Automatic Classification of Conversational Humor with a focus on COVID-19 tweets

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by

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CERTIFICATE

It is certified that the work contained in this thesis, titled "***Automatic Classification of Conversational Humor with a focus on COVID-19 tweets*** " by Gayatri Purigilla, has been carried out under my supervision and is not submitted elsewhere for a degree.

Date

Adviser: Prof. Radhika Mamidi

To Guruvugaru.

Acknowledgments

To the place that has shaped me into who I am today,
To the people who are now family, I can say,
To the sleepless nights that paved the way,
And to everything and everyone who have been a part of my day.

To thank you all, with this poem, I start,
As sadly, this is where we part.
The ups and downs have been etched in my heart
Which is what I believe has made me into this piece of art.

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"See, the dreamers need the realists to keep them from soaring too close to the sun."

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Abstract

We, humans, are social beings, and our communication is the most evolved and well-structured form of a communication system that we are aware of. An essential aspect of human communication that helps humans bond faster and develop a sense of closeness is the use of humor. Humor that occurs as part of a conversation is known as conversational humor. Conversational humor is a type of humor that is unique and contrary to what it may seem like. It is more than just plugging canned jokes into a conversation. It requires the use of certain techniques and the presence of at least two interlocutors who understand the context of the conversation.

The first step towards understanding conversational humor is to identify the different types into which it can be categorized and the techniques that are used to generate each type of humor. Current studies on this front either consider only a subset of these types and techniques or are domain specific. To tackle these challenges, we first propose a hierarchical annotation schema which allows us to get a comprehensive overview of conversational humor. For this task, we use a famous Telugu play, Kanyasulkam, and consider humorous utterances from this play as the dataset. This schema includes tags for type, technique, and benignity and considers cultural nuances in the text, making it an extensive schema for conversational humor.

Further, to test the universality of the schema, we built a dataset of a different domain (Covid-19-based humor) and language (English). This dataset was annotated using a part of the annotation schema containing the type and technique tags. Two more tags viz. “Situation” and “Relevance” were added in the schema to help make the dataset more valuable as a standalone dataset which can be used by researchers from other fields like marketing, sociology, etc.

The effectiveness of this dataset is tested with the help of various experiments for binary as well as multi-label multi-class classification using state-of-the-art ML models including but not limited to BERT, RoBERTa, BerTweet, etc. Based on the accuracy and analysis from the experiments, we can show that the annotation schema is universal in terms of language and domain. Such a classification of data can be used to accelerate the annotation process for humor data, and this annotated data can be used for various purposes like marketing, connecting with

a target audience based on the relevance tag, and aiding research in the field of conversational humor for building humorous chatbots, and more human-like interactive systems.

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Chapter 1

Introduction

Humor has always been an integral part of human communication. From a young age, we are taught to recognize and appreciate jokes, puns, and other forms of humor. As we grow older, humor becomes an increasingly important part of our social interactions, especially in conversational settings. Conversational humor can take many forms, including puns, one-liners, sarcasm, and irony, among others. Humor can also be used for different purposes, such as breaking the ice, easing tension, and building rapport.

Humor is a complex phenomenon, and its classification and analysis are challenging tasks. The ability to recognize and produce humor is an essential aspect of social intelligence, and it is often used as a measure of mental agility and creativity. Thus, the study of conversational humor is of significant interest to researchers in various fields, including linguistics, psychology, and artificial intelligence. Linguists have long been interested in the structure and function of humor, focusing on the linguistic devices used to create and express humor. They have been concerned with finding patterns and defining rules about what we find funny. More specifically, many linguists find interest in studying how grammatical manipulations affect humor generation. Sociologists are interested in how it influences society at large. Psychologists have studied humor from a cognitive and affective perspective, examining how people perceive, process, and respond to humorous stimuli. Meanwhile, researchers in artificial intelligence and natural language processing have explored the potential of computational methods for analyzing and generating humor.

What do humans find funny? The highly subjective nature of this question and the difficulty which comes with generalizing the answer is what makes research about humor interesting. Humor in the past had not ever been considered a subject of importance. Starting with the ancient Greek philosophers to the scholars of the 20th century, everyone disregarded humor research as a fruitful field of study or went a step ahead and associated humor with negative connotations of being evil, mocking, or even violent. While this was the general notion until the 20th century, humor research has recently been gaining the attention of various scholars.

Humor is defined as the ability of something to be amusing and, in turn, cause humans to smile or laugh. The source of this amusement can be something seen, heard, read, or even thought about. This is the basis of the broadest and most widely accepted forms of humor categorization. i.e., slapstick humor (seen), conversational humor (heard), canned jokes (read), etc. Conversational humor, which is of importance to us, has first been defined by Coates as humorous talk occurring in the informal conversation of friends. This definition was later extended by Dynel to include various discourses which happen during conversations in order to amuse the participants or the listeners.

While conversational humor is also based on the general theories of humor and may have the same basic structure of a joke, there are also a few significant differences that call for studies specific to conversational humor. While canned jokes are often rehearsed or heard before, conversational ones are created on the fly. Further, conversational jokes are told in one's turn during a conversation without any preface or warning, like in the case of canned jokes. Furthermore, conversational jokes are strongly dependent on the context, which makes them unique in their nature.

With the increasing use of social media and human interactions, we can notice the importance that humor holds in a conversation. It not only lightens the mood but also helps break the ice between strangers, makes faster and more robust connections, and fosters trust between individuals. However, it is important to understand the implications of culture and context on humor for the above to be relevant.

Early research on humor classification focused on identifying the linguistic features that distinguish humorous from non-humorous texts. Studies found that humor often involves the use of unexpected or incongruous elements, such as puns, wordplay, and double entendres. Researchers also identified the importance of context and social knowledge in the interpretation of humor. For instance, jokes that rely on cultural references or shared knowledge are more likely to be understood and appreciated by people who share that knowledge.

In recent years, advances in natural language processing (NLP) and machine learning (ML) have enabled researchers to develop algorithms capable of automatically classifying and analyzing conversational humor. Researchers have explored the potential of machine-learning approaches for classifying conversational humor. These approaches typically involve training a classifier on a dataset of annotated examples of humorous and non-humorous conversational exchanges. The classifier can then be used to classify new conversational exchanges as humorous or non-humorous automatically. Some studies have also explored the use of deep learning techniques, such as recurrent neural networks and transformer models, for conversational humor classification. These algorithms have a wide range of applications, from improving chatbots' conversational abilities to analyzing large datasets of social media conversations.

The main research question addressed in this thesis is: Can machine learning algorithms be used to automatically classify conversational humor? Specifically, we aim to develop and evaluate a machine learning-based approach to automatically classify conversational humor based on linguistic features and contextual information.

1.1 Motivation

The fast-increasing pace of technology in today's world has led us to a point where the presence of another human is no longer necessary in order to carry out a conversation. Conversational agents and chatbots are becoming increasingly common in various domains, including customer service, education, and entertainment. These systems rely on natural language processing and machine learning techniques to understand and generate human-like responses. However, they often struggle with understanding and generating humor, which can make interactions with users less engaging and enjoyable. A possible solution would be to add more human touch to the usual machine-like unemotional responses. And one sure-shot way of developing a feeling of connection is to add an element of humor. By developing machine learning-based approaches to conversational humor classification, we can improve the performance of conversational agents and chatbots and make them more effective and enjoyable to use. Further, developing these technologies to be used by the common man in India requires diversification in terms of language and also a thorough understanding of the various cultures, given its heavy influence on humor.

Humor is a complex and multifaceted phenomenon that has been studied extensively in psychology, linguistics, and sociology. However, much of this research has focused on humor in monologues or written contexts rather than in conversational settings. By developing machine learning-based approaches to conversational humor classification, we can gain insights into the linguistic and social factors that contribute to the production and reception of humor in conversation. This can help us better understand the nature of humor and its role in human communication.

Humor is an important coping mechanism that can help individuals reduce stress, improve mood, and enhance social connections. By developing conversational agents and chatbots that can generate and understand humor, we can potentially improve the mental health and well-being of users. For example, conversational agents that can generate humorous responses to stressful situations, such as exams or job interviews, may help individuals cope better with these situations and reduce their levels of anxiety.

Given these needs, comprehensive data annotation methods, which are neither constrained by domain nor by language, are a necessity. Furthermore, given the extensive use of ML models for executing the above-mentioned advancements, we can foresee the need for a massive amount of data. Annotation of this data manually is a herculean task as well as a futile undertaking. The use of state-of-the-art models to automatically tag data is hence, a prerequisite in order to smoothly carry out this task.

1.2 Key Contributions

- **Comprehensive annotation schema for conversational humor**: We propose a hierarchical annotation schema for classifying occurrences on conversational humor based on the Telugu play Kanyasulkam. The annotation schema classifies based on whether the utterance is a monologue/ dialogue, the type of humor, the technique used and benignity of the utterance.

- **Annotated dataset of humorous tweets related to Covid-19:** A dataset of 3000+ tweets in the domain of Covid-19 pandemic is contributed to aid humor research. Tweets for the purpose of this study are considered to be conversations either between two individuals or between a user and his audience on the internet. Of these, 1400+ tweets have been identified to be humorous whereas the rest of the tweets are non-humorous.

- **State-of-the art ML models to run experiments and automatically tag a given sentence using the hierarchical annotation schema:** Finally, we designed experiments using state-of-the-art ML models for multi-label multi-class classification of any humorous sentence to automatically tag a given sentence using the hierarchical annotation schema. The results from these experiments are further analyzed for insights into the data as well as the models.

1.3 Challenges

Humor research intrinsically involves challenges like the subjective nature of humor, differences in humor perception, and resource limitations for languages other than English. These challenges are described in detail below.

1.3.1 Subjectivity of humor

One of the primary challenges of conversational humor classification is the subjectivity of humor itself. Humor is a complex and multifaceted phenomenon that can take many forms, and what one person finds funny, another may not. This subjectivity poses a significant challenge for machine learning-based approaches to classify conversational humor.

Humor is often context-dependent, and its success depends on the social and cultural factors surrounding the interaction. For example, a joke considered hilarious in one culture may not be funny at all or even offensive in another. Similarly, the success of humor in conversation can depend on the relationship between the participants and their respective personalities, interests, and experiences.

Another aspect of humor that contributes to its subjectivity is its reliance on linguistic devices such as wordplay, sarcasm, irony, and ambiguity. These devices often involve playing with the meaning of words or phrases, which can be challenging to detect and interpret using machine learning algorithms. Additionally, the success of these devices in generating humor often depends on the expectations and prior knowledge of the participants.

Given the subjectivity of humor, there is no one-size-fits-all approach to conversational humor classification. Instead, researchers must develop techniques that can capture the context-specific and culturally-specific factors that contribute to the production and reception of humor in conversation.

1.3.2 Resource limitations

Another significant challenge of conversational humor classification is the availability of resources. Developing accurate classification models requires access to large and diverse datasets of conversational exchanges that have been labeled as humorous or non-humorous. Additionally, creating these datasets requires a significant amount of time and effort, as each exchange must be analyzed and labeled by human annotators.

However, the availability of such datasets is often limited, particularly for languages other than English. This scarcity of resources can make it challenging to train and evaluate classification models, as they may not be able to capture the full range of humorous expressions and contexts.

Furthermore, the complexity of humor as a phenomenon means that accurately classifying humorous exchanges requires advanced natural language processing techniques, which can be computationally expensive. These techniques often require large amounts of computing power and memory, making them inaccessible for researchers with limited resources.

Another area for improvement is the need for more diversity in the humor classification datasets. Often, datasets used for training and evaluation of humor classification models are based on humor from a specific source, such as stand-up comedy or sitcoms. This narrow focus can limit the generalizability of the models, as they may not be able to classify humor accurately from other sources, such as everyday conversations or different cultural contexts.

1.3.3 Complexity of chosen domain

The availability of labeled data for classification models that are tailored to specific domains, such as humor in the context of customer service interactions, may be limited. These data sources are critical to developing specialized classification models for use in practical applications.

Building a dataset for humorous tweets in the domain of Covid-19 presents several challenges for researchers. Covid-19 is a serious and sensitive topic, and humor related to the pandemic can be controversial and potentially offensive. Therefore, creating a dataset that is both representative of humorous content related to Covid-19 and socially acceptable can be a challenging task.

1.4 Thesis overview

- The current chapter, provides an introduction to the work done in this thesis along with the motivation behind such a study and the challenges faced.

- Chapter 2 discusses related research studies that focus on humor in general and conversational humor in particular. Work done in the field of computational linguistics to aid humor research by identifying, classifying and generating humor is also discussed.

- Chapter 3 provides a comprehensive view on the work done in building a hierarchical annotation schema for conversational humor using the Telugu play "Kanyasulkam" to understand the cultural implications. Further, we describe the dataset building process for validating the above annotation schema and explain the collection using APIs, preprocessing and annotation of Twitter data. Fine tuning the annotation schema and relevance for such a dataset is also discussed.

- Chapter 4 focuses on the technical aspects of building different models and running experiments on the annotated data. Analysis of the results to gain and understanding of the data and the working of the models to classify humor into multi-class labels are the key points of this chapter.

- Chapter 5 is a concluding chapter which provides a brief overview of the results and the insights gained from this study. Possible directions for future work and how this contribution can assist it is also discussed.

Chapter 2

Related Work

2.1 Conversational Humor

Conversational humor is a rich and diverse field that draws on insights from linguistics, psychology, anthropology, and sociology. A few linguistic, psychological and sociological approaches are as discussed below.

2.1.1 Linguistic approaches

Linguistic approaches to conversational humor have focused on identifying the linguistic devices and mechanisms that speakers use to create humorous effects. For example, researchers have examined the role of ambiguity, puns, irony, sarcasm, and wordplay in generating humor. They have also analyzed the structure and organization of humor, such as the setup and punchline structure of jokes, and the use of timing and delivery to enhance humorous effects.

Some linguistic theories have emphasized the importance of context in understanding humor. For example, the Relevance Theory proposed by Sperber and Wilson (1986) [81] suggests that humor arises when a speaker violates the cooperative principle in a way that creates an unexpected but relevant interpretation. Other theories have focused on the role of incongruity, which occurs when two ideas clash in a surprising or unexpected way, leading to humor.

A vast majority of research in the field of humor has had its primary focus on punchline-based 'canned jokes.' Though humor research has been an integral part of the study of linguistics, up until the 20th century, humor in interactions or conversational humor has only been sparingly mentioned. [65]. One influential framework is the "cooperative principle" proposed by Grice (1975)[35], which suggests that humor is a form of indirect communication that violates conversational norms in a playful and non-threatening way. Other linguistic theories have explored the role of linguistic ambiguity, incongruity, and wordplay in generating humorous effects. [5].

Some of the earliest works related to conversational humor started with discussions about irony as a form of humor. Grice's work which discusses irony as a violation of his conversational maxims, was one such noteworthy contribution. However, this work did not discuss irony as a form of humor. Later works by Colston and O'Brien (2000a,b)[17][18], Dews et al. (1995) [23], Dews and Winner (1995)[24], Gibbs (2000) [30], Kreuz et al. (1991) [47], Kreuz and Roberts (1995) [48] and Roberts and Kreuz (1994) [75] discuss the possibility of irony being used as a medium of conversational humor.

In 1991, Raskin and Attardo's General Theory of Verbal Humor [72] was a game changer. This theory took into account the pragmatics of humor to explain why we find something funny. Following this, Giora [32] in 1995 developed a discourse based theory of humor. This theory bases itself on information flow but is again focused on irony. Mulkay's (1988) [61] work provided a comprehensive analysis of humor in modern society, exploring its nature, functions, and social implications. It also helped lay the groundwork for understanding humor as a form of communication. More recent work by Marta Dynel attempts to draw the differences between canned jokes and conversational humor. Dynel [26] defines conversational humor as 'verbal chunks' which may or may not be true to meaning, spoken for amusing the listeners. The annotation schema developed as part of this paper is in tune with Dynel's work which discusses the definition and different types of conversational humor.

2.1.2 Psychological and Sociological approaches

Psychological approaches to conversational humor have examined the cognitive processes involved in understanding and appreciating humor. The incongruity theory of humor suggests that humor arises from the clash of two incongruous concepts or frames of reference. According to this theory, humor is a cognitive response that requires the individual to recognize the incongruity, resolve the tension between the two ideas, and experience a feeling of pleasure or relief. Suls' (1972) [84] two-stage model proposed that humor appreciation involves both the detection of incongruity and its resolution. This model became influential in understanding the cognitive processes underlying humor comprehension.

Other psychological theories have focused on the role of emotion, motivation, and personality traits in humor appreciation. For example, the "Benign Violation Theory" proposed by McGraw and Warren (2010) [57] suggests that humor arises when a situation violates our expectations or norms but in a benign or non-threatening way, leading to a feeling of relief and pleasure. According to this theory, humor is a way of coping with social and cognitive challenges, such as uncertainty, ambiguity, and incongruity.

Sociological approaches to conversational humor have explored the cultural and social factors that shape humor production and reception. These approaches have emphasized the role of social identity, power dynamics, and cultural norms in shaping the use and interpretation of humor (Davies, 1998) [20]. Morreall's (1983) [60] work explored the role of humor in social interactions, focusing on its communicative aspects and the importance of context in understanding and interpreting humor. Norrick's (1993) [64] conversational joking approach provided insights into the ways humor functions in everyday conversations, emphasizing the significance of social context and shared knowledge. Davies (1998) [20] examined the connection between humor and societal structures, offering valuable insights into the role of humor in reinforcing or challenging social norms and values.

2.2 Humor in times of distress

Another important aspect of the work presented in this thesis is the use of humor as a coping mechanism during adversity. Humor as a coping strategy against the adverse psychological outcomes of a worldwide pandemic is advocated by numerous research scholars. Reizer et al. ([73]) for example, studies the direct and indirect associations between humor and optimism in predicting well-being during Israel's lockdown period. Their findings suggest that individuals who maintained a sense of humor during this challenging period experienced better psychological well-being and were better equipped to handle the stress and uncertainty associated with the lockdown. Alarcon et al., ([3]) Martin and Ford ([54]), Kuiper ([49]) are some of the few others who strongly favor arguments emphasizing the vital role of humor in managing stress and fostering resilience during crises. This explained why we had noticed that a considerable chunk of the social media content that we came across falls under the category of humor which is of our interest. The prevalence of humor-related content on social media platforms during the pandemic suggests that individuals were actively seeking out and engaging with humorous content to cope with the stressful circumstances brought on by the pandemic.

A related class of humor that would be apt to be discussed here is Black comedy. This is a style of comedy to make fun of topics that are generally considered to be off-limits, such as taboos or subjects that are typically serious or painful to discuss. One such example of black humor is Holocaust humor. Ostrower[67] discusses in her work the use of humor as a defense mechanism to endure the atrocities of the Holocaust. Another noteworthy work in this field of study is by Dundes and Hauschild[25]. They discuss Auschwitz jokes, a form of bravado and defence mechanism for alleviating fears through humor.

Research has also shown that individuals who use humor as a coping mechanism tend to have better psychological and physical health outcomes. Humor has also been found to improve quality of life and reduce symptoms in individuals with chronic pain [85]. The positive impact of humor on health outcomes can be attributed to several factors. First, humor has been shown to have physiological effects, such as reducing cortisol levels and increasing the production of endorphins, which can help alleviate stress and enhance overall well-being ([8]. Second, humor can serve as a cognitive coping strategy, allowing individuals to reframe negative events in a more positive light and gain a sense of mastery over their circumstances ([77]. Finally, humor can facilitate social bonding and support, which are essential for maintaining mental health and fostering resilience during challenging times [34].

There are research studies which have identified humor to be one of the healthiest and most powerful coping mechanisms in times of stress and difficulty. Research has also been done on the relation between time and humor in a crisis situation [76]. A notable outcome of one such study by McGraw et al. ([58]) was that they had noticed that following the onset of a crisis, there was an increase in perceived humor, leading to a peak, and finally a decrease again. They attributed this to the 'benign violation theory' which posits that humor arises when a situation is perceived as a violation of expectations or norms but is also seen as benign or non-threatening [57].

Humor has been found to be particularly effective in helping individuals cope with illness. In one study, individuals with chronic illnesses reported using humor as a way to cope with the emotional and physical challenges of their condition [56]. These individuals reported that humor helped them to maintain a positive outlook, reduce stress, and feel more connected to others. Another study found that individuals with cancer who used humor as a coping mechanism had better psychological outcomes than those who did not use humor [52].

Finally, a study similar to ours had been conducted by de Haas ([21]) during the Ebola crisis. While they discuss the change in humor styles during the Ebola crisis, we aim to do a similar study during the Covid-19 pandemic and compare and contrast results. This comparison may help illuminate potential differences in humor styles and coping strategies across different crises and shed light on the adaptive nature of humor as a coping mechanism. Our study additionally considers factors like contextual knowledge and tries to find a correlation not just between the stage of development of the crisis and the type of humor but also between the type of humor and the topic being discussed. By examining these relationships, the current research hopes to provide a more nuanced understanding of how humor functions during a crisis and how its use may evolve over time in response to changing circumstances.

2.3 Humor perception

Humor is a universal phenomenon and the ability to perceive humor is critical for successful communication and socialization. However, it is perceived differently by people all over the world. Culture, social group, gender, language, cognitive factors etc. are all significant parameters in understanding humor. Humor perception involves the cognitive and affective processes that individuals use to understand and appreciate humorous stimuli. The perception of humor is a complex process that involves a variety of cognitive and affective factors, including cognitive flexibility, perspective-taking, social norms, and individual differences [53].

Studies have shown that humor perception involves a series of cognitive steps, including detection, interpretation, and evaluation [53]. During the detection phase, individuals must first recognize that a stimulus is intended to be humorous. Next, during the interpretation phase, individuals must understand the intended meaning of the humor. Finally, during the evaluation phase, individuals must assess the humor's quality and decide whether it is funny or not.

Several factors influence humor perception, including individual differences, social norms, and cultural differences. Individual differences in humor perception are thought to be influenced by a variety of factors, including cognitive flexibility, openness to experience, and sense of humor [53]. Social norms and cultural differences can also influence humor perception, as what is considered humorous in one culture may not be considered humorous in another culture. Yue et al and Jiang et al. [95], [45] discuss the differences in the perception of humor between cultures. Perception and usage of humor among westerners and easterners is discussed in detail and it is evident that the difference in the importance given to humor in both the cultures has a direct impact of humor perception as well.

Research has also shown that humor perception is influenced by contextual factors, such as the timing and delivery of the humor (Martin, 2014) [53]. Studies have shown that humor is more effective when it is delivered at an appropriate time and in a socially appropriate manner. Additionally, the source of the humor can also influence humor perception, as individuals tend to perceive humor as funnier when it is coming from a trusted source.

A pattern is also noticed in how certain humor types and techniques are more acceptable socially as compared to others. For example, difference in the perception of different types humor among genders has been researched extensively. Thorne et al. [87], Crawford [19], Herzog and Anderson [39], Samson and Meyer [78] have reported in different studies how men tend to accept and like humor which is dark, sexual, aggressive, etc. more than women [2]. Kotthoff's (2006) [46] work highlighted the importance of gender as a significant factor in the production and reception of humor, analyzing how humor contributes to the construction and negotiation of gender identities in various social contexts. While these results invariably differ among different cultures, such studies validate the argument that perception of humor is highly individualistic.

2.4 Computational analysis

All the above mentioned research studies discuss the importance and relevance of humor in everyday life. In the preset day scenario, the increase in online activity, web content, internet and social media, etc., drives researchers in the field of computer science to take up humor research for analysing humongous amounts of data and understanding the role of humor in the modern day. Further, the growing use of chatbots and voice assistants drives the need to improve these technologies to sound more human-like. Computational approaches to conversational humor involve the development of automated systems that can understand and generate humorous responses in conversation. These systems typically rely on natural language processing techniques to analyze the language used in conversations and identify humorous content [82]. Given that humor is a part of everyday social interaction between humans [40] , building systems which not only generate but also understand humor can go a long way by making the interaction between humans and computers more pleasant. [9], [83], [43], [4]

Computational humor analysis and recognition is a slightly more complex task as the perception of humor as discussed above varies largely from person to person. However, some of the earliest attempts for automatic humor recognition were contributions of Taylor and Mazlack (2004) [86] ; Mihalcea and Strapparava (2005) [59].

For any work on humor recognition to be fruitful, it needs to be paired with an accurate analysis of why something is funny. Bali et al. [1] address this question of what makes us laugh in their work. Similarly, Mihalcea et al. [59] study humor specific stylistic features like alliteration, antonymy and slang for charecterizing humorous texts. Analysis, detection and generation of humor are required to achieve the above-mentioned objectives and these areas of research have gained huge prominence in the recent past.

Early research in computational humor focused on the task of generation. Evidence of researchers attempting to write algorithms which create humor and replicate human creativity in telling jokes can bee seen right from the early 1990s. Noteworthy contributions in this field come from jokes in the form of question and answers (Raskin and Attardo, 1994 [72]; Binsted and Ritchie, 1994 [10]; Ritchie et al., 2007 [74]; Sjöbergh and Araki, 2008 [79]; Hong and Ong, 2009 [41]; Labutov and Lipson, 2012 [50]), narrative jokes (Sjöbergh and Araki, 2009 [80]; Yu et al., 2018 [94]), jokes through lexical replacement (Stock and Strapparava, 2005

[83][66], Sjöbergh and Araki, 2008 [79]) or witty analogies (Petrović and Matthews, 2013 [69]).

One approach to computational studies in conversational humor is to develop rule-based systems that use predefined rules to identify and generate humorous content [59]. These systems typically rely on linguistic features and heuristics to identify humor in text. For example, one rule-based approach is the use of the incongruity theory of humor, which suggests that humor arises from the unexpected or surprising juxtaposition of concepts or ideas (Carvalho et al., 2019) [14]. Rule-based approaches also use lexical and syntactic features, such as puns, sarcasm, and irony, to identify humorous content [93].

Another approach is to develop machine learning-based systems that can learn from data to identify and generate humorous content [82][88]. These systems typically use large datasets of annotated humor to train machine learning algorithms to recognize and generate humorous content. Machine learning-based approaches involve training algorithms on a dataset of labeled examples to learn patterns and features of humorous text. These approaches use various techniques such as natural language processing, feature engineering, and deep learning algorithms to identify humor in text [38].

For example, one study used support vector machines and random forests to classify humor in Twitter posts based on linguistic features such as sentiment, polarity, and word frequency [29]. Another study used convolutional neural networks to classify humor in Reddit posts based on text and image features [13].

In addition to rule-based and machine learning-based systems, researchers have also explored the use of deep learning techniques for humor recognition and generation [42]. Deep learning models, such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and transformers, have shown promising results in various natural language processing tasks, including humor analysis.

For instance, one study used an LSTM-based model to predict humor in short texts by capturing the sequential dependencies in the text and its context. Another study employed a transformer-based model, BERT (Bidirectional Encoder Representations from Transformers), to classify humor in tweets, taking advantage of BERT's pre-trained contextual word embeddings [22].

Moreover, researchers have attempted to address the challenges associated with the subjectivity and context-dependency of humor by incorporating additional contextual information into their models. Cultural differences and variations in humor perception have been acknowledged in computational humor studies. To address this challenge, researchers have experimented with cross-cultural and multilingual humor datasets. One such example is the work by Potash et al. (2017) [70], who developed a cross-cultural humor dataset containing jokes from various countries and languages and employed machine learning algorithms to classify humor across different cultures.

Despite the progress made in computational humor analysis, several challenges remain. These include the need for larger and more diverse annotated humor datasets, the development of models that can better capture the subtleties and nuances of humor, and the integration of contextual information into humor recognition models.

Chapter 3

Data and Annotation

3.1 Introduction

Laughter that is induced by conversational humor is not based on just the language that is being used. Conversations are usually considered funny because of visual cues like hand gestures and audio clues like voice modulation, laughter, etc. Due to this reason, most datasets for conversational humor are multi-modal in nature. Further, most datasets use dialogues from TV series or plays where the dialogues are well crafted and rehearsed to make the audience laugh. Humor in everyday conversations is comparatively different regarding spontaneity and situational context. While the humor in sitcoms is expected, humor in the latter context happens in a more mundane setting.

Numerous studies have been conducted on the types of humor in both canned jokes as well as conversational humor. There are innumerable classification schemes and a wide variety in the set of types given in each study. [37], [55], [26] and many others have each come up with a new set of types in their studies. While Hay [37] agrees with the need for a unified theory and a thorough, well-defined taxonomy; they also argue that most taxonomies are designed for a specific context and fail to provide adequate coverage of different datasets.

Keeping these challenges in mind, we have worked on creating a hierarchical annotation schema that captures various aspects like the type of humor, the technique used to generate humor, the benignity of the utterance, etc. This annotation schema was developed using the Telugu play, Kanyasulkam, based dataset. This dataset contained 6645 segments, including 2710 utterances that were classified as humorous.

Further, to validate the schema using a different domain and language, we worked on creating a Covid-19 jokes dataset using tweets. The use of tweets in a dataset for conversational humor is unique and uses only text/language-based cues to detect humor. This makes the humor detection task relatively difficult as other cues which are available in a multi-modal dataset are absent in this case. Annotation of such data is also critical as capturing the context, relevance, etc., from the text is complex. These are important for annotation as humor is highly subjective, and understanding the relationship between which section of the population finds what funny must be considered when creating the dataset.

3.2 Covid-19 tweets dataset

Given that Covid-19 is a relatively recent phenomenon, to the best of our knowledge, this dataset of jokes revolving around the pandemic is the first and only publicly available dataset. However, creating such a dataset comes with its own challenges. Creating a humorous tweets dataset in the domain of Covid-19 requires careful consideration of these challenges to ensure that the content is appropriate, ethical, and relevant to the current situation. Covid-19 is a serious and sensitive issue that has affected people's lives worldwide. Therefore, creating humorous content around such a topic can be perceived as insensitive, inappropriate, and even offensive. Creating funny tweets requires a deep understanding of the context, audience, and cultural nuances. In the case of Covid-19, it can be challenging to create humorous content that resonates with people across different regions, cultures, and languages. Humorous content about Covid-19 can easily cross the line and become offensive, discriminatory, or even spread misinformation. Therefore, ensuring that the content is ethical, responsible, and respectful is also essential.

Further, humor is often time-sensitive, and Covid-19 is an ever-evolving situation that requires up-to-date information. Therefore, creating humorous tweets about Covid-19 requires continuous monitoring of the situation and quick responses to the latest developments. Finally, finding a sufficient amount of humorous tweets related to Covid-19 is also challenging due to the limited availability of such content.

The annotation schema developed based on the Telugu play Kanyasulkam was intended to be a regulated and unified schema that could be used across domains. The Covid-19 tweets dataset, created as part of this project, serves a significant purpose of validating the schema. The dataset is quite different in terms of structure, domain, language, and even cultural context. While the Kanyasulkam dataset contains dialogues, the latter includes shorter tweets. It is to be noted that for the purpose of this study, we have considered tweets as conversational humor. Twitter as a platform allows retweeting, commenting, quoting others' tweets, etc. which is essentially people engaging in a public conversation. Hence, all the tweets we have in the database are part of a more extensive conversation.

Further, the previously created annotation schema was improved and modified to include situation and relevance tags to make the schema more standardized and inclusive. Apart from validating the previously mentioned annotation schema, this dataset has also been used to analyze the type of humor which peaked at each moment in the development of the Covid-19 pandemic. We attempt to find a correlation between the tweets of a certain kind of humor and the situation of the pandemic to understand if it is possible to deduce a trending topic, either universal or culture-specific, concerning the pandemic, based on the humor type. The use case for the findings of this study includes but is not limited to individuals or organizations which are involved in discussions regarding crises, brands for building digital marketing strategies, and behavioral researchers.

3.3 Data collection

This Covid-19 tweets dataset contains 1395 humorous tweets and 3723 non-humorous tweets comprising news items, country-wise statistics, etc. We collected the humorous data using Twitter scrapers to extract tweets using keywords related to the pandemic, like "corona jokes," "pandemic humor," and other similar words. The output was then manually filtered to remove non-humorous tweets like news articles, sub-tweets without context, external links, etc. These keywords were selected based on the understanding that if they were found as hashtags in the tweet, then the tweet would most likely be humorous. This further reduced the task of manually filtering the non-humorous tweets from the scrape results. The results contained tweets from the general public from all over the world, as no location filter was implemented. For the non-humorous data, we used tweets from various news channels and official accounts reporting statistics or country-wise updates regarding the pandemic.

The time period over which tweets were collected ranged from February 2020, around which time the virus was first detected, to December 2021. The tweets collected during this span captured various stages of the pandemic, including the three major waves, vaccination drives, lockdown situations, travel bans, etc.

3.4 Hierarchical annotation schema

The main objective of this study was to improve and validate the hierarchical annotation schema presented in our previous work. Fig. 3.1 shows the original schema containing 4 levels.

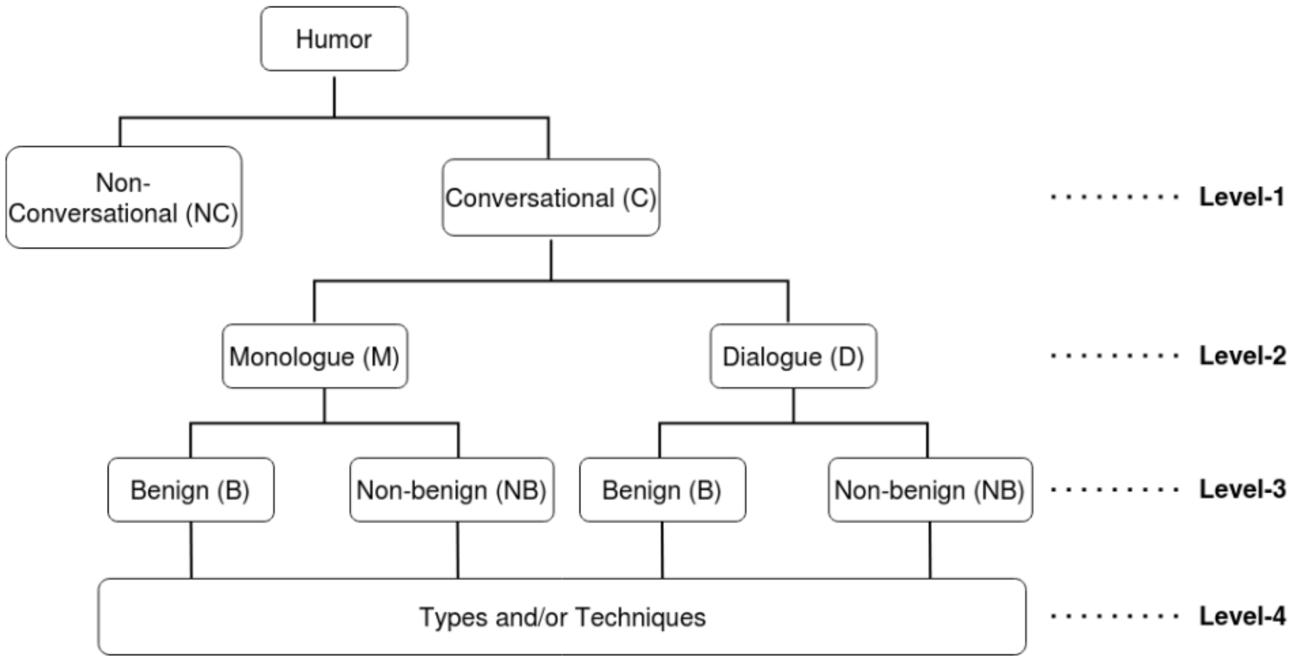

Figure 3.1: Annotation Schema containing four levels [68]

- Level-1 : Conversational/ Non Conversational
- Level-2 : Monologue / Dialogue
- Level-3 : Benign/ Non- Benign
- Level-4 : Types and/or Techniques

For the task of refining the schema, we have taken into consideration the type and technique tags and added the tags of situation and relevance to the same level. These tags give contextual information, which, as discussed earlier, is crucial in understanding why and to whom an utterance is humorous. Accordingly, the data from the Covid-19 tweets dataset was annotated using six tags for each tweet. The tags were first to identify if the tweet was humorous or not. Next, we identify the type and if the technique used to make the tweet funny is direct or indirect. Further, we also specify the exact direct/ indirect technique used. The fifth tag identifies the situation on which the tweet is based. This gives us an idea about the status of the pandemic. And the last relevance tag identified whether the tweet is universally relevant or is only specific to a particular culture. Fig 3.2 shows the refined schema containing three levels.

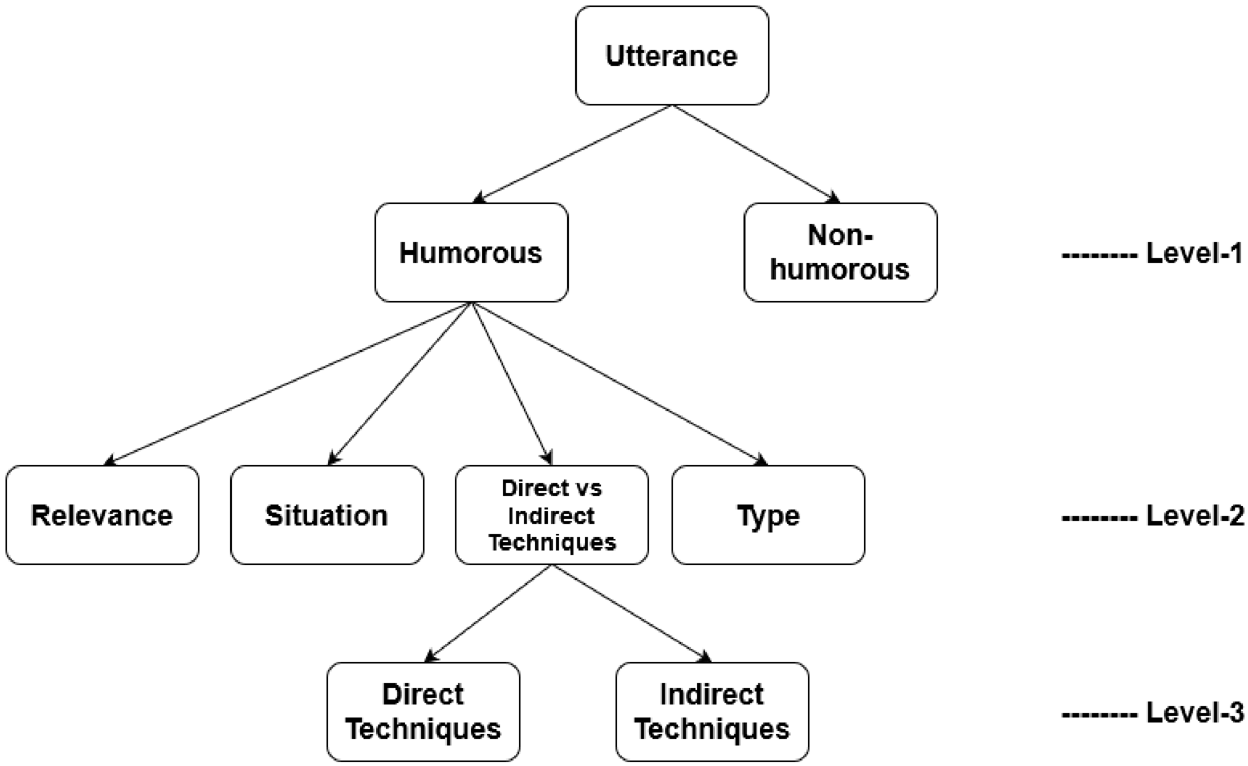

Figure 3.2: Modified schema containing three levels

3.4.1 Level-1 Humorous vs Non-humorous

The Covid-19 tweets dataset contains 1395 humorous tweets and 3723 non-humorous tweets. The first level of annotation was to classify the tweets as humorous or not. However, this level itself is not as seemingly straightforward. Apart from humor's subjective nature, the chosen domain stands as a problem in this case. The pandemic was a grave time for a majority of the population all around the world. Millions of people fell sick, and a significant majority of people lost their lives. Though light-hearted, creating humor in such cases may sometimes come across as insensitive. Hence, tagging such data even manually comes with a lot of challenges, and automating the process further is undeniably arduous.

3.4.2 Level-2 Type

This study focuses on four types of humor generated by the utterances: Teasing, Retort, Banter, and Schadenfreude. Understanding these humor types is essential for analyzing the social dynamics and psychological effects of humor in various contexts.

Teasing is a form of humor where the speaker playfully provokes or makes fun of a person or situation. According to Radcliffe-Brown (1940) [71], teasing is traditionally seen as involving overtly feigned hostility or aggression, which in reality signals genuine friendliness. The underlying principle of teasing is based on Bateson's (1955, 1972) [6] [7] concept of a meta-communicative "this is play" message. By engaging in teasing, individuals can establish rapport, challenge social norms, and navigate interpersonal boundaries in a light-hearted and playful manner.

Retort, on the other hand, refers to a humorous response or comeback to a tease. This type of humor allows the receiver of the tease to demonstrate their wit and engage in the playful exchange. Retorts can help balance power dynamics, promote social bonding, and create an atmosphere of friendly competition between the individuals involved. Individuals can deflect potential negativity and maintain a positive social atmosphere by responding with humor.

Banter is a form of humor that involves repeated exchanges of teasing and retorts between individuals. This type of humor is characterized by its back-and-forth nature and often consists of a degree of verbal sparring. Banter can foster camaraderie, enhance group cohesion, and create a sense of shared enjoyment among the participants. By engaging in banter, individuals can navigate complex social interactions and develop deeper connections with their peers through a shared understanding of humor and playfulness.

Finally, Schadenfreude is a type of humor defined as the pleasure derived from another's misfortune [89]. This form of humor can be seen as a coping mechanism for individuals dealing with adversity or a way to assert social dominance. Schadenfreude may also serve as a means of finding humor in difficult situations by allowing individuals to distance themselves from the negative aspects of the situation and focus on the incongruity or absurdity of the circumstances.

The table 3.1 shows examples for each type tag.

Type	Example
Teasing	Feb : Ok, Boomer. April : Are you OK, Boomer?
Retort	I'll try being nicer if you'll try being smarter
Banter	Exchange of teases and retorts
Schadenfreude	"We became like the money in our banks. Existing but untouchable!"

Table 3.1: Examples for each 'type' tag

3.4.3 Level-2 Direct vs Indirect techniques

Humor techniques can be broadly classified into two categories: direct and indirect. These approaches play a vital role in shaping how the audience conveys and interprets humor. The classification is based on the presence of pretense or any hidden meaning in the utterance. This is further classified into more specific techniques in Level-3 of the annotation schema.

Direct humor techniques are characterized by their straightforward and unambiguous nature, with no hidden meaning or pretense. In these cases, the meaning of the utterance is taken at face value, without any need for interpretation or inference.

Ex: From “Lockdown may get extended” to “Lockdown extended to May.”

In this case, using wordplay causes the utterance to be classified as humorous. Further, the wordplay technique is considered a direct technique as there is no hidden intention that is different from the direct meaning of the sentence.

On the other hand, indirect humor techniques involve an element of pretense or subtlety, with the intended meaning of the utterance differing from its literal interpretation [62]. In these instances, the speaker tries to convey something more than the apparent meaning of the utterance.

Ex: During this lockdown, I have figured out that the key ingredients for any cooking are onions, tomatoes, some veggies, and a camera.

In this case, the technique being used to generate humor is satire. This is classified as an indirect technique as the speaker intends to ridicule social media users by saying a camera is a key ingredient for cooking. This aspect of ridicule is understood because of context and is not directly expressed in the meaning of the utterance.

Note: Only one of the type/ technique categories is mandatory, and there can be more than one technique used in each tweet. [68])

3.4.4 Level-2 Situation

The situation tag can be explained as the topic that is being discussed as part of the conversation/ joke. This tag gives us an idea about the stage of development in the pandemic. For example, if the topic is about the lockdown, we can understand that the pandemic is just developing, and the virus is spreading rapidly. However, if the topic is about reopening schools and offices, we know that it is only towards the end of a wave when cases have started to decline.

We have tagged our dataset using the following topic tags. Health/ Hygiene, Lockdown, Testing/ Vaccination, Quarantine, Government Orders, Eating Habits, Online School, Work From Home (WFH), Hoarding Groceries, Social Media, Social Distance, and Miscellaneous.

To be able to make any assumptions from a trending topic or even to be able to find the tweet funny and deduce a trending topic from it, contextual knowledge and an awareness of what is happening around the world are fundamental. This trending topic can be universally significant or only be confined to a specific culture. It is found in this study that there is a high interdependence between the type of humor and the trending topic.

Table 3.2 shows the examples for each situation tag.

Situation	Example
Lockdown	It's time for an exciting adventure, move to the other side of the couch.
Health/ Hygiene	1665 - learnt about the existence of microorganisms 1892 - discovered viruses 1928 - discovered Penicillin (the first antibiotic) 2020 - learnt how to wash hands properly
Work From Home	Somebody stole my lunch out of the fridge at work today. The worst part about it... I'm working from home.
Social distance	Practice social distancing? Buddy, I've doing that my whole life!
Government	2019: Netflix and chill 2020: Government coronavirus press conference and cry
Eating habits	Nothing says pandemic desperation like eating a pint of Cinnabon frosting with your bare hands...
Testing/ Vaccine	I got my COVID test today, it says 50. What does that mean? Also, my IQ test came back positive.
Hoarding Groceries	Kinda wish I hadn't rid myself of those yellow and white pages. They would have come in handy for toilet paper..... and reading material.
Social Media	It's time we extended the curfew to Whatsapp Groups.
Quarantine	Chuck Norris got the Coronavirus. The virus is now in quarantine for a month.
Online School	There will be no homeschooling for the rest of the month due to technical difficulties. Technically I'm finding it difficult to be good at it.
Misc	Every time I see my email inbox, I feel flattered that so many brands that I don't even use are so sincerely standing by me during this crisis.

Table 3.2: Examples for each 'situation' tag

3.4.5 Level-2 Relevance

The importance of context in humor cannot be understated, as it significantly impacts how jokes are processed and appreciated. This final tag provides information about the significance of a trending topic across the globe, shedding light on the contextual and cultural aspects that influence humor perception. According to Heather et al., understanding the contextual factors that shape humor appreciation is essential for both researchers and practitioners, as it helps identify culture-specific topics that may be humorous within a particular cultural context but not necessarily to those outside that culture.

The significance of context in humor has important implications for content creators and marketing agencies. By understanding the cultural nuances and contextual factors influencing humor appreciation, these professionals can create relatable content that resonates with their target audience [36]. For example, a marketing campaign that leverages humor effectively by taking into account the target audience's cultural context and shared experiences is more likely to capture attention, generate engagement, and foster a positive brand image [28].

Furthermore, recognizing the importance of context in humor can also help content creators and marketing agencies avoid potential pitfalls associated with cultural misunderstandings or offense. A joke that may be considered humorous within one cultural context could be perceived as insensitive or offensive in another, leading to negative backlash and potential damage to the brand [96]. By being mindful of the contextual factors that shape humor appreciation, content creators and marketing agencies can mitigate these risks and create content that appeals to diverse audiences while respecting cultural sensitivities.

This understanding has practical implications for content creators and marketing agencies, who can leverage the power of humor more effectively by considering the cultural and contextual factors that shape humor appreciation. By doing so, they can create relatable content that resonates with their target audience, fosters engagement and enhances brand image while avoiding potential pitfalls associated with cultural misunderstandings or offense.

3.4.6 Level-3 Techniques

Direct humor techniques include exaggeration, fallacious reasoning, allusion, profanity, and stylistic figures. Exaggeration involves the use of hyperbole or overstatement to create a humorous effect by emphasizing certain aspects of a situation or subject [27]. Fallacious reasoning involves presenting illogical or absurd arguments as if they were legitimate, often to highlight the absurdity or contradiction inherent in a particular situation or belief [91]. An allusion is a technique that involves referencing a well-known event, person, or cultural artifact, requiring the audience to recognize the reference and its relevance to the context in order to appreciate the humor [11]. Profanity involves the use of taboo language or subject matter for humorous purposes, often by exploiting the shock value or social transgression associated with such content [44]. Stylistic figures, such as metaphors, similes, or puns, involve the manipulation of language to create humorous effects by highlighting unexpected connections, contrasts, or ambiguities [90].

Indirect humor techniques often require the audience to engage in cognitive processes, such as inference and interpretation, in order to appreciate the humor [84]. Utterances employing indirect humor techniques can be further classified as either satire or sarcasm. Both satire and sarcasm involve the use of irony to mock or criticize a particular subject, but they differ in their focus and tone [16] [31]. Satire is often employed as a tool for social commentary, targeting institutions, individuals, or societal norms. At the same time, sarcasm typically focuses on specific targets, often with a more biting and negative tone [33].

Table 3.3 shows the examples for each technique tag.

Technique	Example
Exaggeration	Weird year this is. January ended in a couple of weeks, February finished in just a few days, while March dragged on for about a year.
Fallacious Reasoning	Cancelled all my weekend plans because of coronavirus. Staying home. Once this dumbass idiot coronavirus goes away, then I'll think of other reasons to cancel plans.
Allusion	An Englishman, an Irishman and a Scotsman walk into a bar. Ah, those were the days...
Profanity	Covid-19 is like my dick. It suddenly shows up and ruins peoples' lives.
Stylistic Figures	From "Lockdown may get extended" to "Lockdown extended to May".
Sarcasm	Really looking forward to being bad at making eye contact again.
Satire	If you want people in Mumbai to stay at home, announce elections instead of lockdown.

Table 3.3: Examples for each 'technique' tag

3.5 Inter-annotator agreement

This dataset was tagged manually by two annotators, A1 and A2. Cohen's Kappa values for each class were calculated separately. For level-1, i.e., identifying humorous tweets, the Kappa value was calculated to be 0.92 (almost perfect agreement). This can be attributed to the fact that determining the non-humorous data came with no ambiguity. Any instances of news, statistics, etc., could be directly tagged as non-humorous. Further, since the humorous tweets were scraped using specific keywords, the instances where either one of the annotators found such a tweet unfunny though it existed were significantly low.

At the second level, the Kappa values for Relevance and Situation were relatively higher, with 0.9 and 0.85, respectively. Since both the annotators have similar cultural backgrounds in terms of age, educational background, country, social background, etc., identifying cultural nuances in the humorous tweets posed no ambiguity. The tags for the situation were also straightforward. Since there could be more than one tag situation tag associated with each tweet, it could be possible that either annotator failed to recognise the second situation resulting in a slightly lesser score.

The Kappa value for identifying the type of humor was calculated to be 0.52 (Moderate agreement). The issue discussed by Pamulapati et al. [68], which resulted in the low Kappa value for the Type tag, is seen in this case as well. Namely, the failure to identify a particular type and giving the NULL tag, and an overlap between retort and teasing tags stand as the main concerns. Finally, the identification of direct and indirect techniques resulted in a Kappa value of 0.62 (Substantial agreement). And the tagging of the specific techniques resulted in a Kappa value of 0.58(Moderate agreement). This can be attributed to issues like a failure to recognise allusion, misunderstanding wordplay, differences in humor perception in cases like exaggeration, etc.

3.6 Analysis

Based on the analysis of our tagged dataset, it has been observed that satire and sarcasm are the most prevalent humor techniques, accounting for 27.1% and 27.3% of the total data, respectively. Schadenfreude, defined as the pleasure derived from others' misfortune, emerged as the most common humor type, with 29.5% of the utterances being tagged as such. This observation can be justified considering the context and timing of these jokes, which occurred amidst panic and chaos caused by the global crisis. The presence of schadenfreude aligns with

Situation	No. of occurrences	Most frequent type/ technique	Frequency
Lockdown	460	Schadenfreude	204
Misc.	278	Schadenfreude/ Satire	63
Health/hygiene	271	Sarcasm	84
Work from home	77	Sarcasm	27
Social Distance	75	Schadenfreude	24
government	64	Satire	52
Eating Habits	45	Schadenfreude	27
Hoarding groceries	40	Satire	13
testing/vaccine	39	Satire	14
Social media	17	satire	10
Quarantine	14	Sarcasm/ Stylistic figures	4
Online school	14	Schadenfreude	8

Table 3.4: No. of occurrences of each situation tag and the most frequent type/technique tag for each situation tag

the benign violation theory discussed by McGraw et al. (2010)[57], which posits that humor arises when a situation is perceived as both a violation of norms and benign simultaneously. The prevalence of satire and sarcasm can also be explained by previous studies that have analyzed humor during challenging times, revealing similar trends.[21] [12].

Our data supports the idea that humor development follows a pattern of an initial increase after the onset of a crisis, followed by a decrease. This observation can be substantiated by examining the number of occurrences of each trending topic. For instance, the beginning of the crisis was marked by a high number of jokes related to the lockdown situation. However, the frequency of such jokes gradually decreased as vaccines became available and the situation evolved.

The next most frequently occurring tags in our dataset were stylistic figures and allusion. These categories encompass statements made by influential individuals as well as a significant portion of one-liners that follow a particular template, such as “two guys walked into a bar” or “Chuck Norris” jokes. The popularity of these humor techniques can be attributed to their ability to convey complex ideas or critiques in a concise and entertaining manner, often relying on shared cultural knowledge or references to enhance their impact.

Furthermore, our analysis revealed a clear correlation between the type of humor and the topic being discussed. As demonstrated in Table 3.4, conversations about the lockdown situation have a high occurrence of schadenfreude, possibly reflecting individuals' attempts to cope with the challenges and frustrations brought about by the restrictions. In contrast, conversations about the government and its policies are often characterized by satirical humor, which serves as a means of critiquing and questioning the decisions made by those in power.

In conclusion, examining our tagged dataset provides valuable insights into the humor techniques and types employed during times of crisis, highlighting the prevalence of satire, sarcasm, and schadenfreude as ways of coping with the challenges and uncertainties faced by individuals and societies. The observed correlations between humor types and the topics being discussed underscore the role of humor as a versatile tool for communication, critique, and emotional regulation in the face of adversity.

3.7 Conclusion

In conclusion, the use of humor as a coping mechanism during adversity is a well-documented and valuable area of research. The studies mentioned in Chapter-2 collectively highlight the importance of humor in managing stress, improving psychological outcomes, and fostering a sense of connectedness among individuals facing challenging circumstances. The present study aims to expand upon this body of knowledge by examining humor styles and contextual factors during the Covid-19 pandemic, providing further insights into the role of humor as a coping strategy during global crises.

Humor during tough times is what keeps us going. As Chiodo et al. [15] mention in their work, "tone it down, but don't turn it off." Especially during a pandemic situation, the only solution for which is to avoid social situations. It is essential to stay connected. And humor is what takes us that extra mile. Be it just a friendly stranger on the internet or a heartwarming ad campaign claiming to stand by your side during tough times, relatability and contextual humor bring us together. It creates a feeling of relatability in people's minds, and this makes people know that they are not alone, making it extremely helpful, especially in crisis situations such as this Covid-19 pandemic.

As the world continues to face unprecedented challenges, understanding the role of humor as a coping mechanism becomes increasingly relevant. By examining the use of humor during crises such as the Covid-19 pandemic, researchers can gain valuable insights into how individuals and communities adapt to adversity and develop strategies for promoting resilience and well-being in the face of future crises. Further, using this study to understand and analyze trends in the time, type, and topic of humor to be used will stand as a very efficient tool for marketing and content creators. The importance of context is also to be noted, especially in the case of marketing using humor in order to make an impact on the masses as, in order to make sense of such humor, contextual knowledge plays an extremely important role, and one must stay up to date with what is happening in the world. Ultimately, this research may contribute to a greater understanding of the power of humor to help individuals and communities navigate through difficult times and emerge more robust and more resilient.

For future work, code-mixed data or data from other languages can be included in the dataset to see the effect of such trends and how they might influence local-level marketing for brands and content creators. This study may be extended to larger datasets and then be used to build computational models which can detect the stage of a crisis, or the level of seriousness, based on the type of social media content.

Chapter 4

Multi-class multi-label classification

4.1 Introduction

The study of humor detection and classification has been a prominent area of research in recent years, with scholars delving into the nuances of humor identification and understanding the different aspects that contribute to what we perceive as funny. While many studies have primarily focused on humor detection, i.e., determining whether a given text is humorous or not, there is a growing need for more advanced classification systems that can capture the various dimensions of humor. As Bali et al. [1] argue, humor classification is a challenging task, primarily due to the lack of consensus among scholars about what humor actually is. Furthermore, humor is highly subjective, and its interpretation depends on a wide range of factors, such as the speaker's identity, the context of the joke, the cultural backgrounds of both the speaker and the listener, and more. The subjective nature of humor makes it difficult for humans to reach a consensus on what is humorous, which in turn complicates the task of automatic humor detection due to inconsistencies in data annotation.

Researchers have previously tackled humor detection tasks by framing them as binary classification problems and training Bert-based models to achieve satisfactory accuracies. However, classifying humor based on its characteristics, such as type and technique, presents an even more daunting challenge, particularly given the absence of a formal taxonomy of humor characteristics [92]. It is also important to note that most humor detection tasks have been performed on canned jokes, one-liners, and similar sources, resulting in more homogeneous data sets.

Refining this binary classification approach to not only detect humor but also classify humorous utterances based on their type and technique and further understanding the context and relevance of these utterances is crucial for gaining a comprehensive understanding of humor. Such classification systems can also provide insights into topics that may be considered sensitive or potentially offensive to specific sections of society.

In this study, we go beyond the binary classification of humor and attempt multi-class, multi-label classification on a manually annotated dataset of Covid-19-related tweets. We categorize each utterance into three binary and three multi-label classes. This chapter will discuss the data preprocessing, methodology, models used, and results obtained from this comprehensive analysis of humor in the context of the Covid-19 pandemic.

Developing a more detailed understanding of humor classification and its various dimensions can have significant implications for a wide range of applications, from content creation and marketing to understanding social dynamics and cultural preferences. By exploring the subtleties of humor and its classification, we can build more robust models that can better capture the diverse nature of humor and account for the various factors that influence its perception and interpretation.

In order to train accurate and reliable models, a substantial amount of high-quality, annotated data is required. However, as humor is inherently subjective, ensuring consistency and reliability in data annotation presents a significant challenge. Researchers must employ rigorous methods to minimize inconsistencies and account for the various factors that can impact the perception of humor.

In addition to refining humor classification models, future research can also explore the role of context in humor perception and appreciation. As previously mentioned, factors such as the speaker's identity, the context of the joke, and the cultural backgrounds of both the speaker and the listener can all play a crucial role in determining whether a given utterance is perceived as humorous. By incorporating context-aware approaches into humor classification models, we can develop more sophisticated systems capable of better understanding and predicting humor across a wide range of situations and cultural contexts.

Overall, the study of humor detection and classification is an essential and growing field of research that has the potential to contribute significantly to our understanding of humor and its various manifestations in society. By continuing to refine our models and explore the complexities of humor, we can develop more accurate and versatile systems that can help us better understand and appreciate the diverse ways in which humor manifests itself in our everyday lives. These advancements can have far-reaching implications in various domains, such as entertainment, marketing, communication, and social interaction.

Moreover, the study of humor in the context of challenging situations, such as the Covid-19 pandemic, can provide valuable insights into how people use humor as a coping mechanism during crises. Understanding the trends and patterns in humor usage during difficult times can help us better support individuals and communities in navigating through adversity.

As artificial intelligence and natural language processing technologies continue to evolve, researchers have the opportunity to develop even more advanced humor classification systems that can capture the complexities and subtleties of humor. These systems could potentially be integrated into various applications, such as chatbots, virtual assistants, and other conversational agents, to enhance their ability to engage with users more naturally and human-like.

4.2 Methodology

The process of analyzing and understanding humor in the context of Covid-19 related tweets begins with the preprocessing of the dataset, which is a crucial step in ensuring that the data is suitable for training a machine learning model. The dataset includes both humorous and non-humorous tweets, many of which contain elements that may interfere with the model's ability to recognize and process the humor present. These elements include external links, hashtags, emojis, and other non-textual components that are not directly relevant to the humor analysis task at hand. Consequently, these elements must be carefully removed during the data preprocessing step, ensuring the dataset is cleaned and ready for annotation.

Once the data has been cleaned, it is then annotated to provide valuable information about the humor present in each tweet. The annotation process involves categorizing tweets according to different dimensions of humor, such as type, technique, and situation. However, given the low number of humorous tweets available in the Covid-19 domain, some adjustments had to be made to the annotated tags to ensure the model could be effectively trained. For instance, the dataset contained only eight instances of tweets utilizing the technique of profanity and only 14 instances of tweets with the situation tag "Quarantine," as seen in the table 3.4. Such low representation of specific tags can lead to imbalanced data, which may adversely affect the model's ability to generalize and accurately predict the corresponding labels.

All tags with fewer than 50 instances were re-categorized during the annotation process to address this issue. In the case of situation tags, they were labeled as miscellaneous, while for type and technique tags, they were marked as unknown or null. This approach allowed for more balanced training data and helped improve the model's ability to accurately predict humor-related categories across a broader range of tweets. The edited dataset's statistics containing the labels and the number of occurrences of each label in each tag can be found in the table 4.1.

Two different types of machine learning models were employed to approach the binary classification task for identifying humorous tweets, classifying techniques as direct or indirect, assigning relevance tags, and the multi-label classification for type, technique, and situation. The first type consisted of basic models using K-Nearest Neighbors (KNN) and decision trees.

These models, while relatively simple, can provide valuable insights into the relationships between different types and techniques of humor and their relevance to specific situations. Using these basic models, the study aimed to establish a foundation for more advanced approaches to humor classification.

The second type of models employed in the study included three BERT-based models: BERT, RoBERTa, and BERTweet. These advanced models leverage pre-trained language representations and fine-tuning techniques to achieve state-of-the-art performance on a wide range of natural language processing tasks. By utilizing these BERT-based models, the study aimed to capture more nuanced aspects of humor and gain a deeper understanding of the various dimensions of humor present in Covid-19 related tweets.

Tag	Labels	No. of occurrences
Type	Schadenfreude	449
	No value	943
Technique	Sarcasm	387
	Satire	376
	Stylistic Figures	189
	Allusion	164
	Exaggeration	50
	No value	226
Situation	Lockdown	562
	Health/ Hygiene	368
	Misc	295
	Work from home	100
	Government	67
Cultural Relevance	Universal	1237
	Cultural	155

Table 4.1: Frequencies of each tag after data manipulation

4.3 Data preprocessing

Before feeding the data to the ML models, the text data goes through several preprocessing steps.

- Cleaning: This is done to clean and normalize the text data. It converts all text to lowercase, replaces common contractions and abbreviations with their full forms, removes non-word characters, and trims extra whitespace. This helps ensure that the model is not affected by capitalization, punctuation, and spacing variations.

- Data extraction: The necessary columns are extracted from the input dataset using pandas, and null values are replaced with "No value."

- Label encoding: The categorical labels are converted into numeric codes using pandas' Categorical data type. This step is necessary as most machine learning models work with numerical data.

- Text vectorization: The cleaned text data is then converted into numerical vectors using the Term Frequency-Inverse Document Frequency (TF-IDF) technique. The TF-IDF Vectorizer is set to extract a maximum of 3,000 features (words) and ignore terms with a document frequency higher than 0.85, which helps filter out common words that do not provide much information.

4.4 KNN and Decision trees

4.4.1 K-Nearest Neighbor

The K-Nearest Neighbor (KNN) algorithm is a machine learning algorithm used for both classification and regression tasks. In classification tasks, it is used to classify new data points based on their similarity to the labeled data points in the training dataset.

The basic idea behind the KNN algorithm is to measure the similarity between the new data point and the labeled data points in the training dataset and then classify the new data point based on the class label of the K nearest labeled data points. The value of K is a hyperparameter that specifies the number of nearest neighbors to consider.

In the context of humor classification, the KNN algorithm can be used to classify jokes based on their similarity to labeled jokes in the training dataset. To use the KNN algorithm for humor classification, we first need to represent each joke numerically. We use a TF IDF vectorizer for this purpose. A TF-IDF vectorizer takes a corpus of text documents as input and creates a matrix where each row represents a document, and each column represents a term in the corpus. The value in each cell of the matrix is the TF-IDF value for the corresponding term in the corresponding document.

Once the jokes are represented in numerical form, we can use the KNN algorithm to classify new jokes based on their similarity to the labeled jokes in the training dataset. We first calculate the distance between the new joke and each labeled joke in the training dataset to do this. We can use a distance metric such as Euclidean distance or cosine similarity to calculate the distance.

Next, we select the K nearest labeled jokes based on the calculated distances. We then assign the new joke to the most frequent class among the K nearest labeled jokes. This algorithm can be used for both binary as well as multiclass classification.

4.4.2 Decision trees

A decision tree is a popular machine-learning algorithm used for classification and regression tasks. It is a tree-like model that uses a set of if-else conditions to classify data into different classes. Each node in the decision tree represents a feature or attribute of the data, and each edge represents a decision or a condition on that feature. The leaf nodes of the tree represent the final output or classification decision.

In the context of humor classification, decision trees can be used to classify jokes based on their features, such as the use of puns, sarcasm, irony, or wordplay. The goal is to create a decision tree that can accurately predict the class label of a new joke based on its features.

To build a decision tree for humor classification, we need a labeled dataset of jokes with features or attributes that can be used to distinguish between different classes of humor. We can then use this dataset to train the decision tree model.

The decision tree algorithm recursively splits the dataset into smaller subsets based on the features that provide the most information gain or discriminative power. The information gain measures the data's reduction in entropy or impurity after splitting based on a particular feature. The feature with the highest information gain is selected as the splitting criterion at each node of the decision tree.

The decision tree continues to split the dataset until it reaches a stopping criterion, such as a maximum depth of the tree or a minimum number of samples required to split a node. The final decision tree consists of a set of if-else conditions that can be used to classify a new joke based on its features.

Once the decision tree is trained, we can use it to classify new jokes by traversing the tree based on their features until we reach a leaf node with a final classification decision.

4.5 BERT based models

4.5.1 Model overview

A brief overview of the three pre-trained models, viz., BERT, RoBERTa and BERTweet which we have used for the multi-label multi-clasas classification task in this study is discussed below.

4.5.1.1 BERT

BERT (Bidirectional Encoder Representations from Transformers)[22] is a pre-trained language model that uses the Transformer architecture to understand the contextual relationship between words in a sentence. BERT is trained on a large amount of data, including Wikipedia articles and books, to predict the next word in a sentence based on its context.

In the context of humor classification, BERT can be used to classify whether a given text is humorous or not. The BERT algorithm first involves tokenizing the input text into individual words and converting them into numerical vectors that the model can process. BERT then processes the text using a series of bidirectional transformers to capture the contextual relationship between the words in the sentence.

After processing the input text, BERT outputs a vector representation of the entire sentence. This vector representation is then fed into a classification layer, predicting whether the sentence is humorous or not.

4.5.1.2 RoBERTA

RoBERTa (Robustly Optimized BERT Pre-training Approach)[51] is an extension of the BERT algorithm that was designed to improve upon some of its limitations. RoBERTa uses a more extensive training dataset and modifies the training process to improve the quality of the pre-trained language model.

The working of RoBERTa in humor classification is similar to BERT. It first tokenizes the input text and processes it through a series of bidirectional transformers to capture the contextual relationship between the words in the sentence. However, RoBERTa uses a different pre-training approach than BERT.

RoBERTa is pre-trained on a large corpus of text, including books, Wikipedia articles, and web pages. The pre-training process involves training the model to predict missing words within a sentence, similar to BERT. However, RoBERTa uses dynamic masking, which randomly masks out different parts of the input sequence during each training epoch. This forces the model to learn more generalizable representations of language, which may improve its ability to detect humor.

Overall, RoBERTa is a more robust and powerful language model than BERT, and it may be able to achieve higher accuracy in humor classification due to its improved training process.

4.5.1.3 BERTweet

BERTweet is a pre-trained language model that is specifically designed for analyzing text on social media platforms such as Twitter [63]. It is based on the BERT architecture but has been trained on a large dataset of tweets, allowing it to understand better the unique language and grammar used on social media.

The working of BERTweet is similar to BERT, but it has been optimized for the characteristics of Twitter data. First, BERTweet tokenizes the input tweet into individual words and converts them into numerical vectors that the model can process. It then processes the tweet using a series of bidirectional transformers to capture the contextual relationship between the words in the tweet.

BERTweet has been specifically trained to handle the challenges of Twitter data, such as the use of emojis, abbreviations, and hashtags. It also has a higher character limit than traditional BERT models, which allows it to capture the nuances of longer tweets better.

Overall, BERTweet is a powerful tool for humor classification on social media platforms like Twitter. It is designed to handle the unique language and grammar used on these platforms and can capture the nuances of humor in tweets more accurately than traditional BERT models.

4.5.2 Model architecture

For this task of humor classification, we have used three pre-trained BERT-based models, namely, BERT, RoBERTa, and BERTweet, as mentioned above, from the transformers library as the backbone. The architecture for each of these models can be divided into the following components.

The input layer consists of a sequence of token IDs, which are integer representations of the input tokens. The input layer has a shape of the maximum length of input sequences. This layer has a data type of int32.

The BERT layer is extracted from a pre-trained transformer model. It takes the input_ids as input and returns two outputs: token-wise hidden states and a pooled output. The pooled output is a fixed-size representation of the input sequence, which is the final hidden state of the [CLS] token after applying the BERT model. Our architecture extracts the pooled output by indexing the BERT output.

A dropout layer is applied to the pooled output to prevent overfitting during training. The dropout rate is specified by the BERT configuration. The dropout layer is applied with the training flag set to False to ensure that dropout is not applied during inference.

For each classification task, a Dense layer is created. Each Dense layer has several units equal to the number of unique values for each category in the dataset. The layers use the Truncated Normal initializer with a standard deviation specified by the BERT configuration. These layers are applied to the pooled output from the BERT model and are responsible for predicting the different categories for each label.

Figure 4.1 gives a graphical representation of the above-mentioned architecture

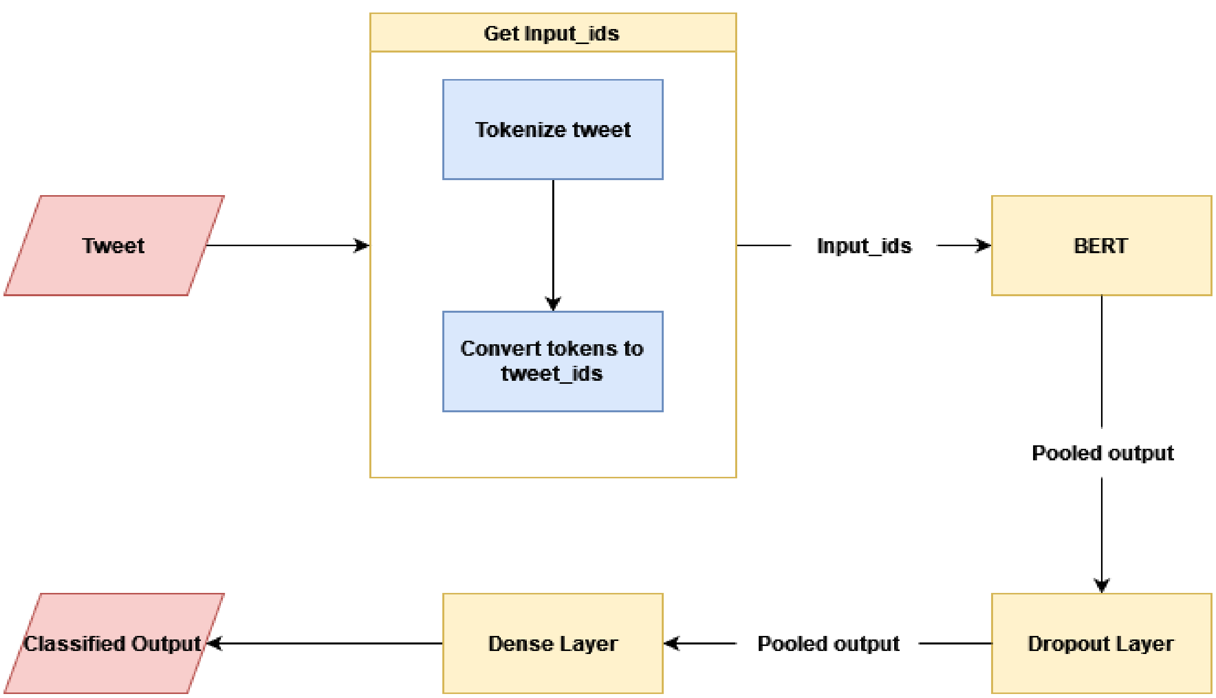

Figure 4.1: Flowchart depicting the model architecture

4.6 Results and analysis

The results and analysis for binary as well as multi-label multi-class classification pertaining to different levels of the annotations schema is discussed below.

4.6.1 Level - 1

As mentioned earlier, binary classification was done initially to classify the tweets as humorous or non-humorous. This is the first level of classification. The accuracy of multiple models in classifying the tweets as humorous or non-humorous could be seen in table 4.2. It can be seen that the BERT-based models perform better in this case.

Model	Humorous vs non-humorous
KNN	0.94
Decistion tree	0.89
BERT	0.88
RoBERTa	0.98
BERTweet	0.98

Table 4.2: Accuracy for humorous vs non-humorous classification

4.6.2 Level - 2 and Level - 3

The next level of classification is the multi-label multi-class classification. Tweets are classified into multiple labels at level - 2 and level - 3 of the aforementioned hierarchical annotation schema. At the second level, type, situation, and relevance are predicted. At the third level, the model classifies the tweets under the technique label. Classification into these four labels is done using a single classifier. Out of these four labels, type and cultural relevance have binary classes, whereas technique and situation have multiple classes. The accuracy for each of the five models in predicting the four labels is shown in the table 4.3. While similar results are obtained by both BERT-based and non-BERT models in the case of binary classification, the former outperforms in the case of multi-class classification. An attempt to increase the accuracy further was made by using various fine-tuning techniques on the pre-trained BERT-based models. The fine-tuning methods and the accuracy obtained are discussed in the next section.

Model	Type	Technique	Situation	Universal vs cultural
KNN	0.68	0.29	0.29	0.88
Decision tree	0.57	0.29	0.21	0.86
BERT	0.68	0.46	0.45	0.85
RoBERTa	0.67	0.44	0.48	0.88
BERTweet	0.67	0.41	0.37	0.88

Table 4.3: Accuracy for multi-class multi-label classification

4.6.3 Fine-tuning BERT based models

We have used pre-trained BERT-based models for the classification task so far. However, the pre-trained BERT models are not task-specific, meaning they do not have any knowledge about the specific task that they are being used for. Fine-tuning is the process of taking the pre-trained BERT model and adapting it to a particular task by training it on a smaller dataset that is specific to the task. This process allows the model to learn the nuances of the task and improve its performance on that task. Though we used the BERTweet model designed explicitly for analyzing tweets, it is not specific to humor classification; hence, fine-tuning is essential. During fine-tuning, the model learns to associate particular words or phrases and sentence patterns with the tweet's class and adjusts its weights accordingly. This results in a model that is specifically trained for the task at hand, and fine-tuned models usually outperform the pre-trained BERT models.

We fine-tune the three BERT-based models we have by taking multiple small steps.

- Attention pooling: We employ attention pooling technique to aggregate information from different tokens in the sequence. This is done to better capture the humor-related aspects of the text by focusing on important tokens.

- Focal loss: The data we have is highly imbalanced for the labels “Cultural Relevance” and “Situation” as can be seen in table 4.1. Hence, it becomes extremely important to tackle the imbalance carefully to prevent the model from being skewed to a particular class. Focal loss is an improved version of CrossEntropy loss which concentrate on the samples that are “harder” to train. It down-weighs easy examples so that their contribution to the overall loss is reduced.

- Setup an optimizer: We set an optimizer with learning rate and warmup scheduler rather than using the default optimizer which helps in adapting the learning rate during training.
- We increase the maximum length of tokens to allow the model to consider a larger context when processing text. This is particularly important for humor classification, as humor often relies on context to be understood.
- We also employ techniques such as stratifying, label smoothing, and early stopping which facilitate efficient training.

Table 4.4 shows the accuracies obtained after fine-tuning the three BERT-based models.

Model	Type	Technique	Situation	Universal vs cultural
BERT	0.70	0.49	0.46	0.89
RoBERTa	0.65	0.48	0.55	0.93
BERTweet	0.69	0.43	0.41	0.89

Table 4.4: Accuracy for multi-class multi-label classification after fine-tuning

4.6.4 Analysis

The results obtained show that the BERT-based models outperformed the classic ML models, such as KNN and Decision trees. This is because the BERT-based models use BiDirectional Encoder Representations, as mentioned earlier, to understand the context of the tweet and nuances of the language, which is essential for understanding humor. They capture long-range dependencies between words, making them better suited for understanding the context of the tweet and nuances of language in humor classification.

Traditional machine learning models like KNN and decision trees performed well in binary classification tasks because they can learn to distinguish between two classes based on a set of input features. As there are only two possible outcomes in binary classification, it becomes easier for these models to learn the decision boundary that separates the two classes. However, they struggle in the multi-class multi-label classification as it requires more complex decision boundaries.

Fine-tuning the pre-trained BERT-based models for our specific task improved the models' accuracy as we added a few layers on top of the existing ones specific to our task. This process allowed the models to adjust their weights and parameters to understand the context better and identify patterns in the data. We also dealt with issues such as imbalances in the data, capturing humor-related aspects in the tweet, etc., by using fine-tuning techniques. As a result, the accuracy of all the models had increased for multi-class labels by around 5%, which is significant considering the size of the dataset at hand.

4.7 Conclusion

In conclusion, this chapter has explored the challenges and complexities associated with multi-class, multi-label humor classification in the context of Covid-19 tweets. By implementing a range of machine learning models, including KNN, decision trees, and BERT-based models, we have delved into the intricacies of humor classification and furthered our understanding of the factors that contribute to humor perception.

Our analysis has highlighted the effectiveness of various models in classifying humor types, techniques, and situations. The study showed that BERT-based models, in particular, were able to capture the nuances of humor effectively, outperforming the traditional KNN and decision tree models. By utilizing state-of-the-art natural language processing techniques and pre-trained models like BERT, RoBERTa, and BERTweet, we have significantly improved our ability to identify and categorize humorous content.

Additionally, while the BERT-based models have shown promising results, there is still room for improvement. Future work could focus on fine-tuning these models for specific types of humor, exploring alternative deep-learning architectures that offer even better performance, or adding more data to our dataset. Moreover, incorporating additional features, such as user metadata or network-based features, could enhance the models' predictive capabilities and help capture the intricacies of humor in online conversations more effectively.

In summary, this chapter has made significant strides in the field of multi-class, multi-label humor classification by applying a range of machine-learning models to a unique dataset of Covid-19 tweets. Our findings contribute to the broader understanding of humor perception, its complexities, and its role in communication during challenging times. Through further research and refinement, we can continue to unravel the intricacies of humor and develop more accurate and robust classification models that can be applied across diverse contexts and datasets.

Chapter 5

Conclusion and future work

5.1 Conclusion

To summarise, the study of humor detection and classification is an important and growing research area with significant potential to expand our understanding of humor and its various manifestations in society. By refining classification models, incorporating context-aware approaches, and exploring humor across diverse cultural settings, researchers can contribute to developing more sophisticated systems that can better capture and appreciate the complexities of humor. This, in turn, can have far-reaching implications for various applications, from entertainment and marketing to enhancing communication and social interactions.

The enhancement of the annotation schema for conversational humor through the addition of 'situation' and 'relevance' tags, and its subsequent validation on the Covid-19 tweets dataset, has resulted in a more comprehensive schema that accounts for the influence of culture on humor perception. By successfully validating this schema on a unique dataset of humorous tweets related to Covid-19, we have not only demonstrated its wide applicability but also created a valuable resource for future research. This updated annotation schema captures the nuances of humor across different contexts and cultures, thus paving the way for deeper insights into the nature of humor in a global context.

Furthermore, understanding humor across different cultures and languages is another area of research worth exploring. Humor is inherently tied to a cultural context, and understanding the nuances of humor in different cultural settings can help develop more culturally sensitive and adaptable models. This can also aid in fostering cross-cultural understanding and appreciation of humor, bridging gaps between different societies.

Incorporating both basic and advanced machine learning models in the humor classification process allowed the researchers to leverage the strengths of each approach, ultimately leading to a more accurate and comprehensive understanding of humor in the context of Covid -19 related tweets. By refining these classification models and exploring the relationships between different dimensions of humor, researchers can contribute to the development of more sophisticated systems for humor detection and analysis, which can have far-reaching implications in various applications and fields.

The successful application of various machine learning models and the development of a comprehensive annotation schema has provided valuable insights and set the stage for future research in this area. As we continue to explore the complexities of humor classification and its implications for communication, we can unlock new opportunities for fostering connection, empathy, and resilience in an increasingly interconnected world.

5.2 Future work

In this work, we have explored the multi-class, multi-label classification of humorous tweets based on Covid-19, providing valuable insights into the types, techniques, and humor situations present in these tweets. While the study has made significant progress in understanding and classifying humor during the pandemic, there remains ample room for further exploration. This chapter outlines several avenues for future work that can enhance the current study and contribute to a more comprehensive understanding of humor in the context of Covid-19 related tweets.

The current study has relied on a relatively small dataset, which might not capture the full spectrum of humor related to Covid-19. Future work could focus on expanding the dataset by collecting and annotating more tweets, ensuring a diverse and representative sample. This would allow for more robust and generalizable models and improve the classification performance across various dimensions of humor.

The current study has primarily focused on the textual content of tweets for humor classification. However, contextual information such as the author's profile, tweet engagement (likes, retweets, and replies), and surrounding discussions can provide valuable insights into the humor present in a tweet. Future work could incorporate these contextual features into the classification models, potentially leading to improved performance and a more nuanced understanding of humor.

While the current study has employed BERT-based models for classification, many other advanced NLP techniques and models are available, such as GPT-3, T5, and XLNet. Future research could investigate the performance of these models in the context of humor classification, potentially leading to further improvements in classification accuracy and generalizability.

The current study's classification models can be used to identify potentially offensive or harmful humor, enabling the development of targeted interventions to mitigate the adverse effects of such humor. Future work could focus on designing and implementing interventions to promote responsible humor during crises, ensuring that humor is used effectively and ethically.

By leveraging the power of natural language processing and machine learning, we can also gain a deeper understanding of humor's role in shaping public discourse and how people engage with sensitive topics. This knowledge can inform the development of more effective communication strategies and tools that foster empathy, understanding, and resilience in times of crisis.

Moreover, the insights from this research can also inform the design of artificial intelligence systems and conversational agents capable of engaging in humorous interactions with humans. By incorporating humor understanding and generation capabilities, these AI systems can become more relatable, engaging, and effective in various applications, ranging from customer service to mental health support.

Overall, the multi-class, multi-label classification of humorous tweets related to Covid-19 represents a significant step forward in understanding humor's complex and dynamic nature in the context of crises. By pursuing the future research directions outlined in this chapter, we can continue to advance our knowledge in this area and improve the classification models and their applications.

Related Publications

- Pamulapati, Vaishnavi, **Gayatri Purigilla**, and Radhika Mamidi. "A novel annotation schema for conversational humor: Capturing the cultural nuances in kanyasulkam." Proceedings of the 14th Linguistic Annotation Workshop. 2020.
- **Gayatri Purigilla** and Radhika Mamidi. "Variation of Humor Type in Tweets amidst the Covid-19 Pandemic". Presented virtually at the 11th Humor Research Conference organized by Texas A&M University, 2021.
- **Gayatri Purigilla** and Radhika Mamidi. "Automatic classification of humor using COVID-19 related tweets". Submitted to the 4th workshop on Computational Approaches to Discourse, ACL 2023.

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