Yandex

UNIVERSITEIT VAN AMSTERDAM

Dialogue systems

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Plan

- Types of dialogue systems
- Task-oriented
- General conversation: generative
- General conversation: retrieval-based
- Hack of the day (real-life story inside!)

An example of a dialogue system

Где я?

Я думаю, примерно тут:
Шотландия, Эдинбург.

ПОКАЗАТЬ НА КАРТЕ

Какая здесь погода?

Сейчас в Эдинбурге

+6 °

ясно от +6 до +9

Утро	День	Вечер
+6	+8	+4

Да это же кружка с рапунцией.

НАЙТИ ЭТО В ЯНДЕКСЕ

ПОСМОТРЕТЬ ПОХОЖИЕ КАРТИНКИ

А кто такая рапунцель?

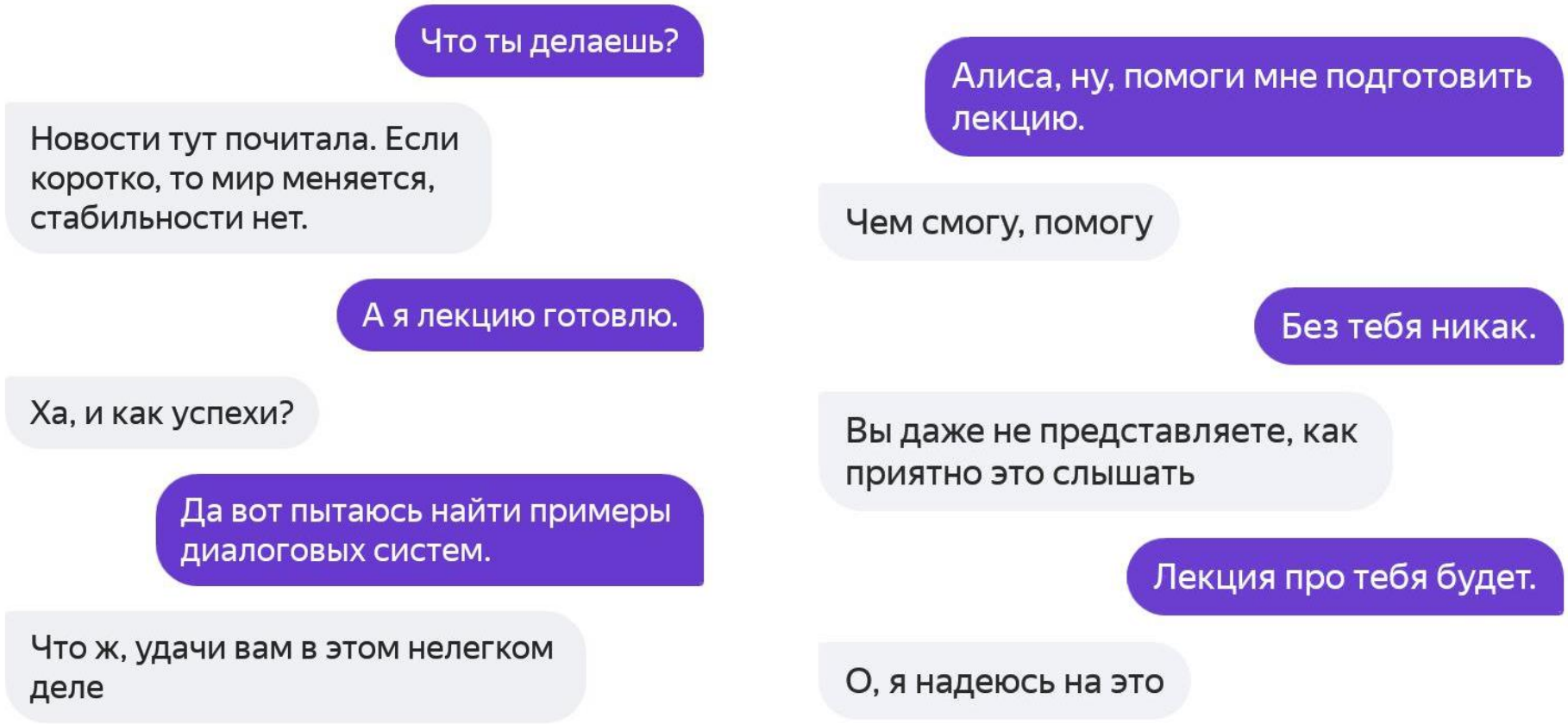
Рапунцель

Сказка о девушке с очень длинными волосами, которая была заточена в высокой башне. Была записана братьями Гримм. В системе классификации народных сказок Аарне-Томпсона этот сюжет имеет номер 310: «Дева в башне».

ru.wikipedia.org

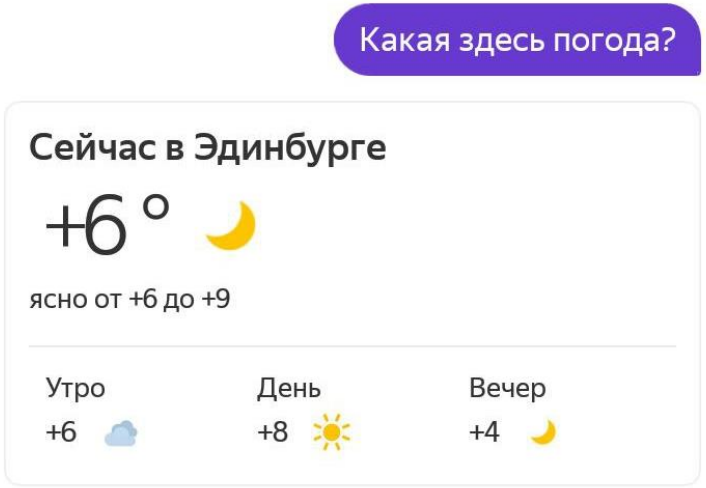
ОТКРЫТЬ В ПОИСКЕ

An example of a dialogue system



Task-oriented

Goal: solve a task for a user



General conversation

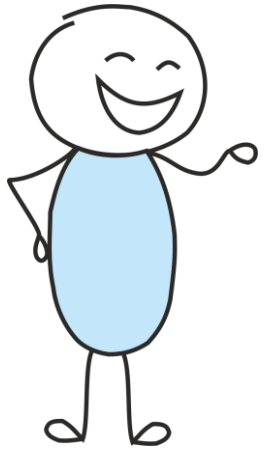
Goal: conversation itself

It has to be enjoyable!

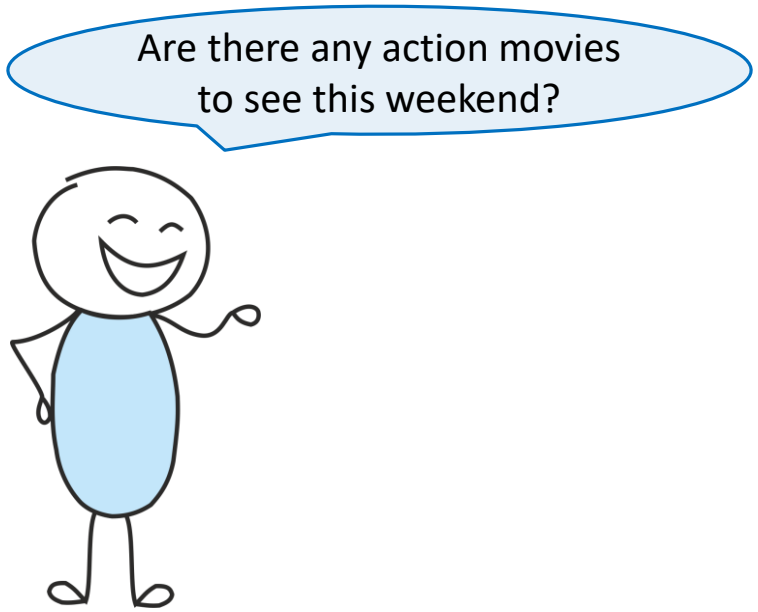
Task-oriented

AKA GOAL-ORIENTED

Task-oriented dialogue system



Task-oriented dialogue system



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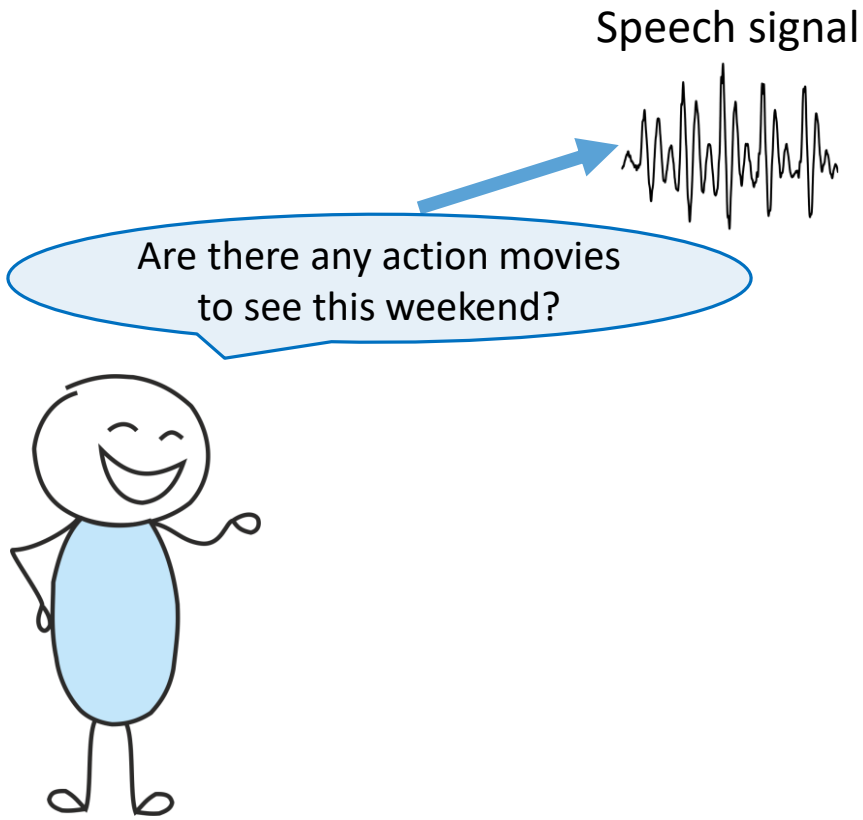
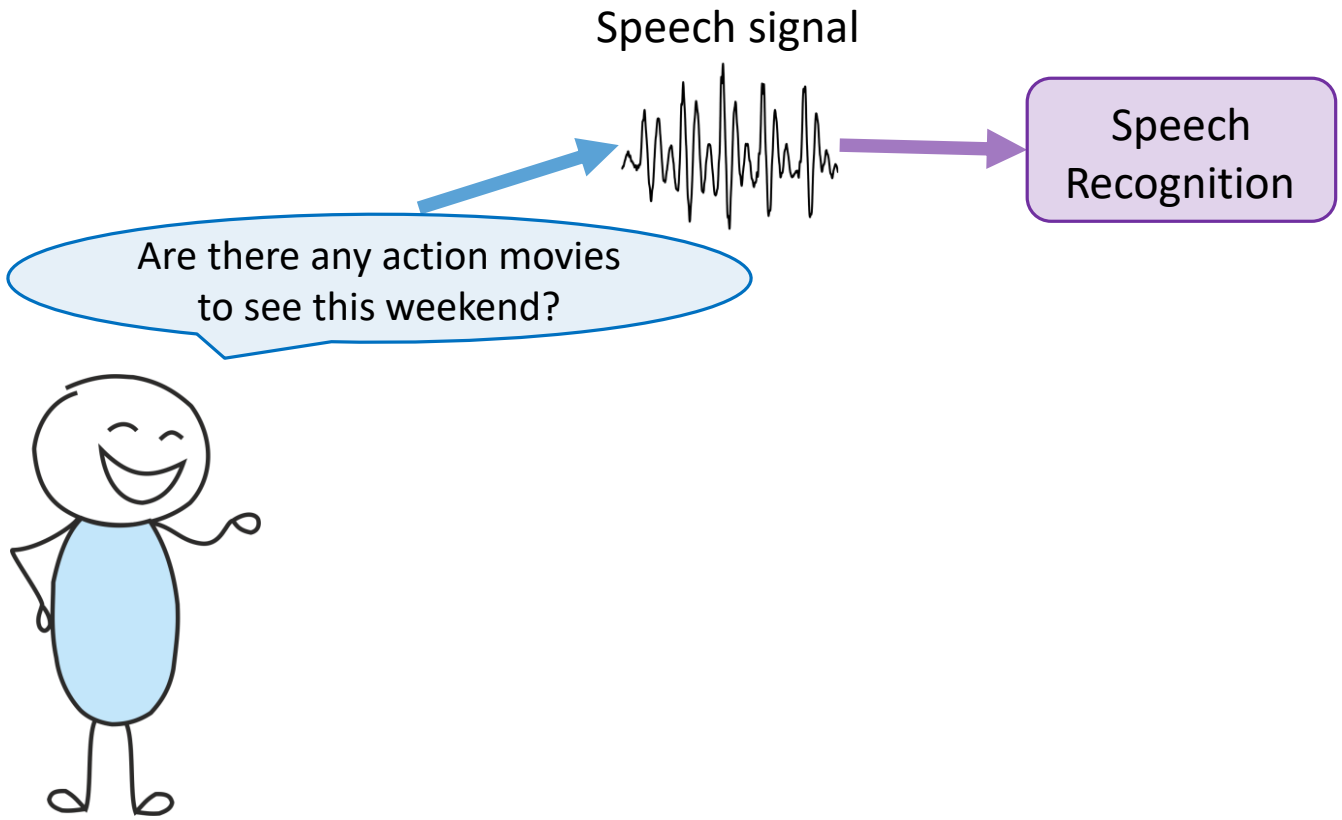


Task-oriented dialogue system



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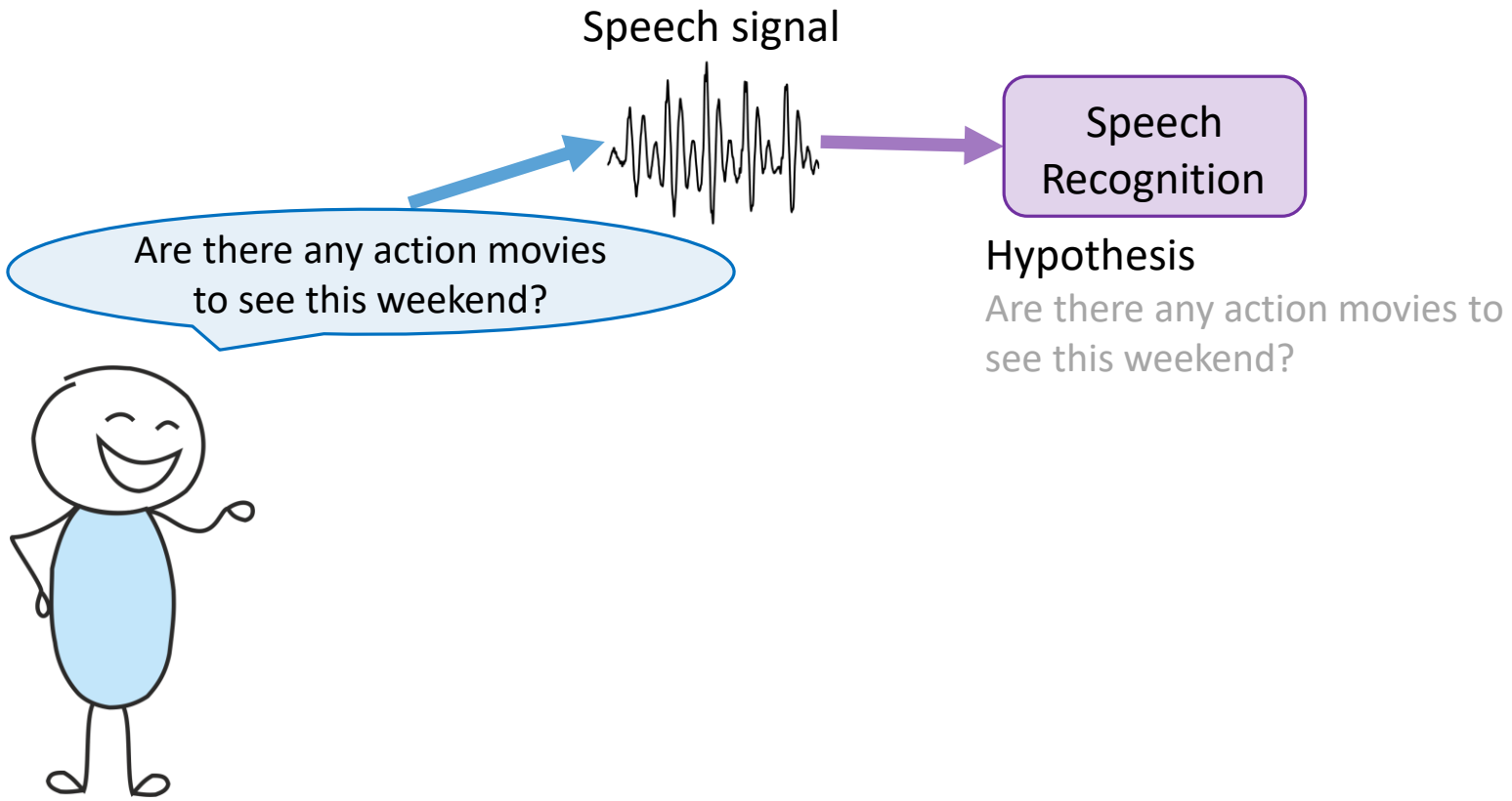

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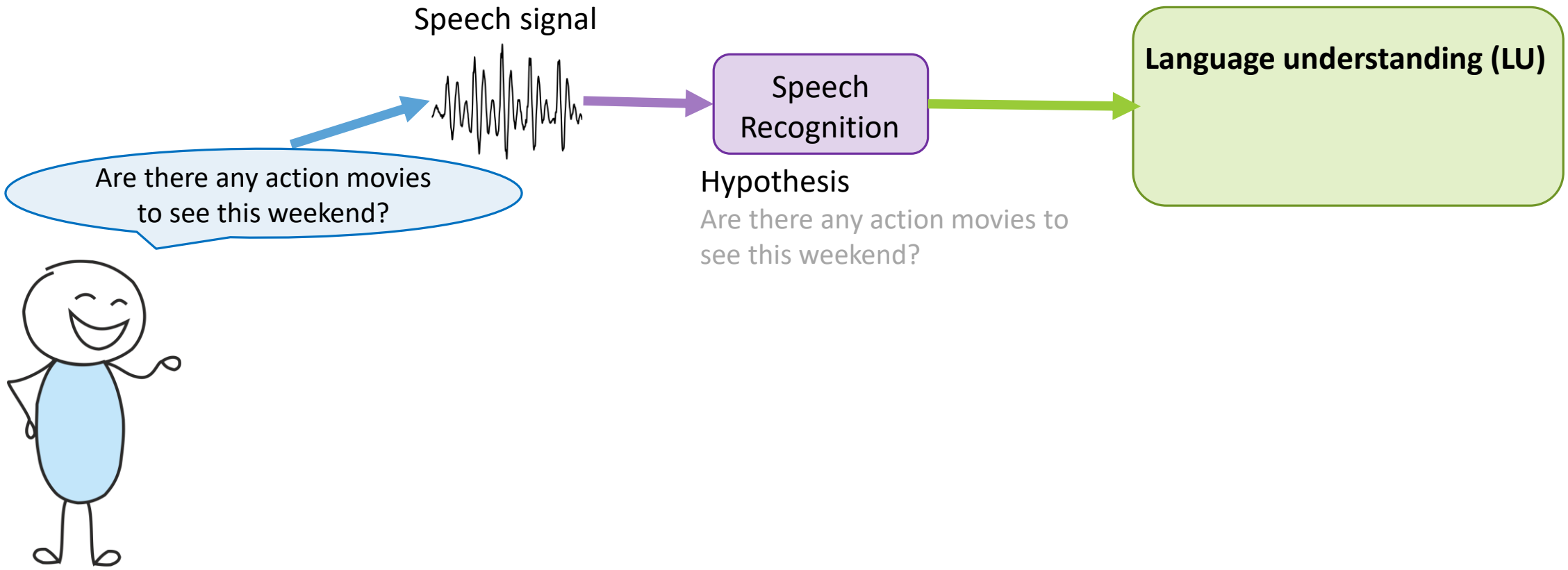

Based on http://deepdialogue.miulab.tw

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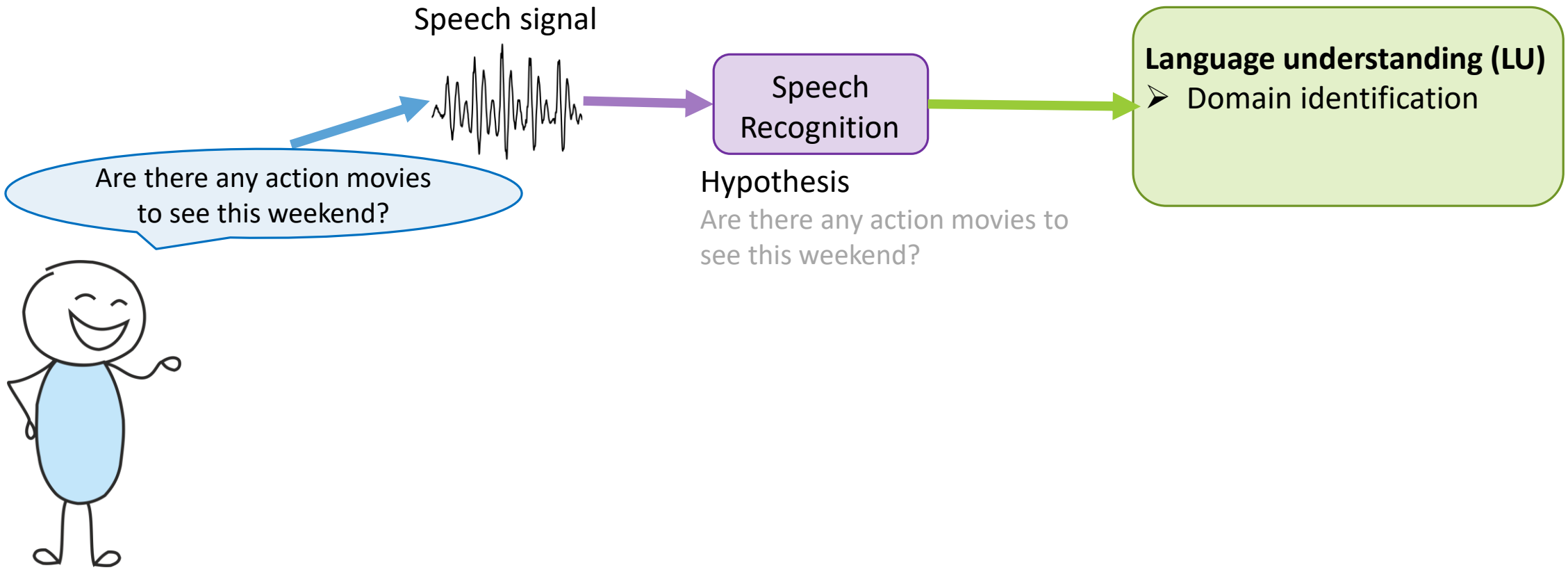

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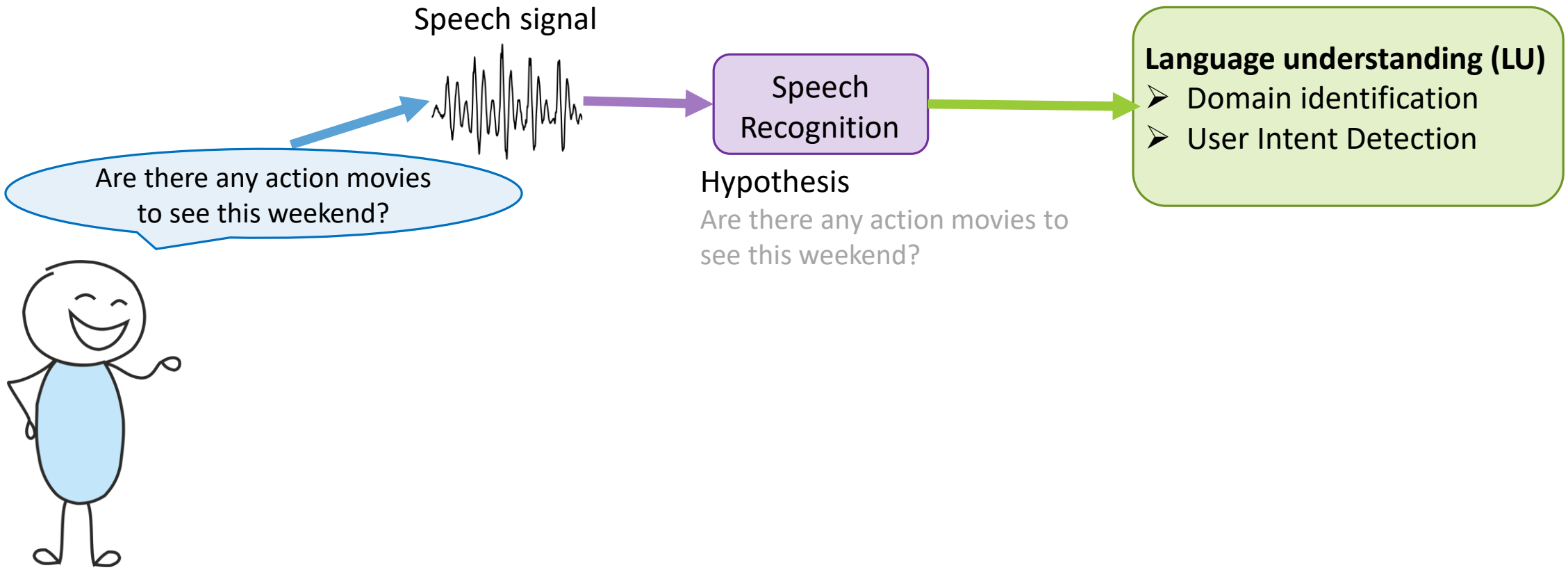

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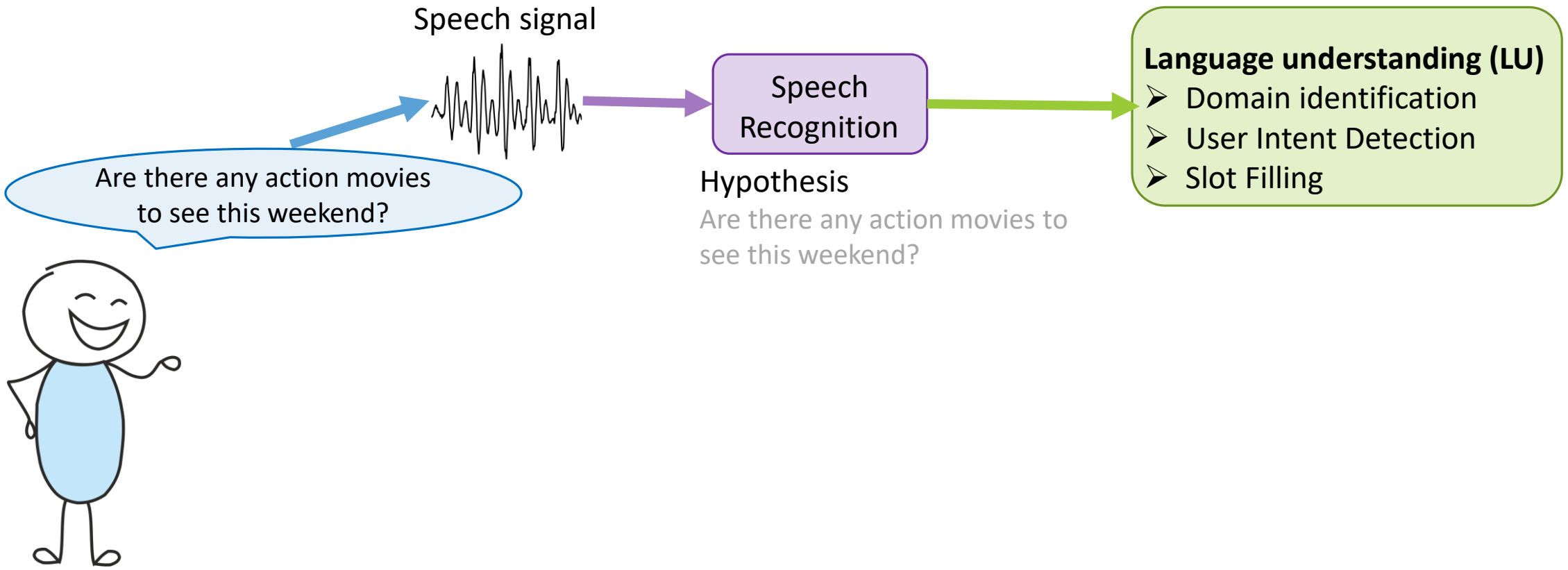

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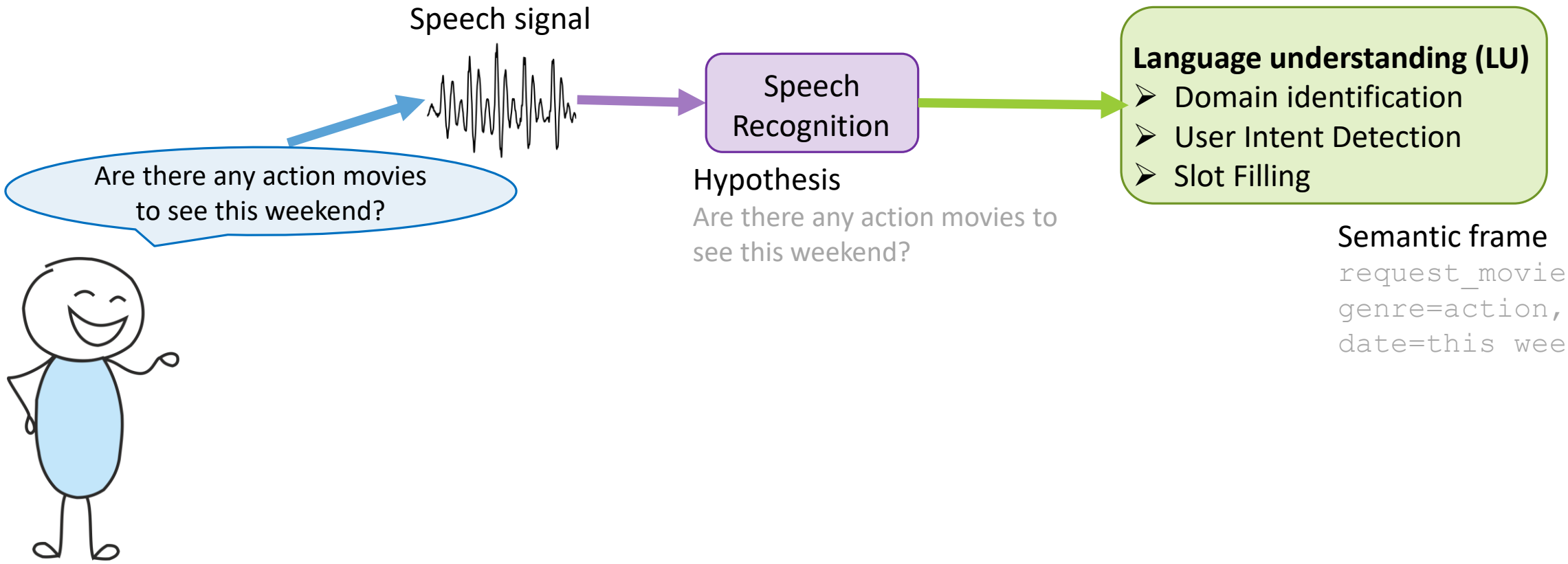

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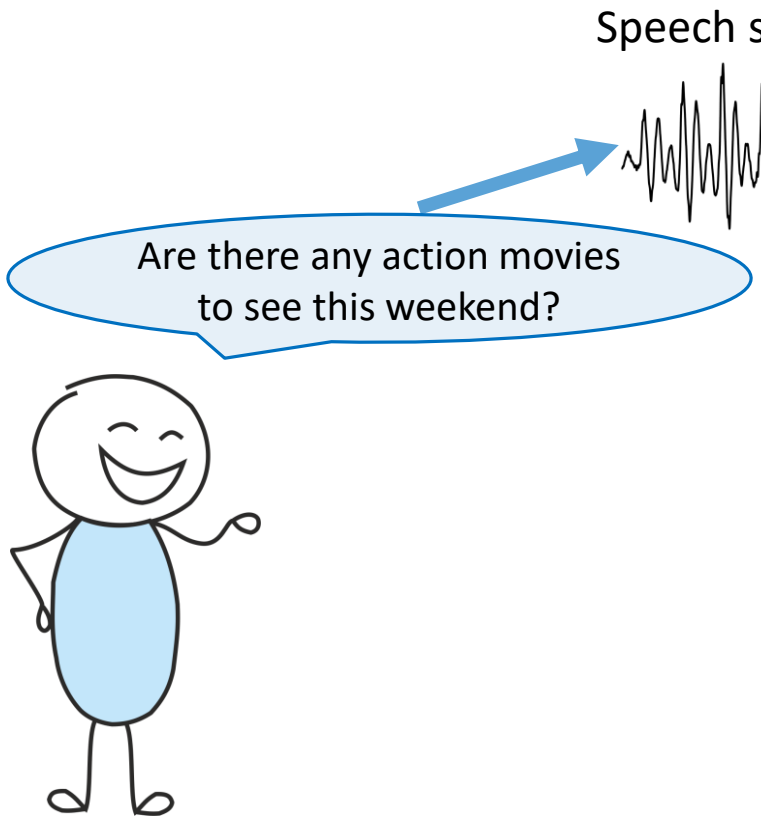


Speech signal

Speech Recognition

Hypothesis

Are there any action movies to see this weekend?

Language understanding (LU)

- Domain identification
- User Intent Detection
- Slot Filling

Semantic frame

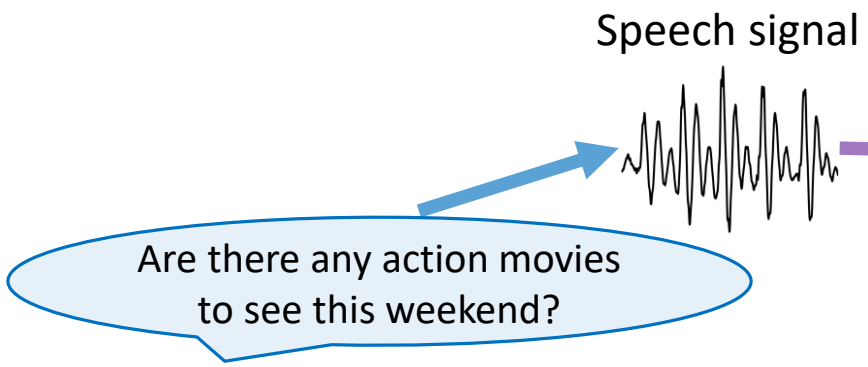
```
request_movie
genre=action,
date=this weekend
```

Dialogue management (DM)

- Dialogue State Tracking
- Dialogue Policy

Based on http://deepdialogue.miulab.tw

Task-oriented dialogue system



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Backend knowledge

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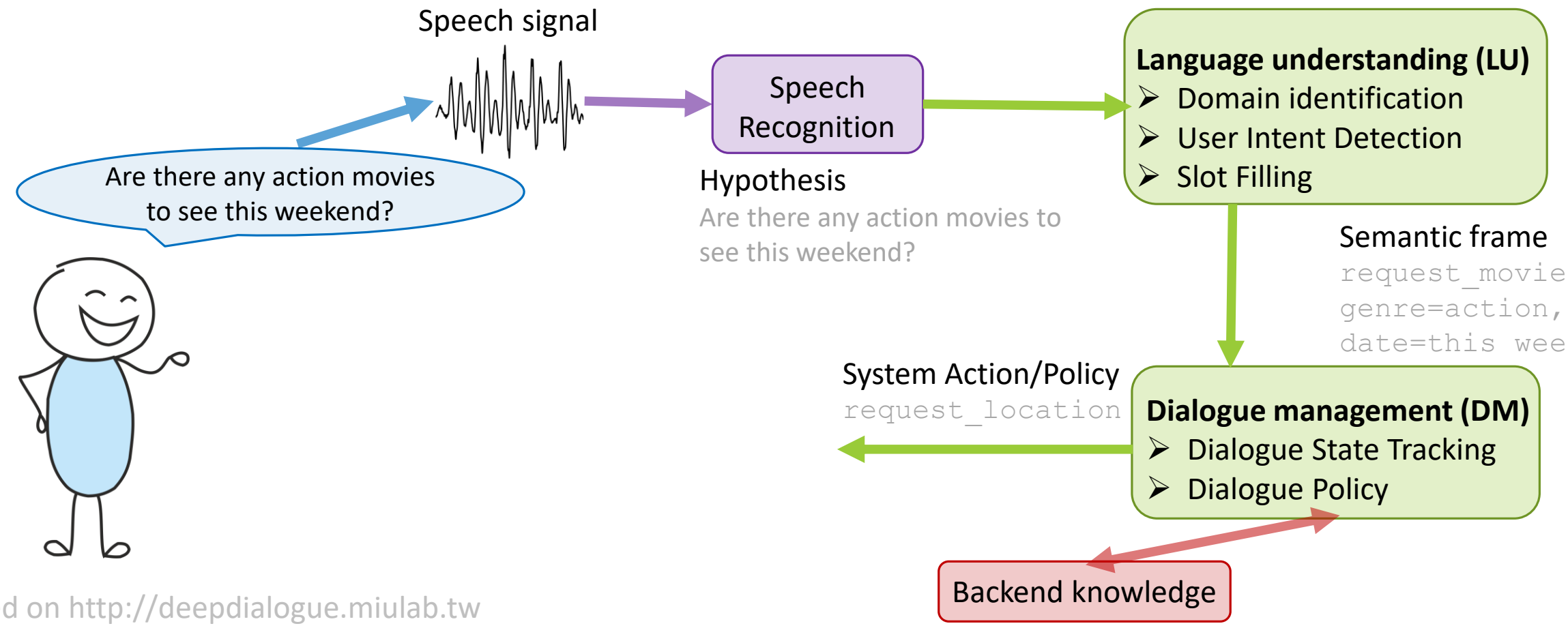

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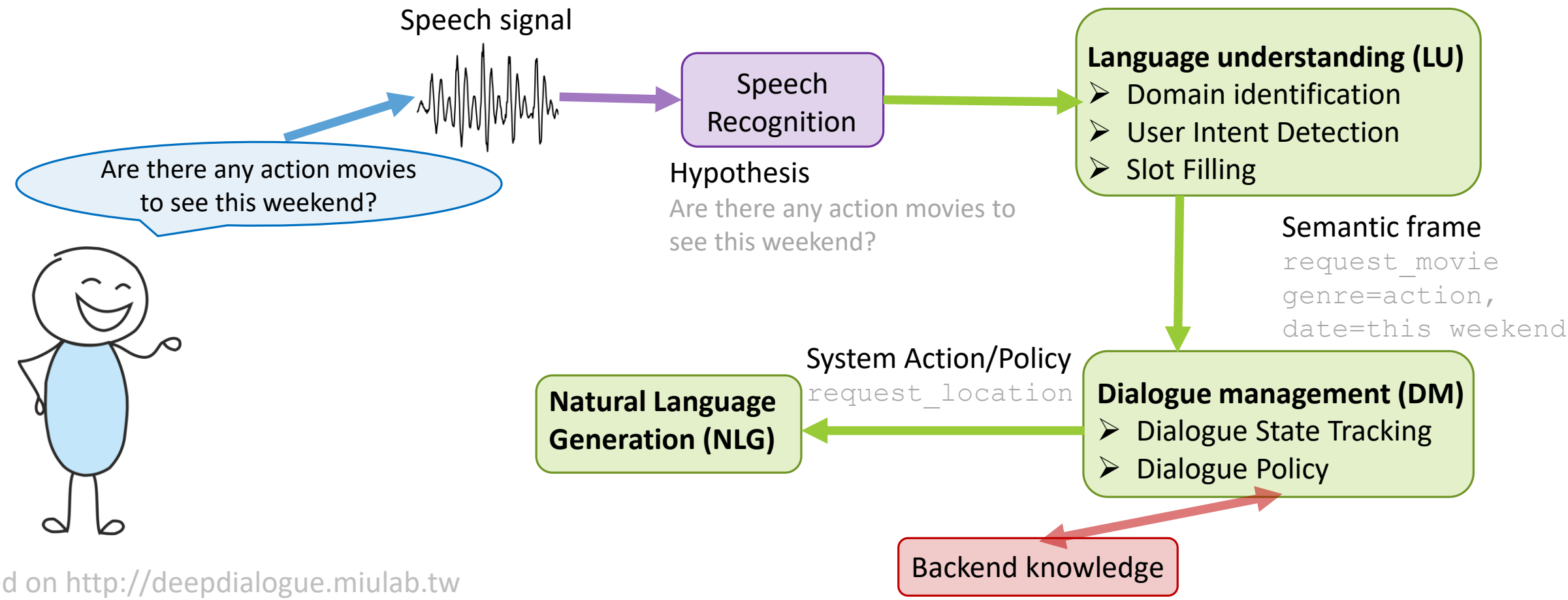

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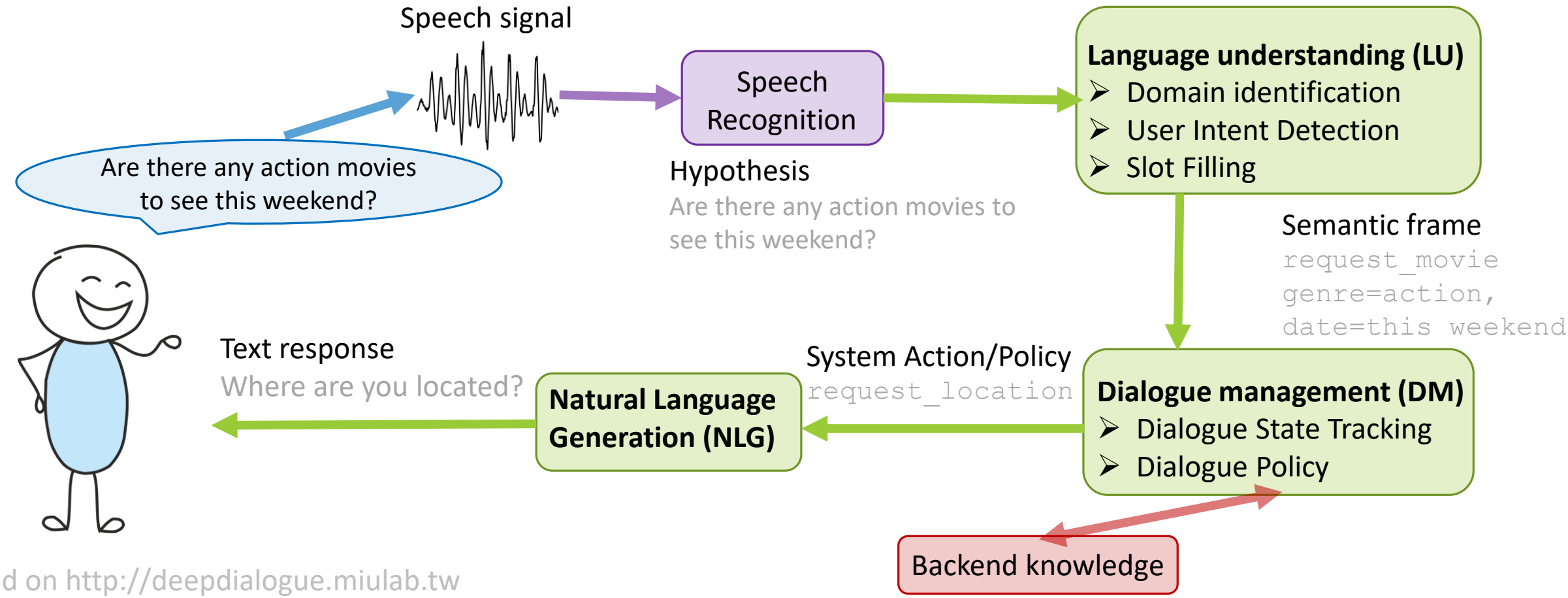

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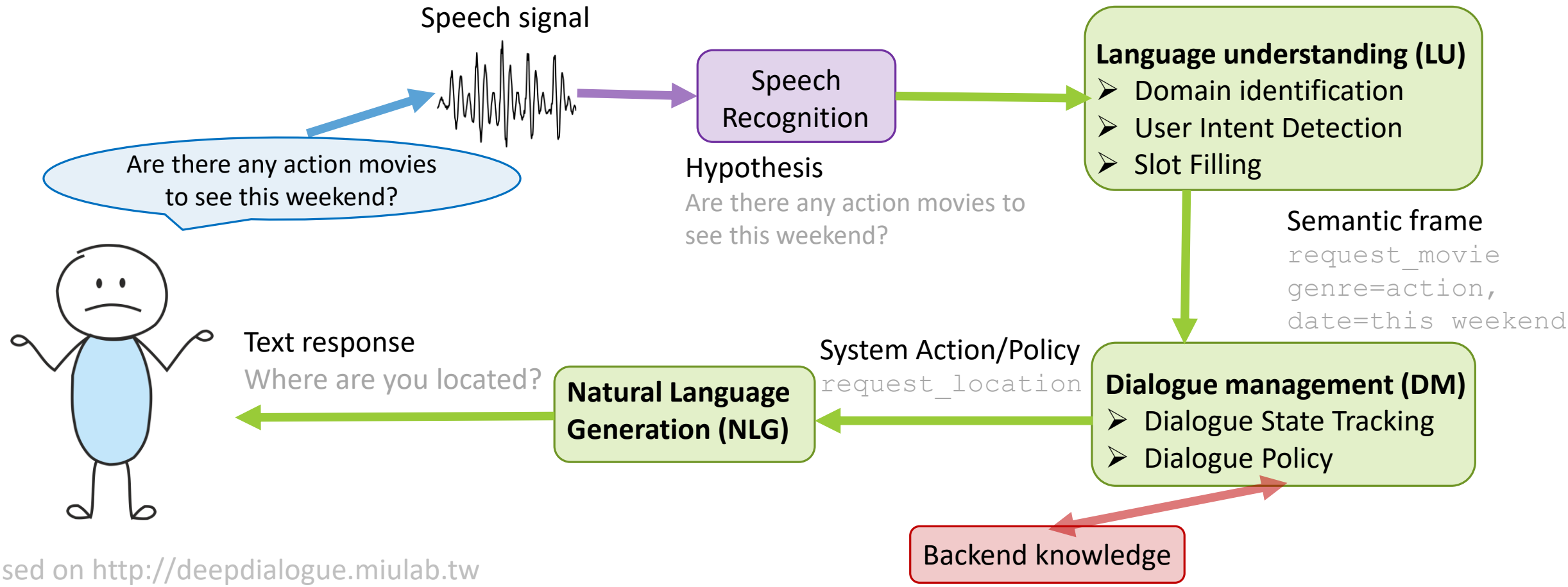
Task-oriented dialogue system



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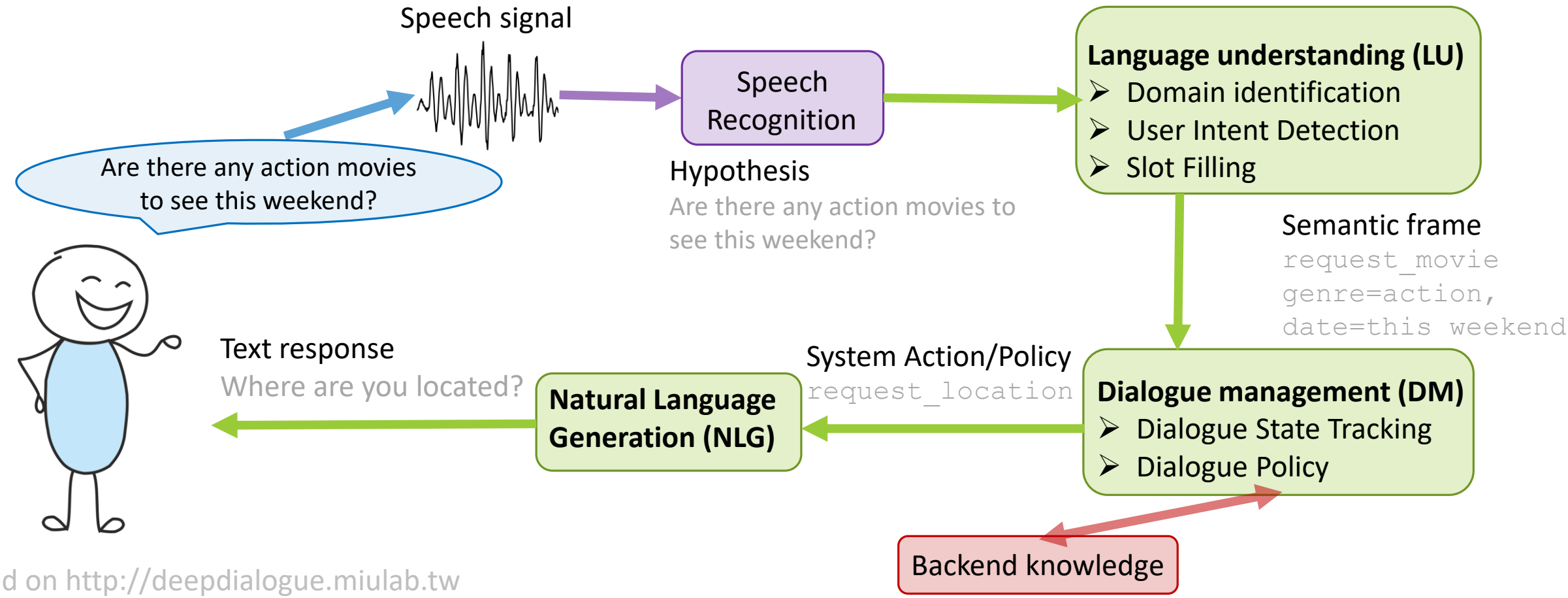
Language Understanding

Task-oriented dialogue system



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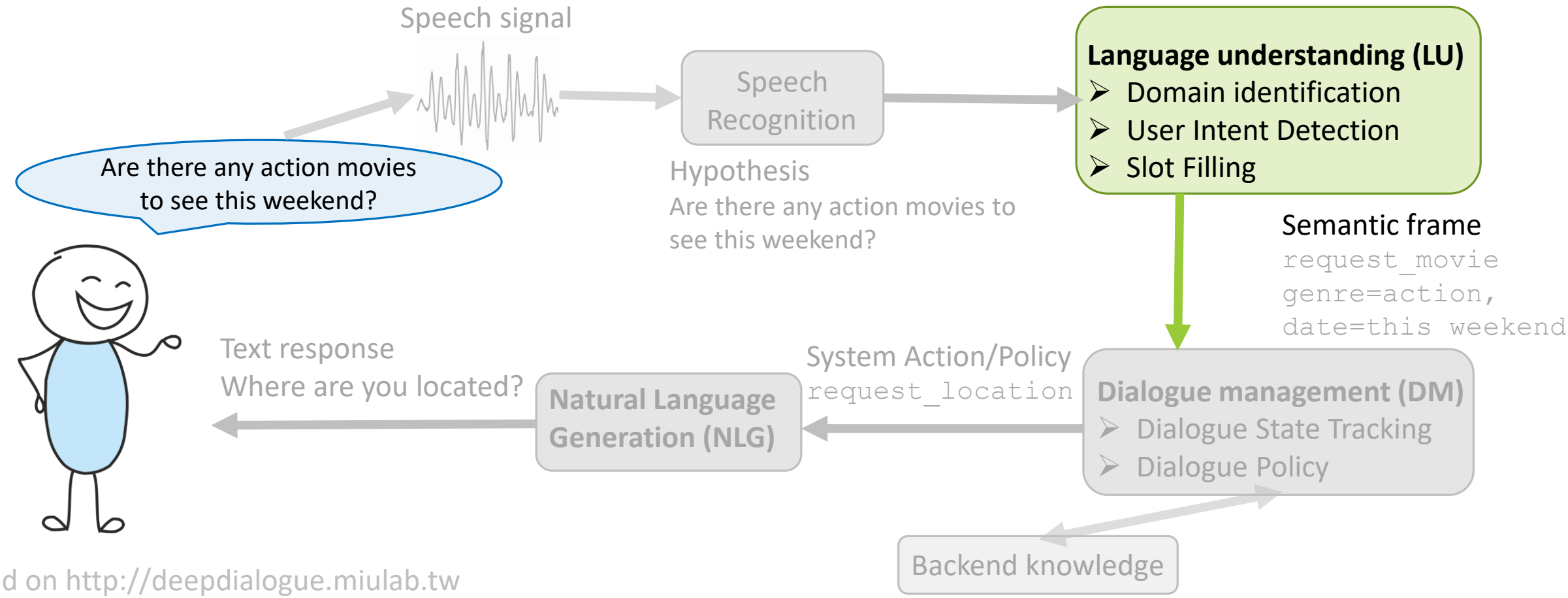

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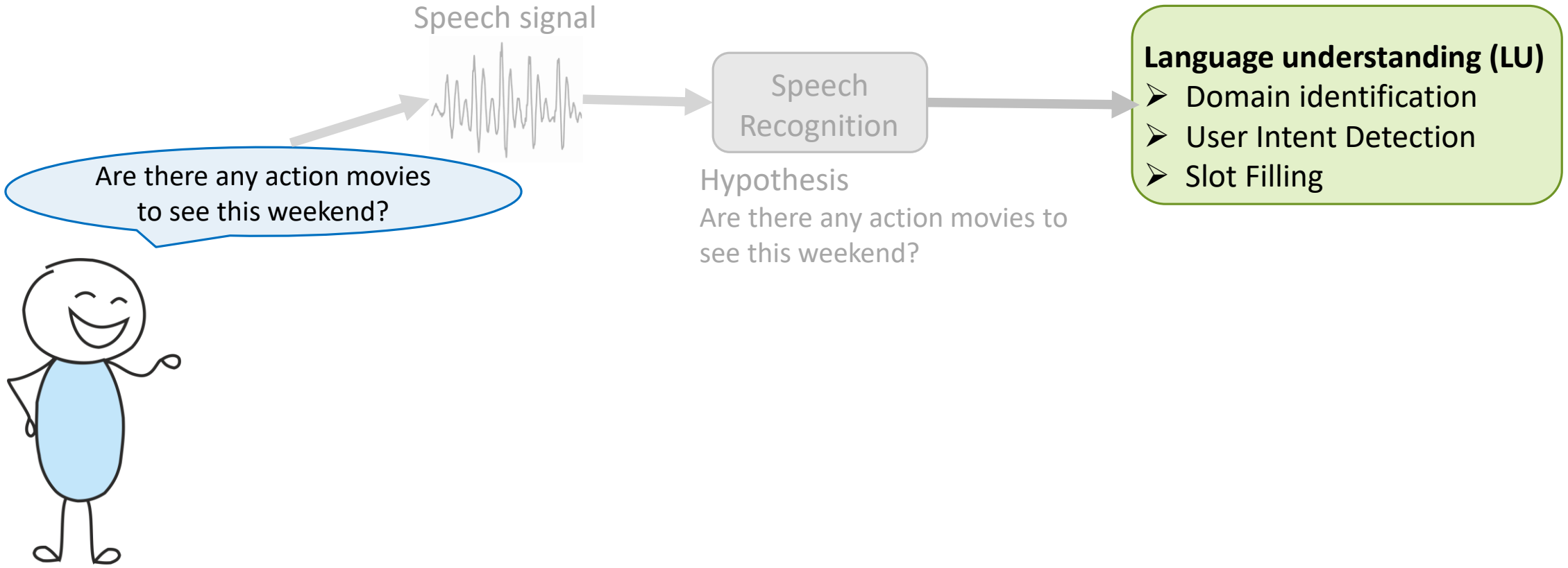

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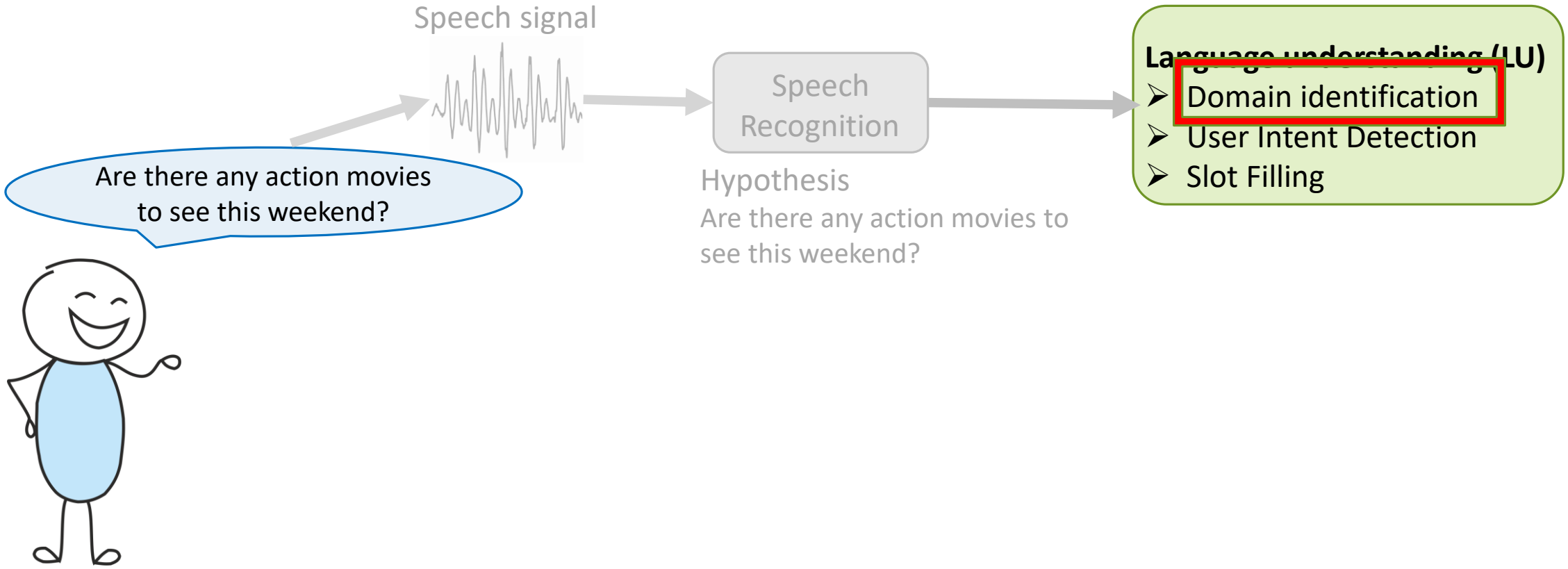
Domain Identification



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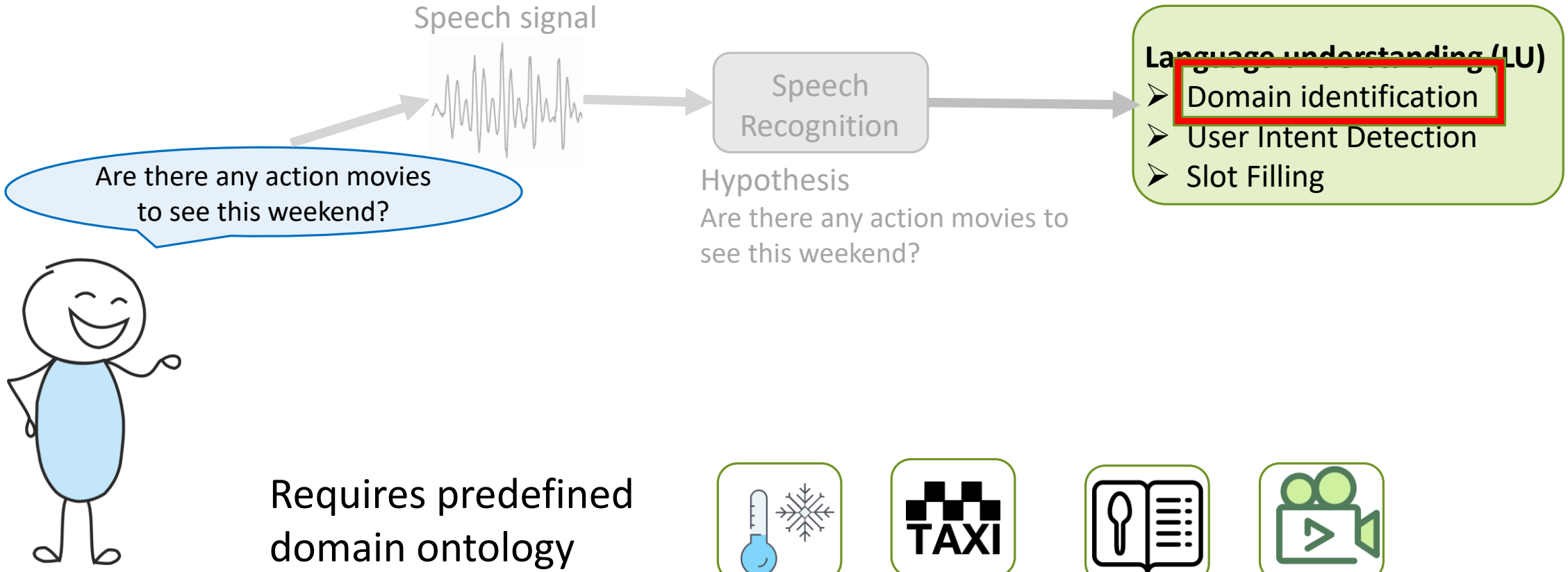

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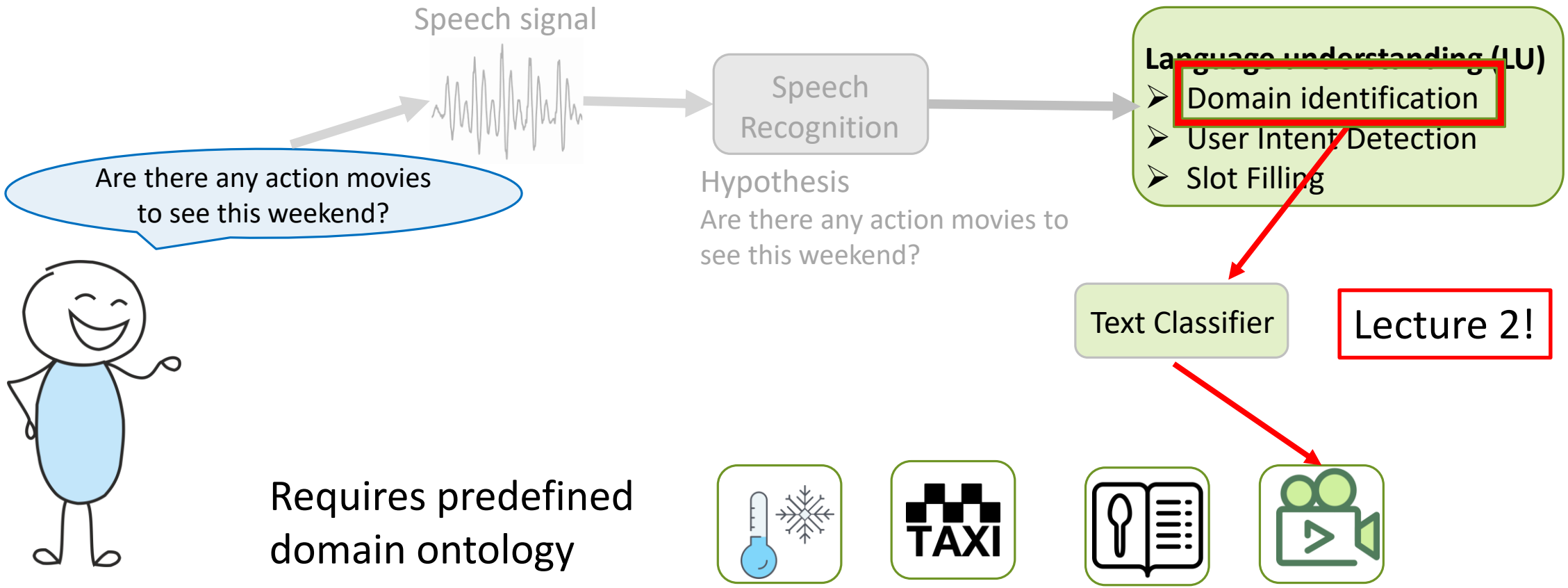

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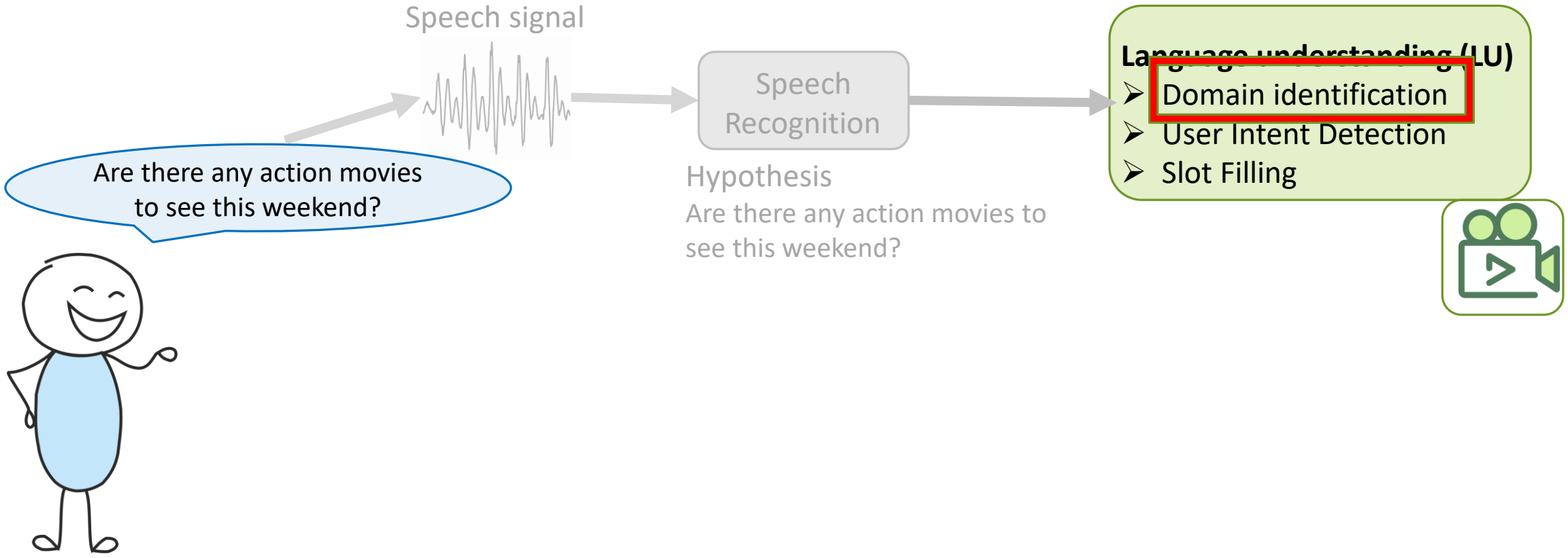

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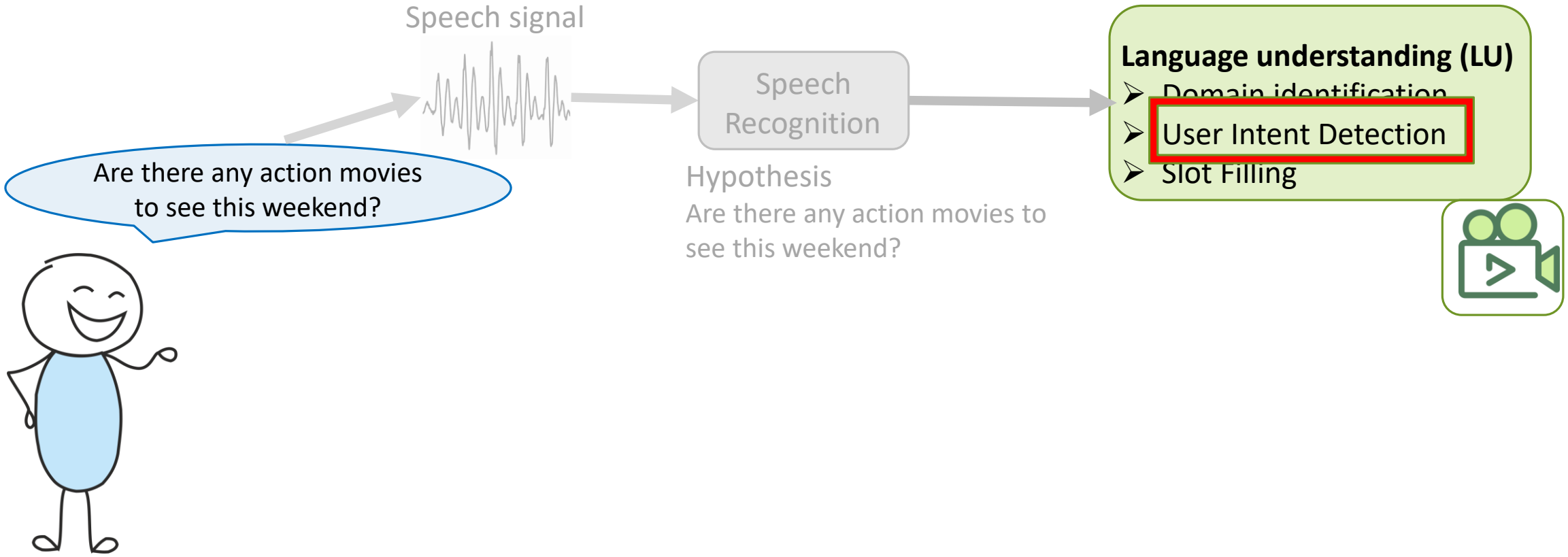
User Intent Detection



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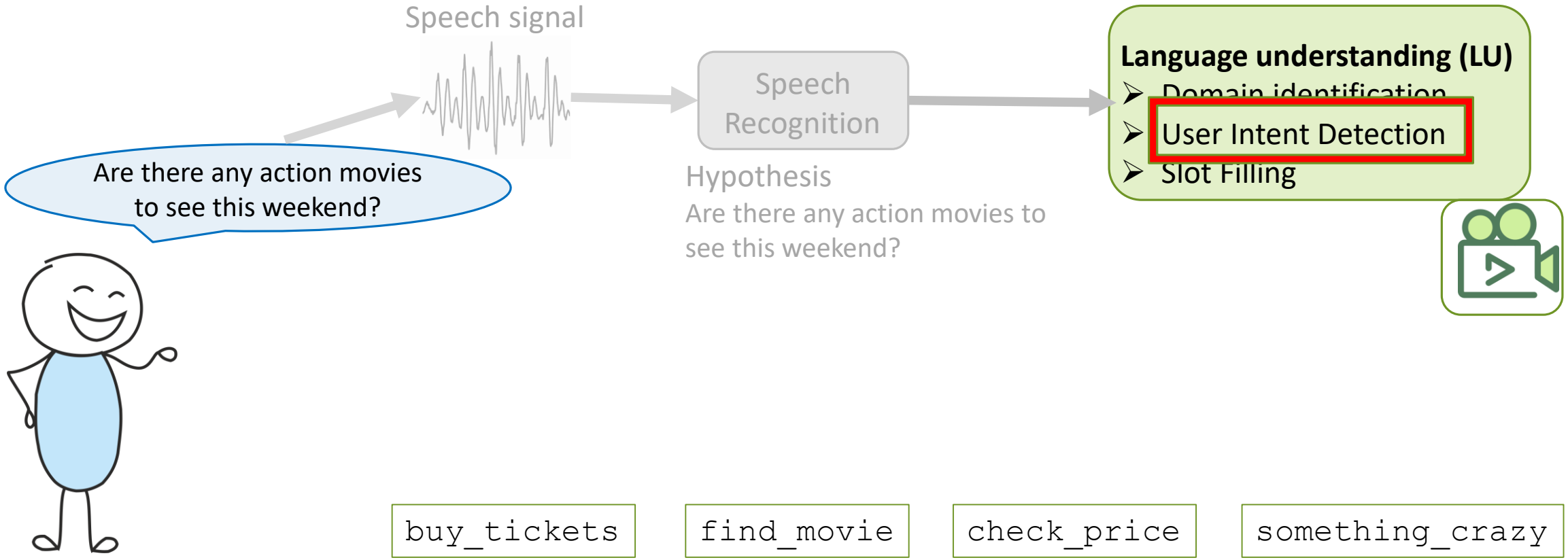
User Intent Detection



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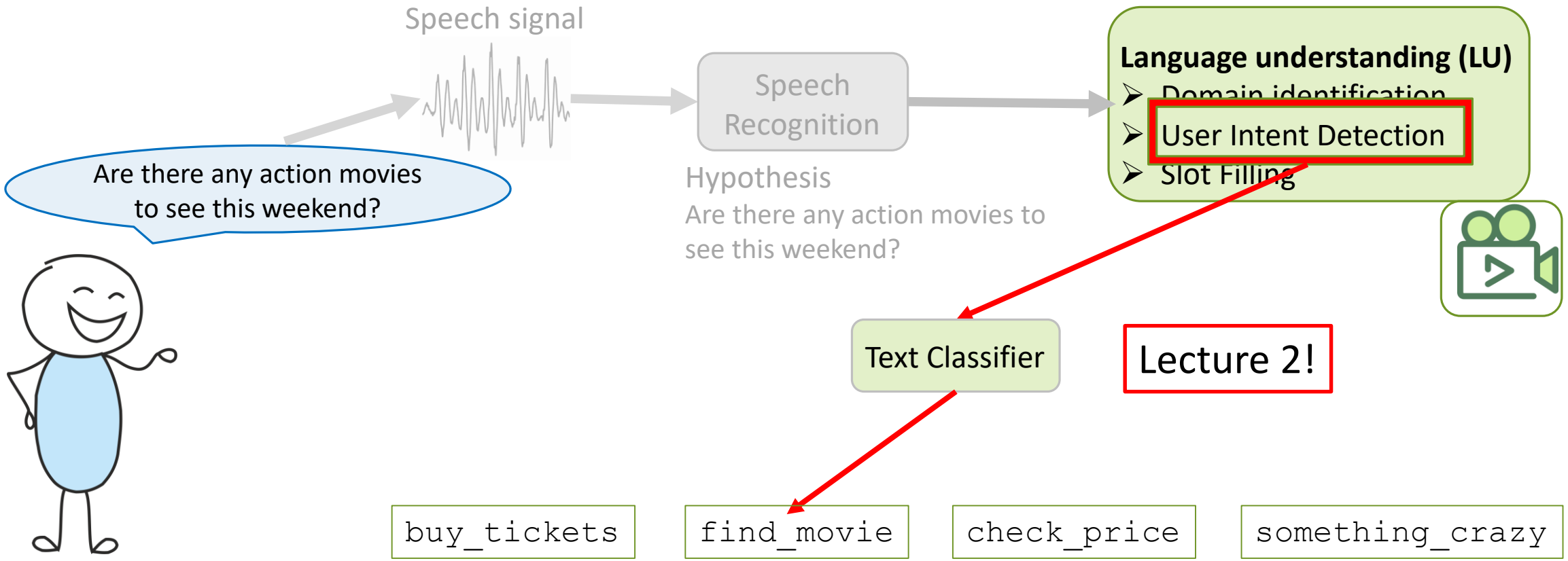

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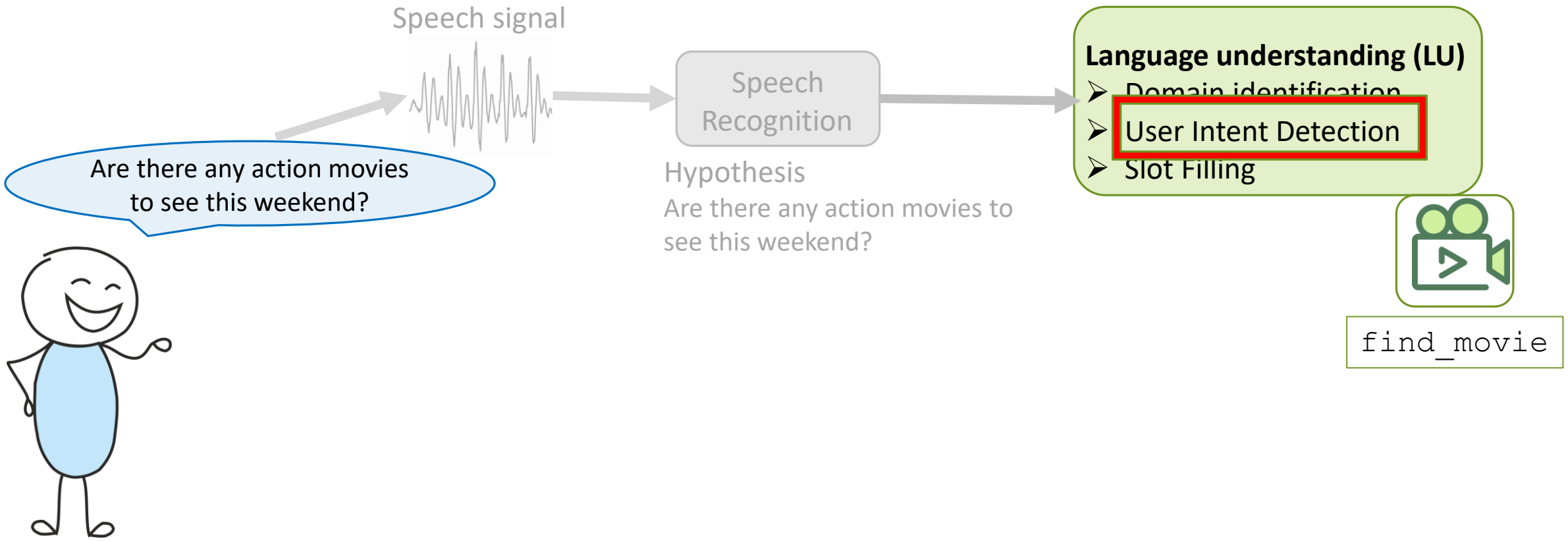

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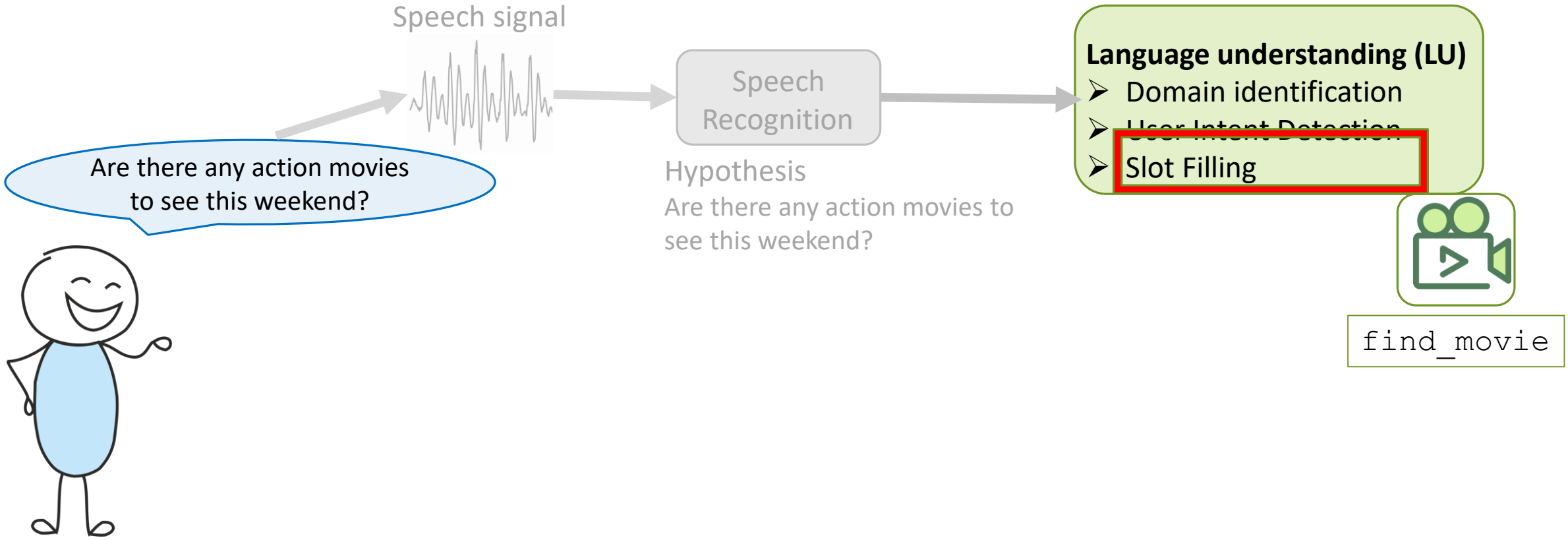
Slot Filling



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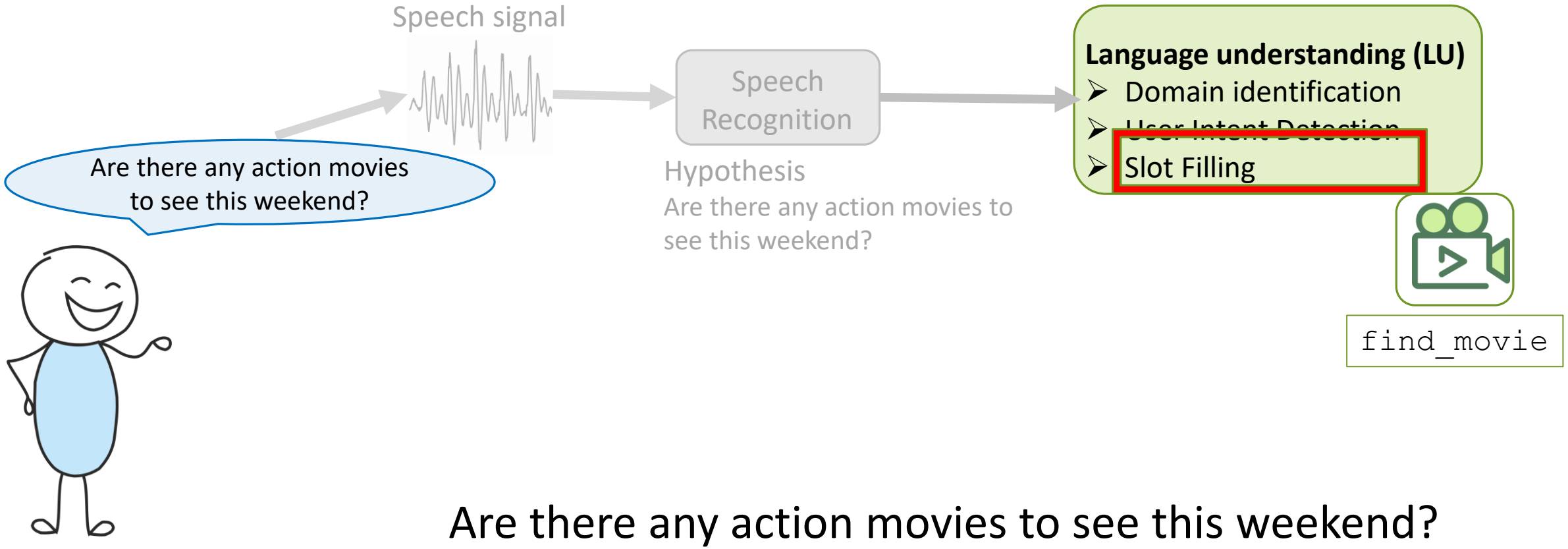
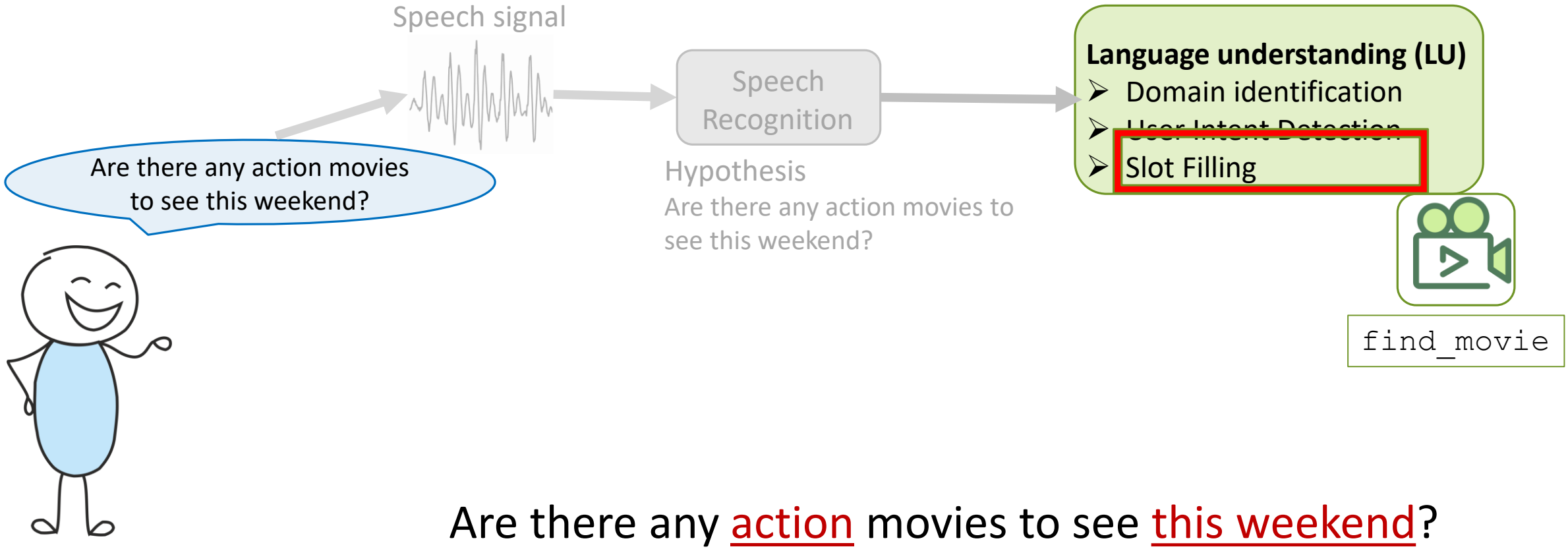


Are there any action movies to see this weekend?

Based on http://deepdialogue.miulab.tw

Slot Filling



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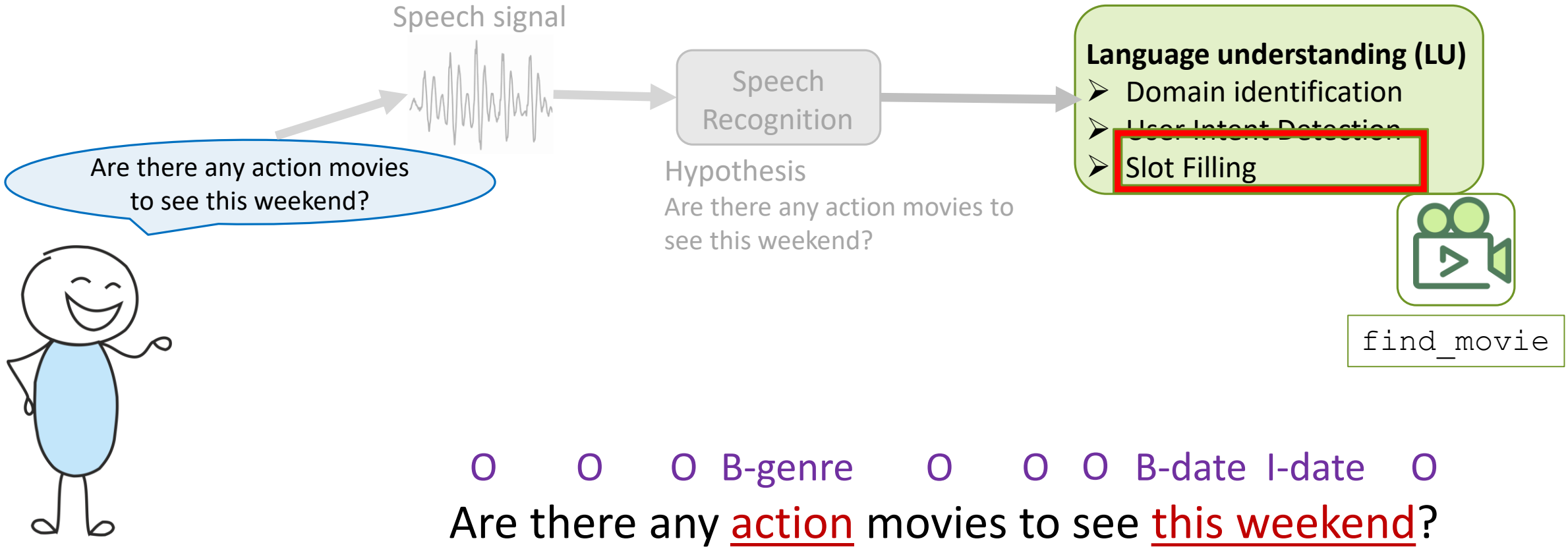

O O O B-genre O O O B-date I-date O

Are there any action movies to see this weekend?

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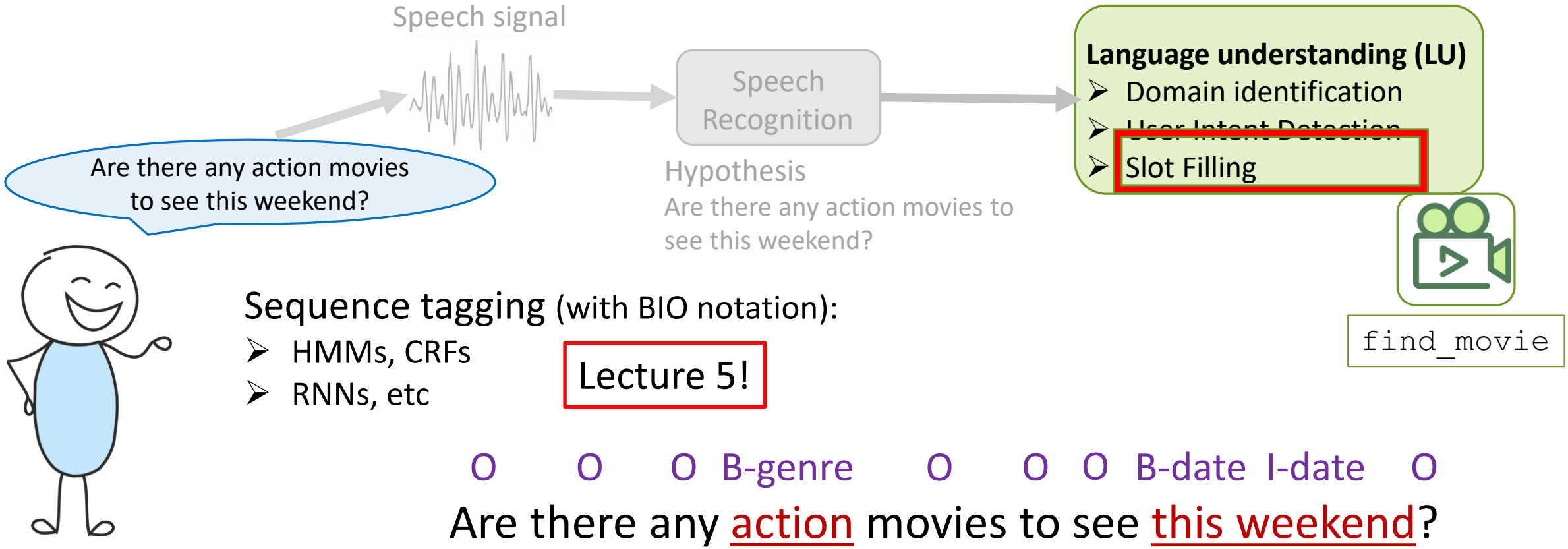
Slot Filling



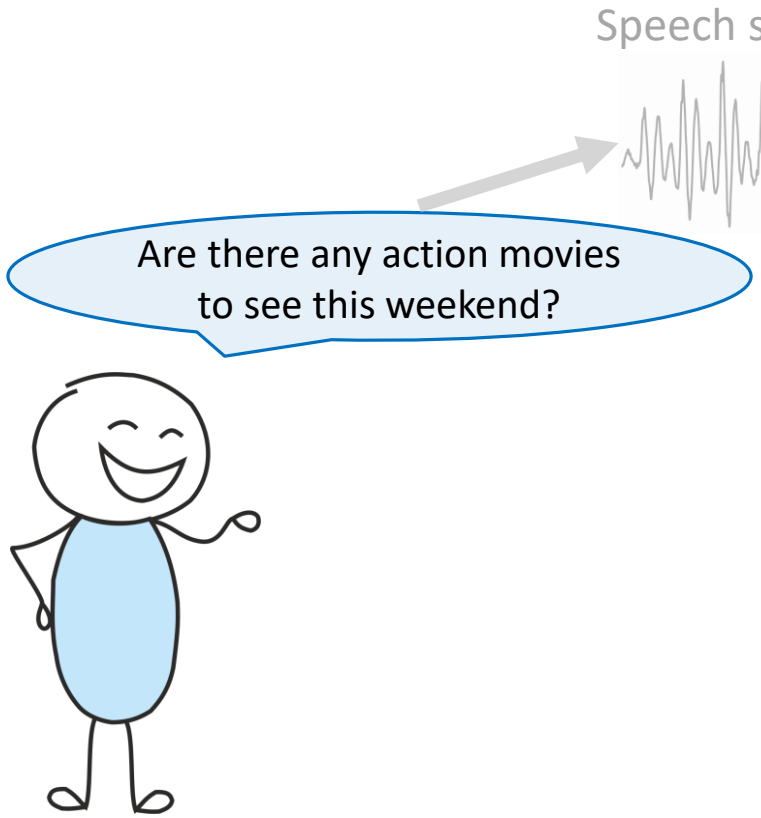
Sequence tagging (with BIO notation):

- HMMs, CRFs
- RNNs, etc

Lecture 5!

O	O	O	B-genre	O	O	O	B-date	I-date	O
Are	there	any	action	movies	to	see	this	weekend	?

Language Understanding



Speech signal

Speech Recognition

Hypothesis

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Language understanding (LU)

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`find_movie`

Semantic frame

```
find_movie
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date=this weekend
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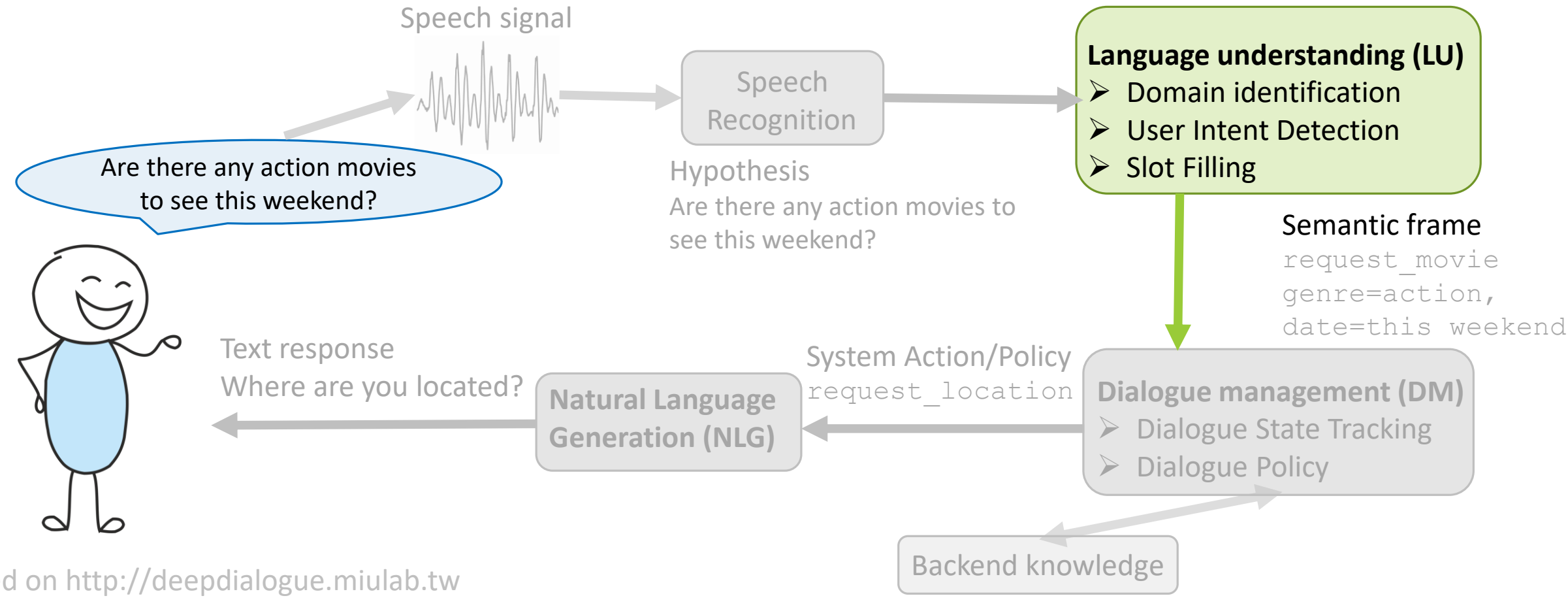
Dialogue Management

Language Understanding



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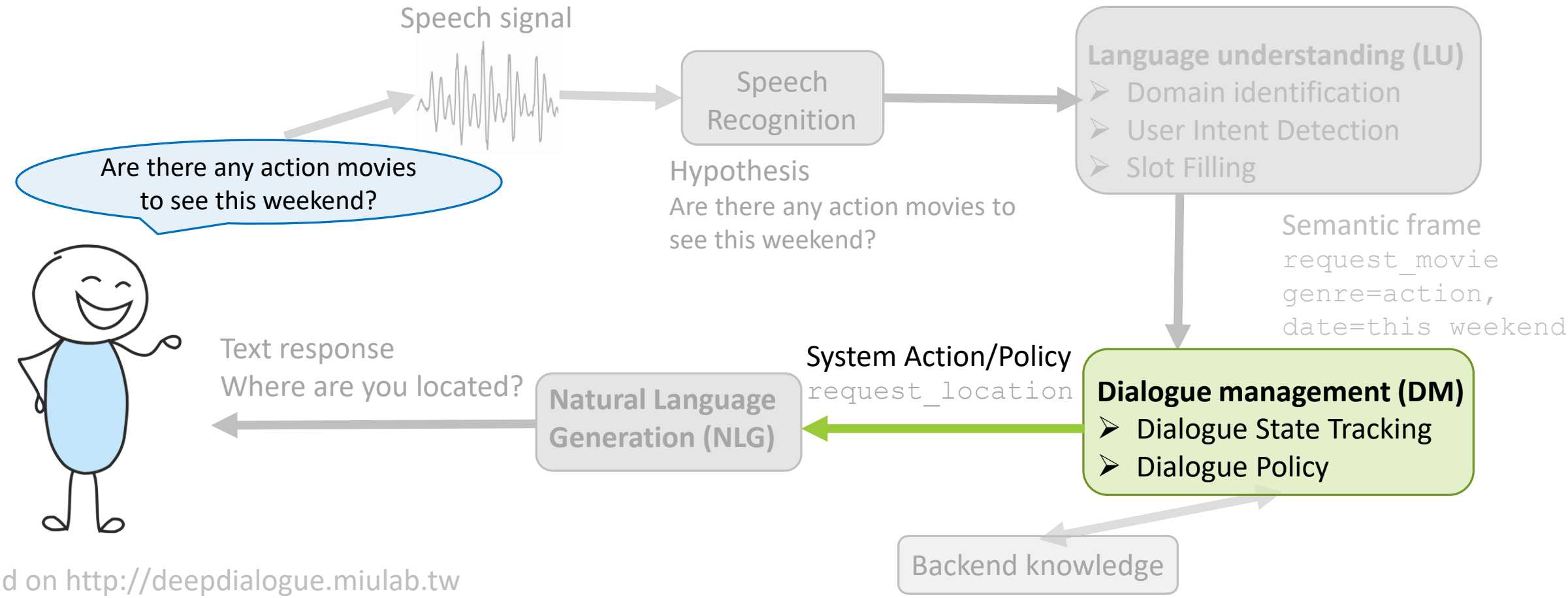
Dialogue Management



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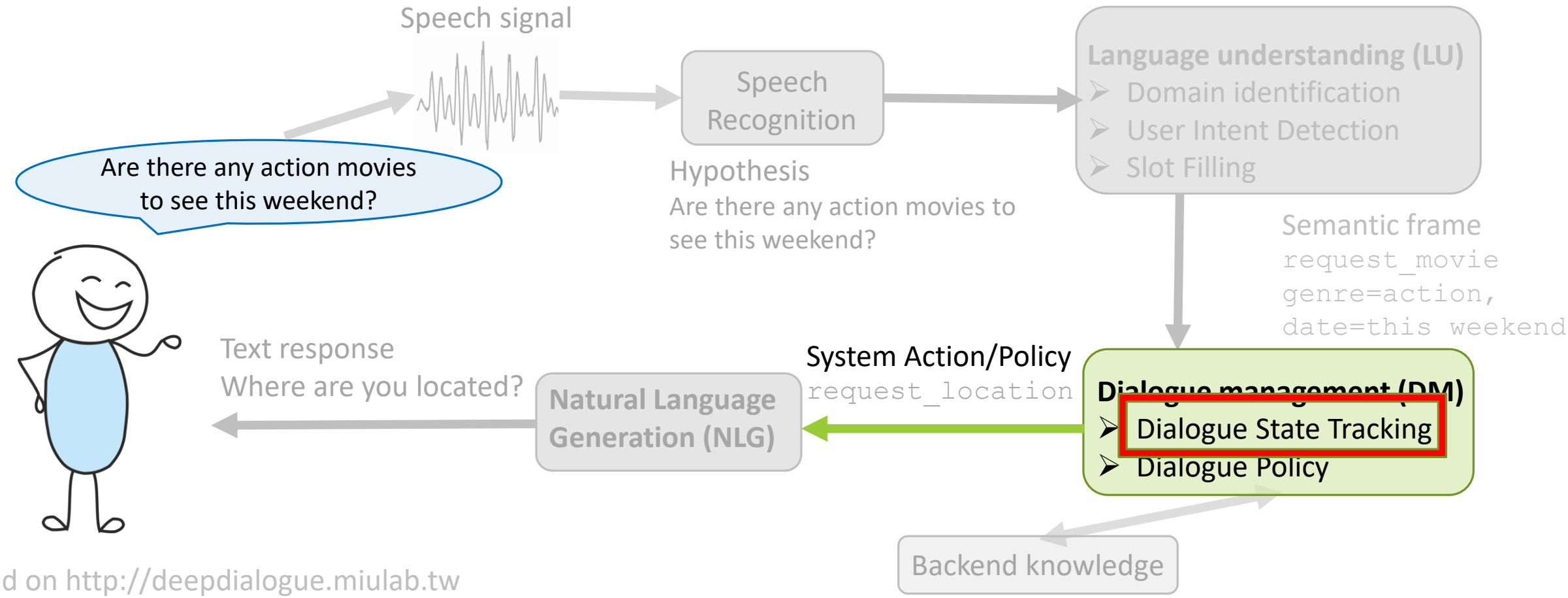
Dialogue Management



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Dialogue State

- goal constraint – constraints from a user
  - Some value
  - “Dontcare” – no preference
  - None – need to be specified
- requested slots – slots that are to be specified
- search method – how a user interacts with a system
  - constraints
  - alternatives
  - finished

	SLU output		Dialog State
Turn 1			
a: What part of town did you have in mind? *request(area)*	0.7 0.2 0.1	*null()* *inform(food='north african')* *inform(area=north)*	**goal constraints** *area=north* **requested slots** – **search method** *by constraints*
u: The North area *inform(area=north)*			
Turn 2			
a: Which part of town? *request(area)*	0.8 0.2	*inform(area=north, pricerange=cheap)* *inform(area=north)*	**goal constraints** *area=north* *pricerange=cheap* **requested slots** –
u: A cheap place in the North *inform(area=north, pricerange=cheap)*			**search method** *by constraints*

Review of ML for DST: https://storage.googleapis.com/pub-tools-public-publication-data/pdf/44018.pdf

Dialogue State

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  - None – need to be specified
- requested slots – slots that are to be specified
- search method – how a user interacts with a system
  - constraints
  - alternatives
  - finished

Turn 3				
a:	Da Vinci Pizzeria is a cheap place in the North. *inform(name='Da Vinci Pizzeria', area=north, pricerange=cheap)*	0.7 0.3	*reqalts(area=west)* *reqalts()*	**goal constraints** *area=west* *pricerange=cheap* **requested slots** – **search method** *by alternatives*
u:	Do you have anything else, but in the West? *requestAlternatives(area=west)*			
Turn 4				
a:	Cocum is a cheap place in the West. *inform(name=cocum, area=west, pricerange=cheap)*	0.6 0.3 0.1	*request(phone, address)* *request(phone)* *request(address)*	**goal constraints** *area=west* *pricerange=cheap* **requested slots** *address* *phone* **search method** *by alternatives*
u:	What is their number and address? *request(address, phone)*			

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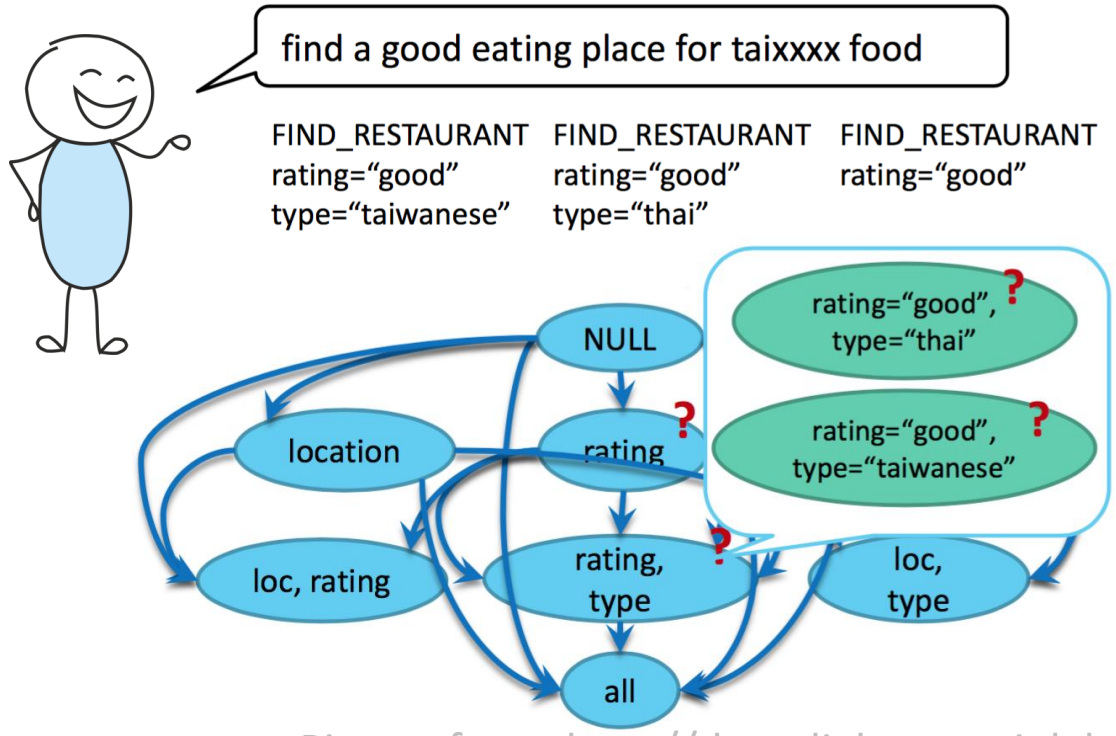
Dialogue State Tracking

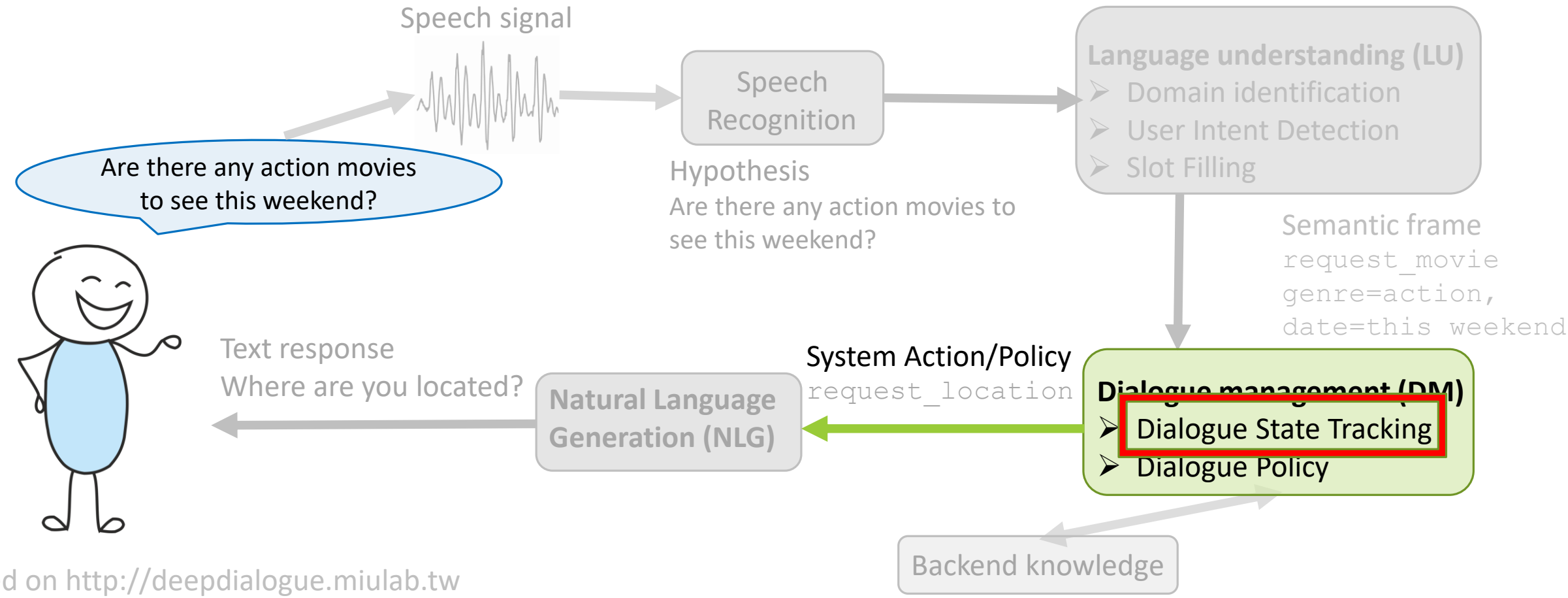
Maintain a distribution over multiple hypotheses of the true dialog state:

- robust sets of handcrafted rules
- conditional random fields
- maximum entropy models
- web-style ranking
- Deep learning: RNNs, LSTMs, etc



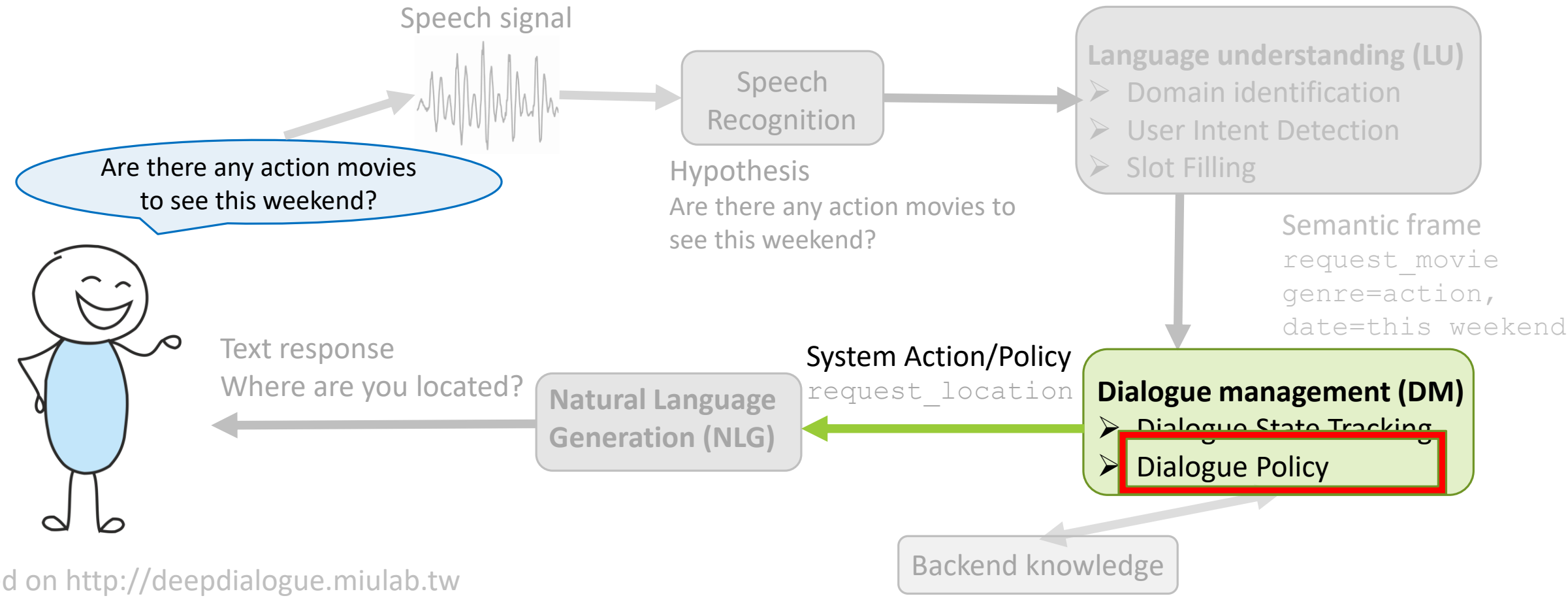
Picture from: http://deepdialogue.miulab.tw

Dialogue Management



Based on http://deepdialogue.miulab.tw

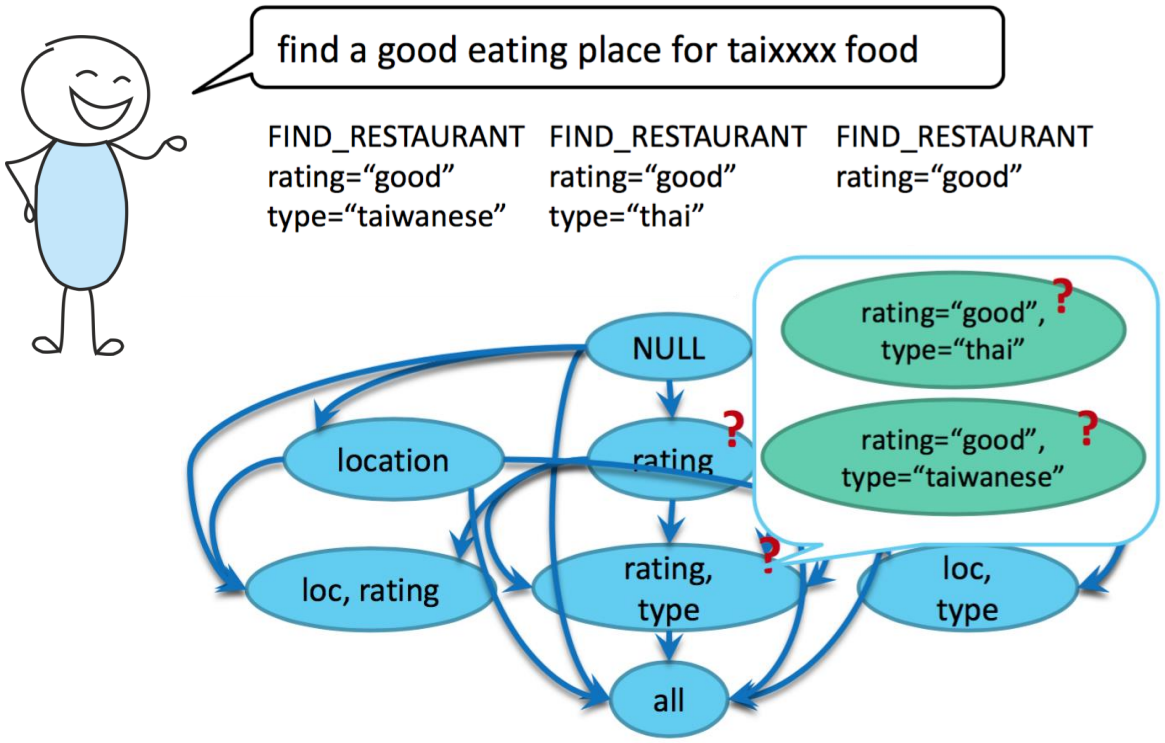
Dialogue Management



Based on http://deepdialogue.miulab.tw

Dialogue Policy

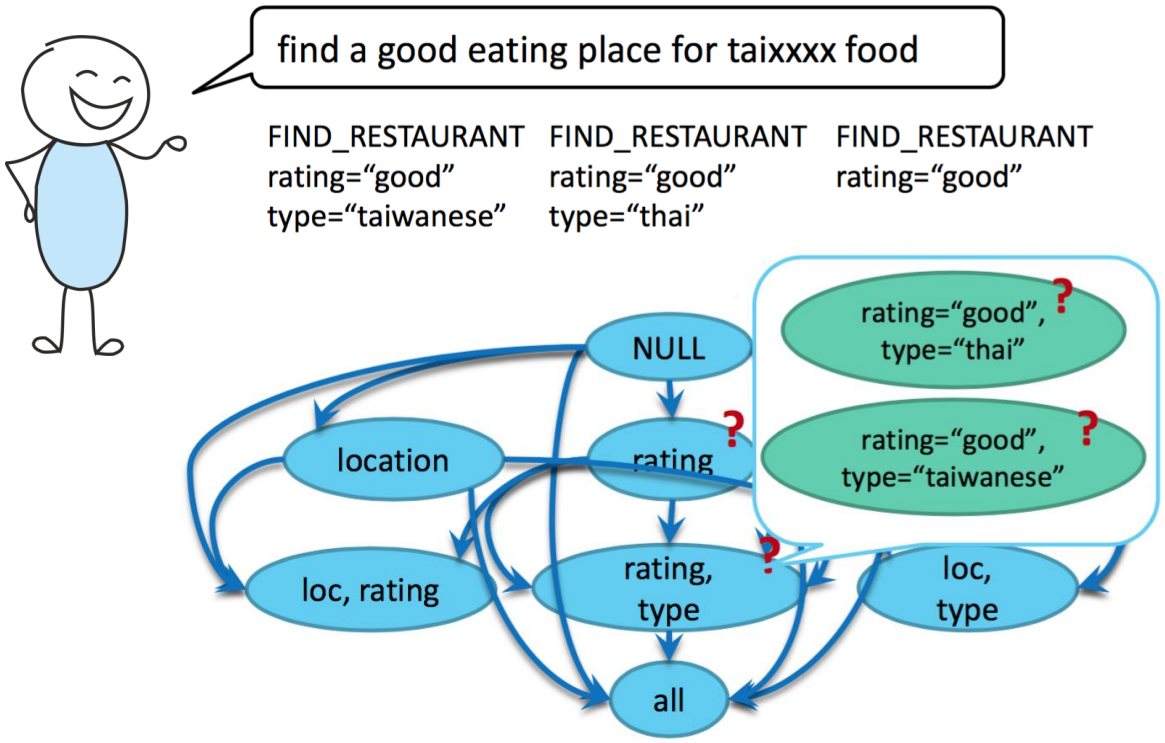
Dialogue State



Picture partially from: http://deepdialogue.miulab.tw

Dialogue Policy

Dialogue State



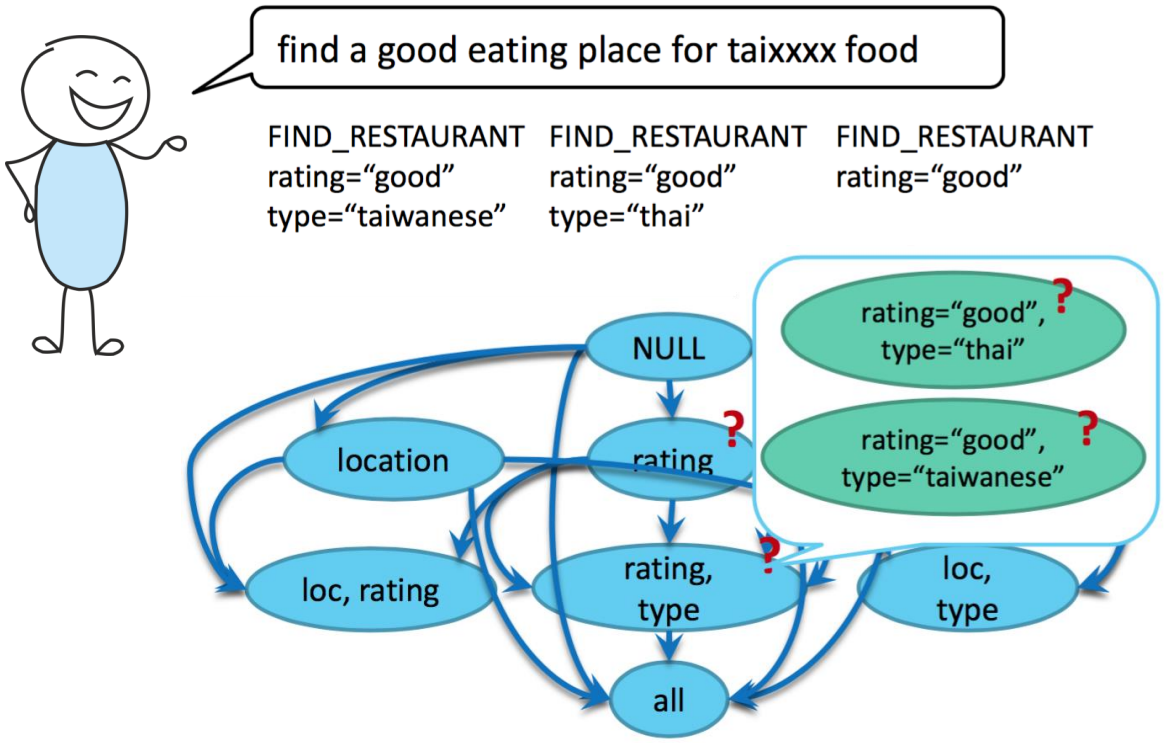
Agent Action

- Inform(location="Taipei 101")
  - "The nearest one is at Taipei 101"
- Request(location)
  - "Where is your home?"
- Confirm(type="taiwanese")
  - "Did you want Taiwanese food?"

Picture partially from: http://deepdialogue.miulab.tw

Dialogue Policy

Dialogue State



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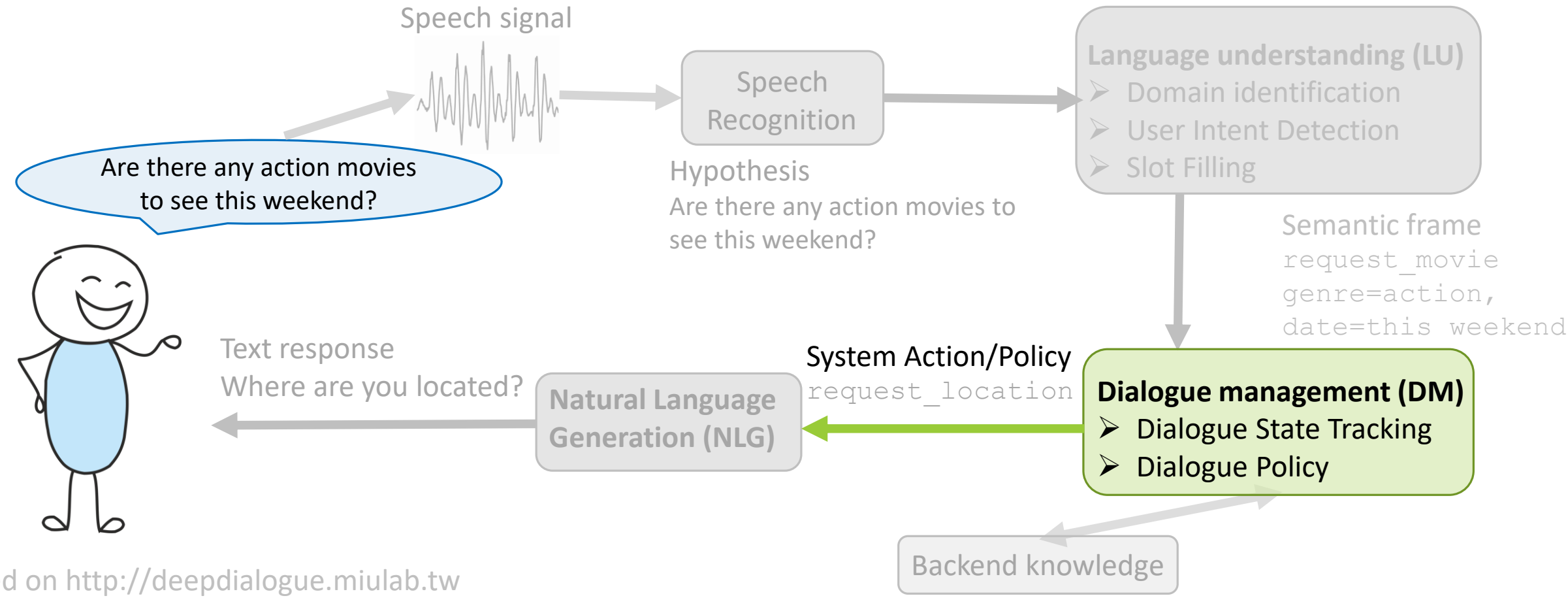
A lot of methods for optimizing policy will be in the RL course (4 semester)!

Picture partially from: http://deepdialogue.miulab.tw

Natural Language Generation

Dialogue Management



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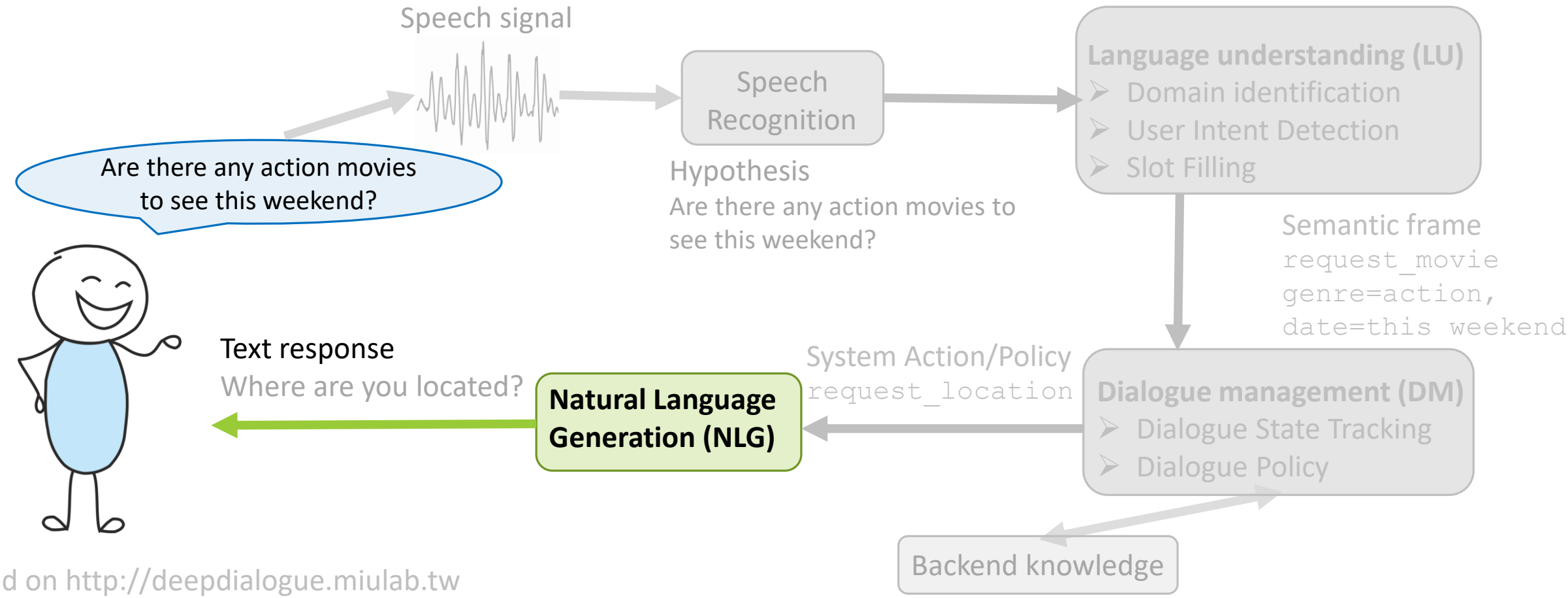
Natural Language Generation



Based on http://deepdialogue.miulab.tw

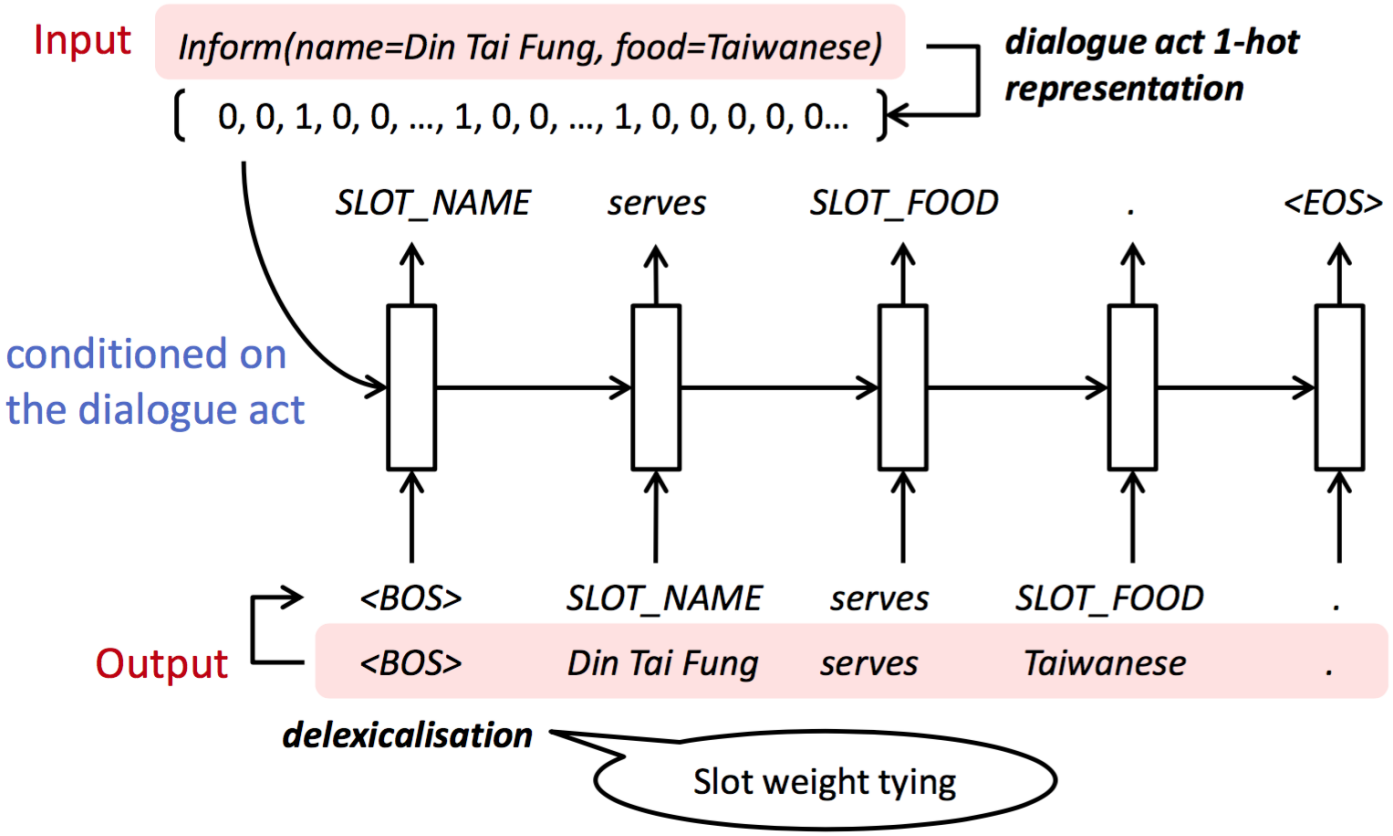
Natural Language Generation

Generate natural language response given a dialogue action

Inform(location="Taipei 101")	→	"The nearest one is at Taipei 101"
Request(location)	→	"Where is your home?"
Confirm(type="taiwanese")	→	"Did you want Taiwanese food?"

Example from: http://deepdialogue.miulab.tw

RNN-Based LM NLG

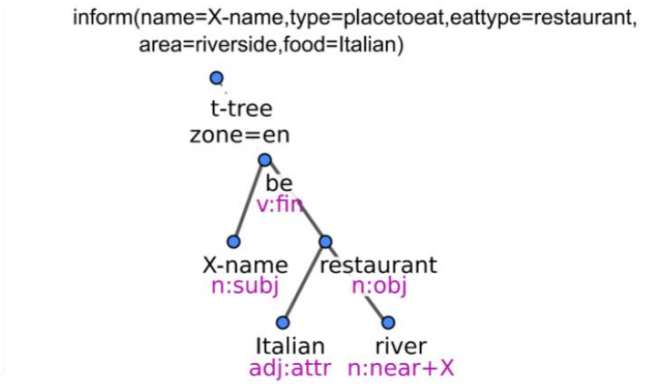


Picture from: http://deepdialogue.miulab.tw , paper: http://www.anthology.aclweb.org/W/W15/W15-46.pdf#page=295

Structural NLG

Goal: NLG based on a syntax tree

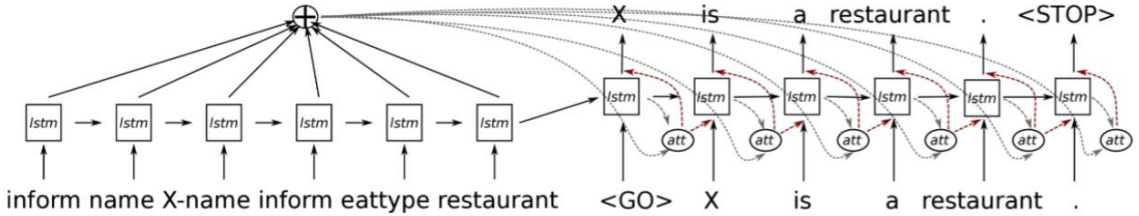
- Encode trees as sequences
- Seq2Seq model for generation



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

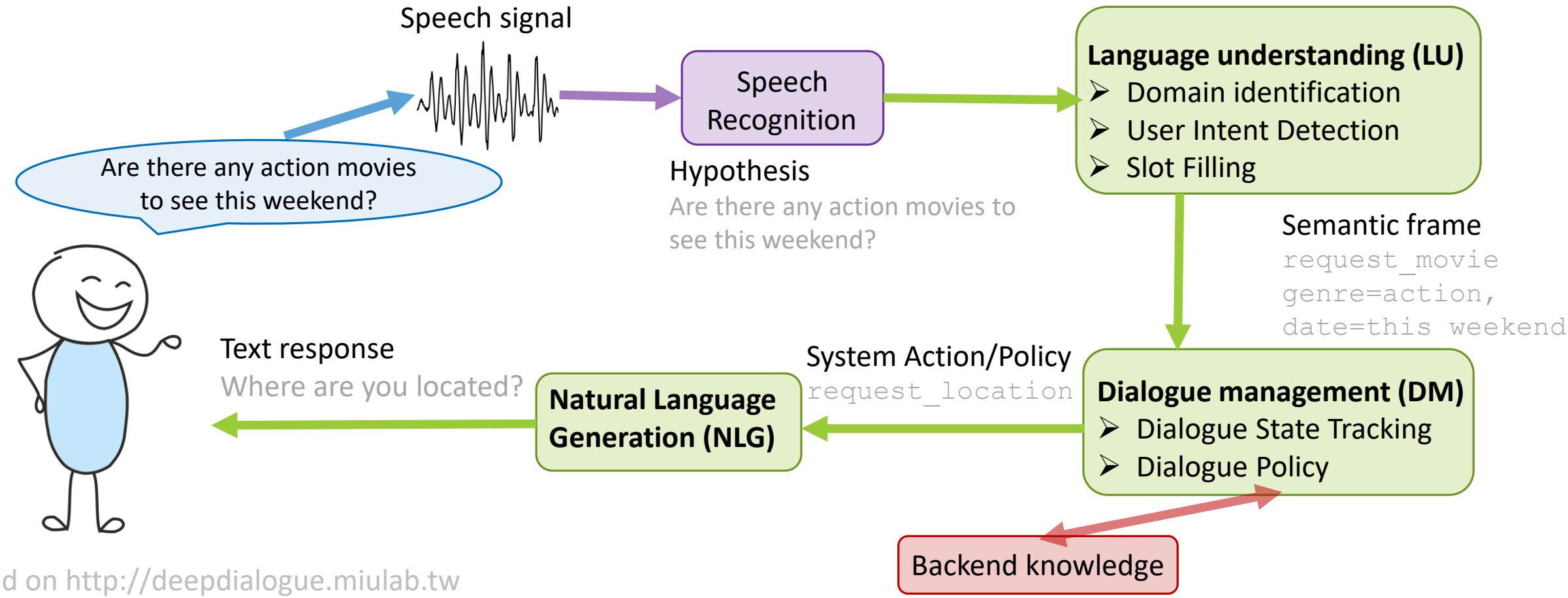
X-name n:subj be v:fin Italian adj:attr restaurant n:obj river n:near+X

X is an Italian restaurant near the river.



Picture from: http://deepdialogue.miulab.tw , paper: https://www.aclweb.org/anthology/P/P16/P16-2.pdf#page=79

Task-oriented dialogue system



Based on http://deepdialogue.miulab.tw

General conversation

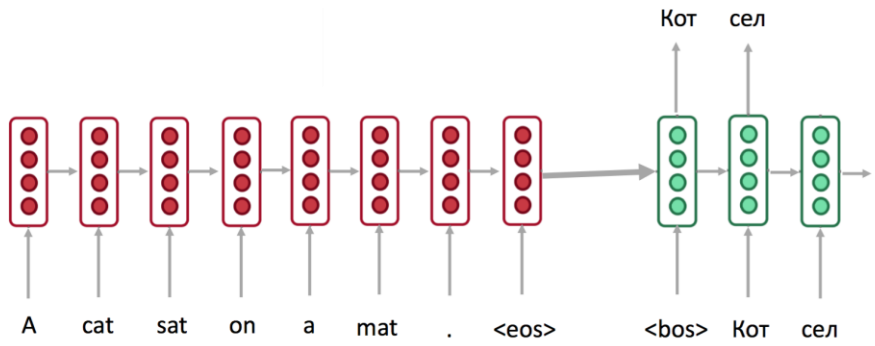
AKA CHIT-CHATS

Retrieval-based (extractive)

Select a response from a database

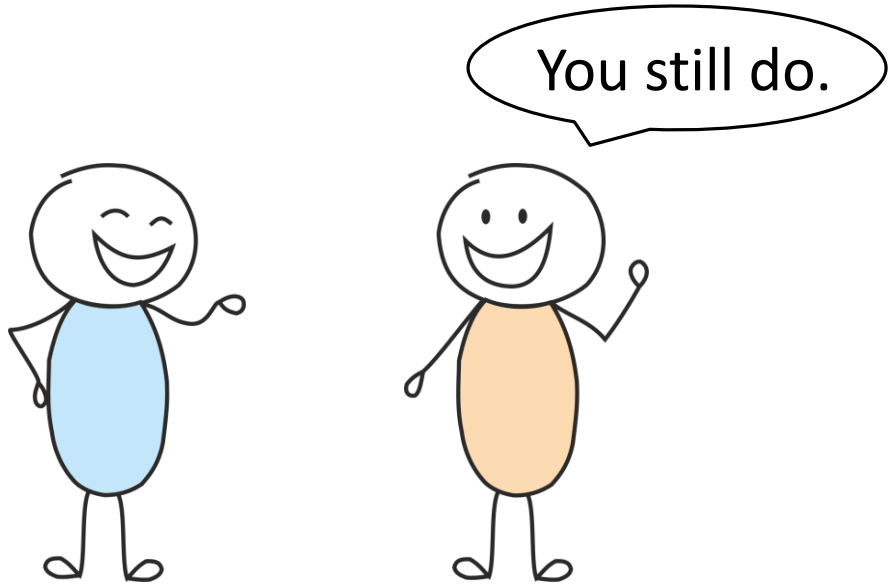
Generative (abstractive)

Generate a response with some model



Generative Models for General conversation

Storyline 1. The importance of context.



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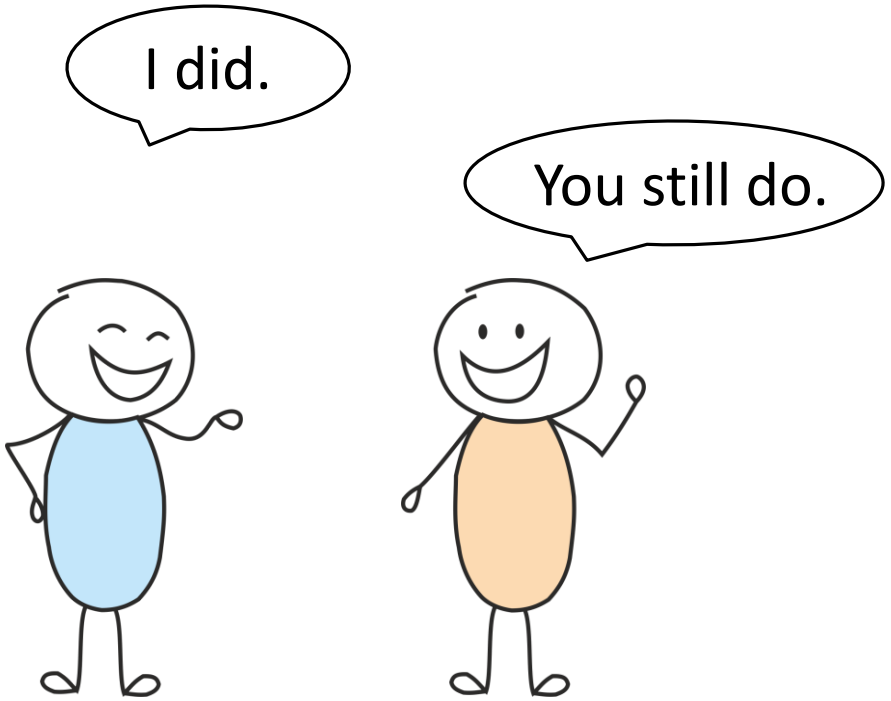

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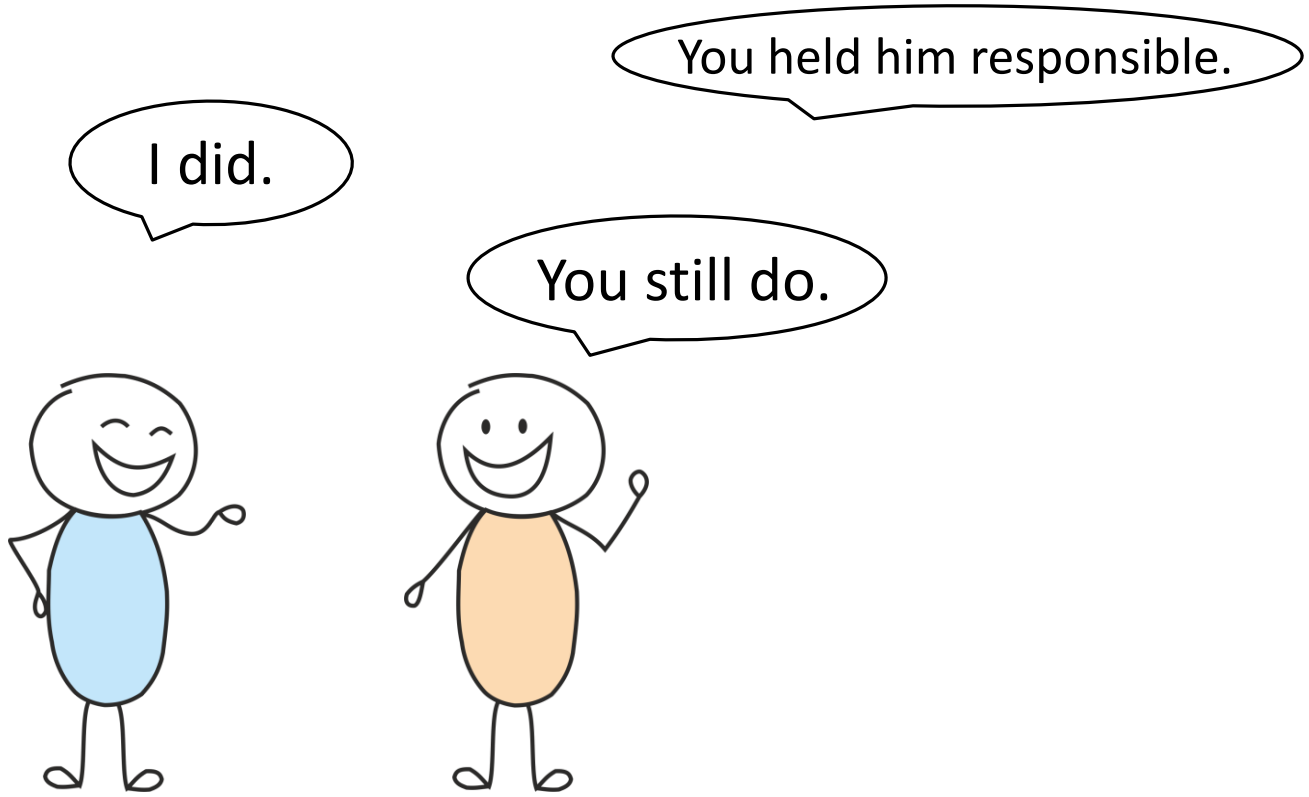

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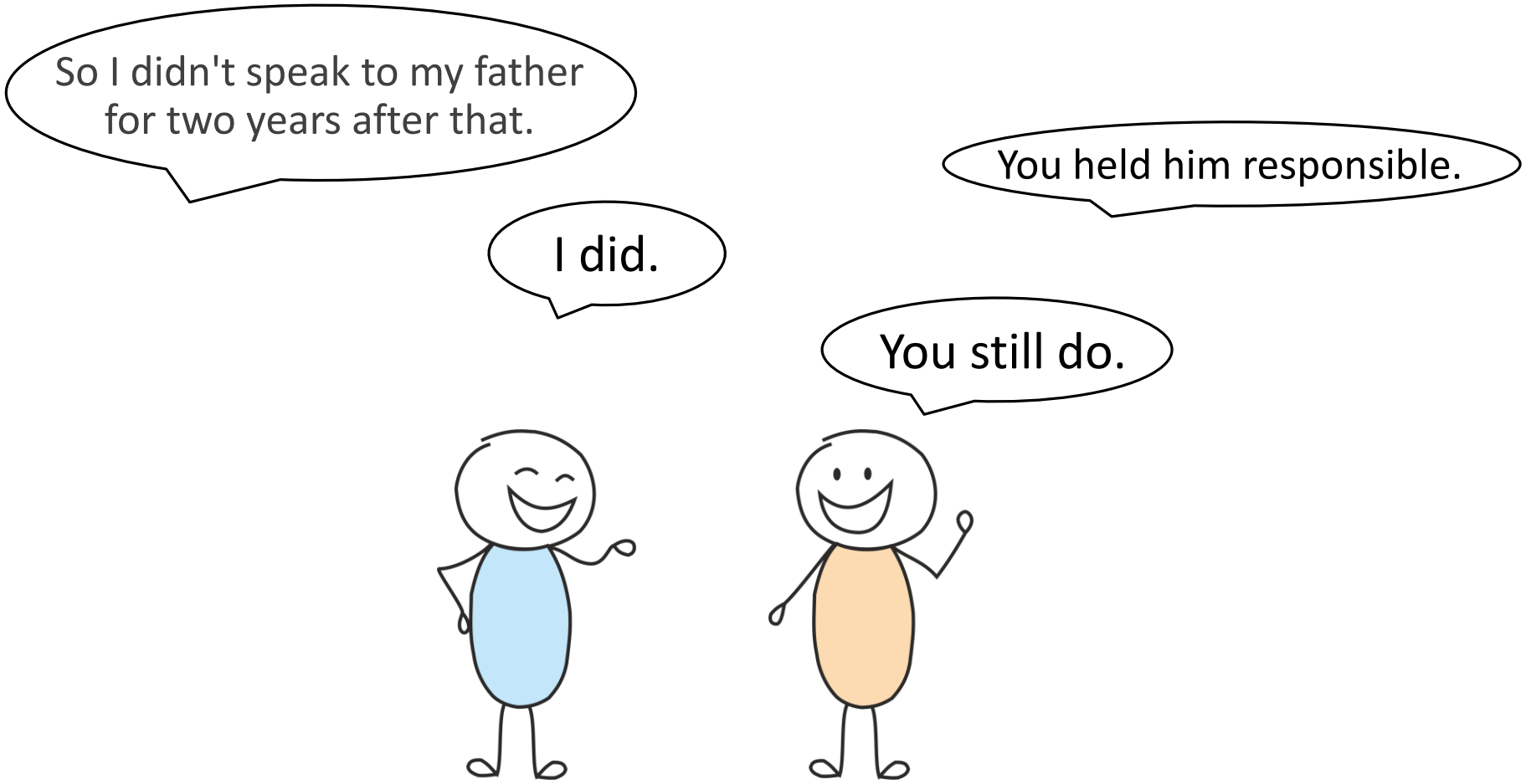
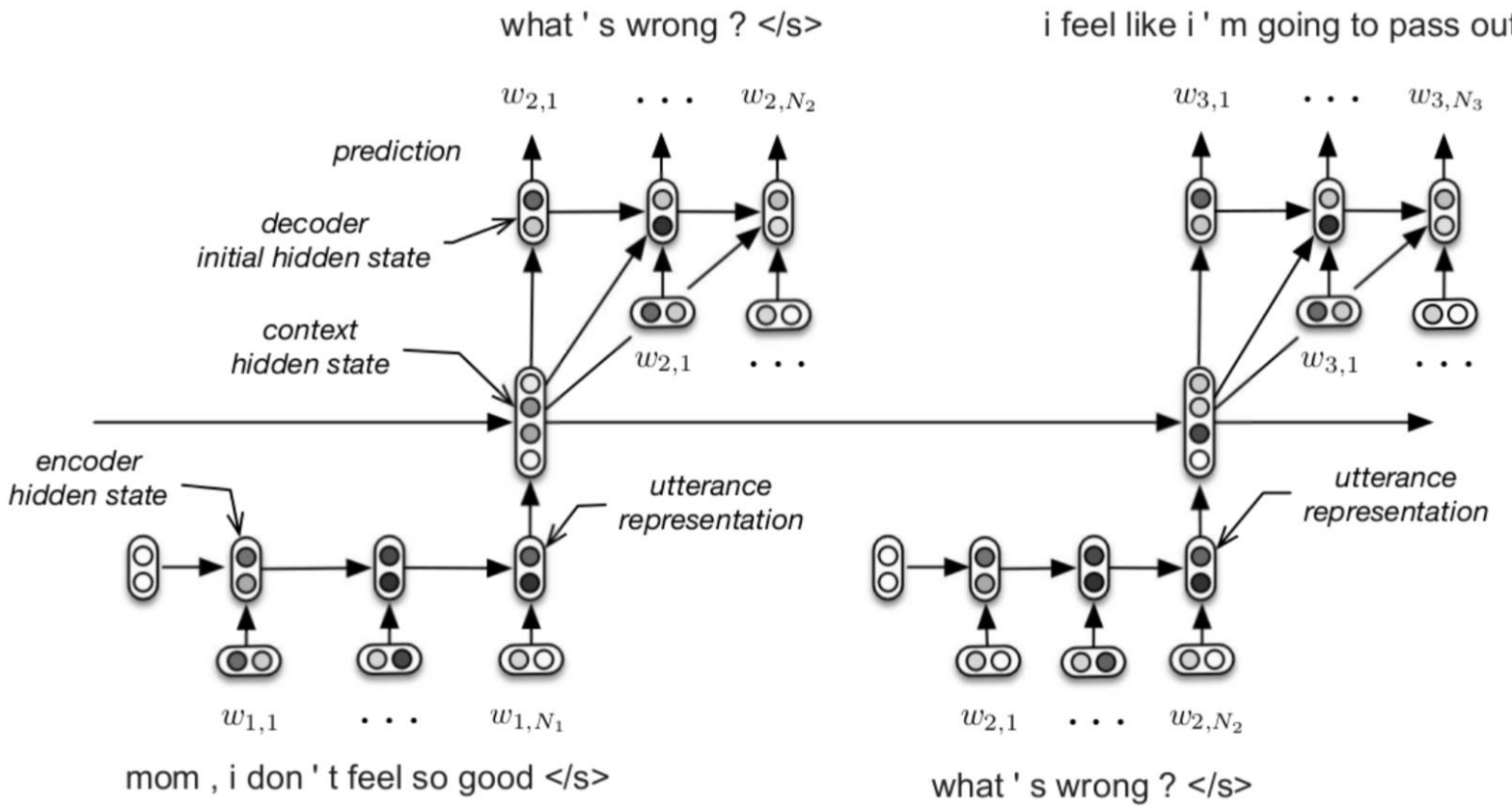


Building End-To-End Dialogue Systems Using Generative Hierarchical Neural Network Models



Serban et al, https://arxiv.org/pdf/1507.04808.pdf

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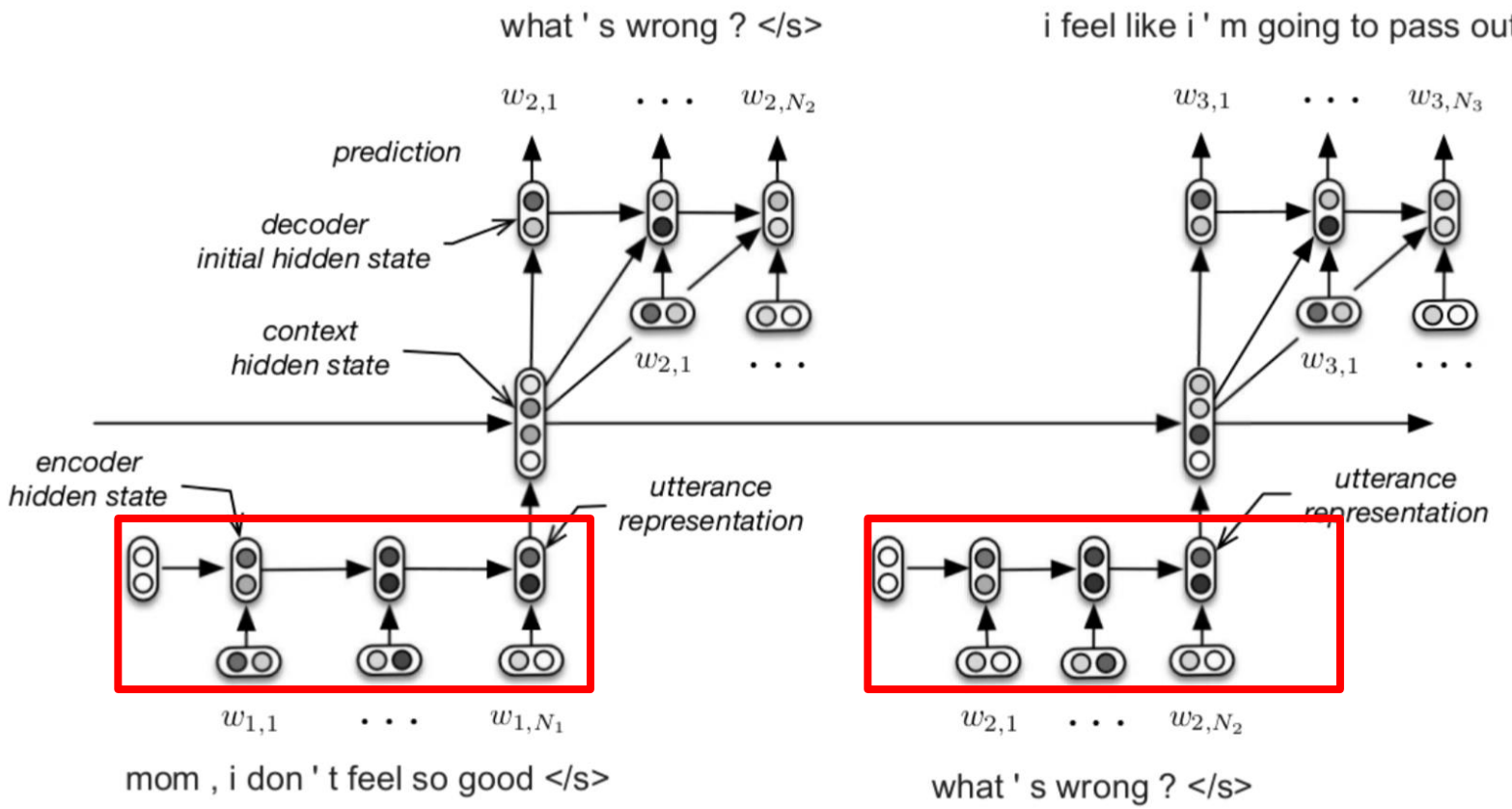

Word-level RNN

Serban et al, https://arxiv.org/pdf/1507.04808.pdf

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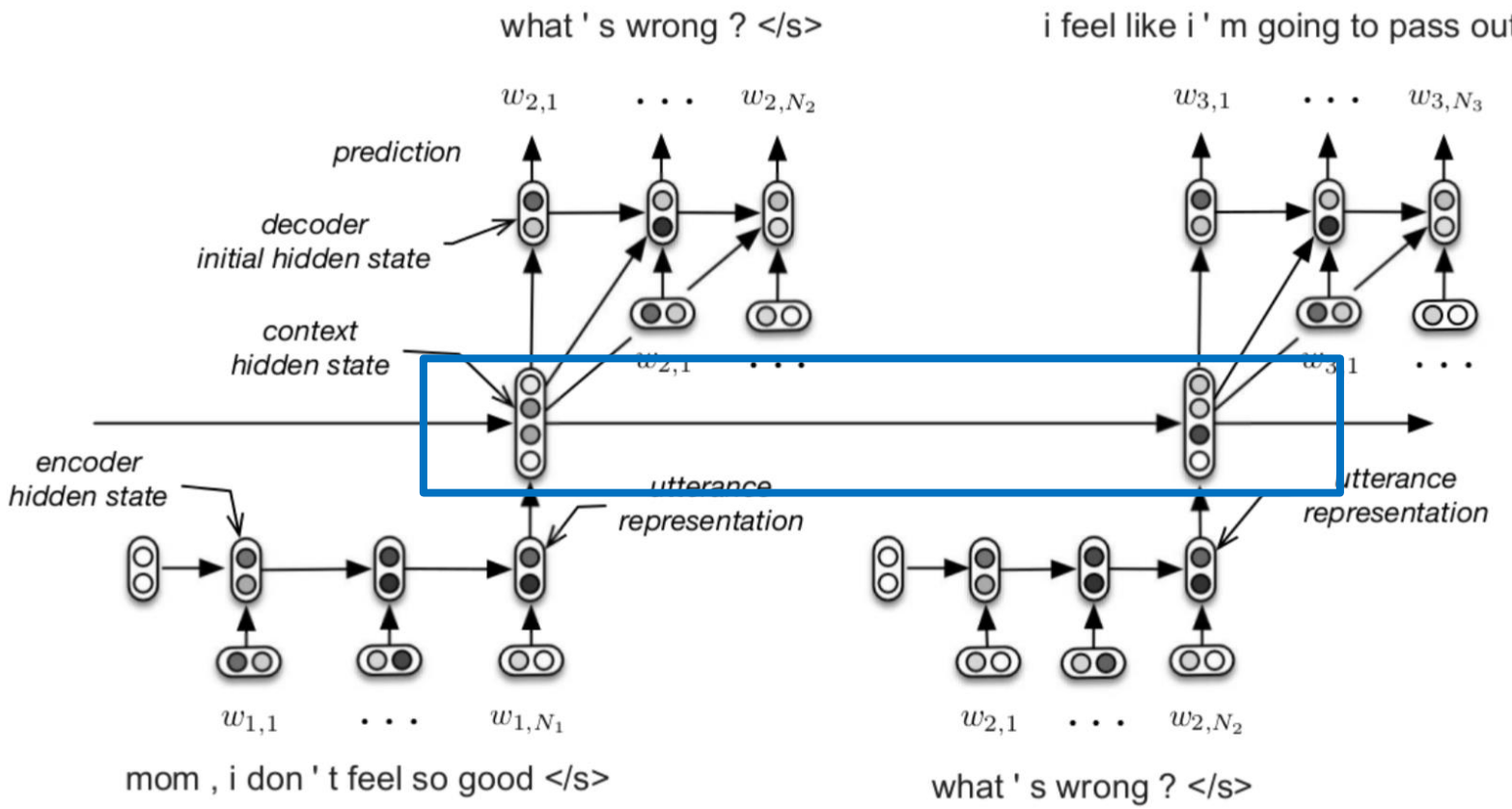
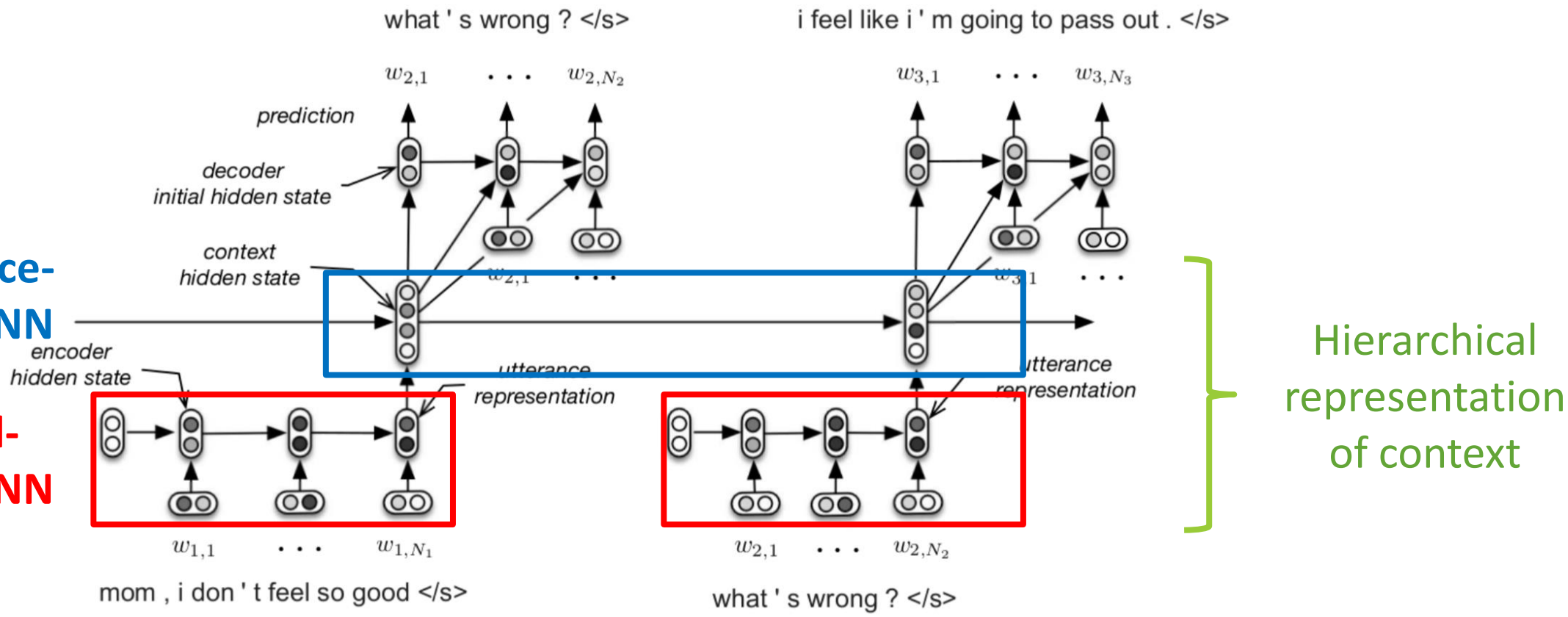


Sentence-level RNN

Serban et al, https://arxiv.org/pdf/1507.04808.pdf

Building End-To-End Dialogue Systems Using Generative Hierarchical Neural Network Models



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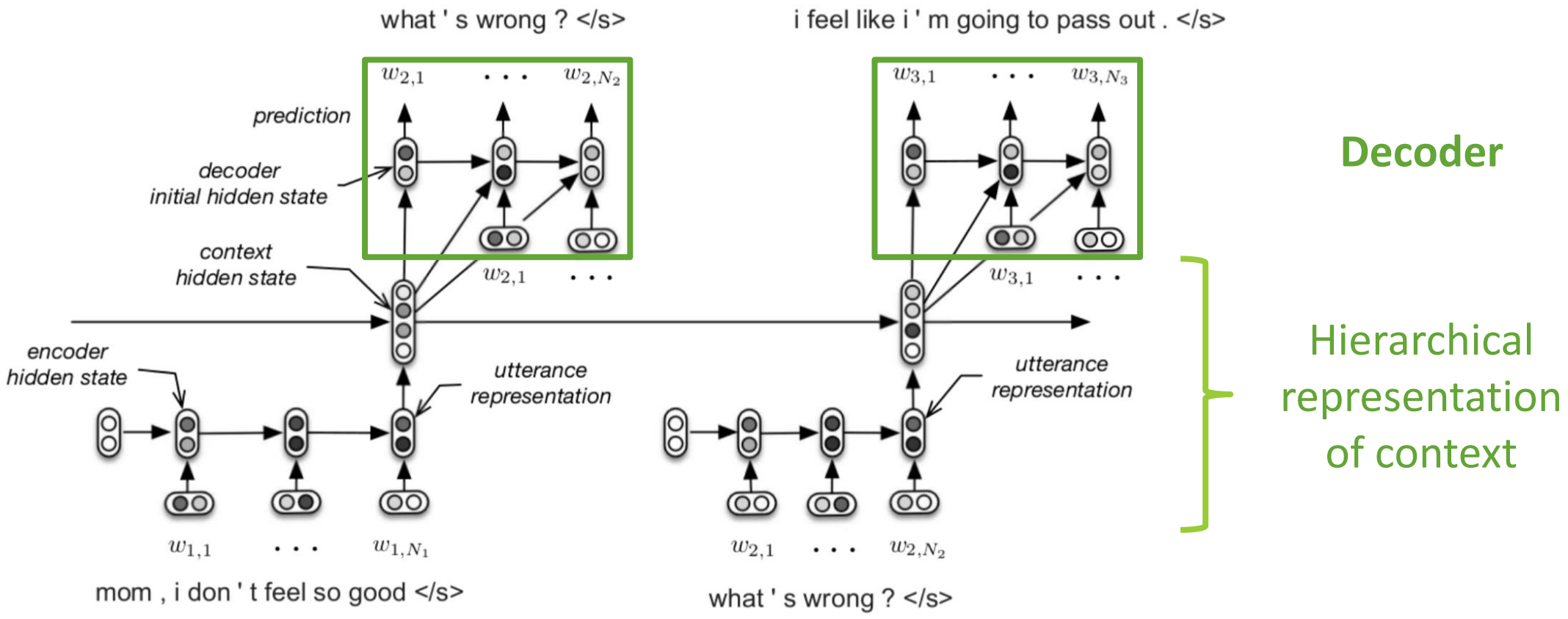

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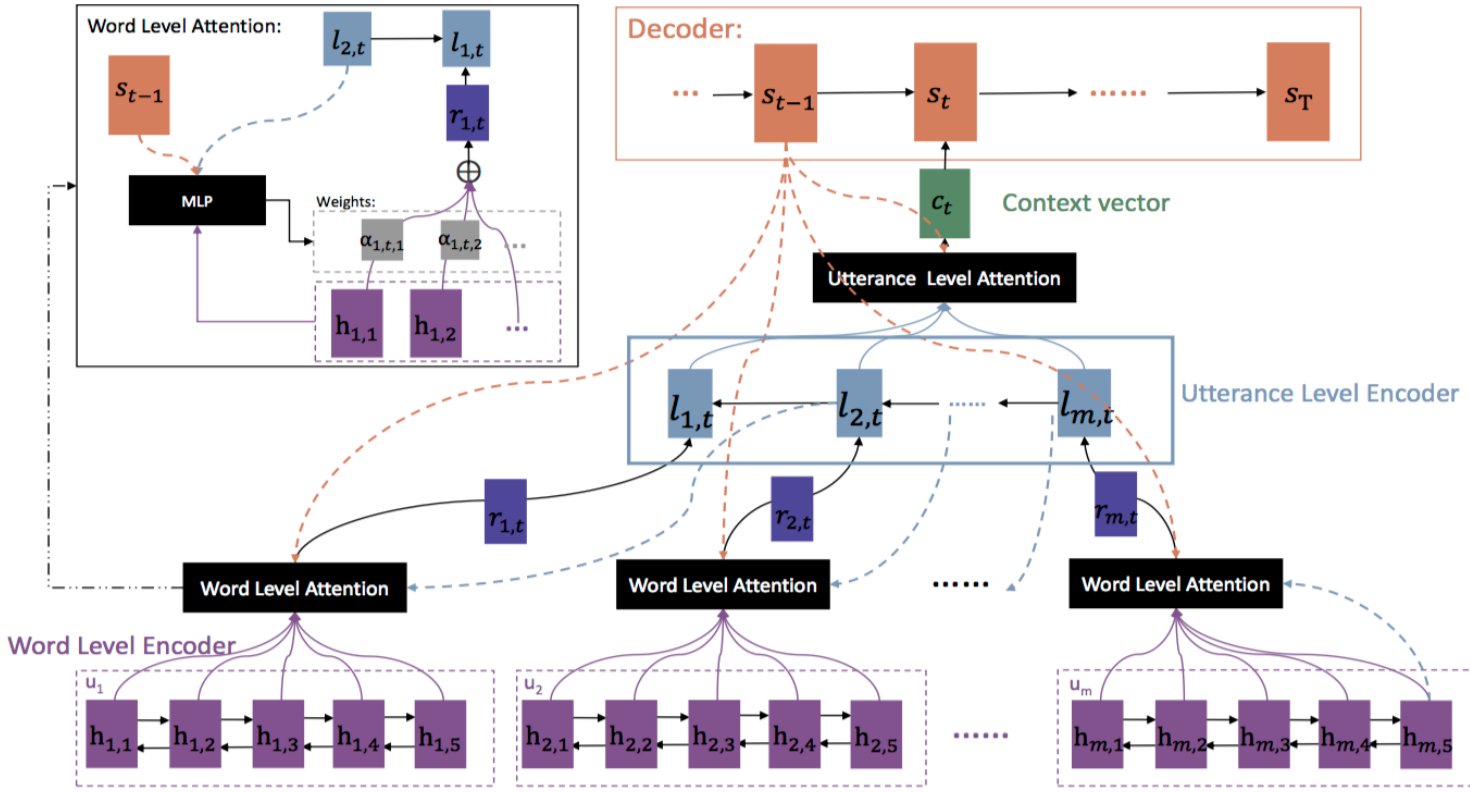
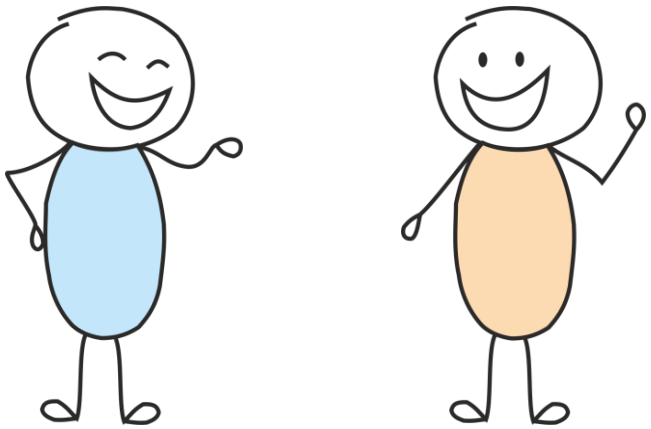
Hierarchical Recurrent Attention Network for Response Generation



Hing at el, https://arxiv.org/pdf/1701.07149.pdf

Storyline 2.
The importance of response diversity.



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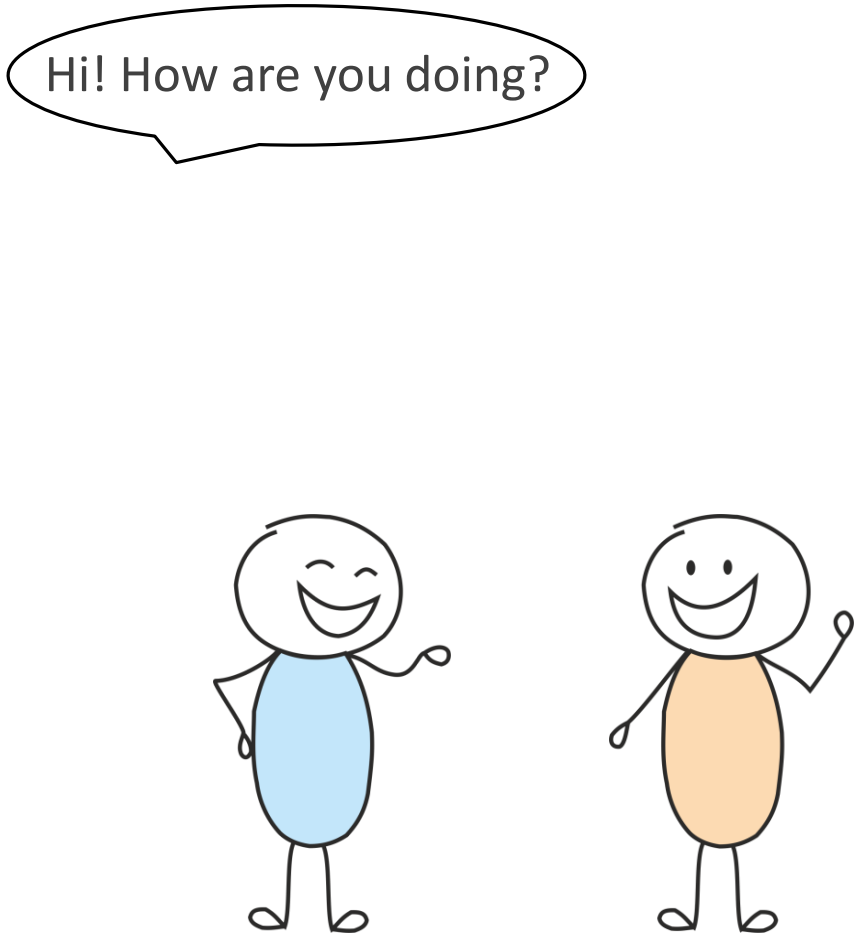

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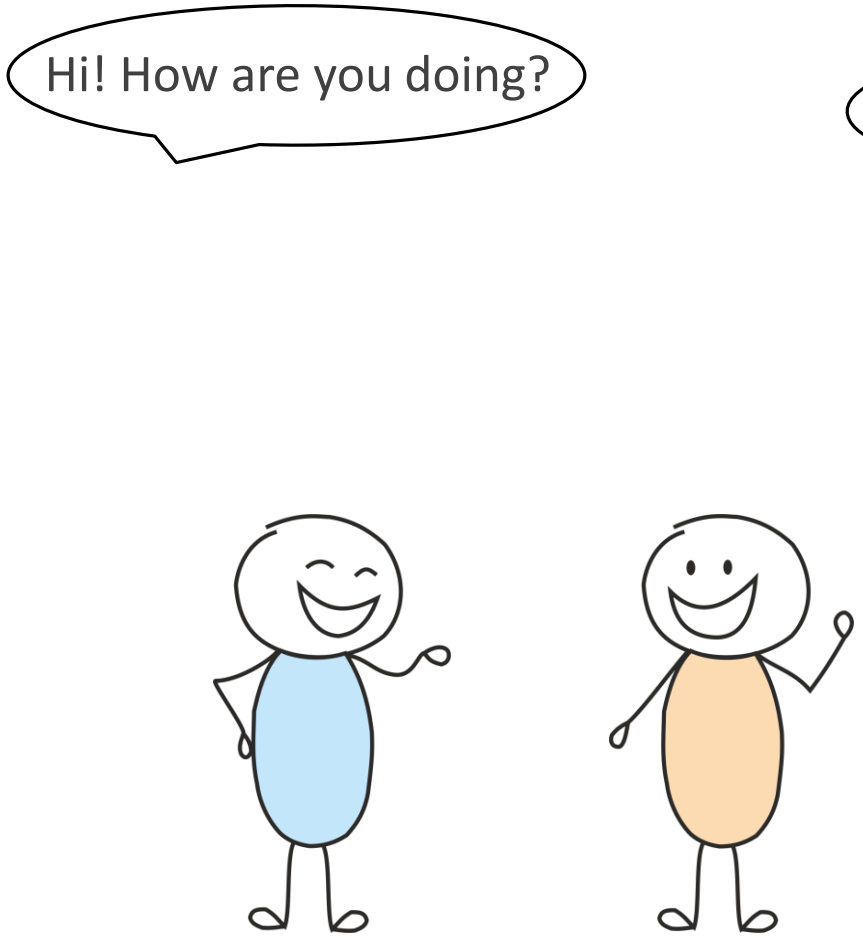

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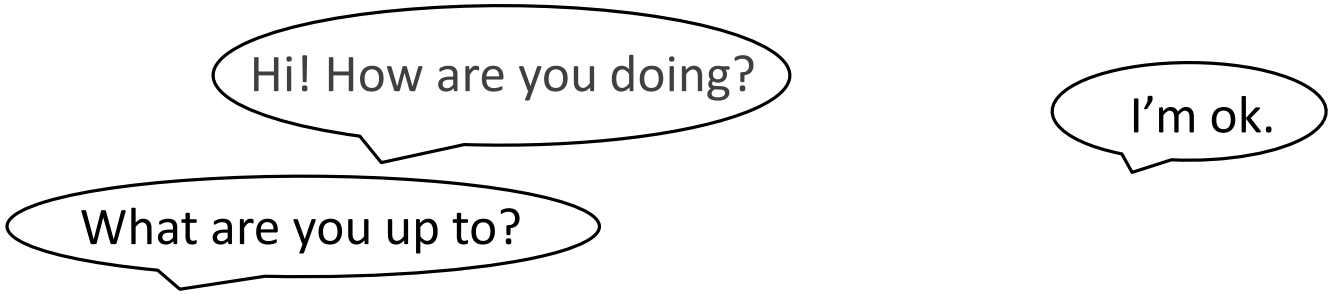

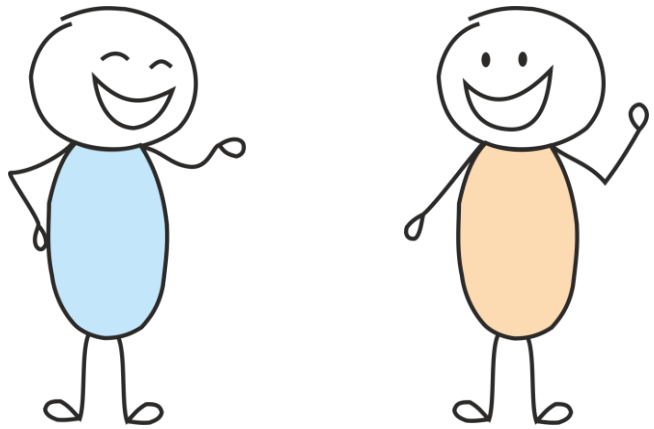

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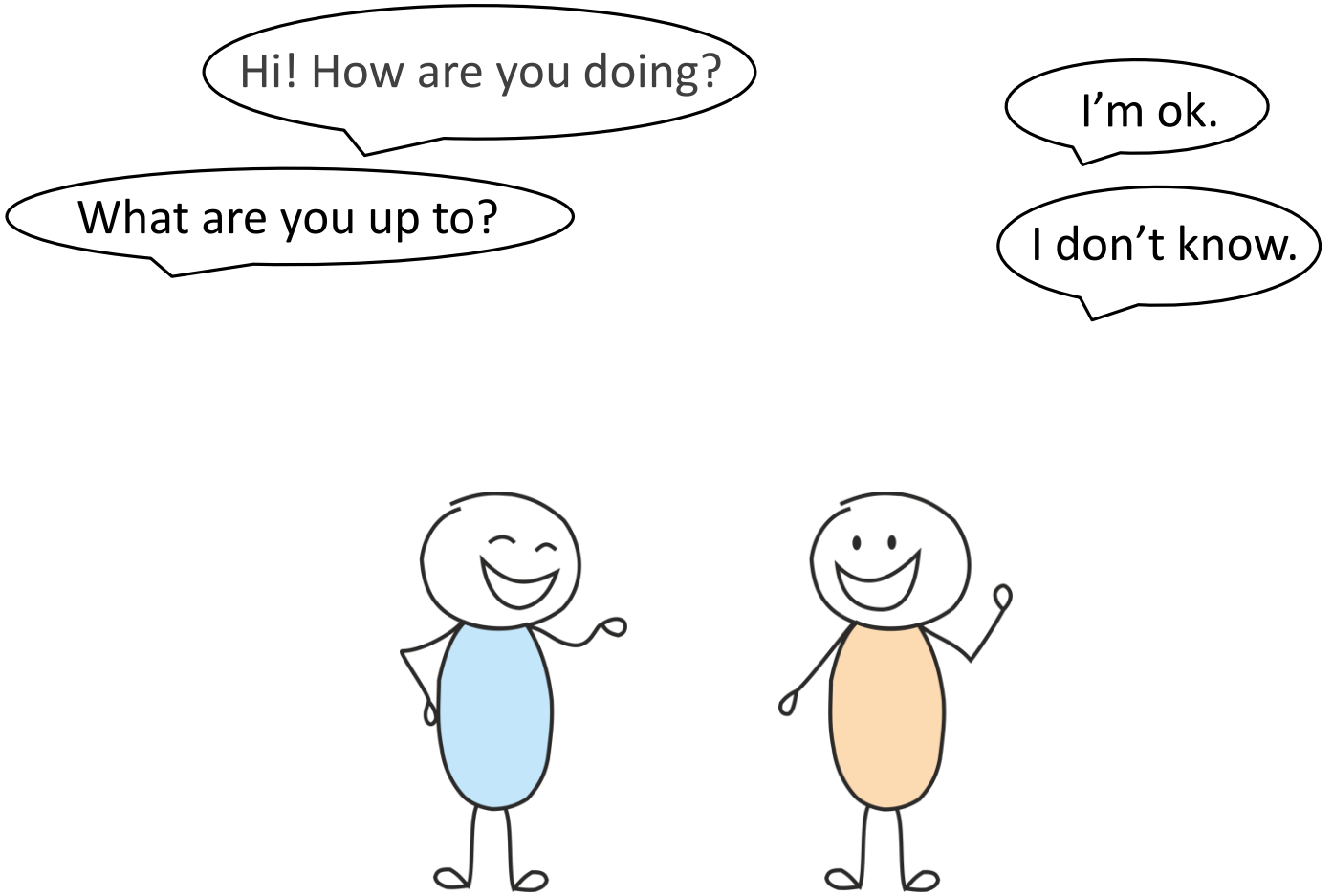

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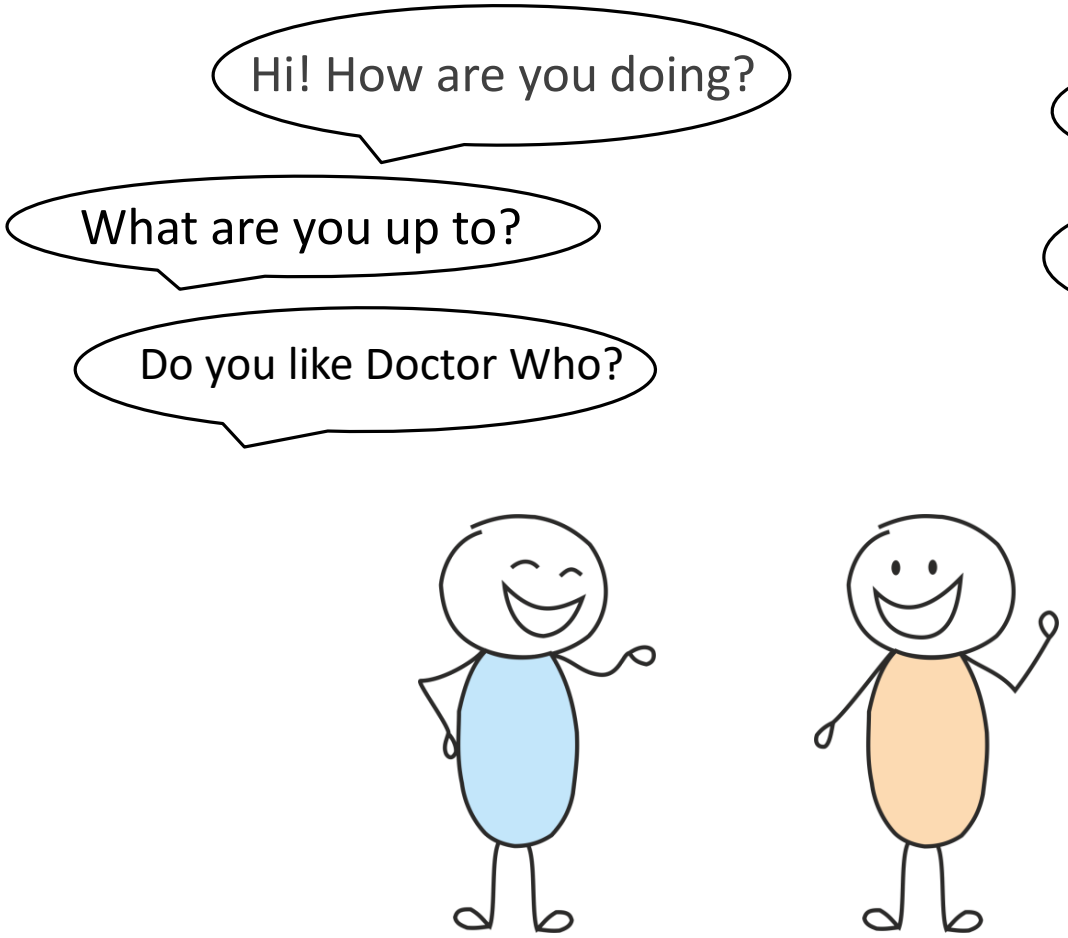

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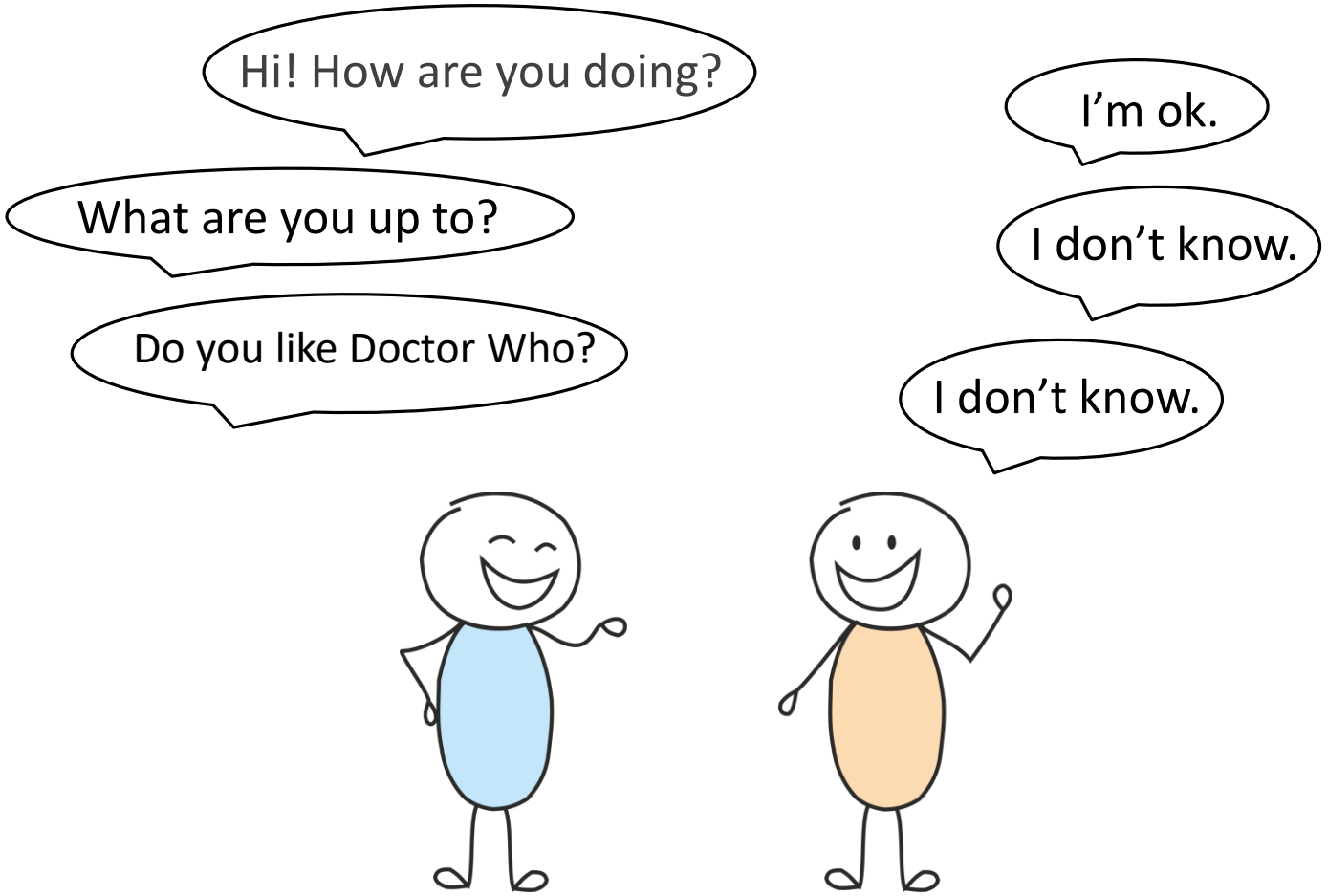

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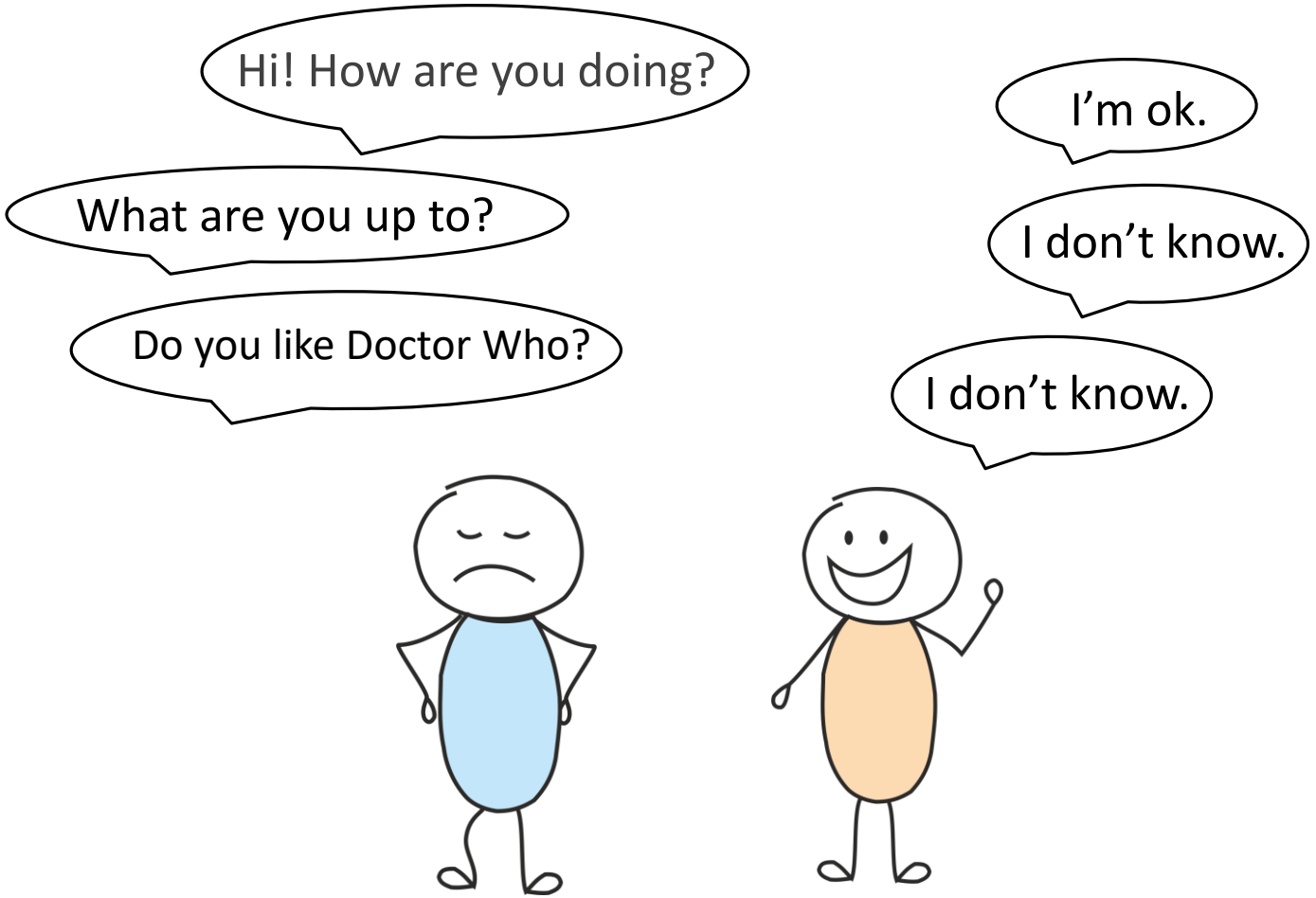

A Diversity-Promoting Objective Function for Neural Conversation Models

Input: What are you doing?			
−0.86	I don't know.	−1.09	Get out of here.
−1.03	I don't know!	−1.09	I'm going home.
−1.06	Nothing.	−1.09	Oh my god!
−1.09	Get out of the way.	−1.10	I'm talking to you.
Input: what is your name?			
−0.91	I don't know.	...	
−0.92	I don't know!	−1.55	My name is Robert.
−0.92	I don't know, sir.	−1.58	My name is John.
−0.97	Oh, my god!	−1.59	My name's John.
Input: How old are you?			
−0.79	I don't know.	...	
−1.06	I'm fine.	−1.64	Twenty-five.
−1.17	I'm all right.	−1.66	Five.
−1.17	I'm not sure.	−1.71	Eight.

Table 1: Responses generated by a 4-layer SEQ2SEQ neural model trained on 20 million conversation pairs take from the OpenSubtitles dataset. Decoding is implemented with beam size set to 200. The top examples are the responses with the highest average probability log-likelihoods in the N-best list. Lower-ranked, less-generic responses were manually chosen.

Standard seq2seq: $\hat{T} = \arg\max_{T} \{ \log p(T|S) \}$

Ji et al, NAACL 2016, http://www.aclweb.org/anthology/N16-1014

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Mutual information between source and target: $\log \frac{p(S,T)}{p(S)p(T)}$

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Maximum Mutual Information (MMI): $\hat{T} = \arg\max_T \{ \log p(T|S) - \log p(T) \}$

Penalize frequent answers

Ji et al, NAACL 2016, http://www.aclweb.org/anthology/N16-1014

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−1.17	I'm all right.	−1.66	Five.
−1.17	I'm not sure.	−1.71	Eight.

Table 1: Responses generated by a 4-layer SEQ2SEQ neural model trained on 20 million conversation pairs take from the OpenSubtitles dataset. Decoding is implemented with beam size set to 200. The top examples are the responses with the highest average probability log-likelihoods in the N-best list. Lower-ranked, less-generic responses were manually chosen.

Standard seq2seq: $\hat{T} = \arg\max_T \{ \log p(T|S) \}$

Mutual information between source and target: $\log \frac{p(S,T)}{p(S)p(T)}$

Maximum Mutual Information (MMI): $\hat{T} = \arg\max_T \{ \log p(T|S) - \log p(T) \}$

Generalized version: $\hat{T} = \arg\max_T \{ \log p(T|S) - \lambda \log p(T) \}$

Bayes Theorem: $\hat{T} = \arg\max_T \{ (1-\lambda) \log p(T|S) + \lambda \log p(S|T) \}$

Ji et al, NAACL 2016, http://www.aclweb.org/anthology/N16-1014

A Diversity-Promoting Objective Function for Neural Conversation Models

message	SEQ2SEQ	MMI $P(T\|S) - \lambda P(T)$
I did not get the report from an mi-6 agent.	I don't think that's a good idea.	You did the right thing, did you?
You haven't been given an assignment in this case.	I don't know what you are talking about.	I've been looking all over for you.
I'm losing my grip.	I don't know what you are talking about.	I'm the only one in the world.
I am ready to help.	Come on, come on	I have something we need to talk about.
You programmed me to gather intelligence. That's all I've ever done.	You know that, don't you?	You do have fun, don't you?
I mean, we'd have to talk to him.	I mean, I don't know.	I mean, he's a good guy.
This has nothing to do with him.	You don't know anything about him, do you?	I know him as much.
How come you never say it?	I don't know	Because I don't want to hurt you
He is the one behind this scheme to crash x-net.	I don't know what you are talking about	Yes, he is, isn't he?
How much time do you have here?	I don't know.	Not long enough. Sorry, sir.

Table 4: Responses from the SEQ2SEQ baseline and MMI-antiLM models on the OpenSubtitles dataset.

Ji et al, NAACL 2016, http://www.aclweb.org/anthology/N16-1014

Diverse Beam Search

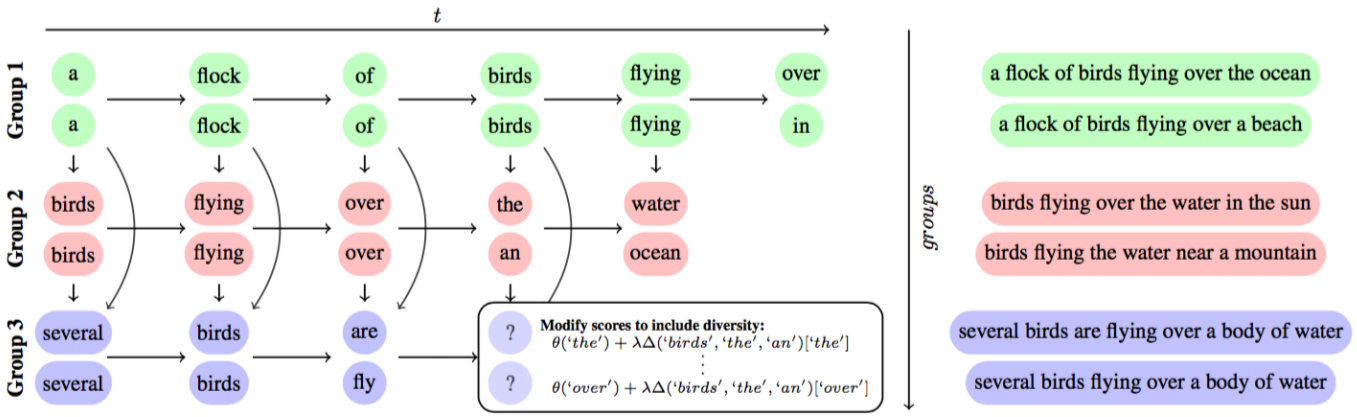


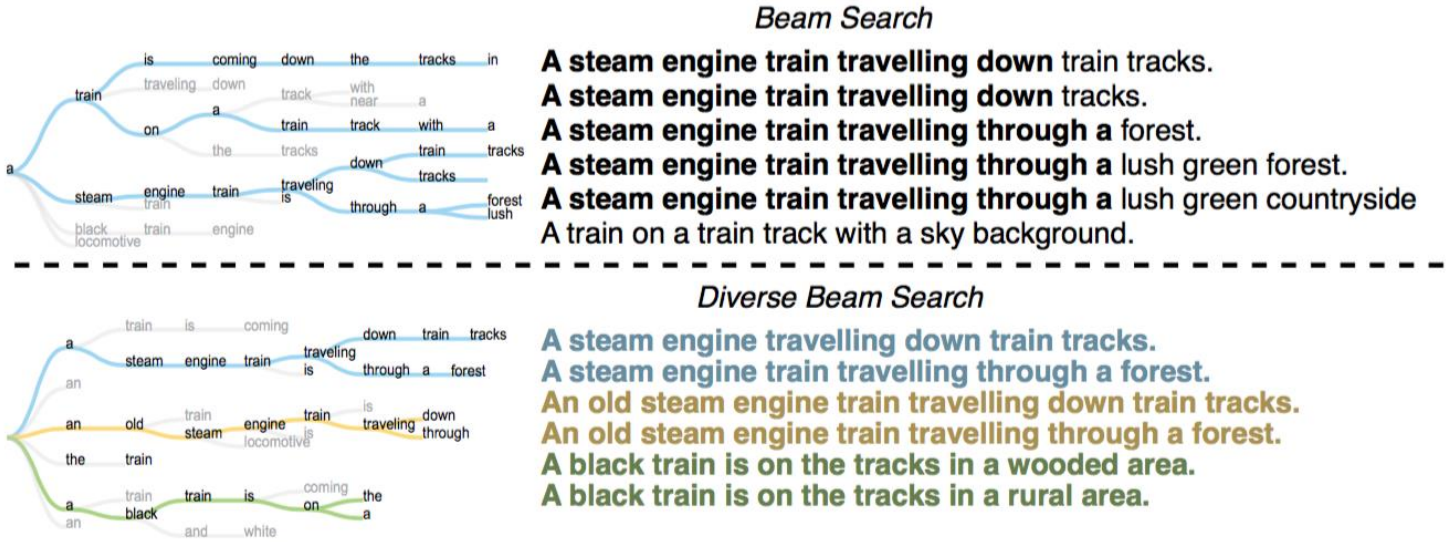
Figure 2: Diverse beam search operates left-to-right through time and top to bottom through groups. Diversity between groups is combined with joint log-probabilities, allowing continuations to be found efficiently. The resulting outputs are more diverse than for standard approaches.

- Divide beam on several groups
- Optimize each group keeping other fixed
- Add dissimilarity term

$$\Delta(\mathbf{y}_{[t]}, Y^g_{[t]}) = \sum_{b=1}^{B'} \delta\left(\mathbf{y}_{[t]}, \mathbf{y}^g_{b,[t]}\right)$$

Vijayakumar et al, https://arxiv.org/pdf/1610.02424.pdf

Diverse Beam Search



Ground Truth Captions

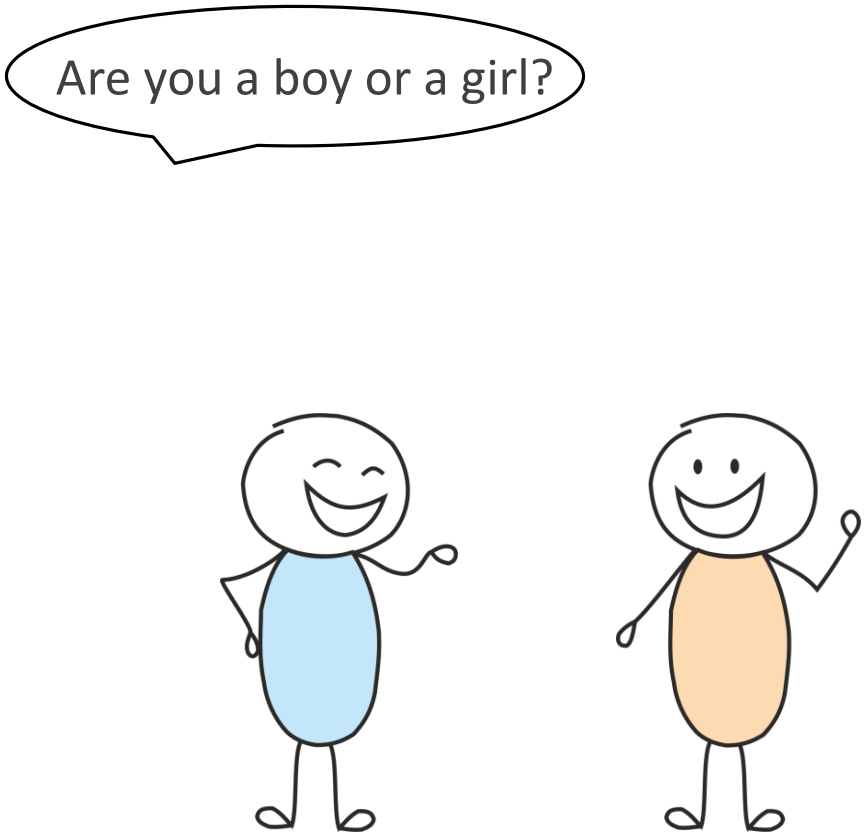
Single engine train rolling down the tracks.
A steam locomotive is blowing steam.

A locomotive drives along the tracks amongst trees and bushes.
An old fashion train with steam coming out of its pipe.

An engine is coming down the train track.
A black and red train moving down a train track.

Vijayakumar et al, https://arxiv.org/pdf/1610.02424.pdf

Storyline 3.
The importance of coherence.



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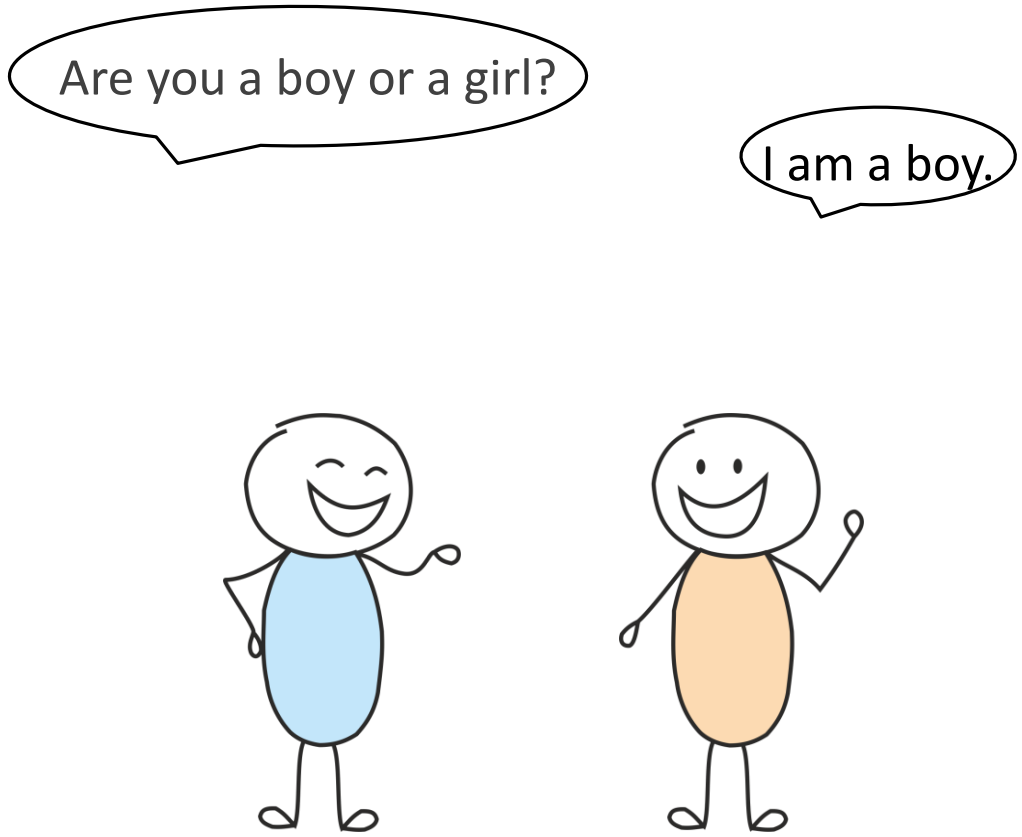

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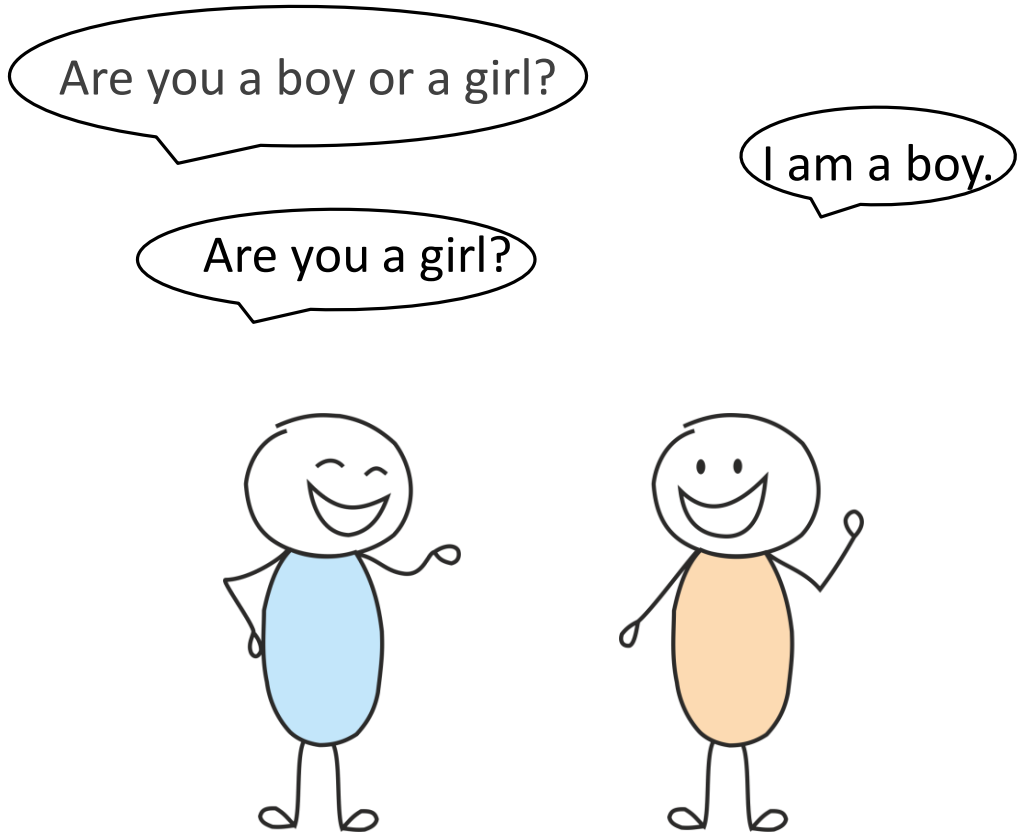

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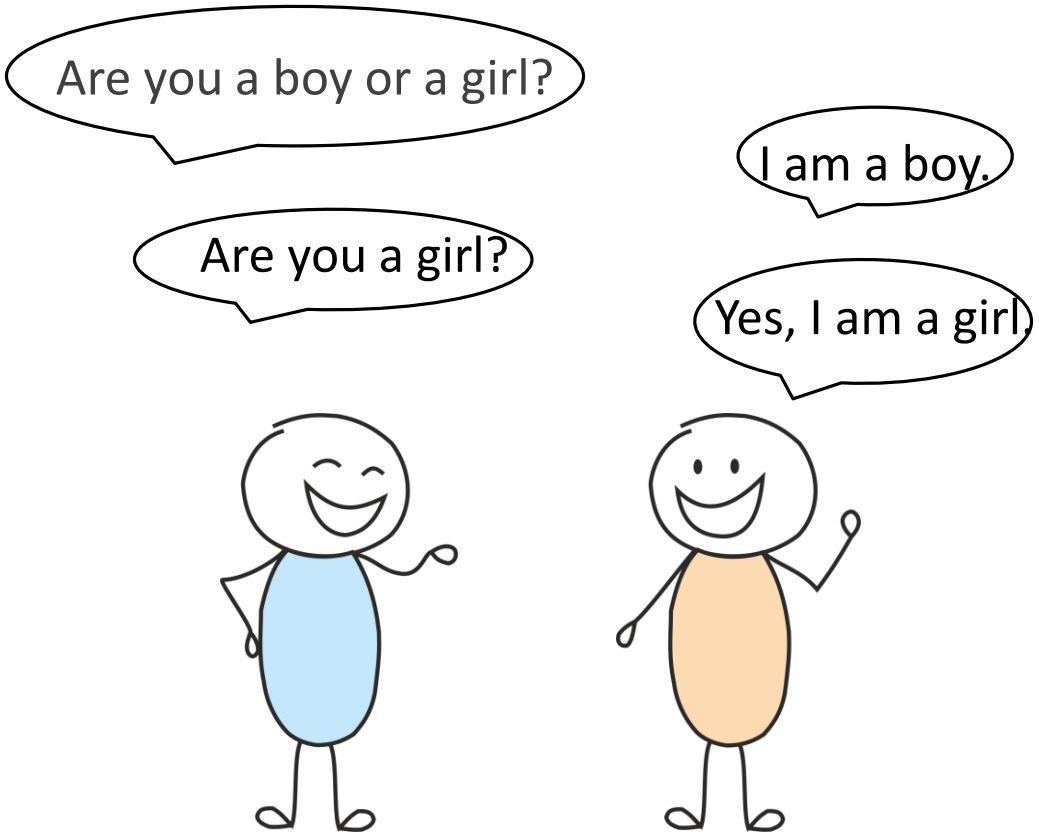

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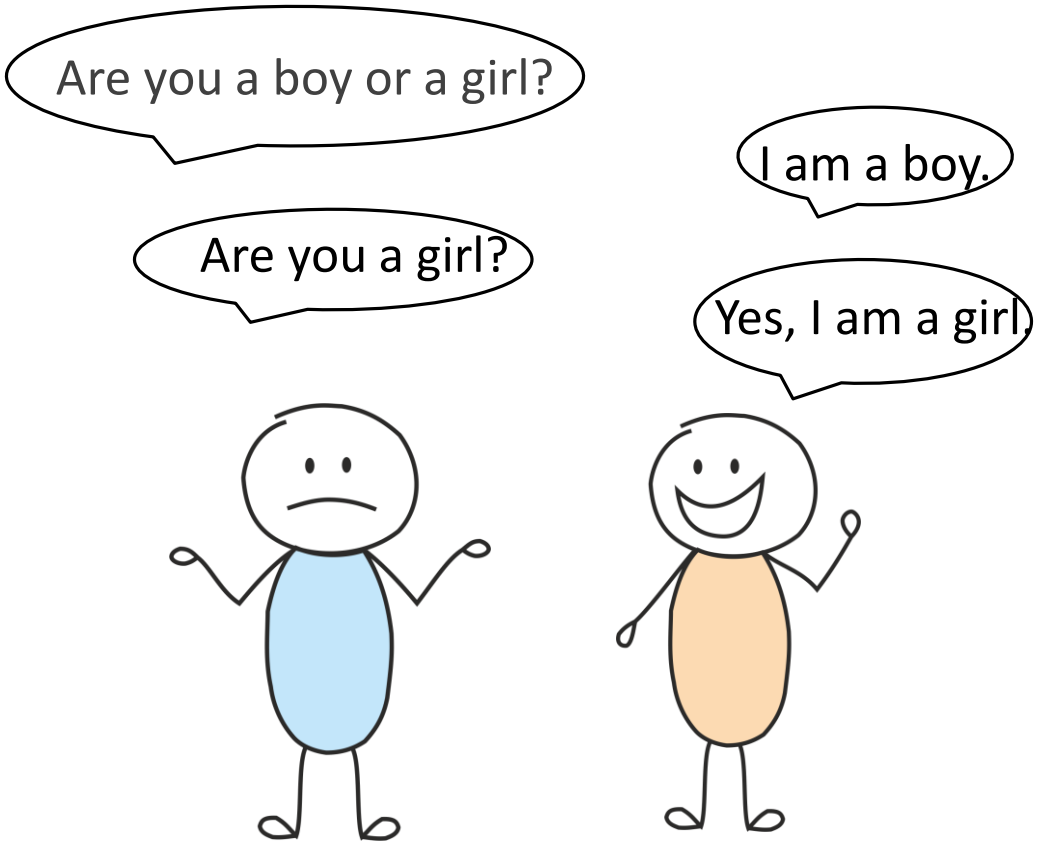
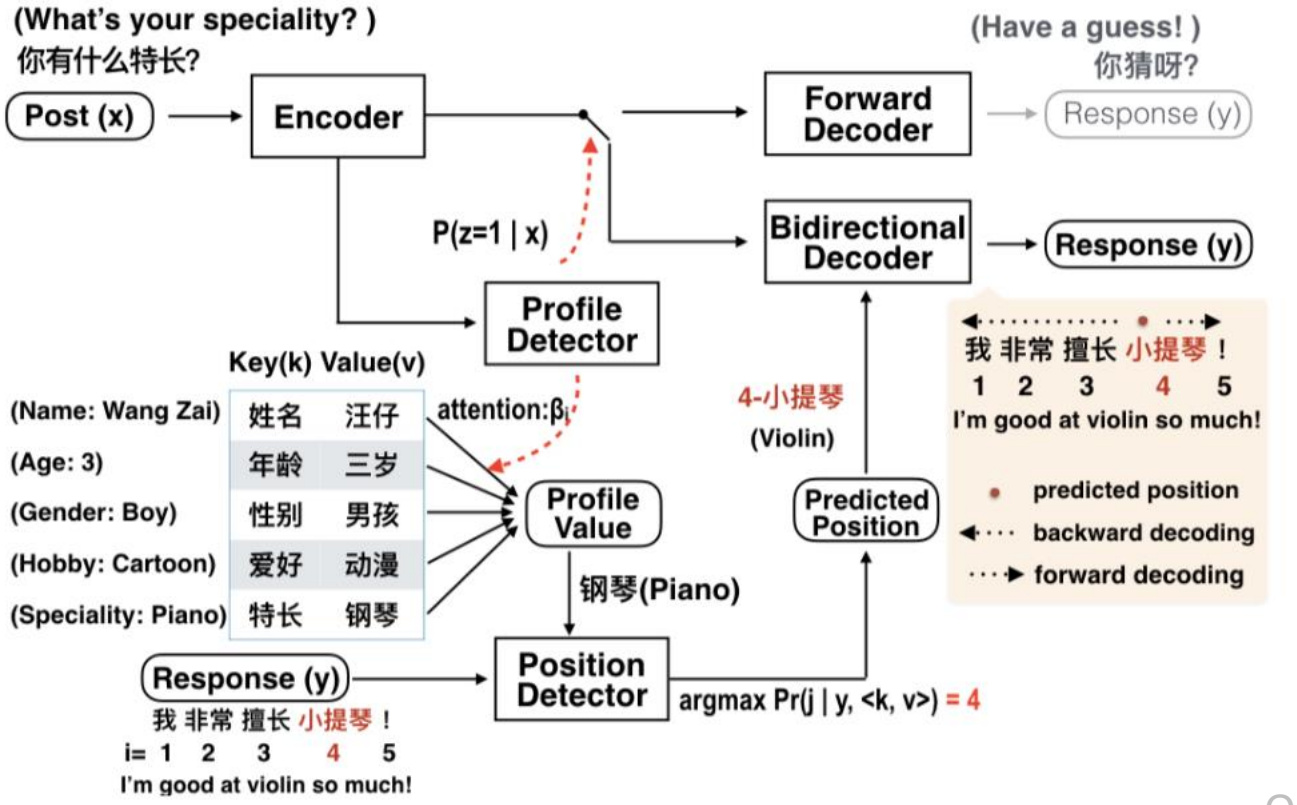


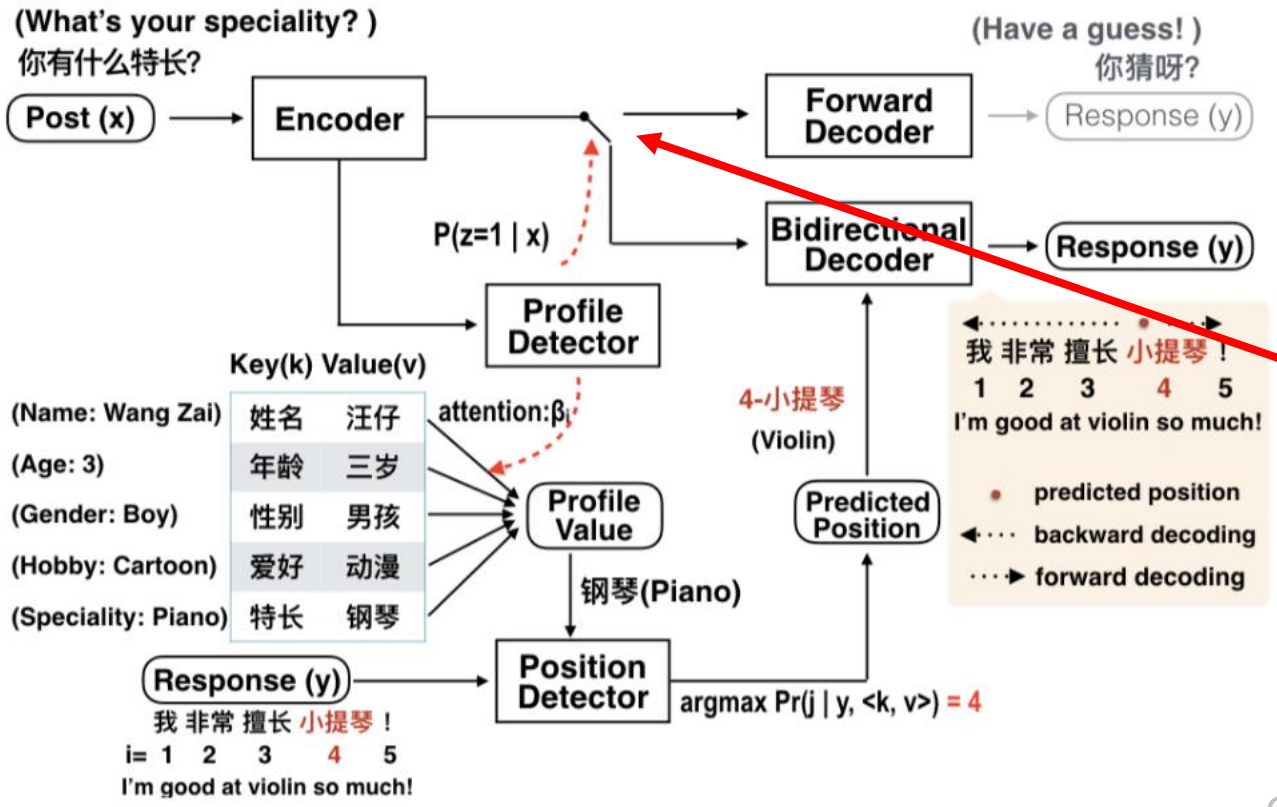
Assigning Personality/Identity to a Chatting Machine



Goal: to generate responses that are coherent to its prespecified identity/personality

Qiao et al, https://arxiv.org/pdf/1706.02861.pdf

Assigning Personality/Identity to a Chatting Machine

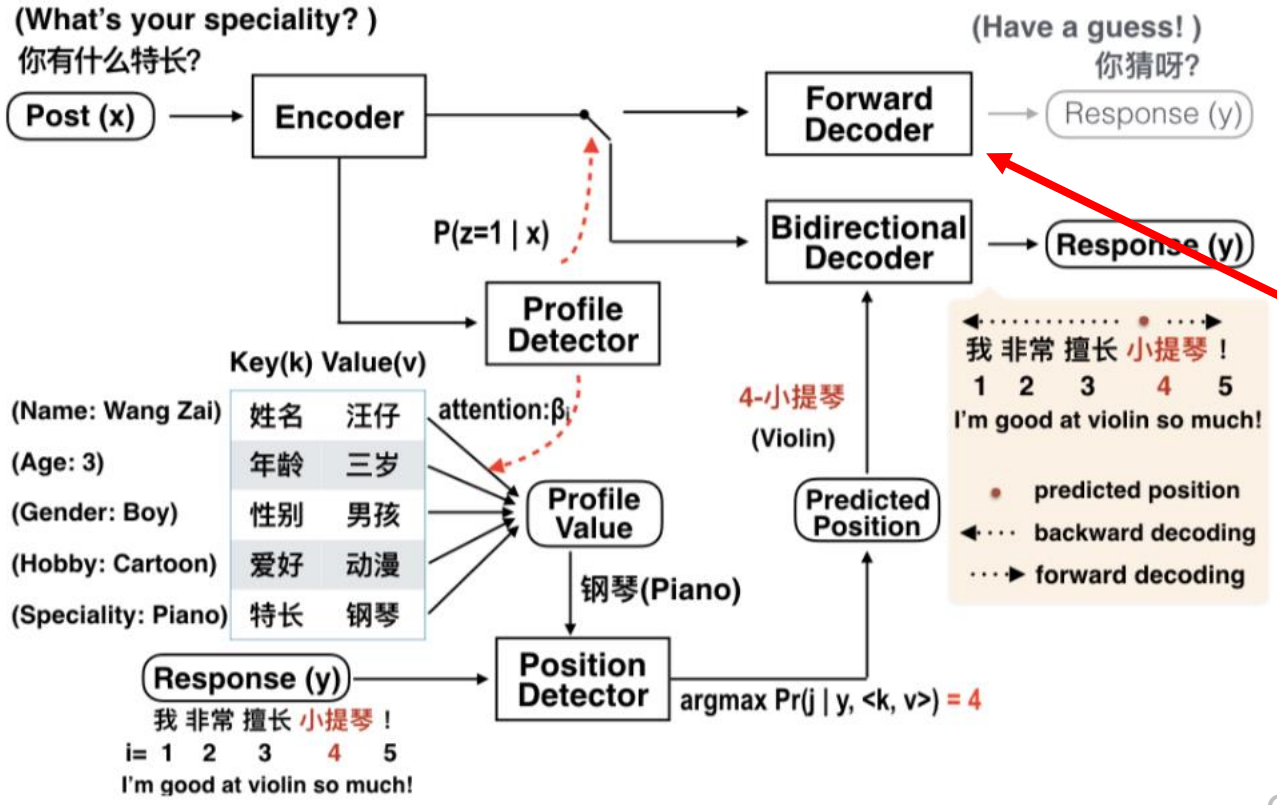


Goal: to generate responses that are coherent to its prespecified identity/personality

Decide if we need profile

Qiao et al, https://arxiv.org/pdf/1706.02861.pdf

Assigning Personality/Identity to a Chatting Machine

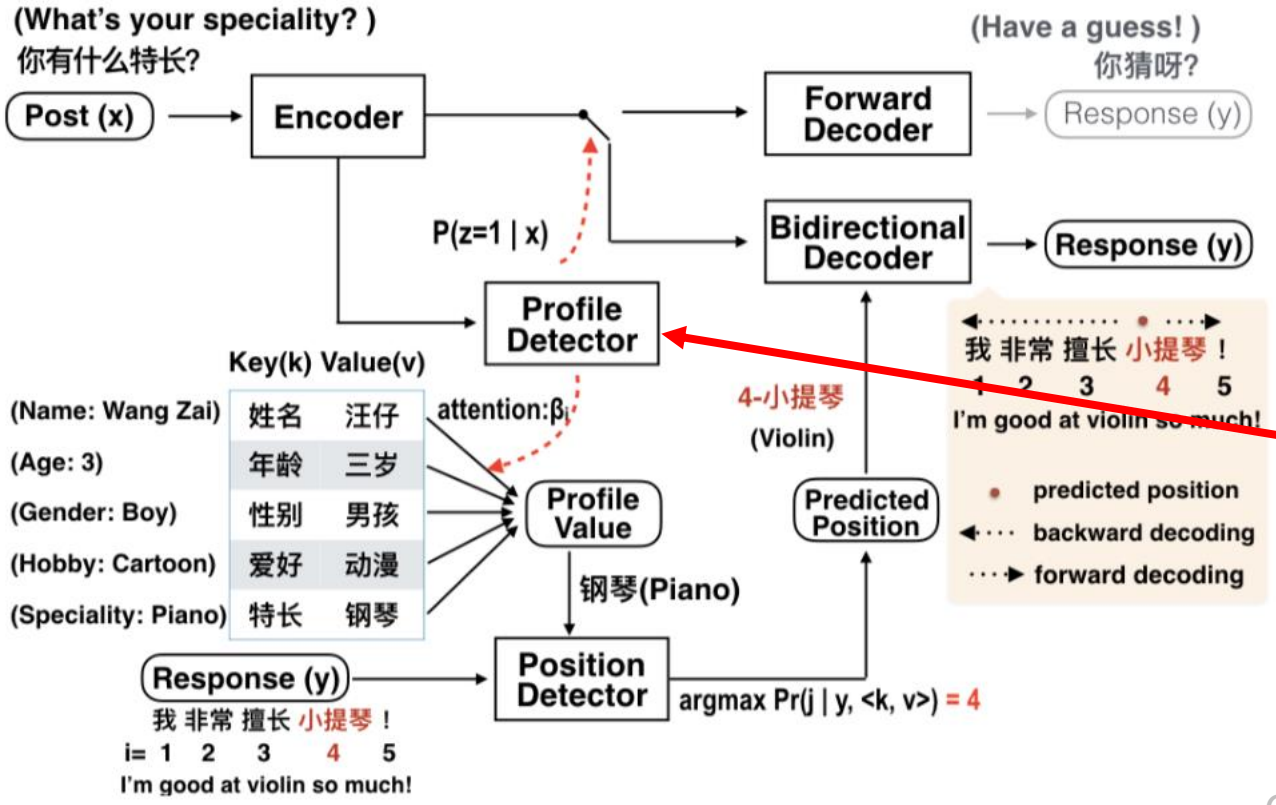


Goal: to generate responses that are coherent to its prespecified identity/personality

If don't need, use general decoder

Qiao et al, https://arxiv.org/pdf/1706.02861.pdf

Assigning Personality/Identity to a Chatting Machine

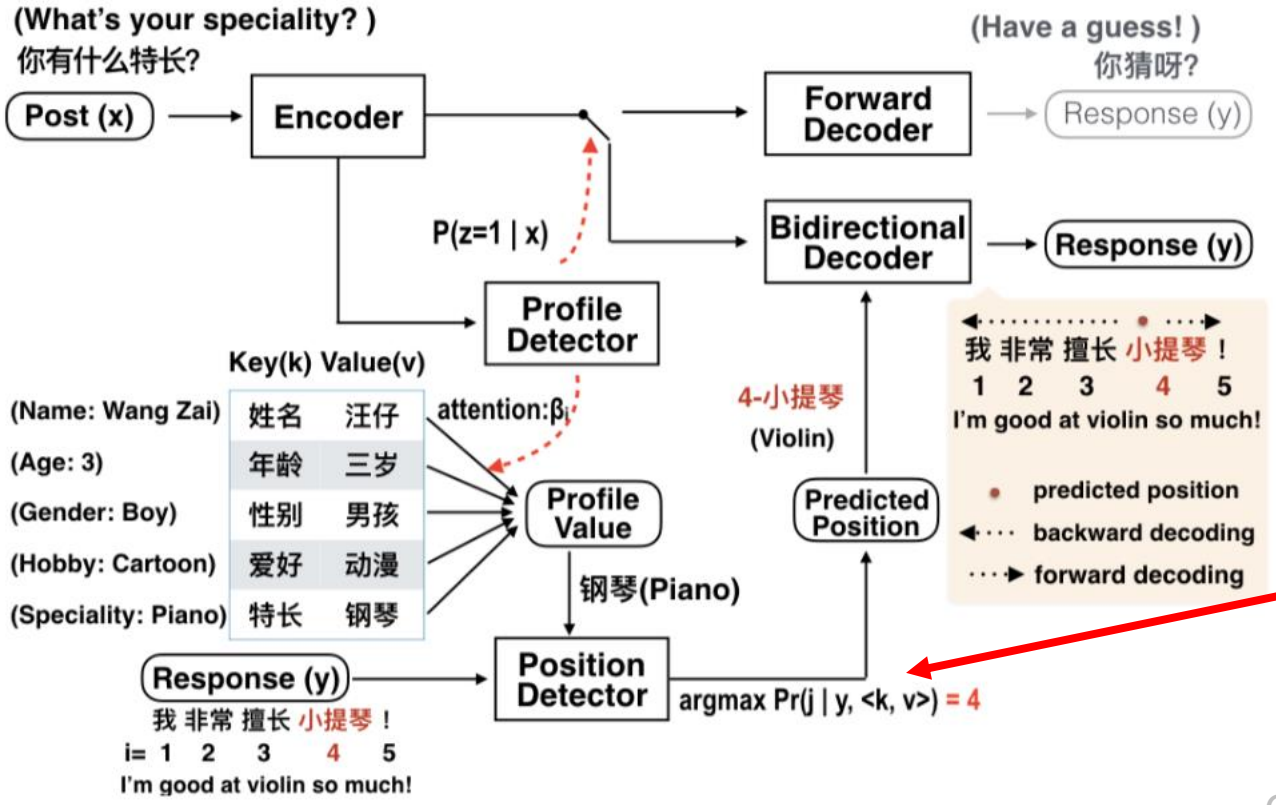


Goal: to generate responses that are coherent to its prespecified identity/personality

If need, pick profile value

Qiao et al, https://arxiv.org/pdf/1706.02861.pdf

Assigning Personality/Identity to a Chatting Machine

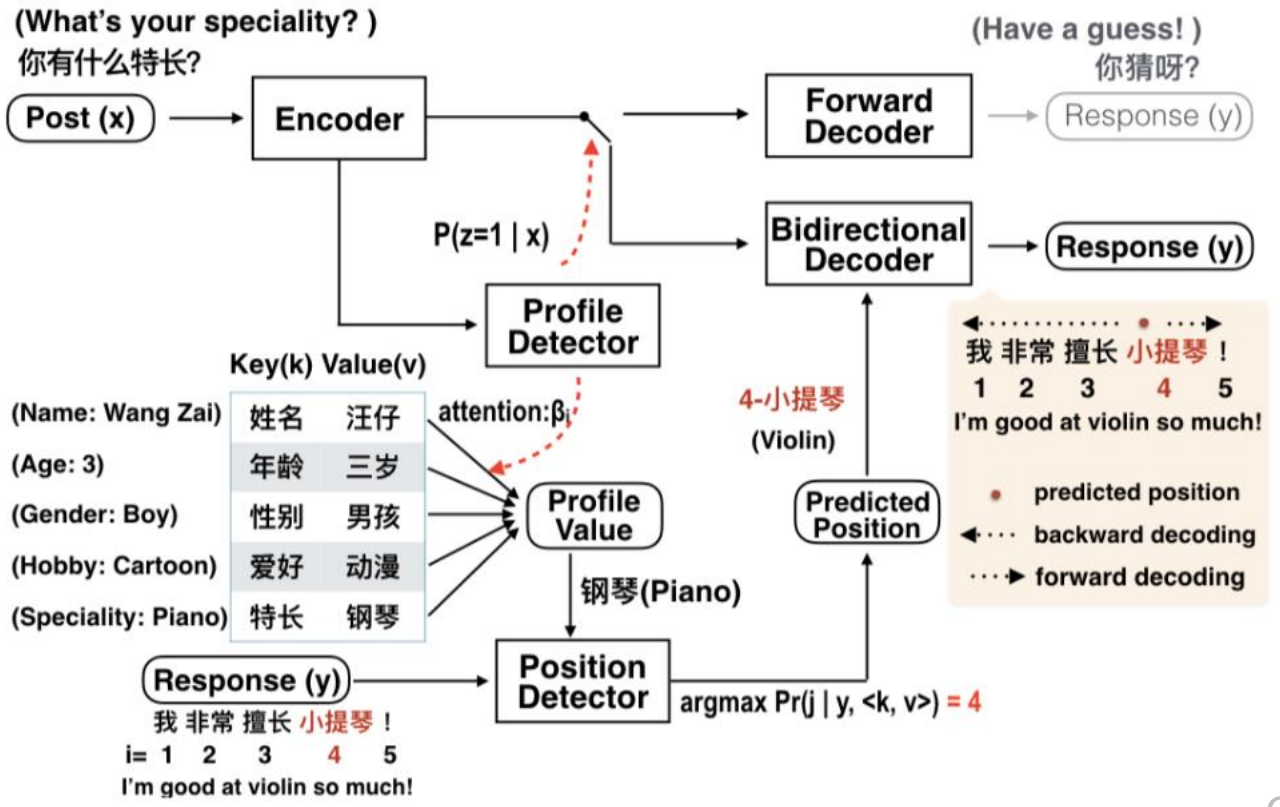


Goal: to generate responses that are coherent to its prespecified identity/personality

Predict position for the profile value

Qiao et al, https://arxiv.org/pdf/1706.02861.pdf

Assigning Personality/Identity to a Chatting Machine



Goal: to generate responses that are coherent to its prespecified identity/personality

Generate from this position both ways

Qiao et al, https://arxiv.org/pdf/1706.02861.pdf

Assigning Personality/Identity to a Chatting Machine

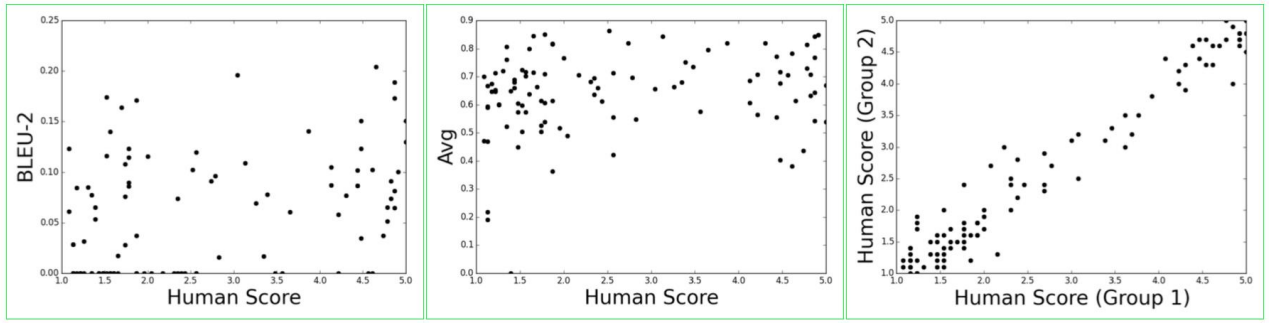
Chinese	English(Translated)
U:你还没说你几岁呢	U:You haven't told me your age.
S:我三岁了	S:I'm three years old.
U:你今年有15了不	U:Are you 15 years old or not?
S:我还没到呢	S:I'm not yet.
U:你多大啦	U:How old are you?
S:3岁了	S:Three years old.

Table 5: Samples of consistent conversations generated by our model. U/S indicates User/System.

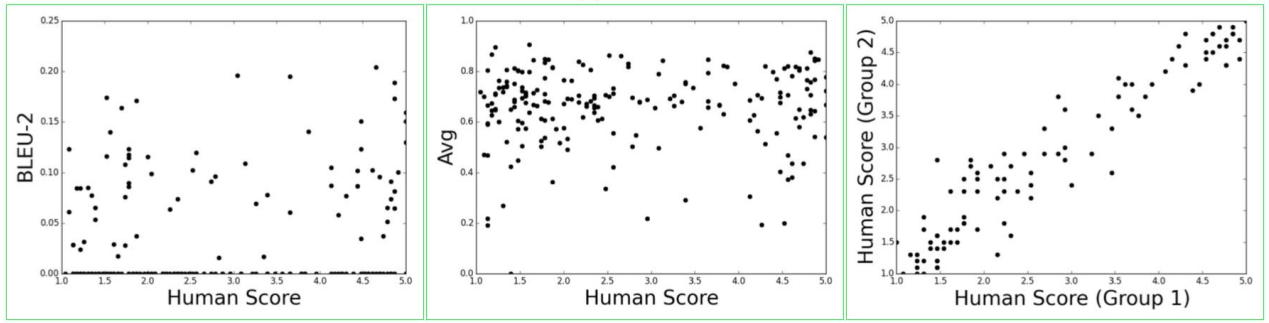
Goal: to generate responses that are coherent to its prespecified identity/personality

Qiao et al, https://arxiv.org/pdf/1706.02861.pdf

How NOT To Evaluate Your Dialogue System



(a) Twitter



(b) Ubuntu

Figure 1: Scatter plots showing the correlation between metrics and human judgements on the Twitter corpus (a) and Ubuntu Dialogue Corpus (b). The plots represent BLEU-2 (left), embedding average (center), and correlation between two randomly selected halves of human respondents (right).

All metrics show either weak or no correlation with human judgements

Liu et al, https://arxiv.org/pdf/1603.08023.pdf

How NOT To Evaluate Your Dialogue System

Context of Conversation
Speaker A: Hey John, what do you want to do tonight?
Speaker B: Why don't we go see a movie?
Ground-Truth Response
Nah, I hate that stuff, let's do something active.
Model Response
Oh sure! Heard the film about Turing is out!

Table 1: Example showing the intrinsic diversity of valid responses in a dialogue. The (reasonable) model response would receive a BLEU score of 0.

Liu et al, https://arxiv.org/pdf/1603.08023.pdf

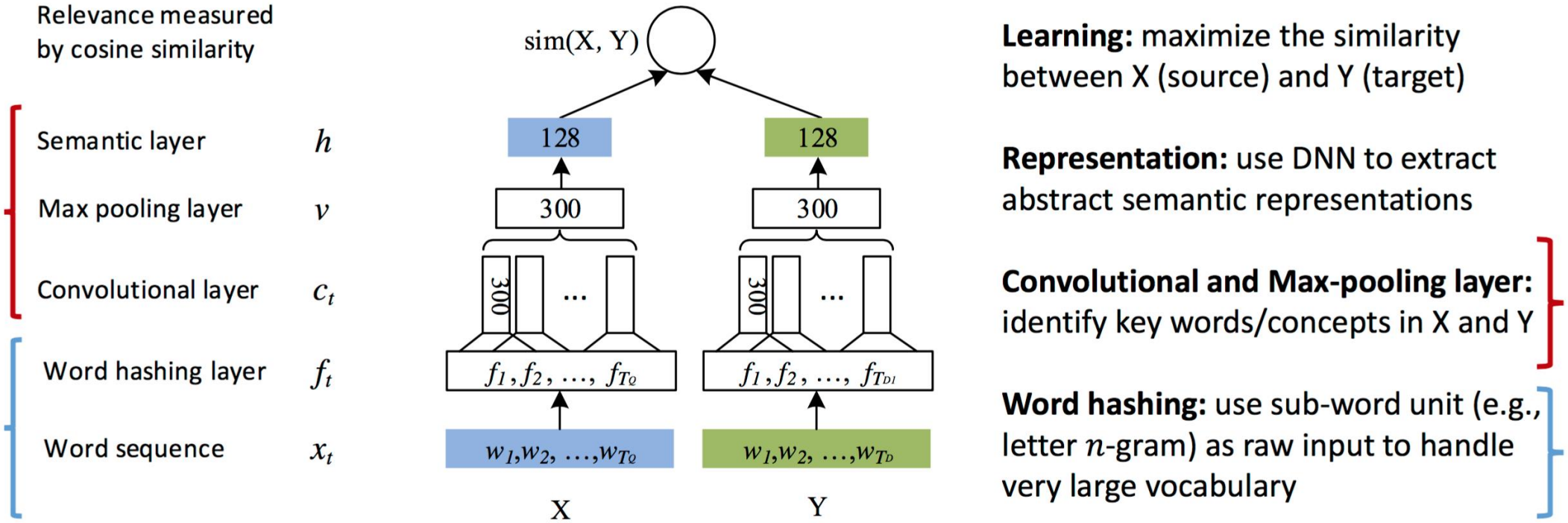
What else tried to improve?

- Improve diversity using latent variables
- Topic consistency
- Use outside knowledge base
- Learn through interaction
- Evaluation (BLEU, word2vec metrics are bad)

More details and links here: https://arxiv.org/pdf/1711.01731.pdf

Retrieval-based methods for General conversation

Deep Semantic Similarity Model (DSSM)



Learning: maximize the similarity between X (source) and Y (target)

Representation: use DNN to extract abstract semantic representations

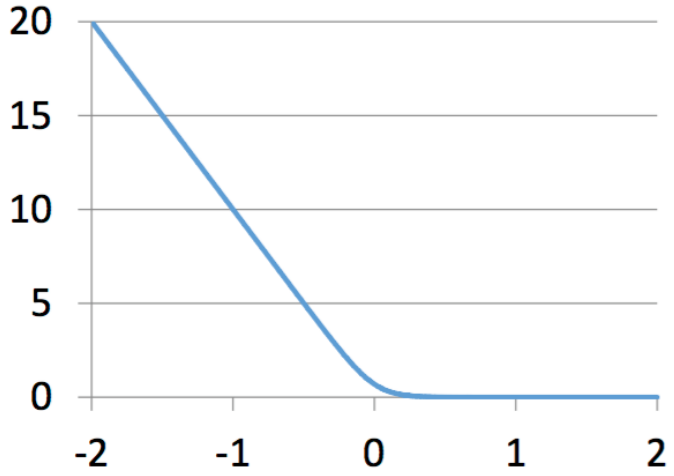
Convolutional and Max-pooling layer: identify key words/concepts in X and Y

Word hashing: use sub-word unit (e.g., letter n-gram) as raw input to handle very large vocabulary

http://emnlp2014.org/material/presentation-EMNLP2014002.pdf

Deep Semantic Similarity Model (DSSM)

- Consider a query X and two examples Y^+ and Y^-
  Assume Y^+ is better than Y^- for query X
- $sim_\theta(X, Y^-)$ is the cosine similarity of X and Y in semantic space, mapped by DSSM parameterized by θ
- $\Delta = sim_\theta(X, Y^+) - sim_\theta(X, Y^-)$
- $Loss(\Delta, \theta) = \log(1 + \exp(-\gamma\Delta))$



What can be different?

- Ways to encode sentences (utterances, documents, etc.) – CNNs, RNNs, MLP, etc
- Loss functions
- Choice of number of context sentences and ways to encode them
- Negative sampling schedule (Yadex.Search experience)

But it’s just a matching task!

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- Ways to encode sentences (utterances, documents, etc.) – CNNs, RNNs, MLP, etc
- Loss functions
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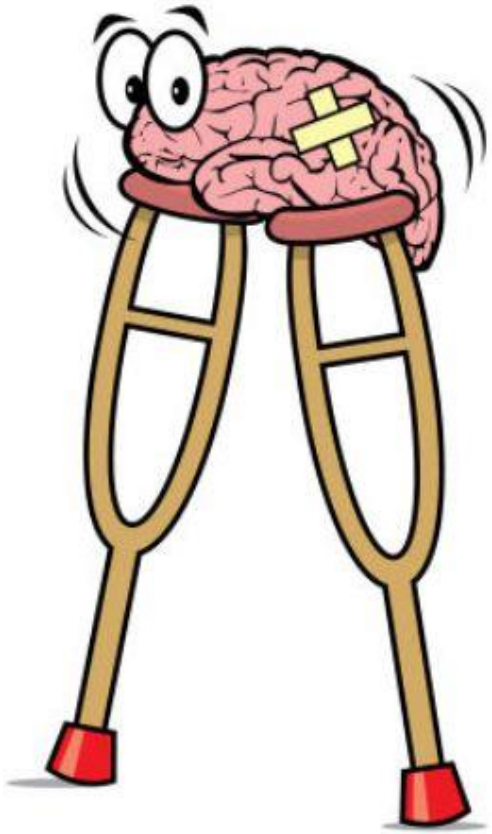
But it’s just a matching task!

- web search query and clicked document
- utterance and response in dialogue
- user profile and article
- document and key phrases to be highlighted
- key phrase and entity with it’s wiki page

Hack of the day



Negative examples

Recall how we train DSSM:

- $\Delta = sim_\theta(X, Y^+) - sim_\theta(X, Y^-)$
- $Loss(\Delta, \theta) = \log(1 + \exp(-\gamma\Delta))$

We want a true answer to be closer to query, than a wrong one

How do we get Y^-?

Negative examples

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How do we get Y^-?

Usually, it's a random example (remember for example word2vec?)

Problem

How do we get Y^-?

Usually, it's a random example (remember for example word2vec?)

We want a true answer to be closer to query, than a wrong one

What if you have plenty of examples, and only a few good ones?

Problem

How do we get Y^-?

Usually, it's a random example (remember for example word2vec?)

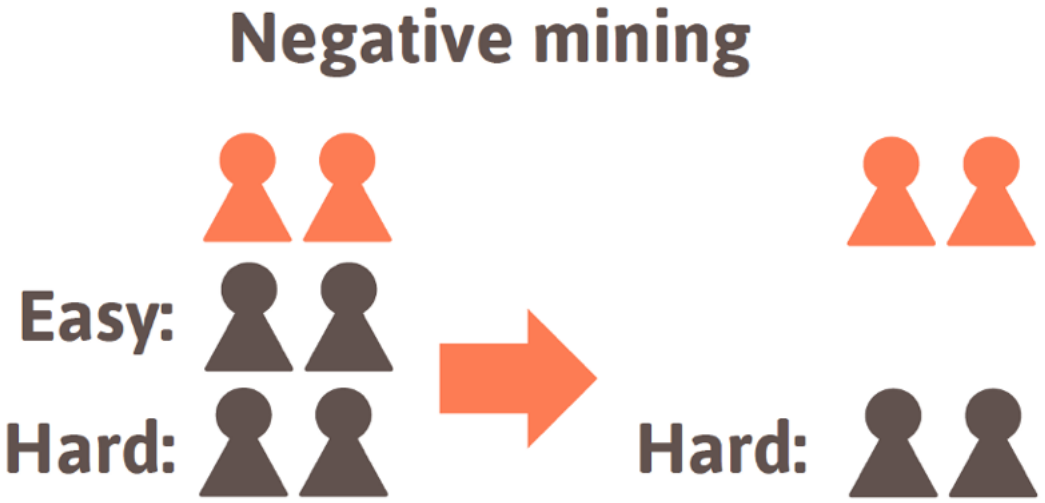
We want a true answer to be closer to query, than a wrong one

What if you have plenty of examples, and only a few good ones?

Would it be so hard to distinguish between a **true** answer and a **random** example?

Hard-Negatives!

Give as “negative” those negative examples, for which your network gives high score (thinks that they’re good)



Hard-Negatives!

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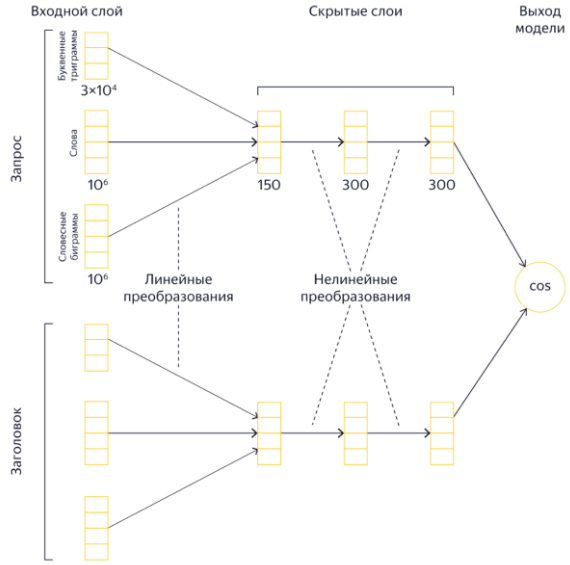
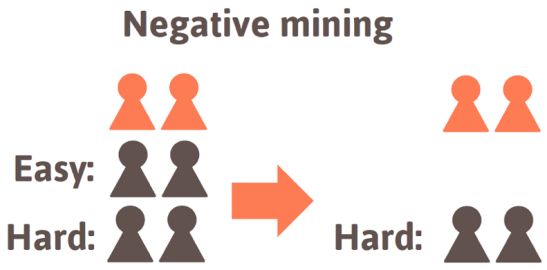
Real-life story: Yandex.Search and DSSM

https://habr.com/company/yandex/blog/314222/





That’s all for today!

Always yours,
Yandex Research

That’s all for today!

In the next episode:

- Adversarial methods in NLP

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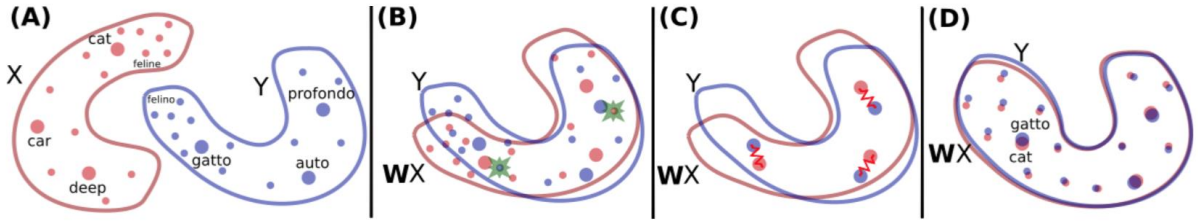
That’s all for today!

In the next episode:

- Adversarial methods in NLP
  + unsupervised embedding space mapping!



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