A Hierarchical Reasoning Graph Neural Network for The Automatic Scoring of Answer Transcriptions in Video Job Interviews

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Abstract

We address the task of automatically scoring the competency of candidates based on textual features, from the automatic speech recognition (ASR) transcriptions in the asynchronous video job interview (AVI). The key challenge is how to construct the dependency relation between questions and answers, and conduct the semantic level interaction for each question-answer (QA) pair. However, most of the recent studies in AVI focus on how to represent questions and answers better, but ignore the dependency information and interaction between them, which is critical for QA evaluation. In this work, we propose a Hierarchical Reasoning Graph Neural Network (HRGNN) for the automatic assessment of questionanswer pairs. Specifically, we construct a sentence-level relational graph neural network to capture the dependency information of sentences in or between the question and the answer. Based on these graphs, we employ a semantic-level reasoning graph attention network to model the interaction states of the current QA session. Finally, we propose a gated recurrent unit encoder to represent the temporal question-answer pairs for the final prediction. Empirical results conducted on CHNAT (a real-world dataset) validate that our proposed model significantly outperforms text-matching based benchmark models. Ablation studies and experimental results with 10 random seeds also show the effectiveness and stability of our models.

Introduction

Recent years have witnessed the rapid advancement of online recruitment platforms. With the increasing amount of online recruitment data, more and more interview related studies have emerged such as person-job (or talent-job) fit (Shen et al. 2018; Qin et al. 2018; Luo et al. 2019b; Bian et al. 2019) and automatic analysis of asynchronous video interviews (AVIs) (Hemamou et al. 2019b,a; Suen, Hung, and Lin 2019), which aim to enable automated job recommendation and candidate assessment. Among these studies, person-job fit is to casting the task as a supervised text match problem. Given a set of labeled data (i.e., person-job match records), it aims to predict the matching label between the candidate resumes and job description. More recently, deep learning has enhanced person-job fit methods by training more effective text match or text representations models (Xu

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et al. 2017; Jiang et al. 2019). AVI is to determine whether the candidate is hirable by evaluating the answers of interview questions. In AVIs, an interview is usually considered as a sequence of questions and answers containing salient socials signals. To evaluate the candidates more comprehensively, AVI models will extract the features of video (or image), text, and voice in the process of answering questions. In this work, we focus on the scoring of multiple QA pairs, we only extract the features of text modality and define this task as the scoring competency of candidates rather than the score of whether or not to be employed. Based on the anatomy of the human interviewers' evaluation process, the solutions consist of two stages: (1) analyzing and evaluating individual QA pair one by one, then acquiring the evaluation status, and (2) grading the competency of the candidate based on the evaluation status of multiple QA pairs.

For the first stage, existing methods tend to employ text matching or attentional text matching algorithms to evaluate QA pairs (Hemamou et al. 2019b; Suen, Hung, and Lin 2019), which feeds the concatenated representation of the question and the answer to the subsequent classifier. As we all know, questions in an asynchronous video interview are not limited to specific domains. That is to say, candidates can answer questions according to their work or study experience. In this way, the candidates' answers will be varied and it is difficult to evaluate the answer accurately only by text matching. Intuitively, it is more reasonable to evaluate QA pairs through the semantic interaction between questions and answers. A critical challenge along this line is how to reveal the latent relationships between each question and answer.

Graph neural networks (GNNs, (Dai, Dai, and Song 2016; Yao, Mao, and Luo 2019; Ghosal et al. 2019)) can learn effective representation of nodes by encoding local graph structures and node attributes. Due to the compactness of model and the capability of inductive learning, GNNs are widely used in modeling relational data (Battaglia et al. 2018; Schlichtkrull et al. 2018; Pan et al. 2020) and logical reasoning (Luo et al. 2019a; Jiang and Han 2020). Recently, Zhang et al. (2020a) proposed a GNN variant, Named ExpressGNN, to strike a nice balance between the representation power and the simplicity of the model in probabilistic logic reasoning. Ghosal et al. (2019) constructed the DialogeGCN to address context propagation issues present

in the RNN-based methods. Specifically, they leverage self and inter-speaker dependency of the interlocutors to model conversational context for emotion recognition. Inspired by (Ghosal et al. 2019), we present a sentence-level relational GCN to represent the internal temporal and QA interaction dependency in the process of answering questions.

For the second stage of grading the candidate, based on the representation of QA pairs, exists methods (Hemamou et al. 2019b,a) prefer to encoder question-answer pairs as a sequence directly. However, this kind of approaches lead to insufficient interaction between the semantic information of question and answer pairs. Therefore, it is difficult to ensure the rationality and explainability of the evaluation. To mitigate this issue, in the first stage, we present a semantic-level graph attention network (GAT) to model the interaction states of each QA session.

To this end, we propose a Hierarchical Reasoning Graph Neural Network (HRGNN) for the automatic scoring of answer transcriptions (ASAT) in job interviews. Specifically, the proposed sentence-level relational graph convolutional neural network (RGCN) is used to capture the contextual dependency, and the semantic-level Reasoning graph attention network (RGAT) is applied to acquire the latent interaction states. And the contribution of our work can be summarized as follows:

- We propose a relational graph neural network to remedy the lack of QA interaction in previous assessment methods. Specifically, the relation of internal temporal dependency in each question/answer is helpful for context understanding. And the relation of QA interaction dependency can establish the latent semantic interaction of question-to-answer and answer-to-question.
- To our knowledge, we are the first one to construct a hierarchical graph neural network for ASAT to model the relation between sentences in the question and its homologous answer, and interact and infer at the semantic level. Although we just evaluate the competence of candidates on textual features, it greatly improves the rationality and accuracy of the evaluation.
- Our model can outperform all existing benchmark approaches on a Chinese real-world dataset. Ablation studies and experimental results with 10 random seeds show the effectiveness and stability of our models.

Related Work

Asynchronous Video Interviews The asynchronous video interview is considered as one of the most essential tasks in talent recruitment, which forms a bridge between employers and candidates in fitting the eligible person for the right job (Shen et al. 2018; Hemamou et al. 2019a,b). Shen et al. (2018) developed a joint learning system to model job description, candidate resume, and interview assessment. It can effectively learn the representation perspectives of the different job interview process from the successful job interview records and then applied in person-job fit and interview question recommendation. Hemamou et al. (2019b) takes an interview process as a sequence of questions and answers and proposed a hierarchical attention model named

HireNet to predict the hireability of the candidates. As far as we know, these approaches ignore the deep dependency between interview questions and answers.

Short Answer Scoring Automatic short answer scoring (ASAS) (CLAUDIA and CC-rater 2003; Sultan, Salazar, and Sumner 2016; Lun et al. 2020; Goenka et al. 2020) is a research subject of intelligent education, which is a hot field of natural language understanding. Methods for ASAS are driven with the help of deep learning techniques (Mueller and Thyagarajan 2016; Zhao et al. 2017) and domain-specific knowledge (Conneau et al. 2017; Goenka et al. 2020). Recently, Saha et al. (2019) have used InferSent (Conneau et al. 2017) and neural domain adaptation to obtain state-of-the-art results in the ASAS task. Lun et al. (2020) proposed multiple data augmentation strategies to learn language representation and achieved a significant gain over benchmark models. It should be emphasized that, in ASAS tasks, the answer text is short and the domain is specific. For the ASAT task which contains several opendomain interview questions, the scoring of long-text answers is much more challenging.

Graph Neural Network Graph neural networks have been successfully applied to several natural language processing tasks, such as text classification (Veličković et al. 2017; Yao, Mao, and Luo 2019; Zhang, Liu, and Song 2018; Zhang et al. 2020b), machine translation (Marcheggiani, Bastings, and Titov 2018), question generation (Pan et al. 2020; Chen, Wu, and Zaki 2020) and fact verification (Zhou et al. 2019). Zhou et al. (2019) propose a graph-based evidence aggregating and reasoning (GEAR) framework which enables information to transfer on a fully-connected evidence graph and then utilize different aggregators to collect multi evidence information. Pan et al. (2020) constructed a semantic-level graph for content selection and improved the performance over questions requiring reasoning over multiple facts. Inspired by previous researches, we proposed a hierarchical reasoning graph neural network to alleviate the issues of lacking interaction and semantic reasoning between questions and answers in the video job interview.

Methods

We now introduce the proposed Hierarchical Reasoning Graph Neural Network (HRGNN) for the automatic scoring of answer transcriptions in the job interview. HRGNN consists of four integral components — Gated Recurrent Unit Encoder, Sentence-level GCN Encoder, Semantic-level GAT Encoder, and Competency Classifier. An overview of HRGNN is shown in Fig. 1. We first give some detailed explanation about Problem Formalization.

Problem Formalization

We represent the automatic scoring of answer transcriptions in video job interview as an object composed of n questionanswer pairs $\{\{Q_1,A_1\},\{Q_2,A_2\},...,\{Q_n,A_n\}\}$. In our model, the ith question Q_i is a sequence of c_{Q_i} sentences (sub-questions) $\{q_1^i,q_2^i,...,q_{c_{Q_i}}^i\}$, where c_{Q_i} represents the count of sentences in question i. Subsequently, the j-th sentence q_i in the question Q_i can be formulated as

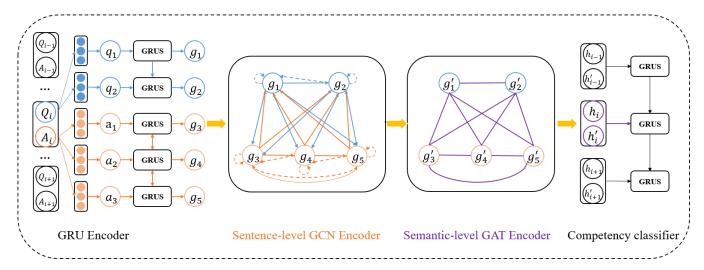


Figure 1: An overview of the proposed HRGNN. As an example, upon a QA session in the interview, every sentence node updates itself from its neighbors. In the sentence-level GCN, each updated node contains dependency information and will be aggregate by the subsequent GAT encoder on the semantic-level. Finally, a GRU network is employed to represent the global interview for competency prediction.

 $\{w_1^{q_j}, w_2^{q_j}, ..., w_{l_{q_j}}^{q_j}\}. \text{ Here } l_{q_j} \text{ is the number of words in sentence } j. \ A_i \text{ denotes the sequence of words } \{a_1^i, a_2^i, ..., a_{c_{A_i}}^i\} \text{ describing the } i\text{th answer. And } c_{A_i} \text{ denotes the number of sentences in the } i\text{th answer. In a same way, the } j\text{-th sentence } a_j \text{ in the answer } A_i \text{ is a sequence of } l_{a_j} \text{ words } \{x_1^{a_j}, x_2^{a_j}, ..., x_{l_{a_j}}^{a_j}\}. \text{ And } l_{a_j} \text{ denotes the length of the } j\text{-th sentence } a_j \text{ in the answer } A_i.$

Gated Recurrent Unit Encoder

For the sentence in the question and the answer, we follow previous work (Jang et al. 2019; Wang et al. 2020) and represent each word as a vector using the pre-trained GloVe word embedding denoted as $E=\{e_i:i\leq l_q,e_i\in\mathcal{R}^{300}\}$ and $F=\{e_j:j\leq l_a,e_j\in\mathcal{R}^{300}\}$, where l_q and l_a indicate the number of embedded words in the sentence of question or answer.

To obtain contextual representations to aggregate temporal information and enhance reasoning ability, we employ two independent Gated Recurrent Unit (GRU) (Chung et al. 2014) to each sentence in the questions and the answers separately. To reduce the cost of information in the longer answer, we set the encoder of the answer to bidirectional. The generated question sentence features $V_q \in \mathcal{R}^{l_q \times d}$ and answer sentence features $V_a \in \mathcal{R}^{l_a \times d}$ denote as:

$$V_q, v_{l_q} = \overrightarrow{GRU}(E, \theta_{GRU}),$$
 (1)

$$V_a, v_{l_a} = \overleftarrow{GRU}(F, \theta_{GRU}),$$
 (2)

where v_{l_q} and v_{l_a} are the outputs of the last hidden units which represent the global features of the two sentences in the question and the answer.

Sentence-level GCN Encoder

We propose the Sentence-level GCN Encoder module to capture the dependency information in the process of answering questions. Effectively modeling the context of the long-text answer requires capturing the inter-dependency and self-dependency among sentences in the question and the answer. Therefore, we construct a directed graph from the sequentially encoded sentences to capture the dependency between the question and the answer. Furthermore, we propose a neighborhood-based convolutional feature transformation process to create contextually features. The framework is detailed here.

First, we introduce the following notation: a single QA session is represented as a directed graph $\mathcal{G}=(\mathcal{V},\mathcal{E},\mathcal{R},\mathcal{W})$, with vertices $v_i\in\mathcal{V}$, labeld edges (relations) $r_{ij}\in\mathcal{E}$ where $r\in\mathcal{R}$ is the relation type of the edge between v_i and v_j , and α_{ij} is the weight of the labeled edge r_{ij} , with $0\leq\alpha_{ij}\leq1$, where $\alpha_{ij}\in\mathcal{W}$ and $i,j\in[1,2,...,c_Q]$ and $[1,2,...,c_A]$, respectively.

Graph Construction The graph is constructed from the sentences in the following way.

Vertices: Each sentences in the question or answer is represent as a vertex $v_i \in \mathcal{V}$ in \mathcal{G} . Each vertex v_i is initialized with the corresponding sequentially encoded feature vector h_i , for all i in $[1, 2, ..., c_Q]$ or $[1, 2, ..., c_A]$. We denote this representation vector as the vertex feature. Here, vertex features are subject to update downstream, when the transformation process is used to encode the context of QA pair.

Edges: Construction of the edges \mathcal{E} depends on the context of the current question and answer to be modeled. As mentioned, in this scenario, we need to evaluate several QA pairs in the interview session. And to acquire the ideal job opportunity, candidates would like to answer each subquestion more clearly, which leads to the answer text contains many sentences. It will be computationally quite expensive to construct the graph neural network through a full connection. Therefore, inspired by Ghosal et al. (2019), we employ a more efficient way to construct the edges by keep-

ing a past context window size of p and a future context window size of f. Hence, each vertex v_i has an edge with the immediate p sentences of the past: $v_{i-1}, v_{i-2}, ..., v_{i-p}$, f sentences of the future: $v_{i+1}, v_{i+2}, ..., v_{i+f}$ and itself: v_i .

Meanwhile, as the graph is directed, vertices from the question or the answer or both can have edges in both directions with different relations.

Edge Weights: We apply a similarity based attention module to acquire the edge weights. The attention function is computed in a way such that, for each vertex, the total weight of the incoming edges is 1. Considering the past and future context window size of p and f, respectively, we calculated the weights as below,

$$\alpha_{ij} = softmax(g_i^T W_e[g_{i-p}, ..., g_{i+f}]),$$

 $for \ j = i - p, ..., i + f.$ (3)

where W_e represents the parameter to be learned. In this way, it can be ensured that the incoming edges of vertex v_i receives a total weight contribution of 1.

Relations: The relation r of an edge r_{ij} is designed in two aspects:

Internal temporal dependency In the i-th question/answer, especially, the i-th answer, the relation depends on the relative position of occurrence of u_i and u_j in the question/answer: whether u_i is appeared before u_j or after. Therefore, there can be c_{Q_i} (sentences in Q_i) * c_{Q_i} + c_{A_i} (sentences in A_i) * c_{A_i} = $c_{Q_i}^2$ + $c_{A_i}^2$ relation types r in the graph $\mathcal G$ for context understanding.

Question-Answer interaction dependency The relations also depends upon the interaction dependency between the question and answer in the QA session. To establish the latent semantic interaction relationships of question-to-answer and answer-to-question, we define the relation of Question-Answer interaction. There will be $c_{Q_i} * c_{A_i} + c_{A_i} * c_{Q_i} = 2c_{Q_i}c_{A_i}$ relation types r in the graph $\mathcal G$ for reasoning. Thus, the total number of distinct relation types in the graph $\mathcal G$ is $c_{Q_i}^2 + c_{A_i}^2 + 2c_{Q_i}c_{A_i} = (c_{Q_i} + c_{A_i})^2$.

Relation	$Q(u_i), A(u_j)$	i < j	(i,j)
1	Q,Q	Yes	(1,2)
2	Q,Q	No	(1,1),(2,1),(2,2)
3	Q,A	-	(1,3),(1,4),(1,5),(2,3),(2,4),(2,5)
4	A,Q	-	(3,1),(3,2),(4,1),(4,2),(5,1),(5,2)
5	A,A	Yes	(3,4),(3,5),(4,5)
6	A,A	No	(3,3),(4,3),(4,4),(5,3),(5,4),(5,5)

Table 1: $Q(u_i)$ and $A(u_j)$ indicate the source of sentence u_i and u_j . The question and the answer in the current session imply $(2+3)^2=25$ distinct relation types. '-' means the connection between the question and the answer is independent of the index. The rightmost column denotes the indices of the vertices of the constituting edge which has the relation type indicated by the leftmost column.

As we all know, the total assessment in an interview is affected by each QA session, and the evaluation of a single QA session should be based on the semantic interaction

state between the question and the answer. Therefore, we hypothesize that explicit declaration of such relational edges in the graph would benefit in capturing the latent Relation of Question-Question (RQQ), Answer-Answer (RAA), and Question-Answer (RQA) among the QA session, which in succession would facilitate the total assessment of the whole interview.

As an illustration, let the question Q and the answer A in a QA session have 5 sentences, where u_1, u_2 are two subquestions in Q, and u_3, u_4, u_5 are sentences in A. Then the edges and relations will be constructed as shown in Table 1.

Feature Transformation The additive attention based sentence encoder mentioned the previous subsection provides effective sentence-level features h_i^0 for initialing the i-th node. Beyond that, the graph provides more dependency information between sentences in questions and answers. A more desirable way is to aggregate these information at the graph-level to get semantic status. A new feature vector $h_i^{(l+1)}$ is computed for vertex v_i by aggregating local neighbourhood information through the relation specific transformation inspired from (Schlichtkrull et al. 2018; Ghosal et al. 2019):

$$h_i^{(l+1)} = \sigma(\sum_{r \in \mathcal{R}} \sum_{j \in N_i^r} \frac{\alpha_{ij}}{c_{i,r}} W_r^{(l)} g_j + \alpha_{ii} W_0^{(l)} g_i)$$

$$for \ i = 1, 2, ..., N.$$
(4)

where σ is an activation function, and $W_0^{(1)}$ and W_r^1 are learnable parameters of the transformation. α_{ii} and α_{ij} are the weights of the edges, N_i^r represents the neighbouring indices of vertex i under relation $r \in \mathcal{R}$. $c_{i,r}$ is the normalizer equal to $|N_i^r|$.

Semantic-level GAT Encoder

In order to reason on the semantic level, we employ a graph attention network to gather information from the nodes of the sentence-level graph and obtain the final hidden state h' of each sentence. With the feature vector $\boldsymbol{h}_i^{(l+1)}$ for initialing the i-th node in reasoning GAT, we can get the updated node representation $\tilde{\boldsymbol{h}}_i^{(l+1)}$:

$$\tilde{h}_{i}^{(l+1)} = \sum_{j \in N(i)} \tilde{\alpha}_{i,j} \tilde{W}^{(l)} h_{i}^{(l)}$$
(5)

where $\tilde{\alpha}_{i,j}$ is the attention score between node i and node j:

$$\tilde{\alpha}_{i,j} = softmax(e_{ij}),$$
(6)

$$e_{ij} = \tilde{\sigma}(a^T[\tilde{W}\tilde{h}_i||\tilde{W}\tilde{h}_j]) \tag{7}$$

where $\tilde{\sigma}$ is the LeakyReLu activation function and \tilde{W} denotes a learnable hyperparameter. After the sentence nodes are sufficiently updated on the semantic level, they are aggregated to a graph-level representation for the QA pair, Based on which the global representation of the interview can be obtained by a GRU encoder. We define the readout function as:

$$h_{\mathcal{G}} = \frac{1}{|\tilde{\mathcal{V}}|} \sum_{i \in \tilde{\mathcal{V}}} \tilde{h}_i \tag{8}$$

Competency classifier

Once the graph representation $h_{\mathcal{G}}$ of each QA pair is obtained, we feed it into a GRU encoder to capture the global representation V_{final} of the interview. Then we feed it into a softmax layer to classify candidates:

$$\hat{y}_{\mathcal{G}} = softmax(W_{final}V_{final} + b_{final}), \qquad (9)$$

where W_{final} is a weight matrix and b_{final} is the bias. As the problem we focused on the a binary classification, we apply the binary cross-entropy as our loss function.

Experiments

Data and Metrics

We evaluate our method on a real-world Chinese answer transcription (CHNAT) in the video job interview. The type of job is sales positions. And the answer transcriptions are obtained from an automatic speech recognition algorithm. Three experts are invited to annotate the same candidates, and we proceed with a majority vote to obtain the golden category. The CHNAT dataset split contains 2,313/289/290 candidates for training, validation, and test. To simplify the ASAT task, we set up a binary classification: based on the understanding of the textual answer, candidates who have been liked are considered part of the competent class and others part of the incompetent class. Some statistics of the dataset are listed in Table 2. Although we are authorized by the candidates to use their interviews, the dataset will not be released to the public due to high privacy constraints.

Dataset	CHNAT
Training set	2,313
Validation set	289
Test set	290
Questions per Candidate (mean)	5.45
Hireable label propotion	63.30%
Total length	507M
Length per question (mean)	64
Length per answer (mean)	256
Vocab size	21,128

Table 2: Descriptive table of CHNAT: number of candidates in each set and overall statistics of the dataset

Besides traditional evaluation metrics such as precision, recall, F1-score, and accuracy (ACC), we use the concordance correlation coefficient (CCC) proposed by (Lawrence and Lin 1989) to evaluate our model. In statistics, the concordance correlation coefficient measures the correlation and agreement between the predicted results of the model and the ground-truth distribution (Deyo, Diehr, and Patrick 1991; Tzirakis et al. 2017).

Settings and Hyper-parameters

For fair comparisons with other methods, we take a consistent hyper-parameters to train our proposed model. We trained our baseline models for about 20 epochs - this is similar to the proposed HRGNN model. We limit the vocabulary

to 21,128 and initialize tokens with 300-dimensional GloVe embeddings (Pennington, Socher, and Manning 2014). While training, we set the word embeddings to be trainable. We filter stop words and punctuations when creating sentence nodes and truncate the input sentence in the question and its corresponding answer to a maximum length of 50 and 295 separately. We set the batch size to 128, and initialize the GRU size with 50 and the attention size with 100. In RGCN and RGAT the sentence nodes with d_s =256 and edge features with d_e = 50. We set the RGCN and RGAT layer to 1. And each RGAT layer is 16 heads. We applied dropout with a rate of 0.1. With the initial learning rate 0.001, learning rate decay 0.97, Adam optimizer (Kingma and Ba 2014) was used. Hyperparameters were optimized using grid search.

For all the experiments with HRGNN and our benchmark models, the scores (precision, recall, F1-score, ACC, and CCC) we present on the validation set and test set are mean values with 10 runs initialized by different random seeds.

Baselines

In this section, we describe the baseline models in our experiments. 1) Non-sequential methods: Similar to the state-of-the-art model-HireNet (Hemamou et al. 2019b) in AVIs, for the ASAT task, we first employ a non-sequential (Non-seq, for abbreviation) model based on Doc2vec (Le and Mikolov 2014) to represent the questions and answers, with three classic learning approaches (namely Ridge regression, Random Forest, and SVM) for classification. Best of the three approaches is shown. 2) Sequential methods: Then two conventional neural network based models named AGRU+FC and HireNet (Hemamou et al. 2019b) are employed for comparison. AGRU+FC is an intuitive baseline for ASAT. To obtain a better representation of the candidate's answer, An attention mechanism is utilized to extract the importance of each moment in the sequence representing the answer. Then, in the comparison with the known HireNet, to explore whether it is reasonable to encode question-answer pairs as a sequence, we employ a fullyconnected classifier to make the final prediction. HireNet is built relying on a hierarchical architecture. The low-level layer is constructed with an additive attention mechanism based GRU to encoder the local QA context, and the highlevel layer consists of a global context encoder driven by another additive attention. With the hypothesis of the job titles are important for the job interview, HireNet includes vectors that encoder this contextual information. Due to we focus on the scoring of QA pairs in this work, we implement a variant of HireNet without the encoder for job titles. 3) **BERT+GRU** As BERT (Devlin et al. 2018) has achieved promising performance on several NLP tasks, we also implement one baseline method via fine-tuning BERT in the claim verification task. The GRU encoder in the low-level layer of HierNet is replaced by a BERT encoder. And in the high-level layer, we also employ GRU to encoder the question-answer pairs.

Compared with Baseline Models

We evaluated our proposed HRGNN on the validation and test set of CHNAT. To reduce the impact of random-

Model	Validation Set				Test Set					
	P	R	F1		CCC	P	R	F1	ACC	CCC
Non-seq (Le and Mikolov 2014)	76.00	83.06	79.37	72.66	39.10	76.60	78.69	77.63	71.38	37.94
AGRU+FC	75.12	88.68	81.23	74.12	42.50	75.22	87.65	80.84	73.91	43.90
HireNet (Hemamou et al. 2019b)	75.86	91.39	82.88	76.08	44.31	75.77	91.09	82.69	75.96	44.38
BERT+GRU	77.04	91.11	83.36	7 6.99	46.73	76.31	90.99	82.87	76.38	45.43
HRGNN	76.87	91.82	83.55	77.12	46.82	78.25	91.47	84.25	78.49	50.78

Table 3: Automatic evaluation on CHNAT validation and test sets using precision (P), recall (R), F1, Accuracy (ACC) and CCC (Concordance Correlation Coefficien).

ness on HRGNN and baseline models, for all the experiments, the scores (precision, recall, F1-score, ACC, and CCC) we present are mean values with 10 runs initialized by different random seeds. Table 3 presents the performance of our model as well as the baselines. We observe that conventional neural network based sequential methods (AGRU+FC, HireNet) generally outperform Non-sequential models, suggesting that the sequential model benefits to the representation of questions and answers. Further, on the validation set and test test, HierNet with sequential GRU based classifier achieves (1.89%, 2.14%, and 1.91%) and (1.85%, 2.05%, and 0.48%) of improvement in F1-score, ACC and CCC, respectively, compared to AGRU+FC model which employs fully-connected based classifier in the second stage of grading candidates. It indicates that it is reasonable to encode question-answer pairs as a sequence. Comparing the performance of HireNet and BERT+GRU, we can find that the pre-training based BERT+GRU model outperforms HireNet about (0.24%, 0.73%, and 2.32% on the validation set) and (0.18%, 0.42%, and 1.03% on the test set) in F1score, ACC, and CCC, respectively. Intuitively, it shows that BERT has a stronger ability to represent text.

Besides, based on the results of all benchmark models, we can see that compared with the validation set, most of the performance of the non-sequential model, sequential model, and the fine-tuned BERT have variable degrees of decline in the test set. It may indicate that even if the model has a strong ability of text/context representation, it is difficult to transfer the ability to evaluate candidates from the validation set to the test set, without the deep interaction between questions and answers. On the test set, Compared to models which only driven by a sequential encoder, our model employs sentence-level GCN for constructing relational dependency and semantic-level GAT for QA reasoning, which brings (3.41%, 4.58%, and 6.88%) and (1.56%, 2.53%, and 6.40%) gains over AGRU+FC and HireNet in F1, ACC, and CCC, respectively. Although, the proposed HRGNN only outperforms pre-training based BERT+GRU about 0.11%, 0.13%, and 0.09% in F1, ACC, and CCC separately. HRGNN achieves promising improvement against BERT+GRU on the test set. It indicates that the proposed model based relational dependency and QA reasoning has higher discrimination ability for unseen data. It further verifies the effectiveness of HRGNN.

Figure 2 illustrates the F1-score and accuracy of different models with different random seeds. We can see that the most affected by random seed is AGRU+FC, followed by

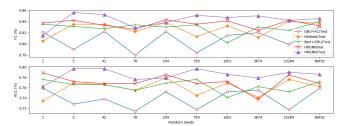


Figure 2: F1-score and accuracy of different models with different random seeds on the test set. To analysis the transferability of HRGNN, we additionally plot a polyline of HRGNN on the validation set. "A/val" or "A/test" represents the performance of model A on the validation set or test set, respectively.

HireNet. On the test set, in most cases, HRGNN performs best and achieves the highest performance. Empirically, our proposed HRGNN was least affected by random seeds. As far as we know, it is almost impossible for the training set to contain all variable samples, models on the validation set tend to perform better than the test set. However, compared to the performance of HRGNN on the validation set (HRGNN/Val) and the test set (HRGNN/Test), we can observe that HRGNN/Test is higher than HRGNN/Val 7 times and 8 times in the F1-score and accuracy separately. It reveals that the semantic interaction and reasoning between questions and answers can improve the generalization ability of the evaluation model.

Ablation Study

We also perform ablation studies to assess the impact of different modules and different relation types on the model performance against text matching based model. Experimental results on the CHNAT dataset are shown in Table 4 and 5, respectively.

• Impact of sentence-level RGCN. When we add the sentence-level relational GCN to the baseline model (HireNet, (Hemamou et al. 2019b)), with the promotion of precision and recall, the F1-score of our model increases to 83.22% (on the validation set) and 83.81% (on the test set), which indicates the necessity of building relational graph to model the dependency between questions and answers. Particularly, on the test set, the CCC increased from 44.38% to 48.70%, which shows that the proposed

Model	P	R	F1	ACC	CCC
Baseline (Hemamou et al. 2019b)	75.86	91.39	82.88	76.08	44.31
+RGCN	76.17	92.01	83.22	76.51	45.10
+RGAT	77.30	90.40	83.30	77.02	47.20
HRGNN	76.87	91.82	83.55	77.12	46.82
Baseline (Hemamou et al. 2019b)	75.77	91.09	82.69	75.96	44.38
+RGCN	77.51	91.63	83.81	77.72	48.70
+RGAT	77.78	90.72	83.72	77.72	49.10
HRGNN	78.25	91.47	84.25	78.49	50.78

Table 4: Ablation studies on the validation set and the test set of CHNAT using precision (P), recall (R), F1, Accuracy (ACC) and CCC (Concordance Correlation Coefficien). The upper and lower parts of the table correspond to the results of the validation set and the test set, respectively. We add each module separately and explore their influence on our model. '+' means we add the module to the baseline model.

RGCN has a stronger capability to learn the logic of human scoring.

- Impact of semantic-level RGAT. Using a reasoning graph attention network to encode the semantic-level information of the QA pair, performance in F1, ACC, and CCC increase to (83.30%, 77.02%, and 47.20% on the validation set) and (83.72%, 77.72%, and 49.10% on the test set), respectively, showing the contribution of semantic interaction over the QA pair.
- Impact of integration of two Graphs When we employ the RGCN and RGAT on the top of the baseline method, HRGNN achieves the best performance in F1 and ACC. Meanwhile, we find that the improvement brought by the integration of RGCN and RGAT is not as high as that by a single module. We suspect that sometimes the relational dependency of the QA pair plays a similar role with the semantic interaction.

Realtion Type	P	R	F1	ACC	CCC
HRGNN	76.87	91.82	83.55	77.12	46.82
-RQQ	76.89	91.42	83.38	76.92	46.39
-RAA	77.53	89.78	83.02	76.75	46.59
-RQA	74.89	92.84	82.80	75.57	42.16
HRGNN	78.25	91.47	84.25	78.49	50.78
-RQQ	77.91	91.37	84.00	78.07	49.75
-RAA	78.34	90.27	83.73	77.93	49.80
-RQA	76.46	92.35	83.53	77.04	46.56

Table 5: Ablation studies of relation types on the validation set and the test set of CHNAT using precision (P), recall (R), F1, Accuracy (ACC), and CCC (Concordance Correlation Coefficient). We remove different relation types and explore their influence on our model. '-' means we remove the corresponding relation type from the original HRGNN.

• Impact of relation types. To investigate the influence of relation types during the update process, we analyzed the performance of HRGNN under different relation types in Table 5. First, we can observe that when we remove the relation connection of sentences in the question, the results drop about (0.17% and 0.2% on the validation set)

and (0.25% and 0.42% on the test set) in F1 and ACC, respectively. When we remove the relation type of RAA, the performance drops about (0.53% and 0.37%) and (0.52% and 0.56%) in F1 and ACC, which is invariably larger than the drop on -RQQ. The reason is that the answer contains more sentences and more semantic information. Further, when we remove the relation type of RQA, the performance drops more than that on -RAA. It suggests that the dependency between sentences in the question and the answer is more critical than that between the answer sentences for QA evaluation.

Conclusion

In this paper, we propose a hierarchical reasoning graph neural network (HRGNN) for the automatic scoring of answer transcriptions (ASAT) in the video job interview. The ASAT task is to score the competency of candidates based on several textual question-answer pairs. Unlike other matching based methods or frameworks, HRGNN can utilize the relational dependency of sentences in the questions and answers, and aggregate them in the semantic level with reasoning flow between different graph layers. Particularly, the proposed relational graph convolutional network (RGCN) module constructs internal temporal dependency and questionanswer interaction dependency to represent the relations between sentences in the question and the answer. And in the graph-based reasoning part, we propose a graph attention network to further aggregate semantic interactions between the question and the answer. Finally, we apply a GRUbased classifier to discriminate the candidate is competent or not. Empirical results with 10 random seeds show that our model achieves state-of-the-art on a Chinese real-world dataset (CHNAT).

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