
Customer : Doesn't matter too much. I'd like 517a
Help Desk : I'd recommend 517a
Customer : Could you give me their phone number? I would like to verify that they have free parking.

Next turn

Restaurant	Hotel	Attraction	Hospital	Police	Train	Taxi	Bus
------------	-------	------------	----------	--------	-------	------	-----

Please **modify** the following answers based on the latest customer response:

- What does the user want?

Is the user looking for a specific hotel **by name**?

What is the **hotel type** the user wants?

What is the **area** the user wants?

What is the **price range** the user wants?

What is the **star of the hotel** the user wants?

Does the user need **internet** ?

Does the user need **parking** ?

Lookup

Help Desk : **(Your response)**

you need to fill in the questionnaires above first.

System response

 end-of-dialogue?**Submit the HIT**

Database GUI

Annotation of system turns

How to acquire high-quality labels for a very specific and challenging task even for NLP practitioners?

Annotation of system turns

How to acquire high-quality labels for a very specific and challenging task even for NLP practitioners?

Two step-approach improves the quality - turkers are asked to annotate an illustrative, long dialogue which covered many problematic examples.

The chosen subset of well-performing turkers were given more detailed instructions and required to go through the test again.

John	Hi Anna, how can I help you?	
Anna	I want to arrive by 11:30 at Cambridge.	
	<h2>Dialogue context</h2>	<div style="background-color: #d3d3d3; padding: 5px; margin-bottom: 10px;"> Booking Restaurant Hotel Attraction Taxi Train Hospital Police More help? Greetings Goodbye You're welcome Not sure </div> <p style="text-align: center;">Train domain</p> <p>John is requesting: day <input type="checkbox"/> departure place <input type="checkbox"/> destination place <input type="checkbox"/> leave after <input type="checkbox"/> arrive by <input type="checkbox"/> people <input type="checkbox"/> informing about <input checked="" type="checkbox"/></p> <p>people <input type="checkbox"/> possible choices <input checked="" type="checkbox"/> 3 <input type="checkbox"/> departure place <input type="checkbox"/> destination place <input type="checkbox"/> leave after <input type="checkbox"/> arrival by <input checked="" type="checkbox"/> 6:43, 8:43, 10:43 <input type="checkbox"/> day <input type="checkbox"/> reference <input type="checkbox"/> trainID <input type="checkbox"/> ticket price <input type="checkbox"/> travel time <input type="checkbox"/> </p> <p>offering to book a train <input checked="" type="checkbox"/></p> <p>people <input type="checkbox"/> possible choices <input type="checkbox"/> departure place <input type="checkbox"/> destination place <input type="checkbox"/> leave after <input type="checkbox"/> arrival by <input type="checkbox"/> day <input type="checkbox"/> reference <input type="checkbox"/> trainID <input type="checkbox"/> ticket price <input type="checkbox"/> travel time <input type="checkbox"/> </p> <p>is asking to select train(s) <input type="checkbox"/></p> <p>informing that no trains are available <input type="checkbox"/></p> <p>informing that train was booked <input type="checkbox"/></p>
Turn 1 John	There are three trains, one arrives at 6:43, one at 8:43, and one at 10:43, which would you like to book?	

John	Hi Anna, how can I help you?	
Anna	I want to arrive by 11:30 at Cambridge.	<h2>Domains</h2> <p>Booking Restaurant Hotel Attraction Taxi Train Hospital Police More help? Greetings Goodbye You're welcome Not sure</p> <p>Train domain</p> <p>John is requesting: day departure place destination place leave after arrive by people informing about ✓</p> <p>people possible choices ✓ 3 departure place destination place leave after arrival by ✓ 6:43, 8:43, 10:43 day reference trainID ticket price travel time </p> <p>offering to book a train ✓</p> <p>people possible choices departure place destination place leave after arrival by day reference trainID ticket price travel time </p> <p>is asking to select train(s)</p> <p>informing that no trains are available</p> <p>informing that train was booked</p>
Turn 1	There are three trains, one arrives at 6:43, one at 8:43, and one at 10:43, which would you like to book?	
John		

John	Hi Anna, how can I help you?	
Anna	I want to arrive by 11:30 at Cambridge.	
	<h2>Dialogue context</h2>	<p>Domains</p> <p>Booking Restaurant Hotel Attraction Taxi Train Hospital Police More help? Greetings Goodbye You're welcome Not sure</p> <p>Train domain</p> <p>John is requesting: day departure place destination place leave after arrive by people informing about ✓ people possible choices ✓ 3 arrival by ✓ 6:43, 8:43, 10:43 destination place leave after ticket price travel time offering to book a train ✓ people possible choices departure place destination place leave after arrival by day reference trainID ticket price travel time </p> <p>Slot-value pairs</p> <p>Dialogue acts</p> <p>informing that no trains are available informing that train was booked</p>
Turn 1	There are three trains, one arrives at 6:43, one at 8:43, and one at 10:43, which would you like to book?	
John		

Annotation of system turns

act type	inform / request / select / recommend/ / not found request booking info / offer booking / inform booked / decline booking welcome /greet / bye / reqmore
slots	address / postcode / phone / name / no of choices / area / pricerange / type / internet / parking / stars / open hours / departure destination / leave after / arrive by / no of people / reference no. / trainID / ticket price / travel time / department / day / no of days

WOZ vs M2M

M2M data collection:

- Full control over the dialogue flow
 - Paraphrase data collection UI is simpler to build
 - Easier to engineer particular behaviours
 - Crowdsourceers don't have to label data
-
- Notation of dialogue acts while developing the dialogue flow
 - Simulating both users and the hand-crafted system
 - No interesting system behaviours learned; everything is expected

WOZ vs M2M

WOZ data collection:

- No explicit dialogue act annotations
- System policy can be learned directly from the data
- Interesting and diverse system behaviours (but long-tail...)

- Not easy to control the system behaviour
- Black box during system development
- User task simulation has to be created
- Complex UI for data annotation
- Difficult to scale to large domains (for now)

Metric	DSTC2	SFX	WOZ2.0	FRAMES	KVRET	M2M	MultiWOZ
# Dialogues	1,612	1,006	600	1,369	2,425	1,500	8,438
Total # turns	23,354	12,396	4,472	19,986	12,732	14,796	115,424
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Avg. tokens per turn	8.54	8.79	11.24	12.60	8.02	8.24	13.18
Total unique tokens	986	1,473	2,142	12,043	2,842	1,008	24,071
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# Values	212	1847	99	3871	1363	138	4510

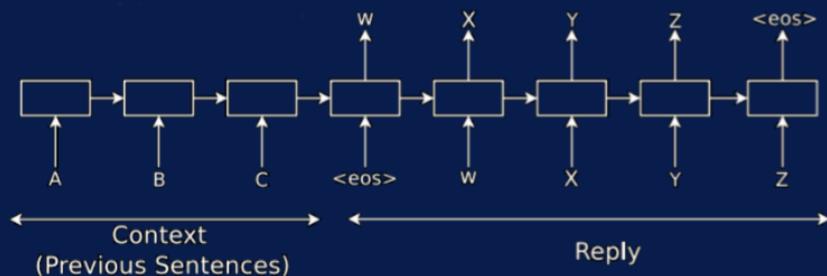
Slot	WOZ 2.0	MultiWOZ (restaurant)	MultiWOZ (all domains)
Overall accuracy	96.5	89.7	97.2
Joint goals	85.5	80.9	25.8

End-to-end
dialogue modelling

Sequence-to-Sequence Conversational Model

Social Chatbots (Chit-chat dialogue systems)

[Vinyals et Le, 2015]



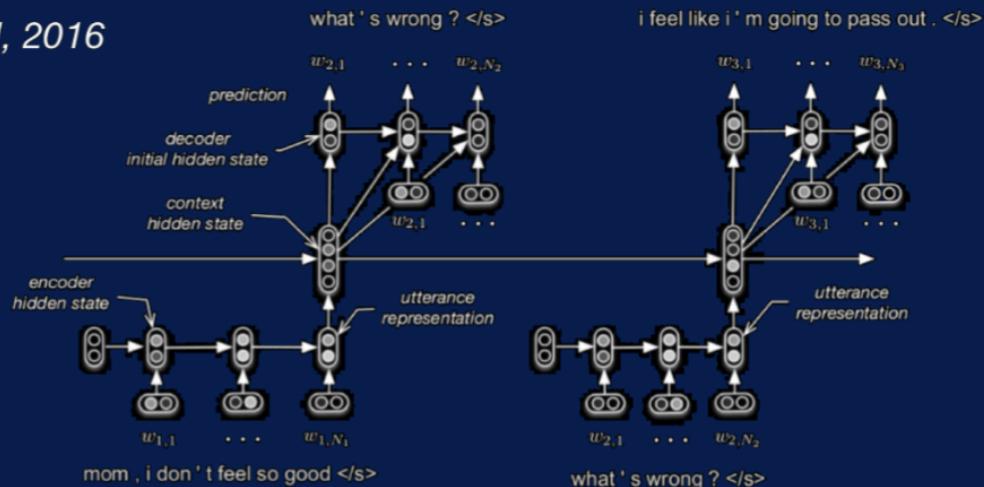
Human: what do you think about tesla ?
Machine: he 's a good conductor .
Human: what do you think about bill gates ?
Machine: he 's a good man .
Human: What do you think about messi ?
Machine: he 's a great player .
Human: what do you think about cleopatra ?
Machine: oh , she 's very regal .
Human: what do you think about england during the reign of elizabeth ?
Machine: it was a great place .

Human: what is the purpose of life ?
Machine: to serve the greater good .
Human: what is the purpose of living ?
Machine: to live forever .
Human: what is the purpose of existence ?
Machine: to find out what happens when we get to the planet earth .
Human: where are you now ?
Machine: i 'm in the middle of nowhere .
Human: what is the purpose of dying ?
Machine: to have a life .
Human: what is the purpose of being intelligent ?
Machine: to find out what it is .
Human: what is the purpose of emotions ?
Machine: i don 't know .

- Ignore the structure of the problem.
- A simple sequence-to-sequence model to learn a context-to-response mapping.
- Maximising a conditional probability $p(\text{response}|\text{context})$
- Large model with huge data.
- Can learn to generate interesting responses.

Hierarchical RNN for Dialogue

Serban et al, 2016



Reference (U_1, U_2)	MAP	Target (U_3)
U_1 : yeah , okay . U_2 : well , i guess i ' ll be going now .	i ' ll see you tomorrow .	yeah .
U_1 : oh . <continued_utterance> oh . U_2 : what ' s the matter , honey ?	i don ' t know .	oh .
U_1 : it ' s the cheapest . U_2 : then it ' s the worst kind ?	no , it ' s not .	they ' re all good , sir .
U_1 : <person> ! what are you doing ? U_2 : shut up ! c ' mon .	what are you doing here ?	what are you that crazy ?

Problems: Generic, difficulty keeping coherence, lack of integration into KBs or 3rd party services... **not very useful for business use cases** (task oriented dialogues)

And more...

- New objective function with penalty [Li et al., NAACL-HLT'16]
- Latent Variable HRED (VHRED) [Serban et al., AAAI'17]
- A framework to unify different structures [Tian et al., ACL'17]
- DPP-Augmented decoder [Song et al., AAAI'18]
- Incorporating multi-head attention schema into conversations [Tao et al., AAAI'18]
- Extension to memory network for long term dependency [Chen et al., WWW'18]
- Hierarchical recurrent attention network [Xing et al., AAAI'18]

And more...

- Persona modeling is one way to solve the conversational consistency problem [Li et al., ACL'16]
- Topic alignment in conversation is important [Xing et al., AAAI'17]
- Personality shall be fixed attributes [Qian et al., IJCAI'18]
- Speaker-Interaction RNN [Zhang et al., AAAI'18]
- EMoji distributions in conversations [Zhou et al., ACL'18]
- Emotional chatting machine [Zhou et al., AAAI'18]
- Personality shall be fixed attributes [Qian et al., IJCAI'18]

But...

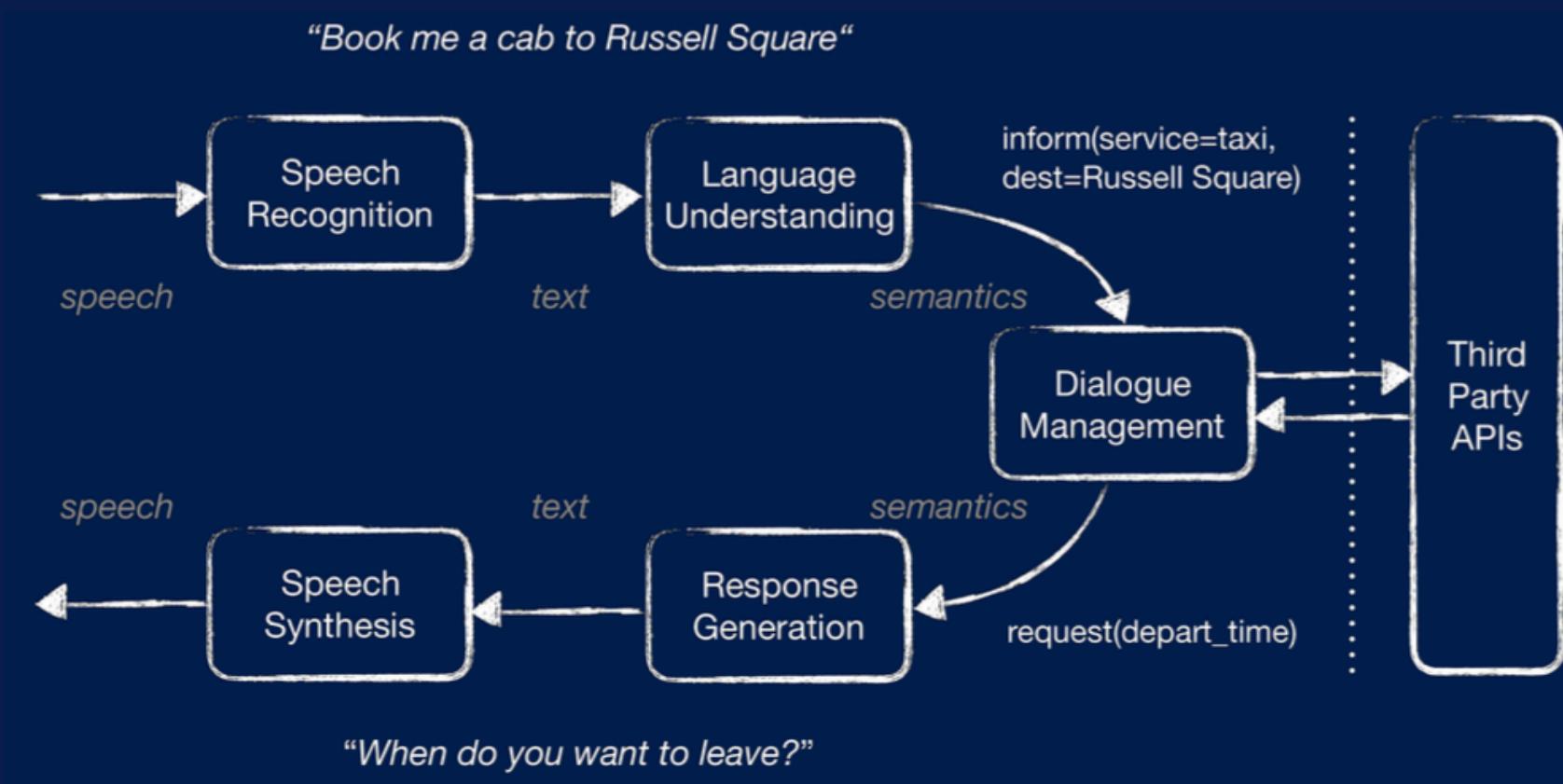
M: Hello, welcome to the Cambridge dialogue system, What kind of food would you like?
H: Yeah I want to find a restaurant that serves European food.
M: Hotel du Vin and Bistro is a nice place. It serves European food.
H: Uh what is the address and phone number?
M: Hotel du Vin and Bistro is a nice place. Their address is XXX and their phone is YYY.
H: Thank you goodbye.
M: Thank you for using this system.

[Su et al, 2016]

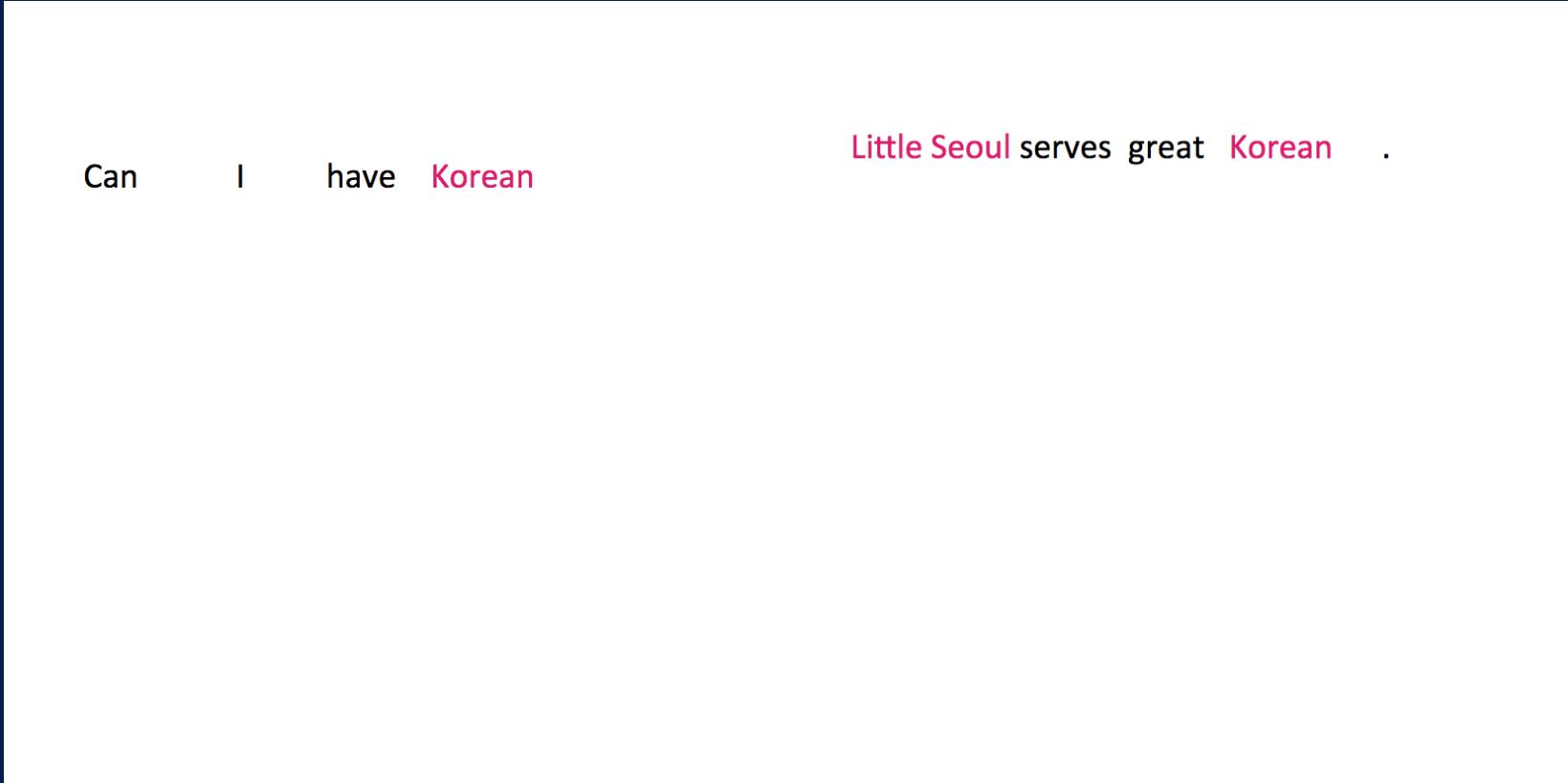
A: How old are you ?
B: I'm 16. Why are you asking ?
A: I thought you were 12.
B: What made you think so ?
A: I don't know what you are talking about.
B: You don't know what you are saying.

[Li et al, 2016]

Task-Oriented Dialogue Systems



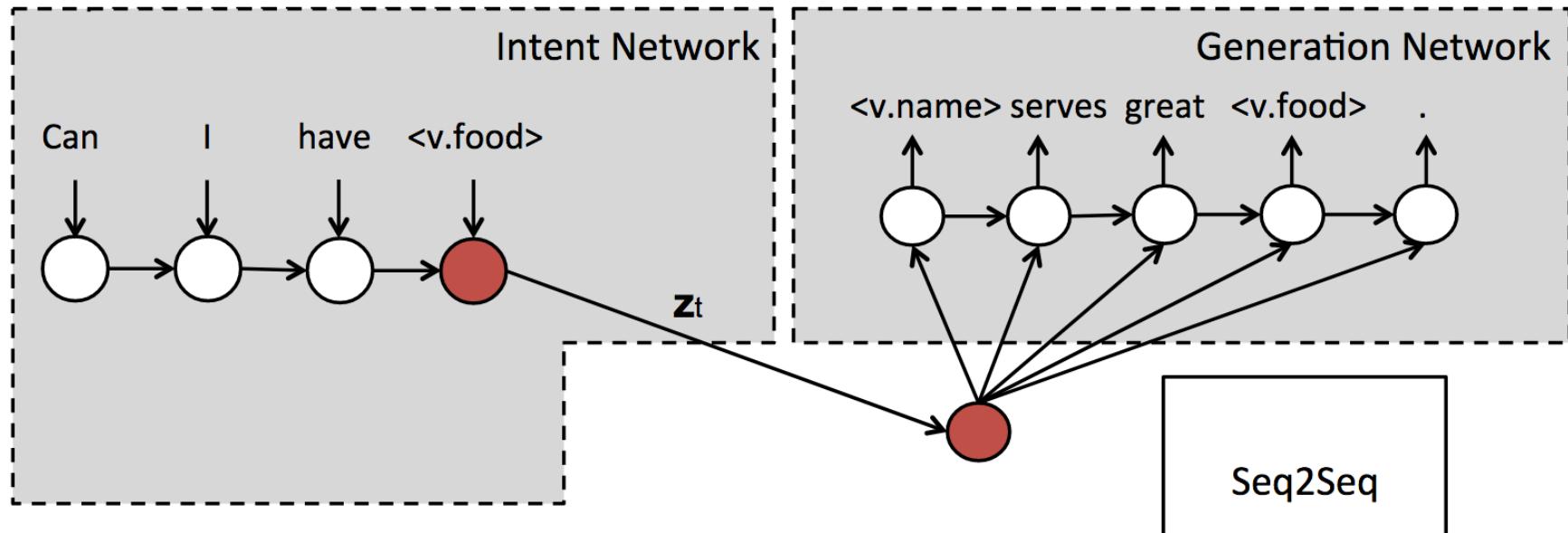
Wen et al (2016)

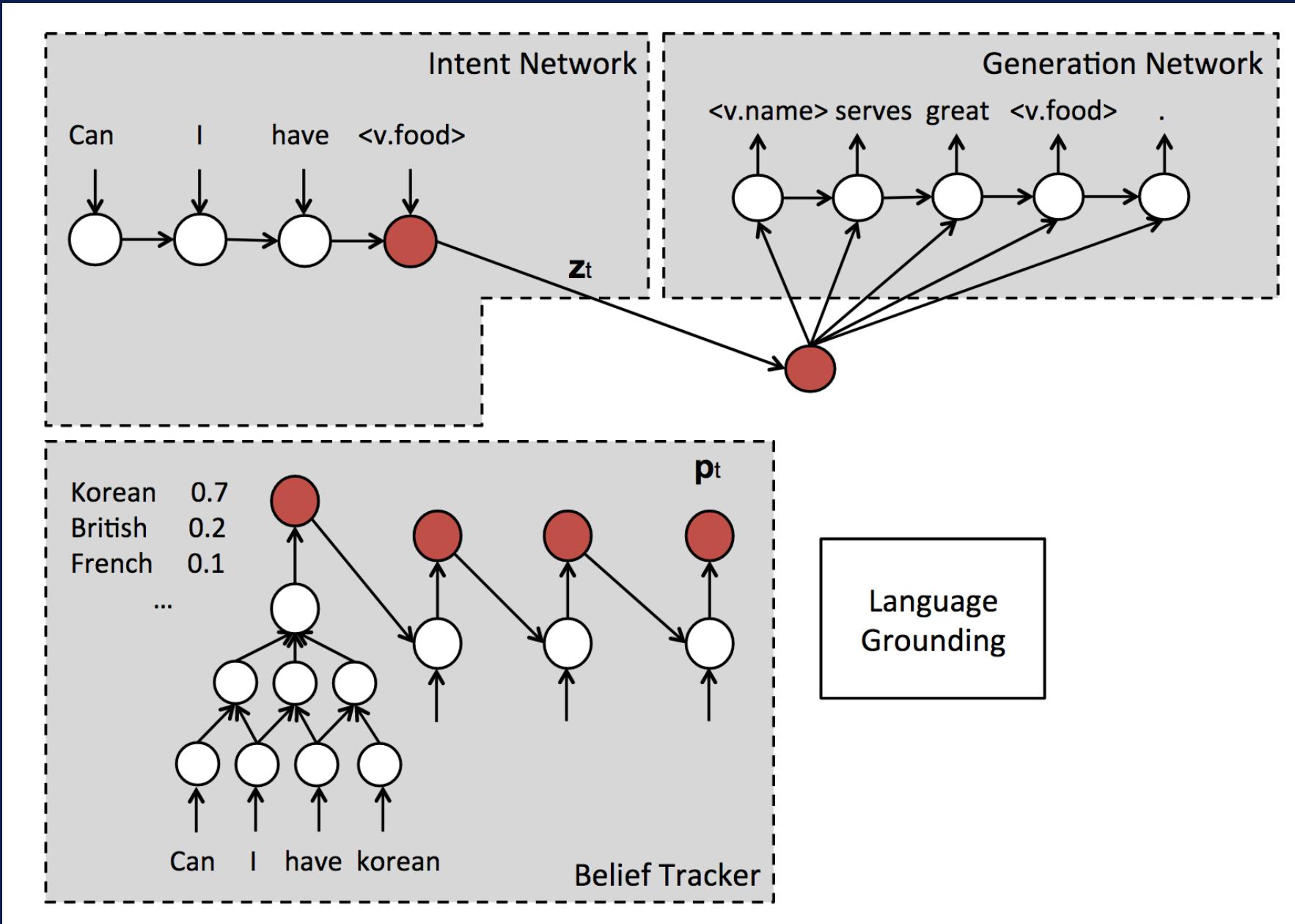


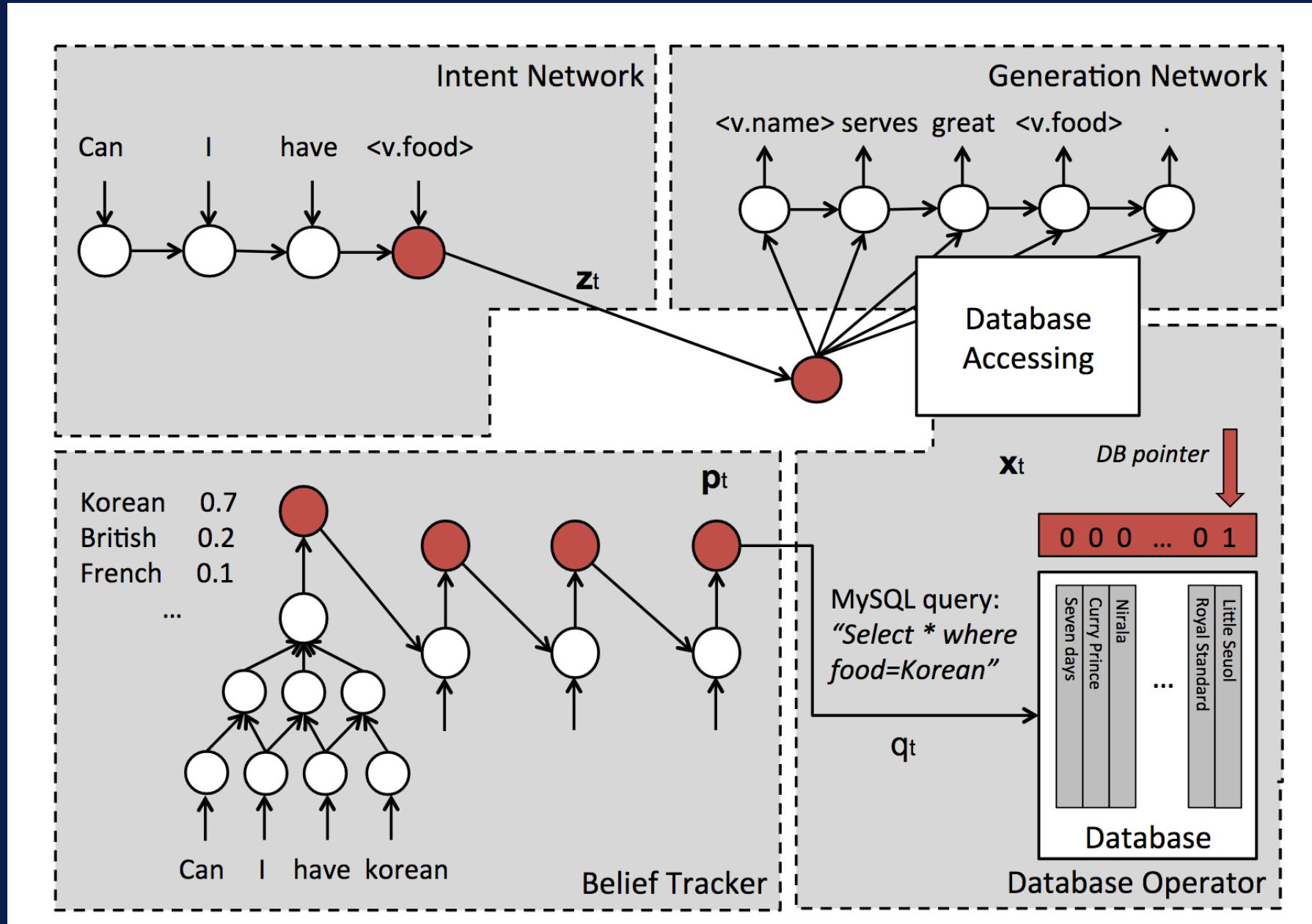
Can I have <v.food>

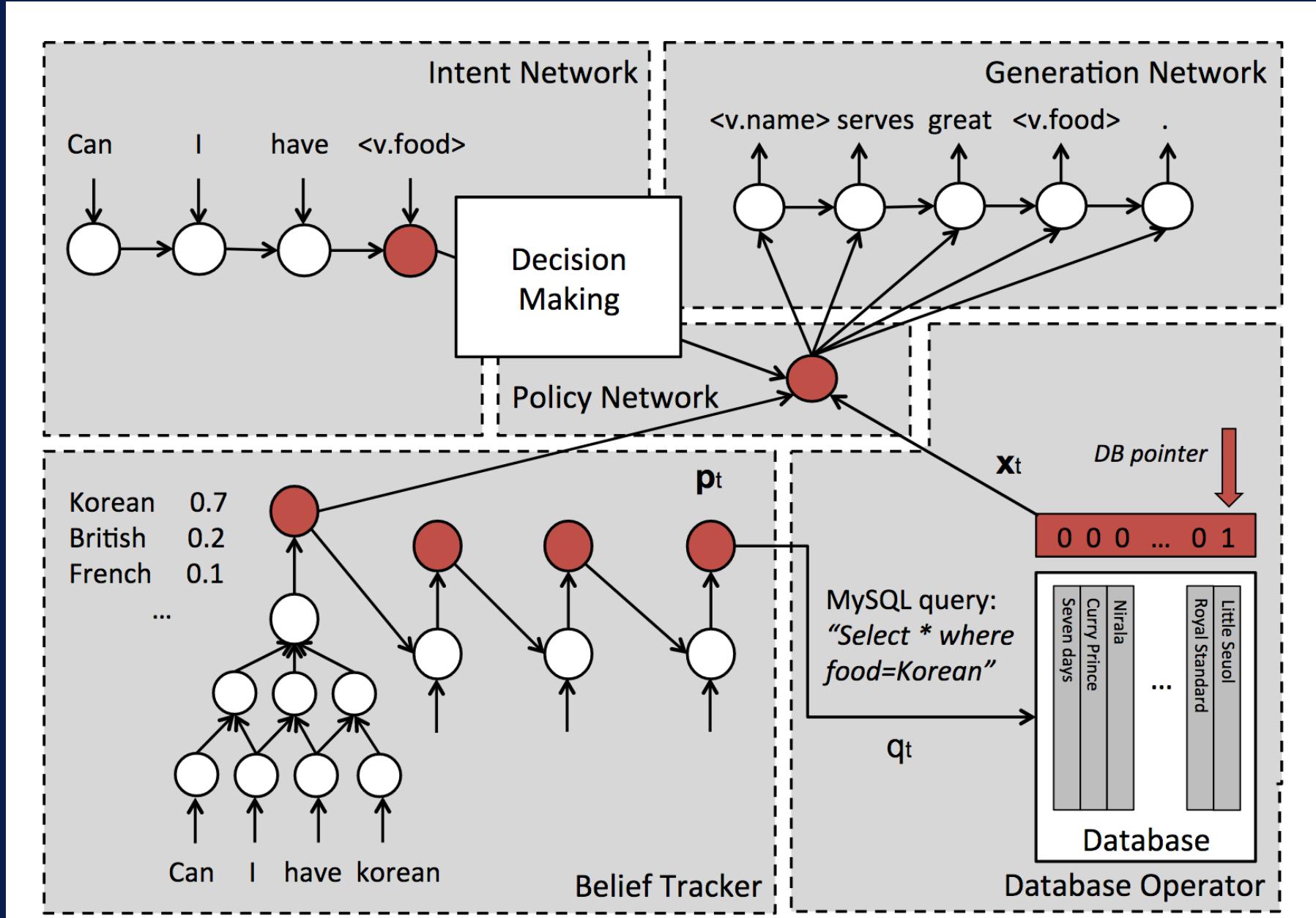
<v.name> serves great <v.food> .

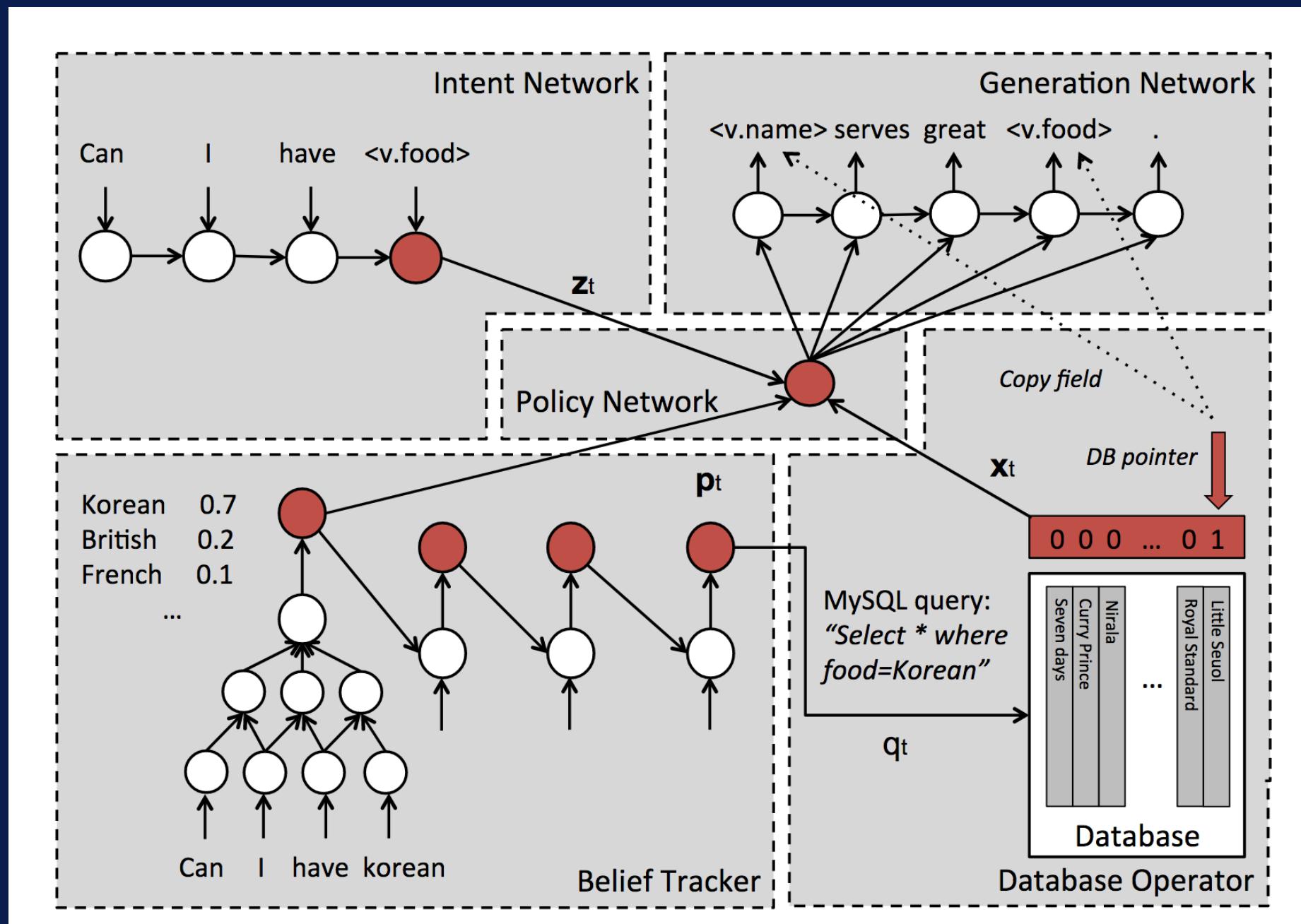
Delexicalisation



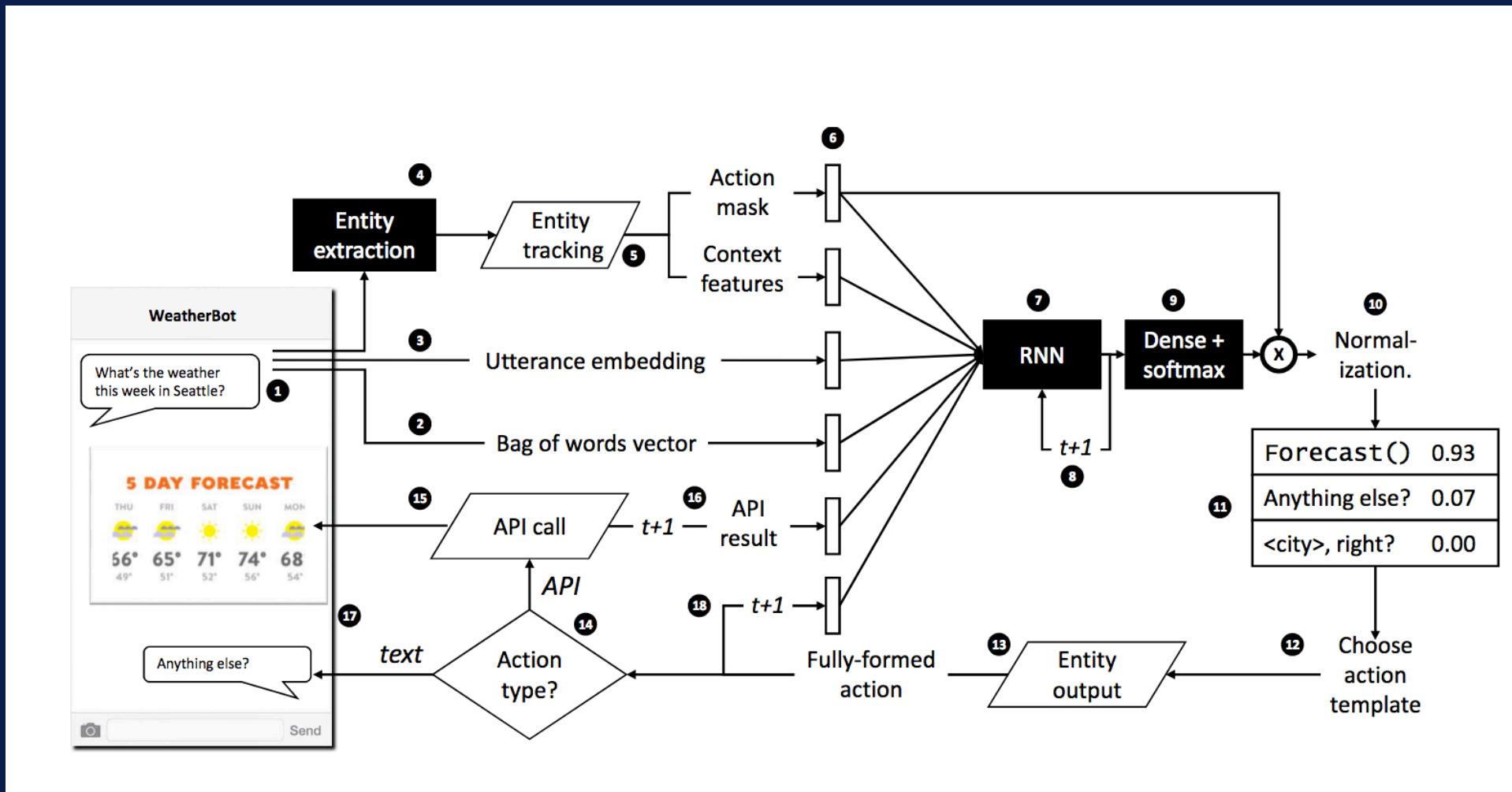








Williams et al (2017)



Zhao et al (2017)

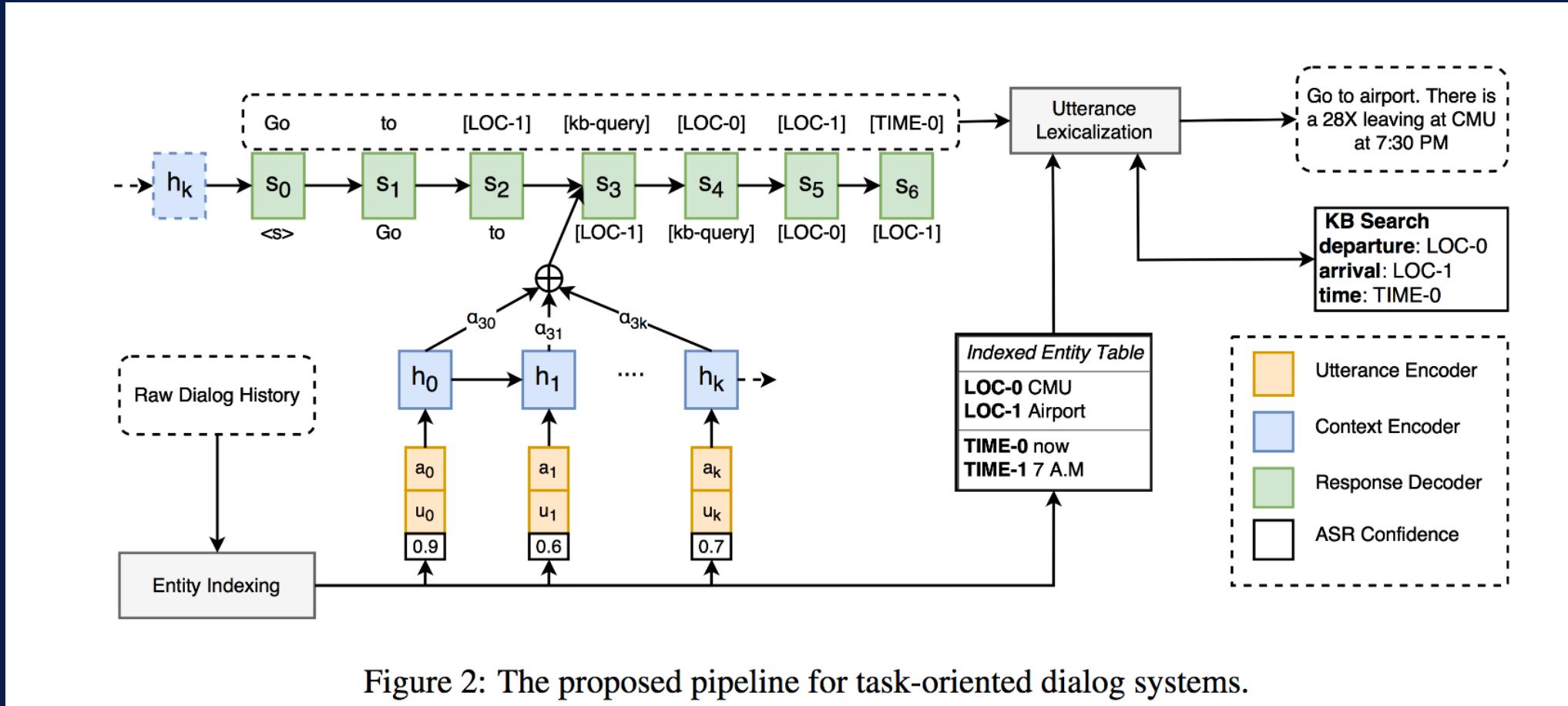


Figure 2: The proposed pipeline for task-oriented dialog systems.

Leveraging Chat Data to Improve OOD Recovery :

- studies shows that open-domain conversations help improves the performance
- original data set (CMU Let's Go Bus IS) extended using publicly available chat corpus
- extension follows simple idea:

Sys: Where are you leaving from?

Usr: How is your day?

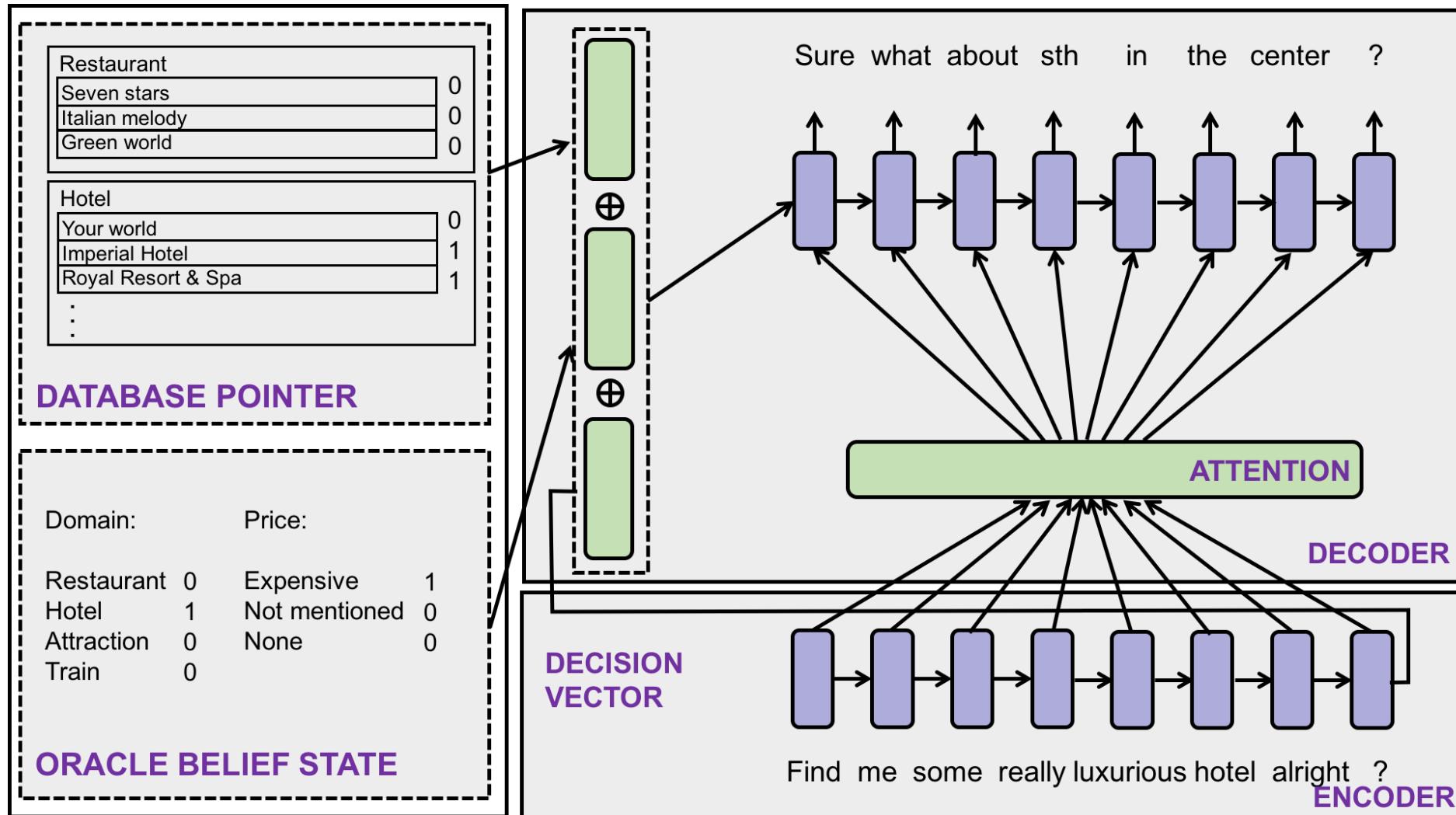
Sys: I am doing great. Where are
you leaving from?

Usr: I am leaving from CMU

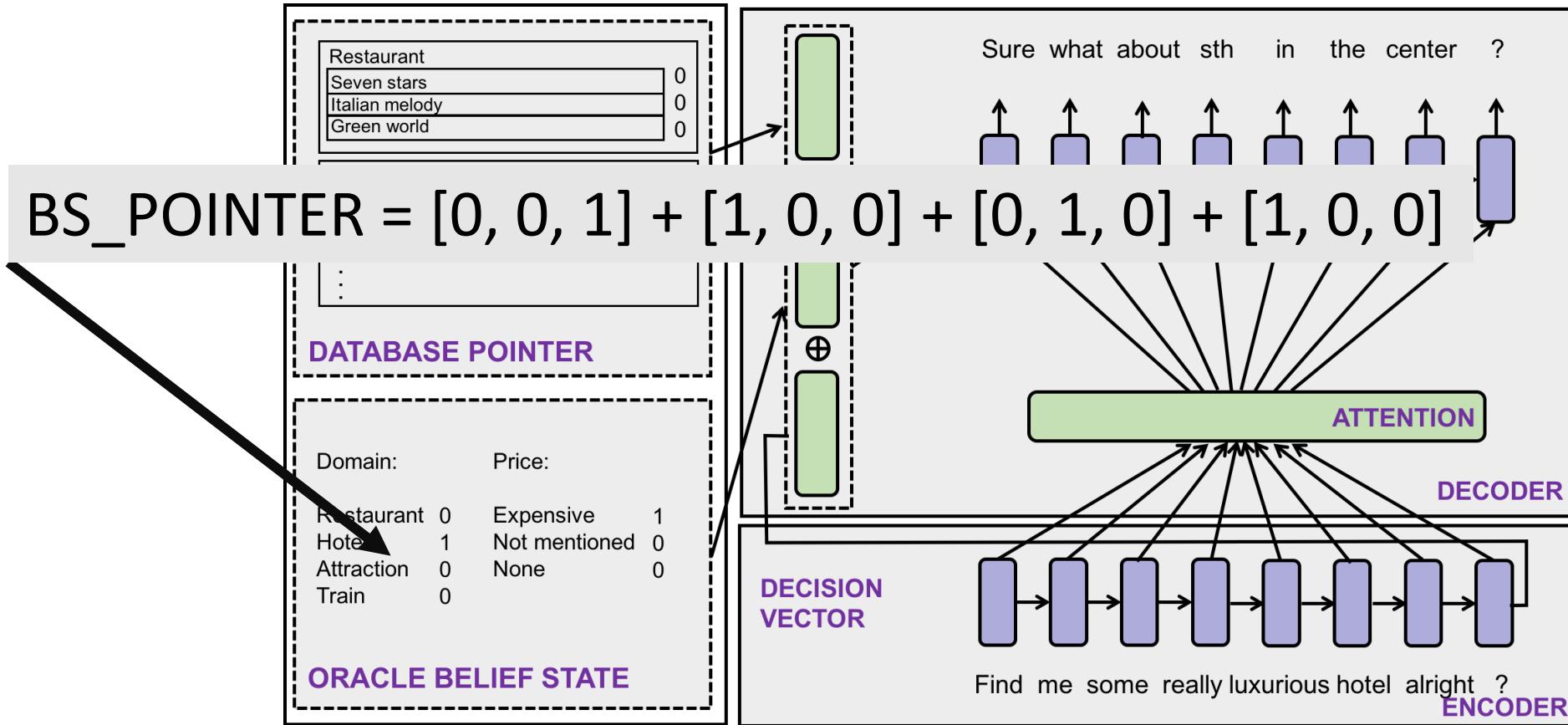
Sys: Ok, what's your destination?

Augmented Turn

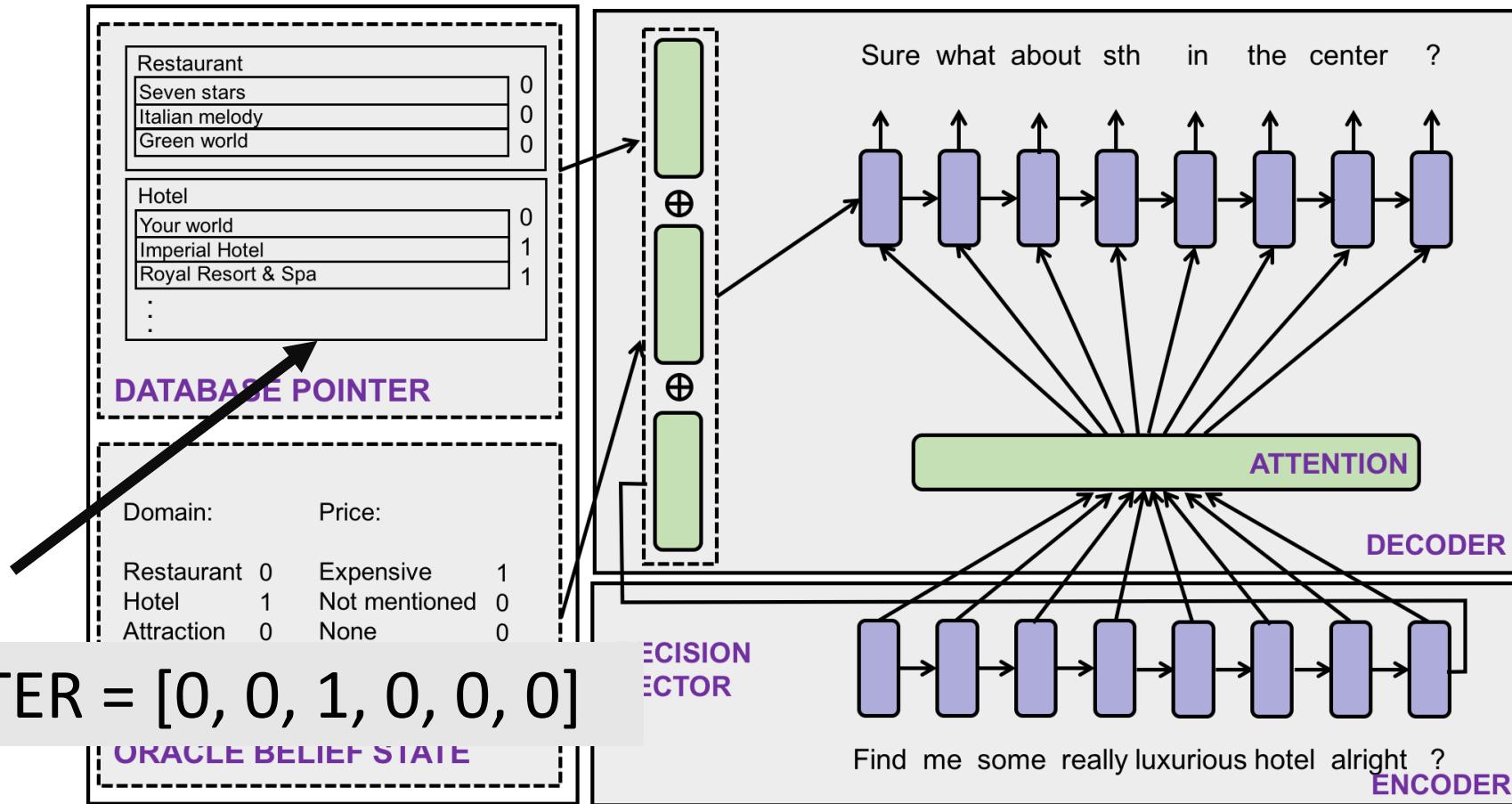
Coding sessions



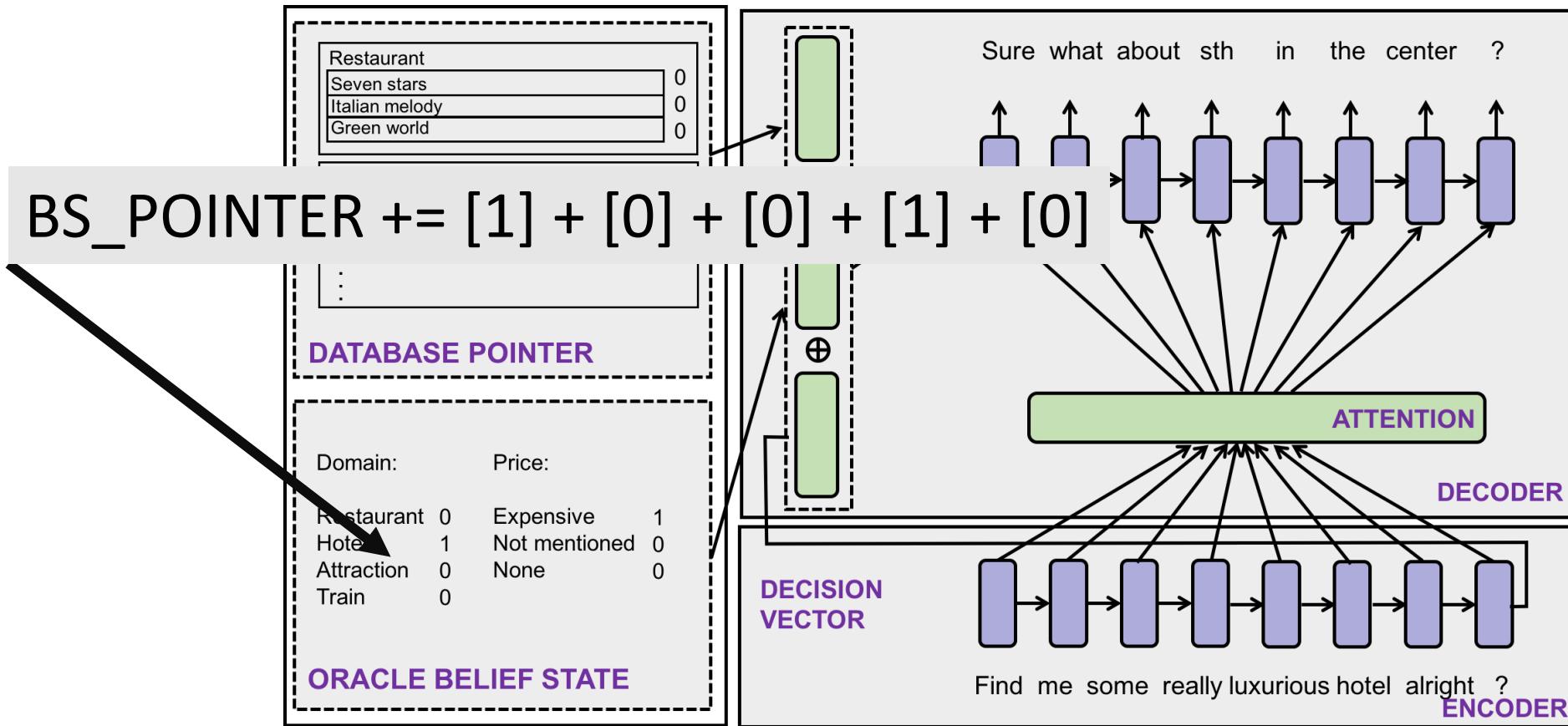
TASK 1



TASK 2



TASK 3



TASK 4

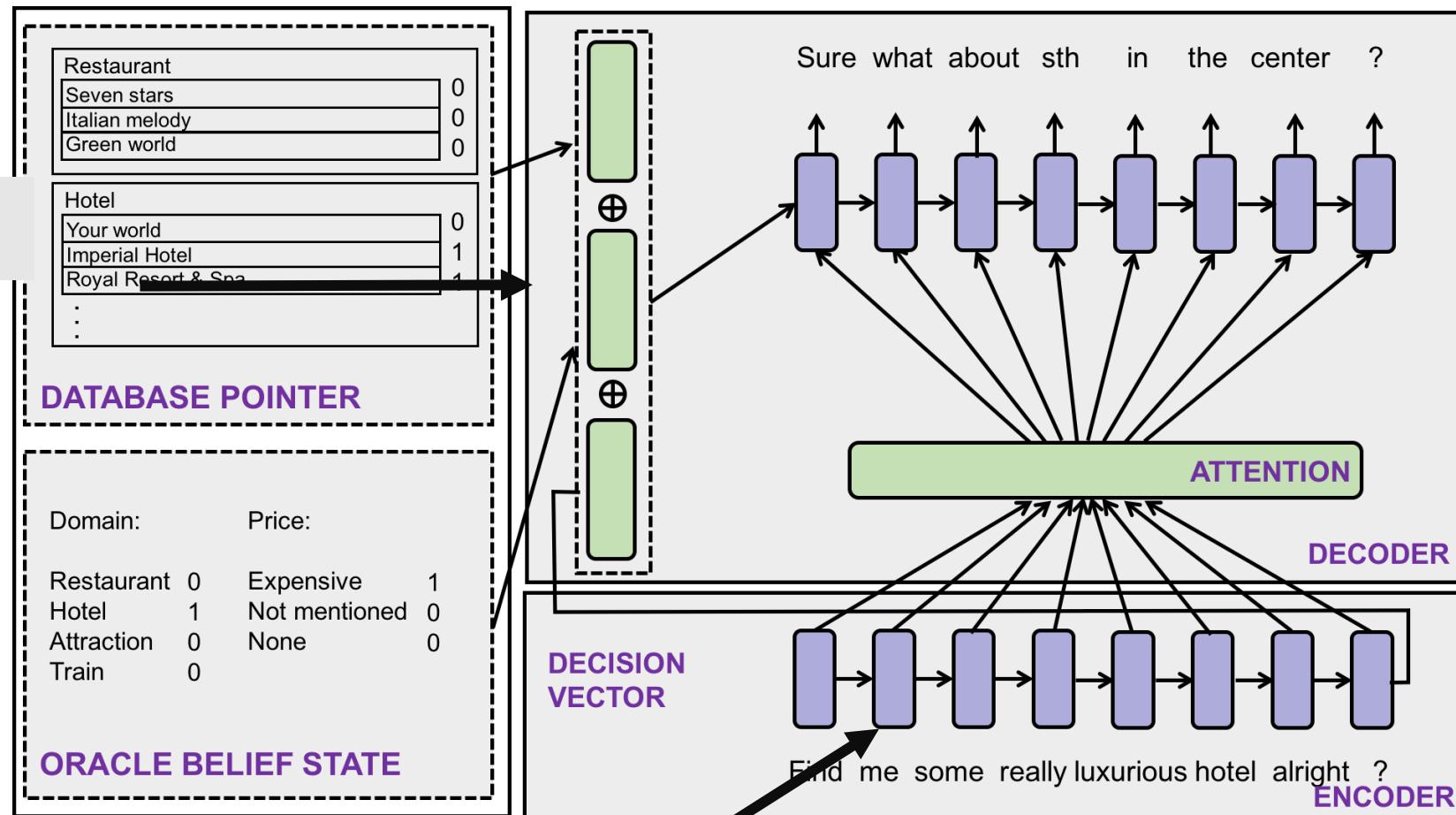
I want a cheap restaurant in the centre of the town.

====>

I want a [value_pricerange] restaurant in the [SLOT_A] of the town.

TASK 5

POLICY



ENCODING