CSE 3021 - SOCIAL AND INFORMATION NETWORKS

PROJECT REPORT

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<u>TOPIC</u>: SENTIMENT ANALYSIS USING EMOTICONS

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ABSTRACT

Emoticons, such as :) ;) :-) and :(, are frequently used online in social media, IM (e.g., Skype), blogs, forums, and other kinds of online social interactions. Because they are commonly used in online communications and they are often direct signals of sentiment, emoticons in text were widely used by NLP researchers in tasks such as sentiment analysis as features to machine learning algorithms or as entries of sentiment lexicons for rule-based approaches. Emoticons (e.g., :) and :( ) have been widely used in sentiment analysis and other NLP tasks as features to machine learning algorithms or as entries of sentiment lexicons. While emoticons are strong and common signals of sentiment expression on social media, the relationship between emoticons and sentiment polarity are not always clear. Thus, any algorithm that deals with sentiment polarity should take emoticons into account but extreme caution should be exercised in which emoticons to depend on. Different online communities and tools may elicit varied degrees of emoticon usage. Twitter, a microblogging site, is one of most popular social media. For researchers and businesses, having access to its huge amount of user-generated data is critical for understanding user behaviour and the sentiment expressed.

In *sentiment analysis*, polarity of sentiment (e.g., positive, negative or neutral) is of particular interest to researchers and business applications. However, the emotions expressed by the emoticons often cannot be captured by the three polarity categories. Many emoticons do not belong to exactly one of the categories. For example, :/ is often used to express an emotional state of annoyed and uneasy, which could be an indication of negative sentiment for some people but neutral for others.

INTRODUCTION

Sentiment Analysis refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. Sentiment analysis is widely applied to voice of the customer materials such as reviews and survey responses, online and social media, and healthcare materials for applications that range from marketing to customer service to clinical medicine.A basic task in sentiment analysis is classifying the polarity of a given text at the document, sentence, or feature/aspect level—whether the expressed opinion in a document, a sentence or an entity feature/aspect is positive, negative, or neutral. Advanced, "beyond polarity" sentiment classification looks, for instance, at emotional states such as "angry", "sad", and "happy".

Precursors to sentimental analysis include the General Inquirer, which provided hints toward quantifying patterns in text and, separately, psychological research that examined a person's psychological state based on analysis of their verbal behaviour.

Subsequently, the method described in a patent by Volcani and Fogel, looked specifically at sentiment and identified individual words and phrases in text with respect to different emotional scales. Many other subsequent efforts were less sophisticated, using a mere polar view of sentiment, from positive to negative, such as work by Turney, and Pang who applied different methods for detecting the polarity of product reviews and movie reviews respectively. This work is at the document level. One can also classify a document's polarity on a multi-way scale, which was attempted by Pang and Snyder among others: Pang and Lee expanded the basic task of classifying a movie review as either positive or negative to predict star ratings on either a 3- or a 4-star scale, while Snyder performed an in-depth analysis of restaurant reviews, predicting ratings for various aspects of the given restaurant, such as the food and atmosphere (on a five-star scale).

First steps to bringing together various approaches—learning, lexical, knowledge-based, etc.—were taken in the 2004 AAAI Spring Symposium where linguists, computer scientists, and other interested researchers first aligned interests and proposed shared tasks.

LITERATURE REVIEW

Sentiment analysis is the multidisciplinary field of study that deals with analyzing people's sentiments, attitudes, emotions and opinions about different entities such as products, services, individuals, companies, organizations, events and topics and includes multiple fields such as natural language processing (NLP), computational linguistics, information retrieval, machine learning and artificial intelligence. It is set of computational and NLP based techniques which could be leveraged in order to extract subjective information in a given text unlike factual information, opinions and sentiments are subjective [1].

Despite the recent surge of interest in sentiment analysis since the term was coined by Nasukawa et al. [2] in 2003, the demand for information on sentiment and opinion during decision-making situations dates back to long before the widespread use of the World Wide Web. Opinions are central to almost all human activities as they could influence our behaviors specially when making a decision.

For example, many of us may have asked their friends to recommend a dishwasher or to explain who they might vote for during elections, or even requested reference letters from colleagues regarding job applications.

Now, opinions and experiences of numerous people that are neither our acquaintances nor professional critics are readily available thanks the Internet and the Web [3]. This is not limited to individuals only; businesses, organizations and companies are also eager to know consumers' opinions about their products and services. In the past, when a business needed consumer opinions, it conducted surveys and opinion polls. Nowadays, one is no longer limited to asking friends and family or conducting surveys for opinions about products; instead one can use volumes of user reviews and discussions in public forums on the Web [1]. Indeed, the Web has dramatically changed the way that people express their opinions about products, services, companies, individuals and social events. There are now many Internet forums, discussion groups, blogs and even micro-blogs that are well suited
for the users to freely post reviews about products and express their views on almost anything online. These users-generated contents and word-of-mouth behavior are sources of information with many immediate and practical applications.

The research on sentiment analysis appeared even earlier than 2003 [4, 5, 6, 7, 8, 9], while there were also some other earlier work [10, 11] on beliefs as frontiers or later work [12, 13, 14, 15, 16, 17, 18, 19] on interpretation of metaphors, sentiment adjectives, subjectivity, view points, affects and related areas [1, 3]. In contrast to the long history of linguistics and NLP, the area of analyzing people's opinions and sentiments has been virtually untrodden before the year 2000. However, since then, the literature witnessed literally hundreds of studies [20, 21, 22, 23, 24, 25, 26, 27, 28] due to several factors, including: (1)the rise of machine learning techniques in natural language processing and information retrieval; (2) access to datasets for training machine learning techniques because of the World Wide Web and specifically review-aggregation Websites, and; (3) realizing the huge applications in industry that the area started to offer [3]. This rapid growth of sentiment analysis and, more importantly its coincidence with the explosive popularity of the social media, have made the sentiment analysis the central point in the social media research [1]. Research on sentiment analysis has been investigated from different perspectives.

Perhaps the most popular perspective is to categorize these studies into three levels, document level, sentence level, and entity and aspect level [1] described as follows:

_ Document level: The aim here is to determine the overall sentiment of an entire document. For example given a product review, the task is to determine whether it expresses positive or negative opinions about the product. This level looks at the document as a single entity, thus it is not extensible to multiple documents.

_ Sentence level: This level of analysis is very close to subjectivity classification and the task at this level is limited to the sentences and their expressed opinions. Specifically, this level determines whether each sentence expresses a positive, negative or neutral opinion.

_ Entity and aspect level: Instead of solely analyzing language constructs (e.g. documents, paragraphs, sentences), this level (a.k.a feature level) provides finer grained analysis for each aspect(or feature) i.e., it directly looks at the opinions for different aspects itself. The aspect-level is more challenging than both document and sentence levels and consists of several sub-problems. It finds different

available sentiment. Sentiment analysis methods could be categorized into two groups, language processing based and application oriented methods. We describe the state-of-the-art approaches in each category and highlight their contributions. Then we conclude this section with a brief overview on visual analytics approaches in sentiment analysis.

PROPOSED METHODOLOGY

- **Data Collection**

Customers usually express their sentiments on public forums like the blogs, discussion boards, product reviews as well as on their private logs – Social network sites like Facebook and Twitter. Opinions and feelings are expressed in different way, with different vocabulary, context of writing, usage of short forms and slang, making the data huge and disorganized. Manual analysis of sentiment data is virtually impossible. Therefore, special programming languages like 'R' are used to process and analyze the data.

- **Text Preparation**

Text preparation refers to the filtering of the extracted data before analysis. It includes identifying and eliminating non-textual content and content that is irrelevant to the area of study from the data.

- **Sentiment Detection**

At this stage, each sentence of the review and opinion is examined for subjectivity. Sentences with subjective expressions are retained and that which conveys objective expressions are discarded. Sentiment analysis is done at different levels using common computational techniques like Unigrams, lemmas, negation and so on.

- **Sentiment Classification**

Sentiments can be broadly classified into two groups, positive and negative. At this stage of sentiment analysis methodology, each subjective sentence detected is classified into groups-positive, negative, good, bad, like, dislike.

- **Presentation of Output**

The main idea of sentiment analysis is to convert unstructured text into meaningful information. After the completion of analysis, the text results are displayed on graphs like pie chart, bar chart and line graphs.

Carrying out sentiment analysis is an important task for all the product and service providers today.

PROCEDURE OF SENTIMENT ANALYSIS

Step 1: Get some sentiment examples

As for every supervised learning problem, the algorithm needs to be trained from labeled examples in order to generalize to new data.

Step 2: Extract features from examples

Transform each example into a feature vector. The simplest way to do it is to have a vector where each dimension represents the frequency of a given word in the document.

Step 3: Train the parameters

This is where your model will learn from the data. There are multiple ways of using features to generate an output, but one of the simplest algorithms is logistic regression. Other well-known algorithms are Naive Bayes, SVM, Decision Trees and Neural Networks, but I'm going to use logistic regression as an example here.
In the simplest form, each feature will be associated with a weight. Let's say the word "love" has a weight equal to +4, "hate" is -10, "the" is 0 ... For a given example, the weights corresponding to the features will be summed, and it will be considered "positive" if the total is > 0, "negative" otherwise. Our model will then try to find the optimal set of weights to maximize the number of examples in our data that are predicted correctly.

If you have more than 2 output classes, for example if you want to classify between "positive", "neutral" and "negative", each feature will have as many weights as there are classes, and the class with the highest weighted feature sum wins.

Step 4: Test the model

After we have trained the parameters to fit the training data, we have to make sure our model generalizes to new data, because it's really easy to overfit. The general way of regularizing the model is to prevent parameters from having extreme values.

Going further

One of the big cons of our model is that it doesn't take into account the order of words in the document, since the feature vector is showing only the frequency of the words. For example, the sentences "good guy beats bad guy" and "bad guy beats good guy" have the same feature representations but have a different sentiment.
One way to overcome this problem is to generate more features, like the frequency of n-grams or the syntactic dependency between words. But my favorite model by Socher et al. takes a completely different approach. It uses the syntactic structure of the document to build up a vector representation by combining recursively the vector representations of words.

APPENDICES (RESULTS, CODE, SNAPSHOTS)

CODE:

```
import nltk
import numpy as np
from sklearn.utils import shuffle
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from sklearn.linear_model import LogisticRegression
from bs4 import BeautifulSoup


ps = PorterStemmer()

positive_reviews = BeautifulSoup(open('positive.review').read())
positive_reviews = positive_reviews.findAll('review_text')

negative_reviews = BeautifulSoup(open('negative.review').read())
negative_reviews = negative_reviews.findAll('review_text')
diff = len(positive_reviews) - len(negative_reviews)
idxs = np.random.choice(len(negative_reviews), size=diff)
extra = [negative_reviews[i] for i in idxs]
negative_reviews += extra

def my_tokenizer(s):
    s = s.lower()
    tokens = nltk.tokenize.word_tokenize(s)
    tokens = [t for t in tokens if len(t) > 2]
    tokens = [ps.stem(t) for t in tokens]
    tokens = [t for t in tokens if t not in set(stopwords.words('english'))]
    return tokens

word_index_map = {}
current_index = 0
orig_reviews = []
```

```
positive_tokenized = []
negative_tokenized = []
for review in positive_reviews:
    orig_reviews.append(review.text)
    tokens = my_tokenizer(review.text)
    positive_tokenized.append(tokens)
    for token in tokens:
        if token not in word_index_map:
            word_index_map[token] = current_index
            current_index += 1

for review in negative_reviews:
    orig_reviews.append(review.text)
    tokens = my_tokenizer(review.text)
    negative_tokenized.append(tokens)
    for token in tokens:
        if token not in word_index_map:
            word_index_map[token] = current_index
            current_index += 1
def tokens_to_vector(tokens, label):
    x = np.zeros(len(word_index_map) + 1)
    for t in tokens:
        i = word_index_map[t]
        x[i] += 1
    x = x / x.sum()
    x[-1] = label
    return x

N = len(positive_tokenized) + len(negative_tokenized)

data = np.zeros((N, len(word_index_map) + 1))
i = 0
for tokens in positive_tokenized:
    xy = tokens_to_vector(tokens, 1)
    data[i,:] = xy
    i += 1

for tokens in negative_tokenized:
    xy = tokens_to_vector(tokens, 0)
    data[i,:] = xy
    i += 1

orig_reviews, data = shuffle(orig_reviews, data)
```

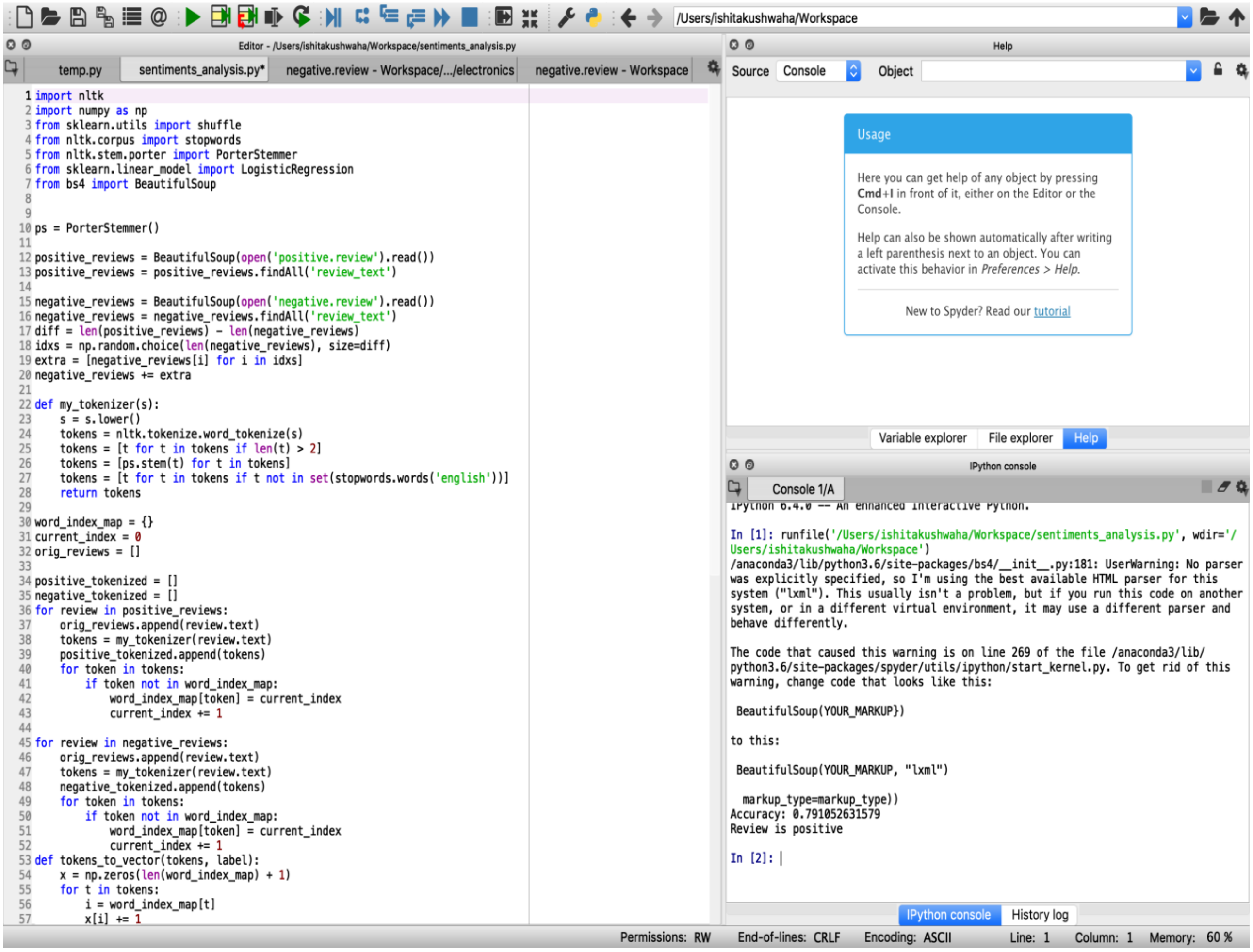
```
x = data[:,:-1]
y = data[:,-1]

Xtrain = x[:-100,]
Ytrain = y[:-100,]

model = LogisticRegression()
model.fit(Xtrain, Ytrain)
print("Accuracy:", model.score(Xtrain, Ytrain))

preds = model.predict(x)
p = model.predict_proba(x)[:,1]
prob = p.sum()/len(p)
if(prob>0.6):
   print("Review is neutral")
elif(0.4<prob<0.6):
   print("Review is positive")
else:
   print("Review is negative”)
```

OUTPUT:


/Users/ishitakushwaha/Workspace
Editor - /Users/ishitakushwaha/Workspace/sentiments_analysis.py
temp.py
sentiments_analysis.py*
negative.review - Workspace/.../electronics
negative.review - Workspace
import nltk
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from sklearn.utils import shuffle
from nltk.corpus import stopwords
from nltk.stem.porter import PorterStemmer
from sklearn.linear_model import LogisticRegression
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negative_tokenized = []
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tokens = my_tokenizer(review.text)
positive_tokenized.append(tokens)
for token in tokens:
if token not in word_index_map:
word_index_map[token] = current_index
current_index += 1
for review in negative_reviews:
orig_reviews.append(review.text)
tokens = my_tokenizer(review.text)
negative_tokenized.append(tokens)
for token in tokens:
if token not in word_index_map:
word_index_map[token] = current_index
current_index += 1
def tokens_to_vector(tokens, label):
x = np.zeros(len(word_index_map) + 1)
for t in tokens:
i = word_index_map[t]
x[i] += 1
Help
Source
Console
Object
Usage
Here you can get help of any object by pressing Cmd+I in front of it, either on the Editor or the Console.
Help can also be shown automatically after writing a left parenthesis next to an object. You can activate this behavior in Preferences > Help.
New to Spyder? Read our tutorial
Variable explorer
File explorer
Help
IPython console
Console 1/A
In [1]: runfile('/Users/ishitakushwaha/Workspace/sentiments_analysis.py', wdir='/Users/ishitakushwaha/Workspace')
/anaconda3/lib/python3.6/site-packages/bs4/__init__.py:181: UserWarning: No parser was explicitly specified, so I'm using the best available HTML parser for this system ("lxml"). This usually isn't a problem, but if you run this code on another system, or in a different virtual environment, it may use a different parser and behave differently.
The code that caused this warning is on line 269 of the file /anaconda3/lib/python3.6/site-packages/spyder/utils/ipython/start_kernel.py. To get rid of this warning, change code that looks like this:
BeautifulSoup(YOUR_MARKUP})
to this:
BeautifulSoup(YOUR_MARKUP, "lxml")
markup_type=markup_type))
Accuracy: 0.791052631579
Review is positive
In [2]:
IPython console
History log
Permissions: RW
End-of-lines: CRLF
Encoding: ASCII
Line: 1
Column: 1
Memory: 60 %

IPython console

Console 1/A

```
IPython 6.4.0 -- An enhanced Interactive Python.

In [1]: runfile('/Users/ishitakushwaha/Workspace/sentiments_analysis.py', wdir='/
Users/ishitakushwaha/Workspace')
/anaconda3/lib/python3.6/site-packages/bs4/__init__.py:181: UserWarning: No parser
was explicitly specified, so I'm using the best available HTML parser for this
system ("lxml"). This usually isn't a problem, but if you run this code on another
system, or in a different virtual environment, it may use a different parser and
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python3.6/site-packages/spyder/utils/ipython/start_kernel.py. To get rid of this
warning, change code that looks like this:

 BeautifulSoup(YOUR_MARKUP})

to this:

 BeautifulSoup(YOUR_MARKUP, "lxml")

  markup_type=markup_type))
Accuracy: 0.791052631579
Review is positive

In [2]:
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<u>LIST OF STOPWORDS</u>

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itself
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myself
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whats
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whos
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CONCLUSION

Sentiment analysis or opinion mining is a field of study that analyzes people's sentiments, attitudes, or emotions towards certain entities. It tackles a fundamental problem of sentiment analysis, sentiment polarity categorization. Online product reviews from Amazon.com are selected as data used for this study. A sentiment polarity categorization process has been proposed along with detailed descriptions of each step. Experiments for both sentence-level categorization and review-level categorization have been performed. We have found the positive and the negative reviews for the products and then trained them for the overall prediction. The overall score can be positive, negative or neutral depending on the number of reviews obtained.

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