

Marketing on YouTube

05.11.2022

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Overview

Youtube has slowly become one of the leading entertainment/media conglomerates worldwide. The entertainment/media company opened its “doors” in 2005, and has been making steady progress in captivating all types of audiences. As of today, YouTube boasts impressive numbers, such as 122 million active users daily (1), 2.6 Billion monthly active users (2), and 1 billion hours of view time per day (3). This success has made YouTube one of, if not, the most influential entertainment/media platforms in the world. One of the side effects of this success is gardening a large and broad audience, which includes people all over the world. Over 71% of Canadian citizens visit the site on a monthly basis (4), making Youtube a viable platform for advertisers. Youtube’s advertising revenue hit 28.8 billion in the year 2021 (5), and with 500 hours of new videos of content being uploaded every day, there is an untapped market in identifying popular videos before they get popular.

Our mission is to provide customers with an opportunity to effectively advertise to a larger audience by discovering videos that will captivate audiences around Canada before they reach the trending page. Our analysis uses real time data from YouTube’s Trending section to understand what videos make it to the most viewed page on the site. Our approach is to analyze the real time data to determine the most effective ways of getting videos to the trending page, such as; time of day to post, best category of videos, useful tags and descriptions, and optimal thumbnails to catch a user’s interest.

Our goal is that we want to identify the videos that will reach the largest audience before they get to the trending page. This way your company can reach more viewers for less money than if you waited until the video got to the trending page. We know that this analysis will help your company reach more audiences around Canada, and therefore help your company's advertising goals.

Why do we need Big Data?

To perform our analysis, we have made use of several techniques that are commonly used in a Big Data paradigm. Big Data is an overarching term that encompasses all kinds of data, however, the most common and technical definitions of Big Data aim to define it within the scope of the ‘Three V’s’. The ‘Three V’s’ of Big Data are Volume, which refers to the size of data that we are dealing with, Variety, which refers to the variation in the fields of the available data, and Velocity, referring to the speed at which the data is collected or accumulated.

The need for our company to utilize Big Data approaches for our analysis is due to the size and variation within the dataset at hand, two of the three “V’s”. Without these

approaches, it becomes almost impossible to ingest and subsequently operate on this data using traditional data processing methods.



To ingest and operate upon the YouTube video dataset, we are making use of the Pyspark framework. The primary reason for the use of Pyspark is to take advantage of Pandas' extremely efficient capabilities of reading and loading data, while overcoming Pandas' inability to perform or support distributed system operations in cases where we might need additional processing power to support our growing data.

In simple terms, Pandas runs data processing operations on a single machine where as Pyspark runs these operations in a distributed manner, on multiple machines and hence, can give much faster computation times and processing speeds as compared to Pandas, thereby finding extensive application in the fields of Data Science, Analytics and Machine Learning.

For our specific application, the data set we used was over 835MB and included several variations in the data field, per country. This made it incredibly difficult to operate on the data using regular data processing techniques and hence, Pyspark was the go-to solution.

The Data

The Dataset that we are using for this analysis is the Youtube Trending dataset from Kaggle. The Data is split up into 9 different countries, but for our analysis we are using the Canadian dataset, given that the companies we are pitching to want to advertise to Canadian citizens. Our hope is that with the success of this project we will be able to increase our efforts to other countries, and to gain access to all of YouTube's data, not just the Trending data.

The dataset we have spans from 2020-07-27 to 2022-04-24 for all videos that were on Canada's Trending dataset. The features we have are:

```

video_id|      title|      publishedAt|      channelId|      channelTitle|categoryId|
trending_date|      tags|view_count| likes| dislikes| comment_count|
thumbnail_link|comments_disabled|ratings_disabled|      description

```

The dataset we are working with looks like:

[30]	video_id	title	publishedAt	channelId	channelTitle	categoryId	trendi
	KX06ksuS6Xo	Diljit Dosanjh: C...	2020-08-11T07:30:02Z	UCZRdNleCgW-BGUJf...	Diljit Dosanjh	10	2020-08-12T00
	J78aP33VyNs	I left youtube fo...	2020-08-11T16:34:06Z	UCYzPXprv15Y-Sf0g...	jacksepticeye	24	2020-08-12T00
	M9Pmf9AB4Mo	Apex Legends St...	2020-08-11T17:00:10Z	UC0zV6M2THA81QT9h...	Apex Legends	20	2020-08-12T00
	3C66w5Z0ixs	I ASKED HER TO BE...	2020-08-11T19:20:14Z	UCvtRTOMP2TqYqu51...	Brawadis	22	2020-08-12T00
	VIUo6yapDbc	Ultimate DIY Home...	2020-08-11T15:10:05Z	UCDVPcEbVLQgLZX0R...	Mr. Kate	26	2020-08-12T00
	ua4QMfQATco	CGP Grey was WRONG	2020-08-11T17:15:11Z	UC2C_jShtL725hvb...	CGP Grey	27	2020-08-12T00
	gi3VMMiFHVg	Giannis Gets Ejec...	2020-08-12T02:30:32Z	UC9-OpMMVoNP5o10...	Bleacher Report	17	2020-08-12T00
	7rlwxSPUcQk	ON EST POSITIF AU...	2020-08-11T16:00:31Z	UCpWaR3gNAQGsX48c...	Tibo InShape	17	2020-08-12T00
	49Z6Mv4_WCA	i don't know what...	2020-08-11T20:24:34Z	UCtinbF-Q-fVthA0q...	CaseyNeistat	22	2020-08-12T00
	p7HGUZWq_8s	Doing Doja Cat's ...	2020-08-11T19:00:09Z	UCucot-Zp428OwkyR...	James Charles	24	2020-08-12T00
	w-aidBdvZo8	I Haven't Been Ho...	2020-08-11T20:00:04Z	UC5zJwsFtEs9WYe3A...	Professor Live	24	2020-08-12T00
	kXLn3HKpjaA	XXL 2020 Freshman...	2020-08-11T16:38:55Z	UCbg_UMjHJg_19SZ...	XXL	10	2020-08-12T00
	AcBd_RH9Jsw	PASSER UNE NUIT D...	2020-08-11T10:55:22Z	UCU17mwOyySfZzUkq...	LeBouseuh	24	2020-08-12T00
	jbgRowa5tIk	ITZY "Not Shy" M/...	2020-08-11T15:00:13Z	UCaO6TYt1C8U5ttz6...	JYP Entertainment	10	2020-08-12T00
	GTp-0S82guE	Time to Talk...	2020-08-11T12:04:40Z	UCGcLoMYIyP0U56dE...	Chloe Ting	26	2020-08-12T00
	nt3VVyv5pxQ	Try Not To Laugh ...	2020-08-11T17:00:31Z	UCYJPby9DRcTeedh5...	Smosh Pit	22	2020-08-12T00
	DF5T7HJ0Xug	Barra Swapped GT3...	2020-08-11T20:14:12Z	UCXIYLGIp6DYZHjMU...	Adam LZ	2	2020-08-12T00
	gPdUsIndvVI	Our Farm Got Dest...	2020-08-11T23:00:06Z	UCuxlXCfVvY-i5YLL...	Cole The Cornstar	22	2020-08-12T00
	I6hswz4rIrU	Rainbow Six Siege...	2020-08-11T17:13:53Z	UCBMvc6jvuTxH6TNo...	Ubisoft North Ame...	20	2020-08-12T00
	9AecsACTkB4	Watch Secret Serv...	2020-08-10T22:29:23Z	UCi7Zk9baY1tvd1gx...	CTV News	25	2020-08-12T00

Our analysis is solely focused on why videos reach and stay on Youtube's Trending page.

Exploratory Data Analysis

The primary aim of our research is to provide our clients with the ability to maximize their discoverability on YouTube and with it, produce substantial improvements in return on investment (ROI) on AdSense (official Google/YouTube partner program) revenue.

One of the major factors to ensure maximum ROI on each video is to advertise on videos with the maximum interactions. Interactions on YouTube are of several different types, including likes, comments, dislikes and most importantly, views.

The AdSense program on Youtube runs in the following manner: once a particular creator has been accepted to the YouTube Partner Program they can switch on the 'monetization' feature on each one of their videos. By monetizing a video, a content creator allows different advertisers to run their advertisements on the video. Advertisements are of varying length and may or may not provide the option to skip through them. For every view the advertisement gets, the advertizer typically pays between \$0.18 to \$0.31 to Google.

Google in turn, pays around 68% of this money to the publisher of the original video. The advertisement payments are varying but the average out to somewhere between \$18 to \$31 per 10,000 views for a content creator.

Hence, the most quantifiable metric to measure the popularity of a video is the number of views that a video garners. There are obviously other factors that could affect the popularity of a video such as the number of subscribers on a channel. However, the most robust metric is still the number of views on a video and our analysis would largely revolve around the same.

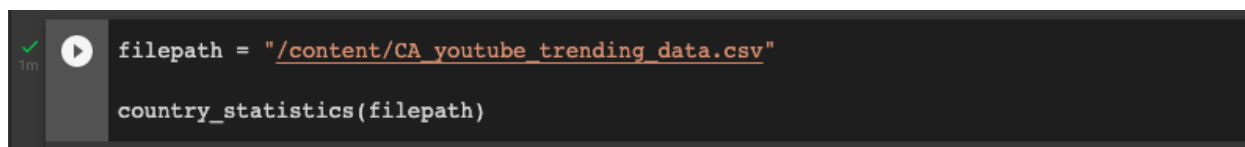
Another feature that YouTube offers, is a list of trending videos for each day of the week, and this is the dataset that we would be working with.

Videos are classified as trending on YouTube based on certain criteria, such as new and upcoming creators or artists, the growth in the number of views on a certain video, and what part of the world views come from. This implies that a particular video with the maximum view count for a day would appear on the countries trending video page. Trending videos however, provide us with the optimal dataset to work with in order to expand discoverability. These are the videos that everyone is watching, or everyone will watch at some particular point in time, and hence, advertising on these videos will almost certainly be a guarantee for success.

1. Most Popular Video Categories:

As part of our analysis, we first aim to find the categories of videos that perform the best in terms of the average view count for that category, and the number of videos created within that category.

In order to generate and subsequently visualize this data, we first need to clean up our data set by dropping any null values. After this, we need to ensure that all values listed within the category column are in the appropriate numerical format which can be used for further analysis. Once these checks are complete, we can move forwards with visualizing the data.

A code editor snippet with a dark background. On the left, there is a green checkmark icon and a play button icon. The code text is as follows:

```
filepath = "/content/CA_youtube_trending_data.csv"  
country_statistics(filepath)
```

```
filepath = "/content/CA_youtube_trending_data.csv"  
country_statistics(filepath)
```

The available data set has categories denoted by numerical values between 1 and 30, with each number mapping out to a particular category. However, upon further analysis of the data, it was found that the actual labeled data only contained a subset of these values.

Since there was no way of artificially generating synthetic labels for the available data, we have to work with what is available.

Based on the available data, the most popular categories for Canada were as shown below

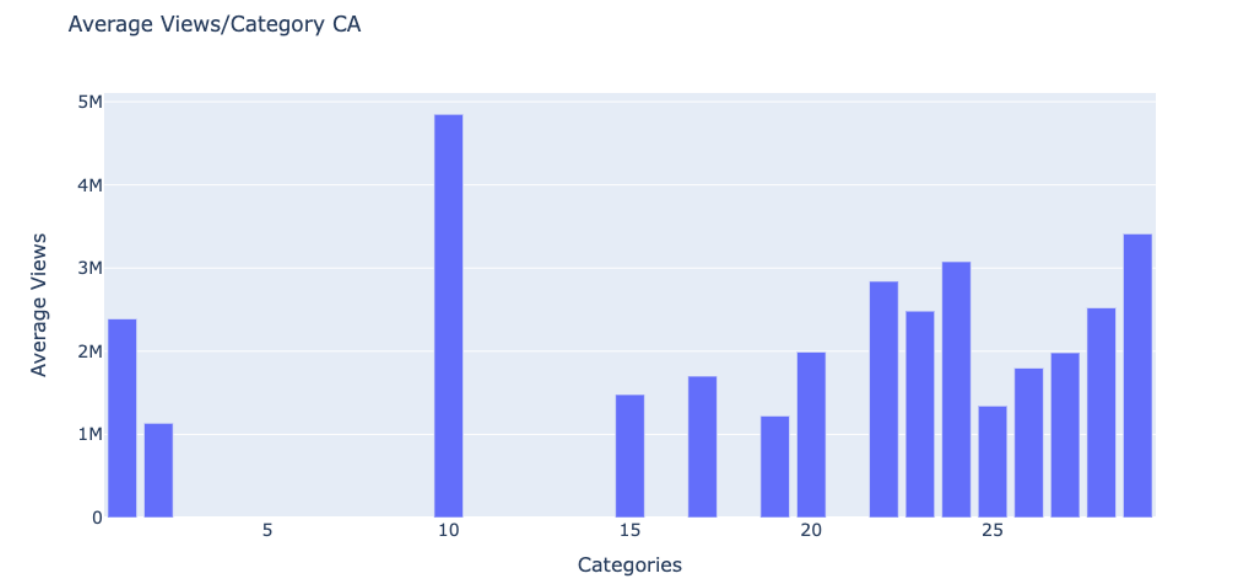


Fig: Graph depicting most popular categories by average views

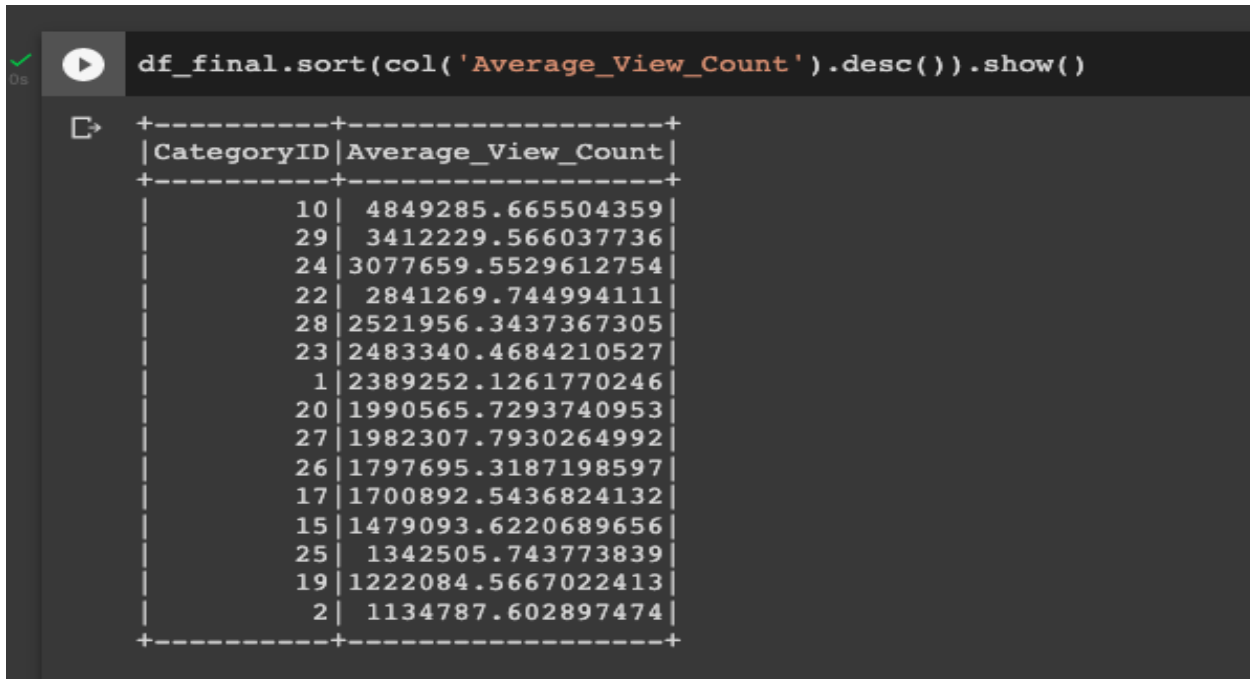


Fig: List of most popular categories by average view count

From the plot, we can clearly see that videos belonging to category 10, perform the best on average in terms of their view counts and those belonging to category 2 do not have great performance. Based on the labeled data available for Canada, category 10 is 'Comedy' and Category 2 is 'Music'.

This goes against our presumptions about categorical popularity, as we assumed Music videos would do pretty well in terms of their popularity and therefore provide the perfect marketplace for advertisement, however, the reality is that Music videos actually seldom make it on to the trending page on YouTube and hence, other avenues should be explored to advertise. We acknowledge that this may also be due to the data being misclassified, but based on the available evidence, our clients might want to steer clear of music videos when looking for advertisement opportunities!

Furthermore, we also provide a pictorial representation of the number of videos produced per category

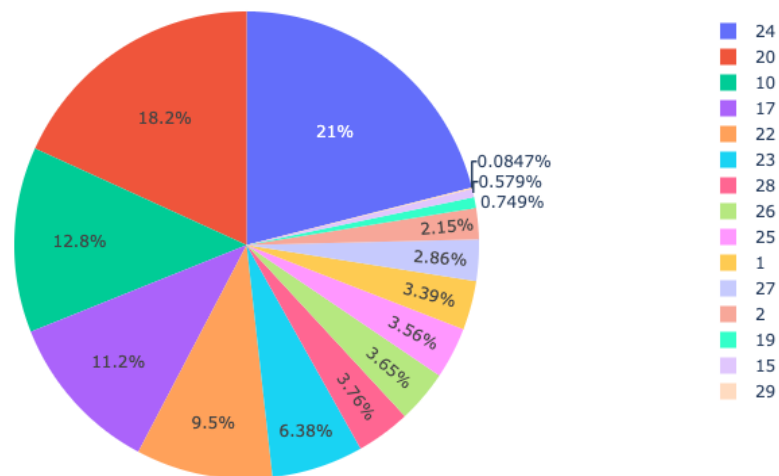


Fig: Chart showing distribution of videos per category

The plot shows that in terms of distribution, category 24 seems to be the most popular category amongst content creators. Category 24 for Canada is 'Family'. This makes sense as most YouTubers aim to produce family friendly content and we could imagine why a large number of videos from other categories such as 'Kids' or even 'Comedy' may fall into this category. In terms of the average view count however, category 24 lies third on the list.

This graph also highlights our second surprise in the analysis. As we can see from the plot, category 29 has the fewest number of videos produced. Even still, it ranks 2nd on the list of most popular categories by average view count. This implies that almost every video in that category is a guarantee to garner a large chunk of viewers. Category 29 is 'Shorts', which is a new feature implemented by YouTube. Multiple content creators could get paid from this category under a new 'Shorts Fund' created by YouTube, but the avenues for advertising on these videos are limited.

2. Popular Times:

As the second part of our analysis, we aim to find out if the time of day a video is posted has any relation with whether or not the video makes it onto the trending page. We select the entire data set available for Canada, filter down the rows containing null values, and then work on the 'publishedAt' column.

We firstly convert this column into the DateTime format by using the 'unixtime' function within the `pyspark.sql.functions` library. Then, we split up the values within this column to create a new column containing the corresponding hours.

```
df_new = df_new.withColumn('Time', regexp_replace('publishedAt', 'T', ' '))
df_new = df_new.withColumn('Time_', regexp_replace('Time', 'Z', ''))
df_new = df_new.drop('Time')
df_new = df_new.withColumn("Hour", from_unixtime(unix_timestamp(col("Time_"), "yyyy-MM-dd HH:mm:ss"), "HH"))
```

Fig: Pyspark code snippet of time transformation

We then classify the hours into four different parts of the day, i.e, Morning - 5am to 11am, Afternoon - 12pm to 4pm, Evening - 5pm to 8pm and Night - 9pm to 4am. These are the local times. Based on this bifurcation, we create a pie chart depicting the most common timeframe in which a video is posted, such that the video also makes it onto the trending page.

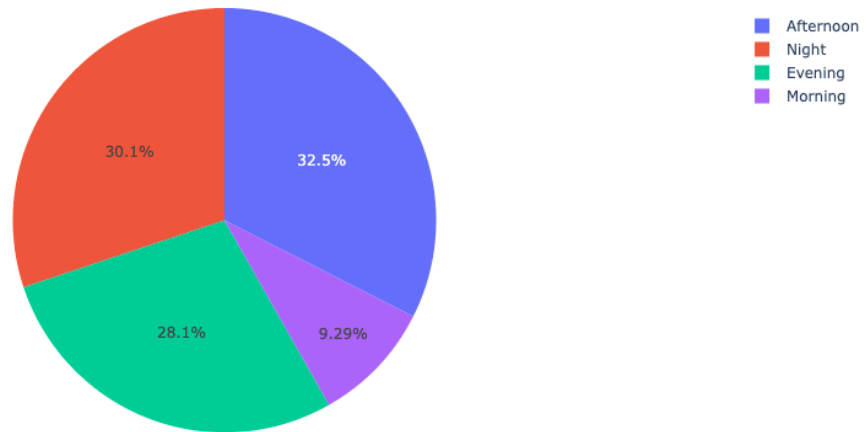


Fig: Chart showing the most common times for publishing trending videos

We can see here that most videos that make it on to the trending page in Canada are actually posted during the afternoon. This provides a great opportunity for advertising, if we keep a track of which videos are being posted during the afternoon times, and identify certain creators or artists that are most likely to make it to the trending page, this could give us a head start in identifying prospective advertisement avenues.

3. Popularity - Factors

As the next part in our analysis, we aim to identify the factors that affect the popularity of a video the most. The popularity of a video, as defined by us, depends upon the three major mediums of interaction with YouTube videos, i.e, number of Views, Likes, and Comments. We do not consider the number of Dislikes on a video to be a useful metric because YouTube discontinued Dislikes from 2022 onwards, and hence, the dataset would be unnecessarily skewed.

Before we delve into this analysis, it is essential to understand that we use Popularity as a separate metric. This implies that just because a certain video makes it onto the trending page, does not necessarily mean that video is 'popular'. As defined earlier, trending videos are those which show the maximum growth in terms of number views over a particular day, further, the trending page also accommodates new artists and creators each day, and their content might not necessarily be the most viewed. Advertising on trending videos

might be a good way to reach the maximum audience for a given day, but over the long term, advertising on videos with the maximum number of views seems to be the more robust metric.

The data set itself did not provide a binary classification between popular and not-popular videos, this classification was synthetically created by using a Pyspark UDF.

```
popularity_detector = f.udf(lambda x,y,z: (1.0 if x > (500000) and y > (10000) and z > (5000) else 0.0), returnType= FloatType())
popularity_detector_likes = f.udf(lambda x: (1.0 if x > (10000) else 0.0), returnType= FloatType())
popularity_detector_comments = f.udf(lambda x: (1.0 if x > (5000) else 0.0), returnType= FloatType())
df_sea = df_sea.withColumn('Popularity', popularity_detector('Views','Likes','Comment_Count1'))
```

Fig: Pyspark code to show how a video was classified as popular

Intuitively, one would think that since the Popularity column has been synthetically created using three other columns from the dataset, all three of them would have equal correlation to the popularity metric, however, this was not observed.

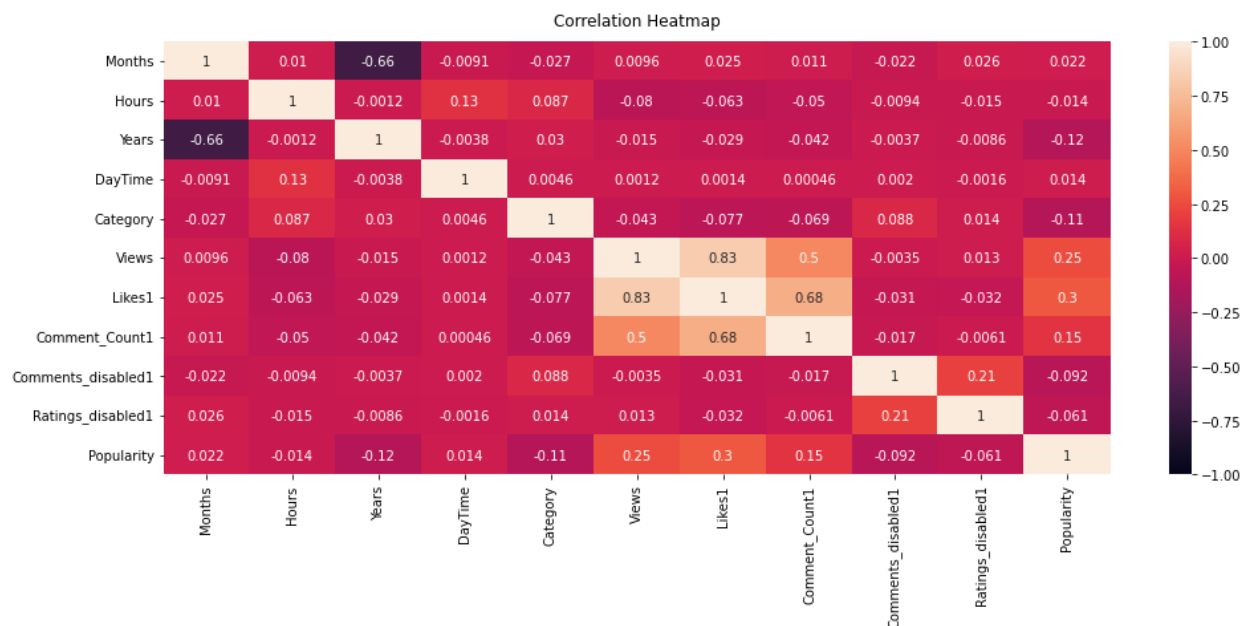


Fig: Heatmap showing feature correlation

Our intuition was somewhat correct, the features, Likes, Views and Comments do have the most correlation with popularity. However, it is observed that videos that are well liked are pushed further by YouTube's algorithm and are more likely to garner a larger number of views in the long run. Hence, while looking for long term advertisement opportunities, it would make sense to keep track of videos with a large number of likes as these will provide a good return on long time investment.

We noticed that the popularity metric we created does not correlate well with any one metric, which is expected given that it was created by using multiple metrics. However, we do observe some positive correlation between the popularity of a video and the month within which it is posted. This forms the basis for the last part of our analysis.

4. Target Months:

As the final part of our analysis, we aim to find the months during which most videos make it onto the trending page on YouTube. Our assumption is that holiday months are usually the most popular for content creators and consumers alike. AdSense revenues are also sky high during these months and hence, we expect maximum production to be during the months from October to February. Let's see if the analysis corroborates this claim.

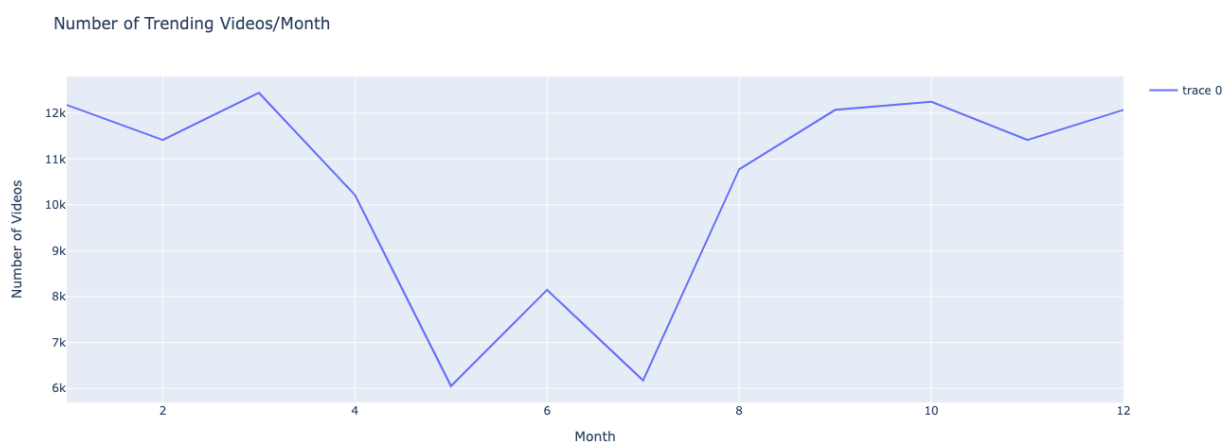


Fig: Line Chart showing video distribution by month

From the plot, we can see that it is in fact the month of March which is the most popular for uploading videos in Canada, and more specifically, videos that actually make it onto the trending page. However, this particular statistic should be viewed with a lower priority, and here is why. As we mentioned earlier, our data set runs from January of 2020 to April of 2022. This means that for the month of 2022, we only consider 4 months, i.e, January, February, March and April. This could possibly skew the data. However, even with the additional data, October still remains our second most popular month to upload a YouTube video with the best chance to make it onto trending, and the predicted trend of the holiday months being a gold mine for YouTubers and advertisers alike is maintained!

As there could be a possible skew in the data, we would choose the second most popular month by video count, i.e October for our further analysis.

The next bit of analysis we perform is we select our target month (October), and find out if there is a specific time of the day which gives a video the best possible chance to make it onto YouTube's trending page. We had observed earlier that for Canada, a majority of videos were posted between 12pm - 4pm, closely followed by night time, ie, between 8pm and 4am. This should give us some intuition as to what the expected trend should be.



Fig: Line Chart showing video distribution by hour for October

Videos posted in the timeframe of 3pm to 5pm are the ones most likely to make it onto the trending page on YouTube which is updated daily at 00:00:00 UTC. Similarly, we can also visualize how many of these videos are actually popular as per our predefined popularity metric and compare if the trend follows a similar pattern.



Fig: Line Chart showing popular video distribution by hour for October

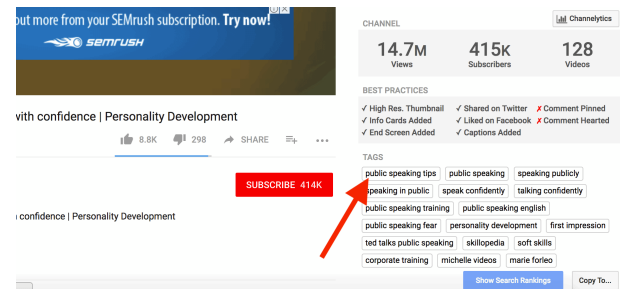
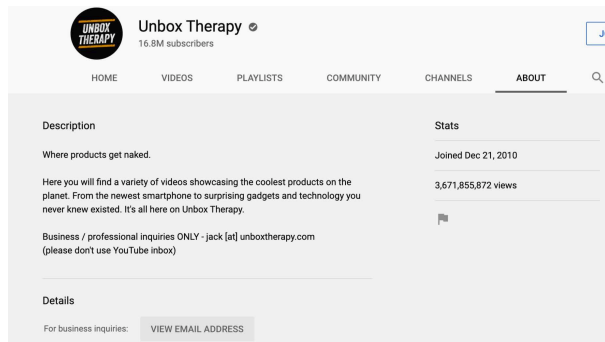
Videos posted between the times of 3pm to 8pm have the best chance of appearing on the trending page, and qualifying as generally popular videos.

These analyses give our clients the best possible metrics for identifying advertisement opportunities and capitalizing on the same. Based on what we have learnt from these visual representations is that a video belonging to the 'Comedy' category, posted in the month of October, and in the 3pm to 8pm timeframe, might be the best possible target for a company looking to maximize their discoverability through advertisement.

These analyses however are very numerical and static, through the rest of our report, we go through other techniques such as identifying key tags and descriptions of videos which contribute to their popularity.

Tags and Description

The Tags and Description section of YouTube is a creator's ability to describe what their video is about, information about links to other videos, or the ability to promote their channel/other channels that they have. These tags and descriptions are very important to the success of a video, as they help draw people to click on a video given the short buzzwords, and encourage people to watch and stay engaged with the videos with a lively description. Throughout the datasets, we were able to do more analysis on these tags and descriptions with the aim of uncovering the perfect tags and descriptions to get viewers to watch videos.



Tags:

The tags of the videos can be anywhere from 0 tags for a video up to 50 unique tags for a single video. Our analysis of the tags for a video started by identifying the amount of unique tags in the Canadian dataset. There are 153,619 unique tags in the trending dataset. The top tag for all of the videos is the tag “funny” with 7026 unique instances. We use techniques of MinHash LSH that we learned in class in order to determine the similarities between tags of different videos. We tried many different NGram combinations, but the one that gave the most telling results was a Ngram of 2. Using this we were able to get the Jaccardian distances for the tags:

JaccardDistance	channel_Title_1	Title_1 view_count1 categoryId1	channel_Title_2	Title_2 view_count2 categoryId2
0.0250000000000000022	MTV	BTS Reveals the M...	MTV	BTS Performs "Tel...
0.02857142857142858	Chelsea Football ...	Tottenham 0-3 Che...	Chelsea Football ...	Chelsea 3-0 Aston...
0.02857142857142858	Cleetus McFarland	We Just Made the ...	Cleetus McFarland	The Freedom Facto...
0.02857142857142858	Ed Sheeran	Ed Sheeran - Shiv...	Ed Sheeran	Ed Sheeran - Shiv...
0.02941176470588236	Dude Perfect Plus	Unreleased Footag...	Dude Perfect Plus	Build A Raft Batt...
0.02941176470588236	Dude Perfect Plus	UFC Golf Battle (...	Dude Perfect Plus	Build A Raft Batt...
0.02941176470588236	Dude Perfect Plus	Submarine Minefie...	Dude Perfect Plus	Build A Raft Batt...
0.02941176470588236	Dude Perfect Plus	Remote Control Ta...	Dude Perfect Plus	Build A Raft Batt...
0.02941176470588236	Dude Perfect Plus	Chainsaw Carving ...	Dude Perfect Plus	Build A Raft Batt...
0.02941176470588236	Dude Perfect Plus	Dude Perfect Corn...	Dude Perfect Plus	Build A Raft Batt...
0.02941176470588236	Dude Perfect Plus	TY QUIT DUDE PER...	Dude Perfect Plus	Build A Raft Batt...
0.030303030303030276	NLE CHOPPA	NLE Choppa - Jigg...	NLE CHOPPA	NLE Choppa - Brys...
0.030303030303030276	NLE CHOPPA	NLE Choppa - Jigg...	NLE CHOPPA	NLE Choppa - Done...
0.030303030303030276	FitMC	The Mystery of 2b...	FitMC	2b2t Griefers Jus...
0.030303030303030276	FitMC	Why Are 2b2t Play...	FitMC	2b2t Griefers Jus...
0.030303030303030276	FitMC	The History of 2b...	FitMC	2b2t Griefers Jus...
0.030303030303030276	FitMC	2b2t's Final Meth...	FitMC	2b2t Griefers Jus...
0.032258064516129004	JxmyHighroller	We Thought This W...	JxmyHighroller	The NBA Is Gettin...
0.032258064516129004	Paramount Pictures	Scream Official...	Paramount Pictures	Scream (2022) - F...
0.03333333333333326	ScreenCrush	LOKI 1x05: Every ...	ScreenCrush	LOKI 1x04: Every ...
0.03333333333333326	Gucci Mane	Gucci Mane - Seri...	Gucci Mane	Gucci Mane - Like...
0.03333333333333326	Gucci Mane	Gucci Mane - Like...	Gucci Mane	Gucci Mane - Bloo...
0.03448275862068961	Kodak Black	Kodak Black - Pur...	Kodak Black	Kodak Black - Aug...
0.03448275862068961	Kodak Black	Kodak Black - Pur...	Kodak Black	Kodak Black - Hal...
0.03448275862068961	Kodak Black	Kodak Black - Pur...	Kodak Black	Kodak Black - Clo...
0.03448275862068961	Kodak Black	Kodak Black - Pur...	Kodak Black	Kodak Black - I W...
0.03448275862068961	JGOD	Warzone Pacific T...	JGOD	Huge Stealth Chan...
0.03448275862068961	JGOD	Played Warzone Pa...	JGOD	Huge Stealth Chan...
0.03448275862068961	Kodak Black	Kodak Black - Sup...	Kodak Black	Kodak Black - Pur...
0.03448275862068961	Kodak Black	Kodak Black Ft. R...	Kodak Black	Kodak Black - Pur...
0.03448275862068961	Kodak Black	Kodak Black Ft. C...	Kodak Black	Kodak Black - Pur...
0.03448275862068961	Kodak Black	Kodak Black - Sen...	Kodak Black	Kodak Black - Pur...

Here we can see that the tags that are the most similar are the ones from similar channels. When we filter out the Jacardian distances between videos from the same channel:

JaccardDistance	channel_Title_1	Title_1 view_count1 categoryId1	channel_Title_2	Title_2 view_count2 categoryId2
0.03448275862068961	Parrot	Can I Solve this ...	Spoke	1,037 Creepers VS...
0.03448275862068961	Parrot	Can I Solve this ...	Spoke	1,017 Withers VS ...
0.03703703703703709	TommyInnit	I met KSI in real...	TommyOutit	I met George in r...
0.00000000000000036	MoreTalkFCB	Ronald Koeman SPE...	TalkFCB	Koeman tells Luis...
0.07017543859649122	KBS World	TWICE(트와이스) - I C...	KBS WORLD TV	TWICE(트와이스) - ...
0.0714285714285714	JYP Entertainment	TWICE The Feels M/V	TWICE	TWICE The Feels C...
0.0714285714285714	TWICE	TWICE The Feels O...	JYP Entertainment	TWICE The Feels M/V
0.08333333333333337	ITZY	ITZY Performance ...	JYP Entertainment	ITZY Not Shy Albu...
0.08333333333333337	JYP Entertainment	ITZY "Not Shy" M/V	ITZY	ITZY Performance ...
0.08333333333333337	JYP Entertainment	ITZY "Not Shy" M/...	ITZY	ITZY Performance ...
0.08333333333333337	ITZY	ITZY Not Shy Stag...	JYP Entertainment	ITZY Not Shy (Eng...
0.08333333333333337	ITZY	ITZY Performance ...	JYP Entertainment	ITZY Not Shy (Eng...
0.08333333333333337	Sleepy Hallow	Sleepy Hallow x S...	Sheff G	Sheff G - Start S...
0.09090909090909094	NMIXX	[NMIXX] 占 (TANK) ...	JYP Entertainment	NMIXX 0.0 M/V
0.09090909090909094	NMIXX	[NMIXX] 占 (TANK) ...	JYP Entertainment	NMIXX 0.0 M/V Teaser
0.09999999999999998	NMIXX	[NMIXX] 0.0 Perfo...	JYP Entertainment	[NMIXX] Debut Tra...
0.09999999999999998	Simon and Martina	What Happened to ...	Eatyourkimchi Studio	Moving to Japan ...
0.09999999999999998	Simon and Martina	What's Inside a C...	Eatyourkimchi Studio	Moving to Japan ...
0.0204081632653061	ITZY	ITZY Not Shy Danc...	JYP Entertainment	ITZY Not Shy Albu...
0.0204081632653061	JYP Entertainment	ITZY "Not Shy" M/V	ITZY	ITZY Not Shy Danc...
0.0204081632653061	JYP Entertainment	ITZY "Not Shy" M/...	ITZY	ITZY Not Shy Danc...
0.0204081632653061	ITZY	ITZY Not Shy Danc...	JYP Entertainment	ITZY Not Shy (Eng...
0.0344827586206895	SEVENTEEN	[Choreography Vid...	Big Hit Labels	SEVENTEEN (세븐틴) ...
0.0810810810810811	FIFATV	Tanzania v Congo ...	FIFA	Egypt v Senegal [...]
0.0810810810810811	FIFATV	Tanzania v Congo ...	FIFA	Senegal v Egypt [...]
0.0810810810810811	FIFATV	Tanzania v Congo ...	FIFA	Algeria v Cameroo...
0.0810810810810811	FIFATV	Djibouti v Algeri...	FIFA	Algeria v Cameroo...

Where we can see that the videos with the most similar tags are the ones that are from channels of the same creators. This tells us that the tags are very unique to each channel. We can draw from this that the channels that are constantly getting to the Trending page are using their own tags that help them get to the top of their respective categorical charts. We now looked at the tags for the top 10 channels for each category, to help us know what tags the Content creators can use to help model their tags for their videos to help get a following. The results of this data for the Canadian categories that were present in the trending data is:

These tags are crucial for creators in these categories to get to the top view counts, and stay on the trending page with all of their new videos. These tags will be the baseline for your employees to help them accrue a following to their videos.

The Description place gives a creator more freedom to describe the content of their video, which means there will be more variety in the descriptions of different videos. We use the same technique that we used with the tags to see if there are any similarities between videos in the trending set. Yet again we see very similar results for the Jacarian Distances between descriptions for videos:

And when we filter out videos that are from different channels:

JaccardDistance	channel_Title_1	Title_1	view_count1	categoryId1	channel_Title_2	Title_2	view_count2	categoryId2
0.0520833333333333	SMTOWN	[STATION] TEN 텐 '...	1520815	10	SM STATION	[STATION] TEN 텐 '...	5384634	10
0.07002801120448177	Jurassic World	Jurassic World Do...	447161	24	Universal Pictures	Jurassic World Do...	9410344	24
0.0755555555555556	Miley Cyrus	Miley Cyrus - Liv...	3685672	24	Foo Fighters	Foo Fighters - Li...	439238	10
0.0755555555555556	Miley Cyrus	Miley Cyrus - Liv...	903935	10	Foo Fighters	Foo Fighters - Li...	439238	10
0.08492201039861347	MoneyBagg Yo	Moneybagg Yo - Fr...	639078	10	MoneybaggYoVEVO	Moneybagg Yo - Fr...	772427	10
0.08571428571428574	Colleen Ballinger	PREGNANCY MUKBANG...	928878	23	Colleen Vlogs	I CAN FINALLY TAL...	992526	24
0.08571428571428574	Colleen Ballinger	PREGNANCY MUKBANG...	928878	23	Colleen Vlogs	Holding The Twins...	1567423	24
0.08571428571428574	Colleen Ballinger	PREGNANCY MUKBANG...	928878	23	Colleen Vlogs	BRINGING MAISY HO...	2435850	24
0.08571428571428574	Colleen Ballinger	PREGNANCY MUKBANG...	928878	23	Colleen Vlogs	BRINGING WESLEY H...	1973041	24
0.08571428571428574	Colleen Ballinger	PREGNANCY MUKBANG...	928878	23	Colleen Vlogs	First Trimester N...	562426	24
0.08571428571428574	Colleen Ballinger	PREGNANCY MUKBANG...	928878	23	Colleen Vlogs	Finding Out I'm P...	708850	24
0.08571428571428574	Colleen Vlogs	Rumors About TRIP...	1387209	24	Colleen Ballinger	PREGNANCY MUKBANG...	928878	23
0.08571428571428574	Colleen Vlogs	Visiting my babie...	1756877	24	Colleen Ballinger	PREGNANCY MUKBANG...	928878	23
0.0861244019138756	SidemenShorts	Why Harry wore ta...	668134	22	MoreSidemen	SIDEMEN 8 YEAR AN...	2966055	22
0.0861244019138756	SidemenShorts	The Brown Variant	885290	22	MoreSidemen	SIDEMEN 8 YEAR AN...	2966055	22
0.08823529411764708	UnspeakablePlays	Testing Illegal M...	930621	20	Unspeakable	Can You Land In T...	2790011	22
0.08823529411764708	UnspeakablePlays	Testing Illegal M...	930621	20	Unspeakable	LAST To LEAVE 100...	4242056	22
0.08823529411764708	UnspeakablePlays	Testing Illegal M...	930621	20	Unspeakable	ESCAPING 100 LAYE...	3581598	22
0.08823529411764708	UnspeakablePlays	Testing Illegal M...	930621	20	Unspeakable	EVERY STEP, YOU K...	2385647	22
0.08823529411764708	UnspeakablePlays	Testing Illegal M...	930621	20	Unspeakable	I Bought A REAL T...	3318312	22
0.08823529411764708	UnspeakablePlays	Testing Illegal M...	930621	20	Unspeakable	100 Buttons but O...	4602973	22
0.08823529411764708	UnspeakablePlays	Testing Clickbait...	2560841	20	Unspeakable	Can You Land In T...	2790011	22
0.08823529411764708	UnspeakablePlays	Testing Clickbait...	2560841	20	Unspeakable	LAST To LEAVE 100...	4242056	22
0.08823529411764708	UnspeakablePlays	Testing Clickbait...	2560841	20	Unspeakable	ESCAPING 100 LAYE...	3581598	22
0.08823529411764708	UnspeakablePlays	Testing Clickbait...	2560841	20	Unspeakable	EVERY STEP, YOU K...	2385647	22
0.08823529411764708	UnspeakablePlays	Testing Clickbait...	2560841	20	Unspeakable	I Bought A REAL T...	3318312	22
0.08823529411764708	UnspeakablePlays	Testing Clickbait...	2560841	20	Unspeakable	100 Buttons but O...	4602973	22
0.08823529411764708	UnspeakablePlays	STRANDED ON AN IS...	819695	20	Unspeakable	Can You Land In T...	2790011	22
0.08823529411764708	UnspeakablePlays	STRANDED ON AN IS...	819695	20	Unspeakable	LAST To LEAVE 100...	4242056	22
0.08823529411764708	UnspeakablePlays	STRANDED ON AN IS...	819695	20	Unspeakable	ESCAPING 100 LAYE...	3581598	22
0.08823529411764708	UnspeakablePlays	STRANDED ON AN IS...	819695	20	Unspeakable	EVERY STEP, YOU K...	2385647	22
0.08823529411764708	UnspeakablePlays	STRANDED ON AN IS...	819695	20	Unspeakable	I Bought A REAL T...	3318312	22
0.08823529411764708	UnspeakablePlays	STRANDED ON AN IS...	819695	20	Unspeakable	100 Buttons but O...	4602973	22
0.08823529411764708	Unspeakable 2.0	We Put A BOAT In ...	611549	22	UnspeakablePlays	Testing Illegal M...	930621	20
0.08823529411764708	Unspeakable 2.0	We Put A BOAT In ...	611549	22	UnspeakablePlays	Testine Clickbait...	2560841	20

What we learned from this information is that there is no formula to a description that would help garner more views. Tags are the bigger driving force in a video's success and accumulating videos. The last aspect of our analysis focuses on thumbnails, and how they impact a video's popularity.

Object Detection using AWS Rekognition

One of the interesting features in the youtube dataset was the thumbnail link column.

A video thumbnail is the viewer's first impression of the video, as it is the first thing that a user sees. A great video thumbnail can mean the difference between thousands of views and just a few. Various thumbnail items can entice the user to play a specific video. Hence, we decided to leverage this feature and used AWS Rekognition to recognize objects from the thumbnails.

Rekognition is an AWS service that analyzes your photographs using deep learning. By sending an image or video to the AWS Rekognition API, you can easily incorporate Rekognition into your application. Objects, people, language, scenes, and activities will be identified by the service. Face analysis and recognition are also incredibly accurate with Amazon Rekognition. Face detection, analysis, and comparison are available for a range of applications, including user identification, cataloging, people counting, and public safety.

Our goal is to identify which objects can grab a user's interest quickly.

```
%matplotlib inline
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
import boto3
import time
final = []
client=boto3.client('rekognition',region_name='us-east-1')
for i in range(114869,us_df.shape[0]):
    imageFile=str(i)+'.jpg'
    try:
        img=mpimg.imread(imageFile)
        with open(imageFile, 'rb') as image:
            %time response = client.detect_labels(Image={'Bytes': image.read()})

        print('Detected labels in ' + imageFile + ':\n')
        objects = []
        for label in response['Labels']:
            obj = label['Name']
            objects.append(obj)
    except Exception as e:
        print('Not detected labels in ' + imageFile + ':\n')
        objects.append([])
    final.append(objects)
```

Streaming output truncated to the last 5000 lines.

CPU times: user 6.84 ms, sys: 176 µs, total: 7.02 ms

Wall time: 253 ms

Detected labels in 123893.jpg:

CPU times: user 4.77 ms, sys: 1.34 ms, total: 6.11 ms

Wall time: 392 ms

Detected labels in 123894.jpg:

CPU times: user 4.98 ms, sys: 1.07 ms, total: 6.05 ms

Wall time: 223 ms

Detected labels in 123895.jpg:

Highest object count per category:

We can see that a human/person dominates the count for each category. Rekognition often gives an extensive list of synonymous objects which can cause some objects to occur together very frequently. In the given snapshot, it can be seen that person and human are categorized as different entities, even though they indicate the same thing. This analysis does not provide any detail about how the objects play a role in determining views but it does give an idea that almost every image has a human in it.

We can get a deeper understanding of the objects by ranking them and see how they are scattered for each category.

```
dfwords=df.withColumn('obj',split(col('objects'),''))\
.withColumn('object',explode(col('obj')))\
.drop('objects','obj').groupBy('object','categoryId').agg(count('object')\
.alias('count')).orderBy(['count',ascending=False])
df_find = dfwords.withColumn("category", recode('categoryId', category))
df_find = df_find.select('category','object','count')
df_find.show()
```

category	object	count
Entertainment	Person	19463
Entertainment	Human	18339
Gaming	Person	15843
Gaming	Human	15009
Music	Person	11581
Music	Human	10838
Sports	Person	10631
Sports	Human	10110
People & Blogs	Person	8612
People & Blogs	Human	8274
Entertainment	Performer	7814
Entertainment	Face	7003
Entertainment	Advertisement	6959
Entertainment	Poster	6444
Entertainment	Clothing	6179
Entertainment	Apparel	6151
Gaming	Performer	6128
Comedy	Person	5991
Entertainment	People	5949
Gaming	Advertisement	5880

only showing top 20 rows

Top 5 ranked objects :

After exploding the dataset, we ranked each object and extracted the top 5 ranked individual objects that appear for each category. Even though all of them have a lot of commonalities, some unique objects do stand out for each category. As you can see, in the category how to & style, females in the thumbnails attract more users. We can leverage this point to advertise female centric products in this category. In the Autos & Vehicles category, Sedan cars dominate over every type of car. Hence, this can again be useful to target a specific set of audience.

Ranking based on individual objects gives an insight as to how objects on its own dominate each category.

category	collect_set(object)
Science & Technology	[Human, Text, Electronics, Phone, Person]
Howto & Style	[Human, Clothing, Female, Apparel, Person]
Education	[Human, Text, Advertisement, Poster, Person]
People & Blogs	[Human, Face, People, Performer, Person]
Film & Animation	[Human, Text, Art, Performer, Person]
Gaming	[Human, Text, Advertisement, Poster, Person]
Travel & Events	[Human, Face, People, Person, Sitting]
Pets & Animals	[Canine, Mammal, Pet, Person, Animal]
Sports	[Human, Crowd, People, Sport, Person]
Comedy	[Human, Clothing, Face, Performer, Person]
Music	[Human, Crowd, Apparel, Performer, Person]
News & Politics	[Human, Electronics, Crowd, Performer, Person]
Entertainment	[Human, Face, People, Performer, Person]
Nature	[Human, Text, Face, [], Person]
Autos & Vehicles	[Human, Vehicle, Sedan, Person, Car]

Top ranked grouped objects:

The next we tried to see was which set of objects frequently together. This will give us a more specific idea about the videos which trend. As it can be inferred, videos containing Iphones topped the Science and Technology category, Film and Animation is dominated by Angry Birds and so on.

Thumbnails do matter when it comes to influencing views. We may deduce from the analysis that each category has a distinct set of objects that appeal to the user. Advertisement corporations can leverage their knowledge of such objects to target specific audiences.

category	collect_set(objects)
Science & Technology	[Phone, Electronics, Mobile Phone, Cell Phone, iPhone]
Howto & Style	[Electronics, Phone, Mobile Phone, Cell Phone, Person, Human]
Education	[Art, Graphics, Symbol, Sign, Light, Lighting]
People & Blogs	[Sitting, Person, Human, Indoors, Crowd, People, Performer, Clothing, Apparel, Hair, Pants, Office, Music Band, M]
Film & Animation	[Angry Birds]
Gaming	[Pac Man]
Travel & Events	[Person, Human, Sweets, Confectionery, Food, Text, Word, Face, People, Dating, Performer, Banner, Birthday Cake,]
Pets & Animals	[Golden Retriever, Canine, Animal, Mammal, Dog, Pet, Puppy, Sitting, Person, Human, Animal, Golden Retriever, Do]
Sports	[Person, Human, Sport, Sports, Boxing, Crowd, Person, Human, Press Conference]
Comedy	[Person, Human, Performer, Hair, People, Poster, Advertisement, Face, Crowd, []]
Music	[Painting, Art, Person, Human, Performer, Person, Human, Head, Face, Hair, Advertisement, Poster, Haircut, Miner]
News & Politics	[Person, Human, Crowd, Performer, Press Conference]
Entertainment	[Person, Human, Face, Water, Animal, People, Aquarium, Sea Life, Outdoors, Photography, Photo, Advertisement, Bi]
Nature	[Blonde, Female, Teen, Person, Girl, Woman, Kid, Human, Child, Tie, Accessories, Accessory, Hair, Dress, Clothing,]
Autos & Vehicles	[Sports Car, Car, Vehicle, Transportation, Automobile, Coupe, Race Car, Mustang, Sedan]

Conclusion

We have seen throughout our analysis that there are a multitude of factors that contribute to the overall popularity of a Youtube video. Our company has identified qualities of videos that drive success and overall popularity, such as posting in a Family category, posting in the month of March, tags that match the top 50 per category, and thumbnails that include people. We are confident that we can identify videos that will reach the broadest audience in Canada before they become popular, thus cutting down on the expenses associated with advertising on videos, and making sure we advertise as early as possible. We will be able to test this analysis on upcoming videos throughout the year, and be able to expand our efforts as we receive more information about Youtube videos.

We are excited for the opportunity to help your company grow and to have your product reach a whole new audience of Canadian citizens. As we grow together, we will make your product one of the most popular around the world.

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- (7)
- (8)