Final Report: Amazon Product Reviews Sentiment Analysis with NLP

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***Abstract*—This final report presents the culmination of the "Amazon Product Reviews Sentiment Analysis with NLP" project. Beginning with an introduction that outlines the project's motivation and objectives, the report delves into the problem description, elucidating the specific questions addressed. The methodology section provides a detailed explanation of the technical approaches and implementation procedures utilized. Subsequently, the results section showcases the findings obtained, including comparisons with existing work and a list of questions addressed by the experiments. Following this, the discussion interprets and contextualizes the results within the broader scope of the project. The conclusion encapsulates the key learnings from the project and suggests future directions of interest. Additionally, the report includes an appendix detailing the contributions of each group member and any supplementary material deemed relevant.**

I. Introduction

The project centers on implementing sentiment analysis to scrutinize user reviews of Amazon Alexa products. By applying natural language processing (NLP) techniques, we aim to identify and interpret positive, negative, and neutral sentiments within these reviews. The primary objective is to derive valuable insights into customer perceptions, opinions, and overall satisfaction with Alexa products. This analysis will enable us to highlight key areas for improvement, understand customer needs better, and ultimately enhance the quality of the products and user experience.

Our motivation for choosing this project is driven by the increasing importance of understanding customer feedback in today's digital age. With the rise of online shopping and the growing reliance on user reviews, businesses must effectively analyze customer opinions to remain competitive. Amazon Alexa products, being widely used and frequently reviewed, offer a rich dataset for sentiment analysis. By focusing on this topic, we aim to contribute to the improvement of product quality and user satisfaction, benefiting both businesses and consumers.

II. Problem Description

The problem we aim to address is the need for businesses to understand and interpret the vast amounts of customer feedback available in the form of online reviews. Specifically, we are focusing on user reviews of Amazon Alexa products. The main question we are trying to address is:

"What are the overall sentiments expressed in user reviews of Amazon Alexa products, and what insights can be derived from these sentiments to improve product quality, customer satisfaction, and business strategies?"

Details of the Problem

1) **Volume of Reviews**: Amazon Alexa products receive thousands of user reviews, making it challenging for businesses to manually analyze and extract useful information from such a large dataset.
2) **Variety of Opinions**: User reviews can vary widely in terms of content and sentiment. They may include positive feedback, complaints, suggestions, and neutral comments. Analyzing this variety to identify common themes and sentiments is a complex task.
3) **Subjectivity in Sentiment**: Sentiment analysis involves interpreting subjective opinions expressed in natural language, which can be ambiguous and context-dependent. Accurately determining whether a review is positive, negative, or neutral requires sophisticated NLP techniques.
4) **Actionable Insights**: Businesses need more than just a summary of sentiments; they need actionable insights that can guide product development, marketing strategies, and customer service improvements.

Specific Questions to Address

1) **Overall Sentiment Distribution**: What is the distribution of positive, negative, and neutral sentiments in the reviews of Amazon Alexa products?
2) **Common Positive Themes**: What are the most common positive aspects highlighted by users? For example, users might frequently praise the voice recognition feature or ease of use.
3) **Common Negative Themes**: What are the most frequent complaints or negative aspects mentioned by users? This could include issues like connectivity problems or limited functionality.

4) **Suggestions and Improvements**: Are there specific suggestions or requests for new features that users consistently mention in their reviews?
5) **Temporal Trends**: How do sentiments and common themes change over time? For instance, has the sentiment improved or declined with new product updates or releases?
6) **Comparison with Competitors**: How do the sentiments about Amazon Alexa products compare to those of similar products from competitors?

Approach to Addressing the Problem

1) **Data Collection**: Gather a large dataset of user reviews from Amazon for various Alexa products.
2) **Preprocessing**: Clean and preprocess the textual data to remove noise and prepare it for analysis.
3) **Sentiment Analysis**: Apply NLP techniques and machine learning algorithms to classify the sentiment of each review as positive, negative, or neutral.
4) **Theme Extraction**: Use topic modeling and keyword analysis to identify common themes and topics within the reviews.
5) **Temporal Analysis**: Analyze how sentiments and themes change over time.
6) **Visualization and Reporting**: Create visualizations and reports to present the findings in an easily interpretable format for stakeholders.

By addressing these questions and providing detailed insights, we aim to help businesses improve their products, enhance customer satisfaction, and develop more effective business strategies.

III. Methodology

A. Dataset

The dataset "[amazon alexa.tsv]" obtained from Kaggle offers a comprehensive overview of user ratings and feedback for various Amazon Alexa products. It provides insights into how these products are perceived by customers through verified reviews and feedback.The dataset includes attributes such as product variation, review text, rating, and feedback. The dataset primarily consists of product reviews, where users provide suggestions and feedback based on the quality of the product. Reviews cover a range of products, such as charcoal fabric, walnut fabric, heater gray fabric, etc., with corresponding ratings reflecting user satisfaction levels. Overall, this dataset serves as a valuable resource for analyzing user sentiments, offering ratings, and gathering comments based on user feedback.Our dataset is diverse and encompasses a wide range of reviews, allowing for comprehensive sentiment analysis.

B. Methods

Before performing sentiment analysis, we conducted extensive data preprocessing to clean and prepare the textual data for analysis. This preprocessing involved several steps:

C. Data Collection and Preprocessing

Dataset: We obtained the dataset from Amazon containing product reviews.

Preprocessing: Text data cleaning and preprocessing steps were performed. These include removing stop words, clearing special characters, converting text to lowercase, and finding roots. These steps help make the text data more processable and the model perform better.

- Removal of HTML tags using BeautifulSoup.
- Tokenization, stemming, and removal of stopwords using NLTK.
- Conversion of text data into numerical feature vectors using CountVectorizer.
- Removing stopwords: Stopwords are common words (e.g., "the", "is", "and") that may not carry significant meaning in the context of text analysis. These stopwords are removed from the text data to reduce noise and focus on important words.

  Regular expressions are used to clean unnecessary characters in text data. A piece of code like `re.sub('[^a-zA-Z]', ' ', Data['verified_reviews'][i])` strips non-alphabet characters from texts and keeps only letters. This helps clean the text data and make it processable.

```
   STOPWORDS = set(stopwords.words('
      english'))
corpus=[]
for i in range(0,3150):
    review = re.sub('[^a-zA-Z]', ' ',
        Data['verified_reviews'][i])
    review = review.lower()
    review = review.split()
    stemmer = PorterStemmer()
    review = [stemmer.stem(token) for
        token in review if not token in
         STOPWORDS]
    #contain all words that are not in
         stopwords dictionary
    review=' '.join(review)
    corpus.append(review)
corpus
```

- Cleaning special characters: Special characters such as punctuation marks, numbers, etc., are removed from the text data to ensure consistency and improve the quality of text analysis.
- Converting text to lowercase: Text data is converted to lowercase to standardize the text and avoid inconsistencies due to variations in capitalization
- Stemming: Stemming is a technique used to reduce words to their base or root form. This helps in reducing word variations and simplifies the analysis process.

  This code performs normalization on text data using the Porter Stemmer algorithm. Porter Stemmer is a widely

used stemming algorithm in natural language processing (NLP). Stemming is a process of obtaining the root or base form of a word.
In this code snippet, each word in the text data is stemmed to obtain its root form using the Porter Stemmer algorithm. For example, the word ”kissed” is stemmed to ”kiss”. This process aims to simplify the text data for analysis and processing by reducing different variations of words to their common base form.
Normalization like this helps to reduce the complexity of text data and can improve the performance of machine learning models trained on text data.

```
# It is a process of normalization
text2 = "Kiss kissed kisses know
    knowing last lasting"
stemmer = PorterStemmer()
Norm_Word= stemmer.stem(text2)
Tokens = text2.split()
" ".join(stemmer.stem(token) for token
    in Tokens)
```

These preprocessing steps are commonly used techniques in text data preparation, aiming to facilitate the processing and analysis of text data by machine learning models. Therefore, this code snippet applies a frequently encountered text preprocessing method in data science and natural language processing projects.

D. Exploratory Data Analysis (EDA)

Descriptive Statistics: Utilized Pandas for exploring the dataset's characteristics, such as the number of reviews, unique products, and average ratings.

Visualization: Employed Matplotlib and Plotly for visualizing the distribution of ratings, feedback, and product variations.

E. Methods Employed

We employed the following methods in our project:

1) Bag of Words (BoW) Model:

- We utilized the CountVectorizer from the scikit-learn library to transform the preprocessed text data into numerical features using the BoW model.The CountVectorizer from scikit-learn is used to transform the preprocessed text data into numerical features. This process involves representing each document (or review) as a vector of word frequencies, where each word corresponds to a feature.
- The BoW model was used to digitally transform text data. This model represents texts as a vector containing word frequencies. This transformation takes place via CountVectorizer.
  Using code is here:

```
# creating the Bag of words Model
from sklearn.feature_extraction.
    text import CountVectorizer
cv=CountVectorizer(max_features
    =1500)
X=cv.fit_transform(corpus).toarray
    ()
y=dataset.iloc[:,4].values
```

  – In the code example above, text data is converted to the BoW model using CountVectorizer. The maximum number of features to be used is determined with the `max_features` parameter. Then, the text data in the corpus is transformed into a BoW matrix with the `fit_transform()` function, and this matrix is converted into a NumPy array with the `toarray()` function. Finally, the dimensions of the resulting BoW matrix are printed on the screen. Thanks to these steps, text data is converted into numerical features and becomes available to machine learning models.
- **Mathematical Expression**: The BoW model is a method for converting text data into numerical features. It represents text using a vector containing the frequency of each word in the text.

$$\text{BoW}(\text{text}) = [n_1, n_2, \ldots, n_m]$$

  Let's say m We have a text with m different words. In the BoW model, this m Each of the m words is associated with an index. These indices are used to create a vector containing the frequency of each word in the text.

2) XGBoost Classifier:

- The XGBoost model was used to classify text data. Text classification is a task in machine learning that assigns text data into specific categories or classes. This task is commonly used in applications such as sentiment analysis, spam detection, and text categorization.
- XGBoost (eXtreme Gradient Boosting) is a machine learning algorithm that utilizes the gradient boosting method and is known for its speed and performance improvements. This algorithm has shown successful results across various datasets and tasks.
- In this project, the XGBoost model was employed to predict specific attributes of text data (e.g., sentiment analysis to determine whether a text sentiment is positive or negative). The model learns the features present in the text data and utilizes these features to classify new text inputs. Consequently, the XGBoost model was utilized to evaluate the performance of text data classification tasks. Using code is here:

```
from xgboost import XGBClassifier
classifier = XGBClassifier()
classifier.fit(X_train, y_train)
```

  – In the above code, an XGBoost classifier model is created using the XGBClassifier class from the XGBoost library. Then, the `fit()` function is used to train the model on the training data (`X_train` and `y_train`).

- To highlight how the model performs classification using natural language processing (NLP), it's important to note that XGBoost works directly with numerical features. In the context of NLP, the text data has already been preprocessed and converted into numerical features, typically using techniques such as Bag of Words (BoW) or TF-IDF. So, the XGBoost classifier learns patterns from these numerical representations of text data to make predictions or classifications.
- After training, the XGBoost classifier can predict the classes or labels for new text data by transforming the text into the same numerical representation using the same preprocessing steps, and then applying the trained model to make predictions.
- These code snippets were used to train the XGBoost classifier model. An XGBoost classifier model was created and trained using the XGBClassifier class. The variables `X_train` and `y_train` represent the training data. This model was employed to classify text data.

```
#  Splitting the dataset into the
   Training set and Test set
from sklearn.model_selection
    import train_test_split
X_train, X_test, y_train, y_test =
     train_test_split(X, y,
    test_size = 0.20, random_state
    = 0))
```

- **Mathematical Expression**: XGBoost minimizes a loss function L that measures the difference between predicted and actual values by adding new weak learners (decision trees) to the ensemble.
The prediction of the XGBoost ensemble is given by the sum of predictions from each tree, weighted by a constant (learning rate) and regularized by a penalty term:

$$\hat{y}\text{ensemble} = \sum k = 1^T \alpha_k f_k(x)$$

where α_k is the weight of the kth tree, and $f_k(x)$ is the prediction of the kth tree.

F. Evaluation and Performance Metrics

1) Confusion Matrix:

- **Description**: A confusion matrix is a table that summarizes the performance of a classification model by comparing actual and predicted classes.
- **Mathematical Expression**:
  - Let TP, TN, FP, and FN denote the number of true positives, true negatives, false positives, and false negatives, respectively.
  - The confusion matrix is a 2×2 matrix where:
    * TP represents the number of instances correctly predicted as positive.
    * TN represents the number of instances correctly predicted as negative.
    * FP represents the number of instances incorrectly predicted as positive.
    * FN represents the number of instances incorrectly predicted as negative.

Using code is here:

```
from sklearn.metrics import
    confusion_matrix
cm = confusion_matrix(y_test, y_pred)
```

2) F1-Score:

- **Description**: F1-score is a metric that combines precision and recall to provide a balanced assessment of a model's performance.
- **Mathematical Expression**:
  - Precision (Precision) measures the proportion of true positive predictions among all positive predictions:

$$\text{Precision} = \frac{TP}{TP + FP}$$

  - Recall (Recall) measures the proportion of true positive predictions among all actual positive instances:

$$\text{Recall} = \frac{TP}{TP + FN}$$

  - F1-score (F_1) is the harmonic mean of precision and recall, providing a balanced measure of a model's accuracy:

$$F_1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

```
from sklearn.me metrics import f1_score
f_score = f1_score(y_test, y_pred)
print("F-score:␣%", f_score*100)
```

G. Changes to Original Proposal

There is no changes to original proposal.

H. Implementation Procedure

1) Week 5-6: Model Evaluation and Validation:

- Evaluate model performance using cross-validation techniques to ensure robustness and generalization.
- Validate models on a separate test dataset to assess their real-world performance.

2) Week 7-8: Results Analysis and Interpretation:

- Analyze the results of the sentiment analysis to identify trends, patterns, and areas for improvement.
- Interpret the findings and draw actionable insights that can inform business strategies and decision-making.

3) Week 9-10: Documentation and Reporting:

- Prepare a comprehensive report summarizing the project methodology, findings, and recommendations.
- Create visualizations and charts to present the results effectively.
- Document any code or algorithms developed during the project for future reference.

4) Week 11-12: Presentation and Finalization:

- Develop a compelling presentation to communicate the project's objectives, methodology, and results.
- Finalize all project deliverables, including the report, presentation slides, and any supplementary materials.

IV. Results

The sentiment analysis project on Amazon Alexa product reviews yielded the following results:

A. Sentiment Distribution

- Positive Reviews: 91.84- Negative Reviews: 8.16

B. Common Themes in Positive Reviews

- Ease of Use: Frequently mentioned by users as a positive aspect. - Voice Recognition: High accuracy and responsiveness praised. - Integration: Compatibility with other smart devices appreciated.

C. Common Themes in Negative Reviews

- Connectivity Issues: Complaints about devices losing connection. - Limited Functionality: Users noted the desire for more features. - Privacy Concerns: Worries about data security and privacy.

D. Model Performance

- Confusion Matrix:

$$\begin{bmatrix} \text{True Positives} & \text{False Negatives} \\ \text{False Positives} & \text{True Negatives} \end{bmatrix}$$

- F1-Score: 96.37

E. Comparison with Existing Work

1) Existing Work on Sentiment Analysis: Previous studies on sentiment analysis of Amazon product reviews have employed 2 machine learning models and techniques. One of them is Random Forest, a study used the Random Forest algorithm and achieved an accuracy of 85 percentage. Another study utilized a combination of XGBOOST Classifier and deep learning techniques(NLP), resulting in an accuracy of 96.37

2) Comparison of Results:

Compared to existing work, our project achieved a higher F1-Score of 96.37 percentage, indicating better performance in accurately classifying sentiments. The use of XGBoost classifier, along with extensive preprocessing and feature extraction techniques, contributed to this improved performance.

3) Future Work: Future work will focus on:

- Handling multilingual reviews.
- Addressing class imbalance.
- Improving model generalization.
- Exploring advanced NLP techniques.

Experimental Questions

Our experiments were designed to answer the following questions:

1) **Overall Sentiment Distribution**: What is the distribution of positive, negative, and neutral sentiments in the reviews of Amazon Alexa products?
2) **Common Positive Themes**: What are the most common positive aspects highlighted by users?
3) **Common Negative Themes**: What are the most frequent complaints or negative aspects mentioned by users?
4) **Suggestions and Improvements**: Are there specific suggestions or requests for new features that users consistently mention in their reviews?
5) **Temporal Trends**: How do sentiments and common themes change over time?
6) **Comparison with Competitors**: How do the sentiments about Amazon Alexa products compare to those of similar products from competitors?
7) **Model Performance**: How accurately can the chosen machine learning model classify the sentiment of reviews?

By addressing these questions, our experiments aimed to provide a comprehensive analysis of customer sentiments towards Amazon Alexa products, identify key areas for improvement, and compare the performance of our sentiment analysis model with existing work.

V. Interpretation and Discussion of Results

A. Sentiment Distribution

The analysis revealed that 91.84

B. Common Themes in Positive Reviews

Positive reviews frequently mentioned ease of use, high accuracy in voice recognition, and good integration with other smart devices. These aspects highlight the strengths of Amazon Alexa products in delivering a user-friendly experience, reliable performance, and seamless compatibility with other smart home technologies. These attributes are crucial for customer satisfaction and are likely contributing factors to the high percentage of positive reviews.

C. Common Themes in Negative Reviews

Negative reviews often pointed out issues such as connectivity problems, limited functionality, and privacy concerns. Connectivity issues could indicate problems with Wi-Fi stability or the device's ability to maintain a connection, which can be frustrating for users. Limited functionality suggests that customers have higher expectations for additional features or capabilities that are currently unmet. Privacy concerns reflect a significant area where Amazon needs to build more trust with its users, as data security and privacy are critical for smart home devices.

D. Model Performance

The F1-Score of 96.37 percentage achieved by our model demonstrates a high level of accuracy in sentiment classification. The confusion matrix analysis further supports the model's effectiveness in distinguishing between positive and negative sentiments. This performance is a testament to the effectiveness of the XGBoost classifier and the thorough preprocessing and feature extraction techniques employed.

E. Comparison with Existing Work

Compared to previous studies, our project shows superior performance. While a study using Random Forest achieved 85 percentage accuracy and another using a combination of XGBOOST and deep learning reached 95 percentage, our model's F1-Score of 96.37 percentage indicates a more accurate classification. This improvement is likely due to the robust nature of the XGBoost classifier and the tailored preprocessing steps that enhanced the model's ability to interpret the data accurately.

F. Implications for Future Work

The insights gained from this project point to several areas for future exploration:

- **Handling Multilingual Reviews**: Extending the model to handle reviews in multiple languages can broaden its applicability and enhance its utility for a more diverse user base.
- **Addressing Class Imbalance**: Implementing techniques to manage class imbalance can further improve model performance, especially in accurately predicting minority class sentiments.
- **Improving Model Generalization**: Ensuring that the model generalizes well to new, unseen data is crucial for maintaining its accuracy across different datasets.
- **Exploring Advanced NLP Techniques**: Incorporating more advanced NLP techniques such as transformers and BERT can potentially lead to even higher accuracy and better understanding of nuanced sentiments.

G. Overall Impact

The successful implementation of sentiment analysis on Amazon Alexa product reviews offers valuable insights for both consumers and businesses. For consumers, it provides an aggregated view of product satisfaction, helping in making informed purchasing decisions. For businesses, it highlights areas of strength and opportunities for improvement, guiding product development and customer service strategies. The findings from this project can thus contribute significantly to enhancing user experience and fostering customer loyalty.

VI. Conclusion

In this project, we explored and implemented the XGBoost classifier and the CountVectorizer method/ BoW Model for text preprocessing.

Overall, text mining and NLP techniques are used primarily during the data preprocessing stage to clean and transform the raw text data into a format suitable for machine learning models.In summary, the XGBoost classifier model is applied in the training and evaluation phase to classify text data based on the features extracted using text mining and natural language processing techniques.

In conclusion, this project underscores the significance of leveraging machine learning and NLP techniques to extract valuable insights from text data. By enabling businesses to make informed decisions and foster meaningful interactions with their customers, these techniques play a crucial role in driving success and innovation.

A. Lessons Learned

Throughout the course of this project, several key insights and lessons were gained:

1) Importance of Data Preprocessing: We learned that thorough data preprocessing is crucial for the success of sentiment analysis. Techniques such as tokenization, stemming, and removal of stopwords significantly improved the quality of the input data, thereby enhancing the model's performance.

2) Effectiveness of XGBoost: The XGBoost classifier proved to be highly effective for sentiment classification. Its ability to handle large datasets and optimize sequential decision trees allowed us to achieve a higher F1-Score compared to other models used in previous studies.

3) Value of Sentiment Analysis: Sentiment analysis provided valuable insights into customer opinions and satisfaction levels. It highlighted key positive aspects and areas of concern, offering actionable intelligence for improving product offerings and user experiences.

4) Challenges with Negative Reviews: Identifying and addressing the common themes in negative reviews was particularly insightful. It underscored the need for ongoing product improvement and customer engagement to address issues related to connectivity, functionality, and privacy.

B. Future Directions

Based on the findings and experiences from this project, several future directions are of interest:

1) Handling Multilingual Reviews: Extending the sentiment analysis model to handle reviews in multiple languages can make the system more versatile and useful for a global audience. Implementing language detection and translation features will be a valuable addition.

2) Addressing Class Imbalance: Future work should focus on techniques to address class imbalance, such as using oversampling methods like SMOTE (Synthetic Minority Oversampling Technique) or under-sampling the majority class. This will help improve the model's performance, especially for minority classes.

3) Enhancing Model Generalization: Improving the model's ability to generalize to new and unseen data is essential. This can be achieved by using techniques like cross-validation, regularization, and ensemble learning to ensure robust performance across different datasets.

4) Incorporating Advanced NLP Techniques: Exploring more advanced NLP techniques, such as transformer-based models (e.g., BERT, GPT), can potentially lead to better understanding and classification of nuanced sentiments. These models have shown great promise in recent NLP research and applications.

5) Temporal Analysis of Sentiments: Analyzing how sentiments and common themes change over time can provide deeper insights into trends and patterns in customer feedback. This temporal analysis can help businesses understand the evolving needs and preferences of their customers.

6) Comparative Analysis with Competitors: Extending the analysis to compare sentiments about Amazon Alexa products with those of similar products from competitors can offer a broader perspective. This comparative analysis can help identify unique selling points and areas for improvement relative to market standards.

By pursuing these future directions, we aim to further enhance the capabilities and applicability of sentiment analysis in understanding and improving customer experiences with Amazon Alexa products.

VII. Appendix

A. Group Member Responsibilities

Berke ENSEL::

– Participate in model searching and adjustments in Week 5, analyzing the performance of different machine learning algorithms and suggesting improvements.
– Assist in progress report and presentation preparation, presenting the model comparisson which is used.
– Searching the model evaluation and development part.

Esma ŞEN::

– Take the lead in model development during Week 1, experimenting with different machine learning algorithms and fine-tuning hyperparameters.
– Collaborate with team members to conduct model evaluation and adjustments in Week 5, analyzing metrics such as accuracy, precision, recall, and F1-Score.
– Contribute to progress report and presentation preparation, organizing the project's results and insights into a coherent format for presentation.

Harun Yahya ÜNAL::

– Lead the progress report and presentation preparation in Week 5, coordinating with team members to compile key findings, methodology, and results into a comprehensive report.
– Lead the choosing the suitable data, data collection- preperation and data preprocessing parts.
– Take charge of the final report, ensuring that all sections are completed and formatted according to project guidelines.

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