CS 224U

Bake-off 2: Sentiment Analysis

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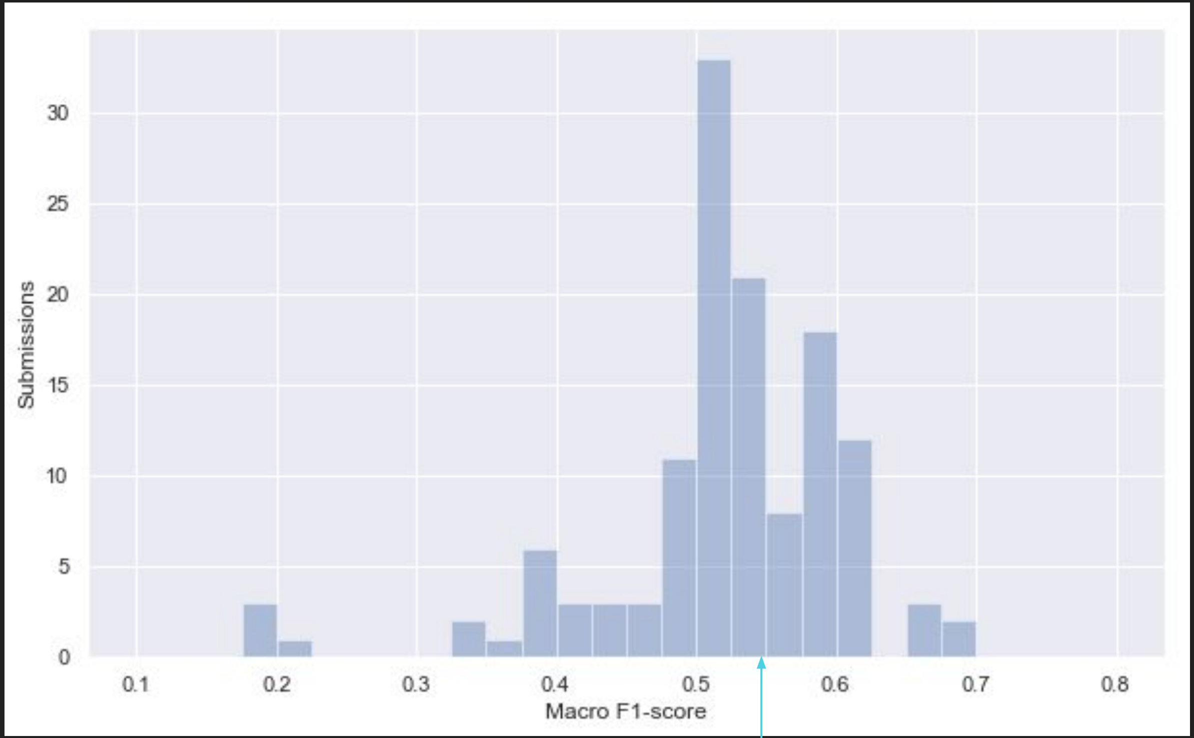
Cindy & Jayadev

Task

- Sentiment analysis with 3 classes: positive, neutral, negative
- Evaluation: Stanford Sentiment Treebank Test Set
  - 2210 sentences in test set
- Evaluation metric: Macro F1 score (**NOT** micro F1 or weighted macro F1)
  - ~900 positive, ~400 neutral, ~900 negative
  - In general, worst performance seen on “neutral” class

Histogram of scores



unigrams_phi + softmax

What distinguishes the high scorers?

High o/e for top scorers (>= 0.58)

	top	bottom
dev	2.061939	0.326789
y_dev	2.034808	0.343988
f	2.004663	0.363099
sst_train	1.996595	0.368213
sst_dev	1.979760	0.378886
bert_sentence_phi	1.963751	0.389035
y_train	1.958842	0.392147
torch.long	1.952593	0.396108
hidden_size	1.946218	0.400150
t.leaves	1.923450	0.414583
X_bert_train_mean	1.921352	0.415913
train	1.914657	0.420157
/	1.911065	0.422435
X_str_train	1.910325	0.422903
X_bert_train	1.907963	0.424401
batch	1.905052	0.426247
X.mean	1.905052	0.426247
BERT	1.899154	0.429986
context	1.899154	0.429986
X_bert_dev	1.892795	0.434017

High o/e for low scorers (<0.58)

	top	bottom
np_func	0.181509	1.518879
score	0.195754	1.509848
rnn_phi	0.204557	1.504267
feats	0.213304	1.498722
glove_subtree_phi	0.226090	1.490617
lookup	0.229404	1.488516
np.sum	0.230127	1.488057
sst_glove_vocab	0.289769	1.450247
0.05	0.303226	1.441716
DATE_HOME	0.305796	1.440087
0.001	0.306836	1.439428
sst_train_vocab	0.310245	1.437267
get_vocab	0.315603	1.433870
avg	0.318200	1.432224
vector	0.332571	1.423114
iter	0.334110	1.422138
10000	0.336186	1.420822
words	0.350329	1.411856
6B	0.351467	1.411135
negative	0.358882	1.406434

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Using BERT for feature extraction and fine-tuning seems to be very effective.

🥇 Group 13 (Di B., Yipeng H., Zijian W.) Score: 0.692

Balanced Dataset + End-to-end BERT

- Data preprocessing:
  - Balance the dataset by oversampling
  - Filter sentences to rejoin contractions and punctuation:

```
def sent_filter(sent):
    return sent.replace(" 's", "'s").replace(" .", ".").replace(" ,", ",").replace("`` ", "''") \
            .replace(" ''", "''").replace(" 'm", "'m").replace(" 've", "'ve") \
            .replace(" 't", "'t").replace(" 're", "'re")
```

- End-to-end BERT:
  - Train the model using the [pretrained BERT model in PyTorch]
  - Use hyperparameter settings from original BERT paper

🥈 Group 51 (Hanoz B., Angelia R. W.)
Score: 0.651

BERT + TorchShallowNeuralClassifier + Balanced Dataset

- BERT encoder:
  - Fine-tune BERT on the SST
  - Run inference to generate features for each sentence
- Classifier:
  - Use TorchShallowNeuralClassifier
  - Up-sample the instances with class 'neutral' during training to ensure roughly balanced dataset

Other interesting approaches

Group 9
Score: 0.69 using the subtree labels (disallowed in the competition but interesting in general)

Seq2seq

- Intuition:
  - Strings containing sentence annotations and tree structure as input sequence
  - Sentiment label as output “sequence”
- Architecture:
  - 2-layer bidirectional LSTM encoder/decoder with multiplicative attention

Other interesting approaches

Feature engineering

- All top systems this year relied on deep learning
- Last year's top 2 systems both used hand-built features + logistic regression
    - Note: scores below are on the binary task
    - First place (Jayadev's team!)
        - Score: 0.831
        - Preprocessing: Remove punctuation
        - Features: Character n-grams, tf-idf weighting
        - Classification: Logistic regression with balanced class weight
    - Second place (Lucy's team!)
        - Score: 0.821
        - Preprocessing: Remove stopwords
        - Features: Unigrams/bigrams, negation words, sentiment lexicon, part of speech, sentence length, GloVe