MATH-328 Project

David Oniani

May 02, 2021

## Setup

library(emmeans)  
library(ggplot2)  
library(multcomp)

## Loading required package: mvtnorm

## Loading required package: survival

## Loading required package: TH.data

## Loading required package: MASS

##   
## Attaching package: 'TH.data'

## The following object is masked from 'package:MASS':  
##   
## geyser

library(sjmisc)

## Initial Data Exploration and Analysis

# Load the data  
data = read.csv("data.csv")  
  
# Get rid of unwanted columns (will come in handy when designing models)  
data[c("trt\_id", "X\_hue", "X\_bright", "X\_price")] = NULL  
  
# Make hue, bright, and price factors  
data$hue = factor(data$hue)  
data$bright = factor(data$bright)  
data$price = factor(data$price)  
  
# Show first 6 and last 6 rows  
head(data)

## quality hue bright price  
## 1 2.1774 1 1 1  
## 2 4.9506 1 1 1  
## 3 4.8796 1 1 1  
## 4 4.9565 1 1 1  
## 5 6.2517 1 1 1  
## 6 5.0488 1 1 1

tail(data)

## quality hue bright price  
## 223 2.8811 2 2 2  
## 224 2.3638 2 2 2  
## 225 1.6588 2 2 2  
## 226 2.7048 2 2 2  
## 227 3.6134 2 2 2  
## 228 1.1509 2 2 2

# Show the structure of the data  
str(data)

## 'data.frame': 228 obs. of 4 variables:  
## $ quality: num 2.18 4.95 4.88 4.96 6.25 ...  
## $ hue : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...  
## $ bright : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...  
## $ price : Factor w/ 2 levels "1","2": 1 1 1 1 1 1 1 1 1 1 ...

# Are factors crossed?  
is\_crossed(data$hue, data$bright)

## [1] TRUE

is\_crossed(data$hue, data$price)

## [1] TRUE

is\_crossed(data$bright, data$price)

## [1] TRUE

# Are factors nested?  
is\_nested(data$hue, data$bright)

## [1] FALSE

is\_nested(data$bright, data$hue)

## [1] FALSE

is\_nested(data$hue, data$price)

## [1] FALSE

is\_nested(data$price, data$hue)

## [1] FALSE

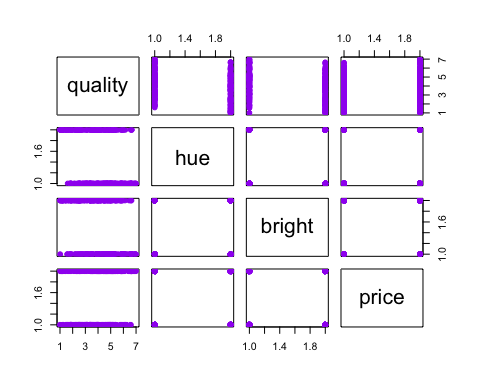
is\_nested(data$bright, data$price)

## [1] FALSE

is\_nested(data$price, data$bright)

## [1] FALSE

# Scatterplot matrix  
plot(data, pch = 20, cex = 1.5, col = "purple")



The data has three categorical variables: hue, bright, and price and one response variable: quality. We will treat hue, bright, and price as factors. The dataset is then suitable for a 3-factor experiment of online shopping. It contains three categorical factors: web page hue (1 = Blue, 2 = Red), Brightness (1 = Dark, 2 = Bright), and Price (1 = Low, 2 = high). Sample sizes are unbalanced. We will analyze when and how the response value - perceived quality - changes with brightness, hue, and price.

Exploratory analysis above prints first and last 6 rows of the data as well as shows the overall structure of the data. We also made hue, bright, and price factor variables. This will help using these variables properly, as factors, in models that we will develop.

Thus, our response variable is quality, which is a perceived quality of the product. Our predictor variables are hue, bright, and price - all of them are categorical variables. Since we do not have any quantitative predictors, we do not have covariates.

Factors hue and bright are crossed. Factors hue and price are also crossed. Factors bright and price are crossed too.

There is no nesting among the factors.

Since the investigators controlled the levels for all factors, all of the factors are fixed. Hence, factors hue, bright, and price are fixed (not random).

The scatterplot matrix is also shown. At a first glance, it does not seem to give us any signficant/important insights, so we can move on with our analysis.

## Fitting Full Model

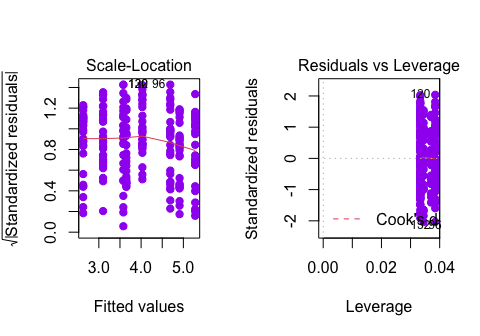
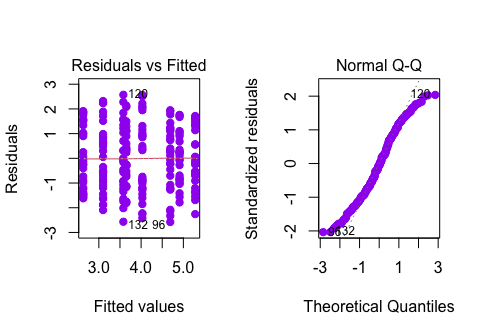
# Fit the initial model with three-way  
fit1 = aov(quality ~ .^3, data)  
  
# Report the summary  
summary(fit1)

## Df Sum Sq Mean Sq F value Pr(>F)   
## hue 1 48.1 48.08 29.016 1.84e-07 \*\*\*  
## bright 1 48.1 48.11 29.034 1.82e-07 \*\*\*  
## price 1 34.1 34.08 20.564 9.47e-06 \*\*\*  
## hue:bright 1 11.7 11.71 7.064 0.00844 \*\*   
## hue:price 1 8.6 8.57 5.169 0.02396 \*   
## bright:price 1 14.1 14.13 8.530 0.00386 \*\*   
## hue:bright:price 1 9.0 8.97 5.414 0.02088 \*   
## Residuals 220 364.6 1.66   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

# Estimates  
fit1$coefficients

## (Intercept) hue2 bright2 price2   
## 4.03000667 -0.45000282 -0.38001051 1.25000000   
## hue2:bright2 hue2:price2 bright2:price2 hue2:bright2:price2   
## -0.09999333 0.07998875 -0.20999615 -1.58999926

# Residual analysis  
par(mfrow = c(1, 2))  
plot(fit1, pch = 20, cex = 1.5, col = "purple")



par(mfrow = c(1, 1))

We start with the full model, including all two-way and one three-way interactions.

Residuals vs Fitted plot shows fairly constant variance. The red line follows the dotted line closely, further corroborating our hypothesis. Thus, the constant variance assumption is not violated.

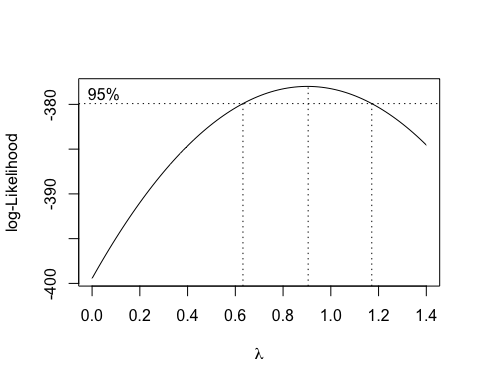
The Normal Q-Q plot shows that most of the points, except for at the tails, of the plot do follow the dotted line. However, at both tails, there is some deviation from the dotted line which suggests some non-normality. This is more of a judgment call, but to me it seems to be approximately normal. Hence, the normality assumption for ANOVA is met.

Scale-Location plot does have some decreasing trend toward the end of the plot, but the variance does seem to be constant.

Residuals vs Leverage does not show any significant outliers.

Given our analysis, let us now perform a Box-Cox analysis in order to find an appropriate power transformation for the response variable.

# Box-Cox analysis for the power transformation  
MASS::boxcox(fit1, lambda = seq(0, 2, 0.7))



From the plot, we can see that the lambda value is approximately 0.9. This means that we have two options:

1. Leave the response as is
2. Raise the response to the 0.9 power

We will first try raising the response to 0.9 power and see if it helps. If the results are similar, we will go with the original model (without the power transformation).

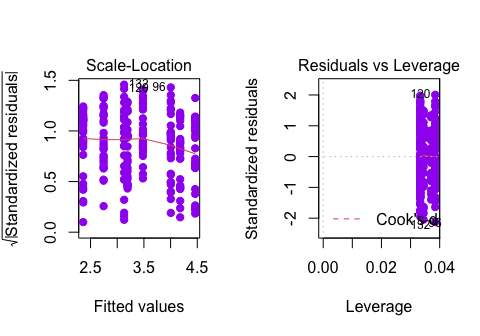
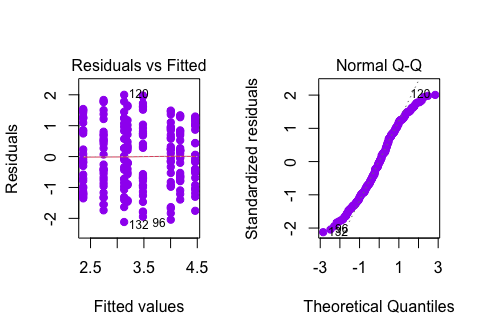
# Refit the model, applying the right power transformation  
fit2 = aov(quality^0.9 ~ .^3, data)  
  
# Summary  
summary(fit2)

## Df Sum Sq Mean Sq F value Pr(>F)   
## hue 1 30.29 30.291 29.293 1.62e-07 \*\*\*  
## bright 1 30.07 30.070 29.080 1.79e-07 \*\*\*  
## price 1 20.74 20.735 20.052 1.21e-05 \*\*\*  
## hue:bright 1 7.74 7.736 7.481 0.00674 \*\*   
## hue:price 1 5.28 5.281 5.107 0.02481 \*   
## bright:price 1 8.96 8.962 8.667 0.00359 \*\*   
## hue:bright:price 1 5.67 5.668 5.481 0.02012 \*   
## Residuals 220 227.50 1.034   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

# Estimates  
fit2$coefficients

## (Intercept) hue2 bright2 price2   
## 3.48215957 -0.35249192 -0.28902182 0.97895364   
## hue2:bright2 hue2:price2 bright2:price2 hue2:bright2:price2   
## -0.09602526 0.07114438 -0.16838508 -1.26376789

# Residual analysis  
par(mfrow = c(1, 2))  
plot(fit2, pch = 20, cex = 1.5, col = "purple")



par(mfrow = c(1, 1))

After applying the transformation, all four plots look similar and the summary also shows approximately the same p-values and estimates (coefficients). For this reason, we will stick with our initial model - fit1.

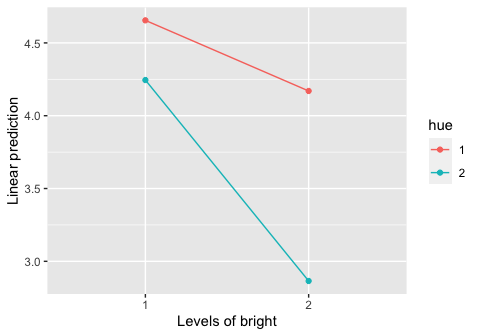
Since all of our interactions are significant, we do not have any insignificant interactions to remove and we do not need to apply a stepwise regression to remove non-significant effects.

## Results

We start by analyzing the interaction plots of significant effects. Since all of the two-way interactions were significant and we have three factors, we will analyze three plots. This would also be the highest order interactions as due to the nature of the study that collected the data, including three-way interaction would not be appropriate.

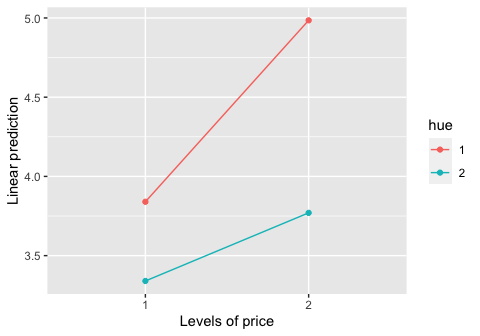
# Interaction plots  
emmip(fit1, hue ~ bright)

## NOTE: Results may be misleading due to involvement in interactions



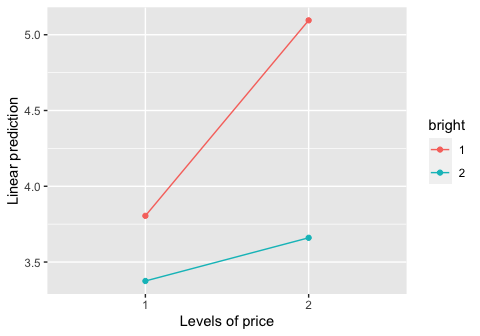
emmip(fit1, hue ~ price)

## NOTE: Results may be misleading due to involvement in interactions

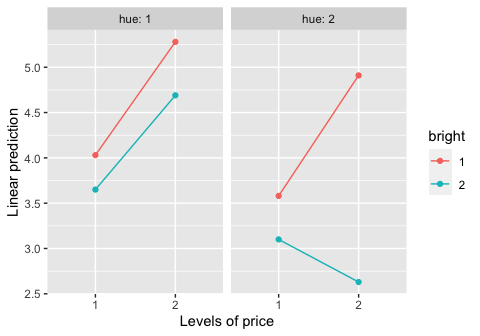


emmip(fit1, bright ~ price)

## NOTE: Results may be misleading due to involvement in interactions



emmip(fit1, bright ~ price | hue)



In terms of interactions plots, all four interaction plots show some degree of interaction between the variables. The lowest degree of interaction seems to be between variables hue and price (lines are relatively parallel with respect to each other). The highest degree of interaction seems to be between variables bright and price (lines are not relatively parallel with respect to each other). That being said, in all three plots, two lines would cross each other if extended and thus, the interactions are significant. Finally, the three-way interaction plots also show some interactions which can be more difficult to assess, but the lines are definitely not parallel with respect to each other in either of the plots (hue: 1 and hue: 2 plots). Further analysis will show the degree of these interactions in more detail.

# Report the summary  
summary(fit1)

## Df Sum Sq Mean Sq F value Pr(>F)   
## hue 1 48.1 48.08 29.016 1.84e-07 \*\*\*  
## bright 1 48.1 48.11 29.034 1.82e-07 \*\*\*  
## price 1 34.1 34.08 20.564 9.47e-06 \*\*\*  
## hue:bright 1 11.7 11.71 7.064 0.00844 \*\*   
## hue:price 1 8.6 8.57 5.169 0.02396 \*   
## bright:price 1 14.1 14.13 8.530 0.00386 \*\*   
## hue:bright:price 1 9.0 8.97 5.414 0.02088 \*   
## Residuals 220 364.6 1.66   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

# Estimates  
fit1$coefficients

## (Intercept) hue2 bright2 price2   
## 4.03000667 -0.45000282 -0.38001051 1.25000000   
## hue2:bright2 hue2:price2 bright2:price2 hue2:bright2:price2   
## -0.09999333 0.07998875 -0.20999615 -1.58999926

The summary report confirms our conclusions based on interaction plots. Indeed, hue and price interaction seems to be the least significant one (but still significant as the p-value is approximately 0.02 < 0.05) with the p-value of 0.02. The interaction between bright and price, as observed, is most significant with the p-value of approximately 0.004. The interaction between hue and bright is also significant with the p-value of approximately 0.008. Finally, the three-way interaction between hue, bright, and price is also significant with the p-value of approximately 0.02.

Variables hue, bright, and price are all significant with the p-values of 1.84e-07, 1.82e-07, and 9.47e-06 respectively.

The estimate of hue is approximately -0.45. The estimates for bright and price are -0.38 and 1.25 respectively.

The intercept is approximately 4.03, which means that the mean quality when all factors are null is 4.03.

cld(emmeans(fit1, ~ hue | bright), Letters=LETTERS)

## NOTE: Results may be misleading due to involvement in interactions

## bright = 1:  
## hue emmean SE df lower.CL upper.CL .group  
## 2 4.24 0.177 220 3.90 4.59 A   
## 1 4.66 0.166 220 4.33 4.98 A   
##   
## bright = 2:  
## hue emmean SE df lower.CL upper.CL .group  
## 2 2.86 0.166 220 2.54 3.19 A   
## 1 4.17 0.174 220 3.83 4.51 B   
##   
## Results are averaged over the levels of: price   
## Confidence level used: 0.95   
## significance level used: alpha = 0.05

cld(emmeans(fit1, ~ hue | price), Letters=LETTERS)

## NOTE: Results may be misleading due to involvement in interactions

## price = 1:  
## hue emmean SE df lower.CL upper.CL .group  
## 2 3.34 0.172 220 3.00 3.68 A   
## 1 3.84 0.172 220 3.50 4.18 B   
##   
## price = 2:  
## hue emmean SE df lower.CL upper.CL .group  
## 2 3.77 0.171 220 3.43 4.11 A   
## 1 4.99 0.168 220 4.65 5.32 B   
##   
## Results are averaged over the levels of: bright   
## Confidence level used: 0.95   
## significance level used: alpha = 0.05

cld(emmeans(fit1, ~ bright | price), Letters=LETTERS)

## NOTE: Results may be misleading due to involvement in interactions

## price = 1:  
## bright emmean SE df lower.CL upper.CL .group  
## 2 3.37 0.172 220 3.04 3.71 A   
## 1 3.81 0.172 220 3.47 4.14 A   
##   
## price = 2:  
## bright emmean SE df lower.CL upper.CL .group  
## 2 3.66 0.168 220 3.33 3.99 A   
## 1 5.09 0.171 220 4.76 5.43 B   
##   
## Results are averaged over the levels of: hue   
## Confidence level used: 0.95   
## significance level used: alpha = 0.05

# We compare bright based on levels of price and hue  
cld(emmeans(fit1, ~ bright | price | hue), Letters=LETTERS)

## price = 1, hue = 1:  
## bright emmean SE df lower.CL upper.CL .group  
## 2 3.65 0.252 220 3.15 4.15 A   
## 1 4.03 0.235 220 3.57 4.49 A   
##   
## price = 1, hue = 2:  
## bright emmean SE df lower.CL upper.CL .group  
## 2 3.10 0.235 220 2.64 3.56 A   
## 1 3.58 0.252 220 3.08 4.08 A   
##   
## price = 2, hue = 1:  
## bright emmean SE df lower.CL upper.CL .group  
## 2 4.69 0.239 220 4.22 5.16 A   
## 1 5.28 0.235 220 4.82 5.74 A   
##   
## price = 2, hue = 2:  
## bright emmean SE df lower.CL upper.CL .group  
## 2 2.63 0.235 220 2.17 3.09 A   
## 1 4.91 0.248 220 4.42 5.40 B   
##   
## Confidence level used: 0.95   
## significance level used: alpha = 0.05

Above find the appropriate pairwise comparisons for the significant effects.

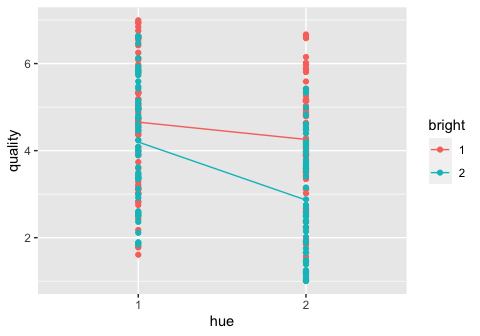
Let us first analyze emmeans with hue and bright interaction. We see that the mean response (quality value) is the lowest with high brightness and red hue (2.86). The mean response is the highest when brightness is low and hue is blue (4.66). When bright = 1 (low brightness) and hue = 2 (red), the emmean is 4.25 and when bright = 2 (high brightness) and hue = 1 (blue), the emmean is 4.18.

In hue - price interaction, the highest emmean value is achieved when price is high and hue is blue, the value is 4.98. The lowest emmean value is when price = 1 (low price) and hue = 2 (red), the value is 3.76. When price is low and hue is blue, the emmean value is 3.85. When price is high and hue blue, the emmean is 3.76.

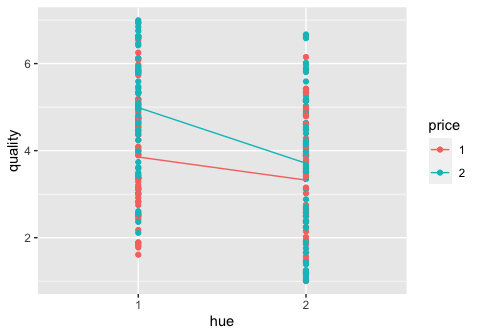
In price - bright interaction, the biggest emmean of 5.08 is when bright = 1 and price = 2 (high brightness and low price). The lowest emmean value is when price is low and brightness is high (price = 1, bright = 2). When both brightness and price are low, the emmean is 3.82 and when both price and brightness are high, the emmean is 3.66.

Analyzing brightness, based on levels of price and hue, we got that the highest emmean value is with high price, blue hue, and low brightness (price = 2, hue = 1, bright = 1) and the lowest emmean value is 2.64 with the price is high, hue is red, and brightness is high (price = 2, hue = 1, bright = 2). The rest of the values are shown in the table.

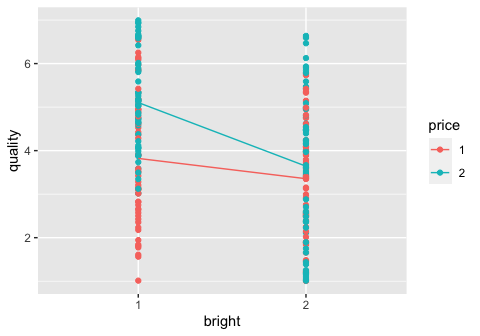
# Hue - Bright  
qplot (hue, quality, data = data, color = bright) +   
 stat\_summary(fun = mean, geom = "line", aes(group = bright))



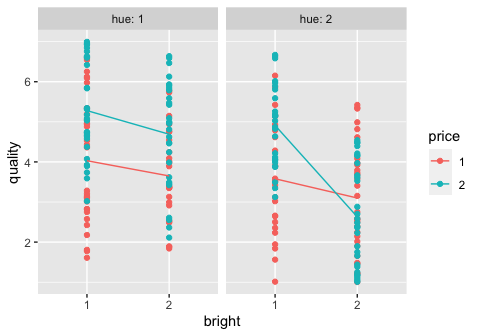
# Hue - Price  
qplot (hue, quality, data = data, color = price) +   
 stat\_summary(fun = mean, geom = "line", aes(group = price))



# Bright - Price  
qplot (bright, quality, data = data, color = price) +   
 stat\_summary(fun = mean, geom = "line", aes(group = price))



# Bright - Price - Hue  
qplot (bright, quality, data = data, color = price) +   
 stat\_summary(fun = mean, geom = "line", aes(group = price)) +  
 facet\_wrap(vars(hue), labeller="label\_both")



Above find some qplots which are similar to emmip plots that we had previously, but also shows the data points. Obviously, these plots do not change our observations in any way as the data and the model are the same, but they do provide another way of looking at the interactions between the variables. Similar to the emmip interaction plots, all interactions seem significant as the lines are not approximately parallel in any of the plots.

Finally, we state several conclusions. In order for me to explain the conclusions, I will use analogies - high brightness (think blinding website/packaging/etc), high hue (think same as high brightness, with blue being less bright/darker and red being brighter/lighter/blinding in extreme cases), high price (think something that might have high quality, but that would depend on interaction with hue and brightness).

* Products with high brightness and high hue have the lowest perceived quality - makes sense, blinding brightness and high hue does not leave good impressions
* Products with low brightness and low hue have the highest perceived quality - makes sense low brightness and low hue probably means more elegant website and is therefore, more attractive in general)
* Products with high price and low hue have the highest perceived quality - makes sense, low hue would probably mean more elegant website and high price would mean that the product is probably high quality (hence, higher perceived quality)
* Products with low price and high hue have the lowest perceived quality: makes sense, low price on already not very elegant looking website might be very attractive.
* Products with high price and low brightness have the highest perceived quality - makes sense, products presented with low brightness and high price will probably look more elegant and attract more users
* Products with high hue and high brightness have the lowest perceived quality - makes sense, products presented with blinding colors and low price are not very attractive