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Analysis of Thai text from social media for mass customization

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Abstract

Knowledge extraction from social media data is a crucial problem when the derivatives of Thai text are concerned, such as using the wrong word, miss-spelling, and using various symbols. Due to the speed and competitiveness of business operations and the dynamic change of customer behaviour, extracting the core and optional attributes from customers was the research objective. One solution for supporting mass customization marketing (MC) is to identify the core attributes and optional attributes from customers posted via social media since the customers should express their needs, wants and demand in their message, which led to the factual data. To analyse these data, the principle of Text Mining and Regular Expression was used at the word level. Additionally, conditional probability was used to identify the significant words for supporting MC on the core and optional product components. The samples were collected from 1,400 posted data in the year 2019 from the Facebook fan page of Swensen's ice cream because the brand is a popular brand, and there are many branches in Thailand. According to the objective, the results showed that the related words to MC production with the conditional probability of the season were as high as 0.66 and 0.48 for summer and winter products, respectively. The core attribute "durian ice cream" had a probability of 0.548, while the optional attributes for ice cream in winter were strawberry and sticky rice in the summer. Finally, the firm can use the findings for supporting product design as customized style.

Introduction

Marketing in an era of technological advancements allows studies to concentrate on customer insight, needs and wants, which are crucial for developing competitive marketing strategies. Moreover, access to consumers' feedback is beneficial with the modern use of mobile devices, primarily through social media. Using the native language to express a customer's requirement to consume a product is a practical way of marketing communication. Considering modern marketing communication practices, practical knowledge to enhance a product design can be extracted from natural language as textual data. The extracted textual data can also facilitate co-creation or co-design by the customer (Deng et al., 2013). Consequently, a marketer can use this data to analyse and interpret market strategies and achieve effective

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global market competitiveness. Moreover, the depth text mining applied to extract the critical product attributes will strengthen marketing practices from a mass customization or personalization dimension.

The combination of the emergence of a more open world economy, the globalization of consumers' tastes, and the development of worldwide commercial accessibility has increased the interdependency and interconnections of markets around the globe. In such environments, businesses should develop their marketing strategy around two key dimensions: (1) mass customization (MC); and (2) personalization (Salvador et al., 2009). MC is the action of customizing, creation, or adaptation (of something) according to the customer's requirements (Deng et al., 2013). Current globalization and robust competitiveness have pushed companies to offer a variety of products to meet the needs of various customers' demands.

Customer demands widely vary and are often sensitive to small changes in the product attributes such as colour, package size, and functionality, and usually will require a substantial redesign of the product. The uncertain nature of customer behaviour and attitudes pressures companies to invest heavily in creating new product designs. Small markets with different needs slowly will replace large homogeneous markets (Fogliatto & Silveira, 2007). Proven solutions are offering the broadest range of products possible, which consistently increases unwanted overheads.

MC is a combination of production-oriented and customer-oriented concepts by finding the core attribute as the primary need, and the optional attributes as the supplement attribute (Tseng et al., 2010). For example, the automobile industry that uses MC strategy agrees to conduct the product design part into two modules: (1) the core module consists of the engine, car body parts; and (2) the optional module consists of accessories or wheels, etc. (Vinodh et al., 2010). With the modern technological capabilities, such as 3-D or visualization, the customers can design car parts and ornaments following customers' preferences. MC value was categorized as producers' and consumers' perspectives (Fogliatto & Silveira, 2007). The critical success factors for the producers' category were cost structuring and market value enhancement (Aigbedo, 2009), while these keys for the customer's group were supporting customer's confidence with co-creator's experience. To fulfil customer demands, the influence of value drivers on customers' willingness to purchase MC products should be validated. Moreover, the use of technology for supporting customers as co-creator and improvement of product design is also considered to enhance MC. Research on MC has involved multi-dimensional considerations such as the operational aspects (Salvador et al., 2009), the heavy use of web-based configurators, and customer interaction-oriented product design. However, exploring and extracting customers' knowledge; needs, wants, and demand, by using their communication in their virtual community, is a good and challenging solution to enhance product design. The study results using questionnaires often cast doubt on the reliability of the data due to the respondent's lack of intention or the unclear question. Most previous research on customization was conducted on data from questionnaire or depth interview (Fogliatto & Silveira 2007; Vinodh et al., 2010). Our study was a new idea of the multidiscipline context and was more challenging than previous works.

The success of mass customization thus depends on how to extract core and optional attributes from the customer dialogue and social media messages. However, since customers always communicate using native languages, the identification of relevant content for MC deployment remains different, mainly in each case, depending upon the natural language process applied to each specific language. This led to our research questions; how to extract core and optional attributes, and what are the ice-cream core and optional attributes.

To implement an MC strategy, product manufacturers must be able to identify parts of the main product, called the core attribute. For example, in car production, the main features are the body and the engine, while the supplements are the rear light, console, and tires, etc (Aigbedo, 2009; Vinodh et al., 2010). A massive production on core attributes leads to the effect on cost reduction. On the optional product attributes view with small demand, businesses can use the technology to design and produce on customer's wants or use outsourcing to be an alternative way for MC management. This type of administration has advantages. The warehouse will have only the main components of the product. As for the composition of the product, the part that the customer wants will only be produced when the customer sends in the demand (Vinodh et al., 2010).

Few works of literature have developed frameworks to assess the likelihood of success in pursuing text processing-based MC. Most previous studies, such as Sunikka and Bragge (2012), combined a text-mining approach for knowledge creation of personalization and customization marketing strategies. In the other application of a product design, searching as image retrieval via natural language is conducted on text processing analysis. Text processing is the fundamental of information extraction from unstructured textual data and Natural Language Processing (NLP). Besides the application of information retrieval, Thai text processing on the paradigm of knowledge extraction, causality, and procedural knowledge, were studied by Pechsiri et al. (2017). In 2017, Piriyakul et al. (2017) using principal components to analyse Thai text from customers' comment posts, and the results showed that there are two product images: symbolic and functional view. Each natural language has its own pre-processing differences. In English text, the step consists of stemming data and verb transformation while the Thai language is the word segment, name identification, and language parser. After the step of pre-processing, all multicultural languages use the generic logic pattern for knowledge extraction. Besides solving the problem of the pre-processing process, the dynamic language from social media with the time device constraints is added to this sub-task.

However, to study Thai text, the processing of unique Thai language features must be handled, such as the lack of space use in writing. Furthermore, there are no delimiters to identify the end of the sentences. Due to the online message composers, it is not only the Thai language, but also other languages, and symbolic representation for written words that need to be considered. For example, in using these styles " ♥ " is for love, "5555" for "Happy," and performing repetitive character extensions of a word is to express emphasis (e.g., I am very hungryyyyyyyyy). From an analytical perspective, analysis of text form social media communications is, therefore, tricky. To overcome this problem, an effective way is constructing the filter rules for detecting noise and cleaning data, by observing the behaviour of data. These research gaps are made prevalent upon investigating marketing management practices in Thailand and motivated this study. Therefore, this study aimed to conduct an empirical survey of customers' communication with regards to their product preferences and their feedback on the "Swensen's fan page." This study explored: (1) the theoretical aspects of the problem-solving in the text as diversity data and the temporal variations thereof; and (2) practical point of relevance knowledge identification for MC on the dimension of core and optional product attributes. This paper was organized in different sections. Previous work is discussed in the literature review. The section of the methodology consists of the explanation of various steps and techniques of Thai text mining. The results present the data analysis and application. The final part is conclusions, discussion, and future work.

Literature Review

Mass Customization (MC)

Since our research is integrating between text mining as a tool for knowledge extraction for further product design based on MC strategy, the previous studied divided two parts: the concept and prior work of MC and the technique in text mining.

Gone are the days when customers run behind specific products or services for their needs; today, differentiation for choice has become very important. That is where the new age MC has come into practice as a viable marketing strategy. Every customer is unique with their set of needs, wants, and demands. Identification of uniqueness in customer's demands and catering to them is a viable strategy to attract customers (Tseng et al., 2010). It is arguable from an economic perspective that a closer fit between preferences and product attributes brings about increased utilities for the customer. Vinodh et al. (2010) stated that the customization is the new strategic branding as it plays an important role in increasing efficiency, ensures maximum optimization of resources at hand, & cutting down unwarranted wastage (Aigbedo, 2009). Within the MC strategy, a company that cannot adapt quickly to change may find itself left behind, and once a company starts to lose market share, it can fall rapidly (Fogliatto & Silveira, 2007). Finally, to sustain and expand on business profitability, the concept of agile manufacturing is to keep a company ahead of the competition so that consumers think of that company first.

Regardless of progress, innovation must be continued and introduce new products because it is financially stable, and it has a strong customer support base (Hume & Gillian, 2010). MC is often divided to four types: (1) Collaborative MC with customer interaction in the stage of design; (2) Transparent MC, which product is adapted to customer according to a prior requirement; (3) Adaptive MC in which after the product has been purchase and the customer can adapt the product; and (4) Cosmetic in which the product attributes are produced to meet the customer's requirement base (Hume & Gillian, 2010). In the product design context, customization, generally, can be carried out on four levels: style, fit, comfort, and functionality. And the cost of mass customization demands on the options or adjustments offers for those product features and value by the customer. Thus, the critical questions are: which characteristics of a product are core and choice (option) from a customer's point of view?

From figure 1, the core attribute represents elements of needs, and optional attribute represents elements of wants with satisfying on the constraint of demand. The general representation of the product categorized as two sub-set: core attribute set: C= {C1, C2, …, Ck} and an optional attributes or selected subset: O = {O1, O2,…, On} due to each customer requirement. Core attributes are the necessary basis to satisfy needs while the optional or extra attributes satisfy wants and demand of consume perspective.

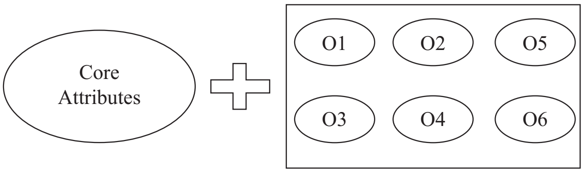

Figure 1 Component of Product: Core attributes and Optional Attributes

Companies that want to switch to the use of agile manufacturing can take advantage of marketers who specialize in helping companies convert and improve existing systems based on customers' knowledge. The knowledge developed from customer's comments or co-creation can offer advice and assistance tailored to the industry involved, and they usually focus on making companies competitive with proven agile techniques within the MC context. Furthermore, handling customers' information is often difficult. Salvador et al. (2009) quantified customer profiles, while Fogliatto and Silveira (2007) conducted preference modelling and applying eco-consumer clustering to configure personal choice menus. Another technique is using live chat software as a tool that creates a better customer experience. The message from the live chat is the same structure as the text from social media. A good point of using marketing communication through live chat or social media is the freedom to express customers' requirements. Therefore, choosing Facebook is a good data source because the properties of message are suitable for our study.

Thai Text Mining

Text mining, in general, is a set of processes to select, identify, and extract the relevant and significant patterns to explore knowledge from textual data. Text mining is an integration of multidisciplinary science: machine learning, statistics, data mining, and computational linguistics. In 2019, Kazi and Kahanda (2019) developed a human-powered doctor-patient conversation transcript annotator and obtained a gold standard dataset through the NAMI. Consequently, they model the task of classifying parts of conversations into six broad categories, such as medical and family history, as a supervised classification problem. Zhang et al. (2007) let customers stated their preferences in natural language, perform semantic analysis, and then predicted customers' preferences using associative classification rules. Previous works in text mining have enhanced business management practices through customer segmentation, customer relationship management, fraud detection, social media analysis on fake news and sentiment analysis. Unfortunately, none of the above studies lead to a marketing application by using content analysis to support MC.

Customers can send their requirements to the product owner in their respective native. Due to the communication that requires speed and emotional response, the messages are, therefore, different from the official written language, such as the use of symbols, images, or characters and joint English and Thai language together. Also, the message uses a number or unique symbol as abbreviations such as "2 you" or "See you @ Siam," "น่ากินนนนนน" ("Look deliciousssss"). The variation of text, as shown in these examples, whence greatly increases the difficulty in every language processing.

Methodology

The knowledge extraction system focused on the evidence of "Swensen's ice cream" with the objectives to extract the core attributes and optional attributes for supporting MC. The process was as follows: (1) Data collection and preparation from Swensen's customers posted in the year 2019 because it was a suitable time of normal consumption, then followed by automatic word segmentation; (2) Filtering incorrect word segments by using the rules formulated from learning behavior of the experimental data; and (3) Synthesis of the information gained by finding words related to the seasonal dimension to perform a product design on time-variant and ingredients, and Knowledge creation.

Results and Discussion

Data Preparation Output

One thousand and four hundred posted messages were collected from Swensen's customers via Facebook in the year 2019. Then the documents were used to process a word segment by LexTo (an open software for the Thai word segment), and such represented a variance length of 1400 feature vectors to formulate our experimental data set.

Filter Rules for Noise Reduction

Since there is an incorrect segment caused by word spellings and ellipsis, using wrong grammar and mixed languages affect software stability. Then, we constructed a set of filter rules to identify the relevant words by exploring the data patterns (such as critical characters and the distance of adjacent words). The filter rules are illustrated in Table 1. Rule filters play a role as reconstructing a complete word, icon or ellipsis transformation, and truncate non-relevant words. The filter rules lead to the data analysis for further MC product design.

Formulation of Related Words

Since Thai words related to the season use many forms such as "winter," "summer," and the other terms (festival or events), our study constructed groups of the seasonal word, namely "S1" and "S2". Our system also used query expression to retrieve the elements. Finally, the two sets were S1 = {winter, Christmas, December, January, February, New-Year}, and S2 = {summer, Songkran, semester-break, summer-break, durian-season, mango-season}. Thailand's ice-cream consumption behavior is often seasonal, the study, therefore, retrieved all words with the concept of time-domain as a knowledge base for further product design.

Knowledge Creation and Implementation

Besides, the information on the time dimension, the system explored more, deep knowledge related to core and optional product attributes. Table 2 illustrates the probability of each pair of words in the document, e.g. "|new year| |strawberry|' is 0.050 (70/1400).

Using the results from set S1 and S2, we defined A = {S1, S2} and B = {b1, b2, b3}; where element, b1 = "สตรอเบอร์รี่" (strawberry) b2 = "ทุเรียน" (durian) and b3 = "มะม่วง" (mango).

The query expression to access any substring from the data is Q = {(S1, B), (S2, B), (B, S1), (B, S2)} as shown in Table 2. The objective of this step was to find the substring which is composed of seasonal words and type of fruit or vice versa in each post. This step aimed to calculate the conditional probability to answer the temporal dimension of product design. The notation of probability was defined as follows:

P(AB) = P (A and B) = P (B and A); where A is seasonal word set and B is type of fruit.

P (B|A) = P(AB)/P(A). The example calculation is as shown below:

P(B = b1|A = S1) = P (B = b1 and A = S1)/P(A = S1) = (120/1400)/ (250/1400) = 0.48.

Table 1 Filter Rules Synthesis for Data Cleaning

<table>
<tr><th>Word in text</th><th>Problem</th><th>Word Segment Result</th><th>Filter Rules</th></tr>
<tr><td>Strawberry</td><td>English word</td><td>| Strawberry|</td><td>If search (substring is | Strawberry|) or |strawberry| then the word is |สตรอเบอรี่| (|strawberry|)</td></tr>
<tr><td>🍓</td><td>Icon
Representation</td><td>| 🍓 |</td><td>If search (substring is | 🍓 |) then the word is |สตรอเบอรี่|
(|strawberry|)</td></tr>
<tr><td>ไอติม (ittim)</td><td>misspell</td><td>| ไอติม | (|itim|)</td><td>If search (substring is | ไอติม |) the word is | ไอศกรีม | (|ice-cream|)</td></tr>
<tr><td>ไอศกรีมทุเรียน
(Isacreamdurian)</td><td>misspell</td><td>| ไอ|| ศ || ครีม || ทุเรียน |
|i|||s||cream||durian|</td><td>If search (substring is | ไอ| (|i|) the word is | ไอศกรีม | (|ice-cream|)
and drop the next three adjacent words</td></tr>
<tr><td>สตอร์เบอรี่
(storeberry)</td><td>misspell</td><td>| สตอ | ร์เบอร | รี่ |
(|store||ber||ry|)</td><td>If search (substring is | สตอ |) then the word is |สตรอเบอรี่|
(|strawberry|) and drop the next two adjacent words</td></tr>
<tr><td>สตรอเบอรี่
(stroberry)</td><td>misspell</td><td>| สต | รอ | เบอร | รี่ |
(|st||ro||ber||ry|)</td><td>If search (substring is | สต|) then the word is |สตรอเบอรี่| (strawberry|)
and drop the next three adjacent words</td></tr>
<tr><td>ไอศกรีมหมอนทอง
(Isacreammonthong)</td><td>Ellipsis
(Durian)</td><td>| ไอศกรีม | หมอน | ทอง |
(|ice-cream||mon||thong|)</td><td>If search (substring is | ไอศกรีม | หมอน | ทอง |) (|ice-cream||mon||thong|)
or (| หมอน | ทอง | ไอศกรีม |) (|mon||thong||ice-cream|) then the
compound word is "|ไอศกรีม|ทุเรียน|" (|ice-cream||durian|) and drop the
next two adjacent words)
word in this case is the noun phrase</td></tr>
</table>

Note: The notation |word| refers to word segment.

Table 2 The related words to the season

Substring in data	Frequency	Frequency	Probability
| new year | …. | strawberry|S1	70	-	0.050
| strawberry |…| winter| S1	20	-	0.014
| Christmas| …. | strawberry | S1	30	-	0.022
winter and strawberry		120	0.086
Amount of" winter" word occurs in the data set		250	
| duration | durian | produce | S2	10	-	0.007
|summer |…. | durian | S2	140	-	0.100
|April |…. | durian| S2	110	-	0.079
| summer-break |…. | durian | S2	150	-	0.107
summer and durian		410	0.293
|summer |…. | mango | S2	40	-	0.029
|semester-break |…. | mango | S2	30	-	0.021
summer and mango		70	0.050
Amount of "summer" word occurs in the data set		620	

The example explanation from Table 3 is *"If the season is summer, then the most popular fruit that customers like to eat is "Ice-Cream and Durian." (Probability = 0.66)."*

Table 3 Conditional Probability

Conditional Probability	Probability
P(B = b1|A = S1)	0.48
P(B = b2|A = S2)	0.66
P(B = b3|A = S2)	0.11

We found that the season had an effect on the type of fruit to design ice cream in the style of mix or match. Thus, the question arises whether the kind of fruit should be used as either the ingredient or the topping. Because of the influence of the season on consumers' behavior, MC strategy should take this variable on the first level of product design.

To construct the module of product attributes as core and optional attributes using regular expression and conditional probability the regular expression is generated based on the pattern of three related words. In the context of MC, customizable food items such as pizza, sandwiches and salads, are often sold using a mixing and matching system. For example, WooCommerce restaurant, which is an online food store, designs orders by allowing customers to select Pizza toppings and filling for baking as the customer prefers. In our research, the mix items are comparable to core attributes, and match items are optional attributes that can lead to creating alternatives for customers to design their products. To examine words or set of words to indicate the core and the optional attributes, we observed the language pattern. The processing consisted of two parts, the detail of which are as follows:

Part 1.

In the general pattern, the rule of fetching is selecting the keyword " ice-cream," followed by a sequence of words of V and B, unless if the language missed a word of set V. To construct set V, our process was learning by the pattern. Examples of text such as "| ice- cream | made | from | durian |," " | ice-cream | made | of | durian |" and "|durian| ice cream|" are the same concept- the ice-cream made from durian. This can be compared to the English grammar: | ice-cream | <noun> | made | <adj> | from | <prep> | durian | <noun>. In the process of substring retrieval, we apply query language regular language expression, and the sample of successful implementation display as follows: Query = |N|V|B|;

where N = | ice-cream |; V= (| |, |made| |with|, |made| |from|, | made |, |flavor|) ; | | is empty word, and B = (|strawberry|, |durian|, |mango|, | Mornthong durian|)

The results after completing part 1, are illustrated in Table 4.

The lists of substrings in Table 4 are the same meaning: |durian ice cream| with the occurrence probability of 0.243, and the most likely result is | ice cream | durian |—most working on seasonal product design improved by the addition of prior information from Table 2. The following computation uses posterior probability under the condition of S2 = summer.

P (Q| S) = P (Q and S)/ P(S); Q is Query expression denoted as |N|V|B|.

Table 4 The probability of substring using query expression (|N|V|B|)

Substring	Frequency	Probability (n =1400)
| ice cream | made | from | durian |	30	0.021
| ice cream | made | with | durian |	30	0.022
| ice cream | made | from | Monthong durian |	20	0.021
| ice cream | made | by | durian |	10	0.007
| ice cream | flavors | durian |	40	0.029
| ice cream | durian |	210	0.157
Total	340	0.243

P (Q|S = S2) = P (Q and S = S2)/ P(S = S2) = (340/1400)/(620/1400) = 340/620 = 0.548.

Due to the probability value, approximately 55 percent of seasonal dimensions, the core product design, is producing ice cream by mixing with durian as an ingredient. The conclusion of part 1 is the core attributes of ice- cream is “durian ice cream”.

Part 2

We established a framework to identify the choice (optional) attributes. This phase focused on extracting keywords with matching between ice cream and other product attributes such as hot fudge, sprinkles, peanut, fruit (mango, strawberry, durian), and wafer. The substrings are retrieved in the same way as part 1, by formulating query language expression: |N|M|P| and |P|M|N|. And the criteria in each expression list are as follows:

N = (|strawberry|, |durian|, |durian ice cream|, |mango|, |ice cream|)

M = (|pair| |with|, |pair| |together|, |see|, |put|, | pour |, |add|, | topping |)

P = (| sticky rice | | stream |, |cream|, |sticky rice|, |wafer|)

Set M, can be broken down into groups, namely: Match (coupled with) = (|pair| |with|, |pair| |together|,|see|), and Augment(supplement) = (|see|, |put|, | pour |, |add|, | topping |). With MC deployment, element in M is an optional product attribute. Table 5 provides the occurrence of relevance substring.

Knowledge Representation for MC

The knowledge tank in Figure 2 presents that during the winter, product design is traditional ice cream and match attributes are strawberry, wafer, or cream. And in the summer season, the core attributes are ice cream made from durian or traditional ice cream, coupled with sticky rice or mango. Our process of knowledge extraction from customer message, can be applied in general product.

Table 5 The frequencies of substring using query expression (|N|M|P| or |P|M|N|)

Category	Substring	Probability
1	|strawberry| |see| |ice cream |	0.021
2	|ice cream ||add| ||strawberry| |	0.029
3	|strawberry| |put | |ice cream|	0.057
4	|strawberry| |topping| |ice cream |	0.014
	ice cream and strawberry	*0.121*
5	|ice cream||pour||cream|	0.021
6	|ice cream||topping||wafer|	0.043
	ice cream topped with cream or water	*0.064*
7	| sticky rice | | stream |, |pair| |with|, |durian ice cream|	0.122
8	|durian ice cream| |pair| |together|	0.057
	durian ice cream couple with sticky rice	*0.179*
9	|ice cream|, |pair| |with|, |mango|	0.014
	ice cream couple with mango	*0.014*

Note: The highest frequency of this category is probability 0.179.

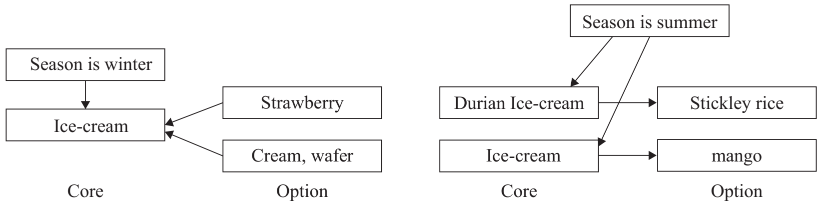

Figure 2 The component of Knowledge-Based for supporting the MC strategy

Conclusion and Recommendation

The result of the study classifies two managerial implications. The first one is product design according to the time dimension, namely, the festival or season, and the second is how to design core and optional product attributes. The core attributes may be compared to mixing the components of the ingredients, while the optional attributes are the supplement as the product composition. The knowledge creation using Thai text posted online from Swensen's ice cream customers is value-added to enhance MC in competitive markets. Additionally, the analysis is quite entirely independent of Thai grammar and flexible on consumers who voluntarily post messages. This type of data collection has advantages over other methods, such as using a questionnaire or interviews as customers may not express all their needs and wants in person.

Conflict of Interest

There is no conflict of interest.

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