CS6120 Project Presentation

Time series analysis of COVID-19 related emotion detection using natural language processing

Chia-Wei Lin

Khoury College of Computer Sciences
Northeastern University, Seattle, WA

Outline

- Motivation
- Goals
- Approach
  - Data
  - Evaluation Method
  - Baseline
  - Experimental Details
- Results
- Analysis
- Conclusion

Motivation

- The outbreak of COVID-19 has changed everyone's life
- Influence human's physical health and mental health
- COVID-19 risk factors, transmission, incubation, diagnostics, therapeutics…
- NLP tasks:
    - Detecting Symptoms, Extracting Diagnosis for Electronic Health Records
    - QA system, Chatbot
    - Fact Check
    - Research summarization
- Semantic analysis and Emotion

Goals

Analyze the association between the global COVID-19 confirmed case number and the emotional response of English Twitter users over time.

Approach

- Build a model with a labeled dataset
  - SVM, LSTM, bi-LSTM ...
- Use the model to detect emotion on real-world tweets
  - Hydrate tweet from collected COVID-19 related dataset

https://competitions.codalab.org/competitions/17751#learn_the_details-datasets
https://github.com/echen102/COVID-19-TweetIDs

Labeled Data

- SemEval-2018 Task 1: Affect in Tweets (AIT-2018), EI-oc datasets

	Train Set	Dev Set
Anger	1701	388
Fear	2252	389
Joy	1616	290
Sadness	1533	397
Total	7102	1464

Evaluation Method

- Classification Task
- Train classifiers on 7102 tweets, evaluate on 1464 tweets
- Evaluate models with dev set accuracy

Baseline

- Random Guess
  - Accuracy = 0.25
- SVM with raw unigram
  - Accuracy = 0.30

Experimental Details: Tweet Pre-processing

- decode_emoji (😞 => disappointed face)
- decode_HTML (& => &)
- remove_mention
- remove_URL
- remove_punctuation
- to_lowercase
- lemmatize
- remove_stop_words

Experimental Details: Tweet Pre-processing

- Result:
  - SVM with unigram (without pre-processing): 0.30
  - SVM with unigram (with pre-processing): 0.35

Experimental Details: FastText Classifier

- FastText
  - Facebook AI Research (FAIR) lab, 2016
  - A library for text classification and learning of word embeddings

Experimental Details: FastText classifier

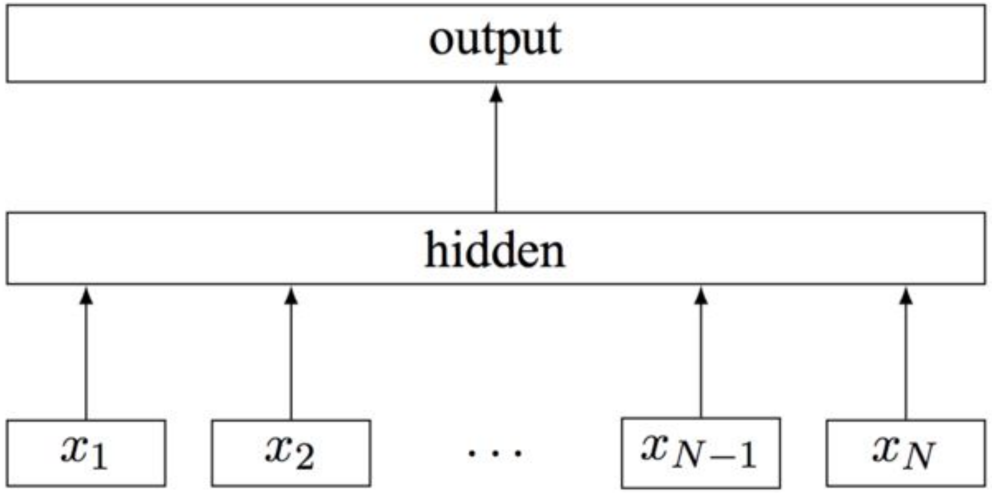
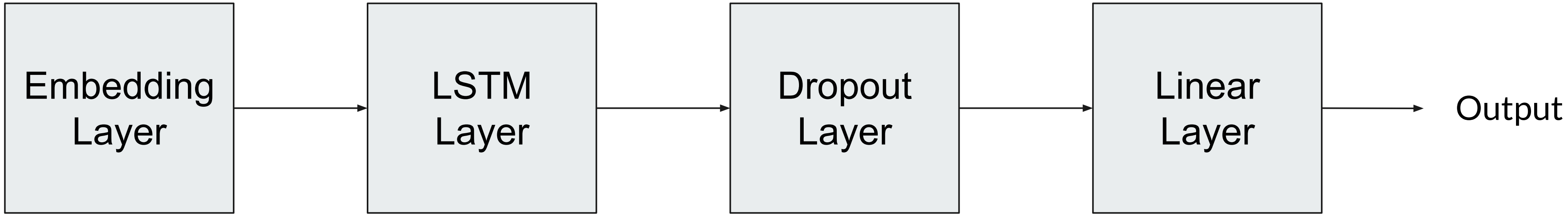


Figure 1: Model architecture of `fastText` for a sentence with N ngram features $x_1, \ldots, x_N$. The features are embedded and averaged to form the hidden variable.

- FastText supervised classifier
  - Accuracy: 0.46

Experimental Details: LSTM and Bi-LSTM

- Model structure



Fixed
Pre-trained
FastText
Embedding

wiki-news-300d-1M.vec
embedding dim: 300

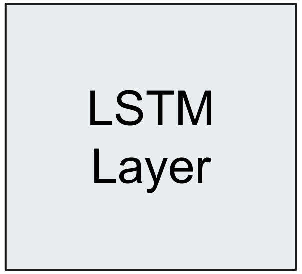
hidden_dim = 128
no_layers = 4
bi_directional= True

dropout = 0.2

256 - > 4

Experimental Details: LSTM Layer

- LSTM Layer



1. Each input is padded to length n (n = max_len of sentences in a batch)
2. Take mean of first n words as the output (n = sentence length)

Fixed vs trainable embedding

- Embedding with Trainable weight: Accuracy: 0.4877
- Embedding Fixed weight: Accuracy: 0.4900

LSTM vs Bi-LSTM

- LSTM Accuracy: 0.4709
- Bi-directional LSTM Accuracy: 0.5044

Experimental Details: Nodes, Layers, Dropouts

		Hidden Nodes / Number of Layers								
		16 / 1	16 / 2	16 / 3	32 / 1	32 / 2	32 / 3	64 / 1	64 / 2	64 / 3
Dropout	0.0	0.4347	0.4962	0.4511	0.4313	0.4942	0.4976	0.4463	0.4969	0.5085
	0.1	0.4278	0.4949	0.5017	0.4238	0.4968	0.4990	0.4532	0.5064	0.5079
	0.2	0.4224	0.4409	0.4539	0.4217	0.4928	0.4928	0.4504	0.4997	0.5085
	0.3	0.4244	0.4915	0.4908	0.4320	0.4962	0.5044	0.4484	0.4907	0.5058
	0.4	0.4210	0.4915	0.5079	0.4254	0.4976	0.5051	0.4457	0.5037	0.5099
	0.5	0.4176	0.4867	0.4266	0.4231	0.5010	0.4990	0.4470	0.4997	0.5010

Experimental Details: Nodes, Layers, Dropouts

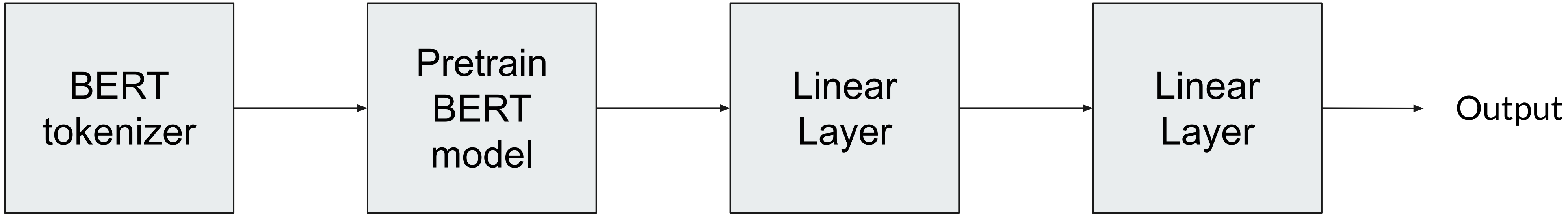
		Hidden Nodes / Number of Layers									
		128 / 1	128 / 2	128 / 3	128 / 4	128 / 5	256 / 1	256 / 2	256 / 3	256 / 4	256 / 5
Dropout	0.0	0.4545	0.5010	0.5113	0.5099	0.4532	0.4662	0.4566	0.4983	0.4484	0.5037
	0.1	0.4545	0.4949	0.5031	0.4915	0.4443	0.4778	0.5051	0.5099	0.4792	0.3794
	0.2	0.4668	0.5000	0.5100	0.5120	0.4477	0.4730	0.5051	0.5058	0.5065	0.4498
	0.3	0.4621	0.5058	0.5017	0.5106	0.4442	0.4566	0.5092	0.5072	0.4334	0.4901
	0.4	0.4600	0.4983	0.5072	0.4463	0.5071	0.4819	0.5017	0.5085	0.4545	0.4560
	0.5	0.4710	0.5000	0.5099	0.4580	0.3944	0.4566	0.5031	0.5044	0.4402	0.2659

Experimental Details: Learning rate, etc.

- Different learning rates, different weight_decay, different optimizers
- No specific gain on dev set accuracy

Experimental Details: BERT

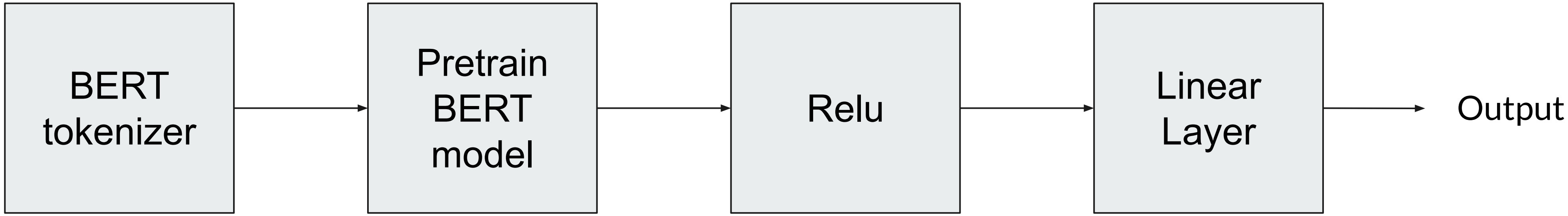
- Model structure



- Accuracy: 0.28

Experimental Details: BERT

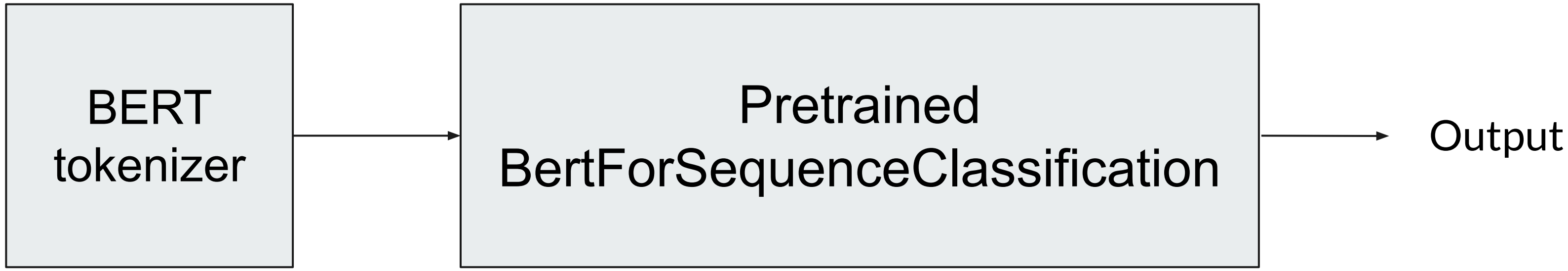
- Model structure



- Accuracy: 0.22

Experimental Details: BERT

- Model structure



- Accuracy: 0.23

Result: The Best Model

- bi_LSTM(

    (embedding): Embedding(12910, 300)

    (lstm): LSTM(300, 128, num_layers=4, batch_first=True, bidirectional=True)

    (drop): Dropout(p=0.2, inplace=False)

    (fc): Linear(in_features=256, out_features=4, bias=True))
- AdamW (

    lr: 0.002

    weight_decay: 0.0005)
- Accuracy

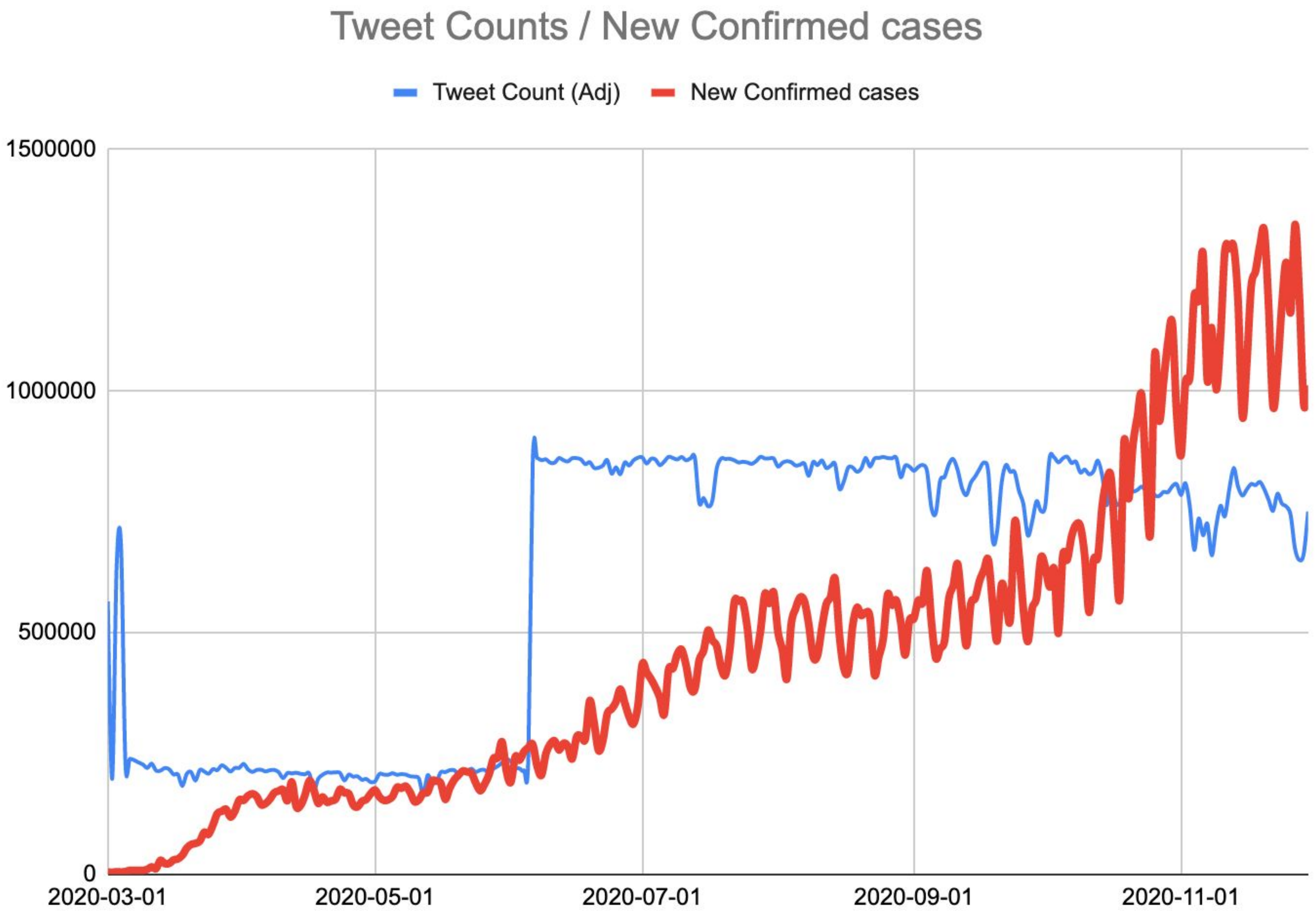
    0.5120

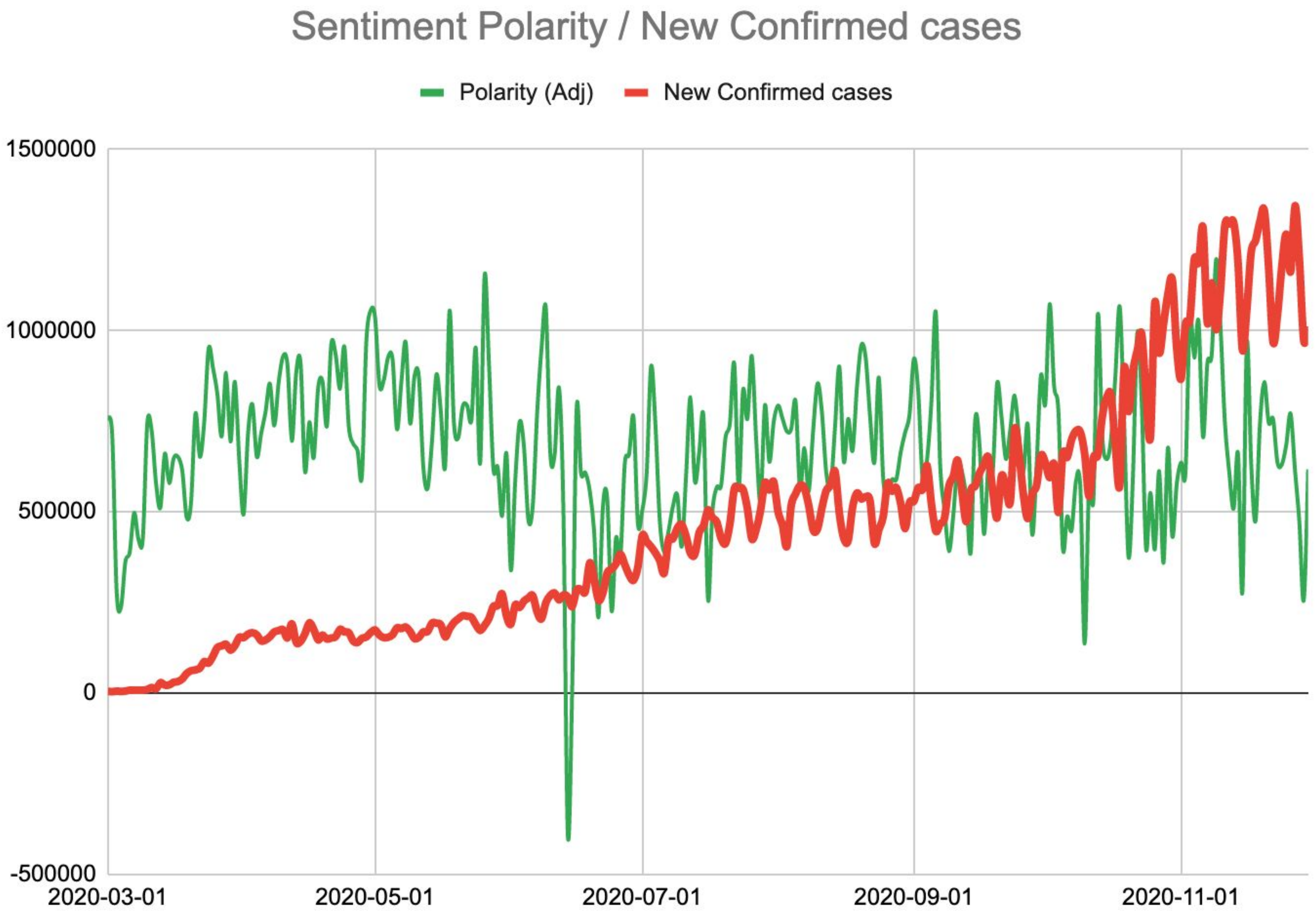
Result: The Best Model

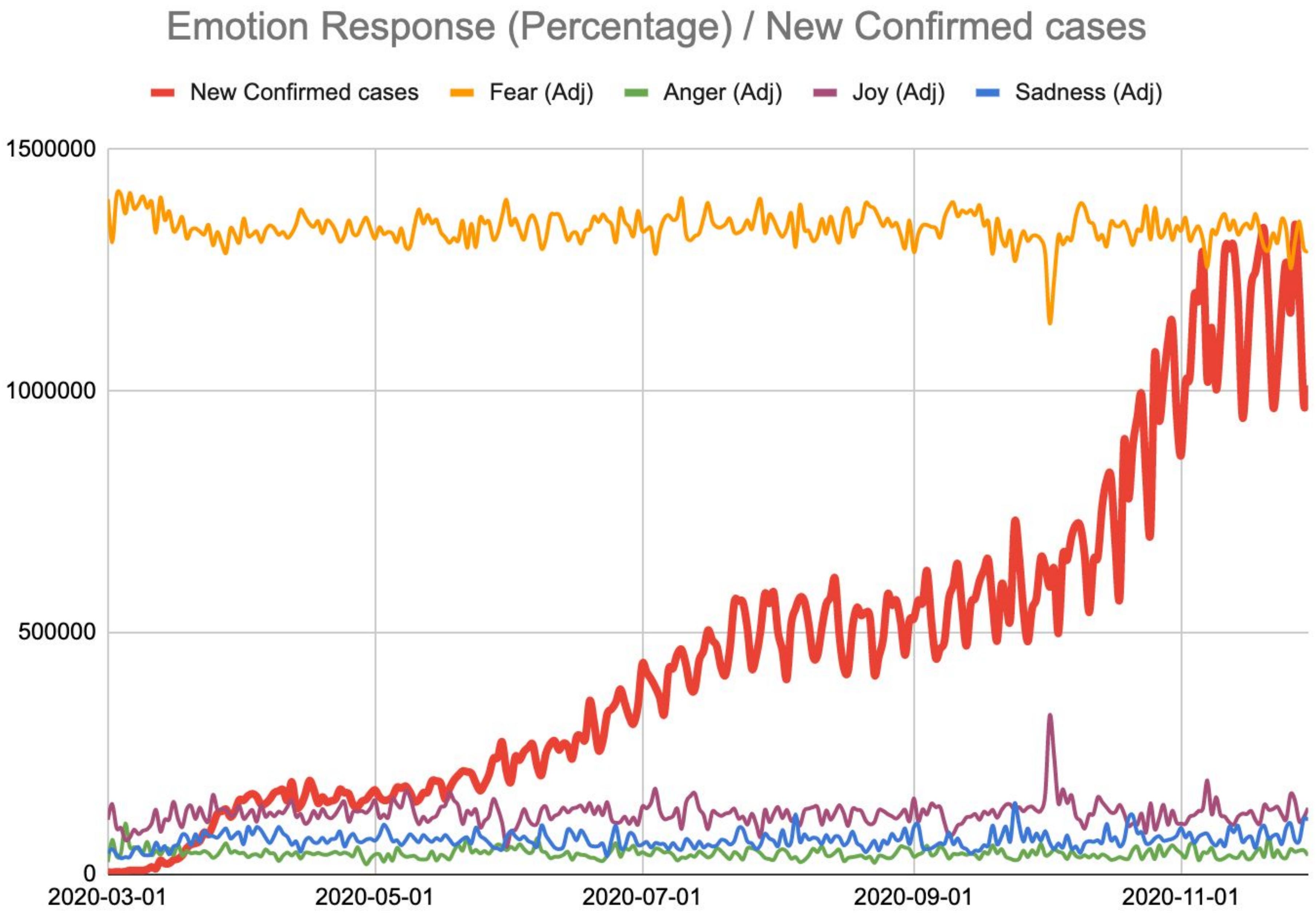
	Precision	Recall	F1-score	Support
Anger	0.49	0.43	0.46	388
Fear	0.40	0.58	0.47	389
Joy	0.76	0.71	0.74	290
Sadness	0.47	0.35	0.40	396
Accuracy			**0.51**	1463
Macro-Avg	0.53	0.52	0.52	1463
Weighted-Avg	0.52	0.50	0.50	1463

Analysis: Real-world Tweets

- Source: COVID-19-TweetIDs (https://github.com/echen102/COVID-19-TweetIDs)
  - Ongoing collection of tweets ID associated with COVID-19 from Jan 28, 2020
  - Keywords: Coronavirus, covid, stay home, etc.
  - Total number of tweet ID: 836, 949, 388
- Collect and Hydrate tweets from Mar 1 to Nov 30
- Sample 2000 English tweets per day
- Use TextBlob to determine the sentiment polarity of tweets
- Use our best Bi-LSTM model to determine the emotion class of tweets


Tweet Counts / New Confirmed cases
Tweet Count (Adj)
New Confirmed cases
1500000
1000000
500000
0
2020-03-01
2020-05-01
2020-07-01
2020-09-01
2020-11-01


Sentiment Polarity / New Confirmed cases
Polarity (Adj)
New Confirmed cases
1500000
1000000
500000
0
-500000
2020-03-01
2020-05-01
2020-07-01
2020-09-01
2020-11-01


Emotion Response (Percentage) / New Confirmed cases
New Confirmed cases
Fear (Adj)
Anger (Adj)
Joy (Adj)
Sadness (Adj)
1500000
1000000
500000
0
2020-03-01
2020-05-01
2020-07-01
2020-09-01
2020-11-01

Conclusion

- Trained classifiers for multi-class emotion detection.
- Classified the tweets into four emotions and investigating the trend of emotions in relation to the COVID-19 new confirmed case number.

Challenges

- Emotion analysis
  - Less work on emotion analysis in text compared with sentiment analysis.
  - Lack of labeling for supervised learning
- Tweet messages
  - Diverse and may include a rich ensemble of emotions, sentiments and moods.
    - May include neutral emotion, no emotion, or more than one emotion
  - Casual Twitter language, length limitation and noise
    - Dictionary size: 12909
    - Unknown words: 2348 (eg. 'inyourneighborhoodnotdc', ‘hhaapppyyybday’)
  - Large numbers of potential features
    - Affective Lexicon-based features, POS, etc.

Thank you