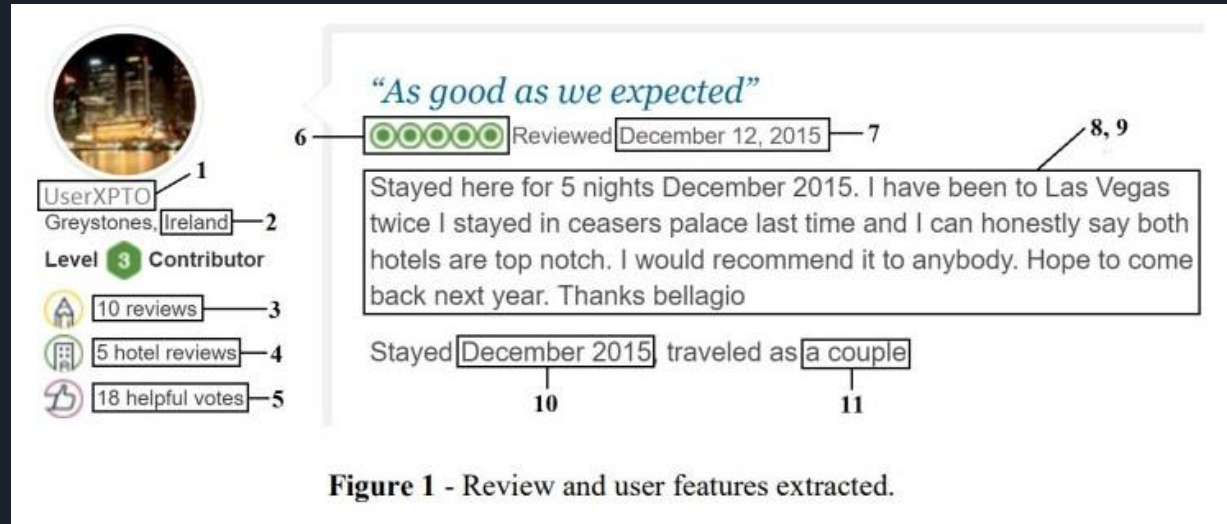
A decorative graphic on the left side of the slide consisting of two overlapping parallelograms. The front one is blue and the back one is light green. They are positioned diagonally, with the blue one partially covering the green one.

What factors are most influential in predicting a Las Vegas Hotel's online rating?

By: Omer Canca, Ben Caggiano, Sarvjot Baxi, Ray Chen

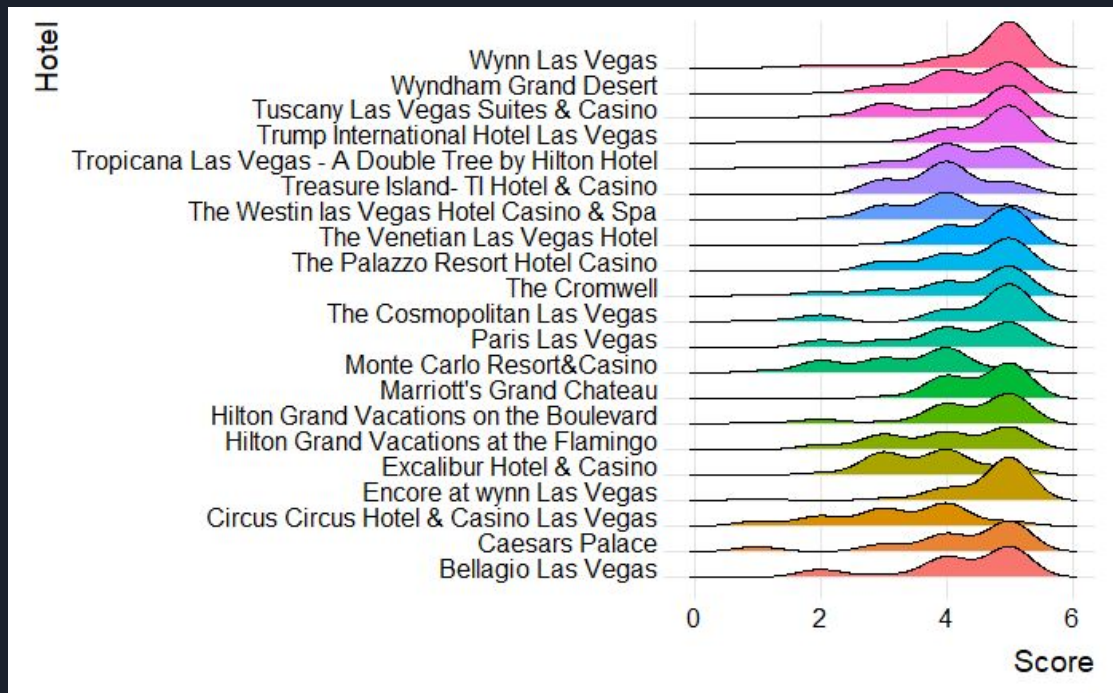
About the Data Set

- Reviews taken from 21 hotels on the Las Vegas Strip
- Two reviews selected per month from 2015
 - 24 reviews per hotel, 504 total reviews
- 20 features



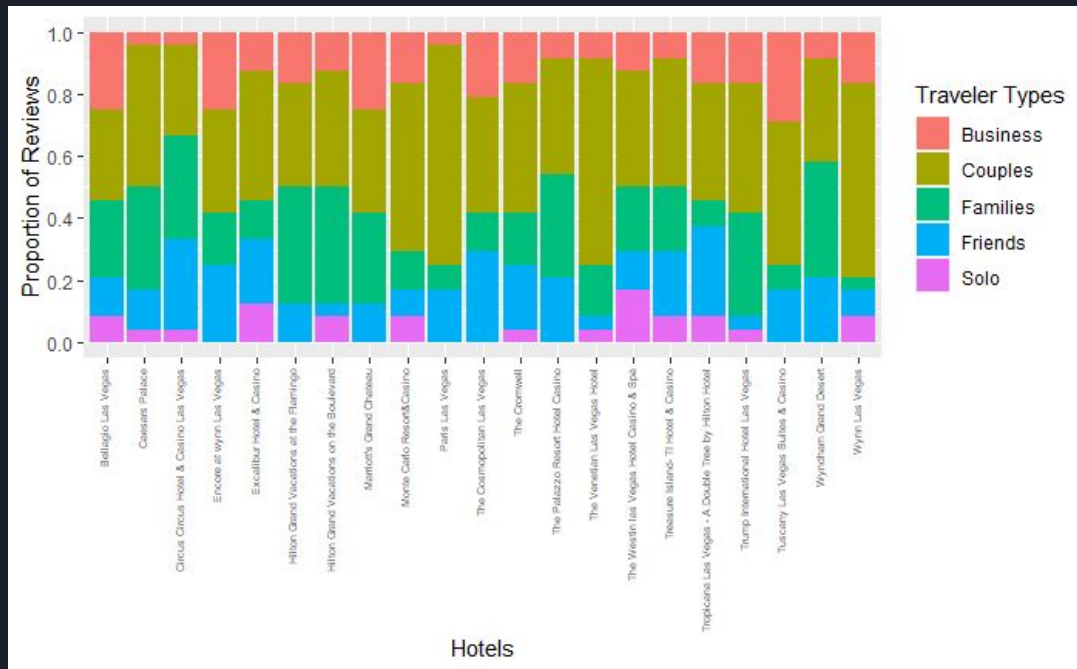
Score Distribution of All Hotels

```
ggplot(hotel_review_df,  
  aes(x = Score,  
    y = Hotel.name,  
    fill = Hotel.name)) +  
  geom_density_ridges() +  
  theme_ridges() +  
  labs("Hotel Rating Distribution") +  
  ylab("Hotel")+  
  theme(legend.position = "none")
```



Score Distribution of All Traveler Types

```
ggplot(hotel_review_df,  
       aes(x = Hotel.name,  
           fill = Traveler.type)) +  
  geom_bar(position = "fill") +  
  theme(axis.text.x =  
        element_text(angle = 90, vjust =  
        0.1, hjust = 1, size = 5)) +  
  scale_y_continuous(breaks = seq(0, 1,  
    .2)) +  
  labs(y = "Proportion of Reviews", x =  
        "Hotels", fill = "Traveler Types")
```



Simple Linear Regression

Coding Variables

Spa = 1 for yes; 0 for no
Gym = 1 for yes; 0 for no
Pool = 1 for yes; 0 for no
Casino = 1 for yes; 0 for no
Free.internet = 1 for yes; 0 for no
Tennis.court = 1 for yes; 0 for no

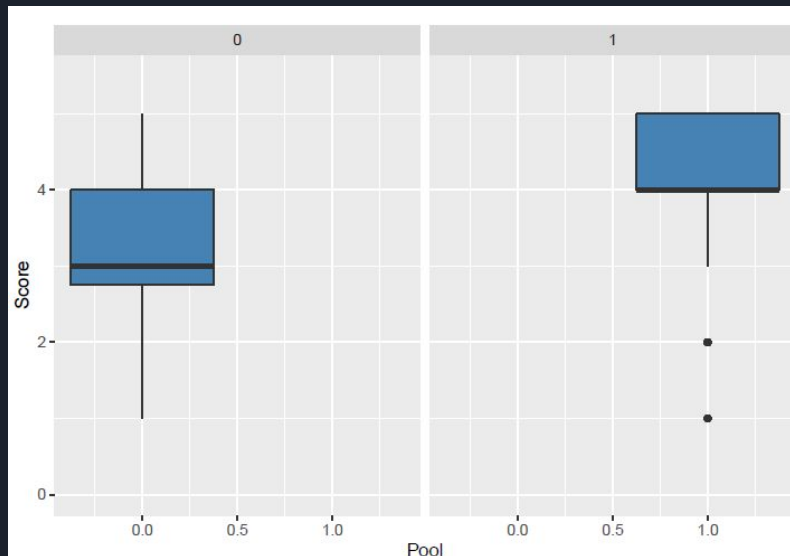
```
data$Spa<-ifelse(data$Spa=="YES",1,0)
data$Gym<-ifelse(data$Gym=="YES",1,0)
data$Pool<-ifelse(data$Pool=="YES",1,0)
data$Casino<-ifelse(data$Casino=="YES",1,0)
data$Free.internet<-ifelse(data$Free.internet=="YES",1,0)
data$Tennis.court<-ifelse(data$Tennis.court=="YES",1,0)
df <- dplyr::select_if(data, is.numeric)
```

```
## Subset selection object
## Call: regsubsets.formula(Score ~ ., data = df, nvmax = 1, method = "backward")
## 11 Variables (and intercept)
## Forced in Forced out
## Nr..reviews FALSE FALSE
## Nr..hotel.reviews FALSE FALSE
## Helpful.votes FALSE FALSE
## Pool FALSE FALSE
## Gym FALSE FALSE
## Tennis.court FALSE FALSE
## Spa FALSE FALSE
## Casino FALSE FALSE
## Free.internet FALSE FALSE
## Nr..rooms FALSE FALSE
## Member.years FALSE FALSE
## 1 subsets of each size up to 1
## Selection Algorithm: backward
## Nr..reviews Nr..hotel.reviews Helpful.votes Pool Gym Tennis.court Spa
## 1 (1) " " " " " " "*" " " "
## Casino Free.internet Nr..rooms Member.years
## 1 (1) " " " " " " " "
```

Our results tell us that Pool is the most significant variable.

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
## (Intercept)	3.2083	0.2015	15.920	< 2e-16 ***
## Pool	0.9604	0.2065	4.651	4.23e-06 ***



Multiple Linear Regression

```
## Casino           FALSE      FALSE
## Free.internet    FALSE      FALSE
## Nr..rooms        FALSE      FALSE
## Member.years     FALSE      FALSE
## 1 subsets of each size up to 5
## Selection Algorithm: forward
##      Nr..reviews Nr..hotel.reviews Helpful.votes Pool Gym Tennis.court Spa
## 1 ( 1 ) " "      " "                  " "      "*" " " " "      " "
## 2 ( 1 ) " "      " "                  " "      "*" " " " "      " "
## 3 ( 1 ) " "      " "                  " "      "*" " " " "      " "
## 4 ( 1 ) " "      " "                  " "      "*" "*" " "      " "
## 5 ( 1 ) " "      " "                  " "      "*" "*" " "      "*"
##
##      Casino Free.internet Nr..rooms Member.years
## 1 ( 1 ) " "      " "      " "      " "
## 2 ( 1 ) " "      "*"      " "      " "
## 3 ( 1 ) " "      "*"      " "      "*"
## 4 ( 1 ) " "      "*"      " "      "*"
## 5 ( 1 ) " "      "*"      " "      "*"

```

```
model2 = lm(Score ~ Pool + Free.internet, data = df)
model3 = lm(Score ~ Pool + Free.internet + Member.years, data = df)
model4 = lm(Score ~ Pool + Free.internet + Member.years + Gym, data = df)
model5 = lm(Score ~ Pool + Free.internet + Member.years + Gym + Spa, data = df)

```

AIC

We will use AIC to determine which model is the best of the three. AIC is a score that is used to determine which model is best based on prediction error. A lower AIC is better

AIC(model2)

```
## [1] 1402.934
```

AIC(model3)

```
## [1] 1404.342
```

AIC(model4)

```
## [1] 1405.88
```

AIC(model5)

```
## [1] 1407.411
```

Analysis of Variance Table

```
##
```

```
## Model 1: Score ~ Pool + Free.internet
```

```
## Model 2: Score ~ Pool
```

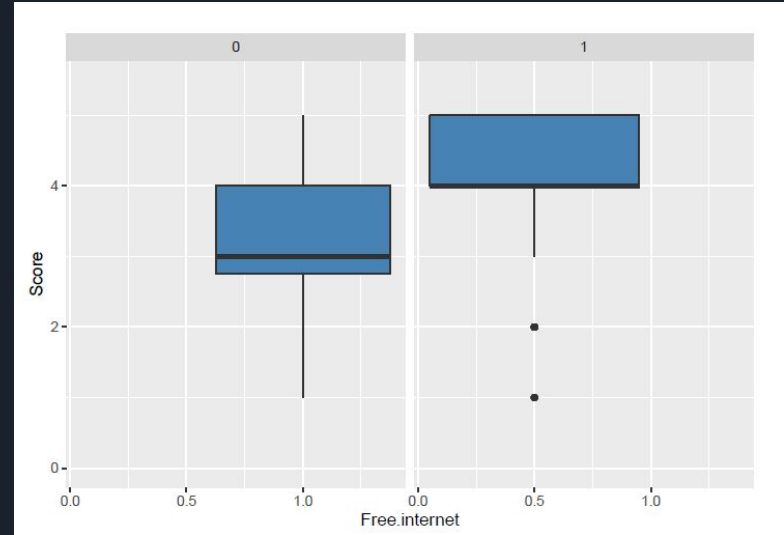
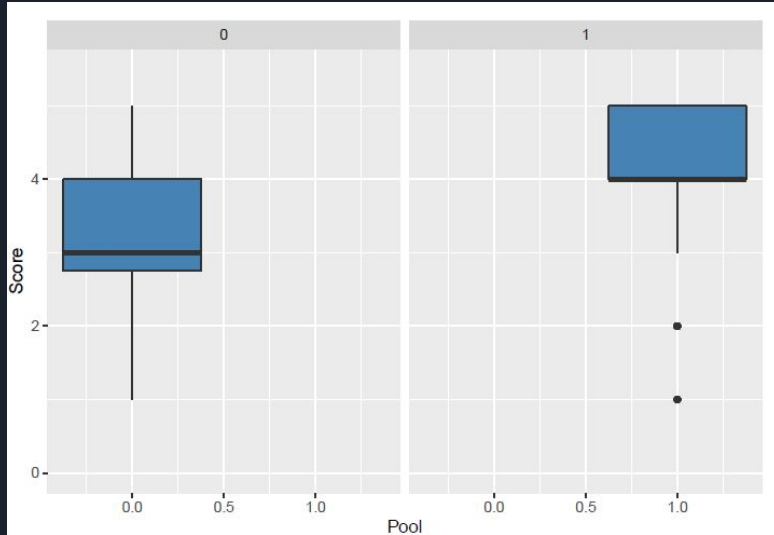
```
##   Res.Df    RSS Df Sum of Sq    F    Pr(>F)
## 1     501 469.86
## 2     502 489.29 -1   -19.434 20.723 6.671e-06 ***
## ---
```

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

```

Our results tell us that the extra predictor in model2 is significant.

Multiple Linear Regression 2



Conclusion

Our final model includes free internet and pool as the best predictors for score. This tells us that when looking for a hotel in Vegas, we should look for these two predictors to find the hotels with the best experience.

Dimensionality reduction through PCA

We did some dimensionality reduction and clustering too

Here we can see the actual PCA we get, there are 4

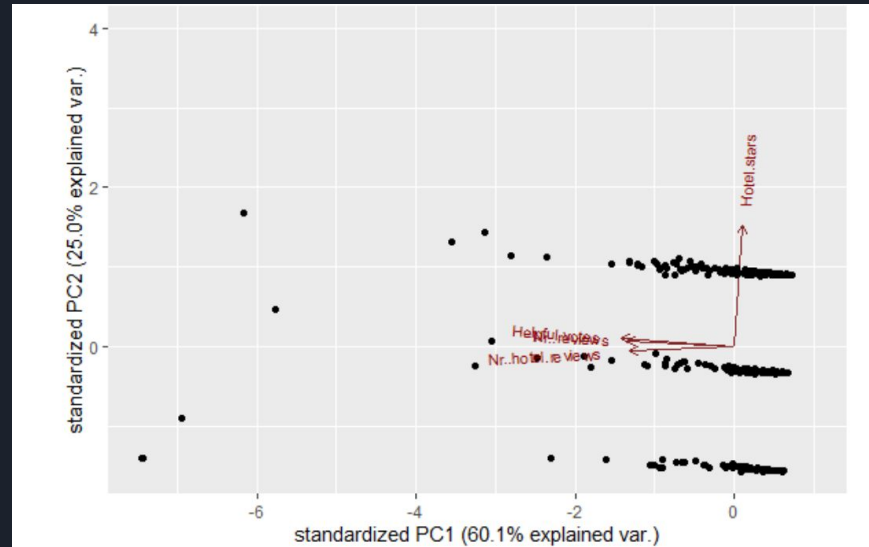
```
[1] 0
Importance of components:
```

	PC1	PC2	PC3	PC4
Standard deviation	1.5501	1.0007	0.6369	0.43597
Proportion of Variance	0.6007	0.2504	0.1014	0.04752
Cumulative Proportion	0.6007	0.8511	0.9525	1.00000

1-variability_explained, within 3 PCA we get 90% of variability in the dataset

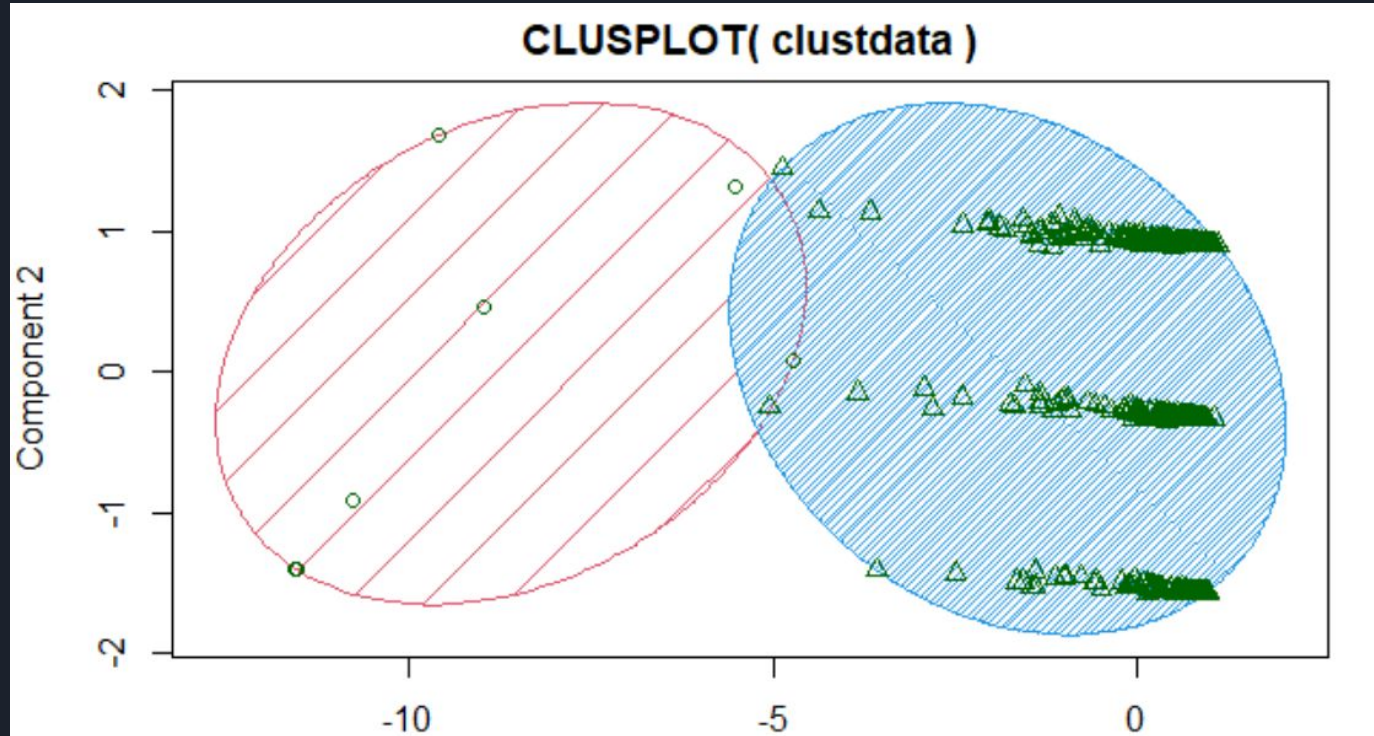
```
[1] 0.3992821 0.7496315 0.8986044 0.9524820
```

Most of the predictors contribute to PC2
and only Hotel.Stars contributes to PC1



Some clustering

We also tried k-means clustering on our data set to see if there were any more trends or patterns within it



We found that 2 clusters can be clearly identified both of which when combined can explain 85.11% point variability in the data



Feature Selection (Remove Irrelevant Variables)

- `Model <- lm(data = LasVegas, Score ~ Pool + Gym + Tennis_court + Spa + Casino + Free_internet)`
- We can use Adjusted R squared, AIC and BIC to see which model is the best fit.
- Backward Stepwise Selection: Begins with the full least squares model containing all p predictors, and then iteratively removes the least useful predictor, one-at-a-time.
- Forward Stepwise Selection: Starts with a model with no predictors and then we add predictors to the model one-at-a-time until getting the complete model (all the predictors). At each step we add the variable that gives the greatest additional improvement to the fit: usually R^2 or RSS.

Backward Stepwise Selection

```
regfit.bwd = regsubsets(Score ~ Pool + Gym + Tennis_court + Spa + Casino + Free_internet, data = LasVegas, nvmax = 6, method="backward")
reg.summary <- summary(regfit.bwd) #get the summary

par(mfrow=c(2,2))
#rss plot - NOT USEFUL
plot(reg.summary$rss, xlab="Number of Variables", ylab="RSS", type="l")

#adjr2 plot
plot(reg.summary$adjr2, xlab="Number of Variables", ylab="Adjusted RSq", type="l")
max_adj_r2 <- which.max(reg.summary$adjr2)
points(max_adj_r2, reg.summary$adjr2[max_adj_r2], col="red", cex=2, pch=20)

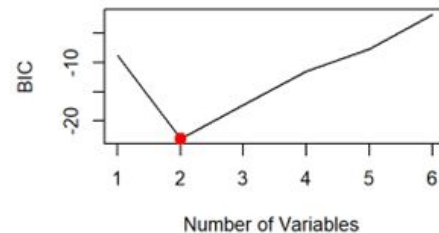
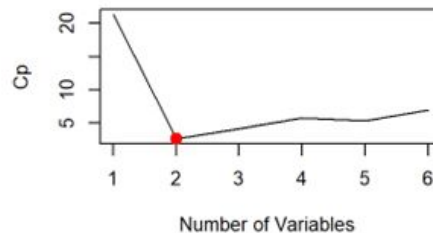
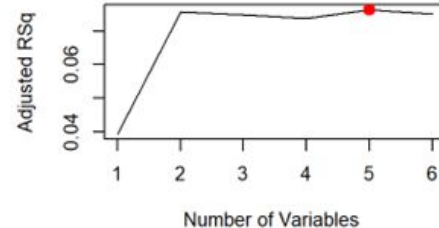
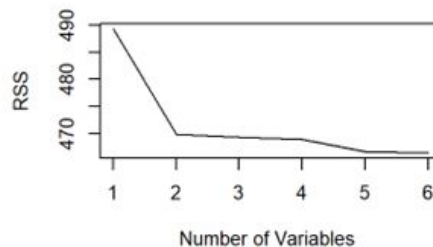
# AIC criterion (Cp) to minimize
plot(reg.summary$c_p, xlab="Number of Variables", ylab="Cp", type="l")
min_cp <- which.min(reg.summary$c_p)
points(min_cp, reg.summary$c_p[min_cp], col="red", cex=2, pch=20)

# BIC criterion to minimize
plot(reg.summary$bic, xlab="Number of Variables", ylab="BIC", type="l")
min_bic <- which.min(reg.summary$bic)
points(min_bic, reg.summary$bic[min_bic], col="red", cex=2, pch=20)
```

Adjusted R-Square highest at 5 variables. (2 ~ 6 variables are about the same)

C(p) lowest at 2 variables.

BIC lowest at 2 variables.



Forward Stepwise Selection

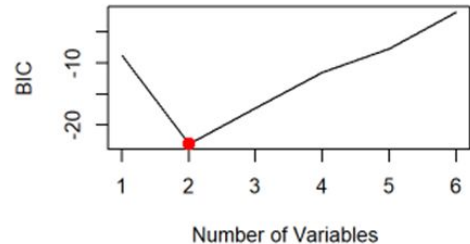
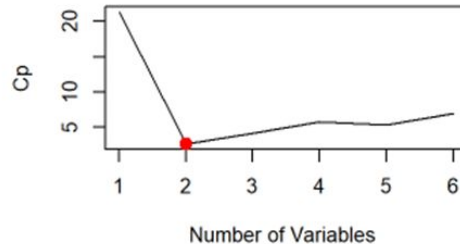
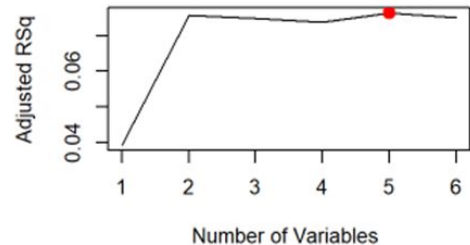
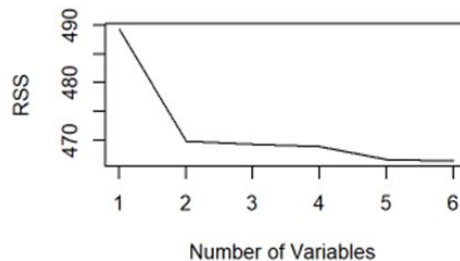
```
regfit.fwd = regsubsets(Score ~ Pool + Gym + Tennis_court + Spa + Casino + Free_internet, data = LasVegas, nvma
x = 6, method="forward")
reg.summary <- summary(regfit.fwd) #get the summary

par(mfrow=c(2,2))
#rss plot - NOT USEFUL
plot(reg.summary$rss, xlab="Number of Variables", ylab="RSS", type="l")

#adjr2 plot
plot(reg.summary$adjr2, xlab="Number of Variables", ylab="Adjusted RSq", type="l")
max_adj_r2 <- which.max(reg.summary$adjr2)
points(max_adj_r2, reg.summary$adjr2[max_adj_r2], col="red", cex=2, pch=20)

# AIC criterion (Cp) to minimize
plot(reg.summary$cp, xlab="Number of Variables", ylab="Cp", type="l")
min_cp <- which.min(reg.summary$cp)
points(min_cp, reg.summary$cp[min_cp], col="red", cex=2, pch=20)

# BIC criterion to minimize
plot(reg.summary$bic, xlab="Number of Variables", ylab="BIC", type="l")
min_bic <- which.min(reg.summary$bic)
points(min_bic, reg.summary$bic[min_bic], col="red", cex=2, pch=20)
```



Adjusted R-Square highest at 5 variables.
(2 ~ 6 variables are about the same)
C(p) lowest at 2 variables.
BIC lowest at 2 variables.

Summary

Best Subsets Regression

Model	Index	Predictors
1		Pool
2		Pool Free_internet
3		Pool Gym Free_internet
4		Pool Gym Spa Free_internet
5		Pool Gym Spa Casino Free_internet
6		Pool Gym Tennis_court Spa Casino Free_internet

Model 2 will be the best model based on Adj.R-Square, C(p), AIC, and SBIC. The predictor variables that are relevant to the hotel score are Pool and Free internet.

Subsets Regression Summary

Model	R-Square	Adj. R-Square	Pred R-Square	C(p)	AIC	SBIC	SBC	MSEP	FPE	HSP	APC
1	0.0413	0.0394	0.0327	21.3393	1421.3607	-9.0646	1434.0284	491.2390	0.9785	0.0019	0.9663
2	0.0794	0.0757	0.0666	2.6319	1402.9336	-27.3161	1419.8240	472.6707	0.9434	0.0019	0.9316
3	0.0802	0.0747	0.062	4.1646	1404.4630	-25.7659	1425.5758	473.1758	0.9463	0.0019	0.9345
4	0.0811	0.0737	0.06	5.7207	1406.0154	-24.1892	1431.3509	473.7051	0.9492	0.0019	0.9374
5	0.0855	0.0763	0.0626	5.3233	1405.5917	-24.5376	1435.1497	472.3811	0.9484	0.0019	0.9366
6	0.0861	0.0750	0.0598	7.0000	1407.2640	-22.8293	1441.0446	473.0258	0.9516	0.0019	0.9397

$$\widehat{\text{Score}} = 2.29 + 1.01(\text{Pool}) + 0.92(\text{Free_internet})$$

Yes = 1
No = 0

For example, a hotel with free internet but no pool, the score would be $2.29 + 0.92 = 3.21$