Neural Dialog Models: A Survey
- Imitation Learning Approach -

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Neural Language models

• Feed-forward LM [Bengio et al., 2003]
  • Next word predictor
• RNN-based LM [Mikolov et al., 2013]
Encoder-decoder approach for sequence learning

1. (Sutskever et al., 2014) The tail output of encoder is the initial state of decoder

2. (Cho et al., 2014) The tail output of encoder is referred at all output prediction

3. (Bahdanau et al., 2014) The weighted combination of encoder outputs is referred at all the output prediction (attention model)
A Neural Conversation Model [Vinyals and Le 2015]

• An example dialog using IT Helpdesk data [Vinyals and Le 2015]
  • **Describe your problem:** i am having issues accessing vpn
  • **Machine:** could you please let me know what are the operating systems you are using ?
  • **Human:** i am using linux
  • **Machine:** ok it was in the ssl vpn on which you stated it was broken
  • **Machine:** please check if you are logged in to corp network
  • **Machine:** what is the error that you are running please
  • **Human:** i am seeing an error related to vpn
  • **Machine:** what is the error message that you are getting when connecting to vpn using network connect ?
  • **Human:** connection refused or something like that
  • **Machine:** may i know the version of network connect you connect ?
A Neural Conversation Model
[Vinyals and Le 2015]

• Although NN just mimic the utterances of human operators, it looks solving the problem.
  • ....
  • **Machine:** try this
  • **Machine:** goto <URL> page and enter your
  • name and password
  • **Human:** done
  • **Machine:** try logging in with <NAME> and
  • check if its working fine now
  • **Human:** yes, now it works!
  • **Machine:** great
  • (The <URL> indeed contains information about vpn access.)

• Special tokens indicating turn taking and actor.
• Perplexity: 8 (Neural) vs. 18 (n-gram model)
Imitation learning for dialog system

• Conventional approach: goal-driven dialog for travel assistance, technical support, etc.
  Requires 1) a measurable goal and 2) task-specific annotated conversations

• Imitation learning approach: mimic human conversations
  • Can be applicable to tasks which are not easy to numerically evaluate the result of conversations (difficult reward design)
  • Can be a unsupervised representation learning for goal-driven dialog system
  • Can be a human simulator for POMDP-based dialog system
Generation task is difficult to evaluate

• Evaluation metrics so far
  • BLEU/METEOR over reference response [Sordoni+ 2015]
  • Perplexity / word classification [Vinyals 2015] [Serban+ 2015]
  • Human evaluation [Shang+ 2015]
  • Response selection task [Lowe+ 2015]
  • Dialog act prediction task [Kalchbrenner+ 2013]
HRED: hierarchical recurrent encoder decoder [Serban+ 2015]

Figures are cited from original paper
Bidirectional HRED
[Serban+ 2015]

• Bidirectional RNN for utterance representation
  • Model 1
    - Forward pass
    - backward pass
    - L2 pooling

• Utterance representation

Model 2
  - Forward pass
  - Backward pass
  - L2 pooling
Experimental results [Serban+ 2015]

• MovieTriples dataset: 3 consecutive utterances between two interlocutors from movies
  • 196,308 triples for training, 53 tokens/triples

• Pre-training
  • word embedding (word2vec)
  • 5M Q-A pairs (movie subtitles)

• Results: Note that the majority of the predictions are generic, such as I don’t know or I’m sorry.

<table>
<thead>
<tr>
<th>Model</th>
<th>Perplexity</th>
<th>Perplex..@U₃</th>
</tr>
</thead>
<tbody>
<tr>
<td>RNN</td>
<td>27.09 ± 0.13</td>
<td>26.67 ± 0.19</td>
</tr>
<tr>
<td>HRED</td>
<td>27.14 ± 0.12</td>
<td>26.60 ± 0.19</td>
</tr>
<tr>
<td>HRED-Bi.</td>
<td>26.81 ± 0.11</td>
<td>26.31 ± 0.19</td>
</tr>
</tbody>
</table>

Table is cited from original paper
Attention-based decoder for one round of conversation [Shang+ 2015]

- Dynamically select and linearly combine different parts of the input utterance

Figures are cited from original paper
Response Selection Task (1)

- The Ubuntu Dialogue Corpus: A Large Dataset for Research in Unstructured Multi-Turn Dialogue Systems [Lowe+ 2015]
- Best response selection corresponding to a given dialog context
  - BLEU can provide a very low score for reasonable responses
  - Avoid the direct evaluation of generation task

<table>
<thead>
<tr>
<th>Context</th>
<th>Response</th>
<th>Flag</th>
</tr>
</thead>
<tbody>
<tr>
<td>well, can I move the drives?</td>
<td>I guess I could just get an enclosure and copy via USB</td>
<td>1</td>
</tr>
<tr>
<td><strong>EOS</strong>  ah not like that</td>
<td></td>
<td></td>
</tr>
<tr>
<td>well, can I move the drives?</td>
<td>you can use &quot;ps ax&quot; and &quot;kill (PID #)&quot;</td>
<td>0</td>
</tr>
<tr>
<td><strong>EOS</strong>  ah not like that</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figures are cited from original paper
Response Selection Task (2) [Lowe+ 2015]

- Encoders for both context and response (no decoder)

<table>
<thead>
<tr>
<th>Method</th>
<th>TF-IDF</th>
<th>RNN</th>
<th>LSTM</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 in 2 R@1</td>
<td>65.9%</td>
<td>76.8%</td>
<td>87.8%</td>
</tr>
<tr>
<td>1 in 10 R@1</td>
<td>41.0%</td>
<td>40.3%</td>
<td>60.4%</td>
</tr>
<tr>
<td>1 in 10 R@2</td>
<td>54.5%</td>
<td>54.7%</td>
<td>74.5%</td>
</tr>
<tr>
<td>1 in 10 R@5</td>
<td>70.8%</td>
<td>81.9%</td>
<td>92.6%</td>
</tr>
</tbody>
</table>

Figures are cited from original paper
Dialog Act Prediction Task (1)

- Recurrent Convolutional Neural Networks for Discourse Compositionality [Kalchbrenner+ 2013]

<table>
<thead>
<tr>
<th>Dialogue Act Label</th>
<th>Example</th>
</tr>
</thead>
<tbody>
<tr>
<td>Statement</td>
<td>And, uh, it’s a legal firm office.</td>
</tr>
<tr>
<td>Backchannel/Acknowledge</td>
<td>Yeah, anything could happen.</td>
</tr>
<tr>
<td>Opinion</td>
<td>I think that would be great.</td>
</tr>
<tr>
<td>Abandoned/Uninterpretable</td>
<td>So, -</td>
</tr>
<tr>
<td>Agreement/Accept</td>
<td>Yes, exactly.</td>
</tr>
<tr>
<td>Appreciation</td>
<td>Wow.</td>
</tr>
<tr>
<td>Yes–No–Question</td>
<td>Is that what you do?</td>
</tr>
<tr>
<td>Non–Verbal</td>
<td>[Laughter], [Throat-clearing]</td>
</tr>
</tbody>
</table>

Figures are cited from original paper
Dialog Act Prediction Task (2) [Kalchbrenner+ 2013]

Figures are cited from original paper
Dialog Act Prediction Task (3) [Kalchbrenner+ 2013]

- A dialogue and its nearest neighbors over discourse vector
  - semantically different
  - pragmatically similar

<table>
<thead>
<tr>
<th></th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RCNN</td>
<td>73.9</td>
</tr>
<tr>
<td>LM-HMM trigram</td>
<td>71.0</td>
</tr>
<tr>
<td>LM-HMM bigram</td>
<td>70.6</td>
</tr>
<tr>
<td>LM-HMM unigram</td>
<td>68.2</td>
</tr>
<tr>
<td>Majority baseline</td>
<td>31.5</td>
</tr>
<tr>
<td>Random baseline</td>
<td>2.4</td>
</tr>
</tbody>
</table>

Figures are cited from original paper.
RNN-based Natural Language Generation for Conventional Dialog System (1) [Wen+ 2015]

• Task: Mapping an abstract dialogue act into an appropriate surface text

• Data: dialogues collected in a user trial of a statistical dialogue manager

Example Dialogue Acts and Realizations from SF Restaurant Domain

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.

Figures are cited from original paper
RNN-based Natural Language Generation for Conventional Dialog System (2) [Wen+ 2015]

- Semantically Conditioned LSTM-based Natural Language Generation for Spoken Dialogue Systems
  - Additional gated memory for dialog act into LSTM
- Real user assessment

<table>
<thead>
<tr>
<th>Method</th>
<th>Informativeness</th>
<th>Naturalness</th>
</tr>
</thead>
<tbody>
<tr>
<td>+deep</td>
<td>2.58</td>
<td>2.51</td>
</tr>
<tr>
<td>sc-lstm</td>
<td>2.59</td>
<td>2.50</td>
</tr>
<tr>
<td>rnn w/</td>
<td>2.53</td>
<td>2.42*</td>
</tr>
<tr>
<td>classlm</td>
<td>2.46**</td>
<td>2.45</td>
</tr>
</tbody>
</table>

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Discussion (1)

• Currently they do not care about error propagation
  • Once a dialog system returns wrong response, it have to handle states not observed in human response logs (training data).
Scheduled Sampling for Sequence Prediction with Recurrent Neural Networks [Samy Bengio+, 2015]

• Randomly select the true previous token or an estimated token coming from the model itself.

• However, it is not trivial to get true human utterance after erroneous system utterance.

Figures are cited from original paper
References

• Neural dialog models

• Response Selection

• Dialog Act Prediction

• Natural Language Generation for Conventional Dialog System

• Imitation Learning Issue
Other related work
