

Report

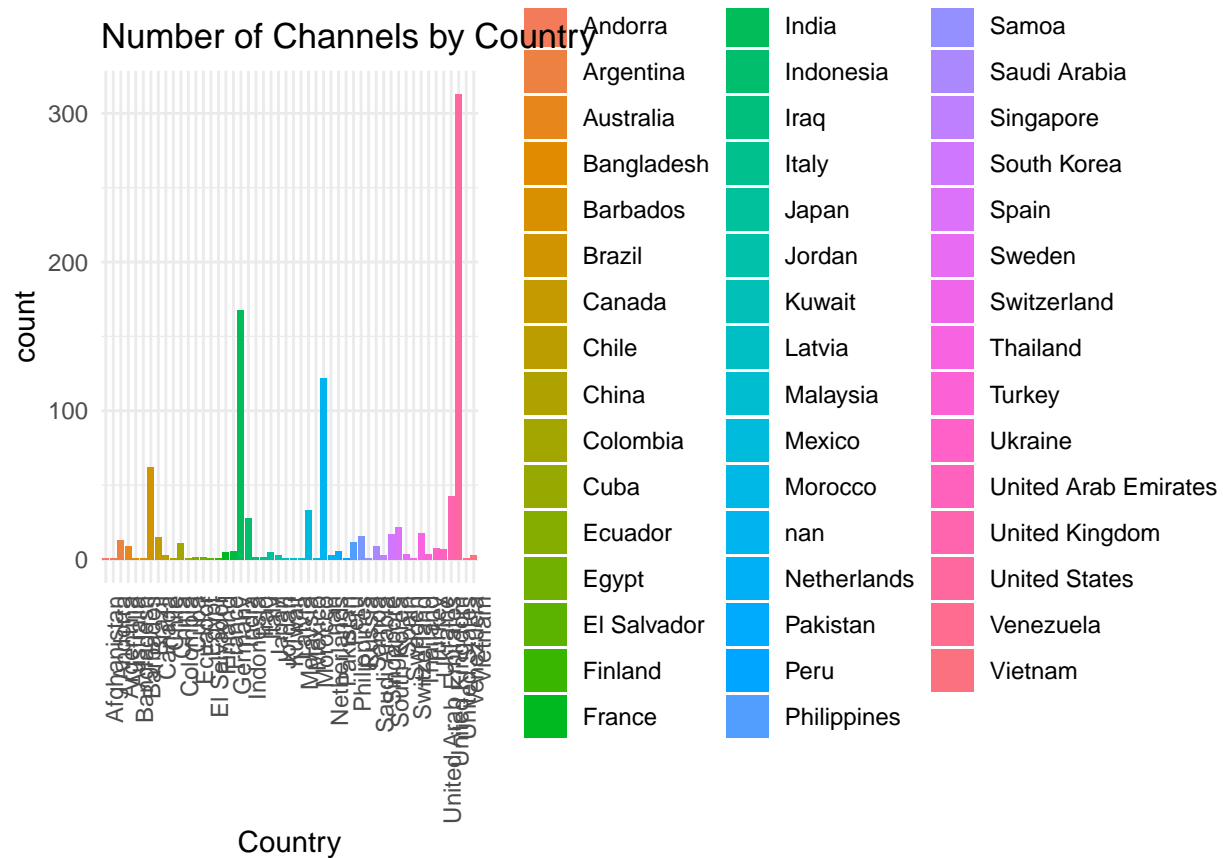
2023-12-14

This dataset examines data from 995 YouTube channels and contains values for a variety of variables, such as a channel's number of uploads or its country of origin. We can categorize most of the dataset's variables into two categories: predictors of video success (e.g. date of channel creation, education level of country of origin) or measurements of video success (e.g. total views, highest yearly earnings). The high number of variables in the first category allows us to examine highly detailed models for predicting the success of a channel, while the high number in the second category enables us to determine if our results are robust to different measures of success.

First, we will do some exploratory data analysis. Here, I will plot a histogram of the number of channels by country and by channel category. Below, we plot the number of channels by category and by country (see produced figure in repository if this one is difficult to read).

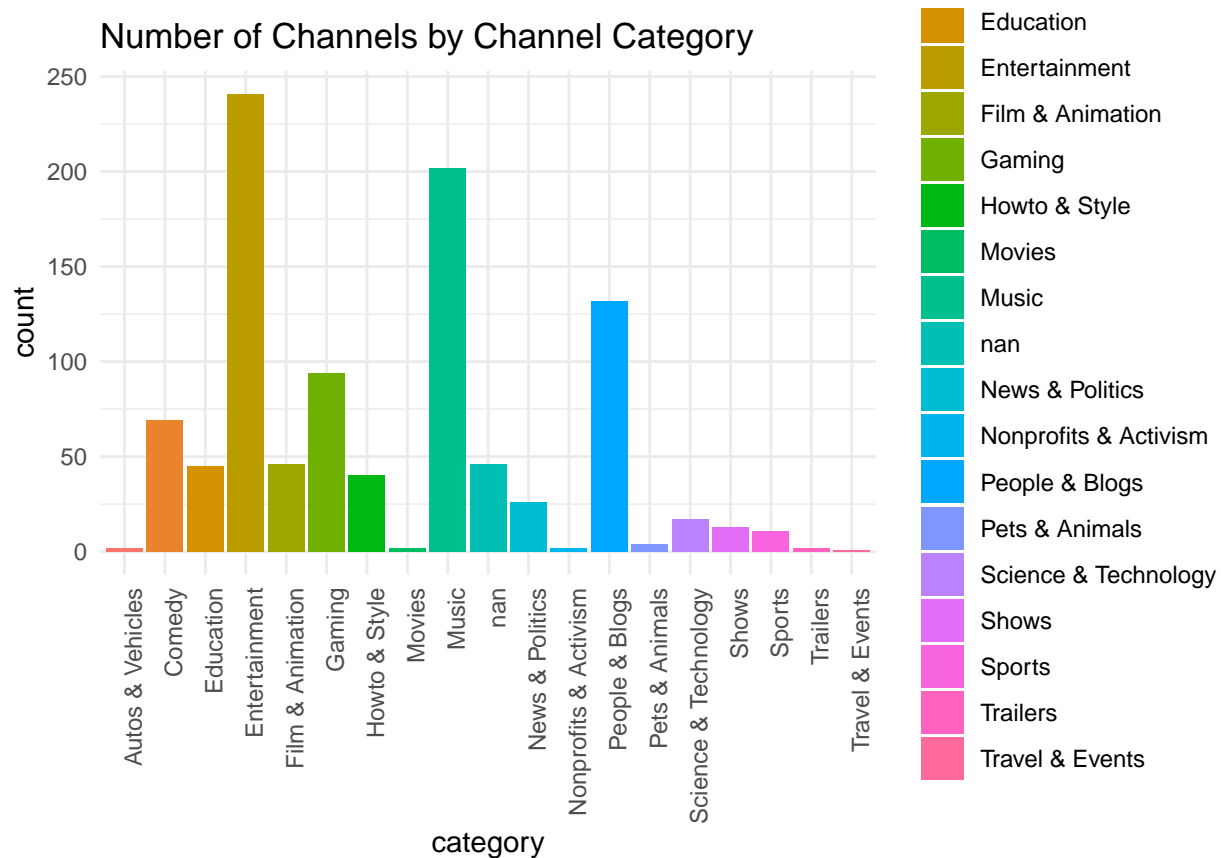
```
library(ggplot2)
youtube<- read.csv("~/Desktop/Global YouTube Statistics.csv")
ggplot(youtube, aes(x = Country, fill = Country)) +
  geom_histogram(stat = "count") +
  labs(title = "Number of Channels by Country", xlab = "Country", ylab = "Number of Channels") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))

## Warning in geom_histogram(stat = "count"): Ignoring unknown parameters:
## `binwidth`, `bins`, and `pad`
```



```
ggplot(youtube, aes(x = category, fill = category)) +
  geom_histogram(stat = "count") +
  labs(title = "Number of Channels by Channel Category", xlab = "Country", ylab = "Number of Channels")
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))
```

```
## Warning in geom_histogram(stat = "count"): Ignoring unknown parameters:
## `binwidth`, `bins`, and `pad`
```



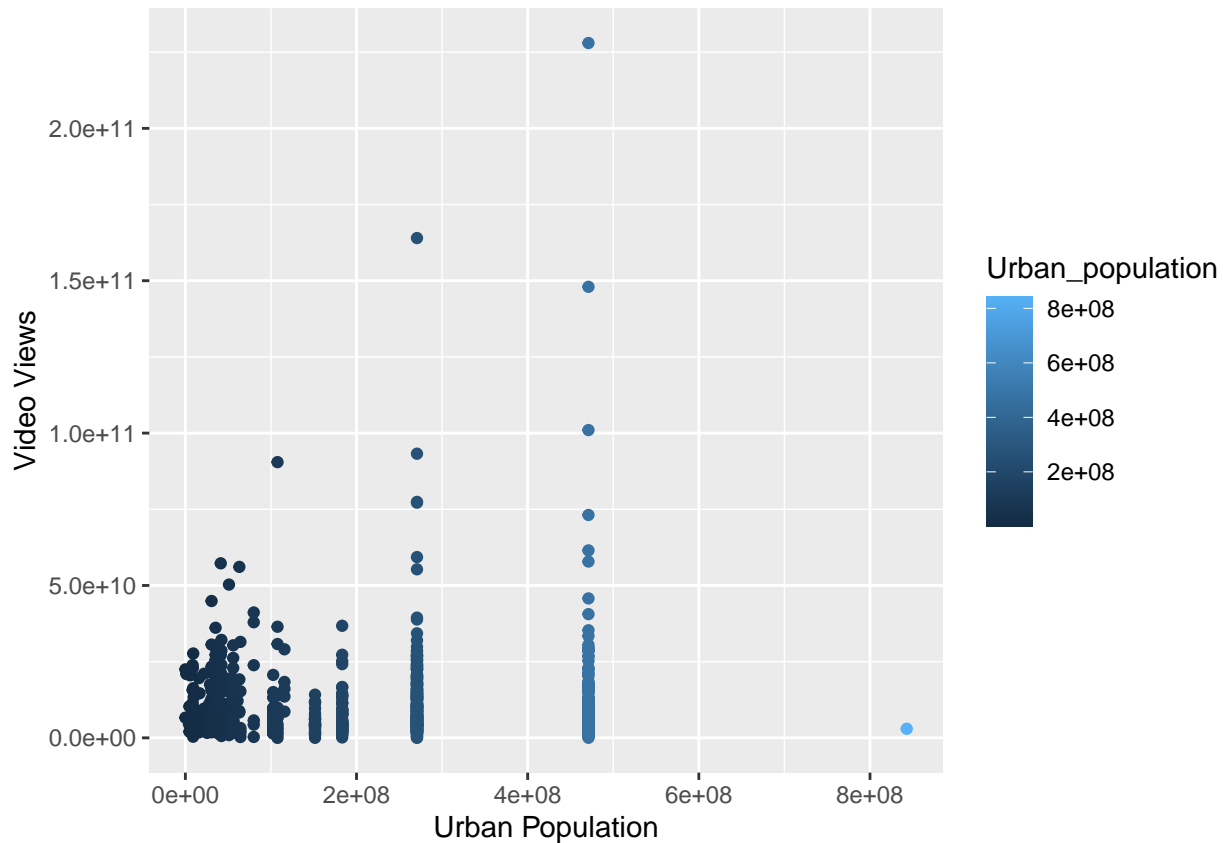
Based on the first histogram, the most popular country of origin for YouTube channels in this dataset is the United States. India was the second most common source of YouTube channels, followed by Brazil and the UK. Based on the second histogram, the most common channel categories are entertainment and music. A large number of channels do not have an associated country because they are Youtube's own channels. Although these channels are actually channels, unlike most of the other channels, they merely aggregate videos across various categories rather than creating their own videos. Aggregator channels are also missing values for variables such as "category", "Country", and "video.views". Therefore, we will restrict our analysis to channels with a focus on creation.

```
channels_only <- subset(youtube, video.views != 0)
```

Next, we will attempt to determine the impact of the urban population of a channel's home country on the number of views that channel receives. We create a scatterplot to examine the relationship between the urban population of a channel's associated country and video views.

```
ggplot(channels_only, aes(Urban_population, video.views)) +
  geom_point(aes(color = Urban_population)) +
  labs(x = "Urban Population", y = "Video Views")
```

```
## Warning: Removed 117 rows containing missing values (`geom_point()`).
```



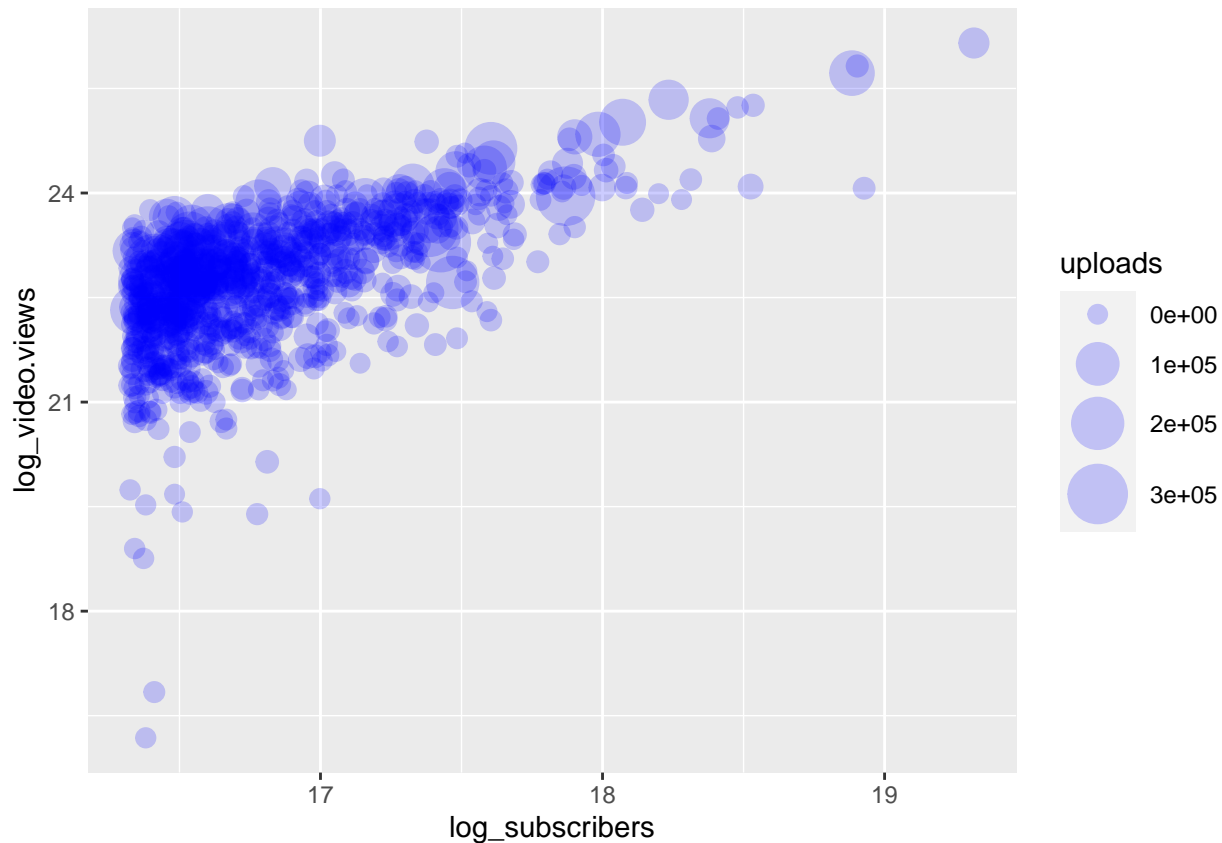
```
cor(channels_only$Urban_population, channels_only$video.views, use = "complete.obs")
```

```
## [1] 0.07723294
```

Although we do not observe a strong effect of urban population on video views, with countries showing mostly similar distributions regardless of urban population, we observe that the channels with the highest numbers of video views are almost exclusively created by channels that hail from countries with large urban populations. Thus, a country's urban population may not have any effect on the success of its channels unless those channels become extremely popular, in which case a high urban population may be modestly associated with more total video views.

Other factors which could plausibly impact the overall success of a channel are its subscriber count and its total number of uploads. To illustrate the impact of these two factors simultaneously, we will create a bubble plot. We apply to a log transformation to the variables representing total video views and total subscribers due to the exponential growth rate typically associated with both.

```
channels_only$log_video.views<- log(channels_only$video.views)
channels_only$log_subscribers<- log(channels_only$subscribers)
channels_only<- subset(channels_only, log_video.views > 15) #Remove outliers
ggplot(data = channels_only, aes(x = log_subscribers, y = log_video.views, size = uploads)) +
  geom_point(alpha = 0.2, color = "blue") +
  scale_size_continuous(range = c(3, 10))
```



```
cor(channels_only$log_subscribers, channels_only$log_video.views, use = "complete.obs")
```

```
## [1] 0.6048599
```

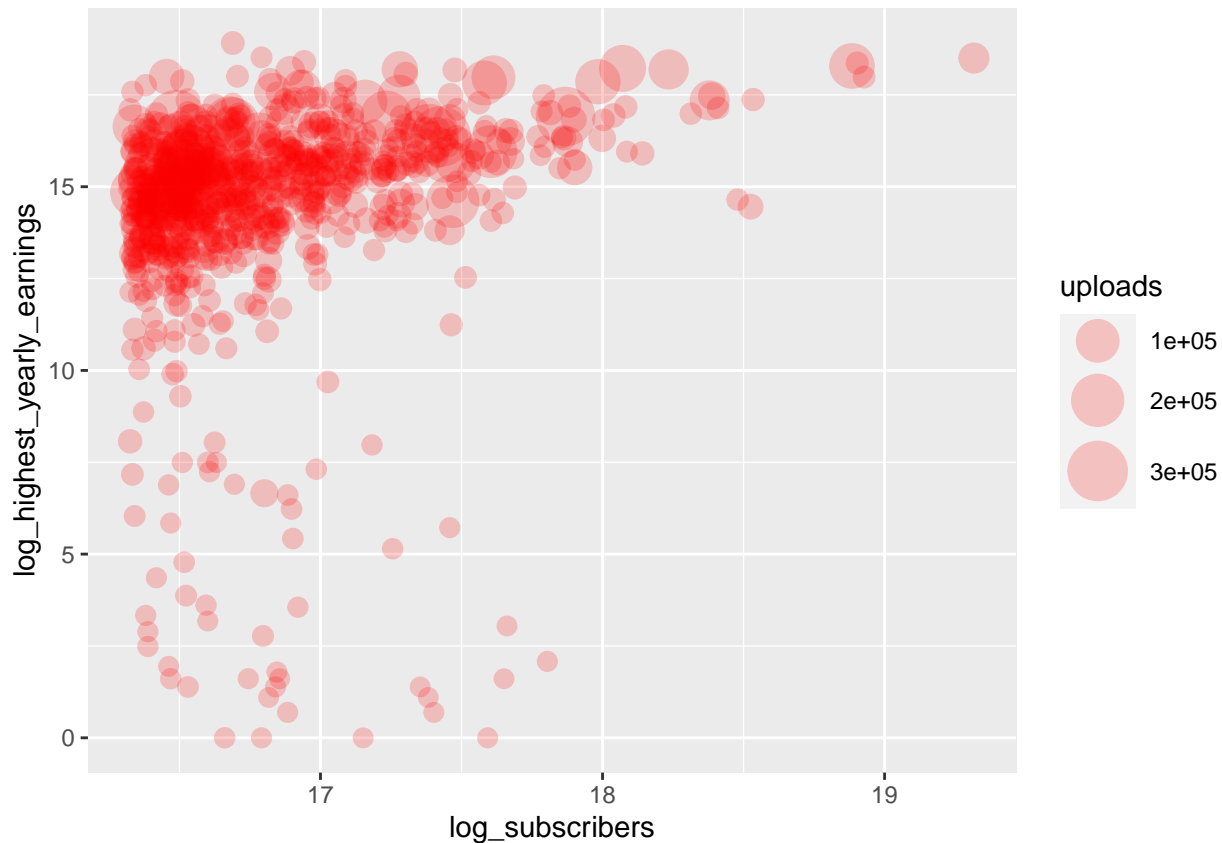
```
cor(channels_only$uploads, channels_only$log_video.views, use = "complete.obs")
```

```
## [1] 0.178092
```

Total number of subscribers and the total number of uploads seem to be positively correlated with channel success (as measured by the total number of video views), albeit to varying degrees. A channel's total number of uploads modestly predicted the total number of video views it received, possibly because a greater number of uploads gives a channel more opportunities to receive views. A channel's total number of subscribers was a substantially stronger predictor of the number of video views it received. There are two plausible (non-mutually exclusive) explanations: 1) channels which have more subscribers receive more views because more potential viewers are exposed to their content or 2) high viewership leads to a high number of subscriptions because people often subscribe to a channel after watching a video.

To ensure that our analysis is robust, we should examine the relationship of our predictors to a different measure of channel success, log transformed yearly earnings (specifically, the highest yearly earnings a channel has received).

```
nonzero<- subset(channels_only, highest_yearly_earnings >= 1) #Remove values equal to zero, as they can
nonzero$log_highest_yearly_earnings<- log(nonzero$highest_yearly_earnings)
ggplot(data = nonzero, aes(x = log_subscribers, y = log_highest_yearly_earnings, size = uploads)) +
  geom_point(alpha = 0.2, color = "red") +
  scale_size_continuous(range = c(3, 10))
```



```
cor(nonzero$uploads, nonzero$log_highest_yearly_earnings, use = "complete.obs")
```

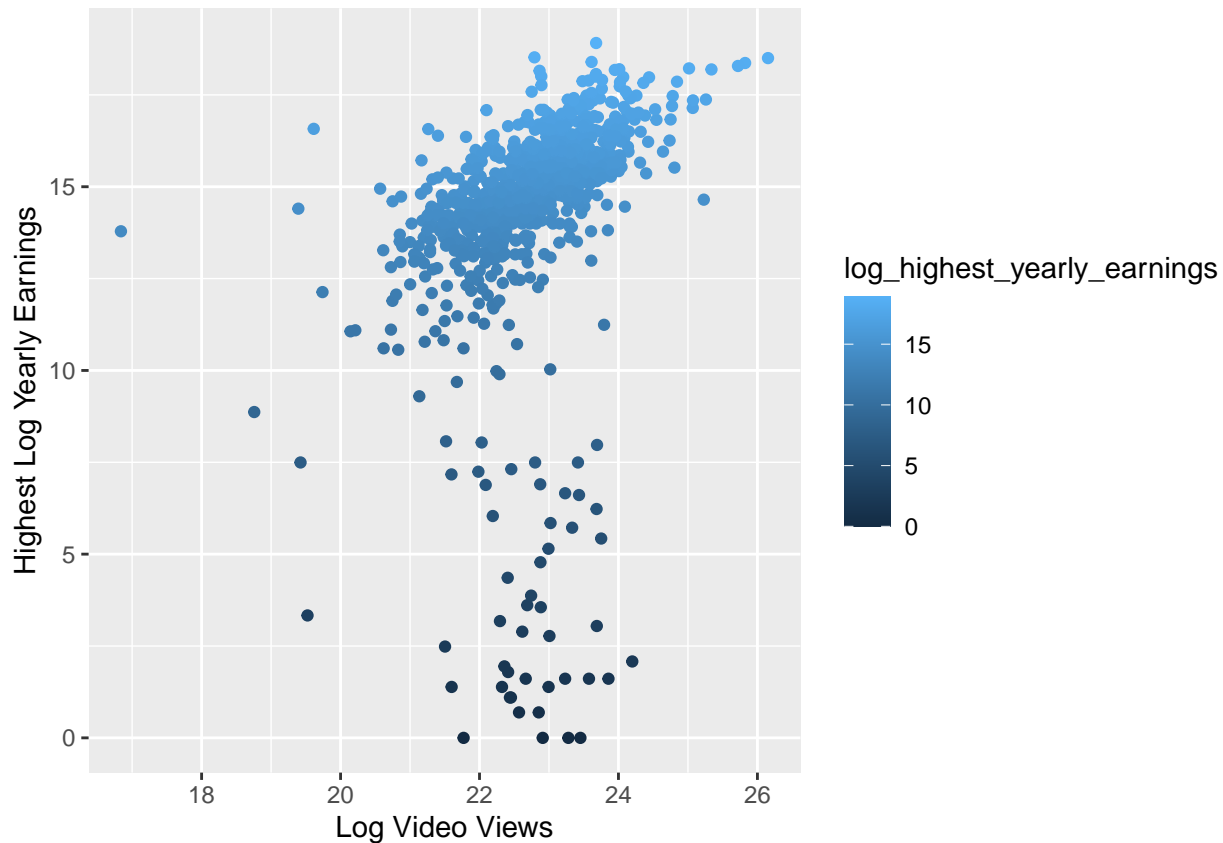
```
## [1] 0.1457022
```

```
cor(nonzero$log_subscribers, nonzero$log_highest_yearly_earnings, use = "complete.obs")
```

```
## [1] 0.1743523
```

We observe similar results when using the highest amount of log-transformed yearly earnings as our measure of channel success; therefore, our results are robust to different measures of channel success. However, the strength of the relationship between log-transformed subscriptions and log-transformed yearly earnings is significantly lower than the strength of the one between log-transformed subscriptions and log-transformed video views. We might observe this effect because some channels may mostly contain high numbers of highly-watched videos that are unable to be monetized for various reasons (e.g. explicit content, copyright violations). To test this hypothesis, we will examine the relationship between log-transformed video views and the highest amount of log-transformed yearly earnings a channel has received.

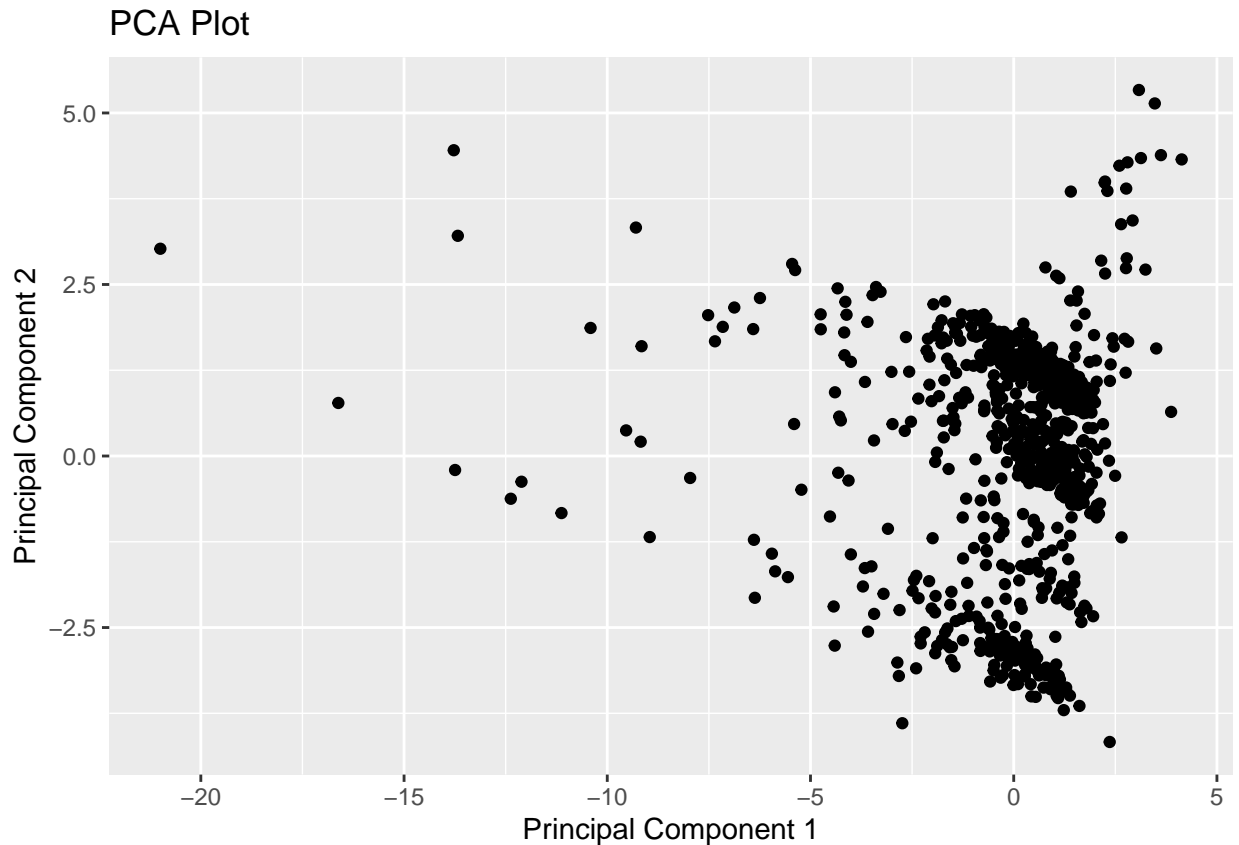
```
ggplot(nonzero, aes(log_video.views, log_highest_yearly_earnings)) +  
  geom_point(aes(color = log_highest_yearly_earnings)) +  
  labs(x = "Log Video Views", y = "Highest Log Yearly Earnings")
```



We observe a similar effect: a strong, positive, linear correlation between log transformed video views and log transformed yearly earnings for the majority of datapoints but a lack of correlation among channels which earn little compared to their peers. This effect provides further evidence that large-scale video demonetization creates the heterogeneous relationship between subscriptions and earnings.

Finally, because many of our variables are related to each other, we will explore the possibility of dimensionality reduction for our dataset. We conduct principal component analysis (PCA) on all numerical variables.

```
channels_only<- subset(channels_only, select = -c(subscribers_for_last_30_days)) #Remove the "subscribers_for_last_30_days" variable
channels_only<- channels_only[complete.cases(channels_only$country_rank), ] #Remove channels without a country rank
youtube_numeric<- channels_only[sapply(channels_only, is.numeric)]
youtube_numeric <- na.omit(youtube_numeric)
youtube_numeric <- subset(youtube_numeric, select = -c(subscribers, video.views)) #Remove variables that are highly correlated
pca_result <- prcomp(youtube_numeric, scale = TRUE)
scores <- as.data.frame(pca_result$x[, 1:2])
ggplot(scores, aes(x = PC1, y = PC2)) +
  geom_point() +
  labs(title = "PCA Plot",
       x = "Principal Component 1",
       y = "Principal Component 2")
```



```
summary(pca_result)
```

```
## Importance of components:
##              PC1      PC2      PC3      PC4      PC5      PC6      PC7
## Standard deviation  2.345  1.7461  1.6521  1.36084  1.27346  1.05807  0.99933
## Proportion of Variance 0.275  0.1524  0.1365  0.09259  0.08109  0.05598  0.04993
## Cumulative Proportion 0.275  0.4274  0.5639  0.65650  0.73758  0.79356  0.84349
##              PC8      PC9      PC10     PC11     PC12     PC13     PC14
## Standard deviation  0.96215  0.83195  0.6856  0.57751  0.54630  0.36921  0.35364
## Proportion of Variance 0.04629  0.03461  0.0235  0.01668  0.01492  0.00682  0.00625
## Cumulative Proportion 0.88978  0.92438  0.9479  0.96456  0.97949  0.98630  0.99255
##              PC15     PC16     PC17     PC18     PC19     PC20
## Standard deviation  0.30253  0.19596  0.13714  0.01118  0.006868  0.001263
## Proportion of Variance 0.00458  0.00192  0.00094  0.00001  0.000000  0.000000
## Cumulative Proportion 0.99713  0.99905  0.99999  1.00000  1.000000  1.000000
```

The first two principal components explain approximately 43% of the variance in the data. We observe three major clusters of data in regions centered around (0, -3), (1.25, 0), and (1, 1.25). An increase in the value of PC1 is associated with a decrease in the value of PC2 within each of these clusters. We will examine some of the clusters below.

```
cluster1_indices <- which(pca_result$x[, 1] > -2 & pca_result$x[, 2] < -2.5)
cluster1_data <- youtube_numeric[cluster1_indices, ]
summary(cluster1_data)
```

```
##      rank      uploads      video_views_rank      country_rank
## Min.   : 79.0    Min.   :   29    Min.   :   88    Min.   :   1.00
## 1st Qu.:450.5    1st Qu.:  477    1st Qu.:  527    1st Qu.:  75.00
```



```

## Median :655.0   Median : 1476   Median : 1033   Median :100.00
## Mean :636.3    Mean : 16732   Mean : 11928   Mean : 91.91
## 3rd Qu.:828.5   3rd Qu.: 5673   3rd Qu.: 2886   3rd Qu.:113.00
## Max. :995.0    Max. :296272   Max. :772571   Max. :125.00
## channel_type_rank video_views_for_the_last_30_days lowest_monthly_earnings
## Min. : 1.00     Min. :8.378e+05   Min. : 0
## 1st Qu.: 28.50   1st Qu.:3.086e+07   1st Qu.: 7050
## Median : 47.00   Median :7.865e+07   Median :18200
## Mean : 72.29    Mean :1.219e+08    Mean :25153
## 3rd Qu.:125.00   3rd Qu.:1.404e+08   3rd Qu.:34800
## Max. :172.00    Max. :2.292e+09    Max. :94800
## highest_monthly_earnings lowest_yearly_earnings highest_yearly_earnings
## Min. : 0        Min. : 0          Min. : 0
## 1st Qu.: 113150   1st Qu.: 84850    1st Qu.: 1350000
## Median : 291600   Median : 218700    Median : 3500000
## Mean : 402050    Mean : 300440     Mean : 4828413
## 3rd Qu.: 556500   3rd Qu.: 417350    3rd Qu.: 6700000
## Max. :1500000    Max. :1100000     Max. :18200000
## created_year created_date Gross.tertiary.education.enrollment....
## Min. :2006      Min. : 1.0        Min. :28.10
## 1st Qu.:2012     1st Qu.: 9.5      1st Qu.:28.10
## Median :2015     Median :18.0      Median :28.10
## Mean :2014       Mean :16.6        Mean :28.49
## 3rd Qu.:2017     3rd Qu.:23.0      3rd Qu.:28.10
## Max. :2022       Max. :31.0        Max. :50.60
## Population      Unemployment.rate Urban_population Latitude
## Min. :1.081e+08   Min. :2.150       Min. : 50975903   Min. : -0.7893
## 1st Qu.:1.366e+09 1st Qu.:5.360      1st Qu.:471031528 1st Qu.:20.5937
## Median :1.366e+09 Median :5.360      Median :471031528 Median :20.5937
## Mean :1.338e+09   Mean :5.313       Mean :465256765   Mean :20.2978
## 3rd Qu.:1.366e+09 3rd Qu.:5.360      3rd Qu.:471031528 3rd Qu.:20.5937
## Max. :1.398e+09   Max. :5.360       Max. :842933962   Max. :35.8617
## Longitude      log_video.views log_subscribers
## Min. : 78.96     Min. :16.18       Min. :16.33
## 1st Qu.: 78.96   1st Qu.:21.82     1st Qu.:16.43
## Median : 78.96   Median :22.52     Median :16.54
## Mean : 80.12     Mean :22.25       Mean :16.61
## 3rd Qu.: 78.96   3rd Qu.:22.93     3rd Qu.:16.74
## Max. :121.77     Max. :23.86       Max. :17.48

```

```

cluster2_indices <- which(pca_result$x[, 1] > 0 & pca_result$x[, 2] < 0.75 & pca_result$x[, 2] > -0.75)
cluster2_data <- youtube_numeric[cluster2_indices, ]
summary(cluster2_data)

```

```

##      rank      uploads    video_views_rank    country_rank
## Min. : 53.0    Min. : 3    Min. : 113    Min. : 1.00
## 1st Qu.:459.0  1st Qu.: 377    1st Qu.: 648    1st Qu.: 6.00
## Median :672.0  Median : 825    Median : 1472    Median : 17.00
## Mean :642.4    Mean : 2414    Mean : 50706    Mean : 90.15
## 3rd Qu.:840.0  3rd Qu.: 1888    3rd Qu.: 2897    3rd Qu.: 34.00
## Max. :994.0    Max. :64496    Max. :4039216    Max. :4651.00
## channel_type_rank video_views_for_the_last_30_days lowest_monthly_earnings
## Min. : 1.0      Min. : 7          Min. : 0
## 1st Qu.: 35.0    1st Qu.: 21072000   1st Qu.: 4100
## Median : 87.0    Median : 43007000   Median : 9900

```

```
## Mean : 180.7      Mean : 60158691      Mean : 12515
## 3rd Qu.: 143.0    3rd Qu.: 76903000      3rd Qu.: 18100
## Max. : 7638.0     Max. : 757789000      Max. : 57200
## highest_monthly_earnings lowest_yearly_earnings highest_yearly_earnings
## Min. : 0          Min. : 0          Min. : 0
## 1st Qu.: 65600     1st Qu.: 49200      1st Qu.: 787600
## Median :158000     Median :118500      Median : 1900000
## Mean : 200205      Mean : 150152       Mean : 2401309
## 3rd Qu.:289000     3rd Qu.:216700      3rd Qu.: 3500000
## Max. : 915600      Max. : 686700       Max. : 11000000
## created_year      created_date      Gross.tertiary.education.enrollment....
## Min. : 2005        Min. : 1.00         Min. : 9.00
## 1st Qu.: 2011      1st Qu.: 8.00       1st Qu.: 51.30
## Median : 2013      Median : 17.00      Median : 60.00
## Mean : 2013        Mean : 16.44        Mean : 62.17
## 3rd Qu.: 2015      3rd Qu.: 25.00      3rd Qu.: 81.90
## Max. : 2022        Max. : 31.00        Max. : 113.10
## Population         Unemployment.rate Urban_population      Latitude
## Min. : 5.520e+06    Min. : 3.040        Min. : 4694702      Min. : -38.42
## 1st Qu.: 5.171e+07  1st Qu.: 3.850      1st Qu.: 42106719    1st Qu.: -14.23
## Median : 1.004e+08  Median : 5.930      Median : 64324835    Median : 23.89
## Mean : 1.318e+08    Mean : 7.711        Mean : 105530510     Mean : 22.58
## 3rd Qu.: 2.126e+08  3rd Qu.: 12.080     3rd Qu.: 183241641   3rd Qu.: 52.13
## Max. : 1.366e+09    Max. : 14.720       Max. : 471031528     Max. : 61.92
## Longitude          log_video.views log_subscribers
## Min. : -106.35      Min. : 18.90        Min. : 16.33
## 1st Qu.: -74.30     1st Qu.: 21.85      1st Qu.: 16.42
## Median : -51.93     Median : 22.34      Median : 16.53
## Mean : -21.99       Mean : 22.29        Mean : 16.60
## 3rd Qu.: 10.45      3rd Qu.: 22.82      3rd Qu.: 16.73
## Max. : 133.78       Max. : 23.79        Max. : 17.65
```

```
cluster3_indices <- which(pca_result$x[, 1] < 0 & pca_result$x[, 2] > 0.75 & pca_result$x[, 2] < 1.875)
cluster3_data <- youtube_numeric[cluster3_indices, ]
summary(cluster3_data)
```

```
## rank      uploads      video_views_rank      country_rank
## Min. : 1.0    Min. : 15.0    Min. : 1.00    Min. : 1.00
## 1st Qu.:122.5  1st Qu.: 386.8  1st Qu.: 95.75  1st Qu.: 6.00
## Median :214.0  Median : 765.0  Median : 195.50 Median : 51.50
## Mean : 270.6   Mean : 6428.5   Mean : 704.74   Mean : 59.12
## 3rd Qu.:363.8  3rd Qu.: 2659.2  3rd Qu.: 376.75  3rd Qu.: 94.75
## Max. : 971.0   Max. : 200933.0 Max. : 40117.00 Max. : 176.00
## channel_type_rank video_views_for_the_last_30_days lowest_monthly_earnings
## Min. : 1.00      Min. : 4.564e+07      Min. : 11400
## 1st Qu.: 16.00    1st Qu.: 1.451e+08      1st Qu.: 36250
## Median : 42.50    Median : 2.068e+08      Median : 51700
## Mean : 46.60      Mean : 3.293e+08      Mean : 82321
## 3rd Qu.: 68.75    3rd Qu.: 3.687e+08      3rd Qu.: 92225
## Max. : 163.00     Max. : 2.258e+09      Max. : 564600
## highest_monthly_earnings lowest_yearly_earnings highest_yearly_earnings
## Min. : 182600     Min. : 136900         Min. : 2200000
## 1st Qu.: 580200    1st Qu.: 435200       1st Qu.: 6925000
## Median : 827350    Median : 620550        Median : 9900000
## Mean : 1315489     Mean : 988962          Mean : 15807143
```

```

## 3rd Qu.:1475000      3rd Qu.:1100000      3rd Qu.: 17675000
## Max. :9000000      Max. :6800000      Max. :108400000
## created_year created_date Gross.tertiary.education.enrollment....
## Min. :2005 Min. : 1.00 Min. :23.90
## 1st Qu.:2009 1st Qu.: 8.00 1st Qu.:88.20
## Median :2013 Median :15.00 Median :88.20
## Mean :2013 Mean :15.35 Mean :82.26
## 3rd Qu.:2016 3rd Qu.:22.00 3rd Qu.:88.20
## Max. :2021 Max. :31.00 Max. :94.30
## Population Unemployment.rate Urban_population Latitude
## Min. :2.870e+05 Min. : 3.04 Min. : 89431 Min. : -38.42
## 1st Qu.:1.444e+08 1st Qu.:10.00 1st Qu.:107683889 1st Qu.: 37.09
## Median :3.282e+08 Median :14.70 Median :270663028 Median : 37.09
## Mean :2.621e+08 Mean :12.57 Mean :209317064 Mean : 31.14
## 3rd Qu.:3.282e+08 3rd Qu.:14.70 3rd Qu.:270663028 3rd Qu.: 37.09
## Max. :1.366e+09 Max. :14.72 Max. :471031528 Max. : 61.52
## Longitude log_video.views log_subscribers
## Min. : -106.35 Min. :19.61 Min. :16.33
## 1st Qu.: -95.71 1st Qu.:23.12 1st Qu.:16.85
## Median : -95.71 Median :23.51 Median :17.09
## Mean : -68.08 Mean :23.47 Mean :17.14
## 3rd Qu.: -74.30 3rd Qu.:23.85 3rd Qu.:17.33
## Max. : 127.77 Max. :26.15 Max. :19.32

```

Interestingly, we observe that channels appear to cluster by country. Cluster 1 (the one centered around (0, -3)) is entirely composed of channels associated with India (although it does not include every channel associated with India). Cluster 2 (the one centered around (1.25, 0)) contains a high number of channels associated with Brazil, while cluster 3 is mostly comprised of channels associated with the United States.