Author(s): Khriyenko, Oleksiy

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Customer Perception Driven Product Evolution
Facilitation of Structured Feedback Collection

Oleksiy Khriyenko
Industrial Ontologies Group, Agora Center and Department of Mathematical Information Technology, University of Jyväskylä, P.O. Box 35, FIN-40014, Jyväskylä, Finland
oleksiy.khriyenko@jyu.fi

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Abstract: Competitive environment not only requires effective advertising strategies from the product producers and service providers, but also to do comprehensive and sufficient analysis of their customers to understand their needs and expectations. Successfully involving customers into a product/service co-creation process, companies more likely increase their future revenue. Customer feedback analysis is widely applied in marketing and product development. Among other challenges (e.g. customer engagement, feedback collection, etc.) automation of customer feedback analysis becomes very demanding task and requires advance intelligent tools to understand customers' product perception and preferences. Since, mining of free text feedbacks (which is still the most representing form of the real voice of the customer) is challenging, this work presents an approach towards customer-supported transformation of feedback into structured data. Further analysis and manipulation with semantically enhanced customer feedback and product/service description makes possible to automatically generate useful changes in existing products or even a new product description that takes into account actual needs and preferences of customers.

1 INTRODUCTION

For years, many companies have been implementing data mining tools and methods to discover various indicators to be predictive about and proactive with their customers. Along with data mining tools, organizations implement a variety of technologies to analyse customer data, including: business intelligence (BI) tools, data discovery and warehouses, predictive analytics, data and text mining, social media analytics, customer data and behaviour management, and more. Becoming "customer centric" is a top priority for companies in highly competitive markets nowadays. Companies experience customer analytics technologies to find best practices to improve customer intelligence, reach customer-centric goals and increase their revenue through customer satisfaction growth. Customers do much more than simply buy products or services. With digitalization of communication channels, they are able to discuss and share information about a product through social media networks, to write reviews and leave comments to reviews of others.

Nowadays, many of product developers and service providers, as well as retailers, are pretty much focusing at pushing their products to the customers, making them willing to buy. Consumers will not buy a product under uncertainty: whether product matches their preferences or whether quality is good as it is advertised. Since, consumers are more likely to rely on other users than on seller-generated information or even third-party experts, consumer review systems have become extremely popular, and have been found to affect the sales of a variety of products (Chen and Xie, 2008; Chevalier and Mayzlin, 2006; Ghose and Ipeirotis, 2011; Ehrmann and Schmale, 2008). Definitely, intelligent strategies towards proper selection of user's reviews to be shown for customer to increase its willingness to buy may bring expected benefit. But, many customers more likely would like to buy a product or service that satisfies customer's needs and expectations rather than just simply choose something suitable from what is offered. Advanced analytics technologies, modern data management and integration systems are enabling organizations to gain far greater depth and breadth of knowledge about customers; to understand sentiment drivers; to identify features for the best segmentation; to measure brand reputation; to make faster strides in predicting retention, attrition, and return rates; to discover patterns and anticipate customers' problems with products or services. Outcome of such analytical tools is further used by domain experts to develop new marketing and advertisement strategies, to improve existing and to create new products and services.

Product and service providers always aim to attract new customers. At the same time, reducing customer churn is a very crucial problem for most of the companies who are doing business in highly competitive environment. Customers are different. They have own perception, own opinion and own preferences. Therefore, not always actual product or service meets personal expectations of a customer. Big difference in ideal, actual and perceived product/service may cause customer loss. Automated distance measuring between ideal-actual-perceived products will allow us to predict the level of customer satisfaction and analyse a risk of that loss. Using various methods and approaches, companies are trying to engage customer to the feedback provisioning process to be able to hear the real voice of a customer. To apply intelligent analytics on top of customer feedbacks, they should be converted into a structured machine readable form. Therefore, we have to elaborate techniques and tools that automate customer feedback gathering in structured form that allows its further automated intelligent analysis. This will speed up corresponding response towards customer expectations from product/service providers and facilitate customer involvement into development of new products and services via shearing own preferences and ideas.

Thus, the paper proposes a solution for facilitation of structured customer feedback collection process and automated generation of preferable/ideal product and services from a customers' perspective. It will expand automated part of a product adaptation and evolution lifecycle, and allow system to perform responsive product optimization. In other words, we try to facilitate adaptation of products and services towards customers' expectations. The next section (Section 2) concerns the main contribution of the paper and presents: motivation for structured feedback collection; semantically enriched digital content as enabler for customer-driven preference definition; and the mechanism for triple-based feedback collection. Section 3 presents the ways structured feedback could be used to facilitate further product development and targeted advertisement. Finally, the paper shortly refers to the planned future enhancement of proposed solution, as well as concludes the proposed work.

2 STRUCTURED CUSTOMER FEEDBACK COLLECTION

Customers are a wealth of information. To create successful innovative business and succeed with new product or service, company must listen to the real voice of a customer based on analysis of customer feedbacks. Collecting human knowledge has been a common goal since ancient times. With appearance of the Internet and the World Wide Web, people have got a possibility to generate and share almost unlimited amount of information. Therefore, automated arrangement of user-generated datasets is crucial. Since ordinary people mainly generate data in text-based unstructured form, transformation of this data into structured datasets enables further automated processing by machines.

Many collaborative systems, having own internal data models, insist users to create data accordingly. For example, the Wikipedia articles are further organized by contributors into structured information, including keyword lists in the infobox, classes, and directories. Their structured information is entity based and follows a predefined schema. With a purpose to not frighten users away with possible complexity of internal data model and to make system more user-friendly, automated text-analysis techniques are used instead. But, since customer feedback analysis domain is very sensitive to possible mistakes and low efficiency of automated natural language processing, fully automated text analysis could become a bottleneck of a system. It is very hard, if not impossible, for any automatic technique to achieve perfect accuracy due to the difficulty of natural language understanding. Systems that need near-perfect solutions require convenient user-friendly mechanism for human involvement to correct errors made by automatic techniques. Even, involvement of a domain expert (which can be costly) into the process at the stage of feedback analysis does not guarantee that a real voice of a customer will not be distorted. It is much more reasonable to ask user (customer) what (s)he meant, rather than to ask some external expert about the same later. Therefore, we still need to engage customer into the process of structured feedback provisioning, and it is a real challenge to make it unobtrusive and attractive for him/her.

According to the analysis of various methods and strategies that help to make a customer willing to provide a feedback (Khriyenko, 2015a), to get comprehensive feedback or suggestion from customers, company should target those customers who are interested in product/service improvement and who believe that his/her feedback (suggestion, preferences, etc.) will be taken into account. Customers are interested in co-creation of a new product/service (that is about to meet their expectations and preferences) as well as concerned with improvement of existing services they use. Therefore, it is preferable to allow customer to provide a feedback/comment at the moment and the place considered by customer as the most appropriate one. Customer should be able to make it for things (product/service parts, properties or functionalities, etc.), which are considered as important for him/her. There are a lot of customer feedback support systems which are mostly based on predefined feedback forms (Kampyle, OpinionLab, PollDaddy, Feedbackify, Survey Monkey, Zoomerang, Survey Gizmo, etc.). Since the forms are created by (or according to) product/service providers, they consist of issues that are important for them, and only unstructured free text forms become a place for actual concerns of a customer. Therefore, talking about digital environment, we have to provide a possibility to a customer, through pointing at any part of visual representation of a product or via selecting certain concept or piece of a text related to it, to access feedback provisioning tool with respect to associated feature/functionality of the product or service.

Reference to product's features and functionalities implies existence of domain data model and structured product description. Semantic Web technology (Berners-Lee et. al., 2001; Semantic Web, 2001) allows us to define domain knowledge and data model in structured form via Ontology. Then products' descriptions, as well as feedbacks provided by customers, could have structured RDF based representations. Definitely, we cannot expect average customer be a knowledge modeling expert able to provide semantically annotated content. Therefore, it is crucial to support feedback providers with easy to use interfaces that simplify the annotation process, placing annotation in the context of their feedback provisioning process. At the same time, all the digital content should be enhanced with possibility to provide a feedback on-the-fly. Talking about web content, we facilitate it with extra JavaScript functionality that implements semantically facilitated structural feedback provisioning.

2.1 Structured Feedback Collection - Enabled Digital Content

Semantic Feedback -enabled Digital Content is a digital content which is facilitated by JavaScript based functionality (*SCF.js plus SCF.css)* and optionally contains already semantically annotated pieces of texts and visual elements. The idea of such annotation is not to just present the same information in semantic form and put it in line with an initial content. For this purpose we may use RDFa notation (Adida et. al., 2015) for example. The idea is to imbed entity annotations to provide more intuitive and accurate guidance for customers during feedback provisioning stage later. The mechanism for customer driven structured feedback provisioning allows user to select peace of a text or visual element of the page, and access to the associated with it product features (presented in domain ontology and description of the product). With a text fragment selection, tool performs semantic annotation of the text. The annotation module is built using Stanford NLP (Manning et. al., 2014) and GATE (Cunningham et. al., 2002) Enabled Java libraries that allow text annotation using domain ontology and product/service description in RDF as an annotation schema. As a result, user sees a list of associated concepts/entities from ontology and products descriptions in the order of their relevance. To avoid errors of an automated annotation, some annotations of digital content (text or visual elements) could be imbedded to the Semantic Feedback -enabled Digital Content by product provider in advance. It could be done via Semantic Feedback -enabled Digital Content Creation tool (SFeDCC tool). In this case, pre-annotated concepts (associated with corresponding selection) will get higher priority in the list. At the same time, imbed entity annotations are required in case we associate them with visual elements of our content, since automated extraction of any semantics from visual content is very complicated task. Therefore, visual content should be enriched with corresponding annotations via SFeDCC tool at the digital content preparation stage.

SFeDCC tool helps to make digital content Semantic Feedback -enabled via enrichment with semantic annotations. Using the tool, product or service provider, who is versed in the product more than any customer, can edit automatically created

```
<p>Main body of the kettle is blue and made of metal. Kettle has gray plastic handle and black dock station. The length
of the dock station wire is 0.5 meters. </p>
```

Initial Digital Content

Enriched Digital Content

```
<head>
  …
  <link rel="stylesheet" type="text/css" href="http://scfDomain.com/scf/scf.css">
  <script type="text/javascript" src="http://scfDomain.com/scf/scf.js"></script>
  </script>
    addSource(http://example.com/domainOntology.n3);
    addSource(http://example.com/productDescription.rdf);
  </script>
</head>
…
<p><span data-scfURI="pD:mainBodyOfKettle1">Main body of the kettle</span> is <span data-scfURI="dOnt:blue">blue</span> and made of <span data-scfURI="dOnt:metal">metal</span>. <span data-scfURI="pD:kettle1">Kettle</span> has <span data-scfURI="dOnt:gray">gray</span> <span data-scfURI="dOnt:plastic">plastic</span> <span data-scfURI="pD:handleOfKettle1">handle</span> and <span data-scfURI="dOnt:black">black</span> <span data-scfURI="pD:dockStationOfKettle1">dock station</span>. The <span data-scfURI="dOnt:hasLength">length</span> of the <span data-scfURI="pD:wireOfDockStationOfKettle1">dock station wire</span> is 0.5 meters. </p>
```

Figure 1: Semantic enrichment of textual content.

annotation more efficiently. Tool highlights automatically recognized concepts/instances and allows expert to check it and make necessary corrections. At the same time, expert has a possibility to manually annotate text fragment if concepts/instances are not recognized automatically. Tool simply allows to select a visual element or text fragment and provides graph based concept browser to choose an appropriate instance from connected semantic products descriptions or corresponding entity from domain ontology in RDF format (these sources are added to the script via *addSource()* method). The browser is enhanced with text-based search functionality to facilitate navigation inside a graph. Corresponding annotation is imbedded into the initial html page via html *<span>* element with *data-scfURI* attribute. Figure 1 shows us an example of initial text that describes a "kettle" product and semantically annotated version of corresponding Semantic Feedback -enabled Digital Content. Result text is split up by *<span>* elements that bring semantic annotation to automatically recognized or manually selected entities.

In case of image annotation, tool gives a possibility to select particular area of the image and provides the same annotation tool with graph-based browser as it was in the case of text annotation. As a result, corresponding html image element is extended to image map structure with *data-scfURI* attribute that refers to annotation class or instance from domain ontology or RDF based product description (see Figure 2). If an image has a link, it will be repeated in each image map area to be visible.

2.2 Triple Based Feedback Collection

Depending on user's selection, system creates a list of entities (instances, classes, properties and their values) associated with it. To be more intelligent and user friendly, system range the list in the order of entity relevance. Assuming that everything is represented in RDF triple based structure "subject-predicate-object", system presents customer feedback as a triple based description of an ideal product. Since a customer feedback is a form of expression of his/her own opinion about product properties or functionalities (which are product properties as well), in most of the cases, user selection will cover "object" (the value of property/functionality) and less it will cover "predicate" as such. If we take a look at product description in our example (see Figure 1) and decide to provide a feedback about properties of the kettle and its parts (their colors, materials they are made of, the length of the kettle's dock station's wire, etc.), most probably we select such fragments of texts like: "blue", "metal" or "made of metal", "plastic handle", "black dock station", "length" and "0.5 meters". In most of the cases they are "objects" (values) or "subject-object" pairs, and only few of them consist of "predicate" (e.g. "length", "made of"). It means that system should automatically derive missing parts of triples using Ontology and

```
<a href="http://www.someLink.com" target="_blank">
    <img id="img_kettle" src="kettle.png" width="150" height="200" alt="Kettle" >
</a>
```

Initial Digital Content

Enriched Digital Content

```
<a href="http://www.someLink.com" target="_blank">
    <img id="img_kettle" src="kettle.png" width="150" height="200" alt="Kettle"
                usemap="#kettleMap" data-scfURI="pD:kettle1">
</a>
<map name="kettleMap">
    <area id="img_kettle_area1" shape="rect" coords="0,170,150,200" alt=""
                onmouseover="scfShowMenu(this);" onmouseout="scfHideMenu(this);"
                data-scfURI="pD:dockStationOfKettle1" href="http://www.someLink.com" target="_blank">
    <area id="img_kettle_area2" shape="poly" coords="30,40,100,40,100,170,30,170" alt=""
                onmouseover="scfShowMenu(this);" onmouseout="scfHideMenu(this);"
                data-scfURI="pD:mainBodyOfKettle1" href="http://www.someLink.com" target="_blank" >
    <area id="img_kettle_area3" shape="poly" coords="30,10,150,10,150,170,100,170,100,40,30,40" alt=""
                onmouseover="scfShowMenu(this);" onmouseout="scfHideMenu(this);"
                data-scfURI="pD:handleOfKettle1" href="http://www.someLink.com" target="_blank" >
...
</map>
```

Figure 2: Semantic enrichment of visual content.

RDF based descriptions of the products, as well as take into account availability of potential candidates in the text. In our example, we have a text with detailed description of the product, and of course, it contains a lot of “objects” and “predicates”. In case, when page does not present product description, but just has a mention of a product, selection brings us only a “subject”. Then, it become much challenging to guess user’s intention, the issue (s)he would like to comment on. We cannot expect that user has any experience with knowledge engineering and is able to compose triple based feedback through browsing domain ontology and product descriptions as it could be done by expert via SFeDCC tool. Thus, system tries to derive triples on-the-fly while user provides a feedback in a free text form.

Figure 3 presents triple based feedback provision supporting tool. The purpose is to help user to generate triple based feedback by presenting it in a human readable form. For example, if we select “plastic handle” fragment of the text, system recognize “handle” as a part of the kettle product and derive corresponding URI of the resource (*pD:handleOfKettle1*) as a subject for the triple. At the same time, associating word “plastic” with corresponding instance (*dOnt:plastic*) of the class *dOnt:Material* in ontology, system derives most suitable predicate for the triple (*dOnt:madeOf*), based on domain and range definitions of the property and available records in RDF product description (*pD:* and *dOnt:* prefixes refer to the namespace of product related definition and domain ontology correspondently). To present a triple in human readable form, system use text based representation associated with corresponding entities in ontology via *scf:hrForm* property (*scf:* prefix is used to represent semantic customer feedback ontology). It is not the same as *rdfs:label* property, even though it might also have the same value. The value of this property is not just a meaningful and human readable part of entity’s URI (e.g “color”, “made of”, etc.), but is the most suitable textual representation of entity to make textual version of a triple more natural for human (e.g. triple like “handle - is - gray” instead of “handle - color - gray”). If all three components of a triple are derived, then system represents the triple and expects changes of “object” from the user. If only subject component was recognized by system, then it is assumed that user will define predicate and assign the value (object). Search of appropriate components of a triple is done via analysis of textual input from the user. Depending on what user is typing in the text field, system modifies the order of suitable entities to be chosen from the list. Any time, when user would like to change the current status of the triple’s component and deletes it from the triple, system shows him/her a list of suitable options and uses user’s input from the text field as a context to order the list. If user would like to reset whole triple and remove all three components, then text field is associated with the whole triple rather than with particular parts of it. Very often feedback consists of relative evaluation rather than absolute meaning.

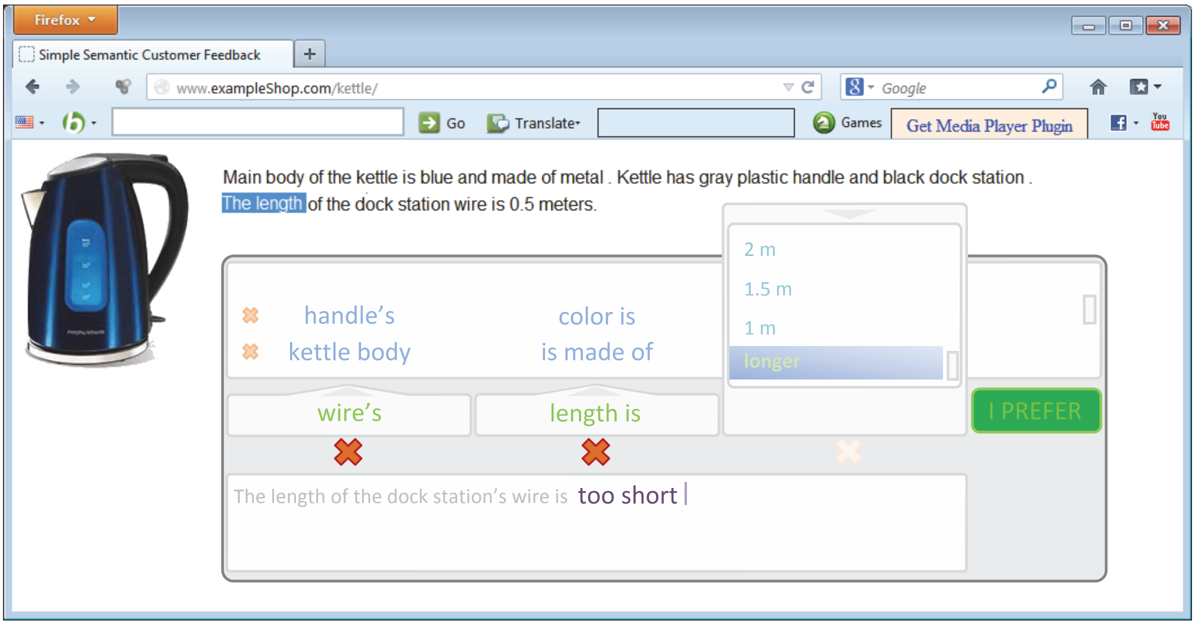

Figure 3: Structured feedback collection interface.

Customer may say that the wire of the dock station is too short for him/her rather to define concrete length of it. Therefore, ontology should consider not just absolute values (e.g numerical value, color's or material's names, etc.), but also define relative values or values defined via its property (e.g. "longer", "too small", "stronger", "more sticky" "softer", etc. Thus, customer may express his/her filling about the product. For example, customer may say that "handle is too dark" meaning that (s)he would prefer more lighter color of it, or say that "the main body of the kettle is too hot" meaning that (s)he prefers it made of some other material with smaller heat conduction. Based on such feedbacks system can build customer perceived and preferable (ideal) versions of a product description.

3 CUSTOMER FEEDBACK DRIVEN DESIRED/IDEAL PRODUCT GENERATION

Having new preferable values for product properties or new set of useful features based on customer feedbacks, theoretically we may use them to substitute initial ones in the product description. Unfortunately, we cannot just simply populate initial product description with new values (perceived or preferable) of the properties, since such values might not exist in the domain ontology and their use might be restricted by property constrains. Therefore, we introduce *scf:CustomerPreference* class (as a class similar to *rdf:Statement)* to represent triple based feedback of the customer. Similarly to RDF Statement, each instance of this class has three main properties: *scf:subject*, *scf:predicat* and *scf:object*. Additionally, it might have optional property *scf:domain* that refers to either particular instance (product or its part) or more general class of things (in case we represent aggregated customer preference with respect to a class of products or a concept). This extra property may simplify further aggregation of preferences. *scf:subject* and *scf:predicat* properties refer to corresponding instance of a product description and its property. In turn, *scf:object* may refer to an entity from a domain ontology and represent preferable for customer value, or to an entity of semantic customer feedback ontology that extends a set of usual values with such uncertain, relative values as: *scf:longer*, *scf:stronger*, *scf:hotter*, *scf:lighter*, etc.

As you noticed, transformation from customer perception (that could be expressed via free text during feedback provisioning (see Figure 3) to customer preference (which is actually submitted by customer through his/her feedback) is done automatically by system and only preference related value is suggested for "object" value to be assigned. In Figure 3 user expressed his/her perception about the wire's length of the dock station, which is too short in his/her opinion. System makes corresponding transformation and suggests the most suitable value ("longer") to describe user's preference - "wire's - length is - longer". Thus, when user submits this preference, corresponding instance will be created (see *cp:customerPreference_03* in Figure 4).

Further, based on such customer preferences and initial description of the product, we are able to generate corresponding description of a desired product. Knowing initial values for the properties, system may reason about relative values in the customer preference description and select reasonable values from existing options. Uncertainty of the values makes an advantage when we perform collaborative generation of potentially the best product configuration in the context of preferences of all the customers who belongs to the selected target group. In this case, if some customers expressed the preference to have lighter color and some customers specified exact values, system is able to calculate average value using color distribution palette. With respect to the materials' properties (e.g. hardness, durability, etc.), the absolute value (the name of material) could be calculated based on suggested values (relative and absolute) and corresponding properties from the ontology of materials.

Assuming that RDF based description of the product/service is used for software-driven automation process and could not be considered as a proper final result used by human (decision maker), decision support system should present results in more human readable form. Therefore, we need visualization tools that are able to build visual model of a product based on its RDF description. Some tools just would need to transform our RDF based product description into internal format of the tool. In more challenging cases, when full transformation

```
@prefix cp: <www.example.com/customer_preferemce/>.
@prefix rdf:<http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
@prefix pD: <www.example.com/productDescription/>.
@prefix dOnt: <www.example.com/domainOntology/>.
@prefix scf: <www.example.com/semCustomerFeedback/>.

cp:customerPreference_03
 rdf:type scf:CustomerPreference;
 scf:domain pD:kettle1;
 scf:subject pD:wireOfDockStationOfKettle1;
 scf:predicate dOnt:hasLength;
 scf:object scf:longer.
cp:customerPreference_02
 rdf:type scf:CustomerPreference;
 scf:domain pD:kettle1;
 scf:subject pD:mainBodyOfKettle1;
 scf:predicate dOnt:hasMaterial;
 scf:object dOnt:plastic.
cp:customerPreference_01
 rdf:type scf:CustomerPreference;
 scf:domain pD:kettle1;
 scf:subject pD:handleOfKettle1;
 scf:predicate dOnt:hasColor;
 scf:object scf:lighter.
…
```

Figure 4: RDF based customer preferences representation.

is not possible due to limitation of the tool's data model, we might need to apply more advance resource visualization techniques. For example, one of the relevant researches (Khriyenko, 2015b) presents an approach towards automated creation of semantically personalized user interface. Something similar might be applied to build domain independent product visualization tool.

With respect to analytical support, we are able to calculate similarity distance between actual and desired products based on their descriptions presented in unified form. Therefore, having statistical measurement of a threshold for customers churn and predicting a level of customers' satisfaction, system will warn product/service provider and suggest appropriate tailoring (customization) of the offering to what customer(s) want. Moreover, collected and aggregated customer's preferences can become a part of a personal customer profile. Matching preferences from the customer profile with descriptions of available products and services, provider can push personalized advertisements to potential customers.

4 FUTURE WORK

Elaboration of supporting tool for customer-driven extension of the ontology could be considered as a logical extension of current solution. Currently, system works with property values ("objects") available in existing domain ontology(ies) and some initial set of extra "relative" values (presented in semantic customer feedback ontology). Assuming that customers may express preferences, which are not covered by mentioned ontologies, and even suggest new part(s) and property(ies)/feature(s) of a product, we have to provide an appropriate support for ontology extension (Witte et. al., 2010). Such extension has dual side effect. From one hand, it requires more sophisticated and intelligent tool to support it, taking care of similarity matching (Shvaiko and Euzenat, 2012; Jain et. al., 2010) to avoid an ambiguity and appearance of several entities for the same notion. From the other hand, it becomes very important for customer feedback consumers, since it might bring something new (new functionality or property of a product) that had not been considered by them before.

Another planned direction of further research is to apply results towards customer reviews management. Usually, readers of reviews try to infer from review content to which extent their preferences overlap with the reviewer's preferences

(Bailey, 2005). Thus, having structured representation of preferences in the users' profiles, it becomes possible to automate review clustering and facilitate proper review selection.

5 CONCLUSIONS

Since, individual creativity and personal experiences will always be critical components of marketing decisions. The role of customer analytics is not necessarily to replace these, but to help decision makers to come to the fact-based conclusions through better knowledge of the organization's customers and markets. One of the challenges for the product/service providers is customer feedback collection and analysis, since it is associated with a real voice of a customer. Among other challenges (e.g. fruitful customer engagement to feedback provisioning process), processing of unstructured text based feedbacks becomes very challenging and does not provide sufficient result. Therefor current research presents an approach towards structured customer feedback gathering that further facilitates automated generation of preferable/desired product description. The main achievements of the proposed solution are: enrichment of digital content (web-based product or service description) with semantic annotations; mechanism for customer driven structured feedback provisioning; free text based feedback transformation into RDF based structured data; automated creation of a new or improved product/service description with respect to expectations and preferences of a customer.

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