model_CA_Kyock.R

atchirc

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```r
library(MASS)
library(car)
library(DataCombine)   # Pair wise correlation
library(stargazer)
library(dplyr)         # Data aggregation
library(glmnet)
source('../atchircUtils.R')


data    <- read.csv('../../intrim/eleckart.csv')


# KPI selection
# units, product_mrp, list_mrp, COD, Prepaid are factors
# Insig : Affiliates corr OnlineMarketing
# Insig : Radio  corr Other
# Insig : Digitial, ContentMarketing corr SEM
# delivery(b/c)days are corr, lets choose deliverycdays
# will use marketing levers rather TotalInvestment

# Filter significant KPIs
model_data <- subset(data, product_analytic_sub_category=='CameraAccessory',
                     select = -c(product_analytic_sub_category,product_mrp,
                                 units,COD,Prepaid,deliverybdays,
                                 TotalInvestment,Affiliates,Radio,Digital,
                                 ContentMarketing,sla,procurement_sla))

model_data_org <- model_data
model_data[,c(8:12)] <- model_data[,c(8:12)]*10000000


# # ***************************************************************************
# #                   FEATURE ENGINEERING -PASS2  ----
# # ***************************************************************************
#
# # . . . . List Price Inflation ----
model_data$chnglist <- c(0,diff(model_data$list_mrp))
#
# # . . . . Discount Inflation ----
model_data$chngdisc <- c(0,diff(model_data$discount))
#

# # . . . . Lag GMV ----
# # Lag weekly avg discount by 1 week
model_data$laggmv <- data.table::shift(model_data$gmv)
```

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    PROCs:

Linear, Ridge and Lasso Model are wrapped with abstract functions. This would facilitate readable code for model building and Model otpimization. Set Class definitions

```
setOldClass('elnet')
setClass(Class = 'atcglmnet',
         representation (
           R2 = 'numeric',
           mdl = 'elnet',
           pred = 'matrix'
         )
)
```

```
setOldClass('lm')
setClass(Class = 'atclm',
         representation (
           R2 = 'numeric',
           mdl = 'lm',
           pred = 'matrix'
         )
)
```

Finding min lambda from 1000 iterations Function to find Min Lambda using bootstrap method. minlambda identified over 1000 cross validation trails. observed minlambda used for Ridge and Lasso regression.

```
findMinLambda <- function(x,y,alpha,folds) {
  lambda_list <- list()
  for (i in 1:1000) {
    cv.out <- cv.glmnet(as.matrix(x), as.vector(y), alpha=alpha,
                        nfolds=folds)
    lambda_list <- append(lambda_list, cv.out$lambda.min)
  }
  return(min(unlist(lambda_list)))
}
```

Linear Model with Regularization Wrapper function for Ridge and Lasso regression. functions performs Ridge/Lasso regression and returns R2, Model and Predicted values as `atcglmnet` object

```
atcLmReg <- function(x,y,l1l2,folds) {
  # l1l2 = 0 for L1,  1 for L2

  if (l1l2) { # Lasso/L2
    min_lambda <- findMinLambda(x,y,1,folds)
  } else { # Ridge/L1
    min_lambda <- findMinLambda(x,y,0,folds)
  }
  mdl        <- glmnet(x,y,alpha=l1l2,lambda = min_lambda)
```

```
  pred       <- predict(mdl,s= min_lambda,newx=x)

  # MSE
  mean((pred-y)^2)
  R2 <- 1 - (sum((y-pred )^2)/sum((y-mean(pred))^2))
  return(new('atcglmnet', R2 = R2, mdl=mdl, pred=pred))
}
```

*

MODELING

```r
# Prune KPI as part of model optimization
model_data <- na.omit(model_data)
model_data <- subset(model_data,select=-c(TV,SEM,discount))
```

Linear Model:

```r
mdl      <- lm(gmv~., data=model_data)
step_mdl <- stepAIC(mdl,direction = 'both',trace = FALSE)

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

```
##
## Linear Regression Results
## ================================================================================
##                                         Dependent variable:
##                      -----------------------------------------------------------
##                                                 gmv
##                                  (1)                            (2)
## --------------------------------------------------------------------------------
## week                   -15,830.260 (36,360.060)
## deliverycdays         306,554.800 (281,106.800)
## n_saledays            253,295.800 (168,608.700)
## Sponsorship           157,093.800** (70,845.050)    127,208.100** (48,686.410)
## OnlineMarketing             0.025 (0.035)                0.039** (0.015)
## Other                       0.014 (0.018)
## NPS                        -0.004 (0.021)
## list_mrp                  0.0003* (0.0002)            0.0003*** (0.0001)
## chnglist                -0.00002 (0.0001)
## chngdisc               48,071.470 (30,365.970)      47,057.540 (28,705.300)
## laggmv                     -0.029 (0.160)
## Constant             1,602,058.000 (13,005,702.000) -679,652.000 (1,194,947.000)
## --------------------------------------------------------------------------------
## Observations                    51                             51
## R2                            0.573                          0.532
## Adjusted R2                   0.452                          0.491
## Residual Std. Error    1,756,903.000 (df = 39)      1,693,640.000 (df = 46)
## F Statistic             4.756*** (df = 11; 39)       13.066*** (df = 4; 46)
## ================================================================================
## Note:                                              *p<0.1; **p<0.05; ***p<0.01
```

```r
knitr::kable(viewModelSummaryVIF(step_mdl))
```

var	Estimate	Std.Error	t-value	Pr(>|t|)	Significance	vif
chngdisc	4.706e+04	2.871e+04	1.639	0.1080	NA	1.026482
list_mrp	3.364e-04	1.065e-04	3.159	0.0028	**	1.144765
OnlineMarketing	3.879e-02	1.534e-02	2.528	0.0150	*	1.333567
Sponsorship	1.272e+05	4.869e+04	2.613	0.0121	*	1.344181

```r
pred_lm <- predict(step_mdl, model_data)
```

Regularized Linear Model:

```r
x = as.matrix(subset(model_data, select=-gmv))
y = as.vector(model_data$gmv)

ridge_out <- atcLmReg(x,y,0,3)  # x, y, alpha, nfolds
lasso_out <- atcLmReg(x,y,1,3)  # x, y, alpha, nfolds
```

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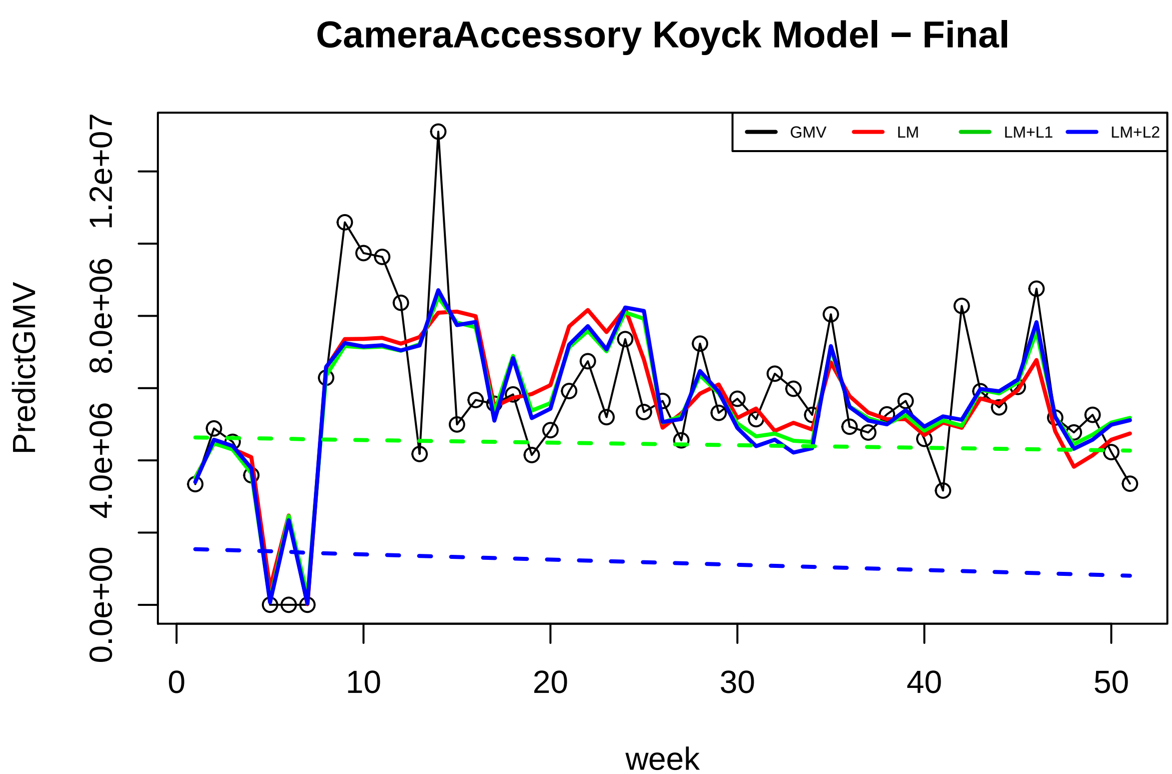
PLOTTING MODEL RESULTS

Plot Model prediction and base sales:

```
plot(model_data$gmv,main = 'CameraAccessory Koyck Model - Final',
     xlab='week',ylab='PredictGMV')
lines(model_data$gmv)
lines(pred_lm,col='red',lwd=2)
lines(ridge_out@pred,col='green',lwd=2)
lines(lasso_out@pred,col='blue',lwd=2)
lines(step_mdl$coefficients['(Intercept)']+step_mdl$coefficients['week']*model_data$week,
      lty=2,lwd=2,col='red')
lines(ridge_out@mdl$a0+ridge_out@mdl$beta['week',1]*model_data$week,
      lty=2,lwd=2,col='green')
lines(lasso_out@mdl$a0+lasso_out@mdl$beta['week',1]*model_data$week,
      lty=2,lwd=2,col='blue')
legend('topright',inset=0, legend=c('GMV','LM','LM+L1','LM+L2'),horiz = TRUE,
       lwd = 2, col=c(1:4), cex = 0.5)
```



*

*Model Coefficients:**

```
coeff_lm <- as.data.frame(as.matrix(coef(step_mdl)))
coeff_l1 <- as.data.frame(as.matrix(coef(ridge_out@mdl)))
coeff_l2 <- as.data.frame(as.matrix(coef(lasso_out@mdl)))


lm_df=data.frame('x'=rownames(coeff_lm),'y'=coeff_lm)
colnames(lm_df) = c('coeff','lm')
l1_df=data.frame('x'=rownames(coeff_l1),'y'=coeff_l1)
colnames(l1_df)= c('coeff','l1')
l2_df=data.frame('x'=rownames(coeff_l2),'y'=coeff_l2)
colnames(l2_df) <- c('coeff','l2')

smry <- merge(lm_df,l1_df,all = TRUE)
smry <- merge(smry,l2_df,all=TRUE)

print(smry)
```

```
##              coeff            lm            l1            l2
## 1      (Intercept) -6.796520e+05  4.647915e+06  1.569911e+06
## 2         chngdisc  4.705754e+04  4.523498e+04  4.799591e+04
## 3         chnglist            NA  2.107435e-05 -1.143964e-05
## 4    deliverycdays            NA  1.961366e+05  2.937839e+05
## 5           laggmv            NA -4.375425e-04 -2.498224e-02
## 6         list_mrp  3.364383e-04  2.840922e-04  3.437029e-04
## 7       n_saledays            NA  2.264429e+05  2.518722e+05
## 8              NPS            NA -8.706021e-03 -4.325675e-03
## 9  OnlineMarketing  3.879036e-02  1.913505e-02  2.504169e-02
## 10           Other            NA  8.041489e-03  1.316946e-02
## 11     Sponsorship  1.272081e+05  1.333025e+05  1.564098e+05
## 12            week            NA -7.121912e+03 -1.440102e+04
```

```
print(paste0('Ridge regression R2 : ',ridge_out@R2))
```

```
## [1] "Ridge regression R2 : 0.569012425320424"
```

```
print(paste0('Lasso regression R2 : ',lasso_out@R2))
```

```
## [1] "Lasso regression R2 : 0.572870730106967"
```

```
print(paste0('Linear Mode      R2 : ',getModelR2(step_mdl)))
```

```
## [1] "Multiple R-squared:  0.5319,\tAdjusted R-squared:  0.4912 "
## [1] "Linear Mode      R2 : Multiple R-squared:  0.5319,\tAdjusted R-squared:  0.4912 "
```

*

Significant KPI

Lasso(LM+L2) regression results a simple explainable model with significant KPIs as `Discount Inflation`, `Deliverycday`, `sale days`, `Sponsorship week`,`discount`,

```
# Model Optimization
```

```
# coeff             lm           l1            l2
# 1      (Intercept) -4.298317e+06  5.794557e+06  2.441952e+06
# 2          chngdisc           NA  2.540553e+04  1.292035e+04
# 3          chnglist           NA  1.401253e-05  0.000000e+00
# 4     deliverycdays           NA  1.634303e+05  1.131055e+05
# 5          discount  7.349317e+04  2.748224e+04  4.521718e+04
# 6            laggmv           NA -1.719029e-02 -3.629628e-02
# 7          list_mrp  3.394976e-04  2.577053e-04  2.832874e-04
# 8        n_saledays  2.476512e+05  2.283399e+05  2.439161e+05
# 9               NPS           NA -1.209985e-02 -8.154427e-03
# 10 OnlineMarketing  3.826100e-02  2.476685e-02  3.161093e-02
# 11            Other           NA  7.390478e-03  1.108746e-02
# 12              SEM -5.215457e-02 -3.435368e-02 -4.995371e-02
# 13      Sponsorship  2.577525e+05  2.008037e+05  2.753698e+05
# 14               TV           NA -1.929945e+05 -4.687682e+05
# 15             week           NA -1.500513e+04 -1.048237e+04
# [1] "Ridge regression R2 : 0.610734183034274"
# [1] "Lasso regression R2 : 0.623163910472765"
# [1] "Multiple R-squared:  0.6006,\tAdjusted R-squared:  0.5461 "
# [1] "Linear Mode      R2 : Multiple R-squared:  0.6006,\tAdjusted R-squared:  0.5461 "
```

```
# coeff             lm           l1            l2
# 1      (Intercept) -6.796520e+05  4.902846e+06  1.579565e+06
# 2          chngdisc  4.705754e+04  4.466822e+04  4.797107e+04
# 3          chnglist           NA  2.532189e-05 -1.008472e-05
# 4     deliverycdays           NA  1.829073e+05  2.898561e+05
# 5            laggmv           NA  3.852542e-03 -2.355309e-02
# 6          list_mrp  3.364383e-04  2.764882e-04  3.425742e-04
# 7        n_saledays           NA  2.220402e+05  2.514192e+05
# 8               NPS           NA -9.020384e-03 -4.332059e-03
# 9  OnlineMarketing  3.879036e-02  1.877191e-02  2.490978e-02
# 10            Other           NA  7.327572e-03  1.300734e-02
# 11      Sponsorship  1.272081e+05  1.300052e+05  1.561283e+05
# 12             week           NA -6.177148e+03 -1.397800e+04
# [1] "Ridge regression R2 : 0.567908635526672"
# [1] "Lasso regression R2 : 0.572846210681951"
# [1] "Multiple R-squared:  0.5319,\tAdjusted R-squared:  0.4912 "
# [1] "Linear Mode      R2 :
#          Multiple R-squared:  0.5319,\tAdjusted R-squared:  0.4912 "
```