Twitter Sentiment Analysis

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Motivation

With the massive volume of tweets being generated by Twitter every second, sentiment analysis can help determine the overall opinion of a particular topic or issue. It is a valuable technique for analyzing the opinions, emotions, and attitudes expressed by individuals over text since companies and other entities have interest in tracking public support behind their products.

Data Description

- 1.6 million tweets tagged with sentiment associated with them.
    - 0 = Negative Sentiment
    - 2 = Neutral sentiment
    - 4 = Positive sentiment

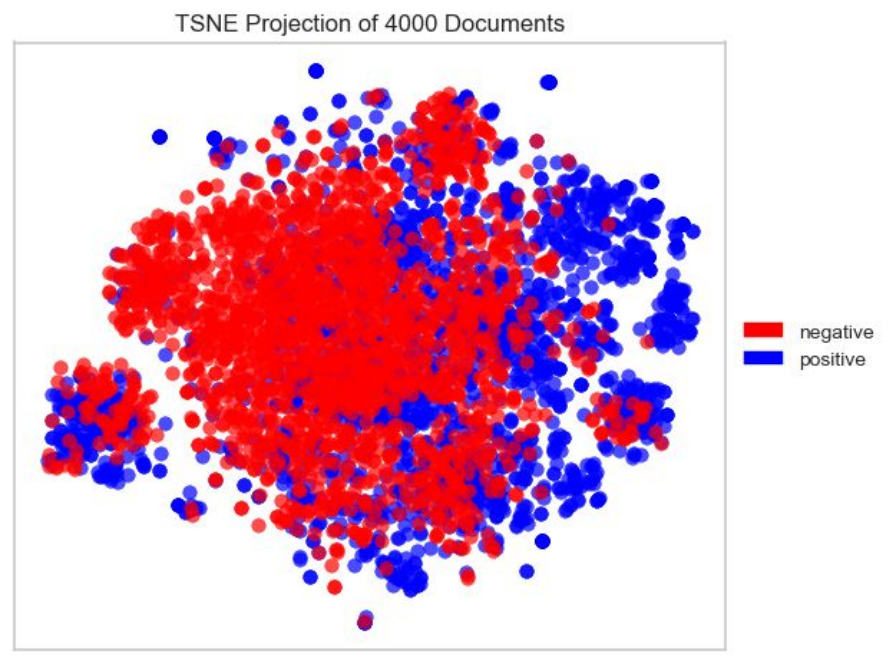
- preprocessing steps for data

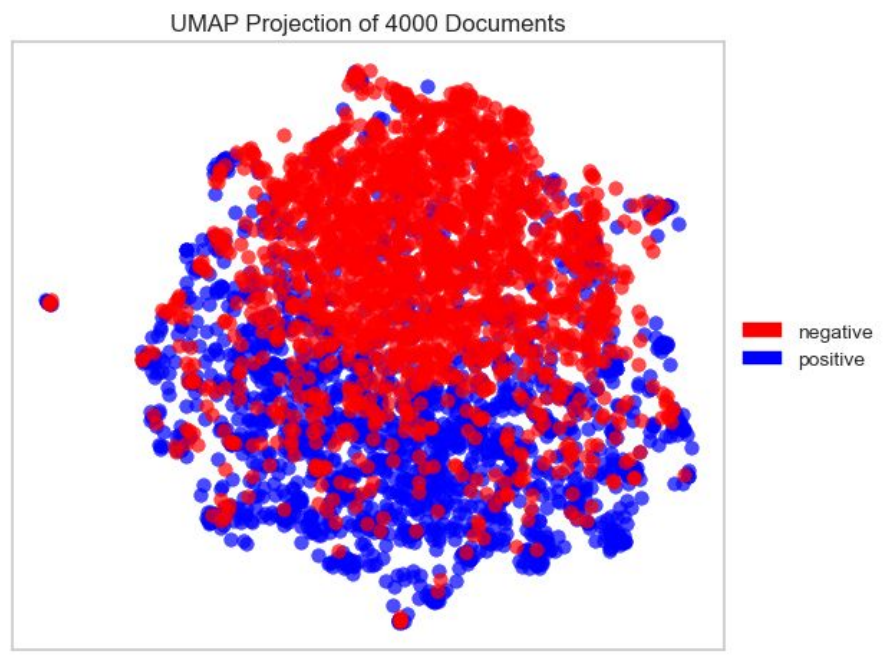
1. remove links remove @'s, punctuation
2. lower-case all text
3. remove stopwords
4. tokenize words per row
5. stem words per row

	target	ids	date	flag	user	raw_text	process_text
0	0	1467810369	Mon Apr 06 22:19:45 PDT 2009	NO_QUERY	_TheSpecialOne_	@switchfoot http://twitpic.com/2y1zl - Awww, t...	[httptwitpiccom2y1zl, awww, thats, bummer, sho...

Modeling

UMAP/tSNE


TSNE Projection of 4000 Documents
negative
positive


UMAP Projection of 4000 Documents
negative
positive

Logistic Regression

- Our basic Logistic Regression model returned an accuracy score of approximately 78% along with an F1 score of approximately 79%
- A confusion matrix seemed to indicate a very slight lean for the model predicting more positive results

```
F1 Score:  0.7873475438327454
Accuracy:  0.7833270833333333

              precision    recall  f1-score   support

           0       0.80      0.76      0.78    240539
           1       0.77      0.80      0.79    239461

    accuracy                           0.78    480000
   macro avg       0.78      0.78      0.78    480000
weighted avg       0.78      0.78      0.78    480000

Confusion Matrix:
 [[183461  57078]
 [ 46925 192536]]
```

SVM

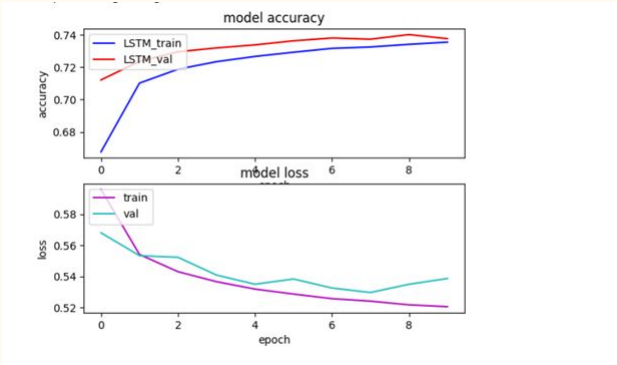
- We built a base SVC model to predict whether a tweet was positive or negative
- We were able to achieve approximately 77% Accuracy with this base model
- Ultimately, we ended up needing to scale our overall dataset to 10% due to multiple issues with memory and computing unit shortages
- We defined a custom tokenizer that also functioned as a tool to make sure the strings were in lower case and converted the text data using TF-IDF
- To ensure the best classification model, we also have built out multiple SVM models utilizing different kernels
- We have also built out multiple Hyper-Parameter Tuners
    - Grid
    - Random
    - Bayes

*Screenshot of Hyperparameters and models in appendix

LSTM Predictions

- We built an LSTM to predict whether a certain string (Tweet) was positive or negative.
- We were able to reach around 73% accuracy with 10 epochs.
- Used GloVe (Global Vectors for Word Representation) Embedding From Stanford.
    - Helps the LTSM understand the information we are feeding it.

*LSTM details in appendix



VADER

-Valence Aware Dictionary and sEntiment Reasoner
-Rule-based sentiment analysis
-Trained on social media data

```
Index: 5314
Text: @SouthwestAir My husband a first time flyer with you has had the worst experience on board a aircraft just a few minutes ago.
Compound Score: -0.62
Positive Score: 0.00
Negative Score: 0.16
Neutral Score: 0.84
```

```
Index: 2342
Text: @united I JUST ASKED MY BOYFRIEND TO PROM OVER THE LOUDSPEAKER ON FLIGHT 494 HE SAID YES!!!! BEST DAY EVER!!! THANK U SO MUCH!!!!!!
Compound Score: 0.95
Positive Score: 0.44
Negative Score: 0.00
Neutral Score: 0.56
```

Takeaways

Conclusion

- SVM and Logistic Regression outperformed our LSTM model.
- UMAP and tSNE struggled with differentiation, showing that this is a rather complex problem
- Large data is hard to parse through and used a lot of computational resources that limited our ability to fully train out some models.

Appendix

SVM

```
# Scale overall dataset to 10% to try to resolve computing issues
df_sampled = pre_processed_data.sample(frac=0.1, random_state=42)
X_train, X_test, y_train, y_test = train_test_split(df_sampled["process_text"], df_sampled["target"], test_size=0.3, random_state=39)

# Define a custom tokenizer function
def my_tokenizer(text):
    tokens = text.lower().split()  # Split text into words
    return tokens

# Convert text data into numerical features using TF-IDF representation
vectorizer = TfidfVectorizer(tokenizer=my_tokenizer)

X_train_list = X_train.tolist()
X_test_list = X_test.tolist()

X_train_tfidf = vectorizer.fit_transform(X_train_list)
X_test_tfidf = vectorizer.transform(X_test_list)

svc_model = SVC()
svc_model.fit(X_train_tfidf, y_train)
y_pred = svc_model.predict(X_test_tfidf)

test_acc = accuracy_score(y_test, y_pred)
print(test_acc)

svc_cfm = confusion_matrix(y_test, y_pred)
print(svc_cfm)
```

```
[ ]  #GRID SEARCH
     param_grid = {'C': [0.1, 1, 10], 'kernel': ['linear', 'rbf']}

     grid_search = GridSearchCV(INSERT_MODEL_HERE_FOR_SVM, param_grid, cv=5)
     grid_search.fit(X, y)

     best_params = grid_search.best_params_
```

```
[ ]  #RANDOM SEARCH
     param_distributions = {'C': loguniform(0.1, 1, 10), 'kernel': ['linear', 'rbf']}
     random_search = RandomizedSearchCV(INSERT_MODEL_HERE_FOR_SVM, param_distributions, n_iter=10, cv=5)
     random_search.fit(X, y)

     best_params = random_search.best_params
```

```
[ ]  #BAYES SEARCH
     param_space = {'C': (0.1, 10.0, 'log-uniform'),
                    'kernel': ['linear', 'rbf'],
                    'gamma': (1e-6, 1e+1, 'log-uniform'),
                    'degree': (1, 8, 'uniform')}

     opt = BayesSearchCV(INSERT_MODEL_HERE_FOR_SVM, param_space, n_iter=50, cv=5, n_jobs=-1)
     opt.fit(X_train, y_train)

     best_params = opt.best_params_

     best_svm = SVC(**best_params)
     best_svm.fit(X_train, y_train)

     accuracy = best_svm.score(X_test, y_test)
     print("Best SVM :", best_params)
     print("Accuracy :", accuracy)
```

LTSM Details

- Input layer with maximum string length of 30 allowed
- embedding layer mapping each integer index to a dense vector of fixed size.
- 1D spatial dropout to the embedding sequences, randomly dropping out entire 1D feature maps in the embedding tensor, to reduce overfitting.
- 1D convolutional layer to the output of the spatial dropout layer, with 64 filters of size 5 and a ReLU activation function, to extract local features from the sequence.
- bidirectional LSTM layer to the output of the convolutional layer, with 64/512 hidden units, and dropout and recurrent dropout rates of 0.2, to capture long-term dependencies in the sequence.
- Dense layer to the output of the LSTM layer, with 64/512 hidden units and a ReLU activation function, to learn a higher-level representation of the sequence.
- Dropout layer dropping 50% of hidden units
- Another dense layer to the output of the dropout layer, with 64 hidden units and a ReLU activation function.
- Final dense layer to the output of the second dense layer, with a single output and sigmoid activation function.