Analysing Toxicity in Formula 1 Fandom - Computational Analysis of Communications Final

Author: Leon Knorr

Matr-Nr: 1902854

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Introduction

Formula 1 is the highest class of international racing for open-wheel single-seater formula racing cars and is generally considered the most competitive, fastest and hardest class of motor racing. Since it's first season in 1950, Formula 1 is visiting a diverse list of many different countries, where the best drivers in the world are racing against each other in teams of two drivers to determine the best driver and the best team on the Formula 1 grid (Lowrey, 2019). These events are visited by thousands of Fans, with millions more following them on television and social media. With the 2021 season being one of the closest and most entertaining seasons in the history of Formula 1, where Red Bulls Max Verstappen beat Mercedes driver Lewis Hamilton in the grand finale of the season under controversial circumstances after a full season of controversy, drama and intense on track battles and with the release of Netflix Drive To Survive, Formula 1s popularity is growing rapidly. But, reports of Toxic and abusive Fan behavior at events and in comment sections on social media are accumulating, and casts an ugly shadow over Formula 1s latest successes (Woodhouse, 2022). As the reports over toxic and abusive fan behaviours in social media and at live events are rising, Formula 1 as well as Fans and drivers are taking a stand against toxicity in the Formula 1 community. However, an independent and scientific analysis of this topic is missing and therefore the accusations are sort of hanging in the air without a solid scientific foundation. Therefore, in order to tackle this problem research into the toxicity of Formula 1 fandom is a necassety to gain valuable insights into understanding the problem, where it originates from and to build a foundation for future measures to make attending Formula 1 events as well as the media around it a safer and more enjoyable experience. To take the first step into this direction, this thesis will analyse Youtube comments of the Formula 1 channel in order to determine:

- If the Formula 1 fandom is toxic
- Has Toxicity risen over the years?
- Is the toxicity a "self-made" problem of Formula 1 and where is the toxicity originating from?

Fundamentals

In this chapter the necessary fundamental knowledge is presented.

Formula 1

Formula 1 is the worlds most prestigous motor racing competition, as well as the world's most popular annual sporting series (Lowrey, 2019). It marks the highest class of international open-wheel single-seater formula racing. The first Formula 1 competition was held in 1950, since then the competiton for the world drivers championship (wdc) which determines the worlds best driver and the world constructors championship (wcc) which determines the best team, is held annualy and is sanctioned by the Fédération Internationale de l'Automobile (FIA). During the competition (also called a season), Formula 1 visits a variety of different countries and racing tracks, each event (Grands Prix) is attended by thousands of people with millions watching from home ("Formula One," 2023). All rights of the Formula 1 brand and the competition itself is owned by Formula One World Championship Limited, which is a corporation, that provides media distribution and promotion services, besides that, it controls the contracts, distribtution, and commercial management of rights and licenses of formula 1 (*Formula One World Championship Ltd - Company Profile and News - Bloomberg Markets*, n.d.). The term Formula 1 is used to describe the corporation, as well as the competition, as they can't exist without each other.

What is Fandom

According to Cornel Sandvoss Fandom is a community of people that are regularly, consuming a given popular narrative or text with great emotional involvement ("What Is Toxic Fandom?" n.d.). The members of the community are called fans, which is a short form of "fanatic" (Arouh, 2020). In other words, a fandom is a community of people that are fanatic about a popular narrative or text such as a tv series, movie franchise or sports.

Becoming a fan starts with the adoption of a fan identity about a fan object, thus fandom can be a powerful of defining the self. The fan object can be anything that people can be fanatic about, this may be a simple object such as trains or a virtual asset such as a movie franchise. Therefore, by taking part in a fandom, people are expressing themselfs through an identity they've chosen for themselfs. As a result, fans may lead to see the fan object as an extension of themselfs and thus react personally threatened if the fan object is facing a threat such as accusations etc ("What Is Toxic Fandom?" n.d.). In addition to creating a strong part of their own identity, fans feel more connected or socialised through their fandom, as studies indicate, that even if fans don't interact with other members of a fan community, they still perceive themselfs as part of that community. Because of that, fans not only become personally invested in their fandom, they become socially invested as well ("What Is Toxic Fandom?" n.d.).

As a result of the strong connection fans build up to their fan object, the time-frame in which this self identity has been chosen is also playing a role. As an example, many people build a fandom in their childhood about a tv series, franchise or sport, this often leads to them feeling entitled to having their fan object preserved as they deem acceptable. This behaviour is also called fan entitlement. A good example for this behaviour are the news movies and series in the Lord of the Rings and Star Wars franchises, as most fan communities of these franchises have been outraged about the new characters and story lines, where many people claimed that this "ruined their childhood" ("What Is Toxic Fandom?" n.d.).

From an economic point of view, fandom and fan cultures are seen as the ideal costumers. They are eager to get their hands on the newest products and they are stable with re-occuring purchases, since intense consumption is considered a part of the fan identity (Arouh, 2020).

Defining Toxic Fan behaviour

In the first place, toxic fandom is a buzzword, that is widely used throughout media to describe or identify fans who engage in behaviors that are considered negative or unaccaptable. This behavior can range from simple negative responses to bullying other members of a fandom or those involved in the creation of the fan object ("What Is Toxic Fandom?" n.d.). Most of this behaviour can be observed online in social media, there are however reports of toxic behaviour in real-life as well, such as abusive behaviour at events.

The word toxic itself however is defined as "of relating to, or caused by a toxin," "of the nature of a poison; poisonous" (Arouh, 2020). This definition originally originates from medival latin, where it refers to poisoned arrows or to being imbued with poison. Following this definition, it is an *external* substance that is toxic and not a person or their behaviour. However in recent years the understanding of this definition has shifted, today someones actions or the emotions experienced or types of character are now understood as poisonous or "toxic" (Arouh, 2020). This definition is closely related to the definition of the word fan, as explained earlier, fan originates from fanatic, which is traditionally linked to madness and demonic posession. This traditional and long obselete link is often exploited by media outlets to mark fans as psychopaths whose frustrated fantasies of intimate relationships or unsatisfied desires with the fan object take violent and ant-social forms (Arouh, 2020). In order to maintain this hypothesis, media often picks the most miserable and negative or “click-bait” examples of fan behaviour, as it creates the most attention and keeps the viewing figures high (Arouh, 2020), (Proctor & Kies, 2018). These circumstances are additionally amplified by social media plattforms, as they promote toxic behaviour, because it usually creates a lot of interactions. Therefore, it is our overall understanding of what a fan is that marks a him as a toxic “other”.

What is also observed, is that “toxic” fans often fall back to racist and mysogenistic behaviour compared with hate speech in order to defend their fan object or view point. This often comes with a feeling of “power loss” for the “toxic fan”. Because of that, current social-, ideological- and political conflicts are becoming more and more frequent as a topic in toxic behaviour (Proctor & Kies, 2018), (Arouh, 2020), (“What Is Toxic Fandom?” n.d.). For some members of the fan communities, this feeling of power loss is amplified by current political circumstances where they feel a feeling of disempowerment at their loss of priviliged status in society because of gender discussions or woman rights movements. Thus toxic fans are often painted as angry white, heterosexual men or members of the “alt-right” community. However in many cases, fan communities are used as a plattform to spread this hatered or ideological ideas because it creates a lot of attention in social networks as well as from the media. The media then progresses to paint fandom and online culture as more and more toxic because it creates “maximum cultural penetration” (Proctor & Kies, 2018). This trend has led to the phenomenon of *progressive toxicity*, where other fans “rush to prove one’s moral superiority by speaking out against some racist, sexist or otherwise hurtful sentiment, the sentiment is often amplified on a scale that wouldn’t have been possible had people not taken the bait” (Proctor & Kies, 2018). This rush to prove morally better than the toxic other often leads to toxic behavior by the defender itself. Because of that, toxic practices more and more frequently are instantiations of larger political or cultural polarizations and they depict the current socio-political climate. Thus toxic fan behaviour is often observed as a conlflict between the “political correct” pro-diversity crowd, which are also called social justice warriors (SJWs) and the members of the so-called “alt-right” hell-bent (Proctor & Kies, 2018).

However toxic fan behaviour is not limited to racist, misogynistic comments that can also include hate-speech. Some toxic fan are even going as far as to writing death or rape threats, doxing people (doxing refers to leaking personal information online) or to show abusive and harassing behaviour in public against other groups (Proctor & Kies, 2018), (Arouh, 2020).

The Dataset

The dataset that will be used throughout this thesis consists of 40200 Comments with replys from 500 youtube videos that were uploaded since 2020 of the formula 1 youtube channel. To obtain this data, the Youtube API V3 was used.

First up, the API has to be initialised, for this an api key is needed, that has to be stored in a .env file in the same directory as the jupyter notebook. This api key is then read in the following code cell and the youtube api is initialized through googles official googleapiclient library.

```
from dotenv import dotenv_values
import googleapiclient.discovery
import pandas as pd

api_keys = dotenv_values("keys.env")
api_service_name = "youtube"
api_version = "v3"
api_key = api_keys["YOUTUBE_API_KEY"]
max_results = 1000
youtube_api = googleapiclient.discovery.build(api_service_name, api_version, developerKey =
```

Now request to the Youtube API V3 can be made. Before we can scrape comments, the video id of the video that comments want to be obtain from is needed. Therefore, data about all videos since 2020 until now are requested. However the api will only retrieve 50 items per request, if there are more items that fit the search query the response is paged and contains a *nextPageToken*, that can be used to obtain the next 50 items. Requesting all videos since 2020 allows the dataset to span a timeframe of three years and will allow to analyze toxicity over time as well and will also paint a broader picture of how the F1 fandom developed. After obtaining all video information, the video ids are extracted and safed into a list, which is used later to obtain the actual comment threads.

```
Formula1_official_channel = youtube_api.channels().list(part='snippet' ,forUsername='Formula
videos_after_2020 = youtube_api.search().list(channelId=Formula1_official_channel["id"],
        maxResults=max_results,
        publishedAfter="2020-01-01T00:00:00Z",
        part='id').execute()
video_ids_after_2020 = [item['id']['videoId'] for item in videos_after_2020['items']]
while len(video_ids_after_2020) < max_results and "nextPageToken" in videos_after_2020.keys(
        videos_after_2020 = youtube_api.search().list(channelId=Formula1_official_channel["i
        maxResults=max_results,
        publishedAfter="2020-01-01T00:00:00Z",
        part='id',
        pageToken=videos_after_2020["nextPageToken"]).execute()
        video_ids_after_2020 = video_ids_after_2020 + [item['id']['videoId'] for item in vid
```

Besides the list of video ids, the data is also parsed into a dataframe. This allows to take general video information such as like count, video title, the overall comment count etc. into consideration for the final analysis.

```
df_list = []
for video_id in video_ids_after_2020:
    video_data = youtube_api.videos().list(part='snippet, statistics', id=video_id).execute(
```

```
    snippet = video_data['items'][0]['snippet']
    statistics = video_data['items'][0]['statistics']
    df_list.append(
    {
        "video_id":video_id,
        "title": snippet['title'],
        "description": snippet['description'],
        "channel": snippet['channelTitle'],
        "published_at": snippet['publishedAt'],
        "tags": snippet['tags'] if "tags" in snippet.keys() else None,
        "like_count": statistics['likeCount'],
        "favorite_count": statistics['favoriteCount'],
        "comment_count": statistics['commentCount'] if "commentCount" in statistics.keys() e
    })

videos = pd.DataFrame(df_list)
videos
```

Now that all the necessary video information has been obtained, the actual comments and replys can be requested. In order to achieve this, for every video id that has been retrieved earlier, a list of 15 comment threads is requested. Every comment thread consists of a topcomment, that has a number of replys associated with it. Because of the maximum quota of 10000 request units per day, for each video only 15 comments can be obtained, as each comment request costs one unit, for all 500 videos for 15 commenthreads per video, a quota usage of 7500 applies. Now for each retrieved top comment a maximum of 10 replies are requested. The corresponding data, is then parsed into one large dataframe, that contains the comment text as well as administrative information like the video id as well as the comment id and further useful information like the number of likes a comment / reply has or the publishing date. This additional information allows to further reason about the amount of interaction the particular comment got.

```
df_list_comments = []
for video_id in video_ids_after_2020:
    if videos.loc[videos['video_id'] == video_id].comment_count.iloc[0] == 0:
        continue
    top_level_comments = youtube_api.commentThreads().list(part="snippet",
        maxResults=15,
        order="relevance",
        videoId=video_id).execute()['items']
    for top_level_comment in top_level_comments:
        replies = youtube_api.comments().list(part="snippet",
            maxResults=10,
            parentId=top_level_comment['snippet']['topLevelComment']['id']).execute()['items
        df_list_comments.append(
        {
```

```
                "video_id": video_id,
                "id": top_level_comment['snippet']['topLevelComment']['id'],
                "text": top_level_comment['snippet']['topLevelComment']['snippet']['textDisplay'
                "user": top_level_comment['snippet']['topLevelComment']['snippet']['authorChanne
                "like_count": top_level_comment['snippet']['topLevelComment']['snippet']['likeCo
                "published_at": top_level_comment['snippet']['topLevelComment']['snippet']['publ
                "reply_count": top_level_comment['snippet']['totalReplyCount']
            })
            for reply in replies:
                df_list_comments.append(
                {
                    "video_id": video_id,
                    "id": reply['id'],
                    "text": reply['snippet']['textDisplay'],
                    "user": reply['snippet']['authorChannelId']['value'],
                    "like_count": reply['snippet']['likeCount'],
                    "published_at": reply['snippet']['publishedAt'],
                    "reply_count": 0
                })

comment_df: pd.DataFrame = pd.DataFrame(df_list_comments)
comment_df
```

Last but not least the dataset is saved into a “pickle” file, which allows efficient storage of dataframes. This is especially useful if the notebook has to be restarted because the dataset doesn't has to be build from scratch and no quota or api access is required to perform analysis on the dataset.

```
videos.to_pickle("datasets/video_data.pkl")
comment_df.to_pickle("datasets/comment_data.pkl")
```

```
videos: pd.DataFrame = pd.read_pickle("datasets/video_data.pkl")
comment_df: pd.DataFrame = pd.read_pickle("datasets/comment_data.pkl")
```

```
videos
```

Dataset limitations

Because of the quoate limit google has set for the youtube api, the dataset is only depicting a small section of the actual circumstances in the Formula 1 fandom. For example, for one video, a maximum of $15 * 10 = 150$ comments will be retrieved.

```
videos.comment_count = videos.comment_count.astype(int)
videos.comment_count.mean()
```

However, on average a video has 1250 comments. Thus a lot of fan interaction will be missed and is not included in this dataset. In addition to that, the dataset only uses the Youtube API as a source, however Formula 1 fandom spans over multiple platforms, especially Twitter, Instagram and Reddit. Thus it is possible that depending on the plattform toxic user interactions may be more frequent as they are governed differently. Also, as Formula 1 is an international sport, comments may not be in english, the dataset therefore must be considered multilingual, which can be problematic depending on the methods used. Nevertheless the dataset spans over a total of 40200 comments that can be analysed.

Dictionary Analysis

As the first method to analyze the dataset, a dictionary analysis is performed. For this, the following three different online available dictionaries are used:

- Othrus Lexicon for Toxicity (Orthrus-Lexicon, 2022), to classify toxic texts directly
- the Grievance Dictionary (Vegt et al., 2021), to classify different categories of negative or unacceptable behaviour
- a dictionary of ethnic slurs based of wikipedia ("List of Ethnic Slurs," 2023), to find toxic behaviour based on racism

In order to achieve a fast and reusable way of analysing comments with any of the given dictionaries, each dictionary and comment text will be represented as a set. Between those two sets, the set intersection is computed, which contains all words that are found in the dictionary and in the comment text. Thus it essentially checks for word occurence. The number of words from the dictionary is then added to the result dataframe. In addition to that, a global counter tracks the number of overall occurences of each dictionary word. This allows for the analysis of language biases or trends in Formula 1 fandom. This method is used for all given dictionaries.

```
import numpy as np
from collections import Counter
from typing import Tuple
from nltk import word_tokenize

def dictionary_analysis_over_set_intersection(dict_name: str, dict_set: set, data: pd.DataFr
    dict_word_counter: Counter = Counter()
    dict_word_count: list = []
    for row in data.text:
        dict_words_in_comment: set = set(word_tokenize(row)).intersection(dict_set)
        dict_word_counter.update(dict_words_in_comment)
        dict_word_count.append(len(dict_words_in_comment))
    data[f"{dict_name}_word_count"] = dict_word_count
    return data, dict_word_counter
```

Othrus-Lexicon for Toxicity

The Othrus-Lexicon for Toxicity is a dictionary containing words often used throughout the internet in toxic content (Orthrus-Lexicon, 2022). It contains about 1900 words that include slurs, insults and common internet abbreviations and obfuscations, such as “sh*t”, which are used to bypass automatic content moderation systems. Other then the Github page, nothing else can be found on the internet about this dictionary, therefore nothing is known about creation process or if and how the dictinoary has been validated. Nonetheless it will be used during this thesis to provide additional insights into the toxicity of Formula 1 fandom as it fits the topic perfectly but its results have to be treated with caution.

In order to use the Othrus-Lexicon for Toxicity, the dictionary has to be read from the provided “toxic_words.txt” text file and is then converted into a set. The set conversion will remove duplicates and ensures compatibility with the previously introduced method of set intersection for word occurence, which is used to analyse the dataset.

```
with open("dictionaries/toxic_words.txt") as toxic_words_file:
    set_of_toxic_words: set = set([word.strip() for word in toxic_words_file.readlines()])
set_of_toxic_words
```

```
comment_df, toxic_word_counter = dictionary_analysis_over_set_intersection(dict_name="toxic'
comment_df.loc[comment_df["toxic_word_count"] > 0]
```

```
toxic_word_counter
```

Grievance Dictionary

The Grievance Dictionary proposed by van der Vegt et. al. aims to provide a method to automatically understand language use in the context of grievance-fuelled violence threat assessement (Vegt et al., 2021). It has been created out of informed suggestions from experienced threat assesement practitioners in combination with subsequent humand and computational word list generation. The resulting dictionary includes 20502 words which were annotated by 2318 participants. In its validation process, it was applied to texts written by violent and non-violent individuals. The results showed strong evidence for a high classification performance (Vegt et al., 2021).

The dictionary itself is composed of multiple categories which depict different forms of grievance, for example jealousy or threat. Each category includes a number of word stems, annotated with weights, which indicate how important or meaningful the given word is for the category it is included in. There are two version of the dictionary available, one which includes words with weights of five or higher and one which includes words with weights of seven or higher. During this thesis the dictionary with weights higher than five will be used, as it can hypothetically cover more infrequent and domain specific words. The dictionary can support three different approaches to text classification (Vegt et al., 2021):

- **Proportional Scoring**: Proportional scoring or wordcount-based classification, calculates the proportion of grievance fueled words in the given texts. This proportion is then used as a classification measure.

- **Weight-based**: During this approach, the assigned word weights are used to obtain a weight average for each given text, which is used as the classification measure.
- **Word inclusion**: Word inclusion checks if and how often the given words from the dictionary are included in the text.

In order to be able to analyse the dataset with the grievance dictionary, all comment texts have to be stemmed. For that, the Porterstemmer, word_tokenize and TreebankWordDetokenizer from the natural language toolkit will be used. First, the comment dataset will be copied, this ensures, that the original texts won't be affected by the applied dictionary specific processing. Then, the text column will be manipulated through the swifter module, which ensures efficient and automatic parrallelization. During manipulation, the text is split up into tokens, then converted to its word stem by the Porterstemmer and detokenized by the TreebankWordDetokenizer. This process essentially converts the original text into the same text sequence but it is composed of word stems instead of the actual words.

```
from nltk.stem import PorterStemmer
from nltk import word_tokenize
from nltk import TreebankWordDetokenizer
import swifter

stemmer: PorterStemmer = PorterStemmer()
detokenizer: TreebankWordDetokenizer = TreebankWordDetokenizer()
stemmed_comments: pd.DataFrame = comment_df.copy()
stemmed_comments["text"] = stemmed_comments.text.swifter.apply(lambda text: detokenizer.deto
stemmed_comments
```

After preprocessing the dataset, the grievance dictionary can be loaded. As it is stored in a .csv file, the pandas read_csv function can be used to read the dictionary into memory. However, the csv includes a seperate unnamed index, which needs to be dropped.

```
from collections import defaultdict
from typing import Dict

grievance_dict_df = pd.read_csv("dictionaries/grievancedictionary/dictionary_versions/dictio
grievance_dict_df.drop(["Unnamed: 0"], axis=1, inplace=True)
categorys = grievance_dict_df.category.unique()
categorys
```

As the dictionary made up of several categories, a set for each dictionary category has to be created in order to ensure compatibility with the dictionary over set intersection function, that was presented earlier. Now for each category, the texts are analyzed using this method. However instead of saving one counter, that counts word occurences, a dictionary which stores each counter for its given category.

```
from tqdm import tqdm
grievance_set_dictionary: Dict[str, Counter] = defaultdict(Counter)
for category in tqdm(categorys):
    curr_category_set = set(grievance_dict_df.loc[grievance_dict_df.category == category].wo
    stemmed_comments, grievance_set_dictionary[category] = dictionary_analysis_over_set_inte
stemmed_comments
```

Last but not least, the results stored in the stemmed dataset needs to be merged into the original one using the pd.merge function.

```
comment_df = pd.merge(comment_df, stemmed_comments[["deadline_word_count", "desperation_word
       'grievance_word_count', 'hate_word_count', 'help_word_count', 'honour_word_count', 'i
       'loneliness_word_count', 'murder_word_count', 'paranoia_word_count', 'planning_word_c
       'soldier_word_count', 'suicide_word_count', 'surveillance_word_count', 'threat_word_c
       'weaponry_word_count']], left_index=True, right_index=True)
len(comment_df)
```

Ethnic Slurs

The third dictionary to be used has been created out of a scrape of the wikipedia page for ethnic slurs ("List of Ethnic Slurs," 2023). The page list all known ethnix slurs in alphabetical order, including their targets, meaning and origin. In order to scrape the website, the webbased tool wikitable2csv has been used. This tool allows the conversion of tables on wiki websites into .csv files. As Wikipedia lists every slur in alphabetical order with one table per letter, a total of 26 .csv files are created. Thus, in order to use the dictionary, all .csv files are in the directory are listed and loaded into their own dataframe, which are then concatinated to form one big dictionary of ethnic slurs.

```
from os import listdir
import os.path

dict_files: list = list(filter(lambda f: f[-4:] == ".csv" ,listdir("dictionaries/ethnic_slur
dict_df: pd.DataFrame = pd.DataFrame()
for file in dict_files:
    part = pd.read_csv(os.path.join("dictionaries/ethnic_slurs", file))
    dict_df = pd.concat([part, dict_df])
dict_df.reset_index(inplace=True, drop=True)
dict_df
```

Now, to be able to reuse the dictionary over set intersection method, the list of terms / slurs in the dictionary are converted into set and then passed onto the method alongside the comment dataset.

```
ethnic_slurs_set: set = set(dict_df.Term.to_list())
comment_df, ethnic_slurs_counter = dictionary_analysis_over_set_intersection(dict_name="ethn
comment_df.loc[comment_df["ethnic_slurs_word_count"] > 0]
```

```
ethnic_slurs_counter
```

After the dataset has been analysed with all three dictionaries, the resulting dataframe, that includes the dictionary word overlap counts per comment, is saved to disk. This allows for efficient reloading without the need of reexecution for the analysis of the acquired data.

```
comment_df.to_csv("datasets/comment_df_dicts.csv" ,index=False)
```

Transformer Classifiers

As the second method for analysing the dataset, two transformer based text classifiers are used. One which classifies the sentiment of a given comment by marking it positive or negative and one which classifies the comment as hate speech or not.

A Transformer is an attention based machine learning architecture, that is made of multiple layers of encoders and decoders. A given text is first transformed into a basic numerical representation, which is enriched with positional information. This representation also called encoding, is then passed on to the stack of n encoders, which compute an information rich embedding. This embedding represents the texts meaning, words and other metadata in multi-dimensional space. It is then injected into the decoder stack, which generates a new text sequence, based of already generated characters and the embedding from the encoders (Vaswani et al., 2017). Today, many variations of the original transformer architecture exist, some are only using the encoder stack, while others only use the decoder stack. The most well known variations are BERT (Bi-directional Encoder Representations for Transformers) and Open-AIs GPT (Generative Pre-Trained Transformer).

In order to use the dataset with transformer models, some pre-processing has to be applied. It consists of removing html or other structured script language content, links and anonymizing user mentions. In addition to cleaning the input texts, some comments have to be removed from the overall dataset, as they are either in a different language or consist of unreadable gibberish, which leads to issues while running some transformer models.

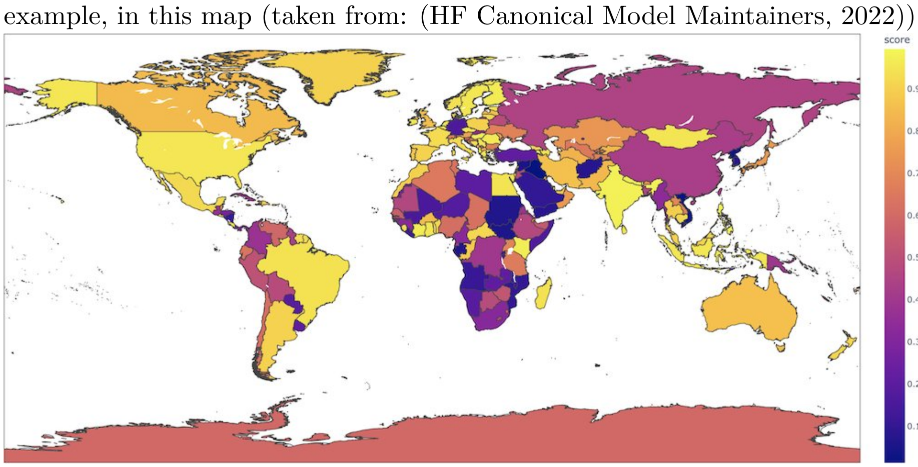
```
from transformers import AutoModelForSequenceClassification, AutoTokenizer, AutoConfig
import numpy as np
from scipy.special import softmax
import swifter
from bs4 import BeautifulSoup

def preprocess(text):
    new_text = []
    text = BeautifulSoup(text, "lxml").text
    for t in text.split(" "):
        t = '@user' if t.startswith('@') and len(t) > 1 else t
        t = 'http' if t.startswith('http') else t
        new_text.append(t)
```

```
    return " ".join(new_text)

# Delete unreadable comments that result in the models crashing
comment_df.drop([14603], inplace=True) # comment is full of random characters
comment_df.drop([27224, 27223], inplace=True) # comment is not in english
comment_df.reset_index(drop=True)

comment_df_for_transformers = comment_df.copy()
comment_df_for_transformers["text"] = comment_df_for_transformers.text.swifter.apply(lambda
comment_df_for_transformers
```

Sentiment

The first transformer model is used to classify the sentiment of a given comment into positive or negative. Even though this is not a direct classification of typical toxic behaviour like racism or hate speech as sorrow text will also be classified as negative, it still hints towards the overall sentiment inside Formula 1 fandom.

The text-classification transformer used in this thesis is the "distilbert-base-uncased-finetuned-sst-2-english" (HF Canonical Model Maintainers, 2022) model. It is a fine-tuned version of the "DistilBERT-base-uncased" on the SST-2 (Stanford Sentiment Treebank corpus) (Socher et al., 2013) for sentiment classification. The model has been validated on SST-2 as, well as on the GLUE (General Language Understanding Evaluation Benchmark)(Wang et al., 2019). On both Datasets, the model reaches scores over 0.9 (1 being the highest possible score) across the board, with scores around 0.98 in all metrics for sentiment classification (HF Canonical Model Maintainers, 2022). However it can only work with english text. Besides the proven classification performance, the model can produce biased predictions. As an example, in this map (taken from: (HF Canonical Model Maintainers, 2022)):



the prediction scores for producing a positive sentiment per *country name* are depicted. It can be observed, that the probabilisty vary drastically between different countries. It has been shown, that for the sentence "This film was filmed in COUNTRY”, “France” will produce a positive label with a probability of 0.89 but “Afghanistan” will only produce a positive label with a probability of 0.08, even though nothig in the text hinted at a semantic shift (HF Canonical Model Maintainers, 2022). As these kind of models are trained unsupervised, this is an unintentional side-effect. Nonetheless, the model is a powerful, reliable and well tested sentiment classifier and will thus be used during this thesis.

An alternative to the distilbert-base-uncased-finetuned-sst-2-english are models like the “cardiffnlp/twitter-roberta-base-sentiment-latest” (Barbieri et al., 2020) model, that has been trained to classifiy tweets this included working with emojis, irony, offensive language and hatespeech, which would in theory be a better fit for the domain of this research. However, the model has been shown to produce scores around 0.65 or lower, which is comparatively low for sentiment classification tasks. Besides that, no bias analysis has been done on the model or the train dataset (Barbieri et al., 2020), which poses a risk in using this model, especially as twitter has been shown to be a plattform that includes a lot of toxicity and hateful content [arouh_toxic_2020]. In addition to that, the tokenizer of the model has been trained without a truncation token ([TRUNC]), which is used to trim text sequences that are longer than the supported maximum length of the model. In the initial release, this hasn’t been a problem as the average tweet in the dataset is reported to be 100 tokens long, and the models maximum length is at 512 tokens. However, the Youtube comments included in the acquired dataset have often shown to produce longer sequences than 512 tokens and thus are in need to use the truncation token. But, using the truncation token produces a vocabulary length mismatch between the tokenizer and the model, which leads to the model crashing during processing.

In order to implement the distilbert-base-uncased-finetuned-sst-2-english the common “Huggingface”, also called “pytorch-transformers” library is used. It enables fast and easy access to hundreds of models available on the Huggingface model hub. First up, the tokenizer, config and model are initialized with the pre-trained weights available on the model hub for the distilbert-base-uncased-finetuned-sst-2-english model. Now every comment is fed sequentially into the model by first encoding it with the tokenizer and then passing the encoded input through the actual transformer model. This will return a tensor with classification information as well as further metadata. The classification data is extracted from the model und run through a softmax to obtain the actual prediction scores for the classes, which are represented by their vector positions. The vector is then sorted via an argsort to obtain the highest vector position, which is converted into the actual label. Both the score and the label are then appended to a score and label list, which are injected into the global data frame at the end of the processing loop.

```
from tqdm import tqdm

MODEL = "distilbert-base-uncased-finetuned-sst-2-english"
config = AutoConfig.from_pretrained(MODEL)
```

```
tokenizer = AutoTokenizer.from_pretrained(MODEL)

model = AutoModelForSequenceClassification.from_pretrained(MODEL)

label_list = []
score_list = []

for text in tqdm(comment_df_for_transformers.text.to_list()):
    encoded_input = tokenizer(text, return_tensors='pt', padding=True, truncation=True, max_
    output = model(**encoded_input)
    scores = output[0][0].detach().numpy()
    scores = softmax(scores)
    label_list.append(config.id2label[np.argsort(scores)[::-1][0]])
    score_list.append(max(scores))

comment_df["sentiment"] = label_list
comment_df["sentiment_score"] = score_list
comment_df

comment_df.to_csv("datasets/comment_df_sentiment_transformer.csv" ,index=False) # df cachin
```

Hate Speech

The second transformer classifier used during this thesis is the "Hate-speech-CNERG/dehatebert-mono-english" transformer. It aims to classify into hate speech containing texts and texts without hate speech (Aluru et al., 2020). As hate speech is part of content that is considered toxic, the classification results are a direct indicator if Formula 1 fandom is toxic or not.

The model is a derivative of the BERT transformer family and can only work with english texts (Aluru et al., 2020). It has been trained on a combined dataset from 6 publicly available hate speech datasets, which include examples from sources like Twitter and Stormfront. During validation and testing, the model achieved a score of 0.71, with that being the highest score reached over all models tested. It has been shown, that it performs best in high ressource settings, where the dataset has to contain more then 256 datapoints. During model development, Aluru et. al. conducted research into trying to understand based on which text fragments, the model makes it predictions. This research suggested, that the model is not heavily influenced by the presence of certain keywords, it rather looks for the context in which the words appear in (Aluru et al., 2020). Thus, verbs like hunt or expel are receiving higher attention values from the model, then a direct insult. However, the presence of a verb which could be bad is not enough to lead the model to classify text as hate, only if a verb is paired with an insult or a direct target or in other words if the context fits, the model will predict hateful content. As an example, "Mexicans are f**king great people" will be classified as non-hate even though it contains the word f**ck. However, "I f**king hate ni**ers!" will be classified as hate speech. In addition to that, the model can understand internet obscurtions in insults, such as “f**ck”. It can also connect text sequences to background knowledge, such that “6 million was not enough. Next time ovens will be the last of your concerns” will be classified as hate speech, even though no insult or direct attack was given (Aluru et al., 2020). The model however is able to understand the unmentioned target of the sequence in this case jews and that it relates to the crueltys during the holocaust in germany.

For the actual implementation, the same process as for the sentiment classifier is reused, as only the model id needs to be changed and model weights etc. will be loaded automatically.

```
MODEL = "Hate-speech-CNERG/dehatebert-mono-english"
tokenizer = AutoTokenizer.from_pretrained(MODEL)
config = AutoConfig.from_pretrained(MODEL)

model = AutoModelForSequenceClassification.from_pretrained(MODEL)

label_list = []
score_list = []

for text in tqdm(comment_df_for_transformers.text.to_list()):
    encoded_input = tokenizer(text, return_tensors='pt', padding=True, truncation=True, max_
    output = model(**encoded_input)
    scores = output[0][0].detach().numpy()
    scores = softmax(scores)
    label_list.append(config.id2label[np.argsort(scores)[::-1][0]])
    score_list.append(max(scores))

comment_df["hate_speech_label"] = label_list
comment_df["hate_speech_score"] = score_list
comment_df
```

```
comment_df.to_csv("datasets/comment_df_hate_speech_transformer.csv", index=False)
```

Results

In this chapter the the three research questions:

- Is Formula 1 Fandom Toxic?
- Has toxicity risen over the years?
- Is Toxicity in Formula 1 a self-made problem?

Will be answered.

Is Formula 1 Fandom Toxic?

In order to answer this question, the following figure, which shows the relative counts for indications of toxic behaviour across all comments in the dataset will be analyzed. With toxic indications beeing defined as evidence from the dictionary and transformer based analysis, that point to the possibility that a given comment is toxic. For example, if the dictionary analysis finds a toxic word from the toxic words dictionary, this is considered a toxic indication. The term of toxic indications for relative counts is defined as a binary variable, that is either true or false. Therefore, it does not matter how much evidence can be found in a comment in order to compute the relative counts. It only counts, that evidence has been found and then the comment is considered to include toxic indications.

```
import pandas as pd
comment_df_dictionarys = pd.read_csv("datasets/comment_df_dicts.csv")
comment_df_hate_speech = pd.read_csv("datasets/comment_df_hate_speech_transformer.csv")
comment_df_sentiment = pd.read_csv("datasets/comment_df_sentiment_transformer.csv")
videos: pd.DataFrame = pd.read_pickle("datasets/video_data.pkl")

print(len(comment_df_dictionarys))
print(len(comment_df_hate_speech))
print(len(comment_df_sentiment))

comment_df = pd.merge(comment_df_dictionarys, comment_df_hate_speech[["hate_speech_label", '
comment_df = pd.merge(comment_df, comment_df_sentiment[["sentiment", "sentiment_score"]], le
comment_df
```

```
import matplotlib.pyplot as plt
import swifter

relative_counts = []
columns = ['toxic_word_count', 'deadline_word_count',
       'desperation_word_count', 'fixation_word_count',
       'frustration_word_count', 'god_word_count', 'grievance_word_count',
       'hate_word_count', 'honour_word_count',
       'impostor_word_count', 'jealousy_word_count',
       'murder_word_count', 'paranoia_word_count',
       'soldier_word_count', 'suicide_word_count',
       'surveillance_word_count', 'threat_word_count', 'violence_word_count',
       'weaponry_word_count', 'ethnic_slurs_word_count', 'hate_speech_label', 'sentiment']

# calculate relative counts
for column in columns[:-2]:
    relative_count = (comment_df[column].swifter.progress_bar(False).apply(lambda c: 1 if c
    relative_counts.append(relative_count)

relative_counts.append((comment_df["hate_speech_label"].swifter.progress_bar(False).apply(la
relative_counts.append((comment_df["sentiment"].swifter.progress_bar(False).apply(lambda l:

relative_counts.append(pd.Series(relative_counts).mean())
```

```
columns.append("average_count")

ax = pd.DataFrame(
    {
        "relative_counts": relative_counts,
        "columns": columns
    }
).plot(kind="barh", x="columns", y="relative_counts", figsize=(15,12), xlabel="%", title="Re
ax = ax.bar_label(ax.containers[0])
```

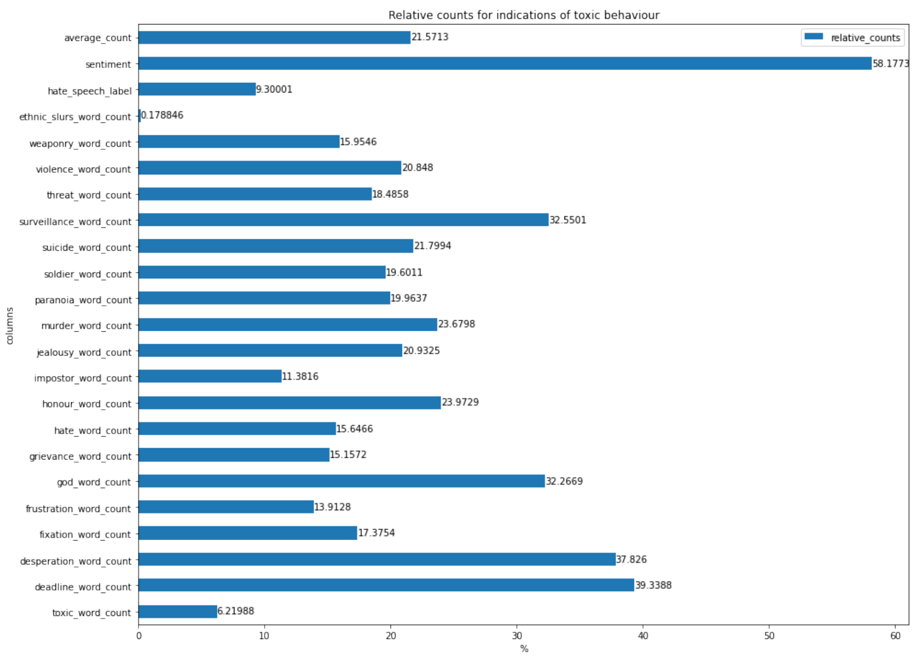


Figure 1: png

As shown in the plot, on average across all categorys tested, with all tests being weighted equally, 21% of all comments show indications for toxic behaviour. However, if the figure is broken down to the individual categories, each test paints a different picture. The tests, that can directly detect parts of toxic behaviour such as hate speech, ethnic slurs to detect racism and the toxicity dictionary all show low percentages of comments that actually contain these direct indications. 9% of comments have been flagged as hate speech, 0.1 % of comments contain ethnic slurs directly and 6% of comments contain toxic words. Therefore, the fraction of comments with direct evidence for toxic behaviour is really low, especially in terms of containing racism. However, the results for the categories of the grievance dictionary are much higher, ranging from 11% for impostor words and up to 39% for words in the deadline category. The grievance dictionary showed an especially high occurence for words regarding, surveillance, god, desperation and frustration. Which is in the context of the sport not suprising, as Formula 1 is a highly competitive, popular and dangerous sport which is government by the FIA, which has been at the center for a lot of controversy in the last two seasons (2021 & 2022) (Richards, 2022). Therefore, the main talking points in Formula 1 at the moment are the FIA, teams bending rules, announcements, team errors and recent crashes of drivers. Because of that, it is not unsurprising that surveillance, god, desperation and frustration are the categories with the highest percentages, as they are a natural and direct consequence of the sports characteristics. All other occurences for the other categorys are ranging between 10% to 20%, which is not an inconsiderable amount, if the topics of some categorys are taken into consideration. Almost 20% of comments show indications for suicide, murder, threat, and violence, weaponry and hate. This is not an inconsiderable amount, it means that on average every 5th comment contains life threatening and hateful content. Also almost 60% of comments show a negative sentiment. Even though this metric is not representing toxicity directy, it clearly shows, that Formula 1 fandom is not in a positive frame of mind, regardless of the discussion topic. In summary, every 5th comment shows clear indications for toxic content, with 60% percent of comments being negative. Therefore, one could make the assumption that Formula 1 fandom is indeed toxic, especially because of the frequency that one can observe comments with toxic behaviour. However, the situation is not as bad on social media as reports might suggest. The overall current negativity in Formula 1 fandom is amplifying the perception of toxicity in Formula 1 fandom as most people connect toxic behaviour not just with racism, misogyny and hate speech but rather with overall negative behaviour ("What Is Toxic Fandom?" n.d.). Therefore, most people will consider current Formula 1 fandom as toxic, especially paired with recent reports of toxic and abusive behaviour during events and online (*3 Times F1 Drivers Addressed Toxic Fan Behavior*, n.d.) (Woodhouse, 2022).

Has toxicity risen over the years?

In order to conclude if Formula 1 fandom got more toxic in recent years, the number of toxic indications per year will be analyzed.

```
comment_df["contains_toxic_indications"] = comment_df[["sentiment", "hate_speech_label"]].sw
grouped = comment_df[["video_id", "contains_toxic_indications"]].groupby(by="video_id").sum(
grouped.index = grouped.index.astype(str)
videos.video_id = videos.video_id.astype(str)
videos = pd.merge(videos, grouped, left_on="video_id", right_index=True)
videos.published_at = pd.to_datetime(videos.published_at)
videos.info()
```

```
videos.groupby(by=videos.published_at.dt.year).sum().plot(kind='bar', figsize=(8,5))
```

```
<AxesSubplot: xlabel='published_at'>
```

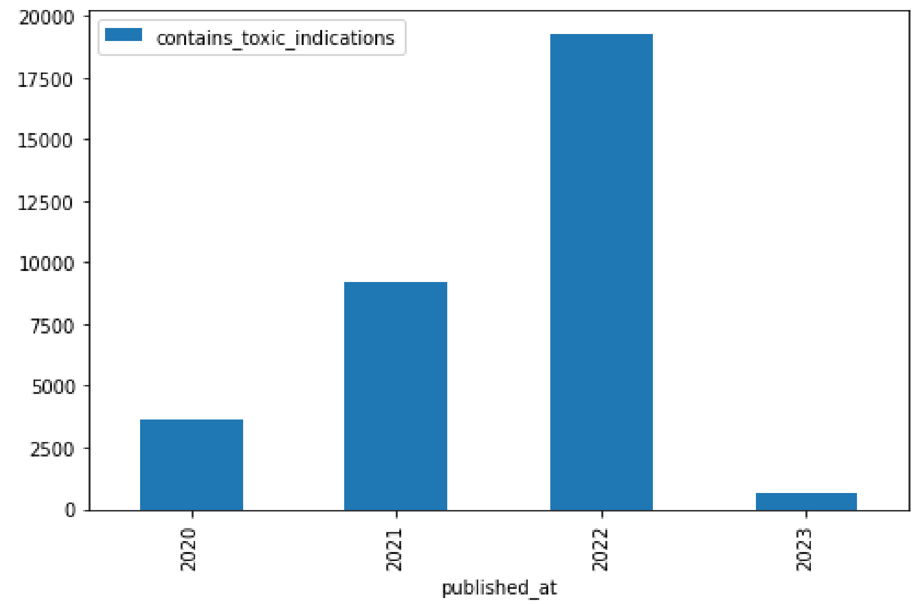


Figure 2: png

As shwon in the Figure above, the overall number of comments with toxic indications have risen drastically over the years. Jumping from around 3.500 comments with toxic indications to around 18.000 comments with toxic indications. This marks an increase of over 500%, or in other words, the amount of comments with toxic ambivalences have **quintupled**. This figure becomes even more alarming if the data in the following figure is taken into consideration as well.

```
fig, ax = plt.subplots(figsize=(10,5))
videos.comment_count = videos.comment_count.astype(int)
videos.like_count = videos.like_count.astype(int)
ax2 = ax.twinx()
videos[["published_at", "comment_count"]].groupby(by=[videos.published_at.dt.year ,videos.pu
videos[["published_at", "like_count"]].groupby(by=[videos.published_at.dt.year ,videos.publi
x = np.arange(32)
y = videos.groupby(by=[videos.published_at.dt.year ,videos.published_at.dt.month]).mean().co
z = np.polyfit(x,y,2)
p = np.poly1d(z)
ax.plot(x, p(x), linestyle="dashed", label="trend")
ax.axvline(0, color="red", label="2020 season")
ax.axvline(10, color="green", label="2021 season")
ax.axvline(22, color="orange", label="2022 season")
lns = ax.get_lines() + ax2.get_lines()
ax.legend(ax.get_lines() + ax2.get_lines(), [l.get_label() for l in lns])
```

```
ax.axvline(8, color="red")
ax.axvline(19, color="green")
ax.axvline(30, color="orange")
ax2.get_legend().remove()
```

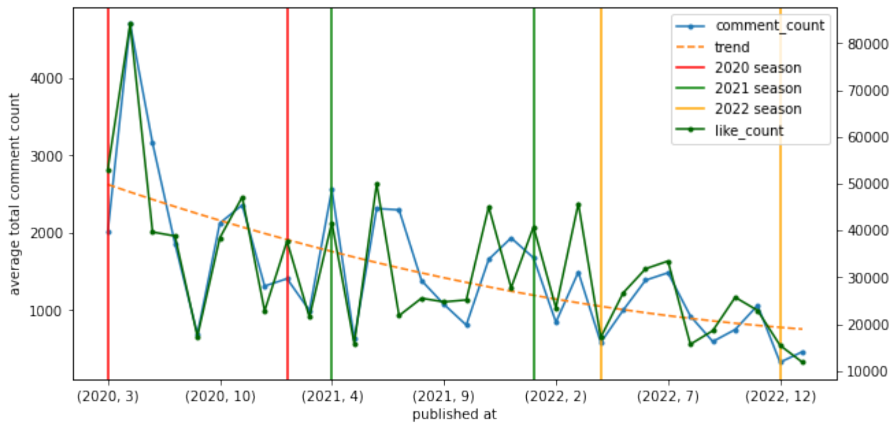


Figure 3: png

The figure shows the amount of comments and likes each video got over the past 2 years. The comment count and like count together, can be seen as an indicator about how much attention and interaction each video got. As shown in the figure by the blue and green line, the curve of the amount of comments and likes are almost identical, with the yellow trend line showing a clear negative or decreasing trend, that is becoming shallower towards the end. With the data about the amount of toxic indications in comments per year, this data paints an alarming picture, as toxicity in comments quintupled, while the overall interactions and attentions each video got has been declining to around 21% of its level from the beginning of the 2020 season. This indicates, that the relative amount of toxicity in Formula 1 Fandom could be even higher then displayed through the dataset. In summary then, Toxicity in Formula 1 Fandom has been rising, especially between 2021 and 2022, with the trend line predicting an increase for the future as well, as depicted by the following figure.

```
ax = videos[["published_at", "contains_toxic_indications"]].groupby(by=[videos.published_at.
x = np.arange(32)
y = videos.groupby(by=[videos.published_at.dt.year ,videos.published_at.dt.month]).sum().con
z = np.polyfit(x,y,1)
p = np.poly1d(z)
ax.plot(x, p(x), linestyle="dashed", label="trend")
ax.axvline(0, color="red", label="2020 season")
ax.axvline(8, color="red")
ax.axvline(10, color="green", label="2021 season")
ax.axvline(19, color="green")
```

```
ax.axvline(22, color="orange", label="2022 season")
ax.axvline(30, color="orange")
ax.legend()
```

```
<matplotlib.legend.Legend at 0x328fec5e0>
```

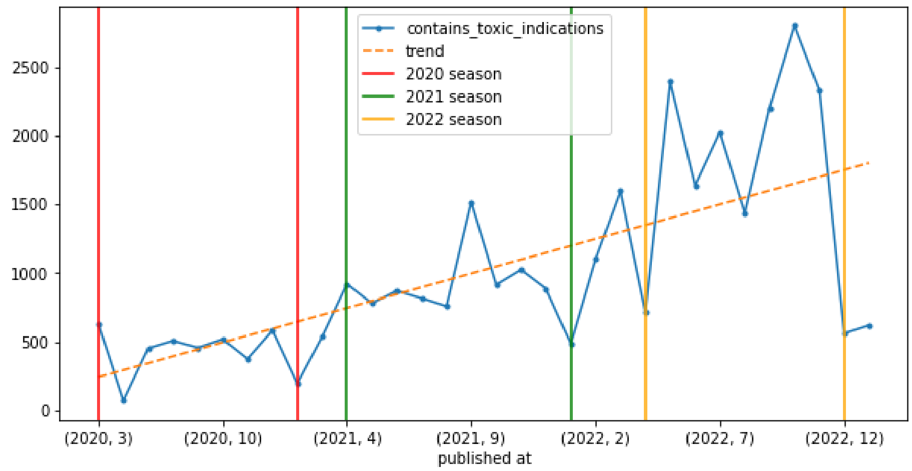


Figure 4: png

```
grouped.mean()
```

```
contains_toxic_indications    52.708696
dtype: float64
```

Is toxicity a self-made problem?

Whether toxicity is a self-made problem of Formula 1 is hard to reason about. However, Formula 1 is a public company, that makes money based on sponsorships, advertising and viewing numbers (*Formula One World Championship Ltd - Company Profile and News - Bloomberg Markets*, n.d.). Therefore, it is essential for Formula 1 to keep the amount of entertainment and interactions high, as well as having an increasingly large fan base or fandom. However, as shown in the following figure (Statista, n.d.), the amount of viewers were steadily decreasing from 2011 to 2017. During this time Formula 1 entered a new era of technical regulations, which has been called the hybrid era, which has been dominated by Mercedes AMG Petronas for seven consecutive years.

Which lead many people to leave the sport, as a lot of the entertainment factor was missing. Which lead to Formula hitting an all time low in 2017. As a result to that worrying development, in 2017 Formula 1 signed an aggressive exclusivity deal with Netflix for an exclusive documentary reality show called "Drive to Survive" which should portray the amount of controversy, excitement

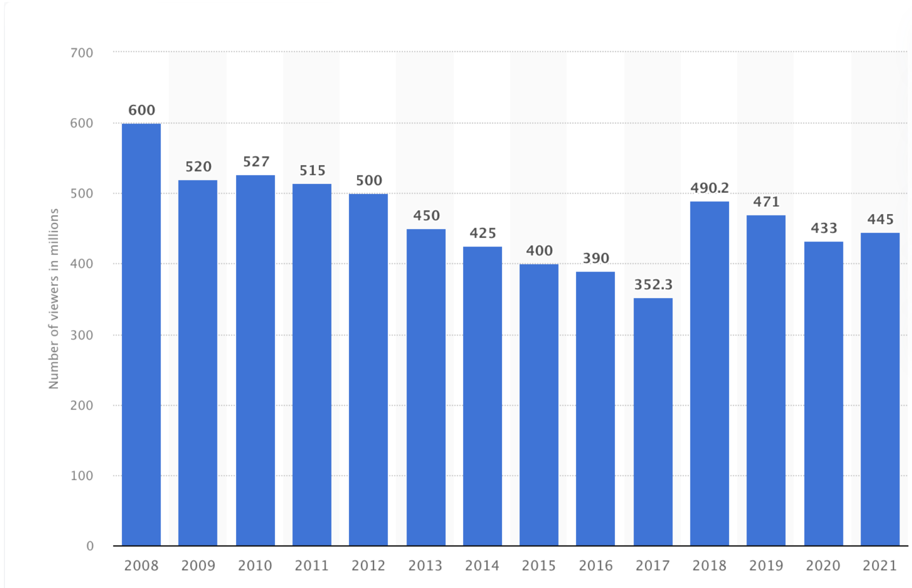


Figure 5: F1 TV viewing figure

and high class racing that Formula 1 is, while simultaneously showing off exclusive behind the scenes content and making Formula 1 more accessible by the average Netflix viewer (Goodman, 2022). The first season that aired on Netflix was an instant hit and lead to a surge in Formula 1s popularity across the globe, as reflected in the data showed in the figure above. The series was especially successfull in the USA, as Formula 1 never really got a foothold in the USA in the past, the series lead to F1s popularity skyrocketing. ESPNs F1 viewing figures increaed by 170% (from approx. 550.000 to 935.000) (Goodman, 2022) and the 2022 American Grand Prix breaking the record for the highest amount of spectators ever recorded (F1Destinations, n.d.). However, as the seasons progressed, the series became more and more a reality show about Formula 1 and the documentary aspect moved more and more in the background. As a result, many controversies, rivalrys and aspects of the sport are now artificially amplified, not fully narrated or told in a queer and distorded way and sometimes it goes as far as artificially creating rivalries where there never has been any (Milburn, 2020). Which lead to a rivalry between old Formula 1 fans and the new ones attracted by drive to survive but also between Fans of different teams and drivers. Also the term “DTS fan” which is an abbreviation for a fan that is following F1 because of Drive to Survive becoming a common insult in Formula 1 fandom for fans making assumptions that are not true or just don’t fit into an older fans perspective of the sport. In addition to that, decisions and actions of the governing body of Formula 1, the FIA became more and more questionable since 2021 (Richards, 2022), with a prime example, that is still discussed a lot today, being the championship decider in 2021. During this race, a late safety car lead to a lot of controversy, as the race director "interpreted" the a rule which stated that "any" lapped cars must over take the safety car to unlap themself and allow for a clean restart. However, in order to allow for one lap of thrilling and exciting racing, the race director only allowed the cars between the championship rivals to unlap themself and restarted the race afterwards. This allowed Max Verstappen to overtake Lewis Hamilton and secure his first ever drivers championship. Many similar incidents and inconsistencies from the governing body in regards to race decisions followed (Race, n.d.). This lead not only to an increasing rivalry between fans of different teams and drivers, but also to a lot of fans attacking the FIA. In summary then, is the Toxicity in Formula 1 Fandom a self-made problem? Well, one could certainly argue that it is. Formula 1 as a corporation needs the amount of entertainment and attention, controversies create. The same applies to Drive to Survive. Formula 1 needs Drive to Survive to draw more people into the sport and to reach its key performance indicators. The toxicity in Formula 1 fandom is just a side effect of the strategies Formula 1 is following. In addition to that, Formula 1 is becoming more and more political with campaigns against racism, or for environmentally friendly programs, which adds another friction point between fans if they don't agree with portrayed political views.

Result Validity

The results are only valid for the given dataset, which has been shown to have its limitations, as presented earlier. The transformer predictions have an average of 88% - 95% certainty. Therefore, the likelihood of the predictions being correct is quite high.

```
comment_df.sentiment_score.mean()
```

```
0.9551236870340416
```

```
comment_df.hate_speech_score.mean()
```

```
0.8822260307092021
```

However, the dictionary results contain a lot of False positives, as words of the dictionary are overlapping with Formula 1 domain language. For example mick is a word of the toxic words dictionary but it is also the name of a driver for the HAAS Formula 1 team. As a consequence, every comment that is about Mick Schumacher is automatically flagged as toxic. The same applies for some of the categories of the grievance dictionary. As explained in the result section, crashes and dangerous incidents are part of the sport. Therefore verbalizations about god, or death are really common as they can also express relief that a driver didn't die.

In addition to that, I, as the authot of this report, certainly have biased opinions on some of the discussed topics myself. As I am part of Formula 1 fandom and a Redbull Racing supporter. Because of that, an unbiased review of comment classification with toxic indications by unbiased annotators should be conducted in the future.

Conclusion

In this thesis, the toxicity in Formula 1 has been analysed based on a custom dataset of 40200 comments from 500 videos of the official Formula 1 Youtube channel. First the fundamentals about what fandom and toxic behaviour is have been layed out. After that, the dataset creation process has been presented. Then the three dictionarys used, along with the dictionary analysis method have been shown. In addition to that, two transformer classifiers have been applied to the dataset in order to detect comment sentiment and hate speech in comments. The results showed, that on average every 5th comment in the dataset contained toxic indications which are often connected to life threatening and hateful behaviour, which concluded the first research question, as Formula 1 Fandom was deemed to be toxic. Following this discussion, it has been analyzed if Toxicity in Formula 1 Fandom has risen over the years. The results showed, that the amount of comments with toxic indications quintupled from 2020 to 2022, while simultaneously the videos were receiving less interactions. This marks a dark future for Formula 1 and Formula 1 Fandom, as the trend curves are both predicting a similar picture for the future. Last but not least, it has been discussed if toxicity in Formula 1 Fandom is a self-made problem of Formula 1. It has been argued, that indeed Formula 1s strategy to fan and economic growth, paired with the increasing amount of political topics addressed by Formula 1 are certainly playing a role in the rise of toxicity and may well be one of the reason. Therefore it was concluded, that yes toxicity is (at least partially) a self-made problem.

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