Chapter 7

Text Analysis of Open-ended Survey Responses

7.1 Introduction

In the previous chapter, we gave a brief summary of the developments in the area of (statistical) text analysis. Although we illustrated the technique Latent Semantic Analysis by means of a realistic example, this example was so simple that the usual difficulties encountered in the analysis of textual data did not come to light. In this chapter we analyze open-ended survey responses. Many of the topics mentioned in the previous chapter will pass in review. The analyses in this chapter clearly illustrate the difficulties encountered when analyzing the written word.

One of the main interests in consumer research is the identification of products which are liked best. Whilst consumers can be expected to rate their overall liking for products, experience has shown that they are often not able to say why, in a way meaningful to product developers (Elmore et al., 1999). If people like a product, they tend to rate it highly on associated attributes and vice versa, the so-called halo effect. Often, key sensory drivers of liking are studied with preference maps that use objective data from trained panel assessment of product characteristics. In preference mapping, sensory attributes are either projected in a low dimensional representation of the preference scores (internal mapping), or alternatively, preferences are projected in a low dimensional representation of the sensory scores (external mapping). Generally, this low dimensional representation of the scores

This chapter is a slightly adapted version of Ten Kleij and Musters (2003).

results from a singular value decomposition (Carroll, 1980). Although preference maps are informative both for product developers and marketers, this approach of linking sensory data to consumer preferences has some shortcomings. First, the liking scores and the sensory assessments come from different groups. Although the sensory panel is highly trained and selected on sensitivity, so that objective product characterization is warranted, their assessments have to be extrapolated to consumers. Labels given to attributes upon which the panel scores products may not be the same words that an average consumer would use. Second, in linking sensory data to preferences, the relationships between the scores have to be specified upfront (i.e. linear, quadratic, or other). Two products can have similar liking scores, but a world of difference may be between them in terms of sensory characteristics. Unfortunately, there is no theoretical framework for assuming a specific type of relation.

In part, these shortcomings could be tackled by complementing preference maps with an analysis of the statements that consumers make to motivate their liking scores. This mode of analysis has the advantage that the liking scores as well as the motives for these scores are given by the same people and, more importantly, are stated in consumer language. Thus, results can be applied directly in marketing the products under consideration. In addition, no functional relation between liking scores and product attributes has to be assumed, since this relation is articulated by the consumers themselves. However, free-text responses explicitly stated by consumers, such as in the form of open-ended questions, are not often used for detailed analysis. Rather, these responses are used for developing other questions, or for reducing the frustration of the respondents by allowing them to explain their responses to other survey items (Looker et al., 1989). However, these free-text responses undoubtedly contain very rich information and may underscore and complement quantitative findings. Since language is a common channel through which emotion is communicated, it is likely that intrinsic information is embedded in this type of data. The richness inherent to textual data makes it extremely interesting to analyze, but when dealing with a large number of texts, it becomes almost impossible for human coders to stay consistent and keep an overview. Whereas techniques for analyzing numerical data have become more and more advanced, the analysis of textual data is still time-consuming and labor-intensive. Although text processing software is emerging, its application is often not fully exploited. The speed and data-handling capabilities of specialized software and computer technology may aid in the detection of themes or patterns in textual data that might otherwise go unnoticed (Mossholder et al., 1995).

We exploit the currently available software capabilities to facilitate text processing. By counting words, we develop an idea of the main topics consumers talk about. Since we are also interested in differences between 'I like the product' and 'I do not like the product', we also take word combinations into account. We construct a product-by-words matrix, showing the frequency of particular word combinations consumers used to describe the products. Correspondence analysis will be applied to this matrix, to construct a visual representation of the relationship between word usage of consumers and products. The correspondence map, just like a preference map, visualizes the relationship between product liking and product attributes. This whole data analysis process will be outlined in section 7.3.

The aim of the present study is to illustrate an approach to integrate the analysis of textual data into the common process of linking sensory data to liking scores with preference maps. In our opinion, both marketing and product development will benefit from incorporating the consumer statements in the analysis. Whereas text analysis is a broad concept and can be applied in many ways, our approach will be mainly quantitative, that is, we will be concerned as little as possible with issues arising in the field of linguistics, semantics, syntax, and so on. The ultimate benefit of the analysis of these responses would be to obtain a better understanding of the emergence of particular preference patterns, to clarify and strengthen quantitative findings, and maybe even to reveal aspects of the products that were not covered by the other survey items. We discuss some exploratory results from analyzing the statements which give insight into when and why consumers start talking about a product in section 7.4. Our main focus, however, is the comparison between the results obtained by preference mapping and those obtained by analyzing the textual statements by means of correspondence analysis. Besides showing how textual data enrich and complement numerical data, we also discuss the difficulties and limitations in section 7.5. We start, however, with a description of the materials and methods used in this study.

7.2 Materials and methods

7.2.1 Samples

During an in-hall test at three different sites, 13 different prototypes of mayonnaise were evaluated. The products were selected to be different in mouthfeel characteristics. Before evaluating the prototypes, each consumer was presented a dummy product as a warm up sample. The products were offered according to a balanced design; one of the products was offered twice to evaluate the reproducibility of the scores.

7.2.2 Panelists

In total, 165 respondents were selected who use mayonnaise at least once every two weeks in several applications, at least in one where it is not mixed with other ingredients. Furthermore, an equal part of the the group of respondents were male and female, and the respondents were equally distributed over three age groups of 20-34, 35-49, and 50-69 years.

7.2.3 Consumer surveys

Respondents had to give liking scores for the products. Responses were given on a 10-point scale, where 1 = 'do not like at all', and 10 = 'like very much'. After each assessment, respondents were allowed to write down remarks, enabling them to explain why they gave particular liking scores, or to express whatever crossed their mind. Since this research was done in the Netherlands, the remarks were in Dutch. These responses were spontaneous, respondents were not forced to give an explanation. We emphasize that all the analyses in this chapter are carried out on the original textual data in Dutch, we only translate the results. To give an idea of the type of statements respondents made, we give a few examples:

'Good color, right thickness. Everything in balance, perfect.'
'This one is soft and creamy.'
'Very sour, tastes like a salad dressing. Very white color.'
'Good taste, color could be a bit more yellow.'
'A very nice and creamy taste.'
'Looks a bit fatty, taste is good.'
'A little bit too sour.'

7.2.4 Quality of the data

To evaluate the quality of these data and to check the representativeness of the panelists, we did some exploratory analyses. Since respondents were not forced in any way to comment on their liking scores, it is interesting to know whether the fact that a respondent does or does not make a remark after assessing a product tells something about how he or she appreciates the product. We therefore look at the differences between the liking scores from respondents who made a remark (72% of the cases) and those who did not (28% of the cases). The results are summarized in table 7.1.

Table 7.1. Number of people with a particular liking score who do or do not make a remark (row percentages are in brackets)*.

liking	1	2	3	4	5	6	7	8	9	10
no remark	3 (.4)	18 (2.6)	26 (3.7)	50 (7.1)	86 (12.2)	141 (20.1)	179 (25.5)	125 (17.8)	57 (8.1)	18 (2.6)
remark	30 (1.7)	59 (3.3)	108 (6.1)	171 (9.6)	259 (14.5)	309 (17.3)	380 (21.3)	303 (17.0)	136 (7.6)	29 (1.6)

* 1='dislike extremely', 10='like extremely'

A simple t-test shows that there is a difference between the average liking score of 6.1 from respondents who made a remark and an average liking of 6.5 from those who did not ($p = 0.001$). There is a clear separation between respondents giving high liking scores and those giving low liking scores. A χ^2-test indicates that the liking scores and the variable indicating whether a respondent does or does not make a remark are dependent ($p = 0.002$). Respondents who use the liking scores 1 through 5 more often give a remark than respondents who use the liking scores 6 through 10. For the respondents who do not give a remark it is just the other way around. It seems that people who are more negative about a product, in terms of the liking score, are more inclined to make a comment than people who are more positive in their judgement.

A related issue is whether respondents make more remarks about particular products than about other products. We hereby also have to take into account that not all products were evaluated the same number of times, because of the presence of duplo products. We therefore look at the relative number of statements per product, that is, the number of statements per product divided by the number of times that product was evaluated. These results are summarized in table 7.2. The last column of this table summarizes the average liking score across respondents for each of the products.

Table 7.2. Number of statements per product.

product	relative number of statements in %	average liking score
A	66	7.0
B	72	6.7
C	74	6.5
D	78	6.4
E	73	6.4
F	66	6.4
G	70	6.2
H	77	6.1
I	71	6.1
J	70	6.0
K	72	5.9
L	72	5.8
M	83	5.3

Table 7.2 clearly reveals that product M is most often made a comment on, which perfectly agrees with the previous result that people who comment on their liking score are more negative than people who do not, since product M is the most disliked product (in terms of the average liking score across respondents). Respondents say relatively little about the products A and F, where the former is the product liked most (again in terms of the average liking score).

Summarizing, we see that respondents make more comments on their dislikes than on their likes. This could either be because they find that easier, or because they are more motivated. One could argue that this causes the sample to be unrepresentative. The results will be somewhat biased, in the sense that we get to know more about why a consumer dislikes a product than why he or she likes it. However, as we saw, the differences are only small, so that the results will be only slightly biased.

7.2.5 Expert panel

A descriptive QDA (Quantitative Descriptive Analysis) panel consisting of 9 persons, assessed the products sensorially. Each of the products was assessed twice by the panelists. These panelists were trained extensively in describing and assessing the sensory aspects of mayonnaise. In total, 37 sensory attributes were evaluated. The significant product differences in terms of sensory attributes, based on an analysis of variance followed by a Student-Newman-Keuls test, can be found in appendix 7.A.

Figure 7.1 shows a biplot representation constructed from the data summarized in appendix 7.A. This so-called internal preference map is constructed by using Principal Components Analysis (see, e.g., Carroll and Chang, 1970). The product attributes are projected in this map by means of regression. Figure 7.2 shows the external preference map, that is, the projection of the consumers in this biplot with the vector model vector model (see, e.g., Carroll, 1972).

The preference map shows that product *H* is perceived as being yellow with high taste and odor intensity. Product *C* is relatively fat, and the products *G* and *J* are very spreadable.

7.3 Data analysis

Using the textual statements, our aim is to typify each of the products in terms of word usage. There is a risk involved that a small number of consumers use particular words many times. However, we carefully examined the statements consumers made to make sure that this was not the case. Preliminary analyses showed that individual words are not sufficient. For example, ’taste’ is the most frequently used word, but this word is not interesting on its own: we want to know what is said about the taste, e.g., ‘the taste is too sour’, or ‘it tastes very creamy’. That is why we take word co-occurrences into account. By counting word combinations, we construct a matrix showing how often particular co-occurrences of words are used to describe each of the products. This matrix will then be analyzed by means of correspondence analysis, to visualize the relationship between products and product characteristics verbalized by the respondents. To come to this matrix we have to ‘clean’ the textual statements and make some practical choices, which we describe in the following subsections. The actual word counting was done using WordStat, a content analysis module specifically designed to process

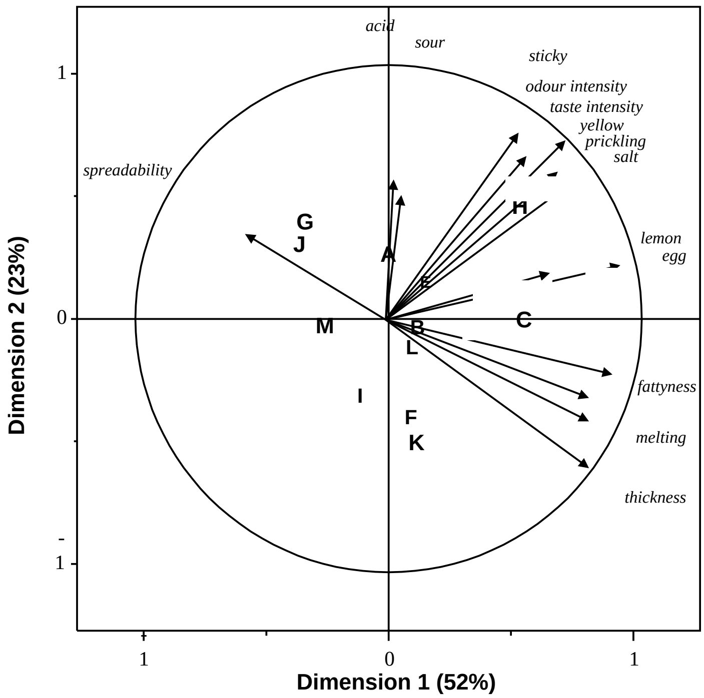

Figure 7.1. Biplot representation (internal preference map). The length of each attribute vector in this figure is proportional to the amount of variance captured by the dimensions in the figure. Attributes lying on the circle are fully represented in the figure (i.e. variance explained is 100%).

textual information such as responses to open-ended questions, interviews, titles, journal articles, public speeches, etc. (`www.simstat.com/wordstat.htm`).

7.3.1 Preprocessing

As described in subsection 6.2.1, text analysis normally starts with preprocessing, the 'cleaning' of a text, that is, removing typing mistakes, dealing with digits, punctuation marks, hyphens, and the case of letters. In the next step, words with low content, also called stopwords, (e.g., the, and, for, on) must be filtered out, thereby removing the noise in the remarks. After a short glance at the textual data, it is immediately clear that the customary

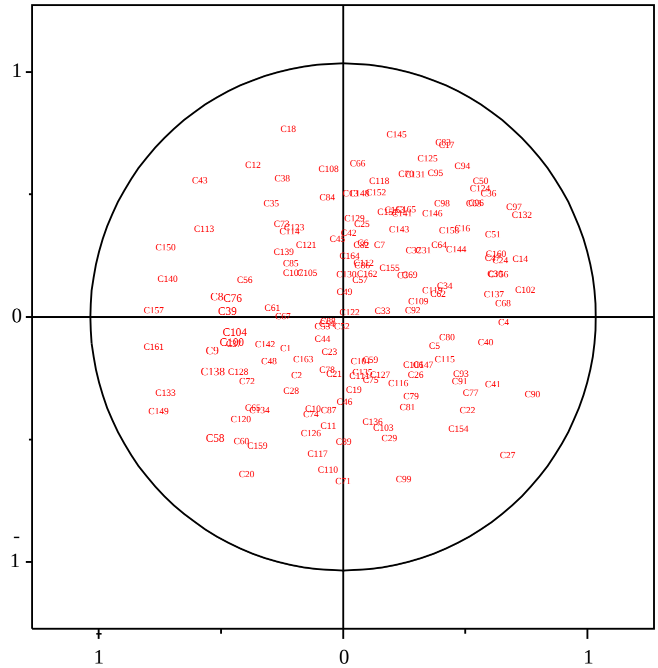

Figure 7.2. Projection of consumers in the biplot representation (external preference map).

stoplists, which can be found in a number of standard books on text analysis (e.g., Manning and Schütze, 1999), do not apply. Statements from consumers are short sentences, often not well-constructed, full with negations (e.g., no, not), and qualifiers (e.g., very, some). The word 'not', for example, appears on most stoplists, since this word does not bear a lot of meaning on its own. This will generally be true, but in consumer remarks this word is extremely important: 'like' and 'not like' is of course a big difference! Similar reasoning applies to words such as 'too', 'very' and 'no'. Adverbs, adjectives and negations are often left out of consideration in text analysis, but in consumer statements they may be the most important, at least in combination with the words they belong to. This means that we have to do more than just counting words, the combinations of words make these texts interesting. We therefore did not include negations and qualifiers on the stoplist. Stemming, i.e. grouping together derivatives of the same word, is the final preprocessing step. Stemming makes that, for example, ‘sour’, ‘sourish’ and ‘sourishness’ comprise the concept ‘sour’. Synonyms are also important, ‘acid’ for instance also means ‘sour’. We did the stemming manually, also taking into account synonymy. Stemming is not a subjective task and is straightforward. In general, handling synonyms is an important aspect on consumers-driven vocabularies and contains a subjective element. Therefore, we only considered synonyms that were free of discussion, that is, we only grouped those words which obviously belonged together. In total, 25579 words were counted, 496 of which were unique concepts.

The short, disconnected sentences also cause problems, since sometimes the subject changes suddenly within a statement, for example: ‘nice color, smells very sour’. Although ‘color’ and ‘sour’ are used within one response, they do not have anything to do with each other. To solve this problem, we split the statements, assuming that a comma and the word ‘and’ indicate that respondents begin to talk about a different product attribute. We accept the mistakes that are made when using this rule and assume that most of these very short statements now deal only with one subject. The original 1818 statements were split up into 4130 shorter statements this way.

7.3.2 Selection of keywords

When analyzing the textual statements, we first filtered out words that have a frequency of occurrence less than 30 and obtained a number of 55 terms, summarized in table 7.3. We had to set the cut-off value because the usefulness of correspondence analysis declines if the matrix is very sparse. A correspondence map showing a large number of word combinations is difficult to interpret. We set this somewhat arbitrary threshold supposing that the remaining words bear most of the content of the remarks. Words occurring relatively infrequently are not expected to be very important. Furthermore, these 55 terms cover more than 70% of the total word frequency, which justifies our choice to disregard the remaining words.

As mentioned before, we are particularly interested in the combinations of words. Besides knowing which product characteristics respondents find important (e.g., the color), it is as least as interesting to know how they evaluate these characteristics (e.g., the color is too yellow). Since we are not that ambitious to extract the exact meaning of the statements[1], we limited

[1] We feel that this should be left to researchers in the area of, for example, linguistics, semantics and syntax.

Table 7.3. Frequency of words occurring at least 30 times.

word	frequency	word	frequency	word	frequency
taste	1047	odor	133	less	51
too	593	fairly	123	strong	51
nice	454	see	121	yellow	48
good	451	fresh	103	salt	43
be	398	no	101	structure	42
sour	373	little	95	seem	37
not	372	extremely	84	nasty	37
color	334	product	79	sit	37
creamy	269	have	77	flat	35
fat	240	beautiful	71	spicy	35
a little	232	sauce	70	pallid	34
aftertaste	210	white	70	really	34
very	182	firm	69	stay	34
thick	177	a lot	68	neutral	33
mayonnaise	175	full	68	sweet	31
a bit	174	thin	63	common	30
do	170	find	62	(to) taste	30
soft	156	can	56		
light	144	pleasant	55		

ourselves to using simple measures. Our aim is to visualize the relationship between products and word usage by means of correspondence analysis, and in order to do this, we need a table showing how often particular word combinations were used to describe each of the products. In the following we describe how the interesting word combinations were selected and how this table was constructed.

Because we are interested in word combinations, we can examine how often the 55 selected words co-occur. This means, however, that we have to look at almost 3000 word combinations, which is a tedious task and probably not very informative. Therefore, we selected, from the list of 55 keywords, 15 product features we considered most important. These product features are: ‘thick’, ‘thin’, ‘yellow’, ‘smell’, ‘color’, ‘light’, ‘aftertaste’, ‘creamy’, ‘taste’, ‘firm’, ‘fatty’, ‘full’, ‘white’, ‘soft’, and ‘sour’. We realize that this selection contains a subjective element and that we have to take this into account when interpreting the results. We constructed a 55×15 word-by-feature matrix of all statements, showing how much each of the 55 keywords co-occurred with the feature within the statements. A small part of this word-by-feature matrix (the first 5 rows and columns) is given by table 7.4. For each of the 15 product features, we selected the 5 most frequent co-occurring words.

Table 7.4. Small part of the matrix of word (rows) and feature (columns) combinations.

	thick	creamy	color	sour	fat
bit	30	10	32	101	33
not	14	13	10	28	56
too	60	11	63	132	66
very	9	20	25	20	31
taste	0	53	8	90	46

Subsequently, we collected the frequency of all the word combinations for each product separately. In other words, we counted how often, for example, the word combination ‘too fat’ was used by consumers to describe product *A*. From these frequencies we constructed a product-by-words matrix, showing the number of times the selected word combinations occurred in the statements for each of the products. This matrix has 75 rows (15×5 word combinations) and 13 columns (the products), so that it is not surprising that it is very sparse. These zero entries cause difficulties in correspondence analysis. To overcome this problem, we chose to group the qualifiers ‘very’ and ‘too’ (so that ‘very yellow’ has the same meaning as ‘too yellow’), ‘a bit’ and ‘a little’, ‘very’ and ‘a lot’, the adjectives ‘good’, ‘nice’, and ‘fine’, and the negations ‘no’ and ‘none’. In addition, we deleted those rows that have a row total less than 10. These decisions are not unreasonable and made the analysis practicable. The number of rows was in this way reduced to 48. For illustration, table 7.5 shows a small part of this matrix.

Table 7.5. The first 5 rows of the matrix of products and word combinations.

	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*
not thick	5	3	26	2	3	10	1	7	1	0	6	2	3
taste creamy	4	8	13	7	1	3	3	3	1	2	5	2	1
nice color	17	17	16	4	10	5	5	13	5	6	7	7	7
sour aftertaste	2	5	0	7	2	3	1	1	2	1	0	5	2
bit fat	5	4	7	9	12	12	19	2	8	7	6	5	5

7.3.3 Visualization

One of our aims is to visualize the relationship between products and word combinations, and since we are dealing with counting data, correspondence analysis is an appropriate technique. Correspondence analysis provides a method for representing data from a two-dimensional contingency table spatially, so that the results can be visually examined for structure (Greenacre, 1984). Both the row variables and the column variables are represented in the same geometrical space.

7.4 Results

Figure 7.3 shows the perceptual map resulting from correspondence analysis of the contingency table constructed as described in section 7.3. Products are scaled relative to their liking score. We see that the first dimension explains 44% of the total variation, while the second dimension explains 33%. Unfortunately, it is not straightforward to interpret the resulting dimensions.

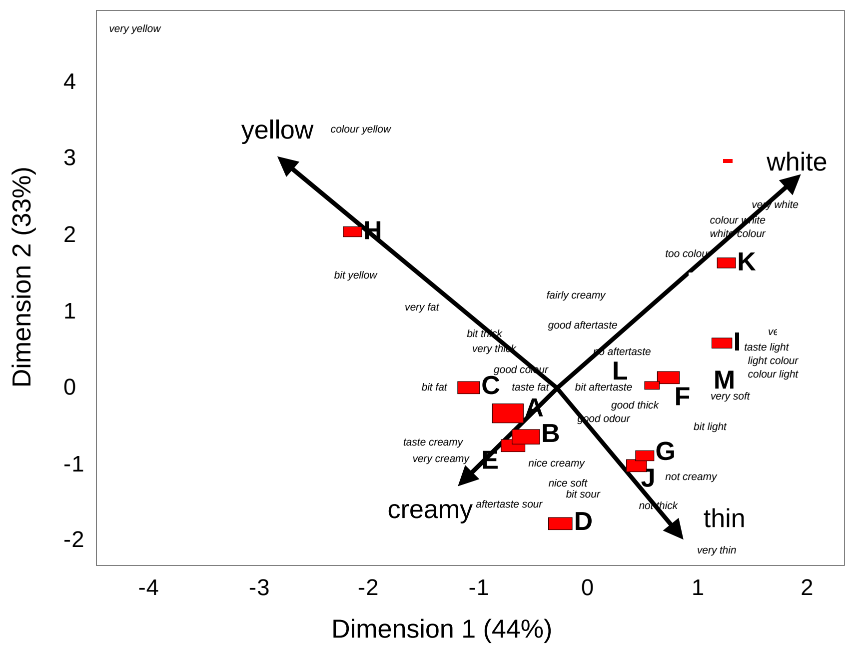

Figure 7.3. Correspondence analysis plot of word usage across products. Markers for the products are scaled relative to their liking score.

Product *H* is clearly associated with 'yellow', while product *I* is evaluated as having a very light color, just like product M. Product D has a sourish aftertaste, while product C is relatively fat. The products G and J are relatively thin, the products A, E and B point in the same direction as word combinations with 'creamy' and are therefore associated. Notable is also the position of 'creamy' compared to 'color', 'taste', and 'thickness'. This confirms that in consumer terms, creaminess is associated with all these attributes (Elmore et al., 1999, Richardson-Harman et al., 2000).

The products with the highest average liking scores point in the same direction as 'very creamy' and 'creamy', confirming the relative importance of the creaminess attribute of mayonnaise. Although evoking negative associations, the most liked products are also associated with 'bit fatty', 'taste fat', 'bit sour' and 'sour aftertaste', implying that mayonnaise that is a bit fat and/or sour need not be disliked. The color attribute appears to be rather important, since there is a clear separation between the products which have a light color and a low average liking score, and the more yellow products with a somewhat higher average liking score. Since the color and fattyness attribute are correlated ($r = 0.54$), the added value of this analysis is that we can separate the influence of these attributes on product liking.

It is extremely interesting to compare the results from the correspondence analysis with those from the preference map depicted in figure 7.1. There are some striking similarities between the correspondence analysis plot and the preference map, which justify the somewhat arbitrary choice of product features as described in section 7.2. Product H is most associated with 'yellow', as we saw in figure 7.3, which agrees with the preference map, where we can see that it loads high on the 'yellow-axis'. According to the preference map, product C is most fat, and we can see on the correspondence analysis map that this product is indeed associated with 'bit fat' and 'very fat'. We can also infer from the preference map that the products G and J are spreadable and, thus, not very thick. This once again matches perfectly with the text analysis results, since these products point in the same direction as 'very thin' and 'not thick' on the correspondence analysis map.

Recapitulating, we can say that the correspondence map gives some valuable insights in the way consumer preferences are realized. For product development, the map stresses that mayonnaise needs to be creamy and that creaminess is associated with the color, taste, and thickness of mayonnaise. For marketing, the map states that terms that have a negative association at first sight, such as 'bit fat' and 'sour taste', need not interfere with preference as the most preferred products are described by these terms. Thus, these terms can be used in communicating the taste of our prototypes without invoking negative associations. Quantitative results from the preference map are corroborated, with the additional advantage that product characteristics are now available in consumer language, which in turn facilitates the task of a marketer in positioning the products. No explicit mapping is needed to link the sensory attributes to the liking scores. This relationship is stated in a natural way by the consumers themselves.

7.5 Discussion

One of the keys to successful text analysis is the availability of suitable preprocessing software. The main difficulty we encountered during the analyses was the very labor-intensive preprocessing stage, in which spelling mistakes were removed and morphologically related words and synonyms were grouped. In a new study this has to be done again, since the vocabulary used by respondents will differ, especially if other products are considered. Preprocessing is one of the crucial stages in text analysis, and to remove the subjective element in this task it should be automated. However, even with the most sophisticated software, it remains to be seen whether the processing will ever be completely automatic and rule-driven (Mossholder et al., 1995).

We only considered combinations of two words while it is obvious that often the combination of more than two words represents what a respondent intends to say (e.g., 'I miss the yellow color'; it is the combination of 'miss', 'yellow' and 'color' that contains the relevant information in this statement). Therefore, the real interest is in semantic units. Semantic parsing refers to the attempt to build a meaning representation of a sentence from its syntactic parse in a process that integrates syntactic and semantic processing (Ng and Zelle, 1997). However, as stated before, our main approach was quantitative, and we therefore did not adopt such a sophisticated approach. We feel this should be left to researchers in the area of linguistics, semantics, syntax, and so on. Text analyses on consumer data may greatly benefit from the junction of the strengths of knowledge from these research areas with the knowledge from the field of statistics.

7.6 Conclusions

We have shown that text analysis does provide useful insights and strengthens quantitative findings, despite the difficulties mentioned in the previous section, such as the labor-intensive and subjective preprocessing task, and the non-inclusion of semantic considerations. By counting words and looking at word combinations, we were able to construct an alternative way of uncovering the relationship between product liking and its motives. The resulting correspondence map corroborated the quantitative findings found by preference mapping. Although the correspondence map of the textual consumer responses was constructed by making some arbitrary choices, its resemblance with the preference map based on judgements from the sensory panel was striking.

An important advantage of our new approach is that products are positioned in terms of consumer language. Creaminess was often mentioned in the spontaneous responses, and is thus relevant for consumers. The textual map also confirmed the current knowledge about consumer understanding regarding the attribute creaminess. Another conclusion we drew from the correspondence map is that 'color' appears to be more relevant than 'fat', something which cannot be inferred from preference mapping since these attributes are highly correlated. We also learned from the open-ended survey responses that people comment more on their dislikes than on their likes.

The existing software products for text analysis certainly facilitate the processing of textual data and aid in giving a quick overview of the main topics in a collection of texts. When analyzing texts at a more detailed level, however, the human brain is essential, since computers are not able (yet) to understand a text. To improve our approach in order to obtain a better understanding of the written word, it is our strong belief that the inclusion of semantics is necessary. Combining semantic and statistical knowledge may be a successful approach to the analysis of textual data.

7.A Sensory characterization of the 13 prototypes

Table 7.6. Significant product differences in terms of sensory attributes. Presented scores are mean scores.

	A	*B*	*C*	*D*	*E*	*F*	*G*	*H*	*I*	*J*	*K*	*L*	*M*
odor													
prickling	24	24	31	23	30	19	26	40	20	24	20	23	23
intensity	44	46	54	44	50	38	47	55	35	49	43	45	45
mouthfeel													
burning	15	11	12	15	15	11	10	18	6	12	8	15	10
thickness	44	54	63	31	49	59	25	58	48	30	60	49	37
gloss	75	74	69	63	68	55	77	74	79	70	60	68	67
particles	3	2	2	2	2	2	2	3	2	2	3	2	2
mealy	3	9	10	3	6	12	10	11	11	3	14	10	12
sticky	26	36	46	19	26	27	18	41	30	16	32	35	25
melting duration	39	49	58	33	40	43	29	53	45	31	47	51	39
fatty	46	47	65	40	54	52	38	61	45	26	47	53	37
spreadability	68	72	61	71	64	60	76	66	75	75	62	67	69
appearance													
jelly	22	20	36	28	28	24	18	32	25	16	34	26	16
yellow	25	16	28	15	22	10	16	43	9	17	8	11	12
curdled	4	8	4	3	3	10	3	10	1	4	10	2	9
green	4	3	3	4	5	3	5	5	2	5	2	3	3
airy	20	16	12	15	16	23	17	15	11	14	21	11	23
salmon	3	3	6	2	5	2	3	5	1	4	1	2	2
taste													
acid	17	15	16	15	21	15	20	20	11	19	15	19	16
bitter	18	14	12	12	15	11	13	17	14	13	11	15	13
lemon	15	16	22	18	23	16	12	25	12	19	16	21	12
egg	29	30	35	22	31	26	23	38	21	17	23	26	19
fruity	6	15	15	13	17	12	12	10	8	13	12	10	12
cardboard	5	5	5	4	4	3	4	8	4	8	3	4	4
cheesy	5	4	3	4	2	5	2	6	5	3	3	3	2
artificial	11	10	10	14	11	14	12	13	8	13	9	11	10
mustard	11	9	13	11	11	12	9	11	6	12	7	9	7
old oil	3	4	4	6	2	5	2	5	3	2	2	3	2
pepper	11	8	9	10	11	9	8	10	5	9	5	10	9
creamy	29	28	27	27	30	26	48	61	42	52	45	52	53
synthetic	15	19	17	17	20	17	12	15	18	19	19	23	15
fishy	5	2	5	3	7	3	4	8	4	5	3	4	4
sweet	37	44	44	35	36	35	41	39	28	33	35	34	37
salt	34	29	35	30	30	26	28	40	25	28	23	32	22
dairy	11	9	11	16	8	8	10	9	16	14	17	12	13
sour taste	34	28	24	31	33	28	29	36	19	34	25	33	26