Final report draft

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Introduction

This report investigates 'Trending YouTube Video Statistics', which was has records from 2008 and was last updated on 2019-06-02. The primary aim of the dataset is for use in determining the year's top trending Youtube videos. Whilst it includes data specific to 10 different countries, we have chosen to explore the dataset for Canada only.

The dataset contains rows of trending videos which include features like category, trending date, tags, number of views, likes, dislikes, shares and descriptions of videos.

The primary aim of this investigation is to determine the relationship between video category, number of views it recieves, likes/dislikes and comment count? Specificially, we aim to investigate whether the number of views on Youtube videos correlate with the number of likes or dislikes on a video.

About data

Below are the number of rows and columns for the dataset.

```
nrow(CAN)
```

```
## [1] 40881
```

```
ncol(CAN)
```

```
## [1] 16
```

The following are data types of the columns in the dataset.

```
features <- CAN %>% colnames() %>% tibble()
types <- CAN %>% sapply(class) %>% tibble()
feature_type <- cbind(features,types)
colnames(feature_type)<-c("Features","Type")
kable(feature_type)
```

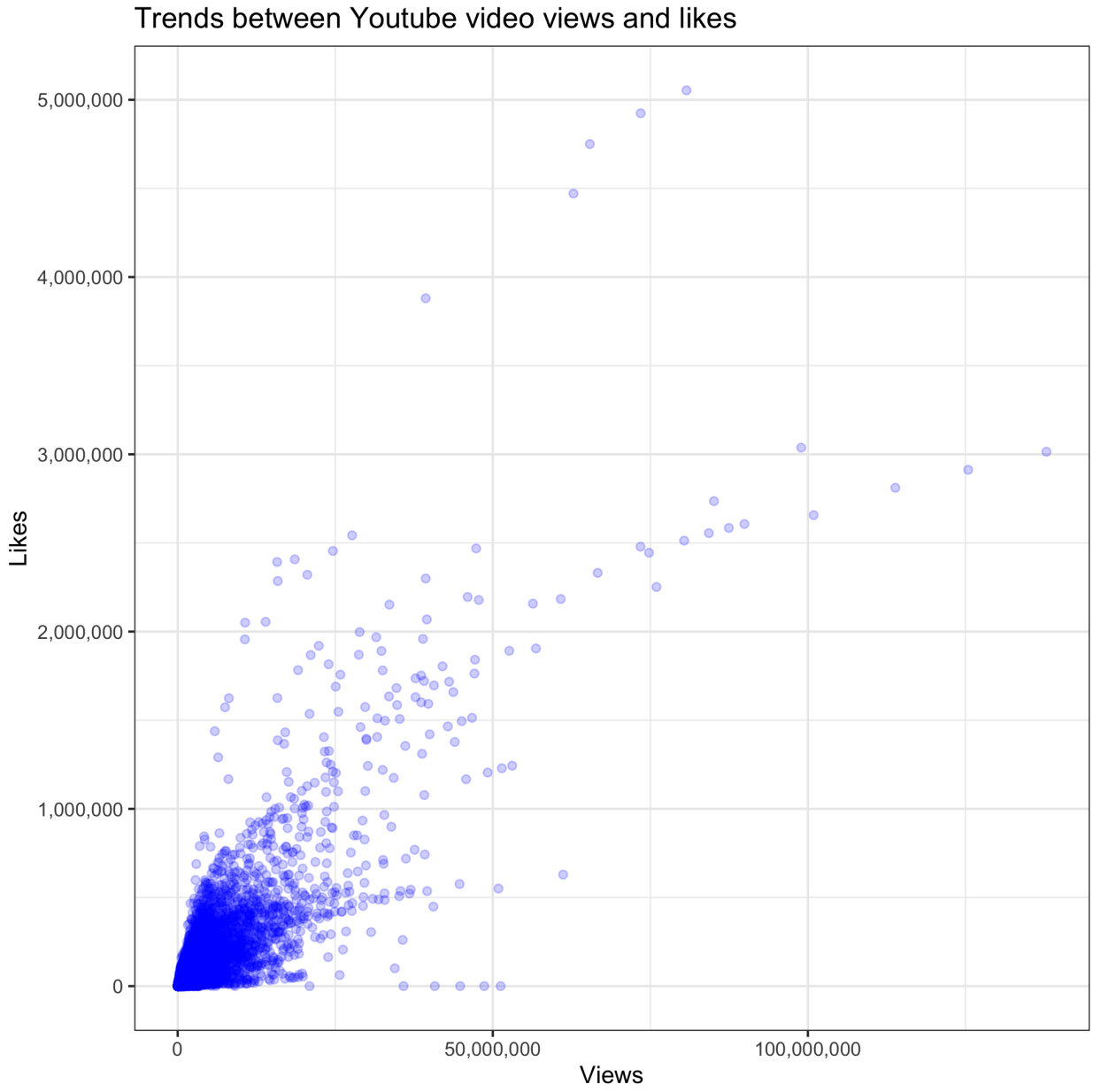
Features	Type
video_id	character
trending_date	Date
title	character
channel_title	character
category_id	numeric
publish_time	logical
tags	character
views	numeric
likes	numeric
dislikes	numeric
comment_count	numeric
thumbnail_link	character
comments_disabled	logical

Features	Type
ratings_disabled	logical
video_error_or_removed	logical
description	character

EDA

Trend in views and likes

Below we plot number of likes as a function of views.

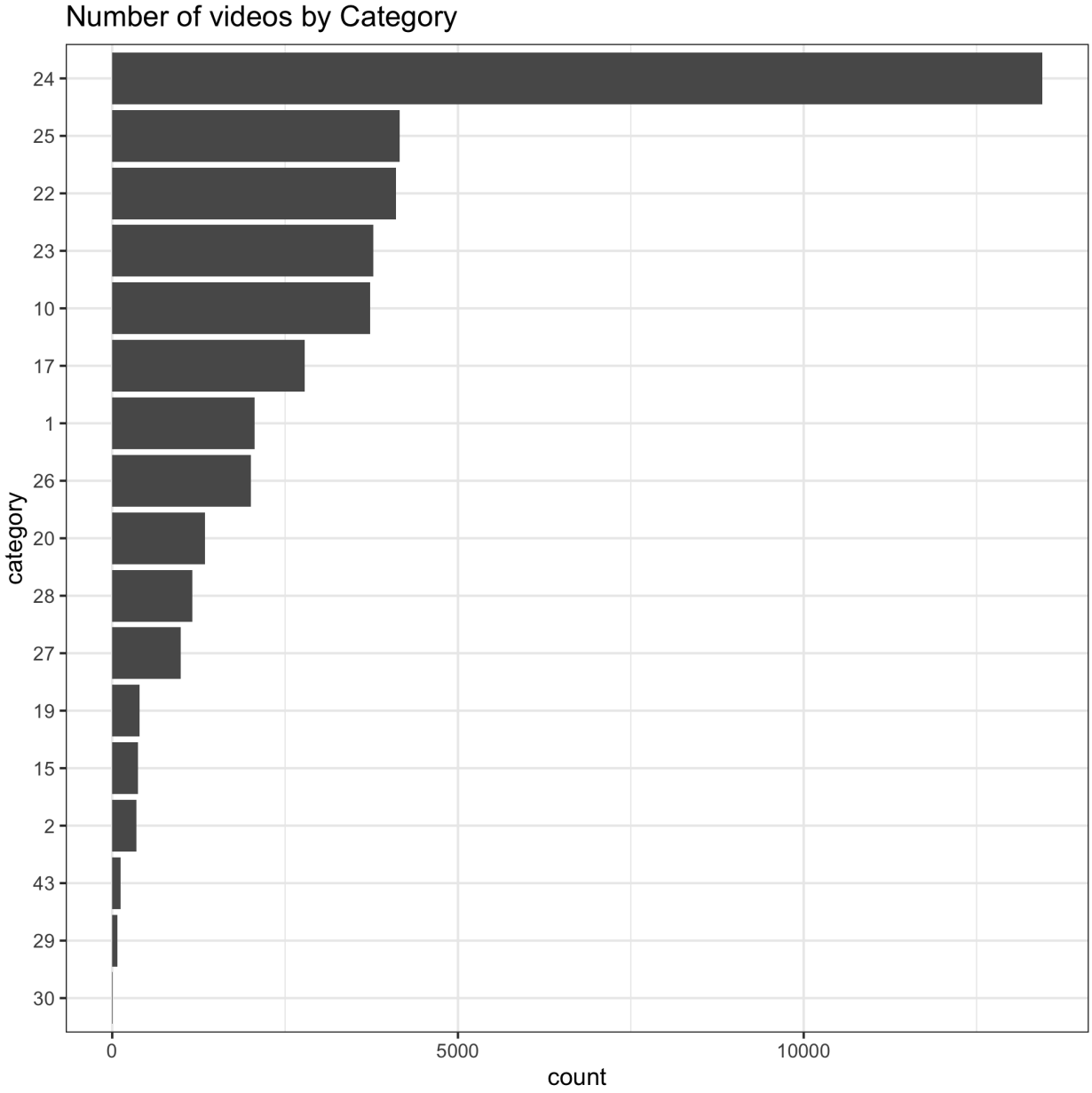


We see that in general the number of likes increase as we have more views. The points are concentrated at

the bottom left corner (there are more videos with number of views less than 50 million, and likes less than 1 million).

Number of videos in each category.

We explore how many videos are in each category.



The category corresponding to its ID can be found here.

Top 5 Categories are:

- Category 24: Entertainment
- Category 25: News and Politics
- Category 22: People and Blogs
- Category 23: Comedy

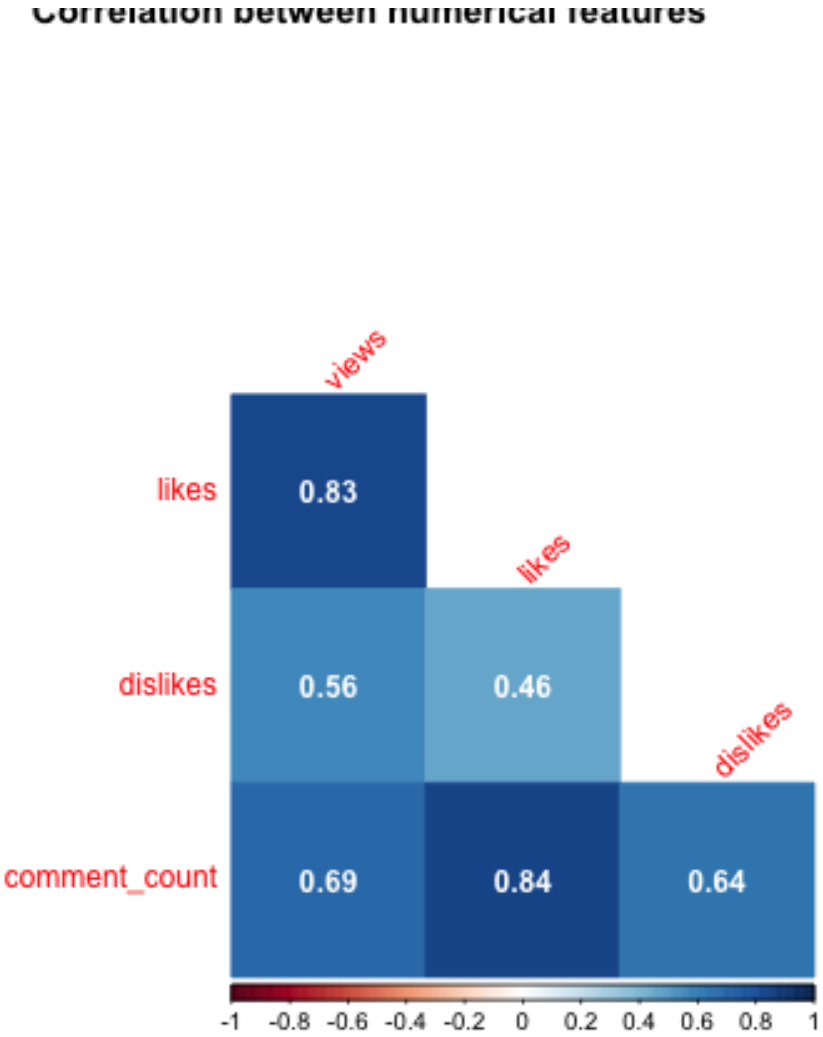
- Category 10: Music

Bottom 5 Categories are:

- Category 30: Movies
- Category 29: Nonprofits & Activism
- Category 43: Shows
- Category 2: Autos and Vehicles
- Category 15: Pets and Animals

Correlation plot

Next, we explore correlation between numerical columns.



We note the highest correlation between the number of likes and number of comments, and the lowest correlation beetween number of views and number of dislikes.

Analysis methods

We explore the relationship between the number of views and number of likes and dislikes. We aim to build a regression model of `views` as a function of `likes` and `dislikes`. It is reasonable to assume that the dependent variable is `views` and the explanatory variables are `likes` and `dislikes`. One could switch these response and explanatory variables depending on their interpretation.

We use linear regression to fit the model.

```
fit.lm <- readRDS(file="../rds/lm.rds")
```

We also use poisson regression method. We choose this method because the response variable `views` is actually a count data, and may follow Poisson distribution.

```
fit.glm <-readRDS(file="../rds/glm.rds")
```

Results

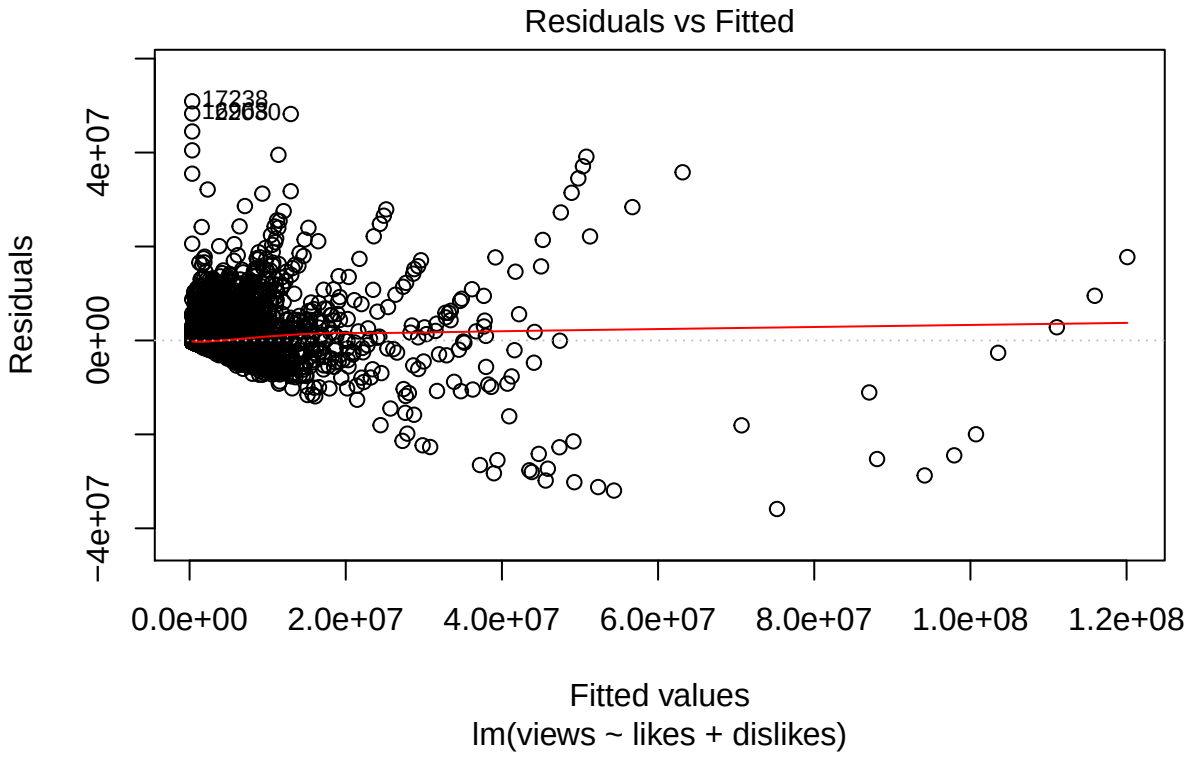
We check the summary of the linear model. `r.squared` denotes the goodness of fit of the data, measured by the ratio between the variance of the fitted values and variance of the actual values (response variable = `views`). We see that it is close to 0, which means the data is poorly fitted.

```
glance(fit.lm)
```

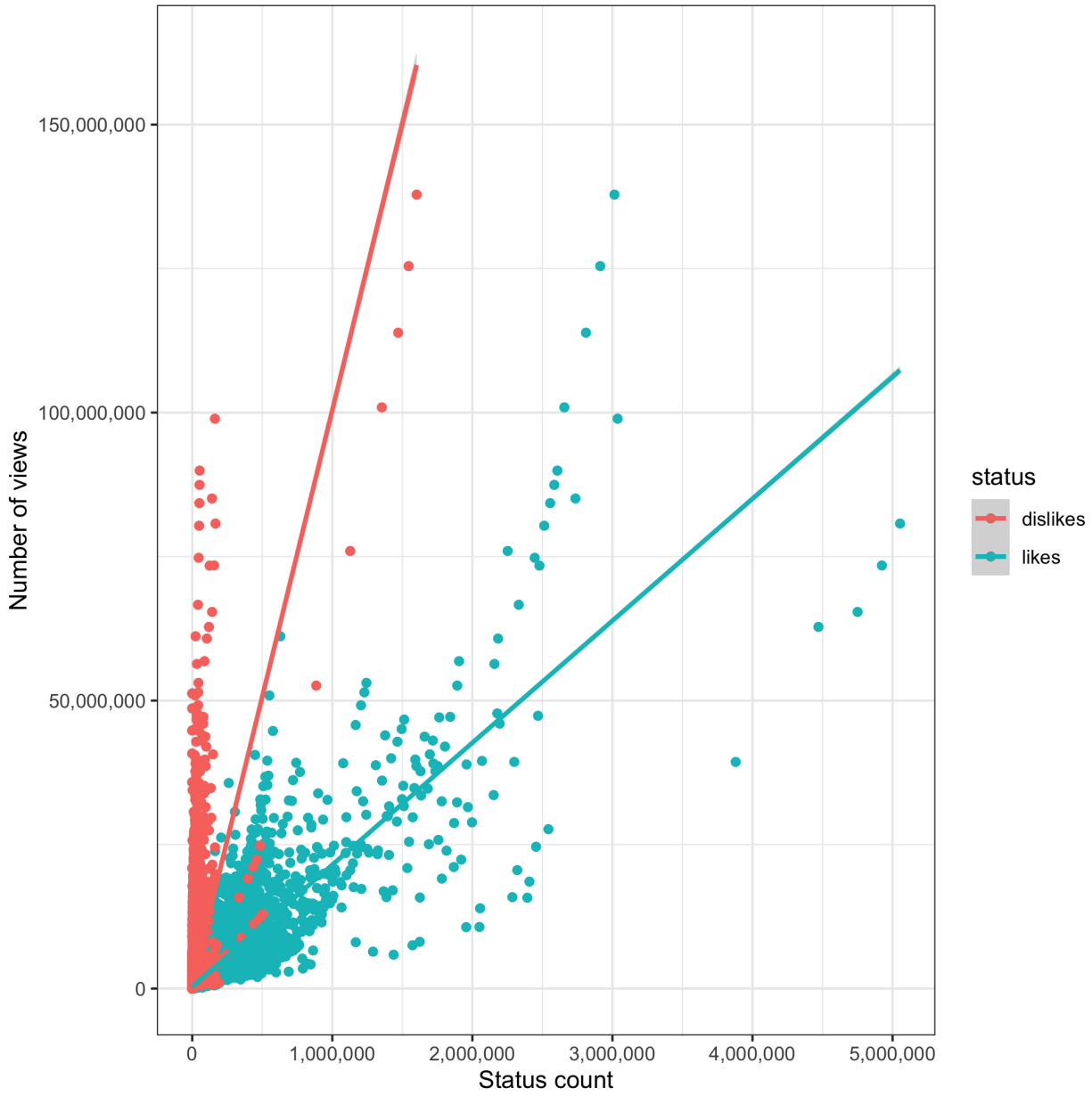
```
## # A tibble: 1 x 11
##   r.squared adj.r.squared  sigma statistic p.value    df  logLik    AIC
##       <dbl>         <dbl>  <dbl>     <dbl>   <dbl> <int>   <dbl>  <dbl>
## 1     0.726         0.726 1.77e6    54283.       0     3 -6.46e5 1.29e6
## # ... with 3 more variables: BIC <dbl>, deviance <dbl>, df.residual <int>
```

Below is the diagnostic plot of the linear model, showing residual vs. fitted values. We see that the fitted values are aggressively clustered at lower end with low residual. We have a number of outliers.

```
plot(fit.lm,which=1)
```



Here is a plot that performs linear regression on views with one explanotory variable each, `likes` and `dislikes`.



Although we see a poor fit, we see that it does capture the trend that as number of likes or dislikes increase, the views also increase.

Discussion/Conclusion