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Master's Thesis in Informatics

Deep Learning for Sentiment Analysis

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Deep Learning Methoden für Sentiment Analysis Probleme

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I confirm that this master's thesis in informatics is my own work and I have documented all sources and material used.

Munich, Germany, Ankit Bahuguna
September 15, 2015

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Abstract

Word vector representations or word embeddings, learned using deep neural network models prove extremely useful at capturing semantically similar words and phrases. Recent work in the area, utilize semantic word vector spaces and sentiment compositionality to classify sentiment better. One of the biggest constraints with these methods, is need of manually labeled sentiment for phrases in parse trees of sentences making its use challenging for languages with constrained resources.

Moreover, traditional methods do not efficiently leverage the use of semantic word vector spaces and word context in overall sentiment classification. In this report, we first present a broad overview of the problem, discuss traditional methods and then introduce Deep Learning based methods for Natural Language Processing which help in understanding the problem of Sentiment Analysis, better than traditional methods. Also presented is the analysis of concatenating various word vector representations which do not necessarily require phrase level labeling, comparisons of their results in various experimental configurations and showing improvement over traditional unsupervised baseline methods and state of the art results. In the same experiment, we also explore in-domain, out-of-domain and mixed-domain data towards training these word vectors and show how each one affects sentiment classification.

We also present promising future work, which may lead to better deep neural network based word representations for various NLP tasks.

Contents

1 Introduction

Romance should never begin with sentiment. It should begin with science and end with a settlement. — Oscar Wilde, An Ideal Husband

1.1 Information Gathering, Opinions and Sentiment

"*What other people think*", has been a very important element in the overall decision making process. This is more relevant in the modern era with the explosion of web and internet based services where the people have a new platform where they can voice their opinions and discuss about day to day things. With the advent of this platform, the subjective information too has grown extremely rapidly over the years.

It is interesting to note that social opinion of users impact a large corpus of audience. A simple case example is, that if a product is negatively perceived in the social circles of the internet, it will not be taken positively by a new user who is interested in purchasing the product. Hence, /this also is a tool for organizations to understand how the product is performing in the public. This, has given rise to a new area of study known as social media monitoring and analysis.

In the modern day, organizations have made significant investments to process this vast amount of data and make sense of the important information contained in it, so that they can leverage their products and services and improve their overall user experience or increase chances of making more profit, by identifying key areas which are causing an indirect impact on the overall profit margin. In the modern world, the organizations which makes the best use of data is the clear winner and it also is an opportunity for the researchers working in the area to aggressively pursue new techniques and algorithms which beat the current state of the art systems, giving the organizations slight edge over their competitors, which can in turn bring millions of dollars in revenue.

1.2 Sentiment Analysis: An Introduction

It's well said that the fundamental difference, between a human and a computer is that, the computer doesn't perceive or express emotions. If someday, this barrier can be overcome, then it will be very hard to distinguish a human conversation from a machine conversation. Thus, the broad goal for the study of Sentiment Analysis, is making computers recognize and express emotions.

First, we present some of the common terms, which are regularly used in context of Sentiment Analysis, viz., **opinion**, **sentiment** and **subjectivity** in text. These can be defined in the following manner:

opinion : *A view or judgment formed about something, not necessarily based on fact or knowledge.*

sentiment : *A view or opinion that is held or expressed.*

subjectivity : *Refers to how someone's judgment is shaped by personal opinions and feelings instead of outside influences.*

The term opinion mining appears in a paper by Dave et al. [69] that was published in the proceedings of the 2003 WWW conference. Interestingly, an ideal opinion-mining tool would "process a set of search results for a given item, generating a list of product attributes (quality, features, etc.) and aggregating opinions about each of them (poor, mixed, good)."

The history of the phrase sentiment analysis parallels that of "opinion mining" in certain respects. The term "sentiment" used in reference to the automatic analysis of evaluative text and tracking of the predictive judgments therein appears in 2001 papers by Das and Chen [66] and Tong [296], due to these authors' interest in analyzing market sentiment. It subsequently occurred within 2002 papers by Turney [298] and Pang et al. [235], which were published in the proceedings of the annual meeting of the Association for Computational Linguistics (ACL) and the annual conference on Empirical Methods in Natural Language Processing (EMNLP). These papers really increased the popularity of the term "Sentiment Analysis" in the Natural Language Processing research community. A number of papers mentioning "sentiment analysis" focus on the specific application of classifying reviews as to their polarity (either positive or negative), a fact that appears to have caused some authors to suggest that the phrase refers specifically to this narrowly defined task. However, nowadays many construe the term more broadly to mean the computational treatment of opinion, sentiment, and subjectivity in text.

If we look in a broad view, the terms sentiment analysis and opinion mining roughly imply the same field of study, which itself can be attributed as the sub field of subjectivity analysis. For the sake of simplicity, we will stick to "sentiment analysis" throughout this work.

1.3 Applications

Sentiment without action is the ruin of the soul. — Edward Abbey

There are a number of application areas of this study, although, in the introduction we have mentioned reviews related to websites and products but in general there are many other possibilities. It is because of all the possible applications, there are a good number of small startups to large organizations which have dedicated teams who look into this subject matter and have it as part of their mission statement.

1.3.1 Review-oriented Search Engine

A classic example can be a review oriented search engine. Consider a product search engine which also utilizes the reviews on the products made. And ranks the result based on the positive polarity of the products. Thus, the products which has maximum positive product reviews are ranked higher than the ones which receives lower reviews. This will help a client who is user of the search engine to have high confidence about the kind of products returned. Such a search engine will in a way give an assurance to the customer that the best reviewed product which are socially favorable and appreciated are shown first to the user, hence making it easy to make the final choice of eventually purchasing the product.

1.3.2 Websites which host Reviews

There is a growing number of opinion hosting websites, for example, epinions.com; along with the booming e-commerce industry which showcase products and offers, there are millions of reviews generated every week. Thus, they are a primary playground for sentiment analysis. These can be a good benchmark for the companies to evaluate how the product is performing in the market. By performing a comprehensive analysis of the reviews which are hosted on these websites, the companies get a fair idea about the pros and cons about their product and also about the competitor, and a general sentiment about the public perception can help organizations make important decisions about how to go or not go about the future iterations of the projects. Some organizations, perform a real time analysis, so that if a feature is causing a universal cry, resources can be quickly put together into immediately fixing the issue and thus leveraging overall user experience, leading to a longer user loyalty retention.

1.3.3 Sub-Component Technology

Sentiment analysis can also be used a sub component leveraging the working of another intelligent computational system. One possibility is the augmentation to a *recommendation system*. Thus, a recommendation system will utilize a sentiment analysis system, which can then not recommend products which receive a lot of negative feedback.

Detection of overheated or agnostic language in emails or any other form of communication is another use of subjectivity detection and classification.

In *online systems and display advertisements*, where its required to display advertisements relevant to the content of the web-page and some may contain sensitive material, it always better is such sensitive websites can be recognized in advance. A more sophisticated system can display an advertisement when more positive statements in content are discovered and nix the same when negative statements begin to appear.

Also in *information extraction* which is heavily based on objectivity in text, can leverage subjectivity detection and discard any subjectivity content, thus improving overall quality of information extracted.

Question Answering systems can also be improved, as the opinion oriented questions can be handled differently. These questions differ in the subjective sense and a pre-analysis of the same can be useful to generate better answers. Similarly, *summarization* can also be made useful in the context of the multiple views points.

In the area of citation analysis, where potentially, one can detect whether the citation done by the researcher in his scientific work is a support or a rebuttal of the cited work.

1.3.4 Business and Government Intelligence

Sentiment Analysis is used effectively as a business intelligence tools. The reviews about the product can be indicative directly what is right or wrong about the product or it may be useful to mine the reviews from all the general domains like opinion websites,blogs, public forms and product pages and summarize each f the review entities corresponding to each product thereby giving a consensus of all the key points relevant in the eyes of the users with respect to the product. The data can also determine what are the current trends in the given business category and can be used to leverage the key insights which in-turn can benefit sales.

With a view point of government Intelligence, such a tool can be used to monitor hostile behavior in a communication. This form of government intelligence can help in also beefing up security if a known threat is determined in advance.

1.3.5 Applications across domains

Sentiment Analysis has not only been cherished by computer and data scientists but also in the political circles of the government. It has actually turned out to be a golden tool in political elections. Knowing what the people think about the candidates in a general election can allow a party to choose the right candidate and also work on its shortcomings in due time, to win the ever significant final elections.

Moreover, There are now e-portals which are facilitating *eRuleMaking*, where a new policy is first open to the public and then based on the various opinions of the general public, the decision to move forward and cement the proposed rules into a law or updating its various sections is taken into consideration. This has proved to be an effective tools to iron out any problems which may exist in a proposed law even before its presented to the democratic authority. Thus, saving both time and resources.

1.4 General Challenges

Often a simple question comes to mind, when discussing Sentiment Analysis: *How is it different from classic text mining and fact based analysis?*

Traditionally, text categorization involves categorizing text into categories. These categories can be topics which are either predefined or looked up as more data is processed. These categories can also be user or application specific. And, for a given task, we might be dealing with wither a two class or binary classification or a multi-class classification (say, among thousands of classes). In contrast, with sentiment analysis, we are usually focused with 3 classes: positive, negative or neutral (coarse grained) or, 5 classes: positive, slightly positive, negative, slightly negative and neutral (fine grained). Thus, the number of classification classes are fairly limited and it generalizes well to many information domains and users. moreover the topics or categories can sometimes be highly non-correlated whereas the sentiments classes are often opposite in nature (in case of binary: positive- negative classification.)

Also, there is fundamentally a difference when it comes to answering opinion oriented questions vs fact based questions. The traditional information extraction methods which work well for a number of facts based templates. An opinion oriented information extraction method too will be a generalized version of the traditional system, as they are focused on similar fields of an opinion expression (holder, type and strength) irrespective of the topic. Although, it may seem the propositions presented above may make the task of sentiment analysis relatively easy, but its far from the actual truth. We will learn next about the difficulties in developing sentiment analysis systems, as compared to traditional fact based text analysis systems.

1.4.1 Difficulty in Sentiment Classification?

First, we start with a simple scenario and a connected question: Given, we have an opinionated sentence in some given language, our task is to classify it into one of positive, negative or neutral classes. How hard is this overall task? Let's start with some examples:

1. It was a great restaurant.
2. It should have been a great restaurant.
3. The restaurant was great in that it will make all future meals seem more delicious.
4. Despite a pleasant experience I can't support the many reviews that it was a great restaurant.

First sentence is a positive sentence, implied by "great restaurant", The rest of the sentences are all negative. But there exists a varying degree of negativeness among them. The second sentence with the phrase "should have been" implies the desired result. Which suggests that the restaurant was expected to be better than it actually was. The third sentence is a classic case of saracasm. This is hardest to spot even for humans; On the first glance we might be mistaken to consider this as positive. Sentence 4, started with a positive vibe "pleasant experience", but the reviewer then retracts his support to all the positive reviews made about the restaurants by others, thus making his overall review negative.

These four sentences just provide a glimpse to how hard is to analyze sentiment. Moreover, apart from detecting polarity in subjective sentences, there is something, which is known as beyond polarity analysis, where the task is to detect more expressive features like anger, happiness, sadness and relaxation in text, these too are very hard to predict and are highly context driven. The context may be based on the expression in the sentence or say, in a conversation among two individuals, their relationships between them. For example, the sentence "Your're a Liar!", may mean either positive or negative given the two individuals and their relationships. Like, a candid conversation between a couple, one may take this in positive sense (not always!), but among politicians it certainly means seems negative.

Then there is also a problem of **entity level sentiment** and **domain specificity**. The sentiment of a reviewer of a product may be dependent on individual entities composing a product. Say, for example: A user is writing a review about a **digital camera**:

"I consider this is as a decent looking camera. The lens is of high quality and performs well in low light condition. Although, the flash is timely, it just seems to fade away the colors. There is

also the issue with the battery which only takes about 100-150 photos on full charge, making periodic recharging necessary. Last, the price is the reason, I won't recommend this camera to anyone, because there are other better cameras for the same specs and lower price which are better buy in the category. "

In the above review, the user is highly positive about the looks and lens of the camera. Thus, the review begins on a positive note and then the user comments about the flash, battery and the price, eventually making the review a negative one. This example is essentially useful in understanding the complexity involved in extracting the overall sentiment of a long review. Such long reviews are common in the real world and thus, this task is harder than it seems. Often, in such cases, it's best to understand what entity or sentence contributes the most to overall sentiment. Although, this is easier said than done!

One may, also find that the specific qualities of the entities, which seem good for a certain product may not be good for another. This is where domain specificity is required. For example,

- "**unpredictable**" may be negative in a car review, but positive in a movie review [Turney, ACL2002]

- "**cheap**" may be positive in a travel/lodging review, but negative in a toys review

In this current work, we are more concerned about determining the orientation of an opinionated text. We assume that the sentences which we analyze are subjective in nature and express opinions. If, that were not the case, we wold have to first filter out opinion-centric sentences from the non - opinionated or objective sentences. This type of analysis is more specifically subjectivity analysis and goes beyond the scope of this work. In simple terms, sentiment classification is a sub-field of subjectivity analysis.

Next, we dig deeper into the problem and discuss some relevant methods which have been developed over the years to solve problems related to sentiment classification.

2 Sentiment Analysis

Till now we have studied about Sentiment Analysis with a general perspective. This chapter starts a more computational view of solving this problem. Before we begin discussing various methods, its important to understand the scope of the problem.

2.1 Sentiment Analysis Levels

The sentiment analysis problem is not a single view problem, rather its can be viewed as multi-level problem. They are discussed as follows:

- **Document Level:** Identifying if the *document* (product review, blog-post, forum post etc.) expresses opinions and if they do, classifying them as positive, negative or neutral. this takes into account the overall sentiment expressed by the opinion holder for the whole document.
- **Sentence Level:** Identifying whether a single *sentence* is positive, negative or neutral.
- **Attribute Level:** Extracting the *object attributes* (image quality, zoom size etc.) that are subject of an opinion and the opinion orientation.

  It is important to note here that as the object becomes more granular, the intensity or difficulty of sentiment analysis increases.

2.2 Document-Level Sentiment Analysis

We start with the traditional methods for document analysis sentiment analysis. It's important to keep in mind few assumptions which come along the way.

- The document is opinionated on a single object
- the opinions are from a single opinion holder.

In real world data, these assumptions don't usually hold. But, for the sake of simplicity, we start with them to make the understanding of the methods easy.

Also, more importantly, this analysis is slightly different from the topic based text classification. In topic classification, heavy emphasis is given to the extraction of the topics. Thus, the *topic words* become very important. Whereas, in sentiment classification, the opinion words are more important. For example: wonderful, fabulous and terrible.

So to start with, a naive sentiment classifier can be based on identification and processing of these opinion words. Opinionated words are also known as sentiment words, opinion lexicon, polarity words or opinion bearing words. They are categorized into two types. First, **Base types**, for example:

Positive: wonderful, elegant, amazing

Negative: horrible disgusting poor

Second, Comparative Types, for example: better, worse etc.

2.2.1 Counting Opinion Words

We start with a simple method. We try to count the opinion words in a given document. We are given an opinion word list which have both positive and negative words. And we assign an **orientation score** (-1,1) to all words in this list. Such that,

Positive opinion words (+1): great, amazing, love ...

Negative opinion words (-1): hate, horrible, etc ...

Strength of these words can also be defined [0,1]

Thus the orientation score for the document, is the sum of the orientation scores of all opinion words found. Lets, take an example review and count the opinion words in the same and calculate overall orientation score for that review. Example:

"My Canon Powershot takes **great** pictures! ... My friend had gotten one about a year ago and she **loves** it. So, after seeing her enthusiasm about it I decided to get one and I will never go back to any other camera. I absolutely **love** this camera. I believe that every person on Earth should own one of these. ... It is **amazing**! ... There is not one thing I **hate** about this product, which is strange because I am a very picky person! ..."

Positive Sentiment Words: great (1), love (2) and amazing (1); Total: 4

Negative Sentiment Words: hate (1); Total: 1

Overall Sentiment Orientation for Review = 4-1 = 3 or **Positive Review Overall**!

After looking at this analysis, lets ask ourselves a question. **Is simply counting the opinion words good enough?**

The answer to that is **NO**! Lets' see why. Just take into consideration the last sentence in the above review.

There is **not** one thing I **hate** about this product. → Not Negative!

This is positive sentence overall. Since, we only captured our negative sentiment word **"hate"**, we labeled this sentence as negative, which is not true. Because of the negation indicator "not", the sentiment is reversed as in **not ... hate** ⇒ **like**.. Thus, an important lesson here is that we need to handle negation. A common pattern of analysis is:

"not ... **negative**" → **positive**
"never ... **negative**" → **positive**

Thus, the overall orientation score of the review is 4 +1 = 5 and not 3 as stated previously.

A word of caution: Negation must be handled very carefully! As, "not" in the pattern: "not only ... but also" does not change the orientation.

2.2.2 Rule Based Method

Another method to compute the overall sentiment of a document is through handcrafted rules which are provided by a trained linguist, based on the identification of linguistic phenomenon which determine sentiment for a given language. We first discuss some related terminology:

- **Pattern / Rule:** A sequence of tokens.
- **Token:** An abstraction of a word, represented using lemma, polarity tag or a part of speech tag. There are two special tokens. TOPIC: an attribute (ex. weight, size etc.) and GAP_DIGIT_DIGIT: How many words can be skipping between two tokens to allow more tolerant matching. Ex GAP_1_2
- **Polarity Tag:** positive, negative, neutral, NOT (negation)
- **POS Tag:** NN (Noun), VB (Verb), JJ (Adjective), RB (Adverb), IN (preposition) ...

Examples of some basic opinion rules, Label Sequential Pattern (LSP) Matching:

- Subject like | adore | want | work TOPIC → positive, e.g. – "I like the old camera"

- Subject is | are great | fantastic | simple | easy → positive, e.g. – "This camera is fantastic"
- TOPIC GAP_0_3 NOT work → negative, e.g. – "The new search still does not work"
- Please do NOT VB → negative, e.g. – "Please do not roll out this new search!"
- NOT GAP_0_3 want | think | believe | need | get → negative, e.g. – "I do not want large size pictures in the Gallery window."
- get | bring | give | put | change GAP_0_3 TOPIC GAP_0_3 back → positive – "Please put the old search and browse back!"

Although this method seems to work pretty well, but there is a fundamental limitation in putting it to use at large scale. Any rule based mining methods are computationally expensive. In this case, only a limited number of opinionated words are found and only a limited number of patterns can be created.

Note: There are methods, which are helpful in generation and classification of these sentiment words automatically, but we do not go deeper into the same. For the more curious, some methods which are used for this purpose are discussed in the works of Turney 2002 which make use of PMI (Point-wise Mutual Information), Dictionary based methods (SentiWordnet), Corpus based Methods (which rely on syntactic or co-occurrence patterns in large text corpora) etc.

TODO: Refer several related papers here!

2.2.3 Supervised Machine Learning Techniques

So, far we have seen simple count based and rule based methods. Although these methods are simple to comprehend and implement, they don't scale well for large corpora. So, to achieve an overall improvement, we make use of machine learning. What machine learning allows is to help find the patterns in known set of documents and then apply those patterns learned on new documents. For the case of supervise learning, we require training and testing datasets. And a set of features to represent documents.

In the case of sentiment analysis the final learning goal is to classify sentence into positive, negative or neutral. A very common way to try out this method is on product reviews dataset. In product reviews, we find that the users review by selecting starts [1,5] or thumbs up or down, where 5 or thumbs up means very good rating and 1 or thumbs down represents very low rating. This can be used his review as positive or

negative and use the same as training data. We can then perform sentiment analysis on those reviews which have not been specifically rated by the user.
An important step in the process is representing these reviews in such a way that its consistent and they are also understood by computers alike. This begins with something known as "Feature Extraction". Some general methods are discussed below:

- **Terms and Frequency**
  - Unigram and more general n-grams.
  - Word Position Information
  - Term Frequency - Inverse Document Frequency (TF-IDF) weighting.
- **Part of Speech Tags:** Adjectives are usually important indicators of subjectivity and opinions.
- **Syntactic Dependencies:** The syntactic structure of a sentence can be captured by representing the sentence as a **Syntax Parse Tree**. See Figure 2.1.

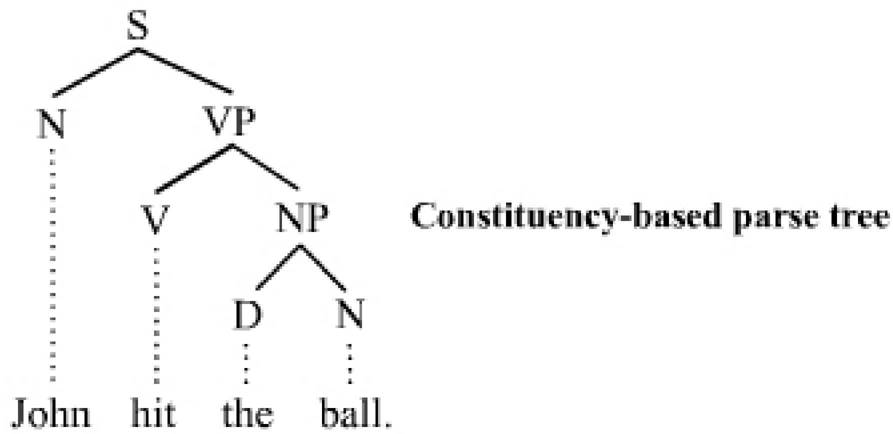

Figure 2.1: Parse Tree for sentence "John hit the ball."

Once we have performed feature extraction, then the next step is to feed the feature input to the machine learning algorithm. There are a number of very successful and efficient supervised machine learning methods. They are described briefly as follows:

- **Naïve Bayes:** A simple probabilistic classifier based on applying the Bayes' theorem with strong (naive) independence assumption.
- **Maximum Entropy (ME):** A probabilistic model that estimates the conditional distribution of the class label

- **Support Vector Machines (SVM)** [Pang et al, EMNLP 2002] A representation of the examples as points in space in which support vectors are computed to provide a best division of points/examples into categories
- **Logistic Regression (LR) Model** [Pang & Lee, ACL 2005] A LR model predicts the classes from a set of variables that may be continuous, discrete, or a mixture.

Since, the topics of this work are focused on exploring unsupervised word representations learned via deep learning and its application to the problem of sentiment analysis, we will not expand this discussion further.

2.2.4 Domain Dependency Problem and Domain Adaptation

When sentiment analysis is performed in real life, a common issue arises. A classifier trained using opinionated documents from domain A often performs poorly when tested on documents from domain B. There are genuine reasons for the same:

1. Reason 1: words used in different domains can be substantially different, e.g.
   - Cars vs. Movies
   - Cameras vs. Strollers
2. Reason 2: some words mean opposite in two domains, e.g.
   - "unpredictable" may be negative in a car review, but positive in a movie review [Turney, ACL2002]
   - "cheap" may be positive in a travel/lodging review, but negative in a toys review

A common way to mitigate this issue is **Domain Adaptation**. It's actually a well studied problem. [Aue & Gamon, RANLP 2005; Blitzer et al, ACL 2007; Yang et al, TREC 2006]. Some of the basic steps involved when perfroming domain adaptation is as follows:

1. Use labeled data from one domain and unlabeled data from both source the target domain and general opinion words as features
2. Choose a set of pivot features which occur frequently in both domains
3. Model correlations between the pivot features and all other features by training linear pivot predictors to predict occurrences of each pivot in the unlabeled data from both domains

Recently, Jochim and Schütze showed improvement in citation polarity classification using product reviews, by making use of Domain Adaptation, their out-of domain data was Amazon's Product Review data-set.

2.3 Sentence-Level Sentiment Analysis

Document level sentiment analysis is too coarse for most applications,☺ or, ☹? Example:

"I bought a new X phone yesterday. The voice quality is **super** and I really **like** it. However, it is a little bit **heavy**. Plus, the key pad is **too soft** and it **doesn't feel comfortable**. I think the image quality is **good** enough but I am **not** sure about the battery life..."

- **Task:** Determine whether a sentence **s** is subjective or objective, and if **s** is subjective, determine whether its orientation is positive or negative
- **Assumptions:** The sentence is opinionated on a single object and the opinion is from a single opinion holder.

It is important to highlight that at sentence level, the syntax becomes of paramount importance. Hence we begin next with understanding syntactic patterns.

2.3.1 Syntactic Pattern Learning

In thier 2003 work, Riloff and Wiebe presented a bootstrapping process that learns linguistically rich extraction patterns for subjective (opinionated) expressions. The proposed process can be explained briefly as follows:

1. Use high precision but low recall classifiers to automatically identify some subjective and objective sentences.
   - A subjective classifier: the sentence contains two or more strong subjective clues
   - An objective classifier: the sentence contains no strong subjective clues
   - Based on manually collected single words and n-grams, which are good subjective clues
2. Learn a set of patterns from subjective and objective sentences identified above
   - Syntactic templates are used to restrict the kinds of patterns to be discovered, e.g. <subject> active-verb ⇒ the customer complained
3. The learned patterns are used to extract more subjective and objective sentences (the process can be repeated)

2.4 Attribute - Level Sentiment Analysis

We have seen from some of the reviews example presented earlier that a positive or a negative labeleed document doesn't imply that the author likes or dislikes all attributes of the product. Thus, an interesting area of study is to analyze what attribute is most positively rated and which one is most negatively rated in a given product review. Also, in a general opinion corpus about a product, another interesting study is the percentage of positive to negative review for a given attribute. This is useful to determine, what exactly about the product do the people love or hate about the product. These attribute can be anything from product properties, the individual components or important topics etc.

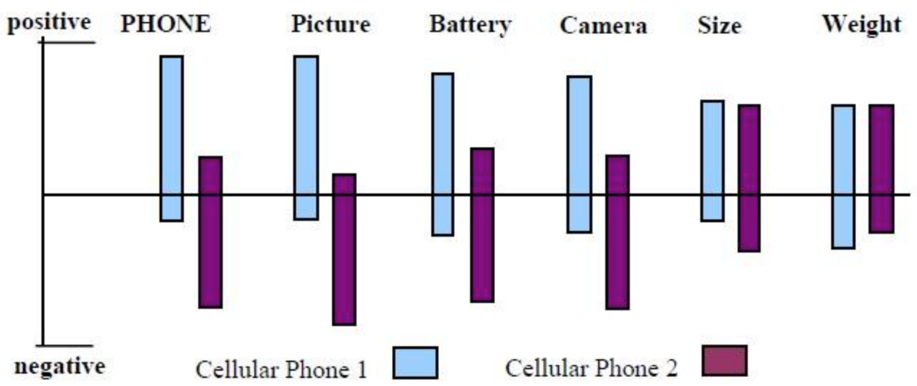

Figure 2.2: Attribute Level Sentiment Analysis Example

The Figure 2.2 shows an example of attribute level sentiment analysis. It displays the comparative analysis of two cellular phone and their individual attributes like positive or negative. Referring to the figure, one can clearly see that Cellphone 1 has overall positive sentiment, and it scores more positively for the attributes: picture, battery and camera. Where as, the size and weight of both the devices has received roughly similar reviews.

Again, there are many methods proposed which allows us to extract these attributes automatically. for the sake of focusing on this work, we will curtail the discussion her.

3 Deep Learning

3.1 Foundations: Neural Networks

3.2 From Neural Networks to Deep Neural Networks

3.3 Applications

4 Deep Learning and NLP: Word Representations and Language Modelling

4.1 Language Modelling

4.2 Word2Vec

4.3 Glove

4.4 Polyglot

4.5 Paragraph Vectors

5 Deep Learning: Modern Apporaches

5.1 RNTN : Recursive Neural Tensor Networks

5.2 MSDA : Marginalized Stacked Denoising Auto Encoders

5.3 CNN : Convoluted Neural Networks

5.4 LSTM : Long and Short Term Memory Networks

5.5 Comparative Evaluation

6 Concatenated Word Representations for Sentiment Classification

6.1 Problem

6.2 Experiments

6.3 Observations

6.4 Result

7 Moving from Text to Speech: Emotion Recognition

7.1 Conventional Methods

7.1.1 GMM: Gaussian Mixture Models

7.1.2 I-Vectors: Total Variability Matrix

7.2 Deep Neural Networks for Emotion Recognition

8 Conclusion

8.1 Section

Citation test [Lam94].

8.1.1 Subsection

See Figure 8.1.

Figure 8.1: An example for a figure.

8.2 Section

See Table 8.1, Figure 8.2, Figure 8.3, Figure 8.4.

Table 8.1: An example for a simple table.

A	B	C	D
1	2	1	2
2	3	2	3

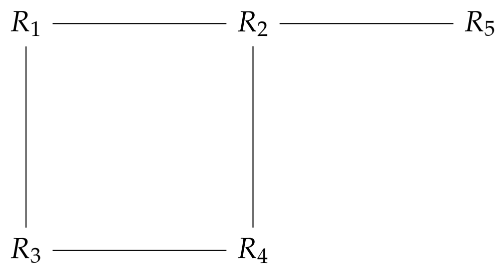

Figure 8.2: An example for a simple drawing.

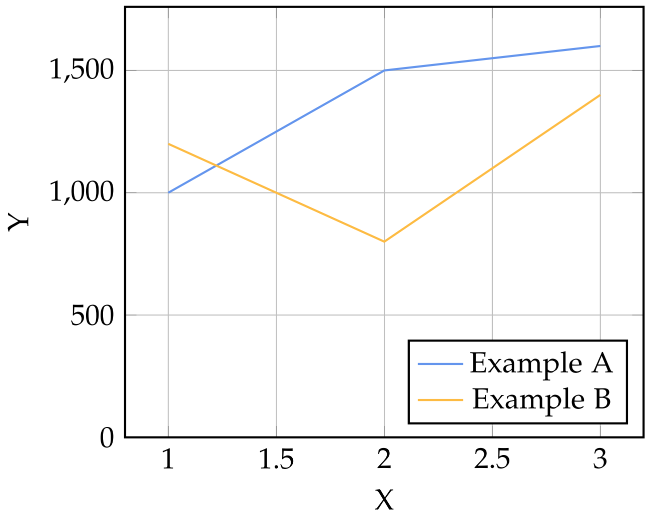

Figure 8.3: An example for a simple plot.

```sql
SELECT * FROM tbl WHERE tbl.str = "str"
```

Figure 8.4: An example for a source code listing.

Glossary

computer is a machine that. . . .

Acronyms

TUM Technische Universität München.

List of Figures

List of Tables

Bibliography

[Lam94] L. Lamport. *LaTeX : A Documentation Preparation System User's Guide and Reference Manual*. Addison-Wesley Professional, 1994.