

Winning the Race:

A Conjoint Analysis of
EarlyRiders and Competition

Jiakang Chen, Yun Xiao,
Chengyu Jiang, and Jade Sinskul
GBA424 - 11B; MSMA Team #A: In-Person
7 December 2020



Executive Summary

From our conjoint analysis, segment 1 contained the largest benefit segmentation.

- Based on price, size, motion, and style, the analysis concluded that a total of three segment groups were appropriate; all three segments have distinct preferences.

Out of the three benefit segments, segment 1 is the only segment that is price sensitive in the toy horse market.

- All three segments had different variations of preferences (price, size, motion, and style).

From our A Priori segmentation of age and gender, the analysis concluded the differences between younger vs. older children and females vs. males.

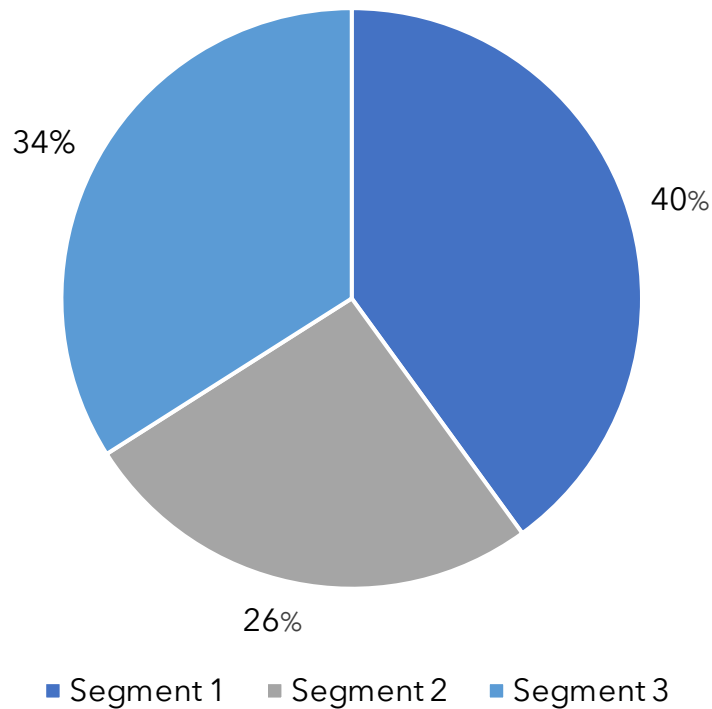
- Younger children and females share similar preferences when choosing a toy horse.

Recommendation: The business impact had concluded six market simulations that could happen to EarlyRiders and competition.

- Based on the analysis, we found that scenario #4 was deemed the best position for EarlyRiders as they would capture the largest market share and profit.

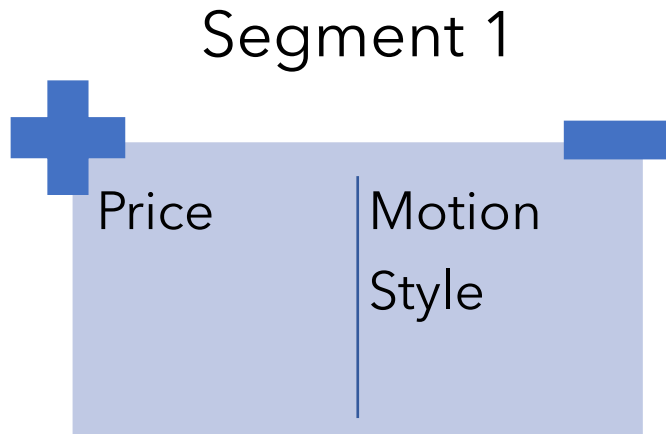
Segment 1 Contains the Largest Benefit Segmentation

Percentage of Customers in Each Segment

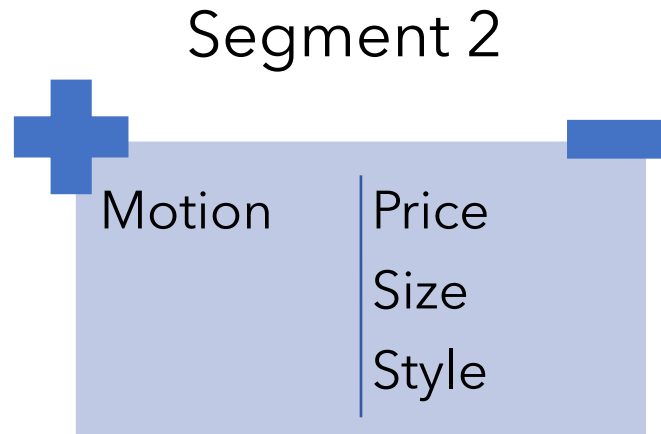


- Out of 200 customers, 3 segments were deemed appropriate based on ratings of:
 - Price
 - Size
 - Motion
 - Style

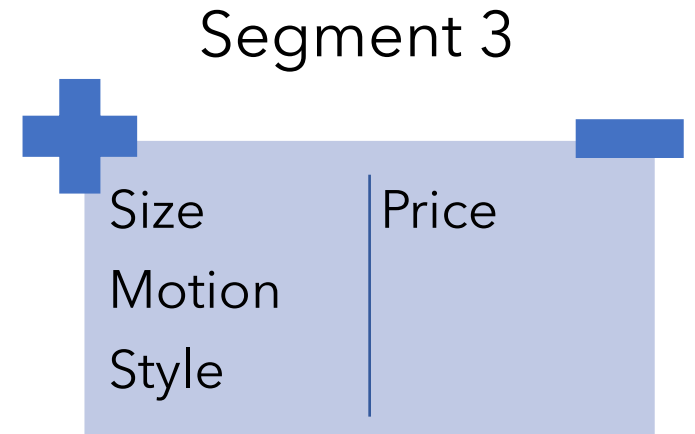
Segment 1 is the Only Segment that is Price Sensitive



- Price sensitive
- Indifferent about size
- Prefers bouncing motion
- Prefers racing style

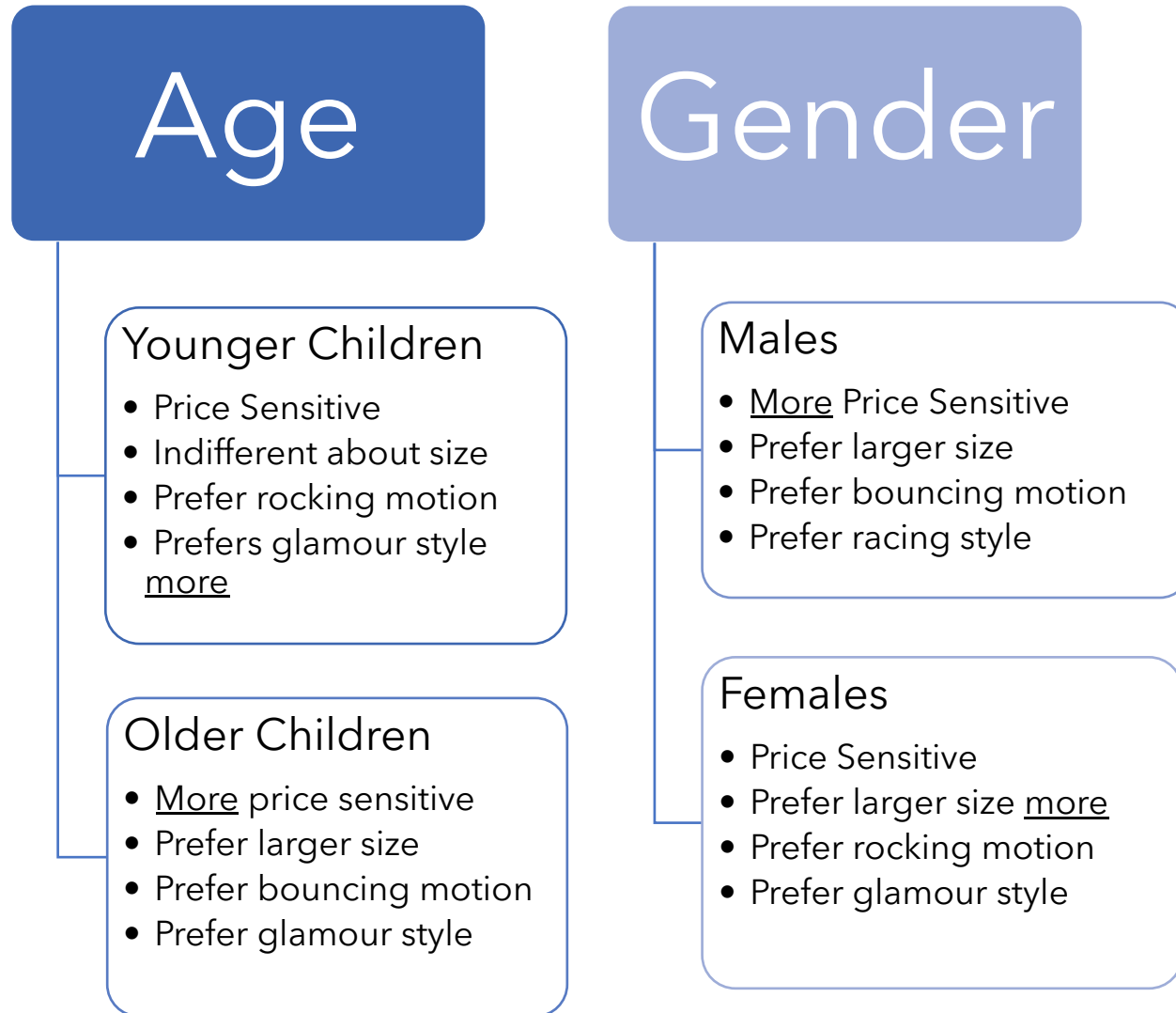


- Price insensitive
- Prefers smaller size
- Prefers rocking motion
- Prefers racing style



- Price insensitive
- Prefers larger size
- Prefers rocking motion
- Prefers glamour style

A Priori Segmentation by Age and Gender



To firmly conclude, on average:

- Females and Younger Children prefer:
 - Price = \$139.99
 - Size = 18
 - Style = Bouncing
 - Motion = Racing

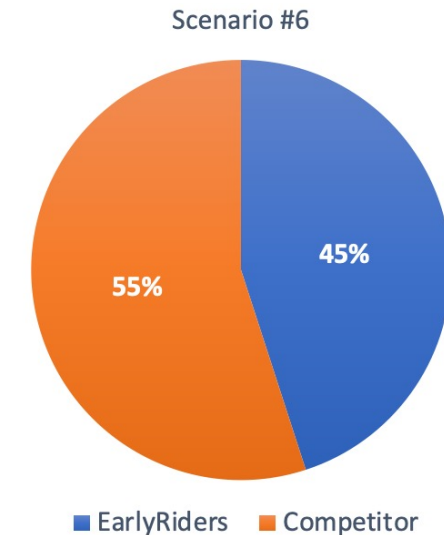
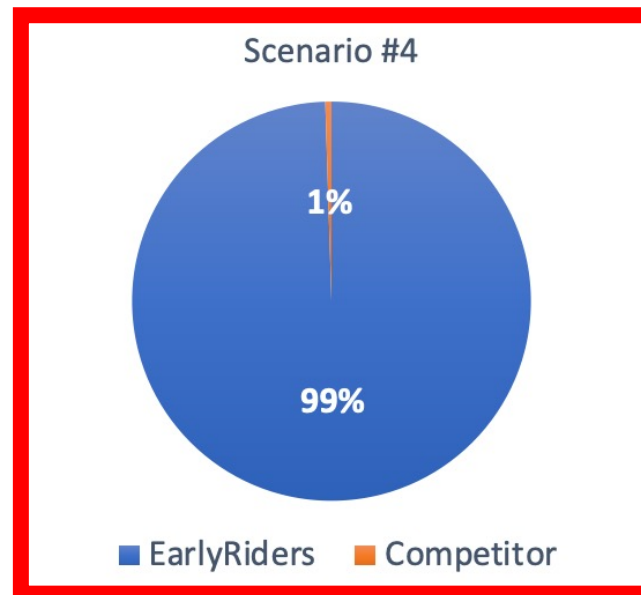
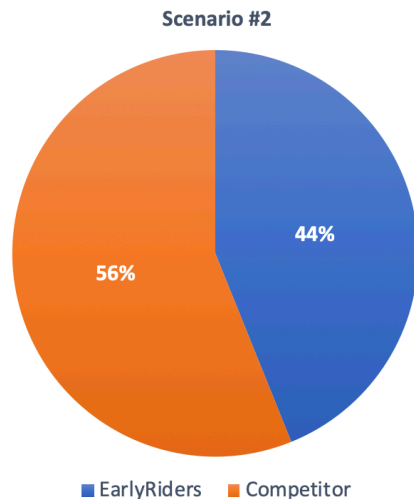
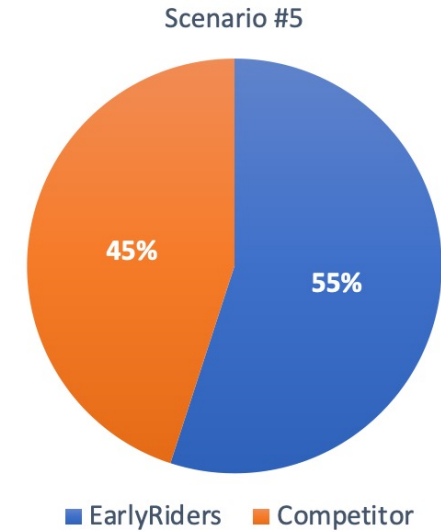
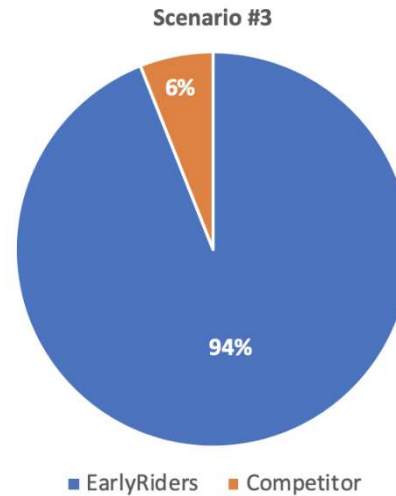
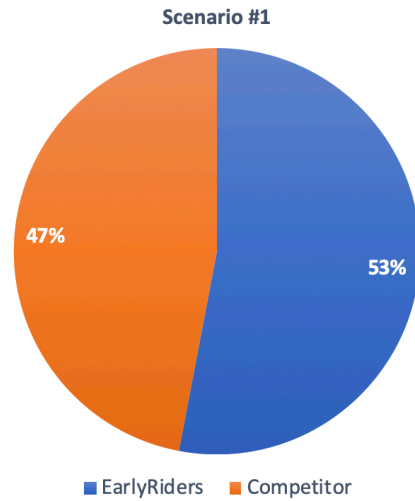
Market Simulations

Scenarios	Description	Offerings
Scenario 1	Don't change anything	Profile #5, #13
Scenario 2	Eliminate worse product, keep best	Profile #5
Scenario 3	Lower price for current products	Profile #6, #14
Scenario 4	Eliminate Profile #13, release 2 new products (targets benefit segments)	Profile #2 (S1), #5 (S2), #15 (S3)
Scenario 5	Targets Age Segmentation	Profile #15 (Younger), #12 (Older)
Scenario 6	Targets Gender Segmentation	Profile #4 (Male), #15 (Female)

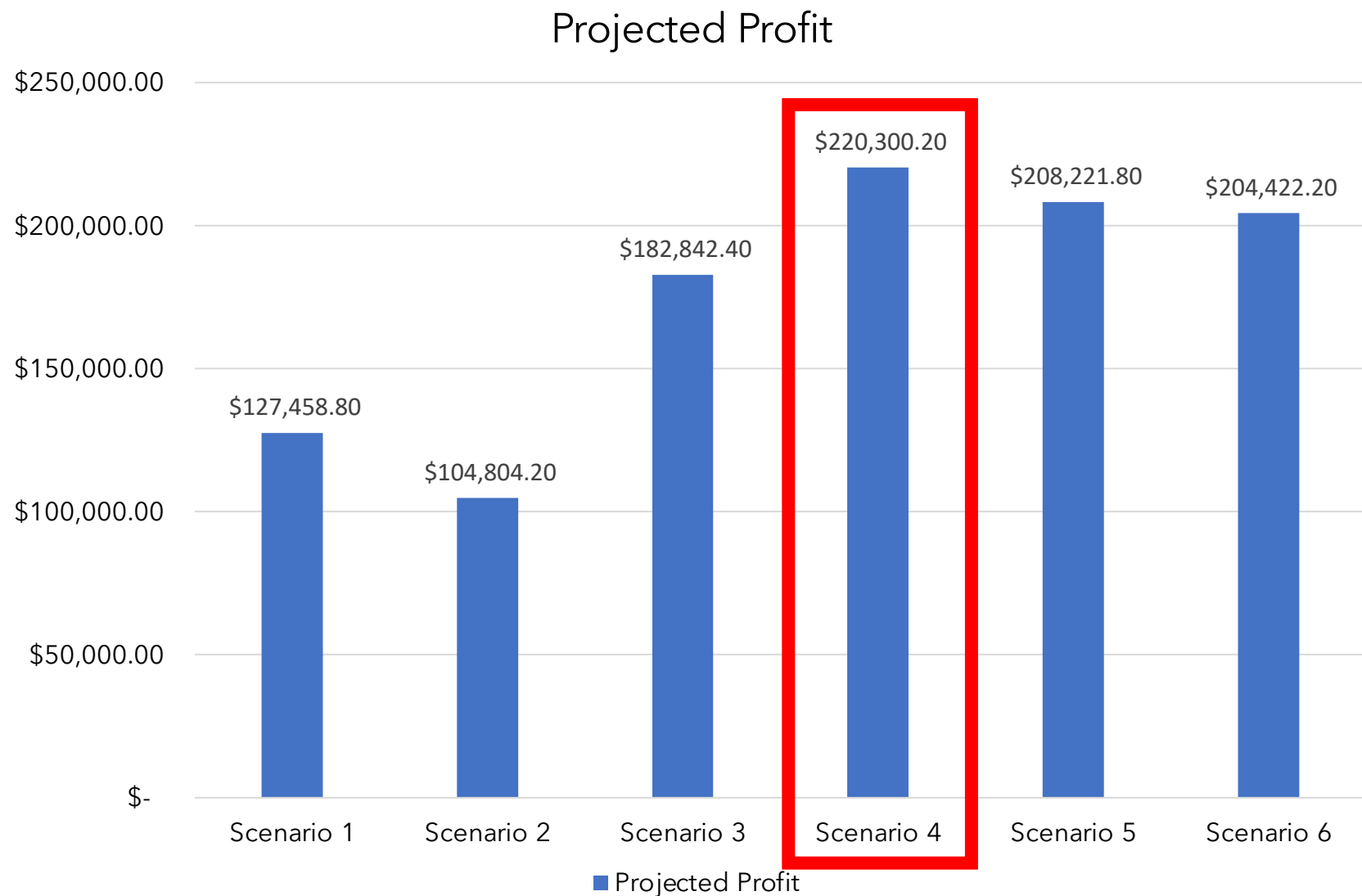
Competitors remains carrying the same product (Profile #7)

Refer to Appendix D for further analysis.

Scenario 4 Offers the Largest Market Share



Scenario 4 Offers the Largest Projected Profit



Winning the Race:

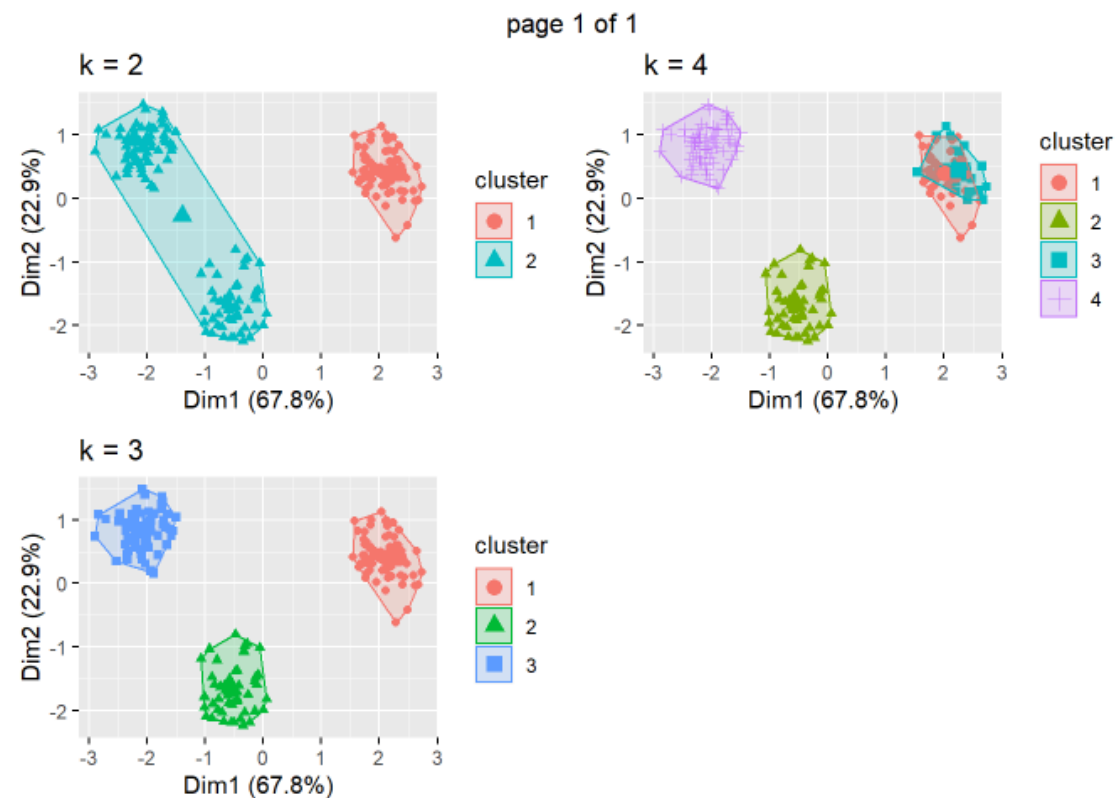
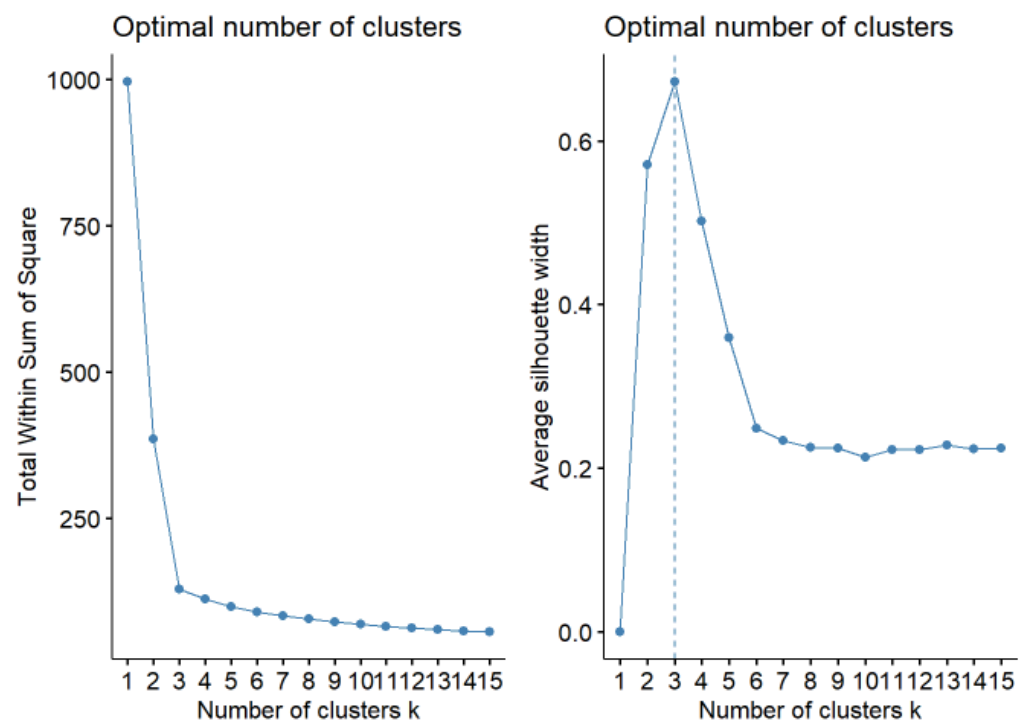
A Conjoint Analysis of EarlyRiders and Competition

Jiakang Chen, jchen156@simon.rochester.edu
Yun Xiao, yxiao28@simon.rochester.edu
Chengyu Jiang, cjiang16@simon.rochester.edu
Jade Sinskul, jsinskul@simon.rochester.edu
GBA424 - 11B; MSMA Team #A: In-Person
7 December 2020



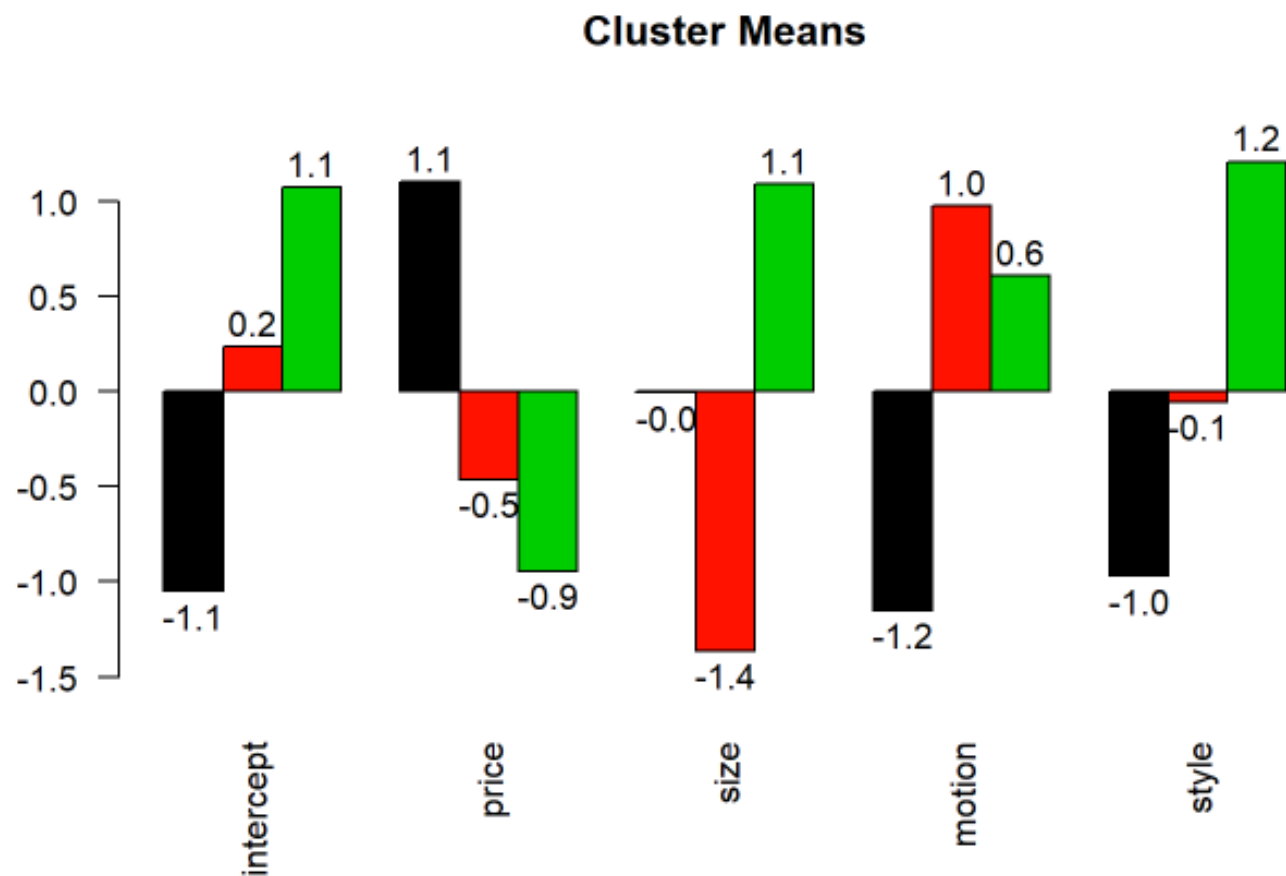
Appendix A

Cluster Analysis



Appendix B

Average Product Preferences



Appendix C

Regression on Age (Younger vs. Older)

```
summary(lm(ratings~price+size+motion+style,data=data[data$age==0,]))
```

```
##
## Call:
## lm(formula = ratings ~ price + size + motion + style, data = data[data$age ==
## 0, ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.3750 -2.1463  0.0385  2.3327  7.1463
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   6.9615     0.2075  33.551 < 2e-16 ***
## price         2.9558     0.1944  15.203 < 2e-16 ***
## size          0.7077     0.1862   3.802 0.000151 ***
## motion        0.5213     0.1862   2.800 0.005191 **
## style         0.1846     0.1862   0.991 0.321685
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.159 on 1183 degrees of freedom
## (396 observations deleted due to missingness)
## Multiple R-squared:  0.1896, Adjusted R-squared:  0.1869
## F-statistic: 69.21 on 4 and 1183 DF, p-value: < 2.2e-16
```

```
summary(lm(ratings~price+size+motion+style,data=data[data$age==1,])) #older
```

```
##
## Call:
## lm(formula = ratings ~ price + size + motion + style, data = data[data$age ==
## 1, ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -7.2380 -2.7562 -0.4616  3.3723  8.3100
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   6.62768     0.23235  28.524 < 2e-16 ***
## price         3.28589     0.21772  15.092 < 2e-16 ***
## size          1.54806     0.20845   7.426 2.1e-13 ***
## motion       -0.06621     0.20845  -0.318  0.751
## style         0.12851     0.20845   0.616  0.538
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.573 on 1207 degrees of freedom
## (404 observations deleted due to missingness)
## Multiple R-squared:  0.2224, Adjusted R-squared:  0.2198
## F-statistic: 86.28 on 4 and 1207 DF, p-value: < 2.2e-16
```

Appendix C (cont.)

Regression on Gender (Female vs. Male)

```
summary(lm(ratings~price+size+motion+style,data=data[data$gender==1,])) #female
```

```
##
## Call:
## lm(formula = ratings ~ price + size + motion + style, data = data[data$gender ==
## 1, ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -8.890 -2.884  0.755  2.767  6.571
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   7.2388     0.2148  33.693 < 2e-16 ***
## price         2.8032     0.2013  13.924 < 2e-16 ***
## size          1.4603     0.1927   7.576 6.76e-14 ***
## motion         0.5459     0.1927   2.832 0.004694 **
## style          0.6447     0.1927   3.345 0.000847 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.416 on 1291 degrees of freedom
## (432 observations deleted due to missingness)
## Multiple R-squared:  0.1876, Adjusted R-squared:  0.1851
## F-statistic: 74.51 on 4 and 1291 DF, p-value: < 2.2e-16
```

```
summary(lm(ratings~price+size+motion+style,data=data[data$gender==0,]))
```

```
##
## Call:
## lm(formula = ratings ~ price + size + motion + style, data = data[data$gender ==
## 0, ])
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -6.4466 -2.1168 -0.5136  1.7305  8.5534
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)   6.2695     0.2028  30.912 < 2e-16 ***
## price         3.4973     0.1900  18.402 < 2e-16 ***
## size          0.7468     0.1820   4.104 4.35e-05 ***
## motion        -0.1526     0.1820  -0.839  0.4018
## style         -0.4171     0.1820  -2.292  0.0221 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.977 on 1099 degrees of freedom
## (368 observations deleted due to missingness)
## Multiple R-squared:  0.2867, Adjusted R-squared:  0.2841
## F-statistic: 110.4 on 4 and 1099 DF, p-value: < 2.2e-16
```

Appendix D

Product Profiles

	profile	price	size	motion	style	priceLabel	sizeLabel	motionLabel	styleLabel
1	1	0	0	0	0	139.99	18 inches	Bouncing	Racing
2	2	1	0	0	0	119.99	18 inches	Bouncing	Racing
3	3	0	1	0	0	139.99	26 inches	Bouncing	Racing
4	4	1	1	0	0	119.99	26 inches	Bouncing	Racing
5	5	0	0	1	0	139.99	18 inches	Rocking	Racing
6	6	1	0	1	0	119.99	18 inches	Rocking	Racing
7	7	0	1	1	0	139.99	26 inches	Rocking	Racing
8	8	1	1	1	0	119.99	26 inches	Rocking	Racing
9	9	0	0	0	1	139.99	18 inches	Bouncing	Glamour
10	10	1	0	0	1	119.99	18 inches	Bouncing	Glamour
11	11	0	1	0	1	139.99	26 inches	Bouncing	Glamour
12	12	1	1	0	1	119.99	26 inches	Bouncing	Glamour
13	13	0	0	1	1	139.99	18 inches	Rocking	Glamour
14	14	1	0	1	1	119.99	18 inches	Rocking	Glamour
15	15	0	1	1	1	139.99	26 inches	Rocking	Glamour
16	16	1	1	1	1	119.99	26 inches	Rocking	Glamour