Towards Different Perspectives in Automatic Human-Computer Conversational Systems

#Go_ChatBots!!

Rui Yan, Peking University

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Brief History

**Keyword Spotting**
(e.g., AT&T)
System: “Please say collect, calling card, person, third number, or operator”

**Early 1990s**

**Early 2000s**

TV Voice Search
e.g., Bing on Xbox

**2017**

**Virtual Personal Assistants**
Apple Siri (2011)
Facebook M & Bot (2015)
Google Home (2016)
Microsoft Cortana (2014)
Amazon Alexa/Echo (2014)
Google Now (2012)
Google Assistant (2016)

**Task-specific argument extraction**
(e.g., Nuance, SpeechWorks)

**User:** “I want to fly from Boston to New York next week.”

**Intent Determination**
(Nuance’s Emily™, AT&T HMIHY)
**User:** “Uh...we want to move...we want to change our phone line from this house to another house”

**Chatbots**
Why Do We Need

• Get things done
  • E.g. set up alarm/reminder, take note

• Easy access to structured data, services and apps
  • E.g. find docs/photos/restaurants

• Assist your daily schedule and routine
  • E.g. commute alerts to/from work

• Be more productive in managing your work and personal life
APP->Bots

- A bot is responsible for a “single” domain, similar to an app

Users can initiate dialogues instead of following the GUI design
GUI -> Conversational UI
## GUI vs. CUI

<table>
<thead>
<tr>
<th></th>
<th>Website/APP’s GUI</th>
<th>Msg’s CUI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Situation</strong></td>
<td>Navigation, no specific goal</td>
<td>Searching, with specific goal</td>
</tr>
<tr>
<td><strong>Information Quantity</strong></td>
<td>More</td>
<td>Less</td>
</tr>
<tr>
<td><strong>Information Precision</strong></td>
<td>Low</td>
<td>High</td>
</tr>
<tr>
<td><strong>Display</strong></td>
<td>Structured</td>
<td>Non-structured</td>
</tr>
<tr>
<td><strong>Interface</strong></td>
<td>Graphics</td>
<td>Language</td>
</tr>
<tr>
<td><strong>Manipulation</strong></td>
<td>Click</td>
<td>mainly use texts or speech as input</td>
</tr>
<tr>
<td><strong>Learning</strong></td>
<td>Need time to learn and adapt</td>
<td>No need to learn</td>
</tr>
<tr>
<td><strong>Entrance</strong></td>
<td>App download</td>
<td>Incorporated in any msg-based interface</td>
</tr>
<tr>
<td><strong>Flexibility</strong></td>
<td>Low, like machine manipulation</td>
<td>High, like converse with a human</td>
</tr>
</tbody>
</table>
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...
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…
Background Knowledge

- Machine learning ≈ looking for a function

Speech Recognition
\[ f(\text{声波信号}) = \text{“你好 (Hello)”} \]

Image Recognition
\[ f(\text{猫}) = \text{cat} \]

Go Playing
\[ f(\text{围棋}) = 5-5 \text{ (next move)} \]

Chat Bot
\[ f(\text{“Where is Westin?”}) = \text{“The address is...”} \]

Given a large amount of data, the machine learns what the function \( f \) should be.
Deep learning is a type of machine learning approaches, called “neural networks”.
A Single Neuron

\[ y = h_{w,b}(x) = \sigma(w^T x + b) \]

**Activation function**

\[ \sigma(z) = \frac{1}{1 + e^{-z}} \]

**Sigmoid function**

\[ w, b \] are the parameters of this neuron
A Single Neuron

\[ y = h_{w,b}(x) = \sigma(w^T x + b) \]

Activation function

Sigmoid function

\[ \sigma(z) = \frac{1}{1 + e^{-z}} \]

\( w, b \) are the parameters of this neuron
How Does It Work?

A single neuron can only handle binary classification

\[ f : \mathbb{R}^N \rightarrow \mathbb{R}^M \]

\[
\begin{cases}
\text{is "2"} & y \geq 0.5 \\
\text{not "2"} & y < 0.5
\end{cases}
\]
A Layer of Neurons

A layer of neurons can handle multiple possible output, and the result depends on the max one.
Deep Neural Networks

Fully connected feedforward network

\[ f: \mathbb{R}^N \rightarrow \mathbb{R}^M \]

Deep NN: multiple hidden layers
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
Categorizations

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RETRIEVAL-BASED CONVERSATION SYSTEM
Dataset

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

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**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.*

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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

  $$\text{match}(x, y) = \langle \Phi_Y(x), \Phi_X(y) \rangle_H$$

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

- **From Linear to Deep**
  - Localness
  - Hierarchy

  Lu et al., NIPS’13
Neural Network Structure

- Connect with topic patterns
  
  \[ T_\ell \]
  
  \[ T_{\ell-1} \]

- Matching architecture

Lu et al., NIPS’13
Convolutions

• Convolutional sentence model

Illustration of convolutional sentence model

Hu et al., NIPS’14
**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

<table>
<thead>
<tr>
<th></th>
<th>Conv-pooling LSTM ((c=4000,K=1))</th>
<th>Conv-pooling LSTM ((c=200,K=50))</th>
<th>Conv-pooling LSTM ((c=400,K=50))</th>
</tr>
</thead>
<tbody>
<tr>
<td>E</td>
<td>66.2</td>
<td>66.4</td>
<td>67.8</td>
</tr>
<tr>
<td>F</td>
<td>64.6</td>
<td>67.4</td>
<td>67.5</td>
</tr>
<tr>
<td>G</td>
<td>66.0</td>
<td>66.1</td>
<td>67.6</td>
</tr>
<tr>
<td>I</td>
<td>67.1</td>
<td>67.6</td>
<td>64.4</td>
</tr>
</tbody>
</table>
CNN+RNN Match + Attention

- Question-Answer Matching
- Attentive matching

\[ m_{a,q}(t) = W_{am} h_{a}(t) + W_{qm} o_q \]
\[ s_{a,q}(t) \propto \exp(w_{ms}^T \tanh(m_{a,q}(t))) \]
\[ \tilde{h}_a(t) = h_a(t) s_{a,q}(t) \]

| 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** |

Tan et al., ACL’16
Positional Matching

- Positional-based match

- Attention-based ranking

Wan et al., AAAI’16

Liu et al., CIKM’16
Recursive Matching

- Fused recursive match
- Recursive match

Liu et al., ACL’16
Wan et al., IJCAI’16

Liu et al., ACL’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

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

Yan et al., SIGIR’16

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Human-Computer Conversation

<table>
<thead>
<tr>
<th>Task Formulation</th>
</tr>
</thead>
<tbody>
<tr>
<td>User query: $q_0 = A_2$</td>
</tr>
<tr>
<td>Context information: $C = {c_1 = A_1, c_2 = B_1}$</td>
</tr>
<tr>
<td>Reformulated queries: $q_1 = A_2 \sqcap A_1, q_2 = A_2 \sqcap B_1, q_3 = A_2 \sqcap A_1 \sqcap B_1, \ldots$</td>
</tr>
<tr>
<td>Top-1 ranked response: $r^* = \text{Reply}_1$</td>
</tr>
</tbody>
</table>
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**

- **Sum-Product Process**

\[
F(q_0, r) = \sum_{i=0}^{\lvert Q \rvert} h(q_0, q_i) \sum_p (f(q_i, r) \cdot g(q_i, p))
\]

Yan et al., SIGIR’16
**Word Sequence Model**

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

Zhou et al., EMNLP’16

```
p_w(y = 1|c, r) = \sigma(h_w + \cdot c_w + \cdot w_w + \cdot r_w)
```
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!

- **Ranking algorithm**

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Li et al., IJCAI’16

![Diagram of the general conversation system](image)
Gossips and Impacts

- Pilot study and state-of-the-art
- News media coverage
  - Been reported within only 3 days after got published on arXiv
  - UK DailyMail, The Stack, Headline Today, China Science, Peking University News and several others

Li et al., IJCAI’16
Re-thinking

• Till now we ALREADY have a well-defined paradigm for conversational systems
  • Given a human utterance as a query, the system returns a response
  • The most standard situation: a single q to a single r
  • Some extensions: many q to a single r for multi-turn conversations [Yan et al., SIGIR’16]

• Query suggestions is important in IR
A New Idea

• What if
  • we borrow the query suggestion solution in conversation systems?
  • E.g. “response ranking” and “next utterance suggestion” simultaneously

• Potential benefits
  • From passive conversation mode to proactive conversation mode
  • Brings information outside users’ scope
  • Improve conversational experiences

• Typical situations
  • Predict something that users might say next
  • New contents to talk about: people are open-minded in chit-chat
A New Task

- **Problem formulation**
  - Given a query $q$
  - Retrieve a candidate response $r$
  - Suggest a next utterance $s$
  - A triple of $\{q, r, s\}$

- Given the candidate responses $r$ and suggestions $s$, we learn to couple them together so as to rank a pair of $(r, s)$ given $q$.

- **A ranking function**
  $$ (r, s)^* = \arg\max_{r,s} \mathcal{F}((r, s)|q) $$
Dual-LSTM Chain Model

- Model framework

Yan et al., SIGIR’17
## Results

### Appropriateness

<table>
<thead>
<tr>
<th>Model</th>
<th>p@1</th>
<th>MAP</th>
<th>nDCG</th>
<th>MRR</th>
<th>Tier</th>
</tr>
</thead>
<tbody>
<tr>
<td>Okapi BM25</td>
<td>0.272</td>
<td>0.253</td>
<td>0.302</td>
<td>0.169</td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>0.259</td>
<td>0.226</td>
<td>0.284</td>
<td>0.156</td>
<td>II</td>
</tr>
<tr>
<td></td>
<td>0.138</td>
<td>0.126</td>
<td>0.187</td>
<td>0.091</td>
<td>III</td>
</tr>
<tr>
<td>ARC-II</td>
<td>0.394</td>
<td>0.294</td>
<td>0.421</td>
<td>0.232</td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>0.387</td>
<td>0.291</td>
<td>0.415</td>
<td>0.217</td>
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</tr>
<tr>
<td></td>
<td>0.255</td>
<td>0.201</td>
<td>0.278</td>
<td>0.142</td>
<td>III</td>
</tr>
<tr>
<td>LSTM-RNN</td>
<td>0.338</td>
<td>0.283</td>
<td>0.371</td>
<td>0.228</td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>0.351</td>
<td>0.300</td>
<td>0.366</td>
<td>0.237</td>
<td>II</td>
</tr>
<tr>
<td></td>
<td>0.206</td>
<td>0.195</td>
<td>0.233</td>
<td>0.128</td>
<td>III</td>
</tr>
<tr>
<td>MV-LSTM</td>
<td>0.435</td>
<td>0.322</td>
<td>0.409</td>
<td>0.308</td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>0.410</td>
<td>0.313</td>
<td>0.414</td>
<td>0.301</td>
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<tr>
<td></td>
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<td>0.251</td>
<td>0.267</td>
<td>0.168</td>
<td>III</td>
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<tr>
<td>Chain-LSTM</td>
<td>0.416</td>
<td>0.328</td>
<td>0.429</td>
<td>0.301</td>
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<tr>
<td></td>
<td>0.422</td>
<td>0.316</td>
<td>0.410</td>
<td>0.307</td>
<td>II</td>
</tr>
<tr>
<td></td>
<td>0.261</td>
<td>0.246</td>
<td>0.298</td>
<td>0.183</td>
<td>III</td>
</tr>
<tr>
<td>Dual-LSTM</td>
<td>0.431</td>
<td>0.339</td>
<td>0.441</td>
<td>0.312</td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>0.442</td>
<td>0.326</td>
<td>0.437</td>
<td>0.319</td>
<td>II</td>
</tr>
<tr>
<td></td>
<td>0.425</td>
<td>0.315</td>
<td>0.419</td>
<td>0.303</td>
<td>III</td>
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</tbody>
</table>

### Component Evaluations

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<th>Tier</th>
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<tbody>
<tr>
<td>-MLP</td>
<td>0.422</td>
<td>0.326</td>
<td>0.432</td>
<td>0.304</td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>0.425</td>
<td>0.320</td>
<td>0.428</td>
<td>0.310</td>
<td>II</td>
</tr>
<tr>
<td></td>
<td>0.271</td>
<td>0.248</td>
<td>0.313</td>
<td>0.216</td>
<td>III</td>
</tr>
<tr>
<td>-Cell</td>
<td>0.426</td>
<td>0.333</td>
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GENERATION-BASED CONVERSATION SYSTEM
RNN Family

- Recurrent Neural Networks
  - Vanilla RNN
  - LSTM
  - GRU

Schmidhuber et al., Neural Computing’97

Chung et al., arXiv’14 Attention Signal
Sequence-to-Sequence

- Basic sequence to sequence

Sequential modeling with bi-directions

Sutskever et al., NIPS’14
Graves et al., ASSP’13
Attention Mechanism

• Attention signal

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

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

\[ e_{ij} = v_a^T \tanh(W_a s_{i-1} + U_a h_j) \]

Bahdanau et al., ICLR’14
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 level)
    - a sequence of words for each utterance
    - a sequence of utterances

Serban et al., AAAI’16

[Diagram showing the hierarchical encoder-decoder model with utterances and predictions.]
**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 $T$

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

Ghosh et al., KDD’16 Workshop
Conditional Generation Network

- Memory type LSTM

Wen et al., EMNLP'16
Conditional Generation Network

- Hybrid type LSTM

\[
\begin{pmatrix}
i_j \\
f_j \\
o_j \\
r_j
\end{pmatrix} = \begin{pmatrix}
\text{sigmoid} \\
\text{sigmoid} \\
\text{sigmoid} \\
\text{sigmoid}
\end{pmatrix} W_{4n,3n} \begin{pmatrix}
m_t \\
w_j \\
h_j \\
h_{j-1}
\end{pmatrix}
\]

\[
\hat{c}_j = \tanh(W_c(w_j \oplus h_{j-1}))
\]

\[
c_j = f_j \odot c_{j-1} + i_j \odot \hat{c}_j
\]

\[
h_j = o_j \odot \tanh(c_j) + r_j \odot m_t
\]

Wen et al., EMNLP’16
Semantically Conditioned LSTM

- Semantic Controlled LSTM

Wen et al., EMNLP’15

\[
\begin{align*}
    i_t &= \sigma(W_{wi} w_t + W_{hi} h_{t-1}) \\
    f_t &= \sigma(W_{wf} w_t + W_{hf} h_{t-1}) \\
    o_t &= \sigma(W_{wo} w_t + W_{ho} h_{t-1}) \\
    c_t &= f_t \odot c_{t-1} + i_t \odot \hat{c}_t + tanh(W_{dc} d_t) \\
    h_t &= o_t \odot tanh(c_t)
\end{align*}
\]
Generation Overview

- Case studies

Wen et al., EMNLP’15

<table>
<thead>
<tr>
<th>#</th>
<th>Example Dialogue Acts and Realizations from SF Restaurant Domain</th>
</tr>
</thead>
</table>
| 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. |

<table>
<thead>
<tr>
<th>#</th>
<th>Example Dialogue Acts and Realizations from SF Hotel Domain</th>
</tr>
</thead>
</table>
| 3   | inform(type=”hotel”,count=”182”,dogsallowed=”don’t care”)
|     | 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

- **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:

\[
\text{PMI}(w_q, w_r) = \log \frac{p(w_q, w_r)}{p(w_q)p(w_r)} = \log \frac{p(w_q|w_r)}{p(w_q)}
\]

• For all the words in the query

\[
\text{PMI}(w_{q_1} \cdots w_{q_n}, w_r) = \log \frac{p(w_{q_1} \cdots w_{q_n}|w_r)}{p(w_{q_1} \cdots w_{q_n})}
\approx \log \frac{\prod_{i=1}^n p(w_{q_i}|w_r)}{\prod_{i=1}^n p(w_{q_i})} = \sum_{i=1}^n \log \frac{p(w_{q_i}|w_r)}{p(w_{q_i})} = \sum_{i=1}^n \text{PMI}(w_{q_i}, w_r)
\]

• 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

\[
p \left( \frac{r_{k-1} \cdots r_1}{r_{k+1} \cdots r_m} \bigg| r_k, q \right) = \prod_{i=1}^{k-1} p^{(bw)}(r_{k-i}|r_k, q, \cdot) \prod_{i=1}^{m-k} p^{(fw)}(r_{k+i}|r_k, q, \cdot)
\]
### Case studies

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

- Hard constraint vs soft constraint
- Does the constraint word really need to exist, explicitly?
Soft Constraint

- Two ways to inject information

- Model
  - Standard GRU
  - Cue word GRU
  - Fusion units

Yao et al., EMNLP’17
## Illustrations

- **An example query**

<table>
<thead>
<tr>
<th>Query (Cue word)</th>
<th>Related Criterion</th>
<th>Labels</th>
</tr>
</thead>
<tbody>
<tr>
<td>The teacher took a photo of me; it was really ugly and people laughed at me. <em>(Photogenic)</em></td>
<td>Logic Consistency</td>
<td>Unsuitable</td>
</tr>
<tr>
<td>Who's photo?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>What did he took the photo?</td>
<td>Implicit Relevance</td>
<td>Neutral</td>
</tr>
<tr>
<td>Give you a hug.</td>
<td>Implicit Relevance</td>
<td>Neutral</td>
</tr>
<tr>
<td>My photos are also ugly!</td>
<td></td>
<td>Suitable</td>
</tr>
</tbody>
</table>

## Visualization

### k-openness

![k-openness chart]

### Correlation

- 内心是崩溃的吧
- 夸奖
- 纸巾
- 说过吗？好像没有说过啊！
- 递纸巾！
- 谢谢夸奖！么么哒！
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
Diversity in Conversation

- **MMI objective**
  \[ \hat{T} = \arg \max_T \{ \log p(T|S) - \log p(T) \} \]

- **Penalty parameter**
  \[ \hat{T} = \arg \max_T \{ \log p(T|S) - \lambda \log p(T) \} \]

- **Bayes theorems**
  \[ \log p(T) = \log p(T|S) + \log p(S) - \log p(S|T) \]

- **Final representation**
  \[ \hat{T} = \arg \max_T \{ (1 - \lambda) \log p(T|S) + \lambda \log p(S|T) \} \]
  \[ = \arg \max_T \{ (1 - \lambda) \log p(T|S) + \lambda \log p(S|T) \} \]

---

**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.

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

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

Li et al., NAACL’16
Emotion in Conversation

- Emotion is important
  - Emotion classification
  - Emotion fusion

<table>
<thead>
<tr>
<th>Post</th>
<th>Model</th>
<th>Response (Original)</th>
<th>Response (Translated)</th>
</tr>
</thead>
<tbody>
<tr>
<td>比情人节更庸俗的事就是，对情人节的接待规格待遇提出要求。What is more vulgar than Valentine's day is to make specific demands on the reception of the Valentine's day.</td>
<td>Seq2Seq</td>
<td>这才是真正的情人节。</td>
<td>This is a real Valentine's day.</td>
</tr>
<tr>
<td>比情人节更庸俗的事就是，对情人节的接待规格待遇提出要求。What is more vulgar than Valentine's day is to make specific demands on the reception of the Valentine's day.</td>
<td>ECM</td>
<td>情人节快乐！</td>
<td>Happy Valentine's Day!</td>
</tr>
<tr>
<td>比情人节更庸俗的事就是，对情人节的接待规格待遇提出要求。What is more vulgar than Valentine's day is to make specific demands on the reception of the Valentine's day.</td>
<td></td>
<td>哈哈，这也太浪漫了吧！</td>
<td>Aha, this is too romantic!</td>
</tr>
<tr>
<td>比情人节更庸俗的事就是，对情人节的接待规格待遇提出要求。What is more vulgar than Valentine's day is to make specific demands on the reception of the Valentine's day.</td>
<td></td>
<td>我也想要这样的情人节。</td>
<td>I also want this kind of Valentine's day, sigh.</td>
</tr>
<tr>
<td>比情人节更庸俗的事就是，对情人节的接待规格待遇提出要求。What is more vulgar than Valentine's day is to make specific demands on the reception of the Valentine's day.</td>
<td></td>
<td>这就是所谓的情人节！</td>
<td>This is the so-called Valentine's day!</td>
</tr>
<tr>
<td>比情人节更庸俗的事就是，对情人节的接待规格待遇提出要求。What is more vulgar than Valentine's day is to make specific demands on the reception of the Valentine's day.</td>
<td></td>
<td>这是赤裸裸的炫耀啊！</td>
<td>This is shameless show-off!</td>
</tr>
</tbody>
</table>
Speaker Model

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

Li et al., ACL’16
Model Extension

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

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

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

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

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

Li et al., ACL’16
Semantically Conditioned LSTM

- **Affect-LM**: customizable affective text generation

Ghosh et al., ACL 2017

![Diagram showing Affect-LM model with context words, affect category, and affect strength.]

Five specific affect categories: $e_{t-1}$

$B$ is affect strength

Mathematical equations for probability distributions:

$$P(w_1, w_2, ..., w_M) = \prod_{t=1}^{t=M} P(w_t|w_1, w_2, ..., w_{t-1})$$

$$P(w_t = i|c_{t-1}) = \frac{\exp(U_i^T f(c_{t-1}) + b_i)}{\sum_{j=1}^{V} \exp(U_j^T f(c_{t-1}) + b_j)}$$

$$P(w_t = i|c_{t-1}, e_{t-1}) = \frac{\exp(U_i^T f(c_{t-1}) + \beta V_i^T g(e_{t-1}) + b_i)}{\sum_{j=1}^{V} \exp(U_j^T f(c_{t-1}) + \beta V_j^T g(e_{t-1}) + b_j)}$$
**Conditional VAE**

- **Conditional Variational Auto Encoder (CVAE)**

  \[
  \mathcal{L}(\theta, \phi; x, c) = -KL(q_\phi(z|x, c)\|p_\theta(z|c)) + \mathbb{E}_{q_\phi(z|c, x)}[\log p_\theta(x|z, c)] \\
  \leq \log p(x|c)
  \]

- **Knowledge-Guided CVAE (kgCVAE)**

  \[
  \mathcal{L}(\theta, \phi; x, c, y) = -KL(q_\phi(z|x, c, y)\|P_\theta(z|c)) + \mathbb{E}_{q_\phi(z|c, x, y)}[\log p(x|z, c, y)] \\
  + \mathbb{E}_{q_\phi(z|c, x, y)}[\log p(y|z, c)]
  \]
Conditional VAE

- Conditional Variational Autoencoder

\[
\log p(x_{bow}|z, c) = \log \prod_{t=1}^{n} \frac{e^{f_{xt}}}{\sum_{j=1}^{V} e^{f_{jt}}}
\]

zhao et al., ACL’17
Mechanism-aware Neural machine for Dialogue Generation

Zhou et al., AAAI 2017

Encoder: returns context $c$
Diverter: calculate distribution over mechanism embeddings and return $[c, m_i]$
Decoder: generate response according to $[c, m_i]$

$$p(y|x) = \sum_{i=1}^{M} p(y, m_i|x) = \sum_{i=1}^{M} p(m_i|x)p(y|m_i, x)$$

$$p(m_i|x) = \frac{\exp g(m_i, c)}{\sum_{k=1}^{M} \exp g(m_k, c)}$$

$$g(m_i, c) = m_i^T W_t t$$
$$t = [\max\{\tilde{t}_{j-1}, \tilde{t}_j\}]_{j=1,2,\ldots,l_c}^T$$
$$\tilde{t} = W_c c$$
Mechanism Aware Generation

\[
\sum_{(x,y) \in D^c} \log p(y|x) = \sum_{(x,y) \in D^c} \log \sum_{i=1}^{M} p(m_i|x)p(y|m_i,x)
\]

\[
p(y, m_l|x) = p(m_l|x)p(y|m_l,x)
\]

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

Interactive learning of grounded verb semantics

\[ \mathcal{E}_i \text{ Initial Environment:} \]
\[ \ldots \text{Has(Kettle1,WATER)} \]
\[ ^\wedge\text{Grasping(Kettle1)} \ldots \]
\[ \mathcal{L}_i \text{ command: } \text{Boil the water.} \]
\[ v_i \text{ boil(WATER)} \]

\[ \overrightarrow{A}_i \text{ Action sequence:} \]
\[ \text{Moveto(Kettle1), Grasp(Kettle1), Moveto(Stove), Keep(Kettle1, on, Stovefire4), Press(Stovefire4)} \]

\[ \mathcal{E}_i' \text{ Final Environment:} \]
\[ \ldots\text{Has(Kettle1,WATER)} \]
\[ ^\wedge\text{Status(WATER,TempHigh)} \]
\[ ^\wedge\text{On(Kettle1,Stove)}^\wedge\text{Near(Robot,Stove)} \]
\[ ^\wedge\text{Status(Stovefire4,On)}^\wedge\text{Grasping(Kettle1)} \ldots \]

The acquired verb representation (i.e., a goal state hypothesis): \( \text{boil(x): Status(x,TempHigh)} \)

An example of acquiring state-based representation for verb semantics

environment \( \mathcal{E}_i \)

a language command \( \mathcal{L}_i \)

primitive action sequence \( \overrightarrow{A}_i \)

final environment \( \mathcal{E}_i' \) that results from the execution of \( \overrightarrow{A}_i \) in \( \mathcal{E}_i \)
Reinforcement Learning

A General Form of one Interaction Episode

Request Action

Provide Feedback

Update:
1) KB
2) $\theta_E$

Provide Demonstration

Update:
1) KB with a new verb
2) $\theta_D$

KB stands for knowledge base

$\theta_E$ stands for Interaction Strategy for Execution

$\theta_D$ stands for Interaction Strategy for Learning
Reinforcement Learning

Interactive learning of grounded verb semantics

<table>
<thead>
<tr>
<th>Only demonstration (She and Chai, 2016)</th>
<th>Interactive learning (this work)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Execution Example</strong></td>
<td><strong>Execution Example</strong></td>
</tr>
<tr>
<td>H1: Boil the water.</td>
<td>H1: Boil the water.</td>
</tr>
<tr>
<td>R1: <em>(select a hypothesis and execute the action accordingly)</em></td>
<td>R1: I see a silver object on the table, is that a pot?</td>
</tr>
<tr>
<td>H2: <em>(provide true/false feedback on whether the execution is correct)</em></td>
<td>H2: Yes.</td>
</tr>
<tr>
<td>R2: Should I leave the pot on the stove after boil?</td>
<td>R2: Yes.</td>
</tr>
<tr>
<td>H3: Yes.</td>
<td>R3: Ok. <em>(select a hypothesis to execute)</em></td>
</tr>
<tr>
<td>R3: Ok. <em>(select a hypothesis to execute)</em></td>
<td>H4: Thank you.</td>
</tr>
<tr>
<td>H4: Thank you.</td>
<td></td>
</tr>
<tr>
<td><strong>Learning Example</strong></td>
<td><strong>Learning Example</strong></td>
</tr>
<tr>
<td>H3: Boil the water.</td>
<td>H5: Boil the water.</td>
</tr>
<tr>
<td>R3: I don’t know how to boil, could you show me an example?</td>
<td>R5: I don’t know how to boil, could you show me an example?</td>
</tr>
<tr>
<td>H4: <em>(human shows the robot how to achieve the corresponding action through a sequence of primitive actions)</em></td>
<td>H6: Ok. <em>(demonstrate the task, at the end put the pot on a heat pad)</em></td>
</tr>
<tr>
<td>R4: <em>(indicate the acceptance and induce a hypothesis to represent verb semantics)</em></td>
<td>R6: So after boiling something, should I put it on a heat pad?</td>
</tr>
<tr>
<td>H7: No, you don’t have to.</td>
<td>H7: No, you don’t have to.</td>
</tr>
<tr>
<td>R7: I sec. <em>(induce goal state hypothesis)</em></td>
<td>R7: I see. <em>(induce goal state hypothesis)</em></td>
</tr>
</tbody>
</table>
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
• Idea of adversarial training: GAN

Generative Adversarial Network

Latent Space → Generator (G) → Real Samples → Discriminator (D) → Is D Correct?

Generator (G) outputs Generated Fake Samples to Discriminator (D) for fine-tuning.
GAN in NLP

- Languages are different from images
  - Consecutive distributions vs. discrete distributions

- SeqGAN
  - NO intermediate reward
  - Policy: to maximize the expected reward of the whole sequence after generation
  - Generator and discriminator

Yu et al., AAAI’17
GAN in Conversation

- **Seq2SeqGAN**
  - With the input sequence, using the idea of SeqGAN

- Generative model with discrimination via policy

- Reward with every generation step

- Adversarial evaluation

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<table>
<thead>
<tr>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vanilla-MLE</td>
<td>i'm not a doctor.</td>
</tr>
<tr>
<td>Vanilla-Sample</td>
<td>well everything you did was totally untrue.</td>
</tr>
<tr>
<td>REINFORCE</td>
<td>i don't know how long it's been.</td>
</tr>
<tr>
<td>REGS Monte Carlo</td>
<td>A few months, I guess.</td>
</tr>
</tbody>
</table>

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<tr>
<th>Input</th>
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<tbody>
<tr>
<td>Vanilla-MLE</td>
<td>so i had the doctors test sammy's response to conditioning.</td>
</tr>
<tr>
<td>Vanilla-Sample</td>
<td>sammy wrote the test sammy wrote the test.</td>
</tr>
<tr>
<td>REINFORCE</td>
<td>objects objects objects objects objects objects objects</td>
</tr>
<tr>
<td>REGS Monte Carlo</td>
<td>i'm not sure that's relevant.</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>Input</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vanilla-MLE</td>
<td>what are you going to do?</td>
</tr>
<tr>
<td>Vanilla-Sample</td>
<td>i'm going to the movies.</td>
</tr>
<tr>
<td>REINFORCE</td>
<td>get him outta here first!</td>
</tr>
<tr>
<td>REGS Monte Carlo</td>
<td>i'm going to get you.</td>
</tr>
</tbody>
</table>

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<thead>
<tr>
<th>Input</th>
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</thead>
<tbody>
<tr>
<td>Vanilla-MLE</td>
<td>they fear your power your intellect.</td>
</tr>
<tr>
<td>Vanilla-Sample</td>
<td>you're the only one who knows what's going on.</td>
</tr>
<tr>
<td>REINFORCE</td>
<td>when they are conquered and you surrender they will control all of us.</td>
</tr>
<tr>
<td>REGS Monte Carlo</td>
<td>i'm afraid i'm not ready yet.</td>
</tr>
</tbody>
</table>

Li et al., EMNLP’17
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

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

Automatic evaluation is crucial to the research of language generation tasks such as:

- Machine translation
  - BLEU, NIST, METEOR, ...
  - Shared tasks for evaluation metrics in WMT
- Text summarization
  - ROUGE, Pyramid, ...
- Dialog systems
  - ????
Typically Used Metrics in Dialog Systems

- **Human evaluation (widely used)**
  - Pair-wise
  - Point-wise

- **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]
Liu et al. (2016) show the weak correlation of existing metrics (e.g., BLEU, ROUGE and METEOR) with human judgments for dialog systems.

- Significant diversity in the space of valid replied to a given input.
- Utterances are typically short and casual in open-domain dialog systems.
ADEM Model

- 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.

Figure 2: The ADEM model, which uses a hierarchical encoder to produce the context embedding $c$. 

\[ \text{score}(c, r, \hat{r}) = (c^T M \hat{r} + r^T N \hat{r} - \alpha)/\beta \]

Lowe et al., ACL’17
**ADEM Results**

<table>
<thead>
<tr>
<th>Context</th>
<th>Reference response</th>
<th>Model responses</th>
<th>Human score</th>
<th>ADEM score</th>
</tr>
</thead>
<tbody>
<tr>
<td>photo to see my television debut go to - some. some on &lt;url&gt; - hehe &lt;url&gt; → it really was you? i thought ppl were recognizing someone who looked like you! were the oysters worth the wait?</td>
<td>yeah it was me. ha ha i’d kinda forgotten about it it was filmed a while ago</td>
<td>1) i’m not sure. i just don’t know what to do with it. 2) you heard the horsepower productions remix of lee scratch perry’s ‘exercising’ off his ‘mighty upsetter’ album? 3) you won’t chug a fuzzy peach navel 4) they were!</td>
<td>3</td>
<td>1.602</td>
</tr>
<tr>
<td>just beat call of duty!! → want a cookie? → yes!! → come get it</td>
<td>im in kenmore at the moment</td>
<td>1) i’m gonna get a new phone some moro 2) no way man. 3) wow i just got a free pizza coupon! get yours before thers no more! &lt;url&gt; 4) i’m going to go to the mall.</td>
<td>5</td>
<td>1.513</td>
</tr>
<tr>
<td>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</td>
<td>any news on meeting our user? i go to the us on friday and i don’t want to miss anything arranged</td>
<td>1) i’m not sure if i’m going to be able to get it. 2) good to see another mac user in the leadership ranks 3) awwww poor baby hope u get to feeling better soon. maybe some many work days at piedmont 4) did you tweet too much?</td>
<td>5</td>
<td>3.274</td>
</tr>
</tbody>
</table>

- **Higher correlations compared with BLEU and ROUGE**
RUBER: a Referenced metric and Unreferenced metric Blended Evaluation Routine for open-domain dialog systems
## RUBER Results

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Retrieval (Top-1)</th>
<th>Seq2Seq (w/ attention)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pearson (p-value)</td>
<td>Spearman (p-value)</td>
</tr>
<tr>
<td>Inter-annotator</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Human (Avg)</td>
<td>0.4927 (&lt;0.01)</td>
<td>0.4981 (&lt;0.01)</td>
</tr>
<tr>
<td>Human (Max)</td>
<td>0.5931 (&lt;0.01)</td>
<td>0.5926 (&lt;0.01)</td>
</tr>
<tr>
<td>Referenced</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BLEU-1</td>
<td>0.2722 (&lt;0.01)</td>
<td>0.2473 (&lt;0.01)</td>
</tr>
<tr>
<td>BLEU-2</td>
<td>0.2243 (&lt;0.01)</td>
<td>0.2389 (&lt;0.01)</td>
</tr>
<tr>
<td>BLEU-3</td>
<td>0.2018 (&lt;0.01)</td>
<td>0.2247 (&lt;0.01)</td>
</tr>
<tr>
<td>BLEU-4</td>
<td>0.1601 (&lt;0.01)</td>
<td>0.1719 (&lt;0.01)</td>
</tr>
<tr>
<td>ROUGE</td>
<td>0.2840 (&lt;0.01)</td>
<td>0.2696 (&lt;0.01)</td>
</tr>
<tr>
<td>Vector pool ($s_R$)</td>
<td>0.2844 (&lt;0.01)</td>
<td>0.3205 (&lt;0.01)</td>
</tr>
<tr>
<td>Unreferenced</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vector pool ($s_U$)</td>
<td>0.2253 (&lt;0.01)</td>
<td>0.2790 (&lt;0.01)</td>
</tr>
<tr>
<td>NN scorer ($s_U$)</td>
<td>0.4278 (&lt;0.01)</td>
<td>0.4338 (&lt;0.01)</td>
</tr>
<tr>
<td>RUBER</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Min</td>
<td>0.4428 (&lt;0.01)</td>
<td>0.4490 (&lt;0.01)</td>
</tr>
<tr>
<td>Geometric mean</td>
<td>0.4559 (&lt;0.01)</td>
<td>0.4771 (&lt;0.01)</td>
</tr>
<tr>
<td>Arithmetic mean</td>
<td>0.4594 (&lt;0.01)</td>
<td>0.4906 (&lt;0.01)</td>
</tr>
<tr>
<td>Max</td>
<td>0.3263 (&lt;0.01)</td>
<td>0.3551 (&lt;0.01)</td>
</tr>
</tbody>
</table>

### Diagrams

(a) Human (1 vs. rest)  
(b) Human (Group 1 vs. Group 2)  
(c) BLEU-2  
(d) ROUGE
DISCUSSIONS
Where Are We?

- We are doing well, enough?
- Users have really high expectations
Still A Long Way to Go

- How is AI in NLP now?
- There is still a long way to go
Expectations

• What can we expect in the future?
  • Dialogue challenges
    • Multi-turn understanding
    • Semantic understanding
  • Data challenges
    • Vertical domains
  • Intelligence challenges
    • Reasoning
    • Evolution
Thank You

- Q & A
- Email to