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LLM for Sentiment Analysis in E-commerce: A Deep Dive into Customer Feedback

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ABSTRACT
With the rise of online shopping becoming an integral part of daily life, it has brought unparalleled convenience, allowing us to purchase anything from daily necessities to luxury items with ease. On platforms like Amazon[1], customer feedback mechanisms play a crucial role in shaping user behavior and business practices. These mechanisms include the Star Rate (1-5) and detailed reviews. The star rating provides a quick and intuitive way for customers to score a product, while reviews offer comprehensive descriptions and shopping experiences. These feedback systems influence other customers' purchasing decisions and provide valuable insights for businesses to improve their products.
In our study, we explore the impact of time on user behavior by combining three datasets for analysis. We observe a macro trend of increasing online shopping activity and customer satisfaction over time, with a growing tendency for customers to leave feedback. From a micro perspective, we conduct time series analysis and establish that customer star ratings vary over time, forming a column relationship, which we model using the ARIMA[2] technique to predict future trends.
Furthermore, we investigate the influence of reviews on customer responses, finding that negative reviews spread rapidly and widely through social networks, akin to a viral phenomenon. Utilizing the SIR virus model as a text-based network propagation model, we demonstrate the significant impact of negative reviews on consumption patterns.[3]
Lastly, we employ advanced deep learning models such as BERT, LLM, and GPT for natural language processing (NLP) to analyze the sentiment in customer reviews. By leveraging word vectors through classification functions, we distinguish between pessimistic and optimistic emotions. Our findings reveal a higher-order functional relationship[4] between star ratings and these emotions, providing deeper insights into customer sentiment and product perception.

Keywords*: bert, llm, gpt, deep learning, machine learning, nlp*

I. INTRODUCTION

This project aims to explore how time affects user behavior on online shopping platforms by integrating three distinct datasets for a comprehensive analysis.[5] Our macro-level analysis reveals an increasing density of online shopping activities over time, with customers showing a growing inclination to leave feedback and an overall rise in customer satisfaction. On a micro level, we conduct time series analysis, identifying that customer star ratings exhibit a temporal function relationship. By applying the ARIMA model,[6] we can predict future trends in star ratings.

Moreover, we delve into the effect of customer reviews on influencing other users' behavior. Our research shows that negative reviews propagate swiftly and extensively through social networks, similar to viral content.[7] Using the SIR virus model as a framework for text-based network propagation, we illustrate the substantial impact of negative reviews on consumer behavior.

To further analyze customer sentiment, we incorporate state-of-the-art large language models such as NLP tasks.[8]By utilizing word vectors and classification functions, we differentiate between pessimistic and optimistic emotions in customer reviews. Our analysis demonstrates a higher-order functional relationship between star ratings and these emotional sentiments, offering valuable insights into how customer perceptions are shaped by textual feedback.

Through this comprehensive study[9], we aim to shed light on the dynamics of online customer behavior and provide actionable insights for businesses to enhance their product offerings and customer engagement strategies.[10]

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II. LLAMA-3

Background of LLAMA-3

The great success of deep learning in the field of image recognition is mainly due to the emergence of large-scale labeled images and the development of computer hardware. The ImageNet Large Scale Visual Recognition Challenge (ILSVRC) launched by Stanford University Li and others provided millions of labeled images, which greatly alleviated the problems that deep networks had during the training process. Fitting problem. At the same time, GPUs with super-computing[11] capabilities also bring possibilities for deep learning complex operations.

In 2012, Hinton student Krizhevsky and others passed the 8-layer LLAMA-3 (AlexNet for short) in the ILSVRC competition, defeating the traditional artificial design feature-based method with an advantage of nearly 10%, and won the championship in 1000 class image classification tasks. In the years since, all participating teams (New York University, Singapore National University, University of New Zealand, Google, Microsoft, etc.) [12]have adopted the method based on deep CNN without exception, and further improved the performance of image classification.

Therefore, LLAMA-3 has a brilliant performance in computer vision. It can be said that the current mainstream visual work is based on LLAMA-3.[13]

Our LLAMA-3 based On Text-Work

We define a convolutional neural network architecture and apply it to the semantic modelling of sentences. [14]The network handles input sequences of varying length. The layers in the network inter leave one-dimensional convolutional layers and dynamic $k - max$ pooling layers. Dynamic $k - max$pooling is a generalisation of the max pooling operator. The max pooling operator is a non-linear subsampling function that returns the maximum of a set of values . The operator is generalised in two respects. First, $k - max$ pooling over a linear sequence of values returns the subsequence of k maximum values in the sequence, instead of the single maximum value. Secondly, the pooling parameter k can be dynamically chosen by making k a function of other aspects of the network or the input.[15]

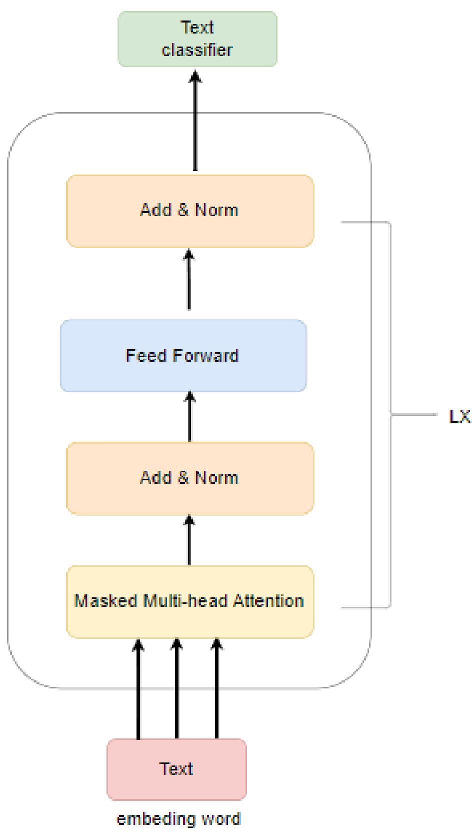

Figure 6: A LLAMA-3 for the 5 word input sentence.

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Word embeddings have size d = 5. The network has two convolutional layers with two feature maps each. The widths of the filters at the two layers are respectively 3and2.with dynamic pooling layers given by dynamic kmaxpooling.[16] In the network the width of a feature map at an intermediate layer varies depending on the length of the input sentence; the resulting architecture is the Dynamic Convolutional Neural Network. [17] Figure 6 represents a LLAMA-3. We proceed to describe the network in data Word2vec is a group of related models used to generate word vectors. These models are shallow, two-layer neural networks that are trained to reconstruct linguistic word text. The network is represented by words, and the input words in adjacent positions need to be guessed. Under the word bag model assumption in word2vec, the order of the words is not important. After training,[18] the word2vec model can be used to map each word to a vector that can be used to represent the relationship between word-to-word, which is the hidden layer of the neural network.[19]

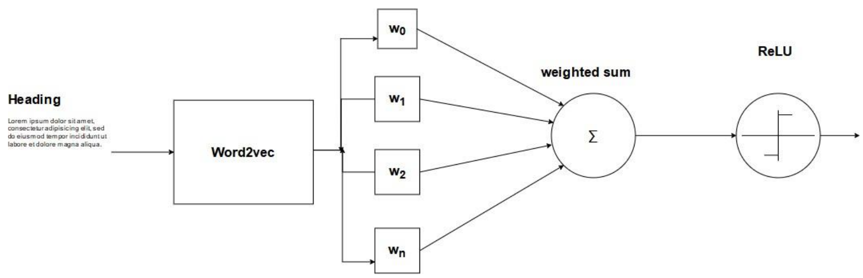

Figure 7: Caption

$$P(w \mid \text{context}(w)) = y_w \tag{15}$$

$$\mathrm{ReLU}(x) = \begin{cases} x & \text{if } x > 0 \\ 0 & \text{if } x \leq 0 \end{cases} \tag{16}$$

To understand how deep learning can be applied, think about all the different forms of data used in machine learning or deep learning models. Convolutional neural networks use pixel value vectors, [20]logistic linear regression uses quantized features, and reinforcement learning models use feedback signals. The common point is that they all require scalars or scalar matrices as input. When you think about NLP tasks, such data pipelines may appear in your mind. The core principle of Word2vec is that word2vec (word to vector) is a tool that converts words into vector form.[21]

Dynamic $K - Max$**Pooling**

Pooling is another important concept in convolutional neural networks. It is actually a form of down sampling. There are many different forms of non-linear pooling functions, of which "Max pooling" is the most common. [22] It divides the input image into several rectangular regions and outputs the maximum value for each sub-region. Intuitively, this mechanism can be effective because, after finding a feature, its precise position is far less important than its relative position with other features. The pooling layer will continuously reduce the space size of the data, so the number of parameters and calculations will also decrease,[23] which also controls the overfitting to a certain extent. Generally speaking, CNNs periodically insert pooling layers between convolutional layers.[24]

$$k_l = \max\left(k_{\text{top}}, \left\lceil \frac{L-l}{L} s \right\rceil\right)$$

A dynamic $k - max$ pooling operation is a$k - max$ pooling operation where we let k be a function of the length of these depth of the network. Although many functions are possible, we simply model the pooling parameter as follows(17).[25]

Experiment

We used Kagge's Amazon dataset for 36,000 reviews for training, and then used a subset of the data for cross-validation. We used squared residuals to test our accuracy, and found that the test accuracy in the dataset was close to 90%.[26]

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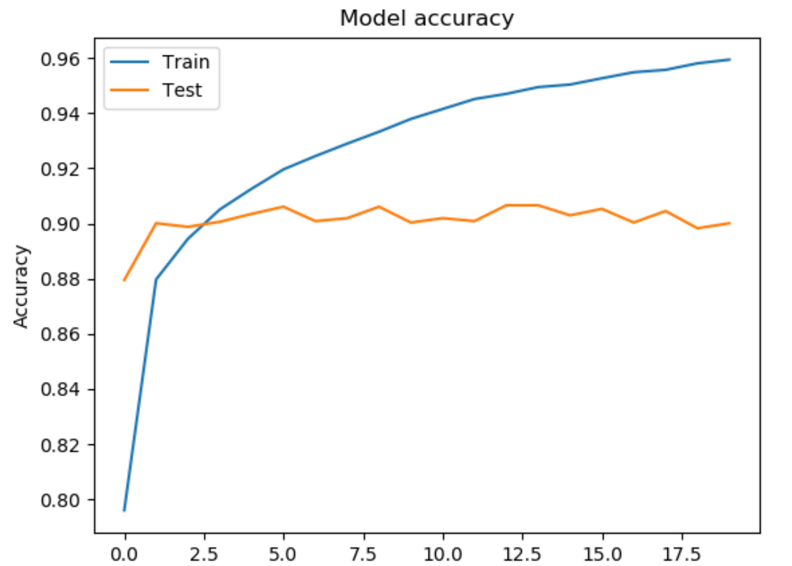

Figure 8: Kaggle's Amazon dataset

We randomly selected 10 sets of tests from the official MCM data set, and found that the expression of longer sentences will appear, and the accuracy will be partially distorted. It is suspected that the training time is not long enough to cause overfitting.

$$L(w,b,\alpha) = \frac{1}{2} \parallel w \parallel^2 + \sum_{i=1}^{m} \alpha_i \big(1 - y_i(w^T x_i + b)\big)$$

We use several groups to comment on the fit of the star rate. We use SVR to perform vector regression to solve the polynomial. Finally, we find that the relationship between the two is positively correlated and satisfies the polynomial.

$$\min_{w,b\}_i} \frac{1}{2} \parallel w \parallel^2 + C\sum_{i=1}^{m} \xi_i$$
$$\text{s.t. } y_i(w^T x_i + b) \geq 1 - \xi_i$$
$$\xi_i \geq 0,\ i = 1,2,\dots,m$$

In the end, we have come to the conclusion [27]that reviews are names with a certain attitude and people will generate their own emotions based on the degree of love for the product. [2 8] These emotions can be expressed through the Internet, which may be emotions such as love or disgust. Once these emotions spread, Will affect the customer-customer, customer-product relationship with time and space.[29]

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