

# **Analysis of Sales Report of a Clothes Manufacturing Outlet**

- Using R ; <Domain: Retail>

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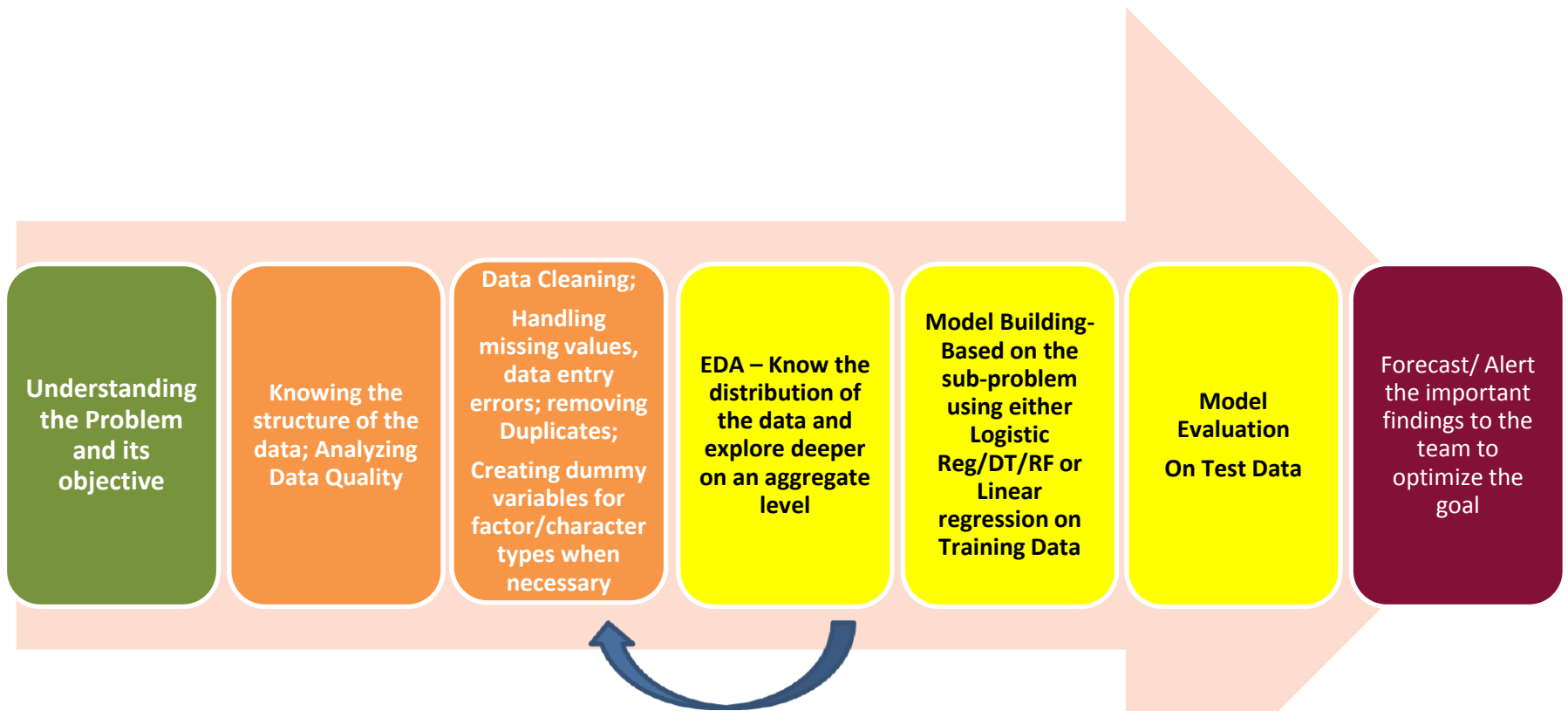
# Preface

- The first few pages will only contain the results pertaining to respective sub-problems of the project
- Appendix will contain the full R code that was used to observe these findings along with comments/logs wherever necessary.

# Background and Objective

- A high-end fashion retail store is looking to expand its products. It wants to understand the market and find the current trends in the industry. It has a database of all products with attributes, such as style, material, season, and the sales of the products over a period of two months.

# Project Workflow



Iteratively going back to Data cleaning step because there are a lot of columns and its best to handle the big dataset as multiple sub-problems using divide and conquer approach

```
str(ATT_DS) // Attribute DataSet ; nrow(ATT_DS) [1] 500 ; ncol(ATT_DS) [1] 14
tibble [500 x 14] (S3: tbl_df/tbl/data.frame)
 $ Dress_ID      : num [1:500] 1.01e+09 1.21e+09 1.19e+09 9.66e+08 8.76e+08 ...
 $ Style         : chr [1:500] "Sexy" "Casual" "vintage" "Brief" ...
 $ Price         : chr [1:500] "Low" "Low" "High" "Average" ...
 $ Rating        : num [1:500] 4.6 0 0 4.6 4.5 0 0 0 0 0 ...
 $ Size          : chr [1:500] "M" "L" "L" "L" ...
 $ Season        : chr [1:500] "Summer" "Summer" "Autumn" "Spring" ...
 $ NeckLine      : chr [1:500] "o-neck" "o-neck" "o-neck" "o-neck" ...
 $ SleeveLength  : chr [1:500] "sleeveless" "Petal" "full" "full" ...
 $ waiseline     : chr [1:500] "empire" "natural" "natural" "natural" ...
 $ Material      : chr [1:500] "null" "microfiber" "polyester" "silk" ...
 $ FabricType    : chr [1:500] "chiffon" "null" "null" "chiffon" ...
 $ Decoration    : chr [1:500] "ruffles" "ruffles" "null" "embroidary" ...
 $ Pattern Type  : chr [1:500] "animal" "animal" "print" "print" ...
 $ Recommendation: num [1:500] 1 0 0 1 0 0 0 0 1 1 ...
```

- **Data entry errors** – need to be rectified e.g. wollen vs woolen, sattin vs satin, summer vs Summer etc. need to be converted as one level. *<highlighted issues in red>*
- **Pool data** in levels that have **insufficient information**. Lets assume a threshold of 10. If any group has less than 10 rows then we will group all that as Other group
- `nrow(distinct(ATT_DS)) - #[1] 499` - we can see that there is a duplicate, that has to be removed from the dataset

**FabricType <Different Levels>; sort(table(ATT\_DS\$FabricType), decreasing = T)**

null	chiffon	broadcloth	worsted	jersey	shiffon	sattin	batik	Corduroy
265	135	31	19	12	9	6	2	2
dobby	poplin	tulle	wollen	flannael	flannel	knitted	knitting	lace
2	2	2	2	1	1	1	1	1
organza	other	satin	terry	woolen	sum(table(ATT_DS\$FabricType)) # 499 # % of Null/none in the total column FabricType > 100*(265/499) # [1] 53.10621			
1	1	1	1	1				

## Decoration <Different Levels>; sort(table(ATT\_DS\$Decoration), decreasing = T)

null	lace	sashes	beading	applique	hollowout	ruffles	bow	sequined
235	70	42	22	21	21	17	15	14
button	embroidary	Pockets	flowers	crystal	rivet	ruched	draped	feathers
6	5	5	4	3	3	3	2	2
none	plain	Cascading	pearls	pleat	Tassel	Tiered	sum(table(ATT_DS\$Decoration)) # 499; # % of Null/none in the total column Decoration 100*237/499 # [1] 47.49499	
2	2	1	1	1	1	1		

## Pattern Type <Different Levels>; sort(table(ATT\_DS`Pattern Type`), decreasing = T)

solid	null	print	Patchwork	animal	striped	dot	geometric
203	108	71	48	21	17	14	5
leopard	plaid	floral	Character	leapord	none	splice	
3	3	2	1	1	1	1	
sum(table(ATT_DS`Pattern Type`)) # 499 # % of Null/none in the total column `Pattern Type` > 100*109/499 # [1] 21.84369							

## Material <Different Levels>; sort(table(ATT\_DS\$Material), decreasing = T)

cotton	Null	polyster	silk	chiffonfabric	mix	nylon	rayon
152	127	99	26	25	12	10	10
milksilk	Spandex	cashmere	acrylic	linen	lycra	microfiber	other
5	5	4	3	3	3	3	2
Shiffon	Viscos	knitting	lace	modal	model	sill	wool
2	2	1	1	1	1	1	1
sum(table(ATT_DS\$Material)) # 499 # % of Null/none in the total column Material 100*127/499 #[1] 25.45							

## waiseline <Different Levels>; sort(table(ATT\_DS\$waiseline), decreasing = T)

natural	empire	null	dropped	princess
304	104	86	4	1
sum(table(ATT_DS\$waiseline)) # 499 # % of Null/none in the total column waiseline 100*86/499 # [1] 17.23				

SleeveLength <Different Levels>; sort(table(ATT_DS\$SleeveLength), decreasing = T)								
sleeveless	full	short	hallsleeve	threequarter	thressqatar	sleeveless	capsleeves	sleeveless
223	97	96	35	17	10	5	3	3
cap-sleeves	NULL	butterfly	half	Petal	sleeveless	threequarter	turndowncollor	urndowncollor
2	2	1	1	1	1	1	1	1
# sum(table(ATT_DS\$SleeveLength)) # [1] 500 ; # % of Null/none in the total column SleeveLength 100*2/500 # [1] 0.4								

NeckLine <Different Levels>; sort(table(ATT_DS\$NeckLine), decreasing = T)								
o-neck	v-neck	slash-neck	boat-neck	Sweetheart	turndowncollor	bowneck	peterpan-collor	sqare-collor
271	124	25	19	14	13	10	6	5
open	NULL	Scoop	backless	halter	mandarin-collor	ruffled	sweetheart	
3	2	2	1	1	1	1	1	
# sum(table(ATT_DS\$NeckLine)) # [1] 499 ; # % of Null/none in the total column NeckLine 100*2/499 # [1] 0.4								

Summer	Spring	Winter	Automn	winter	Autumn	spring	summer
159	122	99	61	46	8	2	1

sum(table(ATT\_DS\$Season)) # 498 # % of Null/none in the total column Season 100\*0/498 #[1] 0; 2 Nas/ Missing values

**Size <Different Levels>;** sort(table(ATT\_DS\$Size), decreasing = T)

free	L	M	s	S	small	XL
173	96	177	1	37	1	15

sum(table(ATT\_DS\$Size)) # 500 # % of Null/none in the total column Size 100\*0/500 #[1] 0;

**Price <Different Levels>;** sort(table(ATT\_DS\$Price), decreasing = T)

Average	Low	low	Medium	very-high	high	High
252	129	45	30	21	15	6

sum(table(ATT\_DS\$Price)) # 498 # % of Null/none in the total column Price 100\*0/498 #[1] 0; 2 Nas/ Missing values

**Style <Different Levels>;** sort(table(ATT\_DS\$Style), decreasing = T)

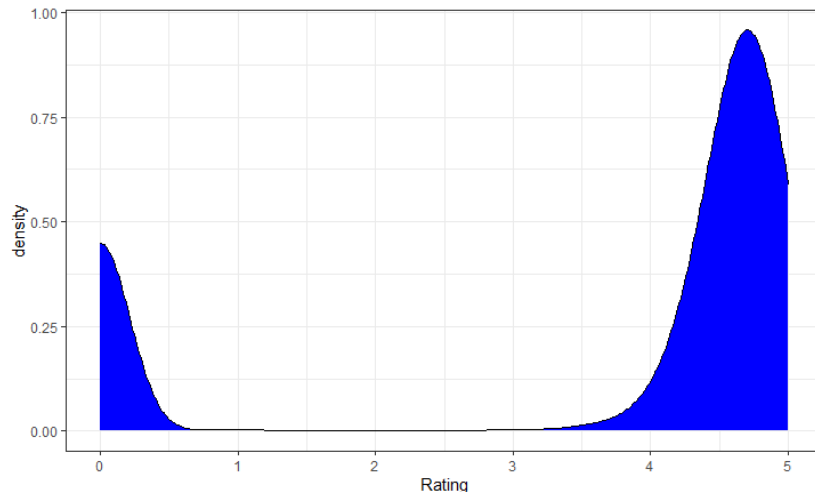
Casual	Sexy	party	cute	vintage	bohemian	Brief
232	69	51	45	25	24	18
work	Novelty	sexy	Flare	fashion	OL	
17	8	7	2	1	1	

sum(table(ATT\_DS\$Style)) # 500 # % of Null/none in the total column Style 100\*0/500 #[1] 0;

**Rating <Different Levels>;** table(ATT\_DS\$Rating)

0	1	3	3.5	3.6	3.7	4	4.1	4.2
120	1	1	1	1	2	7	5	6
4.3	4.4	4.5	4.6	4.7	4.8	4.9	5	
20	27	34	54	84	57	25	55	

# sum(table(ATT\_DS\$Rating)) # [1] 500 ; # % of Null/none in the total column Rating 100\*0/500 # [1] 0



**Rating Class <Different Levels>;**

<=4	>4
133	367

ggplot(ATT\_DS, aes(Rating)) + geom\_density(fill="blue")+theme\_bw()

*# most of the data is 0 -1 or >4, hence best to create RatingClass*

RatingClass = cut(Rating,c(-0.1,4,max(Rating)), labels = c("<=4",">4"))



# More Data Cleaning

- `nrow(distinct(DS_DS))` # 500 - no duplicates as a combination of all columns but
- `length(levels(DS_DS$Dress_ID))` # Dress\_id is only 475, meaning 25 records have more than one same dress\_id - `#[1] 475`
- # an example of one such instance is Dress\_id 560474456
- # We can handle this either of two ways - 1) Taking the average of the duplicate rows or
- # 2) taking the maximum value of the rows by Dress\_id , assuming there was a glitch while entering and
- # max value was supposed to be the final value but instead of making more assumptions,
- # lets take the average which is a decent starting point for such dress\_ids
- If there were any NAs first they were changed to 0 and then average was taken

**Goal1:** To automate the process of recommendations, the store needs to analyze the given attributes of the product, like the style, season, etc., and come up with a model to predict the recommendation of products (in binary output – 0 or 1) accordingly

- For this goal, we can use **Logistic Regression/ Decision Tree/ Random Forest** etc. and **compare** the **metrics** of these algorithms and use the one that has **best Balanced Accuracy**. The metrics of DT/RF are only mentioned here and full details are in appendix in R code with their results as comments. For the solution of this goal 1, here, we are going to explain Logistic alone in full as that was having decent balanced accuracy.
- Logistic regression, also called a logit model, is used to model dichotomous/binary outcome variables. Since we have to automate recommendation which is either 0 or 1 any of these 3 algorithms can be used. Lets start with logistic first.
- #But before doing logit model, lets see vif (**to check for multicollinearity**) for which we will use alias(lm(Recommendation~.))
- # "alias" refers to the variables that are linearly dependent on others (i.e. cause perfect multicollinearity).
- # The **autocorrelated variables** are these mentioned below (found by using alias(myLm))
- # **SeasonAutumn** = 1 - Seasonspring - Seasonsummer – Seasonwinter
- # **Pricevery\_high** = 1 - Priceaverage - Pricehigh - Pricelow – Pricemedium
- # **Style\_work\_dmy** = 1 -Style\_bohemian\_dmy -Style\_brief\_dmy -Style\_casual\_dmy -Style\_cute\_dmy -Style\_fashion\_dmy - Style\_novelty\_dmy -Style\_OL\_dmy -Style\_party\_dmy -Style\_sexy\_dmy -Style\_vintage\_dmy
- # NeckLine\_mandarincollar\_dmy = Style\_OL\_dmy
- # **NeckLine\_open\_dmy** = 1 + Style\_fashion\_dmy -Material\_acrylic\_dmy -Material\_cashmere\_dmy -Material\_chiffon\_dmy - Material\_cotton\_dmy -Material\_knitting\_dmy -Material\_linen\_dmy -Material\_lycra\_dmy -Material\_microfiber\_dmy
- # -Material\_milksilk\_dmy -Material\_mix\_dmy -Material\_modal\_dmy -Material\_nylon\_dmy -Material\_other\_dmy - Material\_polyester\_dmy - Material\_rayon\_dmy - Material\_silk\_dmy - Material\_spandex\_dmy
- # - Material\_viscos\_dmy
- # **NeckLine\_vneck\_dmy** = - Style\_fashion\_dmy -Style\_OL\_dmy + Material\_acrylic\_dmy + Material\_cashmere\_dmy + Material\_chiffon\_dmy + Material\_cotton\_dmy + Material\_knitting\_dmy + Material\_linen\_dmy + Material\_lycra\_dmy
- # + Material\_microfiber\_dmy + Material\_milksilk\_dmy + Material\_mix\_dmy + Material\_modal\_dmy + Material\_nylon\_dmy + Material\_other\_dmy + Material\_polyester\_dmy + Material\_rayon\_dmy
- # + Material\_silk\_dmy + Material\_spandex\_dmy + Material\_viscos\_dmy - NeckLine\_boatneck\_dmy - NeckLine\_bowneck\_dmy - NeckLine\_halter\_dmy - NeckLine\_oneck\_dmy - NeckLine\_peterpancollor\_dmy
- # - NeckLine\_ruffled\_dmy - NeckLine\_Scoop\_dmy - NeckLine\_slashneck\_dmy -NeckLine\_squarecollor\_dmy - NeckLine\_sweetheart\_dmy - NeckLine\_turndowncollor\_dmy

## Answer Goal1: Results of Logit:

Positive influence on Recommendation – Spring season, nylon, cotton and other material.

Negative effect on the response variable – Short sleeve length, Prices (low, high, average) and bow-neck, o-neck neckline. So the positive factors tend to increase the recommendation and the negative factors have a depreciating influence on recommending a dress.

`summary(mylogit)`

`call:`

```
glm(formula = Recommendation ~ Rating + SleeveLengthshort + Seasonspring + Priceaverage + Pricehigh + Pricelow +  
    Style_cute_dmy + Style_OL_dmy + Material_cashmere_dmy + Material_cotton_dmy + Material_nylon_dmy +  
    Material_other_dmy + NeckLine_bowneck_dmy + NeckLine_oneck_dmy + NeckLine_peterpancollor_dmy +  
    NeckLine_squarecollor_dmy + NeckLine_turndowncollor_dmy + Material_acrylic_dmy,  
    family = binomial(link = "logit"), data = Training1)
```

Deviance Residuals:

Min	1Q	Median	3Q	Max
-1.9113	-0.9863	-0.4891	1.0733	2.3082

Coefficients:	Estimate	Std. Error	z value	Pr(> z )
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(Intercept)	0.4921	0.4945	0.995	0.319611
-------------	--------	--------	-------	----------

Rating	0.1057	0.0625	1.692	0.090679 .
--------	--------	--------	-------	------------

SleeveLengthshort	-0.9575	0.3514	-2.725	<b>0.006432 ** // significant</b>
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Seasonspring	0.9848	0.2812	3.502	<b>0.000461 *** very significant</b>
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Priceaverage	-1.6305	0.4479	-3.641	<b>0.000272 *** very significant</b>
--------------	---------	--------	--------	--------------------------------------

Pricehigh	-2.0190	0.6764	-2.985	<b>0.002836 ** // significant</b>
-----------	---------	--------	--------	-----------------------------------

Pricelow	-1.3934	0.4615	-3.019	<b>0.002533 ** // significant</b>
----------	---------	--------	--------	-----------------------------------

Style_cute_dmy	0.7472	0.4118	1.814	0.069629 . //marginally significant
----------------	--------	--------	-------	-------------------------------------

Style_OL_dmy	-17.6394	2399.5448	-0.007	0.994135
--------------	----------	-----------	--------	----------

Material_cashmere_dmy	18.1105	1677.7192	0.011	0.991387
-----------------------	---------	-----------	-------	----------

Material_cotton_dmy	0.5812	0.3055	1.902	0.057112 . //marginally significant
---------------------	--------	--------	-------	-------------------------------------

Material_nylon_dmy	1.7934	0.9386	1.911	0.056030 . //marginally significant
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Material_other_dmy	0.6699	0.3043	2.202	<b>0.027677 * significant</b>
--------------------	--------	--------	-------	-------------------------------

NeckLine_bowneck_dmy	-2.3582	1.2365	-1.907	0.056492 . //marginally significant
----------------------	---------	--------	--------	-------------------------------------

NeckLine_oneck_dmy	-0.4957	0.2571	-1.928	0.053840 . //marginally significant
--------------------	---------	--------	--------	-------------------------------------

NeckLine_peterpancollor_dmy	-16.3605	1063.6762	-0.015	0.987728
-----------------------------	----------	-----------	--------	----------

NeckLine_squarecollor_dmy	-16.4364	1320.2093	-0.012	0.990067
---------------------------	----------	-----------	--------	----------

NeckLine_turndowncollor_dmy	-1.4237	0.8558	-1.664	0.096197 .
-----------------------------	---------	--------	--------	------------

Material_acrylic_dmy	-16.2223	1272.7943	-0.013	0.989831
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Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

Null deviance: 476.2 on 349 degrees of freedom

Residual deviance: 398.0 on 331 degrees of freedom

AIC: 436

Number of Fisher Scoring iterations: 15

There are insignificant terms too in this model, meaning, they could be influential if interactions maybe considered. Tried pooling them to the error degrees of freedom but AIC values started Increasing. So these should be left in the model. For full code, Please refer to the appendix.

# Metrics

LOGIT RESULTS – Training <70 percent of Total data>  
caret::confusionMatrix(a, positive = '1')

Confusion Matrix and Statistics

	predicted	
actual	0	1
0	163	40
1	71	76

Accuracy : 0.6829

95% CI : (0.6313, 0.7313)

No Information Rate : 0.6686

P-Value [Acc > NIR] : 0.306371

Kappa : 0.3295

Mcnemar's Test P-Value : 0.004407

Sensitivity : 0.6552

Specificity : 0.6966

Pos Pred Value : 0.5170

Neg Pred Value : 0.8030

Prevalence : 0.3314

Detection Rate : 0.2171

Detection Prevalence : 0.4200

Balanced Accuracy : 0.6759

'Positive' Class : 1

LOGIT RESULTS – Test Data <30 percent of Total data>  
caret::confusionMatrix(atest, positive = '1')

Confusion Matrix and Statistics

	predicted	
actual	0	1
0	69	17
1	40	23

Accuracy : 0.6174

95% CI : (0.5343, 0.6958)

No Information Rate : 0.7315

P-Value [Acc > NIR] : 0.999119

Kappa : 0.176

Mcnemar's Test P-Value : 0.003569

Sensitivity : 0.5750

Specificity : 0.6330

Pos Pred Value : 0.3651

Neg Pred Value : 0.8023

Prevalence : 0.2685

Detection Rate : 0.1544

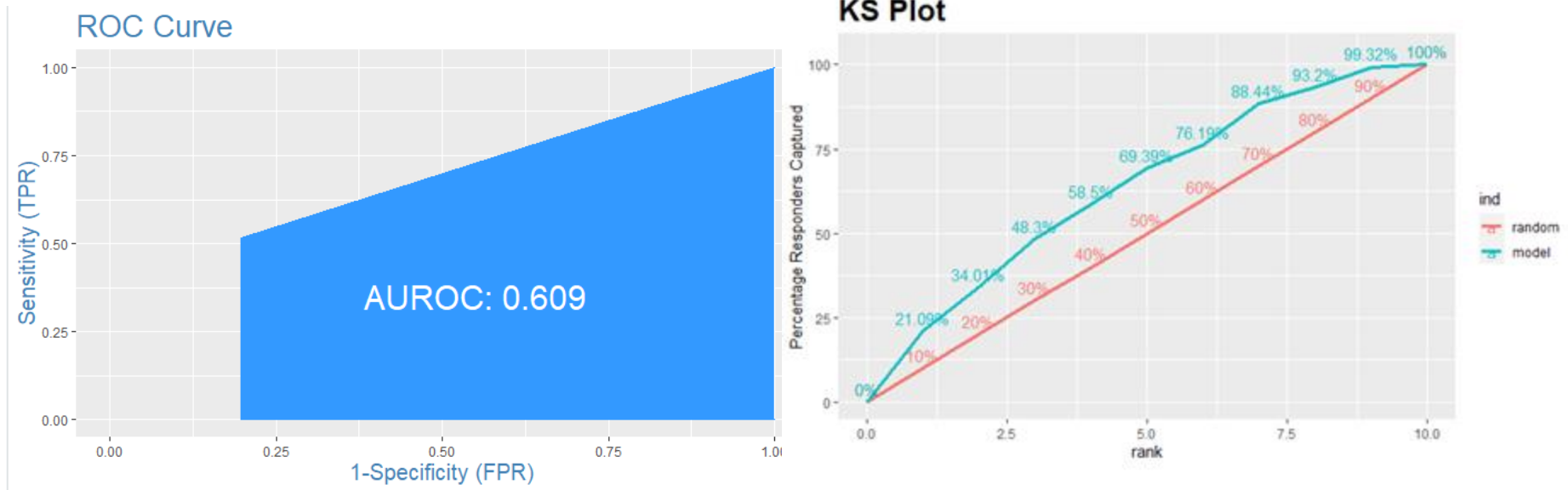
Detection Prevalence : 0.4228

Balanced Accuracy : **0.6040**

'Positive' Class : 1

# LOGISTIC Reg. Model - performance measurement visually

Area Under the ROC curve (AUC) is an aggregated metric that evaluates how well a logistic regression model classifies positive and negative outcomes at all possible cutoffs. AUC 0.61 means there is 61% chance that model will be able to distinguish between positive class and negative class correctly.

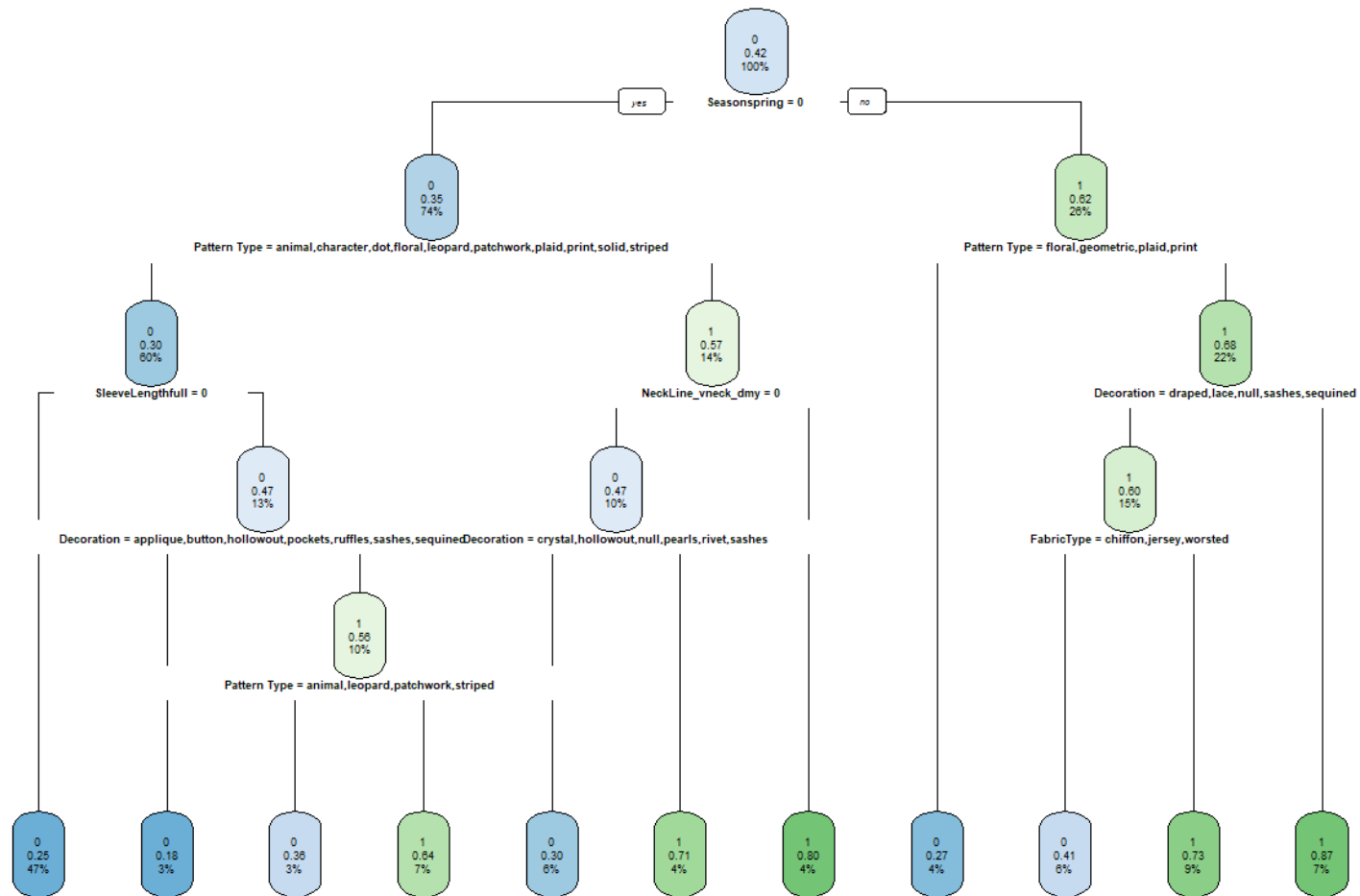


**KS Plot** plots the lift is capturing the responders (Ones) against the random case where we don't use the model.

The **more curvier** (higher) the model curve, the **better is the model**.

# Decision Tree

```
fit = rpart(Recommendation ~ ., method = "class", data = Training1,  
control = rpart.control(minsplit = 30))  
rpart.plot(fit, cex=0.55)
```



# Additional ways of solving Goal 1

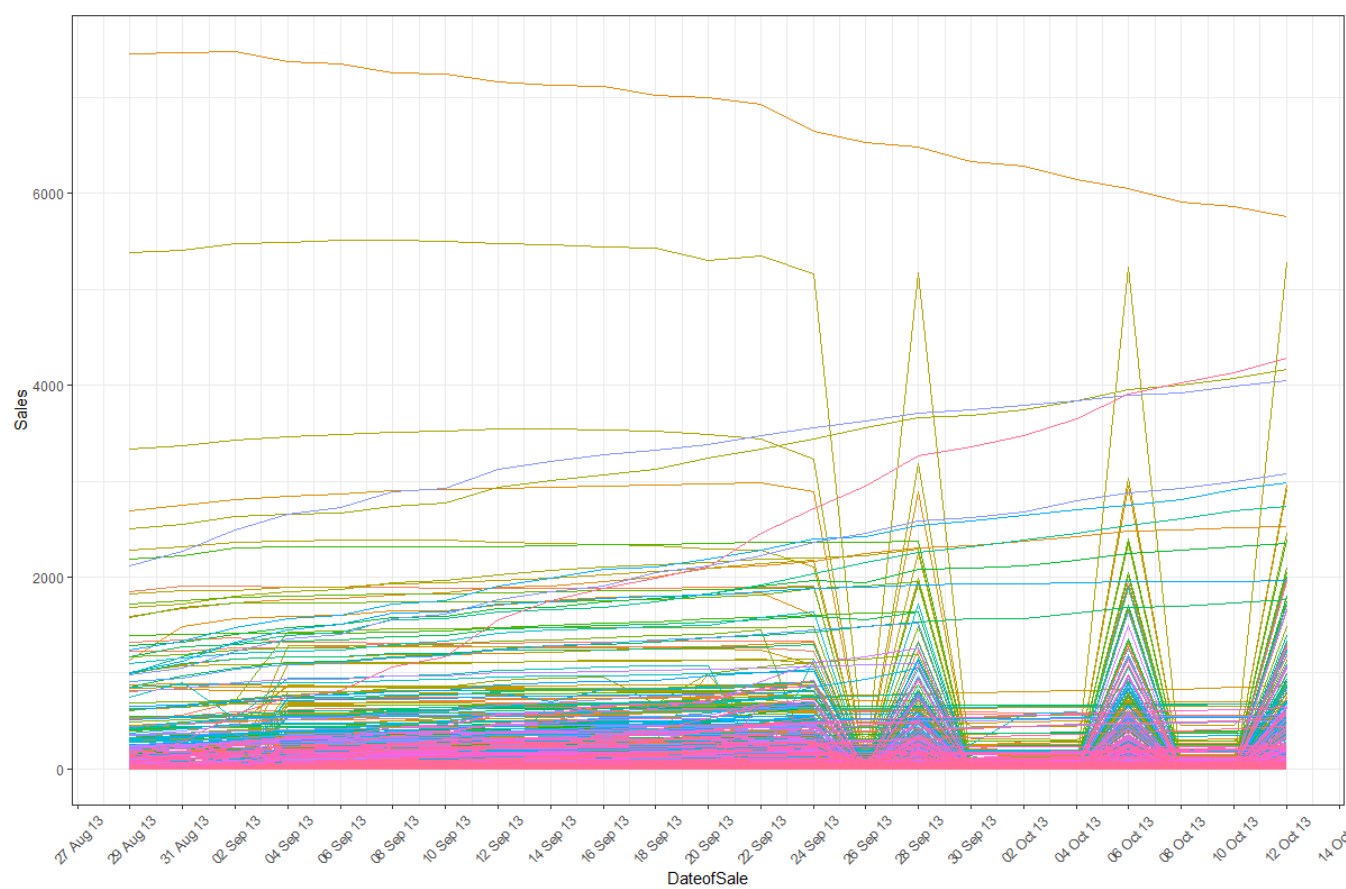
## Decision Tree Metric on Test Data

- `caret::confusionMatrix(a, positive = "1")`
- # Confusion Matrix and Statistics
- #
- # predicted
- # actual 0 1
- # 0 70 16
- # 1 39 24
- #
- # Accuracy : 0.6309
- # 95% CI : (0.548, 0.7084)
- # No Information Rate : 0.7315
- # P-Value [Acc > NIR] : 0.997297
- #
- # Kappa : 0.2049
- #
- # McNemar's Test P-Value : 0.003012
- #
- # Sensitivity : 0.6000
- # Specificity : 0.6422
- # Pos Pred Value : 0.3810
- # Neg Pred Value : 0.8140
- # Prevalence : 0.2685
- # Detection Rate : 0.1611
- # Detection Prevalence : 0.4228
- # Balanced Accuracy : **0.6211**
- #
- # 'Positive' Class : 1

## Random Forest Metric on Test Data

- `caret::confusionMatrix(b, positive = "1")`
- # Confusion Matrix and Statistics
- #
- # predicted
- # actual 0 1
- # 0 64 22
- # 1 31 32
- #
- # Accuracy : 0.6443
- # 95% CI : (0.5618, 0.7209)
- # No Information Rate : 0.6376
- # P-Value [Acc > NIR] : 0.4692
- #
- # Kappa : 0.257
- #
- # McNemar's Test P-Value : 0.2718
- #
- # Sensitivity : 0.5962
- # Specificity : 0.6737
- # Pos Pred Value : 0.5079
- # Neg Pred Value : 0.7442
- # Prevalence : 0.3624
- # Detection Rate : 0.2148
- # Detection Prevalence : 0.4228
- # Balanced Accuracy : **0.6331** <best balanced accuracy>
- #
- # 'Positive' Class : 1

Goal 2: In order to stock the inventory, the store wants to analyze the sales data and predict the trend of total sales for each dress for an extended period of three more alternative days.



### Observations – given data EDA

- Spaghetti plot of observed Sales data – We see some Sale spike on 28Sep/6Oct/12Oct (maybe promotion days?)
- Also we observe one dress sales is consistently decreasing which has the most sales among all dresses.



# Forecasting Algorithms explored

## ETS Exponential Smoothing Algorithm

- (used as a benchmark algorithm to forecast here)
- `fit_ets <- ets(Y)`
- `checkresiduals(fit_ets) #`  
Residual SD :74776.39  
which is high

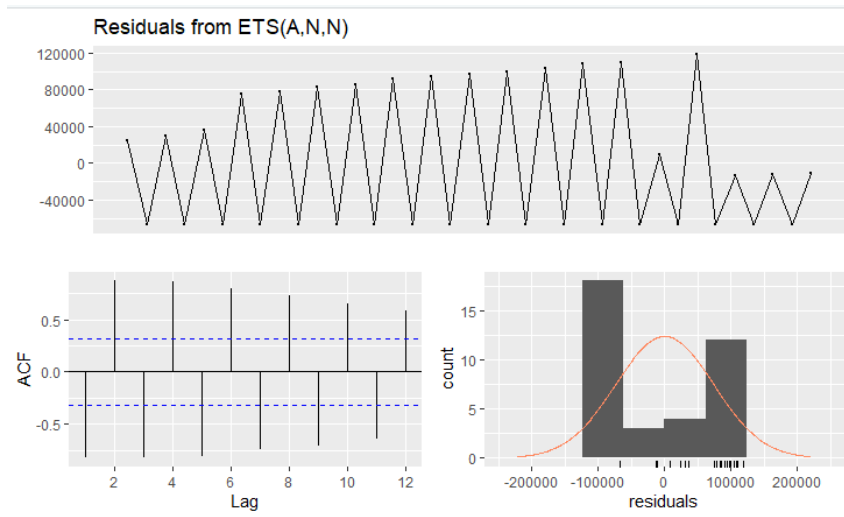
## ARIMA

- `fit_arima <-`  
`summary(auto.arima(Y,`  
`d=1,stepwise =`  
`F,approximation = F,trace =`  
`T)) #residual`  
`sqrt(788991890) ~ 28089`
- ARIMA decreased the residuals drastically

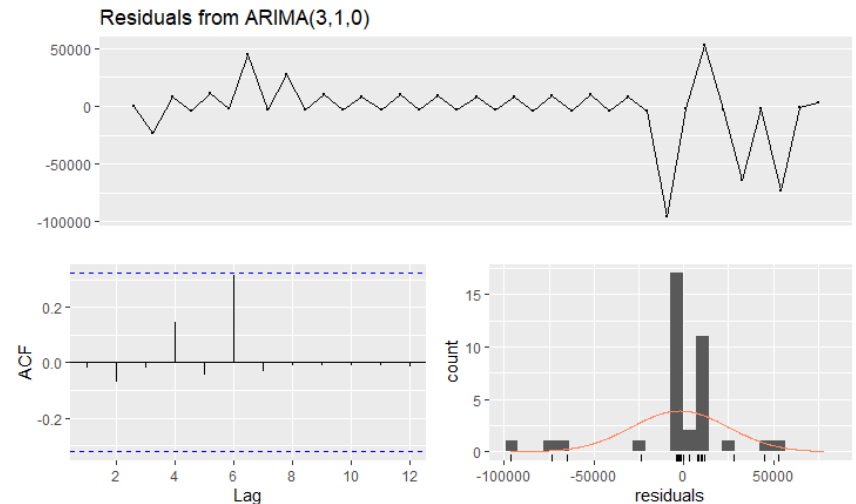
Lets check how ACF or autocorrelation function performed for these in the next page. Autocorrelation measures the linear relation between lagged values of a time series. In the ACF figure (correlogram), we would want the spikes within the blue dashed line, which is the case for Arima, which essentially is good and better than ETS.

# Residual Plots - Forecasting

## ETS



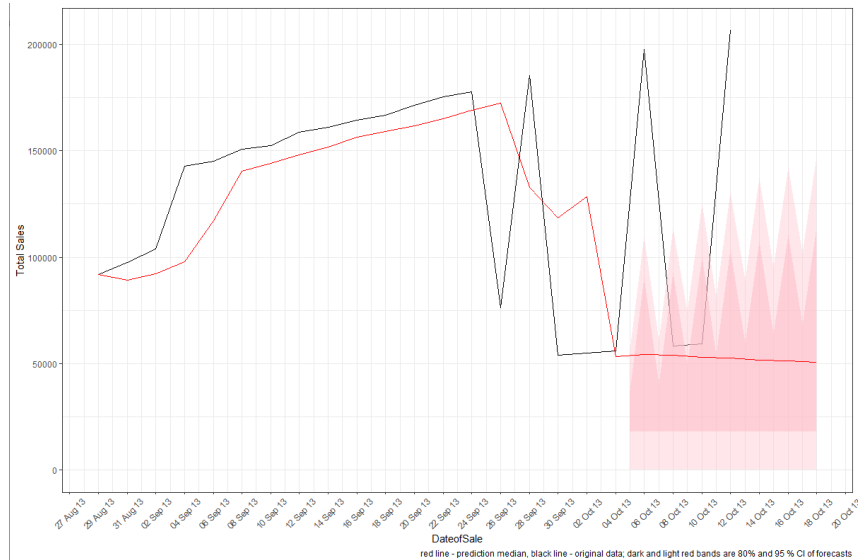
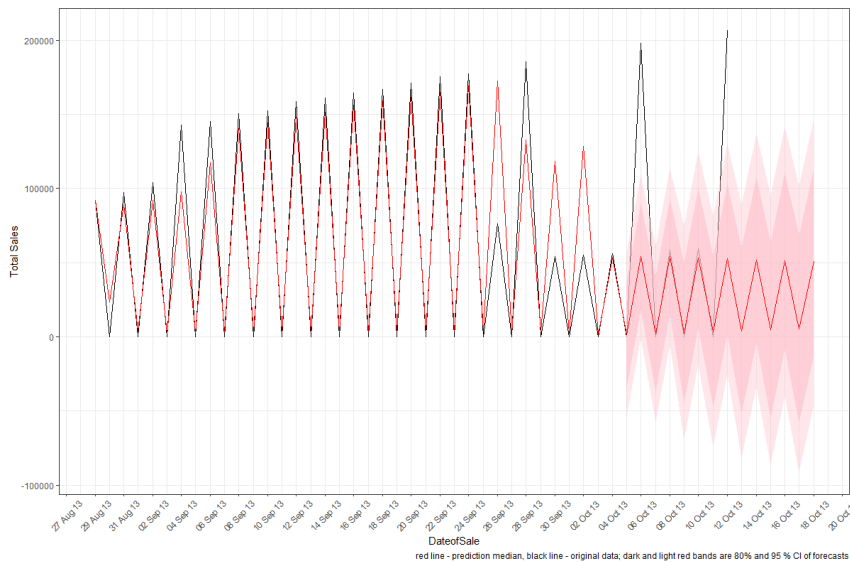
## ARIMA



# Total Sale of all Dresses forecasted for 3 more alternate days using 85:15 train-test split

The spikes on alternate days drop to zero because we don't have information on those days

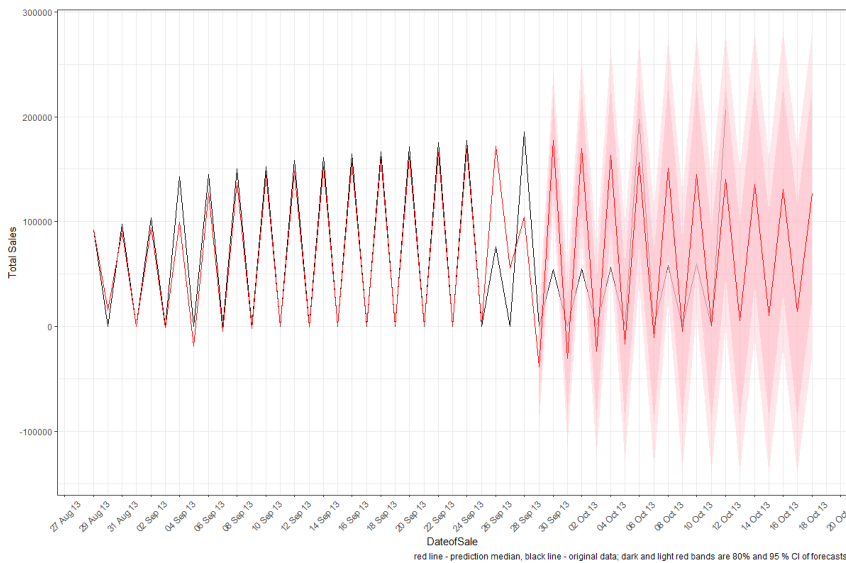
By plotting just alternate days where the information was present, we get



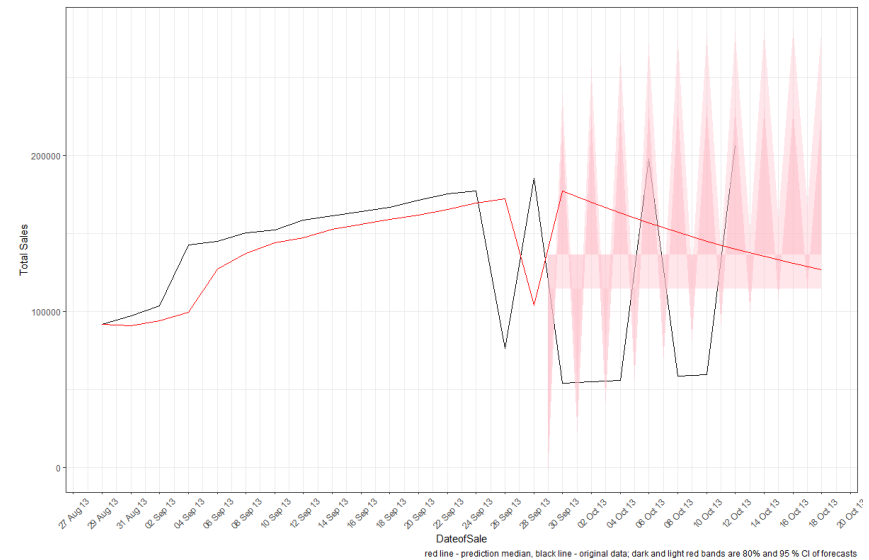
Overall, if we see the predictions are okay but not capturing well on 3 big spikes. Those days could possibly be promotion days where some discount was offered or some national holiday etc. Two possible ways we could improve this prediction i.e. by using another Train:Test split or using another algorithm called Prophet (facebook). Still we haven't solved the goal 2 which was trends asked on an Individual level of every Dress. So for that let's try Prophet assuming that was the best algorithm among the 3. It will capture the promotion/discount days very well.

# Total Sale of all Dresses forecasted for 3 more alternate days using 70:30 train-test split

The spikes on alternate days drop to zero because we don't have information on those days



By plotting just alternate days where the information was present, we get



This looks much better than previous forecast with 85:15 train test split. Still we see that had we known a prior event like 27 Sep date (some public holiday etc.) we could have predicted the drop accurately for 26th Sep instead of 28th Sep. In this split we are over-predicting 30 Sep, 2 Oct and 4th Oct, whereas in the previous split we were more underpredicting the important sales day. So based on the biz decision if under-predicting or over-predicting is more important to the company, we could decide which split to use. In the next page let's see Prophet usage where we will solve the goal 2 (task 2 i.e. on an individual level prediction for 3 more alternate days)

## Prophet R execution

### Without Promotion days coded

```
library(prophet)      library(purrr)

#out of the 23 date records for every dress id, lets consider 70 percent as training and rest as
testing records

train_index <- 1: floor(0.7 * 23 ) # nrow(input) is changed to n as we have already calc for
each SKU

test_index <- setdiff(1:23, train_index) # nrow(input) is changed to n as we have already calc
for each SKU

DS_DS_T <- DS_DS_T %>% group_by(Dress_ID) %>% mutate(SNO = 1:n(), TRAIATESTFIL =
ifelse(SNO <= train_index,"Train","Test")) %>% ungroup()

train <- dplyr::filter(DS_DS_T,TRAIATESTFIL=="Train")

test <- dplyr::filter(DS_DS_T,!TRAIATESTFIL=="Train")

train_all <- train %>%
  group_by(DateofSale,SNO,TRAIATESTFIL) %>%
  summarise(Sales = sum(Sales,na.rm = T)) %>%
  ungroup() %>% dplyr::select(1,2,4,3) %>%
  padr::pad(interval = "day") %>%
  tidyr::fill(SNO,TRAIATESTFIL) %>%
  mutate(Sales = if_else(is.na(Sales), 0, Sales))

test_all <- test %>%
  group_by(DateofSale,SNO,TRAIATESTFIL) %>%
  summarise(Sales = sum(Sales,na.rm = T)) %>%
  ungroup() %>% dplyr::select(1,2,4,3) %>%
  padr::pad(interval = "day") %>%
  tidyr::fill(SNO,TRAIATESTFIL) %>% mutate(Sales = if_else(is.na(Sales), 0, Sales))

d1_all <- train_all %>% rename(ds = DateofSale, y = Sales) %>% # for prophet to work Must
have columns ds (date type) and y, the time series.
  nest() %>% mutate(m = map(data, prophet)) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))

d_all <- d1_all %>% unnest(forecast) %>%
  dplyr::select(ds, yhat, yhat_lower,yhat_upper)

indi_ds_all <- bind_rows(train_all,test_all) %>% mutate(ds = DateofSale)

indi_ds2_all <- left_join(d_all,indi_ds_all) %>% mutate(SNO = 1:n(),
  DateofSale = as.Date(as.character(ds)))

ggplot(data = indi_ds2_all %>% filter(Sales >0) , aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") + ylab("Total Sales")+ geom_line(data =
indi_ds2_all[!(indi_ds2_all$Sales ==0) | (indi_ds2_all$SNO %% 2 ==0 &
is.na(indi_ds2_all$Sales)), , aes(y = yhat), color = "red") + geom_ribbon(data =
indi_ds2_all[!(indi_ds2_all$Sales ==0) | (indi_ds2_all$SNO %% 2 ==0 &
is.na(indi_ds2_all$Sales)) ,], aes(ymin=yhat_lower, ymax=yhat_upper),
  color = "red", alpha =0.3)
```

### With Promotion days coded

```
#now using promotion days to factor in some days to improve the prediction
promotion_days <- data.table::data.table(
  holiday = 'sale discount days',
  ds=as.Date(c('2013-09-28',
    '2013-10-06', '2013-10-12'
  )),
  lower_window = 0, # looks back at 0 days before the last day to shop and get it before sale
  upper_window = 0
)

d1_all <- train_all %>% rename(ds = DateofSale, y = Sales) %>% # for prophet to work Must have columns ds (date type)
and y, the time series.
  nest() %>%
  mutate(m = map(data, ~prophet(.,holidays = promotion_days))) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))

d_all <- d1_all %>%
  unnest(forecast) %>%
  dplyr::select(ds, yhat, yhat_lower,yhat_upper) # in case if we wish to see all variables we can comment this

indi_ds_all <- bind_rows(train_all,test_all) %>% mutate(ds = DateofSale)
indi_ds2_all <- left_join(d_all,indi_ds_all) %>%
  mutate(SNO = 1:n(),DateofSale = as.Date(as.character(ds)))

ggplot(data = indi_ds2_all %>%
  filter(Sales >0) ,
  aes(x = DateofSale)) +geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = indi_ds2_all[!(indi_ds2_all$Sales ==0) |
    (indi_ds2_all$SNO %% 2 ==0 & is.na(indi_ds2_all$Sales)),],
    aes(y = yhat), color = "red") +
  ylab("Total Sales")+geom_ribbon(data = indi_ds2_all[!(indi_ds2_all$Sales ==0) |
    (indi_ds2_all$SNO %% 2 ==0 & is.na(indi_ds2_all$Sales)) ,],
    aes(ymin=yhat_lower, ymax=yhat_upper),
    color = "red", alpha =0.3)

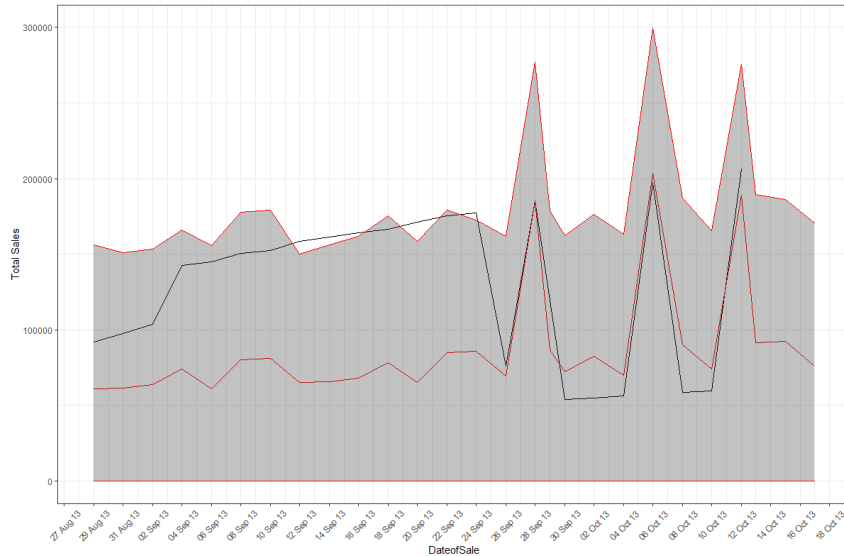
###now also using day seasonality in addition to promotional campaign days
d1_all <- train_all %>% rename(ds = DateofSale, y = Sales) %>% # for prophet to work Must have columns ds (date type) and
y, the time series.
  nest() %>%
  mutate(m = map(data, ~prophet(.,holidays = promotion_days,daily.seasonality=TRUE))) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))

d_all <- d1_all %>%
  unnest(forecast) %>%
  dplyr::select(ds, yhat, yhat_lower,yhat_upper) # in case if we wish to see all variables we can comment this

indi_ds_all <- bind_rows(train_all,test_all) %>% mutate(ds = DateofSale)
indi_ds2_all <- left_join(d_all,indi_ds_all) %>% mutate(SNO = 1:n(), DateofSale = as.Date(as.character(ds)))

ggplot(data = indi_ds2_all %>% filter(Sales >0) ,
  aes(x = DateofSale)) + geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(), axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = indi_ds2_all[!(indi_ds2_all$Sales ==0) |
    (indi_ds2_all$SNO %% 2 ==0 & is.na(indi_ds2_all$Sales)),],
    aes(y = yhat), color = "red") + ylab("Total Sales")+ geom_ribbon(data = indi_ds2_all[!(indi_ds2_all$Sales ==0) |
    (indi_ds2_all$SNO %% 2 ==0 & is.na(indi_ds2_all$Sales)) ,],
    aes(ymin=yhat_lower, ymax=yhat_upper), color = "red", alpha =0.3)
```

# Prophet – Trend Total Sales



- We have captured the event (promotion) days very well using this algorithm.
- The cons are that it is not predicting that well before these days. Arima was better on days leading to event days. This model is kind of over-fitting.
- So depending on the business needs, if we were to understand what is more important i.e. overfitting or under-fitting around these event days, we could choose Arima or this accordingly. Our goal 2 of predicting on an individual level for 3 more additional alternate days is completed (please check the appendix for full code related to that.)
- Previous page included this algorithm on all data (all dresses)
- The code in this page only lists the important piece pertaining to individual level prediction. i.e. nesting by Dress\_Id

## Answer Goal 2: on individual level

```
d1 <- train %>% rename(ds = DateofSale, y = Sales) %>%
# for prophet to work Must have columns ds (date type) and y, the time series.
  nest(-Dress_ID) %>%
  mutate(m = map(data, prophet)) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))
d <- d1 %>%
  unnest(forecast) %>%
  dplyr::select(ds, Dress_ID, yhat, yhat_lower, yhat_upper)
```

## Goal/Task 3

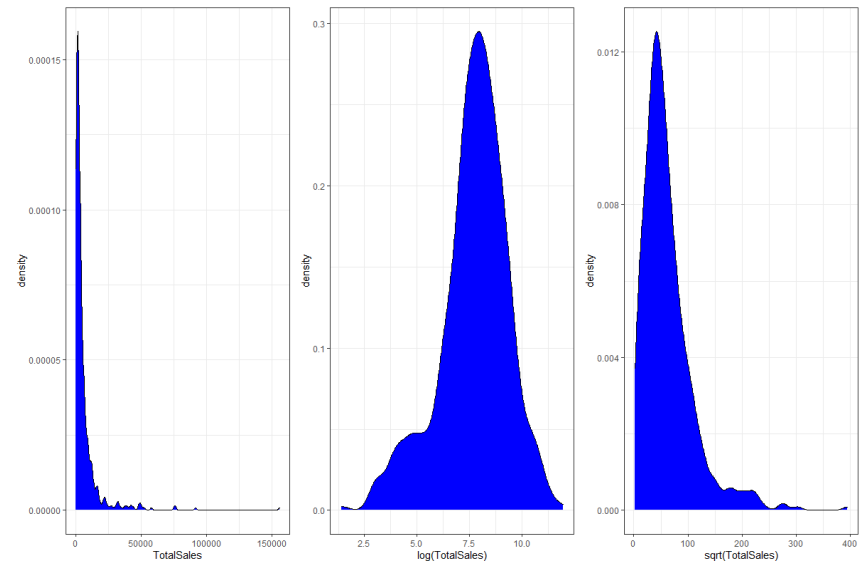
To decide the pricing for various upcoming clothes, they wish to find how the style, season, and material affect the sales of a dress and if the style of the dress is more influential than its price.

- For this task, let's consider the total sales per dress id and do an Linear Regression/ANOVA
- # ANOVA is the statistical model that you use to predict a continuous outcome on the basis of one or more categorical predictor variables
- # we can use lm itself because we have already created dummy variables for categorical variables
- let's explore the response variable TotalSales distribution and see if it is normal; If not use the transformed variable whichever is
- Log transformed looks best. Hence let's model that
- The **autocorrelated variables that will be removed** are these mentioned below (found by using alias(myLm))
- **SeasonAutumn** = 1 - Seasonspring - Seasonsummer - Seasonwinter
- **Pricevery\_high** = 1 - Priceaverage - Pricehigh - Pricelow - Pricemedium
- **Style\_work\_dmy** = 1 - Style\_bohemian\_dmy - Style\_brief\_dmy - Style\_casual\_dmy - Style\_cute\_dmy - Style\_fashion\_dmy - Style\_novelty\_dmy - Style\_OL\_dmy - Style\_party\_dmy - Style\_sexy\_dmy - Style\_vintage\_dmy
- Even after removing these there were some factors that had high VIF >10. These were removed in a step-wise fashion until we had VIF values <5. A high VIF indicates multicollinearity still exists.
- Let's consider alpha value by default 0.05 for all regression problems in this project.

### Answer Goal3:

- Based on the final model with 2-way interactions and just considering these 4 factors asked in the goal3, we see that **season doesn't affect as it has been pooled to error degrees of freedom and low, medium price, cashmere, chiffon, lycra, rayon materials as individual effects are significant. Also high-priced nylon, low-priced cute-style, medium-priced silk material, low-priced rayon material and high-priced cute style affects the total sales in a significant way. Vintage style and low-priced nylon are marginally significant.**
- The ones in green above are influencing in a positive way increasing the sales and the ones in red are decreasing the sales based on the coefficients of the regression.
- **Style of the dress is NOT more influential than its price.** (please see next page linear reg. results as some levels of price have more significance than all style levels, based on p-value).

## Distribution of Response variable



Please note that Adj Rsq here is only 17% and p-val <0.05. So could be biased estimates here. We see that clearly later in the solution of Goal4/5 where rating and other dress attributes are also factored in the model and Adj Rsq. actually improves. Since we didn't consider all factors affecting the model, this one is a biased model. But in the context of comparing style vs price, price is more significant based on p-value.

# Goal 3: Regression results

**First step of Lin Reg., after removing VIF >10 factors; Modeling log(TotalSales) ~**

Residuals:

Min	1Q	Median	3Q	Max
-4.6612	-0.7140	0.1533	0.8534	3.6154

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	7.76788	0.29476	26.354	<2e-16 ***
Seasonspring	-0.09386	0.30462	-0.308	0.7582
Seasonsummer	-0.06357	0.28142	-0.226	0.8214
Seasonwinter	-0.07403	0.28616	-0.259	0.7960
Pricehigh	-0.44247	0.42253	-1.047	0.2958
Pricelow	0.50079	0.19605	2.554	0.0111 *
Pricemedium	-0.95238	0.38777	-2.456	0.0146 *
Style_bohemian_dmy	-0.41881	0.45753	-0.915	0.3607
Style_brief_dmy	0.26802	0.45611	0.588	0.5572
Style_cute_dmy	-0.51047	0.33960	-1.503	0.1338
Style_fashion_dmy	-1.64986	1.53763	-1.073	0.2841
Style_flare_dmy	1.68939	1.69459	0.997	0.3196
Style_novelty_dmy	0.19035	0.59774	0.318	0.7504
Style_OL_dmy	-0.68001	1.57857	-0.431	0.6669
Style_party_dmy	-0.05456	0.30561	-0.179	0.8584
StyleSexy_dmy	-0.03518	0.23846	-0.148	0.8828
Style_vintage_dmy	0.53679	0.38586	1.391	0.1652
Material_acrylic_dmy	-0.25884	1.10752	-0.234	0.8154
Material_cashmere_dmy	-2.06425	0.93461	-2.209	0.0279 *
Material_chiffon_dmy	0.57357	0.42747	1.342	0.1806
Material_knitting_dmy	-0.04894	1.54582	-0.032	0.9748
Material_linen_dmy	0.22779	0.91018	0.250	0.8025
Material_lycra_dmy	-1.98517	1.10440	-1.798	0.0732 .
Material_microfiber_dmy	0.21157	0.89776	0.236	0.8138
Material_milksilk_dmy	0.09030	0.78106	0.116	0.9080
Material_mix_dmy	0.18214	0.71806	0.254	0.7999
Material_modal_dmy	-1.68259	1.09342	-1.539	0.1248
Material_nylon_dmy	-1.41114	0.72656	-1.942	0.0530 .
Material_other_dmy	-0.06351	0.22760	-0.279	0.7804
Material_polyester_dmy	0.01582	0.24481	0.065	0.9485
Material_rayon_dmy	-0.64360	0.57862	-1.112	0.2668
Material_silk_dmy	-0.62744	0.40819	-1.537	0.1253
Material_spandex_dmy	-0.70575	0.79951	-0.883	0.3781
Material_viscos_dmy	-0.14776	1.10108	-0.134	0.8933

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.523 on 318 degrees of freedom  
Multiple R-squared: 0.1506, **Adjusted R-squared: 0.06242**  
F-statistic: 1.708 on 33 and 318 DF, p-value: 0.011

**Last step of Reg., that also contains 2-way interaction.**

Residuals:

Min	1Q	Median	3Q	Max
-5.0113	-0.6128	0.1188	0.8238	3.1419

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	7.6462	0.1079	70.870	< 2e-16 ***
Pricelow	0.4485	0.1736	2.583	0.01022 * significant
Pricemedium	-1.0526	0.3809	-2.764	0.00604 ** very sig.
Style_cute_dmy	0.5006	0.4774	1.049	0.29508
Style_fashion_dmy	-1.5917	1.4372	-1.108	0.26887
Style_vintage_dmy	0.6219	0.3498	1.778	0.07635 . Marginally sig.
Material_cashmere_dmy	-3.9085	1.4372	-2.720	0.00688 ** very sig.
Material_chiffon_dmy	0.8835	0.4233	2.087	0.03763 * significant
Material_lycra_dmy	-3.6208	1.4372	-2.519	0.01223 * significant
Material_modal_dmy	-1.5983	1.0174	-1.571	0.11714
Material_rayon_dmy	-1.3560	0.6141	-2.208	0.02793 * significant
Material_nylon_dmy:Pricehigh	-4.2450	1.4372	-2.954	0.00336 ** very sig.
Style_cute_dmy:Pricehigh	-2.1728	0.9581	-2.268	0.02399 * significant
Pricelow:Style_cute_dmy	-1.7716	0.6717	-2.637	0.00875 ** very sig.
Pricelow:Material_lycra_dmy	3.3093	2.0342	1.627	0.10471
Pricelow:Material_nylon_dmy	-1.5121	0.8393	-1.802	0.07251 . Marginally sig.
Pricelow:Material_rayon_dmy	2.8191	1.1935	2.362	0.01876 * significant
Pricemedium:Style_cute_dmy	1.3510	1.2869	1.050	0.29454
Pricemedium:Material_cashmere_dmy	2.9381	1.7961	1.636	0.10282
Pricemedium:Material_silk_dmy	-3.2381	1.1954	-2.709	0.00710 ** very sig.
Style_cute_dmy:Material_chiffon_dmy	-1.6226	0.9969	-1.628	0.10454

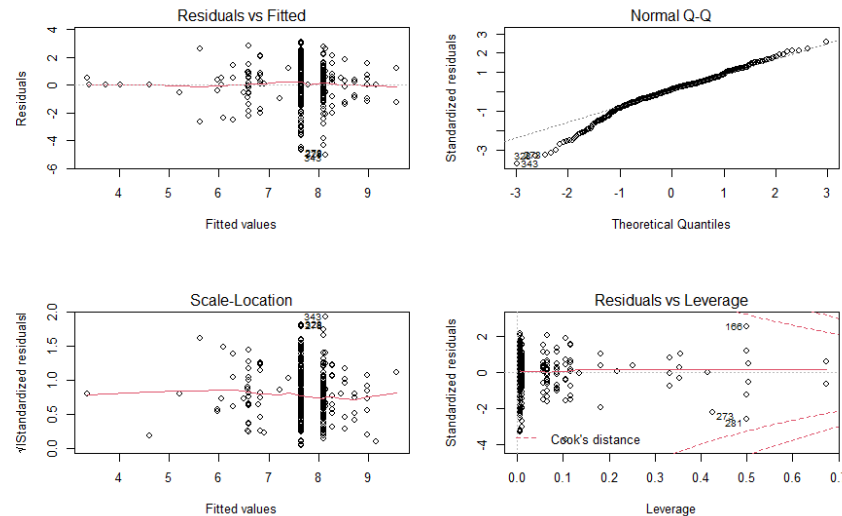
---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.433 on 331 degrees of freedom  
Multiple R-squared: 0.2173, **Adjusted R-squared: 0.17**  
F-statistic: 4.595 on 20 and 331 DF, p-value: 0.000000001098

The adj Rsq 0.17 tells the predictive ability of this model and its not great. Just means we haven't considered all the factors to predict this. The p-val. associated with the model is significant <<<<0.05 (1.1^10-9) indicating we have a significant model nevertheless. It could very well be an under-specified biased model considering only these factors asked in this task but to compare which factors among these impact more , we can consider the p-value of these and numerically sort them in orders of significance with the least values being most significant. The p-values > 0.05 are the ones which are insignificant. Some are slightly >0.05 but not by a lot, so we consider them as marginally significant.



# Goal 3: Results (continued)



- The residual plot indicates there are some influential outliers (Cook's distance) and the q-q plot indicates normal plot overall with some heavy tail where the outliers are perhaps dragging and make it bad.
- But overall the residual plots look good as we don't find any patterns and the residual is homoscedastic. So for this task , we are ok with the regression results for the time being. We will run another run after all the tasks are done to see if we can improve this i.e. removing the heavy tail

```
pred1 <- predict(totsale_lm.19_c.15, newdata = Testing1)
rmse <- sqrt(sum((exp(pred1) - Testing1$TotalSales)^2)/length(Testing1$TotalSales))
c(RMSE = rmse, R2=summary(totsale_lm.19_c.15)$r.squared)
```

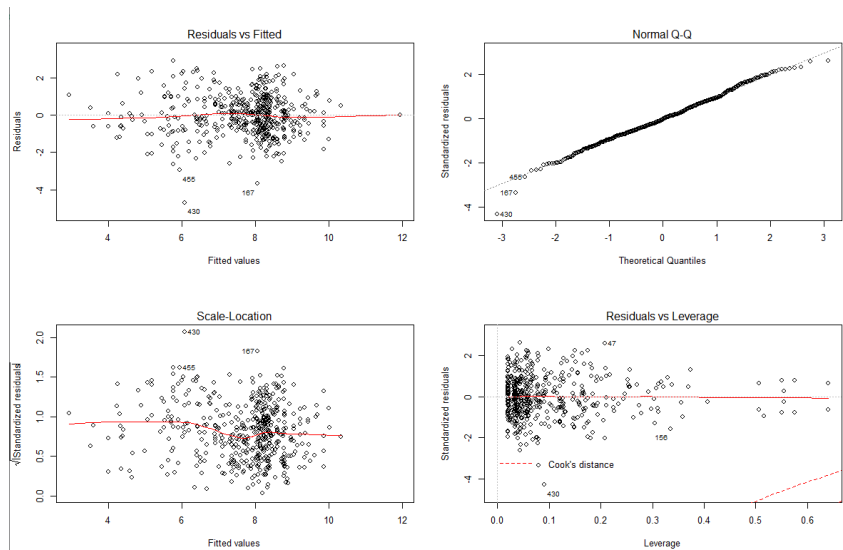
- As the last step, we will predict the 'test' observation and will see the comparison between predicted response and actual response value.
- RMSE explains on an average how much of the predicted value will be from the actual value.
- Based on RMSE = 19749.31, we can conclude that on an average predicted value will be off by 19749.31 from the actual value.
- It is not a great model because we only considered the few factors asked in Task 3 for the modeling of Total Sales

Goal4: Also, to increase sales, the management wants to analyze the attributes of dresses and find which are the leading factors affecting the sale of a dress.

Goal5: To regularize the rating procedure and find its efficiency, the store wants to find if the rating of the dress affects the total sales

- Lets consider both the goal/tasks together and evaluate one single regression. Also instead of just considering these factors alone for regression and to remove bias, lets consider even price , styles as other factors affecting sales as that was significant earlier.
- By using step()/stepAIC(), we found the final model to be used and we have analyzed with 2-way interactions and without interactions as well.
- And the model with 2-way interaction is better and considered as final for now based on the Adj Rsq.

Residual Plots of Overall Total Sales Model with 2 factor interactions- **Looks good**



- Q-Q plot indicates the data is normal with the exception of outliers indicated by cook's D
- The residuals vs fitted points and other plots indicate homoscedastic (equal) variance as there is no pattern and it is evenly distributed
- There are few outliers indicated by Cook's distance but overall the model satisfies the linear regression assumptions and is good to use albeit the Adj. Rsq is just over 50% indicating further factors need to be explored or maybe 3 way interaction level need to be thought of as well.
- But this model of predicting sales has improved considerably after exploring one very significant factor (Rating) which was not evaluated earlier.
- Results of regression in next page

# Coefficients: Main Effects

NOTE: Coefficients of the interaction terms are in the next page

	Estimate	Std. Error	t value	Pr(> t )		
(Intercept)	8.713	0.5205	16.74	< 2e-16	***	<b>INFERENCE</b>
SleeveLengththreequarter	-0.5254	0.5333	-0.985	0.325058		<i>insignificant</i>
SleeveLengthsleeveless	-1.1716	0.4923	-2.38	0.017735	*	<b>significant</b> <i>Sleeveless decreases sales</i>
SleeveLengthshort	-0.8836	0.5013	-1.763	0.078654		<i>marginally significant</i>
SleeveLengthhalfsleeve	-1.2042	0.5307	-2.269	0.023746	*	<b>significant</b> <i>Half-sleeve decreases sales</i>
SleeveLengthfull	-2.397	0.6759	-3.546	0.000432	***	<b>very significant</b> <i>Full-sleeve decreases sales</i>
Priceaverage	0.5847	0.1928	3.033	0.002562	**	<b>very significant</b> <i>Price low, average</i>
Pricelow	0.7513	0.2193	3.426	0.000669	***	<b>very significant</b> <i>increases sales</i>
Style_sexy	-0.1063	0.2289	-0.465	0.64251		<i>insignificant</i>
Material_cashmere	0.9235	0.949	0.973	0.33104		<i>insignificant</i>
Material_linen	1.2258	0.8503	1.442	0.150101		<i>insignificant</i>
Material_mix	0.6347	0.6103	1.04	0.29891		<i>insignificant</i>
Material_modal	-1.8147	0.8221	-2.207	0.027799	*	<b>significant</b> <i>Modal material decreases sales</i>
NeckLine_bowneck	-1.9092	0.5653	-3.377	0.000796	***	<b>very significant</b> <i>Bow-neck decreases sales</i>
NeckLine_ruffled	3.1834	1.1657	2.731	0.006567	**	<b>very significant</b> <i>Ruffled neckline increases sales</i>
Size_L	1.7671	0.5204	3.396	0.000746	***	<b>very significant</b>
Size_M	0.1931	0.1426	1.354	0.176538		<i>insignificant</i> <i>Large and small size</i>
Size_S	1.2033	0.3962	3.037	0.002529	**	<b>very significant</b> <i>increase sales</i>
FabricType_null	-0.2452	0.1222	-2.006	0.045492	*	<b>significant</b> <i>Fabric type if null decreases sales</i>
FabricType_worsted	0.2006	0.3493	0.574	0.56614		<i>insignificant</i>
Pattern_Type_null	-1.7803	0.5011	-3.553	0.000422	***	<b>very significant</b> <i>Pattern Type if null decreases sales</i>
RATINGLE4	-1.7407	0.1973	-8.822	< 2e-16	***	<b>very significant</b> <i>Rating below 4 decreases sales</i>

signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.147 on 447 degrees of freedom

Multiple R-squared: 0.5575, Adjusted R-squared: 0.507

F-statistic: 11.04 on 51 and 447 DF, p-value: < 2.2e-16

# Coefficients: 2-way interaction

//the positive significant coefficients (estimate) improve sales and the negative significant coefficients decrease sales

	Estimate	Std. Error	t value	Pr(> t )	
SleeveLengththreequarter:Size_L	-2.5566	0.7306	-3.5	0.000513	*** <b>very significant</b>
SleeveLengththreequarter:RATINGLE4	-1.1852	0.5407	-2.192	0.028897	* <b>significant</b>
SleeveLengthsleeveless:NeckLine_bowneck	1.778	0.7834	2.269	0.023718	* <b>significant</b>
SleeveLengthsleeveless:Size_L	-1.5114	0.5538	-2.729	0.006596	** <b>very significant</b>
SleeveLengthsleeveless:Size_S	-0.8113	0.5091	-1.593	0.11176	<b>insignificant</b>
SleeveLengthsleeveless:Pattern_Type_null	1.3994	0.5198	2.692	0.007364	** <b>very significant</b>
SleeveLengthsleeveless:RATINGLE4	-0.6317	0.2571	-2.458	0.014368	* <b>significant</b>
SleeveLengthshort:Size_L	-1.13	0.5891	-1.918	0.055729	<b>marginally significant</b>
SleeveLengthshort:Size_S	-1.1741	0.6218	-1.888	0.059641	<b>marginally significant</b>
SleeveLengthshort:Pattern_Type_null	1.9552	0.6129	3.19	0.001523	** <b>very significant</b>
SleeveLengthhalfsleeve:FabricType_worsted	1.9841	1.3743	1.444	0.149507	<b>insignificant</b>
SleeveLengthhalfsleeve:Pattern_Type_null	1.8378	0.6336	2.901	0.003909	** <b>very significant</b>
SleeveLengthfull:Priceaverage	1.0262	0.4533	2.264	0.024057	* <b>significant</b>
SleeveLengthfull:Pricelow	0.938	0.4607	2.036	0.042335	* <b>significant</b>
SleeveLengthfull:Size_L	-0.9438	0.6315	-1.495	0.135738	<b>insignificant</b>
SleeveLengthfull:FabricType_null	0.4693	0.297	1.58	0.11471	<b>insignificant</b>
SleeveLengthfull:Pattern_Type_null	1.9306	0.6355	3.038	0.002523	** <b>very significant</b>
Priceaverage:Material_mix	1.0899	0.7394	1.474	0.1412	<b>insignificant</b>
Priceaverage:Size_S	-0.717	0.4405	-1.628	0.104307	<b>insignificant</b>
Priceaverage:Material_cashmere	-3.0039	1.2782	-2.35	0.019203	* <b>significant</b>
Pricelow:RATINGLE4	1.094	0.2674	4.091	0.000051	*** <b>very significant</b>
Style_sexy:Size_L	1.1392	0.4464	2.552	0.011047	* <b>significant</b>
Style_sexy:Size_M	0.6697	0.3466	1.932	0.053946	<b>marginally significant</b>
Style_sexy:Size_S	1.1038	0.6073	1.818	0.069782	<b>marginally significant</b>
Material_linen:Size_M	2.105	1.4613	1.441	0.150422	<b>insignificant</b>
Material_mix:Size_L	-1.4219	0.8185	-1.737	0.083026	<b>marginally significant</b>
Material_mix:Size_M	-2.0617	0.9718	-2.121	0.034432	* <b>significant</b>
Size_S:FabricType_worsted	-3.7085	1.2779	-2.902	0.003892	** <b>very significant</b>
FabricType_worsted:RATINGLE4	-1.4966	0.7627	-1.962	0.050367	<b>marginally significant</b>
Pattern_Type_null:RATINGLE4	-0.7449	0.2999	-2.484	0.013362	* <b>significant</b>

# Appendix

- R Code that generated these results is mentioned in this section.
- The results of R code are added as R comments using # whenever possible (i.e. for anything except plots/simulations).

```

"-----
# Purpose          : Project 1 (Analysis of Sales Report of a Clothes Manufacturing
Outlet)
# Date             : 12/14/2020 (creation); last edited date: 01/10/2021
# Author           : Harish Ganesan
# Input file(s)    : C:/Users/hganesan/Documents/training/DS_R_lms_proj/Dress
Sales.xlsx
#                  : C:/Users/hganesan/Documents/training/DS_R_lms_proj/Attribute
DataSet.xlsx
# Output file(s)   :
"-----
library(tidyverse)
library(lubridate)
library(scales)
#library(qdap)
library(tm)
library(usdm)

any_column_NA <- function(x){
  any(is.na(x))
}
replace_NA_0 <- function(x){
  if_else(is.na(x),0,x)
}

# Dress Sales DS_DS
path_src1 <- "C:/Users/hganesan/Documents/training/DS_R_lms_proj/Dress Sales.xlsx"
#path_src1 <- "C:/Users/hganesan/Documents/DS_R_lms_proj/Dress Sales.xlsx"

DS_DSh <- readxl::read_excel(path = path_src1 , col_types = "guess", guess_max = 5000,
skip = 0, col_names = F, n_max = 1)
DS_DS <- readxl::read_excel(path = path_src1 , col_types = "guess", guess_max = 5000,
skip = 0, col_names = T)
DS_DSh1 <- DS_DSh %>%
  mutate_at(vars(2,3,10:18), as_date, format = '%d/%m/%Y')
DS_DSh1 <- DS_DSh1 %>%
  mutate_if(is.POSIXct ,as.character) %>%
  mutate_if(is.Date,as.character)
# while checking the values of DS_DSh1, spotted a potential data entry error - while
all columns are talking about 2013 year,
# one alone stands out
# hence correcting that below

DS_DSh1[,22] <- gsub("2010", "2013", DS_DSh1[,22])
str(DS_DSh1)
colnames(DS_DS) <- DS_DSh1[1,]

rm(DS_DSh,DS_DSh1)
str(DS_DS) # some are character types even though they are numeric
DS_DS <- DS_DS%>%
  mutate_if(is.character,as.numeric) %>% # converting some character columns as
numeric
  mutate(Dress_ID = factor(Dress_ID))

# Attribute DataSet ATT_DS
path_src2 <- "C:/Users/hganesan/Documents/training/DS_R_lms_proj/Attribute
DataSet.xlsx"
#path_src2 <- "C:/Users/hganesan/Documents/DS_R_lms_proj/Attribute DataSet.xlsx"
ATT_DS <- readxl::read_excel(path = path_src2 , col_types = "guess", guess_max = 5000,
skip = 0, col_names = T)

***** ATT_DS: Factor 1 below*****
*****
table(ATT_DS$FabricType)
#satin, sattin can be clubbed; similarly flannael flannel can be grouped, woollen and
wollen can be grouped, knitted and knitting can be grouped

# batik broadcloth chiffon corduroy dobby flannael flannel jersey
knitted knitting lace null
# 2 31 135 2 2 1 1 12
1 1 1 265

```

```
# organza      other      poplin      satin      sattin      shiffon      terry      tulles
wollen        woolen      worsted
# 1            1            2            1            6            9            1            2
2            1            19
```

```
ATT_DS <- ATT_DS %>% mutate( FabricType = ifelse( tolower(FabricType) %in%
c("flannael"), "flannel",
                                     ifelse( tolower(FabricType) %in%
c("knitting"), "knitted",
                                     ifelse( tolower(FabricType)
%in% c("sattin"), "satin",
                                     ifelse(
tolower(FabricType) %in% c("wollen"), "woolen",
                                     ifelse(
tolower(FabricType) %in% c("shiffon"), "chiffon",
FabricType))))))
```

```
table(ATT_DS$FabricType)
```

```
# batik broadcloth chiffon corduroy dobby flannel jersey knitted
lace null organza other
# 2 31 144 2
1 265 1 1 2 2 12 2
# poplin satin terry tulles woolen worsted
# 2 7 1 2 3 19
sum(table(ATT_DS$FabricType)) # 499
```

```
# % of Null/NA/none in the total column FabricType > 100*(265/499)
# [1] 53.10621
```

```
***** ATT_DS: Factor 2 below*****
***** -----*****
table(ATT_DS$Decoration)
```

```
# applique beading bow button cascading crystal draped
embroidary feathers flowers hollowout lace
# 21 22 15 6 1 3 2 5
2 4 21 70
# none null pearls plain pleat pockets rivet rucked
ruffles sashes sequined tassel
# 2 235 1 2 1 5 3 3
17 42 14 1
# Tiered
# 1
sum(table(ATT_DS$Decoration)) # 499
# % of Null/NA/none in the total column Decoration > 100*237/499
# [1] 47.49499
```

```
***** ATT_DS: Factor 3 below*****
***** -----*****
table(ATT_DS$`Pattern Type`)
```

```
# animal character dot floral geometric leapord leopard none
null patchwork plaid print solid
# 21 1 14 2 5 1 3 1
108 48 3 71 203
# splice striped
# 1 17
ATT_DS <- ATT_DS %>% mutate( `Pattern Type` = ifelse( tolower(`Pattern Type`) %in%
c("leapord"), "leopard", `Pattern Type`))

table(ATT_DS$`Pattern Type`)
# animal character dot floral geometric leopard none null
patchwork plaid print solid splice
# 21 1 14 2 5 4 1 108 48
3 71 203 1
# striped
# 17
```

```
sum(table(ATT_DS$`Pattern Type`)) # 499
```

```
# % of Null/NA/none in the total column `Pattern Type` > 100*109/499
# [1] 21.84369
```

```
***** ATT_DS: Factor 4 below*****
***** -----*****
```

```
table(ATT_DS$Material)
#modal is the fabric not model. similarly shiffon shd be chiffon
```

	acrylic linen	cashmere lycra	chiffon microfiber	chiffonfabric	cotton	knitting	lace
# 3	3	4	25		152	1	1
# milksilk			mix	modal	model	null	nylon
# 5	other	polyster	12	rayon	1	127	10
# 2		99	10	1			
# shiffon			silk	sill	spandex	viscos	wool
# 2		26	1		5	2	1

```
ATT_DS <- ATT_DS %>% mutate( Material = ifelse( tolower(Material) %in%
c("shiffon"),"chiffonfabric",
                                     ifelse( tolower(Material) %in%
c("model"),"modal",
                                     ifelse( tolower(Material) %in%
c("sill"),"silk",
                                     Material))))
```

	acrylic linen	cashmere lycra	chiffon microfiber	chiffonfabric	cotton	knitting	lace
# 3	3	4	27		152	1	1
# milksilk			mix	modal	null	nylon	other
# 5	polyster	12	rayon	silk	127	10	2
# 99		10	27				
# spandex			viscos	wool			
# 5		2	1				

```
# % of Null/none in the total column Material 100*127/499 #[1] 25.45
```

```
***** ATT_DS: Factor 5 below*****
***** -----*****
```

```
table(ATT_DS$waiseline)
# dropped empire natural null princess
# 4 104 304 86 1
```

```
# % of Null/NA/none in the total column waiseline 100*86/499
# [1] 17.23
```

```
***** ATT_DS: Factor 6 below*****
***** -----*****
```

	butterfly NULL	cap-sleeves Petal	capsleeves short	full	half	halfsleeve
# 1	1	2	3	97	1	35
# 2		1	96			
# sleeveless		sleeveless	sleeveless	sleeveless	threequarter	
# 3	threquarter	thressqatar	turndowncollor	urndowncollor		
# 10		5	223	1	17	1

```
ATT_DS <- ATT_DS %>% mutate( SleeveLength = ifelse( tolower(SleeveLength) %in%
c("capsleeves"),"cap-sleeves",
```



```

c("half"), "halfsleeve",
                                     ifelse( tolower(SleeveLength) %in%
%in% c("sleeveless", "sleeveless", "sleeveless"), "sleeveless",
                                     ifelse(
tolower(SleeveLength) %in% c("threequarter", "threequarter"), "threequarter",
                                     ifelse(
tolower(SleeveLength) %in% c("turndowncollor"), "turndowncollor",
SleeveLength))))))
table(ATT_DS$SleeveLength)
# butterfly    cap-sleeves    full    halfsleeve    NULL    Petal
# short    sleeveless    threequarter
# 1          5          97          36          2          1
96          232          28
# turndowncollor
# 2

# sum(table(ATT_DS$SleeveLength)) # [1] 500
# % of Null/none in the total column SleeveLength 100*2/500 # [1] 0.4

```

```

***** ATT_DS: Factor 7 below*****
***** -----*****

```

```

table(ATT_DS$NeckLine)
# backless    boat-neck    bowneck    halter mandarin-collor
# NULL    1    o-neck    19    open    10    1    1
2    271    3
# peterpan-collor    ruffled    Scoop    slash-neck    square-collor
# sweetheart    Sweetheart    turndowncollor
# 1    6    1    2    25    5
13    14    13
# v-neck
# 124
ATT_DS <- ATT_DS %>% mutate( NeckLine = ifelse( tolower(NeckLine) %in% c("square-
collor"), "square-collor",
                                     ifelse(NeckLine %in%
c("Sweetheart"), "sweetheart",
                                     NeckLine)))

table(ATT_DS$NeckLine)
# backless    boat-neck    bowneck    halter mandarin-collor    NULL
# o-neck    open
# 1    19    10    1    1    2
271    3
# peterpan-collor    ruffled    Scoop    slash-neck    square-collor    sweetheart
# turndowncollor    v-neck
# 6    1    2    25    5    15
13    124

# % of Null/none in the total column NeckLine > 100*2/499
# [1] 0.4

```

```

***** ATT_DS: Factor 8 below*****
***** -----*****

```

```

table(ATT_DS$Season)
#
# Autumn Autumn spring Spring summer Summer winter winter
# 61    8    2    122    1    159    46    99

ATT_DS <- ATT_DS %>% mutate( Season = ifelse( tolower(Season) %in%
c("autumn"), "Autumn",
                                     ifelse( tolower(Season) %in%
c("spring"), "spring",
                                     ifelse( tolower(Season) %in%
c("summer"), "summer",

```

```

    ifelse( tolower(Season)
%in% c("winter"), "winter",
Season))))))

```

```
table(ATT_DS$Season)
# Autumn spring summer winter
#    69    124    160    145
```

```
##### ATT_DS: Factor 9 below#####
##### -----#####
```

```
table(ATT_DS$Size)
# In the following s S and small all indicate the same, we need to format the data
# with values (small,s) and
# make it one standard value s
```

# free	L	M	s	S	small	XL
# 173	96	177	1	37	1	15

```
ATT_DS <- ATT_DS %>% mutate( size = ifelse( tolower(Size) %in%
c("s","small"), "s", Size))
```

```
table(ATT_DS$Size)
# Now the following is alright
# free      L      M      S      XL
#   173    96   177    39    15
```

```
##### ATT_DS: Factor 10 below#####
##### -----#####
```

```
table(ATT_DS$Price)
```

# Average	high	High	low	Low	Medium	very-high
# 252	15	6	45	129	30	21

```
ATT_DS <- ATT_DS %>% mutate( Price = ifelse( tolower(Price) %in% c("high"), "high",
                                           ifelse( tolower(Price) %in%
c("low"), "low",
                                           ifelse( tolower(Price) %in%
c("medium"), "medium",
                                           ifelse( tolower(Price)
%in% c("average"), "average",
                                           Price))))))
```

```
table(ATT_DS$Price)
# average  high      low  medium very-high
# 252      21      174     30      21
```

```
##### ATT_DS: Factor 11 below#####
##### -----#####
```

```
table(ATT_DS$Style)
```

# bohemian	Brief	Casual	cute	fashion	Flare	Novelty	OL	party
sexy	Sexy	vintage	work					
# 24	18	232	45	1	2	8	1	51
7	69	25	17					

```
ATT_DS <- ATT_DS %>% mutate( style = ifelse( tolower(style) %in% c("sexy"),"sexy",
                                           ifelse( tolower(style) %in%
c("novelty"),"novelty",
                                           ifelse( tolower(style) %in%
c("brief"),"brief",
                                           ifelse( tolower(style)
%in% c("casual"),"casual",
                                           ifelse(
tolower(style) %in% c("flare"),"flare",
                                           style))))))
```

```
# bohemian    brief  casual    cute  fashion    flare  novelty    OL    party
sexy  vintage  work
#      24      18      232      45      1      2      8      1      51
76      25      17
```

```
***** ATT_DS: Factor 12 below*****
```

```
***** -----*****
```

```
table(ATT_DS$Rating)
```

```
# 0      1      3 3.5 3.6 3.7      4 4.1 4.2 4.3 4.4 4.5 4.6 4.7 4.8 4.9      5
# 120      1      1      1      1      2      7      5      6      20      27      34      54      84      57      25      55
```

```
## -(a)
```

```
# Checking for NAs and replacing (if possible) with measures of central tendency
median/mean (continuous) and mode (categorical/discrete)
# (we can replace continuous missing values by median that is more resistant to
outliers and
# for categorical missing like this below, we can use mode to replace the missing
value)
```

```
lapply(ATT_DS,function(x) { length(which(is.na(x)))})
```

```
# $Dress_ID # [1] 0 #
# $Style # [1] 0 #
# $Price # [1] 2 # categorical column that can be replaced by Mode
# $Rating # [1] 0 #
# $Size # [1] 0 #
# $Season # [1] 2 # categorical column that can be replaced by Mode
# $NeckLine # [1] 1 #
# $SleeveLength # [1] 0 #
# $waiseline # [1] 1 #
# $Material # [1] 1 #
# $FabricType # [1] 1 #
# $Decoration # [1] 1 #
# $`Pattern Type` # [1] 1 #
# $Recommendation # [1] 0
```

```
# Price,Season, NeckLine, waiseline, Material, FabricType, Decoration, Pattern Type
all have NAs
```

```
## -(b)
```

```
# Checking for null or none values which is similar to NA, just that they are NA's
that are predefined as null or none
```

```
lapply(ATT_DS,function(x) { length(which(x %in% c("NULL","null","none"))))})
```

```
# $Dress_ID # [1] 0 #
# $Style # [1] 0 #
# $Price # [1] 0 #
# $Rating # [1] 0 #
# $Size # [1] 0 #
# $Season # [1] 0 #
# $NeckLine # [1] 2 #
# $SleeveLength # [1] 2 #
# $waiseline # [1] 86 #
# $Material # [1] 127 #
# $FabricType # [1] 265 #
# $Decoration # [1] 237 #
# $`Pattern Type` # [1] 109 #
# $Recommendation # [1] 0
```

```
# Based on list -(a) above, we are going to replace the NAs in some columns that can
be replaced which are less in number
```

```
filter(ATT_DS,is.na(ATT_DS$Price ))
```

```
# A tibble: 2 x 14
```

```
# Dress_ID Style Price Rating Size Season NeckLine SleeveLength waiseline Material
FabricType Decoration `Pattern Type` Recommendation
# <dbl> <chr> <chr> <dbl> <chr> <chr> <chr> <chr> <chr> <chr>
# <chr> <chr> <chr> <dbl> <chr> <chr> <chr> <chr> <chr>
#1 6.63e8 party NA 4.8 free winter o-neck sleeveless empire null
null embroidery null 1
```

```
#2 1.09e9 party NA 4.5 L summer NA full NA NA NA
NA NA 1
```

```
table(filter(ATT_DS,ATT_DS$Style == "party" )$Style)
```

```
# party
# 51
```

```
table((filter(ATT_DS,ATT_DS$Style == "party" ) )$Price)
```

```
# average      high      medium very-high
#      18         9         5         17
sum(table((filter(ATT_DS,ATT_DS$Style == "party" ) )$Price))
# [1] 49
```

# So of the 51 party Style records, 2 NA values can be replaced by the mode of the Price column (average ~ 18 occurring most)  
 # since it is a categorical missing value and the number of records to replace is very less.  
 # If this case was similar and like Fabric type i.e. having > 50% of missing values,  
 # we would not be that comfortable assigning mode because that is a lot of assumption replacing the values

```
filter(ATT_DS,is.na(ATT_DS$Season))
# A tibble: 2 x 14
#   Dress_ID Style Price Rating Size Season NeckLine SleeveLength waiseline Material
FabricType Decoration Pattern Type Recommendation
#   <dbl> <chr> <chr> <dbl> <chr> <chr> <chr> <chr> <chr> <chr>
<chr> <chr> <chr> <chr> <chr> <dbl>
# 1 929797706 casu~ low 0 free NA o-neck full natural cotton
null null patchwork 0
# 2 751364623 party aver~ 4.8 L NA sweethe~ sleeveless empire null
null pleat null 1
```

```
table(ATT_DS$Season)
```

```
# Autumn spring summer winter
# 69 124 160 145
```

```
sum(table(ATT_DS$Season)) #[1] 498
```

# So of the 500 Season records, 2 NA values can be replaced by the mode of the Season column (summer ~ 160 occurring most)  
 # since it is a categorical missing value and the number of records to replace is very less.

```
filter(ATT_DS,is.na(ATT_DS$NeckLine))
# A tibble: 1 x 14
#   Dress_ID Style Price Rating Size Season NeckLine SleeveLength waiseline
Material FabricType Decoration Pattern Type Recommendation
#   <dbl> <chr> <chr> <dbl> <chr> <chr> <chr> <chr> <chr>
<chr> <chr> <chr> <chr> <chr> <dbl>
#1 1.09e9 party NA 4.5 L summer NA full NA NA
NA NA NA 1
```

```
table(ATT_DS$NeckLine)
```

```
# backless      boat-neck      bowneck      halter mandarin-collor      NULL
o-neck      open
# 1      19      10      1      1      2
271      3
# peterpan-collor      ruffled      Scoop      slash-neck      square-collor
sweetheart turndowncollor      v-neck
#      6      1      2      25      5
15      13      124
```

```
sum(table(ATT_DS$NeckLine)) #[1] 499
```

```
ATT_DS %>% group_by(NeckLine) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n) %>%
top_n(3)
# `summarise()` ungrouping output (override with `.groups` argument)
# Selecting by n
# # A tibble: 3 x 2
# NeckLine      n
# <chr>      <int>
# 1 o-neck      271
# 2 v-neck      124
# 3 slash-neck   25
```

# So of the 500 NeckLine records, 1 NA value and 2 NULL can be replaced by the mode of the NeckLine column (o-neck ~ 271 occurring most)  
# since it is a categorical missing value and the number of records to replace is very less.

```
ATT_DS %>% group_by(waiseline) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n)
# `summarise()` ungrouping output (override with `.groups` argument)
# Selecting by n
# A tibble: 3 x 2
# waiseline      n
# <chr>      <int>
# 1 natural      304
# 2 empire       104
# 3 null         86
# 4 dropped        4
# 5 princess      1
# 6 NA            1
```

# <https://discuss.analyticsvidhya.com/t/what-should-be-the-allowed-percentage-of-missing-values/2456>

# Theoretically, 25 to 30% is the maximum missing values are allowed, beyond which we might want to drop the variable from analysis if that is not that important of a variable.

# Based on my experience i have usually used central tendencies if the amount of assumption was less than 10-15 percent and the above link

# also backs my experience and intuition with mine being a less bias prone and more strict assumption.

# I am not ok converting the null waiseline as natural value as 17.2 % (86/500) of it is missing.

# For this project i set the threshold as 15%. Anything less than 15% of missing data, i am ok with using central tendency

# So of the 500 waiseline records, 1 NA value can be replaced by the mode of the waiseline column (natural ~ 304 occurring most)

# since it is a categorical missing value and the number of records to replace is very less.

# Also i would test the model with these 86 null as natural values later as a sensitivity analysis and

# see for biases or tradeoffs we may have to take based on the selection/assumption of data

```
ATT_DS %>% group_by(Material) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n) %>%
top_n(3) # 25.4 % of null
# A tibble: 3 x 2
# Material      n
# <chr>      <int>
# 1 cotton      152
# 2 null        127
# 3 polyester    99
```

```
ATT_DS %>% group_by(Material) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n) %>%
slice_tail()
# `summarise()` ungrouping output (override with `.groups` argument)
# # A tibble: 1 x 2
# Material      n
# <chr>      <int>
# 1 NA            1
```

```
ATT_DS %>% group_by(FabricType) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n) %>%
top_n(3)
# FabricType      n
# <chr>      <int>
```

```

# 1 null          265
# 2 chiffon       144
# 3 broadcloth    31

ATT_DS %>% group_by(FabricType) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n) %>%
slice_tail()
# `summarise()` ungrouping output (override with `.groups` argument)
# A tibble: 1 x 2
#   FabricType      n
#   <chr>         <int>
# 1 NA             1

ATT_DS %>% group_by(Decoration) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n) %>%
top_n(3)
# A tibble: 3 x 2
#   Decoration      n
#   <chr>         <int>
# 1 null          235
# 2 lace          70
# 3 sashes        42

ATT_DS %>% group_by(Decoration) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n) %>%
slice_tail()
# `summarise()` ungrouping output (override with `.groups` argument)
# A tibble: 1 x 2
#   Decoration      n
#   <chr>         <int>
# 1 NA             1

ATT_DS %>% group_by(`Pattern Type`) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n)
%>% top_n(3) # 21.6 % 108/500 is null
# A tibble: 3 x 2
#   `Pattern Type`      n
#   <chr>             <int>
# 1 solid              203
# 2 null               108
# 3 print               71

ATT_DS %>% group_by(`Pattern Type`) %>% summarise(n=n()) %>% ungroup() %>% arrange(-n)
%>% slice_tail()
#   `Pattern Type`      n
#   <chr>             <int>
# 1 NA                 1

ATT_DS %>% group_by(SleeveLength) %>% summarise(n= n()) %>% ungroup() %>% arrange(-n)
%>% top_n(3)

ATT_DS %>% group_by(SleeveLength) %>% summarise(n= n()) %>% ungroup() %>% arrange(-n)
# 2 NULLs can be replaced by the mode sleeveless
# A tibble: 10 x 2
#   SleeveLength      n
#   <chr>           <int>
# 1 sleeveless      232
# 2 full            97
# 3 short           96
# 4 halfsleeve      36
# 5 threequarter    28
# 6 cap-sleeves      5
# 7 NULL             2
# 8 turndowncollor   2
# 9 butterfly        1
# 10 Petal           1

ATT_DS <- ATT_DS %>% mutate(Price = ifelse(is.na(Price), "average", Price),
                             Season = ifelse(is.na(Season), "summer", Season),
                             NeckLine = ifelse(is.na(NeckLine) | toupper(NeckLine)
== "NULL", "o-neck", NeckLine),
                             SleeveLength = ifelse(is.na(SleeveLength) |
toupper(SleeveLength) == "NULL", "sleeveless",
                             SleeveLength),

```

```

        waiseline = ifelse(is.na(waiseline),"natural",waiseline),
        Material = ifelse(is.na(Material),"cotton",Material),
        FabricType = ifelse(is.na(FabricType),"null",FabricType),
# even though NA as is or NA changed to null is not that useful, we are trying to
group these as same values
        Decoration = ifelse(is.na(Decoration),"null",Decoration),
# even though NA as is or NA changed to null is not that useful, we are trying to
group these as same values
        `Pattern Type` = ifelse(is.na(`Pattern
Type`),"solid",`Pattern Type`))

table(ATT_DS$Recommendation)

# 0    1
# 290 210

str(ATT_DS)
table(ATT_DS$Recommendation) # 210 have a recommendation as 1; 290 have a
recommendation as 0
# 0    1
#290 210

table(is.na(ATT_DS$Dress_ID))
# FALSE
# 500
table(is.na(DS_DS$Dress_ID))
# FALSE
# 500

nrow(distinct(ATT_DS))
#[1] 499 - we can see that there is a duplicate, that has to be removed

ATT_DS <- distinct(ATT_DS,.keep_all = T)

nrow(distinct(DS_DS)) # no duplicates as a combination of all columns but

length(levels(DS_DS$Dress_ID)) # Dress_id is only 475, meaning 25 records have more
than one same dress_id
#[1] 475

# an example of one such instance is Dress_id 560474456

# we can handle this either of two ways - 1) Taking the average of the duplicate rows
or
# 2) taking the maximum value of the rows by Dress_id , assuming there was a glitch
while entering and
# max value was supposed to be the final value but instead of making more assumptions,
# lets take the average which is a decent starting point for such dress_ids

DS_DS <- DS_DS %>% mutate_if(any_column_NA,replace_NA_0) # changing NAs as 0

DS_DS <- aggregate(. ~Dress_ID, data=DS_DS, mean, na.rm=T) # only 475 unique Dress ID
remain in this dataset

# we can use the Dress_ID as primary key
ATT_DS$Dress_ID <- sapply(ATT_DS$Dress_ID,factor)

ATT_DS <- ATT_DS %>% left_join(DS_DS)

ATT_DS <- ATT_DS %>% mutate(Recommendation = as.factor(Recommendation))

str(ATT_DS)

# now even though there are 499 unique combinations only 475 dress ids are there.
meaning again 24 have multiple records where one or more columns vary
# 560474456 again can be used as one such example where it was purchased in diff
season and the material used for the dress was different

```

```

# Logistic regression, also called a logit model, is used to model dichotomous/binary
outcome variables
library(aod)
library(car)
table(ATT_DS$Recommendation)
# 1:210 0:289
summary(ATT_DS)

#xtabs(~ Recommendation + Style + Price , data = ATT_DS)
# + Size + Rating + Season + NeckLine + SleeveLength + waiseline + Material +
FabricType + Decoration + `Pattern Type`

#estimate a logistic regression model using the glm (generalized linear model)
function
# we are going to assume alpha = 0.05

#ATT_DS$Rating <- factor(ATT_DS$Rating)
# commenting this - we convert Rating to a factor to indicate that Rating should be
treated as a categorical variable just to see how this plays out

#But before doing logit model, lets see vif (to check for multicollinearity) for which
we will use lm()

# ATT_DS2 <- ATT_DS %>%
#   mutate(Style_bohemian_dmy = ifelse(Style == "bohemian", 1, 0),
#   Style_brief_dmy = ifelse(Style == "brief", 1, 0),
#   Style_casual_dmy = ifelse(Style == "casual", 1, 0),
#   Style_cute_dmy = ifelse(Style == "cute", 1, 0),
#   Style_fashion_dmy = ifelse(Style == "fashion", 1, 0),
#   Style_flare_dmy = ifelse(Style == "flare", 1, 0),
#   Style_novelty_dmy = ifelse(Style == "novelty", 1, 0),
#   Style_OL_dmy = ifelse(Style == "OL", 1, 0),
#   Style_party_dmy = ifelse(Style == "party", 1, 0),
#   Style_sexy_dmy = ifelse(Style == "sexy", 1, 0),
#   Style_vintage_dmy = ifelse(Style == "vintage", 1, 0),
#   Style_work_dmy = ifelse(Style == "work", 1, 0),
#   NeckLine_backless_dmy = ifelse(NeckLine == "backless", 1, 0),
#   NeckLine_boatneck_dmy = ifelse(NeckLine == "boat-neck", 1, 0),
#   NeckLine_bowneck_dmy = ifelse(NeckLine == "bowneck", 1, 0),
#   NeckLine_halter_dmy = ifelse(NeckLine == "halter", 1, 0),
#   NeckLine_mandarincollor_dmy = ifelse(NeckLine == "mandarin-collor",
1, 0),
#   NeckLine_oneck_dmy = ifelse(NeckLine == "o-neck", 1, 0),
#   NeckLine_open_dmy = ifelse(NeckLine == "open", 1, 0),
#   NeckLine_peterpancollor_dmy = ifelse(NeckLine == "peterpan-collor",
1, 0),
#   NeckLine_ruffled_dmy = ifelse(NeckLine == "ruffled", 1, 0),
#   NeckLine_scoop_dmy = ifelse(NeckLine == "scoop", 1, 0),
#   NeckLine_slashneck_dmy = ifelse(NeckLine == "slash-neck", 1, 0),
#   NeckLine_squarecollor_dmy = ifelse(NeckLine == "square-collor", 1,
0),
#   NeckLine_sweetheart_dmy = ifelse(NeckLine == "sweetheart", 1, 0),
#   NeckLine_turndowncollor_dmy = ifelse(NeckLine == "turndowncollor",
1, 0),
#   NeckLine_vneck_dmy = ifelse(NeckLine == "v-neck", 1, 0)
#   ) %>% dplyr::select(-c("NeckLine", "Style"))

# usdm::vif((ATT_DS2 %>% dplyr::select(c(36:62))))

mylm <- lm(Recommendation ~
  Style + Price + Size + Rating + Season + NeckLine + SleeveLength +
  waiseline + Material + FabricType + Decoration + `Pattern Type`,
  data = ATT_DS)

alias(mylm)
# 'alias' refers to the variables that are linearly dependent on others (i.e. cause
perfect multicollinearity).

```



# Since NeckLinemandarin-collor is linearly dependent on StyleOL we are going to use stepAIC to remove unimportant factors and reduce the number of factors using MASS package stepAIC()

# Complete :

```
# (Intercept) Stylebrief Stylecasual Stylecute Stylefashion
Styleflare Stylenovelty StyleOL Styleparty Stylesexy
# NeckLinemandarin-collor 0 0 0 0 0
0 1 0 0
# Stylevintage Stylework Pricehigh Pricelow Pricemedium
Pricevery-high SizeL SizeM SizeS SizeXL Rating
# NeckLinemandarin-collor 0 0 0 0 0
0 0 0 0 0
# Seasonspring Seasonsummer Seasonwinter NeckLineboat-neck
NeckLinebowneck NeckLinehalter NeckLineo-neck
# NeckLinemandarin-collor 0 0 0 0
0 0
# NeckLineopen NeckLinepeterpan-collor NeckLineruffled
NeckLinescoop NeckLineslash-neck NeckLinesquare-collor
# NeckLinemandarin-collor 0 0 0
0 0
# NeckLinesweetheart NeckLineturndowncollor NeckLinev-neck
SleeveLengthcap-sleeves SleeveLengthfull
# NeckLinemandarin-collor 0 0 0
0
# SleeveLengthhalfssleeve SleeveLengthNULL SleeveLengthPetal
SleeveLengthshort SleeveLengthsleeveless
# NeckLinemandarin-collor 0 0 0
0
# SleeveLengththreequarter SleeveLengthturndowncollor
waiselineempire waiselinenatural waiselinenull
# NeckLinemandarin-collor 0 0 0
0 0
# waiselineprincess Materialcashmere Materialchiffonfabric
Materialcotton Materialknitting Materiallace
# NeckLinemandarin-collor 0 0 0
0 0
# Materiallinen Materiallycra Materialmicrofiber
Materialmilksilk Materialmix Materialmodal Materialnull
# NeckLinemandarin-collor 0 0 0 0
0 0
# Materialnylon Materialother Materialpolyster Materialrayon
Materialsilk Materialsandex Materialviscos
# NeckLinemandarin-collor 0 0 0 0
0 0
# Materialwool FabricTypebroadcloth FabricTypechiffon
FabricTypecorduroy FabricTypedobby FabricTypeflannel
# NeckLinemandarin-collor 0 0 0
0 0
# FabricTypejersey FabricTypeknitted FabricTypelace
FabricTypenull FabricTypeorganza FabricTypeother
# NeckLinemandarin-collor 0 0 0
0 0
# FabricTypepoplin FabricTypesatin FabricTypepeterry
FabricTypepetulle FabricTypewoolen
# NeckLinemandarin-collor 0 0 0
0
# FabricTypeworsted Decorationbeading Decorationbow
Decorationbutton Decorationcascading Decorationcrystal
# NeckLinemandarin-collor 0 0 0
0 0
# Decorationdraped Decorationembroidary Decorationfeathers
Decorationflowers Decorationhollowout Decorationlace
# NeckLinemandarin-collor 0 0 0
0 0
# Decorationnone Decorationnull Decorationpearls Decorationplain
Decorationpleat Decorationpockets
# NeckLinemandarin-collor 0 0 0
0 0
# Decorationrivet Decorationruched Decorationruffles
Decorationsashes Decorationsequined Decorationtassel
```

```

# NeckLinemandarin-collor 0 0 0 0
0 0
# DecorationTiered `Pattern Type`character `Pattern Type`dot
`Pattern Type`floral `Pattern Type`geometric
# NeckLinemandarin-collor 0 0 0 0
0
# `Pattern Type`leopard `Pattern Type`none `Pattern Type`null
`Pattern Type`patchwork `Pattern Type`plaid
# NeckLinemandarin-collor 0 0 0
0 0
# `Pattern Type`print `Pattern Type`solid `Pattern Type`splice
`Pattern Type`striped
# NeckLinemandarin-collor 0 0 0
0

```

# since we have many categorical values, we are changing them to dichotomous dummy variables

```

ATT_DS2 <- ATT_DS %>% mutate( SleeveLengththreequarter =
ifelse(SleeveLength=="threequarter",1,0),
      SleeveLengthsleeveless =
ifelse(SleeveLength=="sleeveless",1,0),
      SleeveLengthshort= ifelse(SleeveLength=="short",1,0),
      SleeveLengthhalfssleeve =
ifelse(SleeveLength=="halfssleeve",1,0),
      SleeveLengthfull = ifelse(SleeveLength=="full",1,0),
      SleeveLengthcap_sleeves = ifelse(SleeveLength=="cap-
sleeves",1,0),
      Seasonspring= ifelse(Season == "spring",1,0),
      Seasonsummer = ifelse(Season == "summer",1,0),
      Seasonwinter = ifelse(Season == "winter",1,0),
      SeasonAutumn = ifelse(Season == "Autumn",1,0),
      Priceaverage= ifelse(Price == "average",1,0),
      Pricehigh= ifelse(Price == "high",1,0),
      Pricelow= ifelse(Price == "low",1,0),
      Pricemedium= ifelse(Price == "medium",1,0),
      Pricevery_high= ifelse(Price == "very-high",1,0),
      Style_bohemian_dmy = ifelse(Style == "bohemian", 1, 0),
      Style_brief_dmy = ifelse(Style == "brief", 1, 0),
      Style_casual_dmy = ifelse(Style == "casual", 1, 0),
      Style_cute_dmy = ifelse(Style == "cute", 1, 0),
      Style_fashion_dmy = ifelse(Style == "fashion", 1, 0),
      Style_flare_dmy = ifelse(Style == "flare", 1, 0),
      Style_novelty_dmy = ifelse(Style == "novelty", 1, 0),
      Style_OL_dmy = ifelse(Style == "OL", 1, 0),
      Style_party_dmy = ifelse(Style == "party", 1, 0),
      Style_sexy_dmy = ifelse(Style == "sexy", 1, 0),
      Style_vintage_dmy = ifelse(Style == "vintage", 1, 0),
      Style_work_dmy = ifelse(Style == "work", 1, 0),
      Material_acrylic_dmy = ifelse(Material == "acrylic", 1,
0),
      Material_cashmere_dmy = ifelse(Material == "cashmere", 1,
0),
      Material_chiffon_dmy = ifelse(Material
=="chiffonfabric", 1, 0),
      Material_cotton_dmy = ifelse(Material == "cotton", 1, 0),
      Material_knitting_dmy = ifelse(Material == "knitting", 1,
0),
      Material_linen_dmy = ifelse(Material == "linen", 1, 0),
      Material_lycra_dmy = ifelse(Material == "lycra", 1, 0),
      Material_microfiber_dmy = ifelse(Material
=="microfiber", 1, 0),
      Material_milksilk_dmy = ifelse(Material == "milksilk", 1,
0),
      Material_mix_dmy = ifelse(Material == "mix", 1, 0),
      Material_modal_dmy = ifelse(Material == "modal", 1, 0),
      Material_nylon_dmy = ifelse(Material == "nylon", 1, 0),
      Material_other_dmy = ifelse(Material %in%
c("other","null"), 1, 0),

```

```

0),
Material_polyester_dmy = ifelse(Material == "polyester", 1,
Material_rayon_dmy = ifelse(Material == "rayon", 1, 0),
Material_silk_dmy = ifelse(Material == "silk", 1, 0),
Material_spandex_dmy = ifelse(Material == "spandex", 1,
0),
Material_viscos_dmy = ifelse(Material == "viscos", 1, 0),
NeckLine_backless_dmy = ifelse(NeckLine == "backless", 1,
0),
NeckLine_boatneck_dmy = ifelse(NeckLine == "boat-neck",
NeckLine_bowneck_dmy = ifelse(NeckLine == "bowneck", 1,
0),
NeckLine_halter_dmy = ifelse(NeckLine == "halter", 1, 0),
NeckLine_mandarincollor_dmy = ifelse(NeckLine
=="mandarin-collor", 1, 0),
NeckLine_oneck_dmy = ifelse(NeckLine == "o-neck", 1, 0),
NeckLine_open_dmy = ifelse(NeckLine == "open", 1, 0),
NeckLine_peterpancollor_dmy = ifelse(NeckLine
=="peterpan-collor", 1, 0),
NeckLine_ruffled_dmy = ifelse(NeckLine == "ruffled", 1,
0),
NeckLine_scoop_dmy = ifelse(NeckLine == "scoop", 1, 0),
NeckLine_slashneck_dmy = ifelse(NeckLine == "slash-neck",
1, 0),
NeckLine_squarecollor_dmy = ifelse(NeckLine == "square-
collor", 1, 0),
NeckLine_sweetheart_dmy = ifelse(NeckLine
=="sweetheart", 1, 0),
NeckLine_turndowncollor_dmy = ifelse(NeckLine
=="turndowncollor", 1, 0),
NeckLine_vneck_dmy = ifelse(NeckLine == "v-neck", 1, 0) )
%>%
  dplyr::select(-
c("Price", "Season", "SleeveLength", "NeckLine", "Style", "Material"))

library(MASS)
library(caret)

# first creating training and testing of data so that we can validate model later
set.seed(123)
inTrain <- createDataPartition(ATT_DS$Recommendation, p = 0.7, list = FALSE)

Training = ATT_DS2[inTrain,]
Testing = ATT_DS2[-inTrain,]

sum(as.numeric(as.character(ATT_DS$Recommendation)))
#[1] 210

sum(as.numeric(as.character(Training$Recommendation)))
#[1] 147

Training1 <- Training %>% dplyr::select(c(2:8,32:91))
Testing1 <- Testing %>% dplyr::select(c(2:8,32:91))

mylm <- lm(as.numeric(Recommendation) ~ .
          data = Training1)

alias( mylm )
vif(mylm)
#Error in vif.default(mylm) : there are aliased coefficients in the model

# The autocorrelated variables are these mentioned below (found by using alias(mylm))
# SeasonAutumn = 1 - Seasonspring - Seasonsummer - Seasonwinter
# Pricevery_high = 1 - Priceaverage - Pricehigh - Pricelow - Pricemedium

```

```

# Style_work_dmy = 1 -Style_bohemian_dmy -Style_brief_dmy -Style_casual_dmy -
Style_cute_dmy -Style_fashion_dmy -Style_novelty_dmy -Style_OL_dmy -
Style_party_dmy -Style_sexy_dmy -Style_vintage_dmy

# NeckLine_mandarincollor_dmy = Style_OL_dmy

# NeckLine_open_dmy = 1 + Style_fashion_dmy -Material_acrylic_dmy -
Material_cashmere_dmy -Material_chiffon_dmy -Material_cotton_dmy -
Material_knitting_dmy -Material_linen_dmy -Material_lycra_dmy -Material_microfiber_dmy
# -Material_milksilk_dmy -Material_mix_dmy -Material_modal_dmy -Material_nylon_dmy -
Material_other_dmy - Material_polyster_dmy - Material_rayon_dmy - Material_silk_dmy -
Material_spandex_dmy
# - Material_viscos_dmy

# NeckLine_vneck_dmy = - Style_fashion_dmy -Style_OL_dmy + Material_acrylic_dmy +
Material_cashmere_dmy + Material_chiffon_dmy + Material_cotton_dmy +
Material_knitting_dmy + Material_linen_dmy + Material_lycra_dmy
# + Material_microfiber_dmy + Material_milksilk_dmy + Material_mix_dmy +
Material_modal_dmy + Material_nylon_dmy + Material_other_dmy + Material_polyster_dmy
+ Material_rayon_dmy
# + Material_silk_dmy + Material_spandex_dmy + Material_viscos_dmy -
NeckLine_boatneck_dmy - NeckLine_bowneck_dmy - NeckLine_halter_dmy -
NeckLine_oneck_dmy - NeckLine_peterpancollor_dmy
# - NeckLine_ruffled_dmy - NeckLine_Scoop_dmy - NeckLine_slashneck_dmy -
NeckLine_squarecollor_dmy - NeckLine_sweetheart_dmy - NeckLine_turndowncollor_dmy

# In the below glm we have to remove the autocorrelated variables, which we will do
after the following
fit0 = glm(Recommendation ~ ., data= Training1, family = binomial(link = "logit"))
# Got a warning message when i ran the above - it indicates there are too many
variables in the model
# So lets compare correlation between the factors to remove the highly correlated
variables and reduce
# Warning message:
# glm.fit: fitted probabilities numerically 0 or 1 occurred

fit0 <- update(fit0, ~. -SeasonAutumn -Pricevery_high - Style_work_dmy
- NeckLine_mandarincollor_dmy - NeckLine_open_dmy - NeckLine_vneck_dmy)

#we still got the following warning for the above update
# Warning message:
# glm.fit: fitted probabilities numerically 0 or 1 occurred
# since we explored and saw two NAs for the following factors,
# we are going to exclude that as well from the model as these are not significant
factors
# as all of the 350 records are 0
# > table(Training1$NeckLine_backless_dmy)
#
# 0
# 350
# > table(Training1$Style_flare_dmy)
#
# 0
# 350

fit0 <- update(fit0, ~. -NeckLine_backless_dmy - Style_flare_dmy)
# Warning message:
# glm.fit: fitted probabilities numerically 0 or 1 occurred

summary(fit0)
# since there are too many factors lets first use stepAIC to reduce this to only
significant factors

step1 = stepAIC(fit0, direction = "both")

#Last iteration result #Step: AIC=436
#
# Step: AIC=436
# Recommendation ~ Rating + SleeveLengthshort + Seasonspring +

```

```

# Priceaverage + Pricehigh + Pricelow + Style_cute_dmy + Style_OL_dmy +
# Material_cashmere_dmy + Material_cotton_dmy + Material_nylon_dmy +
# Material_other_dmy + NeckLine_bowneck_dmy + NeckLine_oneck_dmy +
# NeckLine_peterpancollor_dmy + NeckLine_squarecollor_dmy +
# NeckLine_turndowncollor_dmy + Material_acrylic_dmy
#
# Df Deviance      AIC
# <none>                398.00 436.00
# - Style_OL_dmy        1 400.60 436.60
# + Style_fashion_dmy   1 396.72 436.72
# + Style_brief_dmy     1 396.81 436.81
# + NeckLine_halter_dmy 1 396.81 436.81
# + NeckLine_ruffled_dmy 1 396.89 436.89
# - Rating              1 400.93 436.93
# + Material_milksilk_dmy 1 396.96 436.96
# + Style_bohemian_dmy  1 397.01 437.01
# + Material_linen_dmy  1 397.09 437.09
# + SleeveLengthfull    1 397.12 437.12
# + Material_modal_dmy  1 397.12 437.12
# - Material_acrylic_dmy 1 401.19 437.19
# + Seasonwinter        1 397.23 437.23
# + NeckLine_boatneck_dmy 1 397.29 437.29
# - NeckLine_turndowncollor_dmy 1 401.30 437.30
# + Material_knitting_dmy 1 397.31 437.31
# + NeckLine_sweetheart_dmy 1 397.32 437.32
# + NeckLine_slashneck_dmy 1 397.33 437.33
# - Style_cute_dmy      1 401.33 437.33
# + Style_party_dmy     1 397.44 437.44
# + SleeveLengththreequarter 1 397.45 437.45
# + Style_sexy_dmy      1 397.52 437.52
# + Material_rayon_dmy  1 397.54 437.54
# + SleeveLengthhalfsleeve 1 397.55 437.55
# - NeckLine_squarecollor_dmy 1 401.64 437.64
# + SleeveLengthcap_sleeves 1 397.65 437.65
# - Material_cotton_dmy 1 401.67 437.67
# + Style_casual_dmy    1 397.73 437.73
# - NeckLine_oneck_dmy  1 401.74 437.74
# + NeckLine_scoop_dmy  1 397.78 437.78
# + Material_viscos_dmy 1 397.80 437.80
# + Seasonsummer        1 397.84 437.84
# + Material_mix_dmy    1 397.84 437.84
# - Material_nylon_dmy  1 401.89 437.89
# + Material_spandex_dmy 1 397.89 437.89
# + Material_polyester_dmy 1 397.91 437.91
# + Style_novelty_dmy   1 397.92 437.92
# + Style_vintage_dmy   1 397.93 437.93
# + Material_chiffon_dmy 1 397.95 437.95
# + Material_silk_dmy   1 397.96 437.96
# + SleeveLengthsleeveless 1 397.98 437.98
# + Material_lycra_dmy  1 397.98 437.98
# + Material_microfiber_dmy 1 397.98 437.98
# + Pricemedium         1 397.99 437.99
# - Material_other_dmy  1 402.91 438.91
# - NeckLine_bowneck_dmy 1 403.21 439.21
# - NeckLine_peterpancollor_dmy 1 403.72 439.72
# - Material_cashmere_dmy 1 403.79 439.79
# + waiseline           4 394.36 440.36
# + Size                4 395.68 441.68
# - SleeveLengthshort   1 406.05 442.05
# - Pricehigh           1 407.51 443.51
# - Pricelow            1 407.93 443.93
# + `Pattern Type`      12 383.91 445.91
# - Seasonspring        1 410.62 446.62
# - Priceaverage        1 412.68 448.68
# + FabricType          14 387.24 453.24
# + Decoration           21 383.82 463.82

#Just checking VIF again as a check
mylm <- lm(as.numeric(Recommendation) ~ Rating + sleeveLengthshort + Seasonspring +
Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
Style_OL_dmy +

```

```

Material_cashmere_dmy + Material_cotton_dmy +
Material_nylon_dmy + Material_other_dmy + NeckLine_bowneck_dmy +
NeckLine_oneck_dmy + NeckLine_peterpancollor_dmy + NeckLine_squarecollor_dmy
+ NeckLine_turndowncollor_dmy + Material_acrylic_dmy

```

```

data = Training1)
vif(myglm)
# Rating SleeveLengthshort Seasonspring
# 1.065692 1.061912 1.074698
# Priceaverage Pricehigh Pricelow
# 2.873957 1.463455 2.866266
# Style_cute_dmy Style_OL_dmy Material_cashmere_dmy
# 1.059598 1.045989 1.107724
# Material_cotton_dmy Material_nylon_dmy Material_other_dmy
# 1.321626 1.078019 1.314816
# NeckLine_bowneck_dmy NeckLine_oneck_dmy NeckLine_peterpancollor_dmy
# 1.105460 1.183940 1.043706
# NeckLine_squarecollor_dmy NeckLine_turndowncollor_dmy Material_acrylic_dmy
# 1.037134 1.068606 1.023906

```

```

# now since we don't have VIF >10 , we can assume these as predictors for glm

```

```

mylogit <- glm(Recommendation ~
Rating + SleeveLengthshort + Seasonspring +
Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
Style_OL_dmy + Material_cashmere_dmy + Material_cotton_dmy +
Material_nylon_dmy + Material_other_dmy + NeckLine_bowneck_dmy + NeckLine_oneck_dmy
+ NeckLine_peterpancollor_dmy + NeckLine_squarecollor_dmy +
NeckLine_turndowncollor_dmy + Material_acrylic_dmy

```

```

# was trying the following in the past - not needed now as the above is
deemed final significant factors to start with

```

```

# Priceaverage +
# Pricehigh +
# Pricelow +
# Pricemedium +
# Pricevery_high +
# Seasonspring +
# Seasonsummer +
# Seasonwinter +
# SeasonAutumn +
# SleeveLengththreequarter +
# SleeveLengthsleeveless +
# SleeveLengthshort +
# SleeveLengthhalfsleeve +
# SleeveLengthfull +
# SleeveLengthcap_sleeves

```

```

data = Training1, family = binomial(link = "logit"))

```

```

summary(mylogit)
#
# Call:
# glm(formula = Recommendation ~ Rating + SleeveLengthshort + Seasonspring +
# Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
Style_OL_dmy + Material_cashmere_dmy + Material_cotton_dmy + Material_nylon_dmy
+ Material_other_dmy + NeckLine_bowneck_dmy + NeckLine_oneck_dmy +
NeckLine_peterpancollor_dmy + NeckLine_squarecollor_dmy +
NeckLine_turndowncollor_dmy + Material_acrylic_dmy, family =
binomial(link = "logit"),
# data = Training1)
#

```

```

# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -1.9113  -0.9863  -0.4891   1.0733   2.3082
#
# Coefficients:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.4921     0.4945   0.995 0.319611
# Rating            0.1057     0.0625   1.692 0.090679 .
# SleeveLengthshort -0.9575     0.3514 -2.725 0.006432 **
#   Seasonspring      0.9848     0.2812   3.502 0.000461 ***
#   Priceaverage     -1.6305     0.4479  -3.641 0.000272 ***
#   Pricehigh       -2.0190     0.6764  -2.985 0.002836 **
#   Pricelow        -1.3934     0.4615  -3.019 0.002533 **
#   Style_cute_dmy    0.7472     0.4118   1.814 0.069629 .
# Style_OL_dmy     -17.6394    2399.5448  -0.007 0.994135
# Material_cashmere_dmy 18.1105    1677.7192   0.011 0.991387
# Material_cotton_dmy   0.5812     0.3055   1.902 0.057112 .
# Material_nylon_dmy    1.7934     0.9386   1.911 0.056030 .
# Material_other_dmy    0.6699     0.3043   2.202 0.027677 *
#   NeckLine_bowneck_dmy -2.3582     1.2365  -1.907 0.056492 .
# NeckLine_oneck_dmy   -0.4957     0.2571  -1.928 0.053840 .
# NeckLine_peterpancollor_dmy -16.3605    1063.6762  -0.015 0.987728
# NeckLine_squarecollor_dmy -16.4364    1320.2093  -0.012 0.990067
# NeckLine_turndowncollor_dmy -1.4237     0.8558  -1.664 0.096197 .
# Material_acrylic_dmy -16.2223    1272.7943  -0.013 0.989831
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.2  on 349  degrees of freedom
# Residual deviance: 398.0  on 331  degrees of freedom
# AIC: 436
#
# Number of Fisher Scoring iterations: 15
vif(mylogit)

# Rating      SleeveLengthshort      Seasonspring
# 1.054771      1.057073      1.041390
# Priceaverage      Pricehigh      Pricelow
# 3.423224      1.615719      3.436006
# Style_cute_dmy      Style_OL_dmy      Material_cashmere_dmy
# 1.061445      1.000000      1.000000
# Material_cotton_dmy      Material_nylon_dmy      Material_other_dmy
# 1.373702      1.082158      1.340865
# NeckLine_bowneck_dmy      NeckLine_oneck_dmy NeckLine_peterpancollor_dmy
# 1.039433      1.120444      1.000000
# NeckLine_squarecollor_dmy NeckLine_turndowncollor_dmy      Material_acrylic_dmy
# 1.000000      1.055415      1.000000

# no multicollinear factors (as vif <10) - which is good
#now we are going to pool the most insignificant term into the error degrees of
freedom

fitA = update(mylogit, .~. -Style_OL_dmy)
summary(fitA)
# glm(formula = Recommendation ~ Rating + SleeveLengthshort + Seasonspring +
#      Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
#      Material_cashmere_dmy +
#      Material_cotton_dmy + Material_nylon_dmy + Material_other_dmy +
#      NeckLine_bowneck_dmy + NeckLine_oneck_dmy + NeckLine_peterpancollor_dmy
#      +
#      NeckLine_squarecollor_dmy + NeckLine_turndowncollor_dmy +
#      Material_acrylic_dmy, family = binomial(link = "logit"),
#      data = Training1)
#
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -1.8592  -0.9845  -0.5002   1.0707   2.3027
#
# Coefficients:
#              Estimate Std. Error z value Pr(>|z|)

```

```

# (Intercept)          0.34667    0.47978    0.723 0.469952
# Rating                0.11254    0.06234    1.805 0.071023 .
# SleeveLengthshort   -0.93085    0.34939   -2.664 0.007717 **
#   Seasonspring          0.99478    0.28005    3.552 0.000382 ***
#   Priceaverage         -1.51381    0.43483   -3.481 0.000499 ***
#   Pricehigh           -1.89949    0.66761   -2.845 0.004438 **
#   Pricelow            -1.27682    0.44875   -2.845 0.004437 **
#   Style_cute_dmy        0.75404    0.41060    1.836 0.066291 .
# Material_cashmere_dmy  18.18322  1673.79498    0.011 0.991332
# Material_cotton_dmy    0.54066    0.30371    1.780 0.075045 .
# Material_nylon_dmy     1.79219    0.93712    1.912 0.055820 .
# Material_other_dmy     0.67130    0.30329    2.213 0.026868 *
#   NeckLine_bowneck_dmy -2.31276    1.22527   -1.888 0.059086 .
# NeckLine_oneck_dmy     -0.48007    0.25648   -1.872 0.061240 .
# NeckLine_peterpancollor_dmy -16.31541  1062.88934   -0.015 0.987753
# NeckLine_squarecollor_dmy -16.37607  1331.12285   -0.012 0.990184
# NeckLine_turndowncollor_dmy -1.37713    0.85106   -1.618 0.105633
# Material_acrylic_dmy   -16.23737  1267.73560   -0.013 0.989781
# ---
#   signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.2  on 349  degrees of freedom
# Residual deviance: 400.6  on 332  degrees of freedom
# AIC: 436.6
#
# Number of Fisher Scoring iterations: 15

vif(fitA)
# Rating                SleeveLengthshort          Seasonspring
# 1.061180                1.053520                1.041168
# Priceaverage            Pricehigh                Pricelow
# 3.247463                1.572441                3.264356
# Style_cute_dmy          Material_cashmere_dmy      Material_cotton_dmy
# 1.061364                1.000000                1.367792
# Material_nylon_dmy      Material_other_dmy        NeckLine_bowneck_dmy
# 1.082365                1.339567                1.037920
# NeckLine_oneck_dmy      NeckLine_peterpancollor_dmy NeckLine_squarecollor_dmy
# 1.123985                1.000000                1.000000
# NeckLine_turndowncollor_dmy Material_acrylic_dmy
# 1.053661                1.000000

fitB = update(fitA, ~. -Material_cashmere_dmy)
summary(fitB)
# Call:
#   glm(formula = Recommendation ~ Rating + SleeveLengthshort + Seasonspring +
#       Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
#       Material_cotton_dmy +
#       Material_nylon_dmy + Material_other_dmy + NeckLine_bowneck_dmy +
#       NeckLine_oneck_dmy + NeckLine_peterpancollor_dmy +
#       NeckLine_squarecollor_dmy +
#       NeckLine_turndowncollor_dmy + Material_acrylic_dmy, family =
#       binomial(link = "logit"),
#       data = Training1)
#
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -1.8934 -0.9870 -0.5844  1.0852  2.2515
#
# Coefficients:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept)    0.54754    0.47564   1.151 0.249660
# Rating          0.09176    0.06111   1.502 0.133216
# SleeveLengthshort -0.95207    0.34801  -2.736 0.006223 **
#   Seasonspring      0.95360    0.27778    3.433 0.000597 ***
#   Priceaverage     -1.55369    0.43373   -3.582 0.000341 ***
#   Pricehigh       -1.96566    0.66635   -2.950 0.003179 **
#   Pricelow        -1.33749    0.44831   -2.983 0.002851 **
#   Style_cute_dmy    0.69720    0.40843    1.707 0.087819 .
# Material_cotton_dmy  0.47177    0.29970    1.574 0.115456
# Material_nylon_dmy  1.71483    0.93623    1.832 0.067005 .

```



```

# Material_other_dmy          0.60293    0.30043    2.007 0.044759 *
# NeckLine_owneck_dmy        -0.49381    0.25503   -1.936 0.052835 .
# NeckLine_peterpancollor_dmy -16.34696 1063.39050   -0.015 0.987735
# NeckLine_squarecollor_dmy   -16.41475 1334.86486   -0.012 0.990189
# NeckLine_turndowncollor_dmy -1.39579    0.85092   -1.640 0.100937
# Material_acrylic_dmy        -16.25407 1280.40697   -0.013 0.989872
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 406.58  on 333  degrees of freedom
# AIC: 440.58
#
# Number of Fisher Scoring iterations: 15

vif(fitB)
# Rating          SleeveLengthshort          Seasonspring
# 1.054818          1.054156          1.039644
# Priceaverage          Pricehigh          Pricelow
# 3.287177          1.580767          3.305692
# Style_cute_dmy          Material_cotton_dmy          Material_nylon_dmy
# 1.051321          1.349244          1.078984
# Material_other_dmy          NeckLine_owneck_dmy          NeckLine_owneck_dmy
# 1.324937          1.044119          1.131673
# NeckLine_peterpancollor_dmy          NeckLine_squarecollor_dmy          NeckLine_turndowncollor_dmy
# 1.000000          1.000000          1.052936
# Material_acrylic_dmy
# 1.000000

fitC = update(fitB, ~. -NeckLine_squarecollor_dmy)
summary(fitC)
# Call:
#      glm(formula = Recommendation ~ Rating + SleeveLengthshort + Seasonspring +
# Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
# Material_cotton_dmy +
# Material_nylon_dmy + Material_other_dmy + NeckLine_owneck_dmy +
# NeckLine_owneck_dmy + NeckLine_peterpancollor_dmy +
# NeckLine_turndowncollor_dmy +
# Material_acrylic_dmy, family = binomial(link = "logit"),
#      data = Training1)
#
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -1.8942  -0.9898  -0.5997   1.0740   2.2593
#
# Coefficients:
#      Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.45653    0.46807    0.975 0.329389
# Rating            0.08383    0.06080    1.379 0.167927
# SleeveLengthshort -0.98408    0.34822   -2.826 0.004712 **
# Seasonspring          0.97022    0.27692    3.504 0.000459 ***
# Priceaverage        -1.49451    0.42317   -3.532 0.000413 ***
# Pricehigh          -1.88071    0.65997   -2.850 0.004376 **
# Pricelow           -1.25546    0.43834   -2.864 0.004182 **
# Style_cute_dmy       0.71755    0.40791    1.759 0.078559 .
# Material_cotton_dmy    0.46934    0.29748    1.578 0.114626
# Material_nylon_dmy    1.73300    0.93587    1.852 0.064063 .
# Material_other_dmy    0.63440    0.29877    2.123 0.033724 *
# NeckLine_owneck_dmy   -1.42779    0.92270   -1.547 0.121767
# NeckLine_owneck_dmy   -0.44909    0.25342   -1.772 0.076375 .
# NeckLine_peterpancollor_dmy -16.27854 1065.20921   -0.015 0.987807
# NeckLine_turndowncollor_dmy -1.33417    0.84929   -1.571 0.116201
# Material_acrylic_dmy  -16.25203 1276.21595   -0.013 0.989840
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#

```

```

# Null deviance: 476.20 on 349 degrees of freedom
# Residual deviance: 410.18 on 334 degrees of freedom
# AIC: 442.18
#
# Number of Fisher Scoring iterations: 15

vif(fitC)
# Rating                SleeveLengthshort                Seasonspring
# 1.050076                1.061667                1.039557
# Priceaverage                Pricehigh                Pricelow
# 3.155762                1.550552                3.174590
# Style_cute_dmy                Material_cotton_dmy                Material_nylon_dmy
# 1.052199                1.340407                1.078509
# Material_other_dmy                NeckLine_bowneck_dmy                NeckLine_oneck_dmy
# 1.316823                1.041896                1.129126
# NeckLine_peterpancollor_dmy NeckLine_turndowncollor_dmy                Material_acrylic_dmy
# 1.000000                1.050858                1.000000

fitD = update(fitC, .~. -Material_acrylic_dmy)
summary(fitD)
# Call:
#      glm(formula = Recommendation ~ Rating + SleeveLengthshort + Seasonspring +
#          Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
#          Material_cotton_dmy +
#          Material_nylon_dmy + Material_other_dmy + NeckLine_bowneck_dmy +
#          NeckLine_oneck_dmy + NeckLine_peterpancollor_dmy +
#          NeckLine_turndowncollor_dmy,
#          family = binomial(link = "logit"), data = Training1)
#
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -1.8960 -0.9796 -0.6046  1.0872  2.2685
#
# Coefficients:
#              Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.43909    0.46550   0.943  0.345542
# Rating            0.08414    0.06046   1.392  0.164046
# SleeveLengthshort -0.95823    0.34757  -2.757  0.005835 **
#   Seasonspring      0.95726    0.27556   3.474  0.000513 ***
#   Priceaverage     -1.52055    0.42232  -3.600  0.000318 ***
#   Pricehigh       -1.87801    0.65932  -2.848  0.004394 **
#   Pricelow        -1.26409    0.43649  -2.896  0.003779 **
#   Style_cute_dmy    0.64548    0.40143   1.608  0.107844
# Material_cotton_dmy  0.50826    0.29635   1.715  0.086333 .
# Material_nylon_dmy  1.75680    0.93507   1.879  0.060273 .
# Material_other_dmy  0.67397    0.29773   2.264  0.023595 *
#   NeckLine_bowneck_dmy -1.40320    0.91997  -1.525  0.127194
# NeckLine_oneck_dmy -0.45402    0.25253  -1.798  0.072198 .
# NeckLine_peterpancollor_dmy -15.27298   645.73236  -0.024  0.981130
# NeckLine_turndowncollor_dmy -1.33303    0.84996  -1.568  0.116801
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20 on 349 degrees of freedom
# Residual deviance: 413.45 on 335 degrees of freedom
# AIC: 443.45
#
# Number of Fisher Scoring iterations: 14

vif(fitD)
# Rating                SleeveLengthshort                Seasonspring
# 1.048515                1.059441                1.043693
# Priceaverage                Pricehigh                Pricelow
# 3.167561                1.549416                3.173094
# Style_cute_dmy                Material_cotton_dmy                Material_nylon_dmy
# 1.055153                1.336955                1.077464
# Material_other_dmy                NeckLine_bowneck_dmy                NeckLine_oneck_dmy
# 1.313407                1.041336                1.129971
# NeckLine_peterpancollor_dmy NeckLine_turndowncollor_dmy
# 1.000000                1.051007

```

```

fitE = update(fitD, ~. -NeckLine_peterpancollor_dmy)
summary(fitE)
# Call:
#       glm(formula = Recommendation ~ Rating + SleeveLengthshort + Seasonspring +
#           Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
Material_cotton_dmy +
#           Material_nylon_dmy + Material_other_dmy + NeckLine_bowneck_dmy +
#           NeckLine_oneck_dmy + NeckLine_turndowncollor_dmy, family =
binomial(link = "logit"),
#           data = Training1)
#
# Deviance Residuals:
#       Min       1Q   Median       3Q      Max
# -1.9019  -0.9833  -0.6134   1.1110   2.2867
#
# Coefficients:
#             Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.35941    0.45860   0.784 0.433211
# Rating           0.08481    0.05996   1.414 0.157239
# SleeveLengthshort -1.00047    0.34676  -2.885 0.003911 **
#   Seasonspring      0.98719    0.27471   3.594 0.000326 ***
#   Priceaverage     -1.50933    0.41590  -3.629 0.000284 ***
#   Pricehigh       -1.81508    0.65550  -2.769 0.005623 **
#   Pricelow        -1.23214    0.42978  -2.867 0.004145 **
#   Style_cute_dmy    0.62214    0.39614   1.570 0.116305
# Material_cotton_dmy  0.48039    0.29488   1.629 0.103294
# Material_nylon_dmy  1.77570    0.93457   1.900 0.057430 .
# Material_other_dmy  0.67125    0.29680   2.262 0.023719 *
#   NeckLine_bowneck_dmy -1.33344    0.91776  -1.453 0.146245
# NeckLine_oneck_dmy -0.38812    0.25072  -1.548 0.121619
# NeckLine_turndowncollor_dmy -1.25268    0.84858  -1.476 0.139889
# ---
#             signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 418.83  on 336  degrees of freedom
# AIC: 446.83
#
# Number of Fisher Scoring iterations: 4

fitF = update(fitE, ~. -Rating)
summary(fitF)
# Call:
#       glm(formula = Recommendation ~ SleeveLengthshort + Seasonspring +
#           Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
Material_cotton_dmy +
#           Material_nylon_dmy + Material_other_dmy + NeckLine_bowneck_dmy +
#           NeckLine_oneck_dmy + NeckLine_turndowncollor_dmy, family =
binomial(link = "logit"),
#           data = Training1)
#
# Deviance Residuals:
#       Min       1Q   Median       3Q      Max
# -2.0211  -0.9723  -0.6231   1.1324   2.1409
#
# Coefficients:
#             Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.6061    0.4245   1.428 0.153322
# SleeveLengthshort -0.9745    0.3441  -2.832 0.004629 **
#   Seasonspring      0.9756    0.2731   3.573 0.000353 ***
#   Priceaverage     -1.4678    0.4128  -3.556 0.000377 ***
#   Pricehigh       -1.7805    0.6499  -2.740 0.006153 **
#   Pricelow        -1.1723    0.4258  -2.753 0.005899 **
#   Style_cute_dmy    0.5822    0.3936   1.479 0.139120
# Material_cotton_dmy  0.4480    0.2930   1.529 0.126245
# Material_nylon_dmy  1.6741    0.9351   1.790 0.073396 .
# Material_other_dmy  0.6707    0.2960   2.266 0.023435 *
#   NeckLine_bowneck_dmy -1.3135    0.9092  -1.445 0.148527

```

```

# NeckLine_oneck_dmy          -0.3488      0.2482  -1.406 0.159826
# NeckLine_turndowncollor_dmy -1.2184      0.8508  -1.432 0.152095
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 420.87  on 337  degrees of freedom
# AIC: 446.87
#
# Number of Fisher Scoring iterations: 4

fitG = update(fitF, ~. -NeckLine_oneck_dmy)
summary(fitG)
# Call:
#      glm(formula = Recommendation ~ SleeveLengthshort + Seasonspring +
#      Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
#      Material_cotton_dmy +
#      Material_nylon_dmy + Material_other_dmy + NeckLine_bowneck_dmy +
#      NeckLine_turndowncollor_dmy, family = binomial(link = "logit"),
#      data = Training1)
#
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -2.1183  -0.9698  -0.6140   1.1091   2.0829
#
# Coefficients:
#      Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.4605      0.4096   1.124 0.260904
# SleeveLengthshort -0.9707      0.3441  -2.821 0.004789 **
# Seasonspring      0.9641      0.2716   3.549 0.000386 ***
# Priceaverage     -1.5378      0.4091  -3.759 0.000171 ***
# Pricehigh       -1.7284      0.6467  -2.672 0.007529 **
# Pricelow        -1.2619      0.4207  -3.000 0.002703 **
# Style_cute_dmy      0.5657      0.3904   1.449 0.147308
# Material_cotton_dmy  0.4752      0.2917   1.629 0.103333
# Material_nylon_dmy  1.7296      0.9241   1.872 0.061264 .
# Material_other_dmy  0.7068      0.2946   2.399 0.016447 *
# NeckLine_bowneck_dmy -1.1242      0.9038  -1.244 0.213554
# NeckLine_turndowncollor_dmy -1.0299      0.8431  -1.222 0.221874
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 422.84  on 338  degrees of freedom
# AIC: 446.84
#
# Number of Fisher Scoring iterations: 4

fitH = update(fitG, ~. -NeckLine_turndowncollor_dmy)
summary(fitH)
# Call:
#      glm(formula = Recommendation ~ SleeveLengthshort + Seasonspring +
#      Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
#      Material_cotton_dmy +
#      Material_nylon_dmy + Material_other_dmy + NeckLine_bowneck_dmy,
#      family = binomial(link = "logit"), data = Training1)
#
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -2.108  -1.018  -0.678   1.115   2.092
#
# Coefficients:
#      Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.4276      0.4080   1.048 0.294618
# SleeveLengthshort -0.9665      0.3429  -2.819 0.004816 **
# Seasonspring      0.9632      0.2703   3.563 0.000367 ***
# Priceaverage     -1.5311      0.4082  -3.751 0.000176 ***
# Pricehigh       -1.7018      0.6463  -2.633 0.008457 **

```

```

#           Pricelow             -1.2419      0.4194  -2.961 0.003065 **
#           Style_cute_dmy        0.5945      0.3897   1.525 0.127151
# Material_cotton_dmy      0.4382      0.2896   1.513 0.130163
# Material_nylon_dmy       1.7421      0.9239   1.886 0.059347 .
# Material_other_dmy       0.7166      0.2938   2.439 0.014731 *
#           Neckline_bowneck_dmy -1.0970      0.9063  -1.210 0.226099
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 424.58  on 339  degrees of freedom
# AIC: 446.58
#
# Number of Fisher Scoring iterations: 4

fitI = update(fitH, ~. -NeckLine_bowneck_dmy)
summary(fitI)

# Call:
#       glm(formula = Recommendation ~ SleeveLengthshort + Seasonspring +
#           Priceaverage + Pricehigh + Pricelow + Style_cute_dmy +
# Material_cotton_dmy +
#           Material_nylon_dmy + Material_other_dmy, family = binomial(link
# = "logit"),
#           data = Training1)
#
# Deviance Residuals:
#           Min       1Q   Median       3Q      Max
# -2.0859 -1.0132 -0.6814  1.1252  2.0960
#
# Coefficients:
#           Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.3544     0.4012   0.883 0.377060
# SleeveLengthshort -0.9453     0.3412 -2.771 0.005592 **
#           Seasonspring      0.9611     0.2693   3.569 0.000359 ***
#           Priceaverage     -1.4878     0.4047  -3.676 0.000237 ***
#           Pricehigh      -1.6424     0.6435  -2.552 0.010708 *
#           Pricelow       -1.1995     0.4155  -2.887 0.003892 **
#           Style_cute_dmy      0.5915     0.3918   1.510 0.131081
# Material_cotton_dmy      0.4457     0.2887   1.544 0.122652
# Material_nylon_dmy      1.7636     0.9234   1.910 0.056131 .
# Material_other_dmy      0.7394     0.2939   2.516 0.011870 *
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 426.24  on 340  degrees of freedom
# AIC: 446.24
#
# Number of Fisher Scoring iterations: 4

fitJ = update(fitI, ~. -Style_cute_dmy)
summary(fitJ)

# Call:
#       glm(formula = Recommendation ~ SleeveLengthshort + Seasonspring +
#           Priceaverage + Pricehigh + Pricelow + Material_cotton_dmy +
#           Material_nylon_dmy + Material_other_dmy, family = binomial(link
# = "logit"),
#           data = Training1)
#
# Deviance Residuals:
#           Min       1Q   Median       3Q      Max
# -2.1006 -1.0098 -0.7043  1.0918  2.0414
#
# Coefficients:
#           Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.3996     0.3979   1.004 0.315148

```

```

# SleeveLengthshort    -0.8856      0.3358   -2.637 0.008366 **
#      Seasonspring      1.0070      0.2676    3.763 0.000168 ***
#      Priceaverage     -1.4648      0.4017   -3.647 0.000266 ***
#      Pricehigh        -1.5912      0.6397   -2.488 0.012863 *
#      Pricelow         -1.1791      0.4133   -2.853 0.004329 **
#      Material_cotton_dmy 0.4189      0.2870    1.459 0.144500
# Material_nylon_dmy    1.6709      0.9201    1.816 0.069370 .
# Material_other_dmy    0.6831      0.2901    2.355 0.018539 *
#
# ---
#      Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 428.52  on 341  degrees of freedom
# AIC: 446.52
#
# Number of Fisher Scoring iterations: 4

fitK = update(fitJ, .~. -Material_cotton_dmy)
summary(fitK)
#
# Call:
#      glm(formula = Recommendation ~ SleeveLengthshort + Seasonspring +
#          Priceaverage + Pricehigh + Pricelow + Material_nylon_dmy +
#          Material_other_dmy, family = binomial(link = "logit"), data =
Training1)
#
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -2.0590 -0.9471 -0.6520  1.1392  1.9469
#
# Coefficients:
#      Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.5379      0.3860    1.393 0.163506
# SleeveLengthshort -0.8711      0.3348   -2.602 0.009264 **
#      Seasonspring      0.9517      0.2631    3.617 0.000298 ***
#      Priceaverage     -1.3991      0.3970   -3.524 0.000425 ***
#      Pricehigh        -1.5736      0.6379   -2.467 0.013626 *
#      Pricelow         -1.1071      0.4085   -2.710 0.006733 **
#      Material_nylon_dmy  1.4823      0.9089    1.631 0.102913
# Material_other_dmy  0.5022      0.2596    1.934 0.053067 .
#
# ---
#      Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 430.66  on 342  degrees of freedom
# AIC: 446.66
#
# Number of Fisher Scoring iterations: 4

fitL = update(fitK, .~. -Material_nylon_dmy)
summary(fitL)
# Call:
#      glm(formula = Recommendation ~ SleeveLengthshort + Seasonspring +
#          Priceaverage + Pricehigh + Pricelow + Material_other_dmy,
#          family = binomial(link = "logit"), data = Training1)
#
# Deviance Residuals:
#      Min       1Q   Median       3Q      Max
# -2.0408 -0.9661 -0.6689  1.1339  1.9321
#
# Coefficients:
#      Estimate Std. Error z value Pr(>|z|)
# (Intercept)      0.5515      0.3853    1.431 0.152338
# SleeveLengthshort -0.8637      0.3333   -2.591 0.009568 **
#      Seasonspring      0.9381      0.2620    3.581 0.000342 ***
#      Priceaverage     -1.3864      0.3960   -3.501 0.000463 ***
#      Pricehigh        -1.3952      0.6180   -2.258 0.023969 *

```

```

#          Pricelow          -1.0712      0.4072  -2.631 0.008512 **
#          Material_other_dmy      0.4595      0.2576   1.784 0.074494 .
# ---
#          signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# (Dispersion parameter for binomial family taken to be 1)
#
# Null deviance: 476.20  on 349  degrees of freedom
# Residual deviance: 433.52  on 343  degrees of freedom
# AIC: 447.52
#
# Number of Fisher Scoring iterations: 4

#Looks like we can't pool any more insignificant terms.
# Material_other_dmy  is marginally significant as it has p-val 0.07 which is not
that far from 0.05 threshold alpha value which we assumed above.
# all of the above independent terms are significant

# But fitL has AIC 447.52 when the last of stepaic was only 436. Hence we need to go
with that itself
# This was just done to check if we could do something to improvise.
# The only possible explanation could be we have just seen main effects
# Probably interaction is needed and some of the insignificant terms could be useful
to make something else significant.
# anyway for now lets consider this mylogit as the final logit run

mylogit$coefficients
# (Intercept)                Rating                SleeveLengthshort
# 0.4921253                0.1057431                -0.9575346
# Seasonspring                Priceaverage                Pricehigh
# 0.9847531                -1.6305465                -2.0189868
# Pricelow                Style_cute_dmy                Style_OL_dmy
# -1.3933465                0.7471881                -17.6393730
# Material_cashmere_dmy                Material_cotton_dmy                Material_nylon_dmy
# 18.1105515                0.5811792                1.7934062
# Material_other_dmy                NeckLine_bowneck_dmy                NeckLine_oneck_dmy
# 0.6699423                -2.3582023                -0.4957287
# NeckLine_peterpancollor_dmy                NeckLine_squarecollor_dmy                NeckLine_turndowncollor_dmy
# -16.3604505                -16.4363868                -1.4237090
# Material_acrylic_dmy
# -16.2223475

mylogit$fitted.values
Pred = predict(mylogit, newdata = Training1[,-7], type= "response") # checking this
with above

sum(mylogit$fitted.values - Pred) # just to show both are equal- diff is 0

#Now to predict the test data
Pred_Test = predict(mylogit, newdata = Testing1[,-7], type= "response")

#This is training datas below
Pred1 = ifelse(Pred <0.5,0,1) # making it binary - converting probability values as 0
and 1

Pred_Test1 = ifelse(Pred_Test <0.5,0,1) # making it binary - converting probability
values as 0 and 1

library(e1071)

a = table(Training1$Recommendation, Pred1, dnn = list('actual','predicted'))

#          predicted
# actual      0      1
# 0          163    40
# 1           71    76

caret::confusionMatrix(a, positive = '1')

predicted

```

```

actual  0  1
0 163  40
1  71  76
> caret::confusionMatrix(a, positive = '1')
Confusion Matrix and Statistics

# predicted
# actual  0  1
# 0 163  40
# 1  71  76
#
# Accuracy : 0.6829
# 95% CI : (0.6313, 0.7313)
# No Information Rate : 0.6686
# P-Value [Acc > NIR] : 0.306371
#
# Kappa : 0.3295
#
# Mcnemar's Test P-Value : 0.004407
#
#           Sensitivity : 0.6552
#           Specificity : 0.6966
#           Pos Pred Value : 0.5170
#           Neg Pred Value : 0.8030
#           Prevalence : 0.3314
#           Detection Rate : 0.2171
#           Detection Prevalence : 0.4200
#           Balanced Accuracy : 0.6759
#
#           'Positive' Class : 1

#Checking the testing dataset
atest = table(Testing1$Recommendation, Pred_Test1, dnn = list('actual','predicted'))
atest
caret::confusionMatrix(atest, positive = '1')

#install.packages("InformationValue")
library(InformationValue)

plotROC(actuals=Training1$Recommendation, predictedScores=Pred1)

#visually inspecting sensitivity plot
sensMat <- plotROC(actuals=Training1$Recommendation, predictedScores=Pred1,
returnSensitivityMat = TRUE)
sensMat

#Sensitivity, also considered as the 'True Positive Rate' or 'recall' is the
# proportion of 'Events' (or 'Ones') correctly predicted by the model,
# for a given prediction probability cutoff score

# For a given probability score cutoff (threshold), precision or 'positive predictive
value'
# computes the proportion of the total events (ones) out of the total that were
predicted
# to be events (ones).

precision(actuals=Training1$Recommendation,
predictedScores=Pred1)
# 0.6551724

# somersD computes how many more concordant than discordant pairs exist divided by the
# total number of pairs. Larger the Somers D value, better model's predictive ability
# Concordance is the percentage of predicted probability scores where the scores of
actual
# positive's are greater than the scores of actual negative's.
# It is calculated by taking into account the scores of all possible pairs of Ones
# and Zeros. If the concordance of a model is 100%, it means that,
# by tweaking the prediction probability cutoff, we could accurately predict
# all of the events and non-events

```



```

somersD(actuals=Training1$Recommendation,
         predictedScores=Pred) # we are using Pred instead of Pred1 (binary values)
because somersD uses actual prediction values
#0.4887571

ks_stat(actuals=Training1$Recommendation,
        predictedScores=Pred)
# [1] 0.3343

ks_plot(actuals=Training1$Recommendation,
        predictedScores=Pred)

# ks_plot plots the lift is capturing the responders (Ones) against the the random
# case
# where we don't use the model. The more curvier (higher) the model curve,
# the better is the model.

#For example, from the above chart for instance, by targeting first 40% of the Dress,
# the model will be able to capture 58.5% of total responders(Ones),
# while without the model, you can expect to capture only 40% of responders by random
# targeting.

# Based on the ks_plot and ROC curve, we have a decent model . Still we are going to
# explore Decision Tree/RF
####Start DT

# first creating training and testing of data so that we can validate model later
set.seed(123)
inTrain <- createDataPartition(ATT_DS$Recommendation,p = 0.7, list = FALSE)

ATT_DS3 <- ATT_DS2 %>%
  mutate(RatingClass = cut(Rating,c(-0.1,4,max(Rating))),
         labels = c("<=4",">4"))%>%
  mutate_if(is.numeric,as.factor) %>%
  mutate_if(is.character,as.factor) # for DT lets use this dataset

Training = ATT_DS3[inTrain,]
Testing = ATT_DS3[-inTrain,]

# since rating is numeric and has 16 values, lets use cut and make it into few groups
# to make it easier to view
# Training %>%
#   dplyr::select(c(2:8,32:91)) %>%
#   mutate(RatingClass = cut(Rating,c(-0.1,1,2,3,4,max(Rating))),
#          labels = c("0-1","1-2","2-3","3-4","4-5"))
# %>%
#   dplyr::select(RatingClass) %>% table()

# 0-1 1-2 2-3 3-4 4-5
# 89   0   1   6 254
# Testing %>% dplyr::select(c(2:8,32:91)) %>%
#   mutate(RatingClass = cut(Rating,c(-0.1,1,2,3,4,max(Rating))),
#          labels = c("0-1","1-2","2-3","3-4","4-5")) %>%
#   dplyr::select(RatingClass) %>% table()
#
# 0-1 1-2 2-3 3-4 4-5
# 32   0   0   5 112

#so max rating is either 4-5 or 0-1 with very few in 3-4; so lets cut it into two >=4
# or less than 4
Training1 <- Training %>% dplyr::select(c(2:8,32:92)) %>%
  dplyr::select(-c(Rating))

Testing1 <- Testing %>% dplyr::select(c(2:8,32:92)) %>%
  dplyr::select(-c(Rating))

# Now for DT, we need rpart and rpart.plot; Referred based on Dec 18 class of Kapi1
library(rpart)
library(rpart.plot)

```

```

fit = rpart(Recommendation ~ ., method = "class", data = Training1) # method = class
for classification tree;
rpart.plot(fit, cex=0.5)

#suppose we wish to prune the tree we could use the option rpart.control below. but
testing the different values, the minsplit of 30 which was the one chosen above
without using the option by default seems to be the best model in this
fit = rpart(Recommendation ~ ., method = "class", data = Training1,
            control = rpart.control(minsplit = 40))## minimum 30 data records need to
be there to split further

rpart.plot(fit, cex=0.5, extra = 1) # using absolute values
rpart.plot(fit, cex=0.7)

#now lets validate the model using Test data

Pred = predict(fit, newdata = Testing1[, -6], type = "class") # without the dependent
column as best practice; Sourcing my model fit to it

table(Pred)
# Pred
# 0    1
# 109  40

a = table(Testing1$Recommendation, Pred, dnn = list("actual", "predicted"))

caret::confusionMatrix(a, positive = "1")
# Confusion Matrix and Statistics
#
# predicted
# actual 0  1
# 0  70 16
# 1  39 24
#
# Accuracy : 0.6309
# 95% CI : (0.548, 0.7084)
# No Information Rate : 0.7315
# P-Value [Acc > NIR] : 0.997297
#
# Kappa : 0.2049
#
# Mcnemar's Test P-Value : 0.003012
#
#           Sensitivity : 0.6000
#           Specificity : 0.6422
#           Pos Pred Value : 0.3810
#           Neg Pred Value : 0.8140
#           Prevalence : 0.2685
#           Detection Rate : 0.1611
#           Detection Prevalence : 0.4228
#           Balanced Accuracy : 0.6211
#
#           'Positive' Class : 1

# Looking at the metrics (62.11% for balanced accuracy) of DT, it looks slightly
better than logistic regression

####end DT

#### Random Forest- lets try another algo as well
library(randomForest)

F1 = randomForest(Recommendation ~ ., data = Training1, ntree = 1000)
#Error in eval(predvars, data, env) : object 'Pattern Type' not found
#Guessing its not accepting spaces in the variable names- hence lets rename that in
both training and test

Training1 <- Training1 %>% rename(Pattern_Type = `Pattern Type`)
Testing1 <- Testing1 %>% rename(Pattern_Type = `Pattern Type`)
set.seed(2345)
F1 = randomForest(Recommendation ~ ., data = Training1, ntree = 3000) #3000 trees used

```

```

aa= predict(F1,Testing1,type ="vote")
aa1 = ifelse(aa[,2]>0.5,"Good","Bad")
table(Testing1$Recommendation,aa1)

aa = predict(F1, newdata = Testing1[,-6], type="class") # without the dependent column
as best practice; Sourcing my model fit to it

table(aa)
# Pred
# 0    1
# 95   54

b= table(Testing1$Recommendation, aa, dnn = list("actual","predicted"))

caret::confusionMatrix(b, positive ="1")
#
# Confusion Matrix and Statistics
#
# predicted
# actual  0   1
# 0  64  22
# 1  31  32
#
# Accuracy : 0.6443
# 95% CI : (0.5618, 0.7209)
# No Information Rate : 0.6376
# P-Value [Acc > NIR] : 0.4692
#
# Kappa : 0.257
#
# Mcnemar's Test P-Value : 0.2718
#
#           Sensitivity : 0.5926
#           Specificity : 0.6737
#           Pos Pred Value : 0.5079
#           Neg Pred Value : 0.7442
#           Prevalence : 0.3624
#           Detection Rate : 0.2148
#           Detection Prevalence : 0.4228
#           Balanced Accuracy : 0.6331
#
#           'Positive' Class : 1

####End Random Forest <best Balanced Accuracy/Sensitivity: 0.6331>;
#There are other metrics too (sensitivity/specificity).
#So depending on what is more important to us for the biz decision, we can choose that
as our model - Lets choose Log Reg as our model
#But Random forest overall performs best among these 3

#### Task 2: In order to stock the inventory, the store wants to analyze the sales
data and predict the trend of total sales for each dress for an extended period of
three more alternative days.

DS_DS_T <- DS_DS %>% group_by(Dress_ID) %>% gather(key = "DateofSale", value =
"Sales",

names(DS_DS)[2:length(names(DS_DS))] ) %>%
  ungroup() %>%
  arrange(Dress_ID)
DS_DS_T <- DS_DS_T %>% mutate(max3rdpart = str_split(DS_DS_T$DateofSale,"-")) %>%
  separate(max3rdpart, c("A", "B","C","D")) %>% dplyr::select(-c(A))
DS_DS_T <- DS_DS_T %>% group_by(Dress_ID) %>%
  mutate(lagD = lag(D)) %>%
  ungroup()
DS_DS_T <- DS_DS_T %>%
  mutate( DateofSale = ifelse((as.numeric(D) - as.numeric(lagD) <=0) &
!is.na(lagD),paste(B,D,C,sep='-'),DateofSale))
DS_DS_T <- DS_DS_T %>% dplyr::select(1:3) %>% mutate(DateofSale =
as.Date(parse_date_time(DateofSale,orders =c("y-m-d"))))

```

```

ggplot(data = DS_DS_T , aes(x = DateofSale, y = Sales)) +
  geom_line(aes(x = DateofSale, y = Sales,color = factor(Dress_ID))) +
  #geom_line(col = "hotpink") +
  #ylim(0, 8000) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none")

library(forecast)
# DS_DS_T2 <- DS_DS_T %>%
#   group_by(Dress_ID) %>% mutate(arima1 = nest(auto.arima(as.ts(Sales)))) %>%
#   ungroup()
# arima1

#out of the 23 date records for every dress id, lets consider 85 percent as training
#and rest as testing records
#inTrain2 <- createDataPartition(DS_DS_T$Sales,p = 0.7, list = FALSE)
train_index <- 1: floor(0.85 * 23 ) # nrow(input) is changed to n as we have already
calc for each SKU
test_index <- setdiff(1:23, train_index) # nrow(input) is changed to n as we have
already calc for each SKU

DS_DS_T <- DS_DS_T %>% group_by(Dress_ID) %>% mutate(SNO = 1:n(), TRAINTESTFIL =
ifelse(SNO <= train_index,"Train","Test")) %>% ungroup()

train <- dplyr::filter(DS_DS_T,TRAINTESTFIL == "Train")
test <- dplyr::filter(DS_DS_T,!TRAINTESTFIL == "Train")

summary(train$Sales)
# Min. 1st Qu. Median Mean 3rd Qu. Max.
# 0.0 5.0 73.0 275.3 275.0 7479.0

library(fpp2)

train_all <- train %>%
  group_by(DateofSale,SNO,TRAINTESTFIL) %>%
  summarise(Sales = sum(Sales,na.rm = T)) %>%
  ungroup() %>% dplyr::select(1,2,4,3) %>%
  padr::pad(interval = "day") %>%
  tidyr::fill(SNO,TRAINTESTFIL) %>%
  mutate(Sales = if_else(is.na(Sales), 0, Sales))

test_all <- test %>%
  group_by(DateofSale,SNO,TRAINTESTFIL) %>%
  summarise(Sales = sum(Sales,na.rm = T)) %>%
  ungroup() %>% dplyr::select(1,2,4,3) %>%
  padr::pad(interval = "day") %>%
  tidyr::fill(SNO,TRAINTESTFIL) %>%
  mutate(Sales = if_else(is.na(Sales), 0, Sales))

#Declaring train as a time-series data

Y <- ts(train_all[,3],start = c(2013, as.numeric(format(train$DateofSale[1], "%j"))),
#starting date
      end = c(2013,as.numeric(format(train$DateofSale[9025], "%j"))), # end
date from last available dt
      frequency = 365)

#####preliminary analysis#####

#Time Plot
autoplot(Y) +
  ggtitle("Time Plot of Sales") +
  ylab("Total Sales")+ theme_bw()

ggplot(data = train_all , aes(x = DateofSale, y = Sales)) +

```

```

    geom_line(aes(x = DateofSale, y = Sales)) +
    scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
    theme_bw() + theme(legend.title = element_blank(),
                        axis.text.x = element_text(angle=45, vjust=0.5)) +
    theme(legend.position = "none")

#There is a slight trend. Investigate transformation
# Take the first difference to remove the trend

DY <- diff(Y)

options(scipen=7) #Do not want scientific notation on plot axis
#Time Plot of the differenced data
autoplot(DY) +
  ggtitle("Time Plot of Change in Sales") +
  ylab("Total Sales") + theme_bw()

#Series appears trend-stationary.

# Next Need to investigate seasonality but since we only have just two months we can
jump to algos, commenting the following hence
# ggseasonplot(DY) +
#   ggtitle("Seasonal Plot: Change in Daily Total Sales") +
#   ylab("Total Sales")+
#   theme_bw()

#ggsubseriesplot(DY)
# Error in ggsubseriesplot(DY) :
#   Each season requires at least 2 observations. Your series length may be too
short for this graphic.

#####
#Use a benchmark method to forecast
# Lets use ETS method as our bench mark
#####

fit_ets <- ets(Y)
print(summary(fit_ets))
# ETS(A,N,N)
#
# Call:
#   ets(y = Y)
#
# Smoothing parameters:
#   alpha = 0.0001
#
# Initial states:
#   l = 67152.9864
#
# sigma: 74776.39
#
# AIC      AICc      BIC
# 967.9949 968.7222 972.8277
#
# Training set error measures:
#           ME      RMSE      MAE  MPE MAPE MASE      ACF1
# Training set -7.099539 72727.33 67310.57 -Inf  Inf  NaN -0.8248643
# ME      RMSE      MAE  MPE MAPE MASE      ACF1
# Training set -7.099539 72727.33 67310.57 -Inf  Inf  NaN -0.8248643

checkresiduals(fit_ets) # Residual SD :74776.39 which is high

# Ljung-Box test
#
# data: Residuals from ETS(A,N,N)
# Q* = 205.63, df = 5, p-value < 2.2e-16
#
# Model df: 2. Total lags used: 7

#####
#Fit arima model - which needs to have stationary data

```

```
#####
fit_arima <- auto.arima(Y, d=1, stepwise = F, approximation = F, trace = T) #residual
sqrt(788991890) ~ 28089
# ARIMA(0,1,0) : 957.8362
# ARIMA(0,1,0) with drift : 960.0804
# ARIMA(0,1,1) : Inf
# ARIMA(0,1,1) with drift : Inf
# ARIMA(0,1,2) : Inf
# ARIMA(0,1,2) with drift : Inf
# ARIMA(0,1,3) : Inf
# ARIMA(0,1,3) with drift : Inf
# ARIMA(0,1,4) : Inf
# ARIMA(0,1,4) with drift : Inf
# ARIMA(0,1,5) : Inf
# ARIMA(0,1,5) with drift : Inf
# ARIMA(1,1,0) : 859.8935
# ARIMA(1,1,0) with drift : 862.2476
# ARIMA(1,1,1) : 861.1228
# ARIMA(1,1,1) with drift : 863.5355
# ARIMA(1,1,2) : 854.3237
# ARIMA(1,1,2) with drift : 856.8826
# ARIMA(1,1,3) : Inf
# ARIMA(1,1,3) with drift : Inf
# ARIMA(1,1,4) : Inf
# ARIMA(1,1,4) with drift : Inf
# ARIMA(2,1,0) : 862.274
# ARIMA(2,1,0) with drift : 864.7811
# ARIMA(2,1,1) : 861.284
# ARIMA(2,1,1) with drift : Inf
# ARIMA(2,1,2) : 857.0318
# ARIMA(2,1,2) with drift : 859.778
# ARIMA(2,1,3) : Inf
# ARIMA(2,1,3) with drift : Inf
# ARIMA(3,1,0) : 849.3568
# ARIMA(3,1,0) with drift : 851.9142
# ARIMA(3,1,1) : 852.0663
# ARIMA(3,1,1) with drift : 854.8084
# ARIMA(3,1,2) : Inf
# ARIMA(3,1,2) with drift : Inf
# ARIMA(4,1,0) : 852.0664
# ARIMA(4,1,0) with drift : 854.809
# ARIMA(4,1,1) : 854.7237
# ARIMA(4,1,1) with drift : 857.7211
# ARIMA(5,1,0) : 854.8037
# ARIMA(5,1,0) with drift : 857.7234
#
#
# Best model: ARIMA(3,1,0)

print(summary(fit_arima))
# Series: Y
# ARIMA(3,1,0)
#
# Coefficients:
# ar1 ar2 ar3
# -0.9865 -0.5833 -0.5749
# s.e. 0.1321 0.1826 0.1267
#
# sigma^2 estimated as 788991890: log likelihood=-420.03
# AIC=848.07 AICc=849.36 BIC=854.4
#
# Training set error measures:
# ME RMSE MAE MPE MAPE MASE ACF1
# Training set -2162.108 26527.26 14634.1 -Inf Inf NaN -0.02084238
# ME RMSE MAE MPE MAPE MASE ACF1
# Training set -2162.108 26527.26 14634.1 -Inf Inf NaN -0.02084238

checkresiduals(fit_arima)
```

```

# data: Residuals from ARIMA(3,1,0)
# Q* = 5.8982, df = 4, p-value = 0.2069
#
# Model df: 3. Total lags used: 7

# Residual dropped from ~74K to ~28K which was good and the ACF plot falls between
# the Confidence interval which is also good and the distribution of the residuals
# is also normal around 0 which is good. So lets use arima as our model to forecast

#####Forecast with ARIMA model####
fcst <- forecast(fit_arima, h =14) # 14 more days to forecast from the last of
training date to get 3 more additional alternate days

autoplot(fcst)+
  theme_bw()
#Looks realistic as the previous few days sales was low, its forecasting low sales
like those first few days of oct
autoplot(fcst, include = 21) +
  theme_bw() # last 21 days or 3 weeks before the prediction period (just
zooming the forecast plot)

check_pred <- bind_rows(train_all,test_all) %>%
  padr::pad(interval = "day", end_val = as.Date("2013-10-18"))
check_pred <- check_pred %>%
  dplyr::mutate(Sales = if_else(is.na(Sales) & check_pred$DateofSale <= "2013-
10-12",
                                0, Sales))

check_pred2 <- data.frame(DateofSale = check_pred$DateofSale,
                          Sales = c(fcst$fitted[1:37],fcst$mean[1:14]))
bandds <- data.frame(DateofSale = filter(check_pred, DateofSale >="2013-10-
05")$DateofSale, LOWER95 = as.numeric(fcst$lower[,2]),
                    UPPER95 = as.numeric(fcst$upper[,2]))
bandds2 <- data.frame(DateofSale = filter(check_pred, DateofSale >="2013-10-
05")$DateofSale,
                     LOWER80 = as.numeric(fcst$lower[,1]),
                     UPPER80 = as.numeric(fcst$upper[,1]))

ggplot(data = check_pred , aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  geom_ribbon(data = bandds,aes(ymin = LOWER95, ymax = UPPER95), fill = "pink",
alpha = 0.4)+
  geom_ribbon(data = bandds2,aes(ymin = LOWER80, ymax = UPPER80), fill = "pink",
alpha = 0.6)+
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() +
  ylab("Total Sales")+
  theme(legend.title = element_blank(),
        axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = check_pred2, aes(y = Sales),color = "red")+
  labs(caption = "red line - prediction median, black line - original data; dark
and light red bands are 80% and 95 % CI of forecasts")

ggplot(data = check_pred %>% filter(Sales >0) , aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  geom_ribbon(data = bandds,aes(ymin = max(LOWER95,0), ymax = UPPER95), fill =
"pink", alpha = 0.4)+
  geom_ribbon(data = bandds2,aes(ymin = max(LOWER80,0), ymax = UPPER80), fill =
"pink", alpha = 0.6)+
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  ylab("Total Sales")+
  geom_line(data = check_pred2[!as.numeric(row.names(check_pred2)) % 2 ==0,],
            aes( y = Sales),color = "red")+
  labs(caption = "red line - prediction median, black line - original data; dark
and light red bands are 80% and 95 % CI of forecasts")

```

```

# Based on the plot just looking at the alternate days (data provided to us),
# looks like the model considering the Train:Test split as 85% doesn't do well as per
the
# Test data as there is a huge fluctuation after the split i.e. after
# max(train$DateofSale) ~ "2013-10-04", there seems to be some promotion or some sale
# or discount or could be some event (public holiday etc.) depending on what location
this
# shop is in. So instead of considering train:test split as 85%, had we considered it
# as 90% or 70%, we might have been able to capture one or both of the two peaks of
the test
# i.e on the 6th oct, lets check once more with 70% train test split
#Repeating the same steps as above

#out of the 23 date records for every dress id, lets consider 70 percent as training
and rest as testing records
train_index <- 1: floor(0.7 * 23 ) # nrow(input) is changed to n as we have already
calc for each SKU
test_index <- setdiff(1:23, train_index) # nrow(input) is changed to n as we have
already calc for each SKU

DS_DS_T <- DS_DS_T %>% group_by(Dress_ID) %>% mutate(SNO = 1:n(), TRAINTESTFIL =
ifelse(SNO <= train_index,"Train","Test")) %>% ungroup()

train <- dplyr::filter(DS_DS_T,TRAINTESTFIL == "Train")
test <- dplyr::filter(DS_DS_T,!TRAINTESTFIL == "Train")

summary(train$Sales)
# Min. 1st Qu. Median Mean 3rd Qu. Max.
# 0.0 16.0 101.0 305.2 318.0 7479.0

train_all <- train %>%
  group_by(DateofSale,SNO,TRAINTESTFIL) %>%
  summarise(Sales = sum(Sales,na.rm = T)) %>%
  ungroup() %>% dplyr::select(1,2,4,3) %>%
  padr::pad(interval = "day") %>%
  tidyr::fill(SNO,TRAINTESTFIL) %>%
  mutate(Sales = if_else(is.na(Sales), 0, Sales))

test_all <- test %>%
  group_by(DateofSale,SNO,TRAINTESTFIL) %>%
  summarise(Sales = sum(Sales,na.rm = T)) %>%
  ungroup() %>% dplyr::select(1,2,4,3) %>%
  padr::pad(interval = "day") %>%
  tidyr::fill(SNO,TRAINTESTFIL) %>%
  mutate(Sales = if_else(is.na(Sales), 0, Sales))

#Declaring train as a time-series data
Y <- ts(train_all[,3],start = c(2013, as.numeric(format(train$DateofSale[1], "%j"))),
#starting date
end = c(2013,as.numeric(format(train$DateofSale[length(train$DateofSale)],
"%j"))), # end date from last available dt
frequency = 365)

#####preliminary analysis#####

#Time Plot
autoplot(Y) +
  ggtitle("Time Plot of Sales") +
  ylab("Total Sales")+ theme_bw()

ggplot(data = train_all , aes(x = DateofSale, y = Sales)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none")

#There is a slight trend. Investigate transformation
# Take the first difference to remove the trend

```



```

DY <- diff(Y)

options(scipen=7) #Do not want scientific notation on plot axis
#Time Plot of the differenced data
autoplot(DY) +
  ggtitle("Time Plot of Change in Sales") +
  ylab("Total Sales") + theme_bw()

#Series appears trend-stationary.

# Next Need to investigate seasonality but since we only have just two months we can
# jump to algos, commenting the following hence
# ggseasonplot(DY) +
#   ggtitle("Seasonal Plot: Change in Daily Total Sales") +
#   ylab("Total Sales")+
#   theme_bw()

#ggsubseriesplot(DY)
# Error in ggsubseriesplot(DY) :
#   Each season requires at least 2 observations. Your series length may be too
# short for this graphic.

#####
#Use a benchmark method to forecast
# Lets use ETS method as our bench mark
#####

fit_ets <- ets(Y)
print(summary(fit_ets))
# ETS(A,N,N)
#
# Call:
#   ets(y = Y)
#
# Smoothing parameters:
#   alpha = 0.0001
#
# Initial states:
#   l = 74836.1411
#
# sigma: 78762.66
#
# AIC      AICc      BIC
# 809.3862 810.2751 813.6882
#
# Training set error measures:
#           ME      RMSE      MAE  MPE MAPE  MASE      ACF1
# Training set -3.338684 76179.57 72414.18 -Inf  Inf  NaN -0.8806181
# ME      RMSE      MAE  MPE MAPE  MASE      ACF1
# Training set -3.338684 76179.57 72414.18 -Inf  Inf  NaN -0.8806181

checkresiduals(fit_ets) # Residual SD :78762.66 which is high

# Ljung-Box test
#
# data: Residuals from ETS(A,N,N)
# Q* = 160.67, df = 4, p-value < 2.2e-16
#
# Model df: 2. Total lags used: 6

#####
#Fit arima model - which needs to have stationary data
#####

fit_arima <- auto.arima(Y, d=1,stepwise = F,approximation = F,trace = T) #residual
sqrt(810727537) ~ 28473.28
# ARIMA(0,1,0) : 801.8936
# ARIMA(0,1,0) with drift : 804.1821
# ARIMA(0,1,1) : Inf
# ARIMA(0,1,1) with drift : Inf

```

```

# ARIMA(0,1,2) : Inf
# ARIMA(0,1,2) with drift : Inf
# ARIMA(0,1,3) : Inf
# ARIMA(0,1,3) with drift : Inf
# ARIMA(0,1,4) : Inf
# ARIMA(0,1,4) with drift : Inf
# ARIMA(0,1,5) : Inf
# ARIMA(0,1,5) with drift : Inf
# ARIMA(1,1,0) : Inf
# ARIMA(1,1,0) with drift : Inf
# ARIMA(1,1,1) : 709.2702
# ARIMA(1,1,1) with drift : 711.451
# ARIMA(1,1,2) : Inf
# ARIMA(1,1,2) with drift : Inf
# ARIMA(1,1,3) : Inf
# ARIMA(1,1,3) with drift : Inf
# ARIMA(1,1,4) : Inf
# ARIMA(1,1,4) with drift : Inf
# ARIMA(2,1,0) : Inf
# ARIMA(2,1,0) with drift : Inf
# ARIMA(2,1,1) : 709.8638
# ARIMA(2,1,1) with drift : Inf
# ARIMA(2,1,2) : Inf
# ARIMA(2,1,2) with drift : Inf
# ARIMA(2,1,3) : Inf
# ARIMA(2,1,3) with drift : Inf
# ARIMA(3,1,0) : Inf
# ARIMA(3,1,0) with drift : Inf
# ARIMA(3,1,1) : Inf
# ARIMA(3,1,1) with drift : Inf
# ARIMA(3,1,2) : Inf
# ARIMA(3,1,2) with drift : Inf
# ARIMA(4,1,0) : Inf
# ARIMA(4,1,0) with drift : Inf
# ARIMA(4,1,1) : Inf
# ARIMA(4,1,1) with drift : Inf
# ARIMA(5,1,0) : Inf
# ARIMA(5,1,0) with drift : Inf
#
#
# Best model: ARIMA(1,1,1)

print(summary(fit_arima))
# Series: Y
# ARIMA(1,1,1)
#
# Coefficients:
#      ar1      ma1
# -0.9644 -0.5525
# s.e.    0.0381    0.1924
#
# sigma^2 estimated as 810727537: log likelihood=-351.17
# AIC=708.35 AICc=709.27 BIC=712.55
#
# Training set error measures:
#      ME      RMSE      MAE MPE MAPE MASE      ACF1
# Training set 3013.953 27060.49 14414.72 NaN Inf NaN 0.09657674
# ME      RMSE      MAE MPE MAPE MASE      ACF1
# Training set 3013.953 27060.49 14414.72 NaN Inf NaN 0.09657674

checkresiduals(fit_arima)

# Ljung-Box test
#
# data: Residuals from ARIMA(1,1,1)
# Q* = 3.471, df = 4, p-value = 0.4823
#
# Model df: 2. Total lags used: 6

# Residual dropped from ~78K to ~28K which was good and the ACF plot falls between
# the Confidence interval which is also good and the distribution of the residuals

```

```

# is also normal around 0 which is good. So lets use arima as our model to forecast

#####Forecast with ARIMA model####
fcst <- forecast(fit_arima, h =20) # 20 more days to forecast from the last of
training date to get 3 more additional alternate days

autoplot(fcst)+
  theme_bw()
#Looks realistic as the previous few days sales was low, its forecasting low sales
like those first few days of oct
autoplot(fcst, include = 21) +
  theme_bw() # last 21 days or 3 weeks before the prediction period (just
zooming the forecast plot)

check_pred <- bind_rows(train_all,test_all) %>%
  padr::pad(interval = "day", end_val = as.Date("2013-10-18"))
check_pred <- check_pred %>%
  mutate(Sales = if_else(is.na(Sales) & check_pred$DateofSale <= "2013-10-12",
0, Sales))

check_pred2 <- data.frame(DateofSale = check_pred$DateofSale,
  Sales = c(fcst$fitted[1:31],fcst$mean[1:20]))

bandds <- data.frame(DateofSale = filter(check_pred, DateofSale >="2013-09-
29")$DateofSale, LOWER95 = as.numeric(fcst$lower[,2]),
  UPPER95 = as.numeric(fcst$upper[,2]))
bandds2 <- data.frame(DateofSale = filter(check_pred, DateofSale >="2013-09-
29")$DateofSale,
  LOWER80 = as.numeric(fcst$lower[,1]),
  UPPER80 = as.numeric(fcst$upper[,1]))

ggplot(data = check_pred , aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  geom_ribbon(data = bandds,aes(ymin = LOWER95, ymax = UPPER95), fill = "pink",
alpha = 0.4)+
  geom_ribbon(data = bandds2,aes(ymin = LOWER80, ymax = UPPER80), fill = "pink",
alpha = 0.6)+
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() +
  ylab("Total Sales")+
  theme(legend.title = element_blank(),
  axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = check_pred2, aes(y = Sales),color = "red")+
  labs(caption = "red line - prediction median, black line - original data; dark
and light red bands are 80% and 95 % CI of forecasts")

ggplot(data = check_pred %>% filter(Sales >0) , aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  geom_ribbon(data = bandds,aes(ymin = max(LOWER95,0), ymax = UPPER95), fill =
"pink", alpha = 0.4)+
  geom_ribbon(data = bandds2,aes(ymin = max(LOWER80,0), ymax = UPPER80), fill =
"pink", alpha = 0.6)+
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
  axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  ylab("Total Sales")+
  geom_line(data = check_pred2[!as.numeric(row.names(check_pred2)) % 2 ==0,],
  aes( y = Sales),color = "red")+
  labs(caption = "red line - prediction median, black line - original data; dark
and light red bands are 80% and 95 % CI of forecasts")

#This looks much better than previous forecast with 85:15 train test split.
# Still we see that had we known a prior event like 27 Sep date (some public holiday
etc)
# we could have predicted the drop accurately for 26th Sep instead of 28th Sep
# In this split we are over-predicting 30 Sep,20Oct and 4th Oct. whereas in the
# previous split we were more underpredicting the important sales day

```

```

# So based on the biz decision if under-predicting or over-predicting is more
# important to the company, we could decide which split to use

# P.S for this Forecasting exercise sought help based on a Youtube video by Adam Check
# His explanation was fantastic for forecasting in R
# https://www.youtube.com/watch?v=dBNy_A6Zpcc

library(prophet)
library(purrr)

####Prophet Check -start
#out of the 23 date records for every dress id, lets consider 70 percent as training
and rest as testing records
train_index <- 1: floor(0.7 * 23 ) # nrow(input) is changed to n as we have already
calc for each SKU
test_index <- setdiff(1:23, train_index) # nrow(input) is changed to n as we have
already calc for each SKU

DS_DS_T <- DS_DS_T %>% group_by(Dress_ID) %>% mutate(SNO = 1:n(), TRAINTESTFIL =
ifelse(SNO <= train_index,"Train","Test")) %>% ungroup()

train <- dplyr::filter(DS_DS_T,TRAINTESTFIL == "Train")
test <- dplyr::filter(DS_DS_T,!TRAINTESTFIL == "Train")

summary(train$Sales)
# Min. 1st Qu. Median Mean 3rd Qu. Max.
# 0.0 16.0 101.0 305.2 318.0 7479.0

train_all <- train %>%
  group_by(DateofSale,SNO,TRAINTESTFIL) %>%
  summarise(Sales = sum(Sales,na.rm = T)) %>%
  ungroup() %>% dplyr::select(1,2,4,3) %>%
  padr::pad(interval = "day") %>%
  tidyr::fill(SNO,TRAINTESTFIL) %>%
  mutate(Sales = if_else(is.na(Sales), 0, Sales))

test_all <- test %>%
  group_by(DateofSale,SNO,TRAINTESTFIL) %>%
  summarise(Sales = sum(Sales,na.rm = T)) %>%
  ungroup() %>% dplyr::select(1,2,4,3) %>%
  padr::pad(interval = "day") %>%
  tidyr::fill(SNO,TRAINTESTFIL) %>%
  mutate(Sales = if_else(is.na(Sales), 0, Sales))

d1_all <- train_all %>% rename(ds = DateofSale, y = Sales) %>% # for prophet to work
Must have columns ds (date type) and y, the time series.
  nest() %>%
  mutate(m = map(data, prophet)) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))

d_all <- d1_all %>%
  unnest(forecast) %>%
  dplyr::select(ds, yhat, yhat_lower,yhat_upper) # in case if we wish to see all
variables we can comment this

indi_ds_all <- bind_rows(train_all,test_all) %>% mutate(ds = DateofSale)
indi_ds2_all <- left_join(d_all,indi_ds_all) %>%
  mutate(SNO = 1:n(),
         DateofSale = as.Date(as.character(ds)))

ggplot(data = indi_ds2_all %>%
  filter(Sales >0) ,
  aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +

```

```

    theme(legend.position = "none") +
    ylab("Total Sales")+
    geom_line(data = indi_ds2_all[!(indi_ds2_all$Sales ==0) |
                                     (indi_ds2_all$SNO %% 2 ==0 &
                                     is.na(indi_ds2_all$Sales))],
              aes(y = yhat), color = "red") +
    geom_ribbon(data = indi_ds2_all[!(indi_ds2_all$Sales ==0) |
                                     (indi_ds2_all$SNO %% 2 ==0 &
                                     is.na(indi_ds2_all$Sales)) ],
              aes(ymin=yhat_lower, ymax=yhat_upper),
              color = "red", alpha =0.3)
#now using promotion days to factor in some days to improve the prediction
promotion_days <- data.table::data.table(
  holiday = 'sale discount days',
  ds=as.Date(c('2013-09-28',
               '2013-10-06',
               '2013-10-12'
              )),
  lower_window = 0, # looks back at 0 days before the last day to shop and get
it before sale
  upper_window = 0
)
d1_all <- train_all %>% rename(ds = DateofSale, y = Sales) %>% # for prophet to work
Must have columns ds (date type) and y, the time series.
  nest() %>%
  mutate(m = map(data, ~prophet(.,holidays = promotion_days))) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))

d_all <- d1_all %>%
  unnest(forecast) %>%
  dplyr::select(ds, yhat, yhat_lower,yhat_upper) # in case if we wish to see all
variables we can comment this

indi_ds_all <- bind_rows(train_all,test_all) %>% mutate(ds = DateofSale)
indi_ds2_all <- left_join(d_all,indi_ds_all) %>%
  mutate(SNO = 1:n(),
         DateofSale = as.Date(as.character(ds)))

ggplot(data = indi_ds2_all %>%
  filter(Sales >0) ,
  aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = indi_ds2_all[!(indi_ds2_all$Sales ==0) |
                                   (indi_ds2_all$SNO %% 2 ==0 &
                                   is.na(indi_ds2_all$Sales))],
            aes(y = yhat), color = "red") +
  ylab("Total Sales")+
  geom_ribbon(data = indi_ds2_all[!(indi_ds2_all$Sales ==0) |
                                   (indi_ds2_all$SNO %% 2 ==0 &
                                   is.na(indi_ds2_all$Sales)) ],
            aes(ymin=yhat_lower, ymax=yhat_upper),
            color = "red", alpha =0.3)

###now also using day seasonality in addition to promotional campaign days
d1_all <- train_all %>% rename(ds = DateofSale, y = Sales) %>% # for prophet to work
Must have columns ds (date type) and y, the time series.
  nest() %>%
  mutate(m = map(data, ~prophet(.,holidays =
promotion_days,daily.seasonality=TRUE))) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))

d_all <- d1_all %>%

```

```

      unnest(forecast) %>%
      dplyr::select(ds, yhat, yhat_lower, yhat_upper) # in case if we wish to see all
variables we can comment this

```

```

indi_ds_all <- bind_rows(train_all, test_all) %>% mutate(ds = DateofSale)
indi_ds2_all <- left_join(d_all, indi_ds_all) %>%
  mutate(SNO = 1:n(),
         DateofSale = as.Date(as.character(ds)))

```

```

ggplot(data = indi_ds2_all %>%
  filter(Sales > 0) ,
  aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = indi_ds2_all[!(indi_ds2_all$Sales == 0) |
                                (indi_ds2_all$SNO %% 2 == 0 &
                                 is.na(indi_ds2_all$Sales))],
            aes(y = yhat), color = "red") +
  ylab("Total Sales")+
  geom_ribbon(data = indi_ds2_all[!(indi_ds2_all$Sales == 0) |
                                  (indi_ds2_all$SNO %% 2 == 0 &
                                   is.na(indi_ds2_all$Sales))],
            aes(ymin=0, ymax=yhat_upper), # yhat_lower has been changed to 0
            color = "red", alpha = 0.3)

```

```
gc() # to clear the memory dump
```

```
#####Check -end
```

```
###
```

```
### We still havent solved the objective which was based on individual Dress ID
#####
```

```

# For that lets explore Facebook's Prophet package to predict the Sales
# (Technically we need to use the algo which gives the least residuals or based on Biz
decision
# for different purposes different algos; Like if say the company wanted to predict
well the
# holiday/sale days well even accepting over-fitting but not under-fitting on those
days
# then our model choice would have been prophet here as that only captures the
promotion
# days well and also captures other days but the range of CI is wide. We would have
liked that
# the model even predict the non-sale days better, hence if the biz wanted to predict
only
# the non-sale days a lot better then probably we would have gone with Arima model
above
# but for didactic purposes lets assume prophet was the best algo better than arima
above overall)

```

```

#out of the 23 date records for every dress id, lets consider 70 percent as training
and rest as testing records
train_index <- 1: floor(0.7 * 23 ) # nrow(input) is changed to n as we have already
calc for each SKU
test_index <- setdiff(1:23, train_index) # nrow(input) is changed to n as we have
already calc for each SKU

```

```

DS_DS_T <- DS_DS_T %>% group_by(Dress_ID) %>% mutate(SNO = 1:n(), TRAINTESTFIL =
ifelse(SNO <= train_index, "Train", "Test")) %>% ungroup()

```

```

train <- dplyr::filter(DS_DS_T, TRAINTESTFIL == "Train")
test <- dplyr::filter(DS_DS_T, !TRAINTESTFIL == "Train")

```

```

d1 <- train %>% rename(ds = DateofSale, y = Sales) %>% # for prophet to work Must have
columns ds (date type) and y, the time series.
  nest(-Dress_ID) %>%
  mutate(m = map(data, prophet)) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))

d <- d1 %>%
  unnest(forecast) %>%
  dplyr::select(ds, Dress_ID, yhat, yhat_lower, yhat_upper) # in case if we wish
to see all variables we can comment this
# d1 %>%
#   + unnest(forecast) %>% names()
# [1] "Dress_ID" "data" "m"
# [4] "future" "ds" "trend"
# [7] "additive_terms" "additive_terms_lower" "additive_terms_upper"
# [10] "weekly" "weekly_lower" "weekly_upper"
# [13] "multiplicative_terms" "multiplicative_terms_lower"
"multiplicative_terms_upper"
# [16] "yhat_lower" "yhat_upper" "trend_lower"
# [19] "trend_upper" "yhat"

indi_ds <- bind_rows(train, test) %>% mutate(ds = DateofSale)
indi_ds2 <- left_join(d, indi_ds) %>%
  group_by(Dress_ID) %>%
  mutate(SNO = 1:n(),
         DateofSale = as.Date(as.character(ds)))
gc()
#A call of gc causes a garbage collection to take place

#Checking randomly for two ids via plot
ggplot(data = indi_ds2 %>% filter(Sales > 0, Dress_ID == "444282011") ,
  aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = indi_ds2[(indi_ds2$SNO <=16 |
                             (as.numeric(format(indi_ds2$DateofSale,
format = "%d")) % 2 == 0 &
                             indi_ds2$SNO >=17)) &
                             indi_ds2$Dress_ID == "444282011",]
    , aes(y = yhat), color = "red") +
  geom_ribbon(data = indi_ds2[(indi_ds2$SNO <=16 |
                              (as.numeric(format(indi_ds2$DateofSale,
format = "%d")) % 2 == 0 &
                              indi_ds2$SNO >=17)) &
                              indi_ds2$Dress_ID == "444282011",]
    , aes(ymin=yhat_lower, ymax=yhat_upper),
    color = "red", alpha =0.3)

#Checking randomly for two ids via plot
ggplot(data = indi_ds2 %>% filter(Sales > 0, Dress_ID == "549401113") ,
  aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = indi_ds2[(indi_ds2$SNO <=16 |
                             (as.numeric(format(indi_ds2$DateofSale,
format = "%d")) % 2 == 0 &
                             indi_ds2$SNO >=17)) &
                             indi_ds2$Dress_ID == "549401113",]
    , aes(y = yhat), color = "red") +
  geom_ribbon(data = indi_ds2[(indi_ds2$SNO <=16 |
                              (as.numeric(format(indi_ds2$DateofSale,
format = "%d")) % 2 == 0 &
                              indi_ds2$SNO >=17)) &
                              indi_ds2$Dress_ID == "549401113",]
    , aes(ymin=yhat_lower, ymax=yhat_upper),
    color = "red", alpha =0.3)

```

```

format = "%d")) %% 2 ==0 &
                                indi_ds2$DateofSale,
                                indi_ds2$SNO >=17)) &
                                indi_ds2$Dress_ID == "549401113",],
aes(ymin=yhat_lower, ymax=yhat_upper),
color = "red", alpha =0.3)

# now lets explore as though the days where total sales was high as sale
days/promotion days
# even b4 forecasting we will feed these dates into the prophet algo
# this will help better estimate the peak threshold days

d2 <- train %>%
  rename(ds = DateofSale, y = Sales) %>% # for prophet to work Must have columns
ds (date type) and y, the time series.
  dplyr::select(-c(SNO, TRAINTESTFIL)) %>%
  nest(-Dress_ID) %>%
  mutate(m = map(data, ~prophet(., holidays = promotion_days))) %>%
  mutate(future = map(m, make_future_dataframe, period = 20, freq = 'day')) %>%
  mutate(forecast = map2(m, future, predict))

d_pro <- d2 %>%
  unnest(forecast) %>%
  dplyr::select(ds, Dress_ID, yhat, yhat_lower, yhat_upper) # in case if we wish
to see all variables we can comment this

indi_ds_pro <- bind_rows(train, test) %>% mutate(ds = DateofSale)
indi_ds2_pro <- left_join(d_pro, indi_ds_pro) %>%
  group_by(Dress_ID) %>%
  mutate(SNO = 1:n(),
         DateofSale = as.Date(as.character(ds)))

#Checking randomly for two ids via plot
ggplot(data = indi_ds2_pro %>% filter(Sales >0, Dress_ID == "444282011") ,
aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = indi_ds2_pro[(indi_ds2_pro$SNO <=16 |
                                (as.numeric(format(indi_ds2_pro$DateofSale,
format = "%d")) %% 2 ==0
                                indi_ds2_pro$SNO >=17)) &
                                indi_ds2_pro$Dress_ID == "444282011",]
          ,aes(y = yhat), color = "red") +
  geom_ribbon(data = indi_ds2_pro[(indi_ds2_pro$SNO <=16 |
                                (as.numeric(format(indi_ds2_pro$DateofSale,
format = "%d")) %% 2
==0 &
                                indi_ds2_pro$SNO >=17)) &
                                indi_ds2_pro$Dress_ID == "444282011",]
          ,aes(ymin=yhat_lower, ymax=yhat_upper),
color = "red", alpha =0.3)

#Checking randomly for two ids via plot
ggplot(data = indi_ds2_pro %>% filter(Sales >0, Dress_ID == "549401113") ,
aes(x = DateofSale)) +
  geom_line(aes(x = DateofSale, y = Sales)) +
  scale_x_date(date_labels = "%d %b %y", date_breaks = "2 days") +
  theme_bw() + theme(legend.title = element_blank(),
                    axis.text.x = element_text(angle=45, vjust=0.5)) +
  theme(legend.position = "none") +
  geom_line(data = indi_ds2_pro[(indi_ds2_pro$SNO <=16 |
                                (as.numeric(format(indi_ds2_pro$DateofSale,
format = "%d")) %% 2 ==0
                                indi_ds2_pro$SNO >=17)) &
                                indi_ds2_pro$Dress_ID == "549401113",]
          ,aes(y = yhat), color = "red") +
  geom_ribbon(data = indi_ds2_pro[(indi_ds2_pro$SNO <=16 |
                                (as.numeric(format(indi_ds2_pro$DateofSale,
format = "%d")) %% 2
==0 &
                                indi_ds2_pro$SNO >=17)) &
                                indi_ds2_pro$Dress_ID == "549401113",]
          ,aes(ymin=yhat_lower, ymax=yhat_upper),
color = "red", alpha =0.3)

```



```

        indi_ds2_pro$Dress_ID == "549401113",]
      aes(y = yhat), color = "red") +
    geom_ribbon(data = indi_ds2_pro[(indi_ds2_pro$SNO <=16 |
      (as.numeric(format(indi_ds2_pro$DateofSale,
        format = "%d")) %% 2
      ==0 &
        indi_ds2_pro$SNO >=17)) &
        indi_ds2_pro$Dress_ID == "549401113",],
      aes(ymin=yhat_lower, ymax=yhat_upper),
      color = "red", alpha =0.3)

#Task 3:
# To decide the pricing for various upcoming clothes, they wish to find how the
# style, season, and material affect the sales of a dress and if the style of the
# dress
# is more influential than its price.

# For this task, lets consider the total sales per dress id and do an Linear
# Regression/ANOVA
# ANOVA is the statistical model that you use to predict a continuous outcome on the
# basis
# of one or more categorical predictor variables
# we can use lm itself because we have already created dummy variables for categorical
# variables

# lets assume alpha value as 0.05 and any p-value < alpha will be
# significant factots contributing to the sales

summ_totsales_ds <- DS_DS_T %>%
  group_by(Dress_ID) %>%
  summarise(TotalSales = sum(Sales, na.rm = T)) %>%
  ungroup()
ATT_DS3 <- left_join(ATT_DS2, summ_totsales_ds)

# lets explore the response variable TotalSales distribution and see if it is normal;
# if not use the transformed variable whichever is
g1 <- ggplot(ATT_DS3, aes(TotalSales)) + geom_density(fill="blue")+theme_bw() # it is
normal because we have more than 20 samples/records but just not like our usual bell
curve
g2<- ggplot(ATT_DS3, aes(log(TotalSales))) + geom_density(fill="blue")+theme_bw() #
more closer to normal
g3 <- ggplot(ATT_DS3, aes(sqrt(TotalSales))) + geom_density(fill="blue")+theme_bw()

gridExtra::grid.arrange(g1,g2,g3, ncol = 3)
# The coefficient for linear regression is calculated based on the sample data.
# The basic assumption here is that the sample is not biased and residuals are normal.
# relation between dependent and independent are linear
# residual variance is homoscedastic equal

# we could have technically used any of the above response variable but i prefer to
# use log transformed as it is close to usual normal bell curve
# first creating training and testing of data so that we can validate model later
set.seed(123)
inTrain <- createDataPartition(ATT_DS3$TotalSales,
  p = 0.7,
  list = FALSE)

Training = ATT_DS3[inTrain,]
Testing = ATT_DS3[-inTrain,]

Training1 <- Training %>% dplyr::select(c(2:7,32:92))
Testing1 <- Testing %>% dplyr::select(c(2:7,32:92))
#just for removing multicollinearity lets use lm
totsale_lm <- lm(data = Training1,
  log(TotalSales) ~ Seasonspring + Seasonsummer + Seasonwinter +
    SeasonAutumn +
    Priceaverage + Pricehigh + Pricelow + Pricemedium +

```

```

style_casual_dmy +
style_novelty_dmy +
style_vintage_dmy +
+
Material_knitting_dmy +
Material_microfiber_dmy +
+
Material_polyster_dmy +
+
Pricevery_high + Style_bohemian_dmy + Style_brief_dmy +
Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
Style_OL_dmy + Style_party_dmy + Style_sexy_dmy +
Style_work_dmy + Material_acrylic_dmy + Material_cashmere_dmy
+
Material_chiffon_dmy + Material_cotton_dmy +
Material_linen_dmy + Material_lycra_dmy +
Material_milksilk_dmy + Material_mix_dmy + Material_modal_dmy
+
Material_nylon_dmy + Material_other_dmy +
Material_rayon_dmy + Material_silk_dmy + Material_spandex_dmy
+
Material_viscos_dmy)

```

```

alias(totsale_lm) # indicates SeasonAutumn, Pricevery_high, Style_work_dmy need to be
removed due to autocorrelation
# The autocorrelated variables are these mentioned below (found by using alias(my_lm))

```

```

# SeasonAutumn = 1 - Seasonspring - Seasonsummer - Seasonwinter

```

```

# Pricevery_high = 1 - Priceaverage - Pricehigh - Pricelow - Pricemedium

```

```

# Style_work_dmy = 1 - Style_bohemian_dmy - Style_brief_dmy - Style_casual_dmy -
Style_cute_dmy - Style_fashion_dmy - Style_novelty_dmy - Style_OL_dmy -
Style_party_dmy - Style_sexy_dmy - Style_vintage_dmy

```

```

vif(totsale_lm)

```

```

#Error in vif.default(my_lm) : there are aliased coefficients in the model

```

```

totsale_lm <- lm(data = Training1,
log(TotalSales) ~ Seasonspring + Seasonsummer + Seasonwinter +
Priceaverage + Pricehigh + Pricelow + Pricemedium +
Style_bohemian_dmy + Style_brief_dmy + Style_casual_dmy +
Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
Style_OL_dmy + Style_party_dmy + Style_sexy_dmy +
Material_acrylic_dmy + Material_cashmere_dmy +
Material_chiffon_dmy + Material_cotton_dmy +
Material_knitting_dmy +
Material_linen_dmy + Material_lycra_dmy +
Material_microfiber_dmy +
Material_milksilk_dmy + Material_mix_dmy + Material_modal_dmy
+
Material_nylon_dmy + Material_other_dmy +
Material_polyster_dmy +
Material_rayon_dmy + Material_silk_dmy + Material_spandex_dmy
+
Material_viscos_dmy)
alias(totsale_lm) # no warning/err

```

```

vif(totsale_lm)
# Seasonspring          Seasonsummer          Seasonwinter          Priceaverage
# 2.542901              2.700566              2.744959              9.468094
# Pricehigh             Pricelow             Pricemedium          Style_bohemian_dmy
# 2.304913              9.418700              2.952570              2.231499
# Style_brief_dmy       Style_casual_dmy       Style_cute_dmy
# 2.156559              8.607728              3.181639              1.100120
# Style_flare_dmy       Style_novelty_dmy     Style_OL_dmy
# Style_party_dmy
# 1.314469              1.632623              1.165004              4.428099

```

```

# Style_sexy_dmy      Style_vintage_dmy      Material_acrylic_dmy
Material_cashmere_dmy
# 5.494190            2.502165            3.121383            4.220774
# Material_chiffon_dmy      Material_cotton_dmy      Material_knitting_dmy
Material_linen_dmy
# 15.938040            79.295952            2.052178            4.099462
# Material_lycra_dmy      Material_microfiber_dmy      Material_milksilk_dmy
Material_mix_dmy
# 3.080968            4.146351            5.070427            6.244475
# Material_modal_dmy      Material_nylon_dmy      Material_other_dmy
Material_polyester_dmy
# 3.101582            7.396789            68.515930            62.652227
# Material_rayon_dmy      Material_silk_dmy      Material_spandex_dmy
Material_viscos_dmy
# 9.134801            18.669394            5.190389            3.082433

```

```

#A variance inflation factor(VIF) detects multicollinearity in regression analysis.
# Multicollinearity is when there's correlation between predictors
# (i.e. independent variables) in a model;
# >10 vif values associated factors need to be removed one at a time from the model
# to remove this multicollinearity

```

```

#removing Material_cotton_dmy first (~79.29 vif)

```

```

totsale_lm <- lm(data = Training1,
  log(TotalSales) ~ Seasonspring + Seasonsummer + Seasonwinter +
    Priceaverage + Pricehigh + Pricelow + Pricemedium +
    Style_bohemian_dmy + Style_brief_dmy + Style_casual_dmy +
    Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
    Style_novelty_dmy +
    Style_vintage_dmy +
    Material_acrylic_dmy + Material_cashmere_dmy +
    Material_chiffon_dmy + Material_knitting_dmy +
    Material_linen_dmy + Material_lycra_dmy +
    Material_microfiber_dmy +
    Material_milksilk_dmy + Material_mix_dmy + Material_modal_dmy
    +
    Material_nylon_dmy + Material_other_dmy +
    Material_polyester_dmy +
    Material_rayon_dmy + Material_silk_dmy + Material_spandex_dmy
    +
    Material_viscos_dmy)
alias(totsale_lm) # no warning/err

```

```

vif(totsale_lm)
# Seasonspring      Seasonsummer      Seasonwinter      Priceaverage
# 2.510237            2.650694            2.709898            9.467003
# Pricehigh          Pricelow          Pricemedium      Style_bohemian_dmy
# 2.304793            9.417106            2.952483            2.231119
# Style_brief_dmy      Style_casual_dmy      Style_cute_dmy
Style_fashion_dmy
# 2.155900            8.604117            3.181527            1.100099
# Style_flare_dmy      Style_novelty_dmy      Style_OL_dmy
Style_party_dmy
# 1.314454            1.632414            1.164906            4.428093
# Style_sexy_dmy      Style_vintage_dmy      Material_acrylic_dmy
Material_cashmere_dmy
# 5.489841            2.502033            1.051401            1.120336
# Material_chiffon_dmy      Material_knitting_dmy      Material_linen_dmy
Material_lycra_dmy
# 1.135140            1.027128            1.084950            1.070396
# Material_microfiber_dmy      Material_milksilk_dmy      Material_mix_dmy
Material_modal_dmy
# 1.079631            1.040156            1.107579            1.025369
# Material_nylon_dmy      Material_other_dmy      Material_polyester_dmy
Material_rayon_dmy
# 1.344171            1.474553            1.543209            1.132127
# Material_silk_dmy      Material_spandex_dmy      Material_viscos_dmy
# 1.226671            1.090327            1.066874

```

```
# we can see that Priceaverage and Pricelow are highly correlated
# the more VIF increases, the less reliable regression results are going to be.

#we removed the priceaverage from the first model due to high vif (even though it was
less than 10 it was still >>5 highly correlated)
# we would have got
```

```
totsale_lm <- lm(data = Training1,
  log(TotalSales) ~ Seasonspring + Seasonsummer + Seasonwinter +
    Pricehigh + Pricelow + Pricemedium +
    Style_bohemian_dmy + Style_brief_dmy + Style_casual_dmy +
    Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
    Style_novelty_dmy +
    Style_vintage_dmy +
    Style_OL_dmy + Style_party_dmy + Style_sexy_dmy +
    Material_acrylic_dmy + Material_cashmere_dmy +
    Material_chiffon_dmy + Material_knitting_dmy +
    Material_linen_dmy + Material_lycra_dmy +
    Material_microfiber_dmy +
    Material_milksilk_dmy + Material_mix_dmy + Material_modal_dmy
    +
    Material_nylon_dmy + Material_other_dmy +
    Material_polyster_dmy +
    Material_rayon_dmy + Material_silk_dmy + Material_spandex_dmy
    +
    Material_viscos_dmy)
alias(totsale_lm) # no warning/err
```

```
vif(totsale_lm)
# Seasonspring          Seasonsummer          Seasonwinter          Pricehigh
# 2.502160              2.650669              2.688577              1.178129
# Pricelow              Pricemedium          Style_bohemian_dmy          Style_brief_dmy
# 1.343921              1.227101              2.207769              2.155373
# Style_casual_dmy      Style_cute_dmy          Style_fashion_dmy
# Style_flare_dmy      3.176479              1.099847              1.313947
# Style_novelty_dmy      Style_OL_dmy          Style_party_dmy
# Style_sexy_dmy        1.164323              4.072482              5.478410
# Style_vintage_dmy      Material_acrylic_dmy      Material_cashmere_dmy
# Material_chiffon_dmy  1.051395              1.120334              1.132027
# Material_knitting_dmy      Material_linen_dmy          Material_lycra_dmy
# Material_microfiber_dmy  1.084856              1.045606              1.060663
# Material_milksilk_dmy      Material_mix_dmy          Material_modal_dmy
# Material_nylon_dmy        1.107303              1.025292              1.342131
# Material_other_dmy      Material_polyster_dmy      Material_rayon_dmy
# Material_silk_dmy        1.541561              1.128407              1.226608
# Material_spandex_dmy      Material_viscos_dmy
# 1.090199              1.039359
#Style casual still has high vif. Even though its not >10 but it is >>5, we try
removing that as well
```

```
totsale_lm <- lm(data = Training1,
  log(TotalSales) ~ Seasonspring + Seasonsummer + Seasonwinter +
    Pricehigh + Pricelow + Pricemedium +
    Style_bohemian_dmy + Style_brief_dmy +
    Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
    style_novelty_dmy +
    style_vintage_dmy +
    Style_OL_dmy + Style_party_dmy + Style_sexy_dmy +
    Material_acrylic_dmy + Material_cashmere_dmy +
    Material_chiffon_dmy + Material_knitting_dmy +
    Material_linen_dmy + Material_lycra_dmy +
    Material_microfiber_dmy +
    Material_milksilk_dmy + Material_mix_dmy + Material_modal_dmy
    +
    Material_nylon_dmy + Material_other_dmy +
    Material_polyster_dmy +
```

```

+
Material_rayon_dmy + Material_silk_dmy + Material_spandex_dmy
+
Material_viscos_dmy)
alias(totsale_lm) # no warning/err

vif(totsale_lm)
# Seasonspring          Seasonsummer          Seasonwinter          Pricehigh
# 2.494244              2.643206              2.682305              1.175266
# Pricelow              Pricemedium          style_bohemian_dmy          style_brief_dmy
# 1.325716              1.222572              1.129676              1.122656
# Style_cute_dmy        Style_fashion_dmy          Style_flare_dmy
Style_novelty_dmy
# 1.154457              1.016183              1.234244              1.056590
# Style_OL_dmy          Style_party_dmy          Style_sexy_dmy          Style_vintage_dmy
# 1.071022              1.364656              1.203716              1.096055
# Material_acrylic_dmy  Material_cashmere_dmy    Material_chiffon_dmy
Material_knitting_dmy
# 1.051382              1.119881              1.131105              1.027035
# Material_linen_dmy    Material_lycra_dmy    Material_microfiber_dmy
Material_milksilk_dmy
# 1.062086              1.045479              1.033318              1.039839
# Material_mix_dmy      Material_modal_dmy      Material_nylon_dmy
Material_other_dmy
# 1.095435              1.024792              1.341953              1.462404
# Material_polyster_dmy  Material_rayon_dmy      Material_silk_dmy
Material_spandex_dmy
# 1.539354              1.128220              1.226605              1.089550
# Material_viscos_dmy
# 1.039207
summary(totsale_lm)

# Call:
# lm(formula = log(TotalSales) ~ Seasonspring + Seasonsummer +
# Seasonwinter + Pricehigh + Pricelow + Pricemedium +
# Style_bohemian_dmy +
# style_brief_dmy + style_cute_dmy + style_fashion_dmy +
# style_flare_dmy +
# style_novelty_dmy + style_OL_dmy + style_party_dmy +
# style_sexy_dmy +
# style_vintage_dmy + Material_acrylic_dmy + Material_cashmere_dmy
+
# Material_chiffon_dmy + Material_knitting_dmy + Material_linen_dmy
+
# Material_lycra_dmy + Material_microfiber_dmy +
Material_milksilk_dmy +
# Material_mix_dmy + Material_modal_dmy + Material_nylon_dmy +
# Material_other_dmy + Material_polyster_dmy + Material_rayon_dmy +
# Material_silk_dmy + Material_spandex_dmy + Material_viscos_dmy,
# data = Training1)

# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6612 -0.7140  0.1533  0.8534  3.6154

# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.76788    0.29476   26.354 <2e-16 ***
# Seasonspring      -0.09386    0.30462  -0.308  0.7582
# Seasonsummer     -0.06357    0.28142  -0.226  0.8214
# Seasonwinter     -0.07403    0.28616  -0.259  0.7960
# Pricehigh        -0.44247    0.42253  -1.047  0.2958
# Pricelow         0.50079    0.19605   2.554  0.0111 *
# Pricemedium      -0.95238    0.38777  -2.456  0.0146 *
# Style_bohemian_dmy -0.41881    0.45753  -0.915  0.3607
# Style_brief_dmy   0.26802    0.45611   0.588  0.5572
# Style_cute_dmy    -0.51047    0.33960  -1.503  0.1338
# Style_fashion_dmy -1.64986    1.53763  -1.073  0.2841
# Style_flare_dmy   1.68939    1.69459   0.997  0.3196
# Style_novelty_dmy  0.19035    0.59774   0.318  0.7504
# Style_OL_dmy      -0.68001    1.57857  -0.431  0.6669
# Style_party_dmy   -0.05456    0.30561  -0.179  0.8584
# Style_sexy_dmy    -0.03518    0.23846  -0.148  0.8828

```

```

# Style_vintage_dmy      0.53679      0.38586      1.391      0.1652
# Material_acrylic_dmy   -0.25884      1.10752     -0.234      0.8154
# Material_cashmere_dmy  -2.06425      0.93461     -2.209      0.0279 *
# Material_chiffon_dmy   0.57357      0.42747      1.342      0.1806
# Material_knitting_dmy  -0.04894      1.54582     -0.032      0.9748
# Material_linen_dmy     0.22779      0.91018      0.250      0.8025
# Material_lycra_dmy     -1.98517      1.10440     -1.798      0.0732 .
# Material_microfiber_dmy 0.21157      0.89776      0.236      0.8138
# Material_milksilk_dmy  0.09030      0.78106      0.116      0.9080
# Material_mix_dmy       0.18214      0.71806      0.254      0.7999
# Material_modal_dmy     -1.68259      1.09342     -1.539      0.1248
# Material_nylon_dmy     -1.41114      0.72656     -1.942      0.0530 .
# Material_other_dmy     -0.06351      0.22760     -0.279      0.7804
# Material_polyester_dmy  0.01582      0.24481      0.065      0.9485
# Material_rayon_dmy     -0.64360      0.57862     -1.112      0.2668
# Material_silk_dmy      -0.62744      0.40819     -1.537      0.1253
# Material_spandex_dmy   -0.70575      0.79951     -0.883      0.3781
# Material_viscos_dmy    -0.14776      1.10108     -0.134      0.8933
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.523 on 318 degrees of freedom
# Multiple R-squared:  0.1506, Adjusted R-squared:  0.06242
# F-statistic: 1.708 on 33 and 318 DF, p-value: 0.011

```

```

Training1s <- Training1 %>% dplyr::select(TotalSales,Seasonspring , Seasonsummer ,
Seasonwinter ,
Pricehigh , Pricelow , Pricemedium ,
Style_bohemian_dmy , Style_brief_dmy ,
Style_cute_dmy , Style_fashion_dmy ,
style_flare_dmy , style_novelty_dmy ,
style_sexy_dmy , style_vintage_dmy ,
style_OL_dmy , style_party_dmy ,
Material_acrylic_dmy ,
Material_chiffon_dmy ,
Material_knitting_dmy ,
Material_linen_dmy , Material_lycra_dmy ,
Material_microfiber_dmy ,
Material_milksilk_dmy , Material_mix_dmy ,
Material_modal_dmy ,
Material_nylon_dmy , Material_other_dmy ,
Material_polyester_dmy ,
Material_rayon_dmy , Material_silk_dmy ,
Material_spandex_dmy ,
Material_viscos_dmy)
totsale_lm.1 <- lm(data = Training1s,
log(TotalSales) ~.-Material_knitting_dmy) # has the highest p-
value- pool to the error deg of freedom as its insignificant
summary(totsale_lm.1)

```

```

# Call:
# lm(formula = log(TotalSales) ~ . - Material_knitting_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6618 -0.7135  0.1532  0.8539  3.6155
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.76757    0.29414   26.408 <2e-16 ***
# Seasonspring     -0.09387    0.30414   -0.309  0.7578
# Seasonsummer     -0.06340    0.28093   -0.226  0.8216
# Seasonwinter     -0.07463    0.28508   -0.262  0.7937
# Pricehigh        -0.44247    0.42187   -1.049  0.2951
# Pricelow         0.50027    0.19505    2.565  0.0108 *
# Pricemedium      -0.95225    0.38714   -2.460  0.0144 *
# Style_bohemian_dmy -0.41860    0.45677   -0.916  0.3601
# Style_brief_dmy    0.26847    0.45518    0.590  0.5557
# Style_cute_dmy     -0.51026    0.33900   -1.505  0.1333
# Style_fashion_dmy  -1.64973    1.53521   -1.075  0.2834
# style_flare_dmy    1.68920    1.69193    0.998  0.3188

```

```

# Style_novelty_dmy      0.19045      0.59680      0.319      0.7498
# Style_OL_dmy           -0.67923      1.57591     -0.431      0.6668
# Style_party_dmy        -0.05448      0.30512     -0.179      0.8584
# Style_sexy_dmy         -0.03483      0.23784     -0.146      0.8837
# Style_vintage_dmy      0.53704      0.38517      1.394      0.1642
# Material_acrylic_dmy   -0.25829      1.10564     -0.234      0.8154
# Material_cashmere_dmy  -2.06343      0.93279     -2.212      0.0277 *
# Material_chiffon_dmy    0.57412      0.42645      1.346      0.1792
# Material_linen_dmy     0.22804      0.90872      0.251      0.8020
# Material_lycra_dmy     -1.98451      1.10248     -1.800      0.0728 .
# Material_microfiber_dmy 0.21216      0.89616      0.237      0.8130
# Material_milksilk_dmy   0.09103      0.77949      0.117      0.9071
# Material_mix_dmy       0.18255      0.71682      0.255      0.7991
# Material_modal_dmy     -1.68220      1.09164     -1.541      0.1243
# Material_nylon_dmy     -1.41064      0.72525     -1.945      0.0526 .
# Material_other_dmy     -0.06308      0.22683     -0.278      0.7811
# Material_polyester_dmy  0.01640      0.24373      0.067      0.9464
# Material_rayon_dmy     -0.64339      0.57767     -1.114      0.2662
# Material_silk_dmy      -0.62676      0.40698     -1.540      0.1245
# Material_spandex_dmy   -0.70522      0.79809     -0.884      0.3776
# Material_viscos_dmy    -0.14719      1.09922     -0.134      0.8936
# ---
#          signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.521 on 319 degrees of freedom
# Multiple R-squared:  0.1506, Adjusted R-squared:  0.06536
# F-statistic: 1.767 on 32 and 319 DF, p-value: 0.007933

totsale_lm.2 <- update(totsale_lm.1, ~.-Material_polyester_dmy) # next highest p-value
removed

summary(totsale_lm.2)

# Call:
# lm(formula = log(TotalSales) ~ Seasonspring + Seasonsummer +
#     Seasonwinter + Pricehigh + Pricelow + Pricemedium +
#     Style_bohemian_dmy + style_brief_dmy + style_cute_dmy + Style_fashion_dmy +
#     Style_flare_dmy + style_novelty_dmy + style_OL_dmy + Style_party_dmy +
#     Style_sexy_dmy + style_vintage_dmy + Material_acrylic_dmy + Material_cashmere_dmy
#     +
#     Material_chiffon_dmy + Material_linen_dmy + Material_lycra_dmy +
#     Material_microfiber_dmy + Material_milksilk_dmy +
#     Material_mix_dmy + Material_modal_dmy + Material_nylon_dmy + Material_other_dmy +
#     Material_rayon_dmy + Material_silk_dmy + Material_spandex_dmy +
#     Material_viscos_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6611 -0.7139  0.1525  0.8491  3.6090
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.77491    0.27274  28.507  <2e-16 ***
# Seasonspring     -0.09406    0.30366  -0.310  0.7570
# Seasonsummer     -0.06601    0.27781  -0.238  0.8123
# Seasonwinter     -0.07287    0.28344  -0.257  0.7973
# Pricehigh        -0.44194    0.42114  -1.049  0.2948
# Pricelow         0.49877    0.19349   2.578  0.0104 *
# Pricemedium      -0.95175    0.38647  -2.463  0.0143 *
# Style_bohemian_dmy -0.41741    0.45572  -0.916  0.3604
# Style_brief_dmy    0.26584    0.45280   0.587  0.5575
# Style_cute_dmy    -0.51098    0.33831  -1.510  0.1319
# Style_fashion_dmy -1.65447    1.53121  -1.080  0.2807
# Style_flare_dmy    1.68849    1.68926   1.000  0.3183
# Style_novelty_dmy  0.19333    0.59434   0.325  0.7452
# Style_OL_dmy      -0.68884    1.56698  -0.440  0.6605
# Style_party_dmy   -0.05459    0.30464  -0.179  0.8579
# Style_sexy_dmy    -0.03381    0.23698  -0.143  0.8866

```

```

# Style_vintage_dmy      0.53576      0.38410      1.395      0.1640
# Material_acrylic_dmy   -0.26314      1.10156     -0.239      0.8113
# Material_cashmere_dmy  -2.07287      0.92075     -2.251      0.0250 *
# Material_chiffon_dmy    0.56829      0.41691      1.363      0.1738
# Material_linen_dmy     0.22157      0.90221      0.246      0.8062
# Material_lycra_dmy     -1.99235      1.09461     -1.820      0.0697 .
# Material_microfiber_dmy 0.20570      0.88962      0.231      0.8173
# Material_milksilk_dmy   0.08395      0.77115      0.109      0.9134
# Material_mix_dmy       0.17540      0.70780      0.248      0.8044
# Material_modal_dmy     -1.68618      1.08833     -1.549      0.1223
# Material_nylon_dmy     -1.41708      0.71779     -1.974      0.0492 *
# Material_other_dmy     -0.06957      0.20500     -0.339      0.7346
# Material_rayon_dmy     -0.64913      0.57045     -1.138      0.2560
# Material_silk_dmy      -0.63316      0.39510     -1.603      0.1100
# Material_spandex_dmy   -0.71145      0.79147     -0.899      0.3694
# Material_viscos_dmy    -0.15382      1.09309     -0.141      0.8882
# ---
#          signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.518 on 320 degrees of freedom
# Multiple R-squared:  0.1506,    Adjusted R-squared:  0.06827
# F-statistic:  1.83 on 31 and 320 DF,  p-value: 0.005631

```

```
totsale_lm.3 <- update(totsale_lm.2, ~. - Material_milksilk_dmy)
```

```

summary(totsale_lm.3)
# Call:
#      lm(formula = log(TotalSales) ~ Seasonspring + Seasonsummer +
#      Seasonwinter + Pricehigh + Pricelow + Pricemedium +
#      Style_bohemian_dmy +
#      style_brief_dmy + style_cute_dmy + style_fashion_dmy +
#      style_flare_dmy +
#      style_novelty_dmy + style_OL_dmy + style_party_dmy +
#      style_sexy_dmy +
#      style_vintage_dmy + Material_acrylic_dmy + Material_cashmere_dmy
#      +
#      Material_chiffon_dmy + Material_linen_dmy + Material_lycra_dmy +
#      Material_microfiber_dmy + Material_mix_dmy + Material_modal_dmy +
#      Material_nylon_dmy + Material_other_dmy + Material_rayon_dmy +
#      Material_silk_dmy + Material_spandex_dmy + Material_viscos_dmy,
#      data = Trainingsls)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6607 -0.7061  0.1520  0.8476  3.6087
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.77768    0.27113   28.686 <2e-16 ***
# Seasonspring     -0.09565    0.30284   -0.316  0.7523
# Seasonsummer     -0.06729    0.27714   -0.243  0.8083
# Seasonwinter     -0.07310    0.28300   -0.258  0.7963
# Pricehigh        -0.44216    0.42049   -1.052  0.2938
# Pricelow         0.49945    0.19309    2.587  0.0101 *
# Pricemedium      -0.95281    0.38575   -2.470  0.0140 *
# Style_bohemian_dmy -0.41883    0.45483   -0.921  0.3578
# Style_brief_dmy    0.26430    0.45188    0.585  0.5590
# Style_cute_dmy     -0.51178    0.33771   -1.515  0.1306
# Style_fashion_dmy -1.65595    1.52879   -1.083  0.2795
# Style_flare_dmy    1.68848    1.68666    1.001  0.3175
# Style_novelty_dmy  0.19140    0.59316    0.323  0.7471
# Style_OL_dmy      -0.69031    1.56451   -0.441  0.6593
# Style_party_dmy   -0.05526    0.30411   -0.182  0.8559
# Style_sexy_dmy    -0.03415    0.23659   -0.144  0.8853
# Style_vintage_dmy  0.53454    0.38335    1.394  0.1642
# Material_acrylic_dmy -0.26472    1.09977   -0.241  0.8099
# Material_cashmere_dmy -2.07470    0.91918   -2.257  0.0247 *
# Material_chiffon_dmy 0.56650    0.41595    1.362  0.1742
# Material_linen_dmy  0.21923    0.90056    0.243  0.8078
# Material_lycra_dmy -1.99404    1.09281   -1.825  0.0690 .
# Material_microfiber_dmy 0.20397    0.88810    0.230  0.8185

```



```

# Material_mix_dmy      0.17423    0.70663    0.247    0.8054
# Material_modal_dmy    -1.68801    1.08653   -1.554    0.1213
# Material_nylon_dmy    -1.41824    0.71661   -1.979    0.0487 *
# Material_other_dmy    -0.07113    0.20418   -0.348    0.7278
# Material_rayon_dmy    -0.65004    0.56951   -1.141    0.2546
# Material_silk_dmy     -0.63491    0.39416   -1.611    0.1082
# Material_spandex_dmy  -0.71276    0.79016   -0.902    0.3677
# Material_viscos_dmy   -0.15566    1.09128   -0.143    0.8867
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.516 on 321 degrees of freedom
# Multiple R-squared:  0.1505,    Adjusted R-squared:  0.07114
# F-statistic: 1.896 on 30 and 321 DF,  p-value: 0.003937

totsale_lm.4 <- update(totsale_lm.3, ~.-Material_viscos_dmy)
summary(totsale_lm.4)

#
# Call:
# lm(formula = log(TotalSales) ~ Seasonspring + Seasonsummer +
# Style_bohemian_dmy + Style_brief_dmy + Style_cute_dmy + Style_fashion_dmy +
# Style_flare_dmy + Style_novelty_dmy + Style_OL_dmy + Style_party_dmy +
# Style_sexy_dmy + Style_vintage_dmy + Material_acrylic_dmy + Material_cashmere_dmy
# + Material_chiffon_dmy + Material_linen_dmy + Material_lycra_dmy +
# Material_microfiber_dmy + Material_mix_dmy + Material_modal_dmy +
# Material_nylon_dmy + Material_other_dmy + Material_rayon_dmy +
# Material_silk_dmy + Material_spandex_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6595 -0.7026  0.1522  0.8479  3.6086
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.77823    0.27069   28.735 <2e-16 ***
# Seasonspring     -0.09547    0.30237   -0.316  0.7524
# Seasonsummer     -0.06854    0.27657   -0.248  0.8044
# Seasonwinter     -0.07436    0.28243   -0.263  0.7925
# Pricehigh        -0.44047    0.41968   -1.050  0.2947
# Pricelow         0.49821    0.19260    2.587  0.0101 *
# Pricemedium      -0.95230    0.38514   -2.473  0.0139 *
# Style_bohemian_dmy -0.41892    0.45414   -0.922  0.3570
# Style_brief_dmy    0.26403    0.45119    0.585  0.5588
# Style_cute_dmy     -0.51241    0.33717   -1.520  0.1296
# Style_fashion_dmy -1.65524    1.52646   -1.084  0.2790
# Style_flare_dmy    1.68553    1.68396    1.001  0.3176
# Style_novelty_dmy  0.19139    0.59226    0.323  0.7468
# Style_OL_dmy       -0.69011    1.56213   -0.442  0.6589
# Style_party_dmy    -0.06095    0.30102   -0.202  0.8397
# Style_sexy_dmy     -0.03669    0.23556   -0.156  0.8763
# Style_vintage_dmy  0.53445    0.38276    1.396  0.1636
# Material_acrylic_dmy -0.26326    1.09805   -0.240  0.8107
# Material_cashmere_dmy -2.07433    0.91777   -2.260  0.0245 *
# Material_chiffon_dmy 0.56765    0.41523    1.367  0.1726
# Material_linen_dmy  0.21910    0.89919    0.244  0.8076
# Material_lycra_dmy  -1.98931    1.09064   -1.824  0.0691 .
# Material_microfiber_dmy 0.20651    0.88657    0.233  0.8160
# Material_mix_dmy    0.17416    0.70555    0.247  0.8052
# Material_modal_dmy  -1.68668    1.08483   -1.555  0.1210
# Material_nylon_dmy  -1.41602    0.71535   -1.979  0.0486 *
# Material_other_dmy  -0.06910    0.20337   -0.340  0.7343
# Material_rayon_dmy  -0.64862    0.56856   -1.141  0.2548
# Material_silk_dmy   -0.63331    0.39340   -1.610  0.1084
# Material_spandex_dmy -0.71271    0.78895   -0.903  0.3670
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

#
# Residual standard error: 1.514 on 322 degrees of freedom
# Multiple R-squared: 0.1505, Adjusted R-squared: 0.07396
# F-statistic: 1.967 on 29 and 322 DF, p-value: 0.002711

totsale_lm.5 <- update(totsale_lm.4, ~.- style_sexy_dmy )
summary(totsale_lm.5)

# Call:
# lm(formula = log(TotalSales) ~ Seasonspring + Seasonsummer +
# Seasonwinter + Pricehigh + Pricelow + Pricemedium +
# style_bohemian_dmy + style_brief_dmy + style_cute_dmy + style_fashion_dmy +
# style_flare_dmy + style_novelty_dmy + style_OL_dmy + style_party_dmy +
# style_vintage_dmy + Material_acrylic_dmy + Material_cashmere_dmy +
# Material_chiffon_dmy + Material_linen_dmy + Material_lycra_dmy + Material_microfiber_dmy
# + Material_mix_dmy + Material_modal_dmy + Material_nylon_dmy +
# Material_other_dmy + Material_rayon_dmy + Material_silk_dmy +
# Material_spandex_dmy, data = Training1s)

# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6879 -0.7089  0.1526  0.8560  3.6088

# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.76641    0.25945  29.934  <2e-16 ***
# Seasonspring     -0.09124    0.30069  -0.303  0.7618
# Seasonsummer     -0.06440    0.27488  -0.234  0.8149
# Seasonwinter     -0.07143    0.28137  -0.254  0.7998
# Pricehigh        -0.43708    0.41848  -1.044  0.2971
# Pricelow         0.49511    0.19129   2.588  0.0101 *
# Pricemedium      -0.95108    0.38448  -2.474  0.0139 *
# style_bohemian_dmy -0.40851    0.44851  -0.911  0.3631
# style_brief_dmy    0.27309    0.44674   0.611  0.5414
# style_cute_dmy     -0.50504    0.33332  -1.515  0.1307
# style_fashion_dmy -1.64757    1.52336  -1.082  0.2803
# style_flare_dmy     1.69709    1.67979   1.010  0.3131
# style_novelty_dmy  0.20066    0.58836   0.341  0.7333
# style_OL_dmy       -0.68245    1.55899  -0.438  0.6619
# style_party_dmy    -0.05327    0.29651  -0.180  0.8575
# style_vintage_dmy  0.54278    0.37844   1.434  0.1525
# Material_acrylic_dmy -0.25796    1.09586  -0.235  0.8141
# Material_cashmere_dmy -2.06626    0.91493  -2.258  0.0246 *
# Material_chiffon_dmy  0.57499    0.41193   1.396  0.1637
# Material_linen_dmy  0.22953    0.89534   0.256  0.7978
# Material_lycra_dmy  -2.00172    1.08609  -1.843  0.0662 .
# Material_microfiber_dmy 0.21303    0.88425   0.241  0.8098
# Material_mix_dmy     0.17878    0.70386   0.254  0.7997
# Material_modal_dmy  -1.67746    1.08158  -1.551  0.1219
# Material_nylon_dmy  -1.42000    0.71381  -1.989  0.0475 *
# Material_other_dmy  -0.06963    0.20303  -0.343  0.7319
# Material_rayon_dmy  -0.64685    0.56759  -1.140  0.2553
# Material_silk_dmy   -0.63362    0.39281  -1.613  0.1077
# Material_spandex_dmy -0.70543    0.78638  -0.897  0.3704
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Residual standard error: 1.511 on 323 degrees of freedom
# Multiple R-squared: 0.1504, Adjusted R-squared: 0.07676
# F-statistic: 2.042 on 28 and 323 DF, p-value: 0.001835

totsale_lm.6 <- update(totsale_lm.5, ~.-style_party_dmy)
summary(totsale_lm.6)

# call:

```

```

# lm(formula = log(TotalSales) ~ Seasonspring + Seasonsummer +
# Seasonwinter + Pricehigh + Pricelow + Pricemedium +
# Style_bohemian_dmy +
# style_brief_dmy + style_cute_dmy + style_fashion_dmy +
# style_flare_dmy +
# style_novelty_dmy + style_OL_dmy + style_vintage_dmy +
# Material_acrylic_dmy +
# Material_cashmere_dmy + Material_chiffon_dmy + Material_linen_dmy
#
# Material_lycra_dmy + Material_microfiber_dmy + Material_mix_dmy +
# Material_modal_dmy + Material_nylon_dmy + Material_other_dmy +
# Material_rayon_dmy + Material_silk_dmy + Material_spandex_dmy,
# data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6744 -0.6990  0.1573  0.8633  3.6098
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.76313    0.25842  30.040 < 2e-16 ***
# Seasonspring    -0.09919    0.29697  -0.334  0.73860
# Seasonsummer    -0.06836    0.27359  -0.250  0.80286
# Seasonwinter    -0.07674    0.27940  -0.275  0.78376
# Pricehigh       -0.45202    0.40952  -1.104  0.27051
# Pricelow        0.50358    0.18511   2.720  0.00687 **
# Pricemedium     -0.94964    0.38382  -2.474  0.01387 *
# Style_bohemian_dmy -0.40182    0.44630  -0.900  0.36860
# Style_brief_dmy   0.28091    0.44395   0.633  0.52734
# Style_cute_dmy    -0.49486    0.32798  -1.509  0.13232
# Style_fashion_dmy -1.64033    1.52055  -1.079  0.28149
# Style_flare_dmy   1.71464    1.67444   1.024  0.30660
# Style_novelty_dmy  0.20805    0.58605   0.355  0.72282
# Style_OL_dmy     -0.67529    1.55616  -0.434  0.66461
# Style_vintage_dmy  0.55114    0.37500   1.470  0.14261
# Material_acrylic_dmy -0.25819    1.09423  -0.236  0.81362
# Material_cashmere_dmy -2.05862    0.91257  -2.256  0.02475 *
# Material_chiffon_dmy  0.57321    0.41119   1.394  0.16427
# Material_linen_dmy  0.23413    0.89363   0.262  0.79349
# Material_lycra_dmy -2.02267    1.07819  -1.876  0.06156 .
# Material_microfiber_dmy 0.20147    0.88059   0.229  0.81918
# Material_mix_dmy   0.18572    0.70175   0.265  0.79145
# Material_modal_dmy -1.67445    1.07983  -1.551  0.12196
# Material_nylon_dmy -1.42631    0.71188  -2.004  0.04595 *
# Material_other_dmy -0.07593    0.19967  -0.380  0.70398
# Material_rayon_dmy -0.65757    0.56360  -1.167  0.24417
# Material_silk_dmy  -0.63406    0.39221  -1.617  0.10693
# Material_spandex_dmy -0.70097    0.78481  -0.893  0.37243
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.509 on 324 degrees of freedom
# Multiple R-squared:  0.1503, Adjusted R-squared:  0.07952
# F-statistic: 2.123 on 27 and 324 DF, p-value: 0.001222

totsale_lm.7 <- update(totsale_lm.6, ~.-Material_microfiber_dmy)

summary(totsale_lm.7)
# Call:
# lm(formula = log(TotalSales) ~ Seasonspring + Seasonsummer +
# Seasonwinter + Pricehigh + Pricelow + Pricemedium +
# Style_bohemian_dmy +
# style_brief_dmy + style_cute_dmy + style_fashion_dmy +
# style_flare_dmy +
# style_novelty_dmy + style_OL_dmy + style_vintage_dmy +
# Material_acrylic_dmy +
# Material_cashmere_dmy + Material_chiffon_dmy + Material_linen_dmy
#
# Material_lycra_dmy + Material_mix_dmy + Material_modal_dmy +
# Material_nylon_dmy + Material_other_dmy + Material_rayon_dmy +
# Material_silk_dmy + Material_spandex_dmy, data = Training1s)
#

```

```

# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6750 -0.6913  0.1562  0.8595  3.6064
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.76514    0.25790   30.109 < 2e-16 ***
# Seasonspring     -0.09569    0.29614   -0.323  0.74680
# Seasonsummer     -0.06666    0.27309   -0.244  0.80731
# Seasonwinter     -0.07491    0.27888   -0.269  0.78840
# Pricehigh        -0.45377    0.40886   -1.110  0.26788
# Pricelow         0.50316    0.18483    2.722  0.00683 **
# Pricemedium      -0.95192    0.38313   -2.485  0.01347 *
# Style_bohemian_dmy -0.40382    0.44556   -0.906  0.36544
# Style_brief_dmy   0.27876    0.44320    0.629  0.52981
# Style_cute_dmy    -0.49690    0.32738   -1.518  0.13004
# Style_fashion_dmy -1.64404    1.51824   -1.083  0.27968
# Style_flare_dmy   1.71219    1.67196    1.024  0.30657
# Style_novelty_dmy 0.20554    0.58509    0.351  0.72560
# Style_OL_dmy      -0.67685    1.55387   -0.436  0.66342
# Style_vintage_dmy 0.54908    0.37435    1.467  0.14340
# Material_acrylic_dmy -0.26067    1.09258   -0.239  0.81158
# Material_cashmere_dmy -2.06094    0.91119   -2.262  0.02437 *
# Material_chiffon_dmy 0.56985    0.41033    1.389  0.16586
# Material_linen_dmy 0.23156    0.89226    0.260  0.79539
# Material_lycra_dmy -2.02713    1.07644   -1.883  0.06057 .
# Material_mix_dmy  0.18173    0.70051    0.259  0.79547
# Material_modal_dmy -1.67795    1.07815   -1.556  0.12060
# Material_nylon_dmy -1.42936    0.71071   -2.011  0.04513 *
# Material_other_dmy -0.07900    0.19893   -0.397  0.69156
# Material_rayon_dmy -0.66014    0.56266   -1.173  0.24156
# Material_silk_dmy  -0.63740    0.39137   -1.629  0.10436
# Material_spandex_dmy -0.70575    0.78339   -0.901  0.36831
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.507 on 325 degrees of freedom
# Multiple R-squared:  0.1502, Adjusted R-squared:  0.0822
# F-statistic: 2.209 on 26 and 325 DF, p-value: 0.0008035

```

```

totsale_lm.8 <- update(totsale_lm.7, ~. -Material_acrylic_dmy)
summary(totsale_lm.8)

```

```

# Call:
#      lm(formula = log(TotalSales) ~ Seasonspring + Seasonsummer +
#      Seasonwinter + Pricehigh + Pricelow + Pricemedium +
#      Style_bohemian_dmy + style_brief_dmy + style_cute_dmy + style_fashion_dmy +
#      style_flare_dmy + style_novelty_dmy + style_OL_dmy + style_vintage_dmy +
#      Material_cashmere_dmy + Material_chiffon_dmy + Material_linen_dmy + Material_lycra_dmy +
#      Material_mix_dmy + Material_modal_dmy + Material_nylon_dmy +
#      Material_other_dmy + Material_rayon_dmy + Material_silk_dmy +
#      Material_spandex_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6751 -0.6878  0.1572  0.8621  3.6062
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.76519    0.25752   30.153 < 2e-16 ***
# Seasonspring     -0.09617    0.29571   -0.325  0.74522
# Seasonsummer     -0.06926    0.27247   -0.254  0.79950
# Seasonwinter     -0.07700    0.27834   -0.277  0.78222
# Pricehigh        -0.45422    0.40826   -1.113  0.26671
# Pricelow         0.50206    0.18450    2.721  0.00686 **
# Pricemedium      -0.95170    0.38258   -2.488  0.01336 *
# Style_bohemian_dmy -0.40273    0.44489   -0.905  0.36601
# Style_brief_dmy   0.25905    0.43480    0.596  0.55174
# Style_cute_dmy    -0.49630    0.32690   -1.518  0.12993

```

```

# Style_fashion_dmy      -1.64149      1.51601    -1.083    0.27971
# Style_flare_dmy        1.71069      1.66953     1.025    0.30628
# Style_novelty_dmy       0.20672      0.58422     0.354    0.72369
# Style_OL_dmy           -0.67503      1.55160    -0.435    0.66381
# Style_vintage_dmy       0.54990      0.37379     1.471    0.14222
# Material_cashmere_dmy   -2.05905      0.90983    -2.263    0.02429 *
# Material_chiffon_dmy    0.57158      0.40967     1.395    0.16390
# Material_linen_dmy      0.23238      0.89096     0.261    0.79440
# Material_lycra_dmy      -2.02534      1.07486    -1.884    0.06042 .
# Material_mix_dmy        0.18658      0.69920     0.267    0.78976
# Material_modal_dmy      -1.67485      1.07651    -1.556    0.12072
# Material_nylon_dmy      -1.42745      0.70964    -2.012    0.04509 *
# Material_other_dmy      -0.07639      0.19835    -0.385    0.70040
# Material_rayon_dmy      -0.65690      0.56168    -1.170    0.24305
# Material_silk_dmy       -0.63551      0.39072    -1.627    0.10481
# Material_spandex_dmy    -0.70492      0.78225    -0.901    0.36817
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.505 on 326 degrees of freedom
# Multiple R-squared:  0.15,    Adjusted R-squared:  0.08486
# F-statistic: 2.302 on 25 and 326 DF,  p-value: 0.0005185

totsale_lm.9 <- update(totsale_lm.8, ~. -Seasonsummer)
summary(totsale_lm.9)

# Call:
# lm(formula = log(TotalSales) ~ Seasonspring + Seasonwinter +
# Pricehigh + Pricelow + Pricemedium + Style_bohemian_dmy +
# Style_brief_dmy + Style_cute_dmy + Style_fashion_dmy +
# Style_flare_dmy +
# Style_novelty_dmy + Style_OL_dmy + Style_vintage_dmy +
# Material_cashmere_dmy +
# Material_chiffon_dmy + Material_linen_dmy + Material_lycra_dmy +
# Material_mix_dmy + Material_modal_dmy + Material_nylon_dmy +
# Material_other_dmy + Material_rayon_dmy + Material_silk_dmy +
# Material_spandex_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6980 -0.6907  0.1494  0.8592  3.6145
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.71537     0.16681  46.253 < 2e-16 ***
# Seasonspring     -0.04669     0.22229  -0.210  0.83376
# Seasonwinter     -0.02749     0.19854  -0.138  0.88996
# Pricehigh        -0.45855     0.40732  -1.126  0.26108
# Pricelow         0.50079     0.18417   2.719  0.00689 **
# Pricemedium      -0.94563     0.38129  -2.480  0.01364 *
# Style_bohemian_dmy -0.40632     0.44403  -0.915  0.36083
# Style_brief_dmy   0.26226     0.43400   0.604  0.54607
# Style_cute_dmy    -0.50429     0.32492  -1.552  0.12162
# Style_fashion_dmy -1.66093     1.51191  -1.099  0.27277
# Style_flare_dmy   1.71555     1.66703   1.029  0.30419
# Style_novelty_dmy  0.21417     0.58265   0.368  0.71342
# Style_OL_dmy      -0.68079     1.54922  -0.439  0.66063
# Style_vintage_dmy  0.54098     0.37161   1.456  0.14641
# Material_cashmere_dmy -2.06278     0.90841  -2.271  0.02381 *
# Material_chiffon_dmy 0.57470     0.40890   1.405  0.16083
# Material_linen_dmy  0.25911     0.88346   0.293  0.76949
# Material_lycra_dmy -2.02438     1.07331  -1.886  0.06017 .
# Material_mix_dmy   0.18805     0.69818   0.269  0.78784
# Material_modal_dmy -1.69366     1.07243  -1.579  0.11524
# Material_nylon_dmy -1.43197     0.70840  -2.021  0.04405 *
# Material_other_dmy -0.07297     0.19761  -0.369  0.71218
# Material_rayon_dmy -0.64511     0.55897  -1.154  0.24929
# Material_silk_dmy  -0.63323     0.39006  -1.623  0.10546
# Material_spandex_dmy -0.70195     0.78104  -0.899  0.36945
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#

```

```
# Residual standard error: 1.503 on 327 degrees of freedom
# Multiple R-squared: 0.1499, Adjusted R-squared: 0.08747
# F-statistic: 2.402 on 24 and 327 DF, p-value: 0.0003286
```

```
totsale_lm.10 <- update(totsale_lm.9, ~. -Seasonwinter)
summary(totsale_lm.10)
```

```
# Call:
# lm(formula = log(TotalSales) ~ Seasonspring + Pricehigh + Pricelow +
# Pricemedium + Style_bohemian_dmy + Style_brief_dmy +
# Style_cute_dmy +
# style_fashion_dmy + style_flare_dmy + style_novelty_dmy +
# style_OL_dmy + style_vintage_dmy + Material_cashmere_dmy +
# Material_chiffon_dmy + Material_linen_dmy + Material_lycra_dmy +
# Material_mix_dmy + Material_modal_dmy + Material_nylon_dmy +
# Material_other_dmy + Material_rayon_dmy + Material_silk_dmy +
# Material_spandex_dmy, data = Training1s)
```

```
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6871 -0.6985  0.1484  0.8555  3.6157
```

```
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.70254    0.13851  55.612 < 2e-16 ***
# Seasonspring     -0.03508    0.20554  -0.171  0.86461
# Pricehigh        -0.46318    0.40534  -1.143  0.25400
# Pricelow          0.50497    0.18141   2.784  0.00569 **
# Pricemedium      -0.95275    0.37724  -2.526  0.01202 *
# Style_bohemian_dmy -0.40173    0.44213  -0.909  0.36422
# Style_brief_dmy    0.25767    0.43208   0.596  0.55136
# Style_cute_dmy     -0.50422    0.32443  -1.554  0.12111
# Style_fashion_dmy -1.64810    1.50681  -1.094  0.27486
# Style_flare_dmy    1.71750    1.66448   1.032  0.30290
# Style_novelty_dmy  0.21595    0.58164   0.371  0.71066
# Style_OL_dmy      -0.68834    1.54594  -0.445  0.65643
# Style_vintage_dmy  0.54197    0.37098   1.461  0.14500
# Material_cashmere_dmy -2.07270    0.90423  -2.292  0.02252 *
# Material_chiffon_dmy  0.57613    0.40816   1.412  0.15904
# Material_linen_dmy  0.27194    0.87728   0.310  0.75677
# Material_lycra_dmy -2.03320    1.06982  -1.901  0.05824 .
# Material_mix_dmy    0.18363    0.69640   0.264  0.79219
# Material_modal_dmy -1.68292    1.06802  -1.576  0.11605
# Material_nylon_dmy -1.43270    0.70732  -2.026  0.04362 *
# Material_other_dmy -0.07098    0.19679  -0.361  0.71857
# Material_rayon_dmy -0.63870    0.55621  -1.148  0.25168
# Material_silk_dmy  -0.63558    0.38911  -1.633  0.10334
# Material_spandex_dmy -0.70285    0.77985  -0.901  0.36811
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
# Residual standard error: 1.5 on 328 degrees of freedom
# Multiple R-squared: 0.1498, Adjusted R-squared: 0.0902
# F-statistic: 2.513 on 23 and 328 DF, p-value: 0.0002008
```

```
totsale_lm.11 <- update(totsale_lm.10, ~. -Seasonspring)
summary(totsale_lm.11)
```

```
# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
# Style_bohemian_dmy + Style_brief_dmy + Style_cute_dmy +
# style_fashion_dmy +
# style_flare_dmy + style_novelty_dmy + style_OL_dmy +
# style_vintage_dmy +
# Material_cashmere_dmy + Material_chiffon_dmy + Material_linen_dmy
# +
# Material_lycra_dmy + Material_mix_dmy + Material_modal_dmy +
# Material_nylon_dmy + Material_other_dmy + Material_rayon_dmy +
# Material_silk_dmy + Material_spandex_dmy, data = Training1s)
```

```
# Residuals:
#      Min       1Q   Median       3Q      Max
```

```

# -4.6787 -0.7040 0.1500 0.8608 3.5900
#
# Coefficients:
# Estimate Std. Error t value Pr(>|t|)
# (Intercept) 7.6975 0.1351 56.979 < 2e-16 ***
# Pricehigh -0.4662 0.4043 -1.153 0.24973
# Pricelow 0.5040 0.1810 2.784 0.00569 **
# Pricemedium -0.9562 0.3761 -2.542 0.01147 *
# Style_bohemian_dmy -0.3982 0.4410 -0.903 0.36717
# Style_brief_dmy 0.2582 0.4314 0.598 0.54996
# Style_cute_dmy -0.5086 0.3230 -1.575 0.11629
# Style_fashion_dmy -1.6430 1.5043 -1.092 0.27553
# Style_flare_dmy 1.6966 1.6575 1.024 0.30678
# Style_novelty_dmy 0.2220 0.5797 0.383 0.70202
# Style_OL_dmy -0.6798 1.5429 -0.441 0.65978
# Style_vintage_dmy 0.5466 0.3695 1.479 0.13999
# Material_cashmere_dmy -2.0653 0.9019 -2.290 0.02265 *
# Material_chiffon_dmy 0.5705 0.4062 1.404 0.16114
# Material_linen_dmy 0.2770 0.8755 0.316 0.75190
# Material_lycra_dmy -2.0452 1.0659 -1.919 0.05589 .
# Material_mix_dmy 0.1666 0.6882 0.242 0.80885
# Material_modal_dmy -1.6773 1.0659 -1.574 0.11655
# Material_nylon_dmy -1.4419 0.7043 -2.047 0.04142 *
# Material_other_dmy -0.0743 0.1955 -0.380 0.70420
# Material_rayon_dmy -0.6505 0.5511 -1.181 0.23865
# Material_silk_dmy -0.6456 0.3841 -1.681 0.09369 .
# Material_spandex_dmy -0.7313 0.7607 -0.961 0.33712
# ---
# signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.498 on 329 degrees of freedom
# Multiple R-squared: 0.1497, Adjusted R-squared: 0.09289
# F-statistic: 2.634 on 22 and 329 DF, p-value: 0.0001203

totsale_lm.12 <- update(totsale_lm.11, ~. -Material_mix_dmy)
summary(totsale_lm.12)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
# Style_bohemian_dmy + Style_brief_dmy + Style_cute_dmy +
# Style_fashion_dmy +
# Style_flare_dmy + Style_novelty_dmy + Style_OL_dmy +
# Style_vintage_dmy +
# Material_cashmere_dmy + Material_chiffon_dmy + Material_linen_dmy
# +
# Material_lycra_dmy + Material_modal_dmy + Material_nylon_dmy +
# Material_other_dmy + Material_rayon_dmy + Material_silk_dmy +
# Material_spandex_dmy, data = Training1s)
#
# Residuals:
# Min 1Q Median 3Q Max
# -4.6796 -0.7072 0.1470 0.8579 3.5859
#
# Coefficients:
# Estimate Std. Error t value Pr(>|t|)
# (Intercept) 7.70260 0.13324 57.811 <2e-16 ***
# Pricehigh -0.46837 0.40367 -1.160 0.2468
# Pricelow 0.49994 0.18003 2.777 0.0058 **
# Pricemedium -0.96001 0.37527 -2.558 0.0110 *
# Style_bohemian_dmy -0.39952 0.44035 -0.907 0.3649
# Style_brief_dmy 0.26887 0.42855 0.627 0.5308
# Style_cute_dmy -0.50961 0.32247 -1.580 0.1150
# Style_fashion_dmy -1.64816 1.50200 -1.097 0.2733
# Style_flare_dmy 1.69328 1.65510 1.023 0.3070
# Style_novelty_dmy 0.21802 0.57865 0.377 0.7066
# Style_OL_dmy -0.68113 1.54064 -0.442 0.6587
# Style_vintage_dmy 0.55375 0.36773 1.506 0.1331
# Material_cashmere_dmy -2.06791 0.90051 -2.296 0.0223 *
# Material_chiffon_dmy 0.56702 0.40540 1.399 0.1629
# Material_linen_dmy 0.27188 0.87398 0.311 0.7559
# Material_lycra_dmy -2.04828 1.06434 -1.924 0.0552 .
# Material_modal_dmy -1.68046 1.06434 -1.579 0.1153

```

```

# Material_nylon_dmy      -1.44362      0.70321    -2.053      0.0409 *
# Material_other_dmy      -0.07859      0.19445     -0.404      0.6863
# Material_rayon_dmy      -0.65619      0.54977     -1.194      0.2335
# Material_silk_dmy       -0.64696      0.38347     -1.687      0.0925 .
# Material_spandex_dmy    -0.73412      0.75955     -0.967      0.3345
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.496 on 330 degrees of freedom
# Multiple R-squared:  0.1496,    Adjusted R-squared:  0.09547
# F-statistic: 2.764 on 21 and 330 DF,  p-value: 0.00007111

totsale_lm.13 <- update(totsale_lm.12, ~. -Material_linen_dmy)
summary(totsale_lm.13)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#   Style_bohemian_dmy + Style_brief_dmy + Style_cute_dmy +
#   Style_fashion_dmy + Style_flare_dmy + Style_novelty_dmy + Style_OL_dmy +
#   Style_vintage_dmy + Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy
# +
#   Material_modal_dmy + Material_nylon_dmy + Material_other_dmy +
#   Material_rayon_dmy + Material_silk_dmy + Material_spandex_dmy,
#   data = Trainings1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6822 -0.7114  0.1501  0.8525  3.5817
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.70892     0.13150   58.623 < 2e-16 ***
# Pricehigh        -0.47187     0.40297   -1.171  0.24244
# Pricelow         0.49562     0.17924    2.765  0.00601 **
# Pricemedium      -0.96416     0.37453   -2.574  0.01048 *
# Style_bohemian_dmy -0.40212     0.43966   -0.915  0.36106
# Style_brief_dmy    0.26527     0.42781    0.620  0.53564
# Style_cute_dmy     -0.51175     0.32196   -1.590  0.11290
# Style_fashion_dmy -1.65448     1.49981   -1.103  0.27077
# Style_flare_dmy    1.68895     1.65278    1.022  0.30758
# Style_novelty_dmy  0.21283     0.57762    0.368  0.71277
# Style_OL_dmy       -0.68330     1.53852   -0.444  0.65724
# Style_vintage_dmy  0.55024     0.36706    1.499  0.13482
# Material_cashmere_dmy -2.07147     0.89921   -2.304  0.02186 *
# Material_chiffon_dmy 0.56338     0.40468    1.392  0.16481
# Material_lycra_dmy  -2.05244     1.06281   -1.931  0.05432 .
# Material_modal_dmy -1.68462     1.06281   -1.585  0.11391
# Material_nylon_dmy  -1.44560     0.70222   -2.059  0.04031 *
# Material_other_dmy  -0.08233     0.19381   -0.425  0.67128
# Material_rayon_dmy  -0.65924     0.54894   -1.201  0.23063
# Material_silk_dmy   -0.64883     0.38289   -1.695  0.09110 .
# Material_spandex_dmy -0.73774     0.75842   -0.973  0.33140
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.494 on 331 degrees of freedom
# Multiple R-squared:  0.1493,    Adjusted R-squared:  0.09794
# F-statistic: 2.906 on 20 and 331 DF,  p-value: 0.00004155

totsale_lm.14 <- update(totsale_lm.13, ~. -Style_novelty_dmy )
summary(totsale_lm.14)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#   Style_bohemian_dmy + Style_brief_dmy + Style_cute_dmy +
#   Style_fashion_dmy + Style_flare_dmy + Style_OL_dmy + Style_vintage_dmy +
#   Material_cashmere_dmy +
#   Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#   Material_nylon_dmy + Material_other_dmy + Material_rayon_dmy +

```



```

#                               Material_silk_dmy + Material_spandex_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6881 -0.7161  0.1503  0.8547  3.5769
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.71798    0.12901   59.825 < 2e-16 ***
# Pricehigh           -0.47784    0.40212   -1.188  0.23556
# Pricelow            0.48913    0.17814    2.746  0.00637 **
# Pricemedium         -0.95861    0.37374   -2.565  0.01076 *
# Style_bohemian_dmy   -0.40735    0.43886   -0.928  0.35398
# Style_brief_dmy      0.25942    0.42696    0.608  0.54387
# Style_cute_dmy       -0.51601    0.32133   -1.606  0.10926
# Style_fashion_dmy   -1.66354    1.49766   -1.111  0.26747
# Style_flare_dmy      1.68177    1.65052    1.019  0.30898
# Style_OL_dmy        -0.69792    1.53600   -0.454  0.64986
# Style_vintage_dmy    0.54379    0.36617    1.485  0.13846
# Material_cashmere_dmy -2.08424    0.89737   -2.323  0.02080 *
# Material_chiffon_dmy  0.55862    0.40395    1.383  0.16762
# Material_lycra_dmy   -2.05826    1.06131   -1.939  0.05330 .
# Material_modal_dmy   -1.69044    1.06131   -1.593  0.11216
# Material_nylon_dmy   -1.44749    0.70128   -2.064  0.03979 *
# Material_other_dmy   -0.08543    0.19338   -0.442  0.65895
# Material_rayon_dmy   -0.66269    0.54814   -1.209  0.22754
# Material_silk_dmy    -0.65221    0.38229   -1.706  0.08893 .
# Material_spandex_dmy -0.74250    0.75733   -0.980  0.32759
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.492 on 332 degrees of freedom
# Multiple R-squared:  0.149,    Adjusted R-squared:  0.1003
# F-statistic: 3.059 on 19 and 332 DF,  p-value: 0.000024

totsale_lm.15 <- update(totsale_lm.14, ~. -Material_other_dmy)
summary(totsale_lm.15)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#   Style_bohemian_dmy + Style_brief_dmy + Style_cute_dmy +
#   Style_fashion_dmy +
#   Style_flare_dmy + Style_OL_dmy + Style_vintage_dmy +
#   Material_cashmere_dmy +
#   Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#   Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy +
#   Material_spandex_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7507 -0.7035  0.1650  0.8629  3.6006
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6952    0.1181   65.170 < 2e-16 ***
# Pricehigh           -0.5048    0.3970   -1.271  0.20445
# Pricelow            0.4868    0.1779    2.737  0.00653 **
# Pricemedium         -0.9584    0.3733   -2.568  0.01068 *
# Style_bohemian_dmy   -0.4101    0.4383   -0.936  0.35007
# Style_brief_dmy      0.2544    0.4263    0.597  0.55101
# Style_cute_dmy       -0.5169    0.3209   -1.611  0.10822
# Style_fashion_dmy   -1.6407    1.4950   -1.098  0.27321
# Style_flare_dmy      1.6739    1.6484    1.015  0.31064
# Style_OL_dmy        -0.6753    1.5333   -0.440  0.65991
# Style_vintage_dmy    0.5357    0.3653    1.467  0.14345
# Material_cashmere_dmy -2.0616    0.8948   -2.304  0.02184 *
# Material_chiffon_dmy  0.5832    0.3996    1.460  0.14535
# Material_lycra_dmy   -2.0343    1.0586   -1.922  0.05551 .
# Material_modal_dmy   -1.6665    1.0586   -1.574  0.11640
# Material_nylon_dmy   -1.4168    0.6970   -2.033  0.04287 *
# Material_rayon_dmy   -0.6337    0.5435   -1.166  0.24449
# Material_silk_dmy    -0.6245    0.3767   -1.658  0.09824 .

```

```

# Material_spandex_dmy    -0.7183      0.7544  -0.952  0.34173
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.49 on 333 degrees of freedom
# Multiple R-squared:  0.1485,    Adjusted R-squared:  0.1025
# F-statistic: 3.226 on 18 and 333 DF,  p-value: 0.00001381

totsale_lm.16 <- update(totsale_lm.15, ~. -Style_OL_dmy)
summary(totsale_lm.16)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#   Style_bohemian_dmy + Style_brief_dmy + Style_cute_dmy +
#   Style_fashion_dmy +
#   Style_flare_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#   Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#   Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy +
#   Material_spandex_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7501 -0.7027  0.1657  0.8620  3.5982
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6945     0.1179   65.248 < 2e-16 ***
# Pricehigh            -0.5051     0.3965   -1.274  0.20358
# Pricelow             0.4865     0.1776    2.739  0.00650 **
# Pricemedium          -0.9951     0.3634   -2.738  0.00651 **
# Style_bohemian_dmy   -0.4063     0.4377   -0.928  0.35386
# Style_brief_dmy      0.2553     0.4258    0.600  0.54922
# Style_cute_dmy       -0.5138     0.3205   -1.603  0.10985
# Style_fashion_dmy    -1.6401     1.4932   -1.098  0.27282
# Style_flare_dmy      1.6751     1.6464    1.017  0.30969
# Style_vintage_dmy    0.5385     0.3648    1.476  0.14081
# Material_cashmere_dmy -2.0364     0.8919   -2.283  0.02305 *
# Material_chiffon_dmy  0.5832     0.3991    1.461  0.14487
# Material_lycra_dmy   -2.0335     1.0574   -1.923  0.05531 .
# Material_modal_dmy   -1.6656     1.0574   -1.575  0.11614
# Material_nylon_dmy   -1.4174     0.6961   -2.036  0.04254 *
# Material_rayon_dmy   -0.6346     0.5429   -1.169  0.24323
# Material_silk_dmy    -0.6202     0.3761   -1.649  0.10004
# Material_spandex_dmy -0.7183     0.7535   -0.953  0.34117
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.488 on 334 degrees of freedom
# Multiple R-squared:  0.148,    Adjusted R-squared:  0.1046
# F-statistic: 3.413 on 17 and 334 DF,  p-value: 0.000007727

totsale_lm.17 <- update(totsale_lm.16, ~. -Style_brief_dmy)
summary(totsale_lm.17)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#   Style_bohemian_dmy + Style_cute_dmy + Style_fashion_dmy +
#   Style_flare_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#   Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#   Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy +
#   Material_spandex_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7641 -0.7162  0.1636  0.8660  3.5942
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.7086     0.1155   66.762 < 2e-16 ***
# Pricehigh            -0.5177     0.3956   -1.309  0.19155
# Pricelow             0.4840     0.1774    2.728  0.00671 **
# Pricemedium          -1.0053     0.3627   -2.772  0.00589 **
# Style_bohemian_dmy   -0.4197     0.4367   -0.961  0.33714

```

```

# Style_cute_dmy      -0.5239      0.3197    -1.639    0.10225
# Style_fashion_dmy   -1.6541      1.4915    -1.109    0.26823
# Style_flare_dmy      1.6658      1.6448     1.013    0.31191
# Style_vintage_dmy    0.5247      0.3637     1.443    0.15006
# Material_cashmere_dmy -2.0437      0.8910    -2.294    0.02242 *
# Material_chiffon_dmy 0.5733      0.3984     1.439    0.15108
# Material_lycra_dmy   -2.0463      1.0561    -1.938    0.05352 .
# Material_modal_dmy   -1.6784      1.0561    -1.589    0.11295
# Material_nylon_dmy   -1.4221      0.6954    -2.045    0.04165 *
# Material_rayon_dmy   -0.6087      0.5406    -1.126    0.26104
# Material_silk_dmy    -0.6277      0.3755    -1.672    0.09553 .
# Material_spandex_dmy -0.7285      0.7526    -0.968    0.33373
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.487 on 335 degrees of freedom
# Multiple R-squared:  0.1471,    Adjusted R-squared:  0.1063
# F-statistic: 3.611 on 16 and 335 DF,  p-value: 0.000004479

totsale_lm.18 <- update(totsale_lm.17, ~. -Style_bohemian_dmy)
summary(totsale_lm.18)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#   Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
#   Style_vintage_dmy +
#     Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy
# +
#     Material_modal_dmy + Material_nylon_dmy + Material_rayon_dmy +
#     Material_silk_dmy + Material_spandex_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7498 -0.7364  0.1655  0.8745  3.5953
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6943      0.1145   67.206 < 2e-16 ***
# Pricehigh        -0.4953      0.3949   -1.254  0.21054
# Pricelow          0.4779      0.1773    2.696  0.00737 **
# Pricemedium      -1.0180      0.3624   -2.809  0.00526 **
# Style_cute_dmy    -0.5099      0.3193   -1.597  0.11130
# Style_fashion_dmy -1.6398      1.4913   -1.100  0.27230
# Style_flare_dmy    1.8345      1.6352    1.122  0.26272
# Style_vintage_dmy  0.5428      0.3632    1.495  0.13593
# Material_cashmere_dmy -2.0209      0.8906   -2.269  0.02389 *
# Material_chiffon_dmy  0.5864      0.3981    1.473  0.14169
# Material_lycra_dmy  -2.0289      1.0559   -1.922  0.05550 .
# Material_modal_dmy  -1.6611      1.0559   -1.573  0.11661
# Material_nylon_dmy  -1.5765      0.6765   -2.330  0.02039 *
# Material_rayon_dmy  -0.6539      0.5385   -1.214  0.22553
# Material_silk_dmy   -0.6132      0.3752   -1.634  0.10309
# Material_spandex_dmy -0.7147      0.7524   -0.950  0.34284
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.487 on 336 degrees of freedom
# Multiple R-squared:  0.1447,    Adjusted R-squared:  0.1065
# F-statistic:  3.79 on 15 and 336 DF,  p-value: 0.00000315

totsale_lm.19 <- update(totsale_lm.18, ~. -Material_spandex_dmy )
summary(totsale_lm.19)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#   Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
#   Style_vintage_dmy +
#     Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy
# +
#     Material_modal_dmy + Material_nylon_dmy + Material_rayon_dmy +
#     Material_silk_dmy, data = Training1s)
#

```

```

# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7421 -0.7303  0.1687  0.8714  3.6283
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6866     0.1142   67.317 < 2e-16 ***
# Pricehigh       -0.4861     0.3947   -1.232  0.21894
# Pricelow        0.4726     0.1772    2.667  0.00801 **
# Pricemedium     -1.0098     0.3622   -2.788  0.00561 **
# Style_cute_dmy   -0.5360     0.3181   -1.685  0.09296 .
# Style_fashion_dmy -1.6321     1.4911   -1.095  0.27447
# Style_flare_dmy   1.8331     1.6350    1.121  0.26300
# Style_vintage_dmy  0.5496     0.3630    1.514  0.13096
# Material_cashmere_dmy -2.0187     0.8904   -2.267  0.02402 *
# Material_chiffon_dmy  0.6013     0.3977    1.512  0.13150
# Material_lycra_dmy  -2.0186     1.0556   -1.912  0.05670 .
# Material_modal_dmy  -1.6508     1.0556   -1.564  0.11882
# Material_nylon_dmy  -1.5674     0.6764   -2.317  0.02108 *
# Material_rayon_dmy  -0.6403     0.5383   -1.190  0.23502
# Material_silk_dmy   -0.5978     0.3748   -1.595  0.11161
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.487 on 337 degrees of freedom
# Multiple R-squared:  0.1424, Adjusted R-squared:  0.1068
# F-statistic: 3.998 on 14 and 337 DF, p-value: 0.00000215

totsale_lm.20 <- update(totsale_lm.19, ~. -Style_fashion_dmy)
summary(totsale_lm.20)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#      Style_cute_dmy + Style_flare_dmy + Style_vintage_dmy +
#      Material_cashmere_dmy +
#      Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#      Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy,
#      data = Trainings1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7326 -0.7398  0.1749  0.8810  3.6340
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6770     0.1139   67.411 < 2e-16 ***
# Pricehigh       -0.4778     0.3947   -1.210  0.22694
# Pricelow        0.4811     0.1770    2.717  0.00692 **
# Pricemedium     -1.0015     0.3623   -2.764  0.00602 **
# Style_cute_dmy   -0.5321     0.3182   -1.672  0.09538 .
# Style_flare_dmy   1.8399     1.6354    1.125  0.26138
# Style_vintage_dmy  0.5563     0.3631    1.532  0.12639
# Material_cashmere_dmy -2.0147     0.8907   -2.262  0.02433 *
# Material_chiffon_dmy  0.6057     0.3978    1.523  0.12881
# Material_lycra_dmy  -2.0133     1.0559   -1.907  0.05742 .
# Material_modal_dmy  -1.6454     1.0559   -1.558  0.12010
# Material_nylon_dmy  -1.5646     0.6766   -2.313  0.02134 *
# Material_rayon_dmy  -0.6357     0.5384   -1.181  0.23852
# Material_silk_dmy   -0.5971     0.3749   -1.593  0.11214
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.487 on 338 degrees of freedom
# Multiple R-squared:  0.1394, Adjusted R-squared:  0.1063
# F-statistic: 4.211 on 13 and 338 DF, p-value: 0.000001614

totsale_lm.21 <- update(totsale_lm.20, ~. -Style_flare_dmy)
summary(totsale_lm.21)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#      Style_cute_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#      Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +

```

```
#           Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy,
#           data = Training1s)
#
# Residuals:
#           Min       1Q   Median       3Q      Max
# -4.7389 -0.7425  0.1764  0.8747  3.6263
#
# Coefficients:
#           Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6833     0.1138  67.522 < 2e-16 ***
# Pricehigh        -0.5049     0.3941  -1.281  0.20103
# Pricelow         0.4663     0.1766   2.640  0.00868 **
# Pricemedium     -1.0084     0.3624  -2.783  0.00569 **
# Style_cute_dmy   -0.5307     0.3183  -1.667  0.09642 .
# Style_vintage_dmy 0.5536     0.3632   1.524  0.12837
# Material_cashmere_dmy -2.0164     0.8910  -2.263  0.02427 *
# Material_chiffon_dmy 0.6062     0.3980   1.523  0.12864
# Material_lycra_dmy -2.0122     1.0564  -1.905  0.05765 .
# Material_modal_dmy -1.6443     1.0564  -1.557  0.12050
# Material_nylon_dmy -1.2524     0.6173  -2.029  0.04325 *
# Material_rayon_dmy -0.6350     0.5386  -1.179  0.23926
# Material_silk_dmy -0.5892     0.3750  -1.571  0.11700
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.488 on 339 degrees of freedom
# Multiple R-squared:  0.1362,    Adjusted R-squared:  0.1056
# F-statistic: 4.453 on 12 and 339 DF,  p-value: 0.000001218
```

```
totsale_lm.22 <- update(totsale_lm.21, ~. -Material_rayon_dmy )
summary(totsale_lm.22)
```

```
# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
#           Style_cute_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#           Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#           Material_nylon_dmy + Material_silk_dmy, data = Training1s)
#
# Residuals:
#           Min       1Q   Median       3Q      Max
# -4.7252 -0.7511  0.1814  0.8884  3.6831
#
# Coefficients:
#           Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6696     0.1133  67.717 < 2e-16 ***
# Pricehigh        -0.5265     0.3939  -1.337  0.18226
# Pricelow         0.4695     0.1767   2.657  0.00826 **
# Pricemedium     -0.9916     0.3623  -2.737  0.00653 **
# Style_cute_dmy   -0.5738     0.3164  -1.814  0.07061 .
# Style_vintage_dmy 0.5292     0.3628   1.458  0.14565
# Material_cashmere_dmy -2.0139     0.8915  -2.259  0.02452 *
# Material_chiffon_dmy 0.6287     0.3978   1.581  0.11491
# Material_lycra_dmy -2.0001     1.0569  -1.892  0.05929 .
# Material_modal_dmy -1.6322     1.0569  -1.544  0.12343
# Material_nylon_dmy -1.2367     0.6175  -2.003  0.04599 *
# Material_silk_dmy -0.5677     0.3747  -1.515  0.13069
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.489 on 340 degrees of freedom
# Multiple R-squared:  0.1326,    Adjusted R-squared:  0.1046
# F-statistic: 4.726 on 11 and 340 DF,  p-value: 0.0000009445
```

```
totsale_lm.23 <- update(totsale_lm.22, ~. -Pricehigh )
summary(totsale_lm.23)
```

```
# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#           Style_vintage_dmy + Material_cashmere_dmy + Material_chiffon_dmy
#           +
#           Material_lycra_dmy + Material_modal_dmy + Material_nylon_dmy +
#           Material_silk_dmy, data = Training1s)
```

```

#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6867 -0.7465  0.1697  0.9067  3.7614
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6311     0.1097  69.587 < 2e-16 ***
# Pricelow         0.5155     0.1735   2.971 0.00318 **
# Pricemedium     -0.9462     0.3611  -2.620 0.00918 **
# Style_cute_dmy   -0.6136     0.3153  -1.946 0.05250 .
# Style_vintage_dmy 0.5536     0.3628   1.526 0.12793 .
# Material_cashmere_dmy -2.0057    0.8925  -2.247 0.02527 *
# Material_chiffon_dmy 0.6520     0.3978   1.639 0.10215 .
# Material_lycra_dmy -1.9846     1.0581  -1.876 0.06156 .
# Material_modal_dmy -1.6168     1.0581  -1.528 0.12743 .
# Material_nylon_dmy -1.3089     0.6158  -2.126 0.03426 *
# Material_silk_dmy  -0.6172     0.3733  -1.653 0.09921 .
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.49 on 341 degrees of freedom
# Multiple R-squared:  0.1281, Adjusted R-squared:  0.1025
# F-statistic: 5.008 on 10 and 341 DF, p-value: 0.0000008435

totsale_lm.24 <- update(totsale_lm.23, ~. -Style_vintage_dmy)
summary(totsale_lm.24)

# Call:
#      lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#      Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy
#      +
#      Material_modal_dmy + Material_nylon_dmy + Material_silk_dmy,
#      data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7239 -0.7327  0.1483  0.9165  3.7544
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6683     0.1071  71.578 < 2e-16 ***
# Pricelow         0.5011     0.1736   2.887 0.00414 **
# Pricemedium     -0.9470     0.3618  -2.617 0.00925 **
# Style_cute_dmy   -0.6438     0.3153  -2.042 0.04194 *
# Material_cashmere_dmy -2.0423    0.8940  -2.285 0.02295 *
# Material_chiffon_dmy 0.6645     0.3985   1.667 0.09635 .
# Material_lycra_dmy -2.0146     1.0599  -1.901 0.05819 .
# Material_modal_dmy -1.6468     1.0599  -1.554 0.12119 .
# Material_nylon_dmy -1.3389     0.6167  -2.171 0.03060 *
# Material_silk_dmy  -0.6372     0.3738  -1.705 0.08919 .
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.493 on 342 degrees of freedom
# Multiple R-squared:  0.1221, Adjusted R-squared:  0.099
# F-statistic: 5.285 on 9 and 342 DF, p-value: 0.0000009274

totsale_lm.25 <- update(totsale_lm.24, ~. -Material_modal_dmy)
summary(totsale_lm.25)

# Call:
#      lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#      Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy
#      +
#      Material_nylon_dmy + Material_silk_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7146 -0.7659  0.1560  0.9231  3.7557
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)

```

```

# (Intercept)          7.6590      0.1072  71.456 < 2e-16 ***
# Pricelow             0.4942      0.1739   2.842  0.00476 **
# Pricemedium          -0.9402      0.3625  -2.593  0.00991 **
# Style_cute_dmy       -0.6358      0.3159  -2.012  0.04496 *
# Material_cashmere_dmy -2.0376      0.8958  -2.275  0.02355 *
# Material_chiffon_dmy  0.6754      0.3993   1.692  0.09163 .
# Material_lycra_dmy    -2.0018      1.0621  -1.885  0.06030 .
# Material_nylon_dmy    -1.3262      0.6179  -2.146  0.03255 *
# Material_silk_dmy     -0.6254      0.3745  -1.670  0.09584 .
# ---
#             signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.496 on 343 degrees of freedom
# Multiple R-squared:  0.1159, Adjusted R-squared:  0.09529
# F-statistic: 5.621 on 8 and 343 DF, p-value: 0.000001035

totsale_lm.26 <- update(totsale_lm.25, ~. -Material_silk_dmy)
summary(totsale_lm.26)
# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#   Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy +
#   Material_nylon_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7078 -0.7424  0.1140  0.9058  3.8365
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6523      0.1074  71.258 < 2e-16 ***
# Pricelow          0.4363      0.1709   2.554  0.01109 *
# Pricemedium      -0.9927      0.3621  -2.742  0.00643 **
# Style_cute_dmy   -0.7099      0.3136  -2.264  0.02422 *
# Material_cashmere_dmy -1.9958      0.8978  -2.223  0.02686 *
# Material_chiffon_dmy  0.7240      0.3993   1.813  0.07064 .
# Material_lycra_dmy  -1.9661      1.0646  -1.847  0.06564 .
# Material_nylon_dmy  -1.2905      0.6191  -2.084  0.03786 *
# ---
#             signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.5 on 344 degrees of freedom
# Multiple R-squared:  0.1087, Adjusted R-squared:  0.09059
# F-statistic: 5.995 on 7 and 344 DF, p-value: 0.000001328

totsale_lm.27 <- update(totsale_lm.26, ~. -Material_chiffon_dmy)
summary(totsale_lm.27)
# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#   Material_cashmere_dmy + Material_lycra_dmy + Material_nylon_dmy,
#   data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7321 -0.7137  0.0878  0.9473  3.7521
#
# Coefficients:
#             Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6766      0.1069  71.810 < 2e-16 ***
# Pricelow          0.4498      0.1713   2.627  0.00901 **
# Pricemedium      -1.0226      0.3629  -2.818  0.00512 **
# Style_cute_dmy   -0.6498      0.3129  -2.077  0.03857 *
# Material_cashmere_dmy -2.0002      0.9007  -2.221  0.02703 *
# Material_lycra_dmy  -1.9972      1.0680  -1.870  0.06233 .
# Material_nylon_dmy  -1.3216      0.6209  -2.128  0.03402 *
# ---
#             signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.505 on 345 degrees of freedom
# Multiple R-squared:  0.1002, Adjusted R-squared:  0.08455
# F-statistic: 6.403 on 6 and 345 DF, p-value: 0.000002074

```

```
totsale_lm.28 <- update(totsale_lm.27, ~. -Material_lycra_dmy)
summary(totsale_lm.28)
# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#     Material_cashmere_dmy + Material_nylon_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.7215 -0.7073  0.0895  0.9601  3.7504
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6660     0.1071  71.554 < 2e-16 ***
# Pricelow         0.4430     0.1718   2.578  0.01036 *
# Pricemedium     -1.0137     0.3642  -2.783  0.00567 **
# Style_cute_dmy   -0.6374     0.3140  -2.030  0.04309 *
# Material_cashmere_dmy -1.9955     0.9040  -2.207  0.02794 *
# Material_nylon_dmy -1.3075     0.6231  -2.098  0.03660 *
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.511 on 346 degrees of freedom
# Multiple R-squared:  0.09108, Adjusted R-squared:  0.07795
# F-statistic: 6.934 on 5 and 346 DF, p-value: 0.000003458
```

#Even though we did 28 steps of linear regression, based on Adjusted R-squared, # ~ 0.1068 for totsale\_lm.19, is the max value. hence that needs to be used as our model in terms of a better prediction  
# even despite some insignificant factors in the model

```
# we can try one more additional run where we consider 2-level interactions of the run
# 19 main effects to see if we can better the model further
totsale_lm.19_b <- lm(formula = log(TotalSales) ~ (Pricehigh + Pricelow + Pricemedium +
+     style_cute_dmy + style_fashion_dmy + style_flare_dmy +
+     style_vintage_dmy +
+     Material_cashmere_dmy + Material_chiffon_dmy +
+     Material_lycra_dmy +
+     Material_modal_dmy + Material_nylon_dmy +
+     Material_rayon_dmy +
+     Material_silk_dmy)^2, data = Training1s)
```

```
summary(totsale_lm.19_b) # looking at the results we are going to remove NA relations
# Call:
# lm(formula = log(TotalSales) ~ (Pricehigh + Pricelow + Pricemedium +
#     style_cute_dmy + style_fashion_dmy +
#     style_flare_dmy + style_vintage_dmy +
#     Material_cashmere_dmy +
#     Material_chiffon_dmy + Material_lycra_dmy +
#     Material_modal_dmy +
#     Material_nylon_dmy + Material_rayon_dmy +
#     Material_silk_dmy)^2, data =
# Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9230 -0.5997  0.0340  0.8567  3.1675
#
# Coefficients: (70 not defined because of singularities)
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.62058     0.11728   64.978 < 2e-16 ***
# Pricehigh        -0.08152     0.44956  -0.181
# 0.85622
# Pricelow         0.54017     0.19515   2.768  0.00597 **
# Pricemedium     -0.97552     0.40315  -2.420
# 0.01609 *
# style_cute_dmy      0.43795     0.51223   0.855
# 0.39321
# style_fashion_dmy -1.56614     1.46230  -1.071  0.28498
# style_flare_dmy   -0.42613     2.06134  -0.207  0.83636
```



# Style_vintage_dmy	0.82813	0.45486	1.821	0.06961	.
# Material_cashmere_dmy	-3.88291	1.46230	-2.655	0.00832	**
# Material_chiffon_dmy		1.22057	0.62994	1.938	
0.05356					
# Material_lycra_dmy	-3.59523	1.46230	-2.459	0.01448	*
# Material_modal_dmy		-1.03994	1.46230	-0.711	
0.47750					
# Material_nylon_dmy	0.75781	1.46230	0.518	0.60466	
# Material_rayon_dmy	-1.53258	0.84967	-1.804	0.07223	.
# Material_silk_dmy	0.92946	1.46230	0.636	0.52549	
# Pricehigh:Pricelow	NA	NA	NA	NA	
# Pricehigh:Pricemedium	NA	NA	NA	NA	
# Pricehigh:Style_cute_dmy	-1.55162	1.37305	-1.130	0.25931	
# Pricehigh:Style_fashion_dmy	NA	NA	NA	NA	
# Pricehigh:Style_flare_dmy	NA	NA	NA	NA	
# Pricehigh:Style_vintage_dmy	NA	NA	NA	NA	
# Pricehigh:Material_cashmere_dmy	NA	NA	NA	NA	
# Pricehigh:Material_chiffon_dmy	NA	NA	NA	NA	
# Pricehigh:Material_lycra_dmy	NA	NA	NA	NA	
# Pricehigh:Material_modal_dmy	NA	NA	NA	NA	
# Pricehigh:Material_nylon_dmy	-4.89567	2.10979	-2.320	0.02095	*
# Pricehigh:Material_rayon_dmy		-1.01067	2.45759	-0.411	
0.68117					
# Pricehigh:Material_silk_dmy	-1.16902	1.94204	-0.602	0.54763	
# Pricelow:Pricemedium	NA	NA	NA	NA	
# Pricelow:Style_cute_dmy	-1.50111	0.73678	-2.037	0.04244	*
# Pricelow:Style_fashion_dmy		NA	NA	NA	
NA					
# Pricelow:Style_flare_dmy	NA	NA	NA	NA	
# Pricelow:Style_vintage_dmy	-0.53901	0.87314	-0.617	0.53746	
# Pricelow:Material_cashmere_dmy	NA	NA	NA	NA	
# Pricelow:Material_chiffon_dmy	-0.66052	0.82013	-0.805	0.42120	
# Pricelow:Material_lycra_dmy	3.21770	2.07056	1.554	0.12118	
# Pricelow:Material_modal_dmy	-1.15723	2.07056	-0.559	0.57663	
# Pricelow:Material_nylon_dmy	-2.33598	1.69435	-1.379	0.16897	
# Pricelow:Material_rayon_dmy	2.92956	1.34482	2.178	0.03012	*
# Pricelow:Material_silk_dmy		-1.22624	1.53181	-0.801	
0.42401					
# Pricemedium:Style_cute_dmy	1.61246	1.36560	1.181	0.23858	
# Pricemedium:Style_fashion_dmy	NA	NA	NA	NA	
# Pricemedium:Style_flare_dmy	NA	NA	NA	NA	
# Pricemedium:Style_vintage_dmy	-1.22903	1.57487	-0.780	0.43574	
# Pricemedium:Material_cashmere_dmy	2.86102	1.83013	1.563	0.11898	
# Pricemedium:Material_chiffon_dmy	NA	NA	NA	NA	
# Pricemedium:Material_lycra_dmy	NA	NA	NA	NA	
# Pricemedium:Material_modal_dmy	NA	NA	NA	NA	
# Pricemedium:Material_nylon_dmy	NA	NA	NA	NA	
# Pricemedium:Material_rayon_dmy	NA	NA	NA	NA	
# Pricemedium:Material_silk_dmy	-3.96883	1.93675	-2.049	0.04127	*
# Style_cute_dmy:Style_fashion_dmy		NA	NA	NA	
NA					
# Style_cute_dmy:Style_flare_dmy	NA	NA	NA	NA	
# Style_cute_dmy:Style_vintage_dmy	NA	NA	NA	NA	
# Style_cute_dmy:Material_cashmere_dmy	NA	NA	NA	NA	
# Style_cute_dmy:Material_chiffon_dmy	-1.77200	1.04277	-1.699	0.09024	.
# Style_cute_dmy:Material_lycra_dmy	NA	NA	NA	NA	
# Style_cute_dmy:Material_modal_dmy	NA	NA	NA	NA	
# Style_cute_dmy:Material_nylon_dmy	NA	NA	NA	NA	
# Style_cute_dmy:Material_rayon_dmy	0.77181	1.75930	0.439	0.66117	
# Style_cute_dmy:Material_silk_dmy	-0.69925	1.03735	-0.674	0.50076	
# Style_fashion_dmy:Style_flare_dmy	NA	NA	NA	NA	
# Style_fashion_dmy:Style_vintage_dmy	NA	NA	NA	NA	
# Style_fashion_dmy:Material_cashmere_dmy	NA	NA	NA	NA	
# Style_fashion_dmy:Material_chiffon_dmy	NA	NA	NA	NA	
# Style_fashion_dmy:Material_lycra_dmy	NA	NA	NA	NA	
# Style_fashion_dmy:Material_modal_dmy	NA	NA	NA	NA	
# Style_fashion_dmy:Material_nylon_dmy	NA	NA	NA	NA	
# Style_fashion_dmy:Material_rayon_dmy	NA	NA	NA	NA	
# Style_fashion_dmy:Material_silk_dmy	NA	NA	NA	NA	
# Style_flare_dmy:Style_vintage_dmy	NA	NA	NA	NA	
# Style_flare_dmy:Material_cashmere_dmy	NA	NA	NA	NA	
# Style_flare_dmy:Material_chiffon_dmy	NA	NA	NA	NA	

```

# Style_flare_dmy:Material_lycra_dmy      NA      NA      NA      NA
# Style_flare_dmy:Material_modal_dmy      NA      NA      NA      NA
# Style_flare_dmy:Material_nylon_dmy      NA      NA      NA      NA
# Style_flare_dmy:Material_rayon_dmy      NA      NA      NA      NA
# Style_flare_dmy:Material_silk_dmy       NA      NA      NA      NA
# Style_vintage_dmy:Material_cashmere_dmy NA      NA      NA      NA
# Style_vintage_dmy:Material_chiffon_dmy  -0.53098  1.64758  -0.322  0.74745
# Style_vintage_dmy:Material_lycra_dmy    NA      NA      NA      NA
# Style_vintage_dmy:Material_modal_dmy    NA      NA      NA      NA
# Style_vintage_dmy:Material_nylon_dmy    NA      NA      NA      NA
# Style_vintage_dmy:Material_rayon_dmy    0.05927  1.74346  0.034  0.97290
# Style_vintage_dmy:Material_silk_dmy     NA      NA      NA      NA
# Material_cashmere_dmy:Material_chiffon_dmy NA      NA      NA      NA
# Material_cashmere_dmy:Material_lycra_dmy NA      NA      NA      NA
# Material_cashmere_dmy:Material_modal_dmy NA      NA      NA      NA
# Material_cashmere_dmy:Material_nylon_dmy NA      NA      NA      NA
# Material_cashmere_dmy:Material_rayon_dmy NA      NA      NA      NA
# Material_cashmere_dmy:Material_silk_dmy  NA      NA      NA      NA
# Material_chiffon_dmy:Material_lycra_dmy NA      NA      NA      NA
# Material_chiffon_dmy:Material_modal_dmy  NA      NA      NA      NA
# Material_chiffon_dmy:Material_nylon_dmy  NA      NA      NA      NA
# Material_chiffon_dmy:Material_rayon_dmy  NA      NA      NA      NA
# Material_chiffon_dmy:Material_silk_dmy   NA      NA      NA      NA
# Material_lycra_dmy:Material_modal_dmy    NA      NA      NA      NA
# Material_lycra_dmy:Material_nylon_dmy    NA      NA      NA      NA
# Material_lycra_dmy:Material_rayon_dmy    NA      NA      NA      NA
# Material_lycra_dmy:Material_silk_dmy     NA      NA      NA      NA
# Material_modal_dmy:Material_nylon_dmy    NA      NA      NA      NA
# Material_modal_dmy:Material_rayon_dmy    NA      NA      NA      NA
# Material_modal_dmy:Material_silk_dmy     NA      NA      NA      NA
# Material_nylon_dmy:Material_rayon_dmy    NA      NA      NA      NA
# Material_nylon_dmy:Material_silk_dmy     NA      NA      NA      NA
# Material_rayon_dmy:Material_silk_dmy     NA      NA      NA      NA

```

```

# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#

```

```

# Residual standard error: 1.458 on 316 degrees of freedom
# Multiple R-squared:  0.227,    Adjusted R-squared:  0.1414
# F-statistic: 2.652 on 35 and 316 DF,  p-value: 0.000004122

```

```

totsale_lm.19_c <- lm(formula = log(TotalSales) ~
  (Pricehigh + Pricelow + Pricemedium +
  Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
  style_vintage_dmy +
  Material_lycra_dmy +
  Material_rayon_dmy +
  Material_modal_dmy + Material_nylon_dmy +
  Material_silk_dmy) +
  Pricehigh:Material_nylon_dmy + Pricehigh:Style_cute_dmy
+
  Pricehigh:Material_rayon_dmy +
  Pricelow:Style_cute_dmy + Pricelow:Style_vintage_dmy +
  Pricelow:Material_lycra_dmy +
  Pricelow:Material_modal_dmy +
  Pricelow:Material_nylon_dmy +
  Pricelow:Material_rayon_dmy + Pricelow:Material_silk_dmy +
  Pricemedium:Style_cute_dmy + Pricemedium:Style_vintage_dmy +
  Pricemedium:Material_cashmere_dmy +
  Pricemedium:Material_silk_dmy +
  Style_cute_dmy:Material_chiffon_dmy +
  style_cute_dmy:Material_rayon_dmy +
  style_cute_dmy:Material_silk_dmy +
  style_vintage_dmy:Material_chiffon_dmy +
  style_vintage_dmy:Material_rayon_dmy
, data = Training1s)

```

```

# Call:
#      lm(formula = log(TotalSales) ~ (Pricehigh + Pricelow + Pricemedium +

```

```

# style_cute_dmy + style_fashion_dmy +
style_flare_dmy + style_vintage_dmy +
# Material_cashmere_dmy +
Material_chiffon_dmy + Material_lycra_dmy +
# Material_modal_dmy +
Material_nylon_dmy + Material_rayon_dmy +
# Material_silk_dmy) +
Pricehigh:Material_nylon_dmy + Pricehigh:Style_cute_dmy +
# Pricehigh:Material_rayon_dmy + Pricehigh:Material_silk_dmy +
# Pricelow:Style_cute_dmy + Pricelow:Style_vintage_dmy +
Pricelow:Material_chiffon_dmy +
# Pricelow:Material_lycra_dmy + Pricelow:Material_modal_dmy +
# Pricelow:Material_nylon_dmy + Pricelow:Material_rayon_dmy +
# Pricelow:Material_silk_dmy + Pricemedium:Style_cute_dmy +
# Pricemedium:Style_vintage_dmy + Pricemedium:Material_cashmere_dmy
+
# Pricemedium:Material_silk_dmy +
Style_cute_dmy:Material_chiffon_dmy +
# Style_cute_dmy:Material_rayon_dmy +
Style_cute_dmy:Material_silk_dmy +
# Style_vintage_dmy:Material_chiffon_dmy +
Style_vintage_dmy:Material_rayon_dmy,
# data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9230 -0.5997  0.0340  0.8567  3.1675
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.62058    0.11728   64.978 < 2e-16 ***
# Pricehigh           -0.08152    0.44956   -0.181  0.85622
# Pricelow            0.54017    0.19515    2.768  0.00597 **
# Pricemedium        -0.97552    0.40315   -2.420  0.01609 *
# Style_cute_dmy       0.43795    0.51223    0.855  0.39321
# Style_fashion_dmy   -1.56614    1.46230   -1.071  0.28498
# Style_flare_dmy     -0.42613    2.06134   -0.207  0.83636
# Style_vintage_dmy    0.82813    0.45486    1.821  0.06961 .
# Material_cashmere_dmy -3.88291    1.46230   -2.655  0.00832 **
# Material_chiffon_dmy  1.22057    0.62994    1.938  0.05356 .
# Material_lycra_dmy   -3.59523    1.46230   -2.459  0.01448 *
# Material_modal_dmy   -1.03994    1.46230   -0.711  0.47750
# Material_nylon_dmy   -1.75781    1.46230   -0.518  0.60466
# Material_rayon_dmy   -1.53258    0.84967   -1.804  0.07223 .
# Material_silk_dmy     0.92946    1.46230    0.636  0.52549
# Pricehigh:Material_nylon_dmy -4.89567    2.10979   -2.320  0.02095 *
# Pricehigh:Style_cute_dmy -1.55162    1.37305   -1.130  0.25931
# Pricehigh:Material_rayon_dmy -1.01067    2.45759   -0.411  0.68117
# Pricehigh:Material_silk_dmy -1.16902    1.94204   -0.602  0.54763
# Pricelow:Style_cute_dmy -1.50111    0.73678   -2.037  0.04244 *
# Pricelow:Style_vintage_dmy -0.53901    0.87314   -0.617  0.53746
# Pricelow:Material_chiffon_dmy -0.66052    0.82013   -0.805  0.42120
# Pricelow:Material_lycra_dmy  3.21770    2.07056    1.554  0.12118
# Pricelow:Material_modal_dmy -1.15723    2.07056   -0.559  0.57663
# Pricelow:Material_nylon_dmy -2.33598    1.69435   -1.379  0.16897
# Pricelow:Material_rayon_dmy  2.92956    1.34482    2.178  0.03012 *
# Pricelow:Material_silk_dmy -1.22624    1.53181   -0.801  0.42401
# Pricemedium:Style_cute_dmy  1.61246    1.36560    1.181  0.23858
# Pricemedium:Style_vintage_dmy -1.22903    1.57487   -0.780  0.43574
# Pricemedium:Material_cashmere_dmy  2.86102    1.83013    1.563  0.11898
# Pricemedium:Material_silk_dmy -3.96883    1.93675   -2.049  0.04127 *
# Style_cute_dmy:Material_chiffon_dmy -1.77200    1.04277   -1.699  0.09024 .
# Style_cute_dmy:Material_rayon_dmy  0.77181    1.75930    0.439  0.66117
# Style_cute_dmy:Material_silk_dmy -0.69925    1.03735   -0.674  0.50076
# Style_vintage_dmy:Material_chiffon_dmy -0.53098    1.64758   -0.322  0.74745
# Style_vintage_dmy:Material_rayon_dmy  0.05927    1.74346    0.034  0.97290
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.458 on 316 degrees of freedom
# Multiple R-squared:  0.227,    Adjusted R-squared:  0.1414
# F-statistic: 2.652 on 35 and 316 DF,  p-value: 0.000004122

```

```

totsale_lm.19_c.1 <- update(totsale_lm.19_c, ~. -Style_vintage_dmy:Material_rayon_dmy)

# Call:
# lm(formula = log(TotalSales) ~ Pricehigh + Pricelow + Pricemedium +
# Style_cute_dmy + Style_fashion_dmy + Style_flare_dmy +
# Style_vintage_dmy + Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy
# + Material_modal_dmy + Material_nylon_dmy + Material_rayon_dmy +
# Material_silk_dmy + Pricehigh:Material_nylon_dmy +
# Pricehigh:Style_cute_dmy + Pricehigh:Material_rayon_dmy + Pricehigh:Material_silk_dmy +
# Pricelow:Style_cute_dmy + Pricelow:Style_vintage_dmy +
# Pricelow:Material_chiffon_dmy + Pricelow:Material_lycra_dmy + Pricelow:Material_modal_dmy +
# Pricelow:Material_nylon_dmy + Pricelow:Material_rayon_dmy +
# Pricelow:Material_silk_dmy + Pricemedium:Style_cute_dmy +
# Pricemedium:Style_vintage_dmy + Pricemedium:Material_cashmere_dmy
# + Pricemedium:Material_silk_dmy +
# Style_cute_dmy:Material_chiffon_dmy +
# Style_cute_dmy:Material_rayon_dmy +
# Style_cute_dmy:Material_silk_dmy +
# Style_vintage_dmy:Material_chiffon_dmy, data = Training1s)

# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9230 -0.5996  0.0412  0.8568  3.1678

# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.62032    0.11683   65.226 < 2e-16 ***
# Pricehigh           -0.08125    0.44878   -0.181  0.85644
# Pricelow             0.54044    0.19469    2.776  0.00583 **
# Pricemedium          -0.97525    0.40243   -2.423  0.01594 *
# Style_cute_dmy        0.43820    0.51137    0.857  0.39214
# Style_fashion_dmy    -1.56588    1.45997   -1.073  0.28429
# Style_flare_dmy      -0.42613    2.05809   -0.207  0.83610
# Style_vintage_dmy     0.83217    0.43841    1.898  0.05859 .
# Material_cashmere_dmy -3.88265    1.45997   -2.659  0.00823 **
# Material_chiffon_dmy  1.22081    0.62890    1.941  0.05312 .
# Material_lycra_dmy    -3.59496    1.45997   -2.462  0.01433 *
# Material_modal_dmy    -1.03968    1.45997   -0.712  0.47691
# Material_nylon_dmy     0.75807    1.45997    0.519  0.60396
# Material_rayon_dmy    -1.51850    0.74077   -2.050  0.04120 *
# Material_silk_dmy     0.92973    1.45997    0.637  0.52470
# Pricehigh:Material_nylon_dmy -4.89594    2.10645   -2.324  0.02074 *
# Pricehigh:Style_cute_dmy -1.55186    1.37087   -1.132  0.25848
# Pricehigh:Material_rayon_dmy -1.01069    2.45371   -0.412  0.68069
# Pricehigh:Material_silk_dmy -1.16929    1.93896   -0.603  0.54691
# Pricelow:Style_cute_dmy  -1.50134    0.73558   -2.041  0.04208 *
# Pricelow:Style_vintage_dmy -0.54304    0.86368   -0.629  0.52996
# Pricelow:Material_chiffon_dmy -0.66074    0.81881   -0.807  0.42030
# Pricelow:Material_lycra_dmy  3.21743    2.06728    1.556  0.12062
# Pricelow:Material_modal_dmy -1.15750    2.06728   -0.560  0.57593
# Pricelow:Material_nylon_dmy -2.33625    1.69166   -1.381  0.16824
# Pricelow:Material_rayon_dmy  2.91548    1.27748    2.282  0.02314 *
# Pricelow:Material_silk_dmy -1.22651    1.52937   -0.802  0.42317
# Pricemedium:Style_cute_dmy  1.61222    1.36343    1.182  0.23790
# Pricemedium:Style_vintage_dmy -1.23307    1.56792   -0.786  0.43220
# Pricemedium:Material_cashmere_dmy 2.86076    1.82723    1.566  0.11843
# Pricemedium:Material_silk_dmy -3.96910    1.93368   -2.053  0.04093 *
# Style_cute_dmy:Material_chiffon_dmy -1.77217    1.04111   -1.702  0.08970 .
# Style_cute_dmy:Material_rayon_dmy  0.75775    1.70729    0.444  0.65747
# Style_cute_dmy:Material_silk_dmy -0.69927    1.03572   -0.675  0.50007
# Style_vintage_dmy:Material_chiffon_dmy -0.53499    1.64076   -0.326  0.74459
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Residual standard error: 1.455 on 317 degrees of freedom
# Multiple R-squared:  0.227, Adjusted R-squared:  0.1441

```

```

# F-statistic: 2.738 on 34 and 317 DF,  p-value: 0.00000243

totsale_lm.19_c.2 <- update(totsale_lm.19_c.1, ~. - Pricehigh)
summary(totsale_lm.19_c.2)

# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#   Style_fashion_dmy + Style_flare_dmy + Style_vintage_dmy +
#   Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy
# +
#   Material_modal_dmy + Material_nylon_dmy + Material_rayon_dmy +
#   Material_silk_dmy + Pricehigh:Material_nylon_dmy +
Pricehigh:Style_cute_dmy +
#   Pricehigh:Material_rayon_dmy + Pricehigh:Material_silk_dmy +
#   Pricelow:Style_cute_dmy + Pricelow:Style_vintage_dmy +
Pricelow:Material_chiffon_dmy +
#   Pricelow:Material_lycra_dmy + Pricelow:Material_modal_dmy +
#   Pricelow:Material_nylon_dmy + Pricelow:Material_rayon_dmy +
#   Pricelow:Material_silk_dmy + Pricemedium:Style_cute_dmy +
#   Pricemedium:Style_vintage_dmy + Pricemedium:Material_cashmere_dmy
# +
#   Pricemedium:Material_silk_dmy +
Style_cute_dmy:Material_chiffon_dmy +
#   Style_cute_dmy:Material_rayon_dmy +
Style_cute_dmy:Material_silk_dmy +
#   Style_vintage_dmy:Material_chiffon_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9225 -0.5984  0.0334  0.8580  3.1733
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6148     0.1126  67.602 < 2e-16 ***
# Pricelow             0.5461     0.1919   2.846  0.00471 **
# Pricemedium          -0.9695     0.4006  -2.420  0.01607 *
# Style_cute_dmy        0.4432     0.5098   0.869  0.38534
# Style_fashion_dmy    -1.5604     1.4574  -1.071  0.28515
# Style_flare_dmy      -0.4261     2.0550  -0.207  0.83586
# Style_vintage_dmy     0.8373     0.4368   1.917  0.05616 .
# Material_cashmere_dmy -3.8771     1.4574  -2.660  0.00820 **
# Material_chiffon_dmy  1.2255     0.6274   1.953  0.05166 .
# Material_lycra_dmy   -3.5895     1.4574  -2.463  0.01431 *
# Material_modal_dmy   -1.0342     1.4574  -0.710  0.47848
# Material_nylon_dmy    0.7636     1.4574   0.524  0.60070
# Material_rayon_dmy   -1.5143     0.7393  -2.048  0.04135 *
# Material_silk_dmy     0.9352     1.4574   0.642  0.52153
# Material_nylon_dmy:Pricehigh -4.9772     2.0550  -2.422  0.01599 *
# Style_cute_dmy:Pricehigh -1.6115     1.3287  -1.213  0.22607
# Material_rayon_dmy:Pricehigh -1.0323     2.4471  -0.422  0.67342
# Material_silk_dmy:Pricehigh -1.2294     1.9074  -0.645  0.51968
# Pricelow:Style_cute_dmy  -1.5087     0.7333  -2.057  0.04048 *
# Pricelow:Style_vintage_dmy -0.5483     0.8619  -0.636  0.52508
# Pricelow:Material_chiffon_dmy -0.6650     0.8172  -0.814  0.41645
# Pricelow:Material_lycra_dmy  3.2118     2.0639   1.556  0.12066
# Pricelow:Material_modal_dmy -1.1631     2.0639  -0.564  0.57344
# Pricelow:Material_nylon_dmy -2.3419     1.6888  -1.387  0.16650
# Pricelow:Material_rayon_dmy  2.9111     1.2753   2.283  0.02311 *
# Pricelow:Material_silk_dmy  -1.2337     1.5265  -0.808  0.41959
# Pricemedium:Style_cute_dmy   1.6029     1.3604   1.178  0.23957
# Pricemedium:Style_vintage_dmy -1.2385     1.5652  -0.791  0.42939
# Pricemedium:Material_cashmere_dmy 2.8550     1.8242   1.565  0.11856
# Pricemedium:Material_silk_dmy -3.9789     1.9300  -2.062  0.04005 *
# Style_cute_dmy:Material_chiffon_dmy -1.7744     1.0395  -1.707  0.08879 .
# Style_cute_dmy:Material_rayon_dmy  0.7540     1.7046   0.442  0.65853
# Style_cute_dmy:Material_silk_dmy -0.6868     1.0319  -0.666  0.50613
# Style_vintage_dmy:Material_chiffon_dmy -0.5394     1.6381  -0.329  0.74218
# ---
#             signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.453 on 318 degrees of freedom
# Multiple R-squared:  0.2269,    Adjusted R-squared:  0.1467

```

```
# F-statistic: 2.829 on 33 and 318 DF, p-value: 0.000001425
```

```
totsale_lm.19_c.3 <- update(totsale_lm.19_c.2, ~. -style_flare_dmy)
summary(totsale_lm.19_c.3)
```

```
# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#   Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#   Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#   Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy +
#   Material_nylon_dmy:Pricehigh + Style_cute_dmy:Pricehigh +
#   Material_rayon_dmy:Pricehigh + Material_silk_dmy:Pricehigh +
#   Pricelow:Style_cute_dmy + Pricelow:Style_vintage_dmy +
#   Pricelow:Material_chiffon_dmy +
#   Pricelow:Material_lycra_dmy + Pricelow:Material_modal_dmy +
#   Pricelow:Material_nylon_dmy + Pricelow:Material_rayon_dmy +
#   Pricelow:Material_silk_dmy + Pricemedium:Style_cute_dmy +
#   Pricemedium:Style_vintage_dmy + Pricemedium:Material_cashmere_dmy
#   +
#   Pricemedium:Material_silk_dmy +
#   Style_cute_dmy:Material_chiffon_dmy +
#   Style_cute_dmy:Material_rayon_dmy +
#   Style_cute_dmy:Material_silk_dmy +
#   Style_vintage_dmy:Material_chiffon_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9225 -0.5984  0.0416  0.8580  3.1733
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6148    0.1125  67.703 < 2e-16 ***
# Pricelow           0.5461    0.1916   2.850  0.00465 **
# Pricemedium       -0.9695    0.4000  -2.424  0.01591 *
# Style_cute_dmy      0.4432    0.5091   0.871  0.38463
# Style_fashion_dmy  -1.5604    1.4552  -1.072  0.28442
# Style_vintage_dmy   0.8373    0.4362   1.920  0.05579 .
# Material_cashmere_dmy -3.8771    1.4552  -2.664  0.00811 **
# Material_chiffon_dmy  1.2255    0.6265   1.956  0.05131 .
# Material_lycra_dmy   -3.5895    1.4552  -2.467  0.01417 *
# Material_modal_dmy  -1.0342    1.4552  -0.711  0.47782
# Material_nylon_dmy    0.5505    1.0321   0.533  0.59413
# Material_rayon_dmy  -1.5143    0.7382  -2.051  0.04104 *
# Material_silk_dmy     0.9352    1.4552   0.643  0.52091
# Material_nylon_dmy:Pricehigh -4.7641    1.7770  -2.681  0.00772 **
# Style_cute_dmy:Pricehigh -1.6115    1.3267  -1.215  0.22538
# Material_rayon_dmy:Pricehigh -1.0323    2.4434  -0.422  0.67296
# Material_silk_dmy:Pricehigh -1.2294    1.9045  -0.646  0.51905
# Pricelow:Style_cute_dmy -1.5087    0.7322  -2.060  0.04017 *
# Pricelow:Style_vintage_dmy -0.5483    0.8606  -0.637  0.52446
# Pricelow:Material_chiffon_dmy -0.6650    0.8160  -0.815  0.41575
# Pricelow:Material_lycra_dmy  3.2118    2.0608   1.559  0.12010
# Pricelow:Material_modal_dmy -1.1631    2.0608  -0.564  0.57287
# Pricelow:Material_nylon_dmy -2.1288    1.3383  -1.591  0.11266
# Pricelow:Material_rayon_dmy  2.9111    1.2734   2.286  0.02290 *
# Pricelow:Material_silk_dmy  -1.2337    1.5242  -0.809  0.41889
# Pricemedium:Style_cute_dmy  1.6029    1.3583   1.180  0.23887
# Pricemedium:Style_vintage_dmy -1.2385    1.5629  -0.792  0.42869
# Pricemedium:Material_cashmere_dmy  2.8550    1.8214   1.567  0.11800
# Pricemedium:Material_silk_dmy -3.9789    1.9271  -2.065  0.03975 *
# Style_cute_dmy:Material_chiffon_dmy -1.7744    1.0379  -1.710  0.08831 .
# Style_cute_dmy:Material_rayon_dmy  0.7540    1.7020   0.443  0.65805
# Style_cute_dmy:Material_silk_dmy -0.6868    1.0303  -0.667  0.50549
# Style_vintage_dmy:Material_chiffon_dmy -0.5394    1.6356  -0.330  0.74180
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.451 on 319 degrees of freedom
# Multiple R-squared:  0.2268, Adjusted R-squared:  0.1493
# F-statistic: 2.925 on 32 and 319 DF, p-value: 0.0000008248
```

```

totsale_lm.19_c.4 <- update(totsale_lm.19_c.3, ~. -
Style_vintage_dmy:Material_chiffon_dmy)
summary(totsale_lm.19_c.4)

# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
# Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
# Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
# Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy +
# Material_nylon_dmy:Pricehigh + Style_cute_dmy:Pricehigh +
# Material_rayon_dmy:Pricehigh + Material_silk_dmy:Pricehigh +
# Pricelow:Style_cute_dmy + Pricelow:Style_vintage_dmy +
# Pricelow:Material_chiffon_dmy +
# Pricelow:Material_lycra_dmy + Pricelow:Material_modal_dmy +
# Pricelow:Material_nylon_dmy + Pricelow:Material_rayon_dmy +
# Pricelow:Material_silk_dmy + Pricemedium:Style_cute_dmy +
# Pricemedium:Style_vintage_dmy + Pricemedium:Material_cashmere_dmy
# +
# Pricemedium:Material_silk_dmy +
# Style_cute_dmy:Material_chiffon_dmy +
# Style_cute_dmy:Material_rayon_dmy +
# Style_cute_dmy:Material_silk_dmy,
# data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9276 -0.5993  0.0445  0.8572  3.1711
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6170     0.1121  67.932 < 2e-16 ***
# Pricelow             0.5444     0.1913   2.846  0.00471 **
# Pricemedium          -0.9715     0.3993  -2.433  0.01553 *
# Style_cute_dmy        0.4461     0.5083   0.878  0.38081
# Style_fashion_dmy    -1.5625     1.4532  -1.075  0.28308
# Style_vintage_dmy     0.7992     0.4200   1.903  0.05795 .
# Material_cashmere_dmy -3.8793     1.4532  -2.669  0.00798 **
# Material_chiffon_dmy   1.1466     0.5781   1.983  0.04818 *
# Material_lycra_dmy    -3.5916     1.4532  -2.472  0.01397 *
# Material_modal_dmy    -1.0363     1.4532  -0.713  0.47628
# Material_nylon_dmy     0.5483     1.0306   0.532  0.59506
# Material_rayon_dmy    -1.5069     0.7368  -2.045  0.04165 *
# Material_silk_dmy      0.9331     1.4532   0.642  0.51218
# Material_nylon_dmy:Pricehigh -4.7641     1.7745  -2.685  0.00764 **
# Style_cute_dmy:Pricehigh -1.6176     1.3247  -1.221  0.22296
# Material_rayon_dmy:Pricehigh -1.0263     2.4399  -0.421  0.67432
# Material_silk_dmy:Pricehigh -1.2304     1.9019  -0.647  0.51812
# Pricelow:Style_cute_dmy -1.5183     0.7306  -2.078  0.03851 *
# Pricelow:Style_vintage_dmy -0.5106     0.8518  -0.600  0.54925
# Pricelow:Material_chiffon_dmy -0.5931     0.7853  -0.755  0.45063
# Pricelow:Material_lycra_dmy   3.2135     2.0579   1.562  0.11939
# Pricelow:Material_modal_dmy  -1.1614     2.0579  -0.564  0.57290
# Pricelow:Material_nylon_dmy  -2.1271     1.3364  -1.592  0.11244
# Pricelow:Material_rayon_dmy   2.9033     1.2714   2.284  0.02305 *
# Pricelow:Material_silk_dmy  -1.2317     1.5221  -0.809  0.41898
# Pricemedium:Style_cute_dmy    1.5982     1.3564   1.178  0.23955
# Pricemedium:Style_vintage_dmy -1.2005     1.5565  -0.771  0.44111
# Pricemedium:Material_cashmere_dmy 2.8570     1.8189   1.571  0.11723
# Pricemedium:Material_silk_dmy  -3.9786     1.9244  -2.067  0.03950 *
# Style_cute_dmy:Material_chiffon_dmy -1.7207     1.0236  -1.681  0.09374 .
# Style_cute_dmy:Material_rayon_dmy  0.7416     1.6992   0.436  0.66281
# Style_cute_dmy:Material_silk_dmy -0.6817     1.0288  -0.663  0.50804
# ---
#              signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.449 on 320 degrees of freedom
# Multiple R-squared:  0.2266, Adjusted R-squared:  0.1517
# F-statistic: 3.024 on 31 and 320 DF, p-value: 0.0000004805

totsale_lm.19_c.5 <- update(totsale_lm.19_c.4, ~. -Material_rayon_dmy:Pricehigh)
summary(totsale_lm.19_c.5)

```

```

# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
# Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
# Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
# Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy +
# Material_nylon_dmy:Pricehigh + Style_cute_dmy:Pricehigh +
# Material_silk_dmy:Pricehigh + Pricelow:Style_cute_dmy +
Pricelow:Style_vintage_dmy +
# Pricelow:Material_chiffon_dmy + Pricelow:Material_lycra_dmy +
# Pricelow:Material_modal_dmy + Pricelow:Material_nylon_dmy +
# Pricelow:Material_rayon_dmy + Pricelow:Material_silk_dmy +
# Pricemedium:Style_cute_dmy + Pricemedium:Style_vintage_dmy +
# Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
+
# Style_cute_dmy:Material_chiffon_dmy +
Style_cute_dmy:Material_rayon_dmy +
# Style_cute_dmy:Material_silk_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9693 -0.5996  0.0484  0.8568  3.1716
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6165     0.1120   68.019 < 2e-16 ***
# Pricelow             0.5455     0.1910    2.856  0.00457 **
# Pricemedium          -0.9697     0.3988   -2.431  0.01558 *
# Style_cute_dmy        0.4883     0.4977    0.981  0.32728
# Style_fashion_dmy    -1.5621     1.4513   -1.076  0.28260
# Style_vintage_dmy     0.8000     0.4194    1.907  0.05738 .
# Material_cashmere_dmy -3.8788     1.4513   -2.673  0.00791 **
# Material_chiffon_dmy  1.1422     0.5772    1.979  0.04870 *
# Material_lycra_dmy    -3.5912     1.4513   -2.474  0.01386 *
# Material_modal_dmy    -1.0359     1.4513   -0.714  0.47591
# Material_nylon_dmy     0.5488     1.0293    0.533  0.59427
# Material_rayon_dmy    -1.5066     0.7359   -2.047  0.04143 *
# Material_silk_dmy      0.9335     1.4513    0.643  0.52054
# Material_nylon_dmy:Pricehigh -4.7641     1.7722   -2.688  0.00756 **
# Style_cute_dmy:Pricehigh -1.9201     1.1110   -1.728  0.08492 .
# Material_silk_dmy:Pricehigh -1.1293     1.8842   -0.599  0.54935
# Pricelow:Style_cute_dmy -1.5701     0.7193   -2.183  0.02977 *
# Pricelow:Style_vintage_dmy -0.5120     0.8507   -0.602  0.54764
# Pricelow:Material_chiffon_dmy -0.5847     0.7840   -0.746  0.45636
# Pricelow:Material_lycra_dmy  3.2124     2.0553    1.563  0.11904
# Pricelow:Material_modal_dmy -1.1625     2.0553   -0.566  0.57204
# Pricelow:Material_nylon_dmy -2.1282     1.3347   -1.595  0.11180
# Pricelow:Material_rayon_dmy  2.9024     1.2698    2.286  0.02292 *
# Pricelow:Material_silk_dmy -1.2403     1.5200   -0.816  0.41512
# Pricemedium:Style_cute_dmy  1.5357     1.3465    1.141  0.25491
# Pricemedium:Style_vintage_dmy -1.2026     1.5545   -0.774  0.43971
# Pricemedium:Material_cashmere_dmy 2.8552     1.8165    1.572  0.11699
# Pricemedium:Material_silk_dmy -3.9993     1.9213   -2.082  0.03817 *
# Style_cute_dmy:Material_chiffon_dmy -1.7439     1.0208   -1.708  0.08853 .
# Style_cute_dmy:Material_rayon_dmy  0.3378     1.4001    0.241  0.80953
# Style_cute_dmy:Material_silk_dmy -0.6235     1.0181   -0.612  0.54068
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.447 on 321 degrees of freedom
# Multiple R-squared:  0.2262, Adjusted R-squared:  0.1538
# F-statistic: 3.127 on 30 and 321 DF, p-value: 0.000000282

totsale_lm.19_c.6 <- update(totsale_lm.19_c.5, ~. -Style_cute_dmy:Material_rayon_dmy)
summary(totsale_lm.19_c.6)

# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
# Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
# Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
# Material_nylon_dmy + Material_rayon_dmy + Material_silk_dmy +
# Material_nylon_dmy:Pricehigh + Style_cute_dmy:Pricehigh +

```



```

#               Material_silk_dmy:Pricehigh + Pricelow:Style_cute_dmy +
Pricelow:Style_vintage_dmy +
#               Pricelow:Material_chiffon_dmy + Pricelow:Material_lycra_dmy +
#               Pricelow:Material_modal_dmy + Pricelow:Material_nylon_dmy +
#               Pricelow:Material_rayon_dmy + Pricelow:Material_silk_dmy +
#               Pricemedium:Style_cute_dmy + Pricemedium:Style_vintage_dmy +
#               Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
+
#               Style_cute_dmy:Material_chiffon_dmy +
Style_cute_dmy:Material_silk_dmy,
#               data = Training1s)
#
# Residuals:
#               Min       1Q   Median       3Q      Max
# -4.9952 -0.5989  0.0464  0.8575  3.1730
#
# Coefficients:
#               Estimate Std. Error t value Pr(>|t|)
# (Intercept)              7.6151      0.1117  68.198 < 2e-16 ***
# Pricelow                0.5464      0.1907   2.865  0.00444 **
# Pricemedium             -0.9689      0.3982  -2.433  0.01551 *
# Style_cute_dmy           0.5156      0.4839   1.066  0.28744
# Style_fashion_dmy       -1.5607      1.4492  -1.077  0.28232
# Style_vintage_dmy        0.7942      0.4181   1.899  0.05841 .
# Material_cashmere_dmy   -3.8774      1.4492  -2.676  0.00784 **
# Material_chiffon_dmy     1.1427      0.5764   1.982  0.04828 *
# Material_lycra_dmy      -3.5898      1.4492  -2.477  0.01376 *
# Material_modal_dmy      -1.0345      1.4492  -0.714  0.47585
# Material_nylon_dmy       0.5502      1.0278   0.535  0.59278
# Material_rayon_dmy      -1.4136      0.6258  -2.259  0.02455 *
# Material_silk_dmy        0.9349      1.4492   0.645  0.51930
# Material_nylon_dmy:Pricehigh -4.7641      1.7696  -2.692  0.00747 **
# Style_cute_dmy:Pricehigh -1.8432      1.0629  -1.734  0.08383 .
# Material_silk_dmy:Pricehigh -1.1686      1.8744  -0.623  0.53345
# Pricelow:Style_cute_dmy  -1.5899      0.7135  -2.228  0.02655 *
# Pricelow:Style_vintage_dmy -0.5058      0.8490  -0.596  0.55179
# Pricelow:Material_chiffon_dmy -0.5828      0.7829  -0.744  0.45715
# Pricelow:Material_lycra_dmy  3.2115      2.0523   1.565  0.11860
# Pricelow:Material_modal_dmy -1.1634      2.0523  -0.567  0.57118
# Pricelow:Material_nylon_dmy -2.1291      1.3327  -1.598  0.11112
# Pricelow:Material_rayon_dmy  2.8099      1.2087   2.325  0.02070 *
# Pricelow:Material_silk_dmy  -1.2384      1.5178  -0.816  0.41514
# Pricemedium:Style_cute_dmy  1.5174      1.3424   1.130  0.25916
# Pricemedium:Style_vintage_dmy -1.1962      1.5520  -0.771  0.44140
# Pricemedium:Material_cashmere_dmy 2.8544      1.8139   1.574  0.11655
# Pricemedium:Material_silk_dmy -3.9917      1.9182  -2.081  0.03823 *
# Style_cute_dmy:Material_chiffon_dmy -1.7647      1.0157  -1.737  0.08326 .
# Style_cute_dmy:Material_silk_dmy -0.6493      1.0110  -0.642  0.52121
# ---
#               signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.445 on 322 degrees of freedom
# Multiple R-squared:  0.226,    Adjusted R-squared:  0.1563
# F-statistic: 3.242 on 29 and 322 DF,  p-value: 0.000000156

totsale_lm.19_c.7 <- update(totsale_lm.19_c.6, ~. -Material_nylon_dmy)
summary(totsale_lm.19_c.7)

# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#               Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#               Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#               Material_rayon_dmy + Material_silk_dmy +
Material_nylon_dmy:Pricehigh +
#               Style_cute_dmy:Pricehigh + Material_silk_dmy:Pricehigh +
#               Pricelow:Style_cute_dmy + Pricelow:Style_vintage_dmy +
Pricelow:Material_chiffon_dmy +
#               Pricelow:Material_lycra_dmy + Pricelow:Material_modal_dmy +
#               Pricelow:Material_nylon_dmy + Pricelow:Material_rayon_dmy +
#               Pricelow:Material_silk_dmy + Pricemedium:Style_cute_dmy +
#               Pricemedium:Style_vintage_dmy + Pricemedium:Material_cashmere_dmy
+

```

```

#               Pricemedium:Material_silk_dmy +
Style_cute_dmy:Material_chiffon_dmy +
#               Style_cute_dmy:Material_silk_dmy, data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9959 -0.6005  0.0444  0.8559  3.1665
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6216     0.1109  68.738 < 2e-16 ***
# Pricelow             0.5399     0.1901   2.840  0.00479 **
# Pricemedium          -0.9754     0.3976  -2.453  0.01469 *
# Style_cute_dmy        0.5098     0.4832   1.055  0.29223
# Style_fashion_dmy     -1.5672     1.4476  -1.083  0.27978
# Style_vintage_dmy      0.7884     0.4175   1.888  0.05990 .
# Material_cashmere_dmy  -3.8839     1.4476  -2.683  0.00767 **
# Material_chiffon_dmy   1.1375     0.5757   1.976  0.04901 *
# Material_lycra_dmy     -3.5963     1.4476  -2.484  0.01348 *
# Material_modal_dmy     -1.0410     1.4476  -0.719  0.47258
# Material_rayon_dmy     -1.4175     0.6250  -2.268  0.02400 *
# Material_silk_dmy       0.9284     1.4476   0.641  0.52173
# Material_nylon_dmy:Pricehigh -4.2204     1.4476  -2.916  0.00380 **
# Style_cute_dmy:Pricehigh -1.8413     1.0617  -1.734  0.08381 .
# Material_silk_dmy:Pricehigh -1.1672     1.8724  -0.623  0.53347
# Pricelow:Style_cute_dmy -1.5847     0.7127  -2.224  0.02687 *
# Pricelow:Style_vintage_dmy -0.5000     0.8480  -0.590  0.55586
# Pricelow:Material_chiffon_dmy -0.5781     0.7819  -0.739  0.46027
# Pricelow:Material_lycra_dmy   3.2180     2.0500   1.570  0.11745
# Pricelow:Material_modal_dmy  -1.1570     2.0500  -0.564  0.57288
# Pricelow:Material_nylon_dmy  -1.5789     0.8476  -1.863  0.06338 .
# Pricelow:Material_rayon_dmy   2.8137     1.2073   2.331  0.02039 *
# Pricelow:Material_silk_dmy  -1.2320     1.5160  -0.813  0.41701
# Pricemedium:Style_cute_dmy    1.5228     1.3408   1.136  0.25693
# Pricemedium:Style_vintage_dmy -1.1904     1.5502  -0.768  0.44309
# Pricemedium:Material_cashmere_dmy 2.8609     1.8118   1.579  0.11532
# Pricemedium:Material_silk_dmy -3.9856     1.9161  -2.080  0.03830 *
# Style_cute_dmy:Material_chiffon_dmy -1.7614     1.0145  -1.736  0.08349 .
# Style_cute_dmy:Material_silk_dmy -0.6481     1.0099  -0.642  0.52149
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.443 on 323 degrees of freedom
# Multiple R-squared:  0.2253, Adjusted R-squared:  0.1582
# F-statistic: 3.355 on 28 and 323 DF, p-value: 0.00000009214

totsale_lm.19_c.8 <- update(totsale_lm.19_c.7, ~.- Pricelow:Material_modal_dmy)

# Call:
#      lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#      Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#      Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#      Material_rayon_dmy + Material_silk_dmy +
#      Material_nylon_dmy:Pricehigh +
#      Style_cute_dmy:Pricehigh + Material_silk_dmy:Pricehigh +
#      Pricelow:Style_cute_dmy + Pricelow:Style_vintage_dmy +
#      Pricelow:Material_chiffon_dmy +
#      Pricelow:Material_lycra_dmy + Pricelow:Material_nylon_dmy +
#      Pricelow:Material_rayon_dmy + Pricelow:Material_silk_dmy +
#      Pricemedium:Style_cute_dmy + Pricemedium:Style_vintage_dmy +
#      Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
#      +
#      Style_cute_dmy:Material_chiffon_dmy +
#      Style_cute_dmy:Material_silk_dmy,
#      data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9966 -0.5961  0.0484  0.8586  3.1631
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)

```

```

# (Intercept) 7.6250 0.1106 68.941 < 2e-16 ***
# Pricelow 0.5300 0.1891 2.803 0.00537 **
# Pricemedium -0.9788 0.3971 -2.465 0.01423 *
# Style_cute_dmy 0.5071 0.4827 1.051 0.29422
# Style_fashion_dmy -1.5705 1.4460 -1.086 0.27824
# Style_vintage_dmy 0.7853 0.4170 1.883 0.06058 .
# Material_cashmere_dmy -3.8873 1.4460 -2.688 0.00755 **
# Material_chiffon_dmy 1.1353 0.5751 1.974 0.04919 *
# Material_lycra_dmy -3.5996 1.4460 -2.489 0.01330 *
# Material_modal_dmy -1.6178 1.0239 -1.580 0.11508
# Material_rayon_dmy -1.4198 0.6244 -2.274 0.02363 *
# Material_silk_dmy 0.9251 1.4460 0.640 0.52279
# Material_nylon_dmy:Pricehigh -4.2238 1.4460 -2.921 0.00373 **
# Style_cute_dmy:Pricehigh -1.8398 1.0605 -1.735 0.08374 .
# Material_silk_dmy:Pricehigh -1.1650 1.8704 -0.623 0.53383
# Pricelow:Style_cute_dmy -1.5767 0.7118 -2.215 0.02745 *
# Pricelow:Style_vintage_dmy -0.4904 0.8469 -0.579 0.56298
# Pricelow:Material_chiffon_dmy -0.5700 0.7810 -0.730 0.46601
# Pricelow:Material_lycra_dmy 3.2279 2.0477 1.576 0.11592
# Pricelow:Material_nylon_dmy -1.5724 0.8466 -1.857 0.06418 .
# Pricelow:Material_rayon_dmy 2.8226 1.2059 2.341 0.01986 *
# Pricelow:Material_silk_dmy -1.2224 1.5144 -0.807 0.42014
# Pricemedium:Style_cute_dmy 1.5266 1.3394 1.140 0.25523
# Pricemedium:Style_vintage_dmy -1.1873 1.5486 -0.767 0.44380
# Pricemedium:Material_cashmere_dmy 2.8643 1.8099 1.583 0.11450
# Pricemedium:Material_silk_dmy -3.9811 1.9140 -2.080 0.03832 *
# Style_cute_dmy:Material_chiffon_dmy -1.7619 1.0134 -1.739 0.08306 .
# Style_cute_dmy:Material_silk_dmy -0.6515 1.0088 -0.646 0.51888
# ---

```

```

# signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#

```

```

# Residual standard error: 1.442 on 324 degrees of freedom
# Multiple R-squared: 0.2246, Adjusted R-squared: 0.1599
# F-statistic: 3.475 on 27 and 324 DF, p-value: 0.00000005417

```

```

totsale_lm.19_c.9 <- update(totsale_lm.19_c.8, ~. -Pricelow:Style_vintage_dmy)
summary(totsale_lm.19_c.9)

```

```

# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
# Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
# Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
# Material_rayon_dmy + Material_silk_dmy +
# Material_nylon_dmy:Pricehigh +
# Style_cute_dmy:Pricehigh + Material_silk_dmy:Pricehigh +
# Pricelow:Style_cute_dmy + Pricelow:Material_chiffon_dmy +
# Pricelow:Material_lycra_dmy + Pricelow:Material_nylon_dmy +
# Pricelow:Material_rayon_dmy + Pricelow:Material_silk_dmy +
# Pricemedium:Style_cute_dmy + Pricemedium:Style_vintage_dmy +
# Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
# +
# Style_cute_dmy:Material_chiffon_dmy +
# Style_cute_dmy:Material_silk_dmy,
# data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9951 -0.6177  0.0743  0.8512  3.1557
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6323    0.1098  69.540 < 2e-16 ***
# Pricelow         0.5064    0.1844   2.746  0.00638 **
# Pricemedium     -0.9863    0.3965  -2.488  0.01336 *
# Style_cute_dmy   0.4982    0.4820   1.034  0.30204
# Style_fashion_dmy -1.5779    1.4445  -1.092  0.27548
# Style_vintage_dmy  0.6665    0.3626   1.838  0.06701 .
# Material_cashmere_dmy -3.8947    1.4445  -2.696  0.00738 **
# Material_chiffon_dmy  1.1481    0.5740   2.000  0.04634 *
# Material_lycra_dmy -3.6070    1.4445  -2.497  0.01302 *
# Material_modal_dmy -1.6134    1.0229  -1.577  0.11569

```

```

# Material_rayon_dmy -1.4040 0.6231 -2.253 0.02491 *
# Material_silk_dmy 0.9177 1.4445 0.635 0.52567
# Material_nylon_dmy:Pricehigh -4.2311 1.4445 -2.929 0.00364 **
# Style_cute_dmy:Pricehigh -1.8416 1.0595 -1.738 0.08312 .
# Material_silk_dmy:Pricehigh -1.1559 1.8684 -0.619 0.53656
# Pricelow:Style_cute_dmy -1.5537 0.7099 -2.189 0.02934 *
# Pricelow:Material_chiffon_dmy -0.5668 0.7802 -0.726 0.46806
# Pricelow:Material_lycra_dmy 3.2515 2.0452 1.590 0.11285
# Pricelow:Material_nylon_dmy -1.5561 0.8453 -1.841 0.06653 .
# Pricelow:Material_rayon_dmy 2.8231 1.2047 2.343 0.01971 *
# Pricelow:Material_silk_dmy -1.1998 1.5123 -0.793 0.42813
# Pricemedium:Style_cute_dmy 1.5381 1.3379 1.150 0.25114
# Pricemedium:Style_vintage_dmy -1.0683 1.5333 -0.697 0.48647
# Pricemedium:Material_cashmere_dmy 2.8718 1.8080 1.588 0.11317
# Pricemedium:Material_silk_dmy -3.9712 1.9120 -2.077 0.03859 *
# Style_cute_dmy:Material_chiffon_dmy -1.7740 1.0122 -1.753 0.08062 .
# Style_cute_dmy:Material_silk_dmy -0.6588 1.0077 -0.654 0.51374
# ---
# signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.44 on 325 degrees of freedom
# Multiple R-squared: 0.2238, Adjusted R-squared: 0.1617
# F-statistic: 3.603 on 26 and 325 DF, p-value: 0.00000003152

totsale_lm.19_c.10 <- update(totsale_lm.19_c.9, ~. -Material_silk_dmy:Pricehigh)
summary(totsale_lm.19_c.10)
# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
# Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
# Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
# Material_rayon_dmy + Material_silk_dmy +
# Material_nylon_dmy:Pricehigh +
# Style_cute_dmy:Pricehigh + Pricelow:Style_cute_dmy +
# Pricelow:Material_chiffon_dmy +
# Pricelow:Material_lycra_dmy + Pricelow:Material_nylon_dmy +
# Pricelow:Material_rayon_dmy + Pricelow:Material_silk_dmy +
# Pricemedium:Style_cute_dmy + Pricemedium:Style_vintage_dmy +
# Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
# +
# Style_cute_dmy:Material_chiffon_dmy +
# Style_cute_dmy:Material_silk_dmy,
# data = Trainings1s)
#
# Residuals:
# Min 1Q Median 3Q Max
# -4.9946 -0.6403 0.0862 0.8505 3.1550
#
# Coefficients:
# Estimate Std. Error t value Pr(>|t|)
# (Intercept) 7.6331 0.1096 69.617 < 2e-16 ***
# Pricelow 0.5039 0.1842 2.736 0.00657 **
# Pricemedium -0.9902 0.3961 -2.500 0.01291 *
# Style_cute_dmy 0.4970 0.4815 1.032 0.30272
# Style_fashion_dmy -1.5787 1.4431 -1.094 0.27479
# Style_vintage_dmy 0.6650 0.3623 1.836 0.06734 .
# Material_cashmere_dmy -3.8954 1.4431 -2.699 0.00731 **
# Material_chiffon_dmy 1.1502 0.5735 2.006 0.04572 *
# Material_lycra_dmy -3.6078 1.4431 -2.500 0.01291 *
# Material_modal_dmy -1.6130 1.0219 -1.578 0.11544
# Material_rayon_dmy -1.3844 0.6217 -2.227 0.02665 *
# Material_silk_dmy 0.2300 0.9216 0.250 0.80307
# Material_nylon_dmy:Pricehigh -4.2319 1.4431 -2.932 0.00360 **
# Style_cute_dmy:Pricehigh -1.9599 1.0411 -1.883 0.06065 .
# Pricelow:Style_cute_dmy -1.5243 0.7077 -2.154 0.03198 *
# Pricelow:Material_chiffon_dmy -0.5699 0.7794 -0.731 0.46521
# Pricelow:Material_lycra_dmy 3.2540 2.0433 1.593 0.11224
# Pricelow:Material_nylon_dmy -1.5544 0.8444 -1.841 0.06656 .
# Pricelow:Material_rayon_dmy 2.8052 1.2032 2.331 0.02034 *
# Pricelow:Material_silk_dmy -0.4946 0.9928 -0.498 0.61872
# Pricemedium:Style_cute_dmy 1.5852 1.3345 1.188 0.23574
# Pricemedium:Style_vintage_dmy -1.0638 1.5318 -0.694 0.48790
# Pricemedium:Material_cashmere_dmy 2.8757 1.8063 1.592 0.11235

```

```

# Pricemedium:Material_silk_dmy      -3.2376      1.4985  -2.161  0.03146 *
# Style_cute_dmy:Material_chiffon_dmy -1.7836      1.0111  -1.764  0.07867 .
# Style_cute_dmy:Material_silk_dmy    -0.7904      0.9841  -0.803  0.42243
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.439 on 326 degrees of freedom
# Multiple R-squared:  0.2228, Adjusted R-squared:  0.1632
# F-statistic: 3.739 on 25 and 326 DF, p-value: 0.00000001835

totsale_lm.19_c.11 <- update(totsale_lm.19_c.10, ~. -Material_silk_dmy)
summary(totsale_lm.19_c.11)
# Call:
#      lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#      Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#      Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#      Material_rayon_dmy + Material_nylon_dmy:Pricehigh +
Style_cute_dmy:Pricehigh +
#      Pricelow:Style_cute_dmy + Pricelow:Material_chiffon_dmy +
#      Pricelow:Material_lycra_dmy + Pricelow:Material_nylon_dmy +
#      Pricelow:Material_rayon_dmy + Pricelow:Material_silk_dmy +
#      Pricemedium:Style_cute_dmy + Pricemedium:Style_vintage_dmy +
#      Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
+
#      Style_cute_dmy:Material_chiffon_dmy +
Style_cute_dmy:Material_silk_dmy,
#      data = Training1s)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.9952 -0.6181  0.0896  0.8547  3.1521
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6360      0.1089  70.134 < 2e-16 ***
# Pricelow              0.5020      0.1838   2.731  0.00665 **
# Pricemedium          -0.9915      0.3955  -2.507  0.01265 *
# Style_cute_dmy         0.4947      0.4807   1.029  0.30420
# Style_fashion_dmy     -1.5816      1.4410  -1.098  0.27321
# Style_vintage_dmy      0.6635      0.3617   1.834  0.06753 .
# Material_cashmere_dmy -3.8983      1.4410  -2.705  0.00718 **
# Material_chiffon_dmy   1.1465      0.5725   2.003  0.04604 *
# Material_lycra_dmy     -3.6106      1.4410  -2.506  0.01271 *
# Material_modal_dmy     -1.6149      1.0204  -1.583  0.11448
# Material_rayon_dmy     -1.3960      0.6191  -2.255  0.02480 *
# Material_nylon_dmy:Pricehigh -4.2348      1.4410  -2.939  0.00353 **
# Style_cute_dmy:Pricehigh -1.9014      1.0129  -1.877  0.06139 .
# Pricelow:Style_cute_dmy -1.5361      0.7051  -2.179  0.03008 *
# Pricelow:Material_chiffon_dmy -0.5660      0.7781  -0.727  0.46751
# Pricelow:Material_lycra_dmy   3.2559      2.0403   1.596  0.11151
# Pricelow:Material_nylon_dmy  -1.5554      0.8432  -1.845  0.06601 .
# Pricelow:Material_rayon_dmy   2.8158      1.2007   2.345  0.01962 *
# Pricelow:Material_silk_dmy    -0.2732      0.4459  -0.613  0.54043
# Pricemedium:Style_cute_dmy    1.5650      1.3301   1.177  0.24021
# Pricemedium:Style_vintage_dmy -1.0637      1.5296  -0.695  0.48728
# Pricemedium:Material_cashmere_dmy 2.8771      1.8037   1.595  0.11166
# Pricemedium:Material_silk_dmy  -3.0301      1.2449  -2.434  0.01547 *
# Style_cute_dmy:Material_chiffon_dmy -1.7772      1.0093  -1.761  0.07922 .
# Style_cute_dmy:Material_silk_dmy -0.7259      0.9481  -0.766  0.44447
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.437 on 327 degrees of freedom
# Multiple R-squared:  0.2227, Adjusted R-squared:  0.1656
# F-statistic: 3.904 on 24 and 327 DF, p-value: 0.000000009273

totsale_lm.19_c.12 <- update(totsale_lm.19_c.11, ~. -Pricelow:Material_silk_dmy)
summary(totsale_lm.19_c.12)

# Call:
#      lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#      Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +

```

```

#               Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#               Material_rayon_dmy + Material_nylon_dmy:Pricehigh +
Style_cute_dmy:Pricehigh +
#               Pricelow:Style_cute_dmy + Pricelow:Material_chiffon_dmy +
#               Pricelow:Material_lycra_dmy + Pricelow:Material_nylon_dmy +
#               Pricelow:Material_rayon_dmy + Pricemedium:Style_cute_dmy +
#               Pricemedium:Style_vintage_dmy + Pricemedium:Material_cashmere_dmy
+
#               Pricemedium:Material_silk_dmy +
Style_cute_dmy:Material_chiffon_dmy +
#               Style_cute_dmy:Material_silk_dmy, data = Training1s)
#
# Residuals:
#           Min       1Q   Median       3Q      Max
# -4.9966 -0.6256  0.0868  0.8480  3.1525
#
# Coefficients:
#               Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6356      0.1088  70.198 < 2e-16 ***
# Pricelow             0.4724      0.1772   2.666  0.00805 **
# Pricemedium          -0.9950      0.3951  -2.519  0.01225 *
# Style_cute_dmy        0.4965      0.4803   1.034  0.30202
# Style_fashion_dmy     -1.5812      1.4396  -1.098  0.27286
# Style_vintage_dmy      0.6715      0.3611   1.859  0.06387 .
# Material_cashmere_dmy -3.8980      1.4396  -2.708  0.00713 **
# Material_chiffon_dmy   1.1457      0.5719   2.003  0.04597 *
# Material_lycra_dmy     -3.6103      1.4396  -2.508  0.01263 *
# Material_modal_dmy     -1.5997      1.0191  -1.570  0.11745
# Material_rayon_dmy     -1.4072      0.6183  -2.276  0.02349 *
# Material_nylon_dmy:Pricehigh -4.2344      1.4396  -2.941  0.00350 **
# Style_cute_dmy:Pricehigh -1.8438      1.0076  -1.830  0.06817 .
# Pricelow:Style_cute_dmy -1.5350      0.7044  -2.179  0.03004 *
# Pricelow:Material_chiffon_dmy -0.5356      0.7758  -0.690  0.49047
# Pricelow:Material_lycra_dmy 3.2854      2.0378   1.612  0.10787
# Pricelow:Material_nylon_dmy -1.5255      0.8410  -1.814  0.07061 .
# Pricelow:Material_rayon_dmy 2.8569      1.1977   2.385  0.01763 *
# Pricemedium:Style_cute_dmy 1.6211      1.3257   1.223  0.22227
# Pricemedium:Style_vintage_dmy -1.0679      1.5282  -0.699  0.48516
# Pricemedium:Material_cashmere_dmy 2.8805      1.8020   1.599  0.11088
# Pricemedium:Material_silk_dmy -2.9722      1.2401  -2.397  0.01710 *
# Style_cute_dmy:Material_chiffon_dmy -1.7785      1.0084  -1.764  0.07871 .
# Style_cute_dmy:Material_silk_dmy -0.8917      0.9078  -0.982  0.32670
# ---
#               signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.436 on 328 degrees of freedom
# Multiple R-squared:  0.2218,    Adjusted R-squared:  0.1672
# F-statistic: 4.065 on 23 and 328 DF,  p-value: 0.000000005182

totsale_lm.19_c.13 <- update(totsale_lm.19_c.12, ~. -Pricelow:Material_chiffon_dmy)
summary(totsale_lm.19_c.13)

# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#   Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#   Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#   Material_rayon_dmy + Material_nylon_dmy:Pricehigh +
Style_cute_dmy:Pricehigh +
#   Pricelow:Style_cute_dmy + Pricelow:Material_lycra_dmy +
Pricelow:Material_nylon_dmy +
#   Pricelow:Material_rayon_dmy + Pricemedium:Style_cute_dmy +
#   Pricemedium:Style_vintage_dmy + Pricemedium:Material_cashmere_dmy
+
#   Pricemedium:Material_silk_dmy +
Style_cute_dmy:Material_chiffon_dmy +
#   Style_cute_dmy:Material_silk_dmy, data = Training1s)
#
# Residuals:
#           Min       1Q   Median       3Q      Max
# -5.0317 -0.6105  0.0954  0.8262  3.1449
#

```

```

# Coefficients:
#           Estimate Std. Error t value Pr(>|t|)
# (Intercept)              7.6432      0.1081  70.687 < 2e-16 ***
#           Pricelow         0.4492      0.1738   2.584  0.01018 *
#           Pricemedium      -1.0020      0.3946  -2.539  0.01157 *
#           Style_cute_dmy     0.5240      0.4782   1.096  0.27403
# Style_fashion_dmy        -1.5888      1.4384  -1.105  0.27017
# Style_vintage_dmy         0.6857      0.3603   1.903  0.05789 .
# Material_cashmere_dmy     -3.9056      1.4384  -2.715  0.00697 **
# Material_chiffon_dmy       0.8808      0.4237   2.079  0.03840 *
# Material_lycra_dmy        -3.6179      1.4384  -2.515  0.01237 *
# Material_modal_dmy        -1.5957      1.0183  -1.567  0.11806
# Material_rayon_dmy        -1.4196      0.6175  -2.299  0.02214 *
# Material_nylon_dmy:Pricehigh -4.2420      1.4384  -2.949  0.00342 **
# Style_cute_dmy:Pricehigh   -1.8844      1.0051  -1.875  0.06169 .
# Pricelow:Style_cute_dmy    -1.5920      0.6990  -2.278  0.02339 *
# Pricelow:Material_lycra_dmy  3.3086      2.0359   1.625  0.10509
# Pricelow:Material_nylon_dmy -1.5099      0.8400  -1.797  0.07319 .
# Pricelow:Material_rayon_dmy  2.8848      1.1961   2.412  0.01642 *
# Pricemedium:Style_cute_dmy  1.5835      1.3235   1.196  0.23238
# Pricemedium:Style_vintage_dmy -1.0828      1.5268  -0.709  0.47872
# Pricemedium:Material_cashmere_dmy 2.8875      1.8005   1.604  0.10974
# Pricemedium:Material_silk_dmy -2.9823      1.2391  -2.407  0.01664 *
# Style_cute_dmy:Material_chiffon_dmy -1.7004      1.0012  -1.698  0.09039 .
# Style_cute_dmy:Material_silk_dmy -0.8629      0.9061  -0.952  0.34165
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.434 on 329 degrees of freedom
# Multiple R-squared:  0.2207, Adjusted R-squared:  0.1686
# F-statistic: 4.234 on 22 and 329 DF, p-value: 0.000000002956

totsale_lm.19_c.14 <- update(totsale_lm.19_c.13, ~. -Pricemedium:Style_vintage_dmy)
summary(totsale_lm.19_c.14)

# Call:
# lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#           Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#           Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#           Material_rayon_dmy + Material_nylon_dmy:Pricehigh +
#           Style_cute_dmy:Pricehigh +
#           Pricelow:Style_cute_dmy + Pricelow:Material_lycra_dmy +
#           Pricelow:Material_nylon_dmy +
#           Pricelow:Material_rayon_dmy + Pricemedium:Style_cute_dmy +
#           Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
#           +
#           Style_cute_dmy:Material_chiffon_dmy +
#           Style_cute_dmy:Material_silk_dmy,
#           data = Training1s)
#
# Residuals:
#           Min       1Q   Median       3Q      Max
# -5.0310 -0.6127  0.1134  0.8236  3.1410
#
# Coefficients:
#           Estimate Std. Error t value Pr(>|t|)
# (Intercept)              7.6471      0.1079  70.868 < 2e-16 ***
#           Pricelow         0.4475      0.1737   2.577  0.01041 *
#           Pricemedium      -1.0727      0.3815  -2.812  0.00522 **
#           Style_cute_dmy     0.5194      0.4778   1.087  0.27781
#           Style_fashion_dmy  -1.5927      1.4373  -1.108  0.26864
#           Style_vintage_dmy  0.6254      0.3498   1.788  0.07475 .
#           Material_cashmere_dmy -3.9095      1.4373  -2.720  0.00688 **
#           Material_chiffon_dmy  0.8828      0.4233   2.085  0.03782 *
#           Material_lycra_dmy   -3.6218      1.4373  -2.520  0.01221 *
#           Material_modal_dmy   -1.5988      1.0175  -1.571  0.11709
#           Material_rayon_dmy   -1.4120      0.6170  -2.289  0.02273 *
#           Material_nylon_dmy:Pricehigh -4.2459      1.4373  -2.954  0.00336 **
#           Style_cute_dmy:Pricehigh  -1.8837      1.0043  -1.876  0.06160 .
#           Pricelow:Style_cute_dmy  -1.5879      0.6984  -2.273  0.02364 *
#           Pricelow:Material_lycra_dmy  3.3104      2.0344   1.627  0.10465

```

```

# Pricelow:Material_nylon_dmy      -1.5120      0.8394    -1.801    0.07257 .
# Pricelow:Material_rayon_dmy      2.8752      1.1951     2.406    0.01669 *
# Pricemedium:Style_cute_dmy       1.6352      1.3205     1.238    0.21647
# Pricemedium:Material_cashmere_dmy 2.9582      1.7964     1.647    0.10056
# Pricemedium:Material_silk_dmy    -2.9351     1.2364    -2.374    0.01817 *
# Style_cute_dmy:Material_chiffon_dmy -1.7026     1.0005    -1.702    0.08974 .
# Style_cute_dmy:Material_silk_dmy  -0.8706      0.9054    -0.962    0.33694
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.433 on 330 degrees of freedom
# Multiple R-squared:  0.2195,    Adjusted R-squared:  0.1698
# F-statistic: 4.419 on 21 and 330 DF,  p-value: 0.000000001671

```

```

totsale_lm.19_c.15 <- update(totsale_lm.19_c.14, ~. -Style_cute_dmy:Material_silk_dmy)
summary(totsale_lm.19_c.15)

```

```

# Call:
#      lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_cute_dmy +
#      Style_fashion_dmy + Style_vintage_dmy + Material_cashmere_dmy +
#      Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#      Material_rayon_dmy + Material_nylon_dmy:Pricehigh +
#      Style_cute_dmy:Pricehigh +
#      Pricelow:Style_cute_dmy + Pricelow:Material_lycra_dmy +
#      Pricelow:Material_nylon_dmy +
#      Pricelow:Material_rayon_dmy + Pricemedium:Style_cute_dmy +
#      Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
#      +
#      style_cute_dmy:Material_chiffon_dmy, data = Training1s)
#
#      Residuals:
#      Min       1Q   Median       3Q      Max
#     -5.0113  -0.6128   0.1188   0.8238   3.1419
#
# Coefficients:
#
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6462    0.1079  70.870 < 2e-16 ***
# Pricelow           0.4485    0.1736   2.583  0.01022 *
# Pricemedium       -1.0526    0.3809  -2.764  0.00604 **
# Style_cute_dmy      0.5006    0.4774   1.049  0.29508
# Style_fashion_dmy  -1.5917    1.4372  -1.108  0.26887
# Style_vintage_dmy  0.6219    0.3498   1.778  0.07635 .
# Material_cashmere_dmy -3.9085    1.4372  -2.720  0.00688 **
# Material_chiffon_dmy  0.8835    0.4233   2.087  0.03763 *
# Material_lycra_dmy  -3.6208    1.4372  -2.519  0.01223 *
# Material_modal_dmy  -1.5983    1.0174  -1.571  0.11714
# Material_rayon_dmy  -1.3560    0.6141  -2.208  0.02793 *
# Material_nylon_dmy:Pricehigh -4.2450    1.4372  -2.954  0.00336 **
# Style_cute_dmy:Pricehigh -2.1728    0.9581  -2.268  0.02399 *
# Pricelow:Style_cute_dmy -1.7716    0.6717  -2.637  0.00875 **
# Pricelow:Material_lycra_dmy  3.3093    2.0342   1.627  0.10471
# Pricelow:Material_nylon_dmy -1.5121    0.8393  -1.802  0.07251 .
# Pricelow:Material_rayon_dmy  2.8191    1.1935   2.362  0.01876 *
# Pricemedium:Style_cute_dmy  1.3510    1.2869   1.050  0.29454
# Pricemedium:Material_cashmere_dmy 2.9381    1.7961   1.636  0.10282
# Pricemedium:Material_silk_dmy -3.2381    1.1954  -2.709  0.00710 **
# Style_cute_dmy:Material_chiffon_dmy -1.6226    0.9969  -1.628  0.10454
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.433 on 331 degrees of freedom
# Multiple R-squared:  0.2173,    Adjusted R-squared:  0.17
# F-statistic: 4.595 on 20 and 331 DF,  p-value: 0.000000001098

```

```

#
#      Residuals:
#      Min       1Q   Median       3Q      Max
#     -5.0113  -0.6128   0.1188   0.8238   3.1419
#
# Coefficients:
#
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6462    0.1079  70.870 < 2e-16 ***
# Pricelow           0.4485    0.1736   2.583  0.01022 *
# Pricemedium       -1.0526    0.3809  -2.764  0.00604 **
# Style_cute_dmy      0.5006    0.4774   1.049  0.29508
# Style_fashion_dmy  -1.5917    1.4372  -1.108  0.26887
# Style_vintage_dmy  0.6219    0.3498   1.778  0.07635 .
# Material_cashmere_dmy -3.9085    1.4372  -2.720  0.00688 **
# Material_chiffon_dmy  0.8835    0.4233   2.087  0.03763 *
# Material_lycra_dmy  -3.6208    1.4372  -2.519  0.01223 *
# Material_modal_dmy  -1.5983    1.0174  -1.571  0.11714
# Material_rayon_dmy  -1.3560    0.6141  -2.208  0.02793 *
# Material_nylon_dmy:Pricehigh -4.2450    1.4372  -2.954  0.00336 **
# Style_cute_dmy:Pricehigh -2.1728    0.9581  -2.268  0.02399 *
# Pricelow:Style_cute_dmy -1.7716    0.6717  -2.637  0.00875 **
# Pricelow:Material_lycra_dmy  3.3093    2.0342   1.627  0.10471
# Pricelow:Material_nylon_dmy -1.5121    0.8393  -1.802  0.07251 .
# Pricelow:Material_rayon_dmy  2.8191    1.1935   2.362  0.01876 *
# Pricemedium:Style_cute_dmy  1.3510    1.2869   1.050  0.29454
# Pricemedium:Material_cashmere_dmy 2.9381    1.7961   1.636  0.10282
# Pricemedium:Material_silk_dmy -3.2381    1.1954  -2.709  0.00710 **
# Style_cute_dmy:Material_chiffon_dmy -1.6226    0.9969  -1.628  0.10454
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.433 on 331 degrees of freedom
# Multiple R-squared:  0.2173,    Adjusted R-squared:  0.17
# F-statistic: 4.595 on 20 and 331 DF,  p-value: 0.000000001098

```

```

# Call:
#      lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_fashion_dmy +
#      Style_vintage_dmy + Material_cashmere_dmy +
#      Material_chiffon_dmy + Material_lycra_dmy + Material_modal_dmy +
#      Material_rayon_dmy + Material_nylon_dmy:Pricehigh +
#      Style_cute_dmy:Pricehigh +
#      Pricelow:Style_cute_dmy + Pricelow:Material_lycra_dmy +
#      Pricelow:Material_nylon_dmy +
#      Pricelow:Material_rayon_dmy + Pricemedium:Style_cute_dmy +
#      Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
#      +
#      style_cute_dmy:Material_chiffon_dmy, data = Training1s)
#
#      Residuals:
#      Min       1Q   Median       3Q      Max
#     -5.0113  -0.6128   0.1188   0.8238   3.1419
#
# Coefficients:
#
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.6462    0.1079  70.870 < 2e-16 ***
# Pricelow           0.4485    0.1736   2.583  0.01022 *
# Pricemedium       -1.0526    0.3809  -2.764  0.00604 **
# Style_cute_dmy      0.5006    0.4774   1.049  0.29508
# Style_fashion_dmy  -1.5917    1.4372  -1.108  0.26887
# Style_vintage_dmy  0.6219    0.3498   1.778  0.07635 .
# Material_cashmere_dmy -3.9085    1.4372  -2.720  0.00688 **
# Material_chiffon_dmy  0.8835    0.4233   2.087  0.03763 *
# Material_lycra_dmy  -3.6208    1.4372  -2.519  0.01223 *
# Material_modal_dmy  -1.5983    1.0174  -1.571  0.11714
# Material_rayon_dmy  -1.3560    0.6141  -2.208  0.02793 *
# Material_nylon_dmy:Pricehigh -4.2450    1.4372  -2.954  0.00336 **
# Style_cute_dmy:Pricehigh -2.1728    0.9581  -2.268  0.02399 *
# Pricelow:Style_cute_dmy -1.7716    0.6717  -2.637  0.00875 **
# Pricelow:Material_lycra_dmy  3.3093    2.0342   1.627  0.10471
# Pricelow:Material_nylon_dmy -1.5121    0.8393  -1.802  0.07251 .
# Pricelow:Material_rayon_dmy  2.8191    1.1935   2.362  0.01876 *
# Pricemedium:Style_cute_dmy  1.3510    1.2869   1.050  0.29454
# Pricemedium:Material_cashmere_dmy 2.9381    1.7961   1.636  0.10282
# Pricemedium:Material_silk_dmy -3.2381    1.1954  -2.709  0.00710 **
# Style_cute_dmy:Material_chiffon_dmy -1.6226    0.9969  -1.628  0.10454
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.433 on 331 degrees of freedom
# Multiple R-squared:  0.2173,    Adjusted R-squared:  0.17
# F-statistic: 4.595 on 20 and 331 DF,  p-value: 0.000000001098

```

```

#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.433 on 331 degrees of freedom
# Multiple R-squared:  0.2173,    Adjusted R-squared:  0.17
# F-statistic: 4.595 on 20 and 331 DF,  p-value: 0.000000001098

```

```

# Residual standard error: 1.433 on 331 degrees of freedom
# Multiple R-squared:  0.2173,    Adjusted R-squared:  0.17
# F-statistic: 4.595 on 20 and 331 DF,  p-value: 0.000000001098

```

```

totsale_lm.19_c.16 <- update(totsale_lm.19_c.15, ~. -Style_cute_dmy)

```

```

summary(totsale_lm.19_c.16)

```

```

# Call:
#      lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_fashion_dmy +
#

```



```

#           style_vintage_dmy + Material_cashmere_dmy + Material_chiffon_dmy
+
#           Material_lycra_dmy + Material_modal_dmy + Material_rayon_dmy +
#           Material_nylon_dmy:Pricehigh + Style_cute_dmy:Pricehigh +
#           Pricelow:Style_cute_dmy + Pricelow:Material_lycra_dmy +
Pricelow:Material_nylon_dmy +
#           Pricelow:Material_rayon_dmy + Pricemedium:Style_cute_dmy +
#           Pricemedium:Material_cashmere_dmy + Pricemedium:Material_silk_dmy
+
#           style_cute_dmy:Material_chiffon_dmy, data = Training1s)
#
# Residuals:
#           Min       1Q   Median       3Q      Max
# -4.7257 -0.6143  0.1155  0.8254  3.1179
#
# Coefficients:
#           Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6701    0.1055  72.734 < 2e-16 ***
# Pricelow             0.4261    0.1723   2.472  0.01393 *
# Pricemedium          -1.0752    0.3803  -2.827  0.00498 **
# Style_fashion_dmy    -1.6157    1.4372  -1.124  0.26174
# Style_vintage_dmy     0.6008    0.3493   1.720  0.08633 .
# Material_cashmere_dmy -3.9325    1.4372  -2.736  0.00655 **
# Material_chiffon_dmy  0.8725    0.4232   2.062  0.04003 *
# Material_lycra_dmy   -3.6448    1.4372  -2.536  0.01167 *
# Material_modal_dmy    -1.6111    1.0175  -1.583  0.11429
# Material_rayon_dmy    -1.2851    0.6105  -2.105  0.03604 *
# Material_nylon_dmy:Pricehigh -4.2690    1.4372  -2.970  0.00319 **
# Pricehigh:Style_cute_dmy -1.7198    0.8554  -2.011  0.04518 *
# Pricelow:Style_cute_dmy -1.3091    0.5068  -2.583  0.01022 *
# Pricelow:Material_lycra_dmy  3.3318    2.0344   1.638  0.10242
# Pricelow:Material_nylon_dmy -1.5136    0.8394  -1.803  0.07227 .
# Pricelow:Material_rayon_dmy  2.7467    1.1917   2.305  0.02179 *
# Pricemedium:Style_cute_dmy  1.8507    1.1956   1.548  0.12258
# Pricemedium:Material_cashmere_dmy  2.9607    1.7962   1.648  0.10023
# Pricemedium:Material_silk_dmy -3.2390    1.1956  -2.709  0.00710 **
# Material_chiffon_dmy:Style_cute_dmy -1.2817    0.9425  -1.360  0.17480
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.433 on 332 degrees of freedom
# Multiple R-squared:  0.2147, Adjusted R-squared:  0.1698
# F-statistic: 4.777 on 19 and 332 DF, p-value: 0.000000000762

totsale_lm.19_c.17 <- update(totsale_lm.19_c.16, ~. -Style_fashion_dmy)
summary(totsale_lm.19_c.17)

# Call:
#           lm(formula = log(TotalSales) ~ Pricelow + Pricemedium + Style_vintage_dmy +
#           Material_cashmere_dmy + Material_chiffon_dmy + Material_lycra_dmy
+
#           Material_modal_dmy + Material_rayon_dmy +
Material_nylon_dmy:Pricehigh +
#           Pricehigh:Style_cute_dmy + Pricelow:Style_cute_dmy +
Pricelow:Material_lycra_dmy +
#           Pricelow:Material_nylon_dmy + Pricelow:Material_rayon_dmy +
#           Pricemedium:Style_cute_dmy + Pricemedium:Material_cashmere_dmy +
#           Pricemedium:Material_silk_dmy +
Material_chiffon_dmy:Style_cute_dmy,
#           data = Training1s)
#
# Residuals:
#           Min       1Q   Median       3Q      Max
# -4.7170 -0.6385  0.1161  0.8312  3.1266
#
# Coefficients:
#           Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.6614    0.1052  72.819 < 2e-16 ***
# Pricelow             0.4343    0.1723   2.521  0.01217 *
# Pricemedium          -1.0669    0.3804  -2.805  0.00533 **
# Style_vintage_dmy     0.6066    0.3494   1.736  0.08343 .
# Material_cashmere_dmy -3.9238    1.4378  -2.729  0.00669 **

```

```

# Material_chiffon_dmy          0.8766      0.4234      2.071  0.03917 *
# Material_lycra_dmy           -3.6361      1.4378     -2.529  0.01190 *
# Material_modal_dmy           -1.6065      1.0179     -1.578  0.11546
# Material_rayon_dmy           -1.2785      0.6107     -2.093  0.03706 *
# Material_nylon_dmy:Pricehigh -4.2603      1.4378     -2.963  0.00326 **
# Pricehigh:Style_cute_dmy     -1.7133      0.8557     -2.002  0.04607 *
# Pricelow:Style_cute_dmy      -1.3093      0.5070     -2.582  0.01024 *
# Pricelow:Material_lycra_dmy   3.3236      2.0352      1.633  0.10339
# Pricelow:Material_nylon_dmy  -1.5131      0.8398     -1.802  0.07247 .
# Pricelow:Material_rayon_dmy   2.7405      1.1922      2.299  0.02214 *
# Pricemedium:Style_cute_dmy    1.8510      1.1961      1.548  0.12267
# Pricemedium:Material_cashmere_dmy 2.9524      1.7969      1.643  0.10132
# Pricemedium:Material_silk_dmy -3.2388      1.1961     -2.708  0.00712 **
# Material_chiffon_dmy:Style_cute_dmy -1.2798      0.9429     -1.357  0.17561
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.434 on 333 degrees of freedom
# Multiple R-squared:  0.2117,    Adjusted R-squared:  0.1691
# F-statistic: 4.968 on 18 and 333 DF,  p-value: 0.000000005564

```

```

#Adj Rsq is starting to decrease so lets stop and consider totsale_lm.19_c.15 as best model
# even though it has some insignificant terms

```

```

# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)    7.6462    0.1079   70.870 < 2e-16 ***
# Pricelow       0.4485    0.1736    2.583  0.01022 *
# Pricemedium    -1.0526    0.3809   -2.764  0.00604 **
# Style_cute_dmy  0.5006    0.4774    1.049  0.29508
# Style_fashion_dmy -1.5917    1.4372   -1.108  0.26887
# Style_vintage_dmy  0.6219    0.3498    1.778  0.07635 .
# Material_cashmere_dmy -3.9085    1.4372   -2.720  0.00688 **
# Material_chiffon_dmy  0.8835    0.4233    2.087  0.03763 *
# Material_lycra_dmy  -3.6208    1.4372   -2.519  0.01223 *
# Material_modal_dmy  -1.5983    1.0174   -1.571  0.11714
# Material_rayon_dmy  -1.3560    0.6141   -2.208  0.02793 *
# Material_nylon_dmy:Pricehigh -4.2450    1.4372   -2.954  0.00336 **
# Style_cute_dmy:Pricehigh    -2.1728    0.9581   -2.268  0.02399 *
# Pricelow:Style_cute_dmy    -1.7716    0.6717   -2.637  0.00875 **
# Pricelow:Material_lycra_dmy  3.3093    2.0342    1.627  0.10471
# Pricelow:Material_nylon_dmy  -1.5121    0.8393   -1.802  0.07251 .
# Pricelow:Material_rayon_dmy  2.8191    1.1935    2.362  0.01876 *
# Pricemedium:Style_cute_dmy    1.3510    1.2869    1.050  0.29454
# Pricemedium:Material_cashmere_dmy 2.9381    1.7961    1.636  0.10282
# Pricemedium:Material_silk_dmy  -3.2381    1.1954   -2.709  0.00710 **
# Style_cute_dmy:Material_chiffon_dmy -1.6226    0.9969   -1.628  0.10454
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.433 on 331 degrees of freedom
# Multiple R-squared:  0.2173,    Adjusted R-squared:  0.17
# F-statistic: 4.595 on 20 and 331 DF,  p-value: 0.000000001098

```

```

par(mfrow=c(2,2))
plot(totsale_lm.19_c.15)

```

```

# based on the residual plots and cooks distance,
# looks like there are couple of outliers hence heavy tail in Q-Q plot at lower quantiles.
# For most part it is normal. If we remove the high leverage points and outliers,
# the model could get better ; but for now this is fine and residuals are homoscedastic (equal variance)
# Adj Rsq also improved from the run totsale_lm.19 where we only had Main effects after the addition of interaction variables
# is this the best model - no and we need to refine further adding more factors into the model based on experimental design

```

```

# To decide the pricing for various upcoming clothes, they wish to find how the

```

```

# style, season, and material affect the sales of a dress and if the style of the
dress
# is more influential than its price -
# So the ones with p-value < alpha =0.05 are significant factors in our model,
# and affect the sales and the weightage how they affect is described by the
coefficient ;
# To answer if style is more influential than price, based on our model,
# the answer is no because two of the price levels ARE significant and
# only Style_vintage is marginally significant.

#validate the regression model using test data
# Till now we were checking training-error but the real goal of the model is to reduce
the
# testing error. As we already split the sample dataset into training and testing
dataset,
# we will use test dataset to evaluate the model that we have arrived upon.
# We will make a prediction based on 'totsale_lm.19_c.15' and will evaluate the model.
# As the last step, we will predict the 'test' observation and will see the comparison
# between predicted response and actual response value.
# RMSE explains on an average how much of the predicted value will be from the actual
value.
# Based on RMSE = 19749.31, we can conclude that on an average predicted value will be
off by 19749.31 from the actual value.
# It is not a great model because we only considered the few factors asked in Task 3
for the modeling of Total Sales. had we considered every possible reasonable factor
then we could have minimized RMSE.
# But we have answered the objective of Task 3 based on what we have created so far
pred1 <- predict(totsale_lm.19_c.15, newdata = Testing1)
rmse <- sqrt(sum((exp(pred1) - Testing1$TotalSales)^2)/length(Testing1$TotalSales))
c(RMSE = rmse, R2=summary(totsale_lm.19_c.15)$r.squared)
# RMSE          R2
# 19749.3077309    0.2172935

par(mfrow=c(1,1))
plot(Testing1$TotalSales, exp(pred1)) # not that great

#now onto tasks 4 and 5
#Task4:
#Also, to increase sales, the management wants to analyze the attributes of dresses
and find which are the leading factors affecting the sale of a dress.

#we are yet to explore Size,Neckline,Sleeve length,waistline,Fabric
type,Decoration,Pattern Type of the dress
# we have already expored the material style and season, so we can add the imp factors
from those later after completing the final task and then refine the model once at
that time

task4lm <- (lm(log(TotalSales) ~ factor(Size) + factor(waiseline) +
                                factor(FabricType) + factor(Decoration) +
                                factor(' Pattern Type')+
                                SleeveLengththreequarter + SleeveLengthsleeveless +
                                SleeveLengthshort + SleeveLengthhalf sleeve +
                                SleeveLengthfull+
                                SleeveLengthcap_sleeves +
                                NeckLine_backless_dmy + NeckLine_boatneck_dmy +
                                NeckLine_bowneck_dmy + NeckLine_halter_dmy +
                                NeckLine_mandarincollor_dmy +
                                NeckLine_oneck_dmy + NeckLine_open_dmy +
                                NeckLine_peterpancollor_dmy +
                                NeckLine_ruffled_dmy + NeckLine_Scoop_dmy +
                                NeckLine_slashneck_dmy +
                                NeckLine_squarecollor_dmy + NeckLine_sweetheart_dmy +
                                NeckLine_turndowncollor_dmy + NeckLine_vneck_dmy
                                , data = ATT_DS3))

vif(task4lm)
# Error in vif.default(task4lm) :
#       there are aliased coefficients in the model
# alias(task4lm)
# Model :
#       log(TotalSales) ~ factor(Size) + factor(waiseline) + factor(FabricType) +

```

```

#      factor(Decoration) + factor(`Pattern Type`) + SleeveLengththreequarter +
#      SleeveLengthsleeveless + SleeveLengthshort + SleeveLengthhalfsleeve +
#      SleeveLengthfull + SleeveLengthcap_sleeves + NeckLine_backless_dmy +
#      NeckLine_boatneck_dmy + NeckLine_bowneck_dmy + NeckLine_halter_dmy +
#      NeckLine_mandarincollor_dmy + NeckLine_oneck_dmy + NeckLine_open_dmy +
#      NeckLine_peterpancollor_dmy + NeckLine_ruffled_dmy + NeckLine_Scoop_dmy +
#      NeckLine_slashneck_dmy + NeckLine_squarecollor_dmy + NeckLine_sweetheart_dmy
+
#      NeckLine_turndowncollor_dmy + NeckLine_vneck_dmy
#
# Complete :
#      (Intercept) factor(Size)L factor(Size)M factor(Size)S factor(Size)XL
# NeckLine_vneck_dmy 1 0 0 0 0
# factor(waiseline)empire factor(waiseline)natural factor(waiseline)null
# NeckLine_vneck_dmy 0 0 0 0
# factor(waiseline)princess factor(FabricType)broadcloth
# NeckLine_vneck_dmy 0 0 0 0
# factor(FabricType)chiffon factor(FabricType)Corduroy factor(FabricType)dobby
# NeckLine_vneck_dmy 0 0 0 0
# factor(FabricType)flannel factor(FabricType)jersey factor(FabricType)knitted
# NeckLine_vneck_dmy 0 0 0 0
# factor(FabricType)lace factor(FabricType)null factor(FabricType)organza
# NeckLine_vneck_dmy 0 0 0 0
# factor(FabricType)other factor(FabricType)poplin factor(FabricType)satin
# NeckLine_vneck_dmy 0 0 0 0
# factor(FabricType)terry factor(FabricType)tulle factor(FabricType)woolen
# NeckLine_vneck_dmy 0 0 0 0
# factor(FabricType)worsted factor(Decoration)beading factor(Decoration)bow
# NeckLine_vneck_dmy 0 0 0 0
# factor(Decoration)button factor(Decoration)cascading factor(Decoration)crystal
# NeckLine_vneck_dmy 0 0 0 0
# factor(Decoration)draped factor(Decoration)embroidary
# NeckLine_vneck_dmy 0 0 0 0
# factor(Decoration)feathers factor(Decoration)flowers
# NeckLine_vneck_dmy 0 0 0 0
# factor(Decoration)hollowout factor(Decoration)lace factor(Decoration)none
# NeckLine_vneck_dmy 0 0 0 0
# factor(Decoration)null factor(Decoration)pearls factor(Decoration)plain
# NeckLine_vneck_dmy 0 0 0 0
# factor(Decoration)pleat factor(Decoration)pockets factor(Decoration)rivet
# NeckLine_vneck_dmy 0 0 0 0
# factor(Decoration)ruched factor(Decoration)ruffles factor(Decoration)sashes
# NeckLine_vneck_dmy 0 0 0 0
# factor(Decoration)sequined factor(Decoration)tassel factor(Decoration)Tiered
# NeckLine_vneck_dmy 0 0 0 0
# factor(`Pattern Type`)character factor(`Pattern Type`)dot
# NeckLine_vneck_dmy 0 0 0 0
# factor(`Pattern Type`)floral factor(`Pattern Type`)geometric
# NeckLine_vneck_dmy 0 0 0 0
# factor(`Pattern Type`)leopard factor(`Pattern Type`)none
# NeckLine_vneck_dmy 0 0 0 0
# factor(`Pattern Type`)null factor(`Pattern Type`)patchwork
# NeckLine_vneck_dmy 0 0 0 0
# factor(`Pattern Type`)plaid factor(`Pattern Type`)print
# NeckLine_vneck_dmy 0 0 0 0
# factor(`Pattern Type`)solid factor(`Pattern Type`)splice
# NeckLine_vneck_dmy 0 0 0 0
# factor(`Pattern Type`)striped SleeveLengththreequarter SleeveLengthsleeveless
# NeckLine_vneck_dmy 0 0 0 0
# SleeveLengthshort SleeveLengthhalfsleeve SleeveLengthfull
# NeckLine_vneck_dmy 0 0 0 0
# SleeveLengthcap_sleeves NeckLine_backless_dmy NeckLine_boatneck_dmy
# NeckLine_vneck_dmy 0 -1 -1 -1
# NeckLine_bowneck_dmy NeckLine_halter_dmy NeckLine_mandarincollor_dmy
# NeckLine_vneck_dmy -1 -1 -1
# NeckLine_oneck_dmy NeckLine_open_dmy NeckLine_peterpancollor_dmy
# NeckLine_vneck_dmy -1 -1 -1
# NeckLine_ruffled_dmy NeckLine_Scoop_dmy NeckLine_slashneck_dmy
# NeckLine_vneck_dmy -1 -1 -1
# NeckLine_squarecollor_dmy NeckLine_sweetheart_dmy NeckLine_turndowncollor_dmy
# NeckLine_vneck_dmy -1 -1 -1
#

```

```

task4lm <- (lm(log(TotalSales) ~ factor(Size) + factor(waiseline) +
               factor(FabricType) + factor(Decoration) +
               factor(`Pattern Type`)+
               SleeveLengththreequarter + SleeveLengthsleeveless +
               SleeveLengthshort + SleeveLengthhalfssleeve + SleeveLengthfull+
               SleeveLengthcap_sleeves +
               NeckLine_backless_dmy + NeckLine_boatneck_dmy +
               NeckLine_bowneck_dmy + NeckLine_halter_dmy +
               NeckLine_mandarincollor_dmy +
               NeckLine_oneck_dmy + NeckLine_open_dmy +
               NeckLine_peterpancollor_dmy +
               NeckLine_ruffled_dmy + NeckLine_Scoop_dmy +
               NeckLine_slashneck_dmy +
               NeckLine_squarecollor_dmy + NeckLine_sweetheart_dmy +
               NeckLine_turndowncollor_dmy
               , data = ATT_DS3))

```

```

vif(task4lm)
# GVIF Df GVIF^(1/(2*Df))
# factor(Size)                2.340937  4      1.112177
# factor(waiseline)            2.528051  4      1.122918
# factor(FabricType)           35.640902 17      1.110825
# factor(Decoration)           129.747578 24      1.106682
# factor(`Pattern Type`)       6.997702 13      1.077701
# SleeveLengththreequarter     8.204722  1      2.864389
# SleeveLengthsleeveless       33.948462  1      5.826531
# SleeveLengthshort            21.422838  1      4.628481
# SleeveLengthhalfssleeve      9.945179  1      3.153598
# SleeveLengthfull             22.041905  1      4.694881
# SleeveLengthcap_sleeves      2.355190  1      1.534663
# NeckLine_backless_dmy        2.040432  1      1.428437
# NeckLine_boatneck_dmy        1.423237  1      1.192995
# NeckLine_bowneck_dmy         1.257232  1      1.121264
# NeckLine_halter_dmy          2.033808  1      1.426117
# NeckLine_mandarincollor_dmy  1.078339  1      1.038431
# NeckLine_oneck_dmy           1.750278  1      1.322981
# NeckLine_open_dmy            1.297945  1      1.139274
# NeckLine_peterpancollor_dmy  1.127475  1      1.061826
# NeckLine_ruffled_dmy         1.151200  1      1.072940
# NeckLine_Scoop_dmy           4.169585  1      2.041956
# NeckLine_slashneck_dmy       1.310494  1      1.144768
# NeckLine_squarecollor_dmy    1.490239  1      1.220753
# NeckLine_sweetheart_dmy      1.941704  1      1.393450
# NeckLine_turndowncollor_dmy  1.217727  1      1.103507

```

```

task4lm <- update(task4lm, ~. - SleeveLengthsleeveless) # removing the vif >5

```

```

vif(task4lm)
# GVIF Df GVIF^(1/(2*Df))
# factor(Size)                2.335705  4      1.111865
# factor(waiseline)            2.524140  4      1.122701
# factor(FabricType)           35.455822 17      1.110655
# factor(Decoration)           126.877531 24      1.106167
# factor(`Pattern Type`)       6.786349 13      1.076431
# SleeveLengththreequarter     1.357291  1      1.165028
# SleeveLengthshort            1.511971  1      1.229622
# SleeveLengthhalfssleeve      1.285793  1      1.133928
# SleeveLengthfull             1.449922  1      1.204127
# SleeveLengthcap_sleeves      1.063690  1      1.031353
# NeckLine_backless_dmy        2.040417  1      1.428432
# NeckLine_boatneck_dmy        1.422589  1      1.192724
# NeckLine_bowneck_dmy         1.255550  1      1.120513
# NeckLine_halter_dmy          2.033289  1      1.425934
# NeckLine_mandarincollor_dmy  1.078334  1      1.038429
# NeckLine_oneck_dmy           1.750260  1      1.322974
# NeckLine_open_dmy            1.297614  1      1.139129
# NeckLine_peterpancollor_dmy  1.127458  1      1.061818
# NeckLine_ruffled_dmy         1.148372  1      1.071621
# NeckLine_Scoop_dmy           4.168900  1      2.041788
# NeckLine_slashneck_dmy       1.308595  1      1.143938
# NeckLine_squarecollor_dmy    1.489482  1      1.220443
# NeckLine_sweetheart_dmy      1.938776  1      1.392399

```

```

# NeckLine_turndowncollor_dmy 1.217720 1 1.103504
# Now we are good have vif <5

# Now we can continue the factor way of handling the categorical variables for lm
# but it is more easier to remove the
# insignificant variables if they were dummy variables -
# hence lets convert these factors that are going to modeled as dummy
# Before that let us also group (pool) the levels of the various factor/character
levels that
# have insufficient
# samples into other group as we can't do much with very few samples in the group.
# This should have been done for the other groups which were already changed to dummy
values but
# lets not change those for now as we have been using them so far as is. Just for
these
# dress levels which are still character/factor we are going to convert now.
# As a threshold, lets set 10 as the minimum count per group if they were to be
considered
# as a group of their own else we will pool them to a value called other

# table(ATT_DS3$Size) # not changing Size as all the levels have atleast 10 in each

# free L M S XL
# 173 96 177 38 15

# table(ATT_DS3$waiseline) # lets change dropped and princess into a level called
other
# dropped empire natural null princess
# 4 104 304 86 1

# table(ATT_DS3$FabricType)
# lets change batik , Corduroy, dobby, flannel, knitted, lace , organza, poplin,
# satin, terry , tulle, woolen into a level called other
#
# batik broadcloth chiffon Corduroy dobby flannel jersey knitted
lace
# 2 31 144 2 2 2 12 2
1
# null organza other poplin satin terry tulle woolen
worsted
# 265 1 1 2 7 1 2 3
19

# table(ATT_DS3$Decoration)
# lets change button , cascading , crystal , draped ,embroidary , feathers,
flowers, none,
# pearls, plain, pleat, pockets, rivet ,ruched, tassel , Tiered to a level called
other
# applique beading bow button cascading crystal draped embroidary
feathers
# 21 22 15 6 1 3 2 5
2
# flowers hollowout lace none null pearls plain pleat
pockets
# 4 21 70 2 235 1 2 1
5
# rivet ruched ruffles sashes sequined tassel Tiered
# 3 3 17 42 14 1 1

# table(ATT_DS3$`Pattern Type`)
# lets change character, floral, geometric, leopard, none, plaid, splice into other
level
# animal character dot floral geometric leopard none null patchwork
# 21 1 14 2 5 4 1 108 47
# plaid print solid splice striped
# 3 71 204 1 17

summary(task41m)
# Call:

```

```

#           lm(formula = log(TotalSales) ~ factor(Size) + factor(waiseline) +
#               factor(FabricType) + factor(Decoration) + factor(`Pattern Type`)
+
#               SleeveLengththreequarter + SleeveLengthshort +
SleeveLengthhalfsleeve +
#               SleeveLengthfull + SleeveLengthcap_sleeves +
NeckLine_backless_dmy +
#               NeckLine_boatneck_dmy + NeckLine_bowneck_dmy +
NeckLine_halter_dmy +
#               NeckLine_mandarincollor_dmy + NeckLine_oneck_dmy +
NeckLine_open_dmy +
#               NeckLine_peterpancollor_dmy + NeckLine_ruffled_dmy +
NeckLine_Scoop_dmy +
#               NeckLine_slashneck_dmy + NeckLine_squarecollor_dmy +
NeckLine_sweetheart_dmy +
#               NeckLine_turndowncollor_dmy, data = ATT_DS3)
#

```

# we are going to create SNO to merge the dataset again after stripping Dress ID and Recommendation before undergoing the dummy variable creation

```

ATT_DS3 <- ATT_DS3 %>% mutate(SNOMERGE = 1:n())
TASK4_DS <- fastDummies::dummy_cols(dplyr::select(ATT_DS3, -
c(Dress_ID, Recommendation)) %>%
  rename(Pattern_Type = `Pattern Type`) %>%
  mutate(
    waiseline = ifelse(waiseline %in%
c("dropped", "princess"), "other", waiseline),
    FabricType = ifelse(FabricType %in% c("batik", "Corduroy",
      "dobby", "flannel", "knitted",
      "lace", "organza", "poplin",
      "satin", "terry",
      "tulle", "woolen"), "other",
      FabricType),
    Decoration = ifelse( Decoration %in% c("button", "cascading",
      "crystal",
      "draped", "embroidary",
      "feathers", "flowers", "none",
      "pearls", "plain", "pleat",
      "pockets", "rivet",
      "ruched", "tassel", "Tiered"),
      "other", Decoration),
    Pattern_Type = ifelse(Pattern_Type %in%
      c("character", "floral", "geometric",
      "leopard", "none", "plaid",
"splice"),
      "other", Pattern_Type)
  ), remove_first_dummy = TRUE)

```

```

TASK4_DS <- left_join(TASK4_DS
, dplyr::select(ATT_DS3, SNOMERGE, Dress_ID, Recommendation))

```

#By default, dummy\_cols() will make dummy variables from factor or character columns only.

#This is because in most cases those are the only types of data you want dummy variables from.

#If those are the only columns you want, then the function takes your data set as the first

#parameter and returns a data.frame with the newly created variables appended to the end of the original data.

#option for dummy\_cols() is remove\_first\_dummy which by default is FALSE.

#If TRUE, it removes the first dummy variable created from each column.

#This is done to avoid multicollinearity in a multiple regression model caused by included all dummy variables.

```

task4lm <- lm(formula = log(TotalSales) ~ Size_L + Size_M +
  Size_S + Size_XL + waiseline_natural + waiseline_null +
  waiseline_other + FabricType_chiffon + FabricType_jersey +
  FabricType_null + FabricType_other + FabricType_worsted +
  Decoration_beading +
  Decoration_bow + Decoration_hollowout +
  Decoration_lace + Decoration_null +

```

```

    Decoration_other + Decoration_ruffles + Decoration_sashes + Decoration_sequined +
    Pattern_Type_dot + Pattern_Type_other + Pattern_Type_null +
    Pattern_Type_patchwork + Pattern_Type_print +
    Pattern_Type_solid + Pattern_Type_stripped +
    SleeveLengththreequarter + SleeveLengthshort +
SleeveLengthhalfsleeve +
    SleeveLengthfull + SleeveLengthcap_sleeves +
NeckLine_backless_dmy +
    NeckLine_boatneck_dmy + NeckLine_bowneck_dmy +
NeckLine_halter_dmy +
    NeckLine_mandarincollor_dmy + NeckLine_oneck_dmy +
NeckLine_open_dmy +
    NeckLine_peterpancollor_dmy + NeckLine_ruffled_dmy +
NeckLine_scoop_dmy +
    NeckLine_slashneck_dmy + NeckLine_squarecollor_dmy +
NeckLine_sweetheart_dmy +
    NeckLine_turndowncollor_dmy, data = TASK4_DS)

```

```

vif(task4lm)
# Size_L          Size_M          Size_S
# 1.432387        1.536966        1.287723
# Size_XL          waiseline_natural    waiseline_null
# 1.184655        1.798530        1.881452
# waiseline_other    FabricType_chiffon    FabricType_jersey
# 1.133072        4.741197        1.476295
# FabricType_null    FabricType_other    FabricType_worsted
# 5.378450        2.053439        1.748252
# Decoration_beading    Decoration_bow    Decoration_hollowout
# 2.328712        1.971131        2.165474
# Decoration_lace    Decoration_null    Decoration_other
# 4.109546        7.407472        3.164365
# Decoration_ruffles    Decoration_sashes    Decoration_sequined
# 1.980412        3.191992        1.769016
# Pattern_Type_dot    Pattern_Type_other    Pattern_Type_null
# 1.929328        1.900682        5.407070
# Pattern_Type_patchwork    Pattern_Type_print    Pattern_Type_solid
# 3.295449        4.150701        7.196751
# Pattern_Type_stripped    SleeveLengththreequarter    SleeveLengthshort
# 1.932287        1.234200        1.416055
# SleeveLengthhalfsleeve    SleeveLengthfull    SleeveLengthcap_sleeves
# 1.244727        1.341314        1.059962
# NeckLine_backless_dmy    NeckLine_boatneck_dmy    NeckLine_bowneck_dmy
# 1.062225        1.232815        1.192466
# NeckLine_halter_dmy    NeckLine_mandarincollor_dmy    NeckLine_oneck_dmy
# 1.056616        1.075163        1.678604
# NeckLine_open_dmy    NeckLine_peterpancollor_dmy    NeckLine_ruffled_dmy
# 1.100550        1.121503        1.147062
# NeckLine_scoop_dmy    NeckLine_slashneck_dmy    NeckLine_squarecollor_dmy
# 1.123392        1.218818        1.154260
# NeckLine_sweetheart_dmy    NeckLine_turndowncollor_dmy
# 1.408604        1.172605

```

```

#Removing high vif >5 variable out

```

```

task4lm <- update(task4lm, ~. - Decoration_null)
vif(task4lm)
# Size_L          Size_M          Size_S
# 1.432153        1.536943        1.285580
# Size_XL          waiseline_natural    waiseline_null
# 1.184613        1.792448        1.862631
# waiseline_other    FabricType_chiffon    FabricType_jersey
# 1.131783        4.665047        1.472194
# FabricType_null    FabricType_other    FabricType_worsted
# 5.256554        2.046386        1.746501
# Decoration_beading    Decoration_bow    Decoration_hollowout
# 1.333053        1.305314        1.157021
# Decoration_lace    Decoration_other    Decoration_ruffles
# 1.241436        1.288986        1.180160
# Decoration_sashes    Decoration_sequined    Pattern_Type_dot
# 1.238657        1.133247        1.908603
# Pattern_Type_other    Pattern_Type_null    Pattern_Type_patchwork
# 1.900682        5.401288        3.294295

```



#	Pattern_Type_print	Pattern_Type_solid	Pattern_Type_stripped
#	4.138395	7.181514	1.932034
#	SleeveLengththreequarter	sleeveLengthshort	SleeveLengthhalfsleeve
#	1.230709	1.414643	1.244706
#	SleeveLengthfull	SleeveLengthcap_sleeves	NeckLine_backless_dmy
#	1.331672	1.059877	1.062210
#	NeckLine_boatneck_dmy	NeckLine_bowneck_dmy	NeckLine_halter_dmy
#	1.216127	1.188428	1.056391
#	NeckLine_mandarincollor_dmy	NeckLine_oneck_dmy	NeckLine_open_dmy
#	1.075102	1.677717	1.082504
#	NeckLine_peterpancollor_dmy	NeckLine_ruffled_dmy	NeckLine_Scoop_dmy
#	1.118218	1.146450	1.097606
#	NeckLine_slashneck_dmy	NeckLine_squarecollor_dmy	NeckLine_sweetheart_dmy
#	1.218781	1.152754	1.408486
#	NeckLine_turndowncollor_dmy		
#	1.170170		

```
task41m <- update(task41m, ~. -Pattern_Type_solid)
vif(task41m)
```

#	Size_L	Size_M	Size_S
#	1.431129	1.534607	1.285561
#	Size_XL	waisseline_natural	waisseline_null
#	1.183945	1.772984	1.857362
#	waisseline_other	FabricType_chiffon	FabricType_jersey
#	1.130897	4.655324	1.468109
#	FabricType_null	FabricType_other	FabricType_worsted
#	5.250691	2.037080	1.746492
#	Decoration_beading	Decoration_bow	Decoration_hollowout
#	1.329165	1.303053	1.154039
#	Decoration_lace	Decoration_other	Decoration_ruffles
#	1.240753	1.276107	1.158506
#	Decoration_sashes	Decoration_sequined	Pattern_Type_dot
#	1.221615	1.128492	1.343024
#	Pattern_Type_other	Pattern_Type_null	Pattern_Type_patchwork
#	1.121031	1.586395	1.238263
#	Pattern_Type_print	Pattern_Type_stripped	SleeveLengththreequarter
#	1.273995	1.134430	1.230626
#	SleeveLengthshort	SleeveLengthhalfsleeve	SleeveLengthfull
#	1.411245	1.240625	1.325156
#	SleeveLengthcap_sleeves	NeckLine_backless_dmy	NeckLine_boatneck_dmy
#	1.059211	1.061926	1.214714
#	NeckLine_bowneck_dmy	NeckLine_halter_dmy	NeckLine_mandarincollor_dmy
#	1.188038	1.055334	1.074958
#	NeckLine_oneck_dmy	NeckLine_open_dmy	NeckLine_peterpancollor_dmy
#	1.666802	1.081935	1.117761
#	NeckLine_ruffled_dmy	NeckLine_Scoop_dmy	NeckLine_slashneck_dmy
#	1.146380	1.097594	1.217812
#	NeckLine_squarecollor_dmy	NeckLine_sweetheart_dmy	NeckLine_turndowncollor_dmy
#	1.152707	1.407439	1.169171

```
task41m <- update(task41m, ~. - FabricType_null)
```

```
vif(task41m)
```

#	Size_L	Size_M	Size_S
#	1.423209	1.520799	1.279703
#	Size_XL	waisseline_natural	waisseline_null
#	1.182514	1.756499	1.851313
#	waisseline_other	FabricType_chiffon	FabricType_jersey
#	1.130793	1.244453	1.086278
#	FabricType_other	FabricType_worsted	Decoration_beading
#	1.184775	1.147812	1.298203
#	Decoration_bow	Decoration_hollowout	Decoration_lace
#	1.302618	1.152715	1.235841
#	Decoration_other	Decoration_ruffles	Decoration_sashes
#	1.274963	1.157802	1.220103
#	Decoration_sequined	Pattern_Type_dot	Pattern_Type_other
#	1.113802	1.343023	1.120951
#	Pattern_Type_null	Pattern_Type_patchwork	Pattern_Type_print
#	1.585991	1.238135	1.263320
#	Pattern_Type_stripped	SleeveLengththreequarter	SleeveLengthshort
#	1.132847	1.229244	1.404493
#	SleeveLengthhalfsleeve	SleeveLengthfull	SleeveLengthcap_sleeves

```

# 1.201575          1.315696          1.058704
# NeckLine_backless_dmy NeckLine_boatneck_dmy NeckLine_bowneck_dmy
# 1.061902          1.214600          1.186221
# NeckLine_halter_dmy NeckLine_mandarincollor_dmy NeckLine_oneck_dmy
# 1.053751          1.072103          1.651747
# NeckLine_open_dmy NeckLine_peterpancollor_dmy NeckLine_ruffled_dmy
# 1.078326          1.115863          1.146354
# NeckLine_Scoop_dmy NeckLine_slashneck_dmy NeckLine_squarecollor_dmy
# 1.097109          1.215168          1.150057
# NeckLine_sweetheart_dmy NeckLine_turndowncollor_dmy
# 1.400279          1.168974
# now since we have vif <5, we are free from multicollinearity and we can proceed in
the modeling

```

```
summary(task41m)
```

```

#
# Call:
# lm(formula = log(TotalSales) ~ Size_L + Size_M + Size_S + Size_XL +
# waiseline_natural + waiseline_null + waiseline_other +
FabricType_chiffon +
# FabricType_jersey + FabricType_other + FabricType_worsted +
# Decoration_beading + Decoration_bow + Decoration_hollowout +
# Decoration_lace + Decoration_other + Decoration_ruffles +
# Decoration_sashes + Decoration_sequined + Pattern_Type_dot +
# Pattern_Type_other + Pattern_Type_null + Pattern_Type_patchwork
+
# Pattern_Type_print + Pattern_Type_striped +
SleeveLengththreequarter +
# SleeveLengthshort + SleeveLengthhalfssleeve + SleeveLengthfull +
# SleeveLengthcap_sleeves + NeckLine_backless_dmy +
NeckLine_boatneck_dmy +
# NeckLine_bowneck_dmy + NeckLine_halter_dmy +
NeckLine_mandarincollor_dmy +
# NeckLine_oneck_dmy + NeckLine_open_dmy +
NeckLine_peterpancollor_dmy +
# NeckLine_ruffled_dmy + NeckLine_Scoop_dmy +
NeckLine_slashneck_dmy +
# NeckLine_squarecollor_dmy + NeckLine_sweetheart_dmy +
NeckLine_turndowncollor_dmy,
# data = TASK4_DS)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.6894 -0.8307  0.1907  1.0211  3.6866
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.2175387  0.2727557  26.462 < 2e-16 ***
#      Size_L          0.7042388  0.2140516   3.290 0.001080 **
#      Size_M          0.3814969  0.1823029   2.093 0.036935 *
#      Size_S          0.2502171  0.3016370   0.830 0.407240
#      Size_XL          0.2617063  0.4504089   0.581 0.561501
# waiseline_natural    0.1430612  0.1921065   0.745 0.456840
# waiseline_null       0.1855573  0.2547932   0.728 0.466826
# waiseline_other      0.4043898  0.7551188   0.536 0.592545
# FabricType_chiffon   0.1795170  0.1741270   1.031 0.303111
# FabricType_jersey   -0.1253488  0.4811578  -0.261 0.794585
# FabricType_other    -0.2694214  0.3345035  -0.805 0.420989
# FabricType_worsted  -0.0079227  0.3959226  -0.020 0.984044
# Decoration_beading  -0.0704926  0.3925302  -0.180 0.857558
# Decoration_bow       0.3094092  0.4727293   0.655 0.513110
# Decoration_hollowout -0.2944195  0.3781896  -0.778 0.436682
# Decoration_lace      -0.0414212  0.2263997  -0.183 0.854914
# Decoration_other     -0.1740817  0.2876327  -0.605 0.545334
# Decoration_ruffles   -0.2449926  0.4195092  -0.584 0.559512
# Decoration_sashes    0.2140791  0.2813764   0.761 0.447155
# Decoration_sequined  -0.2607449  0.4520030  -0.577 0.564316
# Pattern_Type_dot      0.0448991  0.4963397   0.090 0.927961
# Pattern_Type_other    0.2106234  0.4127790   0.510 0.610119
# Pattern_Type_null    -0.7904660  0.2162830  -3.655 0.000287 ***
#      Pattern_Type_patchwork -0.4031408  0.2694251  -1.496 0.135270

```

```

# Pattern_Type_print          0.0673335  0.2275506   0.296 0.767437
# Pattern_Type_stripped      -0.0415812  0.4149635  -0.100 0.920226
# SleeveLengththreequarter -0.3528284  0.3407233  -1.036 0.300974
# SleeveLengthshort          0.2415244  0.2126395   1.136 0.256623
# SleeveLengthhalfssleeve    0.1942378  0.2996442   0.648 0.517165
# SleeveLengthfull           0.0259397  0.2058078   0.126 0.899757
# SleeveLengthcap_sleeves    -0.2899727  0.7306529  -0.397 0.691651
# NeckLine_backless_dmy       1.5358116  1.6296701   0.942 0.346486
# NeckLine_boatneck_dmy       -0.3194972  0.4072784  -0.784 0.433174
# NeckLine_bowneck_dmy        -0.9631927  0.5496681  -1.752 0.080394
# NeckLine_halter_dmy         1.3682439  1.6234035   0.843 0.399771
# NeckLine_mandarincollor_dmy -2.0889568  1.6374790  -1.276 0.202709
# NeckLine_oneck_dmy          0.3986382  0.1826032   2.183 0.029541 *
# NeckLine_open_dmy           -0.4976577  0.9500486  -0.524 0.600657
# NeckLine_peterpancollor_dmy -0.0756365  0.6854543  -0.110 0.912184
# NeckLine_ruffled_dmy        3.5827580  1.6932338   2.116 0.034895 *
# NeckLine_Scoop_dmy          0.6773712  1.1724757   0.578 0.563735
# NeckLine_slashneck_dmy      0.0456119  0.3573807   0.128 0.898500
# NeckLine_squarecollor_dmy   0.2929464  0.7615235   0.385 0.700651
# NeckLine_sweetheart_dmy     -0.0001764  0.4901300   0.000 0.999713
# NeckLine_turndowncollor_dmy 0.1285134  0.4800481   0.268 0.789045
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.58 on 454 degrees of freedom
# Multiple R-squared:  0.1467, Adjusted R-squared:  0.06398
# F-statistic: 1.774 on 44 and 454 DF, p-value: 0.002304

task4lm.1 <- update(task4lm, ~. -NeckLine_sweetheart_dmy)
summary(task4lm.1)

#
# Call:
# lm(formula = log(TotalSales) ~ Size_L + Size_M + Size_S + Size_XL +
# waiseline_natural + waiseline_null + waiseline_other +
FabricType_chiffon +
# FabricType_jersey + FabricType_other + FabricType_worsted +
# Decoration_beading + Decoration_bow + Decoration_hollowout +
# Decoration_lace + Decoration_other + Decoration_ruffles +
# Decoration_sashes + Decoration_sequined + Pattern_Type_dot +
# Pattern_Type_other + Pattern_Type_null + Pattern_Type_patchwork
+
# Pattern_Type_print + Pattern_Type_stripped +
SleeveLengththreequarter +
# SleeveLengthshort + SleeveLengthhalfssleeve + SleeveLengthfull +
# SleeveLengthcap_sleeves + NeckLine_backless_dmy +
NeckLine_boatneck_dmy +
# NeckLine_bowneck_dmy + NeckLine_halter_dmy +
NeckLine_mandarincollor_dmy +
# NeckLine_oneck_dmy + NeckLine_open_dmy +
NeckLine_peterpancollor_dmy +
# NeckLine_ruffled_dmy + NeckLine_Scoop_dmy +
NeckLine_slashneck_dmy +
# NeckLine_squarecollor_dmy + NeckLine_turndowncollor_dmy,
# data = TASK4_DS)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.6894 -0.8307  0.1907  1.0211  3.6866
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)    7.217528   0.270763   26.656 < 2e-16 ***
#           Size_L         0.704238   0.213792    3.294 0.001065 **
#           Size_M         0.381492   0.181513    2.102 0.036126 *
#           Size_S         0.250221   0.301118    0.831 0.406424
#           Size_XL         0.261707   0.449912    0.582 0.561068
# waiseline_natural    0.143063   0.191835    0.746 0.456197
# waiseline_null       0.185565   0.253580    0.732 0.464678
# waiseline_other      0.404371   0.752416    0.537 0.591234
# FabricType_chiffon   0.179514   0.173765    1.033 0.302112
# FabricType_jersey    -0.125348   0.480627   -0.261 0.794363

```

```

# FabricType_other          -0.269428    0.333661   -0.807  0.419807
# FabricType_worsted        -0.007927    0.395338   -0.020  0.984012
# Decoration_beading         -0.070534    0.374820   -0.188  0.850818
# Decoration_bow             0.309410    0.472208    0.655  0.512645
# Decoration_hollowout       -0.294422    0.377715   -0.779  0.436101
# Decoration_lace            -0.041418    0.226018   -0.183  0.854681
# Decoration_other           -0.174097    0.284330   -0.612  0.540642
# Decoration_ruffles         -0.244990    0.418968   -0.585  0.559009
# Decoration_sashes          0.214077    0.281005    0.762  0.446558
# Decoration_sequined        -0.260744    0.451499   -0.578  0.563882
# Pattern_Type_dot           0.044893    0.495479    0.091  0.927847
# Pattern_Type_other          0.210618    0.412038    0.511  0.609486
# Pattern_Type_null          -0.790482    0.211497   -3.738  0.000209 ***
# Pattern_Type_patchwork     -0.403143    0.269083   -1.498  0.134772
# Pattern_Type_print          0.067334    0.227299    0.296  0.767186
# Pattern_Type_stripped       -0.041575    0.414148   -0.100  0.920081
# SleeveLengththreequarter  -0.352820    0.339619   -1.039  0.299417
# SleeveLengthshort          0.241533    0.210947    1.145  0.252813
# SleeveLengthhalfssleeve    0.194246    0.298455    0.651  0.515479
# SleeveLengthfull           0.025947    0.204706    0.127  0.899194
# SleeveLengthcap_sleeves    -0.289961    0.729088   -0.398  0.691035
# NeckLine_backless_dmy       1.535856    1.623191    0.946  0.344551
# NeckLine_boatneck_dmy       -0.319489    0.406147   -0.787  0.431906
# NeckLine_bowneck_dmy        -0.963183    0.548385   -1.756  0.079693 .
# NeckLine_halter_dmy         1.368284    1.617820    0.846  0.398132
# NeckLine_mandarincollor_dmy -2.088948    1.635511   -1.277  0.202167
# NeckLine_oneck_dmy          0.398650    0.179374    2.222  0.026743 *
# NeckLine_open_dmy           -0.497656    0.948990   -0.524  0.600252
# NeckLine_peterpancollor_dmy -0.075626    0.684127   -0.111  0.912026
# NeckLine_ruffled_dmy        3.582774    1.690787    2.119  0.034632 *
# NeckLine_Scoop_dmy           0.677400    1.168538    0.580  0.562405
# NeckLine_slashneck_dmy       0.045632    0.352797    0.129  0.897144
# NeckLine_squarecollor_dmy    0.292963    0.759204    0.386  0.699764
# NeckLine_turndowncollor_dmy 0.128521    0.479107    0.268  0.788628
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.578 on 455 degrees of freedom
# Multiple R-squared:  0.1467, Adjusted R-squared:  0.06604
# F-statistic: 1.819 on 43 and 455 DF, p-value: 0.001655

```

```

task4lm.2 <- update(task4lm.1, ~. - FabricType_worsted)
summary(task4lm.2)

```

```

# Call:
#      lm(formula = log(TotalSales) ~ Size_L + Size_M + Size_S + Size_XL +
#      waiseline_natural + waiseline_null + waiseline_other +
FabricType_chiffon +
#      FabricType_jersey + FabricType_other + Decoration_beading +
#      Decoration_bow + Decoration_hollowout + Decoration_lace +
#      Decoration_other + Decoration_ruffles + Decoration_sashes +
#      Decoration_sequined + Pattern_Type_dot + Pattern_Type_other +
#      Pattern_Type_null + Pattern_Type_patchwork + Pattern_Type_print
+
#      Pattern_Type_stripped + SleeveLengththreequarter +
SleeveLengthshort +
#      SleeveLengthhalfssleeve + SleeveLengthfull +
SleeveLengthcap_sleeves +
#      NeckLine_backless_dmy + NeckLine_boatneck_dmy +
NeckLine_bowneck_dmy +
#      NeckLine_halter_dmy + NeckLine_mandarincollor_dmy +
NeckLine_oneck_dmy +
#      NeckLine_open_dmy + NeckLine_peterpancollor_dmy +
NeckLine_ruffled_dmy +
#      NeckLine_Scoop_dmy + NeckLine_slashneck_dmy +
NeckLine_squarecollor_dmy +
#      NeckLine_turndowncollor_dmy, data = TASK4_DS)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.6884 -0.8306  0.1911  1.0216  3.6868

```

```

#
# Coefficients:
#           Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.21703    0.26931  26.798 < 2e-16 ***
#           Size_L      0.70437    0.21345   3.300 0.001043 **
#           Size_M      0.38183    0.18051   2.115 0.034950 *
#           Size_S      0.25068    0.29991   0.836 0.403682
# Size_XL      0.26140    0.44916   0.582 0.560870
# waiseline_natural 0.14293    0.19152   0.746 0.455855
# waiseline_null    0.18568    0.25323   0.733 0.463778
# waiseline_other    0.40474    0.75136   0.539 0.590371
# FabricType_chiffon 0.17985    0.17276   1.041 0.298406
# FabricType_jersey -0.12493    0.47965  -0.260 0.794625
# FabricType_other   -0.26896    0.33250  -0.809 0.418979
# Decoration_beadings -0.07049    0.37440  -0.188 0.850739
# Decoration_bow     0.30978    0.47133   0.657 0.511352
# Decoration_hollowout -0.29415    0.37706  -0.780 0.435728
# Decoration_lace    -0.04207    0.22346  -0.188 0.850768
# Decoration_other   -0.17393    0.28389  -0.613 0.540413
# Decoration_ruffles -0.24486    0.41846  -0.585 0.558739
# Decoration_sashes  0.21428    0.28052   0.764 0.445347
# Decoration_sequined -0.26084    0.45098  -0.578 0.563282
# Pattern_Type_dot    0.04405    0.49316   0.089 0.928861
# Pattern_Type_other  0.21112    0.41084   0.514 0.607590
# Pattern_Type_null  -0.79030    0.21108  -3.744 0.000204 ***
# Pattern_Type_patchwork -0.40370    0.26736  -1.510 0.131756
# Pattern_Type_print  0.06739    0.22703   0.297 0.766743
# Pattern_Type_stripped -0.04269    0.40996  -0.104 0.917112
# SleeveLengththreequarter -0.35251    0.33889  -1.040 0.298806
# SleeveLengthshort  0.24180    0.21029   1.150 0.250805
# SleeveLengthhalfssleeve 0.19424    0.29813   0.652 0.515032
# SleeveLengthfull   0.02574    0.20423   0.126 0.899754
# SleeveLengthcap_sleeves -0.28950    0.72793  -0.398 0.691033
# NeckLine_backless_dmy 1.53567    1.62138   0.947 0.344071
# NeckLine_boatneck_dmy -0.31937    0.40566  -0.787 0.431522
# NeckLine_bowneck_dmy -0.96275    0.54737  -1.759 0.079268 .
# NeckLine_halter_dmy  1.36856    1.61599   0.847 0.397500
# NeckLine_mandarincollor_dmy -2.08885    1.63371  -1.279 0.201690
# NeckLine_oneck_dmy   0.39861    0.17917   2.225 0.026583 *
# NeckLine_open_dmy    -0.49730    0.94778  -0.525 0.600048
# NeckLine_peterpancollor_dmy -0.07543    0.68331  -0.110 0.912151
# NeckLine_ruffled_dmy  3.58280    1.68893   2.121 0.034432 *
# NeckLine_Scoop_dmy    0.67680    1.16687   0.580 0.562194
# NeckLine_slashneck_dmy 0.04584    0.35226   0.130 0.896517
# NeckLine_squarecollor_dmy 0.29307    0.75835   0.386 0.699336
# NeckLine_turndowncollor_dmy 0.12825    0.47839   0.268 0.788757
# ---
#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.576 on 456 degrees of freedom
# Multiple R-squared:  0.1467, Adjusted R-squared:  0.06808
# F-statistic: 1.866 on 42 and 456 DF, p-value: 0.001174

task41m.3 <- update(task41m.2, ~. - Pattern_Type_dot)
summary(task41m.3)

#
# Call:
# lm(formula = log(TotalSales) ~ Size_L + Size_M + Size_S + Size_XL +
#   waiseline_natural + waiseline_null + waiseline_other +
#   FabricType_chiffon +
#   FabricType_jersey + FabricType_other + Decoration_beadings +
#   Decoration_bow + Decoration_hollowout + Decoration_lace +
#   Decoration_other + Decoration_ruffles + Decoration_sashes +
#   Decoration_sequined + Pattern_Type_other + Pattern_Type_null +
#   Pattern_Type_patchwork + Pattern_Type_print +
#   Pattern_Type_stripped +
#   SleeveLengththreequarter + SleeveLengthshort +
#   SleeveLengthhalfssleeve +
#   SleeveLengthfull + SleeveLengthcap_sleeves +
#   NeckLine_backless_dmy +

```

```

# NeckLine_boatneck_dmy + NeckLine_bowneck_dmy +
NeckLine_halter_dmy +
# NeckLine_mandarincollor_dmy + NeckLine_oneck_dmy +
NeckLine_open_dmy +
# NeckLine_peterpancollor_dmy + NeckLine_ruffled_dmy +
NeckLine_scoop_dmy +
# NeckLine_slashneck_dmy + NeckLine_squarecollor_dmy +
NeckLine_turndowncollor_dmy,
# data = TASK4_DS)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.6872 -0.8279  0.1911  1.0196  3.6881
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.21723    0.26901  26.829 < 2e-16 ***
#      Size_L          0.70451    0.21322   3.304 0.001027 **
#      Size_M          0.38285    0.17996   2.127 0.033922 *
#      Size_S          0.25297    0.29849   0.847 0.397165
# Size_XL          0.26266    0.44845   0.586 0.558356
# waiseline_natural 0.14354    0.19119   0.751 0.453189
# waiseline_null    0.18709    0.25247   0.741 0.459054
# waiseline_other    0.40584    0.75045   0.541 0.588909
# FabricType_chiffon 0.18106    0.17204   1.052 0.293152
# FabricType_jersey -0.12533    0.47910  -0.262 0.793745
# FabricType_other  -0.26957    0.33207  -0.812 0.417333
# Decoration_beading -0.07144    0.37385  -0.191 0.848541
# Decoration_bow     0.31977    0.45738   0.699 0.484829
# Decoration_hollowout -0.29608    0.37604  -0.787 0.431482
# Decoration_lace    -0.04343    0.22269  -0.195 0.845447
# Decoration_other   -0.17633    0.28230  -0.625 0.532525
# Decoration_ruffles -0.24266    0.41728  -0.582 0.561170
# Decoration_sashes  0.21177    0.27881   0.760 0.447913
# Decoration_sequined -0.26187    0.45034  -0.582 0.561187
# Pattern_Type_other  0.20913    0.40979   0.510 0.610055
# Pattern_Type_null  -0.79245    0.20948  -3.783 0.000176 ***
#      Pattern_Type_patchwork -0.40706    0.26441  -1.539 0.124375
# Pattern_Type_print  0.06433    0.22419   0.287 0.774294
# Pattern_Type_stripped -0.04420    0.40916  -0.108 0.914014
# SleeveLengththreequarter -0.35082    0.33799  -1.038 0.299847
# SleeveLengthshort   0.24489    0.20721   1.182 0.237876
# SleeveLengthhalfssleeve 0.19449    0.29779   0.653 0.514023
# SleeveLengthfull    0.02568    0.20400   0.126 0.899879
# SleeveLengthcap_sleeves -0.28926    0.72713  -0.398 0.690952
# NeckLine_backless_dmy 1.53881    1.61924   0.950 0.342448
# NeckLine_boatneck_dmy -0.31693    0.40430  -0.784 0.433503
# NeckLine_bowneck_dmy -0.96215    0.54673  -1.760 0.079106
# NeckLine_halter_dmy  1.37231    1.61369   0.850 0.395536
# NeckLine_mandarincollor_dmy -2.08842    1.63193  -1.280 0.201292
# NeckLine_oneck_dmy   0.39925    0.17883   2.233 0.026057 *
#      NeckLine_open_dmy -0.49877    0.94661  -0.527 0.598516
# NeckLine_peterpancollor_dmy -0.07648    0.68246  -0.112 0.910824
# NeckLine_ruffled_dmy  3.61135    1.65661   2.180 0.029770 *
#      NeckLine_scoop_dmy 0.67521    1.16547   0.579 0.562642
# NeckLine_slashneck_dmy 0.04508    0.35177   0.128 0.898096
# NeckLine_squarecollor_dmy 0.30301    0.74934   0.404 0.686135
# NeckLine_turndowncollor_dmy 0.12698    0.47766   0.266 0.790480
#
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.575 on 457 degrees of freedom
# Multiple R-squared:  0.1467, Adjusted R-squared:  0.07011
# F-statistic: 1.916 on 41 and 457 DF, p-value: 0.0008245

task4lm.4 <- update(task4lm.3, ~. -Pattern_Type_stripped)
summary(task4lm.4)

# Call:
# lm(formula = log(Totalsales) ~ Size_L + Size_M + Size_S + Size_XL +

```

```

# waiseline_natural + waiseline_null + waiseline_other +
FabricType_chiffon +
# FabricType_jersey + FabricType_other + Decoration_beading +
# Decoration_bow + Decoration_hollowout + Decoration_lace +
# Decoration_other + Decoration_ruffles + Decoration_sashes +
# Decoration_sequined + Pattern_Type_other + Pattern_Type_null +
# Pattern_Type_patchwork + Pattern_Type_print +
SleeveLengththreequarter +
# SleeveLengthshort + SleeveLengthhalfssleeve + SleeveLengthfull +
# SleeveLengthcap_sleeves + NeckLine_backless_dmy +
NeckLine_boatneck_dmy +
# NeckLine_bowneck_dmy + NeckLine_halter_dmy +
NeckLine_mandarincollor_dmy +
# NeckLine_oneck_dmy + NeckLine_open_dmy +
NeckLine_peterpancollor_dmy +
# NeckLine_ruffled_dmy + NeckLine_scoop_dmy +
NeckLine_slashneck_dmy +
# NeckLine_squarecollor_dmy + NeckLine_turndowncollor_dmy,
# data = TASK4_DS)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.6843 -0.8266  0.1864  1.0147  3.6853
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          7.21148    0.26341   27.377 < 2e-16 ***
#      Size_L           0.70611    0.21247    3.323 0.000961 ***
#      Size_M           0.38339    0.17970    2.134 0.033409 *
#      Size_S           0.25503    0.29756    0.857 0.391846
# Size_XL              0.26400    0.44779    0.590 0.555779
# waiseline_natural    0.14262    0.19080    0.748 0.455137
# waiseline_null       0.18806    0.25204    0.746 0.455945
# waiseline_other      0.40594    0.74964    0.542 0.588414
# FabricType_chiffon   0.18017    0.17166    1.050 0.294456
# FabricType_jersey   -0.12350    0.47828   -0.258 0.796362
# FabricType_other    -0.27002    0.33168   -0.814 0.416007
# Decoration_beading   -0.06829    0.37231   -0.183 0.854544
# Decoration_bow       0.32243    0.45623    0.707 0.480096
# Decoration_hollowout -0.29239    0.37408   -0.782 0.434845
# Decoration_lace      -0.04108    0.22138   -0.186 0.852882
# Decoration_other     -0.17591    0.28197   -0.624 0.533032
# Decoration_ruffles   -0.24153    0.41670   -0.580 0.562454
# Decoration_sashes    0.21265    0.27839    0.764 0.445359
# Decoration_sequined  -0.25787    0.44833   -0.575 0.565450
# Pattern_Type_other   0.21171    0.40865    0.518 0.604661
# Pattern_Type_null    -0.78900    0.20680   -3.815 0.000155 ***
# Pattern_Type_patchwork -0.40466    0.26319   -1.538 0.124859
# Pattern_Type_print   0.06795    0.22143    0.307 0.759062
# SleeveLengththreequarter -0.34887    0.33715   -1.035 0.301324
# SleeveLengthshort    0.24730    0.20577    1.202 0.230057
# SleeveLengthhalfssleeve 0.19544    0.29734    0.657 0.511328
# SleeveLengthfull     0.02759    0.20302    0.136 0.891973
# SleeveLengthcap_sleeves -0.28812    0.72627   -0.397 0.691767
# NeckLine_backless_dmy 1.54158    1.61729    0.953 0.341000
# NeckLine_boatneck_dmy -0.31585    0.40374   -0.782 0.434441
# NeckLine_bowneck_dmy -0.95978    0.54570   -1.759 0.079278
# NeckLine_halter_dmy  1.37510    1.61174    0.853 0.394007
# NeckLine_mandarincollor_dmy -2.08412    1.62969   -1.279 0.201597
# NeckLine_oneck_dmy   0.39991    0.17853    2.240 0.025567 *
# NeckLine_open_dmy    -0.49888    0.94559   -0.528 0.598040
# NeckLine_peterpancollor_dmy -0.07569    0.68169   -0.111 0.911637
# NeckLine_ruffled_dmy  3.61237    1.65479    2.183 0.029545 *
# NeckLine_scoop_dmy   0.67426    1.16418    0.579 0.562758
# NeckLine_slashneck_dmy 0.04593    0.35130    0.131 0.896034
# NeckLine_squarecollor_dmy 0.30440    0.74842    0.407 0.684399
# NeckLine_turndowncollor_dmy 0.12976    0.47645    0.272 0.785471
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.573 on 458 degrees of freedom
# Multiple R-squared:  0.1466, Adjusted R-squared:  0.07211

```

# F-statistic: 1.968 on 40 and 458 DF, p-value: 0.000572

```
task41m.5 <- update(task41m.4, ~. -NeckLine_peterpancollor_dmy)
summary(task41m.5)
```

```
# Call:
# lm(formula = log(TotalSales) ~ Size_L + Size_M + Size_S + Size_XL +
# waiseline_natural + waiseline_null + waiseline_other +
FabricType_chiffon +
# FabricType_jersey + FabricType_other + Decoration_beading +
# Decoration_bow + Decoration_hollowout + Decoration_lace +
# Decoration_other + Decoration_ruffles + Decoration_sashes +
# Decoration_sequined + Pattern_Type_other + Pattern_Type_null +
# Pattern_Type_patchwork + Pattern_Type_print +
SleeveLengththreequarter +
# SleeveLengthshort + SleeveLengthhalf sleeve + SleeveLengthfull +
# SleeveLengthcap_sleeves + NeckLine_backless_dmy +
NeckLine_boatneck_dmy +
# NeckLine_bowneck_dmy + NeckLine_halter_dmy +
NeckLine_mandarincollor_dmy +
# NeckLine_oneck_dmy + NeckLine_open_dmy + NeckLine_ruffled_dmy +
# NeckLine_Scoop_dmy + NeckLine_slashneck_dmy +
NeckLine_squarecollor_dmy +
# NeckLine_turndowncollor_dmy, data = TASK4_DS)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.6840 -0.8261  0.1862  1.0166  3.6939
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.20766    0.26087   27.629 < 2e-16 ***
# Size_L           0.70743    0.21191    3.338 0.000911 ***
# Size_M           0.38338    0.17950    2.136 0.033225 *
# Size_S           0.25685    0.29679    0.865 0.387260
# Size_XL          0.26625    0.44685    0.596 0.551573
# waiseline_natural 0.14364    0.19037    0.755 0.450920
# waiseline_null    0.18857    0.25172    0.749 0.454159
# waiseline_other   0.40916    0.74827    0.547 0.584780
# FabricType_chiffon 0.18045    0.17145    1.052 0.293140
# FabricType_jersey -0.12322    0.47776   -0.258 0.796590
# FabricType_other  -0.26834    0.33098   -0.811 0.417929
# Decoration_beading -0.06637    0.37151   -0.179 0.858292
# Decoration_bow     0.32341    0.45565    0.710 0.478205
# Decoration_hollowout -0.29116    0.37352   -0.780 0.436078
# Decoration_lace    -0.04028    0.22103   -0.182 0.855472
# Decoration_other   -0.17471    0.28146   -0.621 0.535089
# Decoration_ruffles -0.23939    0.41580   -0.576 0.565087
# Decoration_sashes  0.21335    0.27802    0.767 0.443241
# Decoration_sequined -0.25641    0.44765   -0.573 0.567069
# Pattern_Type_other  0.21252    0.40815    0.521 0.602834
# Pattern_Type_null  -0.78936    0.20656   -3.822 0.000151 ***
# Pattern_Type_patchwork -0.40723    0.26188   -1.555 0.120630
# Pattern_Type_print  0.06819    0.22118    0.308 0.758003
# SleeveLengththreequarter -0.35648    0.32975   -1.081 0.280232
# SleeveLengthshort  0.24540    0.20484    1.198 0.231530
# SleeveLengthhalf sleeve 0.19517    0.29701    0.657 0.511440
# SleeveLengthfull   0.02757    0.20280    0.136 0.891937
# SleeveLengthcap_sleeves -0.28711    0.72543   -0.396 0.692453
# NeckLine_backless_dmy 1.54428    1.61537    0.956 0.339579
# NeckLine_boatneck_dmy -0.31287    0.40241   -0.777 0.437277
# NeckLine_bowneck_dmy -0.95749    0.54472   -1.758 0.079455 .
# NeckLine_halter_dmy  1.37706    1.60991    0.855 0.392793
# NeckLine_mandarincollor_dmy -2.08175    1.62779   -1.279 0.201586
# NeckLine_oneck_dmy  0.40290    0.17630    2.285 0.022753 *
# NeckLine_open_dmy   -0.49646    0.94432   -0.526 0.599325
# NeckLine_ruffled_dmy 3.61684    1.65252    2.189 0.029123 *
# NeckLine_Scoop_dmy  0.67749    1.16256    0.583 0.560341
# NeckLine_slashneck_dmy 0.04806    0.35040    0.137 0.890961
# NeckLine_squarecollor_dmy 0.30711    0.74722    0.411 0.681263
# NeckLine_turndowncollor_dmy 0.13247    0.47531    0.279 0.780596
# ---
```



```

#           signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.571 on 459 degrees of freedom
# Multiple R-squared:  0.1466, Adjusted R-squared:  0.07411
# F-statistic: 2.022 on 39 and 459 DF, p-value: 0.0003917

task4lm.6 <- update(task4lm.5, ~. - sleeveLengthfull)
summary(task4lm.6)

# Call:
# lm(formula = log(TotalSales) ~ Size_L + Size_M + Size_S + Size_XL +
#     waiseline_natural + waiseline_null + waiseline_other +
FabricType_chiffon +
#     FabricType_jersey + FabricType_other + Decoration_beading +
#     Decoration_bow + Decoration_hollowout + Decoration_lace +
#     Decoration_other + Decoration_ruffles + Decoration_sashes +
#     Decoration_sequined + Pattern_Type_other + Pattern_Type_null +
#     Pattern_Type_patchwork + Pattern_Type_print +
SleeveLengththreequarter +
#     SleeveLengthshort + SleeveLengthhalfssleeve +
SleeveLengthcap_sleeves +
#     NeckLine_backless_dmy + NeckLine_boatneck_dmy +
NeckLine_bowneck_dmy +
#     NeckLine_halter_dmy + NeckLine_mandarincollor_dmy +
NeckLine_oneck_dmy +
#     NeckLine_open_dmy + NeckLine_ruffled_dmy + NeckLine_Scoop_dmy +
#     NeckLine_slashneck_dmy + NeckLine_squarecollor_dmy +
NeckLine_turndowncollor_dmy,
#     data = TASK4_DS)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.6699 -0.8233  0.1784  1.0110  3.6968
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.21290    0.25774   27.985 < 2e-16 ***
#           Size_L        0.70634    0.21153    3.339 0.000909 ***
#           Size_M        0.38362    0.17930    2.140 0.032921 *
#           Size_S        0.25894    0.29607    0.875 0.382257
#           Size_XL        0.27372    0.44299    0.618 0.536944
# waiseline_natural    0.14642    0.18907    0.774 0.439056
# waiseline_null      0.19324    0.24910    0.776 0.438287
# waiseline_other      0.41107    0.74734    0.550 0.582555
# FabricType_chiffon    0.17885    0.17087    1.047 0.295777
# FabricType_jersey   -0.12322    0.47725   -0.258 0.796384
# FabricType_other    -0.26432    0.32930   -0.803 0.422584
# Decoration_beading   -0.06532    0.37103   -0.176 0.860340
# Decoration_bow       0.32046    0.45465    0.705 0.481261
# Decoration_hollowout -0.29142    0.37311   -0.781 0.435176
# Decoration_lace      -0.03885    0.22054   -0.176 0.860260
# Decoration_other     -0.17450    0.28115   -0.621 0.535132
# Decoration_ruffles   -0.24001    0.41533   -0.578 0.563639
# Decoration_sashes     0.21128    0.27731    0.762 0.446505
# Decoration_sequined  -0.25863    0.44687   -0.579 0.563037
# Pattern_Type_other    0.21265    0.40771    0.522 0.602222
# Pattern_Type_null    -0.79345    0.20414   -3.887 0.000117 ***
# Pattern_Type_patchwork -0.40491    0.26104   -1.551 0.121563
# Pattern_Type_print    0.06677    0.22070    0.303 0.762361
# SleeveLengththreequarter -0.36514    0.32320   -1.130 0.259163
# SleeveLengthshort     0.23707    0.19525    1.214 0.225297
# SleeveLengthhalfssleeve 0.18754    0.29135    0.644 0.520093
# SleeveLengthcap_sleeves -0.29400    0.72289   -0.407 0.684417
# NeckLine_backless_dmy  1.54452    1.61364    0.957 0.338988
# NeckLine_boatneck_dmy -0.30866    0.40079   -0.770 0.441622
# NeckLine_bowneck_dmy  -0.95570    0.54398   -1.757 0.079606 .
# NeckLine_halter_dmy    1.37292    1.60790    0.854 0.393627
# NeckLine_mandarincollor_dmy -2.08031    1.62602   -1.279 0.201405
# NeckLine_oneck_dmy     0.40463    0.17565    2.304 0.021693 *
# NeckLine_open_dmy     -0.49069    0.94236   -0.521 0.602822
# NeckLine_ruffled_dmy   3.62425    1.64986    2.197 0.028540 *
# NeckLine_Scoop_dmy     0.68000    1.16117    0.586 0.558424

```

```

# NeckLine_slashneck_dmy      0.04505      0.34932      0.129 0.897443
# NeckLine_squarecollor_dmy   0.30846      0.74635      0.413 0.679584
# NeckLine_turndowncollor_dmy 0.13726      0.47350      0.290 0.772035
# ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.57 on 460 degrees of freedom
# Multiple R-squared:  0.1466, Adjusted R-squared:  0.07608
# F-statistic: 2.079 on 38 and 460 DF, p-value: 0.000265

# since there are a lot of params lets make use of stepAIC or step function to choose
a model for us in an automated way based on aic
step(task4lm.6, direction = "both", test = "F")

#just pasting last step from this
# Step: AIC=442.53
# log(TotalSales) ~ Size_L + Size_M + FabricType_chiffon + Pattern_Type_null +
#      Pattern_Type_patchwork + SleeveLengthshort + NeckLine_bowneck_dmy +
#      NeckLine_oneck_dmy + NeckLine_ruffled_dmy
#
# Df Sum of Sq    RSS    AIC F value    Pr(>F)
# <none>                    1163.7 442.53
# - SleeveLengthshort      1      4.943 1168.7 442.65    2.0772    0.150152
# - FabricType_chiffon      1      4.946 1168.7 442.65    2.0785    0.150026
# - NeckLine_bowneck_dmy    1      5.076 1168.8 442.71    2.1330    0.144803
# - Pattern_Type_patchwork  1      5.955 1169.7 443.08    2.5023    0.114326
# + SleeveLengththreequarter 1      2.750 1161.0 443.35    1.1559    0.282840
# + FabricType_other        1      2.640 1161.1 443.40    1.1094    0.292733
# + NeckLine_mandarincollor_dmy 1      2.422 1161.3 443.49    1.0176    0.313589
# + Size_S                  1      2.212 1161.5 443.58    0.9294    0.335504
# + Decoration_sashes       1      2.205 1161.5 443.59    0.9264    0.336276
# + Decoration_hollowout    1      2.016 1161.7 443.67    0.8468    0.357900
# + Decoration_bow          1      1.521 1162.2 443.88    0.6388    0.424535
# + NeckLine_halter_dmy     1      1.452 1162.3 443.91    0.6096    0.435334
# + NeckLine_backless_dmy   1      1.413 1162.3 443.93    0.5933    0.441514
# - Size_M                  1      8.113 1171.8 444.00    3.4093    0.065435
# + SleeveLengthhalfsleeve  1      1.130 1162.6 444.05    0.4743    0.491330
# + Decoration_ruffles      1      1.085 1162.6 444.07    0.4556    0.500002
# + NeckLine_turndowncollor_dmy 1      0.971 1162.7 444.12    0.4076    0.523508
# + Decoration_sequined     1      0.929 1162.8 444.14    0.3900    0.532607
# + NeckLine_open_dmy       1      0.901 1162.8 444.15    0.3780    0.538971
# + NeckLine_boatneck_dmy   1      0.811 1162.9 444.19    0.3402    0.559975
# + Pattern_Type_other      1      0.683 1163.0 444.24    0.2865    0.592711
# + NeckLine_squarecollor_dmy 1      0.672 1163.0 444.25    0.2819    0.595673
# + Size_XL                 1      0.627 1163.1 444.27    0.2629    0.608342
# + NeckLine_scoop_dmy      1      0.613 1163.1 444.27    0.2572    0.612302
# + SleeveLengthcap_sleeves 1      0.468 1163.2 444.33    0.1965    0.657724
# + Decoration_lace         1      0.304 1163.4 444.40    0.1276    0.721133
# + Decoration_other        1      0.272 1163.4 444.42    0.1139    0.735891
# + Pattern_Type_print      1      0.187 1163.5 444.45    0.0784    0.779577
# + Decoration_beading      1      0.156 1163.5 444.47    0.0656    0.797926
# + waiseline_other         1      0.138 1163.6 444.47    0.0577    0.810269
# + waiseline_natural       1      0.123 1163.6 444.48    0.0517    0.820282
# + waiseline_null         1      0.104 1163.6 444.49    0.0435    0.834916
# + NeckLine_slashneck_dmy  1      0.088 1163.6 444.50    0.0370    0.847461
# + FabricType_jersey       1      0.079 1163.6 444.50    0.0333    0.855333
# - NeckLine_ruffled_dmy    1     14.627 1178.3 446.77    6.1465    0.013503 *
**
#      - Size_L              1      22.661 1186.4 450.16    9.5222    0.002145
**
#      - NeckLine_oneck_dmy  1      25.749 1189.5 451.45   10.8201    0.001076
**
#      - Pattern_Type_null   1      43.731 1207.4 458.94   18.3760    0.00002185
***
#
#      ---
#      signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Call:
#      lm(formula = log(TotalSales) ~ Size_L + Size_M + FabricType_chiffon +
#      Pattern_Type_null + Pattern_Type_patchwork + SleeveLengthshort +
#      NeckLine_bowneck_dmy + NeckLine_oneck_dmy +
NeckLine_ruffled_dmy,
#      data = TASK4_DS)

```

```

#
# Coefficients:
#           (Intercept)           Size_L           Size_M
FabricType_chiffon
# 7.3162           0.5874           0.2921           0.2240
# Pattern_Type_null Pattern_Type_patchwork SleeveLengthshort
NeckLine_bowneck_dmy
# -0.7485           -0.3815           0.2568           -0.7339
# NeckLine_oneck_dmy NeckLine_ruffled_dmy
# 0.4729           3.8682

finaltask4 <- lm( log(TotalSales) ~ Size_L + Size_M + FabricType_chiffon +
Pattern_Type_null +
Pattern_Type_patchwork + SleeveLengthshort + NeckLine_bowneck_dmy +
NeckLine_oneck_dmy + NeckLine_ruffled_dmy, data = TASK4_DS)

# Call:
# lm(formula = log(TotalSales) ~ Size_L + Size_M + FabricType_chiffon +
# Pattern_Type_null + Pattern_Type_patchwork + SleeveLengthshort +
# NeckLine_bowneck_dmy + NeckLine_oneck_dmy +
NeckLine_ruffled_dmy,
# data = TASK4_DS)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.9299 -0.7943  0.1948  1.0321  3.5212
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)       7.3162     0.1449   50.497 < 2e-16 ***
# Size_L             0.5874     0.1903   3.086 0.00215 ** <very significant>
# Size_M             0.2921     0.1582   1.846 0.06543 . <marginally
significant>
# FabricType_chiffon 0.2240     0.1554   1.442 0.15003 <insignificant by
itself>
# Pattern_Type_null -0.7485     0.1746  -4.287 0.0000219 *** <very significant>
# Pattern_Type_patchwork -0.3815     0.2412  -1.582 0.11433 <insignificant by
itself>
# SleeveLengthshort 0.2568     0.1782   1.441 0.15015 <insignificant by
itself>
# NeckLine_bowneck_dmy -0.7339     0.5025  -1.460 0.14480 <insignificant by
itself>
# NeckLine_oneck_dmy 0.4729     0.1438   3.289 0.00108 ** <very significant>
# NeckLine_ruffled_dmy 3.8682     1.5602   2.479 0.01350 * <significant>
#
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.543 on 489 degrees of freedom
# Multiple R-squared:  0.1237, Adjusted R-squared:  0.1076
# F-statistic: 7.669 on 9 and 489 DF, p-value: 0.0000000001428

# from the model looks like these are significant if we just consider the main effect
# Pattern_Type_null,NeckLine_oneck_dmy,Size_L,NeckLine_ruffled_dmy,Size_M(marginally)
# So the company can focus on these for campaigns etc. # Still Adj Rsq is just 10
percent
# We need to use the some factors from Task3, this and next Task if significant and
have a cumulative model to predict the sales very well
# we needed to do this on Training and validate on test data but since we know the
concept
# and just to answer task4, we had considered the whole dataset itself for this task

# we can see why the above was given as final model from step function even though
insig factors
# were still present
# by removing the most insig factor based on p-value we see that adj. rsq starts to
decrease at
# this stage. Hence we are going to term the model as final at the above step
summary(update(finaltask4, ~. -SleeveLengthshort)) # just to show adj rsq is starting
to decrease if we remove more

# call:

```

```
# lm(formula = log(TotalSales) ~ Size_L + Size_M + FabricType_chiffon +
# Pattern_Type_null + Pattern_Type_patchwork + NeckLine_bowneck_dmy
# NeckLine_oneck_dmy + NeckLine_ruffled_dmy, data = TASK4_DS)
# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.9740 -0.8008  0.1870  1.0482  3.4481
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)      7.3603     0.1418   51.919 < 2e-16 ***
#      Size_L          0.6163     0.1895    3.253 0.00122 **
#      Size_M          0.3055     0.1581    1.933 0.05384 .
# FabricType_chiffon    0.2242     0.1555    1.441 0.15012
# Pattern_Type_null    -0.7737     0.1739   -4.448 0.0000107 ***
# Pattern_Type_patchwork -0.3774     0.2414   -1.563 0.11858
# NeckLine_bowneck_dmy  -0.7578     0.5028   -1.507 0.13238
# NeckLine_oneck_dmy    0.4729     0.1439    3.286 0.00109 **
# NeckLine_ruffled_dmy  4.0672     1.5558    2.614 0.00922 **
# ---
# Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
# Residual standard error: 1.544 on 490 degrees of freedom
# Multiple R-squared:  0.12, Adjusted R-squared:  0.1056
# F-statistic: 8.35 on 8 and 490 DF, p-value: 0.0000000001198
```

#Task5:

#To regularize the rating procedure and find its efficiency, the store wants to find if the rating of the dress affects the total sales

#Task 5 solution:

# Lets consider ATT\_DS4 dataset with RatingClass column since Rating as a factor (categorical variable is more relevant here as there is a clear distinction about the distribution of Rating Data)

```
ATT_DS4 <- TASK4_DS %>%
  mutate(RatingClass = cut(Rating,c(-0.1,4,max(Rating)),
    labels = c("<=4",">4")))%>%
  mutate_if(is.character,as.factor) %>%
  dplyr::select(-c(Recommendation,SNOMERGE,
    Size, waiseline, FabricType, Decoration,
    Pattern_Type, `2013-08-29`, `2013-08-31`, `2013-02-09`,
    `2013-04-09`, `2013-06-09`, `2013-08-09`,
    `2013-10-09`, `2013-12-09`, `2013-09-14`, `2013-09-16`,
    `2013-09-18`, `2013-09-20`, `2013-09-22`, `2013-09-24`,
    `2013-09-26`, `2013-09-28`, `2013-09-30`, `2013-02-10`,
    `2013-04-10`, `2013-06-10`, `2013-08-10`, `2013-10-10`,
    `2013-12-10`))
```

ggplot(ATT\_DS4, aes(Rating)) + geom\_density(fill="blue")+theme\_bw() # indicates more of 0 -1 or >4, hence best to use RatingClass

```
table(ATT_DS4$RatingClass)
# <=4 >4
# 133 366
```

```
ATT_DS4 <- ATT_DS4 %>% mutate(RATINGLE4 = ifelse(RatingClass=="<=4",1,0),
  RATINGGT4 = ifelse(RatingClass==">4",1,0) # these two
are not needed, just one of them is sufficient, but for consistency creating both of
these
)
```

# we again need to do Training and test but since we know the concept and  
# just want to answer task5, lets consider the whole dataset itself for now  
task5lm <- lm(log(TotalSales) ~ RATINGLE4 + RATINGGT4 ,data = ATT\_DS4)

```
summary(task5lm)
# Call:
# lm(formula = log(TotalSales) ~ RATINGLE4 + RATINGGT4, data = ATT_DS4)
#
```

```

# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.8642 -0.9255 -0.0501  0.9041  4.6135
#
# Coefficients: (1 not defined because of singularities)
# Estimate Std. Error t value Pr(>|t|)
# (Intercept)  8.22763    0.07214   114.05  <2e-16 ***
# RATINGLE4    -1.97718    0.13973   -14.15  <2e-16 ***
# RATINGGT4         NA         NA      NA      NA
# ---
#      Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.38 on 497 degrees of freedom
# Multiple R-squared:  0.2872,    Adjusted R-squared:  0.2857
# F-statistic: 200.2 on 1 and 497 DF,  p-value: < 2.2e-16

task5lm.1 <- update(task5lm, ~. -RATINGGT4)
summary(task5lm.1)

# Call:
#      lm(formula = log(TotalSales) ~ RATINGLE4, data = ATT_DS4)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.8642 -0.9255 -0.0501  0.9041  4.6135
#
# Coefficients:
#      Estimate Std. Error t value Pr(>|t|)
# (Intercept)  8.22763    0.07214   114.05  <2e-16 ***
# RATINGLE4    -1.97718    0.13973   -14.15  <2e-16 ***
# ---
#      Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.38 on 497 degrees of freedom
# Multiple R-squared:  0.2872,    Adjusted R-squared:  0.2857
# F-statistic: 200.2 on 1 and 497 DF,  p-value: < 2.2e-16
# based on the p-value of the model, rating of the dress affects the total sales as
# its is very significant <0.05
# Adj Rsq of 28.57%; adding this factor alone to previous best model from task3 and
# significant factors from task 4 would have improved the model so much

### Now just to complete the model as a one whole one for the retail store, lets
# combine the significant factors from task3,4,5 and create a single model and see how
# the
# adj rs is. we expect it to be better than every task step individually but lets
# validate

#Additional step done by me to predict sales overall
#also in one of the earlier steps we considered interactions as well to improve the
#model
# but just lets take the main effects from these steps and create interactions all
# over again
# and use step/stepAIC to do one single regression model for TotalSales

ADDIT_lm <- lm(data=ATT_DS4,log(TotalSales) ~. - Dress_ID - Rating -RATINGGT4 -
RatingClass)

step(ADDIT_lm, direction = "both", test = "F")

# Call:
#      lm(formula = log(TotalSales) ~ SleeveLengththreequarter +
SleeveLengthsleeveless +
#      SleeveLengthshort + SleeveLengthhalf sleeve + SleeveLengthfull +
#      SleeveLengthcap_sleeves + Priceaverage + Pricelow +
Style_sexy_dmy +
#      Material_linen_dmy + Material_mix_dmy + Material_modal_dmy +
#      NeckLine_bowneck_dmy + NeckLine_ruffled_dmy + Size_L + Size_M +
#      Size_S + FabricType_null + FabricType_worsted + Pattern_Type_null
+
#      RATINGLE4 + Material_cashmere_dmy, data = ATT_DS4)
#
# Coefficients:

```

```

#           (Intercept) SleeveLengththreequarter SleeveLengthsleeveless
# 8.8275          -1.6199          -1.5815
# SleeveLengthshort   SleeveLengthhalfsleeve   SleeveLengthfull
# -1.0749          -1.0387          -1.3517
# SleeveLengthcap_sleeves Priceaverage          Pricelow
# -1.5542          0.6858          1.0835
# Style_sexy_dmy      Material_linen_dmy      Material_mix_dmy
# 0.3279          1.2108          0.7005
# Material_modal_dmy   NeckLine_bowneck_dmy   NeckLine_ruffled_dmy
# -1.7594          -0.9290          2.8326
# Size_L              Size_M              Size_S
# 0.6019          0.2885          0.3885
# FabricType_null      FabricType_worsted      Pattern_Type_null
# -0.1982          -0.5554          -0.5331
# RATINGLE4      Material_cashmere_dmy
# -1.9268          -1.0137

```

```

TOTALSALES_FINAL <- lm(formula = log(TotalSales) ~ SleeveLengththreequarter +
SleeveLengthsleeveless +
      SleeveLengthshort + SleeveLengthhalfsleeve + SleeveLengthfull +
      SleeveLengthcap_sleeves + Priceaverage + Pricelow + Style_sexy_dmy
+
      Material_linen_dmy + Material_mix_dmy + Material_modal_dmy +
      NeckLine_bowneck_dmy + NeckLine_ruffled_dmy + Size_L + Size_M +
      Size_S + FabricType_null + FabricType_worsted + Pattern_Type_null
+
      RATINGLE4 + Material_cashmere_dmy, data = ATT_DS4)
summary(TOTALSALES_FINAL)

```

```

# Call:
# lm(formula = log(TotalSales) ~ SleeveLengththreequarter +
SleeveLengthsleeveless +
# SleeveLengthshort + SleeveLengthhalfsleeve + SleeveLengthfull +
# SleeveLengthcap_sleeves + Priceaverage + Pricelow +
Style_sexy_dmy +
# Material_linen_dmy + Material_mix_dmy + Material_modal_dmy +
# NeckLine_bowneck_dmy + NeckLine_ruffled_dmy + Size_L + Size_M +
# Size_S + FabricType_null + FabricType_worsted + Pattern_Type_null
+
# RATINGLE4 + Material_cashmere_dmy, data = ATT_DS4)

```

```

# Residuals:
#      Min       1Q   Median       3Q      Max
# -5.1765 -0.8716  0.0396  0.8234  3.3445

```

```

# Coefficients:
#           Estimate Std. Error t value      Pr(>|t|)
# (Intercept)      8.8275     0.6741  13.095    < 2e-16 ***
# SleeveLengththreequarter -1.6199     0.6679   -2.425    0.015671 *
# SleeveLengthsleeveless -1.5815     0.6309   -2.507    0.012521 *
# SleeveLengthshort -1.0749     0.6385   -1.684    0.092907 .
# SleeveLengthhalfsleeve -1.0387     0.6586   -1.577    0.115459 .
# SleeveLengthfull -1.3517     0.6396   -2.113    0.035093 *
# SleeveLengthcap_sleeves -1.5542     0.8360   -1.859    0.063621 .
# Priceaverage      0.6858     0.1741    3.939 0.0000940896 ***
# Pricelow          1.0835     0.1928    5.620 0.0000000326 ***
# Style_sexy_dmy     0.3279     0.1617    2.028    0.043128 *
# Material_linen_dmy  1.2108     0.7281    1.663    0.097002 .
# Material_mix_dmy    0.7005     0.3732    1.877    0.061132 .
# Material_modal_dmy -1.7594     0.8842   -1.990    0.047190 *
# NeckLine_bowneck_dmy -0.9290     0.4036   -2.301    0.021797 *
# NeckLine_ruffled_dmy  2.8326     1.2516    2.263    0.024079 *
# Size_L            0.6019     0.1625    3.703    0.000238 ***
# Size_M            0.2885     0.1397    2.065    0.039495 *
# Size_S            0.3885     0.2263    1.717    0.086608 .
# FabricType_null -0.1982     0.1167   -1.699    0.090066 .
# FabricType_worsted -0.5554     0.3075   -1.806    0.071556 .
# Pattern_Type_null -0.5331     0.1460   -3.652    0.000289 ***
# RATINGLE4        -1.9268     0.1289  -14.952    < 2e-16 ***
# Material_cashmere_dmy -1.0137     0.6395   -1.585    0.113580
# ---

```

```

#          signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.237 on 476 degrees of freedom
# Multiple R-squared:  0.4512,    Adjusted R-squared:  0.4258
# F-statistic: 17.79 on 22 and 476 DF,  p-value: < 2.2e-16

#with 2-level interactions # to improve the model further

TOTALSALES_FINAL_W_2INT <- lm(formula = log(TotalSales) ~

                                (SleeveLengththreequarter + SleeveLengthsleeveless +
SleeveLengthshort + SleeveLengthhalfssleeve +
SleeveLengthfull +
                                SleeveLengthcap_sleeves + Priceaverage + Pricelow +
Style_sexy_dmy +
                                Material_linen_dmy + Material_mix_dmy +
Material_modal_dmy +
                                NeckLine_bowneck_dmy + NeckLine_ruffled_dmy + Size_L +
Size_M +
                                Size_S + FabricType_null + FabricType_worsted +
Pattern_Type_null +
                                RATINGLE4 + Material_cashmere_dmy)^2, data = ATT_DS4)

step(TOTALSALES_FINAL_W_2INT, direction = "both", test = "F")
#Pasting last call from step func.
# Call:
#   lm(formula = log(TotalSales) ~ SleeveLengththreequarter +
SleeveLengthsleeveless +
#       SleeveLengthshort + SleeveLengthhalfssleeve + SleeveLengthfull +
#       Priceaverage + Pricelow + Style_sexy_dmy + Material_linen_dmy +
#       Material_mix_dmy + Material_modal_dmy + NeckLine_bowneck_dmy +
#       NeckLine_ruffled_dmy + Size_L + Size_M + Size_S + FabricType_null
#       +
#       FabricType_worsted + Pattern_Type_null + RATINGLE4 +
Material_cashmere_dmy +
#       SleeveLengththreequarter:Size_L +
SleeveLengththreequarter:RATINGLE4 +
#       SleeveLengthsleeveless:NeckLine_bowneck_dmy +
SleeveLengthsleeveless:Size_L +
#       SleeveLengthsleeveless:Size_S +
SleeveLengthsleeveless:Pattern_Type_null +
#       SleeveLengthsleeveless:RATINGLE4 + SleeveLengthshort:Size_L +
#       SleeveLengthshort:Size_S + SleeveLengthshort:Pattern_Type_null +
#       SleeveLengthhalfssleeve:FabricType_worsted +
SleeveLengthhalfssleeve:Pattern_Type_null +
#       SleeveLengthfull:Priceaverage + SleeveLengthfull:Pricelow +
#       SleeveLengthfull:Size_L + SleeveLengthfull:FabricType_null +
#       SleeveLengthfull:Pattern_Type_null +
Priceaverage:Material_mix_dmy +
#       Priceaverage:Size_S + Priceaverage:Material_cashmere_dmy +
#       Pricelow:RATINGLE4 + Style_sexy_dmy:Size_L +
Style_sexy_dmy:Size_M +
#       Style_sexy_dmy:Size_S + Material_linen_dmy:Size_M +
Material_mix_dmy:Size_L +
#       Material_mix_dmy:Size_M + Size_S:FabricType_worsted +
FabricType_worsted:RATINGLE4 +
#       Pattern_Type_null:RATINGLE4, data = ATT_DS4)
#
# Coefficients:
#      (Intercept)                SleeveLengththreequarter
#      8.7130                    -0.5254
#      SleeveLengthsleeveless      SleeveLengthshort
#     -1.1716                    -0.8836
#      SleeveLengthhalfssleeve      SleeveLengthfull
#     -1.2042                    -2.3970
#      Priceaverage                  Pricelow
#      0.5847                      0.7513
#      Style_sexy_dmy                Material_linen_dmy
#     -0.1063                      1.2258
#      Material_mix_dmy              Material_modal_dmy
#      0.6347                      -1.8147

```

```

# NeckLine_bowneck_dmy                    NeckLine_ruffled_dmy
# -1.9092                                3.1834
# Size_L                                Size_M
# 1.7671                                0.1931
# Size_S                                FabricType_null
# 1.2033                                -0.2452
# FabricType_worsted                    Pattern_Type_null
# 0.2006                                -1.7803
# RATINGLE4                            Material_cashmere_dmy
# -1.7407                                0.9235
# SleeveLengththreequarter:Size_L        SleeveLengththreequarter:RATINGLE4
# -2.5566                                -1.1852
# SleeveLengthsleeveless:NeckLine_bowneck_dmy
SleeveLengthsleeveless:Size_L
# 1.7780                                -1.5114
# SleeveLengthsleeveless:Size_S        SleeveLengthsleeveless:Pattern_Type_null
# -0.8113                                1.3994
# SleeveLengthsleeveless:RATINGLE4        SleeveLengthshort:Size_L
# -0.6317                                -1.1300
# SleeveLengthshort:Size_S            SleeveLengthshort:Pattern_Type_null
# -1.1741                                1.9552
# SleeveLengthhalfsleeve:FabricType_worsted
SleeveLengthhalfsleeve:Pattern_Type_null
# 1.9841                                1.8378
# SleeveLengthfull:Priceaverage        SleeveLengthfull:Pricelow
# 1.0262                                0.9380
# SleeveLengthfull:Size_L            SleeveLengthfull:FabricType_null
# -0.9438                                0.4693
# SleeveLengthfull:Pattern_Type_null        Priceaverage:Material_mix_dmy
# 1.9306                                1.0899
# Priceaverage:Size_S            Priceaverage:Material_cashmere_dmy
# -0.7170                                -3.0039
# Pricelow:RATINGLE4                Style_sexy_dmy:Size_L
# 1.0940                                1.1392
# Style_sexy_dmy:Size_M            Style_sexy_dmy:Size_S
# 0.6697                                1.1038
# Material_linen_dmy:Size_M            Material_mix_dmy:Size_L
# 2.1050                                -1.4219
# Material_mix_dmy:Size_M            Size_S:FabricType_worsted
# -2.0617                                -3.7085
# FabricType_worsted:RATINGLE4        Pattern_Type_null:RATINGLE4
# -1.4966                                -0.7449

```

```

TOTALSALES_FINAL_W_2INT <- lm(formula = log(TotalSales) ~ SleeveLengththreequarter +
SleeveLengthsleeveless +
    SleeveLengthshort + SleeveLengthhalfsleeve + SleeveLengthfull +
    Priceaverage + Pricelow + Style_sexy_dmy + Material_linen_dmy +
    Material_mix_dmy + Material_modal_dmy + NeckLine_bowneck_dmy +
    NeckLine_ruffled_dmy + Size_L + Size_M + Size_S + FabricType_null
+
    FabricType_worsted + Pattern_Type_null + RATINGLE4 +
Material_cashmere_dmy +
    SleeveLengththreequarter:Size_L +
SleeveLengththreequarter:RATINGLE4 +
    SleeveLengthsleeveless:NeckLine_bowneck_dmy +
SleeveLengthsleeveless:Size_L +
    SleeveLengthsleeveless:Size_S +
SleeveLengthsleeveless:Pattern_Type_null +
    SleeveLengthsleeveless:RATINGLE4 + SleeveLengthshort:Size_L +
    SleeveLengthshort:Size_S + SleeveLengthshort:Pattern_Type_null +
    SleeveLengthhalfsleeve:FabricType_worsted +
SleeveLengthhalfsleeve:Pattern_Type_null +
    SleeveLengthfull:Priceaverage + SleeveLengthfull:Pricelow +
    SleeveLengthfull:Size_L + SleeveLengthfull:FabricType_null +
    SleeveLengthfull:Pattern_Type_null + Priceaverage:Material_mix_dmy
+
    Priceaverage:Size_S + Priceaverage:Material_cashmere_dmy +
    Pricelow:RATINGLE4 + Style_sexy_dmy:Size_L + Style_sexy_dmy:Size_M
+
    style_sexy_dmy:Size_S + Material_linen_dmy:Size_M +
Material_mix_dmy:Size_L +

```



```

Material_mix_dmy:Size_M + Size_S:FabricType_worsted +
FabricType_worsted:RATINGLE4 +
Pattern_Type_null:RATINGLE4, data = ATT_DS4)

```

```
summary(TOTALSALES_FINAL_W_2INT)
```

```

# Call:
# lm(formula = log(TotalSales) ~ SleeveLengththreequarter +
SleeveLengthsleeveless +
# SleeveLengthshort + SleeveLengthhalfsleeve + SleeveLengthfull +
# Priceaverage + Pricelow + Style_sexy_dmy + Material_linen_dmy +
# Material_mix_dmy + Material_modal_dmy + NeckLine_bowneck_dmy +
# NeckLine_ruffled_dmy + Size_L + Size_M + Size_S + FabricType_null
+
# FabricType_worsted + Pattern_Type_null + RATINGLE4 +
Material_cashmere_dmy +
# SleeveLengththreequarter:Size_L +
SleeveLengththreequarter:RATINGLE4 +
# SleeveLengthsleeveless:NeckLine_bowneck_dmy +
SleeveLengthsleeveless:Size_L +
# SleeveLengthsleeveless:Size_S +
SleeveLengthsleeveless:Pattern_Type_null +
# SleeveLengthsleeveless:RATINGLE4 + SleeveLengthshort:Size_L +
# SleeveLengthshort:Size_S + SleeveLengthshort:Pattern_Type_null +
# SleeveLengthhalfsleeve:FabricType_worsted +
SleeveLengthhalfsleeve:Pattern_Type_null +
# SleeveLengthfull:Priceaverage + SleeveLengthfull:Pricelow +
# SleeveLengthfull:Size_L + SleeveLengthfull:FabricType_null +
# SleeveLengthfull:Pattern_Type_null +
Priceaverage:Material_mix_dmy +
# Priceaverage:Size_S + Priceaverage:Material_cashmere_dmy +
# Pricelow:RATINGLE4 + Style_sexy_dmy:Size_L +
Style_sexy_dmy:Size_M +
# Style_sexy_dmy:Size_S + Material_linen_dmy:Size_M +
Material_mix_dmy:Size_L +
# Material_mix_dmy:Size_M + Size_S:FabricType_worsted +
FabricType_worsted:RATINGLE4 +
# Pattern_Type_null:RATINGLE4, data = ATT_DS4)
#
# Residuals:
#      Min       1Q   Median       3Q      Max
# -4.6935 -0.6899  0.0000  0.7239  2.9308
#
# Coefficients:
#              Estimate Std. Error t value Pr(>|t|)
# (Intercept)          8.7130      0.5205   16.740 < 2e-16 ***
# SleeveLengththreequarter -0.5254      0.5333   -0.985 0.325058
# SleeveLengthsleeveless -1.1716      0.4923   -2.380 0.017735 *
# SleeveLengthshort -0.8836      0.5013   -1.763 0.078654 .
# SleeveLengthhalfsleeve -1.2042      0.5307   -2.269 0.023746 *
# SleeveLengthfull -2.3970      0.6759   -3.546 0.000432 ***
# Priceaverage 0.5847      0.1928    3.033 0.002562 **
# Pricelow 0.7513      0.2193    3.426 0.000669 ***
# Style_sexy_dmy -0.1063      0.2289   -0.465 0.642510
# Material_linen_dmy 1.2258      0.8503    1.442 0.150101
# Material_mix_dmy 0.6347      0.6103    1.040 0.298910
# Material_modal_dmy -1.8147      0.8221   -2.207 0.027799 *
# NeckLine_bowneck_dmy -1.9092      0.5653   -3.377 0.000796 ***
# NeckLine_ruffled_dmy 3.1834      1.1657    2.731 0.006567 **
# Size_L 1.7671      0.5204    3.396 0.000746 ***
# Size_M 0.1931      0.1426    1.354 0.176538
# Size_S 1.2033      0.3962    3.037 0.002529 **
# FabricType_null -0.2452      0.1222   -2.006 0.045492 *
# FabricType_worsted 0.2006      0.3493    0.574 0.566140
# Pattern_Type_null -1.7803      0.5011   -3.553 0.000422 ***
# RATINGLE4 -1.7407      0.1973   -8.822 < 2e-16 ***
# Material_cashmere_dmy 0.9235      0.9490    0.973 0.331040
# SleeveLengththreequarter:Size_L -2.5566      0.7306   -3.500 0.000513 ***
# SleeveLengththreequarter:RATINGLE4 -1.1852      0.5407   -2.192 0.028897 *
# SleeveLengthsleeveless:NeckLine_bowneck_dmy 1.7780      0.7834    2.269 0.023718 *
# SleeveLengthsleeveless:Size_L -1.5114      0.5538   -2.729 0.006596 **
# SleeveLengthsleeveless:Size_S -0.8113      0.5091   -1.593 0.111760

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# SleeveLengthsleeveless:Pattern_Type_null      1.3994      0.5198      2.692 0.007364 **
# SleeveLengthsleeveless:RATINGLE4             -0.6317      0.2571     -2.458 0.014368 *
# SleeveLengthshort:Size_L                       -1.1300      0.5891     -1.918 0.055729 .
# SleeveLengthshort:Size_S                       -1.1741      0.6218     -1.888 0.059641 .
# SleeveLengthshort:Pattern_Type_null            1.9552      0.6129      3.190 0.001523 **
# SleeveLengthhalfsleeve:FabricType_worsted      1.9841      1.3743      1.444 0.149507
# SleeveLengthhalfsleeve:Pattern_Type_null       1.8378      0.6336      2.901 0.003909 **
# SleeveLengthfull:Priceaverage                  1.0262      0.4533      2.264 0.024057 *
# SleeveLengthfull:Pricelow                      0.9380      0.4607      2.036 0.042335 *
# SleeveLengthfull:Size_L                       -0.9438      0.6315     -1.495 0.135738
# SleeveLengthfull:FabricType_null               0.4693      0.2970      1.580 0.114710
# SleeveLengthfull:Pattern_Type_null             1.9306      0.6355      3.038 0.002523 **
# Priceaverage:Material_mix_dmy                  1.0899      0.7394      1.474 0.141200
# Priceaverage:Size_S                           -0.7170      0.4405     -1.628 0.104307
# Priceaverage:Material_cashmere_dmy             -3.0039      1.2782     -2.350 0.019203 *
# Pricelow:RATINGLE4                           1.0940      0.2674      4.091 0.000051 ***
# Style_sexy_dmy:Size_L                         1.1392      0.4464      2.552 0.011047 *
# Style_sexy_dmy:Size_M                         0.6697      0.3466      1.932 0.053946 .
# Style_sexy_dmy:Size_S                         1.1038      0.6073      1.818 0.069782 .
# Material_linen_dmy:Size_M                     2.1050      1.4613      1.441 0.150422
# Material_mix_dmy:Size_L                       -1.4219      0.8185     -1.737 0.083026 .
# Material_mix_dmy:Size_M                       -2.0617      0.9718     -2.121 0.034432 *
# Size_S:FabricType_worsted                     -3.7085      1.2779     -2.902 0.003892 **
# FabricType_worsted:RATINGLE4                  -1.4966      0.7627     -1.962 0.050367 .
# Pattern_Type_null:RATINGLE4                   -0.7449      0.2999     -2.484 0.013362 *
#
# ---
#          Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
#
# Residual standard error: 1.147 on 447 degrees of freedom
# Multiple R-squared:  0.5575,    Adjusted R-squared:  0.507
# F-statistic: 11.04 on 51 and 447 DF,  p-value: < 2.2e-16

par(mfrow=c(2,2))
plot(TOTALSALES_FINAL_W_2INT)

```