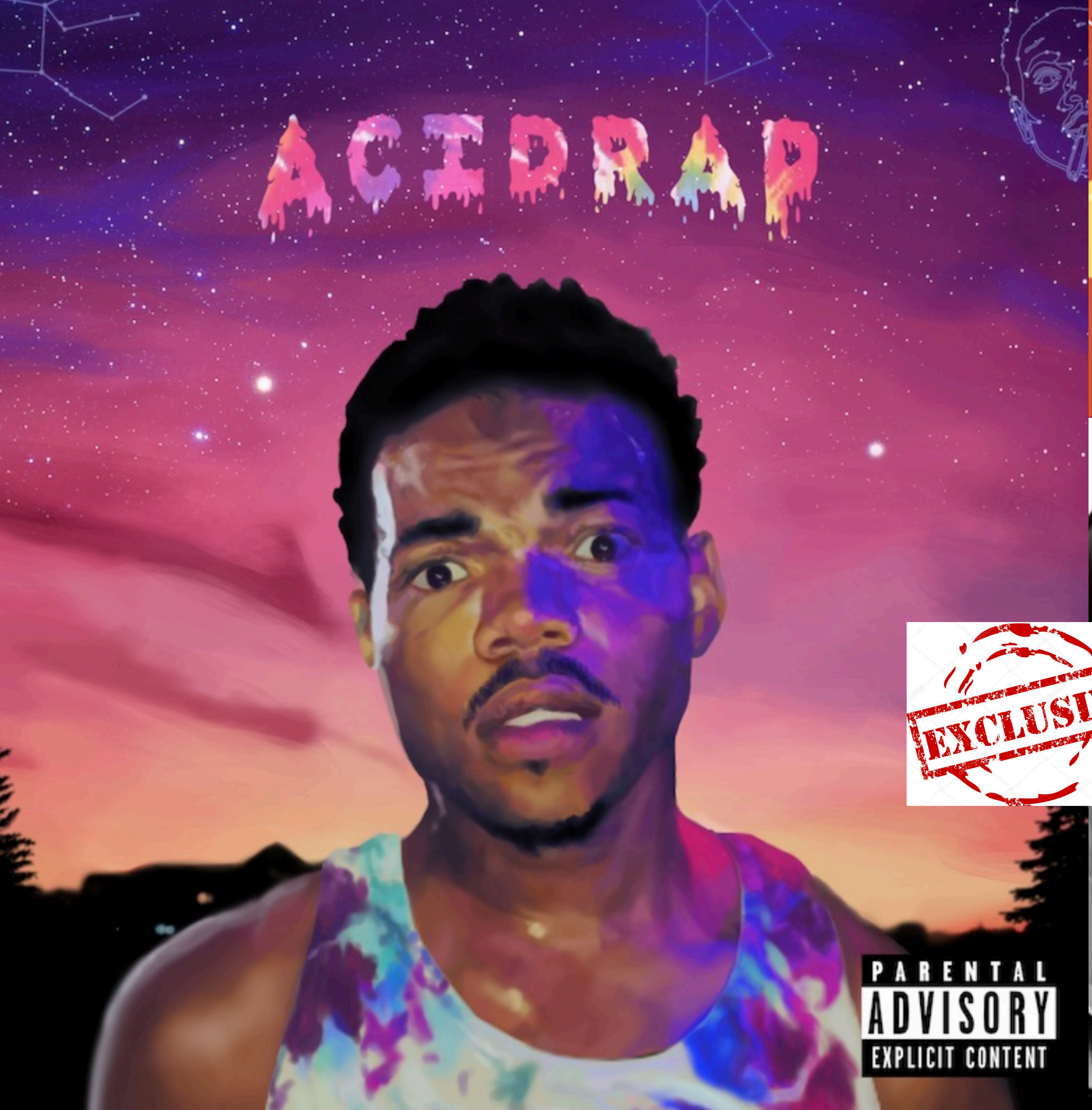
HB model: Part-Worth Estimation


ACIDRAP
EXCLUSIVE
PARENTAL
ADVISORY
EXPLICIT CONTENT


CREATING A
SUCCESSFUL
MARKETING
CAMPAIGN
%
PLAN

Google Play Music

- 30M+ tracks
- default on Android
- up to 320kbps
- “I’m feeling lucky” radio
- $9.99, 4 month free trial

Spotify

- 30M+ songs
- desktop app
- 320kbps
- Playlist radio
- $9.99, 3 months for 99¢

pandora®

- 1M+ tracks
- Thumbprint Radio
- 192kbps
- Music Genome Project
- $9.99, $4.99 plus

MUSIC

- 30M+ songs
- Siri virtual assistant
- 256kbps in AAC
- average recommendations
- $9.99, 3 months trial

ABT

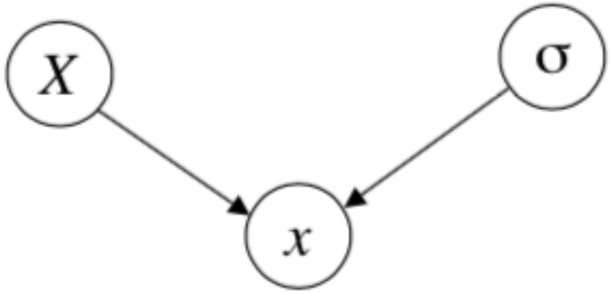
id	profile	setid	brand	catalog	features	bitrate	radio	price	choice
1	1	1	TIDAL	1	4	2	8	8	0
1	2	1	Spotify	7	3	1	6	3	0
1	3	1	AMZN	6	1	2	4	4	1
1	4	1	Deezer	8	3	2	2	7	0
1	5	2	Google	4	2	2	2	2	0
1	6	2	SoundCloud	8	4	1	5	8	0
1	7	2	TIDAL	1	1	2	7	3	0
1	8	2	Apple	5	3	1	4	5	1
1	9	3	Apple	4	4	1	6	7	1
1	10	3	SoundCloud	7	2	2	2	6	0
1	11	3	Spotify	3	3	2	8	2	0
1	12	3	Pandora	8	1	1	2	5	0
1	13	4	Deezer	6	2	1	6	5	0
1	14	4	AMZN	5	4	1	2	3	1
1	15	4	Pandora	7	3	2	7	1	0
1	16	4	Spotify	2	1	1	4	7	0
1	17	5	SoundCloud	6	1	1	8	3	0
1	18	5	Deezer	5	4	2	3	1	1
1	19	5	Apple	1	3	2	2	8	0
1	20	5	Google	8	2	1	1	1	0

$\perp$

Nonhierarchical models have a very simple structure, e.g.,

$$p(X,\sigma \mid x) \propto p(x \mid X,\sigma)\pi(X)\pi(\sigma)$$

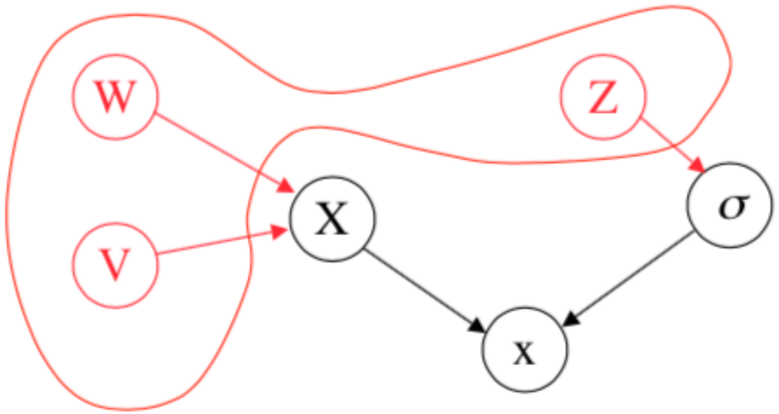
x is stochastically dependent on X and σ



Hierarchical Models

$$p(X,\sigma,W,V,Z \mid x) \propto p(x \mid X,\sigma)\pi(X \mid W,V)\pi(W)\pi(V)\pi(\sigma \mid Z)\pi(Z)$$

- use priors that themselves depend on other parameters not mentioned in the likelihood



BH Modeling

deriving the posterior distribution

$$Y \mid \theta \sim N(\theta, 1).$$

Prior distribution

$$\theta \mid \mu \sim N(\mu, 1)$$

- Hyperparameter: parameter of the prior distribution
- Hyperprior: distribution of a Hyperparameter

$$\mu \sim \mathrm{N}(0,1)$$

$$Y \mid \theta, \mu \sim N(\theta, 1)$$

$$\mu \sim N(\beta, \epsilon)$$

BH Modeling

use of hyperpriors gives more information to make more accurate beliefs in the behavior of a parameter

$$P(\theta, \phi \mid Y) \propto P(Y \mid \theta, \phi) P(\theta, \phi)$$
$$P(\theta, \phi \mid Y) \propto P(Y \mid \theta) P(\theta \mid \phi) P(\phi)$$

Stage I: $y_j \mid \theta_j, \phi \sim P(y_j \mid \theta_j, \phi)$

Stage II: $\theta_j \mid \phi \sim P(\theta_j \mid \phi)$

Stage III: $\phi \sim P(\phi)$

The likelihood, as seen in stage I is $P(y_j \mid \theta_j, \phi)$, with $P(\theta_j, \phi)$ as its prior distribution.

The prior distribution from stage I can be broken down into:

$P(\theta_j, \phi) = P(\theta_j \mid \phi) P(\phi)$ *[from the definition of conditional probability]*

With ϕ as its hyperparameter with hyperprior distribution, $P(\phi)$.

Thus, the posterior distribution is proportional to:

$P(\phi, \theta_j \mid y) \propto P(y_j \mid \theta_j, \phi) P(\theta_j \mid \phi)$ *[using Bayes' Theorem]*

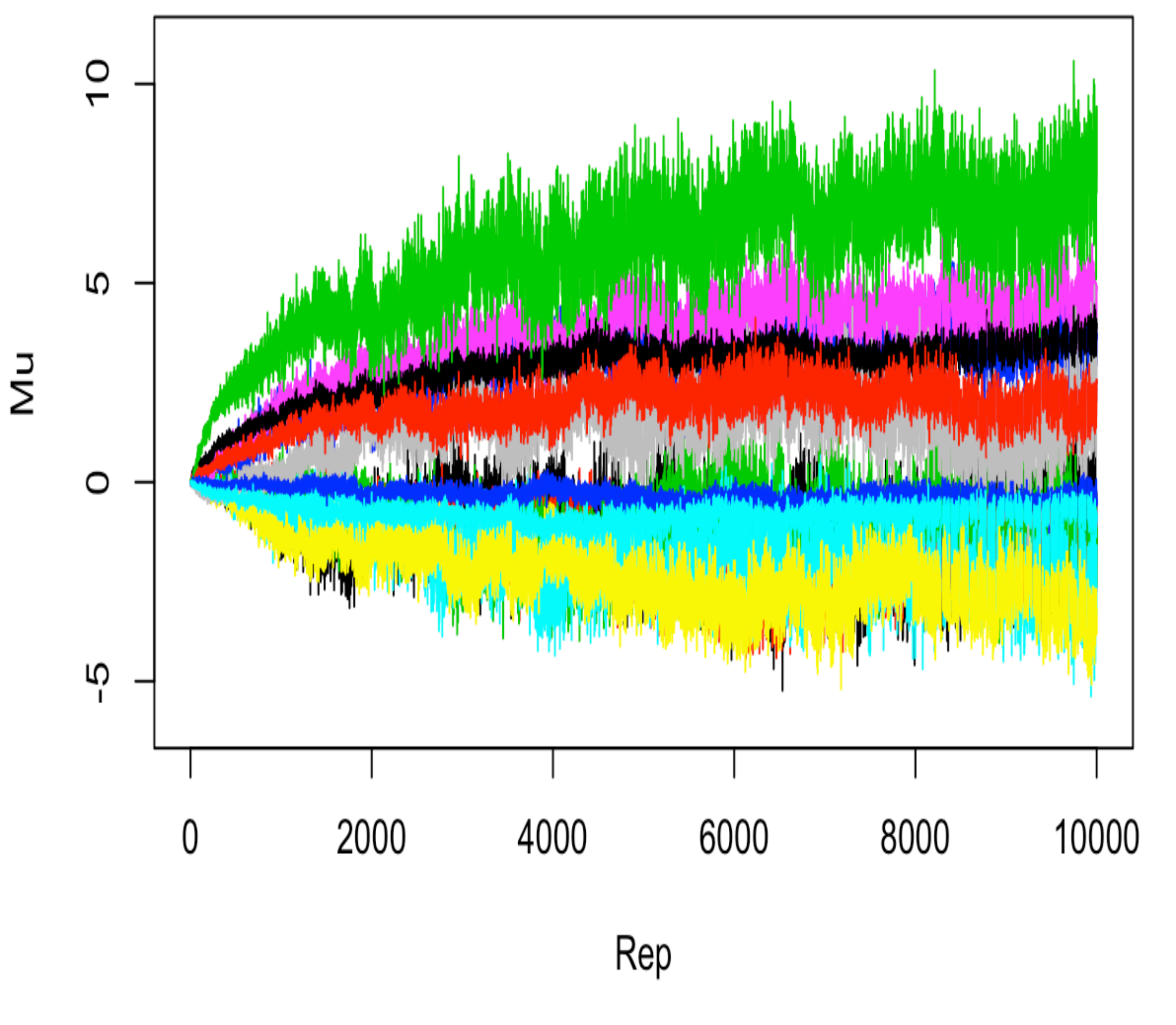
$P(\phi, \theta_j \mid y) \propto P(y_j \mid \theta_j) P(\theta_j, \phi)$[12]

Gibbs MH-MCMC

ChoiceModelR

- MCMC algorithm to estimate a hierarchical multinomial logit model with a normal heterogeneity distribution. The algorithm uses a hybrid Gibbs Sampler with a random walk metropolis step for the MNL coefficients for each unit.

MCMC beta parameter estimates

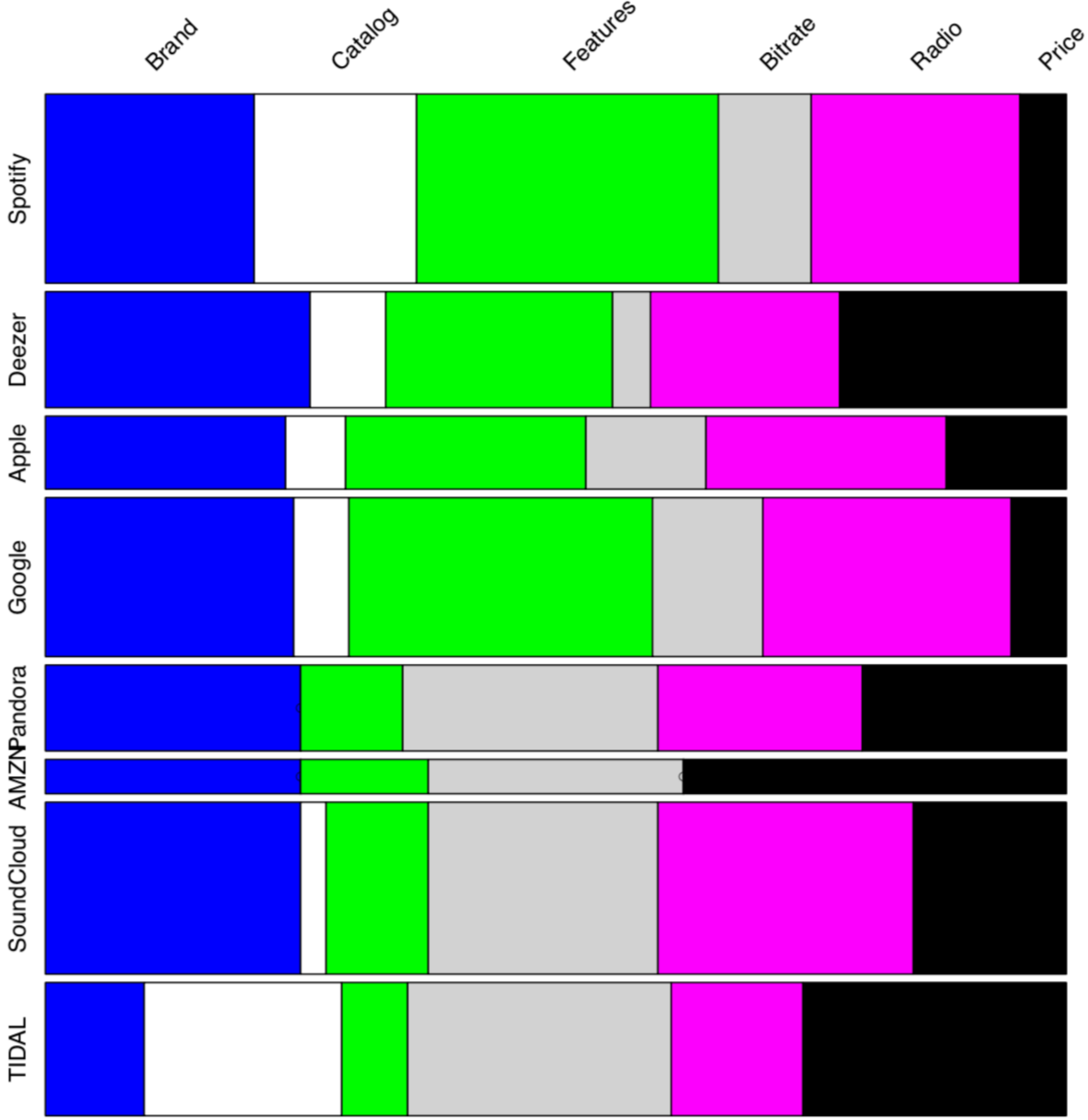


Training and Testing

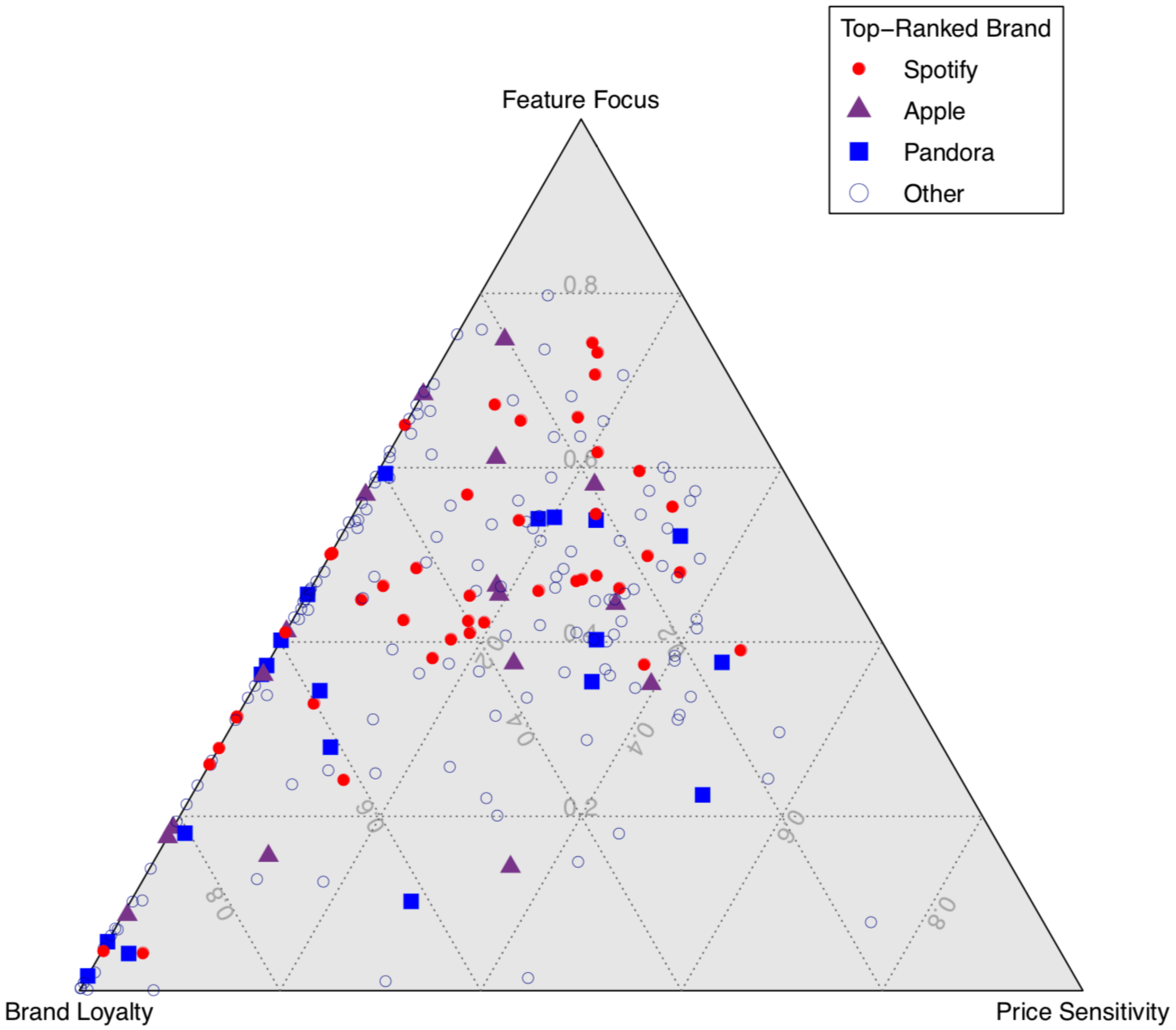
- MCMC algorithm to estimate a hierarchical multinomial logit model with a normal heterogeneity distribution. The algorithm uses a hybrid Gibbs Sampler with a random walk metropolis step for the MNL coefficients for each unit.

```
> # report choice prediction sensitivity for test data
> cat("\n\nTest choice set sensitivity = ",
+   sprintf("%1.1f",test.set.performance$byClass[1]*100)," Percent",sep="")


Test choice set sensitivity = 52.6 Percent
```

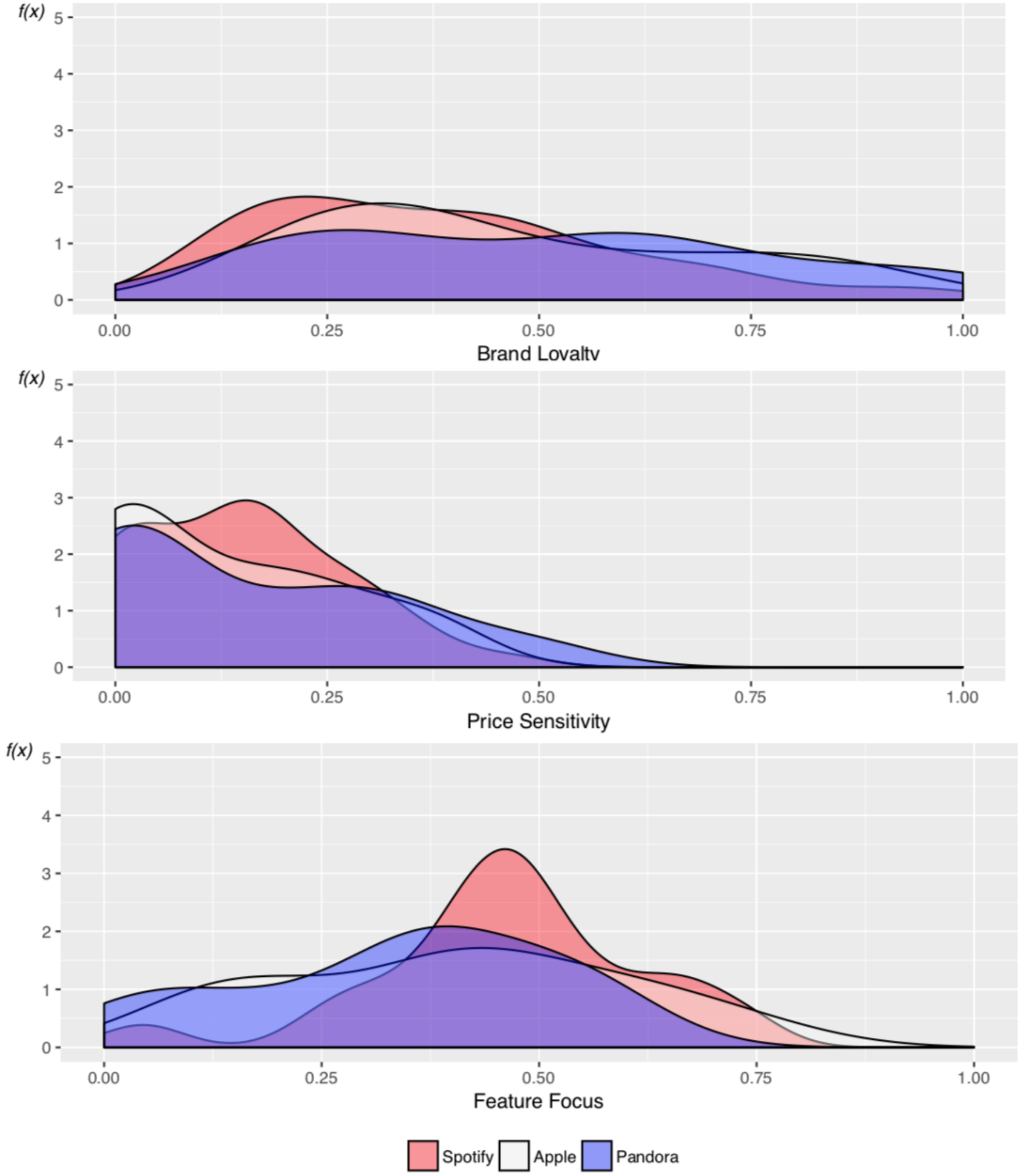
```
> # report choice prediction sensitivity for training data
> cat("\n\nTraining choice set sensitivity = ",
+   sprintf("%1.1f",training.set.performance$byClass[1]*100)," Percent",sep="")


Training choice set sensitivity = 93.7 Percent>
```



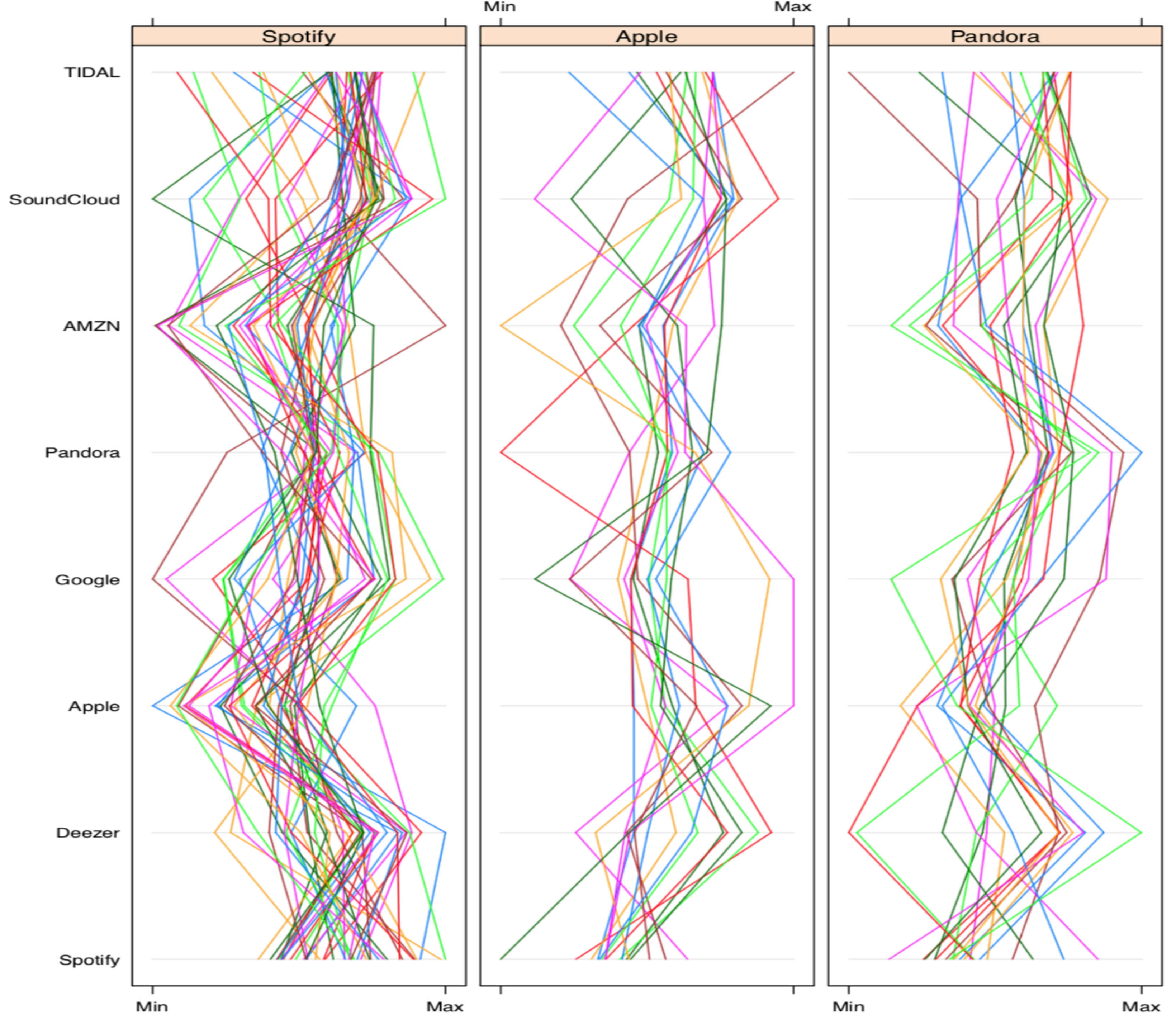
Mosaic of Top-Ranked Brands and Most Valued Attributes



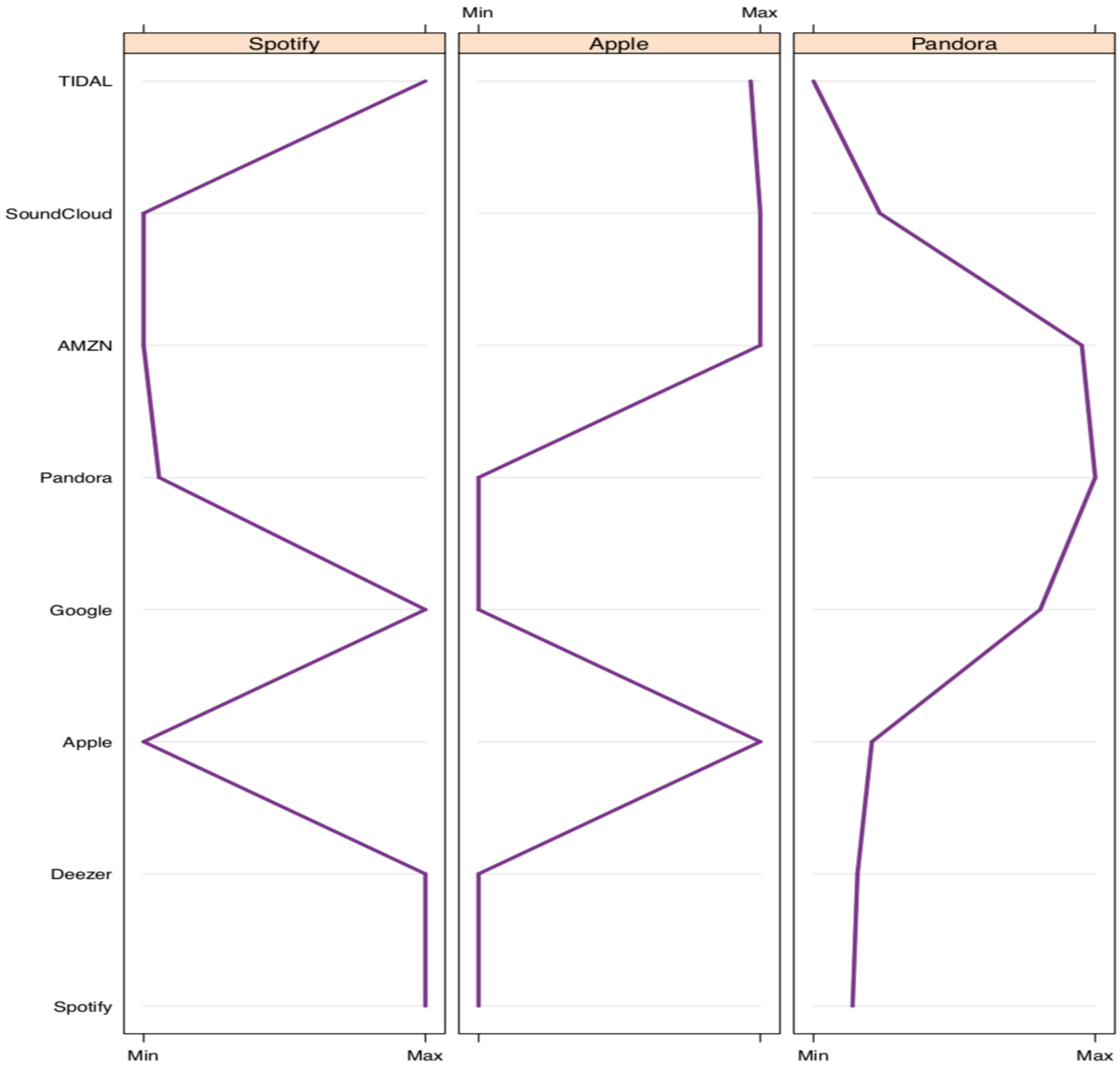
Ternary Plot of User Preference and Choice



Comparing Listeners with Differing Brand Preferences



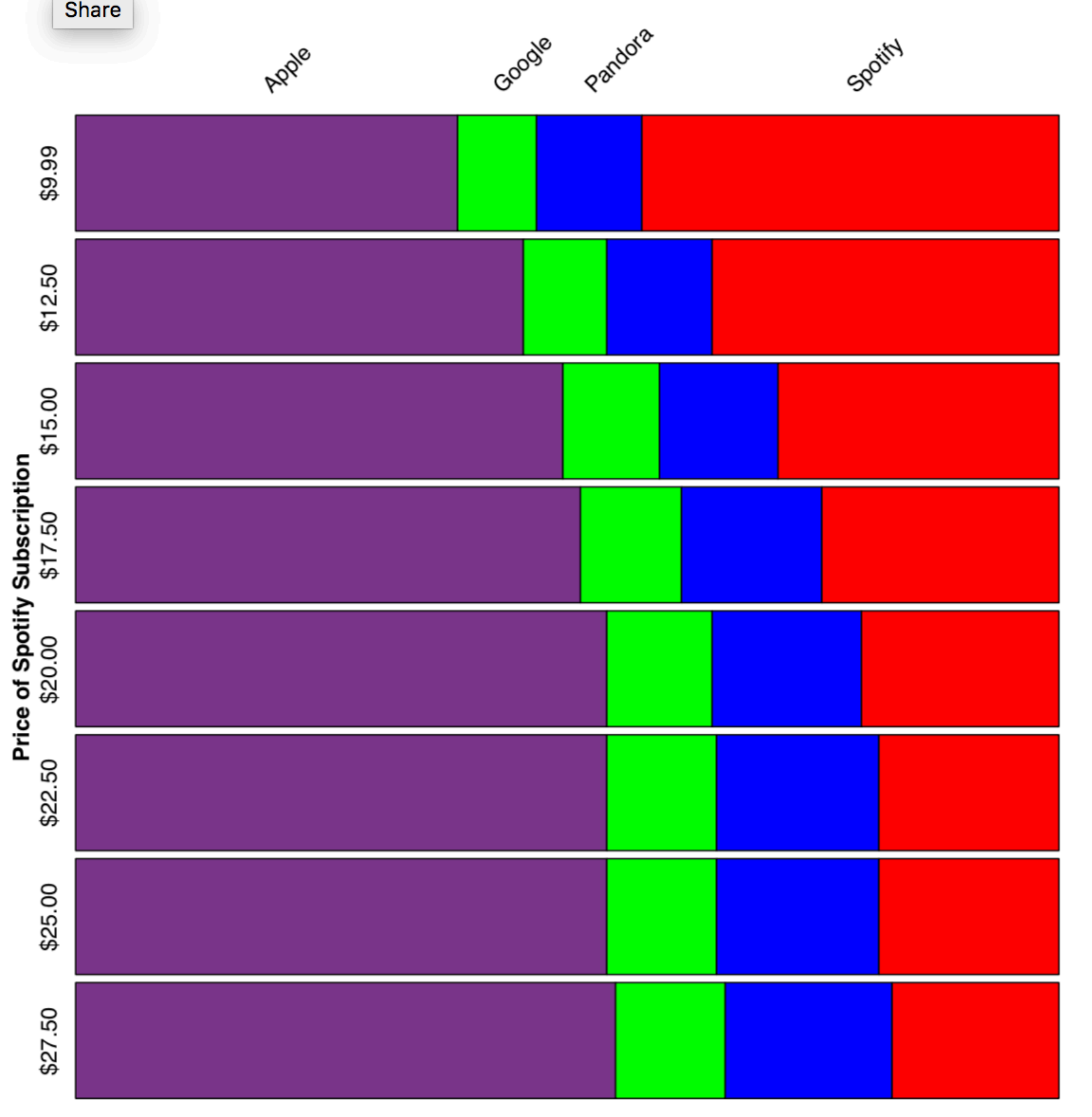
Potential for Brand Switching: Parallel Coordinates for Individual Users



Potential for Brand Switching: Parallel Coordinates for Listener Groups

```
----- Simulation Choice Sets -----

> print(simulation.choice.sets)
   setid   brand catalog features bitrate radio price
1      1   Apple       8        4       2     4     4
2      1  Google       6        2       1     2     2
3      1 Pandora       6        3       2     2     3
4      1 Spotify       5        4       2     1     1
5      2   Apple       8        4       2     4     4
6      2  Google       6        2       1     2     2
7      2 Pandora       6        3       2     2     3
8      2 Spotify       5        4       2     1     2
9      3   Apple       8        4       2     4     4
10     3  Google       6        2       1     2     2
11     3 Pandora       6        3       2     2     3
12     3 Spotify       5        4       2     1     3
13     4   Apple       8        4       2     4     4
14     4  Google       6        2       1     2     2
15     4 Pandora       6        3       2     2     3
16     4 Spotify       5        4       2     1     4
17     5   Apple       8        4       2     4     4
18     5  Google       6        2       1     2     2
19     5 Pandora       6        3       2     2     3
20     5 Spotify       5        4       2     1     5
21     6   Apple       8        4       2     4     4
22     6  Google       6        2       1     2     2
23     6 Pandora       6        3       2     2     3
24     6 Spotify       5        4       2     1     6
25     7   Apple       8        4       2     4     4
26     7  Google       6        2       1     2     2
27     7 Pandora       6        3       2     2     3
28     7 Spotify       5        4       2     1     7
```

Choice Set Input for Market Simulation




```
----- Simulation Results: Preference Share Table -----

> print(table.work)  # print the market/preference share table
  Spotify.Price Spotify Apple Google Pandora
1          1000    42.4  38.8    8.0    10.7
2          1250    35.3  45.5    8.5    10.7
3          1500    28.6  49.6    9.8    12.1
4          1750    24.1  51.3   10.3    14.3
5          2000    20.1  54.0   10.7    15.2
6          2250    18.3  54.0   11.2    16.5
7          2500    18.3  54.0   11.2    16.5
8          2750    17.0  54.9   11.2    17.0
```

Market Simulation: A Mosaic of Preference Shares

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