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VISUALIZING INCONGRUITY: VISUAL DATA MINING STRATEGIES FOR MODELING HUMOR IN TEXT

A Project

Presented to

The Graduate Faculty

Central Washington University

In Partial Fulfillment

of the Requirements for the Degree

Master of Science

Computational Science

---

by

Andrew Smigaj

December 2017

CENTRAL WASHINGTON UNIVERSITY

Graduate Studies

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ABSTRACT

VISUALIZING INCONGRUITY: VISUAL DATA MINING STRATEGIES FOR MODELING HUMOR IN TEXT

by

Andrew Smigaj

December 2017

The goal of this project is to investigate the use of visual data mining to model verbal humor. We explored various means of text visualization to identify key featrues of garden path jokes as compared with non jokes. With garden path jokes one interpretation is established in the setup but new information indicating some alternative interpretation triggers some resolution process leading to a new interpretation. For this project we visualize text in three novel ways, assisted by some web mining to build an informal ontology, that allow us to see the differences between garden path jokes and non jokes of similar form. We used the results of the visualizations to build a rule based model which was then compared with models from tradtitional data mining toi show the use of visual data mining. Additional experiments with other forms of incongruity including visualization of 'shilling' or the introduction of false reviews into a product review set. The results are very similar to that of garden path jokes and start to show us there is a shape to incongruity. Overall this project shows as that the proposed methodologies and tools offer a new approach to testing and generating hypotheses related to theories of humor as well as other phenomena involving opposition, incongruities, and shifts in classification.

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I want to thank my advisor, comittee, family, friends, pets, car, dead relatives, myself,and whoever else is appropriate.

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CHAPTER I

INTRODUCTION

This text describes the results of a several projects with the goal to visualize incongruity and resolution. Incongruity and resolution are a core part of the theory of humor but appear in many other places. We will first show the results of a study to visualize humor in text which was successful and visually shows the resolution process. Then we will look at a study to visualize shilling, or the entry of false reviews into a product review set by a shiller, which ends up visually showing us what incongruity looks like.

While many theories of humor agree that humor often involved the detection of incongruities and their resolution the details remain vague and there is no agreed upon theoretical framework which describes how these incongruities form and are detected by intelligent agents [1]. Our project explored the use of text visualization for modeling humor in text in process known as visual text mining, a subset of visual data mining [2] [3]. In particular our approach visualizes shifts in meaning assignment over time as jokes are processed when compared with non jokes. While this does not fully solve the problem of modeling the specific mechanisms underlying humor, visualization and visual text mining gives us one more data centric tool for detecting features associated with various natural language phenomena Furthermore these approaches can be used to model and detect many other phenomena where incongruities arise within text data.

This text will begin with a quick literature review. We will look look at incongruity-resolution based theories of humor and then garden path humor in particular. We will then look at different means of working with meaning with computers, and then a few projects attempting to use computers to detect humor in text. We will then review some current problems with the state of computational humor which we think could be addressed through data visualization as well as traditional data mining techniques which let the data tell its own story..

This text will then describe the development of the three visualization approaches to model, detect, and classify sequential jokes involving shifts in the interpreted meaning of some ambiguous word. This form of sequential joke has been referred to as a garden path joke to differentiate it from other sequential jokes involving incongruity and resolution which do not involve a shift from on interpretation to the next [4]. The three approaches use a correlation based measure to assign meaning of ambiguous words given the context of the ambiguous word in different parts of a surface level text and relations associated with different meanings of that word as defined in an ontology as a deeper level.

The first visualization shows how meaning correlation scores for two or more opposing meanings are plotted as coordinates using an approach known as collocated paired coordinates [5]. This lets us visually see shifts of meaning associated when given a set of jokes when compared with a set of non jokes which is equivalent to the resolution process where meanings assignment is switched. The next visualization uses heat maps to color code the differences of meaning correlation scores given different time steps. The heat maps for the set of jokes is distinguishable from that of non jokes with respect to these meaning correlation differences. Finally the third visualization displays in two dimensions an entire model space consisting of boolean vectors describing meaning correlation over time. The set of jokes and non jokes are plotted on this space allowing us to see the boundary between what is a joke and non joke. To show the power of this approach we compare the results with traditional data mining approaches which result in models describing the same key features. This text describes all three approaches in detail, including the construction of an informal ontology using web mining to identify semantic relations, and shows how these approaches were used to visualize jokes and non jokes to get experimental results. We then present a fourth visualization which extends this approach to use with more complex jokes where multiple correlation might form in each part of text. Following this we will discuess some other improvements to this method including a different means of establishing and assigning meaning which was developed based on unsupervised learning and ways of automatically selecting keywords to use in search queries for meaning disambiguation.

Whereas the first visualization process shows us what resolution looks like, the next will visualize incongruity as we shift our focus to a study of shilling. Shilling occurs when a shill leaves fake reviews for some gain which createi incongruities within product review sets. We will look at the results of a small toy project involving the simlation of shilling within a movie review time series where combine sentiment analysis with visualization to visualize these incongruities which arise when shilling occurs.

We will present the results of a study to visualize shifts of emotion found within the toy diary of a bipolar patient. This is another phenomena showing shifts between two polar and mutually exclusive classes.

Finally we will conclude with a discussion of our overall findings where we discuss the shape of incongruity.

CHAPTER II

LITERATURE REVIEW

A number of attempts have been made to explore and model humor using computers, most of which can be found within the growing field of Computational Humor. These approaches are very diverse in that they build on different theoretical foundations, look at different subtypes of humor, take different approaches to modeling, vary in their degree of detail, and are used for to solve isolated tasks. The goal of this project is to model and detect instances of sequential humor involving the formation of incongruity and resolution over time in a sequential fashion which this literature review will focus on. We will first describe Incongruity-Resolution based theories of humor, second we will look at different theories of humor which specifically focus on sequential humor such as forced reinterpretation, frame shifting, and garden path humor, third we will look at several computational techniques used to represent and work with meaning using computers, and finally we will discuss some recent approaches to modeling sequential humor using computers which led to viable results. What we have found is not that the models used experimental and diverse but no approach has made use of text visualization.

Incongruity Resolution Theory

One predominant theory of verbal humor states that humor is triggered by the detection and resolution of semantic incongruities that arise during communication. The dictionary defines 'incongruous' as lacking harmony of parts, discordant, or inconsistent in nature. Semantic incongruities form when a reader's interpretation of some concept conflicts with other possible interpretations. Suls [6] coined the term ’incongruity resolution’ which is the terminology we will use.

Take for example the following joke:

Two fish are in a tank. One looks to the other and asks how do you drive this thing?

When a reader initially reads it in the tank is interpreted as an aquarium.When additional information is presented an alternative interpretation arises, that of a vehicle. Some form of resolution process occur to deal with this contradiction.

Theorists argue though as to how these incongruities arise and are resolved. Over the years other theorists have coined other terms as they try to work out the specific nature of incongruity and resolution as it applies to humor from cognitively, sociologically, and linguistical viewpoints. These include Semantic-Script Theory of Humor and Ontological Semantic Theory of Verbal Humor [7] and Theory of False Fuzzy Causation [8]. They have also identified many subtypes of humor involving incongruity and resolution. In this thesis we are focused on sequential humor, where a incongruity arises and then is resolved in a sequential manner, and in particular a pattern of sequential humor involving what is called the garden path mechanism [4].

Opposition

The concept of opposition arises when workingn with incongruity Incongruities often arise when ’opposing’ elements simultaneously occur. One way of describing them are as mutually exclusive classifications. If you are happy then you are not sad, if it is summer then it is not winter, and if the word ’tank’ indicates of ’vehicle’ then it does not indicate an ’aquarium. Raskin used the term ’opposition’ when he developed the concept of ’script opposition’ but the concept has been described in other manners before and since then. Often when things oppose there is a form of negative correlation with respect to some subset of features. For example when it is summer you would go sunbathing more often but less often in the winter while you would go skiing less often and vice versa. Emotions such as happiness and sadness oppose - when you are happy you are more likely to smile and less lilkely to frown. If a product is good then it is not bad.

Garden Path Humor

This paper will focus on a particular humor subtype where there is a shift from some interpretation to some opposing other. Dynel calls these jokes ”garden path” jokes using the garden path metaphor of being misled [4], while other theorists use the terminology of ’forced reinterpretation’ and ’frame shifting’ [1]. These jokes are sequential in nature and describe a certain pattern of incongruity and resolution. With a garden path joke a reader establishes some interpretation A as they read the first part of a joke, the setup, but given new evidence included in the second part, the punchline, they must discard this interpretation and establish a new interpretation B. Our visualizations show this shifting process along with the incongruity.

Representation of Meaning

The computational representation and manipulation of meaning is essential for language processing tasks including humor detection. There are no agreed upon approaches to this and the approaches currently use tend to be of a heuristic and limited nature. To truly pass a turing test for humor detection we not only need to detect the meaning of words and phrases but perform complex tasks of inference and reasoning. We do not solve this problem and limit the experiments in this thesis to jokes requiring no complex processes of inference. We do require a semantic model which can perform surface level lexical disambiguation so have chosen to use a model utilizing distributional semantics. Computational models inspired by distributional semantics have been shown to work for basic tasks such as lexical disambigutation [9]. In this section we will briefly discuss the distributional hypothesis.

The distributional hypothesis is a linguistic theory that similar meanings will have similar contextual distributions [10]. That is, if a meaning is the same you will find it in the same contexts. For example the meaning for the word 'tank' which is that of a fish tank will be found in the same context as 'aquarium'. They will both co-occur at higher than normal frequency with words such as 'gallon', 'water', 'guppies', and so on. The visualizations introduced later will make use of this in that there will be a correlation of contextual frequencies given words with the same meaning.

There have been many computational models which make use of distributional semantics and vary in degrees of complexity. Most of them work with vectors of word frequencies given words which co-occur with different words given a large corpus of natural language data. Some of these such as latent semantic analysis (LSA) will perform some type of dimensionality reduction . Others utilize special techniques for extracting co occuring keyword frequencies from document sets such as the term-frequency to inverse document frequency (TF-IDF) approach which adjusts for the fact that some words just happen to appear more frequently in a document set [11]. The approach we use is very simple one which uses a target web search, making use of special keyword sets associated with specific meanings, use a TF-IDF approach to establish co-occuring web frequencies, and then look only at the top frequencies to reduce noise.

Computational Humor

A number of attempts have been made to explore and model humor within text using computers. Some approaches make use of a joke templates (in a typical generative approach words are fit into specific sentence patterns), while others are less restricted and designed to work with any joke format. Some approaches attempt to generate jokes and other to recognize them, a considerably harder task. Finally they differ in the depth and nature of the underlying model. Some models only work with surface level features while others utilize ontologies and deep semantic processing capabilities to extract meaning from text or generate jokes. Overall these approaches are diverse and disjointed. This section will describe several of these recent attempts..

Raskin and Taylor have seen considerable success in template free detection of jokes with the implementation of systems described in the Ontological Semantic Theory of Verbal Humor. They developed a robust system for extracting text meaning representations from text The program has access to an ontology, describing how the world works, a database of name and historical facts, and a semantic analyzer that uses grammatical and semantic rules to parse meaning. Their ontology though is mostly hand constructed. We are interested in automated approaches to ontology developmen, some of which may reflect how the human mind learns to store and communicate meaning more accurately.

Others have engaged in a number of projects using different experimental designs. Since Computational Humor is a new field with great experimental capacity these researchers work from a diverse variety of theoretical backgrounds.

Working within the framework of the Semantic-Script Theory of Humor [7], Labutov and Lipson [12] modeled incongruity based on the idea of script opposition. In their model a script is a path through a semantic network, and potential humor when cycles form. Divergence, that is having multiple paths to go down to get from one point to another is proposed as a key component to humor. A template based approach is used to insert elements of the script into a text and generated several humorous instances according to a survey.

Strapparrava and Mihalcea [?] took a data analysis/mining approach, analyzing a set of joke setups and punchlines, focusing mostly on features related to semantic similarity. Each entry in the data set has one joke setup, and then a number of possible punchlines of which only one was humorous and the rest chosen as normal non-humorous followups. An underlying hypothesis was that the punchline would be unexpected, leading to the use of similarity metrics. They used both corpus based and knowledge based metrics for similarity. They also include a explored a number of other features including measures of polysemy, alliteration, and features resulting from latent semantic analysis of the joke set. We use a data mining approach but work with correlation of meaning given meaning vectors.

Petrovic and Matthews [13] developed a program for generating jokes of the form I like my X like I like my Y, Z using corpus-extracted word relation metrics. In order to be considered as a possible joke, using their template, several conditions had to be met. First, X and Y are nouns while Z is an adjective. Second, Z must describe both X and Y. Third, Z should be rare. Fourth, Z is often polysemous with multiple words senses. Finally, X and Y should be dissimilar. According to their results, 16 percent of all automatically generated statements matching these criteria were found to be humorous. In this study we have a similar situation where a pair of elements involved in the incongruity should oppose.

Data Visualization And Humor

The approach we proposed was to develop visual data mining techniques for visualizing humor within text, that is the visualization of incongruity and resolution within natural langauge texts. To our knowledge our project is the first attempt to visualize incongruities within text.

CHAPTER III

PROBLEMS

There are a number of problems still to be solved within the domain of computational humor.

First at this point a Turing Test for humor recognition would not be passed. This is partially due to the heuristic and limited nature of models used which lack the ability to perform complex inference and have limited knowledge bases. This is true even with short jokes, which almost all studies have focused on, let alone longer and more complex jokes.

Second, no incongruity-resolution based model of humor has been established that describe how incongruities are detected by the brain. Current researchers take different approaches to modeling and start with different underlying theoretical viewpoints. To resolve these issues new approaches to modeling humor in text should be tried, ones which are more data centric and let the data tell its own story such as visual data miining.

Next, the garden path subtype of incongruity-resolution based jokes remains a unexplored phenomena on its own. Some researchers blindly look at a mix of joke subtypes, including other sequential joke subtypes other than garden path jokes. Modeling of garden path jokes may require other approaches than a mixed bag other subtypes on their own.

Our solution is the use ofvisualization to identify features which let us differentiate between jokes and non jokes, in particular those of the garden path joke subtype, and from them build models. In the next section we will describe the use of visualization to identify model features in various ways, from visualization of the semantic shifts which occur in text to visualization of entire model spaces which allows us to quickly explore various models.

CHAPTER IV

OUR APPROACH

This chapter describes our approach. Parts of this section have been published in [14] and [15].

Establishing Meanings and Meaning Correlations

We chose a vector representation of meaning based on the frequency at which different words occur in the context of some target word. This is a standard approach taken by a number of researchers in the past for dealing with meaning [16]. These vector of word associations form an informal ontology describing entities and their relations. The material used to build these vectors was retrieved via a web search. Below we consider some ambiguous word A with a number of possible meanings $AM_1...AM_n$ and different parts of some text $P_1...P_m$ containing the ambiguous word A.

Establishing vectors of word association frequencies using a web mining approach

For each meaning AM_x we establish a set of disambiguating keywords $K(AM_x)$ which uniquely identify that meaning. While we hand chose our keyword sets these can be established using a variety of resources such as wordnet.

Next we use $K(AM_x)$ as a query for a search engine retrieve the top n documents. Let D(q, n) be a search function which retrieves n documents relevant to some query q. The resulting document set for some meaning AM_x is thus designated $D(K(AM_x), n)$.

Finally we compute frequencies of all words occuring within distance j of A given the document set $D(K(AM_x), n)$. We designate this $F(A, j, D(K(AM_x), n)))$ where F is a function that returns a vector of word frequencies. In this paper F uses the term-frequency to inverse document frequency approach (TF-IDF) to establishing word frequencies [11]. $F(A, j, D(K(AM_x), n)))$ represents the meaning for AM_x as a set of word association frequencies or in other words its contexts. These frequencies are ordered by the lexicographic order of the words. Note that we include the frequency of the given word A itself though have experimented with variants which do not include the ambiguous word.

In a similar fashion we established semantics for the ambiguous word A given the different parts $P_1 ... P_m$ of some text containing A. We denote them as $F(A, j, D(P_1, n))$... $F(A, j, D(P_m, n))$.

Calculating correlation coefficients

We are interested in how the meaning of A given a search for some phrase Px correlates with the meaning of A given the meaning established for each word sense $AM_1 ... AM_n$.

We compute the correlation coefficient given the vector of word frequencies associated with A given a search for some part of text P_i, that is $F(A, D(P_i, n)$, and the vector of word frequencies associated with a search for some meaning AM_x, that is $F(A, j, D(K(AM_x), n)$, using a function C which return the correlation. In our case we use Pearon's correlation coefficient given two vectors. We denote these C_{iy} = $C(F(A, j, D(P_i, n)), F(A, j, D(K(AM_y), n)))$.

All of the jokes in our data set are two part jokes in which two meanings are invoked. Given two meanings of some ambiguous word A and some statement with parts P_1 and P_2 that refer to A, we calculate the following correlation scores:

Given P_1 (part one of some text):

$C_{1x} = C(F(A, j, D(P_1, n)), F(A, j, D(K(AM_x), n)))$ is a correlation of meaning AP_1 with meaning AM_x,

$C_{1y} = C(F(A, j, D(P_1, n)), F(A, j, D(K(AM_y), n)))$ is a correlation of meaning AP_1 with meaning AM_y,

Given P_2 (part two of some text):

$C_{2x} = C(F(A, j, D(P_2, n)), F(A, D(K(AM_x), n)))$ is a correlation of meaning AP_2 with meaning AM_x,

$C_{2y} = C(F(A, j, D(P_2, n)), F(A, D(K(AM_y), n)))$ is a correlation of meaning AP_2 with meaning AM_y.

Calculating correlation coefficient differences given different parts of text

Finally we calculate differences between the correlation coefficients which are useful for joke classification as they describe g correlation movement patterns. For example the difference between C_{1x} and C_{1y} tells us which meaning has greater correlation given P1, the first part of the joke, while the difference between C_{1x} and C_{1y} tells us which meaning has greater correlation given the second part . If $C_{1x} - C_{1y} > 0$ then this meaning meaning x is greater than meaning y given part one. On the other hand the difference between C_{1x} and C_{2x} tells us if a correlation coefficient for some meaning has increased or decreased given part on or part two of some text. If $C_{1x} - C_{2x} > 0$ then the correlation of meaning x has decreased as the text is read in while if $C_{1x} - C_{2x} < 0$ then it has increased.

We calculate the differences between C_{1x}, C_{1y}, C_{2x}, and C_{2y}. The difference $C_{1x} - C_{1y}$ shows which meaning correlates higher given the first part of text, $C_{2x} - C_{2y}$ shows which meaning correlates higher given the second part of text, $C_{1x} - C_{2x}$ shows if meaning X correlates higher in the second part of text compared with the first, and

$C_{1y} - C_{2y}$ shows if meaning Y correlates higher in the second part of text compared with the first.

Building Features from correlation coefficient differences given different time steps

We then define four Boolean variables $x_1 - x_4$ using these differences:

$x_1 = 1$ If $C_{1x} > C_{1y}$, else $x_1 = 0$

$x_1 = 1$ means the correlation with meaning X is greater than meaning Y given the first part of the text.

$x_2 = 1$ If $C_{1x} > C_{2x}$, else $x_2 = 0$

$x_2 = 1$ means the correlation with meaning X decreased going from part one to part two of the text

$x_3 = 1$ If $C_{1y} < C_{2y}$, else $x_3 = 0$

$x_3 = 1$ means the correlation with meaning Y increased going from par tone to part two of the text

$x_4 = 1$ If $C_{2x} < C_{2y}$, else $x_4 = 0$

$x_4 = 1$ means the correlation with meaning Y is greater than meaning X given the second part of the text.

Example

Take a two-part garden path joke J with the parts P_1 = fish in tank and P_2 = they drive the tank that contains the ambiguous word $A = tank$. Let $tankM_1$ and $tankM_2$ be the two meanings invoked at different points while reading J, that of an aquarium and that of a vehicle.

P_1=fish in a tank.

P_2=drives the tank

$K(tankM_1)$ = [aquarium, tank]

$K(tankM_2)$ = [vehicle, panzer, tank]

This is a distilled example of the fishtank joke presented in the section 3. In order to concentrate on the issue at hand, i.e. visualizing incongruity and resolution, we reduced many jokes to simplified form.

We establish vectors for the various meanings of tank using data from searches for $P_1, P_2, K(tankM_x)$ and $K(tankM_y)$ and then calculate the correlation coefficients between these meaning vectors. The meanings for 'tank' found in P_1 and P_2 may or may not be the same as M_1 and M_2. According to the distributional hypothesis, which states that similar meanings will have similar contexts, if they are the same then there should be correlation of context. The correlation of context can be found by comparing the vectors of word associations we extracted via web mining.

Frequent words near 'tank' given a search for 'A fish in a tank.' include (fish,0.328), (clean,0.094), (size,0.092), (water,0.088), (mates,0.059), (aquarium,0.053), (gallon,0.034) etc

Frequent words near 'tank' given a search for 'Drives the tank.' incldue (drive,0.125), (driving,0.111), (battle,0.068), (main,0.057), (war,0.052), (light,0.045), (world,0.041) etc

Frequent words near 'tank' given a search for 'Aquarium tank' include (fish,0.369), (aquarium,0.270), (gallon,0.151), (led,0.117), (kit,0.109), (giant,0.083), (ocean,0.083) etc

Frequent words near 'tank' given a search for 'Vehicle tank' include (gas,0.076), (battle,0.073), (main,0.061), (war,0.051), (fuel,0.048), (light,0.045), (world,0.040) etc

We would expect that the first vector, given a search for the first part of the joke, should correlate with the third vector while the second vector, given a search for the second part of the joke, should correlate with the fourth. So we calculate meaning correlations.

Meaning correlation coefficients given P_1:

$C_{1x} = C(F(tank, 5, D(fish\ in\ a\ tank, 10)), F(tank, 5, D([aquarium, tank], 10))) = 0.824$

$C_{1y} = C(F(tank, 5, D(fish\ in\ a\ tank, 10)), F(; tank, 5, D([vehicle, panzer, tank], 10))) = 0.333$

Meaning correlation coefficients given P_2:

$C_{2x} = C(F(tank, 5, D(drives\ the\ tank, 10)), F(tank, 5, D([aquarium, tank], 10))) = 0.389$

$C_{2y} = C(F(tank, 5, D(drives\ the\ tank, 10)), F(tank, 5, D([vehicle, panzer, tank], 10))). = 0.573$

Over the course of a garden path joke there should be a switch in dominant meaning correlation coefficient. Given the first part correlation with meaning X should be greater and given the second part correlation with meaning Y should be greater.

Data Set used in Visualizations

We collected two part jokes of garden path form containing lexical ambiguities and converted them into a simple form by hand as we want to model incongruity rather than focusing on other issues related to parsing text. Algorithmically selecting relevant parts of text P_1 and P_2 from longer texts that contain a lot of additional material is a valid approach but outside the scope of this research. Thus material not relevant to the interpretation of the ambiguous lexical entity was removed. Thus Two fish are in tank becomes a fish in a tank. as the number of fish has little to do with the lexical ambiguity involed in the incongruity we are attempted to model. In order to focus on developing means of visualizing text we let meaning X to be the meaning indicated in the first part of the text and meaning Y to be the secondary meaning.

For each joke we created a non joke of similar form. It contains the same first part but a different non-humorous second part. We strove to change as little as possible, usually only a noun or verb, to preserve the structure of the statement. The following are some examples of jokes and non jokes contained in the data set.

Joke1:

P_1: Two fish are in a tank.

P_2: They drive the tank.

NonJoke1:

P_1: Two fish are in a tank.

P_2: The swim in the tank.

Meaning X search query: Aquarium tank

Meaning Y search query: Panzer tank

Joke2:

P_1: No charge said the bartender..

P_2: To the neutron.

NonJoke2:

P_1: No charge said the bartender.

P_2: To the customer.

Meaning X search query: Cost charge

Meaning Y search query: Electron charge.

Visualization Approach 1. Collocated Paired Coordinates

Our first visualization uses a visualization technique known as collocated paired coordinates [5]. Given some ambiguous element with multiple possible meanings, we plot meaning correlation scores established given a part of text and the various meanings as points on a coordinate graph. The Y axis measures the correlation with meaning Y, while the X axis measures the correlation with meaning X. Each part of text in a sequence results in a point and these points are connected with arrows representing time. This allows us to visualize correlation patterns over time. A garden path jokes which involves a shift from one meaning to the next should form a line moving away from one axis and towards another as the meaning correlation score for one meaning lessens and another meaning increases. In our visualization we set the X axis to measure correlation with the meaning invoked by the first part of the text and the Y axis to measure the correlation with second meaning invoked in the second part of text so that the arrows should all move in the same direction as a meaning shift occurs.

Visualization overview:

For P_1 and P_2 we plot the meaning correlation coefficients given two opposing meanings for some ambiguous word with AM_x and AM_y as points:

The X axis represents correlation with some meaning AM_x.

The Y axis represents correlation with some meaning AM_y

1. Plot a point representing the meaning correlations given P_1.

2 . Plot a coordinate representing the meaning correlations given P_2.

3. Connect via an arrow indicating time.

4. Color-code green if humorous, red if not, and black if unknown.

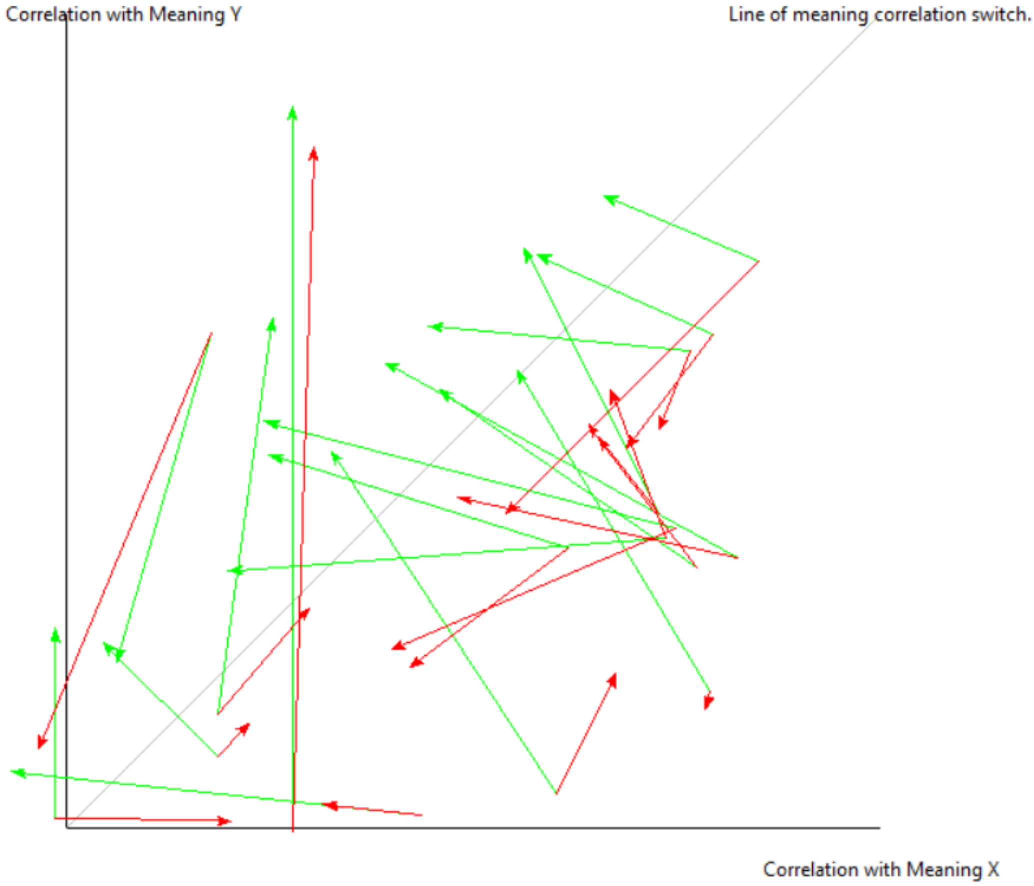


FIGURE 1: Collocated Paired Coordinate Plot of Meaning Context Correlation Over Time. The set of jokes and non jokes plotted as meaning correlation over time using collocated paired coordinates.

Discussion

While there are some examples which fail to match the pattern, it is clear that most jokes involve a shift away from correlation with one meaning and towards the second meaning given part two of the joke. Fig. 1 shows this as the green arrows, representing jokes, move from one axis to another while the red arrows tend to stay closer to the original meaning as there is no meaning change. An analysis of the handful of cases that do not follow this pattern indicates explainable circumstances such as the web search

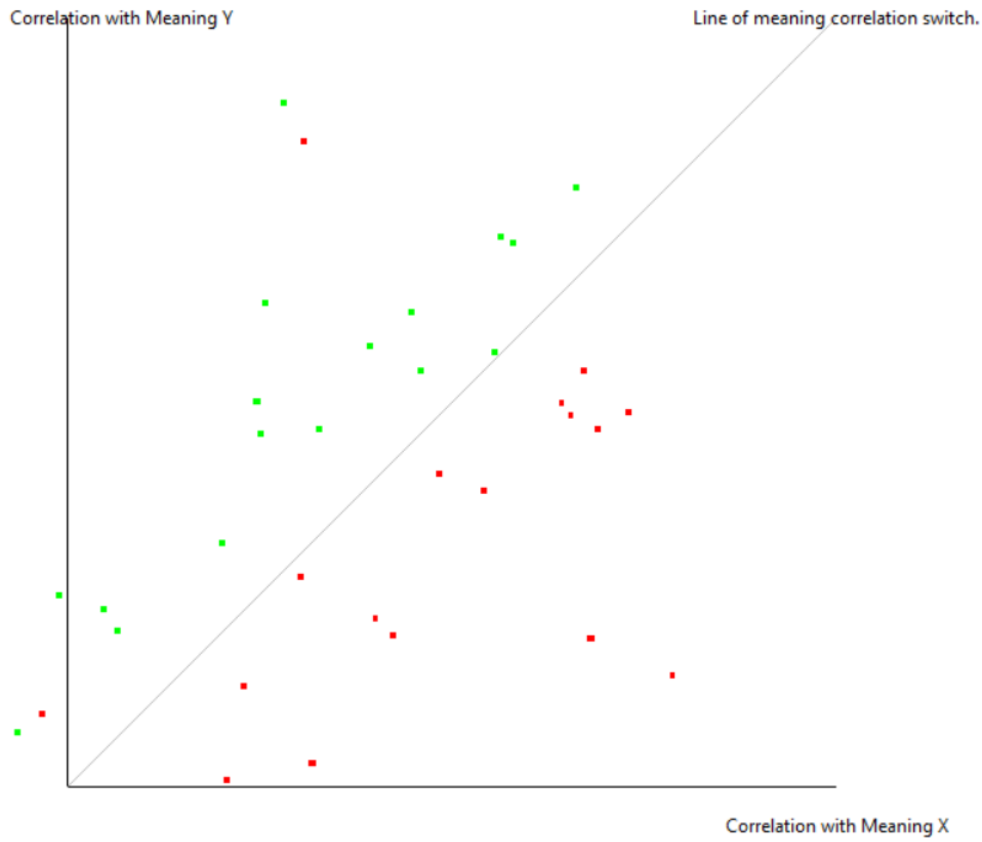


FIGURE 2: Second Endpoint Only. The correlation coefficients given P_2.

returning irrelevant documents due to things like a poor choice in keywords or semantic noise. Methods such as dimensionality reduction including latent semantic analysis may help with this. Fig. 2 only looks at the meaning correlation coefficients given P_2 which clearly shows that there is higher correlation with meaning Y which opposes some meaning X that was initially established.

Visualization 2: Heat Maps

Visualization Overview: In the previous visualization we saw that there is a shift from one meaning correlation being higher to the opposite. To test this intuition we make use of heat maps based on differences in correlation coefficient values given the different meanings and different parts of text. With this approach we can identify potential features that distinguish jokes from non-jokes, assisting in model discovery.

Visualization Algorithm:

1. Organize the correlation coefficient differences as established in Section 4.3 in a data frame along with classification of being a joke or not.

2. Color code the correlation score differences based on value.

3. Sort the rows into groups by classification, that is into two groups of joke and non joke.

4. Identify regions of the heat map where there is a distinguishable difference between the joke and non joke sections in terms of color.

	A	B	C	D
1	name	C1y-C2x	C2x-C2y	class
2	webJoke1	-0.384	-0.012	joke
3	soapJoke1	-0.135	-0.084	joke
4	mouseJoke1	0.039	-0.119	joke
5	terminalJoke1	0.03	-0.129	joke
6	framedJoke1	0.084	-0.138	joke
7	balanceJoke1	-0.2824	-0.1406	joke
8	freeJoke1	0.548	-0.142	joke
9	dogJoke1	0.144	-0.174	joke
10	fishJoke1	-0.056	-0.184	joke
11	chargeJoke1	0.0455	-0.1855	joke
12	chopJoke1	0.096	-0.211	joke
13	potatoJoke1	0.124	-0.256	joke
14	houseJoke1	0.0256	-0.2606	joke
15	bankJoke1	-0.114	-0.375	joke
16	virusJoke1	-0.176	-0.153	joke
17	wavesJoke1	0.158	-0.118	joke
18	catJoke1	-0.283	-0.61	joke
19	webNonjoke1	-0.615	0.639	nonjoke
20	balanceNonJol	-0.635	0.485	nonjoke
21	framedNonjoke	-0.299	0.285	nonjoke
22	dogNonjoke1	-0.139	0.24	nonjoke
23	chopNonJoke1	-0.076	0.224	nonjoke
24	terminalNonjok	-0.08	0.222	nonjoke
25	houseNonjoke	-0.192	0.195	nonjoke
26	potatoNonjoke	-0.03	0.179	nonjoke
27	mouseNonjoke	0.159	0.154	nonjoke
28	soapNonJoke1	-0.318	0.141	nonjoke
29	chargeNonJok	-0.137	0.095	nonjoke
30	fishNonJoke1	-0.146	0.073	nonjoke
31	bankNonjoke1	-0.16	0.027	nonjoke
32	freeNonjoke1	0.645	-0.13	nonjoke
33	catNonjoke1	-0.309	-0.534	nonjoke
34	wavesNonjoke	-0.311	0.128	nonjoke
35	virusNonjoke1	-0.266	0.17	nonJoke

FIGURE 3: Heat Map For Correlation Differences. Column A shows that the first meaning has a higher correlation score than the second given the first part of the joke while Column B show that the second meaning Y has a higher correlation than the first meaning X in the second part of the joke.

Discussion

While this heat map only uses three colors when color coding correlation coefficients by value, clearly we can identify areas where the joke data set differs from the non joke dataset. Lets look at the column representing the difference between $C_{2x} - C_{2y}$. In Fig. 3 this is the column indicating the difference between correlation with meaning X and meaning Y given the second part of the joke. If this value is less than 0 then meaning Y is greater given P_2, if it is greater than 1 then meaning X remains dominant. While we already expected this to happen, the heat map would allow us to automatically identify this value as being a distinguishing feature between classes.

Visualization 3: Visualizing a model space using monotone boolean chain visualizations

In the last viusalization we use a two-dimensional representation of Boolean space based on the plotting of chains of monotonically increasing Boolean vectors [17] to visualize the difference between garden path jokes and non jokes. Vectors are arranged according to their norm, with the all true Boolean vector at one end of the plot and the all false vector at the other. The arrangement of the vectors form chains where monotonicity is preserved, that is as each succeeding vector in the chain is the same as the last except has an additional bit set to one. Each chain describes the change in features. The chains altogether represent a model space based on the Boolean features $x_1 ... x_4$ derived from the meaning correlation coefficient differences described in section 4.4.

Visualization overview:

1. For each joke/nonjoke establish a vector of Boolean values as described in section 4.4.

2. Establish and visualize a 2D Boolean space representation as described in [17].

3. Plot vectors established each joke or non-joke as a dot on the Boolean plot.

4. Color code the dot as green if humorous, red if not humorous.

Fig. 4 and 5 show the resulting visualization using our data set.

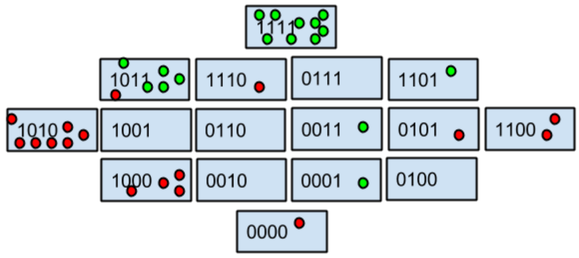


FIGURE 4: Monotone Boolean Plot of Jokes and Non Jokes. Features from the data set of jokes and non jokes describing differences of correlation given different meanings and time steps plotted as Boolean vectors

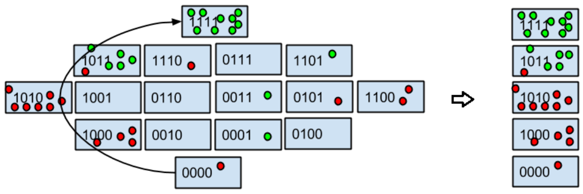


FIGURE 5: Single Chain. Here one chain of monotonically increasing Boolean vectors is isolated to establish a border between humorous and nonhumorous examples in terms of features.

Discussion

Jokes and non jokes can be converted to a vector of Boolean values representing the presence or lack of various features in a such that we can visually distinguish and establish a border between the two classes of humorous and not humorous. By looking at a chains of Boolean vectors that contains examples from each class, each vector containing one additional feature, we can clearly see where non-humorous texts end and humorous ones begin in terms of model features. When looking at chain as shown in Fig. 5 we see that the key difference is the Boolean value which indicates that some second meaning correlated higher than the first given the second part of the text.

Building an expert system from the visualization using visual data mining

We have now visualized the jokes and nonjokes in such a way that we can now build a model. Through a visual inspection of the monotone boolean chain plot we see that jokes fall within areas where the last boolean value is one.

The rules of the system are thus:

If $C_{2x} - C_{2y} < 0$ then the class is humorous.

Comparison with the results using a traditional decision tree based data mining approach

Our analysis of visualizations generated using humorous and non humorous data sets can be compared with the results using traditional data mining approaches. In particular we used a C4.5 decision tree algorithm which resulted in a model indicating the same key features involving changes in meaning correlation as our visualization show.

Resulting C4.5 model:

$IfC_{2x} - C_{2y} < 0.0075$ then class= joke (89.4% of 19 examples) $IfC_{2x} - C_{2y} >= 0.0075$ then class= nonjoke (100.0% of 15 examples)

The C4.5 decision tree results in one key splitting feature which is the same which we found through the visual data mining process. Given a two part garden path joke involving a lexical ambiguity where some meaning for an ambigous word is implied in the first part of the text, another alternate meaning shows higher correlation given the second.

An alternate axis ordering schema: Ordering based on the computer's sequence of interpretations

In the previous visualization we assigned meanings X and Y based on a human reader's sequence of interpretations. This information will not be available to the computer though. In this section we show how the visualizations change if meanings X and Y are ordered based on the computer's sequence of interpretations. The meaning with the higher correlation value given part one of the joke will be assigned to meaning X and the opposing meaning will be assigned to meaning Y.

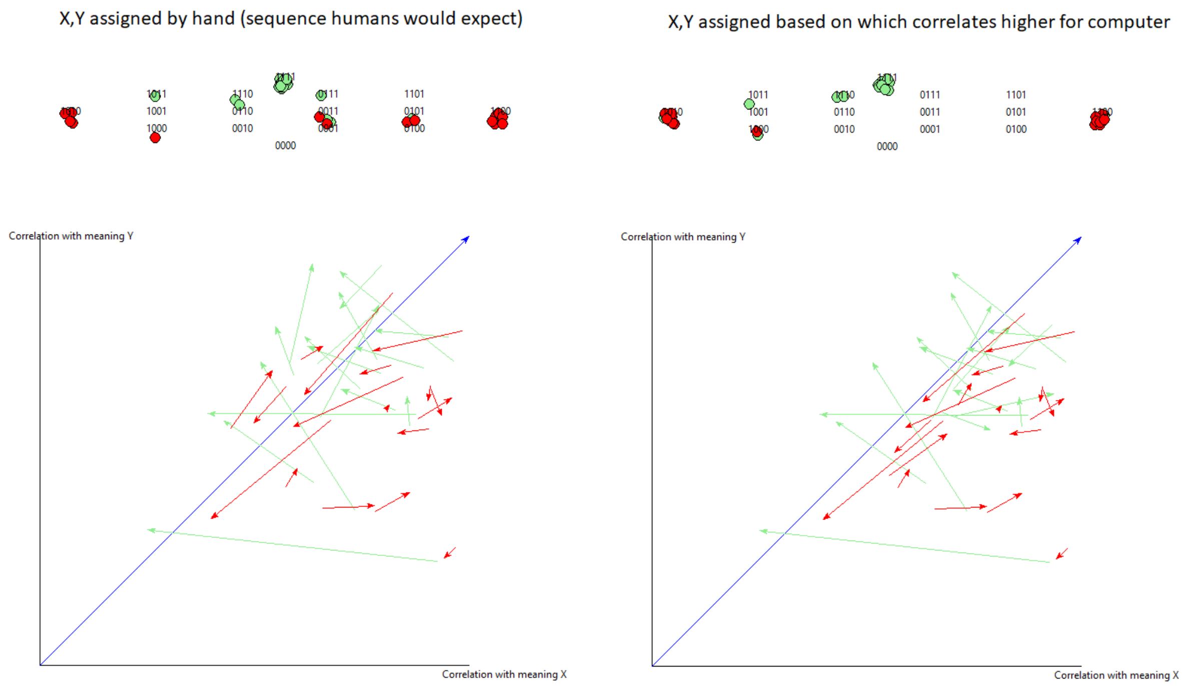


FIGURE 6: Visualization 1 and 3 with both orderings. On the left meaning X and Y are based on the sequence which humans will interpret the meanings while on the right the meanings are ordered based on the computers sequence of interpetation

The addition of the rule which establishes which meaning to assign which axis restricts our potential models. The first boolean value will always be one, thus we can disregard a section of the model space. The rule restricts our model space and we can see this as it moves data points out of that section.

The results with different search parameters, keywords, and search engine

The experiment was run a second time - this time with only 25 sites per search and different keywords using the Google Api rather than Bing. Attached to this thesis is the python scripts and data set used to create this visualization.

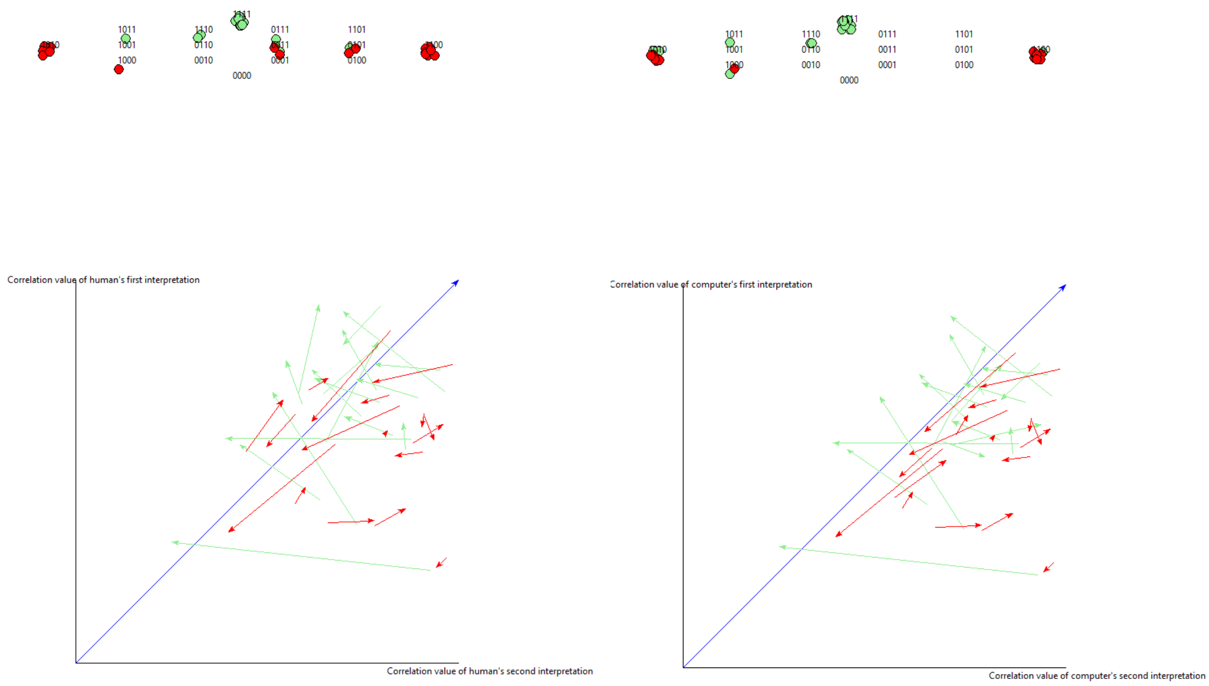


FIGURE 7: Visualization 1 and 3 with both orderings. On the left meaning X and Y are based on the sequence which humans will interpret the meanings while on the right the meanings are ordered based on the computers sequence of interpetation

Discussion

With this second attempt we can see that a number of jokes did not cross the line though you can clearly see the shift. The boolean vector (1,0,1,1) describes shift without crossing the line and a considerable number of jokes plot there. Which model should we use, the one where the is an explicit switch in classification or the one where there is just a significant movement from one class to the other. Ensemble techniques may be interesting by combining the visualizations in a weighted manner based on their accuracy.

CHAPTER V

IMPROVEMENTS TO THE METHOD

Beyond Single Sentence Correlations: Additional Proposed Visualizations

The way correlation with meaning is handled in this data set can be improved since each part of some text may have multiple elements which interact from the ambiguous word in different ways. In collaboration with Boris Kovalerchuk and inspired by the previous visualizations a new visualization was developed which takes into account more complex texts. This visualization also lets us look at shifts with respect to more than two meanings which lets us visualize significantly more data with respect to a joke or non joke.

VIsualizing Shifts in Meaning Given Parts of Text with more than one contextual component

Consider a two part text J.

Each part of text P_i contains some ambiguous word A and two contextual elements P_{i1} and P_{i2}. Let $M_1 ... M_n$ be the different meanings of A. Example: A fish in a saltwater tank. Drives the wartime tank.

A: tank

M_1: vehicle

M_2: aquarium

P_{11}: A fish in

P_{12}: saltwater

P_{21}: drives the

P_{22}: wartime

For each part of the text we use the web search approach to build meaning vectors and calculate the correlation values for each contextual component separately. For example with the first part of the joke we do web search for a fish in a tank and calculate the correlation values for the different meanings and then do the same with a tank full of water. We end up with:

Part one of the joke and meaning 1:

$C(P_{11}, M_1) = C_{111}$ $C(P_{12}, M_1) = C_{121}$

Part two of the joke and meaning 1:

$C(P_{21}, M_1) = C_{211}$ $C(P_{22}, M_1) = C_{221}$

Part one of the joke and meaning 2:

$C(P_{11}, M_2) = C_{112}$ $C(P_{12}, M_2) = C_{122}$

Part two of the joke and meaning 2: $C(P_{21}, M_2) = C_{212}$ $C(P_{22}, M_2) = C_{222}$

Visualization

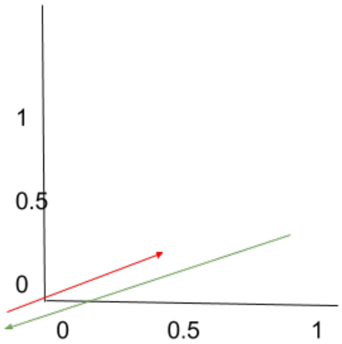
1. Designate the X axis to be the correlation value established using the first contextual component and the Y axis to be the correlation value established using the second contextual component.

2. Plot correlation values with respect to meaning 1 given the first part of a text as a point.

3. Plot the correlation values with respect to meaning 2 given the second part of the text as a point.

4. Connect the points via a line with an arrow indicating time. Results using the humor exploration website to calculate correlation scores.

The resulting visualization:



	Meaning 1 (aquarium)	Meaning 2 (vehicle)
P11 = ‘fish in tank’	0.85	-0.228
P12 = ‘saltwater tank’	0.353	-0.268
P21 = ‘drive the tank’	-0.236	0.462
P22 = ‘wartime tank’	-0.190	0.222

FIGURE 8: Visualizing Shifts in Different Meanings given Jokes With Multiple Contextual Components Per Part. Correlation with the ’vehicle’ while the ’aquarium’ meaning decreases.

Discussion

While the fishtank joke is an ideal candidate for this type of visualization we have shown potential for this new approach. The beauty of this approach is that we can now deal with more than two meanings aside from dealing with more complex jokes. We can add a third arrow for septic tank and a fourth for gas tank and so on.

Automated Keyword Selection

We chose keywords by hand, ones which were representative of the different meanings, but this is not always possible as there are thousands of words in common use. There are a number of methods which could be used to automatically generate the keywords needed to do a disambiguated web search to find document sets. One option are formal and informal ontologies such as Wordnet or OpenCyc. For each word sense wordnet can give you hypernyms and hyponyms, for example the vehicle variant of the word tank has hypernym sets including 'panzer'. We tried out the fishtank joke using the dictionary entries for 'aquarium' and 'tank (vehicle)' and got the same results as using hand selected keywords so it is possible.

An Alternate Means Of Constructing and Assigning Meaning: Semantic Taxonomy Branch Clustering

Problem: Usage of semantic context requires an ontology; in our case web mining is used to establish relations between objects. The problem is that we are trying to deal with inherently ambiguous words thus a web search will result in document sets representing different word senses. The technique used earlier in this paper makes use of disambiguating keywords attached to a search query which allow us to search for documents relevant to a specific word sense. In some cases we do not have a list of disambiguating keywords for a word or even a dictionary entry given new trends.

Solution: Unsupervised learning can be used to cluster semantic data resulting from a web search into meaningful and connected groups. Document clustering has been explored extensively for topic modeling so we are attempting an approach which clusters not documents but rather subtrees of a semantic taxonomy built using web mining. As outlined in [1], recursive construction of a tree based semantic taxonomy using a targeted web search approach really allows us to robustly explore different meaning components in a targeted and isolated manner which reduces the amount of noise and topic mixture for each branch of the taxonomy.

Given a tree based semantic taxonomy built using a web mining approach as described in [1], we can cluster the semantic taxonomy subtrees into meaningful groups representing word sense and usage.

We use the approach described in [1] to build a tree based semantic taxonomy with a depth of 3. The root is an ambiguous word. 15 initial branches represent high frequency bigrams associated with different word senses. Each branch recursively branches 5 ways. Leaves consist of the top 40 keywords given a search for a keyword string formed from the branch path starting at the root.

The resulting 75 leafs keyword sets were then clustered using k-means clustering. I am clustering leaves for now, but whole subtrees could be clustering. I am doing this for time constraints as I could have recursively kept building subtrees but it takes awhile.

Result

Below is a printout of the top four clusters primary keyword sets. We print all keyword which have a centroid value greater than 0.2. We then labeled the clusters by hand.

Cluster number 1 tank top

Significant keywords:// tank, new, top, colors, lace, print, crochet, tops, front, back, neck, shirt, cotton, long, see, size, sleeveless, nursing, basic, nursing_nursing, muscle, added, neckline, white, shop, men, graphic, clothing, related, black, dressy, loose, swim, style, fit, gym, plus_size, plus, comfort, color, colored, wholesale, tunic, tops_wholesale, tops_tops, comfort_tops, colored_tops, cheap, hem, size_tunic, striped, front_plus, hem_plus, ribbed, solid, knit, sheer, love, fashion, fashion_clothing, mesh, top_top, sheer_top, vest, vintage, top_sheer, pink

Cluster number 2 vehicle cluster Significant keywords:

also, tank, used, use, design, new, one, vehicle, main, edit, gun, battle, main_battle, medium, would, heavy, light, first, war, world, best, free, destroyer, us, german, tiger, crew, world_war, production, soviet, type, armor, infantry, armored, development, combat, army, history, could, military, mark, game, tier

Cluster number 3 aquarium cluster Significant keywords: water, also, tank, well, may, new, need, top, fish, one, filter, get, many, size, related, gallon, free, small, aquarium, species, list, acrylic, tropical, large, lighting, gallon_gallon, perfect, ideal, stand, keep, information, led, easy, food, aquarium_aquarium, glass, home, bowl, live, marine, pet, community, kept, make

Cluster number 4 storage tank cluster Significant keywords: water, also, tank, hot, storage, pressure, pump, system, supply, may, used, drinking, use, gas, design, new, potable, need, top, available, fuel, one, bottom, fill, see, air, would, get, size, black, gallon, steel, large, plastic, poly, vertical

Usage for garden path joke detection:

Now that we have an unsupervised method for establishing different meanings for some ambiguous word (as opposed to using disambiguating keywords) that result in clusters of meaning, we can reframe the garden path joke detection problem as a problem of detecting meaning cluster reassignment given clusters of semantic taxonomy subtrees. Clearly the vector associated with fish in tank will be assigned to cluster 3, while the vector associated with military tank will be assigned to cluster 4. Techniques used in the garden path paper can now be used with these new metrics, but rather than meaning correlation we can use distance to cluster center and look at how those distances change over time.

CHAPTER VI

VISUALIZING INCONGRUITY: SHILLING WITHIN PRODUCT REVIEW SETS

A 'shill' is someone, often an company insider or someone who has something to gain, who leaves false reviews for some item. 'shilling' is the act of leaving these reviews. Shilling can occur within product review sets at sites like Amazon.com, during political elections, and is a serious problem on penny stock and cryptocurrency forums. When shilling occurs an incongruity forms - one of sentiment. Positive and negative sentiment generally oppose in that if something is rated high it will not be rated low. When false reviews are left the incongruity forms when these oipposing classes exist simultaneously. As a consumer you must perform some resolution process and decide to ubuy or not.

In this section we use similar forms of visualization that we used for humor to show this incongruity forming. This time rather than plotting 'correlation' of opposing meanings we built a Naive Bayes classifier and plot on one axis the probability of being a positive review and the other axis the probability of being a negative review.

An Experiment Using Toy Data Simulating Shilling

Data set Used

We generated a set of fake movie reviews by hand. The first six are positive sentiment and then the next 6 alternate between positive and negative sentiment simulating a shill.

The Visualization Process

1. Train a Naive Bayes classifier to predict the probability of the text being a positive or negative sentiment text.

Training set used: movie reviews tagged with positive or negative sentiment provided by the NLTK corpus library. [18]

2. For each review in the time series of fake movie reviews:

a. Use the classifier to generate a positive probability and negative probability score.

b. Plot the probabilities as a point using the paired coordinates system but with the addition of a Z axis representing time.

Resulting Visualization

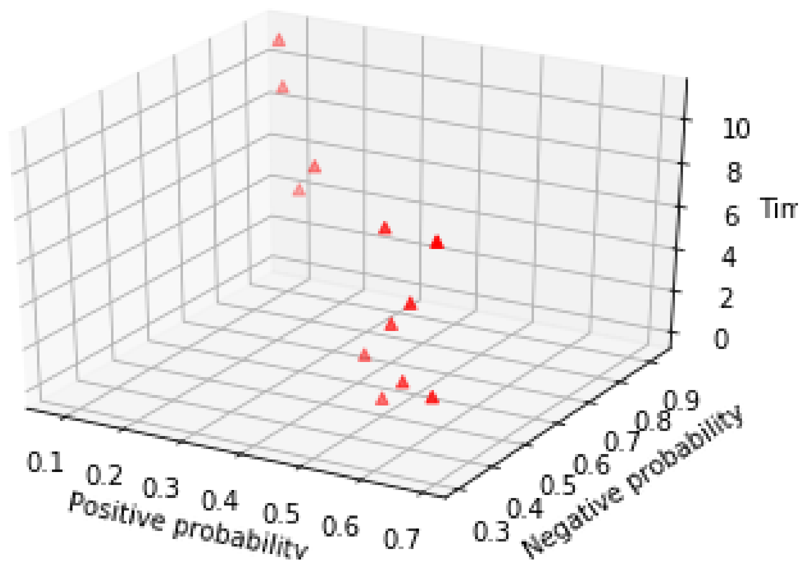


FIGURE 9: Time Series of Movie Review With The Introduction of Shilling. This figure shows the estimated sentiment probability scores for a time series of movie reviews using a Naive Bayes classifier.

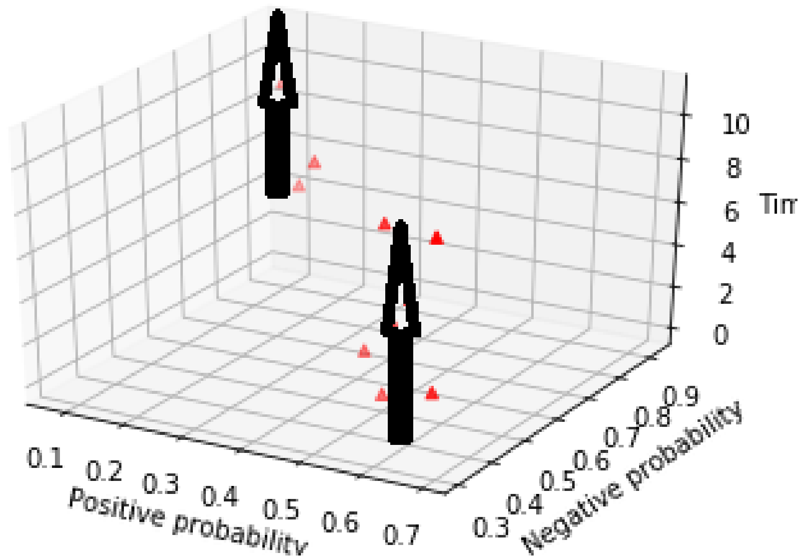


FIGURE 10: Incongruity. When shilling occurs a number of false negative reviews are introduced which oppose the good. We see an incongruity form given the simultaneous presence of the opposing class.

Discussion

Clearly we see the reviews diverge in terms of sentiment. Additionally we see two clusters form, one closer to one class and the other closer to the opposing class. If a movie actually has mixed reviews there would be more mixture. In this case a bimodal distribution forms. This divergence represents and incongruity. Whereas with the garden path visualization we only see the resolution as we don't visualize the stage of humor where the meaing simultaneously exist, in this case we do visualize the incongruiy or simultaneous existence of opposing classes.

One interesting thing to note is that we used a classifier to establish the class probabilities. What type of distance measure we used or the inner workings of the classifier do not matter as long as they work - what matters is the shifts and divergence in sentiment over time. This is a useful way of visualizing phenomena involving patterns of classification.

CHAPTER VII

OTHER USES OF THE VISUALIZATION STRATEGIES

Our project continued with further experiments visualizing incongruities beyond those found in humor. In this section we will look at two of these experiments: visualizing incongruities that form within movie review sets when false reviews are introduced and visualizing the cyclic shifts of emotion given a bipolar author.

Detection of Shifts In Emotion

This sectin looks at another exploration of opposing classification and patterns involving polar shifts. We looked at how the detection and visualization of shifts in emotion over time detected within an authors writing can potentially be used for bipolar detection. First this section will introduce a web mining strategy for obtaining emotionally charged texts, second describe a context based classifier ensemble for emotion detection built using the texts, third and finally will demonstrate its usage for visualizing emotion shifts over time using a positive and negative emotion score coordinate visualization approach toy diaries of bipolar and non bipolar authors

Polar emotion pairs: Emotions can often be grouped into pairings which are communicate whether we are meeting or not meeting some need associated with some internal state. Emotions form a motivational signaling system which both inform us as to our internal need levels associated with some state and motivate us to take action to meet those needs via positive and negative signals. These signals inform us when our behaviors are or are not meeting our needs and guides the evolution of behavioral system. For example when our food levels are low hunger motivates us to find food while satiation tells us we are full. In this case study we will be looking at happiness and sadness levels which are associated with overall meeting of needs and needs being unmet. One can experience multiple emotions as long as they are associated with different internal states and need levels and are not polar pairs.

Mutual exclusion of behaviors given polar emotions: Emotions which are associated with the two poles of some internal need state tend to associate with mutually exclusive behavior. When we are sad we do not engage in behavior when happy and vice versa. Hypothetically there should be a negative correlation between behaviors given two polar emotional states. Through finding orthogonal subsets of behavior we can model differences in emotional state.

Emotional Incongruity and bipolar disorder: A temporal emotional incongruity arises with a bipolar person. Due to differences in brain chemistry they will exhibit polar opposites of behavior given similar contexts. They often cycle through positive and negative moods. The informal hypothesis that temporal incongruity of emotion correlated behavior arises as a bipolar patients cycles through emotional poles. We can test this hypothesis visually using the algorithms used to visualize shifts in meaning presented earlier in this thesis.

Detecting Shifts In Emotion:

This approach is similar to the one we used to detect shifts in meaning.

Rather than looking at some ambiguous word A at some ambiguous indicator of emotion I. For example the words feel, mood, and emotion all indicate that some emotion is being felt but without context the reader does not know which one.

Rather than AM_x which we used to designate some meaning x for the ambiguous word A will call designate IE_x some emotion x for the ambiguous emotion indicator I.

Example: Take for example the word feel. In different emotional contexts you ’feel’ like doing different things. Thus:

I = feel

IM_1 = happy

IM_2 = sad

Web Mining

We mine the web for documents containing some target word within different emotional keyword. For example we want to see what co-occurs with the word ’feel’ in different emotional contexts so we generate the folloing queries.

e1 = happy

e2 = sad

wx = feel

q(e1(wx)) = +happy +feel

q(e2(wx)) = +sad +feel

Visualizing shifts in emotion

Take for example the two part text:

P_1 = I feel like laughing

P_2 = I feel like crying

1. Mine the web for documents containing the target word ’feel’ along with different emotion keywords to find documents relevant to different emotional contexts.

2. Extract frequencies at which words co-occur with the target word. For each document we add a row to a table along with the target emotion label or class.

3. Train a classifier to predict the emotion.

4. Use this classifier to assign emotion scores for a series of texts.

5. Visualize these scores over time using a paired coordinates approach with respect to two different polarly opposed emotions.

Our Classifier of Choice: Decision Trees

Using the count vectors describing n-gram co-occurrence given a search for target phrases along with emotional disambiguators and emotion class labels we trained decision trees using various approaches. Using the sklearn python libraries [19] we tried out several decision tree induction algorithms with various parameters including max depth, minimum leaf size, and n-gram width.

To choose a final classifier we used accuracy on a testing set which was not used during training using a python script.

The best classifier scored 0.74 accuracy on the testing set using bigrams, a max depth of 100 and a minimum leaf size of 2.

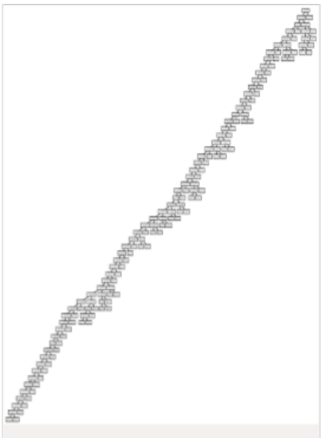


FIGURE 11: The happy/sad emotion classifier. Clearly it is too large to see at this view. The next figure will show just a section.

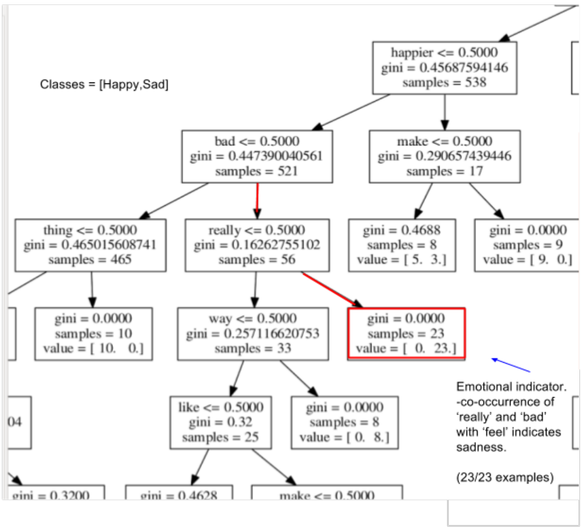


FIGURE 12: One particular branch path indicating sadness.

Third Step: Visualizing emotion assignment scores over time Visualizing patterns of detected emotion over time given polar emotion pairs for exploration of bipolar disorder using collocated paired coordinates with time as a third axis.

Data: Our data set is a hand written toy diary of a bipolar writer to show proof of concept. There will be nuances in real world diaries but in order to focus on initial algorithm development we chose. We wrote these entries without looking at the decision tree model or n-gram sets.

ToyDiary:

d1 = ['feel bad'] d2 = ['feel good'] d3 = ['feel awful'] d4 = ['feel great'] d5 = ['feel like crying'] d6 = ['feel like dancing'] d7 = ['feel sadness'] d8 = ['feel happiness']

Visualization procedure

For each 'feel statement' in the toy diary use the feel classifier to establish emotion scores for the happy/sad emotion pair. For simplicity we only had one contextual component.

Plot each time step as an (x,y,z) coordinate where one axis represents the score for happy and the other sad. Z represents is the time step.

Below is the resulting visualization given our toy diary and emotion detection system:

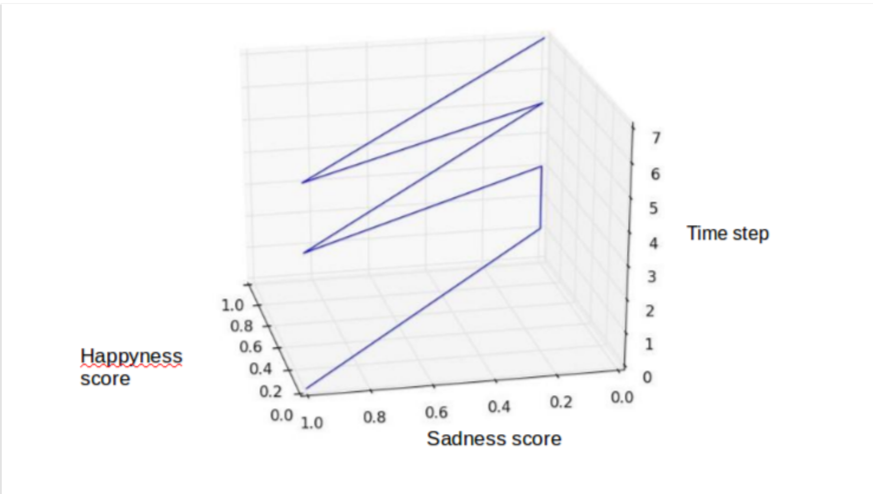


FIGURE 13: Emotion classification over time given an alternating series of happy and sad writings.

Discussion

Whereas in the last section with shilling we plotted class probabilities as points that span a range of possible values adding to one, the decision tree classifier only outputs 0 or 1. A more sophisticated technique could be devleoped which calculates the differrent class leaf counts along the branch path to calculate scores for each class. It still shows we can use this form of visualization to visualize patterns of classification over time associated with phenomena involving shifting and resolution but no incongruity. We see with the toy diary of the bipolar patient there is a cyclic pattern shifting from one opposing state to the other whereas a depressive episode would look different.

CHAPTER VIII

CONCLUSION

Overall the results from this study show that visualization can be used as a valid strategy for approaching the modeling and detection of humor within text as well as other phenomena involving incongruities, characterized by the simultaneous presence of two opposing classifications of state.

The shape of incongruity

Humor theorists argue about how incongruities are formed and resolved. The garden path visualizations clearly shows the resolution that occurs but not the incongruity itself as much as the shilling visualization. The incongruity forms when both meanings are activated, just as with shilling the incongruity foirms when clusters of reviews of opposing sentiment occur simultaneously. We propose that shilling visualization represent incongruity and the the garden path visualization resolution. Incongruity is the stage where the opposing classifications exist simultaneously while resolution comes when one classification occurs. With the garden path jokes we have ’shifting resolution’ which is visualized.

Requirements For The Future

There are several things we would like to see happen. First is the replication of our results using garden path jokes like ours. Development of these very specific data sets, and with them some benchmarks, would be very useful. Second we would like to see the notions of incongruity and resolution formalized both mathematically and visually. We believe there is a shape to incongruity and resolution which is shared by several phenomena that we can capture and make use of. Finally we would like to see continued work on modeling and detecting incongruities beyond humor, both in general and using visualization.

There are many potential uses for visualization and possible studied which could yield interesting results that involve incongruity and resolution. When theorists argue as to some cause incongruities arise within academic document sets. The generation and resolution of these incongruities is how paradigm evolve. Visualization could play an interesting role here. Tasty food involves incongruities, the mind finds the simultaneous presence of opposing tastes and textures appealing, and visualizing recipes using an ontology of tastes and textures might be an interesting way of modeling tastiness. Beyond verbal humor it would be interesting to study nonverbal humor found within comic nonverbal films sequences. With garden path humor of this form the viewer establishes one interpretation but given new clues must establish a new interpretation. In this case computer vision would be needed and our hypothesis is that humorous sequences would involve more scene element misclassifications.

CHAPTER IX

APPENDIX ONE: JOKES AND NON JOKES IN CONDENSED FORM

Jokes

”Two fish are in a tank. One looks to the other and asks: ”how do you drive this thing?””

”I asked the teller at the bank to check my balance, so she pushed me”

”Clean after soap ... addiction.”

”My computer mouse ate some cheese.”

”My computer has a terminal illness.”

”The picture was framed and found guilty.”

”Online on the web the fly got caught up.”

”Are you free for dinner, or will it cost me?”

”The hot dog barked.”

”No charge said the shopkeeper to the neutron.”

”A pork chop is a pig who knows karate”

”We went to the roof as the waiter said it was on the house.”

”A potato that sits around the house is a couch potato.”

”The fish swam by the bank to make a deposit.”

”The computer had a virus. It had malaria.”

”The ocean waves to his friend.”

”I got a cat scan. The cat did not like it.”

Data set of jokes and non jokes after simplifying:

Name, P1, P2, M1, M2, A

Jokes

[”fishJoke”,”fish in a tank”, ”drives the tank”, ”aquarium tank”, ”vehicle tank”, ”tank”],

[”bankJoke”,”check balance at bank”, ”balance when pushed”, ”account balance”, ”stability balance”, ”balance”],

[”soapJoke”,”clean after soap”, ”clean after addiction”, ”wash hands clean”, ”clean and sober”, ”clean”],

[”mouseJoke”,”computer mouse”, ”mouse eats cheese”, ”mouse and keyboard”, ”rodent mouse”, ”mouse”],

[”terminalJoke”,”computer has a terminal”, ”terminal illness”, ”screen terminal”, ”cancer terminal”, ”terminal”],

[”framedJoke”,”picture was framed”, ”framed found guilty”, ”decoration framed”, ”framed go to jail”, ”framed”],

[”webJoke”,”online on the web”, ”fly was caught in a web”, ”web search”, ”spider web”, ”web”],

[”freeJoke”,”are you free for dinner?”, ”free or will it cost me?”, ”free available”, ”free no charge”, ”free”],

[”dogJoke”,”a hot dog”, ”the dog barked”, ”dog and bun”, ”dog and cat”, ”dog”],

[”chargeJoke”,”no charge said the shopkeeper”, ”neutron charge”, ”charge payment”, ”electron charge”, ”charge”],

[”chopJoke”,”pork chop”, ”karate chop”, ”breaded baked chop”, ”martial arts chop”, ”chop”],

[”houseJoke”,”it is on the house”, ”the roof of house”, ”on the house free”, ”construction house”, ”house”], ["potatoJoke","a potato vegetable", "that sits around is a couch potato", "meat and potato", "lazy potato", "potato"],

["bankJoke","the fish swam by the bank", "went to the bank to make a deposit", "bank of a river", "bank account", "bank"],

["virusJoke","the computer had a virus", "malaria virus", "malware virus", "disease virus", "virus"],

["wavesJoke","the ocean waves", "waves to his friend", "water waves", "waves and says hello", "waves"],

["catJoke","got a cat scan", "the cat did not like it", "Computed Axial Tomography cat", "cat and mouse", "cat"]

Non Jokes

["fishNJoke","a fish in a tank", "swims in the tank", "aquarium tank", "vehicle tank", "tank"],

["bankNJoke","check balance at bank", "asked teller to check balance", "account balance", "stability balance", "balance"],

["soapNJoke","clean after soap", "soap and water", "wash hands clean", "clean and sober", "clean"],

["mouseNJoke","computer mouse", "mouse click", "mouse and keyboard", "cat and mouse", "mouse"],

["terminalNJoke","computer has a terminal", "terminal and keyboard", "screen terminal", "cancer terminal", "terminal"],

["framedNJoke","picture was framed", "framed on the wall", "decoration framed", "framed go to jail", "framed"],

["webNJoke","on the web", "web results", "web search", "spider web", "web"],

[”freeNJoke”,”are you free for dinner?”, ”free to meet?”, ”free available”, ”free no charge”, ”free”],

[”dogNJoke”,”eating a hot dog”, ”hot dog with ketchup”, ”dog on a bun”, ”dog and cat”, ”dog”],

[”chargeNJoke”,”no charge said the shopkeeper”, ”free no charge”, ”charge payment”, ”electron charge”, ”charge”],

[”chopNJoke”,”pork chop”, ”pork chop and applesauce”, ”baked chop”, ”martial arts chop”, ”chop”],

[”houseNJoke”,”it is on the house”, ”no charge on the house”, ”on the house free”, ”tiles on the house”, ”house”],

[”potatoNJoke”,”a potato is a vegetable”, ”is a potato used in a stew”, ”meat and potato”, ”lazy potato”, ”potato”],

[”bankNJoke”,”the fish swam by the bank”, ”the bank of the river”, ”stream bank”, ”bank account”, ”bank”],

[”virusNJoke”,”the computer had a virus”, ”computer virus protection”, ”malware virus”, ”disease virus”, ”virus”],

[”wavesNJoke”,”the ocean waves”, ”liquid waves”, ”water waves”, ”waves hello”, ”waves”],

[”catNJoke”,”got a cat scan”, ”cat scan at hospital”, ”Computed Axial Tomography cat”, ”cat and mouse”, ”cat”]

REFERENCES CITED

[1] G. Ritchie, "Developing the incongruity-resolution theory," 1999.

[2] S. J. Simoff, M. H. Böhlen, and A. Mazeika, "Visual data mining: An introduction and overview," in *Visual Data Mining*, pp. 1–12, Springer, 2008.

[3] B. Kovalerchuk and J. Schwing, "Visual and spatial analysis," *Advances In Data Mining, Reasoning, And Problem Solving*, 2005.

[4] M. Dynel, "Garden paths, red lights and crossroads.," *Israeli Journal of Humor Research*, vol. 1, no. 1, p. 289320, 2012.

[5] B. Kovalerchuk, "Visualization of multidimensional data with collocated paired coordinates and general line coordinates," in *IS&T/SPIE Electronic Imaging*, pp. 90170I–90170I, International Society for Optics and Photonics, 2013.

[6] "Jerry m. suls. a two-stage model for the appreciation of jokes and cartoons: an information-processing analysis," 1972.

[7] V. Raskin, *Semantic Mechanisms of Humor.* Studies in Linguistics and Philosophy, Springer Netherlands, 1984.

[8] Y. Wang, "Fuzzy causal patterns of humor and jokes for cognitive and affective computing," *International Journal of Cognitive Informatics and Natural Intelligence (IJCINI)*, vol. 8, no. 2, pp. 34–46, 2014.

[9] R. Navigli, "Word sense disambiguation: A survey," *ACM Comput. Surv.*, vol. 41, pp. 10:1–10:69, Feb. 2009.

[10] Z. S. Harris, "Distributional structure," *¡i¿WORD¡/i¿*, vol. 10, no. 2-3, pp. 146–162, 1954.

[11] A. Rajaraman and J. D. Ullman, "Mining of massive datasets," in *Visual Data Mining*, pp. 1–17, 2011.

[12] I. Labutov and H. Lipson, "Humor as circuits in semantic networks," in *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers-Volume 2*, pp. 150–155, Association for Computational Linguistics, 2012.

[13] S. Petrovic and D. Matthews, "Unsupervised joke generation from big data.," in *ACL (2)*, pp. 228–232, Citeseer, 2013.

[14] A. Kovalerhuck, B Smigaj, "Computing with words beyond quantitative words: Incongruity modeling," in *2015 Annual Conference of the North American Fuzzy Information Processing Society (NAFIPS) held jointly with 2015 5th World Conference on Soft Computing (WConSC)*, pp. 1–6, Aug 2015.

[15] A. Smigaj and B. Kovalerchuk, *Visualizing Incongruity and Resolution: Visual Data Mining Strategies for Modeling Sequential Humor Containing Shifts of Interpretation*, pp. 660–674. Cham: Springer International Publishing, 2017.

[16] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," in *Advances in Neural Information Processing Systems 26* (C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Weinberger, eds.), pp. 3111–3119, Curran Associates, Inc., 2013.

[17] B. Kovalerchuk and F. Delizy, "Visual data mining using monotone boolean functions," in *Visual and Spatial Analysis*, pp. 387–406, Springer, 2004.

[18] S. Bird, "Nltk: the natural language toolkit," in *Proceedings of the COLING/ACL on Interactive presentation sessions*, COLING-ACL '06, (Stroudsburg, PA, USA), pp. 69–72, Association for Computational Linguistics, 2006.

[19] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.