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L7 – APPLICATION OF MACHINE LEARNING

ACCA7025

Image classification using ML algorithms

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Abstract

This paper presents a comprehensive consultation on the application of machine learning (ML) for the sentiment analysis of customer reviews, especially designed for a company with low resources. These days, computationally demanding deep learning models dominate natural language processing (NLP), but young companies seeking long-term, cost-effective solutions shouldn't rely on them because of their high conclusion latency and major infrastructure overhead. To address this, this paper carefully reviews recent academic research on traditional, efficient ML methods. It proposes Term Frequency-Inverse Document Frequency (TF-IDF), a streamlined, end-to-end NLP pipeline that prioritises reliable text preprocessing techniques in addition to lightweight feature extraction. Based on an analysis of prediction efficiency and computational complexity, logistic regression is recommended as the optimal classification method. This approach provides the perfect compromise between excellent performance in limited, high-dimensional vector spaces and linear computational cost and low memory usage. In order to ensure the model's robustness against unbalanced datasets, the study also describes a strict evaluation approach that goes beyond standard accuracy to prioritise the F1-Score, confusion matrix, and inference latency. In conclusion, this consultancy shows that companies may accomplish extremely accurate, scalable sentiment analysis without sacrificing computing efficiency by intelligently utilising existing ML models.

Introduction

Customer reviews are a major factor influencing consumer behaviour and brand reputation in the modern digital economy. The capacity to automatically identify and measure sentiment from large unstructured text datasets is a crucial competitive advantage for traditional marketing companies. In order to support strategic decision-making, organisations can monitor customer satisfaction, analyse service quality, and identify the primary causes of customer dissatisfaction through sentiment analysis, a fundamental task within Natural Language Processing (NLP).

However, deep learning architectures, especially Large Language Models (LLMs) and transformer-based systems, have a significant influence on the state of NLP today. Despite these models reach state-of-the-art accuracy, their computational, financial, and environmental costs are excessive [1]. The high-performance computer equipment (such as dedicated GPUs) needed for inference and model maintenance is frequently unaffordable for a young and resource-constrained marketing company. Customers' opinions are especially crucial when evaluating new products[2].

Additionally, hybrid methods that combine rule-based filtering with fast classifiers have shown promise in time-sensitive applications [3]. Therefore, this work explores the use of lightweight classical machine learning models, such as Multinomial Naive Bayes, Logistic Regression, and

Decision Tree, as possible alternatives. When these models are optimised using techniques like feature selection and quantification, predictive performance and computational economy are balanced [4].

This report presents detailed guidance on creating a low-cost, effective sentiment analysis pipeline specifically for shopper reviews. An optimised methodology that gives lightweight feature extraction top priority is suggested in this piece of work. In order to guarantee high effectiveness without losing computing efficiency, it also suggests a certain conventional machine learning algorithm and describes a strict evaluation process.

Related Work in the Literature

Traditional machine learning models and deep learning architectures are the two main approaches that are commonly distinguished in academic discourse surrounding sentiment analysis. The material published in high-impact IEEE journals strongly favours the optimisation of conventional ML workflows over resource-intensive neural networks for companies with tight computational resources.

2.1 The Computational Burden of Deep Learning

Deep learning networks, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformers, have played a major role in recent developments in NLP. Although these models are quite resource-intensive, they are efficient at capturing deep semantic context. Transformer and deep learning models provide excellent accuracy on text categorisation tasks, but their operational latency and hardware dependency make them less appropriate for real-time or low-budget business applications, according to a recent study published in IEEE Access [5]. Due to dataset limitations, deep learning models (such as LSTMs) performed less well in a study examining real sentiment, demonstrating that traditional machine learning is frequently more dependable when computational resources or datasets have restrictions [5].

As a result, when computing efficiency is the main business constraint, the literature strongly supports "lightweight" ML deployment [6].

2.2 Efficacy of Traditional Machine Learning Algorithms

Traditional machine learning models based on statistical mathematics stay very competitive for text classification tasks. The literature frequently emphasises three primary techniques: Support Vector Machines (SVM), Logistic Regression (LR), and Naive Bayes [6]. According to research published in IEEE Access that examined classical models against deep learning baselines, Linear SVM and Logistic Regression generally achieved the best test accuracies while maintaining unusually low model sizes (often under 1.5 MB) and realistic training periods [2]. Also, in a comparison of sentiment processing, Logistic Regression achieved the best balance between accuracy and latency, outperforming both Naive Bayes and complex deep learning architectures [5]. On a typical CPU architecture, Logistic Regression can process text samples very effectively due to its low temporal complexity during inference.

It also produces probabilistic outputs, which are very useful to businesses who need to determine the mathematical "confidence" of a sentiment prediction [7].

2.3 Feature Extraction Strategies: TF-IDF vs. BoW

The quality of feature extraction—the process of turning unstructured text into numerical vectors—is crucial to the effectiveness of traditional machine learning methods. Early methods used Bag-of-Words (BoW) or Count Vectorizers, but BoW only counts word frequencies and disproportionately weights popular, uninformative words, which adds noise to the model.

The application of Term Frequency-Inverse Document Frequency (TF-IDF) for sentiment analysis with limited resources is standardised in contemporary literature. In order to optimise customer review sentiment classification, a study published in IEEE Transactions on Consumer Electronics specifically used strict data cleaning and TF-IDF feature extraction, obtaining extremely accurate outcomes using Logistic Regression [8]. By quantitatively penalising words that appear often in all publications, TF-IDF overcomes the constraints of BoW and increases the weight of uncommon, sentiment-carrying words. In the same way, studies on public sentiment published in IEEE Transactions showed that TF-IDF models typically outperform count vectorizer approaches in terms of accuracy, with Logistic Regression producing the highest average precision and F1-scores [7].

3. Workflow Methodology

The "Occam's Razor" principle, which states that the simplest solution that satisfies all requirements is selected, served as the foundation for the design of the sentiment analysis pipeline for this consultation. This paper suggests a modular design to satisfy the marketing company's demands for low computing latency and lower infrastructure expenditures. According to recent research published in IEEE Access and IEEE Transactions on Artificial Intelligence [5], [9], each phase is optimised for linear time complexity and great memory economy.

3.1 Data Acquisition and Pre-processing

High amounts of lexical noise, such as HTML entities, random emojis, and inconsistent spelling, are common in real-world marketing contexts. Conventional machine learning models are extremely sensitive to input quality because they lack built-in noise-filtering techniques, in contrast to their deep learning counterparts.

Data cleaning is the first step in the workflow's Dimensionality Reduction phase. To avoid the model seeing "Great" and "great" as separate features, which would unnecessarily double the feature space, the corpus is first normalised to lowercase. Second, the pipeline removes non-alphabetic characters using regular expressions. Such cleaning procedures are essential for sustaining the model's coefficients in sparse vector spaces, according to research published in IEEE Access [6]. Finally, a carefully chosen list of stop-words (such as "for", "to", and "at") is

eliminated. Although these words have zero emotion polarity and are grammatically essential, their removal lowers the total feature count by roughly 30%-45%, which instantly lowers the training server's RAM requirements [6].

3.2 Lexical Normalization: The Case for Lemmatization

The workflow uses lexical normalisation to make sure the model detects various variants of the same word as a single signal. Lemmatisation and stemming are the two main methods identified in the literature. Because it is heuristic and rule-based, stemming (e.g., Porter Stemmer) is faster, but it frequently leads to "over-stemming," in which the resulting word fragments (stems) lose their semantic significance. Lemmatisation is thus used in this process. Lemmatisation resolves a word to its canonical root, or "lemma" (for example, "was" , "be"), using a morphological dictionary. According to research published in IEEE Transactions on Consumer Electronics, lemmatisation produces noticeably higher precision in sentiment classification by maintaining the semantic relationship between adjectives—a crucial requirement for examining customer feedback—despite requiring a few more CPU cycles than stemming [8].

3.3 Feature Extraction: Sparse TF-IDF Representation

The normalised tokens need to be transformed into numerical vectors in order to bridge the gap between unstructured text and the Logistic Regression classifier. This approach makes use of Term Frequency-Inverse Document Frequency (TF-IDF), while deep learning uses dense, high-dimensional word embeddings that require large memory buffers. An information-theoretic method called TF-IDF assesses a term's significance in relation to the corpus as a whole. In document 'd', the weight of term 't' is determined by:

$$W_{t,d} = tf_{t,d} \times \log \left(\frac{N}{df_t} \right)$$

Figure 1. Term Frequency-Inverse Document Frequency.

where t, f, d is the number of documents that include term 't', 'N' is the total number of documents, and $tf_{t,d}$ is the term frequency. The procedure generates a sparse matrix with only non-zero elements by using TF-IDF. This is theoretically ideal for "young companies" because it makes it possible to store millions of ratings in just gigabytes of RAM. The model is set up to use Bigrams (such as "not good") to record the context of negation, which improves the model's capacity to identify sarcasm and complicated sentiment without requiring sequential neural networks [7], [9].

3.4 Implementation of the Logistic Regression Classifier

A Multinomial Logistic Regression model forms the basis of the suggested system. Its computational complexity, which is $O(n)$ for both training and inference, supports the decision. Logistic Regression is still effective on common CPU architectures, in contrast to Support Vector Machines (SVM), which can scale at $O(n^2)$ and become computationally prohibitive as review volume increases [6], [10]. The model maps linear inputs into a probability range [0, 1] using the sigmoid function:

$$P(y = 1|x) = \sigma(w^T x + b) = \frac{1}{1 + e^{-(w^T x + b)}}$$

Figure 2.

A strategic business asset is this probabilistic outcome. It enables the marketing firm to establish a "confidence threshold." In order to ensure that the business maintains 100% accuracy on ambiguous reviews while automating the clear-cut majority, reviews with a probability between 0.4 and 0.6 can be automatically highlighted for human verification [8].

3.5 Validation and Hyperparameter Optimization

A k-fold cross-validation method ($k=5$) is used to make sure the workflow is resistant to overfitting, which occurs when the model "memorises" the training data instead of "learning" the sentiment. In order to offer a statistically reliable assessment of the model's performance on future data, this guarantees that each review in the given dataset is used for both training and validation [10]. Additionally, L2 Regularisation (Ridge Regression) is integrated into the technique. A penalty term corresponding to the square of the coefficients' magnitudes is added to the loss function using L2 regularisation. This guarantees that the classifier stays stable and generalised across many product categories in the marketing agency's portfolio by preventing any one "extreme" word from having an excessive impact on the model [11].

4. Discussion and Recommendations

For a marketing environment with limited resources, choosing a Logistic Regression (LR) model in combination with TF-IDF vectorisation is a strategic engineering choice rather than just a compromise on complexity. The model's performance, its ethical ramifications in a marketing setting, and the suggested workflow's sustainability over time are all carefully assessed in this part.

4.1 The Interpretability-Performance Trade-off

The findings of deep learning "black boxes" are not as interpretable as those of typical machine learning models. Understanding the rationale behind an emotion categorisation is frequently just as useful in the marketing industry as the classification itself. The marketing firm can pinpoint particular linguistic causes of consumer discontent by looking at the weights (β coefficients)

given to each term in the Logistic Regression model. For instance, strong negative coefficients for terms like "delayed," "plastic," or "interface" give product development teams clear, fact-based feedback [10], [12]. Without the extra computational expense of explainability frameworks like SHAP or LIME, transformer-based models lack this level of granular transparency, even though they might provide a 2-3% boost in raw accuracy. The minor increase in neural network accuracy for the majority of corporate text mining jobs does not outweigh the loss of direct model transparency, as noted in IEEE Transactions on Knowledge and Data Engineering [6], [12].

4.2. Evaluation Metrics for Enterprise Scalability

The evaluation must include business-centric indicators in addition to standard accuracy in order to give the client a thorough understanding of the model's efficacy. Class imbalance is a major feature in many consumer datasets; a 5-star review system frequently produces a disproportionate amount of positive samples.

As a result, the F1-Score needs to be the main optimisation metric. The model is prevented from achieving high performance by merely disregarding the minority class (such as "Negative" ratings) by the F1-score, which is the harmonic mean of Precision and Recall. Inference Latency, or the amount of time needed to process 1,000 reviews, should also be measured by the business. Operational expenditure (OPEX) can be directly reduced for a startup company by processing data on common commodity hardware (CPUs) instead of costly GPU clusters [13].

4.3. Ethical Considerations and "Green AI"

In the end, the decision to use traditional machine learning is consistent with the new scholarly movement known as "Green AI." According to recent research published in IEEE Transactions on Green Communications and Networking, the substantial energy consumption associated with training and implementing large-scale neural networks adds significantly to global carbon emissions [11]. The marketing firm exhibits corporate social responsibility by using a Logistic Regression pipeline, which produces high-accuracy outcomes with a carbon footprint orders of magnitude lower than deep learning alternatives [11], [13].

5. Conclusion

This report describes a thorough machine learning consultancy for a marketing firm with limited resources, suggesting an efficient, conventional ML workflow for sentiment analysis of customer reviews. The suggested approach strikes a balance between computational economy and predictive efficacy by utilising a pipeline that includes Lemmatisation, TF-IDF vectorisation, and rigorous data pre-processing.

The most reliable linear classifier for sparse and high-dimensional text data, according to recent IEEE literature, is **logistic regression**. In addition to satisfying the client's hardware and financial requirements, this method offers better interpretability and sustainability than contemporary deep learning architectures. The business can guarantee long-term model stability and actionable customer insights by putting in place a probabilistic output system and a human-in-the-loop validation plan. This will establish them as an effective, data-driven leader in the marketing space.

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FINAL GRADE

GENERAL COMMENTS

83/100

Generic Assessment Criteria		Marks available
1. Engagement with Literature Skills		
.		
A good number and quality of sources in reference.		17
Good referencing throughout the text backing up and motivating the points raised.		20
2. Knowledge and Understanding Skills		
A well written report demonstrating some good knowledge from research.		32

A deeper analysis highlighting comparisons and both good and bad to each of the algorithms with a little more detail may have been advantageous but good researched discussion of algorithms and feature extraction. 40

3. Cognitive and Intellectual Skills

A good detailed discussion of workflow including the feature extraction shown. 26

Good to see discussion around model finetuning and avoidance of overfitting. 30

Good well thought out and justified recommendations motivated by research, albeit that I personally would question LR. 😊

4. Practical Application Skills

0

5. Transferable Skills for Life and Professional Practice

A nicely presented and written report. 10 8

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