Chapter 11 PCA and Perceptual Maps

11.1 Introduction: Why PCA Matters in Marketing Analytics

Marketing datasets often contain many related variables that describe how consumers perceive brands, products, or services. When these attributes are highly correlated, interpretation becomes difficult and redundancy increases. Principal Components Analysis (PCA) is a dimension-reduction technique that helps uncover the underlying structure in such data.

In marketing analytics, PCA is commonly used to:

- Summarize brand image and positioning data
- Reduce large attribute batteries into interpretable dimensions
- Serve as the foundation for perceptual maps

In this chapter, we focus on applying PCA for **interpretation and insight**, not mathematical derivation. We will:

1. Fit a PCA model and evaluate diagnostics
2. Choose an appropriate number of components
3. Interpret component loadings
4. Use PCA results to construct perceptual maps

As a high-level overview, PCA transforms a set of correlated variables into a smaller set of new variables called *principal components*. Each component is a weighted combination of the original variables.

Key ideas:

- Components are ordered by how much variance they explain

- The first component explains the most variance, the second explains the most remaining variance, and so on
- Components are uncorrelated with one another

From a marketing perspective, PCA helps answer: “What are the main dimensions consumers use to differentiate brands?”

11.2 The `greekbrands` Dataset

This chapter uses the `greekbrands` dataset, which contains simulated attribute ratings and brand preference data for ten fictional technology brands. Each observation corresponds to a respondent-brand evaluation.

The dataset includes:

- A brand identifier
- Multiple numeric attribute ratings describing brand perceptions

This type of brand image data is well suited for PCA because many of the attributes tend to be correlated and may reflect a smaller number of latent dimensions.

11.3 Preparing for PCA in a Marketing Context

Before fitting a PCA model, it is important to:

- Use only numeric perceptual attributes
- Exclude identifiers (e.g., brand names, respondent IDs)
- Consider whether PCA should be run at the individual or brand level

For perceptual mapping, brand-level aggregation is typically preferred so that brands (not respondents) appear as points in the map.

11.4 PCA Modeling

11.4.1 Fitting an Initial PCA Model

We begin with an initial PCA fit to evaluate how many components should be retained. This step focuses on diagnostics rather than interpretation. Although PCA is not difficult in base R using the `prcomp()` function, we'll use the `easy_pca_fit()` function from the `MKT4320BGSU` to automate the process for both fitting and a separate function for the final model.

Usage:

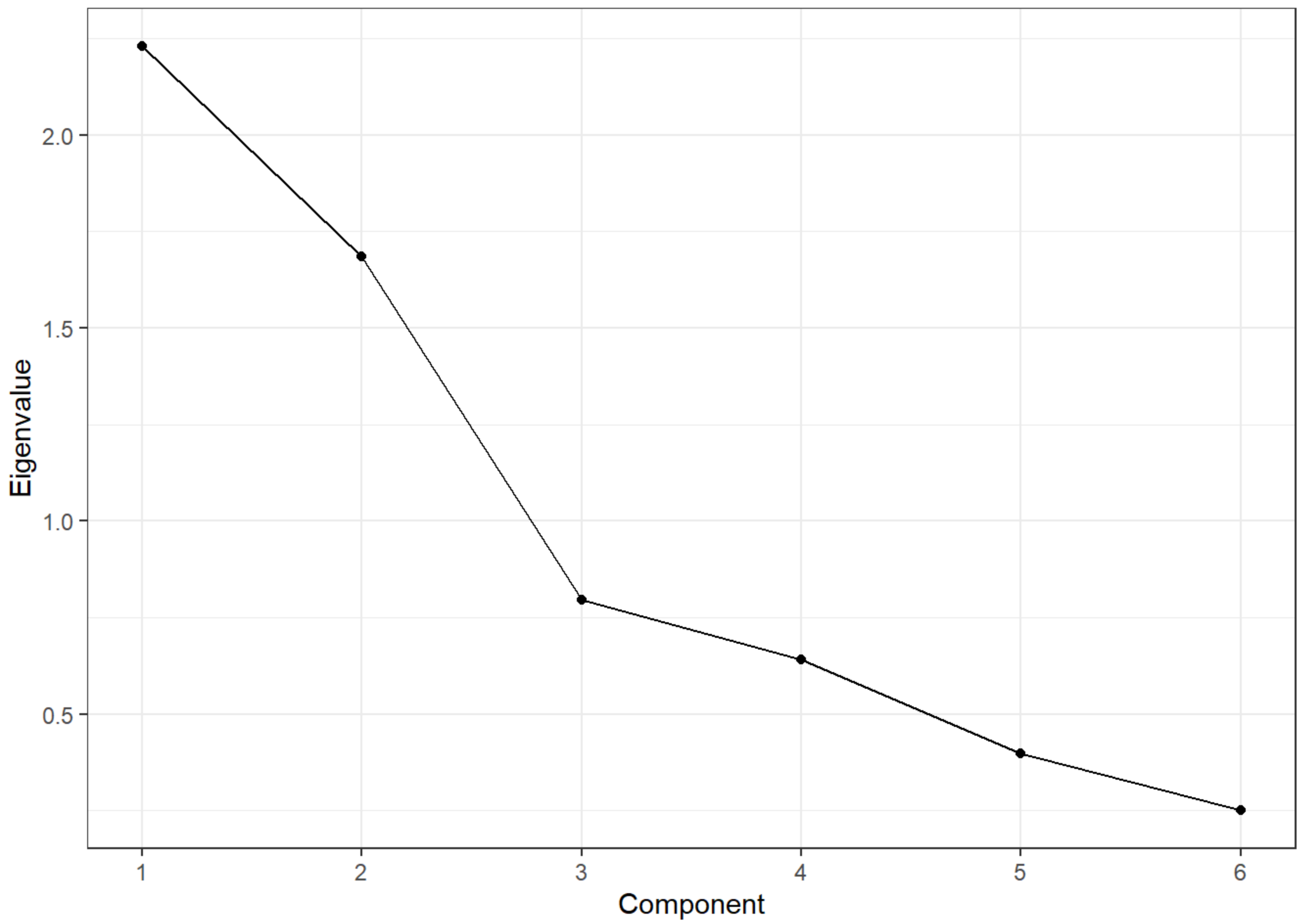
- `easy_pca_fit(data, vars, group = NULL, ft = TRUE)`
- where:
    - `data` is a data frame containing the full dataset.
    - `vars` is a character vector of variable names to use in PCA (required). All variables must be numeric.
    - `group` is an optional character sting of a single variable name to aggregate by before PCA.
    - `ft` is logical; if TRUE, return $table as a flextable (default = TRUE).

In the example below, we do not use the `group` option.

```
attr_vars <- c("perform", "leader", "fun", "serious", "bargain", "value")
pca_fit <- easy_pca_fit(data = greekbrands,  vars = attr_vars, ft=TRUE)
pca_fit$table
```

Component	Eigenvalue	Difference	Proportion	Cumulative
1	2.2293	0.5454	0.3716	0.3716
2	1.6839	0.8876	0.2806	0.6522
3	0.7963	0.1545	0.1327	0.7849
4	0.6418	0.2433	0.1070	0.8919
5	0.3985	0.1484	0.0664	0.9583
6	0.2501		0.0417	1.0000

```
pca_fit$plot
```



The eigenvalue table and scree plot summarize how much variance each component explains. Important columns in the eigenvalue table include:

- **Eigenvalue**: total variance explained by each component
- **Proportion**: share of total variance explained
- **Cumulative**: cumulative proportion of variance explained

Common decision rules:

- Retain components with eigenvalues greater than 1
- Look for an “elbow” where additional components add little explanatory power
- Aim for a solution that balances parsimony and interpretability

There is no single correct answer. Component retention should be guided by marketing judgment as well as statistics.

11.4.2 Final PCA Solution

After deciding how many components to retain, we refit the PCA model and examine the loadings using the `easy_pca_final()` function from the `MKT4320BGSU` package.

Usage:

- `easy_pca_final(data, vars, comp, group = NULL, ft = TRUE)`
- where:
  - `data` is a data frame containing the full dataset.
  - `vars` is a character vector of variable names to use in PCA (required). All variables must be numeric.
  - `comp` is an integer representing the number of components to retain.
  - `group` is an optional character sting of a single variable name to aggregate by before PCA.
  - `ft` is logical; if TRUE, return $table as a flextable (default = TRUE).

In the example below, we again choose not to use the `group` option.

```
pca_final <- easy_pca_final(data = greekbrands, vars = attr_vars,
                            comp = 2, ft=TRUE)
pca_final$rotated
```

Varimax-Rotated PCA Loadings

Variable	Comp_1	Comp_2	Unexplained
perform	0.7243	-0.0750	0.4697
leader	0.8404	-0.0486	0.2914
fun	-0.5475	0.1496	0.6778
serious	0.7849	0.0434	0.3821
bargain	-0.0189	-0.9294	0.1359
value	0.0698	-0.9302	0.1298

We focus on the **varimax-rotated** loadings because they are easier to interpret. A loading represents the relationship between an original attribute and a component:

- Larger absolute values indicate stronger relationships

- Attributes with high loadings on the same component tend to reflect a common underlying dimension

When interpreting loadings:

- Look for patterns across attributes
- Identify which attributes define each component
- Assign descriptive, managerially meaningful names to components

For example:

- A component with high loadings on *perform*, *leader*, and *serious* might be labeled **Performance**
- A component with high loadings on *bargain* and *value* might be labeled **Value Orientation**

11.5 From PCA to Perceptual Maps

PCA components can be used as axes in perceptual maps. Each brand's position on a component reflects how strongly it scores on that underlying dimension.

Perceptual maps translate statistical results into a visual format that is easy to communicate to managers and decision-makers.

11.6 Attribute-Based Perceptual Maps Using PCA

11.6.1 Creating PCA-Based Maps

We now use the retained PCA solution to create perceptual maps. We use the `easy_pca_maps()` function from the `MKT4320BGSU` package to automate the process.

Usage:

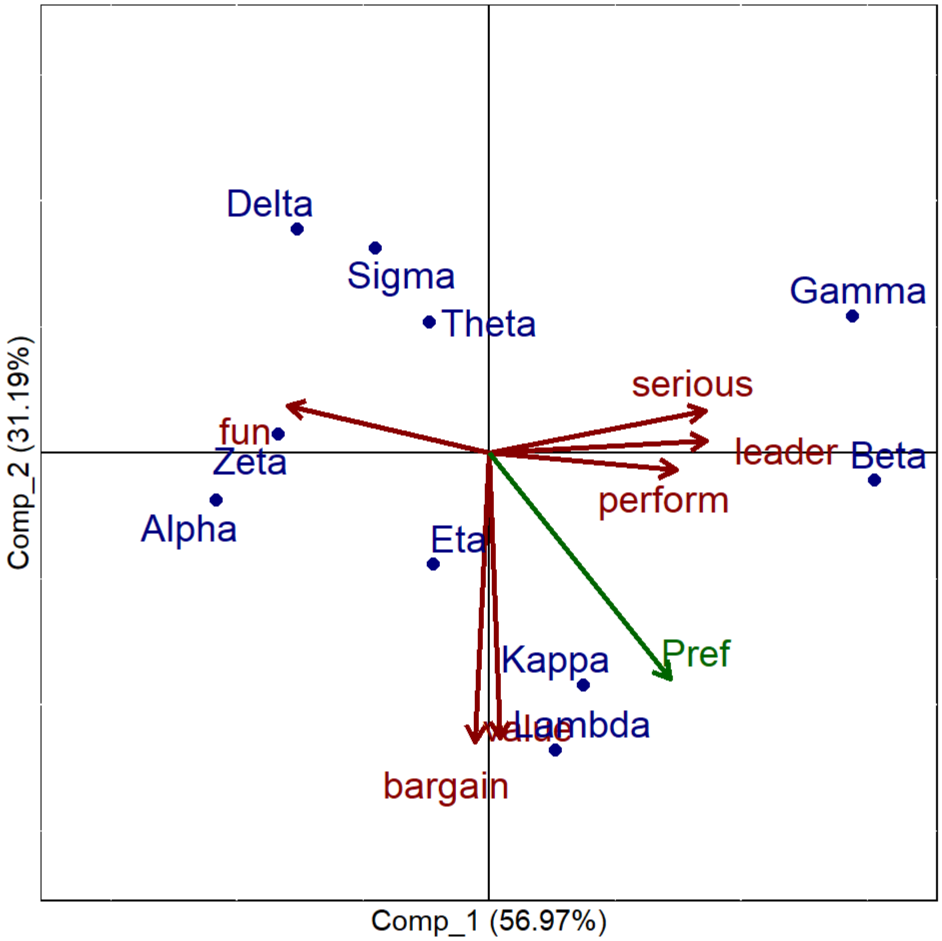
- `easy_pca_maps(data, vars, group, comp, pref = NULL, rotate = TRUE, arrow_scale = 0.75,label_pad = 0.04)`

- where:
  - `data` is a data frame containing individual-level observations.
  - `vars` is a character vector of numeric attribute variable names used in PCA.
  - `group` is a single string specifying the grouping variable (e.g., brand or product name).
  - `comp` is an integer specifying the number of components to retain (must be ≥ 2).
  - `pref` is an optional single string specifying a numeric preference variable name to produce a joint space map with a preference vector (if data is available)
  - `rotate` is logical; if TRUE (default), apply varimax rotation to the retained component space before creating perceptual maps.
  - `arrow_scale` is numeric in (0, 1]; scales arrow lengths relative to the object range (default = 0.75).
  - `label_pad` is numeric; distance (as a proportion of the axis range) used to push attribute arrow labels beyond arrow tips (default = 0.04) for easier viewing of the map.

We'll use the same variables as before, but add in the required `group` and an optional `pref` to create a joint space map.

```
pca_maps <- easy_pca_maps(data = greekbrands, vars = attr_vars,
                          group = "brand", pref = "pref", comp = 2)
pca_maps$plots
```

```
$Comp_1_vs_Comp_2
```



The map displays:

- Brands as points
- Attribute vectors showing how attributes align with the components

Key interpretation guidelines:

- Brands close together are perceived similarly
- Brands far apart are perceived differently
- Attribute vectors indicate the direction of increasing attribute values
- Brands in the direction of an attribute vector score higher on that attribute
- Attribute vectors more parallel with the preference vector (if available) a stronger drivers of preference

Distances are relative and should be interpreted qualitatively rather than precisely.

11.7 Managerial Interpretation and Strategic Insights

PCA-based perceptual maps can help managers:

- Identify direct competitors
- Detect market clusters and white space
- Evaluate whether a brand’s positioning matches strategic intent

These insights can inform:

- Positioning statements
- Advertising and messaging strategy
- Product reformulation decisions

Common Pitfalls and Best Practices

- Do not over-interpret small loadings
- Avoid retaining too many components
- Remember that PCA alone reflects perceptions, not preferences
- Always explain components in clear, non-technical language

11.8 Chapter Summary

In this chapter, we:

- Used PCA to reduce and interpret brand perception data
- Applied diagnostics to choose the number of components
- Interpreted rotated component loadings
- Created perceptual maps to visualize brand positioning

PCA is a powerful bridge between data analysis and strategic insight in marketing analytics.

11.9 What’s Next

In the next chapter, we shift from describing perceptions to testing causal impact.Specifically, we will study A/B testing and uplift modeling, which are tools used to answer questions such as:

- Does a new message, offer, or design actually change behavior?
- How large is the effect of a treatment compared to a control?
- Are some customers more responsive to an intervention than others?

Where PCA and perceptual maps help us understand how consumers see brands, A/B testing helps us evaluate what actions work, and uplift modeling helps us determine for whom they work best. These methods are central to modern data-driven marketing in areas such as digital advertising, pricing experiments, promotions, and personalization.