Analysis of Youtube Trending Videos

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Abstract

In this project we go through the process of collecting, storing and Analysing youtube trending videos from 12th August 2020 till date. We demonstrate the construction of data ingestion pipeline to regularly call the youtube API for trending videos and storing the information on a managed Microsoft Azure instance in a docker container. We further analyze the data to extract insights about the general viewing practice of people furing the COVID-19 Pandemic period. We draw insights about which category of youtube videos are generally seen on the youtube trending tab, we also analyze which channels are regularly seen on the trending tab. Finally, We also train a BERT(Bidirectional Encoder Representations from Transformers) powered model from title of collected youtube videos to estimate the category to which a video belongs to.

1 Overview

Youtube is one of the most popular social media sites with over 122 million daily active users and more than 1 billion hours of content spread across the globe. globalmediainsight.
One of the most popular and important features of the youtube website is unarguably the trending tab (recently name changed to explore). This section contains some of the most popular/upcoming videos of a region. It was one of the first features added to the youtube site which enabled content creators on the platform to reach to a wider audience.

2 Problem Statement

Youtube trending videos dataset is an important asset which allows us to monitor the growth of the platform and change in paradigm of the amount and type of content present on the platform.

But there is a significant problem, there is no publicly available official historical dataset of youtube trending videos. The youtube API only allows for ”mostPopular” video list of the date of the API call.
So this project is aimed to create a tool to regularly query and store youtube trending videos data set so as to eventually create a historical data set and perform analysis on it to understand YouTube usage and content paradigms.

Thus the steps taken to accomplish this are:

1. Create a persistent PostgreSQL database in a docker container on Microsoft Azure cloud platform

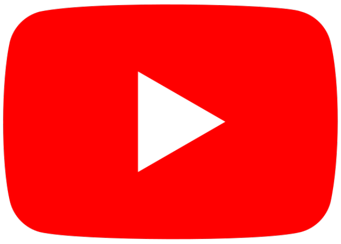
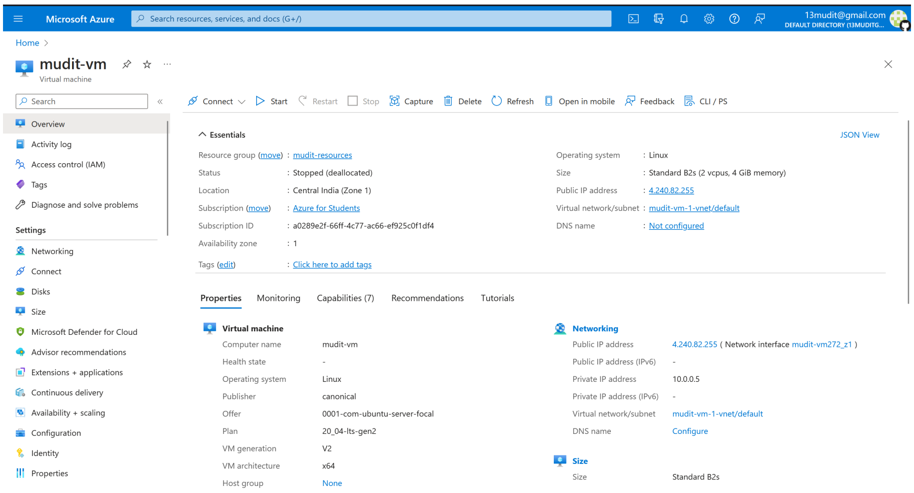


Figure 1: Youtube, the most popular Video streaming service.

Figure 2: Some major cloud service providers.



mudit-vm

Virtual machine

Essentials

Resource group (move) : mudit-resources
Status : Stopped (deallocated)
Location : Central India (Zone 1)
Subscription (move) : Azure for Students
Subscription ID : a0289e2f-66ff-4c77-ac66-ef925c0f1df4
Availability zone : 1
Tags (edit) : Click here to add tags

Operating system : Linux
Size : Standard B2s (2 vcpus, 4 GiB memory)
Public IP address : 4.240.82.255
Virtual network/subnet : mudit-vm-1-vnet/default
DNS name : Not configured

Virtual machine

Computer name	mudit-vm
Health state	-
Operating system	Linux
Publisher	canonical
Offer	0001-com-ubuntu-server-focal
Plan	20_04-lts-gen2
VM generation	V2
VM architecture	x64
Host group	None

Networking

Public IP address	4.240.82.255 (Network interface mudit-vm272_z1)
Public IP address (IPv6)	-
Private IP address	10.0.0.5
Private IP address (IPv6)	-
Virtual network/subnet	mudit-vm-1-vnet/default
DNS name	Configure

Size

Size	Standard B2s

Figure 3: Azure VM console overview.

2. Run a regular cloud edge computing function to query Youtube API and store the current date most popular videos for 10 countries/regions
3. Create an Analysis script to query that data and draw insights from it
4. Train a BERT based Language model to identify the category of a given youtube title

3 Create a Cloud PostgreSQL Server

3.1 Introduction

Cloud services like Microsoft Azure, Google Cloud Platform, AWS, Alibaba Cloud provide a persistent machine running in a server. These machines are very useful for tasks like data storage or edge computing as they are fully maintained and we don't have to rely on our local machine's resources.

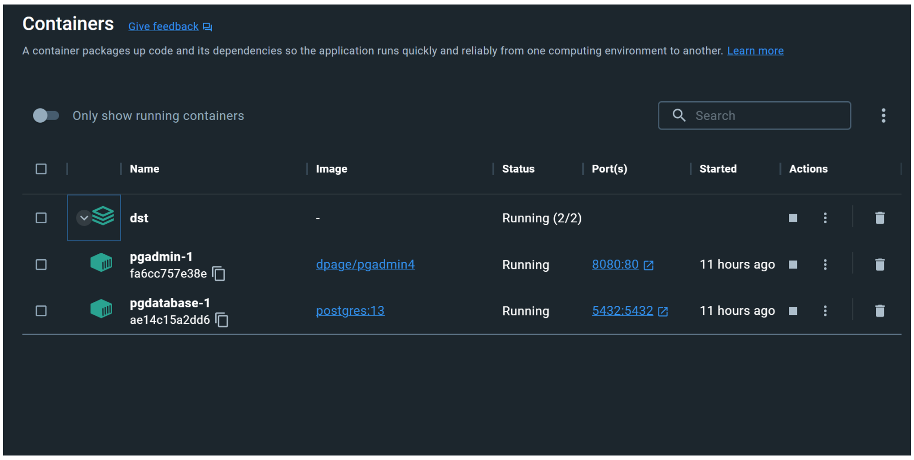
These services are generally aimed at larger organisations as it is much more convenient for them to deploy to a cloud instance than set up their own servers. However, These services can also be very useful for home users who may not have/may not have an incentive to permanently invest in powerful enough hardware that can perform reliable and continuous computation.

3.2 Creating a cloud instance on Azure

Of the popular Cloud Service Providers in 2, we decided to go with Microsoft Azure as it provides a $100 credit to Students enrolled in an accredited institute without the need of any credit card.

To get started with Azure, we created a Microsoft Azure account and started a Cloud Virtual Machine 3

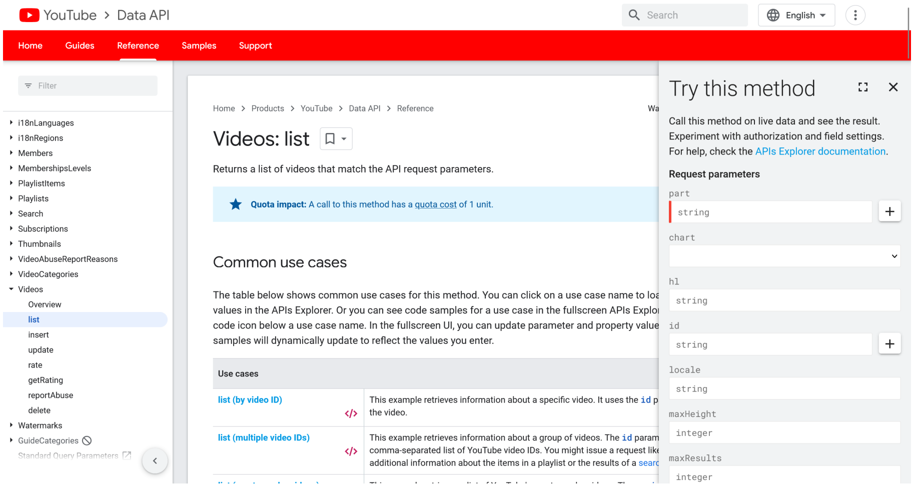
This enabled us to control a virtual machine with 2 Compute cores and 4 GiB of RAM



A container packages up code and its dependencies so the application runs quickly and reliably from one computing environment to another. Learn more

□	Name	Image	Status	Port(s)	Started	Actions
□	dst	-	Running (2/2)			
□	pgadmin-1 fa6cc757e38e	dpage/pgadmin4	Running	8080:80	11 hours ago	
□	pgdatabase-1 ae14c15a2dd6	postgres:13	Running	5432:5432	11 hours ago	

Figure 4: Running docker containers on local machine.



Videos: list

Returns a list of videos that match the API request parameters.

★ **Quota impact:** A call to this method has a quota cost of 1 unit.

Common use cases

The table below shows common use cases for this method. You can click on a use case name to loa
values in the APIs Explorer. Or you can see code samples for a use case in the fullscreen APIs Explo
code icon below a use case name. In the fullscreen UI, you can update parameter and property value
samples will dynamically update to reflect the values you enter.

Use cases	
list (by video ID) </>	This example retrieves information about a specific video. It uses the id p the video.
list (multiple video IDs) </>	This example retrieves information about a group of videos. The id param comma-separated list of YouTube video IDs. You might issue a request like additional information about the items in a playlist or the results of a searc

Try this method

Call this method on live data and see the result.
Experiment with authorization and field settings.
For help, check the APIs Explorer documentation.

Request parameters

part
string

chart

hl
string

id
string

locale
string

maxHeight
integer

maxResults
integer

Figure 5: Youtube Data API v3.

3.3 Create a Docker Container to Host PostgreSQL server

Next step was to start a PostgreSQL server on the created VM. Instead of directly running the PostgreSQL server instance, we checked and monitored its use and performance on our local machine, then to ensure identical behaviour we set up a docker container and deployed that container on the cloud instance.

Docker is a powerful tool used to create isolated systems which allows the user to test their products without any fear of outside intervention/hard to their hardware.

Docker containers, in practice works exactly the same as isolated virtual machines, but a big difference between virtual machines and Docker containers is that docker containers are much quicker to deploy and scale.

4 Interfacing with Youtube API

4.1 Introduction

Yotube API is a part of a multitude of freely available services under Google APIs. Google APIs documentation and reference is very well documented and easy to use. To learn more Google API explorer

4.2 Youtube API

To get started with YouTube API, refer to youtueb api v3 reference

Particularly for Trending videos the API query will look like:

```
request = youtube.videos().list(
    part="snippet,statistics",
    chart="mostPopular",
    regionCode=country_code,
    maxResults=50,
)
response = request.execute()
```

And the response will look like:

```
{
  "kind": "youtube#videoListResponse",
  "etag": etag,
  "nextPageToken": string,
  "prevPageToken": string,
  "pageInfo": {
    "totalResults": integer,
    "resultsPerPage": integer
  },
  "items": [
    video Resource
  ]
}
```

We Also query the the Youtube Video Categories index, which contains the snippet names and category numbers of all the video Categories.

This index can be directly joined with Video List response to get the category name of any given video
Category response query:

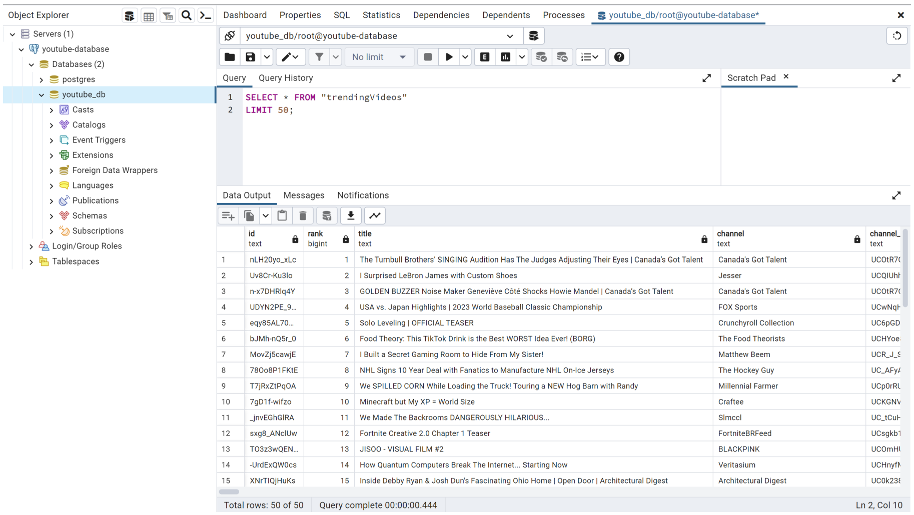
```
def get_video_categories(country_code):
    request = youtube.videoCategories().list(
        part="snippet",
        regionCode=country_code
    )
    return request.execute()
```

Category Response:

```
{
  "kind": "youtube#videoCategoryListResponse",
  "etag": etag,
  "nextPageToken": string,
  "prevPageToken": string,
  "pageInfo": {
    "totalResults": integer,
    "resultsPerPage": integer
  },
  "items": [
    videoCategory resource
  ]
}
```

5 Uploading Data to Cloud Storage

Finally after extracting data we upload the data to the PostgreSQL server in Microsoft Azure using Pandas and SQLalchemy module of python with pyscopg2 binding for SQLalchemy. This packages can be downloaded directly from Python Package Index.
We also use the historical data collected by Rishav Sharma and upload it to the cloud database too.
Due to bandwidth limits and large size of Data, it takes upto 30 mins to upload all the data



```
SELECT * FROM "trendingVideos"
LIMIT 50;
```

	id text	rank bigint	title text	channel text	channel_ text
1	nLH20yo_xLc	1	The Turnbull Brothers' SINGING Audition Has The Judges Adjusting Their Eyes | Canada's Got Talent	Canada's Got Talent	UCOtR7
2	Uv8Cr-Ku3lo	2	I Surprised LeBron James with Custom Shoes	Jesser	UCQIUh
3	n-x7DHRlq4Y	3	GOLDEN BUZZER Noise Maker Geneviève Côté Shocks Howie Mandel | Canada's Got Talent	Canada's Got Talent	UCOtR7
4	UDYN2PE_9...	4	USA vs. Japan Highlights | 2023 World Baseball Classic Championship	FOX Sports	UCwNqH
5	eqy85AL70...	5	Solo Leveling | OFFICIAL TEASER	Crunchyroll Collection	UC6pGD
6	bJMh-nQ5r_0	6	Food Theory: This TikTok Drink is the Best WORST Idea Ever! (BORG)	The Food Theorists	UCHYoe
7	MovZj5cawjE	7	I Built a Secret Gaming Room to Hide From My Sister!	Matthew Beem	UCR_J_S
8	78Oo8P1FKtE	8	NHL Signs 10 Year Deal with Fanatics to Manufacture NHL On-Ice Jerseys	The Hockey Guy	UC_AFyA
9	T7jRxZtPqOA	9	We SPILLED CORN While Loading the Truck! Touring a NEW Hog Barn with Randy	Millennial Farmer	UCp0rRU
10	7gD1f-wifzo	10	Minecraft but My XP = World Size	Craftee	UCKGNV
11	_jnvEGhGlRA	11	We Made The Backrooms DANGEROUSLY HILARIOUS...	Slmccl	UC_tCuH
12	sxg8_ANclUw	12	Fortnite Creative 2.0 Chapter 1 Teaser	FortniteBRFeed	UCsgkb1
13	TO3z3wQEN...	13	JISOO - VISUAL FILM #2	BLACKPINK	UCOmHU
14	-UrdExQW0cs	14	How Quantum Computers Break The Internet... Starting Now	Veritasium	UCHnyfN
15	XNrTIQjHuKs	15	Inside Debby Ryan & Josh Dun's Fascinating Ohio Home | Open Door | Architectural Digest	Architectural Digest	UC0k238

Total rows: 50 of 50 Query complete 00:00:00.444 Ln 2, Col 10

Figure 6: pgadmin connected to PostgreSQL server.

6 Analysis

6.1 Introduction

In this section we will work in a Jupyter notebook to draw insights and train a machine learning model using BERT on the stored database. Some of the packages and technologies we will use are:

1. Transformers model from Huggingface
2. Pytorch module for training our model
3. SQLalchemy for connecting to the database
4. Other common packages and modules including matplotlib, numpy, pandas, etc

6.2 Exploratory Data Analysis

We can very easily extract information regarding youtube usage patterns across different countries for the time period of our data as can be seen in fig 7.

We can see from the graph that the bumps in the views for some countries directly correspond to the lockdown restrictions imposed on those countries. We can also conclude that youtube is predominantly watched in English speaking countries because of the significant lower view counts for countries like Russia, Japan and France as compared to Great Britain, US and India.

We can also do analysis of which category of youtube videos are the most popular and thus generally tend to be on the youtube trending page. As can be seen in fig 8. We can also see from the same graph that alot of video categories do not have any trending videos at all, this is due to the discontinuation of these categories by youtube itself. These exist in the youtube data api solely for analysis of older youtube videos data.

Finally we can check the youtube channels with some of the highest number of days on the youtube trending page

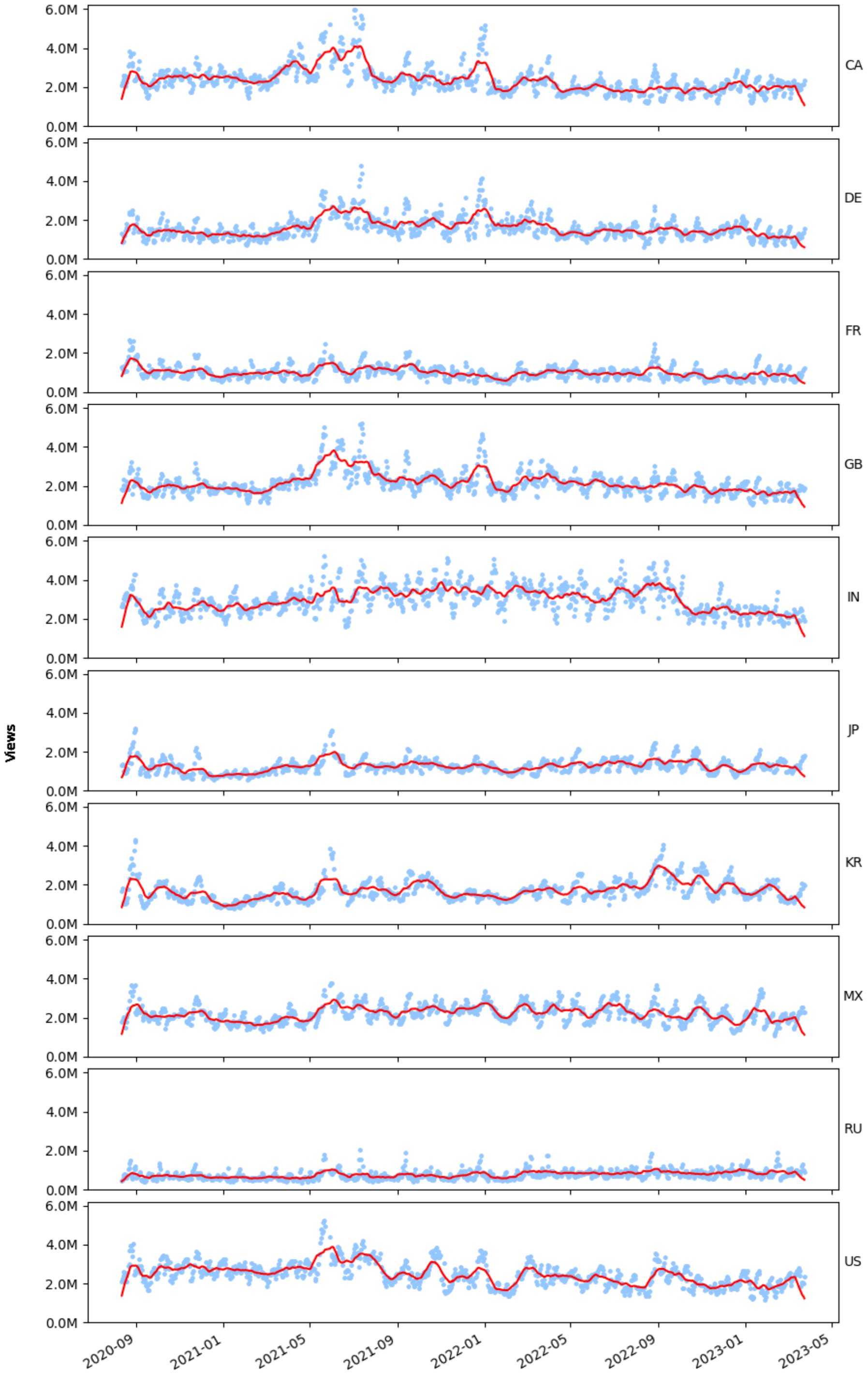


Figure 7: Trend of views per day per country.

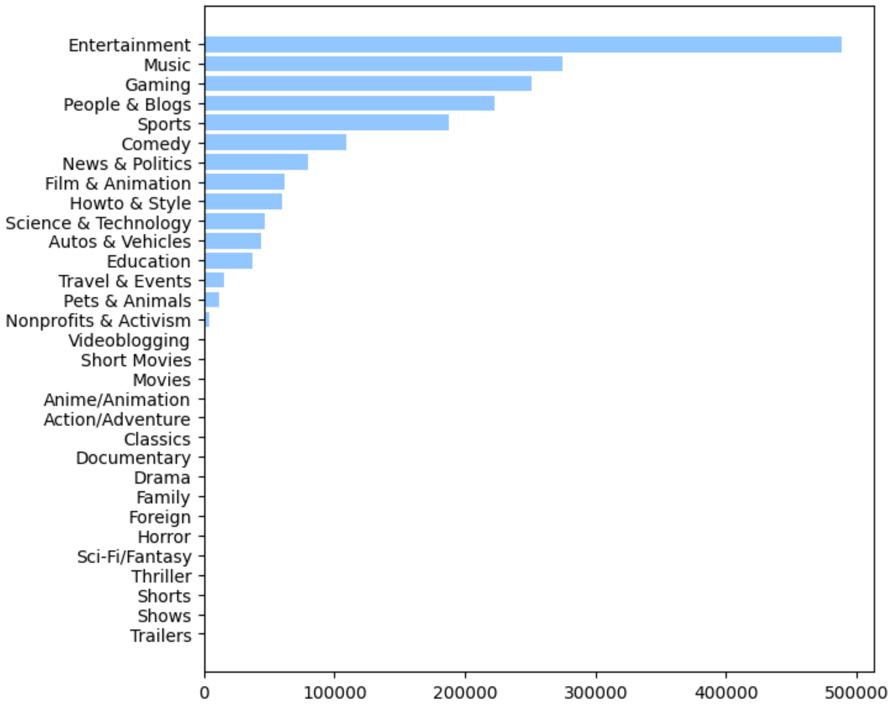


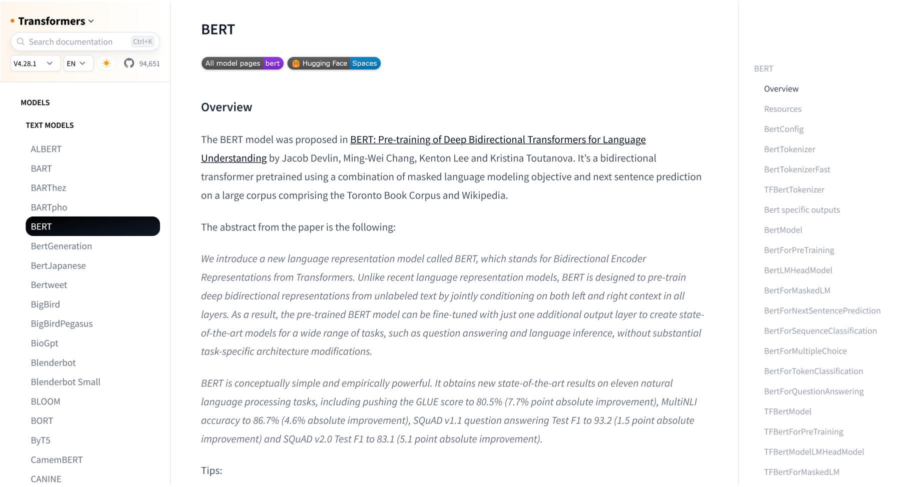
Figure 8: Frequency on the trending tab for different categories.

	channel	trending count	countries	avg views	avg rank
0	BANGTANTV	4312	10	1.096245e+07	106.921614
1	JYP Entertainment	3919	10	1.777034e+07	104.735647
2	SMTOWN	3868	10	1.800122e+07	101.823164
3	HYBE LABELS	3662	10	2.190246e+07	96.327417
4	FORMULA 1	3153	9	4.363194e+06	105.787187
5	NFL	2924	10	6.492250e+06	95.740766
6	東海オンエア	2717	1	1.836095e+06	75.396393
7	BLACKPINK	2701	10	3.475369e+07	94.876342
8	NBA	2578	9	2.223982e+06	101.742048
9	The United Stand	2437	4	3.471158e+05	96.193681
10	Clash of Clans	2421	10	5.883090e+06	99.887650
11	Apex Legends	2347	8	2.797414e+06	97.522795
12	Vijay Television	2245	1	2.411118e+06	84.974165
13	Mnet K-POP	2144	10	3.009970e+06	104.048041
14	MrBeast	2144	9	3.198041e+07	84.438433
15	BT Sport	2124	7	1.248324e+06	84.506121
16	Sky Sports Football	2120	5	8.593057e+05	72.044340
17	TUDN México	2092	6	1.220577e+06	90.370937
18	beIN SPORTS France	2056	5	5.657368e+05	86.535019
19	WWE	2028	8	2.397727e+06	106.636588

The table shows 20 of the most trending channels on youtube, we can infer from this table and from general knowledge, this is very different from the conventionally most subscribed channels on youtube. This is because of the fact that trending video count correlates directly with the number of uploaded videos for a channel.

For instance, the top entries in this table correspond to the very famous Korean pop music channels, whose music is enjoyed across all the countries/regions we have studied for, thus their trending videos count is cumulative across all these regions. Next we can see sports channels in this list which again are enjoyed across a wide location.

Both of these category of videos have in common the fact that their video upload frequency is relatively high and their videos remain on the trending page for multiple days if not weeks.



BERT

Overview

The BERT model was proposed in BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding by Jacob Devlin, Ming-Wei Chang, Kenton Lee and Kristina Toutanova. It's a bidirectional transformer pretrained using a combination of masked language modeling objective and next sentence prediction on a large corpus comprising the Toronto Book Corpus and Wikipedia.

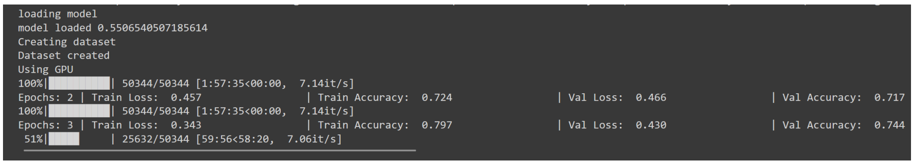
The abstract from the paper is the following:

We introduce a new language representation model called BERT, which stands for Bidirectional Encoder Representations from Transformers. Unlike recent language representation models, BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications.

BERT is conceptually simple and empirically powerful. It obtains new state-of-the-art results on eleven natural language processing tasks, including pushing the GLUE score to 80.5% (7.7% point absolute improvement), MultiNLI accuracy to 86.7% (4.6% absolute improvement), SQuAD v1.1 question answering Test F1 to 93.2 (1.5 point absolute improvement) and SQuAD v2.0 Test F1 to 83.1 (5.1 point absolute improvement).

Tips:

Figure 9: Huggingface BERT landing page.



```
loading model
model loaded 0.5506540507185614
Creating dataset
Dataset created
Using GPU
100%|██████████| 50344/50344 [1:57:35<00:00,  7.14it/s]
Epochs: 2 | Train Loss:  0.457                 | Train Accuracy:  0.724                 | Val Loss:  0.466                 | Val Accuracy:  0.717
100%|██████████| 50344/50344 [1:57:35<00:00,  7.14it/s]
Epochs: 3 | Train Loss:  0.343                 | Train Accuracy:  0.797                 | Val Loss:  0.430                 | Val Accuracy:  0.744
 51%|█████     | 25632/50344 [59:56<58:20,  7.06it/s]
```

Figure 10: Model trained for 3 epochs with accuracy of 74.4%.

6.3 Language Model using BERT

As we have seen, all youtube videos have a category tag associated with them which the video creator specifically chooses for their channel. Thus in practice this dataset can act as a hand labelled dataset for text calssification.

We try to find out whether there is any correlation between the title of a video and the category tag associated with it. If there is we will build a language model to generalize it.

For training this model, we use BERT(Bidirectional Encoder Representations from Transformers) multilingual (fig 9), which supports tokenization in 104 languages, since the nature of our data is by definition multilingual (across 10 countries) this is an appropriate model for us to use.

Our dataset contains upwards of 400k unique category labelled videos, training which requires a GPU, since we donot have access to a GPU we first tested training on CPU using an i7 12th gen processor.

For a sample dataset of only 500 videos, the training took 51 minutes to complete an epoch.

With GPU compute on google colab, we were able to train the model for 3 epochs to get a validation accuracy of 74.4%

7 Conclusion

The project achieved two major accomplishments:

1. The creation of a dataset of historic trending videos on YouTube, which can be used for various analytical purposes. The dataset was deployed on the Microsoft Azure cloud platform in a PostgreSQL database. This indicates that the project team was able to leverage cloud computing technology to store and manage large datasets, which can be accessed and analyzed from anywhere in the world with an internet connection.
2. We also created a language model that can identify the category of a video based solely on its title. It demonstrates the potential of natural language processing (NLP) techniques to automatically classify large amounts of text data. By automating the classification of video

categories, it may be possible to save time and resources that would otherwise be spent manually categorizing videos.

Overall, the project shows that by combining expertise in data management, cloud computing, and natural language processing, it is possible to create valuable insights from large and complex datasets

8 References

1. Majority Youtube trending videos data taken from Rishav Sharma who has been tracking youtube trending videos since 2020 - https://www.kaggle.com/datasets/rsrishav/youtube-trending-video-dataset

2. Hugging face BERT multilingual model - https://dblp.org/rec/journals/corr/abs-1810-04805.bib

3. DataTalksClub data engineering zoomcamp - https://youtube.com/playlist?list=PL3MmuxUbc_hJjEePXIdE-LVUx_1ZZjYGW

4. Microsoft Azure Virtual Machine introduction - https://learn.microsoft.com/en-us/azure/virtual-machines/