Speaker-Conditioned Hierarchical Modeling for Automated Speech Scoring

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ABSTRACT

Automatic Speech Scoring (ASS) is the computer-assisted evaluation of a candidate's speaking proficiency in a language. ASS systems face many challenges like open grammar, variable pronunciations, and unstructured or semi-structured content. Recent deep learning approaches have shown some promise in this domain. However, most of these approaches focus on extracting features from a single audio, making them suffer from the lack of speaker-specific context required to model such a complex task. We propose a novel deep learning technique for non-native ASS, called speaker-conditioned hierarchical modeling. In our technique, we take advantage of the fact that oral proficiency tests rate multiple responses for a candidate. We extract context vectors from these responses and feed them as additional speaker-specific context to our network to score a particular response. We compare our technique with strong baselines and find that such modeling improves the model's average performance by 6.92% (maximum = 12.86%, minimum = 4.51%). We further show both quantitative and qualitative insights into the importance of this additional context in solving the problem of ASS.

KEYWORDS

automated speech scoring, spontaneous speech, end-to-end, hierarchical modeling, multi-modal, interpretability, AI in education

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1 INTRODUCTION

Automated Scoring (AS) of language is one of the most popular applications of artificial intelligence. The first such reporting goes

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back to 1960s for the Project Essay Grade (PEG) by Ellis Page [41]. Since then, the systems have expanded by leaps and bounds and now they grade millions of test-takers per year [3, 23, 31]. The scores given by them are used in important decisions including college admissions, visa approvals, screening interviews, and even highschool exams [3, 23, 38, 67]. Apart from its immense importance in the education and learning domain, automatic scoring also has a large market size of more than USD 110 billion, with a US market size alone of USD 17.1 billion [32, 52, 61, 65].

AS, in general, refers to the act of using computers to convert a candidate's performance on standardized tests to some performance metrics. AS systems are required to interpret and analyse the candidate's response and make a prediction that can be used to infer the person's ability [15]. Automatic Speech Scoring (ASS), a type of AS, assesses the speaking proficiency of a candidate in a language. ASS systems are used for a variety of reasons such as to decide admissions to universities, alleviate the workload of teachers, save time and costs associated with grading, and evaluation of online courses. For instance, a British teacher spends an average of 8 hours per calendar week scoring exams and assignments [20]. This figure is even higher for developing and low-resource countries where the teacher to student ratio is dismal [39]. ASS systems can effectively reduce this workload while still maintaining quality [29]. Due to this reason, schools in Ohio and Utah have already started automated essay scoring for their high school students and would soon require speech scoring systems [23, 38, 67]. Additionally, with the rise of people taking online courses, online platforms require ASS systems to provide immediate results and feedback to the user. On account of all these reasons, much research and development is required in ASS to better the systems which play such an important part in life-changing decisions including university admissions, visas, and job interviews.

Currently, the majority of work in deep learning based AS has been done in the Automatic Essay Scoring (AES) domain. Speech scoring is a much harder problem than essay scoring as we have to model both the content (*what* was spoken) and delivery (*how* it was spoken). We also have to deal with open grammar, unstructured or semi structured content, prosody, fluency and pronunciation variations. Moreover, it has been noted in previous studies that applying AES approaches for ASS results in significant performance drops [33] due to the mentioned issues. To deal with these challenges, most of the previous studies have used handcrafted features for scoring speech. For instance, TOEFL[®] from Education Testing Service (ETS) is a well-known example which uses a rich set of handcrafted features for ASS [76]. However, handcrafted rules are unable to model higher level features such as opinion formation,

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arguments, prose coherence, *etc.* Therefore, recently more and more approaches are moving towards end-to-end deep learning models for scoring speech responses. For instance, Chen et al. [10] combine acoustic and lexical models to perform ASS. Qian et al. [49] and Grover et al. [19] use LSTM-attention and attention fusion, respectively, to score spontaneous speech responses. Recently, research studies have also shown that incorporating speech transformers for scoring improves performance [19, 69].

Contrary to the true classroom settings, a majority of existing feature engineering and deep-learning research treats automatic speech scoring of samples of the same candidate on different prompts¹ to be independent of each other [6, 74]. That is why most of the previous literature reports the performance of *one model per prompt* with no or minimal information sharing between two models. It is well-known that a speaker's performance on different prompts is related. Even in classroom settings, while scoring a response, a teacher knows the subtleties of each pupil on account of her knowledge of the pupil's performance on previous occasions [6, 74]. Therefore, conditioning models on speakers can lead to information sharing across models corresponding to different prompts and hence is expected to improve the models' performance.

Fig. 1 presents the basic idea of speaker-prompt interaction. Response r_{ij} is determined by two factors: speaker s_i and prompt p_j . Speaker s_i remains constant while prompt p_j changes for generating (answering) a response r_{ij} . Therefore, a model finding the score o_{ij} for a response r_{ij} can benefit from sharing speaker s_i 's information with other prompts (p_k s.t. $k \neq j$). The same idea of information sharing through speaker conditioning has been explored directly or indirectly in other tasks including speaker activity detection [13], speaker diarization [50], text-to-speech [22], speech translation [36], and speaker detection [27] in the speech domain, and authorship verification [25], author-based predictive writing [24], sentiment analysis [75], and natural text generation [40] in the NLP domain. Conditioning on speakers improved the performance on all these tasks.

Building on these gaps in existing research, we propose a novel deep learning architecture which relies on speaker-conditioned hierarchical modeling, where the prompts of each user are bundled by the user-specific context. Specifically, we feed our per-prompt models with user-specific context, allowing the models to better understand the user and make a more informative prediction (§3.4). Using an exhaustive set of experiments involving 108 unique modelprompt pairs, we compare our technique with strong baselines and show the superiority of the proposed speaker-conditioned hierarchical models (§4). We also show that audio features along with text-based features can boost the model performance, as audio features capture details such as stress, hesitation, word intensity, word duration, etc. which are not directly captured by text transcripts and hence not modeled by the text based models. In §4.1 we analyze quadratic weighted kappa and mean squared error to see how well our models perform in comparison to the baselines. We analyze how conditioning on other prompts changes the predictions for

high-bias examples. We also note the speaker level accuracy increase by conditioning on speaker for the proposed models. Later, in §4.2, we interpret the results to see how the speaker-conditioned hierarchical models obtain better predictions than the baseline models. For this, we analyze the information-sharing strengths across prompts (§4.2)

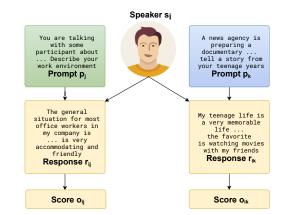


Figure 1: Speaker-Prompt Interaction: Motivation for speakerconditioned models. Speaker s_i gives responses r_{ij} and r_{ik} on prompts p_j and p_k and obtain the score o_{ij} and o_{ik} .

The main contributions of our work are summarised as follows:

- We propose two types of speaker-conditioned hierarchical models for the problem of ASS. To the best of our knowledge, this is the first time speaker conditioning is considered on a multi-prompt dataset in ASS.
- Through extensive experiments on 108 unique model-prompt pairs on a real-life non-native speaker dataset, which contains 7,198 speakers answering 6 prompts each, we show that the proposed models achieve state-of-the-art results on speech scoring. Our method increases average humanmachine agreement by 6.92% (maximum = 12.86%, minimum = 4.51%) over strong baselines.
- Further, using interpretability experiments, we show how our model learns the relations between prompts and individual speaker responses via speaker-conditioned hierarchical embeddings. We find that this also increases the precision for all prompt-specific models. We also find the relative importance of audio and text in ASS.

2 RELATED WORK

Automatic Speech Scoring (ASS): In general, ASS can be of the following types: read-aloud, repeat-aloud, keyword sentence completion, structured narrative, providing an opinion, listen-speak, and conversation-based assessments [16]. Amongst them, structured narrative, providing an opinion, and conversation-based assessments are the most thorough and hence the most challenging ones [16]. In this work, we cover the first two of these three. The range of features covered by this type of assessment is highly comprehensive and include fluency, grammar, vocabulary, discourse coherence, and content, amongst others [73]. Due to the complexity of the task, earlier systems relied on simply measuring automatic

¹Here a prompt denotes an instance of a unique question asked to test-takers for eliciting their opinions and answers in an exam. The prompts can come from varied domains including literature, science, logic and society. The responses to a prompt indicate the creative, literary, argumentative, narrative, and scientific aptitude of candidates and are judged on a pre-determined score scale.

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Prompt	Difficulty	Avg #sec.	Avg #tokens	Score Distribution						
1	B1	57.79	101.91	A2(197)/Low B1(1286)/High B1(5715)						
2	B1	58.82	111.18	A2(400)/Low B1(2697)/High B1(4101)						
3	B2	81.86	151.58	A2(65)/Low B1(463)/High B1(3087)/Low B2(3497)/High B2(86)						
4	C1	104.83	183.83	A2(65)/LB1(463)/High B1(3087)/LB2(3497)/High B2(86)						
5	C1	106.67	199.61	A2(60)/LB1(382)/High B1(2675)/LB2(3945)/High B2(136)						
6	B1	56.15	111.22	A2(56)/Low B1(767)/High B1(6375)						

Table 1: Statistics of the SOPI-SLTI dataset. Difficulty measures the CEFR scale difficulty of each prompt. We report the distribution of each prompt across proficiency levels in the "Score Distribution" column.

speech recognition (ASR) errors on already fixed set of sentences [71].

Over the years, a lot of studies have focused on extracting handcrafted features that cover different aspects of speech such as fluency, rhythm, intonation and stress, vocabulary use, *etc.* [76]. However, these systems are not able to capture complex high-level features such as opinion formation, structure of prose, argument depth, *etc.* Studies have shown that end-to-end systems work better than feature-based systems, while also obviating the need for feature engineering.

Chen et al. [11] were the first to propose an end-to-end network that captures both lexical and acoustic cues to score samples. They used Bi-directional LSTM with attention to generate features from text, and for acoustic cues they used Kaldi ASR's [47] outputs to obtain acoustic model posterior probabilities and word durations, and Praat [8] to obtain pitch and intensity values. They reported an improvement over the conventional method of handcrafted features [76]. Saeki et al. [51] proposed a combination of three models: lexical, acoustic and visual models to score conversation based assessments. Grover et al. [19] proposed a multimodal end-to-end system, which uses a Bi-directional Recurrent CNN and Bi-directional LSTM to encode acoustic and lexical cues from spectrograms and transcriptions, respectively. They applied attention fusion on these features to learn complex interactions between different modalities before final scoring and reported consistent empirical improvements of their system over strong baselines. Qian et al. [48] showed improvements over baselines after including prompt-level information in their models.

Automated Essay Scoring (AES): A task related to ASS is AES. It is one of the most important educational applications of natural language processing (NLP) in the education domain [38, 66, 67]. The first neural network approach was proposed by T&N [63]. They proposed a network which uses Convolutional Neural Network (CNN) to encode local context information, and a long short term memory network (LSTM) to encode long term dependencies. Dong [14] improved this by including the attention mechanism into the network by using attention pooling of CNN features instead of the simple max pooling/average pooling. Tay et al. [64] hypothesized that scoring essays can be improved by computing and using coherence scores of an essay, since coherence is an important dimension of essay quality. They modeled coherence by adding an additional layer to their network which takes in two hidden states of the LSTM network and outputs the similarity or coherence. They used these coherence values to enrich their features and boost their performance.

However, none of the approaches in both AES and ASS have looked into the possible gains after conditioning them on speakers. Our work differs from the current works as we explore speakerconditioned hierarchical modeling, a way to enrich our feature space by providing speaker-specific cues obtained from previously trained models. It has been shown by various previous studies that speaker-conditioned models get better performance across many tasks such as text-to-speech and natural text generation [22, 40].

3 TASK AND DATASET

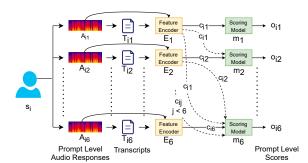
3.1 Dataset

In this study, we use the data collected by Second Language Testing Inc. (SLTI) while administering the Simulated Oral Proficiency Interview (SOPI) Exam for L2 English speakers [19, 58]. The SOPI exam has been operational since 1992 and has a rich research history [58, 60]. Currently, SOPI is used for screening interviews, university admissions, employee training and skill development, university and job placement, and as a test in several online courses [55]. The SOPI offers psychometric advantages in terms of reliability and validity, particularly in standardized testing situations [35].

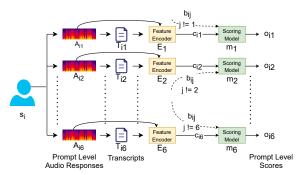
A majority of the speakers in the released dataset are from the Philippines region. The candidates are high school graduates and above. A SOPI test-taker is presented with a question paper containing six prompts on their computer screens, and their responses for each individual item are recorded. The test taker is given approximately one minute to think and two minutes to respond to each question. To answer the questions in the form, the speaker needs to provide arguments and explanations supporting their opinion.

These responses are rated by two expert raters, and in case of a disagreement on the overall score a third rater is asked to resolve the same. The prompts and the rubrics for evaluation follow the guidelines as proposed by the Central European Framework of Reference for Languages (CEFR) [9]. CEFR is an international standard for describing language ability. It describes the language proficiency on a six-point scale, from A1 for beginners to C2 for those who are proficient in the language.

The levels of questions vary from B1 to C1, and the ratings provided to the speakers are upper bounded by the level of the question. The distribution of the dataset and the relevant statistics is provided in Table 1. The dataset consists of 931 hours of speech spoken by 7,198 speakers. The test elicits argumentative, narrative, persuasive and expository skills to answer the questions. For example, the prompt 1 asks candidates to describe their work environment. A candidate gets two types of scores: prompt-level and overall (global)



(a) One Stage speaker-conditioned hierarchical model - Here we use the context vectors c_{ik} from E_k of all the prompts p_k where k < j along with c_{ij} to predict the output score o_{ij} .



(b) Two Stage speaker-conditioned hierarchical model - Here we use the context vectors b_{ik} from baseline encoder E_k of all the prompts p_k where $k \neq j$ along with c_{ij} to predict the output score o_{ij} .

Figure 2: Speaker-conditioned hierarchical models. Above figures show scoring models (m_j) scoring audio responses a_{ij} for speaker s_i on prompt p_j .

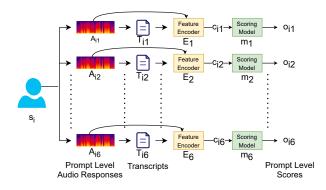


Figure 3: Baseline Modeling Strategy. The figure shows scoring models (m_j) scoring the audio responses a_{ij} for the speaker s_i on prompt p_j . The audio responses a_{ij} are converted to deep embeddings c_{ij} using text and audio encoders E_j .

score. Overall score is computed by combining all the prompt-level scores. Other studies also use the data for various purposes including automated scoring, coherence, *etc.* [5, 19, 45, 56, 57, 59].

3.2 Experimental Setup

We stratify our dataset based on the speaker and global score and then split the candidates in train, validation and test set in 70:10:20 ratio. This ensures that for each prompt we have no speaker intersection in the train, validation and test sets, as required by our speaker-conditioned hierarchical modeling approach. It is noteworthy that this also reflects the real deployment setting. For each prompt, we train our model and report the quadratic weighted kappa (QWK) score on the test set.

We use DeepSpeech2 [1] based ASR system with a trigram language model for transcription of the non-native responses. The ASR system is trained on approximately 1000 hours of audio sampled from CommonVoice [2] and LibriSpeech datasets [42] and further fine-tuned on approximately 22 hours of transcribed nonnative spoken responses from our dataset. The dataset is further augmented with noise using AudioSet [18]. This ASR achieves a word error rate of 16.63%.

We tokenize the transcripts using the Spacy tokenizer [21] and lowercase them. Words not part of the training data vocabulary are mapped to the unknown token (UNK) and initialized to zero vector in the embedding layer. We treat the scoring of the responses as a regression problem such that the output o_{ij} is the normalized score of the speaker s_i 's response r_{ij} to a prompt p_j . The CEFR [9] proficiency levels (N levels) associated with the responses are normalized to the range [0, 1] for training. While testing, we rescale the model output back to the original score range and measure the performance. All our experiments are done using PyTorch [44]. All the plots and hyperparameter tuning were assisted by Weights and Biases [7]. Next, we present our models that were used as feature extractors and the proposed modeling strategies.

3.3 Models

We experimented with several model architectures including Bidirectional LSTM (BDLSTM), Bi-directional LSTM with Attention (BDLSTM+Attn), and BERT based model. We also tried including audio features using wav2vec2.0 [4] with each text encoder model. We demonstrate each of these models with 3 modeling strategies thus showing results for 18 (6*3) different models for 6 prompts. In total, we experiment with 108 (18*6) individual model-prompt pairs. The three modeling strategies are: baseline strategy without any speaker-conditioning (Fig. 3), one stage speaker-conditioned hierarchical modeling (Fig. 2a), two stage speaker-conditioned hierarchical modeling (Fig. 2b). Before explaining the different modeling strategies in §3.4, we first give a brief overview of each of the models.

Bi-Directional LSTM: The Bi-directional LSTM is capable of learning long-term dependencies. A bi-directional network is chosen here to take into account information both from the past and future given the inherent nature of speech and language production. Our model configuration is similar to [11]. The words from the preprocessed transcripts are mapped to their embedding. This word embedding layer is initialized with 300-Dimensional glove embeddings [46] trained on Wikipedia and is optimized during training. We use a single layer of BDLSTM, and assign the hidden layer from the last time step as the context vector (c) for the entire response.

BDLSTM+Attention: The attention mechanism [68] has achieved state-of-the-art on various natural language processing tasks. It enables weighting contextual information learned during each time step, allowing the model to determine which states to pay attention to. We apply attention to the hidden states of a BDLSTM. Given the hidden states of the BDLSTM *h*, we calculate the context vector *c* as follows:

$$e_{t} = W_{a}h_{t}$$

$$a_{t} = softmax(e_{t})$$

$$c = \sum_{i=1}^{T} h_{t}a_{t}$$
(1)

where h_t is the hidden representation at the t^{th} timestep, W_a is the weight matrix for the attention layer which assigns importance scores (e_t) to each hidden state. These scores are then normalised to sum to 1 (a_t) using a softmax layer. The context vector c is a convex combination of the hidden states with weights a_t .

BERT: We use the BERT Tokenizer and the BERT Base model from the huggingface library [72]. Pretrained BERT [12] based embeddings have set a new standard in many natural language processing tasks. The BERT base model has 12 multiheaded self-attention layers with a total of 110M trainable parameters. It produces a 768-dimensional feature vector for a text sequence. We fine tune the last 7 self-attention layers and add a projection layer on top of the features extracted to obtain the context vector (*c*) for a response.

Multi Modal Models: We hypothesise that audio features, along with text-based features can improve the performance of models. We rely on the previous studies that show that audios capture features like stress, hesitation, rhythm, word duration, pitch, intensity, *etc.* which are absent in transcripts and hence text-based features do not give complete information required for scoring [53]. To extract features from audios, we use the pretrained wav2vec2.0 [4] model provided by the huggingface library [72]. Features extracted from wav2vec2.0 have shown SOTA results on various speech tasks [53].

Wav2vec2.0 takes in the raw audio sampled at 16khz, and outputs a 768 dimensional feature vector (v^a), summarising the entire audio. We store these features (v^a) of every audio extracted from wav2vec2.0 and apply a fully connected layer over these features to finetune them and obtain the audio context vector c^a .

$$c^a = W^a v^a + b^a \tag{2}$$

We then concatenate the context vector from the text encoders (c^t) with the audio context vector (c^a) to obtain the multimodal context vector (c) for a response.

$$c = concat(c^t, c^a) \tag{3}$$

3.4 Modeling Strategies

We try out three modeling strategies: baseline strategy without any speaker-conditioning (Fig. 3), one stage speaker-conditioned hierarchical modeling (Fig. 2a), two stage speaker-conditioned hierarchical modeling (Fig. 2b). In the speaker-conditioned hierarchical modeling strategies, we provide other responses (r_{ij} for different values of j) of the same speaker (s_i) on other prompts (p_j) as context (c_{ij}) to the model (m_j) to assist its predictions (o_{ij}). Since a response r_{ij} is dependent on speaker s_i and prompt p_j , we hypothesise that providing the model with a test taker's context can be a crucial element in understanding his/her speech and making a more informed prediction.

Baseline Strategy: This is given by the Fig. 3 where we have 6 models $(m_j, j \in \{1..6\})$, one for each prompt $(p_j, j \in \{1..6\})$. The models are conditioned only on text transcripts (T_{ij}) or a combination of text and audio $(concat(T_{ij}, A_{ij}))$. The text transcripts and audio are encoded by the text and audio encoders $(E_j, j \in \{1..6\})$ explained in the previous section (§3.3). We obtain the context vector c_{ij} from encoder E_j for the response of speaker s_i on prompt p_j . We then pass this context vector through a fully connected layer to obtain the final score o_{ij} .

$$o_{ij} = W_{m_i}c_{ij} + b_{m_j} \tag{4}$$

The models are trained independently of each other using weighted MSE loss until convergence.

One Stage Speaker-Conditioned Hierarchical Model: As we show in Fig. 2a, in this approach, we condition prompt p_j 's scoring model m_j on all the inputs (T_{ik}, A_{ik}) of prompts p_k s.t. k < j. The context of a response is the context vector extracted from the encoder model (*e.g.* final hidden state in BDLSTM).

$$c_{ij} = E_j(T_{ij}, A_{ij}) \tag{5}$$

where c_{ij} is the context vector of a model on the j^{th} prompt for the i^{th} speaker (s_i). We define the new context vector c'_{ij} as:

$$c'_{ij} = concat(c_{i1}, c_{i2}, ..., c_{ij})$$
 (6)

It is the concatenation of context vectors from the previous prompts and the context vector from the current prompt j for a particular speaker s_i . We then pass this new context vector c'_{ij} through a fully connected layer to obtain a score for the sample o_{ij} .

$$o_{ij} = W_{m_i}c'_{ij} + b_{m_j} \tag{7}$$

We train our models sequentially from prompt 1 to prompt 6, and store the context vector for every speaker after the training completes. While training the model on the j^{th} prompt, the context vectors c_{i1} to c_{ij-1} are stored vectors obtained from previously trained models (Fig. 2a). We perform this experiment on all of our models, *i.e.*, BDLSTM, BDLSTM+Attention, BERT, and text encoders with wav2vec2.0.

Two Stage Speaker-Conditioned Hierarchical Modeling: In this approach (Fig. 2b), we assist the training of our model by providing it the context of all the responses of a speaker from the baseline models as shown in Fig. 2b. As modeling non-native users is a harder problem [6, 17, 53], our model needs more user specific context. The context of response is the context vector extracted from the baseline model (*e.g.* final hidden state in BDLSTM) that is then passed through the fully connected layer to score the sample.

$$b_{ij} = E_j(T_{ij}, A_{ij}) \tag{8}$$

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Model	Prompt 1		Prompt 2		Prompt 3		Prompt 4		Prompt 5		Prompt 6		Average	
	QWK	MSE	QWK	MSE	QWK	MSE	QWK	MSE	QWK	MSE	QWK	MSE	QWK	
Baseline Modelling Strategy														
BDLSTM	0.4984	0.2208	0.3298	0.4923	0.4472	0.5847	0.4026	0.7944	0.3718	0.9868	0.3744	0.1534	0.4040	
BDLSTM+Attn	0.5291	0.2284	0.3578	0.4784	0.5050	0.6715	0.5007	0.6277	0.5324	0.5277	0.4254	0.1881	0.4751	
BERT	0.5443	0.2166	0.3566	0.4763	0.5148	0.6305	0.5302	0.5375	0.5494	0.5555	0.4333	0.1777	0.4881	
BDLSTM+Audio	0.5059	0.2336	0.3266	0.4964	0.4732	0.5880	0.4888	0.5951	0.4809	0.6455	0.3922	0.1612	0.4446	
BDLSTM+Attn+Audio	0.5173	0.2464	0.3402	0.5255	0.5390	0.5525	0.5286	0.5724	0.5394	0.5269	0.3859	0.2130	0.4751	
BERT+Audio	0.5385	0.2230	0.3716	0.4704	0.5420	0.5246	0.5289	0.5253	0.5486	0.5239	0.4208	0.1820	0.4917	
		On	e Stage S	peaker-C	ondition	ed Hiera	rchical N	lodelling	Strategy					
BDLSTM	0.4984	0.2208	0.3428	0.4645	0.4390	0.5791	0.4450	0.6548	0.5056	0.5187	0.3398	0.2187	0.4284	
BDLSTM+Attn	0.5291	0.2284	0.3458	0.5125	0.5334	0.5888	0.5330	0.6222	0.5460	0.5805	0.4216	0.1805	0.4848	
BERT	0.5443	0.2166	0.3492	0.4569	0.5772	0.4423	0.5589	0.4479	0.5820	0.4486	0.4726	0.1583	0.5140	
BDLSTM+Audio	0.5059	0.2336	0.3447	0.4810	0.5075	0.5468	0.5258	0.5333	0.5281	0.4865	0.4147	0.1498	0.4711	
BDLSTM+Attn+Audio	0.5173	0.2464	0.3776	0.4481	0.5716	0.5213	0.5657	0.5142	0.5660	0.5241	0.4610	0.1732	0.5099	
BERT+Audio	0.5385	0.2230	0.3746	0.4593	0.5684	0.4642	0.5601	0.4711	0.5770	0.4614	0.4256	0.1938	0.5074	
Two Stage Speaker-Conditioned Hierarchical Modelling Strategy														
BDLSTM	0.4951	0.2194	0.3257	0.4833	0.5307	0.4826	0.5527	0.4256	0.5279	0.4631	0.3040	0.2541	0.4560	
BDLSTM+Attn	0.5350	0.2298	0.3563	0.4437	0.5575	0.5131	0.5592	0.5090	0.5585	0.5326	0.4348	0.1694	0.5002	
BERT	0.5361	0.2243	0.3771	0.4451	0.5911	0.4319	0.5765	0.4527	0.5693	0.5145	0.4701	0.1472	0.5200	
BDLSTM+Audio	0.5422	0.2173	0.3407	0.5028	0.5732	0.4005	0.5872	0.4353	0.5190	0.4857	0.3031	0.2592	0.4776	
BDLSTM+Attn+Audio	0.5104	0.2443	0.3637	0.4332	0.5669	0.5092	0.5614	0.5120	0.5663	0.4801	0.4212	0.1740	0.4983	
BERT+Audio	0.5173	0.2216	0.3464	0.4607	0.5992	0.4204	0.5727	0.4558	0.5927	0.4475	0.4552	0.1827	0.5139	

Table 2: Quadratic Weighted Kappa (QWK) score and Mean Squared Error (MSE) across prompts for different models. We present the results for the three modeling strategies (baseline, one stage speaker-conditioned hierarchical and two stage speaker-conditioned hierarchical) and 6 models (BDLSTM, BDLSTM+Attn, BERT, BDLSTM+Attn+wav2vec2.0, BERT+wav2vec2.0). Bold text represents best modeling technique for the model-prompt pair and green text represents best model for each prompt. It is noteworthy that most green and bold values lie in the proposed one-stage and two-stage speaker-conditioned hierarchical models.

Let b_{ij} be the stored context vector of a trained baseline model trained on the j^{th} prompt for the i^{th} speaker (s_i) . Then the global context vector for s_i be defined as

$$v_i = concat(b_{ii,\forall i \neq i}^6) \tag{9}$$

We define the new context vector c'_{ij} as

$$c_{ij}' = concat(v_i, c_{ij}) \tag{10}$$

as the concatenation of the global baseline context vector v_i and the context vector from the current prompt c_{ij} for a particular speaker. We then pass this new context vector (c'_{ij}) through a fully connected layer to obtain a score for the sample o_{ij} .

$$o_{ij} = W_{m_i} c'_{ij} + b_{m_j} \tag{11}$$

We perform this experiment on all of our models, *i.e.*, BDLSTM, BDLSTM+Attention, BERT, and text encoders with wav2vec2.0 (Fig. 2b).

3.5 Training

We use the weighted mean square loss as our loss function defined as:

$$WMSE(y_{true}, y_{pred}) = \frac{1}{N} \sum_{i=1}^{N} (y_{true}^{i} - y_{pred}^{i})^{2} w_{y_{true}^{i}}$$
(12)

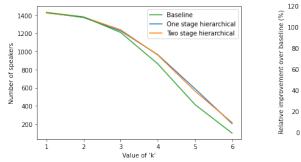
where y_{true}^{i} , y_{pred}^{i} are the scaled ground truth, and predicted grade, respectively. $w_{y_{true}}$ is the weight of the ground truth class. We use the weighted mean squared loss due to class imbalance

in the training data as shown in Table 1. We use the Adam [26] optimizer to minimize our loss over the training data. To prevent overfitting, we train the model with early stopping on the weighted validation MSE loss. We also use the ReduceLROnPlateau scheduler as provided in PyTorch [44] to reduce the learning rate when the weighted validation MSE loss does not improve.

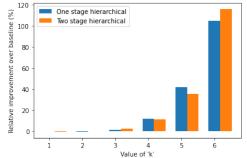
3.6 Evaluation Metric

Similar to previous studies [19, 29, 30, 43, 49, 69, 70], we have used the quadratic weighted kappa (QWK) as our evaluation metric. It measures the level of agreement between two sets of ratings. The metric outputs values between 0 (random agreement between ratings) and 1 (complete agreement between ratings). In cases where the agreement is less than expected by chance, the score can be negative too. To calculate the QWK score, firstly we calculate the confusion matrix O of size CxC, where C is the total number of classes. O_{ii} represents the number of samples with true label i and predicted label *j*. The matrix is normalised to have sum equal 1. We calculate the weight matrix W of size CxC, where $W_{ij} = (i-j)^2/(C-i)^2$ $1)^2$. The weight matrix penalises predictions that are further away from their ground truth more harshly than the ones that are closer to the ground truth. Then we create the histogram matrix of expected grades E of size CxC, which is calculated by taking the outer product of histograms of ground truth and predicted labels. We normalise this matrix such that the sum equals 1. The QWK is calculated as:

$$QWK = 1 - (\sum_{i,j} W_{ij}O_{ij}) / (\sum_{i,j} W_{ij}E_{ij})$$
(13)



(a) Number of speakers for whom output scores of at least k prompts are predicted correctly.



(b) Relative improvement over baseline (in %) in the number of speakers for whom output scores of at least k prompts are predicted correctly.

Figure 4: Speaker level accuracy comparison in the three modeling strategies. For generating these plots, we use the results from BERT model.

Apart from QWK metric, following the recommendations of other studies [30, 34], we analyze the results more comprehensively by calculating speaker-level accuracy, performance on near decision-boundary samples and high-biased samples. In order to gain more intuition, we perform attributions over both modalities and also show information sharing strength across prompts. The results of all these analyses are presented in the next section.

4 RESULTS

Here we present the quantitative and qualitative results for the different models and modeling strategies.

4.1 Quantitative Analysis

QWK Score: In Table 2, we compare the two proposed speakerconditioned hierarchical approaches with baseline strategies on various models. It can be inferred from the table that *speakerconditioned hierarchical modeling consistently improves performance across all the models on all prompts.* This result supports our hypothesis that speaker-specific cues assist the model in making better informed predictions. In table 2, we also report the average QWK for each model which we define as the average of promptwise QWK values for a model. The mean improvement in average QWK across all models is 4.97% (maximum = 7.32%, minimum = 2.05%) and 6.92% (maximum = 12.86%, minimum = 4.51%) in one stage and two stage hierarchical models compared to their baseline counterparts.

Similar to average QWK, we also compute average MSE for each model. As compared to the baseline, we observe a mean decrease in average MSE by 10.03% and 15.21% in one stage and two stage hierarchichal models, respectively.

We see that the two stage speaker-conditioned hierarchical BERT model performs better than the other models in three out of six prompts. For the other three, the one stage speaker-conditioned hierarchical BERT model performs better. This result strongly indicates that conditioning on speakers has improved the results.

Table 2 also contains results for experiments with text and audio features. Similar trends as text-only models are also observed here. First, we see an improvement in performance of 61.11% multimodal models as compared to the text-only models. Our one stage and two

stage speaker-conditioned hierarchical BDLSTM+Attn+Wav2Vec2.0 model beats the BERT text-only model. This shows that our hypothesis of audio-specific features not being captured within text transcriptions was true and including wav2vec2.0's features helped improve the performance. Speaker-conditioning the models further improves the performance by 5.9% as compared to the multi-modal baseline models.

Speaker Level Accuracy: Since our hypothesis is that including speaker-level information from previous models should improve the performance of subsequent models, we also show improvements in speaker-level accuracy. For this, we first compare the mean number of prompts correctly classified for each speaker by the three modeling strategies, *i.e.*, $\frac{1}{N} \sum_{i=1,j=1}^{i=N,j=6} I(y_{true,i,j} = y_{pred,i,j})$ where $y_{pred,i,j}$, $y_{true,i,j}$ are the predicted output and the ground truth for *i*th speaker on *j*th prompt. We found that the mean number of correctly classified prompts for one stage hierarchical and two stage hierarchical models are 4.018 and 4.014, respectively, which is 7.4% better than the baseline mean of 3.740.

To strengthen our claims further for speaker level accuracy, we compare the number of speakers for whom responses on at least k prompts are predicted correctly for the three modeling strategies. Concretely, we measure, $Count_{i=1}^{N}(I(\sum_{j=1}^{6}I(y_{true,i,j} = y_{pred,i,j}) \ge k))$ for different values of k. We present the results in Fig. 4a, where we see that both the one-stage hierarchical model and the two stage hierarchical model outperform the baseline for all the values of k. In Fig. 4b, we can see the significance of this improvement as compared to the baseline model. As the value of k increases, the relative improvements become more significant. This observation suggests that speaker-specific cues used in speaker-conditioned modeling help our model increase speaker level accuracy.

High Bias Samples: We set out to see if conditioning on speakers makes the models avoid errors where the model's predictions are far from the ground truth ($|y_{true} - y_{pred}| \ge 2$). Based on our hypothesis, we expect that given more speaker level information, the models should be able to perform better on such samples. Consequently, we analyze samples which were predicted incorrectly by more than 2 score levels. As compared to baseline models, we observe upto **60**% and **55**% reduction in high-bias errors in one stage

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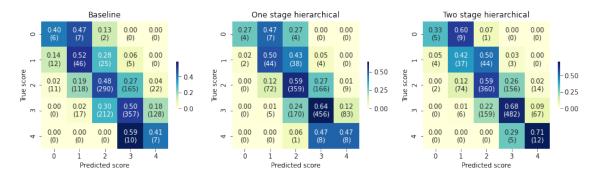


Figure 5: Heatmap on prompt 4, each element e_{ij} depicts percentage (number) of samples predicted in score *j* having ground truth score *i*. The blue patches clearly indicate that there are lesser samples satisfying $|y_{true} - y_{pred}| \ge 2$ in case of our proposed models when compared to the baseline models

and two stage hierarchical models, respectively. Results obtained on prompt 4 are presented in Fig. 5. This shows that giving more speaker-specific context reduces errors on high-bias samples.

Bias Due To Performance On Other Prompts: Since with speaker conditioning, we are giving more speaker context to the models, models might become unfairly biased towards a speaker's previous (good or bad) performance in some prior prompt. For instance, if a speaker performs poorly (well) on some prior prompt but better (poor) on the current prompt, the speaker should not be unfairly penalized (awarded) because of his previous performance.

We analyse the models' predictions for those samples on which the speakers have a high predicted score on prompt i - 1 and low ground-truth scores on prompt *i*. For the other case (where predicted score on prompt i - 1 is low and ground truth on prompt i is high), the number of samples were too less to obtain any statistical inference. We find that one stage and two stage hierarchical models tend to give a higher score than the ground truth score relative to the baseline in 3.5%, 7% samples, respectively. Although this was not consistent across all prompts. Moreover, the average percentage of correctly predicted samples in the one stage and two stage hierarchical models were higher by 10.30% (maximum = 28.00%, minimum = 4.10%) and 10.05% (maximum = 36.34%, minimum = 4.43%), respectively, than the corresponding baseline models. Therefore, despite the increase in predictions observed in 3 out of 6 prompts, the percentage increase in correctly predicted samples is much more significant. This shows that the model extracts speakerspecific features and rather than being biased by it, the model uses it to improve its performance on the current prompt and be more precise. We leave the correction of marginal score change on 3 out of 6 prompts as future work.

Performance On Samples Near Decision Boundary: We define near decision boundary samples as the ones where the two raters disagree on speech scores. Fig. 6 presents the results for both types of samples, *i.e.*, where human raters (i) agree and (ii) disagree with each other. We observe that conditioning on speakers improves the performance on both types of samples. Average accuracy increase is 14.91% and 6.33% in agreements and disagreements for prompts 2, 3, and 5 over the baseline models. Further, we observe that all modelling strategies have a lower accuracy and QWK for samples where the two raters disagree. This is expected

since these samples are hard for both humans and models and can be considered to lie near the model's decision boundary.

4.2 Qualitative Analysis

In Section 4.1, we see an improvement in the QWK score. In order to further probe how our technique helps in improving model performance, we use an attribution method to analyze models' predictions with respect to their inputs. We employ the method of integrated gradients [62] for this purpose:

Given an input *x* and a baseline b^2 , the integrated gradient along the *i*th dimension is defined as:

$$IG_i(x,b) = (x_i - b_i) \int_{\alpha=0}^{1} \frac{\partial F(b + \alpha(x - b))}{\partial x_i} d\alpha \qquad (14)$$

where $\frac{\partial F(x)}{\partial x_i}$ represents the gradient of *F* along the *i*th dimension of *x*. We choose the baseline as empty input (all 0s) since an empty speech sample should get a score of 0 as per the scoring rubrics. For the first experiment on prompt-wise attribution, we took prompt-wise response embeddings as the dimension of attribution. For the second experiment on finding the contribution of modalities, we took text and audio modalities across all prompts, as the two dimensions for finding attributions.

Integrated gradients have been successfully used in the past for various NLP tasks [37, 43, 54]. To calculate these attributions, we used the Captum [28] library and aggregated all attributions of the test set to retain a global view of the importance of different embeddings.

Prompt-wise Attribution: To assess information sharing strength across prompts, we compute prompt-wise attributions on the two stage hierarchical models. The results for this are shown in Fig. 7. Here we observe that the most crucial embedding in predicting each prompt is the embedding from the prompt itself, which is expected since this embedding contains most of the context related to the response of that prompt. Additionally, we can see that there are many lighter patches in Fig. 7. These patches represent the importance of embeddings from other prompts in the current model's predictions. As can be seen in the heatmap, embeddings from prompts 1 and 2

²Defined as an input containing absence of cause for the output of a model; also called neutral input [54, 62].

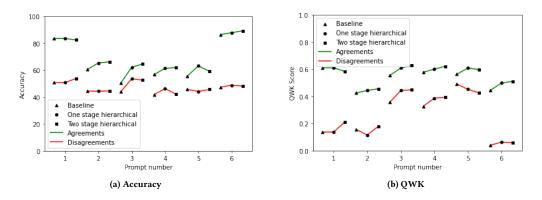


Figure 6: (a) Accuracy and (b) QWK on two types of samples: (i) Where the two expert raters agree (ii) Where the two expert raters disagree

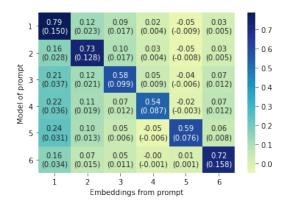


Figure 7: Heatmap for promptwise attributions calculated using BERT two stage speaker-conditioned hierarchical model. Here, each element e_{ij} depicts contibution (attribution value) of prompt j's embeddings in predicting the output score of prompt i

were the most important and contributed significantly in predicting other prompts. This validates our hypothesis that providing a model with rich user specific context via hierarchical modeling can be useful for improving its performance.

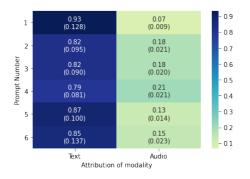


Figure 8: Attribution value of each modality in predicting other prompts calculated using BERT+wav2vec2.0 two stage speaker-conditioned hierarchical model.

Contribution Of Modalities: To understand the importance of text and audio individually in predicting output scores of different prompts, we calculated attribution scores over them (see Fig. 8). We observe that attribution scores are lower for audio as compared to text for all prompts. This demonstrates that our text encoders were able to capture most of the information required for predicting scores and audio embeddings fulfilled the shortcomings of the text encoding process (like pronunciation and prosody which cannot be directly extracted from text transcripts).

We also observe that the relative contribution of audio was the highest for prompts 3 and 4 which are incidentally the most difficult prompts (Table 1). This is expected since for more difficult prompts, apart from content, the presentation also plays an important role. On the other hand, prompts 1 and 6 have the highest contribution of text. These prompts had the lowest difficulty level (B1) and hence content plays a dominant role in the score predictions for them. We observed similar plots for both one stage speaker-conditioned and baseline models.

5 CONCLUSION

In this paper, we have investigated end-to-end deep learning based models for the automated speech scoring task for L2 English speakers. We show that speaker-conditioned hierarchical models perform better than their baseline counterparts. Results indicate that providing the model with additional speaker-specific context helps the model in better understanding the speaker and making a more informed prediction. These models are more precise and less biased than their baseline counterparts. We also show that including audio based features increases models' expressivity and generalisability, which improves the overall performance. In future work, we wish to explore the effectiveness of our technique on AES, offtopic response detection, and individual speech components such as dysfluency and pronunciation.

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