NLP Project Report

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Abstract. *Humor Recognition is one of the long standing goal in the Natural Language Fraternity. In this report we first tackle some of the fundamental ideas of what motivates humor and how it can be generated. Then we move on to humor recognition and deal with some of the important papers which deals with humor recognition. In the end we propose a model which is a hybrid of Humor Generation and Recognition taking the best elements of both.*

Keywords: Humor Generation, Humor Recognition, Classification

Introduction

In this report we tackle the problem of computational humor. We divided the report into 4 chapters. In the first chapter we deal with psychology of humor, in the next chapter we deal with two important applications for generation of humor. We then move on to Humor detection and present two papers which deals with humor as a classification problem. In the last chapter we present a model of our own which mixes the components of humor generation with humor detection.

1 Psychology and Humor

Research on humor remains incomplete if individual differences are not considered. Computational approaches to humor frequently neglected the fact that human tastes are different. Irrespective of whether jokes are created by humans or a computer program they will not always find an appreciative audience. As a result we must look into the domain of personality and how a person appreciates humor and whether or not a person will find the humor funny. Approaches also failed to consider the fact that jokes might fail altogether and humans not only respond exclusively positively to humor but the **"experiential world of the recipient is multidimensional"**. Therefore, testing the quality of computer-generated humor should go beyond consideration of degree of funniness.

The example mentioned in [4] is that if a comedian who tells the same type of jokes and funny stories at all performances irrespective of the audience or the occasion.The chance of him being successful is very less. Again some audiences may find his jokes offensive while some others might not. If he does not want to offend anybody, and plays safe, the remaining sample of jokes might just be plain boring to many. Obviously, such a strategy would not be very successful, and thus a comedian does just what we all do, namely to tailor his attempts of humor to satisfy audiences of different tastes.

This tailoring of jokes is done quite intuitively and no systematic study is known on how people actually do so.

1.1 Reinforcement Learning

If they know the audience well, they might base it on prior experience on what was found funny and what not amusing at all. If not, it is still easy if you have time to learn the taste of the audience. One can use quite diverse jokes initially and see which ones they like and which ones they dont. This is the exploration phase. Then one can put this hypothesis to a test and see whether they actually laugh at a joke that one chooses deliberately because it is similar to a prior successful one. This is the exploitation phase.

1.2 Bayesian Learning

One can take the prior failure with a bad joke and see whether one is equally unsuccessful with a sister joke. Such a procedure will only work if we have the right **taxonomy of jokes; i.e., a rationale that tells which jokes are similar, if not interchangeable (i.e., equal for this given purpose).** If the predictions are all correct one can end the learning stage and has the capacity to optimally serve the audience by calculating the posterior of any other sister jokes.

But this trial and error procedure might not always work. An audience may not be that patient and it might be better to start with a clear idea of what will work out and what not. If one does not have the chance to learn, one still does not need to rely solely on guessing, as we can we infer preference from other salient features of the audience.

1. Their current state,for example if they are very tired then it might be better not to indulge too much into very sophisticated humor.
2. Habitual factors, like gender, socio-economic, ethnic background, are also important. Indeed personality characteristics allow a much better prediction of appreciation of humor than mood of a person and empirical research subsequently provided a scientific foundation for this.

Thus, a more complete view of the humor process should not only involve the analysis of the humorous message but also the states,traits and nature of sender and the receiver, and what they think about each others before and after the massage was transmitted. **Research has shown that on the side of the sender factors like current mood and motivation, and enduring personality as well as intellectual traits determine whether or not somebody will decide to encode humor, how well he or she is able to do so, what the content or tendency will be, and whether or not considerations about potential effects on the audience exist, etc.**

1.3 Taxonomy of Jokes

Intuitive and rational taxonomies typically distinguish only between content classes but factor analytic studies show that structural properties of jokes and cartoons are as important as their content, with two factors consistently appearing: namely, incongruity-resolution (INC-RES) humor and nonsense (NON) humor. Jokes and cartoons of the INC-RES humor category are characterized by punch lines in which the surprising incongruity can be completely resolved. The common element in this type of humor is that the recipient first discovers an incongruity which is then fully resolvable upon consideration of information available elsewhere in the joke or cartoon

Nonsense humor also has a surprising or incongruous punch line, however, the punch line may

1. provide no resolution at all
2. provide a partial resolution (leaving an essential part of the incongruity unresolved),
3. create new absurdities or incongruities.The recipients ability to make sense or to solve problems is exploited; after detecting the incongruity he is misled to resolve it, only to later discover that what made sense for a moment is not really making sense.

Analysis of incongruity-resolution humor yielded a broad set of predictors.

1. The single most potent predictor is conservatism, the major dimension underlying social attitudes. According to a previous research on "dynamic theory of conservatism" this trait reflects a generalized fear of both stimulus and response uncertainty. **This makes more conservative individuals to show greater avoidance and dislike of novel, complex, unfamiliar, incongruous events and to prefer and seek out stimuli which are simpler, more familiar and congruent.** This hypothesis was validated for visual art, poetry, and music. Not surprisingly, then, the hypotheses that conservative persons find incongruity-resolution humor more funny than liberals were substantiated in several countries.
2. The second set of predictors tested the individuals stance towards stimulus uncertainty vs. redundancy more directly using behavioral tests and judgment or creation of art. Again, incongruity-resolution humor is preferred by individuals who generally dislike stimulus uncertainty.
3. Another set of predictors may be circumscribes by inhibitedness, and like stimulus uncertainty it is correlated with conservatism.

1.4 Psychological Analysis

1. Liking of nonsense humor is predicted by liking of complexity in a variety of stimuli. The hypothesis that and nonsense humor is appealing to those generally enjoying or searching for uncertainty was also substantiated in the field of aesthetics. For example, appreciation of nonsense correlated positively with liking complex and fantastic paintings , liking of complexity and asymmetry in freehand drawings and polygons, and also with producing complexity in black/white patterns and enjoying and enhancing visual incongruity when wearing prism glasses which distort the visual field. Liking of nonsense peaks between 20 and 35 years of age and declines thereafter since it has been found to be linked to sexual libido.
2. Conservatism was found to be another predictor for liking non-sense humor. While conservatism does not incorporate the seeking of stimulus uncertainty, the trait of sensation seeking, and in particular the component of experience seeking, does. Experience seeking involves the seeking of stimulation through the mind and the senses, through art, travel, even psychedelic drugs, music,

and the wish to live in an unconventional style, and there is evidence that it is closely related to the novelty and complexity dimensions of stimuli. Therefore it was hypothesized and substantiated in several countries that experience seeking is positively related to appreciation of nonsense humor.

3. Freud (1905) hypothesized that repressed needs find relief in jokes and in dreams. Hence, there will be a negative relationship; people repressing their sexual desires will be the ones appreciating sexual content in humor. Salience theory predicts a positive relationship; funniness of a particular content in humor will increase with increase in salience of this topic in real life. So, the most promising predictor of appreciation of sexual humor is an individuals sexual experience and attitudes towards sex.

Humor Generation

2 JAPE

In this part, we discuss a model of simple question-answer punning, implemented in a program,JAPE- 1[1], which generates riddles from humour-independent lexical entries. The model schemata, uses two main types of structure:

1. schemata which determine the relationships between keywords in a joke
2. templates, which produce the surface form of the joke.

JAPE- 1 succeeds in generating pieces of text that are recognizably jokes, but some of them are not very good jokes.

There are three main strategies used in puns to exploit phonological ambiguity:

1. Syllable substitution:To confuse a syllable (or syllables) in a word with a similar- or identical-sounding word.
   For example: What do short-sighted ghosts wear?
   Spooktacles
2. Word substitution: Word substitution is very similar to syllable substitution. In this strategy, an entire word is confused with another similar- or identical-sounding word.
   For example: How do you make gold soup?
   Put fourteen carrots in it.
3. Metathesis: Metathesis is quite different from syllable or word substitution. Also known as spoonerism, it uses a reversal of sounds and words to suggest (wrongly) a similarity in meaning between two semantically-distinct phrases.
   For example:
   Whats the difference between a very short witch and a deer running from hunters?
   One's a stunted hag and the others a hunted stag.

2.1 Implementation

Lets see the example of:
What do you give an elephant thats exhausted?
Trunkquillizers.
In this joke, the word trunk, which is phonologically similar to the syllable tranq, is substituted into the valid English word tranquillizer. The resulting fake word trunkquillizer is given a meaning, referred to in the question part of the riddle, which is some combination of the meanings of trunk and tranquillizer
The following questions use the same meaning for trunkquillizer, but refer to that meaning in different ways:

1. What do you use to sedate an elephant?
2. What do you call elephant sedatives?
3. What kind of medicine do you give to a stressedout elephant?

On the other hand, these questions are all put together in the same way, but from different constructed meanings:

1. What do you use to sedate an elephant?
2. What do you use to sedate a piece of luggage?
3. What do you use to medicate a nose?

The paper adopted the term schema for the symbolic description of the underlying configuration of meanings and words, and template for the textual patterns used to construct a question-answer pair.

Lexemes A lexeme is an abstract entity, roughly corresponding to a meaning of a word or phrase. Each lexeme has exactly one entry in the lexicon, so if a word has two meanings, it will have two corresponding lexemes. Each lexeme may have some properties which are true of it (e.g. being a noun), and there are a number of possible relations which may hold between lexemes (e.g. synonym,homonym,subclass).

Schemata A schema stipulates a set of relationships which must hold between the lexemes used to build a joke. More specifically, a schema determines how real words/phrases are linked together to make a fake word/phrase, and which parts of the lexical entries for real words/phrases are used to construct the meaning of the fake word/phrase. There are many different possible schemata.For example, the schema in Figure 2 constructs a fake phrase by substituting a homonym for the first word in a real phrase, then builds its meaning from the meaning of the homonym and the real phrase.
For example the instantiated schema is shown below of, Whats green and bounces? A spring cabbage

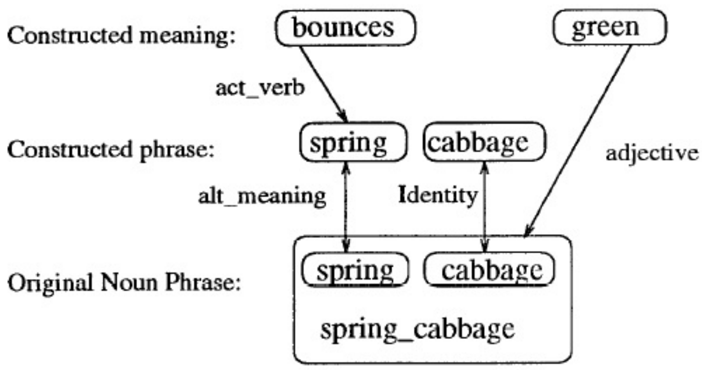


Figure 3: A completely instantiated *lotus* schema

Templates A template is used to produce the surface form of a joke from the lexemes and relationships specified in an instantiated schema. Templates are not inherently humour-related. Given a (real or nonsense) noun phrase, and a meaning for that noun phrase (genuine or constructed),a template builds a suitable question-answer pair. Because of the need to provide a suitable amount of information in the riddle question, every schema has to be associated with a set of appropriate templates. The choice of template influences the choice of lexical relation for the characteristic link.

JAPE 1 main mechanism attempts to construct a punning riddle based on a common noun phrase. It has several distinct knowledge bases with which to accomplish this task: the lexicon (including the homonym base), a set of schemata,a set of templates,and a post-production checker. They chose to generate only word- substitution puns, simply because lists of phonologically identical words (homonyms) are readily available, whereas the other two types (ie syllable substitution and metathesis) require some kind of sub-word comparison.

Since riddles often use certain fixed forms (for example, What do you get when you cross — with — ?), the templates embody such standard forms. A JAPE 1 template consists of some fragments of canned text with slots where generated words or phrases can be inserted, derived from the lexemes in an instantiated schema. What do you get when you cross [text fragment generated from the first characteristic lexeme(s)] with [text fragment generated frown the second characteristic lexeme(s)]? [the constructed noun phrase]. A template also specifies the values it requires to be used for characteristic links in the schema; the describes-all labels in below figure are derived from the syn. syn template. When the schema has been fully instantiated, JAPE-1 selects one of the associated ternplates, generates text fragments from the lexemes, and slots those fragments into the template.

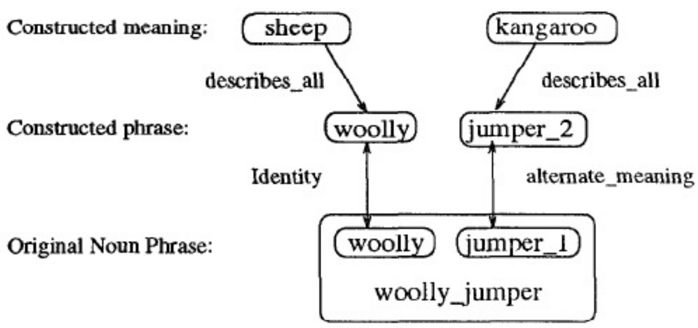


Figure 5: The instantiated *jumper* schema, with links suitable for the *syn_syn* template. Gives the riddle: What do you get when you cross a sheep and a kangaroo? *A woolly jumper.*

2.2 Limitation

1. Some schemata and templates tended to produce better jokes than others. For example, the use-syn template produced several texts that were judged to be non-jokes. For example:
   What do you use to hit a waiting line?
   A pool queue.
2. The problem with this template is probably that it uses the definition constructed by the schema inappropriately. The schema-generated definition is nonsense, in that it describes something that doesnt exist.
3. Still, the word order of the punchline does contain some semantic information (i.e. which of its words is the object and which word describes that object), and it is important for the question to reflect that information. For example, the word queue reflects waiting line.
   On the other hand a more appropriate template, class-has rev, produced this joke:
   What kind of line has sixteen balls? A pool queue.
   This the judges gave an average of two points.
4. Another problem was that the definitions provided by the volunteers were often too general for our purposes.
   For example, the word hanger gave its class as device, producing jokes like: What kind of device has wings? An aeroplane hanger. which scored half a point.

3 HAHAcronym

HAHAcronym1 is the first project concerned with computational humor sponsored by the European Commission[5]. In order to implement this system some general tools have been adapted, or developed for the humorous context. A fundamental tool is an incongruity detector/generator: in practice There is a need to detect semantic mismatches between expected sentence meaning and other readings, along some specific dimension (i.e. in our case the acronym and its context). So if you feed say Massachusetts Institute of Technology, HAHAcronym will output Mythical Institute of Theology(say).

They have identified that deep modeling of humor in all of its facets is not something for the near future. The phenomena are too complex; humor is one of the most sophisticated forms of human intelligence. It is AI-complete. The problem of modeling it is as difficult to solve as the most difficult Artificial Intelligence problems. But some steps can be followed to achieve results.In order to be successfully humorous, a computational system should be able to:

1. recognize situations appropriate for humor
2. choose a suitable kind of humor for the situation
3. generate an appropriately humorous output
4. if there is some form of interaction or control, evaluate the feedback.

One of the purpose of the project was to show that using standard resources (with some extensions and modifications) and suitable linguistic theories of humor (i.e. developing specific algorithms that implement or elaborate theories), it is possible to implement a working prototype.

1. Wordnet and Wordnet Domains: WordNet is a thesaurus for the English language inspired by psycholinguistics principles and developed at the Princeton University by George Miller (Miller, 1990; Fellbaum, 1998). It has been conceived as a computational resource, therefore improving some of the drawbacks of traditional dictionaries, such as circularity of definitions and ambiguity of sense references. It is organized into some 100,000 synonym classes called synsets.
2. Augmenting WordNet with Domain information: Domains have been used both in linguistics (i.e. Semantic Fields) and in lexicography (i.e. Subject Field Codes) to mark technical usages of words. This is useful information for sense discrimination. WordNet Domains is an attempt to extend the coverage of domain labels within an already existing lexical database, WordNet (version 1.6). The synsets have been annotated with at least one domain label, selected from a set of about two hundred labels hierarchically organized. They organized about 250 domain labels in a hierarchy (exploiting Dewey Decimal Classi- fication), where each level is made up of codes of the same degree of specificity: for example, the second level includes domain labels such as Botany, Linguistics, History, Sport,etc.
3. Opposition of semantic fields: They have modelled an independent structure of domain opposition, such as Religion vs. Technology, Sex vs. Religion, etc. to exploit these kind of opposition as a basic resource for the incongruity generator
4. Adjectives and Antonymy Relations: Adjectives play an important role in modifying and generating funny acronyms. So we gave them a thorough analysis. WordNet divides adjectives into two categories. Descriptive adjectives (e.g. big, beautiful, interesting, possible, married) constitute by far the largest category. The second category is called simply relational adjectives because they are related by derivation to nouns (i.e. electrical in electrical engineering is related to noun electricity). To relational adjectives, strictly dependent on noun meanings, it is often possible to apply similar strategies as those exploited for nouns. Their semantic organization, though, is entirely different from the one of the other major categories. In fact it is not clear what it would mean to say that one adjective is a kind of (ISA) some other adjective.
5. Exploiting the hierarchy (e.g. geographic names): It is possible to exploit the network of lexical and semantic relations built in WordNet to make simple ontological reasoning. For example, if a noun or an adjective has a geographic location meaning, the pertaining country and continent can be inferred.
6. Rhymes: The HAHAcronym prototype takes into account word rhymes and the rhythm of the acronym expansion.
7. Parser and grammar : Word sequences that are at the basis of acronyms are subject to a well-defined grammar, simpler than a complete noun phrase

grammar, but complex enough to require a a nontrivial analyzer. In the paper theydecided to use a well established nondeterministic parsing technique (ATN-based parsing). Ordinarily, an ATN parser has three components:

(a) the ATN itself, that represent the grammar in the form of a network
(b) an interpreter for traversing it
(c) and a dictionary (possibly integrated with a morphological analyzer). For the third component they use WordNet integrated with a morphological analyzer.

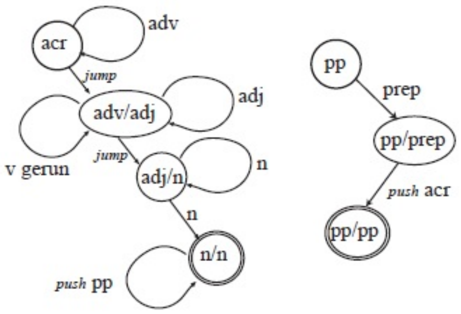


Figure 3: A simplified grammar

(d)

8. A-semantic dictionary The A-semantic dictionary is a **"collection of hyperbolic/epistemic/deontic adjective/adverbs."** This resource is particularly useful when it is necessary to complete a forming acronym (especially during the generation of new acronyms). Some examples of this kind of words are: abnormally, abstrusely, adorably, exceptionally, exorbitantly, exponentially, extraordinarily, voraciously, weirdly,wonderfully. This resource is hand-made using various dictionaries as information sources.

3.1 Implementation

To get an **ironic or profaning re-analysis** of a given acronym, the system follows various steps and strategies. The main elements of the algorithm can be summarized as follows:

1. acronym parsing and construction of a logical form
2. choice of what to keep unchanged (typically the head of the highest ranking NP) and what to modify (e.g. the adjectives)
3. look for possible substitutions
   (a) using semantic field oppositions
   (b) keeping the initial letter, rhyme and rhythm(the modified acronym should sound similar to the original as much as possible)
   (c) for adjectives, basing reasoning mainly on WordNet antonymy clustering
   (d) using the a-semantic dictionary

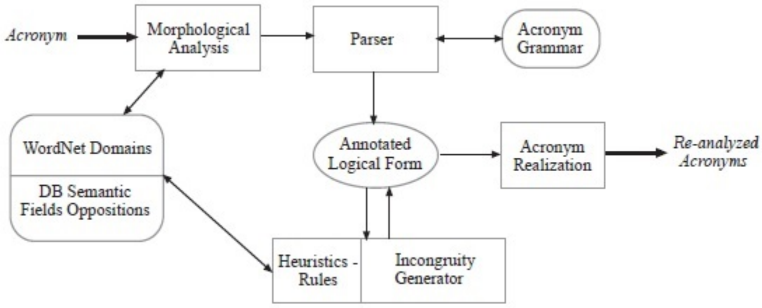


Figure 4: Acronyms Reanalysis: a sketch of the demonstrator architecture

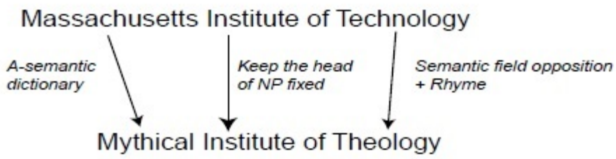


Figure 5: An example of acronym reanalysis

4.

3.2 Limitation

Sometimes HAHAcronym gives you very poor result. For example:
FCCSET - Federal Coordinating Committee for Science, Engineering and Technology Femoral Coordinating Committee for Sword dance Earring and Theology
This example shows how too many modifications can produce a re-analysis that does not resemble the original acronym at all, with poor irony effect.

Humor Classification

Learning to Laugh

In this paper [3] the authors restrict their examination on one-liners only by stating that deep comprehension of humor in all of its aspects is probably too ambitious and beyond the existing computational capabilities.

3.3 One Liners

A one-liner is a short sentence with comic effects and an interesting linguistic structure: simple syntax, deliberate use of rhetoric devices (e.g., alliteration, rhyme), and frequent use of creative language constructions meant to attract the readers attention. While longer jokes can have a relatively complex narrative structure, a one-liner must produce the humorous effect in one shot, with very few words. These characteristics make this type of humor particularly suitable for use in an automatic learning

3.4 Highlights of the Paper

Some of the highlights of the paper is mentioned below:

1. The paper deals with identification of humor from one-liners.
2. This is one of the earliest papers that deals with humor recognition problem as a classification task.
3. The main problems identified by the paper for classification of humorous one-liners from non-humorous one-liners are
   (a) Creation of a clean dataset of humorous one-liners.
   (b) Creation of a non-humorous un-biased dataset that closely resembles the humorous one-liners
   (c) Identifying what features to use to discriminate
   (d) Identifying what classifiers to use
   (e) Limitations where computations fail
   (f) Identifying some core features which characterizes humor in one-liners
4. In the end we must remember that humor is subjective and many of the one-liners may not actually seem funny.

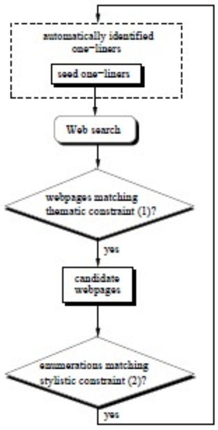


Figure 1: Web-based bootstrapping of one-liners.

1. Large amounts of training data can improve the accuracy of the learning process and affect the classification precision.
2. Employ a bootstrapping procedure to overcome shortage of one-liners available in Web. [2]

1. They start with a short seed list of annotated one-liners.
2. Then they search in the web for web-pages that contains at least one of the seed one-liners.
3. For searching the web pages they use
   (a) **Thematic constraints:** Implemented using a set of keywords of which at least one has to appear in the URL of a retrieved webpage, thus potentially limiting the content of the webpage to a theme related to that keyword
   (b) **Structural Constraints:** This exploits the HTML structure of webpages, in an attempt to identify enumerations of texts that include the seed oneliner. This is based on the hypothesis that enumerations typically include texts of similar genre, and thus a list including the seed one-liner is likely to include additional one-line jokes.
4. Dataset still contains noise of around 9% after removal of duplicates.

1. To make the task of the classifier difficult they chose the one-liners from non-humorous dataset in a careful manner.
2. Four corpora were identified:
   (a) **Reuters**: The titles consist of short sentences with simple syntax, and are often phrased to catch the readers attention (an effect similar to the one rendered by the one-liners).
   (b) **BNC**: A balanced corpus covering different styles, genres, and domains.

(c) **Proverb**: Their property of being condensed, but memorable sayings make them very similar to the one-liners. Some one-liners attempt to reproduce proverbs, with a comic effect, as in the example, **"Beauty is in the eye of the beer holder"** derived from **"Beauty is in the eye of the beholder."**

(d) **OMCS**: Comic effect of jokes is often based on statements that break our usual understanding of the world. OMCS contains commonsense assertions in English as contributed by volunteers over the Web. It consists mostly of simple single sentences, which tend to be explanations and assertions and phrased in a more common language.

3.5 Stylistic Features

For classification of one-liners some of the Stylistic features are listed below:

1. **Alliteration:** Structural and phonetic properties of jokes are as important as their content. In fact one-liners often rely on the readers awareness of attention-catching sounds, through linguistic phenomena such as :
   (a) Alliteration
   (b) Word repetition
   (c) Rhyming
   These produces a comic effect rendering subtlety to jokes. Similar stylistic features are often used in newspaper headlines and in advertisements. For example:
   Infants dont enjoy infancy like adults do adultery.
2. **Antonymy:** Humor often relies on some type of incongruity, opposition, or other forms of apparent contradiction For example:
   A clean desk is a sign of a cluttered desk drawer.

1. **Adult Slang:** Humor based on adult slang is very popular. Therefore, a possible feature for humor recognition is the detection of sexual-oriented lexicon in the sentence. To form a lexicon required for the identification of this feature, they extract from WORDNET all the synsets labeled with the domain SEXUALITY. The list is further processed by removing all words with high polysemy (≥ 4). Next, they check for the presence of the words in this lexicon in each sentence in the corpus, and annotate them accordingly. For example:
   Artificial Insemination: procreation without recreation.
2. **All Three:** There might be sentences were all three are present. For example:
   Behind every $great_{al}$ man_{ant} **is a** $great_{al}$ $woman_{ant}$ **, and behind every** $great_{al}$ $woman_{ant}$ **is some guy staring at her** $behind_{sl}$

3.6 Content Based Features

Apart from looking at stylistic features they formulate humor-recognition task as a traditional text classification problem. For this they identified two classifiers which have performed well on text classification problems as reported in some previous works.

1. **Naive Bayes:** The main idea in a Nave Bayes text classifier is to estimate the probability of a category given a document using joint probabilities of words and documents. Nave Bayes classifiers assume word independence; however, despite this simplification, these algorithms were shown to perform well on text classification.
2. There are several versions of Nave Bayes classifiers, but they use multinomial model, previously shown to be more effective.
3. **Support Vector Machines:** SVM are binary classifiers that seek to find the hyperplane that best separates a set of positive examples from a set of negative examples, with maximum margin.
4. Applications of SVM classifiers to text categorization led to some of the best results reported in the literature.

3.7 Mixture of Two

1. They designed a third experiment that attempts to jointly exploit stylistic and content features for humor recognition.
2. The feature combination is performed using a stacked learner, which takes the output of the text classifier, joins it with the three humor-specific features (alliteration, antonymy, adult slang), and feeds the newly created feature vectors to a machine learning tool.
3. They evaluate the classification using a stratified 10-fold cross-validation.

3.8 Experimental Results

All evaluations are performed using stratified 10-fold cross-validations, for accurate estimates. The baseline for all the experiments is 50%, which represents the classification accuracy obtained if a label of humorous (or non-humorous)would be assigned by default to all the examples in the data set.

1. Below is the result for classification using Stylistic contents.

TABLE 2. Humor-Recognition Accuracy Using Alliteration, Antonymy, and Adult Slang

	One-Liners			
Heuristic	Reuters	BNC	Proverbs	OMCS
Alliteration	74.31%	59.34%	53.30%	55.57%
Antonymy	55.65%	51.40%	50.51%	51.84%
Adult slang	52.74%	52.39%	50.74%	51.34%
All	76.73%	60.63%	53.71%	56.16%

2. Below is the result for classification using Content based features.

	One-Liners			
Classifier	Reuters	BNC	Proverbs	OMCS
Naïve Bayes	96.67%	73.22%	84.81%	82.39%
SVM	96.09%	77.51%	84.48%	81.86%

3.9 Limitation

The areas where the classifier fails are identified below:

1. **Irony:** The humorous effect in about half of the jokes in the sample data was due to irony targeted either to the speaker himself or to entire professional communities, such as lawyers or programmers. For example:**"Criminal lawyer is a redundancy"**.
2. **Ambiguity:** About 20% of the jokes which they manually analyzed had word ambiguity, leading to potential misinterpretations. For instance, the one-liner **"Change is inevitable, except from a vending machine"** exploits the ambiguity, and consequently wrong expectations, induced by the word change. The statement "change is inevitable" refers to change with the meaning of action of changing something, but this meaning is suddenly changed in the second part of the one-liner to that of balance of money. This shift of meaning leads to surprise, which then creates the humorous effect.

1. **Incongruity:**They tried to capture the effect of incongruity modeled through word based antonymy , there are however cases (about 10% in the study corpus) where the classifier failed. For example, **"A diplomat is someone who can tell you to go to hell in such a way that you will look forward to the trip"** is based on the opposition between go to hell and look forward to the trip, which cannot be captured with the help of thesauri or semantic networks such as WordNet.
2. **Commonsense knowledge:** A large fraction of the one-liners (50%) involved understanding of commonsense knowledge, often broken to the effect of creating humor. Many jokes are based on a reinterpretation of the common understanding associated with popular beliefs. For example, the joke **Dont drink and drive. You might hit a bump and spill your drink** is based on the meaning inferred from the phrase dont drink and drive (unsafe for driver) to an unexpected reinterpretation that you might spill your drink.

1. **Idiomatic expressions:** A relatively large number of one-liners (22%) are based on a reinterpretation of idiomatic expressions.
   (a) Idioms are typically noncompositional expressions where the semantics of the idiomatic phrase cannot be fully inferred from the semantics of the component words.

(b) This potential ”disjunction” of meaning can be exploited for creating a comic effect because the meaning expectation created by an idiom can be suddenly changed to the (unexpected) meaning inferred by one of the component words, which results in surprise and consequently humor.

For example, the one-liner **”I used to have an open mind, but my brains kept falling out”** is based on the effect caused by the reinterpretation of the word open in the idiom open mind, with a switch from the meaning of open as receptive to new ideas (intended) to that of open as exposed, uncovered (unintended, but possible).

3.10 What makes us Laugh!

Analyzing the outcome of the experiments the authors came up with a series of suggestions on the features that makes us laugh.

1. **Human-centric vocabulary:** One-liners seem to constantly make reference to human-related scenarios, through the frequent use of words such as you, I, man, woman, guy, etc. For instance, the word ”you” alone occurs in more than 25% of the one-liners , while the word I occurs in about 15% of the one-liners. One example **”Of all the things I lost, I miss my mind the most”**. This supports earlier suggestions made by Freud ,and later on by Minsky, that laughter is often provoked by feelings of frustration caused by our own awkward, behavior.
2. **Negative orientation:** In addition to negative verb forms, one-liners seem to also contain a large number of words with a negative polarity, such as adjectives with negative connotations like bad, illegal, wrong One example **”When everything comes your way, you are in the wrong lane”**, or nouns with a negative orientation, for example, error, mistake, failure.

1. **Negation:** Humorous texts seem to often include negative word forms, such as doesn’t, isn’t, don’t. For instance, about 3,000 of the 16,000 jokes in the collection contain some form of negation.
2. **Professional communities:** Many jokes seem to target professional communities that are often associated with amusing situations, such as lawyers, programmers, policemen.
3. **Human ”weakness”:** This kind of vocabulary relates to theories of humor that explain laughter as an effect of frustration or awkward feelings, when we end up laughing ”at ourselves”. They including nouns such as ignorance, stupidity, trouble or verbs such as quit, steal, lie, drink. One such example is: **”If you can’t drink and drive, then why do bars have parking lots?”**

1. Automatic classification techniques can be successfully applied to the task of humor recognition. Experimental results obtained on very large data sets showed that computational approaches can be efficiently used to distinguish between humorous and non-humorous texts
2. In those cases where the stylistic and content-based features failed some additional knowledge are required to identify humor

New Formulation

In this part we try to formulate a new model which can help us in Humor Recognition. We will look at several aspects of humor recognition and take it not just as classification problem in Machine Learning context.

4 Current Problems

1. Given the approach taken by the Learning to Laugh paper, one of the foremost problem is that it looks at surface level classification of the texts into humorous and non-humorous category.
2. There has to be a richer set of models to represent knowledge.
3. We have to think some way to represent world knowledge (say from wikipedia or twitter) and incorporate them into our model. This is a difficult yet essential task since the knowledge about jokes,puns,riddles,etc is ever changing and ever growing.
4. We have to take into account individual tastes and refine our model according to that.

5 New Model

We have the idea of combining the rich knowledge representation model of JAPE-1 with modification used for Humor generation along with some of the classification techniques used in Learning to Laugh Paper for the identification of one-liners.

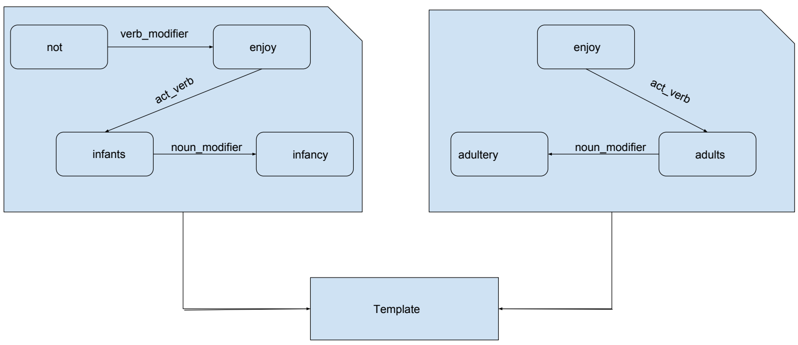
1. We start with the same 3 building blocks as used in JAPE-1.
   (a) Lexeme: Given an input sentence we represent it by the lexemes. A lexeme is an abstract entity, roughly corresponding to a meaning of a word or phrase. Each lexeme has exactly one entry in the lexicon, so if a word has two meanings, it will have two corresponding lexemes. Each lexeme may have some properties which are true of it (e.g. being a noun), and there are a number of possible relations which may hold between lexemes (e.g. synonym,homonym,subclass).
   (b) Schema: A schema stipulates a set of relationships which must hold between the lexemes used to build a joke. More specifically, a schema determines how real words/phrases are linked together to make a fake word/phrase, and which parts of the lexical entries for real words/phrases are used to construct the meaning of the fake word/phrase.
   (c) Templates: A template is used to represent the surface form of a joke from the lexemes and relationships specified in an instantiated schema. Templates here helps to identify how the linkages in the instantiated schema fall into place. For example the alliteration-incongruity template

helps to represent jokes that contain both alliteration and incongruity in parts of the sentences. Every schema has to be associated with a set of appropriate templates. Let's say say that some from of Incongruity is present between two phrases from the same one-liner connected by a conjunction(say and). The template will then take the structure of "—— and ——" , with slots on both sides of the conjunction free where we can fit the phrases with opposite meanings.

2. We actually feel that in human mind the formulation of jokes/one-liners happen this way ie we first form the relationships(schemata) between words(Lexemes) and then cast them into suitable formats(templates) to create a hilarious effect.

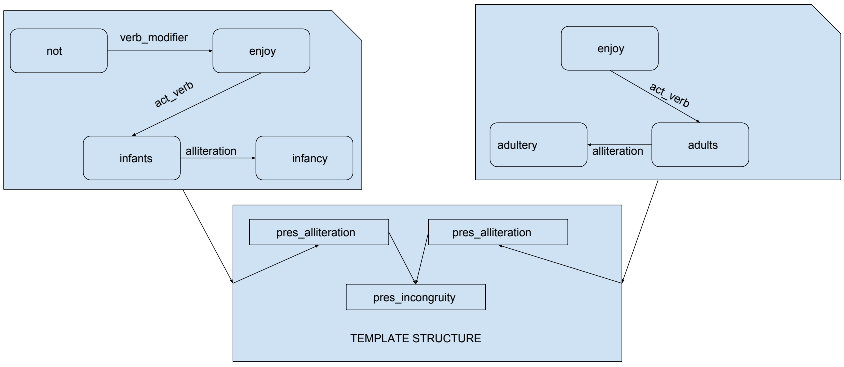
Let us consider the statement: **Infants dont enjoy infancy like adults do adultery.**

1. First we break down the statement into lexemes, with each word being one lexeme with its corresponding Part of Speech Tag, say Noun, Verb, Adjective, etc. associated with it.
2. Then we create the instantiated schema with the links of the words as shown below:



Here the snip rectangles represent the phrases inside the one-liner. This snip rectangles are themselves Lexemes and hence can have linkages between them. The rounded rectangles are the word Lexemes of the one-liner. The linkages between the Lexemes are mentioned in the figure.

3. Ultimately we feed this into our set of templates to find whether this schema fits into any one of our template structure.



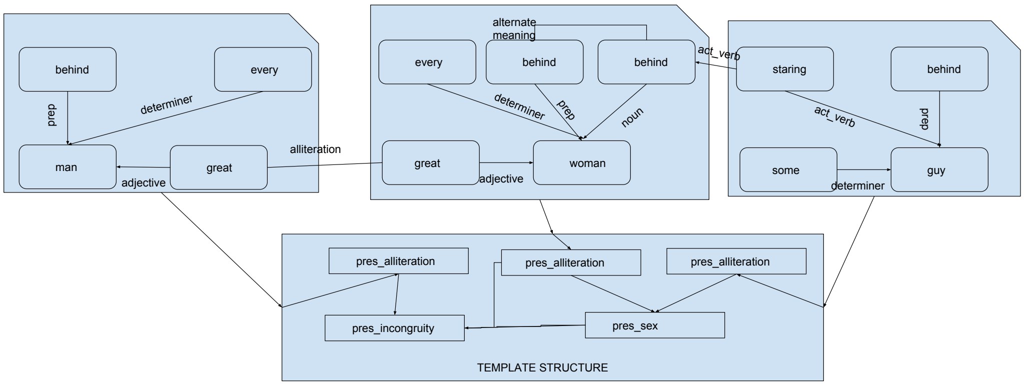
In the above figure this fits into our alliteration-incongruity template structure.The alliteration template looks at whether alliterations are present in the schema or not. In the figure above we have pointed the alliteration linkage found out by the template. The incongruity comes from the fact that some part of the phrase means opposite in its meaning than other parts of the one-liner.

Let us consider another statement: **Behind every** $great_{al}$ man_{ant} **is a** $great_{al}$ $woman_{ant}$ **, and behind every** $great_{al}$ $woman_{ant}$ **is some guy staring at her** $behind_{sl}$

1. First we break down the statement into lexemes, with each word being one lexeme with its corresponding Part of Speech Tag, say Noun, Verb, Adjective, etc. associated with it.

2. Then we create the instantiated schema with the links of the words. Here we see the phrase **"is a great woman"** and **"behind every great woman"** appearing. This two phrases link the first and the last phrase of the one-liner with two meanings of **"behind"**. One is preposition linkage behind while the other is sexual behind(buttock). To represent this linkage the two phrase **"is a great woman"** and **"behind every great woman"** is represented by one Phrase Lexeme with two meanings of the word Lexeme "behind".

3. Ultimately we feed this into our set of templates to find whether this schema fits into any one of our template structure.



This is the final relationship that was found out. In the above figure this fits into our alliteration-incongruity-sexual template structure. The incongruity-sexual template comes from the two meanings of behind whereas the alliteration comes from the usages of "great". Here we also see linkages between phrase lexemes.

6 General Approach

Hence we formulate a general approach to deal with the one-liner humorous sentences.

1. First we break the one liner into word lexemes.
2. We form the phrase lexemes by looking at verb/noun/adjective phrases.
3. We create the instatiated schema with all the relationship linkages
4. We try to reduce phrases by adding extra relationship linkages and word lexemes.
5. We feed the schema/reduced schema to a template structure from a set of template structures present.
6. If the one-liner fits into anyone of the template structure it is classified as a humorous one-liner while if it fails to go into any of the template structure it is branded as a non-humorous sentence.

7 How to learn the Schemata and Templates

The main issue comes is how to learn the template structures and the schema. We can learn the Lexemes by employing a part of speech tagger. In the JAPE-1 model, there are 6 pre-specified schemata that they use. Some ways that we can learn a schemata are

1. Create a set of generalized schemata which fits into most of the known cases of one-liners.

2. In a more generalized setup we can actually learn the schemata from labelled data in a supervised learning setup. We can look into the 16000 one-liners from the Rada dataset which we have discussed before and see how the linkages are established between verbs/nouns/adjectives (say Lexemes) by using a some type of parser say the ATN parser discussed before or the Link parser.

For learning the templates we can fall back to the psychological analysis of humor to see what are the essential characteristics of humor. Some of them as identified by [6]

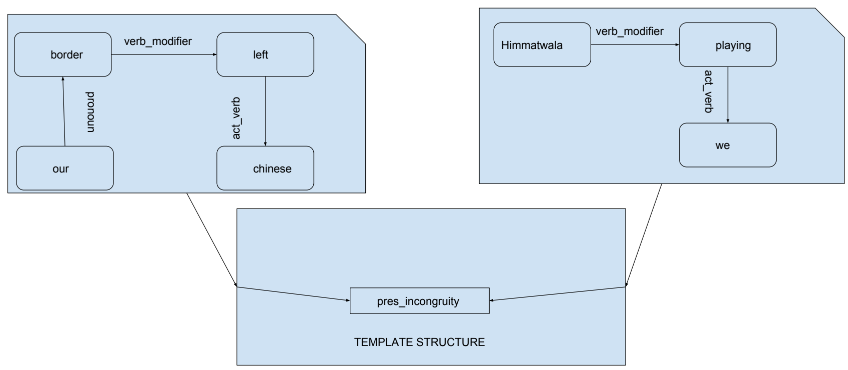
1. Alliteration template: Tries to find alliterations in the schema.
2. Incongruity template: We take both antonymy and different polarity between parts of a one-liner under the same template of Incongruity.
3. Sexual Humor: This contains both adult slangs as well as words having dual(sexual) meanings.
4. Punning Riddles Templates: As used in JAPE-1.
5. Ambiguity: Structural, phonological or morphological ambiguity can be detected by these templates.

8 Incorporate World Knowledge

The domain of jokes, punning riddles is a continuous changing one and the model we proposed needs to get updated accordingly. So we came up with a simple proposition to incorporate world knowledge into the model. As proposed in the Explicit Semantic Analysis setup, we augment each lexeme with as many meanings or forms it can take. To do this we take the help of Wikipedia because it is an ever-changing and growing dictionary grounded in human cognition of the world.

To motivate the need for world knowledge we present the following sentence: **The Chinese left our borders because we were playing Himmatwala.** Proceeding similarly as stated before we break it down into lexemes, then create schema and finally look at suitable templates. But for creating Lexemes, we augment it with the meanings we found out from wikipedia as well. So here Himmatwala will have the meaning "movie" associated with it.

But this is not enough as to detect incongruity ie **The Chinese left our borders** , which has a positive polarity whereas **we were playing Himmatwala** which has a negative polarity these information s also need to be augmented. The detection of these type of incongruity involving world knowledge can be included in the pres-incongruity templates which can resolve it. The diagram below gives an overall view of the scenario.



9 Involving Individual Tastes

Here we must fall back to an important question raised in the 1st chapter. There we talked about how a comedian who tries to deliver the best set of jokes/one-liners at different venues involving different audiences. We know that this task is itself challenging given that the comedian has no prior information about the type of audience present, their state of mind, etc. So what he can do is to follow an exploration and exploitation policy whereby he first dishes out a broad set of jokes/one-liners and thereby depending on the feedback from the environment(audience) he can exploit on the best set of jokes that he delivered till now.

Similarly if we look at our case of humor detection, the one-liners and jokes vary depending on the human tastes and thereby detecting them also becomes difficult. In such a scenario we think that the structure of templates and schematics also needs to be altered/augmented. The question is that how to model the feedback from the environment that will alter the structure. In the training phase when we are dealing with the labelled Rada dataset, we can actually create a policy by which once in the testing phase if the model finds out that it has misclassified a one-liner from the dataset. it can actually go back and alter/augment the templates and schematics to fit the one-liner into any one of its templates.

10 Conclusion

In this report we looked at various aspects of humor , starting from the psychological aspects of humor to humor generation and ultimately ti humor classification. We pointed out the shortcomings of various methods and in the end we proposed a new model which can handle humor in a wide variety of cases and has a stronger knowledge representation model. The model we proposed is an abstract one with its foundations grounded in real world applications of some already existing projects(JAPE-1 and HAHAcronym). But we believe that these applications can actually be used in humor detection as well which can give a much better model than the simple classification of texts used Learning to Laugh paper. With this we conclude the report for the NLP course project. Thank you.

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