MarketMixModeling Models

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Load Libraries:

Load required libraries. Will use `stepAIC` from `MASS` package for model pruning. `vif` variation inflation factor from `car` package

```
library(MASS)
library(car)
library(stargazer)
source('./code/atchircUtils.R')
```

Load Data:

Load blended data from sales and marketing datasets. Data is throughly cleaned, pre-processed for model building. Refer to `DataCleaning.R` script for data preparation steps. For this capstone project we limit our model building focus to `camera_accessory`, `Home_audio` and `Gaming_accessory` product sub-categories. For simplicity will start Linear model building with numerical features, later will consider categorical features.

```
camera_accessory_data_nrm <- read.csv('./intrim/cameraAccessory.csv')
home_audio_data_nrm       <- read.csv('./intrim/homeAudio.csv')
gaming_accessory_data_nrm <- read.csv('./intrim/gamingAccessory')
```

Lets preview the dataset structure. `gmv` gross merchandise values is our target variable, which we would like to maximize with optimal marketing spend across different marketing levers, `discount` is one of the KPI derived from sales data, bunch of other features from marketing spend and NPS datasets.

```
str(camera_accessory_data_nrm)
```

```
## 'data.frame':    52 obs. of  14 variables:
##  $ gmv             : num  18196 3341843 4884098 4514154 3588231 ...
##  $ discount        : num  1.562 -0.276 -0.791 -0.477 -0.397 ...
##  $ sla             : num  -4.772 0.9 0.682 0.302 0.284 ...
##  $ procurement_sla : num  0.101 0.1938 0.0836 0.4656 0.2653 ...
##  $ TV              : num  -1.42 -1.39 -1.39 -1.39 -1.4 ...
##  $ Digital         : num  -0.34291 0.00364 0.00364 0.00364 -0.05181 ...
##  $ Sponsorship     : num  -1.077 -0.948 -0.948 -0.948 -0.984 ...
##  $ ContentMarketing: num  -0.756 -0.756 -0.756 -0.756 -0.756 ...
##  $ OnlineMarketing : num  -1.94 -1.87 -1.87 -1.87 -1.89 ...
##  $ Affiliates      : num  -2 -1.92 -1.92 -1.92 -1.94 ...
##  $ SEM             : num  -0.634 -0.349 -0.349 -0.349 -0.397 ...
##  $ Radio           : num  -0.523 -0.523 -0.523 -0.523 -0.523 ...
##  $ Other           : num  -0.511 -0.511 -0.511 -0.511 -0.511 ...
##  $ NPS             : num  1.28 1.28 1.28 1.28 1.96 ...
```

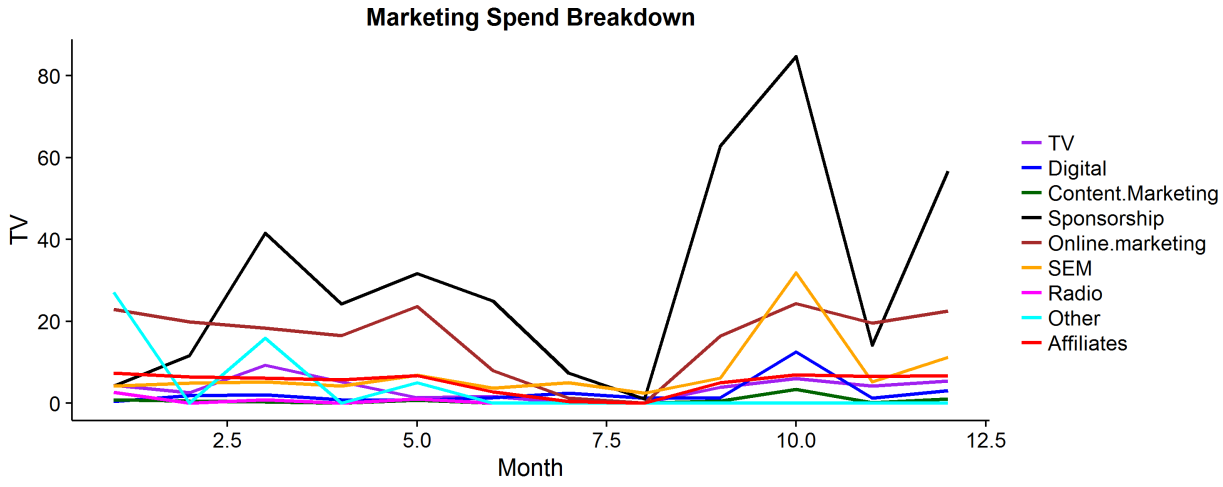
Features distribution: Look at features statistical distributions

```
stargazer(camera_accessory_data_nrm,type='text')
```

```
##
## ================================================================
## Statistic        N      Mean        St. Dev.       Min         Max
```

```
## ---------------------------------------------------------------------------
## gmv              52 5,509,740.000 2,481,745.000 1,397.000 13,102,157.000
## discount         52     0.000         1.000       -3.126       4.616
## sla              52    -0.000         1.000       -4.772       3.169
## procurement_sla  52     0.000         1.000       -4.130       4.646
## TV               52     0.000         1.000       -1.468       2.197
## Digital          52     0.000         1.000       -0.643       3.271
## Sponsorship      52    -0.000         1.000       -1.204       2.198
## ContentMarketing 52     0.000         1.000       -0.756       3.047
## OnlineMarketing  52    -0.000         1.000       -2.019       1.025
## Affiliates       52     0.000         1.000       -2.081       0.936
## SEM              52     0.000         1.000       -0.681       3.221
## Radio            52     0.000         1.000       -0.523       3.004
## Other            52    -0.000         1.000       -0.511       2.876
## NPS              52     0.000         1.000       -1.280       2.640
## ---------------------------------------------------------------------------
```

Marketing Spend Breakdown:



Train and Validation Data:

With one year Sales and Marketing Data, we have 52 obeservations aggreagted at weekly level for each sub-category. Splitting data into training and validation sets would further reduce the training sample size, Moreover the task at hand is to figure out most influential marketing leavers for optimial marketing spend. The goal is to explain the influence of features rather predicting any quantities we can safely utilize the whole dataset for training.

Model Building - Linear Model:

Assumptions:

For simplicity, will consider, each sub-category sales affected from overall marketing spend, where in reality, only a portion of the marketing spend would have been alloted for promoting a certain product category.

Camera Accesory:

Initial Linear Model

```
model_cam1 <- lm(gmv~ .,data=camera_accessory_data_nrm)
```

Auto-Optimize Model

```
step_cam <- stepAIC(model_cam1, direction = "both",trace=FALSE,k=2)
```

Summary

```
stargazer(model_cam1,step_cam, align = TRUE, type = 'text',
          title='Linear Regression Results', single.row=TRUE)
```

```
##
## Linear Regression Results
## ===================================================================================
##                                          Dependent variable:
##                      --------------------------------------------------------------
##                                                  gmv
##                                    (1)                              (2)
## -----------------------------------------------------------------------------------
## discount                 13,381.270 (252,059.500)
## sla                     352,086.700 (319,485.100)       341,307.700 (244,386.300)
## procurement_sla         354,552.400 (260,324.500)       383,522.900 (237,266.500)
## TV                    -2,369,619.000 (4,157,446.000)  -2,660,457.000*** (736,201.100)
## Digital                7,654,649.000 (6,868,969.000)   8,070,851.000*** (2,799,984.000)
## Sponsorship          4,467,389.000*** (1,448,393.000)  4,218,906.000*** (804,623.800)
## ContentMarketing      -3,536,650.000 (4,422,996.000)  -4,920,915.000** (2,060,112.000)
## OnlineMarketing       -5,320,773.000 (5,744,324.000)
## Affiliates             8,122,930.000 (6,602,404.000)   3,725,745.000*** (871,406.200)
## SEM                  -6,451,448.000 (10,803,616.000)  -5,877,756.000** (2,676,528.000)
## Radio                  3,182,333.000 (8,454,713.000)   1,670,248.000*** (607,088.400)
## Other                 -1,638,532.000 (9,560,871.000)
## NPS                     -209,026.500 (1,314,502.000)
## Constant              5,509,740.000*** (235,273.200)   5,509,740.000*** (227,063.500)
## -----------------------------------------------------------------------------------
## Observations                       52                                52
## R2                                0.652                             0.642
## Adjusted R2                       0.533                             0.565
## Residual Std. Error     1,696,579.000 (df = 38)          1,637,378.000 (df = 42)
## F Statistic              5.471*** (df = 13; 38)           8.351*** (df = 9; 42)
## ===================================================================================
## Note:                                                  *p<0.1; **p<0.05; ***p<0.01
```

Variation Inflation Factor

```
knitr::kable(viewModelSummaryVIF(step_cam))
```

var	Estimate	Std.Error	t-value	Pr(>|t|)	Significance	vif
Affiliates	3725745	871406	4.276	0.000107	***	14.444861
ContentMarketing	-4920915	2060112	-2.389	0.021480	*	80.733459
Digital	8070851	2799984	2.882	0.006194	**	149.136230
procurement_sla	383523	237267	1.616	0.113491	NA	1.070890
Radio	1670248	607088	2.751	0.008725	**	7.010936
SEM	-5877756	2676528	-2.196	0.033664	*	136.274821
sla	341308	244386	1.397	0.169874	NA	1.136124
Sponsorship	4218906	804624	5.243	4.82e-06	***	12.315662

var	Estimate	Std.Error	t-value	Pr(>|t|)	Significance	vif
TV	-2660458	736201	-3.614	0.000801	***	10.310149

OBservations:

`Digital` and `SEM` exhibits multi-collinearity, with `Digital` sligthly highly significant. Lets refer marketing spend breakdown

Final Model:

```
model_cam2=lm(formula = gmv ~  Sponsorship + SEM + TV +
     Affiliates, data = camera_accessory_data_nrm)
```

```
getModelR2(model_cam2)
```

```
## [1] "Multiple R-squared:  0.541,\tAdjusted R-squared:  0.5019 "
```

```
knitr::kable(viewModelSummaryVIF(model_cam2))
```

var	Estimate	Std.Error	t-value	Pr(>|t|)	Significance	vif
Affiliates	1381481	339548	4.069	0.000179	***	1.916697
SEM	-1138528	411625	-2.766	0.008088	**	2.816803
Sponsorship	2103163	452193	4.651	2.71e-05	***	3.399378
TV	-679672	369943	-1.837	0.072502	.	2.275208

Understanding Model:

Linear model could explain 56% of revenue from marketing expenditure, but some of the significant features like `TV spending` has negative coefficient term. If we were to explain this, it should mean, `reducing the TV marketing spend would  increase camera Accessory sales`, which doesn't make sense. we can further optimize model by exploring multi-collinearity and pruning features. Hopefully we may end up with a model with better R-Square value and co-efficient terms which makes sense.

Gaming Accesory:

Initial Model

```
model_ga1 <- lm(gmv~ .,data=gaming_accessory_data_nrm)
```

Auto-Optimize Model

```
step_ga <- stepAIC(model_ga1, direction = "both",trace=FALSE)
```

```
stargazer(model_ga1,step_ga, align = TRUE, type = 'text',
          title='Linear Regression Results', single.row=TRUE)
```

```
##
## Linear Regression Results
## =====================================================================================
##                                            Dependent variable:
##                      ----------------------------------------------------------------
##                                                    gmv
##                                    (1)                              (2)
## -------------------------------------------------------------------------------------
## discount             492,264.400*** (170,894.200)    447,874.400*** (159,252.100)
## sla                   -68,255.220 (120,702.100)
## procurement_sla       201,412.100 (132,045.200)        206,101.300 (130,092.400)
## TV                  -1,653,248.000 (1,660,227.000)   -2,593,057.000*** (446,675.800)
## Digital            7,341,960.000** (2,772,307.000)  5,801,867.000*** (1,438,317.000)
## Sponsorship         3,605,580.000*** (629,880.700)   3,721,704.000*** (522,787.300)
## ContentMarketing   -4,868,625.000** (1,838,756.000) -5,671,379.000*** (1,112,845.000)
## OnlineMarketing     -4,191,629.000 (2,585,858.000)   -4,126,524.000 (2,493,308.000)
## Affiliates         6,995,738.000** (2,884,398.000)  7,450,677.000*** (2,458,982.000)
## SEM                 -4,732,325.000 (4,237,833.000)   -2,232,922.000* (1,308,610.000)
## Radio               4,004,619.000 (3,298,355.000)    1,896,536.000*** (319,929.600)
## Other               -2,336,728.000 (3,716,188.000)
## NPS                   520,617.300 (525,942.800)        724,563.100** (330,032.800)
## Constant            3,229,366.000*** (102,965.000)   3,229,366.000*** (101,676.600)
## -------------------------------------------------------------------------------------
## Observations                     53                               53
## R2                              0.794                            0.789
## Adjusted R2                     0.726                            0.733
## Residual Std. Error      749,596.400 (df = 39)           740,216.900 (df = 41)
## F Statistic            11.590*** (df = 13; 39)          13.955*** (df = 11; 41)
## =====================================================================================
## Note:                                                     *p<0.1; **p<0.05; ***p<0.01
```

```
knitr::kable(viewModelSummaryVIF(step_ga))
```

var	Estimate	Std.Error	t-value	Pr(>|t|)	Significance	vif
Affiliates	7450677	2458982	3.030	0.004222	**	573.847014
ContentMarketing	-5671379	1112845	-5.096	8.22e-06	***	117.531605
Digital	5801867	1438317	4.034	0.000233	***	196.333580
discount	447874	159252	2.812	0.007513	**	2.406887
NPS	724563	330033	2.195	0.033849	*	10.337120
OnlineMarketing	-4126524	2493309	-1.655	0.105553	NA	589.980147
procurement_sla	206101	130092	1.584	0.120817	NA	1.606161
Radio	1896536	319930	5.928	5.48e-07	***	9.713913
SEM	-2232922	1308610	-1.706	0.095511	.	162.519650
Sponsorship	3721704	522787	7.119	1.12e-08	***	25.937938
TV	-2593057	446676	-5.805	8.19e-07	***	18.935210

Final Model

```
model_ga2 <- lm(formula = gmv ~ discount + TV + Digital +
Sponsorship + Affiliates +
   Radio, data = gaming_accessory_data_nrm)
```

```
knitr::kable(viewModelSummaryVIF(model_ga2))
```

var	Estimate	Std.Error	t-value	Pr(>|t|)	Significance	vif
Affiliates	596356	229328	2.600	0.012477	*	2.549789
Digital	-707434	225136	-3.142	0.002931	**	2.457422
discount	226427	163744	1.383	0.173400	NA	1.299942
Radio	107078	185543	0.577	0.566680	NA	1.669086
Sponsorship	1008915	258683	3.900	0.000311	***	3.244337
TV	-98236	228435	-0.430	0.669174	NA	2.529967

```
getModelR2(model_ga2)
```

```
## [1] "Multiple R-squared:  0.5371,\tAdjusted R-squared:  0.4767 "
```

Home Accessory

Initial Model

```
model_ha1 <- lm(gmv~ .,data=home_audio_data_nrm)
```

Auto-Opitimize Model

```
step_ha <- stepAIC(model_ha1, direction = "both",trace=FALSE)
```

Summary

```
stargazer(model_ha1,step_ha, align = TRUE, type = 'text',
          title='Linear Regression Results', single.row=TRUE)
```

```
##
## Linear Regression Results
## ========================================================================================
##                                              Dependent variable:
##                         ----------------------------------------------------------------
##                                                      gmv
##                                       (1)                                 (2)
## ----------------------------------------------------------------------------------------
## discount                 2,904,574.000*** (433,630.000)     2,944,063.000*** (412,513.100)
## sla                      1,104,916.000*** (381,902.200)     1,157,871.000*** (343,981.000)
## procurement_sla          -980,968.000*** (275,741.400)      -987,332.200*** (271,781.700)
## TV                       5,141,356.000 (4,299,518.000)      6,109,515.000* (3,163,836.000)
## Digital                 18,481,940.000** (7,612,086.000)  19,884,266.000*** (6,300,980.000)
## Sponsorship              2,746,332.000* (1,382,489.000)     2,394,255.000** (896,178.400)
## ContentMarketing         5,585,090.000 (4,840,766.000)      6,387,531.000 (4,165,723.000)
## OnlineMarketing          -5,610,540.000 (4,991,805.000)    -4,123,055.000* (2,314,829.000)
## Affiliates               1,964,885.000 (5,822,385.000)
## SEM                    -26,003,966.000** (12,087,329.000) -28,405,803.000*** (9,652,125.000)
## Radio                   19,317,311.000* (9,534,118.000)    20,993,554.000** (8,039,993.000)
## Other                  -19,951,450.000* (10,701,862.000)  -21,935,345.000** (8,834,894.000)
## NPS                      -1,105,701.000 (1,176,216.000)     -1,358,797.000 (895,183.600)
## Constant                 5,345,857.000*** (228,263.800)     5,345,857.000*** (225,513.900)
## ----------------------------------------------------------------------------------------
## Observations                         50                                  50
## R2                                 0.748                               0.747
## Adjusted R2                        0.657                               0.665
## Residual Std. Error      1,614,069.000 (df = 36)             1,594,624.000 (df = 37)
## F Statistic               8.205*** (df = 13; 36)              9.097*** (df = 12; 37)
## ========================================================================================
## Note:                                                    *p<0.1; **p<0.05; ***p<0.01
```

```
knitr::kable(viewModelSummaryVIF(step_ha))
```

var	Estimate	Std.Error	t-value	Pr(>|t|)	Significance	vif
ContentMarketing	6387531	4165723	1.533	0.133696	NA	334.395310
Digital	19884266	6300980	3.156	0.003177	**	765.060355
discount	2944063	412513	7.137	1.86e-08	***	3.279102
NPS	-1358797	895184	-1.518	0.137539	NA	15.442006
OnlineMarketing	-4123055	2314829	-1.781	0.083099	.	103.256445
Other	-21935345	8834894	-2.483	0.017696	*	1504.118952
procurement_sla	-987332	271782	-3.633	0.000845	***	1.423377
Radio	20993554	8039993	2.611	0.012957	*	1245.635055
SEM	-28405803	9652125	-2.943	0.005585	**	1795.251766
sla	1157871	343981	3.366	0.001789	**	2.280071
Sponsorship	2394256	896178	2.672	0.011156	*	15.476345
TV	6109515	3163836	1.931	0.061166	.	192.888975

```
model_ha2 <- lm(formula = gmv ~ discount + sla +
                  Sponsorship, data = home_audio_data_nrm)
```

```
knitr::kable(viewModelSummaryVIF(model_ha2))
```

var	Estimate	Std.Error	t-value	Pr(>|t|)	Significance	vif
discount	1850003	290001	6.379	7.8e-08	***	1.251385
sla	865123	287490	3.009	0.004240	**	1.229810
Sponsorship	1022830	263701	3.879	0.000332	***	1.034703

```
getModelR2(model_ha2)
```

```
## [1] "Multiple R-squared:  0.5924,\tAdjusted R-squared:  0.5658 "
```

Observations: