Dialog Systems (2)

Modern Perspective
by
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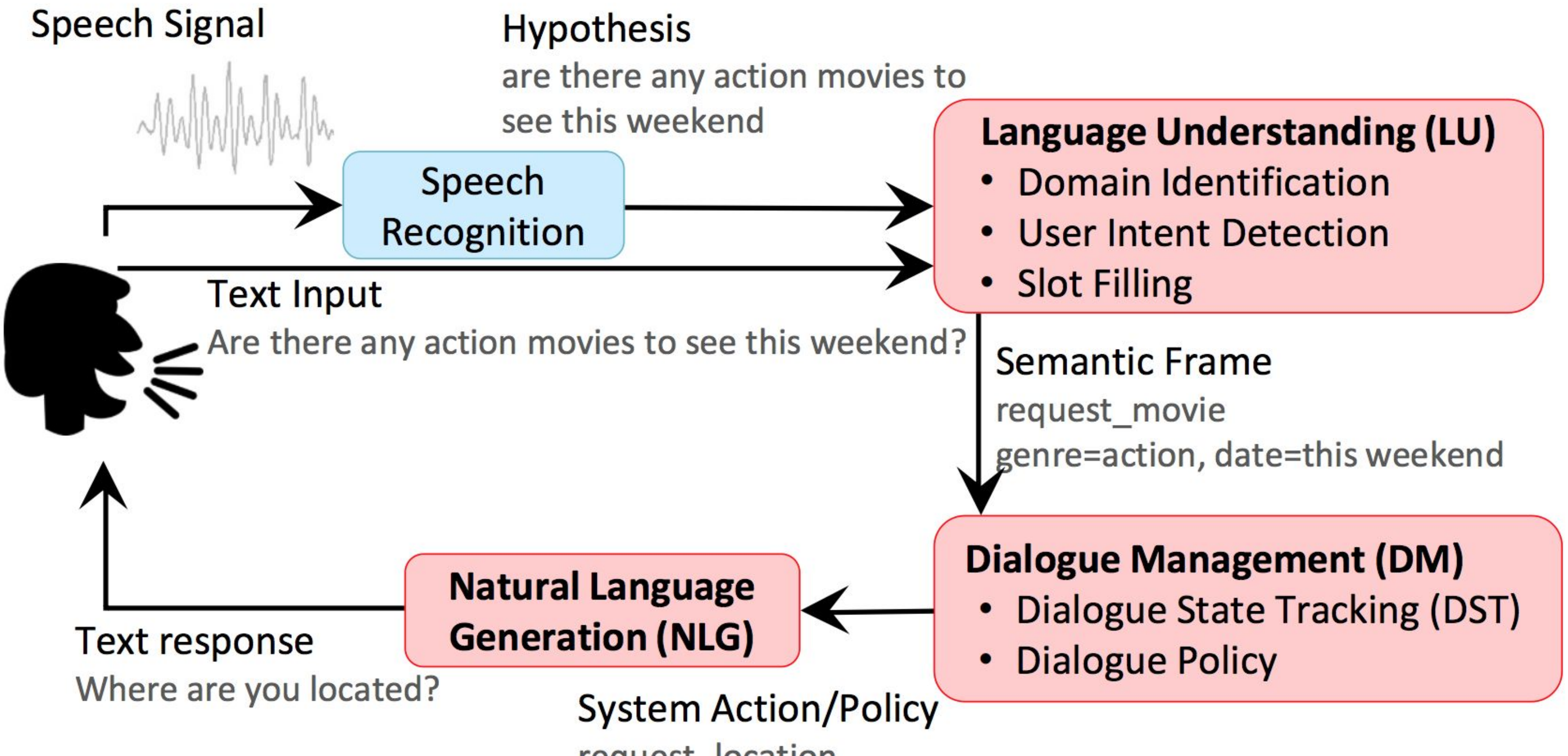
Task-Oriented Dialogue System



Language Modeling

Goal: estimate the probability of a word sequence

$$P(w_1, \cdots, w_m)$$

Example task: determinate whether a sequence is grammatical or makes more sense

recognize speech
or
wreck a nice beach

If P(recognize speech)
> P(wreck a nice beach)

Output =
“recognize speech”

N-Gram Language Modeling

Goal: estimate the probability of a word sequence $$P(w_1, \cdots, w_m)$$

N-gram language model

- Probability is conditioned on a window of (n-1) previous words

$$P(w_1, \cdots, w_m) = \prod_{i=1}^{m} P(w_i \mid w_1, \cdots, w_{i-1}) \approx \prod_{i=1}^{m} P(w_i \mid w_{i-(n-1)}, \cdots, w_{i-1})$$

- Estimate the probability based on the training data

$$P(\text{beach}|\text{nice}) = \frac{C(nice\ beach)}{C(nice)}$$

Count of “nice beach” in the training data

Count of “nice” in the training data

N-Gram Language Modeling

Training data:

- The dog ran ……
- The cat jumped ……

P(jumped | dog) = ~~0~~ 0.0001

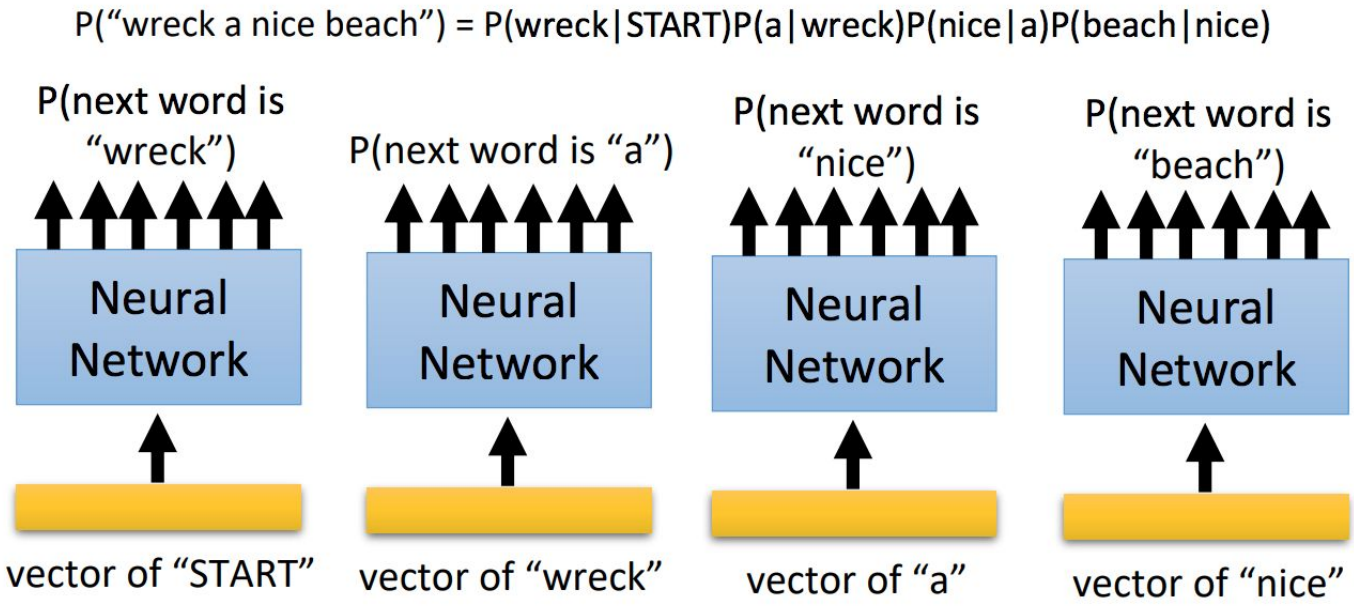
P(ran | cat) = ~~0~~ 0.0001

give some small probability
→ smoothing

- The probability is not accurate.
- The phenomenon happens because we cannot collect all the possible text in the world as training data.

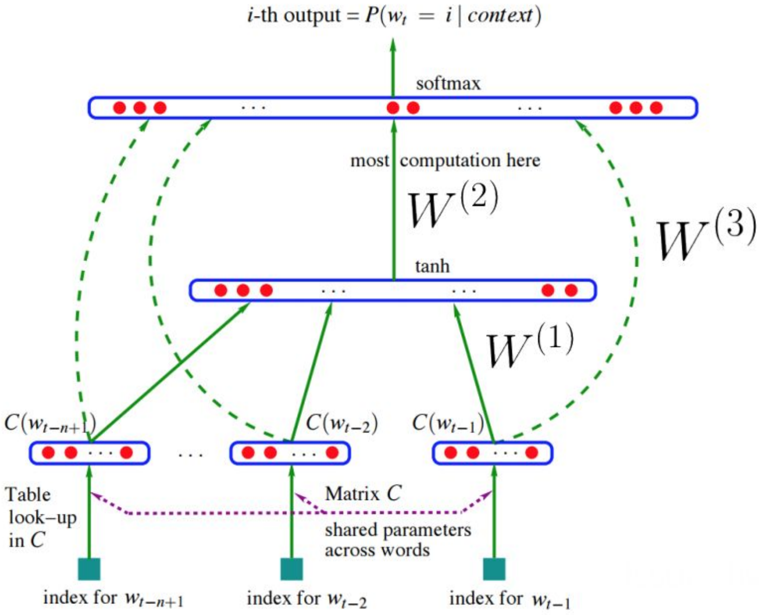
Neural Language Modeling

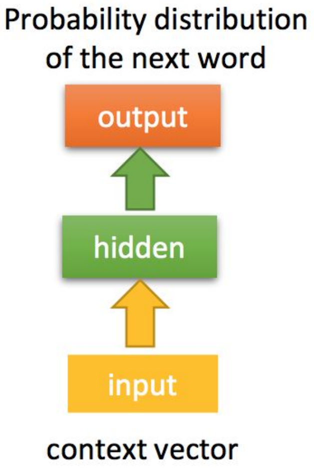
Idea: estimate $P(w_i \mid w_{i-(n-1)}, \cdots, w_{i-1})$ not from count, but from the NN prediction



Neural Language Modeling

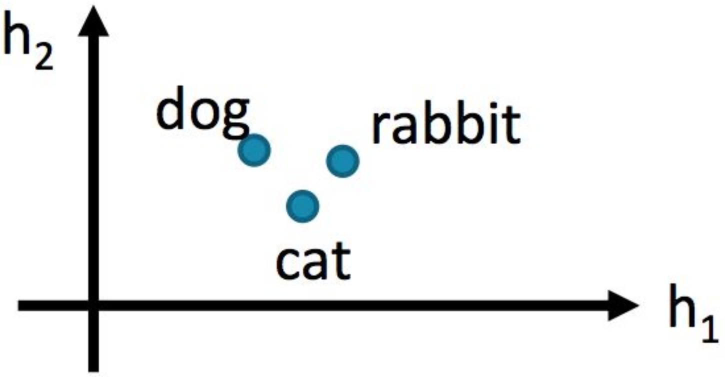
$$\hat{y} = \mathrm{softmax}(W^{(2)}\sigma(W^{(1)}x + b^{(1)}) + W^{(3)}x + b^{(3)})$$





Neural Language Modeling

The input layer (or hidden layer) of the related words are close

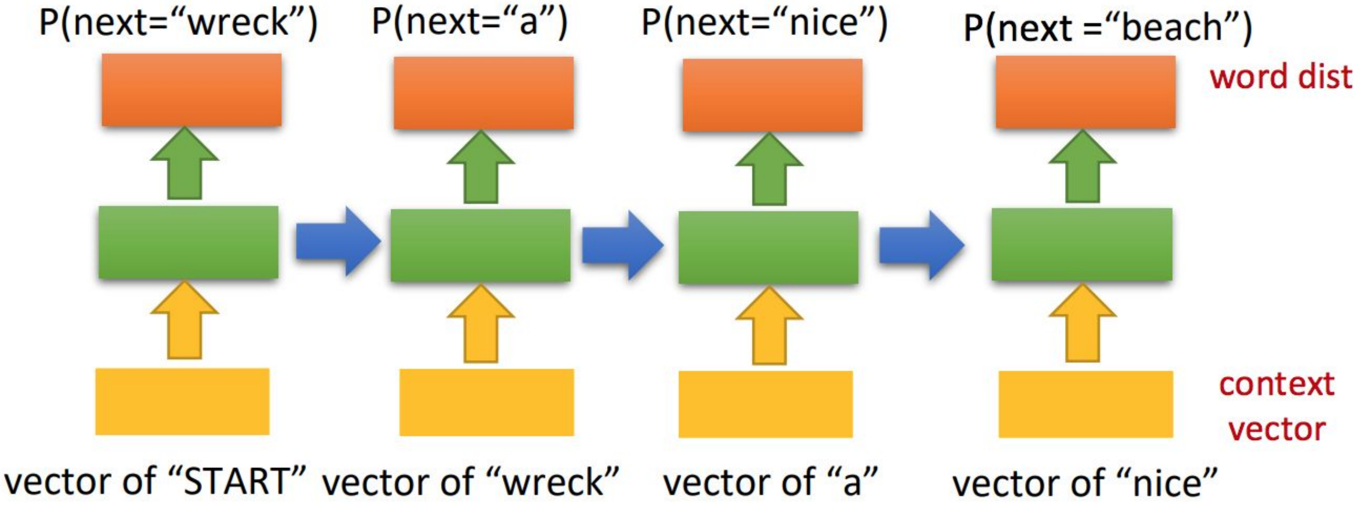


If P(jump|dog) is large, P(jump|cat) increase accordingly (even there is not “… cat jump …” in the data)

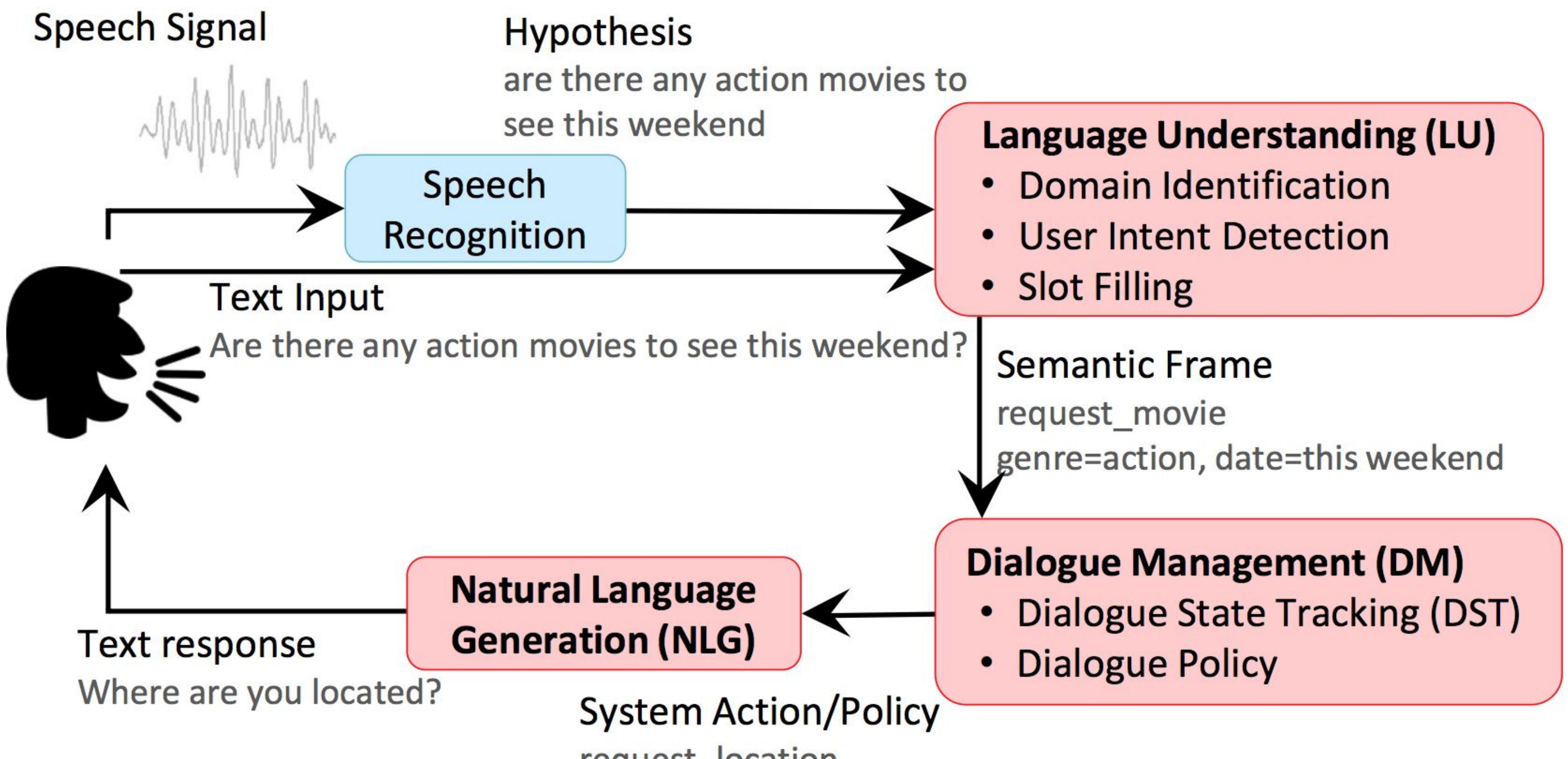
RNNLM

Idea: condition the neural network on all previous words and tie the weights at each time step

Assumption: temporal information matters



Task-Oriented Dialogue System



Natural Language Generation

inform(name=Seven_Days, foodtype=Chinese)

Seven Days is a nice Chinese restaurant

Template-Based NLG

Define a set of rules to map frames to NL

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

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

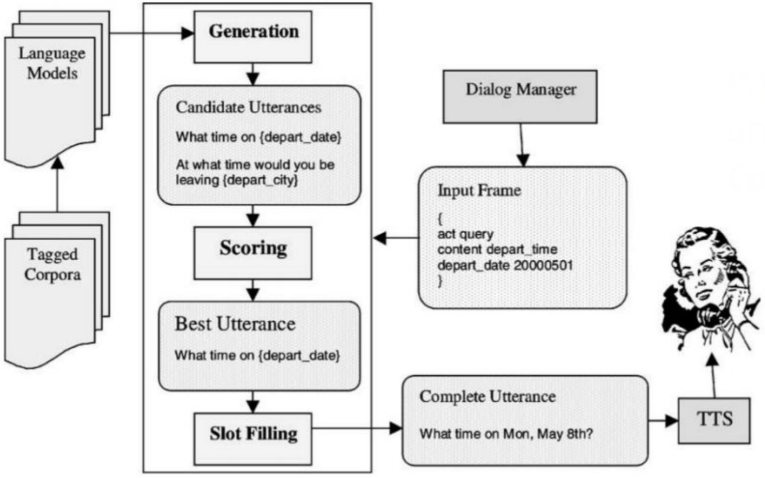
Class-Based LM NLG (Oh and Rudnicky, 2000)

Class-based language modeling

$$P(X \mid c) = \sum_t \log p(x_t \mid x_0, x_1, \cdots, x_{t-1}, c)$$

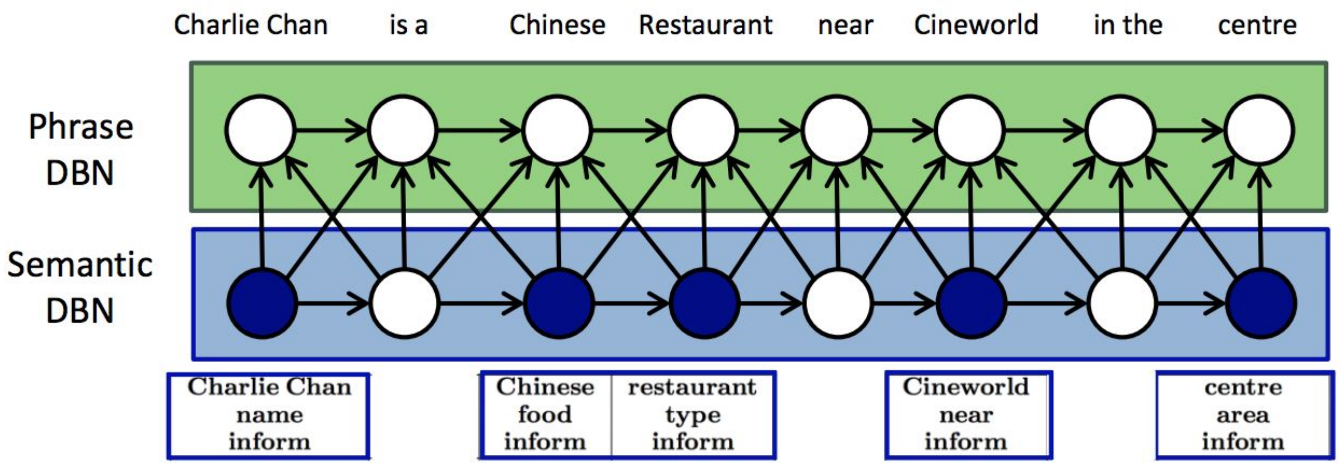
NLG by decoding $$X^* = \arg\max_X P(X \mid c)$$

Classes:
inform_area
inform_address
...
request_area
request_postcode



Pros: easy to implement/ understand, simple rules
Cons: computationally inefficient

Phrase-based NLG



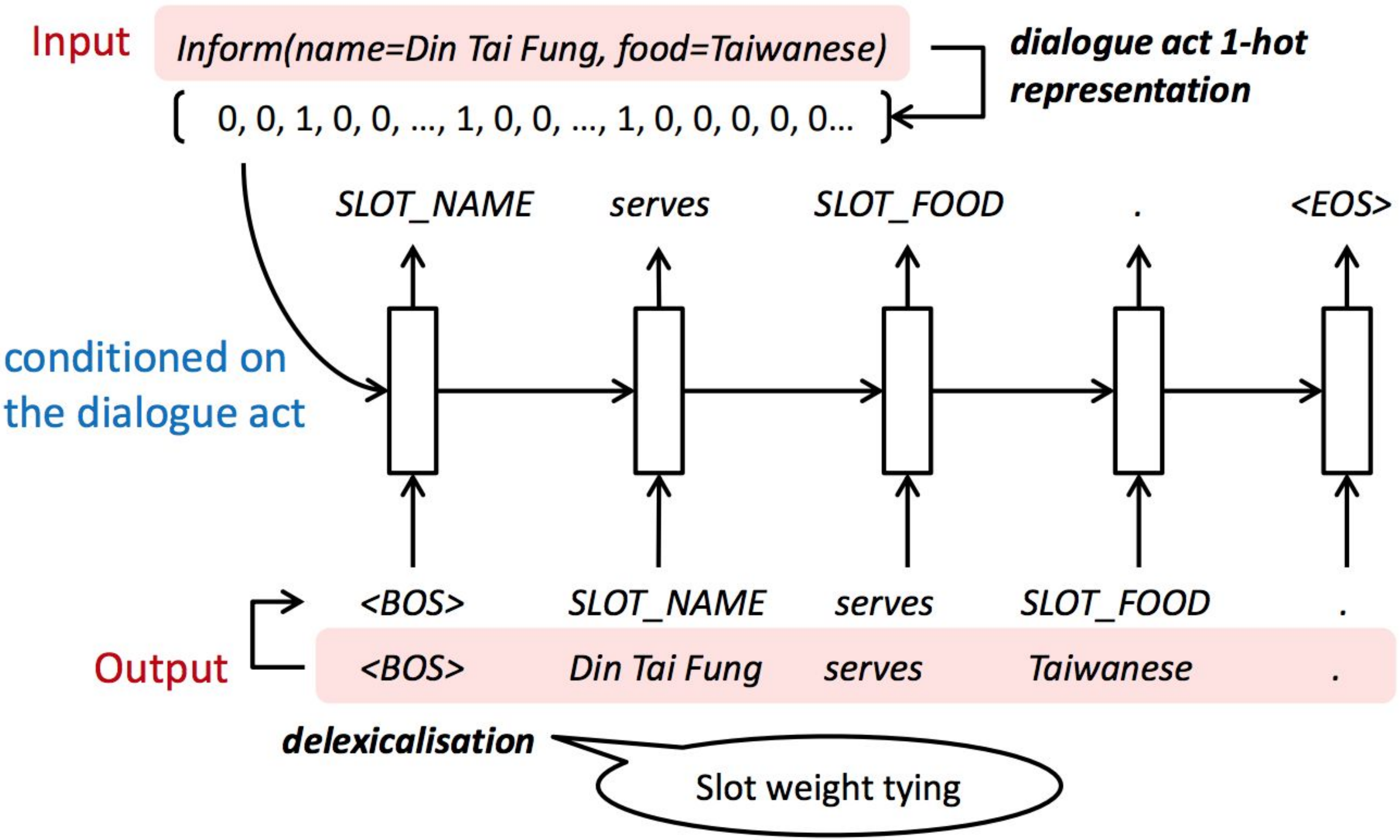
Inform(name=Charlie Chan, food=Chinese, type= restaurant, near=Cineworld, area=centre)

realization phrase   semantic stack

r_t	s_t	h_t	l_t
<s>	START	START	START
The Rice Boat	inform(name(X))	X	inform(name)
is a	inform	inform	EMPTY
restaurant	inform(type(restaurant))	restaurant	inform(type)
in the	inform(area)	area	inform
riverside	inform(area(riverside))	riverside	inform(area)
area	inform(area)	area	inform
that	inform	inform	EMPTY
serves	inform(food)	food	inform
French	inform(food(French))	French	inform(food)
food	inform(food)	food	inform
</s>	END	END	END

Pros: efficient, good performance
Cons: require semantic alignments

RNN-Based LM NLG



RNN-Based LM NLG: an issue

Issue: semantic repetition

- Din Tai Fung is a great *Taiwanese* restaurant that serves *Taiwanese*.
- Din Tai Fung is a *child friendly* restaurant, and also *allows kids*.

Deficiency in either model or decoding (or both)

Mitigation

- Post-processing rules (Oh & Rudnicky, 2000)
- Gating mechanism (Wen et al., 2015)
- Attention (Mei et al., 2016; Wen et al., 2015)

Semantic Conditioned LSTM (Wen et al., 2015)

Original LSTM cell

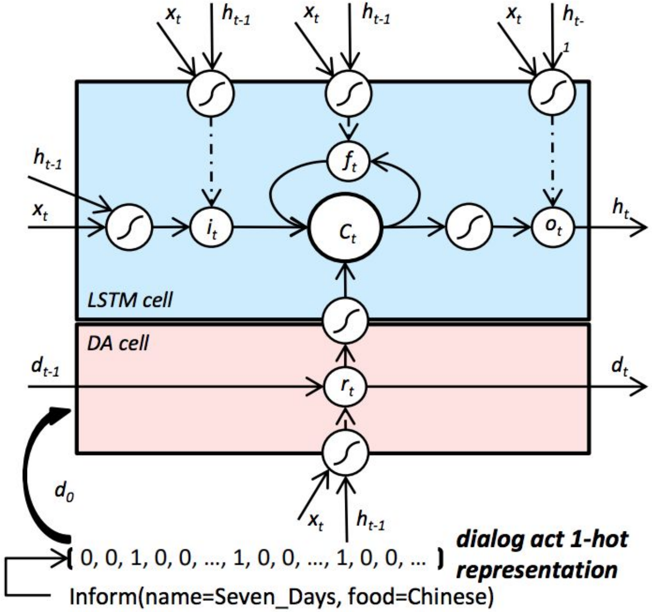
$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{x}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$
$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{x}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{x}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$
$$\hat{\mathbf{c}}_t = \tanh(\mathbf{W}_{wc}\mathbf{x}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t$$
$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t)$$

Dialog Act (DA) cell

$$\mathbf{r}_t = \sigma(\mathbf{W}_{wr}\mathbf{x}_t + \mathbf{W}_{hr}\mathbf{h}_{t-1})$$
$$\mathbf{d}_t = \mathbf{r}_t \odot \mathbf{d}_{t-1}$$

Modify C

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t + \tanh(\mathbf{W}_{dc}\mathbf{d}_t)$$



Attentive Encoder-Decoder for NLG

Slot & value embedding

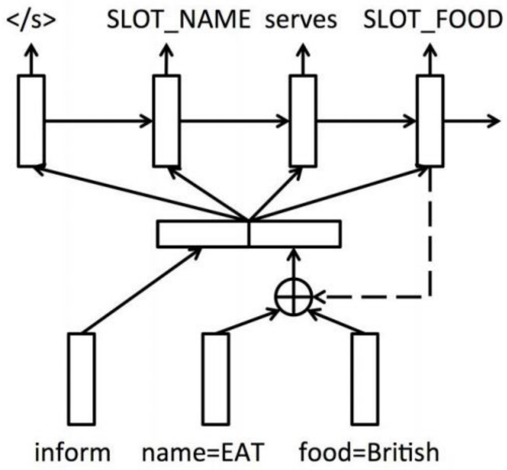
$$\mathbf{z}_i = \mathbf{s}_i + \mathbf{v}_i$$

Attentive meaning representation

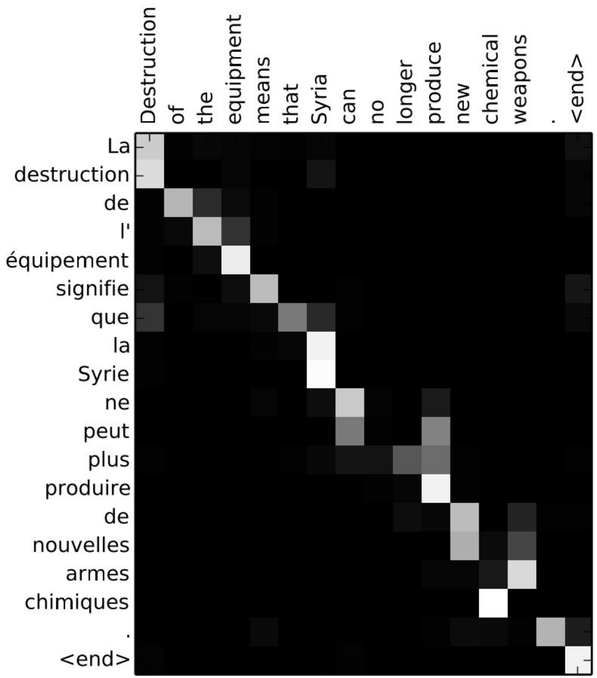
$$e_{ti} = \mathbf{v}^{\mathrm{T}} \tanh(\mathbf{W}_{hm}\mathbf{h}_{t-1} + \mathbf{W}_{zm}\mathbf{z}_i)$$

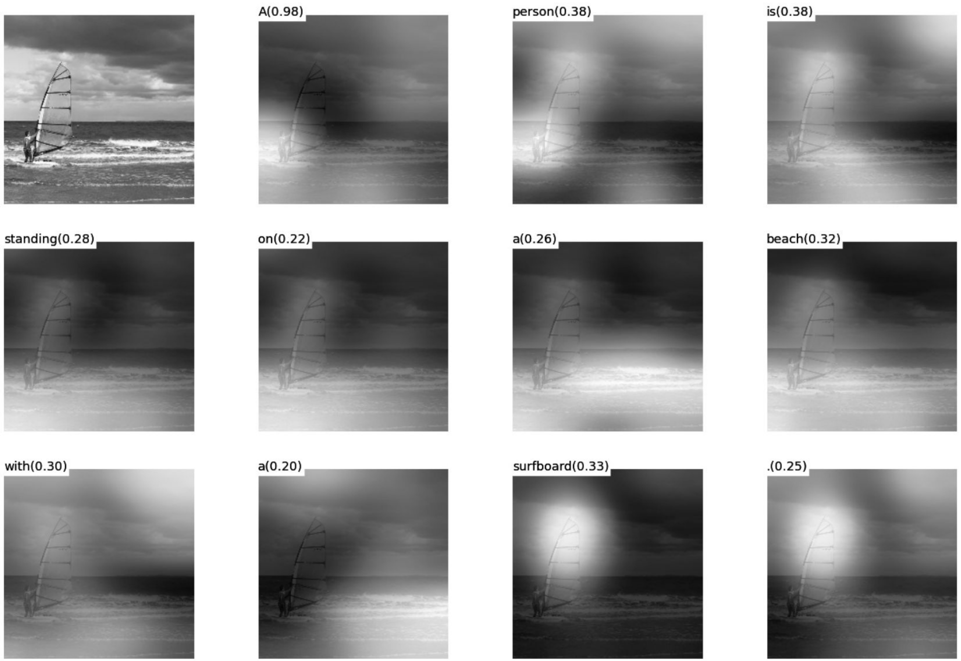
$$\alpha_{ti} = \mathrm{softmax}(e_{ti})$$

$$\mathbf{d}_t = \mathbf{a} \oplus \sum_i \alpha_{ti}\mathbf{z}_i$$



Attention - I

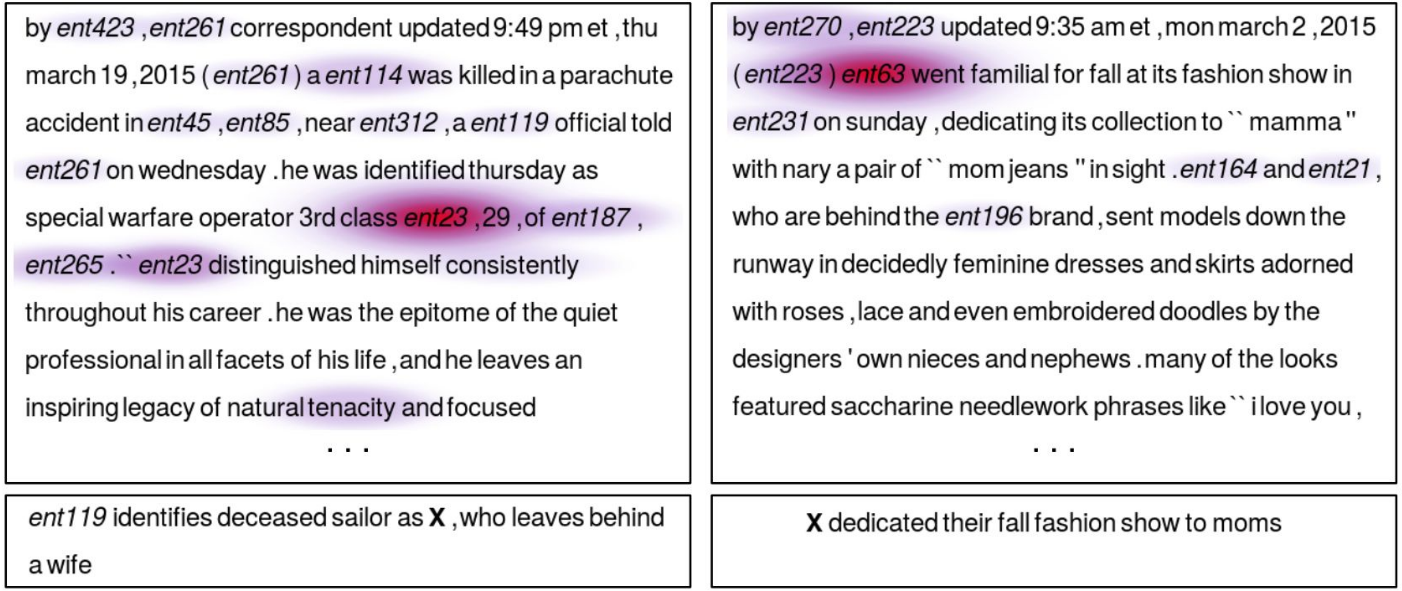




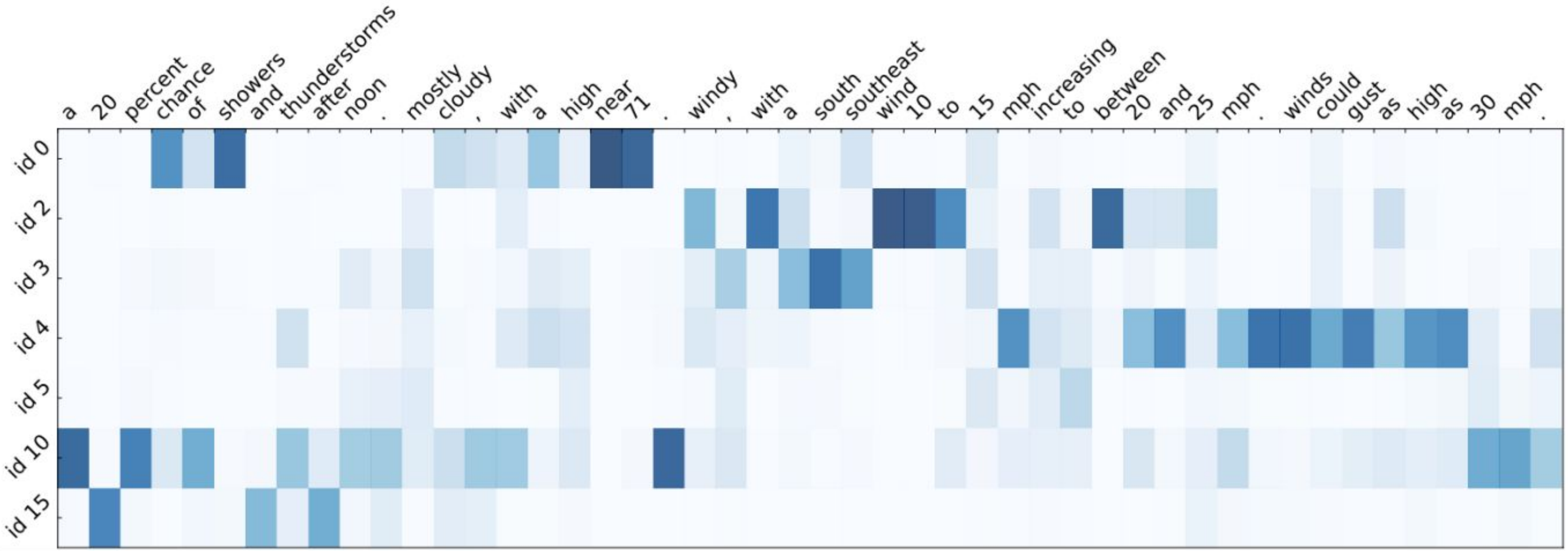
(b) A person is standing on a beach with a surfboard.

Attention - II

Teaching Machine Read and Comprehend (Herman et al. - 2015)



Attention Heat Map



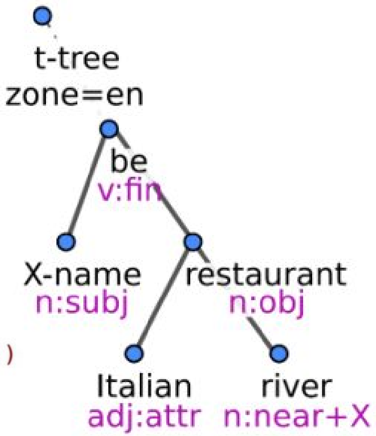
Record details:

id-0: temperature(time=06-21, min=52, mean=63, max=71); id-2: windSpeed(time=06-21, min=8, mean=17, max=23);
id-3: windDir(time=06-21, mode=SSE); id-4: gust(time=06-21, min=0, mean=10, max=30);
id-5: skyCover(time=6-21, mode=50-75); id-10: precipChance(time=06-21, min=19, mean=32, max=73);
id-15: thunderChance(time=13-21, mode=SChc)

Figure 3: An example generation for a set of records from WEATHERGOV.

Structural NLG (Dušek and Jurčíček, 2016)

inform(name=X-name,type=placetoeat,eattype=restaurant,
area=riverside,food=Italian)



Goal: NLG based on the syntax tree

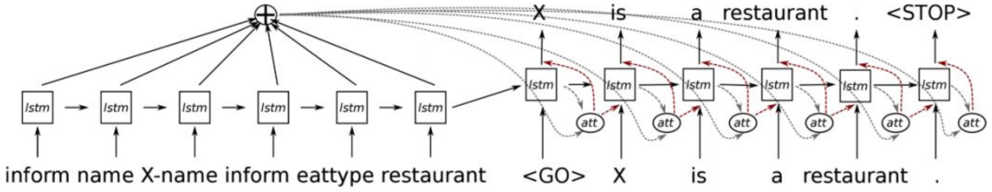
Encode trees as sequences

Seq2Seq model for generation

(<root> <root> ((X-name n:subj) be v:fin ((Italian adj:attr) restaurant n:obj (river n:near+X))))

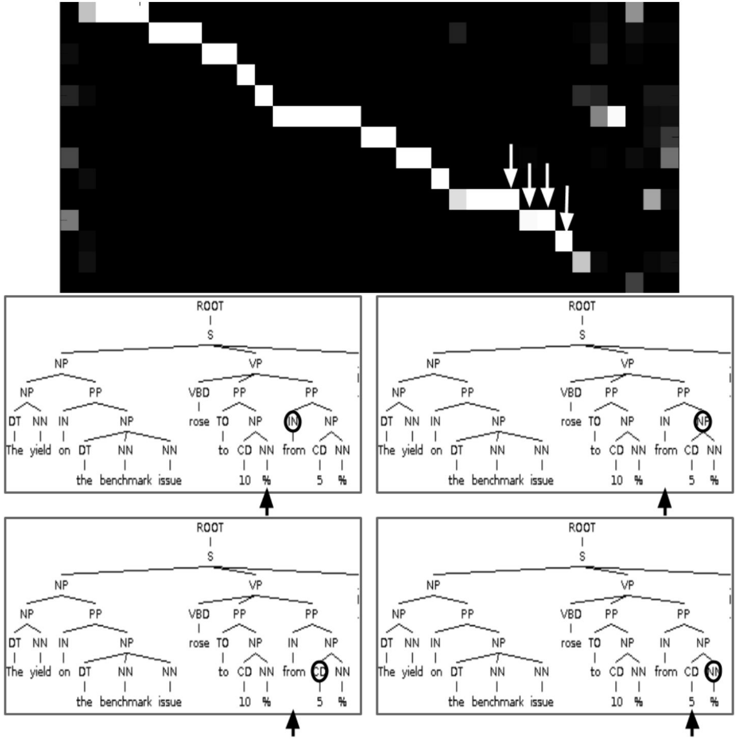
X-name n:subj be v:fin Italian adj:attr restaurant n:obj river n:near+X

X is an Italian restaurant near the river.



Attentive Tree Generator

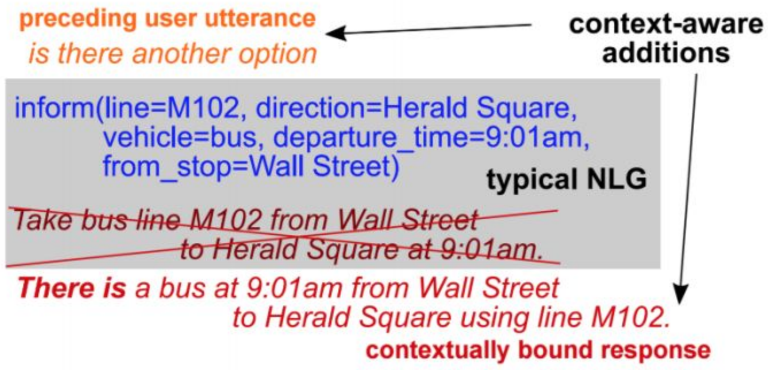
Grammar as a Foreign Language
(Vinyals et al. - 2014)

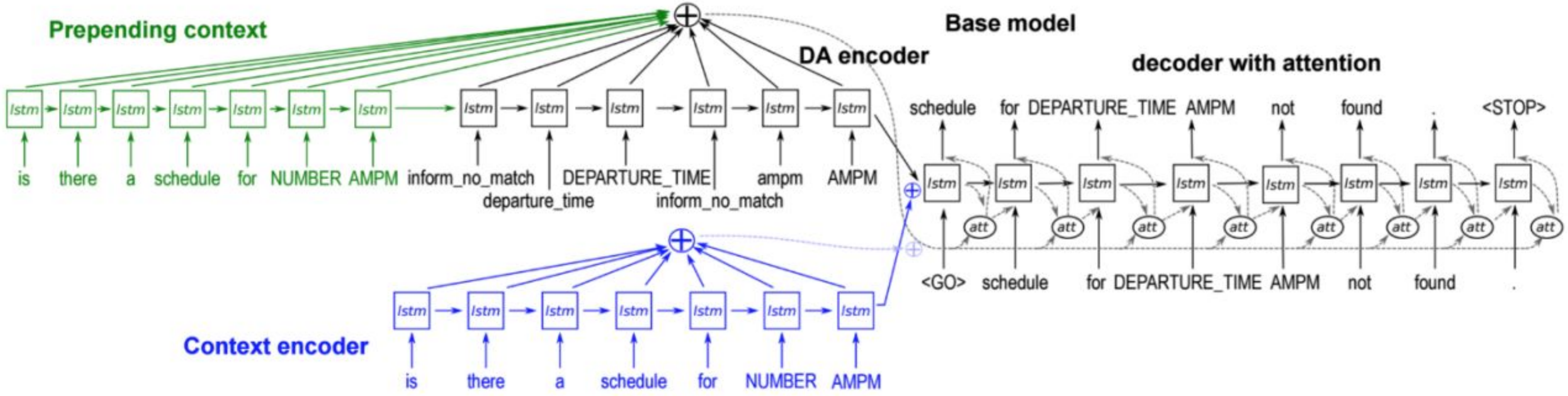


Contextual NLG (Dušek and Jurčíček, 2016)

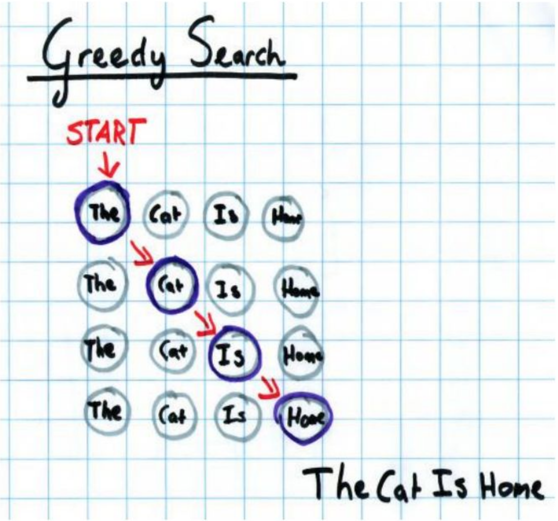
Goal: adapting users' way of speaking, providing contextaware responses

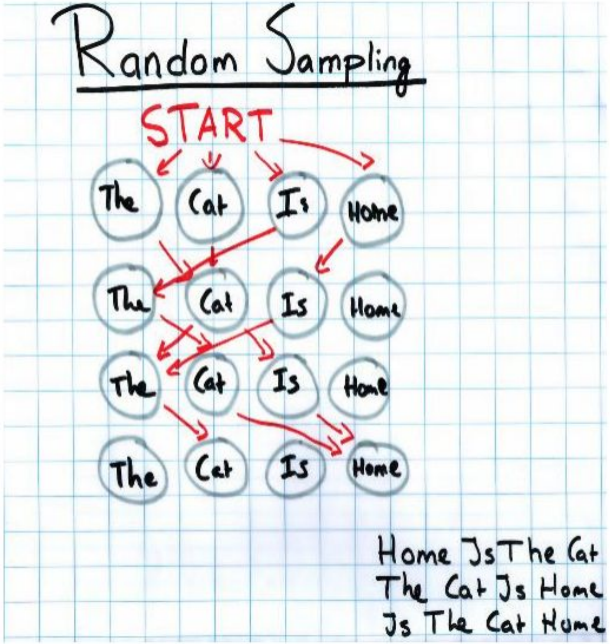
- Context encoder
- Seq2Seq model





Decoder Sampling Strategy

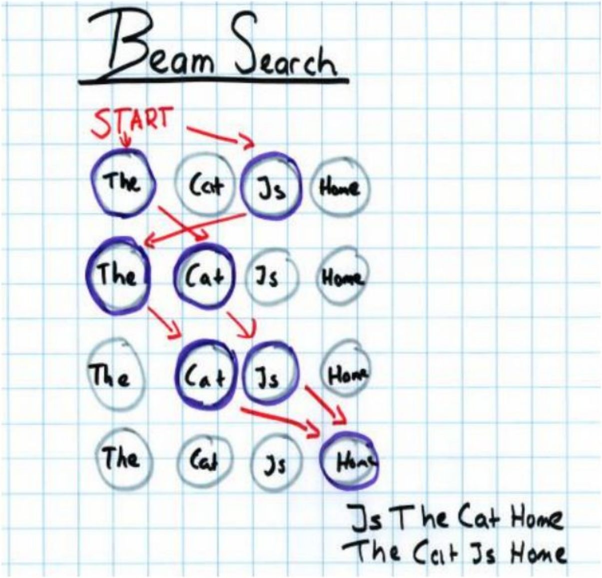


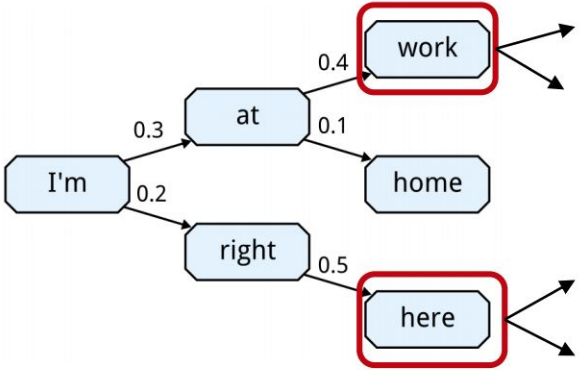


Decoder Sampling Strategy

Beam Search

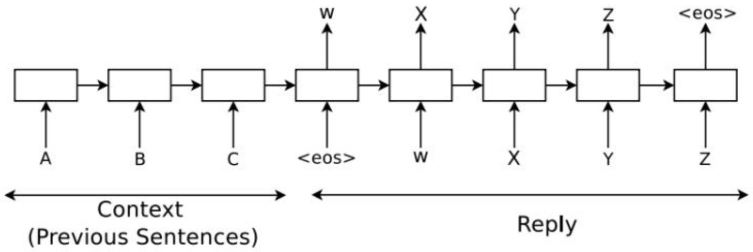
Select the next k-best words and keep a beam with width=k for following decoding





Chit-Chat

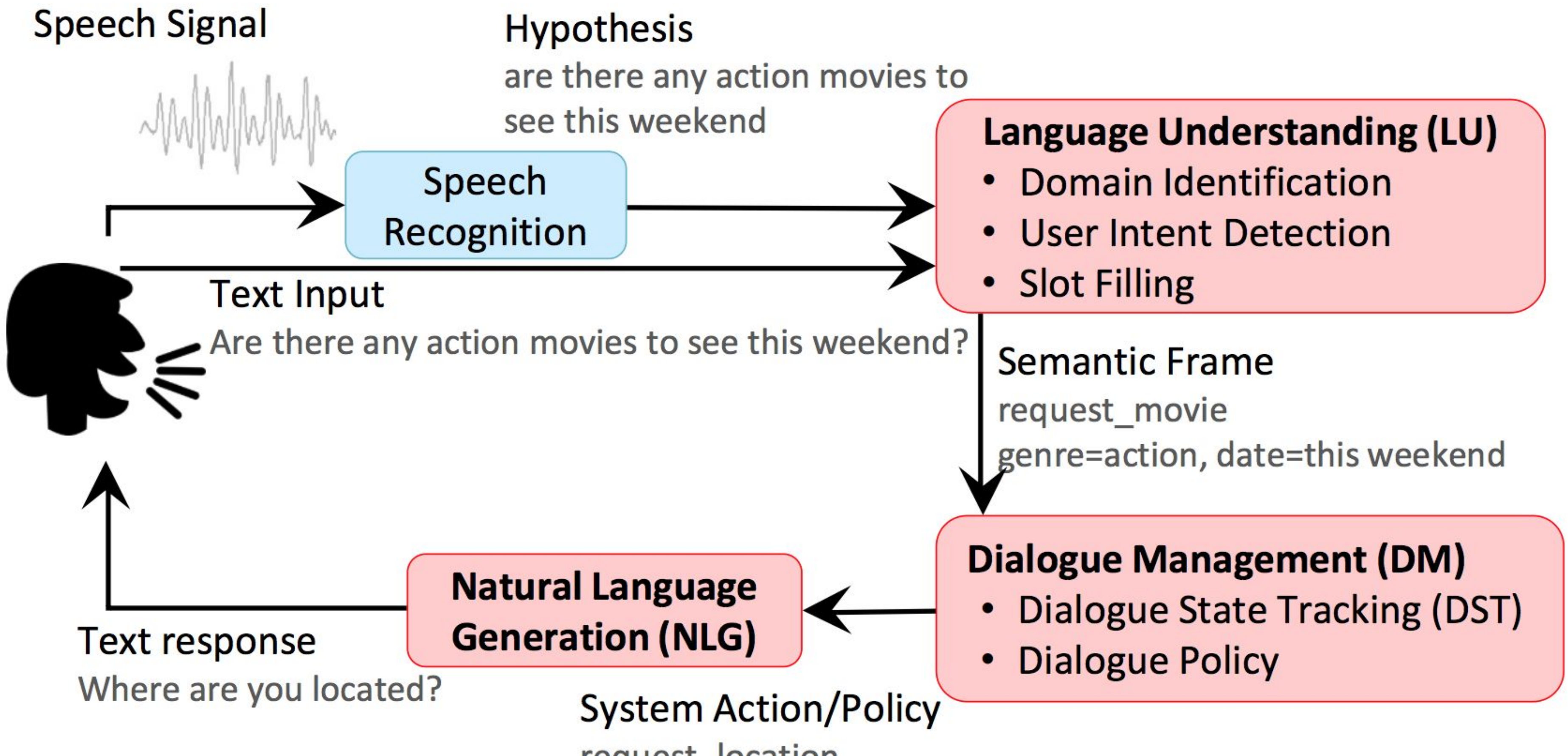
Seq2Seq



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 .*

Task-Oriented Dialogue System



Example Dialog

Hello, how may I help you?

I'm looking for a Thai restaurant. request (restaurant; foodtype=Thai)

What part of town do you have in mind?

Something in the centre. inform (area=centre)

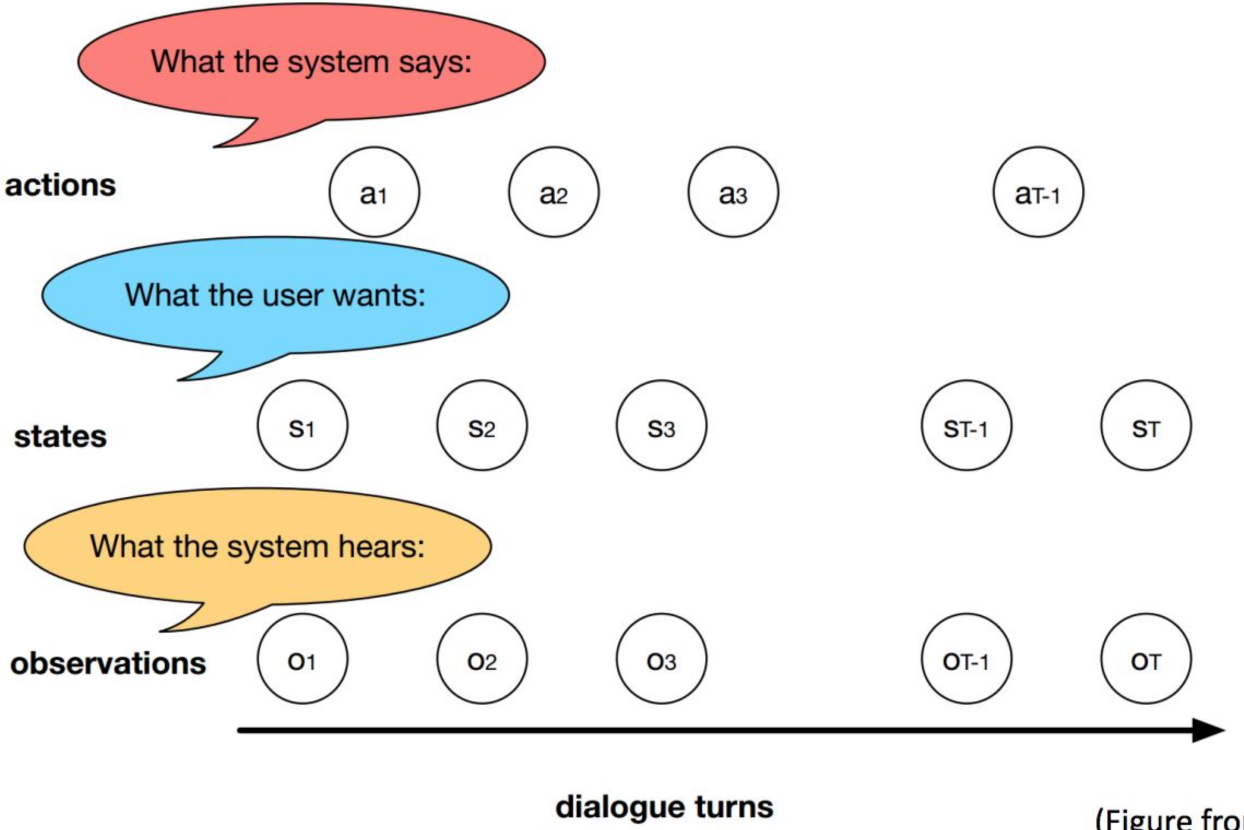
Bangkok city is a nice place, it is in the centre of town and it serves Thai food.

What's the address? request (address)

Bangkok city is a nice place, their address is 24 Green street.

Thank you, bye. bye ()

Dialog Management



(Figure from Gašić)

Dialog State Tracker

Maintain a probabilistic distribution instead of a 1-best prediction for better robustness to recognition errors, ambiguous input, NLU errors

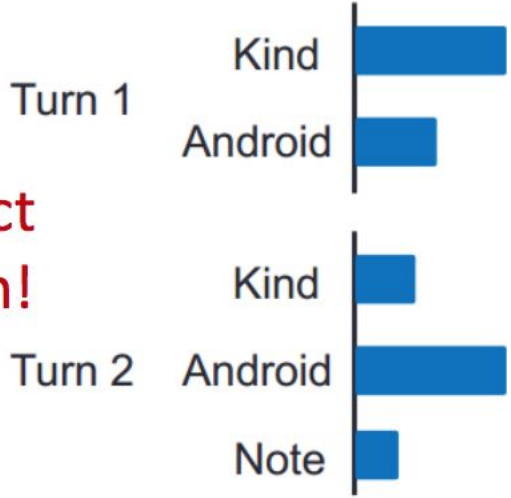
Turn 1
Kind
Android

Turn 2
Note
Android

Turn 1	
Kind	0.5
Android	0.3

Turn 2	
Note	0.4
Android	0.3

Incorrect for both!

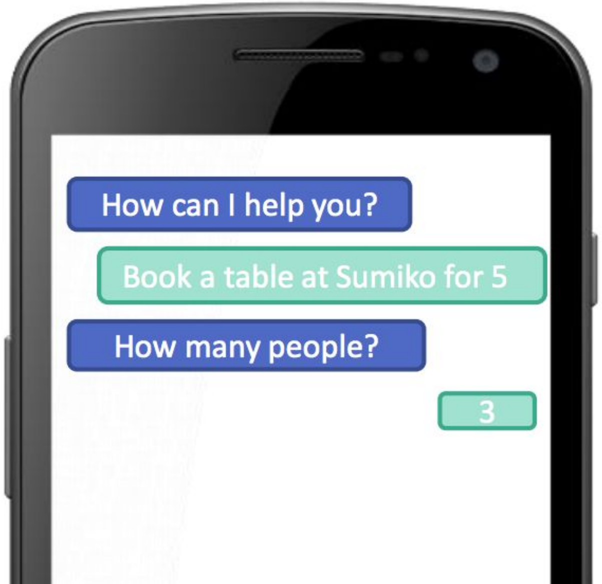


Dialog State Tracker

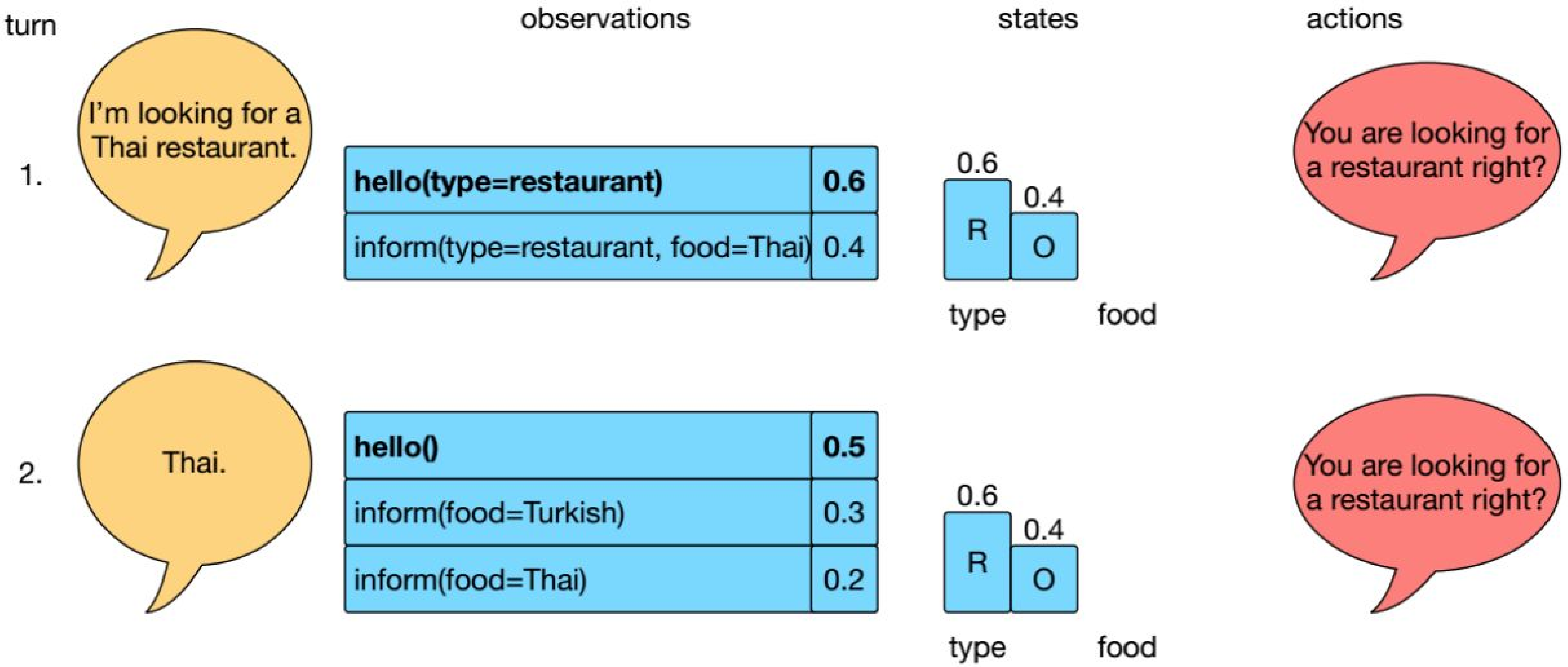
Maintain a probabilistic distribution instead of a 1-best prediction for better robustness to recognition errors, ambiguous input, NLU errors

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

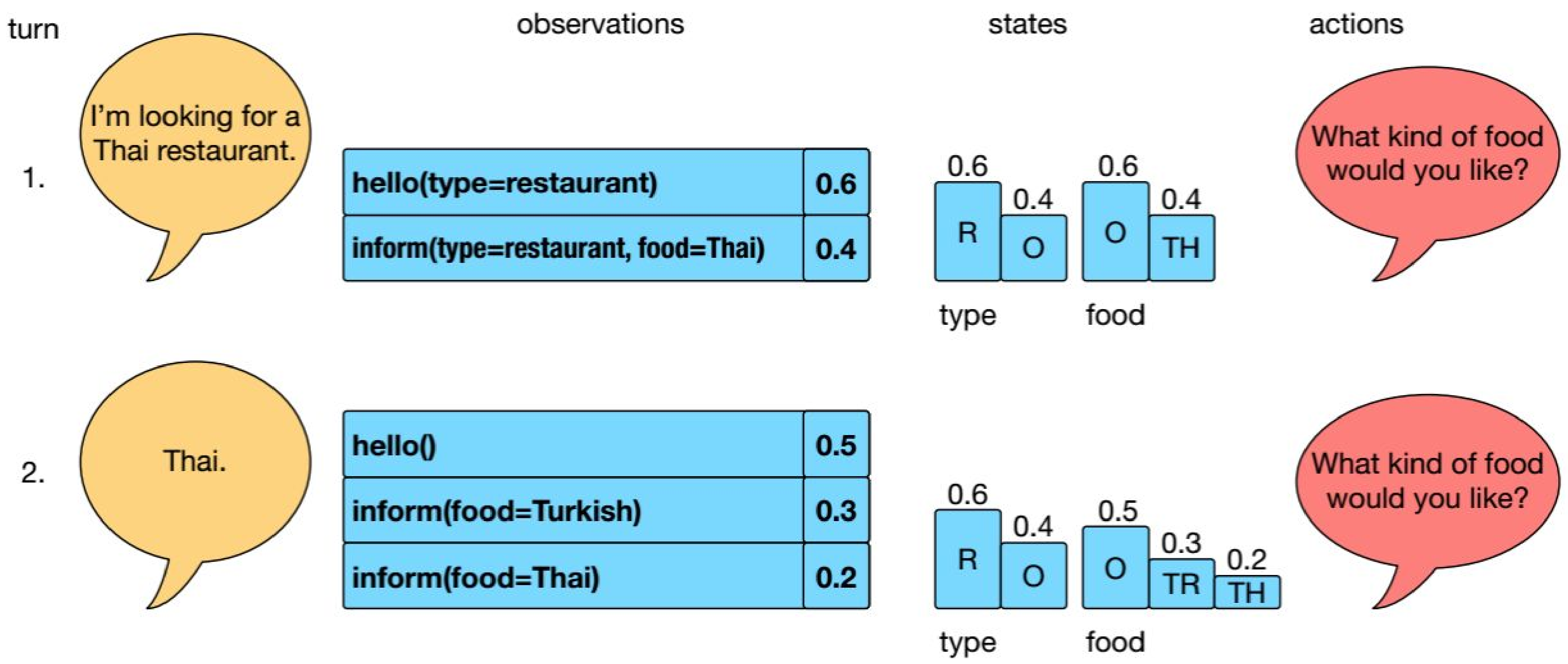
Slot	Value
# people	3 (0.8)
time	5 (0.8)



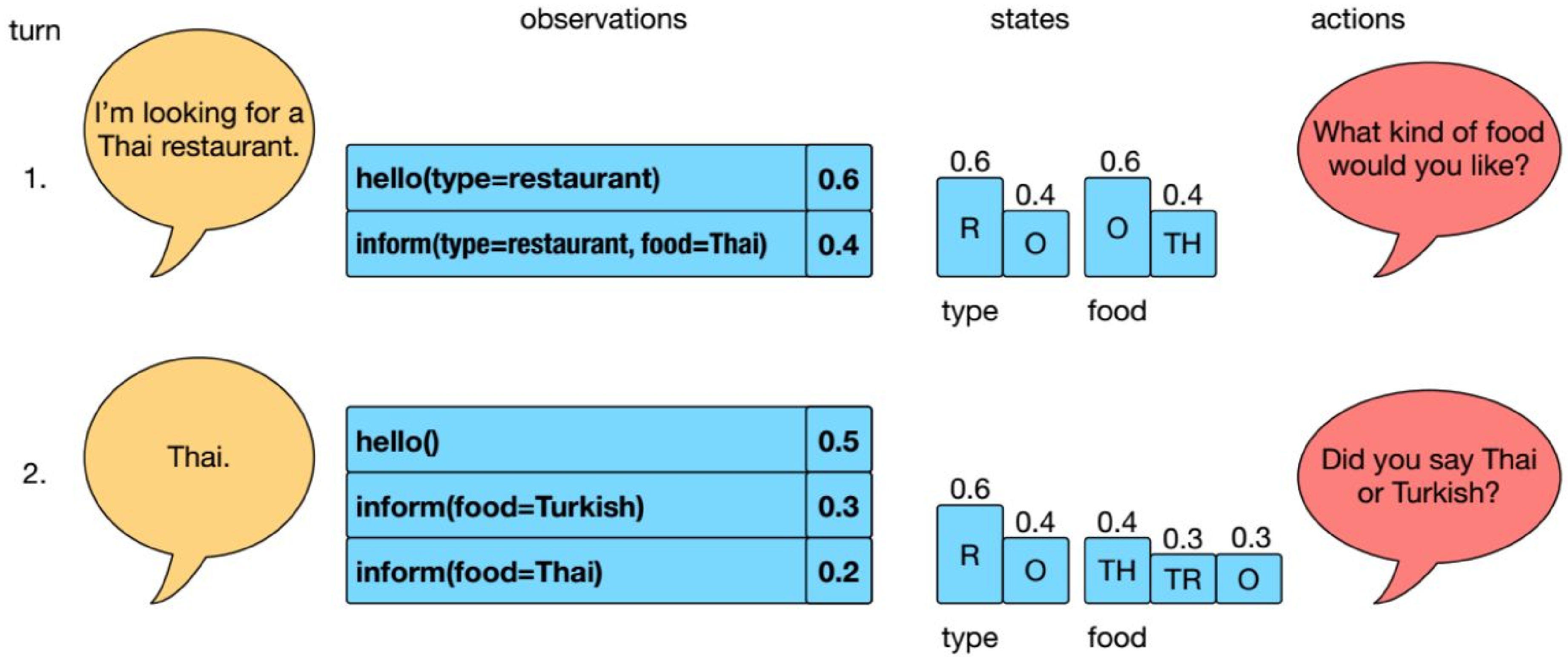
1-Best Input w/o State Tracking



N-Best Inputs w/o State Tracking



N-Best Inputs w/ State Tracking



Dialog State Tracking Challenge

Definition

Representation of the system's belief of the user's goal(s) at any time during the dialogue

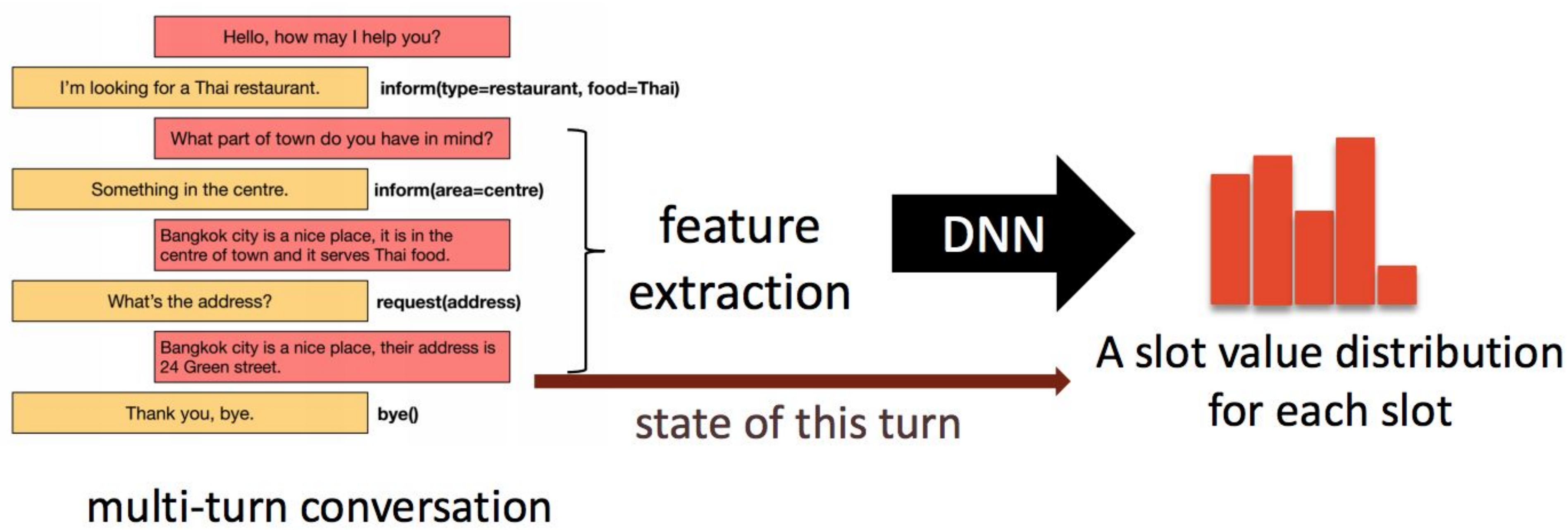
Challenge

How to define the state space?

How to tractably maintain the dialogue state?

Which actions to take for each state?

DNN for DST


Hello, how may I help you?
I'm looking for a Thai restaurant.
inform(type=restaurant, food=Thai)
What part of town do you have in mind?
Something in the centre.
inform(area=centre)
Bangkok city is a nice place, it is in the centre of town and it serves Thai food.
What's the address?
request(address)
Bangkok city is a nice place, their address is 24 Green street.
Thank you, bye.
bye()
feature extraction
DNN
A slot value distribution for each slot
state of this turn
multi-turn conversation

Sequence-based DST

Data

- Sequence of observations labeled w/ dialogue state

Model

- Recurrent neural networks (RNN)

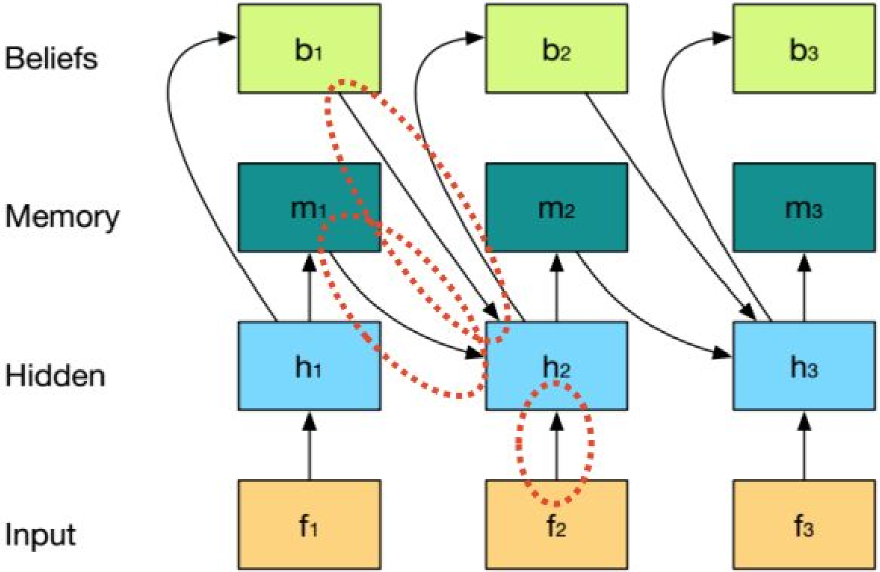
Prediction

- Distribution over dialogue states – Dialogue State Tracking

Sequence-based DST w/ memory

Idea: internal memory for representing dialogue context

- Input
  - most recent dialogue turn
  - last machine dialogue act
  - dialogue state
  - memory layer
- Output
  - update its internal memory
  - distribution over slot values



DST Evaluation

Metrics:

Tracked state accuracy with respect to user goal

L2-norm of the hypothesized dist. and the true label

Machine translation metrics as BLEU, METEOR, etc. do not work.

Recall/Precision/F-measure on individual slots

Questions?

Acknowledgements

I would like to gratefully thank Vivian Chen from Taiwan National University for permission to use her materials to create this presentation.

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