# Fake-EmoReact -2021

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### **Outline**

- 1. Data preprocessing
- 2. Method
- 3. Experiment Result
- 4. Conclusion

# Data Preprocessing

## Steps

- 1. Concatenate tweet with each of it's reply as data points
- 2. Text Processing
  - a. Remove non-ascii
  - b. Convert emoji into meaningful text, ex:  $\Theta \rightarrow \text{red heart}$
  - c. Clean punctuation and contraction, ex: It's  $\rightarrow$  It is
  - d. Replace URL with "\$URL\$", ex: https://xxx  $\rightarrow$  \$URL\$
- 3. Tokenize, build vocabulary and indices

# Method

## Word Embedding

- GloVe: pre-trained word vectors with 840B tokens, dimension 300
- BERT (cased / uncased): contextual embedding
- Fine-Tuned Embedding in training process

### **Models**

- CNN
- (Bi-) RNN
- (Bi-) GRU
- (Bi-) LSTM
- BERT, RoBERTa
- Electra

#### Tackle Data Imbalance

- Data Pairs in Training Data
  - # Real: # Fake= 31799 : 136722 ≈ 1 : 4
- Weighted-Loss during training process

#### **Ensemble**

- Majority voting: every individual classifier votes for a class, and the majority wins
- Soft voting: sum the predicted probabilities for class labels,
  and predict the class label with the largest sum probability
- Reply voting: all data pairs with same source tweet vote for a class, and the majority wins
  - Avg. # reply in training: 4.8 per tweet
  - Avg. # reply in evaluation: 36.9 per tweet

# **Experiment Result**

# Training & Practice - Student Track

Models	BERT(cased)	BERT(uncased)	RoBERTa	Electra
F1-score	0.9777	0.9887	0.995	0.9721

Models	CNN	Bi-RNN	Bi-GRU	Bi-LSTM
F1-score	0.9557	0.9006	0.9501	0.9367

Models	Majority vote	Soft vote
Bert F1-score	0.9932	0.9929
Non-Bert F1-score	0.9576	0.9579



Models	BERT(cased)	BERT(uncased)	RoBERTa	Electra
F1-score	0.5495	0.5962	0.5675	0.501

Models	CNN	Bi-RNN	Bi-GRU	Bi-LSTM
F1-score	0.82	0.6798	0.8099	0.7954

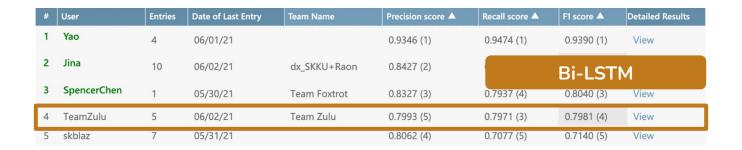
Models	Majority vote	Majority vote + Reply vote
Non-Bert F1-Score	0.8366	0.8703

**OVERFITTING!** 

### **Evaluation - Student Track**

#	User	Entries	Date of Last Entry	Team Name	Precision score ▲	Recall score A	F1 score ▲	Detailed Results
1	ccc_gogo	8	06/02/21		0.8532 (2)	0.8456 (1)	0.8435 (1)	View
2	ChenMian	8	06/01/21	Team Edward	0.8399 (3)	0.8334 (2)	0.8314 (2)	View
3	Papa	11	06/01/21	Team Papa	0.8300 (4)	Bi-LST	M Reply	Voting
4	Yao	1	06/02/21		0.8560 (1)	0.8129 (4)	0.8095 (4)	View
5	TeamZulu	15	06/02/21	Team Zulu	0.8075 (6)	0.8066 (5)	0.8060 (5)	View
6	TeamJuliet	17	06/01/21		0.8002 (7)	0.7997 (6)	0.7998 (6)	View
7	SpencerChen	5	05/31/21	Team Foxtrot	0.8215 (5)	0.7951 (7)	0.7886 (7)	View
8	Brett	13	06/01/21		0.7905 (9)	0.7870 (8)	0.7855 (8)	View
9	yuchingtw	7	06/02/21	Team Victor	0.7442 (16)	0.7211 (9)	0.7162 (9)	View
10	LuoHeZhou	5	06/01/21	Team Charlie	0.7480 (14)	0.7142 (10)	0.7016 (10)	View
11	TeamIndia	9	06/01/21	Team India	0.7726 (10)	0.6981 (11)	0.6725 (11)	View
12	Team_Oscar	4	05/30/21	Team Oscar	0.7941 (8)	0.6851 (12)	0.6490 (12)	View
13	yiching5417	6	06/01/21	Team Mike	0.6565 (25)	0.6489 (16)	0.6432 (13)	View
14	linzinofan	8	06/02/21	team November	0.7394 (18)	0.6664 (13)	0.6353 (14)	View
15	ku4201	1	05/30/21	Team Tango	0.7483 (13)	0.6647 (14)	0.6302 (15)	View

#### **Evaluation - Main Track**



### **Conclusion**

- CNN and BERT have unexpected performance.
- Ensemble
- Properties of different dataset (train, dev, eval)
  - # of replies per tweet
  - o real / fake ratio

## Appendix: Explainable AI - Saliency Map

Saliency score indicates how sensitive the model's final prediction is to each word embedding, which could give us a hint on how much each word embedding contributes to the final decision.

$$w(e) = \frac{\partial(S_c)}{\partial e} \mid_e \qquad S(e) = |w(e)|$$

We implement the saliency map on our trained Bi-LSTM and CNN model.

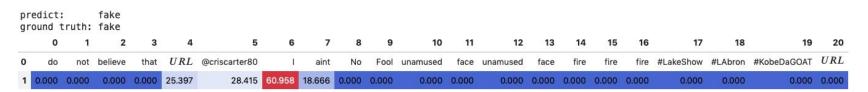


## Appendix: Explainable AI - Saliency Map

#### bi-lstm



#### cnn





## Appendix: Explainable AI - Saliency Map

#### bi-lstm



#### cnn



# **Q & A**