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ANALYSING THE IMPACT OF MEME FORMATS ON REDDIT ENGAGEMENT USING LARGE VISION MODELS

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Abstract

This study, part of a larger group thesis focused on meme engagement on Reddit, examines the interplay between visual and textual elements by categorizing memes into specific comedic formats and analysing their differences in user engagement. Using Large Vision Models, this research aims to capture and analyse the complex, context-dependent elements of memes that previous studies have overlooked. The findings reveal significant variations in engagement levels across different formats, providing insights into the popularity of specific types of memes.

Meme Formats, Reddit, Memes, Python, Ollama, Llava, Large Vision Models, OLS, Zero-Shot Classification

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1. Introduction

Memes have become a significant medium for spreading cultural, social, and political ideas, effectively engaging online audiences through humour, relatability, and adaptability. Understanding what makes a meme successful—often measured by views, likes, and shares—has become essential knowledge, particularly in advertising, political communication, and online content moderation (Barnes et al. 2021). With its topic-focused subreddits and interactive community dynamics, Reddit offers a unique platform for studying meme trends. Its voting and ranking systems amplify posts based on user preferences, enabling memes to spread rapidly and evolve. This dynamic environment provides valuable insights into user engagement across diverse subcultures and contexts (Medvedev, Lambiotte, and Delvenne 2019). As of December 2023, Reddit boasted an average of 73.1 million daily active users and 267.5 million weekly active users, nearly half of whom reside outside the United States. This broad and diverse user base significantly enriches data on meme trends and user interactions with various topics and communities (Statista 2024).

Advances in artificial intelligence, particularly in computer vision and generative AI, have opened new pathways for analysing meme success. Computer vision techniques can identify visual features such as colour patterns, facial expressions, and object presence, which are critical to assessing memes visual appeal and impact (Barnes et al., 2021). Generative AI models like DALL-E contribute to this research by generating images from textual descriptions, enabling a more profound exploration of the synergy between visual and textual meme components (OpenAI 2021).

Previous research highlights how sentiment analysis and machine learning approaches enhance the evaluation and prediction of meme engagement on Reddit. By identifying the emotional tone—such as humour, sarcasm, or motivation—present in memes and comments, sentiment analysis provides valuable insights into user reactions. For instance, one study categorised

memes based on their overall sentiment, showing how this approach helps understand user responses (Hossain et al. 2022). Furthermore, machine learning methods, particularly those integrating multiple data sources, have proven useful for predicting meme virality. For example, a framework combined visual and textual features to determine sentiment across different content types, demonstrating how these technologies collectively forecast meme engagement (Pranesh and Shekhar 2020). Studies reveal that factors like image dimensions, brightness, and text density significantly influence meme popularity on platforms like Reddit (Barnes et al. 2021). These findings underscore the necessity of holistic analysis, as meme success depends on its message, visual design, and contextual relevance.

Predicting meme and comment virality remains challenging, mainly due to the complexity of aligning text and image data with their distinct structures and meanings. Recent advancements in deep learning and computational power have enabled sophisticated analyses that consider both data types, advancing the field of meme research (Ford, Krohn, and Weninger 2023). The highly skewed distribution of meme success further complicates machine learning tasks, necessitating specialised data preprocessing and evaluation techniques to address minority trends without overrepresenting majority classes (Shyalika, Wickramarachchi, and Sheth, 2024). Incorporating rare event prediction methodologies into multimodal AI frameworks holds promise for enhancing the accuracy of meme engagement classification.

Understanding meme dynamics has applications beyond academia, benefiting brands that use memes in advertisements to connect authentically with younger audiences and political campaigns that leverage meme culture to shape opinions and disseminate impactful messages (Ford, Krohn, and Weninger, 2023). Platforms like Reddit have become vital arenas for political and cultural discourse. For example, subreddits like r/PoliticalCompassMemes use humour to critique and discuss ideological perspectives (Colacrai et al. 2024). Additionally, insights into meme success can inform more effective digital communication strategies, as memes are

compelling tools for community building and cultural expression on social media (Nissenbaum and Shifman 2018).

This research adopts a multifaceted approach, integrating computer vision, generative AI, sentiment analysis, and machine learning to examine engagement with memes and comments on Reddit. Using historical data from r/memes, including actual meme images, this study aims to identify key drivers of engagement, enhancing the understanding of meme virality. By analysing the unique features of digital memes—adaptability, emotional resonance, and community-driven evolution—this paper seeks to quantify and model their success based on visual content and contextual data, offering novel insights into the dynamics of meme culture in the digital age.

2. Literature Review

2.1. The Theoretical Foundation of Memes

The idea of a meme was first proposed by evolutionary biologist Richard Dawkins in his work *The Selfish Gene*. Dawkins (1976, 248-249) suggested that evolution occurs because of the survival of self-replicating entities. In the context of biological evolution, the gene is the leading replicator, passing from one generation to the next and driving natural selection. However, the existence of another type of replicator was proposed, the meme, which he defined as a "unit of cultural transmission or a unit of imitation". Etymologically, it is derived from the Greek word *mimeme*, meaning “imitation", and was deliberately shortened to resemble "gene." Dawkins also intended the term to evoke memory, emphasising the role of replication and retention in cultural transmission. This analogy underscores the parallel between genetic and cultural evolution: just as genes propagate through biological organisms, memes spread through human minds, influencing cultural development through imitation.

Although Dawkins' analogy between genes and memes laid the foundation for the study of cultural transmission, it has also faced significant critique for being, according to some, overly

simplistic. For instance, cognitive anthropologist Dan Sperber challenged the notion of memes as replicators like genes in the early 1990s. The author introduced the metaphor epidemiology of representations to compare the spread of ideas and cultural elements to the transmission of diseases within a population (Ananth 2001). Much like diseases are passed between individuals and often mutate, memes are shared and modified during the process of communication. For Sperber, Dawkins's definition failed to account for how individual interpretation and social contexts actively transform these cultural elements during transmission rather than simply replicating them (Caton 1997, 319).

Sperber's critique is just one of the responses to Dawkins' theory. Other scholars, such as Susan Blackmore and Daniel Dennett, chose to expand on Dawkins' ideas rather than challenge them. In *The Meme Machine*, Blackmore supported the concept of memes as true replicators but delved deeper into their influence on human evolution. The author elaborated on the idea of *meme-gene co-evolution*, which suggests that the human brain evolved, at least in part, to become more efficient at imitating and spreading memes (Blackmore 2001, 244). This is because individuals who were better at sharing knowledge and adapting quickly through cultural learning would have gained a survival advantage.

Additionally, the philosopher and scientist Daniel Dennett argued that memes are critical in shaping human consciousness and its sense of self. As individuals encounter memes throughout life, these ideas and behaviours are adopted, either consciously or unconsciously, influencing actions, interactions with others, and the definition of personal identity. Dennett believed that, just as genes shape physical traits, memes shape one's identity (Block 1993).

2.2. Memes in the Digital Era

While the foundational ideas proposed by these authors have guided early discussions around cultural transmission, many of these perspectives were developed before the rise of the modern internet. As a result, there are core ideas that still hold, but they do not fully capture the nuances

of digital memes. Therefore, it is important to explore more recent definitions and frameworks that adapt and add to previous concepts by contextualising them within today's online culture. Limor Shifman, a key figure in defining the concept of internet memes, recontextualises Dawkins' original ideas of longevity, fecundity, and copy fidelity for the digital age (Shifman 2014, 17). The author explains that the internet increases longevity by allowing memes to be archived and rediscovered over time, enhances fecundity by enabling the widespread sharing of memes across platforms, and boosts copy fidelity by making it easier to replicate memes with precision while still allowing for remixes. Shifman also adds to her definition of a meme as a "group of digital items sharing common characteristics", which include content (the ideas conveyed), form (the visual format), and stance (the tone expressed) (Shifman 2014, 41-47). The "Distracted Boyfriend" meme is a well-known example. The form remains the same - a man looking away from his girlfriend - but the content changes based on the labels applied to the characters, such as "Me," "My Responsibilities," and "Procrastination." The stance is usually humorous or sarcastic, although it can vary depending on the message. Shifman also reinforces the idea that memes are not isolated entities by explaining that they are "aware of each other", meaning they remix and reference previous memes. For Shifman, this meme characteristic is fundamental as it differentiates them from viral content, which spreads as identical copies without significant alteration (Shifman 2014, 56-58). In contrast, memes are inherently collaborative and iterative, constantly evolving through user participation, a process greatly facilitated by the internet - something that will be discussed further in the next paragraph.

The emergence of *Web 2.0* transformed the web from a static to an interactive ecosystem, where users became active participants rather than passive consumers. This shift was largely driven by the rise of user-generated content, which empowered individuals to create and share their content, such as memes, across various platforms (Walther and Jang 2012). These platforms

have low barriers to entry, requiring only an internet connection and basic digital literacy, and are often free or low-cost to use (Elkin-Koren 2010). This combination of affordability and accessibility enables users to easily engage with content, thus fostering a highly participatory and interactive online culture that allows memes to evolve dynamically. Memes inherently rely on a dual process of replication and modification, with users copying but also remixing core elements such as images, text, or humour to adapt them to various cultural and social contexts. Therefore, the participatory culture of digital platforms plays a fundamental role in shaping how memes evolve and spread as they serve as the primary environment for meme proliferation.

Among these platforms, Reddit stands out as a central hub for meme creation and circulation, making it an ideal platform for analysing meme dynamics in this research. Reddit is a heterogeneous, crowd-sourced news aggregator and online social platform, originally self-declared as "the front page of the internet" (Eldridge 2024). Launched in 2005, it has consistently attracted over 1 billion monthly visits worldwide since 2023 (Bianchi 2024). Reddit's core structure is built around subreddits, which are interest-based communities that operate independently with their own rules and moderators, where users can post, comment, and engage with content specific to those topics. Posts are subject to a voting system, where upvotes and downvotes determine the visibility and ranking of content, with the most engaging posts rising to the top of the feed. Comments follow a tree-like structure, encouraging in-depth discussions within each post (Medvedev, Lambiotte, and Delvenne 2019). Reddit's large user base and open access make it a rich resource for research (Cauteruccio et al. 2022) across diverse fields, including computer science, health, and social sciences (Proferes et al. 2021). Furthermore, its subreddit structure enables researchers to conduct detailed, topic-specific studies within focused communities, making it easier to analyse niche areas of interest.

2.3. The Role of Memes

With Reddit established as a valuable platform for research, it is equally important to consider

why memes themselves warrant academic attention and, thus, explore their broader significance in the digital age, namely as a dominant form of communication in modern culture. Memes are highly effective in conveying messages because they combine visuals with short, impactful text, making them easy to consume (Holland 2020). This characteristic is particularly valuable in an era where attention spans are shrinking, as memes offer a fast and accessible way to communicate ideas or emotions in a format that is easily absorbed (Fillmore 2025).

Moreover, memes evoke universal emotions, ranging from joy to frustration, that resonate with a wide range of audiences. Their emotional relatability strengthens the connection between the content and the user, making memes an effective channel for conveying emotions. When a meme captures emotions that resonate with personal or collective experiences, it becomes more likely to be shared (Wagener 2021). An example of this emotional connection can be seen during the COVID-19 pandemic, where memes were widely used as coping mechanisms. According to a study on coronavirus-related memes from a dedicated subreddit, these memes allowed individuals to process and share their emotions, helping them cope with the anxiety and uncertainty of the global crisis through humour and creativity (Glăveanu and De Saint Laurent 2021).

Memes also play a significant role in community building and identity formation. Online communities, such as the r/DankMemes subreddit, use memes as a form of in-group communication, where shared cultural references and humour create a sense of belonging and mutual understanding among members (Newton et al. 2022). This shows that users not only relate to the content of memes through the emotions they evoke but also to the community of other users who share the same cultural references, reinforcing a collective identity.

Beyond forming niche communities, memes also act as a global communication medium, transcending cultural barriers as they are easily adapted to many contexts and, thus, can be understood by people from different backgrounds (McGrady and Hamm 2019). Their versatility

allows them to be reshaped, making them a powerful tool for cross-cultural dialogue and global communication.

The focus now shifts to exploring the underlying intentions of meme creators. The dominant function of memes is to entertain, often using humour, satire, or irony to capture attention and provoke laughter or amusement (Milosavljevic 2020). However, their role extends far beyond this, as memes can convey deeper messages. Examining these other intentions provides valuable insights into how memes function not only as sources of entertainment but also as drivers of public discourse and societal change.

Regarding marketing, memes have become a powerful tool in advertising, allowing brands to communicate in a way that is relatable, adaptable, and easily shareable at a lower cost when compared to traditional methods (Ngo 2021). Due to their viral nature, memes can enhance a company's visibility and engagement, especially among younger audiences who spend significant time on social media (Rathi and Jain 2023). Brands often use memes to advertise products by blending humour with cultural references, making their marketing efforts feel more authentic and less intrusive than traditional ads. While meme-based marketing offers brands the potential for significant visibility and engagement, it has risks. The viral and unpredictable nature of memes means that they can sometimes misfire or be misinterpreted, leading to backlash or controversy, as seen in cases like SunnyD's controversial tweet (Morabito 2019). Despite these risks, success stories such as Netflix's creative use of memes in its social media strategy (Beer 2019) prove that, when done correctly, memes can positively impact brand perception.

Just as brands have harnessed the power of memes to promote products, political campaigns, and movements have also embraced meme culture to communicate and engage with the public while promoting their points of view (Milosavljevic 2020). Nevertheless, most often, memes in politics are used to mock or criticise political figures, policies, or ideologies. Memes provide

an accessible and often humorous way to challenge authority and express dissatisfaction, making them a popular tool for political satire and critique (Moody-Ramirez and Church 2019). For instance, during the 2016 U.S. Presidential election, memes were employed as tools for political participation, often aiming to delegitimise political figures like Donald Trump and Hillary Clinton to sway public opinion and achieve a desired political outcome, such as the election of one candidate over another (Ross and Rivers 2017). Political actors themselves are aware of the power of memes and actively use them to shape public opinion. In fact, campaigns frequently hire paid bloggers and commenters to generate meme content, crafting images and narratives that influence how the public perceives political figures or ideologies (Kulkarni 2017). This calculated use of memes in political discourse underscores the recognition of their cultural and persuasive power.

However, that influence can be exploited negatively as well. The same viral qualities that make memes engaging also turn them into effective vehicles for spreading misinformation (Lynch 2022). Memes often oversimplify complex issues, distorting facts or promoting harmful narratives. During events like elections or the COVID-19 pandemic, memes were used to spread conspiracy theories (Basch et al. 2021). Their rapid, anonymous spread makes tracing or correcting false narratives difficult, further fuelling disinformation online.

Beyond the spread of misinformation, memes are being weaponised for harmful purposes, such as cyberbullying and hate speech (Greene 2019, 36), with offensive content often concealed behind humour or visuals. While social media platforms work to detect and moderate such content, traditional automated systems and human moderators frequently struggle to identify nuanced or disguised offensive material. This challenge has led to the development of advanced detection methods, including a recent study using multimodal deep learning models (Ahmed, Bhadani, and Chakraborty 2021) that combine text and image analysis to more effectively identify hateful memes, enabling them to be flagged and removed.

Therefore, although memes are often perceived as light-hearted and humorous, their influence can be profound, with both positive and negative impacts on society.

2.4. Meme Success as Object of Study

As memes continue to play a prominent role in the digital age, researchers have also turned their attention to understanding the factors that drive their success. Some studies emphasise external influences, such as platform algorithms and the amplifying role of social networks, while others focus on the internal attributes of memes, like their content, emotional resonance, and visual design. These varied approaches underscore the complexity of meme success, suggesting that both external dissemination mechanisms and the intrinsic qualities of memes play vital roles in their impact. Rather than being mutually exclusive, these perspectives often intersect, offering a more holistic understanding of meme dynamics.

Beginning with studies that mainly underscore the surrounding environment of memes, Weng, Menczer, and Ahn (2013) explored the role of community structure in meme virality, drawing an analogy to contagions. The authors found that viral memes behave like simple contagions, quickly crossing community boundaries, much like infectious diseases spreading through populations. In contrast, memes confined to a single community act like complex contagions, requiring reinforcement from within the group to spread. Their research emphasised that memes permeating multiple communities are far more likely to go viral, highlighting the importance of network diversity for meme virality. Building on this, their 2014 study expanded the analysis to include additional factors, such as the position of early adopters in the network and the early growth rate of meme adoption, which was found to be the weaker predictor. While the position of early adopters in the social network provides insights into the potential size of its audience, influencing its reach, it was still concluded that community diversity remained the most robust predictor of meme popularity (Weng, Menczer, and Ahn 2014).

Similarly, Ford, Krohn, and Weninger (2023) emphasise the continued importance of

community structure in meme virality but shift focus to the competitive dynamics among memes. The authors view memes as entities vying for limited user attention within social networks. As the number of memes being created and shared increases, the diversity and longevity of individual memes are influenced by the finite attention available from users. This perspective provides a more nuanced understanding, highlighting that meme virality relies not only on reaching diverse communities but also on successfully navigating the competitive pressures of attention economics.

Barnes et al. (2021) also found that neutral memes performed better than extreme sentiments overall, but among extreme sentiments, negative sentiment outperformed positive sentiment in driving upvotes. Building on this focus on sentiment, other studies have demonstrated how tools such as VADER and more advanced machine learning models enable the classification of social media content into sentiment categories (positive, neutral, negative), offering valuable insights into user attitudes and behavioural patterns. For instance, Srinidhi et al. (2024) emphasized that VADER's lexicon-based approach efficiently captures nuanced emotional expressions and is particularly well-suited for analysing short text, such as social media comments.

In practical terms, the conclusions of studies that aim to predict meme success and virality have various applications, as they provide insights into emerging topics that can be useful across multiple areas (Colbaugh and Glass 2011). For instance, in marketing, brands can use these insights to craft meme-based campaigns that resonate with audiences and increase engagement. Political campaigns can also benefit by identifying and leveraging memes that align with their messaging to shape public opinion. Additionally, content moderators can leverage predictive models to anticipate which memes might go viral, enabling them to manage content more effectively and address potential issues before they escalate. On a more relaxed note, communities such as r/MemeEconomy have turned meme success prediction into a form of entertainment, where users speculate and "trade" memes as if they were stocks, betting on which

will rise or fall in popularity (Literat and Van Den Berg 2019).

2.5. Meme Engagement as a Rare Event

All these studies share a common core challenge – they aim to predict a rare event. A rare event is an infrequent occurrence within a dataset that, while uncommon, is expected (Illowsky and Dean 2023, 526). Examples include extreme weather conditions, such as hurricanes or tornadoes, sudden stock market crashes, rare disease outbreaks, or equipment breakdowns in manufacturing environments. It is important not to mistake rare events for anomalies or novelties. While rare events are infrequent yet expected occurrences, anomalies are unexpected deviations from the norm, representing irregularities that break established data patterns, like a sudden spike in network activity indicating potential fraud. On the other hand, novelties refer to entirely new and previously unobserved phenomena that are not present in the training dataset (Carreño, Inza, and Lozano 2020). Substantial meme engagement falls under the rare event category because high levels of engagement, though infrequent, are anticipated within meme datasets. Engagement on social media typically follows a Pareto distribution, where a small number of memes capture most interactions. Therefore, while most memes receive low to moderate engagement, it is expected that, on rare occasions, a select few posts will attract significant attention.

Due to their nature, datasets with rare events lack sufficient data within the minority class. This scarcity can manifest as either absolute rarity, where the minority class has very few instances, or relative rarity, where the majority class outnumbers the minority class. As a result, identifying rare events often requires analysing large volumes of data, which are both time-consuming and computationally expensive, to capture enough minority instances for meaningful learning (Shyalika, Wickramarachchi, and Sheth 2024). Furthermore, the imbalance in the dataset may lead the model to develop a maximum-generality bias, favouring broad patterns that fit the majority class while overlooking the features of the minority class.

Another issue posed by imbalanced datasets is that traditional evaluation metrics, such as classification accuracy, are often unsuitable, as they tend to favour the majority class. For instance, in a dataset with a 100:5 imbalance, a model that misclassifies all minority class instances could still report a high accuracy of 95% despite failing to detect any rare events (Maalouf and Trafalis 2011).

These hurdles have been referred to as the curse of rarity (Liu and Feng 2024). In a study focused on autonomous vehicles, this concept was introduced to illustrate how the scarcity of safety-critical events, such as crashes caused by unexpected obstacles or sudden changes in driving conditions, constrain the model's capacity to learn effectively from these crucial occurrences. Numerous studies have focused on ways to mitigate the curse of rarity.

In terms of data preprocessing, it is essential to use tailored techniques to retain and emphasise critical features that might otherwise be overlooked in imbalanced data, as they may appear redundant or lack sufficient expression in the majority class (Shyalika, Wickramarachchi and Sheth 2024). Feature selection techniques include supervised methods like wrapper-based approaches, such as Recursive Feature Elimination (RFE), which remove less relevant features while preserving patterns linked to rare events. Filter-based methods use statistical measures to detect subtle and low-frequency signals. Intrinsic methods like attention mechanisms and adapted decision trees focus on rare, dispersed features, ensuring critical elements are retained during training. Additionally, feature engineering techniques like data augmentation create synthetic samples to increase the representation of rare patterns, while dimensionality reduction and feature scaling refine the dataset, increasing the detectability of rare event signals and boosting overall model performance.

Recent advancements in predicting rare events focus on approaches to handle imbalanced data effectively (Chen et al. 2024). Data-level methods, like oversampling (e.g., SMOTE) and under-sampling, modify datasets to rebalance classes, while algorithm-level techniques, such as cost-

sensitive learning, enhance models' sensitivity to minority classes by adjusting learning goals to prioritize underrepresented groups. Ensemble learning (e.g., boosting, bagging) merges multiple classifiers to capture minority class patterns, with boosting emphasizing difficult-to-classify instances. Deep learning's long-tail learning addresses deep imbalances, redistributing focus across rare classes.

Finally, performance metrics vary depending on the specific tasks in rare event prediction, including classification, clustering, regression, and simulation (Shyalika, Wickramarachchi, and Sheth 2024). In classification, metrics like G-Mean and Matthews's correlation coefficient (MCC) are preferred as they balance performance across minority and majority classes, providing a more accurate picture in imbalanced scenarios. Clustering tasks use metrics like the Elbow method and Silhouette coefficient to maintain distinct clusters for rare events. For regression, Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are commonly used to measure prediction precision. Simulation tasks rely on probability evaluation, statistical robustness, and confidence intervals to assess model reliability. Selecting the appropriate metric for each task enhances the accuracy and reliability of rare event predictions.

3. Methodology

3.1. Data Collection

3.1.1 Data Sources

Data plays a crucial role in this study, forming the backbone of the analysis and conclusions. The strength and dependability of the data are key to ensuring accurate predictions and great results. Various sources were explored to gather the necessary historical data, primarily focusing on meme-related content on Reddit, specifically within the r/memes subreddit. The Arctic Shift GitHub Repository, the Pushshift Reddit Dataset, and the dataset stored at Regensburg University from the work *A Corpus of Memes from Reddit* were among the valuable resources consulted for this purpose.

Regensburg University Dataset (Schmidt et al. 2023) was helpful for initial testing. However, it only contained the top 1,000 memes (measured by the highest number of upvotes) for each half-year for the 2013-2021 period. By excluding memes with lower or moderate engagement, this dataset fails to capture the full spectrum of meme performance, limiting the ability to generalize findings to the broader meme population. This selection bias could also distort the analysis by inflating the perceived relationships between independent variables and engagement metrics, as it only examines cases where engagement is already high.

On the other hand, Arctic Shift (Heitmann 2023) provided a comprehensive dataset with several advantages for this study. It contains functional URLs for downloading images, which was crucial as some independent variables include visual characteristics of memes. Additionally, the dataset's organization and flexibility allowed for efficient data retrieval using “The Arctic Shift Download Tool”, enabling the selection of specific time frames, subreddits, and distinctions between posts and comments. These features made the Arctic Shift a practical source for data collection, offering a manageable and representative foundation for analysing meme dynamics on Reddit.

It is essential to mention that the data available in the Arctic Shift database reflects the state of Reddit posts and comments when Arctic Shift collected them, not when the dataset was downloaded. Arctic Shift collects Reddit data through periodic snapshots. In April 2023, a retrieved timestamp was added to all posts. This timestamp indicates the specific moment when the content was fetched from Reddit. Fields such as score, or number of comments represent the values at the time of collection rather than their real-time values. Moreover, starting in November 2023, Arctic Shift introduced a secondary retrieval mechanism. A process that revisits collected data 36 hours after the initial retrieval to capture changes, such as post edits, engagement metrics updates, or deletions.

So, the Arctic Shift database is not designed to provide real-time data. When researchers

download a dataset, a historical snapshot of Reddit content is obtained, which may not accurately reflect the present state of the post's score and comments. However, this limitation is acceptable for this study, as engagement on posts typically declines significantly after the first few days of publication (Vassio et al. 2021). This trend occurs mainly because Reddit's algorithm prioritizes newer content, making it more visible to users shortly after posting. As time passes, newer posts take precedence, leading to less attention on older posts.

3.1.2. Subreddit

Reddit has been established as the platform for this study. Given its multitude of subreddits, it is necessary to determine which specific communities will be included in the analysis. Since many subreddits are dedicated to memes, each with distinct user behaviours and approaches to content management, attempting to incorporate data from multiple subreddits could introduce a range of challenges. For instance, one subreddit may enforce strict guidelines against certain memes, while another might actively encourage them. Community size also plays a crucial role, as larger subreddits offer greater post visibility, impacting engagement metrics. To address these challenges and ensure consistency, this research focuses on a single subreddit: r/memes.

Focusing on a single subreddit places greater importance on selecting the right community, as the entire analysis hinges on its characteristics. When multiple subreddits are used, any limitations or biases of one can be balanced out by others, reducing their overall impact. However, with only one subreddit, a poor choice could significantly affect the reliability of the findings. r/memes, regarded as a central hub for meme culture on Reddit, was deemed an appropriate choice based on its characteristics.

Firstly, r/memes was established in 2008, making it one of the oldest meme-focused subreddits on the platform. This longevity has allowed the community to mature and refine its rules, moderation practices, and overall structure, fostering a stable and consistent environment for analysis. Moreover, it has accumulated a substantial subscriber base of over 35 million

members. A large audience reflects broader user behaviours and ensures a significant volume of engagement metrics, providing robust data. Additionally, unlike many meme-focused subreddits catering to specific themes, r/memes encompass various meme content. This generality makes it particularly suitable for analysing overarching trends in meme culture without being constrained by the biases of a specific niche.

3.1.3. Observation Period

The year 2023 was chosen for this analysis because it represents the most recent complete year at the time of the study. Focusing on the latest full year ensures the dataset reflects current trends within meme culture, making the findings more relevant to contemporary digital environments. Another advantage is that 2023 is more comprehensive in data than past years. Older years on the Arctic Shift dataset, 2018 and before, lack details such as whether an author is a premium user, the awards received by the post, or the post's removal status, either because such features did not exist at the time or because the data on them was not retrievable. Moreover, if an older year had been chosen, the analysis would have captured the subreddit during its earlier stages, missing out on the advantages of its current maturity, such as fine-tuned rules and a more extensive subscriber base.

In addition, 2023 offered a manageable dataset size compared to the peak activity years of 2020, and 2021, when Reddit experienced significant surges in traffic, likely driven by global lockdowns that increased online activity during the pandemic (Veselovsky and Anderson 2023). These years represent a unique and atypical context, with user behaviour and engagement heavily influenced by the extraordinary circumstances of the COVID-19 pandemic. The unprecedented spikes in activity during this time may not accurately reflect typical patterns, introducing potential biases into the analysis. By focusing on 2023, the study avoids these irregularities, offering a recent and more representative dataset of standard online behaviour while remaining manageable for analysis.

3.2. Data Preprocessing

The datasets comprising 462,274 posts and approximately 6 million comments from r/memes for the year 2023 were sourced from Arctic Shift. Figure 1 provides an overview of the steps taken to achieve the final datasets used in this research, which are further detailed in this section.

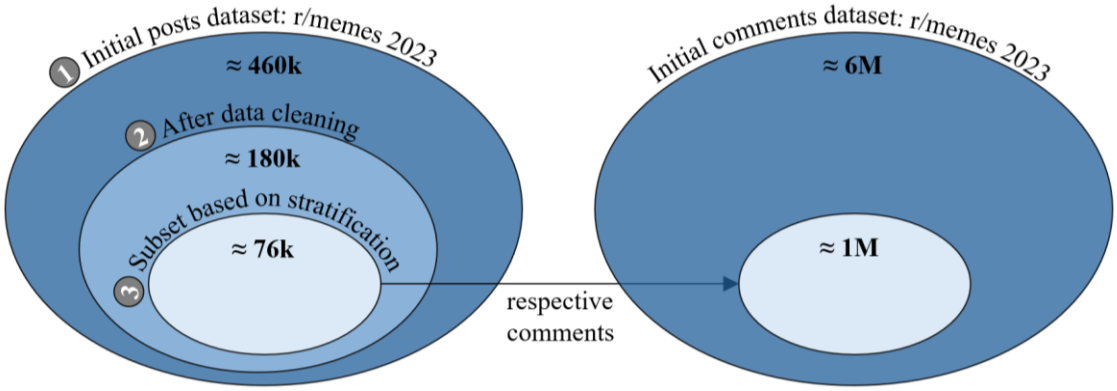

Figure 1: Data Preprocessing for r/memes 2023 posts and comments datasets

3.2.1. Data Cleaning

The preprocessing phase begins with fundamental data cleaning. Video posts were removed, as the study does not focus on video content. Posts submitted on the author's "cake day", the anniversary of their account creation, were also excluded. This decision is based on the understanding that such posts may attract comments unrelated to the meme's content and receive a higher upvote ratio due to the associated event, introducing noise and potential bias into the dataset.

After this initial step, the dataset was reduced to 447,136 posts. However, a problem was identified: not all URLs were valid, which meant the visual content of the memes could not be used due to the absence of accessible images. To address this, a dedicated Python function was developed to verify the URL data for each post and identify those with images available for download. The function checks whether a URL is reachable and points to a valid image file, excluding GIFs, as the analysis focuses on static images. To handle network errors, timeouts, or other issues, the function employs a retry mechanism with exponential backoff, allowing multiple attempts to access a URL while progressively increasing the delay between retries.

This approach ensures that transient issues, such as server overload or network instability, are handled effectively.

To enhance the speed and efficiency of the process, the function employs multithreading, allowing for the concurrent evaluation of multiple URLs. Additionally, it utilises custom HTTP headers, such as a "User-Agent", to emulate browser behaviour and reduce the likelihood of being blocked by websites during the evaluation. For users wishing to monitor progress, the function includes an optional feature to display the status of each URL as it is processed.

Once all posts have been assessed, the results of the status of their image URLs are stored in a new variable called "status", together with the rest of the dataset in a new CSV file.

Posts with URL error status codes of 404 (not found) or 403 (forbidden), with URL missing data, or with other unresolved issues were removed, resulting in 179,161 posts with valid URLs.

3.2.2. Stratification

Although necessary, the cleaning process introduced unintended biases by disproportionately removing posts with specific characteristics. To address this and ensure the dataset represented the entire year, a subset was created based on three key stratification categories, allowing for the selection of a representative sample for analysis.

Comment Category: Posts were categorised based on the number of comments they received, using different levels, such as Low [0-5], Medium]5, 15], High]15+].

Score Category: Posts were also divided into score categories, such as Low [0,10], Medium]10,25], High]25,50], and Very High [50+].

To choose the appropriate numerical intervals for these categories, the percentile distribution of posts for the number of comments and scores had to be examined in the original 2023 dataset (Appendix 1). For the number of comments, 85% of the posts have 5 or fewer comments, 90% have 9 or fewer comments, and 95% have 25 or fewer. For the score, the intervals had to reflect a higher magnitude of values since 85% of the posts have a 32 score or less, 90% have a 73 or

less, and 95% of posts have 325 or less.

Created Month: The posts were also divided into categories of the month they were created, i.e., January to December. From the created UTC data available, the hour of the creation of the post was also extracted. However, this variable proved unusable because of the diversity of users' time zones. This made the month variable the only reliable one regarding posting time.

Using the stratification categories, a representative subset was selected to closely match the distribution of three key variables—Score, Number of Comments, and Month Created—from the original 2023 dataset. The selection process prioritized maximizing the subset's size while ensuring it accurately reflected the original dataset's distribution. This approach resulted in a refined dataset comprising 76,281 posts, which served as the basis for extracting all associated comments and downloading the corresponding meme images.

3.2.3. Images Download

The download_images.py module was developed to manage image downloads for the project efficiently. This module processes pairs of post IDs and previously validated URLs. In the initial stage, images are fetched using the requests library. Next, the format of each downloaded image is verified, and if the format is invalid, the image is processed through a format converter to ensure compatibility. Finally, the validated images are saved in a user-specified folder, with file names corresponding to their respective post IDs.

To optimize performance, these stages are orchestrated by a central function and executed in parallel using the *concurrent.futures* library with the *ThreadPoolExecutor* function. This approach transforms Python's standard single-threaded execution into multi-threaded execution, significantly speeding up the download process by allowing multiple images to be processed simultaneously. In practice, downloading images involves waiting for a network response, during which the program is idle. By using multi-threading, the program can continue downloading and processing other images simultaneously, significantly speeding up the overall

process. This methodology is highly recommended for I/O-bound tasks, as it allows multiple operations to proceed concurrently, reducing idle time and yielding significant improvements in download times.

The preprocessing stages were implemented as functions, enabling easy replication for additional years or different subreddit datasets. By standardizing the process, all researchers involved in the study, whether working with images or other aspects, were provided with a consistent dataset. This alignment ensured greater comparability and coherence across the individual research components.

3.3. Variables

3.3.1 Dependent Variables

In the scope of this analysis, the dependent variables used aim to define meme engagement. However, it is essential to recognise that there is no universally agreed-upon or clear set of measures that should always be used to define it. Researchers may choose different variables to assess it, resulting in various interpretations and approaches. For instance, standard measures often include likes, shares, comments, click-through rates, time spent interacting with the content, frequency of reposts, etc. Furthermore, there is a thin line between studying engagement, success, popularity, and virality, with researchers often using different terms while employing the same dependent variables. The fact that these concepts are frequently used interchangeably underscores the importance of clearly defining how engagement is quantified in this study. Thus, considering the variables provided by the extracted dataset, the following were identified as the most relevant:

Score: The score reflects the cumulative upvotes minus downvotes that a meme receives, providing a measure of its approval among Reddit users. The score serves as a net indicator of community sentiment, where positive engagement (upvotes) and negative engagement (downvotes) combine to reflect overall reception. Higher-scoring memes are more likely to gain

visibility on the platform, increasing their reach to wider audiences (Medvedev, Lambiotte, and Delvenne 2019).

Number of Comments: The volume of comments on a meme captures the level of conversation it stimulates, indicating user interest and depth of engagement. Compared to the score, commenting requires active participation and reflects a more direct interaction with the content, suggesting higher user involvement. Research highlights that content generating significant discourse is often emotionally resonant, controversial, or particularly relevant to its community (Barnes et al. 2021; Weng, Menczer, and Ahn 2014).

Awards: The presence of awards on a meme reflects its recognition and appreciation by the community, indicating a higher level of approval or value placed on the content. Unlike upvotes, a relatively quick and light-hearted form of engagement, awards require users to pay using Reddit Coins purchased with real money. This means that awarding a meme is often a more intentional decision, indicating a stronger endorsement of the content's quality.

3.3.2. Independent Variables

For this study, the variables or attributes used to explain or predict the dependent variables are referred to as independent variables. The predictors are changeable and so, have been carefully developed with the specific aims of the analysis in mind. These variables were selected and developed to find trends in the usage of memes and comments, combining a wide range of attributes on posts and comments while excluding those clearly defined as dependent.

Research in meme engagement seeks to understand the diversity seen in these prediction factors. Common examples include visual features, such as colour palettes and image resolution (Ford, Krohn, and Weninger 2023); textual features, such as sentiment analysis and textual content (Barnes et al. 2021); and contextual features, such as post timing and subreddit-specific features (Shifman 2014). These variables help to establish a baseline for testing patterns of meme engagement and will be explored in greater depth later in this study.

3.3.3. Control Variables

Control variables are factors included in models that, while not the primary focus, account for external influences that might confound the relationship between the independent and dependent variables. By holding these variables constant, the analysis isolates the effects of the primary independent variables and minimizes the risk of results being skewed by external factors (Memon 2024). Since this study focuses on measuring engagement, it is crucial to account for variables that could independently influence user interactions with posts. To select the variables, features that could impact engagement were selected and descriptive statistics were calculated to verify whether those features impacted the dependent variables.

Quarter: Quarters were included as a control variable to account for potential seasonal variations and time-based trends in user activity and engagement on Reddit. Different times of the year can influence the volume and type of content being posted, as well as how users interact with it since meme trends often align with current events or cultural phenomena. Indeed, the data shows notable differences in average scores and comment activity across quarters, (Appendix 2), highlighting the importance of controlling for this variable. However, quarters do not seem to have a significant effect on the proportion of awarded posts in the dataset.

To avoid the dummy variable trap when one-hot encoding, Q4 was excluded from the analysis, becoming the baseline reference category. This aligns with standard practices in regression analysis, allowing the effects of Q1, Q2, and Q3 to be interpreted relative to Q4. By treating Q4 as the reference, we account for the temporal variation in engagement patterns and isolate the unique contributions of each quarter to the dependent variables.

Author premium status: Reddit Premium consists of a paid subscription, and while authors with premium status don’t enjoy a direct impact on the visibility of their posts, the status itself may still influence engagement. Premium users can appear more credible due to exclusive features like custom avatars and badges, which distinguish their profiles and signal their

premium membership. These visual markers may lead other users to view their content as more trustworthy or noteworthy, fostering greater interaction. Premium users' access to exclusive subreddits, such as r/lounge, may provide insights into effective posting practices and trends, potentially enhancing the engagement their posts receive. Moreover, premium users are likely to possess more experience and knowledge about meme culture, increasing the likelihood that their posts achieve high engagement. Looking at the data (Appendix 3) posts by premium authors exhibit distinct engagement patterns compared to those by non-premium authors. While the range of scores is similar for both groups, posts by premium authors receive significantly higher average upvotes, with an increase of over 5763 upvotes compared to non-premium authors. Additionally, premium authors' posts generate more comments, both in terms of range and average, with approximately 24 more comments per post. Furthermore, posts by premium authors are awarded more frequently, with an award frequency of 2.2%, compared to just 0.5% for non-premium authors. These differences highlight the need to account for premium author status as a variable, as it clearly influences engagement metrics and reflects a disparity in user interactions with content based on author type.

Removed: When a post is removed, it is no longer accessible to the public on Reddit, preventing users from interacting with it through actions such as commenting, upvoting, or awarding. This cessation of interaction directly impacts engagement metrics, as any potential future activity on the post is effectively halted. While this may not have a significant impact if the meme had already passed its peak engagement period prior to removal, it could disproportionately affect newer posts that were removed before they had the chance to accumulate interactions. As such, accounting for removal status is essential to ensure a fair analysis of engagement patterns. The data (Appendix 4) reveals a substantial decrease in the average score and number of comments for removed posts, with reductions of approximately 330 upvotes and 14 comments. Interestingly, there is a notable increase in the frequency of awards for removed posts compared

to those that were not removed.

Locked: The locked post variable was included as a control in the analysis for a similar reason. It impacts one of the dependent variables - the number of comments - by preventing further interaction. This influence on overall engagement necessitated careful consideration to avoid overcontrol, a scenario where a control variable removes variation integral to the relationship under study, potentially masking the true effect of the independent variable on the outcome. To address this concern, the analysis assessed whether the locked post variable was part of the causal pathway. For example, if the independent variable affected the number of comments indirectly by influencing whether a post was locked, controlling for the locked post variable could eliminate part of the measured effect. Conversely, omitting the locked post variable would allow both the direct and indirect effects of the independent variable on comments to be observed, including any mediated through locking. It is observable in the descriptive statistics (Appendix 5) that the average score and the frequency of awarded posts between locked and non-locked posts is very similar, while there is a difference in the average number of comments. The control variables outlined above were incorporated into regression models, with a specific set selected for each dependent variable based on their observed effects. For the dependent variable number of comments, the control variables included locked status, author premium status, removal status, and quarters. For score, the control variables were author premium status, removal status, and quarters. Lastly, for awards, the model used author premium status and removal status. The statistical significance of these relationships was evaluated using p-values, with a significance threshold of 0.05.

3.4. Descriptive Statistics

3.4.1 Posts

As Table 1 shows, the dataset contains 76,213 posts. The average number of comments per post is approximately 11.96, with a maximum of 8,383 comments on a single post. Similarly, the

average post score is 211.39, with a maximum score reaching 88,465. These figures highlight the significant disparity in post popularity and the wide range of engagement across the dataset. The large gap between the mean and the maximum values, along with the relatively low medians and high standard deviations, strongly indicates a highly positively skewed data distribution. This is further corroborated by the density plots for both the number of comments (Figure 2) and scores (Figure 3), which reveal that most posts are concentrated near the lower end of engagement metrics. To address this skewness, a logarithmic transformation was applied to the engagement metrics, allowing for a more normalized distribution to do regression analysis. Since the logarithm of zero is undefined, a value of 1 was added to all data points before the transformation. This adjustment ensures that all values are transformed consistently, preventing discrepancies where zero values would otherwise remain unchanged.

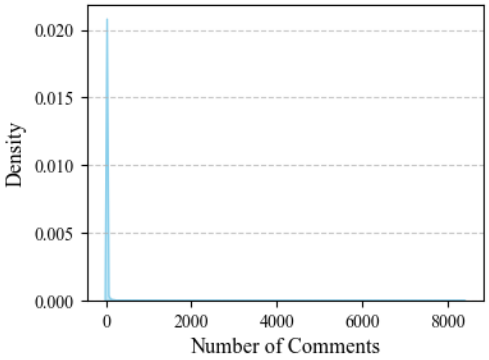

Figure 2: Density Plot for Number of Comments

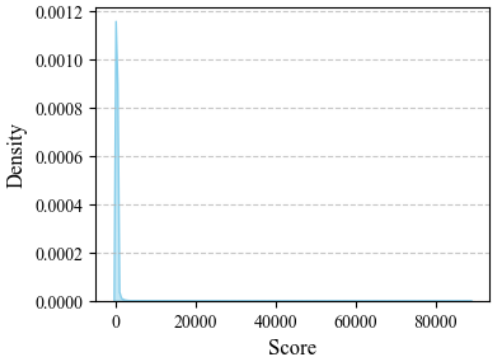

Figure 3: Density Plot for Score

The average number of awards received per post is minimal (0.008), with a maximum of 12 awards on a single post, highlighting the rarity of this phenomenon. Similarly, the proportion of posts made by premium authors is 3.6%, underscoring that most of the activity comes from non-premium users, who represent 97.54% of the user base in this dataset. Both observations are expected, as awarding posts and premium membership generally require payment, and most Reddit users prefer to use the platform for free. Moreover, over half of the posts (57.8%) were removed, suggesting a substantial rate of content moderation in this subreddit.

Table 1: Descriptive Statistics for Posts Dataset

	num_comments	score	locked	author_premium	total_awards_received	has_awards	removed_post
count	76213.000	76213.000	76213.000	76213.000	76213.000	76213.000	76213.000
mean	11.964	211.392	0.076	0.036	0.008	0.006	0.578
std	93.266	2008.409	0.264	0.186	0.148	0.075	0.494
min	0.000	0.000	0.000	0.000	0.000	0.000	0.000
25%	1.000	1.000	0.000	0.000	0.000	0.000	0.000
50%	1.000	1.000	0.000	0.000	0.000	0.000	1.000
75%	3.000	7.000	0.000	0.000	0.000	0.000	1.000
max	8383.000	88465.000	1.000	1.000	12.000	1.000	1.000

Approximately 8% of posts were locked, and around 2% were flagged as containing content suitable only for individuals over 18 years old. The fact that a large number of posts were removed yet only a small proportion were flagged as adult content suggests that r/memes enforce strict content moderation policies extending beyond filtering for explicit material.

The dataset comprises contributions from 46,667 distinct authors, with an average of 1.63 posts per author and a maximum of 2,876 posts by the most prolific contributor.

Regarding seasonality (Figure 4), there are, on average, 6,351 posts per month, with the highest number of posts occurring in January (8,140) and the lowest in May (5,191). The first peaks at the start of the year, followed by a gradual decline, while the second shows a resurgence mid-year, with activity rising again during late summer and early autumn, suggesting that seasonal trends or cultural events may play a role in driving meme creation and engagement. The peak in January might reflect engagement with "New Year, New Me" memes or viral humour about resolutions, which are popular during the start of the year. The mid-year resurgence, particularly in late summer, could align with content surrounding blockbuster summer movie releases such as the *Barbenheimer* trend, which dominated social media discussions (Hamilton 2023).

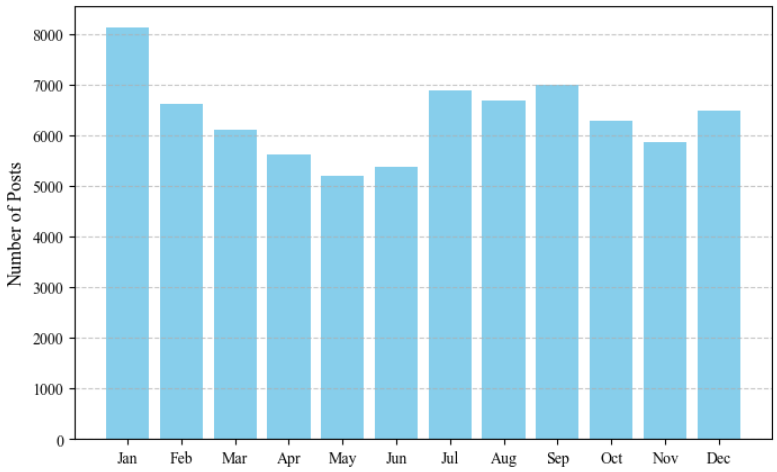

Figure 4: Monthly Distribution of Posts in the Dataset

3.4.2 Comments

As seen in Table 2, the comments dataset contains a total of 279,479 unique commenters who collectively contributed to the discussion threads. The average number of comments per user is approximately 3.45, with a median of 1 comment. However, the standard deviation is 163.41, showing a wide disparity in activity levels, with some users contributing significantly more comments. As visualized in Figure 5, 59.1% of users only commented once, while 30.5% commented between 2 and 5 times. Users contributing between 6 and 10 comments accounted for 5.9%, and users who commented more than 50 times were rare, representing less than 0.3% of the total user base. These figures underscore the skewed distribution of comment activity, with a few highly active users dominating the discussion.

Table 2: Descriptive Statistics for the Comments Dataset

	count	mean	std	min	25%	50%	75%	max
Comments per User	279479.0	3.447175	163.410102	1.0	1.0	1.0	2.0	78056.0
Token Length	963413.0	30.104948	64.336863	1.0	4.0	10.0	23.0	1778.0

Regarding comment length, the average token length of comments shows a notable pattern in Figure 6. Approximately 30.2% of comments were concise, containing 0-5 tokens. Comments with 6-10 tokens accounted for 20%, while comments in the ranges of 11-20 and 21-50 tokens comprised 21.4% and 17% of the dataset, respectively. Lengthier comments with over 100

tokens were rare, accounting for just 6.4% of the total. These statistics highlight that while the dataset captures a wide range of user interactions, most of the activity is concentrated among casual users who contribute with shorter comments.

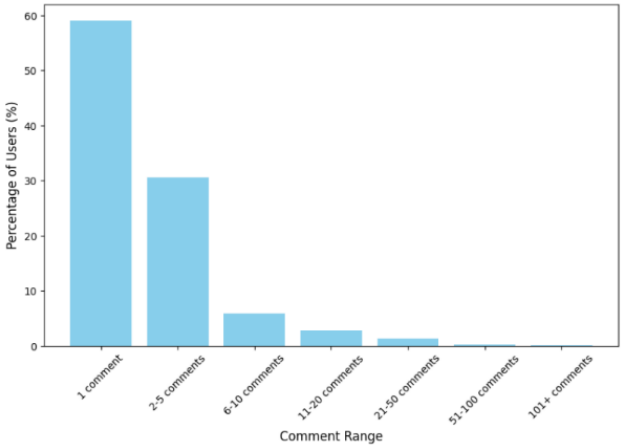

Figure 5: Distribution of User Comment Activity

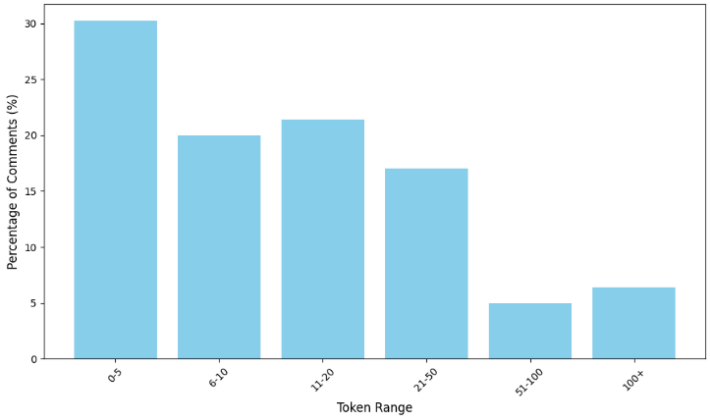

Figure 6: Distribution of Comment Token Lengths

4. Collaboration

4.1 GitHub

The GitHub repository for “reddit-memes” forms the central node around which all prescribed activities for the project take place. It allows easy collaboration and efficient version control among collaborators (https://github.com/martimesteves1/reddit-memes). In designing this project, GitHub was used to host this initiative because it could support a dynamic, iterative, and collaborative development framework yet still maintain high standards of organization, reproducibility, and accessibility (Perez-Riverol et al. 2016). The features of the platform established a dependable basis for managing the diverse demands of a research project characterized by significant scale and complexity, which required thorough data preprocessing, model implementation, and collaborative documentation.

The repository is systematically arranged into a flat layout directory structure that guarantees the distinct separation of essential functionalities while maintaining ease of navigation, therefore being well-suited for the collaborative practices adopted for this project. Inside the reddit memes folder, one can find modules dedicated to data acquisition tasks, like fetching

images or processing URLs and data preprocessing tasks with standardized cleaning and formatting methodologies — things that prove instrumental in constructing datasets for training and testing of the models.

The repository also implements dependency management using “uv”, making it very fast and simple to ensure consistent environments among contributors, reducing versioning conflicts.

Automated dependency checks and installation scripts are also included to make internal onboarding for new contributors easier. Furthermore, the repository incorporates a CI/CD pipeline through GitHub Actions to automate key processes such as running tests, syncing environments, and verifying the compatibility of feature branches. Any contribution made to the repository is thereby safeguarded against the possibility of integration errors while instituting code quality standards.

The repository uses a branching model aimed at allowing concurrent development. The main branch is the stable version of the codebase, and feature-specific branches like “download_images” or “mesteves-sandbox” give the possibility to a developer separate the work on common features from individual research. This practice of branching decreases the possibility of conflicts during the integration of contributions and ensures that the main branch always remains stable.

The scalability of the workflow on the platform itself finally proved to be quite an important asset in overcoming some of the project intricacies, therefore fostering proper collaboration and maintaining the quality of deliverables.

4.2. Programming Languages

This research project uses Python considering the flexible and rich libraries appropriate for data manipulation, distributed processing, and machine learning operations. The ability to enable modular programming and create reusable functions significantly facilitated the preparation of preprocessing scripts. The principles of object-oriented programming further contributed to the

development of modular and scalable components, ensuring the project's architecture remained robust and adaptable to large-scale data analysis. Additionally, Python's extensive library ecosystem proved instrumental in organizing the project workflow effectively (Shaik et al. 2021).

In this project, the centre of Python-based analytics stack is *Pandas*, *NumPy*, *Matplotlib*, *Stargazer*, *TensorFlow*, *scikit-learn*, and *Statsmodels*, where each contributes special capabilities that help to make data management, visualization, and modelling tasks easy. *Pandas* and *NumPy* are perfect for efficient data manipulation and numerical computing. *Matplotlib* makes the visualization of trends quick and intuitive. In addition, *TensorFlow* and *scikit-learn* are the tools used to build, train, and evaluate complex machine learning models, from neural networks to ensemble methods. *Statsmodels* and *Stargazer* complements these resources by supporting traditional statistical modelling, including the use of Ordinary Least Squares (OLS) to perform regression analysis. These libraries together ensure both scalability and efficiency, handling gracefully the difficulties of analysing large datasets from Reddit.

4.3. Code Rules and Quality

Ensuring high-quality code within the "reddit-memes" project is achieved through strict guidelines and automated processes. Pre-commit hooks automatically check for compliance with coding standards, type errors, dependency errors and failing tests before the code is committed. All this helps find and fix problems early within the development process and saves us from pushing errors to the main code repository.

Automated testing is part of the quality assurance process for the project. The repository uses Pytest, a flexible and powerful testing framework, to validate the functionality of individual elements in the codebase. Pytest excels at creating both simple unit tests and more involved functional tests, therefore proving to be an important tool in the verification of the reliability of the software components that are part of the project. Automated testing serves not only to

confirm the correctness of the code but also allows for the fast detection and fixing of errors during development (Hunt 2023, 175–186).

This repository uses MyPy, to enforce data validation and integrity with type annotations. Using MyPy ensures that data is correct according to predefined schemas and dramatically reduces errors caused by malformed or incorrect inputs, that could be more prevalent in commonly worked features.

This also becomes a relevant feature for a project like reddit-memes, since the data is coming from an ever-changing platform like Reddit. If this validation of data structures at runtime didn't happen, MyPy can help to make the data pipeline long-lasting and highly reliable (Hunt 2023, 38) This repository's architecture is based on a modular design philosophy, where scripts and functions are compartmentalized into distinct units performing specific tasks. This will make testing, debugging, and enhancements of the codebase easier to modulate. Further, extensive type annotations and exhaustive docstrings have been integrated throughout the code to enhance readability and provide explicit documentation for developers.

Finally, Ruff is used to lint all code, ensuring that all developed code follows proper code quality standards, making the final product efficient to read and understand between collaborators and future users.

4.4. Documentation

Comprehensive documentation is one of the main backbones of the reddit-memes project, as it makes everything transparent and accessible for all participants. Proper documentation encourages good communication, reduces waste, and helps to handle changes and issues, thus improving both the development process and overall user satisfaction. Modern research emphasizes that good documentation is at the core of successful software engineering practices since it ensures clear communication and simplifies the onboarding process for newcomers (Treude, Middleton, and Atapattu 2020). In addition, sufficient documentation should also be

maintained in agile contexts because this approach balances the need for flexibility with the need for transparency and consistency in project processes (Islam, Hasan, and Eisty 2023).

The README.md document contains detailed information on the project, its goals, results and other key characteristics. Meanwhile, the CONTRIBUTING.md contains detailed information about the workflow, including all the steps in setting up dependencies, initializing the development environment, and submitting any contribution. Besides, this doc emphasizes the importance of running the project in accordance with established coding standards and quality assurance controls.

Inline documentation, especially in the form of thorough docstrings for functions and classes, greatly enhances the accessibility of the codebase. The docstrings follow standard formats, such as NumPy or Google style, with unambiguous descriptions of the intent, parameters, and return values of each function or class. This level of documentation supports understanding and maintenance of the code by both current contributors and future developers. Although agile development generally values functional software over documentation, writing "just enough" documentation is acknowledged as the key to preserving both project efficiency and clarity.

By enforcing linter compliance with Ruff and pre-commit hooks, it is ensured that all code follows a baseline level of code quality, including the creation of proper documentation for the numerous modules, functions, classes and notebooks in the project.

With these methodologies, the highest levels of code quality and operational efficiency are achieved by the reddit-memes initiative. Synergy between extensive documentation, strong validation procedures, and smooth workflows guarantees that the project will retain accessibility, dependability, and scalability while pursuing its goal: creating a complete framework for analysing and predicting meme and comment engagement on Reddit.

4.5. Individual Methodology

The individual methodology was developed and implemented, targeting to meet specific project

goals and improve overall understanding.

In the GitHub repository, Jupyter Notebooks are used by each contributor to document their special research question and approach. A detailed record of preprocessing steps, several feature engineering techniques and multiple model implementations are provided by these notebooks. Not just the specific methodologies employed by the contributors are caught, but also many technical choices are drawing attention to that adjust with the overall objective.

This paper provides an in-depth explanation of the processes and choices made by each contributor above and beyond the code documentation, it helps readers understand their methodologies thoroughly. Many individual contributions become transparent and reproducible, and they easily integrate into the general analysis.

5. Analysing the Impact of Meme Formats on Reddit Engagement Using Large Vision Models

5.1. Introduction

Memes have emerged as a defining mode of expression in digital culture, serving as vehicles for humour, commentary, and social interaction. Unlike traditional media, the effectiveness of a meme lies not only in its visual or textual elements but in the nuanced interplay between the two, often tied to cultural or comedic contexts. Recently, research papers on this topic, such as the work by Ahmed, Bhadani and Chakraborty 2021 and Barnes et al. 2021, have analysed images using Convolutional Neural Networks architectures like ResNet50 and VGG16, with some degree of success. However, such approaches often fail to capture the context-dependent nuances of memes. So, in this research, a new approach to capture the comedic content of memes is explored. By using Large Vision Models, which have rich contextual understanding suitable for problems with limited data, this section aims to understand the engagement in Meme culture through the intrinsic humour and cultural context embedded within meme formats, creating a more holistic approach for Meme image analysis.

5.2. Theoretical Framework

5.2.1. Applying Large Vision Models for Zero-Shot Image Classification

In contrast to previous methodologies, this research implements Zero-Shot learning with Large Vision Models to infer meme categories. This approach has been a growing alternative to traditional image classification techniques since the advent of Large Language Models and Large Vision models in recent years, since these models can infer labels in new domains based on natural language descriptions. Although this approach has not been implemented to the specific domain of Reddit Memes in the past, applications in other domains were used as a basis. One of the first applications of this approach was done by Radford et al. 2021. It was motivated by the fact that traditional computer vision techniques train models to predict a fixed set of labels,

which restricts their ability to generalize to new domains and tasks, as training with new labels would be required. This is the case for CNNs (Convolutional Neural Networks) (Appendix 6), that are trained on large datasets like ImageNet (Deng et al. 2009). ImageNet contains more than 14 million images that are manually labelled across more than 20,000 categories using a hierarchical tree structure (Appendix 7), and usual approaches use transfer learning to apply these architectures to domain specific datasets. Radford et al. developed a new methodology, which pairs an image encoder, typically a Vision Transformer (ViT) or a CNN, with a text encoder, typically a transformer-based model like GPT or BERT. The image encoder and text encoder are trained using large datasets to be able to place image and text pairs in an embeddings space, and Contrastive Learning is applied to distinguish between related and unrelated pairs of image and text. This architecture was therefore named CLIP (Contrastive Language-Image Pretraining) (Appendix 8). In the paper, a dataset of more than 400 million image and text pairs was constructed, and multiple CLIP models were pre-trained using different text and image encoders. The performance of the CLIP models was evaluated across multiple tasks, such as Image and Text Retrieval, Action Recognition in Videos, Geolocation, Object Detection, but most importantly, Zero-Shot learning, against some widely used CNNs and ViTs. The CLIP models zero-shot predictions achieved competitive performance in ImageNet images classification, with an accuracy of 76.2% against 76% of ResNet-50, despite not using any of the ImageNet labelled images in pre-training. More importantly, CLIP and ResNet-50 were also evaluated for 27 domain specific datasets, such as StandfordCars, Food101, Flowers102 and the HatefulMemes datasets, and CLIP either improved the baseline or beat ResNet-50 on 16 out of 27 datasets (Appendix 9). CLIP's features were also fitted using a linear classifier, and the linear classifier outperforms Noisy Student EfficientNet-L2 on 21 out of the 27 datasets, demonstrating that CLIP's features are superior in quality. (Appendix 10).

However, there are some noteworthy limitations to CLIP that are relevant to this research,

namely the fact that CLIP models struggled with fine-grained classification tasks, such as differentiating models of cars, or species of flowers, or for this research, classifying internet meme formats. CLIP's zero-shot capabilities are also very limited on images that are out of the pre-trained distribution, which would likely include many types of internet memes.

Liu et al. 2023 explores a different methodology than CLIP that overcomes some of these limitations. Similarly to CLIP, the LLaVA (Large Language and Vision Assistant) also applies a dual-encoder architecture, using CNNs or ViTs for image encoding and Large Language Models (LLMs) like LLaMA (Large Language Model Architecture) for text encoding. But unlike CLIP, LLaVA adds a fusion layer to align the image embeddings and text embeddings to the same semantic space, by applying techniques such as cross-attention mechanisms, linear projection or prepending the visual tokens to the text tokens. The fused embeddings are then processed through the language model, which uses the visual tokens as input context to generate outputs (Appendix 11). This approach increases the cross-modality integration relatively to CLIP, allowing for more complex contextual knowledge. Not only does this increase the models' capabilities to fine-grained specification tasks in specific domains, but also allow for richer class descriptions and contextual prompts. In the specific domain of Reddit Memes, it is also very common to have text overlayed in the image itself, which can heavily affect the classification of the meme type, so LLaVA is more suited for this domain since it processes the visual and textual elements simultaneously, while CLIP would struggle to "read" the textual elements in memes. Finally, by adding generative capabilities to the model, the models are applicable to tasks such as VQA (Visual Question Answering), image captioning and contextual image analysis, with the drawback of being more computationally heavy to train and infer than CLIP. But since the outputs are richer than CLIP in detail and interpretability, it is possible to apply different evaluation methods for model tuning. In the specific LLaVA architecture implemented by Liu et al., Vicuna was chosen as the LLM and paired with the pre-trained CLIP visual encoder

ViT/14, and a linear projection fusion layer. The model was evaluated using the ScienceQA dataset (Lu et al. 2022), which contains more than 21,000 multimodal multiple-choice science questions from elementary and high school level science curricula (Appendix 12). LLaVA reached an accuracy of 90.92%, just shy of the SoTA (state of the art) model MM-CoT large's 91.68%. Additionally, Liu et al. paired LLaVA with GPT-4 to create ensemble models that were able to surpass the SoTA performance with an accuracy of 92.53%, by generating outputs with LLaVA and GPT-4, and then passing those outputs through GPT-4 again to judge the final outcome (Appendix 13).

In a study by Pratt et al. 2023, a new method was introduced to generate the prompts used to classify the images. The proposed solution, CuPL (Customized Prompts via Language Models), consists of using language models to generate visual descriptions for the given class categories, and then using the generated descriptions to infer. In this specific paper, a standard zero-shot approach using CLIP, pre-trained with image-text pairs with no visual description, e.g. "A photo of a platypus", against pairs with text output from GPT-3, e.g. "A platypus looks like a beaver with a ducks bill" after inputting "What does a platypus look like?" (Appendix 14). Prat et al. tested this approach across 15 different datasets, using CuPL with standard prompts and customized prompts for each dataset, and noticed an immediate improvement of, on average, 0.72% and 1.36% respectively, relative to the standard approach (Appendix 15). This indicates that leveraging the knowledge of LLMs can immediately improve zero-shot capabilities of CLIP models.

5.2.2. Developing a Taxonomy for Internet Memes

The methodology chosen involves developing a customized methodology for Reddit Meme Formats, and the taxonomy suggested by Milner 2012, 83 was used as a starting point. Milner's central research question in this paper was to investigate how broad and inclusive the participation in meme culture was and the diversity of discourse using internet memes. Milner

investigated the processes of meme creation and sharing, who participated in the culture and their perspectives, and the types of conversations that were facilitated by memes. To define the meme creation process, Milner proposed a meme taxonomy, by dividing memes into two main categories, stable and remixed, with stable memes corresponding to memes meant for sharing without much user input, and remixed memes corresponding to images transformed using established set of practices. Within these categories, Milner also defines subcategories. But since 2012, meme culture as shifted greatly, so some of the defined categories were either outdated, such as “Quotes”, “Demotivationals” or “Annotated Stills”, or were too fine-grained, such as “Graphs”, “Drawings”. Still, categories like “Macros”, “Screenshots” and “Stacked Stills” are still very much present in 2023 and other recent years’ meme culture. Milner’s full taxonomy definitions and examples can be consulted in Appendix 16 and Appendix 17.

5.3. Methodology

5.3.1. Data Refinement

For the purposes of this analysis, only the posts dataset was used. In addition to the cleaning, pre-processing and stratified subset selection detailed in section 3.2., an additional resizing step was added to speed up inference times and to comply with the input requirements for the tested models. Figure 17 provides an overview of this process.

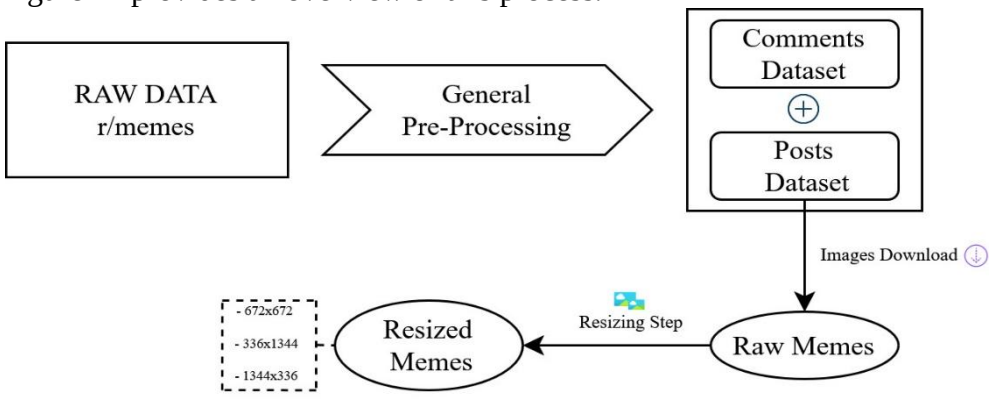

Figure 17: Data Refinement Pipeline

One of the dimensions explored to assess the quality of the images was their dimensions, more specifically the height and the width in pixels, and the aspect ratio (ratio between width and

height). This calculation was done using the *Pillow* library, with parallelized execution using python's built in function *ProcessPoolExecutor* from the *concurrent.futures* module. After calculating these dimensions and plotting their distribution, we can observe in Appendix 18 that most images have appropriate sizes, but a few images have very extreme values. This would create problems in testing some of the planned models, as for example the model LLaVA 1.6 only supported images up to 672x672, 336x1344 and 1344x336 resolutions. One key issue would be resizing the images with unconventional aspect ratios, as resizing would have a greater risk of losing image information. The test in Appendices 20 and 21 showcases this problem, since for the regular aspect ratio image, the LVM was able to capture the same information for the original image and the resized image, while for the aspect ratio outlier the model failed to do so with normal resizing. As observable in Appendix 19, most images have a regular aspect ratio and could therefore be resized, so different resizing dimensions need to be set for the unconventional images. After analysing images with different aspect ratio and the models' behaviour, it was decided that images with an aspect ratio greater than or equal to 0.5 and less than or equal to 2.5 would be resized to the resolution of (336x336), images greater than 2.5 would be resized to 1344x336 and images less than 0.5 would be resized to 336x1344. Resizing was also done using *pillow* and *ProcessPoolExecutor*. In terms of speed improvements, small-scale test with resized height and width outliers showcased big improvements in inference times due to the lower number of pixels processed by the models, so both the quality of the inference and time would be improved with this step. The results can be verified in Appendix 22.

5.3.2. Custom Taxonomy

To infer meme formats, a custom taxonomy was developed, using Milner's work as a basis. The main problem with Milner's work is that it was outdated and too extensive, so it was adapted to better fit the purposes of this research, based on memes in the dataset and some of the meme types documented on the website KnowYourMeme.com. From Milner's taxonomy,

the ‘Macros’ meme types and adaptations of ‘Drawings’, ‘Memes IRL’, ‘Photos’, ‘Shops’ and ‘Screenshots’ were still used, and the same hierarchical structure of ‘Stable’ vs. ‘Remixed’ Images was kept. The **‘Stable’** category represents images that are passed along without transformations and usually are expressed in more traditional formats like screenshots or photos, while **‘Remixed’** memes do suffer transformations by the user, following specific sets of practices that are part of the culture around meme, such as using certain templates or specific joke formats. Within the Stable category, **‘Drawing’** represents artworks that include not only drawings but also photoshopped images; **‘Photo’** refers to unaltered real-world images; **‘Screenshot’** includes images capturing digital media, such as an image of a video game, animated series, an app interface or other equivalent media; and **‘Text’** refers to memes where the primary focus is text, which could be screenshots of text messages, tweets and comment sections, or images consisting of text blocks (also known as wall-of-text memes). Within the **Remixed** category, **‘Comic’** refers to traditional comics with around three to five panels that builds a small comedic story line, but also less conventional variations of stacked images, such as dialog memes using two moments screenshots of a series to simulate a dialog; **‘Emotional Reaction’** for memes that use a face, typically of a human but can also include animals or cartoon characters, to invoke a specific emotional reaction on the user, often in relation to a textual element, usually at the top of the image; **‘Event Reaction’** includes memes that also usually react to textual elements, but the reaction is done with a specific situation or event instead of an emotional expression, such as, for example, using an image of a tornado or an explosion; **‘Macro’** refers to traditional memes that emerged around 2007 in early meme culture, with white text typically in impact font at the top and bottom of the meme and an image in the background, typically from a specific set of popular images like ‘Bad Luck Brian’ or ‘Success Kid’; **‘Meme Character’** includes memes featuring well-known and currently relevant meme characters, such as ‘Pepe the Frog’ and the ‘Wojaks’; **‘Situational’** represents

memes that overlay objects, typically text or heads of characters and people, in specific elements of images in order to simulate absurd comedic situations; and finally **'Template'** for memes that follow the widely used meme templates of recent meme culture, such as the 'Expanding Mind' or the 'Drakeposting' templates. Figure 18 provides a summary and examples of this taxonomy.

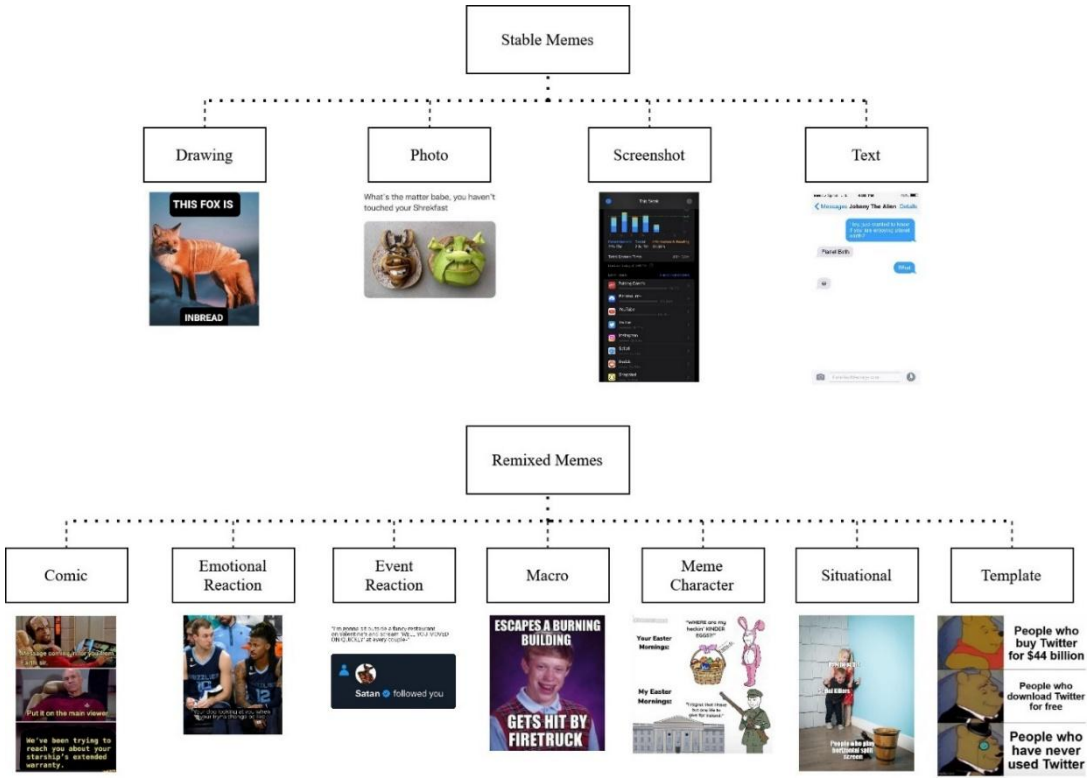

Figure 18: Custom Taxonomy for Meme Formats with Examples

5.3.3. Model Selection

In the inference task, a LVM will be used to infer the lower-level meme types (Comic, Drawing, etc.), by passing a prompt with task instructions and descriptions of each task, using the *ollama* library. An initial selection of LVMs was chosen based on the computational resources available and the performance leaderboards metrics by OpenVLM Leaderboard, which covers more than 150 LVMs. The LVMs selected for testing were llava 1.6 7B, llava-llama3 8B, llava-phi3 8B, minicpm-v 8B, baklava 7B and llama 3.2-vision 11B. To select which model to use, a random sample of 1000 memes was extracted and manually labelled, and each of the models

inferred the meme formats for the sample images using default model parameters and a generic prompt (Appendix 23). The prompt was constructed to include visual features as much as possible, to produce better inference results (Pratt et al. 2023), as well as examples for each type of meme. The instruction section ensured that most inferences would be done correctly, with short responses containing only one label, but in some cases the model would either output labels with different formats, e.g. “Template” and “template”, or include the classification in a longer sentence, e.g. “Because of X element in the meme, it is a photo.”, or even ignore the instructions and produce an invalid output, such as repeating back the labels and descriptions. For those cases, a processing step for the LVM’s output was added, using python’s built-in string methods and regular expressions from the *re* module, ensuring that labels followed a standard format, that inferences inserted in longer outputs would not be wasted and attributing invalid outputs to None, as observable in Figure 19. After inference, the level 1 labels were calculated based on the inference done for the level 2 labels.

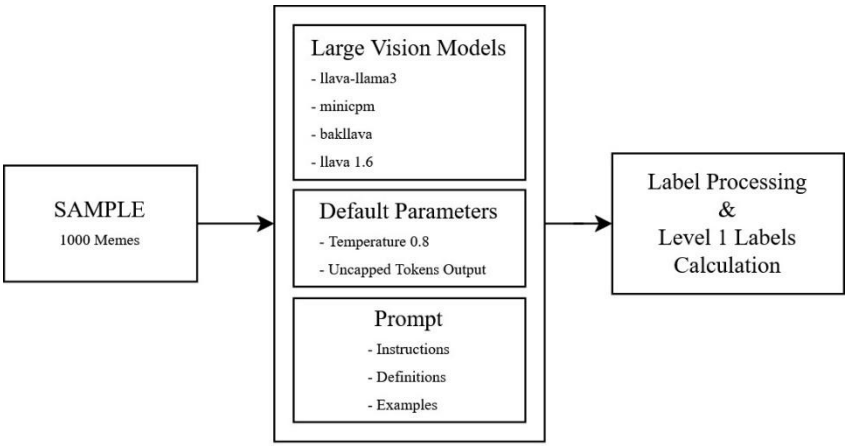

Figure 19: Summary Diagram of Model Selection Process

Table 3: Model Selection Accuracy Results

Model	Accuracy Level 1	Accuracy Level 2	Accuracy Stable	Accuracy Remixed	Number of Nones
llava-llama3	0.27	0.07	0.11	0.33	471
minicpm	0.4	0.18	0.89	0.19	4
bakllava	0.51	0.09	0.39	0.56	53
llava 1.6	0.55	0.18	0.64	0.51	121

From the evaluation results in Table 3, llava 1.6 7B and minicpm-v 8B had the best performance on the level 2 labels, with an accuracy of around 18%. Between those two LVMs, llava had the best performance in the level 1 categories, with an accuracy of approximately 55%, while minicpm only obtained an accuracy of around 40%, so Llava is the chosen model for the main inference. Llava 1.6 did have more None labels, adjustments to the parameters, prompt and inference method were made to reduce invalid inferences. Although the accuracy levels seem low, it is important to remember that the tests were made with a very minimal sample of just 1000 labels, so the goal is to get a general sense of which model is more capable.

5.3.4. Prompt Engineering & Model Parameter Tuning

Before running the main inference, multiple prompts and model parameters were tested to get better inference results. For prompt engineering, three different prompts were tested, each adding an element to the previous: Prompt 1 (Appendix 24) containing only task instructions and meme format definitions, Prompt 2 (Appendix 25) with added examples to the definitions and finally Prompt 3 (Appendix 23) with added contextual information and instruction repetition, same as the Generic Prompt used for the model selection.

For model parameters tuning, the parameters that are relevant for the inference task are the model temperature and the number of predicted tokens. The number of predicted tokens affects the number of tokens the model outputs, which can be beneficial to limit the amount of non-sense responses from the LVM and avoid long inferences. Since the correct output containing only the label usually is limited to around 5 tokens, the parameter was tested with a limit of 5. The model temperature is a very important parameter to test, as it dictates the level of randomness of outputs. LVMs generate outputs by predicting the next token, in relation to the previous, and in each generation, there is a set of possible tokens with calculated raw predictions scores (logits) of being correct (Appendix 26). As observable in the probability function, the Temperature parameter scales the logits, before they are passed to a SoftMax

function that chooses the generated token, so if T=1, the probabilities are taken as is; if T>1, the probability distribution of possible tokens is much more uniform and therefore it is more possible for unexpected tokens to appear, increasing randomness or creativity; and if T<1, the distribution becomes less uniform, making the most probable tokens even more likely to appear, generating more certain or less random outputs. For the inference task, having consistent and accurate classification of meme formats should be prioritized, so temperatures of 0,2, 0,5 and 1 were tested, as it would be likely for the model to disregard instructions or hallucinate formats with high temperature values.

Finally, it was noticed that the same prompt and parameters for the same image could generate different classifications, which could impact the accuracy of classification (Appendix 27). To decrease variability, and to also address the problem of the 'None' inferences, an experiment was done where, for each image, the LVM would infer multiple times, in this case 10 times, and the most popular format would be chosen. In the rare case of a tie, the first appearing label would be chosen.

Table 4: Prompt Engineering, Parameter Tuning and 10x Inference Experiment Results

Configuration	Level 1	Level 2	Stable	Remixed	Number of Nones
Prompt 1	0.59	0.18	0.39	0.67	117
Prompt 2	0.61	0.11	0.14	0.81	146
Prompt 3	0.55	0.13	0.32	0.65	147
Param 1	0.63	0.13	0.34	0.75	26
Param 2	0.61	0.14	0.4	0.7	82
Param 3	0.55	0.13	0.38	0.63	147
llava-10x	0.65	0.24	0.78	0.6	0

Based on Table 4, using a temperature of 0.5 obtained the best accuracy on both levels of labels. It is also worth noting that lower temperatures had less 'None' inferences. For the prompts, despite being less descriptive, Prompt 1 outperformed the other two prompts, while having fewer invalid classifications. Finally, we can also observe very big improvements with the multiple inferences experiment, with an improvement of accuracy to 24% in the level 2

categories and 65% in the level 1 categories, and completely eliminating invalid classifications. So, the main inference on the posts dataset with 76,000 entries was done with the llava 1.6 model, with 0.5 temperature, 5 predicted tokens, using Prompt 1 only containing class definitions and instructions, and with 7 inference runs for each image (reduced from 10 due to computational constraints).

5.3.4. Results

Using the inferred labels, two sets of independent variables were created, set 1 with the level 2 labels (e.g. ‘Comic’, ‘Drawing’, etc.) and set 2 with level 1 labels (‘Stable’ and ‘Remixed’). To avoid falling for the dummy trap when one-hot encoding the labels, in set 1 the ‘Situational’ format was omitted and in set 2 remixed was omitted, since they were the most frequent label. Therefore, since they were removed, they are considered the reference category in their respective regressions. Also, since the format variables are binary variables, the coefficients represent the effect on the dependent variable of having a specific format instead of the reference category.

Table 5: OLS and Logistic Regression Results with Format Independent Variables

	Score (Set 1)	Comments (Set 1)	Awards (Set 1)	Score (Set 2)	Comments (Set 2)	Awards (Set 2)
Q1	1.158***	0.291***		1.161***	0.292***	
Q2	1.002***	0.158***		1.005***	0.159***	
Q3	-0.531***	-0.031***		-0.532***	-0.031***	
Premium Author	0.239***	0.234***	0.981***	0.243***	0.236***	0.985***
Comic	0.029	0.065***	0.282			
Constant	-1.033***	-0.064***	-8.162***	-1.064***	-0.074***	-8.192***
Drawing	-0.227***	-0.089***	-0.595			
Emotional Reaction	-0.092	-0.082**	0.253			
Event Reaction	-0.588	-0.521	-9.569			
Locked Post		0.318***			0.319***	
Macro	-0.009	0.046	0.933**			
Meme Character	-0.127	-0.024	-16.030			
Photo	-0.212***	-0.085***	-0.261			
Removed Post	-1.621***	-0.725***	-1.777***	-1.633***	-0.730***	-1.801***
Screenshot	-0.274***	-0.105***	-0.535			
Stable				-0.079***	-0.035***	-0.062
Template	-0.119***	-0.039***	-0.121			
Text	-0.027*	-0.013	0.036			

Note: *p<0.1; **p<0.05; ***p<0.01

When analyzing the statistically significant results in Table 5 ($p<0.05$), keep in mind that the score and number of comments were log-transformed, changing the meaning of the obtained coefficients into percentage changes. For exact interpretations, these coefficients were converted back to the original scale using the formula in Appendix 28 for better accuracy.

For the log-transformed score with set 1, the **'Drawing'** format has a coefficient of -0.227,

which converted to the original scale suggests an approximately 20.3% decrease in score compared to the reference category; **'Photo'** has a coefficient of -0.212, which translates into a 19.1% decrease in score; **'Screenshot'** has a coefficient of -0.274, suggesting on average a decrease of 24%; **'Template'** has a coefficient of -0.119, so in the original scale reduces the score by 11.2%; and the OLS's **Constant** has a value of -1.033, or -0.644 in the original scale, meaning that on average the OLS predicts situational posts in the 4th quarter to have a slightly negative score, however this is likely due to generally less engagement in the 4th quarter, as the coefficients for the 1st and 2nd quarters are highly positive. With set 2, **'Stable'** got a coefficient of -0.079, translating into a 7.6% decrease in score relative to **'Remixed'** memes, and the **Constant** got a value of -1.064, which converts to an expected score on average of -0.65 for the reference category. Again, the 4th quarter effect is also prevalent in the constant's value. The obtained values indicate that memes in the r/memes subreddit that include user transformation, either by using templates or by overlaying text on image elements in **'Situational'** memes, have more score engagement than memes with less user transformation, like photos or screenshots.

Regarding the number of comments, for set 1, **'Comic'** has a coefficient of 0.065, meaning that comics memes have 6.7% more comments than the reference category; **'Drawing'** has a coefficient of -0.089, indicating a decrease of 8.5% in the number of comments; **'Emotional Reaction'** has a coefficient of -0.082, resulting in a decrease of 7.9% in the number of comments; **'Photo'** has a coefficient of -0.085, meaning a decrease of 8.1%; **'Screenshot'**, has a coefficient of -0.105, translating into a decrease of 10.5%; **'Template'** has a coefficient of -0.039, resulting in a decrease of 3.8%; and the OLS's **Constant** has a value of -0.064, or -6.2 in the original scale, however the quarter effect isn't entirely to blame for, as it is relatively weak. For set 2, **'Stable'** has a coefficient of -0.035, translating into a decrease of 3.5% in the number of comments; and the **Constant** has a value of -0.074, meaning that **'Remixed'** memes

practically have the same number of comments compared to **'Stable'**. It makes sense that memes of the **'Comic'** format and the **'Situational'** format have more comments than the rest, since the comic format is based on creating small storylines within the memes and the situational format creates absurd comedic situations, which may stimulate more discussion in the comments. There are a lot of templates where storylines are built, like the 'Expanding Mind Template', or that deliver controversial opinions, like the 'Change My Mind' and 'Lisa Simpson's Presentation' templates, which might explain why templates have less negative coefficient than the more traditional formats.

Finally, for the awards engagement, in set 2 **'Stable'** does not have a statistically significant coefficient and in set 1 most variables don't have statistically significant results to draw any relevant conclusions, probably due to the high level of rarity of this type of engagement.

5.4. Limitations

The main limitation that affects the validity of the obtained results is the bias in the inference of meme formats. As verifiable in Appendix 29, the chosen inference configuration had a very significant tendency to assign the **'Situational'** format and some bias towards **'Text'** format, while assigning significantly less memes of the **'Macro'**, **'Emotional Reaction'**, **'Meme Character'** and practically no inferences of the **'Event Reaction'** format, which were the formats that had the poorest results. Additionally, multi-agent configurations and heavier models were not tried due to computational constraints, so there could be models and inference configurations better suited to understand the complexity of meme formats that were not explored.

6. Discussion

6.1. Human Faces and Meme Formats: Complementary Roles

The visual presence of human faces and the structural characteristics of meme formats emerged as interconnected factors influencing engagement. While faces alone had mixed effects—modestly increasing scores (+2.15%, coefficient: 0.0215) but slightly reducing comments (-2.03%, coefficient: -0.0203)—their impact was strongly mediated by the meme's format and textual context. For instance, **'Emotional Reaction'** memes, where the main focus is the presence of a face expressing an emotion in reaction to a textual element, have a stronger engagement in comments than meme formats that rarely or never have faces, like **'Drawing'**, **'Photo'** and **'Screenshot'**, but did not have statistically significant effects in the score engagement. **'Situational'** and **'Template'** commonly have prominent facial and textual elements in their construction, and both had stronger performance in score and comment engagement than other categories.

The size and diversity of faces further influenced these factors. Larger faces reduced engagement (coefficient: -0.3838 for score; -0.1951 for comments), likely overshadowing textual and visual harmony. In contrast, emotional diversity in faces, captured by the "mixed emotions" variable, positively influenced both scores and comments, reinforcing the value of visual complexity in driving engagement. **'Situational'** memes that often have mixed emotions have consistent results, as they drive more score and comment engagement than meme formats like **'Emotional Reaction'** and **'Drawing'** that don't often mix emotions.

6.2. Text as a Mediator Between Visual and Structural Elements

Text played a pivotal role in amplifying or modulating the impact of visual and structural features. Memes with text significantly outperformed those without, boosting scores (+30.47%) and comments (+10.85%). Text length exhibited a non-linear relationship, with moderate lengths maximising engagement before diminishing returns set in. The previous pattern aligns

with the role of text in situational memes, where short captions contextualise the visuals without overwhelming them.

Formats that inherently integrate text, such as the **'Template'** and **'Situational** formats, also had significantly more engagement in score and comments than other formats. These rely heavily on textual-enhanced humour, which interacts with visual elements to generate engagement. Conversely, screenshots and photos, which often lack text, had the weakest engagement metrics, underscoring the importance of textual enhancement in visual content.

Effective engagement arises not from any single feature but from the harmonious integration of visual appeal, textual context, and structural clarity.

6.3. Emotional Dynamics and Visual-Textual Interactions

Sentiment analysis showed how emotional and sentimental content in comments interacts with the visual and textual components of memes. Posts that received a higher proportion of highly negative comments, driven by users' strong reactions, were the posts that attracted more engagement in the form of discussions. Positive sentiment, on the other hand, was associated with higher scores and awards, in line with the supportive tone of many situational memes.

These findings illustrate feedback loops: memes that can successfully pair relatable images with succinct text tend to create emotional responses, which then encourage user engagement through commentary, ratings, and recognitions. High-arousal emotions like joy consistently increased all engagement metrics when compared to low-arousal emotions. Anger, as a high-arousal emotion, also attracted engagement in the form of discussions by significantly increasing the number of comments. However, this engagement was not necessarily done with a positive intent. As a result, users, despite being engaged, were less motivated to upvote or award the post. In contrast, sadness as a low-arousal emotion reflected its limited capacity to stimulate meaningful interaction or recognition. Memes that featured emotionally diverse content, such as mixed emotion faces or polarizing comment sentiment, achieved wider

engagement, indicating that diversity in emotional expressions promotes relatability and attracts discussion.

6.4. Exploring Linear and Non-Linear Trends

The machine learning analysis really helped to shift the focus from descriptive results to predictive insights to find linear and non-linear patterns in engagement metrics. Unlike previous analyses, which looked only at direct relationships, this approach used models like Random Forest to explain complex interactions and dependencies between different features. The Random Forest Regressor performed well in predicting log-transformed scores (R-squared: 0.85) and comment counts (R-squared: 0.63), capturing complex relationships. More specifically, the models showed that the interaction between text length, subreddit size, and emotional diversity is non-linear, where certain thresholds increase engagement, while others yield diminishing returns.

Significantly, these models measured the underlying impact of visual characteristics in conjunction with textual and platform-related variables. For example, although an increase in text length initially increases engagement, overextension in length decreases its effect—an effect that is moderated by meme structure and emotional variation. Similarly, the infrequent appearance of awards showed a strong correlation with the diversity of sentiment (entropy), proving the ability of machine learning in identifying subtle factors driving interactions. Such cases were, however, much more challenging for classification tasks. While having high accuracy of 0.99, the models performed poorly with F1-scores of 0.08.

In a nutshell, these machine learning frameworks bring forth the complex, non-linear relationships between visual-textual interactions and emotional dynamics. Taken together with the descriptive analyses, these results show the importance of accounting for the direct and dynamic effects of multimodal features on engagement.

6.5. Multimodal Integration

The results indicate that meme engagement is driven by the dynamic interplay of visual, textual, and emotional elements. Visual features, such as human faces, increase relatability but are highly dependent on contextual integration with textual and structural elements. Text acts as a mediator, contextualizing visuals and eliciting emotions, whose effectiveness is modulated by format and length. Emotional dynamics are amplified in these interactions, while diversity and polarisation bring about broader engagement and deeper user involvement. Adding another layer of understanding, machine learning exposes non-linear patterns and shows how these multimodal features interact in very diverse contexts.

In conclusion, meme engagement is a complex phenomenon where successful meme engagement calls for the integrated function of visual, textual, and emotive elements. These results put into focus the importance of understanding multimodal interactions in creating content for digital platforms—a most valuable message for content creators and researchers.

7. Limitations and Challenges

Despite the increasing complexity of multimodal analytical methodologies, investigations of meme interactions on Reddit still face numerous constraints and challenges. First, memes are inherently dynamic and context-dependent. As cultural markers that frequently rely on humour, societal critique, and relevant references, their impact can shift rapidly with evolving events, linguistic trends, and changes in user demographics (Shifman 2014). Items considered interesting and shareable one day may lose their significance just weeks later, making the task of building reliable predictive models highly challenging. Additionally, advancements in technology and data collection methods continuously expand the range of available engagement metrics. This progress can render older studies less comprehensive or less relevant over time, as they may not account for newly available insights or evolving user behaviours. Such variability necessitates constant updates to methods, feature sets, and analysis frameworks to

ensure that the insights drawn remain accurate and relevant (Adami and Kress 2014).

Similarly, this study was constrained by the engagement metrics available in the dataset, which dictated how engagement could be measured. Ideally, more granular metrics such as separate upvote and downvote counts, time spent viewing a meme, or sharing behaviour could have been included to provide a more comprehensive understanding of user interactions. One of the primary metrics used was score, which, while useful, has its limitations. Score, defined as the difference between upvotes and downvotes, provides an indication of a meme's success but does not fully encapsulate engagement. This is because downvotes, although a form of user interaction, reduce the overall score, potentially underrepresenting the true level of activity. For instance, a meme with high upvotes and equally high downvotes may appear to have low engagement when it has elicited significant user reactions. However, this limitation may be somewhat mitigated by the type of memes typically posted on r/memes. Given the subreddit focus on humour and light-hearted content, it is reasonable to assume that posts are less likely to provoke strong negative reactions that would lead to significant downvoting. This assumption is further supported by the fact that no posts in the dataset have negative scores, suggesting that downvoting is relatively uncommon on this subreddit. As a result, while score remains an imperfect measure of engagement, this focus on generally agreeable content may reduce the distortion caused by downvotes.

A notable characteristic of the dataset is the presence of duplicate memes—identical content posted multiple times but showing varying engagement metrics. This reflects the natural reposting and sharing behaviour common on platforms like Reddit, where memes are frequently recycled for different audiences or timeframes. However, it introduces challenges for analysis by potentially over-representing certain meme formats or themes, which could distort conclusions about engagement trends. The variations in engagement metrics for identical memes highlight the influence of external factors, such as the timing of the post or the level of

competition with other content at the moment of posting, complicating efforts to draw clear conclusions about the intrinsic qualities of memes that drive engagement.

Another factor that may influence engagement metrics is the potential activity of bots on Reddit. Bots can artificially manipulate metrics such as upvotes, downvotes, and awards, distorting the true representation of user engagement. Bots can be sophisticated, mimicking human behaviour in ways that make them difficult to distinguish from genuine users, which makes their identification challenging and not entirely accurate. These automated accounts could either inflate or deflate engagement metrics, for example, by artificially upvoting or downvoting memes or indiscriminately awarding posts. Although some bot accounts were identified in comments during the study, it is difficult to determine the extent of their presence on the dataset, introducing an additional layer of complexity to the interpretation of engagement metrics.

Still on the data perspective, one of the most persistent challenges is the significant skewness in engagement metrics, where a small fraction of memes garners a disproportionately large number of upvotes, comments, and shares, while the majority receives minimal attention. This can lead to two distinct challenges depending on how the dataset is structured (Haibo He and Garcia 2009). In a dataset where high-engagement memes are rare and most memes receive low engagement, machine learning models may lean toward predicting low engagement for most cases to optimise accuracy. On the other hand, if the dataset is artificially balanced—by oversampling high-engagement memes or under sampling low-engagement ones—the model risks overemphasising the trends associated with popular memes. In this scenario, the model may disproportionately focus on the distinct patterns of high-engagement memes, reducing its ability to generalise to the broader meme ecosystem, which primarily consists of low-engagement memes. This challenge was particularly evident for the presence of text, as the number of memes receiving awards was significantly smaller compared to other engagement metrics. Indeed, in many models, the results for this variable were not statistically significant,

likely due to the rarity of memes with awards.

Moreover, the multimodal nature of memes—combining images, overlaid text, and sometimes other media—adds to their analytical complexity. Each modality provides distinct cues, yet the interplay between them often conveys the true essence of a meme message. For instance, an image that appears innocuous on its own may become humorous or politically charged only when paired with accompanying text. Capturing this interdependence requires models capable of effectively integrating heterogeneous data while accounting for the interactions between visual, linguistic, and cultural markers (Zhong et.al. 2024). Without a nuanced understanding of these relationships, predictions of meme engagement risk being oversimplified, potentially overlooking the multidimensional humour and culturally grounded references that drive user interactions.

Finally, another significant limitation of this study lies in the computational challenges associated with analysing meme datasets. Memes are inherently multimodal, combining images, text, and sometimes additional media, which results in large and complex datasets. Processing and analysing such data require substantial computational resources, particularly for tasks like image analysis, text extraction, and sentiment evaluation. Expanding the scope to include multiple subreddits or additional years would dramatically increase the volume of data, further straining computational capacity. These challenges are particularly pronounced when working with image-heavy datasets, as images require more storage, processing power, and advanced feature engineering compared to purely textual data. Consequently, while focusing the main analysis on r/memes and a single year ensures a manageable dataset and consistent scope, it also limits the study's ability to generalize findings or explore broader trends across platforms and timeframes.

8. Applications and Directions for Future Research

The various applications and avenues for future research on Reddit memes are all predicated

on an understanding of the cross-modal interactions between visual, textual, and emotional elements. This study has brought to light the critical nature involved in combining these different facets in meme interactions prediction and evaluation. Of course, there remains further improvement and expansion potential using more sophisticated methodologies that could also test a wider range of contextual factors and engagement metrics.

Future research should centre on the dynamics of content amplification and the effects of meme formats and emotional engagement on interaction with users. Although this paper has emphasized direct analysis of the engagement metrics—scores, comments, and awards—there is still some potential to examine and predict further engagement indicators. More detailed and comprehensive metrics, such as the duration of viewing, patterns of sharing behaviour, or distinct tallies of upvotes and downvotes, might come in handy. Integration of these metrics would help researchers better grasp the complex nature of engagement dynamics and deliver actionable insights for content creators and platform developers.

Although the way that these algorithms work to create or diminish posts based on emotional arousal and content categories was not analysed in this study, investigation of these systems may yield very substantial insights into the incentive structures that guide content creation and dissemination. The existence of algorithmic biases, toward highly emotionally charged or divisive content, certainly warrants more research into their effects on user interactions and platform dynamics in general. For example, evidence has been found that ranking algorithms based on engagement can amplify emotionally charged, out-group hostile content that may affect user perceptions and interactions (Milli et al. 2023).

One important area for further research is the ethical implications of content that evokes powerful emotions and negativity. This study highlighted the ability of memes to provoke high emotional reactions, both in terms of anger and joy, as well as their subsequent effects on engagement metrics. However, more research is required to understand the long-term effects

on individual well-being, societal discourse, and platform engagement. With the rise in emotionally engaging memes, there is a danger that these will further polarize or amplify harmful narratives, which raises critical questions about content platform responsibilities in moderating such phenomena. Research has shown that the diffusion of emotionally charged messages in social media may engender changes in societal values and even have an impact on political attitudes, raising ethical concerns about what content is spread (Steinert 2021).

Building further upon the machine learning methods used in this study, future research should explore more advanced techniques to better capture the non-linear relationships found. For instance, more complex models, such as gradient boosting methods or neural networks, or ensemble models, could potentially offer a deeper understanding of the relationship between sentiment and engagement in different contexts. These models might be particularly well-suited to predicting a broader range of engagement metrics and overcoming some of the limitations of existing models, such as the identified inference disparities and the challenges of handling complicated relationships among multimodal features. Recent multimodal sentiment analysis studies have shown it to be capable of integrating visual and linguistic features to display complex emotions and contexts contained within memes, evidencing the importance of advanced analysis methodologies (Hazman, McKeever, and Griffith 2023).

The expansion of the analysis concerning various types of memes offers a significant avenue for exploration. Existing research indicates complex interactions among meme formats, textual components, and emotional responses. Subsequent investigations might utilize multi-agent inference methodologies to enhance findings further.

For example, sequential inference methods that classify memes as being ultimate or base according to attributes, or model comparisons with better contextual understanding, might bring forth underlying relationships that exist between meme formats and user engagement. More importantly, such approaches would offer the ability to specify exactly how different types of

memes produce disparities in forms of engagement, therefore fostering a more lucid view of their overall impact.

Research on multimodal recontextualization of political memes has shown that presentation modes strongly impact users' perception and forwarding intentions, implying the role of format in meme engagement in a strong way (Bülow and Johann 2023).

Research should also consider the temporal and cross-platform dynamics: as cultural artefacts, memes are likely to evolve with societal trends, whose applicability often depends on timing and context. Longitudinal studies, which utilize years of data or datasets from the multiple social media platforms and other subreddits, could make these dynamics clearer. These papers might outline the changes in meme engagement over time and across users of different demographics. Certainly, bringing advanced computational resources to deal with large-scale complexity in multimodal datasets will add further depth and real-world relevance to such analysis. Subsequent research could look at the influence of cultural, linguistic, and regional differences on meme engagement to find community-specific patterns. Looking at how emotional responses and preferred meme formats differ across different demographic groups could also provide useful information for marketers and platform developers. Finally, understanding the interaction between meme engagement and broader societal events—for example, political and historical events or cultural trends—could help situate the patterns found and explain how memes function as indicators of changes in society. The interaction among user feedback mechanisms, such as comment sentiment and subsequent engagement indicators, needs much more investigation. For instance, knowing whether divisive comments inspire re-engagement or discourage further participation could help platforms develop strategies for productive discussion moderation. Equally, understanding whether an increase in engagement levels with specific meme formats leads to the increased adoption of similar formats may provide insight into changing trends within meme culture.

In summary, future research efforts should not only strive to overcome the limitations acknowledged in this work but also further expand its scope by applying novel methodologies and interdisciplinary approaches. By allowing for a more fine-grained examination and prediction of an expanded range of engagement indicators and exploring details in multimodal interactions, researchers can achieve a better understanding of the digital culture surrounding memes and their impact on users' behaviour, platforms' ecosystems, and social discourse.

9. References

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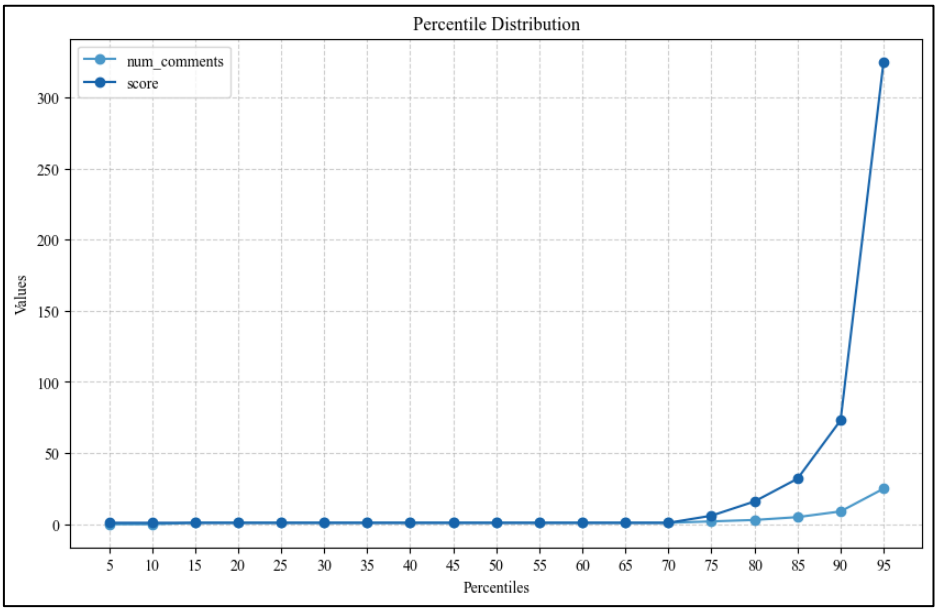
10. Appendices



Appendix 1: Percentile Distribution of Posts for Score and the Number of Comments Original 2023 Dataset

	score								num_comments								awards							
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max
quarter																								
Q1	20862.000	328.495	2391.008	0.000	1.000	4.000	41.000	84714.000	20862.000	18.062	135.103	0.000	1.000	1.000	4.000	8383.000	20862.000	0.008	0.090	0.000	0.000	0.000	0.000	1.000
Q2	16187.000	369.313	2861.488	0.000	1.000	1.000	25.000	88465.000	16187.000	12.133	82.368	0.000	1.000	1.000	2.000	2774.000	16187.000	0.005	0.073	0.000	0.000	0.000	0.000	1.000
Q3	20567.000	34.255	894.764	1.000	1.000	1.000	1.000	59791.000	20567.000	8.792	67.025	0.000	1.000	1.000	2.000	3517.000	20567.000	0.008	0.090	0.000	0.000	0.000	0.000	1.000
Q4	18597.000	138.473	1424.295	1.000	1.000	1.000	1.000	50697.000	18597.000	8.485	65.074	0.000	1.000	1.000	2.000	2355.000	18597.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Appendix 2: Descriptive Statistics for Quarter - Score, Number of Comments and Awards 2023 Dataset

	score								num_comments								awards							
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max
author_premium																								
False	73493.000	190.837	1844.759	0.000	1.000	1.000	6.000	88465.000	73493.000	11.091	84.884	0.000	1.000	1.000	2.000	6724.000	73493.000	0.005	0.071	0.000	0.000	0.000	0.000	1.000
True	2720.000	766.789	4556.197	0.000	1.000	1.000	40.250	77359.000	2720.000	35.552	220.192	0.000	1.000	2.000	6.000	8383.000	2720.000	0.022	0.146	0.000	0.000	0.000	0.000	1.000

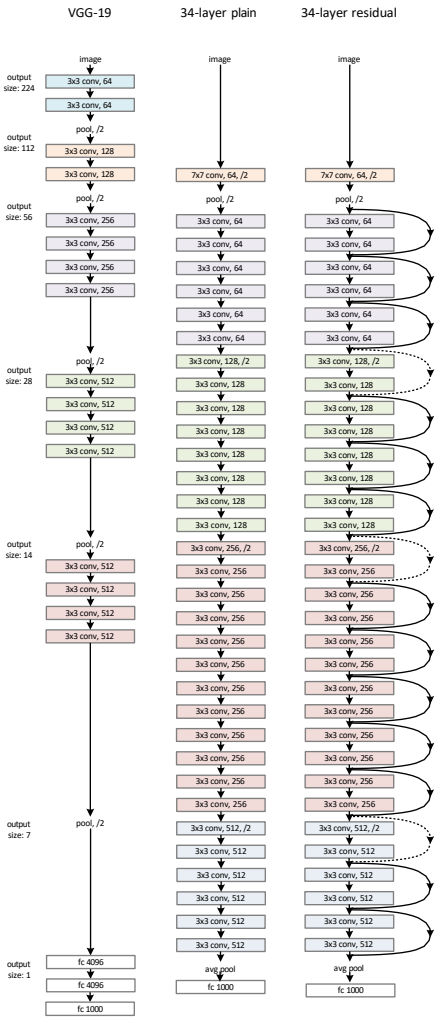
Appendix 3: Descriptive Statistics for Author Premium - Score, Number of Comments and Awards 2023 Dataset

	score								num_comments								awards							
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max
removed_post																								
0	32178.000	403.686	2859.022	0.000	1.000	7.000	46.000	88465.000	32178.000	19.942	116.504	0.000	1.000	3.000	6.000	6724.000	32178.000	0.011	0.104	0.000	0.000	0.000	0.000	1.000
1	44035.000	70.876	980.605	0.000	1.000	1.000	1.000	77359.000	44035.000	6.135	71.107	0.000	1.000	1.000	1.000	8383.000	44035.000	0.002	0.041	0.000	0.000	0.000	0.000	1.000

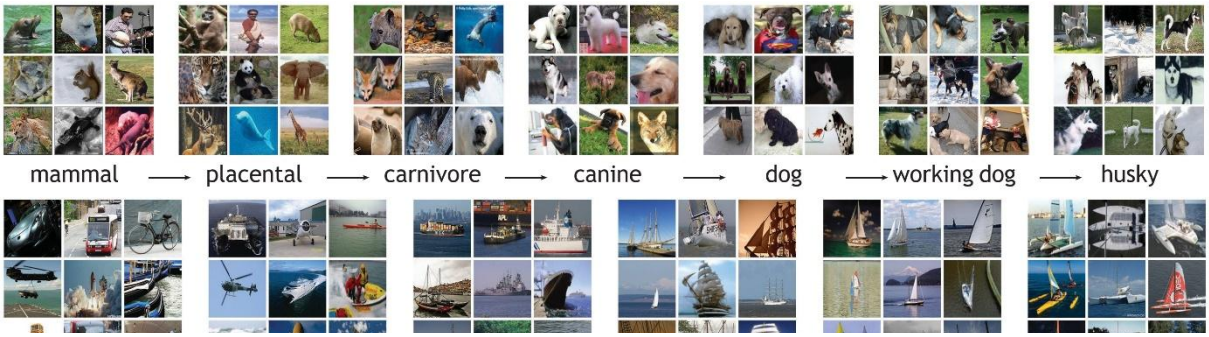
Appendix 4: Descriptive Statistics for Removed Post - Score, Number of Comments and Awards 2023 Dataset

	score								num_comments								awards							
	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max	count	mean	std	min	25%	50%	75%	max
locked																								
False	70452.000	211.352	2018.055	0.000	1.000	1.000	6.000	88465.000	70452.000	11.679	92.947	0.000	1.000	1.000	3.000	8383.000	70452.000	0.006	0.075	0.000	0.000	0.000	0.000	1.000
True	5761.000	211.881	1886.626	0.000	1.000	2.000	9.000	84714.000	5761.000	15.459	97.020	0.000	1.000	1.000	3.000	2568.000	5761.000	0.005	0.073	0.000	0.000	0.000	0.000	1.000

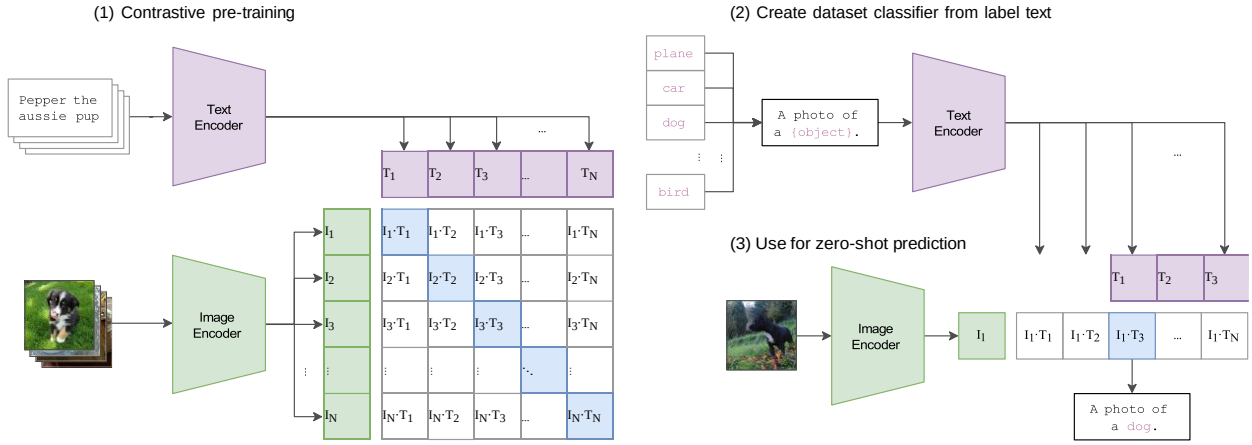
Appendix 5: Descriptive Statistics for Locked - Score, Number of Comments and Awards 2023 Dataset



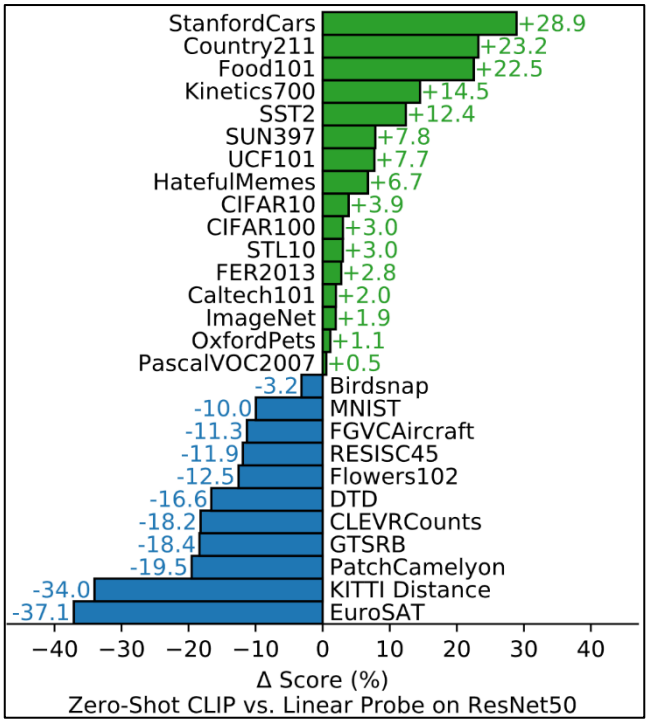
Appendix 6: "Example network architectures for ImageNet. Left: the VGG-19 model [41] (19.6 billion FLOPs) as a reference. Middle: a plain network with 34 parameter layers (3.6 billion FLOPs). Right: a residual network with 34 parameter layers (3.6 billion FLOPs)." (He et al. 2015)



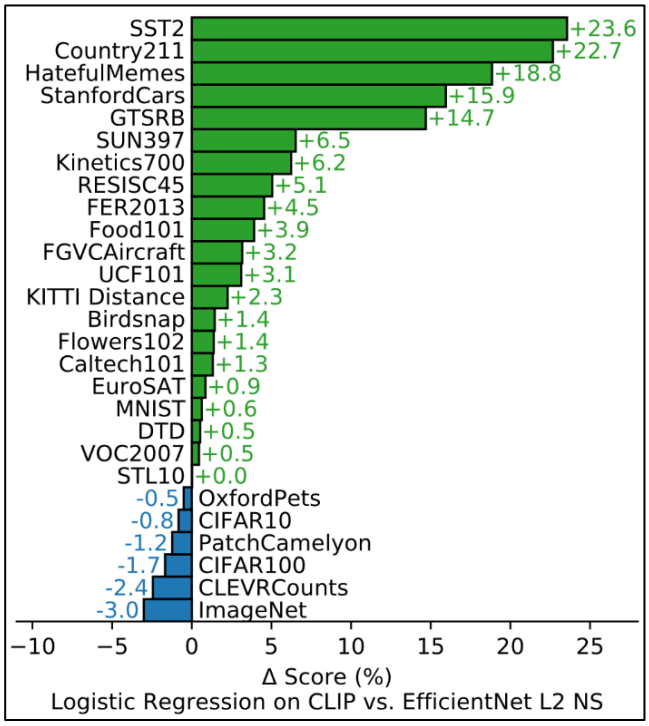
Appendix 7: Example of two root-to-leaf branches of ImageNet: the top from "Mammal" to "Husky" and the bottom from "Vehicle" to "Trimaran", with 9 random images sampled for each label (Deng et al. 2009)



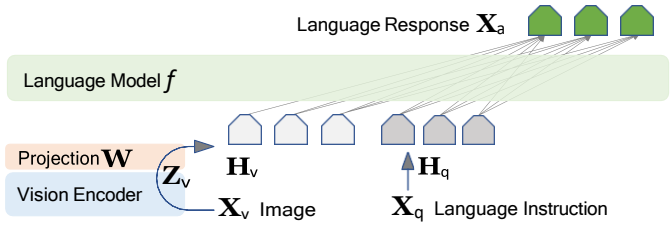
Appendix 8: Summary of the CLIP Architecture and of CLIP's Zero-Shot Prediction Capabilities (Radford et al. 2021)



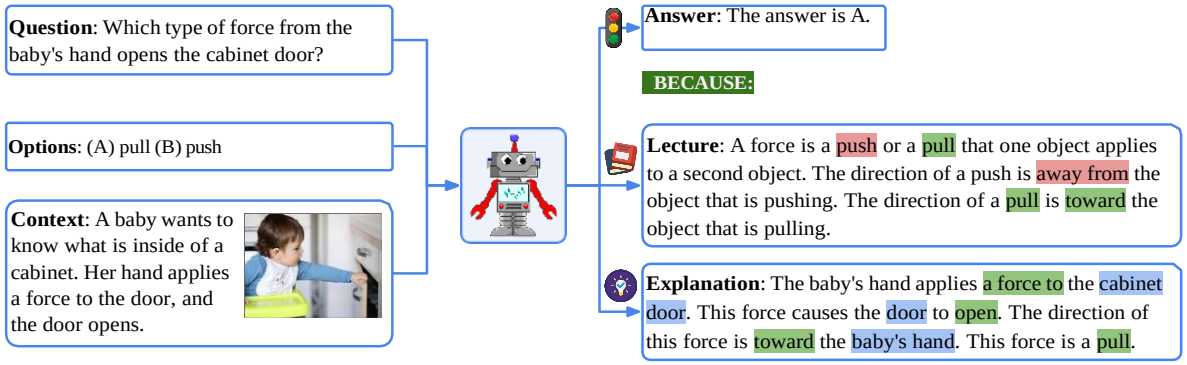
Appendix 9: CLIP's Zero-Shot Prediction Matches or Outpaces the performance of ResNet50 in 16 datasets (Radford et al. 2021)



Appendix 10: CLIP's features fitted with a Logistic Regression outperform the Noisy Student EfficientNet-L2 on 21 out of 27 datasets (Radford et al. 2021)



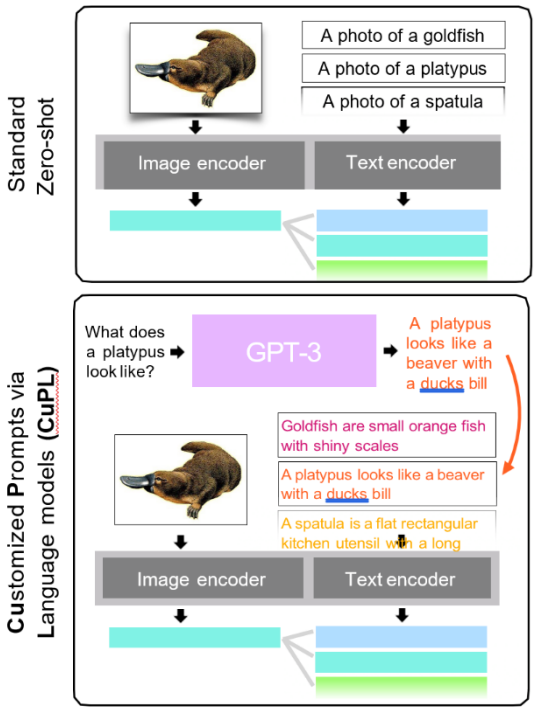
Appendix 11: LLaVA (Large Language and Vision Assistant) Architecture (Liu et al. 2023)



Appendix 12: Multimodal question answering information and the grounded lecture and explanation, used to evaluate QA models chain-of-thought reasoning (Lu et al. 2022)

Method	Subject			Context Modality			Grade		Average
	NAT	SOC	LAN	TXT	IMG	NO	G1-6	G7-12	
Representative & SoTA methods with numbers reported in the literature									
Human	90.23	84.97	87.48	89.60	87.50	88.10	91.59	82.42	88.40
GPT-3.5	74.64	69.74	76.00	74.44	67.28	77.42	76.80	68.89	73.97
GPT-3.5 w/ CoT	75.44	70.87	78.09	74.68	67.43	79.93	78.23	69.68	75.17
LLaMA-Adapter	84.37	88.30	84.36	83.72	80.32	86.90	85.83	84.05	85.19
MM-CoT$_{Base}$	87.52	77.17	85.82	87.88	82.90	86.83	84.65	85.37	84.91
MM-CoT$_{Large}$	95.91	82.00	90.82	95.26	88.80	92.89	92.44	90.31	91.68
Results with our own experiment runs									
GPT-4†	84.06	73.45	87.36	81.87	70.75	90.73	84.69	79.10	82.69
LLaVA	90.36	95.95	88.00	89.49	88.00	90.66	90.93	90.90	90.92
LLaVA+GPT-4† (complement)	90.36	95.50	88.55	89.05	87.80	91.08	92.22	88.73	90.97
LLaVA+GPT-4† (judge)	91.56	96.74	91.09	90.62	88.99	93.52	92.73	92.16	**92.53**

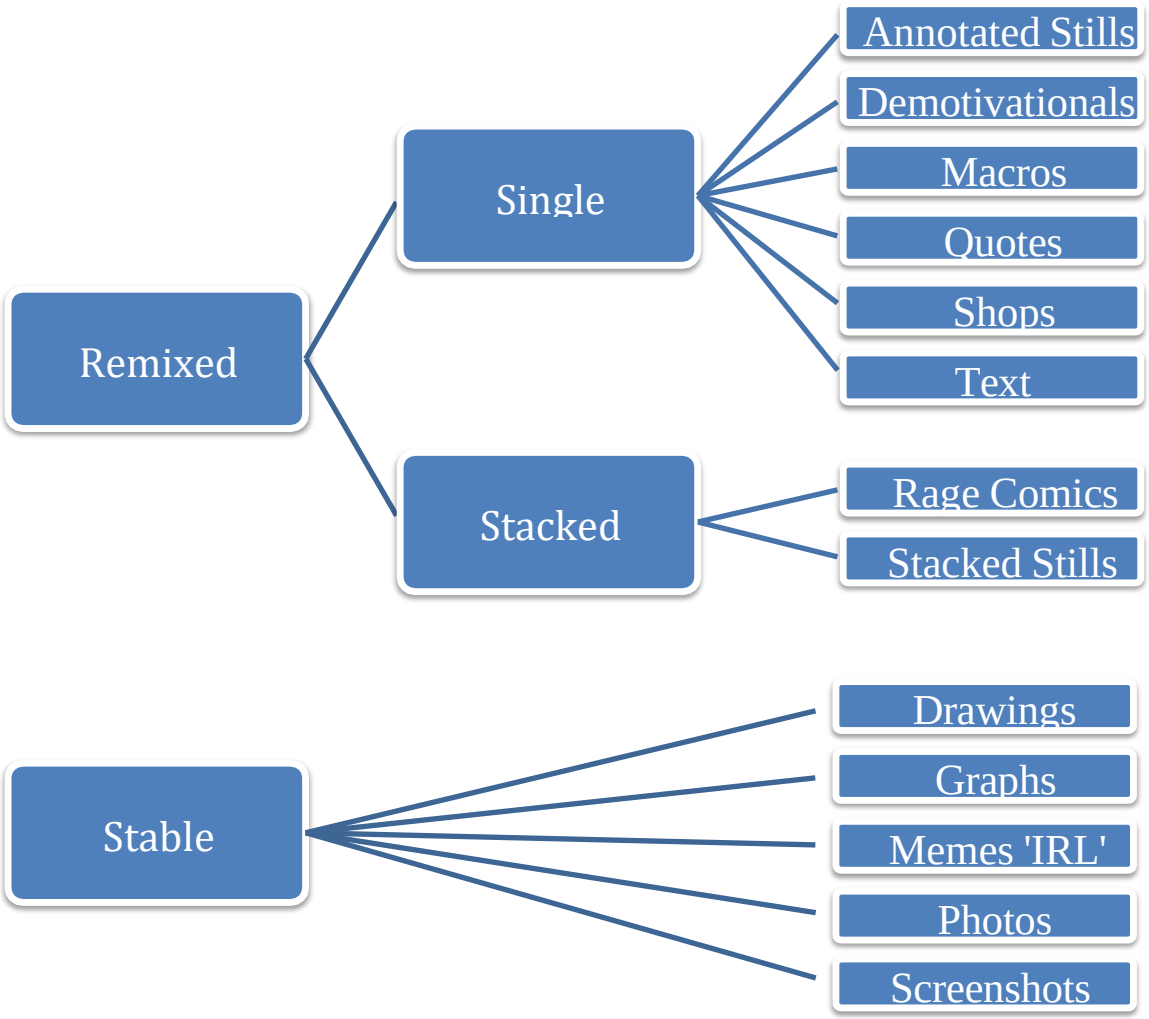
Appendix 13: LLaVA and Derived Ensemble Models performance on the ScienceQA Dataset

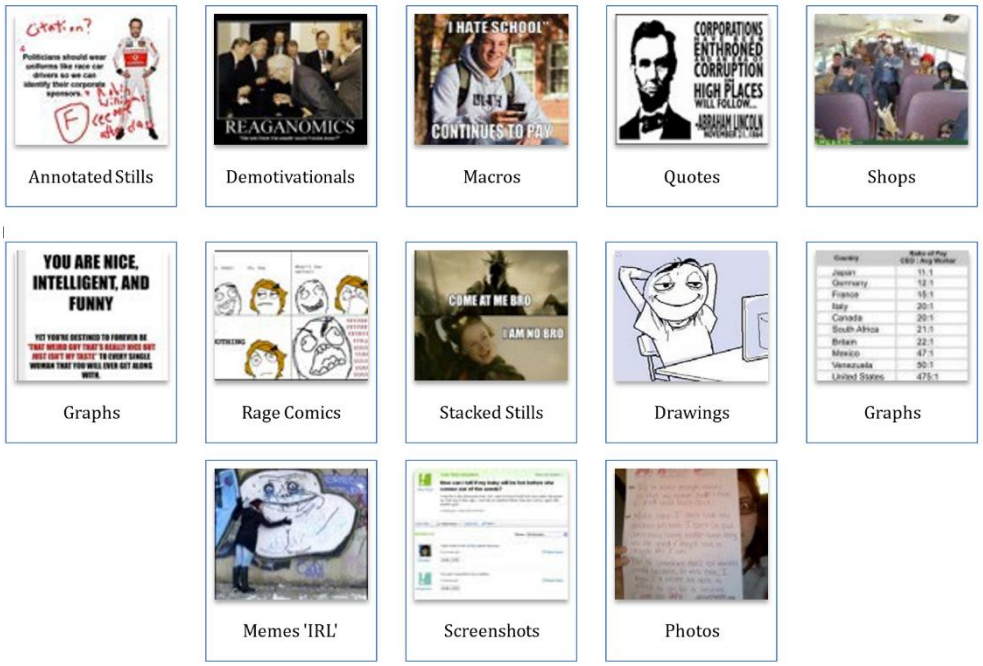


Appendix 14: Schematic of the CuPL (Customized Prompts via Language models) Method (Pratt et al. 2023)

	ImageNet	DTD	Stanford Cars	SUN397	Food101	FGVC Aircraft	Oxford Pets	Caltech101	Flowers 102	UCF101	Kinetics-700	RESISC45	CIFAR-10	CIFAR-100	Birdsnap	mean	Total	Unique
std	75.54	55.20	77.53	69.31	93.08	32.88	93.33	93.24	78.53	77.45	60.07	71.10	95.59	78.26	50.43	73.43		
# hw	80	8	8	2	1	2	1	34	1	48	28	18	18	18	1		268	175
CuPL (full)	76.69	61.70	77.63	73.31	93.36	36.11	93.81	93.45	79.67	78.36	60.63	71.69	95.84	78.57	51.11	74.80		
Δ std	+1.15	+6.50	+0.10	+4.00	+0.28	+3.23	+0.48	+0.21	+1.14	+0.91	+0.56	+0.59	+0.25	+0.31	+0.63			
# hw	5	6	9	3	3	2	2	3	2	5	4	5	3	4	3		59	45
CuPL (base)	76.19	58.90	76.49	72.74	93.33	36.69	93.37	93.45	78.83	77.74	60.24	68.96	95.81	78.47	51.11	74.15		
Δ std	+0.65	+3.70	-1.04	+3.43	+0.25	+3.81	+0.04	+0.21	+0.30	+0.29	+0.17	-2.14	+0.22	+0.21	+0.63			
# hw	3	3	3	3	3	3	3	3	3	3	3	3	3	3	3		45	3

Appendix 15: Performance of CuPL prompts compared to standard hand-written prompts (Pratt et al. 2023)

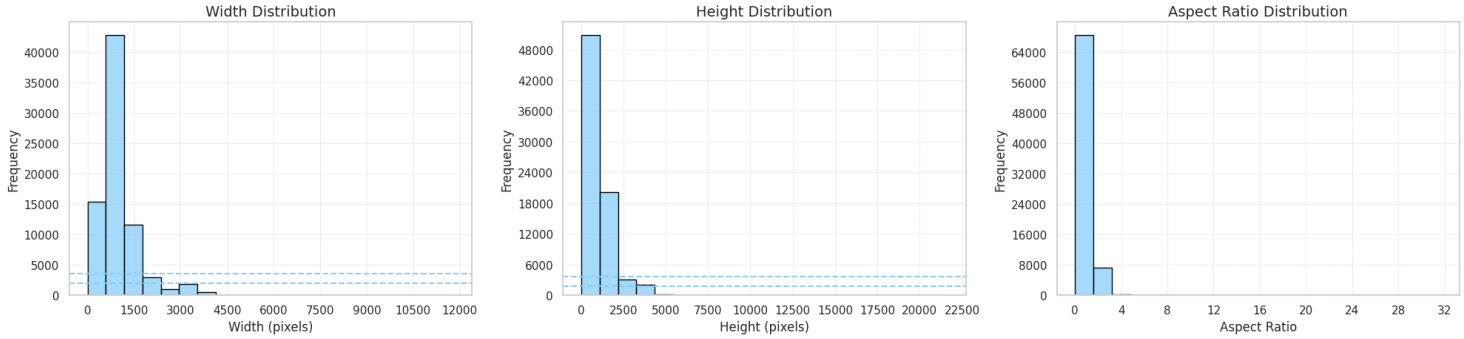




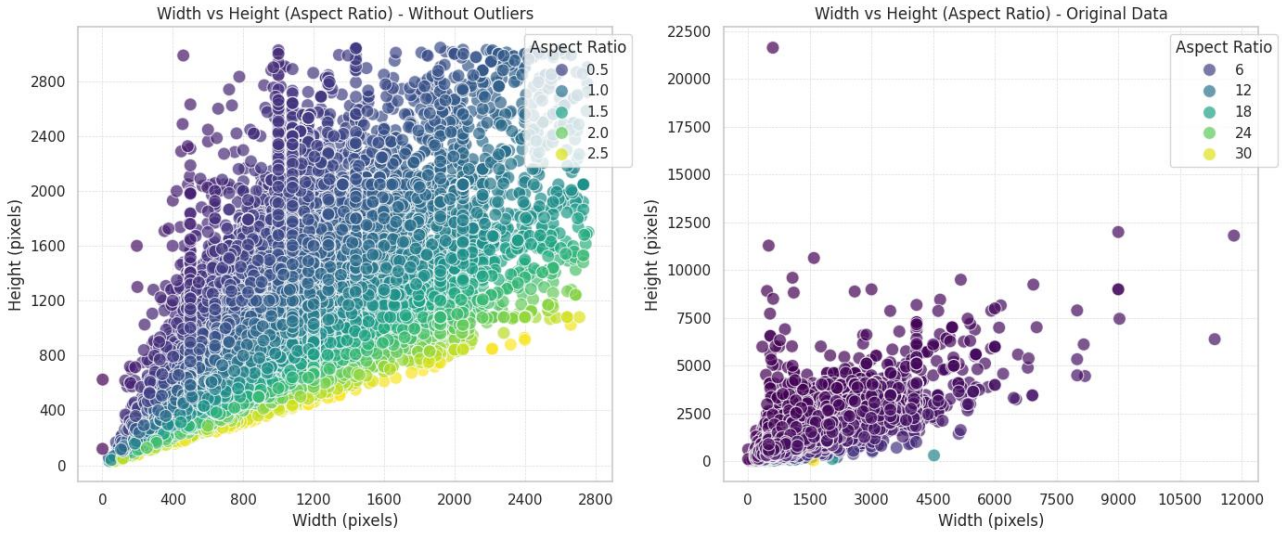
Appendix 16: Taxonomy for Internet Memes & Examples (Milner 2012, 85-86)

Remixed Images	"… transform an image from an established set of practices or established artifacts"
Stable Images	"… passed along without transformation from mediated participants"
Single Images	"… remixes that occur within a single frame."
Stacked Images	"combine multiple single images into a new grouping of images, often to make a more complex point."
Annotated Stills	"Annotated images' interact with the text explicitly, making addendums, adding dialogue bubbles"
Demotivationals	"'Demotivationals' remix image and text in a parody of 'motivational' posters that frame images in a black box"
Macros	"… apply text over the image itself, often a clause on the top of the image to set up a premise and a clause on the bottom to deliver a punch line."
Quotes	"Image and text are also remixed into quotes in meme collectives, often combining a bust of the quoted figure with text from the quote itself."
Shops	"'Shops' (short for 'Photoshops' after the Adobe photo editing application) craft a new image by combining elements of multiple other Images"
Text	"… sometimes image files forego pictures entirely, sharing graphical text only."
Rage Comics	"'Rage Comics' build from a corpus of established 'Rage Faces' and text."
Stacked Stills	"'Stacked stills' take either macros or annotated stills and combine them into multi-panel images."
Drawings	"Drawings are animated images that are used to make or support a point. These can include web comics that are the work of a named or unnamed author rather than built from a remixed core."
Graphs	"Graphs, often adapted from popular press infographics, visually display data. These were predominantly shared in political discussions."
Memes 'IRL'	"…stable images that capture the creation of memes in more traditional aesthetic modes. Making a t-shirt featuring Hipster Kitty or painting him on a wall would be a 'meme IRL'."
Photos	"Unannotated photos are also shared. These are the raw materials by which macros are often made. They can also be transformative extratextually."
Screenshots	"Screenshots are unannotated captures of mediated communication"

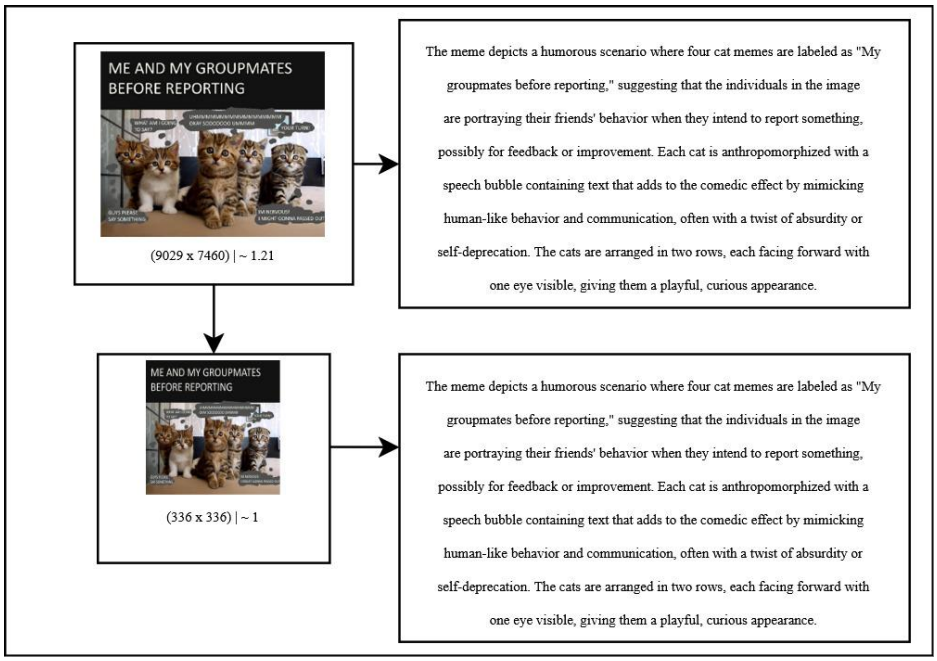
Appendix 17: Definitions for the Taxonomy of Conventional Image Files, quoted from Milner 2012, 83-87



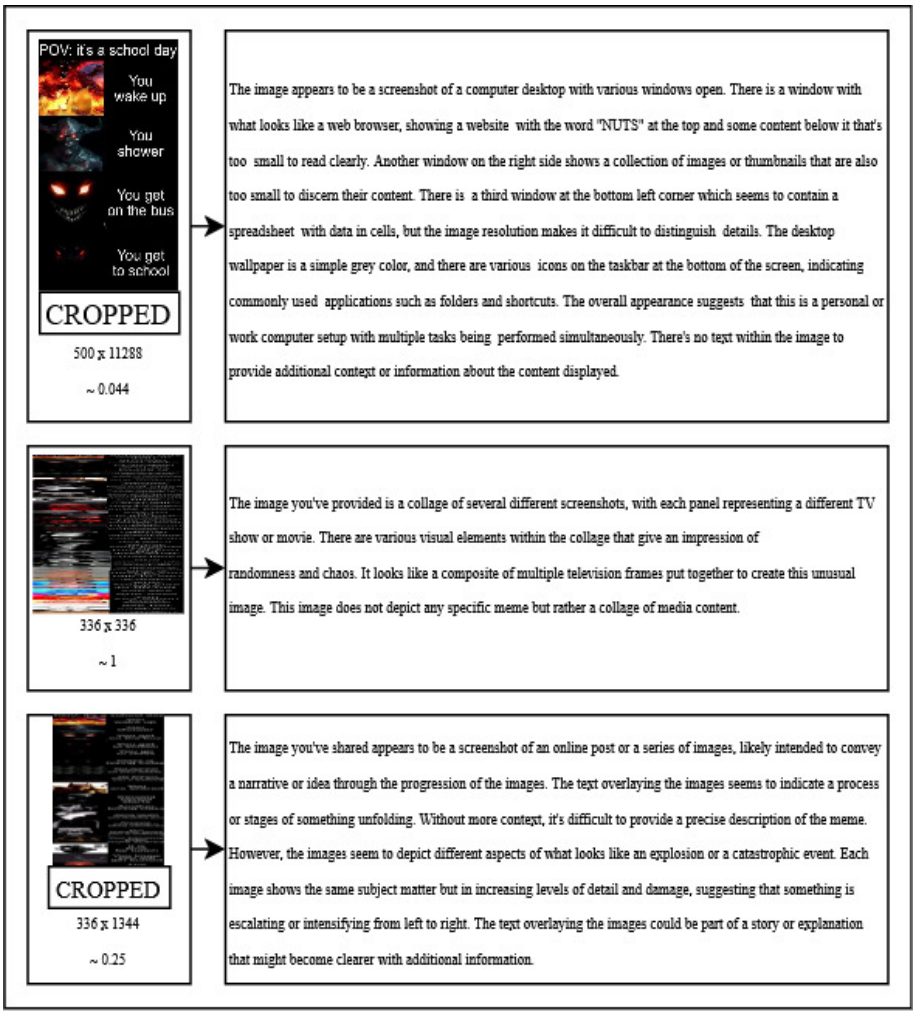
Appendix 18: Size Distributions for Width, Height and Aspect Ratios show most images complying with regular dimensions, but a few images being major outliers (y-axis number of images within a bar's specific range; x-axis pixel count of width and height and their ratio)



Appendix 19: Scatter Plots of all images on the left and non-outlier images on the right, plotting Width (x) against Height (y) in pixels, and with Aspect Ratio colour coded. From the left plot, there is a significant number of height and width outliers that are not aspect ratio outliers, meaning they can be resized without information loss. From the plot on the right, when we exclude outliers there is still a significant number of images with unconventional aspect ratios (below 0.5 or above 2.5)



Appendix 20: Model was able to retain image information after resizing, since it has a normal Aspect Ratio



Appendix 21: Model does not understand the context in the raw size and in the (336x336) resize but has a better understanding with the (336x1344) resize).

Model	Runs	Width Raw	Width Resized	Width Delta	Height Raw	Height Resized	Height Delta	Aspect Raw	Aspect Resized	Aspect Delta
llava:7b	15	0.4	0.37	-0.023 (-5.89%)	0.31	0.24	-0.069 (-22.07%)	0.56	0.26	-0.299 (-53.13%)
llava:13b	15	21.16	10.34	-10.824 (-51.14%)	15.1	11.31	-3.789 (-25.1%)	7.65	7.45	-0.194 (-2.54%)
llava-llama3:latest	15	0.4	0.36	-0.037 (-9.24%)	0.36	0.23	-0.132 (-36.78%)	0.33	0.33	-0.001 (-0.23%)
llava-phi3:latest	15	6.02	6.09	0.069 (1.15%)	7.93	6.9	-1.032 (-13.0%)	6.4	5.85	-0.544 (-8.5%)
minicpm-v:latest	15	0.28	0.22	-0.061 (-22.02%)	0.29	0.27	-0.016 (-5.69%)	0.29	0.21	-0.079 (-27.03%)
bakllava:latest	15	0.39	0.27	-0.123 (-31.63%)	0.17	0.16	-0.004 (-2.44%)	0.3	0.23	-0.072 (-24.01%)
llama3.2-vision:11b	15	82.94	76.1	-6.841 (-8.25%)	63.73	33.53	-30.205 (-47.39%)	44.3	52.5	8.202 (18.52%)

Appendix 22: Small-scale test running inference of outlier images 15x with each model, shows that there is a general decrease in inference times when images are resized

You are a reddit meme expert that is classifying memes using a custom taxonomy. Respond only with one of the following labels: [screenshot, text, photo, drawing, emotional_reaction, event_reaction, macro, situational, comic, meme_character, template]

Context & Instructions

1. screenshot: Images capturing digital media, where content is non-textual.

Example: An image of a video game or animated series.

2. text: Images containing only text.

Example: Walls of text, screenshots of tweets, or messages.

3. photo: Memes where the main focus is an unaltered, organic real-world image, can have text but the image is the primary focus.

Example: A meme featuring a picture of a cat without text or edits.

Class Definition & Example

4. drawing: Artworks or edited images, including photoshopped or illustrated content.

Example: A drawing of a cartoon character or a photoshopped image.

5. emotional_reaction: Memes that often include a text section on top and at the bottom an emotional reaction through an expression.

Example: The Roll Safe Smart Reaction.

6. event_reaction: Similar to emotional reactions but focusing on specific events or situations rather than facial expressions.

Example: A skeleton exploding (an event) or a reaction with a TV series line.

7. macro: Single images with centered text at the top and/or bottom, often in Impact Font, popular in older internet memes.

Example: Success Kid or Bad Luck Brian.

8. situational: Images creating absurd situations by overlaying text over elements of the image (often objects or heads).

Example: An image of a person pouring gasoline on a fire, with text over the gas tank, fire pit, and person.

9. comic: Series of panels or images that tell a story.

Example: Two stacked frames of a movie or a comic strip.

10. meme_character: Memes featuring well-known characters.

Example: Wojak, Chad, Shrek, Troll Face, Rage Characters, Stonks Man, or Pepe.

11. template: Memes following widely popular meme formats.

Example: Expanding mind, Mr. Incredible, Drake, Change My Mind, Distracted Boyfriend, This is Fine, People Raising Hands.

Answer with only the single word from the list. Instruction

Appendix 23: Prompt containing Context Section, Instructions, Class Definitions & Examples and Instruction Reiteration, used for model selection as 'Generic Prompt' and Prompt Engineering as 'Prompt 3'

Label the meme according to these categories. Only return the label } Instructions

1. screenshot: Images capturing digital media, where content is non-textual } Class Definitions

2. text: Images containing only text.

3. photo: Memes where the main focus is an unaltered, organic real-world image, can have text but the image is the primary focus.

4. drawing: Artworks or edited images, including photoshopped or illustrated content.

5. emotional_reaction: Memes that often include a text section on top and at the bottom an emotional reaction through an expression.

6. event_reaction: Similar to emotional reactions but focusing on specific events or situations rather than facial expressions.

7. macro: Single images with centered text at the top and/or bottom, often in Impact Font, popular in older internet memes.

8. situational: Images creating absurd situations by overlaying text over elements of the image (often objects or heads).

9. comic: Series of panels or images that tell a story.

10. meme_character: Memes featuring well-known characters.

11. template: Memes following widely popular meme formats.

Appendix 24: Prompt 1 with Instructions and Class Definitions

Label the meme according to these categories. Only return the label. } Instructions

1. screenshot: Images capturing digital media, where content is non-textual } Class Definition

An example of a screenshot is an image of a video game or animated series } Example

2. text: Images containing only text. An example of a text meme is walls of text, screenshots of tweets, or messages

3. photo: Memes where the main focus is an unaltered, organic real-world image, can have text but the image is the primary focus. An example of a photo is a meme featuring a picture of a cat without text or edits

4. drawing: Artworks or edited images, including photoshopped or illustrated content. An example of a drawing meme is a drawing of a cartoon character or a photoshopped image with face swaps

5. emotional_reaction: Memes that often include a text section on top and at the bottom an emotional reaction through an expression of humans, drawings or animals, to invoke a specific feeling on the user. An example of a emotional_reaction is a meme with text and a face of a person looking surprised or happy or sad

6. event_reaction: Similar to emotional reactions but using images of situations or events as a reaction instead of a facial expression. An example of event_reaction would have at the bottom an image of an explosion, a fight or a specific action

7. macro: Single images with centered text at the top and/or bottom, often in Impact Font, popular in older internet memes. Examples of macro memes use images of the Success Kid or Bad Luck Brian

8. situational: Images creating absurd situations by overlaying text over elements of the image (often objects or heads). An example of situational meme is an image of a person pouring gasoline on a fire, with text over the gas tank (element 1), fire pit (element 2), and person (element 3)

9. comic: Series of panels or images that tell a story. An example of a comic meme is two stacked frames of a movie or comic strips like Rage Comics or Lost

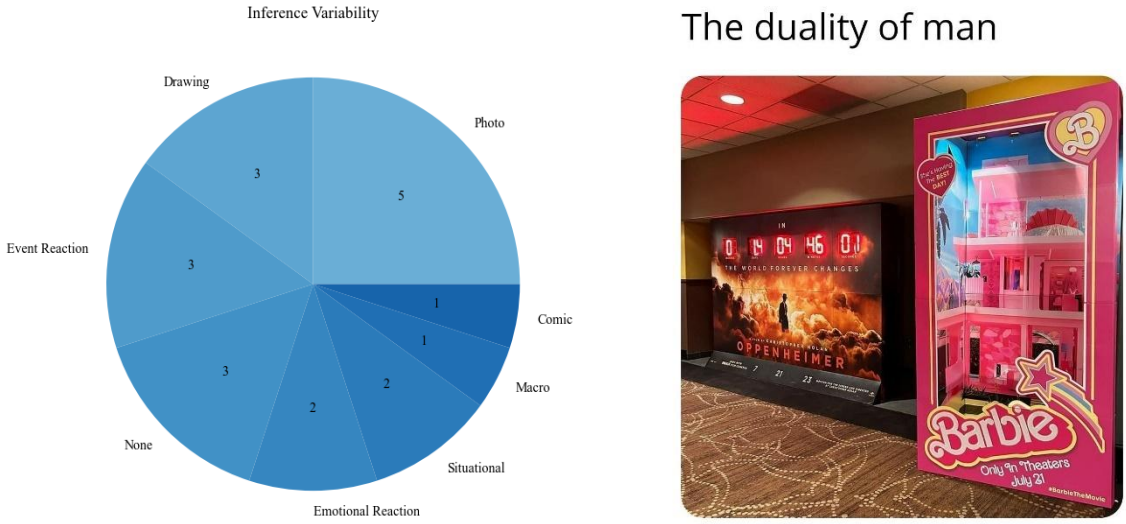
10. meme_character: Memes featuring well-known characters. Examples of meme characters are Wojak, Chad, Shrek, Troll Face, Rage Charactersand Pepe

11. template: Memes following widely popular meme formats, where the user often changes textual. Examples of templates are Expanding Mind, Mr. Incredible Uncanny, Lisa Simpson's Presentation, Drakeposting, Change My Mind, Distracted Boyfriend, This is Fine, People Raising Hands

Appendix 25: Prompt 2 with Instructions, Class Definitions and Examples

$$P(x) = \frac{e^{\frac{z_x}{T}}}{\sum_{j=1}^{n} e^{\frac{z_j}{T}}}$$

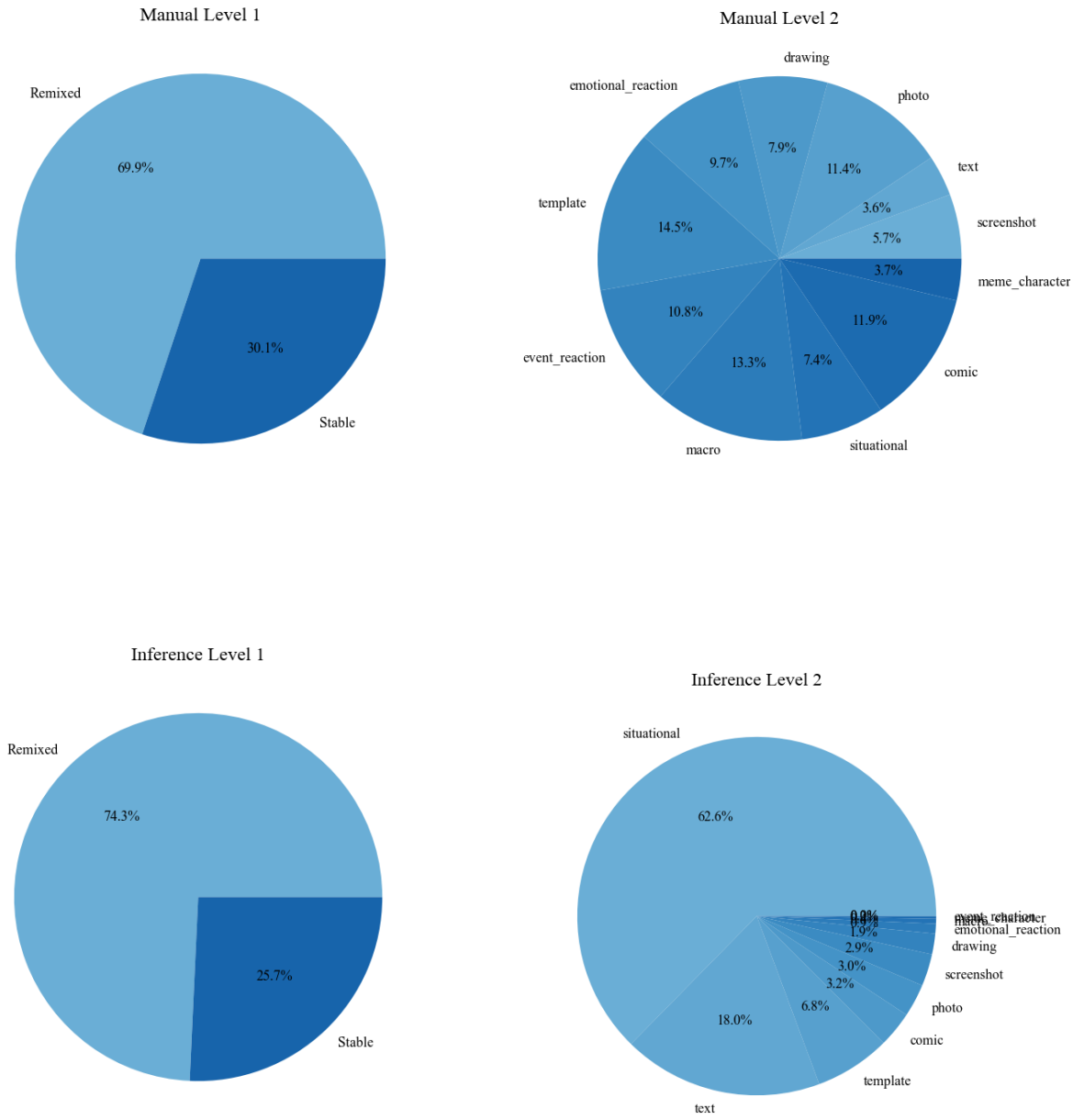
Appendix 26: Probability Function of the next generated output for token i, applied in SoftMax layers of LLMs and LVMs. Temperature influences the equation by acting as a scaler for the logits (zi and zn). T represents temperature and n represents the number of tokens in the vocabulary



Appendix 27: For the meme on the right, inference with the Generic Prompt (Appendix 44) was ran 20 times, showcasing the variability of the models' inference

$$\text{Percentage Change (Dependent Variable)} = (\exp(\beta_i) - 1) * 100$$

Appendix 28: Formula to convert coefficients of regressions with log-transformed dependant variables to the original scale's Percentage Change, advisable when coefficients are large so to not use inaccurate log approximations



Appendix 29: Distributions of Level 1 and Level 2 Formats – Manual vs. Inference. Level 1 formats are relatively close, but the inference has a big bias towards the Situational format, and a slight bias towards text, under classifying all other formats.