Rule-based Opinion Target and Aspect Extraction to Acquire Affective Knowledge

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ABSTRACT

Opinion holder and opinion target extraction are among the most popular and challenging problems tackled by opinion mining researchers, recognizing the significant business value of such components and their importance for applications such as media monitoring and Web intelligence. This paper describes an approach that combines opinion target extraction with aspect extraction using syntactic patterns. It expands previous work limited by sentence boundaries and includes a heuristic for anaphora resolution to identify targets across sentences. Furthermore, it demonstrates the application of concepts known from research on open information extraction to the identification of relevant opinion aspects. Qualitative analyses performed on a corpus of 100 000 Amazon product reviews show that the approach is promising. The extracted opinion targets and aspects are useful for enriching common knowledge resources and opinion mining ontologies, and support practitioners and researchers to identify opinions in document collections.

Categories and Subject Descriptors

H.3.1 [**Information Storage and Retrieval**]: Content Analysis and Indexing—*Linguistic processing*; I.2.7 [**Artificial Intelligence**]: Natural Language Processing—*Language parsing and understanding, text analysis*

Keywords

Opinion mining, opinion target extraction, opinion aspect extraction

1. INTRODUCTION

Opinion mining has received ample attention over the last decade, representing a core component of a growing number of trend mining, campaign tracking, reputation management and business intelligence tools. The research area covers several different methods, e.g. polarity classification for assigning polarity labels to documents, sentences, or phrases; emotion analysis for retrieving a person's feelings; and opinion holder and target extraction. The latter is capable of pinpointing targets in opinionated sentences. Simple opinion target extraction approaches classify text snippets and apply the overall sentiment value of these snippets to particular entities, e.g. nouns from a whitelist. Such low-level approaches are easy to implement, but founder on grammatical subtleties. These limitations call for more sophisticated approaches able to properly handle grammatical structures such as methods that rely a sentence's dependency tree.

Another important line of research is the identification of different opinion aspects. A digital camera (the opinion target) might become desirable thanks to its long battery life and the high quality of its photos (positive opinion aspects) but might suffer from the drawback of a high weight (a negative opinion aspect). The identification of such aspects delivers valuable data for the producer of the company. Instead of being overwhelmed and confused by the abundance of positive and negative statements on the Web, such techniques are capable of revealing the reason for a positive or negative statement. A not too recent example is Apple's antenna problem in the iPhone 4. While companies often receive plenty of feedback for popular products, either by angry customers calling their service lines or public media response, they might find it considerably harder to figure out the reasons for a failed product launch, especially if they are not so obvious. Our approach arms every opinion mining toolkit with a powerful mechanism to solve this problem.

In this paper we present an approach for opinion target extraction using syntactic rules. The presented algorithm is based on a subset of the grammar rules defined by [15]. In contrast to the original method, which is limited by sentence boundaries, we utilize heuristic anaphora resolution to identify opinion targets across sentences. A sentiment propagation technique resembling the technique presented in [15] transfers sentiment values from coreferents back to their targets, which allows to determine the sentiment expressed towards a target even if it is not located in the same sentence. In addition, we extend the method for the extraction of opinion targets with an approach for the identification of aspects. Using information extraction patterns in sentences that contain opinion targets we extract these potential aspects. We have assembled a corpus consisting of 100 000 product reviews, which are fully parsed for evaluating our target and aspect extraction approach.

The rest of this paper is structured as follows: Section 2 provides a brief overview of open information extraction and

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summarizes existing target extraction approaches, followed by Section 3 that presents details of the developed algorithms and their integration in a reliable processing pipeline. Section 4 shows targets and aspects extracted by the approach, and presents a qualitative assessment based on a number of example sentences and aggregated results that outline the most popular opinion targets and aspects. Section 5 concludes the paper with a summary and outlook on planned future work.

2. RELATED WORK

The following section summarizes work on open information extraction and subsequently outlines the current state of the art in the extraction of opinion targets.

2.1 Open Information Extraction

Traditionally, open information extraction focuses on the identification of arbitrary and yet unknown relations from extensive Web corpora [4] based on syntactic and lexical constraints such as part-of-speech patterns or heuristic rules regarding the extraction of relevant relations. Such systems usually either start with pre-defined patterns or learn them based on heuristics or training data provided by a supervisor.

The scalability of these methods explains their success on tasks such as the extraction of relations from Wikipedia articles [18], the extraction of common knowledge [10], and the creation of a Wikipedia-based semantic network representing Wikipedia pages as concepts and providing labeled, ontologized relations between these concepts [13].

Fader et al. [5] identify the following shortcomings of current information extraction systems: (i) they often provide uninformative extractions omitting critical information and (ii) tend to yield phrases without meaningful interpretation. The sentence "'The company made a deal with its main competitor" might only yield the relation `company - made - deal` and sentences such as "'Mr Smith's work was central in uncovering the illegal activities of the company's representative" might return the fragment `was central uncovering`.

Current research focuses on combining and supervising the relation extraction process with background data obtained from more structured data sources. For example, Wu and Weld [18] extract such reference data by applying heuristic matching to Wikipedia infobox attributes.

2.2 Opinion Target Extraction

Opinion target approaches usually invoke strong linguistic pre-processing. One way to tackle the problem of opinion target extraction is automatic semantic role labeling. Such an approach yields acceptable results, but requires the integration of other strategies such as anaphora resolution [16]. [7] extract opinion targets on multiple domains using conditional random fields. Their approach exploits several features, e.g. simple tokens, part-of-speech and dependency parsing. Nakagawa et al. [14] apply a similar approach using conditional random fields and dependency parsing to Japanese and English sentences. In [17], Sayeed et al. connect a-priori sentiment terms with their targets using syntactical relations, derived from suffix-tree data structures. A crowd-sourcing approach helps to overcome the common problem of data sparseness. Qiu et al. define syntactic rules to identify opinion targets [15]. Their approach propagates the value from opinion-bearing words to their targets. After target identification their algorithm connects them with further terms within the sentence, given that the target and the new term have a dependency relation specified in a predefined set of relations. Thus, a freshly identified target can transfer its sentiment value onto other terms. The terms identified in this second step can either be new targets or unknown sentiment terms, ready for inclusion into a sentiment lexicon. The approach presented in this paper uses a subset of the rules compiled in [15]. Since we focus on target extraction rather than the identification of new sentiment terms, double-propagation, i.e. the bidirectional transfer of sentiment values onto targets and back to unknown sentiment terms, is not relevant for the work presented in this paper.

Instead we leverage anaphora resolution for target extraction. [8] report a positive influence of anaphora resolution on opinion mining tasks. [3] state that off-the-shelve solutions for anaphora resolution are still sparse. Thus, they extend the MARS [12] and CogNIAC [1] tools and employ them for opinion mining. The presented work uses an approach similar to the one presented by [9].

3. METHODOLOGY

In contrast to traditional open information extraction techniques, the approach presented in this paper focuses on extracting opinion aspects – i.e., the object of the two abstract relations

1. opinion target $\xrightarrow{\text{good thanks to}}$ sentiment aspect, and
2. opinion target $\xrightarrow{\text{bad due to}}$ sentiment aspect.

In other words, we aim at identifying aspects giving hints why the opinion towards the target is positive or negative. The approach consists of two major steps:

- A technique for the propagation of a sentiment charge from a sentiment indicator (i.e. a term from a sentiment lexicon) onto a target. To overcome sentence-boundaries the approach uses a simple heuristic for anaphora resolution.
- An information extraction component allows the discovery of multi-term sentiment aspects, i.e. the objects in the abstract relation above. These sentiment aspects provide reasons for the target's polarity.

The following chapters outline the steps required for the sentiment aspect extraction.

3.1 Preprocessing

We use the heuristic preprocessing component of the webLyzard framework [1] for sentence splitting and tokenization. Subsequently, we label sentiment indicators and determine dependencies with the Stanford parser[2].

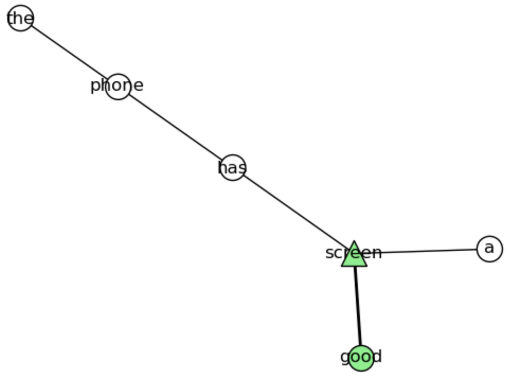
3.2 Cross-sentence sentiment propagation

The sentiment propagation component uses the sentiment annotations and the dependency tree from the preprocessing

[1]www.weblyzard.com

[2]nlp.stanford.edu/software/lex-parser.shtml

Figure 1: Propagation of sentiment charge from a sentiment indicator, in "The phone has a good screen."

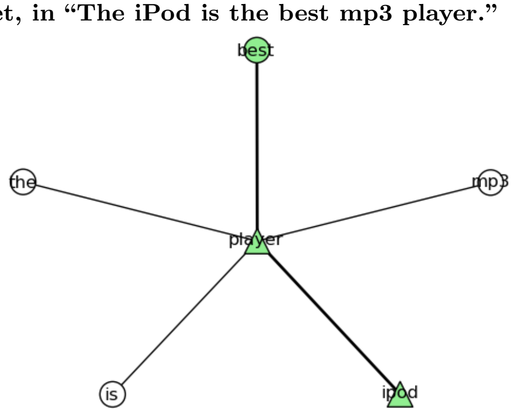


steps and propagates sentiment from the indicators to potential opinion targets. The system uses the first two rules by [15] (single propagation) to identify targets. The first rule propagates a sentiment charge from opinionated terms to noun targets:

$$O \rightarrow O - Dep \rightarrow T, \tag{1}$$

s.t. $O \in \{O\}$, $O{-}Dep \in \{\text{MR}\}$, $POS(\text{T}) \in \{\text{N, NN, NNP}\}$. The application of this rule to the sentence "The phone has a good screen" identifies "good" as an opinionated term and propagates its sentiment charge onto "screen". In other words, "screen" is the target of the "good", as shown in Figure 1.

Figure 2: Propagation of sentiment charge from a target, in "The iPod is the best mp3 player."



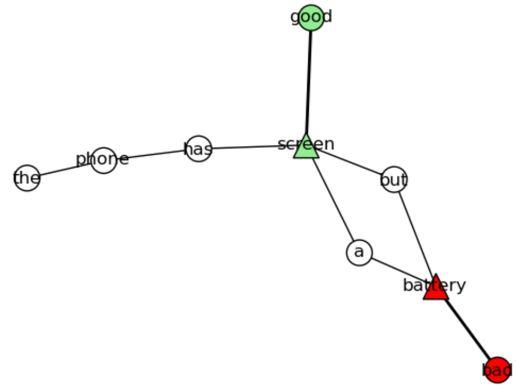
The second rule propagates the sentiment charge of the first identified target onto noun targets in the same sentence:

$$O \rightarrow O - Dep \rightarrow H \leftarrow T - Dep \leftarrow T, \tag{2}$$

s.t. $O \in \{O\}$, $O/T - Dep \in \{\text{MR}\}$, $POS(T) \in \{\text{N}\}$, NN, NNP}; $MR = \{$advmod, amod, rcmod, nsubj, s, obj, obj2, desc, nn$\}$.

With this additional rule, the system is also able to iteratively identify "player" and "ipod" as the targets in the sentence "The iPod is the best mp3 player.", as demonstrated in Figure 2.

Figure 3: Multiple targets with different charge, in "The phone has a good screen but a bad battery."



In contrast to simple opinion target extraction approaches that rely on aggregated sentiment values, this sentiment propagation method is able to differentiate between positive and negative sentiment targets within a sentence.

For instance, the sentence "The phone has a good screen but a bad battery" contains two targets, "screen" (with a positive charge) and "battery" (with a negative charge). The aggregated sentiment value for this sentence is neutral, since "good" and "bad" neutralize each other. Approaches that aggregate the sentiment value over the sentences would, therefore, yield a neutral sentiment for both targets. The rules used in the presented approach provide a solution for this problem. They can easily identify "screen" as the target of "good" and "battery" as the target of bad. Figure 3 shows the graph that corresponds to this example.

The two targets of the previous example, "screen" and "battery", can also be considered as opinion aspects. In this paper we distinguish aspects from targets by the presence of a sentiment indicator in the phrase. We only extract subtle aspect, without an a-priori sentiment charge (e.g. "low weight", "long battery life").

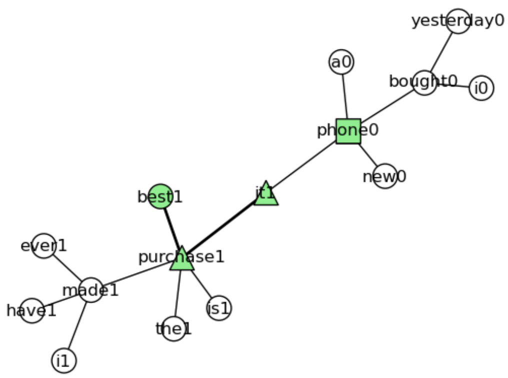
The rules presented above identify several targets within one and the same sentence, but are not able to detect targets across sentences. In the two sentences "Yesterday I bought a new phone. It is the best purchase I have ever made." the noun "phone" is clearly a target with a positive charge, although the first sentence does not contain a sentiment indicator. The sentiment charge comes from the second sentence. The mere application of the two rules (as described in 3.2) cannot identify such targets. To overcome this problem we use a heuristic anaphora resolution that has been inspired by prior work of Lau et al. [9]: in case a sentence starts with a personal pronoun, we assume that this pronoun is connected to the last noun in the previous sentence. For the experiments in this paper we limit personal pronouns to the term "it", since it is particularly relevant in the context of our test corpus. If the pronoun has a sentiment charge (propagated by the rules), we propagate its charge back to the noun of the previous sentence.

The heuristic is capable of identifying coreferents across several sentences. Pronouns at the start of a sentence are connected and receive the sentiment charge from the referring sentence. This strategy is also able to detect ambiguous targets. For instance, an author might write about a target

Table 1: Opinion target extraction patterns for part-of-speech tags. The patterns have been specified using regular expressions.

<table>
<tr><th>Opinion Target Pattern</th><th>Part-of-Speech Pattern</th><th>Description</th></tr>
<tr><td><code>ADJECTIVE* NOUN+</code></td><td><code>(JJ(R|S)?)* (NN(S|PS|P)?)+</code></td><td>adjectival noun phrase</td></tr>
<tr><td><code>ADVERB ADJECTIVE+ NOUN+</code></td><td><code>(RB(R|S)?) (JJ(R|S)?)+ (NN(S|PS|P)?)+</code></td><td>adverbial noun phrases</td></tr>
<tr><td><code>ADJECTIVE* NOUN PREPOSITION \</code>
<code>ADJECTIVE* NOUN+</code></td><td><code>(JJ(R|S)?)* (NN(S|PS|P)? IN) \</code>
<code>(JJ(R|S)?)* (NN(S|PS|P)?)+</code></td><td>extended noun phrase</td></tr>
</table>

Figure 4: Cross sentence propagation in "Yesterday I bought a new phone. It is the best purchase I have ever made."



positively at the beginning of a review and might focus on negative aspects towards the end of the document. Figure 5 illustrates this behaviour. The target "phone" has a positive sentiment repeatedly expressed towards it. However, at the end of the text the author also describes negative aspects of the target, rendering its overall sentiment charge ambiguous.

3.3 Information Extraction Patterns for Sentiment Aspect Extraction

One of the main characteristics of open information extraction approaches is their time complexity of $\leq$O(n) along with a high precision and a rather low recall (due to the use of extraction rules).

Our research applies the philosophy of open information extraction to opinion target extraction. We have identified the following initial part-of-speech patterns for extracting the objects of implicit sentiment aspect relations. (Table 1). The corresponding part-of-speech patterns listed in the table refer to the Penn Treebank II tag sets [11].

We then use the given patterns for combining multiple part-of-speech tags to opinion aspects. For instance, the phrase `ADVERB ADJECTIVE+ NOUN+` yields opinion aspect instances such as *highly efficient battery* or *barely usable software*.

In its current stage, our research focuses on the identification of targets and aspects only, but we plan to extend the information extraction component with an iterative pattern learning algorithm that allows us to discover additional extraction patterns based on the identified sentiment targets.

4. EVALUATION

This chapter provides a qualitative assessment of the opinion target and aspect extraction method. Our experiments draw upon a corpus of of 100 000 Amazon reviews that focus on products from the electronics domain. We consider a star rating below three stars as negative and above three stars as positive. The ratings are distributed equally, i.e. there are 25000 reviews for each star rating except the neutral three stars ratings. We excluded neutral ratings because we expect a more explicit expression of targets and aspects in reviews where the star rating indicates a higher emotive nature.

4.1 Extraction of Opinion Targets

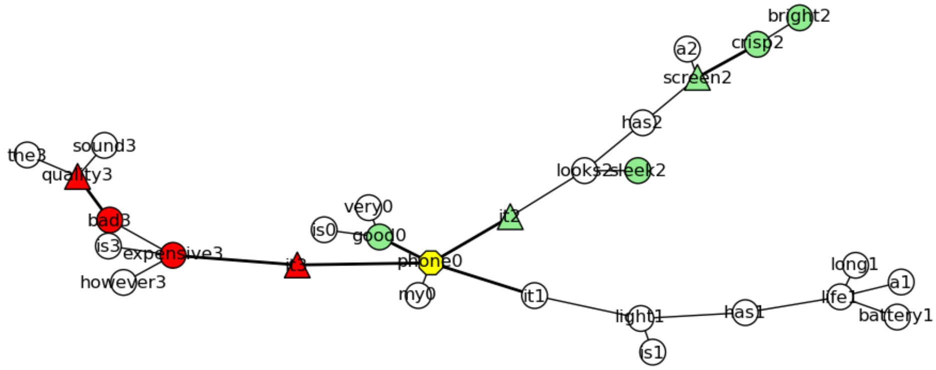
The main reason for applying opinion target extraction is its ability to (i) pinpoint opinion targets and (ii) to summarize the targets in a document collection. We processed the review corpus and applied stopword filtering to its output. This resulted in a list of targets an their frequency in the corpus. Table 2 shows the top 20 targets extracted from the corpus and their corresponding frequencies. Without any further post-processing except for stoplist filtering the terms are meaningful given the domain of the corpus, i.e. electronics reviews from Amazon.

Table 2: The top 20 most frequent positive and negative targets with their respective frequency counts.

Positive targets	Negative targets
quality, 7534	quality, 2708
product, 6429	product, 2227
price, 4486	drive, 2043
sound, 4027	one, 1548
case, 3851	thing, 1505
one, 2350	battery, 1315
thing, 2302	case, 1219
camera, 2258	sound, 1115
picture, 1823	design, 1085
screen, 1805	time, 1072
value, 1624	screen, 1060
cable, 1549	cable, 929
battery, 1547	camera, 906
feature, 1388	unit, 905
device, 1330	software, 715
deal, 1328	price, 712
cover, 1296	something, 689
way, 1293	noise, 642
unit, 1269	plastic, 635
customer, 1230	way, 607

Looking at example sentences revealed both the strengths as well as weaknesses of the presented approach. Table 3 contains a list of sentences where the anaphora heuristic fired. The first three lines contain working examples, whereas the last two lines contain examples showing the

Figure 5: Sentiment propagation across several sentences, exposing the ambiguous polarity of the target "phone"; in "My phone is very good. It is light and has a long battery life. It looks sleek and has a crisp and bright screen. However, it is expensive and the sound quality is bad."



limitation of the heuristic. The first line is an example by an author complaining about a gamepad. While the first sentence contains the sentiment charge in a very subtle way, indiscoverable for the algorithm, the second sentence is more explicit and allows back-propagation using the anaphora heuristic. The second example has a similar structure: the first sentence reveals its sentiment only in a very subtle way whereas the second sentence is far more explicit and thus well-suited for target extraction and sentiment propagation using anaphora resolution.

The third example is worth noting because it shows how the heuristic is able to compensate for the failure of another part of the algorithm. Negation detection is not implemented in that approach, leaving "recommend" untouched and thus ready for propagating a positive value to to "product". However, the system fails to connect these two because of a missing entry in rule dependency set, leaving it neutral where a negative value would have been appropriate. The anaphora heuristic patches this mistake, by back-propagating the negative charge of "waste" onto "product" via "it".

The failed examples in the last two sentences of Table 3 originate from the function of "it" as a dummy pronoun and a placeholder for a noun. Instead of referring to a noun in the previous sentence the function of the pronoun here is merely to provide a noun. The approach cannot detect dummy nouns at the moment but would strongly benefit from the implementation of such a signaling algorithm.

4.2 Extraction of Opinion Aspects

The extraction of opinion aspects focuses on phrases in sentences with opinion targets which do not contain any sentiment indicators themselves. Phrases such as "good battery" or "bad lens" are undeniably aspects as well. However, they can be extracted with the extraction methods presented in Section 3.2. The aspect extraction only focuses on "subtle" phrases, i.e. phrases where no sentiment term indicates its polarity. Table 4 shows sentence examples where the extraction algorithm successfully identified aspect. In the first sentence, the positive target "webcam" has the positive aspect of being able to take "crisp photos". The second line is an example for a negative target: the describing aspect "wimpy feather-weight" serves as an indicator for a low-quality power supply. Aspects are intuitively understandable by humans because of their usage of common sense, but they are hard to assess by computers. Since creating a sentiment lexicon containing all potential aspects for numerous task is far outside the scope of any manual approach, the development of scalable automated methods is highly important to create such language resources.

Table 5 contains a list of the 20 strongest positive and negative aspects. We determine "strength" as the ratio of positive and negative occurrences. Here, the approach reveals its weakness. Whereas the examples for positive aspects are meaningful, the examples for negative aspects seem to be senseless or at least very generic.

Table 5: Top 20 strongest positive and negative aspects

Positive	Negative
sound quality	first time
light weight	first one
sound quality	new one
high quality	other reviews
digital camera	few days
low price	second one
little camera	whole thing
small size	only problem
long battery life	few weeks
remote control	many times
build quality	few months
little device	second time
wide angle lens	big deal
extra money	only reason
audio quality	same thing
spare battery	few minutes
USB port	other reviewers
plus side	few seconds
sound reproduction	other users
video quality	few hours

The current component does not consider negated statements which affects negative sentences, since negative sentiment is often expressed through negation. Another potential reason for the much lower quality of the extracted negative aspects is the strong imbalance between positive and nega-

Table 3: Examples for successful and failed anaphora resolution.

Successful anaphora propagation
I'm playing a lot of Madden NFL 2004 and after every snap my QB moves now to the left even without touching the **pad**. *It* sucks and makes this product useless.
When I bought this Apple charger I thought it was a genuine **product**. However, *it* was fake and a bad one a that.
Bottom line, I wouldn't recommend this **product**. *It* was a waste of money and with only a 30 day warranty, I'm stuck.
Failed anaphora propagation
While this is supposed to be a class 10 card, it's so slow in my digital camera that after taking a pic, it takes an extra sec or two before the **camera** is readied again. It's very surprising, because an older (class unknown) card that I bought 3 years ago didn't have the extra sec or two problem in the same digital camera.
I have examined every possible **aspect** for why it is taking so long for renting/downloading movies. It is absolutely ridiculous...I mean, who gets up in the morning and says "I need to go on Apple TV to rent that movie we want to watch tomorrow night."

Table 4: Example sentences with targets and aspects

Target	Aspect	Sentence
webcam (+)	crisp photos	i love the webcam work really well, clear crips photos.
power supply (-)	wimpy feather-weight	Speaking of power, the Sabrent enclosure comes with a wimpy feather-weight 12V power supply rated at 2A bit I really doubt that is is capable of half that ...
box (+)	effective heat sink	The metal box itself is already a very effective heat sink for the drive.

tive opinion targets. For example, Table 2 shows that the method identified significantly more positive than negative targets. Further experiments will help clarifying this issue and implementing strategies to overcoming this problem (see Section 5). Potential solutions include the refinement of the statistical methods or the inclusion of external resources, such as SenticNet[2], ConceptNet[6], or Freebase.

4.3 Discussion

The qualitative analyses performed in this chapter suggest that the targets and aspects extracted by our approach are intuitive and useful. Future experiments and the inclusion of external knowledge will help to remove existing flaws.

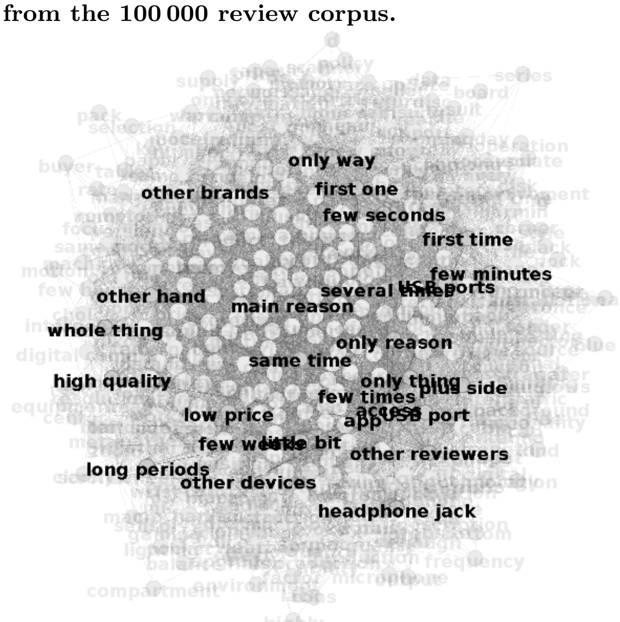
Figure 6 shows a visualization of the relations between opinion targets and aspects that have been extracted from the 100 000 review corpus using the presented method. The extracted relations are well suited for extending language resources with background information on targets and relevant aspects, and for enriching domain-specific ontologies that may be used to support sentiment analysis and target extraction processes.

In addition, the target and aspect extraction provides relations that can be instrumental in summarizing and visualizing the opinions prevailing in documents or document collections.

5. CONCLUSION AND FUTURE WORK

The presented approach uses linguistic rules and anaphora resolution to identify opinion targets in a corpus based on aggregated reviews of electronics products. A subsequent application of part-of-speech information extraction patterns to sentences containing targets reveals aspects of these targets. With this approach we aim at the extraction of subtle aspect without a-priori sentiment charge, such as "long battery life" or "crisp photos".

Figure 6: The target and aspect network extracted from the 100 000 review corpus.



The introduced method yields a network of opinion targets and the corresponding aspects. It facilitates the creation and extension of language resources, and enriches domain-specific ontologies with background information relevant for opinion mining. The extended knowledge resources will contain targets, e.g. products as well as aspects. The aspects, if found in an unknown document, will help to decide if the target obtains a positive or negative sentiment charge. The approach also allows to summarize documents and concisely outline problematic aspects of product. Such a tool is a valuable technique in every toolkit for opinion mining. Future work will focus on optimizing the presented approach by implementing support for the detection of negated statements and providing algorithms for learning aspect extraction patterns based on identified sentiment aspects. From an applied perspective, we plan to use the algorithm across domains and languages. Processing a variety of corpora - e.g., news and social media coverage on political events or tourism destinations - in multiple languages will underscore the generic nature of the approach, and help to evaluate and optimize the underlying methods.

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