Data Science Winter School

Towards Different Perspectives in Automatic Human-Computer Conversation Systems

#Go_ChatBots!!

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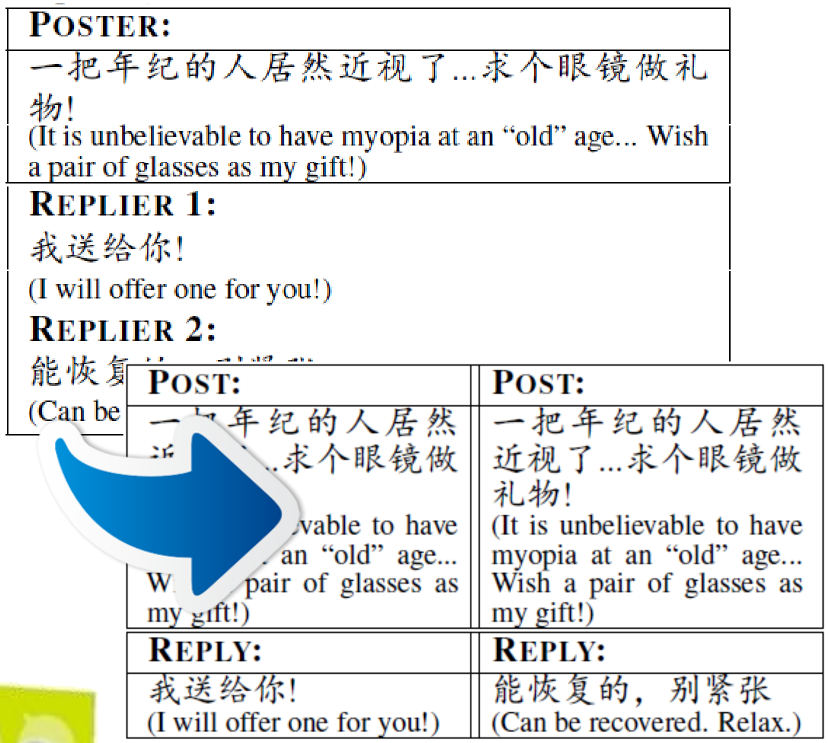
Era of A.I.

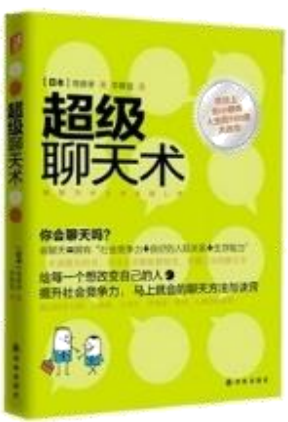
- **Conversation systems with A.I. prevail (>///<)**
  - Virtual personal assistant
    - Apple Siri/Microsoft Cortana/Google Now
  - ChatBot
    - Baidu Duer, Microsoft (Xiaobing, Rinna, Tay)
  - Yet to come: Facebook, Microsoft, more startups…

Hi, I'm Cortana.

Conversation

- **What is conversation**
  - Given **q**, respond with **r**
- **Why is it possible?**
  - It is all about timing
  - Data-driven v.s. big data
    - 10 million is enough?
- **Why is it challenging?**
  - Needless to mention
  - Relevance
  - Interestingness
  - A lot of issues…





Categorizations

- **Domain**
  - Open-domain
  - Vertical domains
- **How to obtain a reply?**
  - Retrieval-based methods
  - Generation-based methods
  - Combination of retrieval- and generation-based methods
- **Scenarios**
  - Single-turn conversation
  - Multi-turn conversation
- **Style**
  - Passive conversation
  - Proactive conversation

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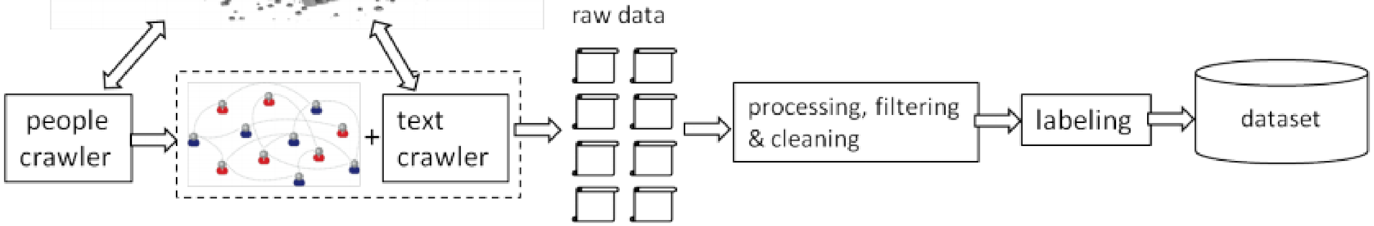
RETRIEVAL-BASED CONVERSATION SYSTEM

Dataset

- **Web provides opportunities with big data**
  - Social media, cQA, BBS forums

Post	
User A:	*The first day at Hawaii. Watching sunset at the balcony with a big glass of wine in hand.*
Responses	
User B:	*Enjoy it & don't forget to share your photos!*
User C:	*Please take me with you next time!*
User D:	*How long are you going to stay there?*
User E:	*When will be your talk?*
User F:	*Haha, I am doing the same thing right now. Which hotel are you staying in?*
User G:	*Stop showing-off, buddy. We are still coding crazily right now in the lab.*
User H:	*Lucky you! Our flight to Honolulu is delayed and I am stuck in the airport. Chewing French fries in MacDonald's right now.*

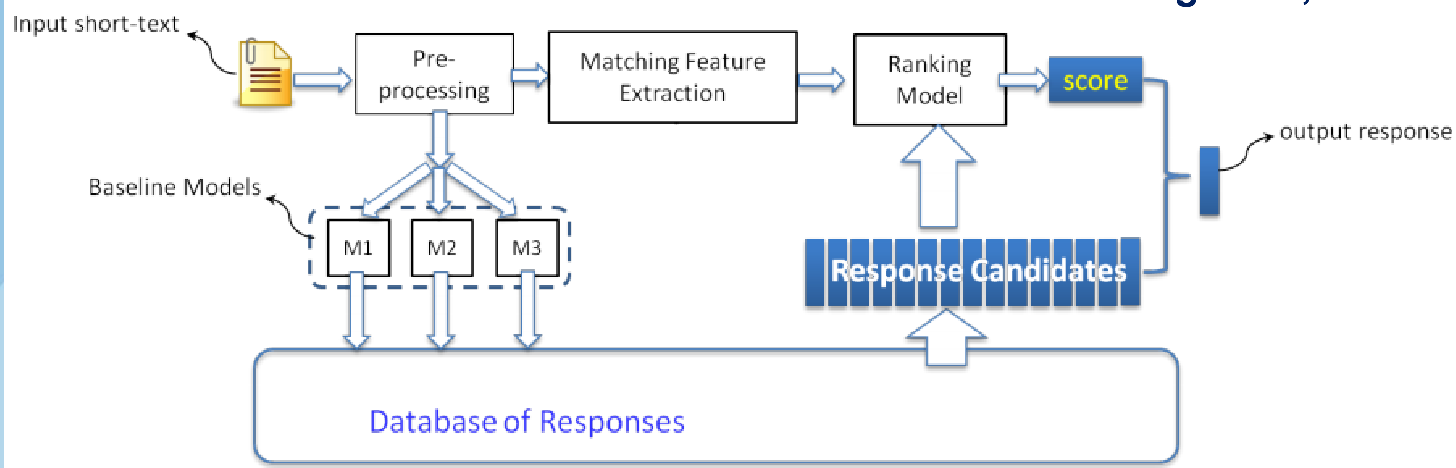
Wang et al., EMNLP'13



Retrieval Process

- **Retrieval model: 2-stage retrieval**
  - Fast retrieval: fast matching
    - Post-response semantic matching (mapping to low-dimension vectors)
    - Post-response similarity (vsm)
    - Post-post similarity
  - Linear match: $$\text{score}(x, y) = \sum_{i \in \Omega} w_i \Phi_i(x, y)$$

Wang et al., EMNLP'13



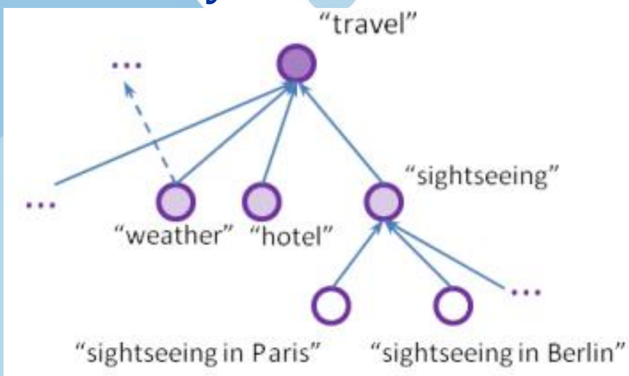
Deep Match

- **Essence**
  - Matching: inner-product of two representing feature vectors

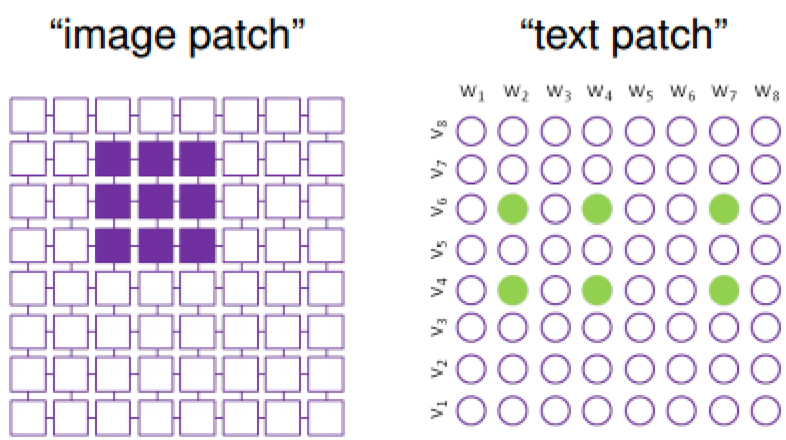
$$\text{match}(x, y) = < \Phi_{\mathcal{Y}}(x), \Phi_{\mathcal{X}}(y) >_{\mathcal{H}}$$

$$\text{match}(\mathbf{x}, \mathbf{y}) = \mathbf{x}^\top \mathbf{A} \mathbf{y} = \sum_{m=1}^{D_x} \sum_{n=1}^{D_y} A_{nm} x_m y_n$$

- **From linear to deep**
  - Localness
  - Hierarchy

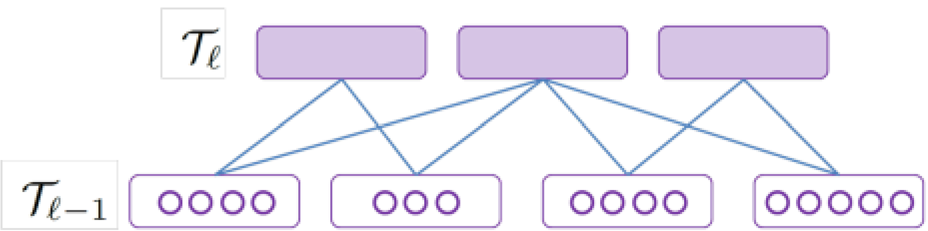


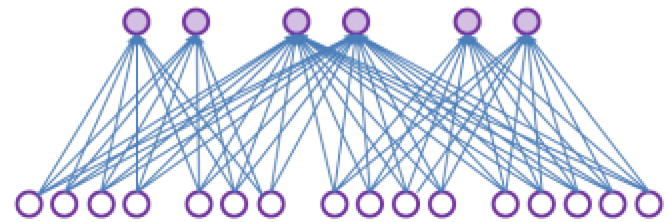
Lu et al., NIPS'13



Neural Network Structure

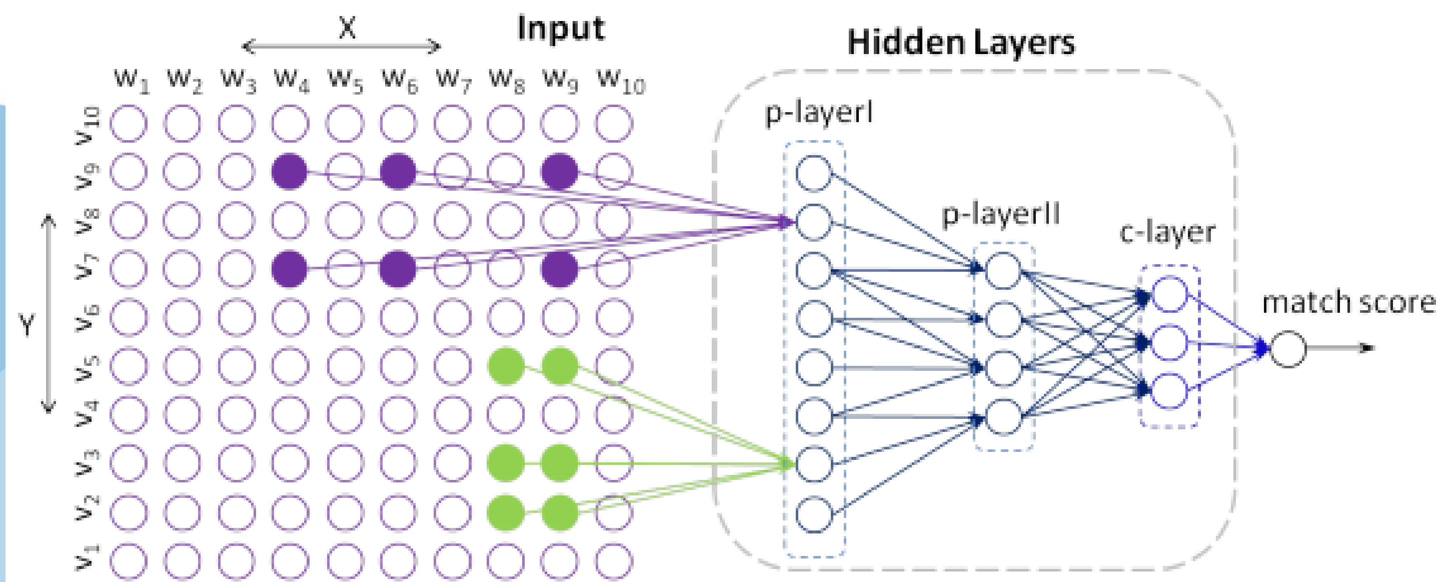
- Connect with topic patterns





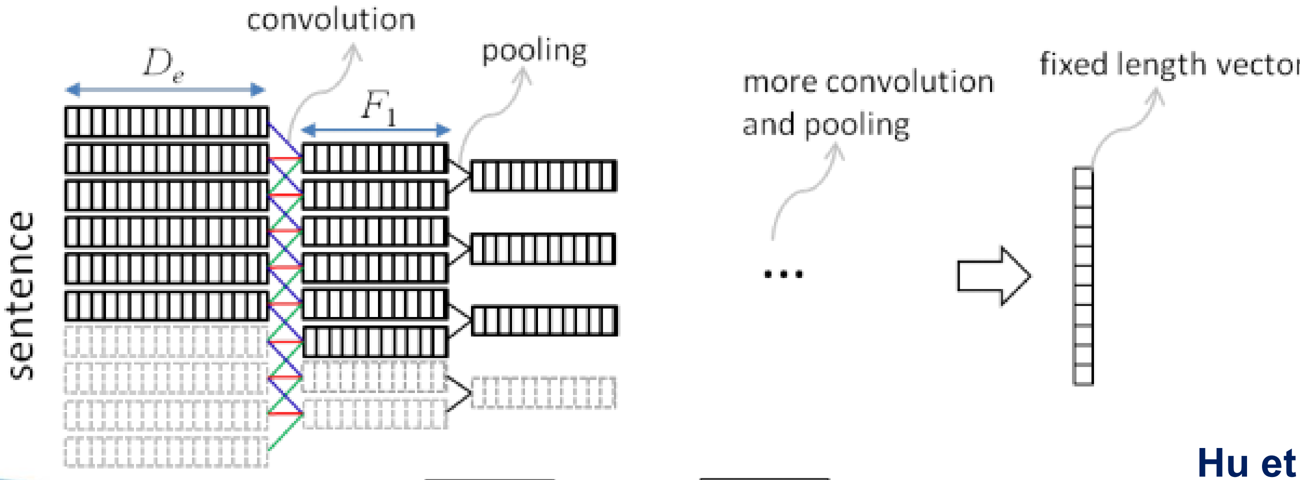
- Matching architecture

Lu et al., NIPS'13

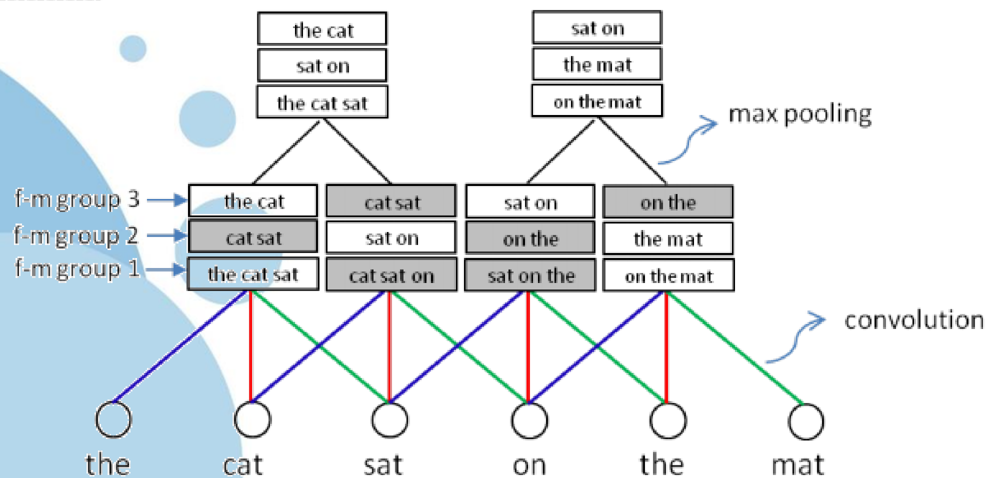


Convolutions

- **Convolutional sentence model**



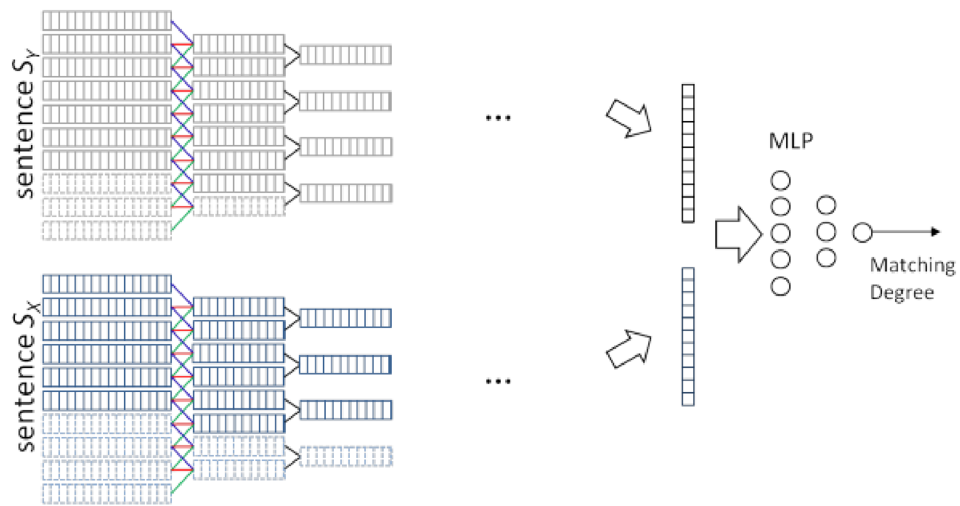
Hu et al., NIPS'14



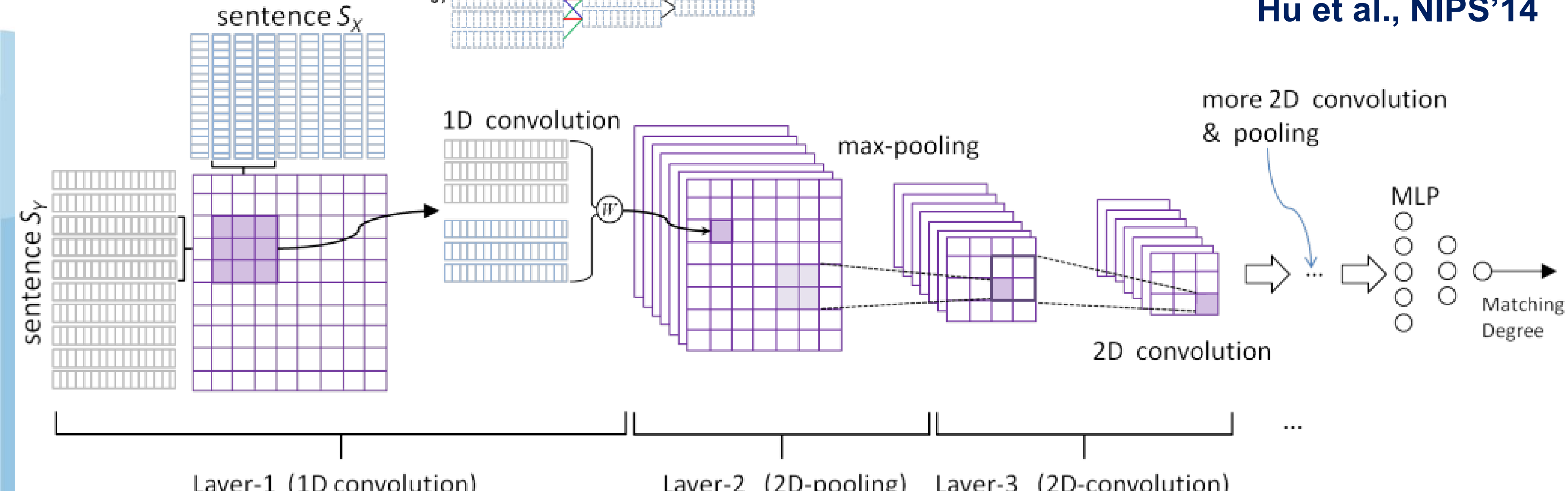
- **Illustration of convolutional sentence model**

Convolutional Match

- **ARC-I and ARC-II matching model**

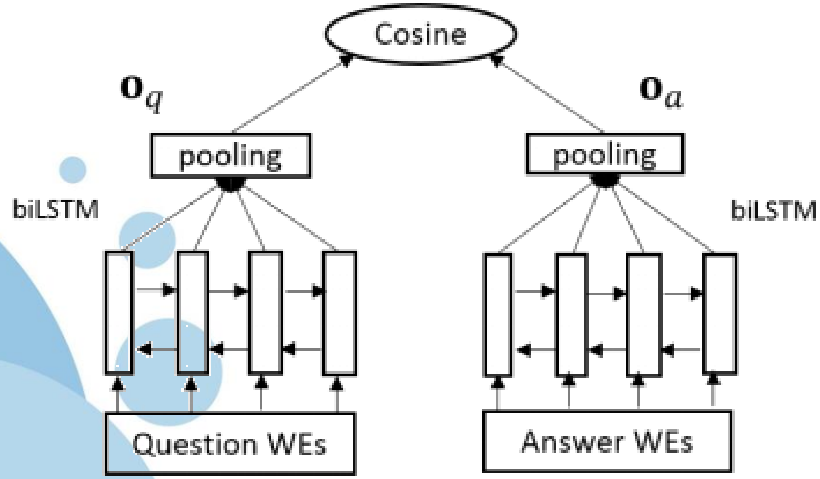


Hu et al., NIPS'14



Recurrent Modeling

- **Question-Answer matching**
  - Standard LSTM
    - Concatenation of the last vectors on both directions of the biLSTM
    - Average pooling over all the output vectors of the biLSTM
    - Max pooling over all the output vectors

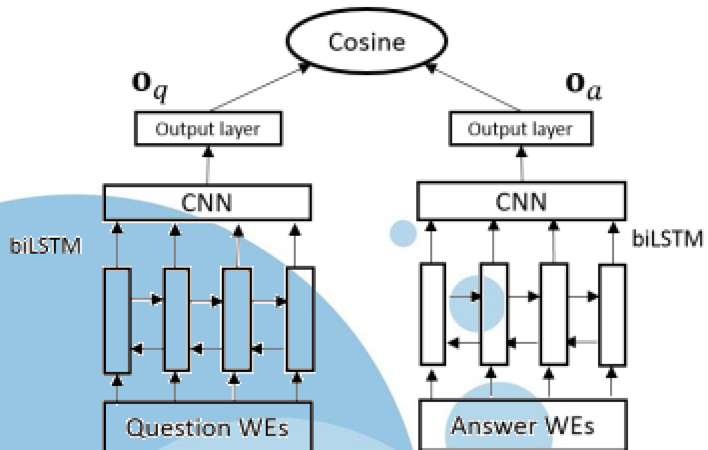


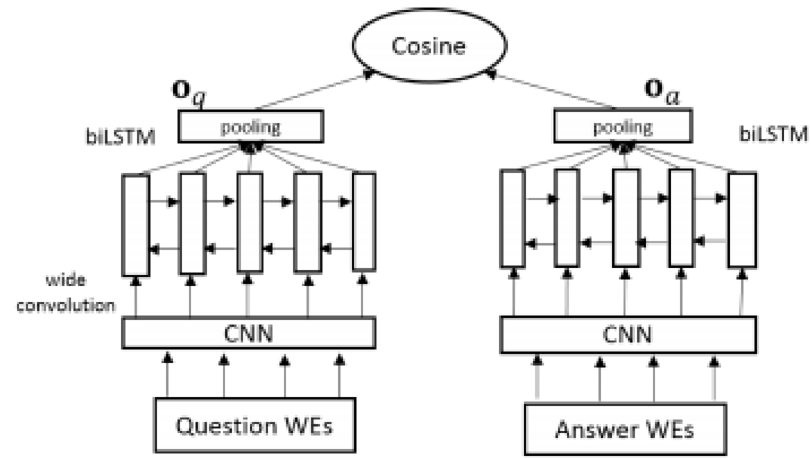
Tan et al., ACL'16

CNN+RNN Match

- **Question-Answer matching**
  - Convolutional LSTM
    - LSTM first, then convolution
    - Convolution first, then LSTM
    - Based on results: more or less the same

Tan et al., ACL'16





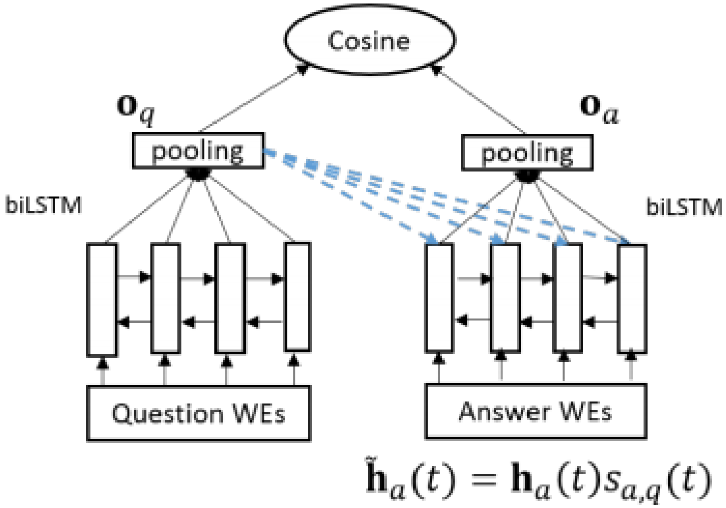
E	Conv-pooling LSTM (c=4000,K=1)	66.2	64.6	62.2
F	Conv-pooling LSTM (c=200,K=50)	66.4	67.4	63.5
G	Conv-pooling LSTM (c=400,K=50)	67.8	67.5	64.4
H	Conv-based LSTM ($\|h\|$=200,K=50)	66.0	66.1	63.0
I	Conv-based LSTM ($\|h\|$=400,K=50)	67.1	67.6	64.4

CNN+RNN Match + Attention

- **Question-Answer matching**
  - Attentive matching

Tan et al., ACL'16

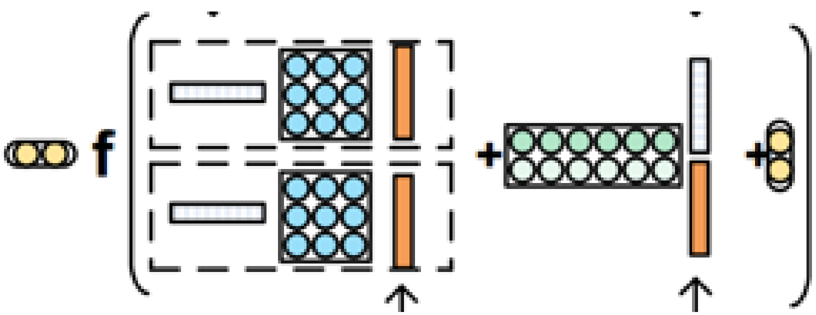
$$\mathbf{m}_{a,q}(t) = \mathbf{W}_{am}\mathbf{h}_a(t) + \mathbf{W}_{qm}\mathbf{o}_q$$
$$s_{a,q}(t) \propto \exp(\mathbf{w}_{ms}^T \tanh(\mathbf{m}_{a,q}(t)))$$
$$\widetilde{\mathbf{h}}_a(t) = \mathbf{h}_a(t)s_{a,q}(t)$$

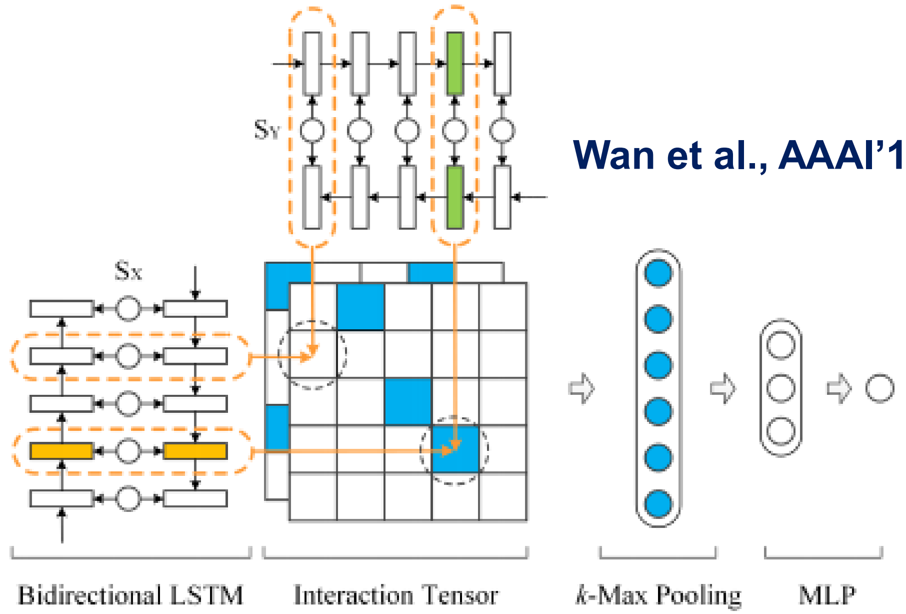


L	Attentive LSTM (avg-pooling K=1)	68.4	68.1	62.2
M	Attentive LSTM (avg-pooling K=50)	68.4	67.8	63.2
N	Attentive LSTM (max-pooling K=50)	**68.9**	**69.0**	**64.8**

Positional Matching

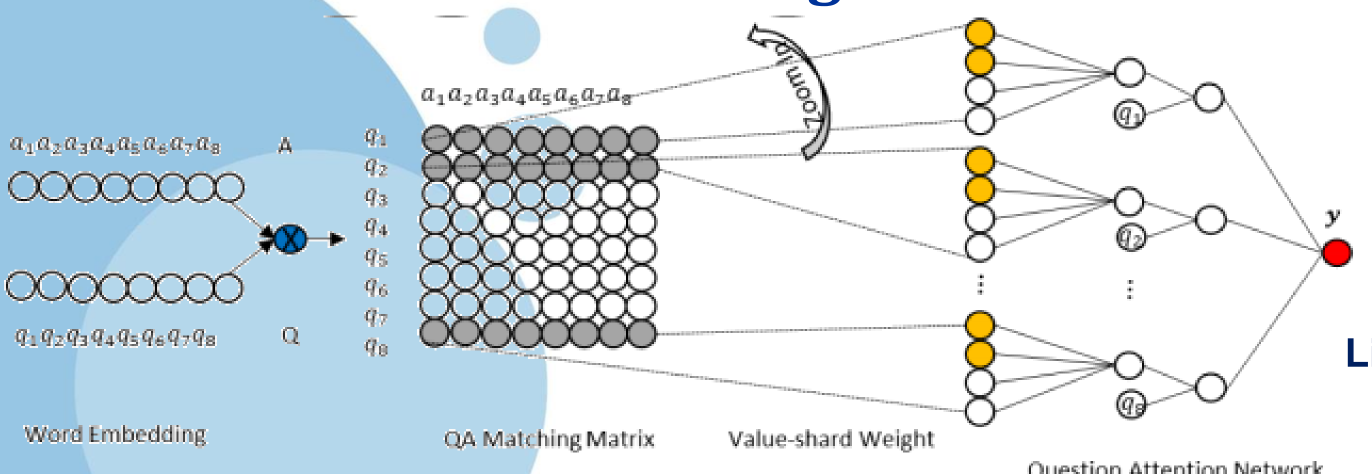
- **Positional-based match**





Wan et al., AAAI'16

- **Attention-based ranking**

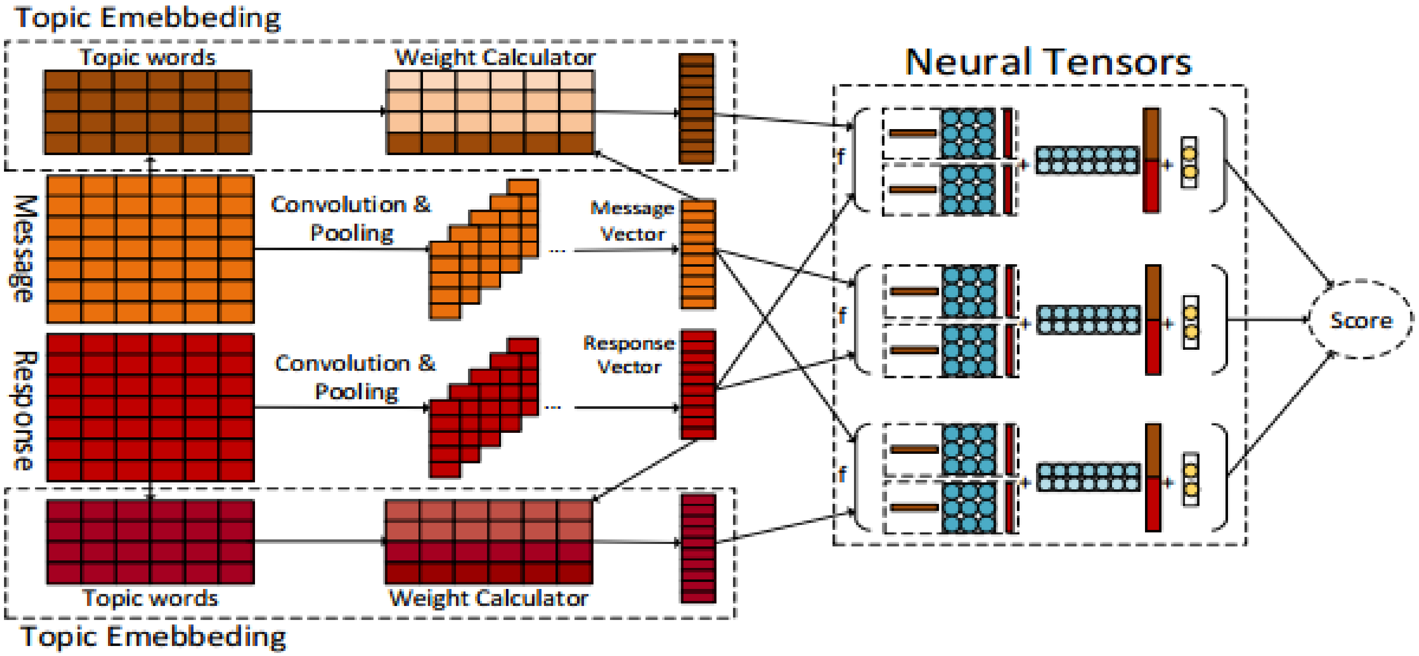


Liu et al., CIKM'16

Matching with Topic Info

- **Additional info might help!**
  - Topic, knowledge, etc
- **Topic information**
  - Topic word generation: LDA
  - Topic-aware neural network

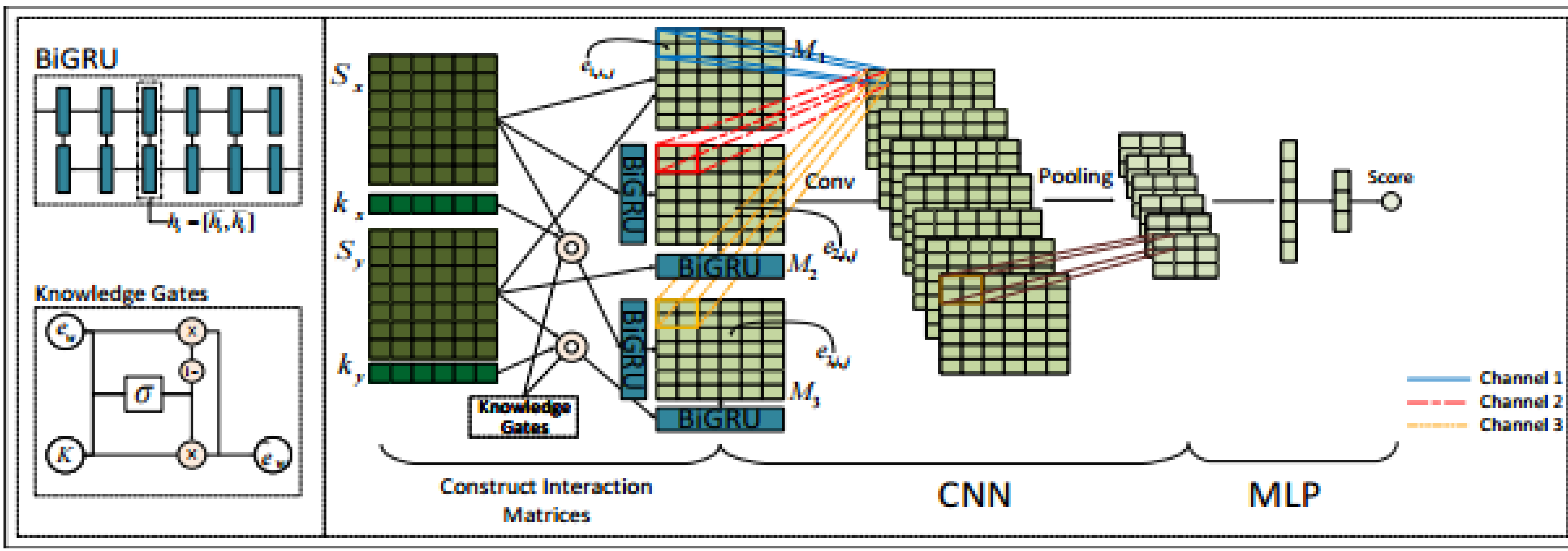
Wu et al., arXiv'16



Matching with Knowledge

- **Here comes the knowledge**
  - Prior knowledge of sentence
    - Tags, keywords, topics, entities, …
  - Fusion of knowledge gate
    - 3 channels: similarity, Bi-GRU match, Bi-GRU with knowledge match

Wu et al., arXiv'16



Multi-Turn Conversation

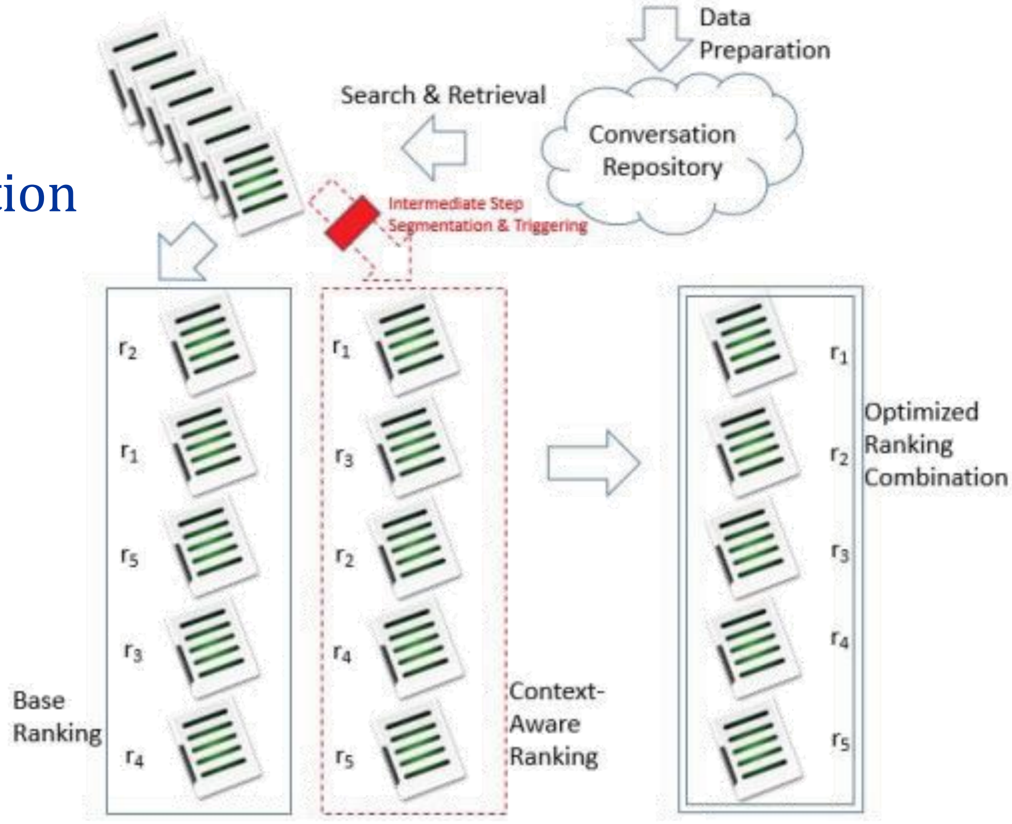
- **2 typical scenarios for a conversation system**
  - Single-Turn Conversation
  - Multi-Turn Conversation

- **Practical Concerns**
  - Effectiveness
  - Efficiency

Yan et al., CIKM'16

Re-ranking Framework

- **Off-line Process**
  - Data preparation: access, cleaning, storage, and indexing
- **Online Process**
  - Search and retrieval
  - Rankings
  - Optimization: rank combination



Yan et al., CIKM'16

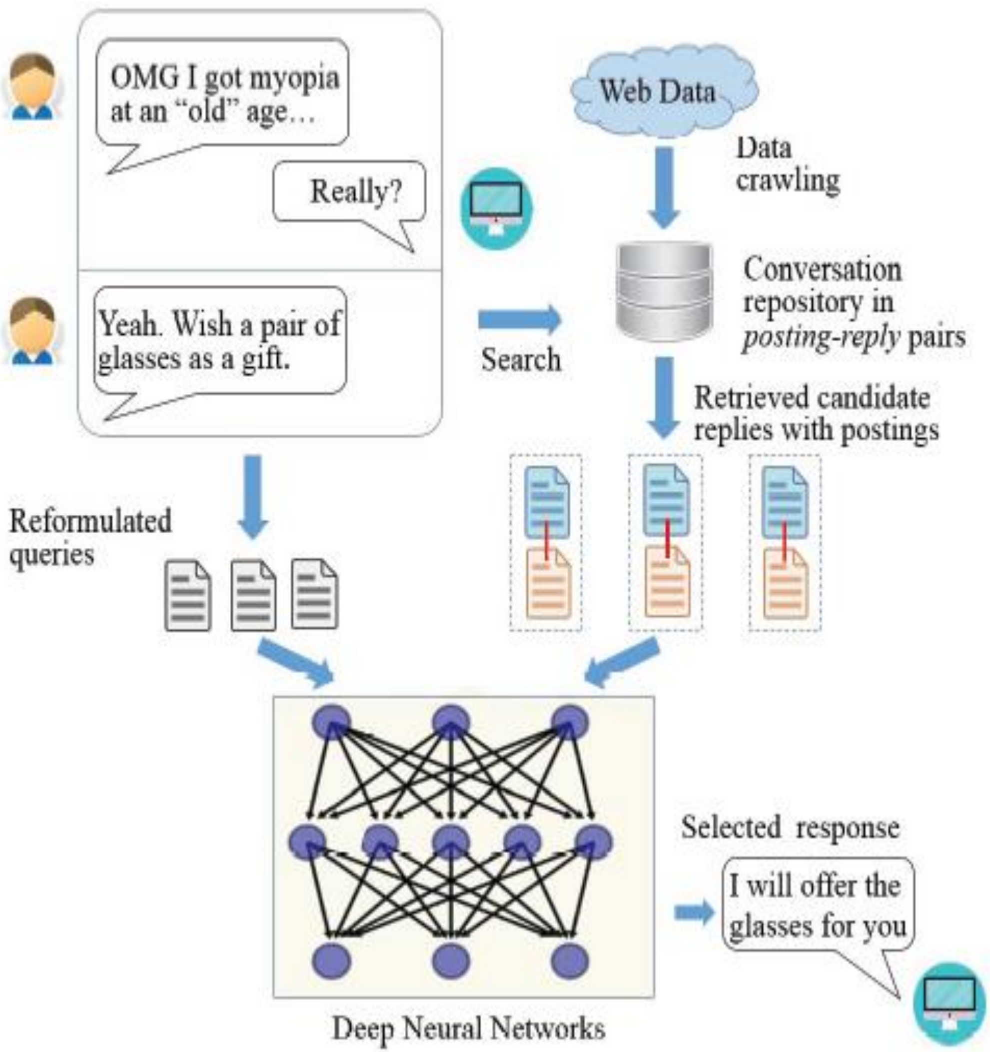
Matching

- **Rankers**
  - Shallow Ranker
    - Representations: term-level, topic-level, entity-level
    - Hand-crafted features: matching score (similarity, mutual information), translation probability, language model, term weighting, length, and fluency
  - Deep Ranker
    - Word Embeddings
    - Bi-Directional LSTM
    - Convolution
    - Pooling
    - Concatenation
    - Matching

Yan et al., CIKM'16

Another View

Yan et al., SIGIR'16



- **Data**
- **Search and retrieval**
- **Contextual reformulation**
  - Possible reformulations

Human-Computer Conversation
A_1: 天哪一把年纪的人居然近视了 (OMG I got myopia at such an "old" age) B_1: 真的吗？ (Really?) A_2:嗯哪。求个眼镜做礼物！ (Yeah. Wish a pair of glasses as a gift.)
B_2:我送你眼镜！ (I will offer the glasses for you!)

Task Formulation
User query: $q_0 = A_2$ **Context information:** $\mathbb{C}=\{c_1=A_1, c_2=B_1\}$ **Reformulated queries:** $q_1=A_2 \boxplus A_1$, $q_2=A_2 \boxplus B_1$ $q_3=A_2 \boxplus A_1 \boxplus B_1, \ldots$
Top-1 ranked response: $r^\star = Reply_1$

Learning to Respond

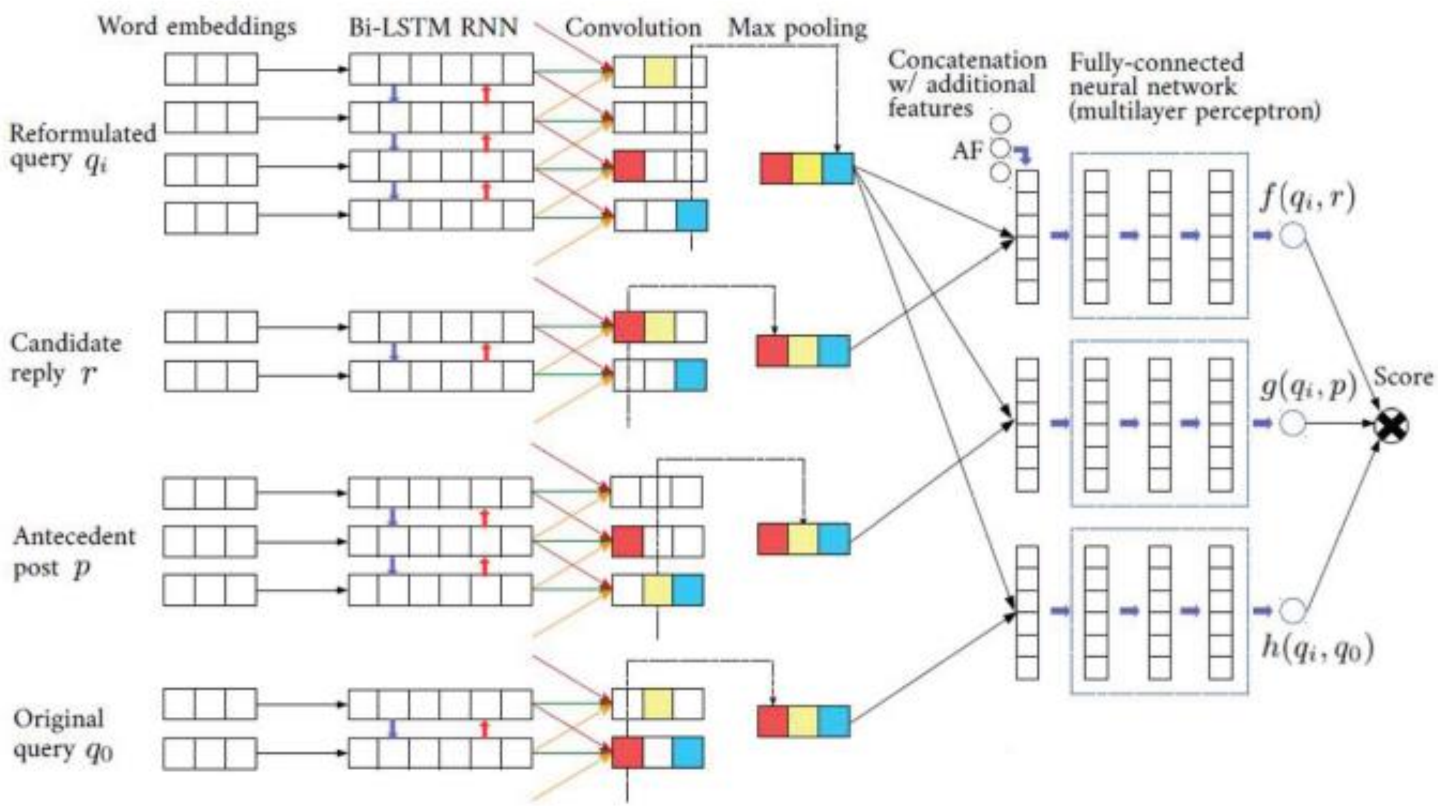
- **Sentence pair matching**
  - f(q,r)
  - g(q,p)
  - h(q,q_0)
- **Representation**
  - Word embedding
  - Bi-Directional LSTM
  - Convolution
  - Pooling
  - Concatenation
  - Matching

Yan et al., SIGIR'16

Deep Learning to Respond

- **Matching metric**

Yan et al., SIGIR'16



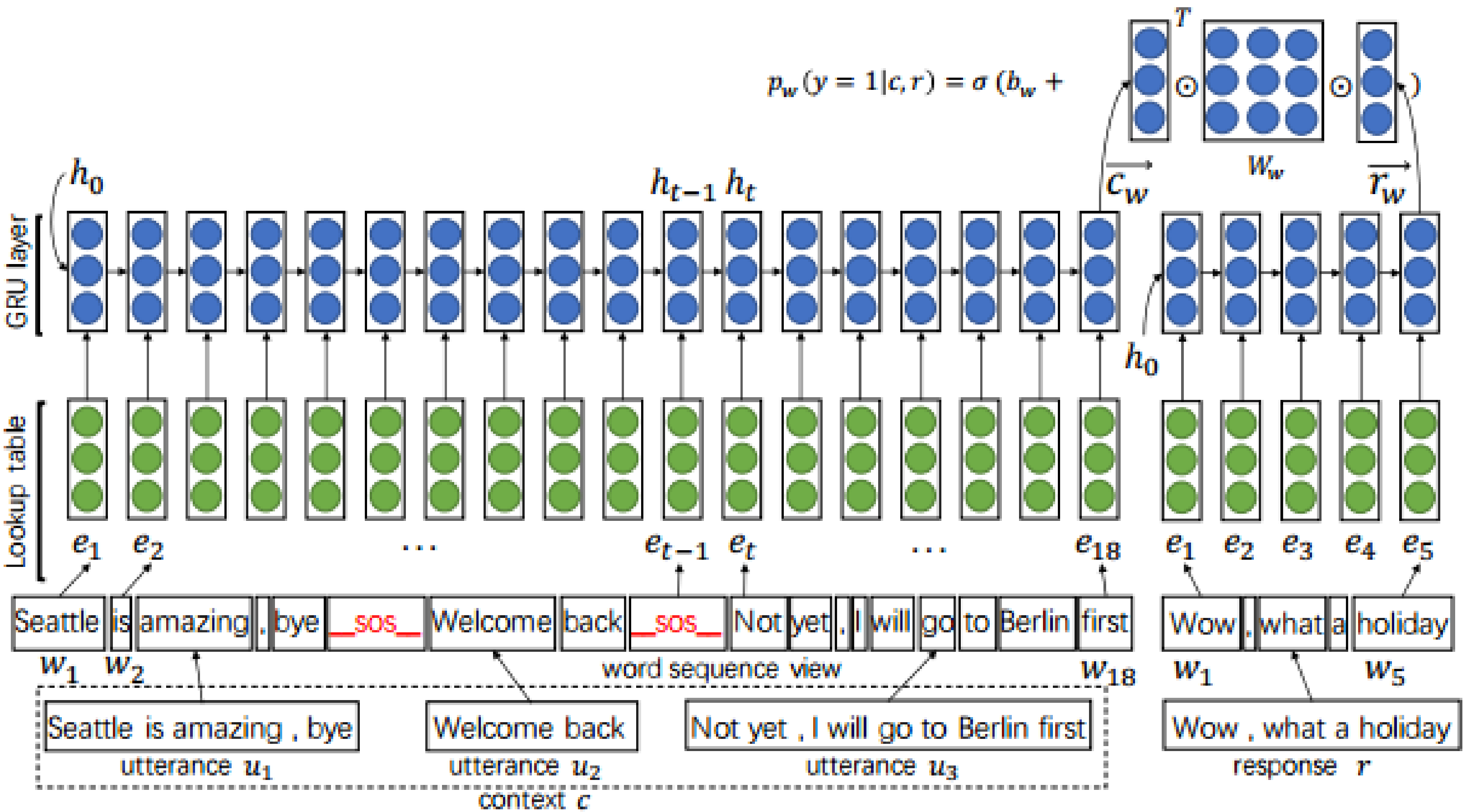
- **Sum-Product Process**

$$\mathcal{F}(q_0, r) = \sum_{i=0}^{|Q|} \left(h(q_0, q_i) \sum_{p} \left(f(q_i, r) \cdot g(q_i, p) \right) \right)$$

Word Sequence Model

- **Response selection**
  - Choose a response given contexts

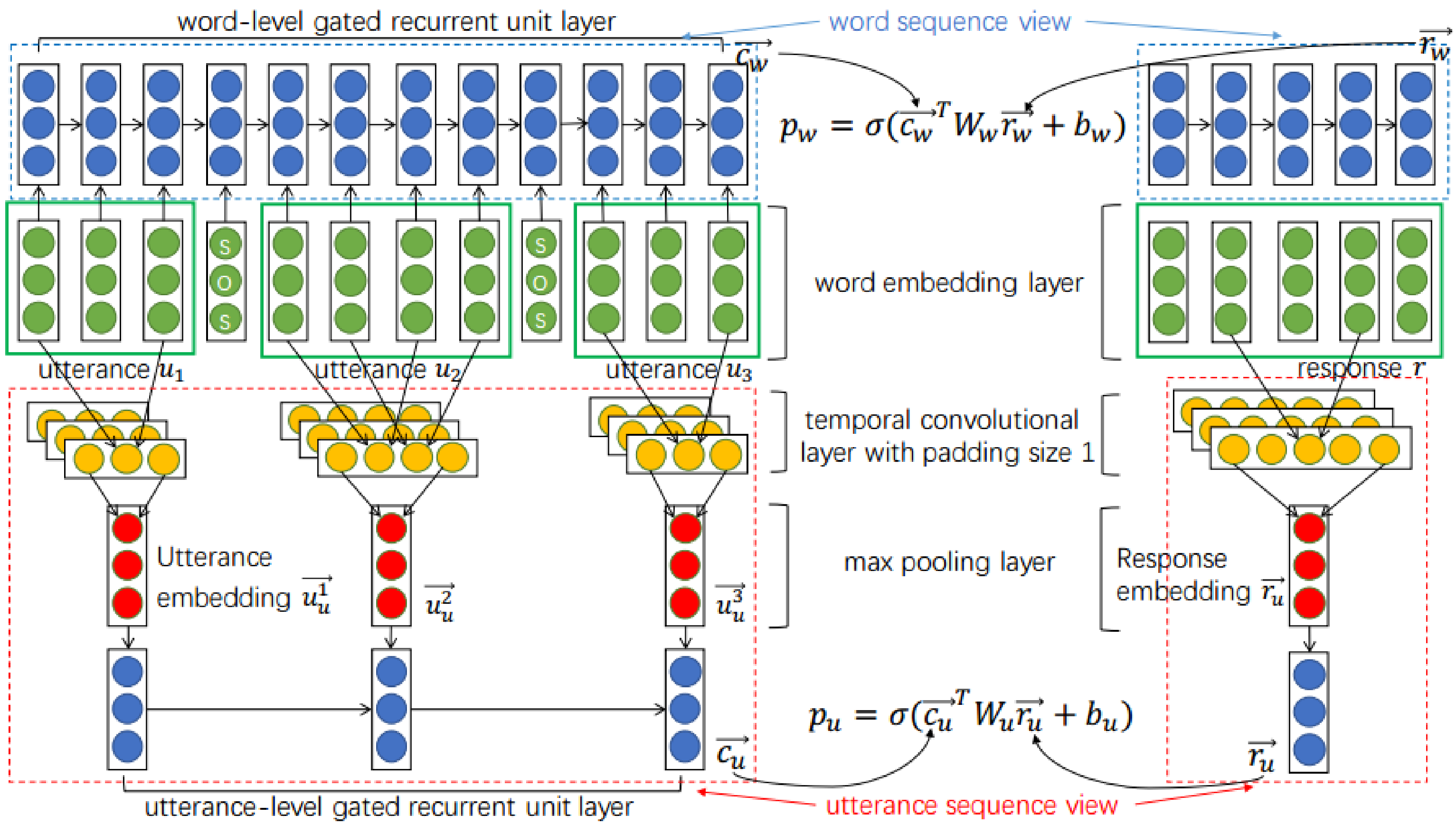
Zhou et al., EMNLP'16



Multi-view Model

- **Views: hierarchical**
  - Word sequence
  - Utterance sequence

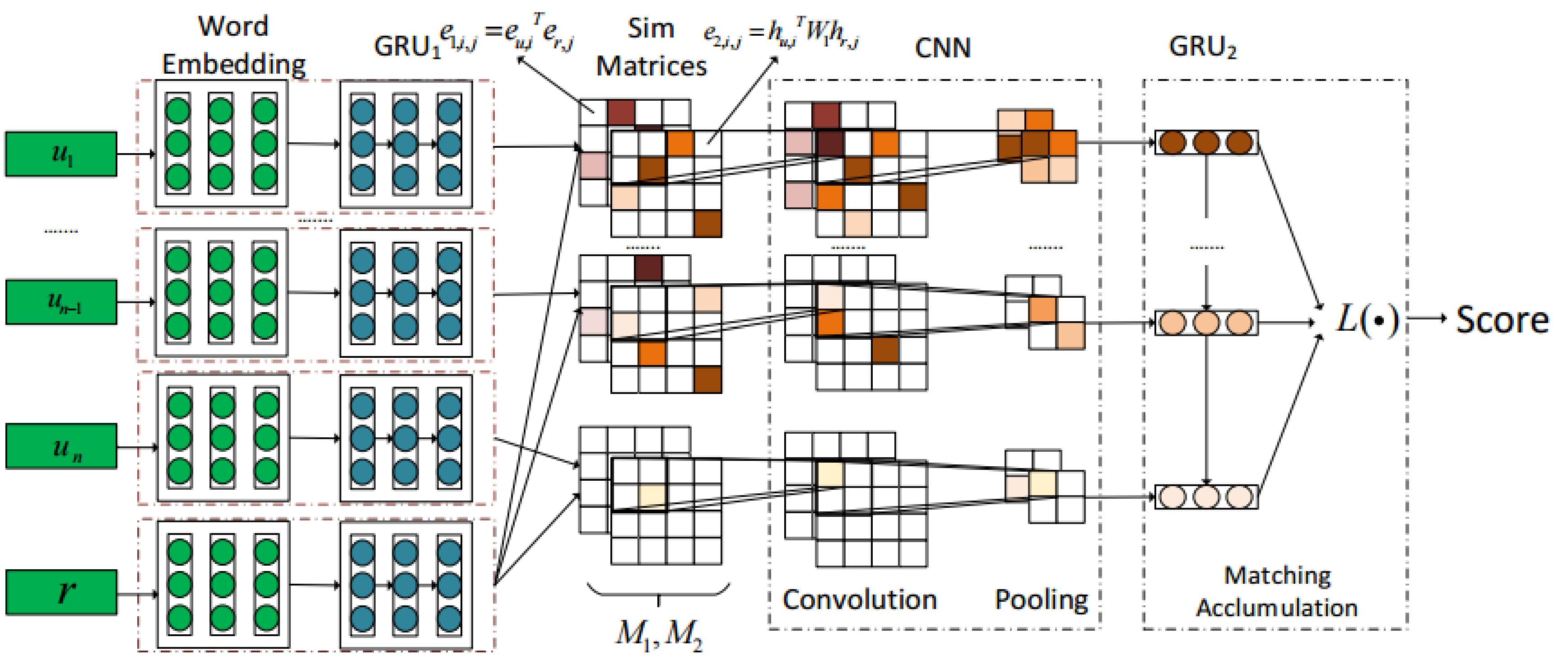
Zhou et al., EMNLP'16



Sequential Match Network

- **Context modeling with sequential utterances**
  - M1: match on the word-level
  - M2: match on the segment-level (based on position)
  - Convolution and pooling
  - Matching sequence

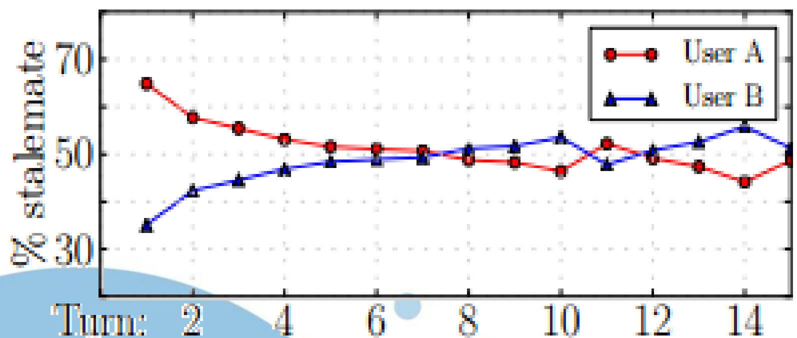
Wu et al., arXiv'16

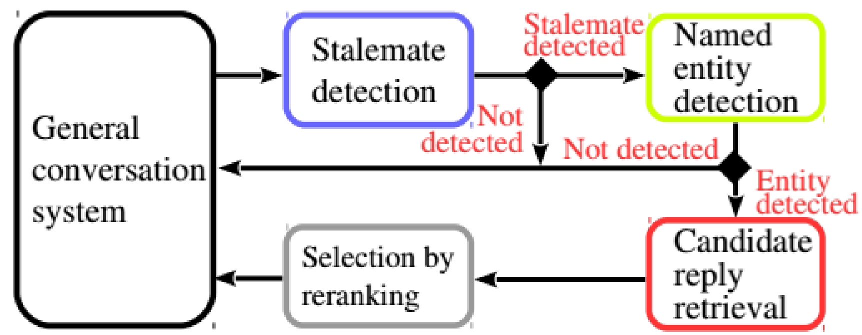


Add-On Component

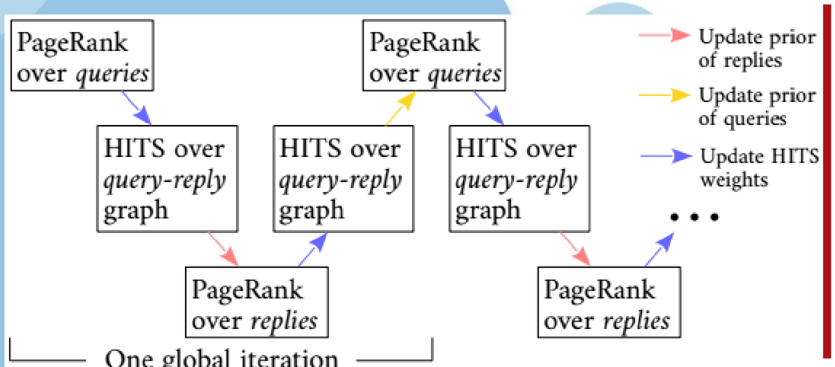
- **StalementBreaker**
- **Human-human conversation**
  - Everyone leads the conversation!

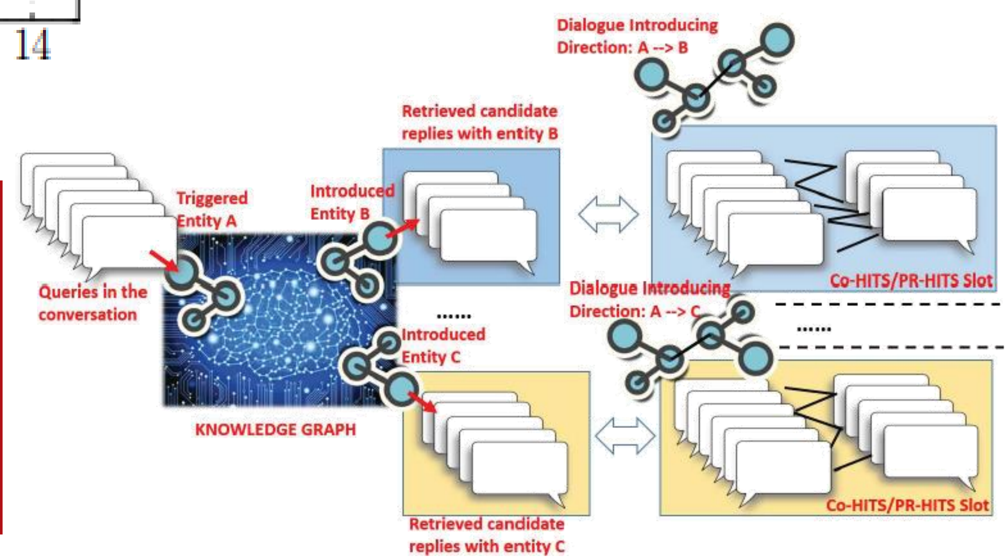
Li et al., IJCAI'16





- **Ranking algorithm**

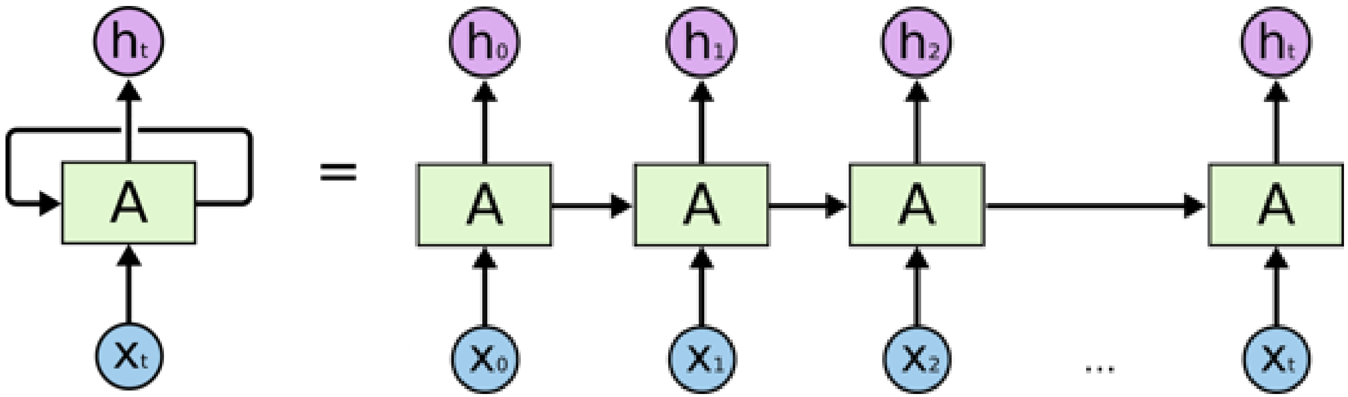




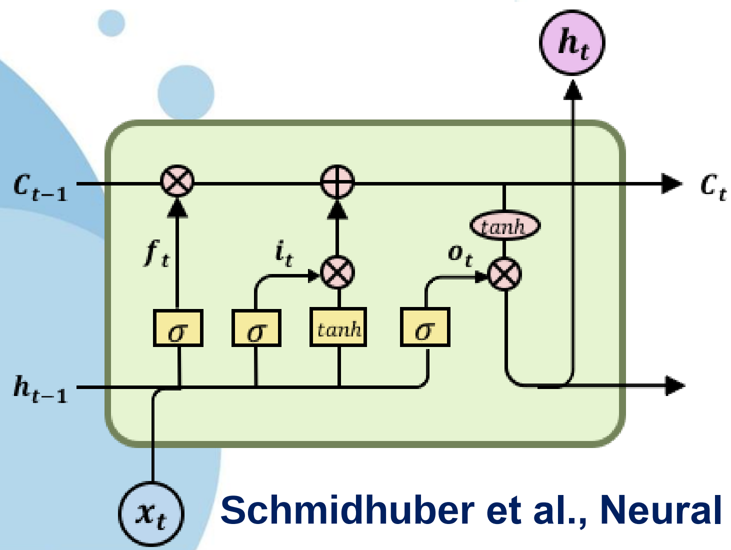
GENERATION-BASED CONVERSATION SYSTEM

RNN Family

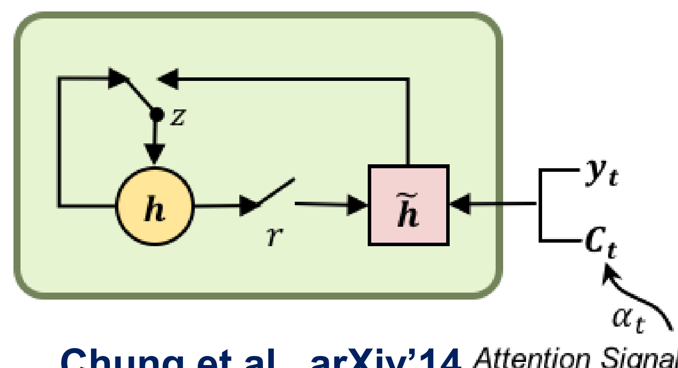
- **Recurrent Neural Networks**
  - Vanilla RNN



  - LSTM
  - GRU



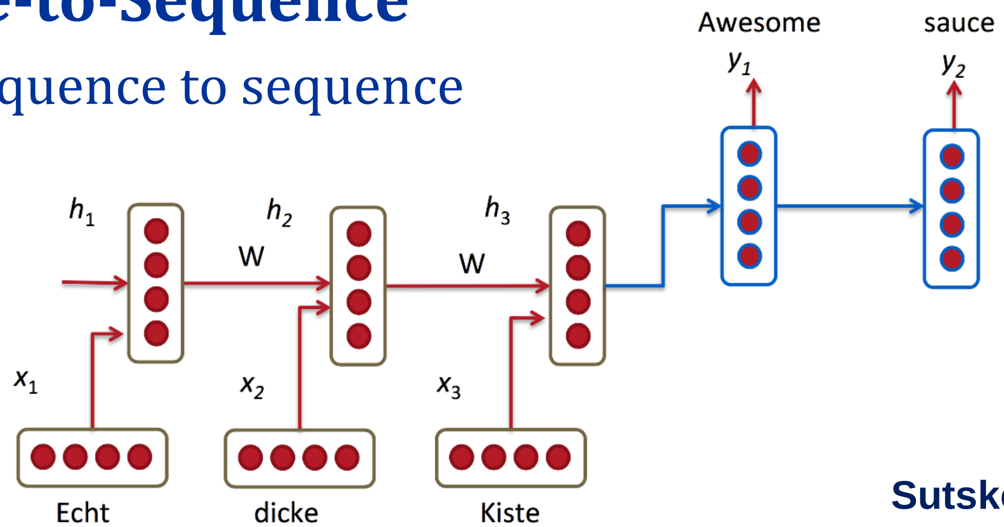
Schmidhuber et al., Neural Computing’97



Chung et al., arXiv’14

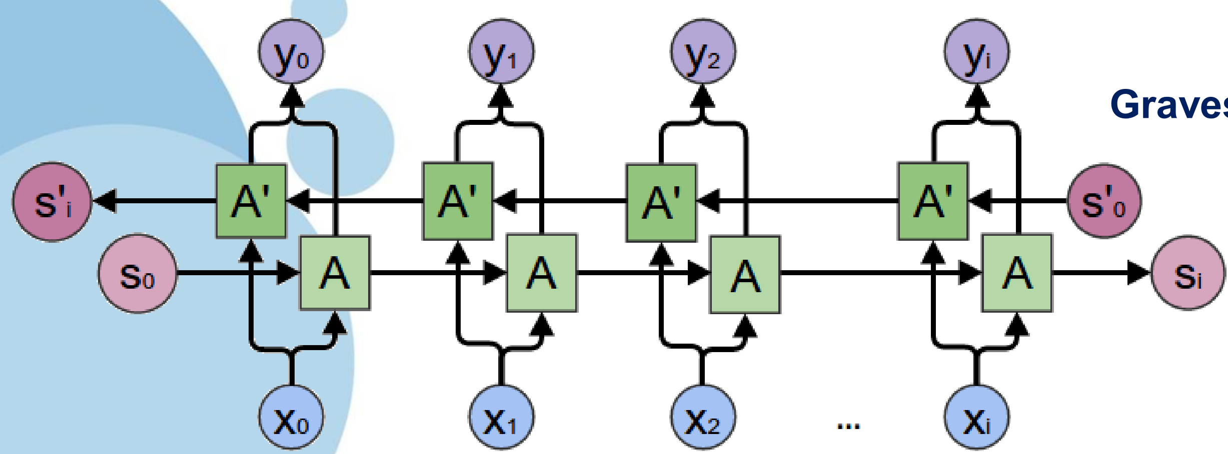
Sequence-to-Sequence

- **Sequence-to-Sequence**
  - Basic sequence to sequence



Sutskever et al., NIPS'14

  - Sequential modeling with bi-directions



Graves et al., ASSP'13

Attention Mechanism

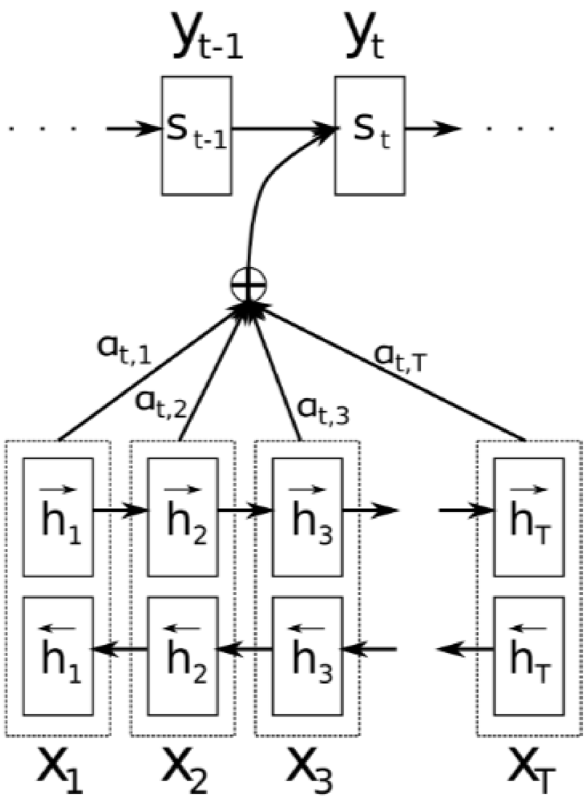
- **Attention signal**

Bahdanau et al., ICLR'14

$$c_i = \sum_{j=1}^{T_x} \alpha_{ij} h_j$$

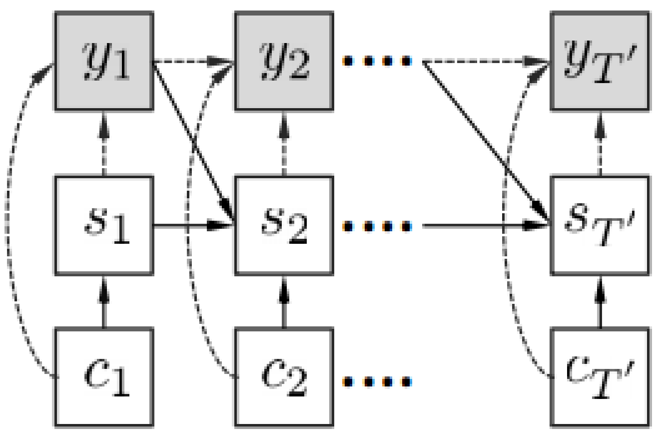
$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_{k=1}^{T_x} \exp(e_{ik})}$$

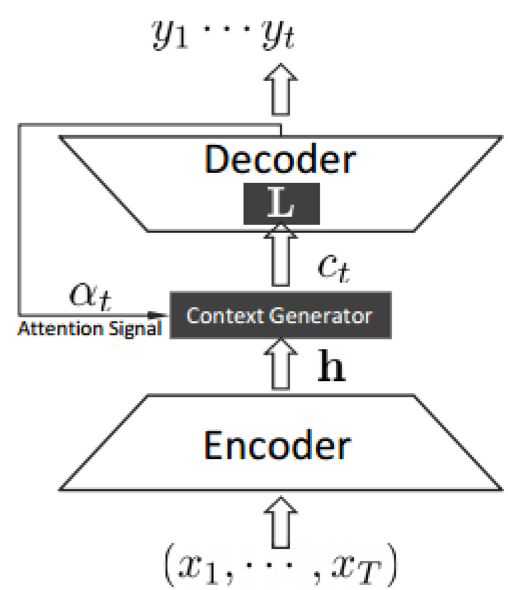
$$e_{ij} = v_a^{\top} \tanh(W_a s_{i-1} + U_a h_j)$$



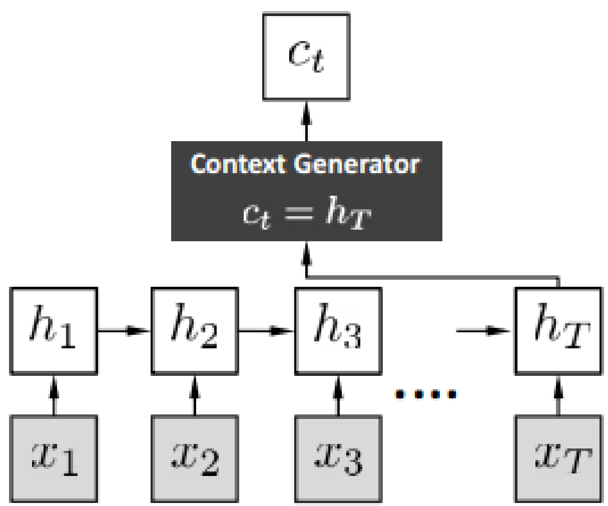
Neural Responding

- **Encoder-decoder with attention signal**
  - Decoder





  - Encoder: global

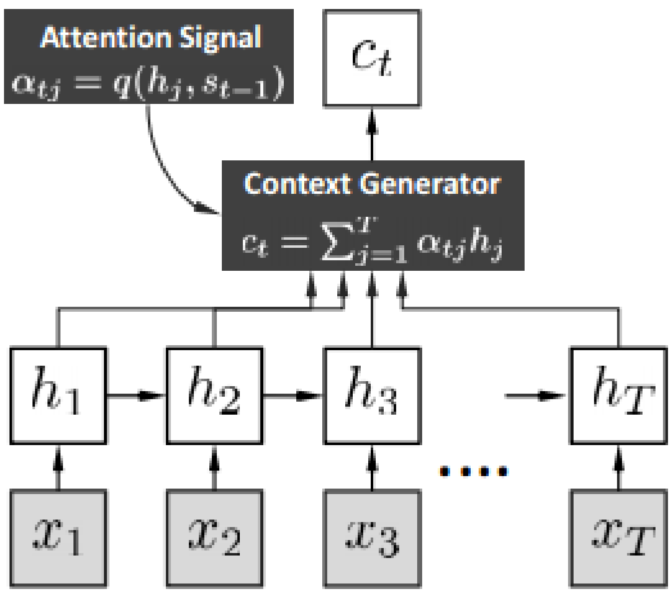


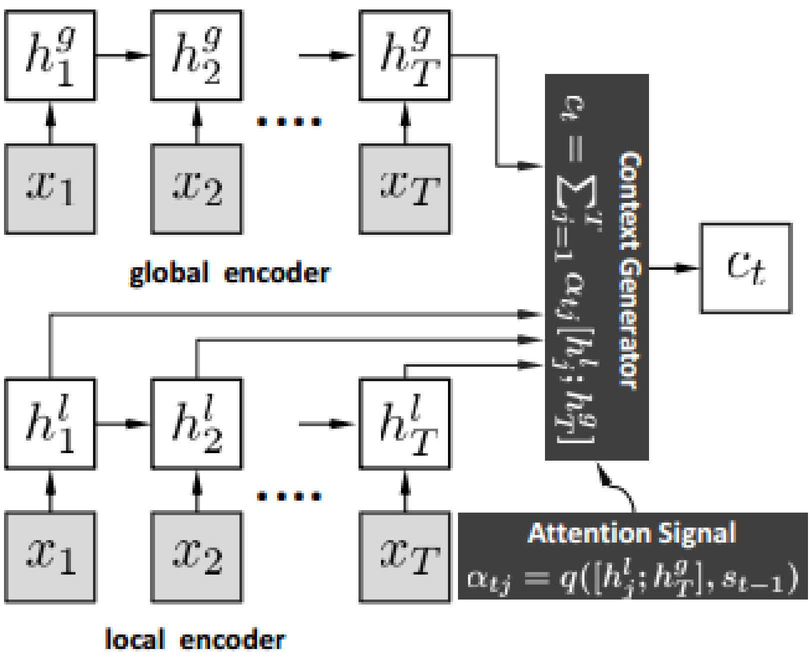
Shang et al., ACL'15

Neural Responding Machine

- **Encoder-decoder with attention signal**
  - More encoders: local schema
  - Combinatory schema

Shang et al., ACL'15

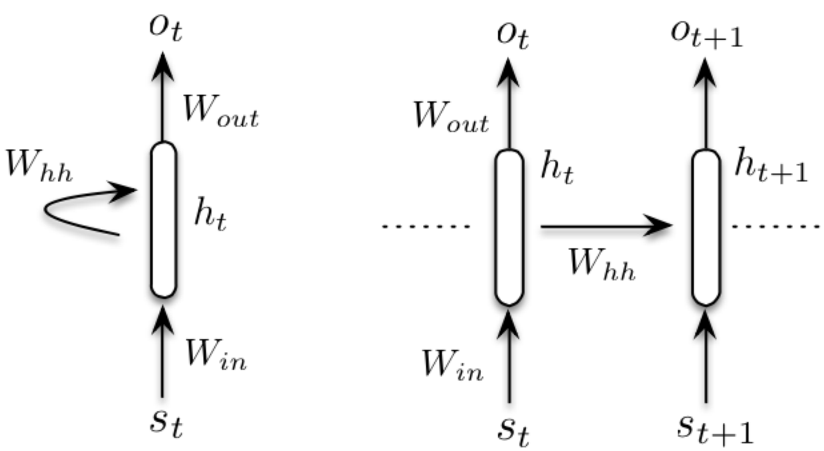


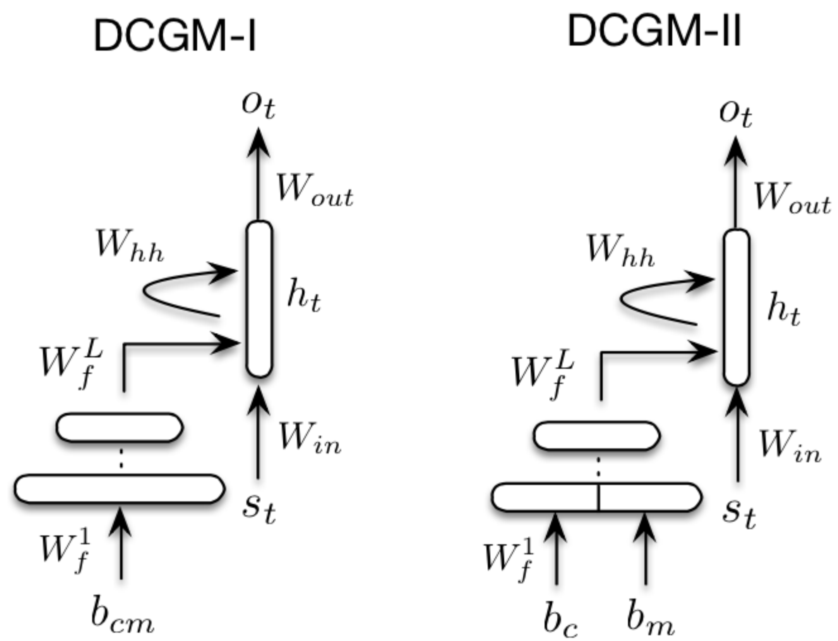


Context-Sensitive Generation

- **Encoder-Decoder with Contextual information**
  - Concatenate each utterance c, m, r into a single sentence s
- **Strengthening the context bias**
  - Bag-of-words
  - Concatenation

Sordoni et al., NAACL-HLT'15

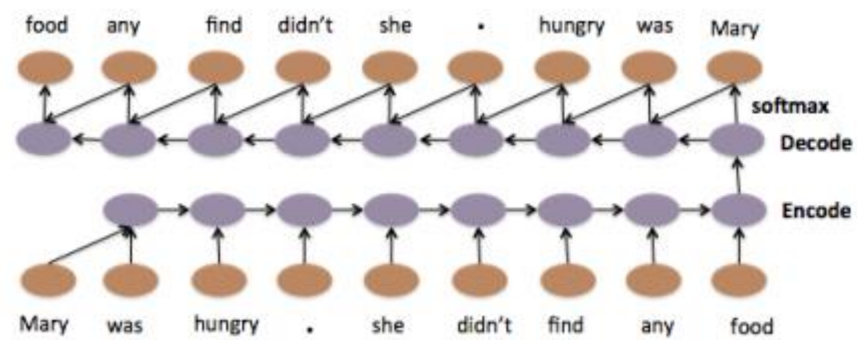


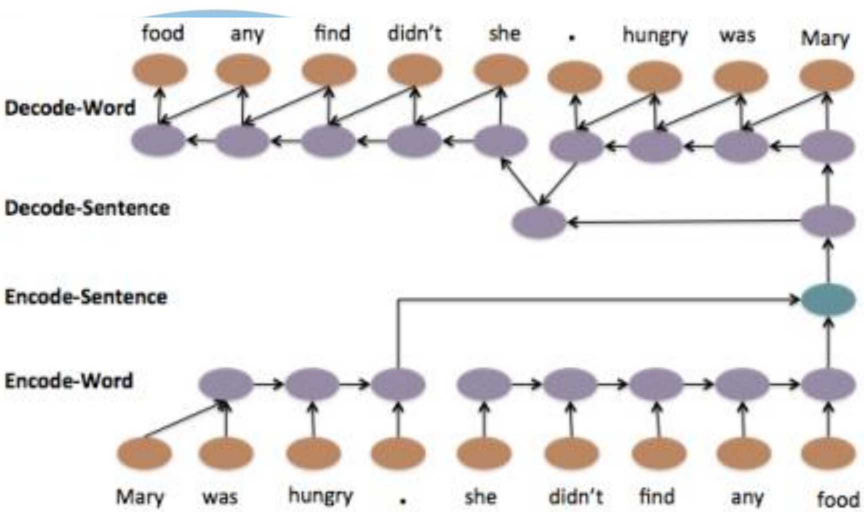


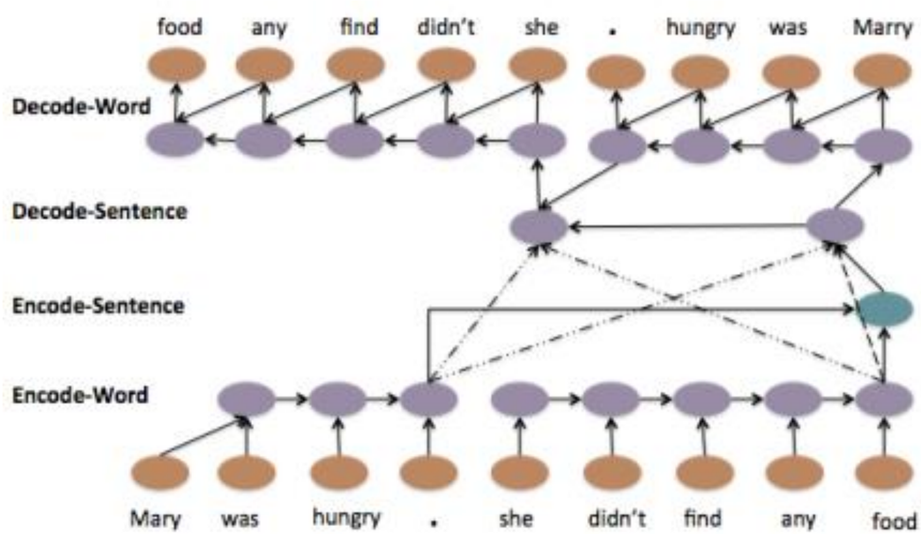
Hierarchical Language Model

- **Hierarchy**
  - Word level
  - Sentence level
- **Auto-Encoder**

Li et al., ACL'15



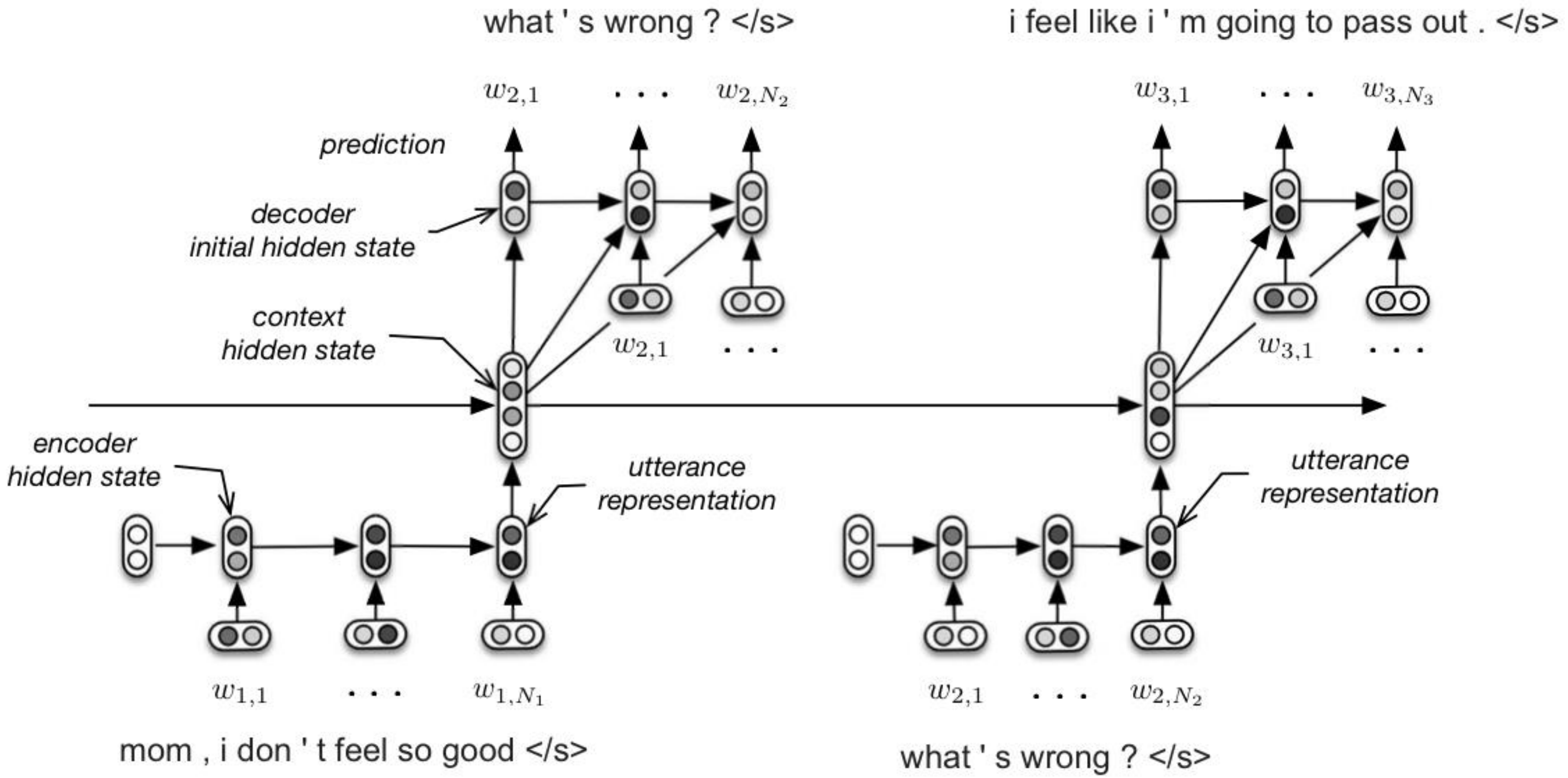




Hierarchical Encoder-decoder

- **HRED (hierarchical recurrent encoder decoder)**
  - Hierarchical architecture (two levels)
    - a sequence of words for each utterance
    - a sequence of utterances

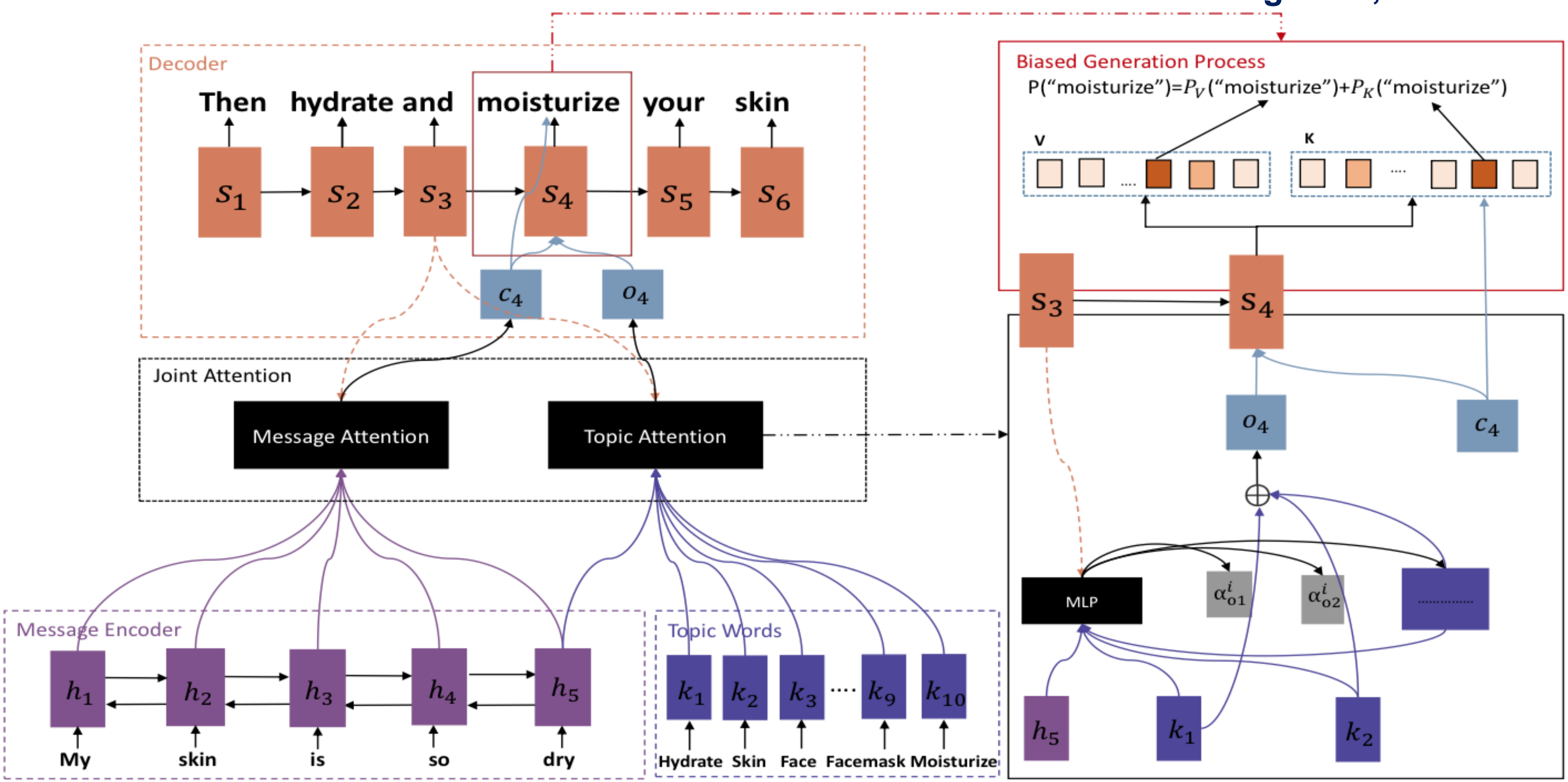
Serban et al., AAAI'16



Topic-Aware Generation

- **TA-Seq2Seq (Topic Aware Seq2Seq)**
  - Topic attention obtained from a pre-trained LDA model

Xing et al., arXiv'16

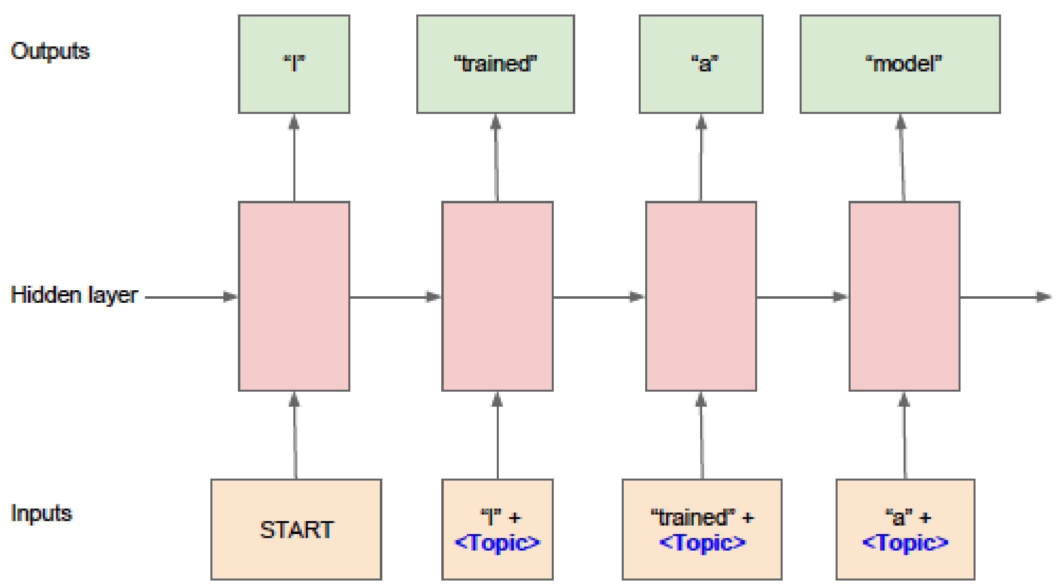


Contextual LSTM

- **Add the topic vector T**

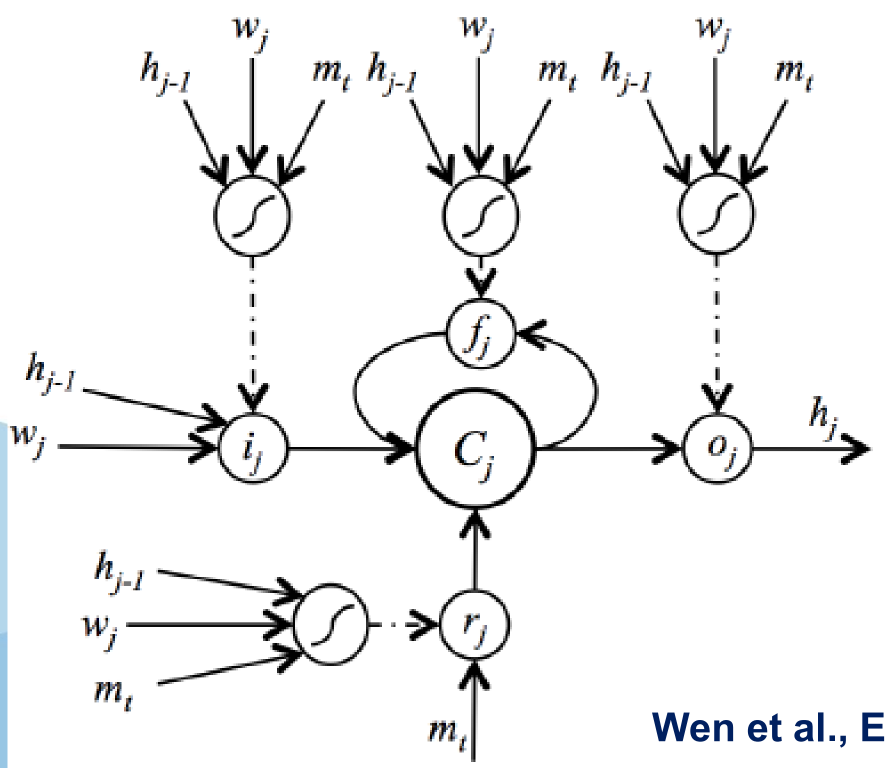
Ghosh et al., KDD'16 Workshop

$$
\begin{aligned}
i_t &= \sigma(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i + \mathbf{W}_{\mathbf{T}\mathrm{i}}\mathbf{T}) \\
f_t &= \sigma(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f + \mathbf{W}_{\mathbf{T}\mathrm{i}}\mathbf{T}) \\
c_t &= f_t c_{t-1} + i_t \tanh(W_{xc}x_t + W_{hc}h_{t-1} + b_c + \mathbf{W}_{\mathbf{T}\mathrm{i}}\mathbf{T}) \\
o_t &= \sigma(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o + \mathbf{W}_{\mathbf{T}\mathrm{i}}\mathbf{T}) \\
h_t &= o_t \tanh(c_t)
\end{aligned}
$$



Conditional Generation Network

- **Memory type LSTM**



$$\begin{pmatrix} \mathbf{i}_j \\ \mathbf{f}_j \\ \mathbf{o}_j \\ \mathbf{r}_j \end{pmatrix} = \begin{pmatrix} \text{sigmoid} \\ \text{sigmoid} \\ \text{sigmoid} \\ \text{sigmoid} \end{pmatrix} \mathbf{W}_{4n,3n} \begin{pmatrix} \mathbf{m}_t \\ \mathbf{w}_j \\ \mathbf{h}_{j-1} \end{pmatrix}$$

$$\hat{\mathbf{c}}_j = \tanh\left(\mathbf{W}_c(\mathbf{w}_j \oplus \mathbf{h}_{j-1})\right)$$

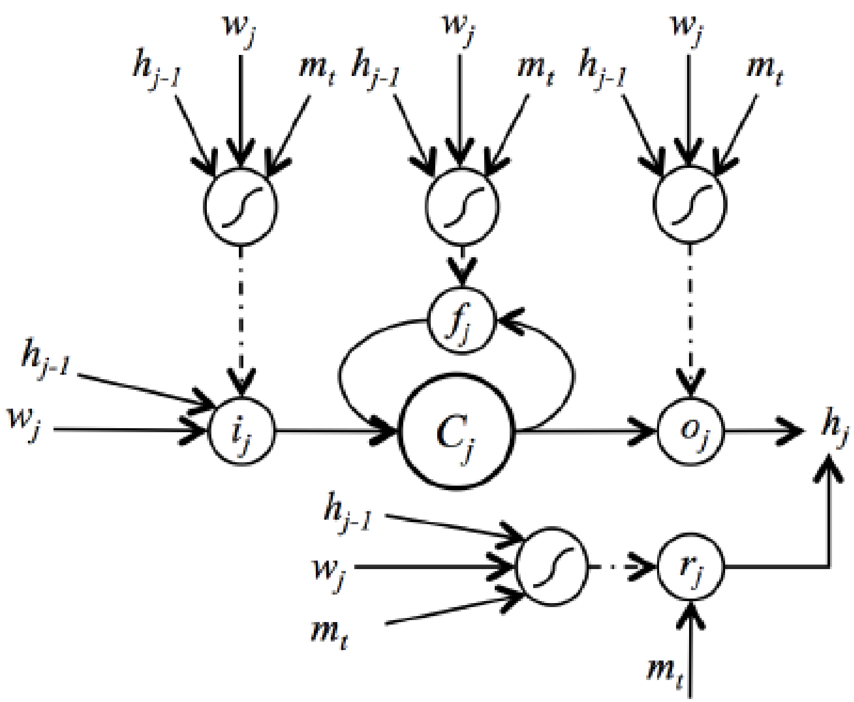
$$\mathbf{c}_j = \mathbf{f}_j \odot \mathbf{c}_{j-1} + \mathbf{i}_j \odot \hat{\mathbf{c}}_j + \mathbf{r}_j \odot \mathbf{m}_t$$

$$\mathbf{h}_j = \mathbf{o}_j \odot \tanh(\mathbf{c}_j)$$

Wen et al., EMNLP'16

Conditional Generation Network

- **Hybrid type LSTM**



$$\begin{pmatrix} \mathbf{i}_j \\ \mathbf{f}_j \\ \mathbf{o}_j \\ \mathbf{r}_j \end{pmatrix} = \begin{pmatrix} \text{sigmoid} \\ \text{sigmoid} \\ \text{sigmoid} \\ \text{sigmoid} \end{pmatrix} \mathbf{W}_{4n,3n} \begin{pmatrix} \mathbf{m}_t \\ \mathbf{w}_j \\ \mathbf{h}_{j-1} \end{pmatrix}$$

$$\hat{\mathbf{c}}_j = \tanh\left(\mathbf{W}_c(\mathbf{w}_j \oplus \mathbf{h}_{j-1})\right)$$

$$\mathbf{c}_j = \mathbf{f}_j \odot \mathbf{c}_{j-1} + \mathbf{i}_j \odot \hat{\mathbf{c}}_j$$

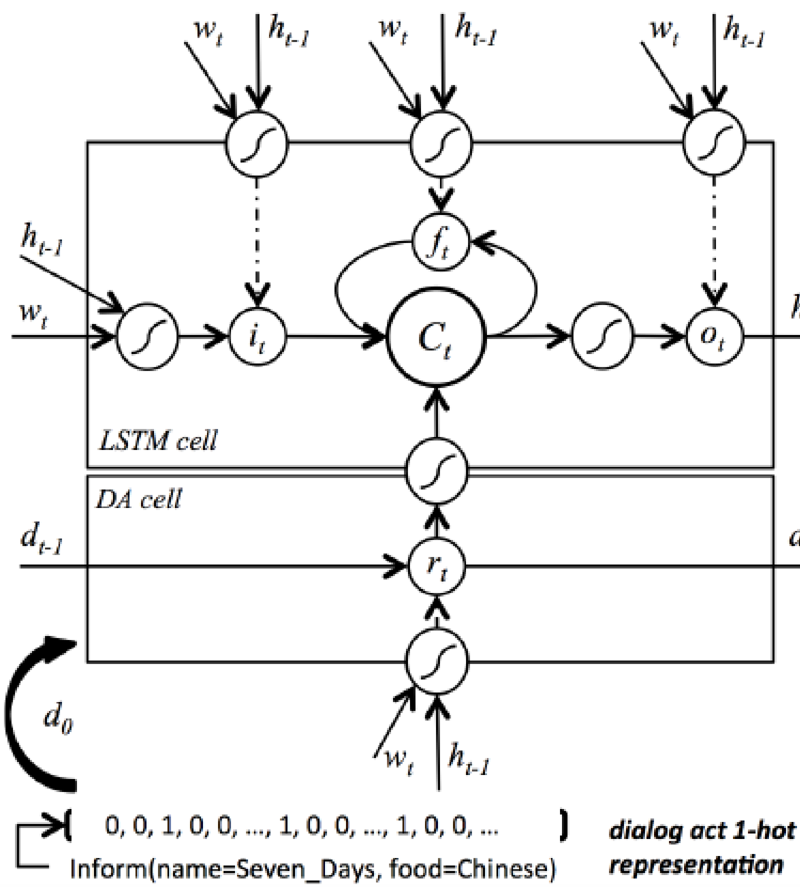
$$\mathbf{h}_j = \mathbf{o}_j \odot \tanh(\mathbf{c}_j) + \mathbf{r}_j \odot \mathbf{m}_t$$

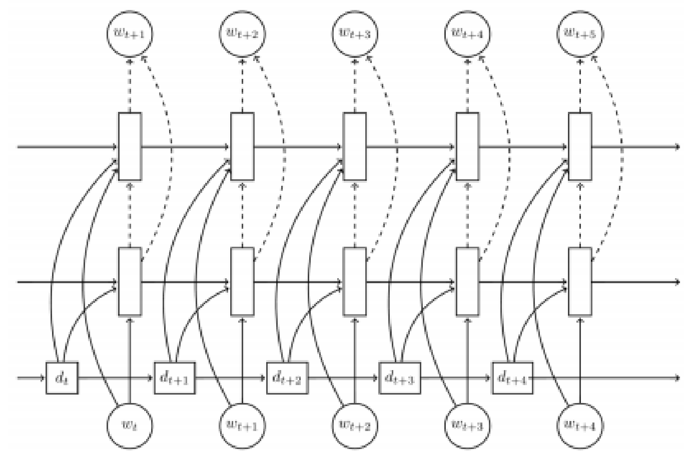
Wen et al., EMNLP’16

Semantically Conditioned LSTM

- **Semantic controlled LSTM**

Wen et al., EMNLP'15





$$\mathbf{i}_t = \sigma(\mathbf{W}_{wi}\mathbf{w}_t + \mathbf{W}_{hi}\mathbf{h}_{t-1})$$
$$\mathbf{f}_t = \sigma(\mathbf{W}_{wf}\mathbf{w}_t + \mathbf{W}_{hf}\mathbf{h}_{t-1})$$
$$\mathbf{o}_t = \sigma(\mathbf{W}_{wo}\mathbf{w}_t + \mathbf{W}_{ho}\mathbf{h}_{t-1})$$
$$\hat{\mathbf{c}}_t = tanh(\mathbf{W}_{wc}\mathbf{w}_t + \mathbf{W}_{hc}\mathbf{h}_{t-1})$$
$$\mathbf{r}_t = \sigma(\mathbf{W}_{wr}\mathbf{w}_t + \alpha\mathbf{W}_{hr}\mathbf{h}_{t-1})$$
$$\mathbf{d}_t = \mathbf{r}_t \odot \mathbf{d}_{t-1}$$
$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \hat{\mathbf{c}}_t + tanh(\mathbf{W}_{dc}\mathbf{d}_t)$$
$$\mathbf{h}_t = \mathbf{o}_t \odot tanh(\mathbf{c}_t)$$

Generation Overview

- **Case studies**

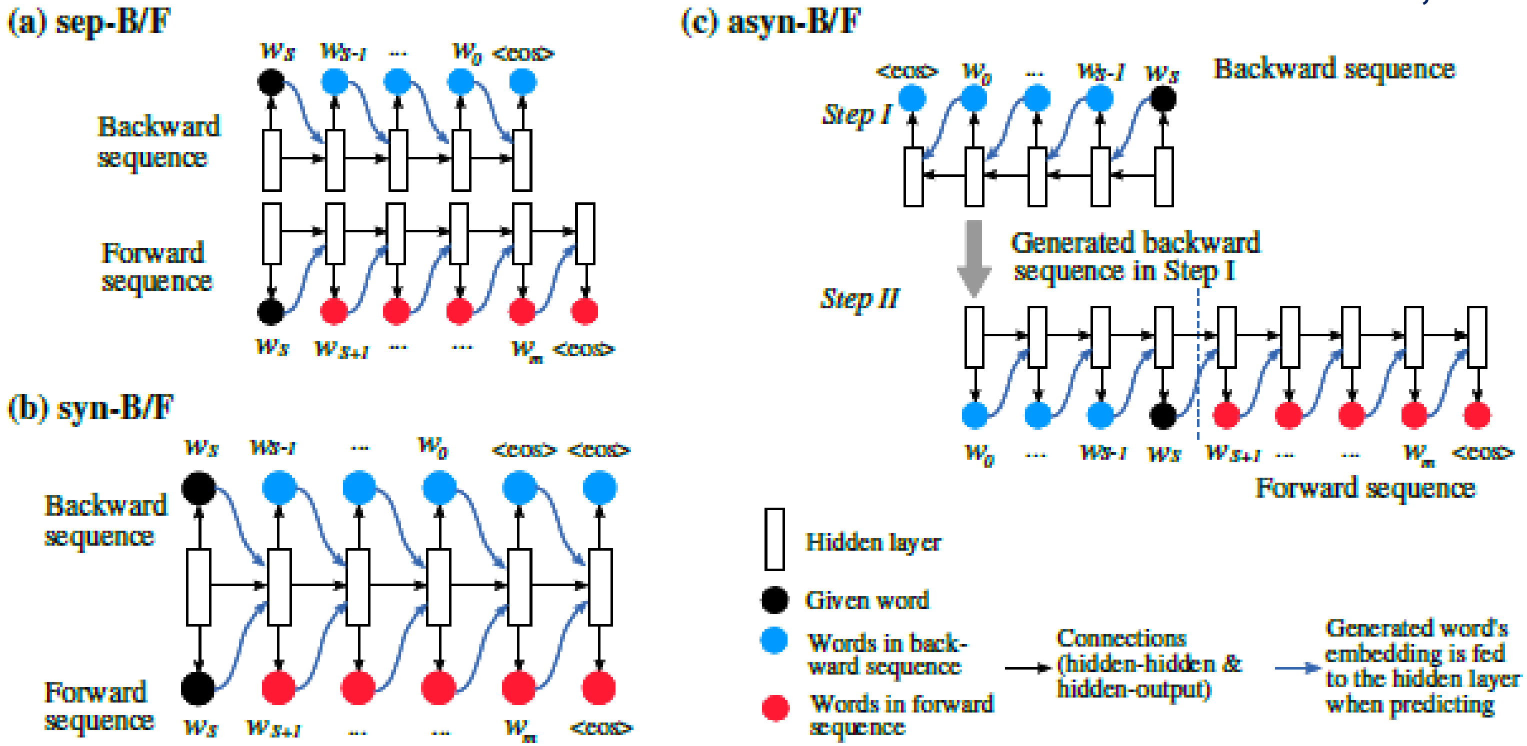
Wen et al., EMNLP'15

#	Example Dialogue Acts and Realizations from SF Restaurant Domain
1	inform(name="red door cafe", goodformeal="breakfast", area="cathedral hill", kidsallowed="no") *red door cafe is a good restaurant for breakfast in the area of cathedral hill and does not allow children .* *red door cafe is a good restaurant for breakfast in the cathedral hill area and does not allow children .* *red door cafe is a good restaurant for breakfast in the cathedral hill area and does not allow kids .* *red door cafe is good for breakfast and is in the area of cathedral hill and does not allow children .* *red door cafe does not allow kids and is in the cathedral hill area and is good for breakfast .*
2	informonly(name="dosa on fillmore and kiss seafood", pricerange="expensive", near="lower pacific heights") *there is no place other than dosa on fillmore and kiss seafood that are expensive near to lower pacific heights .* *dosa on fillmore and kiss seafood is the only expensive restaurant near lower pacific heights .* *the only listed restaurant near lower pacific heights in the expensive price range is dosa on fillmore and kiss seafood .* *i apologize , dosa on fillmore and kiss seafood is the only expensive restaurant near lower pacific heights .* *i apologize , dosa on fillmore and kiss seafood are the only expensive restaurants near lower pacific heights .*
#	**Example Dialogue Acts and Realizations from SF Hotel Domain**
3	inform(type="hotel",count="182",dogsallowed="dontcare") *there are 182 hotels if you do not care whether dogs are allowed .* *there are 182 hotels if you do not care whether they allow dogs .* *182 hotels are available if dogs allowed or not is not an issue .* *there are 182 hotels if allowing dogs or not is not an issue .* *there are 182 hotels if whether dogs are allowed does not matter .*
4	informonly(name="red victorian bed breakfast",acceptscreditcards="yes",near="haight",hasinternet="yes") *red victorian bed breakfast is the only hotel near haight and accepts credit cards and has internet .* *red victorian bed breakfast is the only hotel near haight and has internet and accepts credit cards .* *red victorian bed breakfast is the only hotel near haight that accept credit cards and offers internet .* *the red victorian bed breakfast has internet and near haight , it does accept credit cards .* *the red victorian bed breakfast is the only hotel near haight that accepts credit cards , and offers internet .*

Language Generation

- **Constrained language generation**
- **Models: Backward/Forward Language Modeling**
  - sep-B/F v.s. syn-B/F v.s. asyn-B/F

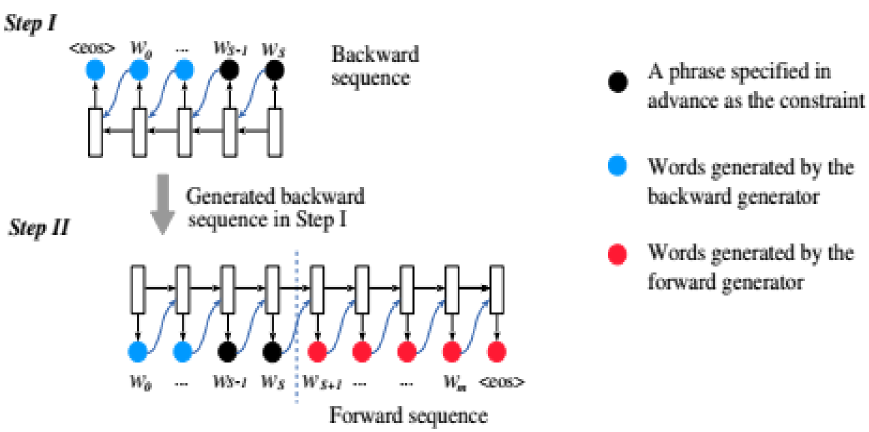
Mou et al., arXiv'15

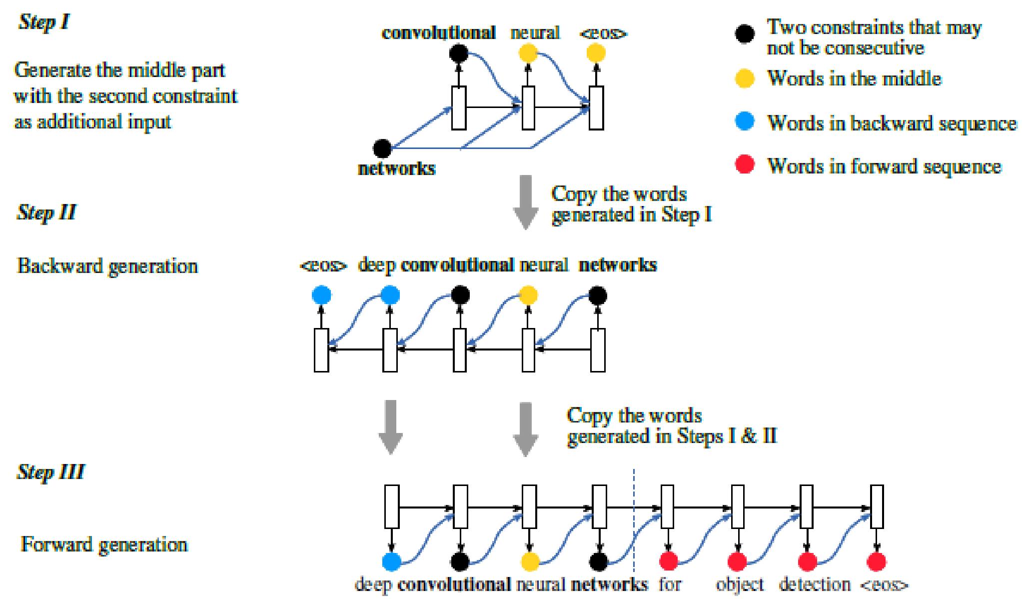


Extensions & Applications

- **Extensions**
  - Constraints of phrases
  - Constraints of multi-terms

Mou et al., arXiv'15





- **Applications**
  - Two-step conversation generation
    - Step 1: keyword generation
    - Step 2: Backward/Forward language generation

2-Step Conversation

- **Overview**
  - Step I: predict a keyword using PMI
  - Step II: sequence generation with the predicted keyword
- **Keyword prediction**
  - For a query word and a reply word:

$$\mathrm{PMI}(w_q, w_r) = \log \frac{p(w_q, w_r)}{p(w_q)p(w_r)} = \log \frac{p(w_q|w_r)}{p(w_q)}$$

  - For all the words in the query

$$\mathrm{PMI}(w_{q_1} \cdots w_{q_n}, w_r) = \log \frac{p(w_{q_1} \cdots w_{q_n}|w_r)}{p(w_{q_1} \cdots w_{q_n})}$$

$$\approx \log \frac{\prod_{i=1}^{n} p(w_{q_i}|w_r)}{\prod_{i=1}^{n} p(w_{q_i})} = \sum_{i=1}^{n} \log \frac{p(w_{q_i}|w_r)}{p(w_{q_i})} = \sum_{i=1}^{n} \mathrm{PMI}(w_{q_i}, w_r)$$

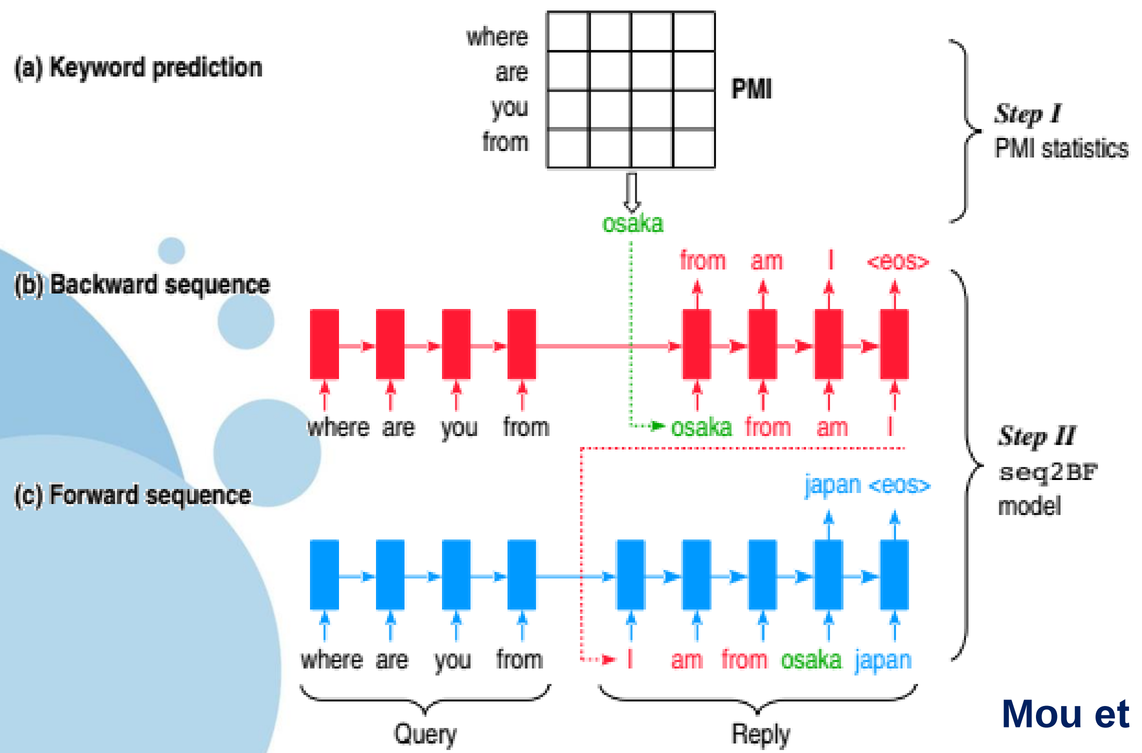
- **PMI prefers a word that is most "mutually informative" with the query**

Mou et al., COLING'16

Content Introducing

- **Generation Process**
  - Backward sequence
  - Forward sequence

$$p\left(\begin{array}{c} r_{k-1}\cdots r_1 \\ \hdashline r_{k+1}\cdots r_m \end{array}\middle| r_k, \boldsymbol{q}\right) = \prod_{i=1}^{k-1} p^{(\mathrm{bw})}(r_{k-i}|r_k, \boldsymbol{q}, \cdot) \prod_{i=1}^{m-k} p^{(\mathrm{fw})}(r_{k+i}|r_k, \boldsymbol{q}, \cdot)$$



Mou et al., COLING'16

Content Introducing Case

- **Case studies**

	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 **rumore**d 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**

Diversity in Conversation

- **A well-known problem for conversation generation**
  - Diversity-promoting
- **Maximum mutual information criterion**
  - Standard objective

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

  - MMI objective

$$\log \frac{p(S,T)}{p(S)p(T)}$$

Li et al., NAACL'16

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

Diversity in Conversation

- **MMI objective**

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

- **Penalty parameter**

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

- **Bayes theorems**

$$\log p(T) = \log p(T|S) + \log p(S) - \log p(S|T)$$

- Final representation

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

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.

Li et al., NAACL'16

Persona in Conversation

- **What is persona and why?**
  - Motivation examples
  - Incoherent personality makes it impossible for current systems to pass the Turing test
  - Embedding based persona

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.

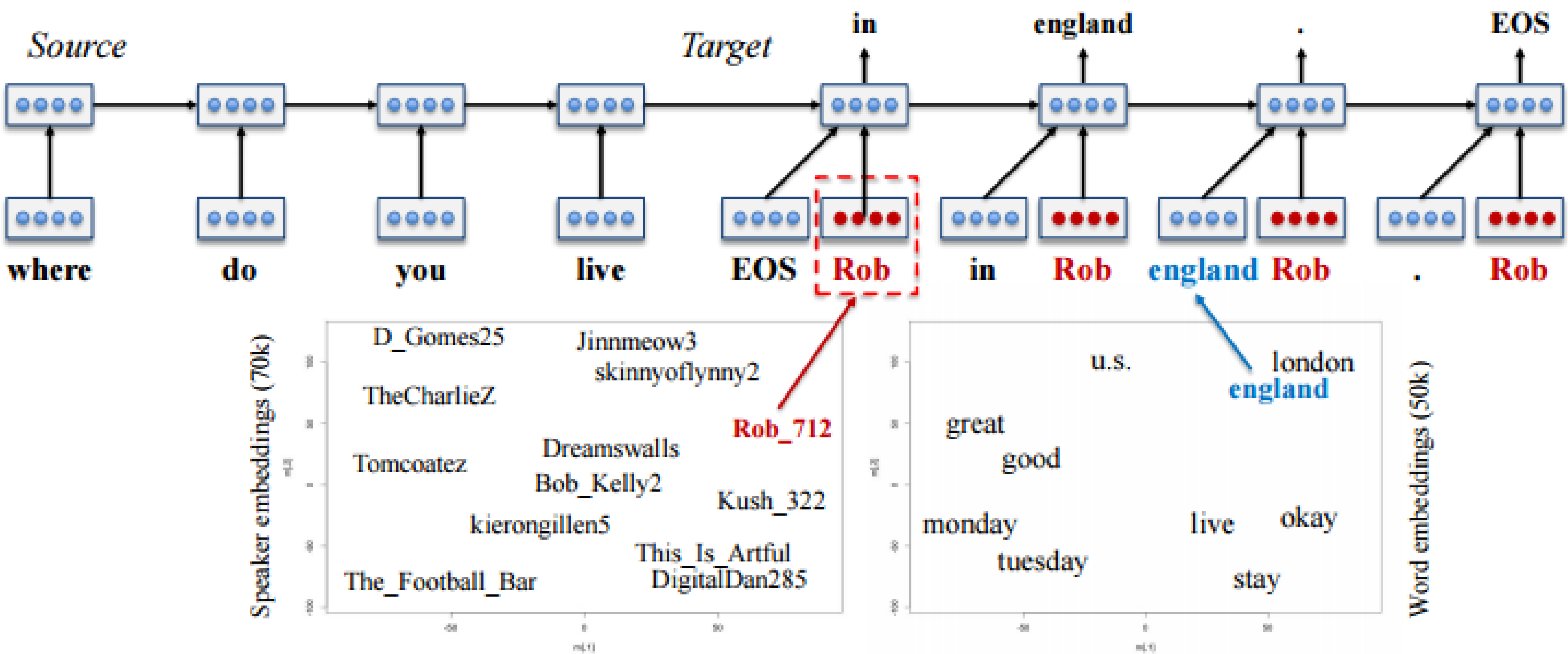
Li et al., ACL'16

Speaker Model

- **What is persona and why?**
  - Persona as additional input
  - Possible benefits: inference in persona

$$\begin{bmatrix} i_t \\ f_t \\ o_t \\ l_t \end{bmatrix} = \begin{bmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{bmatrix} W \cdot \begin{bmatrix} h_{t-1} \\ e_t^s \\ v_i \end{bmatrix}$$

Li et al., ACL'16



Model Extension

- **Speaker-addressee model**
  - Speaker vector
  - Addressee vector

$$V_{i,j} = \tanh(W_1 \cdot v_i + W_2 \cdot v_2)$$

Li et al., ACL'16

- **Reranking**
  - Persona fit?
  - Message fit?
  - Length penalty

$$\log p(R|M, v) + \lambda \log p(M|R) + \gamma |R|$$

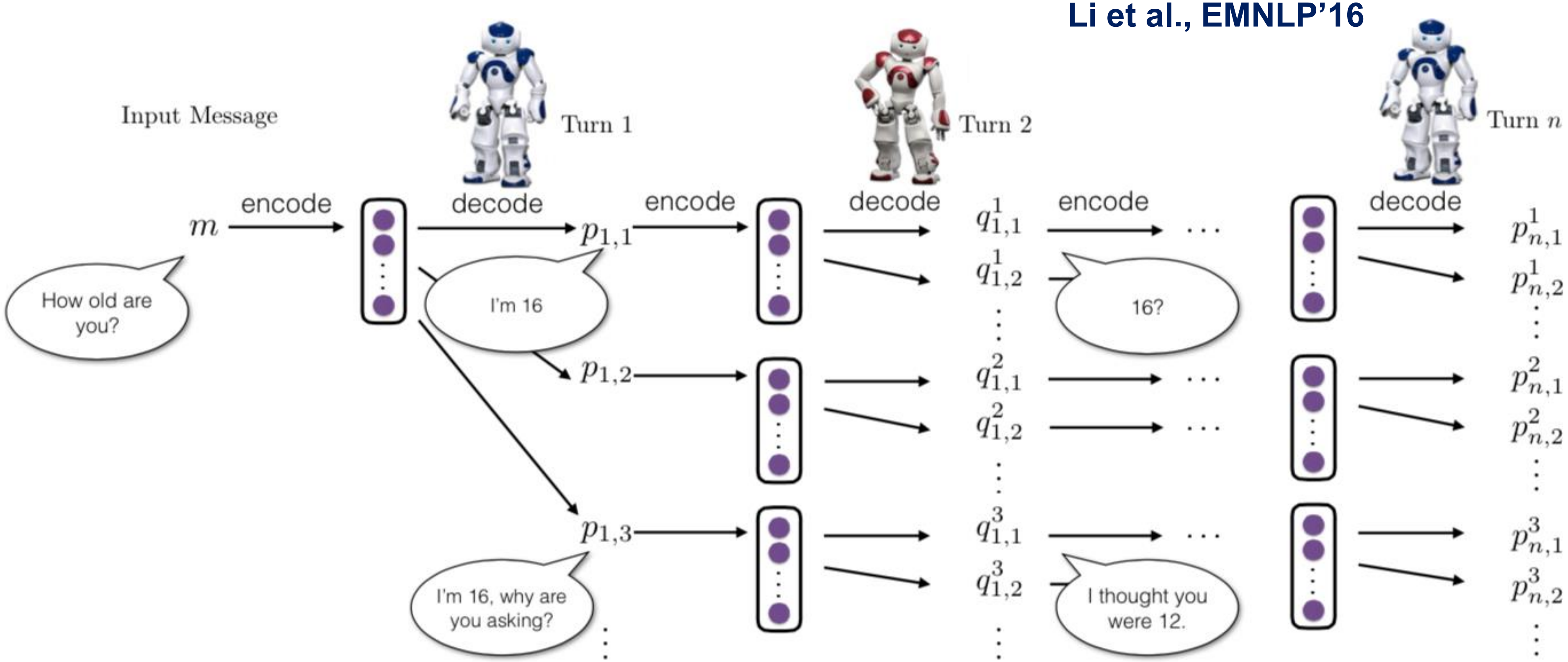
message	Where is your hometown?
baseline	I was born in Canada.
user1	I'm from England.
user2	I'm from Manchester.
user3	I'm from Liverpool.
user4	England. You?
user5	My hometown.
user6	I'm from Texas.
user7	I'm from LA.
user8	England.
user9	I was born here.
user10	I was born in the us.

User1	
message	Where is your hometown?
response	I'm from England.
message	Where are you from?
response	I'm from England.
message	In which city do you live now?
response	I live in London.
message	In which country do you live now?
response	I live in England.
message	What is your major?
response	Business. You?
message	What did you study in college?
response	I did business studies.
message	How old are you?
response	I'm 18.
message	What is your age?
response	I'm 18.

Reinforcement Learning

- **Modeling the future direction by RL**
  - Conversation between two virtual agents
  - Explore the space of possible actions while learning to maximize expected reward

Li et al., EMNLP'16

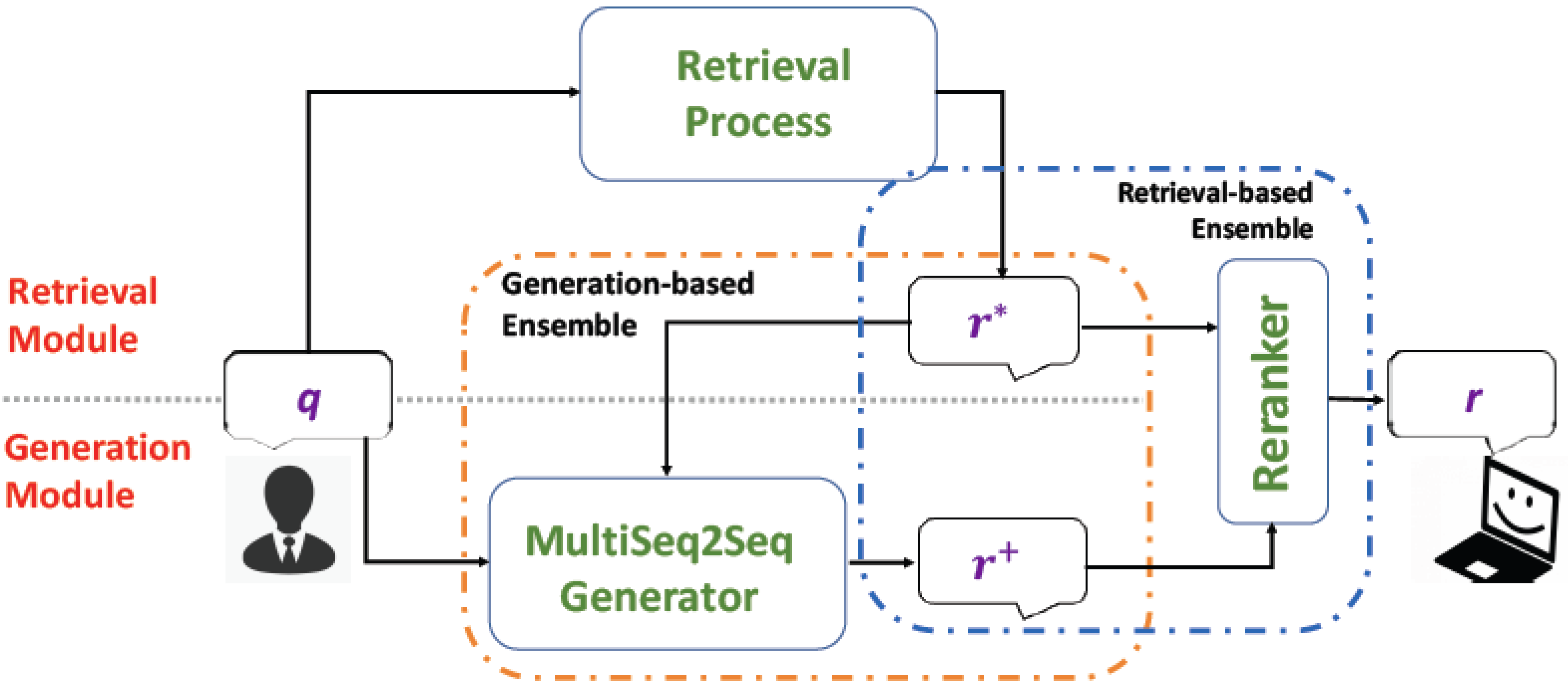


GENERATION + RETRIEVAL CONVERSATION SYSTEM

Motivation

- **Why**
  - Retrieval is not enough?
  - Generation is not enough as well?
- **Retrieval + generation framework**

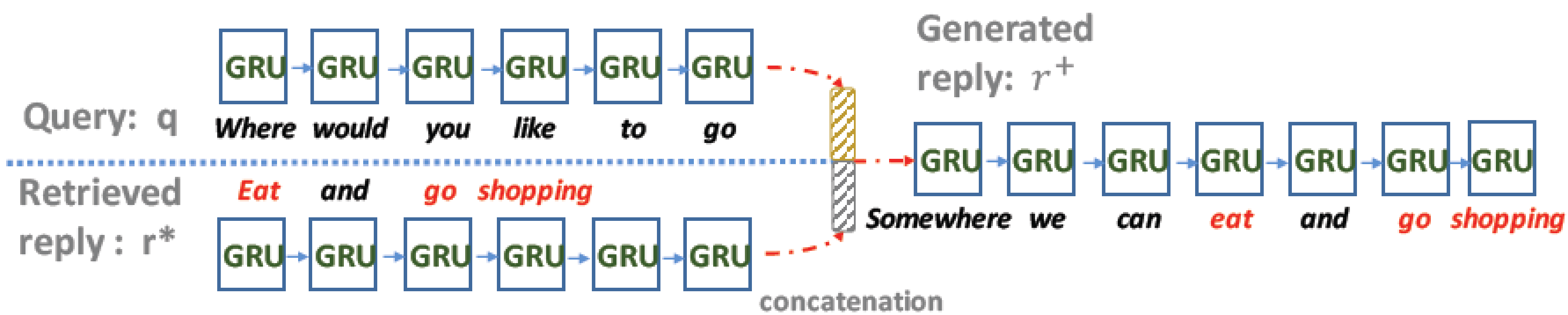
Song et al., arXiv'16



Methodology

- **Generation process**
  - Component ensemble

Song et al., arXiv'16



	Utterance (Translated)	Reranked
Query	这款手机的拍照效果真不错 (This mobile phone's photo effect is pretty good.)	
Retrieved	所以好心动 (I really have a crush on it.)	
biseq2seq	心动不如行动 (Rushing for it rather than having a crush on it.)	√
seq2seq	哈哈 (Haha)	
Query	有给孕妇推荐的保健品啥的么？ (Could you please recommend some health products for pregnant woman?)	
Retrieved	打算上孕妇装？ (Do you want metarnity clothes?)	
biseq2seq	打算买护肤品么？ (Do you want some skin care products?)	√
seq2seq	不好意思 (I'm sorry.)	

Thank You

- Q & A
- Email to:

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