Pricing Solutions - Case Study

Overview of the Data

General Metrics

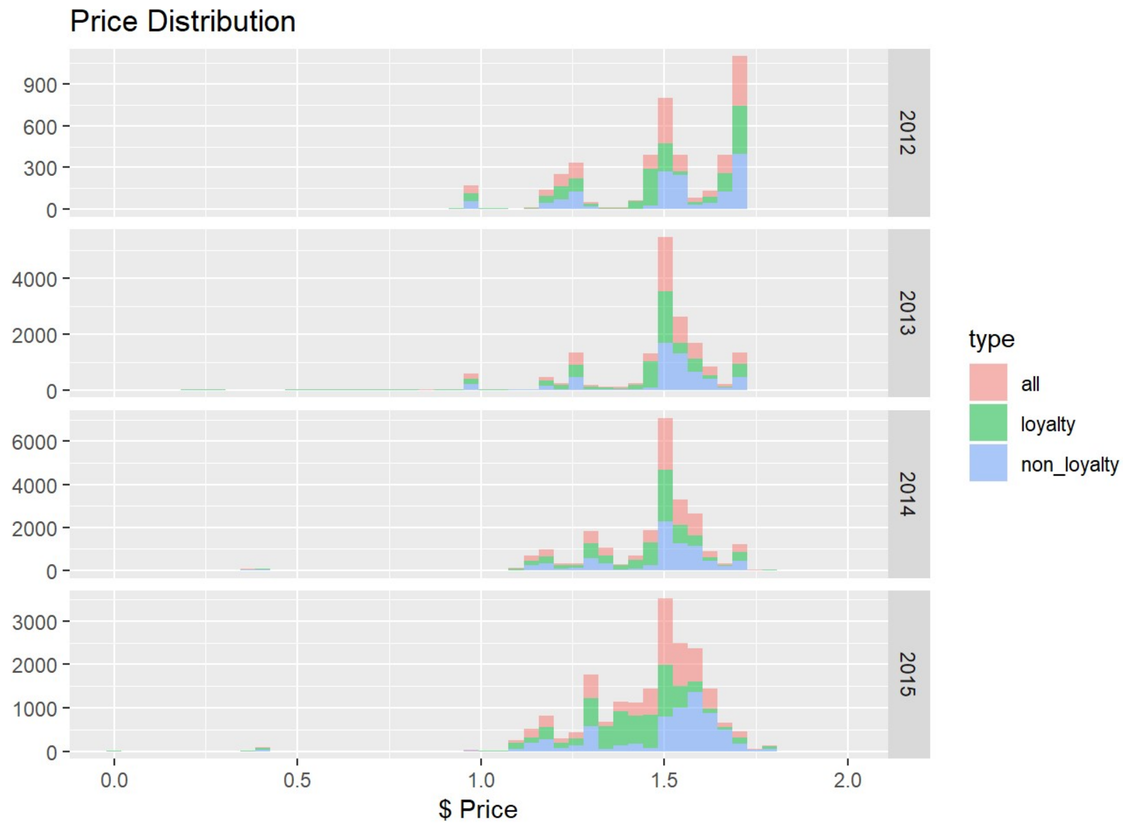
```
apply_to_list(datasets, function(x, n) x %>% summarise(
  `Type`=n,
  `Number of Stores`=max(store, na.rm=T),
  `Number of Products`=length(unique(mstrprodid)),
  `Start Period`=min(year), `End Period`=max(year),
)) %>% arrange(desc(Type))
```

Type	Number of Stores	Number of Products	Start Period	End Period
non_loyalty	511	253	2012	2015
loyalty	511	248	2012	2015
all	511	255	2012	2015

Summary of Price Data

```
apply_to_list(datasets, function(x,n) {
  x %>% select(year, week_num, mstrprodid, price) %>%
    setNames(c("year", "week_num", "pid", n))
}, inner_join) %>%
  gather(type, value, -c(year, week_num, pid)) ->
  psummary
```

```
psummary %>%
  ggplot(aes(
    value,
    fill=type
  )) +
  geom_histogram(alpha=0.5, bins = 50) +
  facet_grid(year~., scales = "free_y")+
  labs(x="$ Price",y="")+
  ggtitle("Price Distribution")
```



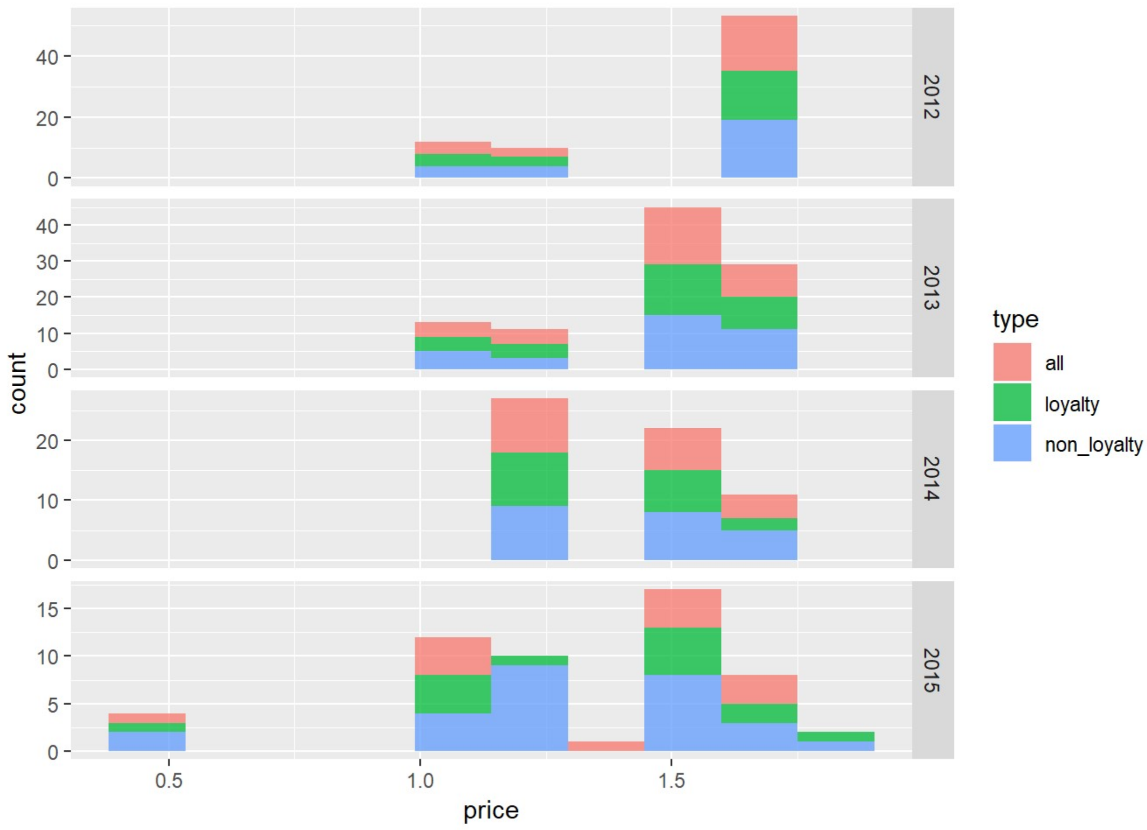

```
psummary %>%
  group_by(year, type) %>%
  summarise(
    Min=min(value, na.rm = T),
    Mean=round(mean(value, na.rm = T), 2),
    Max=max(value, na.rm = T),
    `Na's`=sum(is.na(value)),
    N=n()
  )
```

year	type	Min	Mean	Max	Na's	N
2012	all	0.23	1.50	1.69	0	1447
2012	loyalty	0.12	1.48	1.69	0	1447
2012	non_loyalty	0.99	1.51	1.69	0	1447
2013	all	0.42	1.48	1.69	0	5570
2013	loyalty	0.19	1.45	1.69	0	5570
2013	non_loyalty	0.75	1.50	1.69	0	5570
2014	all	0.00	1.46	1.91	0	8050
2014	loyalty	0.00	1.44	1.99	0	8050
2014	non_loyalty	0.00	1.47	1.99	0	8050
2015	all	0.00	1.46	1.89	0	6604
2015	loyalty	0.00	1.41	1.89	0	6604
2015	non_loyalty	0.00	1.49	1.89	0	6604

```
psummary %>%
  group_by(type, pid, year) %>%
  summarise(
    sd = replace_na(sd(value),0)
  ) %>%
  group_by(type, sd==0, year) %>%
  summarise(
    pids=length(unique(pid))
  ) %>% group_by(year, type) %>%
  spread(`sd == 0`, pids)
```

type	year	FALSE	TRUE
all	2012	83	25
all	2013	104	33
all	2014	173	20
all	2015	194	13
loyalty	2012	85	23
loyalty	2013	106	31
loyalty	2014	175	18
loyalty	2015	193	14
non_loyalty	2012	81	27
non_loyalty	2013	103	34
non_loyalty	2014	171	22
non_loyalty	2015	180	27

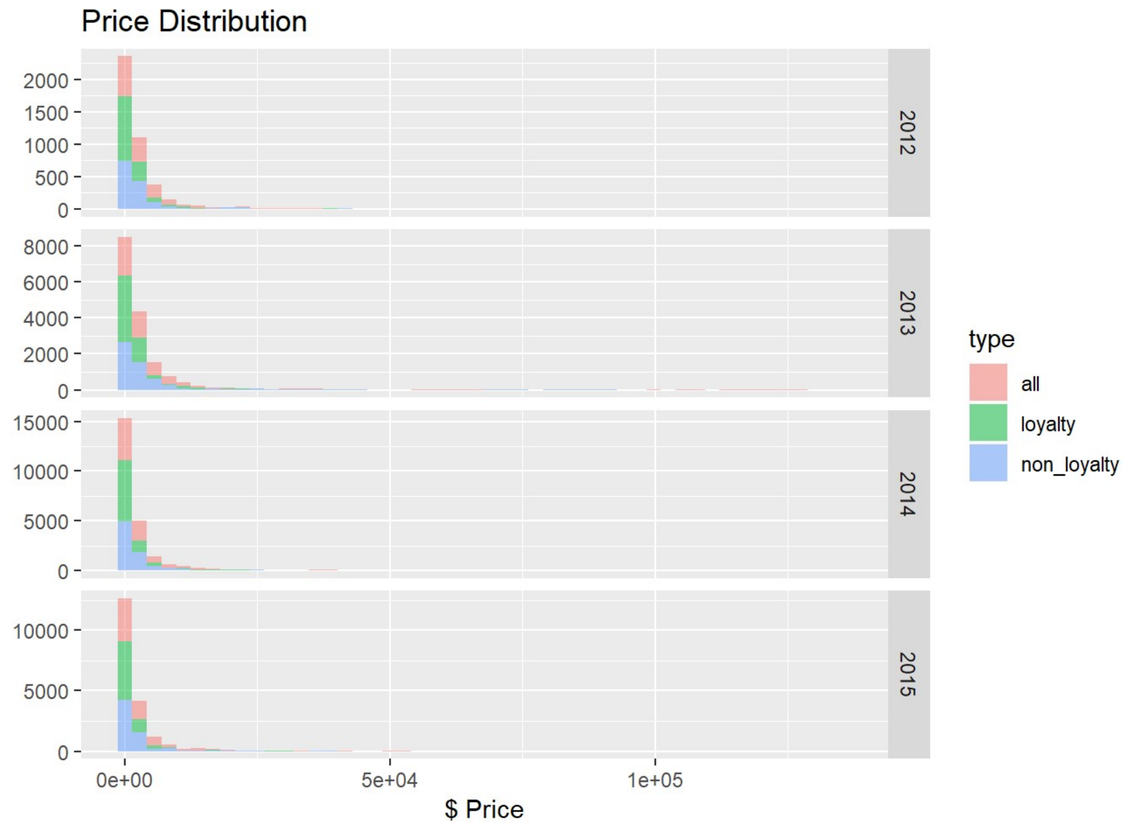
```
psummary %>%
  group_by(type, pid, year) %>%
  summarise(
    price = round(mean(value),2),
    sd = replace_na(sd(value),0)
  ) %>%
  filter(sd==0) %>%
  ggplot() +
  geom_histogram(aes(
    price, fill=type
  ), bins=10, alpha=0.75) +
  facet_grid(year~., scales='free_y')
```



Summary of Quantity

```
apply_to_list(datasets, function(x,n) {
  x %>% select(year, week_num, mstrprodid, qty) %>%
    setNames(c("year", "week_num", "pid", n))
}, inner_join) %>%
  gather(type, value, -c(year, week_num, pid)) ->
  qsummary
```

```
qsummary %>%
  ggplot(aes(
    value,
    fill=type
  )) +
  geom_histogram(alpha=0.5, bins = 50) +
  facet_grid(year~., scales = "free_y")+
  labs(x="$ Price",y="")+
  ggtitle("Price Distribution")
```




```
qsummary %>%
  group_by(year, type) %>%
  summarise(
    Min=min(value, na.rm = T),
    Mean=round(mean(value, na.rm = T), 2),
    Max=max(value, na.rm = T),
    `Na's`=sum(is.na(value)),
    N=n()
  )
```

year	type	Min	Mean	Max	Na's	N
2012	all	2	5813.43	123485	0	1447
2012	loyalty	1	1998.03	38811	0	1447
2012	non_loyalty	1	3815.40	85128	0	1447
2013	all	2	6372.22	133418	0	5570
2013	loyalty	1	2079.61	37634	0	5570
2013	non_loyalty	1	4292.61	95784	0	5570
2014	all	0	4900.20	135707	0	8050
2014	loyalty	1	1642.58	40618	0	8050
2014	non_loyalty	-1	3257.62	95089	0	8050
2015	all	2	4707.53	134403	0	6604
2015	loyalty	1	1912.50	54670	0	6604
2015	non_loyalty	1	2795.03	80594	0	6604

The following had negative units sold

```
qsummary %>% filter(value<0)
```

year	week_num	pid	type	value
2014	45	40886	non_loyalty	-1

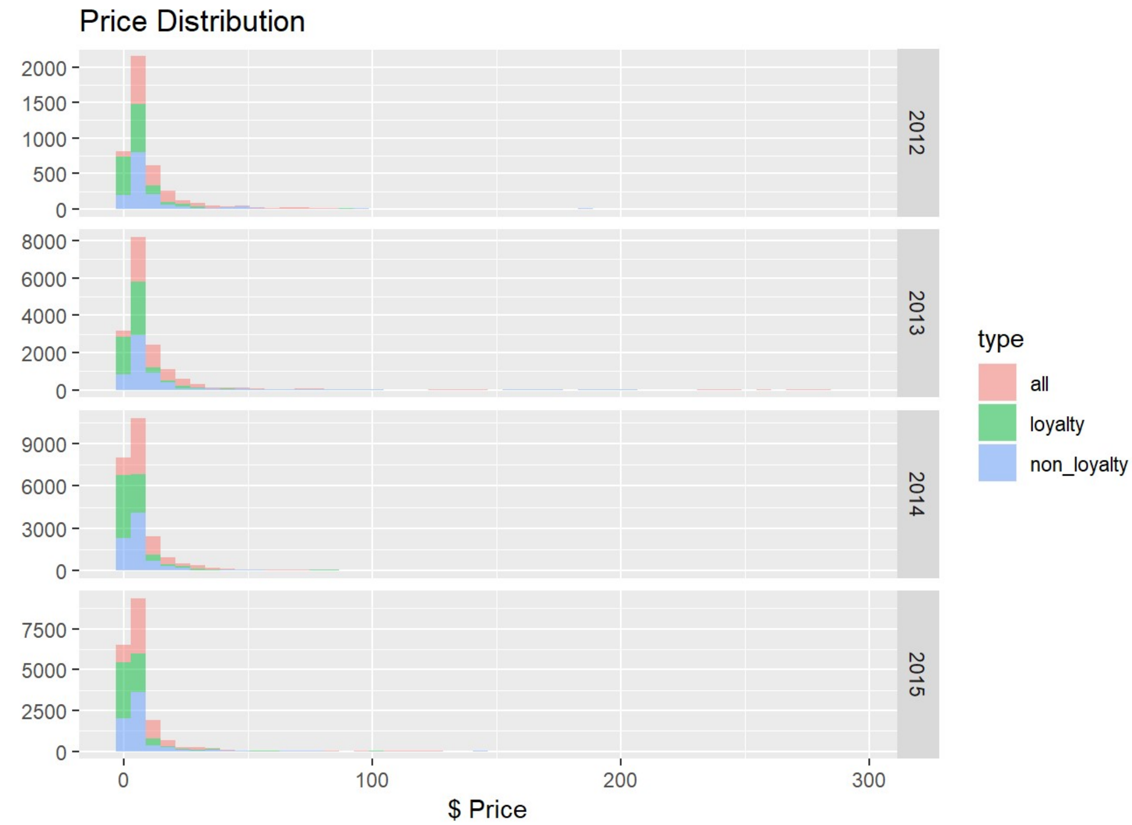
```
qsummary %>% filter(pid==40886) %>%
  group_by(type) %>%
  summarise(qty=sum(value,na.rm=T)) %>%
  spread(type, qty) %>%
  mutate(`CHECK=loyalty+non_loyalty`=loyalty+non_loyalty) %>%
  gather(type, qty) %>% arrange(type)
```

type	qty
all	15784
CHECK=loyalty+non_loyalty	15784
loyalty	4089
non_loyalty	11695

Average Quantity by Store

```
apply_to_list(datasets, function(x,n) {
  x %>% select(year, week_num, mstrprodid, qty_bs) %>%
    setNames(c("year", "week_num", "pid", n))
}, inner_join) %>%
  gather(type, value, -c(year, week_num, pid)) ->
  qsummary
```

```
qsummary %>%
  ggplot(aes(
    value,
    fill=type
  )) +
  geom_histogram(alpha=0.5, bins = 50) +
  facet_grid(year~., scales = "free_y")+
  labs(x="$ Price",y="")+
  ggtitle("Price Distribution")
```



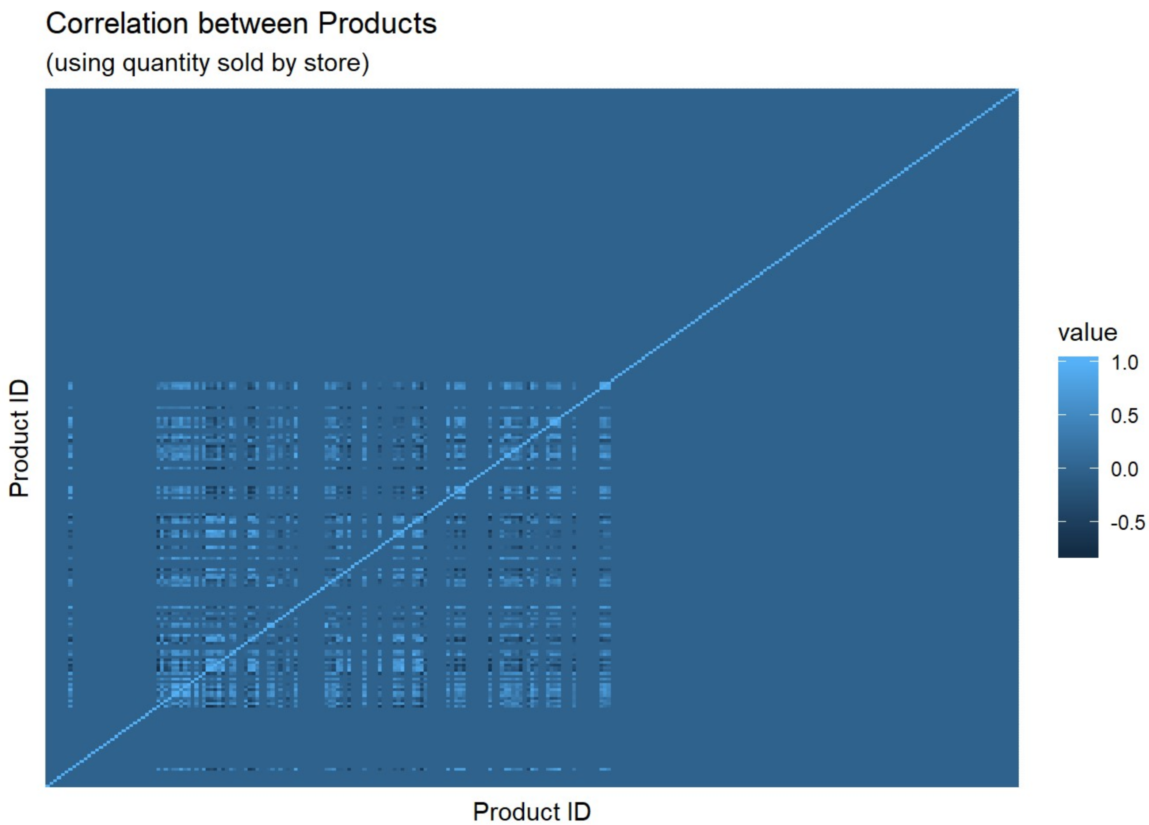

```
qsummary %>%
  group_by(year, type) %>%
  summarise(
    Min=min(value, na.rm = T),
    Mean=round(mean(value, na.rm = T), 2),
    Max=max(value, na.rm = T),
    `Na's`=sum(is.na(value)),
    N=n()
  )
```

year	type	Min	Mean	Max	Na's	N
2012	all	1.0000000	17.95	287.17442	0	1447
2012	loyalty	1.0000000	6.68	89.84028	0	1447
2012	non_loyalty	0.3333333	11.90	197.97209	0	1447
2013	all	1.0000000	17.51	292.58333	0	5570
2013	loyalty	1.0000000	6.23	84.36281	0	5570
2013	non_loyalty	1.0000000	11.93	210.05263	0	5570
2014	all	0.0000000	13.31	283.90586	0	8050
2014	loyalty	1.0000000	5.09	84.97490	0	8050
2014	non_loyalty	-1.0000000	9.12	199.58403	0	8050
2015	all	1.0000000	12.35	270.48589	0	6604
2015	loyalty	1.0000000	5.55	108.61895	0	6604
2015	non_loyalty	1.0000000	7.69	161.86694	0	6604

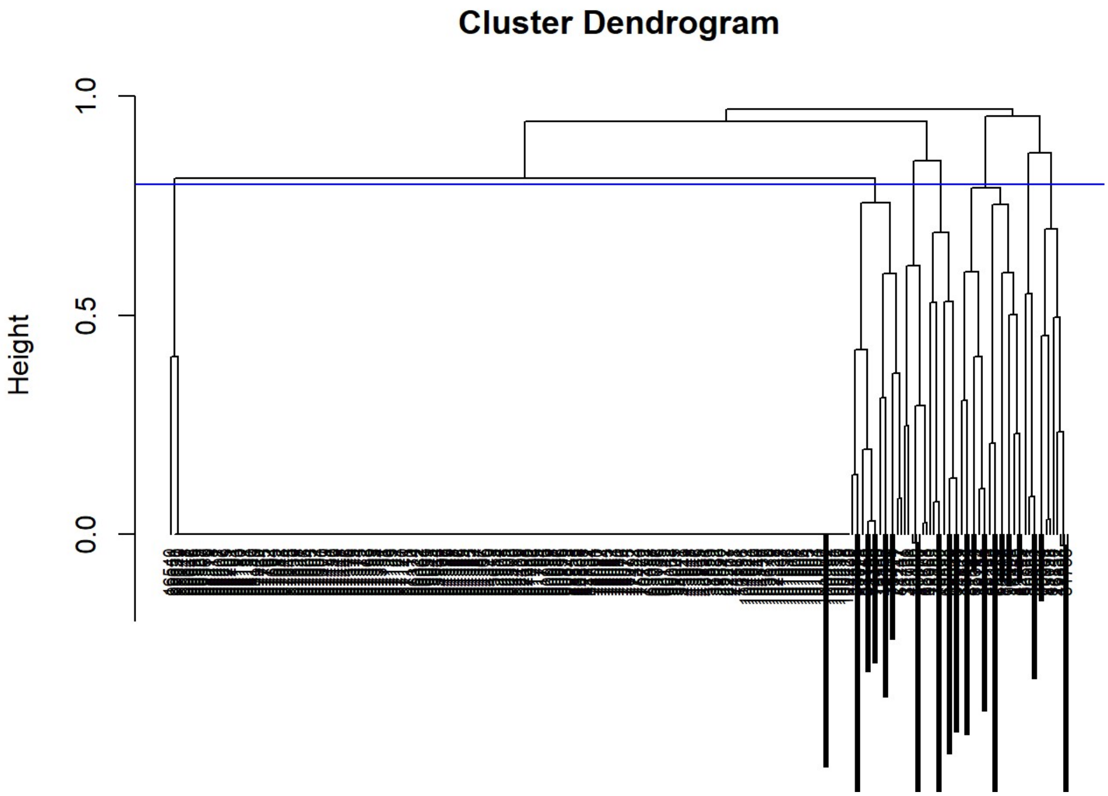
Clustering: Group Generation

Correlation Clustering

```
cor_table %>% ggplot(aes(x=var1,y=var2,fill=value)) + geom_tile() +
  theme(axis.text.x=element_blank(),axis.ticks.x=element_blank(),
        axis.text.y=element_blank(),axis.ticks.y=element_blank()) +
  ggtitle("Correlation between Products",
          "(using quantity sold by store)") +
  labs(x="Product ID",y="Product ID")
```




```
hclst = hclust(cor_dist_matrix, method = 'complete')
plot(hclst, hang = -1, cex = 0.6, xlab='', sub='')
abline(h=0.8, col=4)
```




```r
cutree(hclst, 7) %>% {
  tibble(
    mstrprodid=names(.),
    cor_cluster=as.numeric(.)
  )
} %>% group_by(cor_cluster) %>%
  summarise(N=n())
```

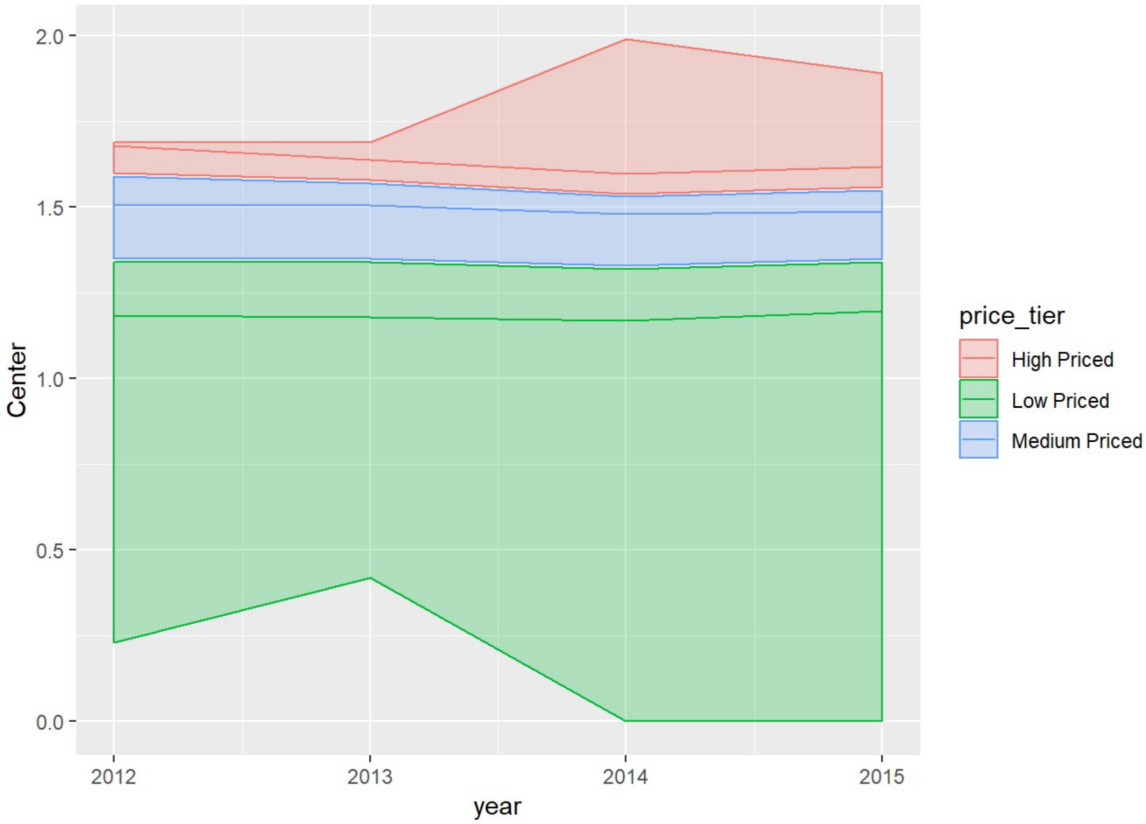
cor_cluster	N
1	193
2	7
3	15
4	18
5	9
6	9
7	4

```
datasets$all %>%
  group_by(cor_cluster_d) %>%
  summarise(
    `Revenue`=sum(price*qty),
    `Number of Products` = length(unique(mstrprodid))
  ) %>%
  mutate(
    `% of Revenue` = scales::percent(Revenue/sum(Revenue)),
    Revenue = scales::dollar(Revenue)
  )
```

cor_cluster_d	Revenue	Number of Products	% of Revenue
1	$34,812,634	193	20.3%
2	$24,447,862	7	14.3%
3	$24,796,277	15	14.5%
4	$27,346,686	18	16.0%
5	$36,126,531	9	21.1%
6	$19,616,166	9	11.5%
7	$4,074,432	4	2.4%

Kmeans Clustering

```
datasets$all %>%
  filter(!is.na(price)) %>%
  group_by(year) %>%
  mutate(
    cluster = kmeans(
      tibble(price), 3
    )$cluster
  ) %>%
  group_by(cluster, year) %>%
  summarise(
    N=n(), `Lower Limit`=min(price),
    `Center`=mean(price),
    `Upper Limit`=max(price)
  ) %>% arrange(year, `Lower Limit`) %>%
  group_by(year) %>%
  mutate(
    price_tier = c("Low Priced", "Medium Priced", "High Priced")
  ) -> price_tiers
price_tiers %>% ggplot(aes(
  x=year, color=price_tier, fill=price_tier
))+
  geom_ribbon(aes(ymax=`Upper Limit`, ymin=`Lower Limit`), alpha=0.25) +
  geom_line(aes(y=Center))
```




```
datasets$all %>%
  group_by(cluster_name) %>%
  summarise(
    `Revenue`=sum(price*qty),
    `Number of Products` = length(unique(mstrprodid))
  ) %>%
  mutate(
    `% of Revenue` = scales::percent(Revenue/sum(Revenue)),
    Revenue = scales::dollar(Revenue)
  )
```

cluster_name	Revenue	Number of Products	% of Revenue
High Priced	$33,969,825	144	19.8%
Low Priced	$10,705,333	139	6.3%
Medium Priced	$126,545,431	178	73.9%

Predictive Models

Model 1: Lagged Price and Quantity

```
joined_dataset %>% group_by(pid) %>%
  arrange(pid, year, week_num) %>%
  mutate(
    last_dqty_bs_all = lag(dqty_bs_all),
    last_price_all = lag(price_all)
  ) %>% ungroup() %>% {lm(
    dqty_bs_all~week_num*last_dqty_bs_all+last_price_all+price_all-1,
    data=.
  )} -> m1

broom::glance(m1)
```

	r.squared	adj.r.squared	sigma	statistic	p.value	df	logLik	AIC	BIC	deviance	df.residual
value	0.0240579	0.0238278	0.3351794	104.5593	0	5	-6909.739	13831.48	13879.25	2382.618	21208

```
broom::tidy(m1) %>% mutate(
  significant=(p.value<0.1)+(p.value<0.05)+(p.value<0.01)+(p.value<0.005)
)
```

term	estimate	std.error	statistic	p.value	significant
week_num	-0.0004893	0.0001538	-3.1803664	0.0014730	4
last_dqty_bs_all	-0.0007206	0.0134289	-0.0536597	0.9572068	0
last_price_all	0.9020981	0.0486432	18.5451977	0.0000000	4
price_all	-0.8761546	0.0487161	-17.9848938	0.0000000	4
week_num:last_dqty_bs_all	-0.0016337	0.0004944	-3.3045307	0.0009529	4

Model 2: Lagged Price and Quality, and clusters

```
joined_dataset %>% group_by(pid) %>%
  arrange(pid, year, week_num) %>%
  mutate(
    last_dqty_bs_all = lag(dqty_bs_all),
    last_price_all = lag(price_all),
    cor_cluster_all=as.character(cor_cluster_all),
  ) %>% ungroup() %>% {lm(
    dqty_bs_all~week_num+last_price_all+
        last_dqty_bs_all+last_price_all+price_all+
        price_tier_all+cor_cluster_all,
    data=.
  )} -> m2

broom::glance(m2)
```

	r.squared	adj.r.squared	sigma	statistic	p.value	df	logLik	AIC	BIC	deviance	df.residual
value	0.0230241	0.0224711	0.3345506	41.63459	0	13	-6865.901	13759.8	13871.27	2372.79	21200

```
broom::tidy(m2) %>% mutate(
  significant=(p.value<0.1)+(p.value<0.05)+(p.value<0.01)+(p.value<0.005)
)
```

term	estimate	std.error	statistic	p.value	significant
(Intercept)	0.1313463	0.0456009	2.880345	0.0039764	4
week_num	-0.0005927	0.0001572	-3.770646	0.0001633	4
last_price_all	0.9019427	0.0492542	18.311995	0.0000000	4
last_dqty_bs_all	-0.0436874	0.0066758	-6.544151	0.0000000	4
price_all	-0.9352148	0.0528943	-17.680814	0.0000000	4
price_tier_allLow Priced	-0.0428171	0.0136004	-3.148217	0.0016450	4
price_tier_allMedium Priced	-0.0276648	0.0063579	-4.351266	0.0000136	4
cor_cluster_all2	-0.0414315	0.0106873	-3.876688	0.0001062	4
cor_cluster_all3	-0.0408147	0.0077007	-5.300127	0.0000001	4
cor_cluster_all4	-0.0421669	0.0071743	-5.877503	0.0000000	4
cor_cluster_all5	-0.0408855	0.0096070	-4.255786	0.0000209	4
cor_cluster_all6	-0.0410463	0.0095575	-4.294679	0.0000176	4
cor_cluster_all7	-0.0415307	0.0139727	-2.972285	0.0029592	4