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SENTIMENT ANALYSIS TO INDICATE CUSTOMER SATISFACTION

Corey B. Holstege

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INTRODUCTION



Consulting experience with Accenture



Senior Manager in Core Finance Transformation



Business Transformation



Complex systems implementation



Masters' student in Data Analytics at Western Governors University

CONTEXT



Internet invented in 1983



Myspace launched in
2003



Currently over 116
unique social media
platforms



How do we keep a pulse
on what our customers
are saying about us?



Customer Satisfaction
Score

PROBLEM STATEMENT & HYPOTHESIS



Problem statement: Can a neural network model be constructed on the dataset to accurately predict customer reviews as positive or negative, allowing these predictions to be used to calculate a customer satisfaction score?



Null hypothesis: a neural network cannot be constructed to accurately predict customer reviews as positive or negative sentiment



Alternative hypothesis: a neural network can be constructed to accurately predict customer reviews as positive or negative sentiment with an accuracy greater than 80%

DATA ANALYSIS PROCESS

Exploratory Data Analysis completed leveraging bar charts, frequency counts, and examining the data's nuances

Data was cleaned: removed punctuation, set all to lowercase, removed stop words, unique strings (xbf, xef, xfd) removed, reviews tokenized, reviews padded

Four models evaluated

Accuracy and loss metrics used to determine which model to use (Model 3)

Social Media reviews imported, cleaned, and model 3 used to predict sentiment

Customer Satisfaction Score calculated across all reviews

EXAMPLE OF CLEANED REVIEW

[illegible]

OUTLINE OF FINDINGS

Model 3 the most accurate at 87%

```
In [454]: print(df_model_metrics)
  model_name  model_description  test_loss  test_accuracy  epoch_stopped_at
0  model_1    2 layers max length    0.358455      0.874080              4
1  model_2    2 layers median length    0.416498      0.839970              3
2  model_3    3 layers max length    0.335516      0.873328              3
3  model_4    3 layers median length    0.407456      0.841322              3
```

Model used to predict sentiment of social media reviews

```
In [482]: print('Original review', df_sm['review'][num_index], '\n')
...: print('Predicted:', 'Negative' if df_sm_predictions[num_index][0] >= 0.5 else 'Positive', 'review')
Original review McDonald\x92s is one of my favorite burgers

Predicted: Positive review
```

Customer Satisfaction of the data calculated to be 48%

```
In [483]: csat_satisfied_df_reviews = sum(df_reviews['rating'] == 1)
In [484]: csat_satisfied_df_sm = sum(df_sm['model_3_prediction'] == 1)
In [485]: csat_all_df_reviews = len(df_reviews['rating'])
In [486]: csat_all_df_sm = len(df_sm['model_3_prediction'])
In [487]: csat = (csat_satisfied_df_reviews + csat_satisfied_df_sm) / (csat_all_df_reviews + csat_all_df_sm) * 100
In [488]: print(f'CSAT score: {round(csat,2)}%')
CSAT score: 48.01%
```

LIMITATIONS OF TOOLS AND TECHNIQUES

Dataset is small at 33,396 rows and 33 rows respectively

Fine tuning of the model

Only four models evaluated

```
In [433]: model_3 = Sequential()
...: model_3.add(Embedding(input_dim=15232, output_dim=11, input_length=273))
...: model_3.add(Flatten()) # https://keras.io/api/layers/reshaping_layers/flatten/
...: model_3.add(Dense(100, activation='relu'))
...: model_3.add(Dense(50, activation='relu'))
...: model_3.add(Dense(25, activation='relu'))
...: model_3.add(Dense(2, activation='softmax'))
...: model_3.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
...: print(model_3.summary())
```


PROPOSED ACTIONS



Gathering more reviews with star ratings to use to train the model, and more social media reviews should be gathered to be evaluated



Hyper tune the model



Design a pipeline

EXPECTED BENEFITS



With the speed of the internet and influencers, a written word can have an outsized impact faster than ever before. This project provides a means and method to collect all those written words, analyze them as positive or negative, and feed that information into a commonly understood metric: customer satisfaction score.



Taken in aggregate, this metric informs company leadership at a wholistic level how the company is perceived. Paired with location data it brings this insight down to the store level where local store leadership can immediately review and act upon it.



Once implemented in a production landscape and paired with a dashboard this model is expected to provide the near real time feedback required to increase customer satisfaction which will ultimately drive repeat and incremental sales.

THANK YOU

Corey B. Holstege