YouTube Trending Video

Data Engineering Capstone Project

Project Summary

The aims of this project is to build an etl pipeline on the daily record of the trending YouTube Videos. the end result is a star-schema model that gives us the possibility to explore and analyze the data in a multidimensional way.

YouTube maintains a list of the top trending videos on the platform. YouTube uses a combination of factors including measuring users interactions (number of views, shares, comments and likes). Note that they're not the most-viewed videos overall for the calendar year".

The source code is found at https://github.com/EngIcaro/YouTube-Trending.

Step 1: Scope the Project and Gather Data

Scope

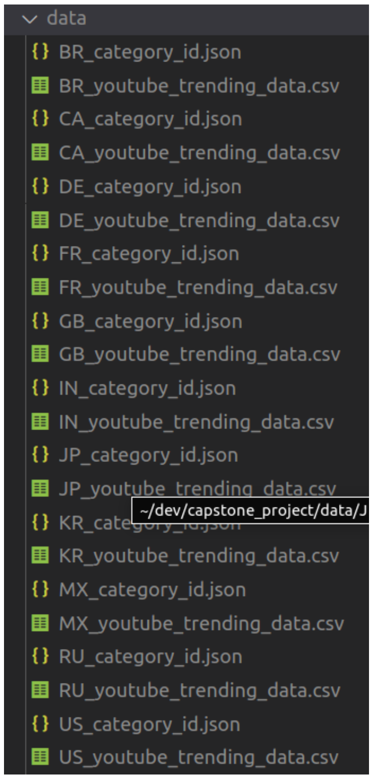
My plan was to extract the data from the .csv and .json sources, transform and clean all data to save in staging tables and finally build an olap cube for further analysis. All tables have been created in a local postgres database.

The dataset used in this project is (https://www.kaggle.com/datasets/rsrishav/youtube-trending-video-dataset?select=BR_youtube_trending_data.csv). This dataset includes several months of data on daily trending YouTube videos. Data is included for the IN, US, GB, DE, CA, FR, RU, BR, MX, KR, and JP regions (India, USA, Great Britain, Germany, Canada, France, Russia, Brazil, Mexico, South Korea, and, Japan respectively)

My end solution is a star schema in a postgres database. I used python, pandas, sql, postgres, docker and git.

Describe and Gather Data

The dataset consists of .csv and .json files. Each region's data is separate by .csv files and the .json files includes a caterogy_id and category_title which varies between regions.



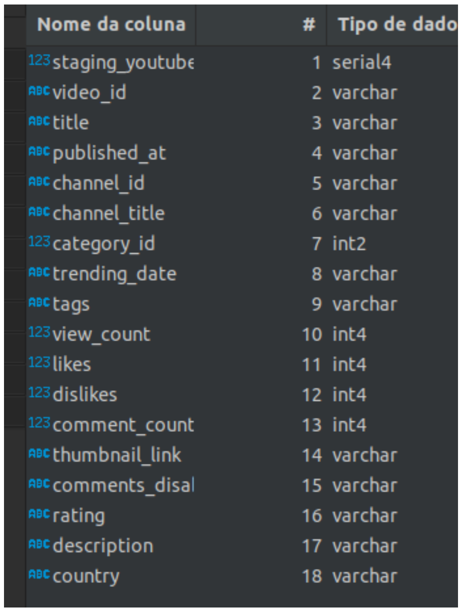
data
- BR_category_id.json
- BR_youtube_trending_data.csv
- CA_category_id.json
- CA_youtube_trending_data.csv
- DE_category_id.json
- DE_youtube_trending_data.csv
- FR_category_id.json
- FR_youtube_trending_data.csv
- GB_category_id.json
- GB_youtube_trending_data.csv
- IN_category_id.json
- IN_youtube_trending_data.csv
- JP_category_id.json
- JP_youtube_trending_data.csv
- KR_category_id.json
- KR_youtube_trending_data.csv
- MX_category_id.json
- MX_youtube_trending_data.csv
- RU_category_id.json
- RU_youtube_trending_data.csv
- US_category_id.json
- US_youtube_trending_data.csv

~/dev/capstone_project/data/J

The data come from The Kaggle DataSet (https://www.kaggle.com/datasets/rsrishav/youtube-trending-video-dataset?

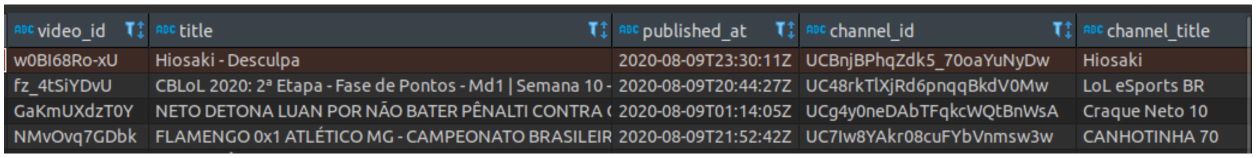
select=BR_youtube_trending_data.csv). Where This dataset was collected using the YouTube API(https://developers.google.com/youtube/v3).

The type of information included in *_youtube_trending_data.csv are :

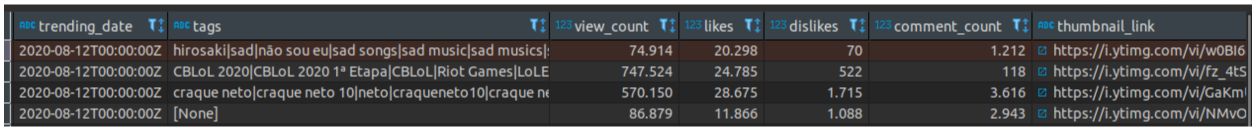


Nome da coluna	#	Tipo de dado
staging_youtube	1	serial4
video_id	2	varchar
title	3	varchar
published_at	4	varchar
channel_id	5	varchar
channel_title	6	varchar
category_id	7	int2
trending_date	8	varchar
tags	9	varchar
view_count	10	int4
likes	11	int4
dislikes	12	int4
comment_count	13	int4
thumbnail_link	14	varchar
comments_disal	15	varchar
rating	16	varchar
description	17	varchar
country	18	varchar

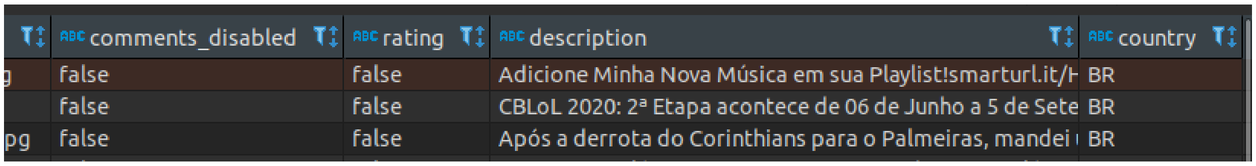
some *_youtube_trending_data.csv samples:



video_id	title	published_at	channel_id	channel_title
w0BI68Ro-xU	Hiosaki - Desculpa	2020-08-09T23:30:11Z	UCBnjBPhqZdk5_70oaYuNyDw	Hiosaki
fz_4tSiYDvU	CBLoL 2020: 2ª Etapa - Fase de Pontos - Md1 | Semana 10 -	2020-08-09T20:44:27Z	UC48rkTlXjRd6pnqqBkdV0Mw	LoL eSports BR
GaKmUXdzT0Y	NETO DETONA LUAN POR NÃO BATER PÊNALTI CONTRA (	2020-08-09T01:14:05Z	UCg4y0neDAbTFqkcWQtBnWsA	Craque Neto 10
NMvOvq7GDbk	FLAMENGO 0x1 ATLÉTICO MG - CAMPEONATO BRASILEIR	2020-08-09T21:52:42Z	UC7Iw8YAkr08cuFYbVnmsw3w	CANHOTINHA 70

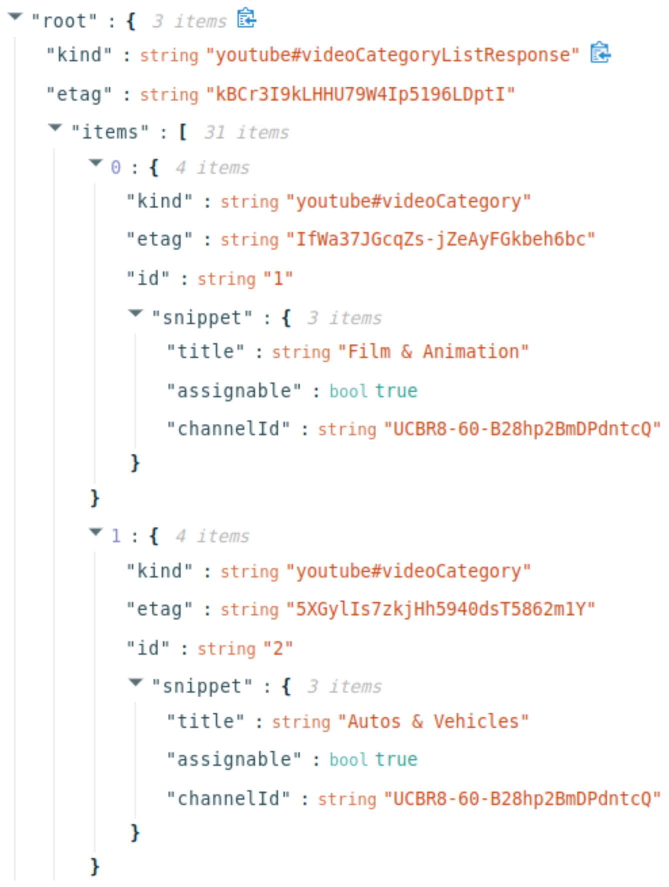


trending_date	tags	view_count	likes	dislikes	comment_count	thumbnail_link
2020-08-12T00:00:00Z	hirosaki|sad|não sou eu|sad songs|sad music|sad musics|	74.914	20.298	70	1.212	https://i.ytimg.com/vi/w0BI6
2020-08-12T00:00:00Z	CBLoL 2020|CBLoL 2020 1ª Etapa|CBLoL|Riot Games|LoLE	747.524	24.785	522	118	https://i.ytimg.com/vi/fz_4tS
2020-08-12T00:00:00Z	craque neto|craque neto 10|neto|craqueneto10|craque ne	570.150	28.675	1.715	3.616	https://i.ytimg.com/vi/GaKm
2020-08-12T00:00:00Z	[None]	86.879	11.866	1.088	2.943	https://i.ytimg.com/vi/NMvO



	comments_disabled	rating	description	country
g	false	false	Adicione Minha Nova Música em sua Playlist!smarturl.it/H	BR
	false	false	CBLoL 2020: 2ª Etapa acontece de 06 de Junho a 5 de Sete	BR
pg	false	false	Após a derrota do Corinthians para o Palmeiras, mandei	BR

The type of information included in *_category_id.json are :



```
▼ "root" : { 3 items
  "kind" : string "youtube#videoCategoryListResponse"
  "etag" : string "kBCr3I9kLHHU79W4Ip5196LDptI"
  ▼ "items" : [ 31 items
    ▼ 0 : { 4 items
      "kind" : string "youtube#videoCategory"
      "etag" : string "IfWa37JGcqZs-jZeAyFGkbeh6bc"
      "id" : string "1"
      ▼ "snippet" : { 3 items
        "title" : string "Film & Animation"
        "assignable" : bool true
        "channelId" : string "UCBR8-60-B28hp2BmDPdntcQ"
      }
    }
    ▼ 1 : { 4 items
      "kind" : string "youtube#videoCategory"
      "etag" : string "5XGylIs7zkjHh5940dsT5862m1Y"
      "id" : string "2"
      ▼ "snippet" : { 3 items
        "title" : string "Autos & Vehicles"
        "assignable" : bool true
        "channelId" : string "UCBR8-60-B28hp2BmDPdntcQ"
      }
    }
```

Step 2: Explore and Asses the Data

Explore the Data

To do this step i created a python script called eda.py. In this script i created a few functions to check nan values, check unique values and explore the data behavior.

```
def check_nan_values(data_base):
    """This function checks if any column has a nan values
    Args:
        data_base (dataframe): database
    """
    for column in data_base:
        print(column,' ', data_base[column].isnull().values.any())
        print(data_base[column].isnull().sum())
```

```
# All columns has repeted values
def check_unique_values(data_base):
    """This functions checks if any column has repeted values
    Args:
        data_base (dataframe): database
    """
    for column in data_base:
        values_list = data_base[column].value_counts().values
        for values in values_list:
            if values > 1:
                print(column, ' Has repeted values')
                break
```

```
def explore_data_base(data_base):
    """This functions explores some columns in the database
    Args:
        data_base (dataframe): database
    """

    print(data_base.info())

    print(data_base['view_count'].describe())
    print(max(data_base['view_count']))

    print(data_base['likes'].describe())
    print(max(data_base['likes']))
    print(data_base[data_base['likes'] == max(data_base['likes'])])

    print(data_base['dislikes'].describe())
    print(max(data_base['dislikes']))
    print(data_base[data_base['dislikes'] == max(data_base['dislikes'])])

    print(data_base['comment_count'].describe())
    print(max(data_base['comment_count']))
    print(data_base[data_base['comment_count'] == max(data_base['comment_count'])])

    print(data_base['thumbnail_link'].describe())

    print(data_base['comments_disabled'].describe())

    print(data_base['ratings_disabled'].describe())

    print(data_base['description'].describe())
```

Cleaning Steps

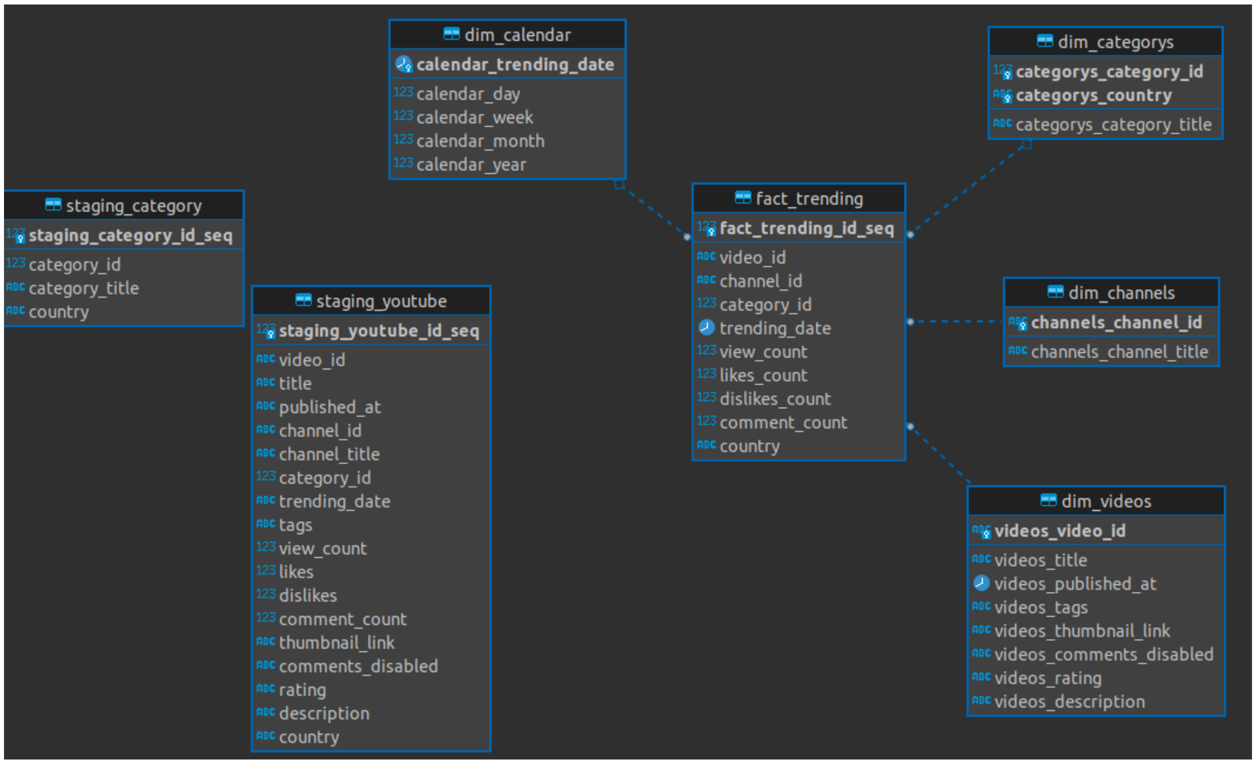
The step to clean the data are:

- Remove rows where ChannelTitle is nan (probably the channel has been removed)
- filter only category_id and category_title from category.json
- Get country by file name

Define the Data Model

Conceptual Data Model

I chose to create a staging area containing the two main sources of the already cleaned data and an area containing a multidimensional modeling of the data.



The multidumensional modeling was builded based on star schema. The star schema is composed of a single, central fact (trending) table that is surrounded by dimension tables (dim_categorys, dim_calendar, dim_videos, dim_channels). Among the main advantages we can mention: good response time, simplier queries, flexibility in the model, low complexity in the model.

another positive point is the possibility of enriching the data with new information. I think in the future to add more information through the youtube API

Mapping Out Data Pipelines

The Steps necessary to pipeline the data into the chosen data model are:

- Create youtube database in postgres

```
def create_database():

    """This function is responsible for creates and connects to the
       youtubedb. As also Returns the connection and cursor to
       youtubedb
    Returns:
        tuple[pg.cursor, pg.connection]: cursor and connection to
        youtubedb
    """
    #establishing the connection
    conn = pg.connect(
        database="postgres",user='postgres', password='postgres', host='localhost', port= '5432'
    )
    conn.autocommit = True
    cursor = conn.cursor()

    # create youtube database with UTF8
    cursor.execute("DROP DATABASE IF EXISTS youtubedb")
    cursor.execute("CREATE DATABASE youtubedb WITH ENCODING 'utf8'")

    conn.close()

    conn = pg.connect(
        database="youtubedb",user='postgres', password='postgres', host='localhost', port= '5432'
    )

    cursor = conn.cursor()
    conn.autocommit = True

    # close connection to default database
    return cursor, conn
```

- Drop pre-existing tables

```
def drop_tables(cur):
    """This function is responsible for dropping
    all tables in the youtubedb database
    Args:
        cur (_cursor): cursor to database session
    """
    for query in drop_table_queries:
        cur.execute(query)
```

- Create all tables

```
def create_tables(cur):
    """This function is responsible for creating all
    tables in the youtubedb
    Args:
        cur (_cursor): cursor to database session
    """
    for query in create_table_queries:
        cur.execute(query)
```

- Read and Clean the Data

```
     # get youtube trending_data
    data_base = read_trending_data("data/")
    # get category_data
    category_data = read_category_data("data/")
    # Remove nan rows of the trending_Data
    remove_nan_rows(data_base,['channelTitle'])
```

- Populating staging tables

```
    # insert youtube_tranding_data in db
    process_trending_data(cursor, data_base)
    # insert category_data in db
    process_category_data(cursor,category_data)
```

- Population Olap tables

```
    # insert olap tables
    insert_tables(cursor)
```

Run pipelines to Model Data

Create the data model

To build the data model I created the create_data_base.py script in which it performs the entire pipeline. this script uses as a base the queries created in the other script (sql_queries.py).

```
Python3 create_data_base.py
```

Data Quality Checks

to ensure that the entire process went as expected, I performed the data quality process in the final data modeling. I checked the integrity of the (unique key), relationships between the tables, number of unique identifiers are the same in the fact table and in the dimension tables.

below are some queries that I used to do the tests: (FOR MORE DETAILS VISIT sql_queries.py)

- Integrity constraints

```
SELECT COUNT(videos_video_id)
FROM public.dim_videos
where videos_video_id is null ;


select count(channels_channel_id)
from public.dim_channels
where channels_channel_id is null;


select count(categorys_category_id)
from public.dim_categorys
where categorys_category_id is null;

select count(calendar_trending_date)
from dim_calendar
where calendar_trending_date is null;
```

- Source/Count checks to ensure completeness

```
select
COUNT(videos_video_id) as CONT
from public.dim_videos;

# EQUAL TO

select
COUNT( distinct video_id) as CONT
from public.fact_trending;
```

```
select
COUNT(channels_channel_id) as CONT
from public.dim_channels;

# EQUAL TO

select
COUNT( distinct channel_id) as CONT
from public.fact_trending;
```

Data dictionary

Field	Description	source
video_id	unique video identifier	dim_videos
video_title	video title	dim_videos
videos_published_at	Video publication date	dim_videos
channels_channel_id	unique channel identifier	dim_channels
channels_channel_title	channel title	dim_channels
categorys_category_id	Channel category identifier	dim_categorys
trending_date	data that was trending videos	fact_trending
videos_tags	videos tags	dim_videos
view_count	number of views on the vídeo	fact_trending
likes	number of likes on the vídeo	fact_trending
dislikes	number of dislikes on the vídeo	fact_trending
comment_count	number of comment on the vídeo	fact_trending
videos_thumbnail_link	link for thumbnail	dim_videos
videos_comments_disabled	boolean if comments is disabled	dim_videos
videos_rating	boolean for videos_rating	dim_videos
videos_description	video text description	dim_videos
country	channel country	fact_trending
categorys_category_title	channel title category	dim_categorys
calendar_day	trending day	dim_calendar
calendar_week	trending_week	dim_calendar
calendar_month	trending_month	dim_calendar
calendar_year	trending_year	dim_calendar

Complete Project Write Up

- Clearly state the rationale for the choice of tools and technologies for the project.
  Python: Python is an accessible language, Python's expansive library of open source data analysis tools, web frameworks, This versatility, along with its beginner-friendliness, has made it one of the most-used programming languages today.
  Postgres: Postgre has many features aimed to help developers build applications, administrators to protect data integrity and build fault-tolerant environments, and help

you manage your data no matter how big or small the dataset. In addition to being free and open sourcePostgreSQL is highly extensible.
Docker: Docker offers many other benefits besides this handy encapsulation, isolation, portability, and control. can use Docker to wrap up an application in such a way that its deployment and runtime issues—how to expose it on a network, how to manage its use of storage and memory and I/O, how to control access permissions—are handled outside of the application itself.

- Propose how often the data should be updated and why.
  Data will be updated once a day, because Trending helps viewers see what's happening on YouTube and in the world. Trending isn't personalized and displays the same list of trending videos to all viewers in the same country. Amongst the many great new videos on YouTube on any given day, Trending can only show a limited number.
- Write a description of how you would approach the problem differently under the following scenarios
  - **The data was increased by 100x:** would use apache spark because of its speed, performance and advanced analytics.If it continues to perform poorly, I would use a distributed data cluster like aws EMR
  - **The data populates a dashboard that must be updated on a daily basis by 7am every day.**

    Would Use Airflow to create a DAG and schedule interval(every day at 7am) for each DAG, which determines exactly when my pipeline is run and update dashboard.
  - **The database needed to be accessed by 100+ people.**

    Would use AWS Redshift becasuse it can handle up to 500 connections