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AN EFFICIENT REVIEW ON ONTOLOGY BASED SENTIMENT ANALYSIS OF PRODUCT AND SERVICE REVIEWS

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ABSTRACT:

With so much opinionated, yet unstructured, information accessible on the Web, sentiment analysis has turned out to be prevalent with the two organizations and analysts. Viewpoint based sentiment analysis goes above and beyond by relating the communicated sentiment in a content to the subject, or perspective, the sentiment is communicated on. This empowers a point by point analysis of the sentiment communicated in, for instance, surveys of items or administrations. In this paper, we propose an information driven way to deal with angle sentiment analysis that supplements customary machine learning techniques. By using normal area learning, as encoded in a cosmology, we enhance the sentiment analysis of a given perspective. The space information is utilized to figure out which words are communicating sentiment on the given angle and in addition to disambiguate sentiment conveying words or expressions. The proposed technique has a very aggressive execution of more than 80% accuracy, fundamentally outflanking the thought about baselines.

Keywords: ontology, sentiment analysis, product reviews, computing aspect sentiment, machine learning .

I. Introduction

With so much opinionated, yet unstructured, information accessible on the Web, sentiment analysis has turned out to be famous with the two organizations and analysts. Its will probably separate the sentiment of substance makers, for example, the authors of buyer surveys, and to total this data into simple to process diagrams, information illustrations, or dashboards. Contingent upon the particular situation, sentiment can be displayed as an arrangement of feelings, or, all the more usually, as a point on an extremity scale going from positive to negative. Extremity can be twofold with simply the positive and negative esteem, or it can be demonstrated as a 5-star score, or even as a genuine number inside a given interim

A philosophy (in data science) compartmentalizes the factors required for some arrangement of calculations and builds up the connections between them.[1][2]

The fields of computerized reasoning, the Semantic Web, frameworks designing, programming building, biomedical informatics, library science, endeavor bookmarking, and data engineering all make ontologies to constrain unpredictability and sort out data. The philosophy would then be able to be connected to critical thinking.

The information thickness of a learning diagram is the normal number of traits and paired relations issued from a given substance and is ordinarily estimated in realities per entity.[3] Although there is no reasonable definition for the term Knowledge chart, it is frequently utilized as the equivalent word for ontology.[4]

What ontologies have in like manner in both software engineering and theory is the portrayal of substances, thoughts and occasions, alongside their properties and relations, as indicated by an arrangement of classes. In the two fields, there is extensive work on issues of ontological relativity (e.g., Quine and Kripke in theory, Sowa, and Guarino in PC science),[6] and discusses about whether a regulating cosmology is feasible (e.g., banters about foundationalism in rationality, and the Cyc venture in AI). Contrasts between the two are to a great extent matters of core interest. PC researchers are more worried about setting up settled, controlled vocabularies, while thinkers are more worried about first standards, for example, regardless of whether there are such things as settled forces or in the case of continuing articles must be ontologically more essential than forms.

Different fields make ontological suppositions that are now and then unequivocally explained and investigated. For example, the definition and metaphysics of financial matters (additionally in some cases called the political economy) is fervently particularly in Marxist economics[7] where it is an essential concern, yet additionally in other subfields.[8] Such concerns cross with those of data science when a reenactment or model is planned to empower monetary choices, for instance, to figure out what capital resources are in danger and by how much (see hazard administration). Some case that every sociology have express cosmology issues since they don't have hard falsifiability criteria like most models in physical sciences and that without a doubt the absence of such broadly acknowledged hard adulteration criteria is the thing that characterizes a social or delicate science

When all is said in done, angle based sentiment analysis strategies can be named information based or as machine learning based [13]. This is obviously not a flawless order, as machine taking in strategies frequently fuse data from word references, for example, sentiment dictionaries. By and by, it is a valuable qualification as machine learning strategies require an adequate measure of preparing information to perform well, while learning based techniques don't. In the quest for superior, machine learning classifiers have turned out to be exceptionally famous to the detriment of information based frameworks. In this paper, we speculate that both have their utilization and that the two techniques are in reality correlative. Utilizing both factual learning and guidelines with an information storehouse is along these lines estimated to work best. Keeping that in mind, we have planned a metaphysics in the eatery space with guidelines to choose what sentiment to appoint in which circumstance, and in addition a sack of-words demonstrate, with extra highlights, for example, a sentiment estimation of the sentence, in view of a Support Vector Machine classifier. With the emphasis being exclusively on the sentiment analysis of viewpoints, the angle identification stage isn't considered in this paper, and consequently, the perspective explanations in the information are utilized as a beginning stage.

II. Related Work

A short diagram of the FIeld of an EFective figuring, which includes sentiment analysis, is displayed in [3]. The creator contends that crossover techniques, joining the instinctive nature and informative energy of learning driven methodologies and the superior of measurable strategies, are the most encouraging approach to enhance the e viability of viable calculations. This structures the exploration theory of this work too, as we consolidate both methodologies in a way that is like [1]. In that work, factual strategies are joined with an arrangement of etymological examples in light of SenticNet [2]. Each sentence is prepared so as to nd the ideas communicated in it. The found ideas are connected to the SenticNet learning store, which empowers the surmising of the sentiment esteem related with the sentence. In the event that there are no ideas communicated in this sentence or if the discovered ideas are not in the information base, at that point a profound learning, pack of-words technique is utilized to decide the sentiment for that sentence. Note this is a sentence-level approach and not an angle based approach like we consider here. Our work has a comparable setup in that it first tries to utilize the learning driven way to deal with make an expectation, utilizing the measurable strategy as a reinforcement when the information base is deficient.

A multi-area way to deal with sentence-level sentiment analysis is displayed in [4]. While the sentiment is doled out to sentences rather than angles, the sentences can originate from various areas, so the proposed strategy needs to disambiguate sentiment words in view of the space the sentence is from. This is like our approach where sentiment words are disambiguated in light of the viewpoint they are about. In an unexpected way, from [4], our philosophy does not highlight a strict division of semantic data and sentiment data. Moreover, [4] utilizes fluffy participation capacities to portray the relations between ideas, sentiment, and spaces, and keeping in mind that this gives all the more demonstrating adaptability, it makes it harder to reason over the information diagram, which is something we need to investigate in this work. Other work that utilizations fluffy ontologies incorporates [8], where a metaphysics is utilized to help in perspective based sentiment analysis. Be that as it may, the utilized philosophy is naturally produced and just catches an idea scientific classification, passing up a major opportunity for the further developed alternatives, for example, utilizing adages for setting subordinate sentiment words.

In [16], a technique is displayed that predicts the sentiment esteem for sentiment-bearing words in light of the setting they are in. For this assignment, a Bayesian model is made that uses the words encompassing a sentiment-bearing word, including the words that mean the perspective, to anticipate the real sentiment estimation of the word given the unique circumstance. Like our approach, it utilizes a two-arrange setup, where a reinforcement technique is utilized when the principal strategy can't settle on a choice. For this situation, if the Bayesian model can't settle on a choice about the sentiment estimation of the word, the past feeling in the content is checked and if there is a conjunction between the two (i.e., no differentiating or nullification words), it will allocate the same sentimental incentive to the present word.

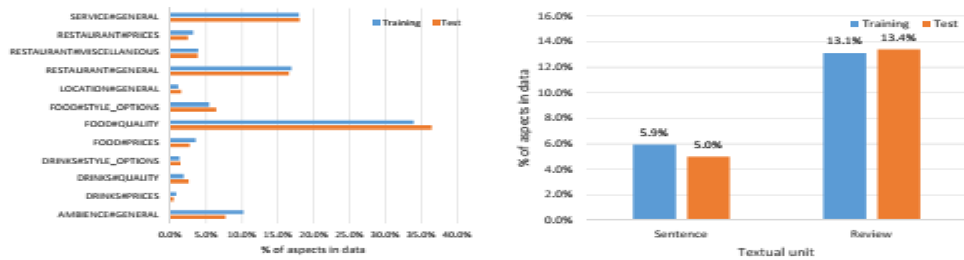
The techniques exhibited in this work enhance our past approach for metaphysics upgraded sentiment analysis, displayed in [14], in two noteworthy ways. Initially, the cosmology is outlined all the more adequately, having the capacity to help both perspective recognition and sentiment analysis better, despite the fact that this work just spotlights on sentiment analysis. This is accomplished by plainly recognizing three kinds of sentiment words: non specific sentiment words that dependably have a similar sentiment esteem paying little mind to the unique circumstance, angle speci c sentiment words that construe the nearness of a solitary perspective and are just relevant to that viewpoint (e.g., \rude" for the administration viewpoint), and setting subordinate sentiment words that are material to in excess of one angle, however not really every one of them, and that may have di erent sentiment esteems for different viewpoints (e.g., \small" being for the most part negative for partitions, yet typically positive for cost). Our past work, while assigning the bland sentiment words in that capacity, does not recognize the second and third sort of sentiment words, which prompts botches.

Last, our past approach used the cosmology inferred data as extra info highlights for the Support Vector Machine (SVM) show, while in the present work we utilize a two-organize approach. In the essential stage, the cosmology is utilized to nd and gather sentiment for the present perspective, and if fruitful, that turns into the expectation of the technique. Just when the cosmology either nds both positive and negative signs, or none by any means, we utilize a SVM model to foresee the sentiment. This optional, or reinforcement, show is a somewhat enhanced pack of-words display that does not utilize metaphysics highlights. For enhanced examination, the execution correlation in Sect. 5 incorporates a SVM show with extra metaphysics highlights, like [14].

III. Specification of Data and Tasks

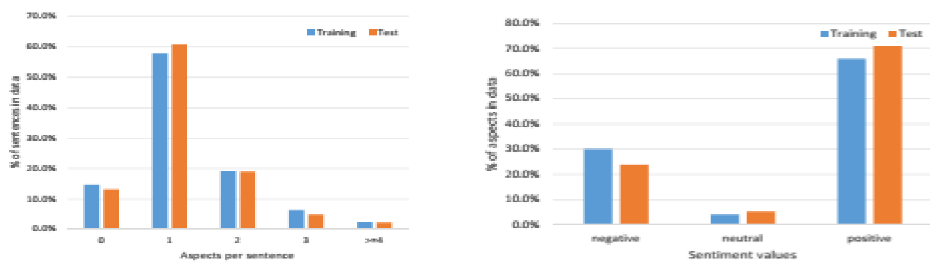
For this examination, the broadly utilized arrangement of eatery audits from SemEval-2015 [12] and SemEval-2016 [11] is utilized. The SemEval-2016 information contains the SemEval-2015 information and comprises of a preparation set of 350 audits inside aggregate 2506 sentiment-named viewpoints and a test set of 90 surveys inside aggregate 859 sentiment-named perspectives. Given that the SemEval-2015 information is a subset of SemEval-2016, it has comparative properties, which are in this way not examined independently. The gave comments al-prepared split the dataset into audits and sentences, and each sentence can be named with at least zero feelings, which is a perspective together with the communicated sentiment identified with that viewpoint.

A few viewpoints are unequivocal, which implies that there is a particular text fragment that communicates that perspective, called the objective articulation, while others are understood implying that there is no such target articulation. The objective articulation, if accessible, is a piece of the gave comments. A few measurements identified with perspectives and sentiment can be found in Fig. 1. In Fig. 1a, the circumstances every class mark shows up is exhibited and in Fig. 1b, the extent of perspectives that have a sentimental esteem that is not the same as the greater part inside the same textual unit is appeared. This gives the base blunder rate for a sentence-level or survey level sentiment analysis framework, individually, as these frameworks are not ready to relegate diverse sentiment esteems to angles inside the same textual unit.



(a) Relative frequencies of each aspect category label

(b) The proportion of aspects that have a polarity that is different from the majority of the aspects within the same textual unit (sentence or review)



(c) The distribution of aspects per sentence

(d) Relative frequencies of each sentiment label

Fig. 1c shows that while most have just one aspect, a signi cant number of sentences contain more than one aspect. This complicates the sentiment analysis as it is not always clear to which aspect a certain sentiment expression pertains. Fig. 1d presents the distribution of sentiment values over aspects, showing that this data set is unbalanced with respect to sentiment.

The task of aspect sentiment classi cation is to give the sentiment value for each aspect, where the aspects are already provided. Thus, all annotations, like the ones given in Fig. 1, are provided, except the values of the polarity elds. The accuracy of the classi er is simply the number of correct classi cations over the total number of aspects to be classi ed.

IV. Methods

All review sentences are preprocessed utilizing the Stanford CoreNLP bundle [9], performing fundamental tasks, for example, tokenization, grammatical feature labeling, lemmatization, syntactic analysis, and in addition sentiment analysis. The last is an officially prepared neural system that allocates a numeric sentiment score to each syntactic constituent in a parse tree.

For the machine learning reinforcement strategy, we settled on a Support Vector Machine (SVM) with an outspread premise work piece, given that SVMs have ended up being exceptionally powerful for text order issues [10]. Since the extremity eld can have three sentiment esteems, a multi-class SVM is prepared that can group an angle into one of three sentiment esteems: positive, nonpartisan, or negative. For this work, the Weka [5] execution of the multiclass SVM is used, which inside performs 1-versus 1 pairwise characterizations.

4.1 Ontology Design

For the metaphysics, the point is to restrain the quantity of stated realities and to utilize the reasoner to deduce the sentiment of a given articulation. The philosophy comprises of three fundamental classes: AspectMention, SentimentMention, and SentimentValue. The last just has Positive and Negative as its subclasses, and the setup is with the end goal that if a specific idea is certain, it is a subclass of Positive and in the event that it communicates a negative sentiment, that idea is demonstrated as a subclass of Negative. The AspectMention class models the notices of viewpoints and SentimentMention models the outflows of sentiment. A schematic review of the metaphysics is appeared in Fig. 2

The SentimentMentions can be separated into three kinds. The principal amass is framed by type-1 SentimentMentions, which dependably mean a positive (negative) sentiment, paying little respect to which angle they are about. In Fig. 3, these are indicated with hexagons. These subclasses of SentimentMention are likewise a sub-class of the sentiment class they express. Consequently, Good is a subclass of both SentimentMention and Positive. Sort 2 SentimentMentions are those articulations that are solely utilized for a specific class of angles, implying that the nearness of the perspective classification can be induced from the event of the SentimentMention. In Fig. 3, these classes are signified with adjusted squares. For example, Delicious is a subclass of SentimentMention, yet additionally of both Sus-tenanceMention and Positive, where SustenanceMention incorporates ideas identified with nourishment and beverages. This implies in the event that we need to anticipate the sentiment estimation of a viewpoint in the administration class, we will overlook the word \delicious" on the off chance that it is experienced in light of the fact that it can't in any way, shape or form be about the present perspective. The third kind (type-3) of SentimentMentions contains context-subordinate sentiment articulations, and this gathering is appeared as a circle in Fig. 3. Here, the deduced sentiment relies upon the angle classification. For example, Small, when joined with Price, is a subclass of Positive, while when it is joined with Portion it is a subclass of Negative. A portion of the words in this gathering are not vague perse but rather are essentially not characteristic of a specific angle class while in the meantime not being for the most part pertinent. An illustration is an idea Fresh, which is constantly positive, yet must be joined with specific viewpoints: it coordinates well with subclasses of Sustenance Mention (e.g., \fresh fixings") and Ambience-Mention (e.g., \a crisp stylistic layout"), however not with subclasses of, e.g., PriceMention or LocationMention.

At the point when a sort 1 SentimentMention is experienced, its sentiment esteem is utilized for the order of all perspectives inside extension (i.e., the sentence). While the extent of the entire sentence can be considered excessively expansive, as non specific sentiment words normally apply to only one perspective, not every one of them, in preparatory investigations, it was demonstrated that restricting the degree to a word window or to ventures over the linguistic diagram is problematic. A sort 2 SentimentMention is utilized for the order of viewpoints that have a place with the inferred perspective classification. For type-3 SentimentMentions, another class is made that is a subclass of both the property class and the viewpoint class. On the off chance that the metaphysics gives any data on that mix, its sentiment esteem can be induced. Something else, the metaphysics does not give any sentiment data to that mix of viewpoint and property.

The cosmology is lexicalized by appending comments of sort lex to every idea. An idea can have numerous lexicalizations, and since this cosmology is intended to work inside a solitary space, there are relatively few equivocal words that would point to in excess of one idea in the metaphysics. Moreover, a few ideas have at least one viewpoint properties, which connect an idea to one of the perspective classifications in the information comments. This implies such an idea, and the majority of its subclasses t inside that viewpoint classification. For example, the Ambience idea has a perspective property with the esteem \AMBIENCE#GENERAL". Last, ideas that are a subclass of SentimentValue have an antonym property that connections that idea to its antonym (e.g., Positive has antonym Negative). This is utilized when discovered metaphysics ideas are liable to invalidation.

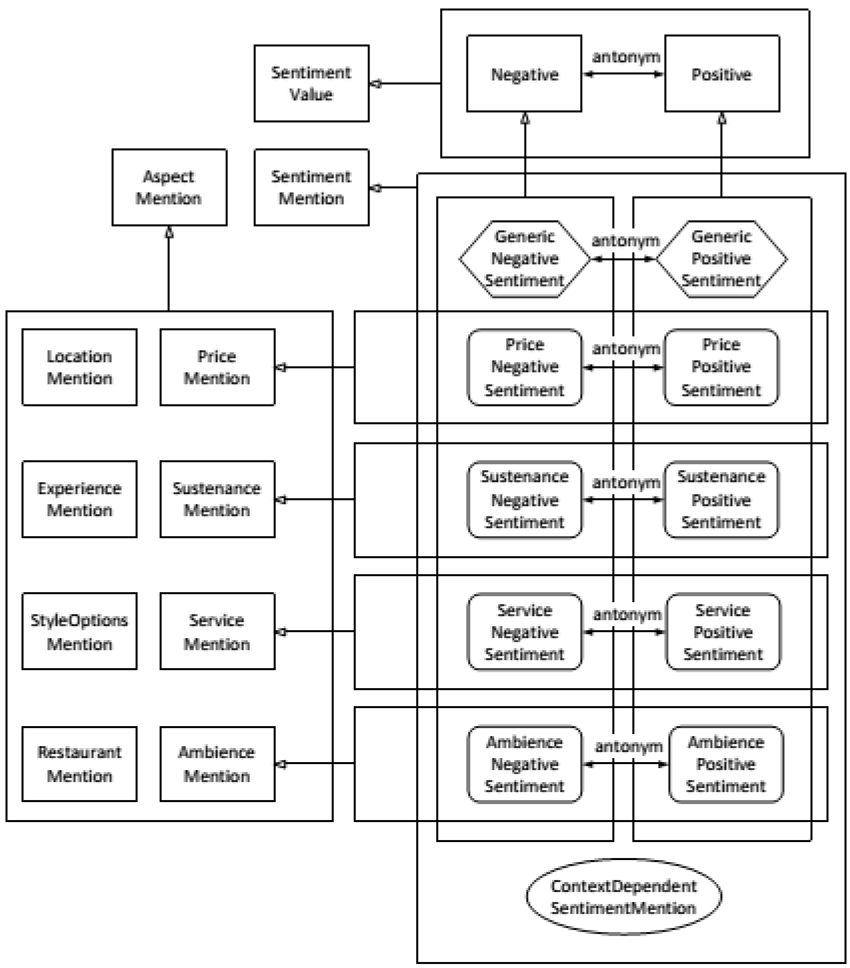


Fig. 2: A schematic overview of the main ontology classes

For this research, a domain ontology is manually constructed using the Onto-Clean methodology [6], and represented in OWL. To demonstrate the usefulness of ontologies, a choice is made for a relatively small, but focused ontology. Hence, it contains about 365 concepts, predominantly AspectMentions, but also includ-ing 53 type-1 SentimentMentions, 38 type-2 SentimentMentions, and 15 type-3 SentimentMentions. The maximum depth of the class hierarchy, not counting owl:Thing at the top, is 7.

4.2 Sentiment Computation

An overview of the sentiment computation method is shown in Alg. 1, outlining the three cases for type-1, type-2, and type-3 sentiment expressions, respectively. The input for sentiment prediction is an ontology, an aspect, and whether or not a bag-of-words model is used as a backup method in case the ontology does not specify a single sentiment value for this aspect. The predictSentiment method starts by retrieving all the words that are linked to the ontology with a URI and that are in the sentence containing the aspect. It also checks whether the current word is negated or not. For this, we look for the existence of a negrelation in the dependency graph, or the existence of a negation word in a window of three words preceding the current word [7].

In the next step, the type of the concept is retrieved from the ontology and, depending on its type, the algorithm will execute one of three cases. As mentioned before, if the concept is a type-2 sentiment expression, then its inferred aspect category has to match with the current aspect, otherwise, it is ignored. For example, when encountering the word \delicious", it leads to the concept Delicious because of the lexical property, which is a subclass of SustenancePositiveProperty.

1. Delicious 9lex.f\delicious"g

2. Delicious v SustenancePositiveProperty

3. SustenancePositiveProperty v Sustenance u Positive

Furthermore, the Sustenance concept is linked to several aspect categories that exist in the annotated dataset by means of an aspect property.

4. Sustenance 9aspect.f\FOOD#QUALITY"g

5. Sustenance 9aspect.f\FOOD#STYLE OPTIONS"g

Hence, when the current aspect for which we want to compute the sentiment is annotated with either one of those two categories, the word \delicious" is considered to be of positive sentiment. For aspects with a different category, the same word is considered to be neutral.

Algorithm 1 Pseudocode for computing aspect sentiment

```
function predictSentiment(Ontology o, Aspect a, boolean useBOW ) : SentimentValue
Set<String> foundURIs = ?
Set<Word> words = getWordsWithURI(getSentence(a))
for all Word w 2 words do
boolean negated = isNegated(w)
String URI = getURI(o, w)
if isType1(o, URI) then
foundURIs = foundURIs [ getSuperclasses(o, URI, negated)
end if
if isType2(o, URI) ^ CategoryMatches(a,URI) then
```

```
foundURIs = foundURIs [ getSuperclasses(o, URI, negated)
end if
if isType3(o, URI) then
for all String relURI 2 getRelatedAspectMentions(w) do
String newURI = addSubclass(o, URI, relURI)
foundURIs = foundURIs [ getSuperclasses(o, newURI, negated)
end for
end if
end for
boolean foundP ositive = (PositiveSentimentURI 2 foundURIs)
boolean foundNegative = (NegativeSentimentURI 2 foundURIs)
if foundP ositive ^ : foundNegative then
return Positive
else if : foundP ositive ^ foundNegative then
return Negative
else if useBOW then
return getBOWPrediction(a)
else
return getMajorityClass // this is Positive in our data sets
end if
end function
```

If the current SentimentMention is generic (type-1) or matching aspect-speci c (type-2), then all superclasses are added to the set of foundURIs. If the current concept is a type-3, or context-dependent, SentimentMention, we need to check if it is related to an AspectMention and whether the combination of those two triggers a class axiom or not. Hence, we create a subclass with both the SentimentMention and the spec mention as its direct superclasses and add all (inferred) superclasses to the set of foundURIs. If there is a class axiom covering this combination, then the set of all inferred superclasses of this new subclass will include either Positive or Negative. When the current word was determined to be negated, the getSuperclasses method will add the antonym of each superclass instead, provided the ontology has an antonym for that class.

A good example of a Type-3 SentimentMention is Small, for which the ontology contains two sentiment-de ning class axioms in the ontology, as well as a property that links the concept to the lexical representation \small".

1. Small 9lex.f\small"g

2. Small u Price v Positive

3. Small u Serving v Negative

Furthermore, Portion v Serving and we assume the review text contains a phrase like \small portions", \portions are small", or something similar. First, the words \small" and \portions" are linked to their respective ontology concepts by means of the lex attribute. Then, since, Small is neither a generic type-1 SentimentMention nor an aspect-specific type-2 SentimentMention, it is paired with related words in the sentence to see if there are any class axioms to take advantage of. In this case, small is directly related to portions, so a new class is created called SmallPortion, that is a direct subclass of Small and Portion:

4. SmallPortion v Small u Portion

This triggers the class axiom de ned earlier, leading to

5. SmallPortion v Negative

Hence, Negative is added to the list of found classes, as all the other superclasses were already known as superclasses from the two individual classes.The last step is to check whether the previous inferences have resulted in finding Positive or Negative. If wend one but not the other, the aspect is determined to have the found sentiment value. If either no sentiment value is found, or both sentiment values are found, the ontology does not give a definitive answer. In that case, if we opt to use a bag-of-words backup model, then it is used here. If bag-of-words is not used, we default to predicting Positive as that is the majority class.

4.3 Bag-of-words model

The bag-of-words model is used both as a baseline, and as a backup model in case, the ontology cannot decide which sentiment to assign. For the most part, it is a classical bag-of-words model with binary features for each lemma in the review that contains the current aspect. In preliminary experiments, this gave better results than using the lemmas from the sentence only. We hypothesize that this might be due to the fact that with more words, it is easier to get the overall sentiment of the review correctly, while for sentences, being a lot smaller, this would be harder. Given that the majority of the aspects follow the overall sentiment of the review, the effect of having more words to work with is larger than the effect of missing out on those aspects with a sentiment value different from the overall review. Furthermore, there is a set of dummy features to encode the aspect category as well as a numerical feature denoting the sentiment of the sentence. This sentiment score is computed by a sentiment component [15] in

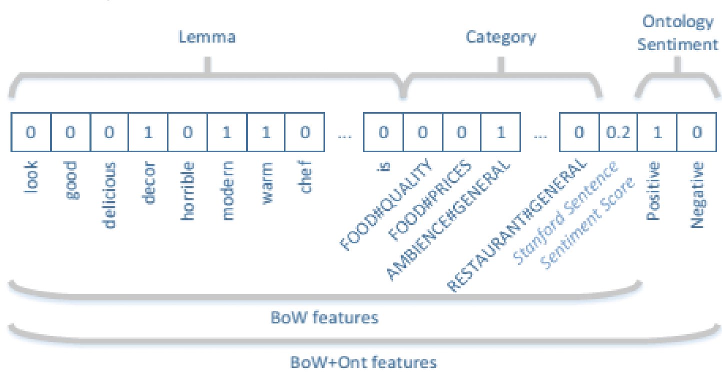


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Fig. 3: Feature vector example for BoW+Ont model

Stanford CoreNLP package and falls roughly in the range of [-1,1]. The model is trained as a multi-class Support Vector Machine that is able to predict positive, negative, and neutral. These last two features are aspect-speci c and sentence-speci c, so the model is technically not bound to predict the same sentiment for all aspects within the same review. The feature vector is illustrated in Fig. 4.

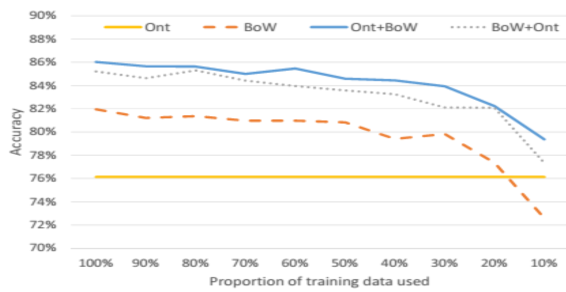

Fig. :4 The accuracy of all four methods at diferent amounts of training data (SemEval-2016)

Table 1: The performance of the ontology and bag-of-words based on whether the Positive and/or Negative concept from the ontology was found or inferred for an aspect

	out-of-sample 2015 data			out-of-sample 2016 data		
	size	acc. ontology	acc. BoW	size	acc. ontology	acc. BoW
Found only Positive	42.7%	**88.1%**	83.7%	55.3%	**93.1%**	87.6%
Found only Negative	9.8%	**94.0%**	85.5%	8.4%	**73.2%**	62.0%
Found both	4.3%	47.2%	**52.8%**	4.1%	62.9%	**68.6%**
Found none	43.2%	33.4%	**77.3%**	33.8%	50.7%	**79.7%**

4.4 Bag-of-words model with ontology features

Other than the run based metaphysics technique utilizing the sack of-words demonstrate as a reinforcement, it likewise bodes well to utilize the pack of-words show as the main model and include cosmology data as extra highlights. Thus, we add two parallel highlights to the pack of-words display, one to indicate that the nearness of the Positive idea and one to signify the nearness of the Negative idea (see Fig. 4). Besides, to keep it in accordance with the manage based cosmology strategy, when both Positive and Negative are available, this is viewed as having no data so the two highlights will be zero.

CONCLUSION

In this paper, a cosmology based strategy for perspective sentiment analysis is presented. It uses space data, encoded in a metaphysics, to nd signs for positive and negative sentiment. At the point when such signs are either not found, or when both positive and negative signals are available, a sack of-words demonstrate is utilized as a reinforcement strategy. The metaphysics based technique and the sack of-words display are appeared to supplement each other, bringing about a half-breed strategy that outperforms both. Since the philosophy based model does not require any preparation information, the execution of the half and half technique additionally depends less on having adequate preparing information, and this impact was shown exactly as well.For future work, we propose investigating growing the cosmology, as there is as yet a substantial gathering of angles for which no sentiment articulation could be found. This procedure could be robotized by scratching eatery reviews from the Web and utilizing the alloted star rating, or something comparable, as sentiment data to characterize discovered articulations as being sure or negative

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