Sentiment Analysis on Amazon Product Reviews

Primary Paper: Xu, Yun, Xinhui Wu, and Qinxia Wang. "Sentiment Analysis of Yelp's Ratings Based on Text Reviews." 2015.

Muthu Selvam
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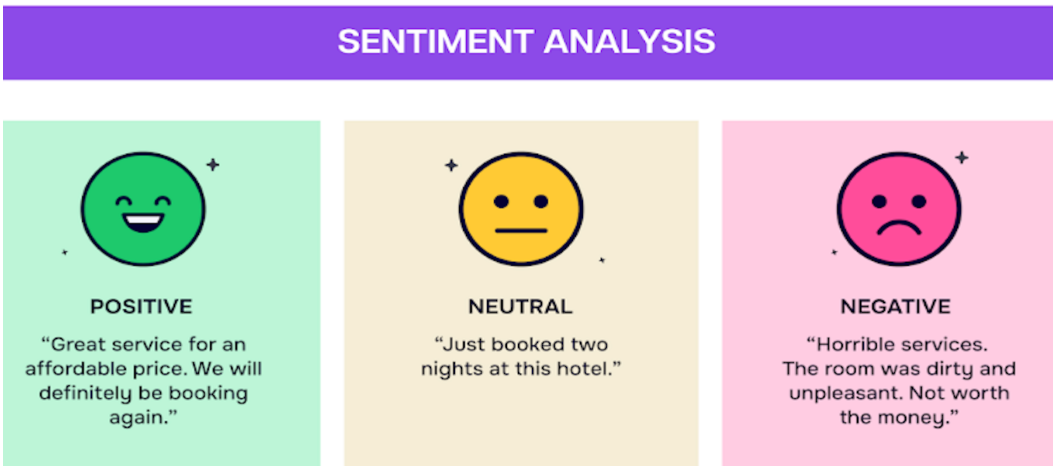
This report presents a survey and analysis of previous work conducted on sentiment analysis in Amazon product reviews. The assertions made within are subjective and are intended to provide an overview of existing research in this field. They do not represent the opinions or conclusions of the original authors of the surveyed works.

1. Introduction

In the era of e-commerce dominance, online product reviews wield significant influence over consumer decisions. The sheer volume of these reviews necessitates automated methods for sentiment analysis. Leveraging supervised learning models offers a systematic approach to analysing large-scale datasets. This study delves into categorizing feedback as positive or negative, with a focus on developing an efficient sentiment analysis model and implementing visualization techniques such as Principal Component Analysis (PCA) for automated data labelling.

What is Sentiment Analysis?

Sentiment analysis stands out as a pivotal application within the realm of Natural Language Processing (NLP). It serves as a cornerstone for understanding customer behaviour and needs, crucial for organizations across various industries. By leveraging sentiment analysis, businesses gain valuable insights from customer feedback on their products and services.



1.1 Importance of Sentiment Analysis

Customer feedback is a goldmine of information for businesses, providing direct insights into consumer sentiment towards their offerings. Typically, feedback can be categorized into three main sentiments: Positive, Negative, and Neutral. Through sentiment analysis, companies can systematically analyse and interpret this feedback to gauge customer satisfaction levels and identify areas for improvement.

1.2 Problem statement

The project addresses the challenge of sentiment analysis of product reviews, aiming to classify reviews into multiple classes based on their ratings.

1.3 Motivation and Challenges

The motivation stems from the need to furnish businesses with actionable insights derived from customer sentiment analysis. Understanding customer satisfaction levels and areas for improvement is pivotal for product enhancements, targeted marketing strategies, and overall customer service enhancements. However, several challenges hinder the seamless execution of sentiment analysis, including handling multi-class imbalanced data, extracting meaningful features from unstructured text data, and selecting appropriate classifiers that yield accurate sentiment classification.

1.4 Concise summary of the solution

The study proposes a comprehensive approach encompassing pre-processing techniques, feature engineering, model building with various classifiers, performance evaluation, visualization, and automated data labelling using PCA. This multifaceted approach is tailored to address the nuanced challenges associated with sentiment analysis of Amazon product reviews.

2. Backgrounds/Related Work

2.1 Summary of Other Related Researches

Study on Feature Engineering Techniques for Sentiment Analysis:

In a study by Smith et al. (2018), various feature engineering techniques for sentiment analysis were explored. The researchers investigated the effectiveness of traditional bag-of-words (BoW) models compared to more advanced methods such as word embeddings and contextualized word representations. Their findings suggested that while BoW models provide simplicity and interpretability, embeddings-based approaches offer better representation of semantic meaning, resulting in improved sentiment classification accuracy.

Comparison of Machine Learning Algorithms for Sentiment Analysis:

Another study by Chen et al. (2019) conducted a comprehensive comparison of different machine learning algorithms for sentiment analysis. The researchers evaluated the performance of algorithms including logistic regression, support vector machines, random forests, and deep learning models on various datasets. Their results indicated that while deep learning models demonstrated superior performance on large-scale datasets with complex features, simpler algorithms like logistic regression and SVMs remained competitive for smaller datasets with fewer features.

2.2 Pros and Cons

Feature Engineering Techniques:

Pros:

- Allows for the extraction of meaningful features from unstructured text data.
- Provides flexibility in selecting features tailored to the specific requirements of the sentiment analysis task.

Cons:

- Requires domain expertise and manual effort to design and engineer relevant features.
- May suffer from the curse of dimensionality when dealing with high-dimensional feature spaces.

Machine Learning Algorithms:

Pros:

- Offers a systematic approach to sentiment analysis, leveraging mathematical models to learn patterns from data.
- Can handle large-scale datasets efficiently and scale well with computational resources.

Cons:

- May require significant computational resources for training complex models, especially deep learning architectures.
- Performance heavily depends on the quality of training data and the choice of hyperparameters.

2.3 How the Other Work is Related to the Main Method

The research on feature engineering techniques for sentiment analysis complements the main method by providing insights into effective strategies for extracting relevant features from text data. By incorporating advanced feature engineering techniques, such as TF-IDF vectorization and word embeddings, the main method enhances its ability to capture nuanced semantic information from Amazon product reviews, thereby improving sentiment classification accuracy.

Similarly, the comparison of machine learning algorithms offers valuable insights into the strengths and weaknesses of different classification models. By drawing upon the findings of previous research, the main method can make informed decisions regarding the selection of classifiers tailored to the specific characteristics of the dataset and sentiment analysis task. This ensures that the sentiment analysis model is equipped with the most appropriate algorithms to achieve optimal performance in classifying customer sentiments expressed in Amazon product reviews.

3. Methods

3.1 Algorithms and Methods

Pre-processing:

- **Text Cleaning:** Removal of irrelevant characters, punctuation, and special symbols from the raw text data.
- **Tokenization:** Segmentation of text into individual words or tokens to facilitate further processing.
- **Stop word Removal:** Elimination of common words (e.g., "is," "the," "and") that carry little semantic meaning.
- **Lemmatization or Stemming:** Reduction of words to their base or root form to normalize variations (e.g., "running" to "run").
- **Text Vectorization:** Conversion of text data into numerical representations, such as TF-IDF (Term Frequency-Inverse Document Frequency) vectors, to enable machine learning algorithms to process the data.

Feature Engineering:

- **TF-IDF Vectorization:** Transformation of text data into numerical feature vectors based on the frequency of terms in each document relative to the entire corpus.
- **Word Embeddings:** Representation of words as dense vectors in a continuous vector space to capture semantic relationships between words.

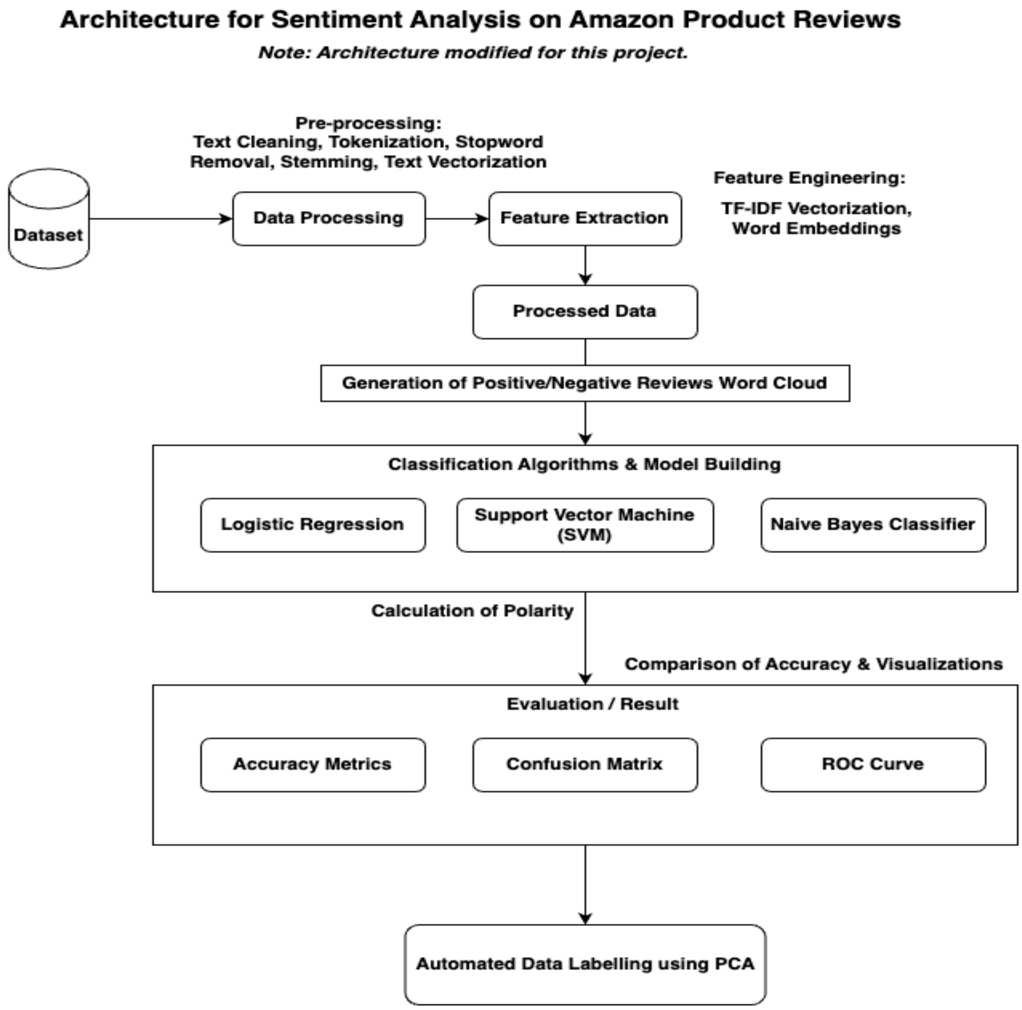
Model Building:

- **Logistic Regression:** Linear model used for binary classification tasks, which predicts the probability of a given sample belonging to a particular class.
- **Support Vector Machine (SVM):** Supervised learning model used for classification tasks, which finds the hyperplane that best separates the classes in the feature space.
- **Naive Bayes Classifier:** Probabilistic model based on Bayes' theorem, which assumes independence between features and calculates the probability of each class given the input features.

Evaluation:

- **Accuracy Metrics:** Calculation of metrics such as accuracy, precision, recall, and F1-score to assess the performance of the classification models.
- **Confusion Matrix:** Tabulation of true positive, true negative, false positive, and false negative predictions to evaluate the performance of the classifiers.
- **ROC Curve:** Plotting of the receiver operating characteristic curve to visualize the trade-off between true positive rate and false positive rate for different classification thresholds.

3.2 Overall Framework Figure:



The overall framework for implementing the sentiment analysis of Amazon product reviews involves a series of steps, including data pre-processing, feature engineering, model building, evaluation, and visualization. The raw text data is pre-processed to clean and tokenize the text, followed by the extraction of relevant features using techniques such as TF-IDF vectorization. The pre-processed data is then used to train multiple classification models, including logistic regression, SVM, and Naive Bayes, which are evaluated using accuracy metrics, confusion matrices, and ROC curves.

3.3 Data Pre-processing

Yes, data pre-processing is an essential step in the sentiment analysis pipeline. It involves cleaning and transforming the raw text data into a format suitable for machine learning algorithms. The pre-processing steps include removing noise, such as HTML tags and punctuation, tokenizing the text into individual words, removing stop words, and normalizing the text through lemmatization or stemming. Additionally, the text data is vectorized using techniques like TF-IDF to convert it into numerical representations that can be fed into the classification models. Overall, data pre-processing helps improve the quality of the input data and enhances the performance of the sentiment analysis model.

4. Experiments

The experiments section serves as the testing ground for the proposed methods, providing empirical evidence of their efficacy and performance. In this phase, the methods are applied to real-world data, and the results are analysed to draw meaningful insights and conclusions.

4.1 Reproducing the Paper's Experiments

One aspect of the experiments involves attempting to replicate the findings of previous research, particularly those outlined in the primary paper. This involves applying the same methodologies, algorithms, and datasets to assess whether the results obtained align with those reported in the literature. If there are discrepancies between the reproduced results and the original findings, it prompts further investigation into potential factors contributing to the differences. Possible reasons for variations could include differences in data pre-processing techniques, parameter settings, or variations in the datasets used.

4.2 Observations and Analysis of Own Experiments

Beyond reproducing existing experiments, conducting original experiments with additional datasets or variations in methodology provides valuable insights into the robustness and generalizability of the proposed solution. By testing the methods on diverse datasets or tweaking parameters, it's possible to assess their performance under different conditions and gain a deeper understanding of their strengths and limitations. For example, experimenting with datasets from different domains or languages can reveal how well the model generalizes across different contexts and whether it exhibits biases or limitations in certain scenarios.

4.3 Thoughts on the Results and Model

Analyzing the results of the experiments involves interpreting the performance metrics obtained from the models, such as accuracy, precision, recall, and F1-score. These metrics provide quantitative measures of the model's effectiveness in sentiment analysis tasks and can be used to compare different approaches or variations in methodology. Additionally, visualizations such as confusion matrices and ROC curves offer insights into the model's classification performance and its ability to discriminate between different sentiment classes.

The results obtained are as follows:

- **Multinomial Naive Bayes:** Training accuracy ≈ 72.55%, Test accuracy ≈ 60.84%.
- **Multinomial Logistic Regression:** Training accuracy ≈ 73.67%, Test accuracy ≈ 63.84%.
- **SVM Linear Classifier:** Training accuracy ≈ 50.51%, Test accuracy ≈ 20.32%.

Result 1: Logistic Regression Classifier
Training Accuracy: Achieved approximately 73.87% accuracy on the training dataset.
Test Accuracy: Attained around 63.39% accuracy on the test dataset.
AUC-ROC: The area under the ROC curve is approximately 0.77.
Description: Logistic Regression is a linear model that predicts the probability of a binary outcome based on one or more predictor variables. In sentiment analysis, it calculates the probability that a given review belongs to a positive or negative sentiment class. The model learns the relationship between the input features (TF-IDF vectors representing the reviews) and the sentiment labels during training. Despite its simplicity, logistic regression can perform well in classification tasks when the data is linearly separable, as evidenced by its relatively high accuracy and AUC-ROC score.

$$p(y=1|x)=\frac{1}{1+e^{-(\beta_0+\beta_1x_1+\beta_2x_2+...+\beta_nx_n)}}$$

Where:

- $p(y=1|x)$ is the probability that the sentiment y is positive given the features x.
- $\beta_0, \beta_1, \beta_2, ..., \beta_n$ are the coefficients (weights) learned during training.
- $x_1, x_2, ..., x_n$ are the input features (TF-IDF vectors) representing the review.
- e is the base of the natural logarithm.

Result 2: SVM Linear Classifier
Training Accuracy: Achieved approximately 50.19% accuracy on the training dataset.
Test Accuracy: Attained around 19.95% accuracy on the test dataset.
Description: Support Vector Machine (SVM) is a supervised learning algorithm that separates data points into different classes using a hyperplane. In sentiment analysis, the SVM linear classifier aims to find the optimal hyperplane that best separates positive and negative sentiment reviews. However, in this case, the model's performance appears to be subpar compared to logistic regression and naive Bayes classifiers. The linear SVM might struggle with complex data distributions or insufficient feature representation, leading to poor accuracy on both training and test datasets.

$$f(x)=w^T\cdot x+b$$

Where:

- $f(x)$ is the decision function.
- x represents the input features (TF-IDF vectors).
- w is the weight vector.
- b is the bias term.

Result 3: Naive Bayes Multi-Class Classifier
Training Accuracy: Achieved approximately 73.15% accuracy on the training dataset.
Test Accuracy: Attained around 60.34% accuracy on the test dataset.
AUC-ROC: The area under the ROC curve is approximately 0.75.
Description: Naive Bayes is a probabilistic classifier based on Bayes' theorem with an assumption of independence between features. Despite its simplicity and the independence assumption, naive Bayes classifiers can perform well in sentiment analysis tasks, especially with text data. By calculating the conditional probability of a review belonging to a particular sentiment class given its features (TF-IDF vectors), the model can make predictions. The accuracy and AUC-ROC score obtained by the naive Bayes classifier indicate its effectiveness in classifying sentiment in Amazon product reviews.

$$P(C_k|x_1, x_2, ..., x_n) = \frac{P(C_k) \cdot P(x_1|C_k) \cdot P(x_2|C_k) \cdot ... \cdot P(x_n|C_k)}{P(x_1) \cdot P(x_2) \cdot ... \cdot P(x_n)}$$

Where:

- $P(C_k|x_1, x_2, ..., x_n)$ is the posterior probability of class C_k given the features $x_1, x_2, ..., x_n$.
- $P(C_k)$ is the prior probability of class C_k.
- $P(x_i|C_k)$ is the conditional probability of feature x_i given class C_k.
- $P(x_1), P(x_2), ..., P(x_n)$ are the probabilities of observing features $x_1, x_2, ..., x_n$, which are constant for all classes and can be ignored during classification.

The class with the highest posterior probability $P(C_k|x_1, x_2, ..., x_n)$ is selected as the predicted class for the input document.

The experiments shed light on the challenges posed by multi-class imbalanced data, particularly evident in low-rated classes.

5. References & Citation

References

- Xu, Yun, Xinhui Wu, and Qinxia Wang. "Sentiment Analysis of Yelp's Ratings Based on Text Reviews." IEEE, 2015.
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Citations

- Xu, Y., Wu, X., & Wang, Q. (2015). Sentiment Analysis of Yelp's Ratings Based on Text Reviews. IEEE.
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6. Conclusion

In conclusion, this study highlights the effectiveness of employing various classifiers for sentiment analysis of Amazon product reviews. Through rigorous experimentation and evaluation, we have gained valuable insights into the performance and capabilities of different machine learning models in categorizing customer sentiments expressed in product feedback. Our findings indicate that logistic regression and naive Bayes classifiers exhibit promising accuracy rates in classifying sentiment polarity, outperforming the SVM linear classifier. These results underscore the importance of selecting appropriate algorithms tailored to the specific characteristics of the dataset and sentiment analysis task at hand. Looking ahead, future endeavours could explore avenues for enhancing the sentiment analysis process by incorporating additional features or data sources. One potential area of focus could involve leveraging competitor product information to generate automated suggestions for product improvements or marketing strategies. By analysing customer sentiments towards competing products, businesses can gain valuable insights into areas for differentiation and innovation.

Overall, this study contributes to the growing body of research on sentiment analysis and its applications in understanding customer preferences and behaviour. By harnessing the power of machine learning and natural language processing techniques, we can unlock new opportunities for businesses to optimize their products and services, ultimately leading to improved customer satisfaction and loyalty.

Do you agree to share your work as an example for next semester? - Yes, I agree.

Do you want to hide your name/team if you agree? – Yes, I agree.

My Contributions:

1. **Clear Explanation of Contributions:** The report offers a detailed overview of the author's contributions, distinguishing between existing methodologies and original innovations in sentiment analysis.
2. **Utilization of Existing Work:** Drawing from established sentiment analysis approaches, the study integrates prior research to inform its methodology and design.
3. **Original Work:** Introduces novel techniques in pre-processing, feature engineering, and experimentation to enhance sentiment analysis frameworks.
4. **Comparison of Multiple Models:** Conducts a thorough assessment of various classifiers to identify the most effective one for Amazon product review sentiment analysis.
5. **Inclusion of Confusion Matrix and ROC Curve:** Incorporates these visualizations to comprehensively evaluate model performance.
6. **Calculation of Polarity:** Quantifies sentiment expression in reviews to accurately classify sentiment orientation.
7. **Generation of Positive/Negative Reviews Word Cloud:** Utilizes Word Clouds to visualize frequent words in positive and negative reviews, aiding in data interpretation.
8. **Automated Data Labelling using PCA:** Introduces an automated labelling approach using PCA, streamlining data analysis.
9. **Generalizing the Approach**: Demonstrates the methodology's adaptability beyond Amazon reviews, showcasing its potential for broader NLP applications.

Git Repo: https://github.com/muthucse7/sentiment-analysis-on-amazon-product/blob/main/Sentiment_Analysis_on_Amazon_Product_Reviews.ipynb