Exploring Recurrent, Memory and Attention Based Architectures for Scoring Interactional Aspects of Human–Machine Text Dialog

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Abstract
An important step towards enabling English language learners to improve their conversational speaking proficiency involves automated scoring of multiple aspects of interactional competence and subsequent targeted feedback. This paper builds on previous work in this direction to investigate multiple neural architectures – recurrent, attention and memory based – along with feature-engineered models for the automated scoring of interactional and topic development aspects of text dialog data. We conducted experiments on a conversational database of text dialogs from human learners interacting with a cloud-based dialog system, which were triple-scored along multiple dimensions of conversational proficiency. We find that fusion of multiple architectures performs competitively on our automated scoring task relative to expert interrater agreements, with (i) hand-engineered features passed to a support vector learner and (ii) transformer-based architectures contributing most prominently to the fusion.

1 Automated Scoring of Text Dialog
There is an increasing demand for dialog-based learning and assessment solutions at scale, given the rapidly growing language learning and online education marketplace. Dialog system technologies are one solution capable of addressing and automating this demand at scale (Ramanarayanan et al., 2016). However, such conversational technologies need to be able to provide useful and actionable feedback to users in order for them to be widely adopted. Automated scoring of multiple aspects of conversational proficiency is one way to address this need. While the automated scoring of text and speech data has been a well-explored topic for several years, particularly for essays and short constructed responses in the case of the former (Shermis and Burstein, 2013; Burrows et al., 2015; Madnani et al., 2017) and monolog speech for the latter (Neumeyer et al., 2000; Witt and Young, 2000; Xi et al., 2012; Bhat and Yoon, 2015)), research on the interpretable automated scoring of dialog has only recently started gaining traction (Evanini et al., 2015; Litman et al., 2016; Ramanarayanan et al., 2017). Further, certain dialog constructs such as those pertaining to interaction – engagement, turn-taking and repair – are a lot less well-studied as compared to others like delivery and language use. Ramanarayanan et al. (2019) recently performed a comprehensive examination of the automated scoring of content of whole dialog responses based primarily on text features, based on a comprehensive multidimensional rubric and scoring paradigm designed specifically focusing on aspects of interaction.

This paper aims to expand on the analysis presented in Ramanarayanan et al. (2019) more comprehensively along two directions. First, we also investigate constructs of text dialog scoring rubric pertaining to topic development along with those pertaining to interaction, aiming to understand, for the first time, how various feature-engineering and model-engineering methods perform on a broader range of scoring dimensions. Second, we propose a more comprehensive experimental setup that explores multiple feature-engineered models (that include novel lexical features from the politeness detection literature (Danescu-Niculescu-Mizil et al., 2013)) and deep learning network architectures – recurrent, attention and memory based – for automated scoring. We specifically study LSTM (Long Short-Term Memory) networks with context attention (Yang et al., 2016), memory networks (Weston et al., 2014; Sukhbaatar et al., 2015), and the BERT (Bidirectional Encoder Representations from Transformers) family of models (Devlin et al., 2018). Finally, we report performance improvements using score-level fusion of multiple models.
Table 1: Human scoring rubric for interaction aspects of conversational proficiency. Scores are assigned on a Likert scale from 1-4 ranging from low to high proficiency. A score of 0 is assigned when there were issues with audio quality or system malfunction or off-topic or empty responses.

| Construct              | Sub-construct | Description                                                                 |
|------------------------|---------------|-----------------------------------------------------------------------------|
| Topic Development      | Topic         | Examines to what extent the responses are uniformly on topic and relevant.   |
|                        | Elaboration   | Examines the extent to which arguments are developed taking into account dialog history and with minimal or no repetition. |
|                        | Structure     | Evaluates the structure of the discourse and chain of reasoning, along with the appropriate use of discourse markers. |
|                        | Task          | Evaluates how well the user accomplished the task over the course of the interaction. |
| Interaction            | Engagement    | Examines the extent to which the user engages with the dialog agent and responds in a thoughtful manner. |
|                        | Turn Taking   | Examines the extent to which the user takes the floor at appropriate points in the conversation without noticeable interruptions or gaps. |
|                        | Repair        | Examines the extent to which the user successfully initiates and completes a repair in case of a misunderstanding or error by the dialog agent. |
|                        | Appropriateness | Examines the extent to which the user reacts to the dialog agent in a pragmatically appropriate manner. |
|                        | Overall Holistic Performance | Measures the overall performance. |

2 Data

2.1 Collection

We analyze a corpus of 2288 conversations of non-native speakers introduced in Ramanarayanan et al. (2019). Here, speakers interact with a dialog application designed to test general English speaking competence in workplace scenarios particularly focusing on pragmatic skills. The application requires participants to interact with their boss and request her for a meeting to review presentation slides using pragmatically appropriate language (see Authors, 2017, for more details). To develop and deploy this application, we leveraged an open-source modular cloud-based dialog system that is compatible with multiple W3C and open industry standards (Anonymous, 2017).

2.2 Human Scoring

Each of the 2288 dialog responses were triple scored by human expert raters on a custom-designed rubric. The rubric defined 12 subconstructs under the 3 broad constructs of linguistic control, topic development and interaction, apart from an overall holistic score. This study investigates the topic development construct for the first time in addition to interaction. See Table 1 for specific details of the constructs examined.

3 Automated Scoring Methods

We first describe the hand-engineered feature set used in conjunction with a linear support vector machine (SVM) classifier. We then describe, in turn, the recurrent, memory and attention based architectures investigated in this paper. We trained all automated scoring models in this paper to predict valid dialog-level scores from 1-4 (we only consider dialogs with a non-zero score to train scoring models 1). An exception to this is in the case of the memory network, where we predict scores at the turn-level, and then report the dialog level score as the median score across all turns of that dialog. We report the mean performance of scoring systems on a 10-fold cross-validation (CV) experimental setup. Finally, we report both accuracy and quadratic weighted kappa (which takes into account the ordered nature of the categorical labels) as metrics.

3.1 Feature Engineering Approaches

We examine two sets of features here. First, we re-implement the features from Ramanarayanan et al. (2019), i.e., features that explicitly capture content (e.g., word n-grams, character n-grams) and gram...
Table 2: Content and grammatical structure features used for machine scoring.

| Feature       | Description                                                                 |
|---------------|-----------------------------------------------------------------------------|
| Word n-grams  | Word n-grams are collected for n = 1 to 2. This feature captures patterns about vocabulary usage (key words) in responses. |
| Character n-grams | Character n-grams (including whitespace) are collected for n = 2 to 5. This feature captures patterns that abstract away from grammatical and other language use errors. |
| Response length | Defined as log(chars), where chars represents the total number of characters in a response. |
| Syntactic dependencies | A feature that captures grammatical relationships between individual words in a sentence. This feature captures linguistic information about “who did what to whom” and abstracts away from a simple unordered set of key words. |
| Discourse strategy | Features based on presence or absence of specific words in the response that represent different discourse strategies (see Table 3 for examples of politeness strategies). |

Second, we introduce nuanced features that are related to the power dynamics of social interactions and are often indicators of whether an interaction went well or not. We hypothesize that features that capture interaction strategies such as gratitude expression or greetings will be particularly useful, given that the corpus involves conversations between a participant and their boss. We therefore focus on features that capture politeness and acknowledgment. These are inspired by Danescu-Niculescu-Mizil et al. (2013), who conducted a very thorough analysis of politeness strategies employed by Wikipedia and Stack Exchange users. Our features capture strategies such as counterfactual modals (“could/would you . . .”), the indicative modal (“can/will you . . .”), deferential back-shift (“I was wondering . . .”), gratitude (“Thank you . . .”), apologies (“I apologize”, “forgive me”), appreciation, especially at the end of the conversation (“sounds good”, “works great”), requests (“please review . . .”), greetings (“Hi, hello miss”), mainly in the beginning of the conversation to build a positive relationship, and hedging (“I suggest . . .”).

2 These features are binary, indicating, whether a dialog consists a specific politeness strategy. Table 3 presents exemplars of politeness strategies observed in our training corpus.

We used SKLL, an open-source Python package that wraps around the scikit-learn package (Pedregosa et al., 2011) to perform machine learning experiments. We report the mean performance of linear support vector machines (SVM) where we used a cross entropy (log-loss) objective function to optimize learner performance, and fine-tuned hyperparameters such as the regularization coefficient using a grid search method.

3.2 Recurrent Architectures (BiLSTMs) with and without Attention

Recurrent architectures, such as Long Short-Term Memory (LSTM) networks, are able to learn long-term dependencies (Hochreiter and Schmidhuber, 1997) and are effective in many NLP tasks related to dialog and turn-taking scenarios (Ghosh et al., 2018; Skantze, 2017). We implement the stacked BiLSTM network architecture with context attention (Yang et al., 2016). Here the output of the first BiLSTM hidden layer is fed as input into the subsequent BiLSTM hidden layer. We experimented with varying depths of the stack and empirically selected depth=2. The attention mechanism is as
follows. Let the number of words in the dialog $d$ be $w$ and the hidden representation for word $w_d$ be $h_d$. We introduce a word-level attention mechanism where the word representation $u_d$ is weighted by measuring similarity with a word level context vector $u_d$, i.e., randomly initialized and jointly learned during the training. Finally, we compute the dialog vector $v_d$ that summarizes the weighted sum of the word annotations based on the weights.

$$u_d = \text{tanh}(W_d h_d + b_w)$$  \hspace{1cm} (1)

$$v_d = \sum_{i \in [1,w]} \alpha_d_i h_d_i$$  \hspace{1cm} (2)

where attention $\alpha_d_i$ is calculated as:

$$\alpha_d_i = \frac{\exp(u_d^T u_d_i)}{\sum_{i \in [1,w]} \exp(u_d^T u_d_i)}$$  \hspace{1cm} (3)

Figure 1 represents the high-level structure of the BiLSTM Attention architecture. Words are represented as embeddings (e.g., GloVe embedding (Pennington et al., 2014), the orange blocks in the Figure 1) and fed to the BiLSTM network. For brevity, we are showing only one BiLSTM layer composed of the forward and backward layer accounting to the hidden layer $h_d$ (green blocks). Next, context vector $u_d$ is utilized to generate word level attention $\alpha_d$ (purple blocks). Finally, the dialog vector $v_d$ passes through a dense+Softmax layer to predict the score of the construct in the given experiment.

To tune the hyperparameters for BiLSTM based experiments, we split the training data for each CV fold into 80% train and 20% dev, and use the dev partition for parameter tuning. We employ the following hyperparameters for the BiLSTM architectures: GloVe embeddings (100D), mini-batch size of 16, recurrent dropout value of 0.3, 10 epochs (with an early-stopping patience of 5), and the Adam optimizer with its default parameters.

3.3 End to End Memory Networks (MemN2Ns)

We also investigated the efficacy of the End to End Memory Network (MemN2N) architecture (Sukhbaatar et al., 2015; Chen et al., 2016) adapted to the dialog scoring task, described in Ramnarayan et al. (2019). See Figure 2. The end to end MemN2N architecture models dependencies in text sequences using a recurrent attention model coupled with a memory component, and is therefore suited to modeling how response and prompt histories contribute to a dialog score. We modified the original MemN2N architecture in the following ways: (i) instead of the original (query, fact history, answer) tuple that is used to train the network, we have an (current response, response history, prompt history, answer) tuple in our case. In other words, we not only embed and learn memory representations between the current response and the history of previous responses, but the history of prior system prompts that have been encountered thus far; (ii) we used an LSTM instead of a matrix multiplication at the final step of the network before prediction; (iii) we train the network at the turn level, and assign the dialog-level score as the median score of all scores predicted by the network at the turn-level, as mentioned earlier.

We tuned hyperparameters of the network using the hyperas toolkit. This included the number of
neurons in the Dense and LSTM layers as well as the addition of Dropout layers after each memory component. We trained the network for 40 epochs (but with an early-stopping patience of 5, so we generally did not exceed 10 epochs in practice). We experimented with 1, 2 and 3 memory hops and found 2 to be optimal. We found that initializing the memory embedding matrices with pretrained word2vec (Mikolov et al., 2013) or GloVe (Pennington et al., 2014) embeddings worked better than randomly-initialized ones for prompt history encoding in particular.

3.4 Transformer Models

The final class of models we explore is the purely attention-based family of transformer models (Vaswani et al., 2017). Attention, as we have seen, is a mechanism in the neural network that a model can learn to make predictions by selectively attending to a given set of data (and if we are making prediction for one part of a data sample using other parts of the observation about the same sample, this is self-attention). The amount of attention is quantified by learned weights and thus the output is usually formed as a weighted average. The transformer family of models allows one to model sequence data without using recurrent network units by leveraging a special scaled dot product attention mechanism in an encoder-decoder framework, and thus may be particularly suited to modeling our dialog time series data.

We primarily experimented with BERT (Bidirectional Encoder Representations from Transformers) pre-trained transformer-based language models (Devlin et al., 2018). We also experimented with two other transformer-based model architectures – RoBERTa (Liu et al., 2019) and DistilBERT (Sanh et al., 2019) – and found them to produce results similar to the standard BERT model, so we report only these results for brevity. We used the HuggingFace transformers library\(^4\) (Wolf et al., 2019) to fine-tune a pre-trained model (bert-base-uncased) on our training data for each fold of our 10-fold cross-validation setup and report performance averaged across all folds. We use the following hyperparameters: number of epochs = 5, learning rate = 5e-5, and Adam epsilon = 1e-8.

4 Observations and Results

Table 4 shows quadratic weighted kappa ($QW_\kappa$) values produced by the different automated scoring methods explored in this study. For a more comprehensive report of both accuracy and $QW_\kappa$ metrics, refer to Table A1 in the Appendix. Notice that all systems generally produce accuracy numbers in the 0.6 – 0.7 range, with the BERT and SVM systems (with hand-engineered content features) performing best individually. The final two columns of Table 4 display two inter-rater agreement statistics – Conger $\kappa$ and Krippendorff $\alpha$ –

\(^4\)github.com/huggingface/transformers
Table 4: Automated scoring performance (as measured by the quadratic weighted kappa or QW$\kappa$) of the 6 systems we explore in this paper. Note that we report results for the fusion system with the best QW$\kappa$ (optimized across all combinations of individual systems). The last two columns present Human Inter Rater Agreements for the same data expressed in Krippendorff $\alpha$ and Conger $\kappa$ (note that this is not directly comparable to the reported QW$\kappa$s).

| Construct          | Sub-construct | 1. SVM | 2. SVM++ | 3. LSTM | 4. LSTM$_{att}$ | 5. MemN2N | 6. BERT | Fusion Results | Human IRR |
|--------------------|---------------|-------|---------|--------|---------------|----------|--------|---------------|-----------|
|                    |               |       |         |        |               |          |        | Best system   | QW$\kappa$ | $\kappa$ | $\alpha$ |
| Topic Development  | Topic         | 0.66  | 0.65   | 0.62   | 0.63          | 0.51     | 0.66   | 1, 2, 3, 4, 5, 6 | 0.69      | 0.70   | 0.73    |
|                    | Elaboration   | 0.69  | 0.68   | 0.63   | 0.67          | 0.62     | 0.68   | 1, 3, 4, 5, 6   | 0.72      | 0.76   | 0.75    |
|                    | Structure     | 0.68  | 0.69   | 0.65   | 0.64          | 0.61     | 0.67   | 1, 5, 6        | 0.72      | 0.75   | 0.75    |
|                    | Task          | 0.71  | 0.72   | 0.65   | 0.69          | 0.62     | 0.71   | 1, 3, 5, 6     | 0.74      | 0.72   | 0.74    |
| Interaction        | Engagement    | 0.70  | 0.70   | 0.68   | 0.67          | 0.66     | 0.70   | 1, 3, 6        | 0.73      | 0.69   | 0.72    |
|                    | Turn Taking   | 0.67  | 0.68   | 0.63   | 0.63          | 0.62     | 0.70   | 2, 5, 6        | 0.72      | 0.71   | 0.74    |
|                    | Repair        | 0.61  | 0.61   | 0.54   | 0.59          | 0.57     | 0.63   | 1, 3, 5, 6     | 0.69      | 0.73   | 0.72    |
|                    | Appropriateness| 0.67  | 0.67   | 0.63   | 0.65          | 0.57     | 0.67   | 2, 6           | 0.69      | 0.70   | 0.72    |
| Overall Holistic Performance | 0.72 | 0.71 | 0.66 | 0.69 | 0.64 | 0.71 | 1, 3, 4, 6 | 0.73 | 0.75 | 0.75 |

Can you review my presentation slides before the meeting

(a) **Topic**

Can you review the presentation slides that I made so we can discuss them ...

(b) **Task**

if you would look over the slides for me that would be great yeah that sounds good ...

(c) **Appropriateness**

friday would be **uni** wonderful **um** do you think sometimes **uh** before the meeting

(d) **Overall holistic score.**

Figure 3: Attention weights for different scoring constructs obtained from the BiLSTM with attention model.
are denoted as systems 1 and 2 respectively for clarity and brevity. We notice that lexicon features capturing politeness help the SVM++ system achieve better accuracy, particularly for the structure, turntaking, and appropriateness constructs, which is in line with our expectations, given that our dialog task requires speakers to use appropriate strategies such as greeting, gratitude, and appreciation, among others, in order to accomplish the task successfully.

The BiLSTMs with attention (marked as $LSTM_{\text{attn}}$ in Table 4 or system number 4) perform better compared to the vanilla BiLSTM networks (system number 3) for all the constructs. We positioned an attention layer on top of the stack networks, which means the attention mechanism is able to identify the key characteristics of the constructs. We analyze the heat maps of the attention weights to obtain a better understanding of the model performance. For brevity, we discuss only a couple of constructs here. Each example depicted in the Figure 3 depicts heat map of the words from a portion of the dialog data corresponding to a request. We chose dialogs which obtained a median human score of 4 (i.e., high proficiency) and were correctly classified by the BiLSTMs with attention model. We observe that words such as “meeting” and “discussion” receive high weights for the topic construct (Figure 3a). Likewise, Figure 3b also shows that the words representing actions, such as “reviewing slides” or “discussion” received the highest weights for the task construct. For appropriateness, we observe words representing positive and respectful tone (e.g., “if you would look”; “great yeah”) receiving higher attention weights (Figure 3c). Finally, in the Figure 3d we observe the heat map for overall holistic performance. Besides key terms such as “Friday” (part of the task as well as the automated agent’s responses), we observe that positive sentiment words such as “wonderful” receive higher attention weights, suggesting that maintaining a positive intonation is weighted more by the BiLSTM with attention model.

Finally, the results from BERT is reported as System 6 in the Table 4. We observe, BERT consistently performs best or comparable to the best model(s) across all the constructs. This verifies the superiority of the transformer architecture, also observed in prior dialog-act classification task (Chakravarty et al., 2019).

5 Implications for Future Work on Automated Dialog Scoring

We have presented, for the first time, a comprehensive set of experiments exploring different architectures for machine scoring of text dialog data. We examined both feature-engineered machine learning models as well as multiple neural architectures – recurrent, memory and attention based – and found that different optimal combinations of these architectures were useful in scoring different constructs of the text dialog. A combination of carefully selected features along with principled attention-based models were particularly effective.

We still need to obtain deeper insights into the relative performance and utility of each system, particularly with respect to interpretability and understandability of the predicted score. Such explainability is particularly crucial in order to deploy such automated scoring systems in the real world. Our initial investigation has provided us with some clues, however. Examining the attention weights in particular provides us with some insights regarding the types of word features that the system “attends” to. Additionally, we conducted a cursory empirical analysis of errors made by each of our systems. We observed that the errors made by the SVM and BERT systems generally involved an underestimation of the median human score, while the Stack BiLSTM and MemN2N generally overestimated it. We need to conduct further research to unpack these findings fully, and will focus on this as an active line of future work.

This work informs two other important future learning and assessment directions and goals in addition to enhancing the interpretability and explainability of our automated scoring models. The first of these is to leverage insights from understanding these models to develop targeted and personalized feedback to language learners interacting with the dialog system. Indeed it is more crucial to provide learners with actionable feedback (as close to something a human teacher might provide them) than just a numeric score if one has to develop effective and widely-adopted learning applications. Second, we would like to extend our modeling and analysis experiments of text dialog to speech and spoken dialog.

We are poised to observe an increase demand for automated scoring of dialog as conversational systems for language learning and assessment continue to burgeon across the global educational land-
scape. While this field is still maturing (relative to automated scoring of essays or monologic speech), this paper puts forth a concrete contribution to our understanding of text dialog scoring, paving the path for more comprehensive solutions going forward.

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Table A1: Complete table of human and machine score performance statistics reporting both accuracy and quadratic weighted kappas.

| Construct        | Sub-construct | 1. SVM ACC | 2. SVM++ ACC | 3. Stack BiLSTM ACC | 4. BiLSTM (attn.) ACC | 5. MemN2N ACC | 6. BERT ACC | Fusion Results Best system ACC | QWκ | Human IRR | Human IRR | Human IRR |
|------------------|---------------|------------|--------------|---------------------|-----------------------|---------------|------------|--------------------------------|-----|-----------|-----------|-----------|
|                  |               | QWκ        | QWκ          | QWκ                 | QWκ                   | QWκ           | QWκ        |                                |     |           |           |           |
| Topic Development| Topic         | 0.71       | 0.66         | 0.70                | 0.65                  | 0.68           | 0.62       | 0.70                            | 0.63| 0.68      | 0.68      | 0.70      |
|                  | Elaboration   | 0.69       | 0.69         | 0.68                | 0.69                  | 0.64           | 0.63       | 0.66                            | 0.67| 0.65      | 0.62      | 0.70      |
|                  | Structure     | 0.68       | 0.68         | 0.69                | 0.69                  | 0.64           | 0.65       | 0.66                            | 0.64| 0.65      | 0.61      | 0.68      |
|                  | Task          | 0.71       | 0.71         | 0.71                | 0.72                  | 0.66           | 0.65       | 0.68                            | 0.69| 0.64      | 0.62      | 0.70      |
| Interaction      | Engagement    | 0.70       | 0.70         | 0.70                | 0.70                  | 0.66           | 0.68       | 0.67                            | 0.67| 0.66      | 0.68      | 0.70      |
|                  | Turn Taking   | 0.69       | 0.67         | 0.70                | 0.68                  | 0.65           | 0.63       | 0.66                            | 0.63| 0.67      | 0.62      | 0.71      |
|                  | Repair        | 0.66       | 0.61         | 0.66                | 0.61                  | 0.60           | 0.54       | 0.63                            | 0.59| 0.64      | 0.57      | 0.65      |
|                  | Appropriateness| 0.67      | 0.67         | 0.68                | 0.67                  | 0.61           | 0.63       | 0.65                            | 0.65| 0.62      | 0.57      | 0.66      |
| Overall Holistic Performance | 0.69 | 0.72 | 0.69 | 0.71 | 0.65 | 0.66 | 0.66 | 0.69 | 0.66 | 0.64 | 0.68 | 0.71 | 1, 3, 4, 6 | 0.70 | 0.73 | 0.75 | 0.75 |

a We report results for the Stack BiLSTM system with the best QWκ (optimized across different types of word and character embeddings).
b We report results for the fusion system with the best QWκ (optimized across all combinations of individual systems).
c Human Inter Rater Agreements expressed in Krippendorff α and Conger κ (note that this is not directly comparable to the reported QWκs).