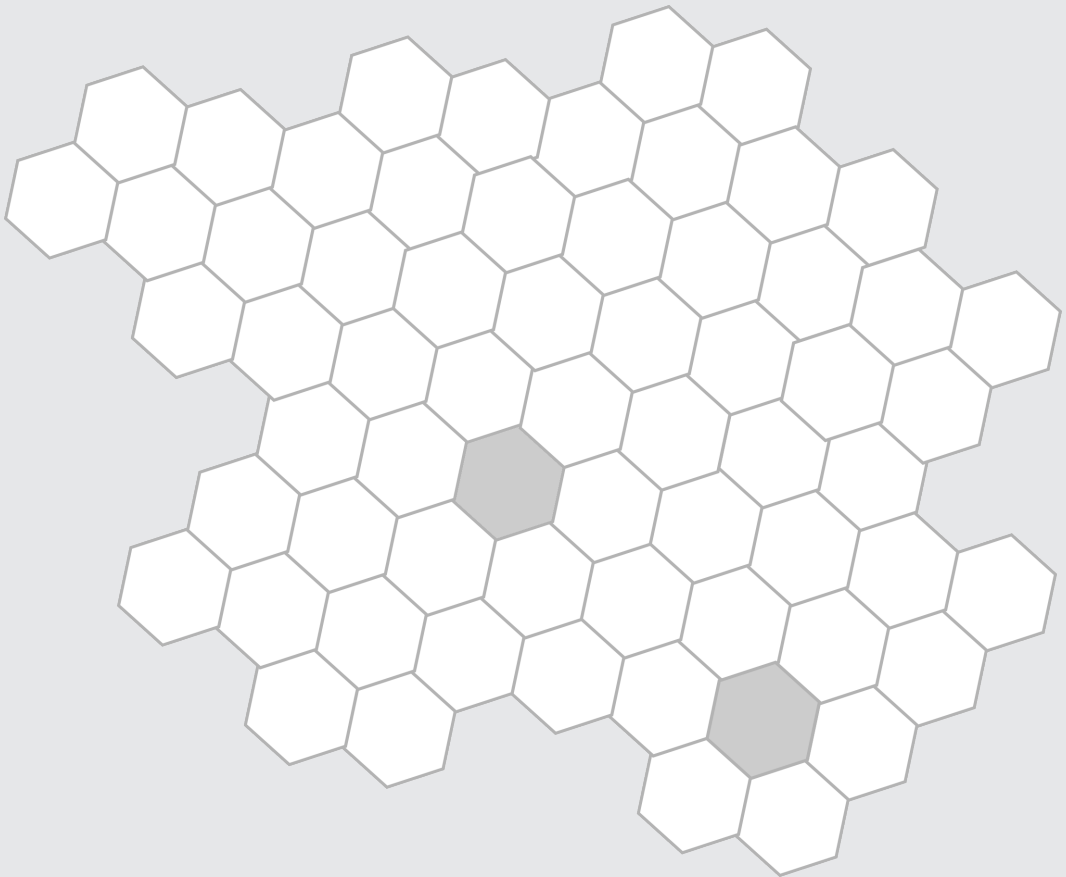


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# The smallest, cheapest, and best: Superlatives in Opinion Mining

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## Abstract

This article introduces superlatives as special indicators for product features in customer reviews. The investigation shows that one type of superlative (called ‘ISA’) is of particular relevance, as instances in this class tend to contain both a feature string and its associated opinion word. An identification of the components of such superlative comparisons can therefore help to solve two Opinion Mining tasks at once: Feature and Opinion Word Identification. The study further introduces and evaluates a novel tool that can reliably identify such superlatives, and extract from them potential product feature strings and opinion words.

## Key words

superlatives; opinion mining; product features; opinion words; adjectives

## Introduction

In recent years, the domain of product reviews has attracted much attention in the area of Sentiment Analysis and Opinion Mining. While the main goal of the former is classification of documents, sentences, phrases or words as positive or negative, the interest in Opinion Mining lies in extracting information about which entities or features of entities are considered as positive or negative, and to summarise this information (HU AND LIU, 2004; POPESCU AND ETZIONI, 2005; CARENINI ET AL., 2005). This is of great benefit not only for companies who want information about customer’s opinions on their products, but also for recommendation systems whose purpose is to assist customers in deciding which product to buy. In general, Opinion Mining systems are required to solve the following main tasks (e.g. HU AND LIU, 2004):

1. Feature Identification
2. Opinion Word Identification
3. Sentiment Classification
4. Opinion Summarisation

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<sup>1</sup> This paper is a printed version of the paper published in the Proceedings of WASSA-2010, see <http://gplsi.dlsi.ua.es/congresos/wassa2010/fitxers/WASSA2010.Proceedings..pdf>.

The first step is to identify features of the products that customers are interested in, usually by using data mining and natural language processing techniques. HU AND LIU (2004) define the term “product feature” as representing both components of an object (e.g. zoom) and their respective attributes (e.g. size).<sup>2</sup> The next step is to identify sentences in the reviews that express opinions about these features. This involves distinguishing opinion words from factual words (subjectivity recognition). To address (3), the system has to determine whether a statement of opinion is positive or negative. Finally, the system also requires techniques for summarising this information (CARENINI ET AL., 2005; CARENINI AND CHEUNG, 2008).

So far, none of the studies in Sentiment Analysis or Opinion Mining have specifically looked at the role of superlatives in these areas. While it has been generally acknowledged that there is a positive correlation between subjectivity and the use of *adjectives* (e.g. HATZIVASSILOGLOU AND WIEBE, 2000), there has not yet been a thorough investigation of *superlative* adjectives and adverbs in this context. This article aims to show that some types of superlative represent a special linguistic means of expressing opinions about products. Consider for example:

- (1) The Panasonic TC-P54G10 is the *best* plasma TV on the market.
- (2) It has the *clearest* picture I have ever seen.

I claim that superlative constructions like (1) and (2) act as special indicators of product features, which contain both the opinion word (the superlative, italicised) and the feature string (underlined). This means that the identification of the components of such superlative comparisons addresses two Opinion Mining tasks at once: Feature and Opinion Word Identification. This article provides evidence for this claim, and introduces a tool which can be used to reliably identify superlatives of interest and extract potential product feature strings from them.

## Previous approaches

Existing work on identifying product features (Task 1) often relies on the simple heuristic that explicit features are expressed as noun phrases. While this narrows down the set of product feature candidates, it is clear that not all noun phrases represent product features. Various approaches to further limiting this set have been proposed. The two most notable ones are HU AND LIU (2004) and POPESCU AND ETZIONI (2005).

HU AND LIU (2004) suggest that nouns or noun phrases that occur frequently in reviews for a particular product are likely to be features. To identify frequent features they use association mining, and then apply heuristic-guided pruning to further refine their results. They further assume that adjectives appearing in the same sentence as frequent features are opinion words, thereby solving Task 2 (however, at the cost of precision). In addition, retrieving nouns and noun phrases that co-occur with these opinion words in other sentences helps their system to identify so-called *infrequent* features, which are also of great interest (PANG AND LEE, 2008).

POPESCU AND ETZIONI (2005), on the other hand, consider product features to be concepts that stand in particular semantic relationships with the product (for

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<sup>2</sup> In this definition, the object itself is also a feature.

example, a camera may have “properties” size, weight, etc., while the lens, flash, etc. stand in a “part” relationship with the camera). Their strategy for identifying such features is to search for corresponding meronymy discriminators. This approach achieves better performance than the one employed by HU AND LIU (2004), but no sentiment analysis is carried out, and opinion words have to be identified in a second step.

Although a previous study by JINDAL AND LIU (2006) investigated graded adjectives in the context of customer reviews, their study is not suitable for identifying product features. They investigate the topic of comparative sentence mining, whose goal is to identify sentences in evaluative texts on the web that express “an ordering relation between two sets of entities with respect to some common features”, and to extract comparative relations from the identified sentences. A follow up study by GANAPATHIBHOTLA AND LIU (2008) builds on these findings and aims to determine which of the extracted entities in a comparison are preferred by its author. However, as JINDAL AND LIU (2006) apply their vector approach to *every* graded adjective in the corpus, this involves a large amount of cases which do not modify “product features” (as identified and annotated by HU AND LIU (2004) in the same corpus). As a consequence, their system is not suitable for the task of identifying product features. Furthermore, even though Jindal and Liu’s system aims to identify the components of superlative comparisons, a closer study showed that their approach does not distinguish between different types of superlatives, leading to incorrect analyses of superlative constructions (SCHEIBLE, 2007). The current study takes different superlative surface constructions into account, and suggests that a particular subclass of superlatives (namely, ‘ISA superlatives’) is especially useful in identifying product features.

## Superlatives in Opinion Mining

Superlatives describe a well-defined class of word forms which (in English) are derived from adjectives or adverbs in two different ways: Inflectionally, where the suffix *-est* is appended to the base form of the adjective or adverb (e.g. *lowest*, *nicest*, *smartest*), or analytically, where the base adjective/adverb is preceded by the markers *most/least* (e.g. *most interesting*, *least beautiful*). Certain adjectives and adverbs have irregular superlative forms: *good (best)*, *bad (worst)*, *far (furthest/farthest)*, *well (best)*, *badly (worst)*, *much (most)*, and *little (least)*. In linguistics, superlatives are usually introduced alongside comparatives as special forms of adjectives or adverbs which are used to compare two or more things, as for example in:

- (3) Bill is *taller* than Sue. [comparative]
- (4) {Joe} is the *tallest* [boy at school]. [superlative]

Superlative constructions like (4) express a comparison between a target entity T (Joe; curly brackets) and its comparison set CS (the other boys at school; square brackets). An investigation of superlative forms showed that two types of relation hold between a superlative target and its comparison set (SCHEIBLE, 2007):

Relation 1: Superlative relation

## Relation 2: IS-A relation (hypernymy)

The superlative relation specifies a property which all members of the set share, but which the target has the highest (or lowest) degree or value of. The IS-A relation expresses the membership of the target in the comparison class (e.g. its parent class in a generalisation hierarchy). For example, in (4), the superlative relation implicitly specifies the property *height*, which applies to all members of the comparison set *boys at school*. Of this set, the target *Joe* has the greatest *height* value. The IS-A relation states that *Joe* is a member of the set *boys at school*. Both relations are of great interest for relation extraction, and SCHEIBLE (2009) discusses their use in applications such as Question Answering (QA) and Ontology Learning. Superlatives occur in a variety of syntactic structures which usually represent different types of comparisons. SCHEIBLE (2009) developed a classification of superlatives based on surface forms (illustrated in Table 1).

Table 1: Superlative classes

	Class	Example
(a)	ISA	ISA-1: The Panasonic TC-P54G10 is the best plasma TV on the market.
(b)		ISA-2: The Samsung is considered the most stylish plasma TV.
(c)	DEF	I bought the cheapest plasma TV.
(d)	INDEF	Plasma TVs represent a most compelling option for home entertainment.
(e)	FREE	The 37" size is best when you are 8-10 feet away from the screen.
(f)	ADV	HD TVs most commonly use progressive scan for 1280×720.
(g)	IDIOM	The 42PC1RR won the Best Plasma TV Award this year.
(h)	PP	The TV weighs about 57 pounds at most.
(i)	PROP	Most cheap TVs have poor quality scalars.

Superlatives belonging to the ISA class are incorporated in a definite NP and contain a clear-cut comparison between a target item and its comparison set. In example (a) in Table 1, the Panasonic TC-P54G10 is compared to other plasma TVs on the market with respect to its overall quality. The difference between the ISA-1 and ISA-2 subclasses lies in the way in which the relation between target and comparison set is expressed. In the case of ISA-1 superlatives, the verb “to be” or appositive form is used, while ISA-2 superlatives involve other forms (e.g. other copula verbs). While superlatives classified as DEF are also incorporated in a definite NP, they differ from members of the ISA class in that the target of comparison is not independently specified in the context. In example (c) the comparison remains ‘implicit’ as the target is not specified in the sentence, except as that which satisfies the superlative NP. When superlative forms are incorporated in an indefinite NP they are classified as INDEF (d). Members of this class are often used as intensifiers. In the FREE class, on the other hand, superlative forms are not incorporated in a noun phrase but occur freely in the sentence. This often makes the comparison less easy to pinpoint: (e) does not compare the 37" size with other screen sizes, but rather the quality of the 37" size viewed from different locations in the room. Superlatives that are derived from adverbs form their own class, ADV (f). Finally, the IDIOM, PP, and PROP classes contain superlatives which do not express proper comparisons: IDIOM contains superlatives that occur as part of

an idiom (g), PP contains so-called PP superlative constructions (h), and PROP includes uses of *most* as a proportional quantifier (i).

This study argues that superlatives of the type ISA are of particular importance in Opinion Mining as they make explicit the IS-A relation that holds between target and comparison set (cf. Relation 2 above). This means that both their target and comparison set are explicitly realised in the text, where the target string often expresses the product, the CS string expresses a feature while the superlative itself expresses the opinion word (as in (a) and (b)). The present study rests on the following claims:

1. ISA superlatives are special indicators for sentences containing product features.
2. The product feature usually appears within their T or CS string, while the superlative expresses its respective opinion word.

The next section briefly describes the data used to support these claims.

## Data

The investigation described in this article uses Hu and Liu's corpus of customer reviews, which was not only the basis of their own study of opinion feature mining HU AND LIU (2004), but has been used as test set by other studies as well, e.g. POPESCU AND ETZIONI (2005). The corpus contains reviews of five products: two digital cameras (Canon G3 and Nikon Coolpix 4300), one mobile phone (Nokia 6610), an mp3 player (Creative Labs Nomad Jukebox Zen Xtra 40GB), and a dvd player (Apex AD2600 Progressive-scan)<sup>3</sup> Sentences in this corpus have been manually annotated with information about product features. Each feature is taken to express an opinion, and labelled as *positive* or *negative* in terms of values on a six-point scale, where [+3] and [+1] stand for the strongest positive and weakest positive opinions, respectively, and [-3] and [-1] stand for the strongest and weakest negative opinions. Hu and Liu's corpus contains 4,259 sentences altogether, of which 1,728 include at least one product feature (40.6%). The remaining sentences in the corpus either contain no product feature (2,217 altogether, 52.1%), or describe a review title, in which case they have been excluded from consideration (314 instances, 7.4%). The corpus contains a total of 230 superlatives in 4,259 sentences, which means that there is around one superlative in every 18 sentences. All 230 superlatives found in the corpus were annotated with class labels as shown in Table 1.

## ISA-Superlatives as product feature indicators

This section aims to provide support for the claim that superlatives are special indicators of product features in customer reviews. In particular, I will show that this especially applies to a subgroup of superlatives (ISA) by analysing the distribution of feature labels across the eight superlative classes in Hu and Liu's corpus of customer reviews. Table 2 shows the overall distribution of superlative classes in

<sup>3</sup> <http://www.cs.uic.edu/~liub/FBS/CustomerReviewData.zip>

Table2: Distribution of features

Class	#S	#T	#F	#N
ISA	71	2	53	16
DEF	45	9	16	20
INDEF	15	10	3	2
FREE	3	1	2	0
ADV	10	0	4	6
IDIOM	12	0	5	7
PP	27	1	13	13
PROP	47	0	23	24
TOTAL	230	23	119	88
	100%	10%	51.7%	38.3%

the corpus (columns 1 and 2). The ISA class is the most frequent with 71 instances (30.9%) (of which ISA-1 accounts for 63 instances, and ISA-2 for 8). The table further shows the proportion of title sentences (T), feature-containing sentences (F), and non-feature containing sentences (N) among the 230 superlative-containing sentences (S) in the corpus. The last row (TOTAL) indicates that the proportion of feature-containing sentences among them is higher (at 51.7%) than the average for all sentences (which is 40.6%, cf. Section 4). What is especially striking is that features are particularly highly represented among sentences containing ISA superlatives: Of 71 ISA superlatives in the data set, 53 occur in a sentence involving a feature (74.6%). This suggests that membership in the ISA class is a good indicator of the sentence containing a product feature.

A closer investigation of the data reveals further interesting results. Among the 119 superlative sentences that contain a feature (column “F”), not all superlatives directly contribute to the evaluation of the feature. For example, the superlative “most” in (5), which belongs to the PROP class, is not directly involved in the evaluation of the feature “firewire” as [-1]. In contrast, the ISA superlative “best” in (6) is directly responsible for the positive [+3] rating of the feature “dvd player”.

(5) it does n’t have firewire, not a real complaint since most windows users do n’t generally have firewire cards themselves . [Creative]

(6) i think , apex is the best [dvd player you can get for the price] . [Apex]

An assessment of all feature-containing sentences with respect to the involvement of the superlative in the feature-rating shows that the IDIOM, PP, and PROP classes are of little relevance, while ISA-1 and ISA-2 clearly are, with the superlative form acting as opinion word evaluating the feature, or acting as intensifier of an opinion word, as for example “complaint” in (7).

(7) [my] biggest [complaint] is the battery life or lack there of . [Creative]

Furthermore, in 34 out of the 46 feature-containing ISA-1 instances (73.9%) and in 6 out of 7 ISA-2 instances (85.7%), the feature is a substring of either the target (as shown in (7) ) or the comparison set spans (6). The importance of the



ISA class is further supported by an investigation which showed that Hu and Liu's annotation is not always consistent. Several of the 16 ISA-1 instances that did not receive a feature label in Hu and Lu's annotation (column "N" in Table 2) do in fact modify a feature. For example, (8) and (9) make a similar positive statement about a camera, however only (8) was annotated with a feature (player[+3]). To be consistent, (9) should receive the same feature label. Example (10), on the other hand, is similar to (7) in that the superlative intensifies a negative evaluation (*drawback* vs. *complaint* in (7)) of a feature (*software* vs. *battery life*), however only (7) received a feature label (battery life[-3]). Given the structural and semantic similarities of the examples, one could clearly argue for adding a feature label "software[-3]" to (10).

- (8) compared to everything else in this category , this is most definitely [the] best [bang for the buck] . [Creative]
- (9) i did a good month 's worth of research before buying this over other similar priced digital cameras , and this is [the] best [buy for the buck] . [Canon]
- (10) [the] biggest [drawback that people have about the zen xtra] is the software . [Creative]

The findings of this section corroborate the claim that ISA superlatives are special indicators of product features. Their identification could simultaneously help to solve Opinion Mining tasks 1 and 2 (see above) as they frequently contain a product feature within their T or CS string, and at the same time express its associated opinion word. As this strategy for finding product features does not depend on frequency (unlike Hu&Liu's approach), ISA superlative identification also represents an efficient way of locating so-called *infrequent* features, which are also of great interest in Opinion Mining.

## Automatic identification of potential product features using superlatives

Having established a positive correlation between ISA superlatives and product features, the following sections describe how instances of this superlative type can be automatically identified and how potential product feature strings can be extracted from them, using Hu and Liu's corpus of customer reviews as data set. The tool used to achieve this is SRE ('Superlative Relation Extractor'), a system implemented in Python3 which can be used to:

- 1) Identify superlatives in text;
- 2) Classify superlative instances according to the surface forms described in Table 1;
- 3) For superlatives classified as ISA-1, identify the spans of the target and comparison sets.

Initially, component 1) (called 'SUP-Finder') is used to find superlative instances in Hu and Liu's corpus of customer reviews. Next, the Classifier in 2)

Table 3: List of abbreviations

Abbreviation	Description
CS	Comparison set of a superlative comparison
T	Target of a superlative comparison
SRE	Superlative Relation Extractor
SUP-Finder	Component of SRE used to identify superlatives in text
SUP-Classifier	Component of SRE used to classify superlative instances according to the surface forms described in Table 1
ISAI-Identifier	SUP-Classifier module used to identify ISAI-superlatives
T/CS-Identifier	Component of SRE used to identify the spans of the target and comparison sets of superlatives classified as ISAI
CS-Identifier	Sub-component of T/CS-Identifier used to identify comparison set spans of ISAI superlatives
T-Identifier	Sub-component of T/CS-Identifier used to identify target spans of ISAI superlatives
CSDet	Determinative phrase of the superlative NP, e.g. <i>the</i> in <i>the best TV on the market</i>
CSHead	Head of the superlative NP, e.g. <i>TV</i> in <i>the best TV on the market</i>

(‘SUP-Classifier’) is used to identify<sup>4</sup> ISAI types among the retrieved superlatives, which are then input into component 3) (‘T/CSIdentifier’) to extract potential product feature strings (which have been shown to occur as substrings of the target or comparison set spans). Table 3 shows an overview of common abbreviations used in the following sections.

The SRE tool was originally developed on a corpus of Wikipedia texts (TextWiki corpus; SCHEIBLE, 2008). It employs a rule-based approach based mainly on tag sequences and dependency relations (using the output of the C&C tools, cf. CLARK AND CURRAN, 2004). SRE employs rules rather than machine learning due to the relatively small size of the gold-standard data set and the low frequency of some superlative types, which would represent a problem for a learner. An additional difficulty concerns the fact that the tools used to obtain the tags and dependency relations will have been optimised to correctly tag frequently occurring phenomena in its target text type, in order to achieve the highest possible performance score. As superlatives are relatively low frequency phenomena, with most types occurring far down the end of low frequency patterns (part of “the long tail”), even a relatively high-performance tagger like C&C may perform poorly at tagging them, because it will make little difference to the tagger’s overall performance score. SRE’s approach involves highly flexible and fine-tuned rules which can take these factors into account wherever necessary.

The following sections describe the three components of SRE and assess their suitability for the purpose of identifying potential product features in customer reviews. As SRE was originally developed on Wikipedia texts, its performance is expected to be affected by the non-standard nature of the data and the tagging/parsing errors that are likely to result from this.

<sup>4</sup> SRE is freely available upon request (email the author of this paper at [Silke.Scheible@manchester.ac.uk](mailto:Silke.Scheible@manchester.ac.uk).)

## Superlative detection

### *Method*

As a first step, superlatives in the corpus are automatically identified using the SUP-Finder component of SRE. As stated earlier, superlatives are derived from their base adjective/adverb in two different ways: inflectionally or analytically. In the first case, the inflectional suffix *-est* is appended to the base form of the adjective or adverb (e.g. *largest*), while in the second case they are preceded by the analytical markers *most/least* (e.g. *most beautiful*). In addition, there is a (limited) number of irregular forms, such as *best*, *worst*, or *furthest*.

Previous automatic approaches to identifying superlatives have mainly focussed on techniques involving a search for the POS tags JJS and RBS (e.g. BOS AND NISSIM, 2006), usually without carrying out a detailed error analysis due to the large amount of manual intervention that is required for a gold standard. The SUP-Finder tool aims to improve on the POS-based approach by using a pattern matcher based on regular expressions and a list of “superlative distractors” (i.e. a list of clear cases of non-superlatives, such as *nest*, *protest*, or *honest*), which are excluded from consideration. As superlatives form a well-defined class with a limited number of irregular forms, this pattern-based search works very well, and has been shown to outperform a POS-based approach by 2-3% with 99.0% precision and 99.8% recall<sup>5</sup> on Wikipedia texts (SCHEIBLE, 2009).

### *Results and discussion*

Unlike the POS-based approach, which has been optimised to work well on a particular text type, SUP-Finder is independent from text type and can be assumed to work equally well on customer review data. With its recall value nearing 100%, SUP-Finder was only assessed for precision in this study. The list of 231 superlatives returned by the tool was manually checked. Only one false positive was found, which had been missing from the list of “superlative distractors” (*hobbyist*, a mistyped version of *hobbyist*). The precision value is therefore 99.6% (230/231).

## Identifying ISA superlatives

### *Method*

The task of the second component of SRE, SUP-Classifier, is to classify superlatives as ISA-1, DEF, INDEF, etc. SUP-Classifier consists of a cascade of modules, each of which applies a set diagnostic tests to determine which class a given superlative instance belongs to. Here the focus is on the module that identifies an instance as belonging to ISA-1, called ISA1-Identifier.<sup>6</sup> This module requires substantial syntactic information, for example on whether the superlative form is bound in a definite NP, and if so, what the indices of the NP head and the determiner are. Furthermore, as the target of comparison needs to be explicitly mentioned in the sentence (cf. Section 3), the ISA1-Identifier component makes extensive use of the Grammatical Relations output of the C&C parser. Two main cases

<sup>5</sup> The only error affecting recall was due to incorrect tokenisation of quotes.

<sup>6</sup> Due to the low frequency of ISA-2 types, I will restrict this investigation to ISA-1 types only.

Table4: GR output for “The Panasonic is the best TV.”

Row	GR output
1	(det Panasonic.1 The.0)
2	(ncmod _ TV.5 best.4)
3	(det TV.5 the.3)
4	(xcomp _ is.2 TV.5)
5	(ncsubj is.2 Panasonic.1 _)

are distinguished: Instances where the IS-A relation between target and comparison set is expressed via the verb “to be”, or via apposition. The strategy for the former case is as follows:

- Step 1: Locate the position of the comparison set head (CSHead) within the sentence
- Step 2: Test whether the relation word between the CSHead and its dependent is a form of “to be”
- Step 3: Find the corresponding target entity

If all three steps succeed, the instance is classified as ISA-I. The first step is addressed by testing whether the head of the superlative NP (CSHead) occurs in subject (ncsubj) or complement (xcomp) position, as for example in (11).

- (11) The Panasonic is the best [TV]CSHead.

The output of the C&C parser for this sentence is shown in Table 4. To fulfil Step 1, the Identifier first searches for a GR tuple where CSHead (here: TV) stands in an xcomp position (Row 4 in Table 4). Step 2 is then met by checking if the item in the second slot of this tuple is a form of “to be”. If it is, Step 3 is addressed by searching the GR list for another tuple where the identified verb stands in an ncsbj relation with another word (the suspected target, cf. Row 5).

Instances where the ISA relation is expressed via apposition receive a different treatment, and the following general steps are applied:

- Step 1: Test whether CSHead stands in a conj relation with any item (but excluding instances of *and*)
- Step 2: Search the GR List for the “linked” item (the suspected target)
- Step 3: Locate the position of the CSHead and the target in the sentence (ncsubj or dobj)

First, the list of Grammatical Relations is searched for tuples where CSHead stands in a conj relation with another word. For example, in the following sentence, Step 1 identifies the comma with index 2 as potential appositive conjunction (cf. Table 5, Row 4):

- (12) The Panasonic, the best [TV]CSHead, has a PC video port.

Table5: GR output for “The Panasonic, the best TV, has a PC video port.”

Row	GR output
1	(det Panasonic_1 The_o)
2	(nmod _ TV_5 best_4)
3	(det TV_5 the_3)
4	(conj ,_2 TV_5)
5	(conj ,_2 Panasonic_1)
6	(nmod _ port_11 video_10)
7	(nmod _ port_11 PC_9)
8	(det port_11 a_8)
9	(dobj has_7 port_11)
10	(nsubj has_7 TV_5 _)
11	(nsubj has_7 Panasonic_1 _)

Table6: Results of SUP-Classifier

Class	Precision	Recall	F-measure
ISA-1	(53/56) 94.6%	(53/62) 85.5%	89.8%
Baseline	(33/115) 28.7%	(33/62) 53.2%	37.3%

Addressing Step 2, the Identifier then searches for another tuple in the list of Grammatical Relations with *conj* in first position and the comma with index 2 in second position (finding the tuple in Row 5). This is identified as a potential “linked” target. Step 3 distinguishes appositions like (12), which appear in subject position, from cases like (13), which appear in object position.

(13) I decided to order the Panasonic, the best TV.

A test is carried out to determine whether both target and *CSHead* stand in a *nsubj* position via the same word. Rows 10 and 11 in Table 5 show that both “TV” and “Panasonic” stand in the required relation via the word “has” with index 7. The Identifier therefore concludes that the superlative appears in an apposition and classifies it as ISA-1.

### Results

SUP-Classifier is tested on the output of SUP-Identifier, i.e. all superlative-containing sentences in Hu and Liu’s corpus (230 altogether).<sup>7</sup> The results are displayed in Table 6.

The results show that SUP-Classifier clearly outperforms a random baseline system. With 94.6% precision and 85.5% recall, it can be reliably used to identify ISA-1 superlatives in customer reviews.

<sup>7</sup> However, five of the 230 instances were excluded from evaluation as the C&C parser failed to parse them.

## Discussion

The non-standard nature of the data in customer reviews does not seem to have had the anticipated negative effect on the performance of the Classifier. Surprisingly, its performance is better on this text type than on the corpus of Wikipedia texts used in SCHEIBLE (2009), where ISA-1 achieved 82.4% precision and 84.3% recall. A closer investigation of the gold-standard ISA-1 superlatives shows that this improvement is likely to be due to a simpler syntactic structure of ISA-1 cases in customer reviews, leading to better parser performance. The C&C tool's inability to handle non-standard language mainly affected recall. For example, (12) was classified as INDEF because the system failed to identify "it 's" as erroneous variant of the possessive pronoun "its" (incorrectly tagged as personal pronoun, PRP, and 3rd person singular present tense verb, VBZ). Example (13) was not recognised by the parser because "about" is interpreted as preposition (IN) rather than as a preceding adverb (RB).

(12) i think this is itPRP 'sVBZ biggest flaw .

(13) if you do any research into digital cameras, you 'll quickly find tha t this camera is justRB aboutIN the best value out there.

## Identification of potential product feature strings

### Method

The third component of SRE, T/CS-Identifier, identifies potential feature-containing strings by extracting the target and comparison set strings of ISA-1 superlatives. The tool consists of two parts: a comparison set span identifier (CS-Identifier), and a target span identifier (T-Identifier). Their goal is to identify all relevant constituents of the T and CS phrases, which is a major challenge because both can have pre- and postmodifiers, the latter of which may be restrictive or nonrestrictive (SCHEIBLE, 2008). To achieve maximum accuracy, T/CS-Identifier uses a fine-grained set of rules based on the lexical annotation output of the C&C tools. This approach was chosen as the GR output by the C&C parser proved to be unreliable due to the non-standard nature of the data. Similar problems are described by Bos AND NISSIM (2006). The present task assumes that both target (T) and comparison set (CS) comprise a single span. The CS span is defined as consisting of a determinative phrase (CSDet) and the main CS phrase (CSMain). To identify the determinative phrase, the tool uses a purely pattern-based approach (based on POS tags). The main CS span is determined by rules which aim to identify all pre- and postmodifiers of CSHed (cf. Section 6.2). Generally, tokens occurring between the superlative form and CSHed are included as premodifiers. Postmodifiers are identified using a set of patterns which were devised to match common types of superlative postmodifiers. Target identification involves locating the target in the sentence, and identifying all restrictive pre- and postmodifiers. The following sentences are examples of superlatives for which T/CS-Identifier is able to correctly identify the target (curly brackets) and comparison set spans (square brackets), with the product feature underlined.

Table7: Performance of T/CS-Identifier (Accuracy)

Component	SRE	Baseline
CS-Identifier	62.9%	17.7%
- CSDet	98.4%	88.7%
- CSMain 64.5%	22.6%	
T-Identifier	66.1%	37.1%

(14) i think , {apex} is [the] *best* [dvd player<sub>+3</sub> you can get for the price] .

(15) in my opinion [the] *worst* [issue on this phone] is {the sidemounted volume control-3}.

### Result

Table 7 shows the results of running T/CS-Identifier on the ISA-1 superlatives in Hu and Liu’s data set. The baseline system assumes “the” as CSDet, and the first word following the superlative as the beginning of the CSMain, and the first word tagged as NN.\* in that sequence as the end. The CS span is marked as correct only if both components CSDet and CSMain are exact matches with the gold standard. The baseline target identifier chooses the sequence of NP chunks closest to the superlative as target span.

Both components clearly outperform their respective baselines.

### Discussion

The majority of errors in the CSMain span were caused by the tagger/parser, in cases where a restrictive “bare” relative clause starting with the pronoun “i” follows the CSHHead. In (16), the parser falsely interprets “i” as the NP head because of its non-standard spelling (which caused it to be tagged as plural noun NNS instead of personal pronoun PRP). A quick test confirmed this: Running the same sentence through the tagger with “I” capitalised resulted in the correct analysis.

(16) {this} is [the] *best* [dvd player i] ’ve purchased .

(17) {this} is [one of the] *niciest* [phones nokia] has made .

Similarly, in (17), the token “nokia” was tagged as common noun (NN) and not recognised as a new NP chunk (“B-NP”) indicating the start of a relative or subordinate clause. In both cases, the CS span breaks off incorrectly (square brackets).

While CS-Identifier performs worse on customer reviews compared to its original domain (Wikipedia texts, where it achieved 88.8%), the situation is the reverse for T-Identifier, despite the nonstandard nature of the data (66.1% vs. 58.4% in Wikipedia). This is largely due to shorter sentences and fewer appositions, which positively affect the target location methods. Furthermore, the target heads are often pronouns (“this”, “it”) or simple NPs such as “Apex” with no pre- or postmodifiers (30 out of 62 instances), which do not represent a problem to T Identifier. The fact that a large proportion of targets are represented by pronouns immediately raises the question of pronoun resolution. However, a first investigation of

the data suggests that the great majority of the pronouns “this” and “it” refer to the entity under review.<sup>8</sup> With respect to the goal of the current investigation (i.e. identifying product features), pronouns in the target string do not represent a problem, as most product features occur in the comparison set string.

## Conclusion and future work

This article established ISA-I superlatives as special indicators of product features in Opinion Mining, which not only contain the feature strings (in most cases as part of the CS), but also the opinion word (usually the superlative itself), addressing two Opinion Mining tasks at once. Although superlatives are of relatively low frequency, the study supports previous findings that superlatives are perceived as interesting and important by people (SCHEIBLE, 2007), and Section 5 highlights their importance in customer reviews. The study further introduced SRE as a tool to reliably identify ISA-I superlatives automatically, and to extract from them potential product feature strings. As this strategy for finding product features does not depend on frequency, it represents an efficient way of locating *infrequent* features, which are also of great interest in Opinion Mining. SRE can be used as a stand-alone system for finding product features involving ISA comparisons, or it could be incorporated as an additional component in an existing Opinion Mining system. While this is unlikely to make a considerable improvement to the overall performance score of such a system due to the relatively low frequency of superlatives, it promises to yield accurate results that are of special interest to the users.

Having automated the detection of ISA-I superlatives and their components, the important final question is how these results can be used to arrive at the product features they are assumed to contain. As previously mentioned, the feature is a substring of either the target or the comparison set in 34 out of the 46 instances (73.9%). As the majority of them (27) occur as part of the comparison set, one strategy would be to assume that the product feature substring is the NP-chunk containing the CSHead. This simple approach would work for 25 of the 27 cases. Crucially, as most of the errors in automatically detecting the CS span were in recognising postmodification, product features can still be correctly identified as they only require identification of the CSHead chunk.

Finally, while this article has focused on the role of ISA-I superlatives in Opinion Mining, another interesting and potentially useful class is represented by DEF, illustrated by (18) and (19), which express positive statements about the features “image quality” and “lens adapter”, respectively.

(18) overall , the g3 delivers what must be considered the *best* image quality of any current > 4 megapixel digicams , from a detail , tonal balance and color response point of view .

(19) they got the *best* lens adapter for the g3-better than canon 's .

While the distribution of product features across the DEF class does not hint at their importance (cf. Table 2), one needs to consider that the DEF class is based

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<sup>8</sup> This claim would however have to be verified by a thorough investigation of the context.



on surface forms and contains a variety of different semantic types, of which only the so-called “relative set comparisons” type may be of interest. Future work will therefore involve finding techniques to distinguish this type from the other semantic types found in the DEF class.

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