Comparing Generic Descriptive Analysis and Temporal Dominance of Sensations of Milk and Dark Chocolates and Effect of Training in Temporal Dominance of Sensations of Chocolates

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ABSTRACT

Temporal Dominance of Sensations (TDS) is a sensory analysis method that measures the order and time that few key attributes are dominant throughout consumption of a product. Dominant attributes are those that catch the attention at a given moment, and are not necessarily related to intensity. A panel of 15 judges was trained first in Generic Descriptive Analysis (GDA) and then in TDS. This panel assessed 8 Guittard chocolates varying in amounts of cocoa solids, sugar, and fat.

Both methods produced similar results. Samples were predominantly separated as milk chocolates and non-milk chocolates. Non-milk chocolates were sorted by attributes associated with cocoa and sugar content. The TDS data complemented the GDA data by providing additional information on how key attributes changed over time.

A group of 98 untrained consumers then performed the same TDS procedure with the same chocolate samples. Both groups produced similar results for sample separation and sorting, but panelist data was superior. Panelists were better able to capture sensory changes over time and had more accurate and consistent understanding of certain attributes.

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1. INTRODUCTION AND LITERATURE REVIEW

Chocolate

Chocolate, an ancient beverage and medicine, was introduced to the "old world" in the early 1500's, but chocolate as a solid food was not produced until the mid 1800's (Hoskin, 1994). Chocolate is made from the cacao bean, which is harvested in pods from the *Theobroma cacao L*. tree. According to the International Cocoa Organization (http://www.icco.org), there are three major types of cacao grown: Criollo, Forastero, and Trinitario. The Criollo tree is particularly high quality but low in yield. It is grown in South and Central America under several varietal names and is typically mixed with other types of cacao to make chocolate. Forastero, fast growing and higher in yield, is considered bulk grade and contributes a majority of the world's cacao. Though mostly grown in Africa, some Central and South American varieties exist and are of better quality. To capture Criollo aroma and Forastero hardiness, the Trinitatio type has been developed through cross breeding. It is grown in Central and South America as well as Asia (http://www.icco.org).

Once harvested, cacao beans undergo a natural fermentation that is a key step in degrading and developing compounds that affect chocolate flavor (Hoskin, 1994). The fungal and bacterial fermenters, as well as enzymes released by the beans, generate glucose, fructose, peptides, amino acids and acetic acid in the cacao (J. C. Kennedy, 2008). The fermented beans change color, lose their surrounding pulp, are less bitter and stringent, and are more acidic. Once dried, the beans are shipped to manufacturers for further processing. The next major process after fermentation is roasting, where Maillard browning and other reactions create deep brown color, complex compounds, and typical cocoa flavor. Extensive research has been done on the many precursors, stages, and products of these reactions, especially in cocoa (Frauendorfer & Schieberle, 2006, 2008; Schnermann & Schieberle, 1997; Stark, Bareuther, & Hofmann, 2005, 2006; Stark & Hofmann, 2005a, 2005b, 2006) Despite these efforts, many of the details are yet to be understood. (Hoskin, 1994)

After roasting, beans are ground into chocolate liquor. This liquor is combined with cocoa butter, sugar, emulsifiers such as lecithin, and vanilla to create solid eating chocolate. Artificial flavors, milk products, and non-cocoa fats can also be added to make milk chocolates or other chocolate-like products. Some chocolate goes through a process called conching, which further mixes the chocolate and has some effect on final sensory characteristics. Sensory panels are often able to note the difference between conched and unconched chocolate, but overall preference does not seem to be affected by this step. Finished solid chocolate of good quality is tempered. Tempering is the control of temperature that allows the formation of beta crystals in the cocoa butter. These crystals have a melting point between 30 and 35C, and contribute to a solid chocolate that has a clean snap and a glossy surface. (Hoskin, 1994)

Chocolate Sensory Research

Because of its popularity worldwide and the complexities of its flavor, chocolate is a common subject of sensory research. Studies have performed sensory analysis on both milk and dark chocolates to determine the effects of cacao cultivar, bean fermentation, processing, sugar and fat ratios, polyphenol content, and nontraditional ingredients such as artificial sweeteners (Guinard & Mazzucchelli, 1999; J. Kennedy & Heymann, 2009; Leite, Bispo, & Santana, 2013; Owusu, Petersen, & Heimdal, 2013; Reed, 2010; Shah, Jones, & Vasiljevic, 2010; William, 1985).

One of these studies, and other reviewed within, suggest that fermentation and roasting affect polyphenol content and that polyphenols are positively correlated with bitter, astringent, and green notes and negatively correlated with fruity notes in chocolate (Leite et al., 2013). This study found that under identical formulation and production conditions, chocolates vary in sensory characteristics simply due to bean cultivar. Different cultivars lead to chocolates that significantly differed in brown color, chocolate odor and flavor, toasted odor and flavor, bitterness, sweetness, and melting quality. These attributes were related to one another, with brown color highly correlated to chocolate odor, toasted odor, bitterness, toasted flavor, chocolate flavor, and firmness (Leite et al., 2013). These findings are generally expected in chocolates that vary in cocoa solids content or processing conditions, but are interesting to see within a sample set that is identical in these variables. It suggests that genotype differences have an effect on the chemical composition of the beans and the chemical changes they go through from harvesting to final production. Another study examined the effects of roasting, conching, and fermentation methods and concluded that roasted samples were generally lower in astringency, and conched samples were lower in banana and fruity notes (Owusu et al., 2013).

While many factors can affect the flavor of cocoa, chocolate also contains sugars, fats, and other ingredients that affect the overall sensory profile. In milk chocolates, Guinard and Mazzuccheli examined the effects of sugar and fat on sensory properties. They found that samples were mostly differentiated by sugar content (PC1 = 82.4%). The 2nd PC (11%) was driven by cocoa butter content. Low sugar chocolates were more bitter, roasted, and gritty in character, and high sugar chocolates were more vanilla/caramel, milky/dairy, sweet, and hard. High fat chocolates melted faster, but there was no correlation between fat levels and fatty/oily texture. Milk solids and chocolate liquor content also varied among the samples. For the most part, milk solids contributed to mouthcoating, and chocolate liquor increased roasted notes.

Kennedy and Heymann (2009) studied the sensory profiles and separation of a variety of chocolates and found that “panelists tended to separate the samples on the basis of milk chocolate versus dark chocolate. Attributes associated with milk chocolate (e.g. sweet and dairy notes) and those with dark chocolate (bitterness and astringency) dominated the 1^{st} PC in the attribute space and accounted for approximately 40% of the variance explained. This finding was consistent across multiple trained and untrained descriptive panels.

Outside of the scientific community, manufacturers have also performed sensory research on chocolate. Cargill employees working on the Wilbur brand have generated a chocolate liquor flavor wheel that separates flavors by degree of roast, degree of fermentation, storage, and other factors (Reed, 2010). They attributed higher levels bitterness, astringency, and green/grassy character to lower fermentation. These same characters are associated with polyphenols (Leite et al., 2013), which are often effected by roasting (Owusu et al., 2013). When Reed, et. al. (2010) examined roasting, low roast samples were mostly characterized by acid and nutty character, medium roast by cocoa and nutty character, and high roast by burnt character. Other attributes correlated with different roast levels are shown in greater detail within the document. Finally, they examined the flavor profiles of cacao bean type and origin. (Reed, 2010).

Little research has been found that focuses on the dynamic chocolate sensory experience or the effect of cocoa content on similar chocolates. Because the samples were purchased commercially, no information is available on the bean cultivar and origin, fermentation, or processing characteristics, or how they may increase variability between the samples.

Sensory Science

Sensory science is the practice of measuring and analyzing human sensory responses in a controlled fashion. These responses involve the senses of sight, smell, touch, taste, and hearing (Stone & Sidel, 2004). A common goal of sensory science is to better understand consumer goods through unbiased human perceptions. If done correctly, the information gathered by sensory scientists can assist those making decisions on formulation, optimization, nutritional, financial, and marketing aspects product development and maintenance. In order to achieve this level of success, a sensory scientist "must understand products, people as measuring instruments, statistical analyses, and interpretation of data within the context of research objectives" (Lawless & Heymann, 2010).

The field of sensory science is divided into three broad types: discrimination, descriptive, and affective. These types focus on differences between products, specific sensory characteristics of products, and consumer liking of products, respectively. Lawless and Heymann (2010) have constructed a useful table to summarize and compare the three types of sensory science, reproduced in Table 1. Because of the nature of this research, focus from here on out will be on descriptive sensory methods.

Table 1. "Classification of test methods in sensory evaluation" (Lawless & Heymann, 2010)

Class	Question of Interest	Type of Test	Panelist Characteristics
Discrimination	Are the products perceptibly different in any way?	Analytic	Screened for sensory acuity, oriented to test method, sometimes trained
Descriptive	How do products differ in specific sensory characteristics?	Analytic	Screened for sensory acuity and motivation, trained or highly trained
Affective	How well are products liked, or which products are preferred?	Hedonic	Screened for products, untrained

Generic Descriptive Analysis (GDA)

Descriptive analysis methods determine the overall profile and sensory experience associated with a set of products and pinpoint sensory differences between them. This information is often used to compare one or more products to competitors, to track changing characteristics over its shelf life, to trouble-shoot consumer complaints, and to correlate sensory and instrumental information (Lawless & Heymann, 2010). In order to collect detailed, reproducible, and valuable information, it is imperative that DA is performed with trained panelists rather than consumers. Because training is time-consuming and costly, corporations use descriptive analysis sparingly.

Many variations of DA exist, and often methods are blended to best suit an investigation. Some of the well-known methods include Flavor Profile, Texture Profile, Quantitative Descriptive Analysis (QDA), and Sensory Spectrum. All of these methods combine qualitative and quantitative information. The qualitative is a list of descriptive terms or attributes that describe products, and the quantitative is a method of scoring the intensity of each of these attributes (Meilgaard, Civille, & Carr, 2007). In this research, Generic Descriptive Analysis was used. It is a blend of QDA and Sensory Spectrum methods, explained in detail below. (Lawless & Heymann, 2010).

Quantitative Descriptive Analysis (QDA)

The Quantitative Descriptive Analysis method uses a panel of 10-12 judges that are trained by exposing them to products within the category of interest. The judges are selected from a larger group based on their ability to discriminate between products in the category. This panel then develops and defines a list of sensory terms to describe the differences between products. These terms are matched with verbal definitions or references to generate agreement across the panel. The panel then practices evaluating the presence and intensities of these attribute terms using 6-inch line scales. Throughout training, the panel leader facilitates discussion and agreement without teaching or influencing the panelists. They are free to use whatever attribute terms they can define and agree on and determine how the group will use the intensity scales. It is important to train panelists to be consistent and objective. The goal is to minimize variation between panelists and between replicates of the same products assessed by each panelist. Objectivity allows panelists to accurately characterize the sensory features of the product regardless of personal preferences or opinions about quality. (Lawless & Heymann, 2010; Meilgaard et al., 2007)

Once fully trained, the panelists evaluate products individually in an isolated and controlled setting. The evaluations are typically done in 2-3 replicates in a balanced experimental design with samples presented monadically. QDA data can be used to focus on one sense or a small list of attributes, but typically a broad spectrum of senses and attributes is examined to avoid the dumping effect. When panelists are asked to evaluate a small portion of the entire sensory experience, they will be frustrated by the inability to rate other attributes they notice but are not asked to assess. These frustrations can be "dumped" into the attributes they are restricted to and give results that differ from their true perception (Lawless & Heymann, 2010).

Sensory Spectrum

Sensory Spectrum, developed by Civille, is one of the most extensive DA methods. It aims to be specific and requires the most training and time to be effectively used. Unlike QDA, the list of terms used is pre-defined and each term has a set of predetermined references for each intensity level. In some cases, panelists can develop new attribute terms, but these are still extensively trained with references at different intensities. Intensity is scored not with a line scale, but numerically, and panelists are trained and calibrated to give as close to identical scores as possible. A compilation of attribute terms, definitions, intensity anchors, and references can be found (Meilgaard et al., 2007).

According to the philosophy of the Spectrum method, results should be absolute and comparable across studies. Some are skeptical that a group of humans can consistently perform as a single, calibrated instrument. In addition to this skepticism, the time and energy costs associated with the method cause it to be rarely used in its full form (Lawless & Heymann, 2010). However, the definitions of attribute terms and intensity references are commonly useful to those creating blended methods such as Generic Descriptive Analysis. The training and development of texture terms from this study was based on such resources (Meilgaard et al., 2007).

Time Intensity (TI)

While DA can gather the intensity of many attributes of a product, the scores recorded are at one point in time or averaged across an entire tasting. Two products may appear similar in terms of average sweetness or bitterness, but could differ greatly in the time that these sensations appear and in how long each sensation lasts. Especially in solid and semisolid foods, the process of consumption can play a role on the temporal sensory experience. The breakdown of food and combination with saliva affects the texture and releases or dissolves various aroma and taste compounds within the food (Fischer, Boulton, & Noble, 1994). In order to capture the dynamic nature of sensory perception, the Time Intensity method was developed.

Since the 1950's researchers have tried a variety of methods and technologies to track the change in intensity of a sensation over time. Depending on the researcher's preference and resources, TI measurements can be taken discretely or continuously. Discrete measurements are taken only at specific points in time, while continuous measurement is non-stop for a period of time. Both types of measurement can be translated to TI curves that show the evolution of a sensation over time. These curves can provide much greater detail and more realistic understanding of single product attributes than descriptive analyses alone. (Cliff & Heymann, 1993)

However, TI has its disadvantages. Because of the concentration required and data collection methods, a panelist can only perform TI on one or two attributes at once. This requires many more sessions and a much longer time than DA to analyze several product attributes. Also, because of the need to consider only one or two attributes at a time, panelists assessing a complex food matrix are likely to succumb to biases such as the halo effect and dumping. These behaviors are caused by a panelist's desire to report more sensations than he or she is asked to assess. If a panelist experiences fruitiness and sweetness he may have difficulty singling out the sweetness alone. He is likely to create a mental "halo" around sweetness that includes flavors such as fruit, caramel, and vanilla, thus reporting these sensations as additional sweetness. Alternatively, He may be frustrated by the inability to report the fruitiness he experiences and dump his frustrations into his intensity scores (Pineau, Schlich et al. 2009).

Temporal Dominance of Sensations (TDS)

To combat the shortfalls of the TI method and to approach the temporality of sensations in a different way, Temporal Dominance of Sensations was more recently developed (Pineau et al., 2012). This method tracks the appearance and duration of dominant perceptions experienced in a given time period (Meyners, 2011). The time period examined may be first sip, mastication, or after swallowing. Alternatively, TDS can take place throughout the entire consumption of a food or beverage, incorporating several of these steps. A unique feature of TDS is the concept of dominance, which must be well understood by all panelists. The concept is sometimes vague, due to use of varying definitions by different researchers (Meyners, 2011). In this study, a dominant sensation is one that is "catching the attention at a given time" (Pineau et al., 2009). The dominant sensation is not necessarily the most intense. It is typically considered a new sensation but may also be reoccurring. To confuse matters, other studies define a dominant sensation as simply the most intense one (Labbe, Schlich, Pineau, Gilbert, & Martin, 2009).

Pineau et al. (2012) reviewed 21 studies using TDS to determine what makes a good attribute list. Based on five parameters related to attribute selection, timing, and consensus, they found that no more than 10 attributes should be assessed at one time. They also found no difference between mixing attribute types such as texture and taste, compared to just one type. Despite that finding, they still recommend separate analyses until further research on this subject is performed. They also reported common practice of using approximately 16 panelists and 2 or 3 replications of each product, but also recommend more research on this topic.

Since its development, the TDS method has been used and expanded upon in a variety of ways. Some of the strategies and methods below are not used in this study, but should be considered in further analysis and future research.

Meyners, while working with Pineau, describes the use of randomization tests to investigate product and panelists (Meyners, 2011). This method allows one to determine the overall quality of the data based on panel agreement on product differences by attribute, point in time, or individual panelist. In addition to selecting the dominant sensation for a given moment, panelists are sometimes directed to rate the intensity of that dominant attribute. Incorporation of intensity scores greatly complicates the procedure for panelists and analysis for researchers, so it often not included (Meyners, 2011; Meyners & Pineau, 2010). When these scores are used, different statistics are needed to analyze data and produce TDS Scores, as done by Labbe et al (2009). Though the inclusion of intensity scores complicates the study for both panelists and researchers, it also aids in the comparison of TDS and Descriptive Analysis data.

Lenfant et al. (2009) found that standardizing or time-scaling TDS data is especially helpful. Their study focused on the textures related to breakdown of wheat flakes through mastication. Since each panelist and each product differed in mastication duration, the time period was changed from fixed time of analysis to the period between the first selection of a dominant attribute and time of swallowing. This change created improved consensus between panelists on the timing of texture changes in each product (Lenfant, Loret, Pineau, Hartmann, & Martin, 2009). Dinnella et al (2013) examined the effect of intensity scores in TDS and the simplification of TDS data into frequency values within specified time intervals. It was found that the inclusion of intensity scores lead to apparent distraction among panelists and decreased product discrimination. They used ANOVA and residual plots to analyze frequency values of TDS data, and found this to be an appropriate, simplified analysis of complex TDS data (Dinnella, Masi, Naes, & Monteleone, 2013).

Rinsing and Warm-up Samples

The procedure for both DA and TDS data collection involved mouth rinsing before and between samples for palate cleansing and the use of a warm-up chocolate sample at the beginning of each session. Mouth rinsing, especially with water, is a commonly used practice in the sensory science field. It is commonly accepted as a good practice, and usually left to the individual panelist to determine the timing and amount of rinsing. The purpose of mouth rinsing is to prevent adaptation by clearing sample residue from the mouth. Adaptation is defined as a "decrease in the sensitivity or responsiveness of an observer as a function of constant stimulation" (Johnson & Vickers, 2004). In tests that involve intensity scores, such as DA, adaptation of a specific taste leads to a decrease in intensity scores of that taste as the session continues. Aside from adaptation, sample residue can also "add to the taste intensity of subsequent products" (Johnson & Vickers, 2004), causing panelists to rate tastes that are not present or detectable in a sample.

Some research has examined the actual effectiveness of different rinsing or resting strategies. O'Mahony has reported and confirmed the findings of several others that rinsing with water between samples is more effective in reducing adaptation than simply resting between samples (O'Mahony and Godman 1974). Although rinsing with water can reduce residuals in the mouth, O'Mahony also found that it takes many rinses in order to completely clear residue (in this case NaCl) from the mouth. When measuring exogenous salt in the mouth, he found that as many as 20 or more mouth rinses were needed to completely clear the palate. Since completely clearing the palate of exogenous salt was so difficult, he also determined that it took about 5 mouth rinses to clear the palate only until residual salt in the mouth had reached concentrations lower than the detection threshold concentration.

The practice of using warm-up samples is not new to descriptive or discrimination testing, but is not widely researched. There are two different versions of the warm-up procedure. One, discussed by O'Mahony, is the "rapid tasting of alternate samples" (O'Mahony, Thieme, &

Goldstein, 1988). It has been shown to help improve sensitivity in discrimination testing by familiarizing panelists with the two samples and the difference(s) between them. Sensitivity can be further improved when judges are asked to describe the difference between the warm-up samples (O'Mahony et al., 1988). The other warm-up procedure is for descriptive testing. An additional sample is analyzed at the beginning of the procedure, often one of the experimental samples, and sometimes the control. No data is collected from this sample, but it improves reliability and performance in two ways. This improvement is from "providing similar testing conditions for the first sample and subsequent samples" "elimination of first sample bias", and "panelist self-calibration" (Plemmons & Resurreccion, 1998). The calibration and overall reliability can be improved with the addition of consensus ratings. These ratings are intensity scores for all attributes in that specific product and are determined during panel training (Plemmons & Resurreccion, 1998). Because of the additional time required to generate consensus ratings, they were not used in this research.

2. COMPARISON OF GDA AND TDS

2.1 Objective

The goal of this study is to determine the similarities, differences, and various benefits of General Descriptive Analysis and Temporal Dominance of Sensations. The former provides a static or averaged sensory profile with many attributes, while the latter produces a dynamic profile that showcases the order and importance of fewer attributes over time. The same panelists and same samples were used for both methods, and the results of each are analyzed with R studio software and compared.

2.2 Material and Methods

Chocolates

All chocolate samples used for data collection were purchased from Chocosphere.com. The chocolates were wafers manufactured by Guittard Chocolate Co. (Burlingame, CA). The varieties are listed in Table 2. The wafers had no identifying marks and were approximately 2cm in diameter and 1.5g each. The chocolates were stored in foil-lined sealed bags at refrigeration temperatures (about 5°C) to maintain freshness for up to 6 months. Samples were allowed to equilibrate to room temperature (20-25°C) for at least 24 hours before panel use. Chocolate discs manufactured by Cordillera were also purchased from Chocosphere.com, but were too large compared to the Guittard samples. These were used for discrimination and training and are listed in Table 3. Other chocolates used for training purposes were purchased at local retailers and are also listed in Table 3.

Table 2. Experimental Chocolate Samples, Distributed by Chocosphere LLC

Product Number	Product Code	Product Name (Manufacturer)	% Fat	% Sugar	Ingredients
P1	C70	E. Guittard Musique Foncee (Dark Music) Wafers, 70% Cocoa	16	12	Cacao beans, pure cane sugar, cocoa butter, soya lecithin, vanilla beans
P2	C55	E. Guittard La Nuit Noire Wafers, 55% Cocoa	14	17	Cacao beans, sugar, cocoa butter, lecithin, vanilla beans
P3	C38	E. Guittard Soleil d'Or Wafers, 38% Cocoa	15	19	Pure cane sugar, full cream milk, cocoa butter, cacao beans, soya lecithin, vanilla beans
P4	C64	E. Guittard L'Etoile du Nord Wafers, 64% Cocoa	16	14	Cacao beans, pure cane sugar, cocoa butter, soya lecithin, vanilla beans
P5	C66	E. Guittard Organic Dark Chocolate Wafers, 66% Cacao	16	14	Cacao beans, evaporated cane juice, cocoa butter, soya lecithin
P6	C72	E. Guittard Coucher du Soleil Wafers, 72% Cocoa	18	11	Cacao beans, sugar, cocoa butter, lecithin, vanilla beans
P7	C58	E. Guittard L'Etoile du Premiere Wafers, 58% Cocoa	15	17	Cacao beans, sugar, cocoa butter, lecithin, vanilla beans
P8	C61	E. Guittard Lever du Soleil Wafers, 61% Cocoa	16	15	Cacao beans, pure cane sugar, cocoa butter, soya lecithin, vanilla beans

Table 3. Discrimination and Training Samples, purchased at local retailers and ordered from Chocosphere

Product Name	Manufacturer	Obtained from	Used in Discrimination?
Cocuy 70% Discs	Cordillera	Chocosphere	Yes
Sumapaz 65% Disc	Cordillera	Chocosphere	Yes
Tayrona 53% Discs	Cordillera	Chocosphere	Yes
Purace 36% Discs	Cordillera	Chocosphere	Yes
Cadbury Dairy Milk	Mondelez	World Market	No
Hershey's Milk Chocolate	Hershey	Rite Aid	No
Hershey's Special Dark Chocolate	Hershey	Rite Aid	No
Lindt Milk Chocolate	Lindt & Sprüngli	World Market	No
Godiva Dark Chocolate	Godiva Chocolatier	Safeway	No

Recruitment and Discrimination Testing

Panelists were recruited from Davis, CA and the surrounding area via email (Appendix). Selection was based on interest and availability to participate as well as ability to discriminate between chocolates. Discrimination testing was performed with a series of triangle tests using FIZZ software version 2.47B (Biosystèmes, Couternon, France). Each panelist performed a total of 10 triangle tests. The first was a warm-up, and the other nine were 3 replicates of 3 different tests that progressed from most easy to discriminate to most difficult. The first test was between chocolates with 70% and 36% cocoa, the second between 65% and 53% cocoa, and the last between 70% and 65% cocoa. Detailed results are shown in Table 4. The group of judges was 100% correct for the first test, 79% correct on the second test, and 49% correct on the third test, which correlates with the increasing difficulty. Out of the 30 potential panelists, 17 were selected based on their discrimination skills (at least 7 out of 9 triangle tests correct) and availability to meet regularly. These panelists were then trained for descriptive analysis.

Table 4. Discrimination Test Results. A ✓ marks a correct answer, and a --- marks an incorrect answer

Judge	Test 1	Test 2	Test 3	Test 4	Test 5	Test 6	Test 7	Test 8	Test 9
J1	✓	✓	✓	✓	✓	✓	---	---	---
J2	✓	✓	✓	✓	---	✓	---	---	---
J3	✓	✓	✓	✓	✓	---	✓	✓	---
J4	✓	✓	✓	✓	✓	✓	✓	---	---
J5	✓	✓	✓	✓	✓	✓	✓	✓	✓
J6	✓	✓	✓	✓	✓	✓	---	✓	✓
J7	✓	✓	✓	✓	---	✓	---	---	---
J8	✓	✓	✓	✓	✓	✓	✓	✓	✓
J9	✓	✓	✓	✓	✓	---	✓	---	---
J10	✓	✓	✓	✓	---	✓	---	---	✓
J11	✓	✓	✓	✓	✓	✓	---	---	---
J12	✓	✓	✓	✓	✓	✓	---	✓	✓
J13	✓	✓	✓	✓	✓	✓	---	✓	---
J14	✓	✓	✓	---	✓	✓	---	✓	✓
J15	✓	✓	✓	✓	✓	✓	---	✓	---
J16	✓	✓	✓	✓	---	✓	✓	✓	---
J17	✓	✓	---	✓	✓	✓	---	---	---

J18	✓	✓	✓	✓	✓	✓	✓	✓	✓
J19	✓	✓	✓	✓	✓	✓	---	✓	✓
J20	✓	✓	✓	✓	---	---	✓	---	---
J21	✓	✓	✓	✓	✓	✓	✓	✓	✓
J22	✓	✓	✓	---	---	---	---	---	---
J23	✓	✓	✓	---	---	✓	✓	✓	✓
J24	✓	✓	✓	✓	✓	✓	✓	✓	---
J25	✓	✓	✓	✓	---	✓	✓	---	✓
J26	✓	✓	✓	✓	✓	✓	---	✓	✓
J27	✓	✓	✓	✓	✓	✓	---	✓	---
J28	✓	✓	✓	---	✓	---	✓	✓	✓
J29	✓	✓	✓	✓	✓	✓	✓	---	---
J30	✓	✓	✓	✓	✓	✓	---	---	---

Generic Descriptive Analysis

The Generic Descriptive Analysis method was used. The 17 selected panelists completed six 50-minute training sessions in groups of 3-8 people. They tasted a variety of chocolates, including some of the samples for data collection, and developed a list of terms to describe the tastes, aromas, textures, and mouth-feel sensations they perceived. The full set of terms was reduced to a list that all panelists agreed on through use of reference standards, Spectrum definitions, and group discussion. This set of attributes is presented in Table 5. While developing and defining the descriptive attributes, the panelists were also trained on the use of 6-inch intensity line scales, a consumption protocol they helped develop, and the FIZZ software program (Appendix). The final hour of training was a practice session under the same conditions as data collection.

Table 5. Attributes and References for Descriptive Analysis

Attribute	Reference or Definition
Sweet	30g sucrose dissolved in 1 L distilled water
Biter	1g anhydrous caffeine dissolved in 1 L distilled water
Sour/Tangy	2g anhydrous citric acid dissolved in 1 L distilled water
Astringent	1.2 g alum dissolved in 1 L distilled water
Cocoa	2 Tbs Ghirardelli premium baking cocoa
Nutty	½ tsp ground Hershey's Dark chocolate, 1 pecan crushed raw, 1 pecan, 1 walnut, 2 almonds, and ¼ Tbs hazelnuts chopped, and 1 pecan, 1 walnut, 2 almonds, and ¼ Tbs hazelnuts chopped and toasted.
Milky	½ Tbs Evaporated milk, ½ Tbs Cream, 1 Oreo filling + 1/8 tsp Cadbury Dairy Milk chocolate
Vanilla	1ml distilled water, 6 drops Spice Supreme Imitation Vanilla Extract, 1 Oreo filling
Caramel	1 Tbs Torani caramel, 1/8 tsp Cadbury Dairy Milk chocolate, 1/8 tsp Hershey's Dark chocolate, stirred into ½ Tbs warm distilled water until homogenous
Mint	1/4 tsp Hershey's Dark chocolate, 1 Tbs chopped fresh spearmint
Coffee	½ Tbs Nestle Taster's Choice, ½ Tbs ground Illy coffee, ½ tsp Hershey's Dark chocolate
Fruity	1 drop each of orange, lemon, strawberry, and cherry flavors, 1/8 tsp ground Hershey's Dark chocolate, 1ml distilled water
Buttery	1.5 Tbs cream, 1/2Tbs Coffee Mate Original, o.25 ml Imitation Butter flavor, 1/8 tsp Cadbury Dairy Milk chocolate
Honey	2 Tbs Sue Bee clover honey
Artificial Sweet /Candy	1 pouch (1g) Splenda Flavors for Coffee Mocha dissolved in 1 ml distilled water
Earthy	1 Tbs orchid bark, 2 ml distilled water, 1 ml canned potato juice
Cherry	1 Tbs of Maraschino cherry juice, 1/4 tsp Hershey's Dark chocolate
Smoke	1 Tbs burned chopped almonds , 3 drops liquid Hickory smoke, 1/8 tsp cocoa powder
Herbal/Tea	¼ tsp dry spearmint, 2 teabags of Twinnings green tea
Hardness	the force required to bite through chocolate
Brittleness	the amount the chocolate snaps rather than deforms/compresses
Roughness	amount of small particles on the surface
Oiliness/ Moistness	amount of oiliness/moistness on surface
Stickiness	amount of chocolate that sticks to teeth and mouth while chewing
Rate of Melt	amount of time to completely melt chocolate
Oily Mouthcoati ng	the amount of oily film left in the mouth after expectorating
Chalky Mouthcoati ng	the amount of chalky film left in the mouth after expectorating
Toothpacki ng	amount of chocolate left in the crevices of teeth after expectorating

Manufacturers: vanilla Gel Spice Co, inc. Bayonne NJ, cocoa Ghirardelli Chocolate company, San Leandro, CA, sugar Domino Foods, Inc. Yonkers, NY, caramel R Torre & Company, So. San Francisco, CA, cherries Safeway Inc. Pleasanton, CA, potatoes Safeway Inc. Pleasanton, CA, coffee creamer Nestle USA Inc. Glendale, CA, instant coffee Nestle USA Inc. Glendale, CA, coffee illy caffe North America Inc. Rye Brook, NY, bark Sun Gro Distribution Inc, Bellevue, WA, Splenda McNeil Nutritionals LLC Fort Washington, PA, Cadbury chocolate Mondelēz International Deerfield, IL, honey Sioux Honey Ass'n Sioux City, IA, Oreo Mondelēz International Deerfield, IL

Definitions for texture attributes are adapted from those used in the Spectrum Descriptive Analysis Method (Meilgaard et al., 2007)

Data was collected using FIZZ software version 2.47B (Screen shot of analysis in the Appendix). The 8 different chocolates were split into two blocks and presented in randomized order via 8x8 Latin squares. Each panelist tasted 3 replicates of each sample over the course of six sessions. In each session, the panelists tasted 5 samples, the first being a warm-up from which no data was analyzed. Warm-up samples were also randomized based on the Latin square design used. Each sample was comprised of three chocolate wafers in a 1-ounce lidded Solo cup coded with a random 3-digit number (Solo Cup Co. Highland Park, IL). Panelists assessed each sample according to the protocol. They were asked to expectorate at all times except when evaluating aftertaste. This was decided, through panel discussion, in order to minimize fatigue while creating a realistic aftertaste experience. Based on previously-mentioned results from O'Mahony and Goldman (1974), a one-minute break including 5 rinses with distilled water was used between each sample. Panelists were also asked to rinse with distilled water to cleanse their palates at the beginning of the session. Fifteen out of the 17 selected panelists completed the full descriptive analysis with the exception of one session for one judge. The data for Judge 13, rep 2, products 4, 6, 8, and 9 were missing. The missing values were imputed in Excel by averaging the scores from the other 2 replicates that the judge completed.

Temporal Dominance of Sensations

The 15 panelists who completed the DA were then trained in 4 50-minute sessions for TDS. They were first introduced to the concepts of TDS and experiencing sensory perceptions over time. Afterward, their training focused on the meaning of dominance. A dominant attribute was defined as the one that is "catching the attention at a given time"(Pineau et al., 2009). Previous studies have used audio recordings to train on temporality and dominance, (Durner, 2011; Sokolowsky & Fischer, 2012) so the panelists practiced selecting dominant attributes first with music (Benjamin Britten's "A Young Person's Guide to the Orchestra"). They then practiced the TDS method with chewing gum.

In their 2nd session, the panelists practiced TDS on paper ballots with chocolate samples and their reduced set of attributes. Past research has shown that panelists cannot effectively perform TDS unless a relatively short list of attributes, no more than 8-10, is used (Pineau et al., 2012). The 7 attributes used in TDS were selected based on ANOVA and CVA analyses of the DA data. This list is shown in Table 6. Although the attributes Hardness and Roughness were considered to have as much impact as the other attributes chosen for the TDS procedure, they were removed during training. Panelists agreed that considering texture and flavor (taste, aroma, astringency) attributes at the same time over-complicated the task. The panelists were also presented with a new consumption protocol (Appendix) that was better suited to the TDS procedure and provided a more realistic consumption experience. Finally, the panelists practiced TDS using chocolates, their new attribute list, and their new consumption protocol. All practice during training was discrete rather than continuous, that is, panelists were asked to report dominant attributes at specific times rather than any number of times throughout a specified time period. The final two training sessions were used to orient the panelists to the continuous nature of the procedure, the format of the program.

Table 6. Attributes, References Definitions for TDS Analysis

Attribute	Reference or Definition
Sweet	30g sucrose dissolved in 1 L distilled water
Biter	1g anhydrous caffeine dissolved in 1 L distilled water
Sour	2g anhydrous citric acid dissolved in 1 L distilled water
Astringent	1.2 g alum dissolved in 1 L distilled water
Cocoa	2 Tbs Ghirardelli premium baking cocoa
Caramel	1 Tbs Torani caramel, 1/8 tsp Cadbury Dairy Milk chocolate, 1/8 tsp Hershey's Dark chocolate, stirred into ½ Tbs warm distilled water until homogenous
Rate of Melt	amount of time to completely melt chocolate

Data was collected using FIZZ software version 2.47B (Appendix). The experimental design is identical to that of the DA procedure. The 8 different chocolates were split into two blocks and presented in randomized order via 8x8 Latin squares. Each panelist tasted 3 replicates of each sample over the course of six sessions. In each session, the panelists tasted 5 samples, the first being a warm-up from which no data was analyzed. Warm-up samples were also randomized based on the Latin square design used. Each sample was comprised of two chocolate discs in a 1-ounce lidded Solo cup coded with a random 3-digit number (Solo Cup Co. Highland Park, IL). Panelists assessed each sample according to instructions and timed prompts that appeared on the screen. They were asked to swallow at the end of each TDS procedure to realistically assess aftertaste and were given a choice between swallowing and expectorating at the end of the melting procedure. A one-minute break including 5 rinses with distilled water was used between each sample. Panelists were also asked to rinse with distilled water to cleanse their palates at the beginning of the session.

2.3 Data Analysis

GDA

All GDA data analysis was performed with R Studio. The data was first analyzed with a 3-way MANOVA (summarized in Table 7) to ensure that the Product factor was significant. The data was then analyzed with ANOVA (full results in Appendix). All attributes considered significantly different among products were then evaluated by lsd to determine differences among product means (full results in Appendix). GDA data was also analyzed with Canonical Variate Analysis (CVA), a factor analysis method to visualize sample separation (Figures 1-6). This method was combined with a one-way MANOVA of the data. Though similar to Principal Component Analysis, CVA combined with simple MANOVA has been shown to provide clearer visuals of sample separation by focusing on attributes most associated with product differences and less on variance caused by interactions, replications, and panelist disagreement (Monrozier & Danzart, 2001). This method is preferable for such sensory data because it "prioritizes the sensory dimensions that maximize product differences while minimizing any other source of information" (Monrozier & Danzart, 2001). Ellipses representing 95% confidence intervals were also added around each product (CVAellipses_new function written by Helene Hopfer, Peter Buffon and Vince Buffalo, edited for aesthetics by Sean LaFond).

Table 7. MANOVA Summary

	Df	**Wilks**	**Approx. F**	**Num DF**	**Den DF**	**Pr(>F)**
Judge	14	0.00000	11.6808	658	2076.2	< 2.2e-16 ***
Product	7	0.00156	4.9297	329	1052.9	< 2.2e-16 ***
Rep	2	0.46465	1.4905	94	300.00	0.006342 **
Judge:Product	98	0.00000	1.6270	4604	7065.6	< 2.2e-16 ***
Judge:Rep	28	0.00006	1.4462	1316	3820.9	< 2.2e-16 ***
Product:Rep	14	0.03387	0.9045	658	2076.2	0.940774

Residuals 196
*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1*

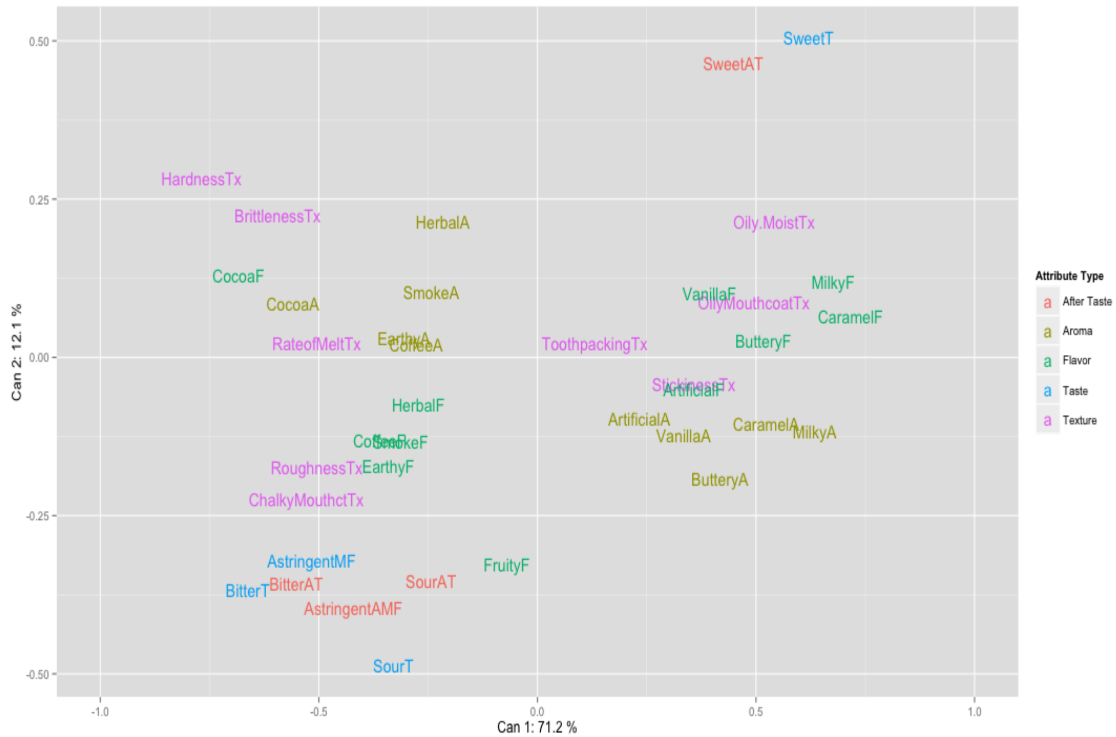

Figure 1. CVA Loadings Plot of GDA Data. Can 1 vs. Can 2

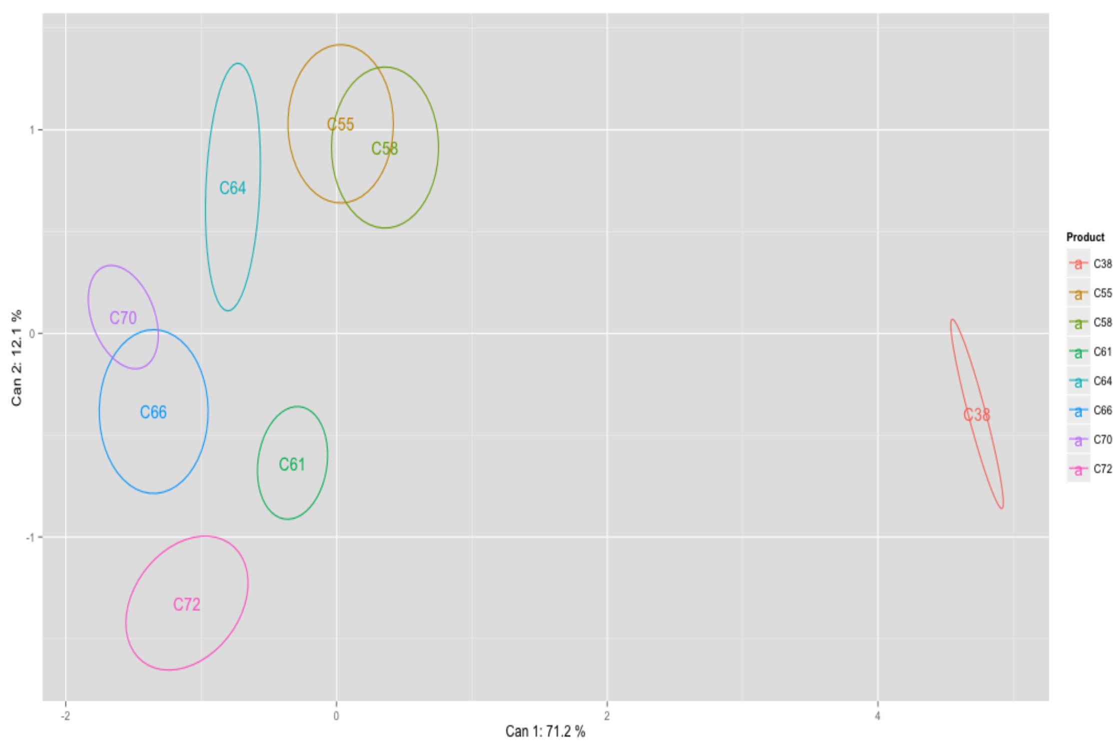

Figure 2: CVA Score Plot of GDA Data. Can 1 vs. Can 2

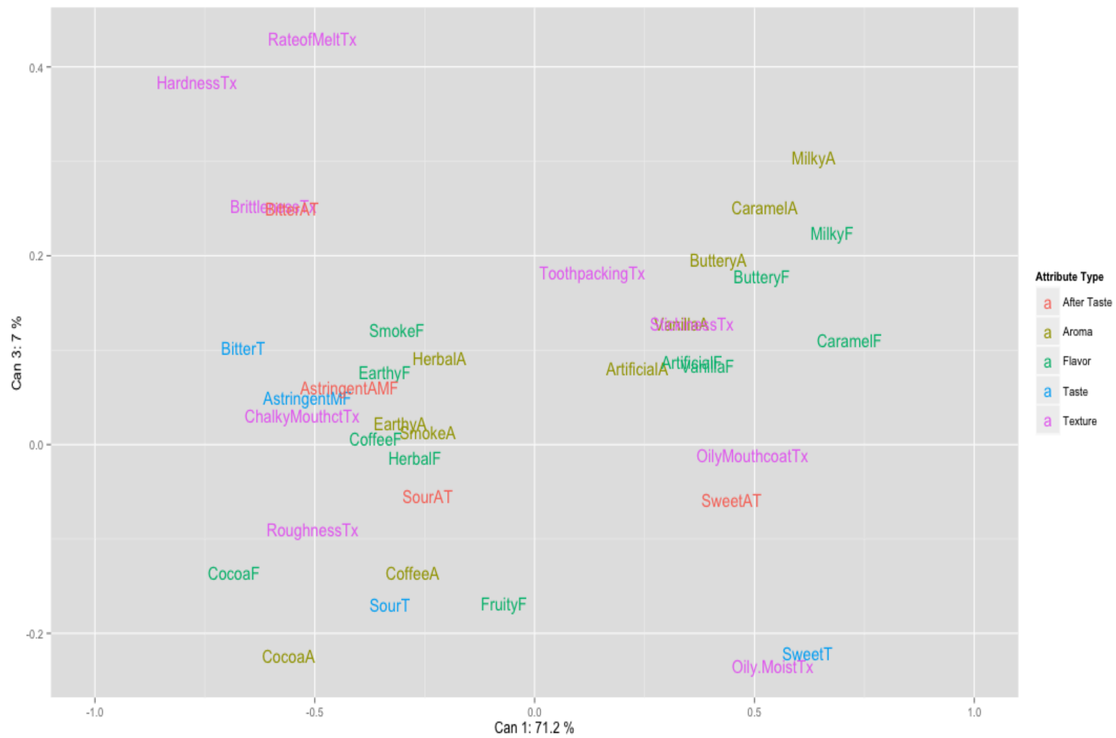

Figure 3. CVA Loadings Plot of GDA Data. Can 1 vs. Can 3

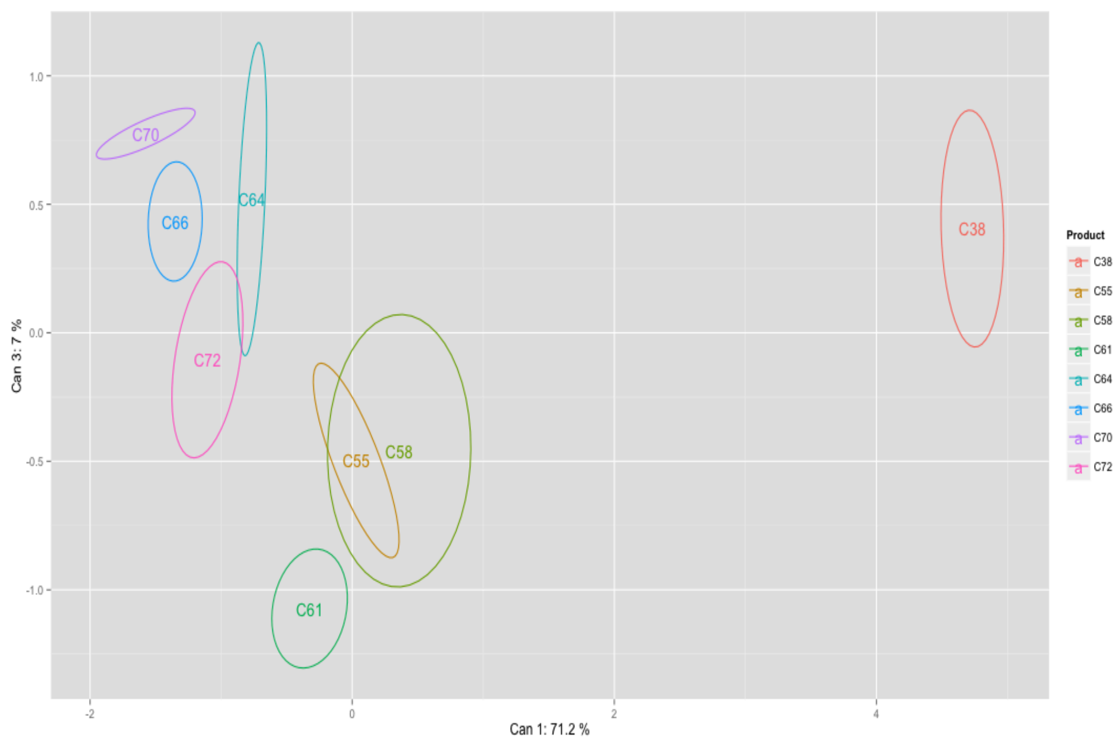

Figure 4. CVA Score Plot of GDA Data. Can 1 vs. Can 3

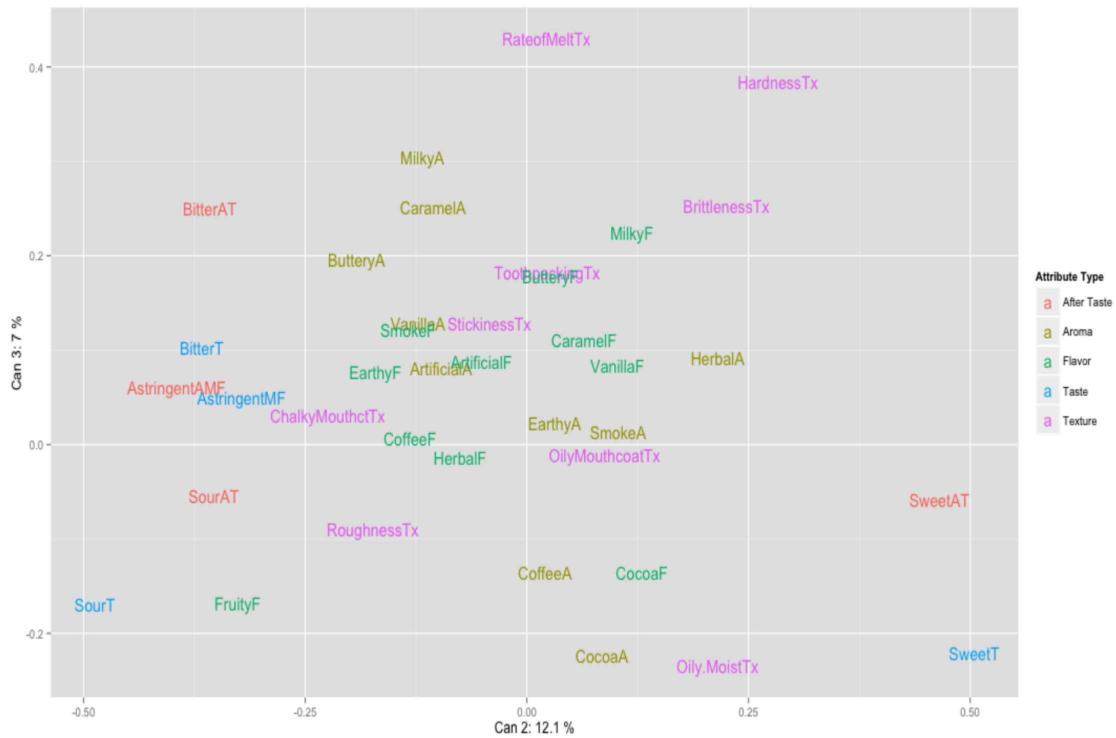

Figure 5. CVA Loadings Plot of GDA Data. Can 2 vs. Can 3

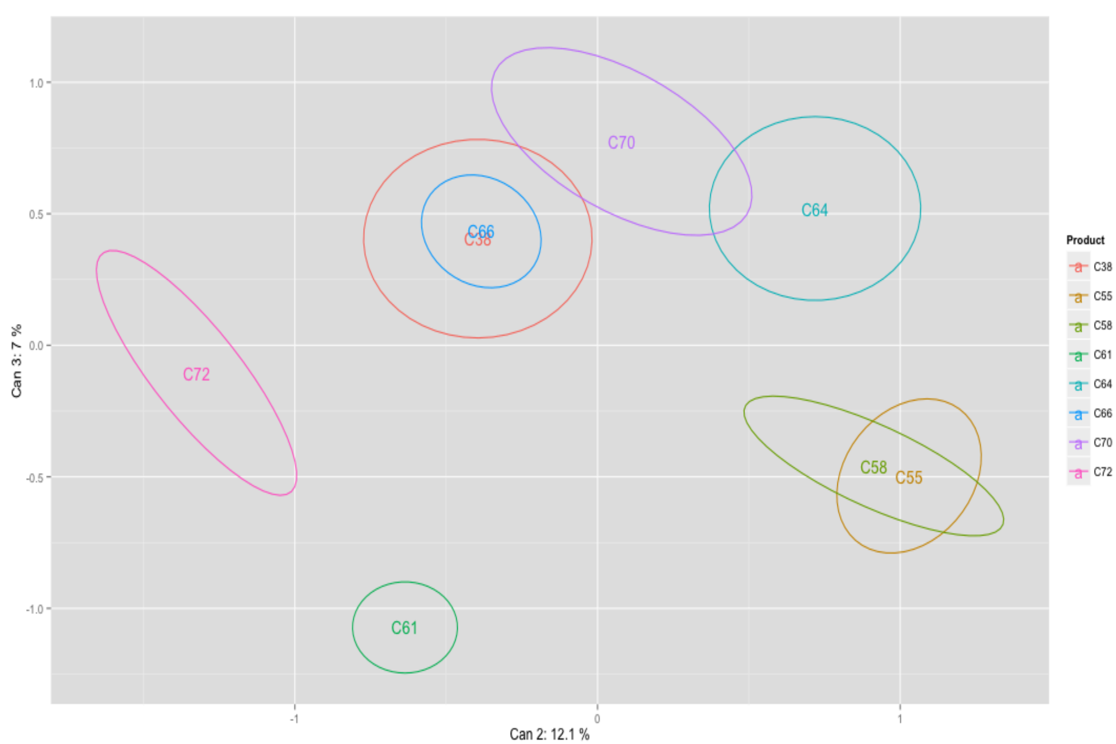

Figure 6. CVA Score Plot of GDA Data. Can 2 vs. Can 3

TDS Curves

Raw TDS data was first converted into traditional TDS curves, which plot dominance rate (DR) over % time. The dominance rate (DR) is a proportion for each attribute/time combination and is calculated NE/NE_{max}, NE is the number of judge/rep combinations that selected a certain attribute as dominant at that particular time, and NE_{max} represents the total of judge/rep combinations at that time. For example, consider a panel of 5 judges who each completed 2 replications, giving a NE_{max} value of 10. When examining the data 30 seconds into the tasting, sweetness is selected as the dominant attribute in 5 out of the 10 possible occasions. This creates a DR value of 0.5. The DR of all attributes for that product in that moment in time should sum to 1. Just as one can plot curves of all attributes for a given product, a figure can also be made for a single attribute in which each curve represents a different product.

The curves are scaled to eliminate periods in which no attributes are chosen. The scaling procedure is similar to that shown by Lenfant (Lenfant et al., 2009). During the procedure, panelists began the one-minute timer by pressing a start button, and afterwards were instructed to select the first dominant attribute once it appeared. They were also given the option to press a stop button before the minute was complete if sensation ended. By scaling the data, time is reported from 0-100% of the tasting rather than 0-60 seconds. This helps capture the period of actual sensation and to standardize this period across all panelists and replications. Trained panel scaled curves are shown in Figures 7-20, and raw, unscaled curves are shown in the Appendix.

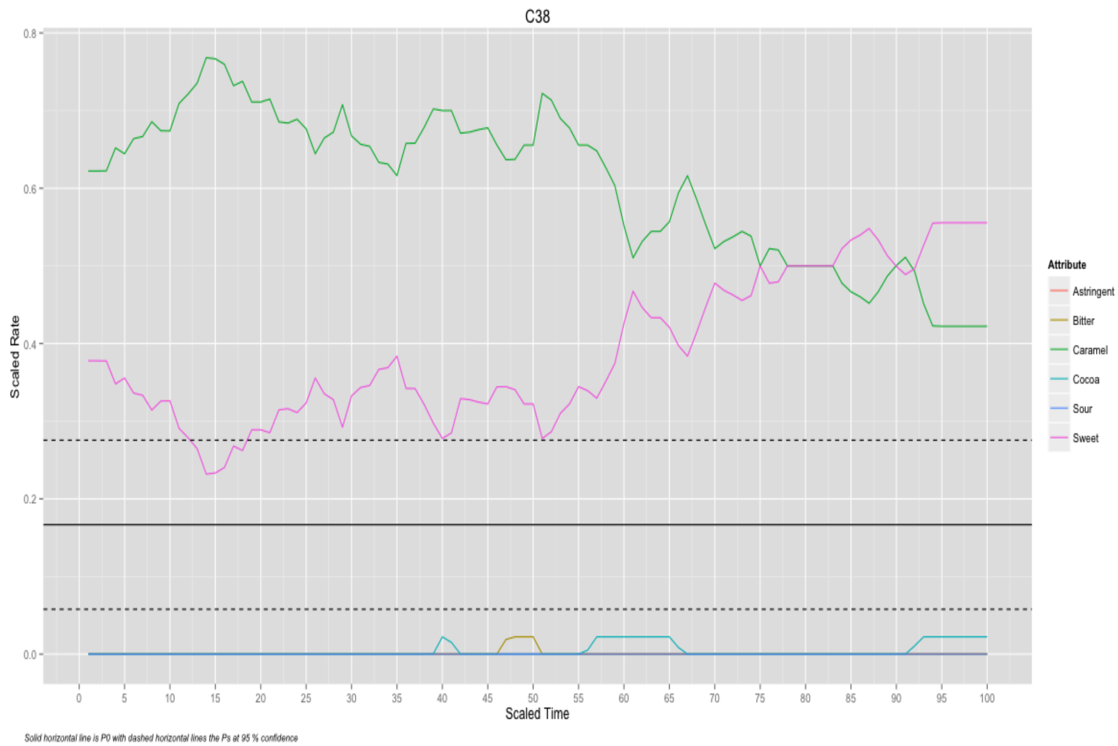

Figure 7. Trained Panel Scaled TDS Curves. Sample C38

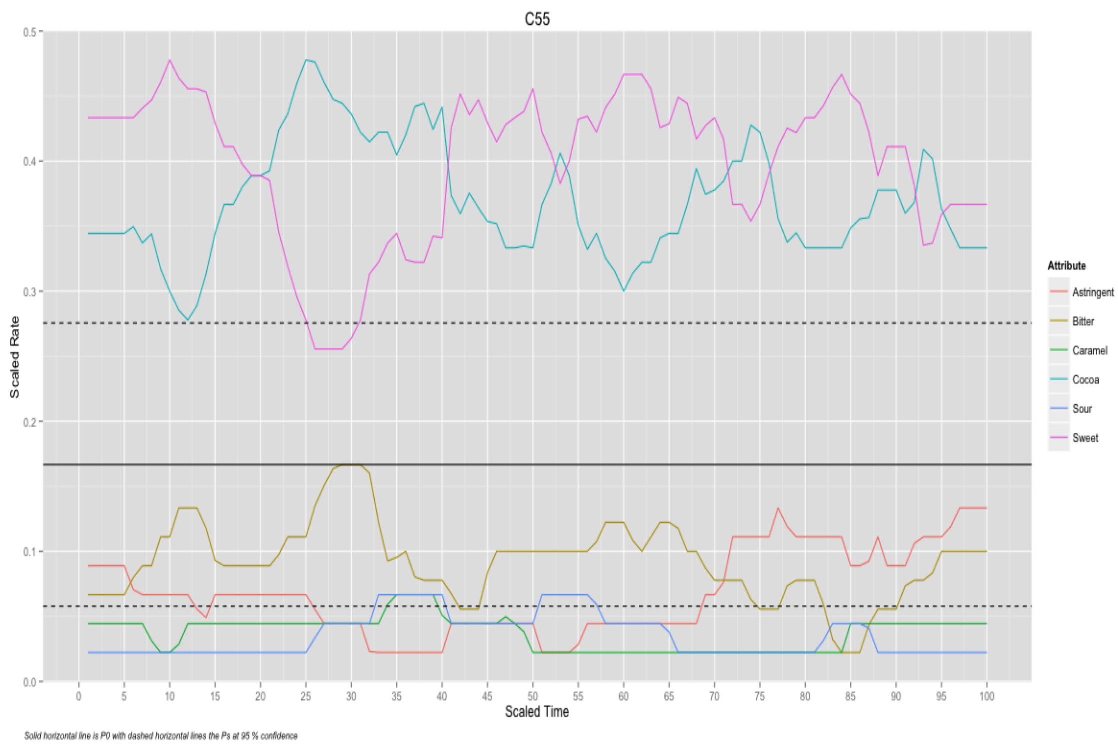

Figure 8. Trained Panel Scaled TDS Curves. Sample C55

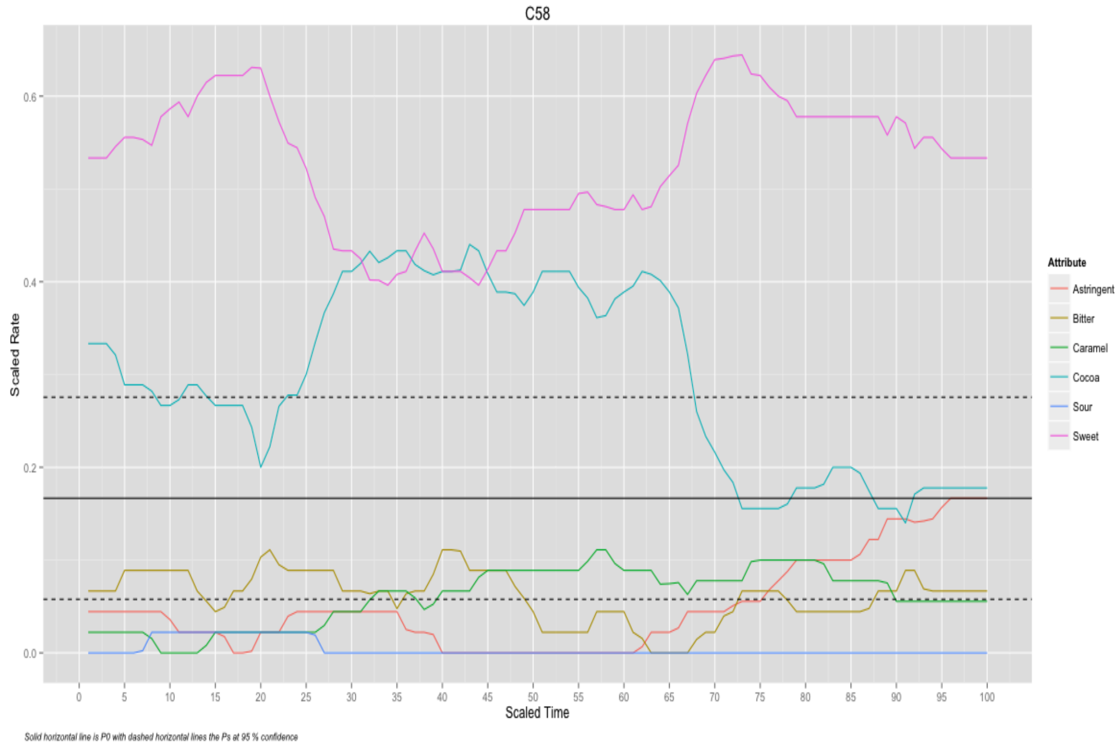

Figure 9. Trained Panel Scaled TDS Curves. Sample C58

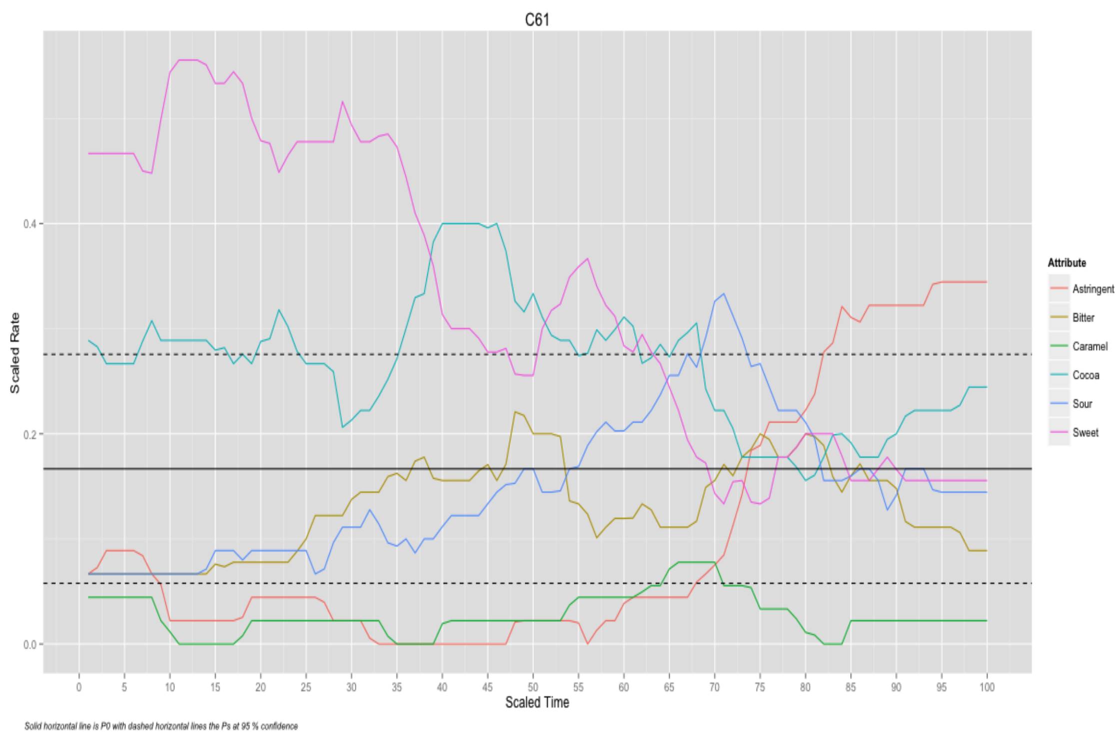

Figure 10. Trained Panel Scaled TDS Curves. Sample C61

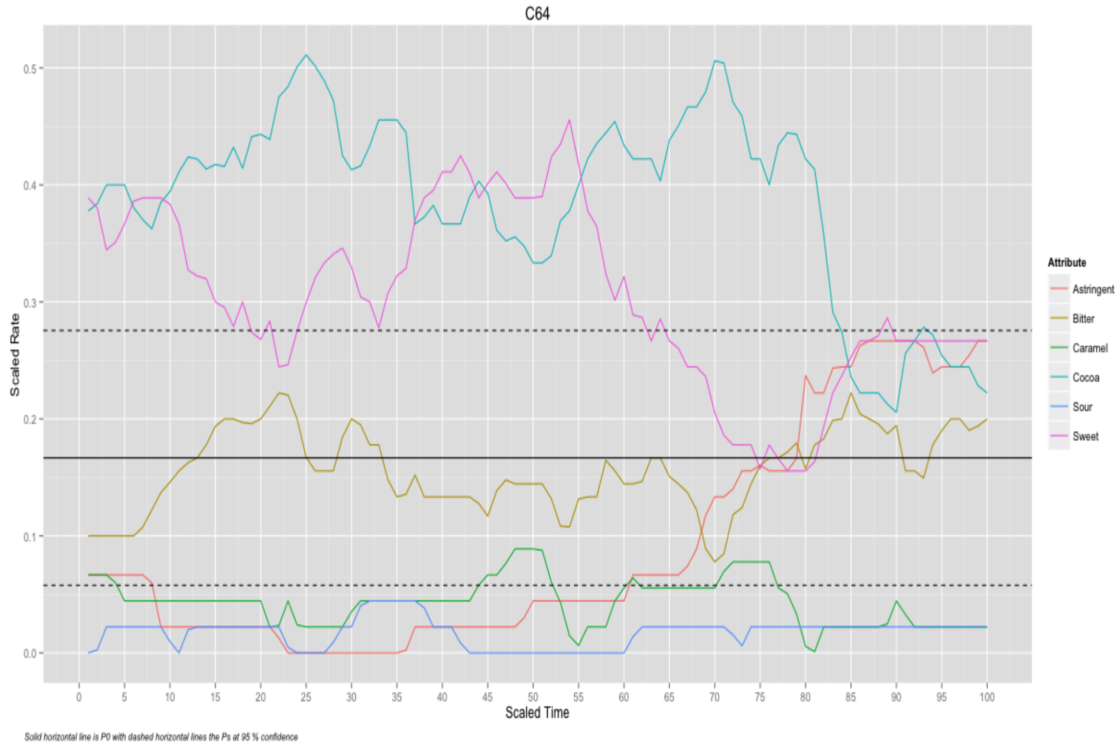

Figure 11. Trained Panel Scaled TDS Curves. Sample C64

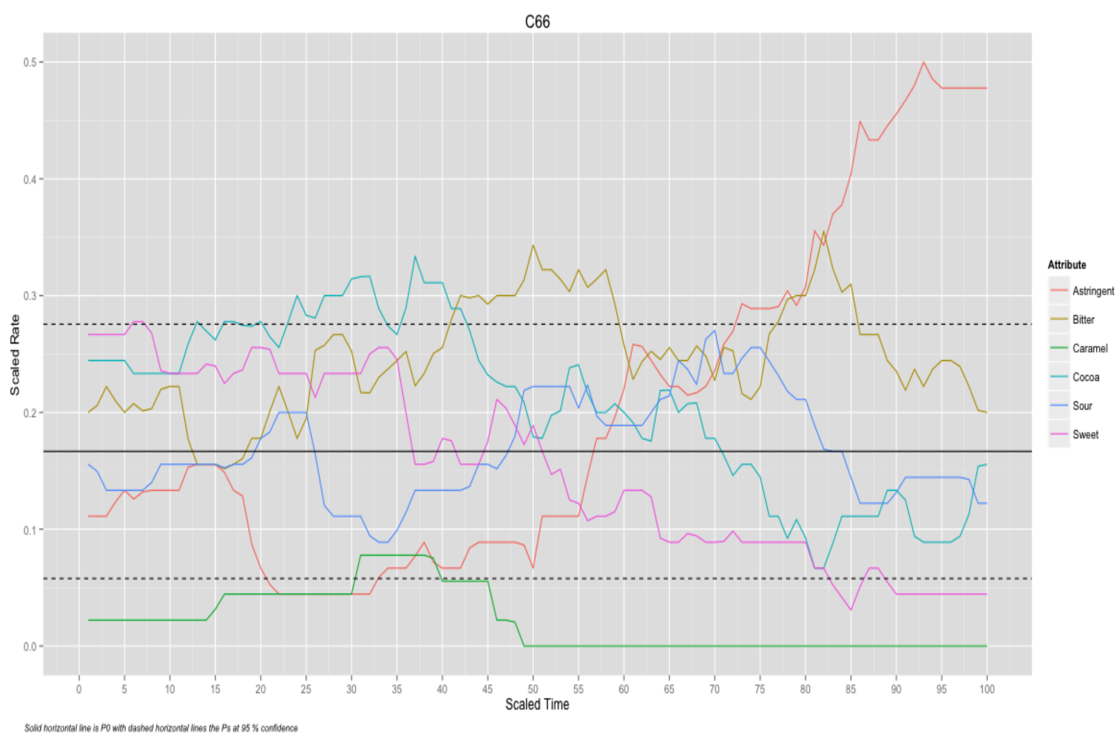

Figure 12. Trained Panel Scaled TDS Curves. Sample C66

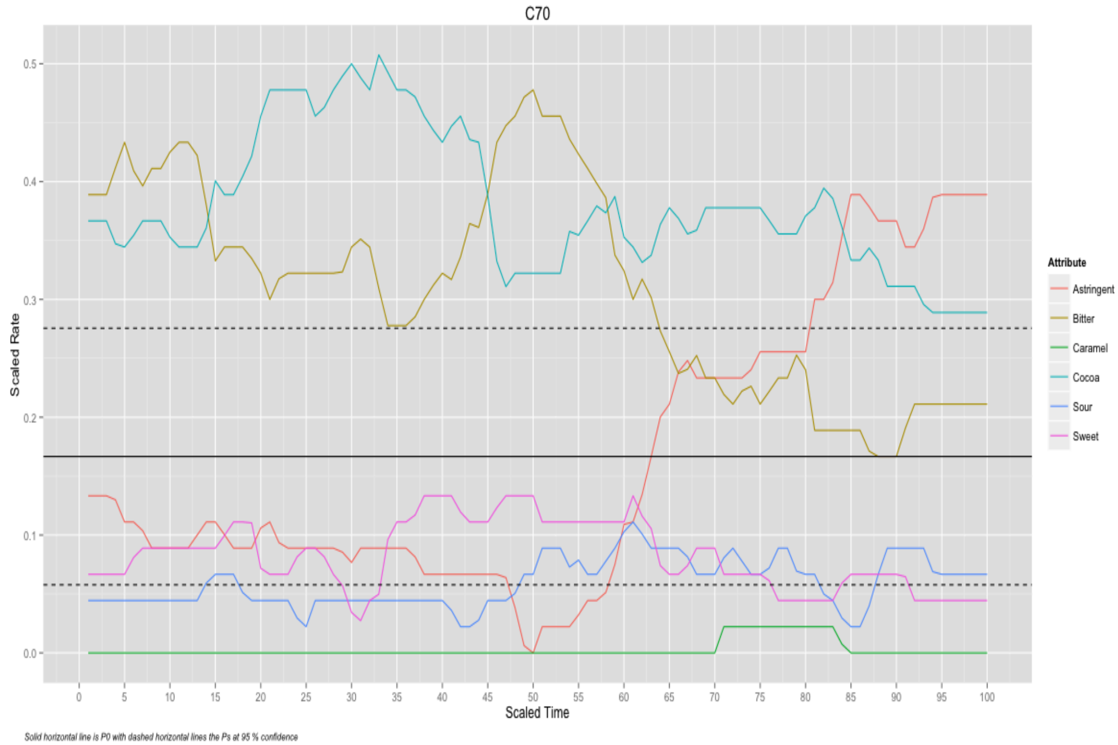

Figure 13. Trained Panel Scaled TDS Curves. Sample C70

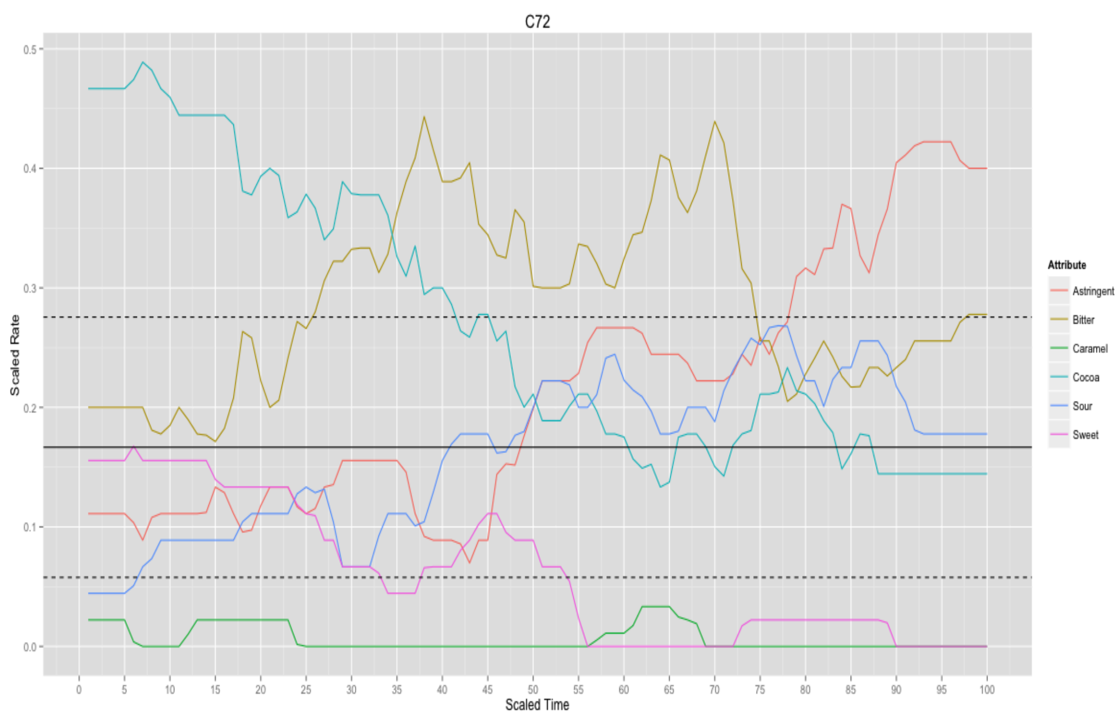

Figure 14. Trained Panel Scaled TDS Curves. Sample C72

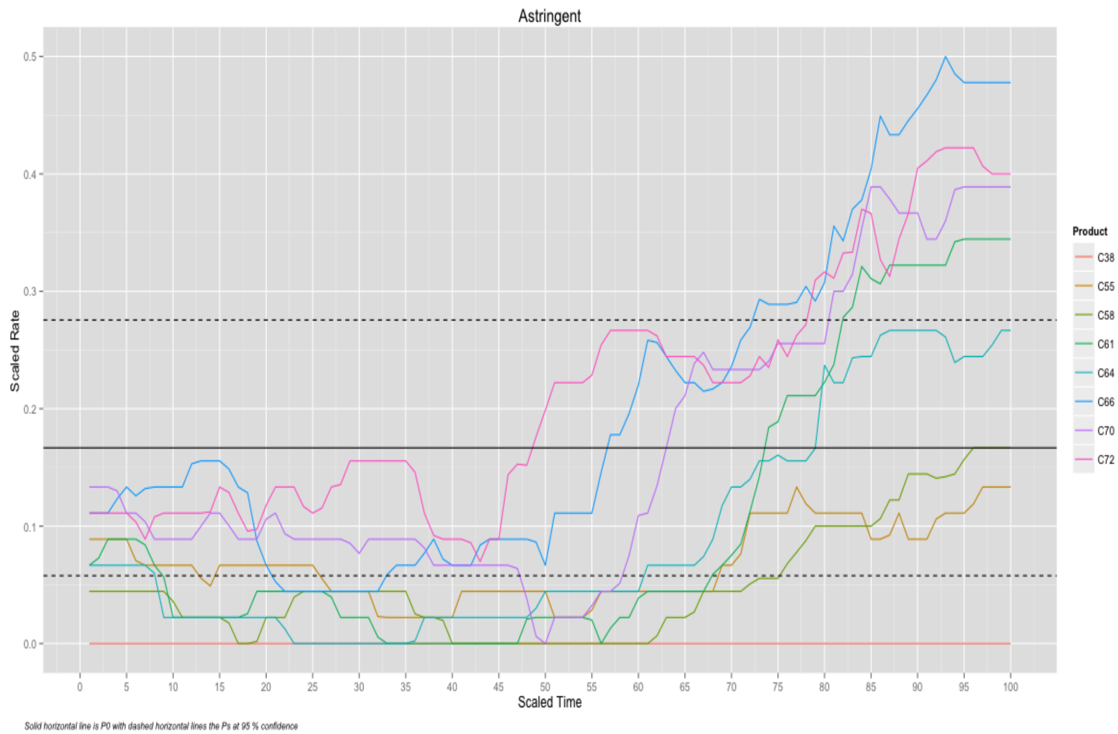

Figure 15. Trained Panel Scaled TDS Curves. Astringency of all samples

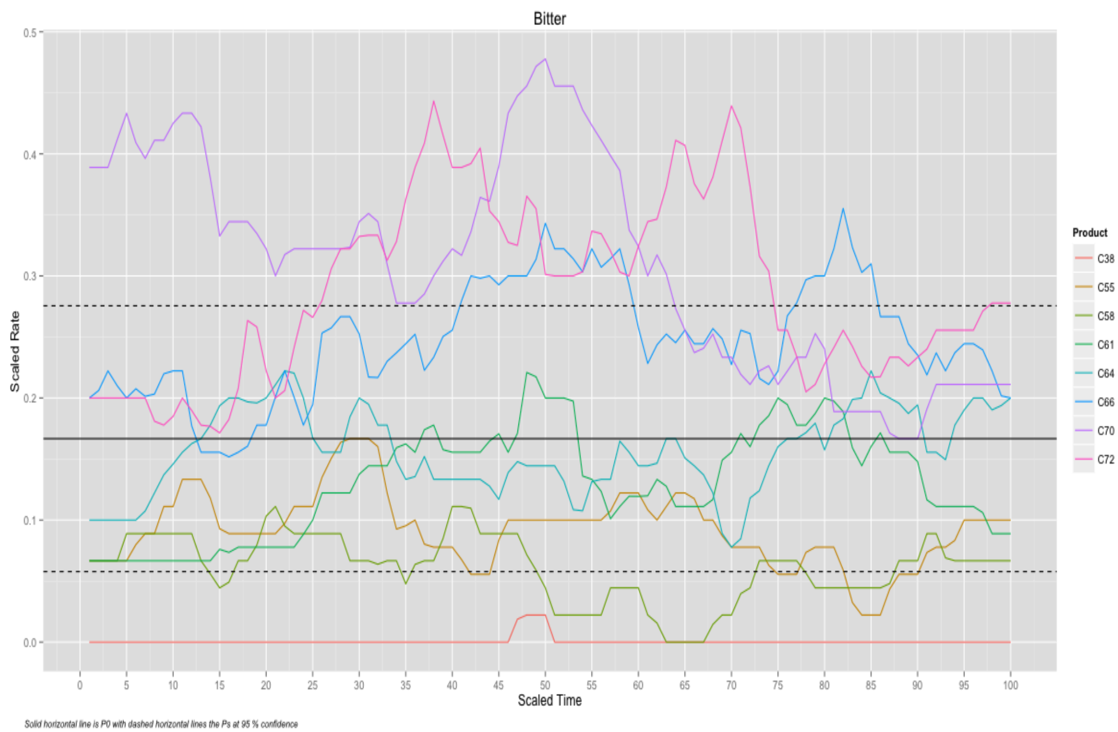

Figure 16. Trained Panel Scaled TDS Curves. Bitterness of all samples

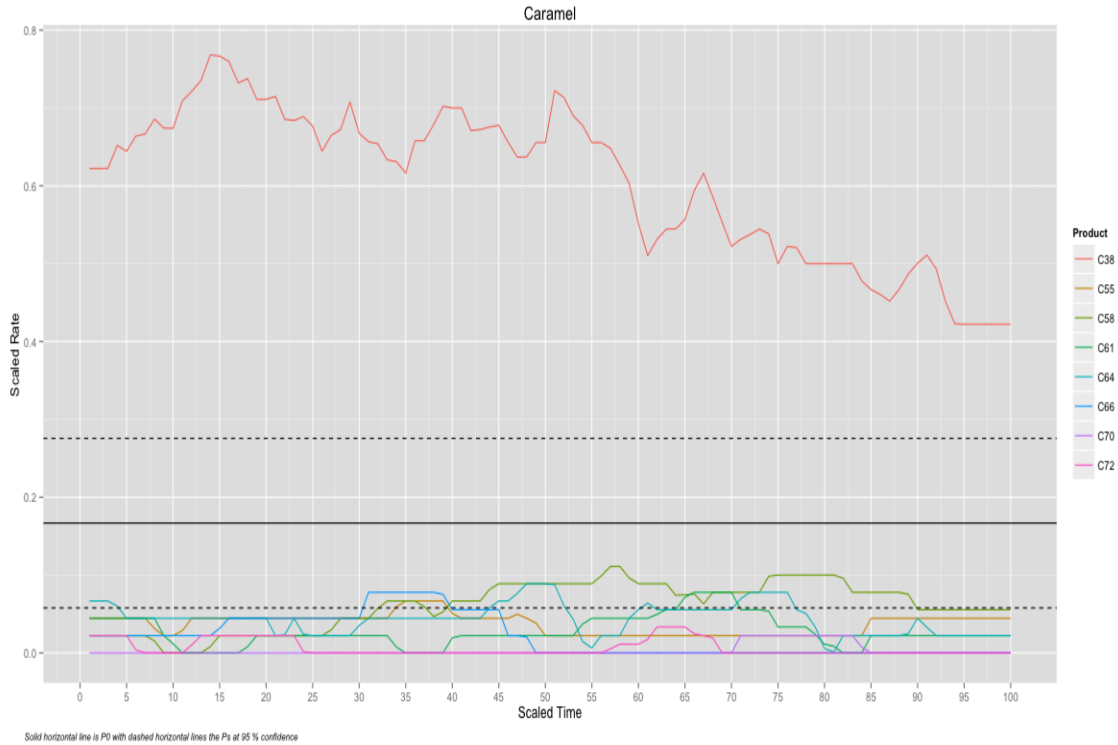

Figure 17. Trained Panel Scaled TDS Curves. Caramel flavor of all samples

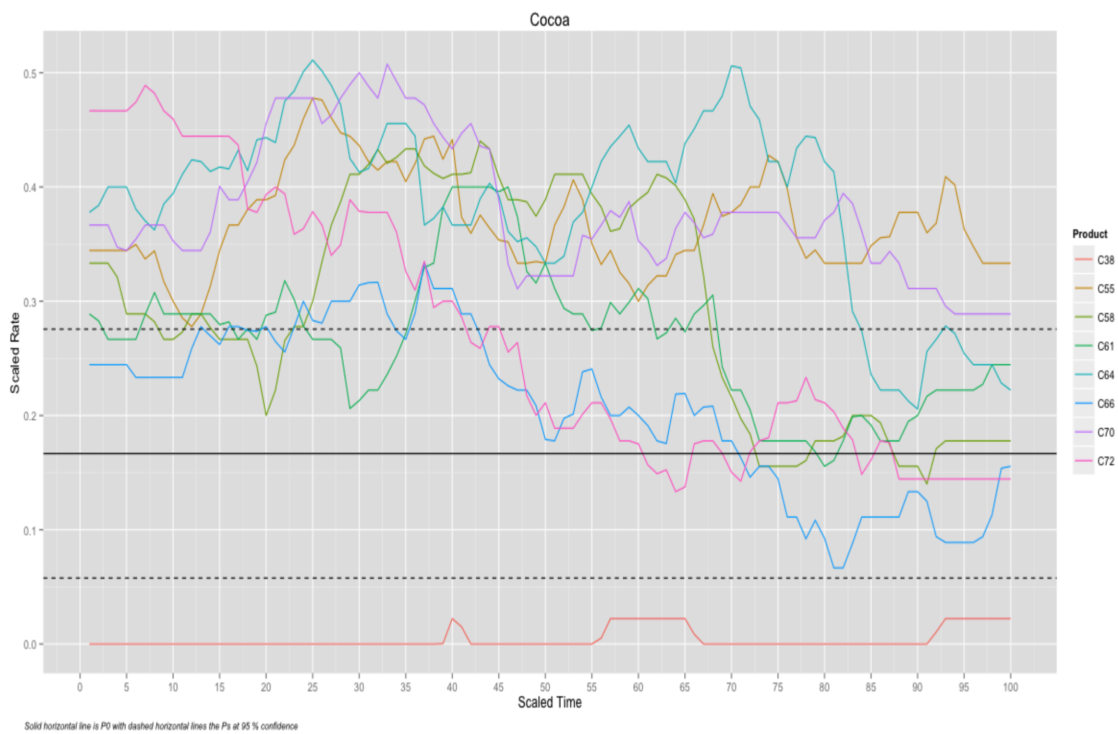

Figure 18. Trained Panel Scaled TDS Curves, Cocoa flavor of all samples

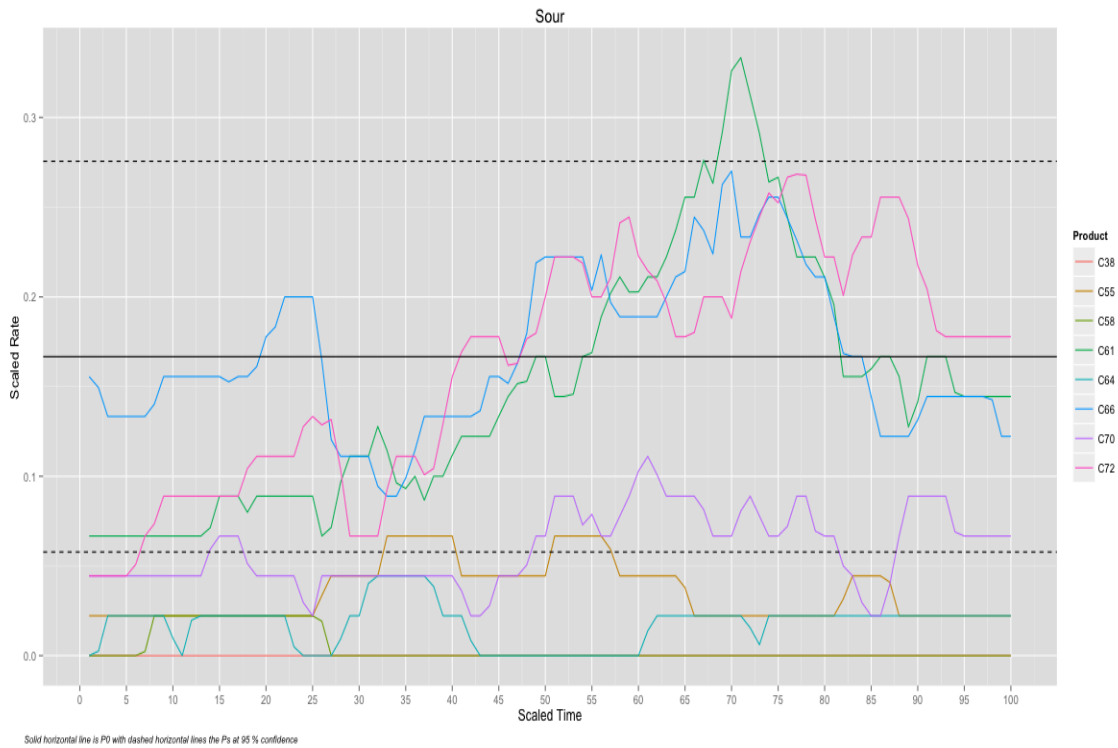

Figure 19. Trained Panel Scaled TDS Curves. Sourness of all samples

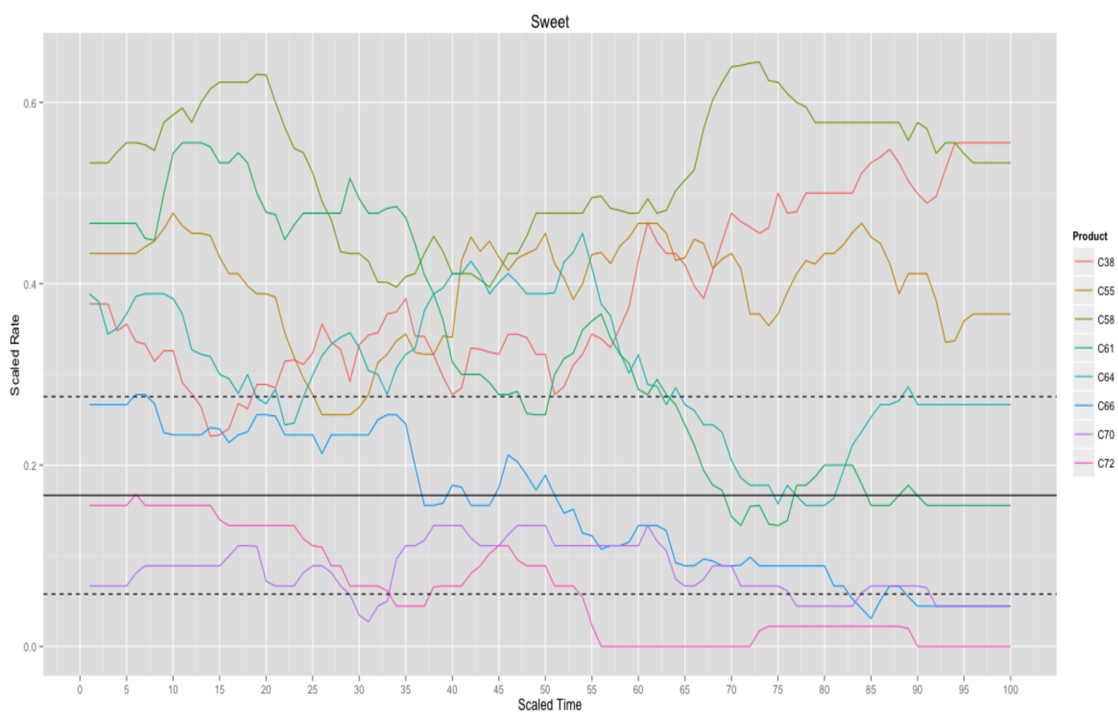

Figure 20. Trained Panel Scaled TDS Curves. Sweetness of all samples

Each TDS curve figure includes three horizontal markers labeled P_0, $P_{s\ low}$, and $P_{s\ high}$. P_0 represents chance and is calculated with 1/p, where p is the number of attributes. Because the curves are scaled, "no selection" is not an option, so p represents the total number of possible selections at any time. Traditionally in TDS, significance is marked with a single P_s, which represents "the minimum value… to be considered as significantly higher than P_0" (Pineau et al., 2009). It is calculated using the confidence interval ($\alpha = 0.05$) of the normal approximation of a binomial proportion. This significance level is calculated with the formula $P_s = P_0 + 1.645\sqrt{(P_0 (1-P_0)/n)}$, where n is equal to the product of judges and replications. (Pineau et al., 2009). In this study, there was equal interest in what was above chance in dominance and below chance in dominance. Therefore, the P_s marker was changed to $P_{s\ low}$ and $P_{s\ high}$ in order to better represent the boundaries of a confidence interval. Points on a TDS curve that fall above $P_{s\ high}$ are considered "significantly dominant". There is 95% confidence that the attribute is truly dominant in that product at that time, and not just by chance. Conversely, points that fall below $P_{s\ low}$ represent an attribute that is "significantly not dominant" in a specific product in that time period. The DR is low enough to say, with 95% confidence, that the attribute is truly not dominant, rather than by chance. This provides additional information about which chocolates or time periods are characterized by the absence of certain traits as well as the presence of others. TDS curves and significance markers were generated by Sean LaFond and based partially on the work by Chatfield and Collins (1980).

PCA Over Time

The scaled TDS data was broken into equal time intervals and summed, a procedure modeled after similar data manipulation by Dinnella (Dinnella et al., 2013). This data was then used to create a PCA of the trajectory of each sample over time. These figures are similar to one created by Lenfant (Lenfant et al., 2009) and are useful for visualizing how samples relate to the attribute space over time Figure 21. The PCA space is created by the relationships between the attributes, and each product has 5 points representing 5 equal time intervals of the tasting. This allows the visualization of how each product changes over time and which attributes best characterize each product throughout the tasting.

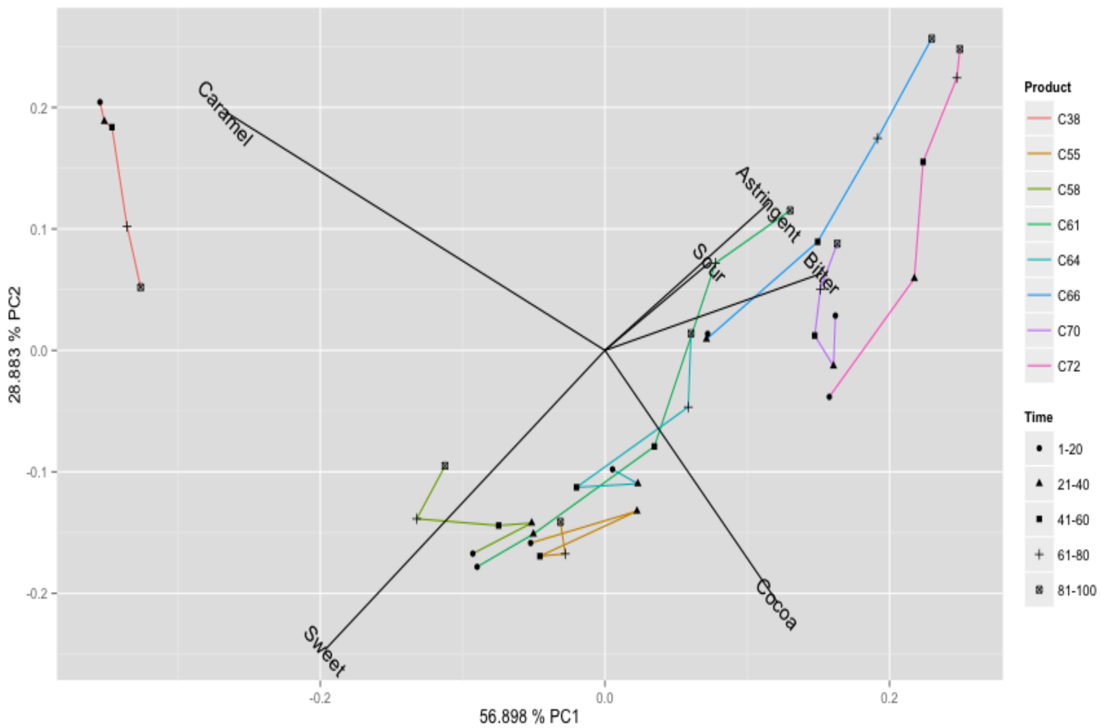

Figure 21. PCA of Trained Panel TDS Data. Split into 5 time intervals

CVA

The data was also plotted via CVA (Canonical Variate Analysis). Figure 22 shows the loadings plot of how the attributes fill the space, and Figure 23 shows where the products fall within that space. Instead of 5 time intervals, each tasting is split into two, for better visualization. Each time period is represented as a mean center point surrounded by a 95% confidence interval (CVAellipses_new function written by Helene Hopfer, Peter Buffon and Vince Buffalo, edited for aesthetics by Sean LaFond).

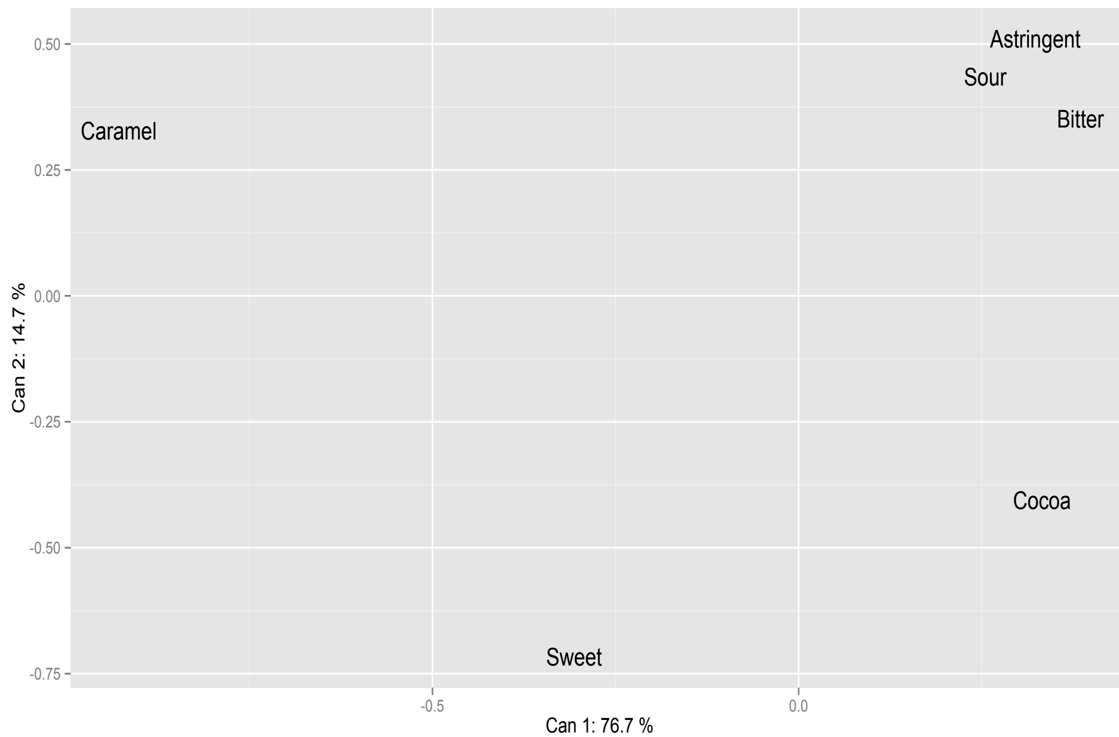

Figure 22. CVA Loadings Plot of Trained Panel TDS Data. Split into 2 time intervals

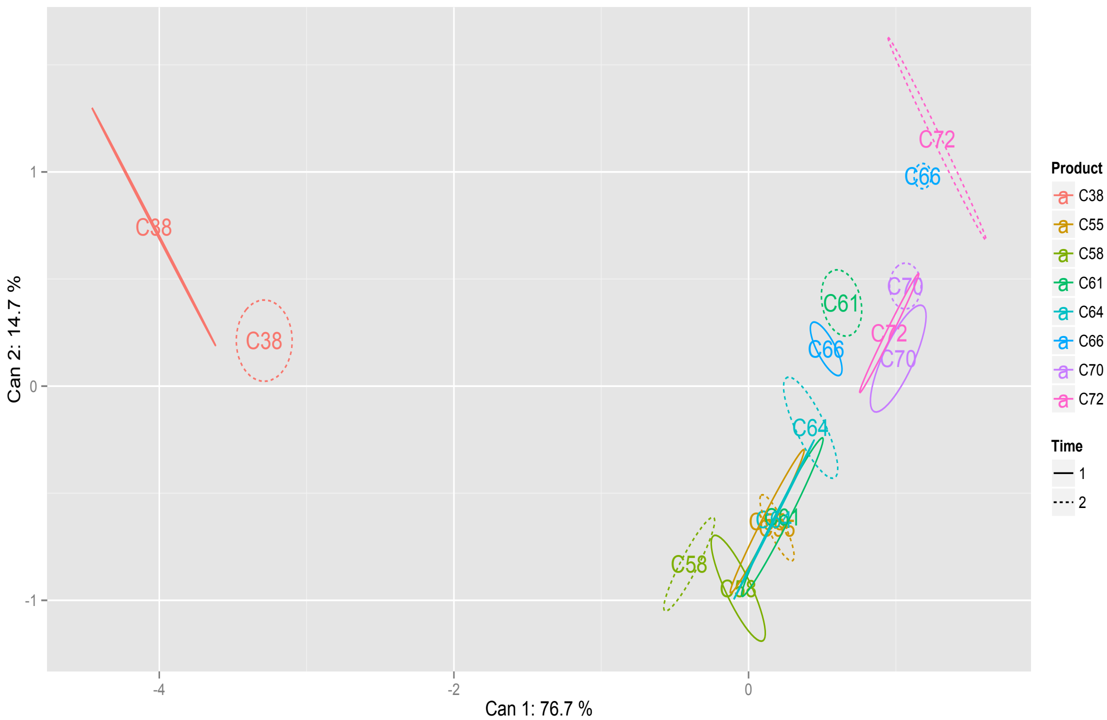

Figure 23. CVA Score Plot of Trained Panel TDS Data. Split into 2 time intervals

2.4 Results and Discussion

GDA ANOVA

Of the 47 attributes used in the Descriptive Analysis, 38 of them were statistically significant among the eight chocolate samples (Table 9). The attributes Nutty Aroma, Fruity Aroma, Honey, Aroma, Cherry Aroma, Nutty Flavor, Mint Flavor, Honey Flavor, and Cherry Flavor were not significant and were not included in Canonical Variate Analysis (CVA) of this data. All of the taste, aftertaste, mouthfeel, and texture attributes were significant, and with the exception of fruity flavor, all of the flavors that were significant also had significant matching aromas. The attributes that were not significant wee likely not necessary in the analysis. These are generally not seen in chocolate descriptive analysis except for nutty flavor and aroma.

Table 8. Significant and Non-Significant GDA Attributes

Significant Attributes	Significant Attributes (Cont'd)	Non-Significant Attributes
Cocoa A	Sweet T	Nutty A
Milky A	Biter T	Mint A
Vanilla A	Sour T	Fruity A
Caramel A	Astringent MF	Honey A
Coffee A	Cocoa F	Cherry A
Buttery A	Milky F	Nutty F
Artificial A	Vanilla F	Mint F
Earthy A	Caramel F	Honey F
Smoke A	Coffee F	Cherry F
Herbal A	Buttery F	
Hardness	Artificial F	
Brittleness	Earthy F	
Roughness	Smoke F	
Oily.Moist	Herbal F	
Stickiness	Fruity F	
Rate of Melt	Sweet AT	
Oily Mouthcoat	Biter AT	
Chalky Mouthcoat	Sour AT	
Tooth Packing	Astringent AMF	

A = aroma, T = taste, MF = mouthfeel, F = flavor, AT = aftertaste, AMF = after-mouthfeel

The Judge and Product factors were highly significant and the Rep factor was moderately significant. Significant Judge factor indicates the judges used the intensity scale differently from one another. This is due to personal habits in terms of scale use, personal differences in sensitivity to certain attributes, and lack of calibration at the level demanded by the Spectrum method. The significant Product factor shows that at least some of the product ratings were different. It does not specify which products are different from one another or in which attributes; an LSD test was performed to determine this. The significant Rep factor indicates that the sessions were not true replicates. Each judge assessed each product on three separate occasions, but those occasions may differ based on variation in the judge or in the test conditions. (Lawless and Heymann 2010)

Three two-way interactions exist: Judge x Rep (JxR), Judge x Product (JxP), and Product x Rep (PxR). The JxR interaction relates to panelist reproducibility. If was significant, meaning at least one of the judges was not reproducible in product rating. The scores given to a product in one replication were different from those given to the same product in another replication. The JxP interaction shows the degree of concept alignment among panelists. Because it was significant, at least one panelist perceived products differently from other panelists. This can usually be caused by lack of understanding of one or more attributes or inadequate training. The PxR interaction is about reproducibility of products. It was not significant, which means the products were consistent across replications. (Lawless and Heymann 2010)

GDA CVA

The first 3 Canonical Variates (labeled as Cans) were examined (Figures 1-6). The first Can explains 71.2% of the variance; the second explains 12.1%, and the third only 7%. In total, the first three Cans explain 90.3% of the variance in the data set. The 1st Can is predominantly driven by caramel flavor, which separates C38 from all other samples. As expected, the caramel flavor is highly associated with buttery and milky flavors, suggesting that these 3 attributes all describe the same character in chocolates. C38 is very far to the right end of the space, and the others are on the left side of the space. On the opposite end of Can 1 are attributes generally associated with very dark chocolates such as bitterness, astringency, and hardness. This shows that the first dimension of the space, Can 1, is closely related to cocoa solids and sugar content of the chocolates, with high cocoa and low sugar chocolates at the left end, and low cocoa and high sugar chocolates (as well as the dairy containing milk chocolate) at the right end. It is less clear what is separating the samples in the 2nd and 3rd dimensions, but it is likely based on sweetness, sourness, and bitterness. There is a definite grouping of C55 and C58, which are not significantly different in any score plots of the first 3 Cans. There is a potential grouping of C72, C70, C66, and C64, depending on which dimensions are examined. Sample C61 seems to be unique because it never overlaps with any other samples. Also, it is sometimes grouped very close to low cocoa and high sugar chocolates and at other times near low sugar and high cocoa chocolates.

Separation of the samples overall is mainly based on the presence of dairy ingredients. If more milk chocolates had been included in the sample set, there would likely be a clear separation between milk chocolates and all other chocolates with higher levels of cocoa solids and no dairy ingredients. Separation by cocoa solids is not clear among the 7 non-milk chocolates. The samples may also differ in type of beans used, processing conditions, and levels of sugar and fat. All of these differences would alter both the flavor ad texture of the chocolates and make separation by cocoa solids alone very difficult.

Rate of Melt

The rate of melt attribute is the most unique in that it involves the unit of time. According to the LSD results, samples C66, C70, and C64 took the most time to melt, and did not differ in this amount of time. Sample C38 took the least amount of time to melt and was different from all other samples, and C72, C58, C61, and C55 were in the middle of that spectrum. There is some apparent inverse relationship between the amount of fat in the chocolate and the time needed to melt it.

To examine how judges interpreted this unusual attribute, a PCA was created of the samples and the judges (Figure 24). The samples are sorted similarly, but have slightly different groups. These groups actually correlate better with the fat and time to melt relationship. Most of the judge vectors suggest that sample C70 had the longest melt time, which was also shown in the LSD results. Some of the judges, especially Judge 7 and Judge 9, were not in agreement with the rest of the panel. It appears that Judge 7 may have used the line scale in the opposite form as everyone else: marking quick-melting chocolates with a high score rather than a low score.

In the TDS analysis, rate of melt was performed separately. This procedure proved somewhat more awkward and difficult for the panelists, and also was not designed to generate a TDS curve. Panelists were asked to press the start button while starting consumption and to press the “Melted” attribute button and then the “Stop” button to mark the time the sample was completely melted. Most panelists reported errors in performing this procedure on multiple occasions. Because of this, the attribute was not examined and not included in the consumer TDS study. It is recommended that future research be performed with a focus on TDS of texture attributes in chocolate, including those related to melting.

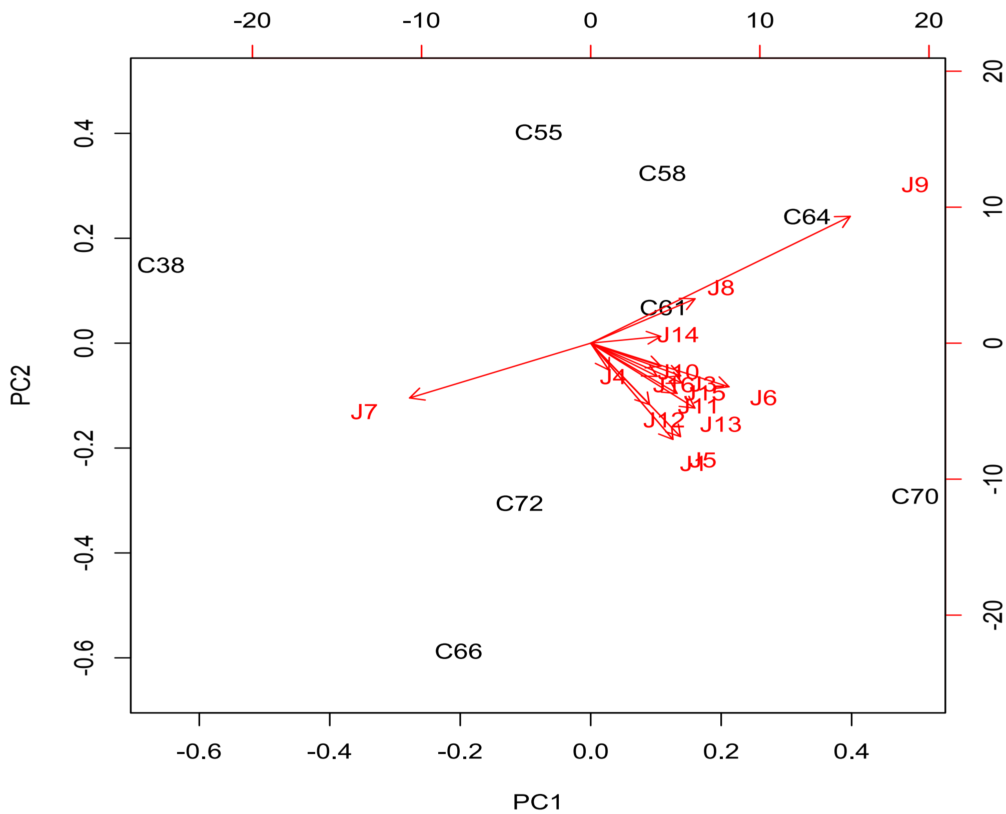

Figure 24. PCA of Judges and Products. Based on GDA rate of melt results.

TDS

In the TDS curves evaluation time is split into two intervals to examine major changes over time. Table 10 shows which attributes are significantly dominant (above $P_{s\ high}$) and significantly not dominant (below $P_{s\ low}$) within each time period for each sample. The raw TDS curves can be found in the Appendix, and scaled TDS curves are shown in Figures 7-20.

Figures 21-13, PCA and CVA plots of TDS data, show similar overall patterns to the CVA plots of GDA data (Figures 1-6). The major separation is that of milk and dark chocolates. Caramel flavor is driving the first dimension, and C38 is well separated from the rest of the samples. Cocoa is opposite caramel in the PCA space, and in the center of the axis separating the other samples. This shows that all chocolates are first split either by being more caramel/dairy in character as milk chocolates or more cocoa in character as all other chocolates. It may also suggest that panelists were most likely to consider cocoa as a dominant attributes in chocolates that are balanced between medium and high cocoa content. As for the other samples, they appear to be sorted along an axis with sweetness at one end and bitterness, sourness, and astringency at the other end. The sorting on this axis is closely related to cocoa and sugar contents of the chocolates. Samples C58 and C55 are far on the sweet end of this axis; C64 and C61 are in the center, and C70, C66, and C72 are on the bitter/sour/astringent end of the axis.

As for the time factor, some of the samples appear more dynamic than others. C55, C58, and C70 do not change as much or progress in a consistent direction throughout the tasting. C38 shows a clear pattern of becoming less dominant in caramel and more dominant in sweetness. C64 stays between the sweetness and cocoa attributes for the first half of the tasting, but then progresses toward the bitter/sour/astringent region in the second half. C66 and C70 are parallel, both starting at the bitter/sour/astringent end of the space and consistently becoming more sour and astringent. Their positions also suggest that C72 is bitterer than C66, which is expected when examining cocoa and sugar content of both samples. C61 appears to be the most dynamic sample, starting in the same region as C55 and C58, but ending near C66 and C70.

The CVA plots very closely match the information in the PCA, but show it in a different form. The evaluation time is split into two intervals, rather than five, and these intervals are shown with 95% confidence interval ellipses. For samples C38, C61, C66, and C72, the ellipses are separated, showing a significant difference between the two intervals of the tasting. For samples C58 and C70, the first and second halves are nearly significantly different because the ellipses just touch. The remaining samples have overlapping ellipses, which suggests that they change more gradually or less consistently throughout tasting.

MFA

Due to the differences in type of data and number of attributes, GDA and TDS data cannot be easily compared. Multifactor Analysis (MFA) is one of the few tools that can compare multiple datasets that have little in common. Figure 25 shows the MFA plot of the GDA data and the TDS data split into two even time intervals. The RV coefficients for this plot are provided in Table 11, and show that roughly 85% of the variance in one method is explained by the other. Figure 10 and Table 11show two different TDS procedures: one by the trained panel and one by untrained consumers. The consumer TDS procedure is discussed in Chapter 3.

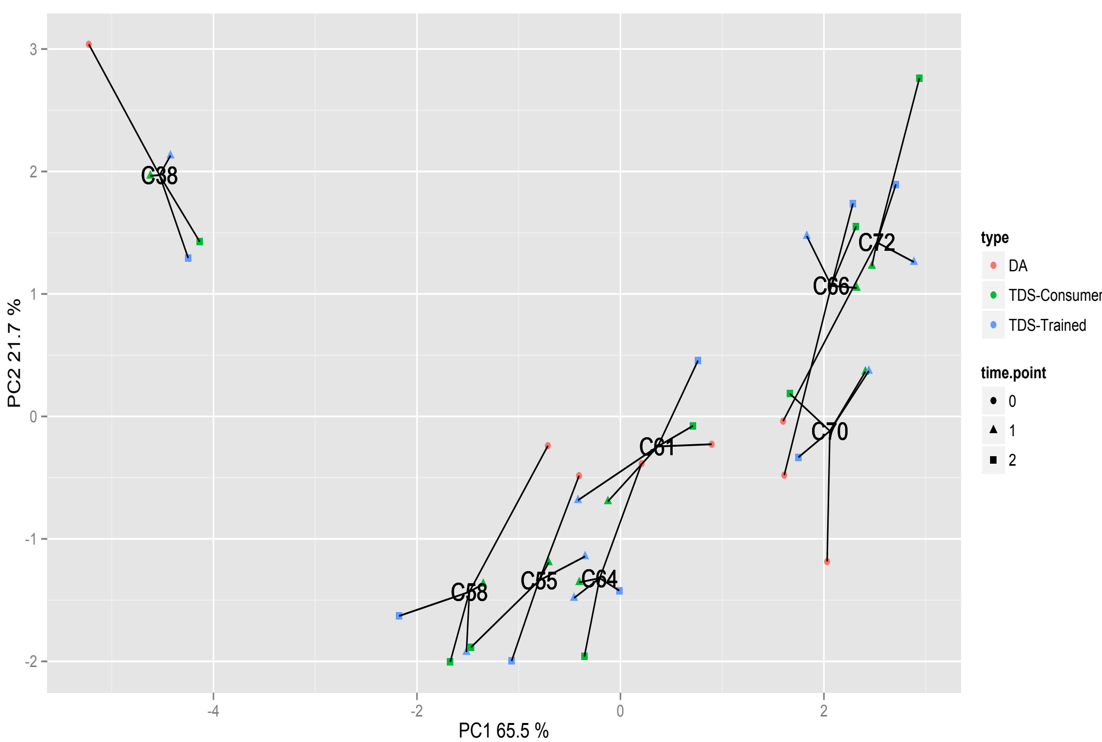

Figure 25. MFA of All 3 Methods. GDA, TDS trained, and TDS untrained. Both TDS methods split into 2 time intervals.

Table 9. RV Coefficients for MFA of GDA, Trained Panel (TP) TDS and Untrained Consumer (UC) TDS

	TDS-UC-1	TDS-UC-2	TDS-TP-1	TDS-TP-2	GDA	MFA
TDS-UC-1	1	0.933	0.972	0.925	0.9	0.984
TDS-UC-2	0.933	1	0.898	0.974	0.842	0.967
TDS-TP-1	0.972	0.898	1	0.901	0.846	0.961
TDS-TP-2	0.925	0.974	0.901	1	0.86	0.97
GDA	0.9	0.842	0.846	0.86	1	0.923
MFA	0.984	0.967	0.961	0.97	0.923	1
Ave	0.943	0.923	0.916	0.926	0.874	0.961

3. TRAINED AND UNTRAINED TDS

3.1 Objective

The goal of this study is to determine the similarities, differences, and various benefits of General Descriptive Analysis and Temporal Dominance of Sensations. The former provides a static or averaged sensory profile with many attributes, while the latter produces a dynamic profile that showcases the order and importance of fewer attributes over time. The same panelists and same samples were used for both methods, and the results of each are analyzed with R studio software and compared.

3.2 Material and Methods

Refer to section 2.2 for information on chocolates, recruitment and discrimination of panelists, generic descriptive analysis, and TDS by trained panel.

TDS by Untrained Consumers

Emails were sent to the university and community in Davis, CA to recruit consumers. (Appendix). The requirements were that all consumers must be at least 18 years old, regular chocolate consumers, and not previously or currently involved in sensory panels or training involving chocolate. Consumers were asked to sign up for one of 6 sessions over the course of two days. For every session, consumers were given a 10-15 minute presentation that explained the basic concepts of TDS, the procedure they were about to perform, and the attributes they would be rating in chocolates. After this presentation and an opportunity to ask questions, the consumers were assigned to individual booths where they performed the analysis with the FIZZ Biosystèmes software, version 2.47B. Each consumer tasted 9 samples, the first being a warm-up from which no data was analyzed. Warm-up samples were also randomized based on the Latin square design used. Each sample was comprised of one chocolate disc in a 1-ounce lidded Solo cup coded with a random 3-digit number (Solo Cup Co. Highland Park, IL). Panelists assessed each sample according to instructions and timed prompts that appeared on the screen. They were asked to swallow at the end of each TDS procedure to realistically assess aftertaste. A one-minute break including 5 rinses with distilled water was used between each sample. Consumers were also asked to rinse with distilled water to cleanse their palates at the beginning of the session. Ninety-eight consumers successfully completed the entire procedure.

3.3 Data Analysis

Refer to section 2.3 for details information on data analysis. All procedures performed are identical, with the exception of additional analyses performed on data generated by untrained consumers performing TDS. The raw consumer TDS curves are shown in the Appendix, and scaled curves are shown in Figures 26-39.

3.4 Results and Discussion

Similarities

At first glance, the two datasets appear very similar. Both groups separate sample C38 from the rest of the samples based on the caramel attribute, while the rest are spread across an axis with sweetness at one end, and bitterness, sourness, and astringency at the other. The ranking and apparent groups within the samples are essentially the same: C72, C70, and C66 as the most bitter, sour, and astringent, C55 and C58 as the sweetest, and C61 and C64 somewhere in-between. These middle samples may also be characterized by more dominant cocoa flavor.

Table 10. Summary of Trained Panel and Untrained Consumer TDS Curves, significantly dominant and not dominant attributes for first and second half of tasting

Panel	1st Half	2nd Half		Consumer	1st Half	2nd Half
C38				**C38**		
Above Ps high	Car, Sw	Car, Sw		Above Ps high	Car, Sw	Car, Sw
Below Ps low	As, Bi, Co, Sr	As, Bi, Co, Sr		Below Ps low	As, Bi, Co, Sr	As, Bi, Co, Sr
C55				**C55**		
Above Ps high	Co, Sw	Co, Sw		Above Ps high	Co, Sw	Co, Sw
Below Ps low	Car, Sr	Car, Sr		Below Ps low	As, Sr	As, Sr
C58				**C58**		
Above Ps high	Co, Sw	Sw		Above Ps high	Co, Sw	Co, Sw
Below Ps low	As, Car, Sr	Bi, Sr		Below Ps low	As, Car, Sr	As, Bi, Sr
C61				**C61**		
Above Ps high	Co, Sw	N/A		Above Ps high	Co, Sw	Co, Sw
Below Ps low	As, Car	Car		Below Ps low	Car, Sr	Car
C64				**C64**		
Above Ps high	Co, Sw	Co		Above Ps high	Co, Sw	Co, Sw
Below Ps low	As, Car, Sr	Ca, Sr		Below Ps low	As, Sr	Ca, Sr
C66				**C66**		
Above Ps high	Co	As, Bi		Above Ps high	Bi, Co	Bi, Co
Below Ps low	Ca	Ca		Below Ps low	Ca, So	Ca, So
C70				**C70**		
Above Ps high	Bi, Co	Co		Above Ps high	Bi, Co	Co
Below Ps low	Car, Sr	Car		Below Ps low	Car, Sr	Car
C72				**C72**		
Above Ps high	Bi, Co	As, Bi		Above Ps high	Bi, Co	N/A
Below Ps low	Ca	Ca, Sw		Below Ps low	Ca	Ca, Sw

As = Astringent, Bi = Bitter, Car = Caramel, Co = Cocoa, Sr = Sour, Sw = Sweet

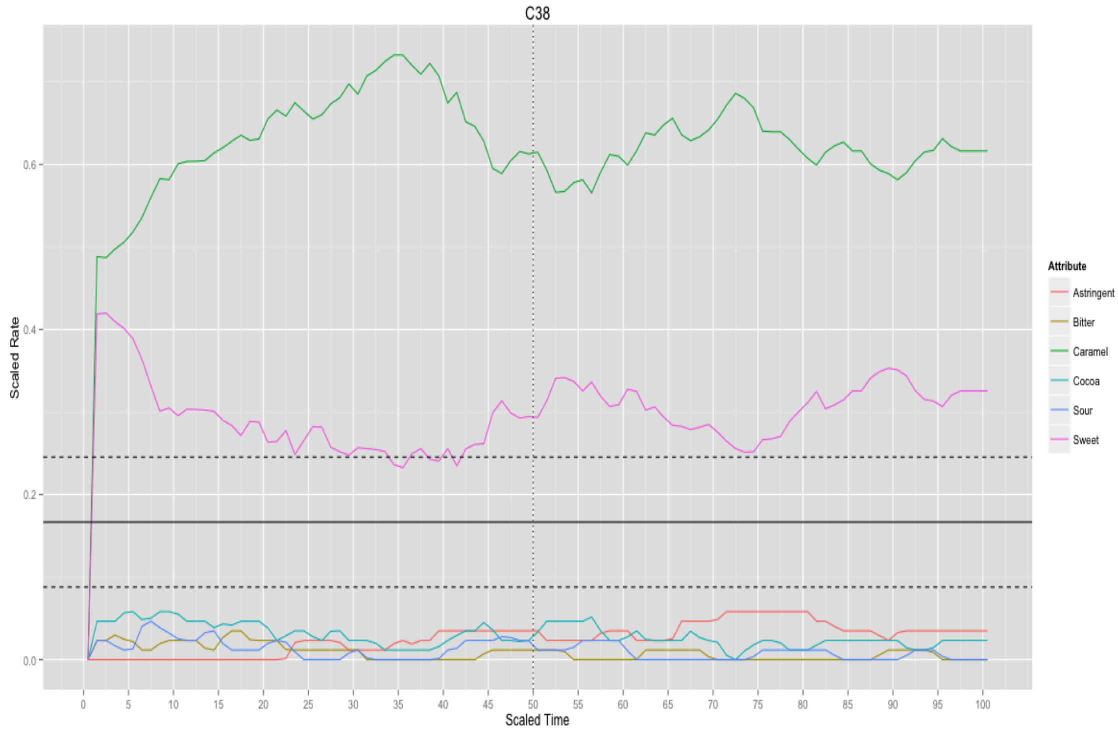

Figure 26. Untrained Consumer Scaled TDS Curves for Sample C38 split into Taste and Aftertaste, including P_0, $P_{s\ Low}$, and $P_{s\ High}$

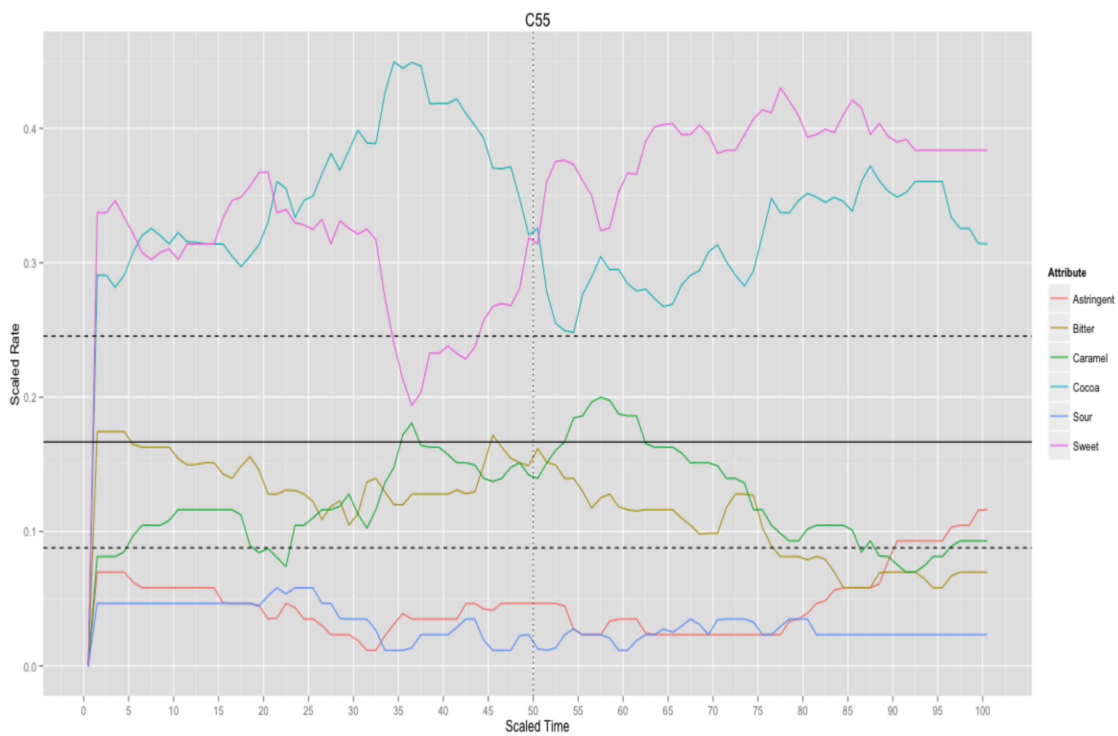

Figure 27. Untrained Consumer Scaled TDS Curves for Sample C55 split into Taste and Aftertaste, including P_0, $P_{s\ Low}$, and $P_{s\ High}$

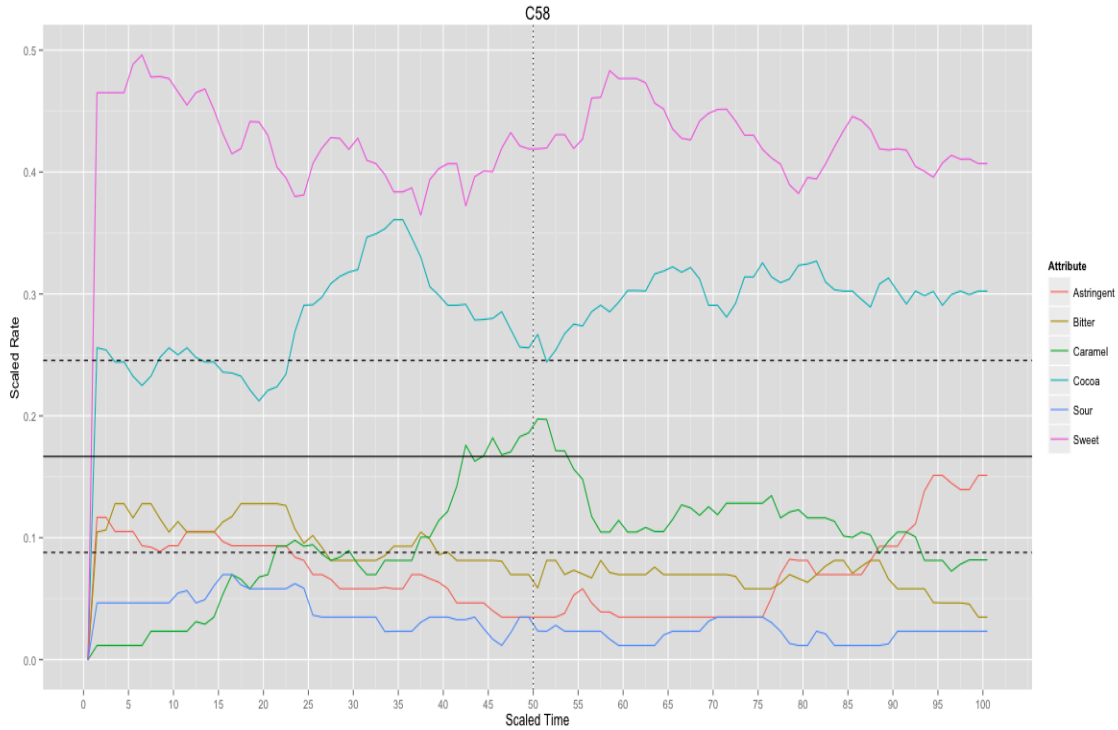

Figure 28. Untrained Consumer Scaled TDS Curves for Sample C58 split into Taste and Aftertaste, including P_0, $P_{s\ Low}$, and $P_{s\ High}$

Figure 29. Untrained Consumer Scaled TDS Curves for Sample C61 split into Taste and Aftertaste, including P_0, $P_{s\ Low}$, and $P_{s\ High}$

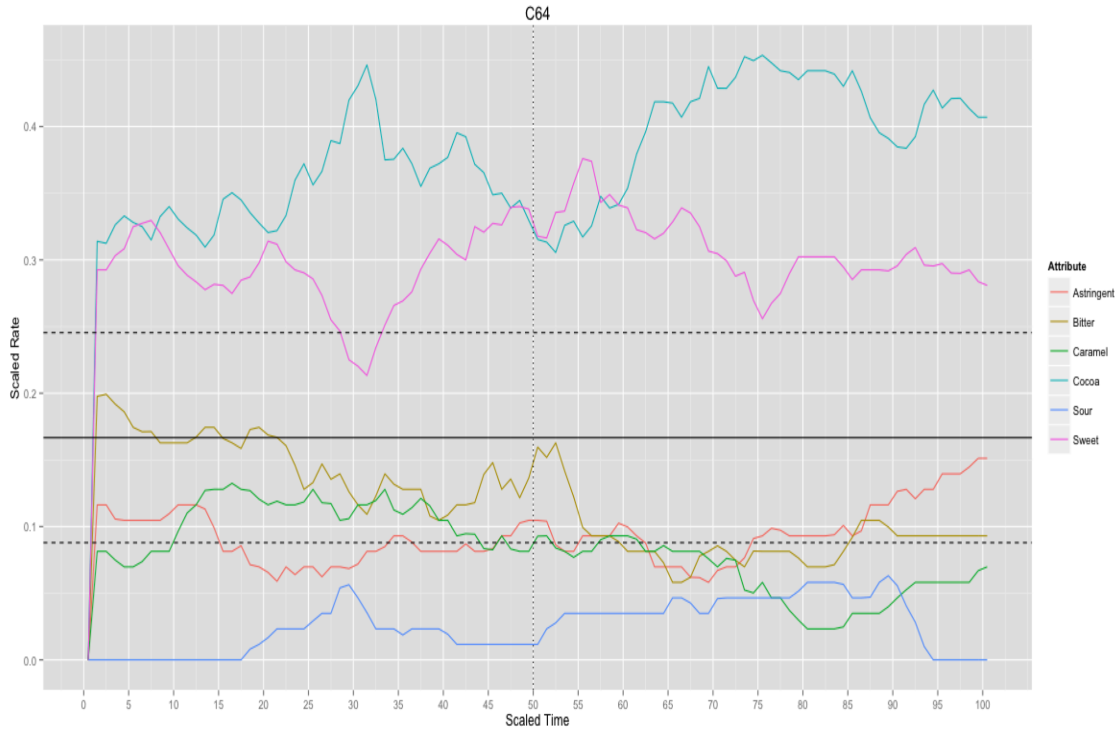

Figure 30. Untrained Consumer Scaled TDS Curves for Sample C64 split into Taste and Aftertaste, including P_0, $P_{s\ Low}$, and $P_{s\ High}$

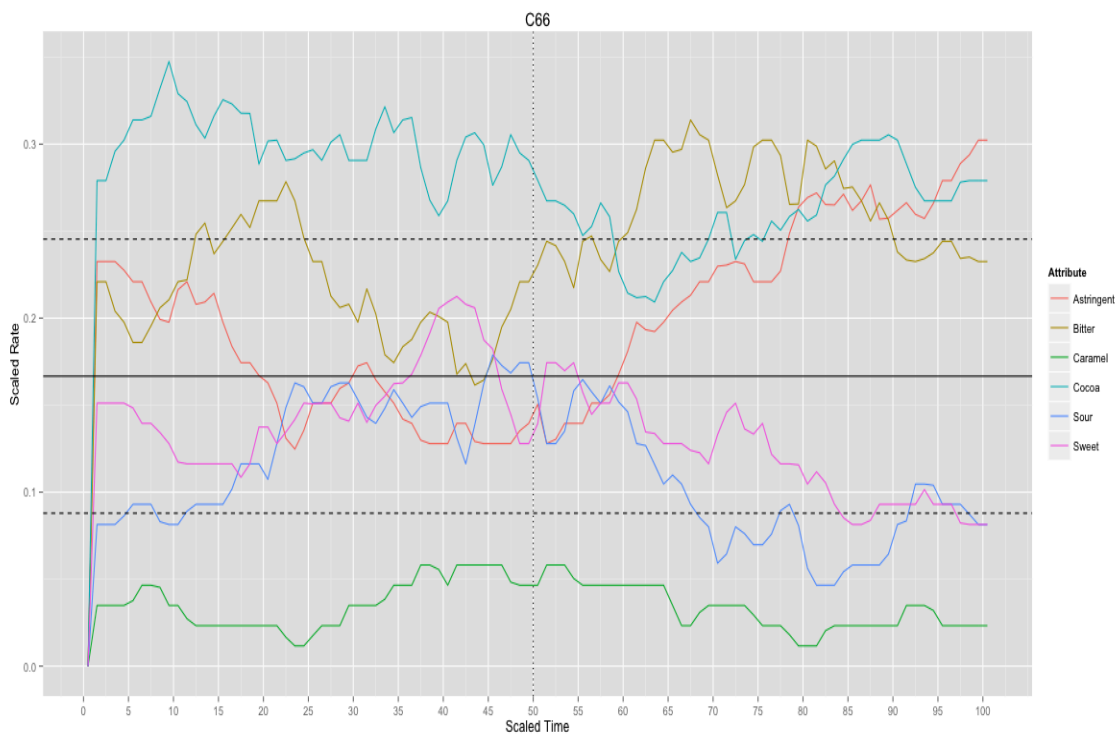

Figure 31. Untrained Consumer Scaled TDS Curves for Sample C66 split into Taste and Aftertaste, including P_0, $P_{s\ Low}$, and $P_{s\ High}$

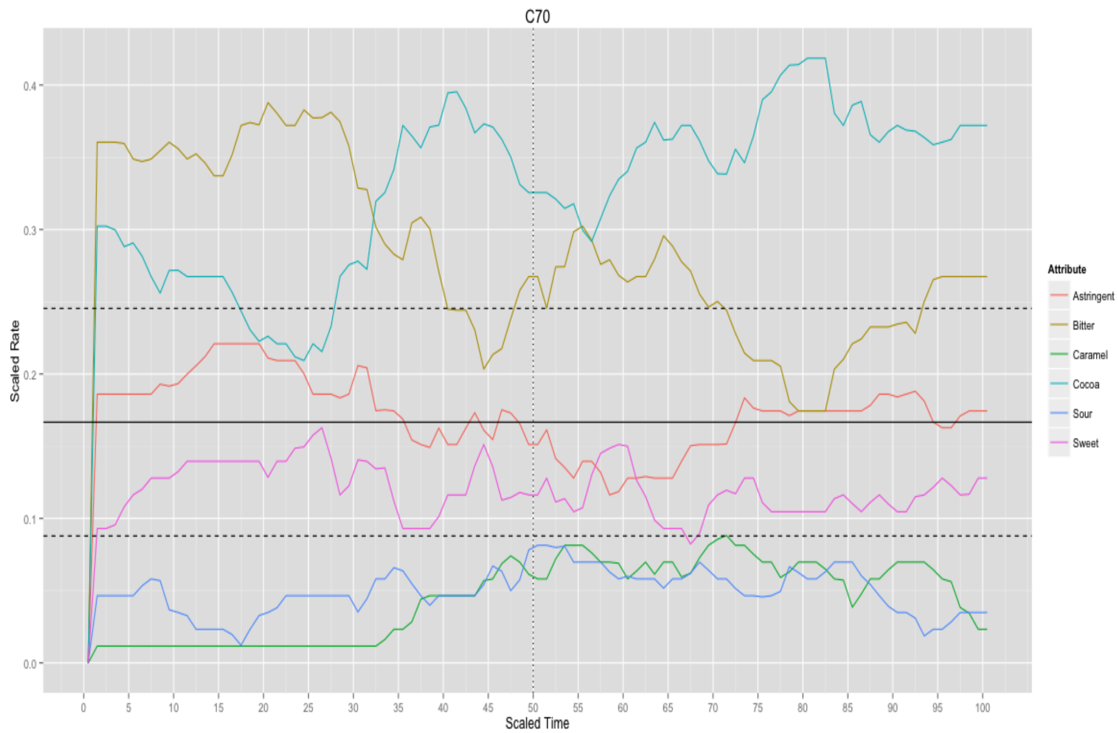

Figure 32. Untrained Consumer Scaled TDS Curves for Sample C70 split into Taste and Aftertaste, including P_0, $P_{s\ Low}$, and $P_{s\ High}$

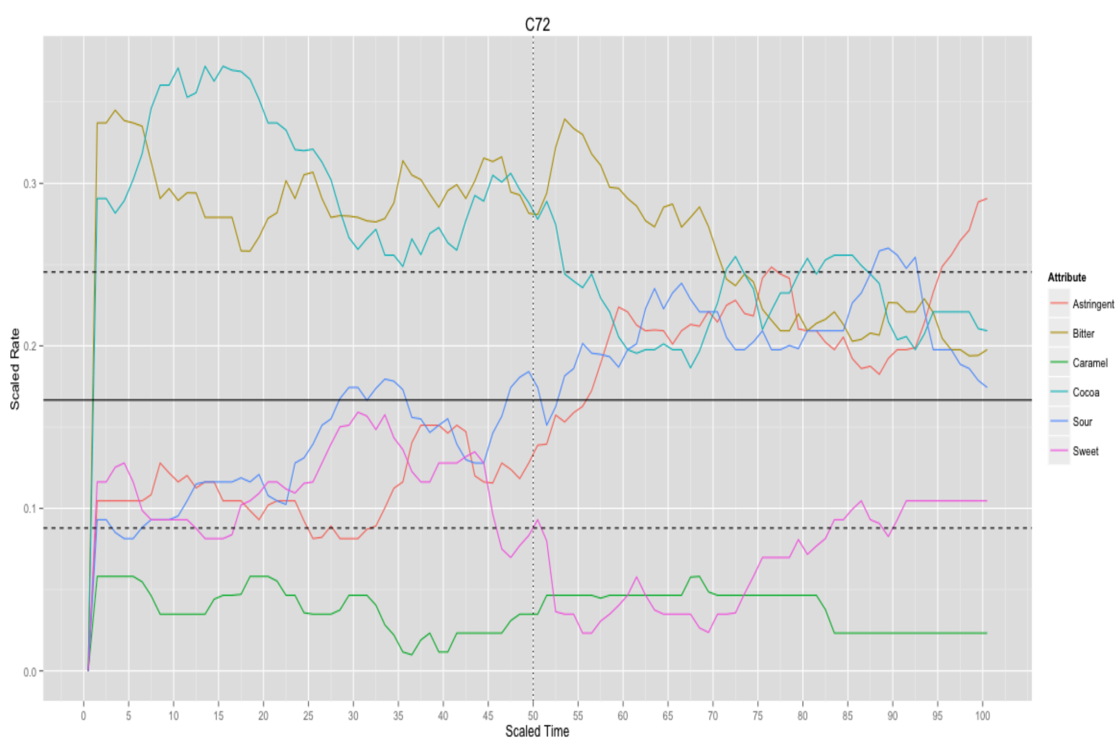

Figure 33. Untrained Consumer Scaled TDS Curves for Sample C72 split into Taste and Aftertaste, including P_0, $P_{s\ Low}$, and $P_{s\ High}$

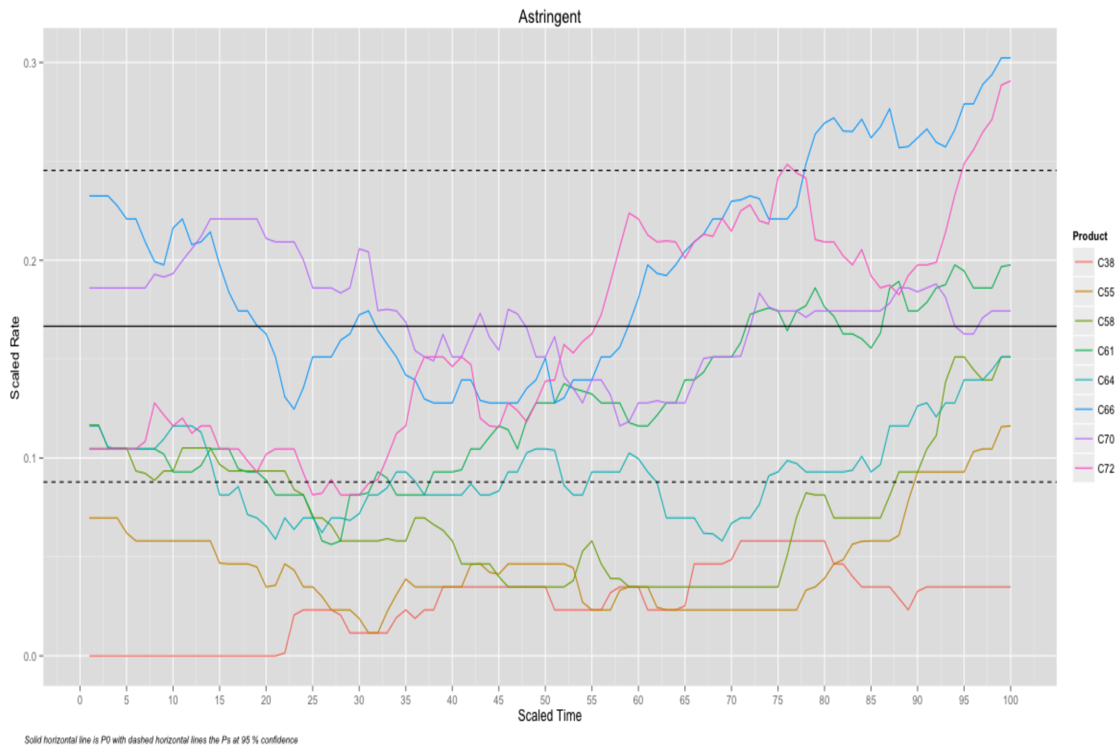

Figure 34. Untrained Consumer Scaled TDS Curves. Astringency of all samples

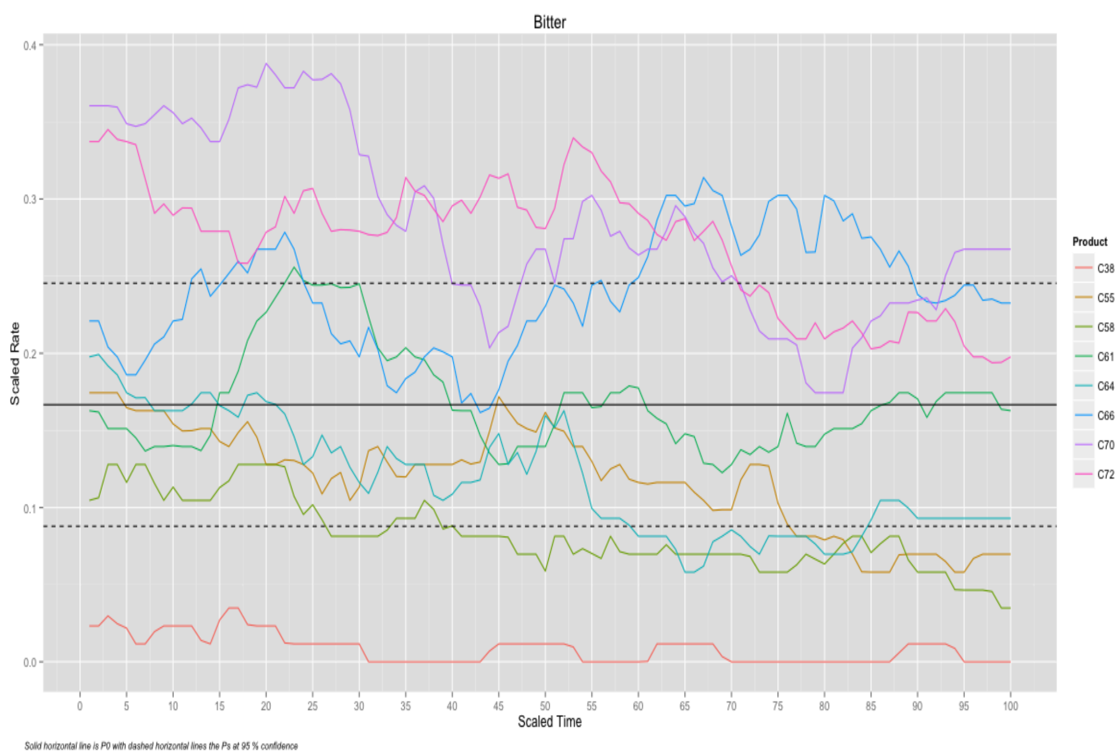

Figure 35. Untrained Consumer Scaled TDS Curves. Bitterness of all samples

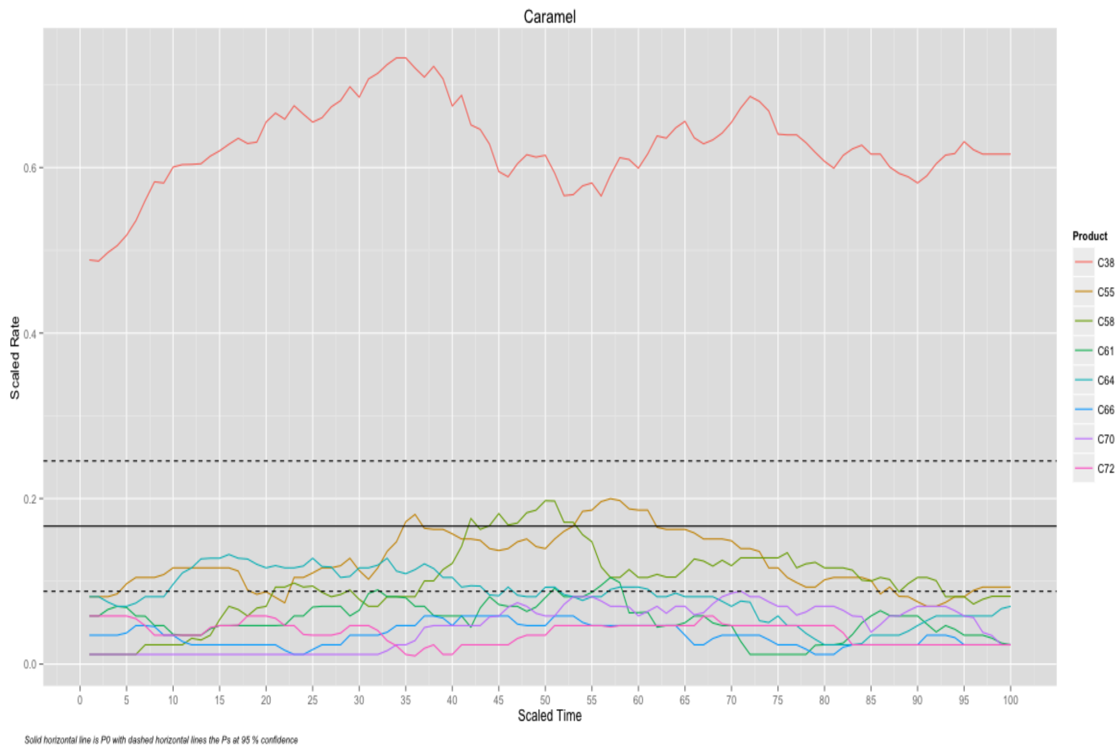

Figure 36. Untrained Consumer Scaled TDS Curves. Caramel flavor of all samples

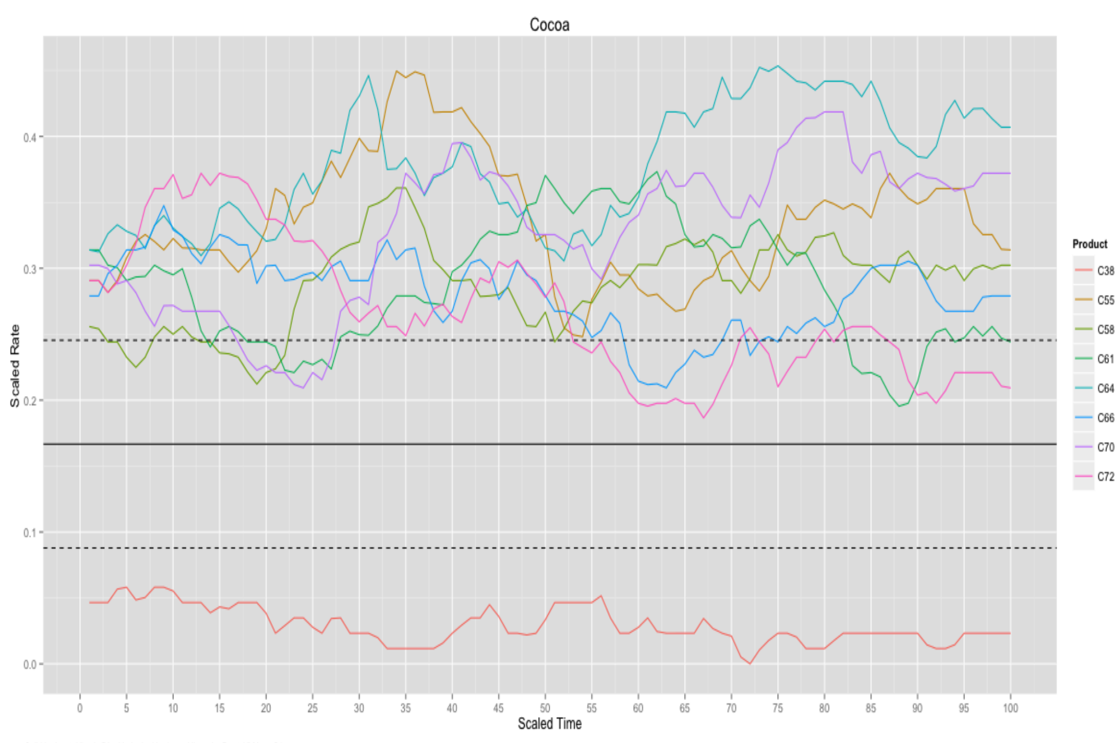

Figure 37. Untrained Consumer Scaled TDS Curves. Cocoa flavor of all samples

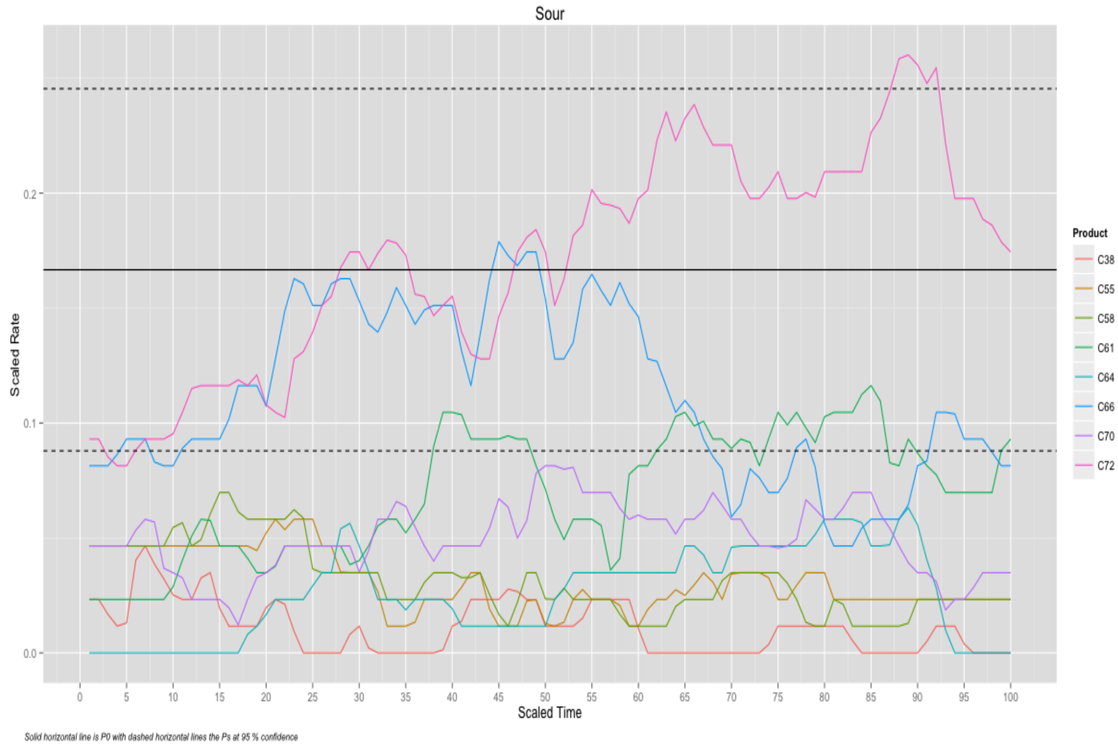

Figure 38. Untrained Consumer Scaled TDS Curves. Sourness of all samples

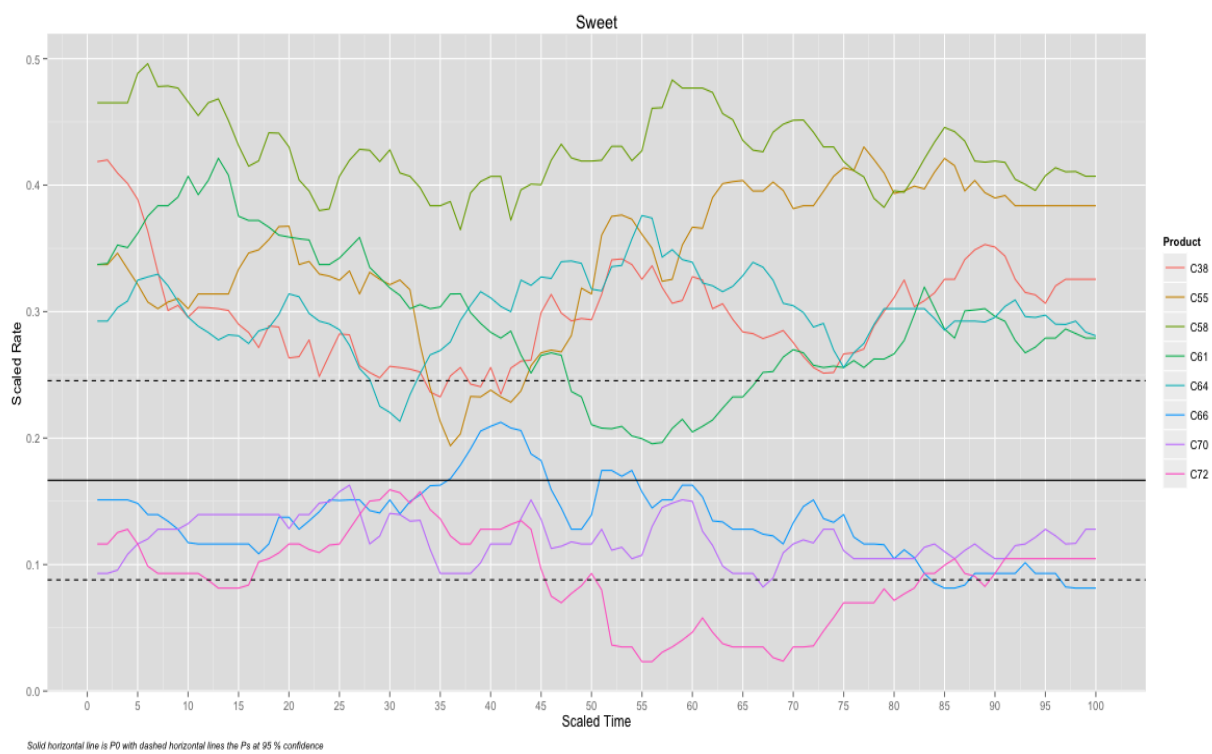

Figure 39. Untrained Consumer Scaled TDS Curves. Sweetness of all samples

PCA Differences

Despite the similarities, there are meaningful differences between the panel and the consumers. Comparing Figures 21 and 40, both the orientation of the attribute vectors and distribution of variance explained are different. It appears that the consumers were more focused on the basic separation of milk and dark chocolates. The caramel attribute dominates the consumer PCA space, and is more closely associated with the first PC, which explains nearly 70% of the total variance. In comparison, the panelists seem to go further beyond this basic division and provide more detail about the differences between the other samples. The caramel attribute is less dominant, and the non-milk chocolates are more spread across the panel PCA space.

Another important difference is the amount of change over time in each sample. The samples in Figure 40 are relatively compact, some doubling back on their path over time and others showing no pattern whatsoever. In contrast, the samples in Figure 21 cover more space, and several of them follow a clear pattern.

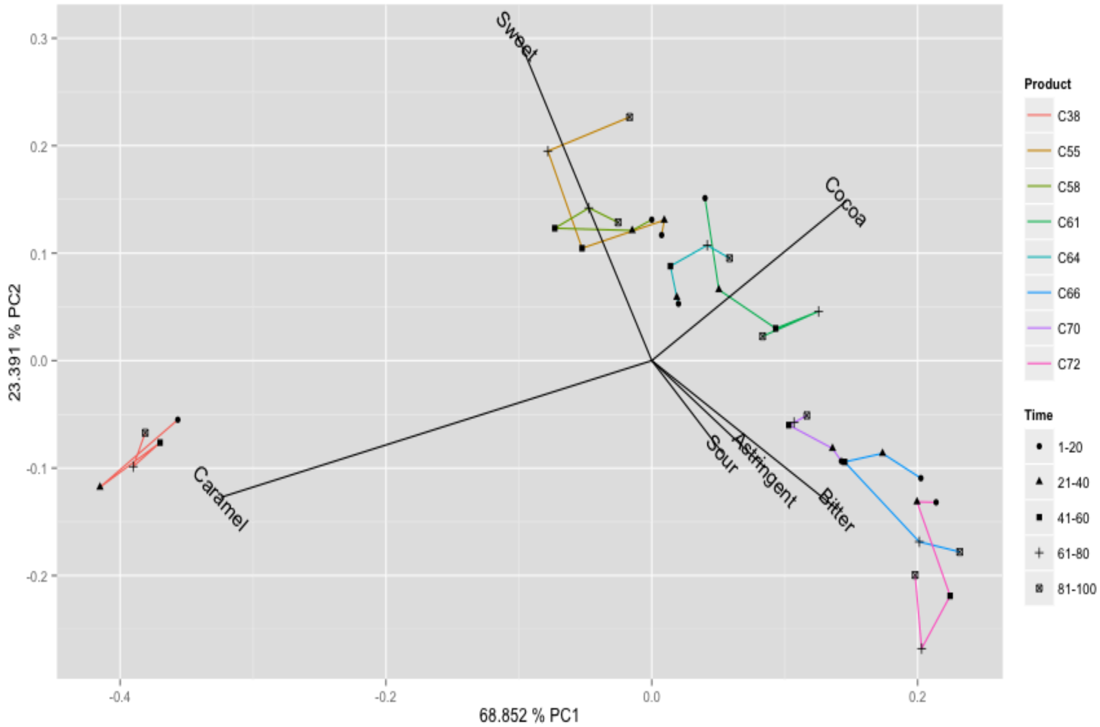

Figure 40. PCA of Untrained Consumer TDS Data. Split into 5 time intervals

CVA Differences

Figures 22, 23, 41 and 42, the CVA plots, are also telling. In the Figure 23, the ellipses for the trained panelists are often smaller and more compact than those of the consumers, suggesting less variability among the panelists. This is especially meaningful because the consumer data is nearly twice as large as the panel data, and thus more powerful. It is expected that more powerful data would lead to smaller ellipses, but this is not the case. Additionally, these figures confirm the differences in change over time. The first and second halves of the tasting by panelists are significantly different (no overlap in ellipses) for 4 of the 8 products, and nearly significantly different (ellipses just touching) for 2 products. Meanwhile, for the consumers, the first and second halves are significantly different for 3 products, and no products have ellipses just touching. Also, Table 12 shows that there is more overlap of ellipses in the consumer plot than in the panel plot, suggesting that the panelists were better able to discriminate between products and between different points of time throughout tasting.

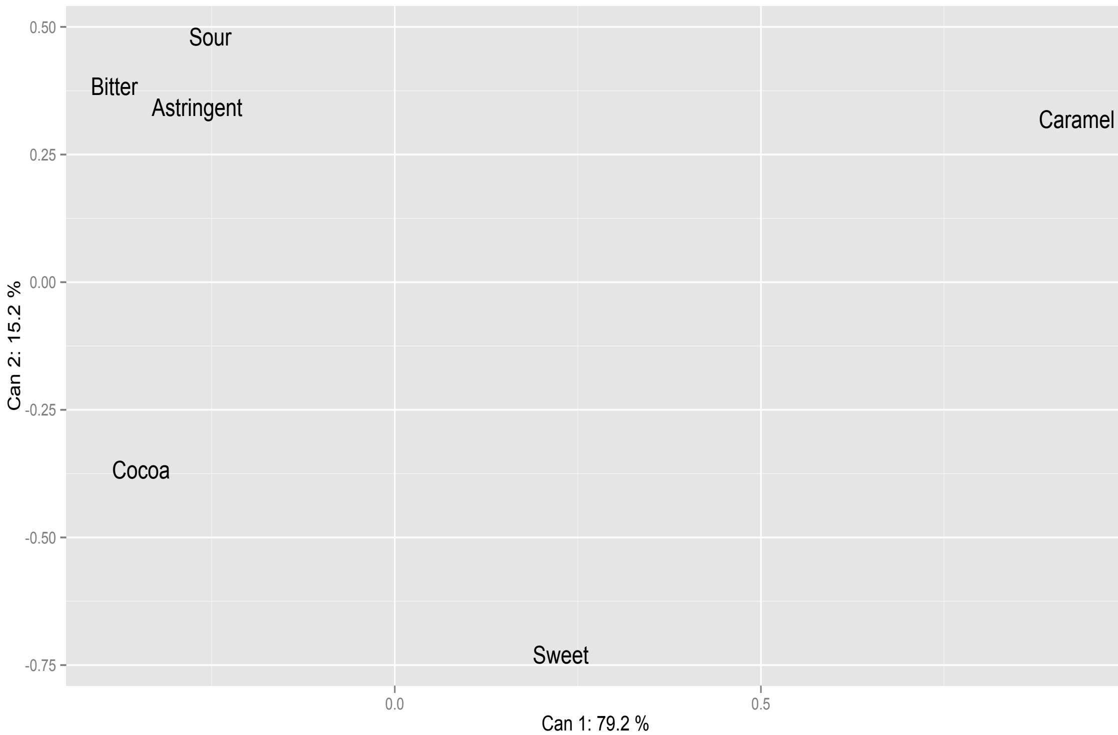

Figure 41. CVA Loadings Plot of Untrained Consumer TDS Data. Split into 2 time intervals

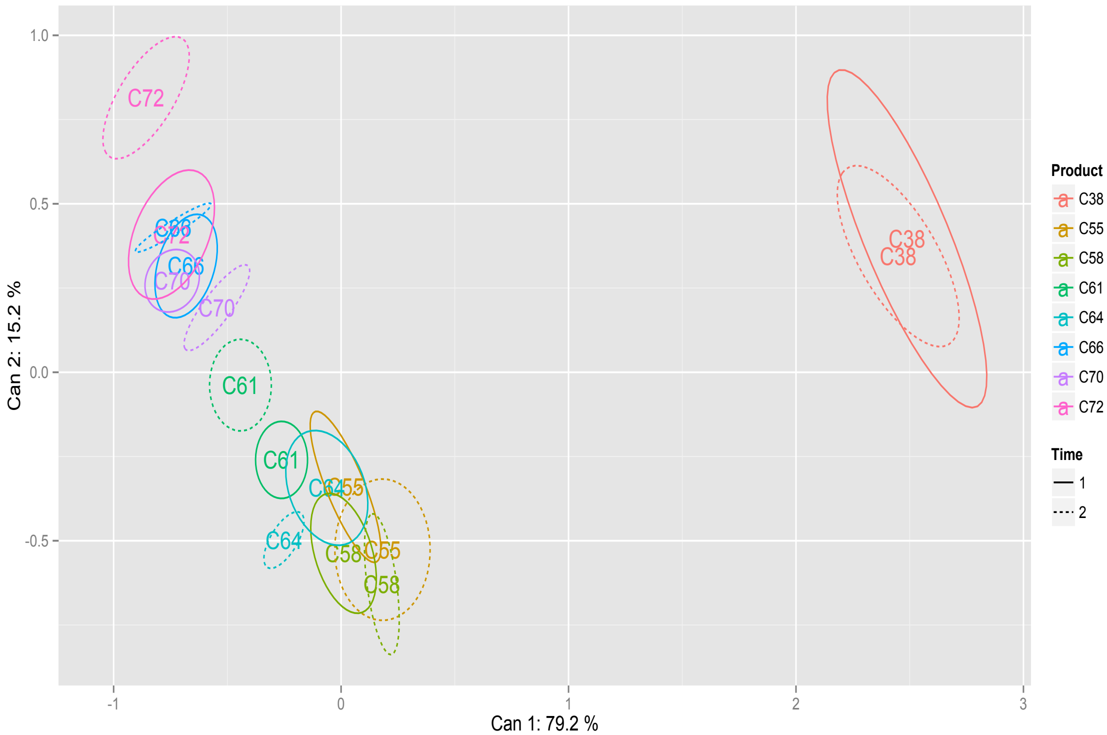

Figure 42. Score Plot of Untrained Consumer TDS Data. Split into 2 time intervals

Attribute Differences

Further differences between the trained panel and untrained consumers can be seen in the TDS curves. The consumers and panelists tended to disagree on the attributes caramel, sour, and astringent. Though both groups had a definite split between C38 and all other samples based on caramel flavor, the consumers were more likely to select caramel as a dominant attribute in samples other than C38. This is likely caused by consumers confusing caramel with sweetness or feeling the need to choose all attributes given regardless of presence. In general, it seems that the panel had a more specific understanding of caramel flavor, and associated it only with chocolate that contained dairy ingredients. As for the sour attribute, the consumers only considered it significantly dominant in C72, while the panelists considered it significantly dominant in C61, C66, and C72. It seems that the consumers were less sensitive to sour taste in chocolates, or that they did not agree on or understand how sour taste would appear in chocolate.

Last and most important, is the difference between groups in astringency. The panelists show astringency curves (Figure 15) that all start at levels significantly below chance and stay consistent for the first half of the tasting period, then dramatically increase throughout the second half of the tasting. By the end of the taste period, 5 of the 8 samples are significantly dominant in astringency. There is also a clear division between the samples at the end of the tasting. Sample C38 has no astringency, C55 and C58 are astringent at a level above chance but below significance, and all other samples end above the P_{shigh} significance marker in astringency.

In Figure 34, the consumers tell a different story. There is a less consistent pattern of astringency over time, and while some samples actually begin with significantly dominant astringency, only 2 of the 8 samples are significantly astringent at the end of the tasting. The consumers also have a less clear division between samples. These differences show that the panelists had a much better and more consistent understanding of what astringency is, and perceive it as a late-onset sensation and dominant aftertaste. The consumers show that they do not agree on what astringency is or when it is sensed during the tasting. This is one of the most obvious differences between the two groups and is likely the cause for the other differences, such as the larger split between the first and second halves of tasting and the general pattern toward astringency seen in the panel data.

4. CONCLUSIONS

Overall, GDA and TDS separate and rank the chocolates in roughly the same way. In both cases, there is an obvious distinction between the milk chocolate, C38, and all other chocolates. As for the remaining samples, the sorting closely follows cocoa content for both datasets. The main differences are seen in samples C61, C66, and C70. In the GDA data, C61 is much farther on the dark chocolate end of the spectrum, which is characterized by sour, bitter, and astringent character. In the TDS data, C61 spans nearly the entire spectrum, starting at the sweet region near C55 and C58, and progressing through to the “dark” region with C66, C70, and C72. TDS is a useful tool to add temporal information to existing descriptive data on food products. It is probably not needed when examining chocolates unless the objective focuses on concepts such as melting and texture changes during mastication, aftertaste and lingering flavors, alternative sweeteners, off-notes that appear at particular stages during consumption, or other temporal concerns.

Additionally, the data show that consumers can understand and perform TDS of chocolates, but they do not perform as consistently or as well as trained panelists. The main effects of training are increased focus on differences other than milk and non-milk chocolates, improved understanding and concept alignment of attributes, especially astringency, and greater changes in samples with clearer patterns of change over time. These effects appear to be related to each other and to the nuances that differentiate similar chocolates with high cocoa content. The main goals of TDS are to capture sensory changes over time and to investigate attributes that appear or disappear during consumption. Because these tasks are weakly performed by consumers compared to trained panelists, the use of consumers for TDS analysis is strongly discouraged.

5. RECOMMENDATIONS

This work served as an exploratory study of chocolate sensory analysis, Temporal Dominance of Sensations, and the effect of training in TDS. It leaves much room for expansion and future work. If this study is repeated, it is recommended to extend panel training time to allow for detailed panel and judge performance analysis and follow-up training as needed. One should also consider developing consensus scores of all chocolates to be used in experimental analysis, not only for more thorough training, but also to use during any descriptive analysis. Panels who were shown consensus scores of their warm-up samples tended to perform analysis with better agreement (O'Mahony et al., 1988). Also recommended for descriptive analysis is the use of fewer attributes. Several of those used in this study were not significant, and several more could be grouped into condensed terms. A slight but obvious flaw in the study is a less diverse mix of milk and non-milk chocolates. Future sensory research on chocolates should either focus solely on one category, or include a more even ratio of milk to non-milk chocolates in the sample set.

This particular research can be expanded upon in several ways. Because the panelists struggled to consider texture simultaneously with flavor and taste, it was not examined in any of the TDS procedures. Once could perform similar analyses, focusing on texture attributes of chocolates with both static and temporal descriptive methods. Other areas of exploration include the use of intensity scores in TDS- both how it compares to static descriptive methods and how it affects performance in trained panelists or untrained consumers. Lastly, TDS and static descriptive analysis could be compared to consumer preference analysis of the same samples to see if either method better predicts preference patterns in consumers.

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APPENDIX

Recruitment Email for Trained Panelists

"Hello previous and potential panelists,

I am recruiting volunteers for a chocolate taste panel that will run Fall Quarter 2013 through Winter Quarter 2014. Panelists should be frequent consumers of milk and dark chocolate and be available to participate 3-4 days per week for both quarters.

If you are interested in participating, please contact me to receive details and to determine meeting times (aboushell@ucdavis.edu). The first meeting will be a brief screening to ensure all volunteers can distinguish between different chocolates.

Thank you,

Audrey Boushell
UC Davis, Food Science and Technology
Heymann Lab
973-670-3271"

DA Training Materials

Training 1 Taste Sheet
Chocolate descriptive analysis

Please record all of the terms that come to mind as you taste the chocolates. Try to describe them in terms that are objective, rather than based on your liking of the chocolate. There is no wrong answer.

	Aroma/Flavor/Taste/Aftertaste	Mouthfeel/Texture
1		
2		

	Aroma/Flavor/Taste/Aftertaste	Mouthfeel/Texture
3		
4		

Training 2 taste sheet
Chocolate descriptive analysis

Please record all of the terms that come to mind as you taste the chocolates. Compare to the list of terms generated during Training Session 1. Be prepared to only share new terms not found on that list.

	Aroma/Flavor/Taste/Aftertaste	Mouthfeel/Texture
1		
2		

	Aroma/Flavor/Taste/Aftertaste	Mouthfeel/Texture
3		
4		

Training 2 Intensity and Line Scales
Training Session 2: Intensity Training

You will be asked to rate chocolates not only on the presence of the attributes you are creating, but also on the intensity of those attributes. Many of the attributes will simply be expressed as high or low intensity. For example, a chocolate may be very high in sweetness, or have only a slight hint of sweetness. The intensity of attributes will cover a broad spectrum with different terms at each end. For instance, the smoothness of a chocolate may cover a spectrum of gritty to silky. These cases need to be discussed and defined within the group.

Below is an example of the line scale you will use to measure intensity. The intensity of the attribute will always go lowest to highest from left to right. Notice that the anchor points are not at the farthest ends of each line. This allows you to mark to the left of the low intensity anchor to denote no detection at all of the attribute, or to mark to the left of the high intensity anchor for extreme cases of intensity. To rate the intensity of an attribute, you simply place a mark on the line at the level of intensity you detect.

Sweetness

Training 3 Reference Scoring Sheet

Chocolate descriptive analysis
Training 3: Reference standards

Taste the references standards in any order, and give a score from 1 to 9.
1 = the same as your concept of the reference standard
9 = furthest away from your concept of the reference standard (i.e. not the same)
Comments: Does this reference remind you of one of the other terms?
Do you think this reference is essentially the same as that for another term?
How specifically is this reference not close to your concept, and how can it be improved?
Have you fond, or do you expect to find, this attribute in chocolate?
Feel free to write a descriptive definition of this term.
Other: If there is a term that you strongly feel should have a reference, tell me what it is and try to provide a descriptive definition or specifics about that term.

Reference standard	**Score (1 = the Same, 9 = Not the same)**	**Comments/ descriptions**
Cocoa		
Hot Cocoa		
Oreo		
Artificial Sweet/ Candy		
Milky 1		
Milky 2		
Honey		
Caramel 1		
Soft		
Chewy		
Grainy/ Chalky		
Brittle		

Chocolate descriptive analysis Training 4: Reference standards

Reference	I would use this word to describe chocolate	This word belongs on its own	This word belongs in the following group	This reference should be mixed with	This is the best example of this reference	Comments
Fruity A						
Fruity B						
Fruity C						
Cherry						
Earthy						
Milky/ Vanilla						
Vanilla/ Artificial						
Artificial						
Vanilla A						
Vanilla B						
Vanilla C						
Milky A						
Milky B						
Milky C						
Milky D						
Caramel A						
Caramel B						
Nutty Raw						
Nutty Toasted						
Copper/ Metallic						
Smoke						
Honey						

<u>**Training 5 Reference Guess Sheet**</u>

Training 5: Naming References

Smell through the references one at a time. All of them are variations of references you have seen so far during training. To the best of your ability, write the name of the reference next to its number.
Please **no** discussing guesses with other panelists or cheating!
If you are unsure of a reference, write what it makes you think of or a question mark.
If you would give the same name to multiple references, feel free to do so.

Reference 1:

Reference 2:

Reference 3:

Reference 4:

Reference 5:

Reference 6:

Reference 7:

Reference 8:

Reference 9:

Reference 10:

Reference 11:

Reference 12:

Reference 13:

Reference 14:

Reference 15:

Descriptive Analysis Chocolate Consumption Protocol

Aroma
Open the container and smell the chocolates without removing them from the container.
Assess for aroma attributes.

Texture
Pick up one chocolate and bite once with incisors.
Assess first bite texture attributes.
Hold the chocolate in your mouth without chewing. Move your tongue back and forth over the chocolate 5 times.
Assess surface texture attributes.
Place the chocolate between your molars and chew five times.
Assess chewing attributes.
Move remaining chocolate back and forth between your tongue and the roof of your mouth until it melts completely.
Assess rate of melt.
Expectorate chocolate, and do not rinse. Feel mouth and tooth surfaces with your tongue.
Assess after-expectorating texture attributes.

Flavor and Taste
Assess flavor attributes throughout this process, using one chocolate.
Pick up one chocolate and place it in your mouth.
Without chewing, move your tongue back and forth over the chocolate 5 times.
Place the chocolate between your molars and chew 5 times.
Move remaining chocolate back and forth between your tongue and the roof of your mouth until it melts completely.
Expectorate chocolate, and do not rinse.

Taste and Mouthfeel
Assess taste and mouthfeel attributes throughout this process, using one chocolate.
*This time, swallow the chocolate to properly assess aftertaste.
Pick up one chocolate and place it in your mouth.
Without chewing, move your tongue back and forth over the chocolate 5 times.
Place the chocolate between your molars and chew 5 times.
Move remaining chocolate back and forth between your tongue and the roof of your mouth until it melts completely.
*Swallow chocolate, and click “Next Screen” button. Do not rinse.
Wait 20 seconds after swallowing to assess aftertaste and mouthfeel.

Break
Thoroughly rinse and spit with water 5 times.
After rinses are complete and one minute has passed, begin assessing the next chocolate sample.

Descriptive Analysis Attribute List

Taste and Mouthfeel: same as Aftertaste and Mouthfeel

1. Sweet
2. Bitter
3. Sour/Tangy
4. Astringent

Aroma and Flavor: presented in order of popularity

1. Cocoa
2. Nutty
3. Milky
4. Vanilla
5. Caramel
6. Mint
7. Coffee
8. Fruity
9. Buttery
10. Honey
11. Artificial Sweet/Candy
12. Earthy
13. Cherry
14. Smoke
15. Herbal/Tea

Texture: presented according to consumption method

First Bite

1. Hardness: the force required to bite through chocolate
2. Brittleness: The amount the chocolate snaps rather than deforms/compresses

Surface

3. Roughness: amount of small particles on the surface
4. Oiliness/Moistness: amount of oiliness/moistness on surface

Chewing

5. Stickiness: amount of chocolate that sticks to teeth and mouth while chewing

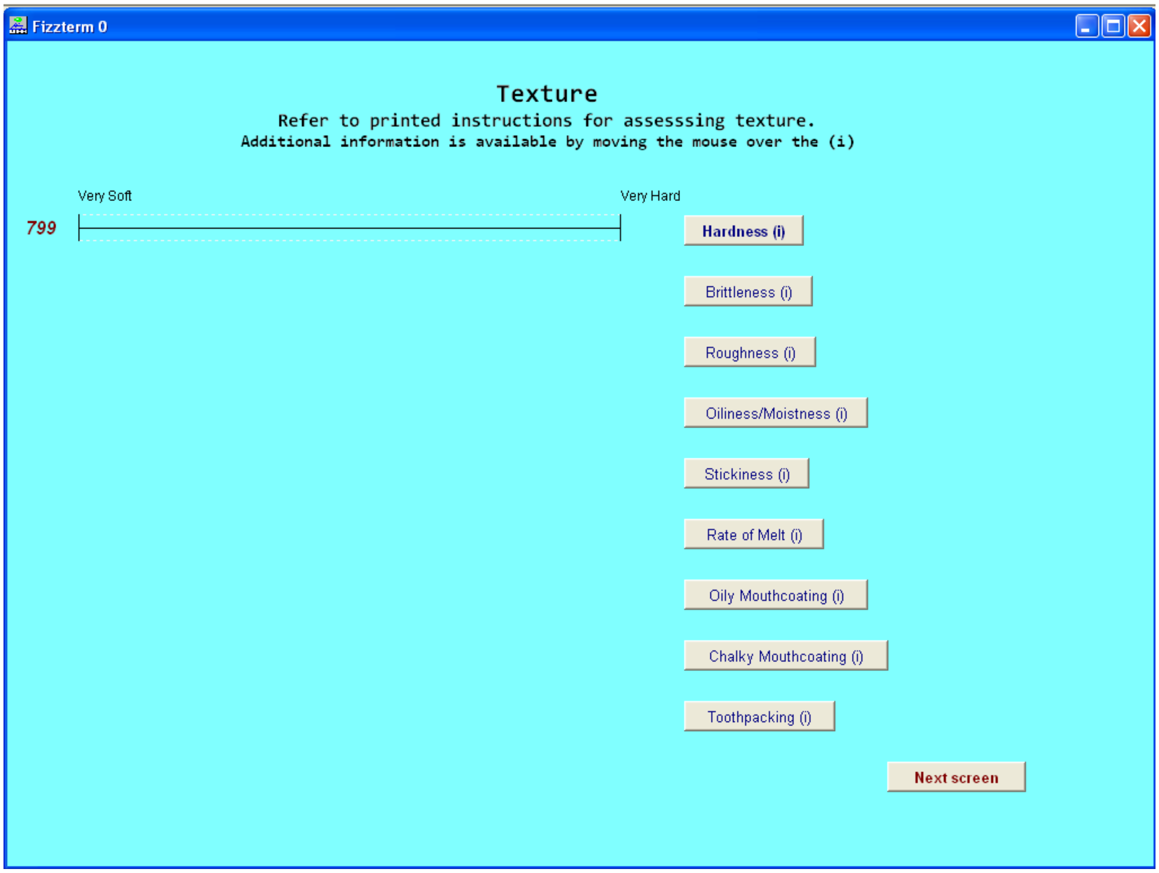
Melting

6. Rate of Melt: amount of time to completely melt chocolate

After Expectorating

7. Oily Mouthcoating: the amount of oily film left in the mouth after expectorating
8. Chalky Mouthcoating: the amount of chalky film left in the mouth after expectorating
9. Toothpacking: amount of chocolate left in the crevices of teeth after expectorating

Example of GDA Analysis on FIZZ Software



TDS Training Materials

Chocolate Panel TDS Training 1

Temporal Dominance of Sensations (TDS)*

Definition: A technique to measure the order and the time that key attributes are dominant throughout the tasting of a product.
Dominance is NOT always intensity, it is *what catches your attention*

Dominance changes when the panelist notices a change, for example:
•A very intense attribute

•An unusual or unexpected attribute

•A flavor burst

•An unpleasant attribute

•A repetitive attribute with a pattern

A relatively low number of attributes will be presented and considered simultaneously. The intensity of these attributes will not be rated in this procedure.
Throughout the timed tasting, panelists will select which attribute is dominant. As a new attribute becomes dominant, that attribute will be selected. The same attribute can be selected multiple times throughout the tasting.

Our first practice of this method will be using music rather than food. The second practice will be using chewing gum.

Definition and notes adapted from FS&T 127 lecture, U.C. Davis , February 5, 2013 by Suzanne Pecore, Principal Scientist Product Guidance & Insights General Mills, Inc.*

Chocolate Panel TDS Training Practice One:
Music and dominant instrumental sections.
Source: "A Young Person's Guide to the Orchestra" written by Benjamin Britten, 1946

INSTRUCTIONS: After the introduction of the 4 instrumental sections, you will hear a performance by the entire orchestra. The recording will be stopped every 10 seconds. While the music is stopped, circle the section that you think was **dominant*** in the 10 seconds you just heard. This process will continue for 1 minute.
The Specify column is optional. If you found that one particular instrument was dominant, you may list that instrument in addition to circling the section to which it belongs.

0-10 seconds	Woodwinds	Brass	Strings	Percussion	Specify:
11-20 seconds	Woodwinds	Brass	Strings	Percussion	Specify:
21-30 seconds	Woodwinds	Brass	Strings	Percussion	Specify:
31-40 seconds	Woodwinds	Brass	Strings	Percussion	Specify:
41-50 seconds	Woodwinds	Brass	Strings	Percussion	Specify:
51-60 seconds	Woodwinds	Brass	Strings	Percussion	Specify:

*Remember that the **dominant** section is the one that most catches your attention. Multiple groups may be playing, or even clearly noticeable, at one time. The dominant section is not necessarily the loudest one. You may find that more than one section is dominant within a 10 second portion of the music. If so, select the one that was dominant for a longer period of time or was the most dominant overall.

Chocolate Panel TDS Training Practice Two:
Chewing gum and dominant flavors and tastes.

INSTRUCTIONS: Take a piece of gum into your mouth, begin chewing at a steady rate, and circle **the dominant* sensation** at the following times.
If you believe a sensation other than fruity tropical, fruity citrus, sweet, sour, or bitter is dominant, name it in the Other section.

Initially (at about 3 chews)	Fruity – Tropical	Fruity – Citrus	Sweet	Sour	Bitter	Other
At 30 seconds	Fruity – Tropical	Fruity – Citrus	Sweet	Sour	Bitter	Other
At 1 minute	Fruity – Tropical	Fruity – Citrus	Sweet	Sour	Bitter	Other
At 1.5 minutes	Fruity – Tropical	Fruity – Citrus	Sweet	Sour	Bitter	Other
At 2 minutes	Fruity – Tropical	Fruity – Citrus	Sweet	Sour	Bitter	Other
At 3 minutes	Fruity – Tropical	Fruity – Citrus	Sweet	Sour	Bitter	Other

*Remember that the **dominant** sensation is the one that most catches your attention. Multiple sensations may be noticeable at one time. The dominant sensation is not necessarily the strongest one. You may find that more than one sensation is dominant within each portion of the chewing process. If so, select the one that was dominant for the longest period of time or was the most dominant overall.

Chocolate Panel TDS Training 2

Reduced set of chocolate attributes

Out of the 47 different aromas, tastes, textures, and other sensations you used to rate chocolates last quarter, 9 of them have been chosen as the most meaningful. You will only be using these 9 attributes to rate chocolates in TDS testing. The 9^{th} attribute, Rate of melt, will be tested separately from the rest since it is based on time and would interfere with the rest of the analysis.

Cocoa
Caramel
Bitter
Sweet
Sour
Astringent
Hardness
Roughness
Rate of Melt

Also, the consumption process has been changed and simplified to better fit the TDS method.

Consumption Protocol
Pick up one chocolate and place it in your mouth. The analysis begins as soon as the chocolate is in your mouth.

0-8 Seconds Hold the chocolate in your mouth without chewing. Move your tongue back and forth over the chocolate.

9-16 Seconds Place the chocolate between your molars and chew at a steady rate.

17-24 Seconds Move remaining chocolate back and forth between your tongue and the roof of your mouth.

25-55 Seconds Swallow chocolate, and do not rinse. Continue to rate any dominant sensation(s) until you no longer sense anything or until the time runs out.

Chocolate Panel TDS Training Practice Three:
Chocolate and dominant sensations.

Sample 652: ____________ Sample 178: ______________

INSTRUCTIONS: Take a piece of chocolate into your mouth and begin the consumption protocol as shown. Circle the **dominant sensation** at the following times. You will be asked to pick a dominant sensation twice for each portion of the consumption protocol. Use one color for each sample and fill in the key above with the corresponding colors.								
0-4 sec. (Not yet chewing)	Cocoa	Caramel	Hardness	Roughness	Sweet	Bitter	Sour	Astringent
5-8 sec. (Not yet chewing)	Cocoa	Caramel	Hardness	Roughness	Sweet	Bitter	Sour	Astringent
9-12 sec. (Chewing)	Cocoa	Caramel	Hardness	Roughness	Sweet	Bitter	Sour	Astringent
13-16 sec. (Chewing)	Cocoa	Caramel	Hardness	Roughness	Sweet	Bitter	Sour	Astringent
17-20 sec. (Melting)	Cocoa	Caramel	Hardness	Roughness	Sweet	Bitter	Sour	Astringent
21-24 sec. (Melting)	Cocoa	Caramel	Hardness	Roughness	Sweet	Bitter	Sour	Astringent
25-39 sec. (After swallowing)	Cocoa	Caramel	Hardness	Roughness	Sweet	Bitter	Sour	Astringent
40-55 sec. (After swallowing)	Cocoa	Caramel	Hardness	Roughness	Sweet	Bitter	Sour	Astringent

Chocolate Panel TDS Training 3

In-Booth Procedure

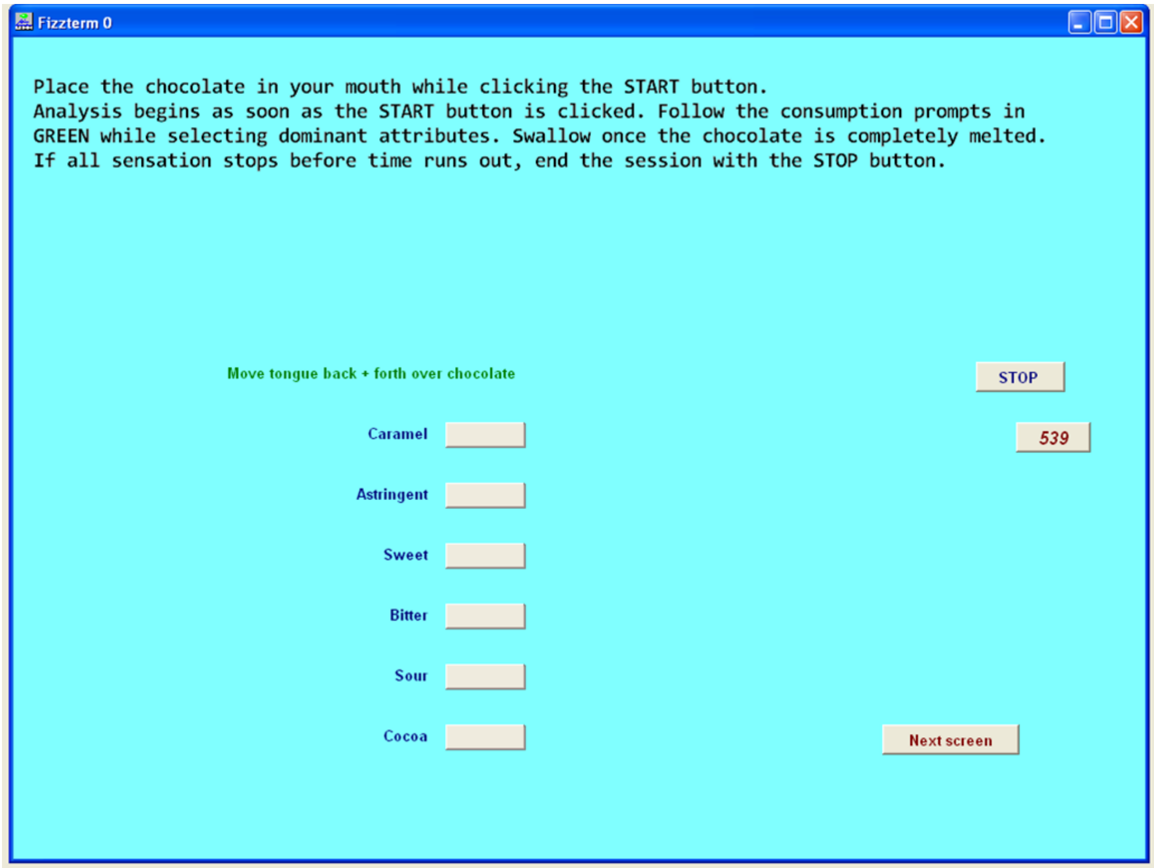
You will be performing an individual practice session today in one of the test booths. This session will be identical in appearance and procedure to the future sessions you will perform. You will be assessing 5 samples, one at a time. For each sample, you will follow the TDS procedure and rate the sample on 7 attributes: Cocoa, Caramel, Sweet, Bitter, Sour, Astringent, and Rate of Melt (this one separately).

To assess the sample, you will consume the chocolate according to prompts on the screen. To start the session, you will need to click the start button while placing the chocolate in your mouth. Throughout consumption, you will need to consider all 6 attributes and determine which one is dominant. To mark an attribute as dominant, you will click on the button that is next to the name of that attribute. When a different attribute becomes dominant, you simply click the button next to the new dominant attribute. If at first you detect nothing, do not feel the need to click any attribute buttons right away. You can use each attribute as many times as you like or not at all. If you no longer sense anything before time runs out, you may use the stop button.

The 7th attribute, Rate of Melt, will be assessed separately. You will consume another chocolate according to the same prompted protocol as before. This time, you will only be considering melting. Once chocolate melts completely, click the Melted button and then the stop button if the consumption process has not ended.

Please be sure to tell me about any errors or difficulties during the practice procedure. Because this procedure is very different, you will be asked to sign up for an additional practice session as well as your 6 data collection sessions. See me after the practice to schedule these or schedule them via email.

Example of TDS Analysis on FIZZ Software



Recruitment Email for Untrained Consumers

Dear students, faculty, staff, and friends,

I would like to inform you about a chocolate consumer study taking place on Saturday and Sunday March 1st and 2nd. Sessions will take place at noon, 2pm, and 4pm each day. A session will take approximately 1.5 hours and have a maximum of 24 panelists. Each session will consist of an information session about the procedure, assignment in booths, and a 20-30 minute tasting of 9 chocolate samples.
All participants will be given snacks as compensation and an information sheet about the study once tasting is complete.

Participants Must:
- Regularly eat and enjoy a variety of chocolate products
- Be 18 years or older
- Have **No** previous training in chocolate sensory analysis or Temporal Dominance of Sensations.

You may sign up on this spreadsheet (https://docs.google.com/spreadsheet/ccc?key=0Ap0Th7FzkO6LdGRGNmRiQWpOS0dFVzJLd3VOeGFYc3c&usp=sharing) for the day and time you would like to attend. Each session will have no more than 24 panelists, and there is a maximum of 120 panelists for the entire study. All sessions will begin on time, so please plan on arriving early.

All participants will meet in the RMI Sensory Theater for the information session, and the tasting will take place in the Heymann lab, room 2003 in the RMI Sensory Building.

Thank you,

Audrey Boushell
FST Masters Student
Heymann Lab
UC Davis

GDA MANOVA Summary

	Df	Wilks	approx F	num Df	den Df	Pr(>F)
Judge	14	0.00000	11.6808	658	2076.2	< 2.2e-16 ***
Product	7	0.00156	4.9297	329	1052.9	< 2.2e-16 ***
Rep	2	0.46465	1.4905	94	300.0	0.006342 **
Judge:Product	98	0.00000	1.6270	4606	7065.6	< 2.2e-16 ***
Judge:Rep	28	0.00006	1.4462	1316	3820.9	< 2.2e-16 ***
Product:Rep	14	0.03387	0.9045	658	2076.2	0.940774
Residuals	196					

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

GDA ANOVA Summary

$CocoaA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Judge	14	404.57	28.898	9.4957	2.637e-16 ***
Product	7	618.20	88.314	29.0196	< 2.2e-16 ***
Rep	1	0.03	0.030	0.0100	0.9205
Judge:Product	98	574.37	5.861	1.9259	3.798e-05 ***
Judge:Rep	14	48.38	3.455	1.1354	0.3282
Product:Rep	7	13.60	1.942	0.6383	0.7239
Residuals	218	663.43	3.043		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$NuttyA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Judge	14	1887.86	134.847	39.8455	< 2e-16 ***
Product	7	63.91	9.130	2.6978	0.01062 *
Rep	1	0.41	0.408	0.1207	0.72864
Judge:Product	98	448.33	4.575	1.3518	0.03574 *
Judge:Rep	14	16.73	1.195	0.3532	0.98549
Product:Rep	7	10.34	1.477	0.4364	0.87859
Residuals	218	737.77	3.384		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$MilkyA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Judge	14	789.73	56.410	19.7740	<2e-16 ***
Product	7	982.81	140.401	49.2166	<2e-16 ***
Rep	1	1.38	1.380	0.4838	0.4874
Judge:Product	98	335.58	3.424	1.2003	0.1371
Judge:Rep	14	20.48	1.463	0.5128	0.9244
Product:Rep	7	18.04	2.577	0.9035	0.5046
Residuals	218	621.89	2.853		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.'0.1' ' 1

$VanillaA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Judge	14	708.22	50.587	25.0975	< 2.2e-16 ***
Product	7	169.85	24.264	12.0380	5.72e-13 ***
Rep	1	0.06	0.057	0.0283	0.8666
Judge:Product	98	242.77	2.477	1.2290	0.1087
Judge:Rep	14	34.65	2.475	1.2279	0.2563
Product:Rep	7	13.39	1.914	0.9493	0.4694
Residuals	218	439.41	2.016		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$CaramelA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Judge	14	835.89	59.706	22.1978	< 2.2e-16 ***
Product	7	654.12	93.446	34.7417	< 2.2e-16 ***
Rep	1	21.24	21.242	7.8972	0.005402 **
Judge:Product	98	368.78	3.763	1.3991	0.022273 *
Judge:Rep	14	36.89	2.635	0.9796	0.475183
Product:Rep	7	31.34	4.477	1.6643	0.119060
Residuals	218	586.36	2.690		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$MintA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Judge	14	115.698	8.2642	11.0412	< 2.2e-16 ***
Product	7	12.911	1.8444	2.4641	0.01881 *
Rep	1	1.426	1.4260	1.9052	0.16891
Judge:Product	98	101.570	1.0364	1.3847	0.02578 *
Judge:Rep	14	34.966	2.4976	3.3368	7.213e-05 ***
Product:Rep	7	0.729	0.1041	0.1391	0.99510
Residuals	218	163.169	0.7485		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

$CoffeeA

	Df	Sum Sq	Mean Sq	F value	Pr(>F)

```
Judge         14 999.11  71.365 23.7539 < 2.2e-16 ***
Product        7 162.54  23.221  7.7290 2.406e-08 ***
Rep            1   0.16   0.155  0.0516    0.8205
Judge:Product  98 329.05   3.358  1.1176    0.2509
Judge:Rep      14  39.71   2.837  0.9442    0.5122
Product:Rep     7  10.47   1.496  0.4980    0.8354
Residuals     218 654.95   3.004
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$FruityA

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 421.91 30.1362 16.1057 < 2.2e-16
***
Product        7  33.94  4.8486  2.5912  0.013800 *
Rep            1   4.51  4.5100  2.4103  0.121990
Judge:Product  98 287.13  2.9299  1.5658  0.003572
**
Judge:Rep      14  20.84  1.4883  0.7954  0.673743
Product:Rep     7   6.46  0.9224  0.4930  0.839146
Residuals     218 407.91  1.8712
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$ButteryA

```
            Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14 1100.67  78.619 47.0319 < 2.2e-16
***
Product        7  398.38  56.911 34.0455 < 2.2e-16
***
Rep            1    2.34   2.340  1.4001    0.2380
Judge:Product  98  387.50   3.954  2.3655 8.546e-08
***
Judge:Rep      14   20.08   1.435  0.8582    0.6052
Product:Rep     7   17.57   2.511  1.5019    0.1678
Residuals     218  364.41   1.672
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$HoneyA

```
            Df Sum Sq Mean Sq F value  Pr(>F)
Judge         14 925.44  66.103 24.8399 < 2e-16 ***
Product        7  13.72   1.960  0.7365 0.64125
Rep            1   2.54   2.542  0.9552 0.32947
Judge:Product  98 212.94   2.173  0.8165 0.87266
Judge:Rep      14  28.00   2.000  0.7517 0.72039
Product:Rep     7  36.18   5.169  1.9425 0.06424 .
Residuals     218 580.13   2.661
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$ArtificialA

```
            Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14 1008.94  72.067 32.8814 < 2.2e-16
***
Product        7   97.18  13.883  6.3341 8.786e-07 ***
Rep            1    0.13   0.126  0.0575   0.81070
Judge:Product  98  285.00   2.908  1.3269   0.04544 *
Judge:Rep      14   28.69   2.049  0.9349   0.52204
Product:Rep     7   24.17   3.454  1.5757   0.14382
Residuals     218  477.80   2.192
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$EarthyA

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 770.43  55.031 17.5850 < 2.2e-16 ***
Product        7 179.29  25.613  8.1844 7.538e-09 ***
Rep            1   1.41   1.411  0.4508    0.5027
Judge:Product  98 344.04   3.511  1.1218    0.2440
Judge:Rep      14  65.10   4.650  1.4858    0.1178
Product:Rep     7  13.32   1.902  0.6078    0.7492
Residuals     218 682.21   3.129
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$CherryA

```
            Df Sum Sq Mean Sq F value  Pr(>F)
Judge         14 578.89  41.349 28.0648 < 2e-16 ***
Product        7  16.81   2.402  1.6304 0.12807
Rep            1   0.00   0.000  0.0001 0.99152
Judge:Product  98 165.31   1.687  1.1449 0.20790
Judge:Rep      14  38.23   2.731  1.8533 0.03284 *
Product:Rep     7   8.39   1.199  0.8137 0.57671
Residuals     218 321.19   1.473
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$SmokeA

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 891.39  63.671 30.1605 < 2.2e-16 ***
Product        7 141.96  20.280  9.6067 2.115e-10 ***
Rep            1   1.15   1.148  0.5439   0.46162
Judge:Product  98 464.85   4.743  2.2469 4.563e-07
***
Judge:Rep      14  55.49   3.964  1.8777   0.03001 *
Product:Rep     7  26.69   3.813  1.8062   0.08727 .
Residuals     218 460.21   2.111
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$HerbalA

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 548.37  39.169 15.6170 < 2.2e-16 ***
```

```
Product        7  93.08  13.297  5.3014 1.298e-05 ***
Rep            1   0.26   0.260  0.1037   0.74777
Judge:Product  98 308.38   3.147  1.2546   0.08749 .
Judge:Rep      14  24.03   1.716  0.6844   0.78855
Product:Rep     7  18.74   2.678  1.0676   0.38538
Residuals     218 546.77   2.508
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$HardnessTx
              Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14  278.53  19.895  6.7923 1.838e-11
***
Product        7 1634.63 233.518 79.7255 < 2.2e-16
***
Rep            1   16.70  16.695  5.7000   0.01782 *
Judge:Product 98  382.39   3.902  1.3322   0.04321 *
Judge:Rep     14   55.48   3.963  1.3529   0.17851
Product:Rep    7   37.65   5.378  1.8362   0.08162 .
Residuals    218  638.53   2.929
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$BrittlenessTx
              Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14  420.93  30.067  8.3052 3.222e-14
***
Product        7 1060.42 151.488 41.8452 < 2.2e-16
***
Rep            1    2.99   2.993  0.8267   0.36425
Judge:Product 98  866.63   8.843  2.4427 2.848e-08
***
Judge:Rep     14   85.43   6.102  1.6856   0.06003 .
Product:Rep    7   41.28   5.896  1.6288   0.12850
Residuals    218  789.21   3.620
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$RoughnessTx
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 599.54  42.824 10.2552 < 2.2e-16 ***
Product        7 653.11  93.301 22.3429 < 2.2e-16 ***
Rep            1   0.13   0.131  0.0313  0.859757
Judge:Product 98 522.03   5.327  1.2756  0.072795 .
Judge:Rep     14 141.89  10.135  2.4271  0.003477
**
Product:Rep    7  17.55   2.508  0.6005  0.755195
Residuals    218 910.34   4.176
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$Oily.MoistTx
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 165.80  11.843  2.7679 0.0008392 ***
Product        7 696.07  99.439 23.2411 < 2.2e-16 ***
Rep            1   2.28   2.281  0.5332 0.4660330
Judge:Product 98 642.26   6.554  1.5317 0.0052865
**
Judge:Rep     14 101.67   7.262  1.6973 0.0576235 .
Product:Rep    7  33.37   4.768  1.1143 0.3550404
Residuals    218 932.73   4.279
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$StickinessTx
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 647.36  46.240 11.5190 < 2.2e-16 ***
Product        7 297.24  42.463 10.5782 1.932e-11
***
Rep            1   0.66   0.661  0.1648  0.685182
Judge:Product 98 645.96   6.591  1.6420  0.001444
**
Judge:Rep     14  65.34   4.667  1.1626  0.305852
Product:Rep    7   9.09   1.298  0.3233  0.942902
Residuals    218 875.09   4.014
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$RateofMeltTx
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 294.30  21.021  6.4898 6.735e-11 ***
Product        7 597.41  85.345 26.3479 < 2.2e-16 ***
Rep            1   0.82   0.817  0.2521    0.6161
Judge:Product 98 622.29   6.350  1.9604 2.389e-05
***
Judge:Rep     14  44.65   3.189  0.9846    0.4700
Product:Rep    7  21.40   3.057  0.9439    0.4735
Residuals    218 706.13   3.239
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$OilyMouthcoatTx
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 576.20  41.157 10.2000 < 2.2e-16 ***
Product        7 515.22  73.603 18.2411 < 2.2e-16 ***
Rep            1   4.11   4.108  1.0181  0.314082
Judge:Product 98 420.24   4.288  1.0627  0.353350
Judge:Rep     14 122.56   8.755  2.1696  0.009799 **
Product:Rep    7  51.67   7.381  1.8294  0.082887 .
Residuals    218 879.63   4.035
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$ChalkyMouthctTx
```

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 982.79  70.199 19.5698 < 2.2e-16 ***
Product        7 846.21 120.887 33.7004 < 2.2e-16
***
Rep            1  28.84  28.843  8.0406  0.005004 **
Judge:Product  98 617.85   6.305  1.7576  0.000343
***
Judge:Rep      14  97.73   6.981  1.9461  0.023232 *
Product:Rep     7  33.26   4.751  1.3245  0.239770
Residuals     218 781.99   3.587
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$ToothpackingTx
            Df  Sum Sq Mean Sq F value  Pr(>F)
Judge         14 1187.80  84.843 26.3111 < 2e-16 ***
Product        7   71.20  10.171  3.1543 0.00339 **
Rep            1    1.43   1.426  0.4422 0.50675
Judge:Product  98  428.71   4.375  1.3566 0.03409 *
Judge:Rep      14   48.64   3.474  1.0775 0.37935
Product:Rep     7   26.86   3.837  1.1900 0.30956
Residuals     218  702.96   3.225
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$CocoaF
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 351.74  25.124 12.5483 < 2.2e-16 ***
Product        7 836.48 119.497 59.6824 < 2.2e-16
***
Rep            1   0.18   0.176  0.0879   0.76712
Judge:Product  98 499.20   5.094  2.5441 6.705e-09
***
Judge:Rep      14  45.78   3.270  1.6332   0.07203 .
Product:Rep     7  20.72   2.960  1.4783   0.17618
Residuals     218 436.48   2.002
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$NuttyF
            Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14 1763.98 125.998 41.6359 < 2.2e-16
***
Product        7   38.31   5.472  1.8083 0.0868566 .
Rep            1    3.48   3.480  1.1500 0.2847402
Judge:Product  98  519.44   5.300  1.7515 0.0003705
***
Judge:Rep      14   78.83   5.631  1.8607 0.0319519 *
Product:Rep     7   16.58   2.368  0.7825 0.6026348
Residuals     218  659.71   3.026
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$MilkyF
            Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14  991.26  70.804 28.2225 < 2.2e-16
***
Product        7 1213.98 173.426 69.1275 < 2.2e-16
***
Rep            1    2.44   2.440  0.9727  0.325113
Judge:Product  98  384.73   3.926  1.5648  0.003612
**
Judge:Rep      14   40.74   2.910  1.1601  0.307886
Product:Rep     7   12.13   1.733  0.6906  0.679983
Residuals     218  546.91   2.509
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$VanillaF
            Df Sum Sq Mean Sq F value  Pr(>F)
Judge         14 708.93  50.638 22.7891 < 2e-16 ***
Product        7 240.89  34.412 15.4871 < 2e-16 ***
Rep            1   1.96   1.962  0.8830 0.34842
Judge:Product  98 290.47   2.964  1.3339 0.04249 *
Judge:Rep      14  29.35   2.097  0.9436 0.51285
Product:Rep     7   4.72   0.675  0.3037 0.95171
Residuals     218 484.40   2.222
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$CaramelF
            Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14  663.87  47.419 17.9081 < 2.2e-16
***
Product        7 1183.14 169.020 63.8308 < 2.2e-16
***
Rep            1    5.58   5.582  2.1079 0.1479806
Judge:Product  98  437.26   4.462  1.6850 0.0008525
***
Judge:Rep      14   16.89   1.206  0.4556 0.9535645
Product:Rep     7    8.66   1.236  0.4670 0.8578056
Residuals     218  577.25   2.648
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$MintF
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 50.146  3.5818 12.1510 < 2.2e-16 ***
Product        7  4.328  0.6183  2.0977  0.044948 *
Rep            1  0.045  0.0454  0.1539  0.695191
Judge:Product  98 47.781  0.4876  1.6540  0.001248
**
Judge:Rep      14  2.790  0.1993  0.6761  0.796473
Product:Rep     7  2.346  0.3352  1.1371  0.340888
Residuals     218 64.261  0.2948
```

```
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$CoffeeF

```
            Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14 1382.28  98.734 29.9471 < 2.2e-16
***
Product        7  341.64  48.806 14.8034 9.358e-16
***
Rep            1    6.53   6.534  1.9818 0.1606224
Judge:Product  98  486.53   4.965  1.5058 0.0070835
**
Judge:Rep      14  127.06   9.076  2.7528 0.0008946
***
Product:Rep     7   17.64   2.520  0.7642 0.6179063
Residuals     218  718.74   3.297
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$FruityF

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 360.50 25.7498 18.1420 < 2.2e-16
***
Product        7  70.53 10.0756  7.0988 1.214e-07 ***
Rep            1   3.24  3.2434  2.2851    0.1321
Judge:Product  98 306.99  3.1325  2.2070 7.990e-07
***
Judge:Rep      14  27.56  1.9683  1.3868    0.1610
Product:Rep     7   7.90  1.1280  0.7948    0.5924
Residuals     218 309.42  1.4193
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$ButteryF

```
            Df  Sum Sq Mean Sq F value    Pr(>F)
Judge         14 1177.06  84.076 45.7379 < 2.2e-16
***
Product        7  555.86  79.409 43.1991 < 2.2e-16
***
Rep            1    0.85   0.852  0.4635    0.4967
Judge:Product  98  354.71   3.619  1.9690 2.126e-05
***
Judge:Rep      14   25.17   1.798  0.9781    0.4767
Product:Rep     7    3.23   0.461  0.2507    0.9716
Residuals     218  400.73   1.838
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$HoneyF

```
            Df  Sum Sq Mean Sq F value  Pr(>F)
Judge         14 1085.02  77.501 35.6271 < 2e-16 ***
Product        7   10.93   1.561  0.7178 0.65700
Rep            1   17.33  17.334  7.9686 0.00520 **
Judge:Product  98  239.70   2.446  1.1244 0.23977
Judge:Rep      14   64.11   4.580  2.1052 0.01262 *
Product:Rep     7    8.04   1.149  0.5282 0.81273
Residuals     218  474.23   2.175
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$ArtificialF

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 826.80  59.057 35.0273 < 2.2e-16 ***
Product        7 204.13  29.161 17.2954 < 2.2e-16 ***
Rep            1   0.42   0.417  0.2471   0.61961
Judge:Product  98 482.31   4.922  2.9190 3.163e-11
***
Judge:Rep      14  37.77   2.698  1.5999   0.08069 .
Product:Rep     7   5.99   0.855  0.5072   0.82858
Residuals     218 367.56   1.686
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$EarthyF

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 662.78  47.341 14.7980 < 2.2e-16 ***
Product        7 262.92  37.559 11.7404 1.164e-12
***
Rep            1   0.43   0.425  0.1329    0.7158
Judge:Product  98 355.47   3.627  1.1338    0.2247
Judge:Rep      14  57.98   4.141  1.2945    0.2122
Product:Rep     7  23.06   3.294  1.0296    0.4112
Residuals     218 697.42   3.199
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$CherryF

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 463.82  33.130 29.4531 < 2.2e-16 ***
Product        7  45.02   6.431  5.7177 4.376e-06 ***
Rep            1   8.07   8.067  7.1714  0.007972 **
Judge:Product  98 312.14   3.185  2.8316 1.101e-10
***
Judge:Rep      14  21.88   1.563  1.3897  0.159590
Product:Rep     7  12.34   1.762  1.5667  0.146588
Residuals     218 245.22   1.125
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1
‘ ’ 1
```

$SmokeF

```
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 828.89  59.206 25.9495 < 2.2e-16 ***
Product        7 208.39  29.770 13.0479  5.29e-14 ***
Rep            1   5.25   5.251  2.3015  0.130700
```

```
Judge:Product  98 347.23   3.543  1.5529  0.004147
**
Judge:Rep      14  77.93   5.567  2.4398  0.003300 **
Product:Rep     7  25.05   3.579  1.5687  0.145971
Residuals     218 497.39   2.282
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$HerbalF
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 428.66 30.6189 16.6071 < 2.2e-16
***
Product        7 123.30 17.6144  9.5537 2.412e-10
***
Rep            1   0.06  0.0570  0.0309    0.8605
Judge:Product  98 337.01  3.4389  1.8652 8.502e-05
***
Judge:Rep      14  35.59  2.5425  1.3790    0.1649
Product:Rep     7  14.85  2.1219  1.1509    0.3325
Residuals     218 401.93  1.8437
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$SweetT
              Df  Sum Sq Mean Sq F value     Pr(>F)
Judge         14  354.30  25.307  9.5902 < 2.2e-16 ***
Product        7 1080.20 154.315 58.4778 < 2.2e-16
***
Rep            1    0.10   0.096  0.0364  0.848912
Judge:Product  98  451.09   4.603  1.7443  0.000406
***
Judge:Rep      14   52.06   3.719  1.4092  0.150255
Product:Rep     7   34.32   4.903  1.8581  0.077730 .
Residuals     218  575.27   2.639
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$BitterT
              Df  Sum Sq Mean Sq F value     Pr(>F)
Judge         14  755.70  53.978 16.8872 < 2.2e-16
***
Product        7 1398.25 199.751 62.4922 < 2.2e-16
***
Rep            1    3.73   3.725  1.1654 0.2815447
Judge:Product  98  545.66   5.568  1.7419 0.0004183
***
Judge:Rep      14   52.72   3.766  1.1781 0.2935521
Product:Rep     7   16.08   2.297  0.7188 0.6562022
Residuals     218  696.82   3.196
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$SourT
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 573.91  40.994 21.4443 < 2.2e-16 ***
Product        7 353.87  50.553 26.4448 < 2.2e-16 ***
Rep            1   0.25   0.247  0.1292    0.7196
Judge:Product  98 510.06   5.205  2.7226 5.222e-10
***
Judge:Rep      14  27.31   1.951  1.0205    0.4338
Product:Rep     7  20.57   2.938  1.5370    0.1560
Residuals     218 416.74   1.912
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$AstringentMF
              Df Sum Sq Mean Sq F value  Pr(>F)
Judge         14 993.49  70.964 19.8405 < 2e-16 ***
Product        7 818.96 116.994 32.7101 < 2e-16 ***
Rep            1  23.56  23.563  6.5878 0.01094 *
Judge:Product  98 441.39   4.504  1.2592 0.08407 .
Judge:Rep      14  98.07   7.005  1.9585 0.02217 *
Product:Rep     7  21.33   3.047  0.8519 0.54555
Residuals     218 779.72   3.577
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$SweetAT
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 818.16  58.440 22.2749 < 2.2e-16 ***
Product        7 662.52  94.646 36.0750 < 2.2e-16 ***
Rep            1   0.64   0.641  0.2442 0.6216901
Judge:Product  98 492.51   5.026  1.9156 4.358e-05
***
Judge:Rep      14 117.65   8.403  3.2030 0.0001293
***
Product:Rep     7  20.64   2.949  1.1241 0.3489140
Residuals     218 571.94   2.624
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$BitterAT
              Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 786.47  56.177 17.5390 < 2.2e-16 ***
Product        7 979.88 139.983 43.7041 < 2.2e-16
***
Rep            1  13.73  13.728  4.2861  0.039604 *
Judge:Product  98 523.02   5.337  1.6662  0.001075
**
Judge:Rep      14 108.08   7.720  2.4104  0.003724 **
Product:Rep     7  24.27   3.467  1.0824  0.375579
Residuals     218 698.25   3.203
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

```
$SourAT
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 483.73  34.552 27.2241 < 2.2e-16 ***
Product        7 120.49  17.213 13.5628 1.598e-14
***
Rep            1   1.12   1.121  0.8830    0.3484
Judge:Product  98 340.61   3.476  2.7385 4.160e-10
***
Judge:Rep      14  19.82   1.416  1.1154    0.3454
Product:Rep     7   8.35   1.193  0.9400    0.4764
Residuals     218 276.68   1.269
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1

$AstringentAMF
            Df Sum Sq Mean Sq F value    Pr(>F)
Judge         14 721.67  51.548 16.5202 < 2.2e-16 ***
Product        7 552.36  78.909 25.2888 < 2.2e-16 ***
Rep            1  30.10  30.104  9.6478 0.0021476 **
Judge:Product  98 541.42   5.525  1.7706 0.0002906
***
Judge:Rep      14  91.13   6.509  2.0861 0.0135900 *
Product:Rep     7  33.31   4.759  1.5252 0.1599057
Residuals     218 680.23   3.120
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1
' ' 1
```

GDA LSD Output

```
library(agricolae)
> #LSD Aromas
> lsd.CocoA =LSD.test(lm(CocoaA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for CocoaA
Mean Square Error: 3.284991
Product, means and individual (95 %) CI

	CocoaA	std.err	r	LCL	UCL	Min.	Max.
C38	3.381395	0.4006260	43	2.590927	4.171864	0.1	9.6
C55	7.237209	0.2834103	43	6.678017	7.796402	0.9	9.8
C58	7.001163	0.3584932	43	6.293825	7.708500	0.8	9.8
C61	7.254651	0.3972804	43	6.470784	8.038519	0.0	10.0
C64	7.311628	0.3494214	43	6.622190	8.001066	0.4	10.0
C66	7.487209	0.2641515	43	6.966016	8.008402	2.3	10.0
C70	7.206977	0.3168819	43	6.581742	7.832211	1.9	9.9
C72	7.482558	0.3273263	43	6.836716	8.128401	0.8	10.0

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7712469
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C66	7.487
a	C72	7.483
a	C64	7.312
a	C61	7.255
a	C55	7.237
a	C70	7.207
a	C58	7.001
b	C38	3.381

```
> lsd.MilkyA =LSD.test(lm(MilkyA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for MilkyA
Mean Square Error: 2.950062
Product, means and individual (95 %) CI

	MilkyA	std.err	r	LCL	UCL	Min.	Max.
C38	6.753488	0.3674815	43	6.0284166	7.478560	0	10.0
C55	2.016279	0.3720276	43	1.2822373	2.750321	0	8.5
C58	2.244186	0.3431065	43	1.5672081	2.921164	0	6.5
C61	1.690698	0.3015981	43	1.0956193	2.285776	0	7.2
C64	2.662791	0.3946209	43	1.8841706	3.441411	0	7.5
C66	1.794186	0.3209474	43	1.1609299	2.427442	0	9.0
C70	1.523256	0.2961891	43	0.9388498	2.107662	0	6.6
C72	2.263953	0.3744813	43	1.5250704	3.002837	0	7.5

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7308731
Means with the same letter are not significantly different.
Groups, Treatments and means

a	C38	6.753
b	C64	2.663
bc	C72	2.264
bcd	C58	2.244
bcd	C55	2.016
cd	C66	1.794
cd	C61	1.691
d	C70	1.523

```
> lsd.VanillaA =LSD.test(lm(VanillaA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for VanillaA
Mean Square Error: 2.193844
Product, means and individual (95 %) CI

	VanillaA	std.err	r	LCL	UCL	Min.	Max.
C38	3.388372	0.4181143	43	2.5633974	4.213347	0	9.2
C55	1.260465	0.2621392	43	0.7432425	1.777688	0	5.7
C58	1.638372	0.2942031	43	1.0578846	2.218860	0	7.9
C61	1.505814	0.3042164	43	0.9055693	2.106059	0	8.3
C64	1.825581	0.3261252	43	1.1821090	2.469054	0	9.3

C66 1.576744 0.3235640 43 0.9383252 2.215163 0 7.9
C70 1.006977 0.1943383 43 0.6235309 1.390423 0 4.7
C72 1.700000 0.3290478 43 1.0507611 2.349239 0 8.8

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.6302737
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C38	3.388
b	C64	1.826
b	C72	1.7
b	C58	1.638
bc	C66	1.577
bc	C61	1.506
bc	C55	1.26
c	C70	1.007

```
> lsd.CaramelA =LSD.test(lm(CaramelA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for CaramelA
Mean Square Error: 3.036071
Product, means and individual (95 %) CI

	CaramelA	std.err	r	LCL	UCL	Min.	Max.
C38	5.397674	0.4425398	43	4.5245061	6.270843	0	10.0
C55	1.709302	0.3708333	43	0.9776171	2.440988	0	7.4
C58	1.366279	0.2597209	43	0.8538280	1.878730	0	6.3
C61	1.632558	0.3791014	43	0.8845593	2.380557	0	10.0
C64	2.525581	0.4209899	43	1.6949330	3.356230	0	7.9
C66	1.413953	0.3336529	43	0.7556282	2.072279	0	7.4
C70	1.148837	0.2421840	43	0.6709879	1.626687	0	6.4
C72	1.767442	0.3522074	43	1.0725070	2.462377	0	9.4

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7414507
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C38	5.398
b	C64	2.526
c	C72	1.767
c	C55	1.709
c	C61	1.633
c	C66	1.414
c	C58	1.366
c	C70	1.149

```
> lsd.CoffeeA =LSD.test(lm(CoffeeA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for CoffeeA
Mean Square Error: 2.844875
Product, means and individual (95 %) CI

	CoffeeA	std.err	r	LCL	UCL	Min.	Max.
C38	0.5302326	0.1681287	43	0.1985004	0.8619647	0	4.4
C55	2.2325581	0.3463258	43	1.5492283	2.9158880	0	8.9
C58	2.1953488	0.3678972	43	1.4694568	2.9212409	0	8.7
C61	2.9034884	0.4007275	43	2.1128194	3.6941573	0	8.8
C64	2.2116279	0.4147904	43	1.3932116	3.0300442	0	8.1
C66	2.8430233	0.4644701	43	1.9265846	3.7594619	0	9.3
C70	2.5837209	0.3888383	43	1.8165102	3.3509316	0	8.4
C72	2.0918605	0.3381105	43	1.4247399	2.7589810	0	9.1

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7177248
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C61	2.903
a	C66	2.843
ab	C70	2.584
ab	C55	2.233
ab	C64	2.212
ab	C58	2.195
b	C72	2.092
c	C38	0.5302

```
> lsd.ButteryA =LSD.test(lm(ButteryA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for ButteryA
Mean Square Error: 1.581187
Product, means and individual (95 %) CI

ButteryA std.err r LCL UCL Min. Max.
C38 4.762791 0.5188584 43 3.7390395 5.786542 0 10.0
C55 1.416279 0.3125633 43 0.7995655 2.032993 0 8.0
C58 1.365116 0.3079940 43 0.7574183 1.972814 0 8.6
C61 2.144186 0.3376569 43 1.4779605 2.810412 0 7.3
C64 2.193023 0.3629795 43 1.4768342 2.909212 0 7.1
C66 1.787209 0.3225774 43 1.1507370 2.423682 0 7.1
C70 1.518605 0.3165997 43 0.8939268 2.143283 0 6.4
C72 1.774419 0.3418258 43 1.0999675 2.448870 0 6.9

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.5350791
Means with the same letter are not significantly different.

Groups, Treatments and means
a C38 4.763
b C64 2.193
b C61 2.144
bc C66 1.787
bc C72 1.774
c C70 1.519
c C55 1.416
c C58 1.365
> lsd.ArtificialA =LSD.test(lm(ArtificialA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for ArtificialA
Mean Square Error: 2.236859
Product, means and individual (95 %) CI

ArtificialA std.err r LCL UCL Min. Max.
C38 3.162791 0.4369306 43 2.3006899 4.024891 0 8.7
C55 1.579070 0.3398514 43 0.9085144 2.249625 0 7.0
C58 1.761628 0.3357107 43 1.0992425 2.424013 0 6.8
C61 1.552326 0.3252606 43 0.9105591 2.194092 0 7.2
C64 1.639535 0.3167376 43 1.0145850 2.264485 0 7.1
C66 1.544186 0.3307983 43 0.8914933 2.196879 0 7.8
C70 1.432558 0.3204150 43 0.8003523 2.064764 0 7.7
C72 2.026744 0.3860323 43 1.2650701 2.788418 0 9.0

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.6364228
Means with the same letter are not significantly different.

Groups, Treatments and means
a C38 3.163
b C72 2.027
b C58 1.762
b C64 1.64
b C55 1.579
b C61 1.552
b C66 1.544
b C70 1.433
> lsd.EarthyA =LSD.test(lm(EarthyA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for EarthyA
Mean Square Error: 3.652918
Product, means and individual (95 %) CI

EarthyA std.err r LCL UCL Min. Max.
C38 0.4488372 0.1465881 43 0.1596066 0.7380678 0 4.1
C55 2.4139535 0.4067207 43 1.6114594 3.2164476 0 9.3
C58 1.7244186 0.3157431 43 1.1014309 2.3474063 0 7.6
C61 2.1418605 0.3904626 43 1.3714449 2.9122760 0 9.3
C64 2.0813953 0.3345756 43 1.4212496 2.7415411 0 8.9
C66 2.2790698 0.3937434 43 1.5021809 3.0559586 0 8.5
C70 3.1116279 0.4075724 43 2.3074533 3.9158026 0 8.7
C72 2.1883721 0.3948199 43 1.4093593 2.9673849 0 9.7

alpha: 0.05 ; Df Error: 182

Critical Value of t: 1.973084

Least Significant Difference 0.8132917
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C70	3.112
ab	C55	2.414
b	C66	2.279
b	C72	2.188
b	C61	2.142
b	C64	2.081
b	C58	1.724
c	C38	0.4488

```
> lsd.SmokeA =LSD.test(lm(SmokeA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for SmokeA
Mean Square Error: 2.321863
Product, means and individual (95 %) CI

	SmokeA	std.err	r	LCL	UCL	Min.	Max.
C38	0.3930233	0.1572323	43	0.08279077	0.7032557	0	5.3
C55	1.7372093	0.3561052	43	1.03458387	2.4398347	0	8.7
C58	1.7837209	0.3908977	43	1.01244693	2.5549949	0	10.0
C61	2.0418605	0.4164161	43	1.22023652	2.8634844	0	10.0
C64	1.8046512	0.3605083	43	1.09333790	2.5159644	0	8.3
C66	1.7360465	0.3663418	43	1.01322330	2.4588697	0	9.9
C70	2.8627907	0.4620842	43	1.95105963	3.7745218	0	9.2
C72	1.3313953	0.2846771	43	0.76970354	1.8930872	0	7.3

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.6484025
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C70	2.863
b	C61	2.042
bc	C64	1.805
bc	C58	1.784
bc	C55	1.737
bc	C66	1.736
c	C72	1.331
d	C38	0.393

```
> lsd.HerbalA =LSD.test(lm(HerbalA~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for HerbalA
Mean Square Error: 2.429137
Product, means and individual (95 %) CI

	HerbalA	std.err	r	LCL	UCL	Min.	Max.
C38	0.6139535	0.1565329	43	0.3051008	0.9228061	0	4.4
C55	1.9930233	0.3497412	43	1.3029545	2.6830920	0	7.7
C58	1.7872093	0.3459427	43	1.1046353	2.4697833	0	8.0
C61	1.3732558	0.2856495	43	0.8096453	1.9368663	0	8.4
C64	1.9581395	0.3500867	43	1.2673890	2.6488901	0	8.0
C66	1.7767442	0.3569875	43	1.0723779	2.4811105	0	9.7
C70	2.3023256	0.3651103	43	1.5819323	3.0227189	0	7.5
C72	1.2802326	0.2436408	43	0.7995087	1.7609564	0	7.2

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.663212
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C70	2.302
ab	C55	1.993
ab	C64	1.958
abc	C58	1.787
abc	C66	1.777
bc	C61	1.373
c	C72	1.28
d	C38	0.614

```
> #LSD Textures
> lsd.HardnessTx =LSD.test(lm(HardnessTx~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for HardnessTx
Mean Square Error: 3.027118
Product, means and individual (95 %) CI

HardnessTx std.err r LCL UCL Min. Max.

C38 1.023256 0.1965043 43 0.6355364 1.410975 0.0 7.1
C55 5.941860 0.3374425 43 5.2760580 6.607663 1.2 10.0
C58 5.659302 0.3534291 43 4.9619570 6.356648 1.4 9.9
C61 4.731395 0.3605783 43 4.0199441 5.442847 0.5 9.3
C64 8.011628 0.2461938 43 7.5258668 8.497389 3.6 10.0
C66 7.320930 0.3257593 43 6.6781797 7.963681 2.7 10.0
C70 7.967442 0.2568383 43 7.4606783 8.474205 3.5 10.0
C72 6.025581 0.3223854 43 5.3894878 6.661675 1.0 10.0

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7403568
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C64	8.012
a	C70	7.967
a	C66	7.321
b	C72	6.026
b	C55	5.942
b	C58	5.659
c	C61	4.731
d	C38	1.023

```
> lsd.BrittlenessTx =LSD.test(lm(BrittlenessTx~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for BrittlenessTx
Mean Square Error: 3.951011
Product, means and individual (95 %) CI

BrittlenessTx std.err r LCL UCL Min. Max.
C38 1.379070 0.2685336 43 0.8492305 1.908909 0.0 7.1
C55 5.083721 0.4200265 43 4.2549733 5.912469 0.2 10.0
C58 5.412791 0.3971699 43 4.6291412 6.196440 0.3 9.8
C61 4.465116 0.3790161 43 3.7172857 5.212947 0.6 10.0
C64 6.160465 0.3707187 43 5.4290060 6.891924 0.6 9.9
C66 6.853488 0.4335890 43 5.9979808 7.708996 0.0 10.0
C70 7.311628 0.4186173 43 6.4856609 8.137595 0.6 10.0
C72 4.973256 0.3534451 43 4.2758789 5.670633 1.4 10.0

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8458249
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C70	7.312
ab	C66	6.853
bc	C64	6.16
cd	C58	5.413
de	C55	5.084
de	C72	4.973
e	C61	4.465
f	C38	1.379

```
> lsd.RoughnessTx =LSD.test(lm(RoughnessTx~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for RoughnessTx
Mean Square Error: 4.25091
Product, means and individual (95 %) CI

RoughnessTx std.err r LCL UCL Min. Max.
C38 1.330233 0.2808691 43 0.7760543 1.884411 0.0 8.7
C55 3.888372 0.3911848 43 3.1165315 4.660213 0.0 9.0
C58 3.745349 0.3537601 43 3.0473504 4.443347 0.0 8.9
C61 5.198837 0.3569919 43 4.4944622 5.903212 0.0 9.1
C64 5.348837 0.4567007 43 4.4477283 6.249946 0.2 9.8
C66 4.590698 0.4262408 43 3.7496887 5.431707 0.5 9.8
C70 5.009302 0.3882524 43 4.2432477 5.775357 0.6 9.5
C72 5.819767 0.4055988 43 5.0194870 6.620048 0.3 9.7

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8773388

Means with the same letter are not significantly different.

Groups, Treatments and means
a C72 5.82
ab C64 5.349
ab C61 5.199
ab C70 5.009
bc C66 4.591
c C55 3.888
c C58 3.745
d C38 1.33

```
> lsd.Oily.MoistTx =LSD.test(lm(Oily.MoistTx~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for Oily.MoistTx
Mean Square Error: 4.625106
Product, means and individual (95 %) CI

	Oily.MoistTx	std.err	r	LCL	UCL	Min.	Max.
C38	8.218605	0.3643173	43	7.499776	8.937433	0.0	10.0
C55	6.618605	0.2708883	43	6.084119	7.153090	0.9	9.2
C58	5.958140	0.2947723	43	5.376529	6.539750	2.4	9.1
C61	5.447674	0.3466536	43	4.763698	6.131651	0.9	9.7
C64	4.988372	0.3849208	43	4.228891	5.747853	0.1	8.8
C66	4.363953	0.4397829	43	3.496225	5.231682	0.2	9.6
C70	3.809302	0.4014759	43	3.017157	4.601448	0.1	9.0
C72	4.310465	0.3409061	43	3.637829	4.983101	0.9	9.1

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.9151393
Means with the same letter are not significantly different.

Groups, Treatments and means
a C38 8.219
b C55 6.619
bc C58 5.958
cd C61 5.448
de C64 4.988
ef C66 4.364
ef C72 4.31
f C70 3.809

```
> lsd.StickinessTx =LSD.test(lm(StickinessTx~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for StickinessTx
Mean Square Error: 4.43774
Product, means and individual (95 %) CI

	StickinessTx	std.err	r	LCL	UCL	Min.	Max.
C38	7.137209	0.3672957	43	6.412504	7.861915	1.4	10.0
C55	4.958140	0.3857402	43	4.197042	5.719237	0.6	9.1
C58	4.824419	0.3319686	43	4.169417	5.479421	0.8	8.4
C61	4.519767	0.3812941	43	3.767442	5.272093	0.0	9.3
C64	4.313953	0.4216009	43	3.482100	5.145807	0.2	9.7
C66	5.048837	0.3696302	43	4.319526	5.778149	0.6	9.5
C70	4.413953	0.4330042	43	3.559600	5.268307	0.4	9.8
C72	4.305814	0.4071353	43	3.502502	5.109126	0.3	9.4

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8964112
Means with the same letter are not significantly different.

Groups, Treatments and means
a C38 7.137
b C66 5.049
b C55 4.958
b C58 4.824
b C61 4.52
b C70 4.414
b C64 4.314
b C72 4.306

```
> lsd.RateofMeltTx =LSD.test(lm(RateofMeltTx~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for RateofMeltTx
Mean Square Error: 3.669963
Product, means and individual (95 %) CI

RateofMeltTx std.err r LCL UCL Min. Max.
C38 2.195349 0.3327784 43 1.538749 2.851949 0.1 9.6
C55 3.962791 0.3166132 43 3.338086 4.587495 0.2 9.3
C58 4.141860 0.3252945 43 3.500027 4.783694 0.5 9.2
C61 4.033721 0.3531174 43 3.336991 4.730451 0.0 8.9
C64 5.948837 0.3787309 43 5.201569 6.696105 0.9 9.9
C66 6.158140 0.3080362 43 5.550358 6.765921 2.4 9.9
C70 6.113953 0.3800038 43 5.364174 6.863733 0.6 9.9
C72 4.827907 0.3173346 43 4.201779 5.454035 0.6 9.2

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8151869
Means with the same letter are not significantly different.

Groups, Treatments and means
a C66 6.158
a C70 6.114
a C64 5.949
b C72 4.828
bc C58 4.142
bc C61 4.034
c C55 3.963
d C38 2.195
> lsd.OilyMouthcoatTx =LSD.test(lm(OilyMouthcoatTx~(Judge+Product+Rep)^2, data=DAChoc), "Product")

Study:
LSD t Test for OilyMouthcoatTx
Mean Square Error: 4.204006
Product, means and individual (95 %) CI

OilyMouthcoatTx std.err r LCL UCL Min. Max.
C38 7.067442 0.3358551 43 6.404771 7.730112 0.4 10.0
C55 4.900000 0.3785500 43 4.153089 5.646911 0.2 9.2
C58 4.459302 0.3566574 43 3.755587 5.163017 0.5 8.9
C61 3.858140 0.3812208 43 3.105959 4.610320 0.1 9.9
C64 3.902326 0.3697218 43 3.172833 4.631818 0.0 9.1
C66 3.443023 0.3745303 43 2.704044 4.182003 0.0 9.7
C70 3.193023 0.3881038 43 2.427262 3.958785 0.0 9.4
C72 3.546512 0.3875606 43 2.781822 4.311201 0.0 9.4

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8724852
Means with the same letter are not significantly different.

Groups, Treatments and means
a C38 7.067
b C55 4.9
bc C58 4.459
cd C64 3.902
cd C61 3.858
d C72 3.547
d C66 3.443
d C70 3.193
> lsd.ChalkyMouthctTx =LSD.test(lm(ChalkyMouthctTx~(Judge+Product+Rep)^2, data=DAChoc), "Product")

Study:
LSD t Test for ChalkyMouthctTx
Mean Square Error: 3.760533
Product, means and individual (95 %) CI

ChalkyMouthctTx std.err r LCL UCL Min. Max.
C38 0.927907 0.1483884 43 0.6351242 1.220690 0.0 4.2
C55 3.402326 0.3949359 43 2.6230838 4.181567 0.0 8.0
C58 3.415116 0.3959811 43 2.6338123 4.196420 0.0 9.1
C61 4.779070 0.4335917 43 3.9235569 5.634583 0.0 8.7
C64 4.997674 0.4679009 43 4.0744667 5.920882 0.1 9.5
C66 4.626744 0.4579081 43 3.7232530 5.530235 0.1 9.5
C70 5.602326 0.4612983 43 4.6921453 6.512506 0.3 10.0
C72 5.972093 0.4524368 43 5.0793972 6.864789 0.0 9.9

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8251846
Means with the same letter are not significantly different.
Groups, Treatments and means

a	C72	5.972
ab	C70	5.602
bc	C64	4.998
bc	C61	4.779
c	C66	4.627
d	C58	3.415
d	C55	3.402
e	C38	0.9279

```
> lsd.ToothpackingTx =LSD.test(lm(ToothpackingTx~(Judge+Product+Rep)^2, data=DAChoc), "Product")
```

Study:
LSD t Test for ToothpackingTx
Mean Square Error: 3.71777
Product, means and individual (95 %) CI

	ToothpackingTx	std.err	r	LCL	UCL	Min.	Max.
C38	3.865116	0.4731423	43	2.931567	4.798666	0	9.9
C55	2.676744	0.3912362	43	1.904802	3.448686	0	9.6
C58	2.802326	0.3684917	43	2.075260	3.529391	0	9.0
C61	2.700000	0.3784183	43	1.953349	3.446651	0	8.8
C64	3.353488	0.4255587	43	2.513825	4.193151	0	9.8
C66	3.202326	0.4452840	43	2.323743	4.080908	0	9.8
C70	2.832558	0.3759627	43	2.090752	3.574364	0	8.9
C72	2.461628	0.3686190	43	1.734312	3.188944	0	9.0

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8204793
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C38	3.865
ab	C64	3.353
abc	C66	3.202
bc	C70	2.833
bc	C58	2.802
bc	C61	2.7
bc	C55	2.677
c	C72	2.462

```
> #LSD Flavors
> lsd.CocoaF =LSD.test(lm(CocoaF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for CocoaF
Mean Square Error: 2.179013
Product, means and individual (95 %) CI

	CocoaF	std.err	r	LCL	UCL	Min.	Max.
C38	3.104651	0.3804607	43	2.353970	3.855332	0.0	9.3
C55	7.672093	0.2986371	43	7.082857	8.261329	0.2	10.0
C58	7.133721	0.3052000	43	6.531536	7.735906	0.8	9.7
C61	7.259302	0.3177399	43	6.632375	7.886230	0.0	10.0
C64	7.620930	0.3074483	43	7.014309	8.227552	1.9	10.0
C66	7.993023	0.2692715	43	7.461728	8.524319	1.0	10.0
C70	7.995349	0.2418770	43	7.518105	8.472592	3.4	10.0
C72	7.823256	0.2840897	43	7.262723	8.383789	1.3	10.0

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.6281397
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C70	7.995
a	C66	7.993
ab	C72	7.823
abc	C55	7.672
abc	C64	7.621
bc	C61	7.259
c	C58	7.134
d	C38	3.105

```
> lsd.MilkyF =LSD.test(lm(MilkyF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for MilkyF
Mean Square Error: 2.795367
Product, means and individual (95 %) CI

MilkyF std.err r LCL UCL Min. Max.
C38 7.516279 0.4026481 43 6.7218206 8.310738 0 10.0
C55 2.983721 0.4210403 43 2.1529729 3.814469 0 9.3
C58 3.125581 0.4122581 43 2.3121615 3.939001 0 7.9
C61 1.819767 0.3167751 43 1.1947436 2.444791 0 6.7
C64 2.776744 0.3891786 43 2.0088621 3.544626 0 8.3
C66 1.994186 0.3300651 43 1.3429398 2.645432 0 8.2
C70 1.732558 0.3574662 43 1.0272473 2.437869 0 9.6
C72 1.487209 0.2865048 43 0.9219113 2.052507 0 7.1

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7114522
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C38	7.516
b	C58	3.126
b	C55	2.984
b	C64	2.777
c	C66	1.994
c	C61	1.82
c	C70	1.733
c	C72	1.487

> lsd.VanillaF =LSD.test(lm(VanillaF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for VanillaF
Mean Square Error: 2.259454
Product, means and individual (95 %) CI

VanillaF std.err r LCL UCL Min. Max.
C38 3.7558140 0.4448587 43 2.8780704 4.633558 0 9.3
C55 1.8023256 0.3332362 43 1.1448225 2.459829 0 6.9
C58 2.1686047 0.3549212 43 1.4683153 2.868894 0 9.1
C61 1.5034884 0.2894815 43 0.9323170 2.074660 0 7.2
C64 1.6046512 0.3009574 43 1.0108370 2.198465 0 6.9
C66 1.8383721 0.3495917 43 1.1485982 2.528146 0 8.4
C70 1.1627907 0.2549406 43 0.6597714 1.665810 0 7.7
C72 0.8418605 0.1854399 43 0.4759719 1.207749 0 4.5

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.6396289
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C38	3.756
b	C58	2.169
bc	C66	1.838
bcd	C55	1.802
bcd	C64	1.605
cd	C61	1.503
de	C70	1.163
e	C72	0.8419

> lsd.CaramelF =LSD.test(lm(CaramelF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for CaramelF
Mean Square Error: 2.761925
Product, means and individual (95 %) CI

CaramelF std.err r LCL UCL Min. Max.
C38 6.8790698 0.3700372 43 6.1489552 7.609184 0 10.0
C55 2.2581395 0.3628549 43 1.5421962 2.974083 0 7.6
C58 2.6895349 0.3968088 43 1.9065977 3.472472 0 8.2
C61 1.7686047 0.3748090 43 1.0290750 2.508134 0 10.0
C64 1.8697674 0.3743808 43 1.1310827 2.608452 0 8.5
C66 1.2779070 0.3042351 43 0.6776256 1.878188 0 7.7
C70 1.0069767 0.2319782 43 0.5492642 1.464689 0 5.9
C72 0.9953488 0.2561093 43 0.4900237 1.500674 0 6.7

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7071838
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C38	6.879
b	C58	2.69
bc	C55	2.258
cd	C64	1.87
cd	C61	1.769
de	C66	1.278
e	C70	1.007
e	C72	0.9953

```
> lsd.CoffeeF =LSD.test(lm(CoffeeF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for CoffeeF
Mean Square Error: 3.420342
Product, means and individual (95 %) CI

	CoffeeF	std.err	r	LCL	UCL	Min.	Max.
C38	0.4348837	0.2137801	43	0.01307764	0.8566898	0	8.9
C55	2.4441860	0.4172008	43	1.62101380	3.2673583	0	8.8
C58	2.1360465	0.4173206	43	1.31263786	2.9594552	0	9.5
C61	3.0151163	0.4341797	43	2.15844325	3.8717893	0	8.8
C64	2.8139535	0.4560481	43	1.91413226	3.7137747	0	8.9
C66	3.3930233	0.4770293	43	2.45180428	4.3342422	0	9.3
C70	3.6255814	0.4889940	43	2.66075520	4.5904076	0	9.6
C72	3.6081395	0.4760369	43	2.66887876	4.5474003	0	9.4

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7869754
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C70	3.626
a	C72	3.608
ab	C66	3.393
abc	C61	3.015
bcd	C64	2.814
cd	C55	2.444
d	C58	2.136
e	C38	0.4349

```
> lsd.ButteryF =LSD.test(lm(ButteryF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for ButteryF
Mean Square Error: 1.687896
Product, means and individual (95 %) CI

	ButteryF	std.err	r	LCL	UCL	Min.	Max.
C38	5.418605	0.5037979	43	4.4245690	6.412640	0	10.0
C55	2.123256	0.3918160	43	1.3501699	2.896342	0	8.1
C58	2.345349	0.3618536	43	1.6313813	3.059316	0	8.2
C61	1.589535	0.3030738	43	0.9915449	2.187525	0	6.9
C64	2.004651	0.3537484	43	1.3066759	2.702626	0	7.5
C66	1.798837	0.3401456	43	1.1277013	2.469973	0	8.7
C70	1.379070	0.2957349	43	0.7955600	1.962580	0	6.6
C72	1.280233	0.3260011	43	0.6370051	1.923460	0	8.1

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.5528397
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C38	5.419
b	C58	2.345
bc	C55	2.123
bc	C64	2.005
bcd	C66	1.799
cd	C61	1.59
d	C70	1.379
d	C72	1.28

```
> lsd.ArtificialF =LSD.test(lm(ArtificialF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for ArtificialF
Mean Square Error: 1.650623
Product, means and individual (95 %) CI

	ArtificialF	std.err	r	LCL	UCL	Min.	Max.
C38	3.737209	0.4729917	43	2.8039568	4.670462	0	9.5
C55	1.418605	0.2869293	43	0.8524690	1.984740	0	6.7

C58 2.024419 0.3651005 43 1.3040446 2.744793
0 8.1
C61 1.480233 0.3055011 43 0.8774531 2.083012
0 7.0
C64 1.451163 0.2977838 43 0.8636102 2.038715
0 8.0
C66 1.381395 0.2777910 43 0.8332904 1.929500
0 6.3
C70 1.248837 0.3147952 43 0.6277198 1.869955
0 6.8
C72 1.573256 0.3559429 43 0.8709506 2.275561
0 9.7

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.5467015
Means with the same letter are not significantly different.

Groups, Treatments and means
a C38 3.737
b C58 2.024
bc C72 1.573
bc C61 1.48
c C64 1.451
c C55 1.419
c C66 1.381
c C70 1.249
> lsd.EarthyF =LSD.test(lm(EarthyF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for EarthyF
Mean Square Error: 3.702717
Product, means and individual (95 %) CI

EarthyF std.err r LCL UCL Min. Max.
C38 0.3581395 0.1139365 43 0.1333332 0.5829459
0 3.3
C55 1.5837209 0.3356277 43 0.9214992 2.2459426
0 7.5
C58 1.2465116 0.2333574 43 0.7860778 1.7069455
0 6.3
C61 2.4918605 0.4069303 43 1.6889528 3.2947682
0 8.9
C64 1.6976744 0.3210325 43 1.0642502 2.3310986
0 8.1
C66 2.5209302 0.4047278 43 1.7223682 3.3194923
0 9.6
C70 3.3488372 0.4652887 43 2.4307834 4.2668910
0 9.8
C72 2.2965116 0.3906734 43 1.5256802 3.0673430
0 9.7

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8188166
Means with the same letter are not significantly different.

Groups, Treatments and means
a C70 3.349
b C66 2.521
bc C61 2.492
bcd C72 2.297
cde C64 1.698
de C55 1.584
e C58 1.247
f C38 0.3581
> lsd.SmokeF =LSD.test(lm(SmokeF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for SmokeF
Mean Square Error: 2.425797
Product, means and individual (95 %) CI

SmokeF std.err r LCL UCL Min. Max.
C38 0.2139535 0.0775155 43 0.06100888 0.3668981
0 2.1
C55 1.3069767 0.3134736 43 0.68846688 1.9254866
0 8.8
C58 0.9197674 0.2485904 43 0.42927773 1.4102572
0 6.5
C61 1.9523256 0.4026661 43 1.15783158 2.7468196
0 9.7
C64 1.6186047 0.3375742 43 0.95254243 2.2846669
0 7.9
C66 1.9197674 0.4056943 43 1.11929846 2.7202364
0 9.9
C70 2.9302326 0.4869224 43 1.96949375 3.8909714
0 9.7
C72 1.9930233 0.3575850 43 1.28747791 2.6985686
0 9.2

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.6627558
Means with the same letter are not significantly different.
Groups, Treatments and means
a C70 2.93
b C72 1.993
bc C61 1.952
bc C66 1.92
bc C64 1.619
cd C55 1.307

d C58 0.9198
e C38 0.214
> lsd.HerbalF
=LSD.test(lm(HerbalF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for HerbalF
Mean Square Error: 2.011952
Product, means and individual (95 %) CI

HerbalF std.err r LCL UCL Min. Max.
C38 0.3767442 0.1103622 43 0.1589903 0.5944981
0 3.4
C55 1.1418605 0.2694737 43 0.6101662 1.6735548
0 7.1
C58 1.2011628 0.2449856 43 0.7177855 1.6845401
0 5.7
C61 2.0732558 0.3655665 43 1.3519624 2.7945492
0 8.3
C64 1.4860465 0.2483741 43 0.9959834 1.9761096
0 6.1
C66 1.9453488 0.3688179 43 1.2176402 2.6730575
0 9.9
C70 2.1883721 0.3516802 43 1.4944775 2.8822667
0 7.5
C72 1.1906977 0.2332023 43 0.7305699 1.6508255
0 5.0

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084
Least Significant Difference 0.6035804
Means with the same letter are not significantly different.

Groups, Treatments and means
a C70 2.188
ab C61 2.073
ab C66 1.945
bc C64 1.486
c C58 1.201
c C72 1.191
c C55 1.142
d C38 0.3767

> #LSD Taste, MF and AfterT/MF
> lsd.SweetT
=LSD.test(lm(SweetT~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for SweetT
Mean Square Error: 2.969907
Product, means and individual (95 %) CI

SweetT std.err r LCL UCL Min. Max.
C38 8.997674 0.2083391 43 8.586604 9.408745 4.8
10.0
C55 7.355814 0.2882202 43 6.787131 7.924497 0.8
9.7
C58 7.318605 0.2106325 43 6.903009 7.734200 4.3
9.9
C61 5.705814 0.3451620 43 5.024780 6.386848 0.3
9.4
C64 6.260465 0.3060870 43 5.656530 6.864401 1.5
8.9
C66 4.369767 0.3984401 43 3.583612 5.155923 0.0
8.4
C70 4.123256 0.3758908 43 3.381592 4.864920 0.4
9.2
C72 4.059302 0.3772249 43 3.315006 4.803599 0.1
8.9

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7333272
Means with the same letter are not significantly different.

Groups, Treatments and means
a C38 8.998
b C55 7.356
b C58 7.319
c C64 6.26
c C61 5.706
d C66 4.37
d C70 4.123
d C72 4.059
> lsd.BitterT
=LSD.test(lm(BitterT~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:

LSD t Test for BitterT
Mean Square Error: 3.568934
Product, means and individual (95 %) CI

BitterT std.err r LCL UCL Min. Max.
C38 0.5139535 0.1791632 43 0.1604494 0.8674576
0.0 7.1
C55 3.7744186 0.3748325 43 3.0348427 4.5139946
0.0 8.5
C58 3.0732558 0.3638204 43 2.3554075 3.7911041
0.0 8.2
C61 5.0941860 0.3981554 43 4.3085920 5.8797801
0.0 9.8

C64 4.8000000 0.4100212 43 3.9909937 5.6090063 0.0 9.8
C66 6.3662791 0.4117217 43 5.5539176 7.1786405 0.0 10.0
C70 6.2627907 0.4379685 43 5.3986420 7.1269394 0.1 10.0
C72 6.7000000 0.3511412 43 6.0071690 7.3928310 0.4 9.6

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8038881
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C72	6.7
a	C66	6.366
a	C70	6.263
b	C61	5.094
b	C64	4.8
c	C55	3.774
c	C58	3.073
d	C38	0.514

```
> lsd.SourT =LSD.test(lm(SourT~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for SourT
Mean Square Error: 1.79739
Product, means and individual (95 %) CI

	SourT	std.err	r	LCL	UCL	Min.	Max.
C38	0.2627907	0.08451695	43	0.09603165	0.4295497	0	2.6
C55	0.8093023	0.16332691	43	0.48704459	1.1315601	0	4.1
C58	1.1697674	0.23471042	43	0.70666406	1.6328708	0	8.2
C61	2.6988372	0.41606875	43	1.87789859	3.5197758	0	8.5
C64	1.2279070	0.28435246	43	0.66685568	1.7889583	0	7.2
C66	2.2779070	0.40636649	43	1.47611172	3.0797022	0	8.2
C70	1.9000000	0.37052236	43	1.16892822	2.6310718	0	9.3
C72	3.2918605	0.44221433	43	2.41933441	4.1643865	0	8.3

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.5704893
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C72	3.292
b	C61	2.699
bc	C66	2.278
c	C70	1.9
d	C64	1.228
d	C58	1.17
de	C55	0.8093
e	C38	0.2628

```
> lsd.AstringentMF =LSD.test(lm(AstringentMF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for AstringentMF
Mean Square Error: 3.871146
Product, means and individual (95 %) CI

	AstringentMF	std.err	r	LCL	UCL	Min.	Max.
C38	0.6883721	0.1644888	43	0.3638218	1.012922	0.0	5.2
C55	2.5534884	0.3582032	43	1.8467234	3.260253	0.0	9.9
C58	3.1813953	0.3453577	43	2.4999756	3.862815	0.0	8.0
C61	4.4581395	0.4088071	43	3.6515287	5.264750	0.0	9.4
C64	4.0093023	0.4566333	43	3.1083264	4.910278	0.0	9.5
C66	5.4651163	0.4453759	43	4.5863521	6.343880	0.0	10.0
C70	4.7953488	0.4441568	43	3.9189902	5.671707	0.0	9.8
C72	5.4790698	0.4574783	43	4.5764267	6.381713	0.1	9.9

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8372326
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C72	5.479
a	C66	5.465
ab	C70	4.795
b	C61	4.458
bc	C64	4.009
cd	C58	3.181

d C55 2.553
e C38 0.6884
> lsd.SweetAT =LSD.test(lm(SweetAT~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for SweetAT
Mean Square Error: 2.5528
Product, means and individual (95 %) CI

SweetAT std.err r LCL UCL Min. Max.
C38 6.216279 0.4449163 43 5.338422 7.094136 0.0 10.0
C55 4.890698 0.3689921 43 4.162645 5.618750 0.4 9.0
C58 5.441860 0.3656520 43 4.720398 6.163323 0.4 9.5
C61 3.443023 0.3868069 43 2.679821 4.206226 0.2 8.7
C64 4.381395 0.3655009 43 3.660231 5.102559 0.2 8.9
C66 3.100000 0.3752740 43 2.359553 3.840447 0.0 8.4
C70 2.860465 0.3738421 43 2.122843 3.598087 0.0 8.8
C72 2.020930 0.2637064 43 1.500615 2.541245 0.0 6.5

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.6798838
Means with the same letter are not significantly different.

Groups, Treatments and means
a C38 6.216
b C58 5.442
bc C55 4.891
c C64 4.381
d C61 3.443
d C66 3.1
d C70 2.86
e C72 2.021
> lsd.BitterAT =LSD.test(lm(BitterAT~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for BitterAT
Mean Square Error: 3.364794
Product, means and individual (95 %) CI

BitterAT std.err r LCL UCL Min. Max.
C38 0.3976744 0.1454549 43 0.1106797 0.6846691 0.0 5.0
C55 2.6465116 0.4129191 43 1.8317875 3.4612358 0.0 8.6
C58 1.6767442 0.3318434 43 1.0219893 2.3314990 0.0 8.3
C61 3.3883721 0.3487553 43 2.7002487 4.0764955 0.0 7.7
C64 3.3930233 0.4407961 43 2.5232956 4.2627509 0.0 9.3
C66 4.9302326 0.4440643 43 4.0540564 5.8064087 0.0 9.8
C70 5.2813953 0.4134003 43 4.4657217 6.0970690 0.1 9.9
C72 5.3186047 0.4043952 43 4.5206989 6.1165104 0.0 9.9

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.7805588
Means with the same letter are not significantly different.

Groups, Treatments and means
a C72 5.319
a C70 5.281
a C66 4.93
b C64 3.393
b C61 3.388
b C55 2.647
c C58 1.677
d C38 0.3977
> lsd.SourAT =LSD.test(lm(SourAT~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")

Study:
LSD t Test for SourAT
Mean Square Error: 1.392982
Product, means and individual (95 %) CI

SourAT std.err r LCL UCL Min. Max.
C38 0.3069767 0.1140416 43 0.08196309 0.5319904 0 4.6
C55 0.5372093 0.1503051 43 0.24064473 0.8337739 0 5.0
C58 0.7244186 0.1725434 43 0.38397588 1.0648613 0 5.0
C61 1.6244186 0.3403445 43 0.95289033 2.2959469 0 8.4
C64 0.9279070 0.2247264 43 0.48450294 1.3713110 0 6.5
C66 1.4116279 0.3222500 43 0.77580156 2.0474543 0 7.0

C70 1.3860465 0.3760490 43 0.64407019 2.1280228
0 9.1
C72 2.0616279 0.3349180 43 1.40080646 2.7224494
0 7.3

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.5022259
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C72	2.062
ab	C61	1.624
bc	C66	1.412
bc	C70	1.386
cd	C64	0.9279
de	C58	0.7244
de	C55	0.5372
e	C38	0.307

```
> lsd.AstringentAMF =LSD.test(lm(AstringentAMF~(Judge+Product+Rep)^2,
+ data=DAChoc), "Product")
```

Study:
LSD t Test for AstringentAMF
Mean Square Error: 3.589914
Product, means and individual (95 %) CI

AstringentAMF std.err r LCL UCL Min. Max.
C38 0.827907 0.2362808 43 0.361705 1.294109
0.0 6.4
C55 1.902326 0.3031486 43 1.304188 2.500463
0.0 7.9
C58 2.018605 0.3297413 43 1.367997 2.669212
0.0 8.5
C61 3.668605 0.4172234 43 2.845388 4.491822
0.0 9.5
C64 3.381395 0.4271808 43 2.538532 4.224259
0.0 8.9
C66 4.338372 0.4727334 43 3.405629 5.271115
0.0 10.0
C70 3.495349 0.3885965 43 2.728615 4.262082
0.0 8.9
C72 4.674419 0.4078832 43 3.869631 5.479206
0.1 9.9

alpha: 0.05 ; Df Error: 182
Critical Value of t: 1.973084

Least Significant Difference 0.8062476
Means with the same letter are not significantly different.

Groups, Treatments and means

a	C72	4.674
ab	C66	4.338
bc	C61	3.669
c	C70	3.495
c	C64	3.381
d	C58	2.019
d	C55	1.902
e	C38	0.8279

Raw TDS Graphs, Trained Panel

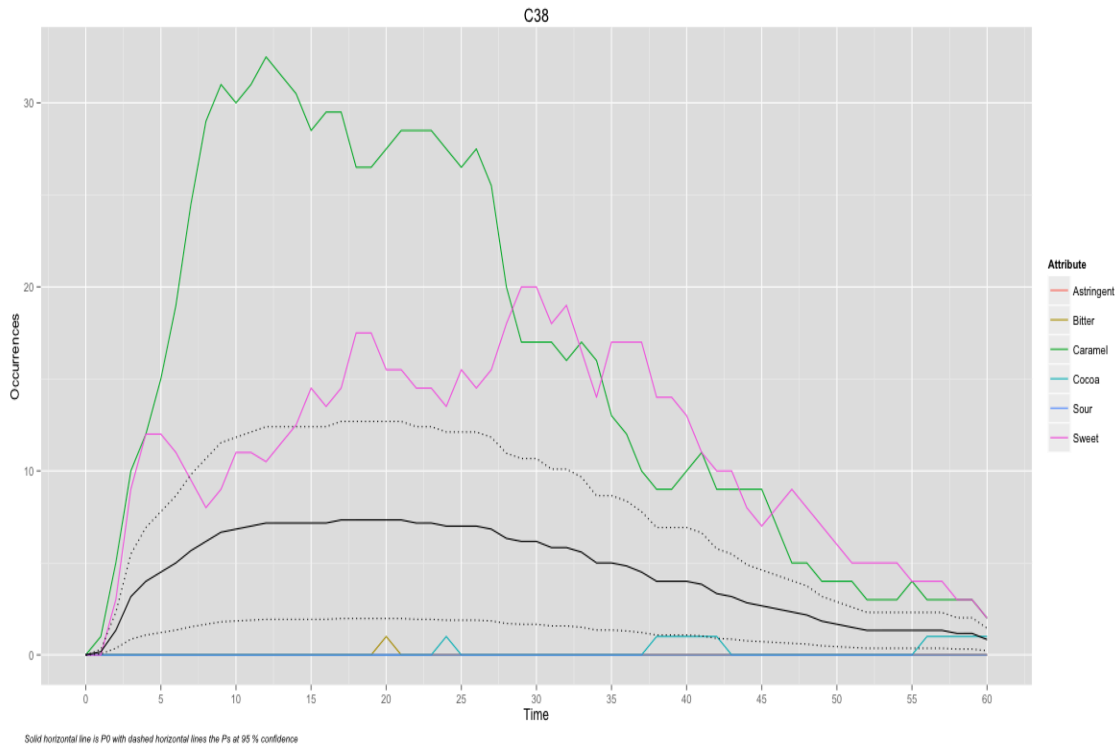


Figure 43. Trained Panel Raw TDS Curves. Sample 38

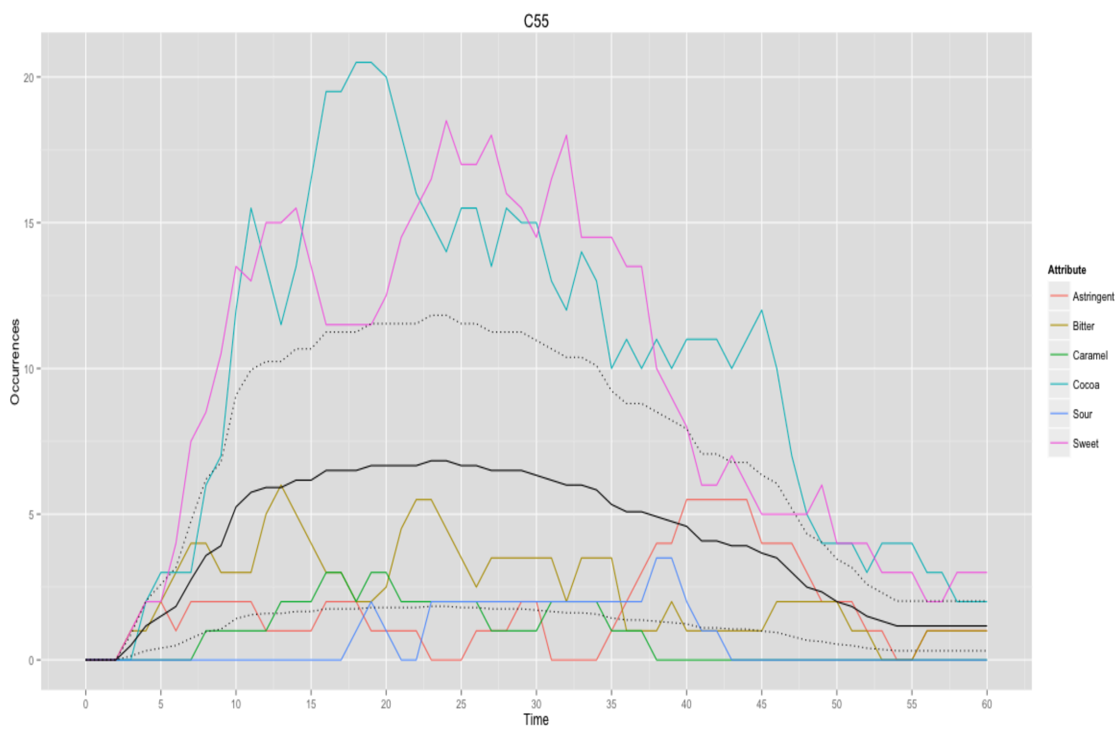


Figure 44. Trained Panel Raw TDS Curves. Sample 55

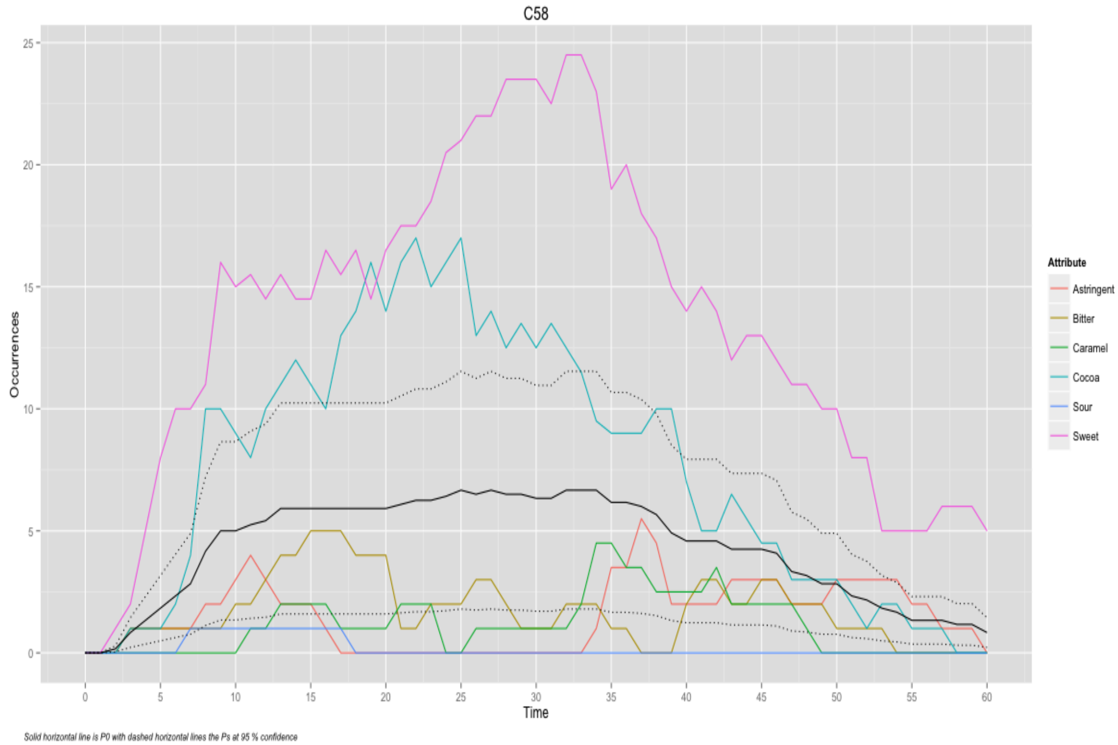


Figure 45. Trained Panel Raw TDS Curves. Sample 58

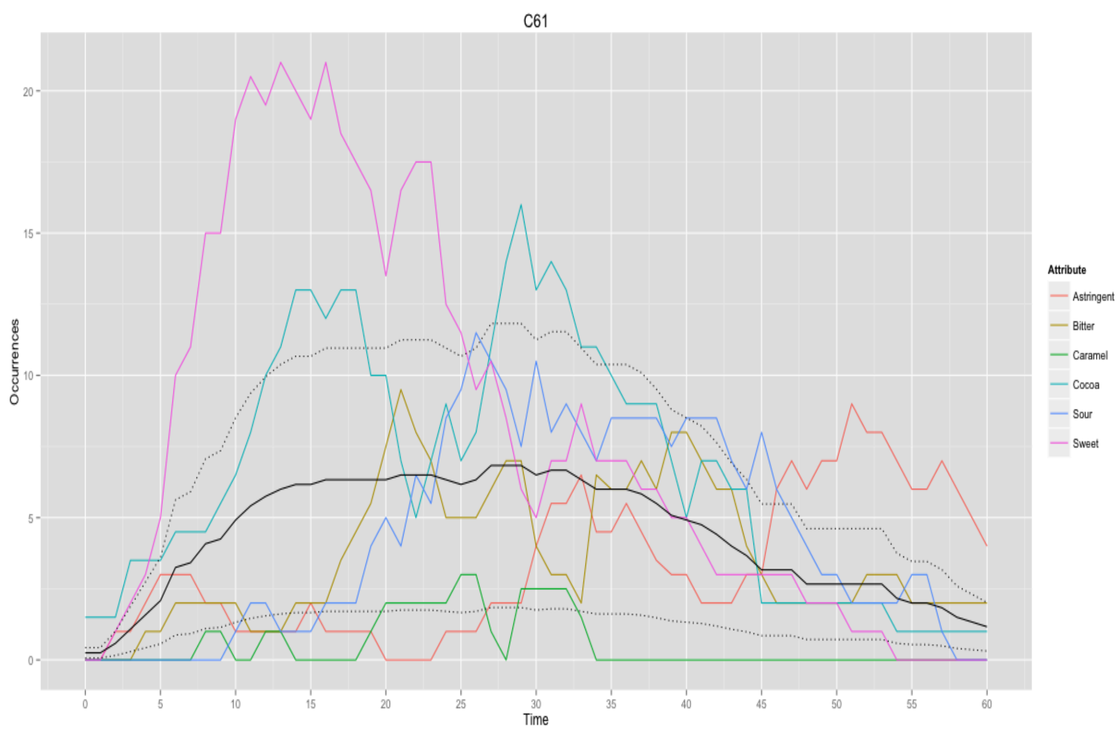


Figure 46. Trained Panel Raw TDS Curves. Sample 61

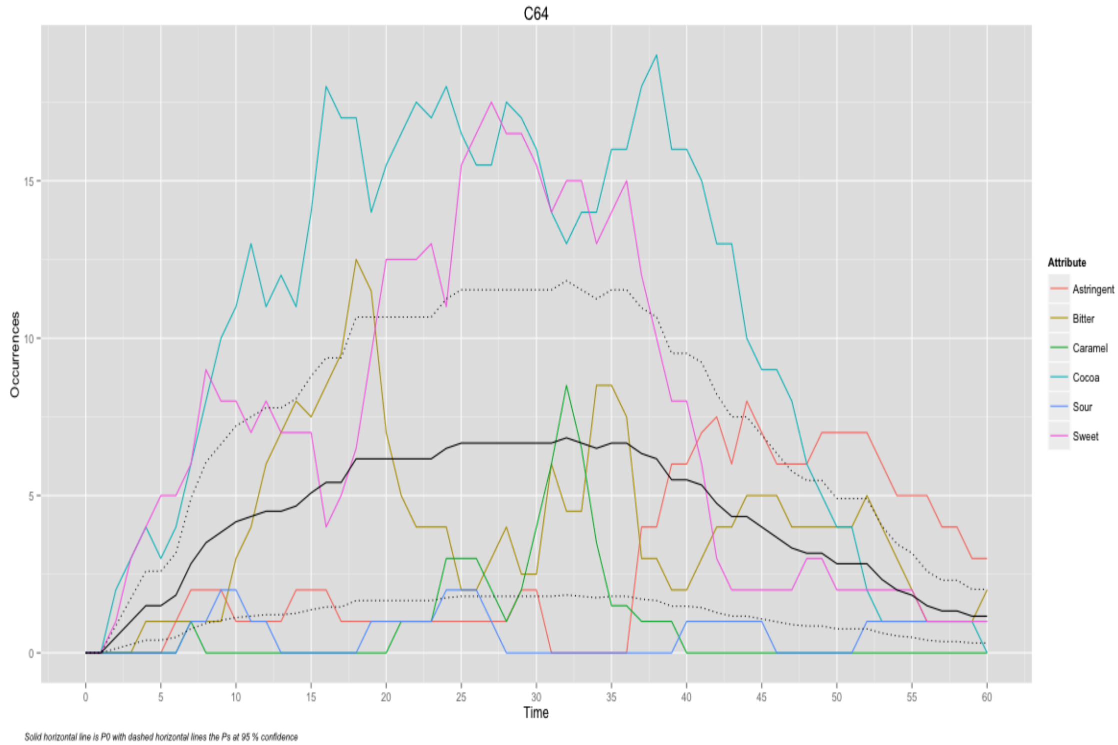


Figure 47. Trained Panel Raw TDS Curves. Sample 64

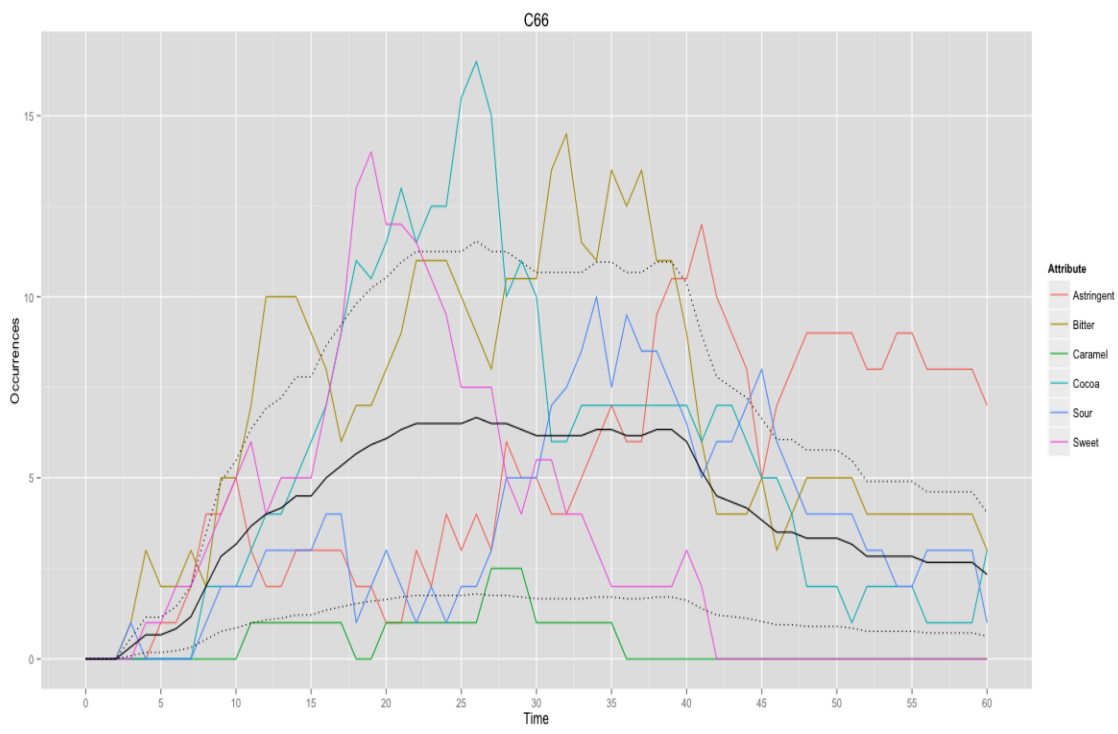


Figure 48. Trained Panel Raw TDS Curves. Sample 66

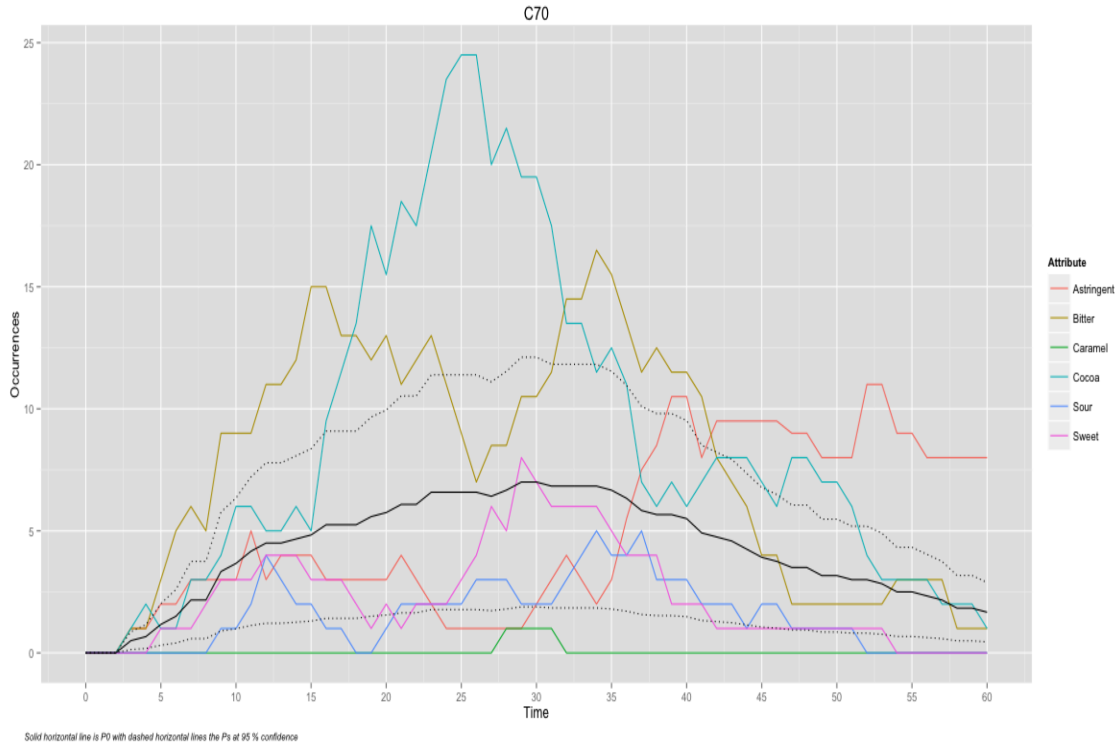


Figure 49. Trained Panel Raw TDS Curves. Sample 70

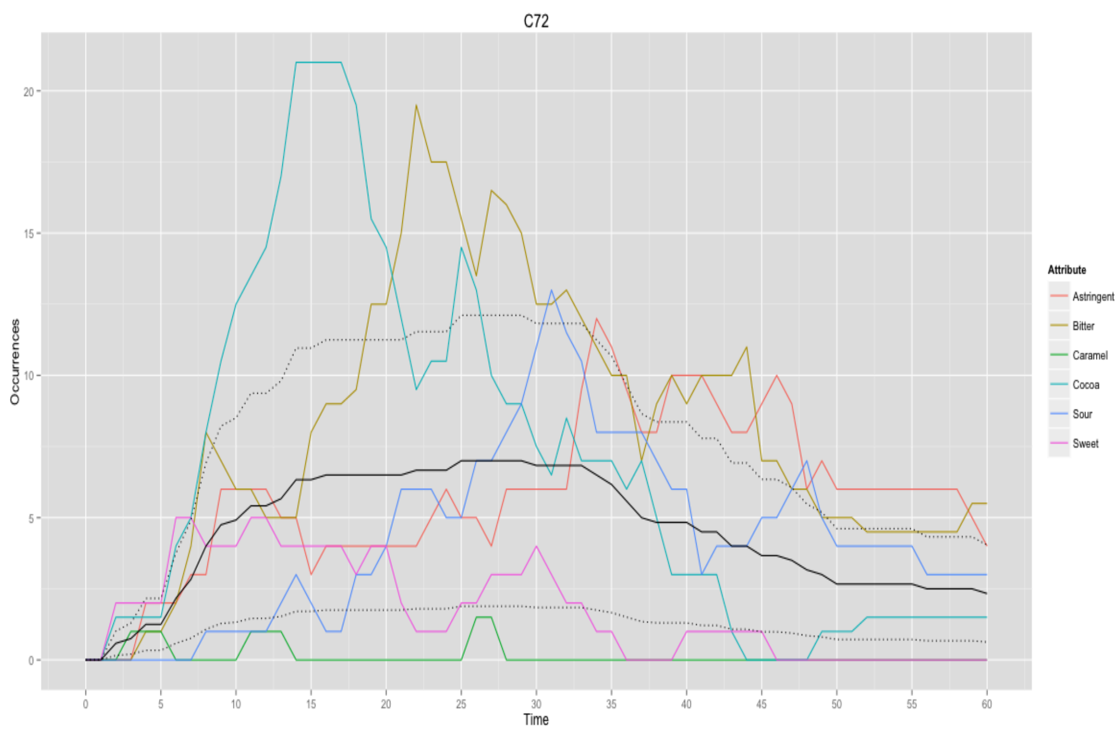


Figure 50. Trained Panel Raw TDS Curves. Sample 72

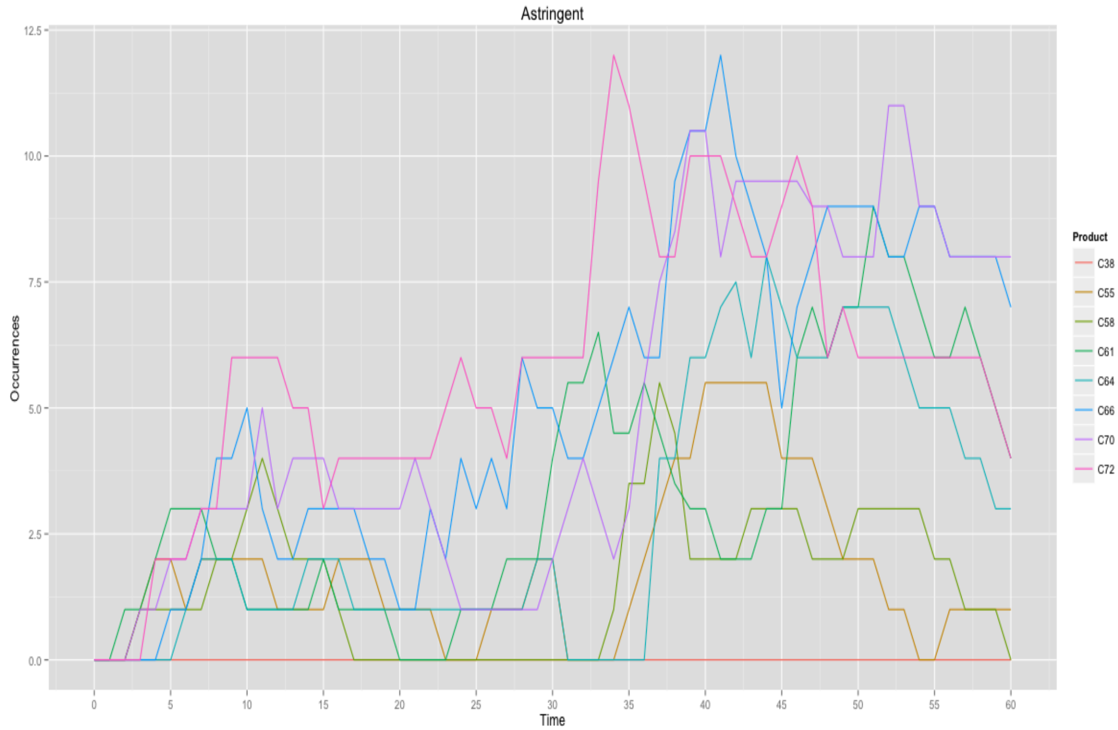


Figure 51. Trained Panel Raw TDS Curves. Astringency of all samples

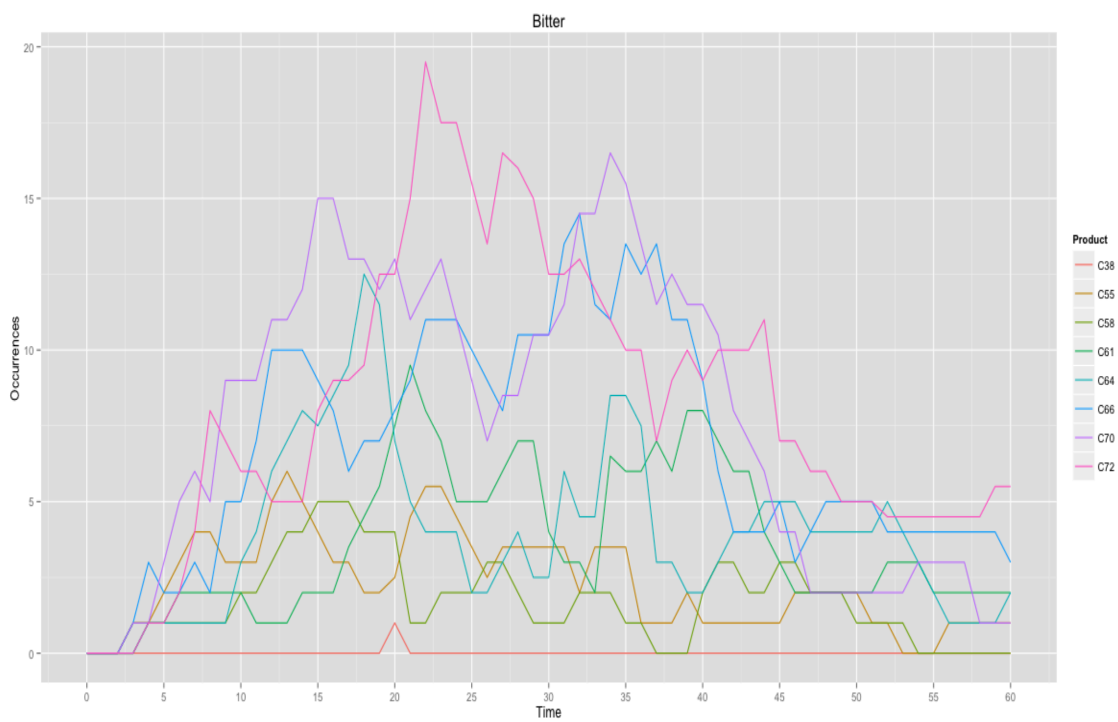


Figure 52. Trained Panel Raw TDS Curves. Bitterness of all samples

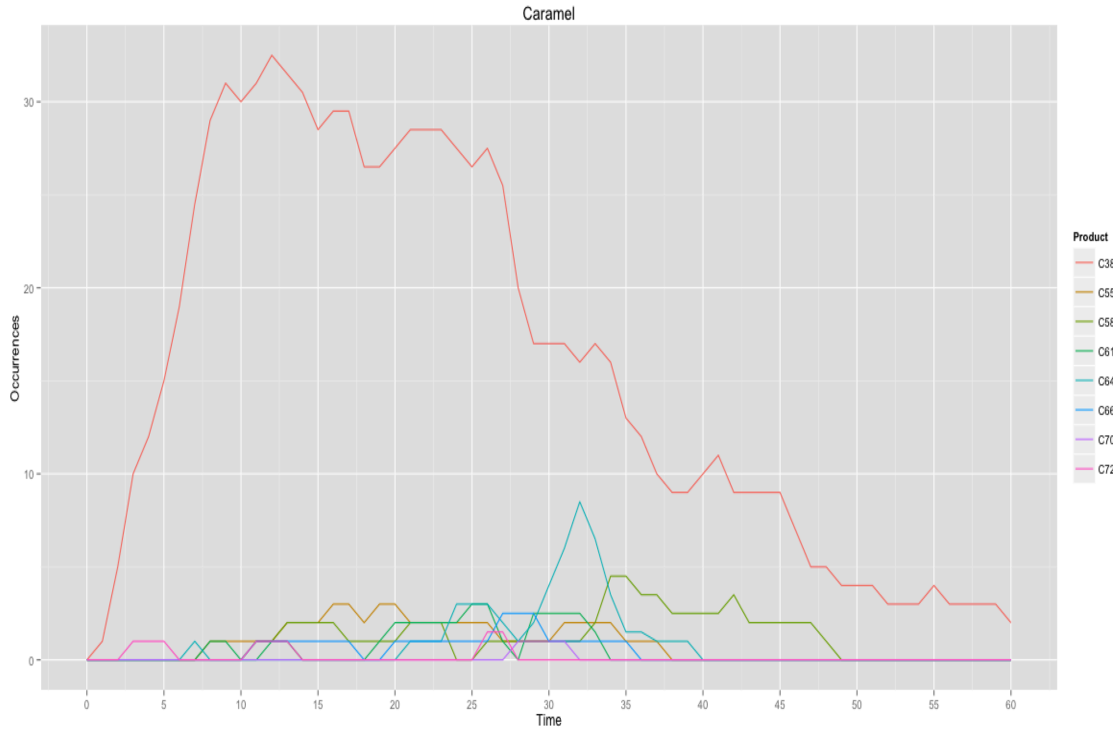


Figure 53. Trained Panel Raw TDS Curves. Caramel flavor of all samples

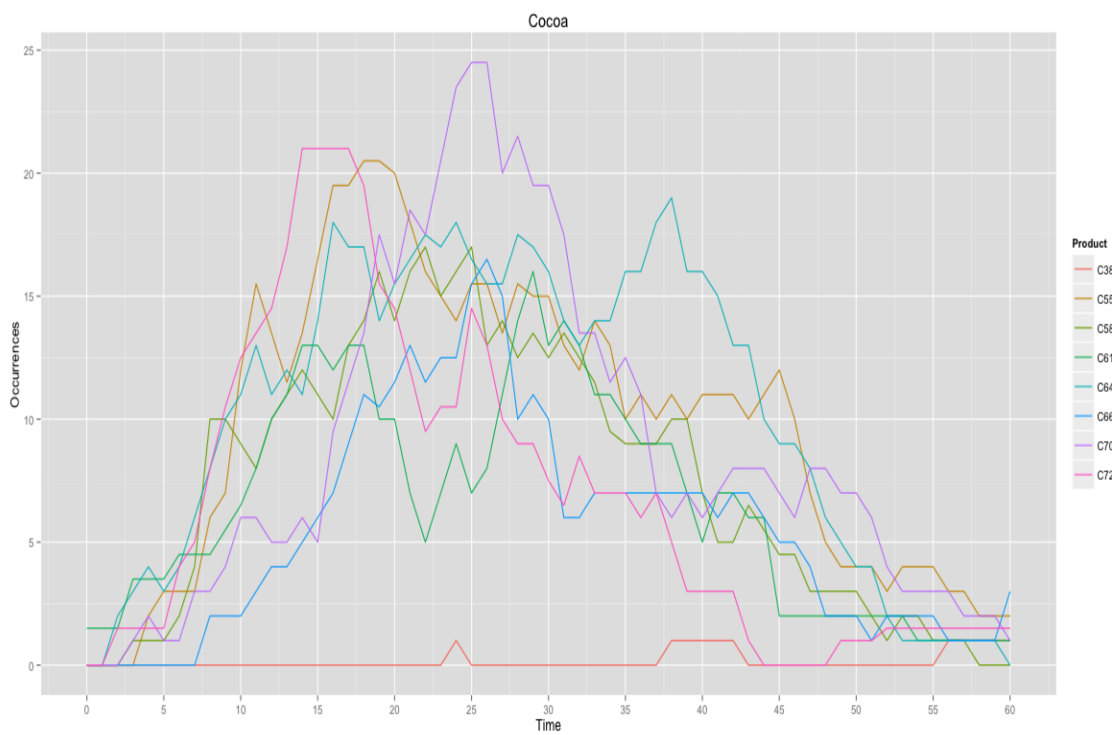


Figure 54. Trained Panel Raw TDS Curves. Cocoa flavor of all samples

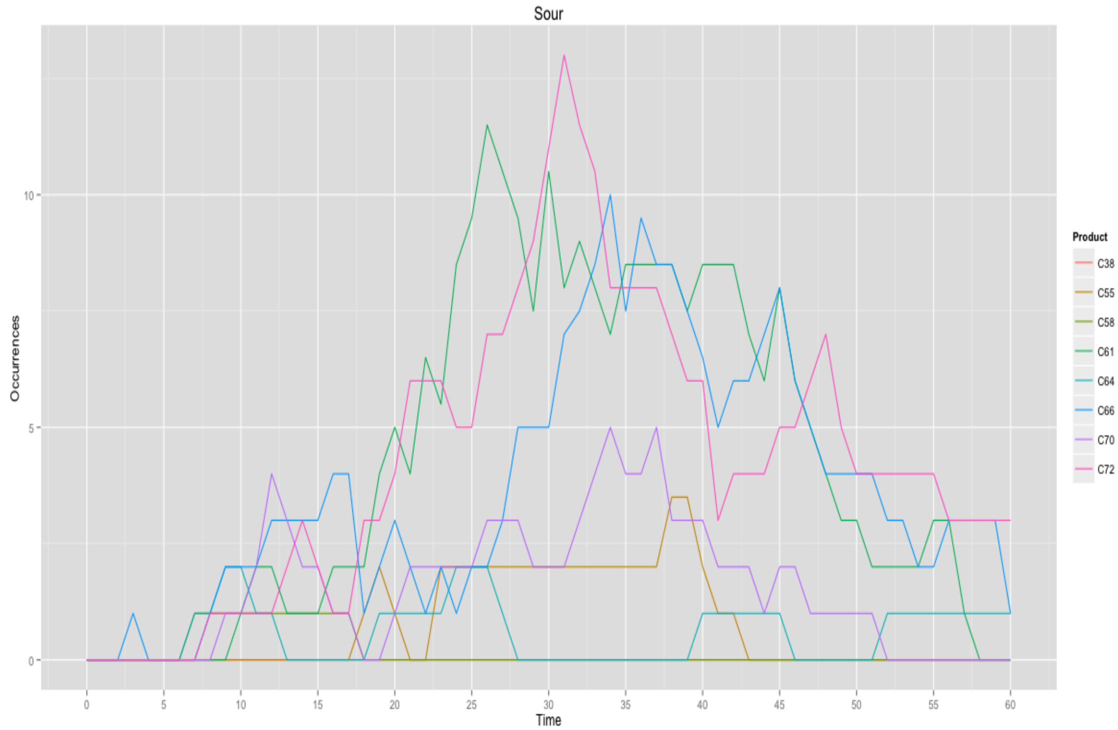


Figure 55. Trained Panel Raw TDS Curves. Sourness of all samples

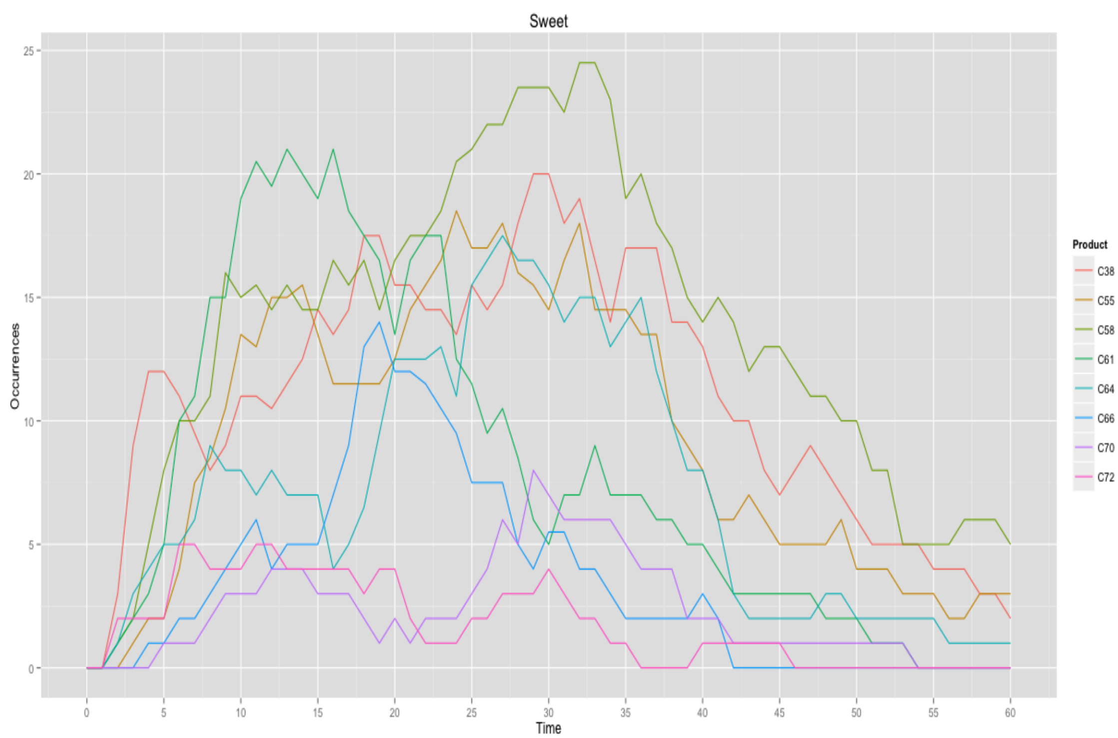


Figure 56. Trained Panel Raw TDS Curves. Sweetness of all samples

Raw TDS Graphs, Untrained Consumers

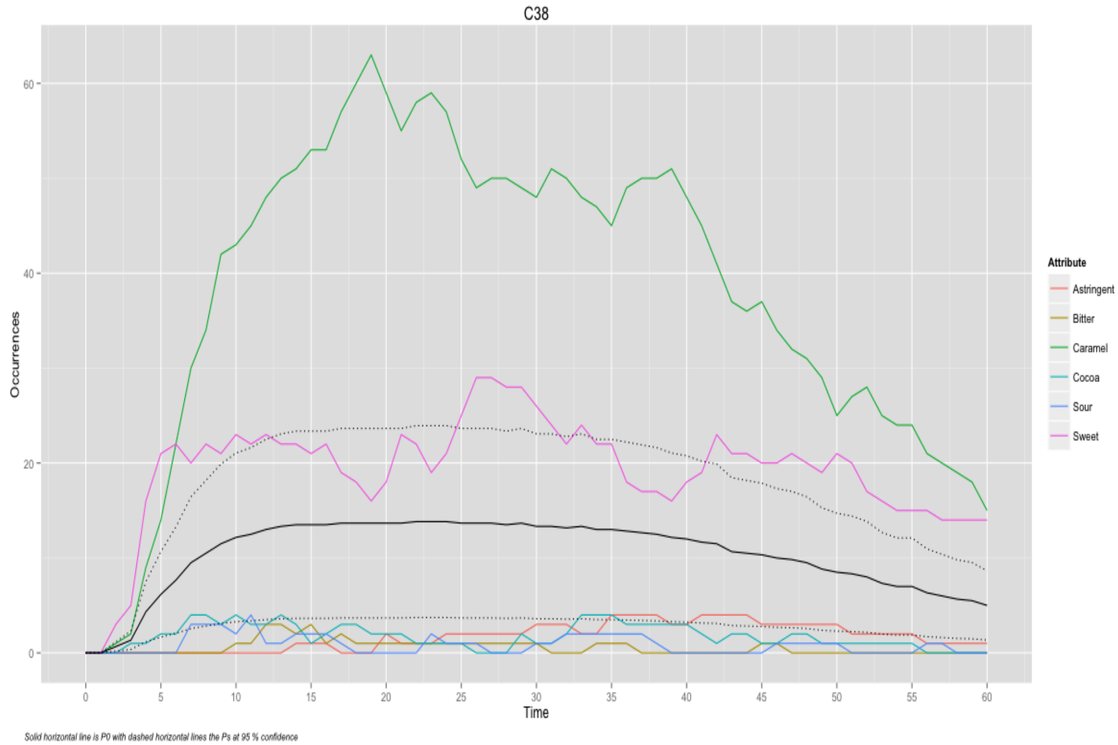


Figure 57. Untrained Consumer Raw TDS Curves. Sample 38

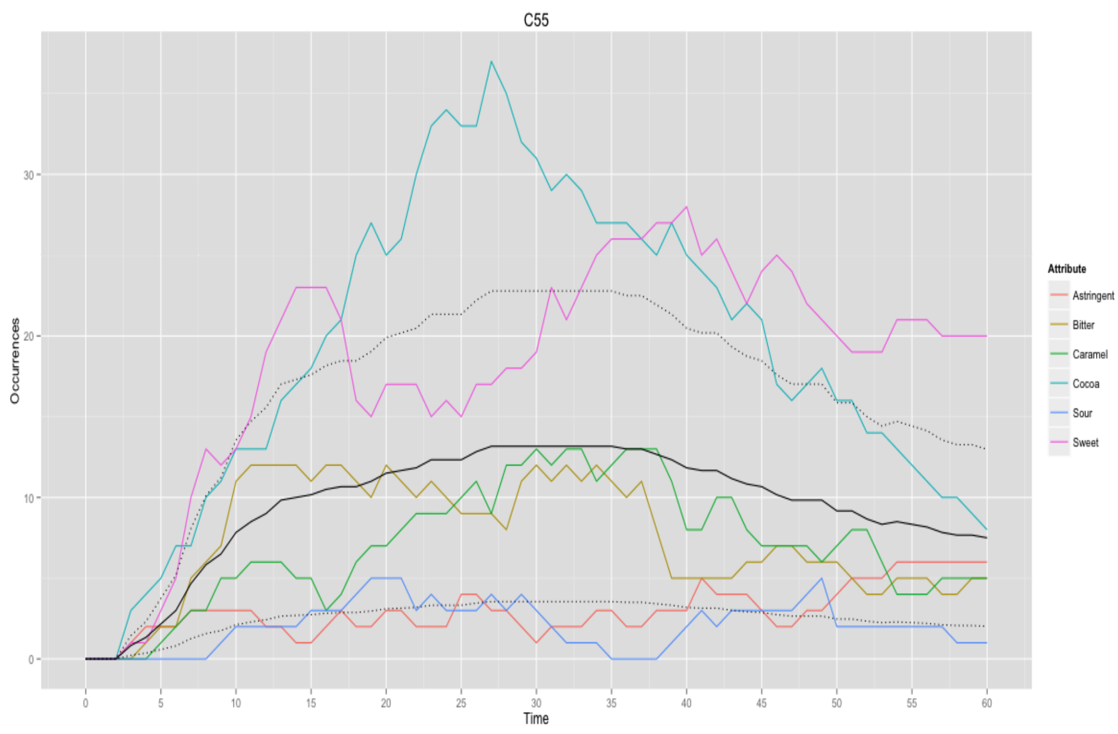


Figure 58. Untrained Consumer Raw TDS Curves. Sample 55

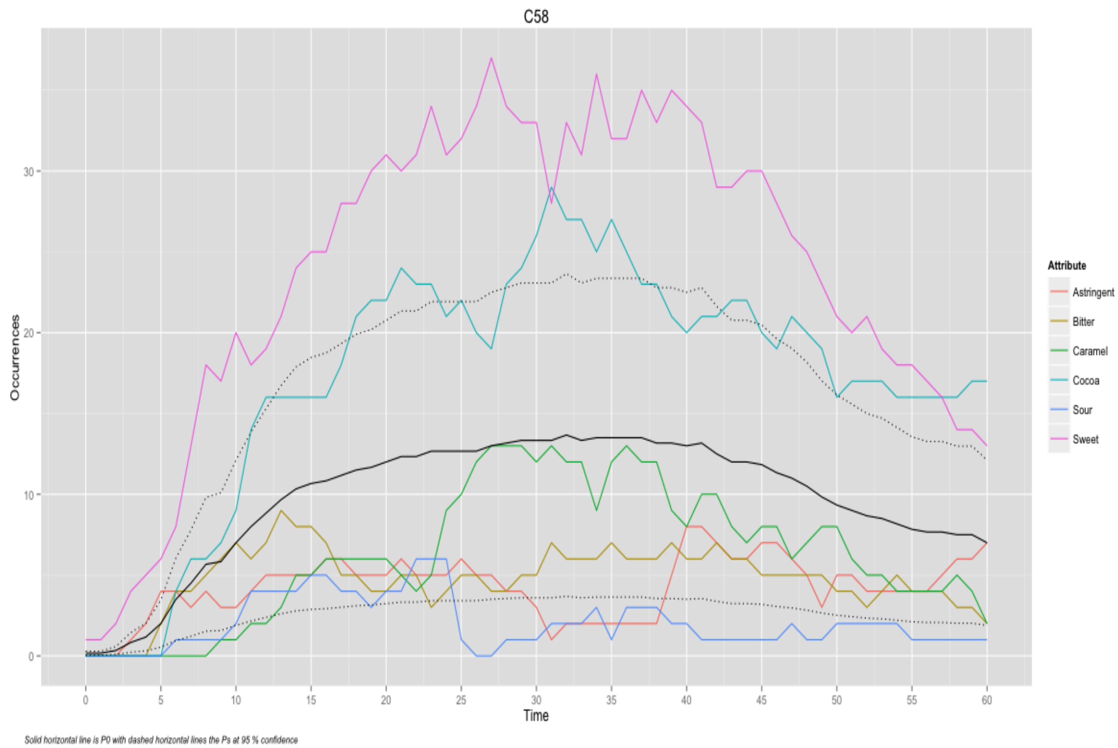


Figure 59. Untrained Consumer Raw TDS Curves. Sample 58

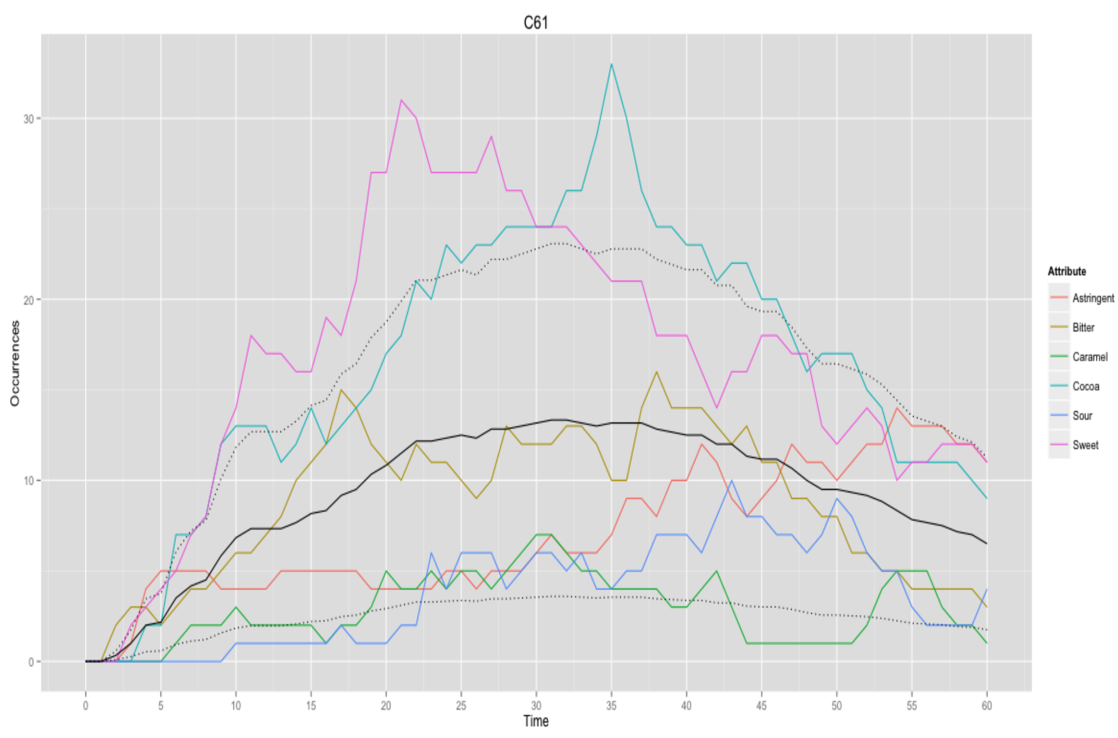


Figure 60. Untrained Consumer Raw TDS Curves. Sample 61

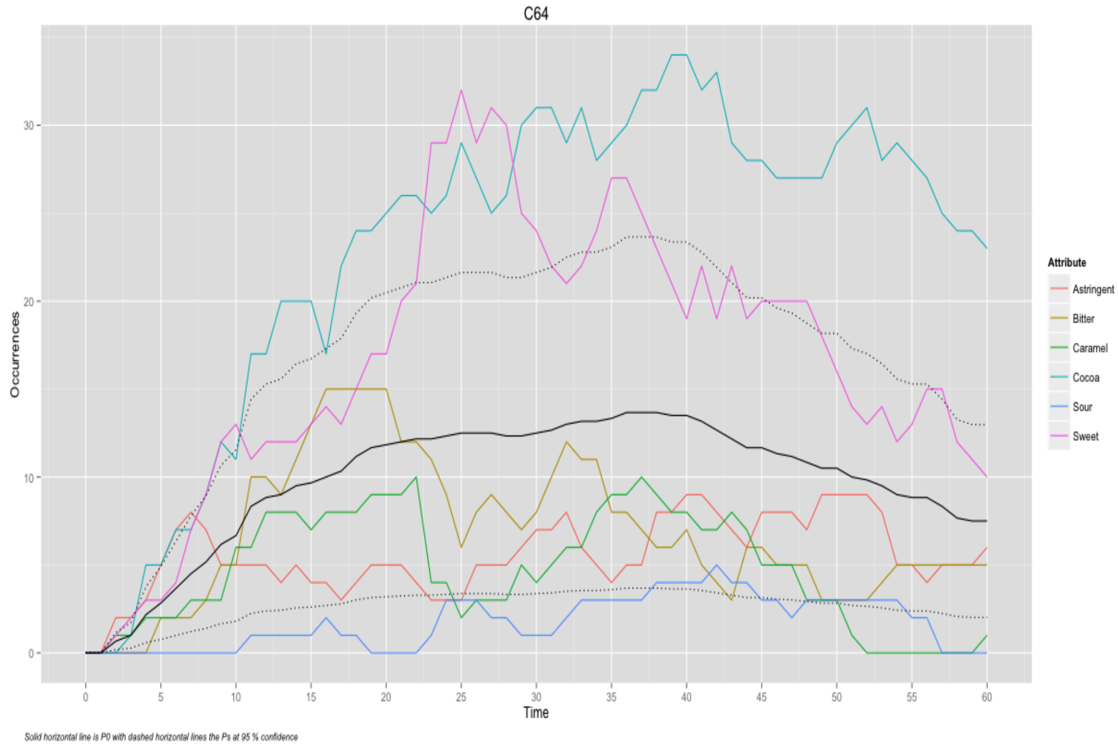


Figure 61. Untrained Consumer Raw TDS Curves. Sample 64

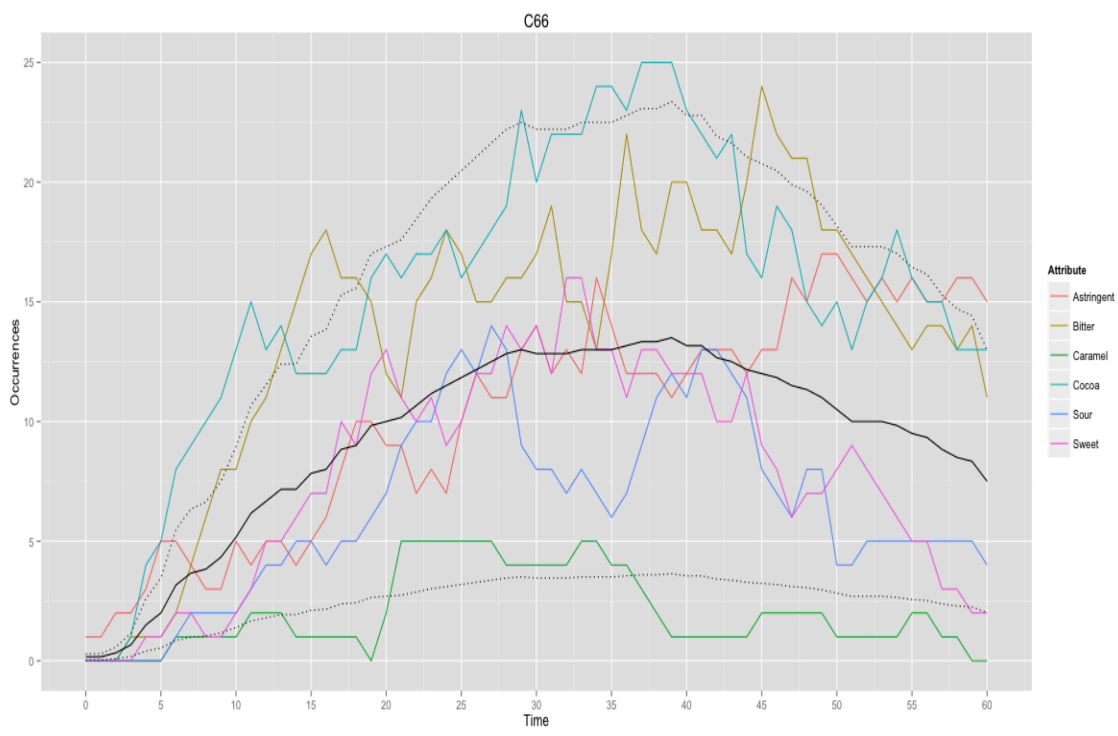


Figure 62. Untrained Consumer Raw TDS Curves. Sample 66

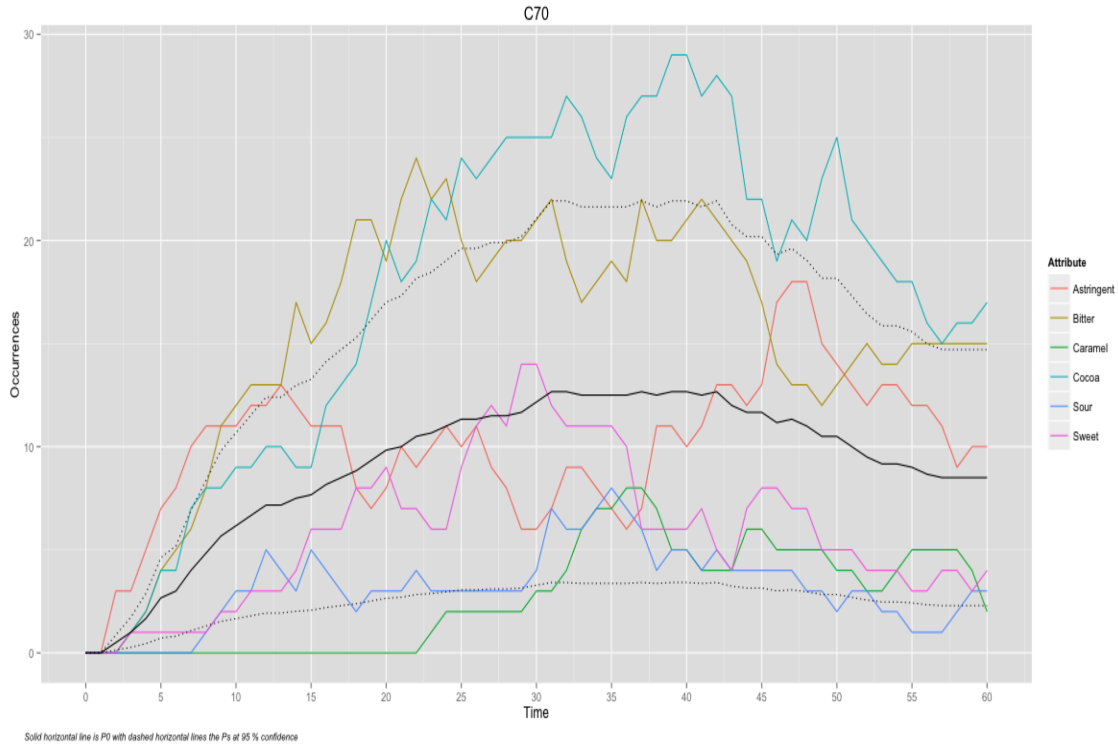


Figure 63. Untrained Consumer Raw TDS Curves. Sample 70

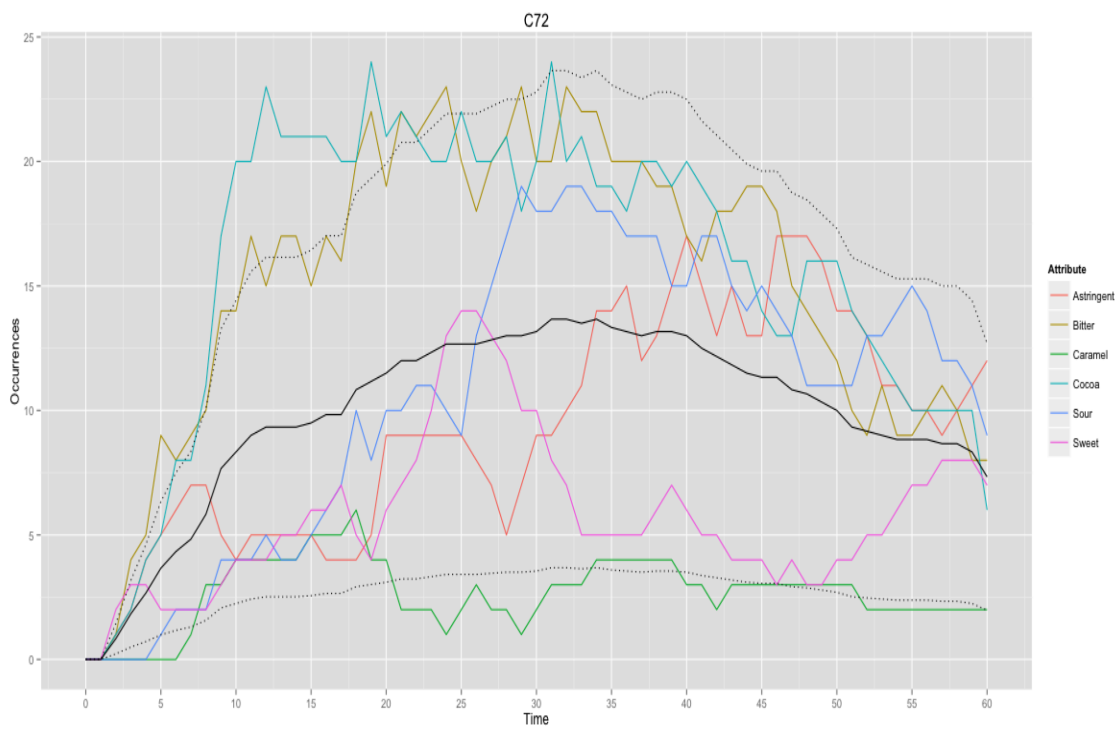


Figure 64. Untrained Consumer Raw TDS Curves. Sample 72

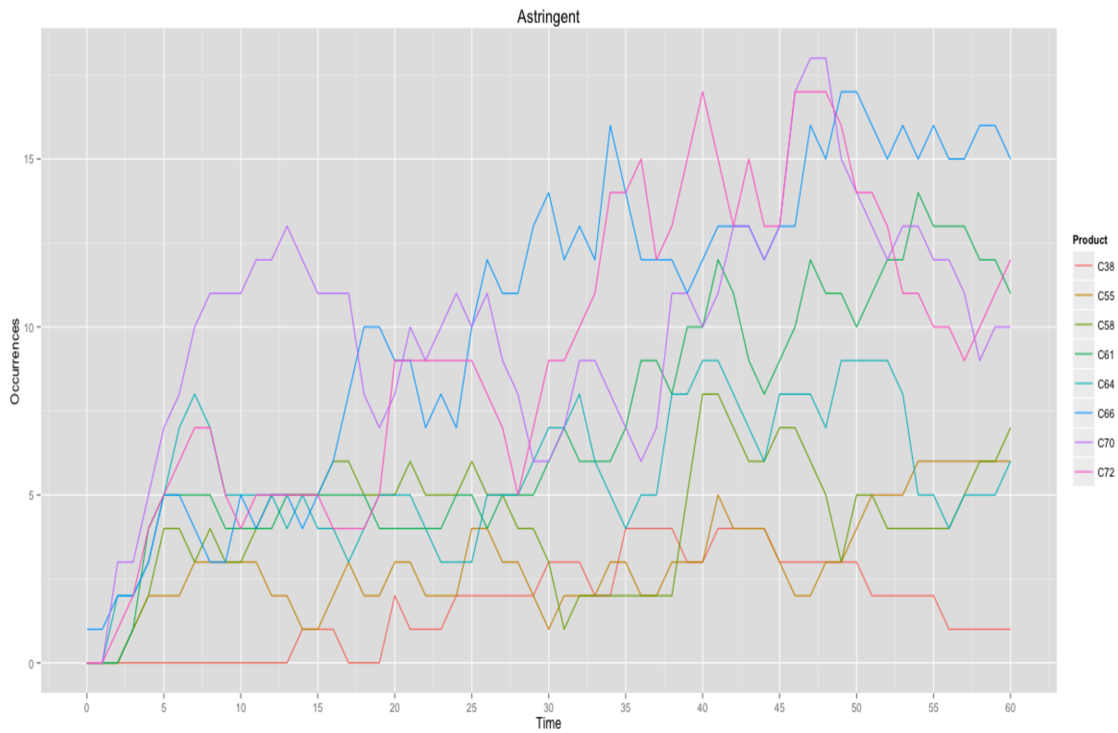


Figure 65. Untrained Consumer Raw TDS Curves. Astringency of all samples

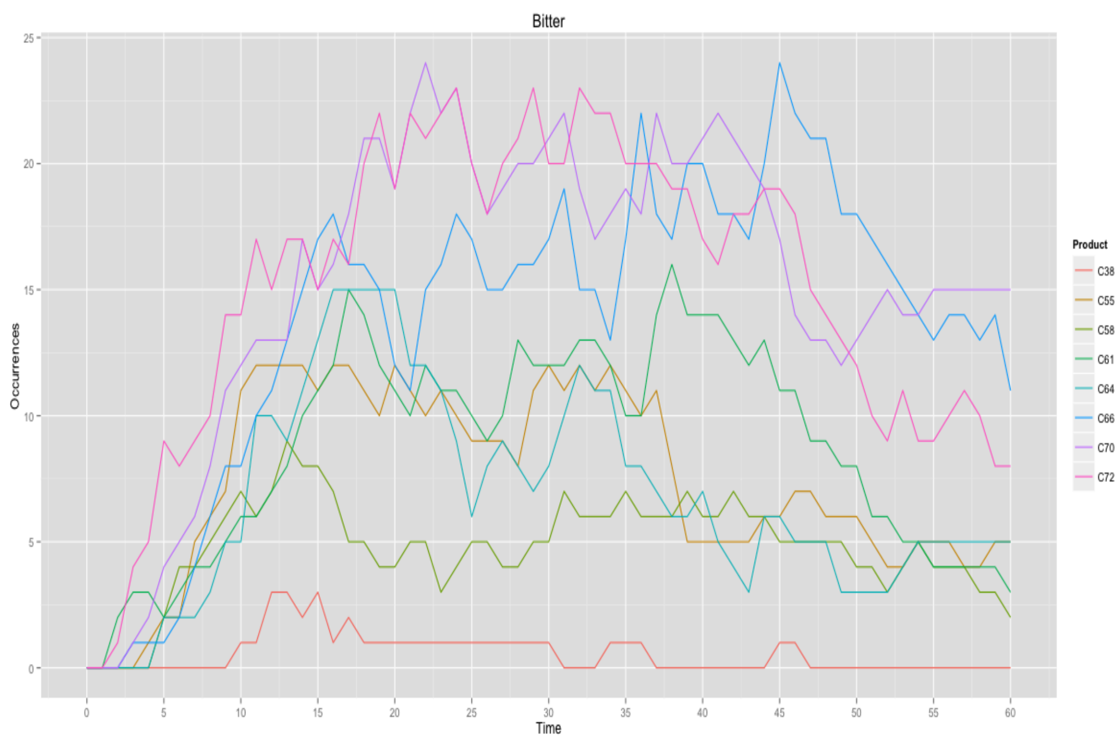


Figure 66. Untrained Consumer Raw TDS Curves. Bitterness of all samples

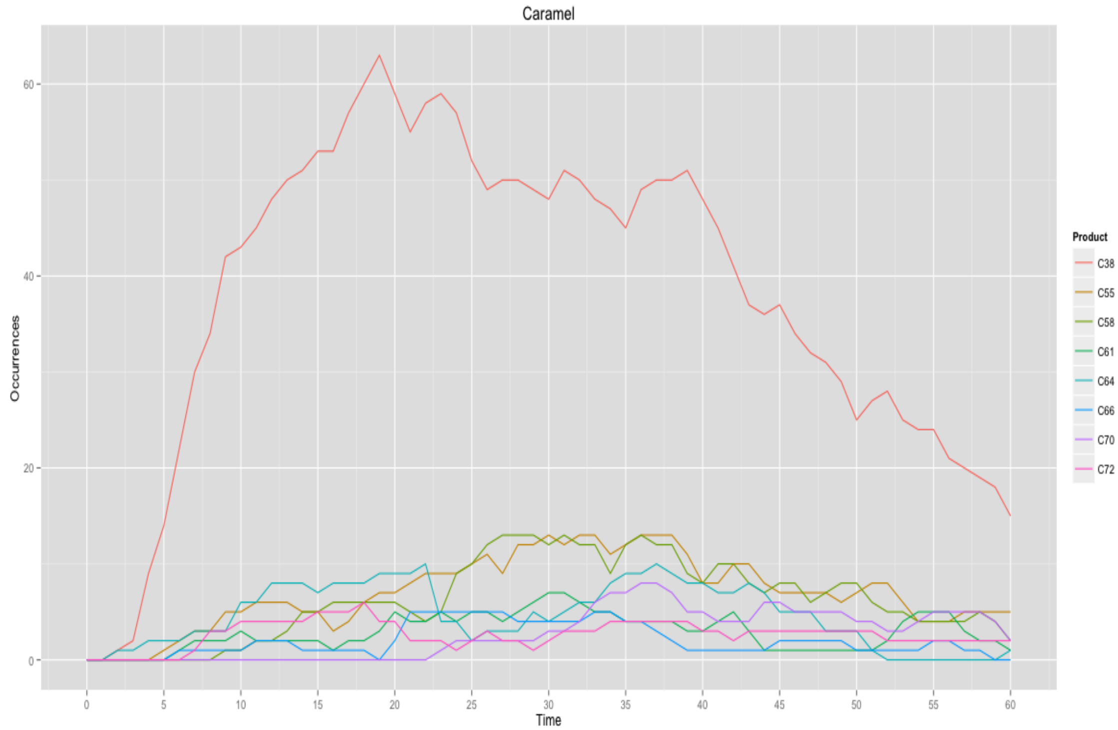


Figure 67. Untrained Consumer Raw TDS Curves. Caramel flavor of all samples

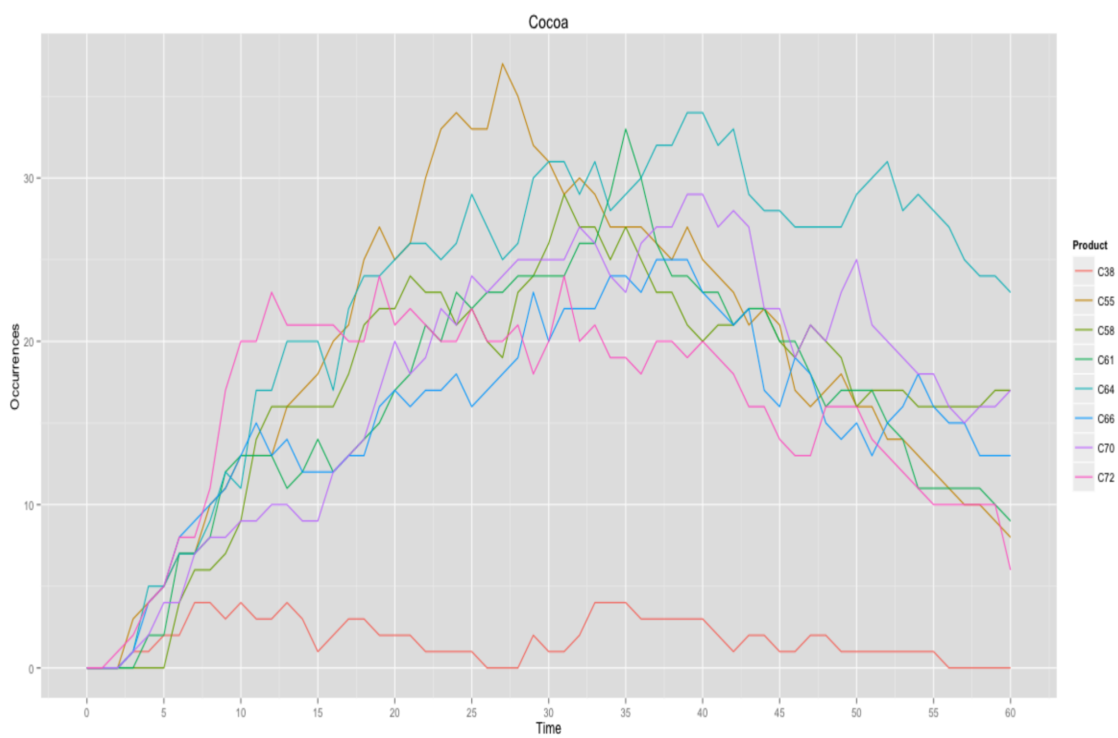


Figure 68. Untrained Consumer Raw TDS Curves. Cocoa flavor of all samples

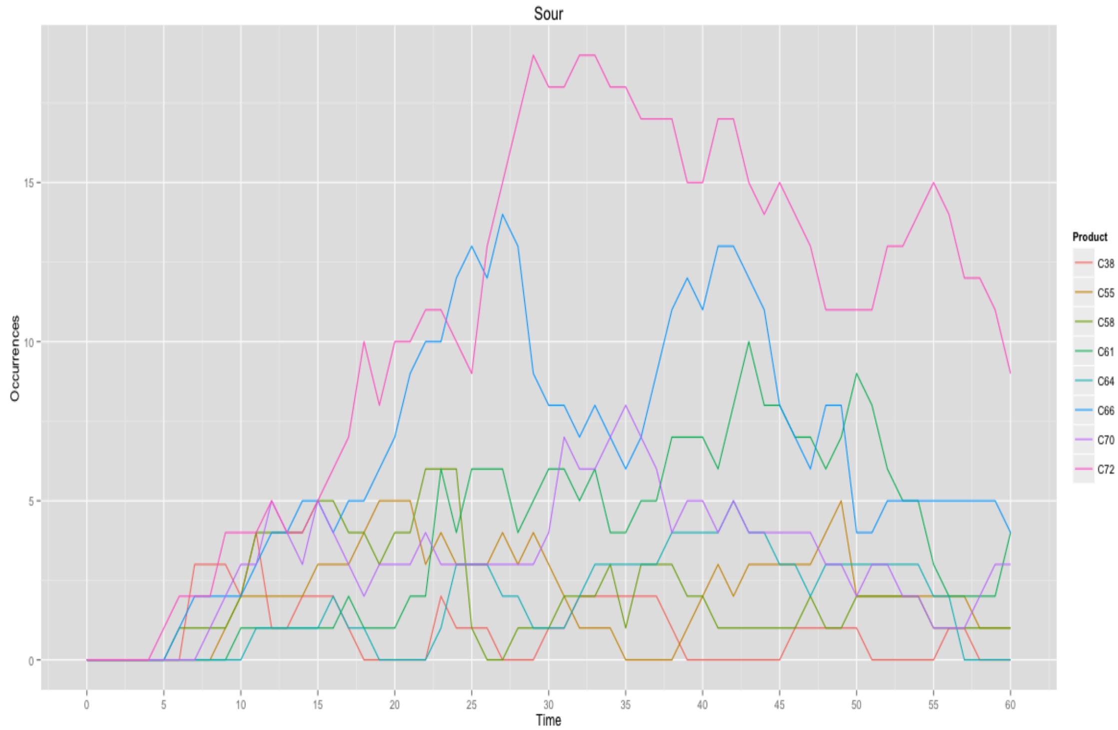


Figure 69. Untrained Consumer Raw TDS Curves. Sourness of all samples

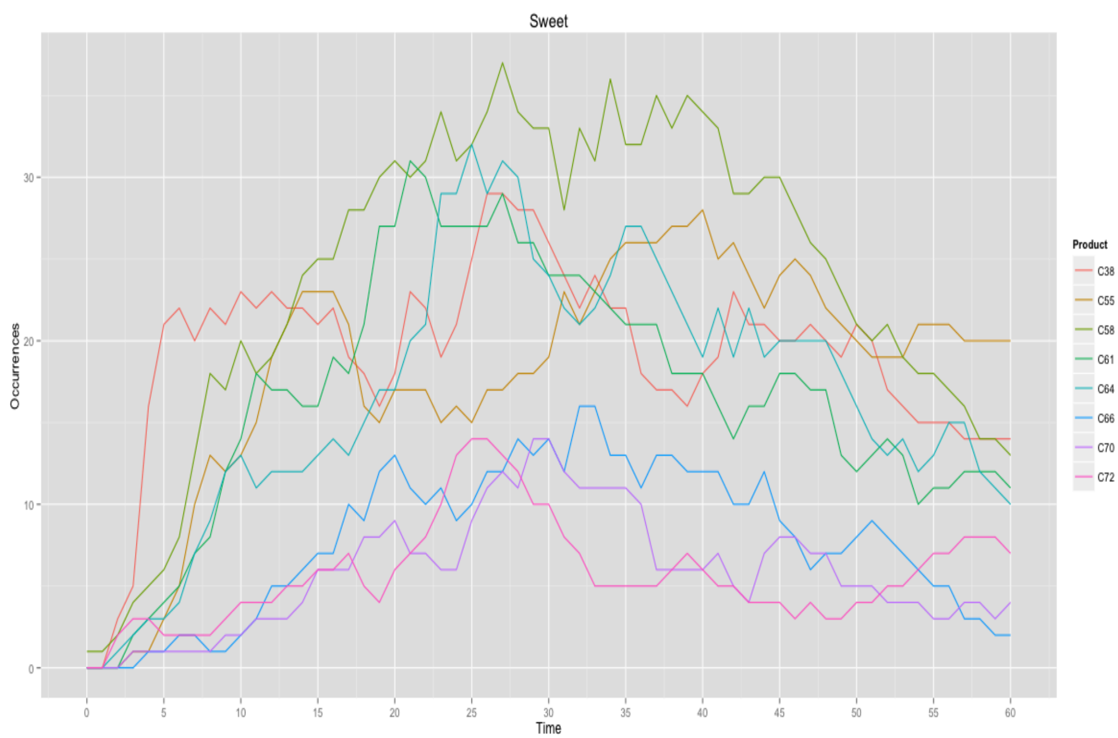


Figure 70. Untrained Consumer Raw TDS Curves. Sweetness of all samples