Deep Chit-Chat: Deep Learning for ChatBots

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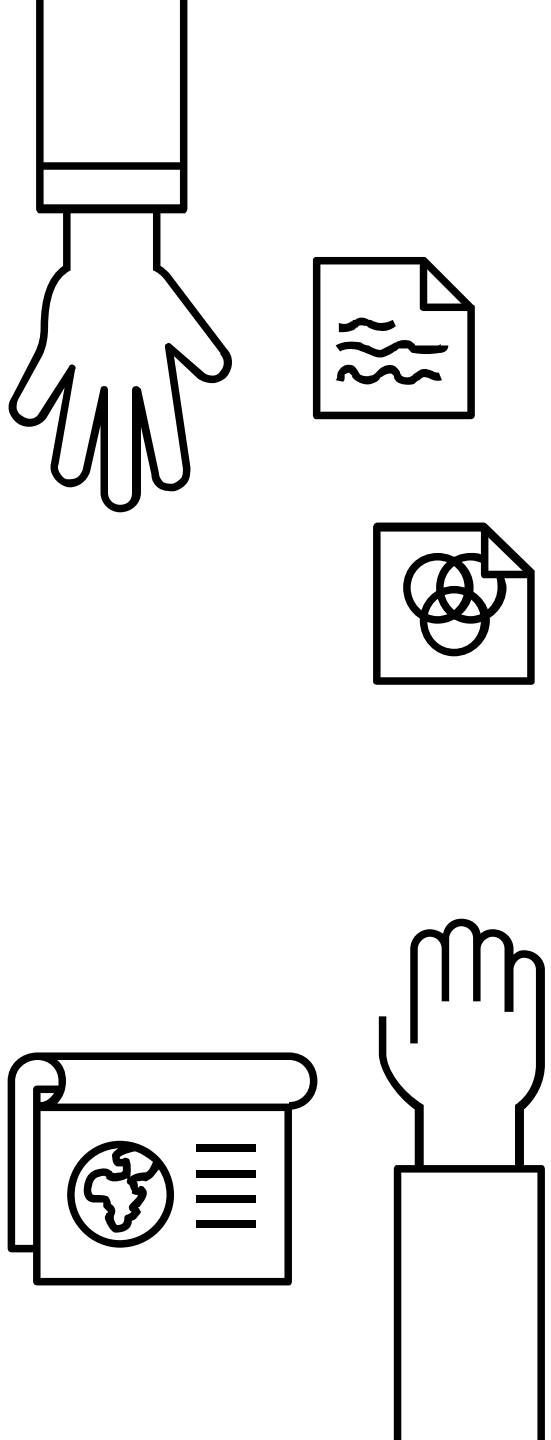
Outline

- Introduction
- Basic Deep Learning Concepts
- Retrieval-based Chatbots
- Break
- Generation-based Chatbots
- Evaluation
- New Trends and Conclusion

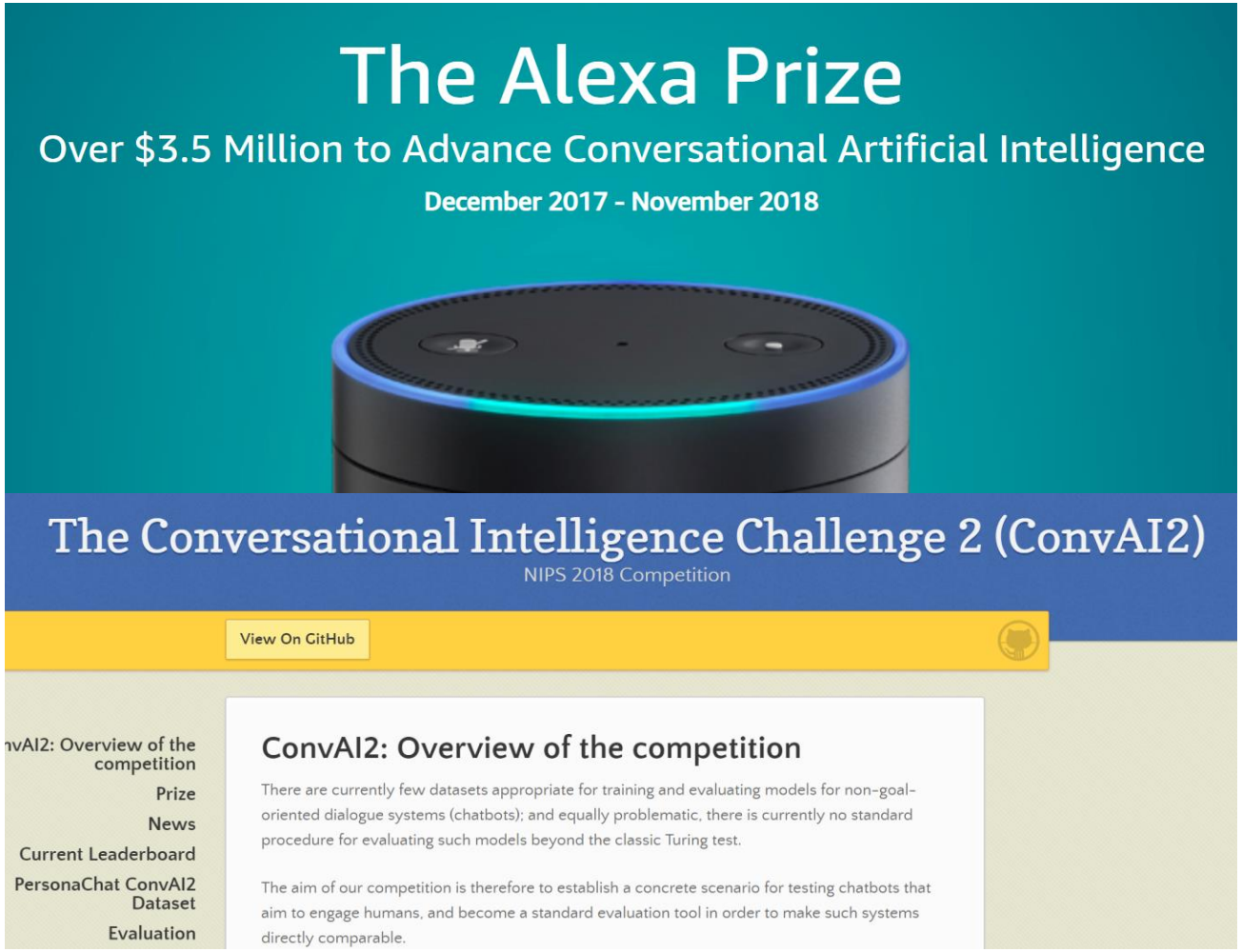
Our Target Audience

- PhD students or researchers working on open domain dialogue systems.
- NLP/IR/ML engineers or scientists with hands-on experience on building chatbots with deep learning techniques.
- Anyone who wants to learn how neural approaches (i.e., deep learning techniques) can be applied to building chatbots.
- Anyone who wants to build chatbots that can chat like humans (better with deep learning background).

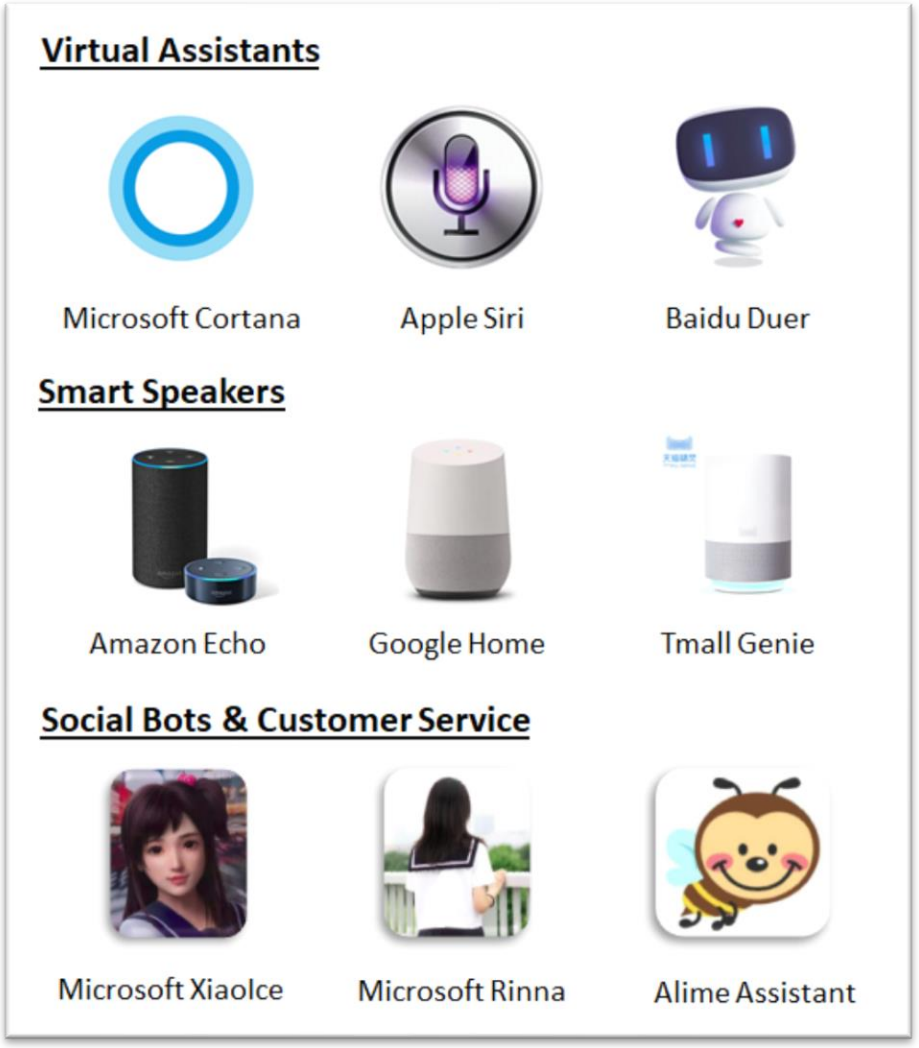


Chatbots are ``HOT''

Academia

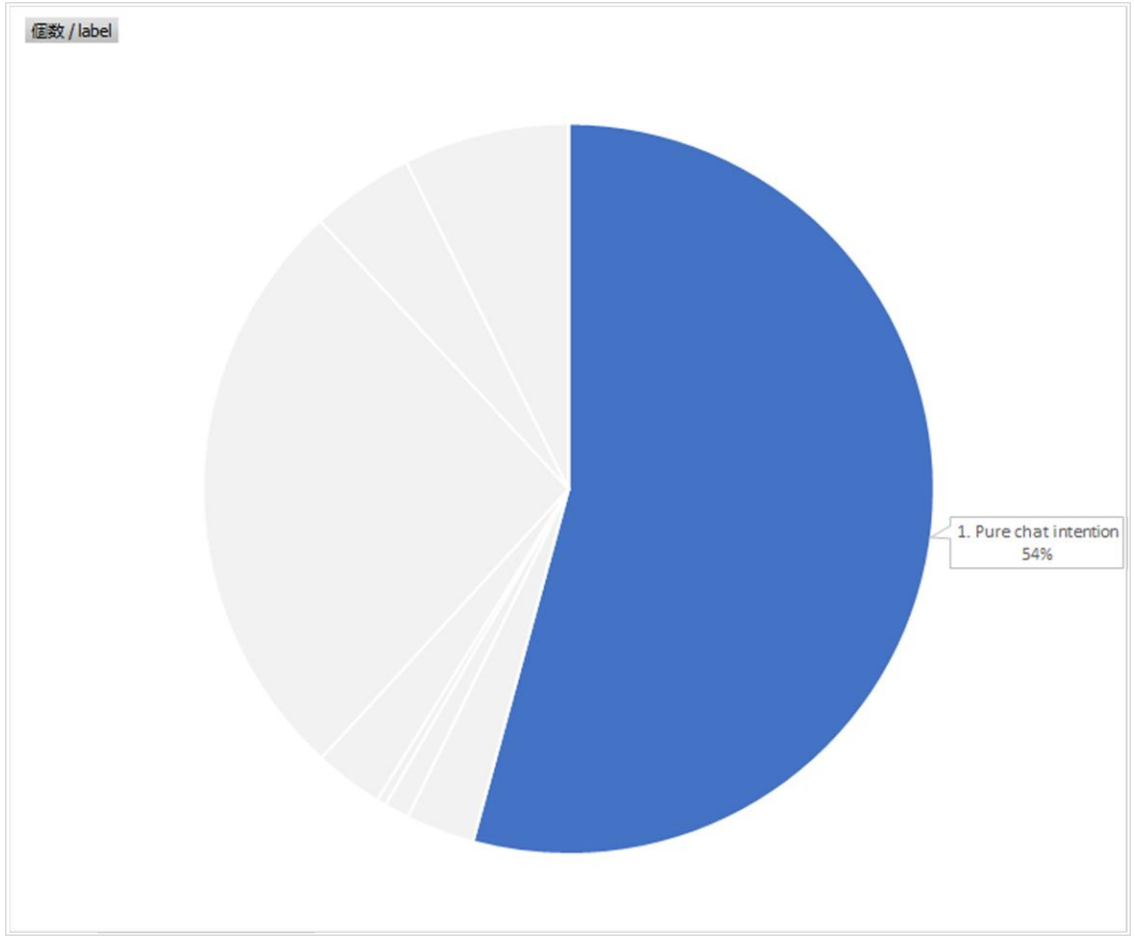


Industry

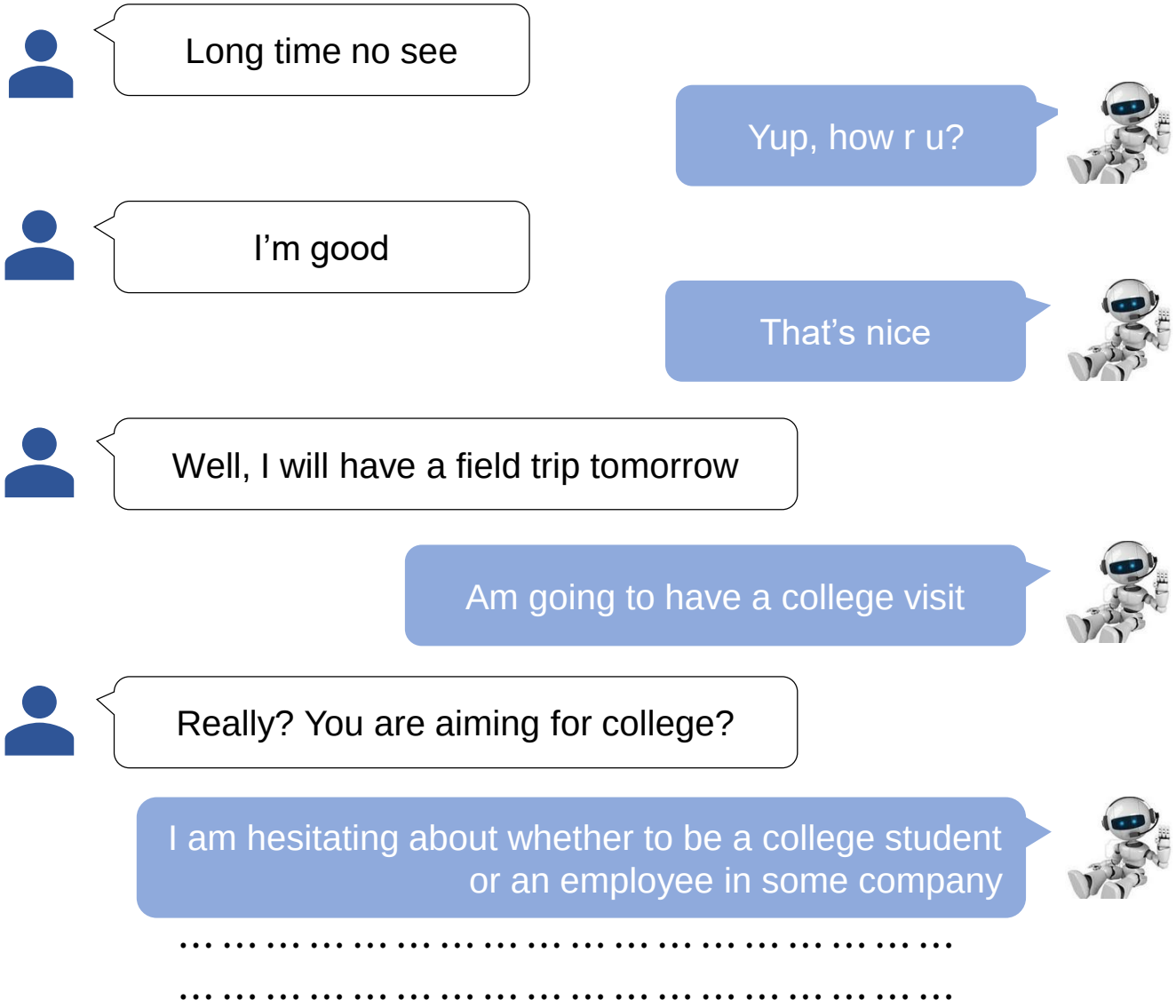


Conversations in a Chatbot

Analysis is done from 100 sessions randomly sampled from the log of Microsoft Rinna, a commercial chatbot with 6M+ users in Japan.



Building A Dialogue System for Human-Machine ``Chat''



- **Chit-chat:** casual and non-goal-oriented
- **Open domain:** the topic of the conversation could be any. Users may jump from topic to topic in the conversation
- **Relevance & Diversity:** the research focuses on automatic replying with relevant (to the context) and diverse (informative) responses to make conversations engaging

Different From Goal-Oriented Dialogues

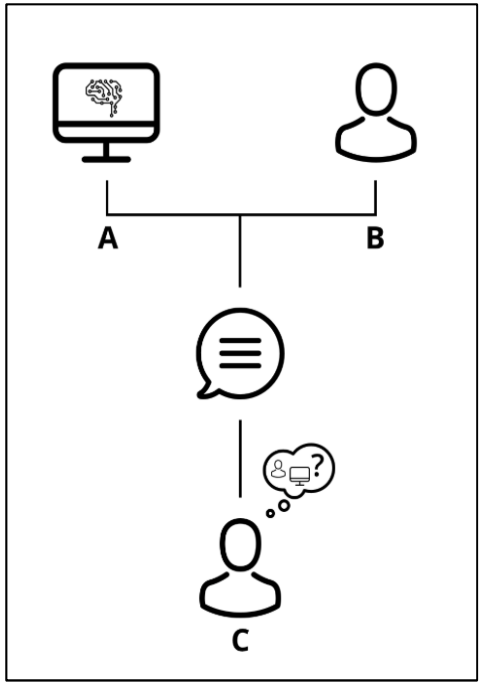
Why People Build Chatbots (In History)

To prove that an AI program can chat like a human.

- One of the first chatbots created at MIT AI Lab in 1966
- Conversation is realized by matching user prompts to scripted responses with patterns.
- Simulation of a Rogerian psychotherapist

ELIZA: is something troubling you?
Human: men are all alike.
ELIZA: what is the connection, do you suppose?
Human: They're always bugging us about something or other.
ELIZA: Can you think of a specific example?
Human: Well, my boyfriend made me here.
ELIZA: Is it important to you that your boyfriend made you come here?
Human: He says I'm depressed much of the time.
ELIZA: I am sorry to hear that you are depressed.
Human: It's true. I am unhappy.
…

Turing Test



Why People Build Chatbots (Recently)

Commercial chatbots with millions of users across different cultures

The Social Bots from Microsoft

Xiaoice
2014,China

Rinna
2015, Japan

Zo
2016, US

Ruuh
2017, India

Rinna
2017, Indonesia

245M+ Users, 30+ Billion Conversations

Services are Connected via Chat in Chatbots

==========From Mid-night (23:43:10)==========

- **Woman**: You don't love me.
- **XiaoIce**: I love you!

Chat

- **Woman**: how much does Honor 6 Plus cost?
- **XiaoIce**: I know this! It's 2,899 RMB.

QA

- **Woman**: You know too much.
- **XiaoIce**: It's my duty~
- **Woman**: My first love
- **XiaoIce**: In most cases, first love cannot move towards marriage.
- **Woman**: why?
- **XiaoIce**: There is no why.

Chat

- *[…more chit-chats happened…]*
- **Woman**: I want to see some handsome boys.
- **XiaoIce**: No problem!【an image of a handsome boy】
- **Woman**: Do you know Lee Minho? (a Korean star)
- **XiaoIce**: 【an image of Lee Minho】

Image Search

- **Woman**: Which cellphone has the best camera?
- **XiaoIce**: You can check your appearance by the screen of the phone.

Recommendation

- **Woman**: What's the price of OPPO R8007?
- **XiaoIce**: I know, it's 2,499 RMB.

QA

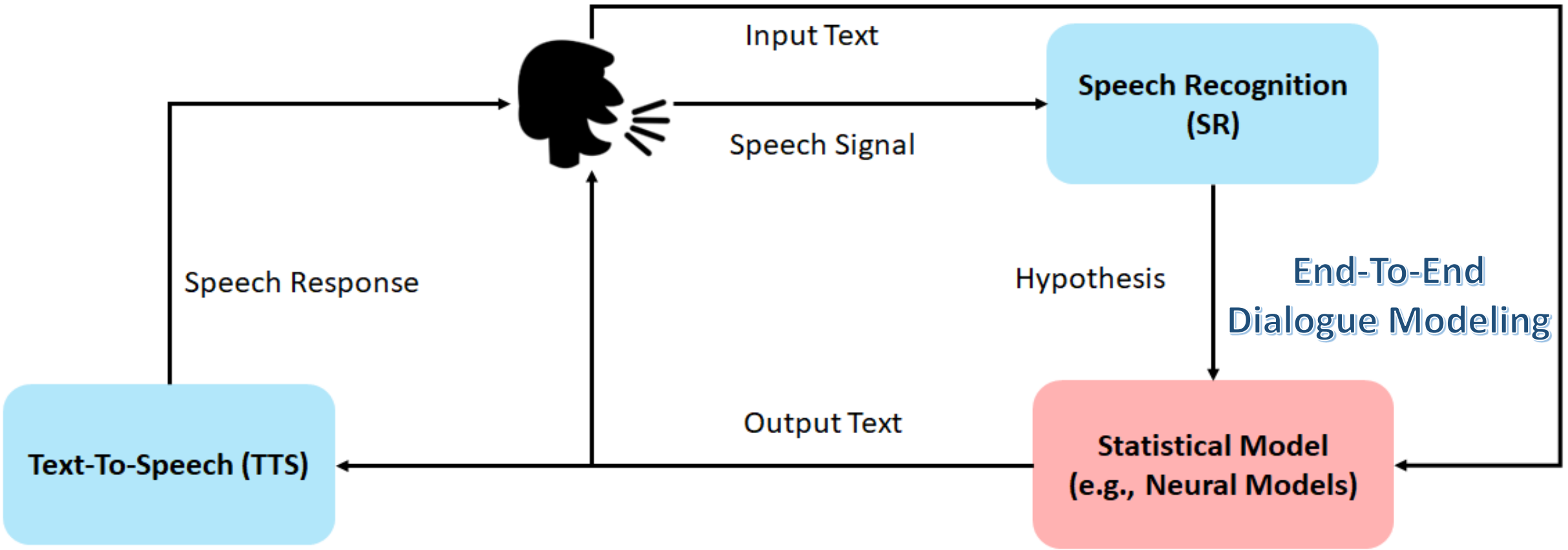
- **Woman**: So expensive.
- **XiaoIce**: It could be better if this is on sale.
- **Woman**: I cannot afford it~
- *[…more chit-chats happened…]*

Chat

Architecture of Dialogue Systems:

Task-Oriented v.s. Non-Task-Oriented

Non-Task-Oriented Dialogue System



Two Approaches for Non-Task-Oriented Dialogue Systems

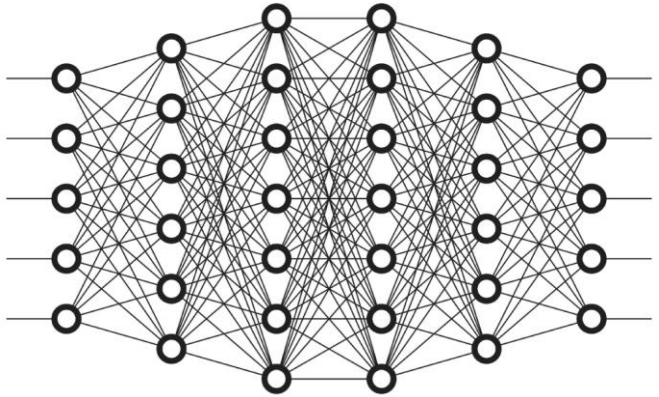
Retrieval-base Methods

Input

Index

Output

Neural Networks

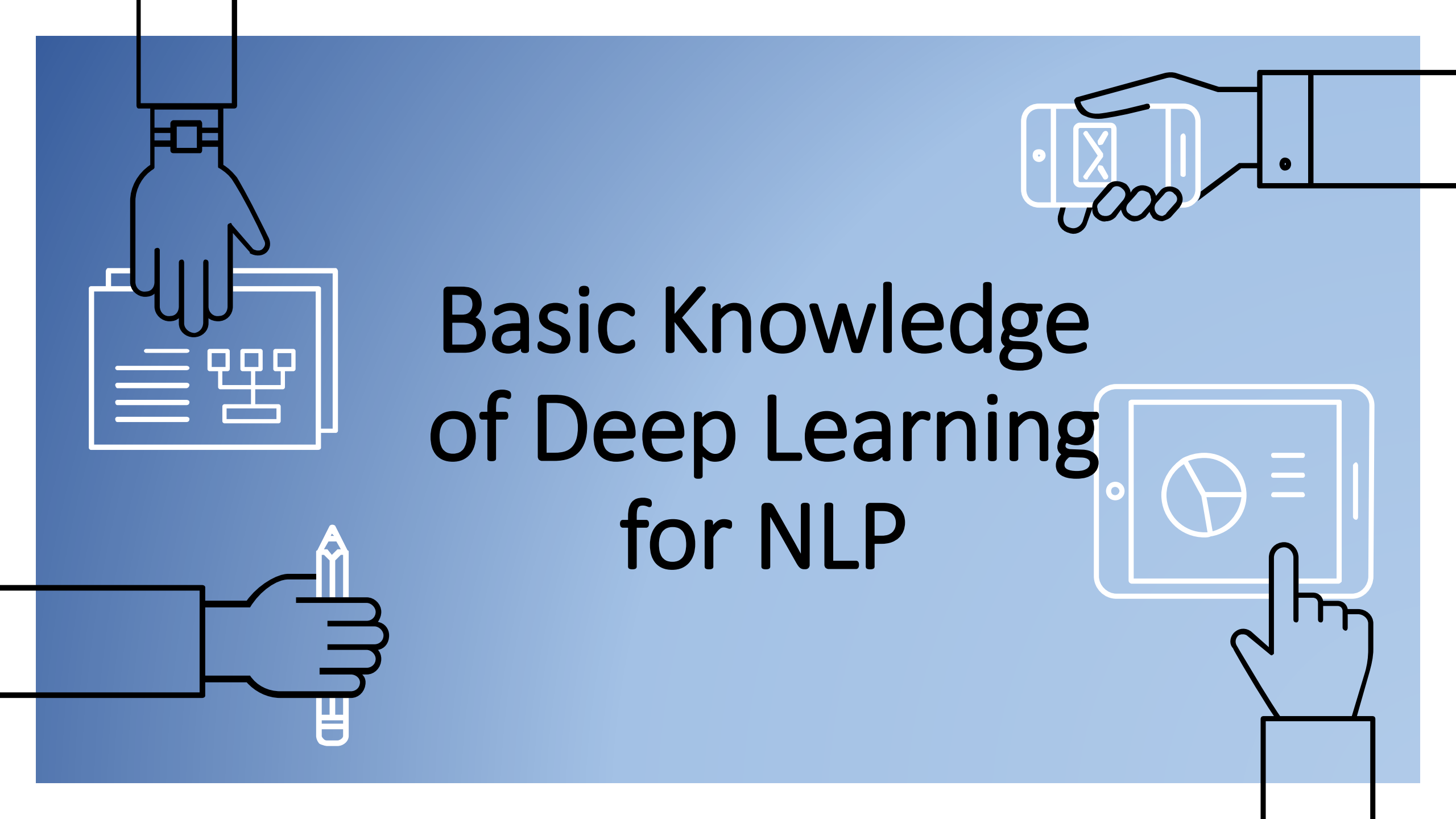


Generation-base Methods

Input

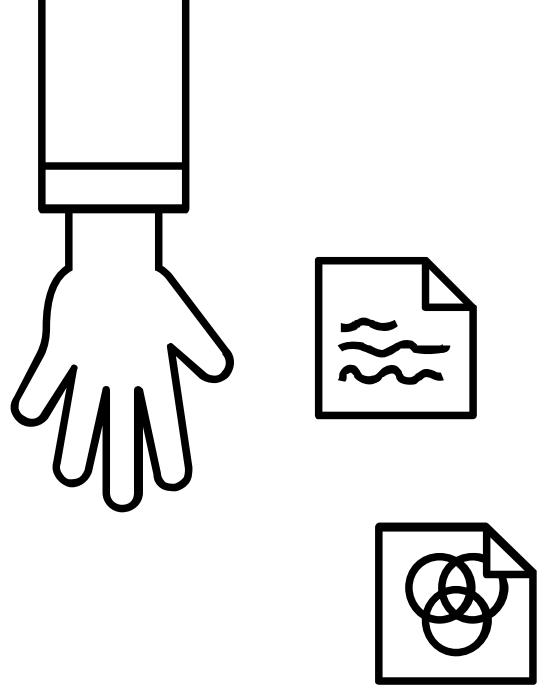
Generation Model

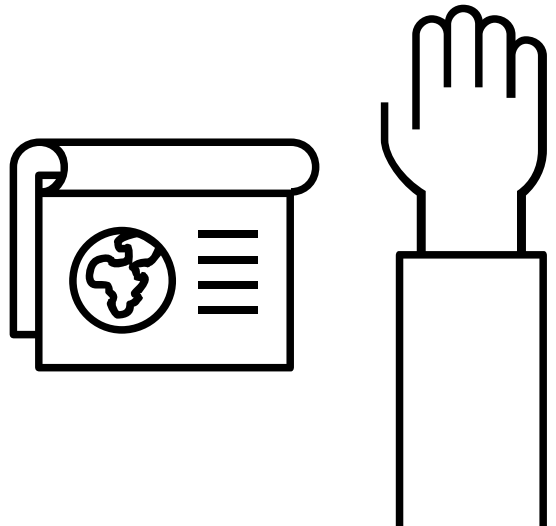
Output


Basic Knowledge
of Deep Learning
for NLP

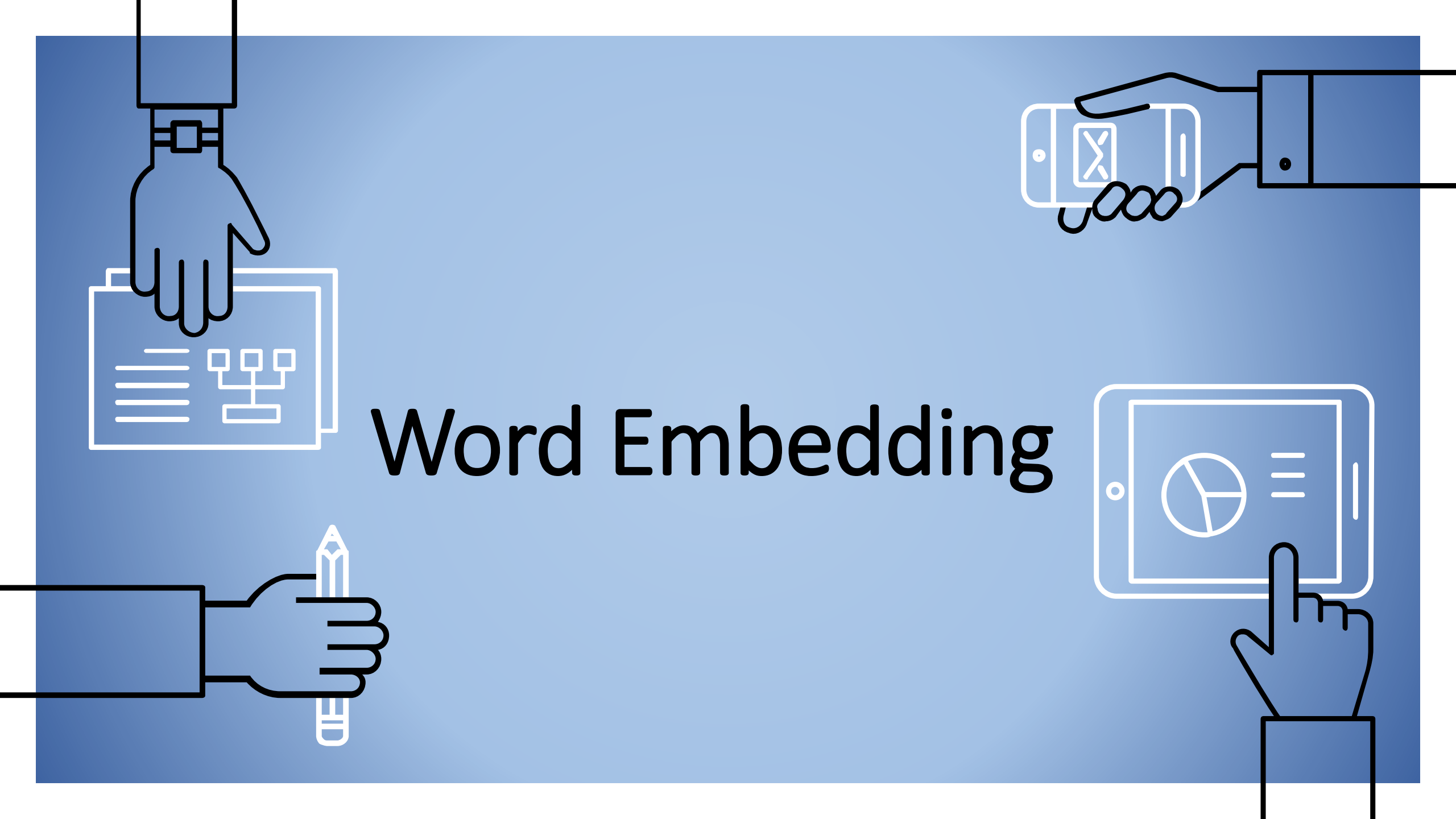
Roadmap

- Word Embedding
- Sentence Embedding
  - Convolutional Neural Network (CNN)
  - Recurrent Neural Network (RNN)
- Application in Dialogue Modeling
  - Sequence-to-Sequence with attention



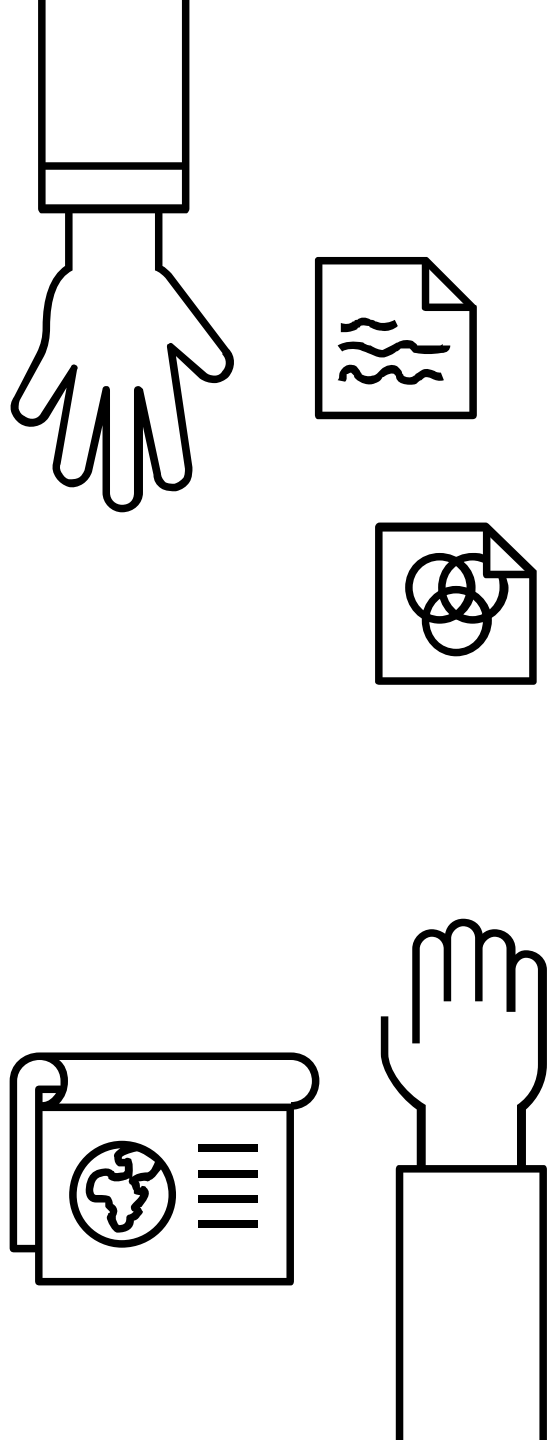


Word Embedding



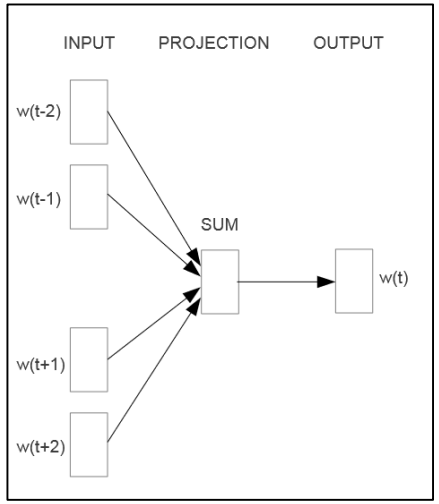
Word Embedding

- **Goal:** representing a word as a dense, low-dimensional, and real-valued vector.
- **Input:** long documents (e.g., articles from Wikipedia) or short texts (e.g., tweets)
- **Output:** word vectors.
- **Usage:** initialization of deep architectures.
- **Assumption:** words co-occur in a context are similar.



Word2Vec

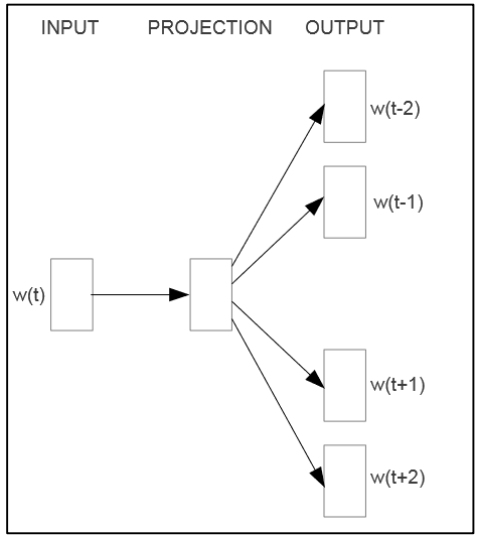
Continuous Bag-of-Words (CBOW)



Predicting a target word (output) with the sum of the words in the context (input)

$$p(w|C) = \frac{\exp\left(v'_w \cdot ave_{w' \in C, w' \neq w}\{v_{w'}\}\right)}{\sum_{w \in V} \exp\left(v'_w \cdot ave_{w' \in C, w' \neq w}\{v_{w'}\}\right)}$$

Skip-gram



Predicting each of other words in the context (output) with the target word (input)

$$p(w|w' \in C) = \frac{\exp(v'_w \cdot v_w)}{\sum_{w \in V} \exp(v'_w \cdot v_w)}$$

- Speed-up:
  - Hierarchical softmax: represent words as leaves of a binary tree. Cost of objective calculation: $V \rightarrow \log(V)$.
  - Negative sampling: approximate the softmax with negative samples. Cost of objective calculation: $V \rightarrow$ # samples.
- Tool: https://code.google.com/archive/p/word2vec/

Tomas Mikolov et al., Efficient Estimation of Word Representations in Vector Space, *Workshop of ICLR'13*

GloVe: Global Vectors for Word Representation

Learning word representations by factorizing a co-occurrence matrix

	w_1	……	w_j	……	w_n
w_1	X_{11}		X_{1j}		X_{1n}
⋮					
w_i	X_{i1}		X_{ij}		X_{in}
⋮					
w_n	X_{n1}		X_{nj}		X_{nn}

X_{ij}: *number of times* w_j *occurs in the context of* w_i

$$Loss = \sum_{i,j}^{V} f(X_{ij})[v_i \cdot \tilde{v}_j + b_i + \tilde{b}_j - logX_{ij}]^2$$

Pre-defined weight function

Factorizing the co-occurrence matrix

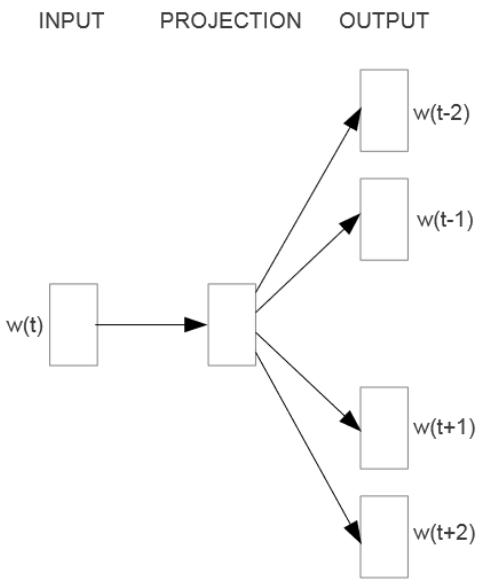
- Tool: https://nlp.stanford.edu/projects/glove/

Jerry Pennington et al., GloVe: Global Vectors for Word Representation, *EMNLP'14*

FastText

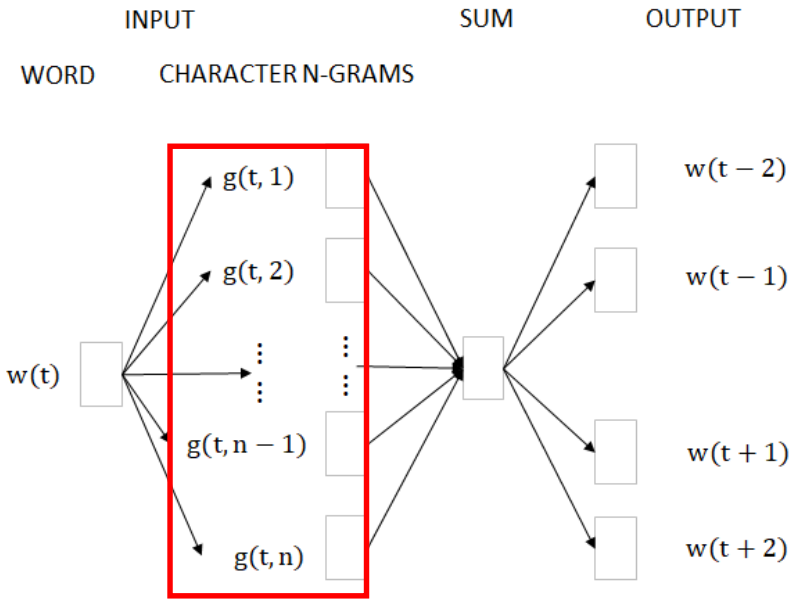
Modeling morphology of words by embedding character n-grams on top of the model of skip-gram.

Skip-gram



$u_w \cdot v_c, c \in \mathcal{C}_w$

FastText (Subword Model)



where → <wh, whe, ere, re>

$\sum_g z_g \cdot v_c, c \in \mathcal{C}_w$

- Tool: https://github.com/facebookresearch/fastText/

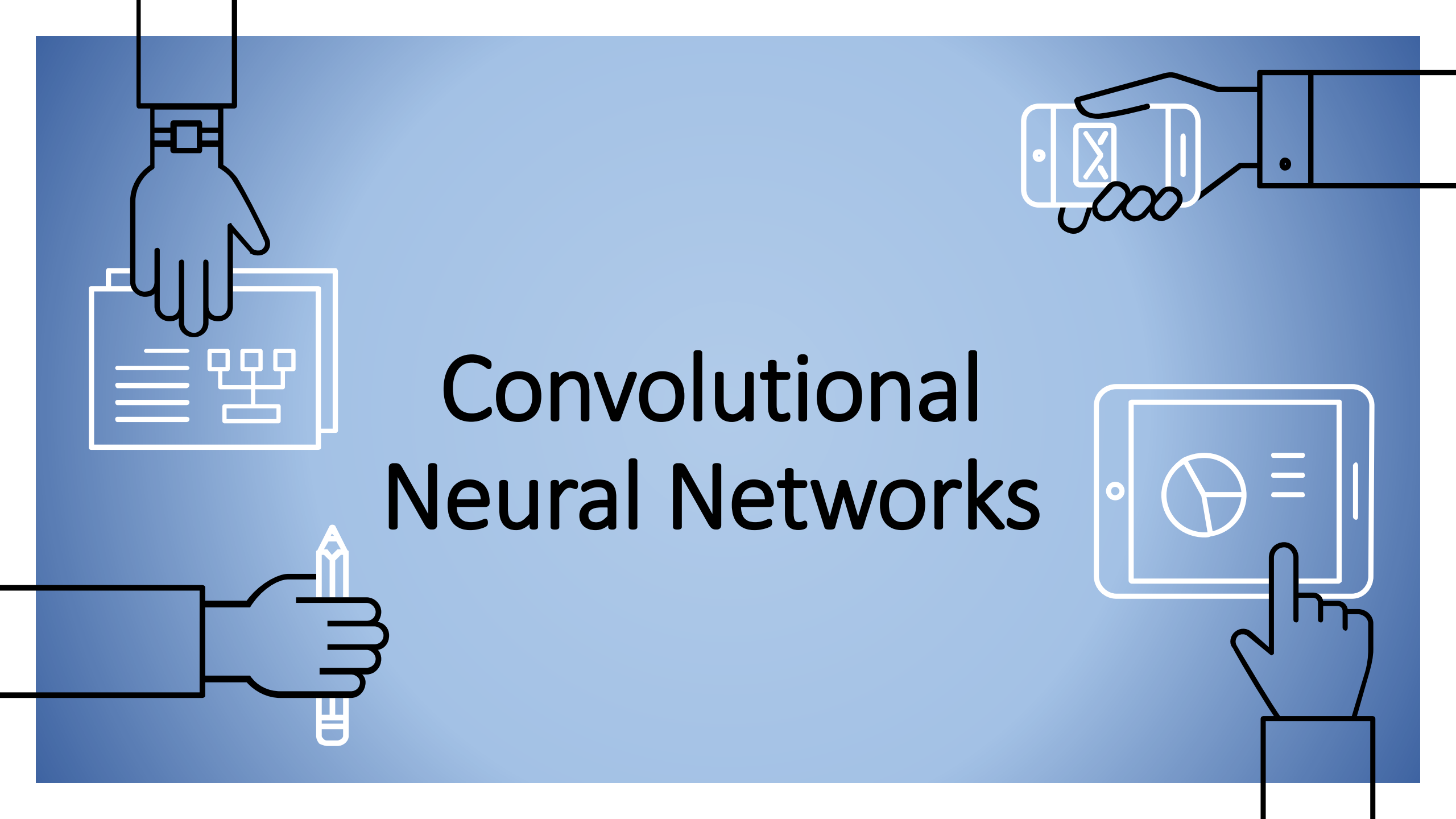
Piotr Bojanowski and Edouard Grave et al., Enriching Word Vectors with Subword Information, *TACL'17*

Comparison of Word2vec, GloVe, and FastText

- **Efficacy on downstream NLP tasks**
  - CBOW < Skip-gram ≈ GloVe < FastText
  - FastText can naturally handle OOV, and is especially better on morphologically rich languages, such as German.

- **Efficiency (training time)**
  - CBOW < GloVe < Skip-gram < FastText

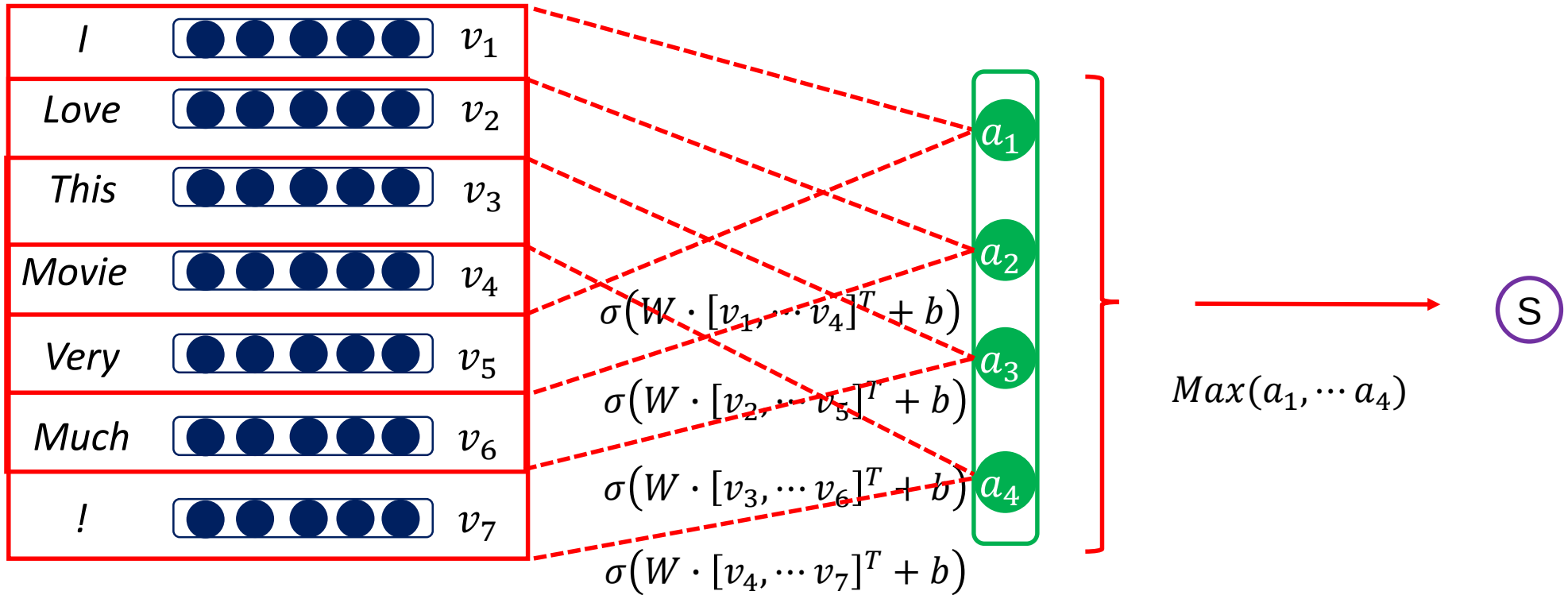
Convolutional Neural Networks



Convolutional Neural Network (CNN)

- **Goal:** representing a sequence of words (e.g., a sentence), or a similarity matrix (word-word similarity) as a dense, low-dimensional, and real-valued vector.
- **Input:** a matrix (e.g., each column is a word vector, or each element is a similarity score of a pair of words).
- **Output:** a vector (or a scalar).
- **Advantage:** encoding semantics of n-grams.

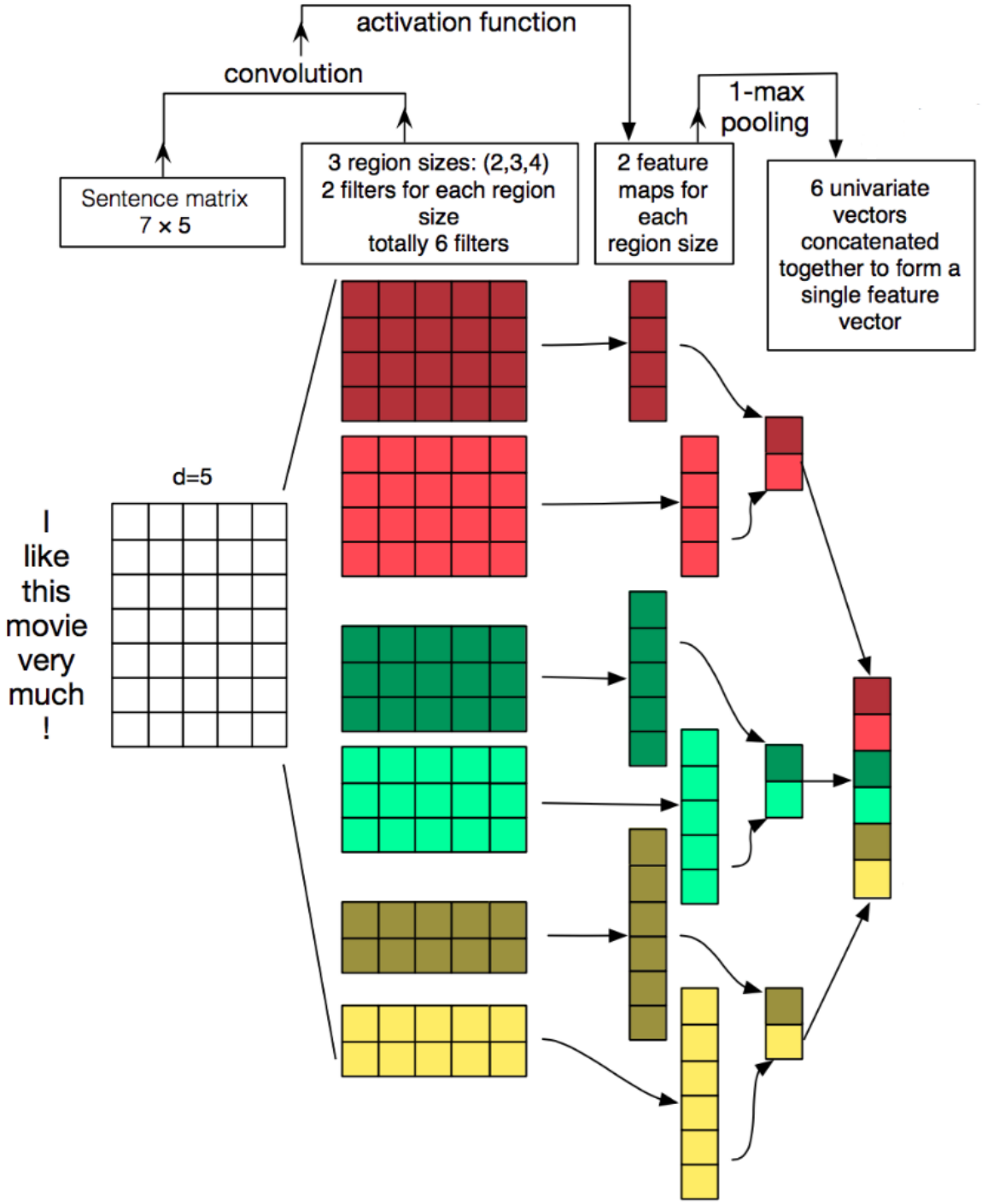
CNN on a Natural Language Sentence



Input: word embedding

Convolution: a *filter* slides a window on the word matrix with a *stride size=1*

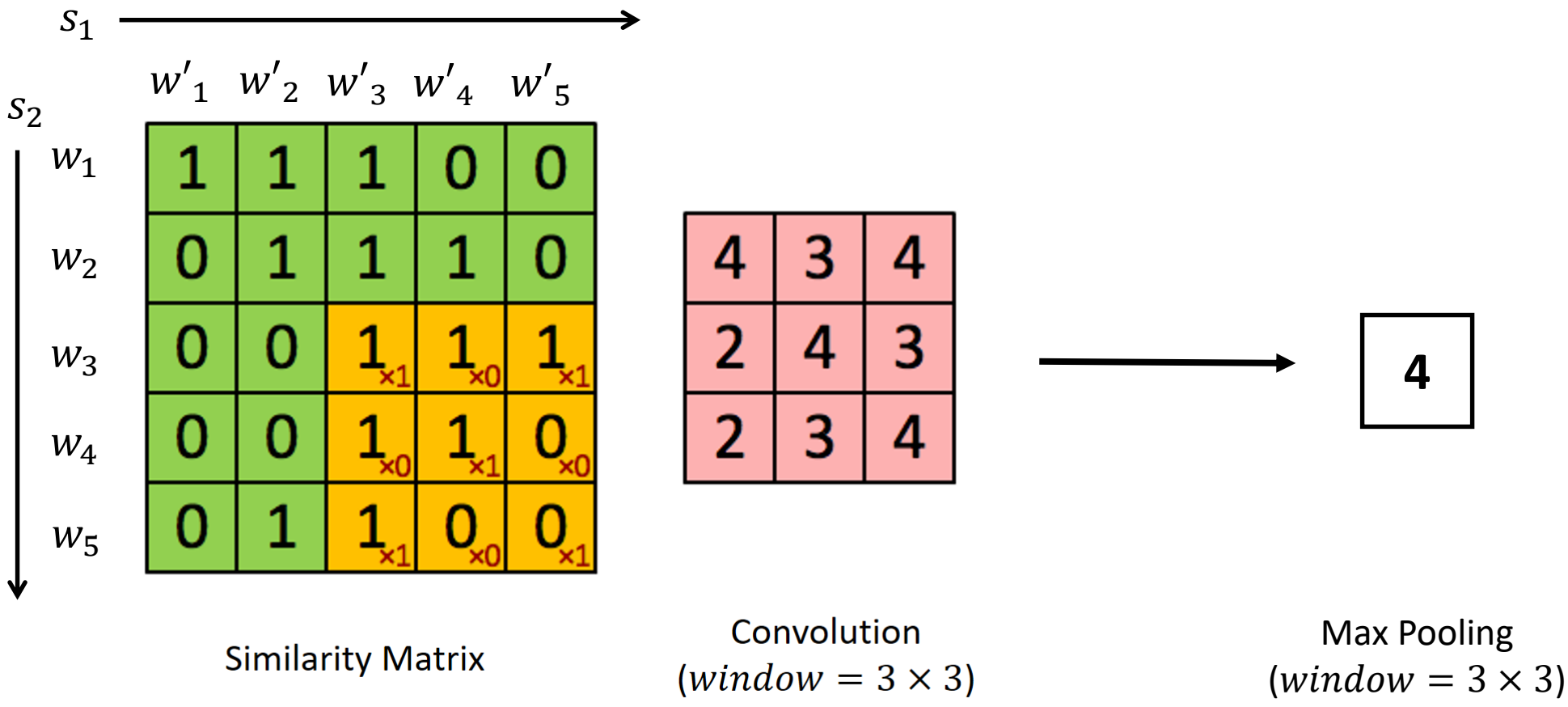
Pooling (max): reducing the result of convolution to a scalar



CNN on a Natural Language Sentence (cont'd)

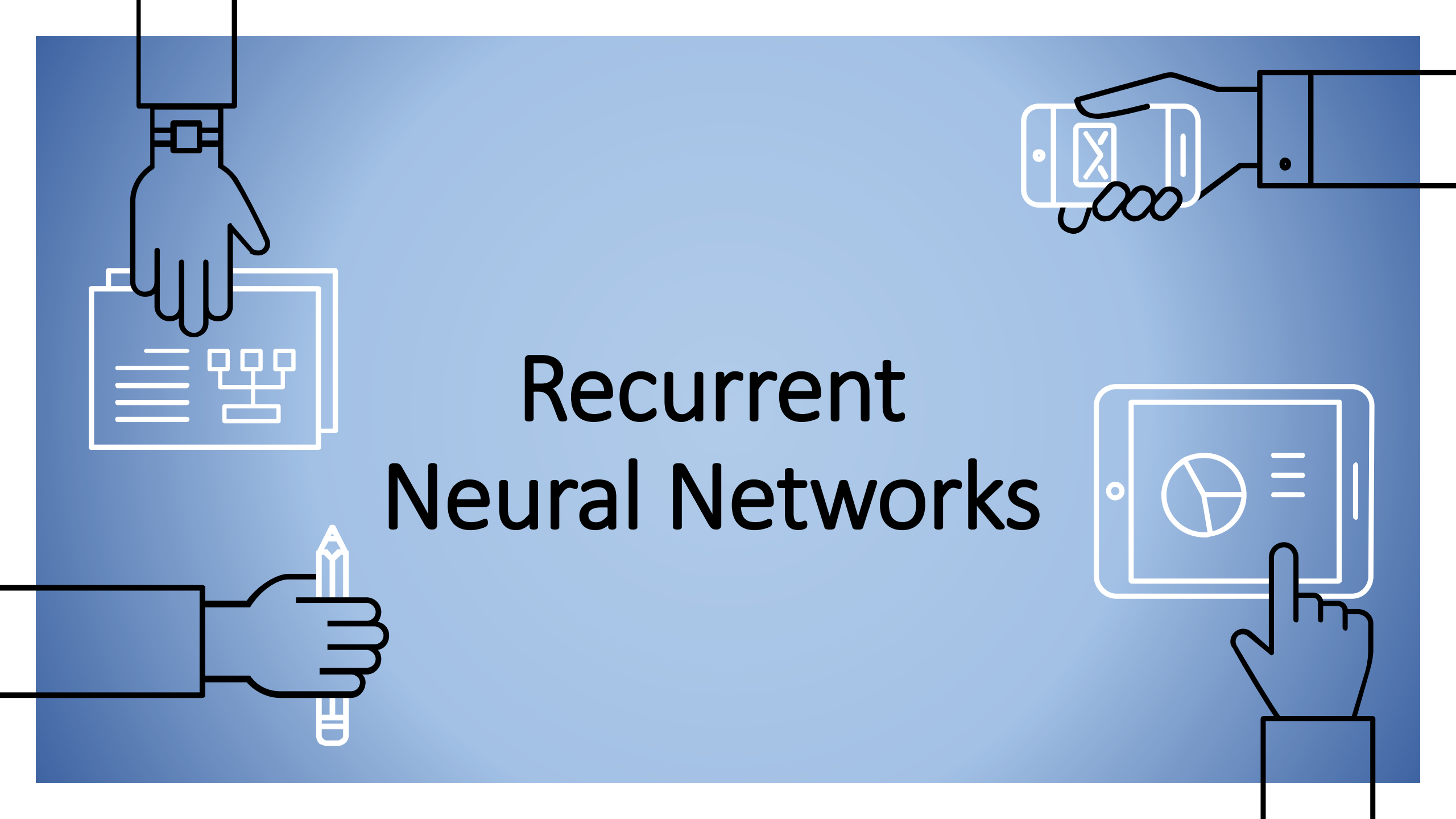
Understanding Convolutional Neural Networks for NLP

CNN on a Similarity Matrix



Understanding Convolutional Neural Networks for NLP

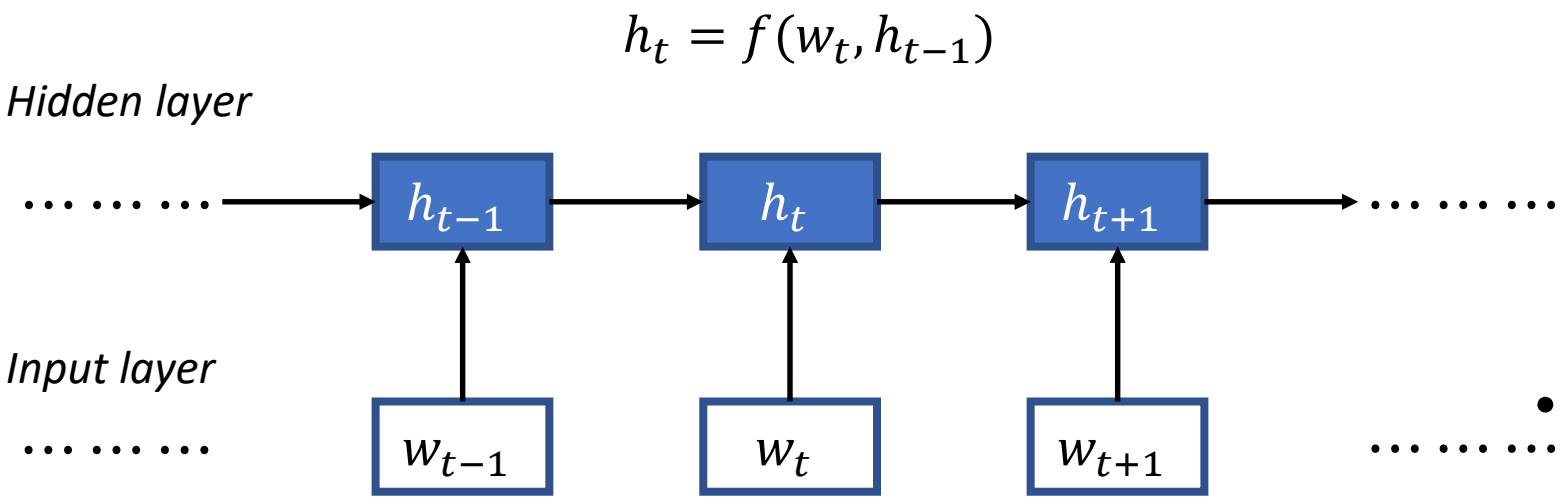
Recurrent Neural Networks



Recurrent Neural Network (RNN)

- **Goal:** representing a sequence of words (i.e., a sentence) as dense, low-dimensional, and real-valued vectors.
- **Input:** a sequence of words (or characters).
- **Output:** a sequence of hidden states with each a representation of the sequence from the beginning to a specific position.
- **Advantage:** encoding sequential relationship and dependency among words.

Architecture of RNN

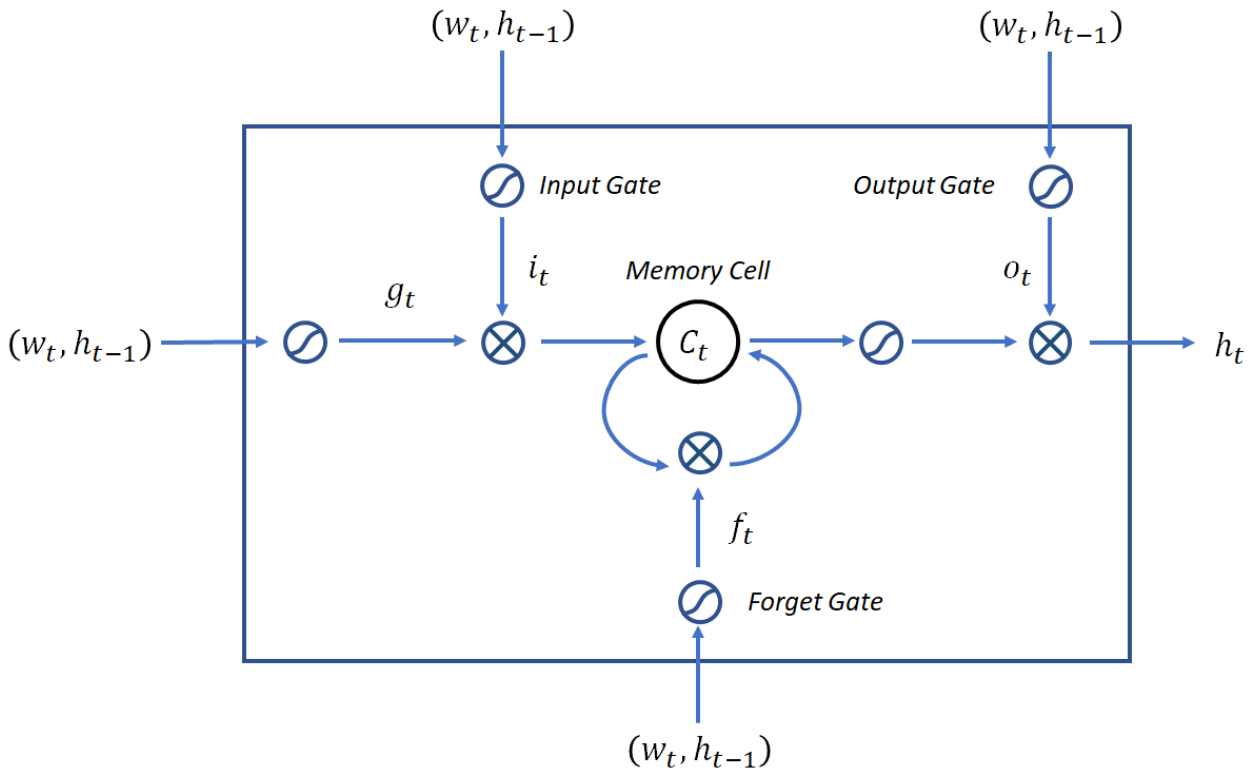


- Similar to **Markov Chain**, the current hidden state depends on the current input and the previous hidden state.
- Learning an RNN with BPTT (Back Propagation Through Time) is not trivial due to the **gradient vanishing/exploding** problem for long sequences.
- The gradient vanishing/exploding problem can be addressed by **defining $\mathbf{f}(\cdot,\cdot)$ with gates**.
- One can **stack many hidden layers** by treating the hidden states in low layers as input

Tomas Mikolov et al., Recurrent Neural Network base Language Model, *INTERSPEECH'10*
Razvan Pascanu et al., On the Difficulty of Training Recurrent Neural Networks, *ICML'13*

RNN with Long Short-Term Memory Units (LSTM)

Define $\boldsymbol{f}(\cdot,\cdot)$ with an input gate, a forget gate, an output gate, and a memory cell for modeling long-term dependency among words.



$$i_t = \sigma(U_i w_t + V_i h_{t-1} + b_i)$$

$$f_t = \sigma\left(U_f w_t + V_f h_{t-1} + b_f\right)$$

$$o_t = \sigma(U_o w_t + V_o h_{t-1} + b_o)$$

$$g_t = \tanh\left(U_g w_t + V_g h_{t-1} + b_g\right)$$

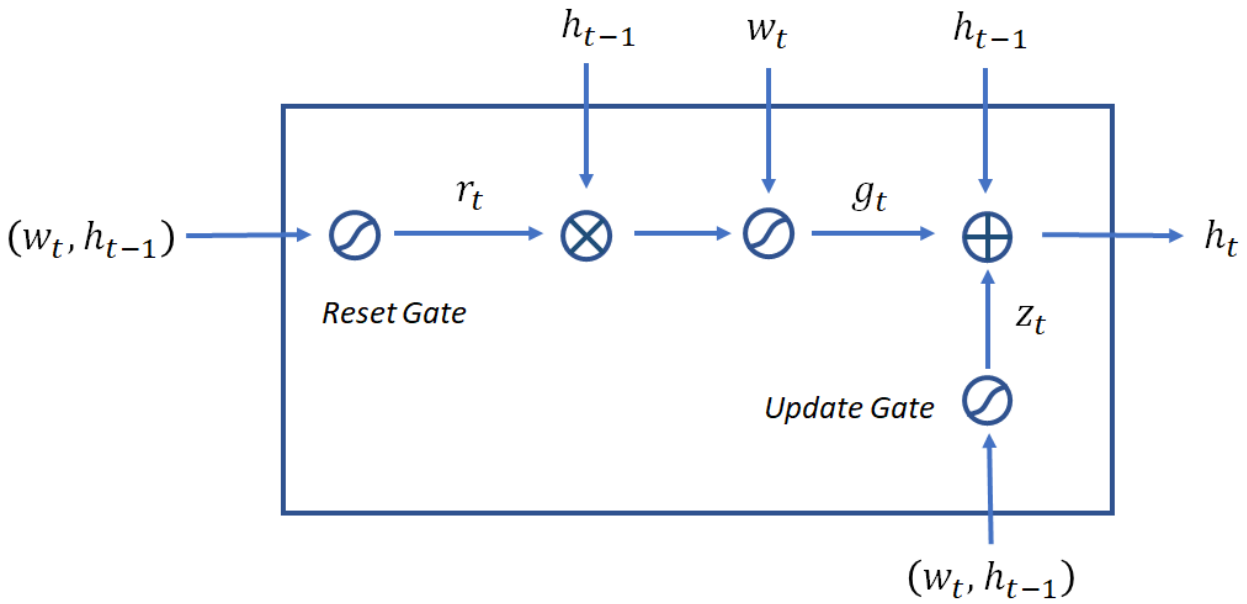
$$C_t = i_t \otimes g_t + f_t \otimes C_{t-1}$$

$$h_t = o_t \otimes \tanh(C_t)$$

Sepp Hochreiter et al., Long Short-Term Memory, *Neural Computation, 1997*

RNN with Gated Recurrent Units (GRU)

- *Define $f(\cdot,\cdot)$ with an update gate and a reset gate.*
- *With a comparable performance with LSTM, but is much simpler.*



$$r_t = \sigma(U_r w_t + V_r h_{t-1} + b_r)$$

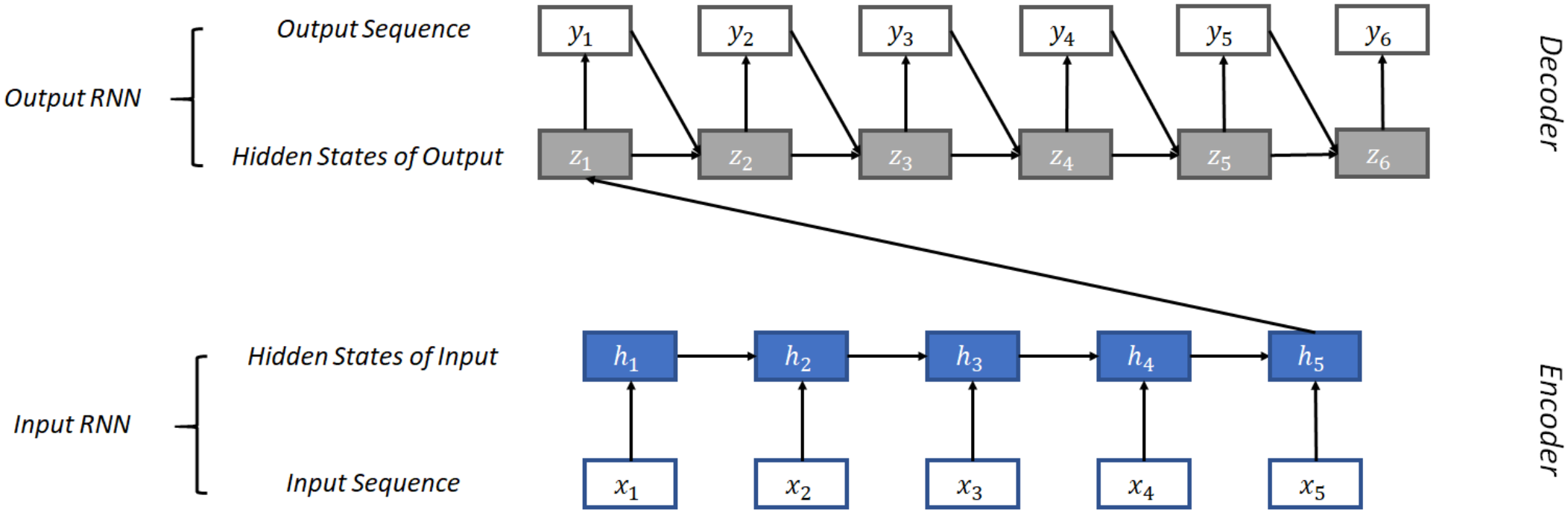
$$z_t = \sigma(U_z w_t + V_z h_{t-1} + b_z)$$

$$g_t = \tanh\left(U_g w_t + V_g (r_t \otimes h_{t-1}) + b_g\right)$$

$$h_t = z_t \otimes h_{t-1} + (1 - z_t) \otimes g_t$$

Kyunghyun Cho et al., Learning Phrase Representations using RNN Encoder-Decoder for Statistical Machine Translation, *EMNLP'14*

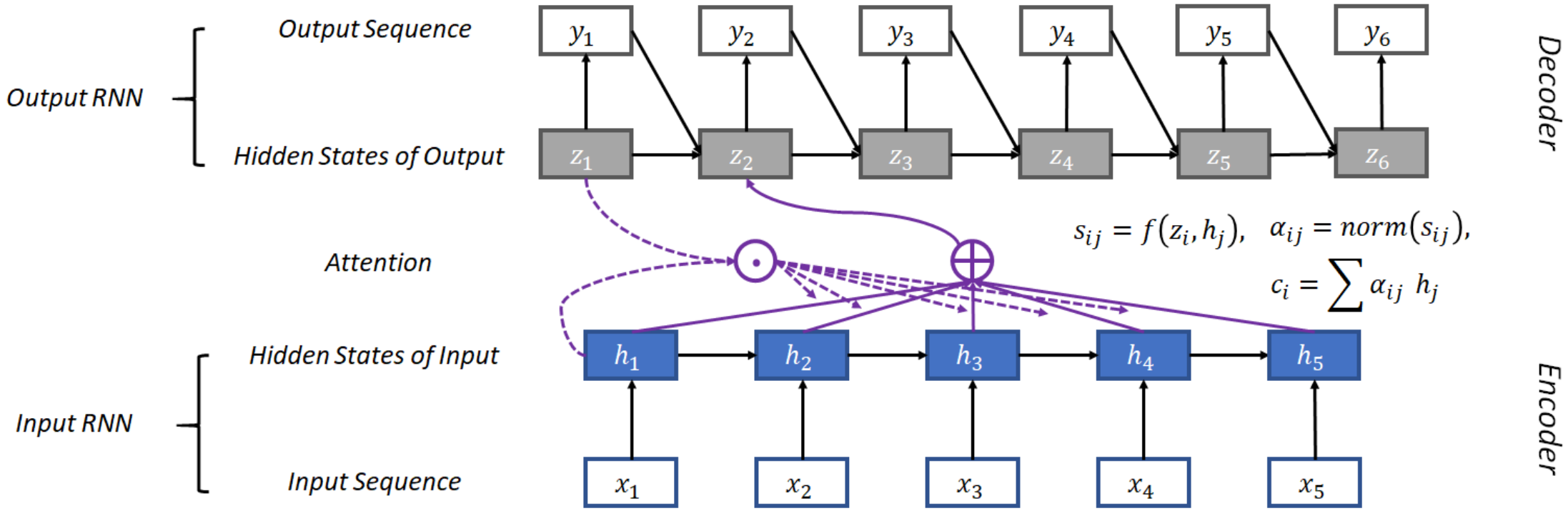
Application of RNN: The Sequence-to-Sequence (Encoder-Decoder) Architecture



- *Prediction of an output sequence conditioned on an input sequence.*
- *Applications: machine translation, response generation in dialogue models, summarization, answer generation, paraphrase generation, etc.*

Ilya Sutskever et al., Sequence to Sequence Learning with Neural Networks, *NIPS'14*

The Encoder-Attention-Decoder Architecture



- *Attention: "pay attention to" different sub-sequences of the input when generating each of the token of the output.*
- *Modeling alignment in machine translation.*

Dzmitry Bahdanau et al., Neural Machine Translation by Jointly Learning to Align and Translate, *ICLR'15*

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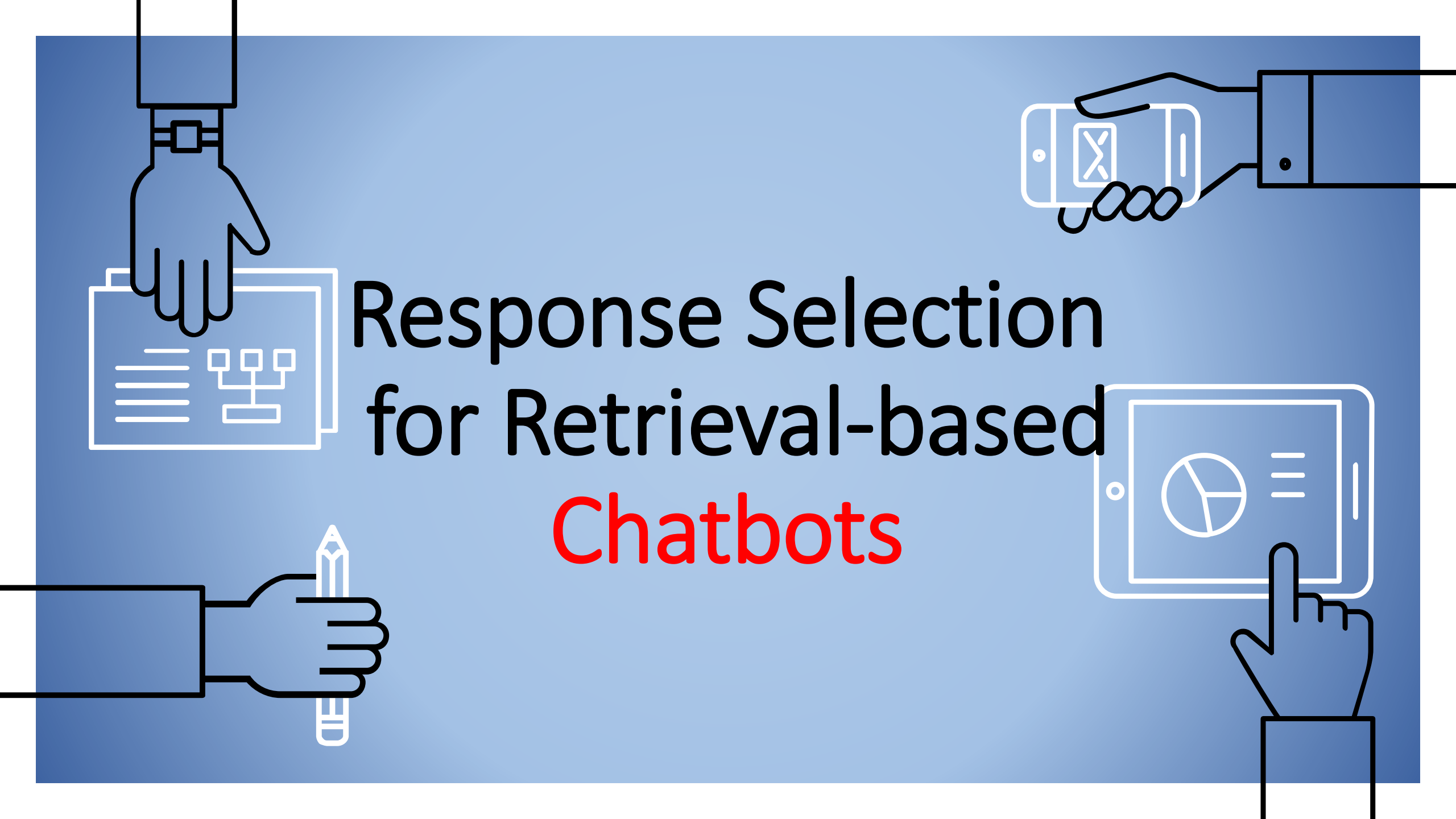
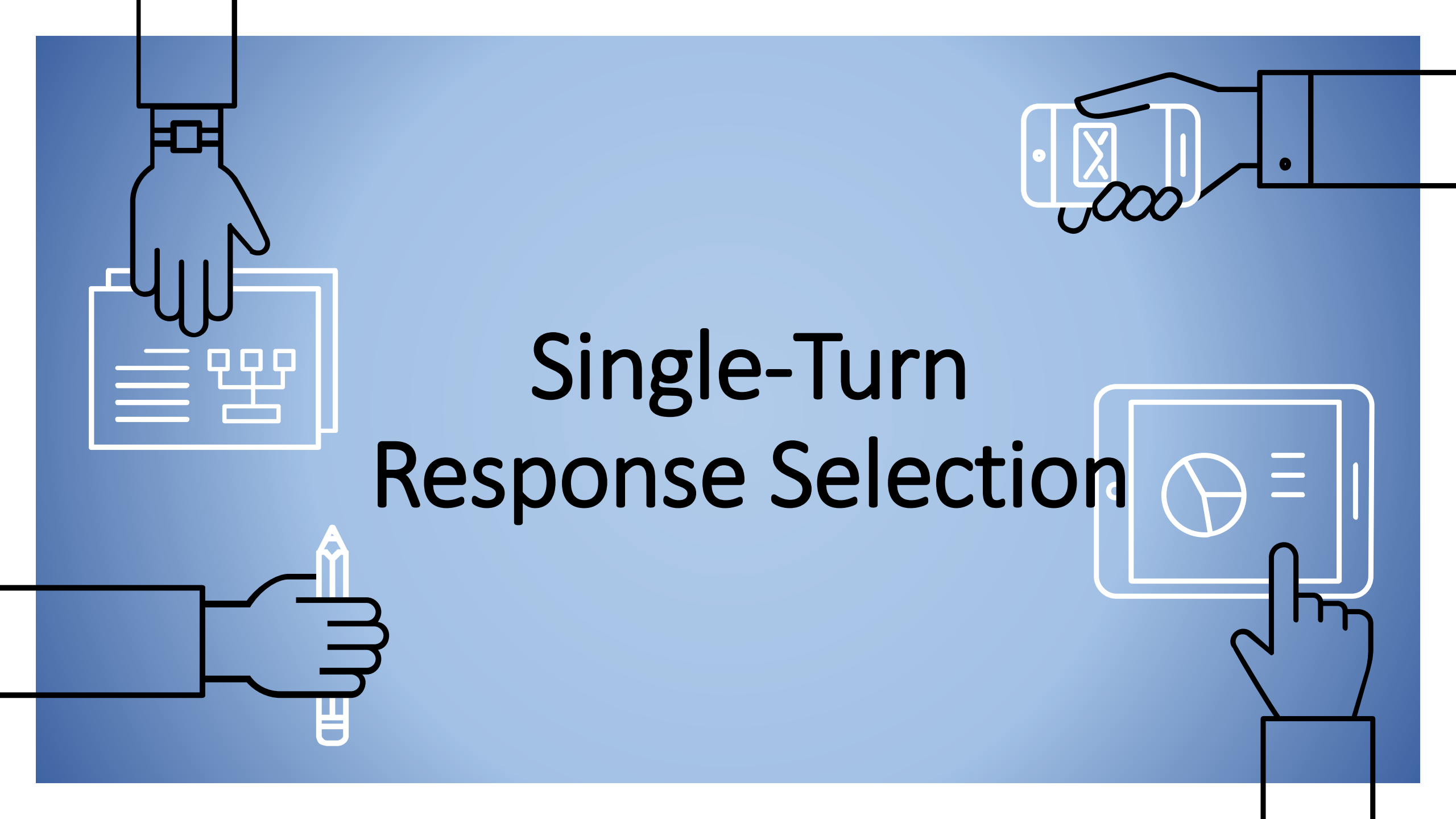
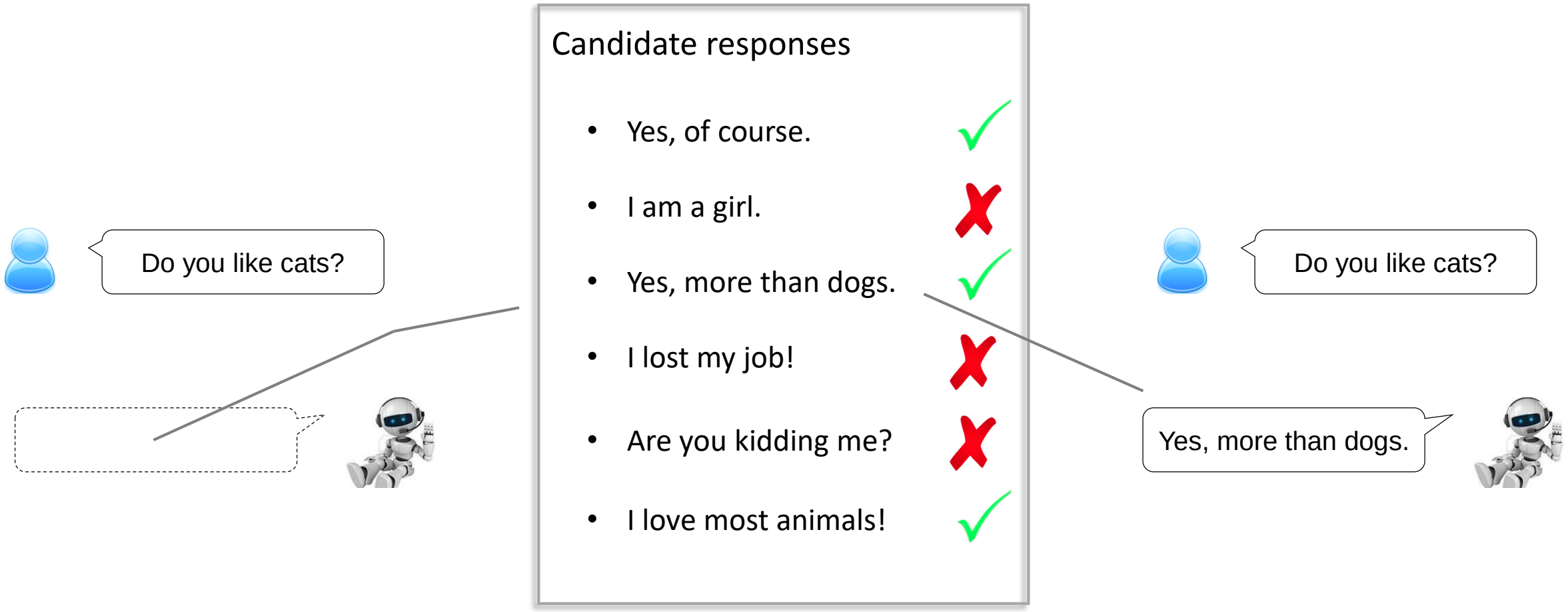

Response Selection
for Retrieval-based
Chatbots

Roadmap

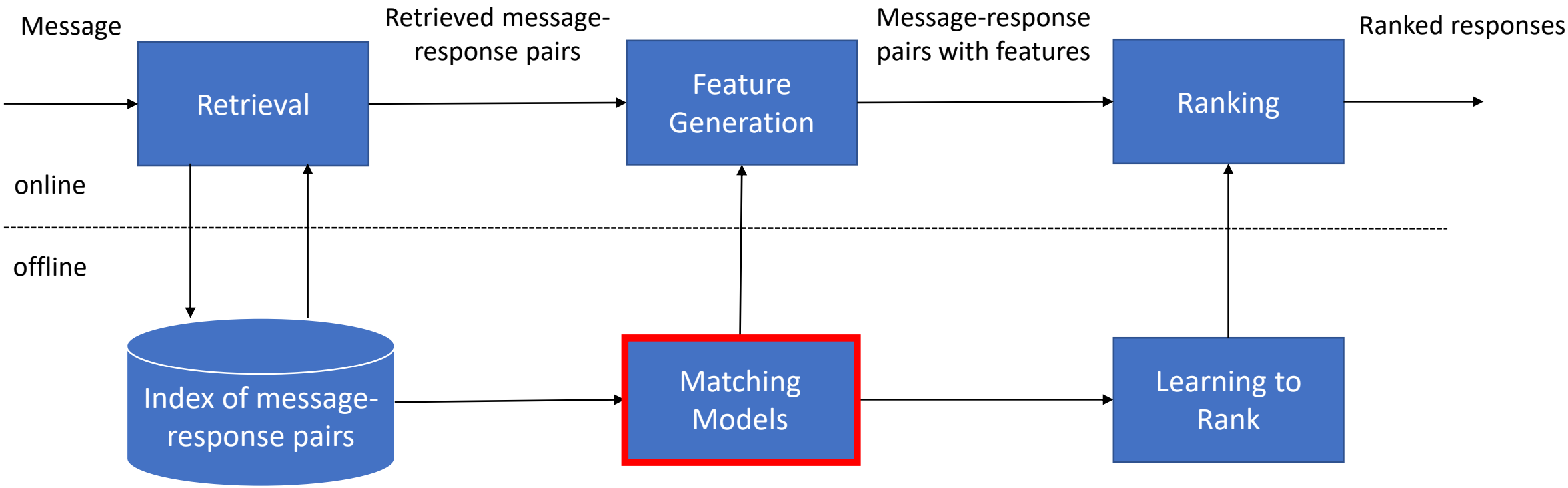
- Message-Response Matching for Single-Turn Response Selection
  - Framework I : matching with sentence embeddings.
  - Framework II: matching with message-response interaction.
  - Insights from empirical studies.
  - Extension: matching with external knowledge.
- Context-Response Matching for Multi-Turn Response Selection
  - Framework I: embedding->matching.
  - Framework II: representation->matching->aggregation.
  - Insights from empirical studies.
- (Some) Emerging Research Topics
  - Matching with better representations
  - Matching with unlabeled data


Single-Turn
Response Selection

Single-Turn Response Selection



System Architecture for Single-Turn Response Selection

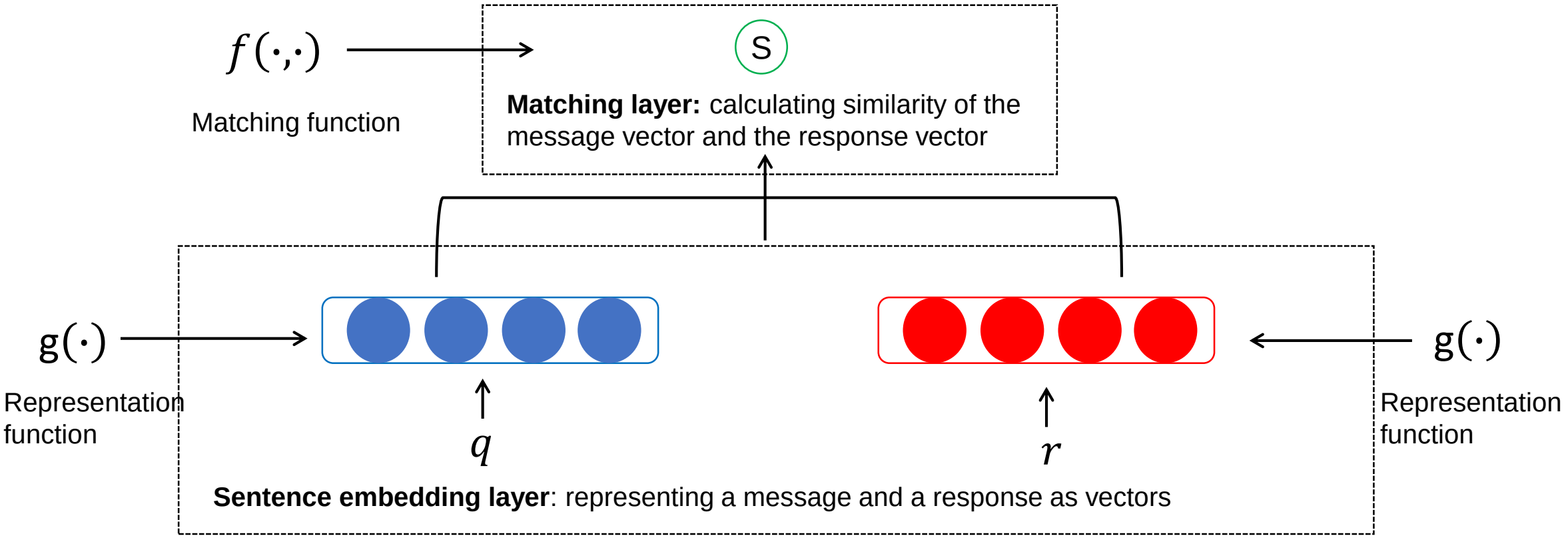


<q>well I hope you fell better smiley</q>
<r> thanks </r>
<q> I was so excited about dying my hair blond</q>
<r> do it </r>
……
……

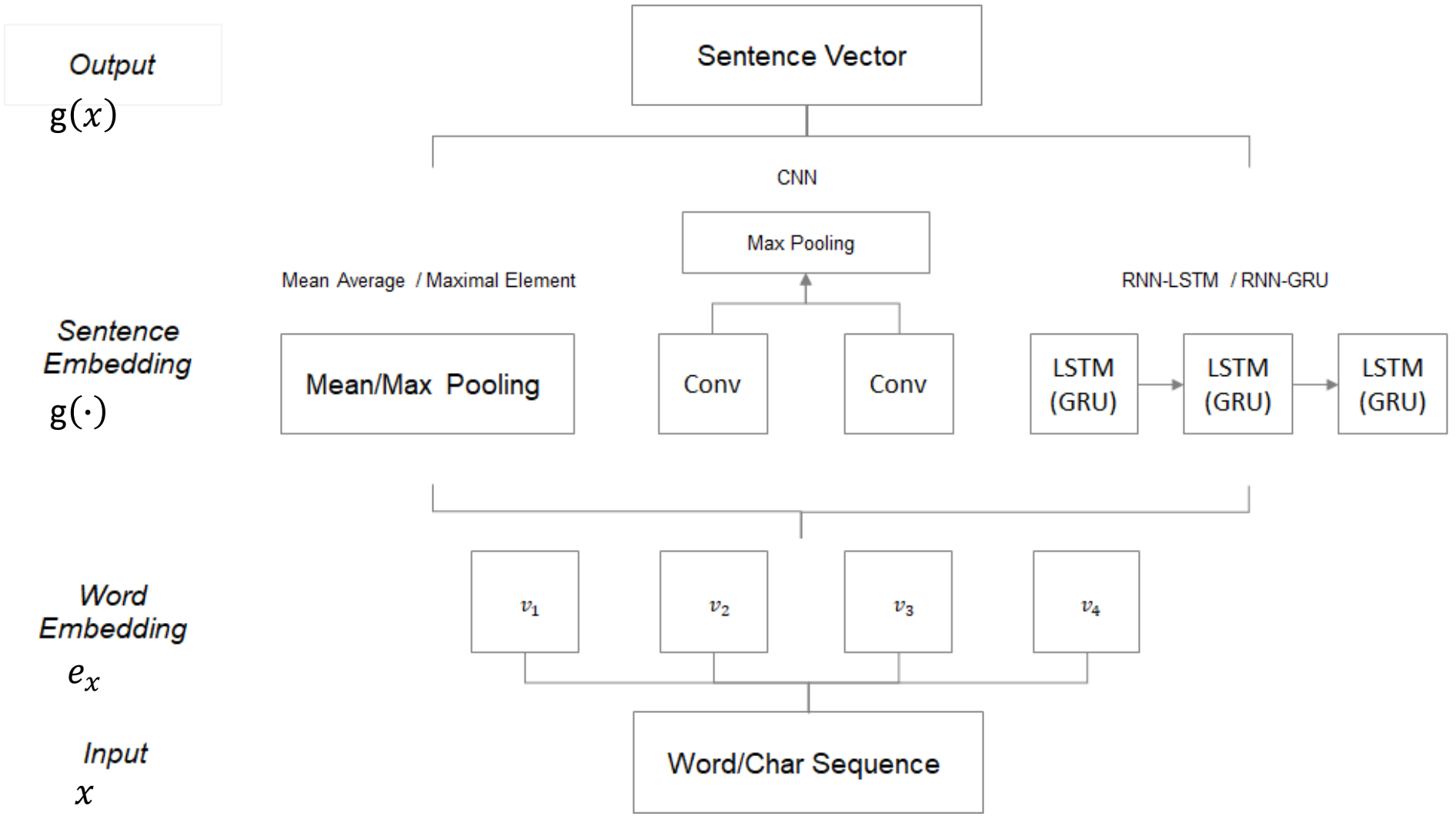
Deep learning based message-response matching

Gradient boosted tree

Message-Response Matching: Framework I



Representation Functions



Matching Functions

Output

$f(q, r)$

Matching Score

Cosine | Bilinear | Multi-layer Perceptron (MLP) | Neural Tensor Network

Matching Functions

$f(\cdot,\cdot)$

$$\frac{q \cdot r}{\|q\| \cdot \|r\|}$$

$$\sigma(q^T \cdot W \cdot r)$$

$$\sigma_2(b_2 + W_2 \cdot \sigma_1(b_1 + W_1 \cdot [q^T, r^T]^T))$$

$$\sigma(q^T \cdot W^{[1:h]} \cdot r + V \cdot [q^T, r^T]^T + b)$$

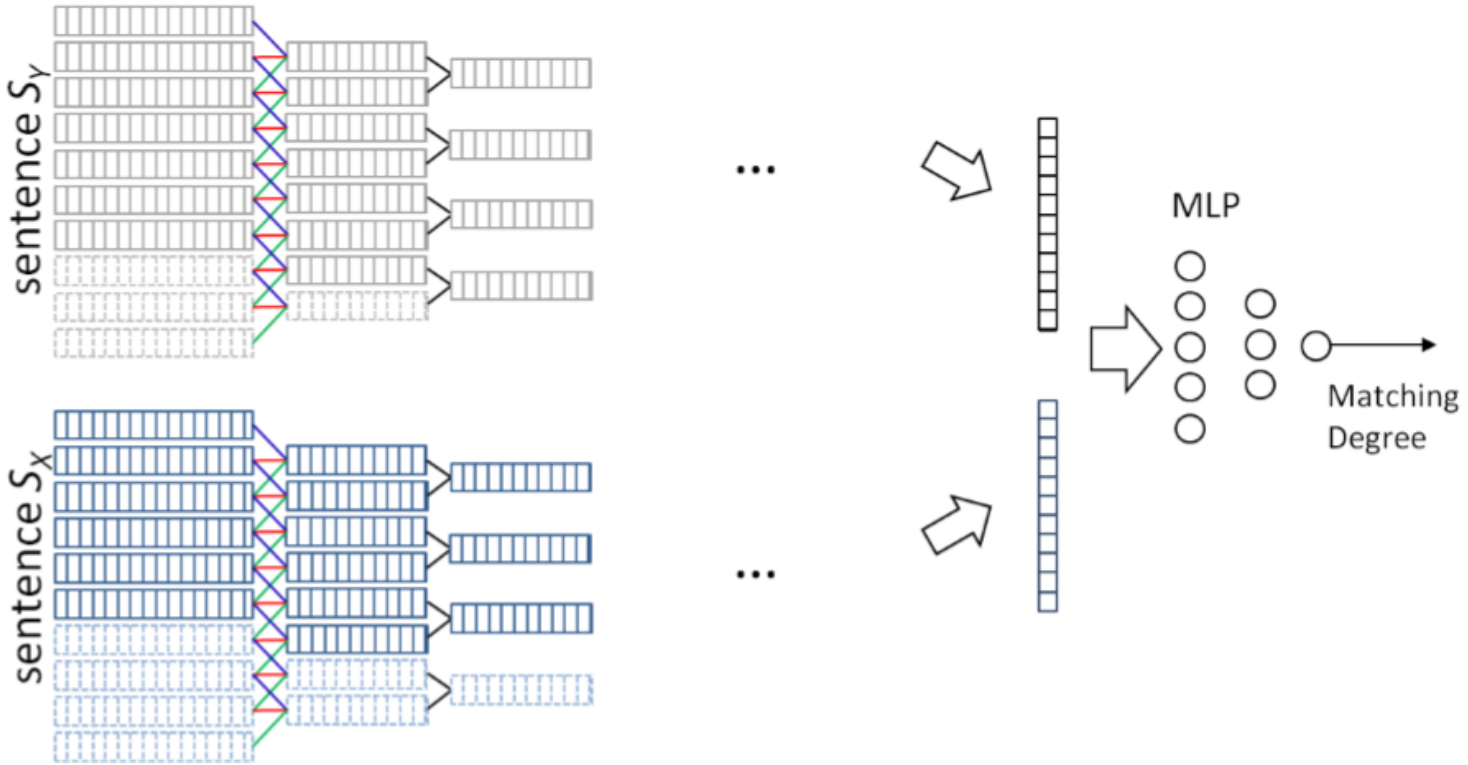
Input

q, r

Sentence Vector

Sentence Vector

Special Case 1: Arc-I



$g(\cdot)$=CNN

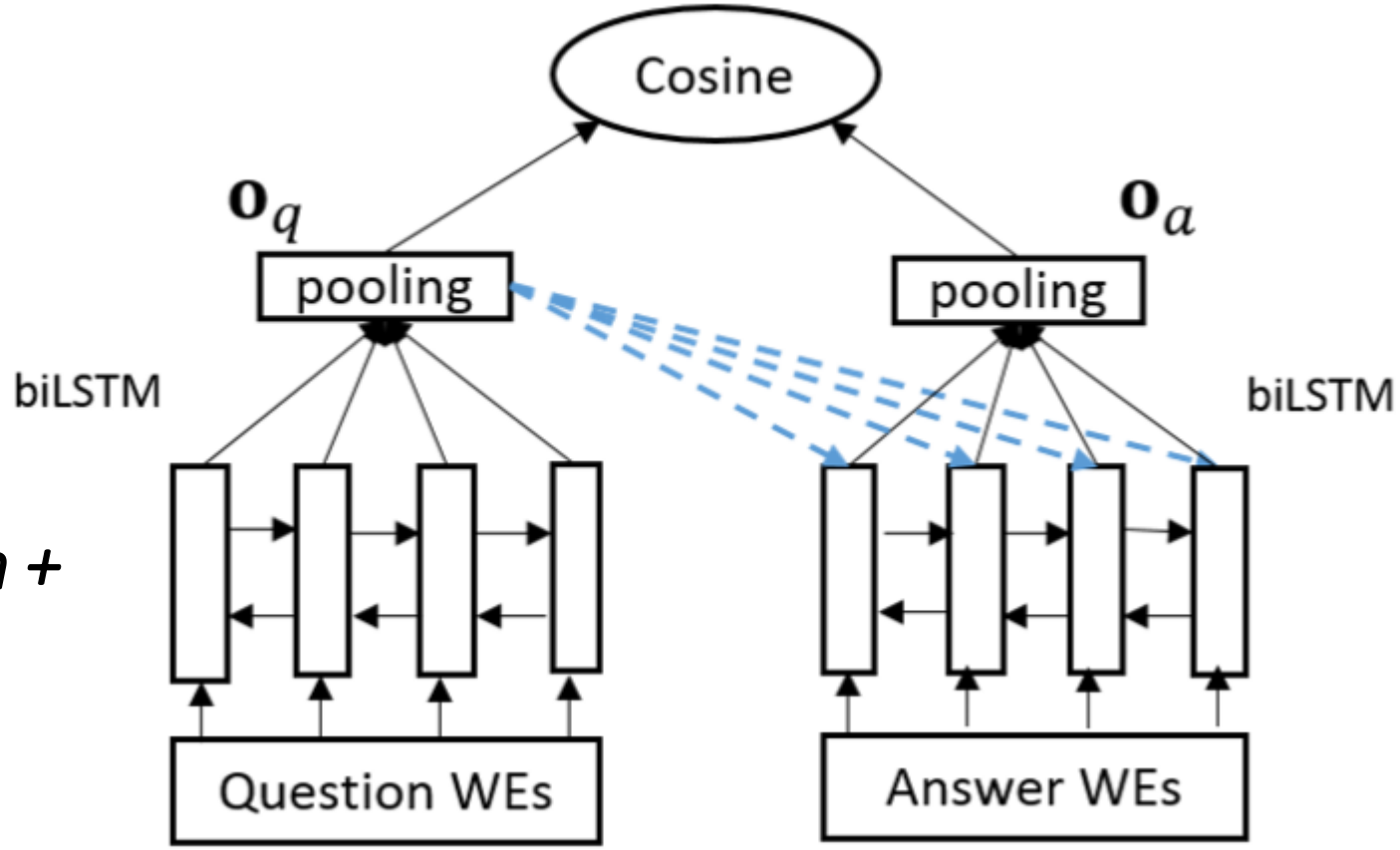
$f(\cdot,\cdot)$=MLP

Baotian Hu et al., Convolutional Neural Network Architectures for Matching Natural Language Sentences, *NIPS'14*

Special Case 2: Attentive LSTM

$f(\cdot,\cdot)$=*Cosine*

$g(\cdot)$=*LSTM + Attention + Pooling*

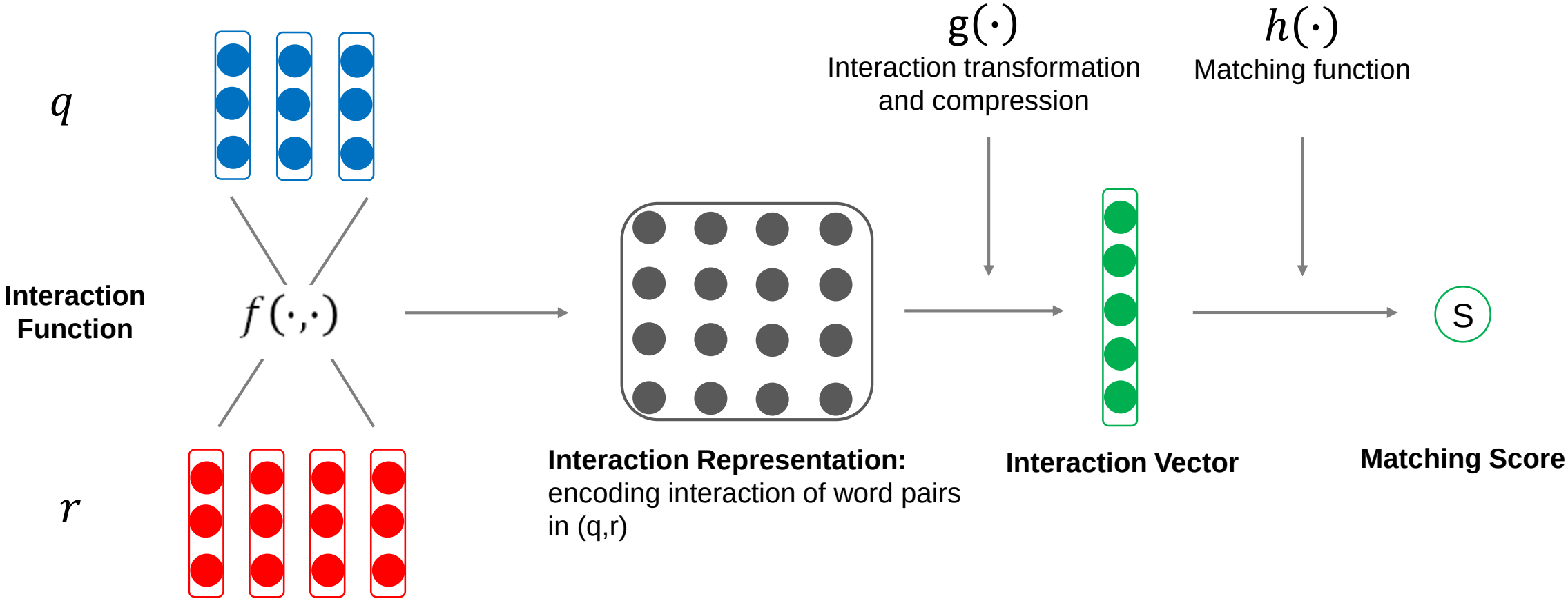


Ming Tan et al., Improved Representation Learning for Question Answer Matching, *ACL'16*

More Methods in Framework I

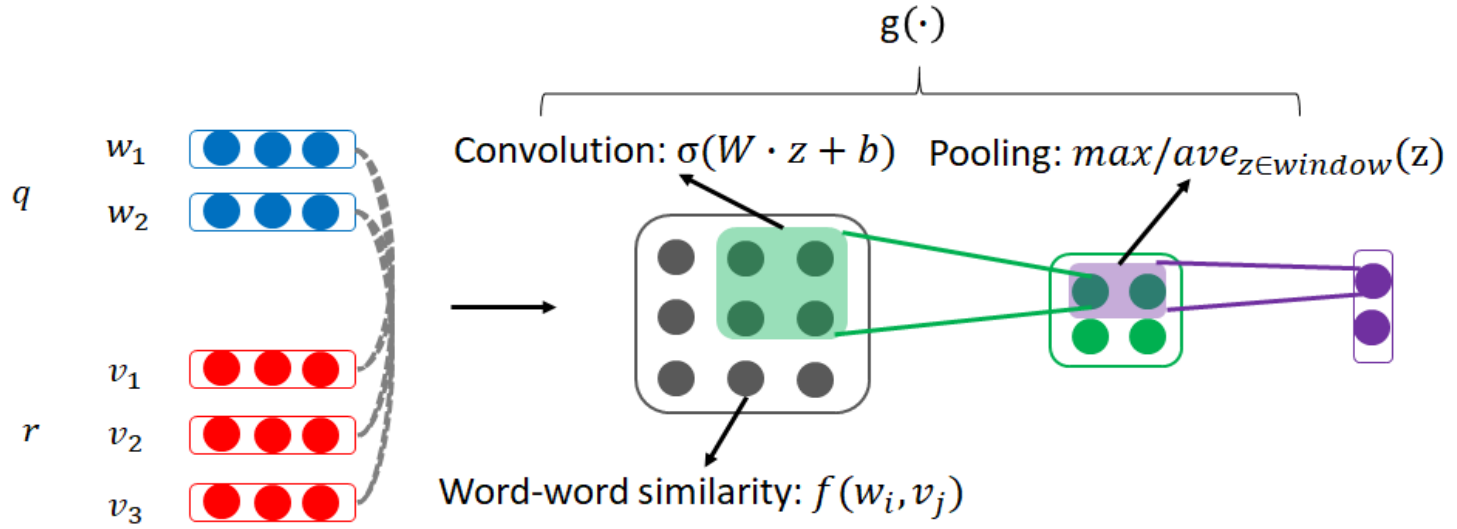
Model	Representation	Matching	Paper
MLP	Mean pooling	MLP	N/A
Arc-I	CNN	MLP	Baotian Hu et al., Convolutional Neural Network Architectures for Matching Natural Language Sentences, *NIPS'14*
CNTN	CNN	Neural Tensor Network	Xipeng Qiu et al., Convolutional Neural Tensor Network Architecture for Community-based Question Answering, *IJCAI'15*
CNN with GESD & AESD	CNN	Dot product & Euclidean distance	Minwei Feng et al., Applying Deep Learning to Answer Selection: A Study and An Open Task, *IEEE ASRU 2015*
Attentive LSTM	BiLSTM (+attention) + mean pooling	Cosine	Ming Tan et al., Improved Representation Learning for Question Answer Matching, *ACL'16*
IARNN	GRU (+attention)	Cosine	Binging Wang et al., Inner Attention based Recurrent Networks for Answer Selection, *ACL'16*

Message-Response Matching: Framework II

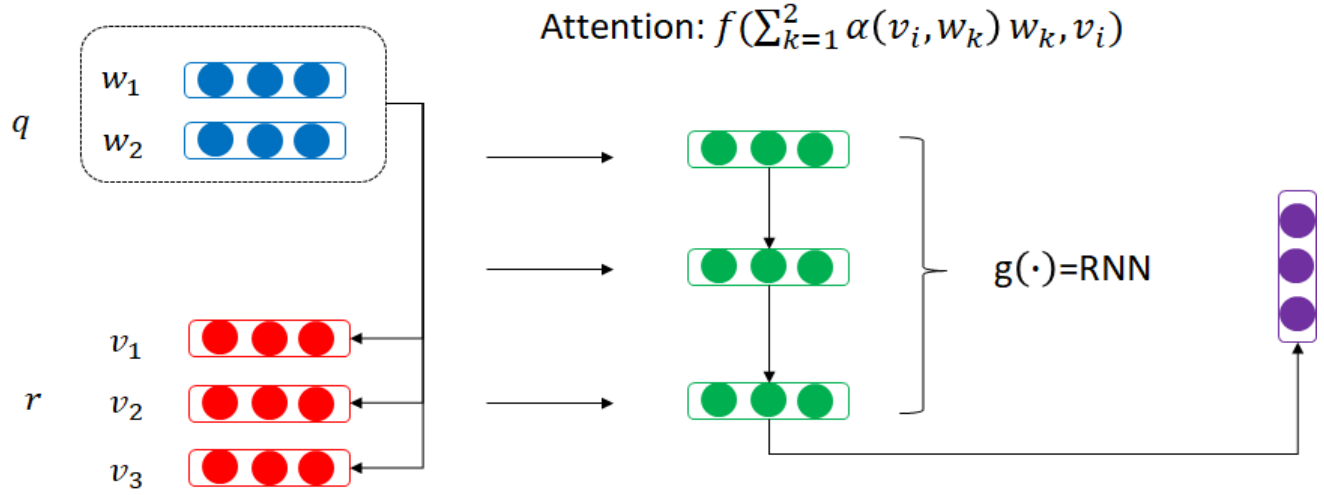


Two Types of Interaction

Similarity matrix-based



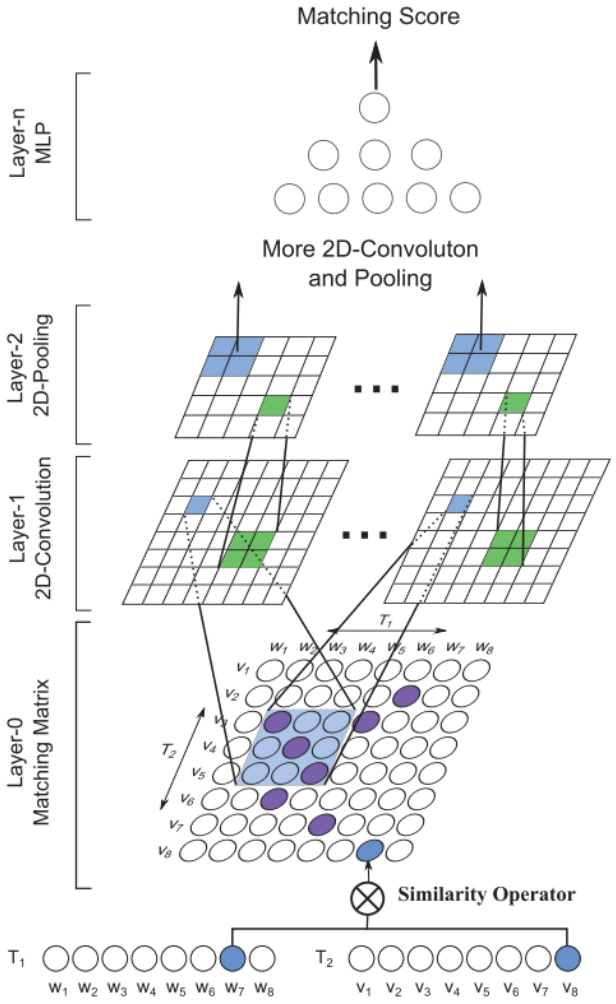
Attention-based



Implementation of Framework II

Input Representation	$f(\cdot,\cdot)$	Interaction Representation	$g(\cdot)$	$h(\cdot)$
Word embedding with random initialization	Cosine/Dot product	Similarity matrices	2D CNN	MLP
Word embedding initialized with Glove	Linear and non-linear transformation	Weighted average (Attention)	RNN	SoftMax
Hidden states of an RNN	Tensor			
	Indicator function			
	Euclidean distance			

Special Case 1: Match Pyramid



$\boldsymbol{h}(\cdot)$: MLP

$\boldsymbol{g}(\cdot)$: 2D CNN

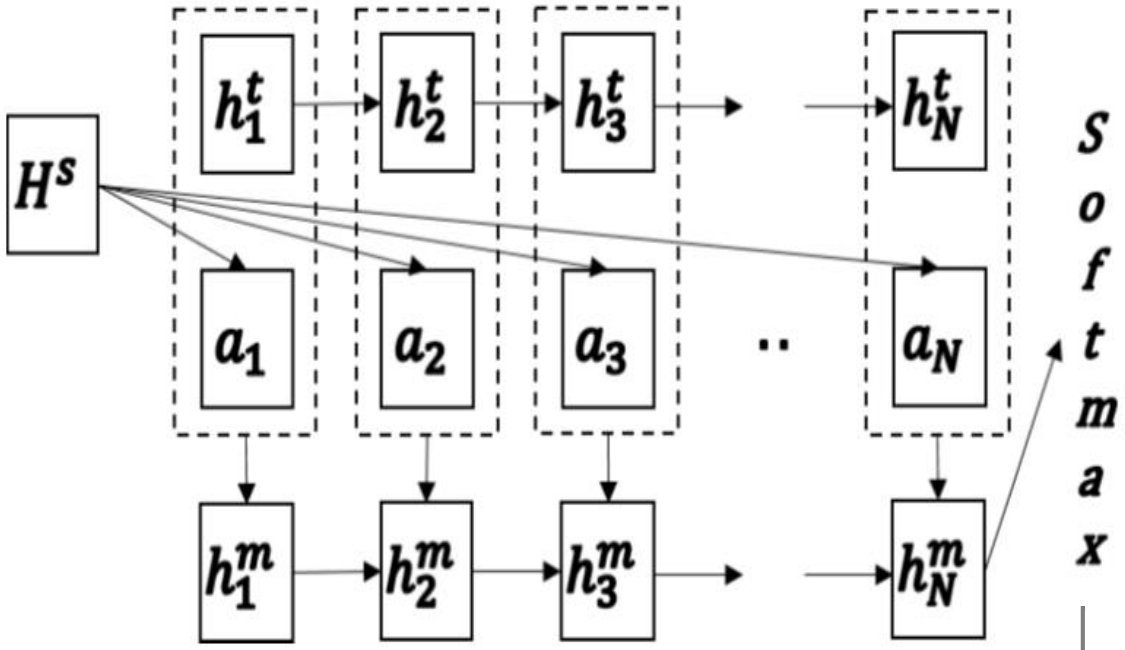
Interaction Representation: similarity matrix

$\boldsymbol{f}(\cdot,\cdot)$: indicator function / dot product / cosine

Input Representation: word embedding with random initialization

Liang Pang et al., Text Matching as Image Recognition, *AAAI'16*

Special Case 2: Match LSTM



Input Representation: hidden states of an RNN that processes the word sequences

$\boldsymbol{f}(\cdot,\cdot)$**:** $w \cdot tanh(A_1 \cdot h_j^s + A_2 \cdot h_k^t + A_3 \cdot h_{k-1}^m)$

Interaction Representation: weighted average

$\boldsymbol{g}(\cdot)$**:** LSTM

$\boldsymbol{h}(\cdot)$**:** softmax

Shuohang Wang & Jing Jiang, Learning Natural Language Inference with LSTM, *NAACL'16*

More Methods in Framework II

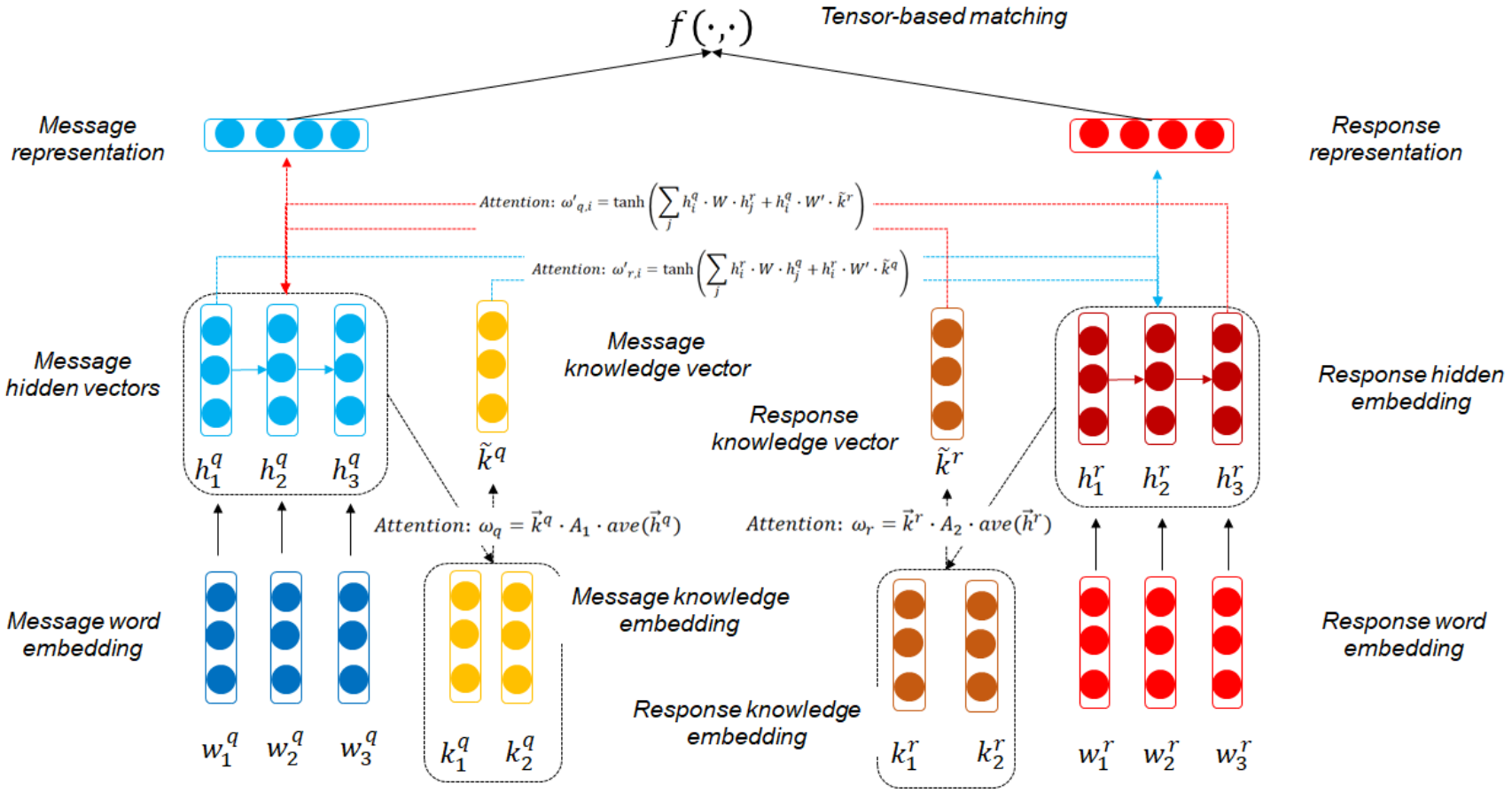
Model	Interaction Representation	$g(\cdot)$	Paper
Arc-II	Similarity matrix (linear & non-linear transformation)	2D CNN	Baotian Hu et al., Convolutional Neural Network Architectures for Matching Natural Language Sentences, *NIPS'14*
DeepMatch_topic	Similarity matrix (linear & non-linear transformation)	MLP	Zhengdong Lu et al., A Deep Architecture for Matching Short Texts, *NIPS'13*
Match Pyramid	Similarity matrix	2D CNN	Liang Pang et al., Text Matching as Image Recognition, *AAAI'16*
Match LSTM	Weighted average	LSTM	Shuohang Wang & Jing Jiang, Learning Natural Language Inference with LSTM, *NAACL'16*
MV-LSTM	Similarity matrix (tensor of hidden states)	K-max pooling	Shengxian Wan et al., A Deep Architecture for Semantic Matching with Multiple Positional Sentence Representations, *AAAI'16*

Comparison between Framework I and II

- Efficacy
  - In general, models in Framework II are better than models in Framework I on published datasets (see later), because matching information in a message-response pair is sufficiently preserved by the interaction in Framework II.
- Efficiency
  - Because the sufficient (and heavy) interaction, models in Framework II in general is more costly than models in Framework I.
  - Because one can pre-compute the representations of messages and responses and store them in index with text, models in Framework I is more preferable when there is strict requirement to online responding time.

Extension of Framework I : Matching with External Knowledge

Topic Aware Attentive Recurrent Neural Network (TAARNN)

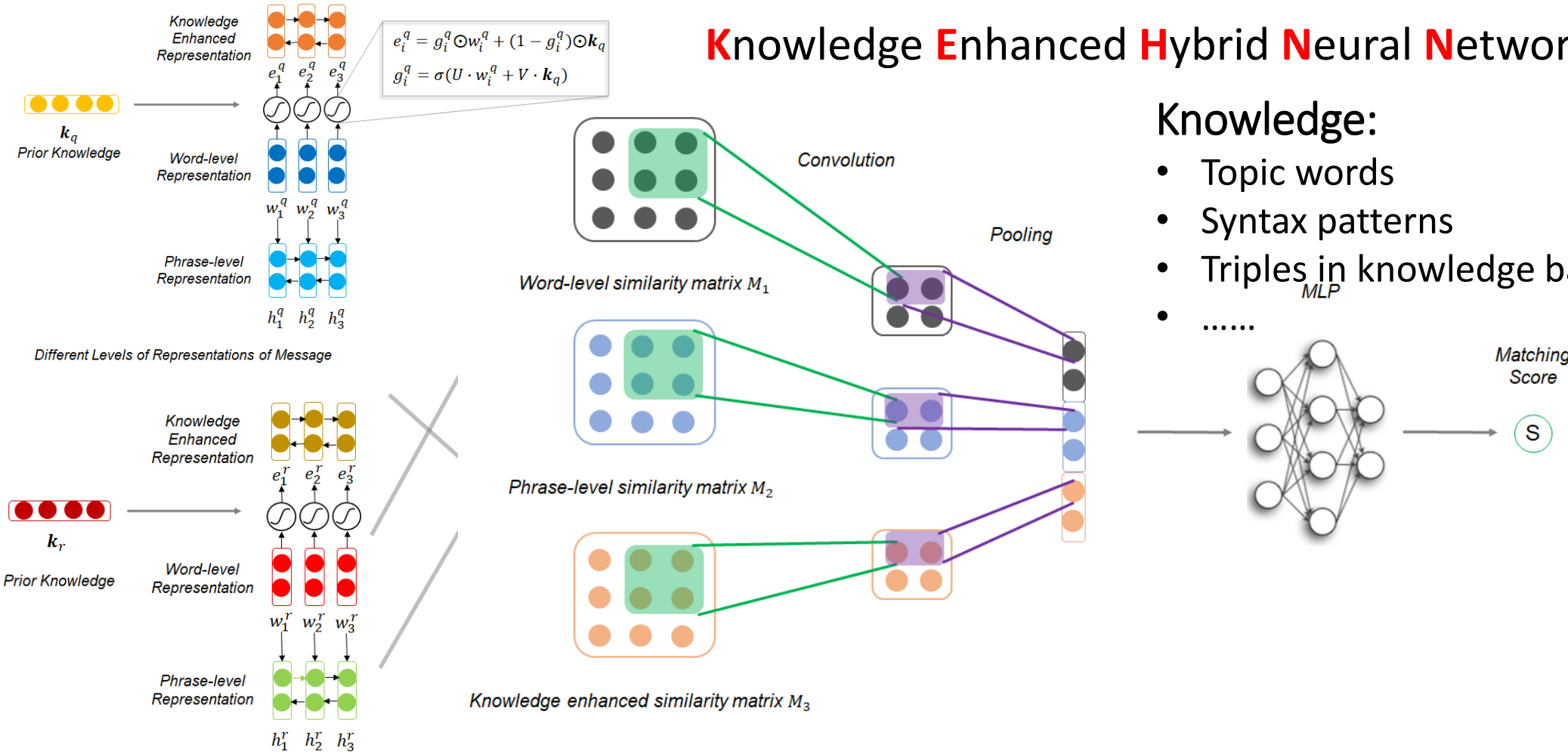


Knowledge:

- Topic words (from LDA)
- Syntax patterns
- Triples in knowledge bases
- ……

Yu Wu et al., Response Selection with Topic Clues for Retrieval-based Chatbots. *Neurocomputing*.

Extension of Framework II : Matching with Multiple Levels of Representations



Knowledge Enhanced Hybrid Neural Network (KEHNN)

Knowledge:

- Topic words
- Syntax patterns
- Triples in knowledge bases
- ……

Yu Wu et al., Knowledge Enhanced Hybrid Neural Network for Text Matching. *AAAI'18*

Datasets for Empirical Studies

- Ubuntu Dialogue Corpus
  - Dyadic English human-human conversations from Ubuntu chat logs.
  - Each conversation has multiple turns (Avg. # turns=7.71). For single-turn studies, we keep the last turn and the response to form a message-response pair.
  - Task = distinguishing the positive response from negative ones for a given message.
  - Train : validation: test = 1M : 0.5M : 0.5M.
  - Positive responses = human responses, negative responses = randomly sampled ones.
  - Positive : negative = 1:1 (train), 1:9 (validation), 1:9 (test).
  - Evaluation metrics = $\mathbf{R_n@k}$. For each message, if the only positive response is ranked within top $\mathbf{k}$ positions of $\mathbf{n}$ candidates, then $\mathbf{R_n@k = 1}$. The final result is the average on messages.

Ryan Lowe et al., The Ubuntu Dialogue Corpus: A Large Dataset for Research in Unstructured Multi-turn Dialogue Systems. *SIGDIAL'15*

Empirical Comparison

Model	Ubuntu			
	$R_2@1$	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$
MLP (I)	0.651	0.256	0.380	0.703
Arc-I (I)	0.665	0.221	0.360	0.684
LSTM (I)	0.725	0.361	0.494	0.801
CNTN (I)	0.743	0.349	0.512	0.797
Attentive-LSTM (I)	0.758	0.381	0.545	0.801
DeepMatch_topic (II)	0.593	0.248	0.376	0.693
Match LSTM (II)	0.685	0.289	0.430	0.701
Arc-II (II)	0.736	0.380	0.534	0.777
Match Pyramid (II)	0.743	0.420	0.554	0.786
MV-LSTM (II)	0.767	0.410	0.591	0.819
TAARNN (I)	0.770	0.404	0.560	0.817
KEHNN (II)	0.786	0.460	0.591	0.819

Insights from the Comparison

- **Neural tensor is a powerful matching function** (CNTN is much better than Arc-I).
- **Attentive LSTM achieves good performance** because the attention mechanism is inherently a kind of interaction.
- **Similarity matrix based interaction is better** than attention based interaction for Framework II (Match LSTM performs badly).
- In similarity matrix based methods, **dot product or cosine is better** as an interaction function (Match Pyramid is better than Arc-II).
- **Input representation that encodes more contextual information can improve** the performance of matching (MV-LSTM is better than Match Pyramid).
- **Topic information is useful** for matching in both Framework I and Framework II (TAARNN performs well).
- **Combining information from multiple sources is beneficial** to matching (KEHNN performs well).

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- Zhengdong Lu and Hang Li. A Deep Architecture for Matching Short Texts. NIPS'13.
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- Minwei Feng, Bing Xiang, Michael R. Glass, Lidan Wang, and Bowen Zhou. Applying Deep Learning to Answer Selection: A Study and An Open Task. IEEE ASRU 2015.
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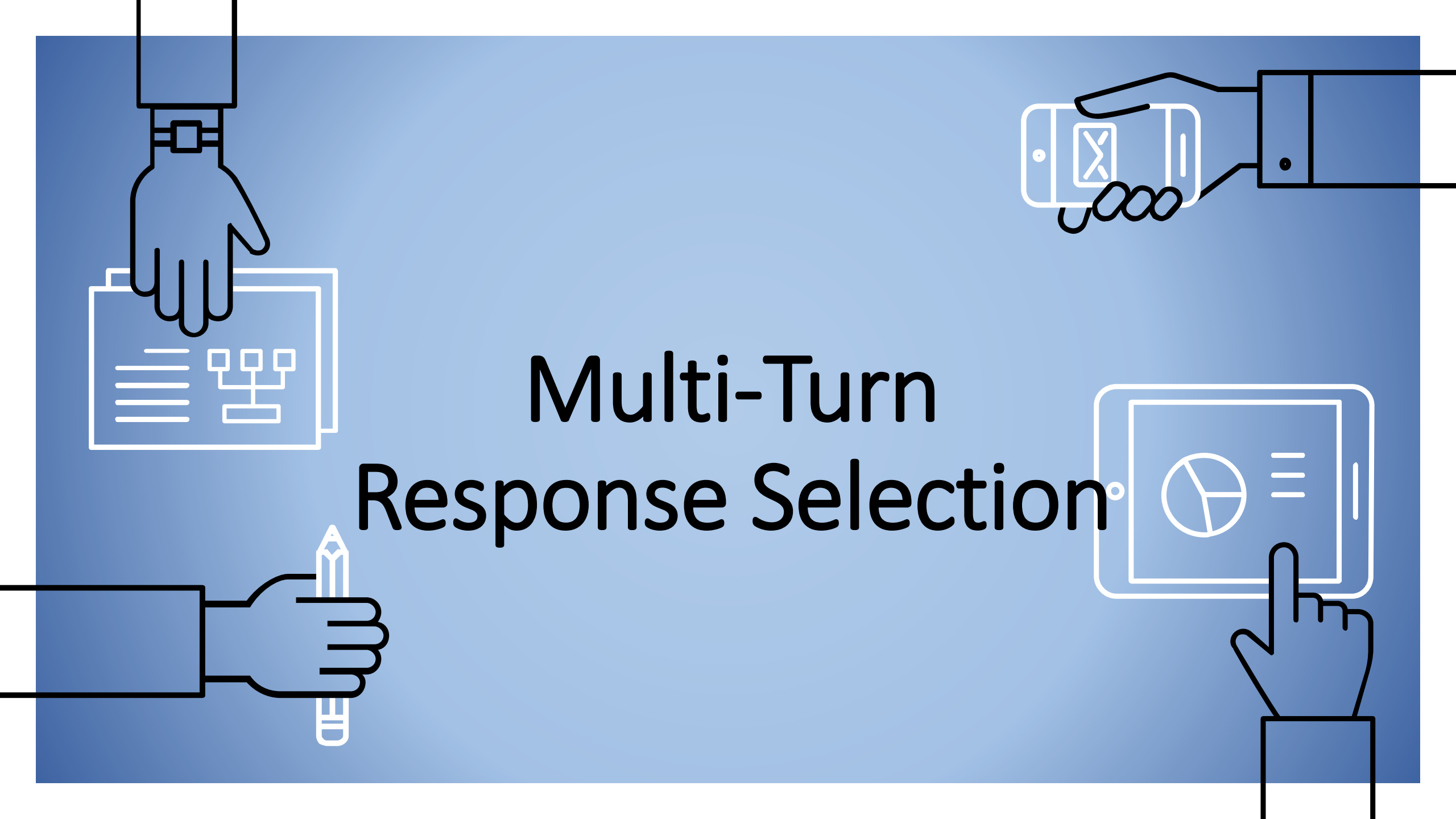
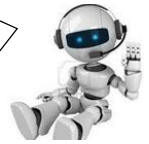
- Yu Wu, Wei Wu, Can Xu, and Zhoujun Li. Knowledge Enhanced Hybrid Neural Network for Text Matching. AAAI'18.


Multi-Turn
Response Selection

Multi-Turn Response Selection

How are you going?

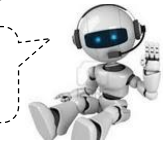
I am going to hold a drum class in Shanghai? Any one wants to join?



Interesting! Do you have coaches who can help me practice drum?

Of course!

Can I have a free lesson?

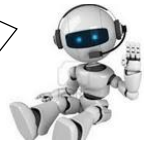


Candidate responses

- Yes, of course. ✓
- What lesson? ✗
- No, no free lessons. ✓
- Yes, please bring your drum ✓
- We do not have coaches. ✗
- Our English lessons are free ✗

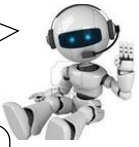
How are you going?

I am going to hold a drum class in Shanghai? Any one wants to join?



Interesting! Do you have coaches who can help me practice drum?

Of course!

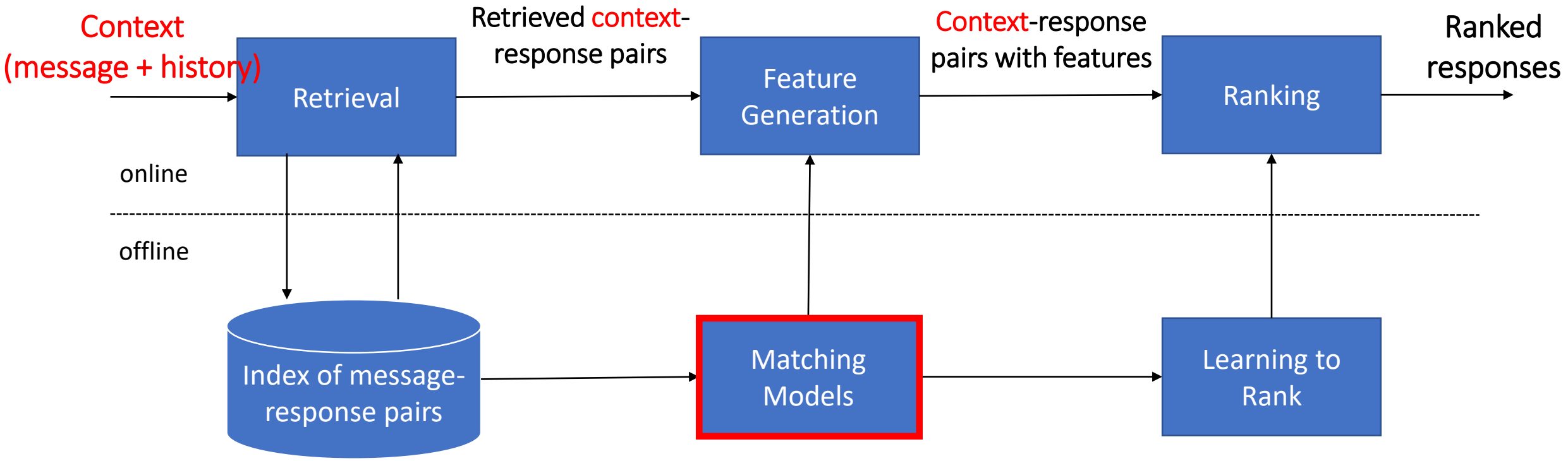


Can I have a free lesson?

Yes, please bring your drum

Candidates in red are good without the context!

System Architecture for Multi-Turn Response Selection



<q>well I hope you fell better smiley</q>
<r> thanks </r>
<q> I was so excited about dying my hair blond</q>
<r> do it </r>
……
……

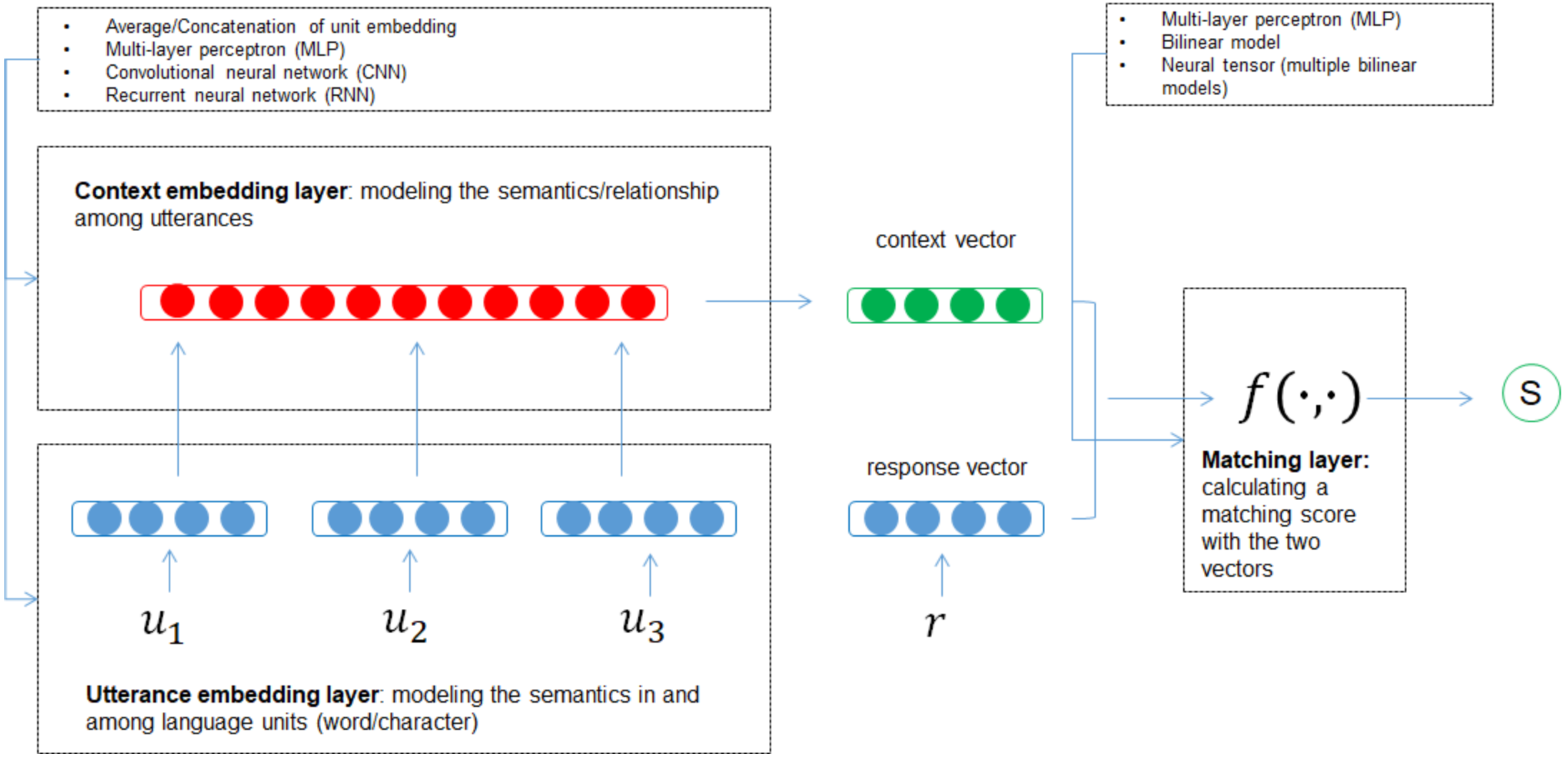
Deep learning based context-response matching

Gradient boosted tree

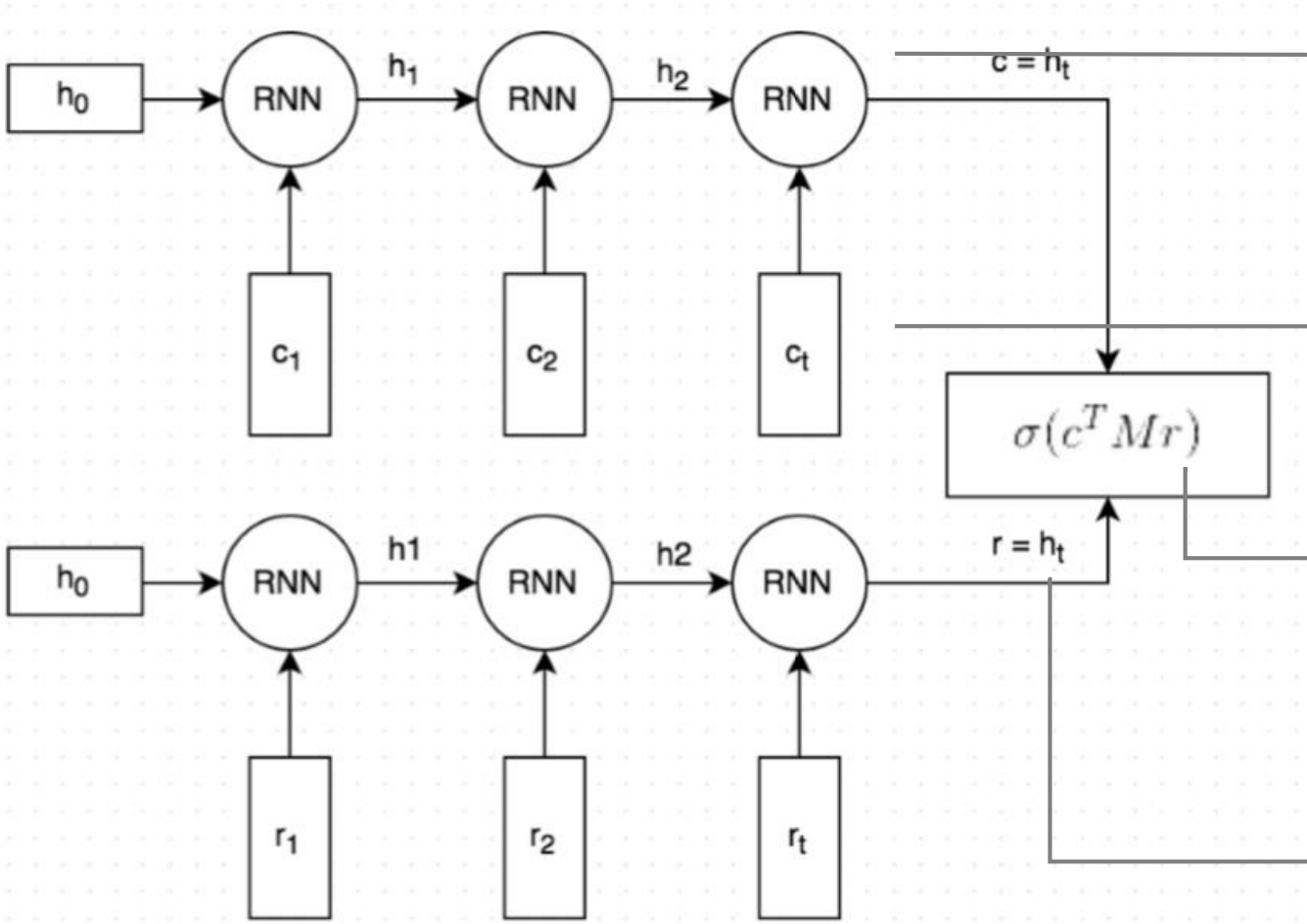
New Challenges with Contexts

- A hierarchical data structure
  - Words -> utterances -> session
- Information redundancy
  - Not all words and utterances are useful for response selection
- Logics
  - Order of utterances matters in response selection
  - Long-term dependencies among words and utterances
  - Constraints to proper responses

Context-Response Matching: Framework I



Special Case 1: Dual-LSTM



Context embedding: LSTM on the concatenation of word vectors

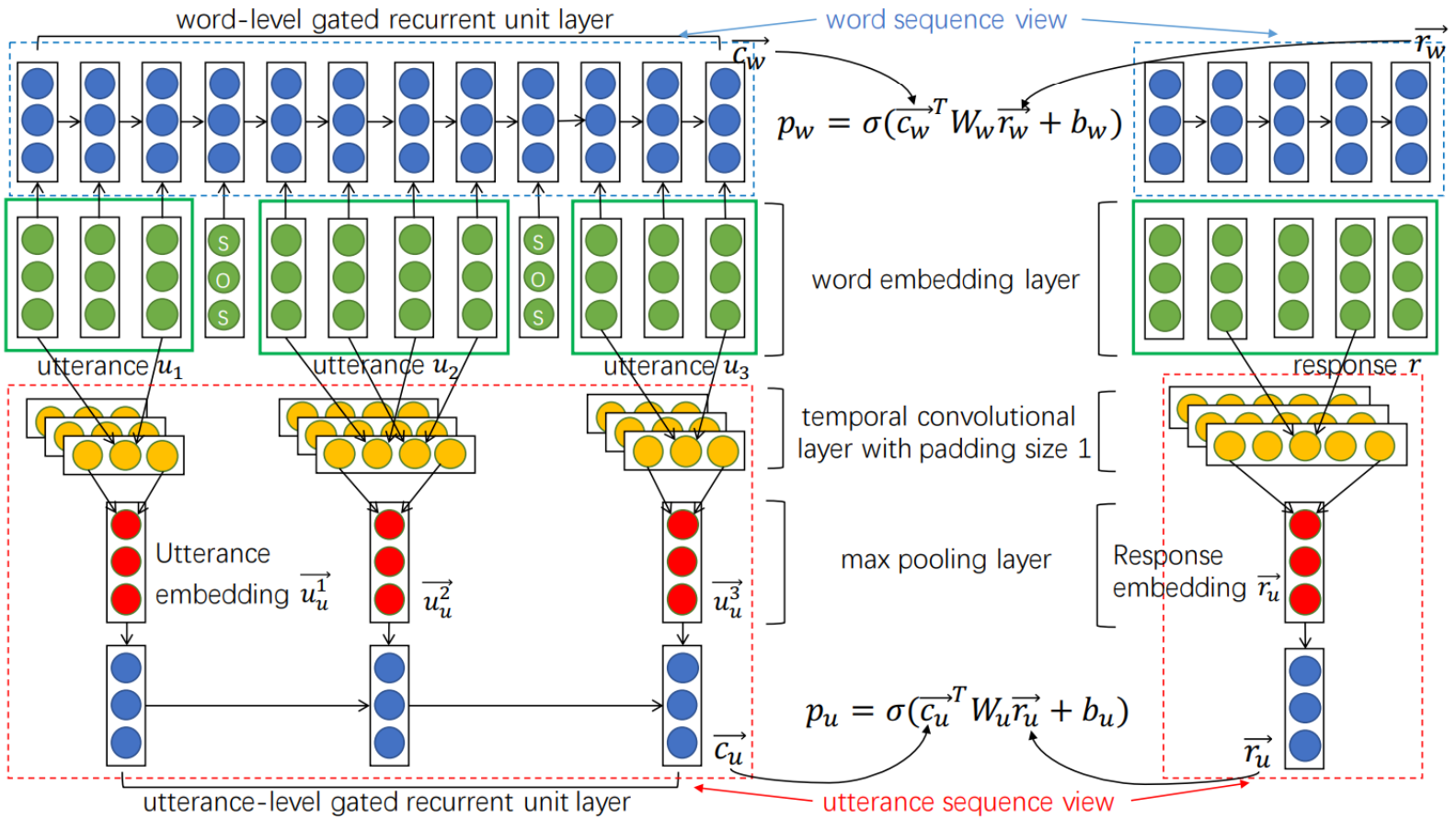
Utterance embedding: word embedding vectors

Matching: Bilinear model

Response vector: last hidden vector of an LSTM

Ryan Lowe et al., The Ubuntu Dialogue Corpus: A Large Dataset for Research in Unstructured Multi-turn Dialogue Systems. *SIGDIAL 2015*

Special Case 2:
Multi-view Response Selection Model



Context embedding (word view): GRU on the concatenation of word vectors

Utterance embedding (word view): word embedding vectors

Response vector (word view): last hidden vector of GRU

Matching: Bilinear

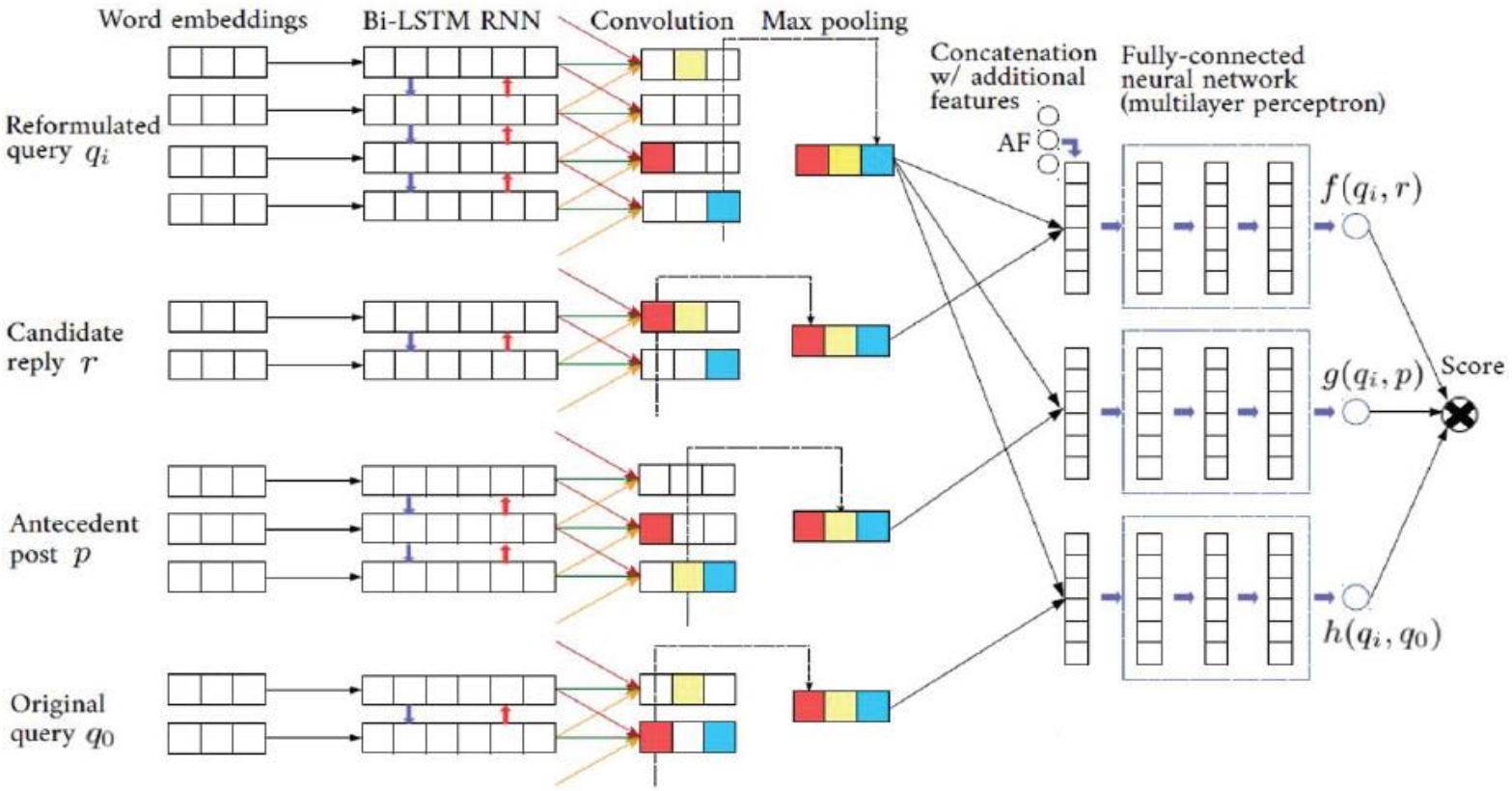
Utterance embedding (utterance view): CNN

Context embedding (utterance view): GRU

Response vector (utterance view): CNN

Xiangyang Zhou et al., Multi-view Response Selection for Human-Computer Conversation. *EMNLP 2016*

Special Case 3:
Deep Learning to Respond (DL2R)



Utterance embedding:
BiLSTM+CNN

Context embedding:
Identity

Matching:
MLP

Response vector:
BiLSTM+CNN

Rui Yan, et al., Learning to Respond with Deep Neural Networks for Retrieval-based Human-Computer Conversation System. *SIGIR'16*.

More Methods in Framework I

Model	Utterance Embedding	Context Embedding	Matching	Paper
Dual-LSTM	Word embedding	LSTM	Bilinear	Ryan Lowe et al., The Ubuntu Dialogue Corpus: A Large Dataset for Research in Unstructured Multi-turn Dialogue Systems. *SIGDIAL'15*
DL2R	BiLSTM+CNN	Identity	MLP	Rui Yan et al., Learning to Respond with Deep Neural Networks for Retrieval-based Human-Computer Conversation System. *SIGIR'16*
Multi-View	Word embedding/CNN	GRU	Bilinear	Xiangyang Zhou et al., Multi-view Response Selection for Human-Computer Conversation, *EMNLP'16*
Coupled LSTM	LSTM (on utterance pair)	LSTM	MAP	Rui Yan et al., Coupled Context Modeling for Deep Chit-Chat: Towards Conversations between Human and Computer, *KDD'18*
Any single-turn model	Word embedding	Message embedding of the model	Matching function of the model	N/A

Analysis of Framework I

Modeling the hierarchy of conversation sessions? ✓

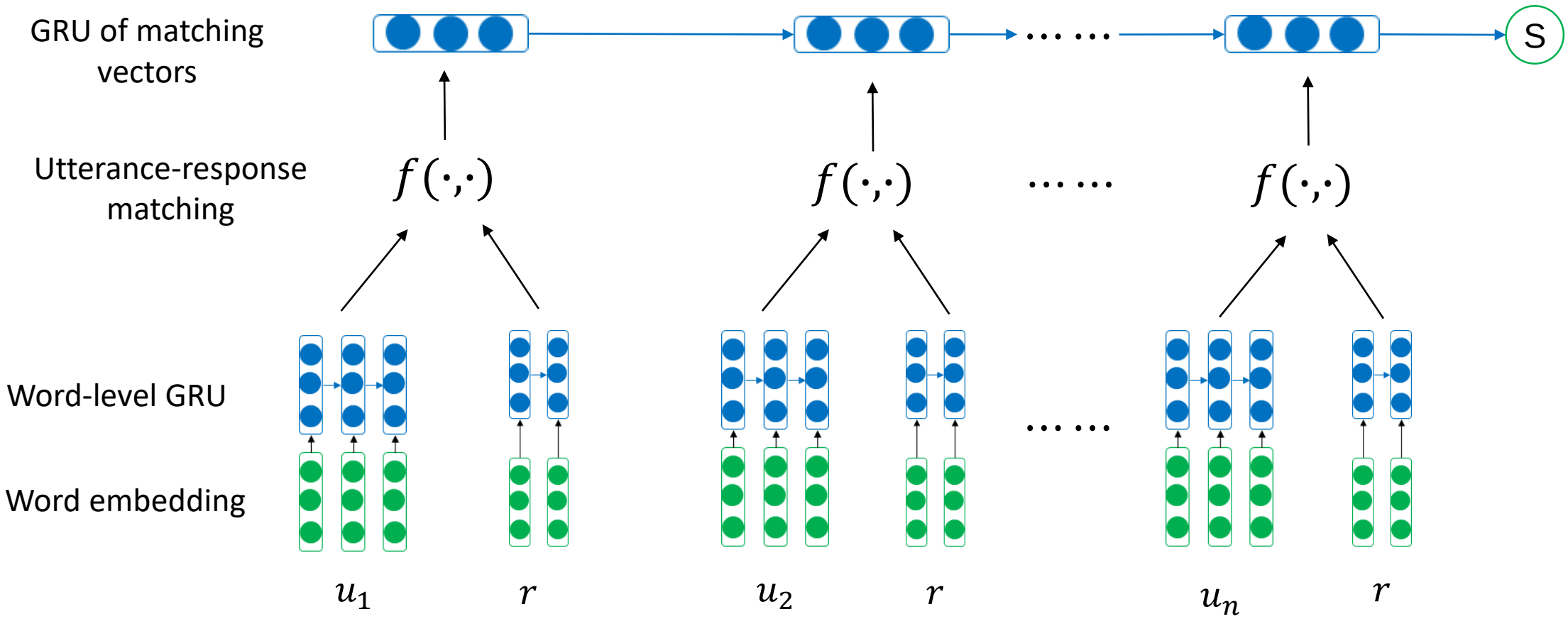
Modeling the relationship/dependency among words? ✓

Modeling the relationship/dependency among utterances? ✓

Modeling word/utterance importance ✗

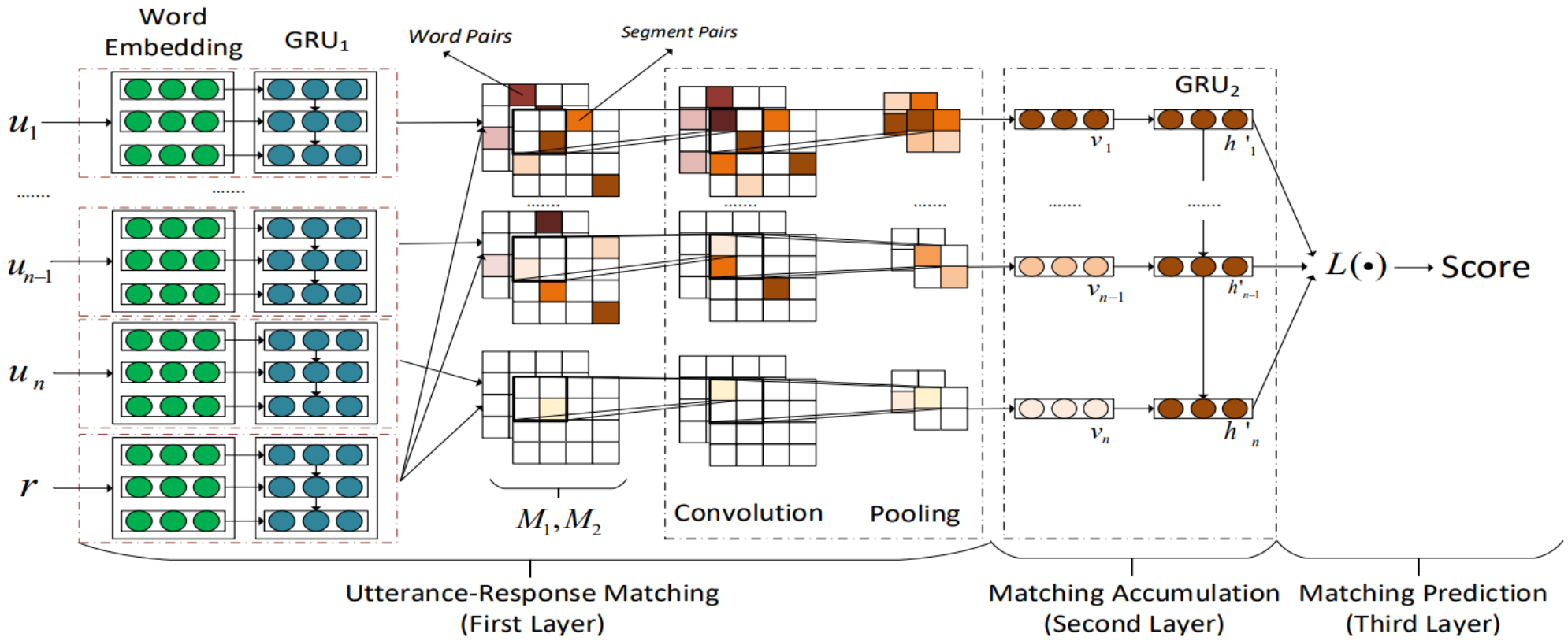
- Every context is compressed to a fixed length vector before matching with the response.
- Utterance representation is independent with the response/other utterances.

Context-Response Matching: Framework II



Yu Wu et al., A Sequential Matching Framework for Multi-turn Response Selection in Retrieval-based Chatbots. *arXiv:1710.11344*

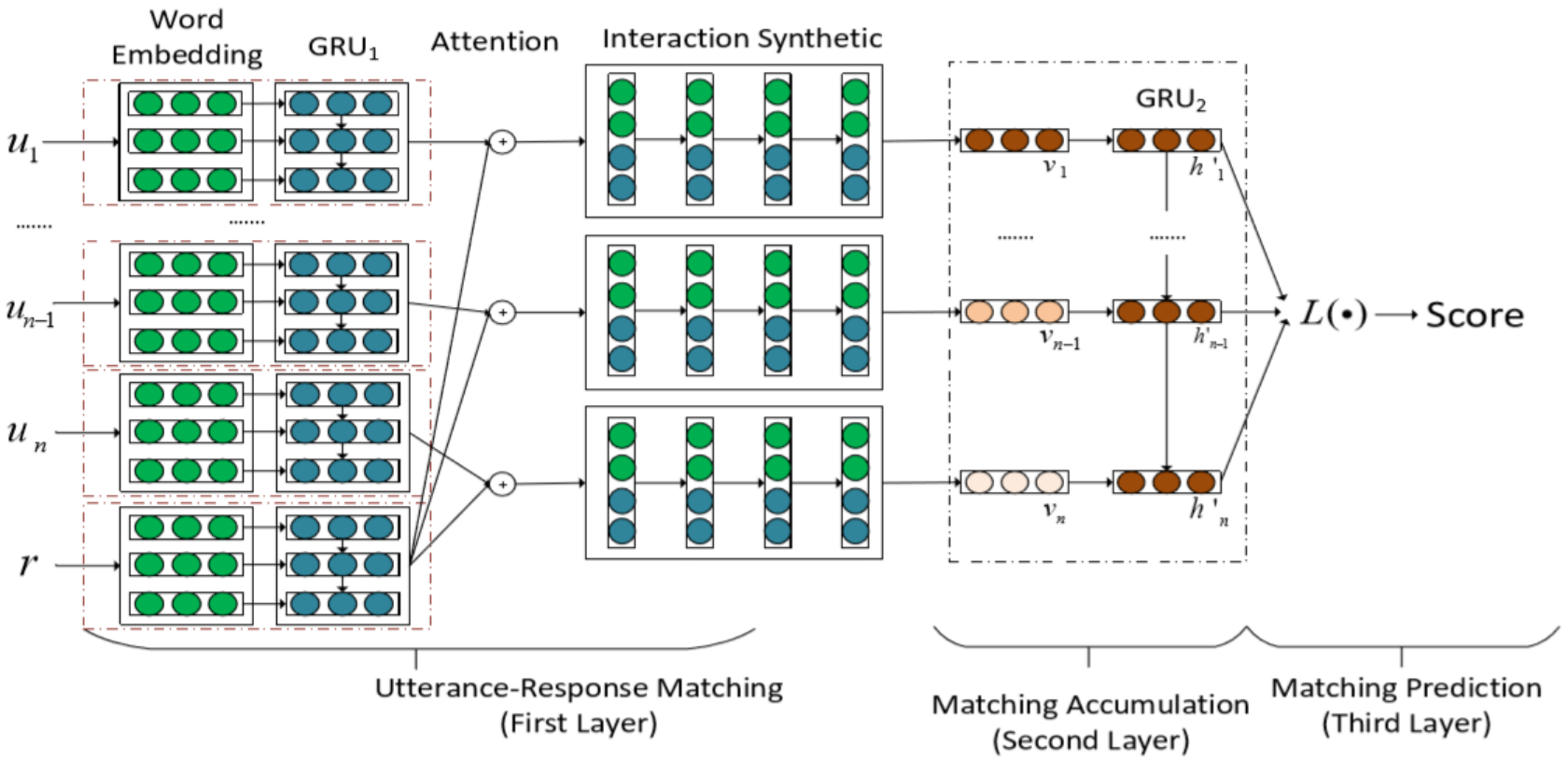
Special Case 1: Sequential Matching Network (SMN)



$$f(u_i, r) = W \cdot [\mathrm{CNN}(M_1) \oplus \mathrm{CNN}(M_2)] + b$$

Yu Wu et al., Sequential Matching Network: A New Architecture for Multi-turn Response Selection in Retrieval-based Chatbots. *ACL'17*

Special Case 2: Sequential Attention Network (SAN)



$$f(u_i, r) = GRU([\mathrm{Att}(r \to u_i) \odot r]_w \oplus [\mathrm{Att}(r \to u_i) \odot r]_h)$$

Yu Wu et al., A Sequential Matching Framework for Multi-turn Response Selection in Retrieval-based Chatbots. *arXiv:1710.11344*

How Framework II Models Word/Utterance Importance

u_1: *How can unzip many rar files (_number_ for example) at once?*

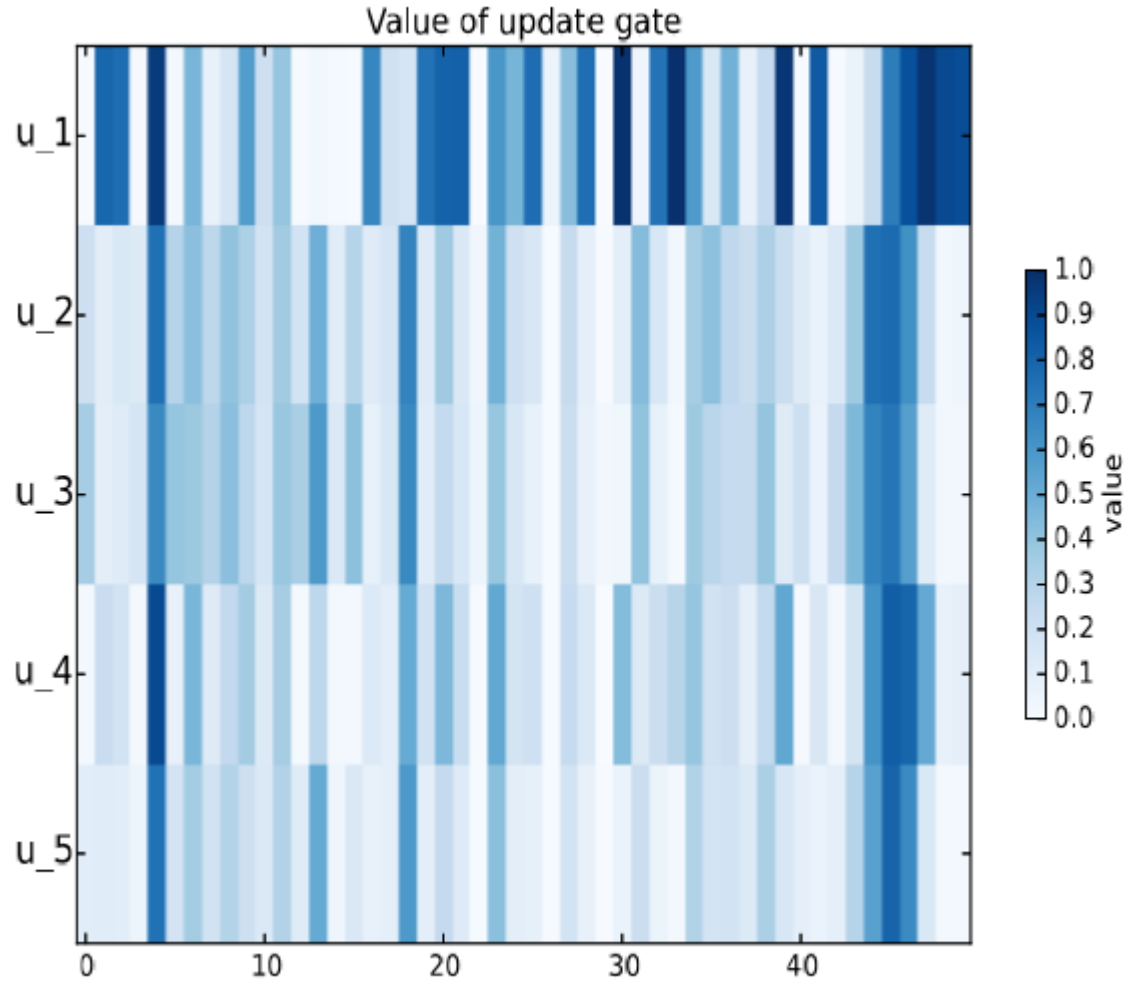
u_2: *Sure, you can do it in bash.*

u_3: *OK, how?*

u_4: *Are the files all in the same directory?*

u_5: *Yes, they all are.*

Response: *Then the command glebihan should extract them all from/to that directory.*



Yu Wu et al., Sequential Matching Network: A New Architecture for Multi-turn Response Selection in Retrieval-based Chatbots. *ACL'17*

Comparison between Framework I and II

- Efficacy
  - In general, models in Framework II are better than models in Framework I on published datasets (see later), because important information in a context is sufficiently distilled and preserved in matching in Framework II.
- Efficiency
  - Because the sufficient (and heavy) interaction, models in Framework II in general is more costly than models in Framework I.
- Interpretability
  - It is easy to understand what models in Framework II have learned via some visualization techniques.

Datasets for Empirical Studies

- Ubuntu Dialogue Corpus
- Douban Conversation Corpus
  - Dyadic Chinese human-human dialogues (comment streams) from Douban group, a popular social networking service in China.
  - Train : validation : test = 1M : 50k : 10k with average turns 6.69, 6.75, and 6.45 respectively.
  - Train & validation : positive responses are human responses, and negative ones are randomly sampled.
  - Test: 10 human judged response candidates per context retrieved from an index.
  - Evaluation metrics: MAP, MRR, and P@1 (from information retrieval)

Yu Wu et al., Sequential Matching Network: A New Architecture for Multi-turn Response Selection in Retrieval-based Chatbots. *ACL'17*

Empirical Comparison

Model	Ubuntu				Douban		
	$R_2@1$	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$	MAP	MRR	$P@1$
TF-IDF	0.659	0.410	0.545	0.708	0.331	0.359	0.180
CNN	0.848	0.549	0.684	0.896	0.417	0.440	0.226
BiLSTM	0.895	0.630	0.780	0.944	0.479	0.514	0.313
MV-LSTM	0.906	0.653	0.804	0.946	0.498	0.538	0.348
Match LSTM	0.904	0.653	0.799	0.944	0.500	0.537	0.345
Attentive-LSTM	0.903	0.633	0.789	0.943	0.495	0.523	0.331
Dual LSTM	0.901	0.638	0.784	0.949	0.485	0.527	0.320
DL2R	0.899	0.626	0.783	0.944	0.488	0.527	0.330
Multi-View	0.908	0.662	0.801	0.951	0.505	0.543	0.342
SMN	0.926	0.726	0.847	0.961	0.529	0.569	0.397
SAN	0.932	0.734	0.852	0.962	0.532	0.575	0.387

Insights from the Comparison

- **Utterance-response interaction at the beginning is crucial**, as models in Framework II (SMN & SAN) are much better than models in Framework I.
- **Ensemble of matching from multiple views are effective**, as multi-view outperforms all other models in Framework I.
- **Selection of interaction functions does not make a clear difference on efficacy**, as long as the function can model word/phrase importance. This is indicated by the comparable performance of SMN and SAN.
- **SMN is more efficient and easier to parallelize than SAN**, due the characteristics of CNN and RNN.

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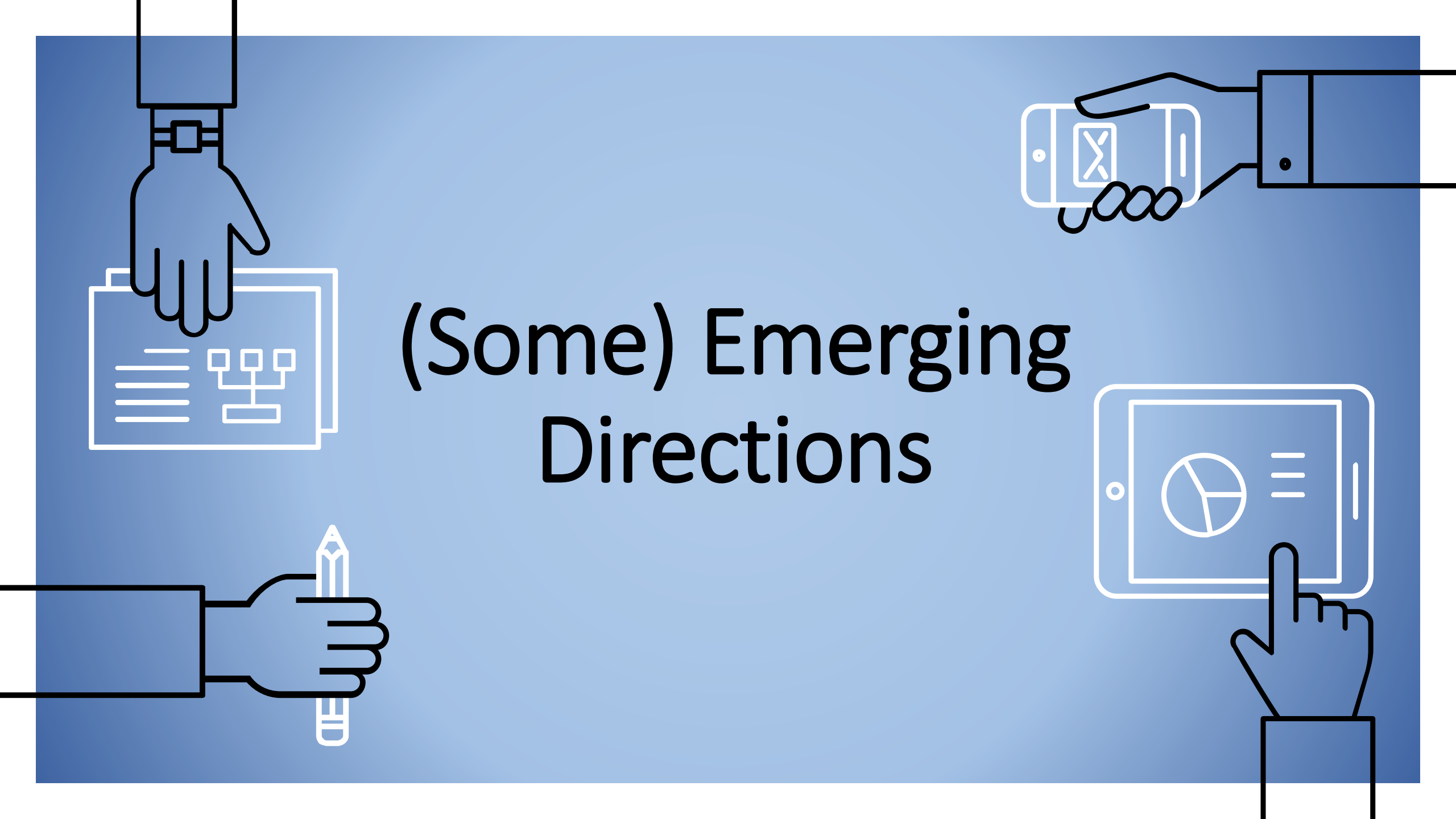
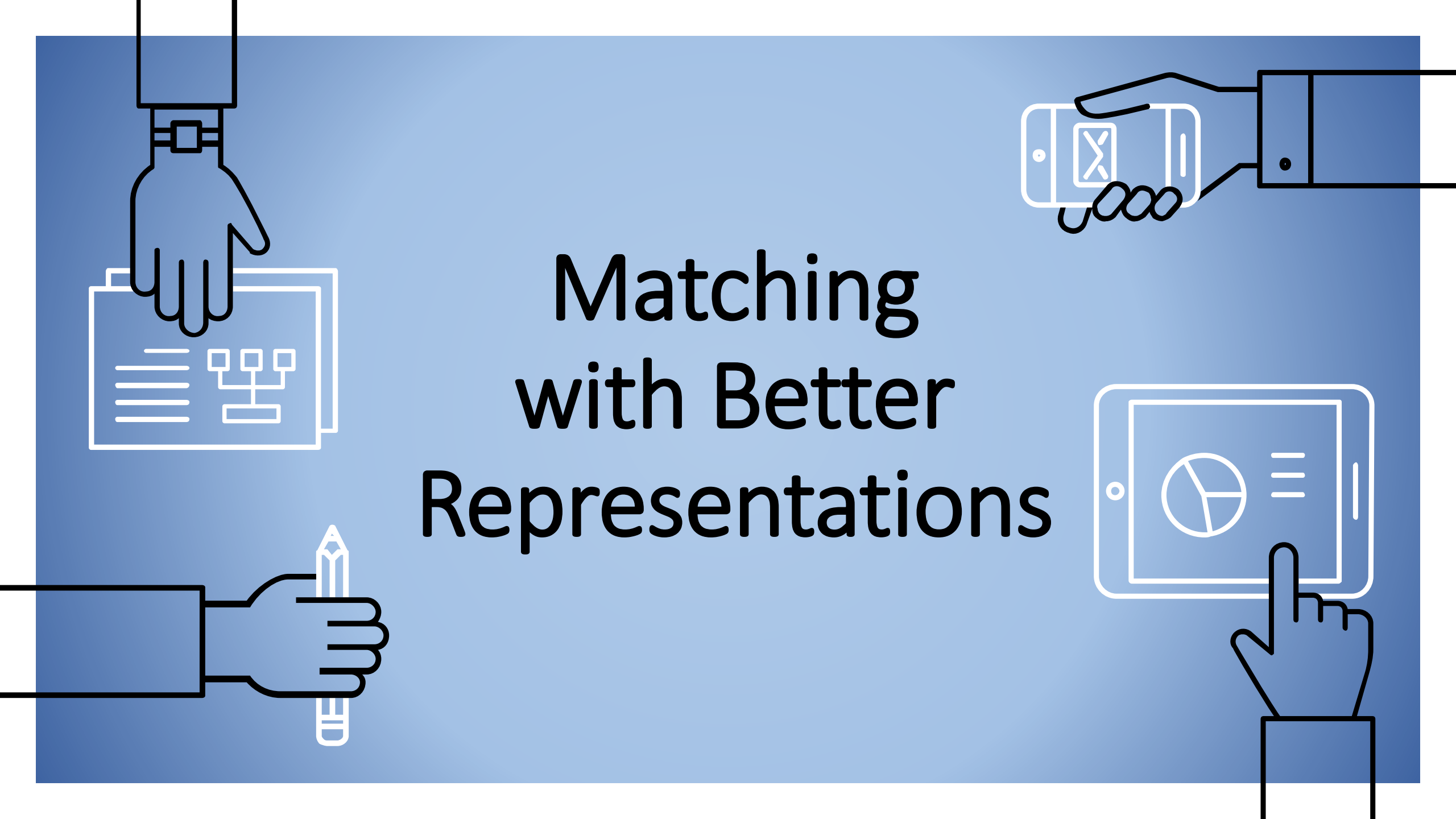
- Zhen Xu, Bingquan Liu, Baoxun Wang, Chengjie Sun, and Xiaolong Wang. Incorporating Loose-Structured Knowledge into LSTM with Recall Gate for Conversation Modeling. IJCNN'17
- Liu Yang, Minghui Qiu, Chen Qu, Jiafeng Guo, Yongfeng Zhang, W.Bruce Croft, Jun Huang, and Haiqing Chen. Response Ranking with Deep Matching Networks and External Knowledge in Information-seeking Conversation Systems. SIGIR'18.

(Some) Emerging Directions

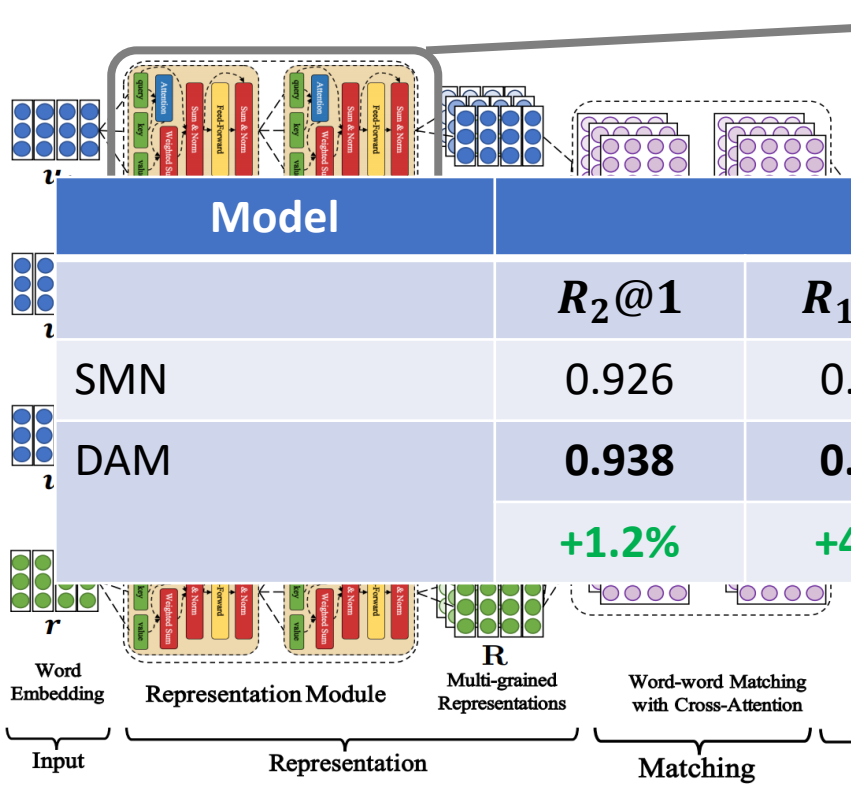


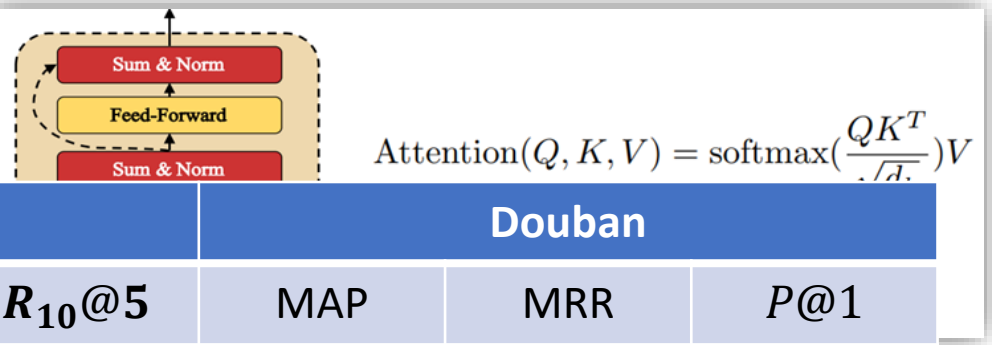

Matching
with Better
Representations

Matching With Better Representations

Self-attention, borrowed from NMT, is powerful in representing contexts and responses.

Deep **A**ttention **M**atching Network (DAM)





Model	Ubuntu				Douban		
	$R_2@1$	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$	MAP	MRR	$P@1$
SMN	0.926	0.726	0.847	0.961	0.529	0.569	0.397
DAM	**0.938**	**0.767**	**0.874**	**0.969**	**0.550**	**0.601**	**0.427**
	+1.2%	+4.1%	+2.7%	+0.8%	+2.1%	+3.1%	+3.0%

- **Cross-attention**: let an utterance and a response attend each other

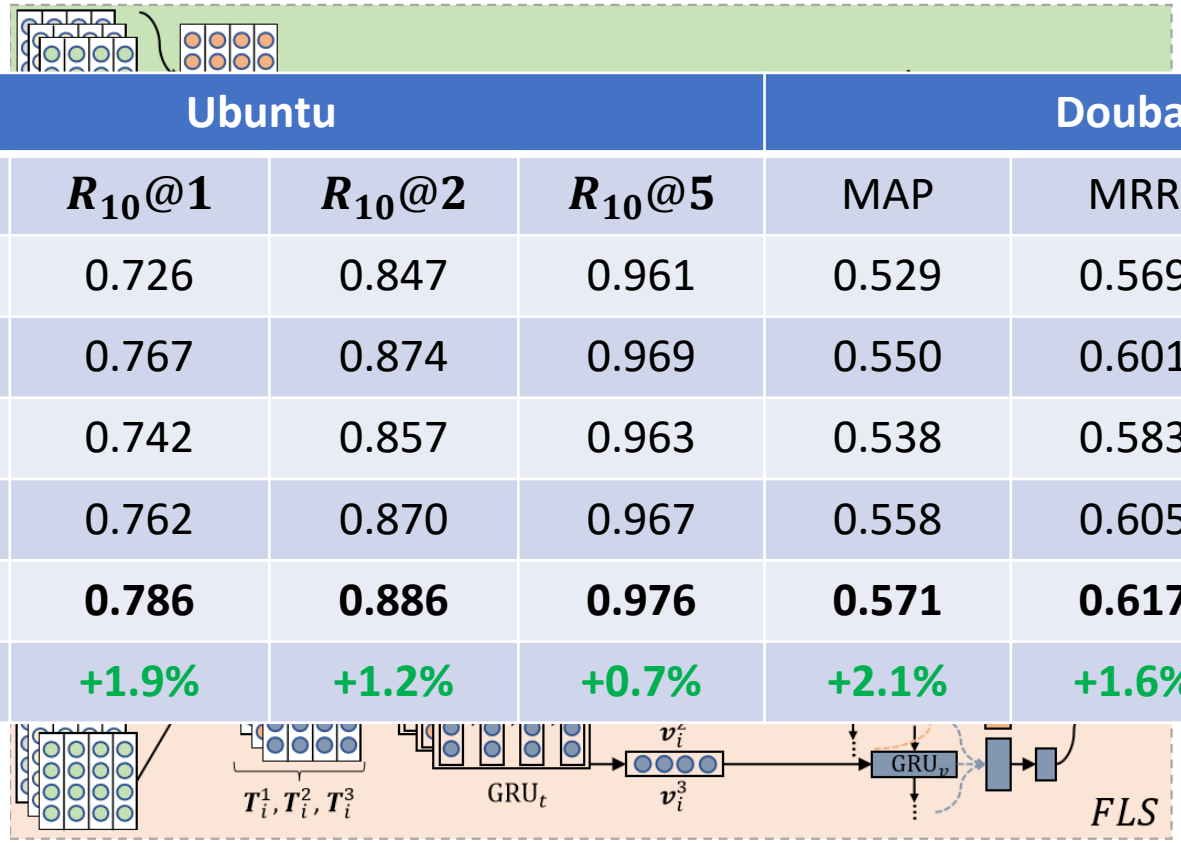
ng-term dependency among words

Xiangyang Zhou et al., Multi-turn Response Selection for Chatbots with Deep Attention Matching Network. *ACL'18*

Matching With Better Representations

Fusing multiple types of representations are helpful, but how to fuse matters.

Multi-Representation Fusion Network (**MRFN**)



Model	Ubuntu				Douban		
	$R_2@1$	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$	MAP	MRR	$P@1$
SMN	0.926	0.726	0.847	0.961	0.529	0.569	0.397
DAM	0.938	0.767	0.874	0.969	0.550	0.601	0.427
MRFN(FES)	0.930	0.742	0.857	0.963	0.538	0.583	0.405
MRFN(FIS)	0.936	0.762	0.870	0.967	0.558	0.605	0.438
MRFN(FLS)	**0.945**	**0.786**	**0.886**	**0.976**	**0.571**	**0.617**	**0.448**
	+0.7%	+1.9%	+1.2%	+0.7%	+2.1%	+1.6%	+2.1%

ut
gation

Chongyang Tao et al., Multi-Representation Fusion Network for Multi-turn Response Selection in Retrieval-based Chatbots. *WSDM'19*

Matching With Better Representations

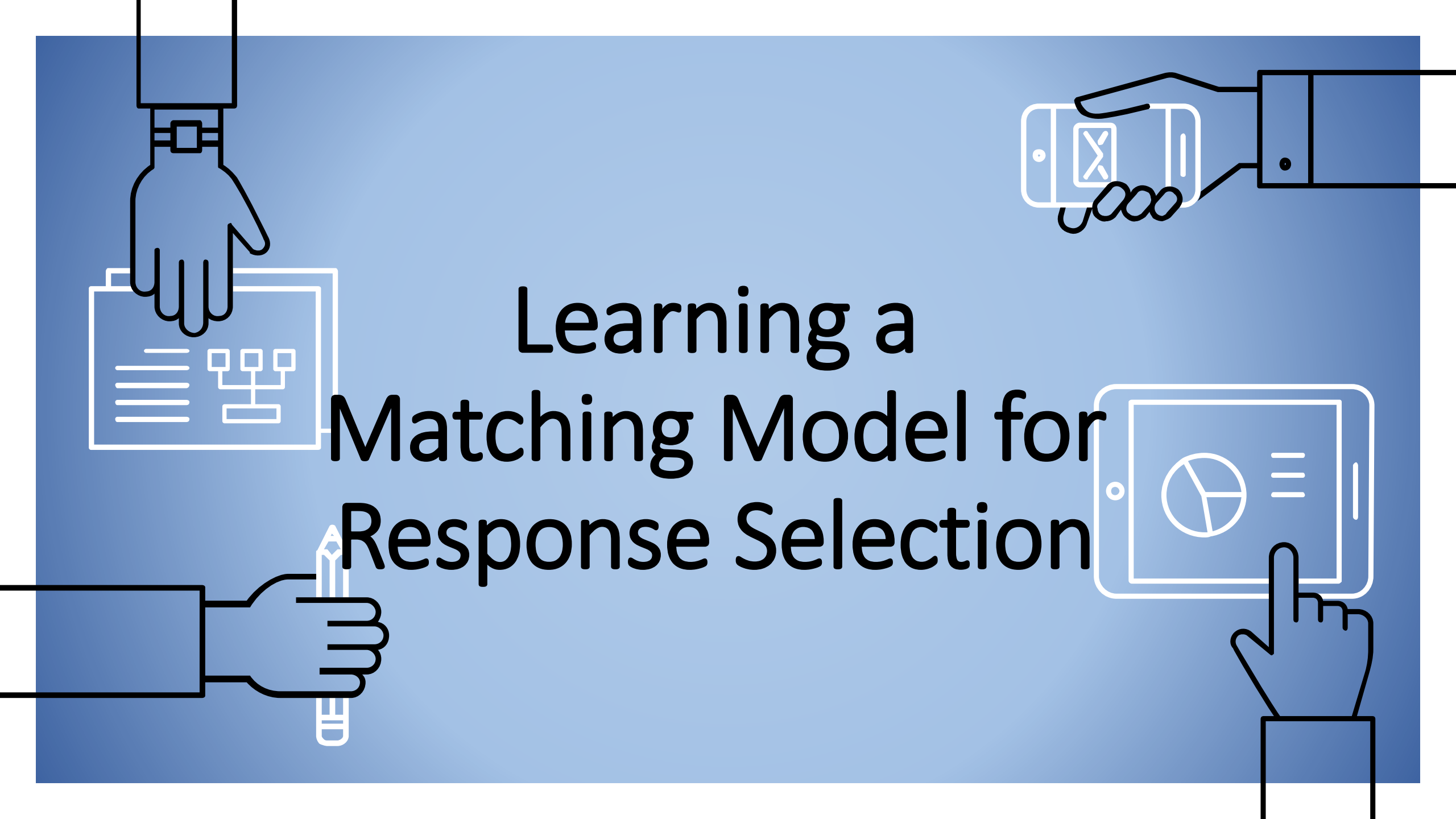
Pre-training neural networks on large scale data sets as representations significantly improve the existing models.

Model	Ubuntu			
	$R_2@1$	$R_{10}@1$	$R_{10}@2$	$R_{10}@5$
SMN	0.926	0.726	0.847	0.961
SMN+CoVe	0.930	0.738	0.856	0.963
	+0.4%	+1.2%	+0.9%	+0.2%
SMN+ELMo	0.917	0.720	0.835	0.953
	-0.9%	-0.6%	-1.2%	-0.8%
SMN+ELMo (fine-tune)	0.922	0.724	0.847	0.957
	-0.4%	-0.2%	+0.0%	-0.4%
SMN+ECMo	**0.933**	**0.755**	**0.866**	**0.975**
	+0.7%	+2.9%	+1.9%	+1.4%

ctors. *NIPS'17*

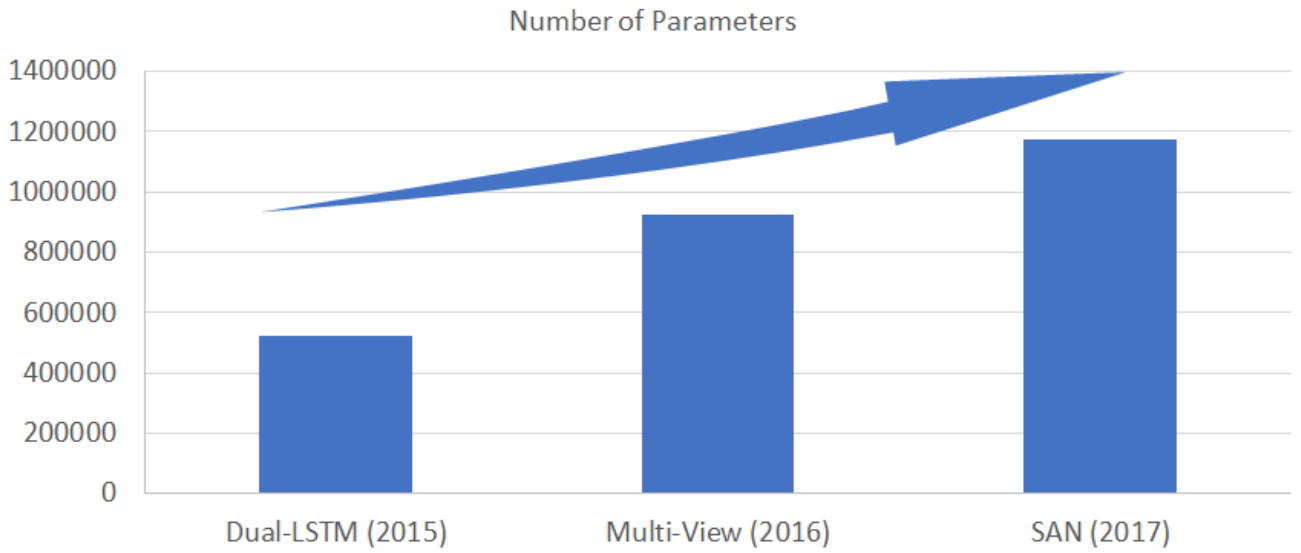
ons. *NAACL'18*

Chongyang Tao et al., Improving Matching Models with Contextualized Word Representations for Multi-turn Response Selection in Retrieval-based Chatbots. *arXiv:1808.07244*


Learning a
Matching Model for
Response Selection

Why Pay Special Attention to Learning?

- Matching models are becoming more and more complicated



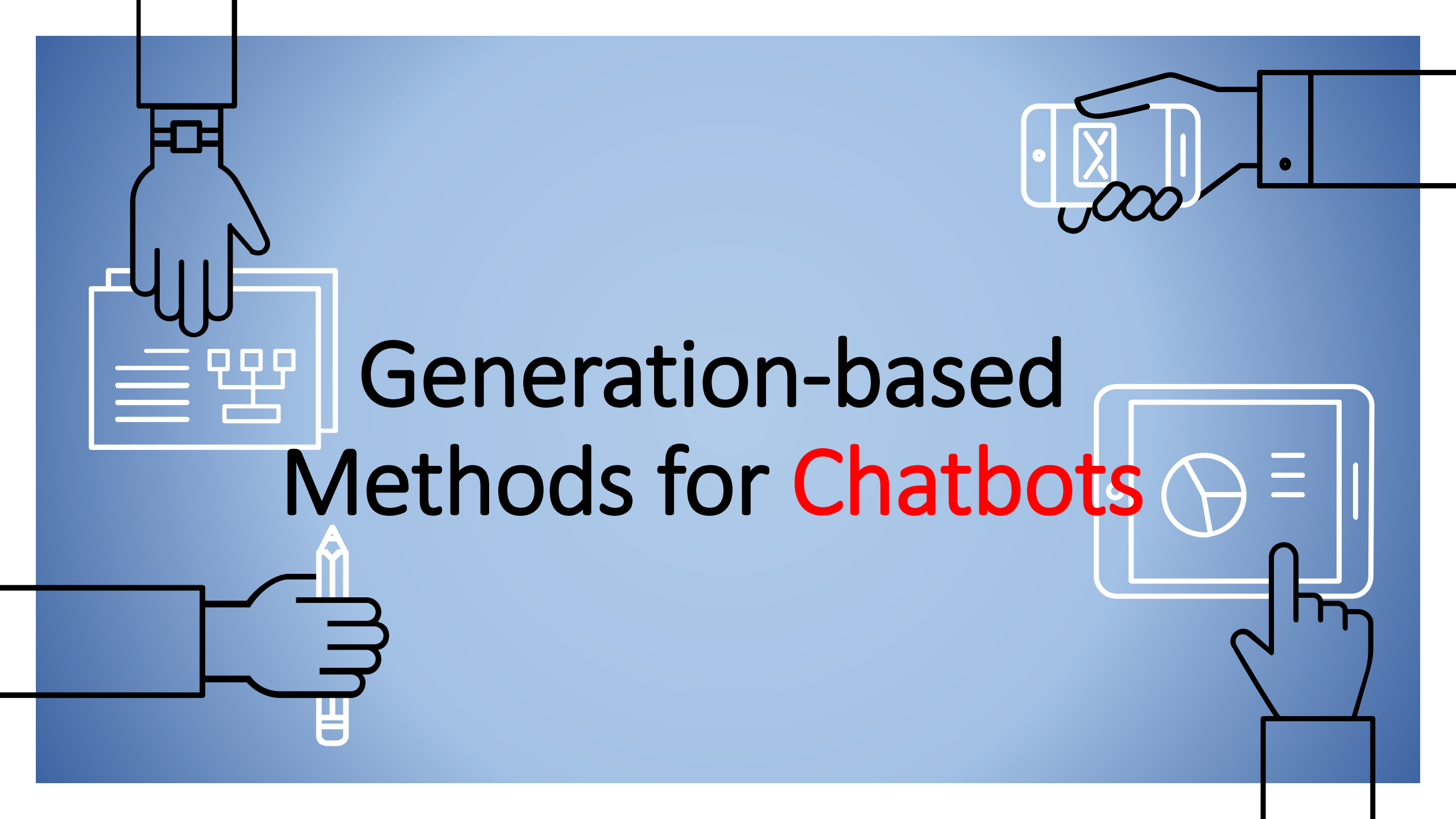
- Training data are randomly constructed with an almost
- fixed size
  - Size: ~million
  - Negative examples are randomly sampled

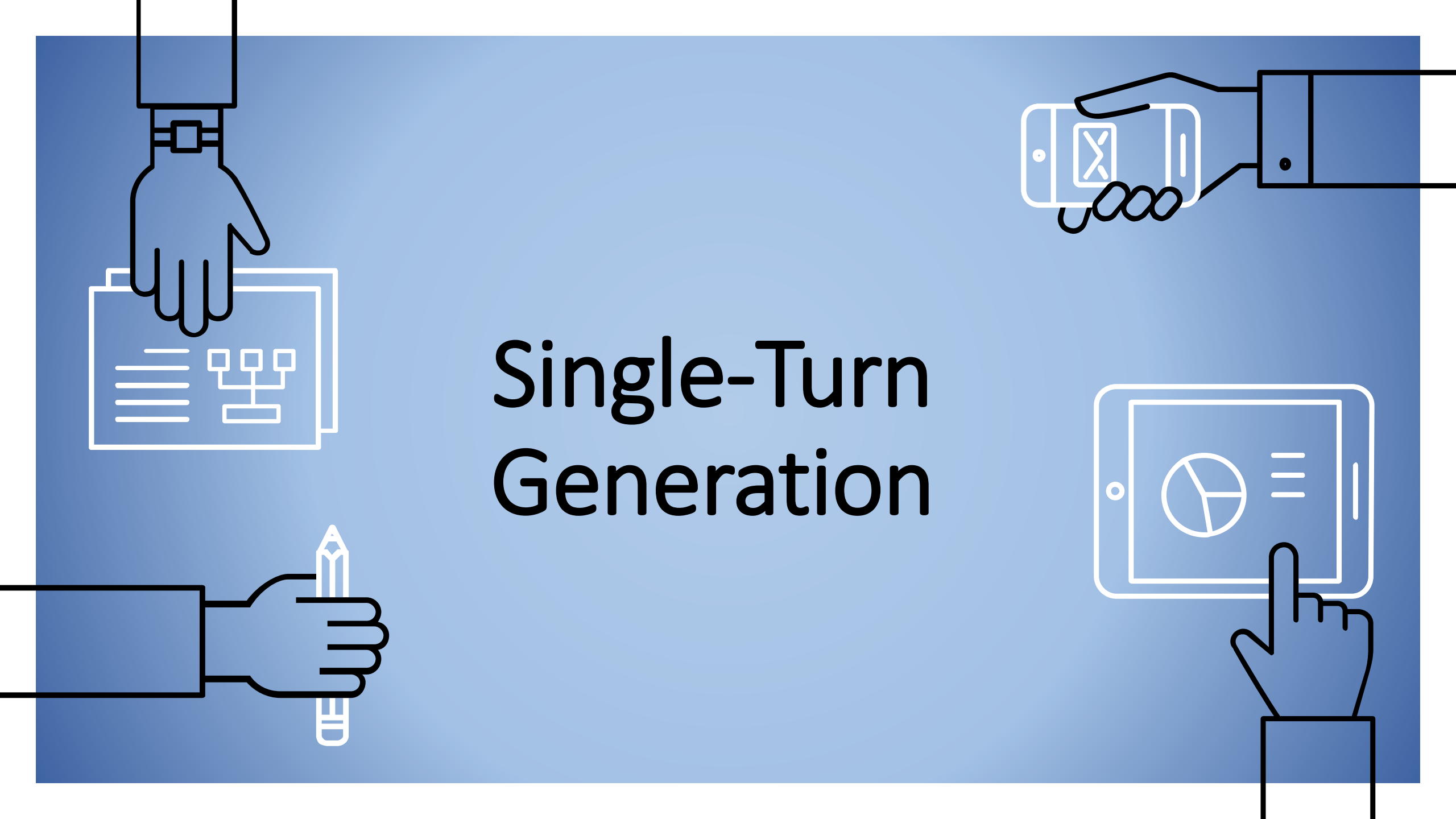
- *More and more easy patterns in training are captured*
- *Gap between training and test is still there*

Learning with Unlabeled Data – Weak Annotator

Model	Douban		
	MAP	MRR	$P@1$
Dual-LSTM	0.485	0.527	0.320
Dual-LSTM+Weak	0.519	0.559	0.359
	+3.4%	**+3.2%**	**+3.9%**
Multi-View	0.505	0.543	0.342
Multi-View+Weak	0.534	0.575	0.378
	+2.9%	**+3.2%**	**+3.6%**
SMN	0.526	0.571	0.393
SMN+Weak	0.565	0.609	0.421
	+3.9%	**+3.8%**	**+2.8%**

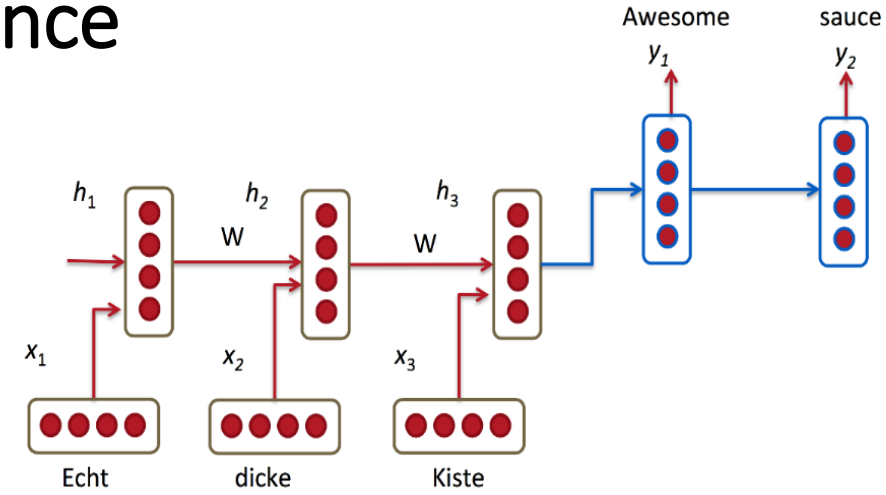
Yu Wu et al., Learning Matching Models with Weak Supervision for Response Selection in Retrieval-based Chatbots. *ACL'18*

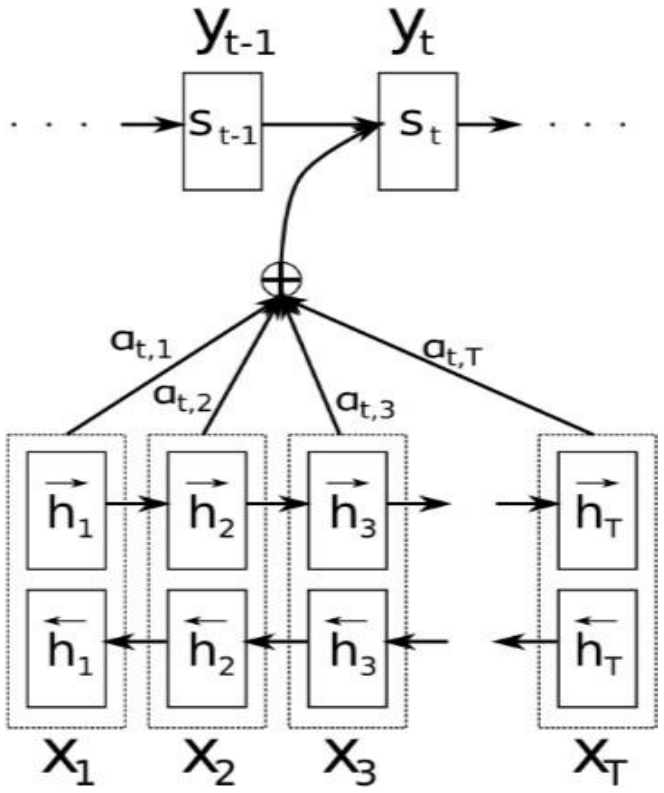

Generation-based
Methods for Chatbots


Single-Turn
Generation

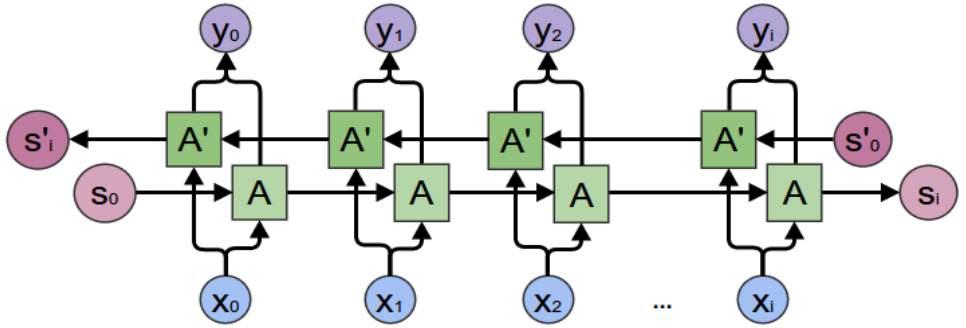
Basic Generation Model

- Sequence-to-sequence
  - Model from MT



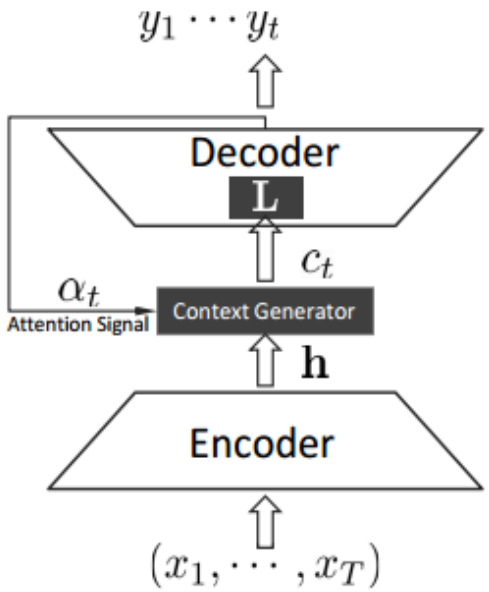


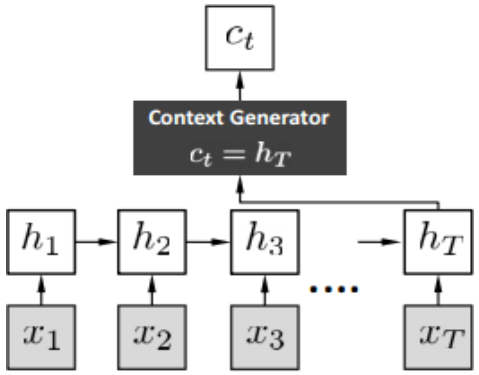
- Attention mechanism
- Bi-directional modeling

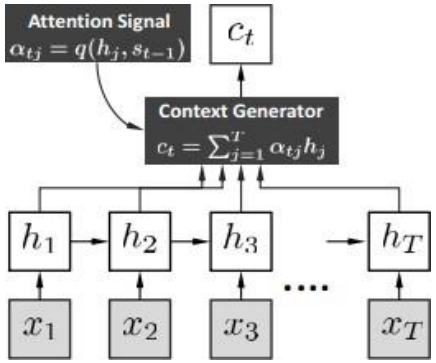


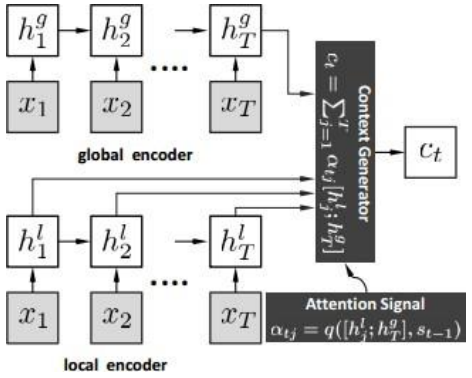
Extension from Seq2Seq

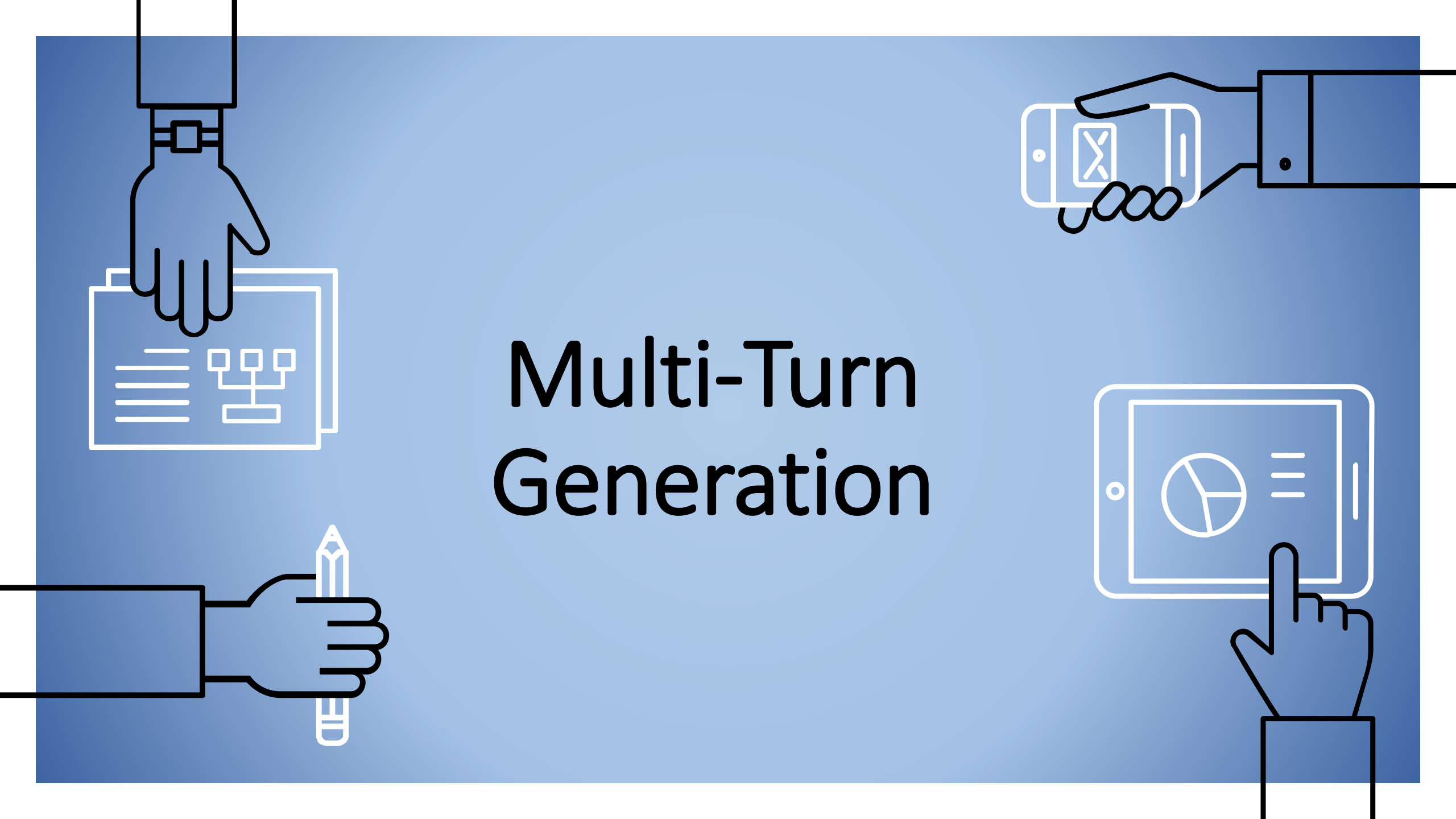
- Neural responding machine [Shang et al., ACL'15]
- Encoding-decoding framework
- Model variants with different attention
  - Local
  - Global
  - Hybrid









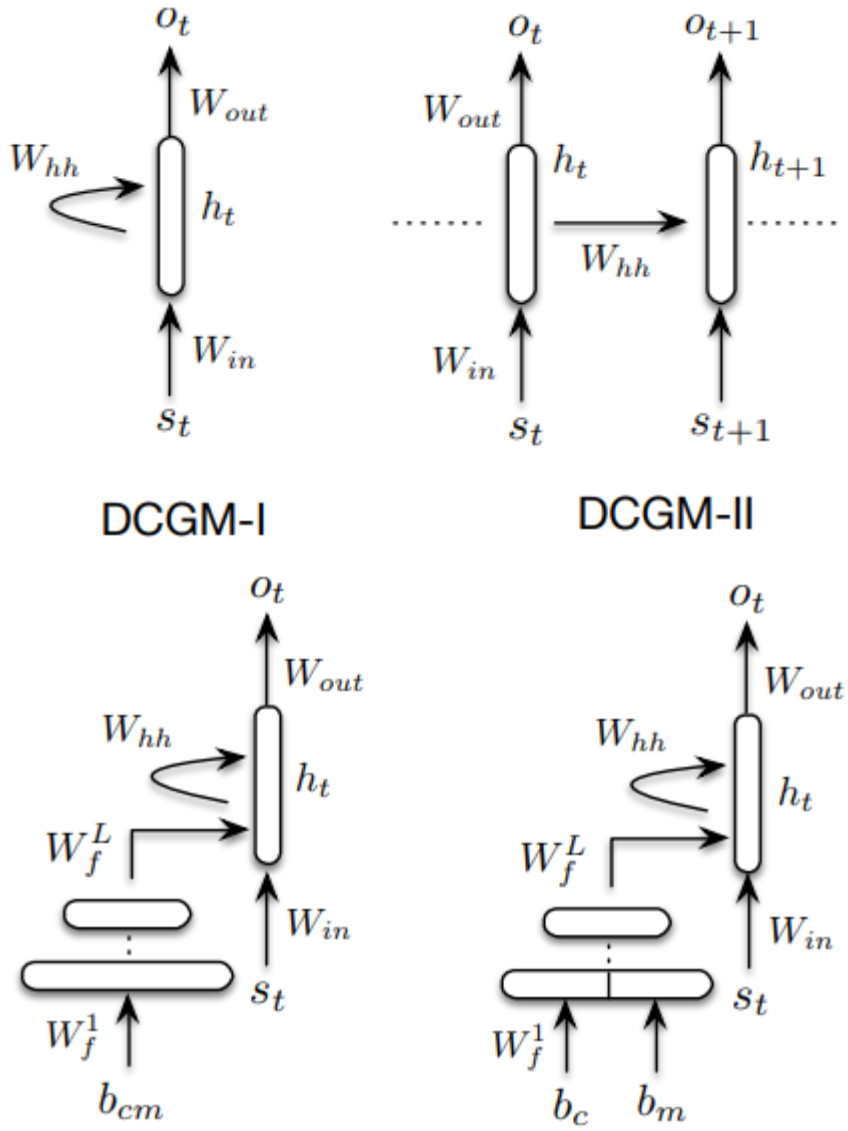

Multi-Turn
Generation

Contexts ARE Important

- A conversation is
  - A consecutive process which includes multiple turns of interactions
  - A session with previous utterances as contexts

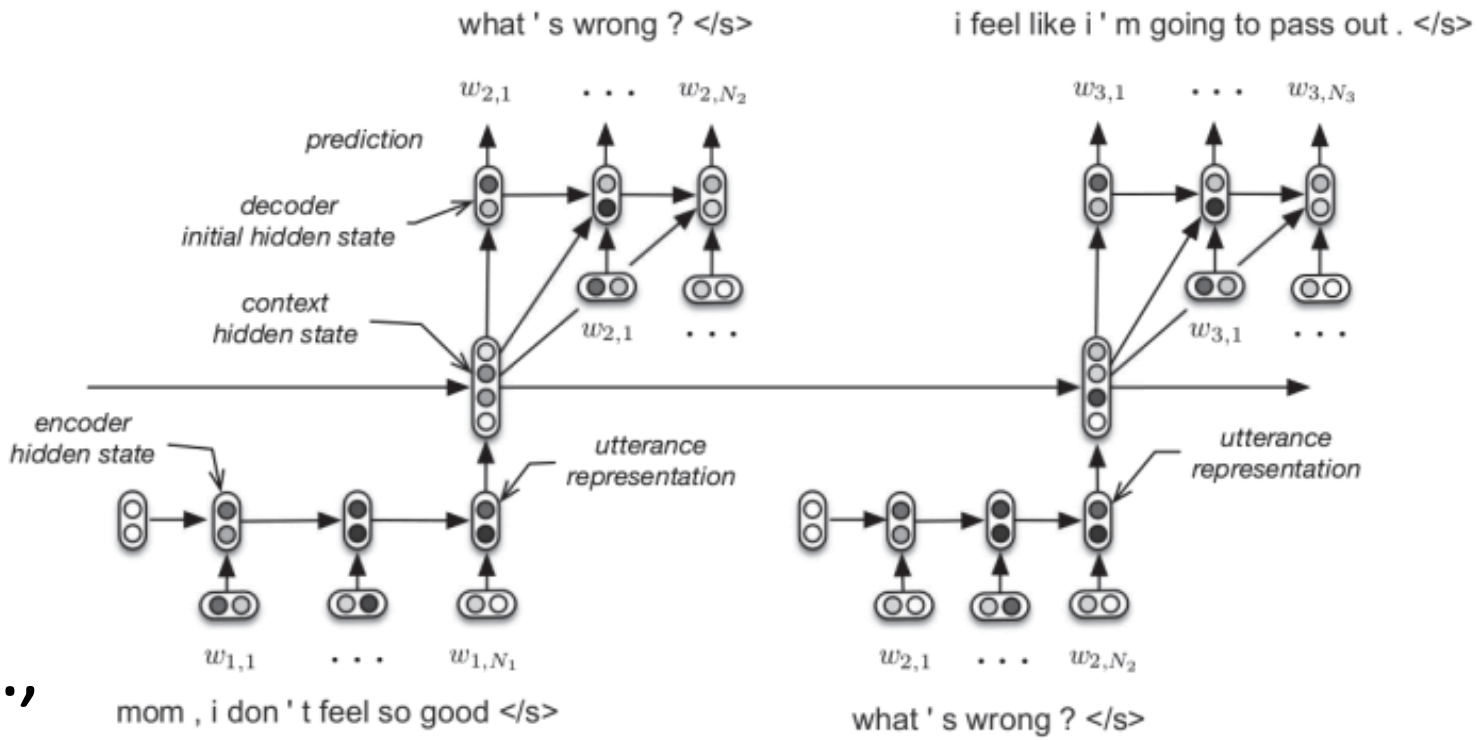
Generation with Contexts

- Context-sensitive models [Sordoni et al., NAACL-HLT'15]
  - *Tripled language model*
    - Concatenate each utterance into a single sentence
    - Problem: long-range representation issue
  - *Dynamic-Context Generative Model*
    - Fixed-length vector: bag-of-words through MLP
    - With order or without order information preserved in context and message



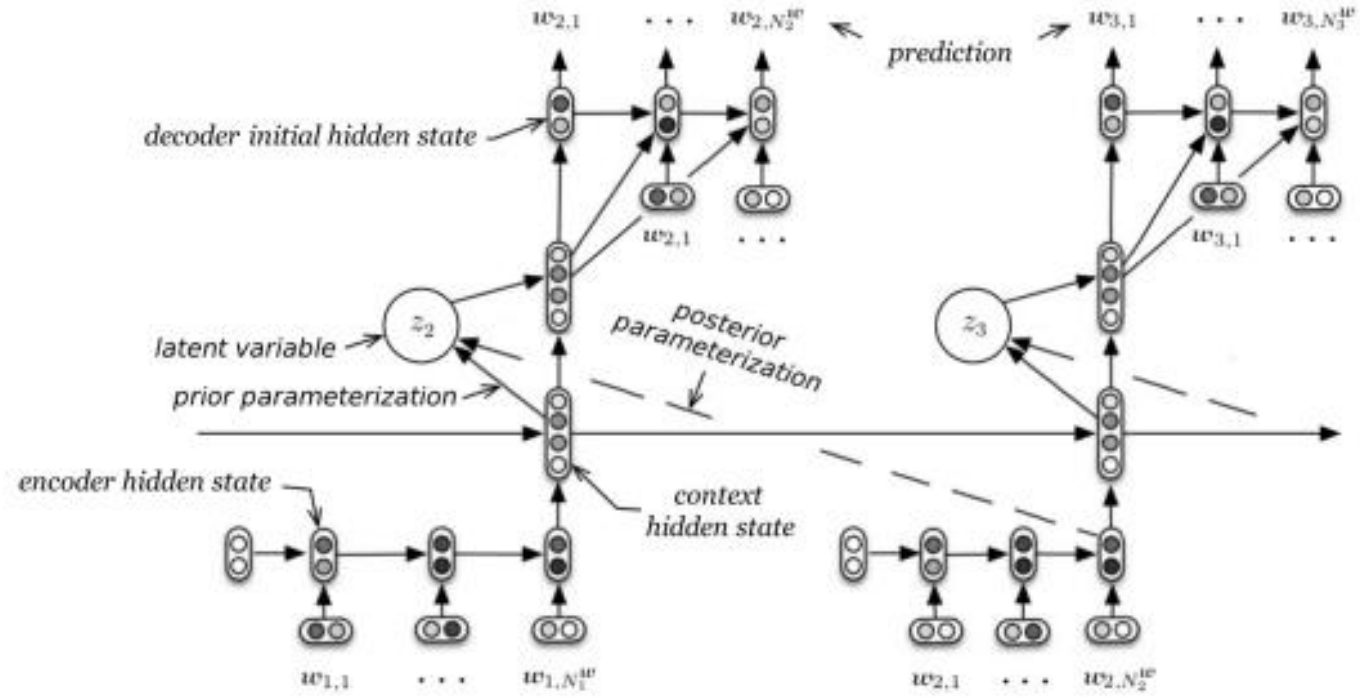
Hierarchical Context Modeling

- Languages are represented as hierarchies [Li et al., ACL'15]
  - Word-level representation AND Sentence-level representation
- Hierarchical recurrent encoder-decoder, HRED [Serban et al., AAAI'16]
  - Context hidden states
  - Global vector of information
- Hierarchical recurrent attention network [Xing et al., AAAI'18]
  - Word-level attention AND Sentence-level attention



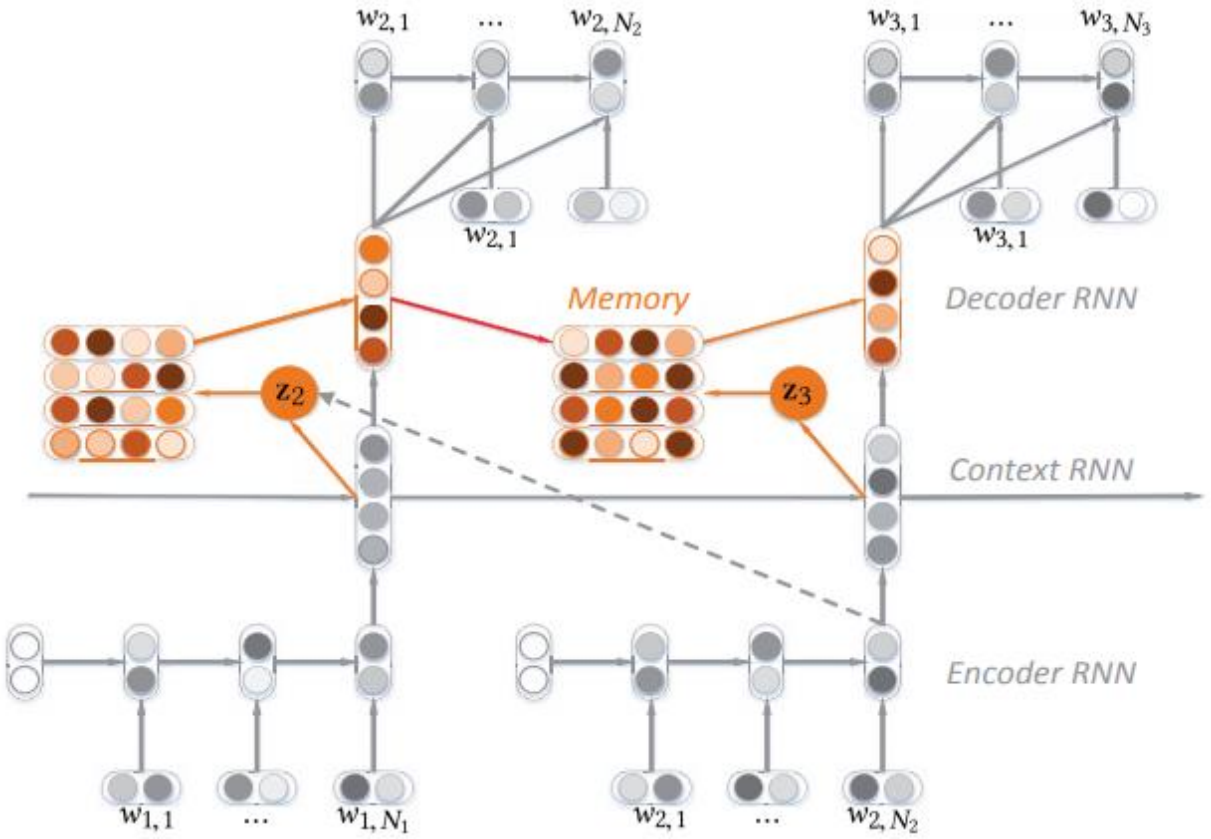
Latent Variable Modeling

- HRED
  - The only source of variation is through the conditional output distribution
- **Latent Variable HRED (VHRED) [Serban et al., AAAI'17]**
  - A stochastic latent variable z conditioned on all previous observed tokens



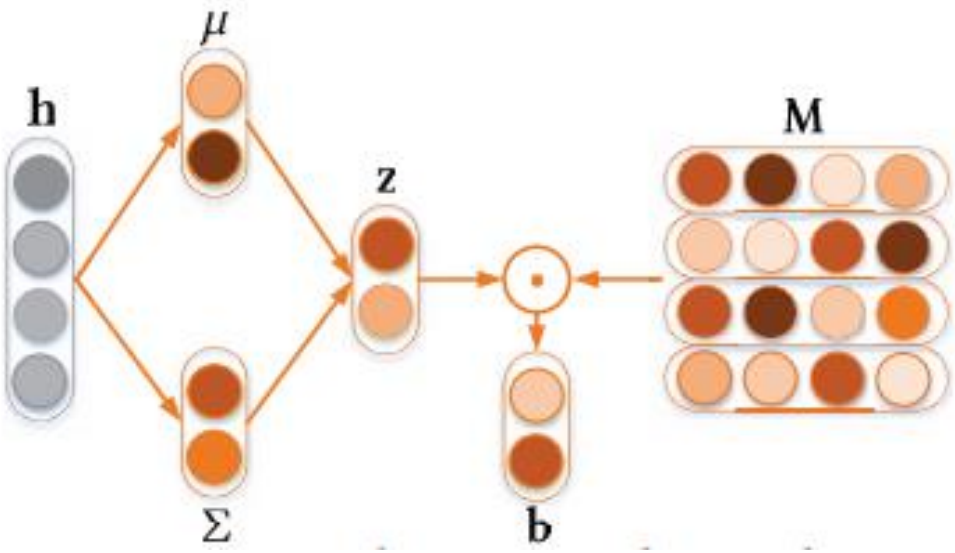
Hierarchical Memory Network

- Extension to memory network for long term dependency [Chen et al., WWW'18]
- Model overview
  - Utterance encoding
  - Variational memory network
  - Decoding

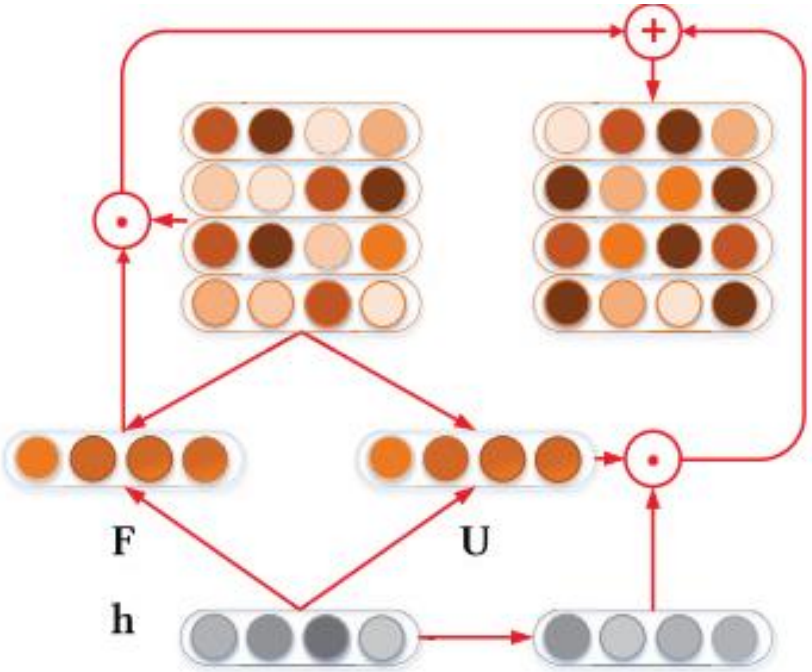


Hierarchical Memory Network (CONT.)

- Memory reading mechanism
  - Reading through latent variable and memory to update bias

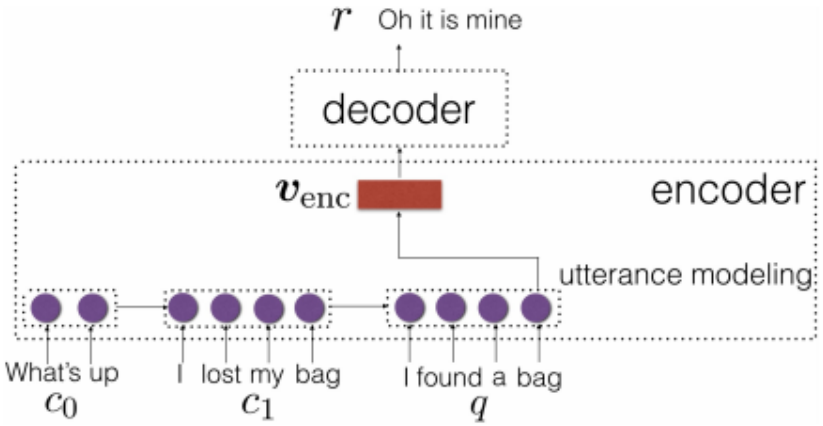


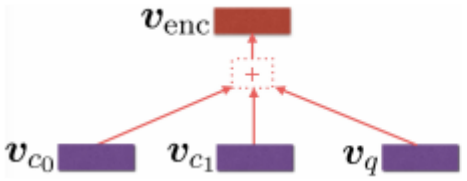
- Memory updating mechanism
  - Forgetting operation
  - Updating operation
  - With the context RNN

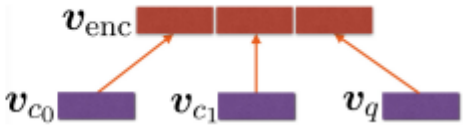


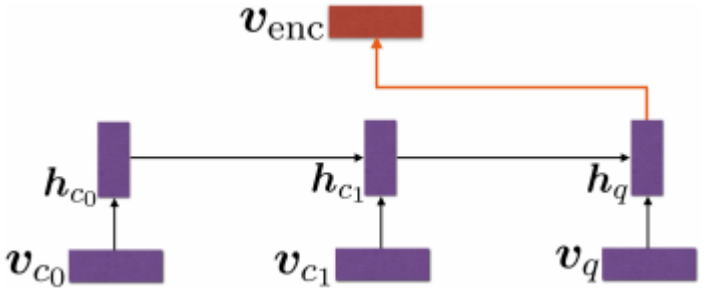
Context Modeling Frameworks

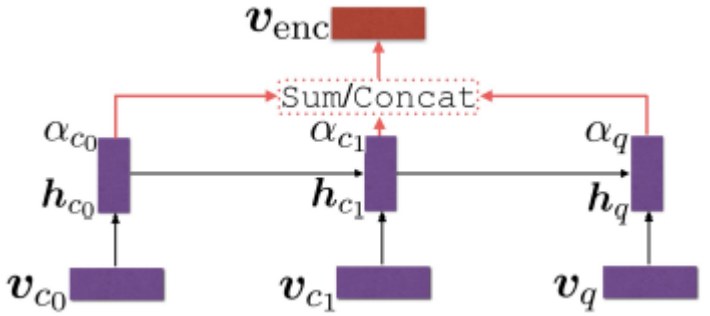
- A framework to unify different structures [Tian et al., ACL'17]
- Non-hierarchical context modeling
- Hierarchical context modeling
  - Sum pooling
  - Concatenation
  - Sequential integration
    - *Weighted sequential integration*












Diversity in
Conversations

Why Diversity

- The unique phenomenon in conversations
  - One-to-many
  - Example
- Diversity issue can be related to either single-turn generation or multi-turn generation
  - Context modeling strategies also applies if any

Objective-Driven Diversity

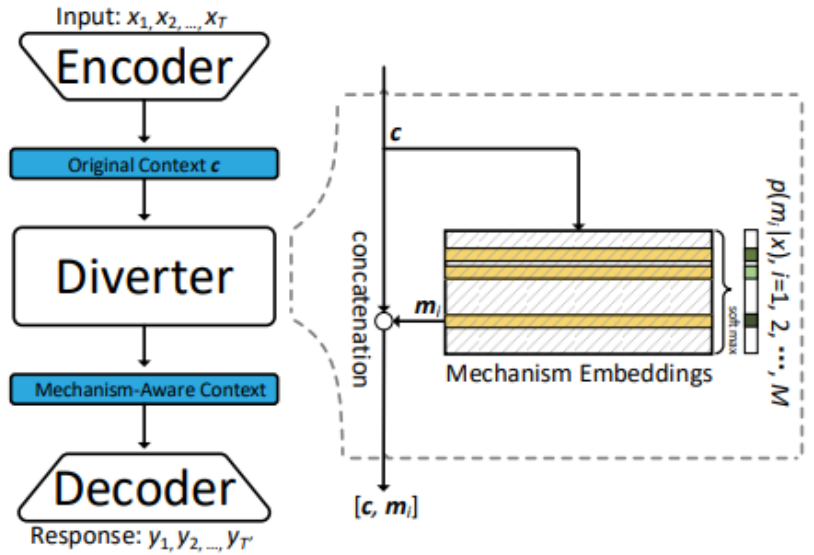
- Why lacks of diversity in end-to-end generation models
  - Driven by data if not supervised in particular
  - "I don't know" and "me too" take up a big proportion in training datasets
- Traditional objective function
  - Maximize the target probability conditioned on the source sequence
- New objective function with penalty [Li et al., NAACL-HLT'16]
  - A penalty factor

$$\hat{T} = \arg\max_{T} \{ \log p(T|S) - \lambda \log p(T) \}$$

Input: What are you doing?
1. I've been looking for you.
2. I want to talk to you.
3. Just making sure you're OK.
Input: What is your name?
1. Blue!
2. Peter.
3. Tyler.
Input: How old are you?
1. Twenty-eight.
2. Twenty-four.
3. Long.

Mechanism-Aware Conversation

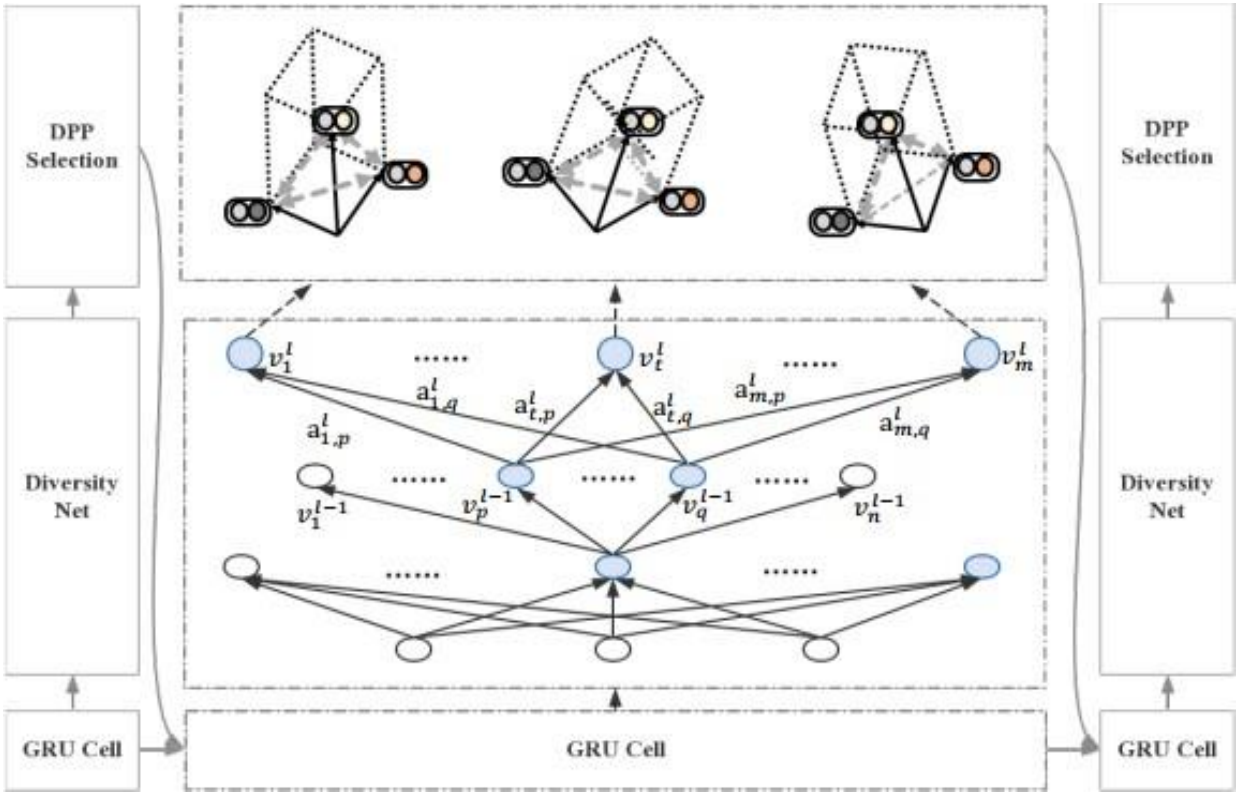
- Mechanism [Zhou et al., AAAI'17]
  - Indicates the latent semantic subspace
  - Hidden categories of utterances
- Incorporating a diverter
  - Seq2Seq -> Seq2Mechanism2Seq



Questions	Mechanism 1	Mechanism 2	Mechanism 3	Mechanism 4
我要坐地铁回家 I take subway back home	好的，路上注意安 Ok, be safe on the subway	真是个不错的选择 That's a good choice	坐车去哪里 Where are you going on the subway	坐车一定要注意安 Be careful on the subway
生活中怎样感到开心快乐 How do I feel happy in my life	开心就来和我聊天 Have a talk with me if you are happy	看来你今天心情很不错 You seem to be happy today	有什么开心的事情 What are the happy things you have experieced	和我聊天就很开心 Talk with me and you will be happy
明天考试、求安慰 I have a test tomorrw, and I need some solace	好好复习就好了 Just work hard on the reviews	我会为你加油的 I will stand by you	你要去哪里试试 Where are you taking the test	我会一直安慰你的 I will always be on your side
上班好累啊 The work is really hard	那就好好休息 Take a good rest	要懂得劳逸结合 You need to balance work and life	你是不是累了 Are you tired	上班就是这样 That is work

Diversity in Rankings

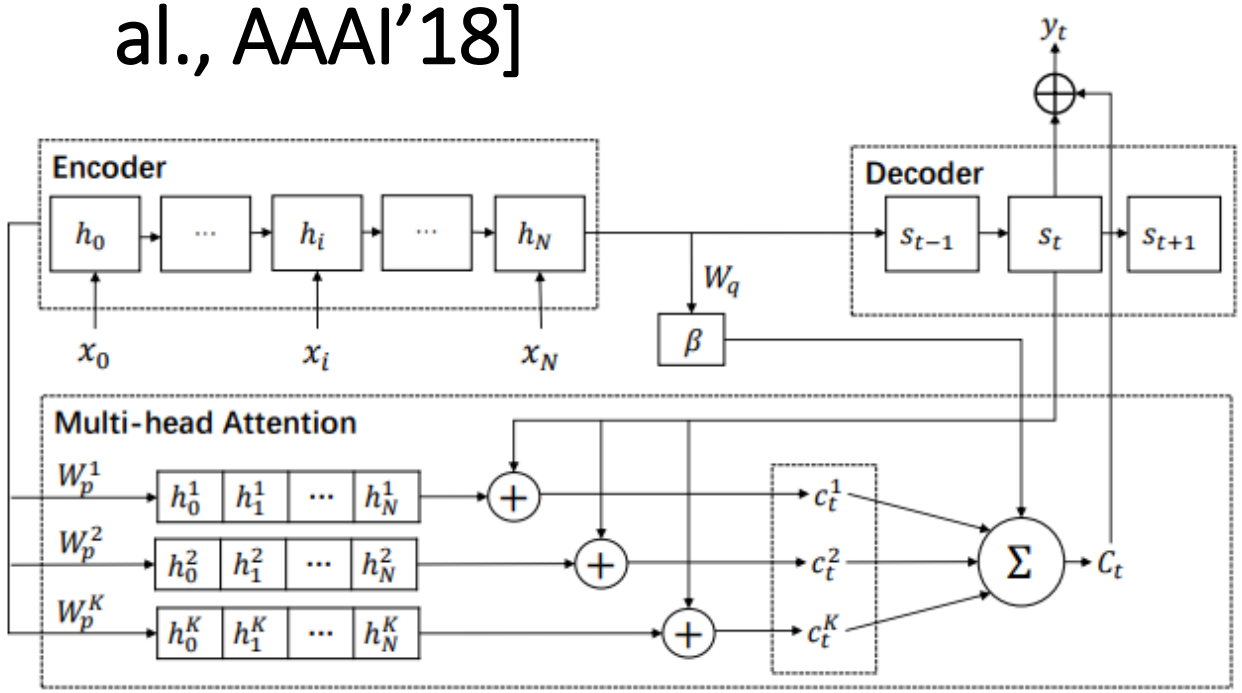
- Generation with candidates as a ranking process
  - Rankers vs Decoders
- Determinantal Point Process
  - A diversity-promoting algorithm: balancing quality and diversity
- DPP-Augmented Ranker vs DPP-Augmented decoder [Song et al., AAAI'18]

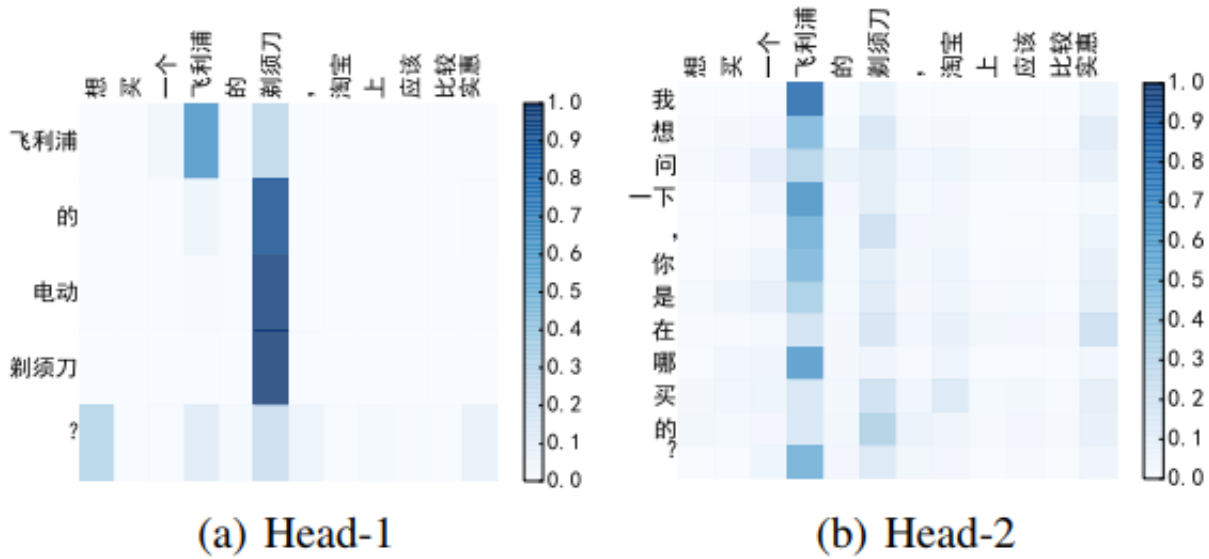


Interpretable Diversity in Conversations

- Why is there diversity in conversations?
- Incorporating multi-head attention schema into conversations [Tao et al., AAAI'18]

Query:	今天下雨，我们一起去吃火锅吧！ It's rainy today, let's go to eat hot pot!
Candidate 1:	我觉得不应该出门，还是在家做饭吧！ I think we shouldn't go out, let's cook at home!
Candidate 2:	好啊，我很久没吃火锅了。 Ok, I have not eaten the hotpot for a long time.
Candidate 3:	开车去还是坐地铁？ drive or take the subway?

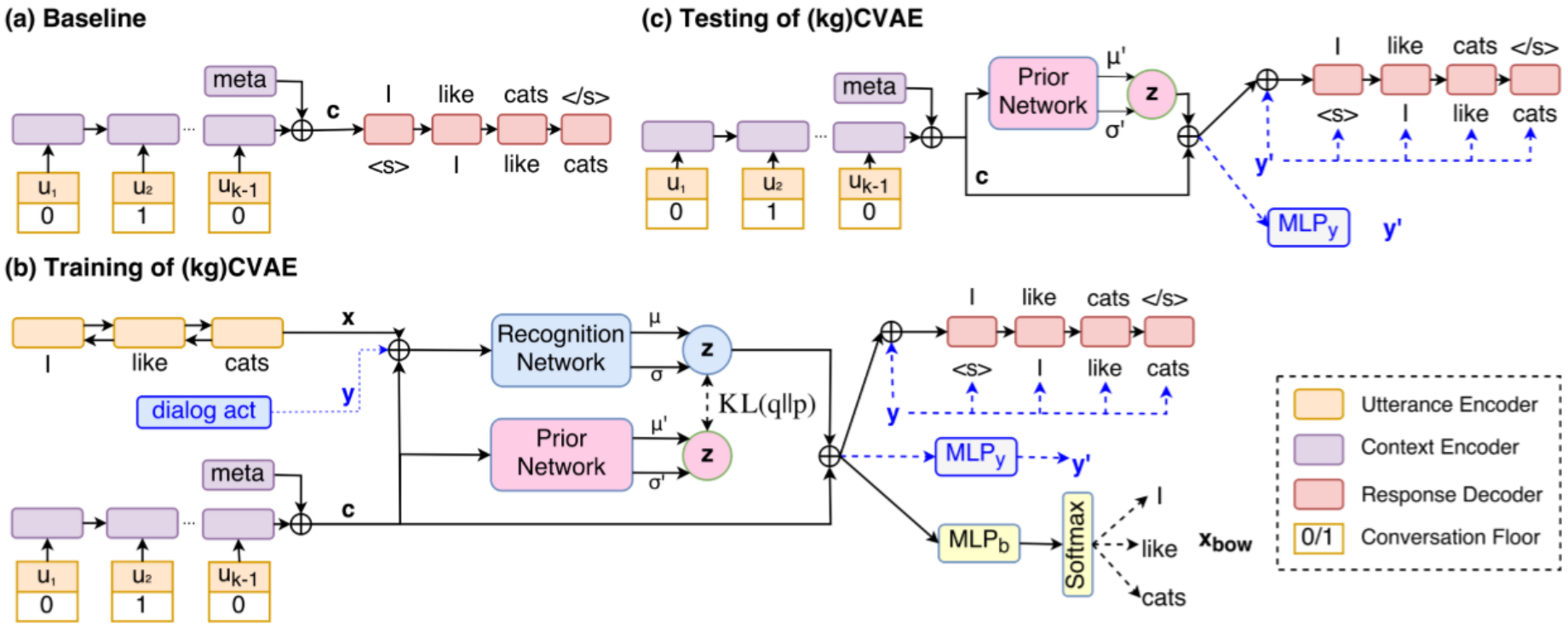




(a) Head-1 (b) Head-2

Diversity with Dialogue Act

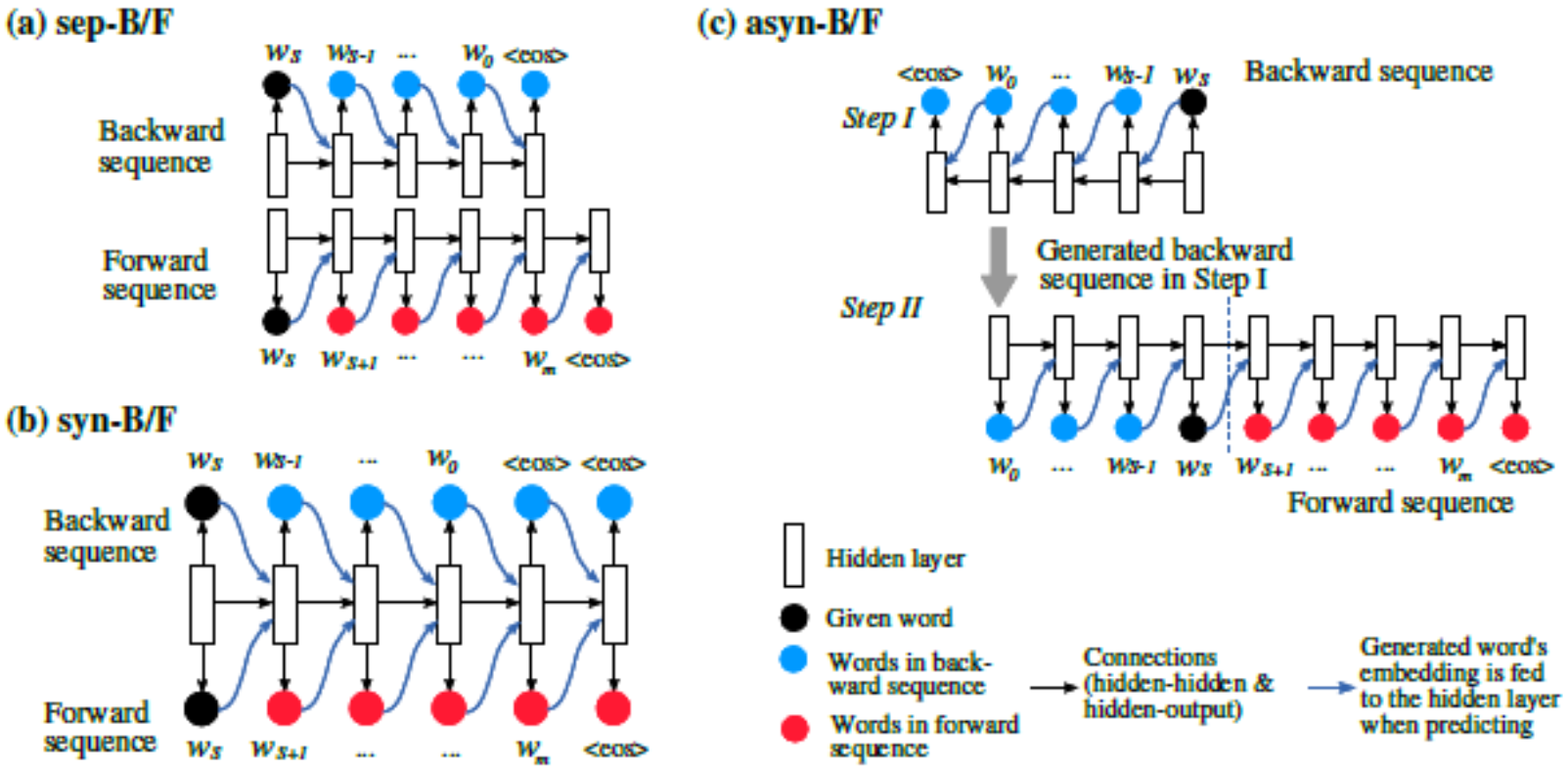
- Conditional VAE
  - Captures the discourse-level diversity during encoding
  - Knowledge-guided CVAE by dialogue acts [Zhao et al., ACL'17]




Content-Introducing

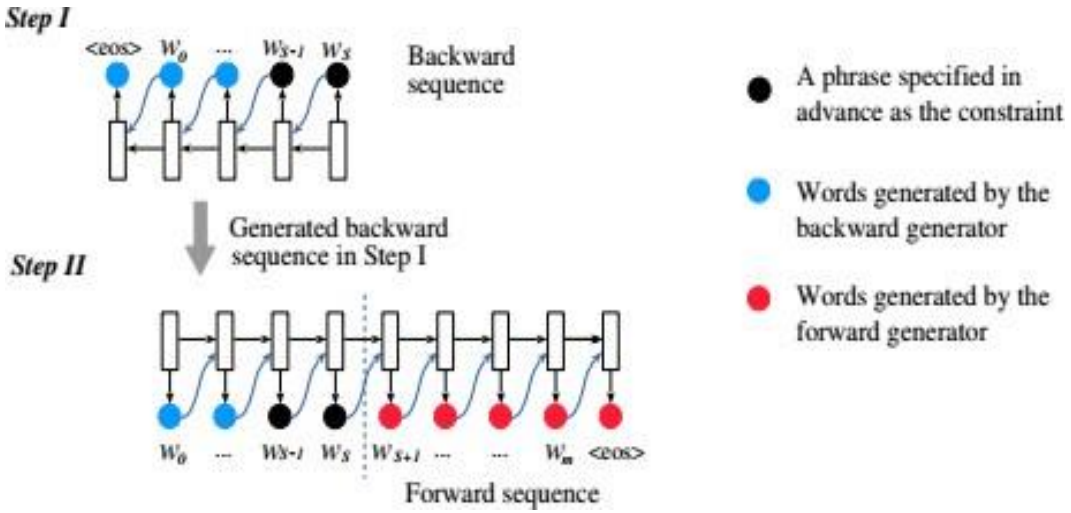
Diversity with Dialogue Act

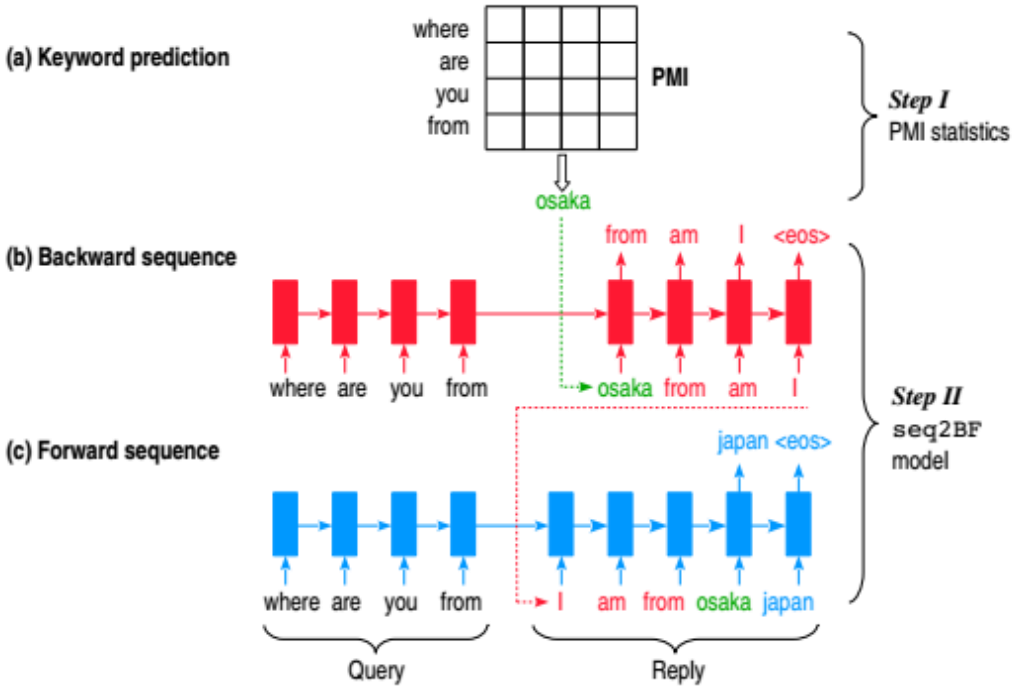
- To generate a sentence with constraint words
- Model variants
  - Sep-B/F
  - Syn-B/F
  - Asyn-B/F



Hard Constraint in Generation

- Controllable generation [Mou et al., COLING'16]
  - Backward and forward generation
- Two-step response generation
  - Keyword generation
  - Hard constraint in generation



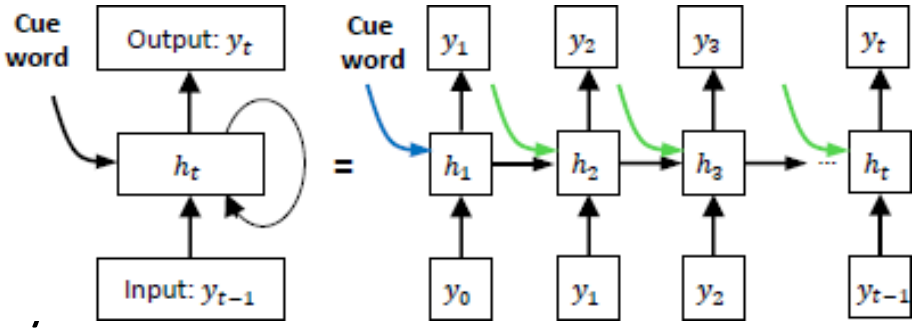


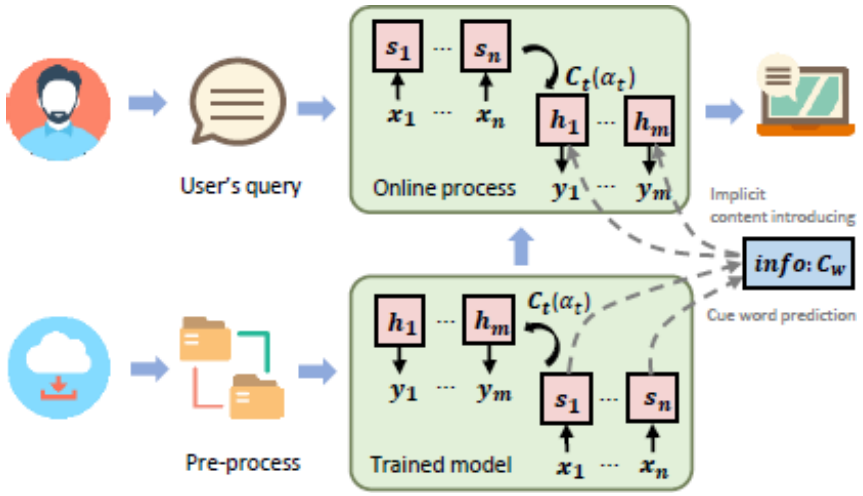
Content Introducing Cases

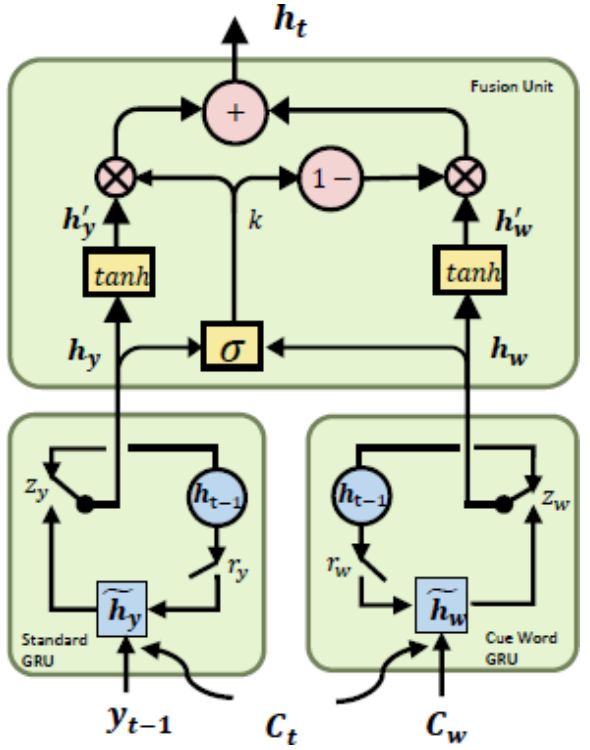
	Chinese	English (translated)
Query	李有男友公开过了	It's known that *Li*† has a boyfriend.
Grountruth	都已经分了 之前李的贴吧都在讨论了	Broken up. There's discussion in her *Tieba*.‡
seq2seq	我是男的	I am a male
seq2BF$_-$	我的男友	My boyfriend
seq2BF$_+$	有**绯闻**男友	Has a **rumor**ed boyfriend
Query	人大复试飘过	Passed second-round exam of Renming Univ.
Grountruth	这么牛，什么专业	Cool, what's your major
seq2seq	我也是！	Me too!
seq2BF$_-$	我也是！	Me too!
seq2BF$_+$	**分数**是什么	What is your **score**
Query	挺漂亮的 祝福祝福	So beautiful, congratulations
Grountruth	下手慢了哈。现在	You're late till now
seq2seq	谢谢	Thank you
seq2BF$_-$	是的，谢谢	Yes, thank you
seq2BF$_+$	谢谢**夸奖**	Thank you for **praising**
Query	我要换头像了！	Want to change a photo
Grountruth	打算换成什么啊～	What do you like...
seq2seq	我是你的头像	I'm in your photo
seq2BF$_-$	我是你的头像	I'm in your photo
seq2BF$_+$	第一张**图像**是谁	Who is in your first **photo**

From Hard Constraint to Soft Constraint

- Implicit content introducing to generate responses [EMNLP'17]
  - Sometimes hard constraints are not necessa
  - Semantics can be incorporated through decoding
    - Standard GRU cell
    - Cue word GRU cell
    - Fusion units

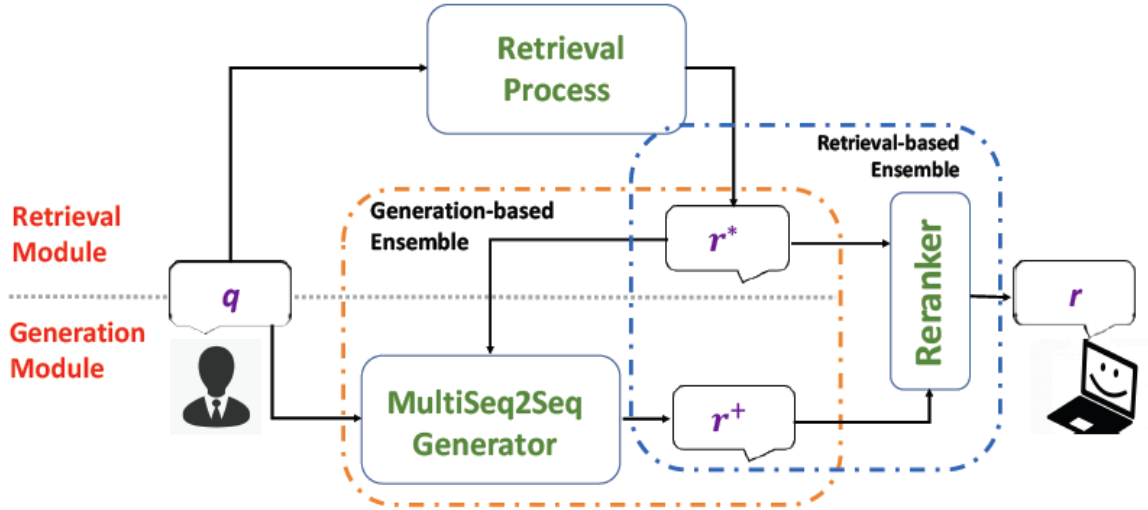


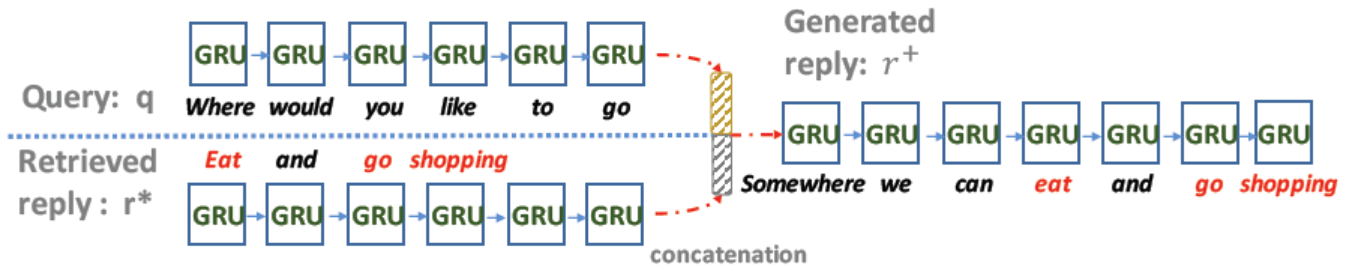




Augmenting Generation with Retrieval

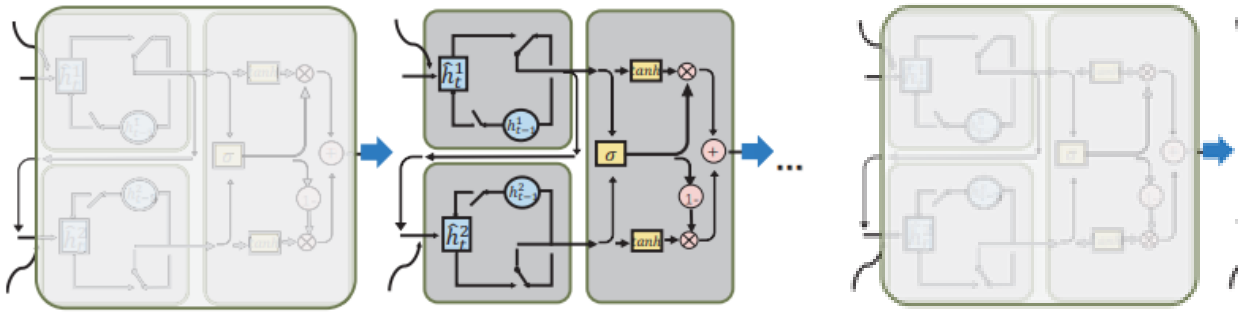
- Pros and Cons in retrieval-based conversations
- Pros and Cons in generation-based conversations
- Optimization using multi-seq2seq [Song et al., IJCAI'18]
  - Retrieved candidates
  - Content augmentation from the multiple sequences

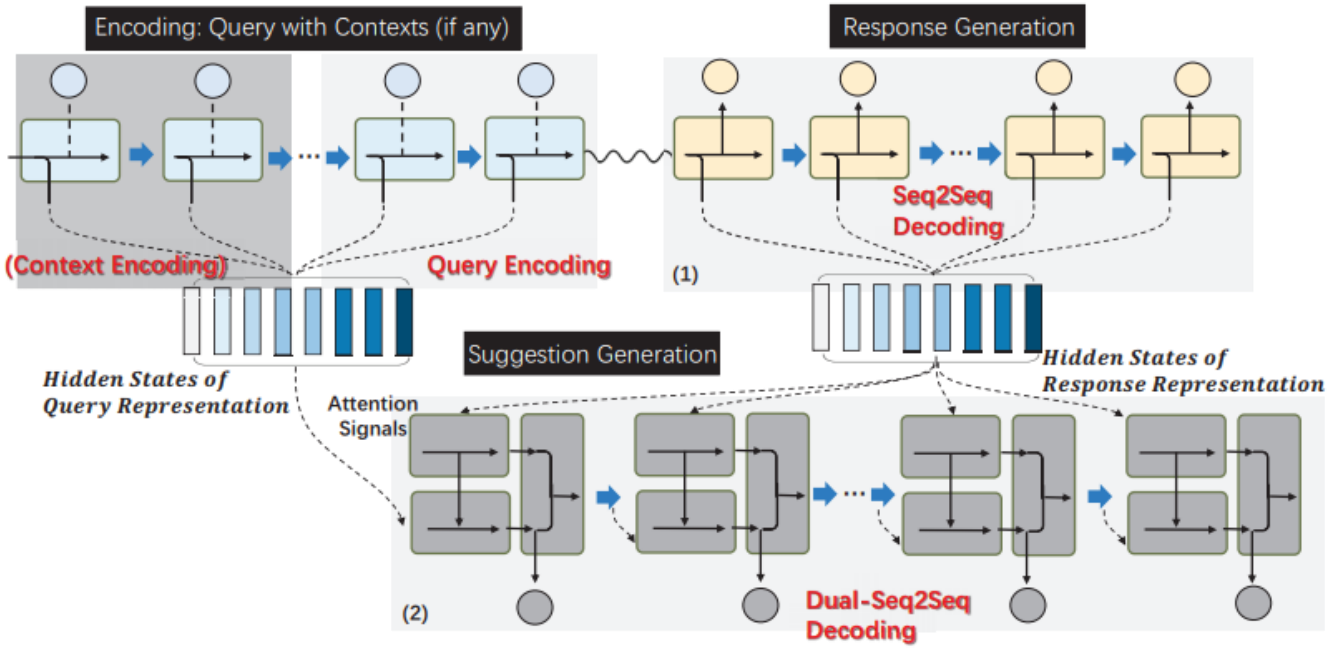


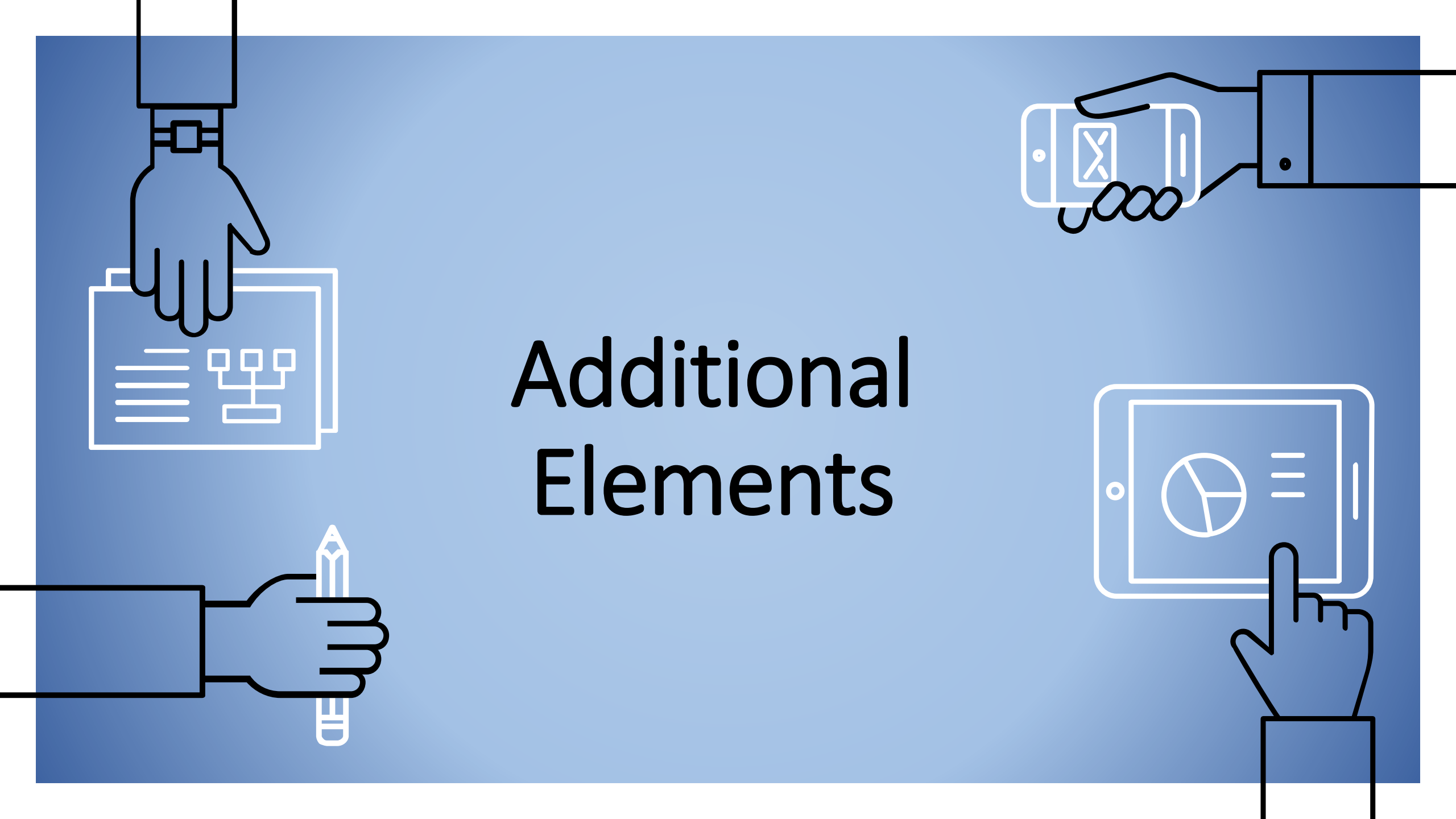


Proactive Suggestion

- A standard conversation paradigm in conversational systems
  - Given a user utterance, a response is provided
- A new conversation paradigm
  - Query utterance, response and suggestion
- Multi-seq2seq process with information fusion as contents [Yan et al., IJCAI'18]

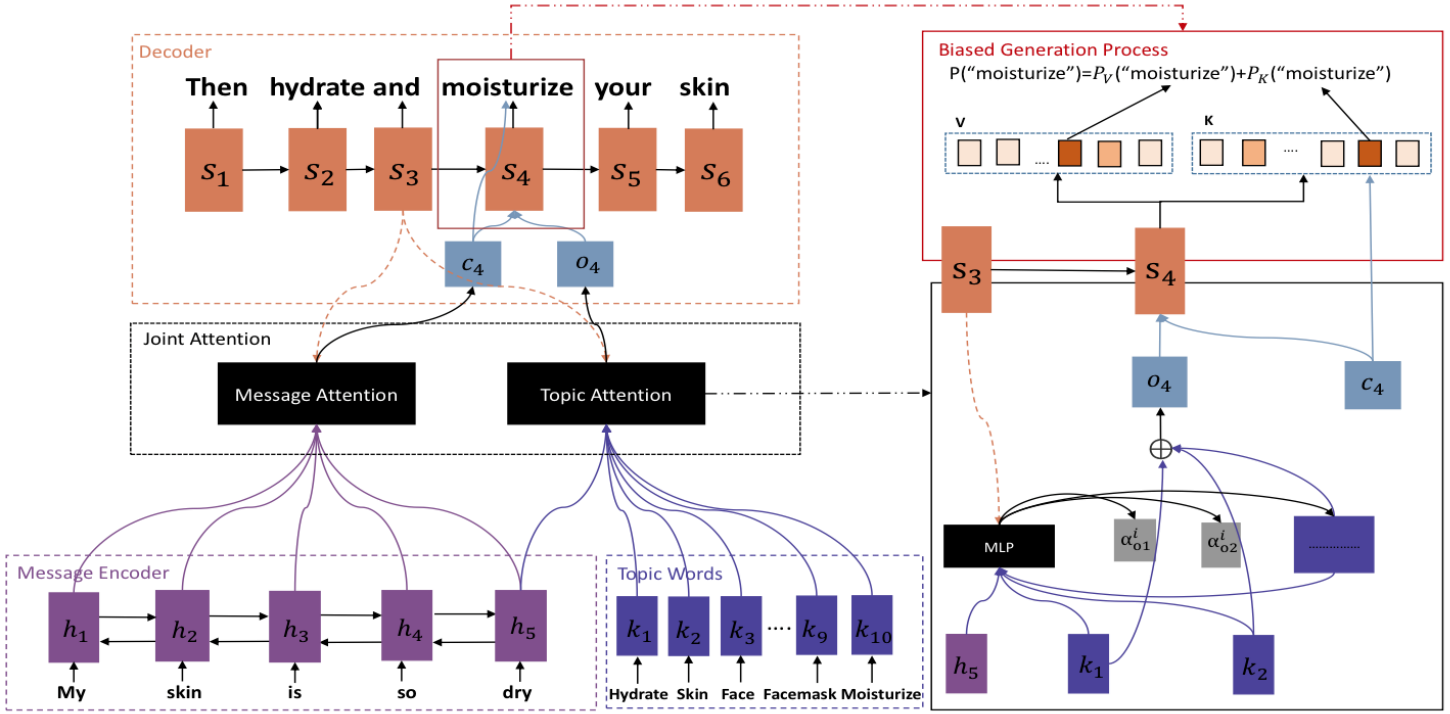





Additional
Elements

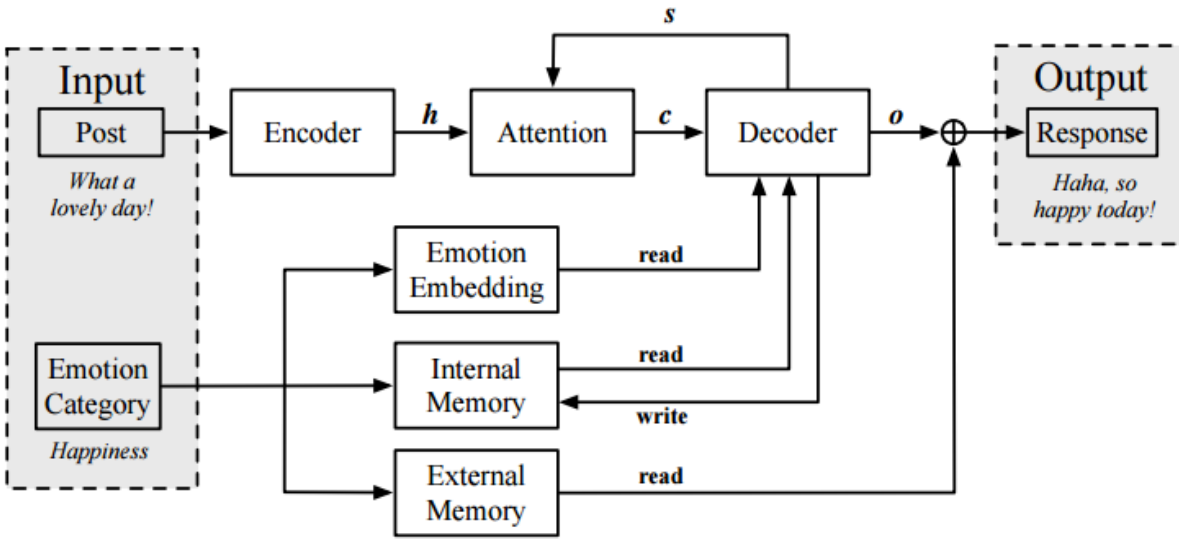
Topics in Conversation

- Topic alignment in conversation is important [Xing et al., AAAI'17]
  - Seq2Seq in the first place
  - With topic alignments
- Decoding with two components



Emotions

- Emotional chatting machine [Zhou et al., AAAI'18]
- Model framework
  - Emotion classifier
  - Emotion expression with an internal memory
  - Emotion control with an external memory

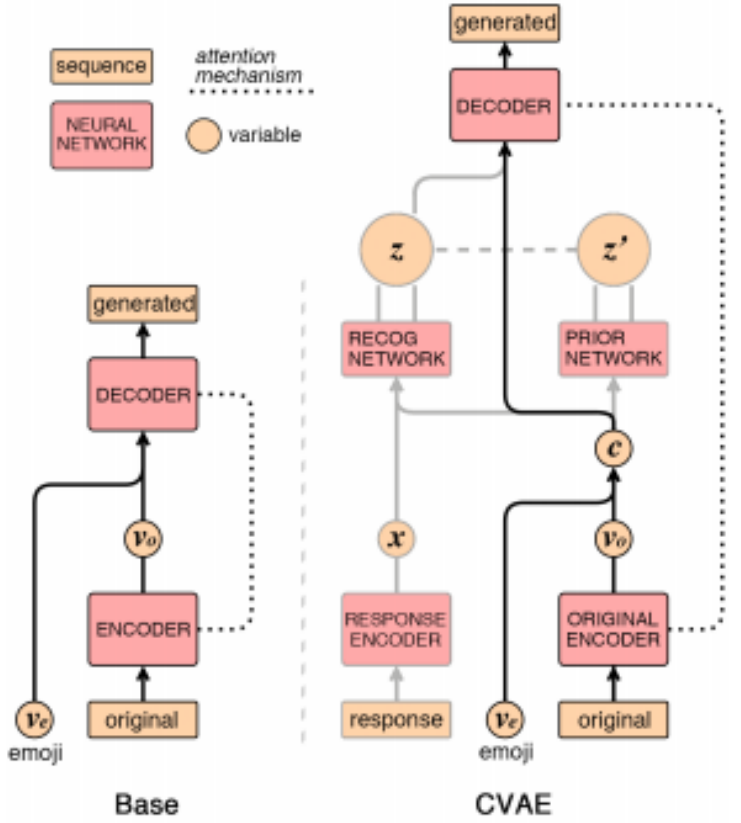


Post	Model		Response(Original)	Response(Translated)
承诺，就是一个骗子说给一个傻子听的。 A promise is what a cheater says to a fool.	Seq2Seq		承诺，就是一个骗子说给一个傻子听的。	A promise is what a cheater says to a fool.
	ECM	Like	承诺是一个**专一**的傻子	Promise is a **single-minded** fool
		Happy	我就是一个**开心**的傻子	I'm just a **happy** fool
		Sad	我就是一个**悲伤**的傻子	I am a **sad** fool
		Disgust	一个**骗子**说给一个**傻子**听	A **cheater** says to a **fool**
		Angry	不管你信不信，反正我信了！	Whatever you believe or not, I trust in it!
知道真相的我眼泪笑下来 Knowing the truth, I laughed myself to tears	Seq2Seq		知道真相的我眼泪掉下来。	After knowing the truth, I burst into tears.
	ECM	Like	太**可爱**了，太**可爱**了！	Too **lovely**, it's too **lovely**.
		Happy	笑得我眼泪都出来了。	I can't help laugh myself to tears.
		Sad	知道真相的我**眼泪**掉下来。	After knowing the truth, I burst into **tears**.
		Disgust	这是真的还是假的？	Is this true?
		Angry	什么意思？没看懂。	What do you mean? I don't understand.

MojiTalk

184,500	9,505	5,558	2,771
38,479	9,455	5,114	2,532
30,447	9,298	5,026	2,332
25,018	8,385	4,738	2,293
19,832	8,341	4,623	1,698
16,934	8,293	4,531	1,534
17,009	8,144	4,287	1,403
15,563	7,101	4,205	1,258
15,046	6,939	4,066	1,091
14,121	6,769	3,973	698
13,887	6,625	3,841	627
13,741	6,558	3,863	423
13,147	6,374	3,236	250
10,927	6,031	3,072	243
10,104	5,849	3,088	154
9,546	5,624	2,969	130

- EMoji distributions in conversations [Zhou et al., ACL'18]
- Generation model
  - Base: Seq2Seq
  - Incrementally using CVAE onto base model
  - Reinforced CVAE
    - *Emoji classifier as reward*



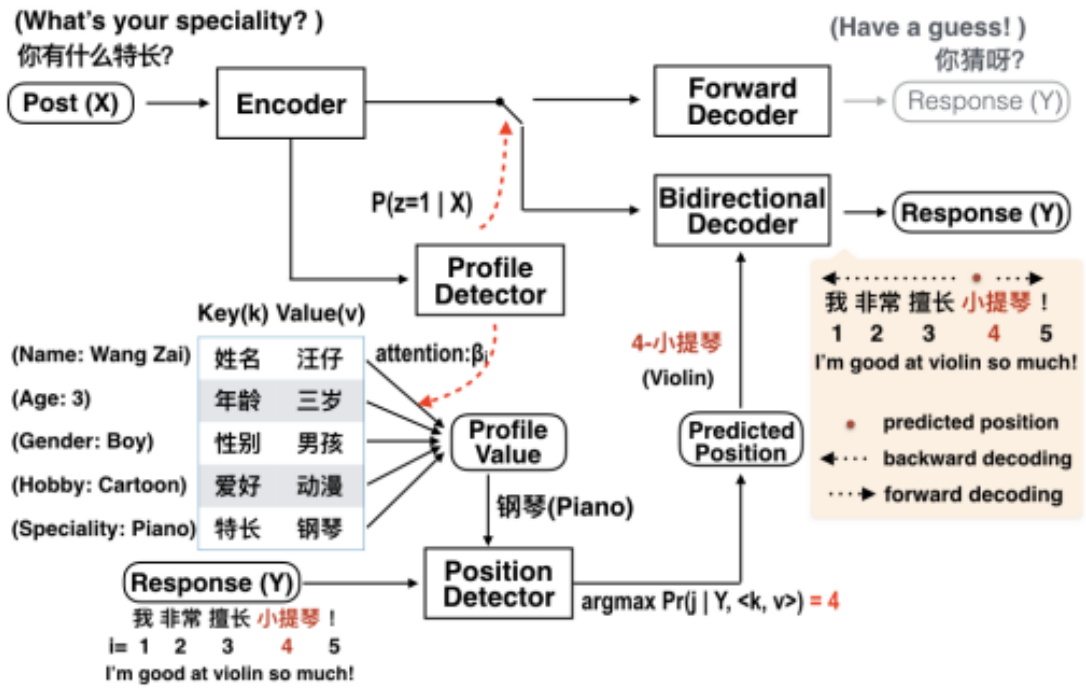
Content	g i needed that laugh lmfaoo
Target Emotion	😊
Base	i 'm glad you enjoyed it
CVAE	good ! have a good time
Reinforced CVAE	thank you for your tweet , you didn 't know how much i guess


Persona in Chat

Personality Assignment

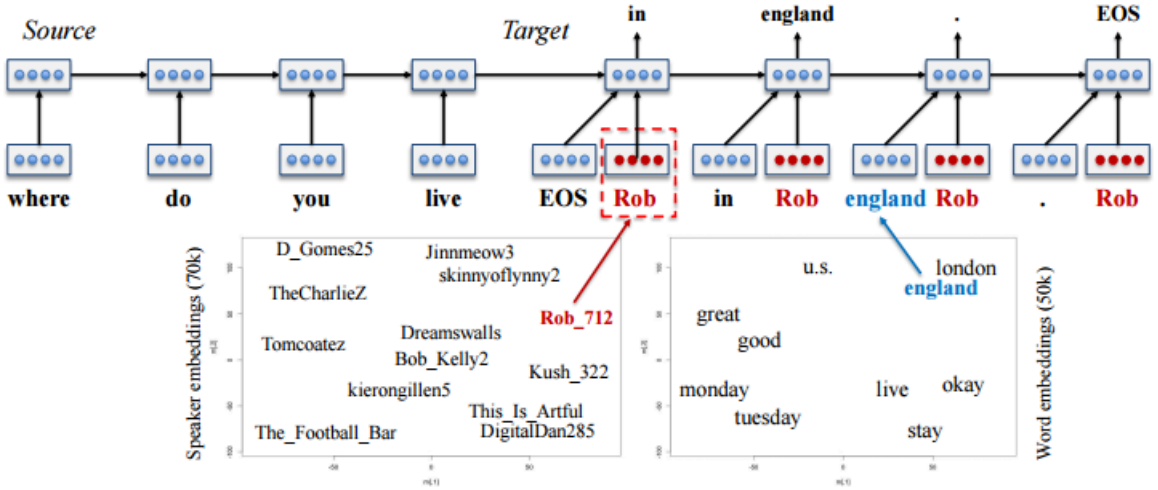
- Personality shall be fixed attributes [Qian et al., IJCAI'18]
- Personality shall be explicitly expressed
  - Rather than implicitly embedded only
- Model framework
  - Encoder
  - Profile detector
  - Bi-directional decoder
  - (Position detector)

General seq2seq model
User: Are you a boy or a girl? Chatbot: I am a boy. User: Are you a girl? Chatbot: Yes, I am a girl.
Our model with personality
User: Are you a boy or a girl? Chatbot: I am a handsome boy. User: Are you a girl? Chatbot: No, I am a boy.



Persona

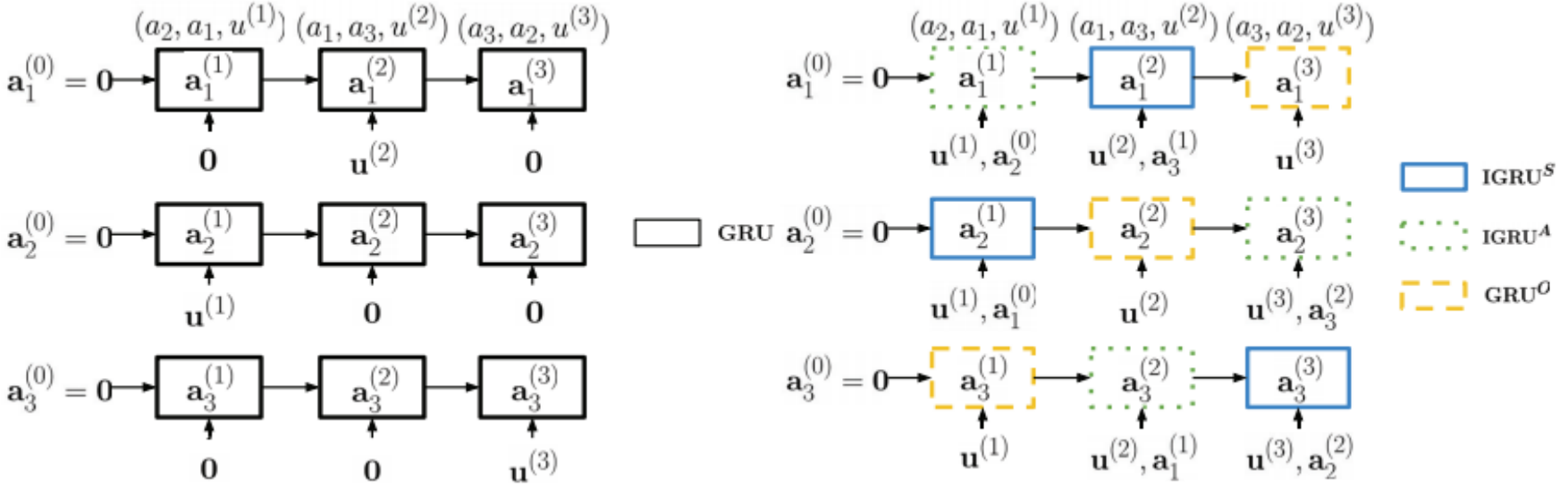
- Consistency is a critical issue
- Persona modeling is one way to solve the conversational consistency problem [Li et al., ACL'16]
- Using language preference as embeddings



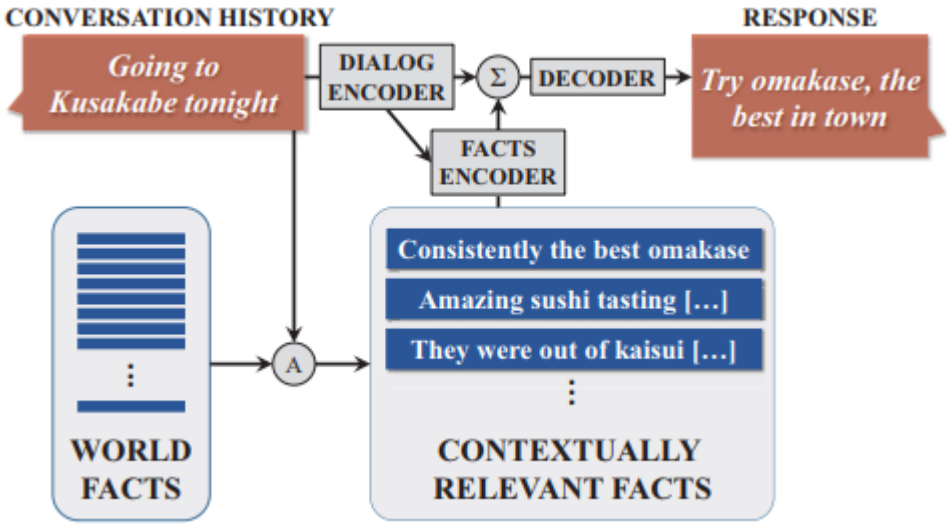
message	Where do you live now?
response	I live in Los Angeles.
message	In which city do you live now?
response	I live in Madrid.
message	In which country do you live now?
response	England, you?
message	Where were you born?
response	I was born in Canada.
message	Where are you from?
response	England, you?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

Speaker-Addressee Modeling

- Dynamic RNN [Ouchi and Tsuboi, EMNLP'16]
  - Speaker embeddings with previous utterances
  - Sentence embeddings are learned based on speaker embeddings
- Speaker-Interaction RNN [Zhang et al., AAAI'18]
  - Interactively learned as different roles: speakers and addressees



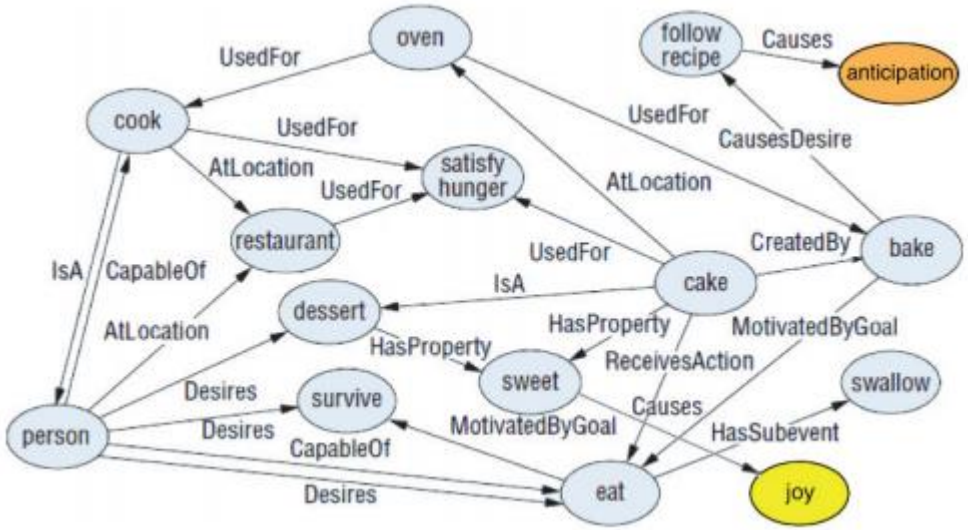
Knowledge

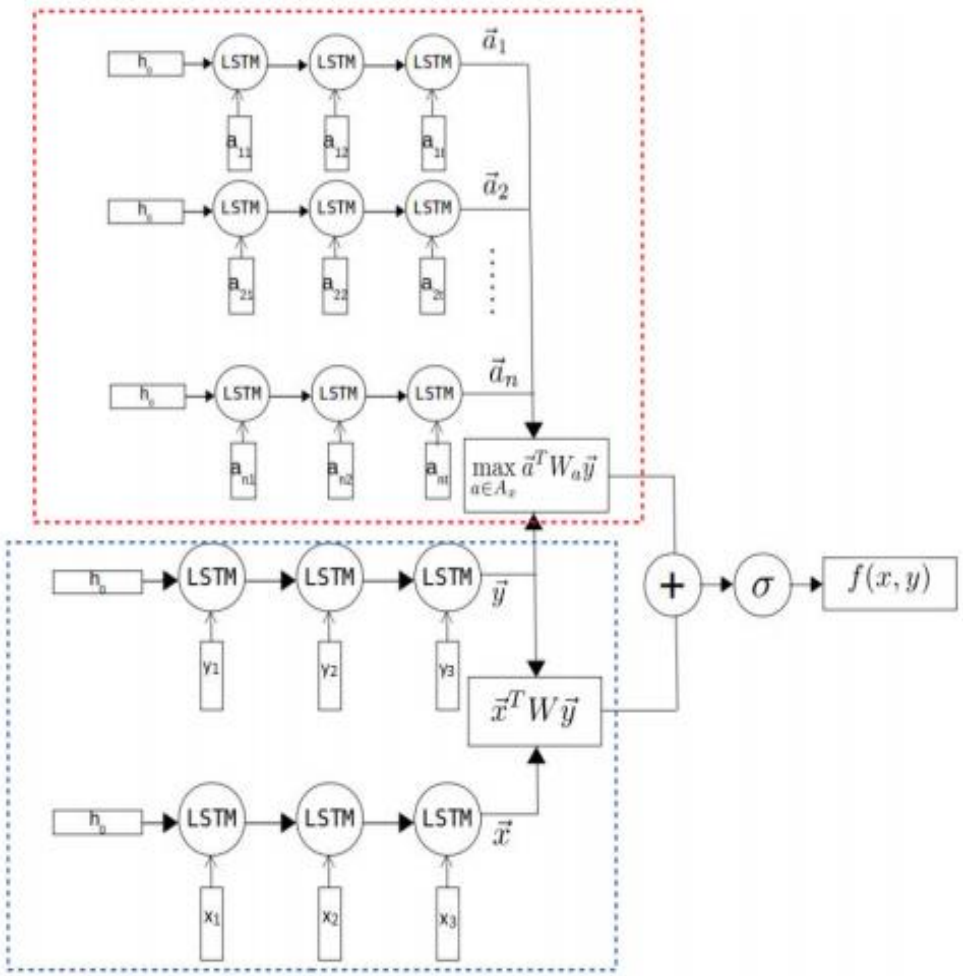


- Grounded response generation [Ghazvininejad et al., AAAI'18]
- Humans have knowledge about conversations
  - Beyond utterances
- Fact encoders
  - Using memory networks to encode facts
  - Based on the conversation history with relevant facts

Commonsense-based Conversation

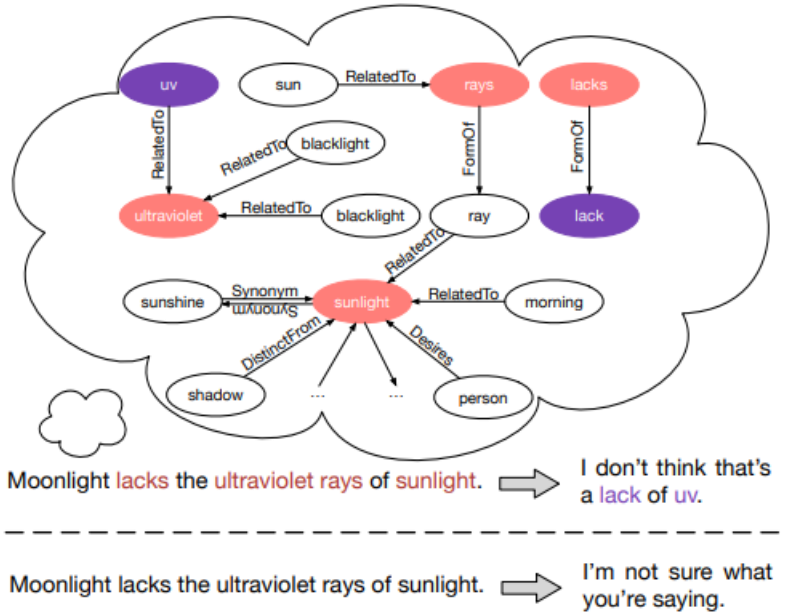
- Commonsense is a knowledge base, too [Young et al., AAAI'18]
  - Commonsense retrieval with all concepts in the utterance
  - Tri-LSTM encoder with a memory network of all commonsense knowledge

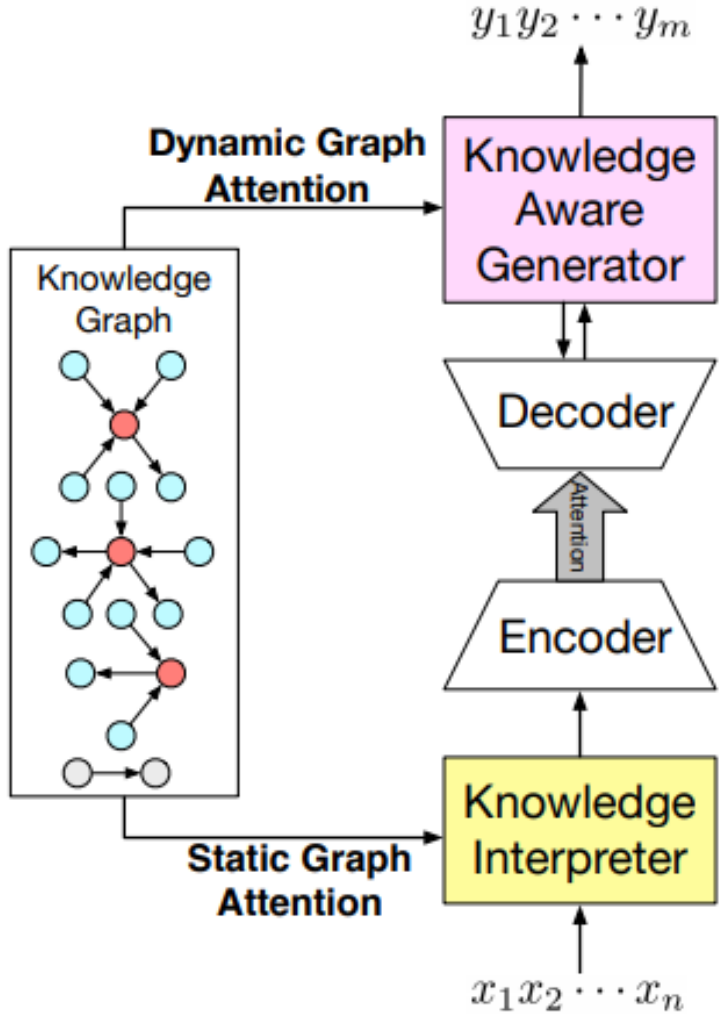




Knowledge Graph based Conversations

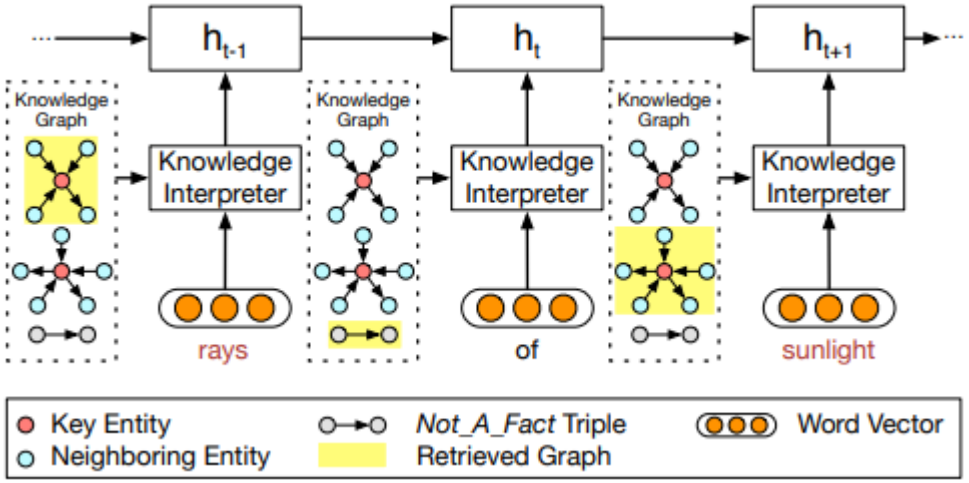
- Knowledge is helpful for human conversations [Zhou et al., IJCAI'18]
- Model components:
  - Encoder-decoder
  - Knowledge interpreter
  - Knowledge generator

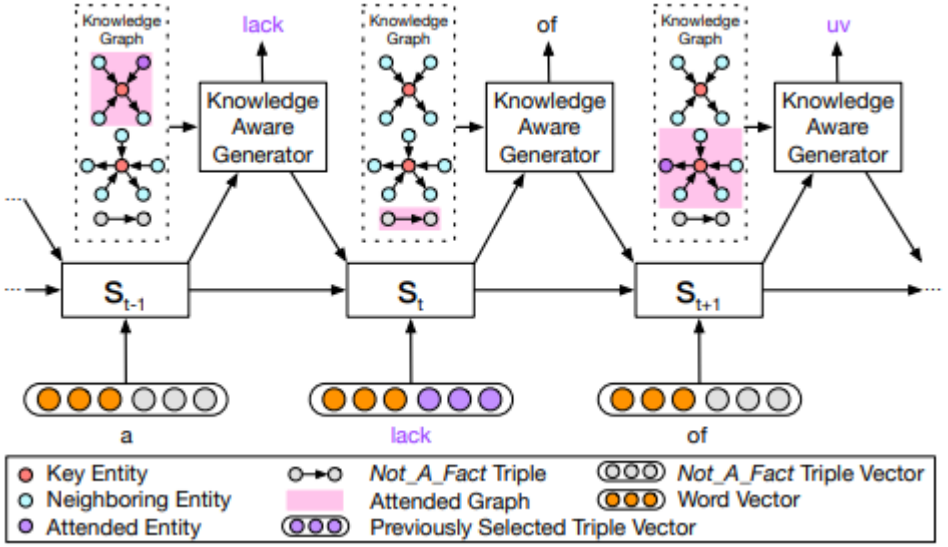


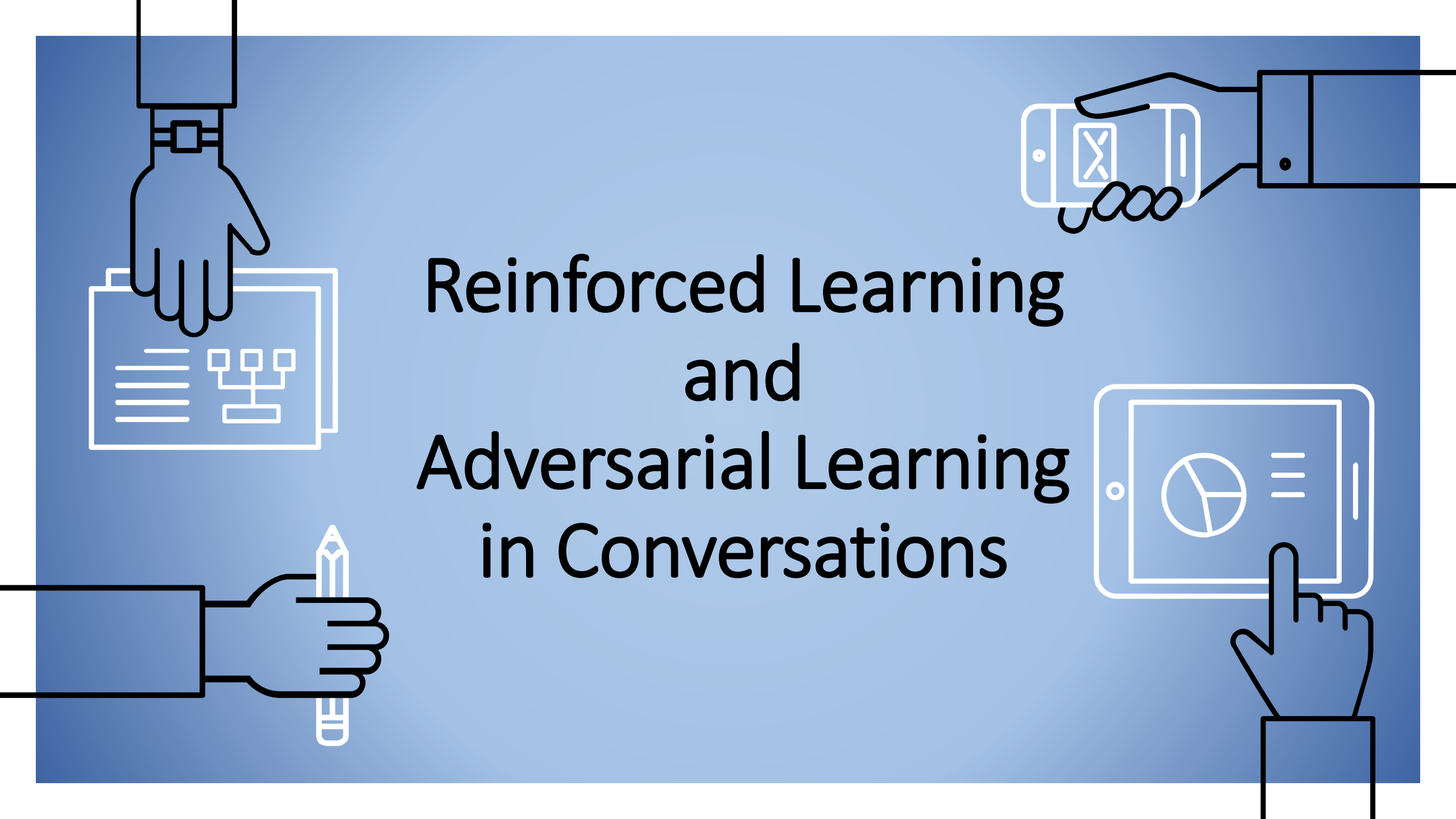


Knowledge Interpreter and Generator (cont.)

- **Interpreter**
  - To understand the utterance
  - Each word as a key node from the graph vector
  - Nodes and neighboring nodes
  - Static graph attention
- **Generator**
  - Read the graph to triples, and then finally to the words
  - Dynamic graph attention

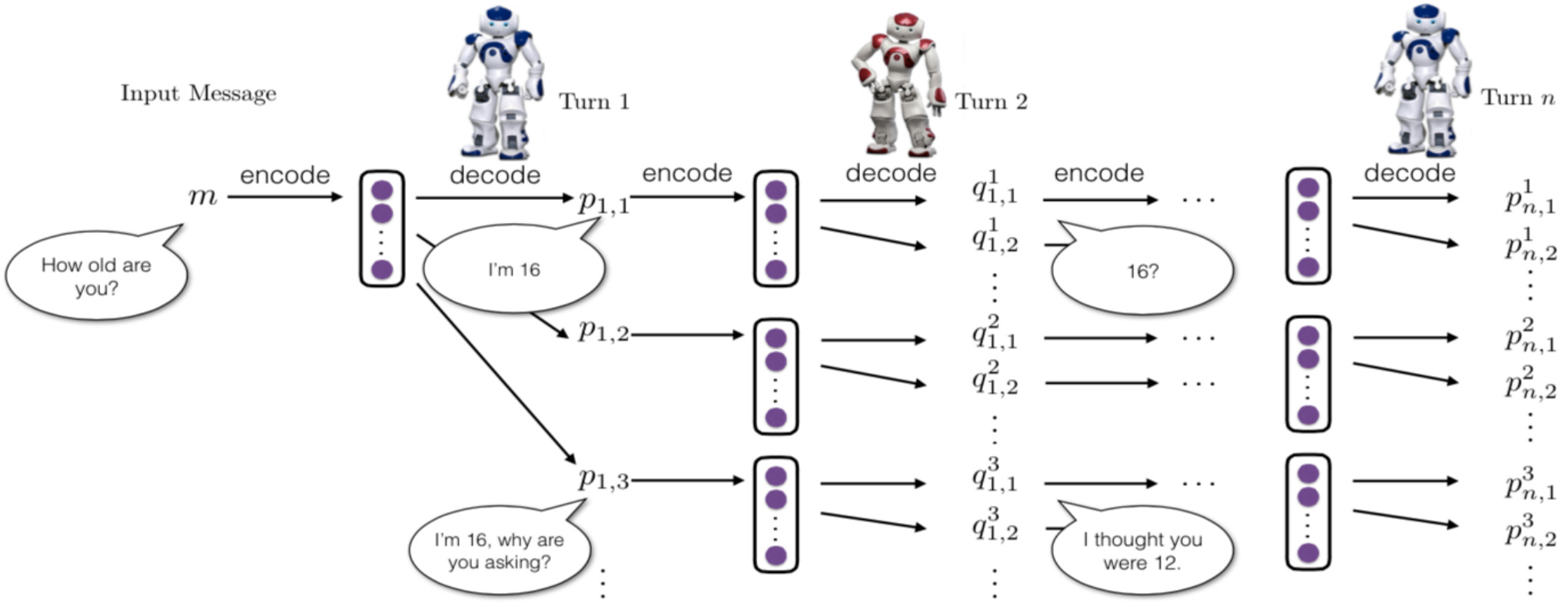





Reinforced Learning
and
Adversarial Learning
in Conversations

Reinforcement Learning in Conversations

- Two virtual agents [Li et al., EMNLP'16]
- Model optimization to maximize rewards



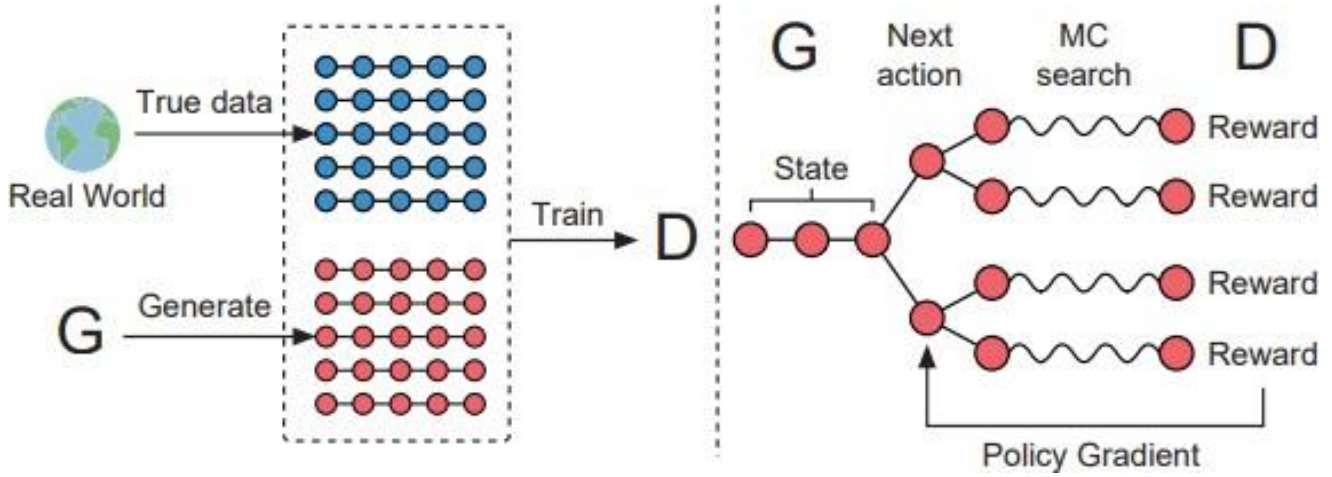
Human-in-the-loop

- Using user implicit feedback [Zhang et al., AAAI'18]
  - Stance reward
  - Sentiment reward
  - Stalemate reward

Baseline RL model (Li et al. 2016c)		**Proposed implicit feedback model**	
A: What are you like?	[1]	A: What are you like?	[1]
B: I'm so confused.	[2]	B: One of your favs.	[2]
A: You know it.	[3]	A: That's so cute.	[3]
B: Thank you !!!	[4]	B: Thank you love.	[4]
A: You're welcome.	[5]	A: You're welcome xoxo.	[5]
B: Lmao I hate this.	[6]	B: You're the best!	[6]
A: What do you mean?	[7]	A: I'll be good to you.	[7]
B: Nah I hate it.	[8]	B: I like you too.	[8]
(Repeat)		A: lol I know.	[9]
...		B: This is true.	[10]
...		A: That's what I'm saying.	[11]
...		(Repeat)	

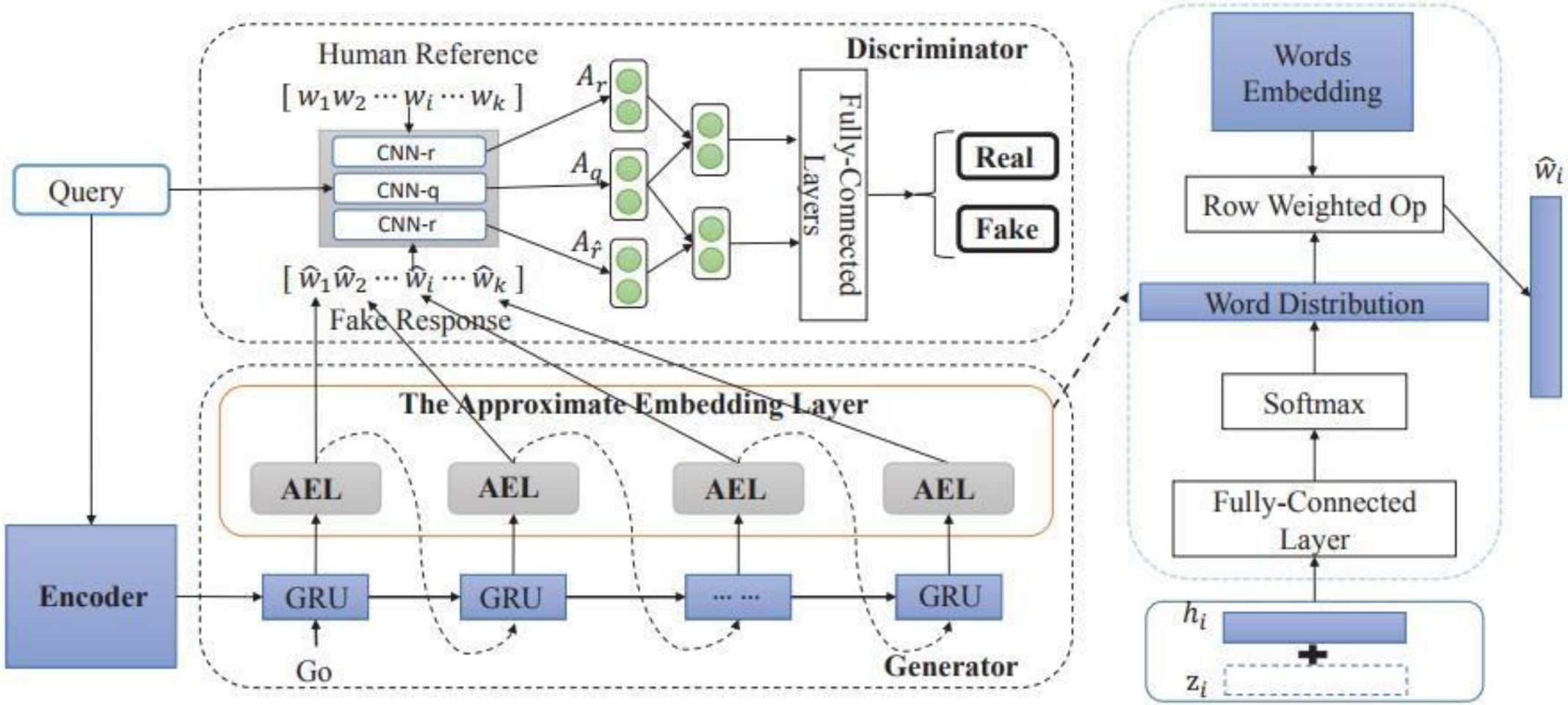
GAN in Conversations

- GAN
- GAN in Sequences
  - SeqGAN [Yu et al., AAAI'17]



- Seq2SeqGAN [Li et al., EMNLP'17]
  - Policy: reward to every generation step
  - Optimize in an adversarial way

GAN in Conversations



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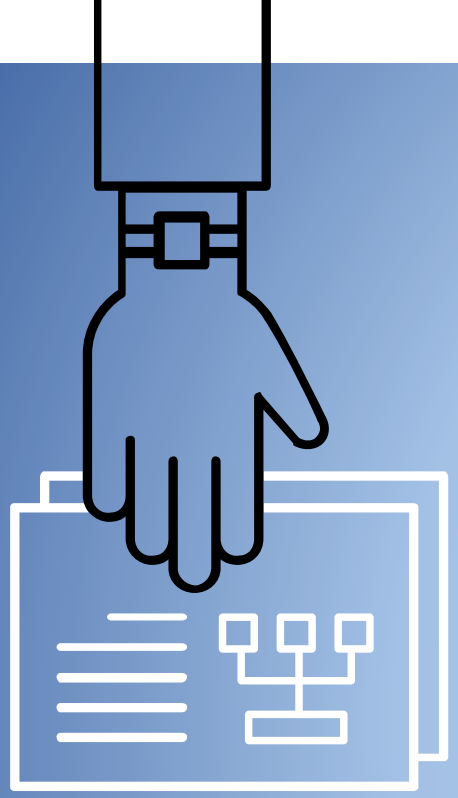
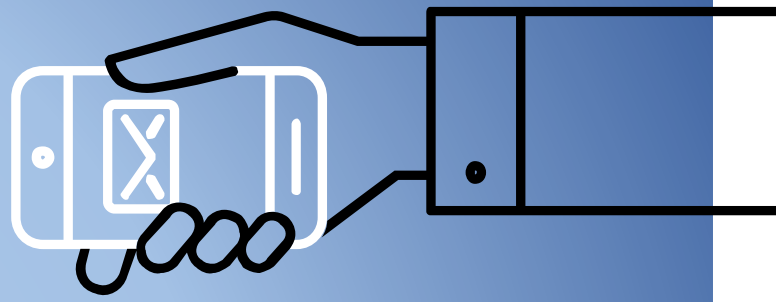
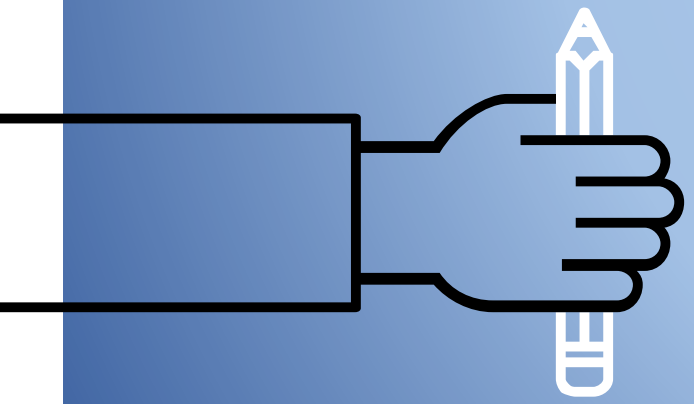
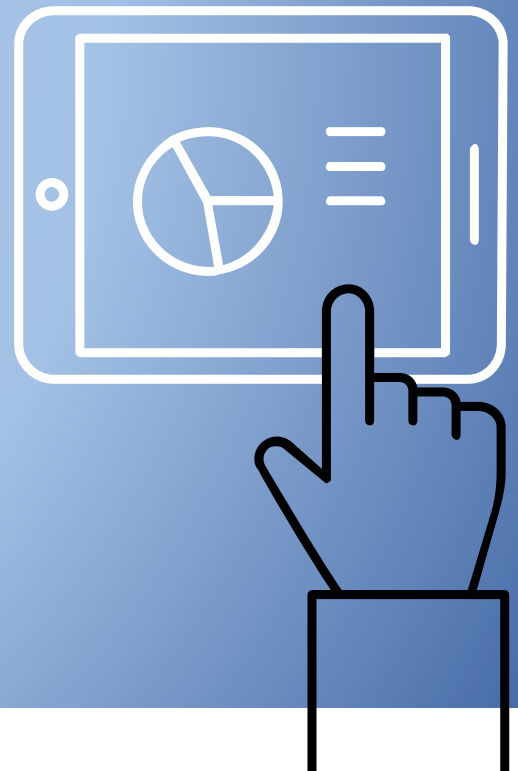
Evaluation



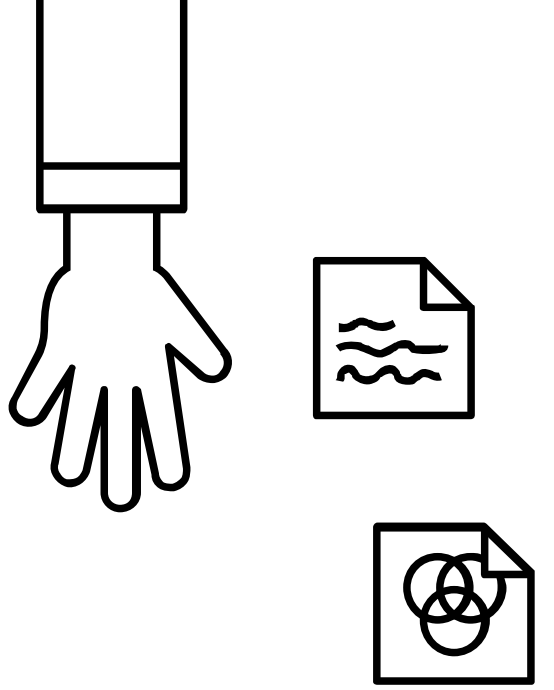


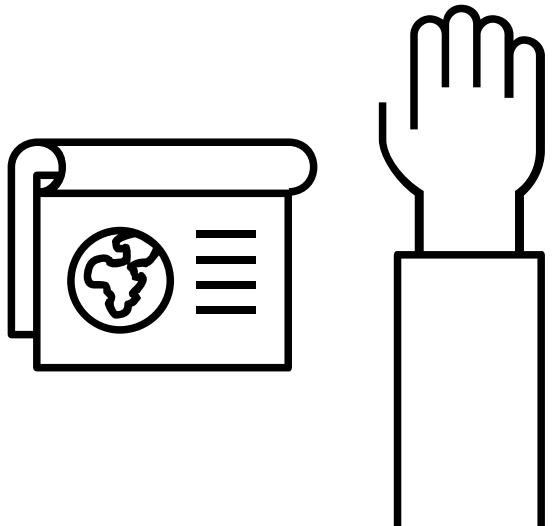




Automatic Evaluation Metric

- Evaluation metrics are crucial to evaluate how we are doing
- Language model
  - Perplexity
- Machine translation
  - BLEU, NIST, METEOR
  - Shared tasks for evaluation in WMT
- Text summarization
  - ROUGE, Pyramid
- Conversational systems: ???





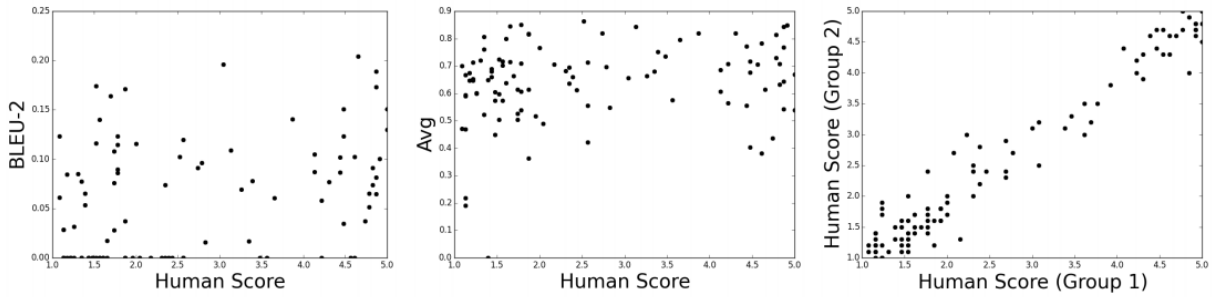
Evaluation Metrics for Conversations

- **Human evaluation**
  - Applicable to almost every NLP task
  - Point-wise evaluation
  - Pair-wise evaluation

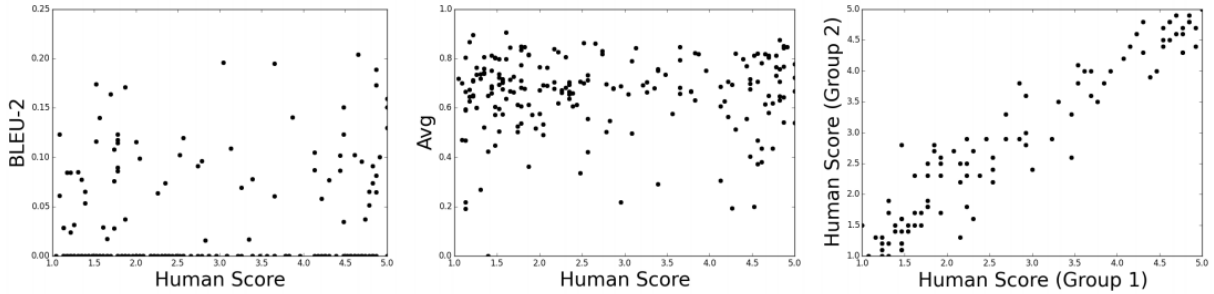
- **Automatic evaluation metrics**
  - BLEU [Ritter et al., 2011; Li et al., 2015; Sordoni et al., 2015; Song et al., 2016]
  - Information: entropy, perplexity [Serban et al. 2016 and Mou et al. 2016]
  - Diversity: distinc-1, distinc-2 [Li et al., 2015]
  - Average response length [Serban et al. 2016, Mou et al. 2016]

How NOT to Evaluate Conversations

- Weak correlation between human evaluation and automatic evaluation metrics [Liu et al., EMNLP'16]
  - Significant diversity in the space of valid replied to a given input.
  - Utterances are typically short and casual in open-domain dialog systems.



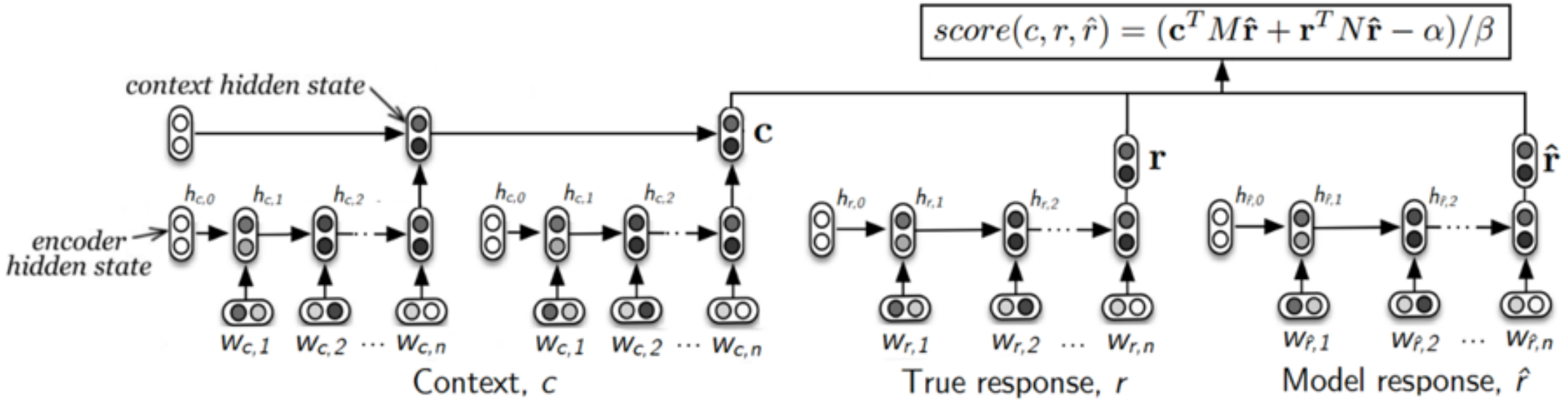
(a) Twitter



(b) Ubuntu

ADEM Model

- ADEM: learnable metric [Lowe et al., ACL'17]
  - Human labeling first
  - Predict a score of a reply given its query (context) and a ground truth reply
  - It requires massive human-annotated scores to train the network

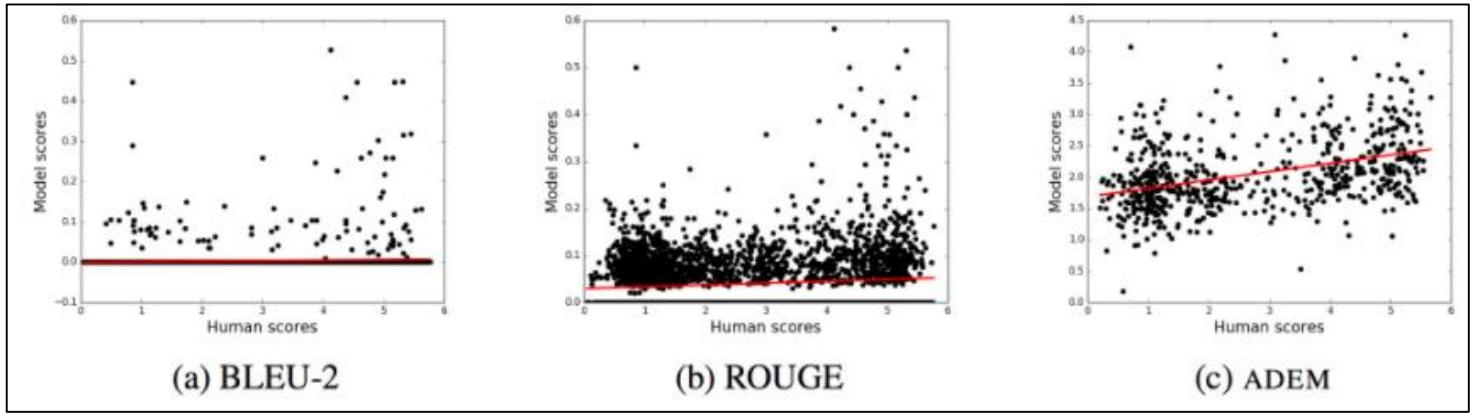


Higher Correlation

Better performance

than BLEU and ROUGE

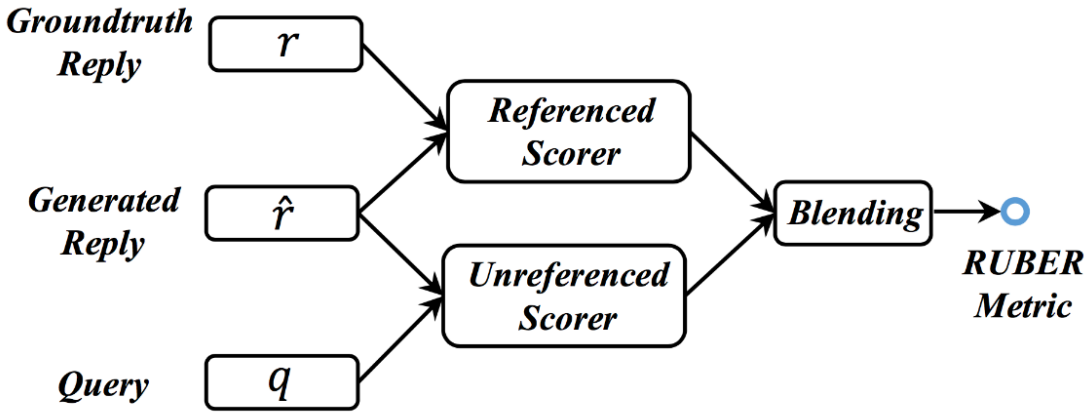
Context	Reference response	Model responses	Human score	ADEM score
photo to see my television debut go to - some. some on <url> - hehe <url> → it really was you? i thought ppl were recognizing someone who looked like you! were the oysters worth the wait?	yeah it was me . haha i 'd kinda forgotten about it it was filmed a while ago	1) i'm not sure. i just don't know what to do with it.	3	1.602
		2) you heard the horsepower productions remix of lee scratch perry's 'exercising' off his 'mighty upsetter' album?	1	1.513
		3) you wont chug a fuzzy peach navel	1	1.744
		4) they were!	5	3.274
just beat call of duty!! → want a cookie? → yes!! → come get it	im in kenmore at the moment	1) i'm gonna get a new phone some moro	1	1.848
		2) no way man.	5	4.265
		3) wow i just got a free pizza coupon! get yours before theres no more! <url>	1	0.921
		4) i'm going to go to the mall.	1	2.634
am i out of twitter jail yet? testing → yeah. i posted bail → thanks. i am a right chatter tweetbox on sundays. same happened last sunday lol	any news on meeting our user ? i go to the us on friday and i don 't want to miss anything arranged	1) i'm not sure if i'm going to be able to get it.	3	1.912
		2) good to see another mac user in the leadership ranks	4	1.417
		3) awww poor baby hope u get to feeling better soon. maybe some many work days at piedmont	2	1.123
		4) did you tweet too much?	5	2.539

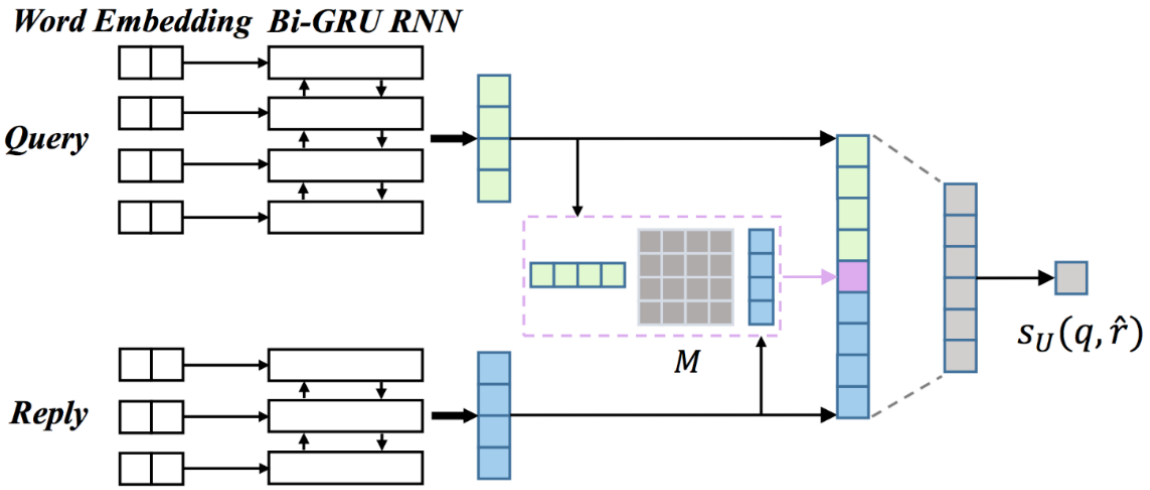


(a) BLEU-2 (b) ROUGE (c) ADEM

RUBER

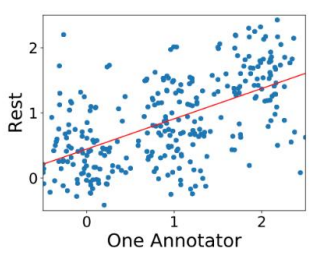
RUBER: a Referenced metric and Unreferenced metric Blended Evaluation Routine for open-domain dialog systems [Tao et al., AAAI'18]



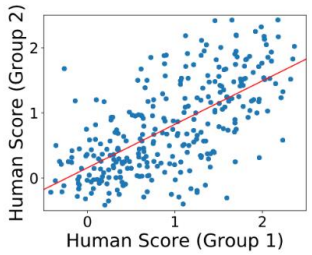


RUBER Results

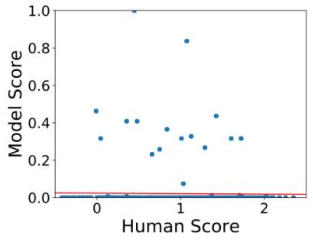
Metrics		Retrieval (Top-1)		Seq2Seq (w/ attention)	
		Pearson(p-value)	Spearman(p-value)	Pearson(p-value)	Spearman(p-value)
Inter-annotator	Human (Avg)	0.4927(<0.01)	0.4981(<0.01)	0.4692(<0.01)	0.4708(<0.01)
	Human (Max)	0.5931(<0.01)	0.5926(<0.01)	0.6068(<0.01)	0.6028(<0.01)
Referenced	BLEU-1	0.2722(<0.01)	0.2473(<0.01)	0.1521(<0.01)	0.2358(<0.01)
	BLEU-2	0.2243(<0.01)	0.2389(<0.01)	-0.0006(0.9914)	0.0546(0.3464)
	BLEU-3	0.2018(<0.01)	0.2247(<0.01)	-0.0576(0.3205)	-0.0188(0.7454)
	BLEU-4	0.1601(<0.01)	0.1719(<0.01)	-0.0604(0.2971)	-0.0539(0.3522)
	ROUGE	0.2840(<0.01)	0.2696(<0.01)	0.1747(<0.01)	0.2522(<0.01)
	Vector pool (s_R)	0.2844(<0.01)	0.3205(<0.01)	0.3434(<0.01)	0.3219(<0.01)
Unreferenced	Vector pool	0.2253(<0.01)	0.2790(<0.01)	0.3808(<0.01)	0.3584(<0.01)
	NN scorer (s_U)	0.4278(<0.01)	0.4338(<0.01)	0.4137(<0.01)	0.4240(<0.01)
RUBER	Min	0.4428(<0.01)	0.4490(<0.01)	**0.4527**(<0.01)	**0.4523**(<0.01)
	Geometric mean	0.4559(<0.01)	0.4771(<0.01)	0.4523(<0.01)	0.4490(<0.01)
	Arithmetic mean	**0.4594**(<0.01)	**0.4906**(<0.01)	0.4509(<0.01)	0.4458(<0.01)
	Max	0.3263(<0.01)	0.3551(<0.01)	0.3868(<0.01)	0.3623(<0.01)



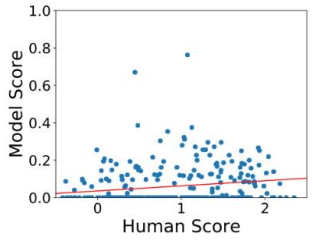
(a) Human (1 vs. rest)



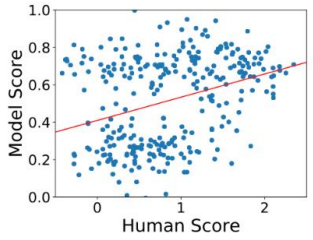
(b) Human (Gropu 1 vs. Group 2)



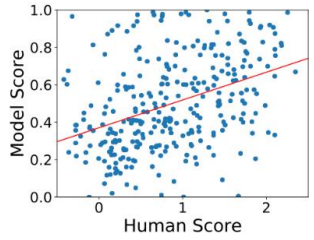
(c) BLEU-2



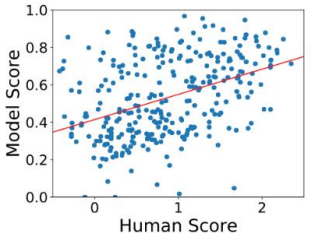
(d) ROUGE



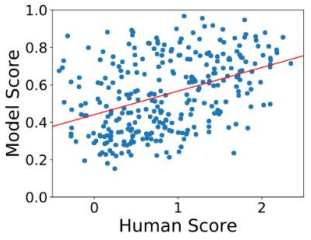
(e) s_R (vector pool)



(f) s_U (NN scorer)



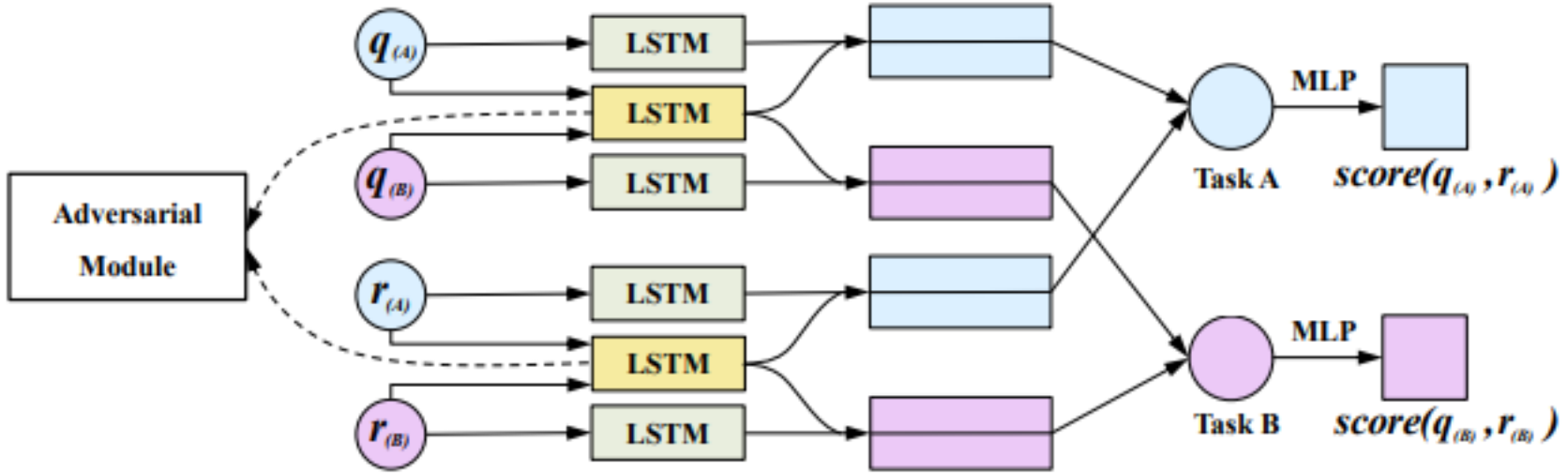
(g) RUBER (Geometric mean)

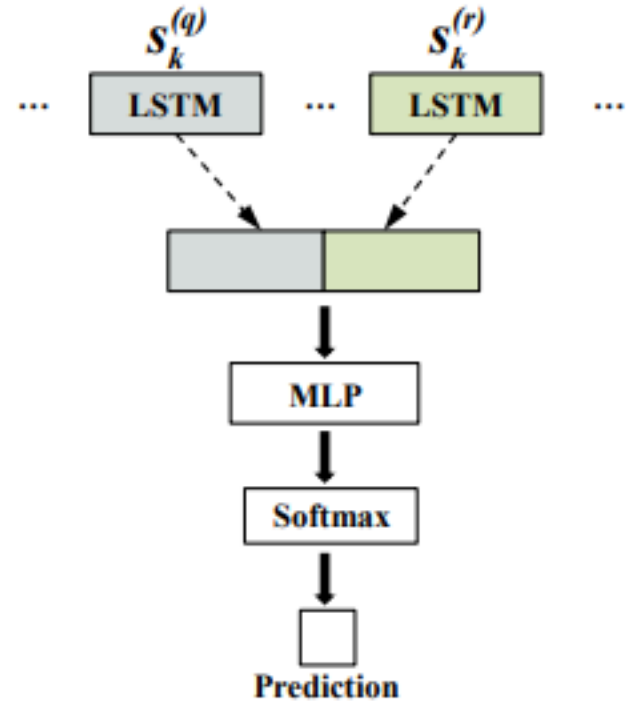


(h) RUBER (Arithmetic mean)

RUBER Plus

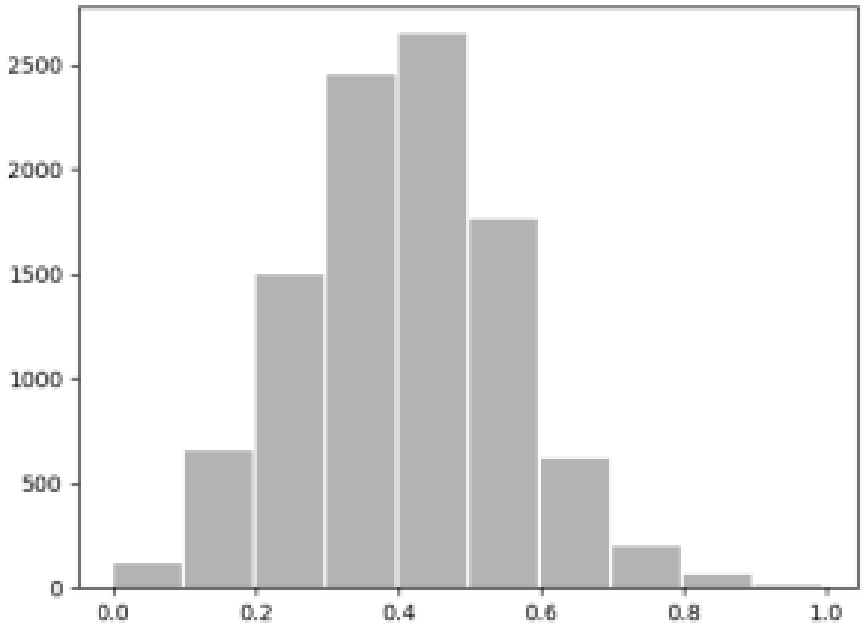
- Multi-linguality in conversations [Tong et al., IJCAI'18]
  - A natural solution with multi-task learning
- Responding patterns are language-insensitive
- Adversarial learning to understand the language-insensitive parts
  - Share-private embeddings





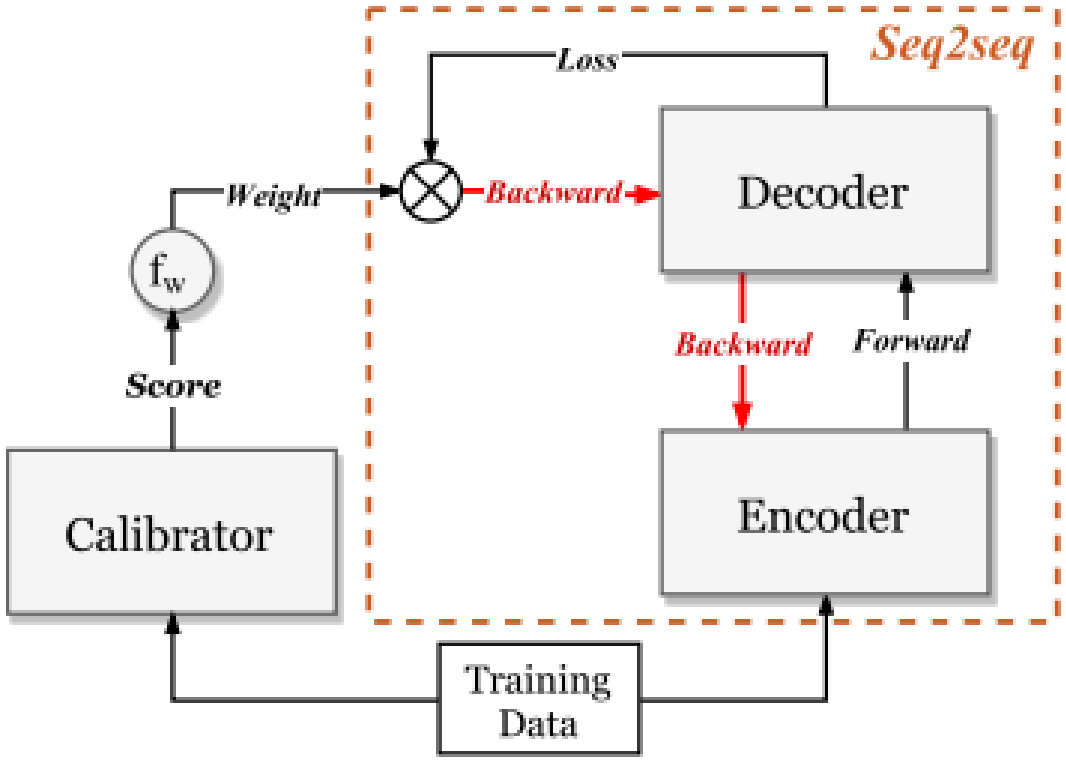
Evaluation-based Generation

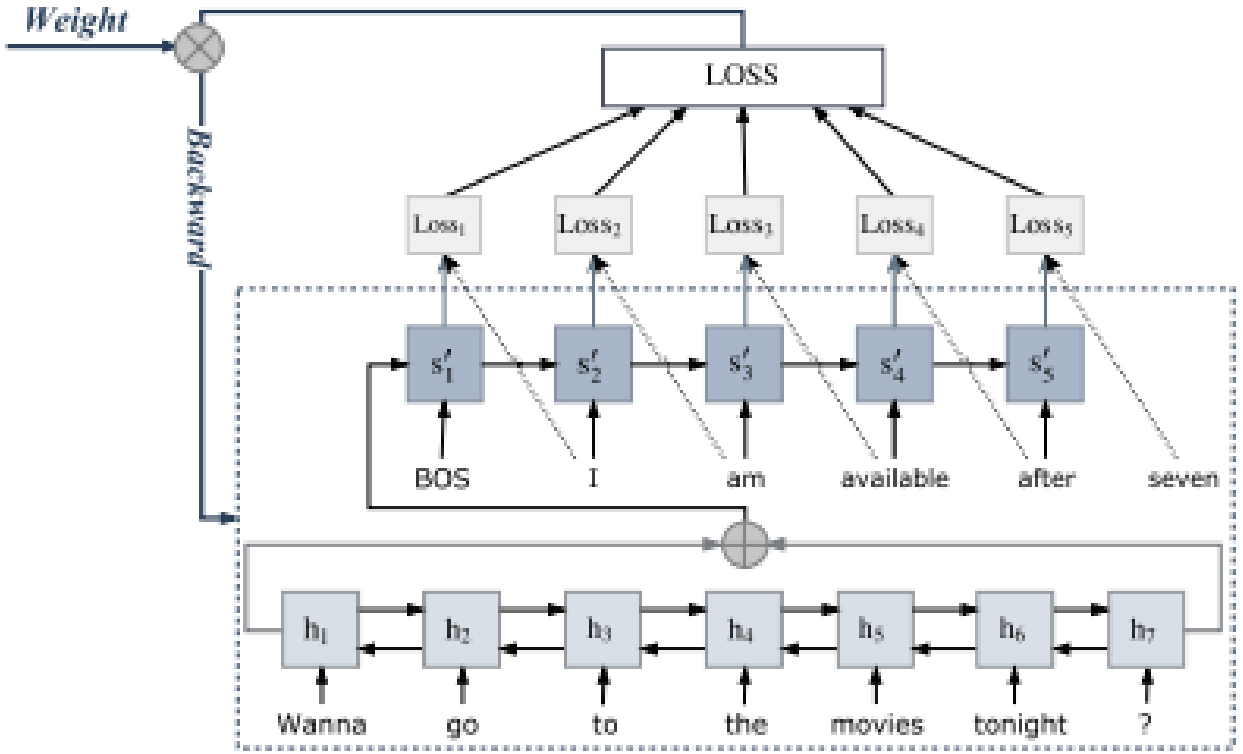
- **Learning to converse with noisy data [Shang et al., IJCAI'18]**
  - Not all training samples are equally important
  - Conversational data are noisy
  - Generation with calibration: using RUBER as the evaluation metric



Evaluation-based Generation (cont.)

- Learning to fit good training samples
  - Instance weighting
- The weights are propagated through loss





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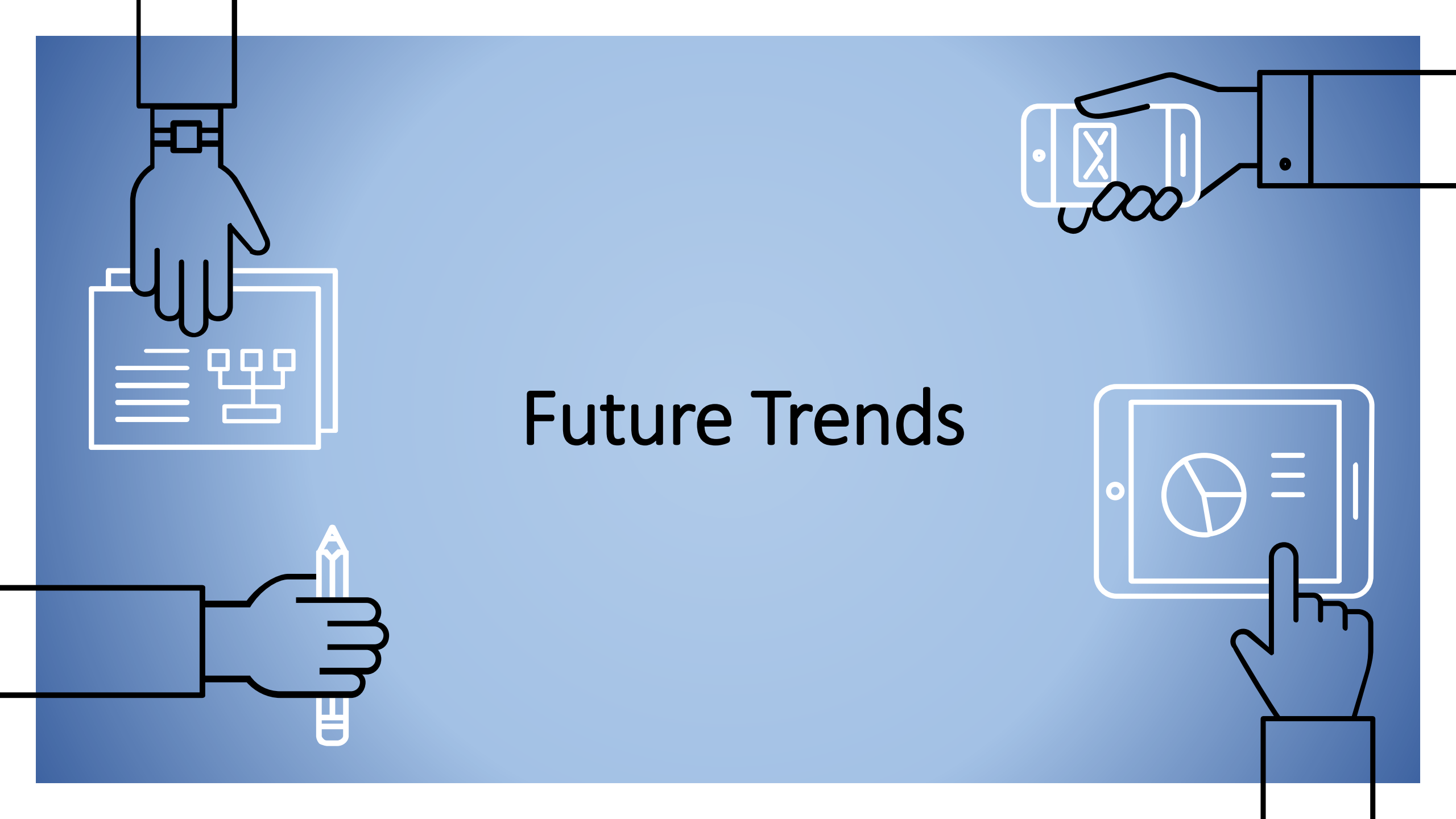
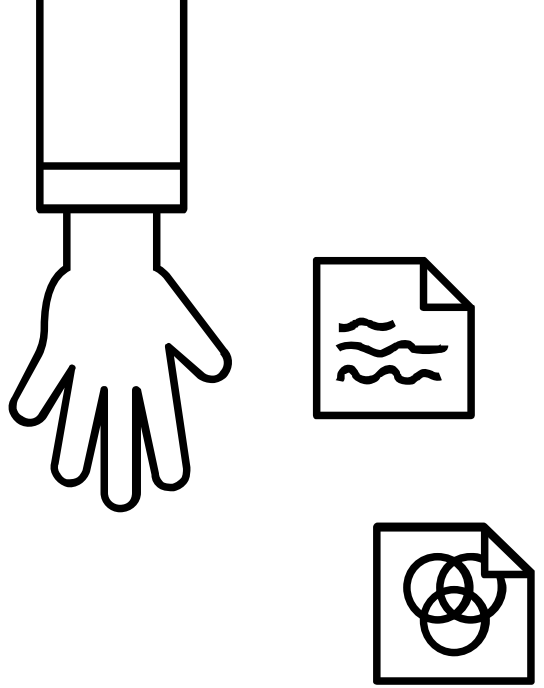
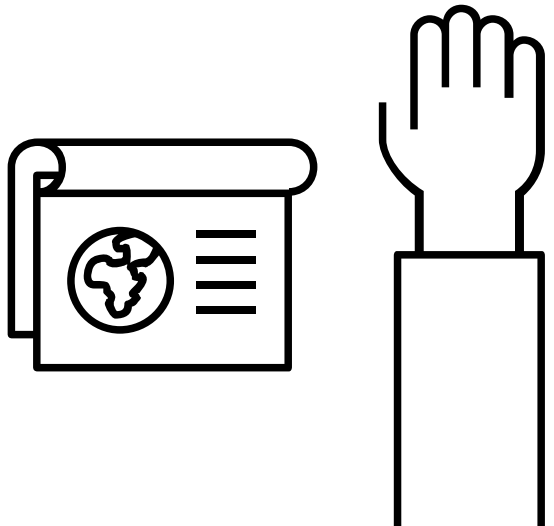
Future Trends



Reminder of Mentioned Trends



- Learning Methods
- Representations



Reasoning in Dialogues

- **Context-based Reasoning**
  - "John picked up the apple."
  - "John walked into the living room."
  - Where is the apple
- **Knowledge**
  - Knowledge graph
- **Commonsense**
  - "I had milk this morning."

X-Grounded Dialogues

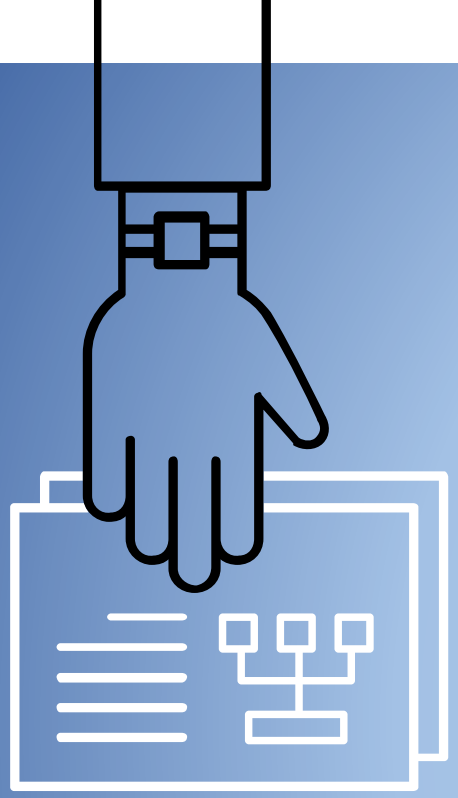
- **Multi-Modal**
  - Vision: image
  - Video
- **Labels**
  - Emotion
- **Texts**
  - Profile
  - Wikipedia
  - Knowledge Graph

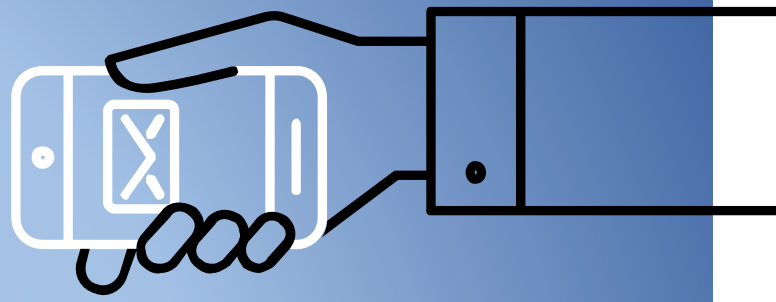
Dialogue Management in Open Domain

- Keyword-based Planning
  - Content-introducing in dialogues
- Dialogue act-based management
- Targets
  - Length
  - Consistency

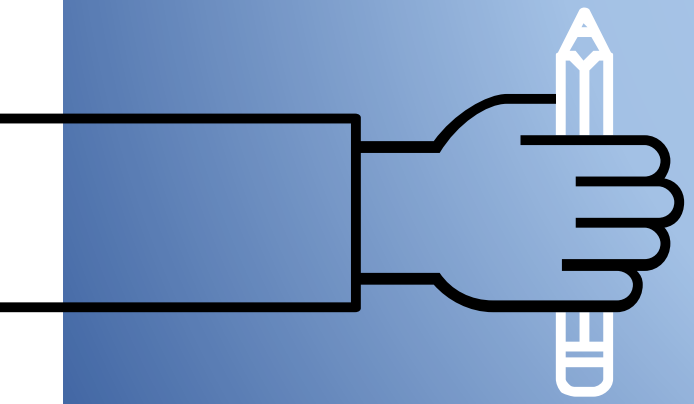
Evaluation & Benchmark Datasets

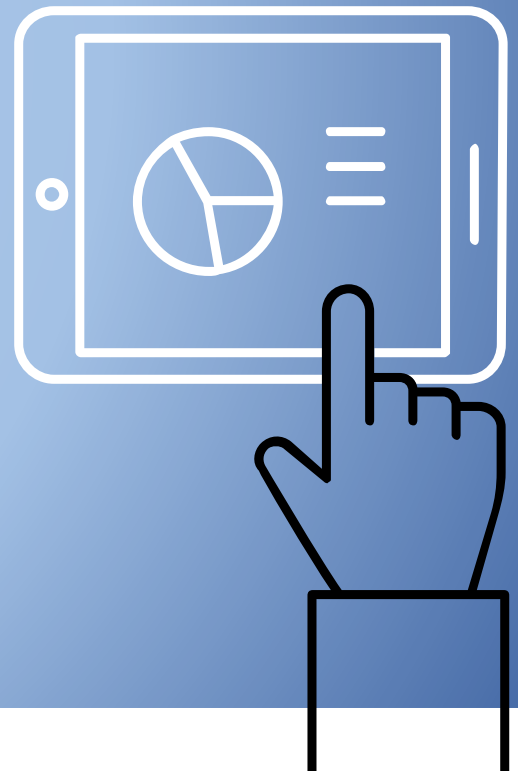
- **Towards better evaluation metrics**
  - From BLEU, ROUGE, to RUBER and ADAM
  - How do you evaluate informativeness, interestingness
- **Benchmark datasets for dialogue generation**
  - Can we have 1 set for all methods?





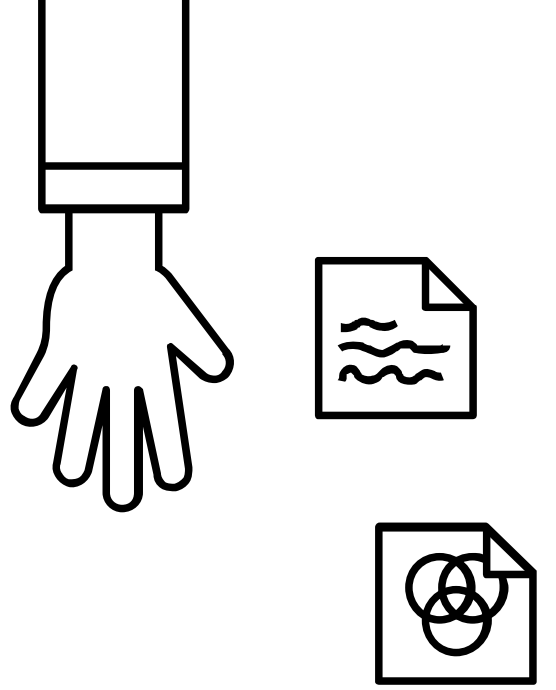
Conclusion

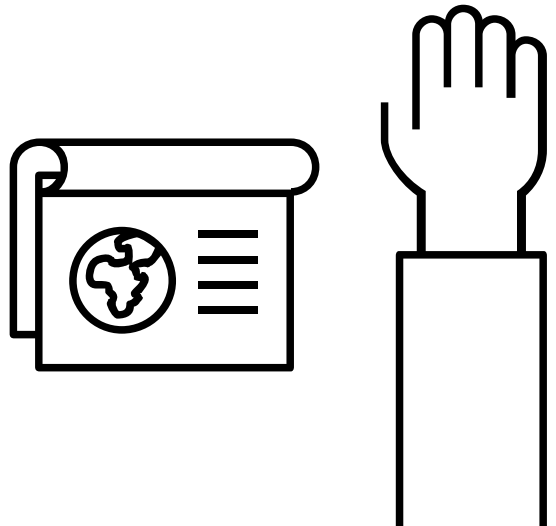


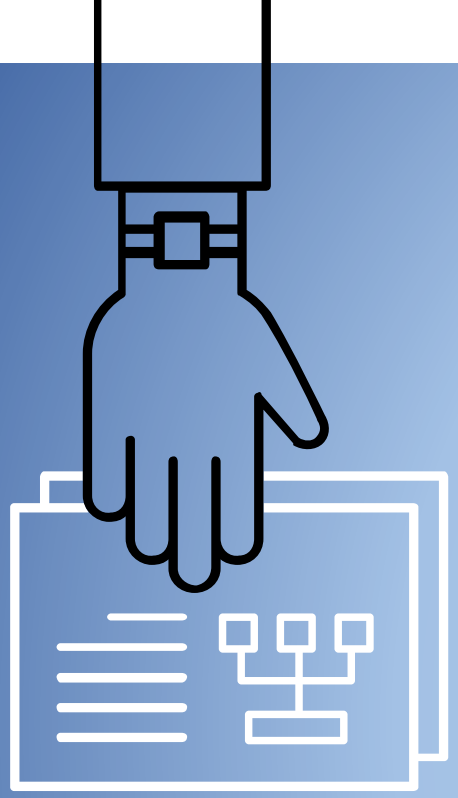


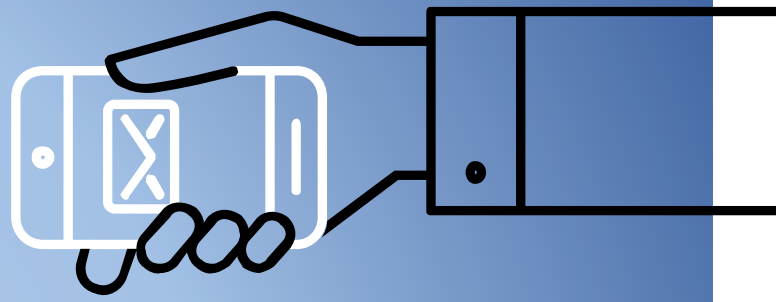
Take-Home Messages

- Background knowledge about dialogues
- Retrieval-based methods
- Generation-based methods
  - Diversity, additional elements
- Evaluations
  - Learnable metrics
- Future trends
  - Grounding, Learning, Reasoning









Thank you for listening

Q&A