Brand Analytics

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Who is this book for?

This guide introduces five key analysis frameworks:

1. Competitive Market Structure Analysis

2. Acquisition Funnel Audit

3. Profiling the Core Consumer

4. Performance-Importance Analysis

5. Basic Brand Vulnerability Matrix

These frameworks help guide strategy development for brands.

In this book we outline a structured approach to understanding a market with a view to aiding the brand planning process, using data that is commonly available from existing survey research, be it continuous, dipstick, or even periodic "Usage and Attitude" (U&A) studies. If such data is not available, it is (these days) relatively inexpensive and time-efficient to get it. We offer these frameworks in the hope that it makes the task of adding value to data easier.

While the process in commercial practice will be more complicated, we've boiled it down into five frameworks:

1. Competitive Market Structure Analysis
2. Acquisition Funnel Audit
3. Profiling the Core Consumer
4. Performance-Importance Analysis
5. Basic Brand Vulnerability Matrix

In terms of what to do when, they are in a broadly sensible order, although it can make sense to do the Basic Brand Vulnerability Matrix immediately after the Acquisition Funnel Audit.

We'll expand on the framework by providing an example of each element in action.

Analysis framework	Tools	Decisions
Competitive Market Structure Analysis	• Switching matrices • Brand attribute grids • Driver analysis • Market Maps with share and dynamics	• Which competitors should we focus on? • What should we say to the market?
Acquisition Funnel Audit	• Performance at different stages of the acquisition funnel • Conversion alations • Breadth versus depth scatterplots	• What goals should we set for our marketing efforts?
Profiling the Core Consumer	• CART • Volumetric analysis	• Who must we sell to?
Importance-Performance Analysis	• Competitive performance in different aspects of the consumption context • Quad maps • Conjoint	• Which aspects of the consumption or purchasing context should we improve?

| Basic Brand Vulnerability Matrix	• Gap analysis • Crosstabs • Significance testing	• How do we support or close gaps between attitude and behavior?

Competitive Market Structure Analysis

Competitive Market Structure Analysis involves overlaying four key pieces of information:

- Who competes with who

- The basis of the competition

- The size of the brands

- The dynamics of the market

Ideally, this is summarized as a single *market map*.

Case study

This case study uses real data but is disguised for reasons of client confidentiality. The map below shows the competitive market structure for the burger market, and the client we are advising is **BURGER CHEF**.

Normalization: Row principal (scaled). Focus: BURGER CHEF
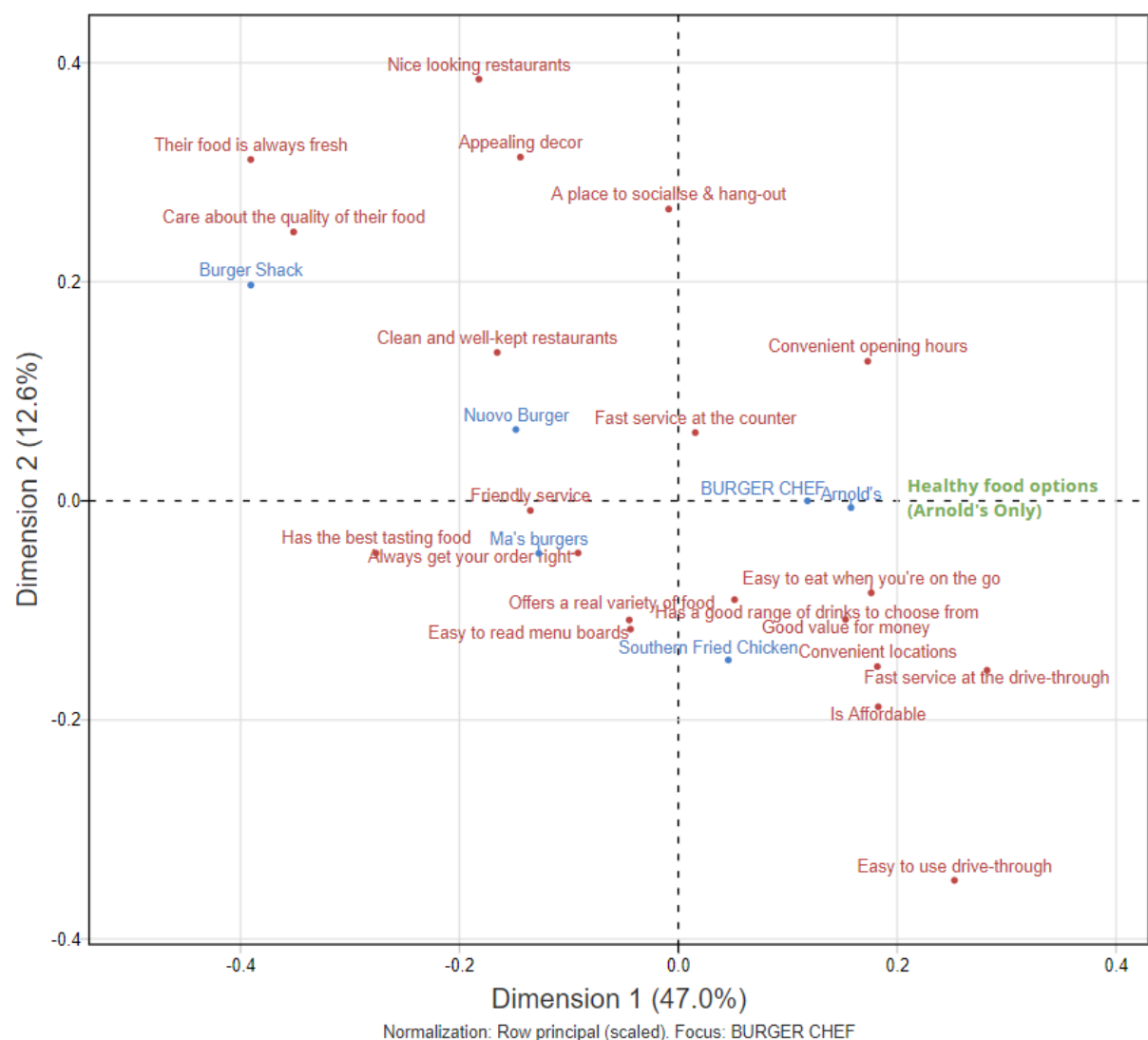
At first glance, the map gives some useful descriptive information:

- Burger Chef competes directly with Arnold's, and then roughly equally with Ma's Burgers, Nuovo Burger, and Southern Fried Chicken.
- The competition with Arnold's and Southern Fried Chicken is in the convenience and value territory.
- Arnold's is uniquely differentiated on the health attribute (this is described in more detail later in this chapter).
- Southern Fried Chicken is more differentiated in terms of variety.
- Ma's burgers and Nuovo Burger, which we might call second-tier burger competitors, have some differentiation on great taste and food quality and freshness.
- While Ma's and Nuovo are as similar to Burger Chef as Southern Fried Chicken, due to Southern Fried Chicken competing on the same core attributes as Burger Chef, in practice it is a more important competitor. Its greater size (see below) also supports this conclusion.
- Burger Shack is very strongly differentiated towards great taste and food quality (so let's call them a third-tier competitor)
- Differentiation in the market operates in two dimensions: there is a quality-versus-convenience dimension, running from the top-left to bottom-right. There is the health dimension, which only Arnold's is competing strongly in.

The question that often arises from the end users of such maps is: what do I do now? By adding more information to the map and the underlying data table, we can get closer to answering this question.

In the map on the next page we have added a bit more about market structure:

1. Bubble size (area) is proportional to market share.
2. Bubble coloring shows dynamics (change in market share by year): the bluer, the greater the growth; the more red, the greater the decline.
3. Text summarizes the groupings of the attributes, making it clearer to see the different competitive territories that the brands compete in: Convenience and Value, Variety, Taste, Food quality, and Restaurant quality.

We can now see Arnold's is the dominant market leader, presumably via its store locations and speed of service (without more information we might assume it has the highest number of distribution points).

BURGER CHEF has done well attracting share over the last 12 months, presumably from its most direct competitors, and possibly via a stronger value or variety. It will be hard to attack Arnold's quickly, given the level of investment required (to build stores, and a "service engine" to run them), but Burger Chef might have more short-term success taking on Southern Fried Chicken, by developing its chicken burger portfolio.

Normalization: Row principal (scaled). Focus: BURGER CHEF
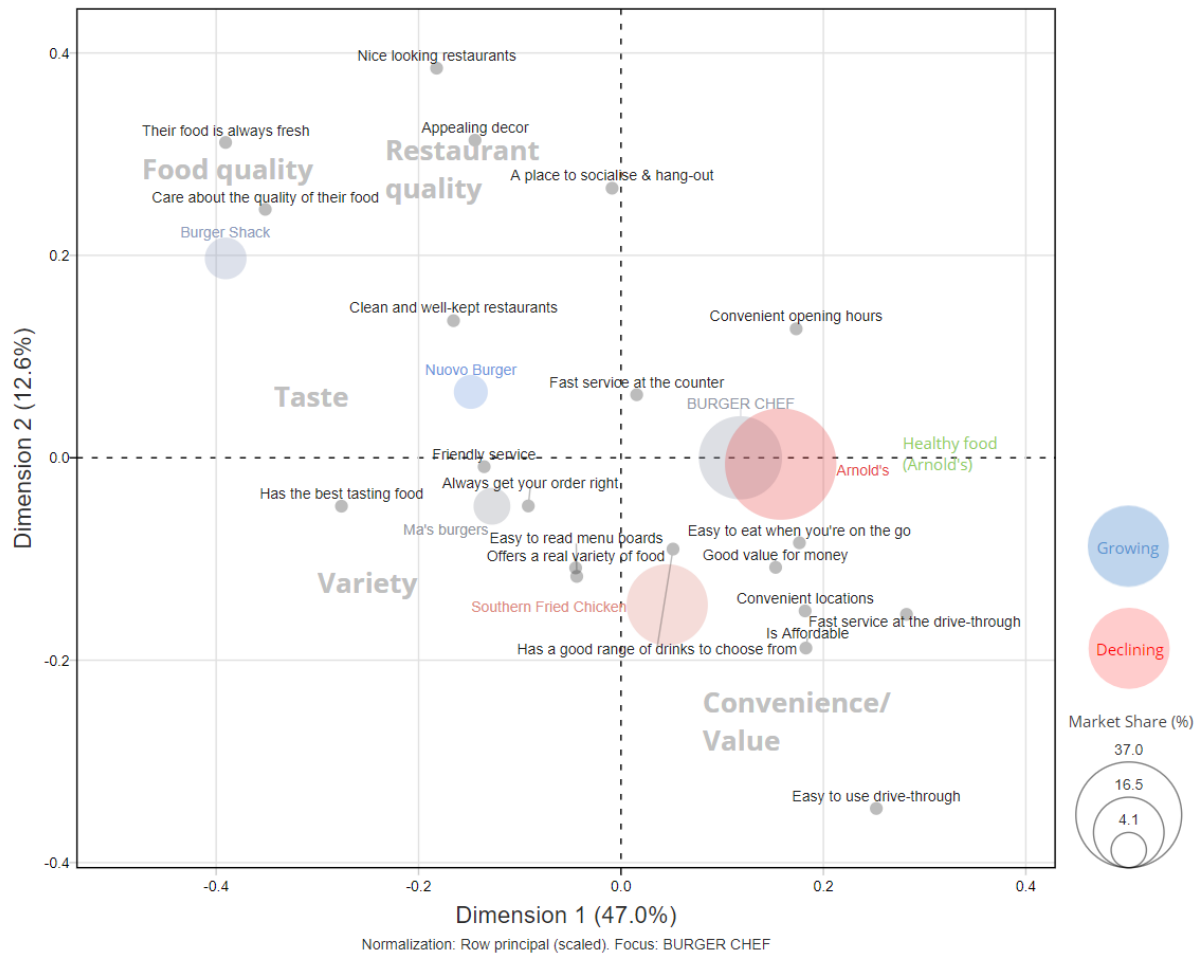
Note also that the Burger Shack and particularly Nuovo Burger are growing. These might be newer players, placing more emphasis on the dining experience or food taste and quality. If share is leaking from the established brands to these players, it could pose a threat to Burger Chef.

While visualizations like the one above are great for summarizing the overall market and are valuable for communicating with all the stakeholders, it is often a good idea to go a bit "old school" and do some cutting and pasting in Excel to create a more detailed review of the competitive structure. Rather than just create a standard crosstab, we instead work quite hard to structure it so that it reflects all our newly acquired knowledge. Within each tier, the columns are deliberately arranged left-to-right based on share ranking; the rows are generally ranked via the market leader's strongest score within each of the seven dimensions. The font colors are the results of significance tests that compare each value to a computed value based on double jeopardy (defined in the next chapter), showing results that are significantly higher (blue) or lower (red) results than what we might expect (given sample size, other results, etc.).

%	TIER 1			TIER 2		TIER 3
	Arnold's	BURGER CHEF	Southern Fried Chicken	Nuovo Burger	Ma's burgers	Burger Shack
Market Share	41	23	22	4	4	6
Change in Market Share	-5	7	-3	26	3	13
CONVENIENCE						
Convenient locations	73	42	40	11	14	13
Convenient opening hours	79	43	29	10	14	18
Easy to use drive-through	66	39	39	9	16	5
Fast service at the drive-through	63	33	27	7	13	4
Easy to eat when you're on the go	57	42	26	12	22	12
Fast service at the counter	48	30	22	12	17	19
VALUE						
Is Affordable	46	30	24	8	15	8
Good value for money	35	24	18	7	12	8
VARIETY						
Has a good range of drinks to choose from	50	41	29	17	25	19
Offers a real variety of food	40	23	21	13	20	15
FOOD QUALITY						
Their food is always fresh	17	14	11	8	14	24
Care about the quality of their food	25	18	15	13	19	30
TASTE						
Has the best tasting food	22	24	27	15	19	31
SERVICE						
Always get your order right	33	29	25	13	19	23
Friendly service	47	32	31	16	24	31
Easy to read menu boards	49	37	35	16	24	26
RESTAURANT QUALITY						
Clean and well-kept restaurants	44	32	25	18	24	33
Appealing decor	30	31	18	15	15	30
A place to socialise & hang-out	37	25	14	11	12	18
Nice looking restaurants	24	22	12	13	11	24
HEALTH						
Has healthy food options	34	24	8	3	9	8

The cell shading has been added manually by us to link to the comments below.

- It looks like the dominance of Arnold's is a function of advantages in access and speed. If the core Burger Chef proposition is deemed to be sound (which we explore below), it may be worth seeking to increase distribution and seek to match or better the leader on speed, in order to take share.
- While Arnold's is winning in terms of health against the other burger brands, the color-coding is relative to the total market, and Arnold's is not overall perceived as being healthy at all (the raw number looks high, but this is inflated due to double jeopardy).

- The top tier brands are battling for ownership of the value dimension, and this is a relative strength for Burger Chef. Some short-term effort or focus would be required here to defend the position.
- The emergent Tier 2 competitors are attacking Burger Chef on variety, a relative strength. Again, some short-term effort or focus is required here.
- Burger Shack is clearly growing via high ground position in food and restaurant quality. This may only ever be a niche position, so may not be worth chasing via what would be a significant investment (something to keep an eye on perhaps).
- The Tier 2 competitors appear to be growing via a focus on food quality and taste. This might reflect an emergent category trend (i.e., it's no longer just about *fast* food), so Burger Chef should at least consider a longer-term play in this space, to nullify the competitive threat.
- So, by adding additional information and structure to simple data, we are getting closer to being able to advise Burger Chef as to where to from here. We will revisit this as we build on the story below.

Identifying potential competitors

In the case study, we focused on five burger brands and a chicken brand. Sometimes it's not so obvious who the key competitors are, and the first step in competitive market analysis is to identify the potential competitors to show on the market map. Peet's coffee, for example, has many levels of competition, as shown in the table below.[1]

The rest of this section describes how to use data to work out who the key competitors are.

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[1] This table was inspired by Donald R. Lehmann and Russell S Winer (Author) (2007), *Analysis for Marketing Planning*, 7th Edition, McGraw-Hill.

Type of competitor	Examples for Peet's Coffee
Specialty coffee shops	Caribou Coffee, Starbucks, Seattle's Best, Millstone, Illy Caffé
Chains selling coffee	Dunkin' Donuts, Krispy Kreme, McDonald's
Grocery coffee brands	Folger's, Green Mountain Coffee, Maxwell House, Nespresso
Beverages	Colas, Energy drinks, Other Sodas, Juice, Water, Tea
Snacks	Gum, Candy, Ice cream, Cookies,
Budget competitors	Netflix, Magazines, iTunes

Step 1: Create a "square" table showing the competitive relationship

A "square" table is a table that contains the same brands in the rows and columns. They are particularly useful for understanding the nature of competition. The ideal square table shows within-occasion brand switching. That is, it shows which brand people switched from and to, where it is known that the switching was for the same occasion. In practice, such data is hard to obtain, so we usually make do with one of the following.

Brand switching matrixes A brand switching matrix shows which brand was purchased at one point of time in the rows, and which was purchased at a subsequent point of time in the columns. The table to the right shows the top-left section of a brand switching matrix from the car market.[2] It shows that 240

	⇕ BMW ▼	⇕ Citroen ▼	⇕ Fiat ▼	⇕ Ford ▼	⇕ GM ▼
BMW	240	2	2	32	18
Citroen	2	226	13	28	22
Fiat	7	30	461	92	51
Ford	63	107	64	4216	629
GM	30	77	32	670	2013

[2] Colombo, Richard, Andrew Ehrenberg, and Darius Sabavala (1993), "The Car Challenge: Diversity in Analyzing Brand Switching Tables," Working Paper.

people who owned a BMW replaced it with a new BMW, 2 switched from a BMW to a Citroen, etc. When using such a table for competitive structure analysis, it is important that the table shows either counts or Total % (i.e., not Row % or Column %).

Common ways of creating such a matrix include:

- Using scanner panel data (e.g., from ACNielsen, IRI, Numerator).
- Using a survey to ask people about their two most recent purchases.
- Using a survey to ask people what they would purchase if their favorite brand wasn't available. An advantage of such *product deletion* questions overlooking historical switching behavior is that historical switching data can be infected due to changes in the buying situation. For example, if you look at the breakfast cereal market, my purchase this week may be for Cheerios for myself, by my previous purchase may have been muesli for my kids.
- Using conjoint analysis and seeing which alternatives a brand's competitors switch to when its price is increased.

Cross-price elasticity matrixes An output of market mix modeling is a square matrix showing the *cross-price elasticities* (i.e., the relative increase in sales or share that a brand will get if a competitor increases its price). From a purely theoretical perspective, this is the ideal data to use for understanding market structure. In practice, however, the estimates from such models tend to be highly unreliable, and brand switching data is typically preferable.

Brand duplication matrixes A *brand duplication matrix* shows the percentage of buyers of one brand who also buy another brand. The table to the right shows a section of a brand duplication matrix obtained from a question asking which fast food brands people said they had consumed in the previous month. The way we read this is that 12% of people had consumed Burger Shack, 6% had consumed Burger Shack and also Burger Chef, etc.

Total %	Burger Shack	Burger Chef	Nuovo Burger	Lucky's Pizza
Burger Shack	12%	6%	2%	4%
Burger Chef	6%	39%	4%	15%
Nuovo Burger	2%	4%	7%	3%
Lucky's Pizza	4%	15%	3%	30%

When using such a table for Competitive Market Structure Analysis, it is important that the table shows either counts or Total % (i.e., not Row % or Column %).[3]

The duplication matrix tends to be the easiest square table to obtain, but it is also generally the least reliable, as the behaviors that are exhibited in the table will tend to show a mix of brand switching, occasion switching, variety seeking, and purchasing for multiple buyers (e.g., children and adult's breakfast cereals).

Brand similarity and sorting matrices
Another form of data that can be used to form square tables is data about the perceived similarity of brands. This is most commonly obtained by getting consumers to performing sorting tasks, where they place similar bands into groups, with the matrices then being formed to summarize this data (e.g., showing the percentage of people who put the two brands in the same group).

Our experience is that this data is often unhelpful, as consumers tend to use simple rational criteria when forming sorting (e.g., proximity in the supermarket, similarity of ingredients). Directly asking about forced substitution is, in our experience, preferable.

Step 2: Remove the non-brand information from the table

Commonly square tables have options like None of These, Other, and Don't Know in the rows or columns. Remove these categories prior to performing any analyses, as otherwise, the analyses focus on comparing these categories to the brands, which is not so informative.

Step 3: Analyzing the square table

A variety of techniques have been developed for analyzing square matrices, including a special variant of correspondence analysis[4], log-linear trees[5], latent class analysis, hierarchical cluster

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[3] More specifically, you need Total % for the analyses described below to be valid. However, the table showing column % can be useful for analysis when eye-balling the data. See Andrew C. Ehrenberg (1988): *Repeat-buying: facts, theory and applications*, 2nd edition, Edward Arnold, London; Oxford University Press, New York.

[4] Michael Greenacre (2000): "Correspondence analysis of square asymmetric matrices", *Journal of the Royal Statistical Society Series C Applied Statistics* 49(3):297-310.

[5] Thomas P. Novak (1993): "Log-Linear Trees: Models of Market Structure in Brand Switching Data", *Journal of Marketing Research,* August.

analysis, log-linear modeling, generalized nonindependence analysis,[6] and, for similarity data, multidimensional scaling. In our experience, the only one of these techniques that is easy to apply by busy non-technical people is correspondence analysis for square tables, so we restrict our discussion to this technique.[7]

The plot below shows the correspondence analysis of a square table produced by Q and Displayr's **Dimension Reduction > Correspondence Analysis of a Square Table.** The key thing that we learn from such an analysis is that most of the brands are in the middle, which is to say that they are not strongly differentiated based on switching behavior.

In the example shown below, the analysis is not particularly informative. There is a large clump of brands all on top of each other, including our brand of interest, Burger Chef. What's gone wrong? The problem relates to the data. The more differentiated brands are just the smaller brands (the table on the left shows consumption in the past month). People that are heavy category consumers tend to buy lots of the brands and are most likely to buy the bigger brands, hence the pattern. As mentioned in the previous section, it is common that analyzing repertoire data is not so insightful and some judgment is required (in this case, the marketing team were of the view that the key competitors were the other burger brands and Southern Fried Chicken, and so these brands are used in the next section).

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[6] Leo A. Goodman (1996): "A single general method for the analysis of cross-classified data: Reconciliation and synthesis of some methods of Pearson, Yule, and Fisher, and also some methods of correspondence analysis and association analysis," *Journal of the American Statistical Association,* Vol. 91.

[7] Our experience is that hierarchical cluster analysis is more widely applied in practice, but that that it is rarely applied correctly. In particular, when applied to brand repertoire/duplication data, it is common for people to inadvertently form segments of big brands rather than similar brands. Multidimensional scaling is easy to apply, but as already discussed, the brand similarity data on which it is based is often uninformative.

Correspondence analysis

	%
Arnold's	65% ↑
Mexican	52% ↑
Pret'a'pane	43% ↑
Southern Fried Chicken	43% ↑
Asian	41% ↑
Burger Chef	39% ↑
Lucky's Pizza	30%
Nero's Pizza	24% ↓
Pizza Heaven	13% ↓
Burger Shack	12% ↓
Ma's burgers	11% ↓
Nuovo Burger	7% ↓
Bread Basket	5% ↓

Q2 Eaten / bought last month SUMMARY
sample size = 4853; 95% confidence level
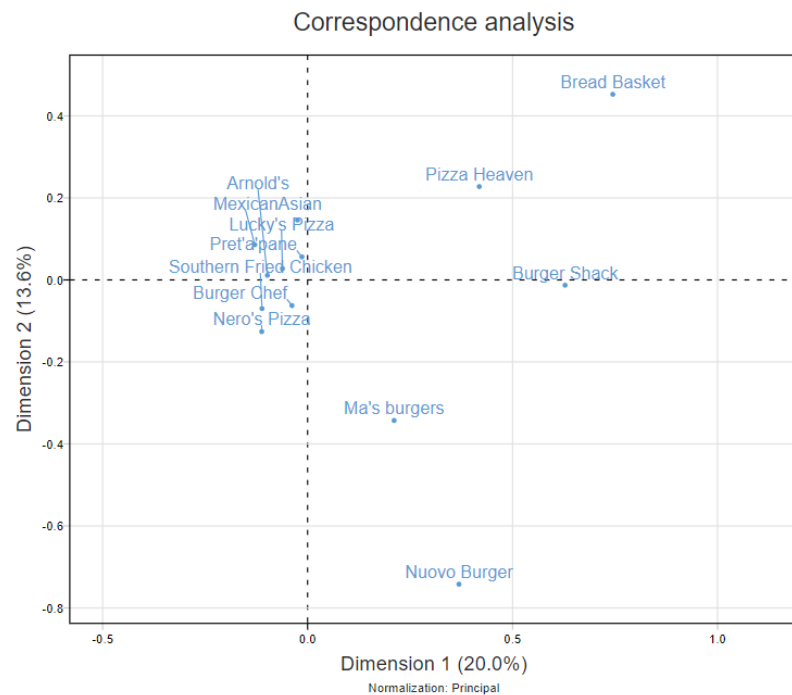
With better quality data you will typically get a more informative analysis, such as the one below, from the earlier car brand switching data. This visualization tells us that the key feature in the data is that Porsche is unique.

Correspondence analysis
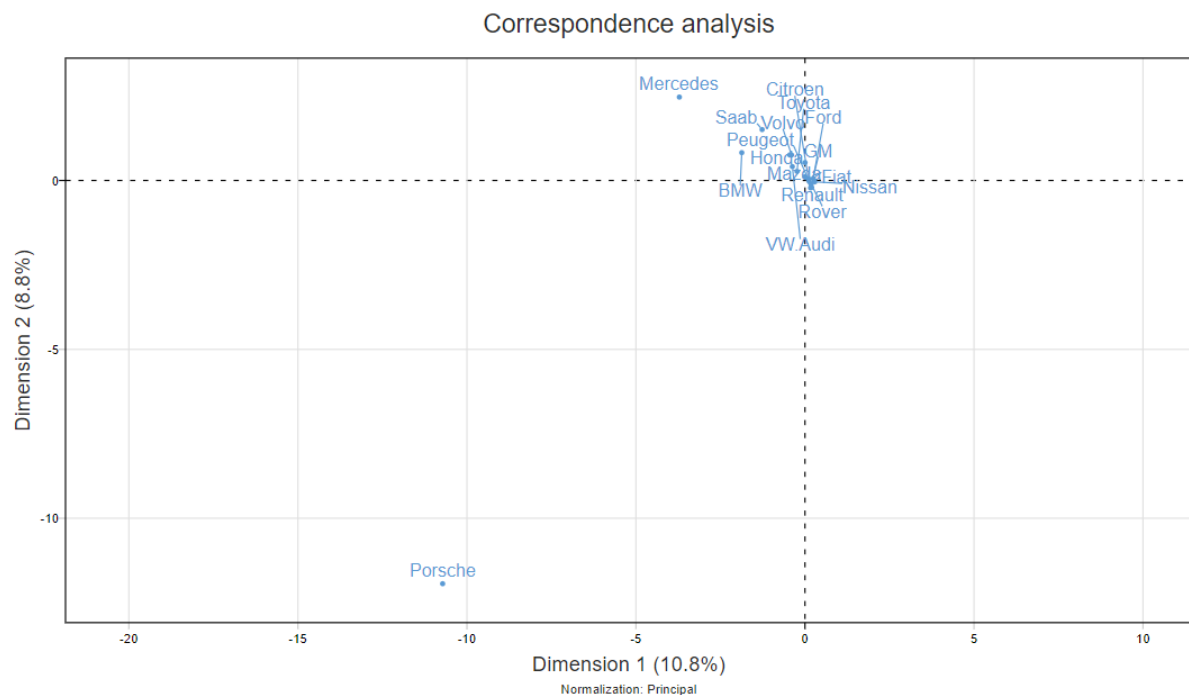
Step 4: Remove non-interesting brands from the table and redo the analysis

It is common with such analyses to find some outlying brands. The next step is to remove the outlying brands from the table and redo the analysis. The resulting map is shown below. This map is an improvement on the map from below, but it only explains 20% of the variance (the sum of the percentages on the bottom and left axes). This tells us that if we keep peeling off additional brands, the position of the brands will keep moving around. There is no magical number about what percentage of variance is desirable; we need to weigh up both statistical and strategic considerations when working out whether to keep removing brands. For example, if our focus was Mercedes, we may leave the map as it is. If Ford, we would remove many of the brands to the left and bottom of the map.

Correspondence analysis

Dimension 1 (11.1%)

Normalization: Principal
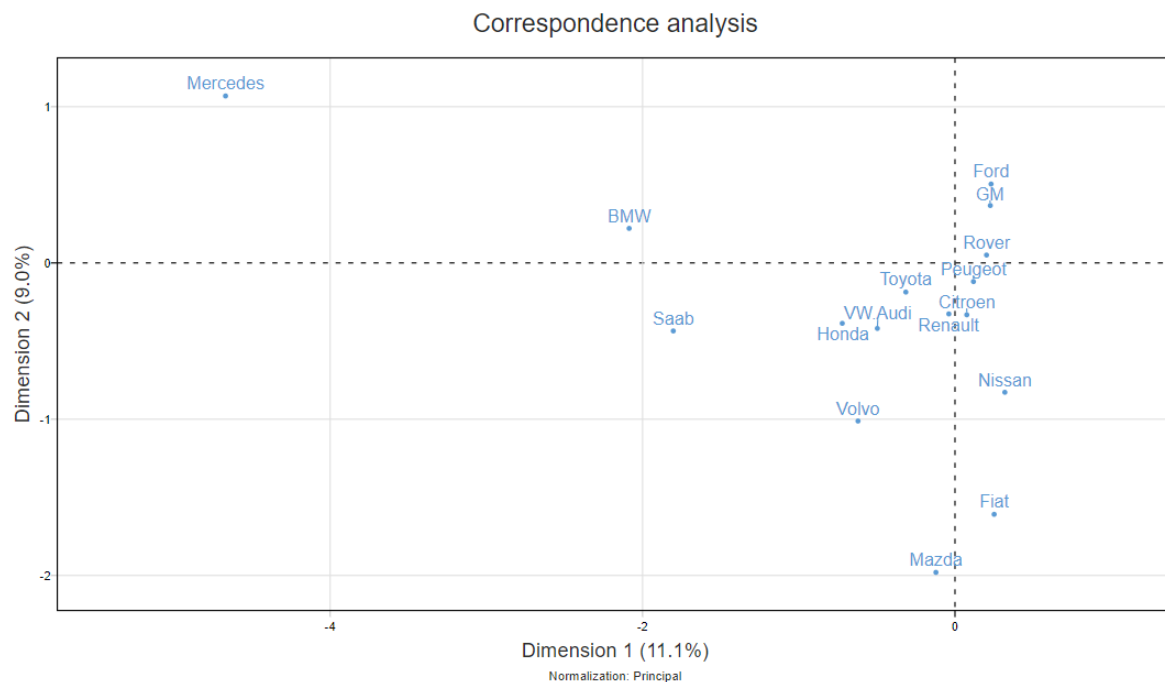
Creating a market map

Step 1 Create a brand attribute table

Once we have identified a preliminary list of competitors, the next step is to create a *brand attribute table,* showing the performance of each brand based on metrics that show how the brands are differentiated. An example of such a table is shown below. This is a part of the table used in the example at the beginning of the chapter.

%	Care about the quality of their food	Good value for money	Has healthy food options	Has the best tasting food	Is Affordable	Their food is always fresh	Has a good range of drinks to choose from	Easy to eat when you're on the go
Burger Shack	30%	8%	11%	31%	8%	24%	19%	12%
BURGER CHEF	18%	24%	7%	24%	30%	14%	41%	42%
Nuovo Burger	13%	7%	3%	15%	8%	8%	17%	12%
Southern Fried Chicken	15%	18%	8%	27%	24%	11%	29%	26%
Arnold's	25%	35%	34%	22%	46%	17%	50%	57%
Ma's burgers	19%	12%	9%	19%	15%	14%	25%	22%

There are a variety of ways of creating brand differentiation tables, including:

- Brand association tables, such as the one above, which are created from surveys and show the percentage of people to associate each table with each brand.
- Brand average or top 2 box tables. These are also created in surveys, where people are asked to rate the performance of each brand on each attribute, and a table formed showing averages or top 2 box scores.
- Brand consumption occasion tables. These are also typically created from surveys and show the percentage of people to consume each brand in each consumption occasion.
- Brand jobs-to-be-done tables. These are also typically created from surveys or qualitative research and show which uses different brands can be put towards. They are most useful in durable and business-to-business markets.
- Expert judgment, where people with knowledge of the brands rate the brands' performance levels.

If you are not able to obtain a brand attribute table, an alternative is to use an analysis of the square table, using judgment to describe the dimensions.

## Step 2: Rotated row-principle correspondence analysis

The standard (and best) way of creating a market map is via correspondence analysis.[8] However, the default settings tend not to be optimized for market maps, and it is desirable to use the following settings:

1. Create a table with the brands in the rows, as in the example above.
2. Run a correspondence analysis by selecting **Dimension Reduction > Correspondence Analysis of a Table** from the **Create** and **Anything > Advanced Analysis** menus in Q and Displayr, respectively.
3. Specify the **Normalization** as **Row Principal (Scaled)**. If your software doesn't have this option, select an option with the word "row" in it (this ensures that the map will be optimized to show the distances between the brands). If all the brands are clustered in the middle of the map, you can manually scale it by just multiplying the brands' coordinates until they appear in a visually pleasing position (this may sound suspect, but it is valid, as the correspondence analysis is just showing relativities rather than absolute values of the coordinates).
4. Rotate the correspondence analysis towards your brand. In Q and Displayr this is done by typing the name of the brand of interest into the **Focus** box.
5. If you are using Excel to create the map, make sure that the *aspect ratio* of the map is at 1. That is, make sure that numbers on the vertical (y) axis and horizontal (x) axis are on the same scale (e.g., if the distance between 0.1 and 0.2 on the vertical axis is one inch, then you want the distance between 0.1 and 0.2 on the horizontal axis to also be one inch). If you do this, you can entirely ignore the information about the relative importance of the two axes, as when the aspect ratio is at 1, it means that this information is conveyed by the position of the points on the map.

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[8] It is common in textbooks to read descriptions of the creation of maps using variants of PCA, discriminant analysis, and variants of multidimensional scaling. These techniques were popular in the 1960s and 1970s, but have long-since been supplanted by correspondence analysis outside of academic circles.

Step 3: Remove outlying brands or attributes and analysis

Sometimes the map will be dominated by an outlying brand or attribute. An example of this occurs below, with Has healthy food options. The effect of this outlying attribute is much stronger than it may first appear. It distorts the position of Arnold's, making Arnold's look substantially stronger in terms of convenience attributes than is the case. The solution is to remove the brand or attribute from the data table and redo the analysis.

Normalization: Row principal (scaled). Focus: BURGER CHEF
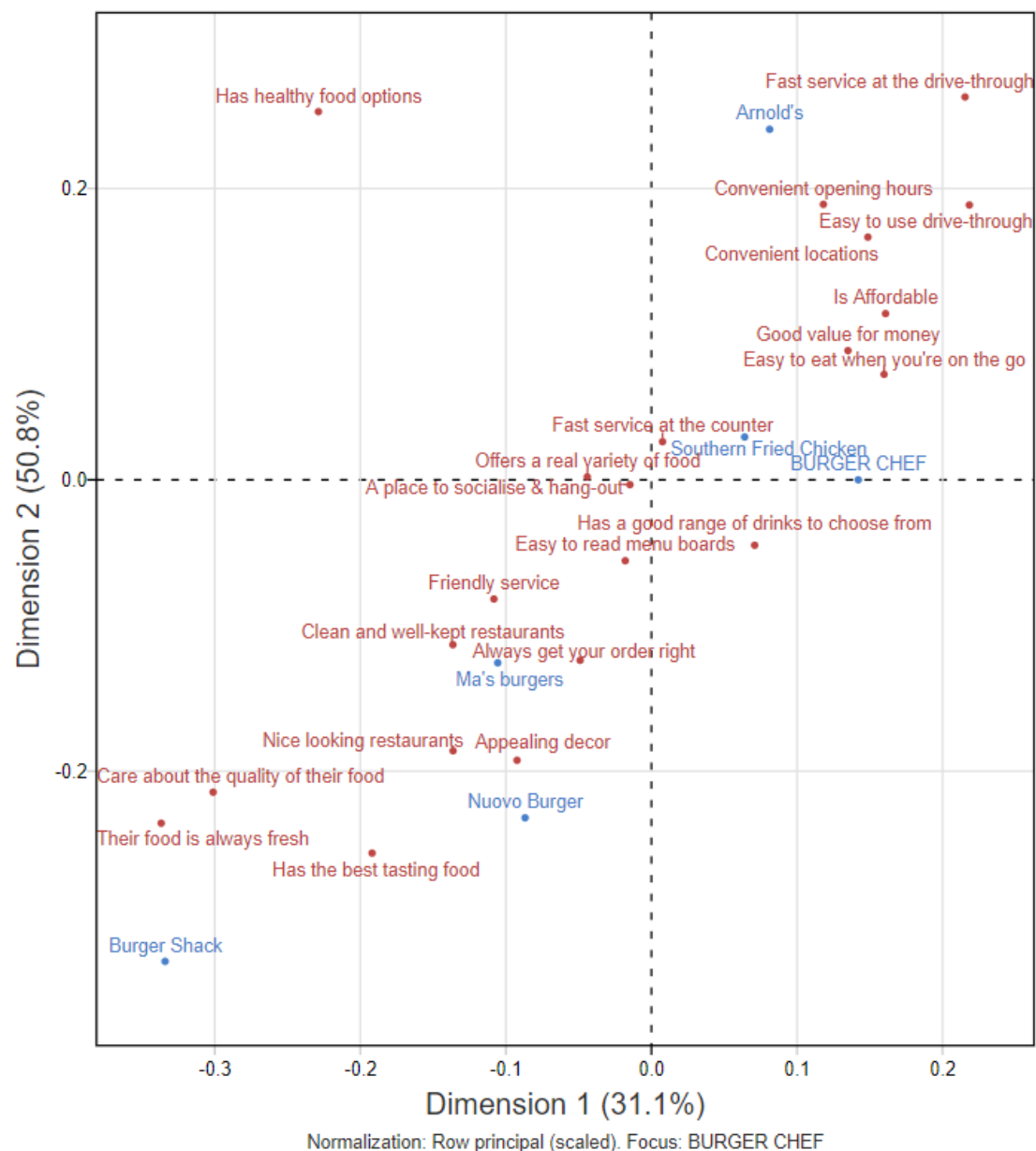
Where attributes are not known to be important, it can be useful to perform a driver analysis and remove non-important attributes from the analysis. Our DIY Driver Analysis book provides more detail about how to do this.

Step 4: Adding share, dynamics, and other commentary

The market map shown at the beginning of the chapter showed the size of brands as bubbles with their growth shown by bubble color. In Q and Displayr this is done by:

1. Creating tables shown market share and change in market share
2. Changing **Output** to **Bubble Chart**
3. Linking **Bubble sizes** and **Bubble colors** to the tables
4. Add commentary using a **Text Box**

Step 5: Check all results in a table

It is common for people to misinterpret market maps. There are two reasons for this:

- The correct interpretation is not obvious to many people. Please see our book DIY Correspondence Analysis for more information about interpretation.
- These maps summarize information very heavily, and this leads to nuances being lost.

The solution is to review all key conclusions from the map by looking at the tables used to create the map, as illustrated in the case study.

Acquisition Funnel Audit

The purchase process is viewed as a series of sequential stages, commonly referred to as an acquisition "funnel."

Insight is gained by understanding the conversion between the stages relative to benchmarks.

Funnel stages

In packaged goods markets (i.e., things sold in grocery stores), people can be viewed as going through a sequence of stages on the journey towards purchasing. For example:

- Ignorance
- Awareness
- Consideration
- Trial
- Regularly purchase
- Main brand

Aware (%)	98
Ever purchased (%)	95
Consider (%)	54
Most recent order (%)	22
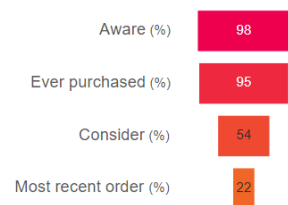
Similar stages can be identified in just about any market. For example, in business-to-business software marketing, it can be useful to define stages more around the sales process than the consumer decision-making process:

- Ignorance
- Visited website
- In the CRM (database)
- Received a demonstration of the software
- Trialed the software
- Purchased the software

The metaphor of the *funnel* is commonly used to describe the stages, with the resulting visualization typically looking a bit like a funnel.

In practice, the metaphor of the funnel is slightly stretched. There are often multiple funnels to be investigated, and they don't always form a meaningful funnel shape (e.g., if some of the stages are related to the frequency of consumption and others to percentages).

Funnel conversion

Most of the insight from the Acquisition Funnel Audit comes from interpreting *conversion* between adjacent stages in the funnel. Conversion is the ratio formed by dividing the metric at one stage of the funnel by the metric at a subsequent stage. For example, the conversion from awareness to ever visiting is 96%.
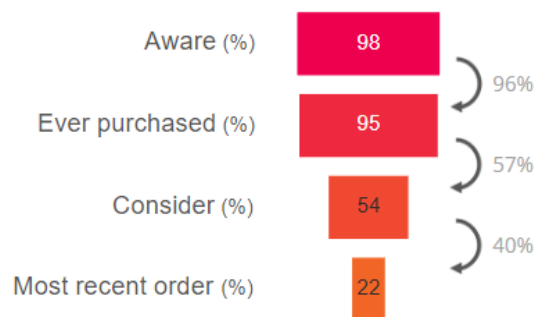

In some industries, benchmark data exists which can be used to assess conversion rates. In email marketing, for example, benchmarks exist for open rates, replies, bounce rates, etc. More commonly, though, there is a need to create benchmarks. There are three main ways of doing this:

- Conducting surveys and benchmarking relative to competitors. Examples of these are presented below.
- Benchmarking against historic data by tracking conversion rates over time.
- Comparing conversion rates by acquisition channels (e.g., paid advertising, email marketing, referrals).

Conversion from consideration to last choice

There are two conversion analyses that often deliver considerable insight. The first is to examine conversion from consideration to the most recent purchase decision. This is shown below for the fast food brands.
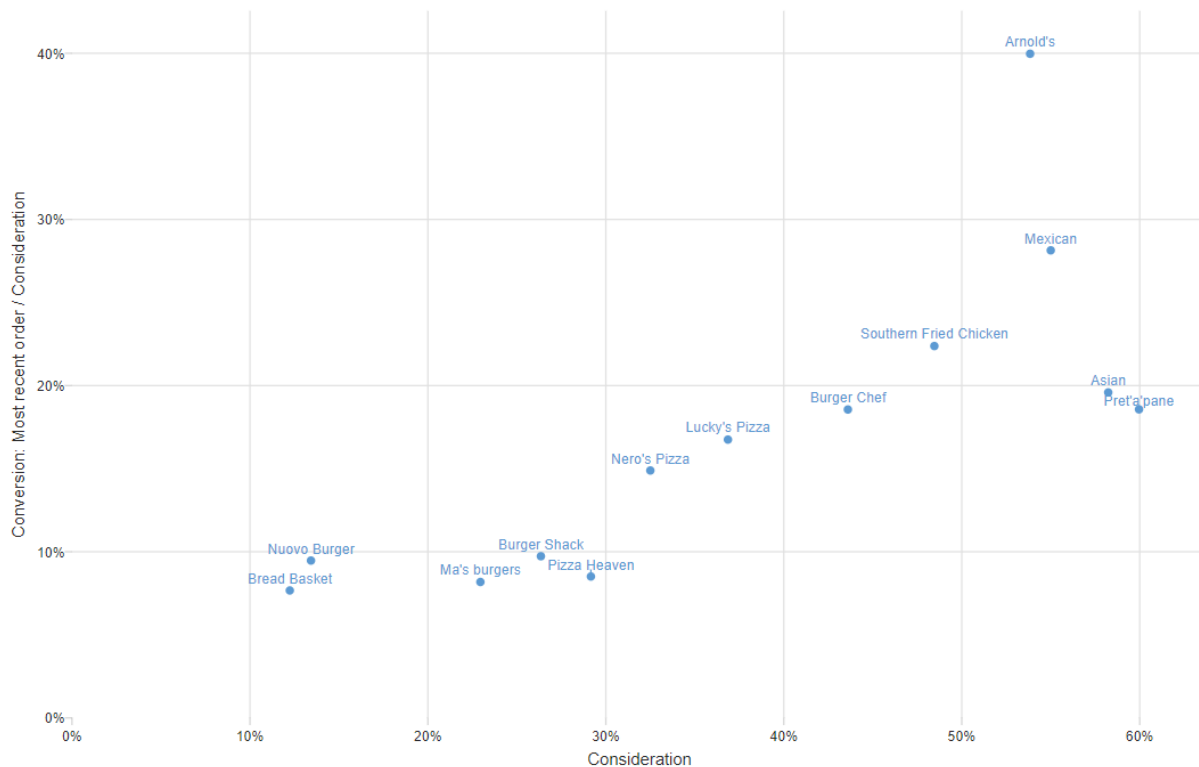
Note that there is a general pattern in the data: brands with higher consideration also have higher conversion ratios. This pattern exists in most conversion data and we discuss it in more detail below. Looking at the chart above we can see that four brands seem to be bucking the trend. Arnold's is doing fantastically well in terms of conversion, as are Nuovo Burger and Bread Basket. By contrast, Pret'a'pane has done very badly, as have the Asian restaurants.

Deviations in conversion rate from the general pattern should be explored, as they tend to have interesting implications. In the case of Arnold's in this example, it's key strength is much stronger distribution, which allows it to convert at a much higher rate.

Distribution is commonly an explanation for conversion rates that are outside of the trend. Another is price. Premium brands can have relatively poor conversion as they may only be purchased for special occasions.

Conversion from penetration to frequency[9]

A second key conversion analysis is to compare the *penetration* of a brand – the percentage of people who purchased within some time period (e.g., last month, last year) – with the frequency of buying among those that did buy.[10]
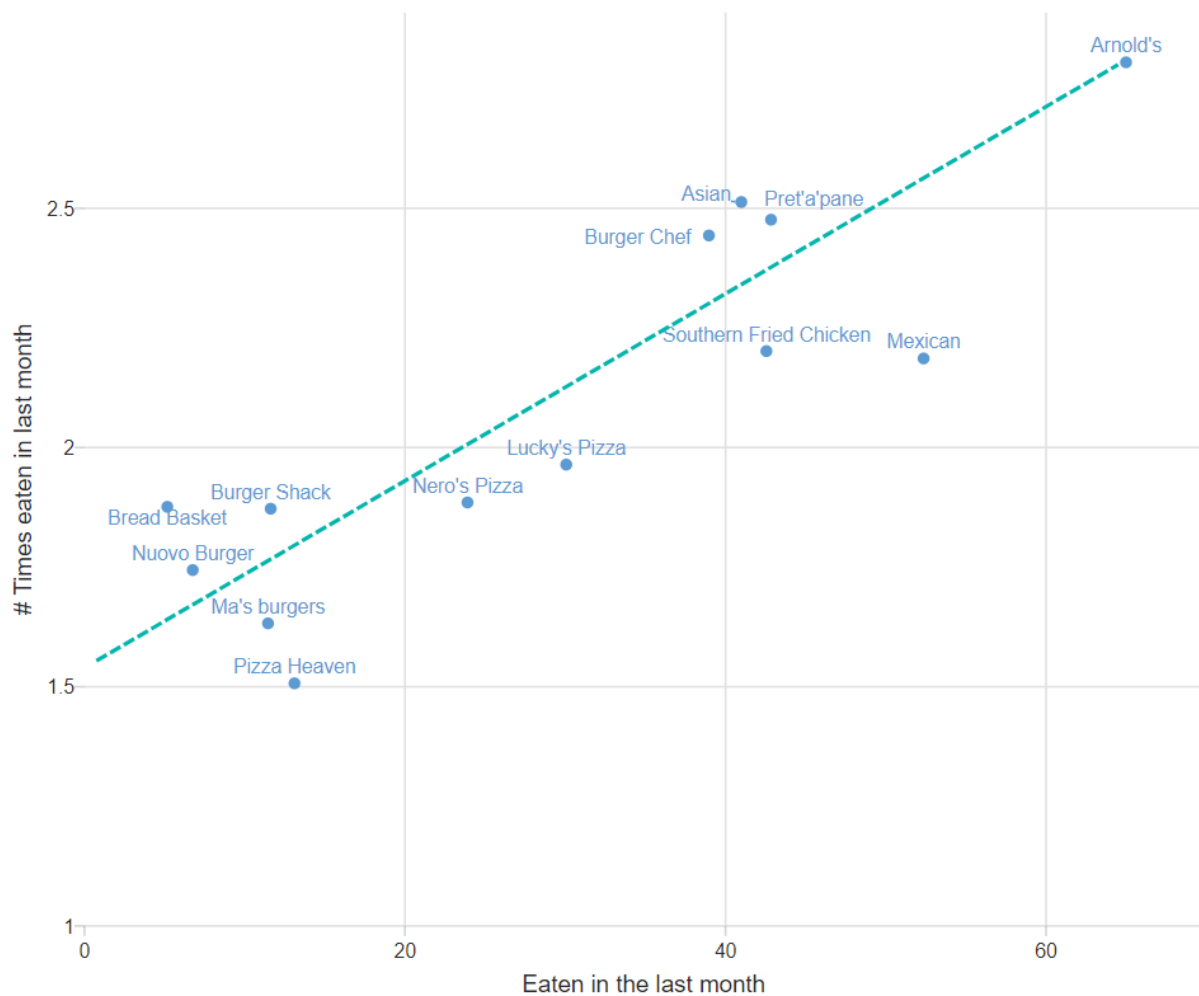
If you just looked at each of these metrics on their own you would conclude that Arnold's is the rockstar, winning on both metrics. When we look at all the data as a scatterplot, we see that the brands all fall around a line. The trick is to assess the performance of brands relative to the line. By this criterion we see some good news for Burger Chef: the frequency of consumption among its buyers is extremely strong. By contrast, we can see that Southern Fried Chicken, for example, is doing relatively poor, suggesting that it is seen as more of a source of variety, suggesting that its market position is a bit more vulnerable than Arnold's.

In terms of implications for Burger Chef, the key one is that it should seek to move to the right on the scatterplot (i.e., increase its proportion of people eating it), rather than seek to increase its frequency of consumption among existing diners.

Note also that the implications of this chart do differ quite a lot to the previous one, with Asian and Pret'a'pane no longer below the line. The earlier chart showed us conversion from consideration to behavior. Once they have succeeded in getting people to buy, they tend to buy relatively regularly, so for these brands, the challenge is to increase monthly penetration.

Creating scatterplots in Displayr and Q

1. Create two tables, one for each of the metrics.
2. Compute conversion as follows:
   a. In Displayr: select the two tables and then select **Calculation > Divide**, and change **Properties > GENERAL > Name** to `conversion`. In Q: Select **Create > R Output** and enter the **R CODE** of `conversion = t1/t2`, replacing the `t1` and `t2` with the names of the tables created in steps 1 and 2 (you can obtain the name of a table by right-clicking in the **Report** and selecting **Reference name**).
   b. Make sure that the brands are listed in the same order in both tables.
3. In Displayr, click **Visualization > Scatterplot** or in Q **Create > Charts> Visualization > Scatterplot**) and set:
   a. **X** to the table created in step 1 (again, use **Ctrl-C** to get its name).
   b. **Y** to `conversion`.

Laws of conversion

Double jeopardy

In the two examples of conversion that we investigated above, we saw that the conversion rates fell on a line. This is a general finding that has been observed with many metrics in many markets. It is known as *double jeopardy.*[11] If a brand is poor on one metric, it will generally be poor on all other metrics. Double jeopardy has various implications when interpreting funnel stages and conversion rates:
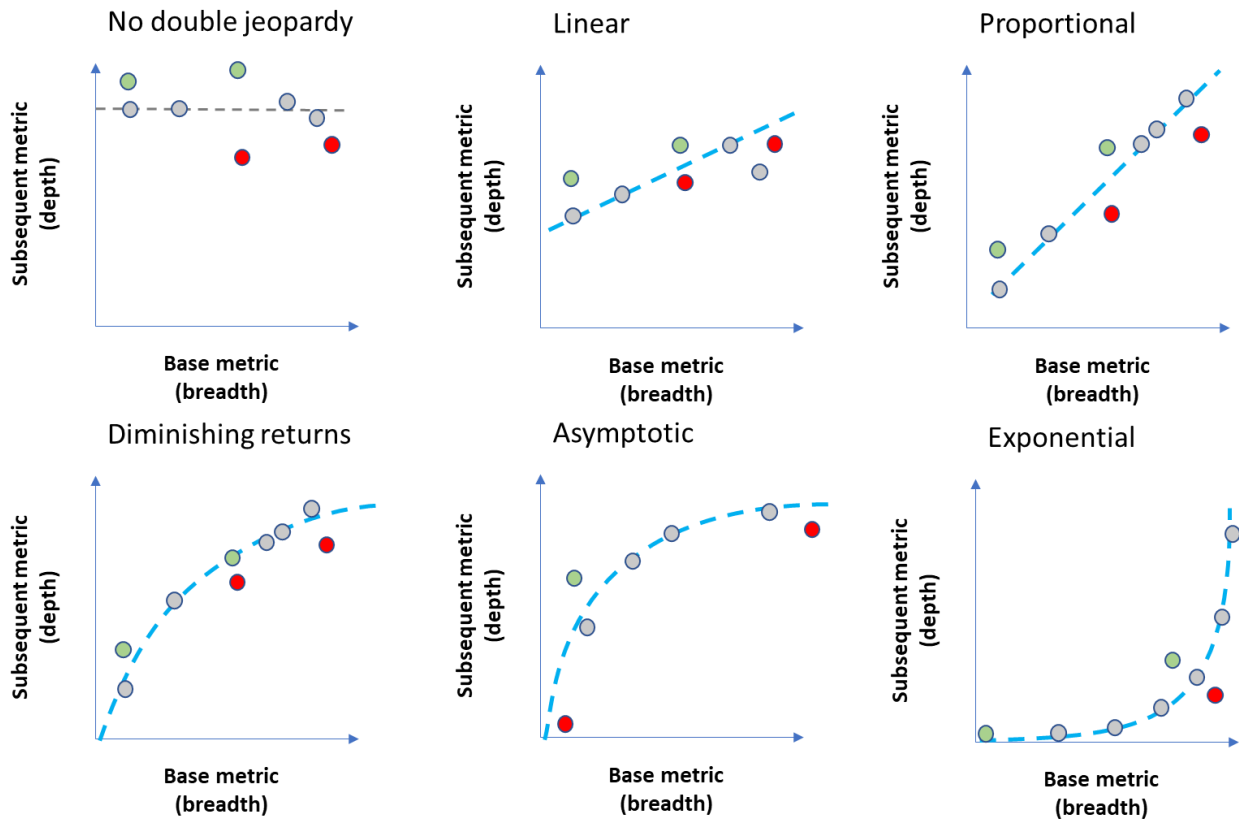
1. Smaller brands tend to do worse in all metrics.
2. Double jeopardy can be viewed as a force, like gravity. Strategies that seek to go against double jeopardy are highly likely to fail. For example, if a brand has poor trial rates, a strategy focused on repeat rates is unlikely to be successful (as double jeopardy means that a brand with poor trial rates will also generally have poor repeat rates).
3. "Easy wins" often relate to rectifying or rectifying areas where a brand is weak relative to the predictions of double jeopardy (more about this below).

The existence of double jeopardy means we need to take it into account whenever we look at conversion rates. Rather than simply compare brands' conversion scores, we need to compare relative to the overall trend.

The double jeopardy pattern shown above is *linear.* Lots of other patterns can occur, and the patterns can give some insight into how the markets work. For example, an exponential pattern may indicate the existence of network effects.

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[11] McPhee, William N (1963), Formal Theories of Mass Behavior. New York: The Free Press of Glencoe

Ehrenberg, Andrew S C, Gerald G Goodhardt, and T Patrick Barwise (1990), "Double Jeopardy revisited," Journal of Marketing, 54 (3), 82-91.

No double jeopardy	Linear	Proportional

Diminishing returns	Asymptotic	Exponential

(All charts: x-axis "Base metric (breadth)", y-axis "Subsequent metric (depth)")

The law of shitty clickthroughs

A second law which is relevant to interpreting conversion rates is *The law of shitty clickthroughs.* It has its origins in internet marketing. And, before you write to us about our use of language, we didn't coin the term. There is no widely used polite way of describing the law. The basic idea is that over time conversion rates tend to get worse and worse (i.e., "shitty" to use the term of art of the practitioners). For example, the clickthrough rate from early banner ads was in 1994 was 78%, whereas by 2011 it was down to 0.05% for Facebook ads.[12]

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[12] https://andrewchen.co/the-law-of-shitty-clickthroughs/

Simultaneously comparing multiple conversion metrics

The *small multiples* of *pyramid charts* shown below show the funnel stages and conversion rates for our fast food restaurant data for four different metrics.
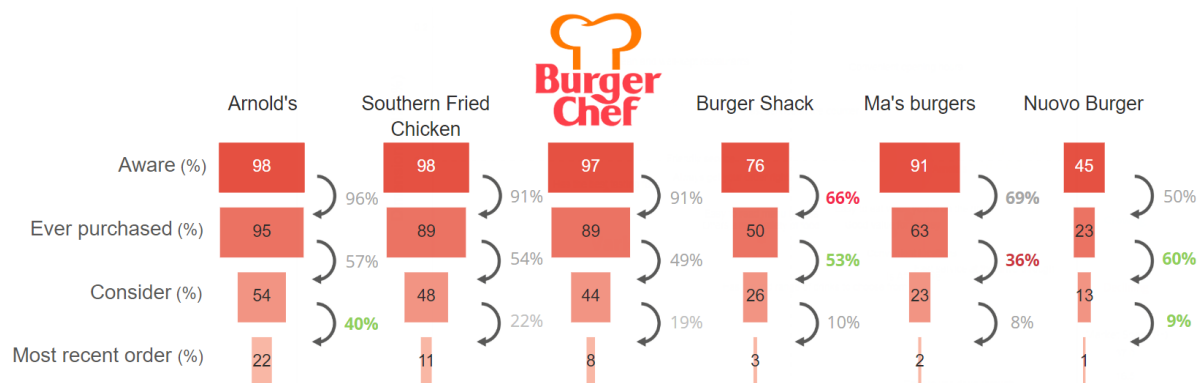
- Arnold's is clearly the benchmark brand – its awareness and penetration (ever) levels are near complete and over half the available population consider using. If we were advising this brand, it would be to maintain its key strengths and nullify or cover any competitive threats to them.

- Southern Fried Chicken is the number two brand. It does an OK job relative to Arnold's in the first two conversions but are doing much worse in terms of conversion from Consider to Most recent order. This tells us that Southern Fried Chicken needs to focus on increasing the frequency of consumption among people that like the restaurant.

- Burger Chef, our client, is largely in the same position as Southern Fried Chicken. Its conversion to Consider is a bit lower, which is in line with double jeopardy. Where it struggles relative to Arnold's is the conversion to Most recent order. Burger Chef needs to focus on increasing frequency. The next three analysis frameworks will help work out how to do this.

- Relative to the category, Burger Shack is doing well in terms of converting trial (ever purchased) to consideration, suggesting that they provide a good experience, which is consistent with what we saw in the Competitive Market Structure Analysis, it is low in awareness as well as the conversion from aware to ever purchased. This suggests it needs to build its proposition, making the brand and what it stands for known to a wider audience (at the same time as building distribution).

- Ma's burgers has terrible conversion from Ever purchased to Consider, suggesting that it's failing to deliver on its core promises.
- Nuovo burger, does well on all the conversions and seems to be a brand that can grow rapidly with more investment.

Steps for simultaneously comparing multiple conversion rates in Displayr and Q

Step 1: Create summary tables for each of the stages

The tables used in the case study are shown below. It's not important that they all have the same set of brands, as the later steps will ensure that only brands with complete information are included in the analysis.

	%
Burger Shack	76% ↓
Burger Chef	97% ↑
Nuovo Burger	45% ↓
Southern Fried Chicken	98% ↑
Arnold's	98% ↑
Ma's burgers	91% ↑

Q1. Aided brand awareness SUMMARY
sample size = 4853; 95% confidence level

	%
Burger Shack	50% ↓
Burger Chef	89% ↑
Nuovo Burger	23% ↓
Lucky's Pizza	82% ↑
Pizza Heaven	69%
Southern Fried Chicken	89% ↓
Arnold's	95% ↑
Nero's Pizza	84% ↑
Pret'a'pane	91% ↑
Ma's burgers	63% ↓
Bread Basket	20% ↓
Asian	81% ↑
Mexican	89% ↑
Other fast food	34% ↓
NET	100% ↑

Q3 Ever Eaten SUMMARY
sample size = 4853; 95% confidence level

	%
Burger Shack	26% ↓
Burger Chef	44% ↑
Nuovo Burger	13% ↓
Lucky's Pizza	37% ↑
Pizza Heaven	29% ↓
Southern Fried Chicken	48% ↑
Arnold's	54% ↑
Nero's Pizza	32%
Pret'a'pane	60% ↑
Ma's burgers	23% ↓
Bread Basket	12% ↓
Asian	58% ↑
Mexican	55% ↑
Other fast food	13% ↓
None of these	1% ↓
NET	100% ↑

Q4 Consider SUMMARY
sample size = 4853; 95% confidence level

	%
Burger Shack	3% ↓
Burger Chef	8% ↑
Nuovo Burger	1% ↓
Lucky's Pizza	6%
Pizza Heaven	2% ↓
Southern Fried Chicken	11% ↑
Arnold's	22% ↑
Nero's Pizza	5% ↓
Pret'a'pane	11% ↑
Ma's burgers	2% ↓
Asian	11% ↑
Mexican	15% ↑
Bread Basket	1% ↓
Other fast food	1% ↓
None of these	0% ↓
NET	100% ↑

Q6 Most recent order SUMMARY
sample size = 4795; total sample size = 4853; 58 missing; 95% confidence level

Step 2: Create the brand health table In Displayr this is done by selecting **Insert > More > Marketing > Brand Health Table**. In Q by **Create > Marketing > Brand Health Table**. But, it can easily be done by cutting and pasting in Excel as well. If using this automatic approach to creating the tables, note that the brands shown are those that appear in the first table.

	Arnold's	Southern Fried Chicken	Burger Chef	Burger Shack	Ma's burgers	Nuovo Burger
Aware	98%	98%	97%	76%	91%	45%
Ever	95%	89%	89%	50%	63%	23%
Consider	54%	48%	44%	26%	23%	13%
Most recent	22%	11%	8%	3%	2%	1%

Step 3: Sort the table by market share or something similar Sort the table so that the columns are ordered by market share, with the biggest brand on the left and the smallest on the right. In applications where there is no market share, such as comparing different acquisition channels, sort by the size of the channel.

If using Q or Displayr, you can do this by either manually ordering the first table and setting **Sort by** to **First table's order** or by setting **Sort by** to the row number that you wish to sort by.

Step 4: Compute conversion

This is done by dividing the numbers in each row by the numbers from the row above. In Q and Displayr this process is automated by setting **Output** to **Conversion**.

Step 5: Identify interesting results

The last step consists of reading along the row and looking for exceptions that defy double jeopardy.

Profiling the Core Consumer

Consumers and potential consumers come in many colors and stripes. For Harley Davidson, they vary from murderers through to Fortune 500 CEOs.

It's not practical to target all of them, which leads to the question of "who is the core consumer" that the brand must make happy?

Defining the core consumer

The core consumer is the archetypal consumer who the marketing efforts should be focused on. The basic idea is that if we succeed with this consumer, we should succeed with the market as a whole.

Whereas segmentation often involves the decision to ignore specific consumers, when we are identifying the core consumer, we are instead working out who to have most clearly in our mind when thinking through our brand strategy. We aren't ignoring everybody else (as potentially in segmentation). Rather, we are finding out who we need to make happy. We still want to make everybody else happy, of course, but if we don't make the core consumer happy, we aren't in the game at all.

Five approaches to defining core consumers are: value, anticipated brand love, innovativeness, opinion leadership, and target segments.

Value

The most widespread approach for defining core consumers is based on how much value (profit) they are expected to provide to the firm. How this is defined varies by market:

- In most food and packaged goods markets, value tends to be equated with how much people buy (*volume*). In the case study we are reviewing in this book, we define value based on the number of meal occasions in burger restaurants in the past month.
- In database marketing, value can be defined based on recency, frequency, and monetary value.
- In financial services, value relates to the profit contribution that a customer provides (e.g., the margin made on their deposits and borrowings less service costs).

Anticipated brand love

When marketing for a new brand, going after value is often not so practical. The biggest brands already own these consumers. Instead, the core consumers can be defined on those who should love the brand. The logic of this approach is that whatever characteristics are shared by the people that best love a brand are also likely to be shared by people who represent the best prospects for the brand.

Common ways of operationalizing anticipated brand love are:

- Judgment. This is all that can be done for brands without consumers.
- Existing customers. This approach is common for products that have CRMs, where they can perform analyses identifying the characteristics of their existing customers.
- Using surveys to identify people that have a highly positive attitude to the brand. For example, people that give giving ratings of 9 or 10 to questions like "How likely are you to recommend this brand to a friend or colleague?". Or, people that say "very disappointed" when asked, "how would you feel if you could no longer use the product?".[13]

Innovativeness

In the early days of a new product, the core consumers can be defined as being innovators. In tech markets, for example, these are the people that are willing to try and gain value from the new tech and aren't too concerned that they will have to modify their workflows.[14]

Influential consumers

In markets with a strong fashion component, such as clothing and music, the core consumers can be defined as people who are influential. This may be based on known influencer status (e.g., the number of followers on social media), celebrity status, or demographics (young and fit looking).

Target segment(s)

The fifth framework is to use segmentation and define the archetypal consumer within a segment as the core consumer. More detail about how to perform segmentation is in our book DIY Market Segmentation.

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[13] https://firstround.com/review/how-superhuman-built-an-engine-to-find-product-market-fit/

[14] Geoffrey A Moore (2014), *Crossing The Chasm*, 3rd Edition, Harperbusiness.

Case study

By applying the previous framework, we learned that Burger Chef needs to get success in convincing heavier consumers who like the product to buy it. For this exercise, we look at the burger category as a whole. However, the same principles can be applied to understanding the various tiers of competition – as above – *within* the category.

To provide a mechanism to understand macro consumer behavior, we will first create a variable to represent it. The target question is one that asks about the number of occasions each restaurant brand has been consumed in the past month.

A new variable was constructed, summing up the occasions where the give burger brands were consumed. We called the newly created variable # Burger Occasions.
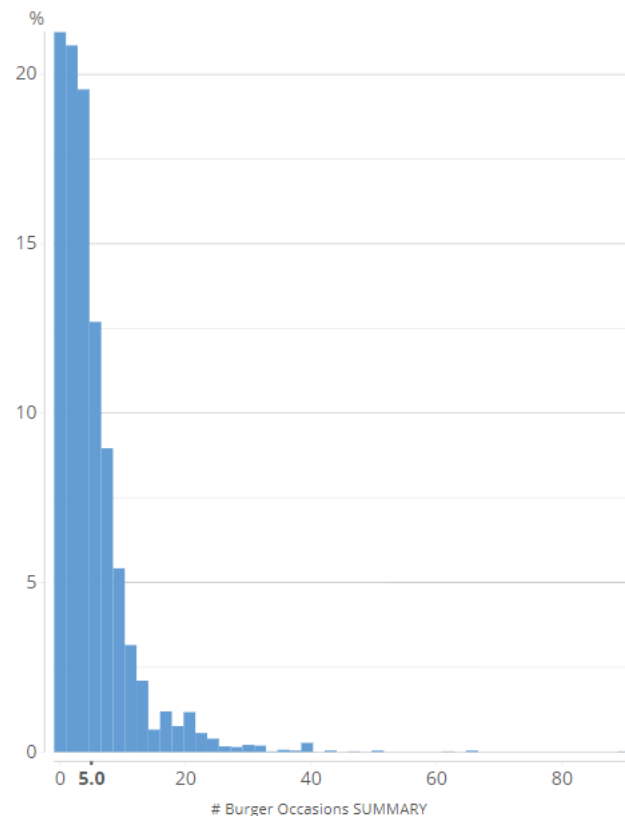
The *histogram* to the right shows the distribution of this new variable. It shows a small number of consumers with more than 50 occasions. While it is theoretically possible to visit a burger outlet for, say, a morning coffee and/or lunch several times a week, we have replaced any values over 50 with the value of 50 (i.e., *capping* the variable). We also re-ran the analyses treating these as missing values, and changing the cap to 20 and 75. All the key conclusions remain unchanged.

Having created our numeric variable defining core consumption, we now need to understand who the people with higher levels of consumption are. Typically, there will be a series of potential demographic and perhaps behavioral and attitudinal variables that can be used to describe the core consumer. Which variables should be used?
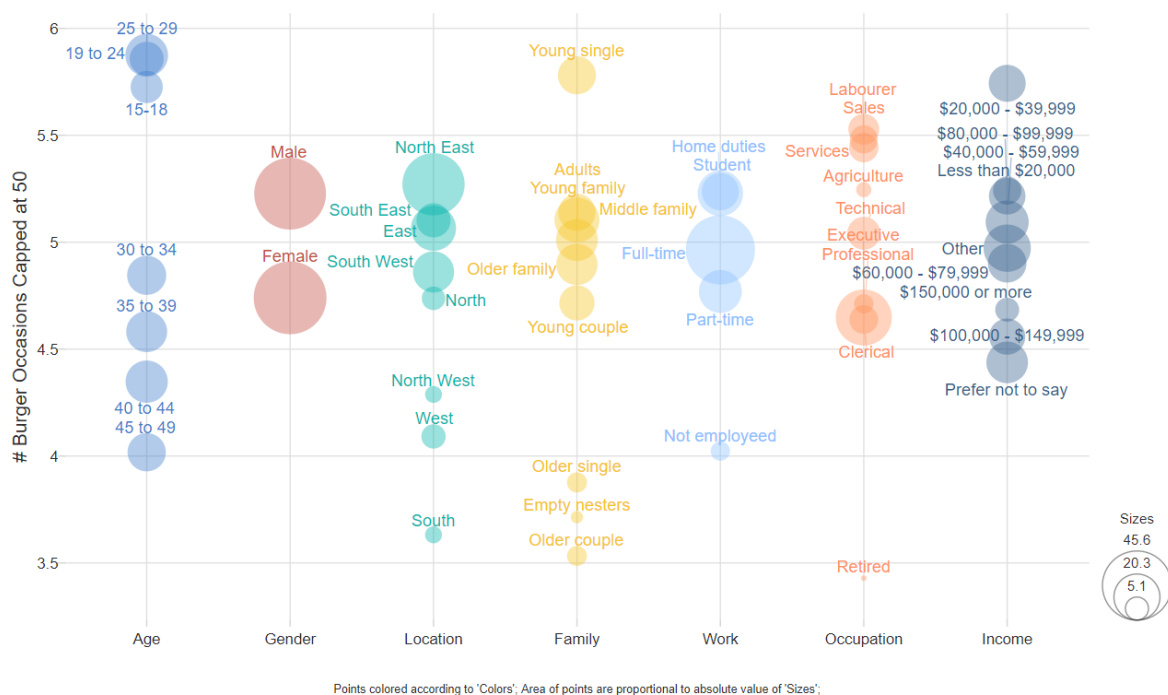
This is a classic predictive modeling problem. Our preferred approach is to use CART. The *Sankey tree* below shows us a very simple model, which tells us to define the core consumer as people aged under 30.
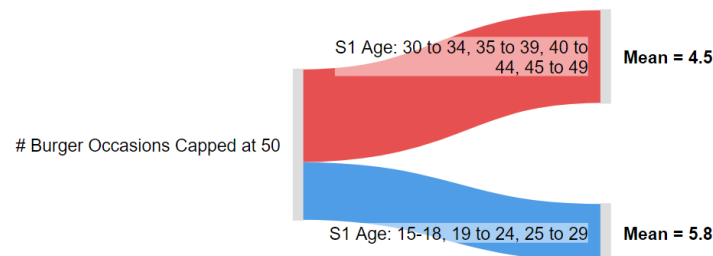
While age is the key defining variable, we need more information to create a richer profile. We find the visualization below is a nice, compact way of visualizing all the key information. Each circle shows the size of different demographic groups, and their height shows the volume. Our core consumer is thus:

- Under 30
- Single
- Works in services, sales, or as a laborer
- Has a low income

And, if we broaden the definition a bit more, they are male.

Points colored according to 'Colors'; Area of points are proportional to absolute value of 'Sizes';

Steps for performing the analysis in Displayr

Creating the variable defining the core consumer

How these need to be done will differ depending on the definition of the core consumer. Typically, it will either involve recoding a variable or creating a new variable, as occurred in the case study. For the example in the case study, it was done as follows:

1. Hover your mouse under **Data Sets**, click the **+** button, and select **Custom Code > R - Numeric**
2. Drag across or type in variable names to sum up the variables. For example: `Q5_1+Q5_2+Q5_7+Q5_10+Q5_7`.
3. Set **Properties > GENERAL > Name** to `volume` and **Label** to `Consumption volume` or whatever else makes sense to you.

For a shortcut you can select the variables under **Data Sets** and then select **Calculation > Sum**.

Creating the histogram

1. Drag the new variable onto a page
2. **Chart > Histogram**

Capping

1. Hover your mouse under **Data Sets**, click the **+** button, and select **Custom Code > R - Numeric**
2. **R CODE:** `ifelse(volume > 50, 50, volume)`
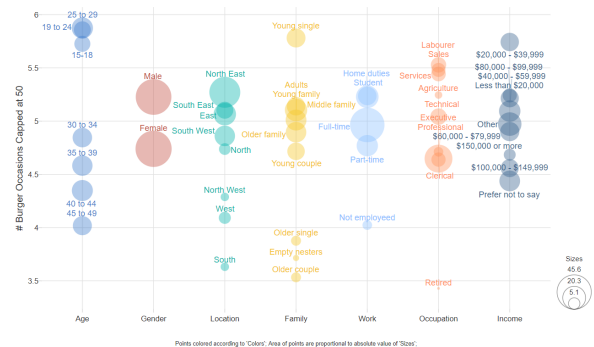3. Set **Properties > GENERAL > Name** and **Label**

CART

1. **Anything > Advanced Analysis > Machine Learning > Classification and Regression Trees (CART)**
2. Select the newly-created variable as the **Outcome variable**
3. Choose all the potential profiling variables as **Predictors**

Volumetric profiling bubble chart

Before explaining how to create the chart, it is useful to look at the underlying data. We are creating a bubble chart like the one to the right. Each bubble is created using five pieces of information:

Points colored according to 'Colors'. Area of points are proportional to absolute value of 'Sizes'.

- Its label. For example, 15-18, Male, or North. In the two tables to the right below, you can see we are showing the labels.
- The size of the bubble. This is shown by the table on the right (only the top of the table is shown).
- The position of the bubble on the y-axis. This is shown by the bubble in the middle.
- The position of the bubble on the x-axis. This is the non-obvious bit. It's shown by the table on the left.
- The color of the bubbles. This is also deduced from the table on the left.

So, to create the bubble chart we need to first create these tables.

X-axis (horizontal):
Category names

[1]	Age
[2]	Age
[3]	Age
[4]	Age
[5]	Age
[6]	Age
[7]	Age
[8]	Gender
[9]	Gender
[10]	Location
[11]	Location
[12]	Location
[13]	Location
[14]	Location
[15]	Location

Y-axis (vertical):
Average consumption

Average	# Burger Occasions Capped at 50
15-18	5.7 ▲
19 to 24	5.9 ▲
25 to 29	5.9 ▲
30 to 34	4.8
35 to 39	4.6
40 to 44	4.3 ▼
45 to 49	4.0 ↓
Male	5.2
Female	4.7
North	4.7
North East	5.3 ▲
East	5.1
South East	5.1

Bubble size
% people

	%
15-18	10% ↓
19 to 24	17% ▲
25 to 29	11% ↓
30 to 34	15%
35 to 39	16% ▲
40 to 44	17% ▲
45 to 49	14%
Male	49% ▲
Female	51% ▲
North	5% ↓
North East	37% ▲
East	11% ↓
South East	19% ▲
South	3% ↓
South West	16% ▲

Creating the bubble size table

We start by creating the table on the right. Once you've identified the profiling variables of interest (e.g., using judgment or **Anything > Report > Crosstabs**):

1. Create a table by dragging the first profiling variable from the **Data Sets** tree (bottom-left of the screen) onto the page.
2. Drag the second variable and release it in the slot underneath the first, as shown to the right.
3. Repeat this process, adding the additional variables.
4. Unchecking the options that will appear to the right of:
   a. **Add sub NETs**
   b. **Add column Spans of variable set names**
5. Click on the table and set **Properties > GENERAL > Name** to `core.sizes`. This stage is not strictly necessary, but it will save time when we create the bubble chart.
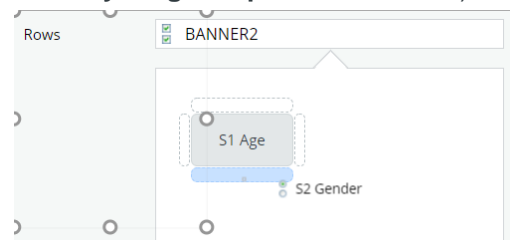
Creating the bubble value table

1. Select the table that has just been created, then press **Home > Duplicate** to copy it.
2. Drag the value variable, releasing it in the **Columns** slot.
3. Click on the table and set **Properties > GENERAL > Name** to `core.y`. This stage is not strictly necessary, but it will save time when we create the bubble chart.

Creating the x-axis table

Click **Calculation** and draw a box on your page. Then enter the following code, where you need to update the names of the categories and the numbers next to them (e.g., the `7` next to `Age` indicates we have 7 age categories):

```
core.x <- c(rep("Age", 7),
            rep("Gender", 2),
            rep("Location", 8),
            rep("Family", 9),
            rep("Work", 5),
            rep("Occupation", 9),
            rep("Income", 9))
```

Creating the bubble chart

Press **Visualization > Scatterplot** and set the options as follows:

1. **DATA SOURCE**
   a. **X coordinates**: `core.x`
   b. **Y coordinates**: `core.x`
   c. **Sizes**: `core.sizes`
   d. **Colors**: `cor.x`
2. **Chart > APPEARANCE > Show labels: On chart**

Steps for performing the analysis in Q

Creating the variable defining the core consumer

How these need to be done will differ depending on the definition of the core consumer. Typically it will either involve recoding a variable or creating a new variable, as occurred in the case study. For the example in the case study, it was done as follows:

1. **Create > Variables and Questions > Variables > JavaScript Formula > Numeric Variable**
2. Double click on type in variable names to sum up the variables. For example:
   `Q5_1+Q5_2+Q5_7+Q5_10+Q5_7`.
3. Set its name to `volume`

For a shortcut, you can select the variables on the Variables and Questions tab, and use **Insert Ready Made Formulas > Mathematical Functions > Sum**.

Creating the histogram

1. Double-click on the variable, which will create a table showing its average
3. **Show data as: Chart > Histogram**

Capping

1. **Create > Variables and Questions > Variables > JavaScript Formula > Numeric Variable**
2. **Expression:** `Math.min(volume, 50)`.

CART

1. **Automate > Browse Online Library > Machine Learning > Classification and Regression Trees (CART)**
2. Select the newly created variable as the **Outcome variable**
3. Choose all the potential profiling variables as **Predictors**

Volumetric profiling bubble chart

Before explaining how to create the chart it is useful to look at the underlying data. We are creating a bubble chart like the one to the right. Each bubble is created using five pieces of information:

Points colored according to 'Colors'. Area of points are proportional to absolute value of 'Sizes'.

- Its label. For example, 15-18, Male, or North. In the two tables to the right below, you can see we are showing the labels.
- The size of the bubble. This is shown by the table on the right (only the top of the table is shown).
- The position of the bubble on the y-axis. This is shown by the bubble in the middle.
- The position of the bubble on the x-axis. This is the non-obvious bit. It's shown by the table on the left.
- The color of the bubbles. This is also deduced from the table on the left.

So, to create the bubble chart, we need to first create these tables.

X-axis (horizontal):
Category names

[1]	Age
[2]	Age
[3]	Age
[4]	Age
[5]	Age
[6]	Age
[7]	Age
[8]	Gender
[9]	Gender
[10]	Location
[11]	Location
[12]	Location
[13]	Location
[14]	Location
[15]	Location

Y-axis (vertical):
Average consumption

Average	# Burger Occasions Capped at 50
15-18	5.7 ▲
19 to 24	5.9 ↑
25 to 29	5.9 ▲
30 to 34	4.8
35 to 39	4.6
40 to 44	4.3 ▼
45 to 49	4.0 ↓
Male	5.2
Female	4.7
North	4.7
North East	5.3 ▲
East	5.1
South East	5.1

Bubble size
% people

	%
15-18	10% ↓
19 to 24	17% ↑
25 to 29	11% ↓
30 to 34	15%
35 to 39	16% ▲
40 to 44	17% ↑
45 to 49	14%
Male	49% ↑
Female	51% ↑
North	5% ↓
North East	37% ↑
East	11% ↓
South East	19% ↑
South	3% ↓
South West	16% ▲

Creating the bubble size table

We start by creating the table on the right. Once you've identified the profiling variables of interest (e.g., using judgment or **Insert > More > Tables > Lots of Crosstabs**):

1. **Create > Banner > Drag and Drop**
2. Drag across the first profiling variable
3. Drag across the second profiling variable, releasing it to the right of the first. Your screen should look like the screenshot shown to the right.

6. Repeat this process, adding the additional variables.
7. Unchecking the options that will appear to the right of:
   a. **Add sub-NETs**
   b. **Add column spans of variable set names**
8. Right-click on the table in the report tree, and click **Rename**, setting the name to `core.sizes`. This stage is not strictly necessary, but it will save time when we create the bubble chart.

Creating the bubble value table

1. Select the table that has just been created, then press **+ Duplicate** to copy it.
2. In the Brown dropdown menu, select the value variable.
3. Rename the table as `core.y`. This stage is not strictly necessary, but it will save time when we create the bubble chart.

Creating the x-axis table

Create> R Output, entering the following code, where you need to update the names of the categories and the numbers next to them (e.g., the `7` next to `Age` indicates we have 7 age categories):

```
core.x <- c(rep("Age", 7),
        rep("Gender", 2),
        rep("Location", 8),
        rep("Family", 9),
        rep("Work", 5),
        rep("Occupation", 9),
        rep("Income", 9))
```

Creating the bubble chart

Press **Create > Charts > Visualization > Scatterplot** and set the options as follows:

1. **DATA SOURCE**
   a. **X coordinates**: `core.x`
   b. **Y coordinates**: `core.x`
   c. **Sizes**: `core.sizes`

d. **Colors**: `cor.x`

2. **Chart > APPEARANCE > Show labels: On chart**

Importance-Performance Analysis

This framework seeks to identify gaps between what people regard as important and how the different brands in the market perform.

Although this type of analysis is most commonly performed in tandem with driver analysis and conjoint, it is often the case that it can be performed with simpler types of data that have already been captured in surveys.

The Importance-Performance Framework and Quad Maps

The basic idea of Importance-Performance Analysis is as follows:

1. Identify a series of possible improvements. These can be just about anything:
    a. Product modifications
    b. Brand imagery
    c. Distribution
    d. Service attributes
    e. Touchpoints
2. For each of the possible improvements, measure performance. This is typically done by getting respondents in a survey to provide ratings of performance (e.g., satisfaction or brand associations), but expert judgment can be used as well.
3. Measure the likely effect of improving performance (i.e., importance). There are many ways of doing this. The three most popular are:
    a. Asking people to rate importance
    b. Driver analysis
    c. Conjoint
    d. MaxDiff
4. Plot the improvements on a scatterplot. This is commonly called a *quad map.* An example of brand personality attributes for Coca-Cola is below. In terms of where to draw the lines between high and low performance, please keep in mind that this is really a simplification for communication. The position of boundaries between high and low are subjective, and you shouldn't be treating the line as a magical cutoff point. Having said that, in the next section we review the burger market, and here there is a natural cutoff value for good performance: Burger Chef's market share (i.e., if a brand has 30% market share, its share of occasions can be benchmarked at 30%).
5. Allocate resources so as to focus on things that are important.
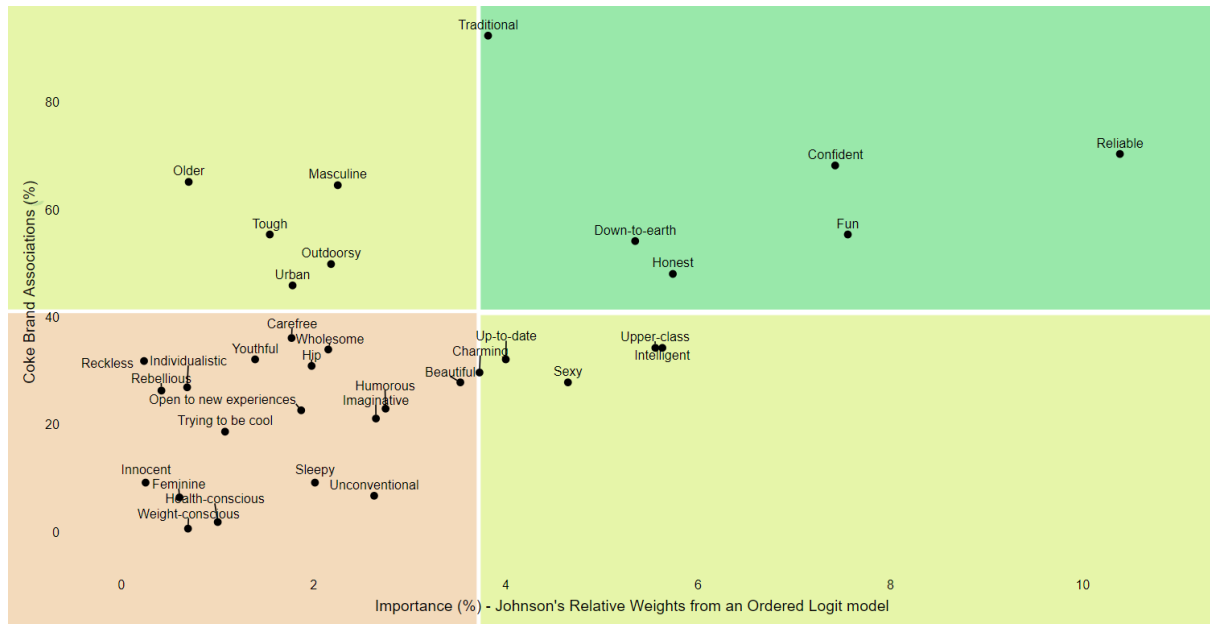
The reallocation of resources follows from the position of the various things shown on the map, as summarized in the diagram on the next page.
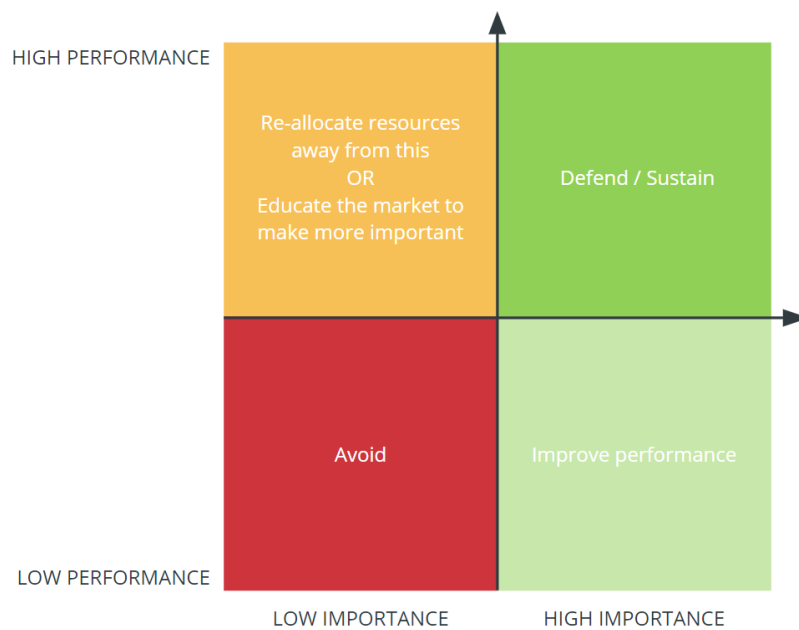
Case study

Food ordered

With the restaurant case study, the key way of defining importance in the data set is the frequency of certain behaviors. The horizontal axis of the chart below shows the frequency with which different food options were chosen by people who ate at a burger restaurant.

We can see that the two most important meal components are, in descending order (i.e., reading from right to left), French fries, beef burgers, chicken burgers, and chicken pieces, chicken nuggets, and tenders.

The vertical axis shows Burger Chef's share of each of these food options among people that ate at a Burger restaurant. The dotted horizontal line shows Burger Chef's market share, which is a useful benchmark to evaluate against.

Importance-Performance Analysis: Food Options
Base: Bought from a burger chain (including Southern Fried Chicken) on last purchase

The performance of beef burgers at first looks pleasing, in that it is both important and performance is above Burger Chef's market share. However, this is only because the data set includes Southern Fried Chicken, which doesn't make beef burgers. If the analysis is limited to only burger chains, Burger Chef's performance on beef burgers is equivalent to the average.

The most interesting results revealed in this chart relate to the chicken. Burger Chef has already managed to get to market parity with its chicken burgers, showing that it has some credibility in this space. But, its nuggets, tenders, and chicken pieces are all very low, despite these being relatively popular food options. There is an opportunity for improvement here. They may not ever lead in this space, but a focus on good "me too" offers or a break-through innovation might drive some incremental business.

The opportunity with chicken nuggets/tenders is the most interesting one strategically. In the Competitive Market Structure Analysis, we identified that we were close competitors to Southern Fried Chicken. So, by ramping up our chicken offer, we both gain advantage relative to other burger restaurants and also to this key non-burger competitor.

Time of Day

Looking at time of day, we can see that Burger Chef is lagging a little behind in the most important meal of the day, dinner.

Importance-Performance Analysis: Time of Day
Base: Bought from a burger chain (including Southern Fried Chicken) on last purchase
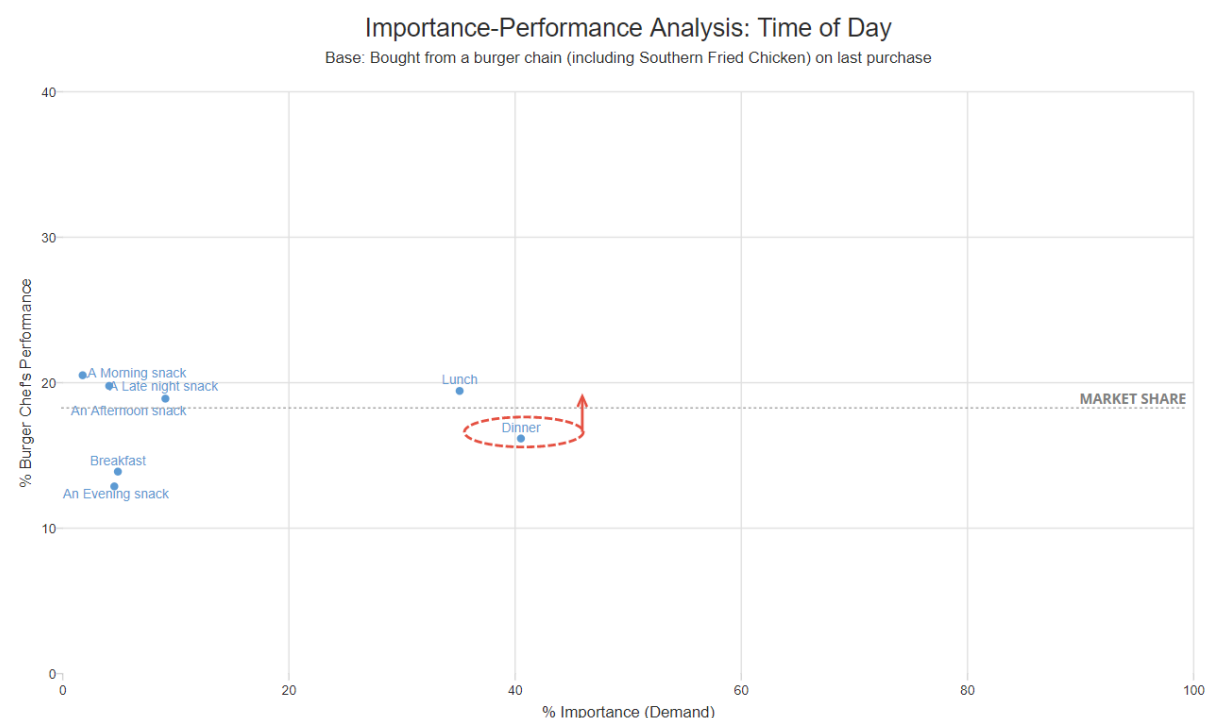
Order Method

The key message here would be for Burger Chef to maintain equal focus on both the Drive Through and Eat in occasions (perhaps tailoring the offer to specific locations e.g. CBD = Dine in, arterial road = Drive Through).

Importance-Performance Analysis: Order Method
Base: Bought from a burger chain (including Southern Fried Chicken) on last purchase
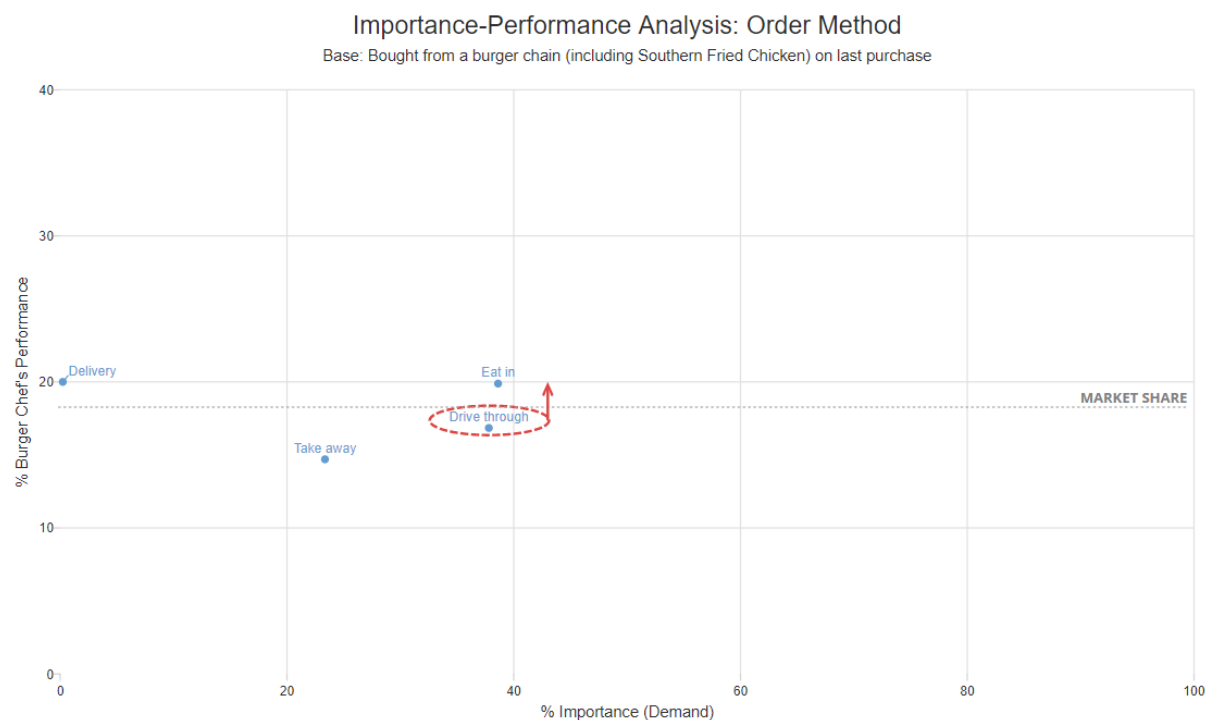
More complicated importance-performance Analyses

In this book, we have focused just on plotting importance by performance for our key brand. However, more insight can be extracted in some studies by doing a more depth analysis, including:

- Comparing multiple brands (e.g., overlaying all the brands on the same chart, to understand perceptions).

- Comparing between different segments. In particular, within Basic Brand Vulnerability Matrix segments, which are introduced in the next chapter.

Steps for performing performance-importance analysis in Q and Displayr

Measuring performance

The measurement of performance is typically taken straight from an average or percentage on a table, perhaps filtered for users of a particular brand.

Measuring importance

Where importance is obtained by directly asking people how important things are, the importance is then computed as an average of a percentage.

A more complex way measurement of performance is called *derived performance,* where it is inferred based on survey data. There are three main approaches:

- **Driver analysis**, where the analysis is based on working out the relationship between measures of performance and a measure of overall performance. Our DIY Driver Analysis book provides more detail about how to do this. This is the main approach used when measuring image attributes and service.
- **MaxDiff**, where people are presented a series of options and asked which they like and do not like. This is the main approach used when there is a large list of possible improvements. Our DIY MaxDiff book provides more detail about how to do this.
- **Conjoint**, where people are presented with hypothetical alternatives and are asked to choose which they would buy. Links to resources for understanding how to do to this are here.

Creating the scatterplot

In Q this is done using **Insert > Chart > Visualization > Scatterplot** and in Display using **Visualization > Scatterplot**.

Basic Brand Vulnerability Matrix

The final analysis framework focuses on identifying gaps between preference and behavior, and understanding how to exploit them.

The *basic brand vulnerability matrix* is typically created by contrasting strength of attitude with frequency or usage. It is typically created as a matrix with nine segments, but there is nothing magical about this number (e.g., a 2 by 2 matrix can work as well).

Brand attitude

	Dislike	Indifferent	Like
Brand usage			
High	Customers who are vulnerable to competitors		Loyal
Medium		Customers who are vulnerable to competitors	
Low	Unlikely target	Competitive customers who are open to our brand	

Sustain

Grow usage

Ignore
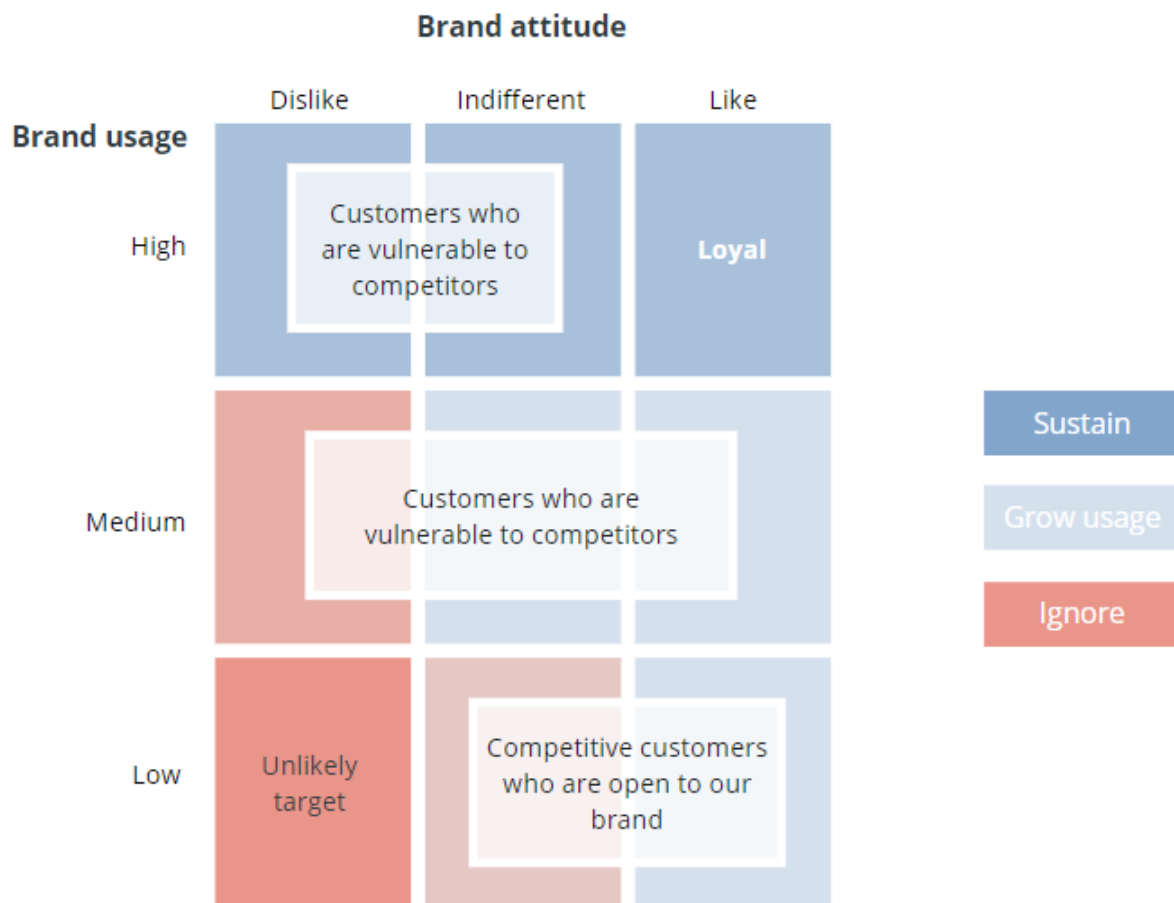
The basic premise of the matrix is that "Loyal customers may be faithful for different reasons, and similarly lack of loyalty can be attributed to a variety of reasons".[15] Discrepancies between attitude and behavior can highlight important characteristics of markets. For example, in markets containing

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[15] Yoram Wind (1978), "Issues and Advances in Segmentation Research", Journal of Marketing Research, Vol. 15, No. 3 (Aug), pp. 317-337.

relatively high levels of price sensitivity we often observe that premium brands have more consumers in the segments at the bottom right corner of the matrix than store brands.

The basic brand vulnerability matrix has several desirable properties. The strategy implications are relatively straightforward. The brand attitude of some segments need to be re-enforced or changed, while for other segments the focus should be more in re-enforcing or removing barriers (e.g., lack of awareness and distribution problems).

Each of the cells in the matrix is then examined to see how it differs from the general population, with a particular focus on:

- Loyalists
- Customers that don't like the brand
- Non-customers that like the brand

Case study

The Basic Brand Vulnerability Matrix for the burger case study is shown on the next page. It contains quite a few interesting insights (this is just a subset: all the insights would have required a much bigger diagram):

- Only 13% of the market is defined as being loyal (the top-right quadrant).
- 10% of the market is buying Burger Chef, despite disliking or being ambivalent towards the brand. These customers are more likely than average to:
  - Be dining at breakfast or late at night
  - Drive through
  - Be in a group of 2
  - Buy a chicken product
  - Buy a snackbox or meal deal
- 13% of the market like Burger chef, but didn't consume at all in the last month. These customers are more likely to:
  - Be eating dinner
  - Eat at Southern Fried Chicken or Mexican
  - Eating chicken or burritos
  - Buy a family box

Brand attitude

Visit in last month	Negative	Average	Positive
Twice or more	Size: 4% Share: 11% - Breakfast- Late night snack - Drive through - Chicken - Snackbox/Meal 2 people	Size: 6% Share: 16% - Drive through - Nuggets	Size: 13% Share: 31% - Drive through - 2 people - Mates - Meal deals - Family box
Once	Size: 4% Share: 11%	Size: 5% Share: 15%	Size: 6% Share: 22% - Family box
None	Size: 31% Share: 0%	Size: 18% Share: 0% - Dinner	Size: 13% Share: 0% - Southern Fried Chicken/Mexican - Chicken/- Burritos - Dinner - Family box

Legend:
- Sustain
- Grow usage
- Ignore

Performing the analysis in Displayr

Creating variables measuring behavior and attitude

The first step is to create one variable that measures behavior and a second variable that measures attitude. There are lots of different ways of doing this, from using questions that directly collect this data in a survey, through to computing new variables that are constructed from other data. In the examples presented in this chapter, for example, behavior is based on the number of visits to Burger

Chef in the past month and attitude based on the number of positive attributes that they assigned to Burger Chef.

It will simplify your analysis if you order attitude from dislike to like, but order behavior in the opposite direction, from heaviest usage to least heavy usage.

Sizing the segments
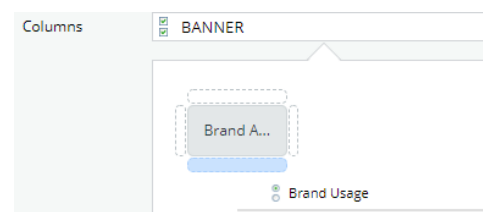
The size of the segments is obtained by:

1. Creating a summary table of attitude by dragging it onto the page
2. Drag the behavior variable on top of the attitude table, releasing in the **Columns** slot.
3. Making sure the table is selected, set **STATISTICS > Cells** to **Total %.**

You should now have a table like the one below, where the cells correspond to the cells in the matrix and the percentages to the sizes of the segments.

Total %	Dislike	Ambivalent	Like	NET
Two or more visits	4%	6%	13%	23%
Visited once	4%	5%	6%	15%
Didn't visit	31%	18%	13%	62%
NET	38%	30%	32%	100%

Computing share within the segments

1. Drag the variable set in the study that measures share onto a page to create a summary table. Typically, this will either be a single variable asking about most recent purchase, or a variable set showing purchase by brand.

2. Drag the attitude variable onto the table in the **Columns** box.
3. Drag the usage variable onto the table, releasing it in the banners slot underneath the attitude column, as showing to the right.
4. If you are using a set of numeric variables to compute share, use **STATISTICS > Cells** to select **% Column Share**. If you are using a single categorical variable, there is no need to do anything.

You should now have a table like the one below, with the behavior variables nested within the attitude variables. The brand shares within segments are shown in the brand's row (in the case study, Burger Chef).

Column %	Dislike			Ambivalent			Like		
	Two or more visits	Visited once	Didn't visit	Two or more visits	Visited once	Didn't visit	Two or more visits	Visited once	Didn't visit
Burger Shack	4%	2%	3%	3%	4%	2%	2%	3%	2%
Burger Chef	11%	11%	0%↓	16%↑	15%↑	0%↓	31%↑	22%↑	0%↓
Nuovo Burger	2%	1%	1%	2%	2%	1%	1%	1%	1%
Lucky's Pizza	5%	3%	7%	7%	6%	6%	4%▼	6%	8%
Pizza Heaven	2%	2%	3%▲	2%	1%	3%	1%	1%	2%
Southern Fried Chicken	16%▲	10%	10%	10%	10%	12%	11%	9%	13%▲
Arnold's	24%	20%	24%▲	20%	21%	22%	18%▼	19%	22%
Nero's Pizza	7%	5%	6%	6%	3%	5%	4%	3%	4%
Pret'a'pane	10%	14%	13%▲	12%	9%	12%	7%▼	9%	10%
Ma's burgers	4%	2%	2%	1%	3%	2%	2%	2%	2%
Bread Basket	1%	2%	1%	1%	1%	1%	0%▼	1%	1%
Asian	7%	11%	14%▲	9%	8%	13%	8%▼	10%	12%
Mexican	5%↓	18%	16%	10%▼	16%	19%▲	10%↓	13%	21%▲
NET	100%	100%	100%	100%	100%	100%	100%	100%	100%

Understanding differences by segments

The last step is to understand the differences between the segments.

1. Click on the page created in the previous section in the **Pages** tree.
2. Press **Duplicate**, which will duplicate the page. If instead something else is duplicated, it means that you skipped the previous step.
3. In **Data sets**, drag across a variable that you wish to profile by segment, dragging it onto the table and releasing it in the **Rows** slot. Blue upward arrows for a segment indicate a statistically significant skew.
4. (Optional) Click on the *banner* that you have just created, which will be at the top of your data set in the **Data Sets** tree and click into its name and rename it as `Attitude & Behavior`.

Quickly profiling lots of tables

If you have a lot of potential variables:

1. Press **Anything > Report > Crosstabs**
2. Select the profiling variables and press **OK**
3. Select the banner variable set that contains attitude and behavior (unless you've changed its name, it will be **BANNERX**, where X is the highest number you can see).
4. Choose **Sort and delete tables not significant at 0.001** (or whatever significance level you like to use)

Performing the analysis in Q

Creating variables measuring behavior and attitude

The first step is to create one variable that measures behavior and a second variable that measures attitude. There are lots of different ways of doing this, from using questions that directly collect this data in a survey, through to computing new variables that are constructed from other data. In the examples presented in this chapter, for example, behavior is based on the number of visits to Burger Chef in the past month and attitude based on the number of positive attributes that they assigned to Burger Chef.

It will simplify your analysis if you order attitude from dislike to like, but order behavior in the opposite direction, from heaviest usage to least heavy usage.

Sizing the segments

The size of the segments is obtained by crosstabbing the attitude and behavior question. You should now have a table like the one below, where the cells correspond to the cells in the matrix, and the percentages to the sizes of the segments.

Total %	Dislike	Ambivalent	Like	NET
Two or more visits	4%	6%	13%	23%
Visited once	4%	5%	6%	15%
Didn't visit	31%	18%	13%	62%
NET	38%	30%	32%	100%

Computing share within the segments

1. In the **Blue Dropdown menu**, select the variable set in the study that measures share. Typically, this will either be a single variable asking about the most recent purchase or a variable set showing purchase by brand.
2. Select the attitude variable in the **Brown Dropdown menu**.
3. Right-click on one of the column headings and select **Create Banner**.

4. Drag the behavior variable so it under the attitude variable.
5. Press OK.
6. If you are using a set of numeric variables to compute share, use **STATISTICS > Cells** to select **% Column Share**. If you are using a single categorical variable, there is no need to do anything.

You should now have a table like the one below, with the behavior variables nested within the attitude variables. The brand shares within segments are shown in the brand's row (in the case study, Burger Chef).

Column %	Dislike			Ambivalent			Like		
	Two or more visits	Visited once	Didn't visit	Two or more visits	Visited once	Didn't visit	Two or more visits	Visited once	Didn't visit
Burger Shack	4%	2%	3%	3%	4%	2%	2%	3%	2%
Burger Chef	11%	11%	0%↓	16%↑	15%↑	0%↓	31%↑	22%↑	0%↓
Nuovo Burger	2%	1%	1%	2%	2%	1%	1%	1%	1%
Lucky's Pizza	5%	3%	7%	7%	6%	6%	4%▼	6%	8%
Pizza Heaven	2%	2%	3%▲	2%	1%	3%	1%	1%	2%
Southern Fried Chicken	16%▲	10%	10%	10%	10%	12%	11%	9%	13%▲
Arnold's	24%	20%	24%▲	20%	21%	22%	18%▼	19%	22%
Nero's Pizza	7%	5%	6%	6%	3%	5%	4%	3%	4%
Pret'a'pane	10%	14%	13%▲	12%	9%	12%	7%↓	9%	10%
Ma's burgers	4%	2%	2%	1%	3%	2%	2%	2%	2%
Bread Basket	1%	2%	1%	1%	1%	1%	0%▼	1%	1%
Asian	7%	11%	14%▲	9%	8%	13%	8%▼	10%	12%
Mexican	5%↓	18%	16%	10%▼	16%	19%▲	10%↓	13%	21%▲
NET	100%	100%	100%	100%	100%	100%	100%	100%	100%

Understanding differences by segments

The last step is to understand the differences between the segments.

1. Press **+ Duplicate**, which will duplicate the page. If instead something else is duplicated, it means that you skipped the previous step.
2. Change the data in the **Blue Dropdown menu**.

Quickly profiling lots of tables

If you have a lot of potential variables use **Create > Tables > Crosstabs**.

Putting it all together

This last chapter summarizes the key learnings identified in the case study form application of the five analysis frameworks.

This approach is not the be-all-and-end-all of data analysis for brand planning. There ought to be other layers to this process – some internal/sales analysis, store count growth, environmental and economic trends, qualitative research, etc.

However, as a *primer* for branding strategy, it has delivered a lot of useful content.

	Short Term	Long Range
Competitive Focus	Take share from Southern Fried Chicken (direct competitor), 2nd Tier players (indirect)	Take share from Arnold's (leader), Protect against potential emergent threats (2nd and 3rd Tier)
Marketing Goal	Increase frequency from current users and considerers	Grow distribution
Strengths to Develop, Defend	Drive Through Convenience, Value	Store location convenience, Value, Food Quality & Taste
Weakness/Gaps to Address	Chicken products Dinner occasion	Distribution and service network
Core consumer	Under 30 Male Single Works in services, sales, or as a laborer. Has a low income.	

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