Le(a)rner Crew

Team 5

Natalie Chen, Daniel Chung, Su Park, Kylene Ye

Meet the Team!

Natalie

Daniel

Kylene

Su

Problem Statement

Client: a boutique eyewear company with 3 main products

Sales Objective
Media Budget:
below $ 70M
Sales volume:
increase by 15%

Audience Engagement
How the audience interact with media?
Does this align with our strategy?

Brand Impact
Understand long term value brand has on sales

Project Overview

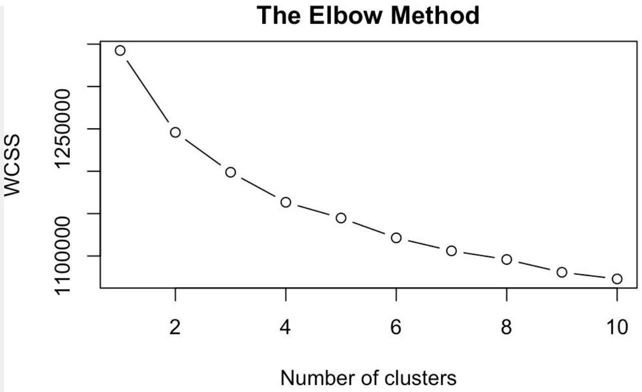
Phase 1	Phase 2	Phase 3	Phase 4
Audience Analysis 1. Identified Groups 2. Target Audience	**Media Analysis** 1. Media Mix 2. Media Efficiency **Sales Analysis** 1. Brand Consideration 2. Weather	**Media Strategy** 1. Competitive Analysis 2. Markov Multi-touch Attribution Model 3. Budget Roll-out Plan 4. Sales Prediction 5. Ad Examples	**Conclusion** 1. KPIs 2. Final Recommendations 3. Appendix

Phase 1: Audience Analysis

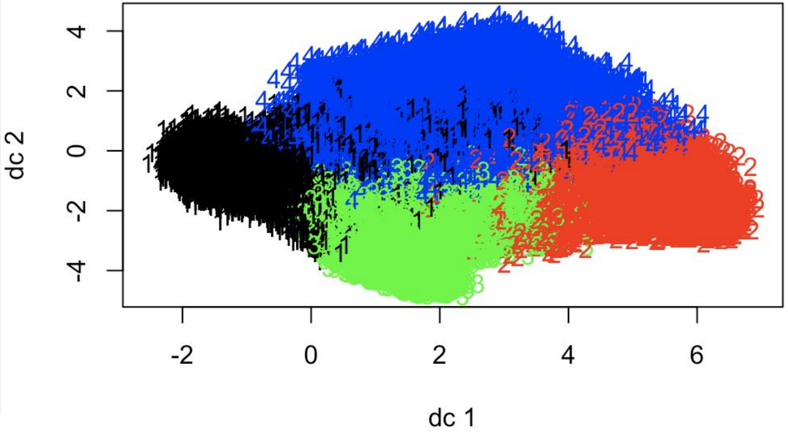
K-means Clustering with
R Tidyverse library.

Identified Groups → Target Audience

Identified Groups



After multiple iterations of clustering and variable selection, we decided to choose K-Means (over K-Modes) and four main clusters to represent the consumer groups in the audience data.



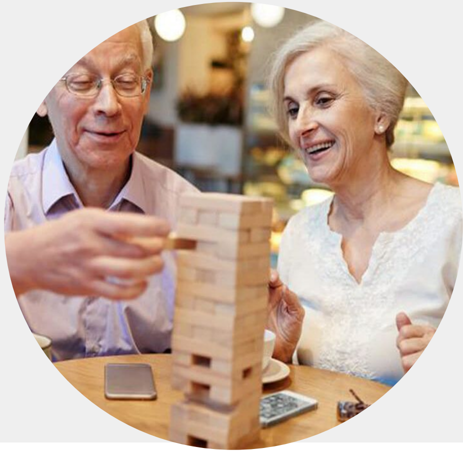
Identified Groups Target Audience

Identified Groups

Boomers and Gen X

Millennials

The Elderly



Unidentified/ Under-represented

Target Audience I

Group 1:
Boomers and Gen X

56% men, 67% parents

Religious, conservative, family-oriented, risk-aversive

Most educated

Most into the outdoors

Avid readers of magazine & newspaper

Prime-time TV watchers

Identified Groups | **Target Audience**

Target Audience II

Group 2: Millennials

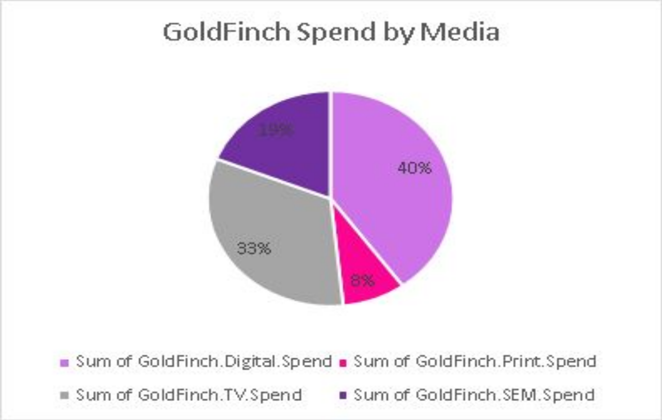
- Risk-taking thrill seekers
- Most trend-conscious
- Enjoys DIY/custom designs
- Most racially diverse
- Carries cell phone everywhere
- Most likely to own a Smart TV
- Listens to Radio & Podcasts
- Women read more magazines

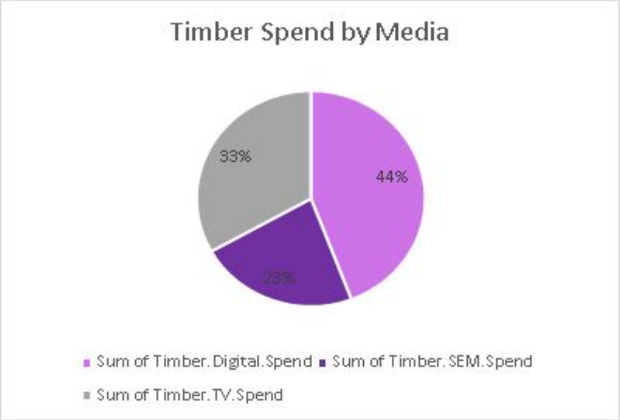
Phase 2: Media Analysis

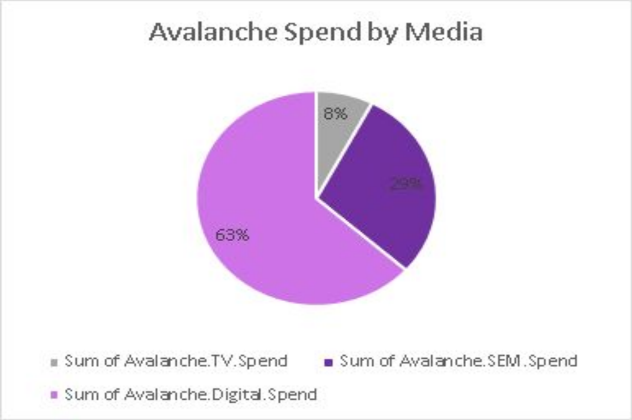
Media Mix → Media Efficiency → Brand Consideration → Weather

Avalanche is only advertised on Digital medium with minimal investment on TV & Print.

Media Mix by Brand

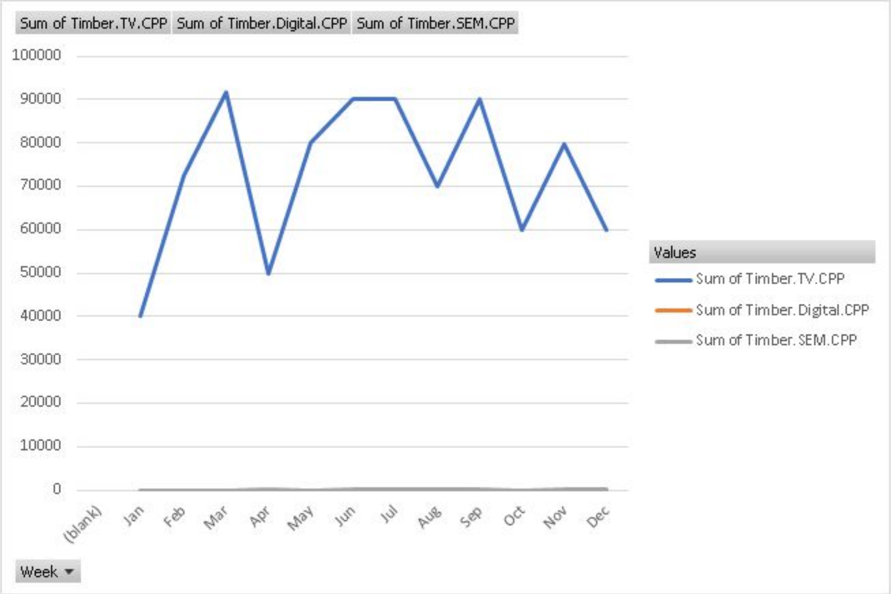






Media Efficiency by Brand

Digital and SEM are the most efficient advertising medium.

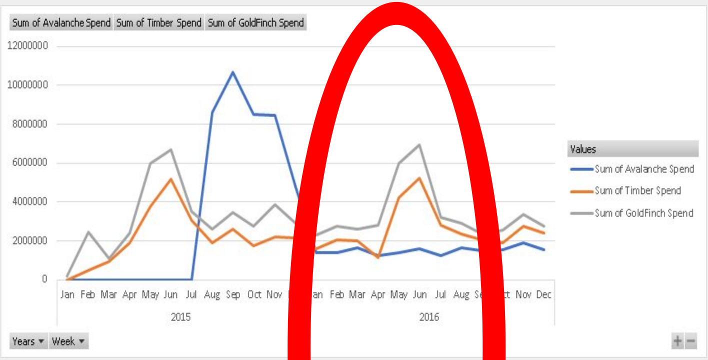


Using Timber as Example

- CPA = Spend / Impression
- Digital > SEM > Print > TV
- Hypothesis: TV's relative inefficiency may be due to heavy reliance on Linear TV which advertises to the general gross public, instead of Programmatic TV which allows targeting based on time, household IP and Geos.

Cross-media advertising is crucial for Brand Consideration.

Total Spend by Brand



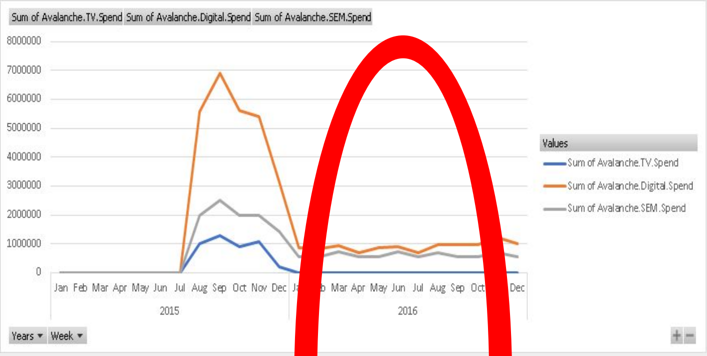
Brand Consideration by Brand

For Avalanche, the decrease in Brand Consideration Rate coincides with pause on TV spend.

- Jan 2016:
  - Stopped spending on TV
- April 2016:
  - Skiing season in North America ends & the brand is no longer visible on TV
- May ~ August 2016:
  - Discount campaigns

Cross-media advertising is crucial for Brand Consideration.

Avalanche Spend by Media



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Average Temperature and Sunshine Duration affect the sales of all three products.

Weather's Impact on Sales

Multivariable Regression with R Glm.

		Golden Finch	**Timber**	**Avalanche**
New York City (Central Park)	**Average Temperature**	Positive ***	Positive ***	Positive ***
	Wind	Negative *	Negative *	Negative
	Average Humidity	Positive *	Positive	Positive
	Sunshine (hrs/day)	Positive	Positive	Negative ***

*$p<.05$ **$p<.01$ ***$p<.001$

Phase 3: Media Strategy

Competitive Analysis → Markov Model → Budget Roll-out Plan → Sales Prediction → Branding

Brands Investigated:

MOSCHINO

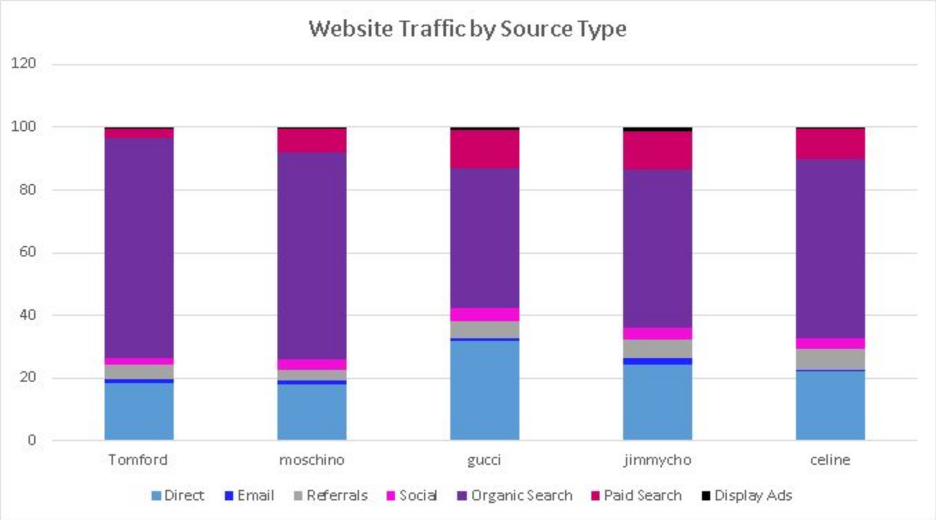
CÉLINE

TOM FORD EYEWEAR

JIMMY CHOO

Display Ads seem to be the initial touch point in the consumer journey,
while Search (Organic & Paid) is the last touchpoint before visiting the website.

Competitive Analysis: Marketing Mix



	Tomford	Moschino	Gucci	Jimmycho	Celine
Direct	18.5%	17.8%	31.8%	24.1%	22.1%
Email	1.2%	1.2%	0.8%	2.4%	0.6%
Referrals	4.4%	3.5%	5.4%	5.8%	6.7%
Social	2.5%	3.6%	4.1%	3.6%	3.5%
Organic Search	70.3%	66.1%	45.0%	50.8%	57.2%
Paid Search	3.0%	7.3%	11.9%	12.2%	9.5%
Display Ads	0.3%	0.5%	0.9%	1.1%	0.5%

Data collected from SimilarWeb Pro (www.similarweb.com) during January 2018 ~ March 2018 (3 months), worldwide.

Purchase Funnel by Media

- Digital (Prospecting)
- TV (programmatic)

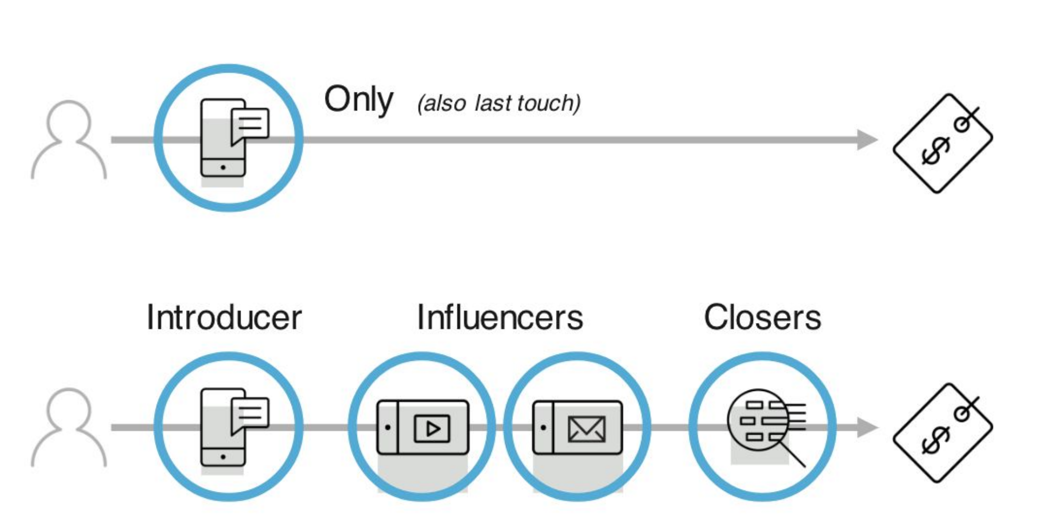
Early
- Print (Content Syndication)

Late
- SEM
- Paid Social
- Digital (Retargeting)

- Review Syndication

Modeled with R Channel Attribution Library.

Multi-touch Attribution Model



Measures digital as a long, nonlinear, interactive journey across multiple marketing tactics & conversions.

Modeled with R Channel Attribution Library.

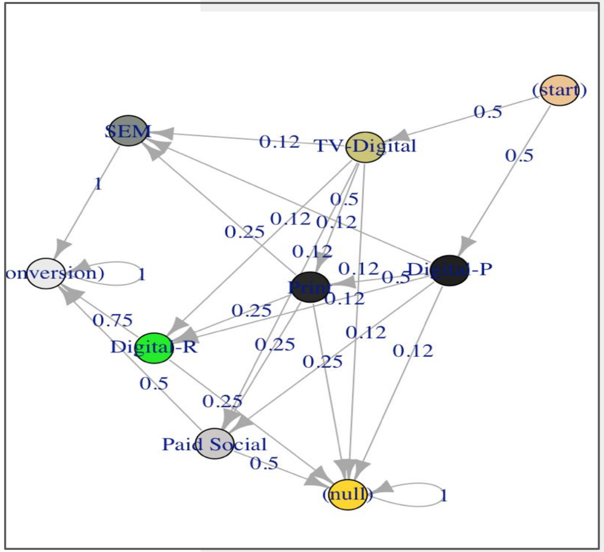
Assumptions

1. No vertical path like 1 —> 2 OR 4 —> 5
2. No reverse path or duplicated channels like 2 —> 1 —> 2
3. Efficiency: Digital > SEM > Print > TV
   a. Source: Sales Analysis
4. Cross-device is more powerful than single-device view. Using cross-device view, consumers convert at 1.4x the rate than if you just viewed from a single device view.
   a. Only SEM & Cross-Device are effective enough to end the user journey in two steps.
   b. Source: Google Analytics Click-Through-Rate Report (2017)
5. All three-step paths will result in conversion.
6. For sportsgear, Print (reputable digital magazines/online sports communities) with detailed description of product functionalities is a key conversion driver.
7. Millenial women consume Print more frequently than millenial men.
   a. Source: Audience Analysis

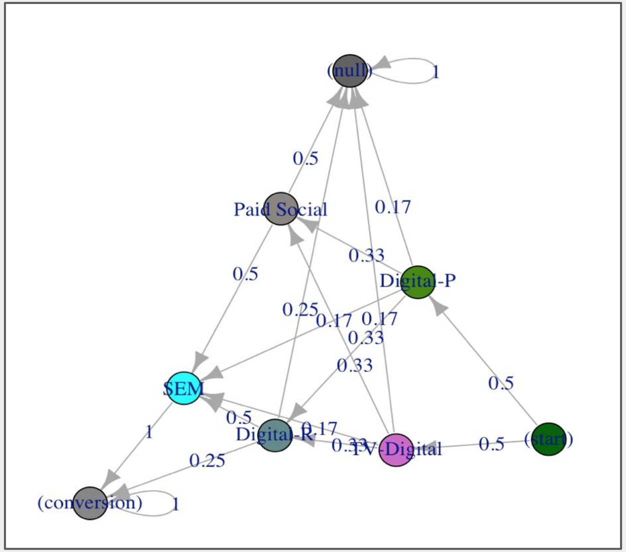
Modeled with R Channel Attribution Library.

Multi-touch Attribution Model

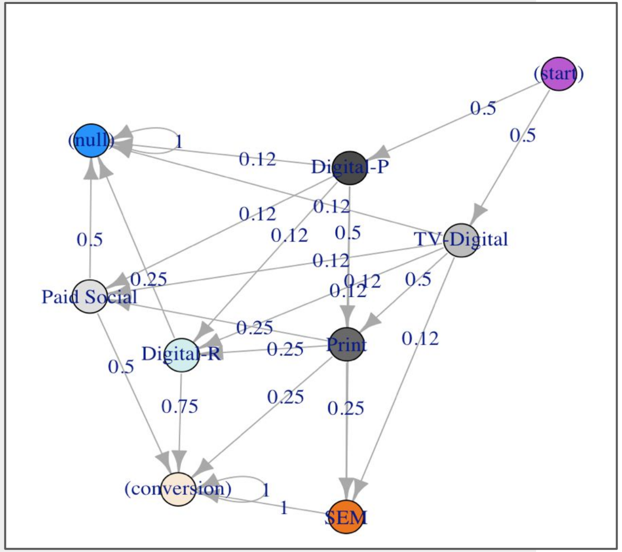
Golden Finch



Timber

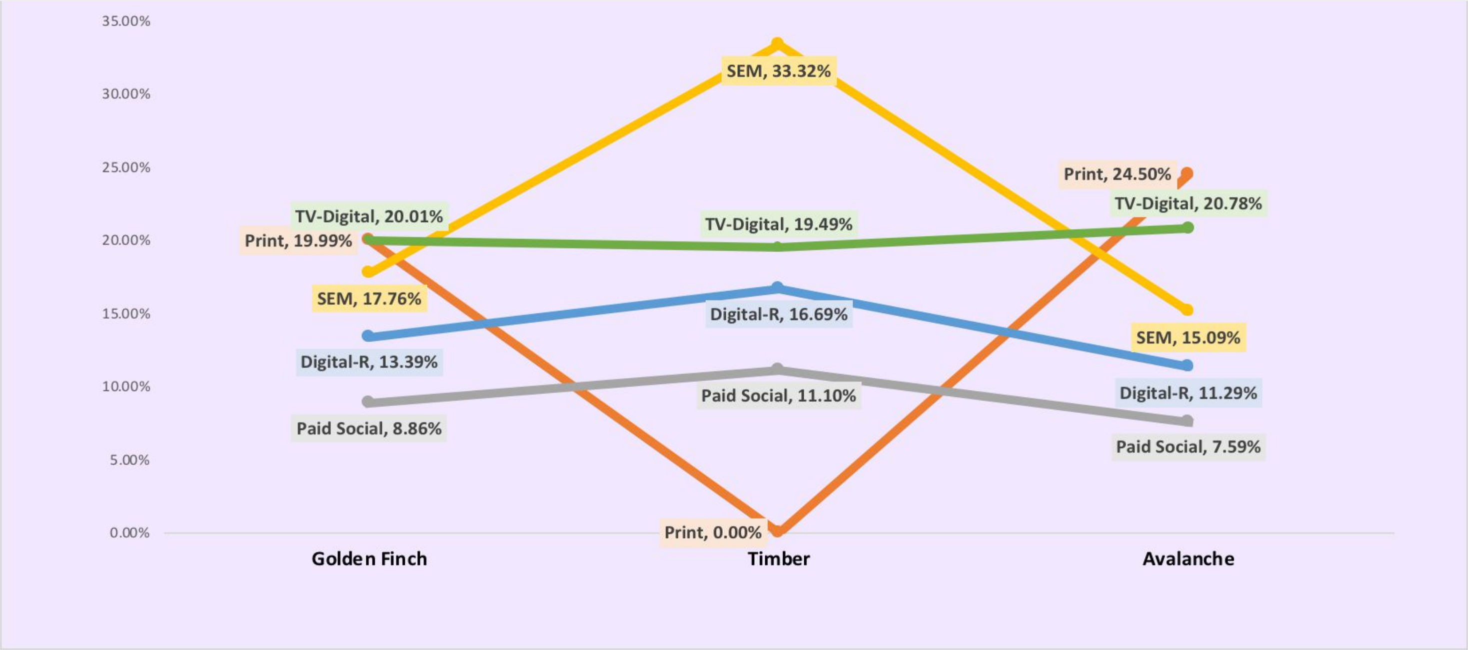


Avalanche

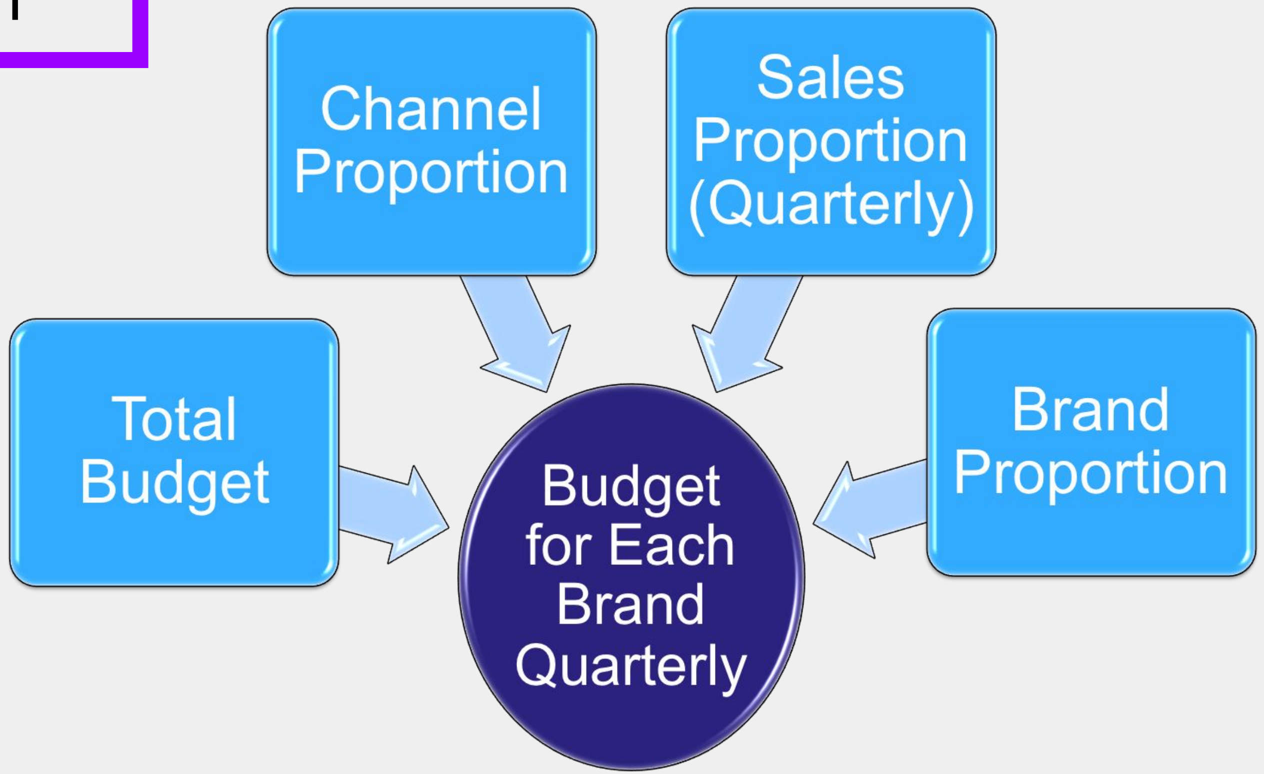


Modeled with R Channel Attribution Library.

Multi-touch Attribution Model



Budget Plan


Channel Proportion
Sales Proportion (Quarterly)
Total Budget
Budget for Each Brand Quarterly
Brand Proportion

Competitive Analysis | Markov Model | **Budget Roll-out Plan** | Sales Prediction | Branding

Budget Plan

Budget for Timber on Digital (Prospecting) in Q1

= $70 Mil *Channel Portion*Brand Sales Portion(Quarterly) * Brand Portion

ex) **$470 K** = $70 Mil * 0.194(Digital-P)* 0.115(1st Quarter Sales within Timber) * 0.316(Timber Portion)

TIMBER

	Q1	Q2	Q3	Q4	Total
Digital-P	$470,002.03	$1,094,195.52	$1,479,893.41	$1,324,214.88	$4,368,305.84
Print	$0.00	$0.00	$0.00	$0.00	$0.00
Paid Social	$268,992.46	$626,232.07	$846,975.43	$757,877.20	$2,500,077.16
SEM	$807,178.21	$1,879,163.73	$2,541,558.59	$2,274,197.38	$7,502,097.91
Digital-R	$404,206.82	$941,019.94	$1,272,724.29	$1,138,839.08	$3,756,790.13
TV-Digital	$472,026.68	$1,098,909.03	$1,486,268.41	$1,329,919.26	$4,387,123.38
Total	$2,422,406.20	$5,639,520.29	$7,627,420.12	$6,825,047.80	**$22,514,394.41**

AVALANCHE

	Q1	Q2	Q3	Q4	Total
Digital-P	$ 525,944.47	$ 574,334.18	$1,022,941.05	$1,430,614.31	$ 3,553,834.00
Print	$ 621,307.54	$ 678,471.17	$1,208,418.44	$1,690,010.10	$ 4,198,207.26
Paid Social	$ 192,478.61	$ 210,187.67	$ 374,363.23	$ 523,558.41	$ 1,300,587.91
SEM	$ 382,495.47	$ 417,687.11	$ 743,938.47	$1,040,420.67	$ 2,584,541.71
Digital-R	$ 286,346.53	$ 312,691.95	$ 556,932.61	$ 778,887.26	$ 1,934,858.34
TV-Digital	$ 526,874.32	$ 575,349.58	$1,024,749.57	$1,433,143.58	$ 3,560,117.05
Total	$2,535,446.93	$2,768,721.65	$4,931,343.37	$6,896,634.33	**$ 17,132,146.28**

GOLDEN FINCH

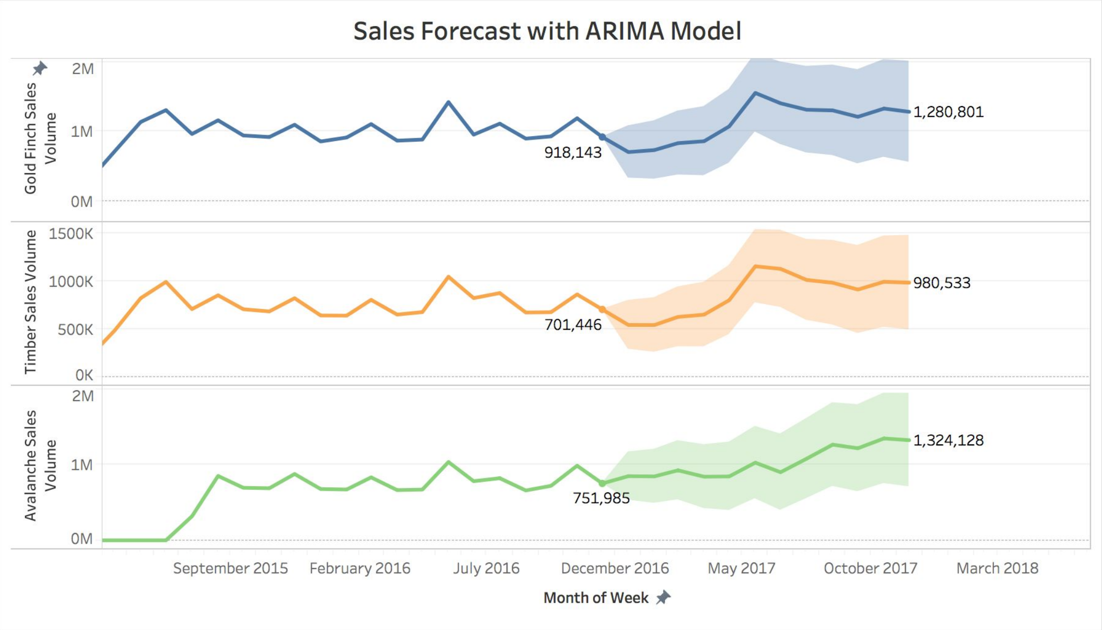
	Q1	Q2	Q3	Q4	Total
Digital-P	$668,967.62	$1,560,043.41	$2,002,501.13	$1,838,804.22	$6,070,316.39
Print	$668,551.57	$1,559,073.16	$2,001,255.70	$1,837,660.60	$6,066,541.03
Paid Social	$296,209.22	$690,764.74	$886,678.64	$814,196.01	$2,687,848.60
SEM	$594,089.76	$1,385,427.01	$1,778,360.24	$1,632,986.00	$5,390,863.01
Digital-R	$447,947.75	$1,044,621.47	$1,340,895.82	$1,231,282.64	$4,064,747.69
TV-Digital	$669,279.08	$1,560,769.73	$2,003,433.46	$1,839,660.33	$6,073,142.60
Total	$3,345,045.01	$7,800,699.52	$10,013,124.98	$9,194,589.80	**$30,353,459.31**

Sales Prediction

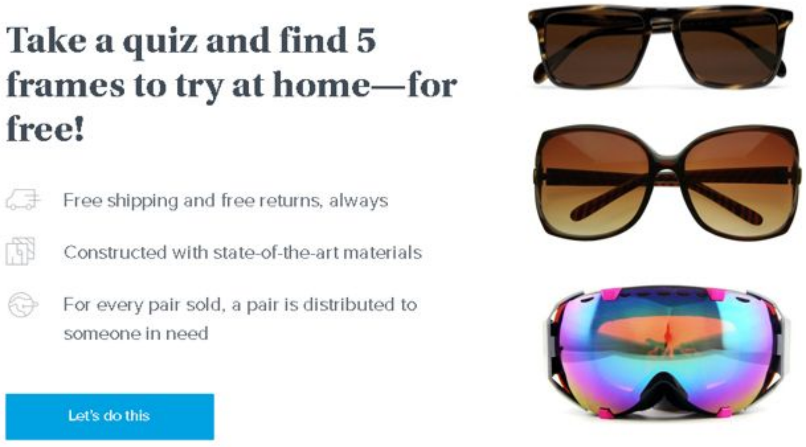
Modeled with R Tsseries Library & Tableau.

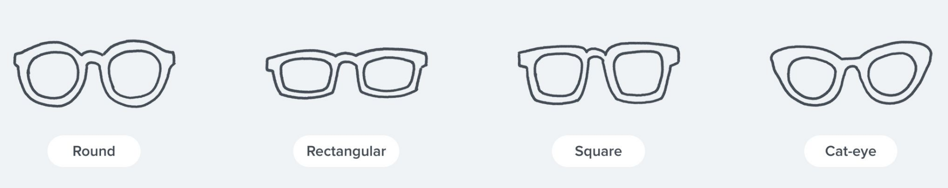
Goal: Increase total sales by 15 % from Dec 2016 to Dec 2017

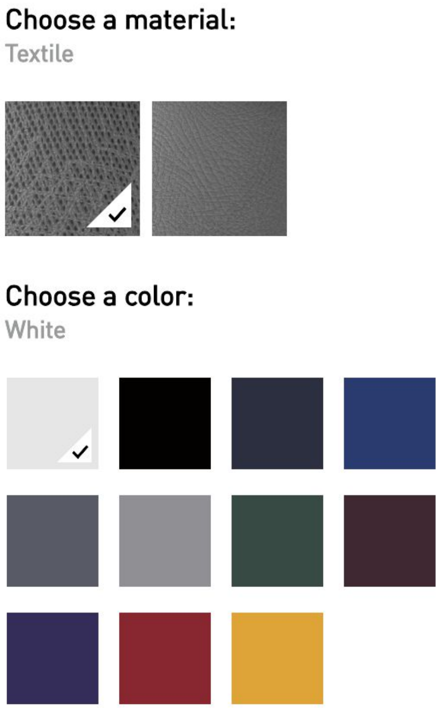
- Golden Finch: 39.50%
- Timber: 39.79%
- Avalanche: 76.08%



Branding Strategy: Personalization

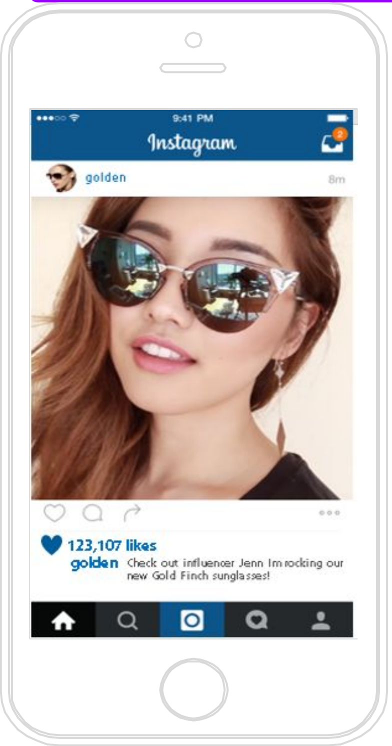






- Landing page personalization
- Interactive Frame Quiz
- Customizable Design
- #wearyou

Branding Strategy:
From Digital to Brick & Mortar



- Influencer Marketing
- Content Syndication
- “Golden Studio” (Showrooms): Transform the brick & mortar store into an interactive experience designed to be tactile, unique and shareable on social media

Branding Strategy: Family Fun

- Partner with Luxurious Ski Resorts & Car Rental Agencies
- RX Ski goggles and RX stylish sunglasses with UV protection
- Family Discounts

Branding Strategy: Rewards Program

- **Members ONLY perks**
  - CSR Campaign
  - Refer a friend & get a promo code
  - Free regular prescription exam
  - Free shipping & Free returns

Phase 4: Conclusion

KPIs > Final Recommendations > Q & A > Appendix

Brand Marketing Goals

Awareness	Consideration	Action	Advocacy

KPIs

Awareness
- Impression/GRP
- Video Completion Rate
- Unique users

Consideration
- Click-Thru Rate
- Video Watch Time
- Item in bag
- Quality Score
- Likes/comments
- Page Views

Action
- Registrations
- Calls/Live Chat
- Sales
- Cost per Acquisition
- Promo redemptions

Advocacy
- Number of Referrals
- Number/rating of Reviews
- Number of tags/hashtags/posts shared
- Net Promoter Score (recommendations)

Final Recommendations

Golden Finch & Timber

- Invest on Cross-Device (TV/Mobile)
- Ramp up Programmatic TV/Radio/Podcast/Music Streaming (Spotify/Pandora)
- Invest in Influencer Marketing
- Customize design quiz for increased personalization and interaction

Final Recommendations

Avalanche

- Expand the audience pool to age 50
- Invest in Print (physical & digital copies)
- Allocate some of SEM budget to Prime-time TV
- Brand Loyalty: Consistently campaign

Thanks!

Any questions?

Appendix

Sources

Slide 21:

Cross-device is more powerful than single-device view. Using cross-device view, consumers convert at 1.4x the rate than if you just viewed from a single device view.

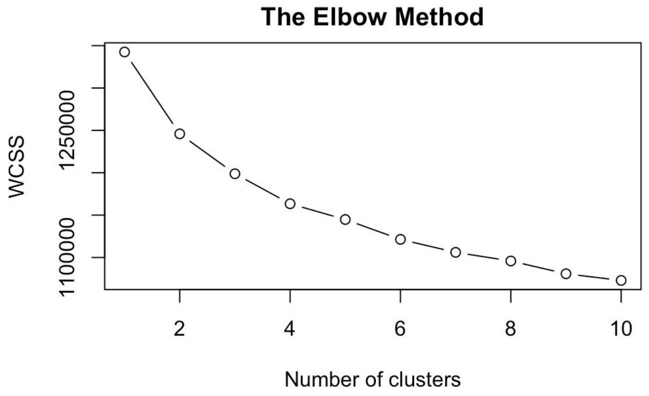
a. https://www.mobilemarketer.com/ex/mobilemarketer/cms/opinion/columns/24660.html

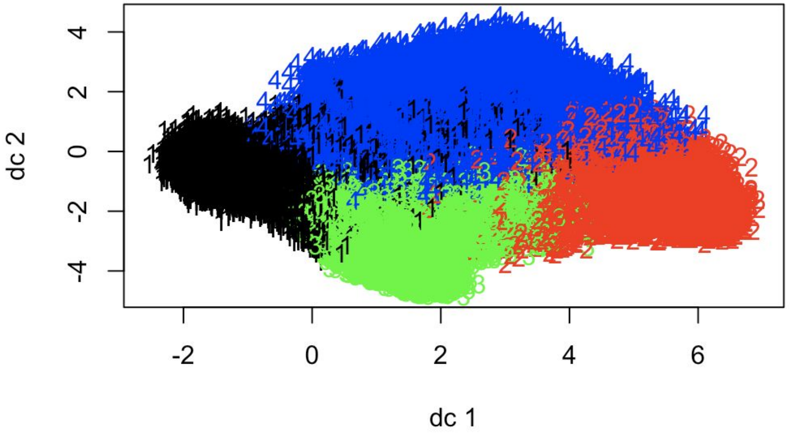
Only SEM & Cross-Device are effective enough to end the user journey in two steps.

b. Google Analytics Click-Through-Rate Report
c. https://www.wordstream.com/blog/ws/2016/02/29/google-adwords-industry-benchmarks

Code

```
#K-means Clustering
```{r}
data<-read.csv('Audience.2.csv')
```
```{r}
# Using the elbow method to find the optimal number of clusters
set.seed(6)
wcss = vector()
for (i in 1:10) wcss[i] = sum(kmeans(data, i)$withinss)
plot(1:10,
     wcss,
     type = 'b',
     main = paste('The Elbow Method'),
     xlab = 'Number of clusters',
     ylab = 'WCSS')
# 4 clusters should be optimal.
```
```{r}
# Fitting K-Means to the dataset
set.seed(29)
kmeans = kmeans(x = data, centers = 4)
y_kmeans = kmeans$cluster
```
```{r}
library(cluster)
library(fpc)
data(data)
```
```





```
# Kmeans clustre analysis
clus <- kmeans(data, centers=4)
# Visualize
plotcluster(data, clus$cluster)
# Visualize more
library(tidyverse)  # data manipulation
library(cluster)    # clustering algorithms
library(factoextra) # clustering algorithms & visualization
fviz_cluster(clus, data = data)d
```

```{r}
# Extract insights from each cluster
# mean
clus_mean <- data %>%
  mutate(Cluster = clus$cluster) %>%
  group_by(Cluster) %>%yyy
  summarise_all("mean")
#write.csv(clus_mean, "clus_mean.csv")
Now on to the personality quiz!
```

```{r}
data.p <- read.csv('/Users/su.min.park@ibm.com/Documents/Mindshare/Audience.Personality.2.csv')
```

```{r}
# remove NA
data.p.final <- data.p[complete.cases(data.p), ]

# Using the elbow method to find the optimal number of clusters
set.seed(6)
wcss = vector()
for (i in 1:10) wcss[i] = sum(kmeans(data.p.final, i)$withinss)
plot(1:10,
     wcss,
     type = 'b',
     main = paste('The Elbow Method'),
     xlab = 'Number of clusters',
     ylab = 'WCSS')

# 4 clusters should be optimal.
```

```{r}
# Fitting K-Means to the dataset
set.seed(29)
kmeans = kmeans(x = data.p.final, centers = 4)
y_kmeans = kmeans$cluster
```

#Multi-touch attribution model
For Golden Finch

```
library(dplyr)
library(reshape2)
library(ggplot2)
library(ggthemes)
library(ggrepel)
library(RColorBrewer)
library(ChannelAttribution)
library(markovchain)
# creating a data sample
PATH1=c('Digital-P','Digital-P > Print','Digital-P > Print > Paid Social','Digital-P > Print > SEM', 'Digital-P > Print > Digital-R','Digital-P > Paid Social', 'Digital-P > SEM','Digital-P > Digital-R','TV-Digital','TV-Digital > Print','TV-Digital > Print > Paid Social','TV-Digital > Print > SEM', 'TV-Digital > Print > Digital-R','TV-Digital > Paid Social', 'TV-Digital > SEM','TV-Digital > Digital-R')
CONV1=c(0,0,1,1,1,0,1,0,0,0,1,1,1,0,1,1)
CONV_NULL1=c(1,1,0,0,0,1,0,1,1,1,0,0,0,1,0,0)
df1 <- data.frame(path = PATH1, conv = CONV1, conv_null = CONV_NULL1)
# calculating the model
mod1 <- markov_model(df1, var_path = 'path', var_conv = 'conv',  var_null = 'conv_null', out_more = TRUE)
# extracting the results of attribution
df_res1 <- mod1$result
df_res1
# extracting a transition matrix
df_trans1 <- mod1$transition_matrix
df_trans1 <- dcast(df_trans1, channel_from ~ channel_to, value.var = 'transition_probability')
### plotting the Markov graph ###
df_trans <- mod1$transition_matrix
df_trans
# adding dummies in order to plot the graph
df_dummy <- data.frame(channel_from = c('(start)', '(conversion)', '(null)'), channel_to = c('(start)', '(conversion)', '(null)'), transition_probability = c(0, 1, 1))
df_trans <- rbind(df_trans, df_dummy)
```

```
# ordering channels
df_trans$channel_from <- factor(df_trans$channel_from,
                               levels = c('(start)', '(conversion)', '(null)', 'Digital-P', 'TV-Digital','Print', 'Paid Social','SEM','Digital-R'))
df_trans$channel_to <- factor(df_trans$channel_to,
                               levels = c('(start)', '(conversion)', '(null)', 'Digital-P', 'TV-Digital','Print', 'Paid Social','SEM','Digital-R'))
df_trans <- dcast(df_trans, channel_from ~ channel_to, value.var = 'transition_probability')
# creating the markovchain object
trans_matrix <- matrix(data = as.matrix(df_trans[, -1]),  nrow = nrow(df_trans[, -1]), ncol = ncol(df_trans[, -1]), dimnames = list(c(as.character(df_trans[, 1])), c(colnames(df_trans[, -1]))))
trans_matrix[is.na(trans_matrix)] <- 0
trans_matrix1 <- new("markovchain", transitionMatrix = trans_matrix)
# plotting the graph
plot(trans_matrix1, edge.arrow.size = 0.65)
```

For Timber

```
# creating a data sample
PATH2=c('Digital-P','Digital-P > Paid Social','Digital-P > Paid Social > SEM','Digital-P > SEM', 'Digital-P > Digital-R','Digital-P > Digital-R > SEM', 'TV-Digital','TV-Digital > Paid Social','TV-Digital > Paid Social > SEM','TV-Digital > SEM', 'TV-Digital > Digital-R','TV-Digital > Digital-R > SEM')
CONV2=c(0,0,1,1,0,1,0,0,1,1,1,1)
CONV_NULL2=c(1,1,0,0,1,0,1,1,0,0,0,0)
df2 <- data.frame(path = PATH2, conv = CONV2, conv_null = CONV_NULL2)
# calculating the model
mod2 <- markov_model(df2, var_path = 'path', var_conv = 'conv',  var_null = 'conv_null', out_more = TRUE)
# extracting the results of attribution
df_res2 <- mod2$result
df_res2
# extracting a transition matrix
df_trans2 <- mod2$transition_matrix
df_trans2 <- dcast(df_trans2, channel_from ~ channel_to, value.var = 'transition_probability')
### plotting the Markov graph ###
df_trans <- mod2$transition_matrix
df_trans
# adding dummies in order to plot the graph
df_dummy <- data.frame(channel_from = c('(start)', '(conversion)', '(null)'), channel_to = c('(start)', '(conversion)', '(null)'),  transition_probability = c(0, 1, 1))
df_trans <- rbind(df_trans, df_dummy)
```

```
# ordering channels
df_trans$channel_from <- factor(df_trans$channel_from, levels = c('(start)', '(conversion)', '(null)', 'Digital-P', 'TV-Digital', 'Paid Social','SEM','Digital-R'))
df_trans$channel_to <- factor(df_trans$channel_to,  levels = c('(start)', '(conversion)', '(null)', 'Digital-P', 'TV-Digital', 'Paid Social','SEM','Digital-R'))
df_trans <- dcast(df_trans, channel_from ~ channel_to, value.var = 'transition_probability')
# creating the markovchain object
trans_matrix <- matrix(data = as.matrix(df_trans[, -1]),  nrow = nrow(df_trans[, -1]), ncol = ncol(df_trans[, -1]),  dimnames = list(c(as.character(df_trans[, 1])), c(colnames(df_trans[, -1]))))
trans_matrix[is.na(trans_matrix)] <- 0
trans_matrix2 <- new("markovchain", transitionMatrix = trans_matrix)
# plotting the graph
plot(trans_matrix2, edge.arrow.size = 0.65)
```

For Avalanche

```
# creating a data sample
PATH3=c('Digital-P','Digital-P > Print','Digital-P > Print > Paid Social','Digital-P > Print > SEM', 'Digital-P > Print > Digital-R','Digital-P > Paid Social', 'Digital-P > SEM','Digital-P > Digital-R','TV-Digital','TV-Digital > Print','TV-Digital > Print > Paid Social','TV-Digital > Print > SEM', 'TV-Digital > Print > Digital-R','TV-Digital > Paid Social', 'TV-Digital > SEM','TV-Digital > Digital-R')
CONV3=c(0,1,1,1,1,0,1,0,0,1,1,1,1,0,1,1)
CONV_NULL3=c(1,0,0,0,0,1,0,1,1,0,0,0,0,1,0,0)
df3 <- data.frame(path = PATH3, conv = CONV3, conv_null = CONV_NULL3)
# calculating the model
mod3 <- markov_model(df3, var_path = 'path',var_conv = 'conv', var_null = 'conv_null', out_more = TRUE)
# extracting the results of attribution
df_res3 <- mod3$result
df_res3
# extracting a transition matrix
df_trans3 <- mod3$transition_matrix
df_trans3 <- dcast(df_trans3, channel_from ~ channel_to, value.var = 'transition_probability')
### plotting the Markov graph ###
df_trans <- mod3$transition_matrix
df_trans
# adding dummies in order to plot the graph
df_dummy <- data.frame(channel_from = c('(start)', '(conversion)', '(null)'), channel_to = c('(start)', '(conversion)', '(null)'), transition_probability = c(0, 1, 1))
df_trans <- rbind(df_trans, df_dummy)
```

```
# ordering channels
df_trans$channel_from <- factor(df_trans$channel_from, levels = c('(start)', '(conversion)', '(null)', 'Digital-P', 'TV-Digital','Print', 'Paid Social','SEM','Digital-R'))
df_trans$channel_to <- factor(df_trans$channel_to,  levels = c('(start)', '(conversion)', '(null)', 'Digital-P', 'TV-Digital','Print', 'Paid Social','SEM','Digital-R'))
df_trans <- dcast(df_trans, channel_from ~ channel_to, value.var = 'transition_probability')
# creating the markovchain object
trans_matrix <- matrix(data = as.matrix(df_trans[, -1]), nrow = nrow(df_trans[, -1]), ncol = ncol(df_trans[, -1]),  dimnames = list(c(as.character(df_trans[, 1])), c(colnames(df_trans[, -1]))))
trans_matrix[is.na(trans_matrix)] <- 0
trans_matrix3 <- new("markovchain", transitionMatrix = trans_matrix)
# plotting the graph
plot(trans_matrix3, edge.arrow.size = 0.65)
```

Weather Regression - Gold Finch

	Gold.Finch.Sales.Volume	Gold.Finch.Sales.Volume	Gold.Finch.Sales.Volume	Gold.Finch.Sales.Volume	Gold.Finch.Sales.Volume	Gold.Finch.Sales.Volume
	B (CI)	*B (CI)*	*B (CI)*	*B (CI)*	*B (CI)*	*B (CI)*
(Intercept)	38079.54 (-74901.44 – 151060.52)	40444.81 (-83308.25 – 164197.88)	6872.80 (-66775.76 – 80521.37)	9219.64 (-117538.90 – 135978.18)	86869.72 (1271.87 – 172467.58) *	165849.73 (72054.77 – 259644.69) ***
wind	780.05 (-5514.89 – 7075.00)	-2567.01 (-9615.49 – 4481.47)		-2374.49 (-9341.71 – 4592.73)	534.22 (-5771.51 – 6839.95)	-6851.76 (-13669.41 – -34.11) *
precp	251.46 (-1058.80 – 1561.71)	-58.95 (-1524.54 – 1406.64)		-245.08 (-1706.78 – 1216.61)	657.76 (-502.18 – 1817.70)	10.97 (-1520.84 – 1542.78)
Sunshine.Hour	-302.55 (-768.43 – 163.33)	505.41 (167.99 – 842.83) **		611.44 (259.27 – 963.62) ***	-364.80 (-822.58 – 92.97)	
avg_temp	3352.68 (2084.99 – 4620.37) ***		2673.77 (1899.78 – 3447.76) ***		3509.85 (2260.49 – 4759.20) ***	
avg_humidity	899.01 (-466.06 – 2264.08)	972.46 (-408.90 – 2353.82)	1122.83 (-62.02 – 2307.67)	1578.64 (67.42 – 3089.86) *		1326.65 (-257.82 – 2911.13)
avg_visibility.mile	-6677.43 (-13425.86 – 70.99)		-7761.87 (-14248.38 – -1275.35) *	-7104.68 (-14709.43 – 500.08)	-4783.85 (-10910.35 – 1342.65)	-2849.59 (-10432.61 – 4733.42)
Observations	104	104	104	104	104	104
R^2 / adj. R^2	.357 / .317	.145 / .111	.345 / .325	.174 / .132	.346 / .312	.074 / .037
Notes	* $p<.05$ ** $p<.01$ *** $p<.001$					

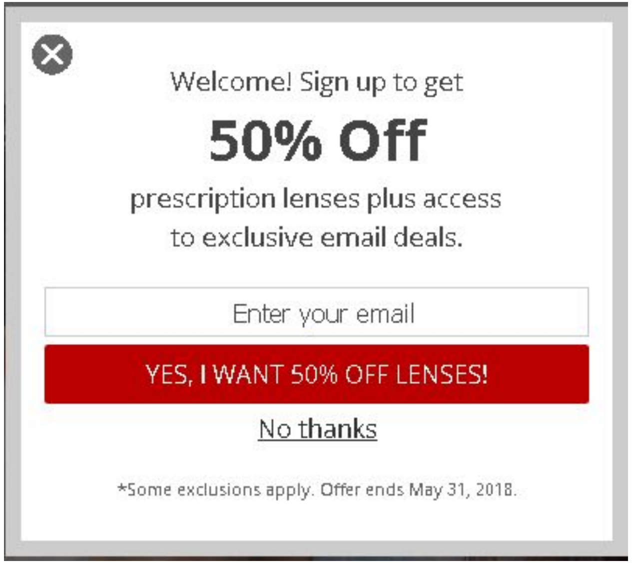
Weather Regression - Timber

	Timber.Sales.Volume	Timber.Sales.Volume	Timber.Sales.Volume	Timber.Sales.Volume	Timber.Sales.Volume	Timber.Sales.Volume
	B (CI)	*B (CI)*	*B (CI)*	*B (CI)*	*B (CI)*	*B (CI)*
(Intercept)	21045.84 (-63597.57 – 105689.25)	21528.00 (-70769.69 – 113825.69)	6098.08 (-48919.59 – 61115.74)	-337.84 (-95073.23 – 94397.56)	55125.78 (-8930.07 – 119181.63)	126215.97 (55480.29 – 196951.66) ***
wind	756.16 (-3959.91 – 5472.22)	-1716.01 (-6972.92 – 3540.90)		-1581.19 (-6788.28 – 3625.89)	584.45 (-4134.35 – 5303.24)	-5198.73 (-10340.27 – -57.18) *
precp	54.59 (-927.03 – 1036.21)	-182.98 (-1276.04 – 910.09)		-313.32 (-1405.75 – 779.11)	338.39 (-529.63 – 1206.42)	-106.43 (-1261.65 – 1048.78)
Sunshine.Hour	-183.19 (-532.22 – 165.84)	419.78 (168.13 – 671.44) **		494.03 (230.83 – 757.24) ***	-226.67 (-569.24 – 115.90)	
avg_temp	2484.16 (1534.43 – 3433.89) ***		2060.31 (1482.11 – 2638.50) ***		2593.94 (1659.01 – 3528.88) ***	
avg_humidity	627.96 (-394.73 – 1650.65)	707.04 (-323.21 – 1737.29)	716.76 (-168.35 – 1601.88)	1131.53 (2.09 – 2260.97) *		927.93 (-267.00 – 2122.86)
avg_visibility.mile	-4658.58 (-9714.38 – 397.23)		-5265.69 (-10111.31 – -420.07) *	-4975.14 (-10658.70 – 708.41)	-3335.91 (-7920.59 – 1248.76)	-1537.13 (-7255.87 – 4181.62)
Observations	104	104	104	104	104	104
R^2 / adj. R^2	.362 / .322	.159 / .125	.353 / .334	.185 / .143	.352 / .319	.069 / .031
Notes						* *p*<.05 ** *p*<.01 *** *p*<.001

Weather Regression - Avalanche

	Avalanche.Sales.Volume	Avalanche.Sales.Volume	Avalanche.Sales.Volume	Avalanche.Sales.Volume	Avalanche.Sales.Volume	Avalanche.Sales.Volume
	B (CI)	*B (CI)*	*B (CI)*	*B (CI)*	*B (CI)*	*B (CI)*
(Intercept)	211392.46 (89146.68 – 333638.25) ***	209561.22 (83867.05 – 335255.39) **	96560.60 (11470.05 – 181651.15) *	188434.11 (58437.53 – 318430.70) **	209224.88 (117411.40 – 301038.36) ***	205019.48 (137643.63 – 272395.33) ***
wind	-293.69 (-7104.84 – 6517.47)	-2933.41 (-10092.45 – 4225.62)		-2803.16 (-9948.35 – 4342.04)	-282.76 (-7046.38 – 6480.85)	
precp	23.33 (-1394.37 – 1441.03)	-245.73 (-1734.31 – 1242.84)		-371.67 (-1870.71 – 1127.37)	5.28 (-1238.89 – 1249.45)	
Sunshine.Hour	-989.75 (-1493.83 – -485.66) ***	-334.40 (-677.11 – 8.32)		-262.65 (-623.83 – 98.52)	-986.98 (-1478.00 – -495.96) ***	-1044.19 (-1520.93 – -567.45) ***
avg_temp	2667.09 (1295.45 – 4038.74) ***		622.70 (-271.54 – 1516.94)		2660.11 (1320.04 – 4000.19) ***	2617.27 (1318.96 – 3915.59) ***
avg_humidity	-39.94 (-1516.95 – 1437.07)	90.57 (-1312.46 – 1493.60)	329.91 (-1039.01 – 1698.83)	500.71 (-1049.11 – 2050.54)		
avg_visibility.mile	-4467.18 (-11769.00 – 2834.64)		-7585.66 (-15079.92 – -91.41) *	-4807.06 (-12606.07 – 2991.96)	-4551.31 (-11122.68 – 2020.07)	
Observations	104	104	104	104	104	104
R^2 / adj. R^2	.179 / .128	.039 / -.000	.046 / .018	.053 / .005	.179 / .137	.163 / .147
Notes						* *p*<.05 ** *p*<.01 *** *p*<.001

Branding Strategy



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