Dataset for Aspect Detection on mobile reviews in Hindi

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Abstract
In recent years Opinion Mining has become one of the very interesting fields of Language Processing. To extract the gist of a sentence in a shorter and efficient manner is what opinion mining provides. In this paper we focus on detecting aspects for a particular domain. While relevant research work has been done in aspect detection in resource rich languages like English, we are trying to do the same in a relatively resource poor Hindi language. Here we present a corpus of mobile reviews which are labelled with carefully curated aspects. The motivation behind Aspect detection is to get information on a finer level about the data. In this paper we identify all aspects related to the gadget which are present on the reviews given online on various websites. We also propose baseline models to detect aspects in Hindi text after conducting various experiments.

1 Introduction
Over the last decade people tend to search for products online rather than physically on stores. This has resulted in a surge of online forums where reviews are available on various products, electronic gadgets being one of the more popular ones. But reading so many long reviews is very time consuming and there is no uniformity on the parameters of reviews. To solve this, research work has been done in this area in the form of Aspect Detection which helps to point out the key specifications of the product in a structured format. But the work is limited to only worldwide languages as English and French. For a multi-lingual country like India, we are still far away in getting these information in the native language. We aimed at creating a dataset in Hindi which has the highest number of native speakers. The dataset is annotated with aspects for mobile reviews.

An aspect is a word in a sentence which has some polarity associated with it. The aspect should hold major meaning of the sentence. Following examples will state what aspect is:

S1: Xiaomi redmi 4A ko pehli baar hath m lene par yeh aapko metal body ka bana lagega.

S1 : शाओमी रेडमी 4ए को पहली बार हाथ में लेने पर यह आपको मेटल बॉडी का बना लगेगा।

Aspect1: “मेटल बॉडी” (metal body) which falls under the “िडज़ाइन” (design) category.

S2: Xiaomi Redmi note m 2 gigahertz octa-core qualcomm snapdragon 625 processor ka isetmal hua hai.

S2: शाओमी रेडमी नोट म 2 गीगाहर्ट्ज़ ऑक्टा - कोर क्वालकॉम स्नैपड्रॉन 625 प्रोसेसर का इस्तेमाल हुआ है।

Aspect: “ऑक्टा - कोर क्वालकॉम स्नैपड्रॉन 625” (Octa core qualcomm snapdragon) which falls under the “स्पेिसिफिकेशन” (specification) category. The aspect tells specifically tells the details of product.

S3: अफसोस यह िक आप उन्हें हटा नहीं सकते।

S3: अफसोस यह कि आप उन्हें हटा नहीं सकते।

Aspect : “NULL” as there is no word which tells about any detail of the product. Hence, it is classified under no aspect category.

2 Related Work
Major work has been done in Aspect Detection when it comes to resource rich languages like English. The work of Aspect Detection has also been followed by Sentiments analysis which plays a major part in Opinion mining. In 2014 SemEval-Task 4, Maria Pontiki (2014) provided the first dataset which con-
sisted of English reviews annotated at sentence level with their aspects followed by their polarity. Some of the systems that emerged who targeted this task were Zhiqiang Toh (2014), Chernyshevich (2014); Joachim Wagner and Tounsi (2014); Giuseppe Castellucci (2014), Shweta Yadav (2015). However, almost all these systems are related to some specific languages, especially English. In 2016, SemEval released new datasets of similar domains (mobile, laptop, restaurant) but in multiple languages. In 2016, the datasets were released in English, Arabic, Chinese, Dutch, French, Russian, Spanish and Turkish.

But this area of field is largely unexplored in Indian languages due to the unavailability of high quality datasets and other tools and resources required. The datasets which were created by research groups mainly by Aditya Joshi (2010); Balamurali A R (2011, 2012) were very less in size and low in quality. Also Google transliteration was used to create data in Indian languages (Akshat Bakliwal, 2012) but dataset created was not rich enough to perform aspect detection with high efficiency. Moreover the datasets available in Hindi were not domain specific which also added to poor results in past.

3 Data Creation

As mentioned, earlier our work is on a specific domain. To build our corpus we scrapped data from various online forums with reviews on mobile phones. We extracted the text from the HTML data with the help of BeautifulSoup library in python. As our language was Hindi, online reviews were very less for which we tried both dynamic and manual crawling of data.

After crawling over 8 websites, we were able to get over 381 reviews. We retrieved 294 mobile reviews (37410 sentences) in a HTML format after extensive removal of noisy reviews. We had 294 HTML files which had raw data between different HTML tags. There was no uniformity in the reviews, even after extraction and tokenization of these reviews,

Table 1: Class Set

| Aspect Class In Hindi                        | Aspect Class In Roman                        | Count |
|-----------------------------------------------|----------------------------------------------|-------|
| सॉफ्टवेयर                                     | software                                     | 52    |
| स्पेिसिफिकेशन और फ़ीचर                    | Specification aur feature                     | 360   |
| हमारा फैसला                                   | hamara faisla                                | 9     |
| कैमरा और बैटरी लाइफ (                   | camera aur battery life                      | 5     |
| स्पेिसिफिकेशन और सॉफ्टवेयर                | specification aur software                   | 137   |
| कैमरा                                         | camera                                       | 76    |
| परफॉमेंस                                       | performance                                 | 826   |
| लुक व बनावट                                   | look vah banawat                             | 26    |
| बैटरी लाइफ                                   | battery life                                 | 1     |
| हमारा फैसला                                   | hamara faisla                                | 300   |
| कैमरा परफॉमेंस                               | camera performance                           | 16    |
| डिजाइन                                       | design                                       | 138   |
| डिजाइन और लुक                               | design aur look                              | 168   |
| NULL                                         | NULL                                         | 352   |
| स्पेिसिफिकेशन                               | specification                                | 139   |
| डिजाइन और बिल्ड                             | design aur build                             | 390   |
| डिजाइन और डिस्प्ले                          | design aur display                           | 49    |
| स्पेिसिफिकेशन , सॉफ्टवेयर और परफॉमेंस | specification, software aur performance      | 40    |
Many reviews had proper headings like specifications, performance, price, design under which two-three paragraphs of text was present. But there were many reviews without any headings. To make it uniform and bring it to sentence level rather than paragraph level, we assigned the heading as labels to every sentence appearing under that heading in the review. This was our first annotation strategy.

While assigning heading as aspects, there were certain sentences which had no heading above them. Such sentences were labelled as NULL. After this initial annotation, we had 18 classes of aspects in total. After doing analysis on our 18 classes, we observed a lot of overlapping between different classes. Some classes had the same name, but due to spelling variations they were assigned different labels. Table 3 gives a clear picture about the overlapping between different classes. We show the counts of highly frequent overlapping class pairs.

| Class1 and Class2                      | Overlap Count |
|----------------------------------------|---------------|
| स्पेसिफिकेशन और फीचर, स्पेसिफिकेशन और सॉफ्टवेर (specification aur feature), (specification aur software) | 441           |
| डिजाइन और लुक, डिजाइन और बिल्ड (design aur look), (design aur build) | 418           |
| स्पेसिफिकेशन और फीचर, स्पेसिफिकेशन (specification aur feature, specification) | 410           |
| डिजाइन, डिजाइन और बिल्ड (design), (design aur build) | 387           |
| स्पेसिफिकेशन स्पेसिफिकेशन और सॉफ्टवेर (specification, specification aur software) | 336           |

Table 3: Overlapping Between Initial Classes

The following decisions to club different classes and provide them a single label were taken based on the percentage of overlapping.

- सॉफ्टवेर (software), स्पेसिफिकेशन और फीचर (specification aur feature), स्पेसिफिकेशन और सॉफ्टवेर (specification aur software), स्पेसिफिकेशन, स्पेसिफिकेशन, सॉफ्टवेर और परफॉर्मैंस (specification, specification, software aur performance) clubbed under one single class called स्पेसिफिकेशन (specification).
- कैमरा और बैटरी लाइफ (camera aur battery life), कैमरा (camera), कैमरा परफॉर्मेंस (camera performance) were clubbed under a class कैमरा (camera).
- लुक व बनावट (look wh banawat), डिजाइन (design), डिजाइन और लुक (design aur look), डिजाइन और बिल्ड (design aur build), डिजाइन और डिस्प्ले (design aur display) categorized under one class डिजाइन (design).
- कैमरा (camera), कैमरा परफॉर्मेंस (camera performance), कैमरा और बैटरी लाइफ (camera aur battery life) were categorized under one class कैमरा (camera).
- NULL and हमारा फैसला (hamara faisla) were merged as into a single class NULL.

After eliminating all these redundancies, we finally had 5 classes or aspects for our mobile reviews.

| Aspect Class | Count |
|--------------|-------|
| डिजाइन (design) | 298   |
| स्पेसिफिकेशन (specification) | 585   |
| NULL         | 489   |
| परफॉर्मेंस (performance) | 459   |
| कैमरा (camera) | 169   |

Table 4: Classwise Distribution

Two annotators were involved in this task. We obtained a Fleiss' ³ score of 0.87 for inter annotator agreement.

4 Experimental Setup

The main task was to predict aspects in every sentence in a review. We used different data.
Table 5: Results Of Models After 5-fold Cross Validation

| Classifier | Feature               | P  | R  | F1-Score |
|------------|-----------------------|----|----|----------|
| MNB        | word uni              | 0.65 | 0.60 | 0.62    |
| MNB        | word uni+bi           | 0.62 | 0.63 | 0.63    |
| MNB        | char 2gram            | 0.72 | 0.65 | 0.67    |
| MNB        | char 2-3gram          | 0.75 | 0.73 | 0.74    |
| MNB        | char 2-4gram          | 0.74 | 0.74 | 0.74    |
| MNB        | char 2-5gram          | 0.73 | 0.75 | 0.74    |
| MNB        | word uni+char2-5gram  | 0.74 | 0.74 | 0.74    |
| MNB        | word uni+bi+char2-5gram | 0.73 | 0.75 | 0.74    |
| SVM        | word uni              | 0.65 | 0.64 | 0.65    |
| SVM        | word uni+bi           | 0.70 | 0.66 | 0.67    |
| SVM        | char2gram             | 0.73 | 0.71 | 0.72    |
| SVM        | char2-3gram           | 0.75 | 0.73 | 0.74    |
| SVM        | char2-4gram           | 0.77 | 0.75 | 0.75    |
| SVM        | char2-5gram           | 0.77 | 0.75 | 0.76    |
| SVM        | word uni+char2-5gram  | 0.74 | 0.73 | 0.73    |
| SVM        | word uni+bi+char2-5gram | 0.75 | 0.73 | 0.74    |

5 Results

The results are shown in table 5. Classifiers and their corresponding features are detailed in this table. We used precision, recall and macro F1-score as the evaluation metric for checking the performance of our models. The words ‘uni’, ‘bi’ refer to the word unigrams and bigrams respectively. char ‘a-b’ gram denotes the combination of character n-grams where n lies in {a, a + 1, a + 2, .., b}

6 Observation

From table 5, we observed that both the classifiers equally perform well on the data. We also observed that character n-grams models are superior than word n-gram models. Combination of word and char n-gram TF-IDF vectors do not significantly improve the performance.

From the values of confusion matrix, we observed that class स्पेसिफिकेशन (specification) has overshadowed classes NULL and कैमरा (camera). It shows that our model is not able to predict between the umbrella class and the child class accurately.

7 Conclusion and Future Work

We annotated aspects for mobile reviews written in Hindi as a part of this work. We also presented baseline models for automatic aspect identification in mobile reviews. The
baseline models will help us to annotate more reviews semi-automatically and can then be integrated to improve our systems. We will explore more into neural network architecture and word embeddings. The next task in this area would be to annotate polarity of the aspects. We can also explore identifying the most informative reviews (Mishra et al., 2017).

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