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ORIGINAL ARTICLE

Leveraging social media to gain insights into service delivery: a study on Airbnb

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Abstract Consumers increasingly rely on reviews and social media posts provided by others to get information about a service. Especially in the Sharing Economy, the quality of service delivery varies widely; no common quality standard can be expected. Because of the rapidly increasing number of reviews and tweets regarding a particular service, the available information becomes unmanageable for a single individual. However, this data contains valuable insights for platform operators to improve the service and educate individual providers. Therefore, an automated tool to summarize this flood of information is needed. Various approaches to aggregating and analyzing unstructured texts like reviews and tweets have already been proposed. In this research, we present a software toolkit that supports the sentiment analysis workflow informed by the current state-of-the-art. Our holistic toolkit embraces the entire process, from data collection and filtering to automated analysis to an interactive visualization of the results to guide researchers and practitioners in interpreting the results. We give an example of how the tool works by identifying positive and negative sentiments from reviews and tweets regarding Airbnb and delivering insights into the features of service delivery its users most value and most dislike. In doing so, we lay the foundation for learning why people participate in the Sharing Economy and for showing how to use the data. Beyond its application on

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the Sharing Economy, the proposed toolkit is a step toward providing the research community with an instrument for a holistic sentiment analysis of individual domains of interest.

Keywords Social media analysis · Sentiment analysis · Sharing Economy · Service delivery

1 Introduction

Social commerce, social sharing, collaborative communities on the Web, changing consumer attitudes towards consumption, and advances in Information Technology (IT) have fueled the rise of the "Sharing Economy" (Owyang 2015; Botsman and Rogers 2010) and "collaborative consumption" (Hamari et al. 2015; Matzner et al. 2015). The umbrella term Sharing Economy describes the socio-economic phenomenon of access-based consumption of otherwise underused assets or services for monetary or other types of benefits (Belk 2014; Botsman 2013). A Sharing Economy business acts as an intermediary in a two-sided market by providing a Web platform that connects peer providers with peer consumers and that handles business transactions (Andersson et al. 2013). The peer providers grant peer consumers temporary access to a physical resource in exchange for a (typically monetary) compensation (Plenter et al. 2017; Belk 2007).

Sharing Economy platforms set the stage for peer providers to deliver services of often inconsistent quality (Hamari et al. 2015), so both the platform provider and consumers face uncertainties regarding the peer providers. The platform provider's revenue stream depends directly on the number of transactions, and indirect on the quality of those offers. Peer consumers must have confidence in the peer provider before they will engage in a transaction, which often involves the sharing of personal resources like—in the Airbnb case—a room in a private home (Andersson et al. 2013). To increase trust in sharing transactions, the platforms encourage users to provide information on the other parties with whom they contract for services through reviews, comments, and ratings. Potential customers and providers will then rely on this information to build trust towards the other party. In effect, reviews are a crucial factor in users' decision to engage in Sharing Economy transactions. They are also of considerable value to the academic community that seeks to understand consumers' motivations and behavior within Sharing Economy business settings.

However, obtaining and analyzing such data using IT is not a trivial task. Websites are diverse and may contain large amounts of relevant customer communication that is encoded in unstructured text, which is not usually easy to decipher by means of IT (Liu 2012). Originating from Natural Language Processing (NLP), the field of sentiment analysis is an actively researched domain that provides the methodological and technological foundation from which to analyze consumers' opinions expressed in unstructured documents (Liu 2015). A sentiment analysis is "the study that analyzes people's opinion and sentiment towards entities such as products [and] services in the text" (Agarwal et al. 2015, p. 1). Nevertheless, scholars who seek to research these opinions have limited access to holistic solutions, as existing solutions are either proprietary and/or not suited for academic research, or focus only on a subset of the steps required for a comprehensive sentiment analysis (Liu 2015).

Against this backdrop, the research objective of our work is to develop a holistic sentiment analysis approach that integrates all necessary steps, from collecting data from multiple sources to analyzing it and to producing human-readable interpretable results. In fact, we present a complete sentiment analysis toolkit that the scientific community can use to gain insights into the sentiments that spread on social media in general and to the specific sentiments that are associated with service delivery in the Sharing Economy. To demonstrate our approach, we use review corpora and tweets, the latter of which frequently serve as a source for sentiment analyses, because they are open to the public, well-adopted, and considered to be a principal source with regard to the provision of live, raw information (Marchand et al. 2017; Yamada et al. 2015).

Our contribution is twofold. Following the design science research paradigm (Hevner et al. 2004), we generate design knowledge by building a toolkit for the extraction and semantic analysis of reviews and tweets. In doing so, we provide researchers with a generic approach that can be applied to a wide range of scenarios. The toolkit allows data scientists to compare and contrast well-formed reviews with short, informally-written tweets. We demonstrate the toolkit's usefulness by applying it to the case of the accommodations provider *Airbnb*[1] with the aim of analyzing, interpreting, and comparing the aspects of service delivery that are most relevant to users. Sharing Economy businesses can use the toolkit to gain insights into their providers' service delivery, which can be used to derive generalizable knowledge about peer consumers' preferences and idiosyncrasies and to inform, educate, and guide peer providers.

This article builds on our previous work published in Hagge et al. (2017) where we describe the architecture and implementation of a toolkit for sentiment analysis of tweets. Hereinafter, we extend our previous work by, first, enhancing and applying the toolkit to review corpora, second, contrasting the findings of reviews and tweets, third, by an in-depth discussion of the results, fourth, by identifying and deriving technical, managerial, and academic implications.

The remainder of this article is structured as follows. Section 2 provides background on sentiment analysis and the Sharing Economy, while Sect. 3 presents the solution's design and its implementation. Section 4 applies the toolkit to the Airbnb case using tweet and review corpora. Section 5 discusses the case results and summarizes its technical and practical implications. This article closes with a summary of its findings and an outlook on future research.

[1] Airbnb website: https://airbnb.com (accessed: 2017-05-19).

2 Foundations and research background

2.1 Sentiment analysis

The sentiment analysis is an NLP technique for identifying opinion and affective states toward subjects in structured documents (Liu 2012). These subjects can be any entity or aspect of the entity about which a sentiment is expressed. The sentiment can be positive, negative, or neutral, or given as numeric rating that represents the strength of positivity or negativity (Agarwal et al. 2015; Pang and Lee 2008). Research in this area has received considerable interest lately because of the rapid growth of online consumer communication using social networks like Twitter and crowd-sourced review websites like Yelp and TripAdvisor (Saif et al. 2016). From a technological standpoint, consumer communication is human language input expressed in unstructured text, which a machine has to process before it can be understood. Central to NLP is the extraction of information from such text by using its grammatical structure (e.g roles and dependencies of the words it contains) (Rajman and Besançon 1998). For a sentiment analysis, it is not necessary to understand the full semantics of a sentence; it is sufficient to identify some of its aspects, such as the sentiments and their target entities or topics (Liu 2015).

Past applications have focused on various levels of analysis, including the document, sentence, and aspect levels (Saif et al. 2016; Liu 2012; Nasukawa and Yi 2003). The document level computes one sentiment for the document as a whole, while an analysis on sentence level categorizes each sentence individually (Liu 2012). However, both approaches are too coarse identify different opinions within a single sentence, which is often the case for customer reviews in which people express mixed views on various aspects pf the service (Saif et al. 2016; Liu 2015). For example, the review "The bedroom is small but the bathroom was spacious" has positive and negative sentiments expressed about two subjects in a single sentence. A sentiment analysis on the feature or aspect level can determine sentiments on different levels regarding an entity and its related hierarchical aspects. It can also generate a structured summary of the opinions towards entities and aspects of them (Liu 2012). In line with related work on examining product reviews (Agarwal and Mittal 2014; Blair-Goldensohn et al. 2008; Hu and Liu 2004), we develop an aspect-based sentiment analysis to extract opinions from tweets and reviews that are related to Sharing Economy transactions.

2.2 The Sharing Economy

The term Sharing Economy refers to the principle concerning peer-providers' and peer-consumers' sharing or collaboratively consuming a resource. Unlike the altruistic "true sharing" (Belk 2010), the Sharing Economy entails some form of compensation for the peer-provider in exchange for the use of the resource by the peer consumer. Typically, transactions in the Sharing Economy use modes of exchange like co-owning, donating, lending, renting, reselling, and swapping (Plenter et al. 2017; Owyang 2013).

In many cases, business models of Sharing Economy services challenge traditional value chains (Walsh 2011). Prominent examples in this respect are Uber and Airbnb, which disrupted the taxi and hotel industries. Such Sharing Economy services dynamically connect individuals who have spare resources or excess capacity (peer providers) with others who need these resources (peer consumers). Sharing idle assets with others leads to a more efficient use of a resource (Belk 2014). The degree of the peer provider's involvement varies among different business models; for example, the peer provider in Uber functions as taxi driver, while a peer provider in Airbnb takes a more passive role by simply providing a resource.

To realize a resource allocation and a related sharing transactions, an exchange of information is required. Internet-based Sharing Economy platforms allow for efficient interaction between platform providers and service users (Plenter et al. 2017). Providers and consumers do not necessarily need to meet in person to exchange information or negotiate terms. Instead, the ubiquitous access to the platform over the Internet (Andersson et al. 2013) and a standardized presentation of offerings, user ratings, and business processes simplify the search process and facilitate transactions, reducing search and transaction costs.

3 Design and implementation

Users of Sharing Economy services often express their experiences with a service in unstructured documents like tweets and reviews. In order to leverage this information by identifying positive and negative aspects of the service delivery in the Sharing Economy, we design and implement a toolkit for the extraction and semantic analysis of reviews and tweets following the design science research guidelines from Hevner et al. (2004). The design of the artifact is manifested in a system that is intended to solve the existing problem of extracting information from unstructured text (with the focus set on tweets and reviews) in an effective way. This problem is also highly relevant to practitioners, as they can use the toolkit to identify the strengths and weaknesses of any product or service (cf. Sect. 5). By rigorously studying, evaluating, and taking into account the related work in the areas of NLP and sentiment analysis, we ensure that our approach lives up to the current state of the art. The resulting toolkit is evaluated by means of a demonstration that provides information for further development and improvements. Given the problem's practical relevance and theoretical foundation, our main outcome is the design and the implementation of an IT artifact (March and Smith 1995).

We substantially enhanced our toolkit (cf. Hagge et al. 2017) to account for the more complex review text corpora. The toolkit is comprised of three components, as visualized in Fig. 1, each of which is dedicated to performing a set of distinct tasks. Some of these tasks adopt and extend existing approaches (cf. Manning et al. 2014; Liu et al. 2005; Hu and Liu 2004).

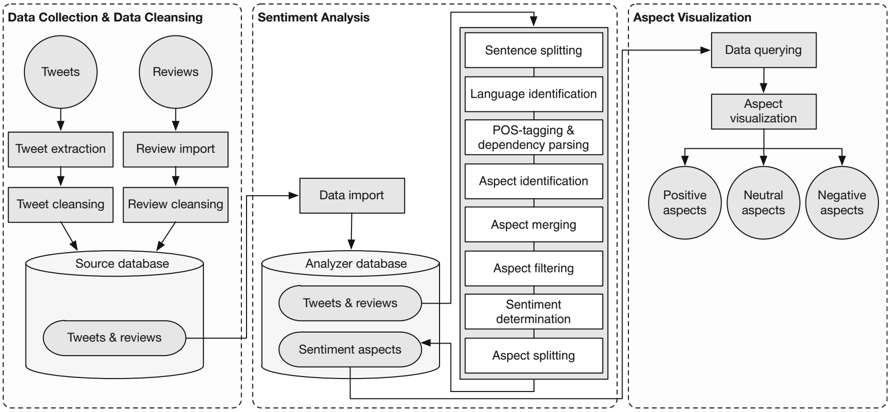


Fig. 1 Toolkit architecture and processing steps

The first component, *data collection and data cleansing*, retrieves data from input sources like text files, relational databases or the Twitter search API to extract content that matches a previously specified query. The query results are then pre-processed by means of data cleansing routines and placed in a database for later analysis. The second component, *sentiment analysis*, loads extracted content and performs an aspect-based sentiment analysis that is realized by means of a serialized processing pipeline. The sentiment analysis component identifies collections of positive, negative, and neutral aspects that are mentioned in the analyzed text documents. The third component, *output visualization*, loads the identified aspects and provides a graphical user interface to support data scientists in the interpretation and derivation of motivations and demotivations for users to engage in the service.

3.1 Data collection and data cleansing

This work's sentiment analysis processes two different types of unstructured documents: reviews and tweets. As for the reviews, the solution imports text corpora from plain-text `.csv` files. Because of the diversity of the websites that contain the reviews, there is no generic approach to extracting reviews from any given website. Therefore, the toolkit does not include a review-retrieval mechanism, but relies on readily available tools like external data providers and Web crawlers that fetch reviews from arbitrary websites. As for the tweets, the toolkit periodically queries the public Twitter search API to collect tweets that match the search criteria [we suggest keyword-based search using hashtags (e.g., "#airbnb")].

However, as opposed to reviews that are a critical reflection on a service experience, Twitter is a generic platform for people to express all kinds of information. Consequently, only a fraction of tweets using the hashtag "#airbnb" actually provides information on service experiences with Airbnb offers. Even worse, in contrast to well-written reviews, tweets are short (Marchand et al. 2017) and have irregular content structure (Saif et al. 2012). Further, the language of tweets has a noisy lexical nature, with inconsistent terminology, colloquialisms, and non-standard abbreviations (Rizzo et al. 2015). We therefore have to apply a specifically tailored data cleansing process on the tweet data. For a detailed description on how our proposed toolkit filters and cleanses the raw tweet data please refer to Hagge et al. (2017).

Review cleansing and also tweet cleansing comprise additional text operations to enhance data quality. Before storing the collected data into the database, the tool inserts whitespace after punctuation, reduces multiple spaces to a single space, and removes all non-ASCII and non-English characters such as Chinese characters and emojis.

3.2 Sentiment analysis

For the aspect-based sentiment analysis, the extracted content traverses through a serialized processing pipeline comprised of eight tasks. The main analysis steps are based to a degree on the execution flow of Stanford's CoreNLP solution, from sentence splitting through Part-of-Speech (POS)-tagging, dependency parsing, and sentiment determination (cf. Manning et al. 2014), but are adapted to the requirements of this article's analysis. As the source data were already pre-processed by the data collection and data cleansing component, documents are directly imported into the analyzer database and fed to the analysis pipeline.

Figure 2 presents an instantiation of the processing tasks for the input tweet "Wohoo that apartment was beautiful. But quite noisy flat!". As this example is a minimal working example, filtering for rarely occurring aspects was omitted. In the following, the single processing tasks are described in greater detail.

POS-taggers usually require single, separated sentences as input, so the individual tweet and review documents are split into sets of sentences using sentence boundary analysis (Manning et al. 2014). The toolkit uses the Apache OpenNLP library,[2] which supports sentence splitting among other common NLP tasks. Identified sentences may contain line breaks leading to misinterpretation by the POS-tagger, so any line breaks in the sentences are removed and replaced with a single space.

Our analysis focuses on English documents. Because of the individual grammatical and linguistic properties of languages, specific algorithms or approaches are necessary (Agarwal et al. 2015). To minimize misinterpretations, the language identification step filters out documents that exceed the configurable threshold of non-English content. For each sentence in a document, the routine calculates the fraction of words that are contained in the English WordNet dictionary, a lexical database for English (cf. Miller 1995) that is commonly used in NLP (Agarwal et al. 2015; Saif et al. 2016). Sentences with a word-in-dictionary-fraction below a configured threshold of 60% are flagged, and if more than half of the sentences in a document are flagged, the document is excluded from further analyses.

POS-tagging and dependency parsing are performed to identify the different roles and relationships of the words in a sentence (Nivre et al. 2016). Lexical ambiguity

[2] Apache OpenNLP website: https://opennlp.apache.org (accessed: 2017-05-19).

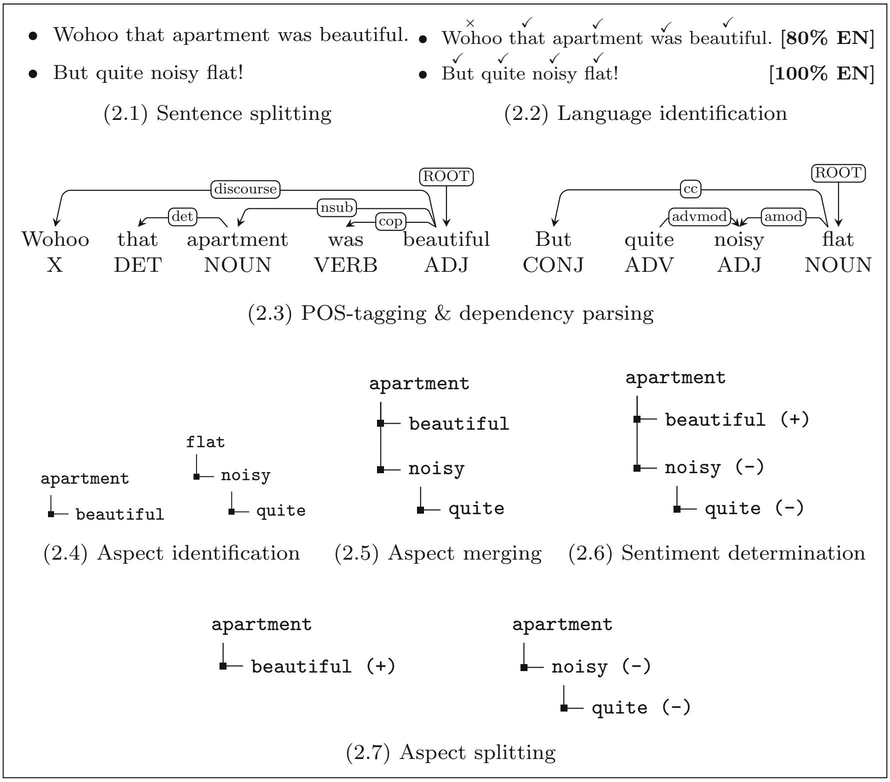


Fig. 2 Exemplary stepwise instantiation of the sentiment analysis

and inflectional morphology make this task challenging to implement, as some words can have different roles in different contexts; for example, "process" can either be a noun or a verb (Rajman and Besançon 1998). The polarity of a word may also change depending on its role in the sentence. For instance, "like" denotes a sentiment only when used as a verb and not as preposition (Nasukawa and Yi 2003). During POS-tagging, each word is tagged with a token that describes the word's syntactic function in the sentence; relations between the tokens determine the words' relationships in the sentence. For each sentence, the dependency parsing yields a directed tree with one (or more) root tokens and dependency relationships between each token and its parent token, such as those trees depicted in Fig. 2.3.

POS-tagging and dependency-annotation approaches usually label the tokens and relations using standardized sets of tags as labels. Our approach uses the common tags from the Universal Dependencies project (cf. Schuster and Manning 2016; Nivre et al. 2016). Given the first sentence in Fig. 2.3, "Wohoo that apartment was beautiful", the adjective *beautiful* is tagged as a root that has *apartment* as its nominal subject. The verb *was* is tagged as copula that links the subject *apartment* to *beautiful*. POS-tagging and dependency parsing are performed by *Parsey McParseface*, which is a pre-trained model to analyze English text that comes with

Google's open-source neural-network NLP framework SyntaxNet (Google Inc 2016).

Opinion words can be of a number of word classes. Most common are adjectives like *beautiful* that carry sentiment information and are related to a noun, which is identified as an aspect in the context of this analysis. As shown in detail in Hagge et al. (2017), we identified and implemented four commonly appearing dependency patterns between adjectives and nouns that are able to extract most sentiment aspects from the documents. Given the sentences in Fig. 2.3, patterns one and two can be applied. The adjective in the first sentence has a direct parental relationship to its nominal subject, i.e *beautiful* is the parent of *apartment* (pattern two). The noun *flat* in the second sentence is the direct parent of the related adjective *noisy*, which itself is modified by the adverb *quite* (pattern one).

Manual inspection of the dependency trees revealed that not all nouns consist of a single token. Instead, nouns can be a combination of multiple tokens such as in *shopping centre*, where the noun is the combination of the two tokens *shopping* and *centre*. In order to extract the noun expression as a whole, we added another pattern that identifies the noun token and its corresponding additional token. As shown in Fig. 3, we can follow the dependency relation "nn" from the additional token to the head noun token. The aspect will then be stored as the concatenation of the two tokens.

The example in Fig. 3 also reveals a weakness in the identification of compounds that are comprised of a preposition and a noun. The expression *underground station* should be identified as a compound noun. However, Parsy McParseface identifies the token *underground* to be the adjective modifying the noun *station*. We further discuss this issue in Sect. 5.1.

Following Liu (2015), the aspects will be stored in a hierarchical form that has the noun as root, the adjective as direct child and the optional adverb and negation as grand- and great-grandchildren. Some aspects such as "very beautiful apartment" and "beautiful apartment" occur multiple times in the documents. The actual token occurrences will be linked at the lowest hierarchical level suitable for the statement. An occurrence of "very beautiful apartment" will be linked to the object "very", while an occurrence of "beautiful apartment" will be linked to "beautiful". Early aggregation of recurring aspects reduces the number of individual sentiment queries to the sentiment determination API. For multiple occurrences of "very beautiful apartment" the sentiment will only be determined once because the sentiment is not determined for the sentence as a whole, but for a set of opinion words and its target. The remaining four tasks (*aspect merging* to *aspect splitting*) are performed on the resulting hierarchical aspect tree structure.

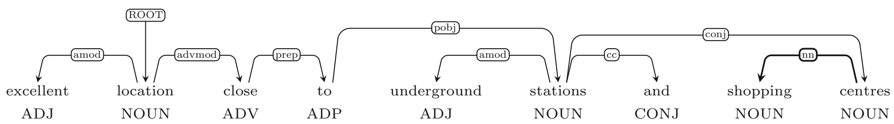


Fig. 3 Identification of combined noun expressions

A variety of words can express the same thing (Liu et al. 2005), so synonymous aspects like *flat* and *apartment* are merged into a common aspect. In order to perform aspect-merging, all aspects are stemmed to the base singular form using the stemming solution from WordNet (Miller 1995). Following Liu et al. (2005), comparing synonyms of all senses would result in too many false matches, so only the two most frequent senses are used for synonym determination. In the solution two aspect names are synonymous when one of the two is a synonym in the two most frequent senses of the other aspect.

Aspect frequency filtering was implemented as part of the processing pipeline, but it is disabled in the default configuration of the solution because enabling would mean that all aspects below a defined frequency threshold would be excluded from further analysis. Based on Liu et al. (2005), more frequently identified aspects might be less likely to be wrong, therefore aspect filtering might help in removing incorrectly identified sentiment aspects.

We employ an online API to determine the polarity of the sentiment aspects. By now, there are multiple online APIs for sentiment determination available on the market, each of which differs from the others in its range of functions, applied algorithms, up-to-dateness, and pricing models. We identified various candidate APIs and ran a small and not statistically relevant benchmark test case. AlchemyAPI by IBM (also known as IBM Watson Developer Cloud)[3] not only performed best in our test but also previously yielded promising results on tweet (cf. Simon et al. 2014; Quercia et al. 2012) and review corpora (cf. Singh et al. 2013). Moreover, AlchemyAPI uses a hybrid approach that on the one hand relies on a sentiment dictionary but also applies machine-learning techniques in order to continuously adapt its dictionary to new language, that is, new expressions, figures of speech, and nuances in text (IBM 2015).

All levels of every sentiment aspect tree are considered to determine the sentiment expressions to be queried. The resulting sentiment score and type is persisted for the aspect at the lowest hierarchical level.

Lastly, it might be necessary to split some aspects since the aspect's tree structures may contain multiple types of sentiment aspects. For our running example, the aspect *apartment* occurs in a positive and a negative statement. A split of the aspect *apartment* is performed to simplify further analyses. As shown in Fig. 2.7, the aspect *apartment* is divided into a positive and a negative aspect, which allows the same aspect noun to be a positive and negative influence on service delivery.

3.3 Aspect visualization

To assist in the evaluation of analysis results, we advanced our graphical user interface (cf. Hagge et al. 2017) to account for the reviews. The solution is build using the self-service in-memory business intelligence software *QlikView*.[4]

[3] AlchemyAPI website: https://www.ibm.com/watson/alchemy-api.html (accessed: 2017-05-19).

[4] QlikTech website: http://www.qlik.com (accessed: 2017-05-19).

The visualization retrieves the results of the analysis,i.e the hierarchical tree structures that contain aspects and sentiments. Interactive visualizations, filtering options, and the ability to drill through the data aid in the process of interpreting analysis results.

Figure 4 shows the user interface. It gives the most frequently mentioned aspects per sentiment type (positive, negative, and neutral) in list views and bar charts. The solution provides time-based filtering on a year, month, day, and weekday basis, which limits the corpus of documents in relation to their creation dates. It further gives the number of occurrences by sentiment types, the most frequently mentioned sentiment words, a quantitative comparison of the most frequently mentioned aspects, the distribution of sentiment types expressed for these aspects in a central bar chart, and the number of documents over time using a line chart. All visualizations are interactive and display results in relation to currently applied filters.

Using the aspect visualizer to examine the results of the aspect-based sentiment analysis we performed, we were able to generate the insights described in the next section.

4 Demonstration

In the following, the developed solution is demonstrated using tweet and review corpora. Twenty thousand reviews from Airbnb users on listings in the US capital city of Washington and the German capital of Berlin were analyzed. These reviews were retrieved from *insideAirbnb*,[5] which provides various Airbnb-related datasets, such as listings and reviews for certain geographic areas and cities. As for the tweets, a total of 83,278 tweets matching the query "#airbnb" were collected over a period of five months of continuous tweet extractions. The applied tweet-filtering reduced the corpus to 11,112 potentially relevant tweets.

The two sets of sentiments extracted from the reviews and tweets are compared with each other to provide a comprehensive picture of positively and negatively perceived aspects of the service experience when users rented an accommodation through Airbnb. In the course of the demonstration, the results yielded from using our toolkit are presented and discussed, and the results for reviews and tweets contrasted.

4.1 Results

The reviews contain 12,262 distinct aspects. The average length of a review is 4.88 sentences, and each sentence contains an average of 15.61 tokens. Each review contains approximately 11.29 distinct aspects, which results in 2.45 distinct aspects per sentence.

In the tweets, 4396 distinct aspects are identified. The average length of a tweet is 1.65 sentences, and the average tweet contains 1.99 distinct aspects. This

[5] *Inside Airbnb* website: http://insideairbnb.com/ (accessed: 2017-05-03).

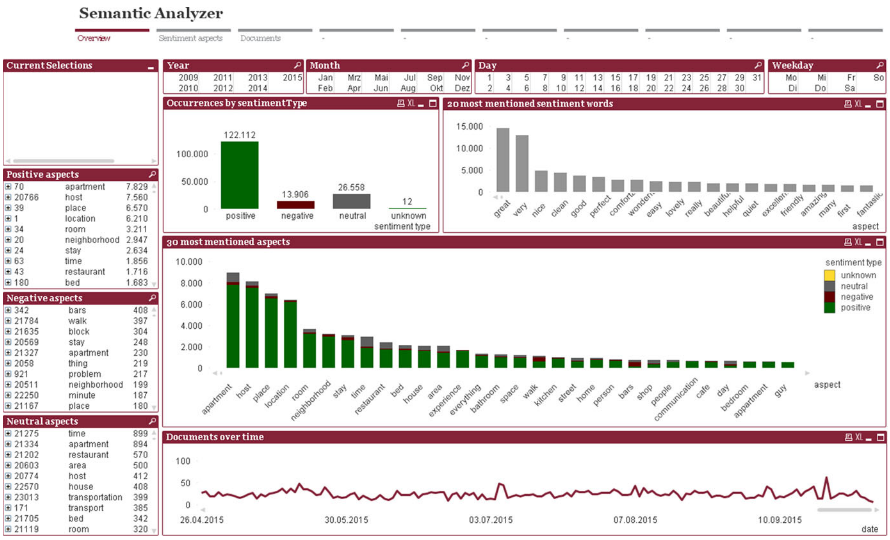


Fig. 4 Interactive visualization of sentiment aspects

comparably short length is due to the fact tweets having a limited length of 140 characters. Each sentence contains approximately 10.23 tokens and an average of 1.21 distinct aspects.

Figure 5 shows the overall sentiment distributions in the reviews and the tweet datasets. In the reviews dataset (Fig. 5.2) 122,112 occurrences (75.11%) of positive aspects are found, which compares to 13,906 occurrences (8.55%) of negative aspects and 26,558 occurrences (16.33%) of neutral aspects. The tweets dataset's sentiment distribution (Fig. 5.1) is similar but slightly less shifted, with 7741 occurrences (58.57%) of positive aspects, 2281 (17.26%) occurrences of negative aspects, and 3194 (24.17%) occurrences of neutral aspects.

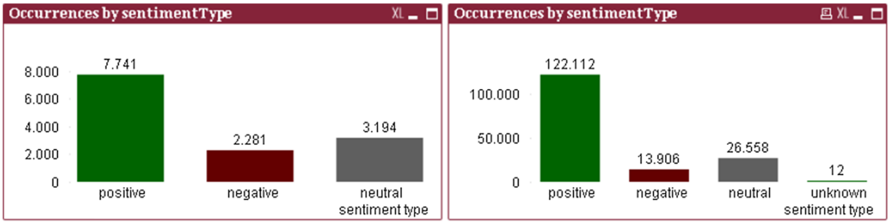
The ten most frequent aspects and their individual counts are given for both, reviews and tweets in Fig. 6. The distribution of sentiments for each aspect is also given.

In the reviews corpus, the aspects identified as being mentioned most often by reviewers are *apartment*, *host*, *place*, *location*, *room*, *neighborhood*, *stay*, *time*, *restaurant*, and *bed*. These aspects, along with their individual sentiment distributions, are depicted in Fig. 6.2.

The most frequently mentioned aspects for tweets are *airbnb*, *place*, *time*, *home*, *day*, *night*, *people*, *view*, *apartment*, and *room* (see Fig. 6.1).

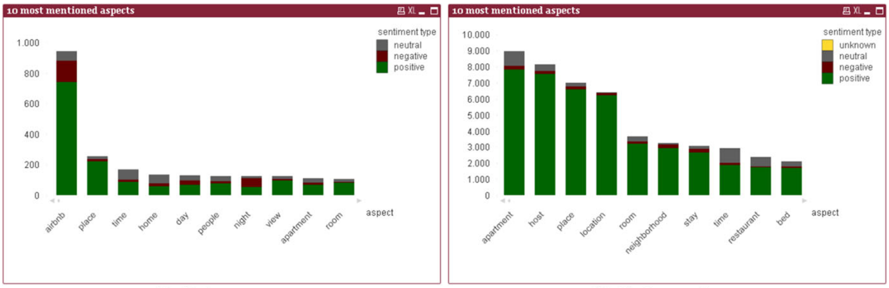
To complement the naming of the ten most frequent aspects, the following lists provide an overview of frequently mentioned positive, negative, and neutral aspects in descending order based on their individual counts.

In the reviews, the most mentioned positive aspects are *apartment*, *host*, *place*, *location*, *room*, *neighborhood*, *stay*, *time*, *restaurant*, and *bed*. Negative aspects most frequently mentioned in the reviews corpus are *bars*, *walk*, *block*, *stay*, *apartment*, *thing*, *problem*, *neighborhood*, *minute*, and *place*. The most frequently



(5.1) in tweets (5.2) in reviews

Fig. 5 Sentiment distribution



(6.1) in tweets (6.2) in reviews

Fig. 6 Ten most frequent aspects

mentioned neutral aspects are *time*, *apartment*, *restaurant*, *area*, *host*, *house*, *transportation*, *transport*, *bed*, and *room*.

The most frequently mentioned positive aspects in tweets are *airbnb*, *place*, *view*, *guest*, *time*, *room*, *experience*, *people*, *day*, and *apartment*. The most frequently mentioned negative aspects are *airbnb*, *rental*, *night*, *term*, *day*, *week*, *minute*, *discrimination*, *housing*, and *place*.The most frequently mentioned neutral aspects are *days*, *time*, *airbnb*, *home*, *week*, *york*, *people*, *day*, *status*, and *house*.

As a side note, the aspects *transportation* and *transport* are in the list of most mentioned neutral aspects because reviewers value the proximity to public transportation. However, the tagging and parsing solution did not consider *public transportation* as one noun expression, but evaluated *public* as being the qualifying adjective for the noun *transportation*, so that the adjective expressing the sentiment (e.g *nearby*) is ignored. A more thorough discussion of current limitations is provided in Sect. 5.

4.2 Interpretation of results

Reviews are an essential mechanism for Sharing Economy services, and on the Airbnb platform, users who engage in a transaction are encouraged to write them. After a user stays with a host, he or she may review the hosts's behavior and offering, while the host reviews his or her experience with the visiting user.

In July 2014, Airbnb changed the review system with the intention of increasing its users' trust in the reviews published on the platform. Since then, reviews are revealed only after the other involved party has also reviewed the transaction, or as soon as the time for submitting the review has expired (cf. Airbnb 2014). Airbnb also urges users to provide honest and accurate feedback and to help increase confidence in reviews on its platform in order to increase trust.

Twitter is used differently. For instance, tweets are often used to communicate status updates and driven by a "desire to maintain positive impressions" (Marwick and Boyd 2011, p. 124) or self-branding (Page 2012). Therefore, people might tend to emphasize on the positive features and, because of the character limit, are not as explicit about their experience.

Comparing the sentiment distributions of tweets (Fig. 5.1) and reviews (Fig. 5.2) makes apparent that positive aspects dominate negative and neutral aspects. Moreover, comparing the general statistics shows that reviews deliver a larger number of insights into the aspects perceived positively and negatively by users than tweets do, probably because of the significantly larger size of a single review and a higher density of relevant information. Reviews contained almost twice as many aspect mentions per sentence than tweets did, and reviews are targeted at describing a particular service, whereas tweets containing "#airbnb" often serve other purposes.

The most frequently mentioned aspect in the tweet corpus is *airbnb* itself, which is obvious, since "#airbnb" was the actual search query. However, the simple occurrence of the terms *#airbnb* or *airbnb* does not qualify as sentiment aspect in itself, as the tweet must contain a sentiment word that targets the respective *#airbnb* or *airbnb* noun. In our case, many users use the word *airbnb* synonymously with apartment (i.e., "my airbnb was awesome").

The most frequently mentioned positive sentiment words for *airbnb* are first, beautiful, new, next, and awesome. We argue that *first*, *new*, and *next* should be considered neutral instead of positive since they might not refer to the apartment or experience itself but to the use of the platform (e.g., "booked my first airbnb"). However, the polarity depends on the context, which cannot be inferred by the sentiment analysis. In general, the analysis is more accurate for reviews. For example, when the user writes "our apartment in Berlin is so nice!" it is clear that he or she is referring to an apartment rented via Airbnb.

We identified more frequent use of time-related aspects in tweets than in reviews. *Time*, *days*, *day*, and *view* are mentioned frequently, which indicates that the purpose of these tweets was to deliver information on what the person composing the tweet was doing at a particular moment, such as enjoying a nice view or reporting on having a good time. As a side note, the presence of both terms *days* and *day* in the most mentioned aspects of the tweet corpus indicates a drawback of our solution. Stemming and merging of aspects does not work flawlessly in every case; clearly, the aspect *days* should have been merged into them stem *day*. (We discuss this and other limitations in Sect. 5.)

In general, the intention in tweeting is most frequently "daily chatter" (Java et al. 2007, p. 57), which fits with the relative prevalence of the aspects mentioned. The reviews, on the other hand, are intended to provide information on the service the current user has received and to aid future users in their decision-making on whether to choose the same service.

Not surprisingly, the most frequently mentioned aspect in the review corpus is *apartment*. Only when drilling down into the aspect does it becomes clear exactly what users valued regarding the apartment. Users positively describe the apartment with the adjectives *clean*, *comfortable*, *nice*, *spacious*, and *great* (see Fig. 7), five adjectives that account for approximately 43% of all positive mentions of *apartment*. With regard to *apartment* as negative aspect, the most frequent mentions include the sentiment words *cheap*, *actual*, *hard*, and *adequate*. However, the tool might have incorrectly attributed these terms to a negative polarity.

Some of the most frequently mentioned aspects, such as *place*, *room*, and *bed*, *location*, *neighborhood*, and *restaurant*—are directly related to the apartment, indicating that the apartment itself is of high importance to the Airbnb user. *Place* is the second most frequently mentioned aspect in the tweet corpus, and it is positively associated with the sentiment words *great*, *new*, *nice*, and *amazing*. Inside the apartment, users of Airbnb seem to value the *room*, *bed*, *bathroom*, and *kitchen* the most. Figures 7 and 8 give an overview of the most frequently mentioned positive and negative aspects and the number of times they occurr.

Regarding the aspect *room*, the most frequent positive aspect mentions are *clean*, *comfortable*, *nice*, *spacious*, and *great*, while examples of negative mentions are *noisy*, *dirty*, and *cold*. The *bed* is most often positively associated with being *comfortable*, *comfy*, *clean*, *great*, and *nice*. On the other hand, it is negatively associated with being *uncomfortable*, *hard*, *dirty*, and *bad*. For the *bathroom* the most frequently mentioned positive aspects mentions are *clean*, *nice*, *great*, *comfortable*, and *spacious* with only minor negative mentions, such as being *post-modern*, *odd*, *tricky*, and *smelly*. The *kitchen* is most often positively associated with

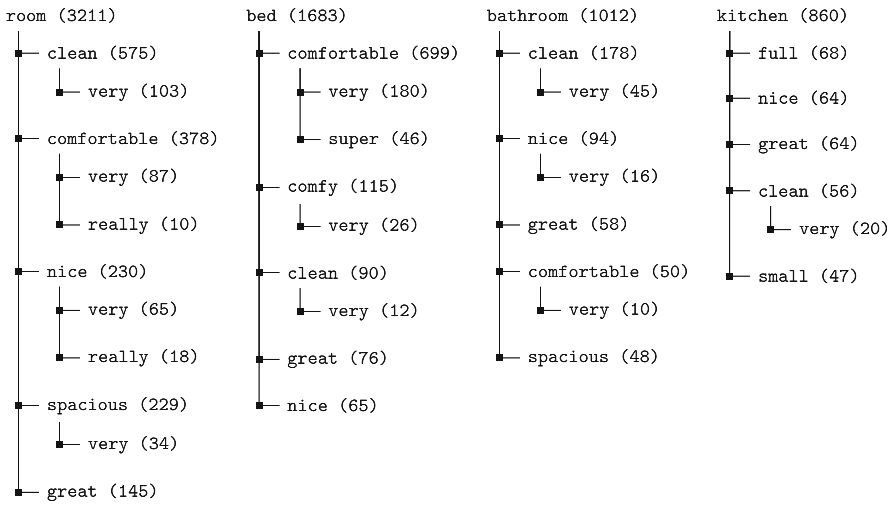


Fig. 7 Selection of positive apartment-related aspects from reviews

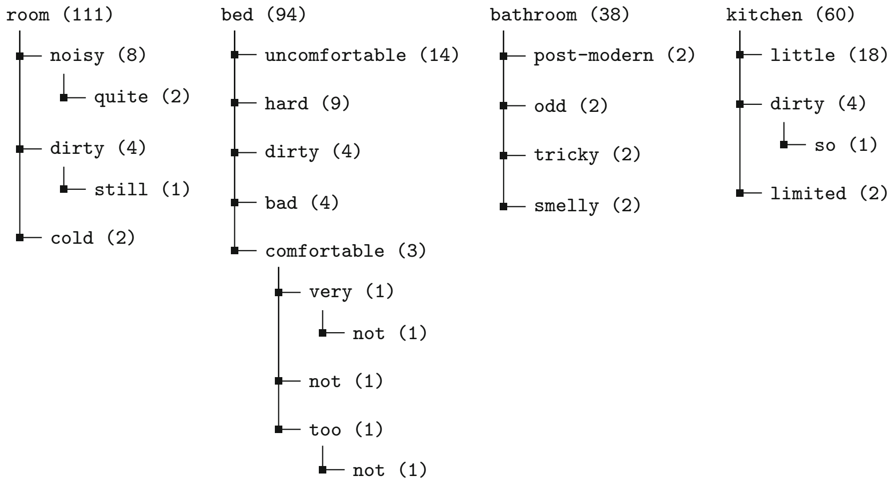


Fig. 8 Selection of negative apartment-related aspects from reviews

full, *nice*, *great*, *clean*, and *small*, and is negatively associated with being *little*, *dirty*, and *limited*.

The *location* of the apartment is mentioned, especially in the reviews corpus. Related aspects are *view*, *neighborhood*, and *public transportation*. The location is valued for being central and close to public transportation, as the following exemplary review excerpt shows:

> "A perfect, central location on a great cobblestone street - only 2 blocks to Warschauer station & lots of super convenient public transportation."

In the tweets, *view* is found as a frequent positive aspect, which is obviously influenced by the apartment's location. In this sense, the users value having a nice view positively. The fact that *public transportation* is wrongfully categorized as a neutral aspect was mentioned earlier, but the proximity to public transportation is frequently mentioned with a positive polarity.

The aspect *host* is the second most frequently mentioned positive aspect in the set of reviews we analyzed. The most frequently mentioned adjectives in this sense are *great*, *friendly*, and *helpful*. In the tweets corpus the aspects *host* and *airbnb host* are also occurring in the twenty most frequently mentioned aspects. One exemplary tweet mentioning the host is given in the following:

> "My first @Airbnb was wonderful. Amazing host, cute house and doggie. Meeting travellers. My heart is happy. #victoria #bc #airbnb"

The high number of occurrences and the found adjectives indicate that the relationship to the host as a person is very important to the users who rented the apartment. No insight can be generated from negative mentions of aspects regarding the host, as the most frequently mentioned sentiment words regarding the host are *flat*, *patient*, and *little*, which appear to be inaccurately categorized as being negative.

Hamari et al. (2015) identify economic gains as a motivator for users to provide their resources to others via Sharing Economy platforms. Mentions of sentiment words that may be related to the users' economic gains, such as *affordable* and *cheap*, account for only 0.18% of the *apartment* mentions, nor is *price* mentioned frequently. Hence, economic gains is not identified as a significant aspect expressed in the documents we analyzed. Some aspect such as *stay*, *time*, *experience block*, *thing*, *problem*, and *rental* are too general or too complex to be used to identify concrete motivators.

The quality of the apartment is a key aspect for Airbnb users. A sufficient degree of cleanliness is crucial, as insufficient cleanliness is often mentioned in negative experiences. For the apartment and its related aspects (room, bed, bathroom, and kitchen), negative mentions are about dirtiness. For the bed it is comfort. The kitchen should be fully equipped. Most uers expect a spacious and comfortable room that is not too noisy or cold. For the bathroom, besides the cleanness, comfort and spaciousness are valued, and it should not be too old or bad-smelling. A nice view from the apartment is also perceived positively, as is a central location in a decent neighborhood with nice bars and restaurants and close proximity to public transportation. On the other hand, a bad, noisy or expensive neighborhood is perceived negatively and may discourage users from choosing a particular listing.

From positive statements one can conclude possible reasons for not using Airbnb services. Several users mentioned that the host was "not intrusive" or "never intrusive", suggesting that an intrusive host would (understandably) contribute to a negative service experience. However, users strongly value their personal relationship to the host, and learning that the host is friendly and helpful can be a motivator to engage in a transaction with the host by renting his or her apartment.

5 Discussion

5.1 Technical implications

Processing natural language and making sense of syntactical and semantic structures remains difficult for machines, so they yield imperfect sentiment analysis results. A detailed discussion of the toolkit's technical limitations with regard to tweet filtering and cleansing is provided in Hagge et al. (2017). From our application to the comprehensive review corpora, we identify further issues related to the semantic analysis and provide suggestions for improvement in the following.

As mentioned before, the POS-tagger SyntaxNet we used identified some compound nouns inaccurately as a combination of an adjective with a noun (e.g *public transport* or *underground station*). As SyntaxNet is still in a beta state and under heavy development, the accuracy of POS-tagging and dependency parsing is expected to increase with future releases. Furthermore, we plan to use a combination of the WordNet dictionary (Miller 1995) with a user-configurable dictionary of compound nouns and idioms, so that compounds will be identified and held together.

A related limitation lies in merging similar concepts. For example, mentions of *public transport* and *public transportation* resulted in the creation of two neutral aspects *transportation* and *transport*, each treating *public* as their adjective. This issue causes less precise analysis results and negatively impacts the interpretation of aspects. In the future, the toolkit will support configurable rule sets for merging specific aspects that overrule the default behavior. Compiling these rules should be done iteratively until the results show no more related, unmerged concepts. Similarly, another viable approach is to construct an ontology that can help to identify semantically similar aspects that may be syntactically different. This solution could be achieved by manually merging related aspects and making use of existing background knowledge and reasoning.

The demonstration yields good results using WordNet as stemming solution. For example, WordNet works well with keys → key, restaurants → restaurant, shops → shop, hosts → host. However, for some words the expected behavior is not achieved, e.g., minutes → minutes and instructions → instructions. This unintended stemming behavior can be explained by the fact that words like instructions and minutes also exist as a stem in the English language. The word *minutes* could also refer to a record of what occurred at a meeting, and *instructions* could also refer to a manual explaining how a product functions. To identify the most likely word stem in a given sentence, future advancements have to take the sentence's semantic context into account.

5.2 The role of context

A human reader unconsciously reasons about a sentence's or a document's context and affective information to evaluate whether an aspect is positive, negative, or neutral and how much weight the aspect has in relation to the whole document. However, context-based polarity determination is a difficult task for machines. The system must first identify, which information makes up the relevant context. This contextual information might be available in the given sentence but might also be encoded in adjacent sentences within the whole document. The relation of the identified context to the sentiment aspect has then to be reasoned upon. We identify three primary issues related to the contextual embedding of aspects.

First, our solution currently performs sentiment determination in isolation from contextual information, which negatively influences the accuracy of our results. The toolkit is meant to analyze large data samples, so measuring the detected sentiment's overall accuracy automatically is impossible because it would require a human to tag each aspect as a benchmark to which to compare the analysis results to. The aspect visualizer component enables users to inspected the results manually. While most sentiment aspects were correctly identified, the sentiment determination API AlchemyAPI we used has a pessimistic bias and tends to incorrectly identify sentiment expressions as negative, although the particular expressions are undoubtedly meant to be neutral or positive. This bias resulted in aspects being included in the most frequent negative aspects that should not have been. Examples inaccurately identified as negative aspect expressions are "[so] many bars", "[very] close bars", "trendy neighborhood", "other neighborhood", and "close neighborhood".

Second, sarcastic remarks and ironic statements skew the results, since these statements switch the general polarity of an aspect into the opposite. While even humans sometimes struggle to identify sarcasm, most automated analyses perform badly (González-Ibáñez et al. 2011). This issue is not limited to our approach but is a widespread issue in sentiment analyses.

Third, without contextual embedding, the importance of a single sentiment aspect in the overall document and the degree of negativity or positivity cannot be inferred (Wilson et al. 2005). However, even with contextual information in place, the severity of individual aspects in a sentence depends on the writer's subjective opinion, as two individuals might weight the exact same sentence differently. Therefore, we do not try to infer the severity of single aspects.

To increase the accuracy of the sentiment analysis, future research should take contextual semantics into account. On the one hand, IBM has introduced a "Tone Analyzer" feature as part of the AlchemyAPI[6] that uses machine learning to infer emotional cues like anger and joy on the document and sentence levels. We imagine triangulating identified polarities with the emotional context to increase the overall accuracy. Recent related work on context-dependent polarity determination also proposes additional ways to include contextual information in the analysis.

5.3 Related work

Agarwal et al. (2015) propose a lexicon-based approach that uses a pre-built dictionary comprised of opinion words and their polarities in combination with the ConceptNet ontology in order to understand domain-specific concepts and their relationships. However, their approach is applied on the document level and does not analyze all sentiment aspects in the document but selects features it deems to be important.

Another lexicon-based approach by Thelwall (2017) combines static domain-specific vocabularies with consideration of contextual cues like emoticons, exaggerated punctuation, and deliberate misspellings. The approach is highly customizable with regard to custom sentiment dictionaries, emotion lists, term blacklists, and language patterns, but it depends heavily on the dictionary's actuality and specifics. Especially for ever-changing lingo in tweet data, this kind of approach poses the risk failing to determine the polarity of each expression.

Saif et al. (2016) pursue a hybrid approach for sentence- and entity-level sentiment analyses. Their algorithm initializes with a given sentiment lexicon. During execution, their algorithm learns from co-occurring patterns and continuously updates the strengths and polarities in the dictionary. While their approach is well-suited to pre-trained entities like a particular product or a politician, its performance degrades for random sentiment aspects such as it is the case in our analysis.

[6] Tone Analyzer website: https://www.ibm.com/watson/developercloud/tone-analyzer.html (accessed: 2017-05-22).

5.4 Managerial and academic implications

Despite the toolkit's technical limitations, its results contribute clarifying what aspects people value or dislike about staying at a stranger's accommodation. Sharing one's home with others is a very personal service, and we provide substantiated information that can serve as a foundation to determine why people engage in such transactions. The toolkit is a prerequisite to answering questions about common motives and issues, so it paves the way to clarifying intrinsic behavior and motivations.

Even though our results may correspond to what one would expect using common sense, the specific numbers of occurrences for the individual aspects unveils what features are considered *most* important. The information that can be extracted from reviews and tweets is especially (but not exclusively) useful for individual Sharing Economy businesses, as it points out what peer consumers value and dislike about using the service. Traditional lodging businesses and other industries use codified quality metrics like the US's AAA diamond rating and European Hotelstars Union's star rating to assure users of a defined service level. Individual providers on Airbnb, however, might deliver varying qualities of service (Hamari et al. 2015). Valuable insights can be extracted by abstracting from the reviews of and tweets about individual offers and instead looking at the overall most common points of criticism and compliments. From a managerial perspective, these insights can then be used to inform and guide prospective and active peer providers on how to improve their offerings and what pitfalls to avoid.

Taking the automated sentiment-analysis approach one step further, platform operators can enhance their presentation of listings with insights from the analyzed data. Users might be able to filter relevant listings by their sentiment scores, and listings can be tagged by extracting specific properties from a given set of domain-specific aspects (e.g., *host*, *bed*, *kitchen*). As for the Airbnb case, users attesting that a listing has a *spacious kitchen* or *comfortable bed* is valuable information for prospective renters. Instead of the binary statements that a kitchen is available or not, qualitative statements can reflect more detailed and hands-on information.

Our sentiment-analysis approach adds to the platform providers' possible set of tools in order to improve the users' experience and to identify and potentially advertise the most positively perceived aspects. In addition, by periodic execution of the sentiment analysis, an early warning system can be put in place that will notify the site operator when a certain threshold of negative sentiments is exceeded so timely countermeasures can be taken. The use case we highlighted is, as is the entire toolkit, not limited to a certain business sector. The toolkit provides an opportunity for optimized and proactive quality assurance to companies that want to learn from their social media communication and user-generated content, as they can build on the toolkit and tailor it to their specific needs instead of buying into a proprietary solution.

In summary, we believe that an important feature of the solution lies in its universality. The tool can be used in multiple settings without major adjustments. Once the process for data collection is configured to collect tweets on other topics such as hashtags, or is provided with review texts, the sentiment analysis generates meaningful output. Thus, various kinds of services and products can be assessed and compared in order to identify crucial characteristics, whether to learn about potential for improvement or to take advantage of positive feedback.

6 Conclusion

This work delivers a state-of-the-art, aspect-based sentiment analysis approach for extracting positive and negative aspects from reviews and tweets composed by users who write about their individual service experiences. A software solution was developed that periodically extracts tweets from Twitter and semantically analyzes the unstructured tweets and other documents (i.e., reviews from Airbnb). With this solution, we conducted a system-based analysis of the aspects most valued by users who engage in service transactions on Airbnb.

The toolkit we developed identifies aspects of a service regarding the perceived service delivery, a valuable source of information for detecting root causes for both problematic and successful services.

The results we achieved by looking at one of the big players in the Sharing Economy can spur further research in the Sharing Economy and specifically the important segment of lodging within the Sharing Economy. Moreover, because of its universality, the approach can be applied to various domains and can support researchers in extracting sentiments efficiently from large text corpora.

In the future, we will further advance the toolkit to increase the accuracy of analysis results. Furthermore, we will transfer and apply the approach to other domains and classify aspects into different stages of the service delivery or a product's life-cycle. In doing so, we envision a solution that can inform both service providers and manufacturers.

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