A Methodological Framework for Dictionary and Rule-based Text Classification

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Abstract: Recent research on dictionary- and rule-based text classification either concentrates on improving the classification quality for standard tasks like sentiment mining or describe applications to a specific domain. The focus is mainly on the underlying algorithmic approach. This work in contrast provides a general methodological approach to dictionary- and rule-based text classification based on a systematic literature analysis. The result is a process description that enables the application of these technologies on specific problems by guidance through major decision points from the definition of the classification goals to the actual classification of texts.

1 INTRODUCTION

Communication via social media and online platforms is steadily rising (Mandal and Gupta 2016). Social networks are a rich source of information, based on opinions freely shared by individuals on specific topics (Walha et al., 2015). The proportion of spoken communication is reduced and is increasingly being replaced by writing in text form. For example, the current user numbers of social media are 2.14 billion people with a rising tendency (eMarketer 2016). As early as 2011, a survey (DHL 2017) confirmed the inclusion of product reviews in purchase decisions. 64% of customers said that their purchase decisions were influenced by reviews and advice from other customers. The increasing popularity of the Internet and social media highlights the need for computer-aided linguistic analysis (Stede 2016).

In companies, this information can be used to identify product enhancements or to fill Product Recommender systems. Similarly, social media provides companies with a good platform to connect with and place advertisements for their customers (Kharde and Sonawane 2016). In order to filter out the relevant content, approaches to text classification such as sentiment mining have been developed
Although the literature deals with different approaches to text classification, it does not offer a uniform reference model or a standardized procedure that support their application. The existing approaches often describe individual cases based on text corpora, which were specifically created for the respective domain. Such resources are difficult to translate to other domains because words in different domains and languages have different meanings. Additionally, there are also domain specific terms that are not covered by standard vocabularies. Thus, there is a need to create new dictionaries and rules for text classification unless machine learning approaches can be applied. However, the latter rely on large annotated datasets for training.

This work aims at providing guidance for the application of dictionary- and rule-based text classification approaches. For this purpose, a systematic literature analysis has been performed which is described in Section 2. The goal of this literature analysis was to identify activities that are described for the implementation of the various presented approaches as well as decisions that have been made with regard to implementation alternatives. Based on the found commonalities, a general process for dictionary- and rule based text classification has been developed. This process is roughly sketched in Section 3. The concluding section 4 provides an overview of the current status of the developed methodological support based on this process and possible future directions.

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2 LITERATURE ANALYSIS

This section documents the conducted systematic literature analysis. It is based on the work of Kitchenham (Kitchenham 2014). There, the selection of studies in connection with a quality control is suggested. The selection process has been performed by means of the snowballing method according to Wohlin (Wohlin 2014). Section 2.1 describes the proposed steps of a literature analysis while Section 2.2 describes the search process and its outcomes in detail. The following Section 2.3 provides an analysis of the found sources with respect to implementation decisions such as the application context and used text classification approaches.

2.1 Snowballing

Wohlin recommends to use Google Scholar[2] for the implementation of snowballing. Google Scholar has widest coverage of scientific literature among available search platforms (Alexander 2016). This avoids the use of biased or subjective research or databases. The advantage of snowballing is that the use of reference lists and citations reduces the noise of non-relevant articles compared to a term based database search as it is suggested by other approaches to systematic literature analysis.

Snowballing initially needs a start set of good quality, relevant publications. The start set should not be too small and if possible cover different clusters, research areas, years and authors in order to bring in a variety of perspectives (Wohlin 2014).

Before starting the snowballing process, inclusion and exclusion criteria have to be defined in order to ensure a consistent selection of literature sources. After the identification of the start set, two phases are distinguished during actual snowballing. These are the backward and the forward snowballing.

Backward snowballing uses the reference list of an already selected publication to identify further relevant publications. Forward snowballing identifies new papers by examining which publications have cited the research paper at hand. In both steps, the selection of candidate publications for the inclusion in the resulting set of the literature analysis is based on author and title first. Then the abstracts are screened. The final decision about inclusion or exclusion should be based on full-text. The next iteration is based on the newly included publications. The search process ends when no new publications are included in an iteration step. (Wohlin 2014)

[2] scholar.google.com

2.2 Literature Selection Process

Criteria for inclusion or exclusion of publications into the analysis process have been based on publication time (from 2008), publication process (scientific review process mandatory), and content. Publications whose content did not contribute to the goals of this work have been excluded. The start set has been found based on a search on Google Scholar querying for *dictionary*, *rule*, and *lexicon* each in combination with "*text classification*". 25 publi-cations have been selected for the start set out of the 703 search results. Table 1 shows the progress of the snowballing iterations that followed.

Table 1: Snowballing Iterations.

Iteration	# Forward	# Backward	# Included
-	-	-	25
1	2652	1066	10
2	245	231	4
	2897	**1297**	**39**

The first iteration resulted in 10 publications that have been added to the analysis set. The second iteration based on this 10 publication lead to 4 additions. A third iteration did not provide further relevant publications. Thus, the final set for literature analysis contains 39 publications. The following discussion is based on them.

2.3 Data Extraction

This section describes the findings with regard to the used text classification approaches and usage contexts.

2.3.1 Classification Approaches

As shown in Figure 1, most of the found approaches are dictionary-based. There are also approaches that combine a rule-based classification with a dictionary. Two publications (Afzaal and Usman 2015, Lee et al., 2011) concentrate on text and document frequencies in a text corpus for text classification. However, they start with an initial dictionary. One publication (Appel et al., 2015) provides a comparison of different approaches including machine learning. Thus, it is separated.

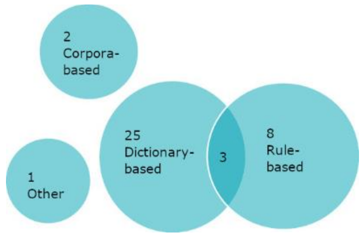

Figure 1: Approaches from Literature.

2.3.2 Application Area

Figure 2 gives an overview of the areas of application that are the subject of research. In addition to the main research areas of sentiment analysis, opinion mining and subjectivity analysis, there are two papers addressing topic mining. The remaining three publications deal with named entity recognition (Yerva et al., 2012), side effects of medication (Nikfarjam and Gonzalez 2011) or just generally describe text classification without a specific application (Darwish et al., 2015).

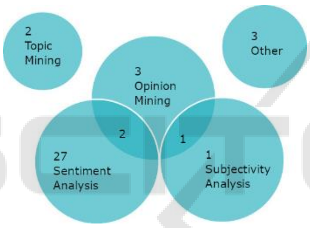

Figure 2: Applications from Literature.

2.3.3 Level of Analysis

There are several possibilities at which level a text analysis could be carried out. Figure 3 shows which levels are addressed by the found publications.

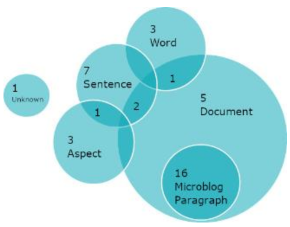

Figure 3: Level of Analysis.

2.3.4 Data Sources

Another important factor in text classification is the quality of the used sources. Microblogging services like Twitter do only provide small pieces of text, using special idioms and sometimes not containing sentences at all. For example, the latter does not allow an analysis at sentence level. Looking at the literature found, Twitter is the most prominent data source (16 publications), followed by web site content (12 publications). 9 publications use special research data sets for text analysis.

With regard to the language of the used sources English has a clear majority (24 publications), followed by Spanish (3 publications). Other language do not have more than 2 occurrences.

3 PROCESS CONSTRUCTION

As shown in the first data extraction from literature analysis (cf. Section 2.3), there are several variance or decision points when implementing a dictionary- or rule-based text classification. Different applications and different text sources require different approaches. The goal of this work was to investigate the possibility of a methodological support for the application of text analysis. In addition to the previous analysis, all selected publications have been screened for activities and alternatives in the implementation of a text analysis. In total, this screening identified 29 activities. None of the publications considered all of them. This underlines the need of an overview of the process, which has been created in this investigation. For reasons of brevity only parts of the complete process can be discussed here. Thus, we concentrate on the parts that are most specific to dictionary- and rule-based text classification compared to text classification in general. These are [1] Scope Definition (Section 3.1), [2] Dictionary Creation (Section 3.2), and [3] Rule Definition (Section 3.3).

3.1 Scope Definition

Not all phases of a text analysis implementation are discussed to the same extent in literature. Above all, the scope definition is not adequately described. The suggested activities are shown in Figure 4b.

Goal Definition: The definition of the analysis objective is the basis for all further steps. When defining the goal, its complexity must be considered. If a classification feature is too complex the rules are complex. Dictionary and rules may become ambiguous (Carstensen et al., 2010). In consequence, there is ambiguity with regard to the actual target question of classification.

Analysis Timeframe Definition: The creation time of texts a crucial criterion for ensuring traceability. To analyze the current market situation, the latest comments, often not more than one month, are to be evaluated.

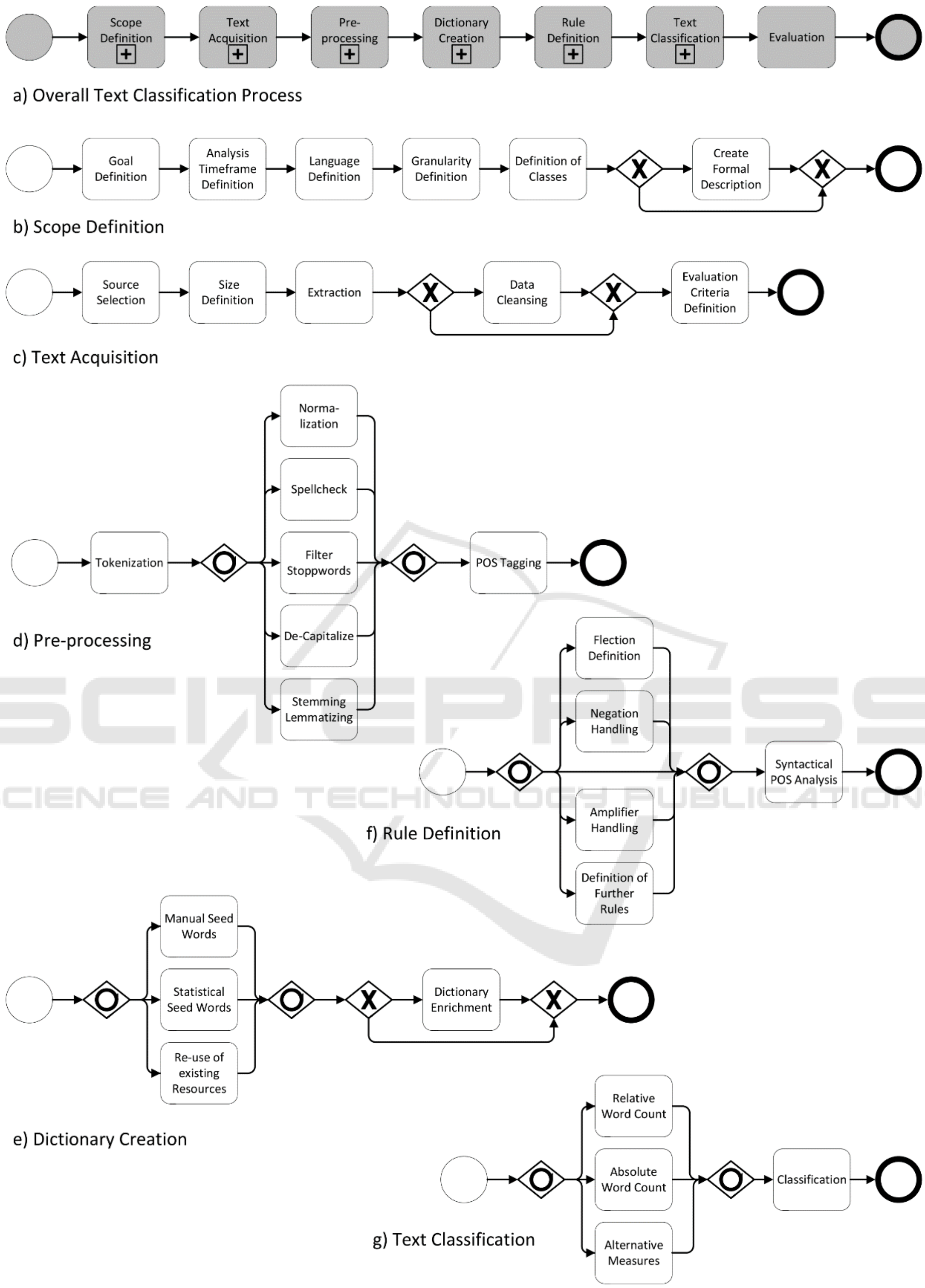

Figure 4: Text Classification Process.

The analysis period is thus derived from the analysis goal.
Language Definition: Language has a great influence on the availability of existing text analysis resources. As shown in Section 2.3.4, a major share of the research concentrates on English language. In the newer language typology, attempts are made to formulate generalizations by means of uniform speech patterns. This can be used to express things expressed in one language in another language (Gunkel et al., 2017). Furthermore attempts are made, to translate texts and to use existing text analysis resources for English language for instance. This approach cannot deal with specific characteristics of a certain language. Furthermore, it is hard to handle domains with a specific vocabulary.
Granularity Definition: As shown in Section 2.3.2 text analysis can be performed at different levels of granularity. Depending on the sources and the goal, the desired level of granularity has to be defined.
Definition of Classes: It needs to be defined which classes and hence how many classes are used to classify the input data. One possibility would be a binary classifier (Stede 2016, Sun et al., 2017). However, there might also be a residual class required (Yerva et al., 2012). When choosing the number of classes, it should be noted that the more classes are used the harder it is to find characteristics for these individual classes and to use them for analysis (Gomez et al., 2016). According to Gräbner et al., (2012) a reduction in the number of classes is always recommended. In conjunction with a larger text set and a larger dictionary, general classification performance can be improved (Gräbner et al., 2012).
Create Formal Description: Some authors (Appel et al., 2015, Noferesti and Shamsfard 2015, Yerva et al., 2012), define a formal framework for the definition of the text classification outcome for further processing.

3.2 Dictionary Creation

The suggested activities for Dictionary Creation are shown in Figure 4e. Dictionaries are domain-specific. Otherwise, differences in the ratings of the affiliation of words to a class, can occur. The domain-specific dictionary is also referred to as the global context (Muhammad et al., 2016). It has to be distinguished from the local context that defines the word meaning or class based on the words in the immediate environment in the text.
The creation of dictionaries can be done in three ways. The first is a purely manual identification of words from the text corpus. The second possibility is a statistical approach in which the individual words are assigned to a class according to their frequency. As a third alternative, it is possible to search for existing dictionary resources and reuse them. The last two options represent an at least partially automated creation approach (Abdulla 2013, Taboada et al. 2011). Despite the time-consuming preparation of dictionaries, especially in the presence of a large body, the dictionaries can later be reused and possibly used in various other domains (Kesharvarz and Abadeh 2017).

In addition, it has to be decided whether the class labels are of a qualitative or quantitative nature. In contrast to the quantitative assessment, qualitative labels do not distinguish degree of class membership. In the case of quantification of labels, a scale must be defined (Asghar et al., 2017). Basically, the choice of a quantitative measure is based on the assumption of statistical linearity. This is necessary so that the results can also be compared in the evaluation phase (Klein et al., 2011) and deviations of extreme values are important.
Depending on the classification scheme, some grammatical parts of speech provide stronger evidence for the class. In the case of sentiment analysis in texts, these are typically adjectives. In an entity classification, the identification of nouns is important (Afzaal and Usman 2015).
Manual Seed Words: Seed words are created based on randomly selected texts by identifying class-specific words from them (Bidulya and Brunova 2016). The first step is to identify relevant content words and assign the associated known class values or labels (Al-Twairesh et al., 2016, Neviarouskaya et al., 2011).The manual approach is very time consuming.
Statistical Seed Words: If classes have already been labelled, a statistical approach that evaluates the word frequencies in the classes can be applied.
Re-use of existing Resources: Depending on the context it might be possible to use a domain independent dictionary for classification. For example, a first seed set of words for sentiment analysis can be derived from SentiStrength (Abdulla 2013). Even foreign language resources can be considered here. In this case a translation of the dictionary to the target language is required (Al-Twairesh et al., 2016, Avanco et al., 2016).
Dictionary Enrichment: This activity describes the possibilities of enriching the dictionary with words that were not previously included in it (Dollmann and Geierhos 2014). The seed words are checked in a dictionary and their synonyms and antonyms identified (Banea et al., 2008, Bidulya and Brunova

2016, Kolchyna et al., 2015, Kontopoulos et al., 2013, Sun et al., 2017) and included in the dictionary. An enrichment of the dictionary is recommended according to (Abdulla 2013). Various experiments were carried out here and found that the results are noticeably worse if the dictionary is too small.

3.3 Rule Definition

The suggested activities for Rule Definition are shown in Figure 4f. Each rule that is created can be represented as a pattern of lexical or syntactic structures of a sentence (Bidulya and Brunova 2016). With the help of rules, the local context given by the text data set is taken into account.

Flection Definition: Based on word flection and grammatical function of words in general, certain aspects of a text can be filtered. For example, (Klein et al., 2011) considers sentiment regarding various financial performance indicators on the financial market. The main concern and goal of the work is, based on the moods, to determine future prices. It is not of interest how these indicators behaved in the past. For this reason, sentences with this grammatical tense form are filtered out. Likewise, conditional clauses are not relevant to their consideration. They often contain no sentiment, but only a condition for the situation. Noferesti and Shamsfard (2015) assume that in addition to conditional clauses, imperative sentences also do not provide sentiment.

Negation Handling: Negations are characterized by words that reverse the polarity of a sentence (Asgarnezhad and Mohebbi 2015, Kolchyna et al., 2015a). Words whose sentiment was originally positively affected are shifted into the negative or vice versa (Tan et al., 2015). A careful handling of negations is important e.g. in sentiment mining.

Amplifier Handling: Considered here are words that have a weighting influence on subsequent words (Anta et al., 2013). This is true both in the positive sense of amplification and in the negative sense of attenuation (Vilares 2013). The advantage of handling amplifiers and attenuators separately is that it is a limited set of words that can be easily identified (Silva et al., 2012).

Definition of Further Rules: Besides the already discussed types of rules, more ideas for rule definition are suggested in the literature. Mao et al., (2015) discuss the idea of including rules such as the number of nouns, exclamation marks, question marks, adjectives and the length of a document in the evaluation. In some publications Dependency Parsing is presented as a kind of basic form for the identification of further rules. Here, a dependency tree is created that reflects the grammatical-syntactic structure of a sentence with the relationships between features (Asgarnezhad and Mohebbi 2015, Sun et al., 2017). In Noferesti and Shamsfard (2015) a dependency tree was used to split up the individual clauses and to analyse the conjunctive structure of the sentences.

Syntactical PoS Analysis: In addition to the previously discussed rules, it is possible to define rules based on grammatical patterns based on the PoS tagging. For example, rules can be defined based on a combination of nouns and adjectives in order to determine the stance towards certain entities.

4 CONCLUSION AND OUTLOOK

This work presents a process for the implementation of a text classification using dictionary- and rule-based approaches. This process has been derived from a systematic literature analysis. Although it was possible to collect general consideration for such an endeavour, at some points literature research does not provide clear decision rules. The use of certain techniques for classification depends on the context. However, the context is not described to an extent that would allow the definition of clear decision rules. Still, the range of implementation options and influence factors for their selection can be described. A part of the presented research project that has not been discussed here is a worksheet that guides through the process and helps to document decisions which might be used in future for some deeper investigation with regard to design decisions for text classification implementations.

From a methodological perspective, roles and cooperation forms in the process should also be described. However, this topic is barely addressed in the literature. Still, when applying the presented approaches in specific domains, the integration of domain experts in the process seems to be an important issue. This should be considered for future research.

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