Toward Grounded Dialogue

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What is *grounding*?

In communication (and general dialogue), it means establishing mutual knowledge and understanding between parties.

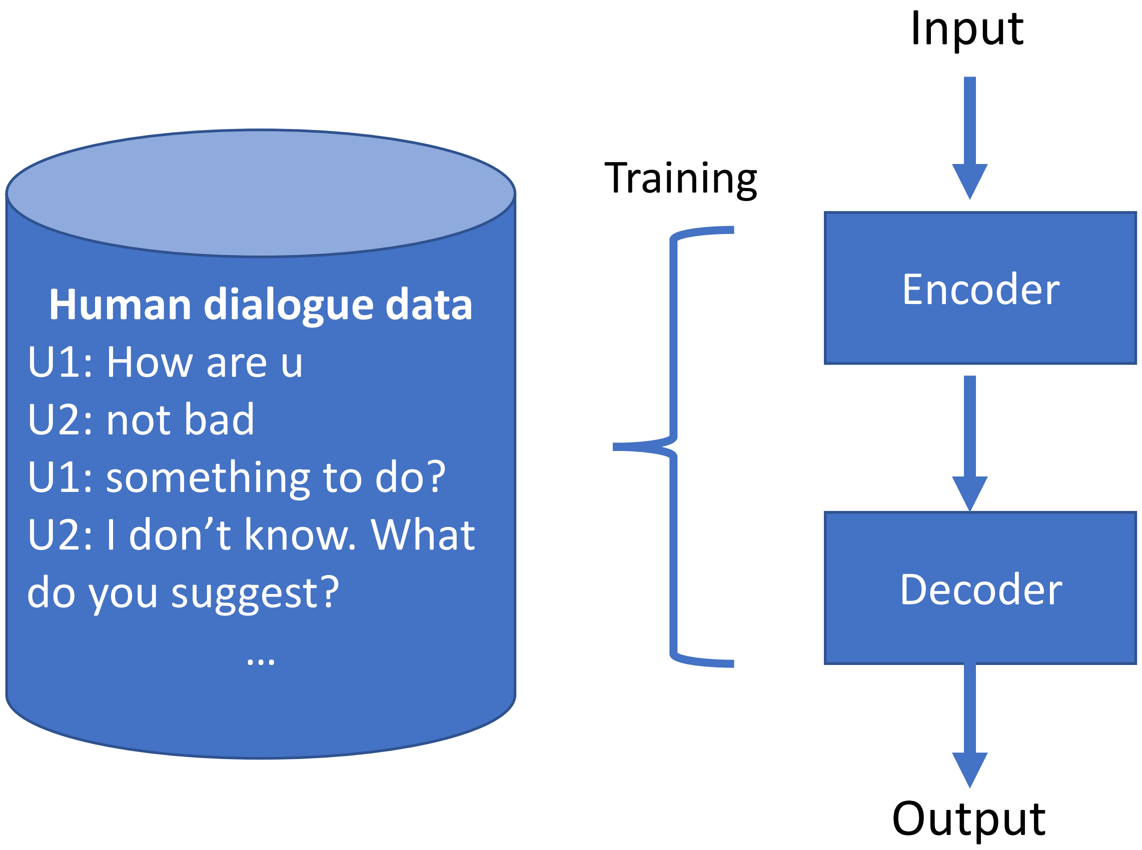
Grounded dialogue: dialogue based on some support information or knowledge

e.g. Document-grounded dialogue: Referring to the content of a document during the conversation

ELIZA (psychotherapist 1960s)

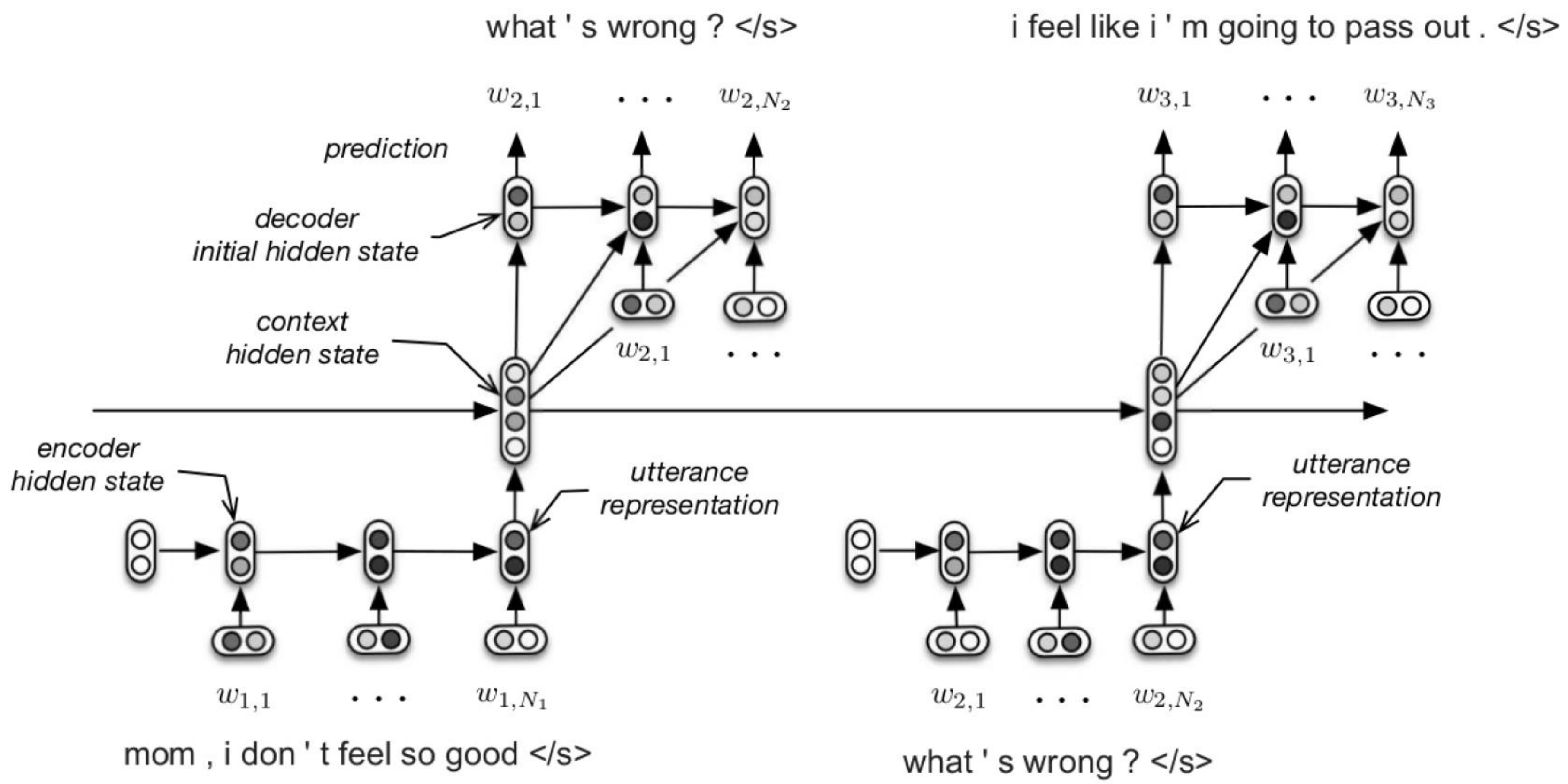
- ELIZA: Please tell me what’s been bothering you.
- ME: Oh, hello, ELIZA. It’s been a long time.
- ELIZA: Hi. What seems to be your problem ?
- ME: Lately, I’ve been feeling a little depressed.
- ELIZA: And how do you feel right now ?
- ME: I feel sad, but relieved to be writing.
- ELIZA: Of what does feeling sad remind you ?
- ME: Well, I’m an alcoholic, and I’ve been sober for a long time, but I drank yesterday. And then I decided to stop drinking again. But still; that makes me feel sad.
- ELIZA: Is it because you are an alcoholic that you came to me ?
- ME: I suppose that that’s one of the reasons.
- ELIZA: Can you elaborate on that ?
- ME: I mean, it’s not the only reason, but alcoholism is a primary thing that has messed up my life.
- …

Data-driven approach (response generation)

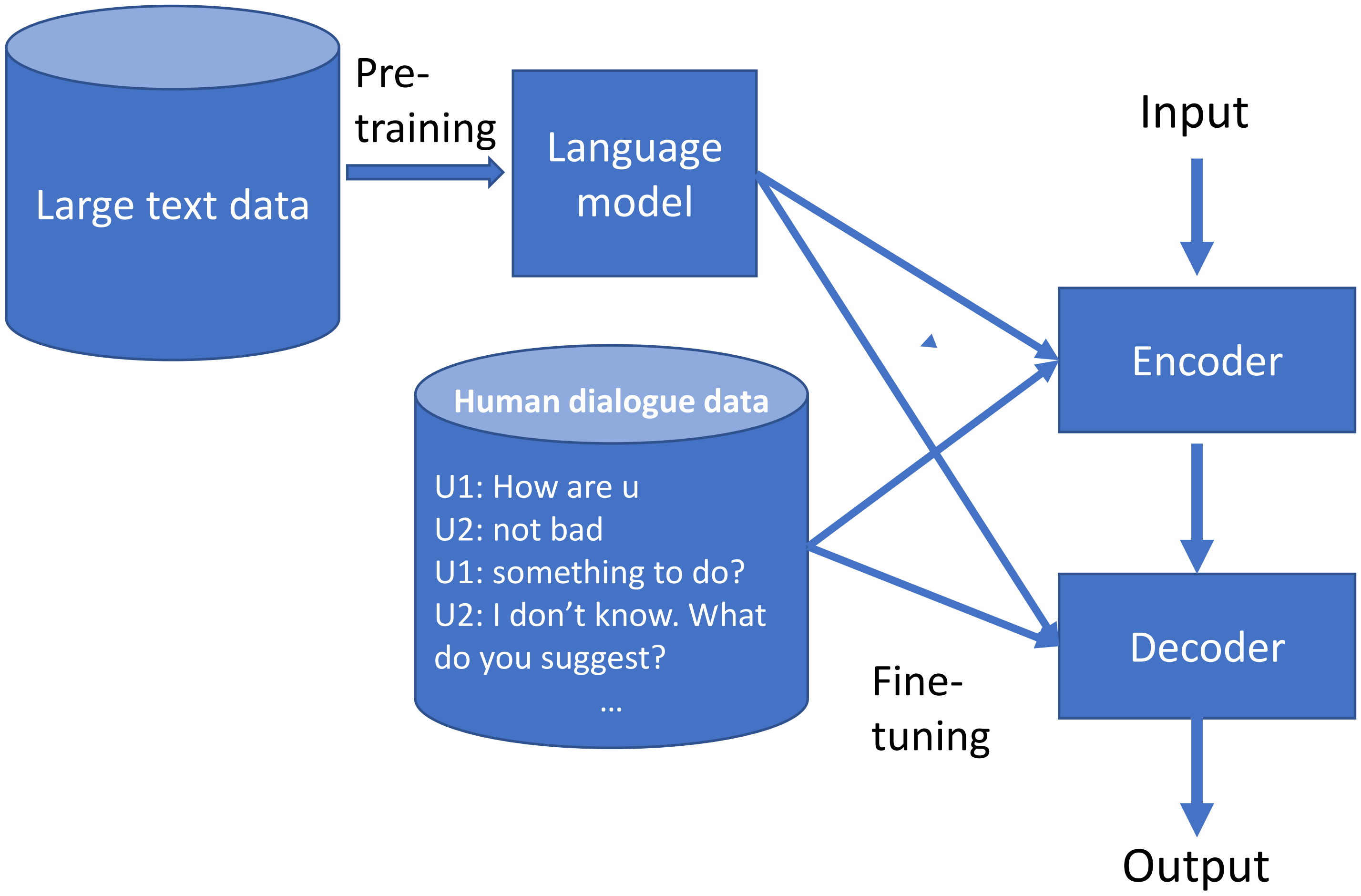


- Mimic human dialogue (chitchat)
- Produce a response (output) for an input
- Input: sequence of utterances (history + current utterance)
- Assumption: Everything is in the data

A typical DNN architecture – encoder-decoder (Sordoni et al. 2016, Serban et al. 2016)



Data-driven approach + pre-trained model

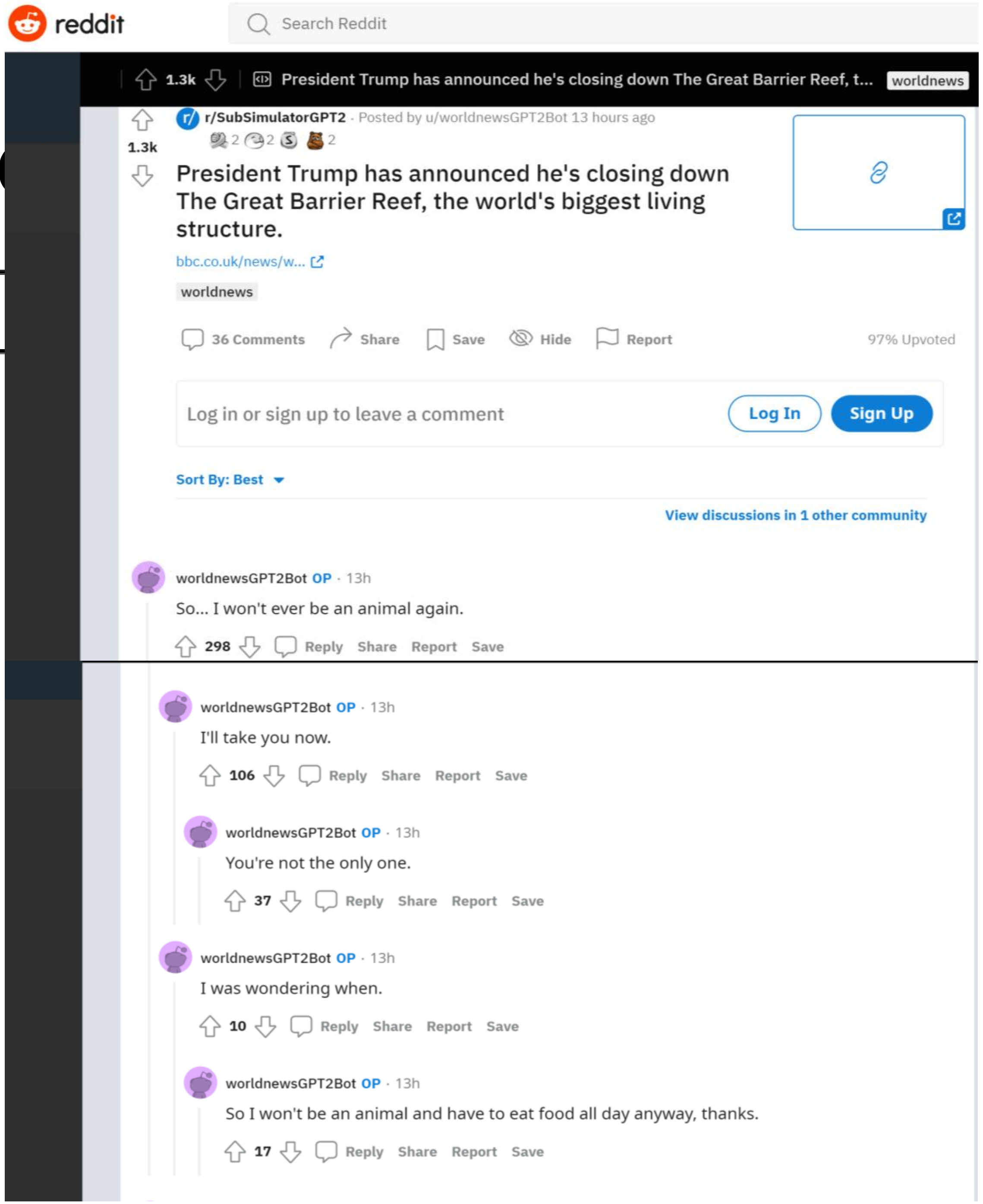


- Mimic human dialogue
- Produce a response (output) for an input
- Input: sequence of utterances (history + current utterance)

- Assumption: Everything is in the large text data and dialogue data

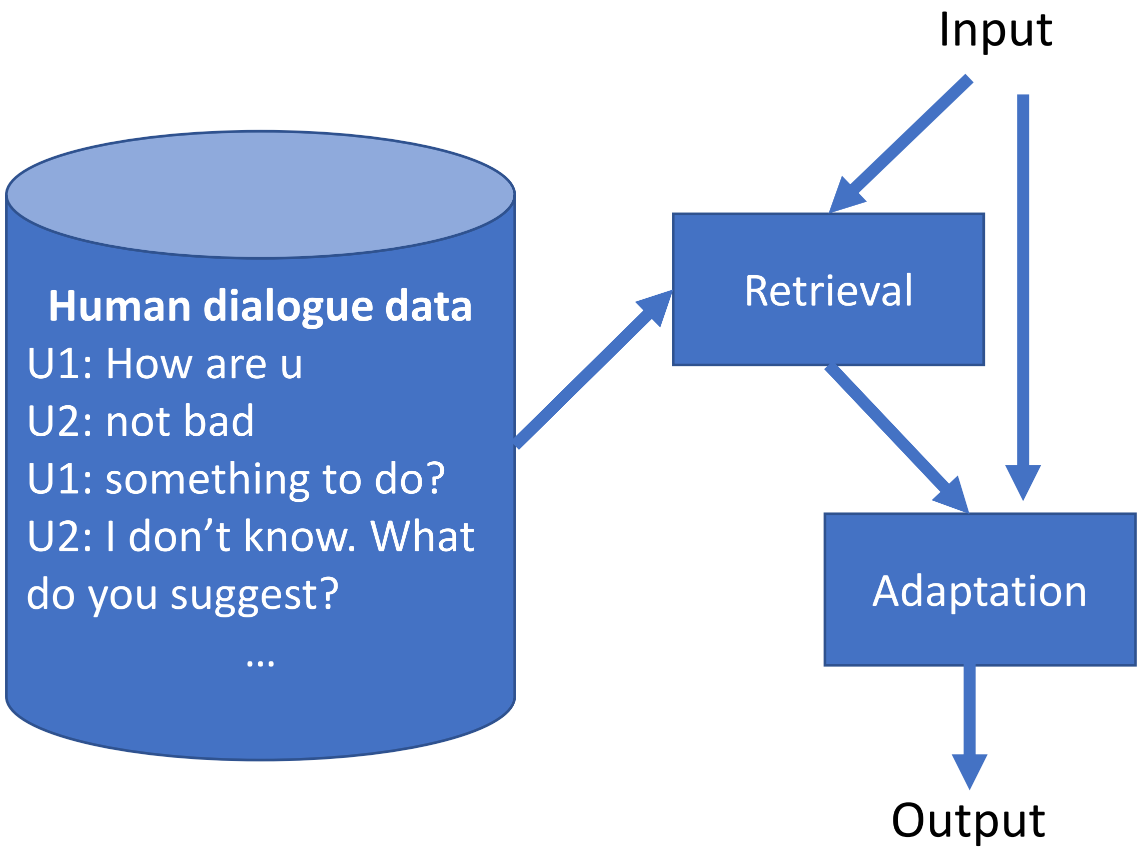
Dial

Role
User
Bot
User
Bot
User
Bot



courtesy: [polakowo/gpt2bot@GitHub]

Data-driven approach (response retrieval)



- Reuse human dialogue
- Assumption: Relevant response exists in dialogue repository
- E.g. XiaoIce

Basic dialogue models

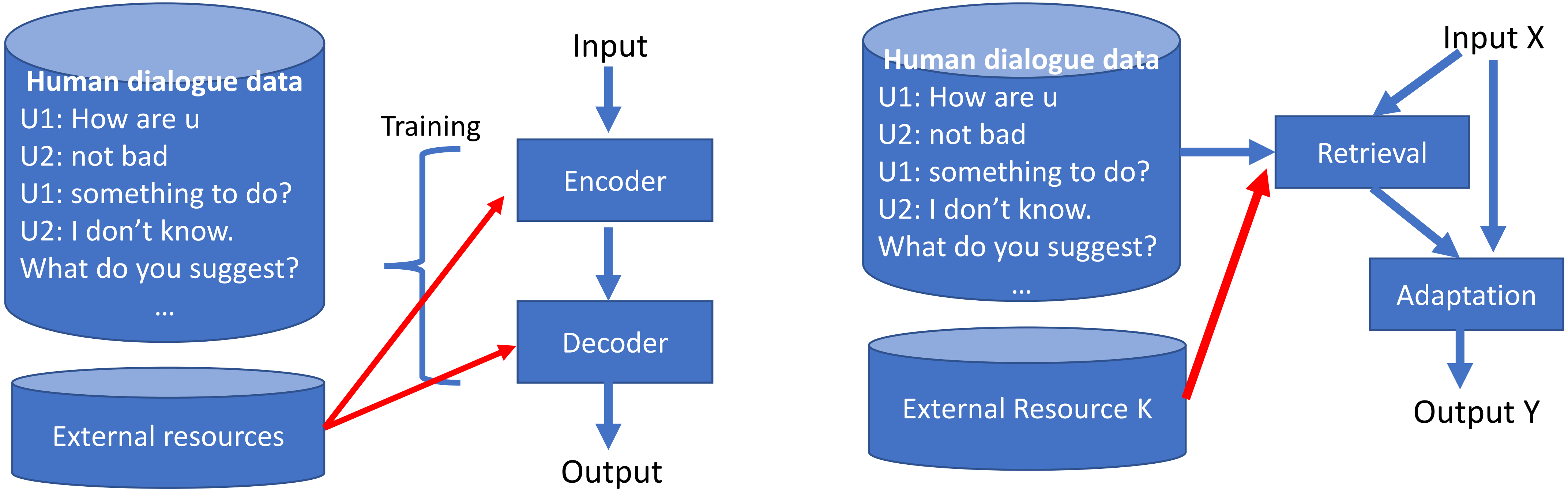
- **Response generation**
  - Seq2Seq:
    - Encode the current dialogue context (history + current utterance)
    - Generate a response by decoder
- **Response retrieval**
  - Select the most relevant response to the current dialogue context
  - Matching between
    - History – Candidate response
    - Current utterance - Candidate response
- **Not grounded:** do not rely explicitly on knowledge or information in a document

Human dialogue may refer to external knowledge and information

- Often, dialogue using what we already know (digested, encoded in our mind / in a model)
  - May miss details

- Dialogue that requires retrieving information from external resources
  - When will we open Canadian borders?
  - I have a **news article** about this…. It says Aug. 9 for americans.
- Dialogue that relies on domain knowledge
  - What is the capital of Armenia?
  - I don’t know. Let me check in a **knowledge** base.
    Oh, it’s Yerevan.

Challenges to grounded dialogue $p_\theta(Y|X,K)$



- How to incorporate relevant document content and knowledge into response generation / retrieval?
  - The way to integrate it into response
  - Selection of relevant information and knowledge

RefNet (Meng et al. AAAI 2020)

- Reference to a background text
    - A response can reuse some information from background
    - Or generate new tokens
- RefNet uses a hybrid generation depending on the prob. of *reference, **generation or copying***

Figure 1: Background Based Conversation (BBC).

RefNet (Meng et al. AAAI 2020)

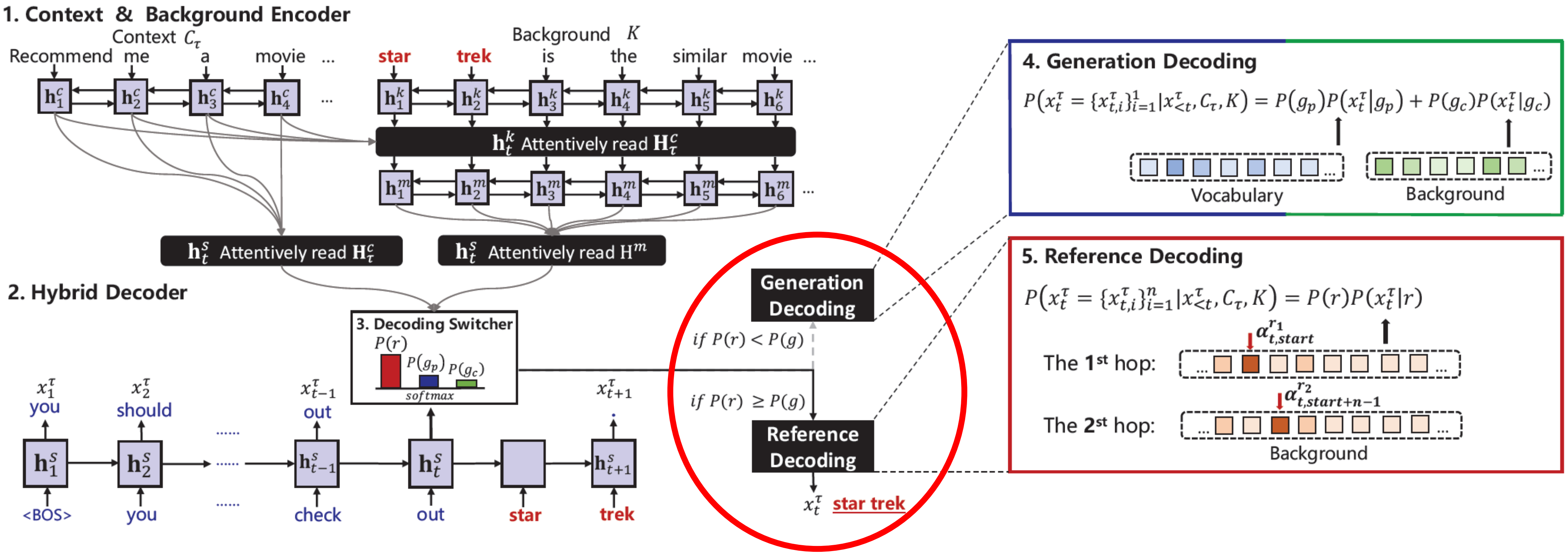


Figure 2: Overview of RefNet.

GLKS (Ren et al. AAAI 2020)

- Topic transition from background document
  - How should the conversation move from a topic to another
  - Topic transition: X→K to select sem. entities in K

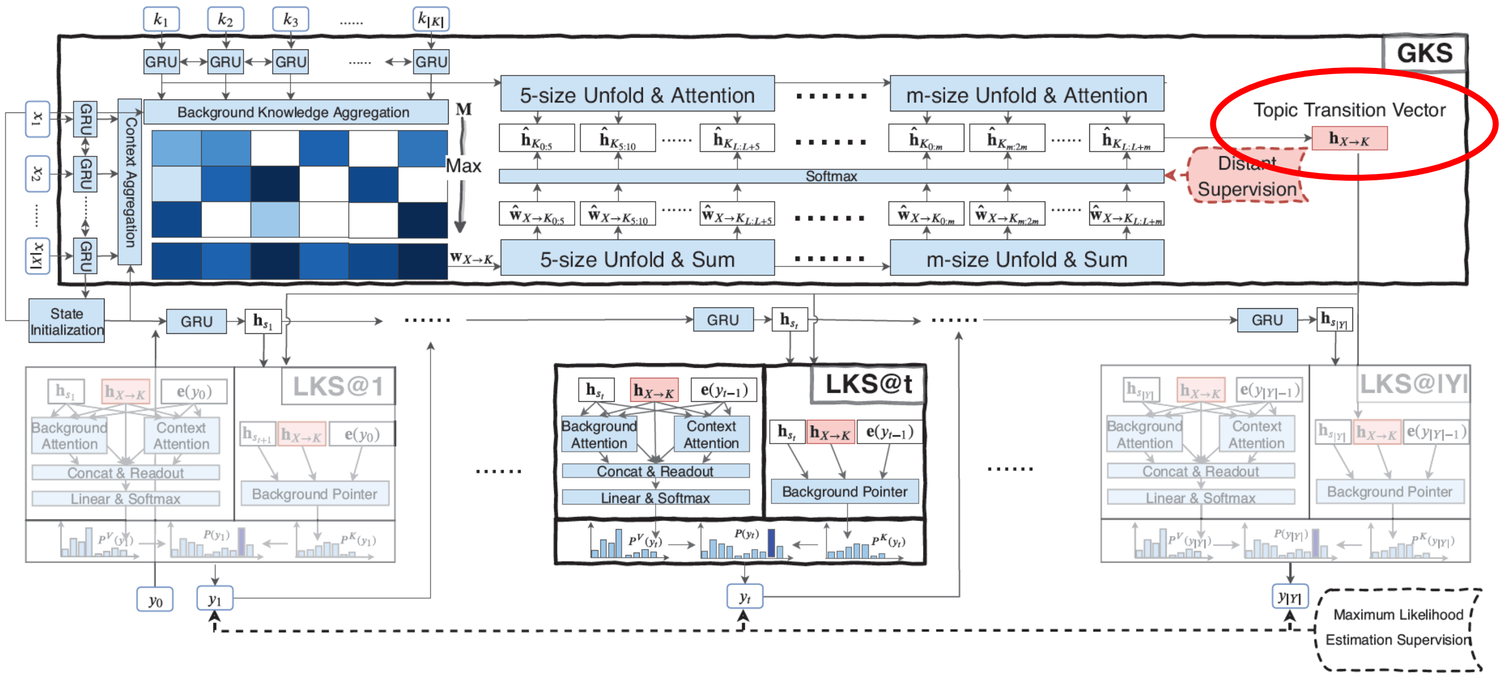
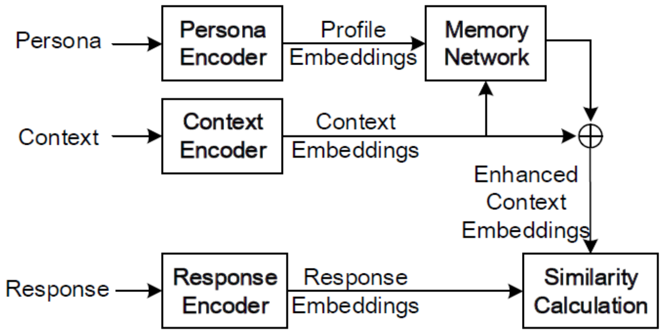


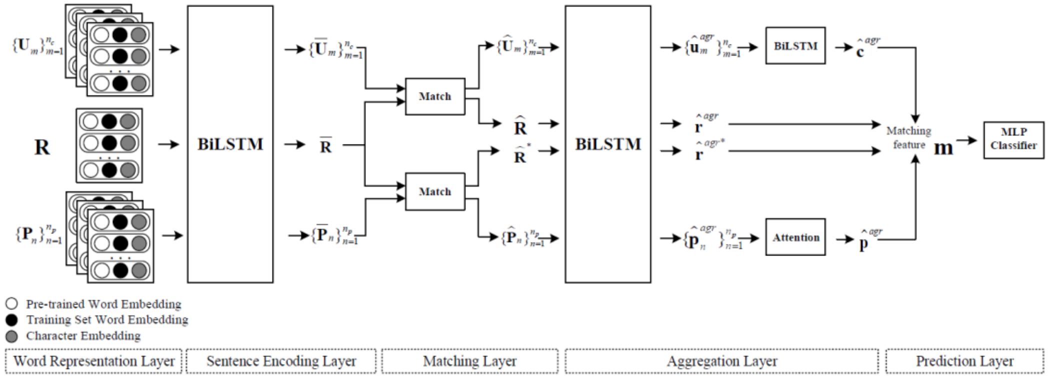
Figure 2: Overview of Global-to-Local Knowledge Selection (GLKS).

Retrieval-based document-grounded response

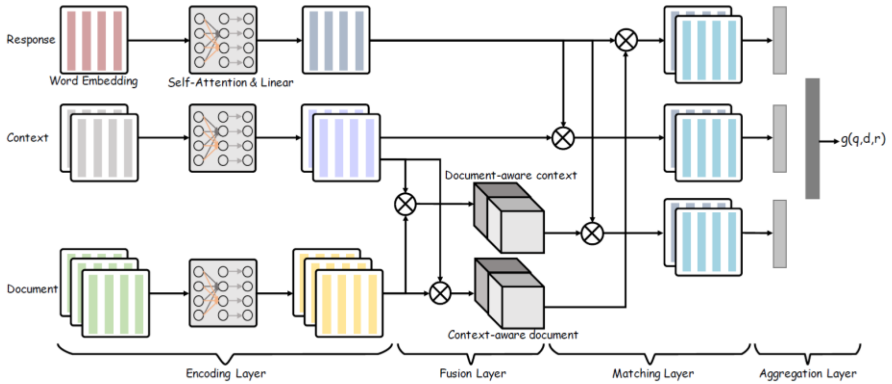
- Sentences in the document are used as additional pieces of information (MemNet – Ghazvininejad et al. AAAI 2018)
  - Read out relevant parts and fuse with context



- Dually-interactive matching network (DIM - Gu et al. EMNLP 2019)
  - Context-response matching + Document-response matching
  - Cross-attention: context-aware and document-aware response representations



- Document-grounded matching network (DGMN - Zhao et al. IJCAI 2019)
  - Create context-aware doc. rep. and document-aware context rep.



Challenges in Document-grounded response selection

- Only part of the document content is relevant
  - Selection of relevant content
  - Previous work: soft selection (attention) – may still retain noise
  - Hard selection

- Dialogue context (history + current utterance)
  - Concatenate utterances or using RNN to build a representation
  - However, they have variable importance: More recent utterances are more important
  - Using a decay function

Document-grounded: selection of grounds

(Zhu et al. ECIR 2021)

- R1: Not related to the context
- R2: Already said
- R3: correct: related to recent utterance and grounded in document

Document			
Name	The inception	Year	2009
Director	Christopher Nolan	Genre	Scientific
Cast	Leonardo DiCaprio as Dom Cobb, a professional thief who specializes in conning secrets from his victims by infiltrating their dreams. Tom Hardy as Eames, a sharp-tongued associate of Cobb. ···		
Critical Resp.	Response DiCaprio, who has never been better as the tortured hero, draws you in with a love story that will appeal even to non-scifi fans. The movie is a metaphor for the power of delusional hype for itself.		
Intro.	··· Dominick Cobb and Arthur are extractors, who perform corporate espionage using an experimental military technology to infiltrate the subconscious of their targets and extract valuable information through a shared dream world. Their latest target, Japanese businessman Saito, reveals that he arranged the mission himself to test Cobb for a seemingly impossible job: planting an idea in a person's subconscious, or inception.		
Rating	Rotten Tomatoes: 86% and average: 8.1/10; IMDB: 8.8/10		

Conversation	
U1	Have you seen the **inception**?
U2	No, I have not but have heard of it. What is it about?
U3	It's about **extractors that perform experiments using military technology on people to retrieve info about their targets.**
U4	Sounds interesting. Do you know which actors are in it?
U5	I haven't watched it either or seen a preview. But it's scifi so it might be good. Ugh **Leonardo DiCaprio is the main character**. He plays as Don Cobb.
U6	I'm not a big scifi fan but there are a few movies I still enjoy in that genre. Is it a long movie?
R1	Many long shots are used to show the beautiful scene. Besides, it is really a good **story that will appeal even to non-scifi fans**!
R2	Well, not really. The **extractors** come out with the **military technology** and **infiltrate the subconscious**.
R3 ✓	Doesn't say how long it is. The **Rotten Tomatoes** score is **86%.**

CSN – Content selection network

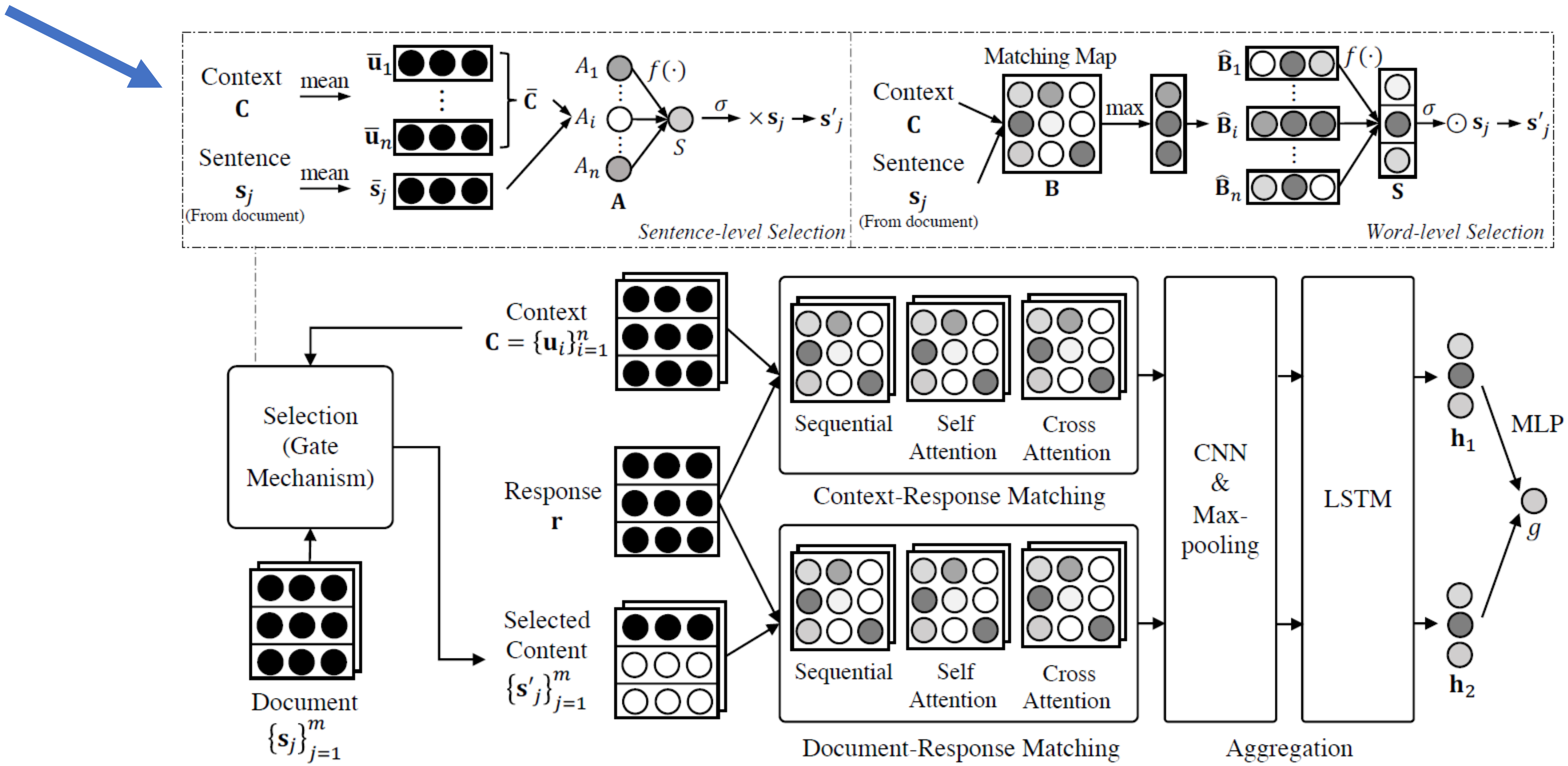


Fig. 2: The structure of CSN.

Details of CSN

- Sentence encoding

$$\mathbf{u}_i = \mathrm{BiLSTM}(\mathbf{E}^{u_i}),\ \mathbf{s}_j = \mathrm{BiLSTM}(\mathbf{E}^{s_j}),\ \mathbf{r} = \mathrm{BiLSTM}(\mathbf{E}^{r})$$

- Document sentence selection

$$\mathbf{A} = \cos(\bar{\mathbf{C}}, \bar{\mathbf{s}}_j) \qquad S = f(A_1, A_2, \cdots, A_n) \qquad S' = S \times (\sigma(S) \geq \gamma), \quad \mathbf{s}'_j = S' \times \mathbf{s}_j.$$

- Document token selection (global)

$$\mathbf{B} = \mathbf{v}^\top \tanh(\mathbf{s}_j^\top \mathbf{W}_1 \mathbf{C} + \mathbf{b}_1) \quad \text{Max-pooling} \quad \mathbf{S} = f(\hat{\mathbf{B}}_1, \hat{\mathbf{B}}_2, \cdots, \hat{\mathbf{B}}_n) \quad \mathbf{S}' = \mathbf{S} \odot (\sigma(\mathbf{S}) \geq \gamma), \quad \mathbf{s}'_j = \mathbf{S}' \odot \mathbf{s}_j$$

matching *aggregation* *Filetering & Scoring*

- Fusion with decay (on recency of utterances in context)

$$A_i = A_i * \eta^{n-i}, \quad \text{(sentence-level)} \qquad \hat{\mathbf{B}}_i = \hat{\mathbf{B}}_i * \eta^{n-i}. \quad \text{(word-level)}$$

Details of CSN

- Matching with response
  - Context-response and document-response

$$\mathbf{M}_1^{cr} = \mathbf{C}\mathbf{H}_1\mathbf{r}^\top \oplus \cos(\mathbf{C}, \mathbf{r}), \qquad \mathbf{M}_1^{dr} = \mathbf{D}\mathbf{H}_1\mathbf{r}^\top \oplus \cos(\mathbf{D}, \mathbf{r}),$$

  - Matching with self-attention representation

$$\mathbf{M}_2^{cr} = \hat{\mathbf{C}}\mathbf{H}_2\hat{\mathbf{r}}^\top \oplus \cos(\hat{\mathbf{C}}, \hat{\mathbf{r}}), \qquad \mathbf{M}_2^{dr} = \hat{\mathbf{D}}\mathbf{H}_2\hat{\mathbf{r}}^\top \oplus \cos(\hat{\mathbf{D}}, \hat{\mathbf{r}})$$

  - Cross-attention (context-aware response rep., document-aware response rep.)

$$\tilde{\mathbf{C}} = f_{\mathrm{ATT}}(\mathbf{C}, \mathbf{r}, \mathbf{r}), \qquad \tilde{\mathbf{r}}^c = f_{\mathrm{ATT}}(\mathbf{r}, \mathbf{C}, \mathbf{C}),$$

$$\tilde{\mathbf{D}} = f_{\mathrm{ATT}}(\mathbf{D}, \mathbf{r}, \mathbf{r}), \qquad \tilde{\mathbf{r}}^d = f_{\mathrm{ATT}}(\mathbf{r}, \mathbf{D}, \mathbf{D}).$$

$$\mathbf{M}_3^{cr} = \tilde{\mathbf{C}}\mathbf{H}_3\tilde{\mathbf{r}}^{c\top} \oplus \cos(\tilde{\mathbf{C}}, \tilde{\mathbf{r}}^c), \qquad \mathbf{M}_3^{dr} = \tilde{\mathbf{D}}\mathbf{H}_3\tilde{\mathbf{r}}^{d\top} \oplus \cos(\tilde{\mathbf{D}}, \tilde{\mathbf{r}}^d)$$

  - Flatten and aggregation

$$\mathbf{h}_1 = \mathrm{LSTM}(\mathbf{v}^{cr}), \quad \mathbf{h}_2 = \mathrm{LSTM}(\mathbf{v}^{dr})$$

  - Output

$$g(c, d, r) = \sigma\big(\mathrm{MLP}(\mathbf{h}_1 \oplus \mathbf{h}_2)\big)$$

Experiments

- Task: retrieve the correct response from 1:19 positive:negative mixture

Soft selection

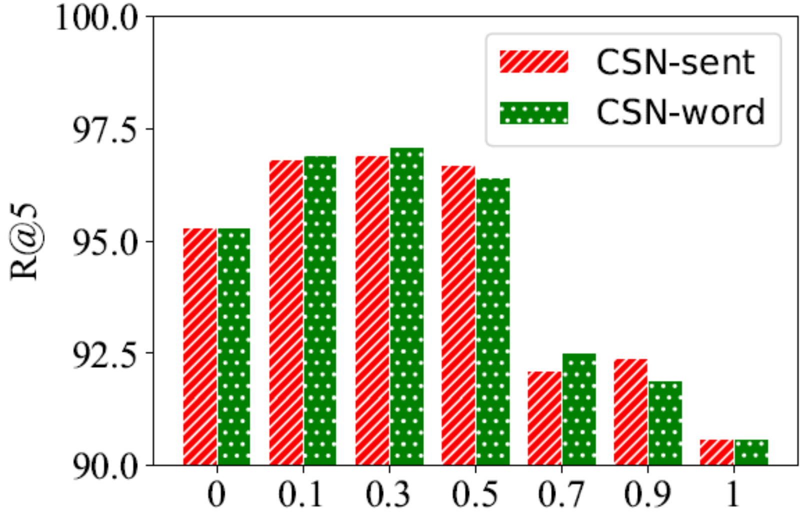
Table 1: Experimental results on all datasets.

	PersonaChat-Original			PersonaChat-Revised			CMUDoG		
	R@1	**R@2**	**R@5**	**R@1**	**R@2**	**R@5**	**R@1**	**R@2**	**R@5**
Starspace	49.1	60.2	76.5	32.2	48.3	66.7	50.7	64.5	80.3
Profile	50.9	60.7	75.7	35.4	48.3	67.5	51.6	65.8	81.4
KV Profile	51.1	61.8	77.4	35.1	45.7	66.3	56.1	69.9	82.4
Transformer	54.2	68.3	83.8	42.1	56.5	75.0	60.3	74.4	87.4
DGMN	67.6	81.3	93.3	56.7	73.0	89.0	65.6	78.3	91.2
DIM	75.5	87.5	96.5	68.3	82.7	94.4	59.6	74.4	89.6
CSN-sent	77.5	88.8	96.8	70.1	83.4	95.1	**70.1**	82.5	**94.3**
CSN-word	**78.1**	**89.0**	**97.1**	**71.3**	**84.2**	**95.5**	69.8	**82.7**	94.0

Personal profile as document

Movie wiki as document

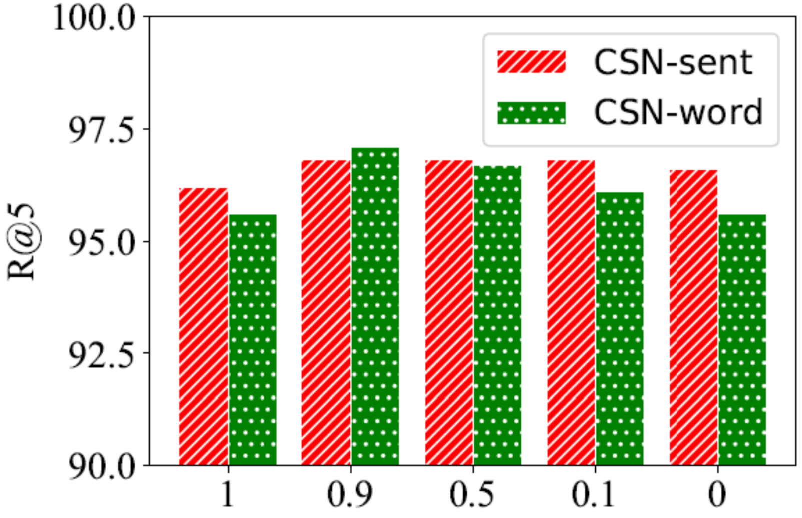
Effect of document content selection and dialogue history decaying



(a) Effect of γ.

No selection, only weighting

No document grounding



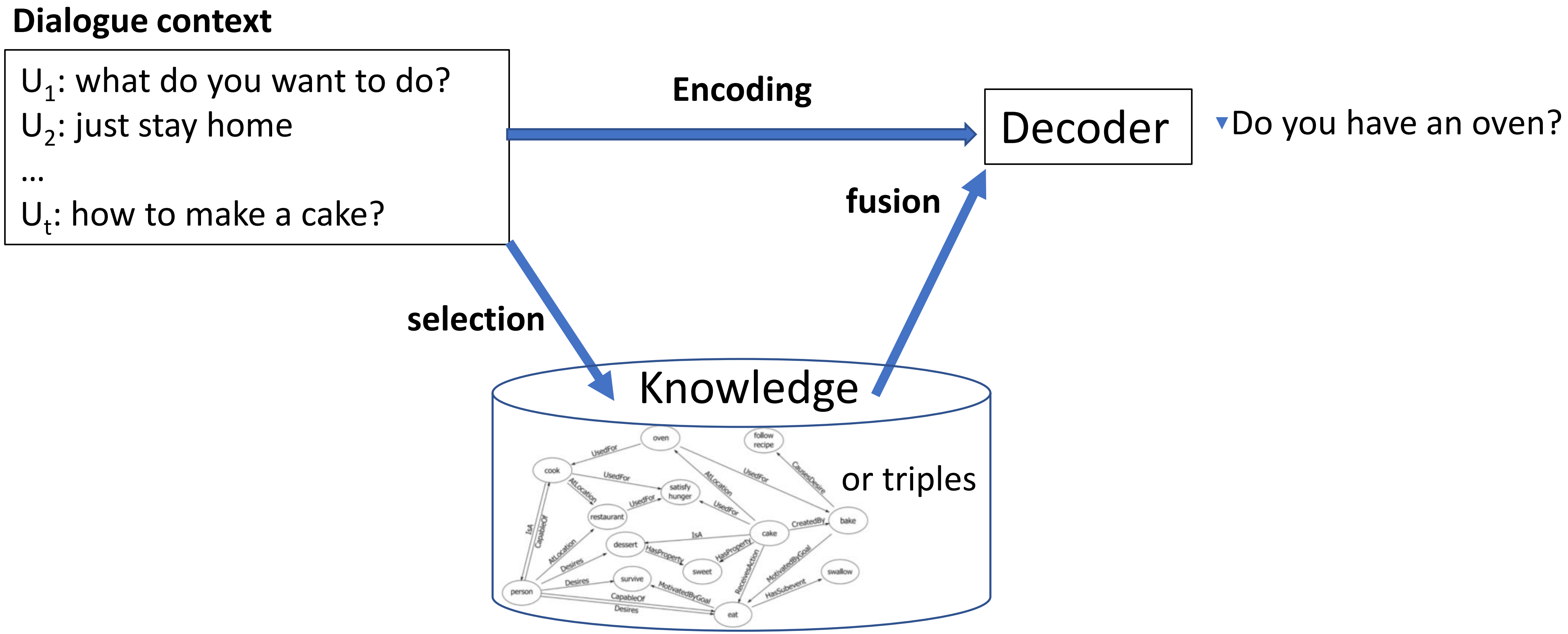
(b) Effect of η.

No decay

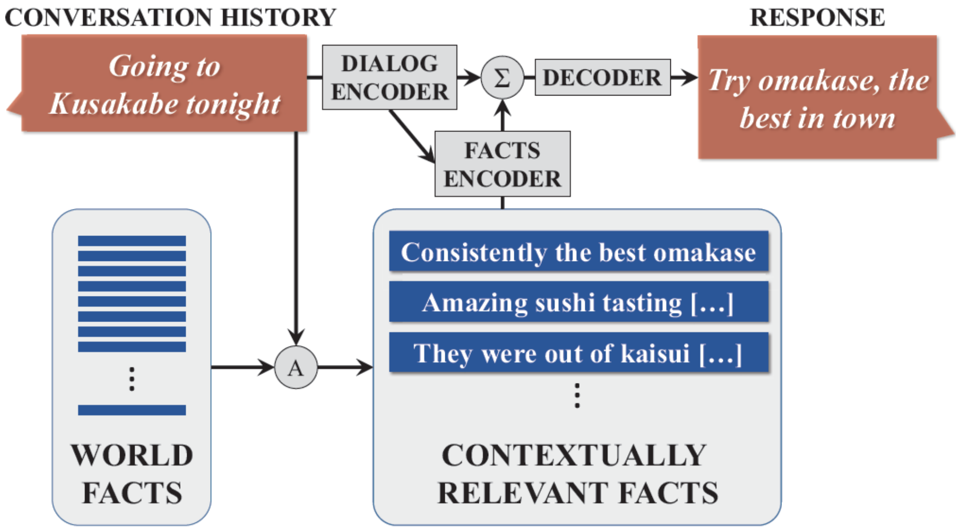
Only last utterance

Knowledge-grounded dialogue

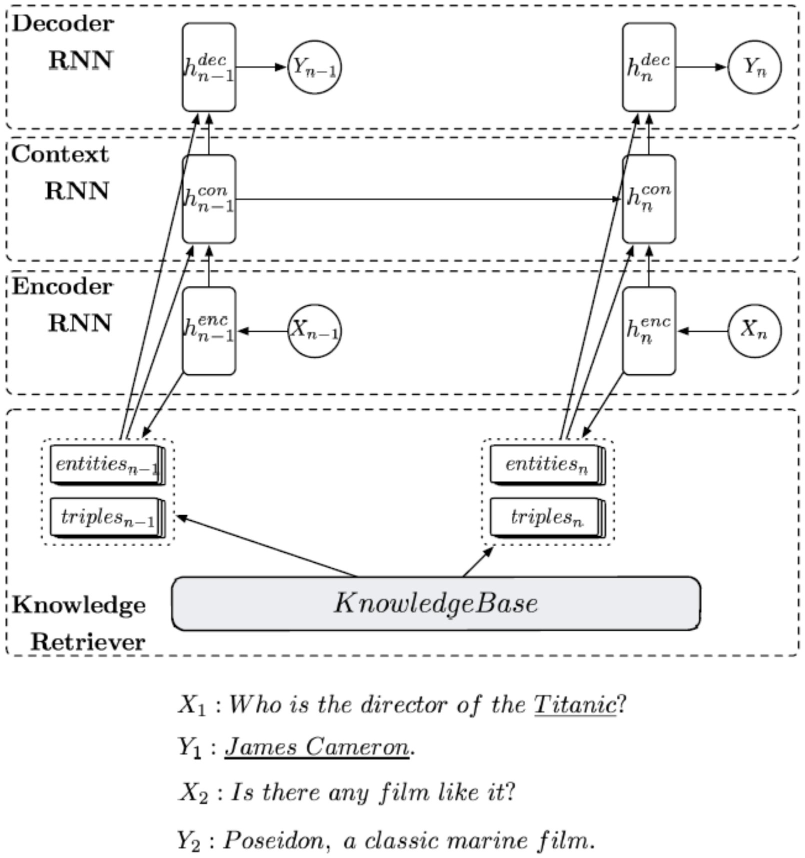
Knowledge as a graph or as a set of triples



Knowledge-grounded dialogue - approaches



- Store knowledge in a memory
  - read-out using context as query



- Knowledge fusion (Liu et al. ACL 2018)
  - Retrieve pieces of knowledge corresponding to the entities in context
  - Fusion in decoder: generate a token from common vocabulary or knowledge

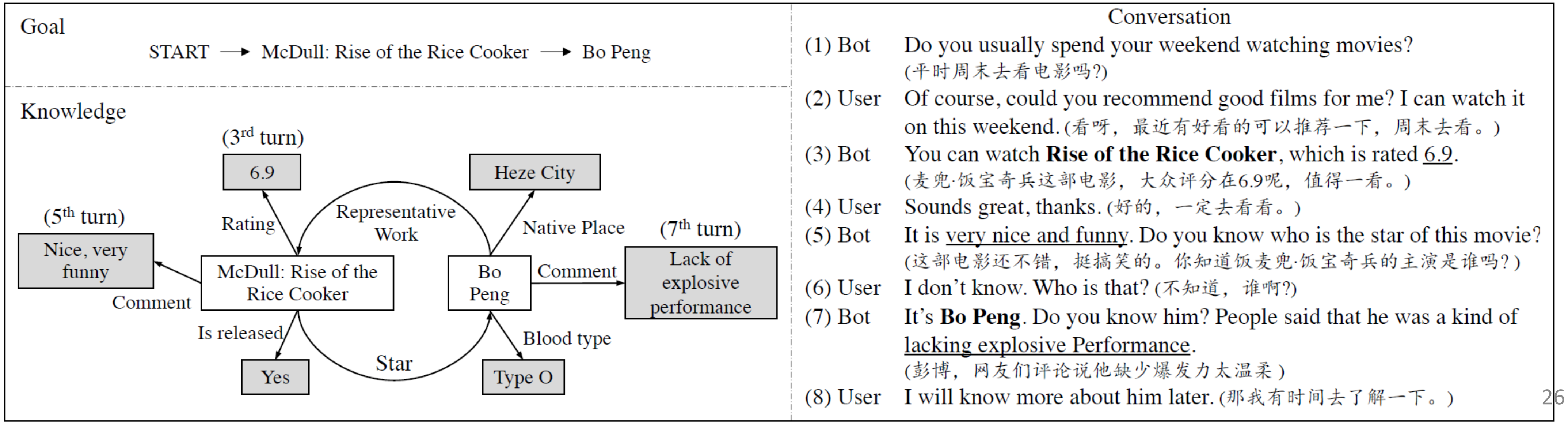
Key issues in knowledge-grounded dialogue

- How to fuse a piece of knowledge into response?
  - Gating, …
- What pieces of knowledge are relevant (to ground the response)?
  - Selection by soft matching/weighting (attention), or entity
  - Usually trained implicitly (end-to-end)

  → Difficult to know if knowledge has been selected correctly

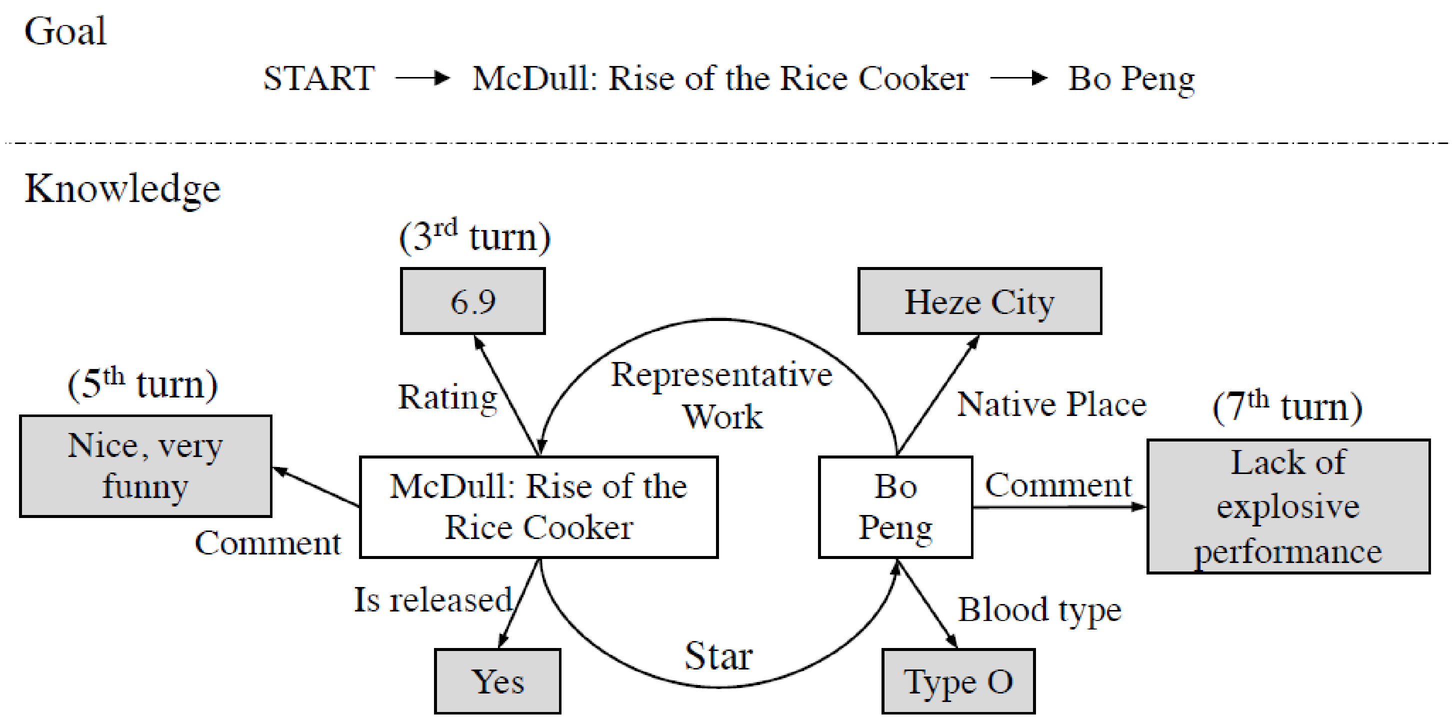
Proactive knowledge-grounded dialogue
(Zhu et al. SIGIR 2021)

- Dialogue grounded in domain knowledge (movie domain)
- Goal-driven dialogue: lead conversation to some goal
  - Goal = a set of entities to mention (Wu et al. 2019)
- Task: Select the right candidate response



Knowledge-grounded proactive conversation

- Movie domain knowledge
- The chatbot should lead the conversation to discuss about some entities (movie, actor, …)



Desired conversation (DuConv)

Goal
START → McDull: Rise of the Rice Cooker → Bo Peng

(1) Bot Do you usually spend your weekend watching movies?
(平时周末去看电影吗?)

(2) User Of course, could you recommend good films for me? I can watch it on this weekend. (看呀，最近有好看的可以推荐一下，周末去看。)

(3) Bot You can watch **Rise of the Rice Cooker**, which is rated 6.9.
(麦兜·饭宝奇兵这部电影，大众评分在6.9呢，值得一看。)

(4) User Sounds great, thanks. (好的，一定去看看。)

(5) Bot It is very nice and funny. Do you know who is the star of this movie?
(这部电影还不错，挺搞笑的。你知道饭麦兜·饭宝奇兵的主演是谁吗?)

(6) User I don't know. Who is that? (不知道，谁啊?)

(7) Bot It's **Bo Peng**. Do you know him? People said that he was a kind of lacking explosive Performance.
(彭博，网友们评论说他缺少爆发力太温柔)

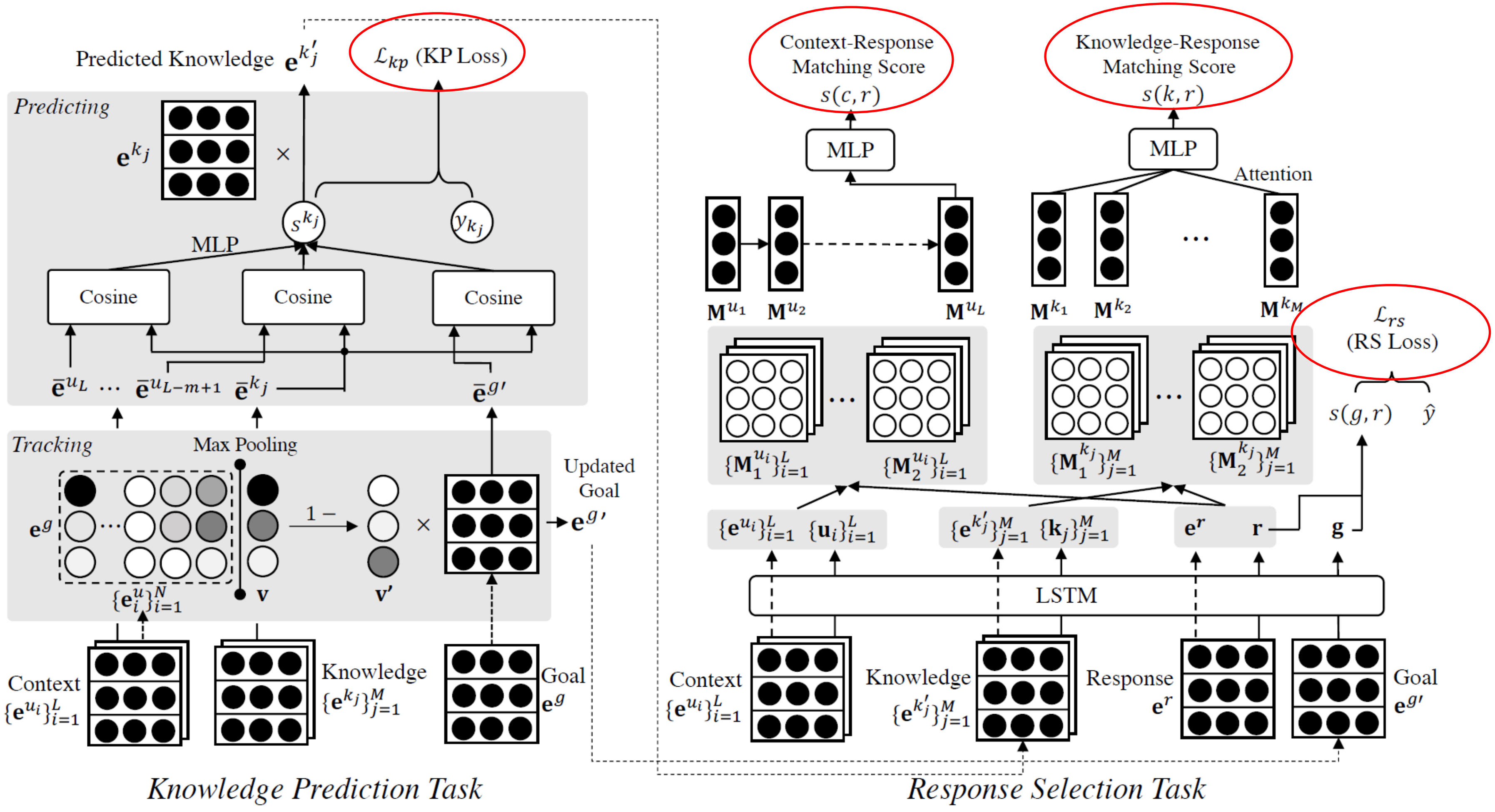
(8) User I will know more about him later. (那我有时间去了解一下。)

KPN – Knowledge Prediction Network

- **Explicit model for knowledge selection**
  - Previous work: implicit selection
    - Does not provide clear signal to knowledge selection
    - Wrong response can be due to wrong knowledge selection or wrong response selection
  - Training signal: Knowledge used in gold responses
- **Goal tracking: what goal to achieve next?**
- Interactive matching with response
  - Context-response
  - Goal-response
  - Knowledge-response
- Multi-task learning: knowledge selection + response selection

KPN architecture

- What knowledge is relevant?
- What goal to achieve?
- Context and goal encoding



Some details

- Goal tracking
  - Goal-context matching $\mathbf{m}_{ij} = \cos(\mathbf{e}_i^g, \mathbf{e}_j^u).$
  - Degree of satisfaction $v_i = \mathrm{ReLU}(\mathrm{Maxpooling}(\mathbf{m}_{i,:}))$
  - Remaining goal $\mathbf{v}' = \mathbf{1} - \mathbf{v} \qquad \mathbf{e}^{g'} = \mathbf{v}' \cdot \mathbf{e}^g$

- Explicit knowledge prediction
  - Similarity to context and to goal $s_{g'}^{k_j} = \cos(\bar{\mathbf{e}}^{g'}, \bar{\mathbf{e}}^{k_j}), \quad s_i^{k_j} = \cos(\bar{\mathbf{e}}^{u_i}, \bar{\mathbf{e}}^{k_j}),$
  - Prediction probability $s^{k_j} = \sigma\left(\mathrm{MLP}([s_0^{k_j}; s_{L-m+1}^{k_j}; \cdots; s_L^{k_j}])\right),$

    $\mathbf{e}^{k_j'} = s^{k_j} \mathbf{e}^{k_j},$
  - Prediction loss $\mathcal{L}_{kp} = -\frac{1}{|\mathcal{D}|} \sum \left(y_{k_j} \log s^{k_j} + (1 - y_{k_j}) \log(1 - s^{k_j}) \right)$

  - Knowledge labeling: k_i is used (label 1) if its *object* appears in gold response

Some details

- Response selection
  - Word-level matching
  - Setence-level matching

$$\mathbf{m}_1^{u_i} = [\mathbf{e}^{u_i}\mathbf{A}_1\mathbf{e}^r; \cos(\mathbf{e}^{u_i}, \mathbf{e}^r)],$$

$$\mathbf{m}_1^{k_j} = [\mathbf{e}^{k'_j}\mathbf{A}_1\mathbf{e}^r; \cos(\mathbf{e}^{k'_j}, \mathbf{e}^r)],$$

$$\mathbf{u}_i = \text{LSTM}(\mathbf{e}^{u_i}), \quad \ldots$$

$$\mathbf{m}_2^{u_i} = [\mathbf{u}_i\mathbf{A}_2\mathbf{r}; \cos(\mathbf{u}_i, \mathbf{r})],$$

$$\mathbf{m}_2^{k_j} = [\mathbf{k}_j\mathbf{A}_2\mathbf{r}; \cos(\mathbf{k}_j, \mathbf{r})],$$

  - Concatenation

$$\mathbf{m}^{u_i} = [\mathbf{m}_1^{u_i}; \mathbf{m}_2^{u_i}], \qquad \mathbf{m}^{k_j} = [\mathbf{m}_1^{k_j}; \mathbf{m}_2^{k_j}].$$

  - CNN and max-pooling

$$\mathbf{v}^u = [\mathbf{v}^{u_1}, \cdots, \mathbf{v}^{u_L}]; \quad \mathbf{v}^k = [\mathbf{v}^{k_1}, \cdots, \mathbf{v}^{k_M}].$$

  - Scoring

$$\mathbf{h}_1 = \text{LSTM}(\mathbf{v}^u), \qquad s(c,r) = \text{MLP}(\mathbf{h}_1).$$

$$\alpha_i = \text{ReLU}(\text{MLP}(\mathbf{v}_i^k)) \qquad \mathbf{h}_2 = \sum_{i=1}^{k_M} \frac{e^{\alpha_i}}{\sum_{j=1}^{k_M} e^{\alpha_j}} \mathbf{v}_i^k, \qquad s(k,r) = \text{MLP}(\mathbf{h}_2).$$

$$\mathbf{g} = \text{LSTM}(\mathbf{e}^{g'}), \qquad \mathbf{h}_3 = [\mathbf{g}_{[-1,:]}; \mathbf{r}_{[-1,:]}], \qquad s(g,r) = \text{MLP}(\mathbf{h}_3).$$

  - Final score

$$\hat{y} = (s(c,r) + s(k,r) + s(g,r))/3.$$

- Training $\mathcal{L} = \lambda\mathcal{L}_{kp} + \mathcal{L}_{rs},$

Experiments (1:9 mixture to selection)

	Hits@1	Hits@3	MRR	BLEU1	BLEU2	KLG. P	KLG. R	KLG. F1	KLG. Acc.	Goal Acc.
DuConv										
Ground-truth	-	-	-	1.00	1.00	38.24	9.20	14.83	100.00	100.00
DuRetrieval	50.12	75.68	63.13	0.47	0.32	30.11	7.24	11.68	53.64	58.90
KPN	**66.94**	**87.52**	**78.30**	**0.56**	**0.42**	**33.45**	**8.05**	**12.97**	**57.82**	**77.58**
+ MemNet	52.54	78.70	67.90	0.50	0.34	29.24	7.03	11.34	50.90	72.36
+ PostKS	39.98	65.70	57.09	0.48	0.33	28.55	6.87	11.07	50.42	69.44
+ NKD	56.42	81.54	70.77	0.50	0.35	29.40	7.07	11.40	52.94	74.62
DuRecDial										
Ground-truth	-	-	-	1.0	1.0	52.64	3.76	7.02	100.00	100.00
DuRetrieval	77.38	89.02	84.47	0.46	0.39	43.42	3.10	5.79	94.90	78.34
KPN	**91.50**	**98.86**	**95.18**	**0.61**	**0.51**	**52.55**	**3.76**	**7.01**	**95.35**	**84.96**
+ MemNet	75.34	93.92	85.00	0.51	0.39	41.04	2.93	5.48	94.32	82.58
+ PostKS	82.45	96.60	89.58	0.53	0.41	43.70	3.12	5.83	94.90	83.12
+ NKD	82.74	97.03	89.96	0.53	0.41	42.87	3.07	5.72	94.81	83.93

Goal-oriented Dialogue on movies

Conversational recommendation on food, movie, …

DuRetrieval:
- BERT-based context and response rep.
- Goal as additional knowledge
- Selection by attention with context

MemNet, PostKS, NKD: Only knowledge weighting

Effect of knowledge selection and goal

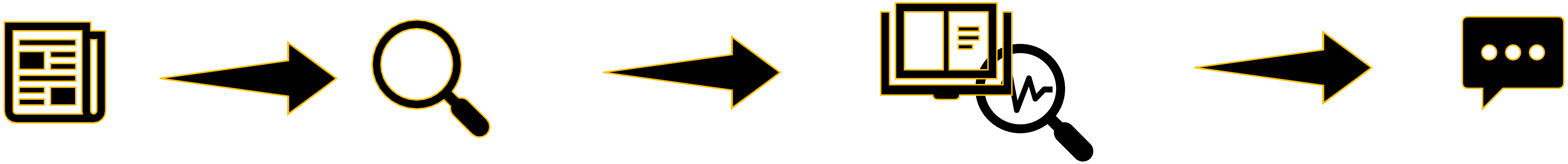
- Knowledge is useful
- Goal is useful (less than knowledge)
- Using goal as a piece of knowledge does not perform well

	KPN	*w/o* K.	*w/o* G.	G. as K.
Hits@1	**66.94**	38.28	62.32	61.94
Hits@3	**87.52**	32.88	85.14	84.56
MRR	**78.30**	55.83	75.20	74.90
BLEU1	**0.56**	0.48	0.53	0.53
BLEU2	**0.42**	0.32	0.39	0.39
KLG. P	**33.45**	28.99	33.07	32.21
KLG. R	**8.05**	6.97	7.95	7.75
KLG. F1	**12.97**	11.24	12.82	12.49
KLG. Acc.	**57.82**	48.80	55.52	56.22
Goal Acc.	**77.58**	67.88	74.42	74.70

Table 2: Ablation test for KPN on DuConv dataset. "*w/o* G." means the goal is not used. "G. as K." means using the goal as a knowledge triplet.

Grounded answer in Open-domain QA:

- Open domain QA: find answer from many texts



Retriever: retrieve a set of texts (documents/ paragraphs/sentences) for a question

Reader: Machine reading comprehension (MRC) to find an answer from the selected documents

Key issue: Retriever and Reader disconnected

Illustration Example

Question: **What Russian emigre to the U.S. is credited with inventing the helicopter ?**
Ground Truth: **Igor**

		r	a	Passages
✗	P_1	1	0	Wright brothers: Orville and Wilbur Wright, were the two Americans who are credited with inventing and building the world's first successful airplane.
?	P_2	1	1	The fellow Russian emigre, ~~Igor~~ Ivanovich Sikorsky, was an American aviation pioneer in both helicopters and fixed-wing aircraft, who was credited with many other accomplishments...
	P_3	0	1	~~Igor~~ Ivanovich Sikorsky was an orthodox chiristian.
✓	P_4	1	1	His paternal grandfather, Leo Shoumatoff, was the bussiness manager of ~~Igor~~ Sikorsky's aircraft company, where **Igor** developed the first helicopter and the first passenger airplane.

- Ranking by retriever: P2 > P4 > P1 > P3
- Some of the passages contain query words, but do not contain the answer (P1) or do not support the answer (P2)
- Idea: Select passages that are relevant and may contain the answer

Adding an answer-oriented passage selector

- Passage reranking: Relevance + Containing possible answer (lightweight reader)

Retriever: retrieve a set of texts (documents/ paragraphs/sentences) for a question

Ranker: select/rerank passages according to relevance + possible answer

Reader: Machine reading comprehension to find an answer from the selected documents

Training of Ranker with noisy data

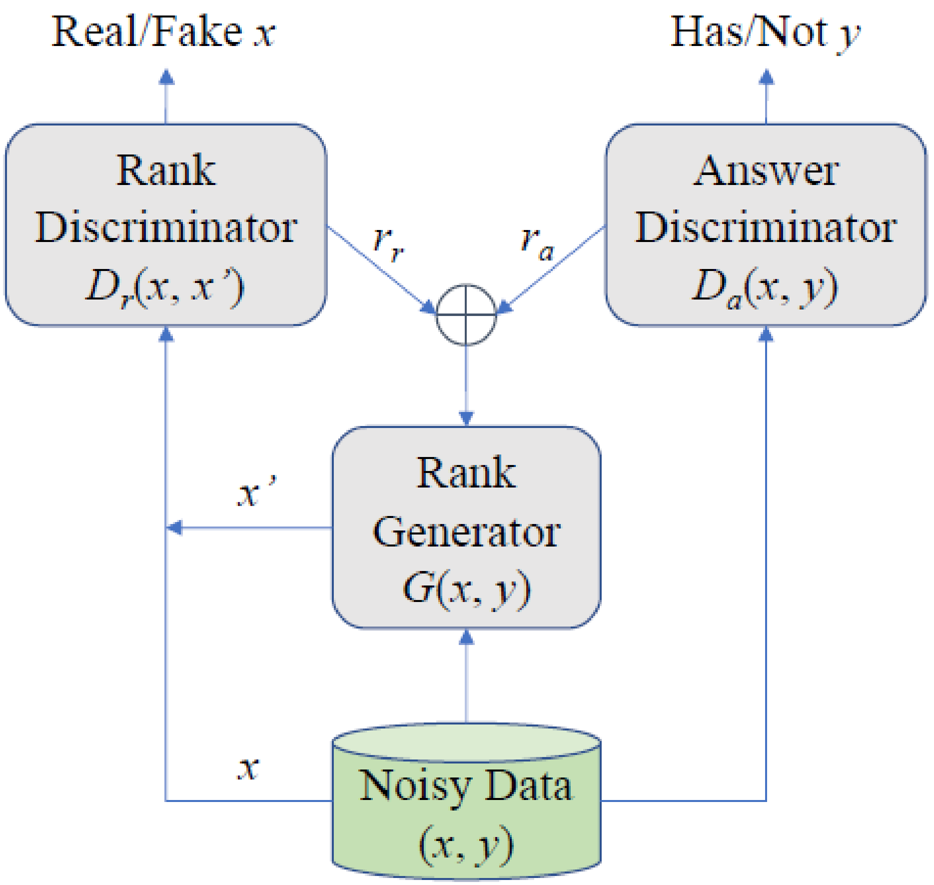
- Available data: Question-answer pairs
- Assumption in previous work: a passage containing the answer is a good passage
- A good passage is the one that contains the answer and a support to the answer (relevance)

	r	a	Passages
Question:			**What Russian emigre to the U.S. is credited with inventing the helicopter ?**
Ground Truth:			**Igor**
	r	**a**	Passages
P_1	1	0	Wright brothers: Orville and Wilbur Wright, were the two Americans who are credited with inventing and building the world's first successful airplane.
P_2	1	1	The fellow Russian emigre, ~~Igor~~ Ivanovich Sikorsky, was an American aviation pioneer in both helicopters and fixed-wing aircraft, who was credited with many other accomplishments...
P_3	0	1	~~Igor~~ Ivanovich Sikorsky was an orthodox chiristian.
P_4	1	1	His paternal grandfather, Leo Shoumatoff, was the bussiness manager of ~~Igor~~ Sikorsky's aircraft company, where **Igor** developed the first helicopter and the first passenger airplane.

GAN-based training

- Adversarial training: Try to separate good and bad examples
- General GAN:
  - Generator – learns the distribution of true data
  - Discriminator – tries to separate true and fake data

- Extended GAN framework
  - Generator
  - 2 discriminators: relevant and contain answer?



Some formulas

- Overall objective
$$J = \min_{\theta} \max_{\phi,\xi} \sum_{n=1}^{N} \Big(\mathbb{E}_{d\sim p_{true}(d|q_n,a)}[\log D^r_\phi(d|q_n)] +$$
$$\mathbb{E}_{d\sim p_\theta(d|q_n,a)}[\log(1 - D^r_\phi(d|q_n))] -$$
$$\lambda_1 \cdot \mathbb{E}_{d\sim p_\theta(d|q_n,a)}[\log D^a_\xi(d|q_n)] +$$
$$\lambda_2 \cdot \mathbb{E}_{d\sim p_{true}(d|q_n,a)}[\log \frac{p_{true}(d|q_n,a)}{p_\theta(d|q_n,a)}] \Big)$$
- Generator: $p_\theta(d|q_n, a)$
- Rank discriminator (relevance): D^r_ϕ
- Answer discriminator: D^a_ξ
- Regularizer: $\mathbb{E}_{d\sim p_{true}(d|q_n,a)}[\log \frac{p_{true}(d|q_n,a)}{p_\theta(d|q_n,a)}]$

Some more formulas for losses

- Rank discriminator:

$$\mathcal{L}_{D^r_\phi} = -\sum_{n=1}^{N} \Big(\mathbb{E}_{d\sim p_{true}} [\log(\sigma(f_\phi(d, q_n)))] + \mathbb{E}_{d\sim p_{\theta^*}} [\log(1 - \sigma(f_\phi(d, q_n)))] \Big)$$

- Answer discriminator:

$$\mathcal{L}_{D^a_\xi} = -\sum_{n=1}^{N} \Big(\sum_{d\in A^+} \log \sigma(f_\xi((d, q_n))) + \sum_{d\in A^-} \log(1 - \sigma(f_\xi(d, q_n))) \Big)$$

- Generator:

$$\mathcal{L}_{p_\theta} = \sum_{n=1}^{N} \Big(\mathbb{E}_{d\sim p_\theta} [\log(1 - \sigma(f_{\phi^*}(d, q_i)))] - \lambda_1 \mathbb{E}_{d\sim p_\theta} [\log \sigma(f_{\xi^*}(d, q_n))] - \lambda_2 \mathbb{E}_{d\sim p_{true}} [\log p_\theta(d|q_n, a)] \Big)$$

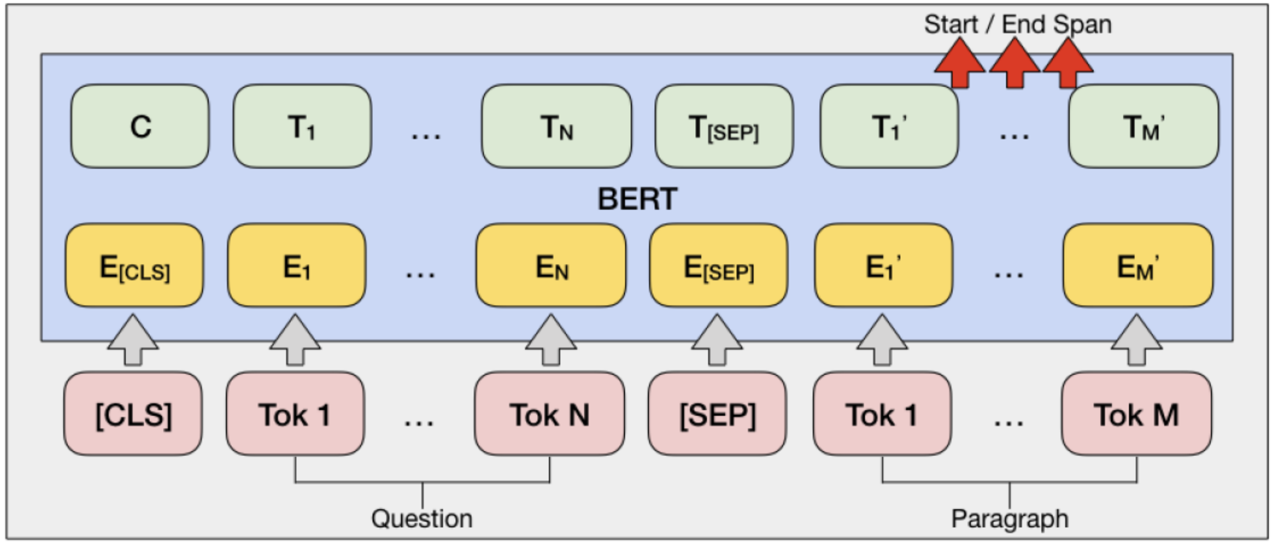
Training

- Document and question encoding: BiLSTM + self-attention
- Score functions in discriminators: $f_\phi(d_i, q) = p(d_i|q) = \text{softmax}(\max_j(\hat{d}_i^j W q)),$
- Score by generator: $f_\theta(d_i, q) = p_\theta(a|q, d_i) = \max_{j,k} p_s^j(a|q, d_i) p_e^k(a|q, d_i)$
- REINFORCE algorithm for training

Retriever and Reader

- Retriever: BM25
- Our ranker
- Reader: A reader based on 12-layer BERT

$$P(s, e, i) = P(d_i) \cdot P(s|d_i) \cdot P(e|d_i)$$
$$P(s|d_i) = \mathrm{softmax}(d_i w_{start})_s$$
$$P(e|d_i) = \mathrm{softmax}(d_i w_{end})_t$$
$$P(d_i) = \mathrm{softmax}(\hat{D}^T w_{doc})_i$$



Some experimental results

- Test collections

Dataset	#Train	#Dev	#Test	#Psgs/Que
Quasar-T	37,012	3,000	3,000	100
SearchQA	99,811	13,893	27,247	~49.6
TriviaQA	87,291	11,274	10,790	100
CuratedTREC	1,353	133	694	Wikipedia (50)
Nat.Question	79,168	8,757	3,610	Wikipedia (50)

- Reranking (part)

	Quasar-T			SearchQA		
	BM25	DSQA	Ours	BM25	DSQA	Ours
Hits@1	*6.3*	*27.7*	**35.2**	*13.7*	*59.9*	**63.9**
Hits@3	*10.9*	*36.8*	**52.0**	*24.1*	*69.8*	**83.0**
Hits@5	*15.2*	*42.6*	**59.5**	*32.7*	*75.5*	**88.8**
Hits@20	-	-	**72.3**	-	-	**97.5**
Hits@50	-	-	**74.8**	-	-	**99.8**

Final answer

	Quasar-T	SearchQA	Cur.Trec	Trivia	NQ_{sub}
BM25	41.6	57.9	*21.3*	*47.1*	26.7
R^3	*35.3*	*49.0*	*28.4*	*47.3*	-
DSQA	*42.2*	*58.8*	*29.1*	*48.7*	-
DPR	-	-	*28.0*	*57.0*	27.4
Ours	**45.5**	**61.2**	**29.3**	**60.7**	**29.5**

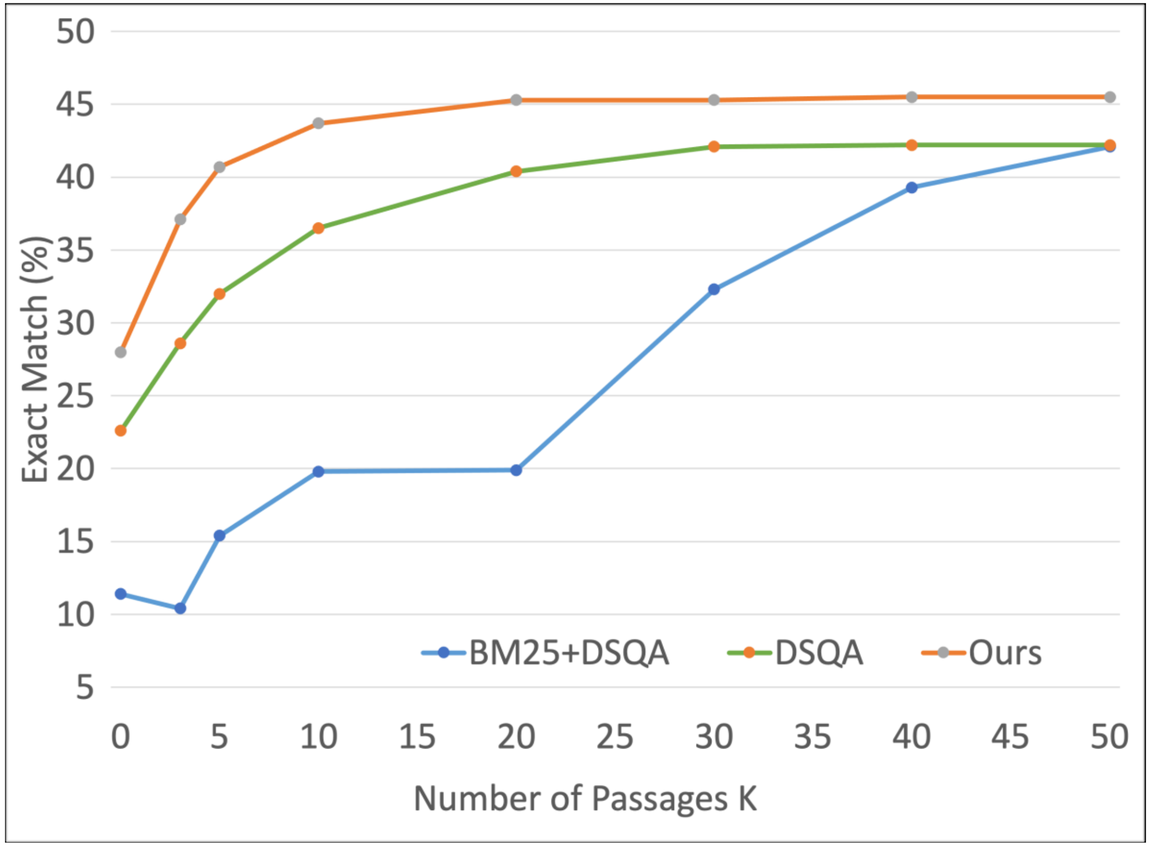
Example

Question: **What Russian emigre to the U.S. is credited with inventing the helicopter ?**
Ground Truth: **Igor**

	r	a	Passages	DPR Score	Our Score
P_1	1	0	Wright brothers: Orville and Wilbur Wright, were the two Americans who are credited with inventing and building the world's first successful airplane.	71.7	242.9
P_2	1	1	The fellow Russian emigre, ~~***Igor***~~ Ivanovich Sikorsky, was an American aviation pioneer in both helicopters and fixed-wing aircraft, who was credited with many other accomplishments...	**75.6**	286.8
P_3	0	1	~~***Igor***~~ Ivanovich Sikorsky was an orthodox chiristian.	57.7	178.1
$\mathbf{P_4}$	1	1	His paternal grandfather, Leo Shoumatoff, was the bussiness manager of ~~***Igor***~~ Sikorsky's aircraft company, where **Igor** developed the first helicopter and the first passenger airplane.	74.4	**292.3**

How does reranking helps in overall efficiency?

- Only a few reranked passages are sufficient
- Lightweight ranker: a fraction of retrieval and machine reading time
  - Retriever: 3.3 ms
  - Ranker: 0.5 ms
  - Reader: 57.3 ms



Conclusions

- Grounded dialogue (and QA) is an important problem
- Key questions:
  - How to select a relevant piece of knowledge / document content?
  - How to incorporate it into response generation / selection?
  - How to ground an answer in QA?
- In this talk
  - Retrieval-based dialogue grounded in document / knowledge
  - Finding grounding passages for QA
- Other interesting questions not covered
  - Grounded Generation-based dialogue
  - Incorporating pre-trained models
  - More types of grounding: Emotion, …
  - Using GNN
  - Explicit reasoning process (symbolic + neural)
  - How to evaluate a dialogue system?