MobASA: Corpus for Aspect-based Sentiment Analysis and Social Inclusion in the Mobility Domain

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Abstract

In this paper we show how aspect-based sentiment analysis might help public transport companies to improve their social responsibility for accessible travel. We present MobASA: a novel German-language corpus of tweets annotated with their relevance for public transportation, and with sentiment towards aspects related to barrier-free travel. We identified and labeled topics important for passengers limited in their mobility due to disability, age, or when travelling with young children. The data can be used to identify hurdles and improve travel planning for vulnerable passengers, as well as to monitor a perception of transportation businesses regarding the social inclusion of all passengers. The data is publicly available under: https://github.com/DFKI-NLP/sim3s-corpus

Keywords: Aspect-based Sentiment Analysis, Crowdsourcing, Mobility, Social Inclusion, Social Responsibility

1. Introduction

Social inclusion is of great importance for building stable societies and public transportation companies play a particularly substantial role for ensuring equal participation in society. Unfortunately, accessing trains, buses, or stations is often a challenge for people limited in their mobility due to a physical or cognitive impairment, age or when traveling with young children. It is important to enable those groups to use public transport in a self-reliant way by providing facilities (lifts or ramps for walking disabled people, etc.), services (visual info for deaf and acoustic info for blind people, etc.), as well as systems informing about the state of these forms of assistance (if lifts are available, etc.) in order to identify unexpected hurdles and improve travel planning. Natural language processing provides means to aid such systems by the automatic extraction of information from texts about the condition of relevant facilities and services. For example, given the input text:

A lift at the Berlin Hbf station has been already defective for two days! This is really annoying!

it would be helpful to have a system that is able to determine that (a) the availability of lifts at public transportation stations is mentioned and (b) their state is described as malfunctioning. The extracted information can be used to inform transport operators as well as passengers limited in their mobility about a problem of a specific facility, trigger a process solving or mitigating the problem (e.g. fixing broken lifts, proposing an alternative traveling route).

In this paper we devote our attention to the question of supporting such systems by adapting the aspect-based sentiment analysis task. Sentiment analysis aims at extracting and quantifying subjective information. A standard version of the sentiment detection classifies the sentiment of a whole sentence, while the aspect-based sentiment analysis (ABSA) focuses on the sentiment towards predefined aspects such as specific products or services. Therefore, ABSA allows a more fine-grained mining of opinions. We cast our problem of extracting information on the state of facilities and services relevant to the barrier-free accessibility of public transport as an aspect-based sentiment task. We consider facilities and services as main aspects, their properties as aspect subcategories, and statements about those properties as phrases potentially expressing or implying a sentiment. For the example above, we assume a main category lift, a subcategory availability (of the lift), and a negative sentiment towards the aspect Lift#Availability.

As a result of our work we present MobASA, a German-language dataset for the detection of sentiment towards aspects relevant for users of public transport limited in their mobility. To the best of our knowledge there is no other dataset, English or German, which covers the topic of travel accessibility in a fine-grained way. Our contributions are:

- We provide a publicly available German-language dataset for the detection of aspect-based sentiment towards barrier-related aspects in the public transport domain.
- The dataset can benefit building inclusive public transportation systems as described in the introduction. Therefore, we add to research aiming to deploy various NLP tasks in support of equality and social responsibility of businesses.

2. Related Work

Aspect-based Sentiment The annotated datasets for developing ABSA models are still scarce, and they mostly cover only the standard domain of product or service reviews (e.g. SCARE corpus by [Sänger et al., 2016], SemEval 2015 by [Pontiki et al., 2015], USAGE by [Klinger and Cimiano, 2014], GESTALT by [Ruppenhofer et al., 2014]). In contrast, the GermEval 2017 dataset (Wojatzki et al., 2017) comprises social media texts annotated with opinions on the biggest railway company in Germany. It lists barrier-free accessibility as one coarse-grain aspect, however more refined labels are needed to model information needs of different target groups (e.g. blind vs. deaf people).
Recent neural approaches based on pre-trained language models (e.g., BERT (Devlin et al., 2019)) have shown impressive results for the task when fine-tuned on supervised datasets. However, the state-of-the-art transformer based ABSA models currently achieve an F1-score of only 0.53 on the GermEval 2017 dataset (Allenmacher et al., 2021) and 0.61 on the SemEval 2016 laptop-dataset (Ponnuru et al., 2016; Li et al., 2019), for example, meaning there is still much room for improvement.

Inclusive NLP Natural language processing (NLP) technologies already support the efforts of inclusion in various domains, for example, sign-language-to-text translation systems (Nunnari et al., 2021) to benefit deaf people, domain-specific translation systems to support migrants when communicating with authorities (Xu et al., 2018), as well as applications predicting readability to help content providers with adjusting their published texts to the needs of people with cognitive disabilities (Evans et al., 2016). The systems target mostly language and communication barriers.

3. Dataset

3.1. Data Collection

To collect the relevant data we crawled German-language tweets based on a predefined list of 11 Twitter channels of public transportation companies, channels related to barrier-free accessibility as well as a set of 68 keywords relevant to the barrier-free travel of handicapped passengers, older people or parents with small children. The list contained German-language keywords equivalent to words such as: barrier-free, escalator, guiding system for the blind, etc. We collected 3,128,639 tweets between 2019-2021, and from that data we sampled tweets for the annotation.

3.2. Annotation Schema and Guidelines

The MobASA labels structure and annotation guidelines are partly based on the instructions of GermEval 2017 and SemEval 2015 datasets. The set of meta-labels (relevance, sentiment, category, polarity, from, to) as well as the XML data format originate from GermEval 2017.

Relevance for Public Transportation Each tweet has binary labelling regarding its relevance to public transport. The relevance value is true, if a tweet contains any phrase related to public passenger transport of any type. For example, the text in Figure 1 contains mentions of a metro station.

Aspect-based Sentiment We defined a base catalog of 19 aspect categories relevant to the barrier-free travel. We included aspects important for the walking disabled passengers, people with a vision or hearing impairment, as well as the elderly, and parents traveling with small children. The category catalog is based on interviews with those target groups, guidelines for travel accessibility by the government and interest groups, information provided by the biggest German railway operator, as well as topics mentioned in our data. Each aspect category consists of two parts: a main aspect and its subcategory. The main aspect references mostly a specific assistance form (facility or service) such as lift, lighting or acoustic info. The subcategory captures various relevant features of the main aspect such as its availability among others. The subcategory might also be labelled Main if no multiple, specific subcategories are identified. We defined up to two subcategories for each aspect. The category Others was annotated if an unanticipated or less frequent but relevant topic was not covered in the base catalog. For example, very short-term announcements of platform changes for departing trains might result in people impaired in their mobility missing their train. Examples of the annotation of various subcategories for tweets, which referenced a main aspect are given in Table 2.

Furthermore, each aspect is annotated along with a polarity value neutral, positive or negative. The value indicates either stated sentiment towards an aspect or, more broadly, it indicates the described state of that aspect. For example, the polarity of the category GeneralBarrier#Main is usually positive if a station or a train is stated as being handicapped accessible, negative if it is not, and neutral if the degree of accessibility is stated as unknown or is described as neither positive nor negative for other reasons. The texts might contain opinionated statements such as bad or good, however, this is not required, i.e. we also accept polarities implied by the state of the aspect (e.g. a faulty lift implies a negative polarity as in the example in Figure 1). Furthermore, we asked to annotate the value regarding the most recent described or announced state of the aspect, i.e. if the lighting was faulty, but it is stated as already repaired, then the sentiment is positive. This approach was chosen with the aim in mind to support systems which focus on solving the latest problems when using public transport. The target of an annotated aspect and its polarity is a text span referencing the main aspect, e.g. phrases Aufzug denoting the main aspect Lift. The offsets of the target span are marked by the labels from and to.

Document-level Sentiment Each tweet is labeled with a document-level sentiment. Its value aggregates the polarities of the opinions in a given text. If the polarity set is {positive, neutral} or {negative, neutral} then the document-level sentiment is set to positive or negative, respectively, otherwise the value is neutral (as illustrated by the example in Figure 1). If a text is irrelevant, then the document-level sentiment is neutral by default.

3.3. Annotation process and quality

Expert annotation A subset of tweets is fully annotated by trained experts using the platform Inception.

The final expert subset of the corpus includes only annotations, for which two annotators agreed or the disagreement was resolved by the third annotator. The annotation is based on guidelines, which were developed in an iterative process and take into account discussions with the experts. The annotators were given definitions of relevance and the aspects along with multiple examples. The annotation of aspect-
based sentiment was only considered for the data annotated as relevant. The inner-annotator agreement for the various annotation layers is: 1) relevance: Cohen’s $\kappa = 0.96$, 2) aspect-based sentiment: Cohen’s $\kappa = 0.73$ on annotated tokens only. Therefore we achieved nearly perfect agreement in the relevance annotation and substantial agreement in the aspect-based sentiment annotation.

**Crowdsourcing** An additional subset of tweets was annotated by crowdworkers using the platform Crowd[1]. First, the workers labelled tweets as relevant or irrelevant for the public transportation topic. Subsequently, the tweets were annotated regarding aspect-based sentiment. In order to choose relevant candidates for the aspect annotation, first we sampled tweets already labeled or automatically determined as relevant for public transportation. For the automatic detection we systematically collected phrases referring to transportation types from a subset of relevant tweets, and used those phrases to filter the potentially relevant data. In the next step we automatically pre-annotated text spans with the main aspect category (e.g. word *Fahrtstuhl* with main category *Lift*) by matching text spans to target strings annotated in the expert subset. Then we showed crowdworkers texts, where a pre-annotated main aspect was highlighted, and we asked if a specific subcategory regarding the highlighted aspect is discussed in a given text, and if so with which polarity. The task was designed as a multiple-choice questionnaire. For the crowdsourcing we focused on aspects most relevant to various target groups (e.g. *Escalator#Availability*), and excluded rare or less relevant aspects (e.g. *TactileContrastOrientation#Main, Lift#Tidiness*). For the annotation of both tasks we provided short guidelines as well as many examples. Each tweet was processed by two workers. To ensure a higher quality of the crowdsourcing process we prepared a qualification test, inserted trapping questions, and set a minimum time for solving the task. We blocked all users, who failed the tests from further tasks. Finally we included only annotations, for which two workers agreed on. We reviewed a sample of the crowd-sourced labels included in the final data. We estimated the accuracy of the relevance labels as very high having 99.6% correct labels of 1000 sampled tweets. Regarding aspect-based sentiment we reviewed 1950 answers having 99.6% correct labels of 1000 sampled tweets. We also publish an extended version of the train set (Table 3). The dev and test and train BASE split contain data, in which all relevant tweets are annotated by the experts, and the irrelevant data is partially labeled by the crowdworkers. We also publish an extended version of the train corpus, trainPLUS, which additionally contains the

| aspect                           | description                                                                 |
|----------------------------------|-----------------------------------------------------------------------------|
| AccidentsMobilityGroups#Main     | risks of injury for people with limited mobility (e.g. falls of wheelchair users into track bed) |
| AcousticSignal#Main              | acoustic signals for blind people (acoustic warning or signals for finding train doors, etc.) |
| ConstructionSite#Main            | construction sites and their impact on the public transport (e.g. accessing of stations) |
| Demonstration#Main               | demonstrations and their impact on the public transport (e.g. accessing of stations) |
| Escalator#Availability           | operational status of escalators (e.g. if they exist and function properly) |
| Escalator#Tidiness               | cleanliness of escalators (also smell or similar) |
| GeneralBarrier#Main              | general mentions of barrier-free accessibility in public transport |
| GroundLevelAccess#Main           | ground level access to stations or vehicles of public transport |
| InfoAcoustic#Availability        | availability of announcements or operational state of loudspeakers |
| InfoDisplay#Availability         | availability of displayed information or operational state of display boards |
| Info#Others                      | availability and quality of information on public transport in apps, e-mails, etc. |
| Lift#Availability                | operational status of lifts |
| Lift#Tidiness                    | cleanliness of lifts (also smell or similar) |
| Lighting#Availability            | operational status of lighting |
| Ramp#Availability                | operational status of ramps |
| Security#Main                    | security at stations (e.g. important for older or handicapped people) |
| SpaceMobilityGroups#Main         | space available for people limited in their mobility (e.g. wheelchair bay) |
| TactileContrastOrientation#Main  | tactile or high-contrast guiding routes for blind people, info in braille, etc. |
| main category#Others             | not anticipated or less frequent subcategories (e.g. InfoDisplay#Others for correctness of displayed info) |
| BarrierOthers#Main               | other topics related to barrier-free accessibility (e.g. assistance during traveling) |

Table 1: Definition of aspect categories related to barrier-free accessibility

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https://www.crowdee.com/
Sag mir mal, wenn es geht, ob die Anzeigetafeln am Hbf wieder gehen! :D
(Tell me if the displayboards at the main station are working again! :D)

Die Anzeigetafeln am Hauptbahnhof Bremen laufen wieder
(The displayboards at Bremen Central Station are functioning again)

S2 08:02 ab Bernau fährt nicht weil? [...] keine Anzeige. Scheiß!
(S2 08:02 from Bernau is not coming because? [...] no info displayed. Crap!)

Shahn fällt 3x aus, [...] schrift auf anzeigenfalte ist verkehrt herum
(Shahn canceled 3x time, [...] text on displayboard is upside down)

@jhnio Komm mit der Bahn so um 12.06 an, lass uns dann bei der
Anzeigetafel treffen.
(@jhnio Arrive by train around 12.06, then let’s meet at the displayboard.)

Table 2: Examples of the annotation of texts containing the main aspect InfoDisplay (original texts and English translations)

| aspect                  | polarity | example                                                                 |
|-------------------------|----------|-------------------------------------------------------------------------|
| InfoDisplay#Availability| neutral  | Sag mir mal, wenn es geht, ob die Anzeigetafeln am Hbf wieder gehen! :D |
| InfoDisplay#Availability| positive | Die Anzeigetafeln am Hauptbahnhof Bremen laufen wieder                  |
| InfoDisplay#Availability| negative | S2 08:02 ab Bernau fährt nicht weil? [...] keine Anzeige. Scheiß!        |
| InfoDisplay#Others      | negative | Shahn fällt 3x aus, [...] schrift auf anzeigenfalte ist verkehrt herum   |
| (no relevant aspect)    | -        | @jhnio Komm mit der Bahn so um 12.06 an, lass uns dann bei der Anzeigetafel treffen. |

crowd-sourced annotations of the aspect-based sentiment.
The inclusion of primarily expert annotation in dev and test set ensures a more robust selection and evaluation of the models, since the expert annotation introduces less noisy labels. That approach follows the suggestions of a careful design of the test data to not misrepresent model performance [Alt et al., 2020] [Bowman and Dahl, 2021].

Table 3: Statistics of the data splits

| aspect          | total | dev | test | train BASE | train PLUS |
|-----------------|-------|-----|------|------------|------------|
| GeneralBarrier#Main | 3010  | 807 | 2203 |            |            |
| Lift#Availability    | 2918  | 1586 | 1332 |            |            |
| Escalator#Availability | 1615  | 769 | 846  |            |            |
| InfoDisplay#Availability | 1545  | 351 | 1194 |            |            |
| ConstructionSite#Main    | 1069  | 103 | 966  |            |            |
| Lighting#Availability    | 786   | 509 | 277  |            |            |
| InfoAcoustic#Availability | 686   | 231 | 455  |            |            |
| Ramp#Availability        | 434   | 101 | 333  |            |            |
| InfoDisplay#Others      | 349   | 349 | 0    |            |            |
| Demonstration#Main      | 232   | 232 | 0    |            |            |
| others                  | 889   | 889 | 0    |            |            |
| total                   | 13533 | 5927| 7606 |            |            |

Table 4: Statistics of 10 most frequent aspect categories

| aspect                  | total | expert | crowd |
|-------------------------|-------|--------|-------|
| GeneralBarrier#Main     | 3010  | 807    | 2203  |
| Lift#Availability       | 2918  | 1586   | 1332  |
| Escalator#Availability  | 1615  | 769    | 846   |
| InfoDisplay#Availability| 1545  | 351    | 1194  |
| ConstructionSite#Main   | 1069  | 103    | 966   |
| Lighting#Availability   | 786   | 509    | 277   |
| InfoAcoustic#Availability| 686   | 231    | 455   |
| Ramp#Availability       | 434   | 101    | 333   |
| InfoDisplay#Others      | 349   | 349    | 0     |
| Demonstration#Main      | 232   | 232    | 0     |
| others                  | 889   | 889    | 0     |
| total                   | 13533 | 5927   | 7606  |

Table 5: Statistics of the aspect-based sentiment

| polarity | doc level | span level |
|----------|-----------|------------|
| neutral  | 19660     | 1652       |
| positive | 1968      | 2361       |
| negative | 7818      | 9520       |
| total    | 29446     | 13533      |

4. Conclusion and Future Work
Most of the inclusive NLP systems focus on overcoming communication barriers. In contrast, we show how NLP can be used by public transportation businesses to mitigate barriers resulting from broken travel facilities or services, and in result to support inclusion of all passengers. We presented a corpus of tweets annotated with sentiment towards aspects related to barrier-free travel. In future work, we want to refine the aspect catalog, and integrate the detection of aspect location and time, to which the sentiment refers.

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