(Authors' names blinded for peer review)

Existing works have predicted user behavior on social media using either image or text data. This research
takes a further step with a methodology to combine image and text data for predicting user behavior
on social media. The methodology is applied to 350k Facebook firm-generated content (FGC) posts. This
research demonstrates that the proposed methodology that utilizes both text and image data for predicting
user behavior outperforms text-only or image-only models for predicting user likes, shares, comments, and
comment sentiment. The results validate the need for using both image and text data for predicting user
behavior on social media.

Key words: add,keywords,here

1. Introduction

1.1. Machine Learning on Social Media Data

Existing research recognizes the value of modeling user behavior on social media using
machine learning models Li et al. (2015), Straton et al. (2017), Ohsawa and Matsuo (2013),
Liu (2012), Li et al. (2015). This pattern of research reflects the desire to understand
consumer behavior on social media Fisher (2009). These studies have focused on particular
metrics, including user click-through rates Li et al. (2015), user interaction with Facebook
posts Straton et al. (2017), predicting user tendency to follow pages Ohsawa and Matsuo
(2013), and user sentiment Liu (2012), Wang et al. (2015). A large amount of research is
concerned with better understanding user behavior on social media.

The existing research understands user behaviors through behavior models, which often
include machine learning models Li et al. (2015), Straton et al. (2017), Ohsawa and Matsuo
(2013), Liu (2012), Li et al. (2015). Examples include statistical models Li et al. (2015),
neural networks Straton et al. (2017), text idf models Ohsawa and Matsuo (2013), opinion
mining Liu (2012), and sentiment analysis of images Wang et al. (2015). Each example

demonstrate the common methodology of modeling user behavior using machine learning models in order to better understand social analytics and user behavior. Modeling user behaviors can provide beneficial research insights about social analytics.

Convolutional Neural Networks (CNNs) perform well at working with images and are used in correspondence with social media images. They have been used for gender classification Hassner and Tal (2015), for visual sentiment Segalin et al. (2017), Xu et al. (2014), to detect sarcasm on Twitter Poria et al. (2016), for detecting stress in social media images Lin et al. (2014), to perform social media profiling Segalin et al. (2017), to predict social media popularity Gelli et al. (2015), and to predict which posts will receive the post clicks Khosla et al. (2014). CNNs are the standard in the realm of social media for image analysis Hassner and Tal (2015).

Models trained on text data exist to understand user behavior. Facebook likes have been predicted for hospital data using only post text data Straton et al. (2017). Research has used NLP to predict the likelihood a user will follow a Facebook page Ohsawa and Matsuo (2013). Other models have used text data for opinion mining Liu (2012). Text data is also frequently used for modeling user behavior on social media.

1.2. Gap

However, a gap exists in current research when modeling user behavior with social media data because researchers fail to incorporate multiple data types, despite the availability of both image and text data. An example is performing sentiment analysis of posts with images Wang et al. (2015) but failing to incorporate the post's text into the model. The same is true for using text-data to predict a post's CTR but ignoring its associated image data Li et al. (2015). The gap in research is a failure to utilize multiple available data types when modeling user behavior on social media.

The gap is demonstrated in the failure for image-based models to incorporate text data. Each of the CNN models fails to incorporate text data in their models for predicting gender classification, detecting sarcasm, profiling, and predicting social media popularity Hassner and Tal (2015), Poria et al. (2016), Segalin et al. (2017), Gelli et al. (2015). Image-based social media models fail to incorporate text-data in their methodology.

1.3. Applied Model for Advertising and Forecasting User Behavior

This research applies its methodology to a use case of predicting user behavior in response to advertising. We feel this use case is relevant to the Marketing Science Journal because

of it demonstrates a method for improving models of user behavior on social media in response to advertising. Such topics might be utilized to provide advertisers with a competitive advantage, or alternatively used in future research to improve marketing models on social media. This paper provides marketing science about user behavior with regard to advertisements on social media.

Advertisers are most concerned with social media metrics, especially those that promote engagement Tiago and Verissimo (2014), which include click-through rate (CTR), brand awareness, and word-of-mouth buzz. Advertisers associate these with advertisement return on investment (ROI), which is known as the Holy Grail of social media Fisher (2009). However, advertisers calculate ROI, which often includes an increase in user interaction Romero (2011), Schacht et al. (2015). This study successfully models user engagement, which is of great interest to advertisers and social media platforms.

Advertisers want to impact future sales from the untapped market Guo et al. (2020). Their goals include creating brand stickiness, improving user relationship quality, creating unique visitors, increasing average time per visit to their website, get repeated visitors, and increase visit frequency Bhat et al. (2002). There are many ways to improve advertisement campaign performance, such as influencing both its content and content type Imsa and Irwansyah (2020). However, neither of these provides a direct forecast of the advertisement's performance. Given the cost of showing ads, quicker feedback mechanisms that can predict advertisement performance is useful in curating content and publishing on the platform with a great degree of confidence concerning the advertisement's performance Hu et al. (2016). Therefore, this study is helpful in that it provides improved mechanisms for forecasting advertisement performance on social media.

Forecasting user response to advertisements is important because advertisers view social media as a method for creating both tangible and intangible firm value that improves business performance Authors (2013). Tangible benefits include a decreased time needed for users to make a buying decision Authors (2013). Intangible benefits include how advertisements influence buyer decisions Authors (2013). In addition, with better forecasting, advertisers can improve planning their sales cycles and projected revenue Imsa and Irwansyah (2020). This paper provides details on improved user behavior forecasting, which is beneficial to advertising revenue.

Social media serves as a platform where brands can create and maintain an online presence Greenwood et al. (2016). Social media can create tangible value that improves business performance Authors (2013). The desire is that tangible user engagements result in faster user conversions Authors (2013). Social media can serve as a platform for influencing their target audiences and increase their bottom-lines.

1.4. Research Summary

Our research provides a method for combining text and image data for modeling user behavior on social media. We demonstrate the successful implementation of a model combining image and text data and demonstrate its improved performance over single-data type models. The chosen method makes use of an ensemble model whose input is a text-based NN and image-based CNN. The combined model outperforms the text and image models when predicting user click, share, comment, and comment sentiment. The results of the sixteen machine learning models are provided in the results section and the discussion provides insights concerning the model's performance and its application to advertising social media data. Future social media studies should adopt the combined model methodology when modeling user behavior on social media.

The remaining paper consists of five sections. The related works will cover existing studies that model user behavior on social media and will delineate studies relying on text data or image data. We also include methodologies for processing text and image data within the related works section. The methodology section will describe the creation of the sixteen machine learning models, four text-only, four image-only, and eight combined models with different architectures. The result section outlines the result of the combined model, juxtaposed with text-only and image-only models. The discussion delineates why the combined model produces an improved performance. The conclusion and future work outline ways future research can adopt these methods to better model user behavior on social media.

2. Related Work

2.0.1. Text-based Social Media Models Text models exist to predict user interaction on Facebook Straton et al. (2017). The predicted user metrics include page likes, shares, and comment counts from this data. The analysis categorizes all posts into engagement categories, e.g., low, medium, and high. The Neural Network trains with on the text and

time data. The model can accurately predict for lower user engagement but fails to predict for higher levels of engagement. The study's sample size was 100k posts and did not incorporate images or comment text in its predictions. Nevertheless, the study found that text data can predict limited levels of user engagement.

A CTR study focuses on predictions based on user interests Li et al. (2015). The study is essential because it models the likelihood of user behavior based on user interests with advertiser data. The study performs its prediction by modeling the Twitter feed and the click rates for each type of user interest. As a result, the study successfully predicted user click-through rates based on how well user interests coincide with the advertisement's content.

Research exists that to measure user sentiment using either text or image data. Text data is useful for opinion mining Liu (2012), where opinion mining uses keywords as sentiment indicators. Fortunately, existing sentiment lexicons are available for predicting sentence sentiment Georgiou et al. (2015). In contrast, there is research that detects image sentiment by clustering images Wang et al. (2015). Methods exist that use either text or image data to predict user sentiment. However, there are no cases of using a combination of image and text data to predict user sentiment on social media.

2.0.2.   Image-based Social Media Models Many studies use Convolutional Neural Networks (CNN) for image analysis. The use cases are varied, and include: age and gender classification Hassner and Tal (2015); image polarity Poria et al. (2016); sarcasm detection Poria et al. (2016); and image popularity classification Khosla et al. (2014). Existing research has produced visual sentiment classifiers with CNNs Segalin et al. (2017), Xu et al. (2014) to identify stress within social media images, Lin et al. (2014), use supervised CNNs to performed social profiling to identify personality traits Segalin et al. (2017), perform sentiment analyses and estimated social media popularity with CNNs Gelli et al. (2015), use images to predict which types of images are popular on social media Gelli et al. (2015), and predict which posts will receive the most clicks Khosla et al. (2014). CNNs are frequently used in combination with images on social media for understanding user behavior.

2.1.   Industry need for Modeling User Behavior

Companies calculate social media revenue return on investment (ROI) via their advertisement performance on the platform Fisher (2009). Therefore, ROI is the Holy Grail of

social media Fisher (2009). When asked which social media metrics marketing managers care about most, they replied with brand awareness, word-of-mouth buzz, customer satisfaction, user-generated content, and web analytics Tiago and Verissimo (2014). However, ROI is difficult to track Schacht et al. (2015). Most companies are unable to get revenue or cost savings from social media Romero (2011). Instead, ROI is measured via user consumption Schacht et al. (2015). The study performed a cross-platform analysis of ROI on Facebook, Twitter, and Foursquare. Schacht proved that tweets could predict rising Foursquare check-ins.

Users visit social media sites to gain information Fisher (2009)—for example, 34% of participants post products about opinions on blogs. Moreover, traffic to blogs keeps increasing 50% alone that year, compared to 17% at CNN, MSNBC, and the New York Times. 70% of consumers visit social media sites for information. 49% of the 70% buy based on social media content. 36% of participants better rate companies with blogs. 60% of users pass along social media data to other users. Persons use social media to learn and gain opinions about products and brands.

2.1.1. Research Questions Research_Question: Can a combination of text and image data better predict user engagement on social media using machine learning?

When predicting user engagement on social media, models trained using both text and image data outperform either text or image models.

The question explores the existing gap in using a machine learning architecture that digests both image and text data to predict user engagement. Such an architecture might include text-based NN, CNNs, and popular models like decision trees. The predicted user engagement consists of the count of likes, comments, shares, and comment sentiment. Models that predict numbers use regression and mean-squared error (MSE) as their loss function. This research explores whether model architectures that combine text and image better produce a model with a lower loss than their text and image counterparts.

Research_Question: Why are images better than text data for predicting user comment sentiment using machine learning?

Models trained on image data better predict user comment sentiment than models only trained on text data.

Existing studies use images in CNN models to predict visual sentiment Segalin et al. (2017), Xu et al. (2014). If a relationship exists between visual sentiment and user response,

we expect image-based CNNs to perform well at predicting user sentiment. Nevertheless, text-data provides a great deal of the post's content. It is worthwhile to juxtapose how well text-based and image-based models compare. This research question will examine the ability for image-based models to predict the sentiment of users, via their comments.

Research_Question: To what extent can machine learning predict which of any two social media advertisements will perform best?

Machine learning models perform statistically significantly better at predicting ad performance than random guessing

Machine learning models that predict user engagement might be able to select, from a group of advertisements, which one will perform the best. The ability to select the best performing advertisement beforehand allows brands to better select advertisement content. One implication is the ability to choose the best post. A further implication might be A/B testing with different variations of the same advertisement. Brands can use the machine learning model to better tweak their advertisement so it best performs on social media. As far as we are aware, successful selection of the best performing advertisement, from a group of ads, has not been done with machine learning models with social media advertisements. This paper explores whether the curated machine learning models can predict which advertisement, will perform best on social media.

3. Methods

The method section describes the data context, collection, and steps for processing, obtaining, and evaluating results by this study. The first section will describe the data collection of advertisements from Facebook and Hootsuite. The second section will describe the data processing, both the cleaning of both text and image data, including sentiment data, and their transformation into machine learning vectors. Afterwards we will cover the machine learning models, their architectures, and the method for their evaluation. The methods section will provide an overview of this study's process for answering each of the research questions.

3.1. Data Collection

The research studies Facebook posts on company Brand pages. These brand pages consist of Firm-Generated Content that users may interact with. Brand pages are often public company pages where brand-content is posted in order to influence user behavior and often
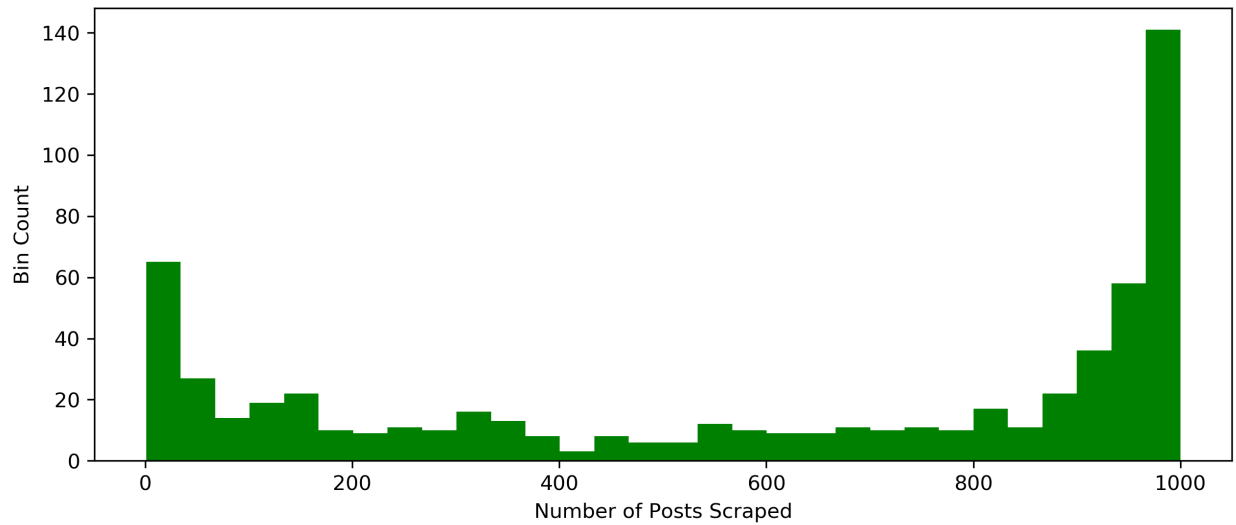
Figure 1 **Histogram of the Number of Posts Scraped Per Facebook Page**

for the purpose of building the company's brand. Given the public nature of these pages they are an easier source of advertising data that can easily be scraped from the Facebook. The study looked at public Brand pages and examined the posts and the resulting user response.

The research obtains a set of brand URLs to Facebook from AdEspresso. Hootsuite owns the website and is a social media management platform created in 2008 (https://www.hootsuite.com). The website features over one-hundred-thousand demo Facebook advertisements. This paper scraped the links of 281,090 available advertiser pages linked on this website. This research discovered URLs to public company-brand pages on Facebook by using the AdEspresso website.

A Python web scraper crawls the Facebook brand pages via the Facebook Graph API, which is a public-use API. This research scrapes the most recent one-thousand posts from each brand page, though many brand pages contain fewer than one-hundred posts. The histogram for the number of posts scraped per brand page are shown in Figure 1. In total, the study collected 366,415 Facebook posts and 1,305,375 million comments. This study collects a great deal of brand-page data via more than 350k Facebook posts and 1.3 million comments.

3.2. Data Processing

This study follows standard text processing steps Camacho-Collados and Pilehvar (2019), including text cleaning, creating tokens, using a port stemmer, part-of-speech tagging,

lemmatization, and transforming text sentences into a td-IDF vectorizer. First, the program split data into word tokens using whitespace as a delimiter. The program grouped these tokens into sentences, and both lowercased and removed common English stopwords and words with three or fewer characters. A port stemmer creates stems for all the words. A POS tag library performed parts-of-speech tagging. The program then extracted stems with a word lemmatizer, which takes the stem and the POS tag as input. Finally, the program fed the lemmatized text sentences to a td-IDF vectorizer. This created word vectors for training the neural network.

Given that images are inherently highly dimensional, we took several steps to reduce each image's dimensionality. First, we used principal component analysis. The number of dimensions to keep was set at 20 since the image variance is lower after denoising, reducing noise and data size. Image denoising can further reduce noise. Second, the research applied a Gaussian blur with a standard deviation of five to each image, which applies image blurring and emphasizes edges. Dilation and erosion are also applied to the image to remove noise in the edge space.

This study analyzes the text sentiment of text from both comments and posts. The post text denotes the text associated with the brand's FGC text. The comment text includes all comments made on the FGC post. Each text is scored from -1 to 1 for its positivity. The comment sentiment is averaged for each post and represents the user sentiment toward the post. Figure-4 shows a histogram of comment sentiments for the Facebook posts. The study rates the sentiment of user response toward a Facebook post as the average sentiment of its comments.

This study uses the Python library VADER to perform text sentiment analysis. Text sentiment rates the orientation of the text as either negative or positive and machine learning tools are commonly used for generating text sentiments Haddi et al. (2013). VADER is a a parsimonious, rule-based model for Sentiment Analysis for social media text data Gilbert. VADER's output is a score between -1 and 1 to denote the text's positive or negativity, where 1 denotes a positive sentiment, 0 is neutral, and -1 denotes a negative sentiment. The machine learning models predict the average user sentiment for the Facebook post. The post's user sentiment is the average sentiment of all user comments, as scored by VADER. This output serves as the target value for the machine learning models. Models

predict the average comment sentiment for each Facebook post. The study uses an existing text-sentiment library, which is made for social media text, to measure text sentiment.

The result dataset consists of 366,415 posts. These posts contain comment count, share count, and comment sentiment data. The research subsets this data for training on user comment sentiment, for which it uses 201,215 posts. Of those posts, the study collected and trained on 1,305,375 million user comments. The study collected many Facebook brand posts and many more user comments.

Three brand variables have correlations worth noting: the number of users talking about a brand page, the fan count, and the comment count. The research found an adjusted R-Squared of 0.22 beteen talking about count and share count and 0.38 between talking about count and fan count. An initial analysis of brand pages found that the count of users talking about a brand page is correlated with share count and fan count. Brand pages that receive more user attention tend to have a higher fan count and share count.

The metrics for comment count and share count are correlated. This correlation is sensible, considering that users talk about shared content. Moreover, the shared content is interesting. Shared content also creates more interesting content. Linear models also found a correlation between fan count and share count. The more fans a page has, the more opportunities exist for people to share the content. Alternatively, people are fans of the page because they like the content and if people like content, they are more likely to share it.

Linear models also discovered a correlation between comment count and comment sentiment. Posts that receive many comments are likely to receive positive comments. We can infer that happier users comment at a higher rate, or positive content elicits more comments, which are also likely to be positive. Interestingly, comment count was not correlated to share count. One might infer that just because a post draws attention and comments does not mean they are likely to get shared. It might also mean that happier content, which receives more comments, does not cause users to share that content. Page metrics are also not correlated with comment count, i.e., a famous or less popular page did not necessarily generate more or fewer comments. The study uses the lack of correlation to justify comparing posts across Facebook pages.

3.3. Modeling

There are three types of models, text, image, and combined models. The text model uses a neural network architecture with seven hidden layers and the CNN uses the VGG16 architecture. There are two types of combined models, a decision-tree based model and an ensemble of the NN and CNN models. There are three training datasets for share count, comment, count, and comment sentiment. Training each of the four architectures on the three data types makes for a total of twelve models. This study trains four model architectures, based on different data types.

The study uses standard deep-learning architectures to train its NN and CNNs. These architectures are freely available to import and train via Keras, a Python machine learning library. The CNN model uses VGG16 (https://keras.io/api/applications/) and the NN is a generic Keras, deep NN with seven hidden layers. Each model, its use, and methods for training and testing are publicly available on Github at https://github.com/cpluspluscrowe/Masters_Thesis. Each model is iteratively trained with large batch sizes of 256 until the test dataset stops learning or its performance decreases. This research initially experimented with word vector sizes from 1k-400k. Good performance and fast training occurred with a word vector size of 10k. The NN models used 10k as the word vector size. CNNs took weeks to train with a GPU, with the NN models training in a few days. The ensemble combined model concatenates both text-based NN and image-based CNN. The The use of existing performant NN and CNN architectures gives us confidence the deep learning models will satisfactorily learn the data. Moreover, future research can also train with these models for extending this research.

Given the study's data contains continuous variables, such as the count of shares, comments, and range of comment sentiment from -1 to 1, the study uses regression to optimize the ml models. The study uses Mean Squared Error (MSE) as its loss function for the machine learning models, which heavily penalizes values straying from the observation. The result are models with a smaller prediction range but which is able to predict which posts will outperform others. The study trains regression ml models that learn to predict if a post will perform well on social media.

4. Results

The results display the MSE for the twelve ml-models. The twelve models use a combination of different data types as input, including only-text, only-video, and a combination of text

Metrics / Model	Text-Based NN	Image-Based CNN	Combined Decision Tree	Combined NN
Share Count	3.44	1.01	2.58	1.00
Comment Count	1.02	1.01	1.29	1.00
Comment Sentiment	1.42	1.14	4.20	1.00

Table 1   Model Mean Squared Error Reported as a Ratio to the Best Model's Performance

and video data. The relative MSE for the twelve models is shown in Table 1. The combined models include a decision tree and an ensemble CNN and NN. The study provides relative MSE performance across both different architectures and combinations of input data types. Rather than provided raw MSE across all models, we provide ratios. We also provide a histogram of the MSE to provide an understanding of how well the model performs on the test datasets.

The combined model best predicted all user behavior metrics. Each machine learning model had its lowest MSE predicting for share count. The CNNs achieved a lower MSE than the NN on all metrics. Moreover, the CNN performance is best on data exhibiting a higher variance. Figure 3 and 4 show the predicted vs actual distribution for the combined model.

The decision tree performed far worse than the combined model. While the exact reason is unknown, there are a few differences between the two models. First, the combined model closely integrates with the text-based NN and image-based CNN. Second, when the combined model trains, it also trains its two-parent models. As a result, the decision tree did not learn alongside its inputs. Likely, parent models compensate for mistakes by training together.

4.1. Discussion

4.1.1. RQ 1: Ability to Predict User Engagement Comment count and share count are correlated, which implies that posts which are shared more often also receive a greater number of comments. The relationship between comment count and share count is senisble since users will share content they find interesting to talk about. The same correlation is also seen with fan count, which makes intuitive sense since more users following a page results in a larger number of user interactions. Alternatively, people are fans of the page because they like the content and if people like content, they are more likely to share it.

There also exists a higher correlation between comment count and comment sentiment. Posts that receive many comments are likely to receive positive comments. We can infer
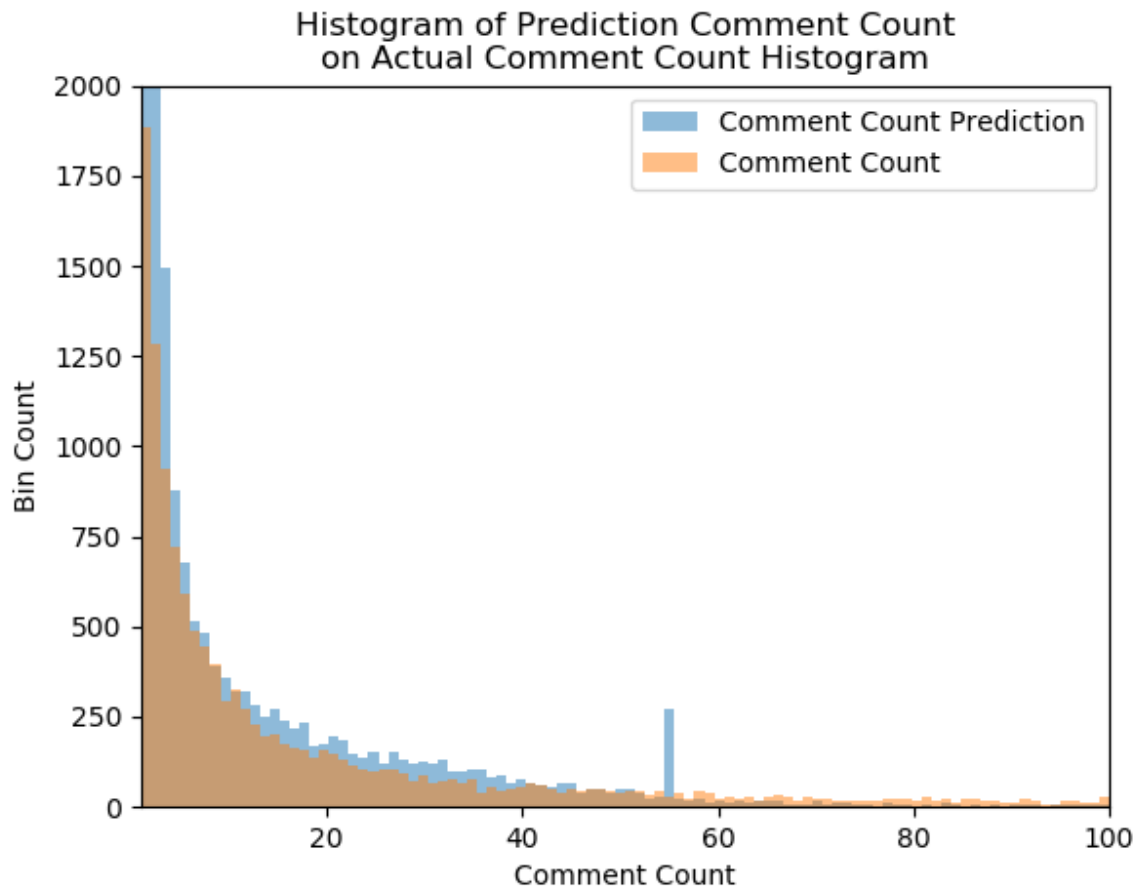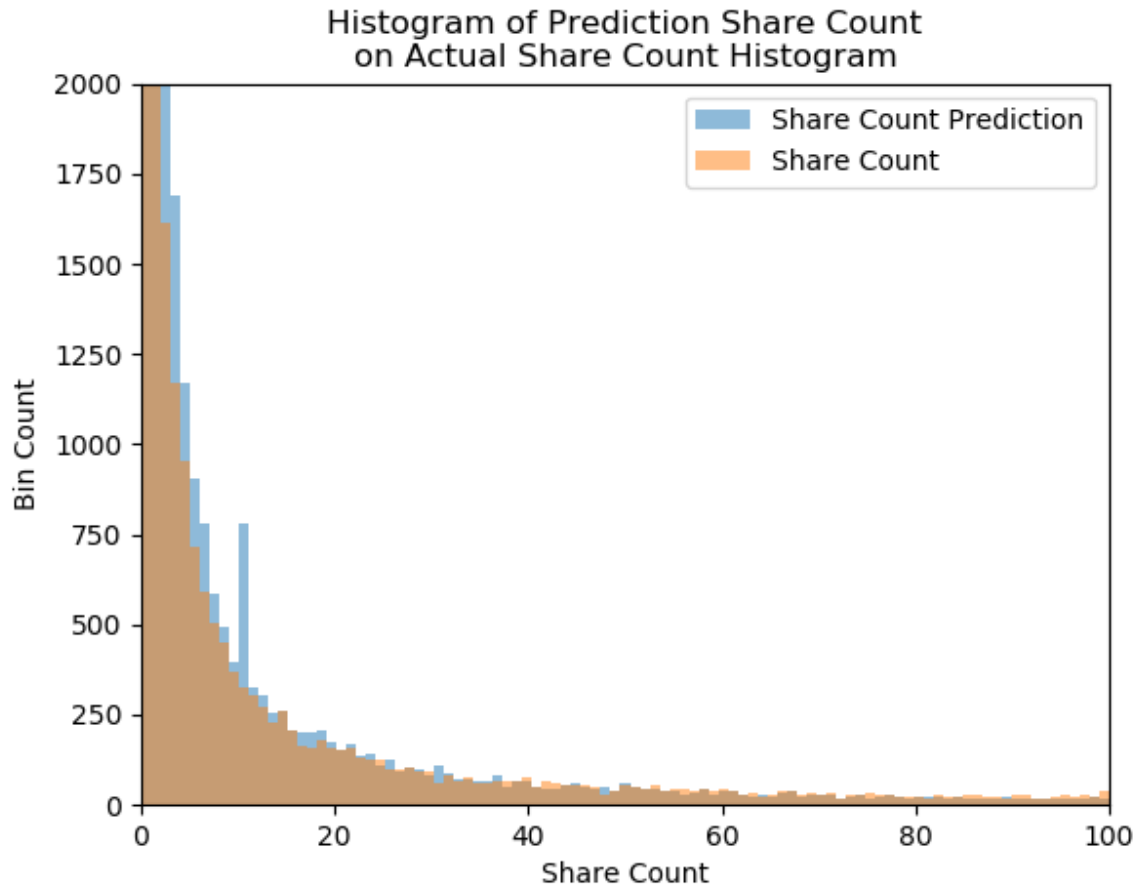
Figure 2   Actual vs Predicted Comment Count Histogram

that happier users comment at a higher rate or positive content elicits more comments. In turn, one might expect that highly positive posts might elicit positive comments. Posts that receive many comments tend to contain an overall more positive comment sentiment.

Comment count is not correlated with share count. This infers that posts with many comments do not necessitate users share the post. This might occur on interesting content that is less relevant to other users. Otherwise, some types of content might exhibit different share rates. The study found little relationship between comment count and share counts.

Popular pages do not generate more comments per post. This might capture a phenomenon where brands receive many followers but produce less interesting content. At the same time, some brands have entire social media teams and produce higher quality content, which in turn generates a lot of engagement. Generating many followers is not equivalent to generating engaged users. Many brands have many followers but generate very little user engagement on their posts.

**Histogram of Prediction Share Count
on Actual Share Count Histogram**

Figure 3   **Actual vs Predicted Share Count Histogram**

The study found a relation in the propensity to share a post and the resulting comment sentiment. Posts that reciprocate positive sentiment are more likely to be shared. Brands should consider how to increase user sentiment, which will result in users also sharing the post more frequently. The study found a strong relationship between user comment sentiment and the propensity to share the post.

4.1.2.   RQ 2: Performance of Images vs Text Related work includes sections on key-point descriptors and neural networks. CNNs detect image features and key points during repeated pooling and filter stages. This replaces the usefulness of image descriptors. Applied research uses CNNs in favor of image descriptors. Moreover, CNNs were faster to train than comparing image descriptors between images. This research trained with as many as eight layers and as few as one hidden layer. Model depths above three trained to a similar degree of accuracy. The models experimented with different convolutional size sequences.
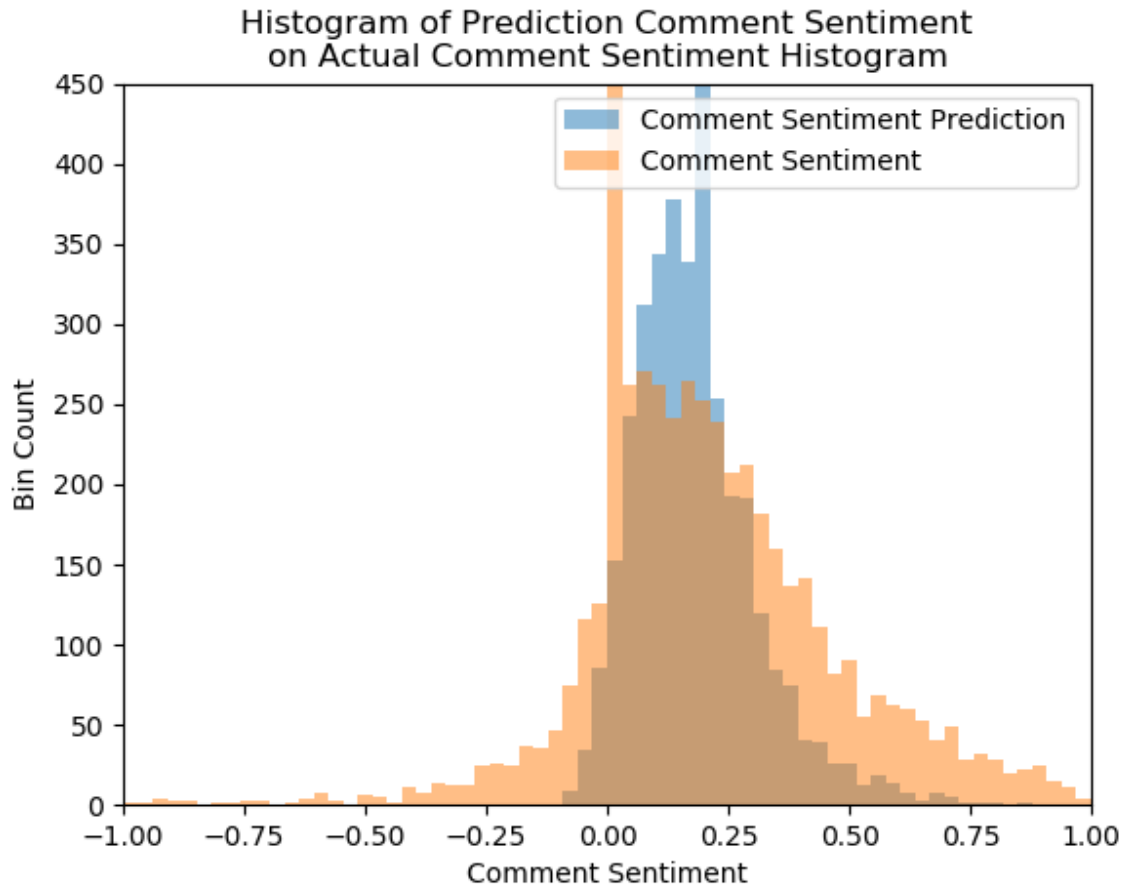
Figure 4   Actual vs Predicted Comment Sentiment Histogram

The experiments include doubling in size, usually from 64 to 128, with a 2x2 filter. The alternative was reduced by size in half with a 2x2 filter. Models with a 2x2 filter that decreased their size by half produced the highest accuracies. The final model contained four hidden layers. This research used this CNN configuration for all CNN model training. The final image-based model performed with a better loss than the text-based NN model on all metrics.

Image-based models performed better than text-based models on all metrics, likely because it emphasizes images' importance for predicting user interaction on social media. Text-based models were poor predictors for many metrics. Text-based models did especially badly in prediction share counts. One may guess that users are sharing content they consider worthy of sharing.

4.1.3.   RQ 3: Ability to Distinguish Between Higher and Lower Performing Ads In light of the newly created data, there are no other baseline measures for what constitutes

good model performance. One goal was to produce a model that performed better than random guessing. Random guessing alone is not representative of the data. A better guess is based on the input's distribution. A good random guess would consider the data's value at each point along with its distribution. Such a distribution would weigh each value by the frequency of data. This calculation is the expected value. For a normal distribution, the expected value is equal to the mean. Also, each output in the research resembles the normal distribution after a log transformation. If the model always predicts the mean, the MSE is equal to the data's variance. The variance is a squared order of the data's distance from the mean. The MSE is also a squared order of the model's prediction from the actual value. Producing a model whose loss is below the variance is a general measure of demonstrating the model is doing a significant amount of learning. Fortunately, the combined model's performance was always much lower than each output data's variance.

Models with a higher variance achieved the worst overall loss/variance ratio. It seems that the larger the data variance, the higher the resulting mode's MSE. Share count had the highest variance of all the measured metrics, 1000x more than the comment count. The high MSE likely reflects that share counts are less related to the image and text data. Share counts might be a factor of other features, like page popularity.

4.1.4.   Use Case The research applied the models in a real-world application. The application explored a use case to demonstrate the model's ability to choose which two advertisements would have the best performance. The research only compares advertisements with a significant value difference, where a significant difference is anything more than one standard deviation, as defined by the data distribution. The research found that models are unlikely able to differentiate between advertisements with similar performances. The combined model performs all predictions since it performed best across all metrics. Moreover, the application is the most useful if it can detect poor-performing and best-performing advertisements.

The scenario is predicting user engagement for advertisements. The scenario pairs Facebook posts together. The model predicts user engagement for all posts. The program scores how often the model correctly predicted for greater user engagement. The program reports the result for each metric. The score is the number of correct predictions over incorrect predictions. This research compared the score with a random model. The random model

produced the correct answer 50% of the time. The combined model scored 93% for comment sentiment, 65% for comment count, and 63% for share count.

The model performance shows its applicability in the real world. Platforms could employ the models to aid advertisers in choosing the best performing advertisement before paying to advertise it on social media. The model can tell advertisers which ads would perform best on the platform, which allows advertisers have their ads vetted. The vetting could prevent advertisers from spending large amounts of money showing worse ads. Moreover, the vetting would allow advertisers to only show ads that will perform best. In the context of billions, 93%, 65%, and 63% accuracy is a substantial monetary difference.

4.2. Study Contributions

The research found that machine learning with both image and text data results in enormous improvements for predicting comment sentiment.

The research serves as a case study for combining text and image data.

The study provides performant model hyperparameters in model depth, dropout rate, and word vector sizes.

The expected results will be generalizable to other studies and encourage others to explore understanding advertisement performance on social media.

The research demonstrates that ml models trained on both text and image data outperform single-data type models. The methodology trains four model architectures on three user metrics. Across all metrics, architectures using both image and text data outperform single data type models. The result demonstrates that architectures exist for combined models that improve predictions for social media data.

4.3. Limitations and Future Work

The study is not able to acquire existing ml models and study data concerning single-data type models. The data and models are not for public use. The result is that this study made use of existing, high-performing model architectures for both CNN and NN. This allows the study to ensure its results are repeatable. Using pre-existing model architectures also ensures that existing research's best practices for ml models and architectures are included within this study. The study is not able to show the improved benefit of the combined model on pre-existing study data or models, however, the study makes use of well-known architectures to ensure model performance and study replicability.

Given that share count and comment-sentiment have a coefficient of determination over 0.4, the share count model is likely a good input for predicting comment sentiment. Future research can incorporate this input to improve future models when predicting user behavior. In addition, future research could overcome existing Facebook API scraping problems. Another avenue for research is collecting comment sentiments for the 350k Facebook posts and using the new data to train better models. Moreover, future work can incorporate the combined text and image model with the image-based CNN and text-based NN into an ensemble model to see if it improves performance.

The models created from this research could generate data to train a generative model. The generative model could transform images and text into advertisements that should generate more user interaction. The transformed and original advertisements could both be shown on social media and their user interactions compared. Thus, the study might demonstrate that generative models generate and improve existing advertising content.

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