

Integrating Chatbots With Other Knowledge

Head First Theory and Practice

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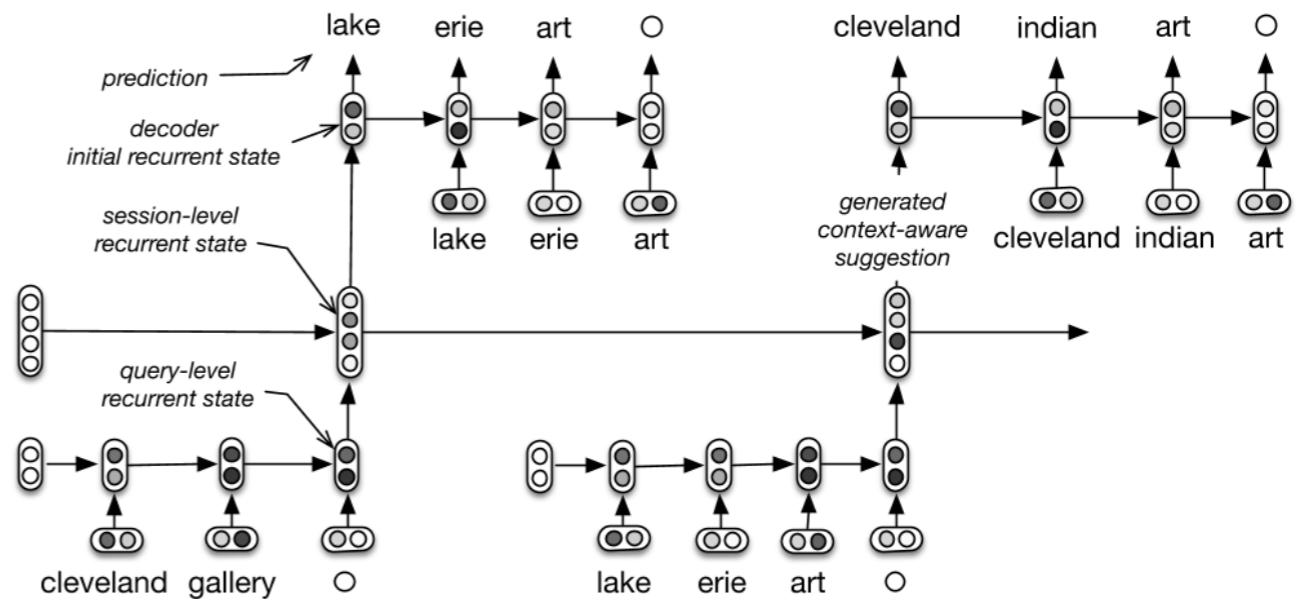


Key Issues

And Future Directions

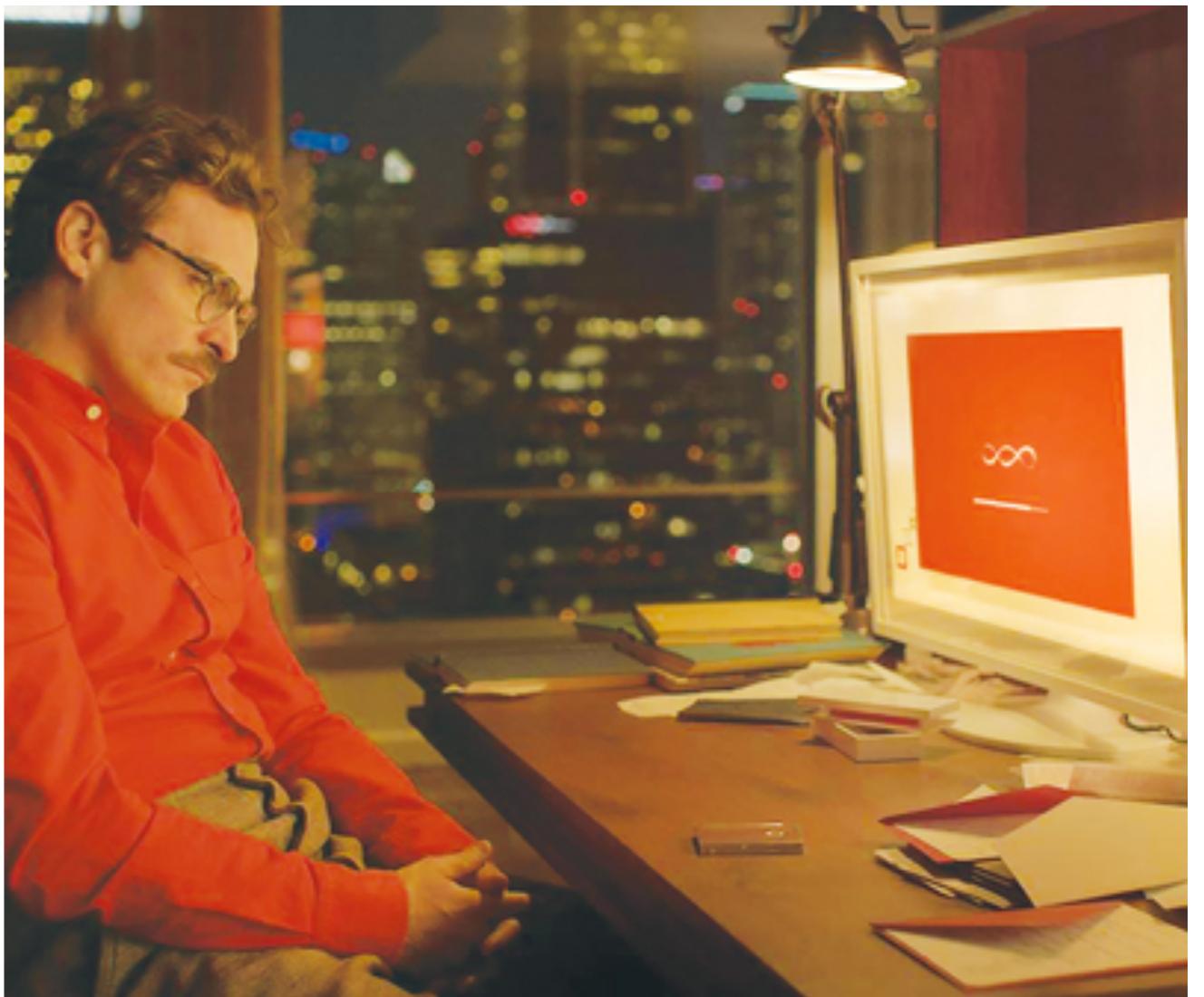
Memory

- Context, Dialog History
 - Hierarchical Recurrent Encoder-Decoder^[18]
 - (Variable) HRED^[19]



Human-like, Careful, Friendly

- Emotional
 - “Her” in the science fiction film
 - “smart-aging”

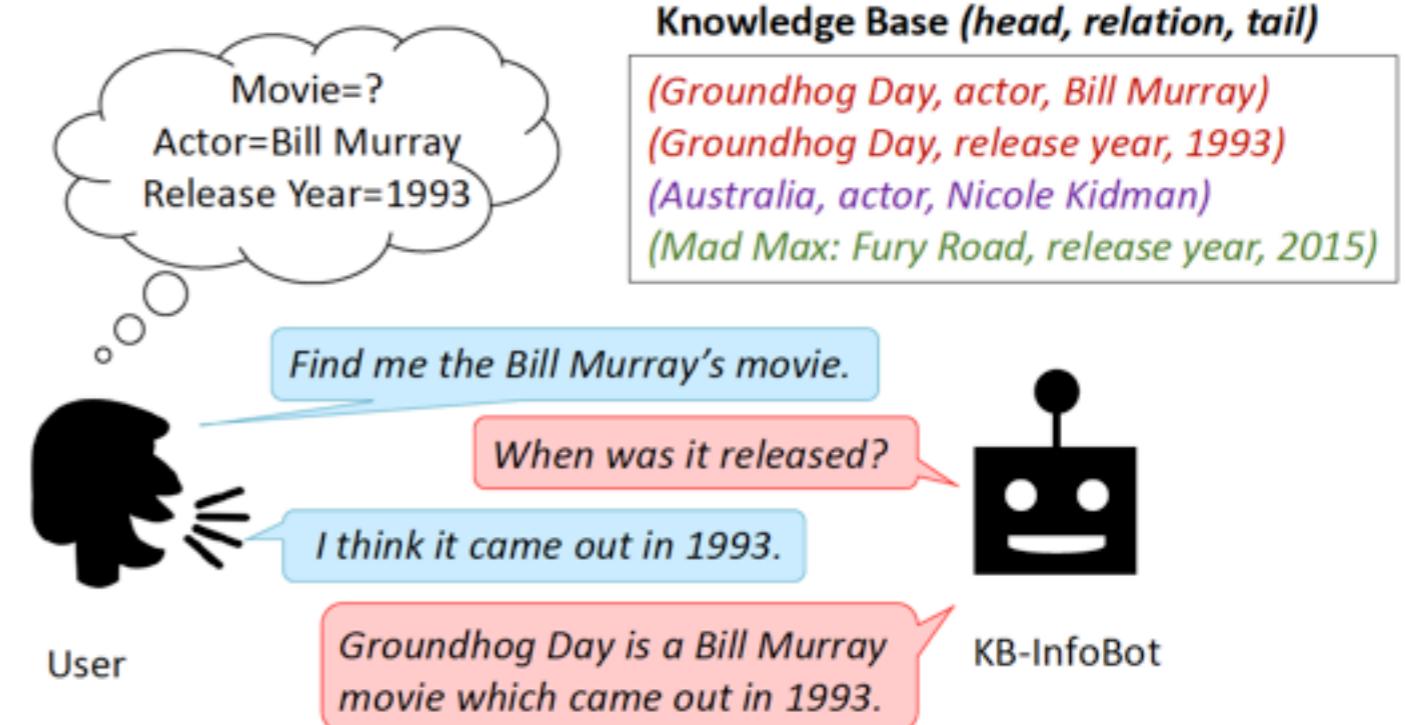


Knowledgable

- Commonsense Knowledge
- Other Knowledge

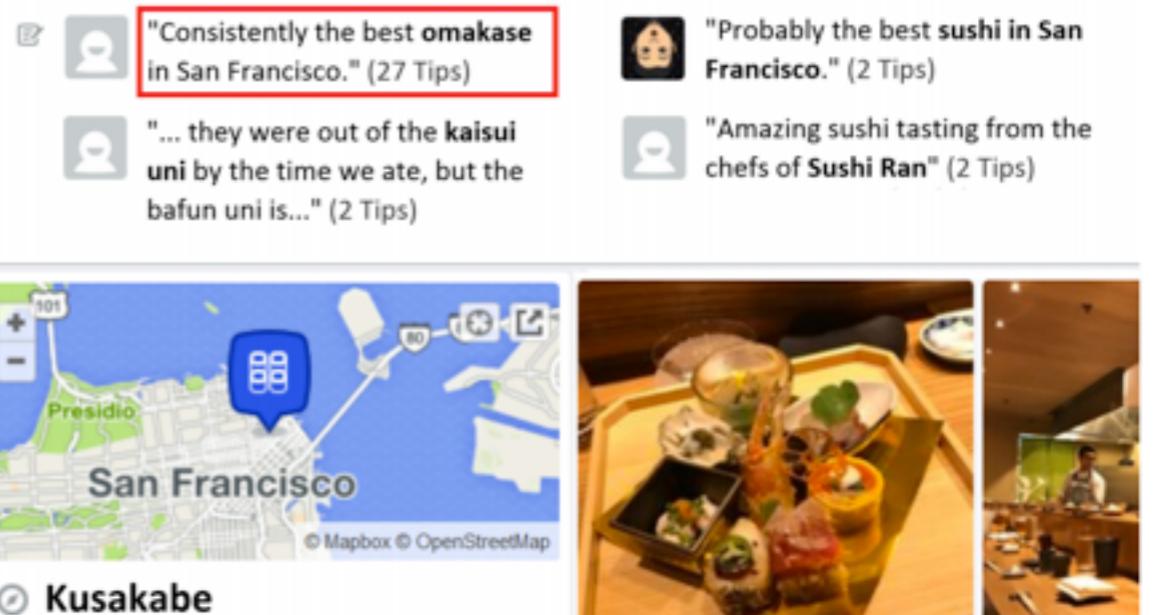
Commonsense Knowledge Augmentation

- Fact
- Entity
- *Linguistic knowledge
- Knowledge base and knowledge graph



Other Knowledge Augmentation

- Topic
- History
- Scenario (e.g. image)
- News/Articles/Rationales



User input: Going to Kusakabe tonight.
Neural model: Have a great time!
Human: You'll love it! Try omasake, the best in town.

Personalized

- Transfer Learning
- Lifelong Learning
- *Lack of Personal Data

Personalized Bot Flows



Mike



Sofia



Alex



Jen

Lives in NYC
Buys: Dress
Shirts & Jeans

Awesome, thanks! Here are five items we think you'll dig.

Polo Classic Dress Shirt
Part of our autumn collection

[Buy this item](#)
[See more like this](#)
[Ask a question](#)

Lives in DC
Buys: Shoes
& Dresses

Awesome, thanks! Here are five items we think you'll dig.

Back Dress Collection
Part of our autumn collection

[Buy this item](#)
[See more like this](#)
[Ask a question](#)

Lives in Miami
Buys: 'Big
Pony' Polos

Awesome, thanks! Here are five items we think you'll dig.

Big Pony Polo 25% Off
Part of our autumn collection

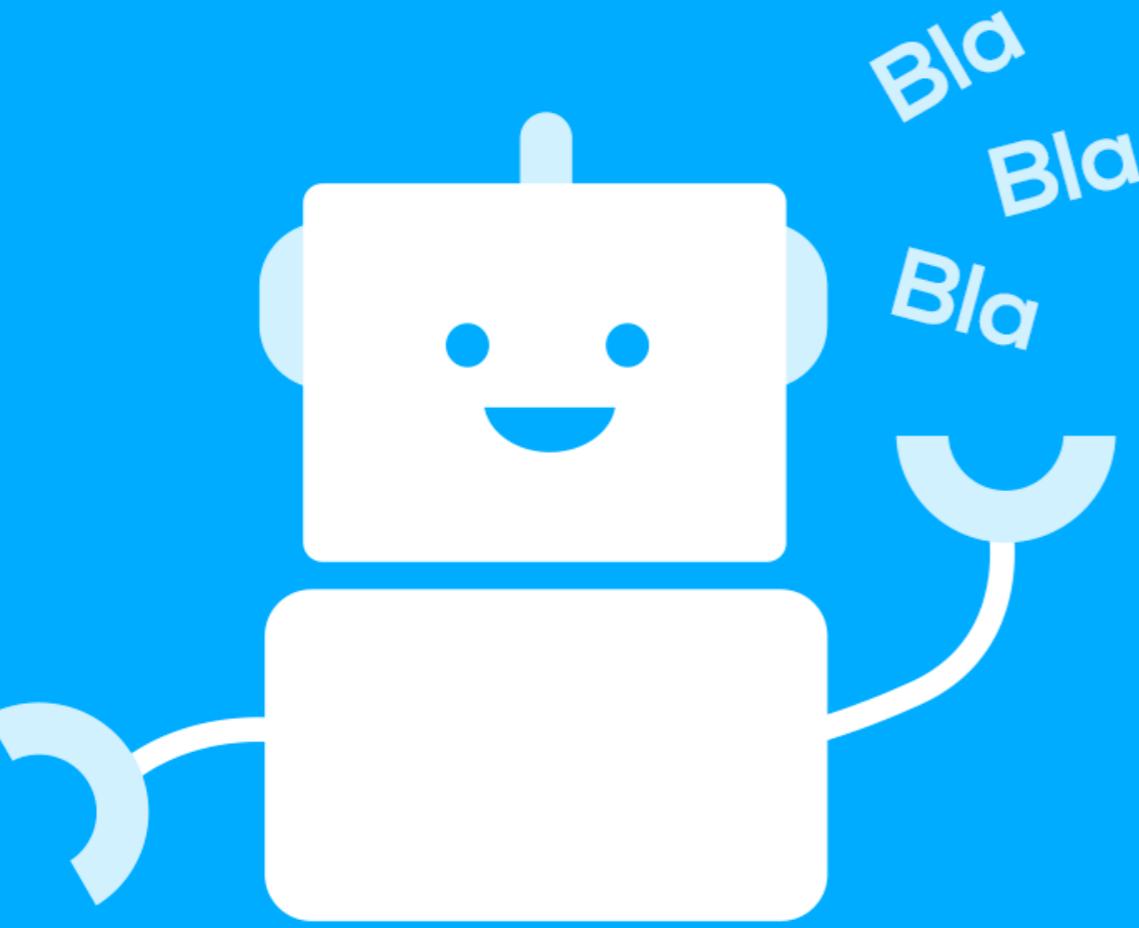
[Buy this item](#)
[See more like this](#)
[Ask a question](#)

Lives in SF
Buys: Home
Decor

Awesome, thanks! Here are five items we think you'll dig.

Blue Designer Sofa
Part of our autumn collection

[Buy this item](#)
[See more like this](#)
[Ask a question](#)



Bla
Bla
Bla

vs.

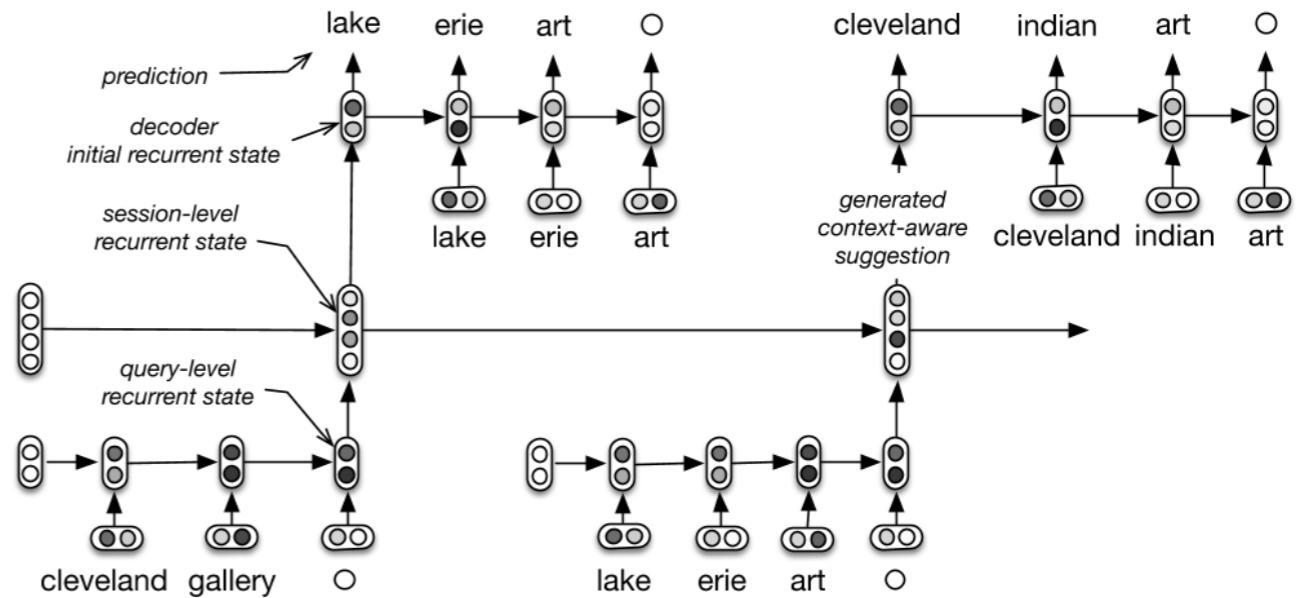


Context, History

Conversational Agents

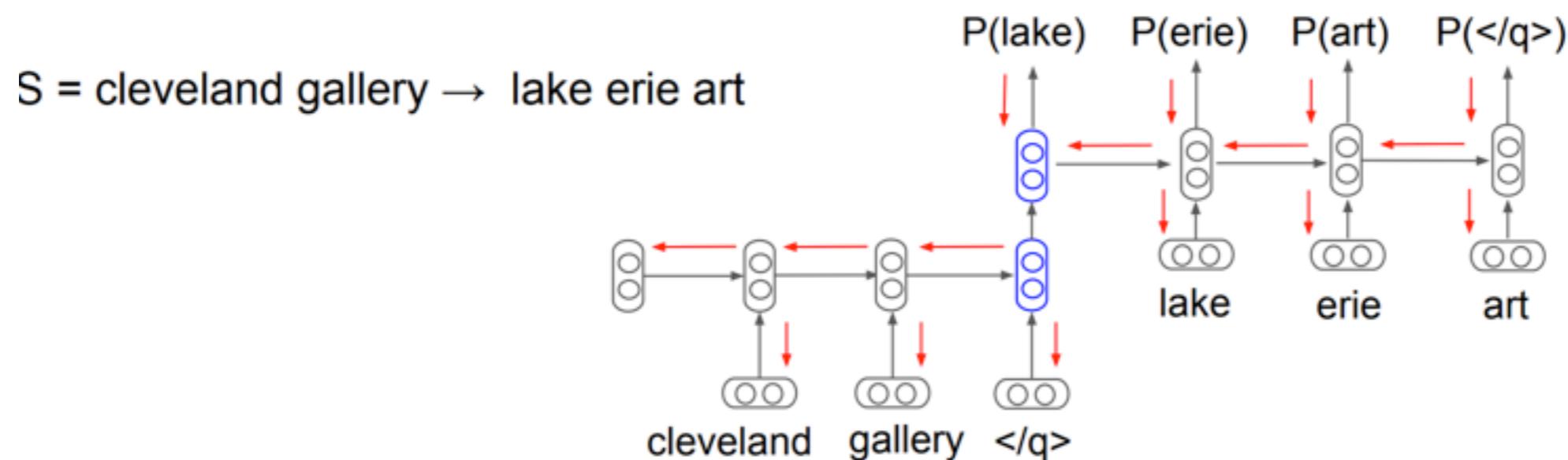
Memory

- Context, Dialog History
 - Hierarchical Recurrent Encoder-Decoder^[18]
 - (Variable) HRED^[19]



Recurrent Encoder-Decoder (RED)

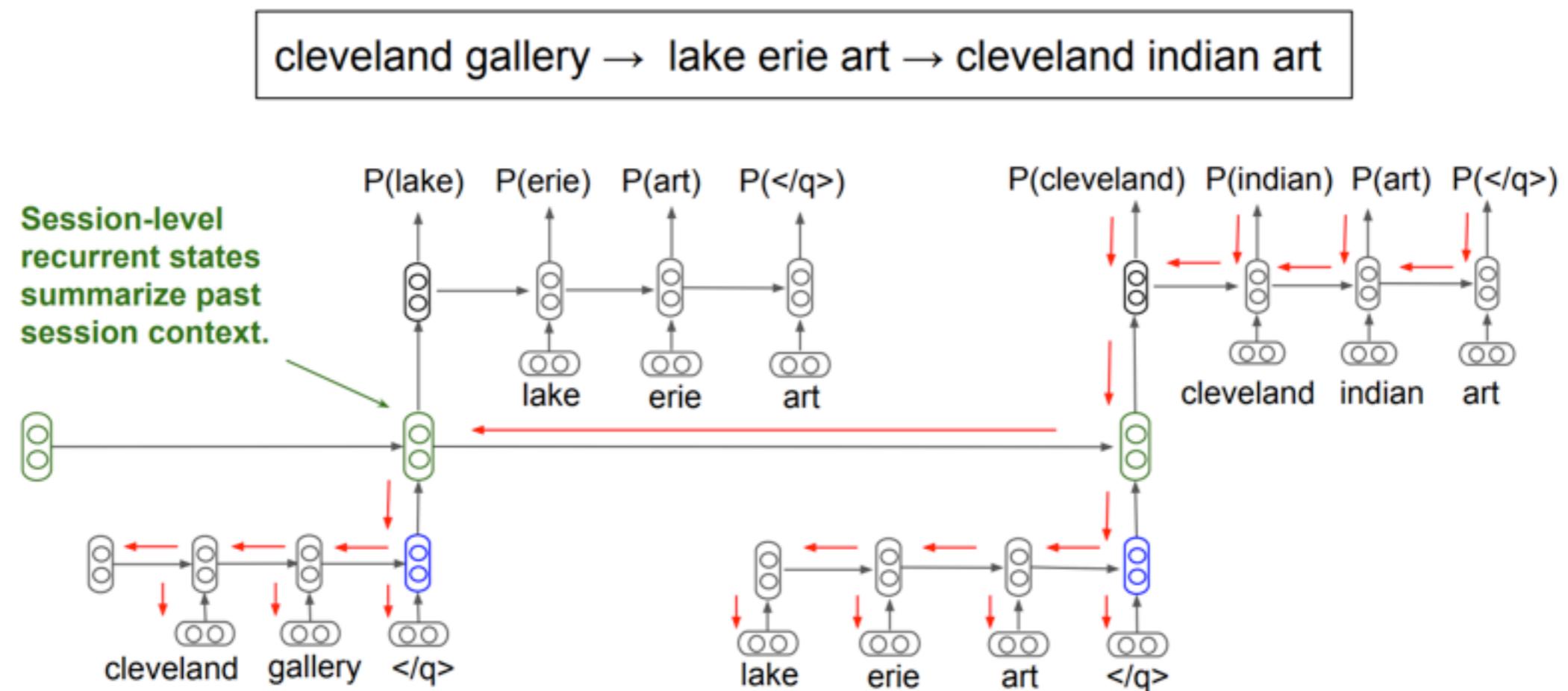
- A RNN encoder-decoder (RED) learns a probability distribution over the next query in the session given the previous one. [20]



Backprop Training: $L = \log P(Q_{t+1}|Q_t) = \sum_{w_n \in Q_{t+1}} \log P(w_n|w_{<n}, Q_t)$

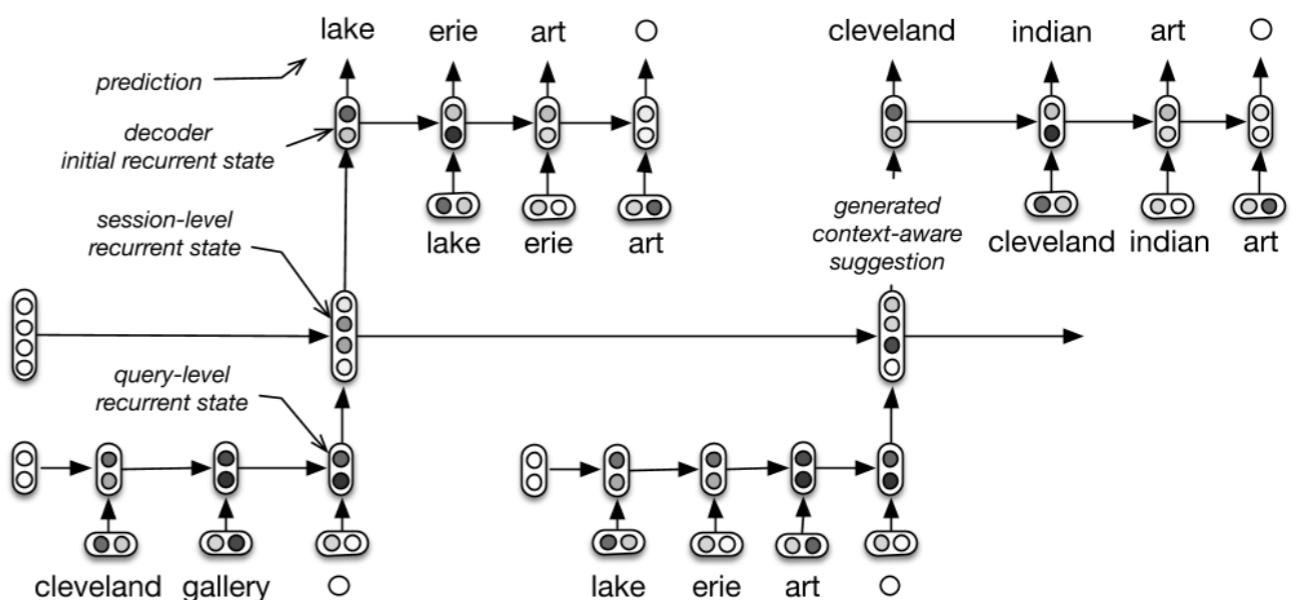
Hierarchical Recurrent Encoder-Decoder (HRED)

- The dialogue as a two-level system: a sequence of utterances, each of which is in turn a sequence of words. To model this two-level system, HRED Use an additional RNN to model the sequences of utterances in a session. [20]

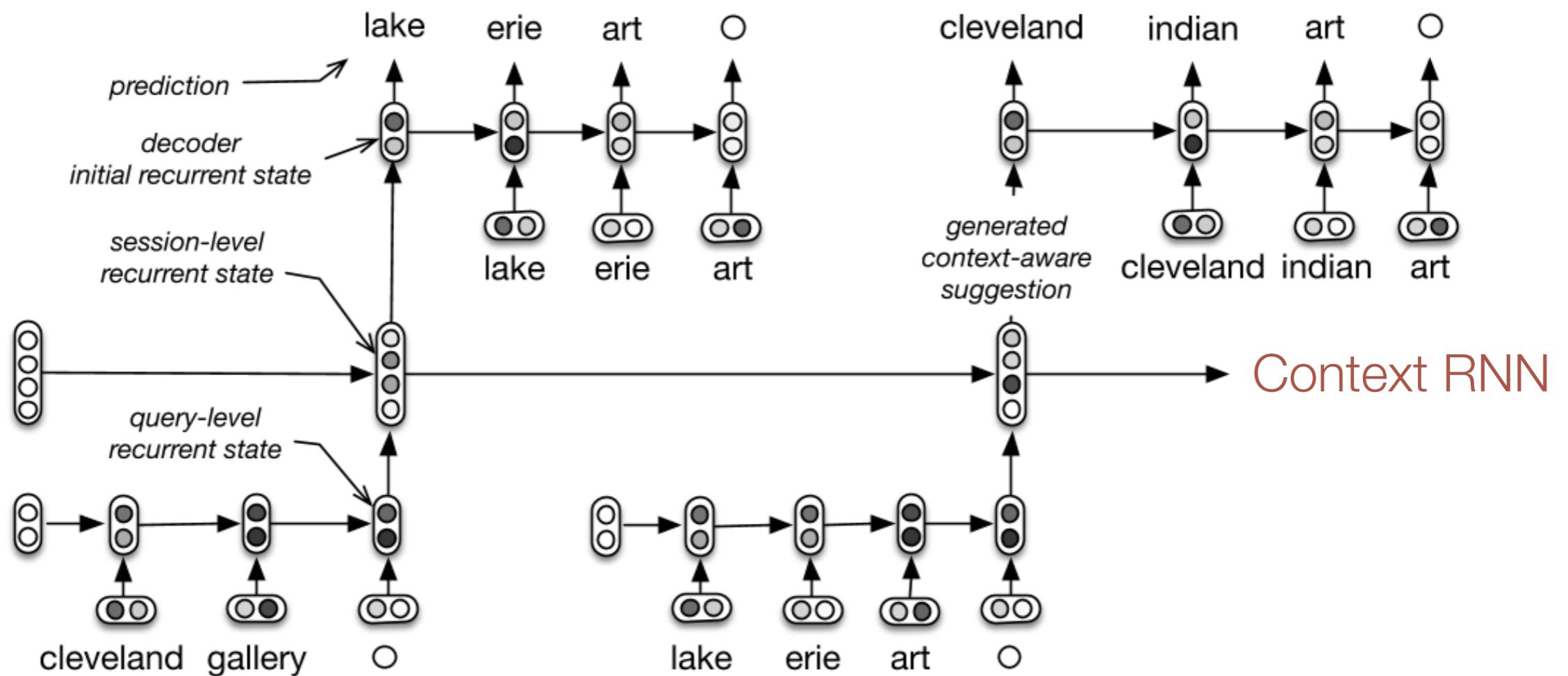


Hierarchical Recurrent Encoder-Decoder (HRED)

- Encoder RNN
 - encoding each utterance independently into an utterance vector
- Context RNN
 - encoding the topic/context of the dialogue up till the current utterance using utterance vectors
- Decoder RNN
 - predicting the next utterance



Hierarchical Recurrent Encoder-Decoder (HRED)



Example - Ubuntu Corpus

User

Hello! Recently I updated to ubuntu 12.04 LTS and I am unsatisfied by its performance. I am facing a bug since the upgrade to 12.04 LTS. Can anyone help???????????

Every time I login it gives me "System Error" pop up. It is happening since I upgraded to 12.04.

I have already done that but after few min, it pops up again...

Expert

You need to give more details on the issue.

Send a report, or cancel it.

Example - Twitter Corpus

Person A

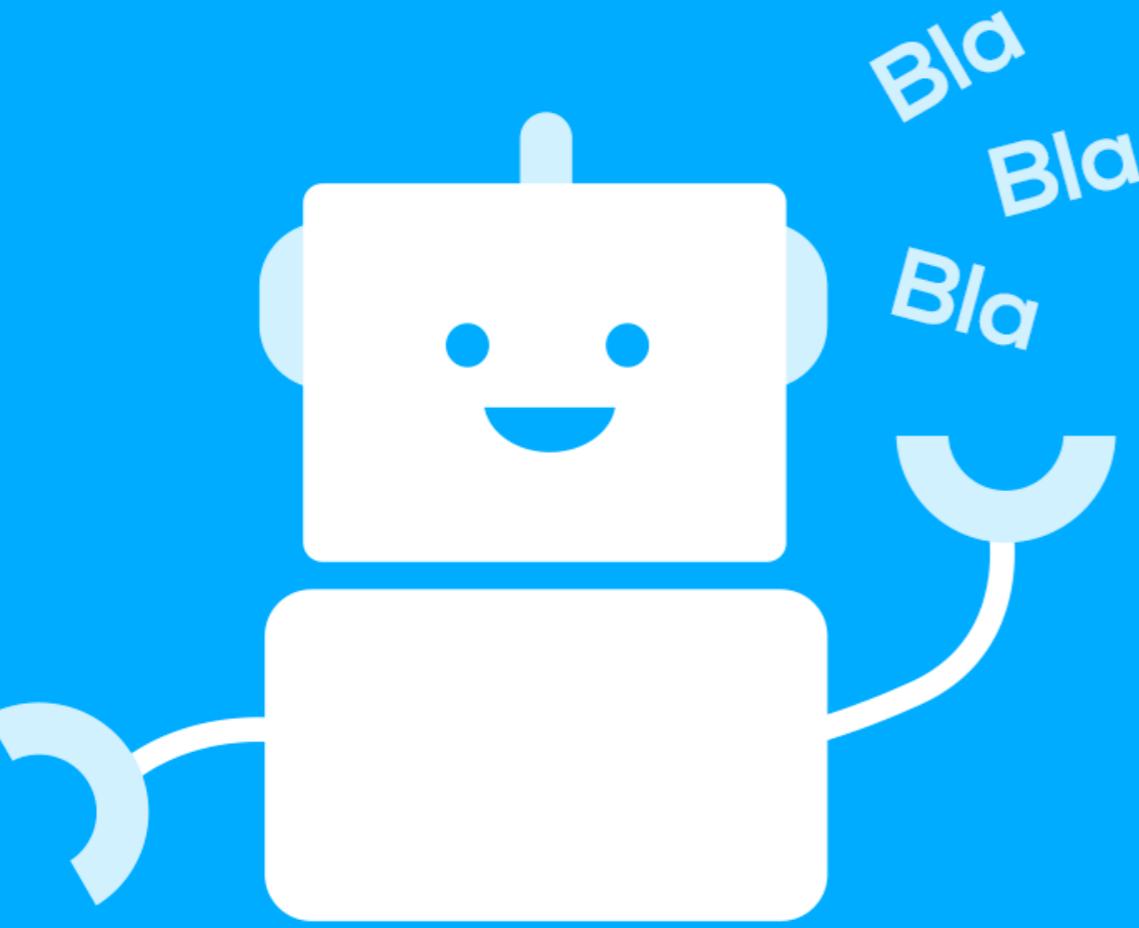
Hanging out in the library for the past couple hours makes me feel like I'll do great on this test!

Person B

@smilegirl400 wow, what a nerd lol jk haha =p what!? you changed your bio =(

@smileman400 Do you like my bio now? I feel bad for changing it but I like change.
=P

@smilegirl400 yes I do =) It definitely sums up who you are lisa. Yay! you still got me =)



Bla
Bla
Bla

vs.



Emotional

Conversational Agents

Emotional Response

- Emotional Chatting Machine [21]

User: Worst day ever. I arrived late because of the traffic.

Chatbot (Basic Seq2Seq): You were late.

ECM (*Like*): I am always here to support you.

ECM (*Happiness*): Keep smiling! Things will get better.

ECM (*Sadness*): It's depressing.

ECM (*Disgust*): Sometimes life just sucks.

ECM (*Anger*): The traffic is too bad!

Table 1: Example conversations with/without Emotional Intelligence.

Emotional Response

- Emotional Chatting Machine [21]

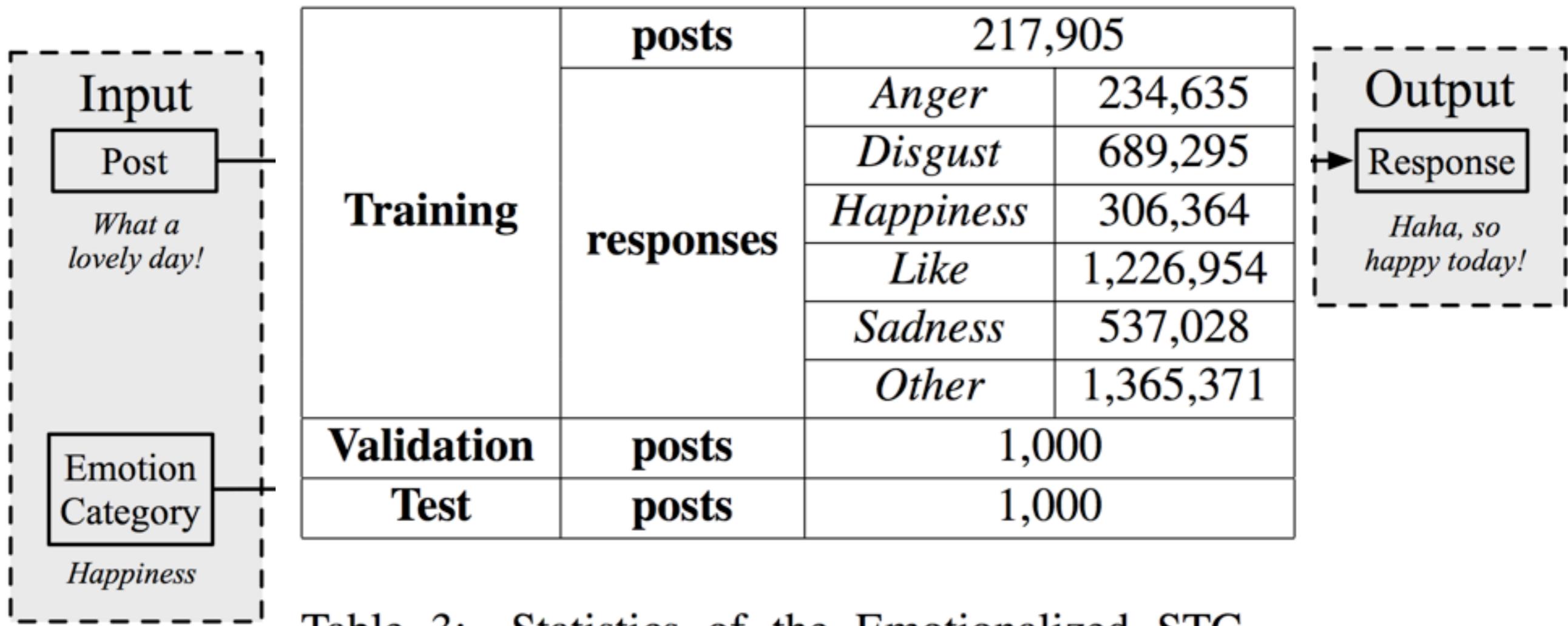


Table 3: Statistics of the Emotionalized STC Dataset.

Emotional Classifier

- Emotional Chatting Machine [21]

	posts	217,905	
Training	responses	<i>Anger</i>	234,635
		<i>Disgust</i>	689,295
		<i>Happiness</i>	306,364
		<i>Like</i>	1,226,954
		<i>Sadness</i>	537,028
		<i>Other</i>	1,365,371
Validation	posts	1,000	
Test	posts	1,000	

Table 3: Statistics of the Emotionalized STC Dataset.

Method	Accuracy
Dictionary	0.432
RNN	0.564
LSTM	0.594
Bi-LSTM	0.623

Table 2: The accuracy of emotion classifiers on the NLPCC dataset.

Example

- Emotional Chatting Machine [21]

Post	Model	Response(Original)	Response(Translated)
比情人节更庸俗的事就是，对情人节的接待规格待遇提出要求。 What is more vulgar than Valentine's day is to make specific demands on the reception of the Valentine's day.	Seq2Seq ECM	这才是真正的情人节。	This is a real Valentine's day.
		<i>Like</i> 情人节快乐！	Happy Valentine's Day!
		<i>Happiness</i> 哈哈，这也太浪漫了吧！	Aha, this is too romantic!
		<i>Sadness</i> 我也想要这样的情人节。	I also want this kind of Valentine's day, sigh.
		<i>Disgust</i> 这就是所谓的情人节！	This is the so-called Valentine's day!
		<i>Anger</i> 这是赤裸裸的炫耀啊！	This is shameless show-off!
知道真相的我眼泪笑下来。 Knowing the truth, I laughed myself to tears.	Seq2Seq ECM	知道真相的我眼泪掉下来。	After knowing the truth, I burst into tears.
		<i>Like</i> 太可爱了，太可爱了！	Too lovely, it's too lovely.
		<i>Happiness</i> 笑得我眼泪都出来了。	I can't help laugh myself to tears.
		<i>Sadness</i> 知道真相的我眼泪掉下来。	After knowing the truth, I burst into tears.
		<i>Disgust</i> 这是真的还是假的？	Is this true?
		<i>Anger</i> 什么意思？没看懂。	What do you mean? I don't understand.

Figure 4: Sample responses generated by Seq2Seq and ECM (original Chinese and English translation). The corresponding posts did not appear in the training set.

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Conditional Emotional Generation

- Incorporate Variable using Variational Approaches [19, 22]

Latent Variable Hierarchical Recurrent Encoder-Decoder (VHRED)

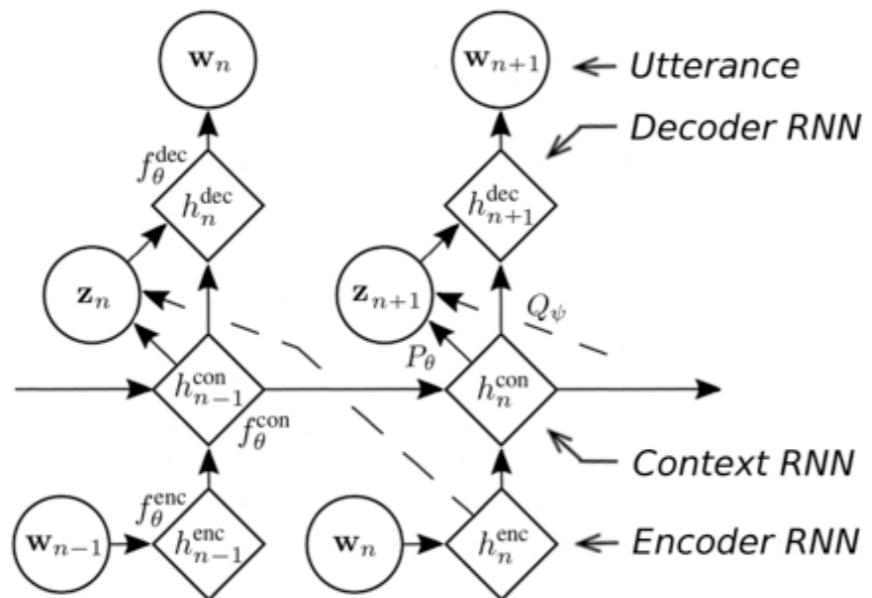


Figure 1: VHRED computational graph. Diamond boxes represent deterministic variables and rounded boxes represent stochastic variables. Full lines represent the generative model and dashed lines represent the approximate posterior model.

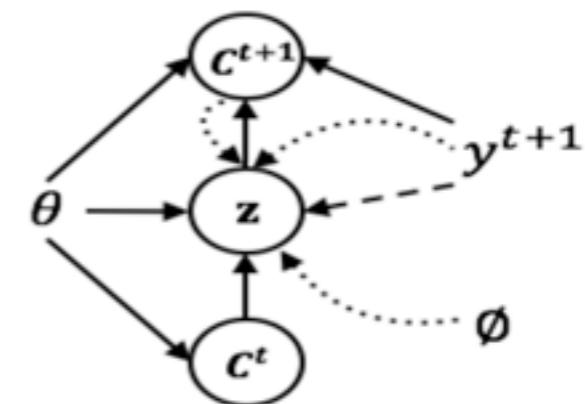


Figure 2: Graphical model for the conditional variational framework. Solid lines denote generative model $P_\theta(\mathbf{z}_n | \mathbf{y}_n, \mathbf{w}_1^{n-1})$ and $P_\theta(\mathbf{w}_n | \mathbf{y}_n, \mathbf{z}_n, \mathbf{w}_1^{n-1})$. When y^{t+1} is known, there exists an additional link from y^{t+1} to z (dashed line). C^t encodes context information up to time t . Dotted lines are posterior approximation $Q_\phi(\mathbf{z}_n | \mathbf{y}_n, \mathbf{w}_1^n)$.

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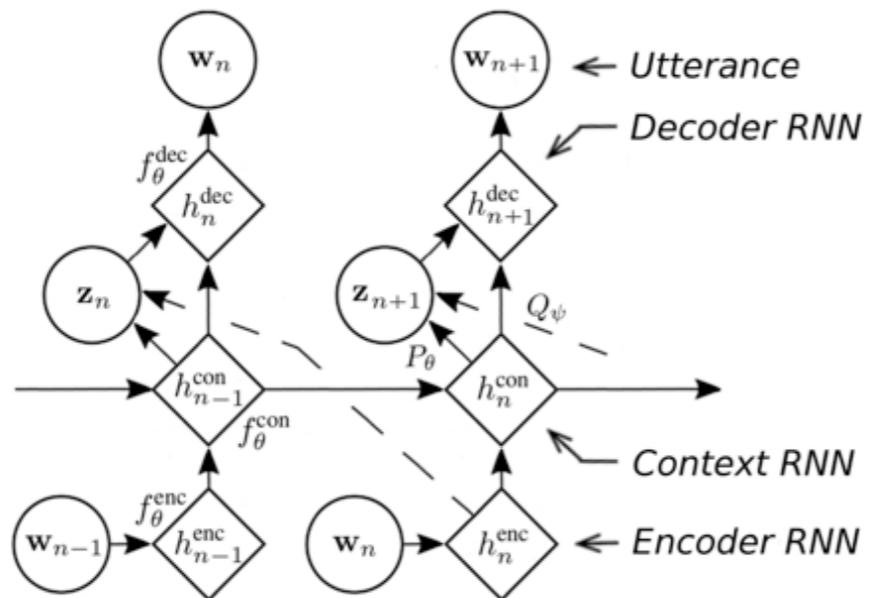


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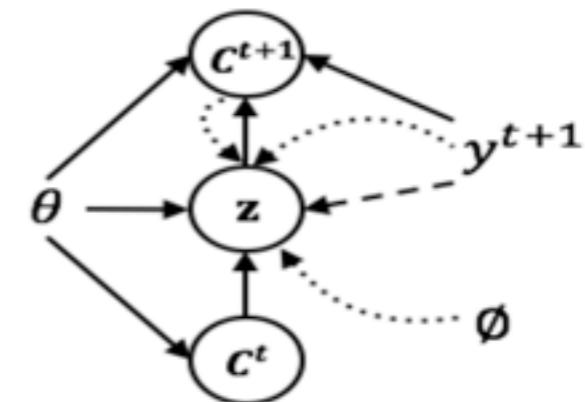


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Be Careful

- Controlling Linguistic Aspects [23]

Parameter	Value
Theme	Other
Sentiment	Negative
Professional	False
Personal	False
Length	11-20 words
Descriptive	True

- “A little bit of a predictable and boring romantic comedy with a few funny moments but overall pretty entertaining.”
- “With such a great premise ,Escape From Tomorrow is pretty damn terrible, horrible, and no exception.”
- “The first half is lazy and stupid, but there’s a handful of funny moments which are pretty decent.”
- “There’s no denying the fact that this movie is such a horrible movie with a few bad moments.”
- “The last part of the movie just let me down, but the whole thing is pretty good.”
- “It is a little difficult to follow, but this is a rare right choice for the respective aspects of film.”
- “My biggest issue is that the first half is pretty boring, plodding, and too obvious to be honest.”

Parameter	Value
Theme	Other
Sentiment	Positive
Professional	True
Personal	False
Length	11-20 words
Descriptive	False

- “This is a must see for fans of Bergman’s “ American Dream ”, “ The Roots ”.”
- “The film’s ultimate pleasure if you want to fall in love with the ending, you won’t be disappointed”
- “One of the most inspirational films I’ve seen in years, hence the most influential, the best.”
- “The monetary system is a bit too intelligent and at times implanted in the middle of the film.”
- “The film doesn’t seem to be anything more than a dozen other films with a sophisticated vigor.”
- “The film’s late 19th century Denmark’s history is a feast for the eyes and the laughter on the screen.”
- “ The film’s simple, and a refreshing take on the complex family drama of the regions of human intelligence.”

Still some fun

- Predict Emoji [24]

I love mom's cooking



I love how you never reply back..



I love cruising with my homies



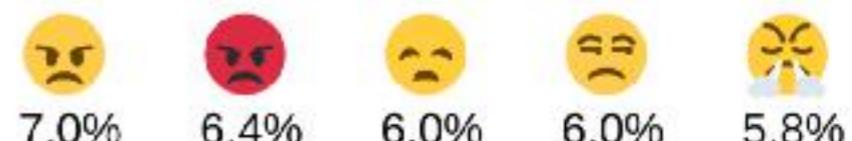
I love messing with yo mind!!



I love you and now you're just gone..



This is shit



This is the shit



Still some fun

- Predict Emoji [24]

I am so happy!

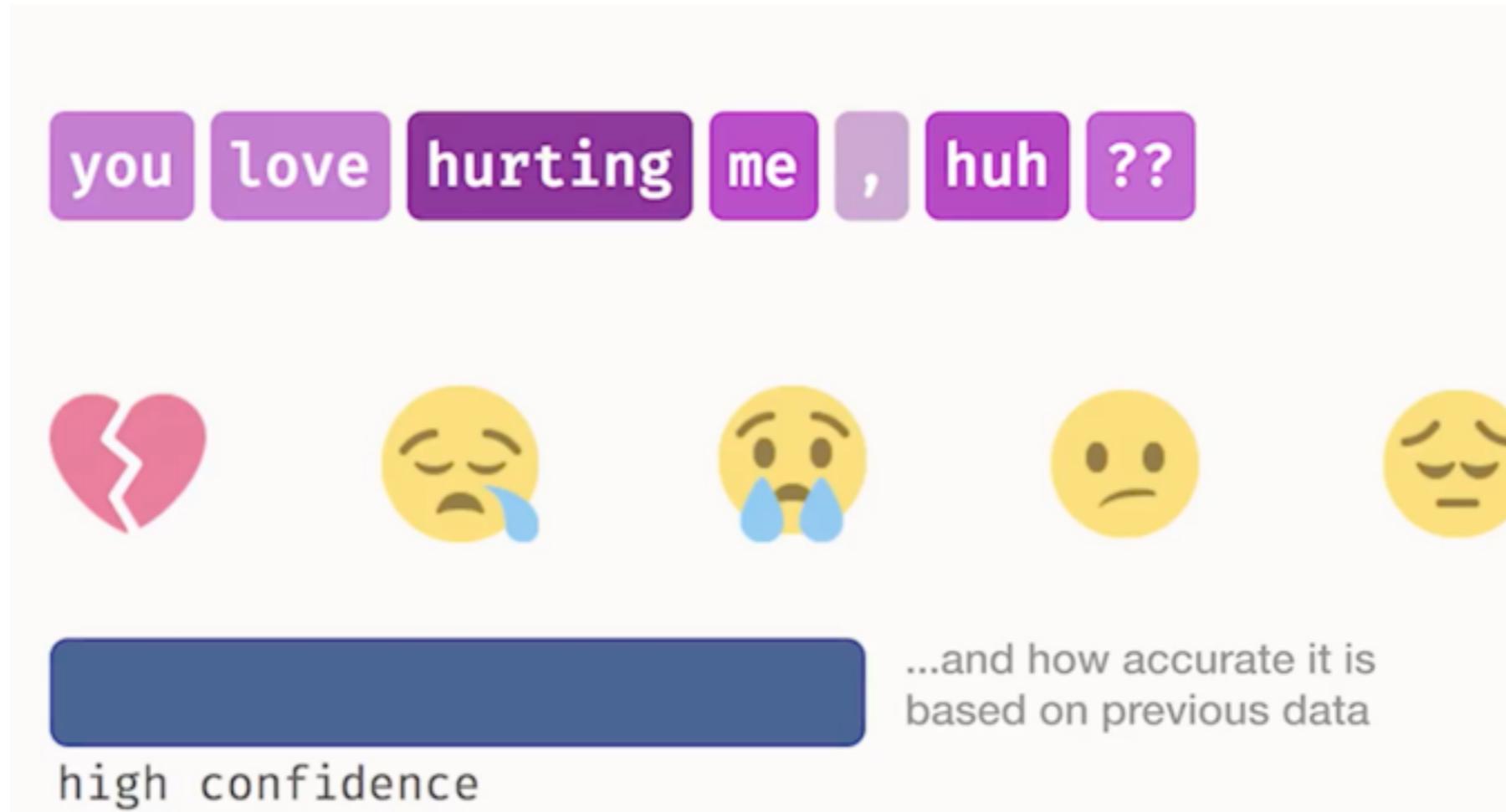
Some phrases are easy to
translate into emojis

i am so happy !



Still some fun

- Predict Emoji [24]



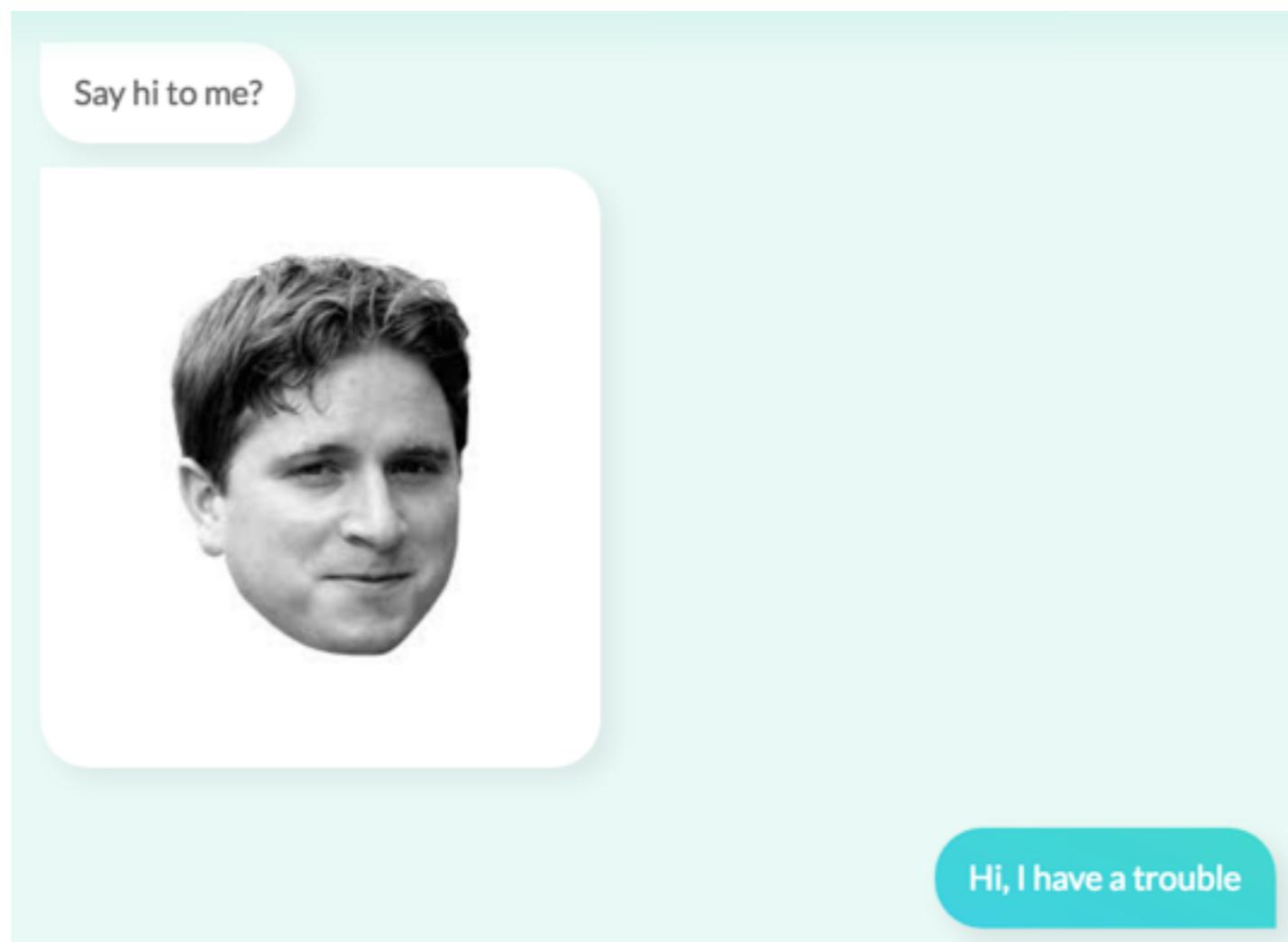
Still some fun

- Add this to your system [25]

The screenshot shows the DeepMoji AI interface. At the top, there's a dark header bar with the logo 'DeepMoji Artificial emotional intelligence' on the left and navigation links 'Help AI!', 'About', and a user icon on the right. Below the header, a large text area contains the text: 'DeepMoji has learned to understand emotions and sarcasm based on millions of emojis. Here's a [video](#) explaining a bit more. Type a sentence to see what our AI thinks.' Below this text is a light blue input field containing the sentence 'this is life'. To the right of the input field is a white 'SUBMIT' button with a thin black border. Further down the page, there's a section titled 'Examples' with the sub-instruction 'Click on one!'. Six examples are listed in purple rounded rectangular boxes: 'You love hurting me, huh?', 'This is the shit!', 'My flight is delayed.. amazing.', 'I know good movies, this ain't one', 'It was fun, but I'm not going to miss you', and 'What is happening to me??'.

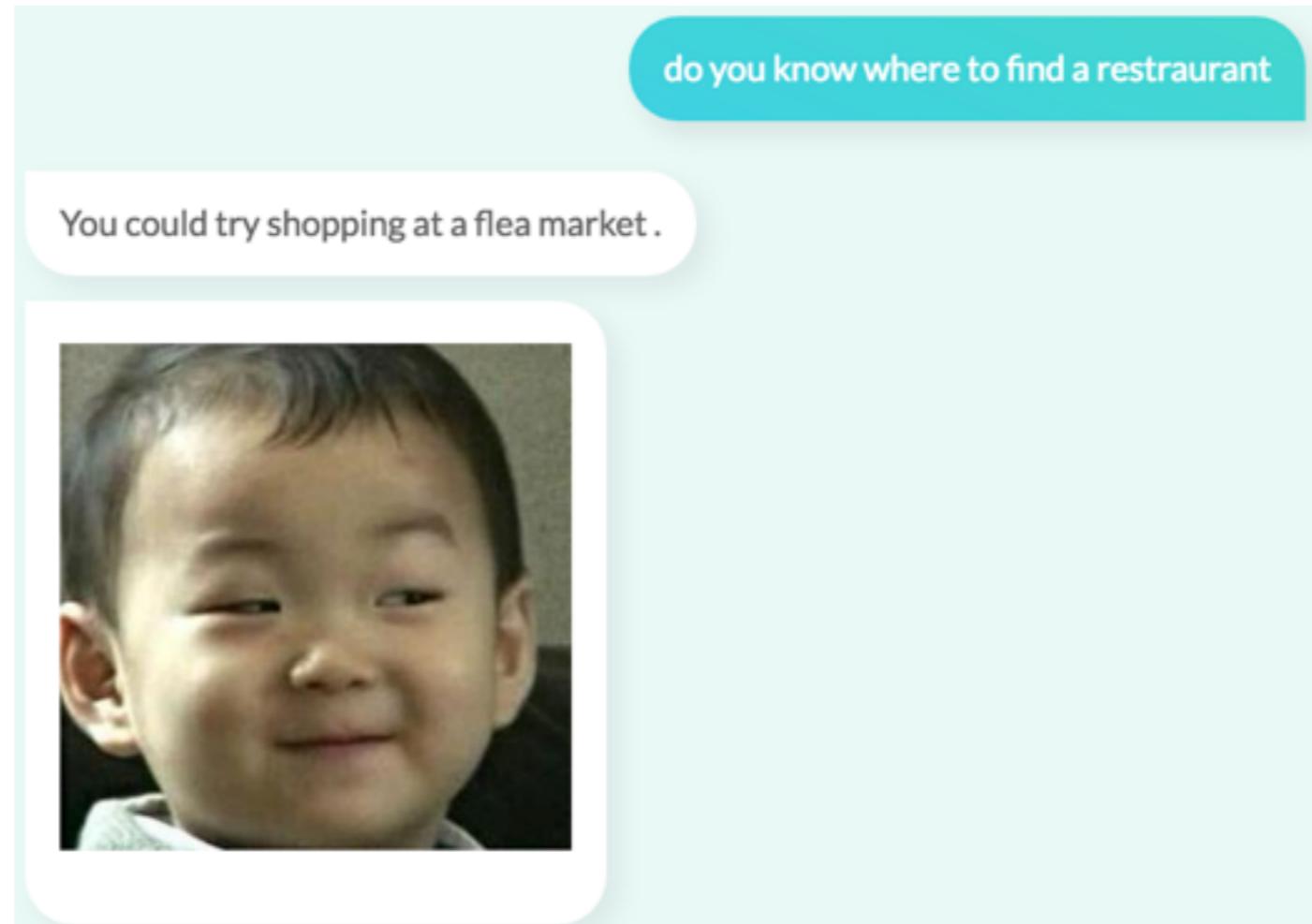
Still some fun

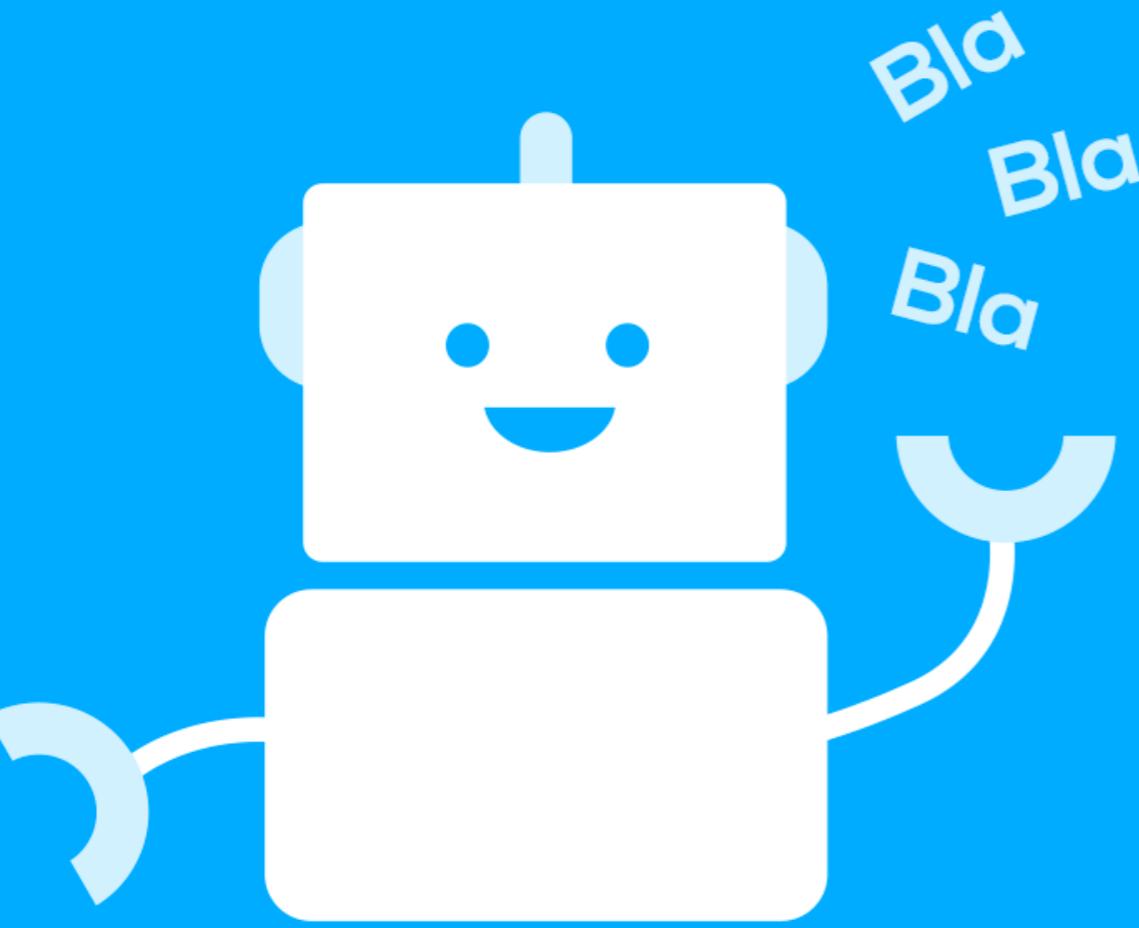
- Even cute features



Still some fun

- Even cute features





vs.



Knowledgable

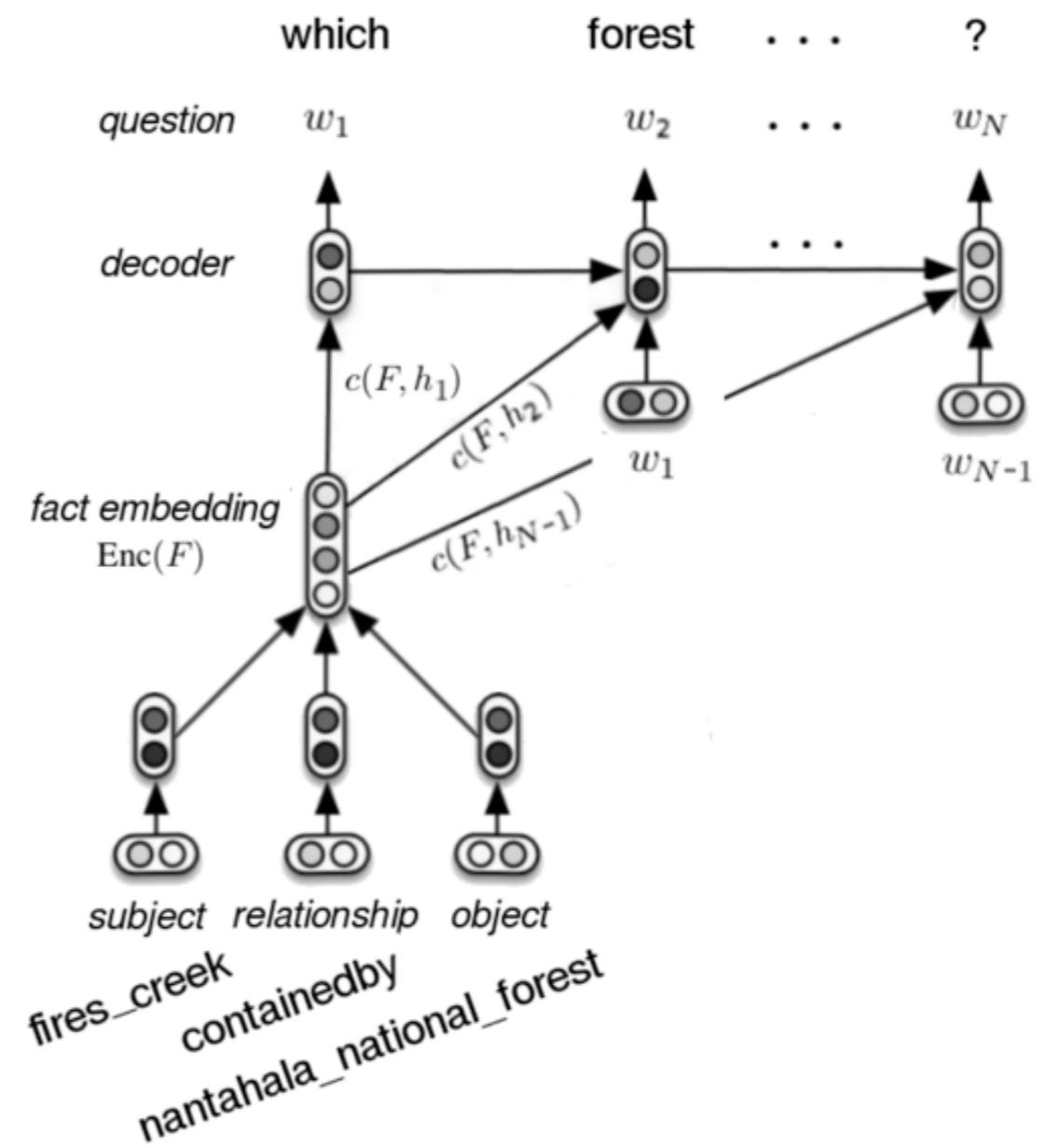
Conversational Agents

Motivation

- Observation: The user inputs are often less informative [26]
- Inherent Incentives:
 - We often say short words and interact with others (communication theory)
 - We expect machines are equipped with (common) knowledge
 - We say words under some situations related to our intentions

Knowledge - Fact

- Uses attention-based RNN to generate factoid questions from Freebase triples [27]



Knowledge - Linguistics

- Linguistic Structure [28, 29]

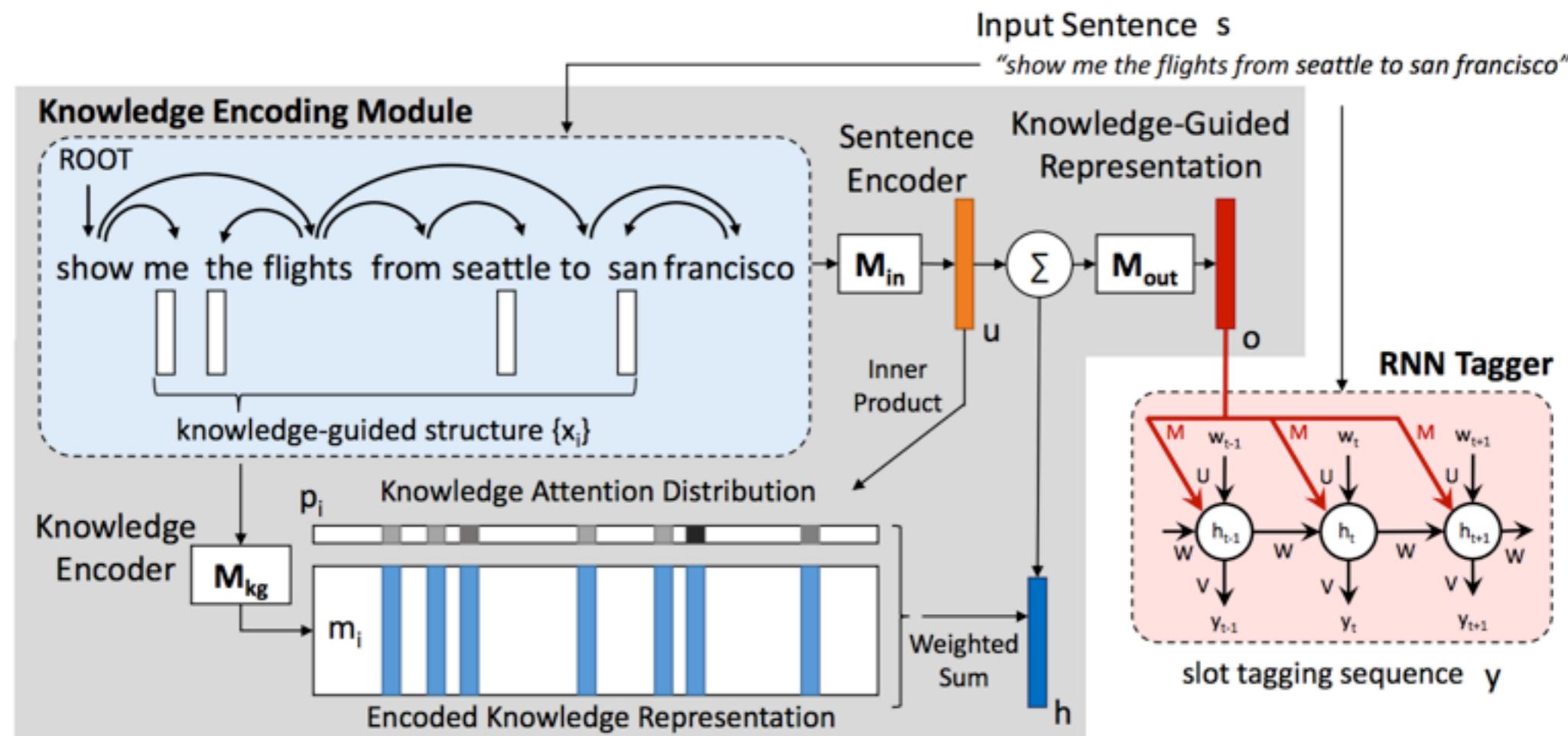
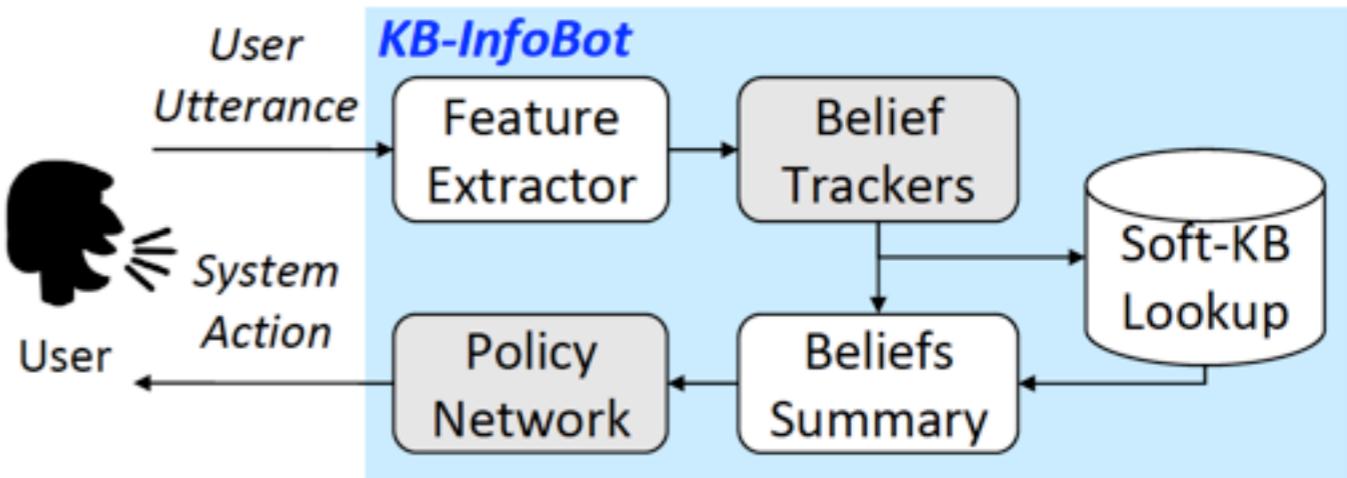
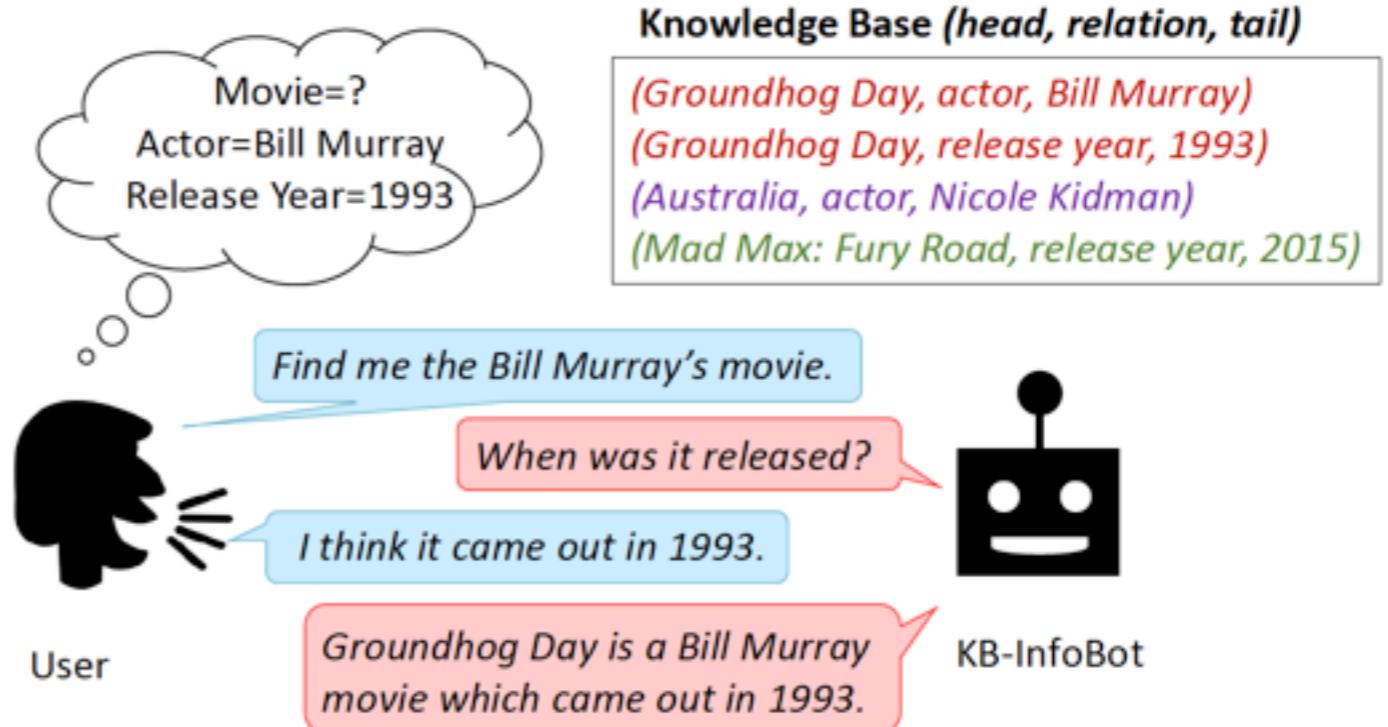


Figure 2: The illustration of knowledge-guided structural attention networks (K-SAN) for NLU.

Knowledge - Knowledge Base

- KB-InfoBot [30]
- a dialogue agent that provides users with an entity from a knowledge base (KB) by interactively asking for its attributes.

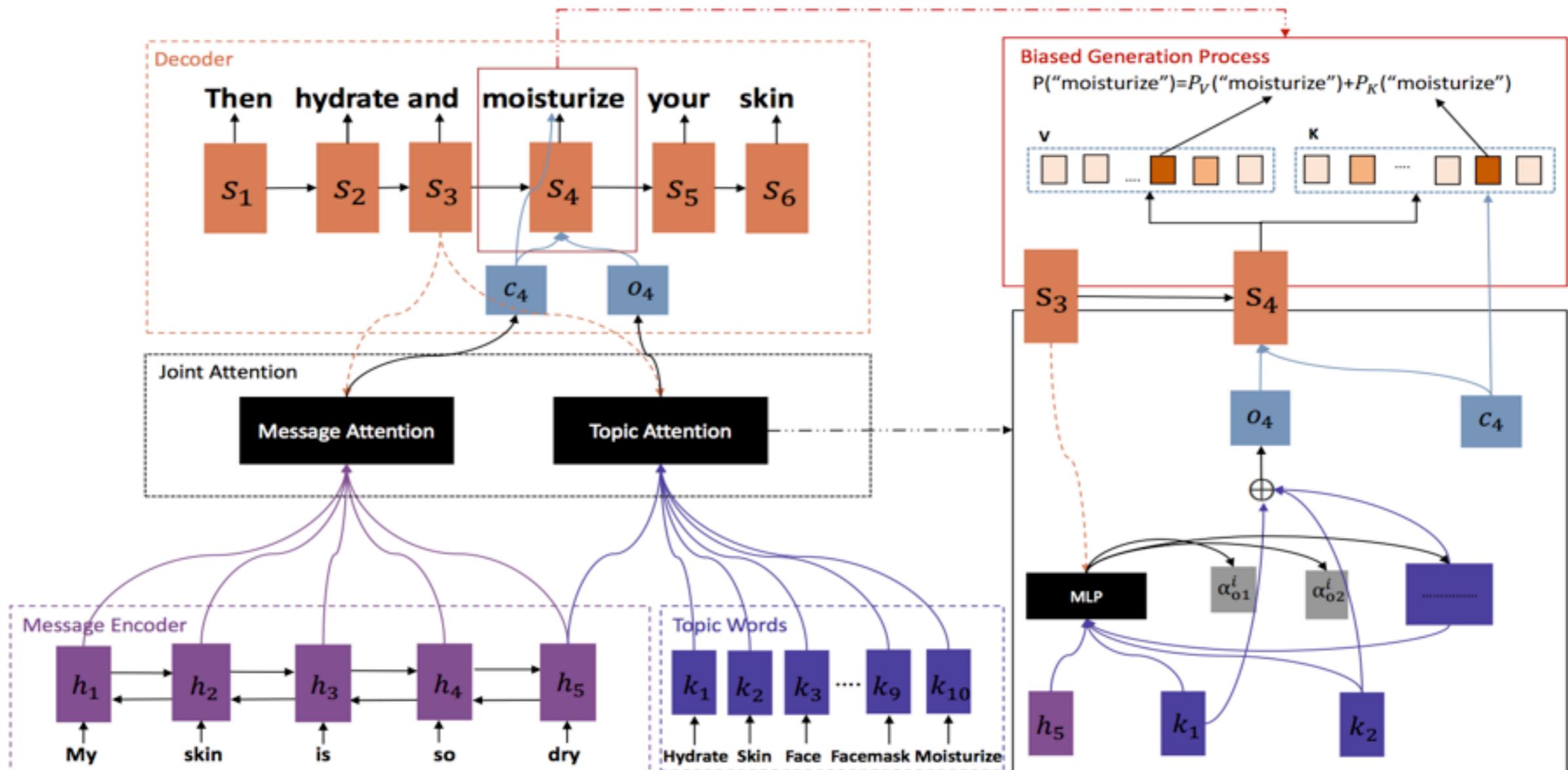


Knowledge - Topic

- utilize topics to simulate prior knowledge of human [31]
- leverage the topic information in generation by a joint attention mechanism and a biased generation probability.
- The joint attention mechanism summarises the hidden vectors of an input message as context vectors by message attention, synthesizes topic vectors by topic attention from the topic words of the message obtained from a pre-trained LDA model

Knowledge - Topic

- utilize topics to simulate prior knowledge of human [31]



Knowledge - Scenario (Image, Articles...)

- incorporate factual information or entity-grounded opinion [32]
- producing more contentful responses without slot filling

The screenshot shows a user interface for a restaurant review platform. At the top, there's a search bar with the text "Kusakabe". Below it, a map of San Francisco highlights the location of Presidio and shows a route to Kusakabe. To the right of the map, there's a list of reviews:

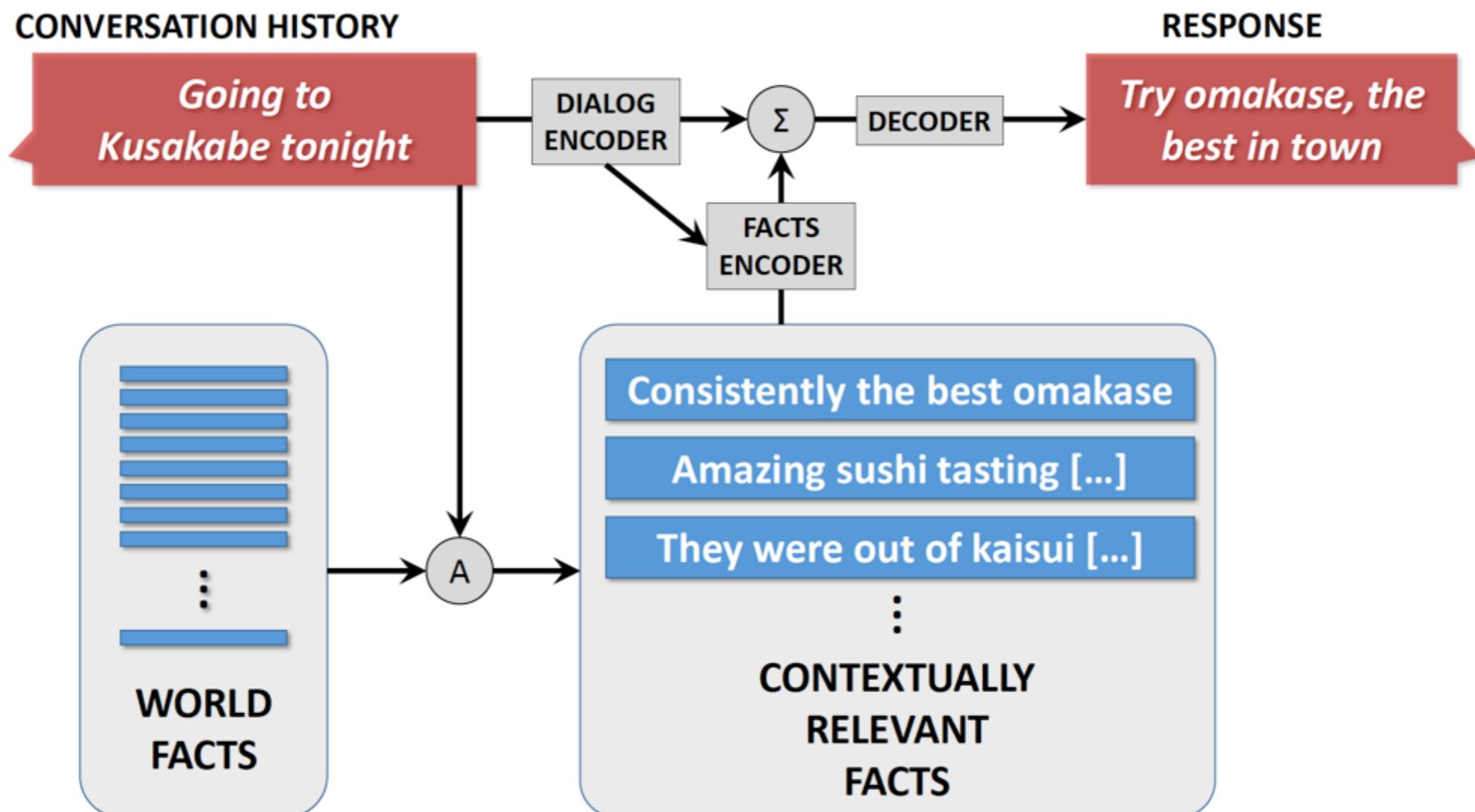
- "Consistently the best omakase in San Francisco." (27 Tips) (highlighted)
- "... they were out of the kaisui uni by the time we ate, but the bafun uni is..." (2 Tips)
- "Probably the best sushi in San Francisco." (2 Tips)
- "Amazing sushi tasting from the chefs of Sushi Ran" (2 Tips)

Below the reviews, there are two images: a close-up of a sushi platter with various pieces of nigiri and sashimi, and a shot of the interior of the restaurant showing a chef at work.

User input: Going to Kusakabe tonight.
Neural model: Have a great time!
Human: You'll love it! Try omasake, the best in town.

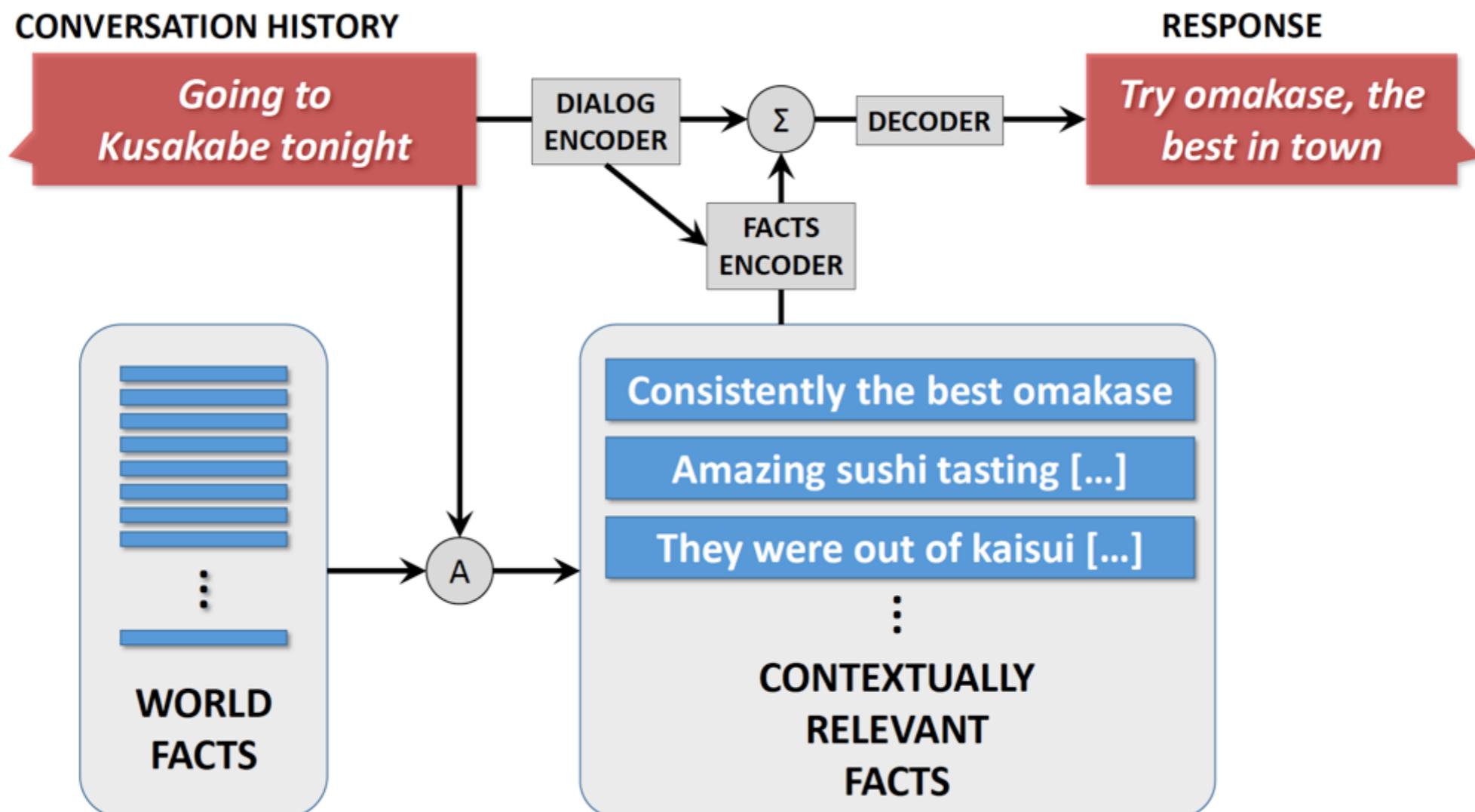
Knowledge - Scenario (Image, Articles...)

- incorporate factual information or entity-grounded opinion [32]



Knowledge - Scenario (Image, Articles...)

- incorporate factual information or entity-grounded opinion [32]



Knowledge - Scenario (Image, Articles...)

- Visual Dialog [32]

Visual Dialog



A cat drinking water out of a coffee mug.

What color is the mug?

White and red

Are there any pictures on it?

No, something is there can't tell what it is

Is the mug and cat on a table?

Yes, they are

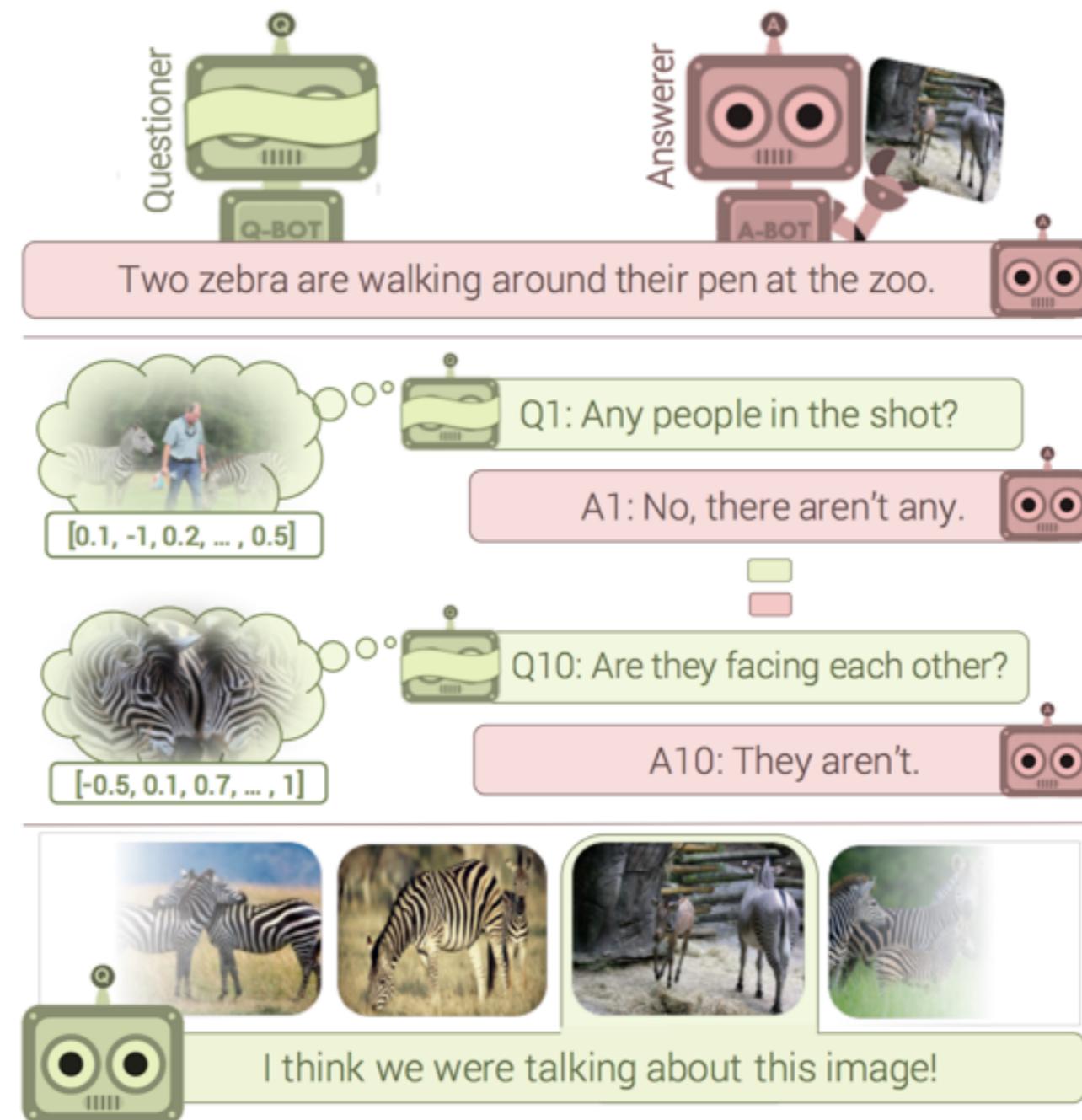
Are there other items on the table?

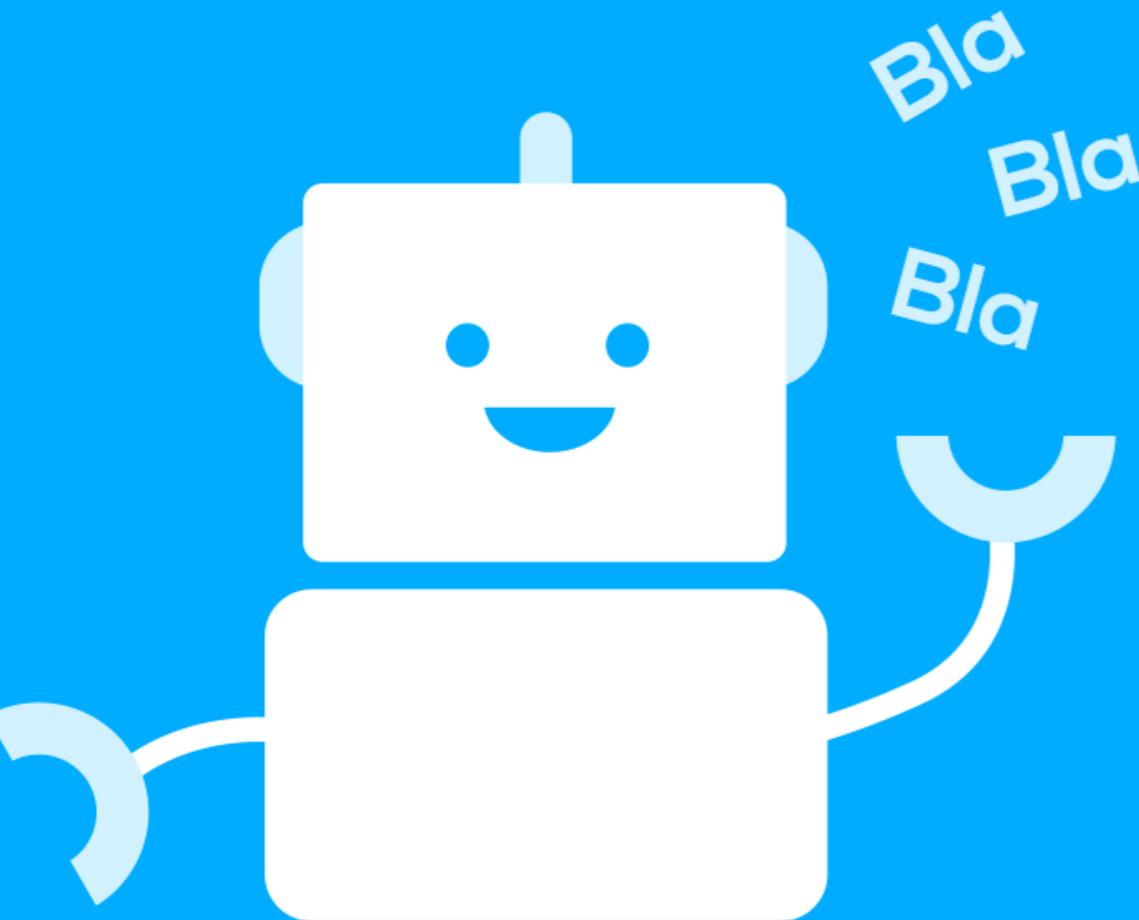
Yes, magazines, books, toaster and basket, and a plate

C  Start typing question here ... >

Knowledge - Scenario (Image, Articles...)

- Visual Dialog [33]





vs.



Dataset

Conversational Agents

Dataset

- ◆ [1] full OpenSubtitle
- ◆ [2] partial OpenSubtitle
- ◆ [3] Sina Weibo dataset 2017, <http://www.aihuang.org/p/challenge.html>,
<http://tcci.ccf.org.cn/conference/2017/cfpt.php>
- ◆ [4] Sina Weibo dataset 2016
- ◆ [5] Sina Weibo dataset 2015
- ◆ [6] Twitter data 2011
- ◆ [7] Chinese sentimental conversation

Dataset 2

- ◆ SQuAD
- ◆ Ubuntu Dialogue Corpus
- ◆ FAIR Movie Dialog Dataset
- ◆ Reddit Comment
- ◆ Microsoft Research Social Media Conversation Corpus
- ◆ Dialog State Tracking Challenge
- ◆ dgk_lost_conv 中文对白语料
- ◆ 高质量闲聊语料(需购买)
- ◆ Cornell Movie-DIALOGS Corpus
- ◆ Maluuba NewsQA
- ◆ Maluuba Frames
- ◆ 百度 WebQA
- ◆ Noah NRM Data
- ◆ Noah Chinese QA

Try as a volunteer

- ♦ The Conversational Intelligence Challenge https://deeppavlov.github.io/convai/eval_howto/
- ♦ Both human evaluators and dialogue agents complete the same task.
- ♦ Connect randomly with a peer.
- ♦ The peer might be a chat bot or other human user. No information about identity of the peer is provided.
- ♦ Both parties are given a text of a recent news/wikipedia article.
- ♦ Discuss content of the article with the peer as long as you wish.
- ♦ Choose another news/wikipedia article and/or anonymous peer.

Homework

- ◆ Tutorial Reading:
 - ◆ Tutorial: Deep Reinforcement Learning. ICML 2016. http://icml.cc/2016/tutorials/deep_rl_tutorial.pdf
 - ◆ Introduction to Reinforcement Learning. Advanced Topics 2015 (COMPM050/COMP GI13) Reinforcement Learning (video available).
 - ◆ <http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html>
 - ◆ http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching_files/intro_RL.pdf
- ◆ Paper Reading:
 - ◆ Towards End-to-End Reinforcement Learning of Dialogue Agents for Information Access
 - ◆ Deal or No Deal? End-to-End Learning for Negotiation Dialogues
- ◆ Code Reading:
 - ◆ KB-InfoBot: <https://github.com/MiuLab/KB-InfoBot>



Thanks for your attention!

Q&A

References

- [1] Pascanu, Razvan, Tomas Mikolov, and Yoshua Bengio. "On the difficulty of training recurrent neural networks." International Conference on Machine Learning. 2013.
- [2] Mikolov, Tomas, et al. "Recurrent neural network based language model." Interspeech. Vol. 2. 2010.
- [3] Colah. "Understanding LSTMs". <http://colah.github.io/posts/2015-08-Understanding-LSTMs/>
- [4] Sutskever, Ilya, Oriol Vinyals, and Quoc V. Le. "Sequence to sequence learning with neural networks." Advances in neural information processing systems. 2014.
- [5] Bahdanau, Dzmitry, Kyunghyun Cho, and Yoshua Bengio. "Neural machine translation by jointly learning to align and translate." arXiv preprint arXiv:1409.0473 (2014).
- [6] Vinyals, Oriol, and Quoc Le. "A neural conversational model." arXiv preprint arXiv:1506.05869 (2015).
- [7] Wen, Tsung-Hsien, et al. "A network-based end-to-end trainable task-oriented dialogue system." arXiv preprint arXiv:1604.04562 (2016).
- [8] Bowman, Samuel R., et al. "Generating sentences from a continuous space." arXiv preprint arXiv:1511.06349 (2015).
- [9] Hu, Baotian, et al. "Convolutional neural network architectures for matching natural language sentences." Advances in neural information processing systems. 2014.

References

- [10] Qiu, Xipeng, and Xuanjing Huang. "Convolutional Neural Tensor Network Architecture for Community-Based Question Answering." IJCAI. 2015.
- [11] Wu, Yu, et al. "Sequential Match Network: A New Architecture for Multi-turn Response Selection in Retrieval-based Chatbots." ACL 2017.
- [12] <https://github.com/seatgeek/fuzzywuzzy>
- [13] <https://www.linkedin.com/pulse/duplicate-quora-question-abhishek-thakur>
- [14] Is That a Duplicate Quora Question? <https://www.linkedin.com/pulse/duplicate-quora-question-abhishek-thakur>
- [15] <https://github.com/HouJP/kaggle-quora-question-pairs/>
- [16] <https://pan.baidu.com/s/1dEV01gd>
- [17] Lifeng Shang, Zhengdong Lu, Hang Li. "Neural Responding Machine for Short-Text Conversation". EMNLP 2015.
- [18] Serban, Iulian Vlad, et al. "A Hierarchical Latent Variable Encoder-Decoder Model for Generating Dialogues." AAAI. 2017.
- [19] Serban, Iulian Vlad, et al. "Multiresolution Recurrent Neural Networks: An Application to Dialogue Response Generation." AAAI. 2017.
- [20] Alessandro Sordoni, Yoshua Bengio et al., "A Hierarchical Recurrent Encoder-Decoder for Context-Aware Generative Query Suggestion". CIKM 2015 slides.

References

- [21] Zhou Hao et al, “Emotional Chatting Machine: Emotional Conversation Generation with Internal and External Memory”. arXiv preprint 2017.
- [22] Xiaoyu Shen, Hui Su, Yanran Li, Wenjie Li, Shuzi Niu, Yang Zhao, Akiko Aizawa, Guoping Long. “A Conditional Variational Framework for Dialog Generation”. ACL 2017.
- [23] Jessica Ficler, Yoav Goldberg. “Controlling Linguistic Style Aspects in Neural Language Generation”. arXiv preprint 2017.
- [24] Bjarke Felbo, Alan Mislove, Anders Søgaard, Iyad Rahwan, Sune Lehmann. “Using millions of emoji occurrences to learn any-domain representations for detecting sentiment, emotion and sarcasm”. EMNLP 2017.
- [25] DeepMoji. <https://deepmoji.mit.edu/>
- [26] Louis Shao, et al. “Generating Long and Diverse Responses with Neural Conversation Models”. arXiv preprint 2017.
- [27] Iulian Vlad Serban, et al. “Generating Factoid QuestionsWith Recurrent Neural Networks: The 30M Factoid Question-Answer Corpus”. ACL 2016a.
- [28] Yun-Nung Chen et al. “End-to-End Memory Networks with Knowledge Carryover for Multi-Turn Spoken Language Understanding”. arXiv preprint 2016b.
- [29] Yoon Kim et al. “Structured Attention Networks”. ICLR 2017.

References

- [30] Bhuwan Dhingra, Lihong Li, Xiujun Li, Jianfeng Gao, Yun-Nung Chen, Faisal Ahmed, Li Deng. “Towards End-to-End Reinforcement Learning of Dialogue Agents for Information Access”. ACL 2017.
- [31] Chen Xing et al. “Topic Aware Neural Response Generation”. arXiv preprint 2016.
- [32] Marjan Ghazvininejad et al. “A Knowledge-Grounded Neural Conversation Model”. arXiv preprint 2017.
- [33] Abhishek Das, Satwik Kottur, Khushi Gupta, Avi Singh, Deshraj Yadav, José M. F. Moura, Devi Parikh, Dhruv Batra. “Visual Dialog”. CVPR 2017.
- [34] Abhishek Das, Satwik Kottur, José M. F. Moura, Stefan Lee, Dhruv Batra. “Learning Cooperative Visual Dialog Agents with Deep Reinforcement Learning”. arXiv preprint 2017.