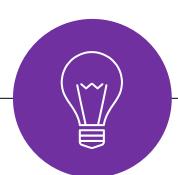
End-to-End Conversational Al

June 7th, 2021 http://adl.miulab.tw



Slides credited from NeurIPS 2020 Tutorial









Why and When We Need? 2

- "I want to chat"
- "I have a question"
- "I need to get this done" "What should I do?"

Turing Test (talk like a human) Social Chit-Chat Information consumption **Task-Oriented** Task completion Dialogues **Decision support**

- What is today's agenda?
- What does NLP stand for?
- Book me the train ticket from Kaohsiung to Taipei
- Reserve a table at Din Tai Fung for 5 people, 7PM tonight
- Schedule a meeting with Vivian at 10:00 tomorrow
- Is this course good to take?

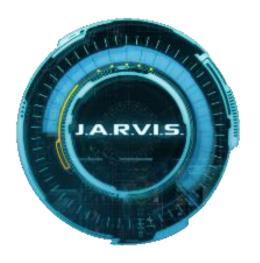












Task-Oriented

Single-domain, system-initiative



Knowledgegrounded seq2seq models

End-to-end learning, massively multi-domain

Multi-domain, contextual, mixed-initiative



Vanilla Seq2Seq ConvAI: How

A simple 4-step recipe:

4

- Choose the data: Human-to-human conversations
- 2. Choose the model: Large pre-trained language models are preferable
- Train the model with the data: Supervised learning 3.
- Evaluate your model: Automatic or human evaluation



Vanilla Seq2Seq ConvAI: Datasets 5

<u>Human1</u>: Ok, I'll try that.

<u>*Human2*</u>: Is there anything else bothering you?

<u>Human1</u>: Just one more thing. A school called me this morning to see if I could teach a few classes this weekend and I don't know what to do.

<u>*Human2*</u>: Do you have any other plan this weekend?

Human1: I'm supposed to work on a paper that's due on Monday.

Slido: #ADL2021

Human-to-Human Conversations:

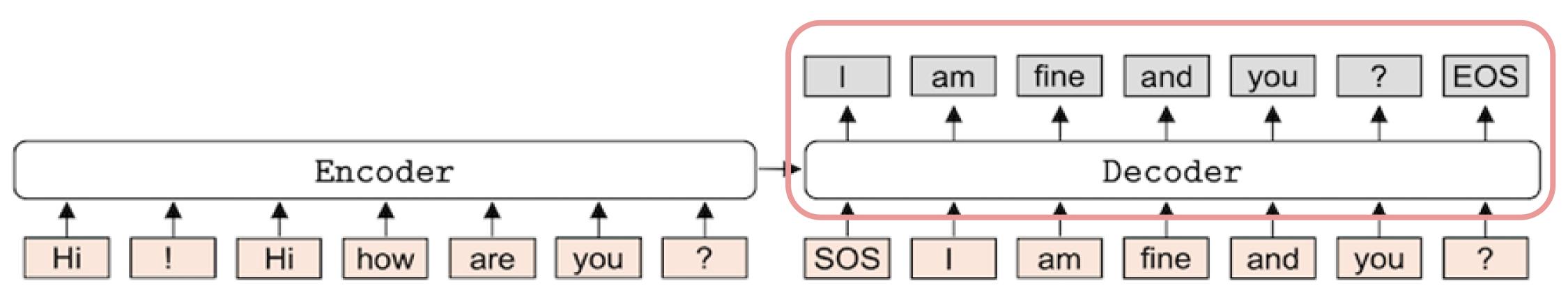
- Daily Dialog
- Ubuntu Dialogue Corpus
- **Twitter Conversations**
- **Reddit Conversational Data**
- **OpenSubtitles**

These datasets are pre-processed to have only 2 speakers \Rightarrow usually no more than 2 turns

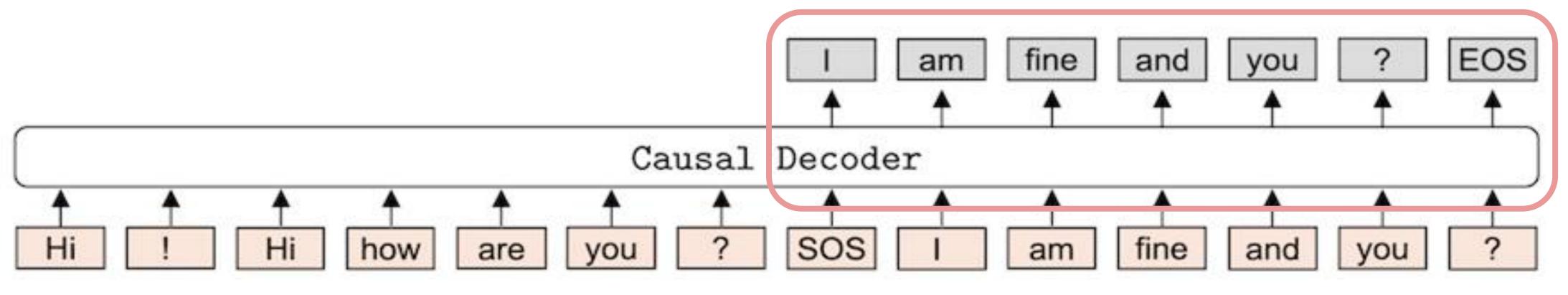








Vanilla Seq2Seq conversational model (Vinyals and Le et.al., 2015, Shang et al., 2015)



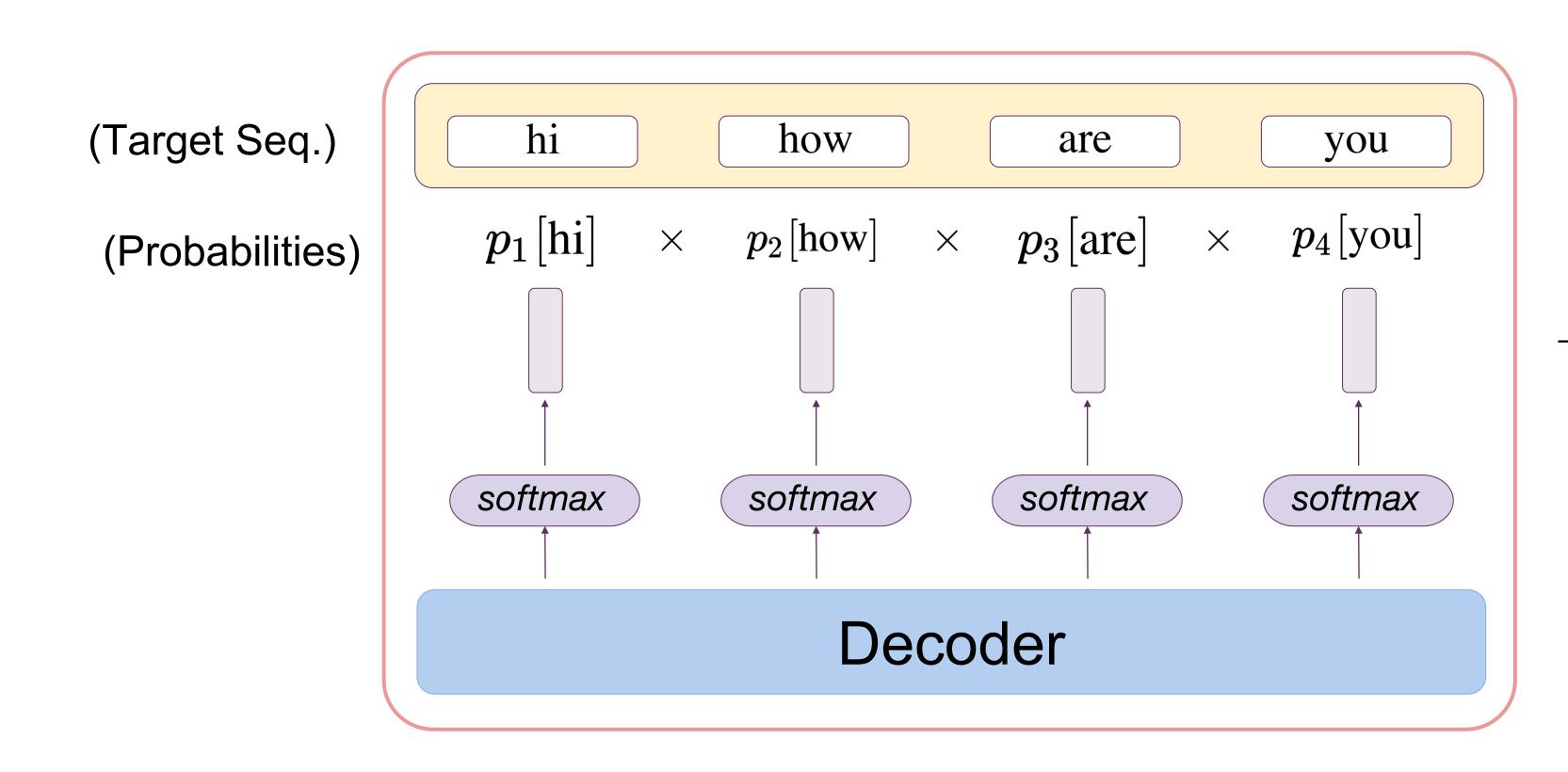
Causal Decoder (Wolf et.al. 2019, Radford et.al. 2018)



Slido: #ADL2021 Vanilla Seq2Seq ConvAl: Supervised Learning

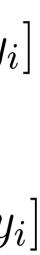
Maximum Likelihood Estimation (MLE) \Rightarrow maximizing the conditional probability of the response given the history \Rightarrow The model output is a probability distribution over the vocab

7

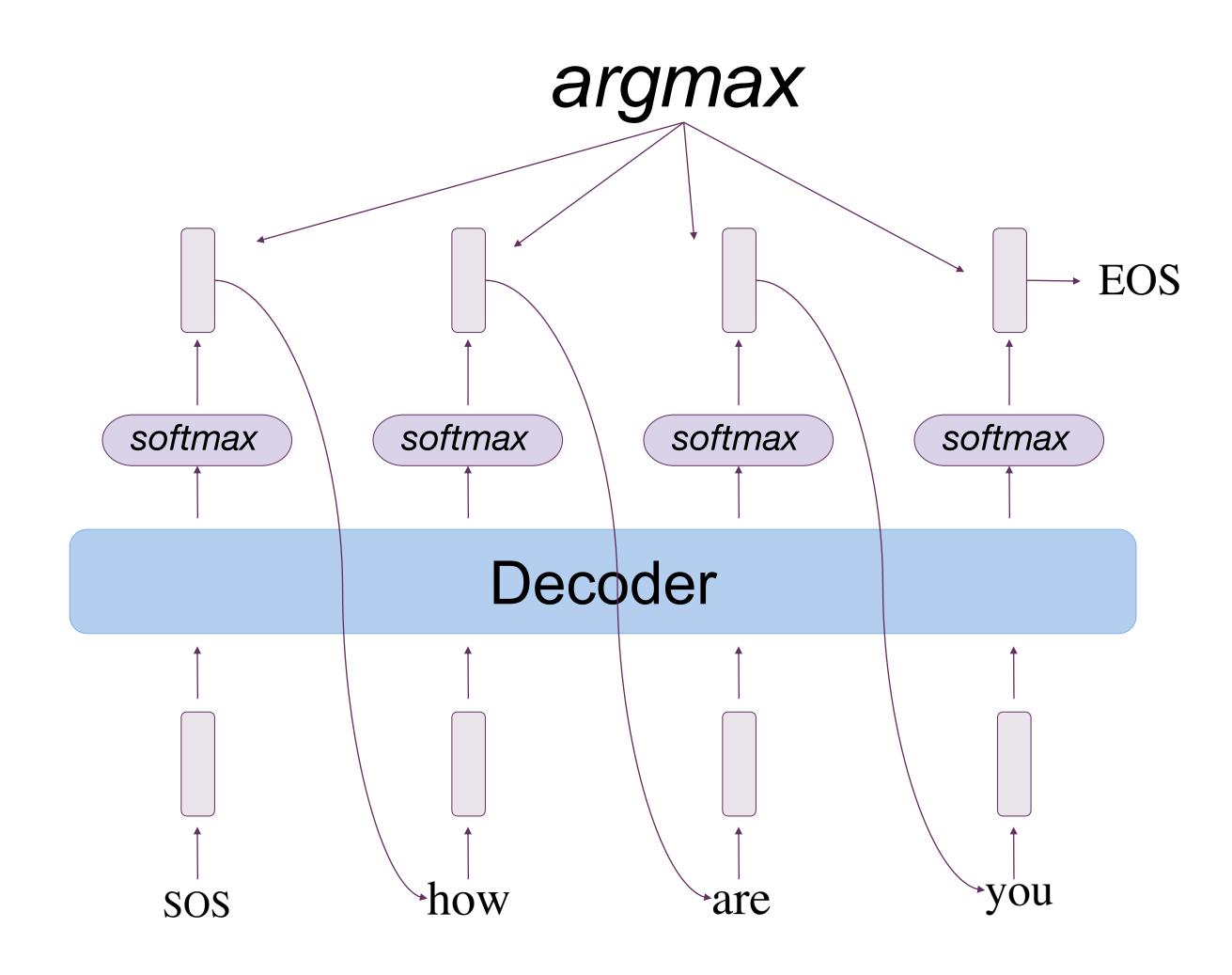


$$\mathbb{P}(y_1, \dots, y_m) = \prod_{i=1}^m p_i[y_i]$$
$$\log \mathbb{P}(y_1, \dots, y_m) = -\log \prod_{i=1}^m p_i[y_i]$$
$$= -\sum_{i=1}^n \log p_i[y_i]$$





Slido: #ADL2021 Vanilla Seq2Seq ConvAI: Greedy Decoding 8



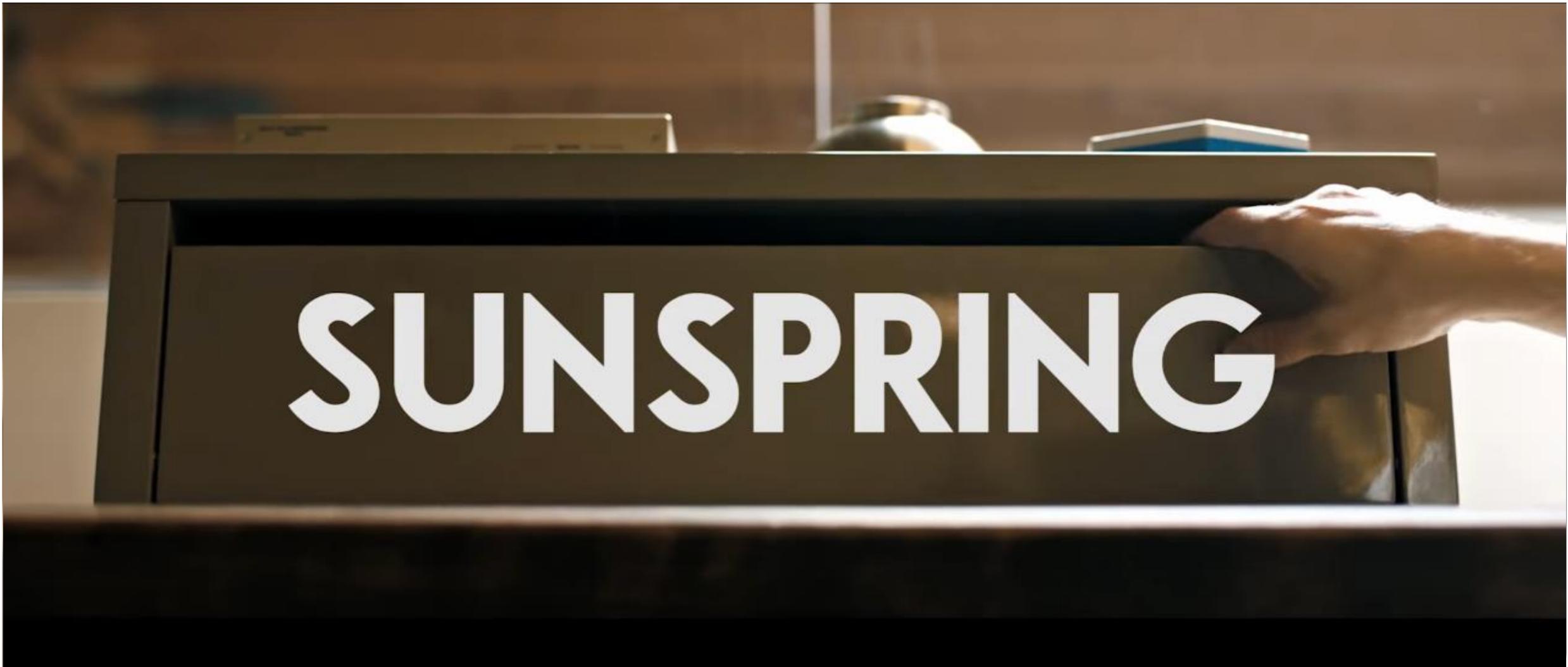


Vanilla Seq2Seq ConvAI: How 9

- A simple 4-step recipe:
- Choose the data: Human-to-human conversations
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- Train the model with the data: Supervised learning 3.
- Evaluate your model: Automatic or human evaluation







Slido: #ADL2021

https://www.youtube.com/watch?v=LY7x2Ihqj





Human: What are you doing today? System: I don't know Human: What is your name? System: I don't know Human: What is your favourite food? System: I don't know





Human: Where were you born? System: I was born in Canada. <u>Human</u>: Where are you from? <u>System</u>: England, you? <u>Human</u>: Where did you grow up? System: I grew up in Texas.





Human: What is the weather like today? System: I don't know, maybe sunny? the weather is good. System: Who is Taylor Swift?

Human: Okay, never mind.

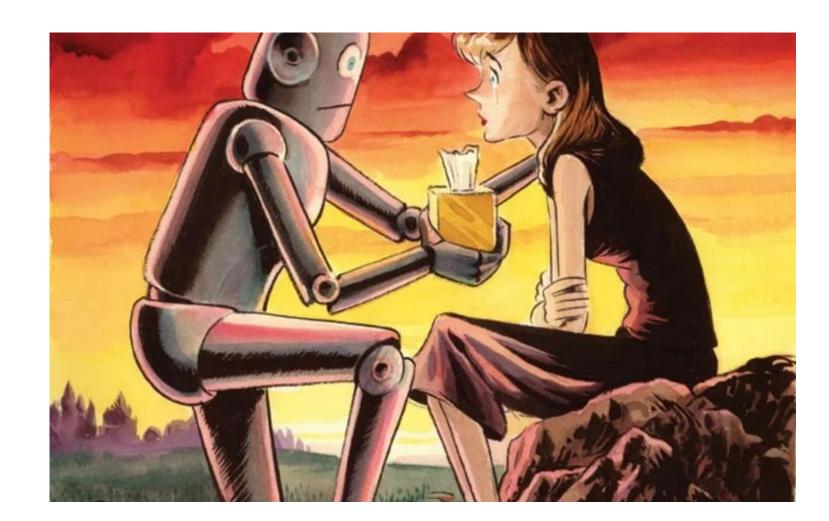
- Human: I am going out to Taylor Swift's concert today, I hope







<u>Human</u>: I messed up my project today. System: What is your project? <u>Human</u>: I think I might get fired... <u>System</u>: Then you need to find another job! Human:







Human: Hi, how are you?

Model1: I am good thanks

Model2: I had really a bad day

Model3: I am okay, how was your day?

swimming pool

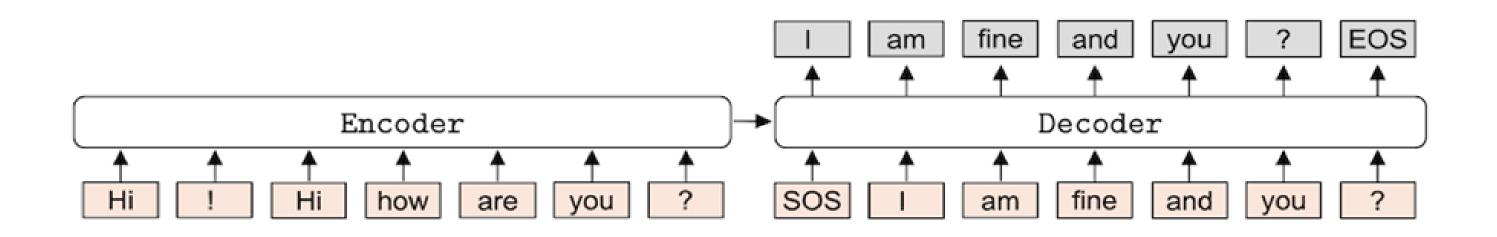
Slido: #ADL2021

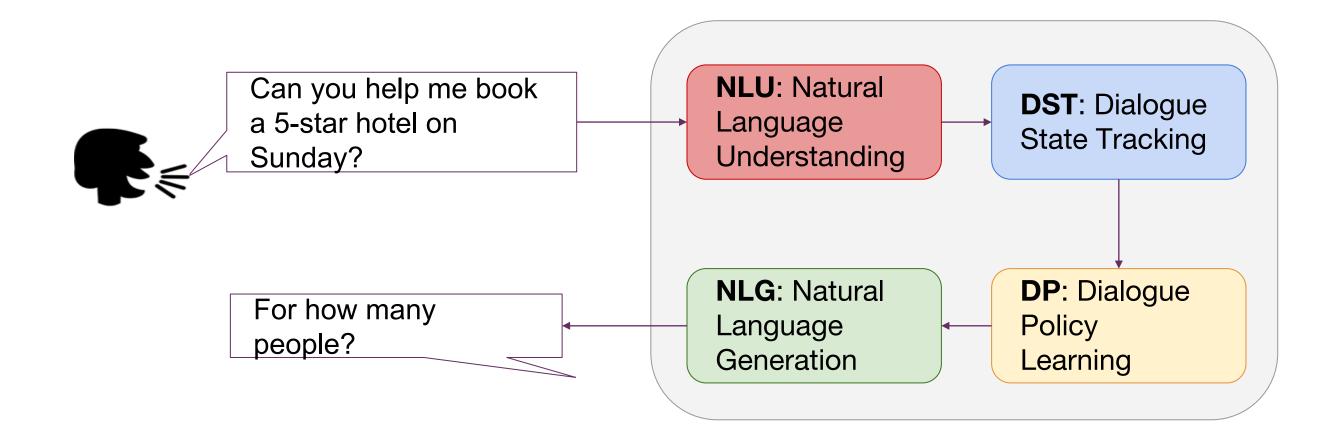
Model4: I am okay, I just finished my training session in the

 \rightarrow no control for style, topics, engagement, toxic and inappropriate responses









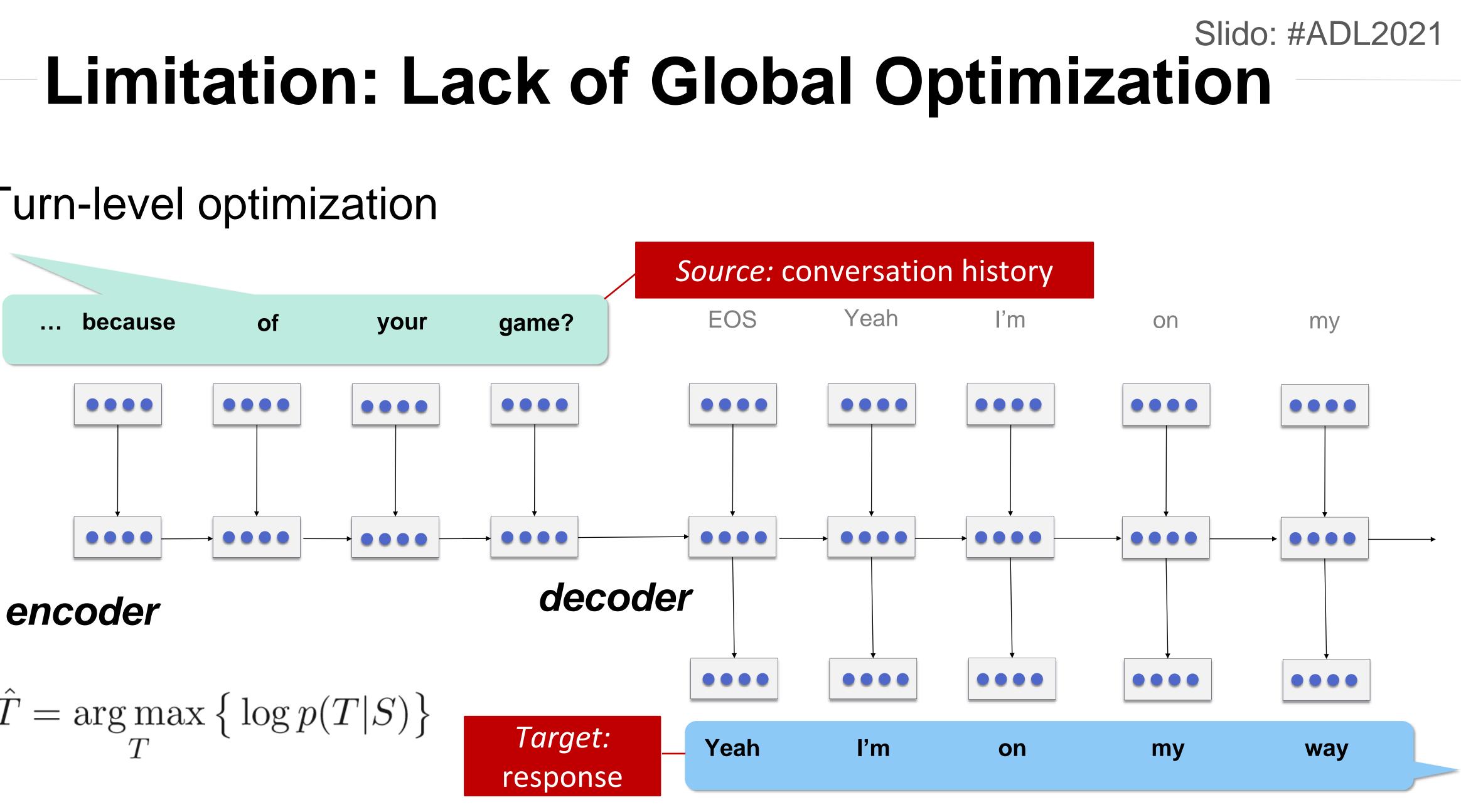
Slido: #ADL2021

\rightarrow cannot handle task-oriented conversations due to API requirement





Turn-level optimization



 $\hat{T} = \arg\max\left\{\log p(T|S)\right\}$

Slido: #ADL2021 Limitations of Vanilla Seq2Seq: Summary 18

- 1. Lack of diversity
- 2. Lack of consistency
- 3. Lack of knowledge
- 4. Lack of empathy
- 5. Lack of controllability
- 6. Lack of versatility
- 7. Lack of global optimization
- conversational AI?

These limitations of vanilla seq2seq make human-machine conversations boring and shallow. How can we overcome these limitations and move towards deeper





Slido: #ADL2021 Limitations of Vanilla Seq2Seq: Summary 19

- **1.** Lack of diversity
- 2. Lack of consistency
- 3. Lack of knowledge
- 4. Lack of empathy
- 5. Lack of controllability
- 6. Lack of versatility
- 7. Lack of global optimization
- conversational AI?

These limitations of vanilla seq2seq make human-machine conversations boring and shallow. How can we overcome these limitations and move towards deeper







- Wow sour starbursts really do make your mouth water... mm drool. Can I have one?
 - Of course!
- Milan apparently selling Zlatan to balance the books... Where next, Madrid?
 - I don't know.
- 'tis a fine brew on a day like this! S
 - I'm not sure y
 - Well he was on in Bromley a
 - I don't even know what he's talking about.

Strc	32% responses are general and meaningless <i>"I don't know"</i>
/et,	"I don't know what you are talking about" "I don't think that is a good idea"
wh	"Oh my god"





Solution: Diversify Responses 21

1. Training and Decoding strategy \Rightarrow Maximum Mutual Information (MMI)

$$\hat{T} = \arg\max_{T} \left\{ \log p(T|S) \right\} \quad \Longrightarrow \quad$$

- Model architecture \Rightarrow Conditional Variational Autoencoder (<u>CVAE</u>) 2.
 - $p(T|S) \implies p(T|z,S)p(z|S)$
- More data & Larger models \Rightarrow Large scale pre-training 3.
- Decoding strategy \Rightarrow Top-k sampling, <u>Nucleus Sampling</u> 4.

Slido: #ADL2021

 $\arg \max_{T} \left\{ (1 - \lambda) \log p(T|S) + \lambda \log p(S|T) \right\}$





MMI for Response Diversity (Li et al., 2016)



Wow sour starbursts really do make your mouth water... mm drool. Can I have one?

Well he was on in Bromley a while ago... still touring.

- Of course you can! They're delicious!
- Milan apparently selling Zlatan to balance the books... Where next, Madrid?
 - I think he'd be a good signing.
- 'tis a fine brew on a day like this! Strong though, how many is sensible?
 - Depends on how much you drink!

 - l've never seen him live.



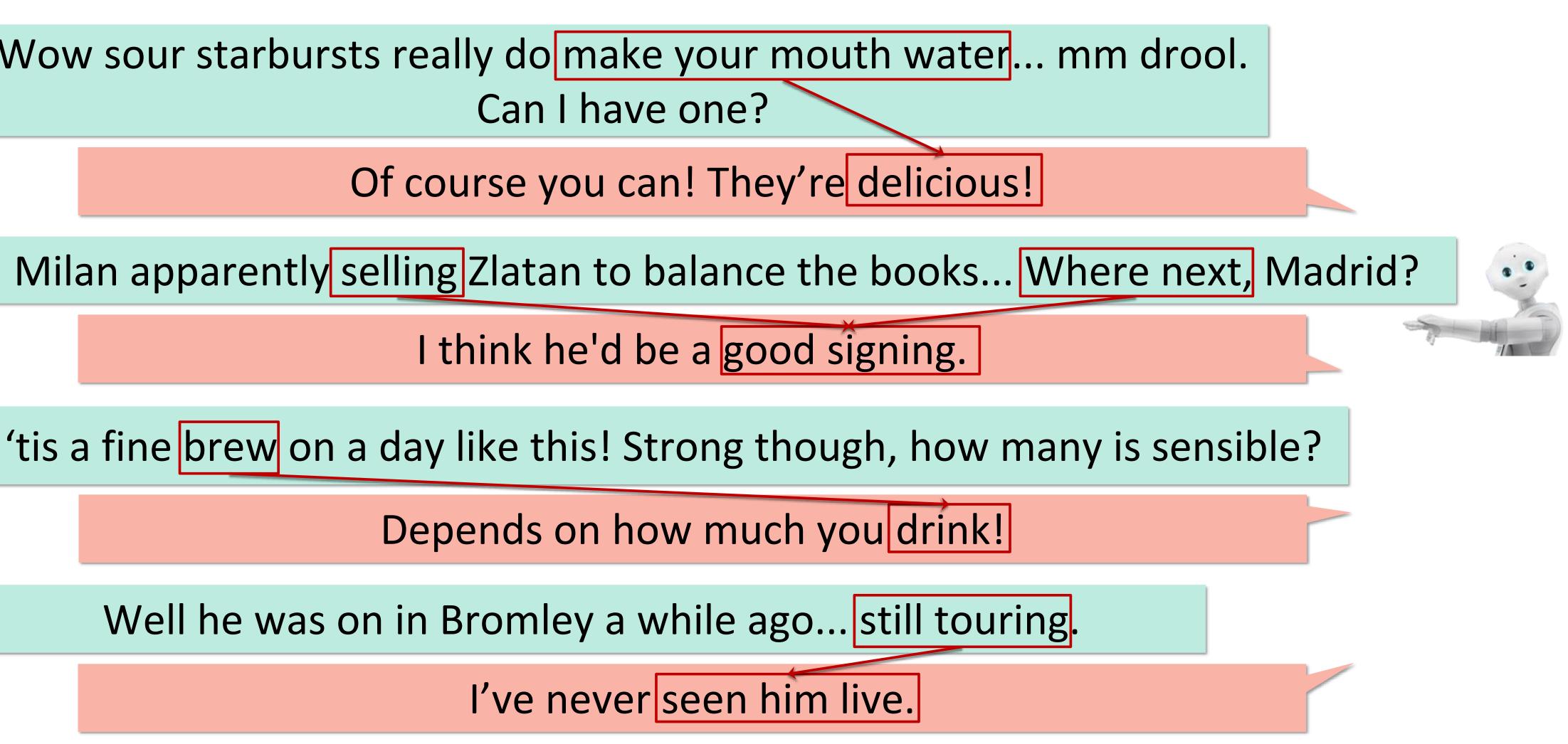


MMI for Response Diversity (Li et al., 2016)

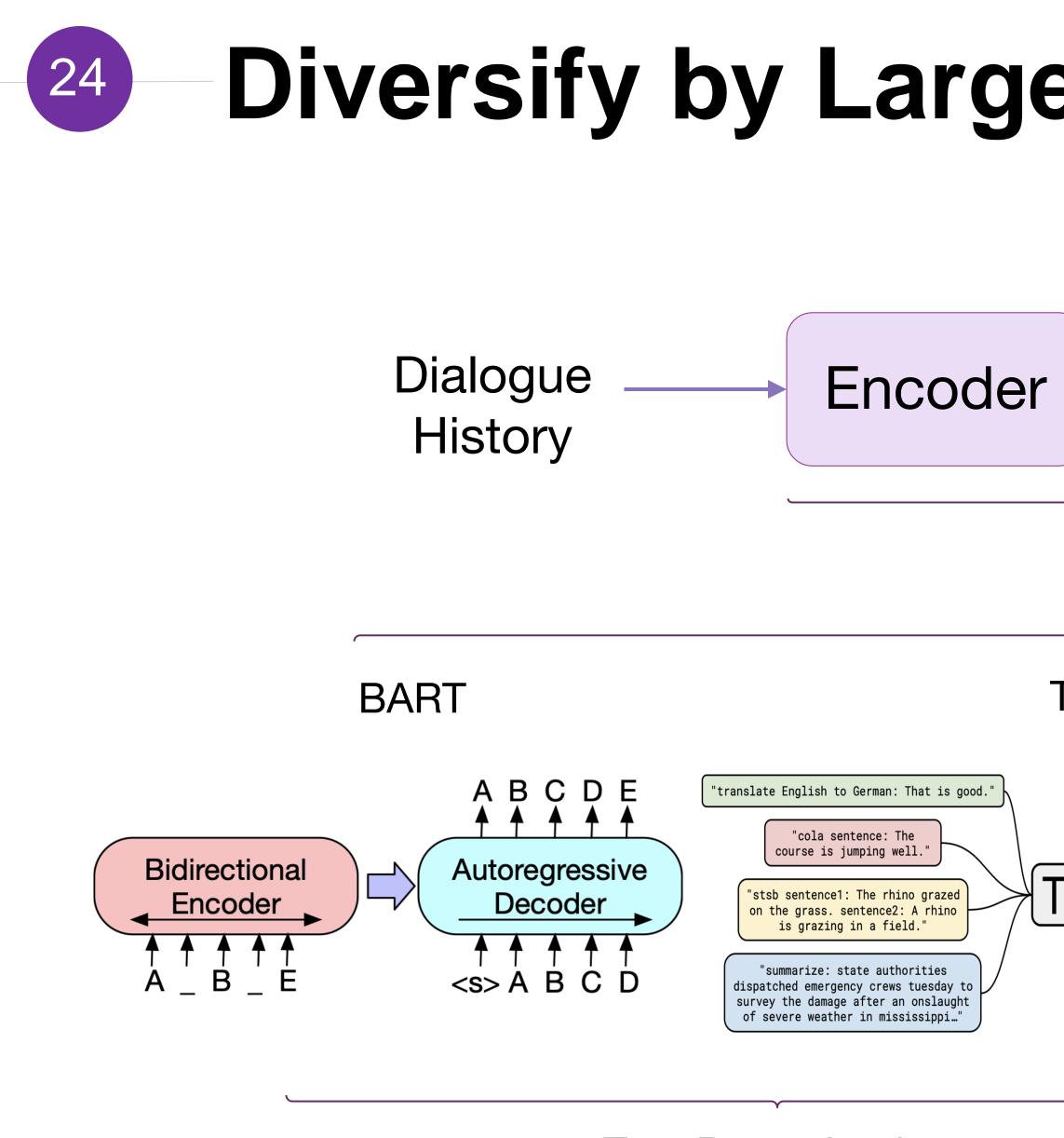


Wow sour starbursts really do make your mouth water... mm drool. Can I have one?

Well he was on in Bromley a while ago... still touring.







Text Pre-trained

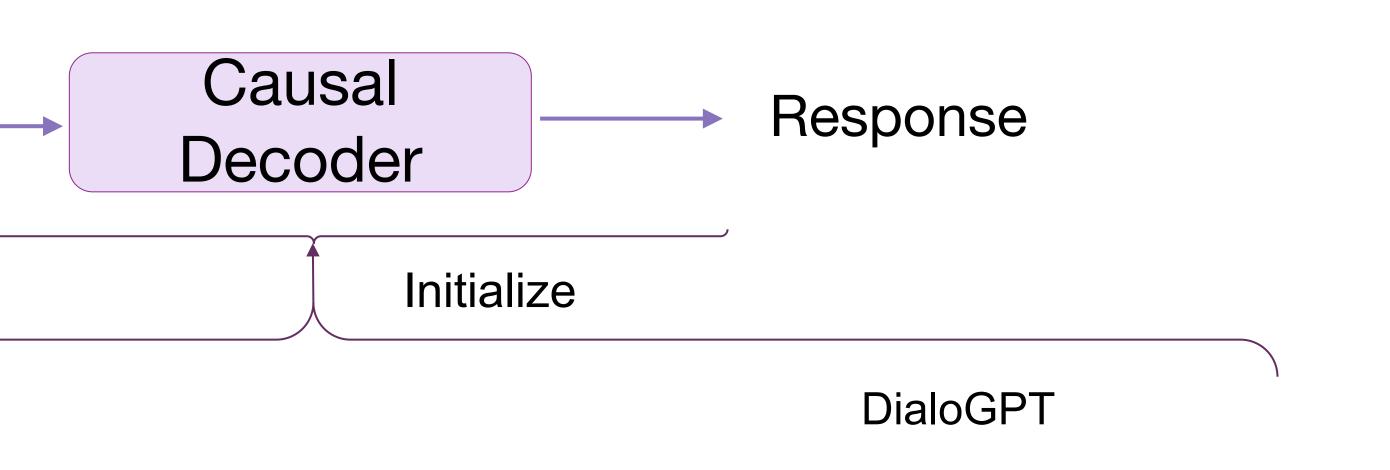
Slido: #ADL2021 **Diversify by Large-Scale Pretraining** Decoder Response Initialize BST T5 Meena "Das ist gut.' Meena BlenderBot T5 "not acceptable" "3.8" "six people hospitalized after a storm in attala county.'

Dialogue Pre-trained

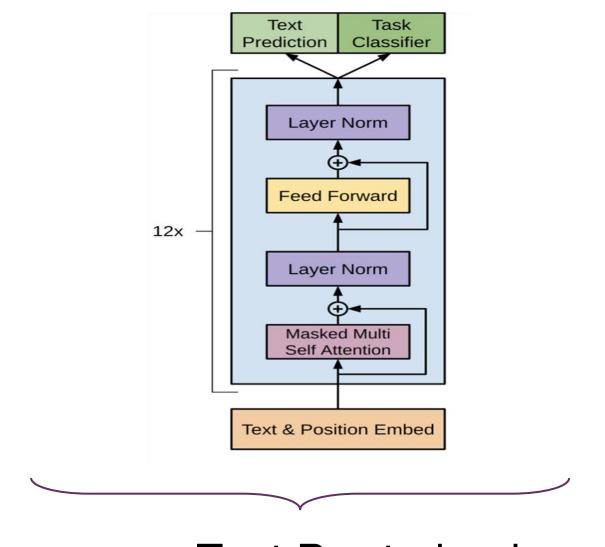








GPT-1/2/3



Text Pre-trained

Diversify by Large-Scale Pretraining



Dialogue Pre-trained



Diversify by Nucleus Sampling 26

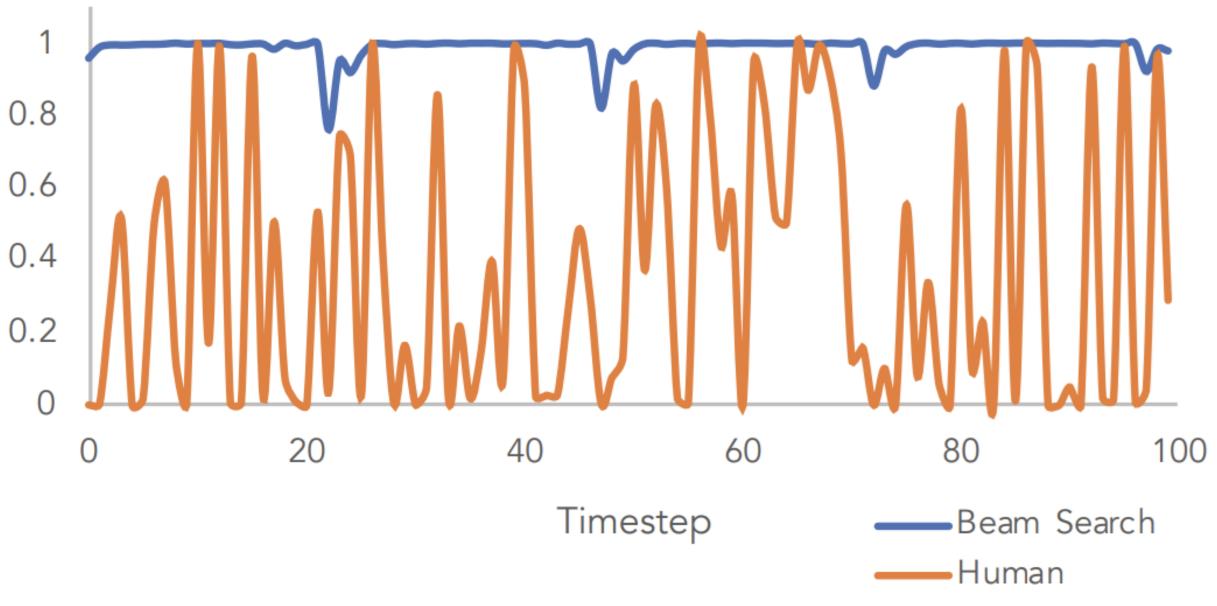
- Compared to beam search, • human are more likely to sample "low probability" tokens.
- Nucleus Sampling try to • recover the human sampling process by sampling from top-N vocabulary $V^{(p)} \subset V$

Probability

 $P(x|x_{1:i-1}) \ge p.$ $x \in V^{(p)}$

Slido: #ADL2021

Beam Search Text is Less Surprising



Ref: <u>The Curious Case of Neural Text Degeneration</u>



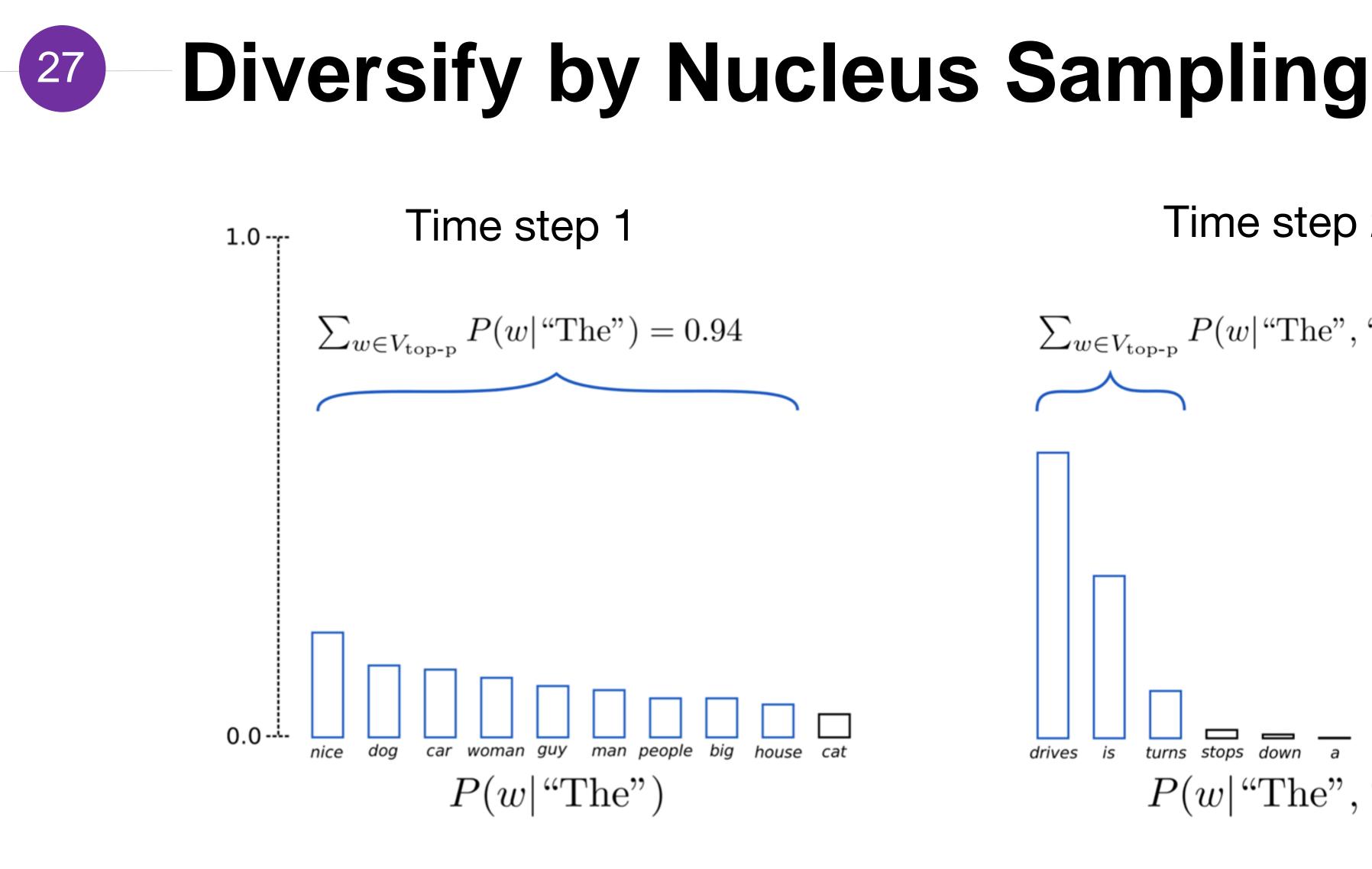
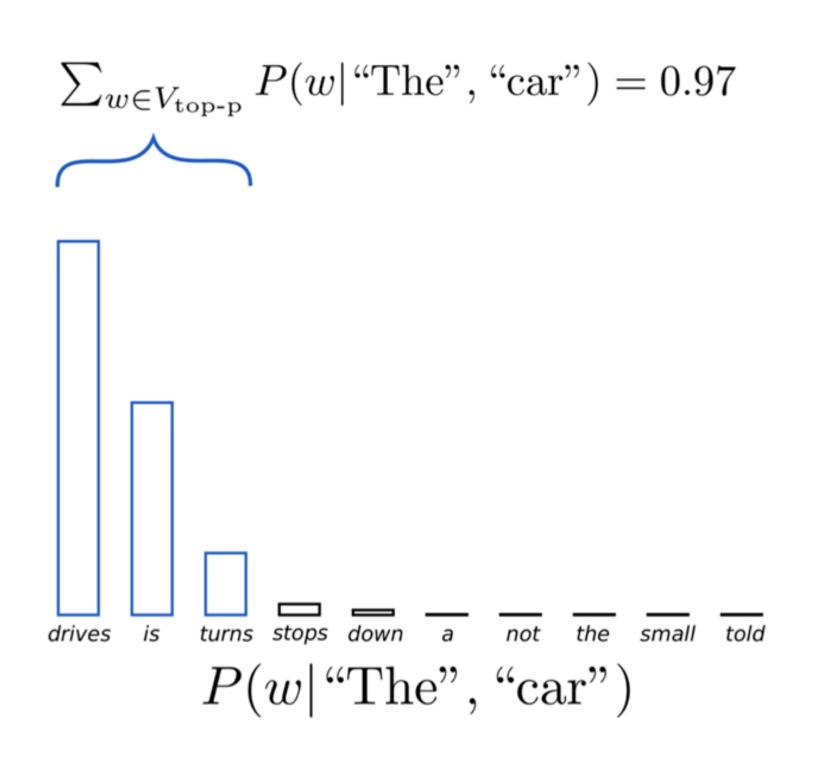


Figure from: <u>https://huggingface.co/blog/how-to-generate</u>

Slido: #ADL2021

Time step 2





Slido: #ADL2021 Limitations of Vanilla Seq2Seq: Summary 28

- 1. Lack of diversity
- 2. Lack of consistency
- 3. Lack of knowledge
- 4. Lack of empathy
- 5. Lack of controllability
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- conversational AI?

These limitations of vanilla seq2seq make human-machine conversations boring and shallow. How can we overcome these limitations and move towards deeper

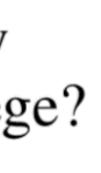




29 Limitation 2: Lack of Consistency

message	Where do you live now?	message	How old are you?
response	I live in Los Angeles.	response	16 and you?
message	In which city do you live now?	message	What's your age?
response	I live in Madrid.	response	18.
message	In which country do you live now?	message	What is your major?
response	England, you?	response	I'm majoring in psychology
message	Where were you born?	message	What did you study in colleg
response	I was born in Canada.	0	English lit.
message	Where are you from?		
	England, you?		
message	Where did you grow up?		
0	I grew up in Texas.	_	







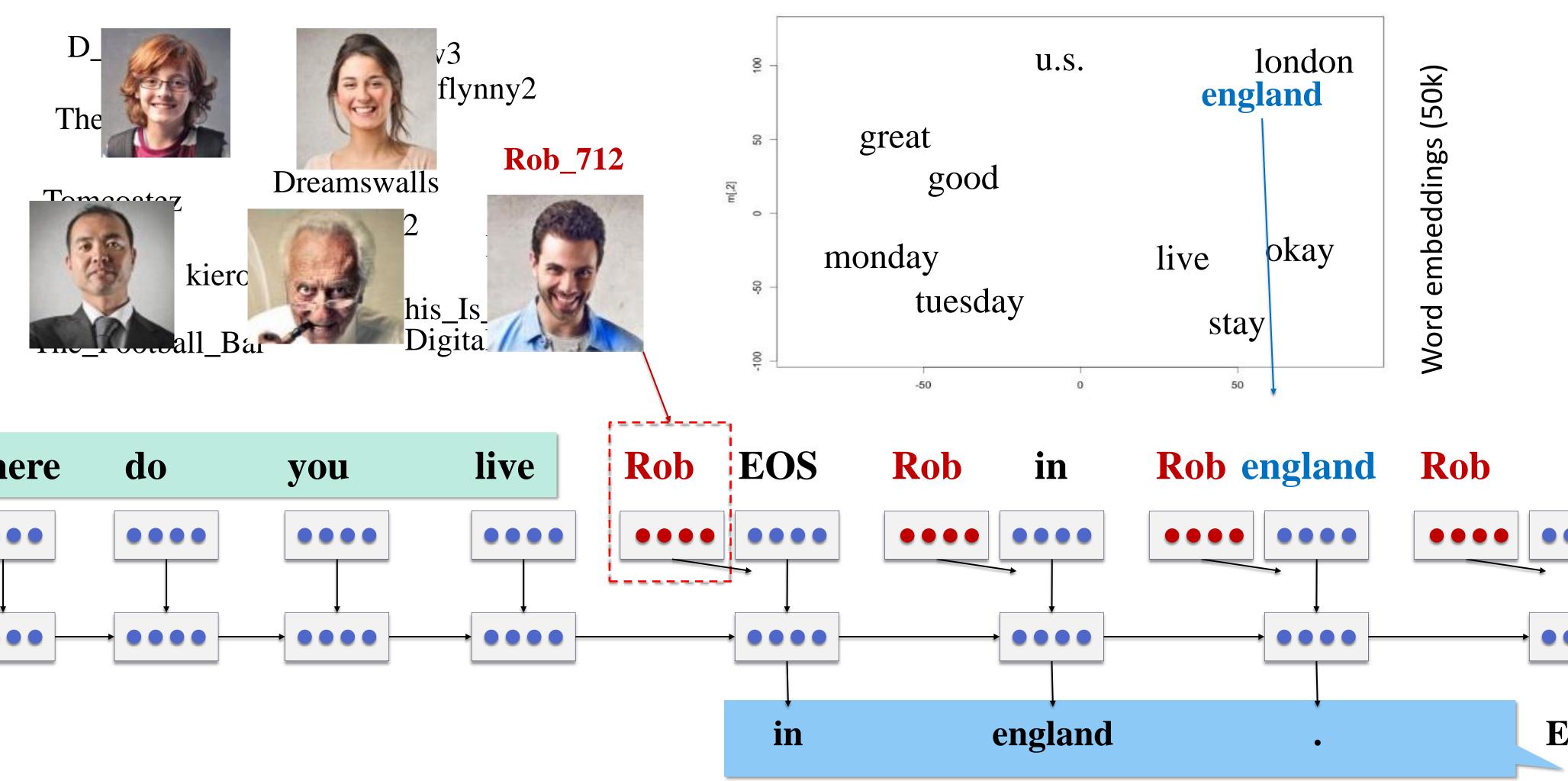
Solution: Personalization

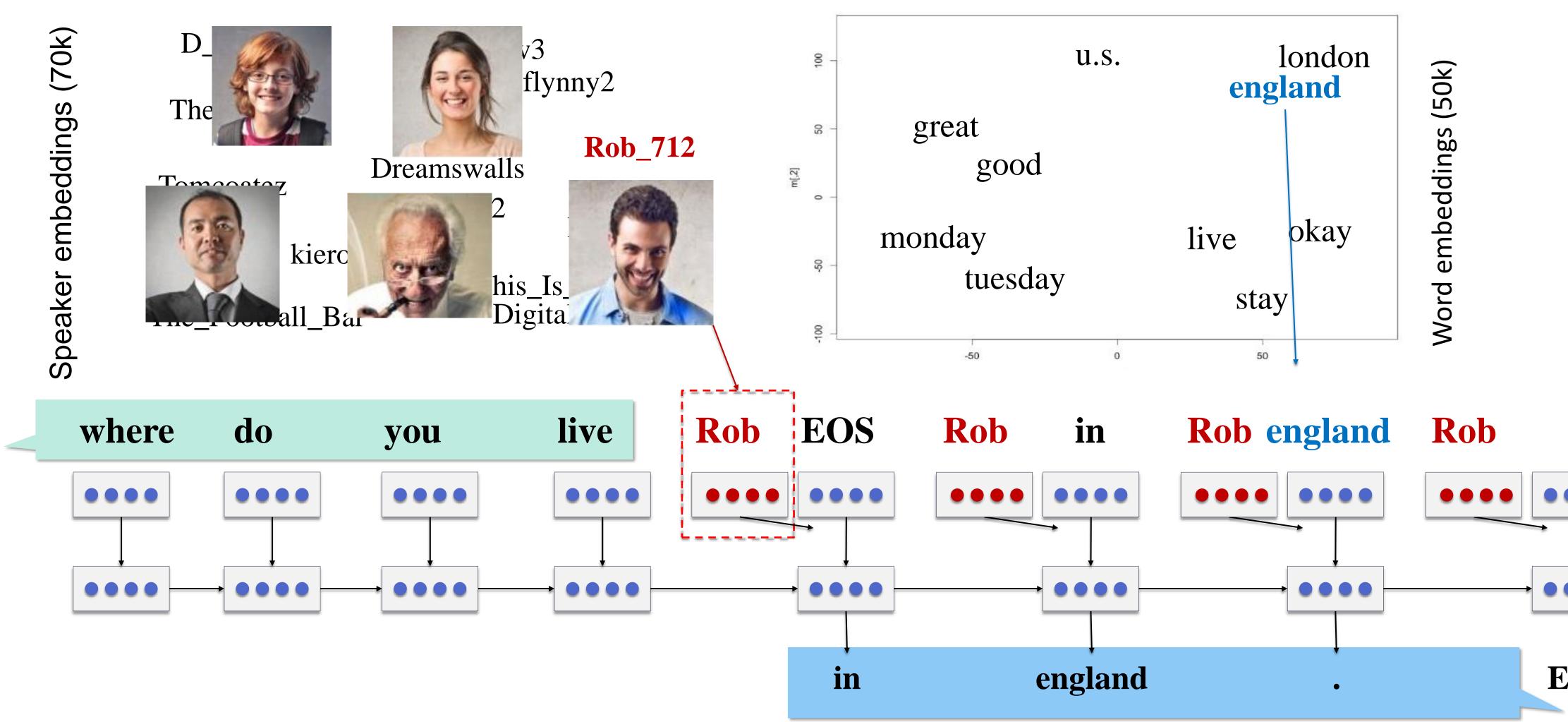
- 1. Learning speaker embedding:
 - Speaker Model
- 2. Conditioning on persona descriptions:
 - PersonaChat Dataset
 - TransferTransfo Model



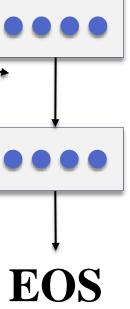












Persona Model for Consistency (Li et al., 2016) 32

Baseline model \rightarrow inconsistency

<i>message</i> Where is your hometown?	<i>message</i> Where is your hometown?
<i>response</i> I live in Indonesia.	response I'm from England.
message Where are you from?	<i>message</i> Where are you from?
response England, you?	response I'm from England.
message In which city do you live now?	message In which city do you live now?
response I live in Jakarta.	response I live in London.
<i>message</i> In which country do you live now?	<i>message</i> In which country do you live now?
response I live in Indonesia.	response I live in England.
message What is your major?	message What is your major?
response Business, you?	response Business. You?
message What did you study in college?	message What did you study in college?
response Psychology, you?	response I did business studies.
message How old are you?	message How old are you?
response I'm 18.	response I'm 18.
message What is your age?	message What is your age?
response I'm 16.	response I'm 18.

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Persona model using speaker embedding \rightarrow consistency





Personalization Datasets 33

Persona Info Human2:

- I like to ski.
- I am 25 years old

<u>Human1</u>: Hi, what do you do in your free time?

<u>Human2</u>: I enjoy going to the mountain and skiing

<u>*Human1*</u>: That's cool, you should be young and strong for this activity!

<u>Human2</u>: oh yeah, I am 25 🛞

Slido: #ADL2021

Human-to-Human Conversations + Persona Features

- Persona Chat
- **Tweeter Personalized**
- Learning Personalized End-to-End Goal-Oriented Dialog

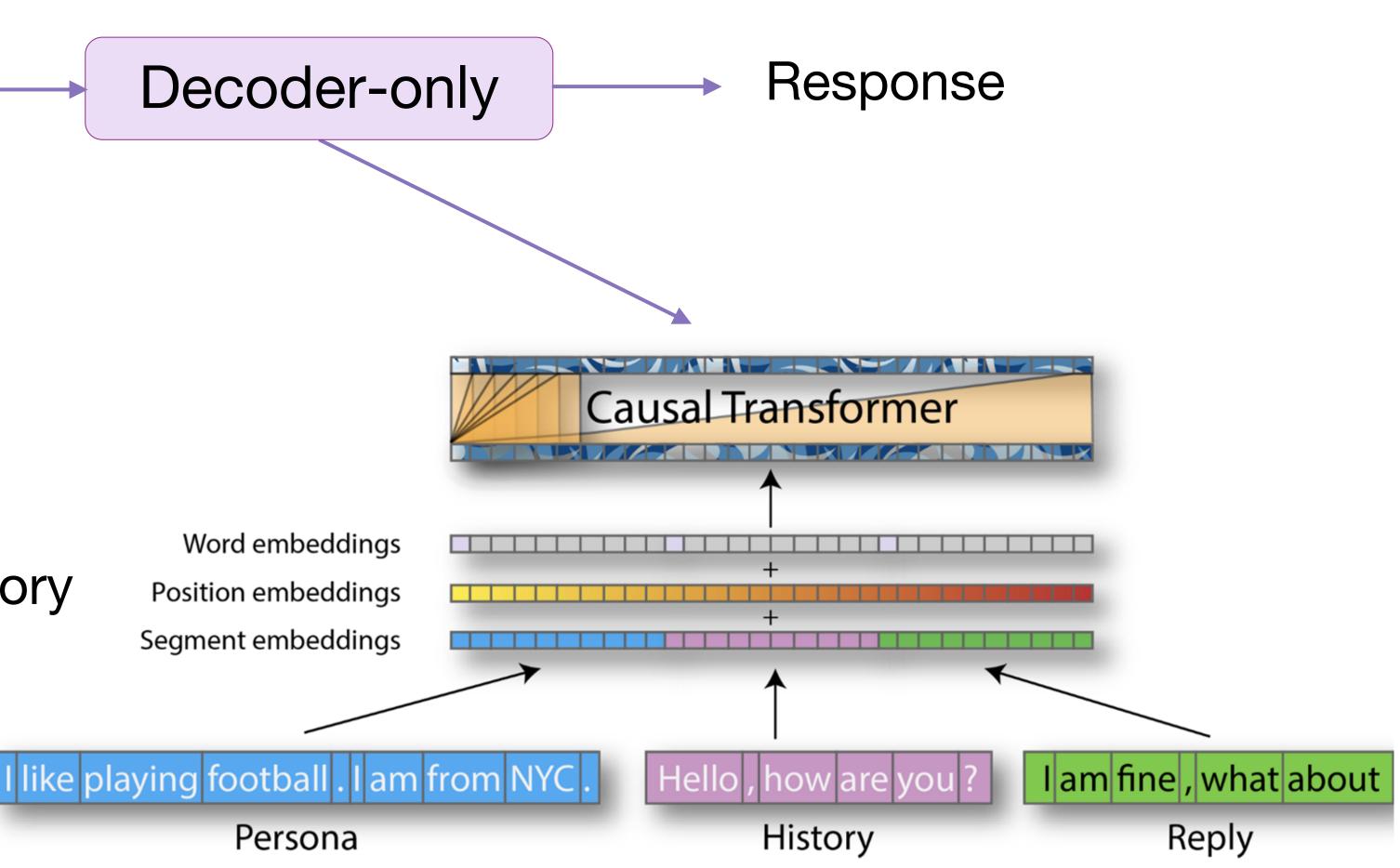




Dialogue History Persona Description

Fine-Tuning GPT with conversational data (Persona-Chat) Formulate persona, history and reply in single sequence

Slido: #ADL2021 **Personalization via TransferTransfo Model**





Slido: #ADL2021 Limitations of Vanilla Seq2Seq: Summary 35

- 1. Lack of diversity
- 2. Lack of consistency
- **3.** Lack of knowledge
- 4. Lack of empathy
- 5. Lack of controllability
- 6. Lack of versatility
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- conversational AI?

These limitations of vanilla seq2seq make human-machine conversations boring and shallow. How can we overcome these limitations and move towards deeper







Social Chat Engaging, Human-Like Interaction (Ungrounded)

The weather is so depressing these days.

I know, I dislike rain too. What about a day trip to eastern Washington?

Any recommendation?



Slido: #ADL2021

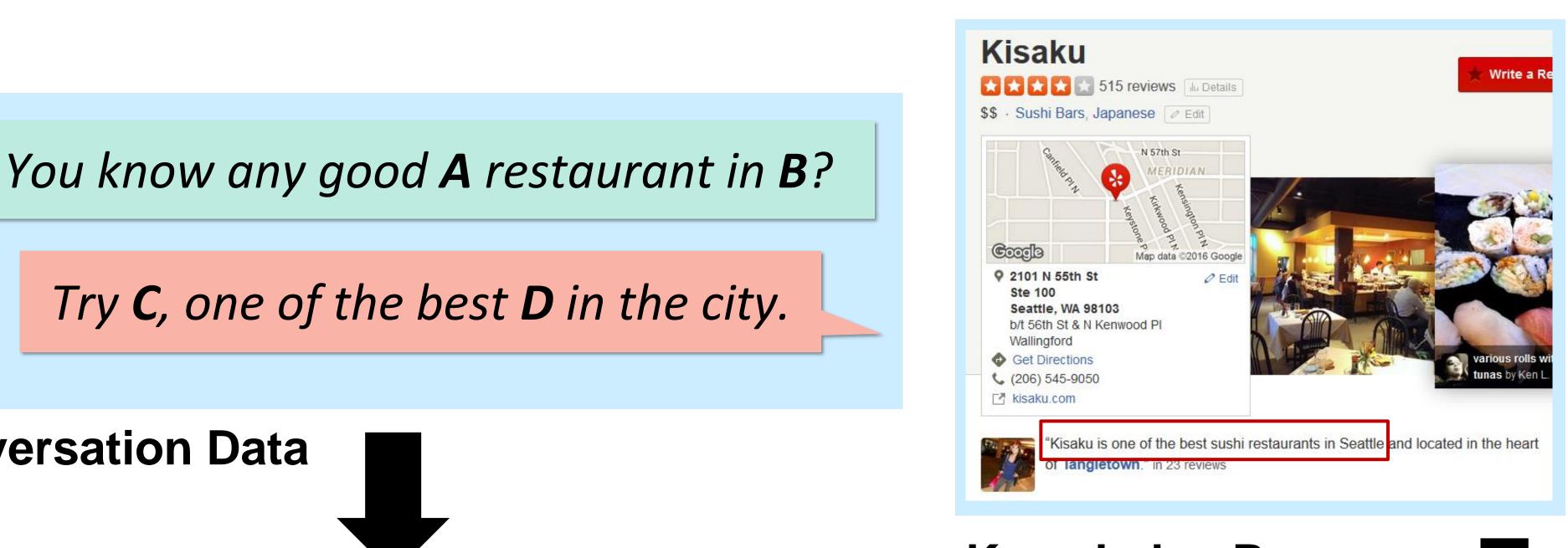
Task-Oriented Task Completion, Decision Support (Grounded)

Try Dry Falls, it's spectacular!











Conversation Data

You know any good Japanese restaurant in Seattle?

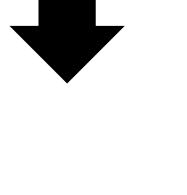




Slido: #ADL2021 **Conversation and Non-Conversation Data**

Knowledge Resource

Try Kisaku, one of the best sushi restaurants in the city.







Solution: Knowledge 38

- Textual Knowledge 1.
 - \Rightarrow Retrieving knowledge from Wikipedia, news, etc.
- Graph Knowledge 2.
 - \Rightarrow Retrieving subgraph from knowledge graphs
- 3. Tabular Knowledge
 - \Rightarrow Incorporate tabular information
- 4. Service API Interaction

 \Rightarrow Generates API query, and incorporate API returns into the response



Textual Knowledge 39

Human: My favorite color is blue.

Wizard: Same! Blue is one of the three

primary colours.

<u>Human</u>: I am trying to recall, where does

blue fall on the spectrum of visible light?

Textual Knowledge:

Blue is one of the three primary colours in the RGB colour model. It lies between violet and green on the spectrum of visible light.

Wizard: It is right between violet and

green.

Slido: #ADL2021

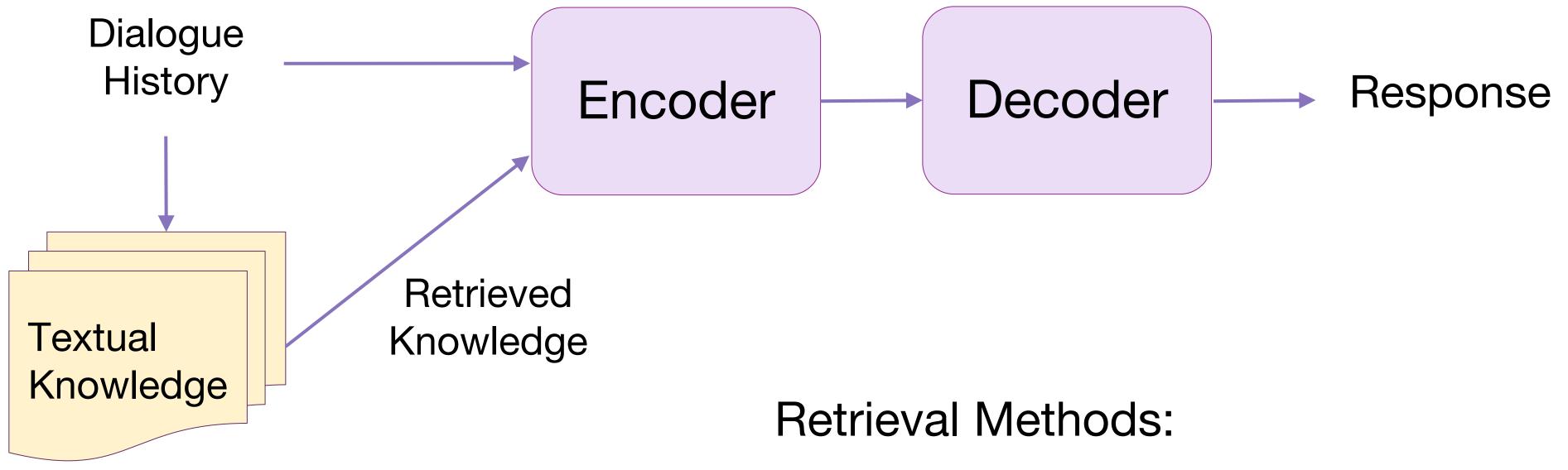
Human-to-Human Conversations + Textual Knowledge

- Wizard of Wikipedia
- CoQA
- **TopicChat**
- CMUDoG
- HollE
- **ConversingByReading**





Models with Textual Knowledge

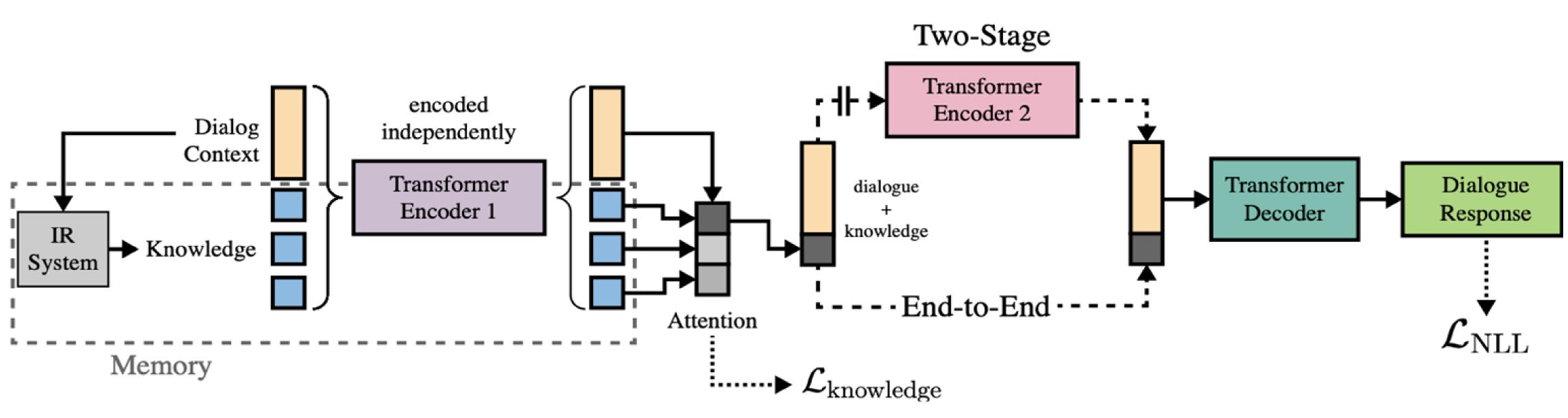


Slido: #ADL2021

IR Systems: TF-IDF, BM25 Neural Retriever: **DPR**





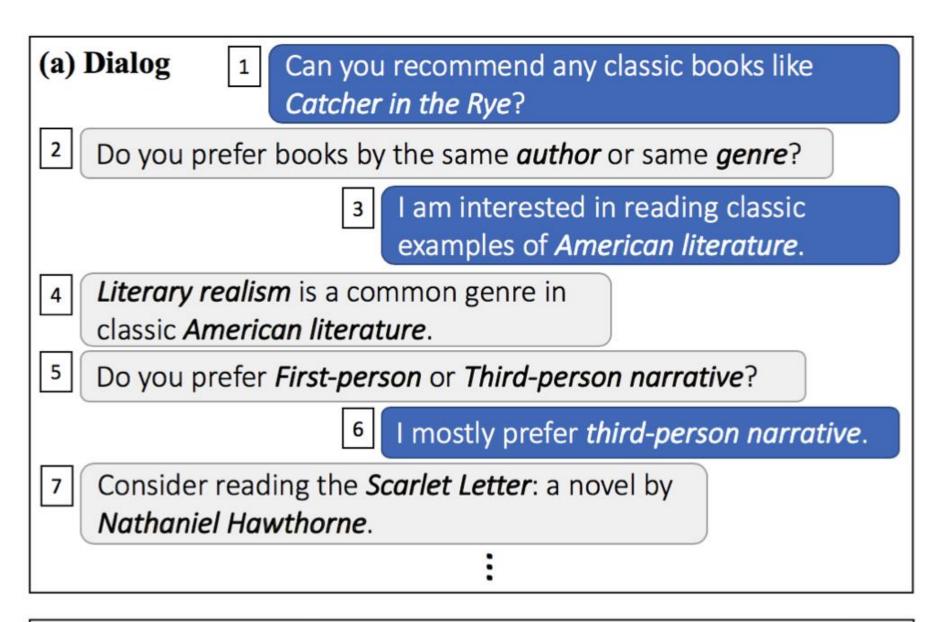


Generative Transformer Memory Network

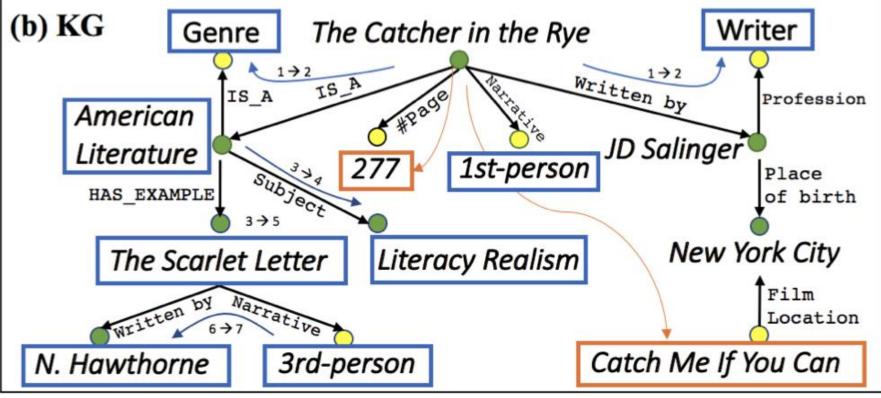
- Use TF-IDF retrieves documents that related to dialogue context
- Encode the retrieved documents independently 2.
- Use dialogue history as query to assign different weights to the documents 3.
- Decoder generates the response



Graph Knowledge

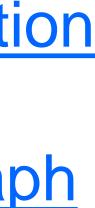


42



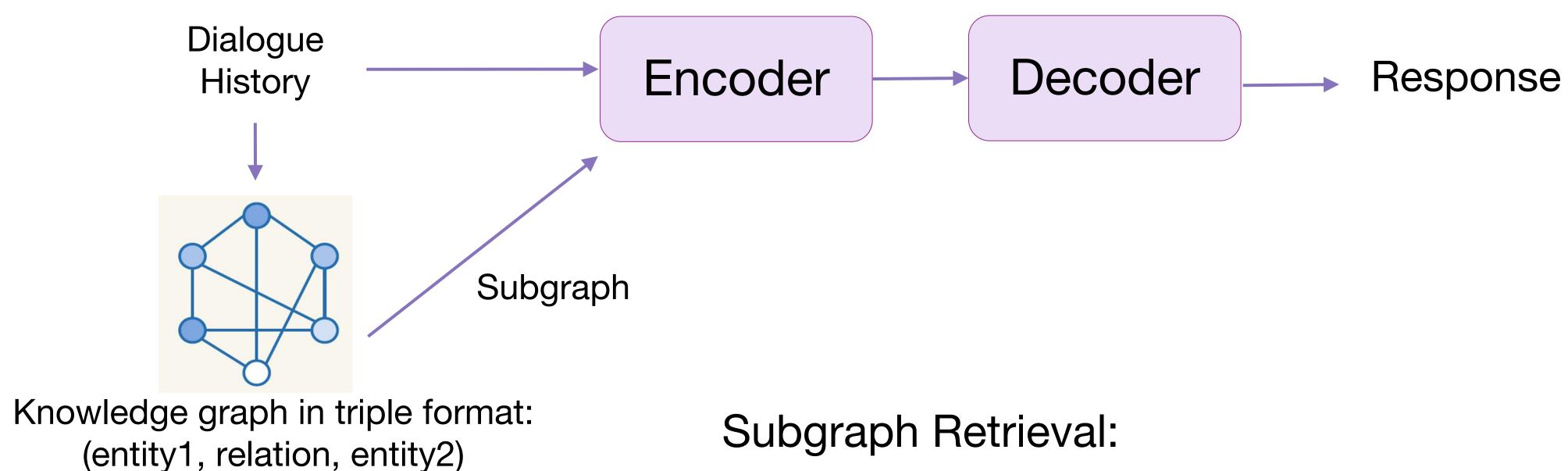
- Human-to-Human Conversations + Graph KG **OpenDialKG**
 - **DyKgChat**
 - KdConv
 - **Commonsense Knowledge Aware Conversation Generation with Graph Attention**
 - Enhancing Dialog Coherence with Event Graph **Grounded Content Planning**







Models with Graph Knowledge



ullet

ullet

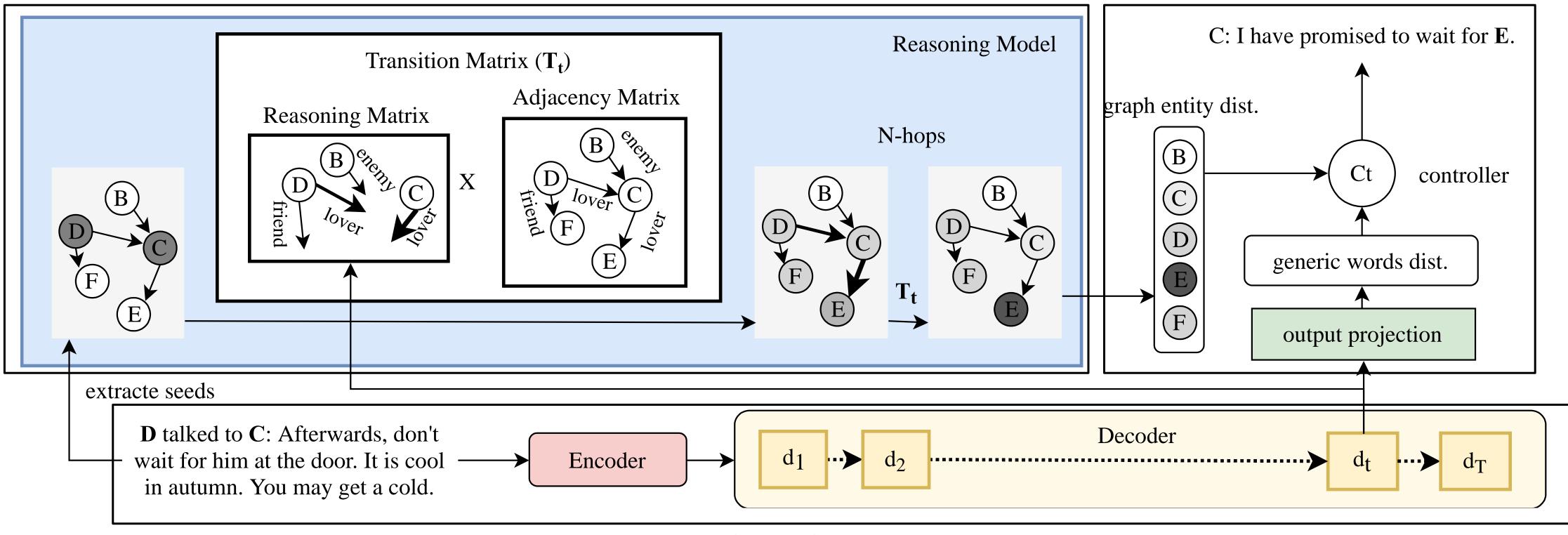
Slido: #ADL2021

All knowledge triples mentioned in a dialogue (1 hop reasoning) Neural Retriever (multihop reasoning)





3. Reasoning model



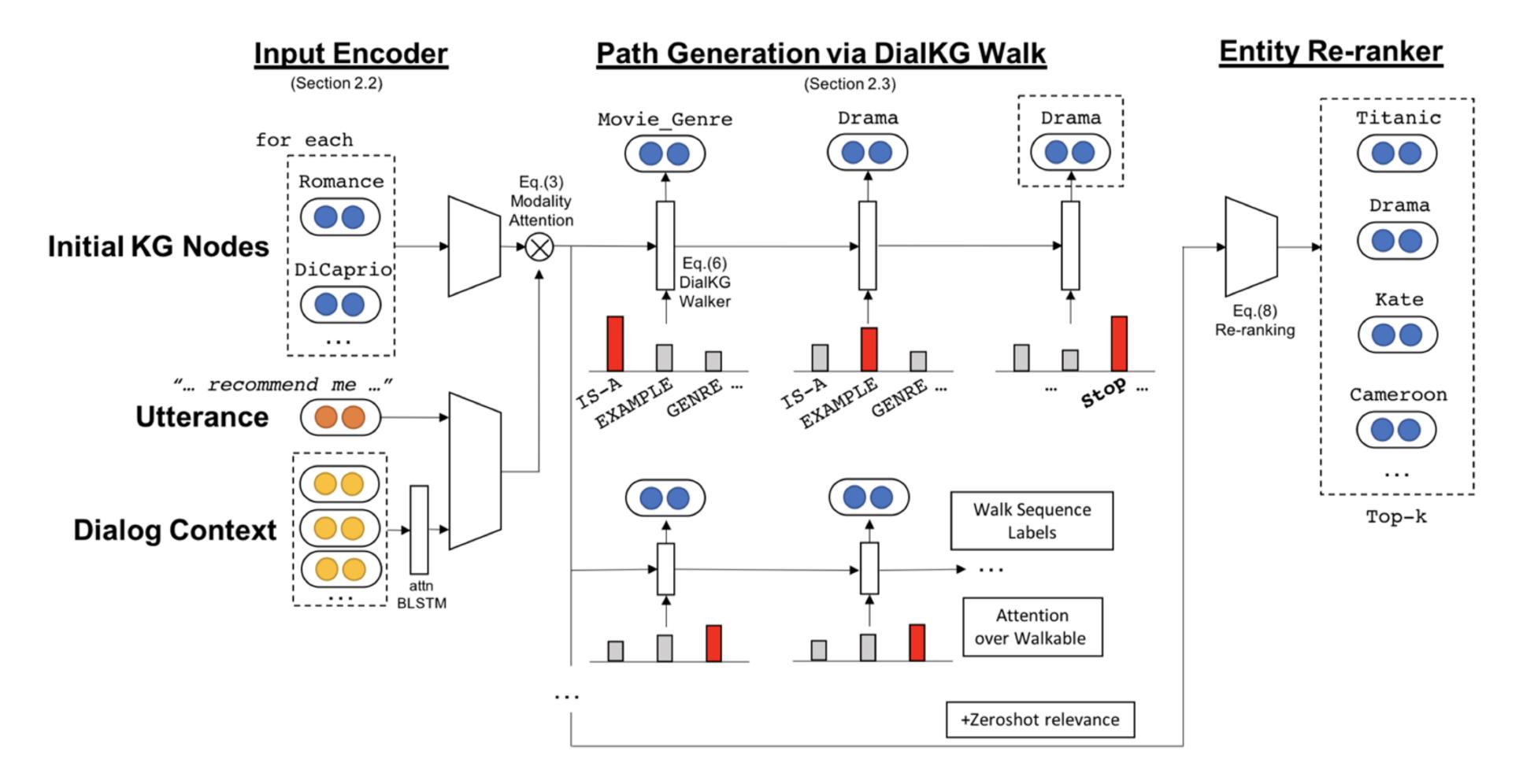
Slido: #ADL2021 **DykgChat:** Quick Adaptive Model (Qadpt)

2. Controller

1. Seq2Seq model







Take all the entities mentioned in dialogue as starting node Supervised learn the reasoning path over graph via graph attention

Slido: #ADL2021 **OpenDialKG Walker: Subgraph Retrieval**



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Tabular Knowledge

Event	Time	Date	Party	Agenda
swimming act.	3pm	the 11th	sister	-
dinner	7pm	the 3rd	mother	-
football	2pm	the 20th	mother	-
lab appt.	10am	the 17th	Jeff	-
•••	•••	•••	•••	•••

DRIVER:	car when is gonna be my next swimming activity?
CAR:	your next swimming activity is on the 11th at 3pm.
DRIVER:	who is gonna attend with me?
CAR:	your swimming activity is on the 11th, one 3pm with sister
DRIVER:	thank you!
CAR:	you are welcome

Slido: #ADL2021



Human-to-Human Conversations + Table Knowledge

- **SMD**
- Camrest
- **bAbl-Dialogues**

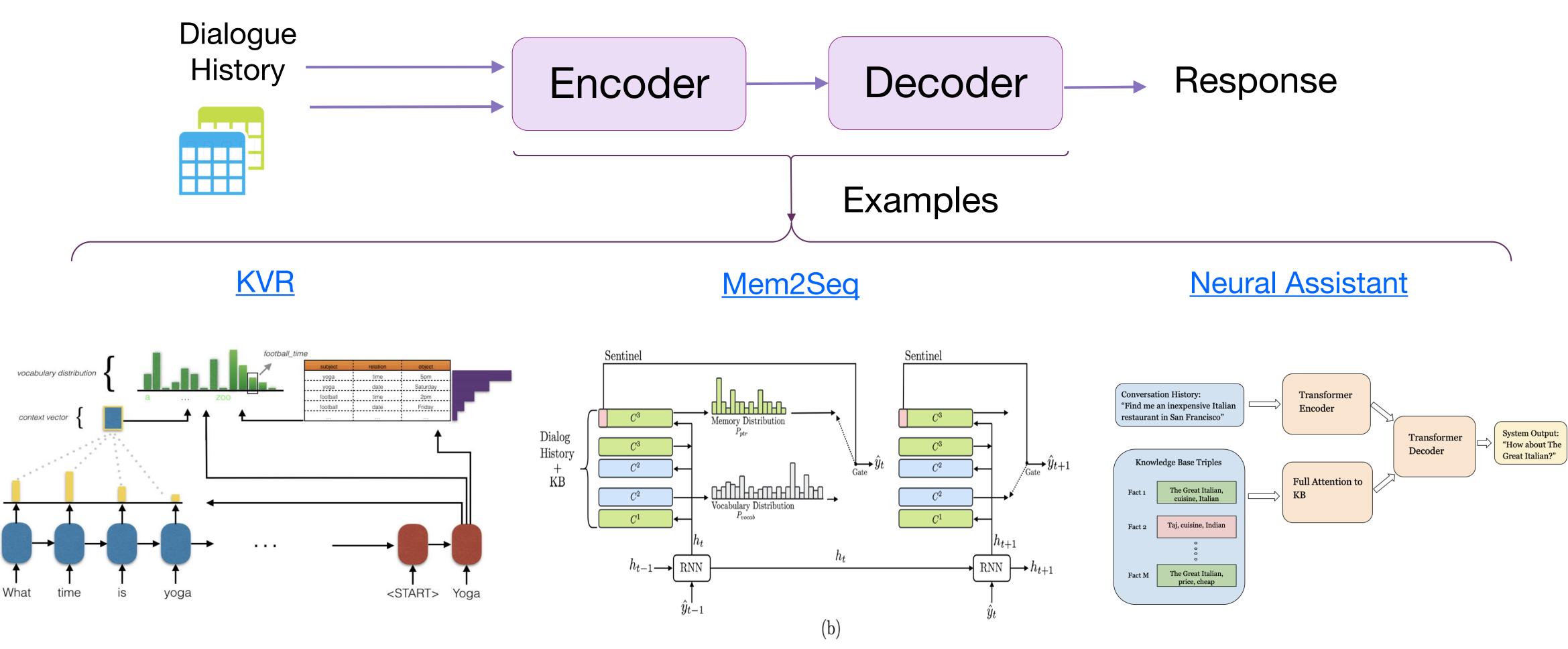
at







Models with Tabular Knowledge







External Service API Interaction

Hi!	TT 11 1 . T1 1 1 9		
TU 1 1'1 / 1 1 /	Hello, what can I help you with today?		
I'd like to book a ta	ble for six people in an expensive price range with British food.		
	I'm on it!		
	Where should it be?		
In London.			
	Ok, let me look into some options for you.		
	<pre>api_call(British, London, Six, Expensive)</pre>		
Actually i would pr	refer for four.		
	Sure. Is there anything else to update?		
No.			
1.0.	Ok let me look into some options for you.		
	api call (British, London, Four, Expensive)		
	* The Place R phone The Place phone		
	* The Place R cuisine british		
	* The Place R address The Place address		
	* The_Place R_location london		
	* The_Place R_availability four		
	* The_Place R_price expensive		
	* The_Place R_rating 7		
	* The_Fancy_Pub R_phone The_Fancy_Pub_phone		
	* The_Fancy_Pub R_cuisine british		
	* The_Fancy_Pub R_address The_Fancy_Pub_address		
	* The_Fancy_Pub R_location london		
	* The_Fancy_Pub R_availability four		
	* The_Fancy_Pub R_price expensive		
	* The Fancy Pub R rating 8		
NT T 1 1/11 /1 /	What do you think of this option: The Fancy Pub		
No, I don't like that			
	Sure, let me find an other option for you.		
	What do you think of this option: The_Place		
Let's do it!			
	Great let me do the reservation.		
Can you provide m			
Can you provide me the address?			
Von real-	Here it is: The_Place_address.		
You rock!	Ta		
	Is there anything else I can help you with?		
No thanks.	Pr		
	You're welcome.		

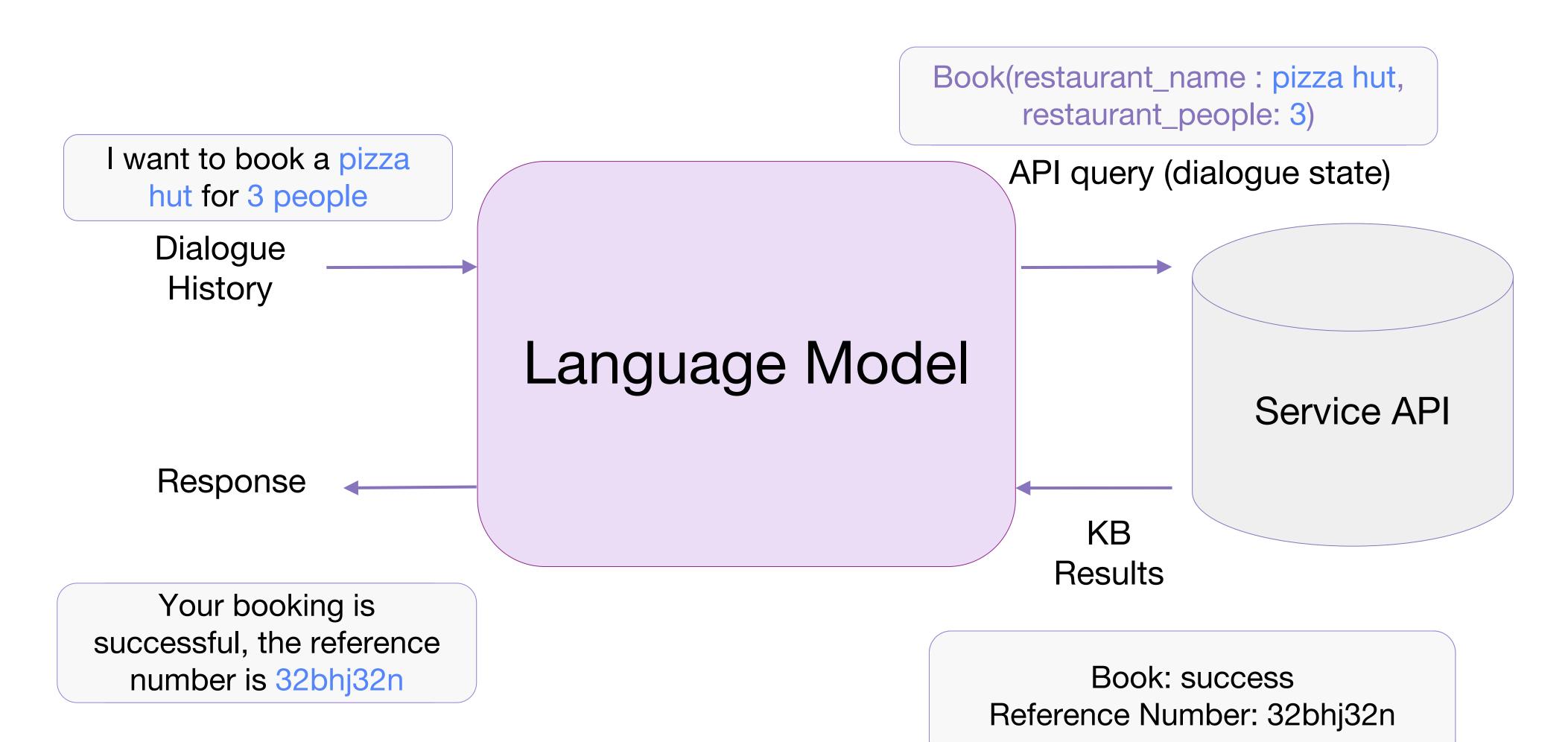
- Human-to-Human Conversations + Table Knowledge
 - . bAbl
 - . Camrest
 - MultiWoz
 - . CrossWoz
 - Schema Guided Dialogue
 - TaskMaster 1-2-3
 - STAR



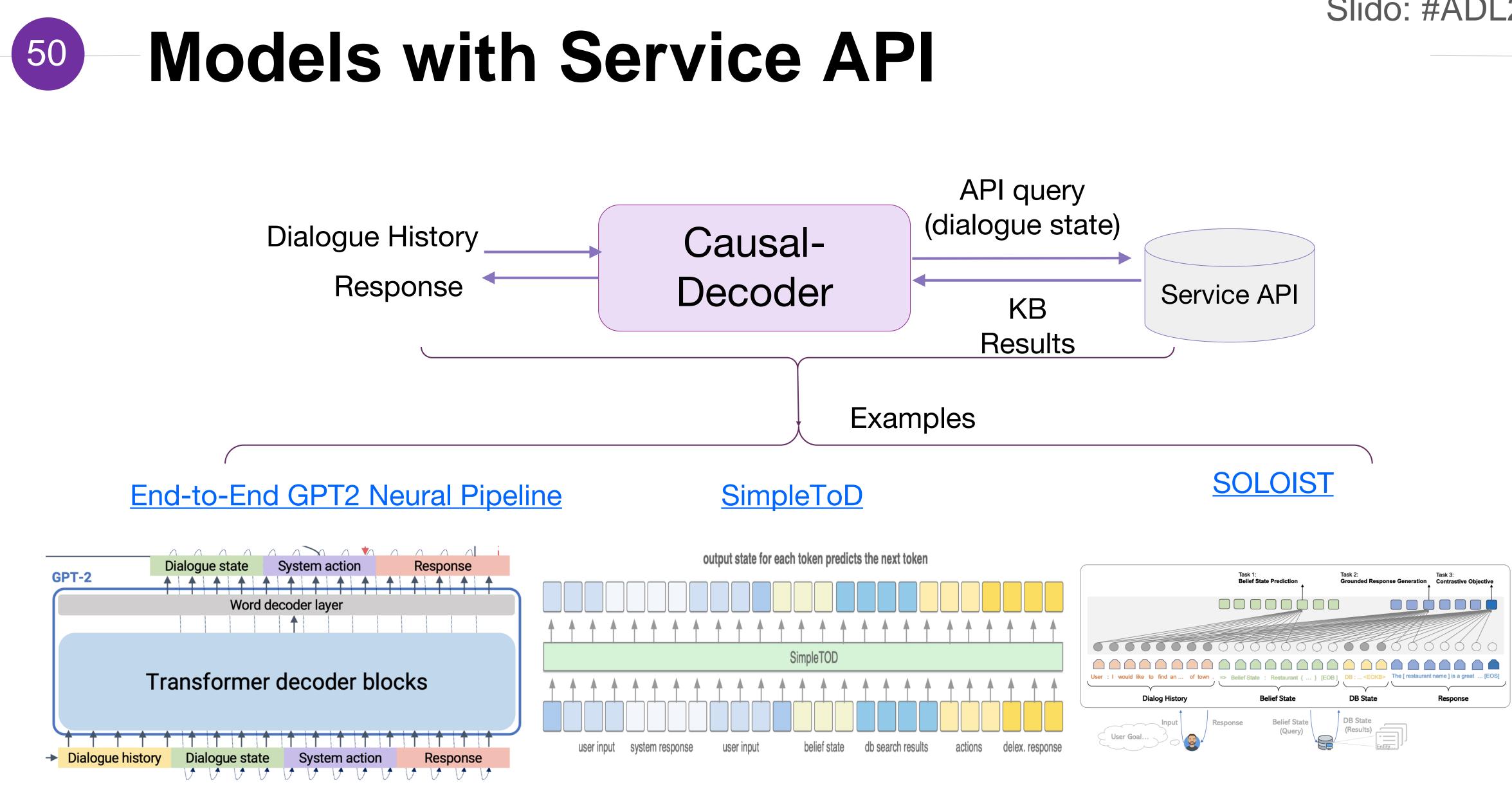




Models with Service API







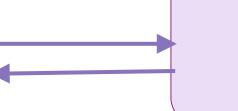




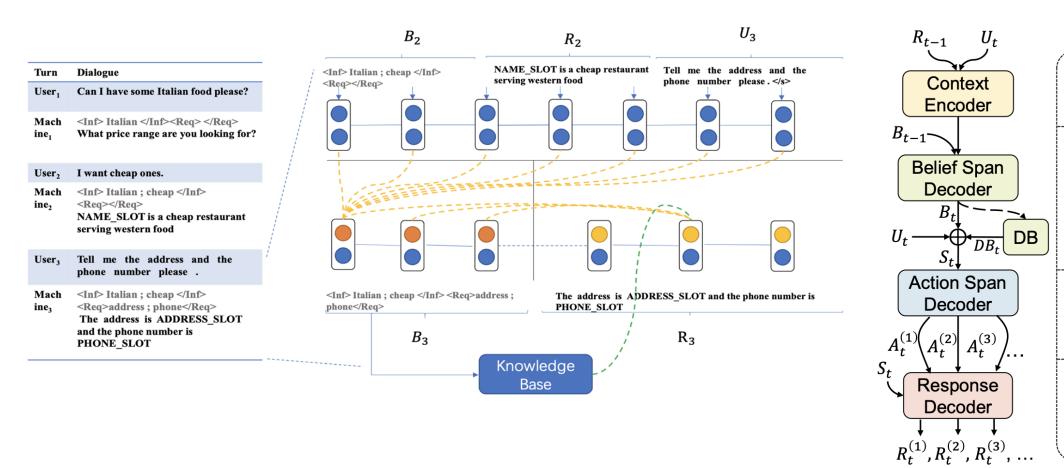
Models with Service API

Dialogue History

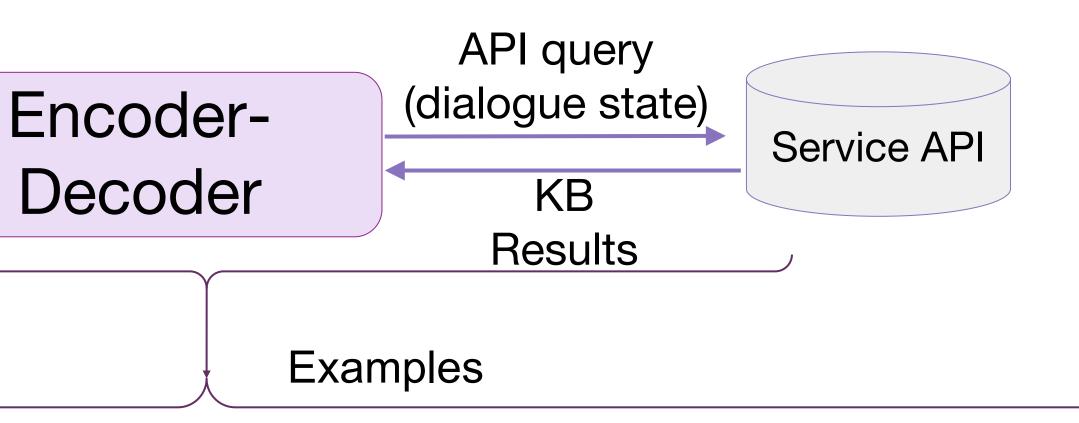
Response



Sequicity



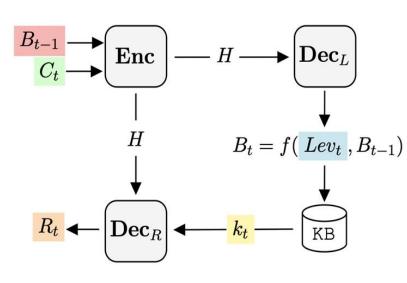
Slido: #ADL2021



DAMD

R_{t-1} : What price range do you want for the hotel? U_t : A cheap one works for me. By the way it should be in the west.					
B_t : [hotel] area west ; price cheap S_t A_t^U : inform					
DB_t : match = 3; booking = available					
name	price	area	Stars	booking	
Avalon	cheap	west	4	available	[]
		•••			[]
$\begin{array}{l} A_t^{(1)} & [hotel] \ [inform] \ name \ [offerbook] \\ A_t^{(2)} & [hotel] \ [request] \ stars \\ A_t^{(3)} & [hotel] \ [recommend] \ name \ wifi \end{array}$					
$R_t^{(1)}$ The <v.name> is a great choice meet your criteria! Do you want me to book it for you? $R_t^{(2)}$ Sure! What star rating do you want? $R_t^{(3)}$ I would recommend the <v.name>! It is</v.name></v.name>					
π _t I wou			ue ∕v.n	ame>! It 1	s

MinTL



[hotel] stars 5 area centre day sunday [restaurant] food thai area centre day sunday name bangkok city <EOB> Can you help me book a 5 star hotel near the restaurant on the same day? <EOU>For how many people? <EOR>10 people <EOU>

<SOB>[hotel] people 10 <EOB>

<KB2> sorry, there are no matches. would you like to try another part of town? <EOR>



Slido: #ADL2021 Limitations of Vanilla Seq2Seq: Summary 52

- 1. Lack of diversity
- 2. Lack of consistency
- 3. Lack of knowledge
- 4. Lack of empathy
- 5. Lack of controllability
- 6. Lack of versatility
- 7. Lack of global optimization
- conversational AI?

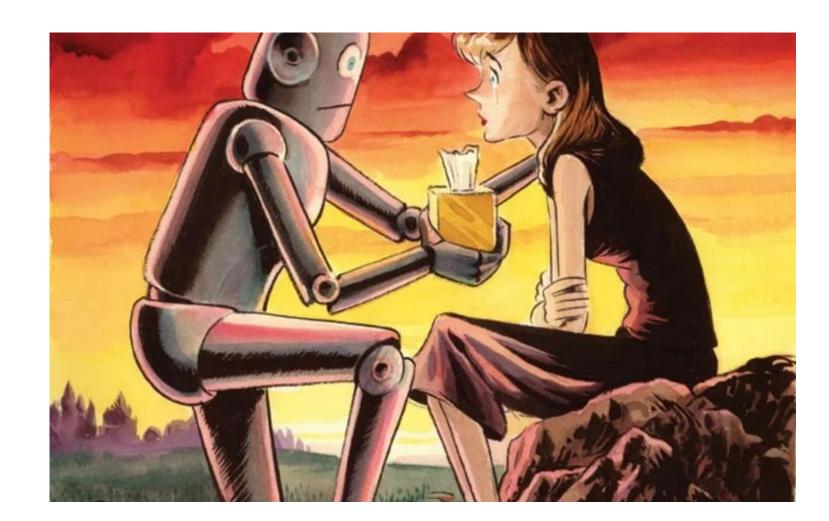
These limitations of vanilla seq2seq make human-machine conversations boring and shallow. How can we overcome these limitations and move towards deeper







<u>Human</u>: I messed up my project today. System: What is your project? <u>Human</u>: I think I might get fired... <u>System</u>: Then you need to find another job! Human:







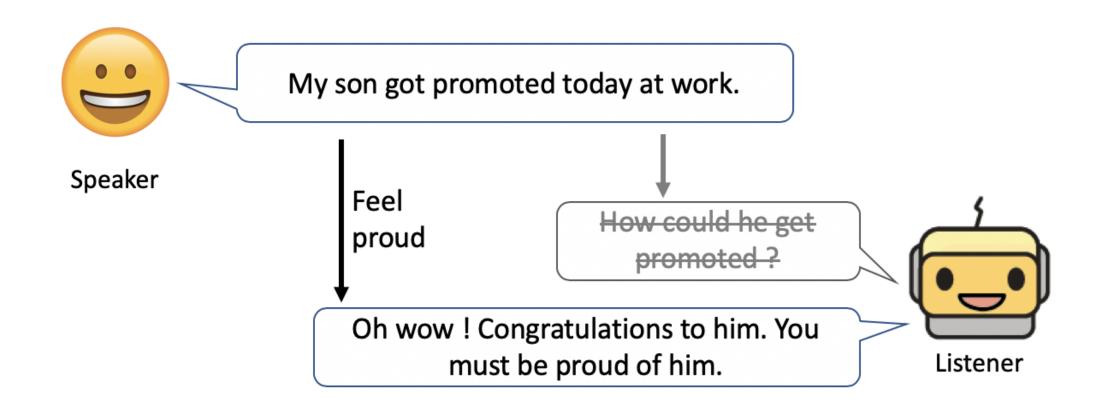
Solution: Empathic Generation

- 1. Emotional response generation:
 - <u>MojiTalk</u>
 - **Emotional Chatting Machine**
- 2. Understand user's emotion, and response accordingly:
 - **Empathetic Dialogues**
 - MoEL
 - Cairebot



55 Empathy Dataset

Empathy: understand the feelings of the conversation partner and replying accordingly.



Label: Afraid

Situation: Speaker felt this when...

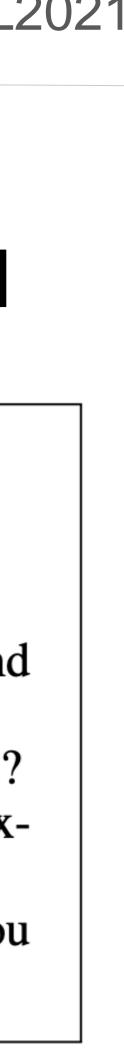
"I've been hearing noises around the house at night" **Conversation:**

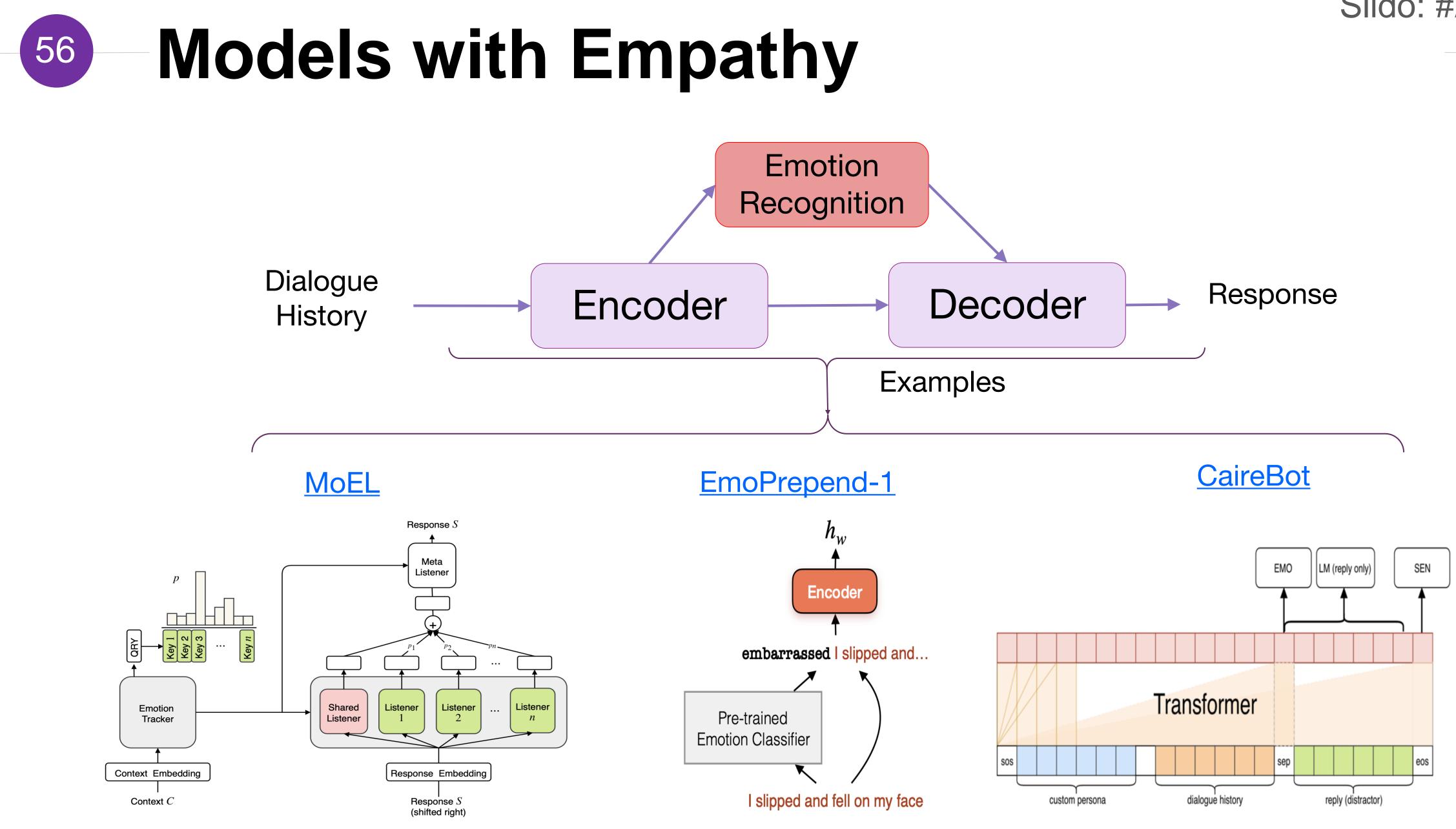
Speaker: I've been hearing some strange noises around the house at night.

Listener: oh no! That's scary! What do you think it is? Speaker: I don't know, that's what's making me anxious.

Listener: I'm sorry to hear that. I wish I could help you figure it out

Dataset: <u>Empathetic Dialogues</u>

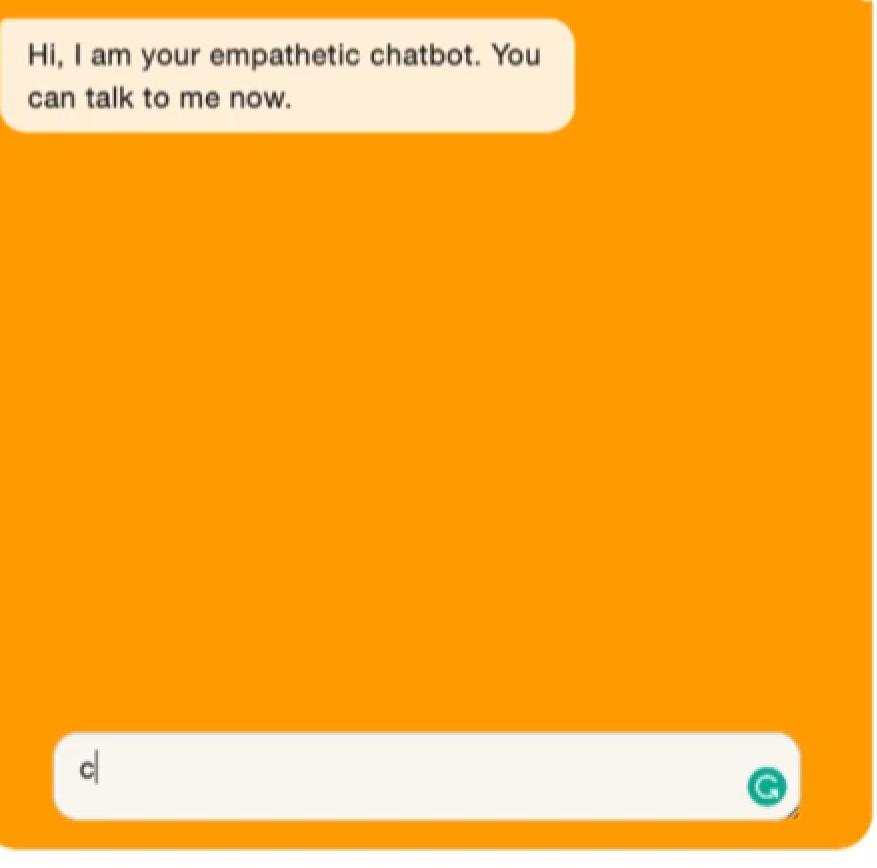






I'm CAiRE, the End-to-End Empathetic Chatbot

CAIRE is implemented by a fully data driven approach as described in this paper. Special acknowledgement to Huggingface for helpful discussions.



Please press the following button to report any ethical issue(s) encountered during the conversation:

Scenario: Happy



https://demo.caire.ust.hk/chatbot



Slido: #ADL2021 Limitations of Vanilla Seq2Seq: Summary 58

- 1. Lack of diversity
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- **5.** Lack of controllability
- 6. Lack of versatility
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- conversational AI?

These limitations of vanilla seq2seq make human-machine conversations boring and shallow. How can we overcome these limitations and move towards deeper



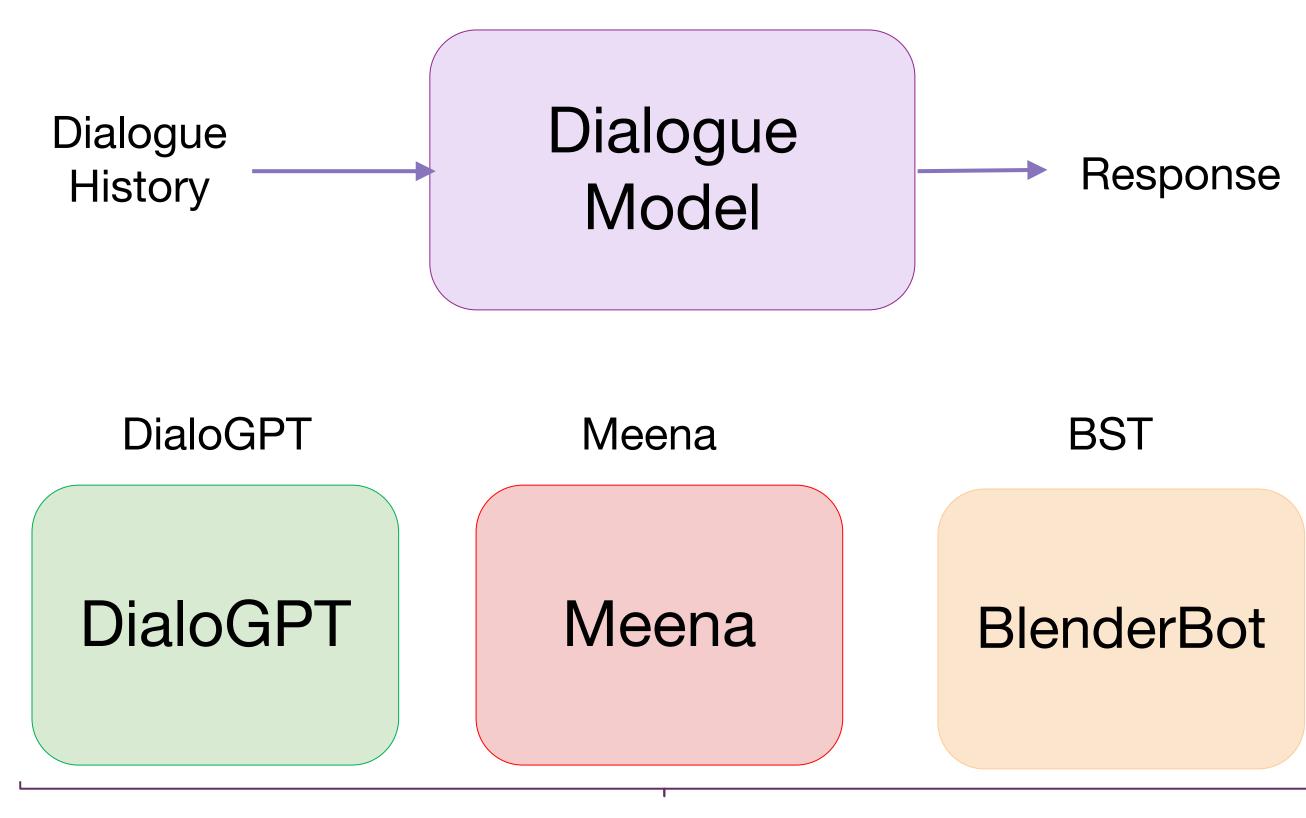


59 Limitation 5: Lack of Controllability

Existing large pre-trained model has no control over

- Response style
- Topics
 - Repetition and specificity
- Response-relatedness

Engagement by proactively asking question



Dialogue Pre-trained



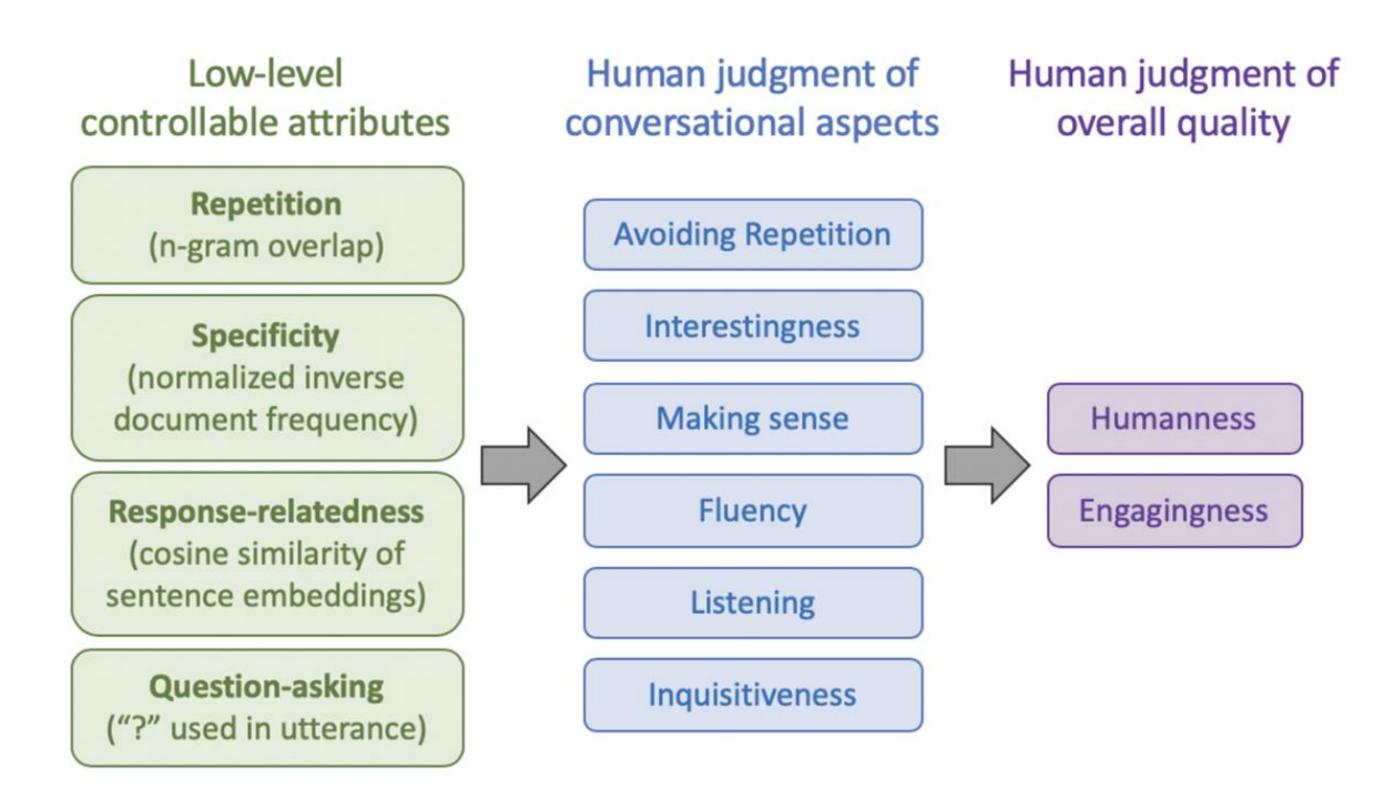


Solution: Controllability

- 1. Controlling low-level attribute
- 2. Controlling by fine-tuning
- 3. Controlling by perturbation
- Controlling by conditioned generation 4.



Controlling Low-Level Attribute 61



Conditional Training + Weight Decoding

What makes a good conversation? How controllable attributes affect human judgments (See et. al. 2019)







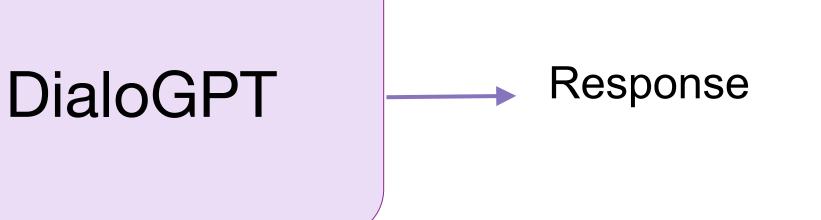


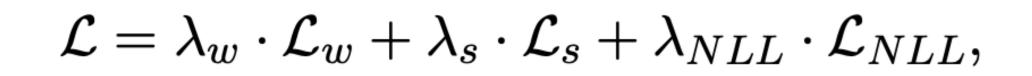
Multitask conversation data with style data

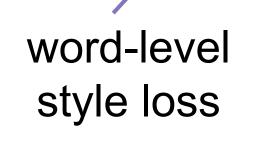
 \Rightarrow No control codes

STYLEDGPT: Stylized Response Generation with Pre-trained Language Models (Yang et. al. 2020)

Slido: #ADL2021





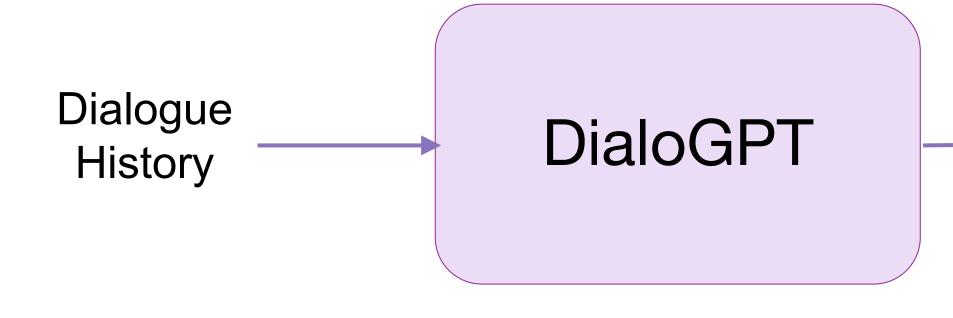


Sentence-level Style loss

Conversational data

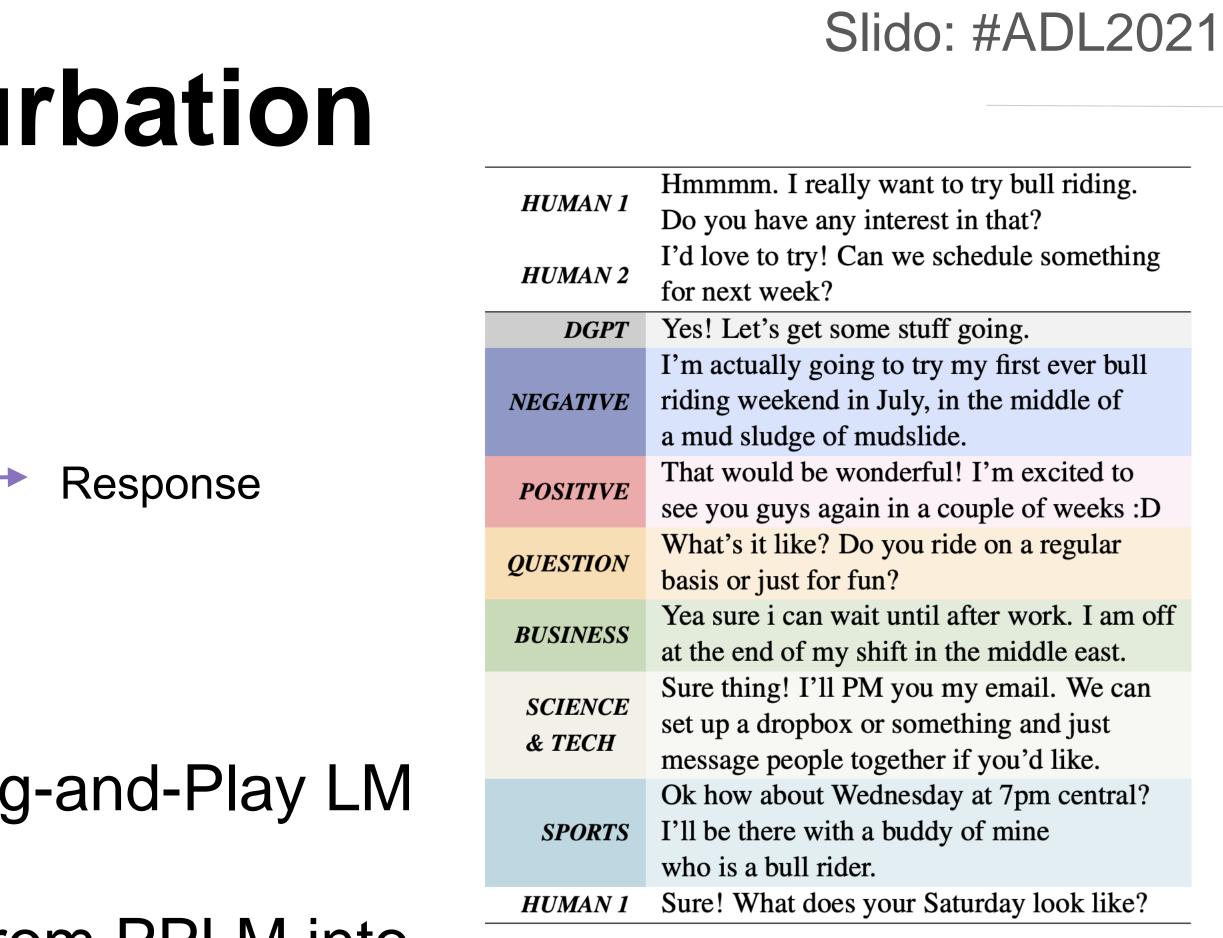


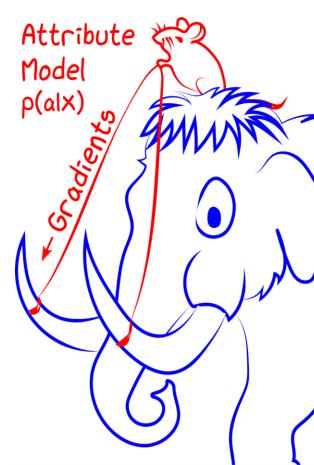




- Control the generated style with Plug-and-Play LM (PPLM) (Dathathri et. al. 2020)
- Distilling the generated responses from PPLM into residual adapter (<u>Houlsby et.al. 2019</u>)
- \Rightarrow Plug-and-Play for 3 style and 3 topic

Plug-and-Play Conversational Models (Madotto et. al. 2020)









Slido: #ADL2021 **Controlling by Conditioned Generation** 64

Controllable generation architectures in open-domain dialogues: retrieval + style-controlled generation (Weston et al. 2018)

- PPLM (Dathathri et. al. 2020)
- CTRL (Keskar et. al. 2019)

200 style labels in <u>ConvAl2</u>, <u>EmpatheticDialogues</u>, <u>Wizard of Wikipedia</u>, and **BlendedSkillTalk**) generated by a classifier trained on **Image-Chat**

Controlling Style in Generated Dialogue (Smith & Gonzalez-Rico et. al. 2020)



Slido: #ADL2021 Limitations of Vanilla Seq2Seq: Summary 65

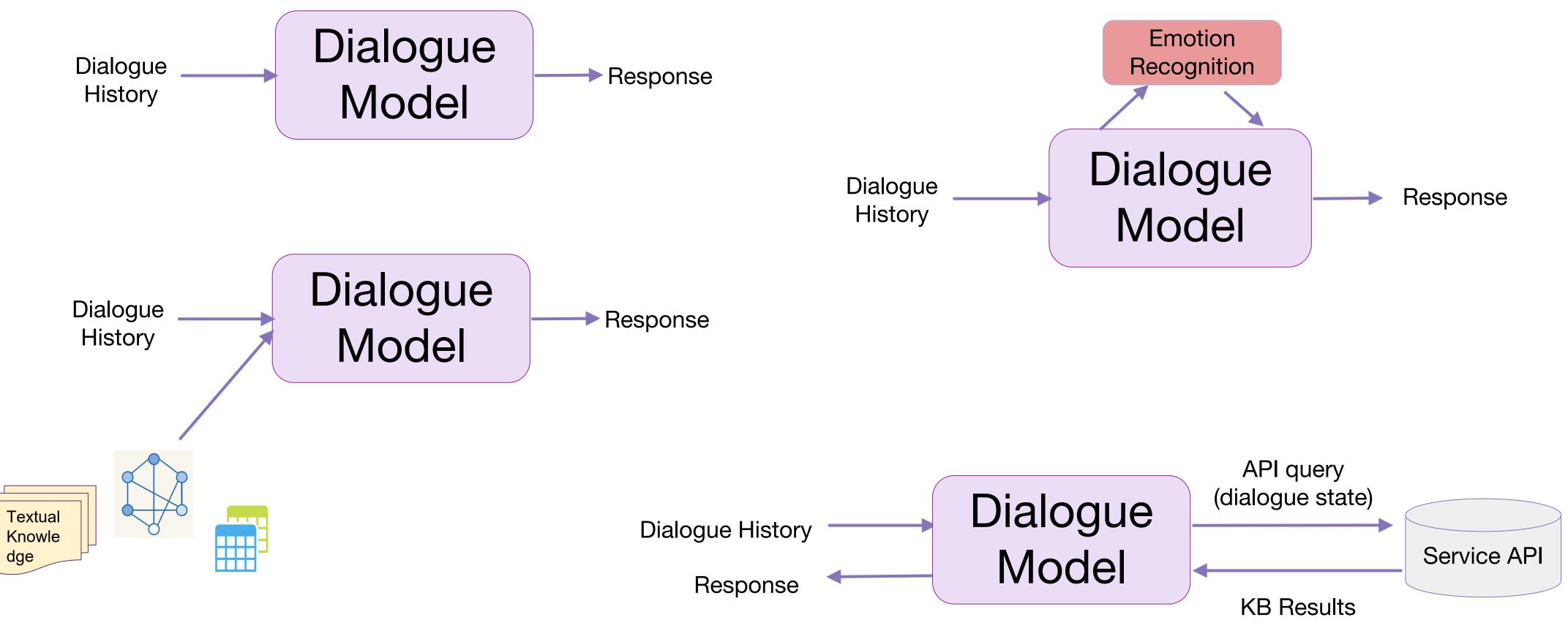
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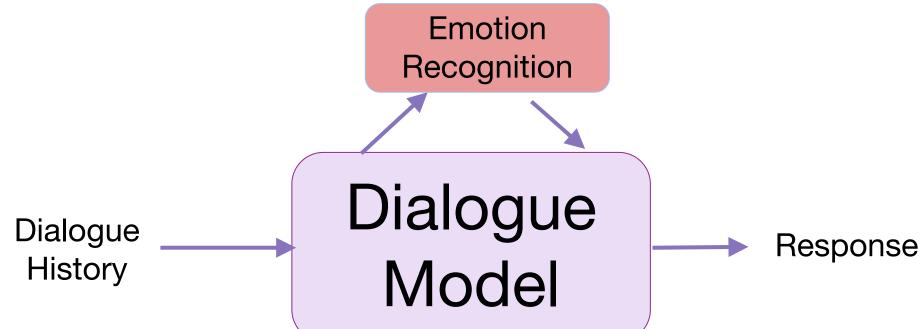
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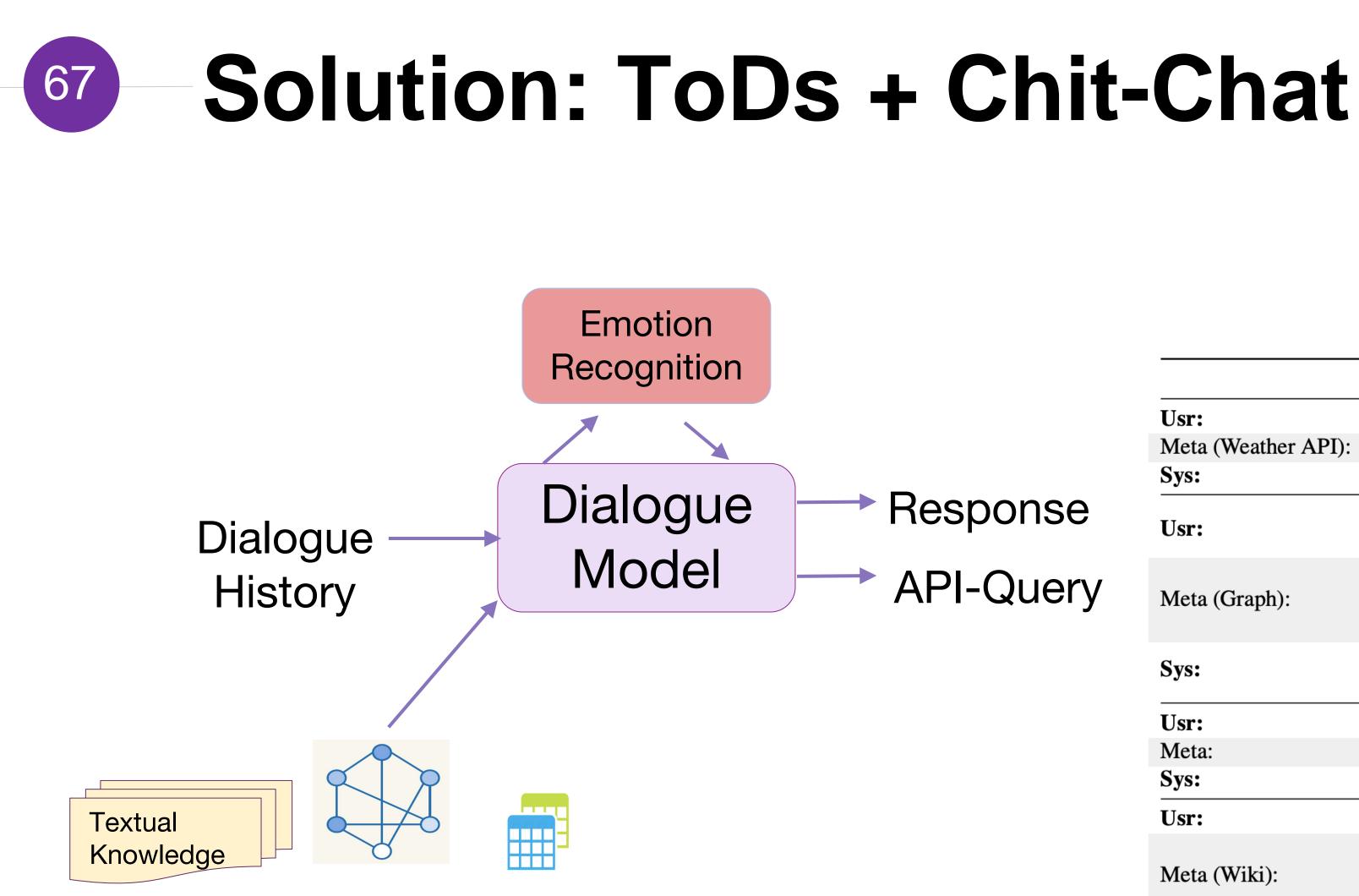












	Dialogue		
Usr:	What is the weather like today?		
Meta (Weather API):	{Weather : Sunny, High : 32 C, Low : 27 C}		
Sys:	Today's weather is sunny with temperature between 27-30 C.		
Usr:	Great, I plan to play basketball this afternoon! I am so excited after watched the match between Golden State Warriors and Houston Ro		
Meta (Graph):	(Golden State Warriors, is_a, Sports Team), (Steve Kerr, Team coached, Golden State Warriors), (Houston Rockets, is_a, Sports Team)		
Sys:	Golden State Warriors is a great basketball team. Steve Kerr is done an incredible job coaching all of that all-star talent.		
Usr:	Haha, you know a lot.		
Meta:	Ø		
Sys:	I try my best to be helpful.		
Usr:	Do you know NBA 2K19?		
	NBA 2K19 is a basketball simulation video game developed by		
Meta (Wiki):	Visual Concepts and published by 2K Sports, based on		
	the National Basketball Association.		
Sys:	Yes, NBA 2K19 is a basketball simulator video game.		





ToDs + Chit-Chat Datasets 68

- Mixing multiple dialogue datasets 1.
- 2. Multiple dialogue skills \Rightarrow Collecting dataset that mix skills
- **3.** Mixing Chit-Chat and ToDs \Rightarrow Collecting data from mixing the two



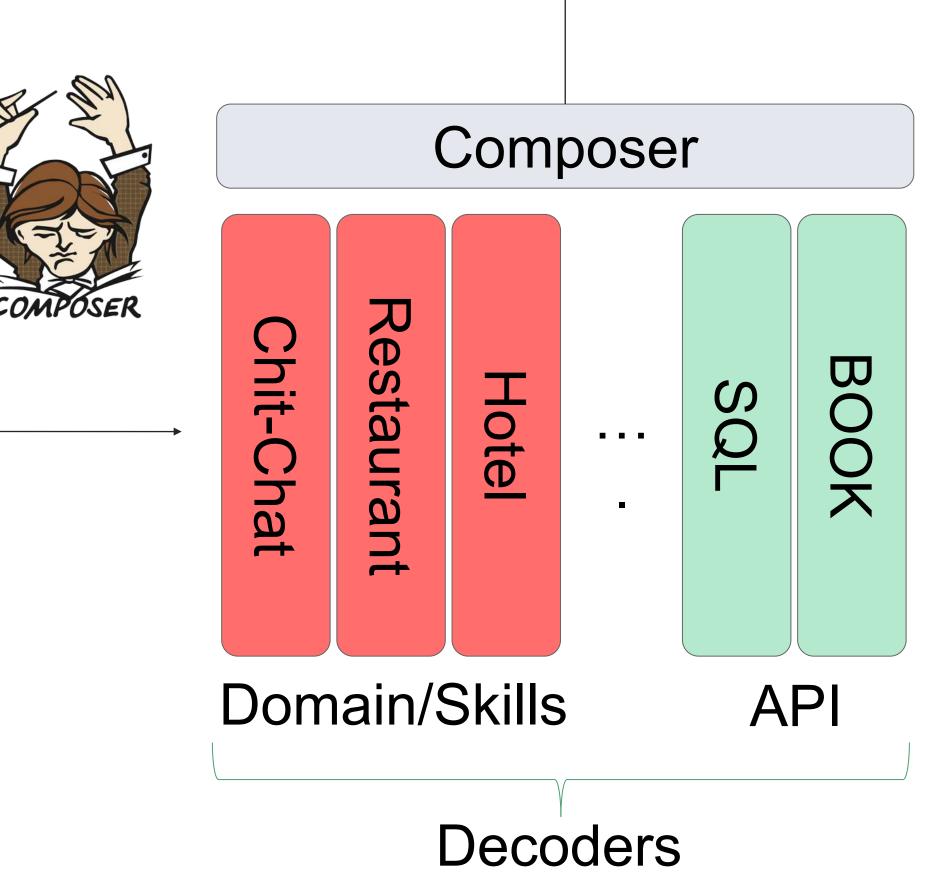




Encoder

Knowledge Base Persona **Dialogue History**



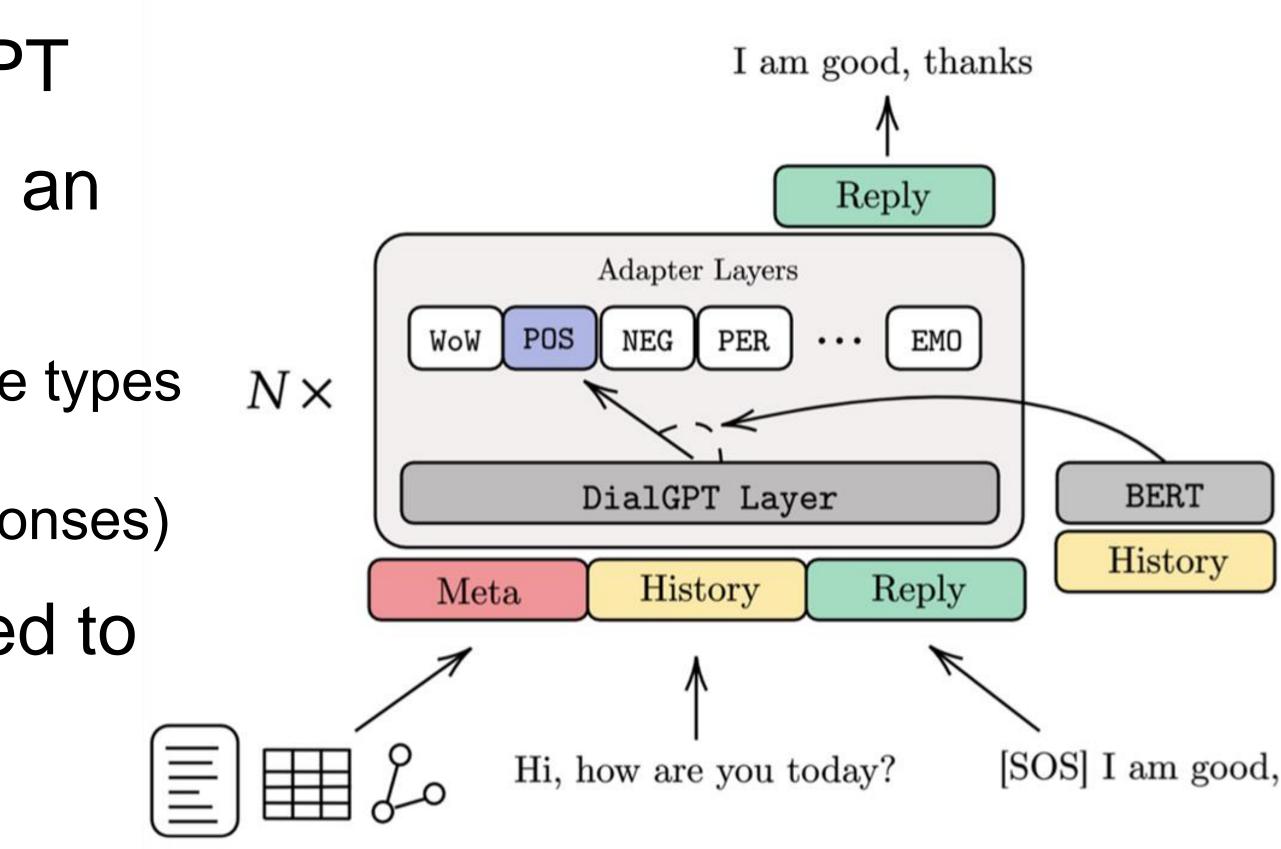






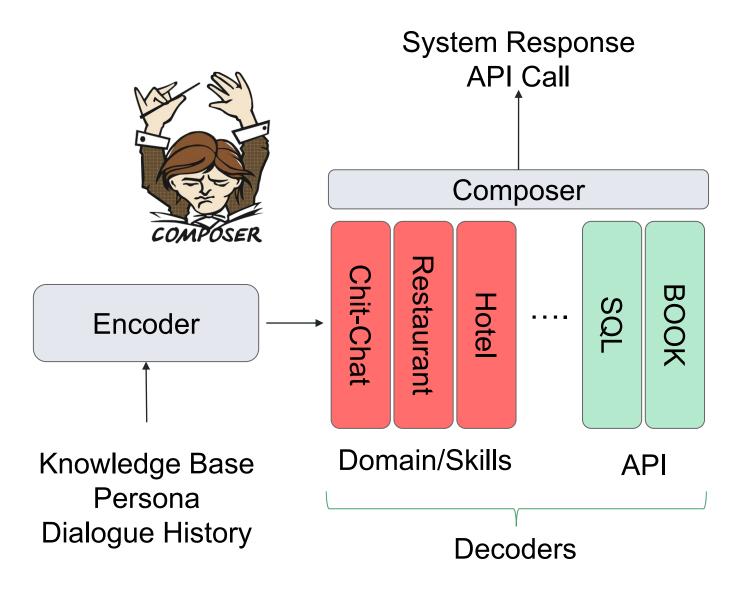
Slido: #ADL2021 Adapter-Bot: All-In-One Controllable Model

- Use a fixed backbone DialoGPT
- Encode each dialogue skill with an • independently trained <u>adapters</u>
 - able to process multiple knowledge types and styles (8 goal-oriented skills + personalized and empathetic responses)
- A skill manager, BERT, is trained to select each adapter







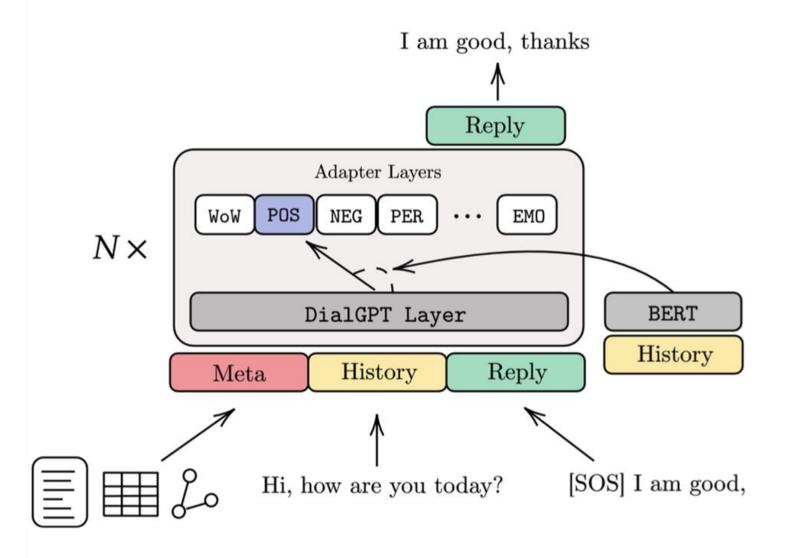


Recipes for building an open-domain chatbot (Roller et.al 2020)

Attention over Parameters for Dialogue Systems (Madotto et.al. 2019)

Slido: #ADL2021

Blender-bot



The Adapter-Bot: All-In-One **Controllable Conversational** Model (Lin & Madotto et.al. 2020)



Slido: #ADL2021 Limitations of Vanilla Seq2Seq: Summary 72

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- 6. Lack of versatility

7. Lack of global optimization

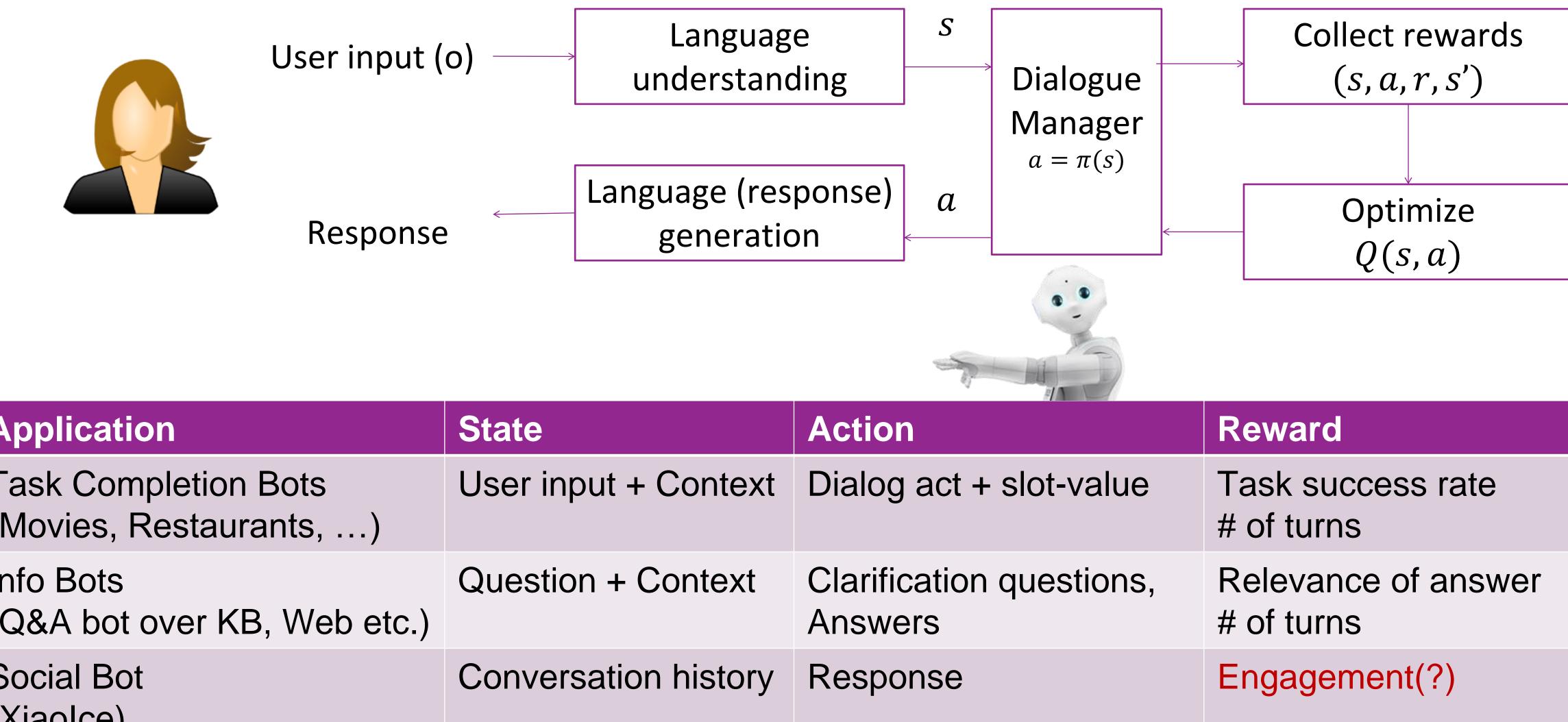
conversational AI?

These limitations of vanilla seq2seq make human-machine conversations boring and shallow. How can we overcome these limitations and move towards deeper









Application	State
Task Completion Bots (Movies, Restaurants,)	User input + Contex
Info Bots (Q&A bot over KB, Web etc.)	Question + Context
Social Bot (Xiaolce)	Conversation histor

Slido: #ADL2021 Limitation 7: Lack of Global Optimization





Solution: Deep RL for Optimization (Li et al., 2016)

Input message	Supervised Learning Agent	Reinforcement Learning Agent
How old are you ?	I'm 16.	I'm 16, why are you asking ?
What's your full name ?	I have no idea .	What's yours ?
I don't want to go home tonight.	Really ?	Why ?
Do you have any feelings for me?	I don't know what you are talking about.	I don 't want to hurt your feelings .
How much time do you have here?	Not long enough. Sorry, sir.	Ten seconds .
Shall we get started ?	Of course !	Yes. We've got a lot of work to do here.
Do you play football ?	No, i don't	Yes. I love football !
We'd have to talk to him.	I mean, he's a good guy	About what ?
How come you never say it?	Because I don't want to hurt you .	I don 't think it 's a good idea to say it.

RL agent generates more *interactive* responses

RL agent tends to end a sentence with a question and hand the conversation over to the user



Concluding Remarks

Limitations of vanilla seq2seq models

1. Lack of diversity

75

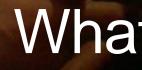
- 2. Lack of consistency
- Lack of knowledge 3.
- Lack of empathy 4.
- 5. Lack of controllability
- 6. Lack of versatility
- Lack of global optimization

Recent trends for addressing above limitations





Her (2013)



What can machines achieve now or in the future?

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