

Product Review Summarization: A Multi-Method Combination Approach with Empirical Evaluation

Project Study

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Declaration of Authorship

I hereby declare that the thesis submitted is my own unaided work. All direct or indirect sources used are acknowledged as references.

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List of Abbreviations

ANOVA	Analysis of variance
GAAC	Group Average Agglomerative Clustering
NLP	Natural Language Processing
NLTK	Python Natural Language Toolkit
POS	Part of speech
SVM	Support vector machine
TF-IDF	Term Frequency – Inverse Document Frequency
TF-ISF	Term Frequency – Inverse Sentence Frequency

1 Introduction

Studies have shown that product reviews have a significant influence on the purchase decisions of customers.¹ With Web 2.0 the amount of reviews is increasing day by day, resulting in information overload if one attempts to read them all.² A customer is therefore in a situation where he is not able to read all reviews about a product and instead focuses on a small amount of reviews, leading to a biased und possibly suboptimal purchase decision.³

The market has recognized this problem and more and more shops are using recommender systems⁴ in order to help their customers make a decision. The problem with this is that the customers do not know how these systems work which results in trust issues.⁵ Therefore a different system is needed that helps customers with their need to process the information in product reviews. For this reason, this paper will present a method to automatically summarize reviews of a given product. Customers read reviews to find unique information about products and reduce the risk of their buying decision.⁶ Summarizing the reviews can thus help the customers make better decisions.

Apart from the practical need for this kind of technology, this problem is also interesting from a research perspective as e.g. “product reviews are the key area that benefits from sentiment analysis.”⁷

This work aims to develop an approach that is usable for any kind of product by combining and modifying existing methods together with new ideas for every sub step of the product review summarization process. The resulting methods are empirically evaluated through a survey to show their applicability. In contrast to other papers, the survey also empirically proves the customer benefit provided by review summaries in addition to the above mentioned theoretical argumentation.

The rest of this work is organized as follows: Chapter 2 will explain the theory behind product reviews and the product review summarization process as well as briefly showing related works. The research approach is described in detail in chapter 3. For every sub step of the summarization process, chapter 4 will describe the papers that this work is based on before

¹ cf. Duric;Song (2012), p. 704.

² cf. Baek et al. (2012), p. 99.

³ cf. Bafna;Toshniwal (2013), p. 143 and cf. Hu;Liu (2004a), p. 168.

⁴ See Lu et al. (2015) for a survey about recommender systems.

⁵ cf. Bafna;Toshniwal (2013), p. 143.

⁶ cf. Burton;Khammash (2010), p. 238f.

⁷ Kurian;Asokan (2015), p. 94.

explaining the methods that are proposed in this work. The evaluation of these methods is conducted in chapter 5. Chapter 6 summarizes the results and explains limitations as well as opportunities for further research.

2 Theory and Related Works

Product review summarization is rooted in natural language processing (NLP) and is typically performed in three steps (excluding preprocessing) (Figure 1): extraction of product features/aspects, sentiment analysis/opinion extraction and creation of the final summary.⁸

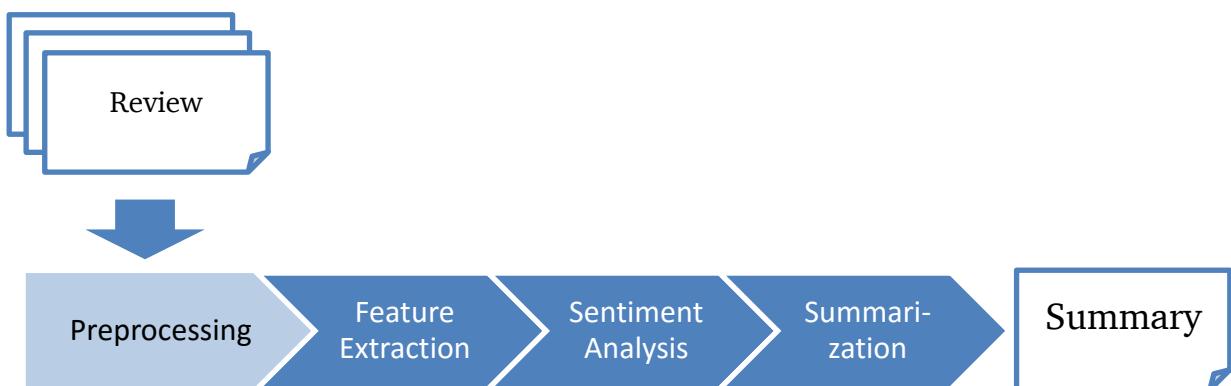


Figure 1: Product Review Summarization Process

The following subsections will briefly describe these steps and the general approaches after describing what a product review actually is.

2.1 Definition and Characteristics of Product Reviews

A “product review” states a user’s opinion about a product and is written by this user. Besides the actual review text explaining e.g. good and bad points about the product, reviews may also contain other elements such as a formal rating of the product on a given score, a count indicating how many other people found the review useful or a link to more information about the review author. As the review text is written by a user, it doesn’t have to follow a specific structure, but may as well be free text. Reviews are for example found in web shops (such as Amazon.com) or other consumer-opinion platforms (like CNet.com).⁹

⁸ cf. Hu;Liu (2004a), p. 168, Wang et al. (2013), p. 28 and Kurian;Asokan (2015), p. 94.

⁹ cf. Burton;Khammash (2010), p. 230f and cf. Baek et al. (2012), p. 99.

User-written reviews are needed because customers may not trust in the information provided by the seller alone when making purchase decisions. Reviews allow finding more detailed information from actual users that may be more relevant than the information provided by the buyer, because customers may perceive them as more trustworthy or because some unique information about a product may only be found there. Thus reviews help customers in their purchase decisions when looking for information about a product or when evaluating alternatives. The aim of reading reviews is to reduce the risk associated with a buying decision and to decrease the necessary time to find the important information about a product. Normally, several reviews are read in order to reduce the risk of being misled by individual sources. But reviews are also a good way for sellers for gaining consumer trust as reviews can indicate that the seller's description is correct. A review is considered to be good if it is subjective (reflecting the real opinion of the writer), readable and linguistically correct.¹⁰

Reviews generally describe both positive and negative parts of a product. Because they are written by humans, a single word in a sentence may influence the meaning of the whole sentence (e.g. a sentence beginning with "but" voids the negative aspects described in the sentence directly before). Furthermore, different terms (synonyms) may be used when talking about the same product aspect. Another characteristic of some reviews is that they provide an overall positive opinion, but start by stating a lot of negative opinions first. After that, it is explained why the negative points are not valid.¹¹

As stated before, the topic of a review is a specific product. Many taxonomies for classifying products exist in literature. One such taxonomy distinguishes between "content-driven" products like books or movies and "use-driven" products like cameras, smartphones or TVs. One of the main differences between these two types of products is that the evaluation of "content-driven" products is very subjective while "use-driven" products can be objectively judged to some degree.¹²

2.2 Product Feature Extraction

A "product feature" or "product aspect" is a component or an attribute of a certain product. For example, features of a smartphone include the battery, the camera and the price. A

¹⁰ cf. Burton;Khammash (2010), p. 233f, 238f and cf. Baek et al. (2012), p. 99f.

¹¹ cf. Najmi et al. (2015), p. 844.

¹² cf. Ibid., p. 847.

product may have a lot of features, some being more important for customers when making a buying decision than others.¹³

“Product Feature Extraction” is the process of extracting the product features from review texts. It is therefore a form of information extraction that aims to extract specific information (the product features) from text documents (the product reviews).¹⁴

There are two broad classes of feature extraction approaches: supervised and unsupervised methods. The difference between those two is that supervised methods need labeled training data. The training reviews are used to train a machine-learning algorithm to become able to extract product features from new reviews. Although supervised methods can be reasonably effective, the result greatly depends on the quality of the training data, but labeling training data is highly time-consuming. Moreover, because of the necessity of training data, supervised methods are often domain-dependent. Unsupervised methods on the other hand rely on heuristics and rules without the need for additional training data and are therefore more flexible.¹⁵

Past studies have shown that product features are generally nouns or noun phrases found in the review bodies. Because of this, a lot of approaches use part-of-speech tagging (apart from other preprocessing like stop word removal, stemming and tokenization¹⁶) in order to extract the nouns and noun phrases.¹⁷

One of the most cited unsupervised approach was developed by Hu and Liu (2004) and further enhanced by Wei et al. (2010) and Bafna and Toshniwal (2013):¹⁸ First, association mining is used in order to find frequently occurring nouns or noun phrases. Second, this initial item list is then pruned in order to remove items that are likely meaningless (compactness pruning; based on the distance between nouns) and lexically subsumed by others (redundancy pruning). Third, infrequent features are discovered by assigning the nearest noun as the product feature to an adjective in a sentence without a frequent feature (see section 2.3 for the rationale behind focusing on adjectives). Wei et al. (2010) enhanced this approach using a manually crafted list of adjectives for a semantic analysis of the reviews to further prune the feature list (features should appear together with adjectives). The

¹³ cf. Zha et al. (2014), p. 1211 and Zhang et al. (2012), p. 10283.

¹⁴ cf. Hotho et al. (2005), p. 5.

¹⁵ cf. Wei et al. (2010), p. 152f and Khan et al. (2013), p. 344

¹⁶ See section 4.1 for an explanation for these preprocessing steps.

¹⁷ cf. Zha et al. (2014), p. 1213, Wang et al. (2013), p. 28 and Hu;Liu (2004b), p. 756ff.

¹⁸ See the following papers for all details: Hu;Liu (2004a), Hu;Liu (2004b), Wei et al. (2010) and Bafna;Toshniwal (2013).

infrequent feature discovery is also improved by using a more sophisticated rule for the assignment of adjective to noun. Bafna and Toshiwal (2013) on the other hand use a probabilistic approach to improve the feature extraction with the assumption that nouns and noun phrases corresponding to product features of a given domain have a higher probability of occurrence in a document of the this domain than in a document of another domain. Further approaches that are used as the basis for this work's approach are described in section 4.2.

A great problem for feature extraction methods are implicit product features and irony.¹⁹ An explicit product feature is a feature whose name (or synonym) appears directly in a sentence. In contrast, implicit feature don't appear directly in a sentence, but can be inferred from the sentence's meaning.²⁰ Example:

- Explicit feature “price”: The price is very low.
- Implicit feature “price”: This product costs only 20 Dollars is therefore very cheap.

Both these sentences talk about the product price. In the first sentence, the feature name “price” directly appears making “price” an explicit feature in this sentence whereas in the second sentence “price” does not appear. Only the word “cheap” and the mentioning of the 20 Dollars make it clear that this sentence talks about the price, making “price” an implicit feature in this case.²¹

This work does not specifically handle implicit product features, but as proven further below, still manages to extract some of them. Irony is not considered in this work.

2.3 Sentiment Analysis

The problem of **sentiment analysis** (sometimes also called opinion mining, appraisal extraction or attitude analysis) consists of detecting whether a given text represents a positive or negative (or neutral) opinion.²² An “**opinion**” is a sentiment, view, attitude, emotion or appraisal about an entity such as a product, a person or a topic or an aspect of that entity from a user or a group of users.²³ When analyzing the sentiment, “**opinion words**” that are

¹⁹ cf. Zhang et al. (2012), p. 10284 and Reyes;Rosso (2012) p, 754ff.

²⁰ cf. Zhang et al. (2012), p. 10283f.

²¹ Note that the mentioning of the 20 Dollars is necessary to establish the context of “cheap” as the price in this example. Otherwise “cheap” could also mean “bad quality”.

²² cf. Medhat et al. (2014), p. 1093f and Ravi;Ravi (2015, in press), p. 1.

²³ cf. Serrano-Guerrero et al. (2015), p. 19.

usually used to express an opinion are examined.²⁴ Most approaches in literature focus on adjective and adverbs as opinion words²⁵, but generally verbs and nouns may also carry sentiment.²⁶

Sentiment analysis can be performed on three different levels of a document: (1) “**Document-level sentiment analysis**” aims to classify a whole document as expressing a positive or negative opinion. (2) “**Sentence-level sentiment analysis**” analyses each sentence of a document individually regarding whether the sentence expresses a positive or negative opinion. In order to do that, it has to be determined first, if the sentence is objective and therefore expresses no opinion or if it is subjective. As sentences can be regarded as small documents, there is no fundamental difference between document-level and sentence-level sentiment analysis. (3) “**Aspect-level sentiment analysis**” aims at classifying sentiment with respect to specific aspects or features of a document. For this, the features have to be identified first. Sentiment analysis with respect to product features is an example for aspect-level sentiment analysis.²⁷

The two main approaches for this task are the “lexical/lexicon-based approach” and the “machine learning approach”: In the **lexicon-based approach** a list of words with known polarity is used. Difficulty arises from complex sentences that contain negation or “but”-clauses. On the other hand, **machine learning approaches** use tagged training data together with a series of feature vectors in order to infer a model that can then be used on new data. Again, creating training data is greatly time-consuming, but by focusing on a single domain, good results are achievable.²⁸

One prominent lexicon used in lexicon-based approaches is SentiWordNet²⁹. SentiWordNet is built on top of WordNet³⁰. WordNet is a network organizing English nouns, verbs and adjectives into synonym sets, called “synsets”. Each synset represents one underlying lexical concept. The synsets are linked by different relations like synonym/antonym-relationship, making it possible to traverse the network.³¹ SentiWordNet is the result of automatic

²⁴ cf. Medhat et al. (2014), p. 1095.

²⁵ Examples: Hu;Liu (2004a), Hu;Liu (2004b), Wang et al. (2013), Baek et al. (2012), Bafna;Toshniwal (2013), Kurian;Asokan (2015) ibid., Zimmermann et al. (2015, in press)

²⁶ cf. Ravi;Ravi (2015, in press), p. 17, Duric;Song (2012), p. 705.

²⁷ cf. Medhat et al. (2014), p. 1093f.

²⁸ cf. Bhadane et al. (2015), p. 808f, Najmi et al. (2015), p. 848f and Zhang et al. (2012), p. 10284.

²⁹ Baccianella et al. (2010)

³⁰ Miller et al. (1990)

³¹ cf. Ibid., p. 235ff.

annotation of every WordNet synsets according to their degree of “positivity”, “negativity” and “neutrality” with respect to sentiment.³²

Analogous to the feature extraction step, irony is also a very hard problem when doing sentiment analysis. One problem is the lack of a formal definition for irony and sarcasm.³³ As said before, irony is not considered in this work.

Pang et al. (2002) use three different machine learning methods, Naïve Bayes, maximum entropy classifier and support vector machines (SVMs), for sentiment classification. The result of their experiment indicates that SVMs perform best and Naïve Bayes performs worst, although the difference is not very large.³⁴ Bhadane et al. (2015) use an SVM together with a domain specific lexicon for sentiment analysis of product reviews of a single product domain.³⁵ Kurian and Asokan (2015) uses cross-domain sentiment analysis to classify the sentiment of products from product domains without labeled data. This uses the sentiment information of another product domain with labeled data to infer sentiment information of a domain without labeled data. The accuracies are comparable to using SentiWordNet.³⁶

The papers on whose ideas this work is based on are described in section 4.3. For a detailed overview about sentiment analysis refer to Medhat et al. (2014) and Ravi and Ravi (2015, in press).

2.4 Summarization

The purpose of **summarization** is to create a smaller version of a document that retains the most important information of the source.³⁷ “Automated text summarization aims at providing a condensed representation of the content according to the information that the user wants to get.³⁸ But the problem with this is, that “it is still difficult to teach software to analyze semantics and to interpret meaning”³⁹.

³² cf. Baccianella et al. (2010), p. 2200ff.

³³ cf. Serrano-Guerrero et al. (2015), p. 20.

³⁴ cf. Pang et al. (2002), p. 81f, 84f.

³⁵ cf. Bhadane et al. (2015), p. 811ff.

³⁶ cf. Kurian;Asokan ibid., p. 96ff.

³⁷ cf. Ramezani;Feizi-Derakhshi (2014), p. 178 and Babar;Patil (2015), p. 354

³⁸ Kiyomarsi (2015), p. 85.

³⁹ Gupta;Lehal (2009), p. 62.

There are two types of summaries: extractive and abstractive summaries. An “**extractive summary**”, as the name implies, extracts sentences from the original text and concatenates them to create the summary. In contrast, “**abstractive summaries**” create new sentences. They therefore have to deeply understand the main concepts of the source text and they have to be able to generate clear natural language sentences. With the difficulty of this task, it is not surprising that most of the works in the area of summarization are following the extractive approach.⁴⁰ This is especially true for product review summarization as in this problem field a summary has to be created from several source documents (multi-document summarization).⁴¹

There are several possibilities in how to decide what sentences should be part of the summary when creating extractive summaries: Machine learning approaches use reference summaries and a number of textual features⁴² (e.g. sentence length or sentence position in a review) to learn rules that lead to the creation of “good” summaries.⁴³ Other approaches score sentences using some metrics and select the sentences based on these metrics. E.g. Nishikawa et al. (2010) assigns a readability and informativeness score to each sentence and solves an optimization problem in order to select the sentences with the highest informativeness and readability while subject to a maximum summary length.⁴⁴ Other systems specifically aimed at product review summarization use the result of the feature extraction and sentiment analysis steps to select sentences.⁴⁵

Existing systems in the domain of product reviews produce text reviews grouped by product features⁴⁶, but there also exist graphical summaries. For example, Kurian and Asokan (2015) display the number of sentences that a product feature is mentioned positively and negatively.

The summarization approaches that this work is based on are described in section 4.4.

⁴⁰ cf. Kurian;Asokan (2015), p. 94, Kiyomarsi (2015), p. 84 and Babar;Patil (2015), p. 354f

⁴¹ cf. Wang et al. (2013), p. 28ff.

⁴² Note that this is different from product features. The textual features are derived from the structure of the text, not its content.

⁴³ cf. Kiyomarsi (2015), p. 85ff.

⁴⁴ cf. Nishikawa et al. (2010), p. 326ff. Note that informativeness and readability may be conflicting goals. Because of this, the system in this paper assigns weights to these two factors.

⁴⁵ Examples: cf. Hu;Liu (2004a), p. 174 and Dave et al. (2003), p. 526.

⁴⁶ Examples: Wang et al. (2013), Hu;Liu (2004a), Dave et al. (2003)

3 Research Approach

The goal of this work is to create a universally usable system for product review summarization. The general approach is to combine various existing techniques for the three steps: feature extraction, sentiment analysis and summarization. In addition, some other techniques that were not implemented in other papers are proposed. The system is implemented in such a way that many different configurations are possible, creating the possibility to find the configuration that results in the best summaries.

For this the feature extraction output is evaluated by manually tagging the features in reviews from different products and calculating a score. Section 5.1 describes this in detail. In addition, all steps are evaluated through an online survey. This survey and the results are described in section 5.2. As the summaries are created for humans, the author believes that a survey is necessary in order to evaluate the quality of the proposed approach.

To the best of the author's knowledge no prior work tried to combine various techniques for the three steps of product review summarization in the way this work does (although there exist very few papers that use a different method as a subsequent tool). In addition, evaluation through customer survey has also been neglected by the majority of papers. Especially no paper was found that verified the need for review summaries not only theoretically but explicitly asked users. The different configurations for the summarization system in this work also far exceed other papers.

This work uses Amazon review data provided by Julian McAuley et al.⁴⁷ consisting of 143.7 million reviews spanning the timeframe of May 1996 until July 2014. The dataset consists of the reviews (including rating, reviewer, helpfulness) and metadata (price, related product information) of 9.45 million products organized in 24 product categories. For evaluation, example products were selected as described in chapter 5.

The following chapter explains the theoretical foundation and subsequent implementation of this work's proposed approach for all steps of the product review summarization process. After that the evaluation of the proposed approach is described.

⁴⁷ McAuley et al. (2015a), McAuley et al. (2015b). Also see: <http://jmcauley.ucsd.edu/data/amazon/>

4 Proposed Method

This section will explain the data preprocessing and the implemented method for feature extraction, sentiment analysis and summary creation.

The method is implemented with Anaconda⁴⁸ for Python 3.4 v2.3.0. The included Python Natural Language Toolkit (NLTK)⁴⁹ is used for some of the text processing, especially the preprocessing as mentioned in the next section.

Example summaries can be found as part of the survey in the appendix.⁵⁰

4.1 Preprocessing

The following nine preprocessing steps are carried out and will in the following be further explained:

1. Sentence Segmentation
2. Tokenization
3. Part of Speech Tagging
4. Case Folding
5. Fuzzy Matching of Nouns
6. Lemmatization and Stemming
7. Negation Tagging
8. Stopword Removal
9. Noun Phrase Tagging

“**Sentence Segmentation**” consists of separating a body of text into individual sentences. A trained machine learning-based sentence tokenizer for English is included in the NLTK and was subsequently used.⁵¹

⁴⁸ <https://www.continuum.io/why-anaconda>

⁴⁹ Bird et al. (2009)

⁵⁰ Especially in the sections “Survey Sentiment Analysis Part (Movie)” and “Survey Sentiment Analysis Part (Smartphone)” of the appendix.

⁵¹ Papers explicitly stating sentence segmentation as a preprocessing step are for example: Babar;Patil (2015), p. 356, Kurian;Asokan ibid., p. 96, Duric;Song (2012), p. 709.

“Tokenization” is the process of converting a string into a list of words (called tokens) based on punctuation marks, whitespaces etc.⁵² Again NLTK’s included tokenizer was used for this step. These first two steps are necessary as the subsequent steps require tokens or sentences represented as a list of tokens as input.⁵³

“Part of Speech (POS) Tagging”, also called grammatical tagging, determines the part of speech (e. g. noun, verb, adjective) for each token based on the token itself and its context, i.e. the relationship with other tokens in the sentence (like its position).⁵⁴ The “Stanford Part of Speech Tagger”⁵⁵ was used to carry out the POS tagging as it was also used in many other papers.⁵⁶ The build-in NLTK-POS-tagger was also tested, but provided unsatisfactory results based on manually checking of the POS-tags of sample data.⁵⁷ The model “english-bidirectional-distsim” was used, as it provides slightly better accuracy than the recommended model, even though it is a bit slower.⁵⁸ In a practical scenario each review must only be POS-tagged once and as the task can be executed in parallel, speed should not be a critical issue.⁵⁹

“Case Folding” means converting all characters to the same letter case (lower case in this work).⁶⁰

“Fuzzy Matching” is used to deal with misspellings (“battery vs. batery”) and word variants (“auto-focus” vs. “autofocus”).⁶¹ A distance function between two strings is defined and two strings are considered equal if their distance is lower than or equal to a given threshold. In this paper the “Levenshtein distance” (sometimes just called “edit distance”) is used. The distance of two strings is equal to the minimum number of single-character edits (insertions,

⁵² cf. Babar;Patil (2015), p. 356.

⁵³ Tokenization was, for example, used in the following papers: ibid., p. 356, Kurian;Asokan ibid., p. 96, Najmi et al. (2015), p. 847

⁵⁴ cf. Bhadane et al. (2015), p. 809f, Hotho et al. (2005), p. 9 and Ravi;Ravi (2015, in press), p. 3.

⁵⁵ Toutanova et al. (2003), Toutanova;Manning (2000), <http://nlp.stanford.edu/software/tagger.shtml>

⁵⁶ cf. for example Bafna;Toshniwal (2013), p. 146 and Najmi et al. (2015), p. 847.

⁵⁷ E.g. in the sentence „This is a powerful light smartphone.” “light” is identified as a noun by the NLTK-POS-tagger while being correctly identified as an adjective by the Stanfort POS-tagger. With the missing comma after “light” both taggers would produce the same result, but errors like missing commas are common in product reviews. As the Stanford POS-tagger performed better for the tested example sentences, it was used instead of the build-in NLTK-POS-tagger

⁵⁸ cf. <http://nlp.stanford.edu/software/pos-tagger-faq.shtml#h>

⁵⁹ The following papers included part of speech tagging in their preprocessing: Hu;Liu (2004b), p. 757, Bhadane et al. (2015), p. 809f, Medhat et al. (2014), p. 1095, Wang et al. (2013), p. 29, Scaffidi et al. (2007), p. 3, Dave et al. (2003), p. 521, Bafna;Toshniwal (2013), p. 146, Kurian;Asokan (2015) ibid., p. 96, Najmi et al. (2015), p. 847, Zhang et al. (2012), p. 10285, Wei et al. (2010), p. 155.

⁶⁰ cf. Gupta;Lehal (2009), p. 63.

⁶¹ cf. Hu;Liu (2004b), p. 757 and Bafna;Toshniwal (2013), p. 145.

deletions, substitutions) necessary to transform one string into the other.⁶² Various threshold values have been tested. The best results were achieved by setting a threshold of one and regarding the transposition of adjacent characters as one edit (resulting in the so called “Damerau–Levenshtein distance”⁶³). Furthermore, only tokens with at least 3 characters are considered. As the noun matching is especially important for feature extraction only nouns are processed.⁶⁴

“**Stemming**” reduces a word to its stem (a natural group of words with equal or very similar meaning), stripping it of its prefixes and suffices (e. g. stripping “ing” from verbs). So stemming emphasizes the semantics of a word. Stemming is normally implemented as a rule-based algorithm. “**Lemmatization**” tries to map nouns to their singular form and verbs to infinitive tense (that is also found in dictionaries), but for that the POS has to be known and the process is slow and error-prone.⁶⁵ This work uses the NLTK’s Snowball stemmer⁶⁶ and WordNet⁶⁷ for lemmatization. But as stemming is preferred by most other papers, this work also mainly uses stemming and only uses lemmatization when using SentiWordNet as lemmatized words are a prerequisite to use SentiWordNet.⁶⁸

Negation words like “not”, “isn’t” etc. change the sentimental direction of the words following them (e. g. “good” vs “not good”). “**Negation Tagging**” is the process of tagging the words whose sentimental direction is reversed by the negation word.⁶⁹ Following the method proposed by Fang and Chen (2011) this work tags every word between a negation word and the first punctuation mark⁷⁰ following the negation word.⁷¹

⁶² cf. Levenshtein (1966).

⁶³ Damerau (1964).

⁶⁴ See section 2.2 for the importance of nouns in feature extraction.

⁶⁵ cf. Hotho et al. (2005), p. 7, Gupta;Lehal (2009), p. 63 and Ravi;Ravi (2015, in press), p. 3.

⁶⁶ Snowball is considered superior to the well-known Porter stemmer according to NLTK (cf. <http://www.nltk.org/howto/stem.html>).

⁶⁷ Miller et al. (1990). „WordNet groups English words into sets of synonyms called synsets and provides short, general definitions, and records the various semantic relations between these synonym sets.” (Bhadane et al. (2015), p. 810).

⁶⁸ Lemmatization is (within the considered literature) only used by Scaffidi et al. (2007), p. 3 and Wei et al. (2010), p. 155. Stemming is for example in the following works: Hu;Liu (2004b), p. 757, Bhadane et al. (2015), p. 809, Babar;Patil ibid., p. 356, Dave et al. (2003), p. 522, Najmi et al. (2015), p. 847,

⁶⁹ cf. Pang et al. (2002) p. 83 and Bhadane et al. (2015), p. 810.

⁷⁰ Used markers: “.: ; ! ?” With the addition of “;” they correspond to the list of Duric;Song (2012), S. 709.

⁷¹ See <http://sentiment.christopherpotts.net/lingstruc.html#negation> for implementation details including a negation word overview. Other works with this approach: Pang et al. (2002), p. 83, Bhadane et al. (2015), p. 810.

“Stopwords” are common words with no semantics that appear in all texts that provide little to no information for the task to be solved. Examples are articles, conjunctions, prepositions, pronouns. “**Stopword Removal**” is the process of removing these words from the text to be analyzed in order to reduce the “noise”.⁷² In this paper the stopword list provided by NLTK is used.⁷³

“Noun phrases”⁷⁴ are word sequences like “a reliable camera”. “**Noun Phrase Tagging**” (or “Noun Phrase Chunking”) is the process of extracting the noun phrases of a text. In this work noun phrases are defined as follows: one optional determiner (“all”, “any” etc.), followed by an arbitrary amount of adjectives, followed by at least one noun.⁷⁵

4.2 Feature Extraction

Before the description of the author’s actual implementation, the general feature extraction ideas of the papers that this work is based on are briefly described.

4.2.1 Wang et al. (2013)

In this paper, noun and noun phrases are considered as potential features and subsequently extracted from the reviews. For each of these terms the “term frequency-inverse sentence frequency” (TF-ISF) is calculated. The 20 terms with the highest TF-ISF score are further examined. If these selected terms have adjectives nearby, they are considered a product feature.⁷⁶ The top five features (with the highest TF-ISF score) are shown to the user.⁷⁷

In other words, nouns and noun phrases near adjectives are ordered by TF-ISF score.

⁷² cf. Gupta;Lehal (2009), p. 63, Hotho et al. (2005), p. 7, Bhadane et al. (2015), p. 810 and Babar;Patil ibid., p. 356.

⁷³ Other works using stopword removal are for example: Hu;Liu (2004b), p. 757, Wang et al. (2013), p. 29, Bhadane et al. (2015), p. 810, Babar;Patil ibid., p. 356, Zhang et al. (2012), p. 10286.

⁷⁴ Product features are often nouns or noun phrases (cf. section 2.2).

⁷⁵ For implementation details refer to Bird et al. (2009), chapter 7.2 (also available online: <http://www.nltk.org/book/ch07.html>) and <https://stackoverflow.com/questions/7619109/nltk-chunking-and-walking-the-results-tree> (last accessed 30.11.2015 21:20).

Papers using noun phrase tagging are for example: Hu;Liu (2004a), p. 171, Wei et al. (2010), p. 154ff, Wang et al. (2013), p. 29.

⁷⁶ See section 2.3: Sentiment is typically carried by adjectives. Therefore terms without nearby adjectives are not considered as no sentiment information can be found for them making them useless in a summary.

⁷⁷ cf. Wang et al. (2013), p. 29. Note that the paper does not explain why they use only the top 20 candidates and show only five features to the user.

4.2.2 Scaffidi et al. (2007) and Ramkumar et al. (2010)

This approach is based on word occurrence probability and uses an external source with statistics about how often terms appear in general English language texts. All single nouns and noun bigrams⁷⁸ are extracted from the review texts of one product category and their number of occurrence n_x is counted. Under the assumptions that the occurrence of a term in a certain position in a text is independent of whether the term occurs in other positions and that the occurrence is independent of the position, the probability that the term would appear n_x times in a random English text containing a series of N noun occurrences is calculated. The Poisson distribution is used as an approximation to the binomial distribution to calculate the probability. The bigram calculation is analogous as under the stated assumptions the probability of the bigram is the product of the individual probabilities. The paper point out that the assumptions don't hold in reality, but the results will still be acceptable. All terms are then ordered by probability.⁷⁹

Ramkumar et al. (2010) extend this approach by clustering terms together. The clustering approach uses lexical analysis like substring matching, bigrams sharing a word and fuzzy matching⁸⁰ for different spellings. WordNet is used to find synonyms in the given terms. Furthermore a semantic similarity matching concept is used to cluster semantically similar words like “power” and “battery”.⁸¹

In other words, noun and noun bigrams are clustered and then ordered by probability of occurrence using external word occurrence statistics.

4.2.3 Author's Approach

This section will explain the modifications to the above mentioned feature extraction methods that are used in this work and one additional feature extraction idea. But first, the reason for not using machine learning is explained.

⁷⁸ A “noun bigram” consist of two successive nouns.

⁷⁹ cf. Scaffidi et al. (2007), p. 3f.

⁸⁰ See section 4.1.

⁸¹ cf. Ramkumar et al. (2010), p. 6864.

4.2.3.1 Why a machine learning approach was not used

One assumption of the author is that while products belonging to the same product group have a lot of common features, each product may also have individual features that are not present in other products. One example that was observed is a mobile phone where the model number, though not necessarily considered a “product feature”, has been mentioned in a lot of reviews. This is thus information that is of interest for a customer. Therefore, only the reviews of one product and not e.g. all reviews in a product category are used as the basis for the feature extraction and subsequent steps in summary generation in this work. Under this assumption and considering the difficulty of training a machine learning approach for this task (due to lack of and cost of producing training data), machine learning approaches are considered unsuitable for the goal of implementing a universally useable summarization approach.

4.2.3.2 Implementation of Wang et al. (2013)

The approach of Wang et al. (2013) has been implemented with the following modifications:

Instead of using TF-ISF “term frequency – inverse document frequency” (TF-IDF) is used. One review is one document in this scenario. After implementing TF-ISF a manual check of the extracted features of three mobile phones and three kitchen utilities (that had been randomly selected under the constraint that the review count is not too high) has been done. The ten features with the highest score and six sentences per feature have been examined. As the quality of this sample result was unsatisfying, TF-IDF has been adopted and examined in the same way. Here the results were much better with more real product features having a high score compared to TF-ISF. One explanation for this is that a feature is rarely present more than once in a sentence, so term frequency and sentence frequency will correlate strongly resulting in a TF-ISF score around one for almost every term.

The manual examination also showed that a lot of terms represent the same product feature. Therefore a second modification is the clustering of candidate terms before calculating the TF-IDF scores in order to subsequently consider all terms in one cluster equal. Two clustering approaches have been tested: The approach by Ramkumar et al. (2010) with some modifications and “Group Average Agglomerative Clustering” (GAAC)⁸². GAAC was chosen as

⁸² GAAC is a bottom-up hierarchical clustering algorithm and generates a dendrogram. It uses Cosine distance (cf. Hotho et al. (2005), p. 8f) to calculate the distance between terms combining two clusters to a bigger one in every step. It is therefore necessary to specify the number of clusters. (cf. Cambria et al. (2014), p. 1519).

it has a very high accuracy when clustering features.⁸³ The modifications to Ramkumar et al. (2010) were as follows: As preprocessing already applies fuzzy matching this step is omitted. Substring matching has been tried but it resulted in some clusters being totally wrong, because of a short term being a substring of another term. The WordNet-synonym check resulted in a very big cluster containing various product features for one product. In the end only the term matching remained. While this approach is conservative, it resulted in the best result (from a subjective point of view) for the examined sample. The outcome of a manual comparison of the clustering results between GAAC and Ramkumar et al. (2010) showed that the modified Ramkumar et al. (2010) approach achieved better clustering results for the regarded sample. Consequently, this approach has been adopted.

The last modification is that not only the 20 terms with the highest TF-IDF score are checked for nearby adjectives, but every term. With this, the system may return an arbitrary amount of features.

4.2.3.3 Implementation of Scaffidi et al. (2007) and Ramkumar et al. (2010)

The approach of Scaffidi et al. (2007) and Ramkumar et al. (2010) has been adopted in the following way:

Terms are clustered as above before calculating the probabilities and only the reviews of the current product are considered instead of all reviews in the current product category. Furthermore, instead of just considering nouns and noun bigrams, noun phrases (containing an arbitrary number of adjectives and at least one noun) are used. Using the independent assumptions of Scaffidi et al. (2007)⁸⁴ the probability calculation formula⁸⁵ has been adapted to handling these n-grams. The statistics in Leech et al. (2001) have been used for the reference noun and adjective probabilities of occurrence.⁸⁶ If a term is not found in the reference statistics, the average probability of the term's POS-group (i.e. noun or adjective) is used.⁸⁷ Again, all terms are ordered by their final score.

⁸³ cf. Cambria et al. (2014), p. 1519.

⁸⁴ See section 4.2.2.

⁸⁵ Scaffidi et al. (2007), p. 4 Eq. 3.

⁸⁶ The statistics are available online: <http://ucrel.lancs.ac.uk/bncfreq/>

⁸⁷ cf. Scaffidi et al. (2007), p. 3.

4.2.3.4 Meta approach

One assumption of the author is that different approaches have different strengths and weaknesses and will therefore rank features or feature clusters differently. As the goal of this work is to develop a universally usable product review summarization system, the bias of each method should be minimized. Therefore, the following “**Meta approach**” has been developed:

Inputs are an arbitrary number of feature extraction algorithms conforming to the following rules:

- The result of the algorithm is an ordered list of features, i.e. each feature must have a score with more extreme scores meaning the feature is more likely to be an actual product feature.
- Each feature is rated with a score between 0 and 1 with 1 meaning that the algorithm regards this feature as having the highest chance of being a real product feature.⁸⁸
- For each feature a list of sentences that contain the feature must be provided.

The Meta approach will then take the results of all input algorithms and calculate the mean score for each feature⁸⁹. All extracted features will be combined in a list ordered by the mean score. The sentence lists for each feature will be combined (in the case that different algorithms consider different sentences to be important for a given feature).⁹⁰ It is possible to assign weights to each input algorithm. The feature scores are then averaged through a weighted mean.

For this paper, the two approaches described in this section are used as input algorithms for the Meta approach. But the concept is applicable to an arbitrary amount of input algorithms.

4.2.3.5 Summary of the feature extraction approach

In summary, there are three implemented feature extraction approaches. Wang et al. (2013) as well as Scaffidi et al (2007) and Ramkumar et al. (2010) have been implemented with some modifications. In addition, a Meta approach that combines the output of these two methods is proposed. The different methods are evaluated in section 5.1 and section 5.2.4.2.

⁸⁸ This is easily achievable by normalizing scores to [0, 1].

⁸⁹ If one algorithm does not extract the given feature, the score of the feature for this algorithm is 0.

⁹⁰ Duplicate entries are prevented.

4.3 Sentiment Analysis

As before, first the general sentiment analysis ideas of the papers that this work is based on are briefly described. Then the author's implementation is described.

4.3.1 Hu and Liu (2004a)

In this paper only adjectives are considered as opinion words that carry the sentiment for a feature. For each sentence of every review that contains a feature, every adjective in the sentence is extracted. Furthermore for every feature in each sentence the nearest adjective is associated to that feature.⁹¹

In order to find the semantic orientation for an adjective, the following strategy is used: Starting with a list of seed adjectives with known orientation, WordNet⁹² is used to expand this list by traversing the WordNet graph. WordNet contains information about synonyms and antonyms for adjectives. Using the idea that the semantic orientation of synonyms is the same and the orientation of antonyms is the opposite, it is possible to discover other adjectives with the same and the opposite semantic orientation when starting with a list with known orientation. Adjectives that WordNet cannot recognize are ignored.⁹³

The semantic orientation of a sentence is predicted as follows: If there are more positive adjectives than negative adjectives the sentence is considered positive. If the negative adjectives are dominant, it is considered negative. If there is an equal amount of positive and negative sentences only the orientation of the nearest adjective per feature is regarded. Negation⁹⁴ is payed attention to.⁹⁵

In summary, this paper uses sentence-level sentiment analysis based on adjectives as opinion words. WordNet is used together with a seed list to generate the opinion word list.

⁹¹ cf. Hu;Liu (2004a), p. 171f.

⁹² See section 2.3.

⁹³ cf. Hu;Liu (2004a), p. 172f.

⁹⁴ See section 4.1 Negation Tagging.

⁹⁵ cf. Hu;Liu (2004a), p. 173f.

4.3.2 Zhang et al. (2012)

This paper uses a manually created list of adjectives and considers only these words to carry sentiment. The words can carry a positive or negative sentiment with a score of “+1” or “-1” respectively. In addition, adverbs of degree like “very” or “a bit” can modify the score of the opinion words. The weights (e.g. 0.5 or 2) were manually defined. The sentiment score is calculated by sentence. If an adverb of degree is in the same clause as an adjective, the adjective score will be multiplied with the adverb of degree’s weight. If a negation word is encountered, the scores of all adjectives in the same clause are multiplied with -1.⁹⁶

In summary, this paper uses sentence-level sentiment analysis based on adjectives as opinion words while considering adverbs of degree to modify the sentiment strength of an adjective. A manually created opinion word list is used.

4.3.3 Najmi et al. (2015)

This paper uses a machine learning approach to classify sentences into either positive, negative or neutral and works in two steps: In step one, one classifier⁹⁷ is used to find neutral sentences that don’t carry sentiment. These sentences are removed for the subsequent analysis. In the second step, another classifier⁹⁸ separates the remaining sentences into positive and negative.⁹⁹

Similar to Hu and Liu (2004a) this paper uses SentiWordNet¹⁰⁰ to find adjectives with known polarity. SentiWordNet runs on top of WordNet and adds three sentiment scores for every term (“positive sentiment”, “negative sentiment” and “neutral sentiment”) that add up to one. The sentiment score for a word is calculated as follows:¹⁰¹

- *positive (+1) \Leftrightarrow positive sentiment – negative sentiment > threshold*
- *negative (-1) \Leftrightarrow negative sentiment – positive sentiment > threshold*
- *neutral (0) \Leftrightarrow |positive sentiment – negative sentiment| < threshold*

⁹⁶ cf. Zhang et al. (2012), p. 10287f.

⁹⁷ The classifier uses features like the word letter case, the POS of a word, the adjectives in the currently regarded sentence etc. For a full list see Najmi et al. (2015), p. 851 Table 3.

⁹⁸ This classifier uses features like the polarity of a word, if the word is a negation word etc. For a full list see ibid., p. 852 Table 4.

⁹⁹ cf. Ibid., p. 851f.

¹⁰⁰ See section 2.3.

¹⁰¹ cf. Najmi et al. (2015), p. 850f.

Like Zhang et al. (2012) this paper considers adverbs of degree (and some nouns like “nothing”) that may modify the sentiment score of a verb by manually creating a list of words and assigning weights. Negation is also considered.¹⁰²

In summary, this paper uses sentence-level sentiment analysis by using a machine learning approach. Adjectives are used as opinion words and a manually created list of words that modify the sentiment score are considered. SentiWordNet is used to calculate the sentiment orientation of adjectives.

4.3.4 Bafna and Toshniwal (2013)

This paper uses adjectives as opinion words. An online available list of adjectives¹⁰³ with known orientation (positive, negative or neutral) is used. If an adjective is not in this list, SentiWordNet is used. If this is also not successful, a human is asked to classify the word.¹⁰⁴

An adjective is assigned to the nearest feature (aspect-level sentiment analysis). The rationale behind this is that the opinion words describing a feature will be the closest ones around the feature. To achieve this, the distance (amount of words in the sentence between two regarded words)¹⁰⁵ of each opinion word to each feature in a sentence is calculated. If two or more features have the same distance, the opinion word is assigned to the feature mentioned first.¹⁰⁶

If a negation word is encountered near an adjective, the adjective’s polarity is reversed. For each feature all positive and negative polarity scores are added up independently to generate a final opinion for each feature.¹⁰⁷

In summary, this paper uses aspect-level sentiment analysis with adjectives as opinion words. An opinion word list and SentiWordNet are used to calculate the sentiment orientation of the opinion words.

¹⁰² cf. Ibid., p. 850ff.

¹⁰³ Opinion Lexicon, see Liu et al. (2005). Online available: <https://github.com/jeffreybreen/twitter-sentiment-analysis-tutorial-201107/tree/master/data/opinion-lexicon-English>

¹⁰⁴ cf. Bafna;Toshniwal (2013), p. 148.

¹⁰⁵ Or put in another way: The amount of words separating the two regarded words in the sentence.

¹⁰⁶ cf. Bafna;Toshniwal (2013), p. 148.

¹⁰⁷ cf. Ibid., p. 149.

4.3.5 Wei et al. (2010)

The aim of this paper is only feature extraction and not sentiment analysis, but opinion words are used to find product features in review texts.¹⁰⁸ As opinion words are considered, some ideas of this paper can be used in sentiment analysis.

In this paper too, a list of adjectives with known polarity (positive or negative) is used as opinion words. The “General Inquirer”¹⁰⁹ is the source for the adjectives, but the list was manually cleaned in order to only contain adjectives that refer to subjective opinions of customers.¹¹⁰

Using verbs with known polarity (positive or negative) in addition to adjectives as opinion words has also been tested in this paper. The source of these verbs is again the General Inquirer. In this paper, using verbs in addition to adjectives has a negative effect on the result. The paper explains this with the possibility that many of the considered verbs are often used to express emotional behavior rather than subjective opinions.¹¹¹

In summary, this paper uses adjectives and (in contrast to the other papers described above) verbs as opinion words when extracting product features, although verbs worsen the result.

4.3.6 Author’s Approach

In this work a combination approach using ideas from the above mentioned five papers is used for sentiment analysis.

4.3.6.1 Why a machine learning approach was not used

Although Najmi et al. (2015) uses a machine learning approach, a lexicon based-approach is used in this work for the following reasons:

As mentioned before¹¹², getting the necessary amount of labeled training data is extremely costly and not feasible in the scope of this work. Although machine learning approaches are

¹⁰⁸ cf. Wei et al. (2010), p.151.

¹⁰⁹ Stone et al. (1966).

¹¹⁰ cf. Wei et al. (2010), p. 156f. An adjective that is used in an objective way is “able” as it is often used to describe a product’s ability to do something. (cf. Ibid., p. 157).

¹¹¹ cf. Ibid., p. 164f.

¹¹² See section 4.2.3 for example.

superior to dictionary-based approaches when implementing them for specific domains¹¹³, the overall goal of this work is the development of a universally usable product review summarization approach not restricted to specific product domains.

One solution to still use machine learning could be to use the review rating (often in the form of a star rating) as an estimator for the user's opinion. For example, Scaffidi et al. (2007) work under the assumption that the rating reflects the user's opinion towards all product features mentioned in his review.¹¹⁴ But it is easy to see that this assumption is wrong.¹¹⁵ Reviews can rate the overall product highly while still criticizing some features of the product. This fact is even admitted in Scaffidi et al. (2007).¹¹⁶ So there is no real alternative to creating training data manually.

4.3.6.2 The implemented approach

The implemented approach for the sentiment analysis will be described from here on: The input of the sentiment analysis is the output of the feature extraction. Any of the methods described in section 4.2.3 may be used.

The general approach is similar to Hu and Liu (2004a) and Zhang et al. (2012): Adjectives are used as opinion words and for each feature each sentence containing this feature is analyzed independently using all found opinion words (sentence-level sentiment analysis). The Negation Tagging step of the preprocessing¹¹⁷ is used to consider negation. If an opinion word is tagged as "negated" the opinion score will be reversed. Opinion words may be positive (score "+1"), negative (score "-1") or neutral (score "0").

The polarity calculation for adjectives works similar to Bafna and Toshniwal (2013): Two sources of adjectives are used¹¹⁸, the Opinion Lexicon also used by Bafna and Toshniwal (2013)¹¹⁹ and SentiWordNet¹²⁰. For SentiWordNet all synsets¹²¹ of the word matching the word's POS-tag are collected. A weighted sum of the positive and negative sentiment scores of

¹¹³ cf. Najmi et al. (2015), p. 849.

¹¹⁴ cf. Scaffidi et al. (2007), p. 4.

¹¹⁵ See for example Najmi et al. (2015), p. 857.

¹¹⁶ cf. Scaffidi et al. (2007), p. 8.

¹¹⁷ See section 4.1.

¹¹⁸ It is possible to use only one of the sources by switching a flag in the source code.

¹¹⁹ Opinion Lexicon, see Liu et al. (2005). Online available: <https://github.com/jeffreybreen/twitter-sentiment-analysis-tutorial-201107/tree/master/data/opinion-lexicon-English>

¹²⁰ Baccianella et al. (2010).

¹²¹ See section 2.3.

all these synsets is calculated. As the synsets in SentiWordNet are ordered by probability, the sentiment scores are weighted accordingly meaning the first synset gets the largest weight. The reason behind this is that any retrieved synsets could possibly be the correct one for the given sentence. Without analyzing the semantics of the sentence, there is no way to know the correct one, but analyzing the semantics is very hard considering the fact that the product domain is not limited to one or two product categories. So an overall sentiment score over all possible synsets considering their probability is calculated instead. If the overall positive score is greater than the overall negative score, the adjective is considered positive (score “+1”). If the overall negative score is great, it is considered negative (score “-1”). If both values are equal, the adjective is considered neutral (score “0”). As there is a lot of uncertainty in this approach, SentiWordNet is only used if the Opinion Lexicon does not contain the adjective. If both Opinion Lexicon and SentiWordNet do not know the adjective, it is considered neutral.¹²²

4.3.6.3 Optional extensions

Similar to Najmi et al. (2015) and Zhang et al. (2012) **adverbs of degree** may modify the sentiment score of opinion words. As no complete list of adverbs was found, a list of 130 adverbs was manually created from several different sources¹²³. Like in the two papers, the weights in this work were also manually assigned. This work uses the interval [0.1, 2.0] in 0.1-steps. The sentiment score modification works as follows: The sentiment score of an opinion word is multiplied with the adverb’s weight. If several adverbs are used their weight is multiplied. If after an opinion word another opinion word follows, its score is also multiplied with the same weight. The rationale behind this is that phrases like “very fast, light and handy” often imply “very fast, very light and very handy”.¹²⁴ If no opinion word follows, the multiplier gets reset to one. Stopwords are ignored.

¹²² As the goal is a fully automatic process for product review summarization, asking a human as done in Bafna;Toshniwal (2013) is no option.

¹²³ Sources: Paradis (1997), <http://www.netdata.com/Netsite/0800d48a/Adverbs-of-Degree-List>, <http://rattanji77.blogspot.jp/2013/08/list-of-adverbs-of-degree-or-quantity-57.html>, http://www.grammar-quizzes.com/adv_degree.html, <https://www.englishclub.com/vocabulary/adverbs-degree.htm>, <http://lognlearn.jimdo.com/grammar-tips/adverbs/intensifiers-adverbs-of-degree/>, <https://en.wikipedia.org/wiki/Intensifier>, <http://www.gingersoftware.com/content/grammar-rules/adverb/adverbs-degree/>. All websites were accessed on 13.12.2015.

¹²⁴ Of course, this is not always the case. But without analyzing the semantic there is no way of knowing what the author meant. Even with analyzing the semantic, the sentence could still be ambiguous.

Using the idea of Wei et al. (2010) there is the option to use **verbs** as additional opinion words. The process is exactly same as for the adjectives (see above). Opinion Lexicon and SentiWordNet are also used to calculate the polarity of the verbs as both these sources also contain verbs.

Another option is to use the **review time** in order to weight the final sentiment score of a feature for a sentence. As time passes, the user's opinion towards a product may change (e.g. because of technological development or newer products), so newer reviews may be more meaningful for customers interested in the product. This idea is proposed by Najmi et al. (2015), but not implemented there.¹²⁵ Here this idea is implemented as follows: The final sentiment score of a feature for a specific sentence is multiplied with a time weight corresponding to the age of a review in relation to the newest review. To achieve this, reviews are grouped by their month and year. The month and year with the newest review gets a weight of 2.5. For every month in the past, the weight is reduced by 0.1 until the minimum weight of 0.1 is reached. Reviews that are older than two years will all be weighted with the same weight of 0.1. But the weighting is only carried out, if the time between the newest and the oldest review is at least four weeks. It is important to note that this does not mean that the newest review's sentences will always have the highest score as the original sentiment score of an older review's sentence for a feature may be so high that it still has a higher score even when considering the review time.

The rationale for this implementation is the following: First of all, if the total time horizon is too short, weighting reviews according to the review time is not reasonable as the time that passed is simply too short to significantly change the customer opinion.¹²⁶ The reason for weighting reviews equally if they are older than two years is that so much time has passed already, that it, for example, doesn't really matter anymore if the review is two and a half or three years old. The opinions will be outdated anyway. Using a linear monthly decrease is only one possibility. Without further analysis it is not possible to determine the best weighting strategy. As this analysis is outside the scope of this work and as no other paper was found that regards review time when doing product review summarization, the linearly decreasing scheme was chosen.

¹²⁵ cf. Najmi et al. (2015), p. 847.

¹²⁶ Of course, there are exceptions to that: A problem with a product that fundamentally changes the customer opinion could be found after one or two weeks. But this situation can be constructed for any number of passed days. So even when only considering two days, the opinions could be quite different in such a situation.

The final option uses the idea of Bafna and Toshniwal (2013) to implement **aspect-level sentiment analysis**. For every opinion word in a sentence, the distance to each product feature associated with the sentence is calculated. Distance is defined as the number of tokens in the sentence from the opinion word to the beginning or end of the product feature.¹²⁷ As features in this work are noun phrases¹²⁸, they may contain more than one token. Therefore the beginning and end of the noun phrase has to be considered when calculating the distance. The sentiment score is in this work also associated with the closest feature. If the distance to two or more features is the same, the score is associated with the feature mentioned first.¹²⁹ One other special case, originating from the fact that features are noun phrases in this work, is that an opinion word may be part of the feature name (e.g. “fast screen”). If the opinion word is part of the feature, the sentiment score is associated with this feature. The last thing to note is that a feature consists of several noun phrases that are clustered together.¹³⁰ Therefore, when calculating the distance all possible noun phrases associated to a feature need to be tested as any of them could be the one in the currently analyzed sentence.

4.3.6.4 Summary of the sentiment analysis approach

In summary, the implemented sentiment analysis system uses two sources of opinion words: Opinion Lexicon and SentiWordNet.¹³¹ Apart from using adjectives as opinion words there are four additional options: (1) using adverbs of degree to modify the sentiment score of following opinion words, (2) using verbs as additional opinion words, (3) weighting the sentiment scores by considering the review time and (4) doing aspect-level sentiment analysis by assigning the sentiment score of an opinion word only to the nearest feature. This makes a total of $2^4=16$ possible configurations for the sentiment analysis.

¹²⁷ Example: “The fast screen is fantastic”. The distance of “fast” and “screen” is one and the distance of “fantastic” and “screen” is two. Stopwords are considered when calculating the distance.

¹²⁸ cf. section 4.2.3.

¹²⁹ This is the same behavior as proposed by Bafna;Toshniwal (2013). See also section 4.3.4.

¹³⁰ cf. section 4.2.3.

¹³¹ As written above, it is actually possible to configure the system to only use Opinion Lexicon or only use SentiWordNet, but as the change to recognize opinion words is higher if both sources are used, this configuration is used.

4.4 Summarization

In this section the summarization approaches of papers that this work is based on are briefly described. Then the implemented approach is explained. The focus is the content of the summaries (i.e. which information is shown) as well as how the content is chosen and the layout of the summaries.

4.4.1 Hu and Liu (2004a)

The approach of this paper is as follows: For each feature all positive and negative sentences are collected and a count with the amount of reviews that mention the feature positively and negatively is calculated per feature. For each feature a short review is created. First the positive sentences of this feature are listed and after that the negative sentences. The paper does not mention an ordering scheme for the individual sentences. For each category (positive, negative) the calculated review count is also shown. As a lot of sentences are shown, they are hidden behind a drop down list. For each sentence, a hyperlink to the original review is created.¹³²

These feature reviews are shown in an ordered list. The default ordering shows the feature that is most talked about, i.e. mentioned in the highest number of reviews, first. Other ordering according to only the positive or only the negative review count is possible. The summaries look like this (Table 1).¹³³

Feature: FEATURE NAME	Legend:
Positive: COUNT	
• SINGLE SENTENCE	• UPPER CASE = is replaced with actual values in the real summary
• SINGLE SENTENCE	• ... = etc.
• ...	
Negative: COUNT	
• SINGLE SENTENCE	
• SINGLE SENTENCE	
• ...	
Feature: FEATURE NAME	
...	

Table 1: Hu, Liu (2004a) Summary Layout

¹³² cf. Hu;Liu (2004a), p. 174.

¹³³ cf. Ibid., p. 174.

In summary, the features are represented in a simple list ordered by the number of reviews that mention them. For each feature positive and negative sentences are listed without any ordering scheme.

4.4.2 Bafna and Toshniwal (2013)

Similar to Hu and Liu (2004a) this paper creates two clusters for each detected feature, one for positive reviews for this feature and one for negative reviews. The corresponding sentences are also extracted here, again without any ordering scheme. The actual graphical representation of the summary is not described.¹³⁴

4.4.3 Dave et al. (2003)

This work shows all found feature names together with their sentiment score at the top of the screen, but they are not ordered. Selecting one of the features will show the corresponding sentences ordered by their sentence-level sentiment score. The interface can also show the context of a sentence and which features in the sentence contribute to the sentence's sentiment score in what way. Positive and negative sentences are shown together, but as the list is ordered by descending sentiment score, the negative sentences are shown after the positive ones. The summaries look like this (Table 2):¹³⁵

FEATURE NAME (TOTAL SCORE)	FEATURE NAME (TOTAL SCORE) ...
FEATURE NAME (TOTAL SCORE)	FEATURE NAME (TOTAL SCORE) ...
...	
FEATURE NAME	Legend:
SCORE: SENTENCE	• UPPER CASE = is replaced with actual values in the real summary
SCORE: SENTENCE	• ... = etc.
...	

Table 2: Dave et al. (2003) Summary Layout

In summary, the feature names are randomly ordered (even though their total sentiment score is shown) and for the selected features all sentences containing the feature are shown ordered by the sentiment score of the sentence.

¹³⁴ cf. Bafna;Toshniwal (2013), p. 149.

¹³⁵ cf. Dave et al. (2003), p. 526 and figure 2.

4.4.4 Wang et al. (2013)

This paper suggests a list of the five top ranked features to the user. The user can then select any combination of them. If a feature is missing, the user is also able to enter one feature name himself. After the selection, the summary is created by calculating a score for all sentences containing the corresponding feature. For each feature only the top-ranked sentence is shown to the user. The score itself is not shown. The selected features are shown in a list without any specific order. The summaries look like this (Table 3):¹³⁶

FEATURE NAME: SENTENCE	Legend: • UPPER CASE = is replaced with actual values in the real summary
FEATURE NAME: SENTENCE	
...	

Table 3: Wang et al. (2013) Summary Layout

In summary, user input is required to create the summary. For each selected features only the sentence with the highest score is displayed. The features are not ordered in the summary.

4.4.5 Author's Approach

The implemented summarization approach is basically a combination of Hu and Liu (2004a) and Dave et al. (2003) with some changes and additions. This means that this work follows an extractive summarization approach¹³⁷ using the results of the previous feature extraction and sentiment analysis steps to select sentences. This approach has been chosen as all previous steps already analyze single sentences (therefore creating a good foundation for extracting relevant sentences) and most other papers also use the extractive approach.¹³⁸ Using the abstractive approach would mean additional complexity, introducing another possible level of error with the task of creating meaningful and grammatically correct sentences.

¹³⁶ cf. Wang et al. (2013), p. 31, figure 2 and figure 3.

¹³⁷ cf. section 2.4.

¹³⁸ cf. section 2.4.

4.4.5.1 The implemented approach

The general input of the summarization step consists of the output of the feature extraction and sentiment analysis steps¹³⁹. From the feature extraction step the n features with the highest score are selected to be part of the summary and they appear in the summary exactly in this order. Like in Hu and Liu (2004a) and Bafna and Toshniwal (2013), sentences belonging to a feature are divided into sentences with positive sentiment and sentences with negative sentences. Objective sentences are not part of the summary as they carry no opinion about a product feature.

Per sentiment polarity and feature at most m sentences (less if there are not enough sentences) are shown. The reason for limiting the sentences, as also done by Wang et al. (2013), is that showing all sentences would make the review too long and therefore run contrary to the goal of a summary, namely saving time. But showing only one sentence would also run contrary as a lot of information would be missed when showing only one sentence per polarity. Because this could lead to a biased decision, m should be greater than one. The m sentences per polarity that are displayed are the ones with the highest positive or negative sentiment score for the regarded features as calculated in the sentiment analysis step. Like Dave et al. (2003), the sentences are ordered by their sentiment score. The reason for this is that the sentences with the most extreme sentiment carry the most meaningful information for the regarded feature and should therefore be read first.

4.4.5.2 Not implemented and implemented optional extensions

The **sentiment score of every sentence** can be optionally displayed and like Hu and Liu (2004a) the number of reviews that mention the regarded feature positively and negative respectively can also be shown, but with the addition of always showing the total number of reviews for the product, too.¹⁴⁰ With this the customer can always put the review count for one feature and polarity in relation to the total review count. The reason for making the display of the numbers optional is that it has to be tested whether customers actually want to see these numbers or would prefer to not see them (see section 5.2 for the customer survey).

It would be easy to add the option to display a **graphical representation** of these optional numbers to follow the idea of Bafna and Toshniwal (2013), but this has not been

¹³⁹ See sections 4.2.3 and 4.3.6.

¹⁴⁰ Example: “30 out of 500” instead of just “30”.

implemented for the following reasons: (1) The only thing graphically displayable would be the above mentioned review counts. While this could give an overview about the general sentiment distribution, it doesn't give any information about the features itself. A user looking at the graphic would still not know exactly what is good or bad with one product feature. It would have no real benefit for assessing the product. (2) As the summaries should have an adequate length, there should be no need to summarize some parts of the summary again. (3) As mentioned above, it is not known whether customers are even interested in these numbers.

There would be the possibility to consider the "**“was this review helpful” statistics**" when choosing which sentences to use in the summary, but this measure is fundamentally biased in three ways and should therefore not be used: Firstly, often reviews are marked as “helpful” even though they are not (imbalance vote bias). Secondly, reviews with an already high amount of positive votes are read more often and receive even more votes (winner circle bias). Finally, earlier reviews are viewed more often compared to newer reviews and can therefore get more votes (early bird bias).¹⁴¹

Instead one additional idea that does not originate from any of the mentioned papers can be used. The idea is to **limit the amount of sentences coming from one review**, so that for all features at most u sentences come from the same review. The rationale behind this is that a single review should not dominate the summary as it would contradict the goal of showing diverse opinions and would instead possibly lead to a biased decision. This idea is implemented as follows: As searching for a global maximum in sentence distribution for all features would need an objective function rating the sentence distribution and a lot of time¹⁴², a greedy approximation is used instead. The feature with the highest score in the feature extraction step is supposed to be the most important feature for customers. It should therefore get the sentences with the most extreme opinions, in order to give customers the best insight in the good and bad sides of this feature. For less important features it is not that big of a problem to get less diverse sentences. The approximation hence first distributes sentences to the most important feature, then to the second most important feature etc.

¹⁴¹ cf. Najmi et al. (2015), p. 856f.

¹⁴² A distribution problem like this normally has an exponentially growing number of possible solutions making the search for a globally optimal solution very time-consuming.

4.4.5.3 Summary layout

The actual summary layout comes in two variants and is described as follows: Both variants start with a header containing the product title, the price, the number of reviews and the review timespan, i.e. the review time of the oldest and newest review. When embedding a summary e.g. into product page in a web shop, title and price are unnecessary as this information is already available on the web page, but these facts are included here as the summary is a stand-alone text. Number of reviews and review timespan may also be available in a web shop. Number of reviews is shown, so that the customer can evaluate the size of information source of the summary. The review timespan is shown, so that the customer knows what kind of information in terms of age he can expect.

After the header the product features are shown in a list in the summary body. The variants differ by how the positive and negative sentences for a review are displayed. In **variant “List”**, the sentences are displayed the same as in Hu and Liu (2004a) starting with the positive sentences. **Variant “Table”** shows positive and negative sentences in a table, so that positive and negative sentences are next to each other. The general layout is as shown in Table 4 and Table 5 (see the appendix sections “Survey Summary Layout Part (Movie)” and “Survey Summary Layout Part (Smartphone)” for actual summaries using these two layouts). Which layout is preferred by the customers will be analyzed in section 5.2.

PRODUCT NAME	<u>Legend:</u>
<u>General Information</u>	<ul style="list-style-type: none"> • UPPER CASE = is replaced with actual values in the real summary • ... = etc. • [] = optional
Price: AA \$	
Number of Reviews: BB	
Review timespan: DD/MM/YYYY - DD/MM/YYYY	
<u>Product Features</u>	
Feature: FEATURE NAME	
(+) Positive:	
[Feature positively mentioned in XX reviews (out of BB)]	
<u>Example sentences:</u>	
<ul style="list-style-type: none"> • SENTENCE [(SCORE)] • ... 	
(-) Negative:	
[Feature negatively mentioned in YY reviews (out of BB)]	
<u>Example sentences:</u>	
<ul style="list-style-type: none"> • SENTENCE [(SCORE)] • ... 	
Feature: FEATURE NAME	
...	

Table 4: Variant "List" Summary Layout

PRODUCT NAME	<u>Legend:</u>
<u>General Information</u>	<ul style="list-style-type: none"> • UPPER CASE = is replaced with actual values in the real summary • ... = etc. • [] = optional
Price: AA \$	
Number of Reviews: BB	
Review timespan: DD/MM/YYYY - DD/MM/YYYY	
<u>Product Features</u>	
Feature: FEATURE NAME	
(+) Positive	(-) Negative
[Feature positively mentioned in XX reviews (out of BB)]	[Feature negatively mentioned in YY reviews (out of BB)]
<u>Example sentences:</u>	<u>Example sentences:</u>
SENTENCE [(SCORE)]	SENTENCE [(SCORE)]
...	...
Feature: FEATURE NAME	
...	

Table 5: Variant "Table" Summary Layout

4.4.5.4 Summary of the summarization approach

In summary, the n most important features will be listed. For each feature the m most positive and m most negative sentences will be shown in either a list or a table. Optionally, the count of reviews mentioning a feature positively or negatively respectively and sentiment scores of the example sentences can be displayed. There is also the option to limit the number of sentences in the summary that can originate from one review.

5 Evaluation

The next section will show the results of the evaluation of the implemented method. Section 5.1 describes process and result of a manual evaluation of the feature extraction for a sample of six products. The survey described in section 5.2 uses products with a lot more reviews compared to the manual evaluation and evaluates all three steps of product review summarization.

5.1 Feature Extraction

First, this section will describe the general description of the evaluation process for the feature selection. After that the results are discussed.

5.1.1 Evaluation Process

In literature, most papers use the measures of recall, precision and F₁-measure (or a subset of these measures) to evaluate their feature extraction. Usually a comparison with other methods that are used as a baseline is performed.¹⁴³ Let c be the number actual product features that the algorithms extracted. Let e be the number of features (actual or not) extracted by the algorithm and let m be the number of actual product features. Then the above measures are defined as follows:¹⁴⁴

- $Recall = \frac{c}{m}$
- $Precision = \frac{c}{e}$

¹⁴³ Papers using (some of) these measures include the following: Hu;Liu (2004b), p. 759f, Ramkumar et al. (2010), p. 6864f, Zhang et al. (2012) ibid., p. 10290 and Table 7, Wei et al. (2010), p. 160ff.

¹⁴⁴ cf. Zhang et al. (2012), p. 10290f and Wei et al. (2010), p. 161.

$$\blacksquare \quad F_1 - Measure = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

The difficulty lies in m as the actual product features are normally not known. Of course, manufacturers write down features in their product description and advertisements, but these lists are not suitable as the source for the product features. Firstly, the lists may not be exhaustive or aspects that some users are interested in could be missing.¹⁴⁵ Secondly, such lists are not always available, e. g. for movies there is hardly information about the picture quality (apart from resolution etc.) available as this matter is very subjective. So the general approach is to extract features by hand which, of course, may introduce errors due to subjectivity and human error. Still, often this is the only choice. This is therefore the approach that is used in this work to evaluate the performance of the different feature extraction methods described above.¹⁴⁶

The approach of this work is as follows: Recall is compared between the methods in the way that each method returns all potential features (no matter the score). The lists are manually checked for the actual features. In addition, the F_1 -Measure is calculated for varying amounts of extracted product features. For each product, the range from one up to the number manually extracted product features is calculated. In order to calculate the F_1 -Measure, the correctly extracted features are again marked manually.

Recall can be increased by sacrificing Precision and vice versa. The F_1 -Measure has the benefit over Precision and Recall that both metrics are considered so that a tradeoff is not possible.¹⁴⁷ The result is therefore more meaningful.

The Meta approach is used with equal weights for the two input algorithms in this evaluation. In addition to these quantitative measures, a qualitative analysis is performed and the feature extraction performance is also analyzed in the survey (see section 5.2.4.2).

¹⁴⁵ cf. Scalfidi et al. (2007), p. 9. For example, in one of the sample products there were quite a few reviews that talked about that the manufacturer provided description of the product is not correct. This is hardly a product feature, but it is still of interest for a customer, as the item description will also be a source of information for him. So this information could also be part of a summary. For another sample product, the model number was often mentioned as a specific model number was sought by the customers. This is also not a real product feature, but is also of interest for a customer.

¹⁴⁶ Papers that extract features by hand include: Hu;Liu (2004b), p. 760, Wei et al. (2010), p. 160, Zhang et al. (2012), p. 10285, 10290, Bafna;Toshniwal (2013), p. 149.

¹⁴⁷ cf. Hotho et al. (2005), p. 10f.

5.1.2 Results

The sample consists of six products: Three mobile phones and three router/networking devices. These categories were chosen as the products are highly structured. It is therefore relatively easy to extract product features by hand. For each product category there is one product with less than ten reviews, one with 30 to 40 reviews and one with more than 60 reviews, but less than 100. These review counts were chosen to evaluate the feature extraction depending on the review count while still being feasible to read all reviews in an appropriate amount of time.

The methods that are tested are described in section 4.2.3. This section also describes the shortcomings of the original methods of Wang et al. (2013) and Scaffidi et al. (2007). Because of these shortcomings only the modified approaches are evaluated. Table 6 shows the achieved **recall** for the above mentioned sample:

	Number of Reviews	Number of manually extracted features	Modified Wang et al. (2013)	Modified Scaffidi et al. (2007)	Meta approach
Mobile Phones:					
Product A	8	8	0.5	0.875	0.875
Product B	37	25	0.88	0.96	0.96
Product C	80	25	0.76	0.8	0.8
Average			0.713	0.878	0.878
Router/Networking Devices					
Product D	6	9	0.556	0.667	0.667
Product E	35	18	1	1	1
Product F	65	17	0.941	0.941	0.941
Average			0.832	0.869	0.869
Total Average			0.773	0.874	0.874

Table 6: Feature Extraction Recall Comparison

For every product of the sample except one Wang et al. (2013) achieves a lower Recall than the other two approaches. This is explainable with the fact that Wang et al. (2013) reduces the number of possible features by searching for nearby adjectives.¹⁴⁸ Scaffidi et al. (2007) does not reduce the feature number. As the Meta approach uses all features of all input algorithms, the Recall is exactly the same as Scaffidi et al. (2007).

¹⁴⁸ See section 4.2.1.

There is no clear trend regarding the influence of the review count recognizable. For the products with less than 10 products a lower Recall is achieved most of the time compared to the other products. This seems to be especially true for Wang et al. (2013). Then again, the sample is too small for a clear statement. It seems plausible that a higher review count could lead to a higher Recall. As most reviews mention more than one product feature, the chance is higher that an actual product feature gets mentioned more often and is therefore easier to recognize for the feature extraction algorithm.¹⁴⁹

With 77 to 87 percent average Recall, all methods perform quite well for the given sample. It is noteworthy that the methods also extract implicit features¹⁵⁰, although the feature name is not always suitable or not as much a general term as a human would choose.

Figure 2 to Figure 7 show the **F₁-Measure** for each product depending on the number of features. Each method extracts the top features (i.e. features with the highest score).

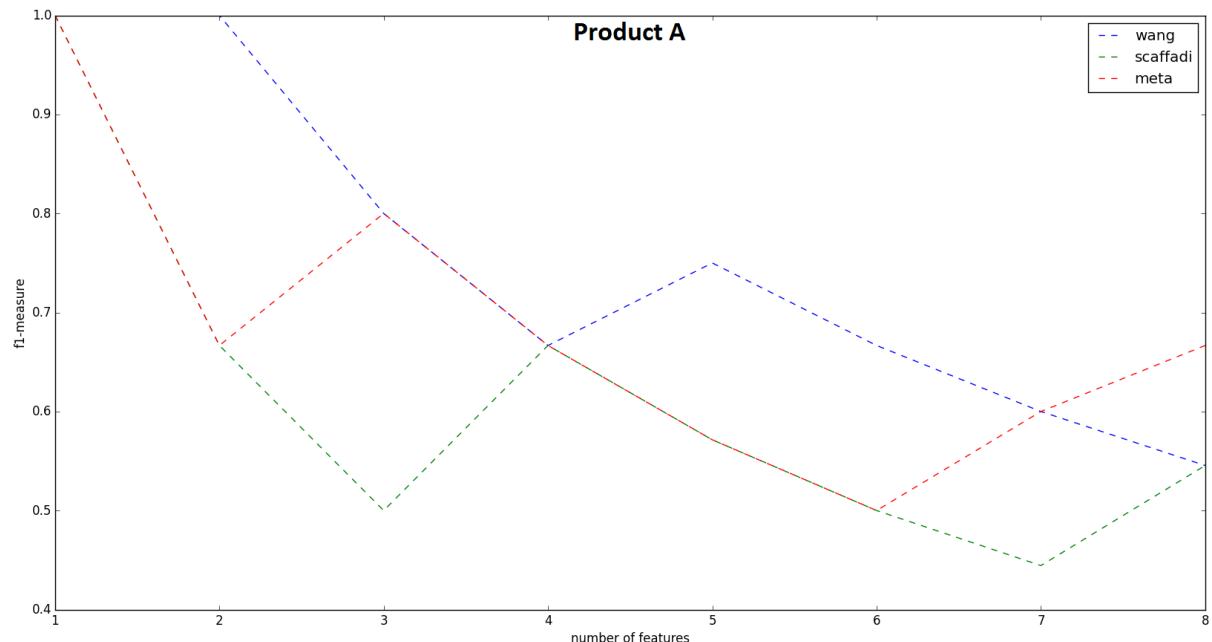


Figure 2: F1-Measure Product A

¹⁴⁹ But on the other hand, every product has short reviews that do not mention any feature in particular.

¹⁵⁰ Implicit features extraction is considered very tough (cf. Zhang et al. (2012), p. 10284).

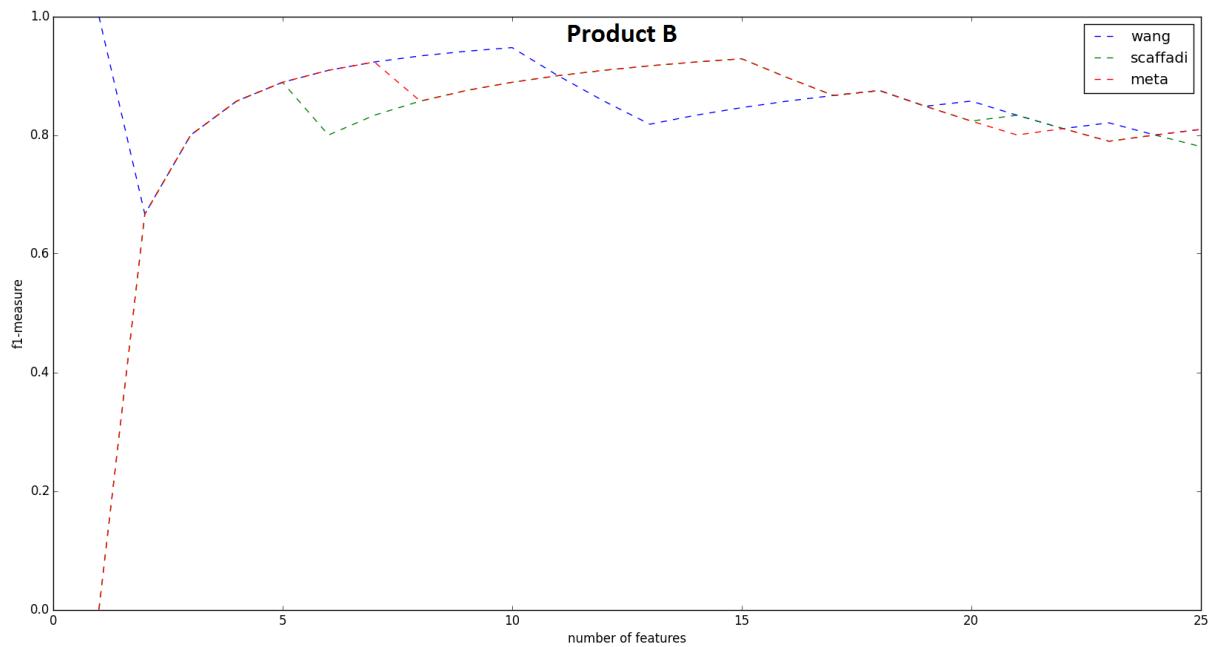


Figure 3: F1-Measure Product B

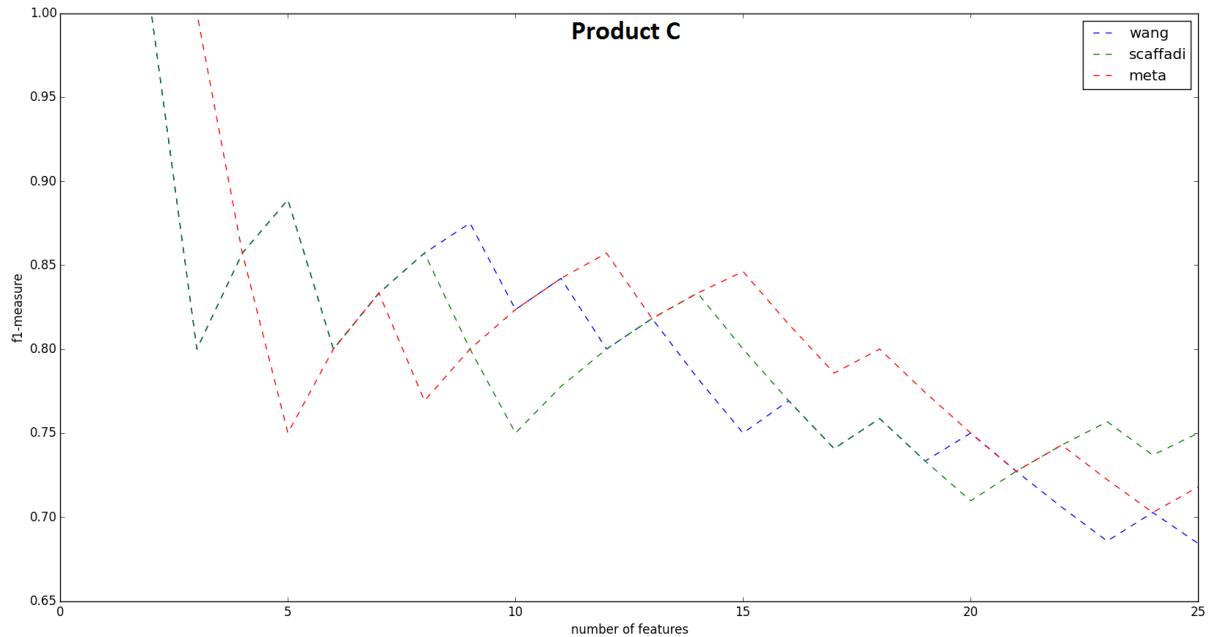


Figure 4: F1-Measure Product C

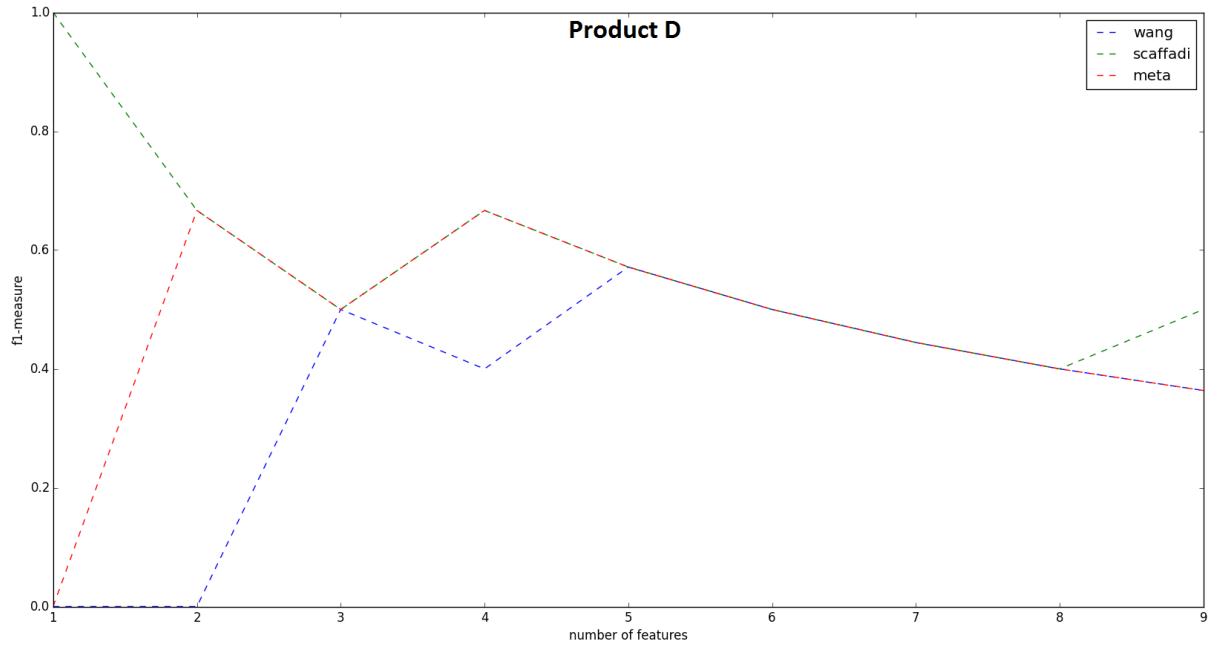


Figure 5: F1-Measure Product D

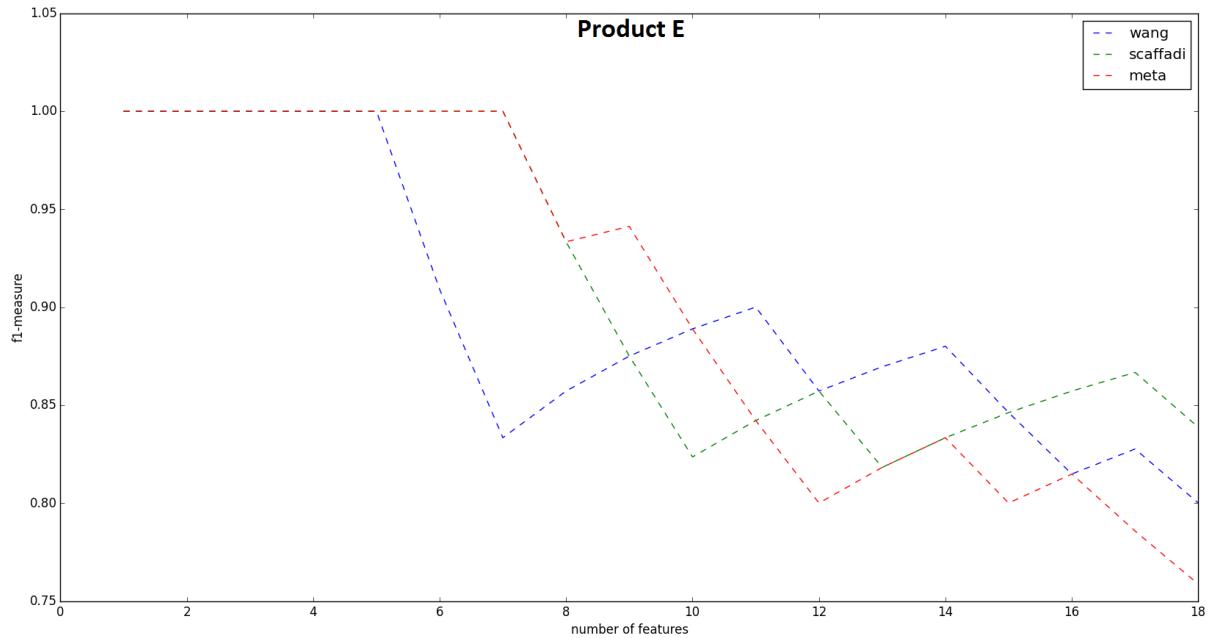


Figure 6: F1-Measure Product E

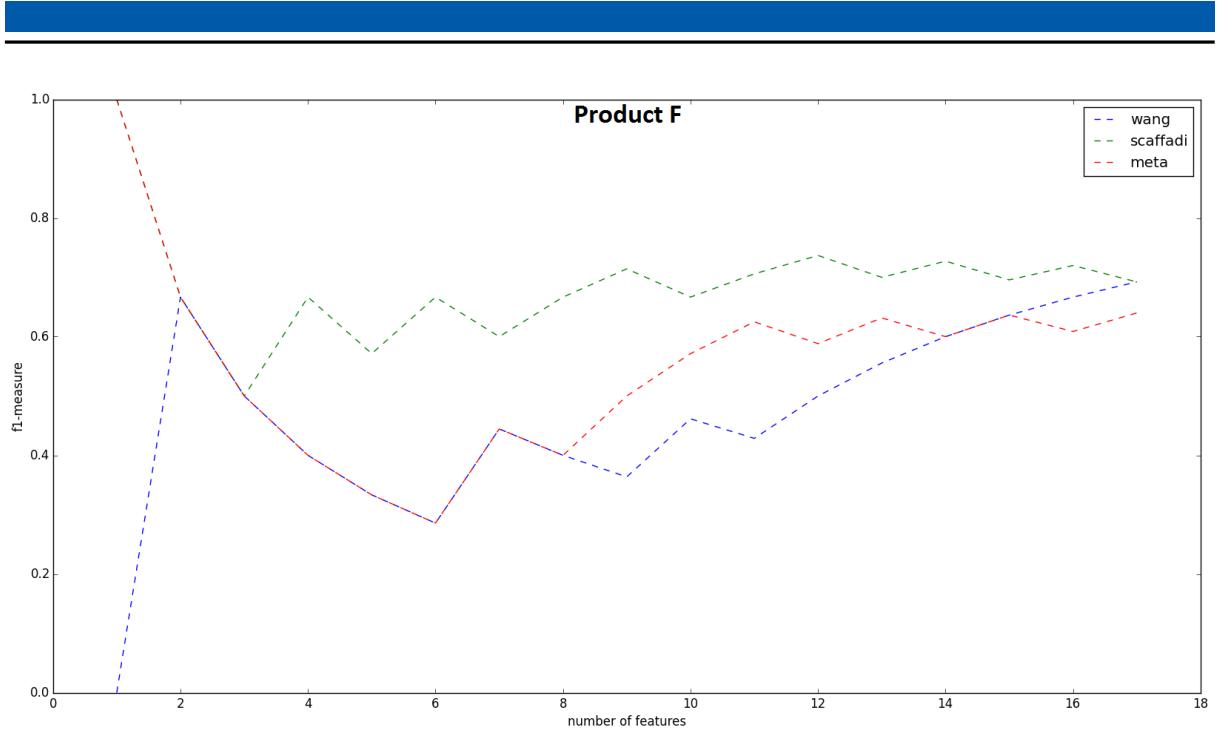


Figure 7: F1-Measure Product F

There is no real trend recognizable. Wang et al. (2013) achieves the best result for product A and is very good for B, but performs worst for C and F for most of the time. For product D and F Scaffidi et al. (2007) seems to perform best, but it performs badly for A for product D. The Meta approach performs best for product C for most of the feature counts. For product E there is no clear winner as depending on the feature count another method has the best performance.

Further manual testing is necessary, but can't be performed in the scope of this work. More products in the same and different categories should be tested and the Meta approach should especially be tested with more input algorithms. Again, this is out of scope for this work. The current result does not clearly show whether the Meta approach can achieve a better performance than each input method. But for some products and feature numbers the Meta approach performs clearly better than each input method. This at least justifies further development and testing.

A qualitative analysis of the extracted features shows two problems: First, the clustering is not perfect, so that the same actual product feature is sometimes returned more than once (although with a different name)¹⁵¹. Future research should develop a better noun phrase clustering as this is the source of this problem in this work. Second, the returned feature name

¹⁵¹ Example: In one mobile phone the extracted features “amazing optical zoom camera feature” and “proper optical zoom lens” both describe the phone's camera and should therefore have been clustered together.

is not always accurate (i.e. it does not perfectly reflect the content of the cluster).¹⁵² This may also be the result of the suboptimal clustering and the current scheme of choosing the longest cluster member as the feature name.

All in all, all feature extraction approaches show satisfying results and are therefore suitable as the basic for the sentiment analysis step of the product review summarization process.

5.2 Survey

This section will describe the survey that was conducted to evaluate the summarization approach. First, the rational for conducting an online survey is explained, then the survey design is explained and finally the results are discussed.

5.2.1 Advantages and disadvantages of doing an online survey

As the aim of this work is to develop a product review summarization approach that will benefit the users, the quality of the generated summaries should be judged by potential users. Therefore an online survey was conducted.¹⁵³ This reasoning is further verified by the fact that there exists no benchmark data and evaluation for review summarization tasks.¹⁵⁴

As the object to evaluate is developed to be used in the Internet, conducting an online survey helps reaching the potential users, namely online shoppers. This paper therefore follows the practice of using an online survey when studying the Internet use and people's opinion about Internet technology.¹⁵⁵

Using online survey instead of other methods like paper survey or interviews offers several advantages, but also has disadvantages. Advantages include the ability to quickly create a survey that is instantly available in the world allowing for a possibly very high number of respondents. The cost for conducting a survey is therefore lower compared to normal paper surveys while offering a greater reach. Online surveys allow fixing the order in which questions should be answered to prevent a possible bias by answering later questions first and they also allow to randomize the question order to prevent systematic bias through the

¹⁵² Example: For the mobile phone's display "great screen" might be a better feature name than "entire screen". Both strings appear in the same noun phrase cluster for this product.

¹⁵³ The used tool to do the survey is <https://www.soscisurvey.de/>

¹⁵⁴ cf. Wang et al. (2013), p. 32.

¹⁵⁵ cf. Selm;Jankowski, p. 436f.

question order. Furthermore, the need to manually input the data into a computer is eliminated which greatly speeds up the data analysis and prevents manual copy errors. Online surveys can force that questions need to be answered before continuing, preventing non-response for certain questions. They also eliminate a possible interviewer bias and are convenient for the respondents as they can choose when to do them or even take breaks in between.¹⁵⁶

The main disadvantage of online surveys is the sampling bias, making it practically impossible to achieve a random sample of Internet users as there is no central register of all users. Furthermore, the Internet population is not representative of the general population, although this is changing as using the Internet becomes more common. As a website makes it possible to track user data without them noticing, privacy concerns could lower response rate of online surveys. Online surveys in general provide relatively low response rates, although the absolute number of respondents could be very high as explained above.¹⁵⁷

As the survey in this work aims at Internet users, the none-representativeness of the Internet population is no problem. Privacy concerns can be reduced with proper survey design¹⁵⁸ and as there is no specific user group that this work targets, an unrestricted sample¹⁵⁹, where the survey is just advertised in the Internet and free for everyone to participate, can be used. So for this work the advantages of online surveys clearly outweigh the disadvantages.

5.2.2 Question Design and Pretest

For the **questions and general survey design criteria** this work follows the guidelines of several works whose key points will be briefly described in the following.¹⁶⁰

Not too many questions should be used, because the users will quit if the survey takes too long. Using double negations etc. may result in users misunderstanding the questions, so easy to understand language should be used. Precise formulation of every question is necessary, to ask about only one specific concept per question without room for interpretation. Violating this may lead to poor results that can't be trusted. Open questions that allow free text

¹⁵⁶ cf. Ibid., p. 437-439 and cf. Evans;Mathur (2005), p. 196ff.

¹⁵⁷ cf. Selm;Jankowski (2006), p. 439 and cf. Evans;Mathur (2005), p. 201f.

¹⁵⁸ cf. Andrews et al. (2003), p. 5f.

¹⁵⁹ cf. Selm;Jankowski (2006), p. 440.

¹⁶⁰ Cf. the following papers for the rest of this section: Andrews et al. (2003), Aschemann-Pilshofer (2001), Gräf (1999), Gräf (2010), p. 74-79.

answers¹⁶¹ can be used after questions with defined answer choices to get additional information about the answers, but are hard to analyze if too many of them are in the survey. In rating questions, the scale has to be complete and without overlaps. Violating this will lead to confusing on where to answer in borderline situations. The aim of the study should be described at the beginning to gain the trust of the user, e.g. by explaining the data usage, thanking him for his help and giving him the context for his answers. Also every question should have an adequate description about what to do if needed. Questions should be formulated in a neutral way to avoid bias and when using ranking scales all options should have an equal distance from each other as otherwise some option could be preferred or disfavored simple because it seems too extreme compared to the other options.

There is no real conclusion to the question whether incentives like vouchers should be used. On one hand, incentives will most probably increase the survey response rate leading to more completed surveys. On the other hand, there is the risk that some people will do the survey multiply times in order to increase their chance to get the price.¹⁶² In order to not risk having duplicate data entries by the same user that can possibly not be distinguished during data analysis, this work refrains from using incentives.¹⁶³

After finishing the first version of the survey, a “pilot” or “pretest” should be conducted. This means letting some users fill out the survey while watching them or collecting their feedback. With this, problems due to questions formulation, misunderstanding, missing answer options, overlapping answer categories, survey structure, survey length etc. can be found and improved before the real survey. This is especially important for online surveys as the additional complexity of having to cope with different operating systems, browsers, screen resolutions etc. has to be considered in order to prevent technical problems in the real survey.¹⁶⁴

This work also did a pretest. The results indicated that the survey was too long, had some superfluous questions and didn’t display correctly on some display resolutions. After resolving these problems the first pretesters were again asked to look over the survey to make sure that no problem remained.

¹⁶¹ cf. Aschemann-Pilshofer (2001), p. 14.

¹⁶² cf. Selm;Jankowski (2006), p. 450f.

¹⁶³ Of course, people may still do the survey more than once, but without an incentive, the probability is very low.

¹⁶⁴ cf. Andrews et al. (2003), p. 15ff, cf. Aschemann-Pilshofer (2001), p. 19f and cf. Gräf (1999), p. 168f, 172.

5.2.3 Survey Description

The actual survey consists of the following five subtopics that are asked in this order:

1. Personal data
2. Motivation/need for using product review summary
3. Comparing the three different feature extraction methods
4. Comparing different summary layouts
5. Evaluating summaries created by using different sentiment analysis configurations

Personal data is used for cross-analysis to compare different user groups. After that some questions are asked about the online shopping experience of the users like how many reviews they normally read for a product, how they feel when reading reviews or if they ever wished to have a summary instead of the reviews. These questions aim to verify the actual **need for automated review summarization** which was disregarded by other papers.

After that, the users are randomly assigned to one of two products. One group will see summaries about a smartphone for the rest of the survey while the other will see summaries of a movie. Those two products were randomly chosen from their respective product categories with the only restriction being that both should have around 300 reviews in order to create summaries for a realistic scenario where they could be needed. A review count of around 300 was chosen to work with a relatively popular product while keeping processing speed in reasonable levels.¹⁶⁵ The two product categories, smartphones and movies, were chosen as they represent completely different product types: Smartphones (an example of a “use-driven” product¹⁶⁶) are very structured and technical, making them easily describable in terms of their different parts like camera or display. This also allows for objectively measuring their quality to some degree like amount main memory, weight, processing speed. Lastly, nowadays, a lot of people have experience with smartphones, making it easier for them to judge the summaries. On the other hand, movies (belonging to the “content-driven” product class) can’t be easily broken down into smaller parts. Although sub-aspects like music or lighting exist, they can’t be objectively measured as everything about movies is subjective opinion. As the aim of this study is a universally useable summarization approach, using

¹⁶⁵ The implementation does not focus on processing speed, but on analyzability of each sub-step and modularity to allow for different configurations and easy extensibility. Therefore processing takes a considerably long time on the author’s computer. In a practical scenario a performance-focused implementation can be used and the possibility to use several servers or a cloud for the analysis exists to greatly speed up the analysis.

¹⁶⁶ See section 2.1.

products from two different product categories makes it possible to at least get an indication whether the approach really works universally. In order to really assess this, a survey that only focuses on this point has to be conducted, e.g. using many products from many different categories. But as this survey focuses more on the different configurations for the summarization approach¹⁶⁷, only two products were chosen.

For the **feature extraction evaluation**, the user gets lists with the top ten feature names together with some other feature members from the three implemented feature extraction methods¹⁶⁸. The user is asked to choose the list that best fits the product and to rate the feature names. The aim is to find the best extraction method according to the user and evaluate the quality of the chosen feature name. A free answer field allows for additional comments.

After that the user should **evaluate the summary layout**. They first have to choose whether the list or table layout¹⁶⁹ is better. After that two questions are asked in random order to eliminate a possible bias through the question order: (1) Do the users prefer to see sentiment scores or not and (2) do they want to see the amount of reviews that mention a feature positively and negatively. The actual content of the summaries is always the same, only the layout differs at this time of the survey. Therefore preference for one option should only come from the actual layout and not the summary content. The shown summaries at this point only have one feature each, so the users are also asked how many features they would like to see per feature and how many sentences per feature the summary should contain. Again, a free answer field can be used for additional comments.

The last part of the survey is used to **evaluate the different sentiment analysis approaches**. For this, the users have to actually read the content of summaries about the smartphone or movie and rate their quality on a seven-point rating scale. As the table layout was randomly chosen for these summaries, these questions are asked after the layout questions in order to prevent bias from being exposed to one layout for a long time. Four different summaries are shown to the user in random order, each with the same layout. The summaries only differ in the used sentiment analysis configuration. Therefore, a difference in the user rating reflects the difference in the quality of the sentiment analysis configurations.

¹⁶⁷ See sections 4.2.3, 4.3.6 and 4.4.5.

¹⁶⁸ See section 4.2.3.

¹⁶⁹ See section 4.4.5.3.

The following four configurations are used:¹⁷⁰

- **Random:** From all sentences associated to a feature, sentences are randomly selected and classified as positive or negative sentences.
- **Base:** Adjectives and adverbs of degree as modifiers are used to calculate a sentiment score for a sentence.
- **Verb:** In addition to the Base-configuration, verbs are also used as opinion words.
- **Aspect:** Using the Base-configuration, aspect-level sentiment analysis is performed instead of sentence-level sentiment analysis.

Random is used as a benchmark for the other three configurations. If the users rate them significantly higher than the Random-configuration, the configurations are able to analyze sentiment. The Base-configuration is used as a minimal configuration for the system. While it is possible to use only adjectives without adverbs, using adverbs is a natural way to make the sentiment analysis more precise. As the result in Wei et al. (2010) indicated that using verbs in addition to adjectives had a negative effect on the sentiment analysis quality, it is interesting to see whether the result will be the same in the method proposed by this work. Lastly, it needs to be analyzed whether aspect-level sentence sentiment analysis has a positive effect on the user rating.

In the pretest two more configurations where tested:

- **Time:** Using the Base-configurations, the sentiment score is weighted according to the review time.
- **All:** Includes all options used in Base-, Verb-, Aspect- and Time-configuration.

As the pretest showed that the survey was too long and the users didn't want to read this many summaries, these two configurations were removed for the following reasons: Evaluating the Time-configuration only really works when creating various summaries with different time reference points. Only like this would the effect of weighting by review time be actually observable. As this would make the survey way too long, this configuration was removed. Still, as discussed in section 4.3.6.3, using the review time should be beneficial in practice. While having an All-configuration would be useful to evaluate interaction effects between the configurations, evaluating the configurations themselves first is more important. Therefore this configuration was also cut from the summary. Additionally, the option to limit

¹⁷⁰ See section 4.3.6 for all possible configurations and details about them.

the amount of sentences from one review¹⁷¹ is also not used for summaries in the survey as this option possibly hinders the sentiment analysis to choose the top rated sentences for a feature. Therefore the user rating could also differ between summaries because less extreme sentences are selected for some features and not only because of the different sentiment analysis configurations. But as discussed in section 4.4.5.2, in a practical scenario this option should be used.

For all summaries created in the survey, a feature extraction method had to be chosen. For this the result of the comparison of six products described in section 5.1 is used. Table 7 shows how often each method has the highest F₁-Measure for five features. A feature count of five has been chosen as it seemed reasonable for the author to include this amount of features into a summary. But as this had to be chosen before conducting the survey, the survey results for the ideal feature count (see section 5.2.4.4) could not be considered.

	Modified Wang et al. (2013)	Modified Scaffidi et al. (2007)	Meta approach
5 features	5/6	5/6	3/6

Table 7: F1-Measure Comparison

For five features Wang et al. (2013) and Scaffidi et al. (2007) perform best. For the survey, one of those two methods should therefore be used as basis for the sentiment analysis questions. As there is no clear winner between the two even when looking at Figure 2 to Figure 7, Wang et al. (2013) has been randomly selected. Still, as all created summaries use the same feature extraction, differences in the rating are still only produced by the different sentiment analysis configurations. Even if Wang et al. (2013) is not the optimal configuration, it should not affect the result of the sentiment analysis configuration comparison.

5.2.4 Survey Results

To find users for the survey, links to the survey were put on several websites including Reddit¹⁷² and Facebook. The full survey for the smartphone and movie respectively can be found in the appendix. The following sections will explain the results of the various survey parts.

¹⁷¹ See section 4.4.5.2.

¹⁷² <https://www.reddit.com/r/SampleSize/>

5.2.4.1 Personal Data and Motivation for Using Product Review Summary

The survey was open for three weeks and was started 214 times. 52 surveys were completed and subsequently used for the evaluation. Figure 8 shows the gender distribution and Figure 9 shows the age distribution. The survey was mainly completed by males between 25 and 29 years. This may stem from the fact that the survey was advertised at places like Reddit and the author's university major's Facebook group where there might be more male than female members. Figure 10 shows the employment situation of the respondents. As the survey was advertised in a university's Facebook page it is not surprising that mainly university students answered the survey. The one person who selected "other" as his occupation stated that he is a solder.

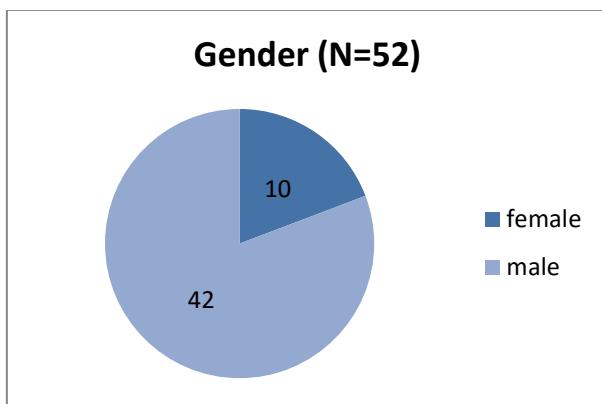


Figure 8: Survey Results - Gender

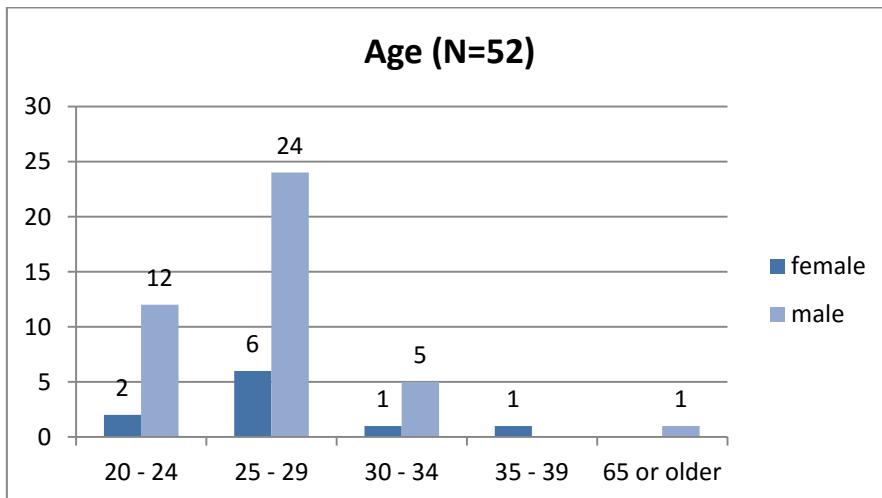


Figure 9: Survey Results - Age

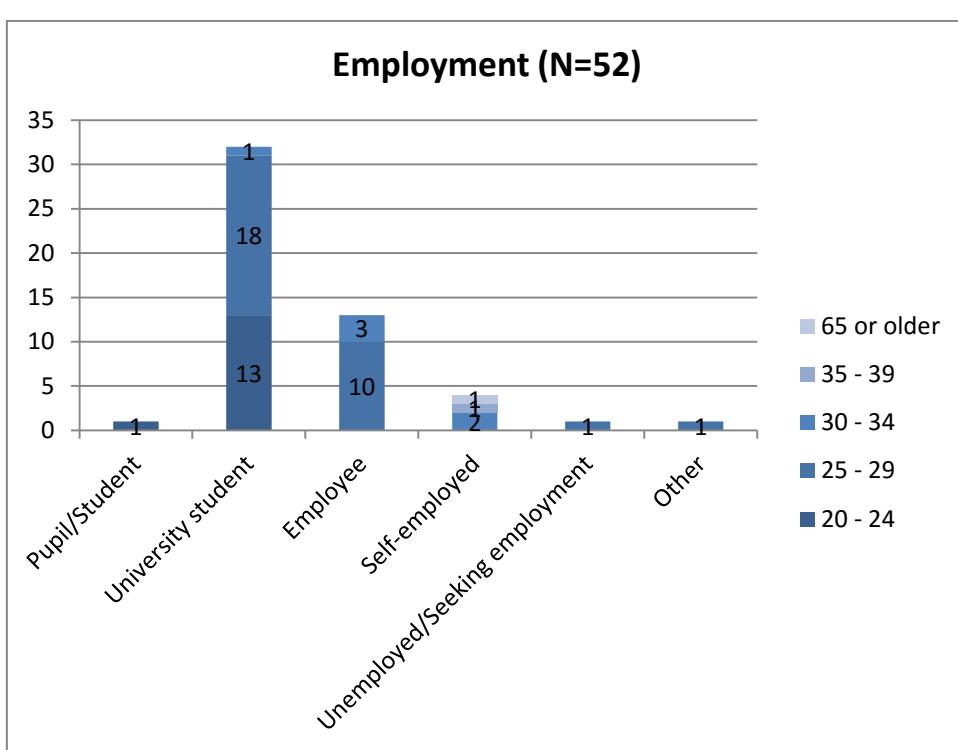


Figure 10: Survey Results - Employment

Every one of the 52 respondents answered that he or she has **experience with online shopping**. Therefore everyone could imagine an online shopping situation making their answers regarding the summaries more trustworthy. When online shopping, the majority of the respondents (28 out of 52) read between five and ten reviews, especially 25 to 29 years old respondents (the largest age group in the survey). Other 17 people read less than five reviews. Only very few respondents (6 out of 52) read eleven or more reviews per product and no one reads more than 30. There is also one respondent who one answered that he or she newer reads reviews (cf. Figure 11).

Figure 12 shows how the respondents **feel when reading product reviews** as percentages of the male and female respondents. Most respondents find reviews interesting and not tiresome, but this could just stem from the fact that most respondents only read up to ten reviews (cf. Figure 11). Taking the products that were part of the survey as an example, reading ten reviews out of around 300 reviews means that only around three percent of the total reviews per product are read in average. With 97 percent missing, the probability of not knowing all important product information when making a purchase decision seems pretty high. This is therefore a good indication that review summaries could be useful for customers.

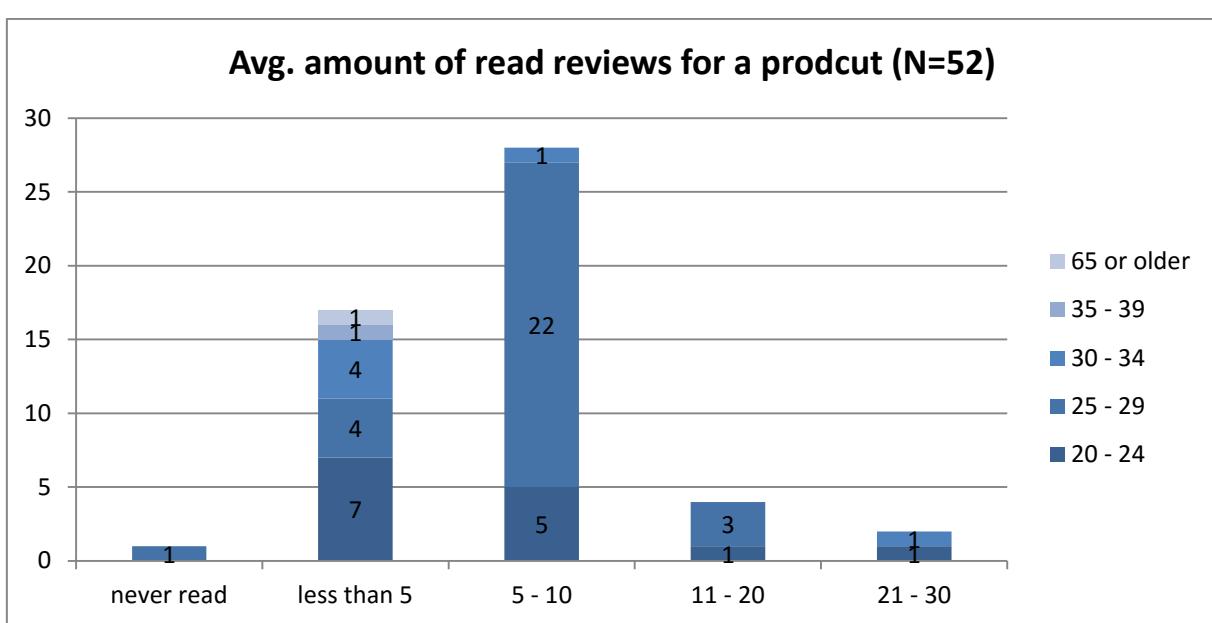


Figure 11: Survey Results - Avg. Number of Reviews Read

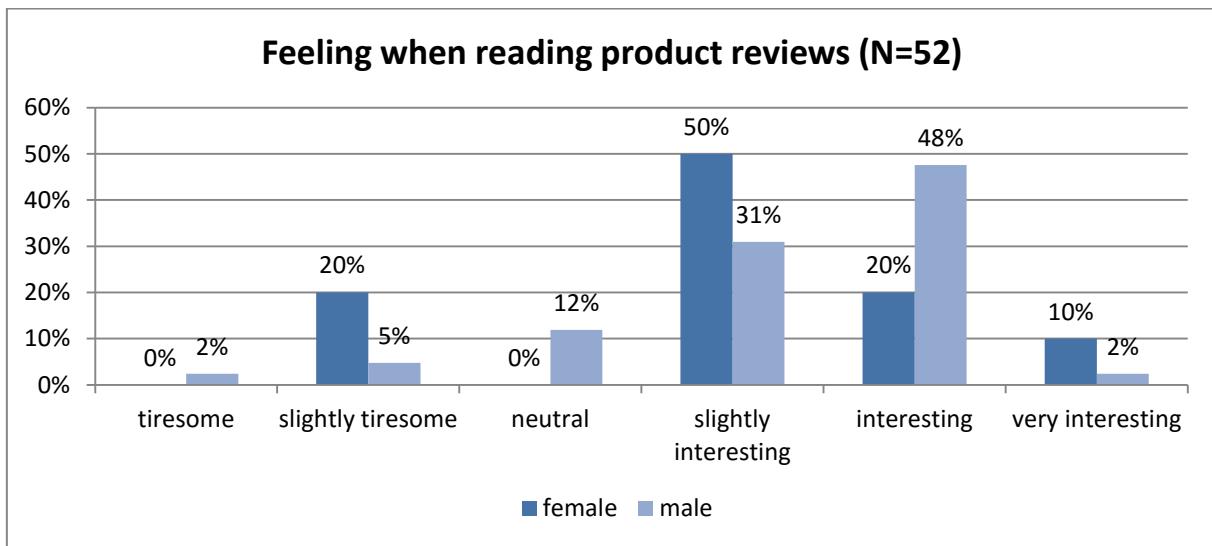


Figure 12: Survey Results - Feeling When Reading Product Reviews

Figure 12 seems to indicate that males feel more interested when reading reviews than females, but as this could just stem from the fact that the sample size between males and females differs, a t-Test was conducted to test whether the mean rating of males and females is equal or not (Table 8). The result indicates that there is no significant difference between males and females in the survey respondents concerning their feeling when reading product reviews.

Feeling when reading product reviews – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H ₀	Mean of male = Mean of females	
	female	Male
N	10	41
Mean Value	5	5.238095238
Empirical Variance	1.555555556	1.06387921
Degrees of Freedom (dF)	12	
t-Statistics	-0.559819751	
Alpha	0.05	
Critical Value t-Distribution	2.17881283	
p-Value	0.585900816 => cannot reject H ₀	

Table 8: t-Test - Feeling When Reading Product Reviews

Lastly, the respondents were directly asked whether they **would like product review summaries** or not. The results indicate that the majority (39 out of 52) would like to have review summaries (Figure 13). This supports the indication described above that there is a need for product review summaries, therefore proving the theoretical derived need for summaries described in the introduction of this paper (see chapter 1).

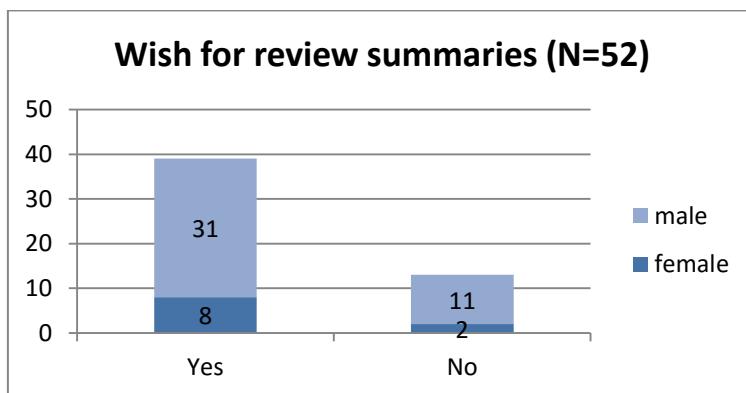


Figure 13: Survey Results - Wish for Product Review Summaries

As above a t-Test was performed to check whether a difference between males and females exists regarding their wish for product review summaries. The result is shown in Table 9 and indicates that there is no significant difference. Together with the results described above, this indicates that there is no difference between male and female customers for the online shopping situation. Everyone finds reading reviews interesting while at the same time only reading a very small amount of reviews. This result together with the explicit wish for summaries proves the need for product review summarization.

Wish for product review summaries – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of male = Mean of females	
	female	Male
N	10	41
Mean Value	1.2	1.261904762
Empirical Variance	0.177777778	0.198025552
Degrees of Freedom (dF)	14	
t-Statistics	-0.412765636	
Alpha	0.05	
Critical Value t-Distribution	2.144786688	
p-Value	0.686030102 => cannot reject H_0	

Table 9: t-Test - Wish for Product Review Summaries

5.2.4.2 Feature Extraction

Figure 14 shows the sample sizes for the two products that were part of the survey: 24 people filled out the survey with the smartphone as their reference product while the 28 people saw the movie. 75 percent of the movie sample knew their product, while only 46 percent of the smartphone sample knew their smartphone (cf. Figure 15). This means that altogether around 62 percent of the survey respondents had knowledge about their product.

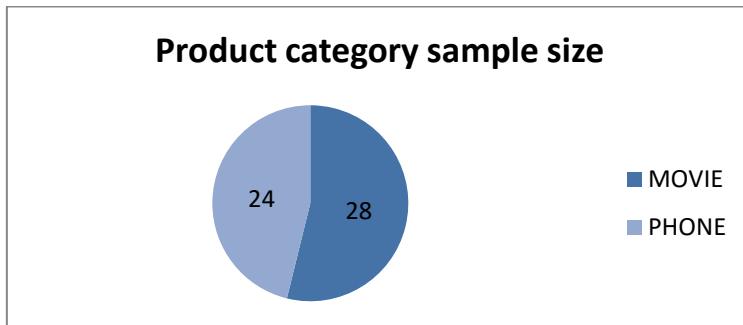


Figure 14: Survey Results - Product Category Sample Size

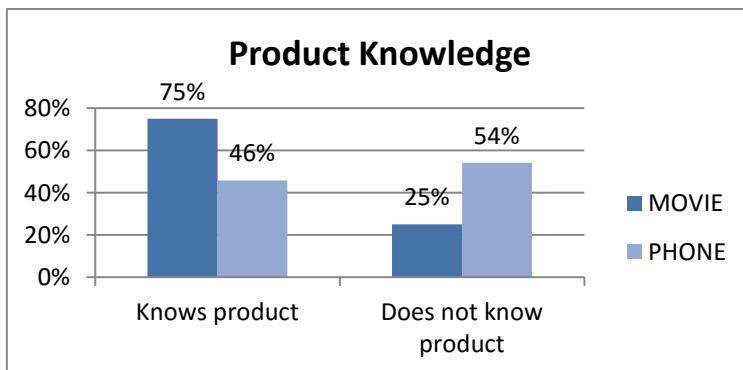


Figure 15: Survey Results - Product Knowledge

Figure 16 and Figure 17 show the results for the **comparison of three different feature extraction methods** implemented in this work¹⁷³. The survey results indicate that the Meta approach performs best in an overall setting.¹⁷⁴ For the movie, the modified Scaffidi et al. (2007) approach performs best, but the Meta approach is close behind. For the smartphone, the modified Wang et al. (2013) approach wins, although it is rated worst when considering both products. For the smartphone, the Meta approach again achieves a good second place. This indicates that while different methods may perform better for different product categories, the Meta approach (through the combination of the various input approaches) is able to achieve the best result when considering all product categories at the same time. It therefore suits the goal of this work, a universally usable summarization approach, best.

Apart from this, 18 percent of the movie sample (five people) and 13 percent of the smartphone sample (three people) consider none of the methods as good. This clearly indicates that the feature extraction approach can be further enhanced, but this also shows that 85 percent of all respondents (44 people) thought that the feature extraction methods are usable. This is therefore great evidence that the implemented approaches can be used in practice.

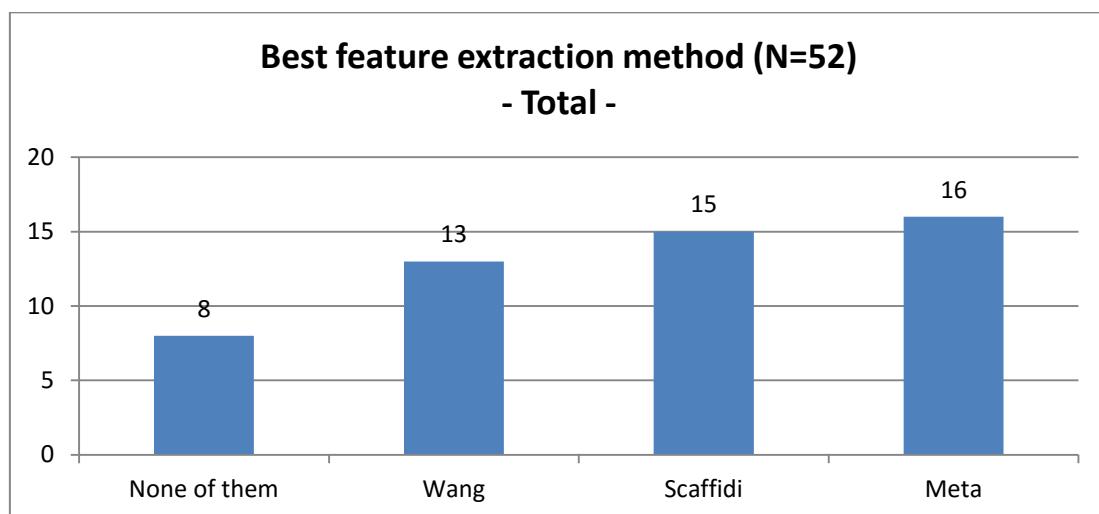


Figure 16: Survey Results - Extraction Method -Total-

¹⁷³ See section 4.2.3.

¹⁷⁴ Although by only one vote.

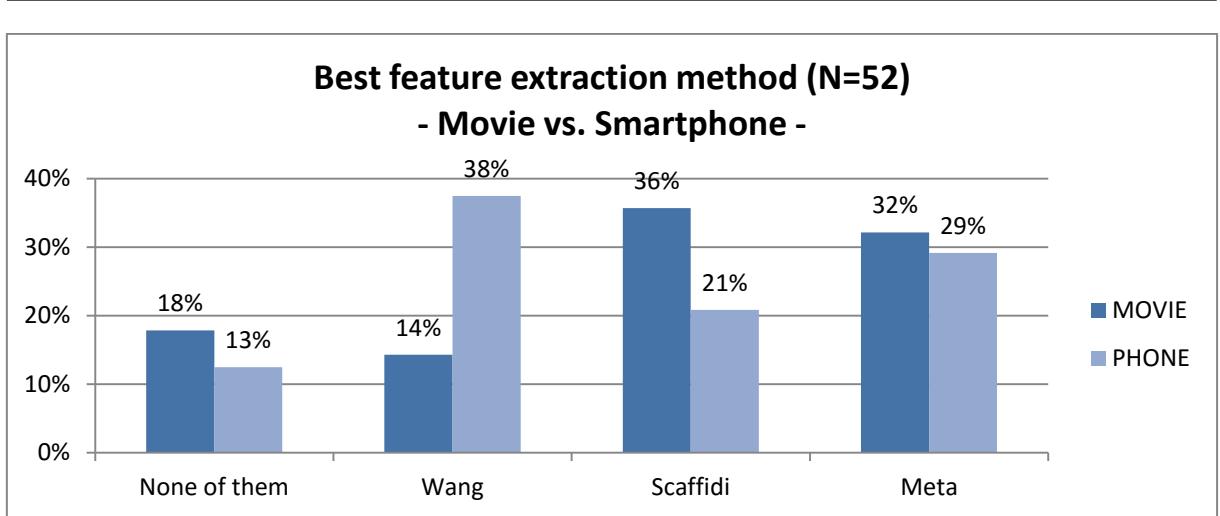


Figure 17: Survey Results - Extraction Method -Movie vs. Smartphone-

Figure 18 shows the result of the feature extraction evaluation when considering the respondent's knowledge about the product. People who know the product consider Scaffidi et al. (2007) as the best method, but the Meta approach is not that far behind. For people without knowledge about the product, both Wang et al. (2013) and the Meta approach perform equally well. This again shows that the Meta approach seems to be the most promising method of the three tested ones as it works well for both groups.

Figure 18 also shows that 19 percent of the respondents who know the product don't like any of the three approaches (vs. only ten percent for respondents without knowledge). This, again, shows that the feature extraction can be further enhanced, but that the methods work around 90 percent of the sample is strong evidence that they can be successfully used in practice.

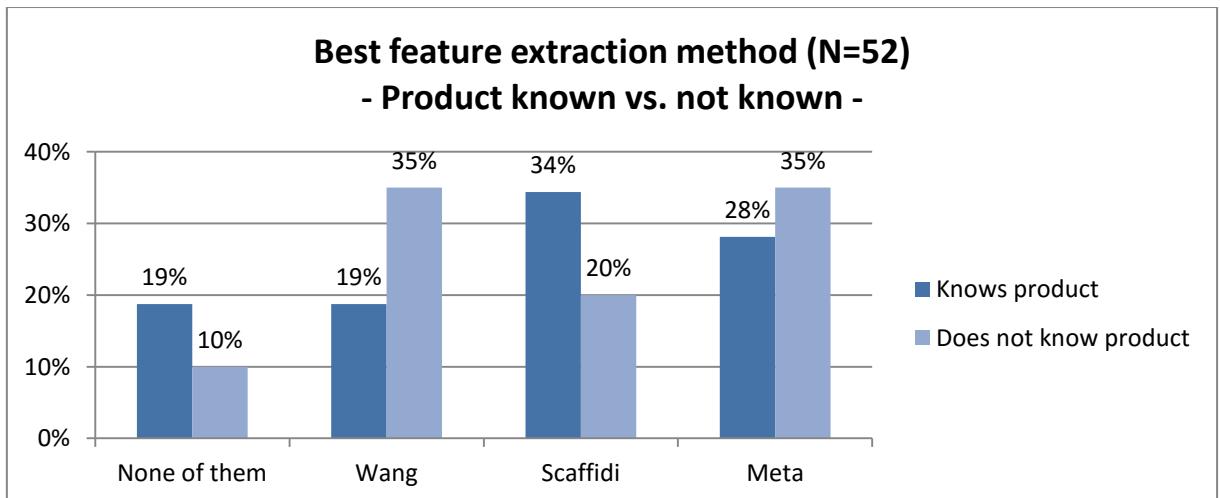


Figure 18: Survey Results - Extraction Method -Product Knowledge-

Figure 19 and Figure 20 show that apart from the general usability of the feature extraction methods, their **quality** is rated positively by around 64 percent of the sample (33 people) and negatively only by 23 percent (12 people). Although this shows that room for improvement is still there (especially as no one rated the quality as “very good”), the methods are still usable in practice as nearly two-third of the sample rate the methods positively. A t-Test (Table 10) shows that there is no significant difference in the rating between the two samples (movie and smartphone).¹⁷⁵ The methods therefore perform equally well for the movie and the smartphone. This is again a good indication that the methods might be universally usable.

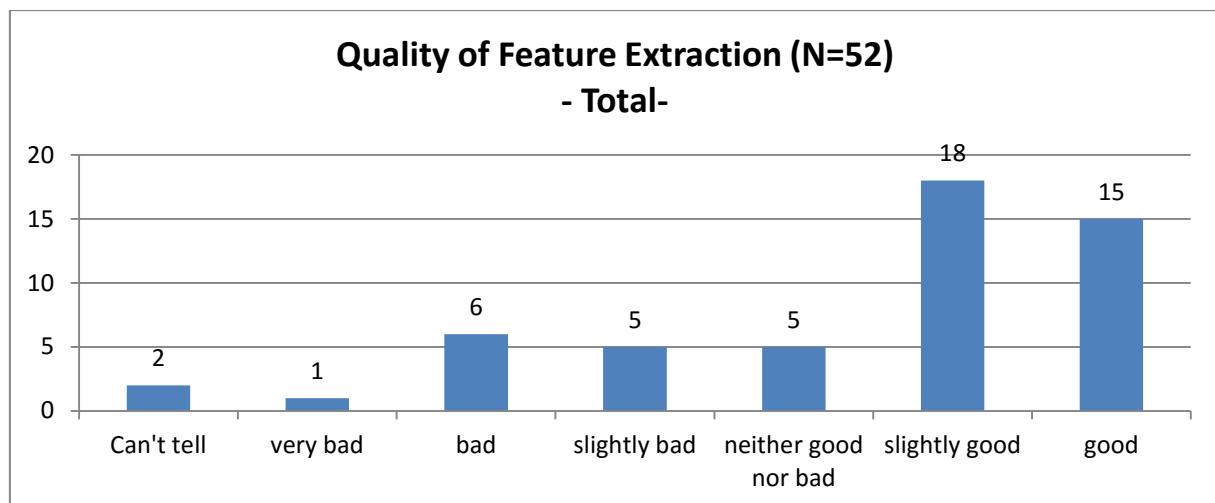


Figure 19: Survey Results - Quality of Feature Extraction -Total-

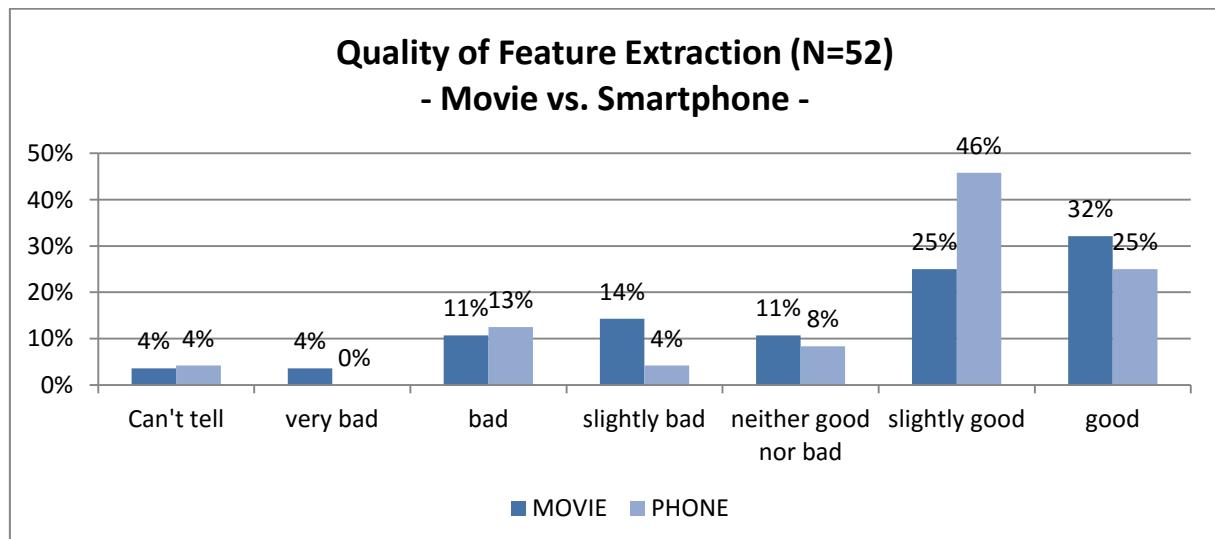


Figure 20: Survey Results - Quality of Feature Extraction -Movie vs. Smartphone-

¹⁷⁵ From each sample, one respondent who answered with „I can't rate the quality” was removed for the t-Test.

Quality of feature extraction – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H ₀	Mean of movie = Mean of smartphone	
N	movie	smartphone
Mean Value	27	23
Empirical Variance	4.444444444	4.695652174
Degrees of Freedom (dF)	28	
t-Statistics	-0.623873598	
Alpha	0.05	
Critical Value t-Distribution	2.010634758	
p-Value	0.535664412 => cannot reject H ₀	

Table 10: t-Test - Quality of Feature Extraction -Movie vs. Smartphone-

When testing whether knowledge about the product has an effect or not, Figure 21 shows that respondents who don't know the product rate the quality of the feature extraction better than respondents who know (70 percent vs. 59 percent with a rating of "slightly good" or better). But a t-Test shows that this difference is not significant (Table 11).¹⁷⁶ The implemented methods therefore work independently from the product knowledge. This proves a universal applicability for all potential users.

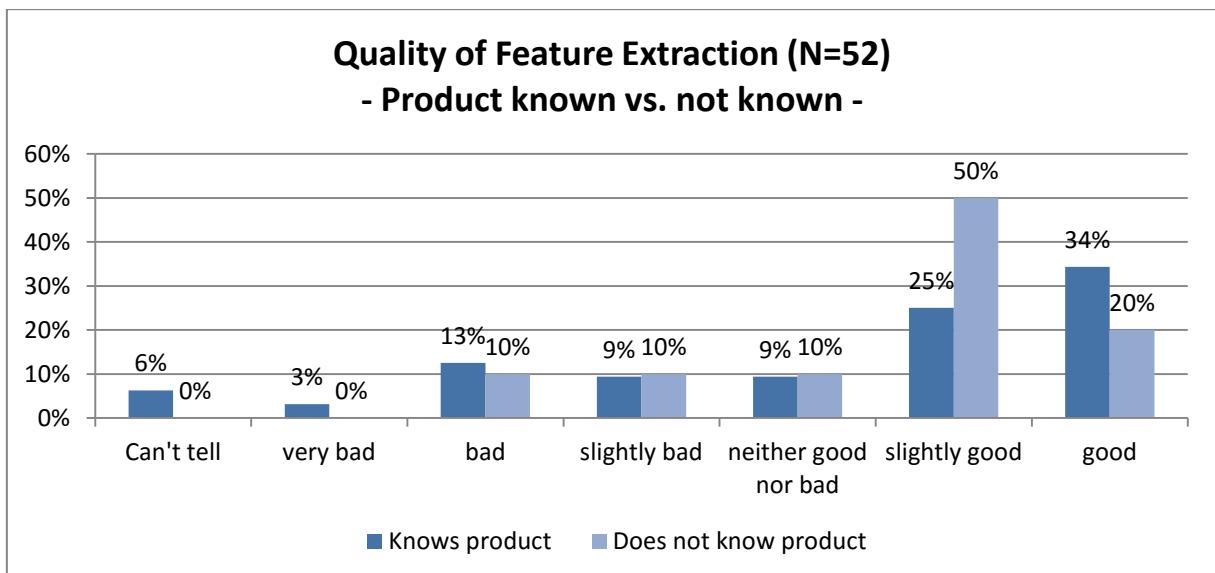


Figure 21: Survey Results - Quality of Feature Extraction -Product Knowledge-

¹⁷⁶ For „knows product“ two people who answered “I can't rate the quality” were removed for the test.

Quality of feature extraction – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H ₀	Mean of knows product = Mean of does not know product	
	Knows product	Does not know product
N	30	20
Mean Value	4.533333333	4.6
Empirical Variance	2.464367816	1.515789474
Degrees of Freedom (dF)	47	
t-Statistics	-0.167752676	
Alpha	0.05	
Critical Value t-Distribution	2.011740514	
p-Value	0.867497608 => cannot reject H ₀	

Table 11: t-Test - Quality of Feature Extraction -Product Knowledge-

Figure 22 and Figure 23 show the results for rating of the **feature names**. Only slightly more than 50 percent (52 percent, 27 people) give a positive rating and around 38 percent (20 percent) give a negative rating. This shows that the feature name selection is a weak point in the implemented feature extraction approaches. A better name selection from the noun phrase clusters should therefore be researched. But as at least half of the sample gives a positive rating, the implemented method can be used, although they are far from being perfect. A t-Test shows that there is no significant difference in the rating between the movie and the smartphone, although the mean rating for the movie feature names is slightly better than for the smartphone feature names (Table 12).¹⁷⁷ This again indicates that the implemented methods seem to be universally applicable for a lot of different product categories.

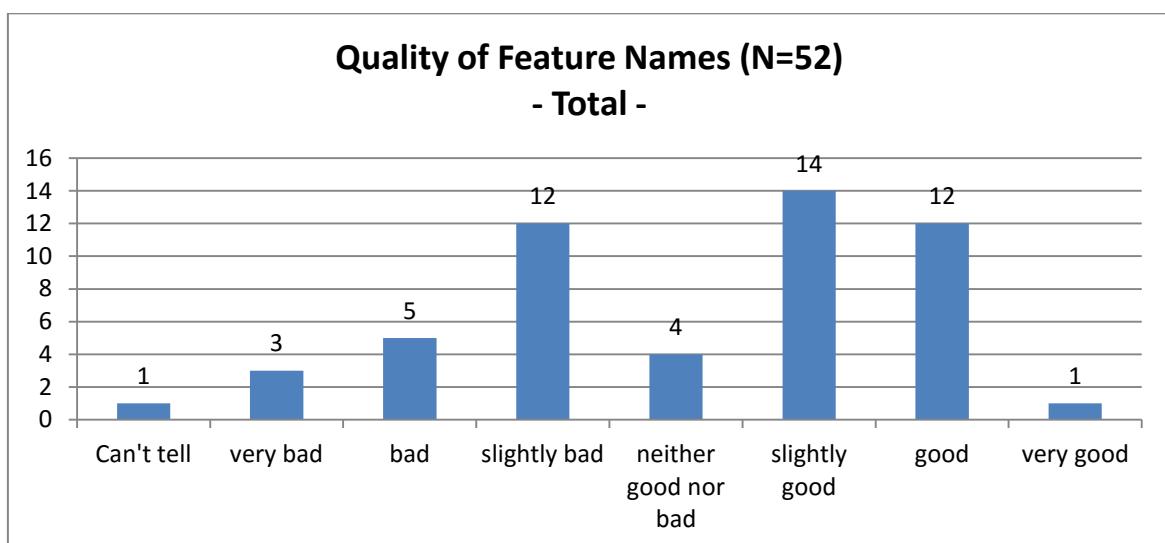


Figure 22: Survey Results - Quality of Feature Names -Total-

¹⁷⁷ From each sample, one respondent who answered with „I can't rate the quality” was removed for the t-Test.

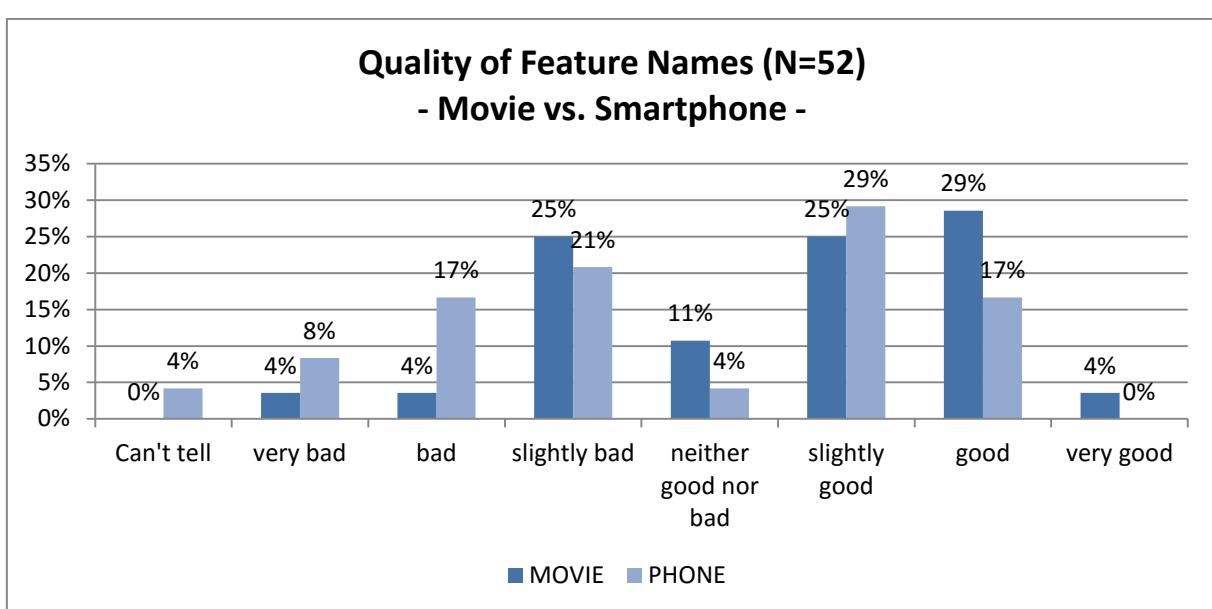


Figure 23: Survey Results - Quality of Feature Names -Movie vs. Smartphone-

Quality of feature names– two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of movie = Mean of smartphone	
N	movie	smartphone
Mean Value	28	24
Empirical Variance	4.5	3.625
Degrees of Freedom (dF)	2.259259259	3.635869565
t-Statistics	44	1.815906189
Alpha	0.05	
Critical Value t-Distribution	2.015367574	
p-Value	0.076202554	=> cannot reject H_0

Table 12: t-Test - Quality of Feature Names -Movie vs. Smartphone-

When controlling for the knowledge about the product (Figure 24), a t-Test shows again no significant difference between people who know the product and people who don't (Table 13). The mean values of both groups are close to the "neither good nor bad"-category which again indicates that the feature names are acceptable, but not really good.

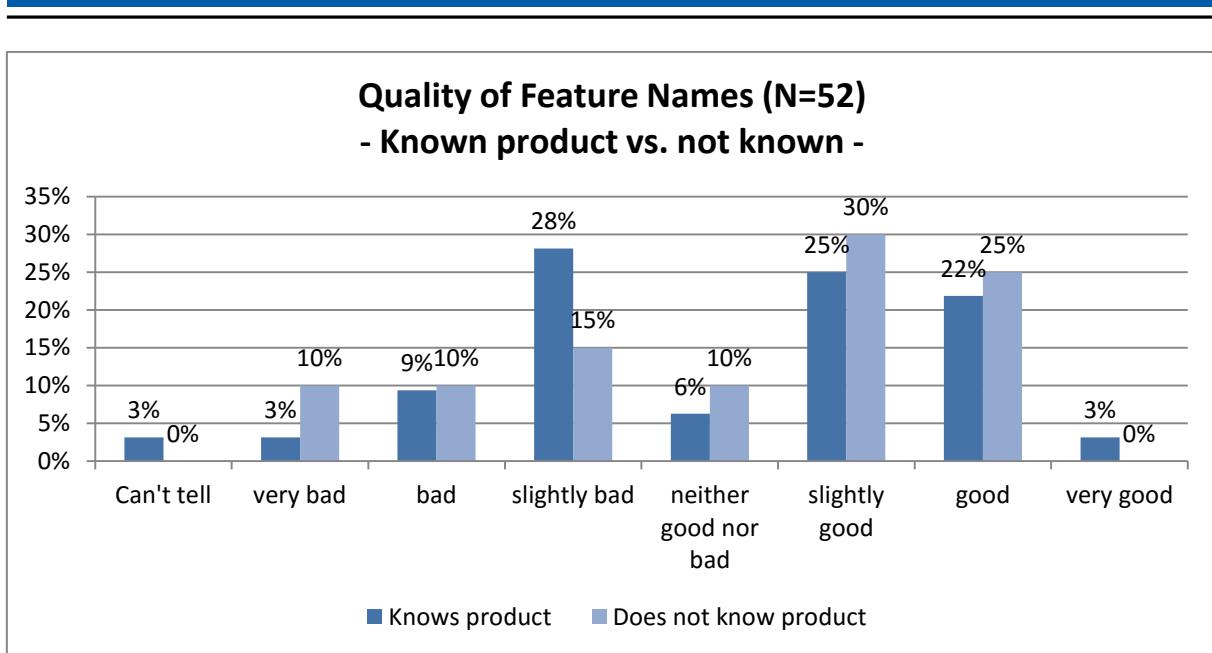


Figure 24: Survey Results - Quality of Feature Names -Product Knowledge-

Quality of feature names – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H ₀	Mean of knows product = Mean of does not know product	
	Knows product	Does not know product
N	31	20
Mean Value	4.225806452	4.15
Empirical Variance	2.447311828	2.871052632
Degrees of Freedom (dF)	38	
t-Statistics	0.160710015	
Alpha	0.05	
Critical Value t-Distribution	2.024394164	
p-Value	0.87317314 => cannot reject H ₀	

Table 13: t-Test - Quality of Feature Names -Product Knowledge-

The **free answers** for the feature extraction indicate the same problems that were already mentioned in section 5.1.2: The noun phrase clustering is not perfect (phrases are clustered together that shouldn't be clustered and clusters are sometimes overlapping) and the feature names are not optimal. As mentioned before, future research should develop a better noun phrase clustering. Although the free answers show these problems, the results explained above still hold, making the implemented feature extraction approaches applicable in practice.

The only other noteworthy comment is one person who wrote that he would prefer feature lists provided by the manufacturer. This person obviously was shown the smartphone in the survey as movies don't generally have a feature list from the manufacturer or producer. As

explained in section 5.1.1 using manufacturer-provided feature lists is not an option for a universally applicable summarization approach which is the goal of this work.

In summary, the three implemented approaches are not perfect, but should be usable in a practical scenario. Especially the Meta approach seems to be universally applicable for different product categories and is therefore best suited for the goal of this work, namely a summarization approach usable for all product categories. Room for improvement includes a better noun phrase clustering that will result in better feature clusters. Also the feature name selection should be improved in future research.

5.2.4.3 Sentiment Analysis

Figure 25 shows the rating of the four tested configurations for the whole sample:

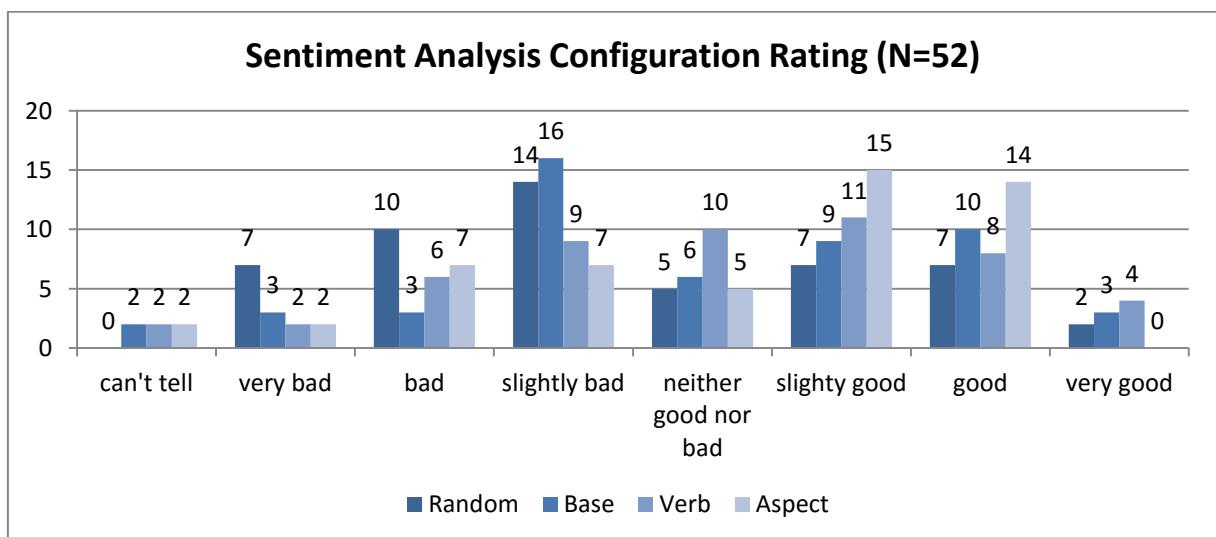


Figure 25: Survey Results - SA Configuration Rating

The interesting question now is if the Verb-, Base- and Aspect-configurations (from here on called “**real configurations**”) are better (i.e. get a higher rating) than the Random-configuration. Figure 26 shows the **mean rating of the whole sample** for the four configurations.¹⁷⁸ It seems that the real configurations could be better than the Random-configuration. In order to test this, analysis of variance (ANOVA) tests were conducted: Table 14 shows that there is a significant difference in the rating of the four configurations and Table 15 shows that there is no significant difference between the three real configurations. This implies that the real rating of the real configurations is significantly different, and in this

¹⁷⁸ “Can’t tell” answers were discarded for the mean calculation.

case higher, compared to the rating of the Random-configuration. This result is also proven by doing t-Tests and comparing the real configurations to the Random-configuration one at a time (see Table 16 to Table 18). Thus the proposed method seems to be capable of doing sentiment analysis.

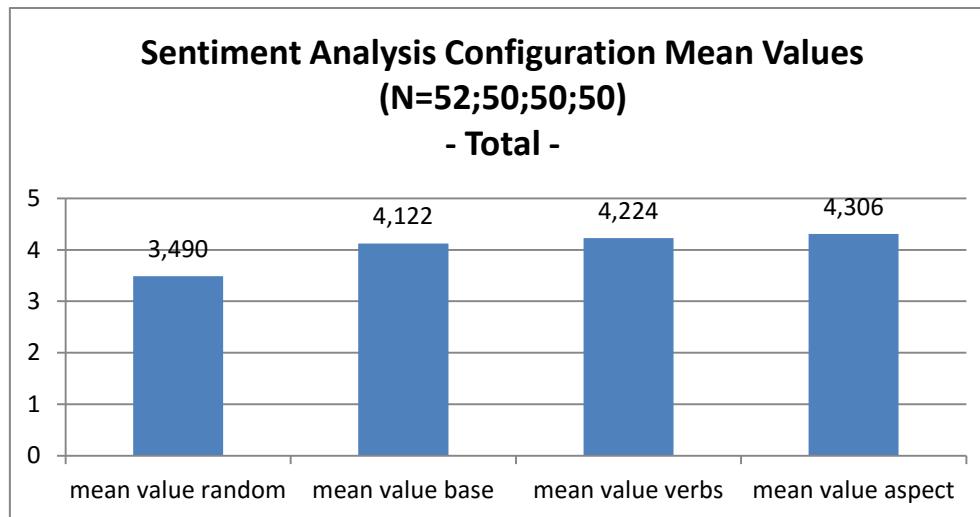


Figure 26: Survey Results - SA Mean Rating -Total-

Mean rating comparison (all configurations, Total) – single factor ANOVA				
Test Hypothesis H_0		Mean of Random = Mean of Base = Mean of Verb = Mean of Aspect		
	Random	Base	Verb	Aspect
N	52	50	50	50
Sum or rating	180	207	212	217
Mean value	3.461538462	4.14	4.24	4.34
Empirical variance	3,037707391	2.653469388	2.594285714	2.473877551
		Square Sum	Degree of Freedom (df)	Mean Square Sum
Variance Between Groups	24.40009139		3	8.133363798
Variance Inside Groups	533.2830769		198	2.693348873
Total	557.6831683		201	
F-statistics				3.019795868
Alpha				0.05
Critical Value F-distribution				2.650209357
p-Value				0.030922834 => reject H_0

Table 14: ANOVA Test – Mean SA rating comparison (all configurations) -Total-

Mean rating comparison (real configurations, Total) – single factor ANOVA			
Test Hypothesis H_0	Mean of Base = Mean of Verb = Mean of Aspect		
	Base	Verb	Aspect
N	50	50	50
Sum or rating	207	212	217
Mean value	4.14	4.24	4.34
Empirical variance	2.653469388	2.594285714	2.473877551
	Square Sum	Degree of Freedom (df)	Mean Square Sum
Variance Between Groups	1	2	0.5
Variance Inside Groups	378.36	147	2.573877551
Total	379.36	149	
F-statistics		0.194259435	
Alpha		0.05	
Critical Value F-distribution		3.057620652	
p-Value		0.82365529 => reject H_0	

Table 15: ANOVA Test – Mean SA rating comparison (real configurations) -Total-

SA Rating (Random vs. Base, Total) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Random = Mean of Base	
	Random	Base
N	52	50
Mean Value	3.461538462	4.14
Empirical Variance	3.037707391	2.653469388
Degrees of Freedom (dF)		100
t-Statistics		-2.031951953
Alpha		0.05
Critical Value t-Distribution		1.983971519
p-Value		0.044810476 => reject H_0

Table 16: t-Test - SA Rating (Random vs. Base) -Total-

SA Rating (Random vs. Verb, Total) two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Random = Mean of Verb	
	Random	Verb
N	52	50
Mean Value	3.461538462	4.24
Empirical Variance	3.037707391	2.594285714
Degrees of Freedom (dF)		100
t-Statistics		-2.343922106
Alpha		0.05
Critical Value t-Distribution		1.983971519
p-Value		0,02106017 => reject H_0

Table 17: t-Test - SA Rating (Random vs. Verb) -Total-

SA Rating (Random vs. Aspect, Total) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Random = Mean of Aspect	
	Random	Aspect
N	52	50
Mean Value	3.461538462	4.34
Empirical Variance	3.037707391	2.473877551
Degrees of Freedom (dF)	100	
t-Statistics	-2.674373685	
Alpha	0.05	
Critical Value t-Distribution	1.983971519	
p-Value	0.008746741 => reject H_0	

Table 18: t-Test - SA Rating (Random vs. Aspect) -Total-

The results also imply that in contrast to the result of Wei et al. (2010) using verbs as opinion words in addition to adjectives (configuration Verb) does not worsen the result. But as shown in Table 15 there does not seem to be a significant difference in rating between the real configurations. Thus using verbs also does not seem to improve the result compared to just using adjectives and modifiers (configuration Base). The same holds for configuration Aspect even though its mean rating is the highest among the four tested configurations. Again, to verify this result, t-Tests were conducted in addition to the ANOVA-test (see Table 19 and Table 20¹⁷⁹). So while every real configuration is better than the Random-configuration when considering the whole sample, there is no significant difference between them. For a practical scenario, there is no real suggestion possible apart from using one of the proposed methods.¹⁸⁰ More research is necessary.

SA Rating (Base vs. Verb, Total) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Base = Mean of Aspect	
	Base	Verb
N	50	50
Mean Value	4.14	4.24
Empirical Variance	2.653469388	2.594285714
Degrees of Freedom (dF)	98	
t-Statistics	-0.308672701	
Alpha	0.05	
Critical Value t-Distribution	1.984467455	
p-Value	0.758225727 => cannot reject H_0	

Table 19: t-Test - SA Rating (Base vs. Verb) -Total-

¹⁷⁹ Note that there is no need to test Verb vs. Aspect as the tests already show that there is no difference between Base and Verb as well as Base and Aspect. Naturally, there can't be a difference between Verb and Aspect.

¹⁸⁰ And as said before: Regarding the review time and limiting the amount of sentences that can originate from one product review should be done (see section 4.3.6.3 and section 4.4.5.2).

SA Rating (Base vs. Aspect, Total) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Base = Mean of Aspect	
	Base	Aspect
N	50	50
Mean Value	4.14	4.34
Empirical Variance	2.653469388	2.473877551
Degrees of Freedom (dF)	98	
t-Statistics	-0.62455206	
Alpha	0.05	
Critical Value t-Distribution	1.984467455	
p-Value	0.533716452 => cannot reject H_0	

Table 20: t-Test - SA Rating (Base vs. Aspect) -Total-

The results change if the **rating is analyzed per product category** (Figure 27). Using ANOVA there is no difference between any of the configurations detectable (Table 21 and Table 22). Because this contradicts the previous result and because the test statistics are very close to being significant on the five percent level, t-Tests were conducted again in which the Random-configuration is tested against each of the real configurations (see Table 23 to Table 25 for the movie subsample and Table 26 to Table 28 for the smartphone subsample). For both subsamples only one configuration is significantly better than the Random-configuration. For the movie the Aspect-configuration is significantly better and for the smartphone the Verb-configuration is rated significantly higher. The survey data does not show why these differences exist, but this result implies that depending on the product category different configurations should be used, but it also implies that at least one of the proposed methods always works.

Again, making a suggestion for a practical scenario is difficult. Choosing the configuration per product category is difficult and not really a universally usable solution. But it at least seems that the Base-configuration is not enough. When regarding the result of the whole sample together with the subsample results, using the Verb- or Aspect-configuration seems promising, but it could be even better to use the Verb- and Aspect-configuration at the same time.¹⁸¹ Maybe this would work for the movie and the smartphone as well as other product categories. As this could not be tested in the scope of the conducted survey, more research is necessary.

¹⁸¹ Together with the review time and the sentence limitation.

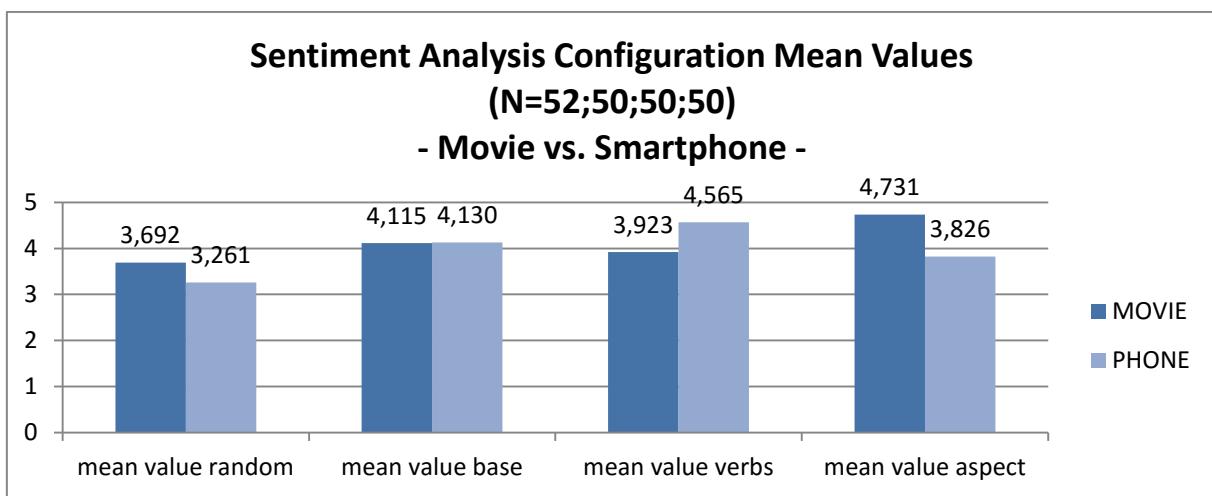


Figure 27: Survey Results - SA Mean Rating -Movie vs. Smartphone-

Mean rating comparison (all configurations, Movie) – single factor ANOVA				
Test Hypothesis H_0		Mean of Random = Mean of Base = Mean of Verb = Mean of Aspect		
		Random	Base	Verb
N		28	27	26
Sum or rating		102	112	102
Mean value		3.642857143	4.148148148	3.923076923
Empirical variance		2.904761905	2.977207977	1.993846154
				Aspect
				27
				129
				4.7777777778
				1.871794872
			Square Sum	Degree of Freedom (df)
Variance Between Groups			19.08638584	3
Variance Inside Groups			254.3487993	104
Total			273.4351852	107
				Mean Square Sum
				6.362128612
				2.445661532
				2.691978638
				0.05
				2.601393745
				0.05601027 => cannot reject H_0

Table 21: ANOVA Test – Mean SA rating comparison (all configurations) -Movie-

Mean rating comparison (all configurations, Smartphone) – single factor ANOVA				
Test Hypothesis H_0	Mean of Random = Mean of Base = Mean of Verb = Mean of Aspect			
	Random	Base	Verb	Aspect
N	24	23	24	23
Sum or rating	78	95	110	88
Mean value	3.25	4.130434783	4.583333333	3.826086957
Empirical variance	3.239130435	2.391304348	3.123188406	2.786561265
	Square Sum	Degree of Freedom (df)	Mean Square Sum	
Variance Between Groups	22.48766574	3	7.495888581	
Variance Inside Groups	260.2463768	90	2.891626409	
Total	282.7340426	93		
F-statistics		2.592274215		
Alpha		0.05		
Critical Value F-distribution		2.705838051		
p-Value		0,057559165 => cannot reject H_0		

Table 22: ANOVA Test – Mean SA rating comparison (all configurations) -Smartphone-

SA Rating (Random vs. Base, Movie) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Random = Mean of Base	
	Random	Base
N	28	27
Mean Value	3.642857143	4.148148148
Empirical Variance	2.904761905	2.977207977
Degrees of Freedom (dF)		53
t-Statistics		-1.092260172
Alpha		0.05
Critical Value t-Distribution		2.005745995
p-Value		0.279659 => cannot reject H_0

Table 23: t-Test - SA Rating (Random vs. Base) -Movie-

SA Rating (Random vs. Verb, Movie) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Random = Mean of Verb	
	Random	Verb
N	28	26
Mean Value	3.642857143	3.923076923
Empirical Variance	2.904761905	1.993846154
Degrees of Freedom (dF)		51
t-Statistics		-0.659700717
Alpha		0.05
Critical Value t-Distribution		2.00758377
p-Value		0.512414159 => cannot reject H_0

Table 24: t-Test - SA Rating (Random vs. Verb) -Movie-

SA Rating (Random vs. Aspect, Movie) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Random = Mean of Aspect	
	Random	Aspect
N	28	27
Mean Value	3.642857143	4.777777778
Empirical Variance	2.904761905	1.871794872
Degrees of Freedom (dF)	51	
t-Statistics	-2.728086068	
Alpha	0.05	
Critical Value t-Distribution	2.00758377	
p-Value	0.008716238 => reject H_0	

Table 25: t-Test - SA Rating (Random vs. Aspect) -Movie-

SA Rating (Random vs. Base, Phone) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Random = Mean of Base	
	Random	Base
N	24	23
Mean Value	3.25	4.130434783
Empirical Variance	3.239130435	2.391304348
Degrees of Freedom (dF)	44	
t-Statistics	-1.801186357	
Alpha	0.05	
Critical Value t-Distribution	2.015367574	
p-Value	0.078529143 = > cannot reject H_0	

Table 26: t-Test - SA Rating (Random vs. Base) -Smartphone-

SA Rating (Random vs. Verb, Phone) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of Random = Mean of Verb	
	Random	Verb
N	24	24
Mean Value	3.25	4.583333333
Empirical Variance	3.239130435	3.123188406
Degrees of Freedom (dF)	46	
t-Statistics	-2.589623591	
Alpha	0.05	
Critical Value t-Distribution	2.012895599	
p-Value	0.012823669 => reject H_0	

Table 27: t-Test - SA Rating (Random vs. Verb) -Smartphone-

SA Rating (Random vs. Aspect, Phone) – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H ₀	Mean of Random = Mean of Aspect	
	Random	Aspect
N	24	23
Mean Value	3.25	3.826086957
Empirical Variance	3.239130435	2.786561265
Degrees of Freedom (dF)	45	
t-Statistics		-1.138328155
Alpha		0.05
Critical Value t-Distribution		2.014103389
p-Value		0.261007704 => cannot reject H ₀

Table 28: t-Test - SA Rating (Random vs. Aspect) -Smartphone-

5.2.4.4 Summary Layout

Figure 28 shows the result for the **preferred layout** of the respondents. The “List”-layout seems to be preferred over the “Table”-layout, although only slightly. In a practical scenario, a good option would therefore be to use a list-based layout as the default option, but giving users the option to change the summary layout to a table-based layout.

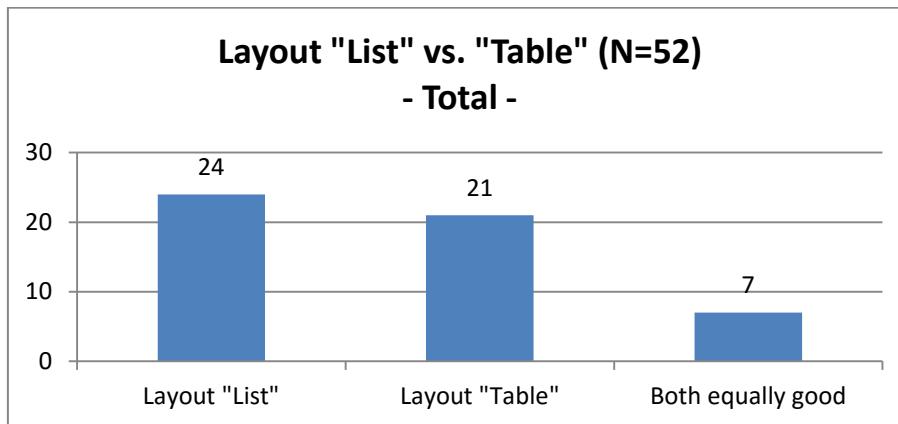


Figure 28: Survey Results - List vs. Table Layout -Total-

As the layout is independent from the summary content, a cross-analysis with the movie and smartphone sample was not performed. Instead it was examined if male and female respondents have a different opinion as shown in Figure 29. It seems male respondents prefer the “List”-layout while female respondents prefer the “Table”-layout, but this result must be interpreted carefully as the female sample size is small. For a practical scenario, the above described configuration is probably still the best option even when considering the difference between male and female respondents. Still, integrating this result is possible: The default

option for unregistered members of a shop is a list-based layout. After registration, once the gender is known, the default layout changes to list-based for men and table-based for women while having the option to change the layout to the other one.

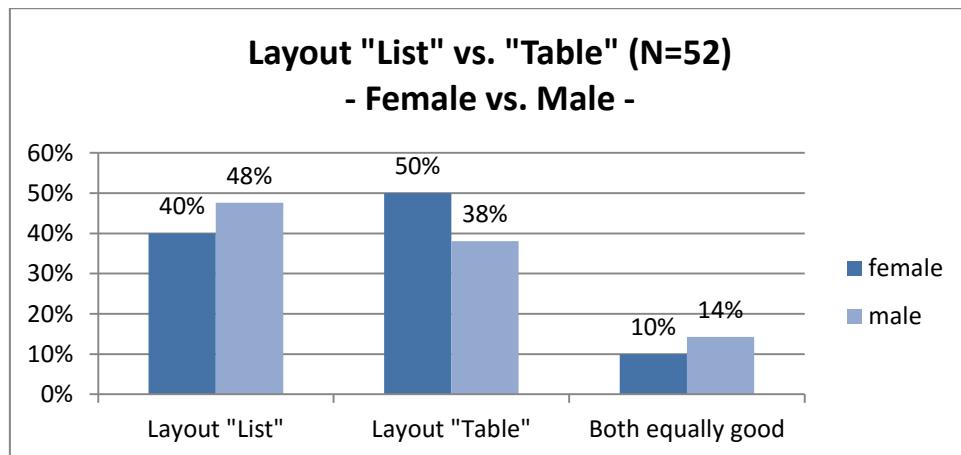


Figure 29: Survey Results - List vs. Table Layout -Female vs. Male-

Figure 30 clearly shows that the **amount of reviews that mention a feature** positively and negatively should be shown in the summary. One explanation for this that it helps put the features importance and opinion into perspective.¹⁸²

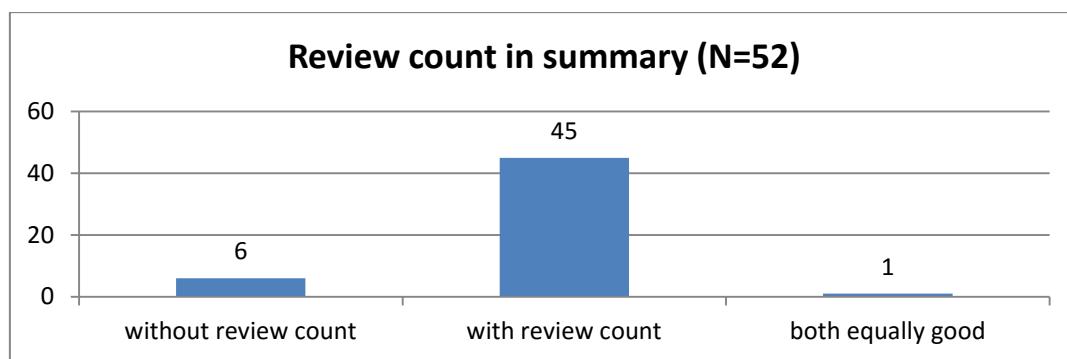


Figure 30: Survey Results - Review Count

Figure 31 shows that most respondents don't want to see the **sentiment analysis score** that indicates how positive or negative a sentence is in the summaries. But the lead is only very small. The reason for not wanting to see the score might be that the interpretation is hard or the general idea that a computer may score the positivity or negativity of sentence might be hard to grasp. One respondent mentioned in a free-text answer that the interpretation is

¹⁸² Also see section 4.4.5.2 for the reason to always show the total review count.

difficult. Another reason might be that the numbers distract from the actual review content. When using summaries in practice, it might be the best option to not show that scores as the default option, but allowing users to display them if they want to see them.

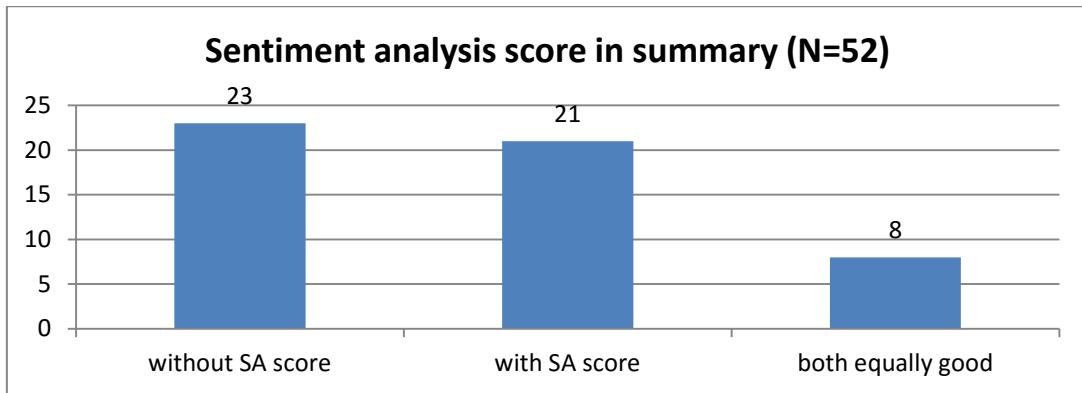


Figure 31: Survey Results - Sentiment Analysis Score

Figure 32 shows that most respondents prefer **five features in a summary**, but 25 percent (13 people) have no preference. When controlling for the product category (Figure 33), a t-Test (without “I don’t care how many features there are”-answers) shows a significant difference between the movie sample and the smartphone sample (Table 29). It seems that for smartphone summaries more features are preferred compared to movie summaries (mean value 6.6 vs. 4.5). This could stem from the fact that smartphones are highly complex with a lot of things to consider when making a buying decision.¹⁸³

The problem that exists now is how to cope with the different preferences in practice as it seems impossible or at least not reasonable to manually find the right feature amount for every product category (e.g. through surveys). Instead the following could be done: Initially, every summary is created with five features, but under each summary, the users have the option to vote for more or less features in the summary. A system could learn from these votes and over time adjust the feature count per product category. A more extreme approach could even learn preferences per user resulting in individual summaries in regard to the amount of shown features.¹⁸⁴

¹⁸³ Controlling for gender shows no difference in preference.

¹⁸⁴ Note that this approach does not increase the computational complexity of the proposed method. The greatest complexity lies in extracting features and analyzing the sentiment. The system could just be configured with a maximum number of features. The only thing that changes is the amount of those features that is shown for products of a certain category and/or individual users. Also note that the greedy approach for selecting sentences if only a maximum number of sentences in the summary may come from the same review (cf. section 4.4.5.2) also works with this method. The only thing that changes is the amount of shown

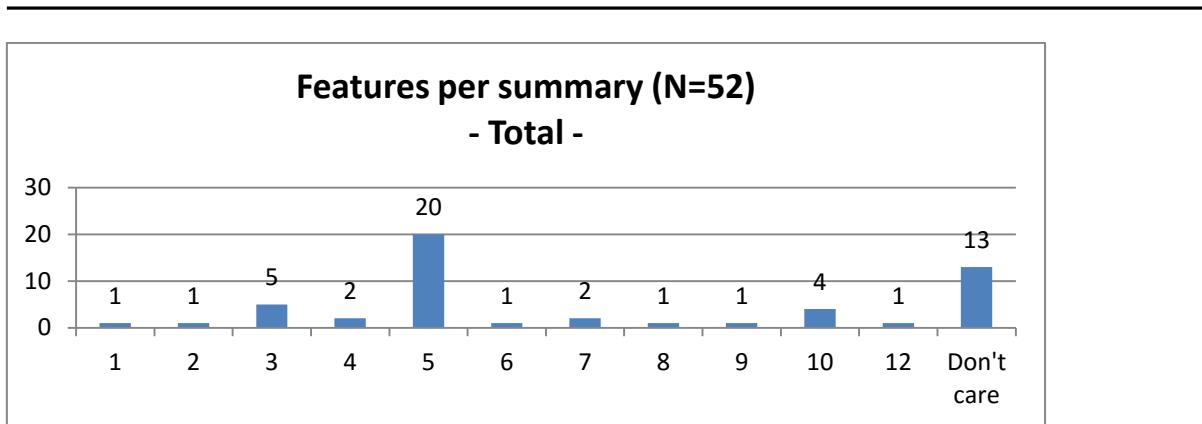


Figure 32: Survey Results - Features per Summary -Total-

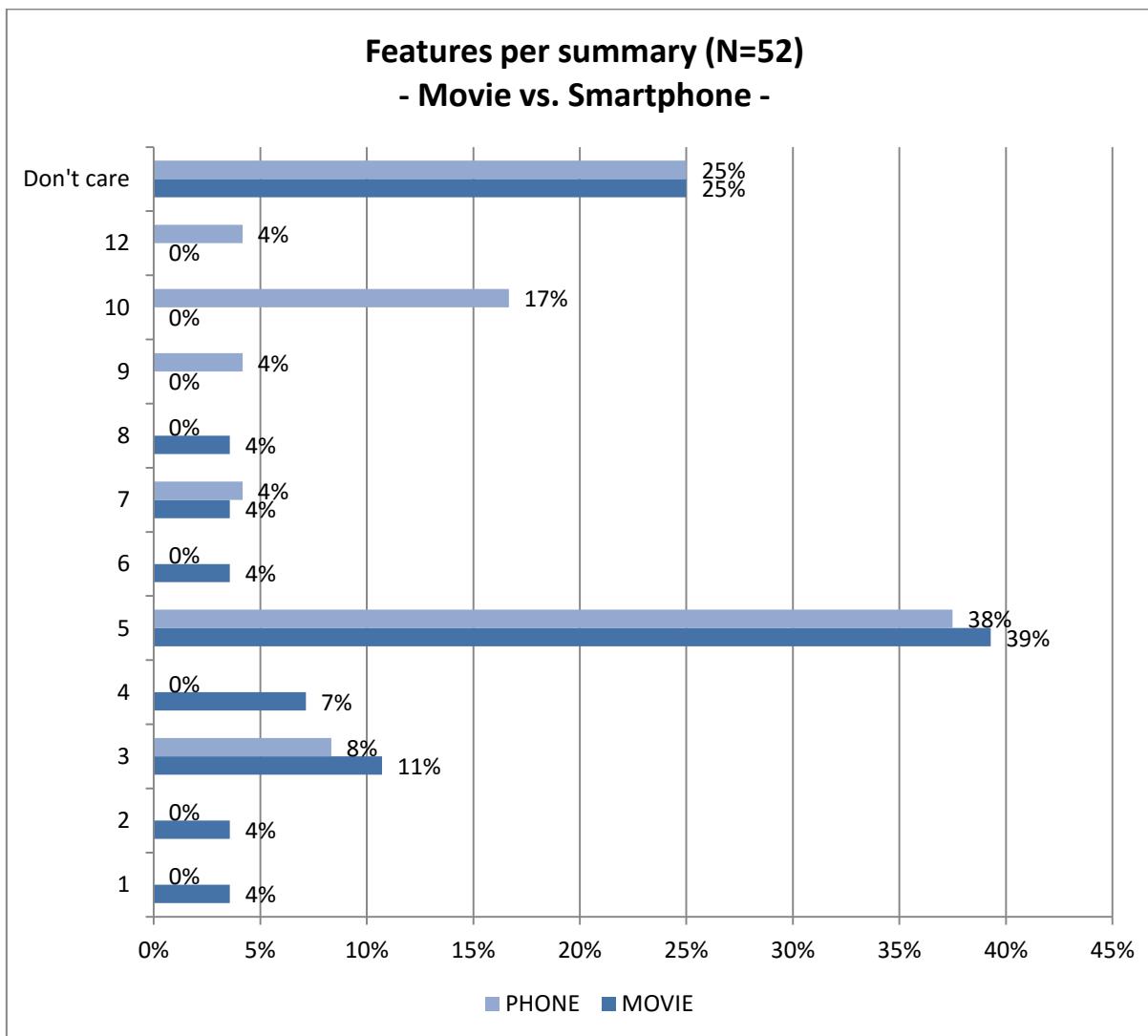


Figure 33: Survey Results - Features per Summary -Movie vs. Smartphone-

features, but the content of the feature summaries is always the same (continue reading the main text to see prove that the number of sentences per feature and sentiment polarity should be the same for all product categories).

Features per summary – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H ₀	Mean of movie = Mean of smartphone	
N	movie	smartphone
N	21	18
Mean Value	4.571428571	6.611111111
Empirical Variance	2.457142857	7.663398693
Degrees of Freedom (dF)	26	
t-Statistics	-2.768612608	
Alpha	0.05	
Critical Value t-Distribution	2.055529439	
p-Value	0.010241266 => reject H ₀	

Table 29: t-Test - Feature per Summary -Movie vs. Smartphone-

Figure 34 indicates that most people seem to prefer seeing only **two sentences per feature and polarity** (positive, negative), but three sentences were also often mentioned. Around 23 percent of all respondents don't have a preference and there is only one respondent who wants more than five sentences. Controlling for the product category (Figure 35) shows no significant difference between smartphones and movies (Table 30). Both samples have a mean value of around three sentences per feature and polarity. This means that in practice, there should be no need to change the sentence amount between different product categories and that two to three sentences per feature and polarity seem best.¹⁸⁵ Controlling for gender did not show significant differences.

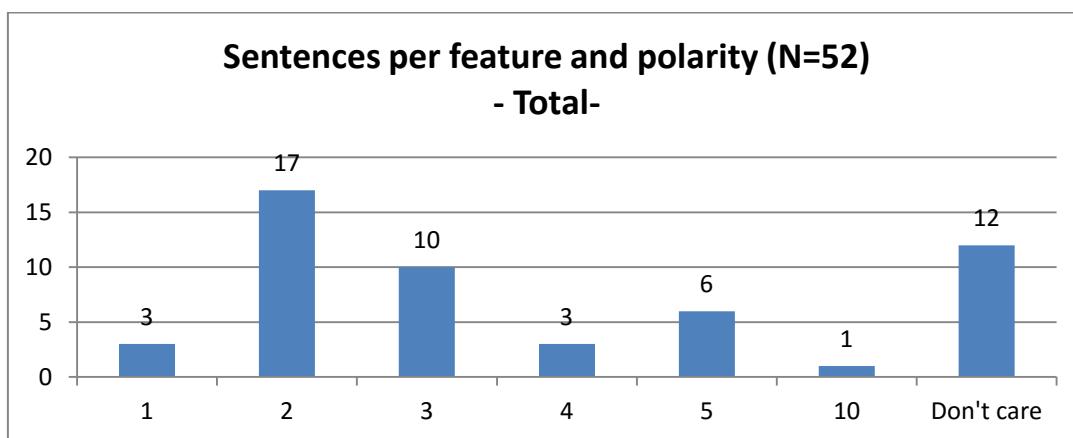


Figure 34: Survey Results - Sentences per Feature and Polarity -Total-

¹⁸⁵ This also benefits the above mentioned way to handle the differences in the amount of features that should be in a summary depending on the product category and/or the user. Were the preferences different, the system would have to create individual summaries for each user as the sentence selection might change if the option to only allow a maximum number of sentences originating from one review is used.

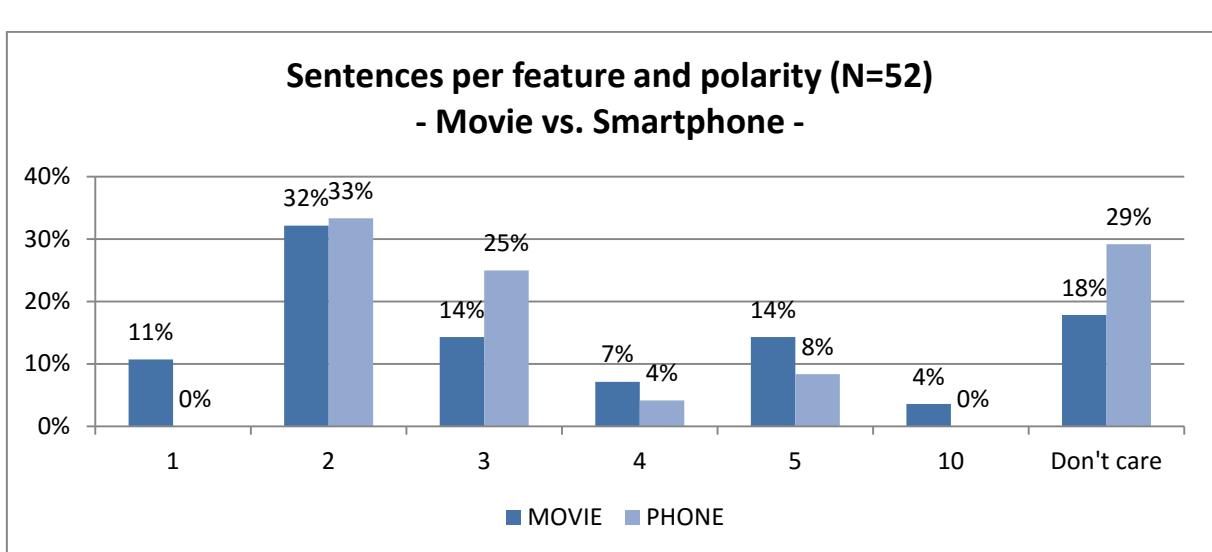


Figure 35: Survey Results - Sentences per Feature and Polarity -Movie vs. Smartphone-

Sentences per feature and polarity – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of movie = Mean of smartphone	
	movie	smartphone
N	23	17
Mean Value	3.086956522	2.823529412
Empirical Variance	3.992094862	1.029411765
Degrees of Freedom (df)	34	
t-Statistics	0.544425489	
Alpha	0.05	
Critical Value t-Distribution	2.032244509	
p-Value	0.589701793 => cannot reject H_0	

Table 30: t-Test - Sentences per Feature and Polarity - Movie vs. Smartphone.

5.2.4.5 Summary of the Results

The survey showed that there is a clear benefit when doing product review summarization for both male and female customers. This work on contrast to other papers proves this empirically and not only theoretically.

The proposed feature extraction methods seem to be universally applicable for all kinds of users and products. While specific methods may perform best for some product category, the Meta approach seems most promising as a universally usable method, performing best when regarding the whole sample. Still, the results could be even better with a better noun phrase clustering and better feature name selection.

Also for sentiment analysis the proposed methods are working, but apart from saying that just the Base-configuration is not enough, it is not possible to give a universal suggestion. More research focusing only at the sentiment analysis has to be conducted. For now, using the Verb- and Aspect-configuration together with the review time and the limitation of sentences originating from one review seems to be the best option.

For the summary layout, a list-based layout with information about how many reviews talk positively and negatively about a certain feature is preferred. For each feature and polarity two to three sentences should be displayed. Depending on the product category, a different amount of features should be shown. A machine-learning approach that automatically solves this problem with the help of the users has been proposed above.

The survey contained one final question asking whether the respondents would **base their buying decision solely on review summaries** like the ones they saw in the survey. Around 50 percent of the people that have an opinion would base their decision only on the summaries (Figure 36). The result is the same when controlling for the product category (Figure 37) and it is statistically significant (Table 31). One respondent wrote in a free-answer question that he also reads manufacturer-provided information besides reviews. It is not hard to image that a lot of people also read the information provided by the shop or manufacturer. Still, half of the respondents would base their decision only on the summaries. This impressive result clearly shows that the proposed methods, while still having flaws and room for improvement, can be successfully used in practice.

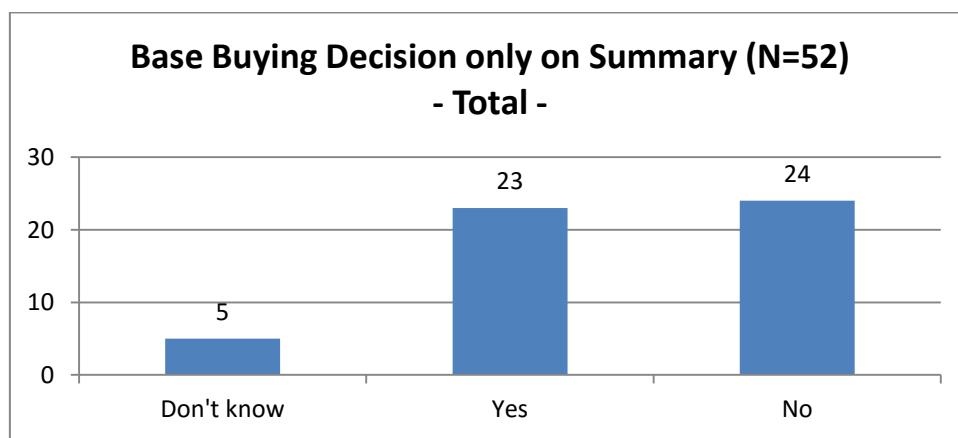


Figure 36: Survey Results - Buying Decision -Total-

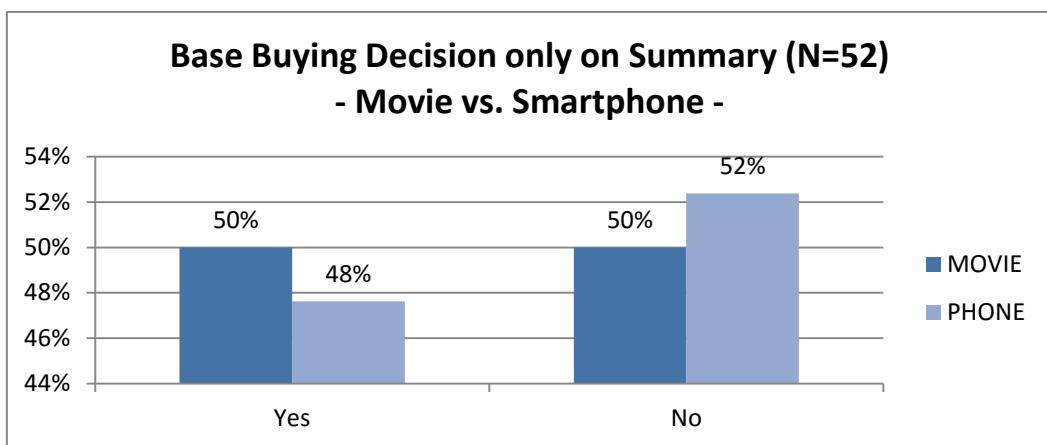


Figure 37: Survey Results - Buying Decision -Movie vs. Smartphone-

Buying Decision – two-sided t-Test for two samples with unequal variance		
Test Hypothesis H_0	Mean of movie = Mean of smartphone	
N	movie	smartphone
Mean Value	1.5	1.523809524
Empirical Variance	0.26	0.261904762
Degrees of Freedom (dF)	43	
t-Statistics		-0.158830234
Alpha		0.05
Critical Value t-Distribution		2.016692199
p-Value	$0.87454627 \Rightarrow \text{cannot reject } H_0$	

Table 31: t-Test - Buying Decision

6 Conclusion

This work proposes and empirically evaluates a product review summarization method that is universally usable and not restricted to certain product categories. In order to do this, existing techniques are modified and combined with each other as well as new ideas for each of the three summarization sub steps (Feature Extraction, Sentiment Analysis, Summarization).

For the feature extraction step, two existing methods were modified and one completely new combination approach (Meta approach) was proposed. While a manual evaluation did not show a clear winner, the conducted survey indicates that the Meta approach is very promising as it seems usable for a large number of product categories.

For the sentiment analysis step, ideas of several papers were combined, resulting in a highly configurable system. This high number of possible configuration of the sentiment analysis is

unique to this work as none of the cited papers has this level of configurability. Apart from this, this work is also the first¹⁸⁶ that actually realizes some ideas that were only proposed in other papers, most notably using the review time when rating sentences in order to penalize sentences from old reviews for being outdated. The empirical evaluation shows the applicability of the proposed methods, but does not give a clear answer to the question of which configuration is best.

For the summarization step, this work proposed a list-based and a table-based layout with optional displayable information. The survey showed that customers prefer the list-based layout with information about how many reviews talk about a product feature in a positive and negative way. This work therefore not only evaluates the general layout of the summaries compared to other papers, it is also the first¹⁸⁷ that directly asks the customers how many features and sentences the customers would like to read. A machine-learning approach is proposed to be able to generate ideal summaries (in terms of layout and feature count) for every product category and customer.

This work is also the only one so far¹⁸⁸ that empirically proves the benefit of review summaries and therefore the need for research in this field. Still, this work is not without limitations and therefore opportunities for further research, the biggest one being that the survey is very limited in the amount of tested products:

The feature extraction step is not perfect. Especially the noun phrase clustering should be improved to provide mutually exclusive clusters. There is also the possibility of errors in the manual evaluation of the feature extraction approaches as the features were extracted by hand. Also only a small sample could be analyzed, so the results may only apply to this sample. Further research should also especially be done on the proposed Meta approach in order to evaluate this approach with more input algorithms and for more product categories.

For the sentiment analysis more research is necessary on which configuration is the best. Not all possible combinations could be tested in the scope of this work and only two product categories with one product each could be tested. The results of the survey may thus be limited to this sample, making further research necessary. Additional options or other implementations for the sentiment analysis could also be explored, e.g. other ways of using the review time to penalize old reviews.

¹⁸⁶ To the best of the author's knowledge.

¹⁸⁷ To the best of the author's knowledge.

¹⁸⁸ To the best of the author's knowledge.

One missing part of the summarization step is the graphical design of the summaries. In this work only the general layout was researched, but not the graphical representation that may have a strong impact on the usability of the summaries in practice. One opportunity for further research is therefore the design and its effect on the perceived quality of the summaries. Apart from that, other layouts, additional graphical information etc. can be researched. The above mentioned possible limited generalizability also applies to the survey results concerning the summarization.

Even with these limitations, the survey has shown that 50 percent of all respondents would base their buying decision only on summaries like the ones they saw in the survey. While this could also only hold for the tested sample, it is still an impressive result that proves the applicability and quality of the proposed methods and other review summarization approaches in practice.

Appendix - Survey

Each respondent only sees the parts for the movie or the parts for the smartphone. After the general part they are randomly assigned to one of those two groups. Please also refer to section 5.2.3 for the other random parts of the survey. The information about which configuration belongs to which summary is only shown here, but was not shown to the survey respondents.

Survey General Part



TECHNISCHE
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0% completed

Welcome!

My name is **Benjamin Tumele**. I am an Information System Master student at TU Darmstadt.

My research focuses on **automated summarization of product reviews** (e.g. from Amazon).
The aim of this study is to evaluate the summarization approach I developed and for this your help is needed!

For this you will be asked to answer questions about your **experience with reading product reviews** and to **rate different summary layouts and summary contents**.

The survey will take about **20 minutes**.

All collected data will only be used in this study and not given to anyone else.
The data will only be analysed on an aggregate level. Individual surveys will not be analysed.

Thank you very much for taking the time to do this survey!

Next

Pause the interview

[Benjamin Tumele](#), Technische Universität Darmstadt – 2016

Please enter some personal data.

1. What is your gender?

- female
- male
- none of the above

2. How old are you?

[Please choose]

3. What do you do professionally?

- Pupil/in school
- Training/apprenticeship
- University student
- Employee
- Civil servant
- Self-employed
- Unemployed/seeking employment
- Other: []

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[Pause the interview](#)

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Your experience with online shopping

Did you ever buy something online (e.g. from Amazon)?

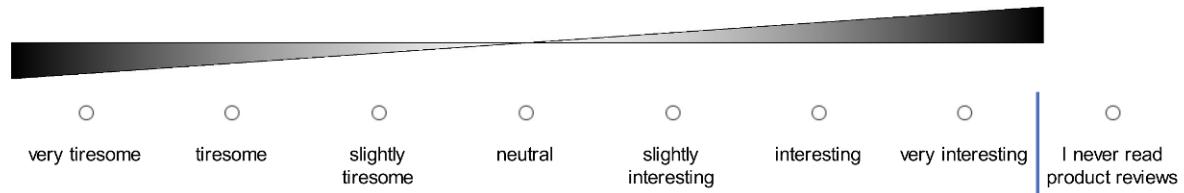
- Yes
- No

4. How many product reviews do you usually read when looking at a product at e.g. Amazon?

- less than 5
- 5 to 10
- 11 to 20
- 21 to 30
- more than 30

I never read product reviews

5. How would you describe your experience with reading product reviews on e.g. Amazon?



6. Think of a time when looking at a product at e.g. Amazon with lots of product reviews.

Did you ever wish you could just read a summary of all product reviews?

- Yes
- No

I have no experience of reading product reviews

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Survey Feature Extraction Part (Movie)

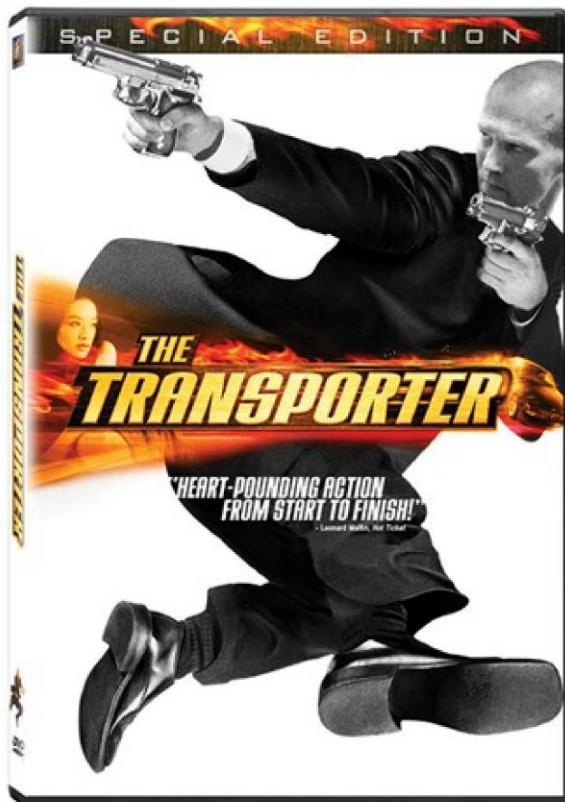


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19% completed

In the rest of the questionnaire you will be asked to answer questions about the **following product**:

The Transporter



Picture Source: www.shuqi.org

Please always think of this movie when answering the following questions!

7. Do you know this product?

- Yes
- No

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Next



Product features

A **product feature** is a characteristic of a product that customers are interested in when looking for the product. For a car product features include the colour, the engine, safety mechanisms, the multimedia system, the price etc.

The following excerpts show the **most important product features** for the product according to different methods to extract them from the product reviews.

The lists are **ordered**, that means the **most important feature** (according to the computer) is **at the top**. After the feature name, some **synonyms** are shown.

After reading them, you will be asked to select the most representative list for the product according to your opinion.

A

Wang

Rank	Feature name	Synonyms
1	official transporter movie website	scary movie, decent action movie, low budget movie
2	serviceable euro-trash action extravaganza	hard action, kick-butt action, genre film
3	professional transportation	transportation service, mercenary transportation, everybody
4	additional fight scene footage	fight footage, unseen action footage,
5	truck cab fight sequence	big chase, fresh car, police chase
6	inevitable breakthrough film	unusual film, film industry, low buget film
7	overall plot development	generic plot, stupid plot idea, great idea
8	british military man	action fan, extra something, fan flick
9	fifth element story line	criminal line, good story, french story
10	long long long time	right thing, time trace, short time, last thing

B

Scaffidi

Rank	Feature name	Synonyms
1	official transporter movie website	scary movie, decent action movie, low budget movie
2	serviceable euro-trash action extravaganza	hard action, kick-butt action, genre film
3	truck cab fight sequence	big chase, fresh car, police chase
4	british military man	action fan, extra something, fan flick
5	fifth element story line	criminal line, good story, french story
6	perpetually-clad-in-armani bad guy	pretty guy, romance, guy film, downright cool guy
7	inevitable breakthrough film	unusual film, film industry, low buget film
8	great roller coaster action flick	serious flick, american gangster flick, solid action flick
9	overall plot development	generic plot, stupid plot idea, great idea
10	professional transportation	transportation service, mercenary transportation, everybody

C

Meta

Rank	Feature name	Synonyms
1	official transporter movie website	scary movie, decent action movie, low budget movie
2	serviceable euro-trash action extravaganza	hard action, kick-butt action, genre film
3	truck cab fight sequence	big chase, fresh car, police chase
4	british military man	action fan, extra something, fan flick
5	professional transportation	transportation service, mercenary transportation, everybody
6	inevitable breakthrough film	unusual film, film industry, low buget film
7	fifth element story line	criminal line, good story, french story
8	overall plot development	generic plot, stupid plot idea, great idea
9	additional fight scene footage	fight footage, unseen action footage,
10	perpetually-clad-in-armani bad guy	pretty guy, romance, guy film, downright cool guy

8. In your opinion, which of the three lists represents the product the most?

Please consider if the features are really features for the product and how they are ranked.

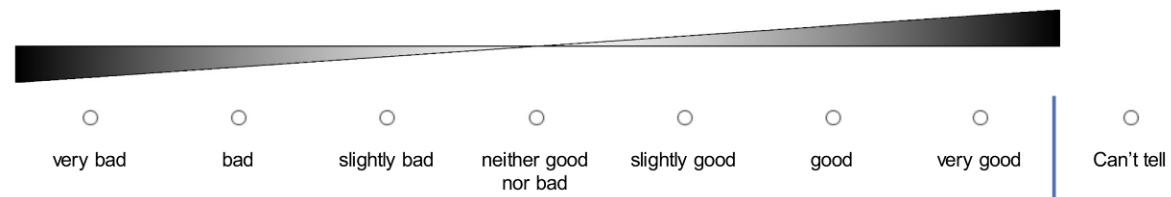
- A
 - B
 - C
-

- None of them

9. Consider your choice from before:

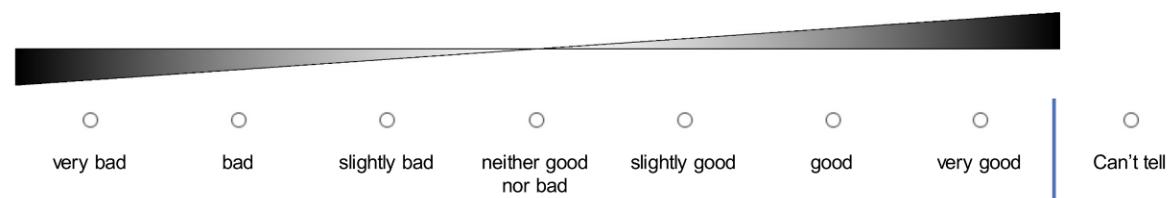
According to your opinion, please rate the quality of the list in terms of whether the important product features are in the list.

Please consider the feature name and the synonyms.



10. Consider your choice from before:

How much do the chosen feature names fit the synonyms?



11. [Optional] Do you have other comments (good or bad) regarding the feature lists?

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Pause the interview

[Benjamin Tumele](#), Technische Universität Darmstadt – 2016

Survey Feature Extraction Part (Smartphone)



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19% completed

In the rest of the questionnaire you will be asked to answer questions about the **following product**:

LG E960 Google Nexus 4 Unlocked GSM Phone 16GB Black



Picture Source: www.amazon.com

Please always think of this smartphone when answering the following questions!

7. Do you know this product?

- Yes
- No

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Product features

A **product feature** is a characteristic of a product that customers are interested in when looking for the product. For a car product features include the colour, the engine, safety mechanisms, the multimedia system, the price etc.

The following excerpts show the **most important product features** for the product according to different methods to extract them from the product reviews.

The lists are **ordered**, that means the **most important feature** (according to the computer) is **at the top**. After the feature name, some **synonyms** are shown.

After reading them, you will be asked to select the most representative list for the product according to your opinion.

A

Wang

Rank	Feature name	Synonyms
1	first generation quad core phone	old tv, generate tv
2	updates unlocked rooted high screen resolution	good screen resolution, great resolution, super high resolution
3	next nexus phone	cover nexus, new nexus, damn cover, fast cover
4	average battery performance	fantastic performance, good performance, battery performance
5	excellent performance superb price	actual price, phenomenal price, factory default config
6	go dialer wont work	stock dialer, won't turn, can't go
7	terrible android implementation	implementation
8	photosphere camera feature	nice camera, app manager, amazing camera, third party android app
9	wonderful mobile device	fast device, big device, android device
10	first smartphone s60 system	nice smartphone, heavy mine, first glass smartphone

B

Scaffidi

Rank	Feature name	Synonyms
1	excellent performance superb price	actual price, phenomenal price, factory default config
2	wonderful mobile device	fast device, big device, android device
3	photosphere camera feature	nice camera, app manager, amazing camera, third party android app
4	first smartphone s60 system	nice smartphone, heavy mine, first glass smartphone
5	external micro sd card	card slot, video card, memory card, micro sim card
6	next nexus phone	cover nexus, new nexus, damn cover, fast cover
7	home internet everyday	protect mode, sleep mode, weak speaker, hq speaker, 2d mode
8	sharp visuals cool product	defect product, awesome product, money
9	third party customization	usb part, volume part, good replacement
10	pesky user interface	micro use, heavy mobile use, smooth interface, simple interface

C

Meta

Rank	Feature name	Synonyms
1	excellent performance superb price	actual price, phenomenal price, factory default config
2	first generation quad core phone	old tv, generate tv
3	wonderful mobile device	fast device, big device, android device
4	photosphere camera feature	nice camera, app manager, amazing camera, third party android app
5	first smartphone s60 system	nice smartphone, heavy mine, first glass smartphone
6	next nexus phone	cover nexus, new nexus, damn cover, fast cover
7	external micro sd card	card slot, video card, memory card, micro sim card
8	sharp visuals cool product	defect product, awesome product, money
9	home internet everyday	protect mode, sleep mode, weak speaker, hq speaker, 2d mode
10	third party customization	usb part, volume part, good replacement

8. In your opinion, which of the three lists represents the product the most?

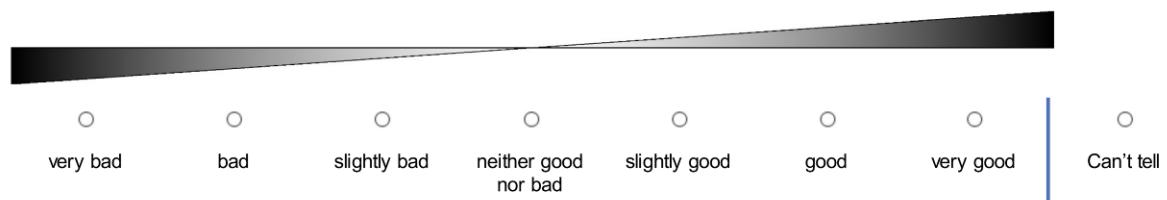
Please consider if the features are really features for the product and how they are ranked.

- A
 - B
 - C
-
- None of them

9. Consider your choice from before:

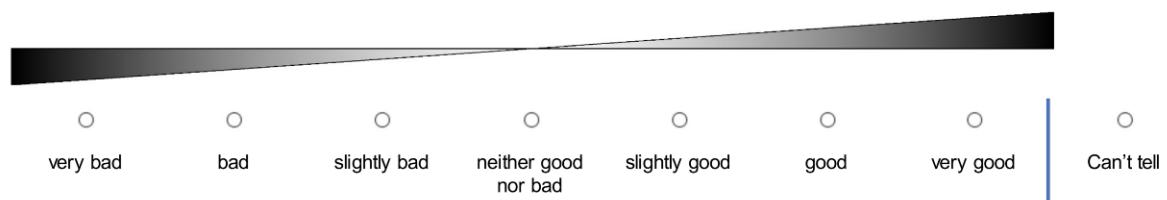
According to your opinion, please rate the quality of the list in terms of whether the important product features are in the list.

Please consider the feature name and the synonyms.



10. Consider your choice from before:

How much do the chosen feature names fit the synonyms?



11. [Optional] Do you have other comments (good or bad) regarding the feature lists?

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[Pause the interview](#)

[Benjamin Tumele](#), Technische Universität Darmstadt – 2016



Survey Summary Layout Part (Movie)



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31% completed

Summary layout and displayed information

The following questions will show you several summaries that only differ in their **layout and displayed information**.

When answering the questions **focus on the layout and displayed information** (e.g. which information is presented in which way) and **not on the design** (e.g. is the summary visually appealing). An appealing summary design is not part of this study. Therefore the summaries look plain.

The actual **summary content** is always the same. You **don't need to read them in detail**.

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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016

Layout "Table"

Summary for: The Transporter

Product features:

Feature: official transporter movie website

(+) Positive	(-) Negative
<u>Example Sentences:</u> You can easily watch this movie over and over again for it's non stop action pace, and very slick direction, but the more discerning viewer, will want to leave the intellect behind, as this is pure adrenaline junky material.	<u>Example Sentences:</u> i got the movie on time with no problems,it was new, it was packaged good,the price was great,i love it
Don't get me wrong: I saw some amazing stuff in this movie, some of the best action scenes I've ever seen.	This movie is just something to pass the time with, it has some unrealistic scenes in it, but overall it's those movies that puts the impossible on the fun side without minding the "that's impossible, he did not just do that".
Good movie, better than XXX (which was also good)	He looked so unnatural (in Michael Jackson kind of sense) that I was sure that he would reveal himself as a woman at the end of the movie.

Layout "List"

Summary for: The Transporter

Product features:

Feature: official transporter movie website

(+) Positive:

Example sentences:

- You can easily watch this movie over and over again for it's non stop action pace, and very slick direction, but the more discerning viewer, will want to leave the intellect behind, as this is pure adrenaline junky material.
- Don't get me wrong: I saw some amazing stuff in this movie, some of the best action scenes I've ever seen.
- Good movie, better than XXX (which was also good)

(-) Negative:

Example sentences:

- i got the movie on time with no problems,it was new, it was packaged good,the price was great,i love it
- This movie is just something to pass the time with, it has some unrealistic scenes in it, but overall it's those movies that puts the impossible on the fun side without minding the "that's impossible, he did not just do that".
- He looked so unnatural (in Michael Jackson kind of sense) that I was sure that he would reveal himself as a woman at the end of the movie.

12. Which summary layout do you prefer?

- Layout "List"
 - Layout "Table"
 - Both are equally good
-
- None of them

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Summary layout and displayed information

Please look at the following two summaries excerpt.

The **second excerpt** shows **how many reviews mention a feature positively and negatively** as additional information.

Layout A

Feature: official transporter movie website

(+) Positive	(-) Negative
Example Sentences:	Example Sentences:
Good movie, better than XXX (which was also good)	He looked so unnatural (in Michael Jackson kind of sense) that I was sure that he would reveal himself as a woman at the end of the movie.

Layout B

Feature: official transporter movie website

(+) Positive	(-) Negative
feature positively mentioned in 147 reviews (out of 304)	feature negatively mentioned in 69 reviews (out of 304)
Example Sentences:	Example Sentences:
Good movie, better than XXX (which was also good)	He looked so unnatural (in Michael Jackson kind of sense) that I was sure that he would reveal himself as a woman at the end of the movie.

13. Which summary layout do you prefer?

- Layout A
- Layout B
- Both are equally good

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[Benjamin Tumele, Technische Universität Darmstadt – 2016](#)

Summary layout and displayed information

Please look at the following two summaries excerpt.

The **second excerpt** shows a computer calculated **score how positive/negative a sentence is** as additional information after a sentence.

Layout A

Feature: official transporter movie website

(+) Positive	(-) Negative
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Good movie, better than XXX (which was also good)	He looked so unnatural (in Michael Jackson kind of sense) that I was sure that he would reveal himself as a woman at the end of the movie.

Layout B

Feature: official transporter movie website

(+) Positive	(-) Negative
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Good movie, better than XXX (which was also good) (6.0)	He looked so unnatural (in Michael Jackson kind of sense) that I was sure that he would reveal himself as a woman at the end of the movie. (-4.2)

14. Which summary layout do you prefer?

- Layout A
- Layout B
- Both are equally good

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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016



Summary layout and displayed information

Imagine that you are in a situation where you would like to **read several movie summaries** of different products one after the other (e.g. because you want to compare several products with each other).

15. How many features and sentences per feature and category (positive, negative) would you like to be displayed in each summary?

Please enter numbers greater or equal to 1.

features per summary	
sentences per feature and category	

Don't care

Don't care

16. [Optional] Do you have other comments (good or bad) regarding the summary layout including the displayed information?

Please don't comment on the design/visual appearance.

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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016



Survey Summary Layout Part (Smartphone)



31% completed

Summary layout and displayed information

The following questions will show you several summaries that only differ in their **layout and displayed information**.

When answering the questions **focus on the layout and displayed information** (e.g. which information is presented in which way) and **not on the design** (e.g. is the summary visually appealing). An appealing summary design is not part of this study. Therefore the summaries look plain.

The actual **summary content** is **always the same**. You **don't need to read them in detail**.

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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016



38% completed

Summary layout and displayed information

Please look at the following **two summaries**.

Please focus on the **layout** of the summaries.

You don't need to read the summaries completely.

Layout "Table"

Summary for: LG E960 Google Nexus 4 Unlocked GSM Phone 16GB Black

Product features:

Feature: first generation quad core phone

(+) Positive	(-) Negative
<u>Example Sentences:</u> great screen, great performance, it has been an excellent purchase so far, i am very pleased with this phone, haven't experienced any problems so far	5Hz and 2G RAM, I cannot see if there is any more powerful thing this one can get run every app just like lighting, and the screen is bigger and better than retina in iPhone4also, I love the app here in the market, even though 90% of them are the same as App store but there are still many amazing app like Light Flow which can give you a total different using experienceAlso, I can trans all my contacts, calendars, and even photo(dropbox) to this phone and it like all the way, no worry to change phone anymore,With the wireless charger, everyone who is passing my desk will give an amazing look at this phoneand I need to mentioned I love the buzz touch for Nexus 4 phone, it is brand new using experience and interaction experience.
All that whining on my part aside, it is a really good phone in terms of voice quality, maps with GPS, taking pretty good photos, doing data stuff "lickey split" on the t-mo network, setting up a personal wifi hot spot, playing music from pandora, amazon, grooveshark, etc.	Q - Is the Nexus 7 future proof?A - Nothing is but considering its beautiful design, high quality manufacturing, the near guarantee of timely software updates, the fact that it is leading Android phone today for the under 5" screen size and that the smart phone technology is approaching 'maturity' it should continue to be a good phone for at least the next 2-3 years.
Since it was unlocked it made it more valuable than to buy it from my phone carriers site, also I needed the phone fast as I was doing a new mobile carrier, so it was great that it was able to ship very fast.	It may not be the best of the best, but it's still very good for phone calls or listening to music or game audio at modest volumes.

Layout "List"

Summary for: LG E960 Google Nexus 4 Unlocked GSM Phone 16GB Black

General information:

Price: 359.99 \$

Number of Reviews: 327

Review timespan: 26/11/2012 - 12/07/2014

Product features:

Feature: first generation quad core phone

(+) Positive:

Example sentences:

- great screen, great performance, it has been an excellent purchase so far, i am very pleased with this phone, haven't experienced any problems so far
- All that whining on my part aside, it is a really good phone in terms of voice quality, maps with GPS, taking pretty good photos, doing data stuff "lickey split" on the t-mo network, setting up a personal wifi hot spot, playing music from pandora, amazon, grooveshark, etc.
- Since it was unlocked it made it more valuable than to buy it from my phone carriers site, also I needed the phone fast as I was doing a new mobile carrier, so it was great that it was able to ship very fast.

(-) Negative:

Example sentences:

- 5Hz and 2G RAM, I cannot see if there is any more powerful thing this one can get run every app just like lighting, and the screen is bigger and better than retina in iPhone4also, I love the app here in the market, even though 90% of them are the same as App store but there are still many amazing app like Light Flow which can give you a total different using experienceAlso, I can trans all my contacts, calendars, and even photo(dropbox) to this phone and it like all the way, no worry to change phone anymore,With the wireless charger, everyone who is passing my desk will give an amazing look at this phoneand I need to mentioned I love the buzz touch for Nexus 4 phone, it is brand new using experience and interaction experience.
- Q - Is the Nexus 7 future proof?A - Nothing is but considering its beautiful design, high quality manufacturing, the near guarantee of timely software updates, the fact that it is leading Android phone today for the under 5" screen size and that the smart phone technology is approaching 'maturity' it should continue to be a good phone for at least the next 2-3 years.
- It may not be the best of the best, but it's still very good for phone calls or listening to music or game audio at modest volumes.

12. Which summary layout do you prefer?

- Layout "List"
 - Layout "Table"
 - Both are equally good
-
- None of them

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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016

Summary layout and displayed information

Please look at the following two summaries excerpt.

The **second excerpt** shows a computer calculated **score how positive/negative a sentence is** as additional information after a sentence.

Layout A

Feature: first generation quad core phone

(+) Positive	(-) Negative
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Since it was unlocked it made it more valuable than to buy it from my phone carriers site, also I needed the phone fast as I was doing a new mobile carrier, so it was great that it was able to ship very fast.	It may not be the best of the best, but it's still very good for phone calls or listening to music or game audio at modest volumes. (-5.6)

Layout B

Feature: first generation quad core phone

(+) Positive	(-) Negative
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Since it was unlocked it made it more valuable than to buy it from my phone carriers site, also I needed the phone fast as I was doing a new mobile carrier, so it was great that it was able to ship very fast. (7.2)	It may not be the best of the best, but it's still very good for phone calls or listening to music or game audio at modest volumes. (-5.6)

13. Which summary layout do you prefer?

- Layout A
- Layout B
- Both are equally good

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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016

Summary layout and displayed information

Please look at the following two summaries excerpt.

The **second excerpt** shows **how many reviews mention a feature positively and negatively** as additional information.

Layout A

Feature: first generation quad core phone

(+) Positive	(-) Negative
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Since it was unlocked it made it more valuable than to buy it from my phone carriers site, also I needed the phone fast as I was doing a new mobile carrier, so it was great that it was able to ship very fast.	It may not be the best of the best, but it's still very good for phone calls or listening to music or game audio at modest volumes.

Layout B

Feature: first generation quad core phone

(+) Positive	(-) Negative
feature positively mentioned in 192 reviews (out of 327)	feature negatively mentioned in 70 reviews (out of 327)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Since it was unlocked it made it more valuable than to buy it from my phone carriers site, also I needed the phone fast as I was doing a new mobile carrier, so it was great that it was able to ship very fast.	It may not be the best of the best, but it's still very good for phone calls or listening to music or game audio at modest volumes.

14. Which summary layout do you prefer?

- Layout A
- Layout B
- Both are equally good

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[Pause the interview](#)

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Summary layout and displayed information

Imagine that you are in a situation where you would like to **read several smartphone summaries** of different products one after the other (e.g. because you want to compare several products with each other).

15. How many features and sentences per feature and category (positive, negative) would you like to be displayed in each summary?

Please enter numbers greater or equal to 1.

features per summary

sentences per feature and category

Don't care

Don't care

16. [Optional] Do you have other comments (good or bad) regarding the summary layout including the displayed information?

Please don't comment on the design/visual appearance.

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Pause the interview

[Benjamin Tumele](#), Technische Universität Darmstadt – 2016



Survey Sentiment Analysis Part (Movie)



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63% completed

Summary content

In the following pages you will be shown **4 different summaries** for the product.

The fundamental idea for the summaries is to show positive and negative aspects of different product features.

The layout will be the same for all reviews, but the **content** for each feature **will vary**.

Some may be better than others. You will be asked to **judge their quality**.

So please read all the summaries carefully!

Please focus on the **content**, not on the design/visual appearance of the summaries!

An appealing visual appearance is not part of this study. Therefore the summaries look plain.

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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016



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DARMSTADT

69% completed

Summary content

Please read the following summary in order to judge its quality:

Summary for: The Transporter

General information:

Price: 16.88 \$
Number of Reviews: 304
Review timespan: 06/10/2002 - 27/06/2014

Configuration „Aspect“

Product features:

Feature: official transporter movie website

(+) Positive	(-) Negative
feature positively mentioned in 102 reviews (out of 304)	feature negatively mentioned in 30 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Good movie, better than XXX (which was also good)	I was extremely disappointed at this movie.
I found the movie to be well shot, extremely stylish, and somewhat substantive.	I warn you however, that once you watch the uncut fight scenes, you may feel a little shortchanged with what was left in the actual movie.
His life is pretty good until he violates one of his most important rules and then gets caught up in a scheme with enough action to keep you on the edge of your seats for most of the movie.	This isn't a brilliant or groundbreaking movie.

Feature: serviceable euro-trash action extravaganza

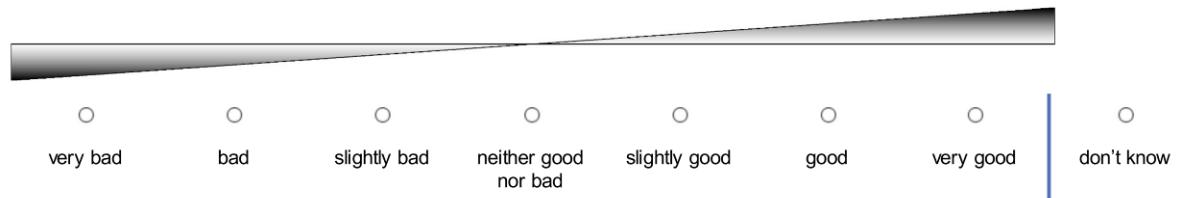
(+) Positive	(-) Negative
feature positively mentioned in 74 reviews (out of 304)	feature negatively mentioned in 30 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
The action was amazing, especially during that oil slick part.. you'll see what I mean... and the car chases were terrific.	With his intense screen presence that can't be ignored, and his impressive athletic ability as showcased in the numerous fight/stunt sequences it's easy to see why Statham is quickly becoming Hollywood's newest action hero.
Don't get me wrong; I saw some amazing stuff in this movie, some of the best action scenes I've ever seen.	Pick a paper-thin, generic plot, add some bland to terrible acting, a bad soundtrack and many ridiculous, over-the-top action scenes.
Basically, the film combines some great European atmosphere (The beautiful southern coast of France) with some incredible fight and action sequences.	I'm not usually a fan of many pure action films, so this one is particularly good.

Feature: professional transportation

(+) Positive	(-) Negative
feature positively mentioned in 21 reviews (out of 304)	feature negatively mentioned in 18 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
The Transporter is a good film if you're looking for terrific action, not for a movie high on plot.	The star is really believable as The Transporter (he reminds you a lot of Bruce Willis in the first "Die Hard" movie - hopefully his career won't be stuck in the same rut though with "The Transporter 2: Transport Harder" and "Transport With A Vengeance" or something).
Nitpicking aside, The Transporter is a fun and intriguing movie well worth picking up for those that enjoy the genre.	The transporter makes the wrong people mad, but he takes care of business.
The original and the best Transporter.	One scene where "The Transporter" tries to commandeer a truck, is almost a identical rip-off of the truck scene in "Raiders of the Lost Ark", only not even half as good (or humorous).

17. How do you rate the quality of the content of this summary?

Please **only consider the content** and not the layout or the design.



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Summary content

Please read the following summary in order to judge its quality:

Summary for: The Transporter

General information:

Price: 16.88 \$
 Number of Reviews: 304
 Review timespan: 06/10/2002 - 27/06/2014

Configuration „Verb“

Product features:

Feature: official transporter movie website

(+) Positive	(-) Negative
feature positively mentioned in 182 reviews (out of 304)	feature negatively mentioned in 86 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
I've seen Jason Statham before this movie and I must say that he gets better each time i see him, I will be looking for him and more movies to come and i think they are suppose to be working on The Italian Job 2	The fact that I have never seen this guy makes it even more thrilling, since I don't think of him as another character (eg, Jackie Chan in "Who am I", I always think of that movie when I see him), I think of Stratham as the Transporter.
Understand that the 5 Stars is for the Action and the Soundtrack if I had to take into account the Plot I would probably take it down to a 3 1/2 - 4 but seeing as it is one I liked enough to say immediatly after the movie I will buy this DVD when it comes out.....	I have never seen him in another movie, but I think he is physically appealing and has what it takes to be the white guy version of Jackie Chan and Jet Li.
This unshaven english bit player grew stubble and used a modicum of talent and facial expression, to become a big star... this was an early film of his and exciting.... he has since made many ok films.. the best of which is , the bank job, dont miss that one.... lately, hes shaven ... and hes not nearly as talented... just shows you.... i tried stubble and got yelled at... in this interesting film, he vies, as an actor, with a wonderfully exciting auto... and often its hard to tell which one wins... worth a watch...	If you just want a movie that will entertain you for 90 minutes and don't care how it makes the world a better place or advances the science of cinema and thesbanism the GET THIS DAMN MOVIE.

Feature: serviceable euro-trash action extravaganza

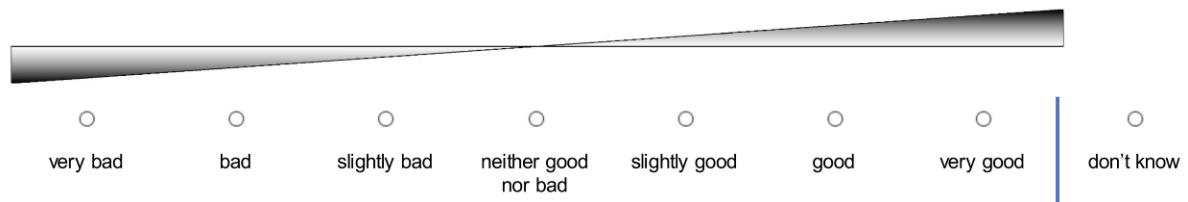
(+) Positive	(-) Negative
feature positively mentioned in 149 reviews (out of 304)	feature negatively mentioned in 49 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Though slight on story, THE TRANSPORTER is creatively choreographed in its fight scenes, contains one of the best car chases ever filmed (aided with the splendid background of Nice, France), and gives full reign to the VERY fine Jason Statham - an actor with enough charisma, looks, and acting ability to put him in the lineup with the best of the usual suspects for these genre films.	With his intense screen presence that can't be ignored, and his impressive athletic ability as showcased in the numerous fight/stunt sequences it's easy to see why Statham is quickly becoming Hollywood's newest action hero.
The action was amazing, especially during that oil slick part.. you'll see what i mean... and the car chases were terrific.	Now what you don't get in a plot or dialogue, you get in beautiful cinematography and flashy action.
There is a woman Qui Shi (Japanese action fans will remember her from "A Man called Hero" fame) that's thrown into his world and with her comes trouble (same ole scenerio)but here is where the plot gets fuzzy and suspended belief needs to come in.	The beginning was slow and there was not enough action (so it gets only 4 stars), but the rest of this film was definitely worth watching, especially the martial arts action and the HOT Chinese girl!

Feature: professional transportation

(+) Positive	(-) Negative
feature positively mentioned in 99 reviews (out of 304)	feature negatively mentioned in 33 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Though slight on story, THE TRANSPORTER is creatively choreographed in its fight scenes, contains one of the best car chases ever filmed (aided with the splendid background of Nice, France), and gives full reign to the VERY fine Jason Statham - an actor with enough charisma, looks, and acting ability to put him in the lineup with the best of the usual suspects for these genre films.	The fact that I have never seen this guy makes it even more thrilling, since I don't think of him as another character (eg, Jackie Chan in "Who am I", I always think of that movie when I see him), I think of Stratham as the Transporter.
The story: Frank Martin (Statham,The Expendables) is a transporter - an expert auto driver and fighting machine who'll deliver anything in his car, even armed bank robbers making their getaway, if the price is right - who finds himself caught up in a deadly game of human trafficking when he finds out that his latest delivery is a kidnapped young woman (Qi Shu,Gorgeous) with knowledge of a massive moving operation of immigrant slaves...	In case you (like most law-abiding citizens) didn't know, a transporter is the guy who not only acts as a high-priced delivery service for such savory folk as mobsters, but also occasionally lands gigs driving the getaway car from the scene of the crime.
The Transporter:Reasonably enjoyable, if completely forgettable, The Transporter rides on the charm of lead Jason Statham and delivers pretty much what could be expected from its bare-bones plot.	Shallow and simple plot aside, The Transporter and its sequels have never been about the story, but about Frank Martin kicking butt and driving a fast car.

18. How do you rate the quality of the content of this summary?

Please **only** consider the content and not the layout or the design.



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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016



81% completed

Summary content

Please read the following summary in order to judge its quality:

Summary for: The Transporter

General information:

Price: 16.88 \$
Number of Reviews: 304
Review timespan: 06/10/2002 - 27/06/2014

Configuration „Random“

Product features:

Feature: official transporter movie website

(+) Positive	(-) Negative
feature positively mentioned in 147 reviews (out of 304)	feature negatively mentioned in 69 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
As the movie progresses it falls flat on its face having the audience hate the dialogue and wishing they had a remote control so that they can fast forward to the action scenes.	Jason Statham is very believable as an action movie star.
this dvd has JASON STATHAM enough saidand the movie is pretty good too	If you're looking for a movie that will enrich your life and make you think- go rent Schindler's List.
Now this is an action movie	Not usually a fan of violent films, I happened on this movie as a desperate attempt to be entertained.

Feature: serviceable euro-trash action extravaganza

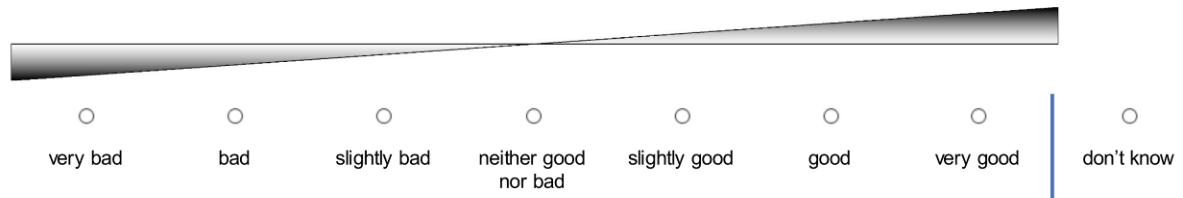
(+) Positive	(-) Negative
feature positively mentioned in 115 reviews (out of 304)	feature negatively mentioned in 56 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
It makes me wonder when a decent action film will arrive in 2002, it seems that each and every attempt falls short.	Their is action in this movie and plenty of it.
Jason Stockam can hold the screen well as an action hero, and he is more than sufficient for the part The Transporter, another in a line of American gangster flick with Hong-Kong style action and directors that began with The Big Hit.	The Transporter has an equal share of drama and action.
Highly recommended to action fans.	Lots of fast-paced action.

Feature: professional transportation

(+) Positive	(-) Negative
feature positively mentioned in 68 reviews (out of 304)	feature negatively mentioned in 40 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
The Transporter	Director Corey Yuen does a great job of jacking up the action in "The Transporter" to make it a fast-faced adventure.
If you are looking for a lot of action, but don't care about plot, "The Transporter" can give you just that.	From the opening scene where he is doing just that, our transporter, Frank Martin, is clearly the best in the business.
My Review of the Transporter: REALLY BAD ACTING.	Jason Stratham plays Frank Martin, a transporter for hire specializing in safely getting items from point A to point B.... for a hefty price of course.

19. How do you rate the quality of the content of this summary?

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Summary content

Please read the following summary in order to judge its quality:

Summary for: The Transporter

General information:

Price: 16.88 \$

Number of Reviews: 304

Review timespan: 06/10/2002 - 27/06/2014

Configuration „Base“

Product features:

Feature: official transporter movie website

(+) Positive	(-) Negative
feature positively mentioned in 147 reviews (out of 304)	feature negatively mentioned in 69 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
You can easily watch this movie over and over again for it's non stop action pace, and very slick direction, but the more discerning viewer, will want to leave the intellect behind, as this is pure adrenaline junky material.	i got the movie on time with no problems,it was new, it was packaged good,the price was great,i love it
Don't get me wrong; I saw some amazing stuff in this movie, some of the best action scenes I've ever seen.	This movie is just something to pass the time with, it has some unrealistic scenes in it, but overall it's those movies that puts the impossible on the fun side without minding the "that's impossible, he did not just do that".
Good movie, better than XXX (which was also good)	He looked so unnatural (in Michael Jackson kind of sense) that I was sure that he would reveal himself as a woman at the end of the movie.

Feature: serviceable euro-trash action extravaganza

(+) Positive	(-) Negative
feature positively mentioned in 115 reviews (out of 304)	feature negatively mentioned in 56 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Though slight on story, THE TRANSPORTER is creatively choreographed in its fight scenes, contains one of the best car chases ever filmed (aided with the splendid background of Nice, France), and gives full reign to the VERY fine Jason Statham - an actor with enough charisma, looks, and acting ability to put him in the lineup with the best of the usual suspects for these genre films.	With his intense screen presence that can't be ignored, and his impressive athletic ability as showcased in the numerous fight/stunt sequences it's easy to see why Statham is quickly becoming Hollywood's newest action hero.
The action was amazing, especially during that oil slick part.. you'll see what i mean... and the car chases were terrific.	The beginning was slow and there was not enough action (so it gets only 4 stars), but the rest of this film was definitely worth watching, especially the martial arts action and the HOT Chinese girl!
The opening of this film is absolutely terrific and it maintains a wonderful action torque throughout its first half.	Some of the acting by the supporting actors is rather bad on the other hand though, Jason Strathan has a very natural and commanding presence on screen and makes an interesting choice for an action hero.

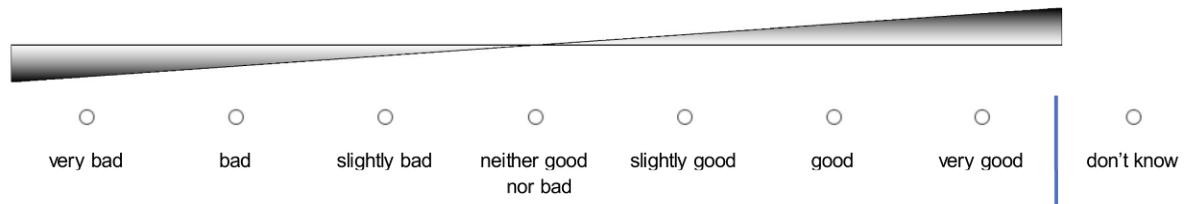
Feature: professional transportation

(+) Positive	(-) Negative
feature positively mentioned in 68 reviews (out of 304)	feature negatively mentioned in 40 reviews (out of 304)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Though slight on story, THE TRANSPORTER is creatively choreographed in its fight scenes, contains one of the best car chases ever filmed (aided with the splendid background of Nice, France), and gives full reign to the VERY fine Jason Statham - an actor with enough charisma, looks, and acting ability to put him in the lineup with the best of the usual suspects for these genre films.	Shallow and simple plot aside, The Transporter and its sequels have never been about the story, but about Frank Martin kicking butt and driving a fast car.
"The Transporter" is pretty good for what it is - a sleek, slick, high-octane action thriller that couldn't possibly expect us to believe anything we are seeing on screen and, quite frankly, doesn't care that we don't.	"The Transporter" is very violent, in a cartoonish way.
The Transporter Reasonably enjoyable, if completely forgettable, The Transporter rides on the charm of lead Jason Statham and delivers pretty much what could be expected from its bare-bones plot.	To make a long story short, the bad guy tries to blow up the transporter.



20. How do you rate the quality of the content of this summary?

Please **only consider the content** and not the layout or the design.



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Survey Sentiment Analysis Part (Smartphone)



63% completed

Summary content

In the following pages you will be shown **4 different summaries** for the product.

The fundamental idea for the summaries is to show positive and negative aspects of different product features.

The layout will be the same for all reviews, but the **content** for each feature **will vary**.

Some may be better than others. You will be asked to **judge their quality**.

So please read all the summaries carefully!

Please **focus on the content, not on the design/visual appearance** of the summaries!

An appealing visual appearance is not part of this study. Therefore the summaries look plain.

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Summary content

Please read the following summary in order to judge its quality:

Summary for: LG E960 Google Nexus 4 Unlocked GSM Phone 16GB Black

General information:

Price: 359.99 \$
Number of Reviews: 327
Review timespan: 26/11/2012 - 12/07/2014

Configuration „Random“

Product features:

Feature: first generation quad core phone

(+) Positive	(-) Negative
feature positively mentioned in 192 reviews (out of 327)	feature negatively mentioned in 70 reviews (out of 327)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
This phone is fast, screen looks great, no carrier specific bloat ware - preloaded with Google apps I would have installed anyway like Chrome, Youtube, & Maps.	Very pleased with this phone
So, the phone is great, the deal is great, and you can get it fulfilled by Amazon....	The best phone ever
1)Poor battery - Battery does not last even for a day, with normal usage , i tried all the setting mentioned over internet, but no much improvement2)The phone does not have any Logo on front panel, at times it is very difficult to know which is top and bottom, especially in sunlight and lot of glare in sun light.	I called LG, they have no estimate for the repair, I have to mail the phone to them..... - all other phones' screens still work after any kind of damage.

Feature: updates unlocked rooted high screen resolution

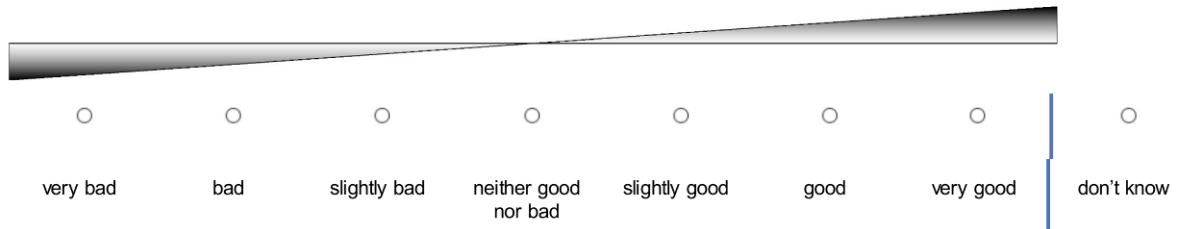
(+) Positive	(-) Negative
feature positively mentioned in 75 reviews (out of 327)	feature negatively mentioned in 23 reviews (out of 327)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
The quality and construction was better than expected (since it was made by LG), but they did a superb job.	very fast, good size good resolution excellent for what I do every day, good camera I just enjoing it a lot
Good luck if you crack this overly fragile screen.	The screen on the Nexus has better resolution (1280x738), and is significantly larger (4).
Pros:Unbelievably fast: the quad-core processor and 2 GB of RAM are certainly noticeableNice size and weight: the screen is large and roomy, without the phone feeling like a tablet and it is very lightElegant design: the phone looks pleasant and professional, with a touch of flairWell-built: it feels very solidCons:Slippery: because the back is glass, the phone can be slippery at times, much like iPhones; however, there is a rubber-like grip around the perimeter of the phone that helpsStorage limitations: there is no slot for expandable storage, which may be a turn-off for some, but utilizing Google's online storage options (like Google Music or Drive) will keep the memory from filling upOverall, I am very pleased with the device and would highly recommend to anyone.	But the quality of the results is a real game changer.

Feature: next nexus phone

(+) Positive	(-) Negative
feature positively mentioned in 37 reviews (out of 327)	feature negatively mentioned in 21 reviews (out of 327)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
A - The Nexus 7 sells for about what you would pay for a 'contract' phone.	Nexus 4
In all honesty the galaxy S4 didn't pair always that great either (come to find out my bluetooth is glitchy, car has now been replaced), but also online people complained about the nexus 4 and bluetooth.	This was not the case with the Nexus 4.
Love my phone :)	c) Connecting to a TV: The Nexus 4 doesn't have a mini HDMI, what it does have is a micro usb which supports slimport.

17. How do you rate the quality of the content of this summary?

Please **only consider the content** and not the layout or the design.



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Summary content

Please read the following summary in order to judge its quality:

Summary for: LG E960 Google Nexus 4 Unlocked GSM Phone 16GB Black

General information:

Price: 359.99 \$

Number of Reviews: 327

Review timespan: 26/11/2012 - 12/07/2014

Configuration „Aspect“

Product features:

Feature: first generation quad core phone

(+) Positive	(-) Negative
feature positively mentioned in 106 reviews (out of 327)	feature negatively mentioned in 19 reviews (out of 327)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
It is a really good phone, nice applications and features.	Simple things that i used to have several products do.... not anymore... also will never have to input contacts into ;my phone again!
This phone would be perfect for me if it wasn't so unreliable.	That's a really expensive if you compare it with iphone screens.
I'm glad lots of people seem to have gotten this to work, but there are enough problems with this phone that I'm not getting any Google or LG designed phones again.	--Nice phone, but too expensive here at Amazon, go to Google Play Store.

Feature: updates unlocked rooted high screen resolution

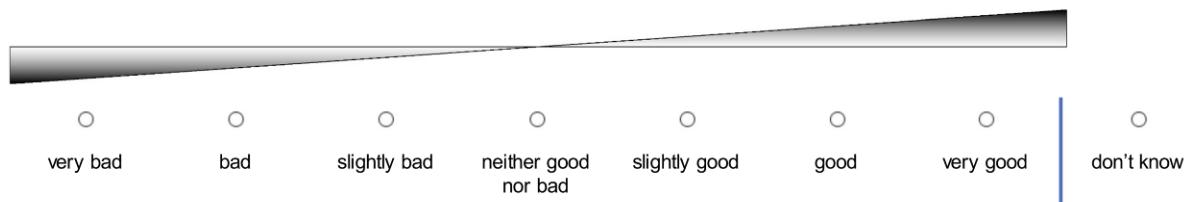
(+) Positive	(-) Negative
feature positively mentioned in 24 reviews (out of 327)	feature negatively mentioned in 7 reviews (out of 327)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
The screen is definitely bigger than what I'm used to with my iPhone, but it looks great.	7" screen is not very good.
The resolution amazing, the screen also amazing.	I told him, I told him also it's a broken screen, they will need just to replace it.
thats a disappointment, but is really beautiful, fast, good screen resolution and cheap!	The quality of the photos isn't any different from my Galaxy SII though (both 8MP).

Feature: next nexus phone

(+) Positive	(-) Negative
feature positively mentioned in 18 reviews (out of 327)	feature negatively mentioned in 11 reviews (out of 327)
<u>Example Sentences:</u>	<u>Example Sentences:</u>
Brand new condition , fast shipping and the phone its self is fast love it thanks a lot best phone I've gotten so far	it's an excellent product, unfortunately a couldn't buy the 16 but in all its aspects is perfect, i can notice how good are the nexus models.
So far, an extremely pleasant experience!Update 6-23-13: The Nexus 4 running Jelly Bean works wonderfully with Glass.	It will get hot also, not burn your skin if you use a good cover though.
Nexus 4 is great, is very fluid and the screen also looks nice.	Just get a damn cover!2.

18. How do you rate the quality of the content of this summary?

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Summary content

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Summary for: LG E960 Google Nexus 4 Unlocked GSM Phone 16GB Black

General information:

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 Number of Reviews: 327
 Review timespan: 26/11/2012 - 12/07/2014

Configuration „Verb“

Product features:

Feature: first generation quad core phone

(+) Positive	(-) Negative
feature positively mentioned in 202 reviews (out of 327)	feature negatively mentioned in 88 reviews (out of 327)
Example Sentences:	Example Sentences:
Pros:Unbelievably fast: the quad-core processor and 2 GB of RAM are certainly noticeableNice size and weight: the screen is large and roomy, without the phone feeling like a tablet and it is very lightElegant design: the phone looks pleasant and professional, with a touch of flairWell-built: it feels very solidCons:Slippery: because the back is glass, the phone can be slippery at times, much like iPhones; however, there is a rubber-like grip around the perimeter of the phone that helpsStorage limitations: there is no slot for expandable storage, which may be a turn-off for some, but utilizing Google's online storage options (like Google Music or Drive) will keep the memory from filling upOverall, I am very pleased with the device and would highly recommend to anyone.	5Hz and 2G RAM, I cannot see if there is any more powerful thing this one can getI run every app just like lighting, and the screen is bigger and better than retina in iPhone+also, I love the app here in the market, even though 90% of them are the same as App store but there are still many amazing app like Light Flow which can give you a total different using experienceAlso, I can trans all my contacts, calendars, and even photo(dropbox) to this phone and it like all the way, no worry to change phone anymore. With the wireless charger, everyone who is passing my desk will give an amazing look at this phoneand I need to mentioned I love the buzz touch for Nexus 4 phone, it is brand new using experience and interaction experience.
Everyone knows the specs of this phone so rather than mentioning those, I'd prefer to talk about my personal experience with the phonePros- The phone is snappy- build quality is excellent- I think the camera is actually good atleast for daytime, outdoor and bright light shots.	Phone performs great, no hangups, great clarity... love the free features including the included inductive charging... BUTBattery life is mediocre at best, OS is nice but not intuitive (I think they are trying to avoid patent fights at the expense of user experience).
The phone is great, and while it does look fragile, believe me: this phone is tougher than it looks, for I am become wreck, the destroyer of phones, and I haven't managed to break this baby.	NFC(I really never find the time to use this feature but it is neat) WIFI HSPA+(I have it on t mobile)Blazing internet speed with up to 11 Mbps ON AVERAGE i feel like my phone is catching up to my home internet everyday!PHOTO SPHERE camera application!

Feature: updates unlocked rooted high screen resolution

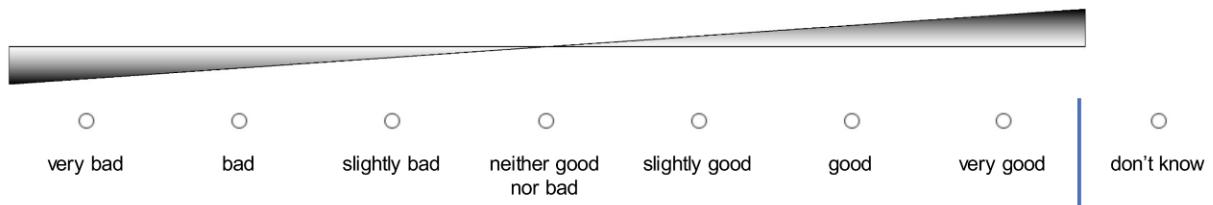
(+) Positive	(-) Negative
feature positively mentioned in 78 reviews (out of 327)	feature negatively mentioned in 25 reviews (out of 327)
Example Sentences:	Example Sentences:
Pros:Unbelievably fast: the quad-core processor and 2 GB of RAM are certainly noticeableNice size and weight: the screen is large and roomy, without the phone feeling like a tablet and it is very lightElegant design: the phone looks pleasant and professional, with a touch of flairWell-built: it feels very solidCons:Slippery: because the back is glass, the phone can be slippery at times, much like iPhones; however, there is a rubber-like grip around the perimeter of the phone that helpsStorage limitations: there is no slot for expandable storage, which may be a turn-off for some, but utilizing Google's online storage options (like Google Music or Drive) will keep the memory from filling upOverall, I am very pleased with the device and would highly recommend to anyone.	5Hz and 2G RAM, I cannot see if there is any more powerful thing this one can getI run every app just like lighting, and the screen is bigger and better than retina in iPhone+also, I love the app here in the market, even though 90% of them are the same as App store but there are still many amazing app like Light Flow which can give you a total different using experienceAlso, I can trans all my contacts, calendars, and even photo(dropbox) to this phone and it like all the way, no worry to change phone anymore. With the wireless charger, everyone who is passing my desk will give an amazing look at this phoneand I need to mentioned I love the buzz touch for Nexus 4 phone, it is brand new using experience and interaction experience.
Everyone knows the specs of this phone so rather than mentioning those, I'd prefer to talk about my personal experience with the phonePros- The phone is snappy- build quality is excellent- I think the camera is actually good atleast for daytime, outdoor and bright light shots.	screen is okay not that great my little brother has a lumia 900 and I think his screen was better and his phone is cheaper and the home and return button take part of the screen so it doesn't feel as big as it is advertised .
Touch screen is flawless, graphics amazing, speed is great, ease of use (Google's Android) is for babies and LG have made a great job as a whole.	I don't feel the quality is the same as an iPhone 5, but it's definitely one of the best on the market.

Feature: next nexus phone

(+) Positive	(-) Negative
feature positively mentioned in 60 reviews (out of 327)	feature negatively mentioned in 20 reviews (out of 327)
Example Sentences:	Example Sentences:
the nexus 4 is a great phone it's OS operates smooth, camera (to me) is awesome, the look and feel is beautiful.	Q - Is the Nexus 7 future proof?A - Nothing is but considering its beautiful design, high quality manufacturing, the near guarantee of timely software updates, the fact that it is leading Android phone today for the under 5" screen size and that the smart phone technology is approaching 'maturity' it should continue to be a good phone for at least the next 2-3 years.
Q - Is the Nexus 4 a good value?A - Considering that for this price all other high end phones come with a contract that usually means high rates and fees for 2 years, yes, it's a good value.	The only thing I don't like in nexus 4, is that memory is 8 gb, and you can't make it bigger.
Brand new condition , fast shipping and the phone its self is fast love it thanks a lot best phone I've gotten so far	I figured the company with the slogan "don't be evil" would understand my difficulties and frustration, since they are noted on my account, and would have helped me get a nexus 5 with some sort of deal, since I have had all these troubles or at least come up with some practical alternative that would help me get a working phone....

19. How do you rate the quality of the content of this summary?

Please **only consider the content** and not the layout or the design.



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Summary content

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Summary for: LG E960 Google Nexus 4 Unlocked GSM Phone 16GB Black

General information:

Price: 359.99 \$
 Number of Reviews: 327
 Review timespan: 26/11/2012 - 12/07/2014

Configuration „Base“

Product features:

Feature: first generation quad core phone

(+) Positive	(-) Negative
feature positively mentioned in 192 reviews (out of 327)	feature negatively mentioned in 70 reviews (out of 327)
Example Sentences:	Example Sentences:
great screen, great performance, it has been an excellent purchase so far, i am very pleased with this phone, haven't experienced any problems so far	5Hz and 2G RAM, I cannot see if there is any more powerful thing this one can get! run every app just like lighting, and the screen is bigger and better than retina in iPhone4also, I love the app here in the market, even though 90% of them are the same as App store but there are still many amazing app like Light Flow which can give you a total different using experienceAlso, I can trans all my contacts, calendars, and even photo(dropbox) to this phone and it like all the way, no worry to change phone anymore,With the wireless charger, everyone who is passing my desk will give an amazing look at this phoneand I need to mentioned I love the buzz touch for Nexus 4 phone, it is brand new using experience and interaction experience.
All that whining on my part aside, it is a really good phone in terms of voice quality, maps with GPS, taking pretty good photos, doing data stuff "lickey split" on the t-mo network, setting up a personal wifi hot spot, playing music from pandora, amazon, grooveshark, etc.	Q - Is the Nexus 7 future proof?A - Nothing is but considering its beautiful design, high quality manufacturing, the near guarantee of timely software updates, the fact that it is leading Android phone today for the under 5" screen size and that the smart phone technology is approaching 'maturity' it should continue to be a good phone for at least the next 2-3 years.
Since it was unlocked it made it more valuable than to buy it from my phone carriers site, also I needed the phone fast as I was doing a new mobile carrier, so it was great that it was able to ship very fast.	It may not be the best of the best, but it's still very good for phone calls or listening to music or game audio at modest volumes.

Feature: updates unlocked rooted high screen resolution

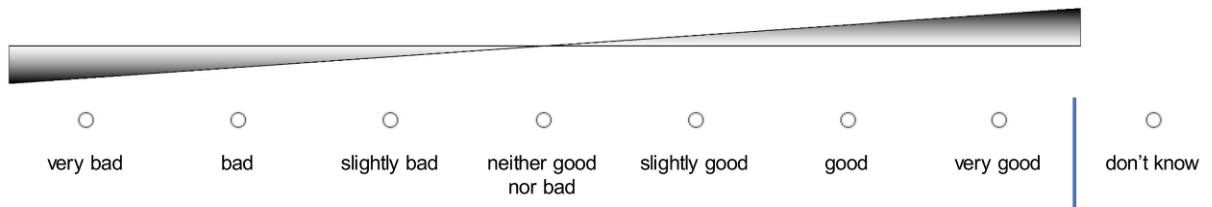
(+) Positive	(-) Negative
feature positively mentioned in 75 reviews (out of 327)	feature negatively mentioned in 23 reviews (out of 327)
Example Sentences:	Example Sentences:
great screen, great performance, it has been an excellent purchase so far, i am very pleased with this phone, haven't experienced any problems so far	5Hz and 2G RAM, I cannot see if there is any more powerful thing this one can get! run every app just like lighting, and the screen is bigger and better than retina in iPhone4also, I love the app here in the market, even though 90% of them are the same as App store but there are still many amazing app like Light Flow which can give you a total different using experienceAlso, I can trans all my contacts, calendars, and even photo(dropbox) to this phone and it like all the way, no worry to change phone anymore,With the wireless charger, everyone who is passing my desk will give an amazing look at this phoneand I need to mentioned I love the buzz touch for Nexus 4 phone, it is brand new using experience and interaction experience.
Touch screen is flawless, graphics amazing, speed is great, ease of use (Google's Android) is for babies and LG have made a great job as a whole.	When I asked them how much it will cost to replace the screen, I just got a response that it will be quite expensive and so it's probably not a good idea to send the phone for repair.
Fast, big screen, nice desing and a good battery!Recommended for everyone a lot!	screen is okay not that great my little brother has a lumia 900 and I think his screen was better and his phone is cheaper and the home and return button take part of the screen so it doesn't feel as big as it is advertised .

Feature: next nexus phone

(+) Positive	(-) Negative
feature positively mentioned in 37 reviews (out of 327)	feature negatively mentioned in 21 reviews (out of 327)
Example Sentences:	Example Sentences:
Brand new condition , fast shipping and the phone its self is fast love it thanks a lot best phone I've gotten so far	Q - Is the Nexus 7 future proof?A - Nothing is but considering its beautiful design, high quality manufacturing, the near guarantee of timely software updates, the fact that it is leading Android phone today for the under 5" screen size and that the smart phone technology is approaching 'maturity' it should continue to be a good phone for at least the next 2-3 years.
the nexus 4 is a great phone it's OS operates smooth, camera (to me) is awesome, the look and feel is beautiful.	The Nexus 4 is not the best phone out there, it does have its flaws, but at \$300 it puts a big fight.
3)Eventhough in papers they have the highest resolution,compared to SAMSUNG 3, i dont see much calarity compared to samsung S3 which is now selling for same nexus price-4)Bluetooth cannot be turned to ON5)Camera is the very worst after battery, very cheap and clarity at worst6)On improvement to android OS, the volume bar and other information can be made to transparent ,because it blocks in middle of the screen.	Q - How does the display compare with other phones?A - I was unable to detect a difference when comparing my Nexus 4 display with the latest iPhone's.

20. How do you rate the quality of the content of this summary?

Please **only consider the content** and not the layout or the design.



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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016



Survey Final Part



TECHNISCHE
UNIVERSITÄT
DARMSTADT

94% completed

Summary content

21. Would you base your buying decision for a product solely on the information found in summaries such as the ones you seen?

(e.g. in situations where you are not sure whether to buy the product or not or in situations where you need to choose between several products)

- Yes
- No

-
- don't know

22. [Optional] Do you have other comments (good or bad) regarding the summary content per feature?

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[Benjamin Tumele](#), Technische Universität Darmstadt – 2016

Thank you for completing this questionnaire!

I would like to thank you very much for helping me.

If you want to further help me, please send the link to this survey to other people you know.

Your answers were transmitted, you may close the browser window or tab now.

[Benjamin Tumele](#), Technische Universität Darmstadt – 2016

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