IMAGE RECOGNITION FOR BRAND REPUTATION

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A thesis submitted in fulfillment of the requirements for the degree of Management and Computer Science in the subject of Business and Marketing Analytics

JUNE 1, 2024
ACADEMIC YEAR 2023/2024
Department of Business and Management

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Abstract

The development of sophisticated image recognition technologies has made it possible to improve brand reputation. This thesis explores the utilization of image recognition models to evaluate the impact on brand reputation given to the increased importance of visual content in shaping consumer perceptions. In the digital age, it is important for firms to analyse and understand their brand identity and image to better understand their market audience.

The images were extracted from Instagram using the Apify Web Scraper API which allowed us to give as input the hashtags of a particular brand we wanted to assess and get as output the URL link of posts which have that hashtag. In total around 120K posts were scraped, of which 72K were in English. The images then would be classified using the Clarifai General Image Recognition model, based on a CNN InceptionV2, which is trained on 20M images and has around 10K concepts.

The research concludes by analysing the labels of each image, running a Topic Parallel Extractor Model (LDA), both for all the images, and afterward a time series-based approach to see if there is continuity in brand perception.

This research aims to contribute to the academic discourse on brand management and provide actionable insights for the industry. Findings reinforce the role of image recognition in brand reputation strategies and underscore the transformative potential of machine learning techniques.

Introduction

1. Background and Motivation

In the modern digital world, brand reputation has become a crucial asset for business, which directly influences consumer behaviour. In general, brand reputation refers to how consumers perceive a brand based on its image, values, and performance. A strong and positive brand reputation can allow a firm to obtain a loyal customer base, which in turn attracts new customers and helps a firm differentiate itself from the competition. Conversely, a negative and tarnished brand reputation can lead to financial losses and long-term damage to a brand's credibility. Brand reputation is not only important from a customer point of view, but it also influences the company’s financial performance such as stock prices and can also be a key factor in the company’s ability to attract and retain employees. A strong brand reputation can also increase employee satisfaction, making them proud to work for a company perceived with a positive message by the market.

Brand reputation is built through time, but it can easily be tarnished overnight by applying unethical business practices, data breaches, environmental violations, and legal troubles. Some key factors that affect brand reputation can be described as the following. The first aspect is based on the quality of products or services. High-quality products and services ensure that customers are satisfied and are an integral part of creating brand loyalty (Vestil, 2023). A superior product makes customers come back, while at the same time allowing for the attraction of new customers due to the Word-of-Mouth. This concept is essential and exceptionally effective, information that comes from someone we trust is more likely to be remembered. Furthermore, when sharing information with others, it strengthens our own beliefs due to social validation. According to a study by Nielsen, 92% of customers trust recommendations from friends and family over all forms of advertising (Nielsen, 2012). Another factor is customer service, customers value excellent communication, responsiveness, and problem-solving (Vestil, 2023). Corporate social responsibility is a crucial aspect of brand reputation. Customers today are much more aware of the social and environmental impacts firms have, thus showing that the company is spending resources and committing to creating a positive impact on society will help with brand reputation (Vestil, 2023).

Traditional methods to analyse and measure brand reputation rely on textual data, such as reviews, and comments, while other measures rely on social media metrics such as engagement, reposts, followers, likes, etc. These methods have been effective, but leave out a valuable aspect, they overlook the information embedded in visual content. Visual information as shown by the study performed by Roger Shepard and Jacqueline Metzler, shows that the speed of processing visual information is significantly faster than processing text-based information (Metzler, 1971). Images can convey emotions and brand messages more powerfully compared to text, thus making them a vital component of a brand’s overall perception. By applying Image Recognition models in the context of brand reputation management, businesses can gain additional information on a brand’s visual presence and make data-driven decisions to enhance their reputation.

2. Scope of the study

The scope of this study will talk about the use of the Clarifai General Image Recognition Model for brand reputation management. Clarifai is an Artificial Intelligence company that specializes in computer vision. This allows them to analyse visual and textual data, making it useful for image and video recognition, facial recognition, and more. The platform provides businesses with the ability to integrate AI capabilities and enhance their data analysis processes, while also easing the scalability and user-friendliness. The data source for this research has been obtained via the use of the Instagram Scraper API of Apify, which allowed us to select all posts starting from 2017 onwards that have a particular hashtag. This will allow the study to ensure the relevance and applicability of the findings to current brand practices. This API only accessed and extracted publicly available information. Instagram has been selected as the social media network on which to perform this study because of its highly active monthly users, around two billion, thus indicating a huge amount of data that is generated daily. We focused on twenty-seven brands belonging to distinct categories, but this study can be expanded to all types of brands that are present on the platform and have enough data in the form of hashtags. Some limitations of this study could be in the form of biases in the image data, reliance on the data extraction via the use of Apify, and reliance on the model performance of Clarifai. The delimitations include the exclusion of other image recognition technologies and the focus on a specific set of brands.

3. Significance of the Study

The significance of this study lies in the potential new aspect of how businesses can track and manage their brand reputation and analyse the brand image in the social media environment. The new digital landscape has made visual content a dominant force in influencing consumer perception and behaviour. Traditional text-based methods of analysing brand reputation, based on text-mining and sentiment analysis, can fail to capture the impact of visual media. Social media platforms are a major resource used by brands to interact with their customers as it allows the latter to feel more connected to the brand via comments, reposts, likes, and engaging with stories. By providing insights into how a brand is visually perceived by its customers, the firm can add additional metrics to data-driven insights. This allows a firm to complement traditional text-based analysis with information extracted from the visual content, offering a more holistic view of brand reputation. From an industry perspective, businesses can leverage these methodologies and findings to enhance their brand monitoring systems, leading to improved reputation management and potential competitive advantage. The ability to proactively manage brand reputation through visual content analysis is an important aspect, especially in this digital age. Analysing the monthly image topics, extracted from the image prediction labels, a firm can analyse the trends and see how customers reacted to marketing campaigns over time. This proactive approach would allow companies to capitalize on positive visual trends and consumer generated content. Another important aspect is related to brand strategy development, understanding visual elements that resonate positively with consumers can inform marketing campaigns, product designs, and overall brand message.

Related Literature and CNNs for Images

1. Literature Review

This study has been inspired by the work done by Dzyabura and Peres 2021 JM titled, Visual Elicitation of Brand Perception. The main idea behind this work is to present an elicitation platform, analysis methodology, and results on consumer associations of U.S. national brands. The authors developed an online brand visual elicitation platform (B-VEP) that asked the users to create a collage of images that represent their relationship with the brand. This created user-generated content which allowed them to create a large-scale brand-mapping process where each collage represented the respondent's perception of the brand itself. This would allow the researchers to obtain associations between users and brands that went beyond the product's category or the company's marketing efforts. After obtaining these collages, they extracted information regarding the visual elements by using image tagging, thus identifying patterns among tags in brand collages. The objective was to see what associations set apart brands from each other and to do so they used a topic modelling approach called Latent Dirichlet Allocation (LDA). The guided LDA would provide a set of topics, where each topic would be distributed over tags.

The key difference between this study and our approach is the way data is collected. As stated previously, our data comes from Instagram hashtags, thus allowing us to obtain a more flexible approach to assess brand reputation, while the studies approach is more user-oriented. The collages created by respondents are substituted with Instagram posts with a determined hashtag.

2. CNNs in Image Recognition

Convolutional Neural Networks (CNNs) have revolutionized the image recognition field, offering accuracy and efficiency in analysing visual content. They are designed to learn spatial hierarchies from the input image, making them ideal for image classification, object detection, and image segmentation. This mathematical operation, called convolution, unlike general matrix multiplication, allows the network to learn hierarchical patterns in data, which is ideal for image processing. The main concept behind CNNs was developed in 1998 by LeCun in their paper Gradient-based Learning Applied to Document Recognition which itself is based on the previous researchers' work. CNNs consist of multiple layers which include, the convolutional layer where, in the case of image application, is used to detect features by creating many feature maps. Afterwards, we have the Activation operation which follows each convolutional layer, also known as a rectifier. We then have a pooling layer where the features are preserved, thus allowing us to find the closest similarities to the features. In this layer, we reduce the size of the image to allow us to get rid of unimportant information and prevent overfitting. The subsequent layer is the Full Connection, which is where we get our output. This last layer classifies the input based on the features detected by the convolutional layers. The general operation runs as follows, we give the CNN the images for the correct output, by backpropagation the neuron in the fully connected layer detects certain features, preserves the value, and communicates this value to both output classes, which then decide if the feature is relevant to them. Afterwards, with forward propagation, we feed the CNN an image, each class has attributes it focuses on, and they give a prediction based on which features the previous layer detects. We can say that it is a vote among neurons on which of the classes the image will be attributed to.

Over the years, there have been developments in CNN architectures which have improved the performance and accuracy of the models. The latest has pushed the boundaries of CNN capabilities by introducing deeper networks, novel layer designs, and innovative training techniques. Some of these new models are GoogleLeNet and ResNet.

3. Applications of Image Classification for Brands

Some potential case studies that could highlight the effectiveness of CNNs could be in tracking a brand's logo, in fact, a study has already been done using Patch-CNN. In the paper, titled

Patch-CNN: Deep Learning for Logo Detection and Brand Recognition, they stated that applications for this technology involve contextual advertisement placement, copyright infringement detection, vehicle logo detection for automated traffic control systems, and for online product-brand management (Yousaf, 2021). An additional use could be in the detection of unauthorized use of the logo, which could also detect counterfeit products across online platforms, including retail websites and social media. Another application could be in the automotive sector, where companies would use CNNs to monitor and analyse the use of their vehicles via images across social media or automotive forums. This would allow them to understand if the vehicle is featured with greater volume compared to their competitors, the general sentiment towards the product, or simply if the vehicle is being used as intended. As we will see further in our analysis, we chose different car companies to see if there was a contrast between their customer bases.

4. Advantages and Disadvantages of CNNs

While the potential of CNNs in brand reputation management is vast, the key limitations can be summarized as follows: there is a need for extensive training data, which itself could be biased, thus painting an inaccurate representation of the full story. In our case, we used a pre-built model that allowed us to apply the research to many different companies, but this also meant that we could not tune the model to our needs. The training data collection itself could be considered a major obstacle when building such models because each image used to train the model would have to be labelled manually, while at the same time being able to collect enough images to train the model could be considered an obstacle itself. Insufficient data can lead to overfitting, meaning that the network fails to generalize to unseen samples. (Kalra, 2023). Another aspect is the computational complexity of training CNNs, they can be computationally expensive especially when using large-scale datasets and deep architecture, which leads to the necessity of using powerful GPUs or distributed computing resources (Kalra, 2023). Lastly, CNNs are often considered black boxes, which makes it difficult to understand the reasoning behind their predictions.

The key advantage of CNNs instead is local feature learning, which allows them to capture meaningful patterns, irrespective of their position in the image. Another aspect is parameter sharing, this allows CNNs to achieve translation invariance, enabling them to recognize patterns regardless of their position in the image. The last important aspect is automatic feature extraction, meaning that CNNs automatically learn relevant features directly from the data, thus eliminating feature engineering. (Kalra, 2023).

As we have seen, this model has various advantages and disadvantages, in our case, we did not encounter these issues, simply because we used a pre-trained model, but we lost a bit of flexibility. On the other hand, a firm could use its resources to outsource the training of a model that is tailored to their specific needs, thus gaining only the positive aspect of CNNs, and in general, image classification.

Empirical Study

1. Data collection

The data used for this study has been obtained via the use of Apify, in particular, the Instagram Scraper module. We collected data for twenty-seven major brands, with the relevant hashtags and additional information which can be found in the below table.

[1] Summary Table

Brand	**Hashtags**	**Number of Posts**	**Brief Description**
Apple	#shotoniphone, #applewatch	29.7M, 7.1M	Campaigns focus on iPhone's camera capabilities and Apple Watch's health features.
Samsung	#samsunggalaxy	2.6M	Galaxy series campaigns emphasize camera connectivity and ecosystem.
Sony	#PlayStation5, #SonyAlpha	3M, 27M	PlayStation 5 launch and promotion of Alpha series mirrorless cameras.
Microsoft	#MicrosoftTeams, #Windows11	150K, 300K	Teams promoted for hybrid work; Windows 11 launch highlights new OS features.
Gucci	#gucciancora	23K	Focus on sustainability and inclusivity alongside high fashion collections.
Louis Vuitton	#lvxyayoikusama	22K	Campaigns revolve around the fusion of high fashion and avant-garde art.

[1] Summary table containing the list of brands, hashtag used, number of posts and brief description. M stands for Million, K for thousand

Ralph Lauren	#RalphLauren, #RalphLaurenPolo	6M, 165K	Celebrate timeless elegance and sophisticated style with Ralph Lauren's latest collection and embrace the iconic Polo lifestyle
Nike	#justdoit	20.6M	Campaign focus on unleashing your potential and embracing the spirit of determination.
Adidas	#ImpossibleIsNothing	535K	Focus on defying limits and achieving greatness.
Mercedes-Benz	#GClass, #MercedesAMG, #MBFanPhoto	1.1M, 5.7M, 717K	Focus on luxury, performance and sharing passion with the community
Ford	#mustangmache, #builtfordtough	83K, 627K	Campaigns emphasize electric vehicles like the Mustang Mach-E and the strength, durability, and reliability.
Tesla	#tesla, #Model3,	7M, 500K,	Marketing relies on media coverage and Elon Musk's personal brand, focuses on Tesla models.
Toyota	#ToyotaHybrid, #LetsGoPlaces, #ToyotaGazooRacing	122K, 1.5M, 300K	Promotions for hybrid models and success in motorsports with Gazoo Racing, while also embracing adventure and exploring new horizons.
Audi	#AudiEtron, #AudiQuattro	175K, 2M	E-tron series and Quattro anniversary campaigns emphasize luxury and electric vehicle innovation.
BMW	#BMWM, #MPower	8M, 6.3M	M Series promotions focus on luxury and performance.
Disney	#disneyplus, #disneymagicmoments	4.6M, 371K	Disney+ streaming service promotion and theme park experiences.
eBay	#ebayfinds	153K	Focus on sustainable shopping and unique second-hand goods.
Amazon	#primeday, #amazonfinds	330K, 4.3M	Prime Day and ongoing benefits of Prime membership.
Coca-Cola	#shareacoke	614K	Campaigns focus on shared moments and happiness, often tied to holidays.
Pepsi	#pepsihalftime	40K	Focus on music and entertainment, leveraging artist partnerships and events like the Super Bowl Halftime Show.
McDonald's	#imlovinit	640K	Focus on iconic menu items and new burgers.
Burger King	#whopperwednesday	5K	Promotions for plant-based options and sustainability efforts.
Purina	#purina	522K	Campaign focused on pet nutrition and love for pets.

H&M	#HMConscious, #HMxME, #HM	31K, 1.4M, 12M	Focus on sustainable fashion, customer engagement, and style diversity
Ikea	#LifeAtHome, #IkeaIdeas	113K, 150K	Campaigns promote practical and inspirational home decor solutions
Rolex	#Perpetual, #OysterPerpetua, #Rolex	233K, 253K, 20M	Emphasizes timeless design, precision, and luxury in watchmaking
Royal Canin	#RoyalCanin	1.1M	Focuses on tailored nutrition for pets and promoting pet health

Table with the summary of each brand, hashtag used and brief description.

In total, we scraped around 150k posts, of which 72,723 were in English. We chose some relevant hashtags for each brand, searched for the URLs of such hashtags on Instagram, and set a constraint on the date, thus only extracting posts more recent than 2017. The basic concept behind the Web Crawler is that it would navigate the Instagram website, would fetch the page, and parse the HTML content of such page. The data subsequently would be extracted and would be given back to us in CSV format. It is important to note that the Web Scraper has mechanisms for handling errors, thus not all the posts with that particular hashtag were effectively extracted. At the same time, as stated by their blog on the legality of Web Scraping, the Instagram Scraper is ethical and does not extract private users' data. Another important aspect is that Apify's Instagram Scraper respects Instagram's robots.txt file and terms of service, by doing so, it has mechanisms that prevent excessive rates that could disrupt the service.

2. Model Description

As we have stated previously, the model used by Clarifai General Image Recognition is based on an InceptionV2 CNN model which has been customized. InceptionV2 is a refined version of the original Inception, also known as GoogLeNet, which incorporates improvements for better performance and efficiency. This model of Convolutional Neural Network architecture was responsible for setting the new state of the art for classification and detection in the ImageNet Large-Scale Visual Recognition Challenge 2014 (Christian Szegedy, 2014). As stated in the paper Rethinking the Inception Architecture for Computer Vision, written by Szegedy, Vanhoucke, Loffe, Shlens, and Wojna, the general design would include the use of factorizing convolutions, which would reduce the computational cost and parameters without degrading performance, and the use of inception modules. These modules are complex building blocks that allow the network to capture multi-scale features by performing convolutions with different filter sizes in parallel, allowing the network to learn and capture features at different scales simultaneously.

The basic difference between a "traditional" CNN and Inception V2 lies in the architecture, convolutional operations are sequential for simple CNNs while in InceptionV2 they are parallel due to the inception modules. The difference between a linear and sequential approach to that of a complex and parallel with multiple paths can be seen in the efficiency of the model and the overall better performance in the image recognition task compared to traditional CNNs, especially useful in our case.

3. Methodology and Application of LDA

The steps to extract the labels for each image using the General Image Recognition module involve taking each image and converting it in Base64 so that the module can extract the labels. To do so, we ran a Python script in the Python Script node in Knime, where the input was a table that contained all the image paths we wanted to label. The script, which can be found in the Appendix A, starts by importing the necessary Python libraries, including the Clarifai API via gRPC (Remote Procedure Call framework) which efficiently connects services in and across data centres (gRPC, s.d.). Subsequently, the prediction function would be executed, the image file would be opened, read into bytes, and then encoded into Base64. Afterward, the request would be made to the Clarifai API using the prepared image data, and it would return labels with their prediction confidence. We chose to keep only those labels above the confidence threshold of 0.9 to obtain better results.

The basic concept behind Base64 encoding is applying the method for encoding binary data (like images) into ASCII characters, which is a 7-bit character set that contains 128 characters (Senast, 2023). This encoding mechanism is rather common in systems that may not handle binary data well, and it is useful for APIs where binary data needs to be embedded into text-based formats. In this case, the Clarifai API requires the image data to be in Base64 format, thus the encoding part is an essential step for ensuring that the image data remains intact and interpretable. The output of this Python Script for 104,661 images belonging to the 72,723 posts would be a table that contained the file ID, the hashtag, the brand, and the prediction labels which would then be used for the LDA topic Extractor which is saved in a CSV file.

By doing a brief exploratory data analysis for the term occurrence of three brands, Pepsi (Appendix B, Pepsi Term Occurrence), Nike (Appendix B, Nike Term Occurrence), and Apple

(Appendix B, Apple Term Occurrence), we can notice the following information. For Pepsi, there is a predominance of the tag people, with a value of 1952. The presence of the tags such as competition, stadium, football, and indoors is due to the hashtag #pepsihalftime, which is referred to the Superbowl. Let us now analyse Nike's term occurrence. We find terms that are associated with sports, such as competition and exercise, but at the same time, we can find terms such as travel and fashion, indicate that Nike is not only a sports brand. Lastly, let us analyse Apple's term occurrence. As expected, the most common terms are no person, business, and technology. On the other hand, we can notice terms such as travel, outdoors, street, nature, and portrait which can be associated with the hashtag, #shotoniphone, showcasing the usage of Apple products as photo cameras and not only as phones. These terms will then be used in the next step to analyse the topic modelling.

4. Application of LDA

Latent Dirichlet Allocation (LDA) is a statistical model used for topic modelling. It is used to identify latent (hidden) topics within a set of documents, which in our case are the images, while the labels predictions are considered as words of this document. Topic modelling has already been used for text mining and data mining techniques with the objective of finding relationships among data and text documents. Researchers have published many articles applying topic modelling in software engineering, political science, medicine, etc. LDA has already been used for brand characteristic identification, especially via the use of text mining on online reviews as demonstrated by the research of Gou, Wang, Xing, and Lu titled "Mining multi-brand characteristics from online reviews for competitive analysis: A brand joint model using latent Dirichlet allocation".

The implementation in Knime of this model is done via the Topic Extractor (Parallel) LDA node, which is based on the work of Newman, Asuncion, Smyth, and Welling titled, "Distributed Algorithms for Topic Models JMLR (2009), with SparseLDA sampling scheme and data structure". LDA assumes the following generative process for each document (which in our case is an image label set):

1) Choose N (number of words or labels in a document)
2) Choose θ, topic distribution for the document, from a Dirichelt Distribution parametrized by α.
3) For each of the N word/labels:
    a. Choose topic z from the Multinomial distribution defined by θ.

b. Choose a word/label from a Multinomial distribution conditioned on the topic z, parameterized by β, a matrix where each entry β_{ij}represents the probability of word j in topic i.

Mathematically, the joint distribution of a topic mixture θ, a set of N topics z, and a set of N words w is given by:

$$p(\theta, z, w|\alpha, \beta) = p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta) p(w_n|z_n, \beta)$$

The goal of LDA is to compute the posterior distribution of the hidden variables given a document:

$$p(\theta, z, w|\alpha, \beta)$$

This distribution is intractable to compute exactly and is typically approximated using Bayes or collapsed Gibbs sampling methods.

The way we chose to tune the hyperparameters was by running a loop with different values of K and α and the choice for the optimal K would be based on the Perplexity, which is a metric commonly used to evaluate the performance of how well the model predicts unseen or held-out documents. Each iteration of the loop would have its perplexity measure, which would then be plotted on a Line Plot. The choice of the K is based on the elbow method rule, but to be more precise we implemented a Python library called Kneed (Satopaa), whose code can be found in the Appendix A. After finding the optimal K, the Topic Extractor (Parallel) LDA node would be executed again giving us the list of topics. The resulting topics would give us a general idea of the information contained in the images with regards to the brand identity. This approach was done both for the general topic modelling and for the monthly topic modelling of five brands that had the longest period.

5. Results

We will now discuss the results of our topic modelling with both methods, the first extracting the topics from all the brands, while the second approach consists in extracting the monthly topic for five brands that had the longest time span.

General Approach

Executing the Topic Extractor (Parallel) LDA on all the labels for the twenty-seven brands we have analysed resulted in the extraction of eighteen topics. We then visualized the data in a bar chart (Appendix B, Bar Chart for General Topic), where each bar represented the frequency of finding that particular topic for the specific brand. This allowed us to not only visualize the most frequent topic for each brand but to also check if there were some unexpected associations. To better help visualize the data in the bar chart, we decided to show the average. The reason behind this choice is due to the fact that some brands have more photos, thus if we showed the occurrence of the topic, it could mislead the viewer into thinking that there is a higher prevalence of some brands compared to others. The results from this Topic Modelling via the use of labels extracted from image classification are promising. We can see that there are dominant topics for specific brands that are coherent with the general view of such brands. For example, we have that for Apple, the most dominant topic is Technology and Electronics, for Ikea, the most dominant topic is Modern Interior Design, for Purina and Royal Canin, which are both pet food-centred brands, we have the most dominant topic being Domestic Animals and Pets. Rolex has the most dominant topic of Watchmaking and Timekeeping followed by Luxury Fashion and Accessories. Instead, if we look at a broad vs. niche focus, we can see that eBay and Amazon show a more diverse association across multiple topics. The reason behind this is that both are an online marketplace, thus it is common to find images that contain a broader range of topics. Conversely, brands like Gucci have high peaks in specific topics that are relevant to their industry. We can see the dominance of the topic Women's Fashion and Portraiture for H&M. Some unexpected associations can also be found, for example, Pepsi has an extraordinarily strong association with Music Festivals and Performance. This can be explained by looking at the choice of hashtags, which in this case involve the Super Bowl. As we can see, the hashtag #pepsihalftime has associated the brand with musical performances, considering the sheer volume of attendance, both in presence and from home, of the Super Bowl, we could say that the marketing choice has allowed Pepsi to cement its presence. Another example of unexpected associations is for both Nike and Adidas, both have a high frequency for Music Festivals and Performances. A strong motivation for this association could be their presence in Pop-Culture and streetwear, which has been embraced by both Adidas and Nike, which can then be seen in how many Pop Artists dress. A concrete example is Nike Jordans, which have been a reference to Pop-Culture since the late 80s (Cole, 2022). You can see the presence of Jordans in music, television, and movies, but recently artist have been having their collaborations with the brand. We have seen the release of Air Jordans 1, Air Jordan 4, and Air Jordans 6 with the collaboration of Travis Scott. Another example of an unexpected association can be seen in the case of Sony. Also in this case, the result has to do with the choice of the hashtag, we can see a similar presence between Music Festivals and Performance, Women's Fashion and Portraiture, and Outdoor Nature and Travel. The hashtag #sonyalpha can incorporate many different topics, simply because a digital camera can capture diverse types of pictures. Sector-specific insights can be seen in the automotive sector, brands like Tesla, BMW, Audi, and Mercedes all have as a strong topic High-Speed Road Driving and Classic Car Shows and Exhibitions. Ford and Toyota on the other hand, have a more even distribution of the automotive topics which also include Industrial Technology and Machinery, suggesting that what sets apart Ford and Toyota from the other car brands is based on customer perception. The use of hashtag #builtfordtough, which is a staple characteristic of Ford's marketing, is aimed at blue-collar US customers who use their trucks for hauling heavy loads, ranching, etc. The same can be said regarding the pickup trucks of Toyota, which are known for their reliability and off-trail capabilities. This later feature is seen with the presence of the topic Outdoor Nature and Travel, which is not very dominant but at the same time has a notable presence. However, we can see that these two brands also have diversified their customer base, as seen by the presence of the topics that are common to Automotive Racing. This is because, even if Toyota and Ford are known for their pickup trucks, both brands offer distinct categories of cars depending on the customer's needs.

This table shows all the twenty-seven brands and their five most occurring topic associations.

[2] Topic per Brand with Decreasing Order of Topic Association

Brand	**Most Frequent Topic Association (Top Five)**				
Adidas	Music Festivals and Performances	Women's Fashion and Portraiture	Outdoor Nature and Travel	Digital Marketing and Design Templates	Automotive Racing and Transportation
Amazon	Digital Marketing and Design Templates	Graphic Design and Retro Illustrations	Women's Fashion and Portraiture	Modern Interior Design	Technology and Electronics
Apple	Technology and Electronics	Women's Fashion and Portraiture	Digital Marketing and Design Templates	Urban Travel and Architecture	Outdoor Nature and Travel

[2] Top 5 Topics per Brand

Audi	Classic Car Shows and Exhibitions	High-Speed Road Driving	Luxury Vehicle Interiors	Automotive Racing and Transportation	Industrial Technology and Machinery
BMW	High-Speed Road Driving	Classic Car Shows and Exhibitions	Automotive Racing and Transportation	Luxury Vehicle Interiors	Industrial Technology and Machinery
Burger King	Culinary and Dining Experiences	Fast Food Trends and Innovations	Urban Eating and Fast-Food Culture	Music Festivals and Performances	Food and Beverage Marketing
Coca-Cola	Digital Marketing and Design Templates	Beverage Marketing and Branding	Music Festivals and Performances	Outdoor Advertising Campaigns	Food and Beverage Marketing
Disney	Women's Fashion and Portraiture	Children's Entertainment	Theme Park Attractions	Animated Films and Media	Domestic Animals and Pets
eBay	Graphic Design and Retro Illustrations	E-commerce Trends and Statistics	Women's Fashion and Portraiture	Online Marketplaces and Auctions	Technology and Electronics
Ferrari	High-Speed Road Driving	Luxury Sports Cars and Automobilia	Automotive Racing and Transportation	Classic Car Shows and Exhibitions	Outdoor Nature and Travel
Ford	Industrial Technology and Machinery	High-Speed Road Driving	Automotive Engineering and Design	Classic Car Shows and Exhibitions	Luxury Vehicle Interiors
Gucci	Women's Fashion and Portraiture	Luxury Fashion and Accessories	High Fashion Events and Shows	Urban Fashion and Lifestyle	Graphic Design and Retro Illustrations
H&M	Women's Fashion and Portraiture	Urban Fashion and Lifestyle	Sustainable Fashion and Eco Trends	Casual and Everyday Fashion	Modern Interior Design
Ikea	Modern Interior Design	Home Furnishings and Decor	Sustainable Living and Eco Solutions	Culinary and Dining Experiences	Urban Travel and Architecture
Louis Vuitton	Women's Fashion and Portraiture	Luxury Fashion and Accessories	High Fashion Events and Shows	Urban Travel and Architecture	Casual and Everyday Fashion
McDonald's	Culinary and Dining Experiences	Fast Food Trends and Innovations	Food and Beverage Marketing	Music Festivals and Performances	Urban Travel and Architecture
Mercedes-Benz	Classic Car Shows and Exhibitions	High-Speed Road Driving	Luxury Vehicle Interiors	Automotive Racing and Transportation	Industrial Technology and Machinery

Microsoft	Digital Marketing and Design Templates	Technology and Electronics	Software Development and Innovation	Women's Fashion and Portraiture	Modern Interior Design
Nike	Music Festivals and Performances	Urban Sportswear and Athletics	Digital Marketing and Design Templates	Graphic Design and Retro Illustrations	Women's Fashion and Portraiture
Pepsi	Music Festivals and Performances	Beverage Marketing and Branding	Food and Beverage Marketing	Digital Marketing and Design Templates	Urban Travel and Architecture
Purina	Domestic Animals and Pets	Veterinary Science and Animal Care	Pet Products and Accessories	Women's Fashion and Portraiture	Graphic Design and Retro Illustrations
Ralph Lauren	Women's Fashion and Portraiture	Luxury Fashion and Accessories	Casual and Everyday Fashion	Urban Travel and Architecture	Graphic Design and Retro Illustrations
Rolex	Watchmaking and Timekeeping	Luxury Watches and Collectibles	Jewelry and High-End Accessories	Men's Fashion and Grooming	Women's Fashion and Portraiture
Royal Canin	Domestic Animals and Pets	Veterinary Science and Animal Care	Pet Nutrition and Health	Women's Fashion and Portraiture	Music Festivals and Performances
Samsung	Urban Travel and Architecture	Technology and Electronics	Digital Marketing and Design Templates	Graphic Design and Retro Illustrations	Women's Fashion and Portraiture
Sony	Music Festivals and Performances	Technology and Electronics	Digital Gaming and Entertainment	Graphic Design and Retro Illustrations	Women's Fashion and Portraiture
Tesla	Classic Car Shows and Exhibitions	Electric Vehicles and Sustainability	Automotive Racing and Transportation	High-Speed Road Driving	Industrial Technology and Machinery
Toyota	Automotive Racing and Transportation	High-Speed Road Driving	Classic Car Shows and Exhibitions	Luxury Vehicle Interiors	Industrial Technology and Machinery

Table with the Top 5 Topic Associations for each Brand

Because the Instagram posts included the caption, we decided to implement Sentiment Analysis via Text Mining. The sentiments captured from the caption were categorized as Positive, Very Positive, Negative, Very Negative, and Neutral. Afterward, we ran a linear correlation on all the data to see if we could find some interesting insights (Appendix B, Linear Correlation Matrix). Overall, between the brands and the topics, we found a positive correlation similar to the results originating from the bar chart. There is a positive correlation, between Rolex and Watchmaking having a value of 0.5289 and Rolex with Luxury Fashion Accessories, with a value of 0.3732. There was no noticeable negative correlation between brands and topics to be noted. Instead, if we look at the sentiment extracted and the correlation present with the brands, there are significant results. The only case in which there was a slight positive correlation is between Rolex and the very positive sentiment, having a value of 0.2405, and the other case is between Amazon and Negative sentiment, having a small positive correlation of 0.1734. We can also notice how the topics do not have a positive or negative correlation between them, indicating that the Topic Extractor model has worked.

Time Serie Approach

This other approach emphasized the possibility of being able to monitor brands and see if it is possible to notice variations in topic association from a customer's perception. The analysis involved five brands that had the longest period; thus, we analysed Burger King, with the first post being from 2017-02-08 and the latest being from 2024-04-03. The other brand is Pepsi, starting from 2019-08-16 to 2024-04-03, then McDonalds with posts from 2020-03-10 until 2024-04-07. The last two brands are Microsoft, starting from 2021-03-25 until 2024-04-09, and lastly, H&M, starting from 2021-10-12 until 2024-04-10. For Microsoft, McDonalds, and H&M the time series approach showed a consistency in the topics, while for Burger King and Pepsi, we noticed a slight change in topic assignment during the time span. In particular, Pepsi has a dominant topic in Creative Design and Fashion industry, which indicates its presence in Pop-Culture with marketing campaigns that involve Pop Artists, for example, Beyonce and Cardi B. At the same time, the launch of Pepsi Music Lab has also helped mark their influence in the music industry, allowing to show them to engage directly with the creative community. The other topic that was found is Sports and Activities, which at first might seem out of place, but analysing the period, we can see the date is 2022-02, the month of the Super Bowl (Appendix B, Super Bowl Mediatic Impact for Pepsi). This is an important discovery, being that Pepsi is the sponsor of the halftime show, we can analyse the virality of the event, having important Pop Artists such as Snoop Dogg, Eminem, Dr. Dre, Kendrick Lamar, etc. For Burger King, we can notice an interesting pattern between the two topics. The first is the general topic of Fast Food and Dining, while the second is Fish and Outdoor Recreation. This last topic is found with a certain consistency during the spring and summer months, suggesting a certain peak in the popularity of fish-based burgers (Appendix B, Burger King Topic Cyclicality).

Conclusions and Further Research

1. Summary of Findings

This thesis explored the application of image recognition technologies, using a pre-trained Convolutional Neural Network (CNN) and Latent Dirichlet Allocation (LDA) to analyse the brand reputation through visual content. This study demonstrated the effectiveness of CNN in labelling images and extracting relevant information associated with brands, which were then analysed using LDA to obtain topics for each brand. Key findings highlighted several dominant themes across distinct brands and the possibility of grouping brands into their industries. LDA revealed consistent patterns in the General Approach which would allow brands to better understand the customer perception, while the Time Series approach allowed us to extract some changes in brand perception. In the case of Pepsi, the mediatic impact of the Super Bowl halftime could have been used to their advantage to push a new flavour of their product. For Burger King instead, the trend of period changes in the topic, going from Fast Food to Fishing, could be used to their advantage to promote their fish-based products.

2. Conclusions

The integration of CNN and LDA presents a robust method for monitoring and analysing brand reputation based on visual content. This approach allows for a deeper understanding of the brand image in an automated, scalable manner, offering significant advantages over traditional manual monitoring methods. The findings affirm that machine learning and topic modelling are invaluable tools for brand management, marketing strategy, and in general brand reputation, enabling brands to adapt more dynamically to changing consumer sentiments.

3. Limitations

While the study provides valuable insights, there are several limitations which must be acknowledged. First of all, the accuracy of the CNN and LDA models is highly dependent on the quality of the input data. Biases in the dataset can skew the analysis and lead to misleading conclusions. Additionally, the choice of the hashtag used for the acquirement of the images could also influence the images obtained, thus altering the results. The use of a pre-trained CNN model may also not capture all nuances specific to different brand images, particularly those from niche or evolving sectors. Another important aspect to consider is the brand's presence in the social media platform and the popularity of the hashtags, thus not allowing this study to be applicable to all types of brands and market segments.

4. Further Research

Given the limitations and the scope of the initial study, several areas for further research can be identified. Extending the analysis to include additional data from multiple platforms could help improve the sentiment analysis could improve the multi-faceted view of brand reputation, encompassing both visual and textual data. The sentiment extracted via the use of the Instagram caption might not capture the complete sentiment towards a particular brand, being that Instagram is based on photo sharing. Exploring more advanced deep learning architecture could also improve the specificity and accuracy of image recognition, which is the essential part of the study on which the topic modelling is based, thus using a better model could improve the overall results.

Appendix A: Code Listings

Knime adjusted code for the image labelling, via the Python Script node.

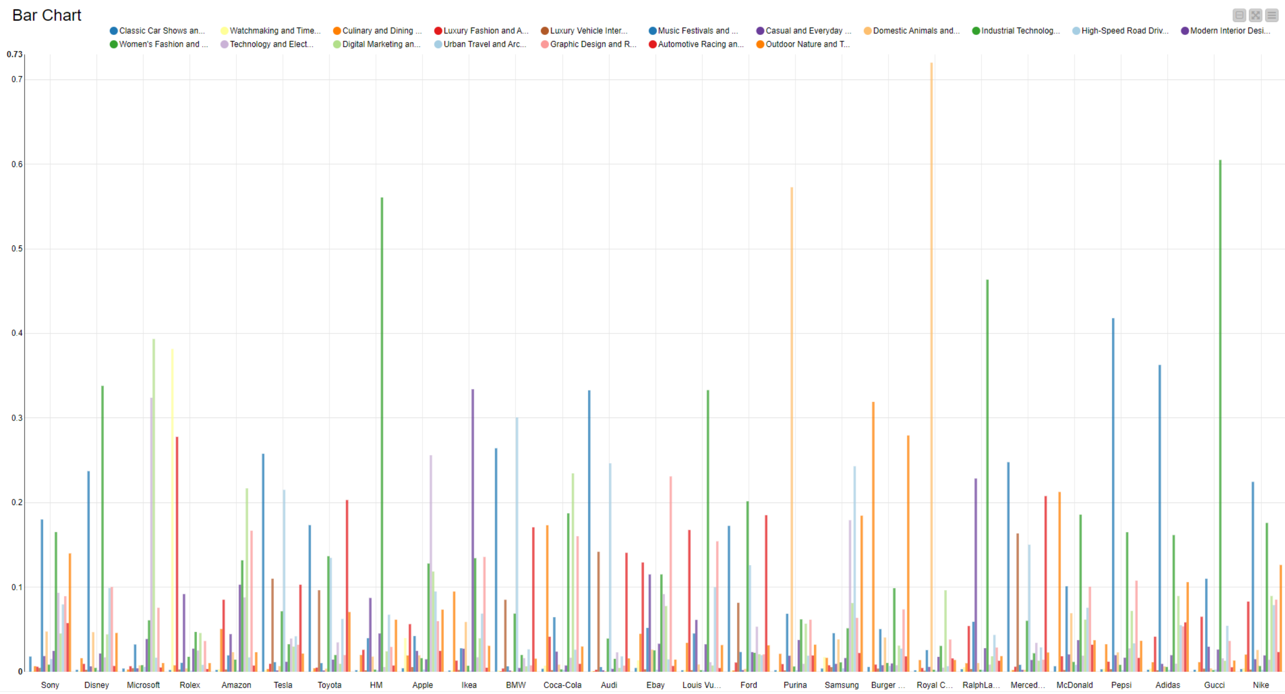
```
import pandas as pd
from clarifai_grpc.channel.clarifai_channel import ClarifaiChannel
from clarifai_grpc.grpc.api import resources_pb2, service_pb2, service_pb2_grpc
from clarifai_grpc.grpc.api.status import status_code_pb2
import knime.scripting.io as knio

# Your PAT and other constants
PAT = 'insert your PAT here'
USER_ID = 'clarifai'
APP_ID = 'main'
MODEL_ID = 'general-image-recognition'
MODEL_VERSION_ID = 'aa7f35c01e0642fda5cf400f543e7c40'

channel = ClarifaiChannel.get_grpc_channel()
stub = service_pb2_grpc.V2Stub(channel)
metadata = (('authorization', 'Key ' + PAT),)
userDataObject = resources_pb2.UserAppIDSet(user_id=USER_ID, app_id=APP_ID)

def predict_image(image_path):
    """Read image and predict using the model, return results as a string."""
    # Check if the input is an FSLocationValue and extract the path
    if hasattr(image_path, 'path'):
        image_path = image_path.path  # Accessing the path attribute directly

    with open(image_path, "rb") as f:
        file_bytes = f.read()
    response = stub.PostModelOutputs(
        service_pb2.PostModelOutputsRequest(
            user_app_id=userDataObject,
            model_id=MODEL_ID,
            version_id=MODEL_VERSION_ID,
            inputs=[
                resources_pb2.Input(
                    data=resources_pb2.Data(
                        image=resources_pb2.Image(base64=file_bytes)
                    )
                )
            ]
        ),
        metadata=metadata
    )
    if response.status.code != status_code_pb2.SUCCESS:
        print(response.status)
        #raise Exception("Post model outputs failed, status: " + response.status.description)
```

```
    predictions = [(concept.name, concept.value) for concept in response.outputs[0].data.concepts if
concept.value > 0.9]
    return ', '.join([f"{name}: {value:.4f}" for name, value in predictions])

# Load the input data from the KNIME workflow
input_table = knio.input_tables[0].to_pandas()
test = input_table['Path']

# Create a new DataFrame from the Series
output_table = pd.DataFrame(test)

# Adding a column for predictions as string, handling FSLocationValue properly
output_table['Predictions'] = output_table['Path'].apply(lambda x: predict_image(x))

# Output the DataFrame to the KNIME workflow
knio.output_tables[0] = knio.Table.from_pandas(output_table)
```

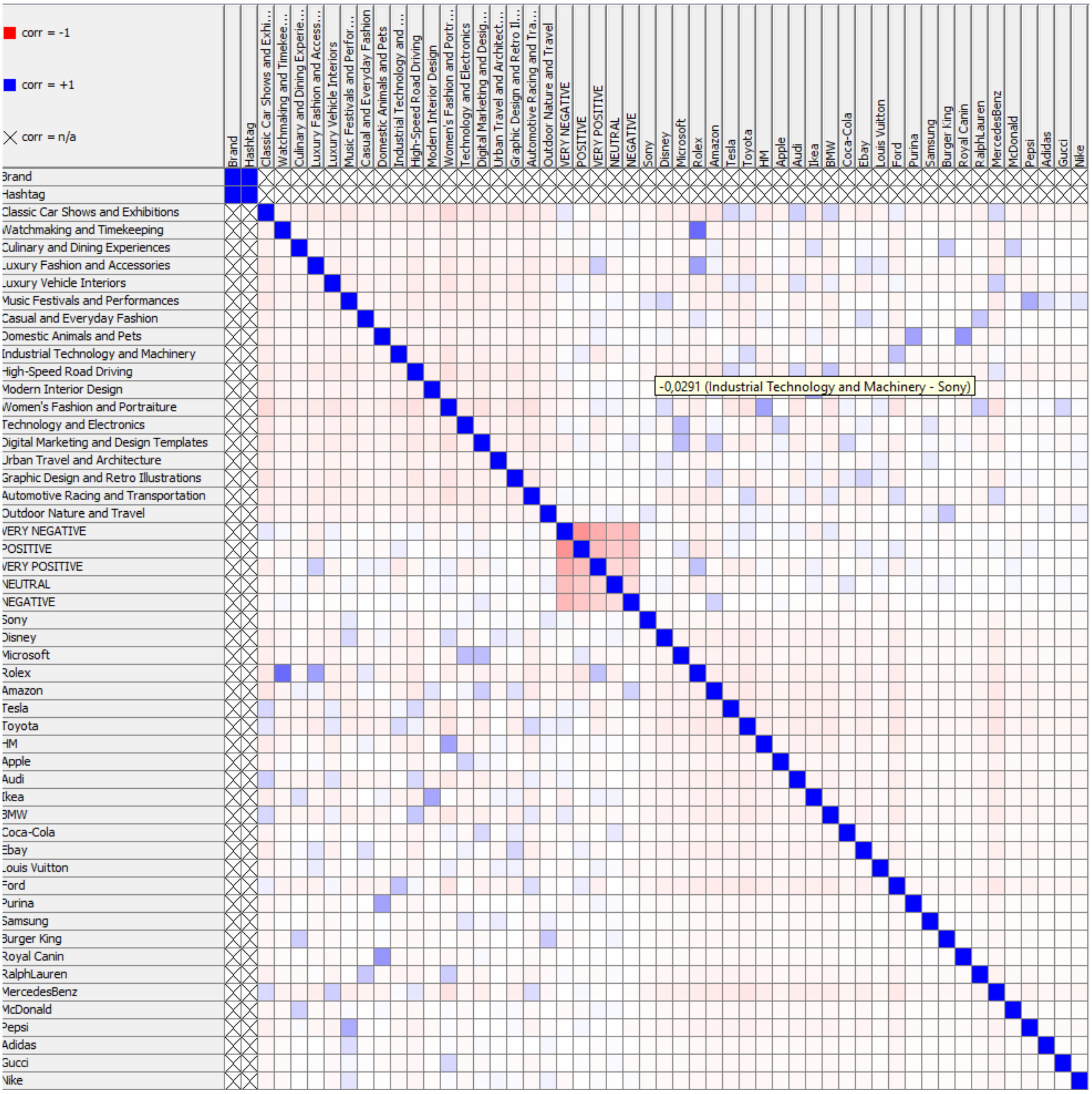
Code for the optimal K via the Kneed Python library using the function KneeLocator.

```
import knime.scripting.io as knio
import numpy as np
from kneed import KneeLocator
import pandas as pd

# This example script simply outputs the node's input table.
test = knio.input_tables[0].to_pandas()

# Convert columns to lists or numpy arrays
x = test["K"].values  # Topic numbers, converted to numpy array
y = test["Perplexity"].values  # Perplexity values, also converted to numpy array

# Find the knee point
knee_locator = KneeLocator(x, y, curve='convex', direction='decreasing')
elbow_point = knee_locator.knee

# Add the elbow point to the DataFrame
test["Elbow Point"] = elbow_point

# Output the DataFrame to the KNIME workflow
knio.output_tables[0] = knio.Table.from_pandas(test)
```

Appendix B: Tables and Data



Bar Chart for General Topic Modelling



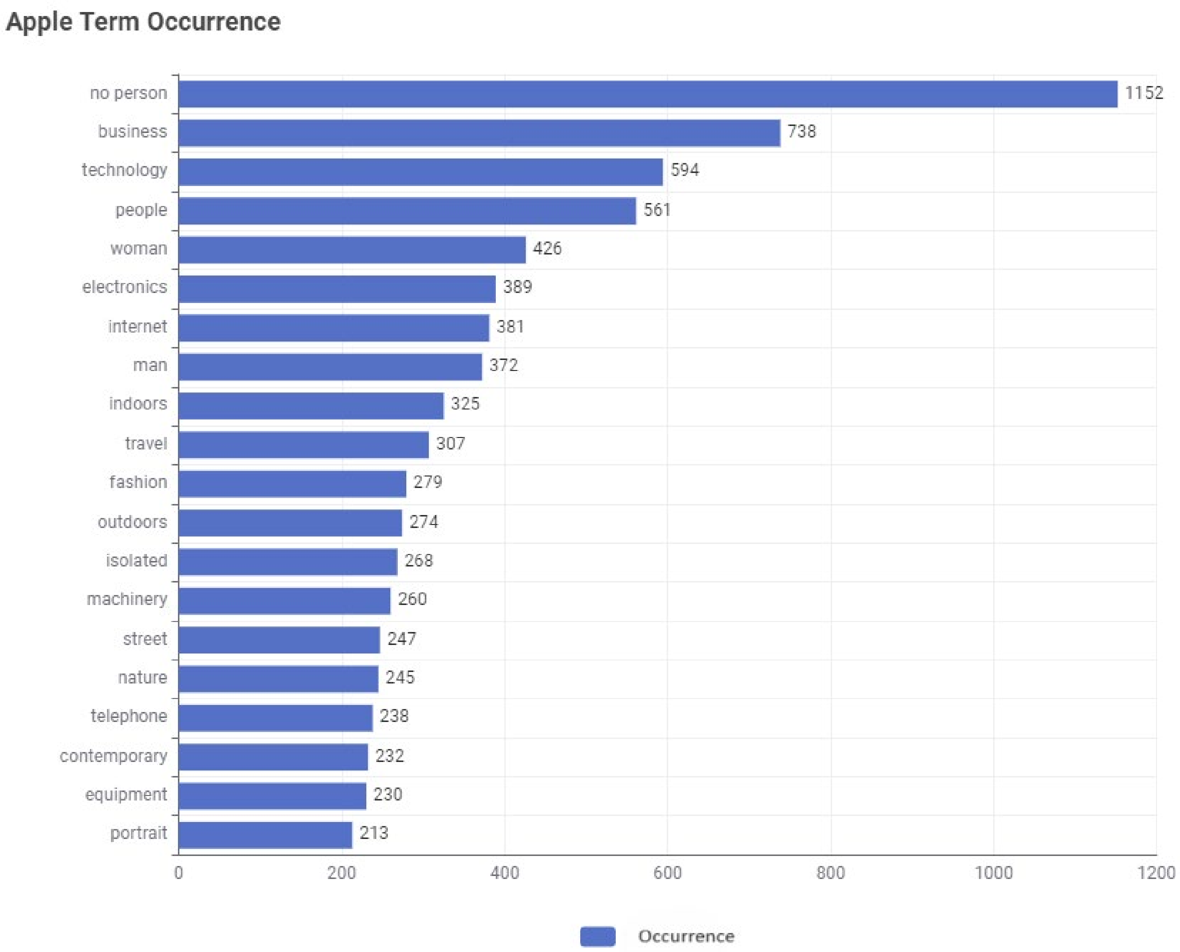
Linear Correlation Matrix

Row...	Brand (String)	Year (Number (integer))	Month (Number (integer))	Mode(Assigned topic (right)) (String)
Row...	Burger King	2021	4	Fishing and Outdoor Recreation
Row...	Burger King	2021	5	Fast Food and Dining
Row...	Burger King	2021	6	Fishing and Outdoor Recreation
Row...	Burger King	2021	7	Fishing and Outdoor Recreation
Row...	Burger King	2021	8	Fast Food and Dining
Row...	Burger King	2021	9	Fast Food and Dining
Row...	Burger King	2021	10	Fast Food and Dining
Row...	Burger King	2021	11	Fast Food and Dining
Row...	Burger King	2021	12	Fast Food and Dining
Row...	Burger King	2022	1	Fast Food and Dining
Row...	Burger King	2022	2	Fast Food and Dining
Row...	Burger King	2022	3	Fishing and Outdoor Recreation
Row...	Burger King	2022	4	Fast Food and Dining
Row...	Burger King	2022	5	Fast Food and Dining
Row...	Burger King	2022	6	Fishing and Outdoor Recreation
Row...	Burger King	2022	7	Fishing and Outdoor Recreation

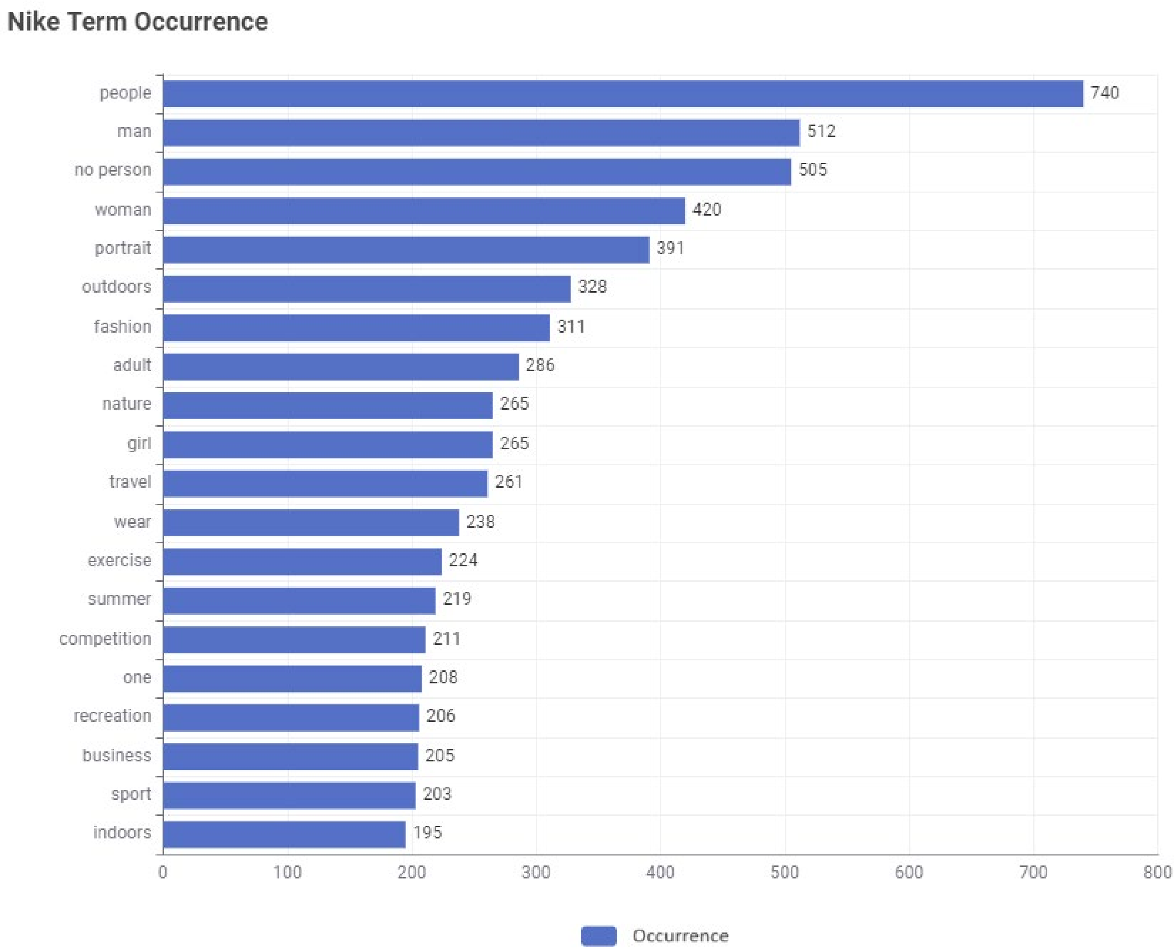
Burger King Topic Cyclicality

Row...	Brand (String)	Year (Number (integer))	Month (Number (integer))	Mode(Assigned topic (right)) (String)
Row...	Pepsi	2019	8	Creative Design and Fashion Industry
Row...	Pepsi	2019	9	Creative Design and Fashion Industry
Row...	Pepsi	2019	11	Creative Design and Fashion Industry
Row...	Pepsi	2021	2	Creative Design and Fashion Industry
Row...	Pepsi	2021	11	Creative Design and Fashion Industry
Row...	Pepsi	2022	1	Creative Design and Fashion Industry
Row...	Pepsi	2022	2	Sports and Activities
Row...	Pepsi	2022	3	Creative Design and Fashion Industry
Row...	Pepsi	2022	4	Creative Design and Fashion Industry
Row...	Pepsi	2022	5	Creative Design and Fashion Industry
Row...	Pepsi	2022	6	Creative Design and Fashion Industry
Row...	Pepsi	2022	7	Creative Design and Fashion Industry

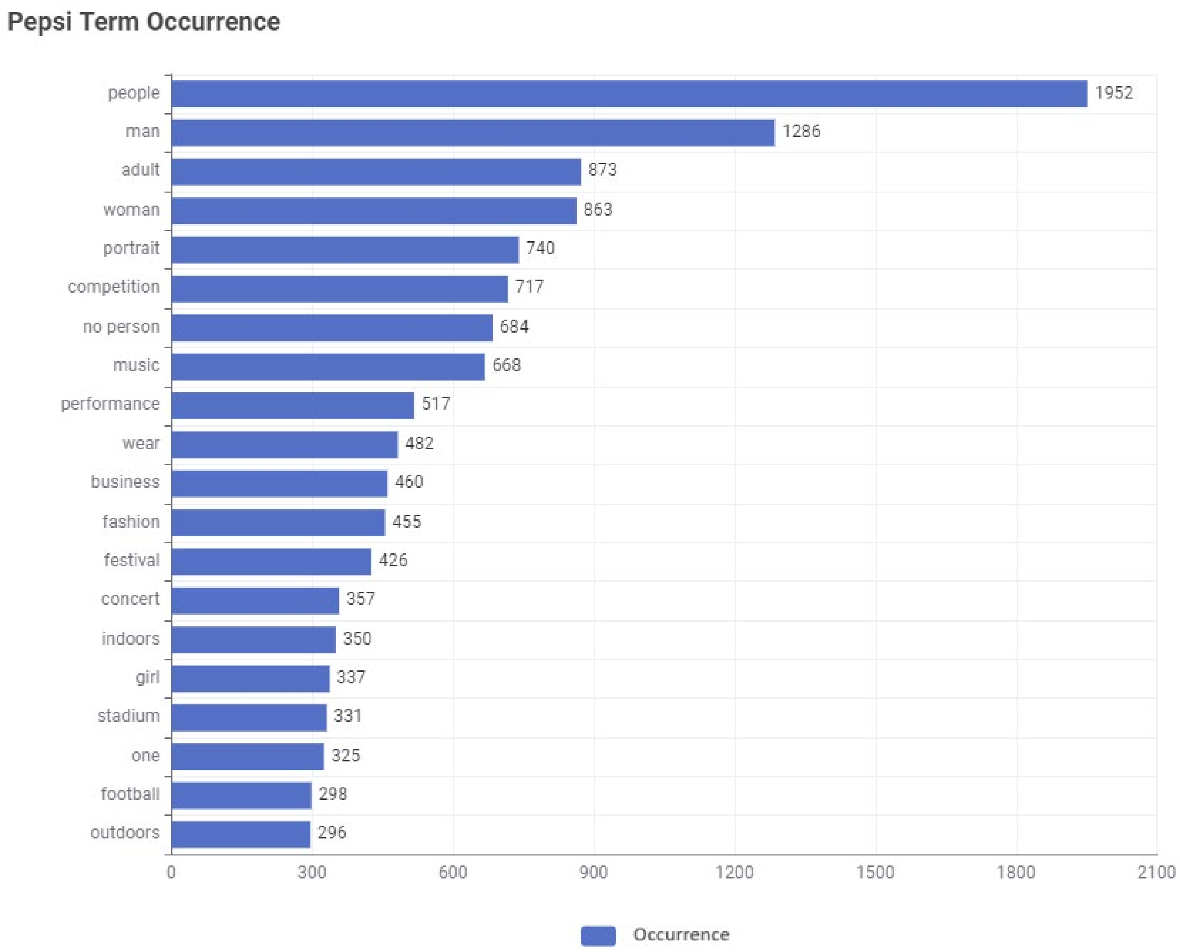
Super Bowl Mediatic Impact for Pepsi



Apple Top 20 Term Occurrence



Nike Top 20 Term Occurrence



Pepsi Top 20 Term Occurrence

Acknowledgements

I'd like to thank my supervisor, Professor Francisco Javier Villarroel Ordenes, for his help and advice throughout this research endeavour. His knowledge in business and marketing analytics has greatly enhanced this experience.

I'd like to thank the Management and Computer Science faculty at LUISS Guido Carli University. Their insightful comments and lessons have contributed considerably to my academic and personal development.

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