

Analysis and Recommendation in Toy Horse Business

2020.02.10



Preview

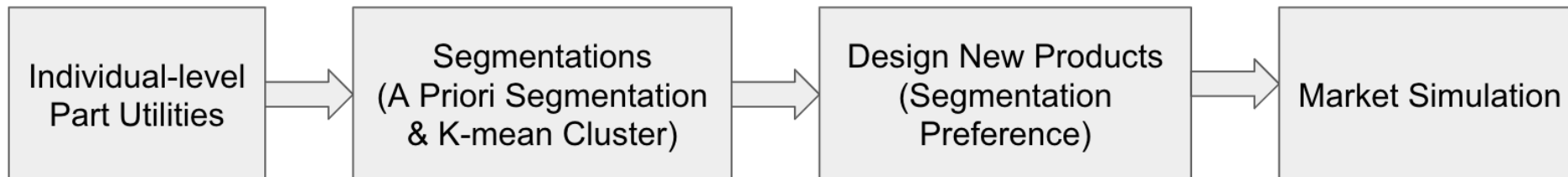
Recommendations:

- Drop current products
- Release 3 new products with key attributes:
 1. \$95.99 Wholesale, 26 inches, Bouncing, Racing (Male)
 2. \$95.99 Wholesale, 26 inches, Rocking, Glamorous(Female)
 3. \$95.99 Wholesale, 18 inches, Rocking, Glamorous
- Packing: Design specific packages toward *different genders*
- Messaging: Emphasize our *low price*

Further Insights:

- Competitor will likely lower prices in response to our strategy
- Main customer segments are **Male** and **Female**
 - Preferences largely differed based on Gender
 - Can generate more profits

Process:



Estimate Individual Preferences of Consumers

- Data: 200 customers ratings of various product profiles
- Utilized individual-level regressions to predict individual preferences
- Predicted ratings of every combination of product attributes

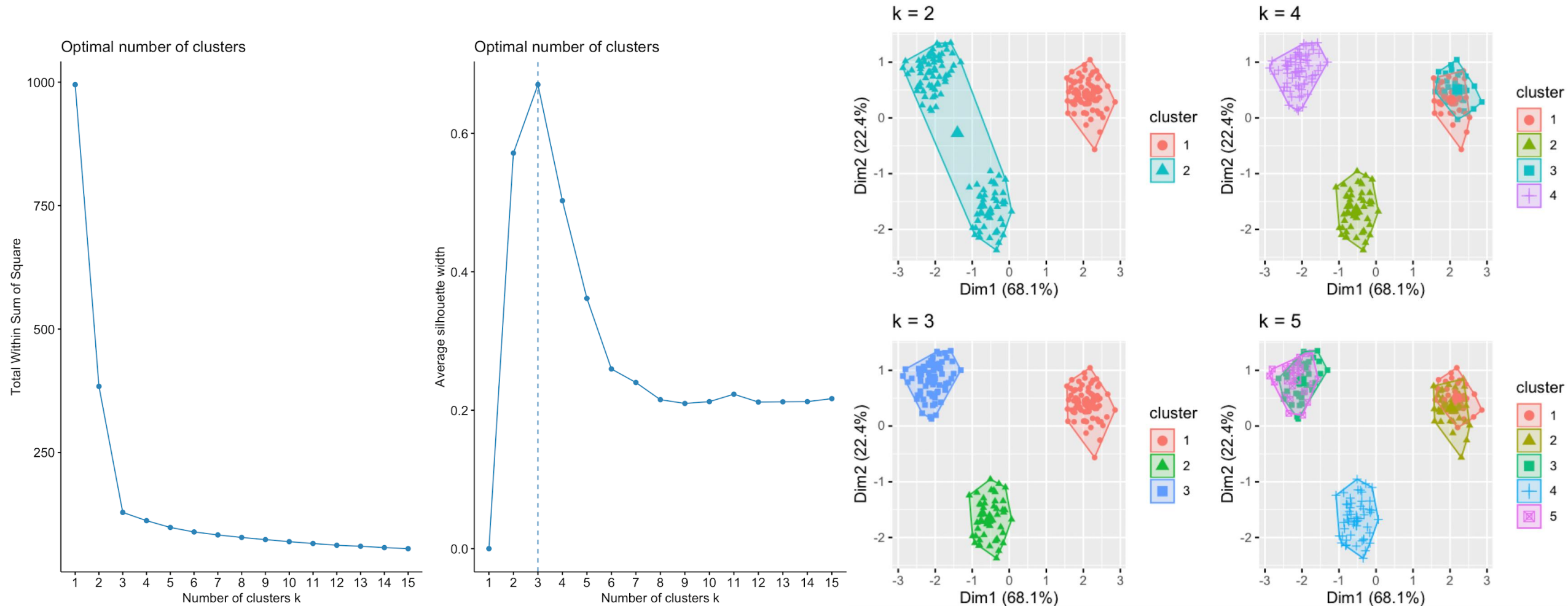
Example:

	(Intercept)	price_low	height_26	motion_rocking	style_glamorous
1	42.16541	8.600463	21.334432	6.289641	11.8153588

This customer prefers a **low priced, 26 inch, rocking** horse that is **glamorously** decorated

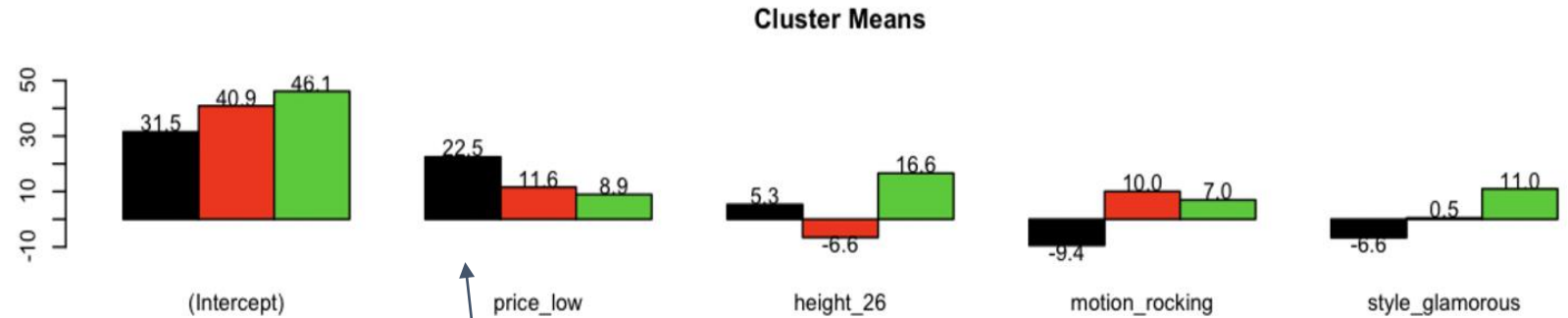
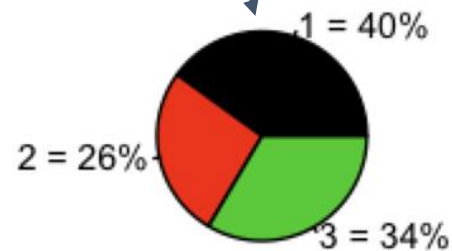
Segmenting Based on Individual Preferences

- Using a K-Means Cluster Analysis, we are able to group customers into *3 distinct segments* based on their innate preferences (rather than physical demographics)



Customer Cluster Overview

Cluster 1 makes up **40%** of our survey respondents



Cluster 1 prefers **low price** the most (highest price sensitivity)

Ideal Products for Each Cluster

Cluster	profile					product
1 ●	low price	26	bouncing	racing		p1(4)
2 ●	low price	18	rocking	glamorous		p2L(14)
3 ●	low price	26	rocking	glamorous		p3(16)

Benefit Segmentation----- a priori segmentation

Call:

```
lm(formula = rating ~ (price_low + height_26 + motion_rocking +  
style_glamorous) * gender, data = merge_df)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	36.5668	0.8801	41.547	< 2e-16	***
price_low	16.8573	0.7872	21.414	< 2e-16	***
height_26	3.8509	0.7872	4.892	1.05e-06	***
motion_rocking	-0.7601	0.7872	-0.966	0.334327	
style_glamorous	-1.8895	0.7872	-2.400	0.016440	*
gender	4.3032	1.1977	3.593	0.000332	***
price_low:gender	-3.3488	1.0713	-3.126	0.001788	**
height_26:gender	3.9046	1.0713	3.645	0.000272	***
motion_rocking:gender	3.6669	1.0713	3.423	0.000627	***
style_glamorous:gender	5.6165	1.0713	5.243	1.68e-07	***

Call:

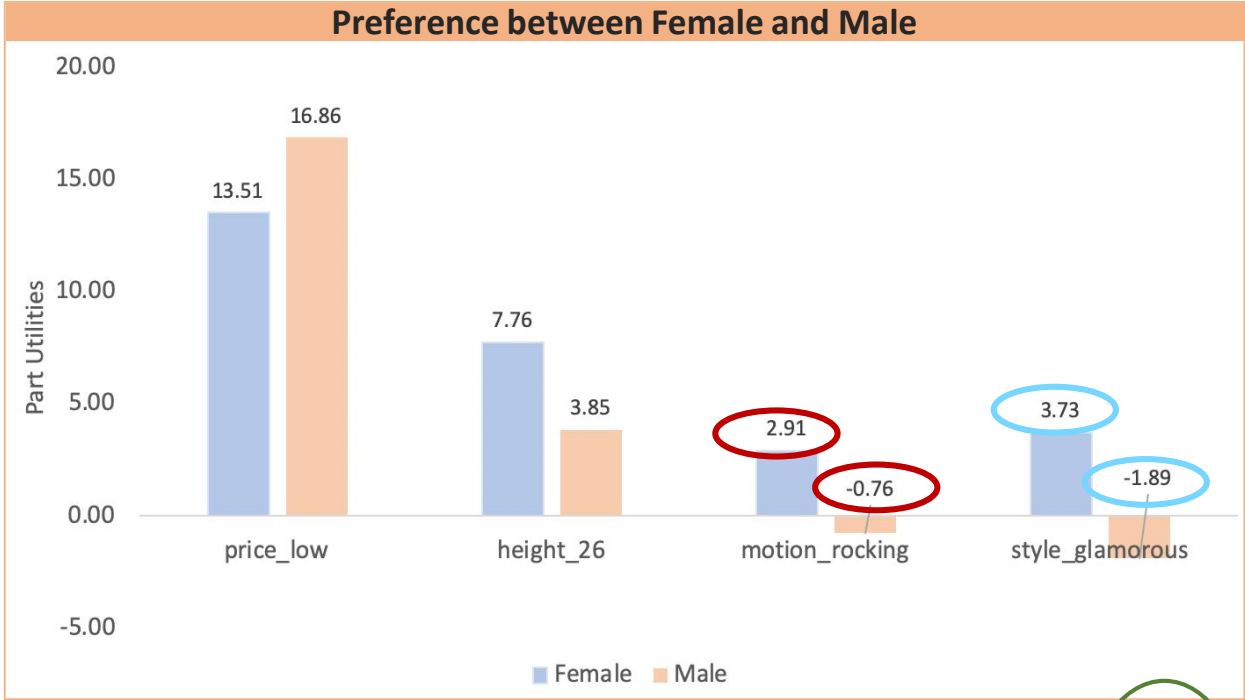
```
lm(formula = rating ~ (price_low + height_26 + motion_rocking +  
style_glamorous) * age, data = merge_df)
```

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)	
(Intercept)	39.5462	0.8917	44.350	< 2e-16	***
price_low	14.4133	0.7975	18.072	< 2e-16	***
height_26	3.8532	0.7975	4.831	1.42e-06	***
motion_rocking	2.7950	0.7975	3.504	0.000464	***
style_glamorous	1.1867	0.7975	1.488	0.136877	
age	-1.2982	1.2548	-1.035	0.300928	
price_low:age	1.2588	1.1223	1.122	0.262095	
height_26:age	4.1708	1.1223	3.716	0.000206	***
motion_rocking:age	-3.1188	1.1223	-2.779	0.005486	**
style_glamorous:age	-0.0857	1.1223	-0.076	0.939140	

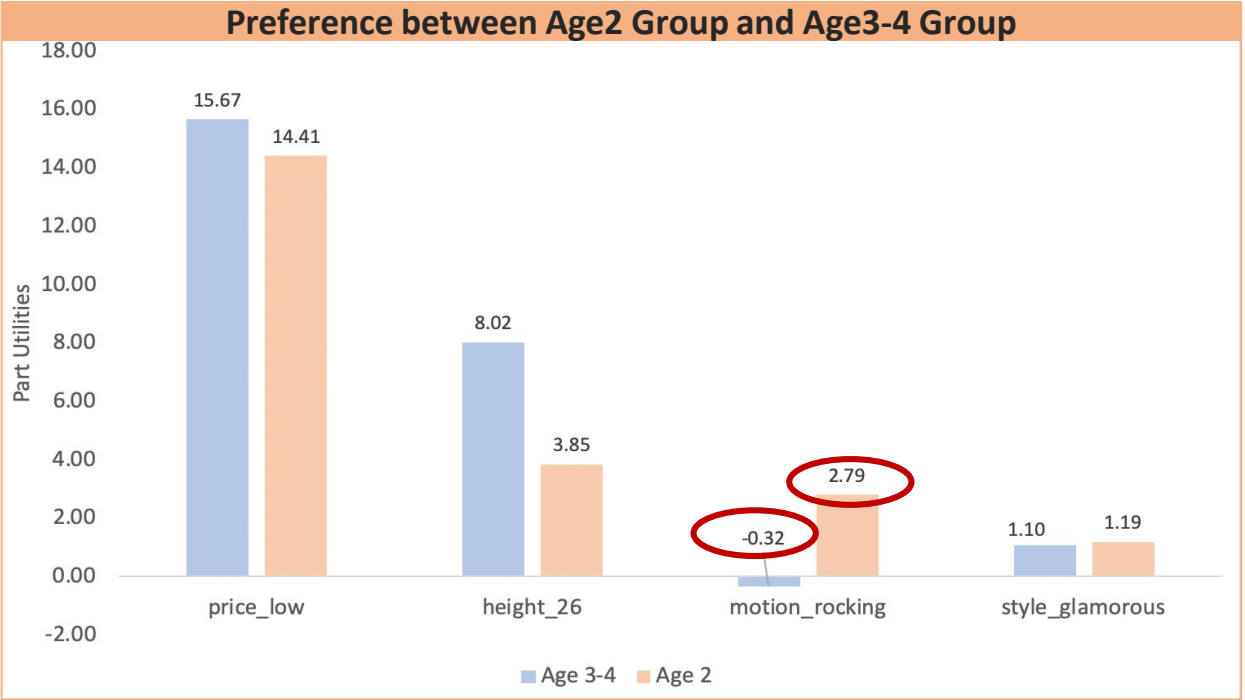
- Creating the interactions of the segment dummies with each
 - The variable gender *affects all* the part-utilities significantly.
 - The variable age only affects *height* and *motion*.
- Using variable gender is a better segmentation scheme but age segment is still meaningful.

Benefit Segmentation-----a priori segmentation



Segmentation	profile				product
Male	low price	26	bouncing	racing	p1
Female	low price	26	rocking	glamorous	p3

- Both gender prefer the *low price* and the *height of 26*.
- female group** prefer the *rocking* and the *glamorous*
- male group** prefer the *bouncing* and the *racing*
- The products that both gender prefer are **match** the products that the cluster 1 and 3 prefer(p1 and p3)



Segmentation	profile				product
Age:2	low price	26	bouncing	glamorous	p4
Age:3-4	low price	26	rocking	glamorous	p3

- Both age group prefer the *low price*, *height of 26* and style of *glamorous*.
- 2-year-old child group** prefer the *bouncing*
- 3~4-year-old child group** prefer the *rocking*

Market Simulation

0) Basic Idea

- Develop scenarios based on the products.
- Calculate market share for each scenario.
- Take fixed cost(\$20,000 per product line) and switching cost(\$20,000* $\frac{1}{3}$ per switched product) into account.
- Profit for both first year and later years.

Competitor's reaction

- Most of the consumers in the market is price sensitive.
- “It is believed the competition will be unlikely to change the product but might respond *by lowering price.*”

1) If competitor assume we have no change:

Competitor's Choice	market situation				Profitability			
	pE(5)	p2E(13)	c1(7)	c2(8)	mkshare	Margin	CurrentFC	CurrentProfit
current pricing	0.22	0.23	0.55	NA	0.55	156200	20000	136200
lowering pricing	0.03	0.05	NA	0.92	0.92	202400	20000	182400

Lowering price
Would increase profit

Market Simulation

2) If competitor can predict our changes in products:

Scenario	p1(4)	pE(5)	c1(7)	p4(12)	p2E(13)	p2L(14)	p3(16)	mkshare	firstYear Profit	laterYear Profit
14	NA	NA	0	NA	NA	0.29	0.7	0.99	243773	250440
9	NA	NA	0.12	NA	0.03	0.86	NA	0.89	241240	241240
5	NA	NA	0	NA	0.04	NA	0.95	0.99	235773	242440
12	0.53	NA	0.06	NA	NA	0.41	NA	0.94	224933	231600
13	NA	NA	0	0.44	NA	NA	0.56	1	223626	236960
7	0.41	NA	0	NA	NA	NA	0.58	0.99	221266	234600
8	NA	NA	0.04	0.78	0.17	NA	NA	0.95	216093	222760
10	NA	NA	0.01	0.7	0.01	0.29	NA	1	215733	222400
19	0.4	NA	0	NA	NA	0.24	0.36	1	211946	225280
20	NA	NA	0	0.42	NA	0.24	0.34	1	211626	224960
16	0.53	NA	0.06	NA	0.02	0.4	NA	0.95	208093	214760
6	0.41	NA	0	NA	0.04	NA	0.55	1	205386	218720
17	NA	NA	0	0.44	0.04	NA	0.52	1	204906	218240
4	0.64	NA	0.14	NA	0.22	NA	NA	0.86	194373	201040
15	0.38	NA	0.04	0.43	0.16	NA	NA	0.97	194306	207640
18	0.33	NA	0	0.12	NA	NA	0.54	0.99	193959	213960
11	0.42	NA	0.08	0.5	NA	NA	NA	0.92	193226	206560
1(current)	NA	0.22	0.55	NA	0.23	NA	NA	0.45	102200	102200
2	NA	NA	0.68	NA	0.32	NA	NA	0.32	81120	81120
3	NA	0.31	0.69	NA	NA	NA	NA	0.31	77960	77960

- Market Simulation based on Competitor 's current product c1(7)

- Launching P2L(14),P3(16)**
 - first-year profit = 243,773
 - later-years profit =250,440

Competitor's Choice	market situation				Profitability			
	p2L(14)	p3(16)	c1(7)	c2(8)	mkshare	Margin	CurrentFC	CurrentProfit
current pricing	0.29	0.7	0	NA	0.01	0	20000	-20000
lowering pricing	0.22	0.37	NA	0.41	0.41	90200	20000	70200

Lowering price
Would increase profit

Market Simulation

Scenario	p1(4)	pE(5)	c2(8)	p4(12)	p2E(13)	p2L(14)	p3(16)	mkshare	firstYear Profit	laterYear Profit
19	0.36	NA	0.1	NA	NA	0.21	0.33	0.9	183226	196560
7	0.36	NA	0.2	NA	NA	NA	0.44	0.8	168106	181440
20	NA	NA	0.21	0.27	NA	0.21	0.31	0.79	153426	166760
18	0.31	NA	0.18	0.1	NA	NA	0.41	0.82	146319	166320
6	0.36	NA	0.19	NA	0.03	NA	0.42	0.81	151906	165240
12	0.4	NA	0.33	NA	NA	0.27	NA	0.67	145853	152520
13	NA	NA	0.31	0.28	NA	NA	0.41	0.69	138146	151480
10	NA	NA	0.31	0.46	0.01	0.23	NA	0.7	132453	139120
17	NA	NA	0.3	0.28	0.03	NA	0.4	0.71	124786	138120
14	NA	NA	0.41	NA	NA	0.22	0.37	0.59	127933	134600
16	0.4	NA	0.33	NA	0.01	0.26	NA	0.67	125853	132520
11	0.32	NA	0.39	0.29	NA	NA	NA	0.61	110146	123480
15	0.32	NA	0.34	0.29	0.06	NA	NA	0.67	109106	122440
8	NA	NA	0.47	0.47	0.06	NA	NA	0.53	98253	104920
5	NA	NA	0.5	NA	0.03	NA	0.47	0.5	96293	102960
4	0.41	NA	0.53	NA	0.06	NA	NA	0.47	82173	88840
9	NA	NA	0.69	NA	0.01	0.3	NA	0.31	57960	57960
2	NA	NA	0.94	NA	0.06	NA	NA	0.06	-1040	-1040
3	NA	0.04	0.96	NA	NA	NA	NA	0.04	-7360	-7360
1(current)	NA	0.03	0.92	NA	0.05	NA	NA	0.08	-14720	-14720

Cluster	profile				product
1	low price	26	bouncing	racing	p1(4)
2	low price	18	rocking	glamorous	p2L(14)
3	low price	26	rocking	glamorous	p3(16)

- Change C1(7) to C2(8)
- **Launching P1(4),P2L(14),P3(16)**
 - first-year profit = 183,226
 - later-years profit = 196,560
- Match the profile combination that we design for our three post-hoc segmentations.
- Some other recommendations: base on gender.
 - E.g. color/packaging style/...



Q&A



Appendix

product	p1	p2E	p3	pE	p4	p5	c1	c2(low)
profile	4	13	15	5	12	14	7	8
VC	29	33	41	33	29	33	41	41
price	96	112	112	112	96	96	112	96
margin	67	79	71	79	67	63	71	55

Some important R code

```
#rename the conjoint data
names(conjointData) = c('ID','profile','rating','price_low','height_26','motion_rocking','style_glamorous')

model = list()
for (i in 1:nrow(distinct(conjointData,ID))) {
  lm = lm(rating~ price_low+height_26+motion_rocking+style_glamorous,data = conjointData[conjointData$ID==i,])
  model[[i]] = lm$coefficients
}

#the final regression table
individualRegression = as.data.frame(matrix(unlist(model),nrow = 200, byrow=T))
names(individualRegression) = names(model[[1]])
individualRegression = cbind(distinct(conjointData,ID),individualRegression)

#predict the NAs
for(id in 1:200){
  conjointData[conjointData$ID==id,][which(is.na(conjointData[conjointData$ID == id,]$rating)),]$rating =
  individualRegression[individualRegression$ID==id,]$`(Intercept)`+
  individualRegression[individualRegression$ID==id,]$price_low*conjointData[conjointData$ID==id,][which(is.na(conjointData[conjointData$ID == id,]$rating)),]$price_low+
  individualRegression[individualRegression$ID==id,]$height_26*conjointData[conjointData$ID==id,][which(is.na(conjointData[conjointData$ID == id,]$rating)),]$height_26+
  individualRegression[individualRegression$ID==id,]$motion_rocking*conjointData[conjointData$ID==id,][which(is.na(conjointData[conjointData$ID == id,]$rating)),]$motion_rocking+
  individualRegression[individualRegression$ID==id,]$style_glamorous*conjointData[conjointData$ID==id,][which(is.na(conjointData[conjointData$ID == id,]$rating)),]$style_glamorous
}
```

Appendix

```
#Complete Ratings
library("reshape")
cast_rating = cast(conjointData[1:3],ID~profile)
cast_rating = cast_rating[-1]

simFCDecisions = function(scen,data){
  inmkt = data[,scen] #construct the subsetting matrix of options
  len = length(scen)
  inmkt$bestOpts = apply(inmkt,1,max)
  for (i in 1:200){
    inmkt[i,1:len] = (inmkt[i,1:len] == inmkt$bestOpts[i])
    inmkt[i,1:len] = inmkt[i,1:len]/sum(inmkt[i,1:len])
  }

  ret = inmkt[1:len]
  names(ret) = names(inmkt[1:len])
  ret #decisions
}

calcUnitShares = function(decisions){
  round(colSums(decisions)/sum(decisions),2) #assumes that total decisions is market size
}

simFCShares=function(scen,data){
  decs = simFCDecisions(scen,data) #determine decisions
  calcUnitShares(decs) #calculate shares and return
}

simFCScenarios = function(scenarios,data,...){
  res = matrix(nrow=length(scenarios),ncol=length(data)) #sets everything to NA by default
  for(i in 1:length(scenarios)){ ##loop over scenarios
    res[i, scenarios[[i]] ] = simFCShares(scenarios[[i]],data,...)## calculate market shares and sa
  }
  res = as.data.frame(res); names(res) = names(data)
  res ##return result table
}
simFCScenarios(scens,cast_rating)
```

Appendix

```
#calculate the FC and profit for 1st year
#Costs = 20,000/year * #products + $20,000/3 *#products not in existing set
newProduct = c(p1,p3,p4,p5)
df1$firstYearFC = NA
for (r in 1:nrow(df1)){
  df1[r,]$firstYearFC = sum(sum(!is.na(df1[r,myProduct]))*20000)+sum(sum(!is.na(df1[r,newProduct]))*6667)
}
df1$firstYearProfit = df1$profit-df1$firstYearFC

#profit after first year
df1$laterYearFC = NA
for (r in 1:nrow(df1)){
  df1[r,]$laterYearFC = sum(sum(!is.na(df1[r,myProduct]))*20000)
}
df1$laterYearProfit = df1$profit-df1$laterYearFC

#calculate the profit for competitor
c1
df1$comMargin = NA
for(r in 1:nrow(df1)){
  df1[r,]$comMargin = sum(profilesData[c1 ,]$margin*df1[r,c1]*4000,na.rm = T)
}

df1$comCurrentFC = NA
for (r in 1:nrow(df1)){
  df1[r,]$comCurrentFC = sum(sum(!is.na(df1[r,c1]))*20000)
}

df1$comCurrentProfit = df1$comMargin-df1$comCurrentFC

#competitor are very likely to lower price
```