DialogueGAT: A Graph Attention Network For Financial Risk Prediction by Modeling the Dialogues in Earnings Conference Calls

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Introduction

- **Financial risk prediction** is an essential task for risk management in capital markets
- More and more studies make use of the **soft information** for financial risk prediction. (e.g., Annual Report, News, Twitter,)
- **Earning conference call** is an increasing important form of voluntary corporate disclosures.
  - Kuaishou Technology's shares tumble after it said more regulations will hurt its revenues during an earnings call, although its revenues jumped 49% in the Q2.

What Is Earning Conference Call?

The earnings conference call is a way for companies to relay information to all interested parties

- **Time**: Typically at the end of each quarter.
- **Participants**: Executives and analysts
- **Part**: Presentation, Question and Answer

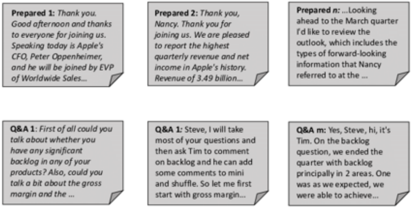

Figure: Example

Related Work

- **ProFET**[3] employs a BiLSTM to learn the representation of presentation, questions and answers respectively.
- **MRQA**[5] uses a multi-round Q&A attention network for considering the dialogue form.

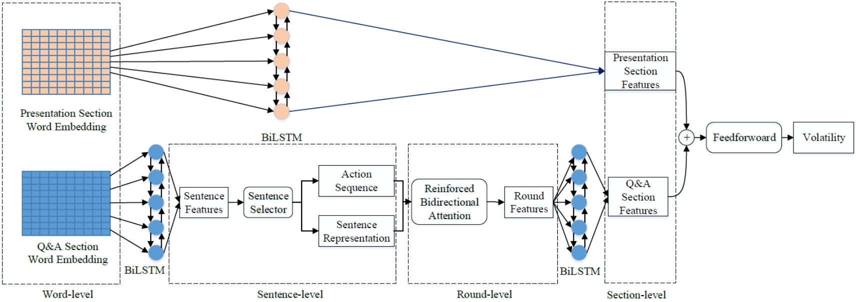

Figure: The Architecture of MRQA

Limitations

- Treat transcripts as long documents
- Without consider the speaker information

Figure: Speaker information is important for a dialogue

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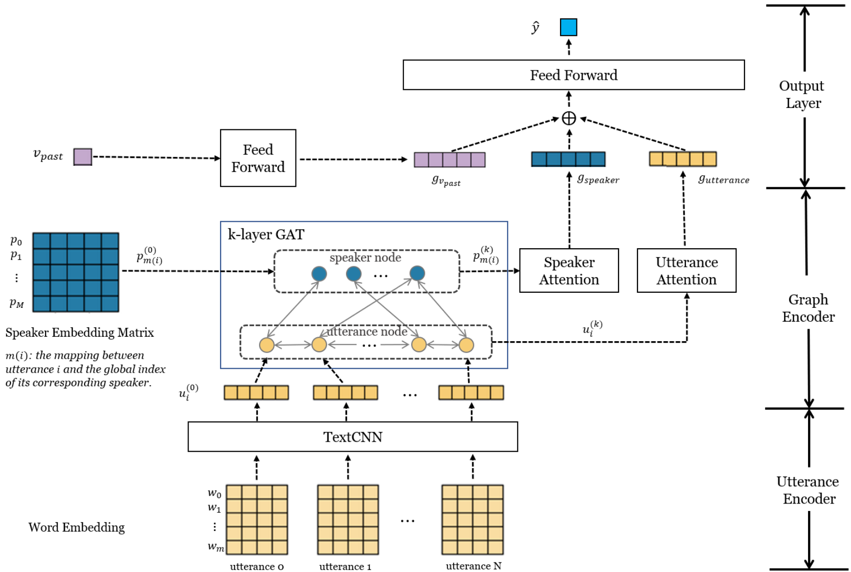
The Architecture of DialogueGAT



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Problem Definition

Financial risk prediction can be seen as **a supervised regression task**:

- **Input**: A dialogue with M speakers and N utterances.
- **Output**: The firm's future stock return volatility $v_{[t,t+\tau]}$
- **Metric**: Mean Squared Error

Definition

The stock return volatility $v_{[t,t+\tau]}$ reflects the degree of variation of stock prices:

$$v_{[t,t+\tau]} = \sqrt{\sum_{i=0}^{\tau} \left(r_{t+i} - \bar{r}\right)^2 / \tau}$$

Dataset

- **Base Dataset**: MAEC dataset
- **Companies**: S&P1500
- **Source**: SeekingAlpha
- **Split**: 7:1:2 on a yearly basis

Table: Descriptive statistics of our extended dataset.

Year	2015	2016	2017 - 2018
Training set (#Samples)	531	968	890
Validation set (#Samples)	75	138	127
Testing set (#Samples)	153	278	255
#Companies	523	897	736
#Speakers	5,840	8,768	7,006
#Utterances	59,549	108,714	79,253
#Sentences	102,142	184,936	145,206

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Result

Table: Model performance in terms of MSE by varying the window size τ.

Year	2015			2016			2017-2018		
Methods	$\tau = 3$	$\tau = 7$	$\tau = 15$	$\tau = 3$	$\tau = 7$	$\tau = 15$	$\tau = 3$	$\tau = 7$	$\tau = 15$
v_{past} [2]	1.0905	0.5441	0.2744	1.3542	0.7300	0.4465	1.1739	0.5681	0.2723
SVR$_{v_{past}}$ [2]	0.6576	0.4393	0.2503	0.6440	0.3810	0.2714	0.5643	0.3634	0.2273
HAN [4]	0.5421	0.4259	0.2516	0.5272	0.3390	0.2501	0.5186	0.3554	0.2231
ProFET [3]	0.5902	0.4297	0.2471	0.5737	0.3717	0.2502	0.5341	0.3605	0.2270
DialogueGCN [1]	0.5376	0.4138	0.2462	0.5209	0.3343	0.2472	0.5019	0.3494	0.2204
MRQA [5]	0.5174	0.4126	0.2407	0.5162	0.3314	0.2286	0.4966	0.3443	0.2240
DialogueGAT	**0.4530**	**0.3236**	**0.1898**	**0.4549**	**0.2884**	**0.1810**	**0.4090**	**0.2886**	**0.2036**

- DialogueGAT is effective for modeling dialogues.
- The textual information is incrementally useful.
- The dialogue structure could further improve the financial risk prediction.

Model Interpretability

Case: AMD's 2015 Q2 earnings conference call [1]

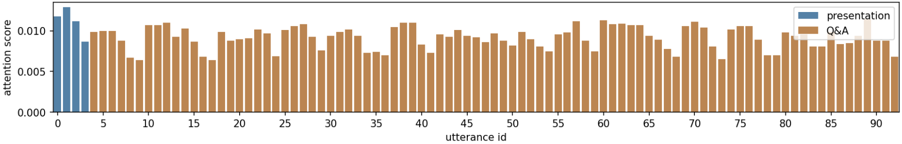

Figure: Utterance Attention

- The utterances in the presentation segment are generally more important than Q&A segment.
- Managers' presentation usually holds more private information and is more informative.

[1] Since the AMD's financial performance in 2015 Q2 is below the market expectation, its stock price drops significantly after the release of earnings conference call.

Model Interpretability

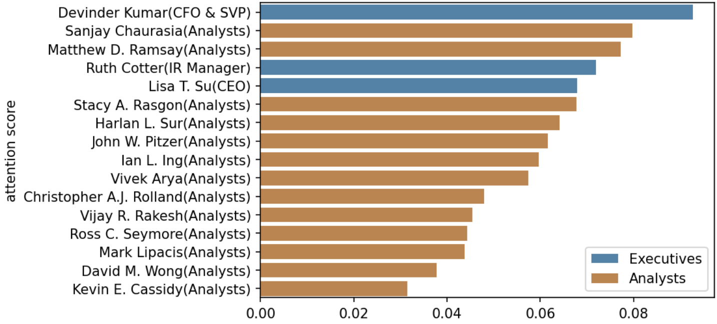

Figure: Speaker Attention

Managers and analysts who ask harsh questions on behalf of public investors are usually more important than the rest analysts.

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Thanks!