

Story-based Multi Aspect Emotion Analysis

Too Seng Wei
1161100643

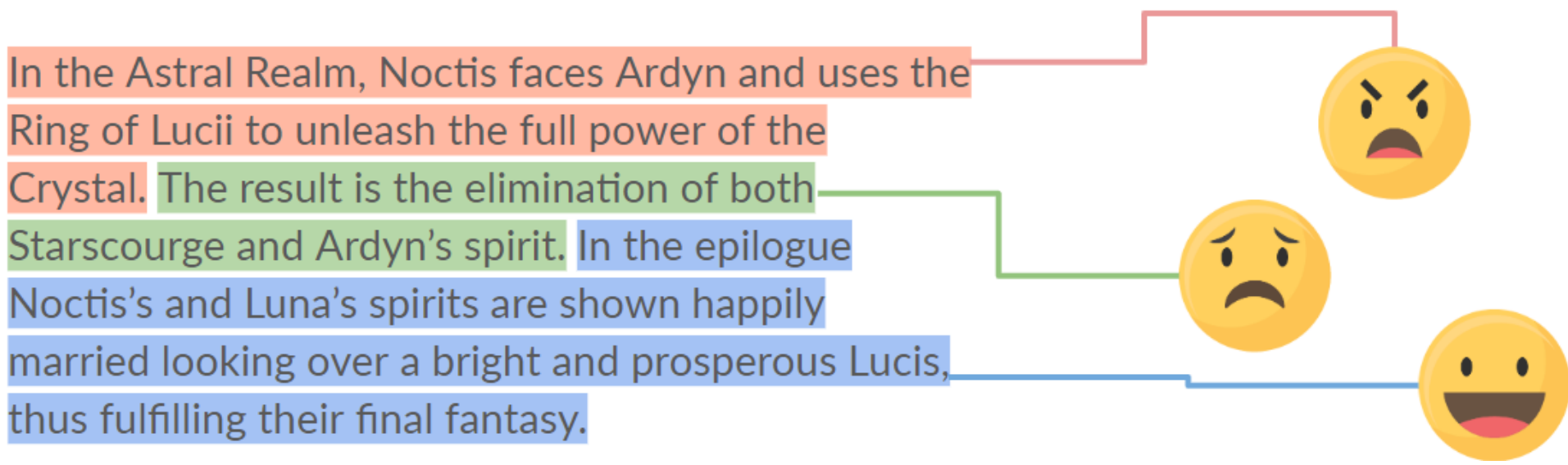
Albert Quek
Supervisor

John See Su Yang
Co-supervisor

Goh Hui Ngo
Moderator

Abstract

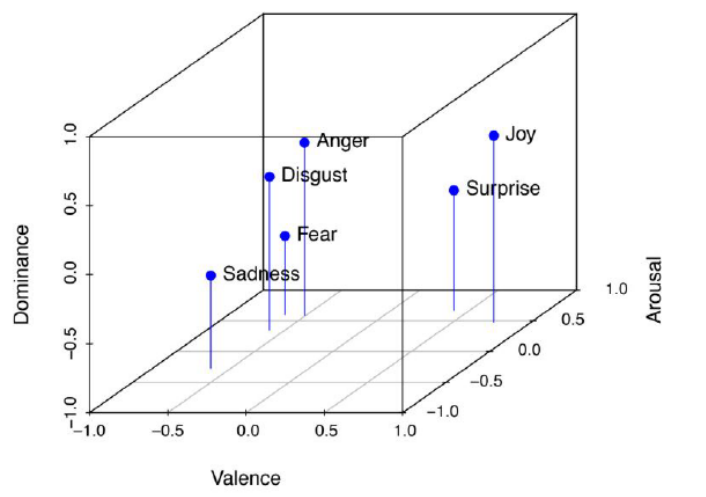
This work study affective analysis in narrative story domain and emotion representation mapping from dimensional schema to the categorical schema using the state-of-the-art architecture and attention-mechanism.



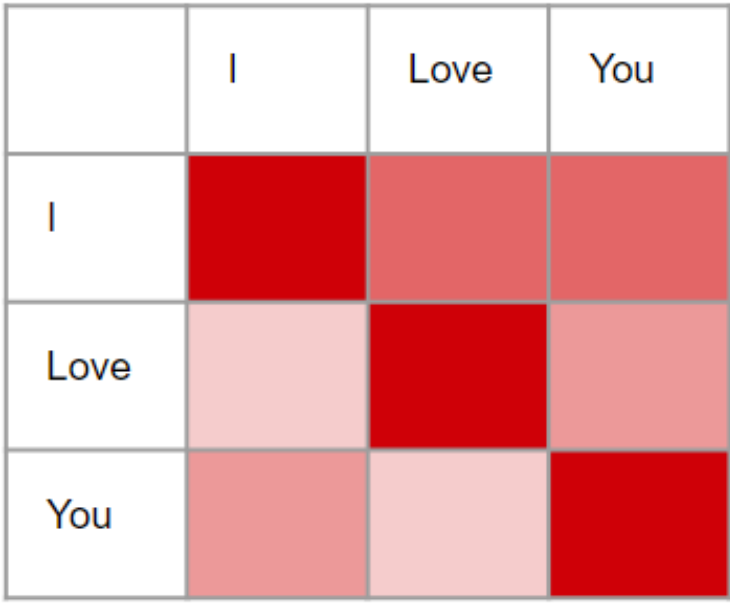
Objectives

1. Use of attention mechanism in Emotion Representation Mapping task and from complex VAD emotion to 8 category
2. Propose an architecture based on the state-of-the-art architecture to perform Affective Analysis(Both Dimensional Space and Categorical Space) in narrative story domain and declared as benchmark result.
3. Experiment the use of emotion representation mapping concept in affective analysis task

Background Study



Valence = Positiveness
Arousal = Strongness
Dominance = Controllability



Self-Attention Mechanism

Methodology

Dataset

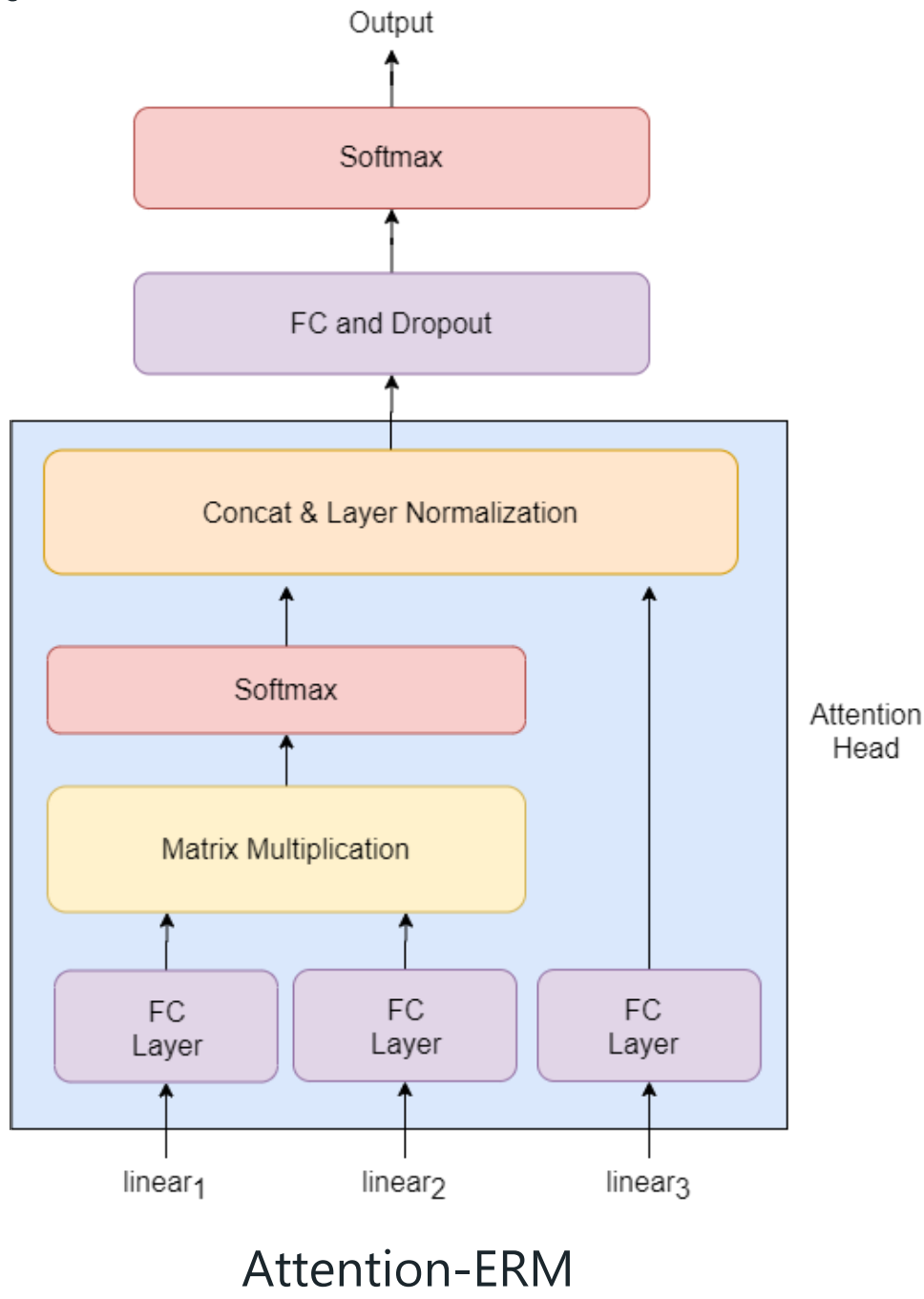
- EmoTales(Francisco et al., 2012).
- ERMDB(Obtained though merging multiple dataset)
- 4000 Stories Sentiment Analysis Dataset

Data Augmentation method:

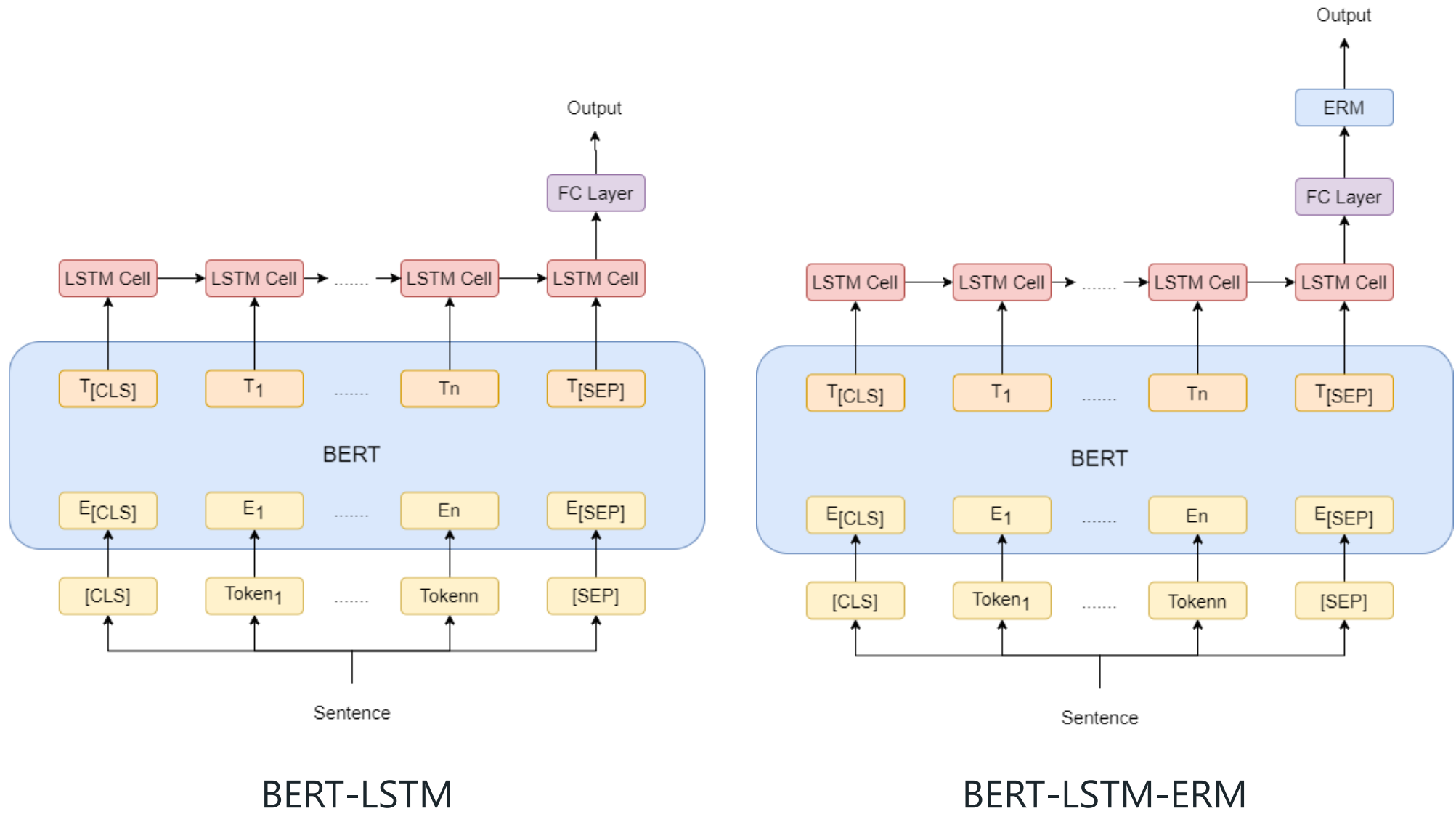
- EDA (Wei & Zou (2019)
- PCA(Krizhevsky et al. (2012))

Proposed Model

1. Attention-ERM
 - Attention helps to learn complex VAD emotion
2. BERT-LSTM
 - BERT as a powerful feature extractor
 - LSTM as a recurrence-oriented decoder
3. BERT-LSTM-ERM
 - Utilized aforementioned Attention-ERM concept to helps in affective analysis



Attention-ERM



Results

Result #1

Model	# of Attention Head	EmoTales	ERMDB		
		F1-score	ρ_{mono}	ρ_{cross}	$\rho_{overall}$
MLP	0	0.37	0.8386	0.8035(0.813)	0.8210
1H-Attention	1	0.59	0.8307	0.8004	0.8166
2H-Attention	2	0.53	0.8228	0.8152	0.8190
4H-Attention	4	0.59	0.8223	0.8110	0.8166
8H-Attention	8	0.51	0.8196	0.8127	0.8167

The leverage of attention improve the performances of an MLP in ERM task and if only the VAD is representing a complex emotion. As a complex emotion relatively carry more information and attention are able to learn the nature of three fundamental dimensions of emotion.

Result #2

Model	EmoTales					120 Stories (Inference Only)	
	8 Category		VAD			VAD	
	# of param	f1-score	# of param	MAE	MSE	MAE	MSE
MLP	12,025k	0.1222	12,008k	0.1069	0.0191	0.1432	0.0262
Attention	20,431k	0.4424	20,430k	0.0923	0.0146	0.1163	0.0260
Trans-LSTM	10,481k	0.4676	10,546k	0.0939	0.0147	0.1153	0.0255
BERT-LSTM	110,565k	0.5287	110,630k	0.0844	0.0124	0.1218	0.0248
BERT-LSTM-ERM	110,779k	0.4784	-	-	-	-	-

In both categorical and dimensional emotion prediction task, BERT-LSTM achieve the best result. However, BERT-LSTM-ERM does not perform as good as expected. Our assumption is that the conversion from hidden state to VAD causes a loss of information and thus making the prediction of category lower.

Testset Sample

Test Sample	True	Predicted
she gave him the mirror in his hand, and he saw there in the likeness of the most beautiful maiden on earth	surprise	happiness
if that is the ladder by which one mounts, i too will try my fortune,	neutral	neutral
suddenly something amazing happened	surprise	surprise
we dare not obey your orders.	fear	fear
the place burnt like fire, and the poison entered into his blood fear	sadness	fear

Conclusions

We believe that it could be interesting to experiment with other types of architecture in affective analysis in the narrative domain or any technique that able to fully utilize the nature of character personalities. As story narrative is usually made up with few characters(either fiction or non-fiction) with well design personalities. By understanding and interpret the personalities or characteristic of a character, it will be great bits of help in understanding the emotional context of a story.

References

Francisco, V., Hervás, R., Peinado, F., & Gervás, P. (2012, Sep 01). Emotales: creating a corpus of folk tales with emotional annotations
Wei, J., & Zou, K. (2019, November). EDA: Easy data augmentation techniques for boosting performance on text classification tasks.
Krizhevsky, A., Sutskever, I., & Hinton, G. E. (2012). Imagenet classification with deep convolutional neural networks