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Sentiment Classification through Category Detection and Imbalanced Data Mitigation Using ML Techniques

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Abstract – **In this paper we consider online consumer reviews to assist purchase-decision making has become increasingly popular. To process the user reviews and find the useful information for making decision of purchase most of existing systems are presented. But one can hardly read all reviews to obtain a fair evaluation of a product or service. A subtask to be performed by such a framework would be to find the general aspect categories addressed in review sentences, for which this paper presents two methods. the first method presented is an unsupervised method that applies association rule mining on co-occurrence frequency data obtained from a corpus to find these aspect categories. While not on par with state-of-the-art supervised methods, the proposed unsupervised method performs better than several simple baselines, a similar but supervised method, and a supervised baseline, with an F1-score of 67%. The second method is a supervised variant that outperforms existing methods with an F1-score of 84%. And also we extend our work to deal with the imbalanced dataset using Synthetic Minority Over-sampling Technique and Modified Synthetic Minority Over-sampling Technique further improving the performance of the system.**

Keywords — **Sentiment Analysis, Co-occurrence Data, imbalanced Data.**

I. INTRODUCTION

Consumer decision-making has always been influenced by word-of-mouth (WoM). Before making any significant purchasing decisions, family members and friends are typically consulted for comments and guidance. Both immediate and long-term effects on consumer decision-making may result from these recommendations [1].

WoM has significantly grown since the advent of the Web. It is now possible for everyone who wants to share their experiences to do so electronically. Social media platforms like Facebook and Twitter make it simple to share opinions about goods, services, and companies. This expanded version of WoM is called electronic WoM (EWoM).

EWoM has grown in popularity during the past few years [2]. Customer reviews of goods and services [3] that are placed online are among the most significant types of EWoM communication. Websites like Yelp provide in-depth customer evaluations of nearby eateries, lodging facilities, and other establishments, while retail giants like Amazon and Bol have a plethora of product reviews that offer a wealth of information. According to research, customers see these reviews as more valuable than editorial recommendations and information created by the market [4]–[6], and they are increasingly employed when making decisions about what to buy [7].

Consumers and businesses alike benefit from the knowledge that can be gleaned from product and service reviews. Businesses can enhance their goods and services by being aware of what has been placed online [8].

However, a framework for the automated summarization of reviews is needed in order to manage the vast quantity of information available in these reviews [9]. Identifying the subjects (i.e., features of the product or service) that people write about would be a crucial challenge for such a system. These subjects may be more general in the case of aspect categories or more specific in the case of aspect-level sentiment analysis.

As can be seen, aspect categories are typically assumed, meaning that the sentence does not specifically state the category names. This is also true for fine-grained elements: whereas the majority are mentioned directly in a sentence, others are just suggested. For instance, the suggested aspect category in the statement below is "service," but the implied fine-grained aspect is "staff."

A supervised machine learning technique to aspect category recognition is possible and produces good results when the aspect categories are known in advance and there is sufficient training data available [11]. There are numerous supervised methods for identifying aspect categories [11]–[14]. But occasionally, the flexibility that comes with an unsupervised approach is preferable.

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In order to identify aspect categories based on co-occurrence frequencies, this research proposes both an unsupervised and a supervised method. The unsupervised approach detects aspect categories by spreading activation on a graph constructed from word co-occurrence frequencies. Furthermore, unlike in [15], it is not necessary to assume that the implicit aspects are always mentioned clearly. By developing a collection of explicit lexical representations for every category, the suggested unsupervised approach makes use of more than simply the actual category label. The collection of aspect categories utilized in the data set is the only information needed. The supervised approach, on the other hand, computes conditional probabilities from which detection rules are mined by using the annotated aspect categories, grammatical relation triples, and word co-occurrences.

Additionally, we expand our work to use the Synthetic Minority Over-sampling Technique (SMOTE) to address unbalanced data. To further enhance performance, we made modifications to SMOTE.

II. RESEARCH METHOD

A) Unsupervised Method

Similar to [15], the suggested unsupervised approach, known as the spreading activation method, employs co-occurrence association rule mining by discovering pertinent rules between the considered categories and notional words—that is, the words in the sentence after stop words and low frequency words have been eliminated. This makes it possible for the algorithm to infer a category from a sentence's words. We provide a collection of seed words for each category, which are words or terms that describe that category, in order to avoid using the ground truth annotations for this and to maintain the method's unsupervised nature.

The lexicalization of the category and its synonyms are taken from a semantic lexicon such as WordNet to find these words or concepts. The seed set {ambience, ambiance, atmosphere}, for instance, is part of the ambience category. The general concept of implicit aspect detection can also be used to detect categories once the seed words are known. The goal is to mine a co-occurrence matrix for association rules of the type [notional term → category]. The frequency degree of two hypothetical words occurring together in the same sentence is represented by each element in this co-occurrence matrix. Less common words and stop words like "and" and "and" are left out because they don't really help identify the categories in review sentences.

The reason why we opt to mine for rules similar to those of [15]'s, and do not analyze all notional terms in the phrase at once to establish the implicit categories, like, is based on the theory that categories are better conveyed by single words. Finding single words like "chicken," "staff," or "helpful" is all that is required to classify sentences if we have categories like "food" and "service."

When there is a strong relationship between a notional word and one of the aspect categories, association rules are mined. The co-occurrence frequency between the category and the notional word is used to represent the strength of the relationship.

We differentiate between two kind of relations: 1) direct relations and 2) indirect relations. The positive conditional probability P(B|A) that word B is present in a sentence given the presence of word A is used to model a direct relationship between two words, A and B. When two words, A and B, have a direct relationship with a third word, C, then there is an indirect relationship between the two words. This suggests that even though A and B may not have the same semantics, they could be used interchangeably. Since they don't frequently occur together, substitutes are typically not recognized without looking for indirect linkages. Fig. 1 provides a graphic representation of an indirect relationship.

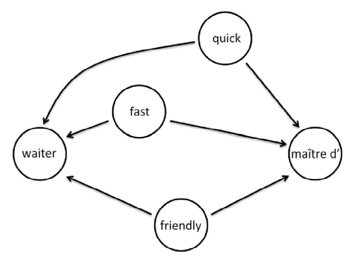

Fig. 1: Example of an indirect relation

The spreading activation algorithm, a technique for finding associative networks, is used to take advantage of the direct and indirect association information between notional words and seed words. In many different sectors, spreading activation has been used with success. This requires a network data structure, as shown in Fig. 1, which is made up of vertices connected by connections. In order to model the relationships between vertices, the vertices are labeled, and the links may be given weights and/or direction. Each vertex is assigned an activation value to start the search for an associative network. As the activation values are iteratively distributed to other, related vertices, these starting values establish the search region.

In this instance, we wish to apply spreading activation to identify a network of words related to the category's set of seed words for every category. This is accomplished by

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creating a network data structure with vertices for every hypothetical word and edges to represent the direct relationships between them. With the exception of the category's seed words, which have positive activation values, all notional words in the network data structure have an initial activation value of zero. Depending on the intensity of the direct association, these positive activation values are distributed to other words that are directly related to the seed words in the first iterative stage of the spreading activation algorithm. High association values are thus given to terms that have close, direct relationships to the seed words. Finding words with strong association values will be the first iterative stage. Once activated, these words will disseminate their activation value to other words that are closely related to them. This also identifies notional terms that have an indirect relationship to one of the seed words. A network of notional words with varying activation values will be the ultimate product; the more activation values a word has, the more closely it relates to the category.

Vertices that represent the notional words and linkages between two vertices that represent a strictly positive co-occurrence frequency will make up the data network structure used for the spreading activation technique. Given that word B appears in a phrase, each link, which reflects the direct relationship between two hypothetical words, is given weight equal to the conditional likelihood that word A and word B co-occur. The data network structure is a co-occurrence digraph, which implies that the links receive direction because the conditional probability is not symmetric.

Rules of the type [notional word → category] can be mined from vertices in these networks, depending on the vertex's activation value, once each category has its own associative network. One word may trigger more than one aspect category since it can appear in several associative networks. A set of rules is activated by the words in the sentence, and the sentence is given the aspect categories that correspond to those words. Using a straightforward example corpus with a firing threshold of 0.4 and a decay factor of 0.9, Fig. 2 shows how the unsupervised approach operates. The example demonstrates the process of identifying and extracting rules from an associative network for the food category.

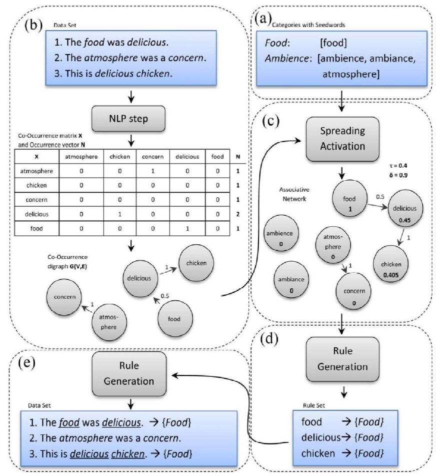

Fig. 2: Example flowchart of the unsupervised method.

i) Algorithm

The method can best be described according to the Algorithm 1.

Algorithm 1: Spreading Activation Algorithm

```
input : category c
input : vertices V
input : seed vertices S_c
input : weight matrix W
input : decay factor δ
input : firing threshold τ_c
output: activation values A_{c,i} for category c
foreach s ∈ S_c do
    A_{c,s} ← 1
end
foreach i ∈ V \ S_c do
    A_{c,i} ← 0
end
F ← S_c
M ← S_c
while M ≠ ∅ do
    foreach i ∈ M do
        foreach j ∈ V do
            A_{c,j} ← min{A_{c,j} + A_{c,i} · W_{i,j} · δ, 1}
        end
    end
    M ← ∅
    foreach i ∈ V \ F do
        if A_{c,i} > τ_c then
            add i to F
            add i to M
        end
    end
end
```

B) Supervised Method

The supervised approach, also known as the probabilistic activation method, uses co-occurrence association rule mining to identify categories, just like the first method did. We use the concept of counting the frequencies of co-occurrence between lemmas and a sentence's annotated categories. However, in order to avoid overfitting, low frequency terms are not included. As in the unsupervised technique, this is

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accomplished with a parameter αL. Additionally, stop words are eliminated.

In addition to counting the co-occurrences of lemmas and aspect categories, the co-occurrences between grammatical dependencies and aspect categories are also counted. Similar to lemmas, low frequency dependencies are not taken into account to prevent overfitting, using the parameter αD. Dependencies, describing the grammatical relations between words in a sentence, are more specific than lemmas, as each dependency has three components: 1) governor word; 2) dependent word; and 3) relation type. The added information provided by dependencies, may provide more accurate predictions, when it comes to category detection. Knowing whether a lemma is used in a subject relation or as a modifier can make the difference between predicting and not predicting a category.

Unseen sentences from the test set are processed after the thresholds and conditional probabilities have been determined. We determine whether any of the lemmas or dependency forms in each unseen sentence have a conditional probability higher than the associated threshold; if so, the sentence is assigned to the appropriate category. Using a very basic test and training set, Fig. 3 shows how the supervised approach operates.

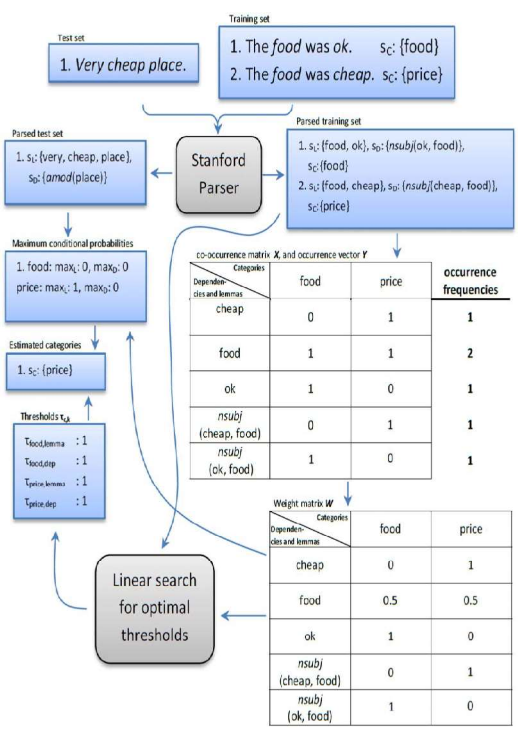

Fig. 3: Example flowchart of the supervised method.

i) Algorithm

The method can best be described according to the following Algorithm 2.

Algorithm 2: Identify Category Set C and Compute Weight Matrix W

```
input : training set
input : occurrence threshold θ
output: category set C, Weight matrix W
C, X, Y ← ∅
foreach sentence s ∈ Training set do
    // s_k are the lemmas/dependecies of s
    foreach s_k ∈ {s_L, s_D1, s_D2, s_D3} do
        foreach dependency forms/lemmas j ∈ s_k do
            // count dependency form/lemma
               occurrence j in Y
            if j ∉ Y then
                add j to Y
            end
            Y_j ← Y_j + 1
            // s_C are the categories of s
            foreach category c ∈ s_C do
                // Add unique categories in
                   category set C
                if c ∉ C then
                    add c to C
                end
                // count co-occurrence (c,j)
                   in X
                if (c,j) ∉ X then
                    add (c,j) to X
                end
                X_c,j ← X_c,j + 1
            end
        end
    end
end
// Compute conditional probabilities
foreach (c,j) ∈ X do
    if Y_j > θ then
        W_c,j ← X_c,j / Y_j
    end
end
```

Predicting the aspect categories for every unknown sentence in the test set is the last stage. For each category c ∈ C, we determine the highest conditional probability P(c|j), as explained in (4), from all lemmas and dependency forms sL, sD1, sD2, and sD3 in sentence s. Then, category c is designated as an aspect category for sentence s if any of these maximum conditional probabilities exceed their threshold τc,k. This step's pseudo-code is displayed in Algorithm 3.

Algorithm 3: Estimating Categories for the Test Set

input : training set
input : test set
input : occurrence threshold θ
output: Estimated categories for each sentence in the test set

$W, C \leftarrow$ Algorithm 2(Training set, θ)
$\tau_{c,L}, \tau_{c,D_1}, \tau_{c,D_2}, \tau_{c,D_3} \leftarrow$ LinearSearch (Training set, W, C)
// Processing of review sentences
foreach *sentence* $s \in$ *test set* **do**
  foreach *category* $c \in C$ **do**
    // Obtain maximum conditional probabilities $P(c|j) = W_{c,j}$ per type, for sentence s
    $\max_{c,L} \leftarrow \max_{l \in s_L} W_{c,l}$
    $\max_{c,D_1} \leftarrow \max_{d_1 \in s_{D_1}} W_{c,d_1}$
    $\max_{c,D_2} \leftarrow \max_{d_2 \in s_{D_2}} W_{c,d_2}$
    $\max_{c,D_3} \leftarrow \max_{d_3 \in s_{D_3}} W_{c,d_3}$
    if $max_{c,L} > \tau_{c,L}$ **or** $max_{c,D_1} > \tau_{c,D_1}$ **or** $max_{c,D_2} > \tau_{c,D_2}$ **or** $max_{c,D_3} > \tau_{c,D_3}$ **then**
      estimate category c for sentence s
    end
  end
end

To do sentiment analysis in this suggested method, we take into account the aspect category balanced dataset. In order to handle unbalanced data in our extension work, we investigate machine learning methods like the Synthetic Minority Over-sampling Technique.

C) Extension Work

i) Problem definition

This issue is common in situations where anomaly detection is essential, such as theft of electricity, bank fraud, the discovery of unusual diseases, etc. The prediction model created in this case with traditional machine learning methods may be skewed and imprecise.

This occurs as a result of the fact that machine learning algorithms are typically made to increase accuracy by decreasing error. As a result, they don't consider the proportion, balance, or distribution of classes.

Electricity theft is one of the biggest issues facing the utility sector today. The third most common type of theft in the world is electricity theft. In order to spot usage trends that point to theft, utility firms are increasingly using machine learning algorithms and advanced analytics.

The enormous amount of data and how it is distributed, however, is one of the main obstacles. Approximately 1-2 percent of all observations are fraudulent, which is a much smaller percentage than typical, healthy transactions. Rather than attaining more general accuracy, the goal is to enhance the identification of the rare minority class.

Unbalanced datasets sometimes result in subpar classifiers from machine learning techniques. If the event to be predicted falls into the minority class and the occurrence rate is less than 5% for any imbalanced data set, it is typically referred to as a rare event.

Example of Imbalanced Data

Let's use an example to better grasp this.

For example: The following information is included in a utilities fraud detection data set:

Total Observations = 1000

Fraudulent Observations = 20

Non Fraudulent Observations = 980

Event Rate= 2 %

The primary query that arises during data analysis is: Given the rarity of certain of these anomalies, how can a balanced dataset be obtained by obtaining a sufficient number of samples for them?

When dealing with unbalanced datasets, the traditional model evaluation techniques are unable to measure model performance effectively.

Conventional classifier techniques, such as Logistic Regression and Decision Trees, are biased toward classes with a high number of occurrences. They often solely forecast data from the majority class. The characteristics of the minority class are frequently disregarded and treated like noise. As a result, the minority class is more likely than the majority class to be misclassified.

The Confusion Matrix, which includes data on the actual and anticipated classes, is used to evaluate the performance of a classification algorithm.

Actual	Predicted	
	Positive	Negative
Positive Class	True Positive (TP)	False Negative (FN)
Negative Class	False Positive(FP)	True Negative(TN)

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Accuracy of Model = (TP+TN) / (TP+FN+FP+TN)

However, accuracy is not a suitable metric to assess model performance when operating in an unbalanced domain. For example, if a classifier labels every instance as belonging to the majority class and obtains a 98% accuracy rate with a 2% event rate, it is not accurate. Furthermore, the 2% minority class observations are eliminated as noise.

ii) Synthetic Minority Over-sampling Technique (SMOTE)

By using this method, overfitting—which happens when exact clones of minority occurrences are added to the main dataset—is prevented. To build new synthetic cases that are similar, a portion of data from the minority class is used as an example. The original dataset is then supplemented with these artificial cases. The classification models are trained using the fresh dataset as a sample.

Total Observations = 1000

Fraudulent Observations = 20

Non Fraudulent Observations = 980

Event Rate = 2 %

Similar synthetic examples are created 20 times using a sample of 15 instances drawn from the minority class.

The data set that follows is produced after the creation of synthetic instances.

Minority Class (Fraudulent Observations) = 300

Majority Class (Non-Fraudulent Observations) = 980

Event rate= 300/1280 = 23.4 %

The benefits of SMOTE generates synthetic examples instead of replicating instances, which mitigates the issue of overfitting brought on by random oversampling. No important information is lost.

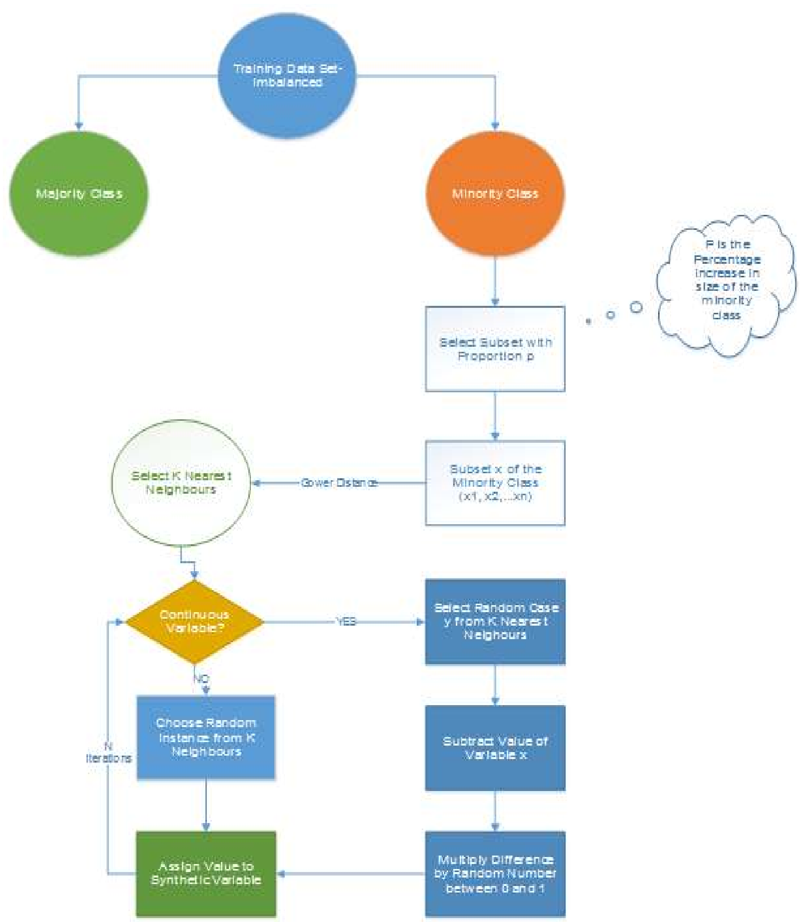

Fig. 4: Synthetic Minority Oversampling Algorithm

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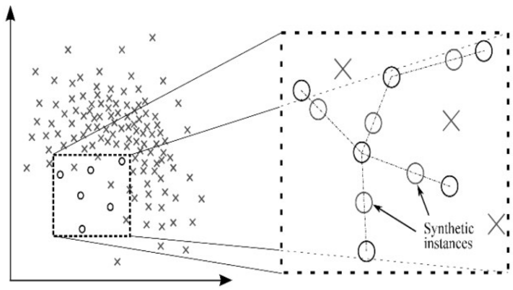

Fig. 5: Generation of Synthetic Instances with the help of SMOTE

iii) Modified SMOTE

It is an altered form of SMOTE. Latent noises in the dataset and the minority class's underlying distribution are not taken into account by SMOTE. A modified technique called MSMOTE is employed to enhance SMOTE's performance.

The samples of minority classes are categorized by this algorithm into three different groups: latent nose samples, border samples, and security/safe samples. The distances between samples of the minority class and samples of the training data are computed to accomplish this.

The data pieces that can enhance a classifier's performance are known as security samples. On the other hand, data points that cause noise can lower the classifier's performance. Border samples are those that are hard to place into one of the two categories.

However, MSOMTE's fundamental flow is identical to SMOTE's (explained in the previous section). The nearest neighbor selection process in MSMOTE differs from that in SMOTE. The algorithm chooses the closest neighbor from the border samples, chooses a data point at random from the k nearest neighbors for the security sample, and ignores latent noise.

III. RESULTS ANALYSIS

The training and test data from SemEval-2014 [10] are utilized to assess the suggested approaches. 800 test sentences and 3000 training sentences drawn from restaurant reviews are included. There are one or more annotated aspect types in every sentence. Every sentence has at least one category, and 20% of the sentences include more than one category, as seen in Fig. 4. Given that 20% of the sentences fall into more than one category, a strategy that can predict numerous categories would be advantageous. Since a single statement might be subject to more than one rule, this is one of the reasons association rule mining is helpful in this situation.

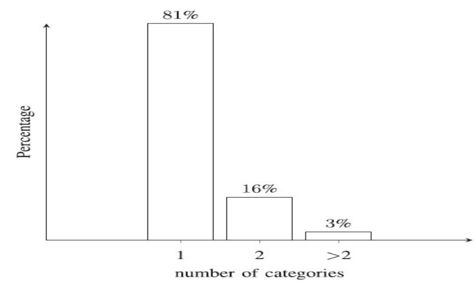

Fig. 6: Distribution of number of aspect categories per sentence.

The proportional frequency of each aspect category is displayed in Fig. 5, which reveals that the two largest categories—food and anecdotes/miscellaneous—appear in over 60% of the sentences. This should make these categories easier to predict than the others, both because there is more information about them and because they are more likely to occur.

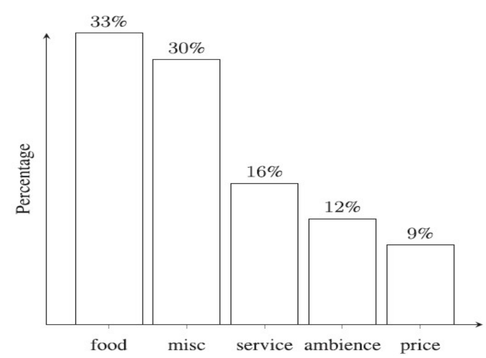

Fig. 7: Relative frequency of the aspect categories.

Finally, the percentage of implicit and explicit aspect categories is displayed in Fig. 6. Given that over three-quarters of the aspect categories are not explicitly addressed in the text, it is evident that employing techniques related to implicit aspect recognition is acceptable in this case.

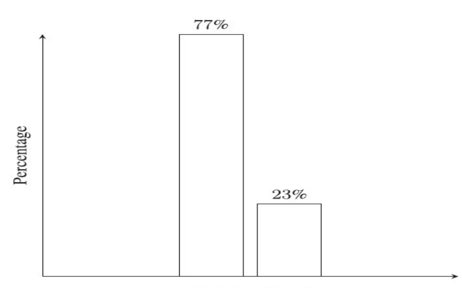

Fig. 8: Ratio between implicit aspect categories and explicitly mentioned ones.

The final category in this data set, anecdotes/miscellaneous, presents a problem because both supervised and unsupervised

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methods perform best for clearly defined aspect categories. The concept of this category is somewhat nebulous, and it is not entirely clear what exactly fits there. Because of this, we have decided not to use any of the real algorithms to allocate this category; rather, the algorithm assigns this category when it finds no alternative category to assign. Given its size and the fact that each sentence comprises at least one category, the features in Fig. 4 further demonstrate that the use of anecdotes/miscellaneous as a "fallback" is warranted.

A) Unsupervised Method

The selected firing threshold and the resulting precision, recall, and F1-score on the test set are shown for each aspect category in Table I. When none of the other four categories are selected in the statement, the category anecdotes/miscellaneous is estimated.

It is clear from Table I that this method struggles to predict the category ambiance. This may be because of the nature of that specific category, which is typically created from a sentence by considering the sentence as a whole rather than being described by a single word.

Table I. Chosen Firing Thresholds and Their Evaluation Scores on the Test Set

Category	TP's	FP's	FN's	τ_c	precision	recall	F_1
food	313	103	105	0.22	75.1%	74.4%	74.8%
service	100	4	72	0.19	96.2%	58.1%	72.5%
ambience	41	10	77	0.09	80.4%	34.8%	48.5%
price	52	16	31	0.09	79.0%	54.2%	64.3%
misc.	163	159	71	-	50.6%	70.9%	59.1%
all	852	157	173	-	70.0%	64.7%	67.0%

B) Supervised Method

After learning the parameters and co-occurrence frequencies on the training set, we assess the supervised technique on the test set. This approach is carried out independently for the dependency indicators, lemma indicators, and a combined version that uses both lemma and dependency indicators, and it is assessed on the test set to see the effect of the dependency indicators. The results are displayed in Tables II–III.

Table II. Evaluation Scores of the Supervised Method with both Dependency and Lemma Indicators on the Test Set

Category	TP's	FP's	FN's	precision	recall	F_1
food	371	51	47	87.9%	88.8%	88.3%
service	159	32	13	83.2%	92.4%	87.6%
ambience	83	28	35	73.8%	70.3%	72.5%
price	74	8	9	90.2%	89.2%	89.7%
anecdotes/misc.	165	38	69	81.3%	70.5%	75.5%
all	852	157	173	84.4%	83.1%	83.8%

Table III. Evaluation Scores of the Supervised Method with Only Dependency Indicators on the Test Set

Category	TP's	FP's	FN's	precision	recall	F_1
food	343	45	75	88.4%	82.1%	85.1%
service	152	27	20	84.9%	88.4%	86.6%
ambience	62	34	56	64.6%	52.5%	57.9%
price	61	5	22	92.4%	73.5%	81.9%
anecdotes/misc.	165	38	69	81.3%	70.5%	75.5%
all	783	149	242	84.0%	76.4%	80.0%

IV. CONCLUSION

Two techniques for identifying aspect categories that are helpful for online review summarization have been provided in this paper. The first, unsupervised approach makes use of both direct and indirect relationships between words by distributing activation throughout a network constructed from word co-occurrence data. As a result, each word has an activation value for each category, which indicates the likelihood that the term will imply that category. This method operates unsupervised, whereas other methods require labeled training data. This method's main disadvantage is that it requires some pre-setting of parameters, particularly the category firing thresholds (i.e., τc), which must be properly calibrated to get good performance. We have provided strategies for setting these parameters.

The second, supervised, approach employs a fairly simple co-occurrence technique in which conditional probabilities are computed using the co-occurrence frequency of annotated aspect categories and both lemmas and dependencies. The category is applied to that sentence if the maximum conditional probability exceeds the corresponding, trained threshold. A high F1-score of 83% is obtained when this method is evaluated on the official SemEval-2014 test set [10].

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