Sentimiento Analysis

Classifying Affect in Mixed Language Tweets

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SemEval-2020 Task 9: Overview of Sentiment Analysis of Code-Mixed Tweets

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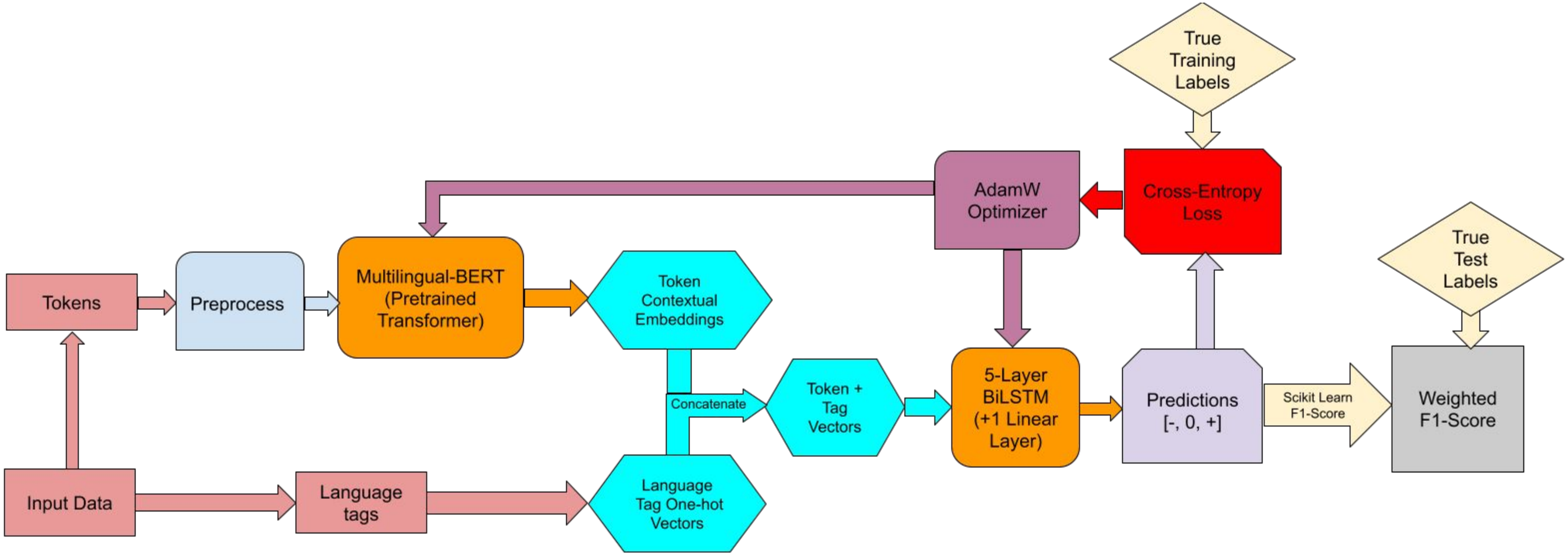
- Sentiment analysis on (Spanglish, Hinglish) tweets
- Categorical output: `[-, 0, +]`
- Adaptation task: Hinglish code mixed tweets

Final System Architecture



Example Input tweet - Hinglish

Original tweet +
lang tags

```
('@', 'O')
('PJkanojia', 'Hin')
('@', 'O')
('ssarwar2', 'Hin')
('Modi', 'Hin')
('ne', 'Hin')
('yagan', 'Hin')
('k', 'Eng')
('politi', 'Eng')
('…', 'O')
('https', 'Eng')
('//', 'O')
('t', 'Eng')
('.', 'O')
('co', 'Hin')
('/', 'O')
('ZVKWrYh8Rg', 'Eng')
('🚨😩', 'O')
```

->

Preprocessed tweet
(URLs, mentions, emojis)

```
('@USER', ['O', 'Hin'])
('@USER', ['O', 'Hin'])
('Modi', ['Hin'])
('ne', ['Hin'])
('yeh', ['Hin'])
('yagan', ['Hin'])
('k', ['Eng'])
('politi', ['Eng'])
('…', ['O'])
('HTTPURL', ['Eng', 'O', 'Eng',
('revolving light', ['O'])
('weary', ['O'])
```

All tags: ['lang1', 'lang2', 'ne', 'ambiguous', 'unk', 'other', 'mixed', 'fw', 'Eng', 'O', 'Hin']

->

Dense contextual embeddings

One-hot language vectors

```
[0.34, 0.12, 0.87, …, 0, 1, 1]
[-0.27, 1.32, 0.23, …, 0, 1, 1]
[1.83, -3.12, 2.15, …, 0, 1, 0]
[3.41, -2.75, 0.19, …, 0, 1, 0]
[0.23, 1.83, -2.37, …, 0, 1, 0]
[-2.34, 4.21, 8.52, …, 1, 0, 0]
[2.83, 1.98, 5.22, …, 1, 0, 0]
[-1.32, 4.83, 9.63, …, 0, 0, 1]
[2.80, 2.64, 2.71, …, 0, 2, 1]
[1.29, 4.74, 2.76, …, 0, 0, 1]
[-2.01, 6.32, 5.01, …, 0, 0, 1]
```

Results - D2/D3

System	**Positive** Precision/Recall F1	**Neutral** Precision/Recall F1	**Negative** Precision/Recall F1	**Avg. F1**
Spanglish Linear SVM (D2)	0.5386 0.7499 0.6252	0.3689 0.2628 0.2971	0.4157 0.1577 0.2233	0.4486
Hinglish Linear SVM (D2)	0.6500 0.6448 0.6432	0.5372 0.4505 0.4838	0.5841 0.6930 0.6302	0.5794
M-BERT - Spanglish (D3)	0.5981 0.6348 0.6159	0.4028 0.4296 0.4158	0.4253 0.2925 0.3466	0.5041
M-BERT - Hinglish (D3)	0.6568 0.6782 0.6673	0.5401 0.4832 0.5101	0.6059 0.6652 0.6342	0.5984

Results - D4 Dev/Eval

System	**Positive** Precision/Recall F1	**Neutral** Precision/Recall F1	**Negative** Precision/Recall F1	**Avg. F1**
M-BERT+BiLSTMClassifier (Spanglish) Dev	0.5767 0.7576 0.6549	0.3791 0.2052 0.2663	0.3963 0.3854 0.3908	0.4815
M-BERT+BiLSTMClassifier (Hinglish) Dev	0.6790 0.6721 0.6755	0.5311 0.5000 0.5151	0.6025 0.6539 0.6272	0.6008

Results - D4 Hinglish Comparison

System	**Positive** Precision/Recall F1	**Neutral** Precision/Recall F1	**Negative** Precision/Recall F1	**Avg. F1**
Baseline	0.728 0.688 0.707	0.562 0.602 0.581	0.691 0.674 0.683	0.654
M-BERT+BiLSTMClassifier (Hinglish) Test	**0.7774 0.7370 0.7567**	**0.6013 0.5936 0.5974**	**0.6894 0.7400 0.7138**	**0.6854**
Top Performer	0.843 0.760 0.799	0.652 0.731 0.689	0.785 0.754 0.769	.750

Results - D4 Spanglish* Comparison

System	Avg. F1
Baseline (M-BERT)	0.5643
M-BERT+BiLSTMClassifier	**0.4849**
Top Performer	0.6126

*separate task; different dataset from original SentiMix

Discussion

a. Issues
    i. Freezing M-BERT layers degraded model performance more than it helped prevent catastrophic forgetting
    ii. Adding dropout to the last LSTM layer degraded model performance more than it helped with overfitting
    iii. Incorporating language tags didn't seem to have much impact
    iv. Skewed data sets = more positive classifications, 55% in Spanglish data positive, 30% neutral, 15% negative
    v. Preprocessing data seemed irrelevant for Spanglish, but helped with Hinglish
b. Successes
    i. End to end NN system, check
    ii. Large file/large model handling
    iii. Beat Hinglish baseline

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Thank you!

[PC: PP]