Survey on Computational Humour

Anirudh Mittal, Diptesh Kanojia, Pushpak Bhattacharyya
Department of Computer Science and Engineering, IIT Bombay,
University of Surrey
{anirudhmittal, pb}@cse.iitb.ac.in, d.kanojia@surrey.ac.uk

Abstract

Humor is an important aspect of human civilisation as it governs our daily lives. A large part of humor we see comes in form of text. Natural Language Processing is a fantastic tool to understand and replicate this phenomenon. Being able to understand humour in text can help machines separate the true meaning from the implied meaning. Humour also has the potential to make machines more human-like. In this work we work attempt to teach machines to detect and generate humor. We build a system to rate the humor quotient in Stand up comedy. Our model is able to predict the funniness on a scale of 0 to 4 with great accuracy (0.84 on Quadratic Weighted Kappa). Creating data sets for automatic measurement of humour quotient is difficult due to multiple possible interpretations of the content. As part of this project we release first tri-modal non-binary data set using English Stand-up comedy. This a valuable resource for the Natural Language Processing and Machine Learning community for multimodal humour and sentiment analysis. We also build a system that can make any sentence hyperbolic and further use that to generate humour. Our first work got accepted to EMNLP 2021 main conference and the second work is getting submitted to EMNLP 2022.

1 Introduction

Humor is one of the most interesting and puzzling research areas in the field of natural language understanding. Recently, computers have changed their roles from automatons that can only perform assigned tasks to intelligent agents that dynamically interact with people and learn to understand their users. When a computer converses with a human being, if it can figure out the humor in human's language, it can better understand the true meaning of human language, and thereby make better decisions that improve the user experience. Developing techniques that enable computers to understand humor in human conversations and adapt behavior accordingly deserves particular attention.

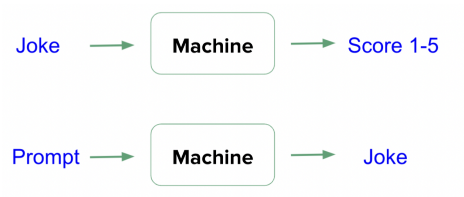

Figure 1: Problem statement

1.1 Problem Statement

We aim to make AI funny through this project. This can be done by achieving two goals:

1. Build a system that, given a joke, is able to identify if there is humor in it and then how funny that joke is.

2. Build a system that given a prompt or some piece of information is able to generate jokes on it.

1.2 Motivation

In Interstellar (2014 movie), a future earth is depicted where robots easily understand and use humor in their connections with their owners and humans can set the level of humor in their personal robots. While we may have a long road toward the astral travels, we are very close in reaching high-quality systems injected with adjustable humor.

Humor, as a potential cause of laughter, is an important part of human communication, which not only makes people feel comfortable, it also creates a cozier environment. Automatic humor detection in texts has interesting use cases in building human-centered artificial intelligence systems such as chatbots and virtual assistants. An appealing use case is to identify whether an input text should be taken seriously or not, which is a critical step to understand the real motive of users' queries, return appropriate answers, and enhance the overall experience of the user with the system. A more advanced outcome would be the injection of humor into computer-generated responses, thus making the human-computer interaction more engaging and interesting. This is an outcome that is achievable by setting the level of humor in possible answers to a desired level, similar to the mentioned movie. The general structure of humor states that a joke consists of a few sentences that concludes with a punchline. The punchline is responsible for bringing contradiction into the story, thus making the whole text laughable. In other words, any sentence in a joke is normally non-humorous in itself, but when we try to comprehend.

1.3 Contributions of the work

As part of this work we make several contributions to the Natural Language Processing and Machine Learning community.

- We release the 3D open mic data. This is the first trimodal data for non-binary classification of humour. This is a valuable resource for mulimodal humour and sentiment analysis.
- We release our model which given video, audio and text can predict the funniness of the content.
- Our work is published in EMNLP 2021 as: Anirudh Mittal, Pranav Jeevan, Prerak Gandhi, Diptesh Kanojia and Pushpak Bhattacharyya, "So You Think You're Funny?": Rating the Humour Quotient in Standup Comedy, EMNLP 21, 7-11 Nov, 2021, Dominican Republic

2 Theory of humor

It's important to understand from a linguistic lens. What makes something funny? Only if we as humans understand it, we can make techniques that will will machines learn how to recognize and generate humor. In this chapter, we try to understand different views overs the last few centuries on how humor works.

An excerpt from (Chauvin, 2015) makes for a great introduction:

"We cannot say that "there is no currently no theory of how humour works". There is a long tradition of trying to account for humour, linguistically but also more generally: the incongruity theory, the superiority theory, the relief theory; Freudian analyses, Aristotelian analyses, Kantian analyses, Bergsonian analyses, etc. What may be true is that there is no recognized theory of how it works, since how and when humour appeared is still very much a mystery."

From the many theories used to understand how humor work, three are widely recognised. (Morreall, 2020) explains the evolution of each of these theories. In this section we discuss each of them.

2.1 Superiority Theory

One of the first explanation was given in the 20th century by the theory called **Superiority theory**. It originally came from Plato and the bible and was further supported by scholars like Hobbes and Descartes. According to this theory - our laughter expresses feelings of superiority over other people or over a former state of ourselves. A contemporary proponent of this theory is Roger Scruton, who analyses amusement as an "attentive demolition" of a person or something connected with a person. "If people dislike being laughed at," Scruton says, "it is surely because laughter devalues its object in the subject's eyes" (in Morreall 1987, 168).

In the 18th century, the dominance of the Superiority Theory began to weaken when Francis Hutcheson (1750) wrote a critique of Hobbes' account of laughter. Feelings of superiority, Hutcheson argued, **are neither necessary nor sufficient for laughter**. In laughing, we may not be comparing ourselves with anyone. If self-comparison and sudden glory are not necessary for laughter, **neither are they sufficient for laughter**.

As an example of how this theory is unable to explain humor, imagine a rich person seeing a beggar. In this case, the rich person might feel superior, but they won't necessarily think of this as a humorous situation. Another example could be in the works of Charlie Chaplin. In his silent movies, there are many situation where he is stuck and manages to get out of the problem. It will be difficult to feel superior in these situations, but many people still find them superior.

2.2 Relief Theory

Weakening of the Superiority theory gave rise to two new theories. One of them is the **Relief theory**.

The Relief Theory is an hydraulic explanation in which laughter does in the nervous system what a pressure-relief valve does in a steam boiler. The theory was sketched in Lord Shaftesbury's 1709 essay "An Essay on the Freedom of Wit and Humor," the first publication in which humor is used in its modern sense of funniness. Scientists at the time knew that nerves connect the brain with the sense organs and muscles, but they thought that nerves carried "animal spirits"—gases and liquids such as air and blood. John Locke (1690, Book 3, ch. 9, para.16), for instance, describes animal spirits as "fluid and subtile Matter, passing through the Conduits of the Nerves."

Shaftesbury's explanation of laughter is that it releases animal spirits that have built up pressure inside the nerves.

The natural free spirits of ingenious men, if imprisoned or controlled, will find out other ways of motion to relieve themselves in their constraint; and whether it be in burlesque, mimicry, or buffoonery, they will be glad at any rate to vent themselves, and be revenged upon their constrainers.

Over the next two centuries, as the nervous system came to be better understood, thinkers such as Herbert Spencer and Sigmund Freud revised the biology behind the Relief Theory but kept the idea that laughter relieves pent-up nervous energy.

Freud's account of "the comic" faces still more problems, particularly his ideas about "mimetic representation." The psychic energy saved, he says, is energy summoned for understanding something, such as the antics of a clown. We summon a large packet of energy to understand the clown's large movements, but as we are summoning it, we compare it with the small packet of energy required to understand our own smaller movements in doing the same thing. The difference between the two packets is surplus energy discharged in laughter. Freud's account of thinking here is idiosyncratic and has strange implications, such as that thinking about swimming the English Channel takes far more energy than thinking about licking a stamp. With all these difficulties, it is not surprising that philosophers and psychologists studying humor today do not appeal to Freud's theory to explain laughter or humor. More generally, the Relief Theory is seldom used as a general explanation of laughter or humor.

2.3 Incongruity Theory

The second account of humor that arose in the 18th century to challenge the Superiority Theory was the **Incongruity Theory**. While the Superiority Theory says that the cause of laughter is feelings of superiority, and the Relief Theory says that it is the release of nervous energy, the Incongruity Theory says that it is the perception of something incongruous—something that violates our mental patterns and expectations. This approach was taken by James Beattie, Immanuel Kant, Arthur Schopenhauer, Søren Kierkegaard, and many later philosophers and psychologists. It is now the dominant theory of humor in philosophy and psychology.

This approach to joking is similar to techniques of stand-up comedians today. They speak of the set-up and the punch (line). The set-up is the first part of the joke: it creates the expectation. The punch (line) is the last part that violates that expectation. In the language of the Incongruity Theory, the joke's ending is incongruous with the beginning. Our laughter "always proceeds from a sentiment or emotion, excited in the mind, in consequence of certain objects or ideas being presented to it". Our laughter "seems to arise from the view of things incongruous united in the same assemblage". The cause of humorous laughter is "two or more inconsistent, unsuitable, or incongruous parts or circumstances, considered as united in one complex object or assemblage, as acquiring a sort of mutual relation from the peculiar manner in which the mind takes notice of them".

The core meaning of "incongruity" in various versions of the Incongruity Theory, then, is that some thing or event we perceive or think about violates our standard mental patterns and normal expectations. (If we are listening to a joke for the second time, of course, there is a sense in which we expect the incongruous punch line, but it still violates our ordinary expectations.) Beyond that core meaning, various thinkers have added different details, many of which are incompatible with each other. In contemporary psychology, for example, theorists such as Thomas Schultz (1976) and Jerry Suls (1972, 1983) have claimed that what we enjoy in humor is not incongruity itself, but the resolution of incongruity. After age seven, Schultz says, we require the fitting of the apparently anomalous element into some conceptual schema. That is what happens when we "get" a joke. Indeed, Schultz does not even call unresolvable incongruity "humor"—he calls it "nonsense." The examples of humor cited by these theorists are typically jokes in which the punch line is momentarily confusing, but then the hearer reinterprets the first part so that it makes a kind of sense. When, for instance, Mae West said, “Marriage is a great institution, but I’m not ready for an institution,” the shift in meanings of “institution” is the incongruity, but it takes a moment to follow that shift, and the pleasure is in figuring out that the word has two meanings. Amusement, according to this understanding of humor, is akin to puzzle-solving. Other theorists insist that incongruity-resolution figures in only some humor, and that the pleasure of amusement is not like puzzle-solving.

2.4 Other theories

There are several other theories that have tried to explain how humor works. even though not as much prevalent as the first three theories, insights from these next theories can be useful in computational research.

Script-based semantic theory of humor
The script-based semantic theory of humor (SSTH) was introduced by Victor Raskin in "Semantic Mechanisms of Humor", published 1985. While being a variant on the more general concepts of the Incongruity theory of humor (see above), it is the first theory to identify its approach as exclusively linguistic. As such it concerns itself only with verbal humor: written and spoken words used in narrative or riddle jokes concluding with a punch line.

The linguistic scripts (a.k.a. frames) referenced in the title include, for any given word, a "large chunk of semantic information surrounding the word and evoked by it [...] a cognitive structure internalized by the native speaker". These scripts extend much further than the lexical definition of a word; they contain the speaker’s complete knowledge of the concept as it exists in his world. Thus native speakers will have similar but not identical scripts for words they have in common.

To produce the humor of a verbal joke, Raskin posits, the following two conditions must be met:

- The text is compatible, fully or in part, with two different [semantic] scripts
- The two scripts with which the text is compatible are opposite [...]. The two scripts with which the text is compatible are said to overlap fully or in part on this text.

Humor is evoked when a trigger at the end of the joke, the punch line, causes the audience to abruptly shift its understanding from the primary (or more obvious) script to the secondary, opposing script.

Ontic-epistemic theory of humor
The ontic-epistemic theory of humor (OETC) proposed by P. Marteinson (2006) asserts that laughter is a reaction to a cognitive impasse, a momentary epistemological difficulty, in which the subject perceives that Social Being itself suddenly appears no longer to be real in any factual or normative sense. When this occurs material reality, which is always factually true, is the only percept remaining in the mind at such a moment of comic perception. This theory posits, as in Bergson, that human beings accept as real both normative immaterial percepts, such as social identity, and neological factual percepts, but also that the individual subject normally blends the two together in perception in order to live by the assumption they are equally real. The comic results from the perception that they are not.

Detection of mistaken reasoning
In 2011, three researchers, Hurley, Dennett and Adams, published a book that reviews previous theories of humor and many specific jokes. They propose the theory that humor evolved because it strengthens the ability of the brain to find mistakes in active belief structures, that is, to detect mistaken reasoning.[50] This is somewhat consistent with the sexual selection theory, because, as stated above, humor would be a reliable indicator of an important survival trait: the ability to detect mistaken reasoning. However, the three researchers argue that humor is fundamentally important because it is the very mechanism that allows the human brain to excel at practical problem solving. Thus, according to them, humor did have survival value even for early humans, because it enhanced the neural circuitry needed to survive.

There are several other theories mentioned (Theories of humor, 2020)in that haven’t been mentioned here.

2.5 Summary

Incongruity theory might require some refinements to be able to explain all aspects of humor. However, as compared to other proposed other theories, it is the one which explains humor the best. It is also close to how comedy, particularly stand up comedy works these days. This principle can be used to analyze sentences and come up techniques to detect and even generate humor. Many works have benefited from leveraging the linguistics of humor and especially the incongruity theory.

3 Data sets

Over the years, many data sets have been proposed to advance research in NLP, particularly detection and generation of humor. Many of these data sets are obtained by crawling through the internet especially websites like Reddit and Twitter as they tend to have humorous content. Further, this data is manually validated and cleaned with help of external annotators.

3.1 16000 one liners

16000 One-Liners data set collected humorous samples from daily joke websites while using formal writing resources (e.g., news titles, proverbs) to obtain non-humorous samples. It was proposed by (Mihalcea and Strapparava, 2005). A one-liner is a joke that usually has very few words in a single sentence with comic effects and interesting linguistic structure. While longer jokes can have a relatively complex linguistic structure, a one-liner must produce the humorous effect with very few words. This data set has been used in many research works between 2005 - Present. It has become one of the base lines for binary detection work.

Figure 2 explains the process followed to create this data set. Even though this data set has been widely used, on manual analysis it looks like it's actually very noisy. Section 3.5 also complains about noise in the data set.

3.2 Pun of the day

Pun of the Day data set was constructed from the Pun of the Day website.This data set was scraped by (Yang et al., 2015) and contains 16001 puns and 16002 not-punny sentences.The pun, also called paronomasia, is a form of wordplay that exploits multiple meanings of a term, or of similar-sounding words, for an intended humorous or rhetorical effect. The negative samples of this data set are sampled from news website.

3.3 Short Jokes Data set

Short Jokes data set, which collected the most amount of jokes, are from an open database on a Kaggle project. It contains 231,657 short jokes with no restriction on joke types scraped from various joke websites and length ranging from 10 to 200 characters. Link: https://www.kaggle.com/abhinavmoudgil95/short-jokes

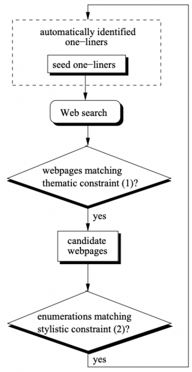

Figure 2: Creation process of 16000 one liners dataset

3.4 PPT Jokes

PTT Bulletin Board System is the largest terminal-based bulletin board system (BBS) in Taiwan. It has more than 1.5 million registered users and over 20,000 boards covering a multitude of topics. Every day more than 20,000 articles and 500,000 comments are posted. Additionally, there is a board called joke that though which (Chen and Soo, 2018) could acquire large amount of Chinese humor samples.

3.5 ColBERT

ColBERT (Khattab and Zaharia, 2020) points out that existing humor detection data sets use a combination of formal texts and informal jokes with incompatible statistics (text length, words count, etc.), making it more likely to detect humor with simple analytical models and without understanding the underlying latent connections. Moreover, they are relatively small for the tasks of text classification, making them prone to over-fit models. These problems encouraged them to create a new data set exclusively for the task of humor detection, where simple feature-based models will not be able to predict without an insight into the linguistic features.

Features for the ColBERT data can be found in 3

Data set contains 200k labeled short texts, equally distributed between humor and non-humor.

GENERAL STATISTICS OF THE COLBERT DATASET (100K POSITIVE, 100K NEGATIVE)

	#chars	#words	#unique words	#punctuation	#duplicate words	#sentences	sentiment polarity	sentiment subjectivity
mean	71.561	12.811	12.371	2.378	0.440	1.180	0.051	0.317
std	12.305	2.307	2.134	1.941	0.794	0.448	0.288	0.327
min	36	10	3	0	0	1	-1.000	0.000
median	71	12	12	2	0	1	0.000	0.268
max	99	22	22	37	13	2	1.000	1.000

Figure 3: Features of the ColBERT Data Set

It is much larger than the previous data sets (4) and it includes texts with similar textual features. Correlation between character count and the target is insignificant (+0.09), and there is no notable connection between the target value and sentiment features (correlation coefficient of -0.09 and +0.02 for polarity and subjectivity, respectively).

Features of all the data sets discussed until now can be found in 4

DATASETS FOR THE BINARY TASK OF HUMOR CLASSIFICATION

	Parts	
Dataset	#Positive	#Negative
16000 One-Liners [22]	16,000	16,002
Pun of the Day [5]	2,423	2,403
PTT Jokes [6]	1,425	2,551
English-Hindi [18]	1,755	1,698
ColBERT	100,000	100,000

Figure 4: Features of data sets available for binary humor classification

3.6 Other data sets

Some other useful data sets are:

- **Reddit+ short jokes+ pun:** Collection of reddit jokes plus the data sets mentioned above.
- **Fun data set:** This dataset is in russian and contains 300,000 short texts.
- **Humicroedit** This dat set has been created by modifying regular new headlines so as to make them funny. It has about 15,095 edited headlines.
- **UR Funny:** This is the first multi-modal data set. It has video, audio and text.

4 Computational work

Research on detection or generation of humor has been a hot topic in the NLP community. From linguistic perspective, it started way back in 1900s, while computational efforts began to surface in the early 2000s. Scarcity of data sets has always been an ongoing challenge limiting the research. However, there have been few data sets that have been made available to the community over the years. Many of them have become for general humor tasks and cited frequently. While there has been research in automatic recognition of humor, computerized generation has seen less progress. This is not surprising, given that humor involves in-depth world-knowledge, common sense, and the ability to perceive relationships across entities and objects at various levels of understanding. Even humans often fail at being funny or recognizing humor. In this chapter, we look at data sets used for humor research, along with different detection and generation techniques proposed over the years.

4.1 Detection

With advances in NLP, researchers applied and evaluated state-of-the-art methods for the task of humor detection. This includes using statistical and N-gram analysis (Rayz, 2004a), Regression Trees (Purandare and Litman, 2006), Word2Vec combined with K-NN Human Centric Features (Yang et al., 2015), and Convolutional Neural Networks (Chen and Soo, 2018; Weller and Seppi, 2019).

(Rayz, 2004b) recognized wordplay jokes based on statistical language recognition techniques, where they learned statistical patterns of text in N-grams and provided a heuristic focus for a location of where wordplay may or may not occur. Similar work can also be found in (Rayz, 2017), which described humor detection process through Ontological Semantics by automatically transposing the text into the formatted text-meaning representation to detect humor. In addition to language features, some other studies also utilize spoken or multimodal signals. For example, (Purandare and Litman, 2006) analyzed acoustic-prosodic and linguistic features to automatically recognize humor during spoken conversations. However, the humor related features in most of those works are not systematically derived or explained.

(Mihalcea and Strapparava, 2005) defined three types of humor specific stylistic features: Alliteration, Antonym and Adult Slang, and trained a classifier based on these feature representations. Similarly, (Zhang and Liu, 2014) designed several categories of humor-related features, derived from influential humor theories, linguistic norms, and affective dimensions, and input around fifty features into the Gradient Boosting Regression Tree model for humor recognition. (Mihalcea and Pulman, 2007) analyzed humorous features in news and blogs; (Raz, 2012) and (Zhang and Liu, 2014) collected and classified humorous tweets; (Radev et al., 2015) predicted humor ranking in The New Yorker Cartoon Caption Contest.

(Bertero and Fung, 2016) focused on predicting humor by using audio information, hence reached 0.750 AUC by using only audio data. It also points that Research on humor in videos has focused on TV sitcoms, using canned laughter as indicators of humor. (Purandare and Litman, 2006) examined speech features of the “FRIENDS” sitcom, while (Bertero and Fung, 2016) built deep learning models with text and speech features to predict canned laughter in “The Big Bang Theory” and “Seinfeld”. However, no study has shown that canned laughter represents the audience’s actual perception of humor. Such information can only tell us what the sitcom producers want the audience to find humorous. Another drawback of this approach is the limitation of the genre; models trained on a particular TV show may not generalize to other shows

With the popularity of transfer learning, some researchers focused on using pre-trained models for several tasks of text classification. Transfer learning in NLP, particularly models like ULMFiT (Howard and Ruder, 2018), Allen AI’s ELMO (Sarzynska-Wawer et al., 2021), and Google’s BERT (Devlin et al., 2018), focuses on storing knowledge gained from training on one problem and applying it to a different but related problem usually after fine-tuning on a small amount of data. Among them, BERT utilizes a multi-layer bidirectional transformer encoder consisting of several encoders stacked together, which can learn deep bi-directional representations. Similar to previous transfer learning methods, it is pre-trained on unlabeled data to be later fine-tuned for a variety of tasks. It initially came with two model sizes (BERT$_{BASE}$ and BERT$_{LARGE}$) and obtained eleven new state-of-the-art results. Since then, it was pre-trained and fine-tuned for several tasks and languages, and several BERT-based architectures and model sizes have been introduced (such as Multilingual BERT, RoBERTa (Liu et al., 2019), ALBERT (Lan et al., 2019) and VideoBERT (Sun et al., 2019)).

Weller and Seppi (2019) focused on the task of detecting whether a joke is humorous by using a Transformer architecture. They approached this problem by building a model that learns to identify humorous jokes based on ratings taken from the popular Reddit r/Jokes thread (13884 negative and 2025 positives). There are emerging tasks related to humor detection. Yang et al. (2019) focused on predicting humor by using audio information, hence reached 0.750 AUC by using only audio data. A good number of research is focused on the detecting humor in nonEnglish texts, such as on Spanish (Chiruzzo et al. (2019), Ismailov (2019), Giudice (2019)), Chinese (Yang et al., 2019), and English-Hindi (Khandelwal et al., 2018).

4.2 Generation

Compared to humor recognition, humor generation has received quite a lot attention in the past decades(Stock and Strapparava, 2005; Ritchie, 2005; Hong and Ong, 2009). Most generation work draws on humor theories to account for humor factors, such as the Script-based Semantic Theory of Humor (Raskin, 1985; Labutov and Lipson, 2012) and employs templates to generate jokes. For example, Ozbal and Strapparava (2012) created humorous neologism using WordNet and ConceptNet. In detail, their system combined several linguistic resources to generate creative names, more specifically neologisms based on homophonic puns and metaphors. Stock and Strapparava (2005) introduced HAHACRONYM, a system (an acronym ironic re-analyzer and generator) devoted to produce humorous acronyms mainly by exploiting incongruity theories (Stock and Strapparava, 2003

4.3 Summary

There has been significant research in the field of humor detection and generation that has happened in the last few decades. Systems have shifted from conventional mechanisms to pre-trained models. However, we’re yet to reach the level when machines will be accurately able to identify humor. One step further for this is machine generating humor which is currently a hot topic.

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