Comparative Search of Entities

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Received 26 March 2017

Revised 27 June 2017

Accepted 22 July 2017

Nowadays, every manufacturer or retailer displays their product information on various websites. The customer has to visit, the number of such web pages to choose the right product, because the information is not available at one place. There are some websites that show such information in one place, but they are product specific and in general information is manually updated. In this paper, we propose a novel concept of web-spreadsheet, which displays product information by crawling through related web pages and generates information like a spreadsheet where each row represents product information and each column represents product attributes. We are extracting the product name of specified product class using decision tree-based classifier by features obtained using Part of Speech (POS) tagging and distance measure. It also extracts the value-measure pairs of preset attributes using distance measure, POS tagging and Data type. This approach will save a lot of time of comparing different products and customers need not have to scan a number of websites for comparison. We present promising results in various product classes which surpass many existing techniques in the literature. The proposed method can work accurately without initial trained labeled data which is expensive to obtain.

Keywords: Entity extraction; attribute value extraction; product comparison; web spreadsheet.

1. Introduction

Fastest growing e-commerce world has provided tremendous opportunities to the customers for purchasing products from different manufacturer or retailers site, such as Amazon.com, Flipkart.com. However, the features and the price of the product are biased towards one site. Single website provides a limited amount of information regarding features (attributes) of the product. For a product, prices

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also may vary from one website to another. Customer will find various values of the features (attributes) as well as prices for a particular product on different retailer sites. Therefore, the customer has to visit various retailer's site to choose the right product.

For a specific product, some websites display the complete information, but they lack in showing the information for other products. In future, if any, change to the product information occurs, information is manually updated by them. There are some websites, which provides the facility to compare the similar class products. The customers pick the products of their choices, compare the features and select the most suitable ones. In this comparison process, generally all the features are taken into consideration. Some customers are mainly interested in specific attributes of the product before purchasing it, which is unhandled in the current comparison process.

A web-spreadsheet view will satisfy the customer and handles all the above discussed scenarios. Hence, in the proposed research, the authors focus on a novel search problem for comparative search of entities (CSE). The main objective of CSE is to extract relevant and attribute level information related to entities along with the entity (product) name in the form of a spreadsheet. Attributes, in which customers are interested, are chosen in advance which will form the columns of the spreadsheet. Product information, i.e. values (consisting of value-measure pair) are extracted efficiently by crawling through related web pages. This approach provides all information (value) for a particular products attribute.

CSE is inspired by Relational Aggregated Search (RAS) which is a new information retrieval area emerging nowadays. In RAS, information is extracted and aggregated in the form of small chunks using their relations. RAS consists of three main components, namely Query Dispatching, Relation Retrieval and Result Aggregation [1]. In the proposed work, authors mainly focus on Relation Retrieval and Result Aggregation operation. In Relation Retrieval, authors targeted on instance-class relation to retrieve complete entity name and instance-attribute relation to extract value-measure pair given predefined attribute and its data type. For example, if a user submits a query for the product class Tablet with attributes such as Price, Display, Camera and Memory then the entities belongs to that product class and attribute values of those entities are retrieved.

This approach would not only reduce the effort of user by crawling through each hyperlink for finding relevant information, but also able to deliver fine grained attribute-value information.

Gathering the information in a consolidated spreadsheet is having following challenges.

- Each webpage consists of descriptions of particular entity, which is stored in a much unstructured manner. The entity name may appear on a webpage in ambiguous form. For example, when user intention is electronic tablet, it may search webpage of medicinal tablet.
- On the web page, the attribute value pair may not be directly specified, so correct value of the attribute has to be extracted.

Considering above challenges, the research work is carried out and the major contributions of it, is summarized as follows:

1.1. Contributions

- A novel complete entity name extraction process is proposed to extract complete entity name from unstructured text.
- A novel value-measure extraction method is designed to extract value-measure pair of the specified attribute and its data types and which works independently of sequencing of attribute and its value.
- Extraction of adjective type values whose attribute is noun are fetched using unique string type value extraction methodology using the Word Net.
- Generating web-spreadsheet dynamically without referring any additional information and irrespective of domain without targeting some specific set of retailer websites.
- To our best knowledge, no other system is designed which extracts entities of specific product class, value-measure pairs for a given preset attributes as we have addressed in this paper. Our web crawler crawls almost all related web pages to efficiently extract entities and value-measure pairs.
- For entity and attribute-value extraction, the proposed method achieves very good accuracy which is measured in terms of precision, recall and F1-measure that is comparable to prominent entity and attribute value extraction methods discussed in the literature.

2. Related Work

Various techniques illustrate the extracting information from unstructured documents that are natural language documents [2, 3]. A template independent wrapper has been developed which exercises labeled news pages from a single site [4]. This wrapper has been used to extract plain texts of news embedded in news article body. The relation between news article and news body is also explored by developing novel features for them. Geographical coordinates and addresses of various organizations from unstructured web sites of organizations are extracted in [5].

Some techniques also deal with semistructured documents [6]. These documents are based on HTML, in which information is stored in different structures like forms, lists, tables. Semantics from semistructured data from web documents using ORA-SS (object- relationship- attribute model) are efficiently extracted [7]. ORA-SS is used to facilitate designing of semistructured databases. A technique [8] of materials knowledge extraction from HTML tables which is based on sibling comparison has been addressed.

Many named entity extraction technique has been proposed in the last few years and still today, named entity extraction is challenging problem because, entities are

scattered over web pages in unstructured and ambiguous manner. Extracting entity (instance) from web pages by identifying instances-class relation is also demanding.

Work presented by [9], addresses domain independent unsupervised named entity extraction method. Using predicates and patterns, named entities are extracted from web corpus. In this work, a set of rules is created using Bootstrapping, which uses domain independent extraction patterns. These rules are applied to extract the information from web pages. Based on mutual information between extracted instances of a class and set of discriminator associated with that class, the accuracy is calculated.

Named entity recognition technique using undirected graphical models called as Conditional Random Fields (CRFs) has been depicted [10]. Automated feature induction method has been used in this work. Initially, atomic features are created by the user. As compared to traditional approaches accuracy is improved. It also reduces feature count. Experimentation has been performed on CONLL-2003 named entity shared task dataset.

Focus on context patterns for extracting named entity from unlabeled data has been worked out [11]. In this work, language independent technique is used. The initial seed list is created and it is expanded gradually by searching more instances for matching context patterns from unlabeled data.

Support Vector Machine (SVM)-based parser has been proposed [12]. Using statistical techniques for an input sequence n -best words are calculated with the features based on their character position and the type. Finally, SVM is used to aggregate character into words and named entity is identified. This work uses CRL NE data for evaluation.

Many researchers have done work in the past few years on extracting features in terms of attributes and their values from web pages. Recent work on extracting pairs of comparative sentences from online reviews of products has been discussed [13]. In this work, features are extracted from pros and cons sentences of the customer views of the product. Using POS tagging, frequent occurrence of noun and noun phrases are treated as features. Frequent feature identification from online reviews is focused [14]. In this work, opinion words are identified initially. Then, semantic orientations (positive or negative) of opinion words are determined using bootstrapping technique, which is based on Word Net. Point of mutual information between noun phrases and related context pattern for extracting product features and opinions from reviews has been calculated [15]. Work done in [16], targets on mining frequent features based on association rule mining technique and natural language processing methods.

Technique for extracting attribute-value pairs from textual product descriptions for implicit and explicit attributes has been addressed [17]. Implicit attributes are semantic attributes which are implicitly mentioned in the product description. While, explicit attributes are physical attributes. Experiments were performed on extracting explicit attributes using Naïve Bayes as a supervised learning and Co-training Expectation Maximization (Co-EM) as a Multiview semi-supervised learning algorithm. Sporting goods category website is used for extracting attribute values.

Work presented in [18], illustrates extracting numerical and textual attribute-value pairs on three variations such as Tweets, Web-Links and Tweets+ Web-Links for 15 events. For extracting numerical attribute-value pairs, splitting of sentences based on a set of delimiters is done. Next, some special cases are handled such as, extracting attribute-value pairs which are mentioned side by side or in a sequence using common noun or proper noun. In this, the word is marked as attribute if it is a noun and coming next to the word. Finally, the remaining sentences (which does not consist of special cases) are handled using dependencies (subject and object concept). Textual attribute-value pairs are extracted based on the relationship with the subject or root word of tweet or preposition dependencies.

Extracting attribute-value pairs using automatically induced Knowledge Base (KB) for a particular category has been demonstrated [19]. In this method, KB is automatically created from tables and other structures which are available in unstructured web pages. Using KB, web pages are annotated automatically. This annotated corpus is used to train the model for extraction. Some attribute value pairs are not present in this model because, annotated corpus is not created manually. Therefore, this extraction model lacks in extracting some attribute value pairs from unstructured test data.

3. Proposed Approach

The proposed approach is described using following sections. These sections give the meaning of definitions and terms used in the Algorithm 1, major steps of the algorithm and explanation of each step of the algorithm.

3.1. Definitions and terms

Class Name (CLNAME): *CLNAME* is a product class name which is provided by the user. For example, value of *CLNAME* can be Tablet, Mobile-Phone, and Mixer-Grinder etc. Final objective is to generate a spreadsheet for class *CLNAME*.

Web Spreadsheet (SP): *SP* is a spreadsheet which consist of $\{T_1, T_2, T_3, \dots, T_n\}$ rows. Consider, D be a set of web pages related to product class, where, $D = \{D_0, D_1, D_2, \dots, D_n\}$ and $n \geq 0$. Algorithm 1, crawls over each D_i one by one and generates one row T_i for spreadsheet *SP*. We define function $f: \mathbb{D} \rightarrow \mathbb{T}$ where, f is injective and onto.

Web Spreadsheet Columns (CL): Let, *AT* consists an array of elements $(\{A_1, DT_1\}, \{A_2, DT_2\} \dots \{A_n, DT_n\})$. Every element of *AT* consists of an attribute and its data type. These attributes, i.e. $A_1, A_2, \dots, A_n$ and data types $DT_1, DT_2, \dots, DT_n$ are user defined. Attributes $A_1, A_2, \dots, A_n$ will be columns of a spreadsheet where, $n \geq 1$.

Web Spreadsheet Row (T_i): It is one of the row of a spreadsheet. T_i consists of $(E_i, IA_{i1}, IA_{i2}, \dots, IA_{in})$ where, E_i is a complete entity name and $IA_{i1}, IA_{i2}, \dots, IA_{in}$ are value-measure information for attributes $A_1, A_2, \dots, A_n$ respectively corresponding to document D_i where, $n, i \geq 1$.

Algorithm 1. Entity and Value-measure extraction

- 1: **Input:** Search Query Specifying class name $CLNAME$, attributes and attribute data types, maximum number of URL's crawled (n) to limit the search space.
 - 2: **Output:** Spreadsheet (SP) indicating product names of the class and attribute values represented as rows of spreadsheet.
 - 3: Prepare Synonym list (SL) for product class name $CLNAME$.
 - 4: Gather URL's from search engine by specifying class name $CLNAME$ and attributes and store in $URLLIST$.
 - 5: Rank the documents pointed by URL based on presence of class name and attribute names. Sort $URLLIST$ based on rank.
 - 6: **for** every document D_i present in $URLLIST$ **do**
 - 7: Remove Stop words, unwanted symbols and perform stemming using Word Net Stemmer.
 - 8: For each word in a sentence construct Feature Vector specified in sections "Entity name extraction" and "Value-measure extraction"
 - 9: Classify word using Decision Tree Classifier for determining entity name (E_i)
 - 10: Classify word using Decision tree Classifier to determine value-measure pair ($IA_{i1}, IA_{i2}, \dots, IA_{in}$) for attributes specified in search query.
 - 11: Prepare row of spreadsheet using results from 9 & 10.
 - 12: **end for**
 - 13: Output: spreadsheet (SP)
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POS tag of a word W_i (POS_Tag): POS tag of word W_i is defined as POS_Tag . POS tag of word is used to categorize the word as nouns, adjectives, verbs, adverbs etc. Following POS tags are used in the proposed work:

CD — Cardinal Number, NN — Noun, singular or mass, NNP — Proper noun, singular

Synonym List (SL): Synonym list for class, $CLNAME$ consists of set synonym words of $CLNAME$. SL is represented as $SW_1, SW_2, \dots, SW_n$ where, $n \geq 1$.

URLLIST: List to store all related URL, returned by search engine.

3.2. Input

Input to the Algorithm is search query mentioning product class name ($CLNAME$), attribute names (A_i), attribute data types (DT_i) and maximum number of URLs (n) which can be crawled to limit the search space. The attribute which is mentioned earlier in the specification is considered to have high priority. For example, to prepare a spreadsheet for tablet, user can specify product class name as Tablet, attributes as Price, Touchscreen, Camera, Processor and RAM.

In the proposed work, the authors define following four data types (value-measure) for the attributes: (A) Alphanumeric (B) Numeric-Alpha (C) String (D) Numeric which is explained as follows:

Alphanumeric (AN): If the word consists of at least one alphabetic letter (A–Z or a–z) and at least one digit (0–9) or combination of digit (0–9) and alphabetic letters then the word falls under alphanumeric category. For e.g. if we take camera as an attribute and its value as 13 MP then type of value of the camera is alphanumeric.

Numeric-Alpha (NA): Numeric-Alpha category is a subset of alphanumeric category. The only difference is value and measure is separated by one or more spaces. i.e. Number/s-Space-Alphabet/s (String). For e.g. 1 MP.

String (ST): If a word is formed using alphabetic letters A–Z or a–Z or combination of both then, word falls under string category. For example large, big, small and little.

Numeric (NU): It consists of pure numbers either in float or as an integer. For e.g. 13, 13.4, etc.

3.3. Preparation of synonym list

We also maintain *SL* for product class name where all the synonym words for product class name are stored. *SL* for class *CLNAME* is created using Word Net. *SL* plays a major role in extracting instance-class relation. The main objective of creating a *SL* is to target only those sentences of a web page, which contains at least one of the synonym words from list *SL*.

Every Retailer describes their products in a different fashion. They also use different words corresponding to class name *CLNAME* to describe the complete name of the product. For e.g. Fig. 1 shows the initial part of product description page for Lenovo Tablet. In this, complete name (Lenovo Tab 2 A8) in the heading part comprises word Tab while in Fig. 2, the complete name (UBI Slate 7CZ Tablet) consists of word Tablet.

While describing the product, retailers use different substring words. These substring words which are basically a part of a complete entity name. For e.g. Fig. 3 shows the part of product description page for the Samsung Galaxy Tablet. The Complete Name of the product is “Samsung Galaxy Tab 4”. The product is described using *n* number of sentences.

Fig. 1. Initial part of product description page for Lenovo Tablet.

Fig. 2. Initial part of product description page for UBI Slate Tablet.

Fig. 3. Product description page for Samsung Galaxy Tablet.

Consider the two sample sentences described as follows:

Sentence 1: “Packed with a host of features, Samsung Galaxy Tab 4 T231 Tablet is a user friendly budget device.”

Sentence 2: “Android operating system and 1.5 GB RAM boosts the performance of this Galaxy Tablet.”

In sentence 1 complete entity name, i.e. “Samsung Galaxy Tab 4 T231” is used while in sentence 2, substring word Galaxy is used. In sentence 1, Tablet and Tab are used as a synonym words while in sentence 2 Tablet is used as a synonym word.

3.4. URL extraction module

Using jsoup 1.8.2 Java library, each URL in the search result which is returned by search query is accessed, parsed and decoded. All child URLs from each search result URL are also extracted, parsed and decoded. Iteration through every URL page and their child URL pages are done and the complete decoded URLs for these pages are stored in a database table. To ensure that, the URL is not visited twice, the presence of a URL in the database table is checked before storing it. If it is not present in the database table, then the URL is stored into the table as well as in list *URLLIST*. Now, the database table as well as list *URLLIST* will consist of unique URLs. These URLs will be given as input to the module Data Preprocessing.

3.5. Ranking of documents

The extracted documents are ranked based on presence of product class name and specified attributes. If more attributes are present then, the rank of the document is higher. If the same number of attributes are present, then document which is having more priority attributes are ranked higher.

3.6. Data preprocessing

In data preprocessing all special symbols, stop words are removed.

3.7. Entity name extraction

3.7.1. Building a classifier using J48 decision tree [Weka] for entity

Classifier is designed by generating feature vector for each word, preparing data for training and using decision tree for classification.

3.7.2. Construction of features vector for each word

Each document, if it is not present in the database table, then, the URL is stored into the table as well as in list D_i is crawled one by one whos URL is already stored in the list $URLLIST$ as mentioned in URL extraction module. Feature vector (Training data) is prepared using Tablet, Washing Machine and Tennis Racket classes by crawling the related website URL of different retailers. Every word in document D_i is represented as feature vector which is shown in Table 1.

Information in Table 1, depicts the particular words Document id, sentence number, the position of the word in a sentence, its POS tag and Label. Label attribute takes two possible values either YES or NO for entity classifier. YES means particular word is an entity or an instance of the respective class otherwise it is labeled as NO. Position of word is calculated with respect to Class Name Word ($CLNAME$) or its synonym word, i.e. $CLNAME$ is given position 0 and first left word is given position -1 and the position is decreased by -1 as we move left side of the sentence. First right word is given position 1 and the position is increased by 1 as we move the right side of the sentence.

Based on the sentence number of the word and position within the sentence, above training data is discretized, which is shown in Table 2.

Table 1. Feature vector representation (entity).

DocId	Attribute word	Sentence_No	Position	POS_Tag	Label
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Table 2. Discretized feature vector representation (entity).

DocId	Attribute word	POS_Tag	Section	Label
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Here, a new attribute section is introduced which is dependent on Sentence_No and Position attribute as follows:

Case 1. If Sentence_No $< \alpha$ and Position $> -\beta$ and Position $< \gamma$ then Section is Nearer.

Case2. If Sentence_No $> \alpha$ and Position $< -\beta$ OR Position $> \gamma$ then Section is Far.

The main purpose of introduction of Section attribute is, to define initial part of the web page. While describing the product on a web page, heading (which consists of the complete name of the product) is placed in the initial part of a web page so, authors concentrated on those sentences placed in the initial part. Here, authors target on the initial part of webpage because, the first occurrence of entity name occurs in the initial part of the web page. A section which comes under initial part is defined as Nearer otherwise the section is Far.

3.7.3. Labeling training data

Those words which belong to instance of product class name in the training data is labeled as either YES or NO. Labeling is done as follows:

Case 1. If POS_Tag = NN or NNP and Section = Nearer then Label is YES.

Case 2. If POS_Tag $\neq$ NN or NNP and Section = Nearer or Far then Label is NO.

Here, we have considered a sufficient amount of features to label the word as an entity. Features such as POS_Tag of a words which are present before and after synonym word, distance of the words with respect to synonym word and Sentence number in which the word appears are taken into consideration.

3.7.4. Extracting the entity name using J48 classifier

For deciding the status of words in the test documents decision tree classifier is used. The decision tree is trained using training data generated from a variety of product classes. Words in the test documents are fed to a classifier to decide the status of the words. The word which is classified as a product class instance forms the entity name of the product class and it will constitute the row label in the spread sheet.

3.8. Value-measure extraction

To decide words for attribute value, classifier is designed by generating feature vector of each word, preparing data for training and using decision tree for classification.

3.8.1. Building a classifier using J48 decision tree for the value-measure

Classifier is designed by generating feature vector for each word, preparing data for training and using decision tree for classification.

For deciding the status of the word, we have preferred decision tree classifier over other types of classifier like SVM [20], Neural Networks [21] and Naïve Bayes [22] because of following reasons:

- The feature vector consists of numeric and categorical attributes.
- The classification decision is sometimes influenced only by some set of attributes rather than all attributes, while in other types of classifiers always all the attributes have influenced classification decisions.
- The decision tree classifier utilizes nonparametric technique and can be trained even if data is less, while other techniques require large data to estimate correct probability distributions.
- The other classifier performance depends on algorithm parameters like kernel function (SVM), activation function (NN) and probability distribution function (Naïve Bayes).

J48 Decision Tree classifier is the Java Implementation of a C4.5 algorithm in Weka tool. Algorithm C4.5 [23] is an extension of ID3 algorithm. One of the first algorithms for Decision tree implementation was an ID3 algorithm. The main reason for choosing C4.5 over ID3 is due to following reasons:

- The ID3 algorithm is over sensitive to features having a large number of values, which is not suitable for the Internet Search activity [24]. In this case, C4.5 is best suitable.
- As our feature vector consists of numeric and categorical attributes, C4.5 is best suitable. ID3 does not handle numerical attributes.
- Algorithm ID3 does not handle missing values, while C4.5 is efficient to handle missing values.
- C4.5 allows post pruning of decision trees. This will help to reduce error rates in unseen testing data. ID3 does not support pruning activity.

3.8.2. Construction of feature vector for each word

Training data is prepared using Tablet, Washing Machine and Tennis Racket product classes by crawling related websites of different retailers. Every word in Document D_i is represented as a feature vector, which is shown in Table 3.

Here, the position of the word is always calculated with reference to the word indicating attribute word. As shown in Table 3, feature word indicates the particular words Document id, sentence number, the position of the word in a sentence, its POS tag and Label. Here DocId, Sentence_No, Position, POS_Tag are independent variable and Label is dependent variable. Label attribute takes two possible values either

Table 3. Feature vector representation (value-measure).

DocId	Attribute word	Sentence_No	Position	POS_Tag	Label
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Table 4. Discretized feature vector representation (value-measure).

DocId	Attribute word	Occurrence	Data Type	Label
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YES or NO. If a particular word is indicating the value of a particular attribute, then it is indicated by YES, otherwise it is indicated as NO. Position of word is calculated with respect to attribute word, i.e. attribute word is given position 0 and first left word is given position -1 and the position is increased by -1 as we move the left side of the sentence. First right word is given position 1 and the position is increased by 1 as we move the right side of the sentence.

Above training data is discretized, which is depicted in Table 4.
Here, a new attribute Occurrence is introduced which is dependent on Position and POS.Tag attribute as follows:

Case 1. If POS.Tag = CD and word is having the first occurrence of the word either from the left side or right side with reference to attribute word then Occurrence is set as First.

Case 2. If POS.Tag = CD and word is not having first occurrence of the word either from left side or right side with reference to attribute word then Occurrence is set as Later.

Case 3. If POS.Tag! = CD then Occurrence is set Random.
A new attribute Data Type is also introduced which is dependent on POS.Tag and Position attribute and its value is set as follows:

Case 4. If POS.Tag = CD then Data type is set as AN (Alphanumeric) or NU (Number).

Case 5. If POS.Tag! = CD then Data type is set as ST (String).

Case 6. If Position = $(-X)$ and POS.Tag = NN or NNP and Position = $(-X - 1)$ and POS.Tag = CD then Data type is set as NA (Numeric-Alpha).

Case 7. If Position = (X) and POS.Tag = CD and Position = $(X + 1)$ and POS.Tag = NN or NNP then Data type is set as NA (Numeric-Alpha).

3.8.3. Labeling training data

Those words which belong to attribute value of product class name in the training data is labeled as either YES or NO. Labeling is done as follows:

Case 1. If Occurrence = First and Data Type = AN or NA then Label is YES.

Case 2. If Occurrence != First or Data Type != AN or NA then Label is NO.

Here, we have considered a sufficient amount of features to label the word as value-measure pair. Features such as an Occurrence of a word which considers distance of the words with respect to attribute word, Data Type of the words which are present before and after attribute word and POS.Tag of the word are taken into account.

3.8.4. *Extracting value-measure pair using J48 classifier*

For deciding the status of words in the test documents, decision tree classifier is used. The decision tree is trained using training data generated from a variety of product classes. Words in the test documents are fed to a classifier to decide the status of the words. The word which is classified as attribute value of the product class instance forms the column value of the row belongs to that instance of the product class in the spreadsheet.

The accuracy of the classifier for entity extraction and attribute value extraction is measured using precision, recall and F1-measure by N-Fold cross-validation and the results are mentioned in Sec. 5.

The proposed algorithm gives a solution to deal with different attribute descriptions about the same feature of the product. When the information about the same product is available on different websites, then instead of reporting aggregate information, the algorithm will add one row from each website. Moreover, if different information is available about the same attribute in the same web page then the algorithm tries to produce the best of all such information if it matches with attribute data type. This feature of algorithm enables the user to get more precise information for product comparison. This can be explained as follows:

Consider the following two sentences taken from two different retailers website for a particular mobile phone (Lenovo K3 Note):

Retailer 1: Sentence 1: “Powerful 64-bit 1.7 GHz processor, camera of 13 MP.”
Retailer 2: Sentence 2: “The device is powered by a Octa core, 1.7 GHz, Cortex-A53 processor paired with 2 GB of RAM.”

Sentences 1 and 2 describe different attribute descriptions for the same feature of the product. Here, feature “processor” is taken into consideration. The proposed algorithm extracts descriptions of an attribute which are at the shortest distance with reference to an attribute word. Consider the “Sentence 1” taken from “Retailer1” website as shown above. After removing stop words and special symbols (as described in Sec. 3.6), sentence 1 will be represented as shown in Table 5.

Our proposed algorithm assigns position 0 for the attribute word “processor”. The other words which are at left and right of the attribute word “processor” are assigned positions accordingly as shown in Table 5. As we move left side from the attribute word processor, the position is decreased by 1 and as we move the right side of the attribute word position is increased by 1.

For Sentence 1, using “Case 1”, “Case 2” and “Case 4” from Sec. 3.8.2, value-measure pair is extracted for attribute “processor” is “64-bit 1.7 GHz” because,

Table 5. Position array for sentence.

Position	−3	−2	−1	0	1	2
Word	Powerful	64-bit	1.7 GHz	Processor	Camera	13 MP
Data type	ST	AN	AN	ST	ST	AN

Table 6. Sample spreadsheet for mobile-phone for “Lenovo K3 Note”.

Entity-name	Price	Camera	RAM	Processor	Touchscreen	Size
Lenovo K3 Note	12,000	13 MP	2 GB	64-bit 1.7 GHz	5.5 inches	Large
Lenovo K3 Note	11,700	13 MP	2 GB	1.7 GHz Cortex-A53	5.5 inches	Large

“1.7 GHz” is shortest distance word (whose Data type is “Alphanumeric”) with reference to “processor” word as compared with the word “13 MP” and “64-bit” is also word whose data type is “Alphanumeric” and is immediate prior word of “1.7 GHz”.

In Sentence 2, using “Case 6” from Sec. 3.8.2, value-measure pair is extracted for attribute “processor” is “1.7 GHz Cortex-A53” because, *POS.Tag* of “1.7 GHz” is “CD” (Cardinal Number) and *POS.Tag* of “Cortex-A53” is “NN”(Noun-Plural).

From all the above scenarios, we conclude that, for a particular feature “processor” our algorithm extracts two different attribute descriptions, i.e. “1.7 GHz” and “1.7 GHz Cortex-A53” from two different retailers web pages for a particular product “Lenovo K3 Note” and stores in a web-spreadsheet as shown in Table 6. Rows 1 and 2 in Table 6 correspond to product information extracted from Retailers 1 and 2 web pages, respectively.

Though the work described in this paper is inspired by RAS, instead of aggregating the information, we are providing all the information so that, the information is not lost and users can perform a better comparison. Here, in our work for a particular product, for e.g. for the product, Lenovo K3 Note, if two different retailers are showing prices on their web pages as 12,000 and 11,700, respectively, then our algorithm extracts the product information (Product Name, Price, Attribute-Value pairs) from two different retailer’s web page and store this information as a two different rows in spreadsheet as shown in Table 6.

As discussed earlier, our algorithm extracts different attribute descriptions for the same feature for the particular product from different retailers web pages and stores this information in a web-spreadsheet. The main purpose of our algorithm is not to lose the different attribute description for the same product feature. Another advantage of performing this task is that, it will save a lot of time of the customers for comparing the same product having different prices because, all the product information (corresponding to all the retailers) along with the prices will be available in spreadsheet so, customers will not only able to do a comparison on the basis of prices but also get a consolidated view of the same product feature attribute description as shown in Table 6.

4. Experimental Setup

Experiments were performed on Windows Server 2012 (R2) and softwares used are as follows:

- NetBeans IDE 8.0.2
- Java JDK 1.7.0.80

- Jsoup1.8.2 API is used, which is used to connect to the web document url and extracts all the sentences.
- Stanford Part Of Speech (POS) tagger v. 2.0 for tagging the terms of web pages.
- Word Net Stemmer for obtaining word stems.
- Java Word Net Interface (JWI) API for accessing Word Net library and obtaining values for an attribute.

5. Results and Discussions

5.1. Building a classifier

Both the Classifiers for entity and value-measure extraction are trained using class names as Tablet, Washing Machine and Tennis Racket. Effectiveness of algorithm which is described in Proposed Approach section is evaluated by calculating classification accuracy (cross-validation) using *N*-Fold cross-validation and 80-20 split i.e. 80% data are used for training and 20% data are used for testing.

5.1.1. Cross-validation for entity extraction

Cross-validation is performed on training as well as testing set and results are described in Tables 7 and 8, respectively.

Total Number of URLs (web documents) crawled are 63. Table 7 indicates the accuracy of the model using *N*-Fold cross-validation, where *N* = 10. The total of number words extracted are 29,999 out of which 1490 words indicate the entity name and 28,509 words are not an entity.

Using *N*-Fold cross-validation (here, *N* = 10), we obtain average precision, recall and F1 for both YES and NO label as 98.7%. A total of 29,6129 words is correctly classified into YES or NO category and 387 words are incorrectly classified.

Accuracy of classifier is also calculated using a 80-20 split technique as depicted in Table 8. In this method, 80% of the total number of words is used for Training and 20% words are used for Testing. Out of 6000 words which are used for testing, 5927

Table 7. Accuracy of classifier built for entity name using 10-fold cross-validation (on complete training set).

10 fold cross-validation	
Total number of URLs crawled	63
Total number of words extracted	29,999
Total number of words indicating the entity name	1490
Total number of words indicating not as entity name	28,509
Correctly classified instances	29,6129 (98.71%)
Incorrectly classified instances	387 (1.29%)
Weighted average precision (for YES and, NO label)	98.7%
Weighted average recall (for YES and, NO label)	98.7%
Weighted average F1 (for YES and, NO label)	98.7%

Table 8. Accuracy of classifier built for entity name using 80-20 split (80% data used for training and 20% data are used for testing).

80-20 split	
Total number of URLs crawled	63
Total number of words extracted	29,999
Total number of words used for training (80%)	23,999
Total number of words used for testing (20%)	6000
Correctly classified test instances (Either YES or NO)	5927 (98.78%)
Incorrectly classified test instances	73 (1.21%)
Weighted average precision (for YES and, NO label)	98.8%
Weighted average recall (for YES and, NO label)	98.8%
Weighted average F1 (for YES and, NO label)	98.8%

words are correctly classified by the classifier into YES or NO category and 73 words are incorrectly classified. Using this method, we obtained average precision, recall and F1 for both YES and NO label as 98.8%.

5.1.2. Cross-validation for value-measure pair extraction

Cross-validation is performed on training as well as testing set and results are described in Tables 9 and 10, respectively.

Total number of URLs (web documents) crawled are 60. Table 9 indicates the accuracy of the model using N -Fold cross-validation, where $N = 10$. Total of number words extracted are 3000 out of which 210 words indicates value-measure pair and 2790 words are not value-measure pairs. Using N -Fold cross-validation (here, $N = 10$), we obtain average precision, recall and F1 for both YES and NO label as 98.92%. A total of 2967 words is correctly classified into YES or NO category and 33 words are incorrectly classified.

Accuracy of classifier is also calculated using a 80-20 split technique as depicted in Table 10. In this method, 80% of the total number of words is used for Training and 20% words are used testing. Out of 3000 words which are used for testing, 594 words are correctly classified by the classifier into YES or NO category and 6 words are

Table 9. Accuracy of classifier built for value-measure pair using 10-fold cross-validation (on complete training set).

10-fold cross-validation	
Total number of URLs crawled	60
Total number of words extracted	3000
Total number of words indicating value-measure	210
Total number of words indicating not as a value-measure	2790
Correctly classified instances	2967 (98.9%)
Incorrectly classified instances	33 (1.1%)
Weighted average precision (for YES and, NO label)	98.92%
Weighted average recall (for YES and, NO label)	98.92%
Weighted average F1 (for YES and, NO label)	98.92%

Table 10. Accuracy of classifier built for value-measure pair using 80-20 split (80% data used for training and 20% data are used for testing).

80-20 split	
Total number of URLs crawled	60
Total number of words extracted	3000
Total number of words used for training (80%)	2400
Total number of words used for testing (20%)	600
Correctly classified test instances (Either YES or NO)	594 (99%)
Incorrectly classified test instances	6 (1.00%)
Weighted average precision (for YES and, NO label)	99.1%
Weighted average recall (for YES and, NO label)	99.1%
Weighted average F1 (for YES and, NO label)	99.1%

incorrectly classified. Using this method, the authors obtained average precision, recall and F1 for both YES and NO label as 99.1%.

5.2. Evaluation on different product classes

The proposed method is used to generate a spreadsheet of product classes of different categories. Accuracy is evaluated using precision, recall and F1 measure. The results of the experimentation of product classes such as Mobile Phone, Mixer Grinder, Television and Electric Timer are described in the following sections.

5.2.1. Product class name: Mobile-Phone

Input: Search query specifying class name *CLNAME* as Mobile-Phone, attributes as Price, Camera, RAM, Processor, Touchscreen and Size, respective data types of the attributes, maximum number of URLs crawled (*n*) to limit the search space as 20.

Output: Spreadsheet *SP* consisting of Price, Camera, RAM, Processor, Touchscreen and Size as Columns and rows of a spreadsheet as their respective value-measure pairs. Sample Spreadsheet *SP* for Mobile-Phone is shown in Table 11.

As mentioned in Table 12, for a particular attribute, “Total Relevant Doc” column corresponds to the total number of relevant documents having product class name as Mobile Phone and the attribute word. “Relevant Docs Retrieved” indicates actual relevant documents retrieved by the algorithm for a particular attribute or entity name. “Total Doc Retrieved” corresponds to the total number of documents retrieved for attribute or entity name. As mentioned in Table 12, we obtained 302 “Relevant Docs” Retrieved, 332 “Total Doc Retrieved”, precision as 0.909, “Total Relevant Doc” as 331, Recall as 0.912 and F1 as 0.910 for entity name. For camera attribute, we obtained 140 “Relevant Docs” Retrieved, 192 “Total Doc Retrieved”, precision as 0.729, “Total Relevant Doc” as 329, Recall as 0.425 and F1 as 0.536. Precision, Recall and F1 is calculated as follows:

$$\text{Precision} = \frac{\sum \text{Relevant Doc's Retrieved}}{\sum \text{Total Doc Retrieved}}, \quad (1)$$

Table 11. Spreadsheet for mobile-phone.

Entity-name	Price	Camera	RAM	Processor	Touchscreen	Size
Samsung galaxy J7	16,900	8 MP front	1.5 GB RAM	Cortex A53	5.5 inches	Large
Intex Aqua Q7	4599	2 MP	1 GB	1.2 GHz	11.43 cm	Small
Lenovo Vibe K5	7499	13 MP primary	2 GB	616 octa core	1280 × 720 pixels	Large
Apple iPhone 7	53,999	12 MP, 7 MP	2 GB	M10 Motion Co-processor	11.938 cm	Large

Table 12. Precision, recall and F1 calculation for mobile-phone class.

Product name: Mobile-phone						
Attribute/ instance name	Relevant docs retrieved	Total doc retrieved	Precision	Total relevant doc	Recall	F1
Entity-name	302	332	0.909	331	0.912	0.910
Camera	140	192	0.729	329	0.425	0.536
RAM	152	179	0.8498	318	0.477	0.610
Processor	99	140	0.707	225	0.44	0.545
Touchscreen	47	95	0.494	122	0.385	0.432
Size	37	38	0.973	74	0.5	0.680
Total	777	976		1399		
Average			0.7961		0.555	0.654

$$\text{Recall} = \frac{\sum \text{Relevant Doc's Retrieved}}{\sum \text{Total Relevant Doc's}} \tag{2}$$

$$F1 = \frac{(2 * \text{Average_Precision} * \text{Average_Recall})}{(\text{Average_Precision} + \text{Average_Recall})} \tag{3}$$

5.2.2. Product class name: Mixer Grinder

Input: Search query specifying class name *CLNAME* as Mixer Grinder, attributes as Price, Warranty, Capacity, Weight, Height, and Size, respective data types of the attributes, maximum number of URLs crawled (*n*) to limit the search space as 20.

Output: *SP* consisting of Price, Warranty, Capacity, Weight, Height, and Size as Columns and rows of a *SP* as their respective value-measure pairs. Sample Spreadsheet *SP* for Mixer Grinder is shown in Table 13.

As mentioned in Table 14, we obtained 320 “Relevant Docs Retrieved”, 381 “Total Doc Retrieved”, precision as 0.839, “Total Relevant Doc” as 380, Recall as 0.842 and F1 as 0.840 for entity name. For warranty attribute, we obtained 200 Relevant Docs Retrieved, 228 “Total Doc Retrieved”, precision as 0.877, “Total Relevant Doc” as 333, Recall as 0.600 and F1 as 0.712.

5.2.3. Product class name: Television

Input: Search query specifying the class name *CLNAME* as Television attributes as Price, Television Size, Response Time, Weight, Angle and Size, respective data

Table 13. Spreadsheet for Mixer-Grinder.

Entity-name	Price	Warranty	Capacity	Weight	Height	Size
Maharaja Whiteline	1899	1 Year	0.7 liter	4.7 kg	16.5 inch	Large
Philips HL1645	3961	2 Years	0.5 l	7 kg	42.2 cm	Large
Butterfly Matchless	3559	3 Years	0.5 liter	6 kg	41.1 cm	Large
Pigeon Gusto	1299	1 Year	0.4 L	2.7 kg	27.99 cm	Small

Table 14. Precision, Recall and F1 calculation for Mixer-Grinder class.

Product name: Mixer-grinder						
Attribute/instance name	Relevant docs retrieved	Total doc retrieved	Precision	Total relevant doc	Recall	F1
Entity-name	320	381	0.839	380	0.842	0.840
Warranty	200	228	0.877	333	0.600	0.712
Capacity	37	45	0.822	91	0.406	0.543
Weight	82	105	0.780	209	0.392	0.521
Height	68	78	0.871	107	0.635	0.734
Size	93	94	0.989	150	0.620	0.762
Total	800	931		1270		
Average			0.859		0.629	0.726

types of the attributes, maximum number of URLs crawled (n) to limit the search space as 20.

Output: SP consisting of Television Size, Response Time, Weight, Weight, Angle, Size as Columns and rows of a SP as their respective value-measure pairs. Sample SP for Television is shown in Table 15.

Table 15. Spreadsheet for television.

Entity-name	Price	Television size	Response time	Weight	Angle	Size
Panasonic	15,699	32 inch	8 millisecond	5 kg	170 degrees	Large
Samsung	11,659	18.5 inch	14 ms	1.8 kg	178 degrees	Big
Sony Bravia	46,482	101.6 cm	14 millisecond	8.7 kg	178 degrees	Large
LG	18,490	80 cm	12 ms	6 kg	175 degrees	Small

As mentioned in Table 16, we obtained 209 “Relevant Docs Retrieved”, 218 “Total Doc Retrieved”, precision as 0.958, “Total Relevant Doc” as 219, Recall as 0.995 and F1 as 0.976 for entity name. For Response time attribute, we obtained 76 “Relevant Docs Retrieved”, 95 “Total Doc Retrieved”, precision as 0.800, “Total Relevant Doc” as 101, Recall as 0.781 and F1 as 0.790.

5.2.4. Product class name: Electric timer

Input: Search query specifying class name $CLNAME$ as Electric Timer, attributes as Price, Timer size, Weight, Humidity, Current and Size, respective data types of the attributes, maximum number of URLs crawled (n) to limit the search space as 20.

Table 16. Precision, recall and F1 calculation for television class.

Product name: Television						
Attribute/instance name	Relevant docs retrieved	Total doc retrieved	Precision	Total relevant doc	Recall	F1
Entity-name	209	218	0.958	219	0.995	0.976
Television size	143	178	0.803	191	0.748	0.774
Response Time	76	95	0.800	101	0.781	0.790
Weight	71	94	0.7551	101	0.702	0.727
Angle	53	60	0.883	62	0.854	0.868
Size	66	78	0.8461	100	0.66	0.741
Total	618	723		774		
Average			0.854		0.798	0.825

Output: *SP* consisting of Timer size, Weight, Humidity, Current, Size as Columns and rows of a *SP* as their respective value-measure pairs. Sample *SP* for Electric Timer is shown in Table 17.

Table 17. Spreadsheet for electric timer.

Entity-name	Price	Timer size	Weight	Humidity	Current	Size
Walnut	1598	17.8 cm	50 gram	4585 rh	80 mah	Small
Intermatic	\$21.37	16.6 cm	46 g	4565 rh	75 mah	Small
Honeywell	\$21.37	18.6 cm	51 g	3898 rh	76 mah	Small
Defiant	\$24.97	17.6 cm	48 g	4445 rh	78 mah	Small

As mentioned in Table 18, we obtained 69 “Relevant Docs” Retrieved, 74 “Total Doc Retrieved”, precision as 0.932, “Total Relevant Doc” as 80, Recall as 0.862 and F1 as 0.895 for entity name. For humidity attribute, authors obtained 5 “Relevant Docs Retrieved”, 7 “Total Doc Retrieved”, precision as 0.714, “Total Relevant Doc” as 13, Recall as 0.384 and F1 as 0.499.

Table 18. Precision, recall and F1 calculation for electric timer class.

Product name: Electric timer						
Attribute/instance name	Relevant docs retrieved	Total doc retrieved	Precision	Total relevant doc	Recall	F1
Entity-name	69	74	0.932	80	0.862	0.895
Timer size	7	12	0.583	15	0.466	0.517
Weight	6	8	0.75	14	0.428	0.544
Humidity	5	7	0.714	13	0.384	0.499
Current	4	9	0.444	11	0.363	0.399
Size	12	12	1.0	17	0.705	0.826
Total	103	122		150		
Average			0.844		0.686	0.756

In the case of entity extraction, Table 19 shows the performance comparison of the proposed method with some of the prominent entity extraction methods

Table 19. Comparison of proposed entity extraction method with the performance of methods in the literature.

Dataset	Algorithm	Class	Precision (%)	Recall (%)	F1-measure (%)
Limited Web corpus	List Extractor (LE)[9]	City	52	NA ^a	NA ^a
		Film	72	NA ^a	NA ^a
		Scientist	64	NA ^a	NA ^a
CONNL-2003 English	Conditional Random Fields (CRFs) [10]	LOC	87.23	87.65	87.44
		MISC	74.44	71.37	72.87
Test Set		ORG	79.52	78.33	78.92
		PER	91.05	89.98	90.51
CONLL-2003	Context Pattern Induction [11]	Location	70	NA ^a	NA ^a
		Organization	85	NA ^a	NA ^a
		Person	88	NA ^a	NA ^a
CRL NE	Support Vector Machine (SVM) [12]	Artifact	NA ^a	NA ^a	50.16
		Organization	NA ^a	NA ^a	80.44
		Location	NA ^a	NA ^a	88.57
		Person	NA ^a	NA ^a	87.81
All related web pages returned by search engine	Proposed algorithm	Mobile Phone	90.9	91.2	91
		Mixer Grinder	83.9	84.2	84
		Television	95.8	99.5	97.6
		Electric Timer	93.2	86.2	89.5

Notes: ^aNot Available.

discussed in the literature. Table 20 shows the performance comparison of the proposed method with some of the prominent attribute-value extraction methods present in the literature. These methods have evaluated their performance on limited web corpus or a single site. We have evaluated the performance of

Table 20. Comparison of proposed value-measure extraction method with the performance of methods in the literature.

Dataset	Algorithm	Class	Precision (%)	Recall (%)	F1-measure (%)
Single site (www.dickssportinggoods.com)	Naïve Bayes [17] co-EM [17]	Football	31.85	45.38	Not Available
			32.04	55.48	Not Available
Only Tweets	POS tagging and Dependency Parsing [18]	Tweets	85.1	38.5	51.6
Only Web-Links		Web-Links	89.1	29.3	42.9
Tweets + Web-Links		Tweets + Web-Links	87.4	46.0	59.5
Single site (www.rakuten.co.jp)	Knowledge Base Induction [19]	Wine and Shampoo	57.05	59.66	58.15
All related web pages returned by search engine	Proposed algorithm	Mobile Phone	73.75	55.49	63.33
		Mixer Grinder	87.27	53.93	66.66
		Television	80.99	73.6	77
		Electric Timer	70.83	48.57	57.62

the proposed method by crawling over almost every manufacturer or retailer websites.

The large improvement in the performance of the proposed algorithm for entity and value-measure extraction as compared with existing approaches (as shown in Tables 19 and 20) is due to application of POS tagging, generation of unique, enhanced, precise, important features and two classifications phased, one for entity extraction and other for attribute extraction. The authors have used the distance measure concept in order to extract the value-measure pair of the specified attribute and its data type. Due to the use of distance measure concept at the word level, extraction of value-measure pairs becomes very fast and accurate as compared with other methods discussed in the literature [17–19]. In [17], Naïve Bayes classifier has been used for classifying the word. The features used in this classifier are the surrounding 8 words of the particular word (unlabeled word) and their corresponding Parts Of Speech (POS) Tags. Naïve Bayes algorithm has to scan and work out on 8 words surrounding an unlabeled word. To improve the performance of Naïve Bayes, co-EM algorithm has been used in [17]. Co-EM is a semi-supervised algorithm, which utilizes 4 words before and 4 words after the particular word and their POS tags. Our proposed algorithm extracts only that word (either on the left side or right side of an attribute word) which is at the smallest distance as compared with attribute word. Due to this scenario, time complexity and accuracy of our proposed algorithm are better as compared with Naïve Bayes and co-EM.

A method for extracting numerical attribute-value pairs (which are mentioned side by side) in [18] is different as compared with the proposed algorithm. In [18], a word is marked as an attribute, if it is a noun and coming next to the word marked as numeric. This scenario is not applicable in every cases. Consider the sentence, “2 MP camera”. Using the method as described in [18], “MP” is marked an attribute for value “2” which is incorrect. Our proposed algorithm marks correctly “2 MP” as a value-measure pair for “camera” attribute. This indicates that accuracy (F1-measure) of our proposed algorithm is more as compared with the technique used in [18] which is shown in Table 20. The accuracy (F1-measure) of the model which uses Knowledge Base (KB) [19] for extracting attribute-value pairs are also less as compared with the proposed algorithm as shown in Table 20.

The authors have also used the distance measure concept as well as “Section” feature to efficiently extract entity name for a particular class. Due to the utilization of “Section” feature, instead of searching complete web page, our proposed algorithm searches only the initial part of a web page which results in fast extraction of entity name as compared with other methods discussed in the literature [9–12]. As shown in Table 19, [9] utilizes List Extraction (LE) method, which initially discovers an exact place of lists of class instances on the web page. Then, for each list, a wrapper is learned and finally, by utilizing these wrappers list elements are extracted. This wrapper induction (rule extraction) technique will not work always because, on each web page, an arrangement of entity names is done in a different fashion. In [10], CRFs are used which utilizes Conditional Probability for extracting entity names.

Unlike our method, this method requires a large amount of hand-labeled training data. In this method, experimentation was performed on only one data set, i.e. “CONLL-2003 English Test Set”. We have performed experimentation on almost all related web pages returned by a search engine. The technique described in [11], automatically extracts entity dictionaries from a large amount of text. However, this method requires complicated induction patterns to extract entity names. Technique addressed in [12] is based on SVM which also requires a large dataset manually labeled for training.

F1-Measure of our proposed algorithm is maximum among all the other models [10, 12, 18, 19]. The higher value of F1-measure represents that our proposed algorithm is more accurate than existing models studied in the literature. The precision of our proposed algorithm is maximum among all other models [9, 11, 17, 19]. The higher value of precision indicates that the proposed algorithm is more robust to remove the unimportant information from the text. A Higher value of recall of the proposed algorithm as compared with [17, 18] indicates that the proposed algorithm is robust to keep the important information from the text.

Works which is described in [13, 15, 16] are different than proposed work which described in this paper in such a way that, in proposed work authors extract value-measure pairs given their attributes and data types. The authors also execute the extraction process on product description pages of different retailers. These pages are highly unstructured as compared to online reviews. Attribute names are often different in online reviews as compared with the retailers product description page. For example, in online reviews, customer mentions picture quality as an attribute, but in the product description, page retailer will mention it as camera as an attribute.

6. Conclusion and Future Work

A big amount of data related to a particular class of product is available online in different web pages. Single retailer site can not satisfy the customer, as it has limited information regarding particular product attributes. Prices of the product may also vary from one site to another. A lot of time will be saved if all the information regarding a particular class of products is consolidated in the spreadsheet. The major challenge to provide such consolidated information is to extract this information from unstructured text using Natural Language Processing.

In the proposed work, the authors have come up with a novel idea of generation of web-spreadsheet for the specified class name. A classifier-based technique for entity extraction and attribute value extraction is also suggested. A classifier is trained using product classes of different categories, which experimentally shows that the classifier built using features can be used for any product classes without the need of trained data of each class.

In the proposed work, nearly every websites of retailers have been crawled. These sites are basically a result returned by search engine for a particular class query

formed by user. Proposed novel algorithm efficiently extracts the entity name and value-measure pairs for related web pages and generates one row for corresponding web page Di. Separate J48 decision tree classifier is used to extract the entity name and value-measure pairs. Authors have used various product classes for generating training data for both the classifiers. Classifier designed for entity, efficiently classifies words from test documents as entity name and the other classifier which is designed for value-measure pair, efficiently classifies words from test documents as value-measure pair. In this work, authors have dealt with attributes, whose value measure pairs belongs to Alphanumeric, Numeric-Alpha and String category.

Experiments were rigorously performed on Mobile-Phone, Tablet, Mixer-Grinder, Television, Washing Machine, Tennis Racket and Electric Timer product classes and promising results are obtained in each category. Tables 19 and 20 show that the proposed method accuracy is superior to many entity and attribute-value extraction techniques.

Immediate future work is to automatically extract attribute and value-measure pairs from unstructured web documents for a particular product class and generate spreadsheet for the same.

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