Opinion Mining in Online Reviews About Distance Education Programs

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Abstract

The popularity of distance education programs is increasing at a fast pace. En par with this development, online communication in fora, social media and reviewing platforms between students is increasing as well. Exploiting this information to support fellow students or institutions requires to extract the relevant opinions in order to automatically generate reports providing an overview of pros and cons of different distance education programs. We report on an experiment involving distance education experts with the goal to develop a dataset of reviews annotated with relevant categories and aspects in each category discussed in the specific review together with an indication of the sentiment. Based on this experiment, we present an approach to extract general categories and specific aspects under discussion in a review together with their sentiment. We frame this task as a multi-label hierarchical text classification problem and empirically investigate the performance of different classification architectures to couple the prediction of a category with the prediction of particular aspects in this category. We evaluate different architectures and show that a hierarchical approach leads to superior results in comparison to a flat model which makes decisions independently.

This work has been performed while the first and last authors were at Bielefeld University.

1 Introduction

Online and distance education has contributed strongly to the accessibility to higher education. Next to relatively new players on the market which focus on distance education like Coursera, edX, and Udacity, traditional campus universities offer online education platforms as well. In Germany, in addition to the largest institution for distance education (Fernuniversität Hagen, with 88000 registered students (Dahlmann, 2013)), several private institutions offer courses, for instance, the Apollon University of Applied Science and Healthcare or the Euro-FH.

The popularity of online courses is demonstrated through annual enrollment rates which continue to exceed the growth rates of traditional higher education (Allen and Seaman, 2010; Allen and Seaman, 2011). Students face an overwhelming challenge to select a program fitting their interests due to the high amount of offers available. Distance education courses have high drop-out rates that are regularly credited to poor matches of students to courses (Brinton et al., 2014). Finding a program that fits ones needs, schedule, learning pace, or financial possibilities is therefore of crucial importance.

An appealing option to find information about a program in addition to official material is relying on the perspective of other fellow students that, in contrast to the distance education providers themselves, have no incentives per se in promoting a particular study program. In fact, the information exchanged about online education programs on the Web (*e. g.* in fora, social media, blogs) has been increasing recently. In reaction to this trend, several providers of recommendation services are turning towards hosting platforms in which students can review their distance education programs and the corresponding institutions offering these programs. One example for such a recommendation service in Germany is the *Online Akademie* (`http://www.fernstudiumcheck.de`, OAK), which maintains information about 4908 courses from 477 institutes (as of May 4$^{\text{th}}$, 2016). Similarly, U.S. News and World Reports (`http://www.usnews.com/education/online-education`) generate ranked lists for different fields of research. The study portal for distance learning (`http://www.distancelearningportal.com/`) is a worldwide search engine for classes and programs and provides structured information. Springtest (`http://www.springest.de`) is a platform for individual education that compares 37870 courses (as of May 4$^{\text{th}}$, 2016).

This exchange of information between students is hard to be assessed at large scale, either by the students themselves or by institutions who could benefit from this feedback to improve their services. One major challenge is that the information exchange is mainly in natural language. Given the fast pace at which the amount of reviews increases (for instance 4785 new reviews in 2013), a comprehensive, manual analysis does not scale to the rate at which reviews are produced. An automated support for analyzing textual reviews automatically is needed.

Towards developing a methodology to analyze such reviews and make their content accessible, we provide the following contributions in this paper and highlight how they address the practical use case: We describe the *methodology* used for the *creation of a corpus of user generated reviews for distance education*. We discuss the agreement on the task between different annotators, and provide a qualitative analysis. Further, we present an approach that automatically extracts the categories and nested aspects within these categories under discussion in a review together with the sentiment expressed towards these. We frame the task as a *multi-label hierarchical classification task* in which relevant aspects, grouped into categories, are given. The task is to predict both the relevant categories as well as the specific aspects under discussion in a review. This is therefore a *closed-domain* approach, similarly to, *e. g.*, the restaurant data set (Ganu et al., 2009). We propose and investigate architectures that take into account the hierarchical structure of the categories and experimentally investigate the impact of classification architectures that couple the prediction of categories and specific aspects that enable the classifiers to exchange information and thus to tie their decisions together. We show that, while a flat model reaches reasonable precision of 79 % on the prediction of aspects (at a recall of 16 % and F_1 measure of 26 %), a hierarchical model in which information from category prediction is propagated to the aspect ("subcategory") prediction increases recall to 44 % at a precision of 71 % and thus an F_1 measure of 54 %.

2 Corpus of Distance Education User Reviews

The data source taken into account are the free text reviews from the website `http://fernstudiumcheck.de/`. We randomly sample 394 reviews from the overall set of 9142 reviews, as of Oct. 10$^{\text{th}}$, 2014. Each sentence is annotated with the aspects discussed and the opinion expressed by the author towards each aspect. An example review is shown in Figure 1.

The annotation of the corpus with aspects was performed by three annotators. Each sentence is assigned a list of pairs of aspect and the polarity of this aspect. More formally, each sentence s_i is associated with a set of tuples (a^i_j, p^i_j).

The polarity p^i_j ranges from -9 to $+9$, with -9 representing a *"very negative opinion"* (for instance *"…the worst experience ever…"*) and $+9$ representing a *"very positive opinion"* with respect to the aspect in question (for instance *"…an outstanding and great…"*). The value 0 corresponds to a neutral opinion (*"it is ok"*). The value 99 has been used in annotation for a mixed polarity (for instance *"…is good but I hate it…"*).

We take into account 32 aspects as values for the variables a^i_j. These aspects have been found to cover all relevant information by preliminary annotation experiments. Each aspect belongs to one of the eight categories *study contents*, *study materials*, *support and organization*, *didactics*, *online campus*, *tuition*, *attendance seminar*, *personal*. The full list of aspects and categories is shown in Table 1. A summary of the statistical properties of the corpus is presented in Section 4.1.

Figure 1: Example review from the website `fernstudiumcheck.de/` (potentially identfying information has been blacked).

3 Models for Automatically Estimating Aspect-Polarity Tuples

We phrase the task of assigning aspects and polarities to sentences as a text classification problem in which dependencies between different classes are reflected in and captured by the model. We first describe the various features used to take a decision with regards to which category or aspect is under discussion in a particular review. Then, we describe the different classification models we investigate.

3.1 Features for Aspect Categorization

In order to classify each sentence as to whether it describes a given aspect or not, our model relies on tf·idf scores for each term (Manning et al., 2008). In addition, we compute the occurrences of word bigrams and trigrams of all sequences of a length of two and three of directly succeeding words. As domain-specific features, the occurrence of terms in manually compiled dictionaries containing specific words frequently associated with a specific aspect, category, or polarity orientation are taken into account.

3.2 Features for Polarity Detection

As cues for polarity tokens and phrases, the English dictionary by Hu and Liu (2004) was automatically translated via Google Translate (`https://translate.google.com`) to German. The feature computed on the basis of this list is the number of polarity words in a sentence. The occurrence of diminishing and intensifying nouns is estimated using manually compiled domain-specific word lists. The GermanPolarityClues dictionary (Waltinger, 2010) is used to determine sentiment priors for individual words and summed up to create an aggregated sentiment score for the entire sentence for positive, negative, and neutral sentiment. Bigrams are used as features as described for aspect detection. For unigrams, negations are taken into account by building features from the cross-product of terms like *not* and *n't*, upon first occurrence, with all succeeding words in the same sentence.

3.3 Model Structures

In our classification approach, we use one binary classifier for each aspect. Each of these classifiers is trained to predict whether the corresponding aspect is mentioned in the sentence the classifier is applied to. In addition, the aspects are grouped into categories.

Assigning a broader category is often easier for a human than assigning a specific category. Further, knowing which category is discussed in a given sentence might simplify the task of predicting which aspects are specifically under discussion. Therefore, we extend the classification-based approach to the category level and train classifiers that predict

Class Label	Occ	Pos	Neg
Study Contents	**397**	**272**	**138**
Average Demand	60	23	25
Up-To-Date	58	35	20
Practical Relevance	50	36	8
Quality of Contents	229	143	66
Exams	77	35	19
Study Materials	**101**	**75**	**20**
Production Quality	7	5	2
Accessibility	22	20	2
Extent of Materials	28	21	3
Exercise Materials	44	29	13
Support and Orga.	**749**	**594**	**125**
Supervision	487	409	61
Revision Time	89	78	10
Organization	173	107	54
Didactics	**527**	**384**	**110**
Teaching Competence	124	101	13
Didactics of Materials	308	220	72
Justified Grading	20	15	3
Revision Quality	75	48	22
Online-Campus	**196**	**129**	**47**
Usefulness	119	84	28
Activity	35	29	6
User-Friendliness	20	8	11
Features	22	18	2
Tuition	**90**	**55**	**20**
Basic Tuition	78	48	17
Additional Charges	10	7	3
Scholarships	2	0	0
Attendance Seminar	**127**	**93**	**22**
Seminar Contents	84	59	14
Management	18	12	5
Locations	9	7	2
Communications	16	15	1
Personal	**572**	**472**	**74**
Flexibility	103	96	2
Recommendation	77	71	4
Personal Benefit	74	61	6
Overall Satisfaction	236	215	17
Learning Effort	82	29	45
Other	**345**	**0**	**0**
No Label	345	0	0

Table 1: Statistics of the annotations of the corpus of 394 reviews.

whether any aspect of a given category is discussed in the respective sentence.

The two classifications can be coupled, so that the classifier performing a decision on the specific aspect under discussion has access to the decision of the classifier predicting which more general category is discussed in the sentence. Coupling these decisions can be implemented via different classifier architectures that we describe below. Similarly, the binary classifiers predicting whether a sentence is neutral, positive or negative can be coupled.

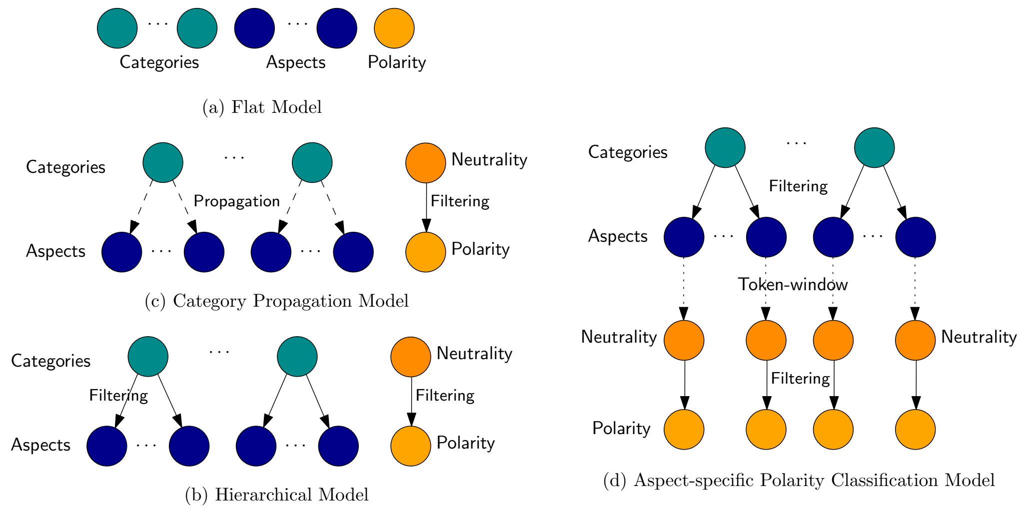
In the *Flat Model* (see Figure 2), each category and each aspect are predicted independently from each other, so that there is no interaction between these classifications. Similarly, the polarity of a sentence is predicted independently of the prediction of the aspect or category classifiers. This model is considered a baseline structure.

In the *Hierarchical Model*, all classifiers for the categories are applied first. An aspect classifier is then only applied if the respective category classifier has predicted that the sentence in question is about the category the aspect belongs to. Besides this hierarchical dependence, there is no direct information flow between the different classifiers. As an example, a prediction that a sentence belongs to the category *Tuition* would prompt the classifiers *Basic Tuition*, *Scholarships*, and *Accessory Charges* to be applied. If the initial prediction of the *Tuition* classifier is negative, none of the above mentioned aspect classifiers would be applied. The polarity detection is independent of the aspect detection in this model, but only applied if a previous model decides for a sentence to be non-neutral. The intuition of this model is that the classifiers on the higher level (categories, neutral/non-neutral) can take into account properties shared between sentences of classes of the lower level (aspects, polarities). On the other hand, classifiers on the lower level can focus on more specific properties and are therefore only trained on sentences of the associated categories.

The *Category Propagation Model* uses the same structure as the *Hierarchical Model*. However, instead of only applying classifiers on the lower level to sentences which have been 'let through' by the upper level, all classifiers are always applied. The information from upper levels is propagated to the lower level by additional features.

The intuition is that the hierarchical model might be too strict. Errors on an upper level would propagate to lower levels. In the propagation model, the predicted categories are used as features in the aspect classifiers. Therefore, these models can 'vote against' the decision of the previous level. However, the task is more challenging for the aspect classifiers, as they take into account all aspects, not only the ones from the same category. The polarity classification remains deterministic and is incorporated in the same manner as before.

In the *Aspect-Specific Polarity Classification Model*, polarity classifiers make the decision based on the textual context of the mention of the respective aspects. Therefore, in this model, different aspects can be assigned different polarities in con-



(a) Flat Model

(c) Category Propagation Model

(b) Hierarchical Model

(d) Aspect-specific Polarity Classification Model

Figure 2: Visualization of the different model structures. The *Flat Model* (a) does not take into account dependencies between aspects or categories. In the *Hierarchical Model* (b), instances are only classified by aspect classifiers if the corresponding category classifier made a positive decision. In the *Category Propagation Model* (c), the output of the category classifiers are used as features in the aspect classifiers. The polarity classifiers are used in the same manner as in the Hierarchical Model. In the *Aspect-Specific Polarity Classification Model* (d), the context defined by an aspect prediction is taken into account for polarity prediction.

trast to the other models. For this purpose, for each aspect the terms with the highest mutual information are assumed to express the respective aspect. The polarity classifier is then only applied on a window of n tokens left and right of the informative tokens for an aspect. For instance, the sentence *"The lecturer was very entertaining but the course work was dreadful"* would be assigned two aspects with opposite polarities.

4 Results

In this section, we describe the properties and distributions of aspects in a manually annotated corpus. This information is valuable on the one hand as it presents results which can be assumed to hold for the whole corpus of all reviews as the subset has been sampled uniformly. On the other hand, it presents results on the task of automatically detecting such aspects in more detail.

4.1 Corpus Statistics and Observations

The corpus has been annotated by three annotators following guidelines that have been agreed upon and incrementally refined along four annotation rounds. The final inter-annotator agreement reached during these rounds has been substantial with a $\kappa = 0.75$ (Cohen, 1960)). In the final corpus, every third review has been annotated by two annotators for quality assurance ($\kappa = 0.77$).

The corpus consists of 394 reviews with 2481 sentences. On average, a review consists of 6.3 sentences. Each sentence was annotated on average with 1.25 aspect-polarity pairs, leading to 3103 annotations altogether.

Table 1 summarizes the overall frequencies of all aspects, categories and polarities. The category with the most frequent mentions is *Support and Organization* (749 mentions), closely followed by *Personal* aspects (572) and *Didactics* (527). These categories can therefore be considered to be of high importance. Surprisingly, the *Tuition* was by far less often discussed (90). Ordering the categories by polarity (*i. e.*, by "positive"−"negative" annotations), this ranked list is not changed, positive mentions are by far more frequent than negative aspect mentions. The category that is most frequently discussed in a negative way is *Study Content*, though this is only the fourth most frequently mentioned category. When normalizing the absolute numbers of mentions by the overall numbers of mentions of a category, the *Study Content* remains on the top of the list of negatively mentioned categories (34 % of all mentions are negative), closely followed by the *Quality of Content* (29 %). The most frequent categories discussed positively are *Personal* (70 %) and *Support and Organization* (62 %).

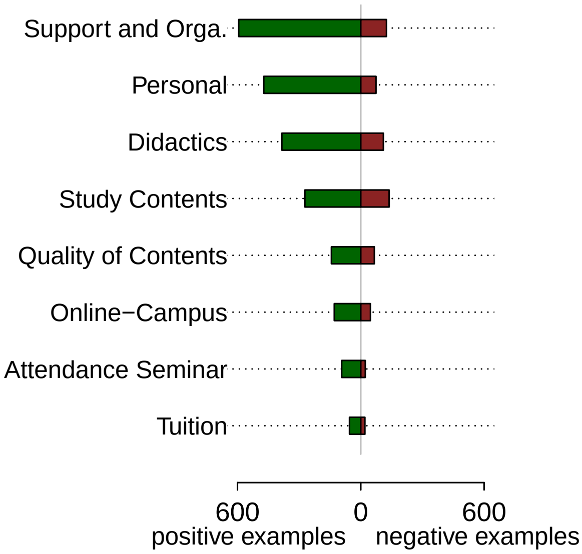


Figure 3: Distribution of positive and negative annotations for individual categories, ranked in a descending order by ratio of positive vs. negative examples.

Going to the more fine-grained level, the *Flexibility*, *Communications*, *Recommendation*, *Overall Satisfaction*, *Accessibility*, *Revision Time*, *Personal Benefit*, *Features* (of online campus), *Support*, *Teaching Competence* are the top 10 aspects with respect to the positive vs. negative ratio. (with percentages of positive mentions ranging from 94 % to 81 %). On the other side, the categories most frequently discussed in a negative manner are the *Learning Effort*, the *User-Friendliness*, *Average Demand*, *Scholarships*, *Exams*, *Up-To-Dateness*, *Organization*, *Revision Quality*, *Exercise Materials* and *Management* (with percentages of positive mentions ranging from 35 % to 66 %).

Notably, there are only three aspects which are more often mentioned negatively than positively, namely the *Average Demand*, the *User-Friendliness*, and the *Learning Effort*.

It is important to mention that this data set is heavily unbalanced, both in the distribution of aspects as well as in the distribution of positive and negative mentions, as depicted in Figure 3.

4.2 Model Evaluation

In the following, we analyze the performance of the different classification model structures with respect to the task of predicting the aspects and the polarity of sentences automatically.

Experimental Setting The evaluation is performed on an independent test set of 104 reviews. The remaining 290 reviews are used for training the models. Note that this split has been the same for the whole engineering phase. The 104 test instances have therefore never been used to improve the performance of the automated system. As performance measures, precision, recall, and F_1 measure are used.

Precision measures the correctness of a prediction of a system: how many of the aspects detected by the system are actually correct? *Recall* expresses how many of the aspects that a sentence actually mentions are also found by the automatic classification system. The F_1-Measure is the harmonic mean of these two measures. Formally, the precision of a system on some data set with respect to one specific aspect is defined as $\text{prec} = \frac{\text{TP}}{\text{TP+FP}}$, the recall is $\text{rec} = \frac{\text{TP}}{\text{TP+FN}}$. The F_1 measure is the balanced harmonic mean of these two values: $F_1 = 2\frac{\text{prec}\cdot\text{rec}}{\text{prec}+\text{rec}}$. TP, FP, and FN denote the number of true positives, false positives, and false negatives, respectively.

The macro-averaged precision, recall, and F_1 measure values are calculated from the respective values for the different aspects. The micro-averaged value is calculated based on the sum of TP, FP, FN for all aspects as the basis for the performance measures. Therefore, the micro-average takes into account the different distributions of the aspects, while the macro-average does not.

Aspects and Categories The results for the aspect and category detection are summarized in Table 2. The micro-averaged values tend to be higher than the macro-averaged scores due to the unbalancedness of the aspect frequencies; this means that the more frequent an aspect is, the more accurately it can be detected. However, the differences between different model structures are similar, such that we focus on the micro-averaged scores in the discussion.

The results for the categories are the same for all model types as this decision is always made independently of other classifiers, i.e., there is no information flow from the aspect classifiers to the category classifiers, but only the other way round. The rows labeled with "Categories (Infer.)" are the performance measures when inferring the category labels from the aspects. For the hierarchical model and the category propagation model, a category is regarded to be relevant for a sentence if at least one

Model	Type	Macro (%) P	R	F	Micro (%) P	R	F
Flat	Categories	70	35	46	72	44	55
	Aspects	79	16	26	72	27	39
Hier.	Categories	70	35	46	72	44	55
	Categ. (Infer.)	71	31	43	72	38	50
	Aspects	71	44	54	61	70	65
Prop.	Categories	70	35	46	72	44	55
	Categ. (Infer.)	73	29	41	75	36	49
	Aspects	74	17	28	65	30	41

Table 2: Results for different model structures. The results for the categories are as predicted for the flat model ("Flat"). In the hierarchical model ("Hier.") and the category propagation model ("Prop."), the category labels as inferred from the aspect prediction are provided in addition.

classifier for an aspect within this category votes for the sentence. Clearly, these inferred values are inferior to the specialized category classifiers. However, when outputting categoric results to a user, contradictions in the results should be avoided and therefore the inferred category labels would be preferred. This occurs particularly in the category propagation model, proving that the capability to overwrite a decision by the category classifier leads to an improved precision (0.75 vs. 0.72).

Altogether, for the category detection, precision is higher than recall. This is the case for the prediction of aspects as well, but to a smaller extent. For the aspect recognition, the flat model has the lowest performance with 0.39 F_1 followed by the category propagation model with 0.41 F_1. The hierarchical model improves this result by 0.24 percentage points to 0.65 F_1. However, the best precision is reached with the flat model. The label propagation model represents a tradeoff between precision and recall with an F_1-Measure of 0.41. It can thus be concluded that the use of categorical information for the aspect recognition enables the aspect classifier to focus on the distinction between aspects of the same category and thus increases recall.

Analyzing results for the respective classifiers, it is notable that specifically the performance for aspects with a small number of training instances is limited: The best results are achieved for *usefulness, supervision, basic tuition, revision time*, and *recommendation* (with an average F_1 of 0.81) with 850 instances. The worst results are achieved for

	Agnostic (%) P	R	F	Specific (%) P	R	F
Positive	78	92	84	76	91	83
Negative	63	60	61	57	40	47
Neutral	75	18	29	86	10	18
Polar	88	99	93	93	100	96

Table 3: Results for polarity and neutrality detection, both aspect-agnostic and aspect-specific.

accessibility, additional charges, communication in attendance seminars, features of the online campus, locations of the attendance seminars with 79 instances altogether.

Polarities The results for the aspect-independent polarity detection (as in the first three model structures) is shown in Table 3. The detection whether one sentence contains a positive or negative statement is close to perfect. The low number of neutral sentences is therefore more difficult to be detected. However, in this task the detection of positive and negative statements is of far greater importance. The detection of positive sentences is satisfactory, with an F_1 of 84 %. The recognition of negative sentences turns out to be more challenging, with 61 % F_1.

In addition, the results show that there is added benefit for distinguishing polar from neutral sentiment for specific aspects compared to computing the polarity at the level of the whole sentence. However, overall, this is a rare phenomenon; only 119 sentences out of 2481 mention more than one aspect. Spanned across the entire problem, this rarity leads to difficulties in learning from the increased granularity. This is expressed in experiments with different window sizes. For aspect-specific detection of all polarities, maximal performance is reached when using the entire sentence for classification.

The aspect-agnostic polarity classification approach delivers correct results in 99.95% of the cases.

5 Discussion

The analysis of the manual annotation of the corpus clearly proves that students have a tendency to discuss positive aspects rather than negative aspects of their distance education programs. This is a bit surprising as one might expect a bias to report negative rather than positive experiences. However, one observes a clear tendency towards discussing positive rather than negative aspects. The relatively high fees of distant education programs might bias people towards a more positive assessment.

In general, the discussions typically revolve around a few categories specific for distance education programs that are generally evaluated positively. The most frequent categories discussed negatively comprise of learning procedures, that is *materials, demand, effort, and quality*. This might suggest that distance education programs are specifically good in their domain but must improve on providing an as solid learning environment as attendance-focused institutions.

The corpus discussed in this work has been used to automatically learn models of different structure. The best performing model indicates that the process of detecting a category first followed by the corresponding aspects is beneficial. The results are satisfactory for frequent aspects.

Our assessment of different model structures discovered that sentences of the same category share properties, which explains the increased recall for the hierarchical model. The best precision is however achieved by the flat model which makes decisions for all aspects independently of each other.

The main use case of our method is to support the processing of reviews in real-time so that feedback about distance education programs can be taken into account in shorter time to support decision making by prospective students. For instance, interested students can select one of the aspects to rank programs and institutions based on that selection. In addition, evidence for specific strengths or weaknesses can be easily retrieved in the form of example reviews or sentences.

In addition to a benefit for potential students, such an approach can help institutions to identify their specific weaknesses. For instance, in order detect which of their programs has most problems regarding management, material quality or other aspects.

6 Conclusion and Future Work

The number of reviews on online education programs is increasing steadily. The reviews from peers contain valuable information that can help students to find the distance education programs that fits their needs best. Given the unstructured nature of such reviews, a systematic and large scale analysis is challenging.

The analysis of the content of such reviews to make their content accessible in a structured manner is a real-world use case for text mining, sentiment analysis and natural language processing. We have proposed a methodology for the automatic and systematic analysis of these reviews. On the one hand, we have proposed a methodology for the manual annotation of reviews in the form of annotation guidelines comprising a taxonomy of aspects that are relevant to distance education programs. On the other hand, we have developed an automatic approach that can automatically identify the aspects under discussion in a given review, and make the sentiment towards these aspects explicit. This automatic approach exploits classifiers trained using machine learning techniques to identify whether a given aspect is discussed in the review under consideration or not. In particular, different model structures for these classifiers have been empirically evaluated. We have shown that the results provided by the classifiers are satisfactory and support the automation of the task. The performance of the polarity detection is satisfying. The recall for aspects of lower frequency in our corpus has space for improvement. However, it can be expected that increasing the size of the corpus with a focus on the infrequent aspects will allow for for an overall improvement of the classification.

Future work includes the enlargement of the corpus and an analysis of the impact of the performance of the classifiers on actual ranking of service providers with respect to specific aspects. The actual acceptance of users of websites supporting the decision which program suits them well will be evaluated.

In addition, the findings should be compared to structured information available for the programs and institutions. One example is the question: Is there a correlation between satisfaction and happiness with the tuition fees and the actual amount of money the program costs?

Furthermore, the current method of propagating information through the hierarchy does not include propagation bottom-up. We will compare the impact of a feed-forward neural network-like setting to address this potential limitation in the current approach.

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