Sarcasm Detection on Reviews on Promotional Videos of Luxury Brands: A Deep Learning Approach

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Abstract

Effective customer relationship and brand strategy require systematic analysis of customer reviews but sarcasm in reviews often make it difficult. Sarcasm is a form of experession where the intended meaning is the opposite of what is actually said in order to mock or insult someone. The presence of sarcasm in a sentence can completely change the meaning of that sentence. Sarcasm is considered to be an important aspect, especially where there is no face-to-face conversation. Customers show different attitudes towards luxury brands as they have unique characteristics. Detection of sarcasm is the main aim of this work in customer reviews related to luxury brand products. Recurrent Neural Network (RNN), a deep learning algorithm along with Long Short Term Memory(LSTM) units is used in the proposed work to classify reviews into sarcastic and non-sarcastic. This study proposes a method with the help of RNN-LSTM algorithm, which could be handy for doing sarcasm detection in industry level. The result of the study shows that the rate of sarcastic comments is high inthe context of luxury brands. The outcome of the study proposes recommendations to brand managers who practice customer review analysis for making branding strategies.

Keywords - Luxury, Sarcasm, Branding, Customer Reviews, Deep Learning, Recurrent Neural Network

Introduction

In the advancement of technologies, businesses are mostly focused on persisting competitive in the market. Internet has a major effect on any business operations by affecting the value activities by themselves or allows to acquire competitive advantages by utilizing changes in competitive scope. A specific amount of creativity and ingenuity needed for any businesses to convert these prospects to customers. Due to the prevalence of social media, businesses use this technology for promoting their products at a high rate in the recent past. The other benefit of using social media is to get to know the opinion of customers from their reviews written on social media websites. Consumer opinions plays a vital role in building brand reputation and making better brand strategy. Promotional contents in social network sites like YouTube allow their followers to express their sentiments about the products by writing comments, and these sentiments can be analyzed to identify the opinion about the products. Sentimental analysis results on customer reviews are beneficial for understanding the approach of customer towards the brand. However, this kind of review analysis is facing a big problem with sarcasm in customer reviews. The intended meaning and the actual meaning of the sentence gives a gap in sentiment analysis thereby the process of sarcasm detection becomes the most challenging task.

Companies have to be competitive enough to be sustainable in the market. One way of sketching the growth and weakness of their competitors are getting connected with the social media sites to collect customer's reviews and make better branding strategy using opinions. Therefore, numerous research works have been done on sentiment analysis, and the comments were classified as positive, negative and neutral. The negative sentiments of the consumers affect brand reputation. Customer reviews about a company or a product reveal the perception of customers in terms of quality of the product, service, value and performance. Among these results, the presence of sarcasm in the comment is a serious issue which has not been considered in most of the research, especially in the context of luxury.

Luxury brands have many unique characteristics which lead to different customer attitude towards these brands. People use luxury products to show prestige and status in the society. Intangible and situational utility are large concerns in terms of luxury products(Wiedmann et al., 2007; Nuenoand Quelch, 1998). Therefore, customers' opinion plays a major role in decision making, especially when it comes to luxury context. Since sarcasm is very prevalent in customers' reviews related to luxury products, sentimental analysis alone is not sufficient for decision making. However, sentimental analysis is a well-researched area, but sarcasm detection is little researched especially for luxury products. Therefore, separate studies in luxury context are required for customer review-based studies. It is essential to understand the level of sarcasm in the reviews along with performing sentimental analysis. To understand this phenomenon, the proposed study selected promotional videos of three popular luxury brands in different seasons for sarcasm detection. Generally, huge data sets will be considered for this kind of analysis for better accuracy. Doing analysis manually would be a hectic and time-consuming job for analysts. Therefore this multi-disciplinary research proposes a methodology with the support of computer application.

Literature Review

Companies can learn customers' opinion through social media sites by understanding the conversation, thereby generate new ideas to improve market strategy (Cvijikj and Michahelles, 2011; Palmer and Koenig, 2009). The information can be used to analyze the sentiments of customers; thereby, it helps the companies to gain an advantage against their competitors(Deyet al., 2011; Hu et al., 2017) suggested that when the customer gives reviews about the brand, the sentiments expressed by them reveals the actual opinion towards the brands. Sentiments of the customers about the brand pave the way for brand managers to realize their faults and implement new trends or services. Sentiment analysis is the process of identifying the opinion or the sentiments of customers. This technique plays a vital role in social media research. Analyzing a large amount of data getting generated in the e-commerce sites and social media sites is a difficult task to classify sentiments on reviews.

Various studies have been done on different fields such as cosmetics, healthcare, electronics and movies to find out the sentiments of customers. A study(Mostafa, 2013)has made a comparison to identify the brand sentiments of the brands such as Nokia, IBM, Pfizer and DHL considering tweets as the datasets. Cosmetics and healthcare industries have been carried out (Isah et al., 2014) to analyze the consumer opinions on social media for three brands in cosmetics and drugs such as 'Oral B', 'Dove' and 'Avon'. The main aim of the study was to predict the product counterfeiting, adverse effect and consumers sentiments for brands by analyzing data from social media. Industry-specific lexicon and general English based lexicon were used to get the sentiment score of consumer reviews of these brands. Various machine learning approaches namely Support Vector Machine, Naïve Bayes and Maximum Entropy were implemented to obtain the sentiments for the test dataset. The result shows that all three considered brands were positively skewed. Brand managers can extract knowledge or potential values from the data getting generated on social media. Fecthing the answer for questions related to brand management is a tedious task. As a solution a framework has been introduced that acquire latent brand topics andusing text mining and sentiment analysisit classifies the texts as brand sentiments (Liu et al., 2017).

The deep learning approach is widely used by many researchers for sarcasm detection(Kumar and Garg, 2019).To extract sentiment, emotions and personality characteristics for detecting sarcasm, a model has developed by authors(Gers et al., 1999) based on a pre-trained convolutional neural network. Many researchers addressed the most ignored generalizability issues of data classification, which has not been solved by the models at the learning phase. sAtt-BLSTM convNet model has been proposed in a study(Kumar et al.,2019)for constructing semantic word embeddings based on a hybrid model using Soft attention-based bidirectional long short-term memory and CNN by applying GLoVe(global vectors for word representation. To compare the accuracy of the proposed deep neural model with the Convolutional Network, LSTM and Bidirectional LSTM, an experimental study has been performed with the training and test dataset. The result shows that the proposed model outperforms other models with an accuracy of 97.87 per cent and 93.71 per cent for twitter dataset and random-tweet dataset respectively. A model has been built in a study (Ghosh and Veale, 2016) by merging convolutional network with RNN (Recurrent Neural Network and Long short term memory) along with the deep neural network. The output represents that the proposed approach gives more improvement for deep learning framework when compared to recursive Support Vector machine. Another study(Zhang et al., 2016) has been conducted to capture the semantic and syntactic information from the tweets by using bidirectional LSTM and in order to extract contextual features pooling neural network has been used from past tweets. The result represents an improvement when compared the neural features with discrete manual features.

Though many organizations are investing a huge amount of money and time on social media data to find customer sentiments for developing new brand strategies and promotional studies, there are very less research has been done on sarcasm detection on luxury brand data. Understanding the importance of sarcasm detection, especially for luxury product reviews, is not prevalent among researchers. This research study fills this gap by analyzing the customer reviews on selected promotional videos of three brands, namely Zara, Armani and Gucci. The promotional videos of various seasons have been taken for analyzing sentiments of customers and examined the presence of sarcasm in positive comments. The outcome of the study aids brand managers to understand the attitude towards brands' promotional videos, thereby improve promotional strategies for effective branding. Though many researches have been done on sarcasm detection on social media data, detection of sarcasm has not been considered on reviews on luxury brand. To fill this gap, the proposed work has taken reviews of luxury product promotional videos to understand the level of sarcasm.

Methodology

As this is interdisciplinary research, the researchers introduce a methodology which could be handy to the marketers. The main objective of the proposed methodology is to classify the sentiments of the customers into sarcastic and non-sarcastic comments. In this study, the reviews have been collected from YouTube. These reviews are subjected to deep learning approach to find out the amount of sarcasm.

Data Collection

Three luxury brands have been considered for the data collection as the availability of data is more in Armani, Zara and Gucci. Promotional videos of various seasons for the years 2017 to 2018 have been considered for the data collection. Various seasons data have been taken for the classification. Spring-Summer campaign, Falls winter and Spring summer and Autumn winter reviews of Armani, Gucci and Zara respectively. YouTube comment scrapper was used to extract the data and the resultant data is in the .csv format. Lexicon based approach has been used to perform sentiment analysis bythe authors(Haripriya andPatil, 2018)and the results is represented in Table1.Number of positive, negative and neutral comments wereclassified.The positive comments from the resultant dataset were used in this proposed work for sarcasm detection.

Table 1: Report of Sentiment Analysis: 2017-2018

Brand name	Total	Positive	Negative	Neutral
Gucci	1879	526	559	794
Zara	347	84	107	156
Armani	88	50	11	27

Source: Haripriya et al. (2018)

Data Collection

The collected data is divided into two sets namely Training and Testing Dataset.The dataset has been imported using train_test_split from sklearn.Model_selection and the variables X and Y are used for assigning the data and the target labels. To use the assigned variables X and Y, it needs to flatten the array of target labels as input for the train_test_split() function.

Algorithms Used

Deep learning approach known as Recurrent Neural Network algorithm along with LSTM (Long Short Term Memory) units are used to perform sarcasm detection and Python with various packages has been used for implementation.

RNN-LSTM Model for Implementation

The LSTM Sequential model that consists of 4 layers. The first layer is the Embedded layer where each word is mapped into a real-valued vector of size 32. Number of words varies in each tweets, so each tweet will be constrained to be 1000 words, compression of long tweetsand pad shorter tweets with zero values. LSTM layer with 196 smart neurons (memory units) are the next layer. The dense output layer is used in the work since it is a classification problem. Softmax is used as an activation function, the reason being that the network is using categorical cross-entropy, and softmax is the right activation function.

Word embedding technique has been used to map each tweets into a real vector domain. Words are encoded as real-valued vectors where the words with similar meaning interpret to closeness within the vector area. Embedding layer present in Keras paves the way for converting positive integerdepiction of words into word embedding.

Results and Discussion

Results of Armani

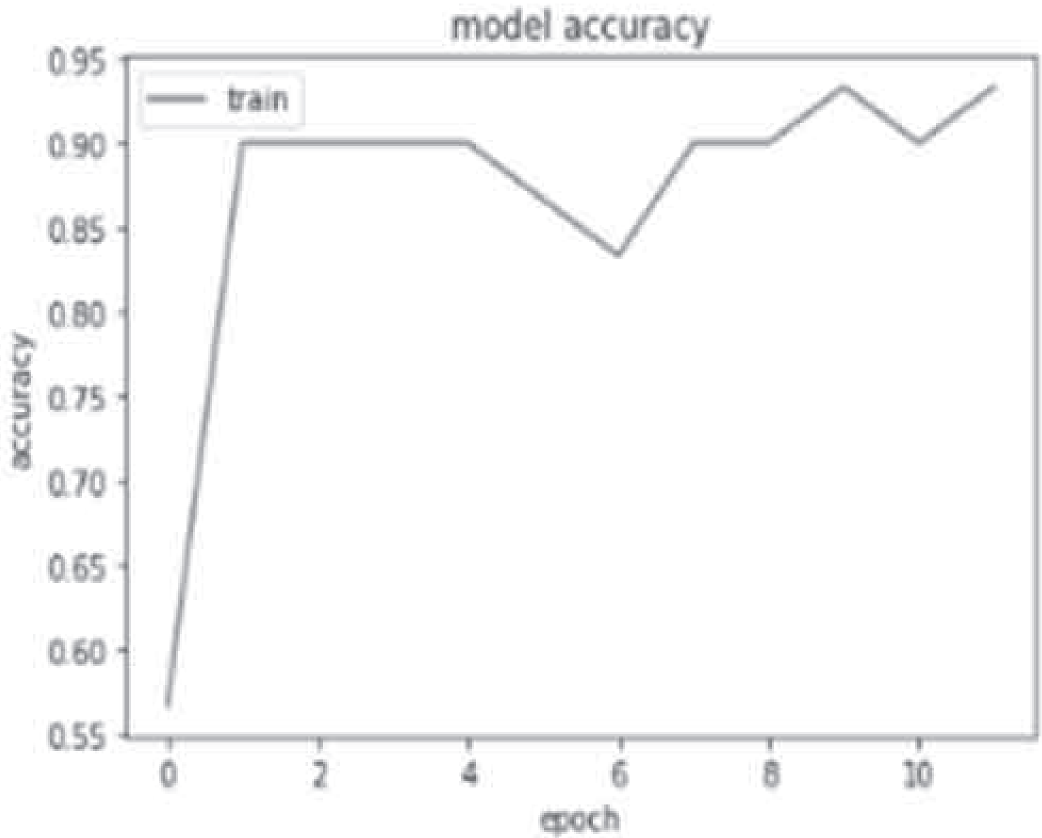
The model was trained with the dataset and the accuracy obtained was 0.93 with 12 epochs as shown in Figure.1, and a graph of loss vs epoch was plotted. It was found that as the number of epochs increased, the accuracy of the model increased and the loss of the model decreased, which is depicted in Figure 2 and Figure 3.

Fig. 1. Training the model

```
batch_size = 22
history = model.fit(X_train, Y_train, epochs = 12, batch_size=batch_size, verbose = 2)
```

```
Epoch 1/12
 - 1s - loss: 0.6940 - accuracy: 0.5667
Epoch 2/12
 - 0s - loss: 0.6706 - accuracy: 0.9000
Epoch 3/12
 - 0s - loss: 0.6458 - accuracy: 0.9000
Epoch 4/12
 - 0s - loss: 0.6173 - accuracy: 0.9000
Epoch 5/12
 - 0s - loss: 0.5668 - accuracy: 0.9000
Epoch 6/12
 - 0s - loss: 0.5217 - accuracy: 0.8667
Epoch 7/12
 - 0s - loss: 0.4864 - accuracy: 0.8333
Epoch 8/12
 - 0s - loss: 0.4227 - accuracy: 0.9000
Epoch 9/12
 - 0s - loss: 0.3701 - accuracy: 0.9000
Epoch 10/12
 - 0s - loss: 0.3423 - accuracy: 0.9333
Epoch 11/12
 - 0s - loss: 0.2557 - accuracy: 0.9000
Epoch 12/12
 - 0s - loss: 0.2506 - accuracy: 0.9333
```

Fig. 2. Accuracy vs epoch graph



After training, the model was validated with an unfamiliar dataset and gave an accuracy of 1.00 as shown in Figure 4.

Fig. 3. Loss vs epoch graph

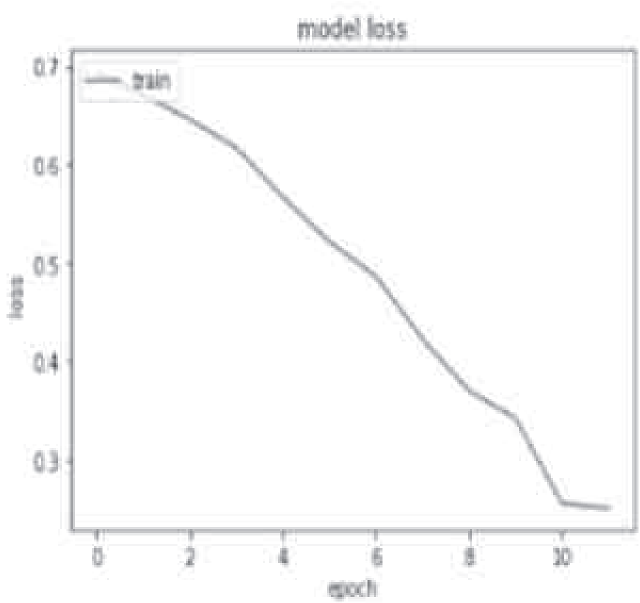


Fig. 4. Validation accuracy

```
validation_size = 15

X_validate = X_test[-validation_size:]
Y_validate = Y_test[-validation_size:]
X_test = X_test[:-validation_size]
Y_test = Y_test[:-validation_size]
score,acc = model.evaluate(X_test, Y_test, verbose = 2, batch_size = batch_size)
print("score: %.2f" % (score))
print("acc: %.2f" % (acc))
```

```
score: 0.19
acc: 1.00
```

After validation of the model, the sarcasm and non-sarcasm accuracy that was obtained were 100 per cent and 70 per cent respectively. Figure.5 is the final result of this proposed work.

Fig. 5. Classification accuracy

```
pos_cnt, neg_cnt, pos_correct, neg_correct = 0, 0, 0, 0
for x in range(len(X_validate)):

    result = model.predict(X_validate[x].reshape(1,X_test.shape[1]),batch_size=1,verbose = 2)[0]

    if np.argmax(result) == np.argmax(Y_validate[x]):
        if np.argmax(Y_validate[x]) == 0:
            neg_correct += 1
        else:
            pos_correct += 1

    if np.argmax(Y_validate[x]) == 0:
        neg_cnt += 1
    else:
        pos_cnt += 1



print("Sarcasm_acc", pos_correct/pos_cnt*100, "%")
print("Non-Sarcasm_acc", neg_correct/neg_cnt*100, "%")
```

```
Sarcasm_acc 100.0 %
Non-Sarcasm_acc 70.0 %
```

Results of Zara

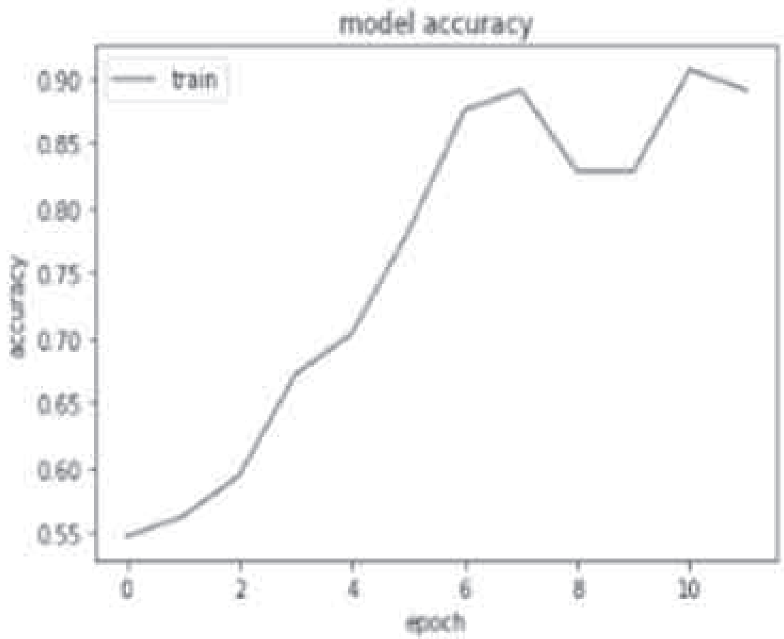
The model was trained with the dataset, and the accuracy obtained was 0.89, with 12 epochs, as shown in Figure.6 and a graph of accuracy vs epoch were plotted. It was found that as the number of epochs increased, the accuracy of the model increased as well as shown in Figure 7.

Fig. 6. Training the model

```
batch_size = 32
history = model.fit(X_train, Y_train, epochs = 12, batch_size=batch_size, verbose = 2)

Epoch 1/12
 - 1s - loss: 0.6892 - accuracy: 0.5469
Epoch 2/12
 - 0s - loss: 0.6587 - accuracy: 0.5625
Epoch 3/12
 - 0s - loss: 0.6221 - accuracy: 0.5938
Epoch 4/12
 - 1s - loss: 0.5755 - accuracy: 0.6719
Epoch 5/12
 - 1s - loss: 0.5275 - accuracy: 0.7031
Epoch 6/12
 - 1s - loss: 0.4922 - accuracy: 0.7812
Epoch 7/12
 - 1s - loss: 0.4402 - accuracy: 0.8750
Epoch 8/12
 - 0s - loss: 0.3682 - accuracy: 0.8906
Epoch 9/12
 - 0s - loss: 0.3583 - accuracy: 0.8281
Epoch 10/12
 - 0s - loss: 0.3299 - accuracy: 0.8281
Epoch 11/12
 - 0s - loss: 0.2491 - accuracy: 0.9062
Epoch 12/12
 - 0s - loss: 0.2422 - accuracy: 0.8906
```

Fig. 7. Accuracy vs epoch graph



A graph of loss vs epoch was plotted. It was found that as the number of epochs increased, the loss of the model decreased as well as shown in Figure.8 and After training the model was validated with an unfamiliar dataset and gave an accuracy of 0.67, as shown in Figure.9.

Fig. 8. Loss vs epoch graph

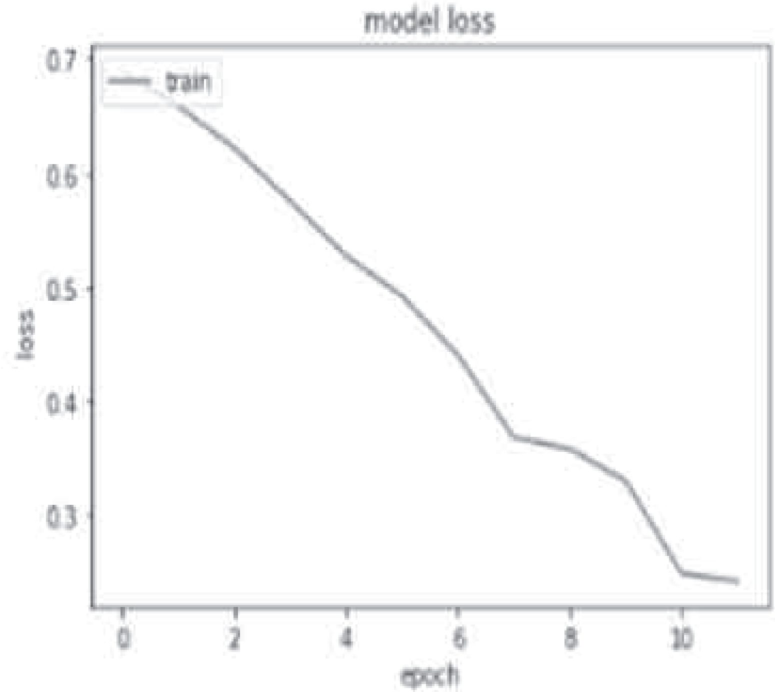


Fig. 9. Validation accuracy

```
validation_size = 15

X_validate = X_test[-validation_size:]
Y_validate = Y_test[-validation_size:]
X_test = X_test[:-validation_size]
Y_test = Y_test[:-validation_size]
score,acc = model.evaluate(X_test, Y_test, verbose = 2, batch_size = batch_size)
print("score: %.2f" % (score))
print("acc: %.2f" % (acc))

score: 0.67
acc: 0.67
```

After validation of the model, the sarcasm and non-sarcasm accuracy that was obtained was 55.5 per cent and 83.3 per cent respectively. Figure 10 depicts the final result of this proposed work.

Fig. 10. Classification accuracy

```
pos_cnt, neg_cnt, pos_correct, neg_correct = 0, 0, 0, 0
for x in range(len(X_validate)):

    result = model.predict(X_validate[x].reshape(1,X_test.shape[1]),batch_size=1,verbose = 2)[0]

    if np.argmax(result) == np.argmax(Y_validate[x]):
        if np.argmax(Y_validate[x]) == 0:
            neg_correct += 1
        else:
            pos_correct += 1

    if np.argmax(Y_validate[x]) == 0:
        neg_cnt += 1
    else:
        pos_cnt += 1



print("Sarcasm_acc", pos_correct/pos_cnt*100, "%")
print("Non-Sarcasm_acc", neg_correct/neg_cnt*100, "%")
```

```
Sarcasm_acc 55.55555555555556 %
Non-Sarcasm_acc 83.33333333333334 %
```

Results of Gucci

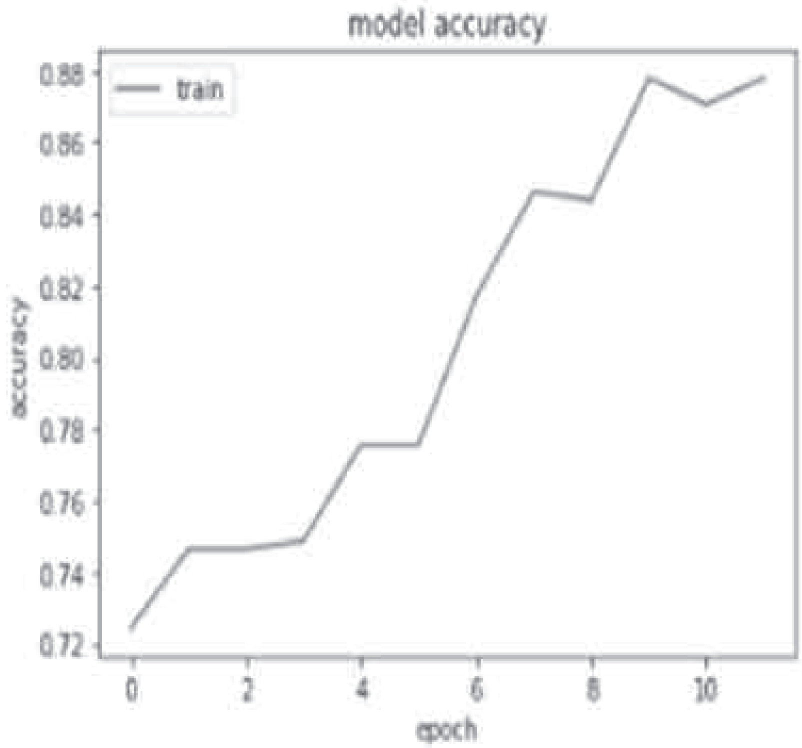
The model was trained with the dataset, and the accuracy obtained was 0.87, with 12 epochs, as shown in Figure.11 and a graph of accuracy vs epoch were plotted. It was found that as the number of epochs increased, the accuracy of the model increased as well as shown in Figure 12.

Fig. 11. Training the model

```
batch_size = 22
history = model.fit(X_train, Y_train, epochs = 12, batch_size=batch_size, verbose = 2)
```

```
Epoch 1/12
 - 3s - loss: 0.6497 - accuracy: 0.7244
Epoch 2/12
 - 2s - loss: 0.5776 - accuracy: 0.7463
Epoch 3/12
 - 2s - loss: 0.5381 - accuracy: 0.7463
Epoch 4/12
 - 2s - loss: 0.4912 - accuracy: 0.7488
Epoch 5/12
 - 2s - loss: 0.4438 - accuracy: 0.7756
Epoch 6/12
 - 2s - loss: 0.4122 - accuracy: 0.7756
Epoch 7/12
 - 2s - loss: 0.3749 - accuracy: 0.8171
Epoch 8/12
 - 2s - loss: 0.3379 - accuracy: 0.8463
Epoch 9/12
 - 2s - loss: 0.3132 - accuracy: 0.8439
Epoch 10/12
 - 2s - loss: 0.2716 - accuracy: 0.8780
Epoch 11/12
 - 3s - loss: 0.2679 - accuracy: 0.8707
Epoch 12/12
 - 2s - loss: 0.2475 - accuracy: 0.8780
```

Fig. 12. Accuracy vs epoch graph



A graph of loss vs epoch was plotted. It was found that as the number of epochs increased, the loss of the model decreased as well as shown in Figure.13 and After training the model was validated with an unfamiliar dataset and gave an accuracy of 0.68 as shown in Figure.14.

Fig. 13. Loss vs epoch graph

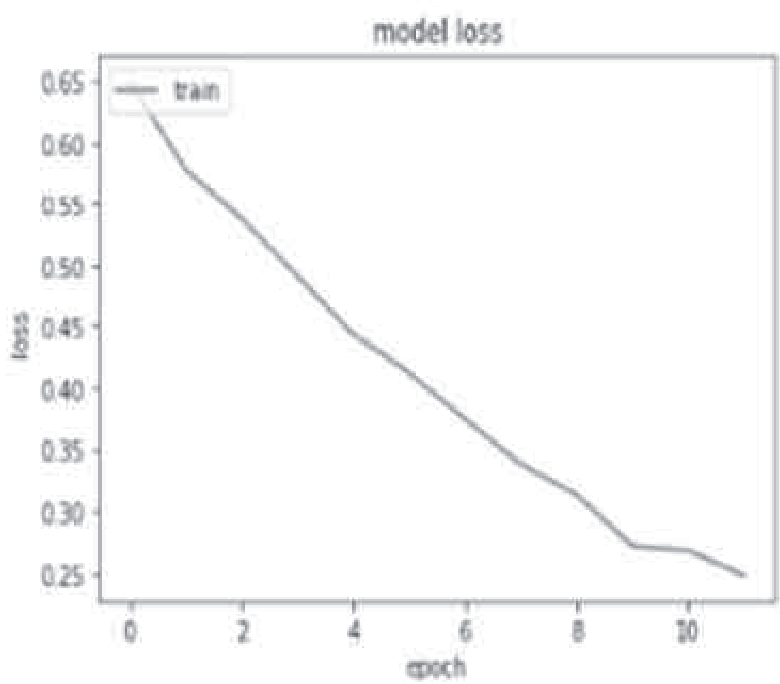


Fig. 14. Loss vs epoch graph

```
In [223]: validation_size = 15

          X_validate = X_test[-validation_size:]
          Y_validate = Y_test[-validation_size:]
          X_test = X_test[:-validation_size]
          Y_test = Y_test[:-validation_size]
          score,acc = model.evaluate(X_test, Y_test, verbose = 2, batch_size = batch_size)
          print("score: %.2f" % (score))
          print("acc: %.2f" % (acc))

          score: 0.72
          acc: 0.68
```

After validation of the model, the sarcasm and non-sarcasm accuracy that was obtained was 84 per cent and 0 per cent respectively. Figure 15 represents the final result of this proposed work.

Fig. 15. Classification accuracy

```
pos_cnt, neg_cnt, pos_correct, neg_correct = 0, 0, 0, 0
for x in range(len(X_validate)):

    result = model.predict(X_validate[x].reshape(1,X_test.shape[1]),batch_size=1,verbose = 2)[0]

    if np.argmax(result) == np.argmax(Y_validate[x]):
        if np.argmax(Y_validate[x]) == 0:
            neg_correct += 1
        else:
            pos_correct += 1

    if np.argmax(Y_validate[x]) == 0:
        neg_cnt += 1
    else:
        pos_cnt += 1



print("Sarcasm_acc", pos_correct/pos_cnt*100, "%")
print("Non-Sarcasm_acc", neg_correct/neg_cnt*100, "%")

Sarcasm_acc 84.61538461538461 %
Non-Sarcasm_acc 0.0 %
```

Implications

This multi-disciplinary study contributes to methodological and managerial implications by suggesting a mechanism for identifying and analyzing customer opinion and showing the level of sarcasm in positive reviews. Analyzing the sentiment, specifically sarcastic comments of consumers, helps to find out the satisfaction level and customers behaviour towards the brands and the products. This helps marketers to create appropriate marketing strategies to establish a healthy relationship with the customers. The result, level of sarcasm in the luxury context, is alerting brand managers that promotional strategies have to be built by considering the fact that many of the audience of the promotional videos are not actually happy with promotional videos. This kind of reviews from the group could create a negative outcome. As the targeted audience of social media is uncontrollable, this could be a challenging task for brand managers and marketers.

The result of a high level of sarcasm in this context is giving a hint to managers to consider this while going for sentimental analysis. This study further gives a mechanism to solve this issue with the help of Recurrent Neural Network algorithm along with LSTM. The results obtained from sarcasm detection will be helpful in areas such as sentiment analysis, natural language processing, opinion mining, business-related decision making or analytics etc.

Conclusion

A brand is a key element that ensures the uniqueness of a business as far as identity is concerned. Customer's opinions are the major factor which affects the sales of luxury brand products. This study has identified the sarcasm in the comments by passing the opinion of customers into deep learning algorithm and the results obtained are satisfactory. By understanding the trend of customer opinion regarding luxury brands' promotional videos will be useful for developing a better branding strategy. Future researchers may consider demographic variables and personality characteristics for obtaining a more accurate result. Moreover, future work can be done on various domain dataset as well as Multi-language social media data. Emojis also can be included along with text data for sarcasm detection.

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