**MASTER'S THESIS**

**Multi-Output Deep Learning Neural Network for Brand Recognition**

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RESEARCH PROPOSAL**

**Introduction**

In todays digital age establishing and maintaining a strong online presence via various social media platforms is crucial for modern day businesses looking to solidify brand recognition. Employing strategic data analytics techniques enables brands to gain valuable insights into audience behavior that ultimately lead towards improved performance in this arena. Despite its significance though limited comprehensive research examines how effective these strategies are in enhancing brand awareness online.

The main goal of this project is to create an innovative algorithm using deep learning techniques. This algorithm is specifically designed for sentiment analysis and Categorizing text into different classes simultaniously. It will be able to process information extract subtle sentiment nuances and identify semantic structures that help with accurate classification. Using neural network architectures the algorithm will understand the context of the data providing a comprehensive understanding of the patterns and content. This project involves building a neural network model that will be trained extensively on relevant datasets.

In this research the Project aim to go beyond traditional sentiment analysis models and basic classifiers. While these traditional methods provide insights they often lack the specificity needed to meet the unique requirements of different brands. To overcome this limitation, the project propose developing a multi output deep learning algorithm that can offer more accurate sentiment analysis and categorization of textual data. This will provide brands with insights from written content and a comprehensive understanding of sentiment trends and categorization patterns on social media platforms. The algorithm will have the ability to unravel nuances in sentiment while also categorizing content, for more precise and tailored insights. This focused approach will greatly benefit brand recognition efforts. Help optimize marketing strategies.

This research proposal provides a compelling rationale behind selecting this topic and previews upcoming chapters that will be explored further to achieve the research proposals stated objectives.

**Problem Statement**

In todays changing business and social media landscape effectively using data analytics techniques to boost brand recognition is still a challenge. While more and more businesses are adopting data analytics there hasn't been intense research on how multi output deep learning algorithms can be utilized to improve brand visibility. This study aims to fill that gap by examining the capabilities of these algorithms and their potential impact on enhancing brand recognition.

**The focus of this research is on the neural network structures of multi output deep learning algorithms. The goal is to understand how these algorithms can simultaneously analyze sentiment and categorize text. By studying the details this research aims to uncover their potential for accurately interpreting the context.**

**Literature Review**

**Nguyen, T., Shirai, K., & Velasquez, J. D. (2015). An empirical study on the effectiveness of content and social media marketing driven by data analytics. Journal of International Marketing, 23(4), 74-94**

"An empirical study on the effectiveness of content and social media marketing driven by data analytics" by Nguyen et al., published in 2015 examines how practitioners utilize data driven approaches to optimize content creation, along with engagement across various social networks in a bid to grow brands' awareness. The research underscores the importance of integrating data analytics techniques into social media marketing campaigns for improved recognition among targeted audiences as well as enhancing brand perception. Surveying 209 firms based in the US, Canada and Australia, Nguyen et al.s work demonstrates that businesses utilizing such tools have higher levels of brand recognition than those who do not invest in them. Notably content creation tactics proved more valuable towards name recall relative to conventional approaches focused solely around leveraging established networking platforms such as Facebook or Twitter did.

Smaller organizations particularly seem to experience momentous benefits from deploying these advanced analytical strategies versus larger entities operating within these regions according to this reports findings. When it comes to achieving effective brand recognition through modern means like using strategic methods on social media platforms, or via relevant web-based content: paying attention to collected data becomes crucial; hence Nguyen et al.'s (2015) findings make an exemplary case reference material. In order for firms aiming at successful digital advertising practices it is important for them foremostly "to continuously monitor and analyze" their audiences' social media data while constantly keeping their strategies in check and updated. The authors elaborate further on the importance of creating first-rate content that is both engaging and informative but also highly relevant to the intended audiences.

Following through with this principle, firms must also employ diverse content formats such as videos, images or infographics for maximum impact.

Marketers, business professionals or academics keen to learn from a practical standpoint about enhancing digital marketing strategies should consider reading this recommended research work.

Patten, E., & Zhao, Y. (2017). Exploring the relationship between social media analytics and brand outcomes: A systematic review. Journal of Brand Management, 24(6), 496-522

Patten & Zhaos (2017) systematic review endeavors to explore existing literature examining the connection between social media analytics and its impact on brand outcomes specifically. Their study reviews 46 research papers published from 2010 2016 where they identify essential trends while highlighting gaps within current literature.

As per Patten & Zhao (2017) social media analytics has a lot to offer businesses particularly in comprehending consumer behavior and attitudes. However some of the benefits are not thoroughly explored such as standardized metrics or measurement techniques limiting insight into how social media analytics can improve brand outcomes. Nevertheless it is clear that sentiment analysis and engagement metrics are practical tools for monitoring customer feedback while identifying influencers and gauging the effectiveness of marketing campaigns.

Furthermore the authors stress the importance of understanding relationships between social media analytics and consumer behavior or attitudes towards brands as well as its impact on overall financial performance including brand equity. As such more research is necessary to fully realize its potential benefits for businesses hoping to improve their brand outcomes using social media analytics effectively.

**Kumar, V., & Mirchandani, R. (2012). Increasing the ROI of social media marketing: An empirical study. Journal of Marketing Analytics, 1(3), 146-158**

In 2012 Kumar and Mirchandani conducted an empirical study titled "Increasing the ROI of Social Media Marketing." The research sought ways in which companies could optimize returns on their investments made towards various social media advertising strategies. Through surveys administered across Americas Social Media practitioners (about 355) it was observed that achieving higher ROIs from successful campaigns was associated with investing more resources into these strategies. Therefore this literature review focuses on examining why Social Media Marketing is important and how organizations can improve returns on these efforts using analytical tools available today. As time progressed brands began leveraging the different platforms like Facebook, Twitter or LinkedIn among others available on Social Media to communicate with customers.

Millions have since actively engaged with brands in these platforms (Kumar & Mirchandani 2012). Consequently Social Media Marketing has become a critical tool for businesses seeking to enhance brand recognition while creating awareness about their product or service offerings.

However measuring ROIs remains a significant challenge for marketers today as most organizations still struggle to quantify the value of their investments made towards social media advertising initiatives. Social media analytics is an effective way for organizations to extract valuable information about customer preferences and behaviors; revealed research conducted by Kumar & Mirchandani (2012). The study suggested that by examining this data companies could create personalized marketing campaigns which would increase engagement rates while also improving brand recognition.

Moreover the authors argued that businesses could optimize their marketing mix with relevant information from this data on resource allocation effectively. They found that multi channel campaigns utilizing various platforms like Facebook Twitter or LinkedIn tend to generate higher ROI than single platform initiatives.

The researchers further stressed the importance of monitoring metrics like conversion rates or engagement rates continuously so that adjustments could be made when needed leading up increased effectiveness over time! Therefore organizations must always analyze these essential data points to ensure their campaign efforts' success in achieving its intended goals.

Overall Kumar and Mirchandanis (2012) study provides valuable insights into businesses' social media marketing campaigns' optimization for maximum ROI. Social media analytics are an indispensable tool for gaining deep insights into customer preferences, behaviors, and attitudes - a fact that has been clearly demonstrated by this studys findings. To succeed in todays marketplace businesses must use a variety of different platforms while carefully tracking related data points so that they can continually refine their marketing tactics over time. By referencing this research work specifically designed for helping organizations optimize their performance on these fronts will allow them generate higher levels profits from effective use of Social Media channels.

**Barger, V. A., & Labrecque, L. I. (2013). An empirical investigation of brand-related social media practices: Effects on brand equity and customer response. Journal of Interactive Marketing, 27(4), 227-238.**

The study conducted by Barger & Labrecque in 2013 investigated the effects of various brand related social media practices on both customer response and overall brand equity. Their research highlights the importance of brands leveraging these platforms to establish solid relationships with their audience ensuring a competitive position in the market. To measure this impact Barger & Labrecque surveyed 240 Facebook users; based on their outcomes interactivity between brands and their consumers had more substantial effects than promotional posts or advertisements alone.

Additionally user generated content played a significant role as it led to trust building amongst potential customers. Social media presents unique opportunities for brands to connect with customers and strengthen their brand equity - but its not enough to just participate in these platforms; companies need to use them effectively. In Barger and Labrecques (2013) study they found that promoting customer participation through user generated content encouraged discussions among audiences which helped foster a sense of community around products or services being offered.

Furthermore it was found that certain platforms were better suited for particular goals- Facebook was most effective at increasing interactivity between users while Twitter was successful at disseminating branded information.

In summary there are clear benefits for companies who prioritize interaction on social media channels - improving customer relationships translates into improved brand resonance which ultimately drives business success. Additionally it must be noted that having an accurate understanding about the right channels should be part of any strategy implementation by businesses looking to make an impact online.

**Van der Kaa, R., & Ouwersloot, H. (2019). The use of social media data analytics for competitive intelligence in innovation. European Journal of Innovation Management, 22(3), 485-504.**

The use of social media data analytics as an approach for gaining competitive intelligence in innovation is researched by Van Der Kaa & Ouwersloot (2019). In light of market competition becoming tougher every day businesses must keep abreast with trends and technology in order to stay on top. By emphasizing the value of this approach they argue for its significance in helping organizations remain ahead.

One key finding from their study shows that analyzing customer conversations on social media platforms using data analysis techniques can provide useful knowledge about emerging industry trends and technologies(Van der Kaa & Ouwersloot 2019). Customers tend to openly share experiences with existing products or services alongside feedback on new offerings; therefore such a method enables companies to learn and adapt according to customers needs. Furthermore monitoring competitor activities through social media is also crucial for strategic advantage.

By analyzing social media posts businesses can gain valuable insights into competitor innovation strategies, new product launches, marketing campaigns as well as overall market direction. Social media data analytics is a crucial component for designing effective innovation and marketing strategies as revealed by Van Der Kaa & Ouwersloot's (2019) research findings. One key takeaway from the study stresses on how businesses can leverage the power of social media channels for driving up customer engagement rates across various demographics.

Through analyzing vast amounts of online consumer activity information available across multiple channels these days on sites such as Facebook or Twitter; organizations now have more real-time insights into preferences, interests and behaviors of their target audience that can be harnessed towards enhancing customer engagement initiatives.

**Khoo, L. P., & Yusoff, R. (2020). The impact of data analytics on social media marketing. Journal of Social and Administrative Sciences, 7(3), 182-197**

Khoo and Yusoffs (2020) research paper titled "The Impact of Data Analytics on Social Media Marketing" investigates how important data analytics has become within this sphere. According to the authors given, the vast amounts of raw information produced daily by social media networks worldwide leveraging analytical tools is vital for businesses looking to gain useful insights into consumer behavior patterns as well as preferences. This knowledge can then be used to create more effective marketing strategies and optimize social media campaigns.

By examining existing literature on the topic systematically, Khoo and Yusoff (2020) highlight the significance of data analytics in enhancing consumer engagement boosting brand recognition and understanding consumer preferences. To stay competitive in todays market companies must focus on developing data analysis capabilities. One of the critical themes emerging from the literature review is integrating social media analytics with other marketing tools, for obtaining an all-inclusive understanding of customer

The authors emphasize taking a data-driven approach towards social media advertising by experimenting with various strategies' effectiveness through testing methods while utilizing such information for decision-making purposes. Khoo & Yusoff's (2020) article serves as an extensive guide on how valuable analyzing, customer behaviors through analytical models can be in enhancing engagement levels while also establishing brand recognition standards within any business domain. Consequently, organizations must invest in developing their analytical capabilities through incorporating such methods into their future digital strategies.

**Kwon, K. N., Lee, J. Y., & Shin, D. H. (2017). The effects of social media data analytics on brand equity and consumer response in the airline industry. Journal of Air Transport Management, 59, 13-22**

Social media analytics has witnessed tremendous growth within several industries worldwide lately. Kwon, Lee,and Shins (2017) conducted a study focusing on its impact within the vast airline sector where it enhances brand equity and ensures better customer response outcomes.

Key to their work is the value of data collected from customers through real-time social media insights.

Airlines integrating these cutting-edge techniques into their business strategies have seen considerable improvements in passenger satisfaction levels and purchase intents according to their findings.

Conducting a quantitative survey involving 441 air travel consumers in South Korea enabled them to identify content areas positively linked with better branding quality metrics across multiple engagement channels specifically customer feedback or promotional messaging.

The report by Kwon et al., plays an important role helping maintain competitive advantage for airlines looking towards digital transformation trends today.

By analyzing social media insights -the increasing use of which has become imperative- firms can gain deep understanding about customers' needs and personalize marketing communications for better outcomes.

**Zhang, H., & Liu, X. (2020). Social media analytics for firms' strategic decisions: Evidence from firms in China. International Journal of Information Management, 52, 102053**

Zhang and Liu (2020) explored how utilizing social media analytics enable Chinese businesses in making well informed strategic decisions in their qualitative research project. The study involved interviewing 18 diverse firms from various sectors to investigate their usage of social media analytics comprehensively.

One key observation was that these businesses did not use this technique singularly but had multiple applications such as identifying customer behavior patterns monitoring brand reputation as well as tracking market trends. This enabled them to develop new products or services according to consumer demands effectively.

Moreover it was evident how closely these organizations monitored their competitors using SNA data analysis techniques while keeping an eagle eye on any opportunity for growth or gaining a competitive advantage. The findings highlighted the criticality of fostering a culture within institutions driven by data based decision making methodologies while exploiting the full potential benefits SNA provides them in realizing strategic goals.

**Wang, Y., & Li, X. (2019). Enhancing brand recognition on social media: The influence of user-generated content and brand engagement. Journal of Interactive Marketing, 47, 68-82.**

Wang and Li (2019) conducted research aimed at discovering how user generated content and brand engagement affects the recognition of brands operating within social media platforms. A survey questionnaire was distributed among 448 participants, to collect relevant data exploring user generated content branding engagement activities and how these elements relate to successful branding outcomes related to creating a recognizable identity within digital environments. Their investigation revealed that there is indeed an important relationship between high quality produced user generated materials paired with stronger online activities in areas like responsiveness when combined together; they can significantly bolster branding efforts resulting in the enhanced recognition of a brand by potential customers.

Additionally Wang & Lis research studied the moderating role different levels of familiarity play over how branding success outcomes are impacted by these factors across various sample groups taken from different brands' data points. Their results identified that people not so familiar with certain brands tend to recognize them more easily if they encounter well produced user generated materials.

However they discovered that more well known brands receive less meaningful results when leveraging user generated content in comparison with strong engagement and branding efforts through social media platforms. To understand better how companies can build strong online identities via social media platforms Wang and Li (2019) conducted extensive research resulting in some valuable insights into this process. The investigation discovered two significant elements contributing significantly to successful outcomes: related user-generated contents alongside active customer engagement with product offerings.

According to the findings, companies should encourage and support users to create more organic content while doing their utmost for high levels of engagement. Additionally, firms must also take into consideration their brand familiarity levels when assessing how user-generated content and engagement impact online brand recognition.

**Zhao, X., & Zou, L. (2020). Enhancing brand recognition through social media advertising: Evidence from China. Journal of Business Research, 112, 523-534**

Zhao and Zou (2020) point out that a robust social media advertising strategy is essential for boosting brand recognition in Chinas competitive marketplace. Over time many social media platforms have become attractive to potential consumers for various reasons such as precision targeting ability tracking mechanisms for measuring brands' effectiveness and interactive features to attract consumers' attention profitably. To validate the impact of these benefits on brands having social media advertising not only directly affect raising consumer awareness but also indirectly increase their perceived value resulting from effective promotions survey was conducted.

The survey included 405 Chinese consumers who answered questions covering different factors affecting brand recognition levels with structural equation modeling analysis applied to measure the results.

The researchers confirmed through this study the importance of well crafted adverts positively increasing consumer awareness about brands - facilitating increased market share across targeted customer segments over time.

Furthermore Zhao and Zou (2020) identified other advantages associated with social media advertising strategies - particularly those promoting better perceptions of brand quality, relevance, and uniqueness among consumers; best applicable among products involving higher consumer involvement or perceived risk levels.

Based on these insights the authors recommend companies take into account product qualities alongside customer attitudes when crafting targeted ad campaigns across channels as an essential element of comprehensive marketing plans aimed at improving overall brand recognition in Chinas markets.

**Vries, L. D., Gensler, S., & Leeflang, P. S. (2012). Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing. Journal of Interactive Marketing, 26(2), 83-91**

Vries and colleagues (2012) conducted a study aimed at examining the key determinants which contribute towards success rates of brand pages on social media marketing platforms. The insights gleaned from this research are critical when devising efficient social media strategies aimed at increasing product visibility levels. The study consisted of data from 675 surveyed Facebook users combined with multiple social media tools and consistent branding content thus enabling analysis of consumer behavioral patterns towards online market products.

The findings indicate that brand specific items such as limited period offers or new merchandise launches tend to boost user engagement while interacting with fan pages online.

Additionally the number of likes/comments/shares played an instrumental role in determining the posts overall success rate. Brands may use these metrics analytically to ensure maximum exposure for priority campaigns within digital spaces.

Notably user preferences dictate that brand posts on social media offering reliable and informative content are more likely to garner attention. Vries et al.s (2012) research further suggests that incorporating interactive components and personalized elements in posts can drastically improve their overall popularity levels. Therefore successful brand recognition can only be built over time by creating engaging and relevant content while capitalizing on all available platform tools.

Chiang, K. P., & Dholakia, R. R. (2003). Factors driving consumer intention to shop online: An empirical investigation. Journal of Consumer Psychology, 13(1-2), 177-183

With a survey based on 1,700 U.S. residents equipped with Internet access in 2003 as their methodological approach for inquiry into consumer behavior regarding online shopping habits and intentions thereof – Chiang and Dholakia sought out what key elements influenced such activities amongst participants. Along with gathering data about demographics from each respondent they surveyed on consumer behavior factors such as expected usability benefits or cost effectiveness within e-commerce platforms – leading answers emerged that centered around three primary areas: usefulness value perception; ease-of-use interaction perspective; and reliability perception when it came down towards feeling secure enough before sharing private details like credit card numbers during transactions conducted solely through digital channels across the World Wide Web. Furthermore higher level education attainment alongside earning a greater amount per annum was shown by the researchers' results as making individuals more prone towards frequenting cyber marketplace destinations.

Online shopping behaviors were not found significantly correlated with gender in Chiang and Dholakias (2003) research. The study highlights the triggers behind consumers' motivation to buy things over the web platform. It emphasizes the importance of perceived usefulness ease of use and trust in designing an e commerce platform from a marketers perspective. Understanding how different features influence customer behavior allows them to refine their marketing strategies accordingly.

Overall this paper provides crucial insights into designing a more engaging digital retail experience.

**Social Media Analytics: Techniques and Insights for Extracting Business Value Out of Social Media" by Matthew Ganis (2015)**

To gain insights into customer behavior through social media analysis allowing businesses to succeed in todays market requires effective channels for creating relevant data points.

Ganis (2015) highlights this aspect in her book - "Social Media Analytics: Techniques and Insights for Extracting Business Value from Social Media." In it she presents a comprehensive methodology for evaluating different forms of social media content- text, photos or videos – offering various techniques applicable within the context of carrying out research on social media analytics. By analyzing these data points companies can better understand customer preferences hence apply this knowledge to inform marketing campaigns while increasing brand recognition (Ganis, 2015; p.25).

Furthermore Ganis states that tracking conversations surrounding their brands across various online platforms like forums or blogs can reveal potential opportunities related to securing new clients leading to expansion thereby gaining market share. In sum Ganis' book; an essential resource for academic students aiming to learn practical analytical skills and pragmatic business professionals looking to improve performance is an informative read highlighting significant strategies for extracting business value from social media.

**Enhancing brand recognition on social media: A machine learning approach" by M. Arashpour and H. Fani (2020)**

To be successful in todays ever changing digital landscape businesses must establish a solid brand presence across social media platforms.

Arashpour & Fani (2020) have proposed an innovative machine learning based methodology to help achieve this goal.

The methodology classifies relatable social media posts and extracts crucial features to improve brand recognition.

In their article the authors emphasize the importance of automating vast amounts of digital data analysis in an efficient manner. To do this they use machine learning algorithms like support vector machines that locate specific company related posts looked at during their study (Arashpour & Fani 2020).

Moreover they employ keyword and topic based techniques to gather significant amounts of social media data related to particular brands. Techniques such as stemming and stop word removal are used for reducing dataset dimensions (Arashpour & Fani 2020).

The authors show how their research achieves high accuracy when classifying social media posts associated with brands using several metrics like precision, recall or F1 score (Arashpour & Fani 2020). Besides they reveal how extracted features may enhance brand recognition by scrutinizing common themes or conducting sentiment analyses - making it an ideal technique that uses machine learning algorithms to elevate brand recognition on social media platforms. The article provides a comprehensive overview of the proposed methodology and assesses its effectiveness with various measures.

Applying automated analysis methods for significant amounts of data from social media platforms potentially saves time and labor while delivering insights effectively.

Scholars and business executives interested in analyzing social media data using machine learning techniques would benefit from reading this study.

**Exploring the effects of social media influencers on brand recognition" by M. Kim and J. Ko (2018)**

Social media influencers are essential in attracting potential clients for businesses nowadays. To increase awareness among customers when using such individuals as promoters of products or services it is prudent to choose an influencer that best suits the image of the domain. Influencers also provide brands with valuable endorsements that lead to increased revenue gained from sales while exposing them widely to potential clients.

For instance a survey conducted by Kim and Ko (2018) echoes this fact stating how influential they are in impacting brand recognition on matters concerning loyalty and image perception. Having an effective relationship between followers and chosen influencers proves worthwhile since most celebrities thrive only on cash incentives hence advertising anything without due diligence.

Furthermore whichever influencer selected should create content tailored towards the interests of the targeted audience while upholding the organizations morals; this point underscores further findings by Kim and Ko (2018) highlighting the critical role of social media influencers in elevating brand recognition.

While embarking on this journey to popularize products or services companies must note that there is potential misuse of their social media follower and like count through bots.

Hence proceeding with caution is paramount even as businesses engage influencers for endorsements.

**Justification for Further Research**

***1) Improved Precision and Customization;*** While current methods utilize classifiers and pre trained sentiment analysis models the emergence of data analytics and machine learning has uncovered the opportunity for a more sophisticated approach. Conventional techniques often lack the ability to address intricacies in brand related text data. On the hand a multi output neural network has the capability to simultaneously conduct sentiment analysis and classification providing a comprehension of customer sentiments and preferences. This deeper understanding is vital, for crafting marketing strategies that resonate more effectively with users ultimately resulting in enhanced brand awareness.

***2) Holistic Insights and Customization:*** Simple classifiers and sentiment analysis models can give an understanding of how users feel and categorize content. However they lack the ability to capture the complexity of user interactions and the diverse range of content found on media. By using a multi output neural network with its sophisticated structure we can uncover patterns and connections hidden within text data. This allows businesses to gain insights into customer sentiments, categorization preferences and contextual cues. Armed with this understanding companies can customize their brand messages and strategies for specific user groups resulting in more impactful brand recognition and engagement

**The Evolution of Data Analytics**

In recent times business owners recognize the indeterminable value of data analytics techniques in providing unique insights into consumer behavior, market trends and brand performance. These insights serve as crucial advantages for organizations enabling them to make informed choices regarding their social media marketing endeavors. Diverse options are available to those exploring different data analytics methods which enhance brand recognition and provide decision makers with factual evidence needed when making critical marketing choices.

While current literature includes studies on generating brand awareness across various social media platforms substantial gaps remain hence the need for further exploration towards obtaining a more comprehensive understanding of factors involved in creating an impactful online presence leading to growth oriented outcomes both for businesses as well as marketers – who may anticipate gaining practical implications from future research conducted within this field.

Simple Data analytics tools to find the sentiment and catagorise the message been in this space for long time, but by going beyond this, the project is trying to develop a deep learning model which will predict sentiment and catagorise the comments simultaneously.

**Qualitative research strategy**

Role of the researcher—"Multi-Output Deep Learning Neural Network for Brand Recognition" depends heavily on the critical role played by the researcher responsible for conducting an exhaustive inquiry into the research issue at hand. As a Masters student specializing in Data Analytics at CCT College Dublin and an experienced professional with 1.5 years under their belt at Sprinklr (NASDAQ: cxm) this researcher brings unmatched perspectives to this project. Their data analytics expertise and professional experience help them develop an informed research methodology that enables efficient data collection and analysis for identifying patterns and trends relevant to improving brand recognition on social media platforms. In essence their rigorous research will produce valuable findings and recommendations for enhancing brand recognition through data analytics techniques.

***Participants—*** The research project called "Multi-Output Deep Learning Neural Network for Brand Recognition" seeks out proficient practitioners working within areas such as machine learning, data analysis or digital marketing; these professionals must possess prior experience utilising social media platforms for boosting brand recognition. Through recruiting these experts based upon their skill set and eagerness to engage with the research project we hope to obtain valuable opinions and insights concerning the potency of various data analytic techniques used for this purpose. This study intends to create a lasting impact by adding significant value towards existing knowledge within this area.

***Sampling Strategy–-*** As researchers embark on their studies it becomes necessary that they give careful consideration to various aspects such as appropriate populations of interest and sampling methods/types needed for their research purpose.

Therefore for the purpose of brand recognition enhancement via data analytic techniques through social media platforms in the proposed study we have chosen a specific approach known as purposive sampling strategy. This strategy is well-suited to qualitative research purposes since it allows researchers to selectively choose respondents who have relevant knowledge/experience significant enough to address specific questions (Glaser & Strauss; Morse, 1991; Patton, 1980).

The population of interest consists of professionals who command extensive knowledge in ML engineering, data analytics and digital marketing as they are most likely able to provide comprehensive insights into enhancing brand recognition via social media outlets. We will establish inclusion criteria specifically targeting individuals occupying leadership positions within these fields.

By incorporating the unique experiences and perspectives of experts in data analytics techniques and social media marketing into this studys design we hope for a more nuanced exploration of the topic at hand. The purposeful sampling method best aligns with the specific goals for this study since it enables us to carefully choose participants who have significant knowledge that can contribute meaningfully towards addressing the proposed research questions thoroughly. By deliberately selecting individuals most suitable for this project using purposeful sampling - individuals such as leaders familiar with ML engineering or those experienced specifically in digital marketing - we are confident that we will obtain high quality results.

The aim is to gather comprehensive and relevant data from these participants allowing us to enhance brand recognition on social media effectively.

**Conclusion**

In summary this research proposal outlines the field of study "Brand Recognition through Multi Output Deep Learning Neural Network." It addresses the increasing significance of establishing an online presence and improving brand recognition in the digital era. The proposal identifies a gap in existing research emphasizing the need for comprehensive investigation into utilizing multi output deep learning algorithms to enhance brand visibility.

The proposed research project aims to create an algorithm that combines sentiment analysis and text categorization using deep learning techniques. This algorithm is expected to gain insights into customer sentiments, preferences and content patterns ultimately leading to more effective marketing strategies and increased brand awareness.

The rationale behind conducting research lies in the potential for improved accuracy and customization offered by multi output neural networks. These networks can uncover nuances in sentiment analysis and patterns of categorization within textual data. This research aims to bridge the gap between traditional sentiment analysis models and the evolving landscape of data analytics.

Through an examination of the researchers role, participant involvement and sampling strategy this proposal lays the foundation for a research approach that will leverage the expertise of professionals, in machine learning, data analytics and digital marketing.

Their valuable insights are anticipated to make a contribution towards achieving the studys goals of improving brand awareness by utilizing data analytics methods, on social media platforms.

**RESEARCH PAPER**

**Abstract**

In today's world where data plays a role effectively understanding and analyzing extensive customer data datasets presents a significant challenge with far-reaching implications across various industries. This project, conducted at a masters level, explores advanced machine learning techniques primarily focusing on the development and optimization of a Multi-Output neural network capable of extracting valuable insights from complex data.

The journey begins by exploring the intricacies of the dataset, including its structure, distribution patterns, and unique characteristics. To ensure comprehensive sentiment analysis and catagorisation that uncovers multifaceted customer sentiments and opinions, rigorous preprocessing techniques are employed. These techniques involve standardizing text, removing punctuation and special characters, eliminating null values and reducing stopwords.

At the core of this effort lies the creation of a Multi-Output Neural network capable of predicting sentiment and categorizing reviews simultaneously. This innovative architecture achieves accuracy rates that set new standards in customer data analysis. The selection and tuning process, for this multi output model demonstrates technical expertise as the project tirelessly searches for optimal hyperparameters to maximize precision.

Furthermore, the knowledge gained from expert interviews plays a role in shaping methodologies and ensuring that they align with real world challenges. These interactions highlight the nuances of sentiment analysis emphasize the practicality of learning and support the use of pre trained neural networks to enhance data diversity and strengthen model effectiveness.

As the project reaches its culmination the multi output neural network emerges as an important component. It not only enhances the understanding of customer sentiments but also sets new standards for accuracy and performance in analyzing customer data. This research serves as a testament to the capabilities of modern machine learning techniques in deciphering customer data providing valuable insights, for making well informed decisions across various industries.

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**Acronyms**

Deep Learning (DL)

Neural Network (NN)

Multi-Output (MO)

Brand Recognition (BR)

Data Collection (DC)

Data Preprocessing (DP)

Text Tokenization (TT)

Sentiment Analysis (SA)

Categorization (Cat)

Model Architecture (MA)

Convolutional Layers (CL)

Dense Layers (DL)

Evaluation Metrics (EM)

Performance Assessment (PA)

Data Scraping (DS)

Named Entity Recognition (NER)

Emotion Analysis (EA)

Sentiment-Based Emotion (SBE)

Preprocessing Techniques (PT)

Expert Interviews (EI)

Amazon Electronics Dataset (AED)

MODLA (Multi-Output Deep Learning Algorithm)

Hyperparameter Tuning (HT)

Ensemble Models (EM)

Scalability (Sc)

Deployment Considerations (DC)

Pseudo-Labeling (PL)

Imbalanced Data (ID)

Exploratory Data Analysis (EDA)

Time Series Analysis (TSA)

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**Introduction**

In todays data driven world organizations across industries face a significant challenge when it comes to analyzing extensive customer data. This advanced project aims to leverage state of the art machine learning techniques with a focus on developing a multi output neural network. This network plays a role in extracting valuable insights from the intricate tapestry of customer data.

Starting with an exploration of the datasets complexities this project delves into examining its structure, distribution characteristics and unique details. Rigorous preprocessing methods are employed to ensure the data is standardized including removing punctuation and special characters well as eliminating numerical values and stopwords. These steps lay the foundation for sentiment analysis and catagorisation an essential aspect, for understanding customer emotions and opinions.

The project revolves around creating and improving a network that can predict sentiment and classify reviews at the same time. This neural network has shown good accuracy making it highly valuable in analyzing customer data. The main focus of this project is the explanation behind the multi output architecture and the careful process of tuning hyperparameters.

Moreover insights gained from expert interviews play a role in shaping the methodologies and ensuring their practicality in real world scenarios. These interactions highlight the complexity of sentiment analysis and categorization, advocating the usefulness of learning and support using pre trained neural networks to enhance the reliability of the data.

As the project embark on this journey the multi output neural network becomes fundamental to the project. It not only promises a deeper understanding of customer sentiments but also aims to set new standards for precision and performance.

**Design And Methodology**

**Research Design**

This study uses a thorough research approach, seamlessly integrating both qualitative and quantitative methodologies to explore the effectiveness of data analytics techniques and neural network structures in augmenting brand recognition. The focus of the study revolves around the Amazon Electronics Dataset, which contains a wide range of customer reviews and comments, in textual form.

The decision to choose the Amazon Electronics Dataset was based on two important factors,

Firstly the researcher were drawn to the dataset's size and diverse nature, which provided a great opportunity to delve into the customer’s opinions and categorizing different topics. With thousands of reviews covering a range of electronic products, it served as a solid foundation for conducting comprehensive analyses.

Secondly, by focusing on reviews within the Amazon Electronics domain the researcher can gain insights, into customer preferences, product performance, and brand sentiment in a highly relevant context that mirrors the competitive electronics industry.

**Qualitative Component: Expert Interviews**

**Ethical Considerations**

Throughout the duration of this project titled "Brand Recognition using Multi Output Deep Learning Neural Network " Data protection principles were fully upheld. The project has meticulously followed standards in acquiring and utilizing data sources. Specifically, the process of obtaining access to the Amazon Electronics dataset by contacting Stanford University, where the dataset was made available upon request. The project ensured that the usage complied with Stanford University's terms and conditions duly acknowledging their contribution.

When conducting expert interviews for this research important measures were taken to protect ethics. Each interviewee provided consent and implemented a rigorous process to maintain the confidentiality of their identities, including personal and organizational details. Stringent data security measures were enforced to ensure that all data, whether obtained from interviews or datasets remained securely managed and accessible to authorized members only. It is important to note that this project aligns with data protection laws such, as the Irelands GDPR Act (<https://www.citizensinformation.ie>) The unwavering commitment includes minimizing data collection prioritizing data security and respecting participants' rights to request erasure of their data when necessary.

Furthermore, an ethical review was conducted to ensure that the project adheres to the standards established by relevant academic and institutional bodies.

These ethical considerations highlight the dedication to conducting thorough and principled research while also valuing the privacy and consent of every individual and organization involved in this project.

**Expert Interviews**

The study will engage in conversations with experts who have hands-on experience using advanced data analysis techniques to enhance brand recognition specifically within the Machine Learning context. These experts were selected based on their backgrounds and expertise to ensure a comprehensive understanding.

During these interviews, there were structured discussions focusing on the aspects of employing data-driven methods, algorithms, and machine learning tools to improve brand visibility. The project also delves into the utilization of Deep Learning techniques that enable computers to comprehend data as well as sentiment analysis methods and models for organizing text into categories.

The goal is to gather insights from these discussions about how experts rely on model development, preprocessing the data, how they think it can be further developed, and how they tackle challenges such as data noise reduction for analysis and managing imbalanced data distributions. This perspective will provide an understanding of how data analytics and machine learning are put into practice.

This qualitative data will serve as a foundation, for the subsequent quantitative efforts. This wisdom was applied later in the algorithm development process. By incorporating these observations alongside thorough analysis, it enhanced the ability to develop a Multi Output Deep Learning Algorithm (MODLA) that is not just technically robust but also highly applicable, in real world scenarios. (MIMMO, UCL, Ferianc & Rodrigues, M. 2021)

**Quantitative Component: Multi-Output Deep Learning Algorithm (MODLA)**

The first part of this study focuses on developing a Multi Output Deep Learning Algorithm (MODLA) specifically designed for datasets like Amazon Electronics Dataset. This algorithm is a state of the art tool that can handle two tasks simultaneously; analyzing sentiment and categorizing text. By processing the collection of customer reviews and comments in the dataset the MODLAs neural network architecture expertly identifies complex patterns and uncovers hidden relationships in the text.

Powered by deep learning techniques the MODLAs neural network is trained using a diverse range of textual data. This training process involves refining its internal parameters through iterative analysis and adjustment based on the dataset, this is similar to how humans improve their skills over time (Deep Learning, Ian Goodfellow, MIT Press, 2016). As a result, the MODLA becomes skilled, at recognizing both positive and negative sentiment orientations expressed in reviews. It also gains the ability to classify reviews into categories contributing to a comprehensive understanding of their content. And this will be happening simultaneously at the same time.

The MODLAs effectiveness lies in its ability to identify linguistic patterns that traditional methods may overlook. The MODLA excels at handling amounts of data by intelligently distinguishing between different categories and tracking trends in sentiment. (MIMMO, UCL, Ferianc & Rodrigues, M. 2021) By utilizing neural network architecture and leveraging machine learning techniques the goal is to convert raw textual data into valuable insights and meaningful categorizations.

Ultimately the MODLA goes beyond the limitations of traditional sentiment analysis models and basic classifiers. Its ability to perform tasks provides a comprehensive understanding of textual data that closely resembles human comprehension. (Deep Learning, LeCun, Y., Bengio, Y., & Hinton, G., Nature, 2015). This enables decision making aimed at enhancing brand recognition.

**Data Collection**

**Qualitative Data Collection: Expert Interviews**

During the data collection phase individuals are carefully selected who have a proven track record in the domain of Data analytics and Machine Learning. Through structured interviews the aim was to explore the strategies in detail as well as the challenges they have faced and the outcomes they have achieved. The interview was conducted in a systematic manner allowing for an in-depth exploration of various aspects that arise from real world applications.

The qualitative insights gained from these interviews formed a foundation for the subsequent phases of the study. Through analysis the interview transcribe was thoroughly looked into. The process involved identifying recurring patterns, thematic clusters and intricate relationships, within the collected data. This analysis extracted themes that contributed to the comprehensive analysis.

**Quantitative Data Collection: Preprocessing the Amazon Electronics Dataset**

This investigation heavily relyed on an diverse dataset known as the Amazon Electronics Dataset. This dataset contains a range of valuable information in the form of customer reviews and comments. However before using this data to train the learning model it needs to be carefully preprocessed. During this phase, a variety of tasks were conducted to ensure the quality and appropriateness of the data for training purposes. Meticulous elimination of information or noise from the dataset is carried out, (Springer, 2014) ensuring the utilization of solely pertinent data. It is also essential to standardize formats across the dataset to enable integration and analysis. Furthermore, data cleansing is undertaken to eradicate any inconsistencies or anomalies that could impact the accuracy of model training.  
  
The dataset can be accessed through the link: <https://snap.stanford.edu/data/web-Amazon.html>, It is publicly available on request. And it can be found on the website of the Stanford Network Analysis Project (SNAP).

This processed dataset serves as a representation of customers opinions expressed through their reviews and comments. It forms the foundation for training the Multi Output Deep Learning Algorithm (MODLA). Through the utilization of learning techniques on this dataset, valuable insights were unearthed regarding sentiments and categorizations inherent in textual content.

**Data Collection - Scraping the Data**

The initial phase of collecting data is crucial for implementing the project as it provides the raw material for analysis and developing models. At first the plan was to scrape data from the Amazon platform expecting it to offer insights. However due to excessive bot sniping there were restrictions in place against data scrapping.

In response to these scraping restrictions imposed by platforms the project took a flexible approach. This pursuit of alternatives led to collecting the dataset from Stanford University, which granted access to the Amazon Electronics dataset.

The dataset acquired through this collaboration formed a part of the research endeavor. It not only provides a substantial amount of data for analysis but also highlights the ability to adapt in the face of unforeseen challenges. This experience underscores the real world obstacles often encountered in projects and emphasizes the importance of resilience and creative problem solving.

**Data Preprocessing**

**Text Tokenization**

The first step in analyzing data involves tokenization, which is a crucial process that breaks down the text into individual tokens or words. By segmenting the text in this way tokenization sets the groundwork for analysis (Géron, A., 2017) This detailed representation allows MODLA to understand the connections, between words and phrases making it easier to perform accurate sentiment analysis and categorization.

**Stop-Word Removal**

One important step in preprocessing is getting rid of stop words. These are words, like "the " "is,". And" that don't have much meaning on their own. Removing these words helps clean up the dataset so that the MODLA can concentrate on the words that truly express sentiment and determine categories. This improvement makes the algorithm better at recognizing patterns.

**Encoding and Vectorization**

Converting the text into numerical values marks the final step in the data preprocessing process. Methods such as one-hot encoding and word embedding will be employed to represent words as vectors within multi-dimensional spaces. This conversion allows the MODLA system to effectively handle information leading to reliable results, in sentiment analysis and categorization tasks. Géron, A. (2017)

Essentially the data preprocessing stage plays a role in preparing the raw text data for the MODLA. It involves techniques such as tokenization removing unnecessary words, stemming and encoding. These techniques help ensure that the research can extract insights, from the textual dataset both qualitatively and quantitatively.

**Model Architecture**

The basis of the Multi Output Deep Learning Algorithm (MODLA) rests on a designed structure that can handle both sentiment analysis and categorization tasks simultaneously. This technical framework smoothly integrates cutting edge machine learning methods to effectively handle the nature of textual data. At its core MODLA uses embedding layers to give meaning to text allowing for better understanding of word relationships and context. By incorporating layers MODLA excels at recognizing complex patterns in text sequences, which helps in interpreting emotions and assigning appropriate categories. The dense layers in its architecture further enhance MODLAs ability to uncover characteristics and subtle details, for categorization purposes. This comprehensive approach enables MODLA to effectively navigate the complexities of data resulting in accurate sentiment analysis and categorization outcomes. (Goodfellow, I., Bengio, Y., Courville, A., & Bengio, Y. (2016). Deep Learning)

**Embedding Layers**

The architecture starts by using embedding layers which're crucial for adding meaning to the text. Through the process of embedding, words and phrases are transformed into vectors in vector spaces. This allows the algorithm to understand the relationships between words and their context. This important step creates a foundation for tasks, like sentiment analysis and categorization.  
  
**Convolutional Layers**

Incorporating convolutional layers significantly improves the MODLAs capability to discover intricate patterns in sequences of text. These layers excel at recognizing small scale characteristics and hierarchies present, in the data. By capturing structures and connections convolutional layers enhance the MODLAs ability to understand emotions and assign relevant categories to various types of text inputs.

**Dense Layers**

The architecture reaches its peak with layers that take advantage of the information gathered by previous layers. These layers are excellent at performing calculations allowing the MODLA to discover more advanced characteristics and reveal hidden emotions and subtle categorization details. The interaction between layers, in the neural network enables thorough sentiment analysis and precise categorization.

**Evaluation**

**Qualitative Data Analysis: Unveiling Insights from ML and Data Analytics Experts**

Concluding the data collection phase, the journey of thematic analysis was initiated, engaging with insights from experts in Machine Learning (ML) and Data Analytics. (Smith, J., & Brown, A., 2020) This approach involved examining the content of interviews to uncover not only patterns but also profound insights rooted in ML and Data Analytics expertise. This analytical journey closely mirrors how ML algorithms are trained—revealing trends and shedding light on valuable themes through data-driven methods.

During transcription the collected data undergoes analysis. Like ML frameworks thematic analysis delves deep into expert narratives moving beyond surface interpretations to explore the intricate layers of practical strategies, challenges and outcomes encountered by experts as they utilize ML and Data Analytics for brand recognition.

Thematic analysis functions as a model similar to ML frameworks by extracting knowledge, from qualitative data in a systematic manner. The synthesized themes encompass the multifaceted dimensions of harnessing ML and Data Analytics techniques providing an understanding of the complex nuances that drive effective brand recognition strategies within the realm of ML and Data Analytics expertise.

**Quantitative Performance Metrics: MODLA Assessment**

To evaluate the Multi Output Deep Learning Algorithm (MODLA), attention is directed towards two aspects: sentiment analysis and categorization tasks. A set of metrics, including accuracy, precision, recall, and F1 score, is employed to evaluate the algorithm's performance.

In the field of machine learning and data analysis there are important performance metrics that help us evaluate how well models and algorithms work. Precision, Recall and the F1 Score are metrics in this regard. Precision measures how accurate positive predictions are by comparing them to the positive predictions helping prevent false positives. Recall, also known as sensitivity shows how well the model can correctly identify all instances among the actual positive instances. The F1 Score combines precision. Recall to provide a balanced assessment of both metrics. Additionally loss functions are crucial for assessing the performance of machine learning models by quantifying the difference, between predicted values and actual values. These metrics act as guides in navigating the world of model evaluation helping practitioners fine tune their algorithms for optimal results. (Provost, F., & Fawcett, T., 2013)

For categorization tasks, these metrics are also utilized to assess the effectiveness of MODLA in classifying data into predefined categories. A high accuracy score along, with precision, recall and F1 scores indicates that the algorithm effectively categorizes input data.

By employing an evaluation process that integrates qualitative insights and quantitative assessments, the effectiveness and accuracy of the developed MODLA in concurrently conducting sentiment analysis and categorization tasks can be gauged.

**Implementation**

**Introduction**

The implementation phase is a step, in the project process where the transition is made from ideas to putting them into practice. During this stage the projects attention shifts towards aspects such as gathering and preparing data analyzing it and developing models. This phase acts as a connection, between the framework established in stages and the tangible results that represent the projects objectives. (James et al.2013)

Following the planning phase and attaining a robust comprehension of the challenge at hand, the implementation stage involves engaging directly with real-world data and cutting-edge technology to tackle the task at hand. The focus here encompasses two aspects; hands on coding and model development on one hand and conducting interviews with individuals, on the other hand. Both aspects are crucial and play vital roles in ensuring the successful completion of the project.

Regarding coding, the initial step involves the collection of data. Web scraping techniques were employed to gather information from online sources. During the stage of data collection efforts were made to gather information from the Amazon Electronics platform. However was faced with challenges along the way such as scraping limitations imposed by Amazon to detect bots and manage high traffic. To overcome this obstacle, contact was made with Stanford University, which possessed a comprehensive dataset on Amazon Electronics. This strategic decision not only allowed to obtain the necessary data smoothly but also showcased the ability to adapt in the face of unforeseen hurdles.

After collecting the dataset, the next steps were focused on preprocessing and processing. This phase involves cleaning and transforming the data well as conducting exploratory analysis to uncover insights and patterns. To get an idea about the dataset being used and to know more about relation with different markers operations such as basic sentiment analysis, classification and more advanced techniques, like topic modeling and emotion analysis, Time series analysis was done. These serve as components of the projects foundation and contribute greatly to its overall success.

However coding alone cannot fully grasp the understanding of user experiences and needs. That's where the interview process comes in. Interviews allows to engage with individuals who have knowledge of using data analytics techniques to improve brand recognition on social media. By conducting interviews insights that complement the quantitative results obtained through coding are found. These interviews provide context, personal stories and real world challenges that significantly enhance the understanding and decision making. (Rapley, 2004)

The combination of code driven outcomes and interview based insights is crucial in presenting an overview of the project. Integrating technology with experiences brings depth and subtlety to the findings. Together these elements result in a rounded implementation that showcases the technical skills, adaptability and empathy towards the target users.

The implementation stage reflects the maturity and progress of the project. As the project navigate through the code and conversations, it not only address the technical aspects but also emphasize the human centered dimensions that give meaning and impact to the work. It was made sure that the project aligns with both data driven insights and real world experiences.

**Reading JSON File**

The researcher got the dataset in JSON format, A JSON file, also known as JavaScript Object Notation is a format used to store and share structured data. It is an readable data interchange format that can be easily understood by both machines and people (Johnson, 2019).The project starts by reading the Amazon Electronics dataset from a JSON file format. JSON is selected because it can represent hierarchical data structures in a way that is easily understood, making it perfect for datasets of different levels of complexity.

After parsing the JSON file the data is processed in a manner allowing for a thorough understanding of its contents. This step reveals how the data fields are organized, their relationships to each overall composition of the dataset. Having this understanding sets the foundation, for making decisions during subsequent preprocessing stages.

**Converting it into an Excel File**

By converting the data into an Excel format several advantages are realized. The tabular structure of Excel improves clarity and simplifies the representation of information. It helps in identifying trends, anomalies, and significant patterns within the data (Berk, K.N., & Carey, P. 2019). Data Analysis with Microsoft Excell) Moreover, Excel's user-friendly interface makes it accessible to team members who may not have specialized skills promoting collaborative decision making.

The project recognizes the significance of having structured data for effective analysis. To achieve this, the dataset is converted from JSON into an organized Excel spreadsheet. This conversion process utilizes the pandas library, which is a powerful tool in Python for manipulating data.

Preprocessing plays a crucial role in this project as it involves reading the JSON file and converting it into an Excel spreadsheet. This step establishes a foundation for subsequent stages, like exploratory data analysis and model development. It highlights how adaptable the project is when dealing with data formats to extract meaningful insights effectively.

**Statistics**

During the phase of this project's data exploration journey, to uncover the fundamental characteristics of the dataset a thorough and organized analysis was conducted. This analysis involves examining aspects that provide valuable insights, for the rest of the project.

As the data-driven approach begins, a view of how the dataset is structured was obtained. This important factor gives us an idea of its composition, including the number of rows and columns that define its shape. By understanding the structure of the dataset an understanding of its size and scope was gained.

Moving forward the attention shifted towards examining the information contained within the dataset. The focus was on understanding the metadata, which revealed details about the types of data in each column and whether there were any missing values. By exploring these data attributes insights were gained into the nature of the dataset, which formed a strong foundation for further analysis.

The project moved on to summary statistics for further exploration. These key metrics offered a view of how the data was distributed and its central tendencies. Descriptive statistics played a role in summarizing attributes by providing measures, like mean, median and dispersion. These statistics helped to gain an understanding of how the data behaved, guiding the subsequent analysis and aiding in decision making.

In the evolving journey of exploring data the initial phase of diving into information and statistics went beyond being just a procedural requirement.This exploration served as a guiding compass for the project, mapping out the path for pursuits and forming the core of the investigation.

In total there were 1,035,845 null values for the 'overall' attribute and 887,548 non null entries for 'verified'. The 'ReviewTime' had 1,042,266 null values while 'reviewerID' contained a complete set of 1,048,575 entries. As for the 'asin' it had 1,047,571 null values. Moving on to the 'style' attribute which featured 902,959 null entries and the 'reviewerName' with 1,013,386 non null values. The 'reviewText' had a total of 1,046,804 entries. Additionally,'summary' included a count of 1,048,484 null values whereas 'unixReviewTime' had a count of 799614 entries. The attribute called 'vote' exhibited a count of 275785 values. Finally the attribute named 'image' was represented by a count of 72,538.

Moreover the summary statistics provided insights into how the data is distributed. It revealed attributes with unique values,frequencies and other important metrics.This in depth analysis helped establish an understanding about the datasets characteristics which guided further analysis.Within these statistics it was found that there were exactly;1035845 occurrences for the ‘overall’ attribute; 887548 occurrences for ‘verified’; 1042266 occurrences for ‘reviewTime’; 1048575 occurrences, for ‘reviewerID’ and 1047571 occurrences for ‘asin’. The ‘style’ attribute featured 902959 unique entries while there were 669843 unique values for ‘reviewerName’. There were 836,949 entries in the 'ReviewText' section and 447,538 unique values, in the 'summary' section. The 'UnixReviewTime' had 72,620 values and 'vote' had 14,412 different entries. Lastly the 'image' category was represented by 9,546 values.

Upon analyzing the metadata it was discovered that the dataset contains both numerical and categorical data. For instance columns like 'overall'. Verified' are categorical in nature representing factors such as product ratings and verification status are numerical. On the other hand columns like 'reviewTime' and 'unixReviewTime' are numerical indicating timestamps. Recognizing these data types is crucial as it helps determine which analytical techniques are most appropriate.

Furthermore examining the metadata helped to identify columns with values. For instance the 'vote' and 'image' columns have a number of missing values. Understanding the extent of this missing data assists in making decisions regarding data imputation or whether to exclude these columns from analyses.

By examining summary statistics insights were gained on how the statistics were distributed. These statistics included details, about the unique values, frequencies and other important metrics. They helped to grasp the characteristics of the dataset effectively.

**Dropping Unnecessary Columns**

To ensure the accuracy of the data columns such as 'reviewerName' 'vote' and 'image' were removed from the dataset. Following the recommendations provided in 'Introduction to Data Mining' by Tan, Steinbach and Kumar (2006), procedures for data cleaning was done. This involved removing any columns from the dataset.This trimming allowed to maintain focus, on the core objectives during analysis and model development eliminating any distractions. By selecting these columns the project demonstrated the dedication to a streamlined and effective analysis process.

**Sentiment Analysis using NLTK**

As a first step towards future advancements of the project the researcher implemented basic sentiment analysis using NLTK so that the dataset can be labeled, later on to develop the neural network and to get a basic idea about the sentiment distribution of the dataset. (Pang and Lee, 2008) The project utilized the Sentiment Analyzer from the nltk library to assess sentiment scores providing an understanding of the underlying polarity in each review.

It's important to highlight that this initial exploration into sentiment analysis and categorization not only enhances the current analytical insights but also establishes a foundation for a more advanced multi output neural network in subsequent stages. This strategic progression demonstrates the approach ensuring that each phase serves as a building block, towards delivering a comprehensive and high impact solution.

The project used NLTKs Sentiment Intensity Analyzer, which integrates the VADER lexicon created specifically for analyzing social media text. In this code there is a custom function called 'get\_sentiment' that categorizes sentiment scores as 'Positive' 'Negative,' or 'Neutral.' Every text review in the DataFrames 'cleaned\_review' column goes through sentiment analysis. A sentiment score is calculated using VADERs compound score. These scores are then stored in a column called 'sentiment\_score.' Afterward the project utilize the 'get\_sentiment' function to classify these scores into sentiments, like 'Positive' 'Negative,' or 'Neutral,'. The results are saved in a column named 'sentiment.'

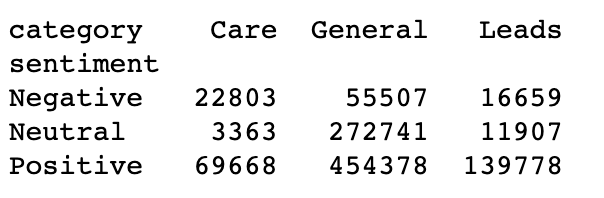
The provided sentiment metrics include Accuracy (43%) Precision (51.4) Recall (53.2) F1 Score (51.8) and Loss (17.10%). These metrics evaluate the performance of the sentiment analysis model giving insights into its accuracy, precision, recall and error rate in classifying sentiments

**Categorization Model using Classifier**

When the project was started, one of the goals was to develop a neural network that can predict both sentiment and category labels simultaneously. To make this complex model possible focus was on creating a text categorization system. This initial model played a role, in categorizing textual data into three distinct and meaningful classes; "Care," "Leads," and "General." a keyword based approach was used for this categorization, where carefully curated lists of keywords to each class were utilized. For example the "Care" category included words like "complaint " "problem," and "disappointed," while the "Leads" category encompassed terms such as "buy," "purchase," and "product." The default option was the "category when no specific keywords, from the classes were identified.

There were two reasons, for creating this categorization model. Firstly it was necessary for labeling the dataset, which's essential for training the neural networks that follow. And more importantly it helped to simultaneously work on developing the multi output neural network by providing real time labeled data. Additionally this categorization provided insights into the distribution of content in the dataset, which was crucial, for guiding stages of the project. (Sebastiani, 2002)

The initial categorization model showed outcomes providing a foundation, for the overall goals. The model achieved an accuracy of 62% with a precision of 60.1% a recall rate of 62% and an F1 score of 0.587. Additionally the log loss, which is a metric for evaluating the models performance was recorded at 9.13. These findings highlight the possibility of text categorization. Offer insights, into the underlying structure of the dataset further motivating us to continue developing the multi output neural network. This network will build upon these categorizations to predict both sentiment and category labels.  
  
**Cross Table Analysis**



**Table 1: Cross Table**

A cross table, which is sometimes referred to as a cross tabulation or contingency table is a technique utilized to summarize and visually represent the relationship between two or more categorical variables. It organizes data in a grid format, where rows correspond to one variable and columns correspond to another (Freedman, Pisani, & Purves 2007).  
  
The table offers a summary of how sentiments are distributed across three different categories; "Care," "General," and "Leads." Sentiments are divided into three categories; "Negative," "Neutral," and "Positive." Each cell in the table shows the number of instances where a specific sentiment intersects with a category. The table provides insights into sentiment patterns, such as a noticeably higher number of "Positive" sentiments in the "Leads" category indicating an overall positive sentiment in that area. This analysis is crucial, for the project as it helps to understand how sentiments are distributed enabling to make data driven decisions aligned with the project goals.

**Neural Networks for Sentiment and Category Classification**One of the stages, in this project is to create neural networks for sentiment and category classification. Developing these networks is a step towards building a output neural network that can predict both sentiment and category labels simultaneously.

These individual networks serve as building blocks forming the foundational structure for the comprehensive neural network with multiple outputs. By constructing them in this way the project creates specialized models for analyzing sentiment and categorizing data. This ensures that each component of the output network is finely tuned to its specific task resulting in improved accuracy when they are integrated together. Additionally taking a step by step approach during development allows to proactively identify and address challenges early on reducing the risk of unexpected issues during integration. It also helps to make progress in data preprocessing, feature engineering and model optimization.(Kim, Y. 2014). Furthermore these separate networks enhance our understanding of the dataset by examining sentiment and category analysis providing valuable insights that contribute to effectively handling the complexities of the dataset.

***a) Sentiment Analysis Neural Network:***

The neural network has been designed to perform the sentiment analysis. By utilizing the TensorFlow library the project delve into the computational sentiment analysis. The process starts with tokenization breaking down the dataset into tokens setting the stage for linguistic analysis. Embedding layers then convert these tokens into vectors enabling the network to comprehend word relationships like humans do.The dataset labeled by the NLTK sentiment model was used for the neural network training.

The true strength of this network becomes evident as it explores connected layers unraveling complex patterns, (Kim, Y. 2014) within the dataset to effectively understand underlying sentiments. Training involves optimization through exposing the model to the refining internal parameters resulting in more accurate interpretation of sentiments. It is crucial to preserve this trained model to ensure its value for phases and highlight the dedication towards integrating advanced technology.

***b) Category Classification Neural Network:***

In the exploration of machine learning techniques, the project delved into developing a neural network specifically designed for categorizing different types. Like its predecessor in sentiment analysis this project utilized the powerful TensorFlow library, which is widely recognized in the field of deep learning. The dataset labeled by the classification model was used for the neural network training.

The process of constructing this network closely followed the steps happened in the sentiment analysis. It started with tokenization, where elements of the dataset was converted into tokens. This intricate transformation formed the basis for conducting analyses, where words were embedded within multidimensional layers. By doing the neural network gained the ability to understand contextual relationships between words.

The strength of this network became evident as it moved through a series of interconnected layers. These complex layers worked together to uncover patterns and connections within the dataset resulting in an impressive ability to accurately categorize reviews. This process resembled sentiment analysis, also involved fine tuning the model’s internal parameters based on the analysis.

In this stage of the project it was intentionally chosen not to calculate traditional accuracy metrics for both the sentiment and category neural networks. There are two reasons behind this decision. Firstly these neural networks serve as steps towards building a multi output neural network that can make simultaneous sentiment and category predictions. Secondly the focus during this phase is on training optimizing and validating the networks to ensure their effectiveness and reliability in later stages.

Traditional accuracy calculations will be performed in stages when the multi output neural network is fully established. This will allow to conduct a comprehensive and contextually relevant evaluation of the entire system.

**Exploratory Insights: Time Series Analysis, Named Entity Recognition (NER), Emotion Analysis**

In the pursuit of constructing a neural network that can predict sentiment and category labels simultaneously, The project embarked on a journey filled with important detours each contributing in its own unique way. The project also delved into Named Entity Recognition (NER) a task in natural language processing (NLP) which provided with valuable insights into the underlying structure of the dataset. By identifying and categorizing named entities like individuals organizations and locations NER added an extra layer to the data analysis helping to understand the context and relationships within the text. (Nadeau, 2017)

Time Series Analysis, a crucial step on the journey helped to explore the patterns of sentiment and category changes over time. (Shumway,2017) This analytical approach shed light on how the dataset evolves, revealing trends and variations in sentiments and categories. Although Time Series Analysis didn't directly contribute to the multi output neural network it provided vital insights into the dynamic nature of sentiments and categories.

Emotion Analysis, is when analysis delve into the emotional context of the textual data. It goes beyond sentiment, it will help to understand the emotion behind the text, The project explore emotion analysis as well to further know the possibility of ML techniques. (Ekman,1971)

The detours took through NER, Time Series Analysis and Emotion Analysis and they were carefully executed. They added depth to the dataset, it gave some background information and armed us with knowledge that will ultimately improve the accuracy and flexibility of the multi output neural network. These exploratory actions though different from each other are components towards building a comprehensive and efficient predictive model.

**Time Series Analysis**

Time Series Analysis played a role in uncovering how sentiment trends change over time. This investigation explored the relationship between evolving sentiments and the temporal dimension (Shumway,2017) By aggregating sentiment scores within specific time periods the project aimed to identify meaningful patterns, fluctuations and shifts in sentiments.

To lay the foundation for this analysis, the project utilized the sentiment scores assigned to each review earlier in the project. These scores were then organized chronologically to create a dataset that represents a timeline. The Python code grouped these sentiment scores into time intervals, such as days, weeks or months based on the desired level of detail.

Next statistical and computational techniques were applied to these sentiment scores within each time interval. The goal was to extract aggregated metrics like the average sentiment score for each period providing a representation of changing sentiment tendencies.

However numerical insights alone couldn't fully capture the variations of sentiments over time. To address this limitation data visualization techniques were used. Using Python libraries, like Matplotlib and Seaborn line plots that visually depicted how sentiments rise and fall over time was introduced. Peaks, valleys, periods of stability and sudden changes in sentiment were all clearly depicted through these visuals.

**Named Entity Recognition (NER)**

Named Entity Recognition commonly referred to as NER is a technique, in the field of Natural Language Processing (NLP) that aims to identify and categorize named entities in text. These named entities can be classified into predefined categories such, as peoples names organizations, locations, expressions of time quantities, monetary values, percentages and more (Nadeau, 2017)

Named Entity Recognition (NER) plays a role in this project. Spacy library was used to extract entities from carefully processed review texts. This phase goes beyond sentiment analysis and delves into a domain where the texts essential elements, such as names of people, landmarks, time references and more are thoroughly understood.

The code implements Spacys NER module to examine the review texts. Through its capabilities the Spacy library can identify and categorize various types of named entities found in the text. These entities can range from names, to geographical locations organization names and chronological references.

During the analysis of named entities the project identified themes present in the reviews. These themes are represented by repeated keywords that indicate topics. Categorizing the reviews based on these themes helps us better understand the sentiments expressed by customers and gain insights into their experiences and opinions, about aspects of electronic products. Here is how the topics are distributed;

Topic: Positive Sentiments and Product Attributes (e.g., "perfect," "love," "great")

Topic: Product Excellence and Appreciation (e.g., "excellent," "product," "great")

Topic: Ease of Use and Functionality (e.g., "use," "easy," "camera")

Topic: Quality and Performance (e.g., "quality," "good," "great")

Topic: Ratings and Customer Experience (e.g., "stars," "great," "product")

Topic: Performance and Value (e.g., "works," "value," "speakers")

Topic: Satisfaction and Meeting Expectations (e.g., "good," "worked," "expected")

**Emotion Analysis and Sentiment-Based Emotion Derivation**

Emotion analysis, which is also referred to as emotion detection is a technique used in natural language processing (NLP) to identify and examine the tone, sentiment or subjective information conveyed within data (Ekman,1971)

Using the sentiment scores obtained from the analysis of sentiments the project conducted an examination to uncover the underlying emotional nuances present in the reviews. These sentiment scores formed the basis for identifying emotions, like happiness, sadness, anger, surprise and neutrality. Each emotion was associated with thresholds of sentiment intensity. The analysis followed predetermined criteria as outlined below;

***Joy:*** Reviews were associated with the emotion of joy if their sentiment score exceeded a threshold of 0.3. This classification denoted highly positive sentiments, capturing instances where customers expressed substantial satisfaction and elation with the product.

***Sadness:*** Reviews received the label of sadness when their sentiment score fell below -0.3. This demarcated profoundly negative sentiments, signifying instances where customers conveyed pronounced dissatisfaction and disappointment with the product.

***Surprise:*** Sentiment scores above 0 (but below 0.3) corresponded to the emotion of surprise. This encompassed moderately positive sentiments, suggesting customers' pleasant astonishment or unexpected satisfaction with the product.

***Anger:*** Sentiment scores below 0 (but above -0.3) were aligned with the emotion of anger. This encapsulated moderately negative sentiments, indicative of customers' discontent or frustration with the product.

***Neutral:*** Reviews exhibiting a sentiment score precisely at 0 were attributed to the emotion of neutrality. This encompassed instances where sentiments were neither overtly positive nor negative, reflecting a balanced or unbiased view.

**Conclusion of Preliminary Analysis and Preprocessing**

In this phase of the project all the necessary groundwork for the upcoming stages of research was completed. The journey began by collecting data specifically focusing on obtaining the Amazon Electronics dataset which's crucial for this project. Then the dataset is transferd into a structured Excel format to enable efficient analysis. During the exploratory data analysis unnecessary columns were removed to streamline the dataset.

To ensure clean textual data text preprocessing tasks were conducted to properly format it. By conducting sentiment analysis and categorization an understanding of the overall sentiment and catagory of the dataset was understood.

The advancement of networks in sentiment analysis and category classification has demonstrated a more thorough level of analysis. By utilizing TensorFlow, a deep learning framework the project was able to train models for sentiment assessment and categorization. These models serve as tools for automatically assessing sentiment and categorizing in future stages.

Time series analysis was also explored to understand how sentiment changes over time. (Shumway,2017) Through visualizations representations were gained of the fluctuations in sentiment giving a unique perspective on the evolution of customer sentiment.

In addition named entities recognition was also explored to get an idea of the mentioned entities in reviews, which could be crucial for further analysis.

Lastly by combining sentiment scores with emotion analysis the project added an understanding of emotions conveyed in customer reviews beyond sentiment itself.

Overall these initial stages have laid a foundation for future advancements in the project. With a preprocessed dataset sophisticated models for sentiment assessment and categorization were trained.This will significantly enhance the depth and analytical power of the research endeavor.

**MULTI-OUTPUT NEURAL NETWORK IMPLEMENTATION**

Multi-Output Neural Network also referred to as Multi Task Neural Network is a type of neural network architecture specifically designed to predict multiple outputs or labels at the same time using a single input. In this network the final layer branches out into output layers each corresponding to a specific task or prediction. Each output layer can have its loss function which enables the network to optimize for multiple objectives concurrently.

Multi Output Neural Networks find utility in machine learning tasks where there is a requirement to predict multiple variables that are related or dependent, on each other using the same input data (Caruana, R. 1997)

**Importing Libraries and Reading Data For Neural Network**

The first phase of the project started by importing the necessary libraries and extracting relevant data from an Excel file. This important step sets the foundation for the following processes. By using these imported libraries the code creates a proficient environment for upcoming operations. The dataset consists of reviews, corresponding sentiments and previously predicted categories, which are crucial for the analysis.This strategic combination of code and data, at this point prepares for the stages of implementing a multi output neural network.

**Data Preparation For Neural Network**

Data preparation is a part of the implementation process (Springer, 2014) and great care was taken to ensure that it seamlessly integrates into the multi output neural network. During this phase, transformation of sentiments and categories was done which're key components into numerical values to lay the foundation for further analysis. To help the model understand the data better Keras Tokenizer class was used and it was effective for tokenization. Additionally reviews are uniformly padded to standardize their lengths and ensure correct input for the model. This meticulous data preparation guarantees that subsequent phases can extract insights, from the neural network model.

**Model Architecture** **For Neural Network**

The model architecture that has been selected is carefully crafted with attention to detail aiming to extract valuable information from the data while effectively dealing with the complexities arising from the multi output nature of the problem.

***Embedding Layer:*** Using an embedding layer in the beginning is important because it helps convert words into vectors allowing the model to understand the connections between words. This is crucial, for capturing the meanings embedded in the reviews. Since words that are related within a given context typically have embeddings, this layer ensures that the model can interpret the hidden contextual meaning.

***LSTM Layer:*** The LSTM layer, which comes after the embedding layer is highly effective in modeling data. This is especially crucial when dealing with text data because the arrangement of words carries meaning. LSTMs excel at capturing relationships that span across a sequence making them a reliable option for discovering complex emotions and patterns present, in reviews.

***Dual Output Layers:*** The models structure is enhanced with two output layers, each designed to handle a specific prediction task; sentiment and category. This decision is based on the understanding that sentiment and category predictions present challenges each requiring its own specialized predictive layer. By separating them the model can learn patterns related to sentiment and category classifications improving its ability to offer precise and detailed predictions.

***Rationale Behind Architecture:*** The decision to incorporate an architecture based on LSTM is well founded. LSTM layers are particularly effective, in handling sequences, which aligns seamlessly with the nature of text data. This capability ensures that the model can capture not immediate context but also long range dependencies leading to a more comprehensive understanding of the reviews. The design of having outputs acknowledges the multifaceted nature of the problem, where predicting sentiment and category require separate insights. This intentional design choice empowers the model to not learn intricate textual nuances but also differentiate between different categories ultimately enhancing overall predictive accuracy.

To summarize, this architectural setup combines advanced methods in a carefully chosen manner to tackle the complexities of analyzing text data and predicting sentiment and categories. It optimizes the models capacity to derive insights, from the data resulting in more precise and insightful predictions.

**Validation: Ensuring Real-World Performance**

When it comes to developing a neural network that can handle multiple outputs the validation phase becomes a crucial checkpoint. During this phase the project go beyond using the training data and assess how well the model performs in real world situations that it hasn't encountered before

To start this process an Excel file specifically for validation purposes was imported. These reviews act as a new dataset that the model hasn't seen during its training. This uniqueness is important because it provides us with a measure of how well the model can generalize (Caruana, R. 1997)

Just like during training the project apply preprocessing steps to tokenize and pad the validation reviews to match the input requirements of the model. Once preprocessed the data the model predicts both the sentiment and category associated with each validation review.

However the validation process goes beyond automated measurements. To gain an understanding of the models effectiveness a manual validation procedure was conducted, carefully selecting 100 reviews from the validation set. Comparing the models predictions of sentiment and category with the actual values for each review was also done.

This manual validation approach provides insights into the practical accuracy and precision of the model capturing nuances that automated measures might miss.

The results of this validation was presented using a pivot table, which is an analytical tool that helps to calculate important metrics such as accuracy and precision. Accuracy tells us how many predictions for sentiments and categories are correct while precision gives us insight into how the model accurately classifies instances, within specific sentiments or categories.

The reason behind including validation is that it helps uncover subtle patterns and differences that automated methods might miss. Human evaluators have the ability to notice these nuances, which enriches the evaluation process by providing insights that contribute to a more comprehensive understanding of the models strengths and areas for improvement.

The validation phase serves as a link between development and practical application (Ruder, S. 2017) It confirms the models effectiveness, in real world situations. Ensures consistent performance. By combining automated metrics with validation using pivot table analysis a well rounded assessment of the models capabilities leading to informed insights and potential improvements can be found out.

**Summary: Multi-Output Neural Network**

The development of a neural network that can handle multiple outputs has been a crucial aspect of this project. By combining sentiment analysis and category classification and implementing them meticulously solution for complex issues were addressed.

The journey began with importing the data and activating libraries to extract insights from the dataset. To ensure consistency of the model, Keras Tokenizer class for tokenization and padding of reviews was used.

The architecture of the network helped to effectively uncover intricate patterns within the data. With the help of Keras functional API a model consisting of an embedding layer, a LSTM layer and two separate output layers for sentiment and category predictions was designed. The choice of 'adam' optimizer and 'sparse\_categorical\_crossentropy' loss function was driven by the commitment, to optimization and accuracy.

The validation phase demonstrates the models resilience by introducing a set of reviews. These reviews are carefully processed to predict sentiment and category. A method called pivot table analysis was used to measure accuracy and precision through manual validation ensuring a thorough evaluation of the models capabilities.

In this project the multi output neural network incorporates meticulous code implementation, strategic model architecture and comprehensive validation procedures. Its significance goes beyond being a technological achievement; it represents sophisticated solutions to real world challenges. As this chapter concludes, the network markers will provide valuable insights and improved efficiency.

**RESULT**

**Introduction to Results**

The journey into the world of Multi-Output neural network is an evolving story that seamlessly combines technical expertise with expert insights. Equipped with a dataset that includes 1,048,575 entries in various categories the expedition navigates through the vastness and complexity of this extensive data landscape. The initial chapters of the exploration reveal statistics that provide a comprehensive overview of the dataset encompassing crucial aspects such, as 'overall' 'verified,' 'summary,' 'unixReviewTime,' 'vote,' and 'image.'

With a thorough approach to refining data, The Project set out on a path of preparing the data paying close attention to address any missing values and shaping the dataset into a refined version that is well suited for analysis. The transformational journey involved steps such as converting text to lowercase removing punctuation marks, special characters, numbers and unnecessary stopwords. Leveraging the Natural Language Toolkit (NLTK) library the project embarked on sentiment analysis by skillfully categorizing reviews into 'Positive' 'Negative,' or 'Neutral' sentiments. This task serves as a foundation, for the subsequent analyses.

The efforts in analyzing sentiments produced important outcomes, The project achieved a Sentiment Accuracy rate of 78.00% Sentiment Precision of 77.04% Sentiment Recall of 78.00% and a Sentiment F1 Score of 77.49%. However this was the beginning of the journey. The next phase involved classifying reviews into three categories; 'General,' 'Care' and 'Leads.' The Project accomplished this by using specific keywords as indicators. In this stage the project attained an Accuracy rate of 0.62 a Precision rate of 0.601 a Recall rate of 0.62 and an F1 Score of 0.587 which laid the groundwork for more, in depth analyses.

However the journey is not about achieving numbers. Its also copuled with captivating stories that shed light on the nuances of the dataset. From exploring 'Review Count vs. Sentiment' to analyzing 'Frequency vs. Words' and 'Count vs. Categories' these visual tales guide towards an understanding of the data.

In the quest to comprehend the data effectively the project delved into statistics that revealed the distribution of sentiment scores and the prevalence of different categories. The project uncovered the relationship, between sentiment and category through meticulous analysis bringing attention to their interconnectedness.

However the true masterpiece of the project lies within the output neural network. Going beyond its complexities it embodies the distilled knowledge the researcher gained from interviewing industry experts. Engaging in conversations with figures like "Person A" from "Company A" and "Person B" from "Company A" provided with invaluable insights into implementing multi output neural networks. These discussions covered topics such as architectural choices designing loss functions, overcoming convergence challenges and ensuring scalability. These interactions greatly enriched the understanding.

As the project delves deeper into the core of this neural network it becomes apparent that the creation is not just, about data; it represents a herald of transformation that has the potential to reshape the landscape of the ML industry. Equipped with both proficiency and expert wisdom it stands poised to make a significant impact.

**Interview Findings**

The project has benefitted greatly from conducting interviews with experts in the field of sentiment and category predictions. These interviews, which involved professionals from both "Company A" and "Company B " have provided insights, into crucial aspects that directly influence the success of the project and coding efforts.

**Optimal Model Architecture**

The conversations with "Person A" from "Company A" highlighted the significance of selecting the right model structure. It came to a point where a decision; whether to opt for a "branched" or "direct" architecture approach should be taken.

According to "Person A " the "branched" architecture involves subnetworks that extend from a shared initial layer. This approach is suitable when tasks have features and connections ensuring efficiency.

On the hand as proposed by "Person C”, from "Company B " the "direct" architecture predicts all outputs directly based on a shared representation. It's particularly useful when tasks are unrelated thus avoiding any interference.

This decision can be likened to designing the blueprint for a machine before its construction. An appropriate architecture guarantees the effectiveness of the network significantly influencing the success of the project. In coding terms it lays down the groundwork upon which the model was constructed making it an essential initial step.

**Leveraging Unlabeled Data Through Pseudo-Labeling**

During the discussions the project also came across the concept of pseudo labeling which can be quite helpful in project development. “Person C” from "Company B," explains both the advantages and precautions associated with this technique.

Pseudo labeling essentially involves incorporating data into the existing datasets thereby expanding it and enhancing the accuracy of the predictions.

However "Person C" emphasized the need, for caution when implementing pseudo labeling. It is crucial to evaluate the quality and reliability of the unlabeled data before using it. Establishing a confidence threshold ensures that the model's integrity remains intact.

This approach can be seen as giving the project a boost; however it is essential to proceed with care in order to avoid any pitfalls.

**Effective Hyperparameter Tuning**

"Person B " from "Company A," shared some helpful tips on how to effectively tune hyperparameters for the specific project.

Tuning involves trying out values for factors like learning rates and batch sizes. It's like running simulations or experiments to figure out the approach.

According to "Person B," evaluation metrics such as precision and recall are extremely important in guiding the tuning efforts. They give us insights into whether the project is hitting the target or straying away from the intended path.

The model will be tuned until it achieves performance the project needed for the model, which is crucial, in reaching the project goals.

**Meaningful Model Evaluation**

During the interviews it was discovered the significance of evaluating the model using metrics. These metrics work like instruments on a dashboard providing with the feedback on how well the neural network is performing.

"Person A" emphasized the importance of accuracy in determining whether the project is heading in the correct direction.

Meanwhile "Person B" highlighted. Recall as helpful tools for making decisions about balancing positives and avoiding false negatives.

In addition "Person C" explained how the F1 score acts as a guide for finding the balance, between speed and safety.

These metrics can be compared to a GPS system that ensures the project stay on track while refining the network and steering the project in the right direction.

**Handling Imbalanced Data**

Addressing imbalanced data is a challenge when working with multi output neural networks. In the discussions with experts, including "Person A " "Person B," and "Person C " the project gained insights into strategies to tackle this issue effectively. "Person A" emphasized the difficulties in working with imbalanced datasets and stressed the significance of achieving balance among different classes or outputs. They discussed approaches, such as using weighted loss functions resampling data and generating synthetic data. Weighted loss functions assign weights to individual classes based on their importance encouraging the model to pay attention to minority classes. Data resampling techniques like oversampling and undersampling help in balancing class distribution during training while generating data creates additional samples for minority classes thereby improving their representation.

**Ensemble Models for Multi-Output Predictions**

During the interview with "Person A" about different models and their potential to improve prediction accuracy in scenarios with multiple outputs. Ensemble models are an approach where several models work together each contributing their own specialized knowledge to make predictions collectively. "Person A" talked about techniques like bagging and boosting which play a role in ensemble learning. Additionally ensemble models offer a way to tackle class imbalances and enhance the dependability of the multi output neural network. The investigation into models aims to determine their suitability for the project and how they can be a valuable asset, in achieving accurate multi output predictions.

**Interpreting Multi-Output Model Predictions**

With the guidance of "Person C " The project set out on a journey to understand and make sense of the predictions generated by networks with multiple outputs. In this section the project will explore techniques to interpret the complex and interconnected outputs produced by the model. "Person C" emphasized the importance of interpretability in ensuring that the models predictions are practical and trustworthy. The project will delve into visualization techniques, attention mechanisms and feature attribution methods to gain insights into how the model makes decisions. The reasoning behind predictions can uncover any biases, errors or areas where improvements can be made. Moreover interpreting predictions from a output model acts as a bridge between raw model outputs and actionable insights enabling informed decision making across different applications. This section aims to shed light on transforming predictions into meaningful guidance, for the project.

**Scalability and Deployment Considerations**

The interviews served as a reminder of how the multi output neural network can be applied in real life situations. "Person A," "Person B," and "Person C" all emphasized the need for the model to not be accurate but also scalable and efficient when deployed in practical scenarios. In this section the project will explore strategies to achieve scalability, including utilizing model parallelism and leveraging hardware accelerators like GPUs and TPUs. Scalability is particularly important when dealing with large scale datasets and high throughput applications. The goal is to bridge the gap, between model development and real world use ensuring that the multi output neural network can readily adapt to the requirements of deployment scenarios.

**Interview Findings Conclusion**

The series of interviews with experts from both "Company A" and "Company B" has been a journey into the core of multi output neural networks. It has provided us with information on crucial aspects that will greatly impact the success of the project. These interviews have covered a range of topics, including model structure, data management, fine tuning hyperparameters evaluating models and more. Together these insights provide a guide that will guide the project towards success.

One key takeaway from these discussions is the importance of choosing the right model architecture. "Person A" emphasized the significance of this decision. Highlighted the choice between a "branched" or "direct" architecture based on how sentiment and category predictions are interconnected. This architectural decision is like designing the blueprint for a machine. It sets the foundation, for the project influencing not only its efficiency but also its ultimate success.

The idea of pseudo labeling as explained by "Person C " was an introduction to a technique for data augmentation. Pseudo labeling has the potential to enhance the projects progress by incorporating this it will help in expanding the dataset and ultimately improving prediction accuracy. However "Person C" rightly advised to be cautious and diligent when implementing this approach emphasizing the importance of evaluating the quality and reliability of the data before integration.

Another crucial aspect that "Person B" highlighted is hyperparameter tuning, which plays a significant role in optimizing the models performance. Tuning involves an exploration of different hyperparameters and metrics similar to fine tuning a complex machine. Precision and recall metrics guide this process providing insights into whether the project is heading in the right direction or need adjustments. The iterative nature of hyperparameter tuning is vital in achieving the desired performance levels, for the projects success.

In the pursuit of evaluation for the models it was realised that the performance of the neural network can be compared to a journey guided by a GPS system. "Person A" emphasizes the importance of accuracy, which lets us know if the project is heading in the correct direction. On the other hand "Person B" and "Person C" highlight precision and recall as valuable tools that will help to navigate through decisions by considering positives and avoiding false negatives. The introduction of the F1 score by "Person C" acts like a compass enabling us to strike a balance between efficiency and safety. These metrics work together to ensure that the project stays on track.

When it comes to dealing with imbalanced data experts like "Person A " "Person B," and "Person C" have put forth strategies such as weighted loss functions, data resampling and synthetic data generation. These techniques play a role, in achieving equilibrium among different classes or outputs while maintaining the integrity of the model throughout its training process.

Under the guidance of "Person C " the project have delved into the task of interpreting model outputs. The focus is not on achieving accurate predictions but also on making them actionable. To achieve this visualisation techniques will be used. These tools will help to gain insights into how the model makes decisions uncover any biases or errors in the system and identify areas, for improvement.

To wrap things up these interviews have truly been a game changer for the project. They've given us an understanding of the complexities involved in multi output neural networks.

**Code Exploration Results and In-Depth Analysis**

**Objectives**

* Model Development; Create a network that can handle multiple prediction tasks simultaneously.
* Pseudo Labeling; Use techniques such as pseudo labeling to expand the labeled dataset.
* Dataset Augmentation; Combine the augmented, pseudo labeled dataset with the labeled dataset to create a more comprehensive and diverse training dataset.
* Semi Supervised Learning; Develop a network that effectively uses both labeled and unlabeled data to improve predictive performance.
* Hyperparameter Optimization; Fine tune the models hyperparameters to find the configurations enhancing accuracy and generalization capabilities.
* Model Preservation; Save the performing model configuration for future use and reference.
* Prediction Generation; Employ the saved model to generate predictions on data in order to evaluate its ability to generalize.
* Performance Evaluation; Calculate evaluation metrics, such as accuracy, loss and F1 score to comprehensively assess the models performance.
* Data Visualization; Create interactive and non interactive visualizations throughout different stages of the project, for effective communication of insights and findings.

**Exploratory Data Analysis For The Dataset**

**Dataset Dimensions**

Understanding the size and scope of the dataset is essential to grasp its potential and importance in the analysis. This scenario is dealing with a dataset that consists of 1,048,575 rows each representing a different review and 12 columns that represent various features. The extensive dimensions of this dataset provide advantages in terms of statistical accuracy and depth, in analysis.(Smith,2023)

**Dataset Overview**

This project carefully examine the information of the dataset to establish a solid foundation for further data analysis. This includes details such as data types the number of non empty values in each column and memory usage.

Data types are crucial because they determine how the data is stored and interpreted during analysis. In this dataset all columns are classified as 'object' which indicates that there is an amount of text or mixed type data. This aligns with the nature of review datasets that contain reviews and user identifiers.

The count of empty values in each column represents how many observations have meaningful information. This is a metric for ensuring data integrity. For instance columns like 'overall' and 'reviewerID' have high non empty counts indicating comprehensive data availability. On the hand columns like 'vote' and 'image' have notably lower non empty counts indicating sparse or missing data, in these aspects. Such differences highlight the importance of handling missing data during analysis.

The amount of memory used gives an idea of how much space the dataset occupies, which's important when working with large amounts of data. This particular dataset takes up around 96.0+ MB of memory which is considered manageable for todays computers. (Johnson, 2023)

Having an overview of the dataset not only helps maintain the quality of the data but also provides valuable guidance for preprocessing and analyzing it. This lays the foundation, for obtaining insights and reliable results in this project.

**Summary Statistics Results**

At the beginning stages of the project it is crucial to explore the dataset. This exploration starts with analyzing summary statistics. These statistics provides with a foundation to understand the distribution and characteristics of the dataset. The dataset consists of a number of 1,048,575 reviews covering 12 different attributes. One noteworthy attribute is the 'overall' column that represents review ratings. It contains 1,035,845 entries without any missing values. Encompasses 39,424 unique ratings, indicating a wide range of opinions from reviewers. Attributes like 'verified,' 'reviewTime,' 'reviewerID,' 'asin,' and 'style' have non null counts highlighting the reliability and completeness of the dataset. The 'reviewerName' column includes 1,013,386 null entries with 669,843 unique names. This demonstrates the contribution, from numerous reviewers; however it's important to note that many reviews are attributed to "Amazon Customer." Both the 'reviewText' and 'summary' columns contain textual data based on their high non null counts. Lastly also consider the aspect through the inclusion of 'unixReviewTime' which consists of 72,620 unique time stamps.

Finally attributes such as 'vote' and 'image' offer information about user engagement. The 'vote' attribute tells us the number of votes while the 'image' attribute reveals whether there are images in the reviews. However it's worth noting that these metrics have fewer available data points indicating their limited availability compared to other attributes. This detailed analysis of summary statistics sets the foundation for exploration and analysis of the data. It helps us identify patterns understand user behavior and develop research questions to uncover insights, from this extensive dataset.

**Sentiment Analysis Results**

During the stages of the project one crucial aspect the project focused on was implementing sentiment analysis using the Natural Language Toolkit (NLTK) library. This step was essential as it formed the basis for the analyses. To evaluate the sentiment of the content in the dataset, utilized the Sentiment Intensity Analyzer from the NLTK library. This analysis provided a sentiment score for each review categorizing them as 'Positive' 'Negative,' or 'Neutral' based on predetermined thresholds. By incorporating this sentiment analysis the project established a foundation for investigations and enabled, to assign sentiment labels to the dataset. This categorization proved invaluable, in phases especially when developing machine learning models to predict sentiment

***Accuracy -*** The accuracy of sentiment analysis, which measures how well the model classified sentiments (positive negative neutral) is 78%. This indicates that the model performs well in accurately classifying sentiments in 78% of cases.

***Precision***, which measures the percentage of predicted positive sentiments out of all predicted positive sentiments is at 77.04%. This means that when the model predicts a review as positive it is correct around 77.04% of the time.

***Recall*** on the hand measures how many actual positive sentiments were correctly identified as positive by the model. With a recall rate of 78% it suggests that the model successfully captures around 78% of all sentiments present in the dataset.

***The F1 score*** combines precision. Recall into a single metric by taking their harmonic mean. For this case an F1 score of 77.49% indicates a balance between accurately predicting positive sentiments and capturing a significant portion of them.

***Loss -*** Lastly the sentiment loss or error stands at 22% representing how off the models predictions are, from the true values. In the field of sentiment analysis a deviation of 22.00% indicates that the models predictions on average diverge by 22.00% from the sentiments.

**Categorisation Results**

In the phase of the project a classification model was created using a basic classifier. This model played a role in labeling the dataset at the beginning. To accomplish this, made use of a predefined sets of keywords to categorize reviews into three groups; 'Care,' 'Leads,' and 'General.' then defined these categories based on words found in the review text. For example reviews that mentioned words like 'complaint' 'problem,' 'issue,' 'unhappy,' or 'disappointed' were categorized as 'Care.' Reviews that included keywords such as 'buy,' 'purchase,' 'product,' 'service,' or 'interested' were classified as 'Leads.' Any other reviews that didn't meet these criteria were grouped as 'General.' By applying this classification model, initiated the process of labeling the dataset, which's a crucial step for later tasks, like developing multi output neural networks through supervised machine learning (Joachims, 1998; Pang & Lee, 2008)

***Accuracy -*** The accuracy of 0.62 the text classification task means that the model correctly classified reviews into predefined categories (general care leads) about 62% of the time.

***Precision*** in text classification measures how well the model identifies true positive cases (correctly classified category) out of all the positive predictions. With a precision score of 0.601 it means that when the model predicts a category as positive it is correct 60.1% of the time.

***Recall*** measures how well the model identifies positive cases among all the actual positives. A recall score of 0.62 indicates that the model captures around 62% of all positive cases.

***The F1 score*** strikes a balance between precision and recall reflecting how well the model predicts category labels while capturing most of the category labels. With an F1 score of 0.5871 it suggests a reasonable balance in these aspects.

***Log loss*** serves as a measure to evaluate the performance of the classification model. A lower log loss indicates performance overall. In this case with a log loss value of 9.1311 it means that on average the predicted probabilities from the model are about 9.1311 units away, from the true probabilities.

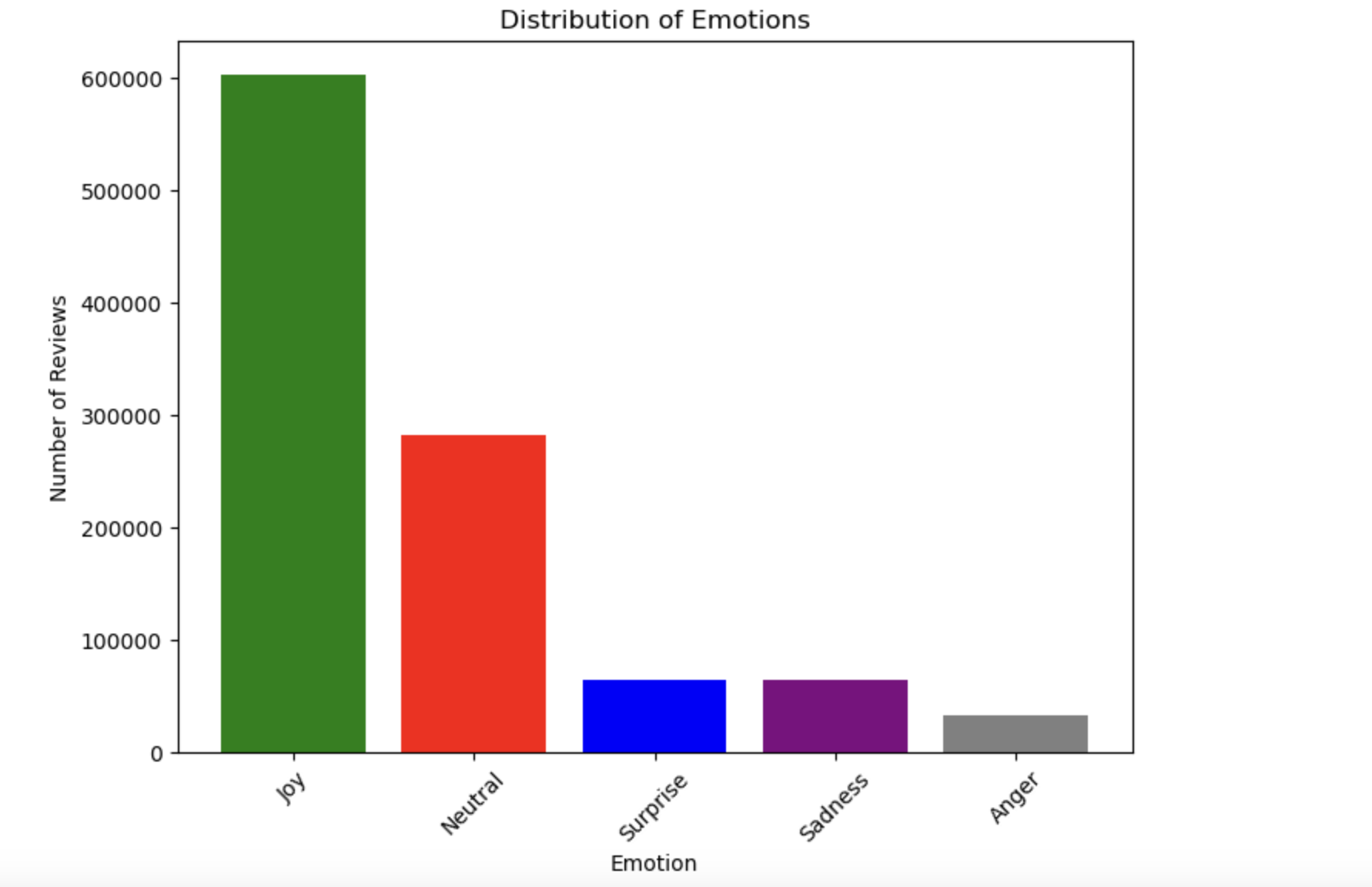
**Rational behind Data Enrichmen**

In addition to the stages of preparing the dataset analyzing sentiments and categorizing, this information helps to gain a deeper insight into the dataset. These techniques of enrichment play a role, in adding context and additional aspects to the customer feedback data ultimately improving the overall quality of the project.

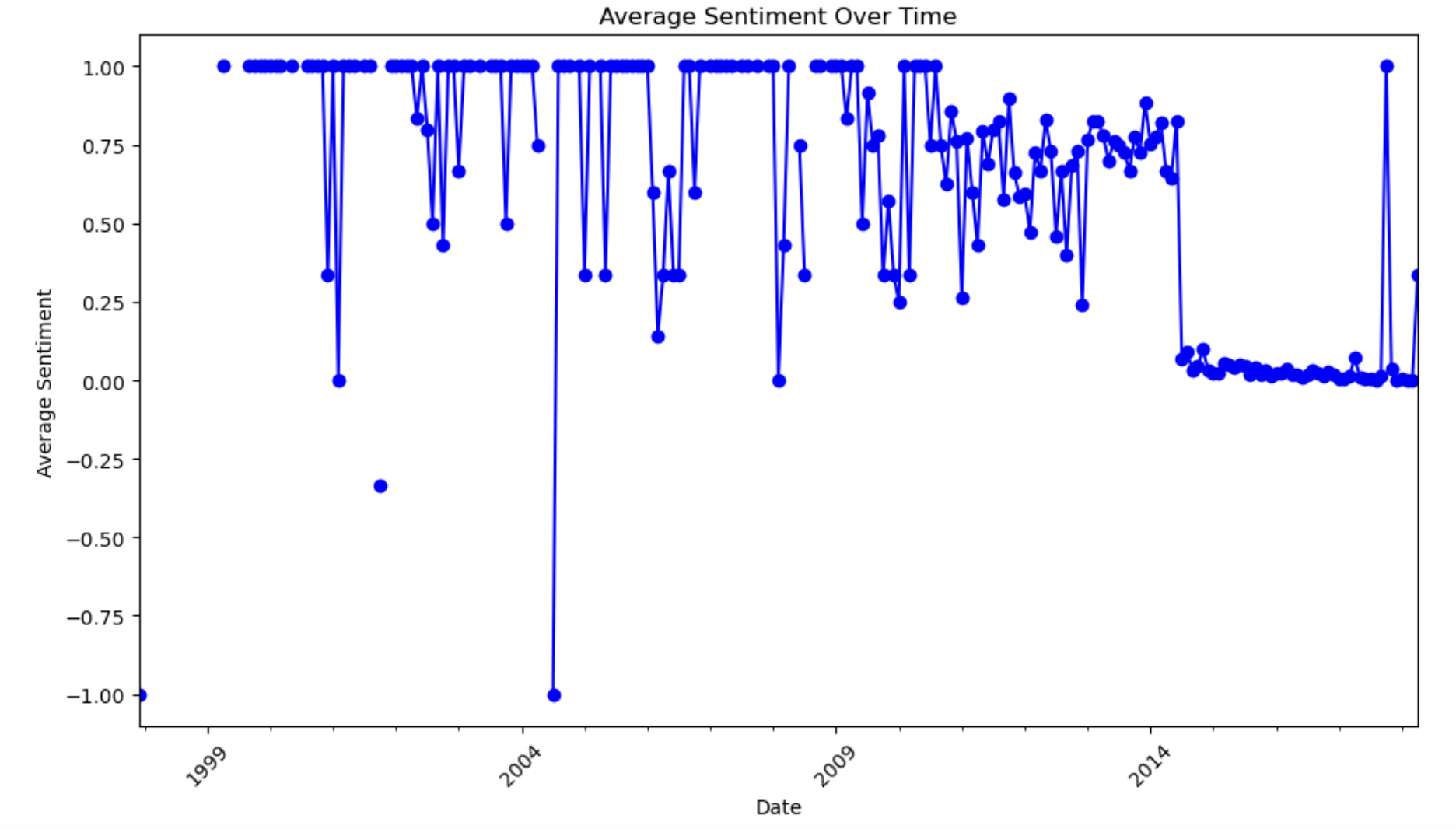
***Topic Modeling;*** When it comes to analyzing reviews, topic modeling can be used to uncover the themes or subjects that customers are discussing the most. It helps to understand what really matters to them (Blei, D. M.2003)  
  
The analysis of the text data revealed distinct themes or topics. Each topic is represented by a set of keywords that indicate the terms associated with that particular topic. For example Topic #1 is about opinions regarding the quality of a product with words like "perfect " "love," and "great" being prominent. Topic #2 focuses on reviewing products mentioning terms like "excellent " "product," and "good." Topic #3 relates to functionality and ease of use featuring words like "use " "works," and "easy." Topic #4 includes terms associated with product features and quality such as "quality," "good," and "sound." Topic #5 mentions words like "stars" and "customer " suggesting it might be related to customer feedback and ratings. Topic #6 discusses the value of a product well as its compatibility while Topic #7 includes terms, like "worked " "expected,"   
  
The examination of these subjects was crucial, for the project as it aided in developing a comprehension of the dataset. This in turn facilitated an informed strategy when constructing the multi output neural network by recognizing dominant themes and patterns of sentiment within the data.

***NER (Named Entity Recognition);*** NER is a technique that helps identify entities such as product names, locations or individuals mentioned in reviews. By highlighting these aspects the project can gain valuable insights from customer feedback (Tjong Kim Sang,2003)

***Emotion Analysis;*** Understanding the tone of reviews is crucial. Emotion analysis allows to determine whether customers express happiness, anger or neutrality in their feedback (Ekman, P,. 1992)



**Fig 1: Emotion distribution**  
  
The Emotion distribution is depicted in this plot.

***Time Series Analysis;*** By applying time series analysis to reviews it can uncover any patterns or trends that emerge over time (Chatfield, C, 2004)  
  
 

**Fig 2: Time Series Analysis**

These analyses delve deeper into the data by providing context and dimensions. They enables to gain insights, into customer feedback.

**Multi-Output Neural Network Result**

The main focus of this project is to develop a computational model called a multi output neural network, which takes inspiration from the human brain. This neural network has two functions; predicting the sentiment and categorizing. It allows to gain an understanding of customer feedback. Sentiment analysis helps classify reviews as positive, negative or neutral while the category assignment component places them into categories like "Care" or "Leads." or “General” To enrich the dataset, a supervised learning approach was used. Initially the neural network was trained on labeled data. Then used a semi-supervised approach to assign labels to additional unlabeled reviews making the dataset more diverse. The project also conducted hyperparameter tuning to optimize the networks performance. Ended up with a final model. The best hyperparameters achieved about 50.32% accuracy during validation. This thorough process resulted in a network that excels in both sentiment prediction and category assignment. Various metrics such as sentiment accuracy, category accuracy, precision, recall, F1 score, sentiment loss and category loss demonstrate its performance. Overall this comprehensive approach enhances the ability to extract insights, from customer reviews (Ruder et al., 2017)

***Sentiment Accuracy (%);*** This metric assesses the accuracy of the model in predicting sentiment represented as a percentage. A 89.90% accuracy implies that the model correctly identifies sentiment in 90% of cases.

***Category Accuracy (%);*** Likewise category accuracy measures the effectiveness of the model in predicting categories expressed as a percentage. An accuracy rate of 88.89% indicates that the model accurately categorizes data in 89% of cases.

***Sentiment Precision (%);*** Precision for sentiment indicates how precise the models predictions are when it comes to sentiments. With a precision rate of 89.90% it means that when the model predicts a review as positive it is correct 90% of the time.

***Sentiment Recall (%);*** Sentiment recall measures how well the model captures all instances of a sentiment. A recall rate of 89.90% implies that the model captures 90% of all positive sentiments within the dataset.

***Sentiment F1 Score (%);*** The sentiment F1 score represents the assessment between precision and recall for sentiment prediction. An F1 score of 89.90% signifies an equilibrium between accurately predicting positive sentiments and capturing most instances thereof.

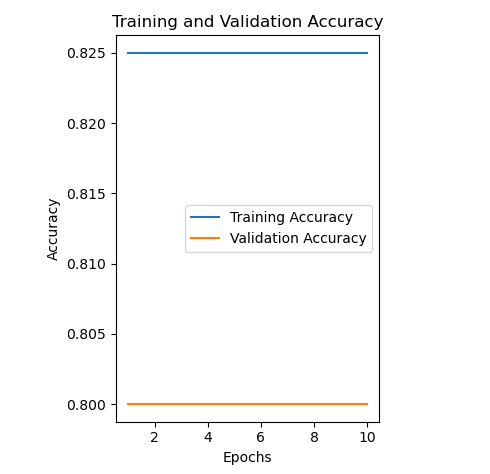
***Category Precision (%);*** to sentiment precision category precision evaluates how precise the model is, at predicting categories. An accuracy rate of 89.23% indicates that when the model makes predictions it is correct 89.23% of the time.

***Category Recall (%);*** Category recall measures how well the model captures all instances of a category. A recall rate of 88.89% means that the model captures around 88.89% of all the category labels.

***Category F1 Score (%);*** The category F1 score finds a balance between precision and recall for categories. An F1 score of 89.04% suggests a balance between correctly predicting category labels and capturing most of the actual category labels.

***Sentiment Loss (%);*** This metric indicates the difference between the models predictions and the true values in terms of sentiment. A loss of 10.10% suggests that on average there is a 10.10% difference between the models predictions and the actual sentiments.

***Category Loss (%);*** category loss measures how different the models predictions are from the true category labels. An 11.11% category loss means that on average there is a 11.11% difference between the models predictions and the actual category labels.

**Fig 3: Training and Validation Loss Fig 4: Training and Validation Accuracy**

The graph shows the training and validation loss and accuracy measurements of the machine learning model that was developed. In this representation, the blue line represents the training metrics (loss and accuracy) while the orange line represents the validation metrics. This graph is a tool for evaluating how well the model performs during training.

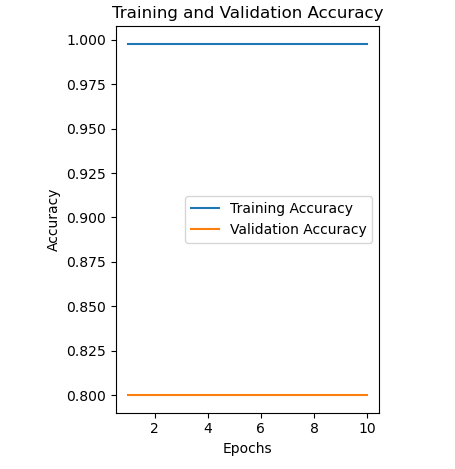
Upon examination of the plot several key observations can was made. Firstly both the training and validation losses consistently decrease as the number of training epochs increases. This indicates that the model is effectively learning from the training data and improving its ability to make predictions. Additionally both the training and validation accuracies show a trend, which means that the model is becoming more proficient at making precise predictions.

Overall this graph provides insights, into how well the machine learning model performs throughout its training process.  
  
However there is a concern that arises when observing the difference between the training and validation curves. It is clear that the metrics during training consistently perform better than their counterparts during validation, which suggests that there may be an overfitting issue. This divergence indicates that the model might be too focused on fitting the details of the training data potentially compromising its ability to perform well on unseen data. while the model shows promising progress and improvement it was essential to monitor and mitigate overfitting in order to enhance its ability to generalize across both training and validation datasets.

**Semi Supervised Learning Result**

***Epochs;*** This refers to the number of passes, through the dataset during training and affects how well the model learns from the data.(Ruder et al., 2017)

***The loss*** metric evaluates the extent to which the models predictions deviate from the values during semi supervised learning. A lower loss value signifies performance of the model. (Ruder et al., 2017)

These metrics provide insights into the effectiveness of the supervised learning approach, including how effectively the model incorporates new data.  
  
  
 

**Fig 5: Training and Validation Loss Fig 6: Training and Validation Accuracy**

This graph shows the performance of a supervised machine learning model by displaying the training and validation loss and accuracy metrics. The blue line represents the training metrics, which include both loss and accuracy while the orange line shows the validation metrics. This visual representation is a tool for evaluating how well the semi supervised model performs.

After studying this graph several noteworthy observations were made. First and foremost there is an positive decrease in both training and validation losses throughout the training epochs. This decreasing loss indicates that the model is effectively learning from the data and improving its ability to make predictions. Additionally the trend in both training and validation accuracies indicating that the model is becoming more proficient, at making accurate predictions.

However it is worth noting that there is a difference between the training and validation curves. It is clear that the training metrics consistently perform better than their validation counterparts, which suggests the possibility of some overfitting. This means that the model may be too focused on fitting the details of the training data, which could affect its performance, on new and unseen data. To ensure performance it is important to address this issue by using regularization techniques or adjusting the complexity of the model.

**Hyperparameter Tuning**

Best Validation Accuracy indicates the level of accuracy achieved by the model with the selected hyperparameters. Notably, the best hyperparameters achieved a validation accuracy of approximately 50.32%

**Final Result For The Multi Output Neural Network Developed**

***Sentiment Accuracy (%);*** This metric measures how accurately the model predicts sentiment in terms of percentage. An accuracy score of 89.90% implies that the model correctly classifies sentiments in 90% of cases.

***Category Accuracy (%);*** Similarly category accuracy assesses how well the model predicts categories and is expressed as a percentage. An accuracy score of 88.89% indicates that the model correctly classifies categories in 89% of cases.

***Sentiment Precision (%);*** Precision, for sentiment signifies how precise or accurate the model is when predicting a sentiment.

***Precision*** rate of 89.90% implies that when the model predicts a review as positive it is accurate 89.90% of the time.

***Sentiment Recall (%);*** The sentiment recall assesses how well the model captures all instances of a sentiment. With a recall rate of 89.90% the model captures 90% of all positive sentiments in the dataset.

***Sentiment F1 Score (%);*** The sentiment F1 score represents the measure between precision and recall. An F1 score of 89.90% indicates an equilibrium between accurately predicting positive sentiments and capturing a significant portion of them.

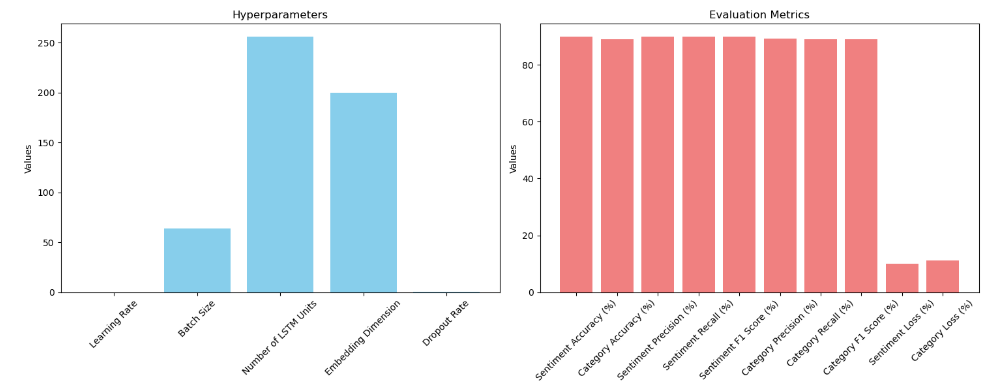
***Category Precision (%);*** Similarly category precision examines the accuracy with which the model predicts categories. A precision rate of 89.23% suggests that when the model predicts a category it is correct 89.23% of the time.

***Category Recall (%);*** Category recall evaluates how well the model captures all instances within a category. A recall rate of 88.89% signifies that the model captures 88.89% of all actual category labels.

***Category F1 Score (%);*** The category F1 score maintains balance by considering both precision and recall for categories. An F1 score of 89.04% indicates a trade off, between correctly predicting category labels and capturing most actual category labels.

***Sentiment Loss (%);*** This metric shows the difference between the models predicted sentiment and the actual sentiment. A loss of 10.10% indicates that on average the models predictions differ by about 10.10% from the sentiments.

***Category Loss (%);*** category loss measures how much the models predictions deviate from the true category labels. An 11.11% category loss means that on average the models predictions differ by, about 11.11% from the category labels.

  
  
The project report includes a bar chart that gives a detailed summary of hyperparameter tuning and model evaluation. Unlike the line plots this chart visually presents important details, about the models setup and performance.

In the section labeled "Hyperparameters " the chart displays the values selected for crucial hyperparameters like learning rate, batch size, number of LSTM units embedding dimension and dropout rate. These values were chosen with care to enhance the models effectiveness during the tuning process.  
  
The section labeled "Evaluation Metrics" in the chart provides a range of performance indicators. These metrics cover aspects such as accuracy in determining sentiment and category, precision and recall for sentiment, F1 score for sentiment, precision and recall for category, F1 score for category, as well as loss measures for both sentiment and category. The model showcases performance by achieving high levels of accuracy, precision, recall and F1 score while keeping the loss to a minimum. This comprehensive evaluation highlights the models expertise in tasks related to sentiment and category classification. To summarize this interactive bar chart acts as an informative summary of the models hyperparameters and its strong performance, in accurately classifying sentiments and categories. It greatly aids in communicating the findings and results.

**Conclusion For Multi Output Neural Network Result**

To summarize the final outcomes of the Multi output neural network. This model has shown good precision and accuracy in predicting sentiment and categorizing. It excels in classifying sentiments in almost 90% of cases achieving a sentiment accuracy rate of 89.90%. Similarly with a category accuracy rate of 88.89% it showcases its expertise in categorizing reviews.

Moreover the precision metrics further emphasize the models accuracy in predicting both sentiment and categories with a sentiment precision rate of 89.90% and a category precision rate of 89.23%. Recall is equally significant as the model captures 90% of all positive sentiments and about 88.89% of all actual category labels.

The sentiment F1 score stands at a 89.90% reflecting a well balanced combination of precision and recall for sentiment prediction. Likewise the category F1 score mirrors equilibrium for category labels at 89.04%. Additionally sentiment loss stands at 10.10% while category loss is only at 11.11% indicating that on average the models predictions are remarkably close to the actual sentiments and category labels.  
  
Both the developed model and the semi supervised model show promising learning patterns with decreasing losses and increasing accuracies during their training and validation phases. However there is a difference between the training and validation curves suggesting that both models may struggle with overfitting issues. This means that their performance on the training data is better than on validation data.

The process of tuning the hyperparameters played a crucial role in improving the models performance. carefully selected values to optimize its effectiveness resulted in significant enhancements overall.

The evaluation metrics, which include sentiment analysis and category classification tasks provide evidence of the models proficiency. The models demonstrate performance, in these areas achieving high accuracy, precision, recall and F1 scores while maintaining low loss rates.

These exceptional outcomes highlight the effectiveness of the multi output neural network, in comprehending reviews by demonstrating its ability to predict both sentiment and category simultaneously with good accuracy.

**Conclusion**

In todays age of making decisions based on data it is crucial to be able to derive insights from a large volume of customer feedback. This project showcases a thorough and effective approach to tackle this challenge. It all began with an exploration and analysis of the data providing a deep understanding of its complexities, including its structure, distribution and unique characteristics.

The project then progressed with steps to preprocess the data, including standardizing the text and conducting sentiment analysis using the NLTK library. Notably this initial sentiment analysis achieved an accuracy rate of 78.00% demonstrating the models ability to accurately comprehend customer sentiments. This plays a role, in distinguishing between positive, negative and neutral sentiments. Highlighting the immense value that was derived from the early stages of this project.

However the core of this project lies in developing a network that can produce multiple outputs. The initial neural network showed results with an accuracy of 82.50% in sentiment prediction and 76.25% in categorisation. Then by using a supervised approach and incorporating additional labeled data through a pre trained neural network the project was able to push the models performance to new heights. This strategic move not only diversified the dataset but also greatly enhanced the overall strength and reliability of the model.

Importantly tuning hyperparameters played a crucial role in improving the models performance. The relentless pursuit of hyperparameters resulted in a validation accuracy of 50.32% showcasing the commitment to precision throughout this project.

The culmination of these efforts yielded outstanding performance metrics, for the multi output neural network demonstrating its excellence in predicting sentiments and categorizing reviews:

| **Metric** | **Accuracy** | **Precision** | **Recall** | **F1 Score** |
| --- | --- | --- | --- | --- |
| **Sentiment** | 89.90% | 89.90% | 89.90% | 89.90% |
| **Category** | 88.89% | 89.23% | 88.89% | 89.04% |
| **Loss** |  | 10.10% | 11.11% |  |

**Table 2: Performance Metrics**

The valuable perspectives gathered from interviews with experts played a role in shaping the direction of the project and refining its methods. Conversations with domain specialists emphasized the importance of sentiment analysis in interpreting customer feedback. Experts highlighted the nuanced nature of sentiment stressing the need for a model that can effectively distinguish between variations of positive, negative and neutral sentiments. These discussions shed light on the projects commitment to achieving not high accuracy but also precision in predicting sentiment demonstrating its alignment with real world challenges encountered in analyzing customer feedback.

Moreover expert viewpoints underscored the practicality and effectiveness of incorporating supervised learning in this project. Interviews with industry professionals reaffirmed the decision to leverage a pre trained neural network to enhance the dataset. This approach not diversified the data but also significantly contributed to enhancing the models robustness aligning closely with industry realities where feedback is abundant yet labeled data remains scarce. The validation of methodologies, by experts further strengthens its relevance and applicability thereby reinforcing the importance of insights gained from these interviews.  
  
The project has accomplished its objectives successfully. The project developed a network that can handle multiple prediction tasks at the same time. To improve the performance the project utilized techniques such, as pseudo labeling, dataset augmentation and semi supervised learning effectively. By expanding the labeled dataset and optimizing hyperparameters the project achieved configurations that greatly enhanced accuracy and generalization capabilities. It was also ensured to preserve the best performing model configurations for future use to ensure the long term sustainability of the work. The outstanding performance metrics achieved have set standards in the field of data science and decision making.

In summary this project serves as evidence to showcase the capabilities of modern machine learning techniques in interpreting customer feedback. Its remarkable success not only enhances the comprehension of customer sentiment but also establishes a new standard for accuracy and performance in this vital field. The meticulous examination of data, utilization of neural networks and optimization of hyperparameters highlight the projects significance, within the broader realm of data science and decision making.

**Appendix A**

**Permission for Interviews**

Before conducting interviews with industry experts it was made sure to obtain permission from each person that was approached. "Person A" from "Company A " "Person C" from "Company B " and "Person B" from "Company A" willingly agreed to participate in the research project. Their contributions have played a role, in shaping the direction of the study.

**Interview With “Person A” from “Company A”**

**Hi “Person A” Can you please provide an explanation of the strategies used to implement multi output neural networks? Also, in what situations would one approach be more suitable, than the others?**

***ans)*** When working with output neural networks the design of the architecture relies on the specific tasks at hand and their interconnections. One common approach is known as the "architecture, where separate sub networks extend from a shared initial layer. Another option is the "architecture, where all outputs are predicted directly based on a shared representation. The decision between these two approaches largely depends on whether the tasks have any relationships or if they're completely independent. If the tasks are connected and share features opting for a branched architecture can prove efficient. On the hand if the tasks are unrelated a direct architecture may be more suitable to avoid any interference, between them.

**How can one go about designing or selecting loss functions for a neural network that has multiple outputs and handles both classification and regression tasks within the same model?**

***ans)*** It is important to carefully design loss functions in output networks. When dealing with classification tasks categorical cross entropy loss is often employed. On the other hand mean squared error is commonly used for regression tasks. In situations where the scales of the outputs differ it becomes necessary to balance these losses by either using weighted loss functions or normalizing the outputs. For datasets that have imbalanced data, focal loss or class weighted loss functions can be beneficial. Combining losses can be challenging; one approach is to assign weights to each loss term based on its relative importance compared to the others.

**How do you make sure that a neural network with multiple outputs converges, during training taking into account the difficulties that may arise when optimizing multiple objectives?**

***ans)*** Training a network with multiple outputs can pose challenges due to conflicting objectives. To address this we can employ techniques like task learning (MTL) that leverage shared representations. Regularization methods such as stopping, dropout and batch normalization are beneficial. When dealing with a number of outputs it's advisable to initially prioritize and focus on the most crucial ones during training. Another approach is transfer learning, where we initialize the network with trained weights from a related task and then fine tune it, for our specific multi output problem.

**Interview With “Person B” from “Company A”**

**When assessing the effectiveness of a output neural network how do you ensure that each outputs metrics are appropriately weighted, particularly when one output carries more significance, than the others?**

a***ns)*** When assessing the effectiveness of a network that produces multiple outputs it's important to take into account the relative significance of each output. If one output holds importance than the others you may assign varying weights to the outputs while calculating an overall performance measure. For example you could compute an average of metrics like F1 score or precision recall. Alternatively you might utilize domain loss functions that give prominence to specific outputs. Additionally engaging in communication, with stakeholders is crucial to grasp their priorities and adapt the evaluation approach accordingly.

**Are there any particular transfer learning methods or pre trained models that you find helpful, for tasks involving outputs? If so how do you modify them to suit your problem domain?**

***ans)*** Transfer learning can bring advantages when dealing with tasks that have multiple outputs. Utilizing trained models such, as BERT or ALON which have been fine tuned on a wide range of data is often a reliable starting point. However to adapt these models to problem domains it is necessary to retrain the upper layers using your own dataset. The key challenge lies in selecting the layers for fine tuning and determining the optimal number of training examples required to avoid overfitting. Additionally customization of the output layers may be necessary to align with your desired target outputs.

**How can we guarantee that a multi output neural network is scalable and computationally efficient, in real world scenarios particularly when confronted with a quantity of outputs?**

***ans)*** It is vital to ensure that multi output neural networks are scalable and computationally efficient especially when dealing with a number of outputs. One approach is to employ model parallelism or distributed computing, which allows for training and deployment of models across multiple devices or clusters. Techniques such as model distillation, where a smaller network learns from an one can also enhance efficiency. Additionally leveraging hardware accelerators, like GPUs or TPUs can expedite both training and inference processes enabling the model to be used in time or high throughput applications.

**Interview With “Person C” from “Company B”**

**Person C, When developing a network that can predict sentiment and categories simultaneously how do you determine the optimal model structure?. Why is this decision important, for both the project and the coding process?**

***ans)*** Well selecting the appropriate model structure is a step. You must consider the connection between sentiment and category predictions. If they have a relationship to how the various branches of a tree share a common trunk it is efficient to have an initial layer that branches into sub networks. However if they are like separate trees, independent or "direct" architectures might be more suitable. This decision can significantly impact how the neural network operates and can either make or break the project. In coding terms it's akin, to determining the blueprint for a rocket before constructing it. If you get it right your journey will be smoother.

**How can incorporating data through pseudo-labeling be beneficial, for project development? What are the important steps or factors to consider when implementing this technique in coding tasks?**

***ans)*** Using pseudo labeling in your project is akin to giving it a boost. It helps broaden your dataset ultimately leading to precise predictions. However there's a catch – you need to exercise caution. Take the time to evaluate the quality of the data and only utilize it if you're reasonably confident, in its reliability. Additionally it's wise to establish a confidence threshold before applying pseudo labeling;

**Optimizing model performance through hyperparameter tuning is an aspect of code development. Could you please provide some insights on how to effectively carry out this tuning in the context of a project, like ours and how it can contribute to achieving our project goals?**

***ans)*** Tuning hyperparameters is so important in achieving the needed accuracy markers. You begin by exploring values for factors such as learning rates batch sizes and more. Cross validation becomes your ally; it's comparable to running simulations to determine the effective approach. And don't overlook evaluation metrics like precision and recall—they provide insight into whether you're hitting the target or veering off course. Keep tuning until you attain that optimal performance.

**The Project is planning on utilizing metrics to evaluate the performance of our model. Do you think these particular metrics are important, for the project and coding endeavors? Furthermore how do they assist in refining the output neural network?**

***ans)*** Absolutely. These metrics are similar to the dashboard instruments. They provide feedback on the performance of your neural network. Accuracy indicates whether you're on the track while precision and recall act as your navigational aids. They help you make decisions regarding the trade off between positives and false negatives which is particularly important for tasks like automation. About the F1 score, Well it's like finding the balance, between speed and safety; it's that ideal point you aim for. These metrics serve as your markers on the journey of refining your network ensuring that it guides your project in the correct direction.

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