IBM Advanced Data Science Capstone Project

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Data Science Peers' Presentation

Contents

Sentiment Analysis of Amazon Customer Reviews

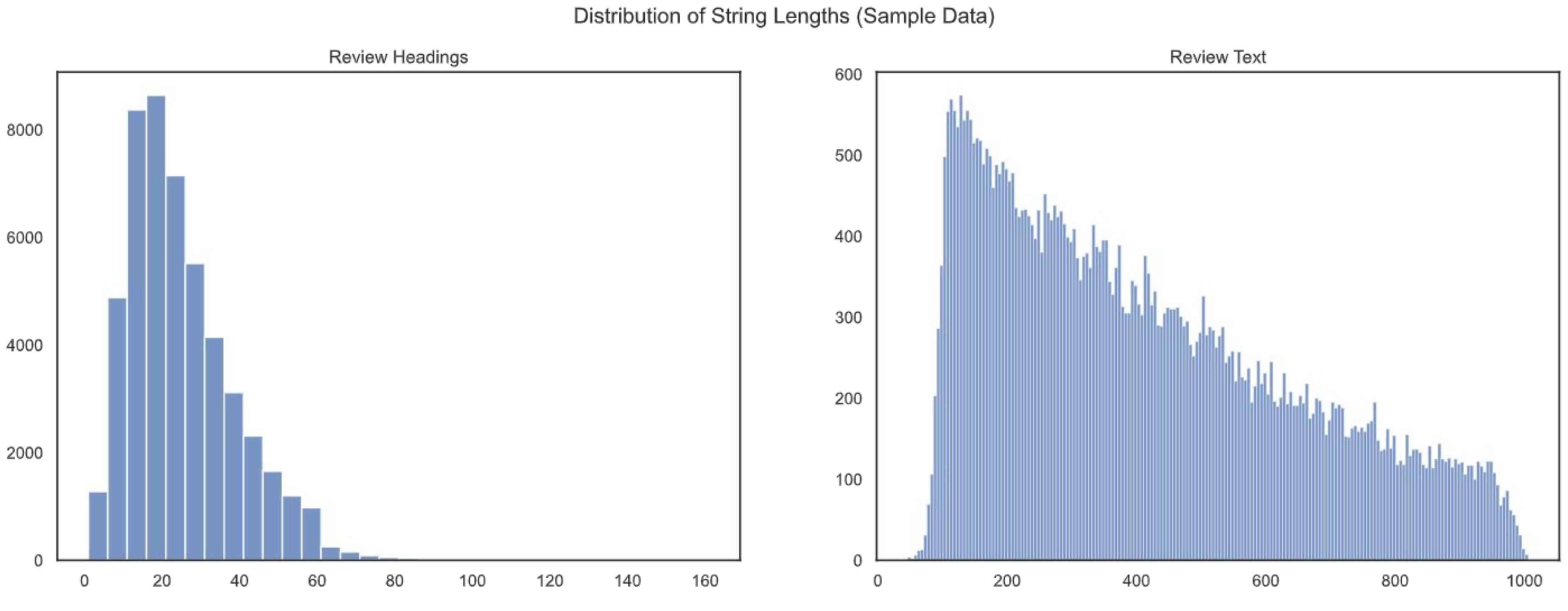
Architectural choices

- **Programming Language - Python**
  - Open-source, huge repository of libraries, fast development, wide community support
- **Data Processing - Spark**
  - Dealing with a relatively large dataset, we chose Spark for data storage and processing
  - Seamless scaling and distributed computing
- **Deep Learning - Keras**
  - An extremely powerful platform for building and deploying deep learning models
- **Data Repository - IBM Cloud Storage**
  - Easy access and secure data repository
- **Development Environment - Jupyter Notebooks**
  - Easy to develop, ability to include data, code and analysis in a single document

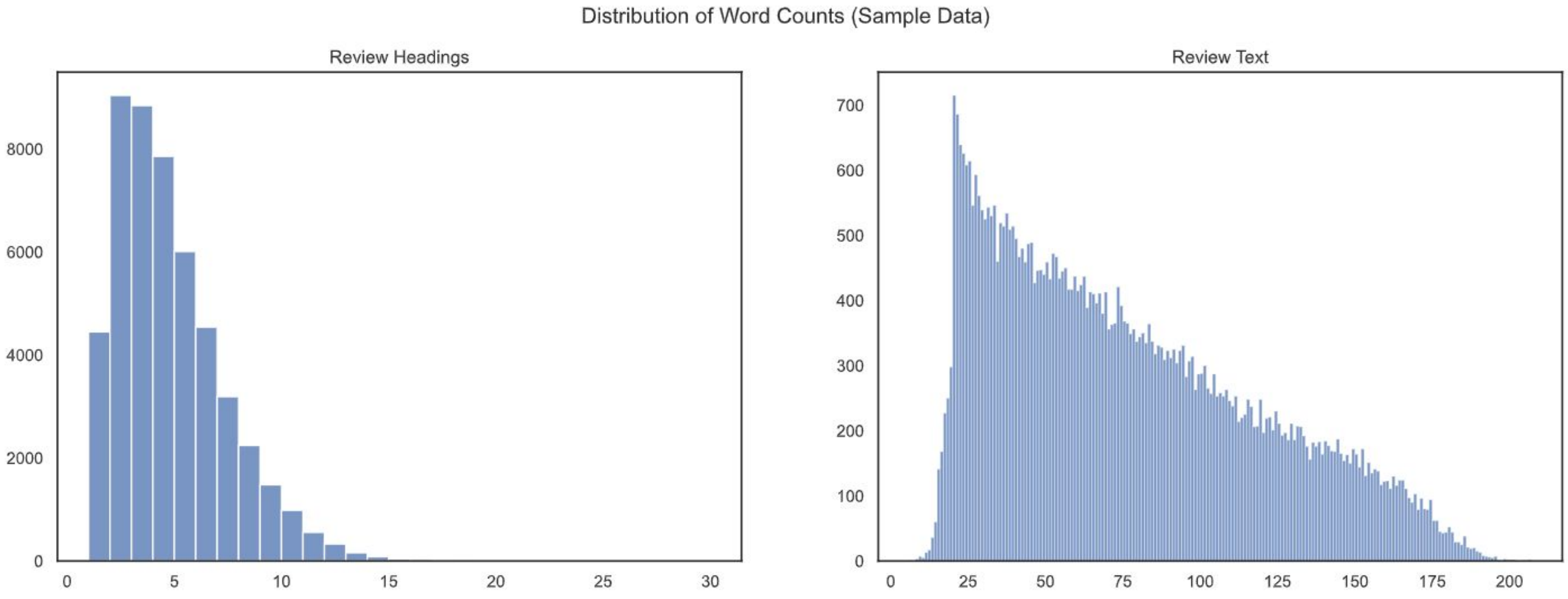
Data preparation – Quality assessment

- **Non-english language reviews**
  - There were ~0.2% non-English language reviews
  - These were removed from the dataset using the ***langdetect*** library in Python
- **Ignoring reviews with Rating = 3**
  - One of the critical issues that wasn't handled was reviews with Rating 3. Since the sentiment of training data was derived from reviews having ratings less than 3 as negative and more than 3 as positive, ~20% of the data was ignored
- **Spelling mistakes, trivial words, etc.**
  - Spelling mistakes and trivial (stop) words were handled using the ***NLTK*** library

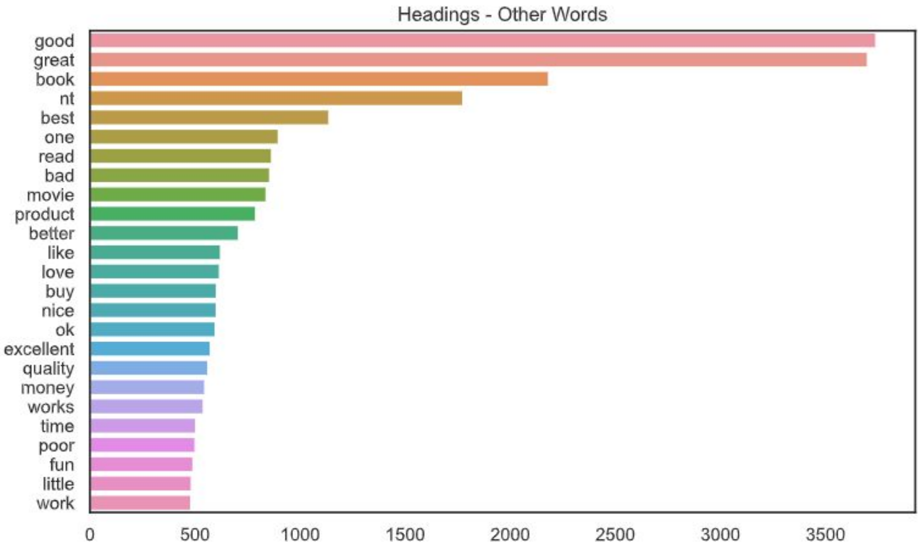
Data preparation – String length distribution

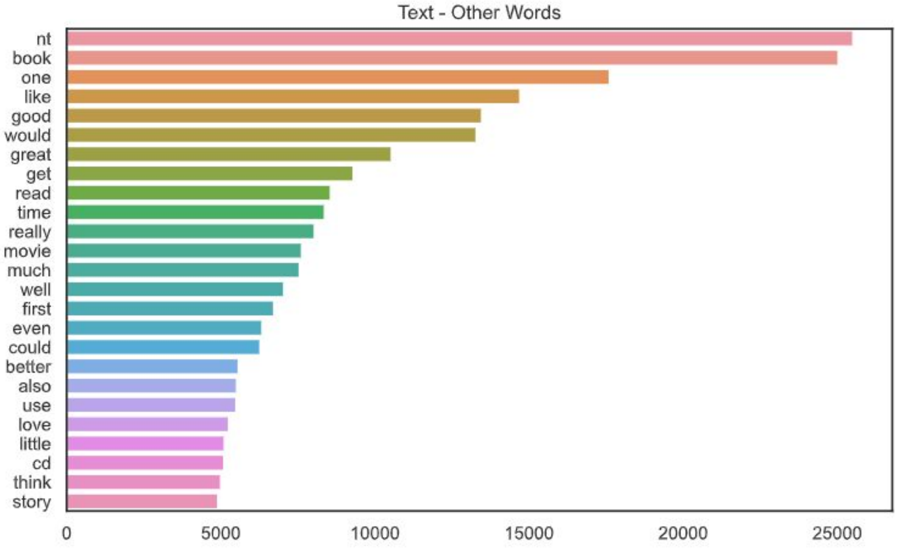


Data preparation – Word count distribution



Data preparation – Top words in reviews





Data preparation – Top word visualization

Data preparation - Pre-processing

- **Removing NAs**
  - All rows where rating/ reviews were NA or Empty were removed from the data
- **Combining Heading and Text**
  - Since the review heading and text both contain relevant information, we combine them into a single column - we are considering the heading as an extension of the overall review body.
- **Tokenization**
  - Reviews were tokenizes into arrays of words after removing special characters, punctuations, etc.
- **Removing stopwords**
  - Words like is, an, the were removed as they do not add any predictive value
- **Lemmatization**
  - Inflected forms of each word were grouped together (such as run, running, ran)
- **Categorical target variable (Review Sentiment)**
  - Negative = Rating < 3; Positive = Rating > 3

Data preparation – Feature extraction

Method 1

TF-IDF Vectorization

- Vectorized the tokens into a sparse matrix using TFIDF Vectorizer
- This is a bag-of-words model that doesn't retain the ordering of words
- The features from this method can be used for training an MLP neural network

Method 2

Padded Sequential Word Vectors

- This method involves replacing each unique word in our vocabulary with an integer value
- Since sentences can be of varying lengths, padding is added (leading zeros) to make all the vectors of the same length

Model algorithm

- We trained two different models using our sample data -
    - Multi-layer perceptron neural network using the TF-IDF sparse vectors
    - LSTM neural network using the padded sequential word vectors
- **Final model selected**
    - LSTM neural network with 2 LSTM layers and 2 fully connected Dense layers

Final model architecture

```
Model: "finalLSTM"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, 147, 128)          4194304
_________________________________________________________________
lstm_2 (LSTM)                (None, 147, 512)          1312768
_________________________________________________________________
lstm_3 (LSTM)                (None, 256)               787456
_________________________________________________________________
dense_6 (Dense)              (None, 256)               65792
_________________________________________________________________
dense_7 (Dense)              (None, 128)               32896
_________________________________________________________________
dense_8 (Dense)              (None, 1)                 129
=================================================================
Total params: 6,393,345
Trainable params: 6,393,345
Non-trainable params: 0
```

Model performance

*Model performance was measured using the **binary accuracy** metric since we are dealing with a **binary classifier** with **balanced class distribution**.*

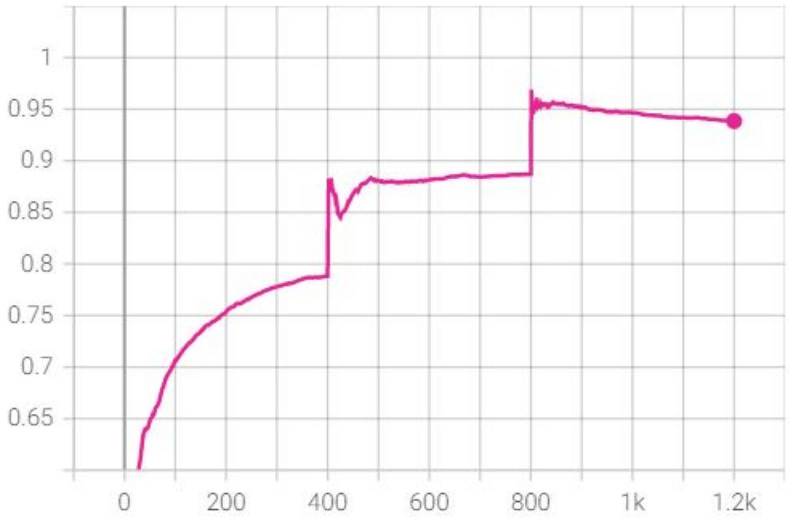
• Naive Bayes model trained on 50k sample data ◦ Baseline model	~50 thousand sample	81.16%
• Sample Multi-layer perceptron neural network ◦ 2 Dense hidden layers with L2 regularization	~50 thousand sample	83.57%
• Sample LSTM neural network ◦ Embedding layer, 2 LSTM layers, 2 Dense layers	~50 thousand sample	82.88%
• Final LSTM neural network ◦ Embedding layer, 2 LSTM layers, 2 Dense layers	~2.4 million dataset	91.79%

Model performance

Multi Layer Perceptron - Trained on 50k sample data

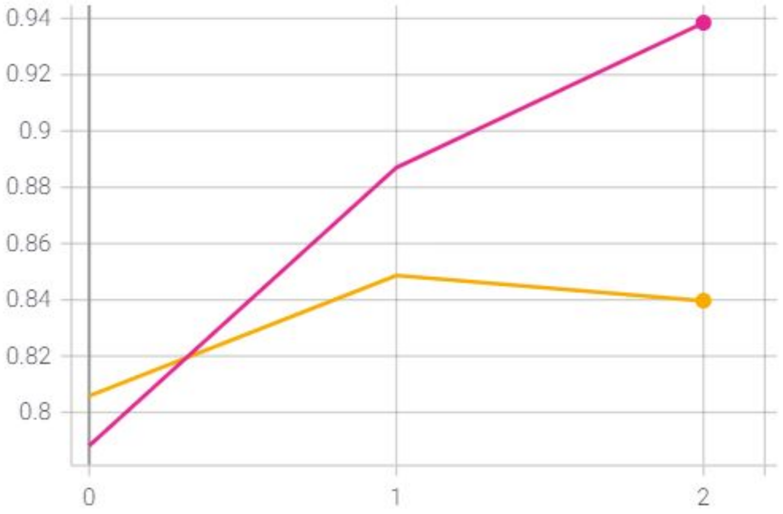
Overfitting can be seen after 2nd training epoch

Training accuracy over 3 epochs



Training vs. Validation Accuracy over 3 epochs

Training
Validation

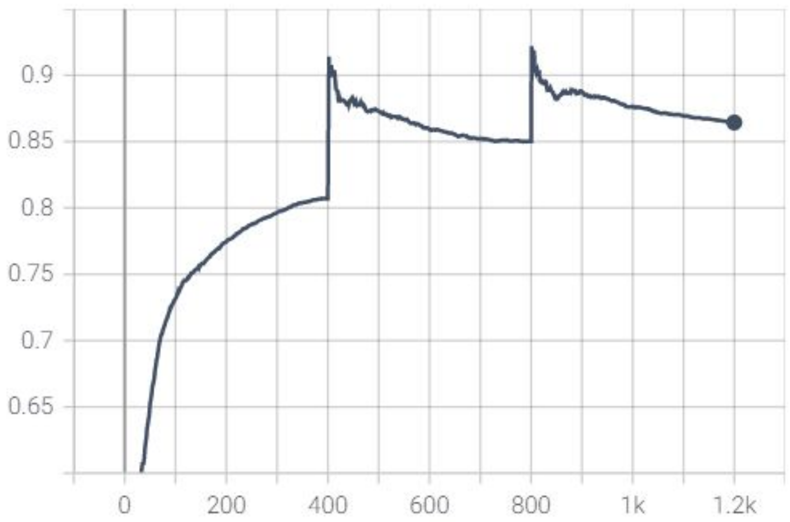


Model performance

Long Short Term Memory Neural Network - Trained on 50k sample data

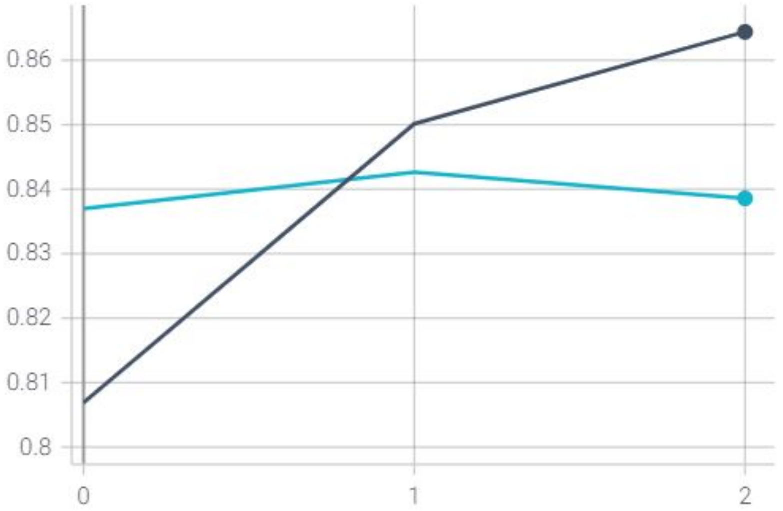
Overfitting can be seen after 2nd training epoch

Training accuracy over 3 epochs



Training vs. Validation Accuracy over 3 epochs

Training
Validation



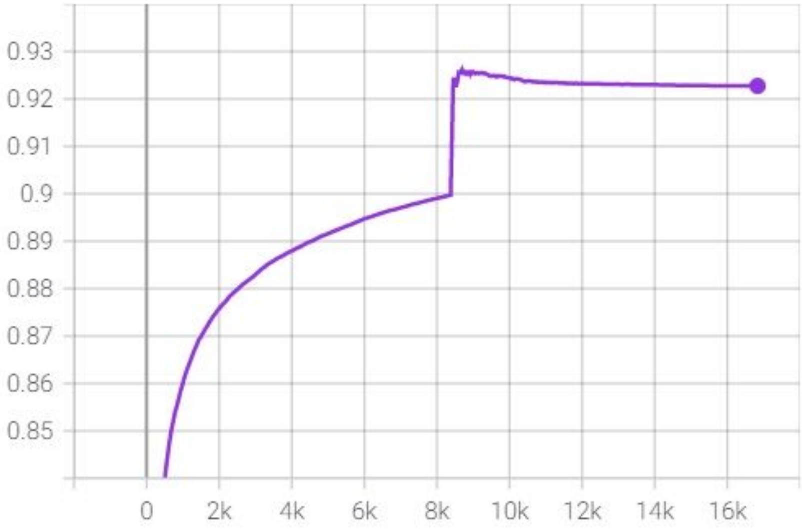
Model performance – Final Model

Long Short Term Memory Neural Network - Trained on 2.6m full dataset

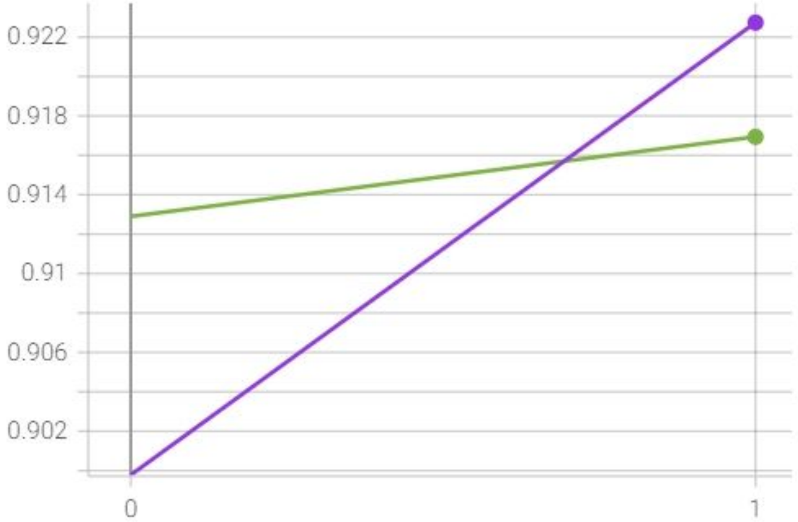
91.79% *binary accuracy achieved on test data*

Training
Validation

Training accuracy over 2 epochs



Training vs. Validation Accuracy over 2 epochs



Next steps...

- **Improve model performance**
  - Hyperparameter tuning was not done due to resource constraints
  - We can improve the model performance by tuning hyperparameters such as -
    - Neural network architecture
    - L2 regularization
    - Learning rate
    - Batch size
- **Deploy model for live streaming data**
  - We can deploy the model in an enterprise environment to predict sentiments of customer reviews for making better business decisions