IMT 547 Team 1 Final Presentation

YOUTUBE GAMING COMMENT TOXICITY

A Comparative Analysis of Action and Non-Action Games Video Comments

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PLAY

Project Overview

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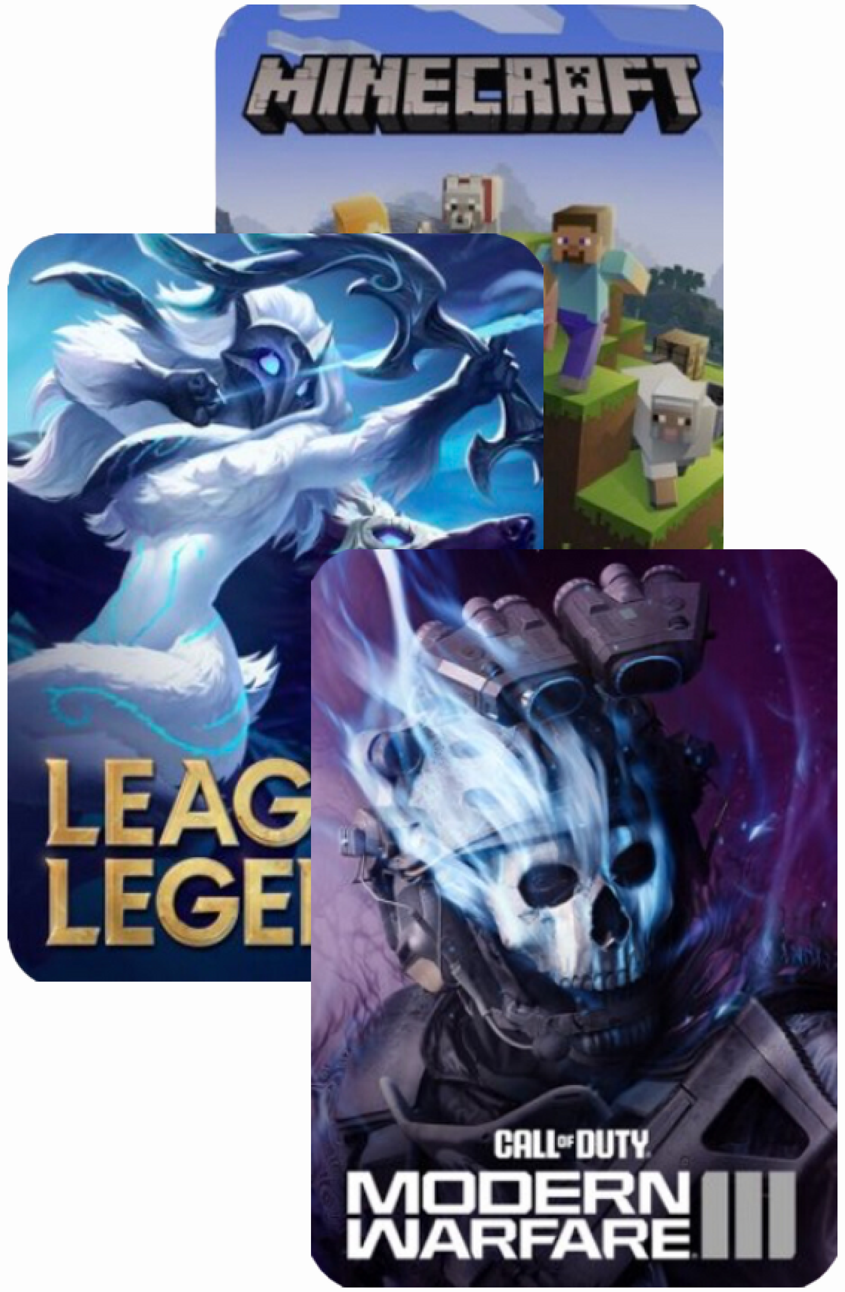
Project Overview



Motivation

Prevalence of Toxic Conversation in Gaming Communities

- Far-reaching harm that extends beyond virtual boundaries

Focus

Out-of-Game Conversations on Social Media

- "An essential part of gamer culture" [1, 2]

Objective

Understand the dynamics of toxicity in YouTube gaming community

Significance

Inform detection and moderation efforts

- Eradicate online toxicity
- Foster a safer and more inclusive online gaming environment

Definitions

“A rude, disrespectful, or unreasonable comment that is likely to make someone leave a discussion” [3]

(PERSPECTIVE API)

Research Questions

RQ #1

Game Genre vs Comment Toxicity

Does the genre of the games (action and non-action) influence the level of toxicity in the comment section?
If so, to what extent?

Action games tend to elicit more toxic comments.

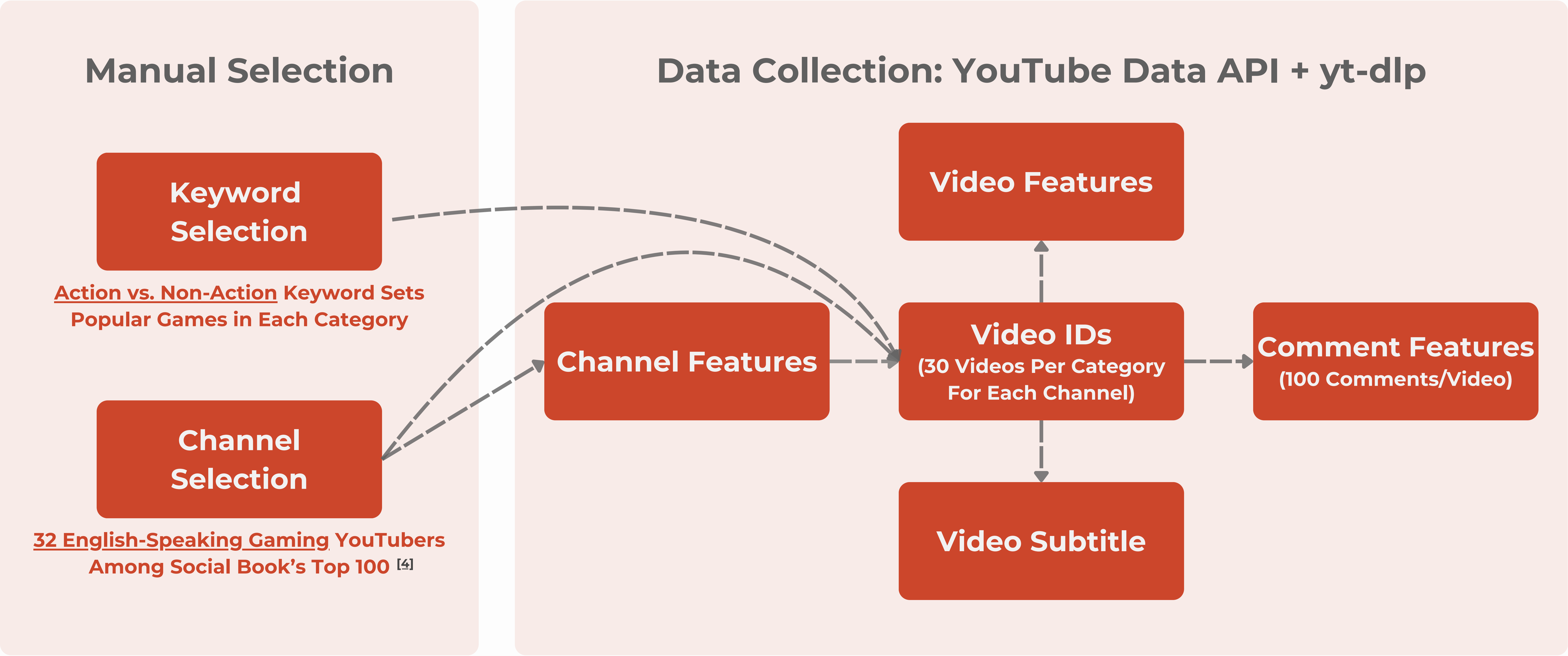
RQ #2

Video Content vs Comment Toxicity

Does the content of the videos influence the level of toxicity in the comment section?
If so, to what extent?

Toxic video transcripts are more likely to generate toxic comments.

Data Collection



Keyword Sets

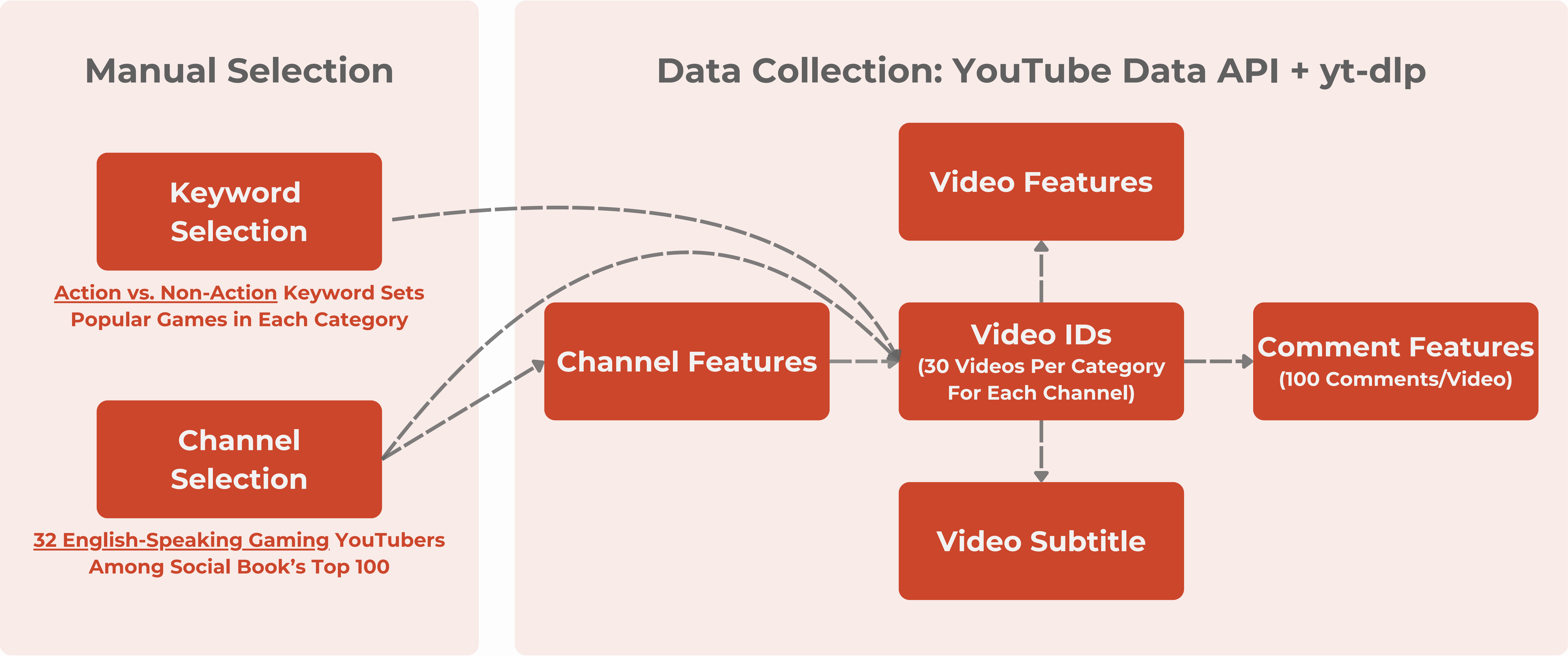
{"call of duty", "gta", "the last of us", "god of war", "assassin's creed", "star wars jedi", "resident evil", "cyberpunk", "fallout", "tomb raider", "elden ring"}

Action Games

{"minecraft", "pokemon go", "just dance", "it takes two", "uncharted", "brawl stars"}

Non-Action Games

Data Collection



Channel List

gamer-100.csv

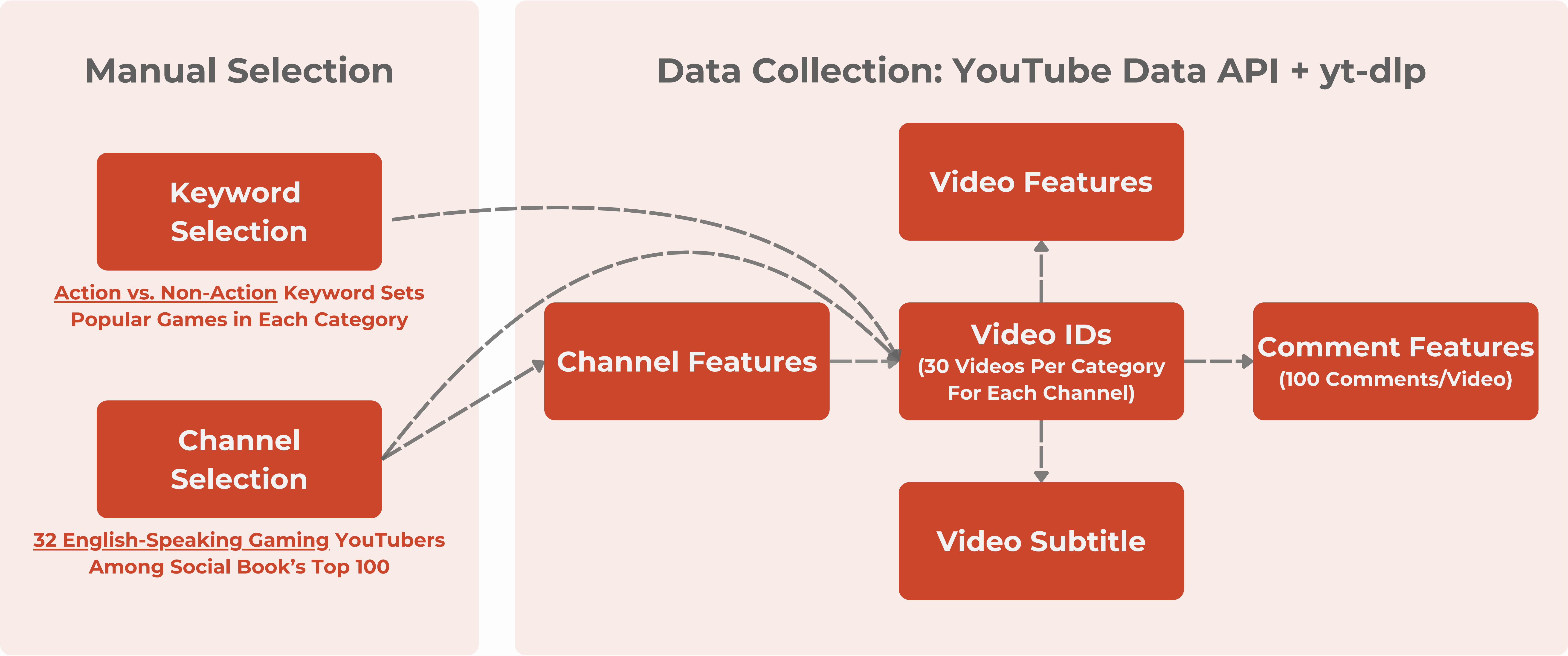
Channel	Channel ID	Gamer	English
PewDiePie	**UC-lHJZR3Gqxm24_Vd_AJ5Yw**	**1**	**1**
A4	UC2tsySbe9TNrI-xh2lximHA	1	0
JuegaGerman	UCYiGq8XF7YQD00x7wAd62Zg	1	0
AboFlah	UCqq5n-Oe-r1EEHI3yvhVJcA	1	0
Markiplier	**UC7_YxT-KID8kRbqZo7MyscQ**	**1**	**1**
Frost Diamond	UC4hGmH5sABOA70D4fGb8qNQ	1	0
SSSniperWolf	**UCpB959t8iPrxQWj7G6n0ctQ**	**1**	**1**
...	...		...
Mythpat	**UCx6F-rETGiz7xf_vkMmX2yQ**	**1**	**1**
Brawl Stars	UCooVYzDxdwTtGYAkcPmOgOw	0	1
Typical Gamer	**UC2wKfjlioOCLP4xQMOWNcgg**	**1**	**1**

English-Speaking

Video Game Players

Focus: English-Speaking Gaming Community

Data Collection



Data Structure

Channel	
PK	**channel_id**
	channel_name
	channel_description
	channel_country
	channel_uploads_id
	channel_viewcount
	channel_subscribercount
	channel_videocount

32 Channels

Video	
PK	**video_id**
FK	channel_id
	video_title
	video_creation_time
	video_description
	video_duration
	video_tags
	video_viewcount
	video_likecount
	video_commentcount
	video_subtitle_path
	video_live

1407 Videos

Comment	
PK	**comment_id**
FK	video_id
	comment_author_id
	comment_text
	comment_time
	comment_likecount
	comment_replycount

136,463 Comments

Methodology

Data Cleaning

- Handle Missing Values
- Check Duplicate & Invalid Entries
- Correct Data Formats

Feature Engineering

- Game in Video
- % Censored Words in Subtitle

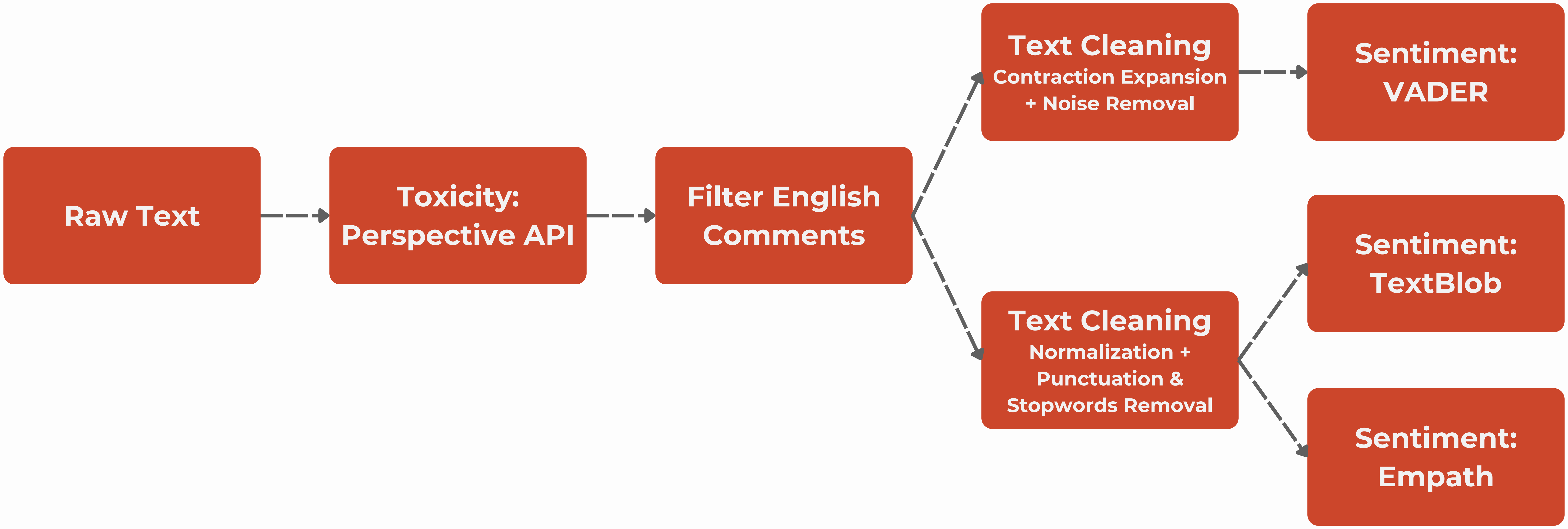
Content Labeling

- Toxicity Annotation
- Sentiment Evaluation

Text Preprocessing

- Filter English Comments
- Text Cleaning

Toxicity & Sentiment



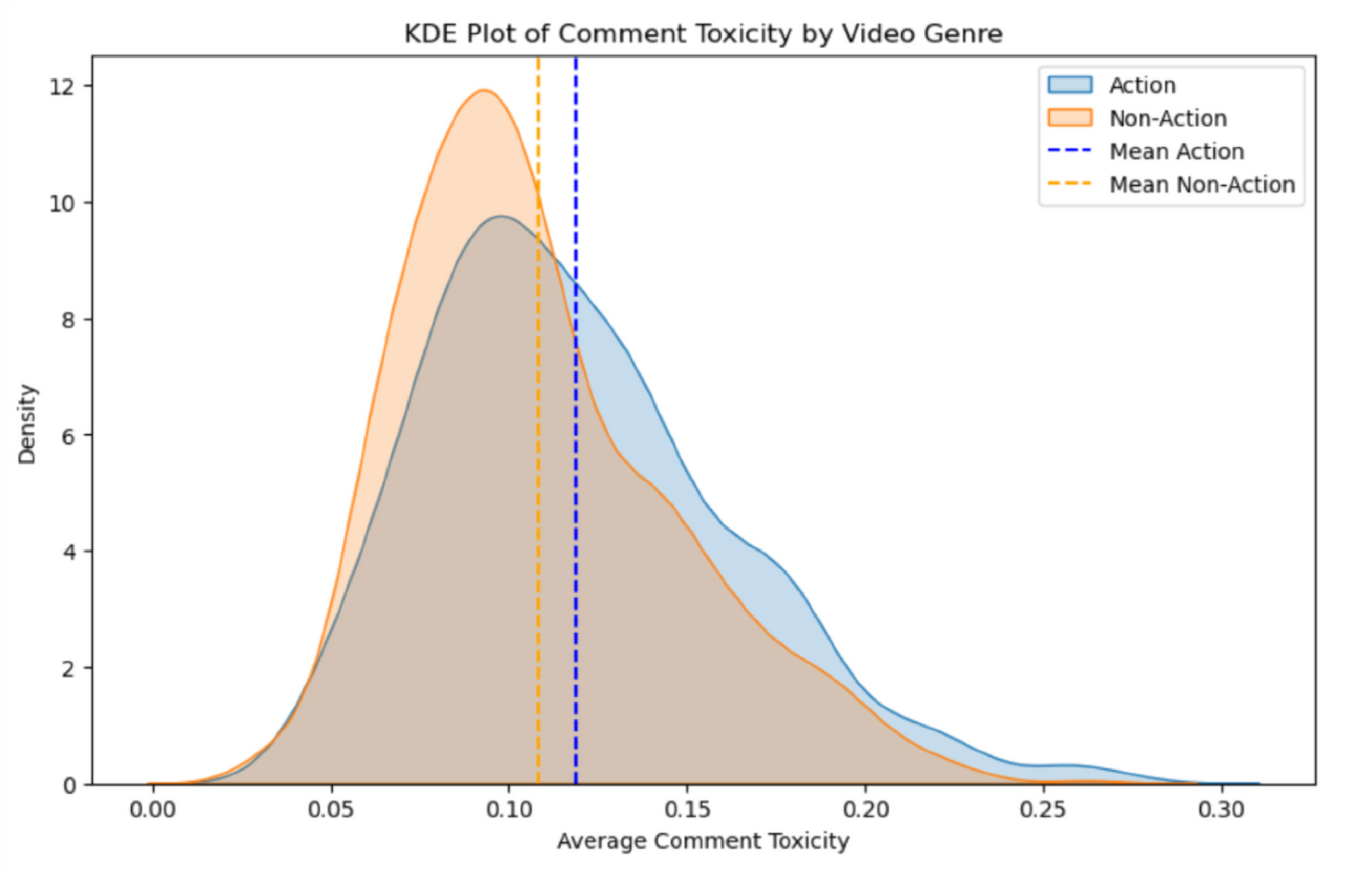
Finding #1

- RQ 1: The influence of game categories on comment sections.
  - Do videos of action games arouse significantly more toxic comments than non-action games in YouTube?

- Our Findings:
  - The comment section of action games has higher toxicity and more negative emotion than non-action games.
  - The YouTubers who post more action games tend to have higher comment section toxicity.
  - Among the most toxic videos, we can observe that the proportion of action games is much higher than among the least toxic videos.

Finding #1

Toxicity distribution in Comment section by Video Genre

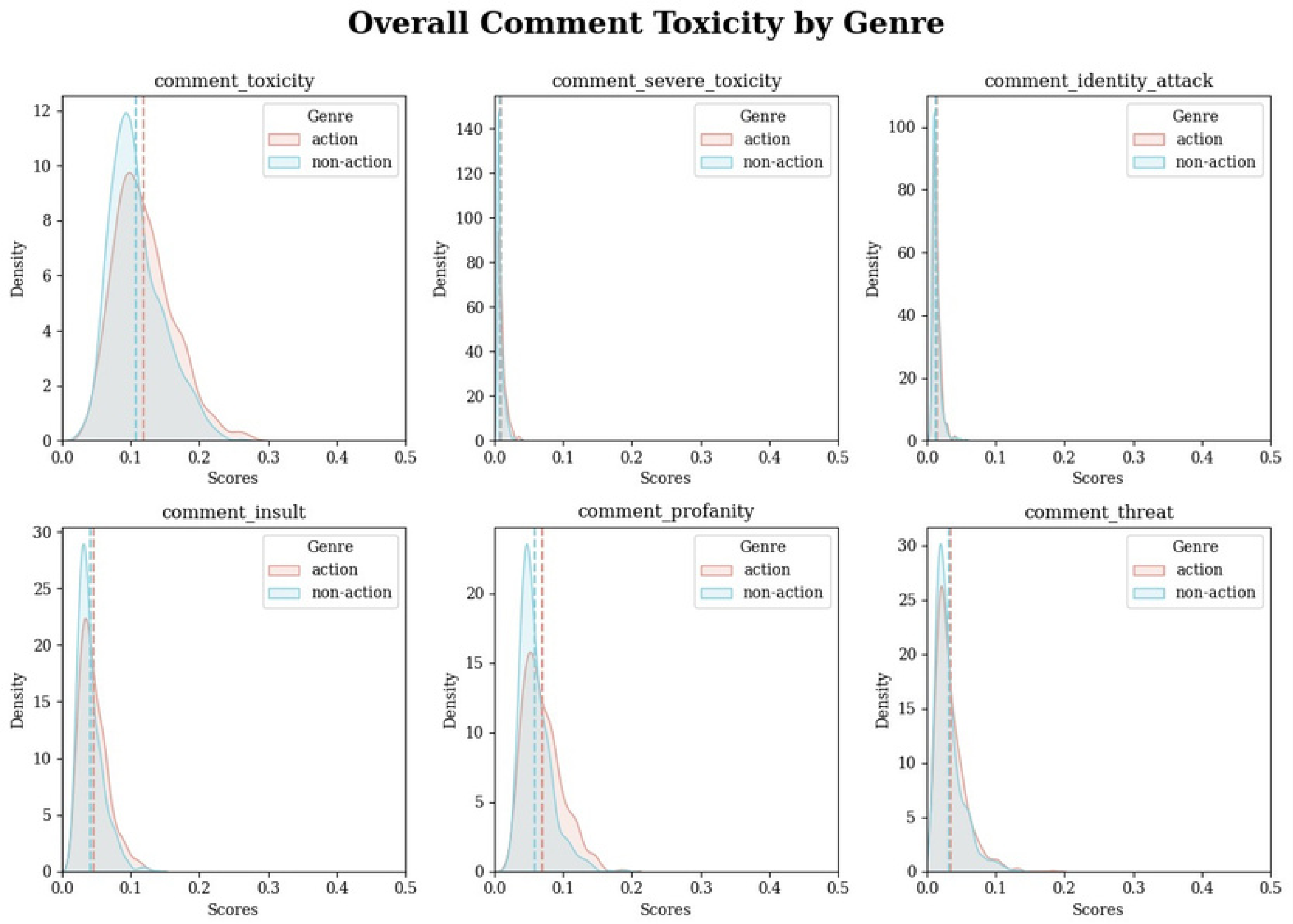


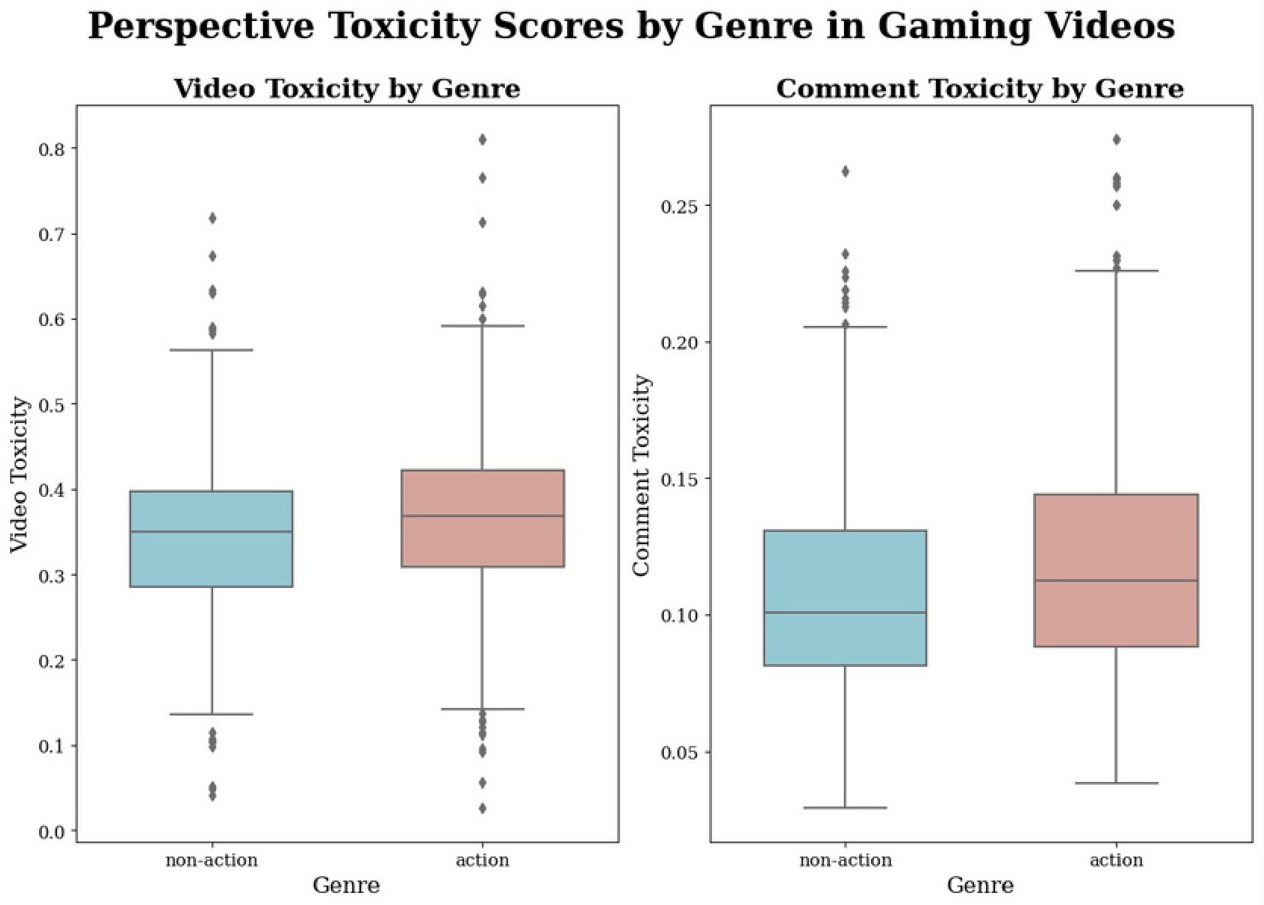
The comment toxicity distribution of Action games has a more gradual and flat curve than Non-Action games.

The center of mass of the Action-game curve is more shifted to the right.

The mean of comment toxicity of Action games is obviously bigger than Non-Action.

Finding #1



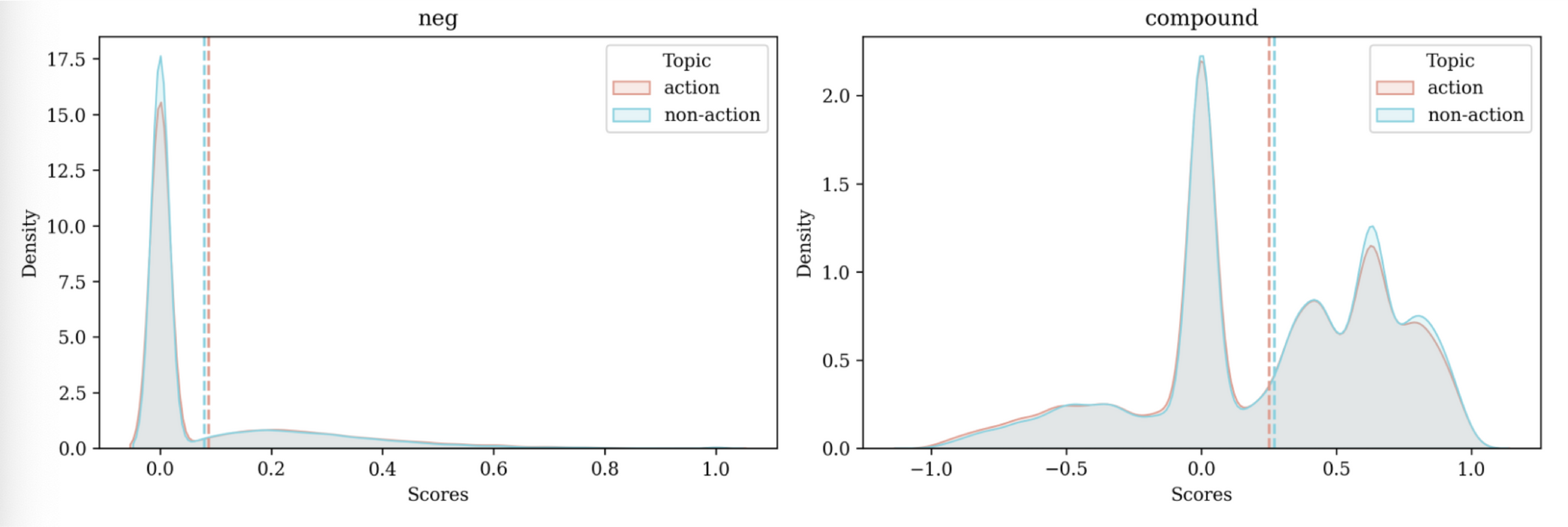


Toxicity Type	MWU Test Statistic	p-value	Non-Action Sample Size	Action Sample Size	Non-Action median	Action Median
comment_toxicity	175475.000000	0.000002	750	551	0.100874	0.112624
comment_severe_toxicity	168427.000000	0.000000	750	551	0.006249	0.008053
comment_identity_attack	182850.000000	0.000192	750	551	0.011633	0.012405
comment_insult	172045.000000	0.000000	750	551	0.035757	0.041462
comment_profanity	158792.000000	0.000000	750	551	0.053160	0.062773
comment_threat	187804.000000	0.002472	750	551	0.025645	0.027943

From the one-tailed Mann-Whitney U test, we can see that the result is statistically signifcant with $p < 0.05$, suggesting that action videos comments are more toxic than non-action video comments across all dimensions

Finding #1

VADER sentiment score by genre

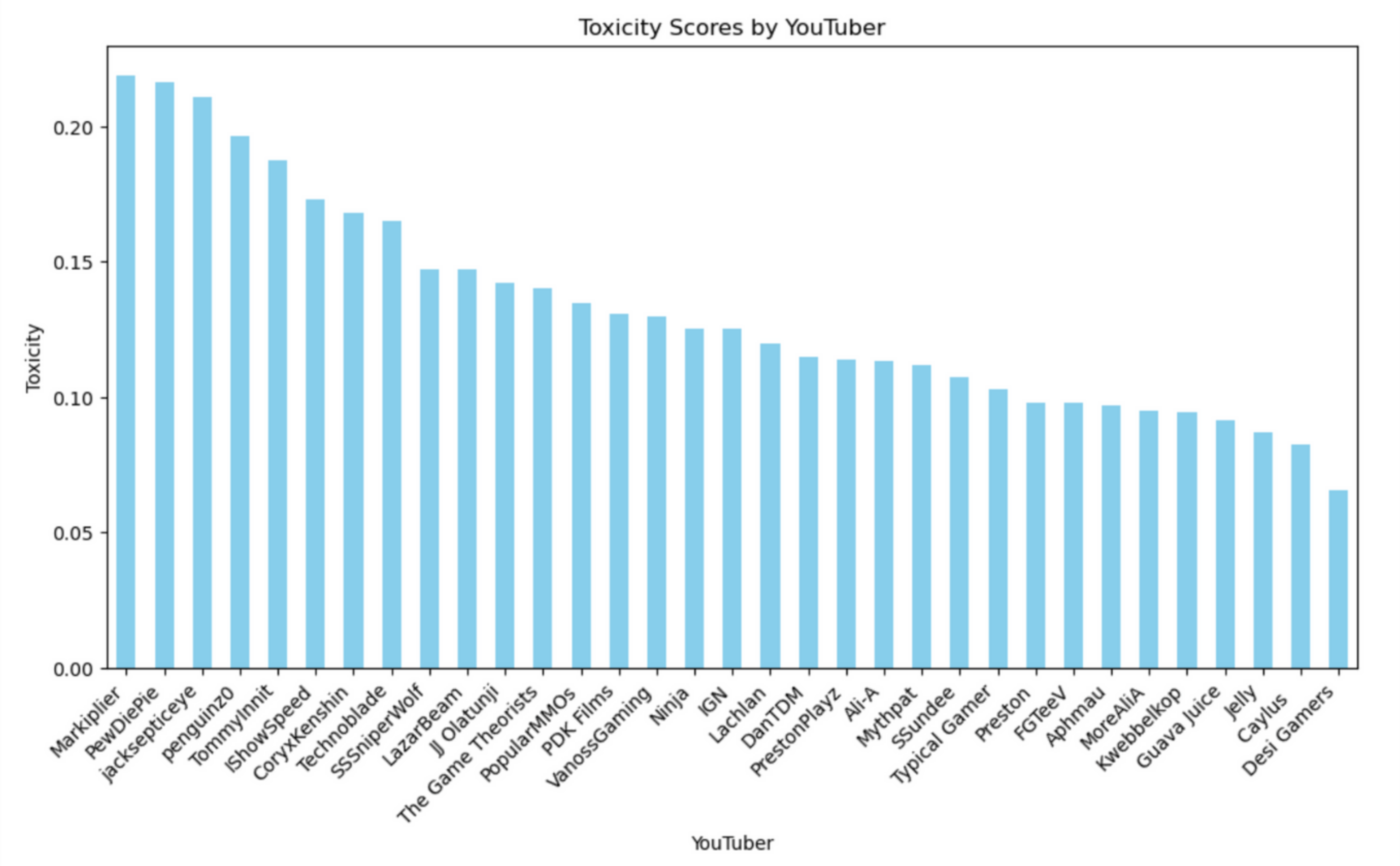


We do sentiment analysis to see the emotion tone of comment section.

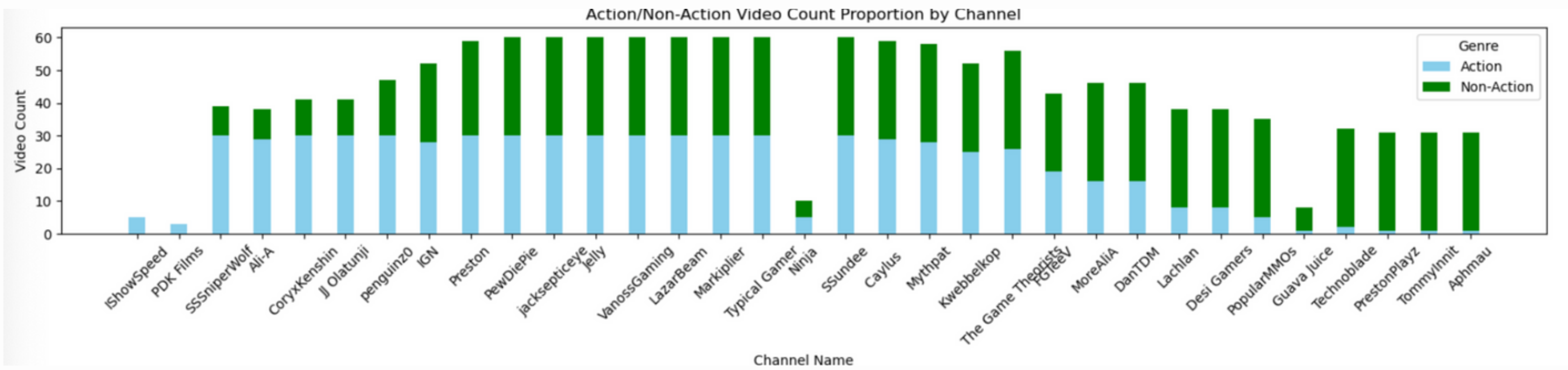
Although the curves are quite similar(Because of the YouTube nature), we can still see action games have bigger mean of VADER neg score and smaller VADER compound score.

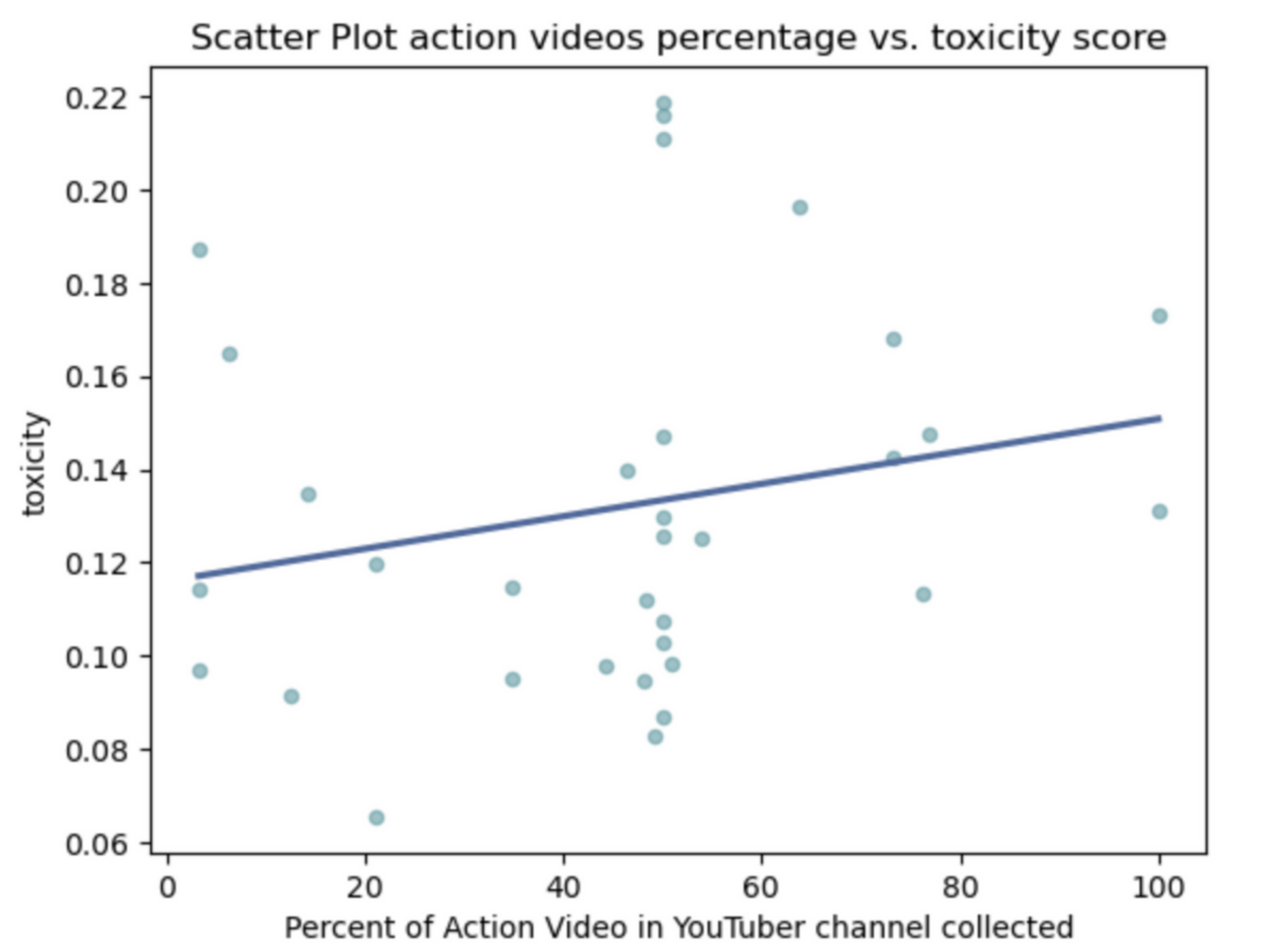
Finding #1

Toxicity by YouTube Channel



Action/Non-Action proportion by Channel

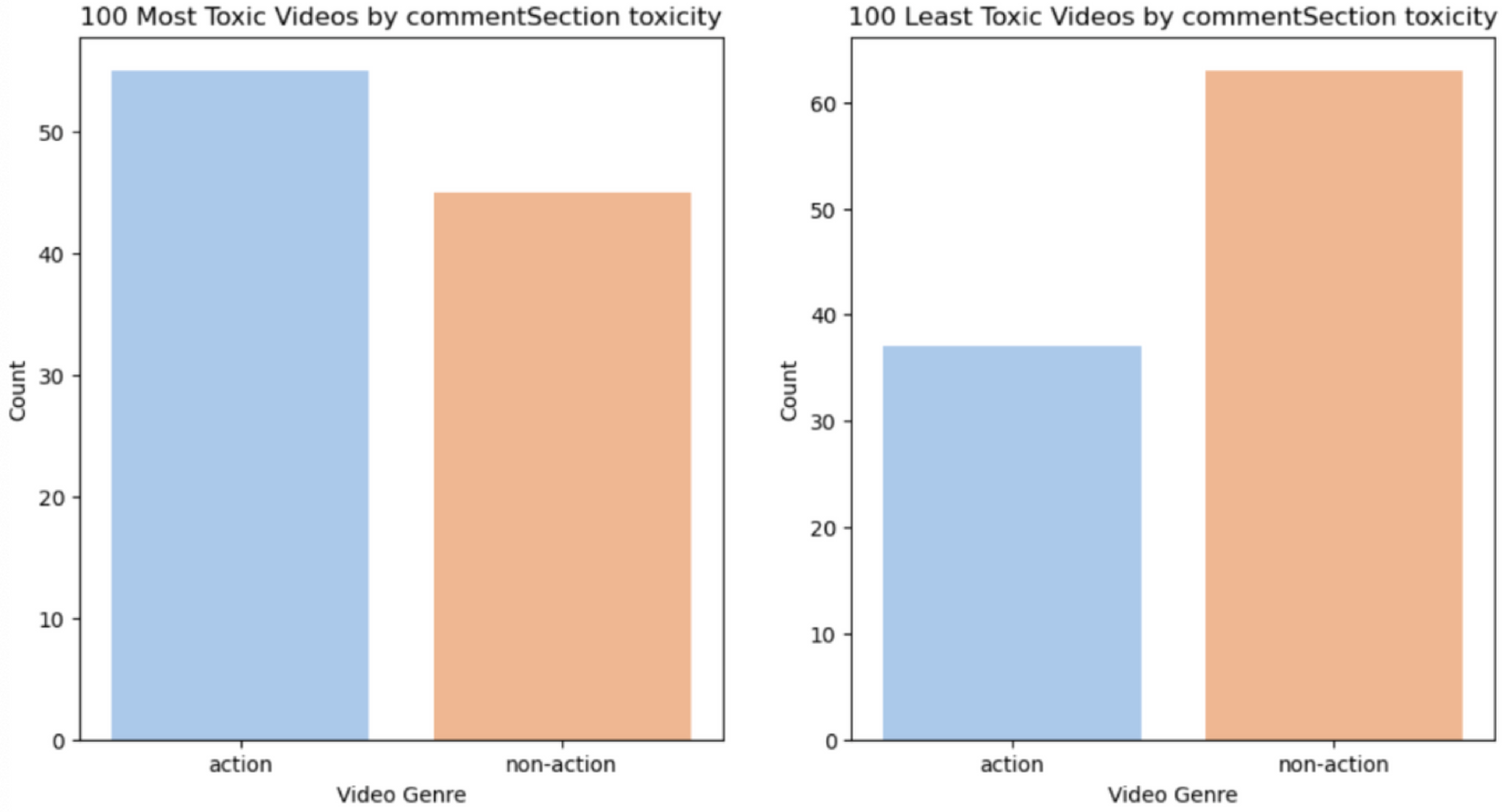




We observe a positive correlation between action-game proportion and comment toxicity

Finding #1

Dive into the most toxic comment section and the least toxic ones



Among the most toxic videos, we can observe that the proportion of action games is much higher than among the least toxic videos.

In the most 100, 55 videos are action and 45 videos are non-action

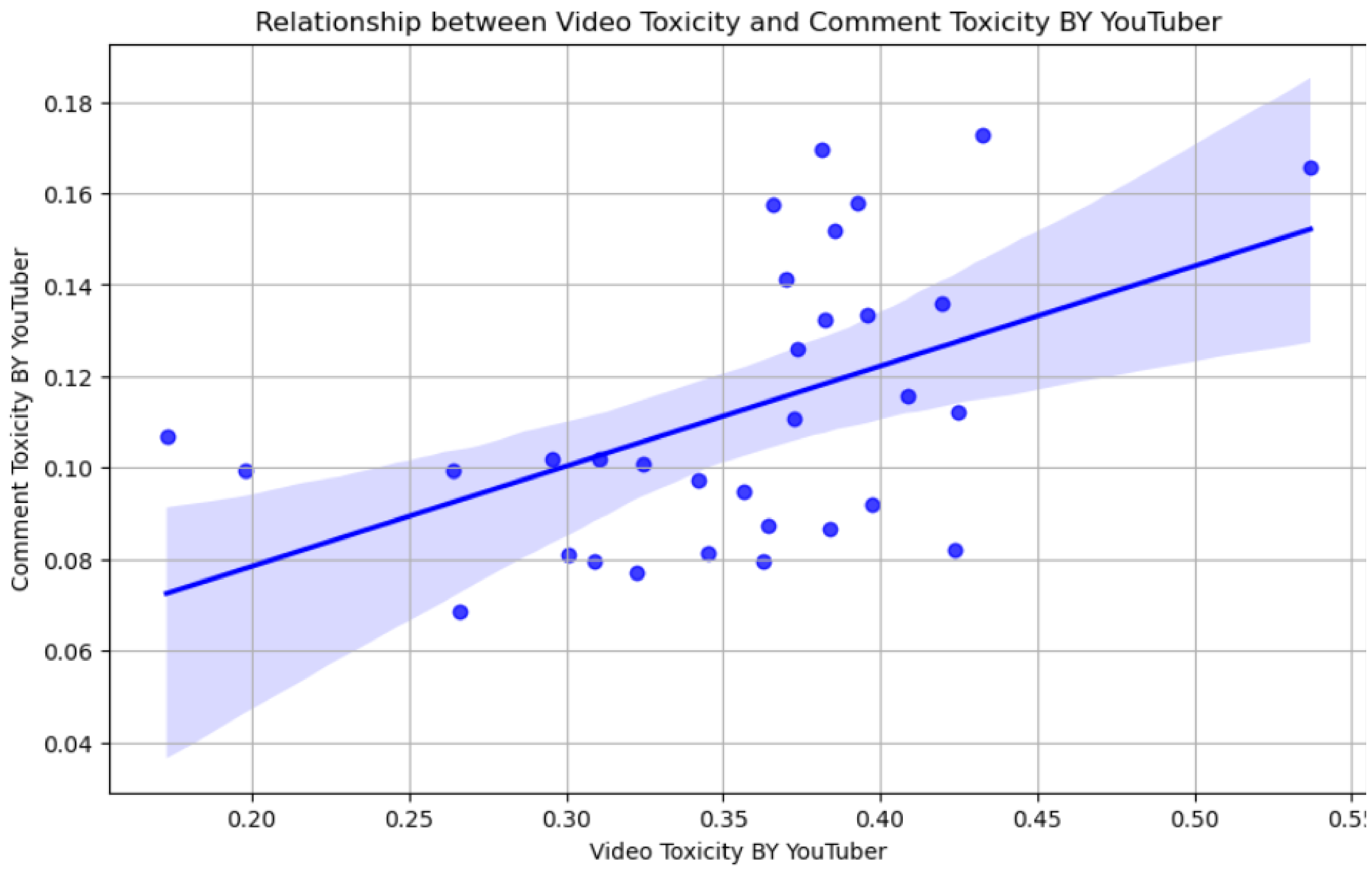
In the least 100, 37 videos are action and 63 videos are non-action

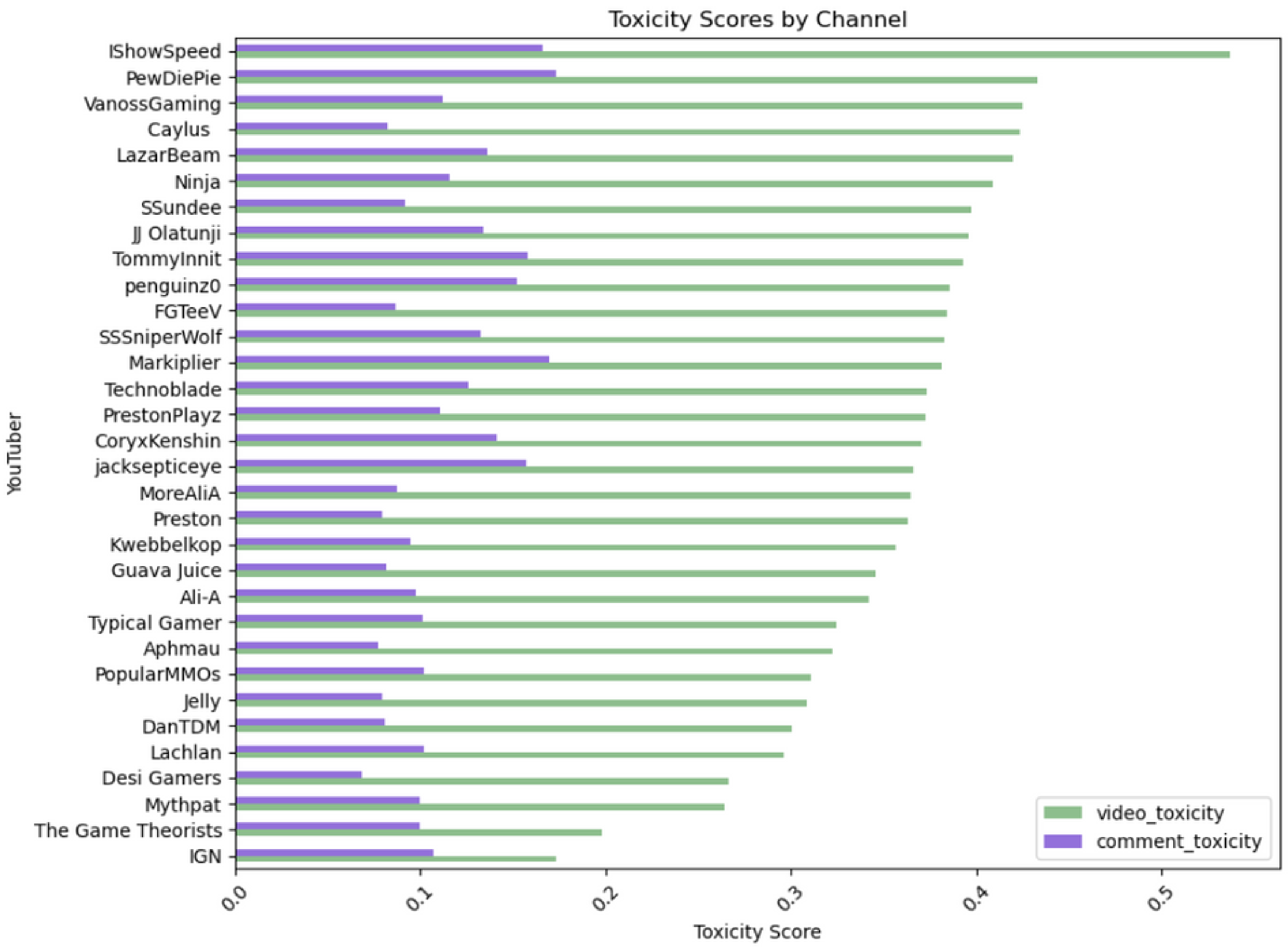
Finding #2

- RQ 2: The influence of video transcripts on comment sections.
  - Does the content of the videos have a substantial influence on the toxicity in the comment section?

- Our Findings:
  - Empath Keywords in toxic videos are expected to involve more violence, war, and fights compared to harmonious videos.
  - Videos with higher toxicity in the transcript are likely to elicit more toxic comments.

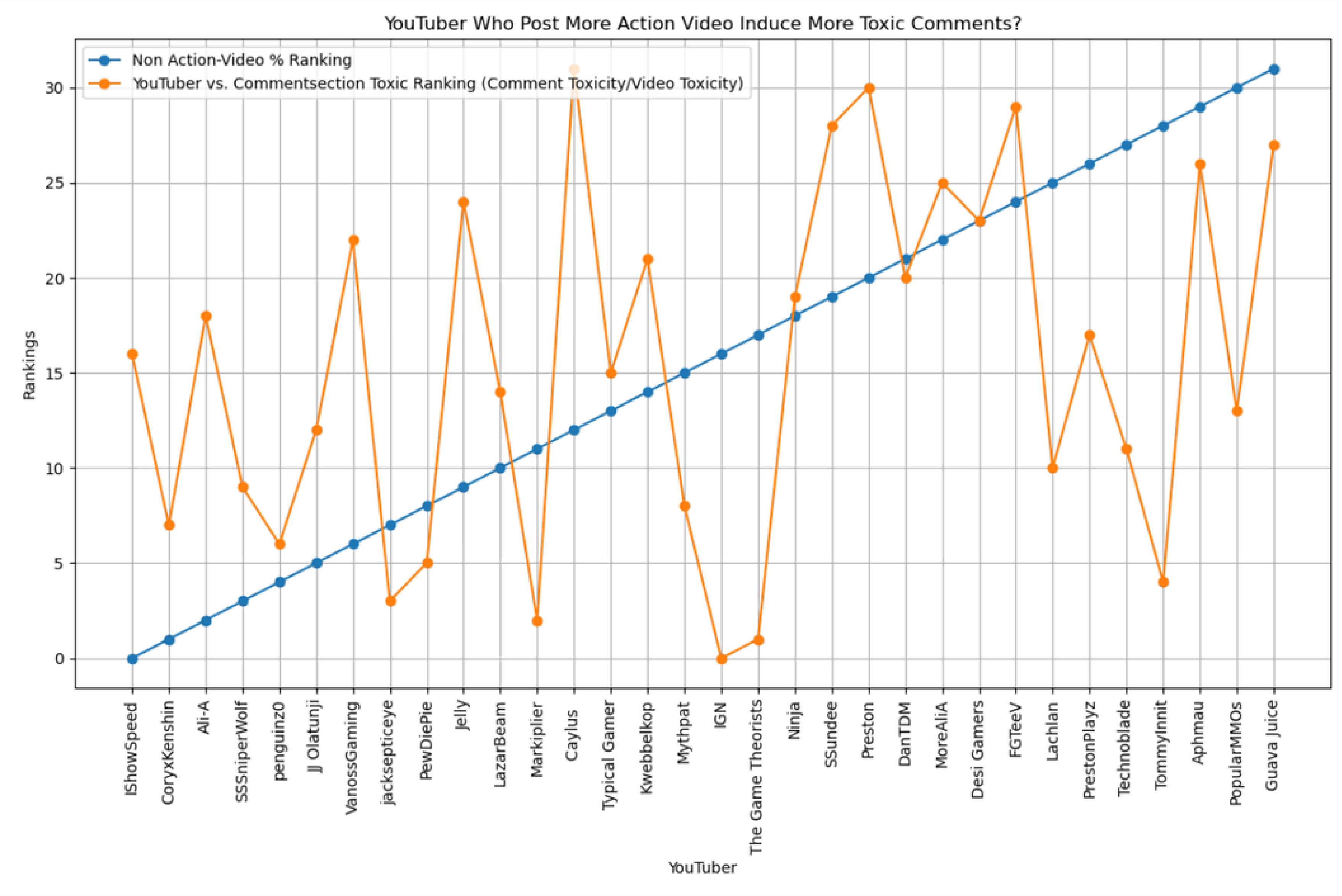
Finding #2

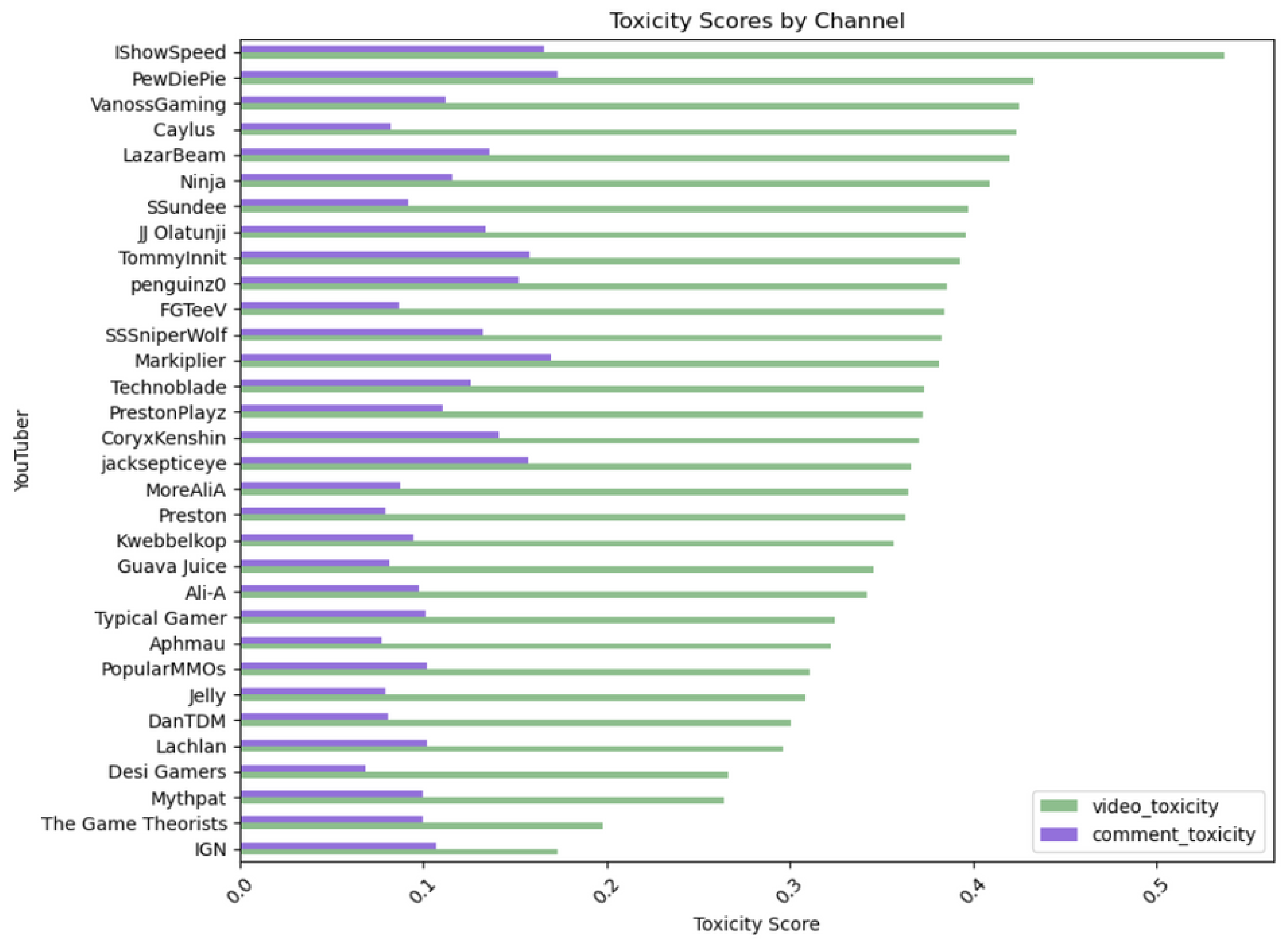




The more toxic the YouTuber's video transcripts
The more toxic the YouTuber's comment sections

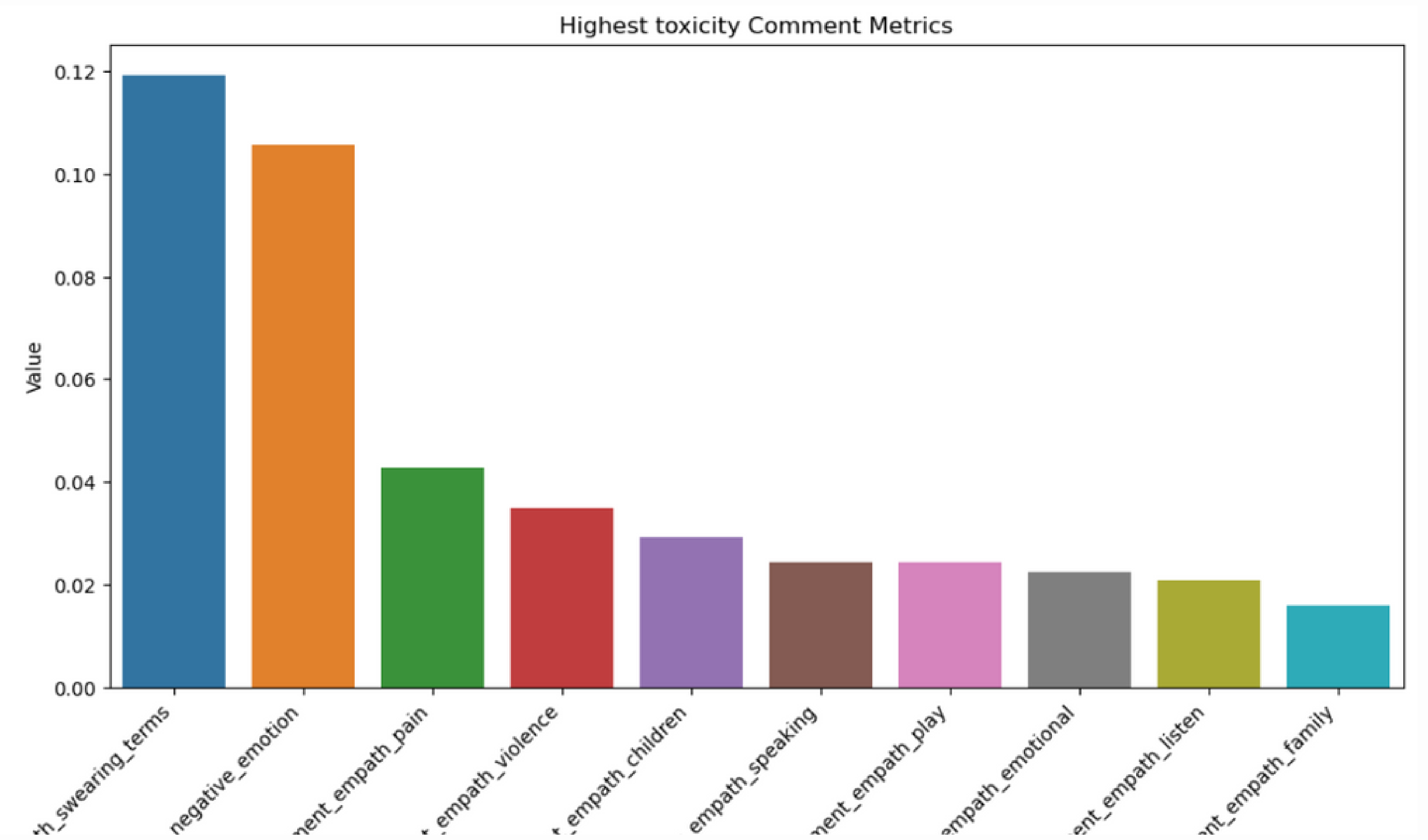
Finding #2

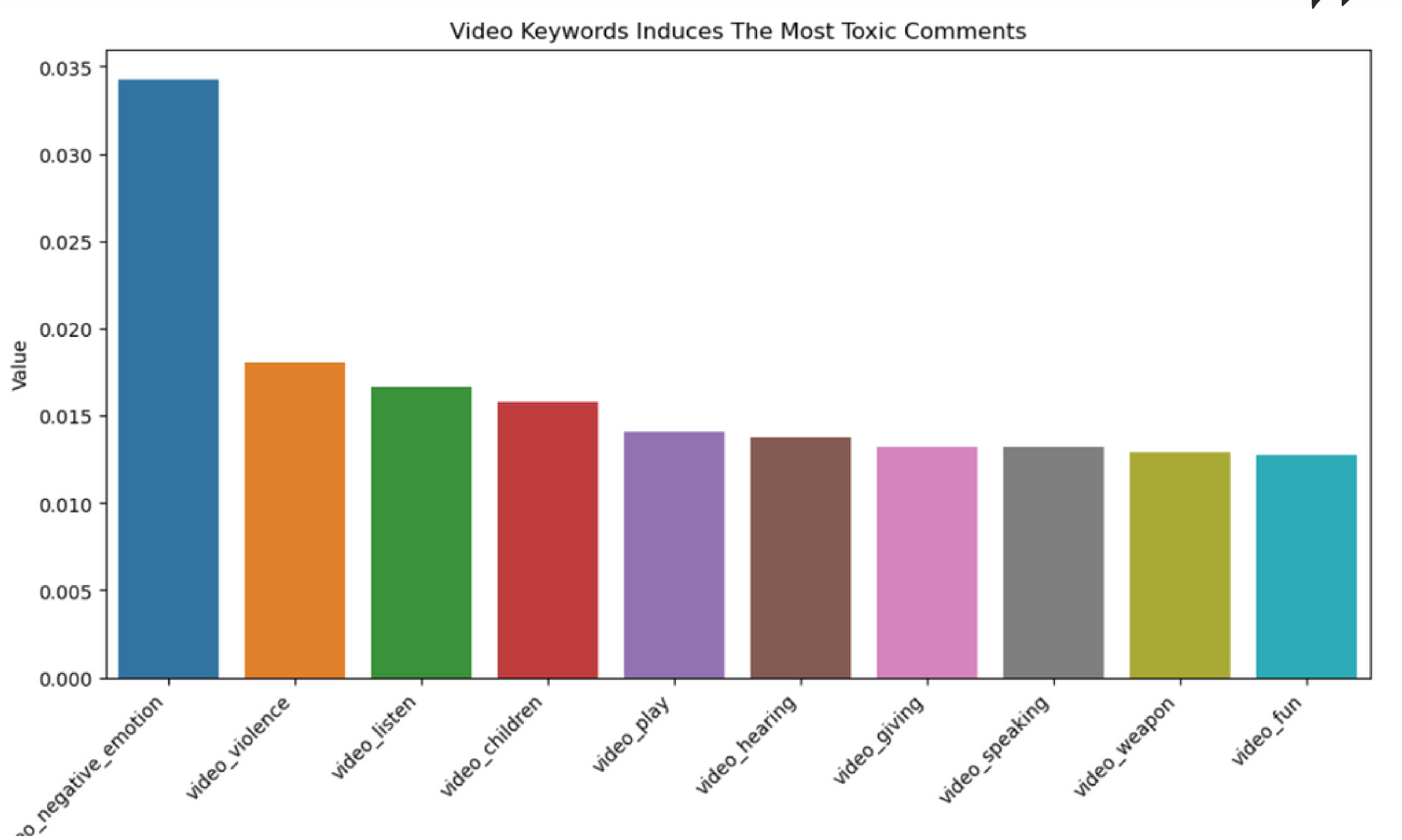




The ranking of Comment Toxicity / Transcript Toxicity Ratio does not seem to correlate with the percentage of non-action videos posted.

Finding #2



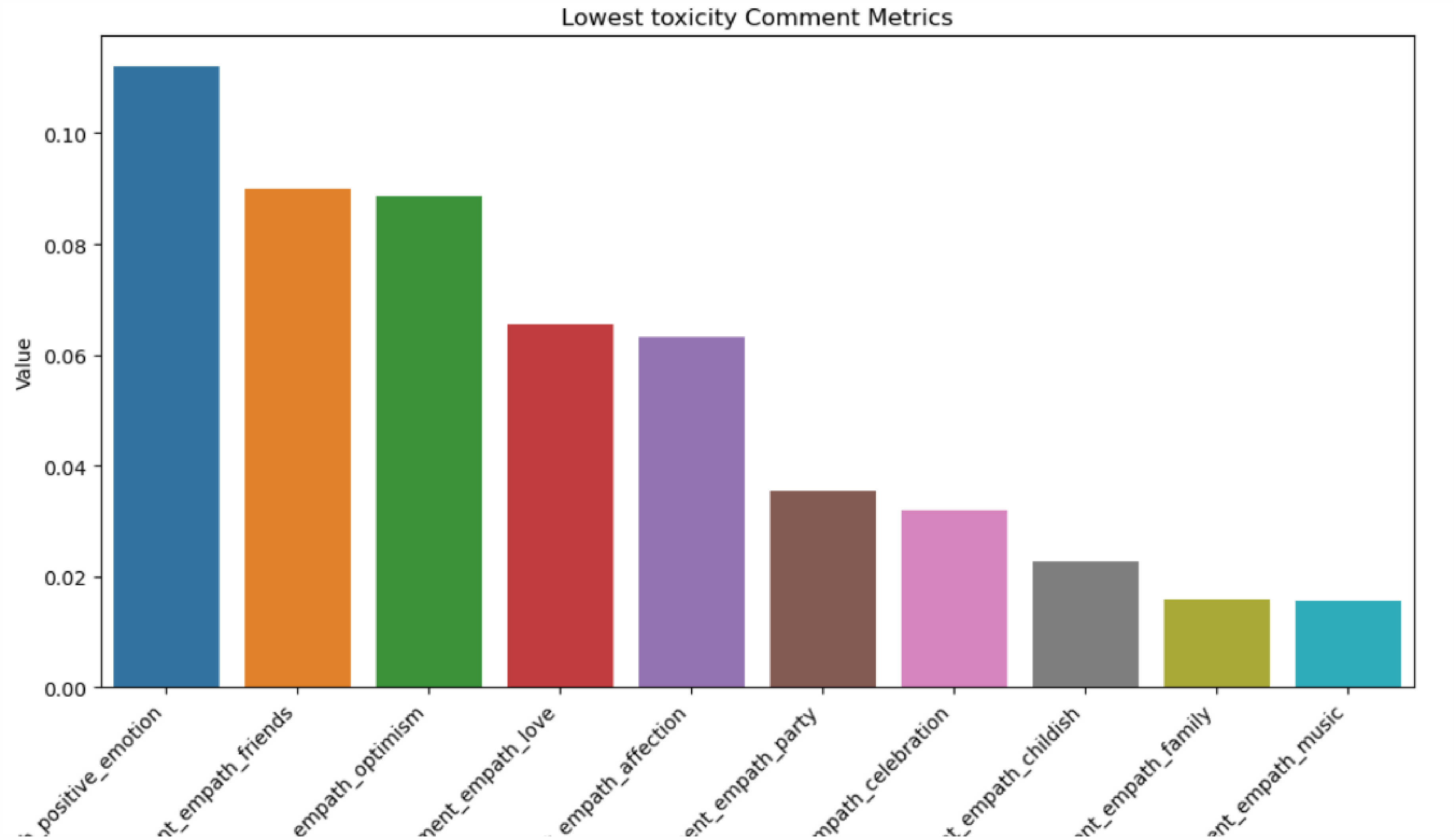


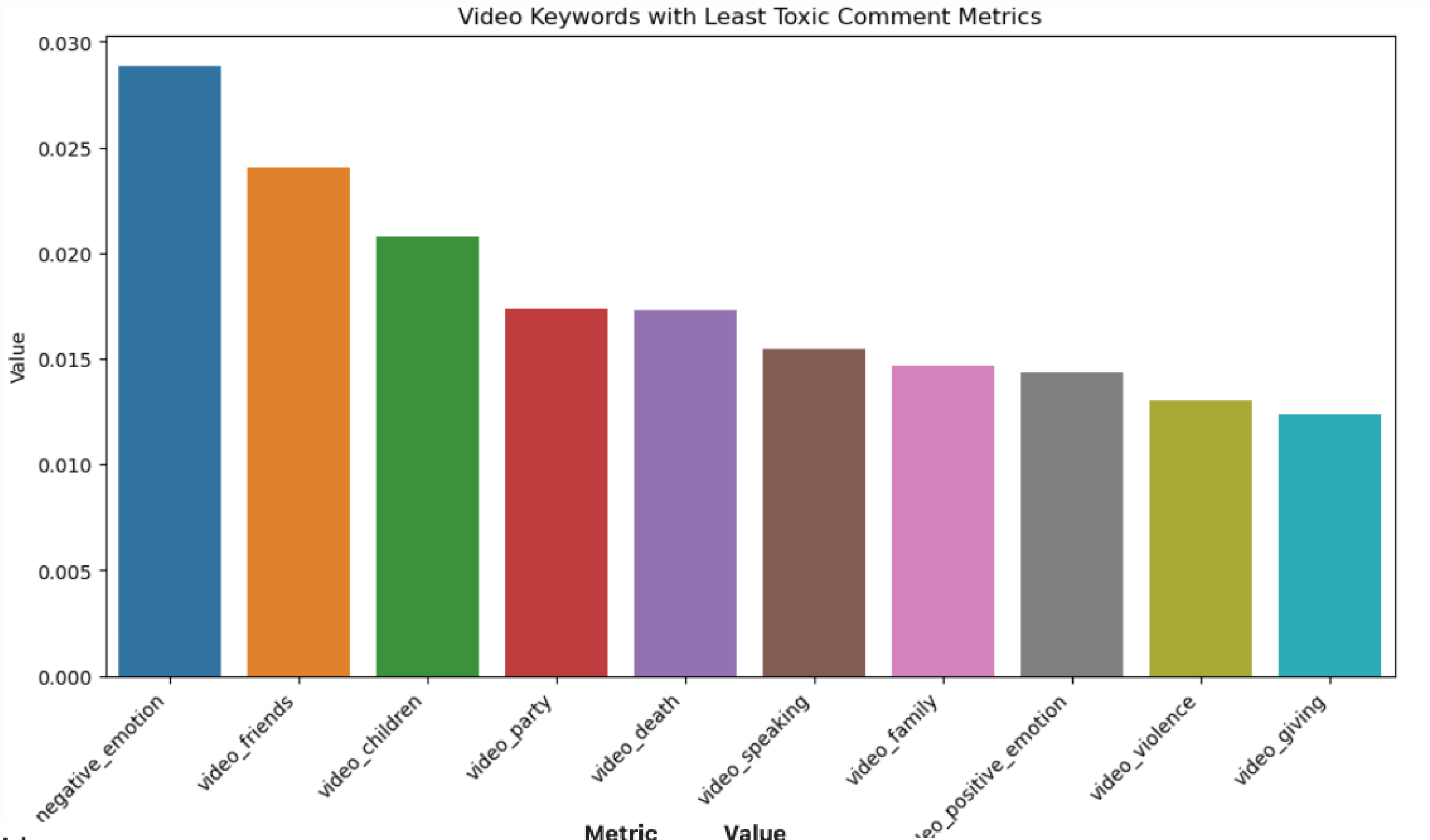
- **Selecting the MOST toxic 100 comment sections;**
- **Investigate what did the video say?**

	Metric	Value
0	comment_empath_swearing_terms	0.119262
1	comment_empath_negative_emotion	0.105787
2	comment_empath_pain	0.042760
3	comment_empath_violence	0.034956
4	comment_empath_children	0.029254
5	comment_empath_speaking	0.024336
6	comment_empath_play	0.024332
7	comment_empath_emotional	0.022333
8	comment_empath_listen	0.020843
9	comment_empath_family	0.015855

	Metric	Value
0	video_negative_emotion	0.034288
1	video_violence	0.018033
2	video_listen	0.016647
3	video_children	0.015752
4	video_play	0.014057
5	video_hearing	0.013755
6	video_giving	0.013190
7	video_speaking	0.013174
8	video_weapon	0.012889
9	video_fun	0.012756

Finding #2





- **Selecting the LEAST toxic 100 comment sections;**
- **Investigate what did the video say?**

	Metric	Value
0	comment_empath_positive_emotion	0.111984
1	comment_empath_friends	0.089857
2	comment_empath_optimism	0.088555
3	comment_empath_love	0.065595
4	comment_empath_affection	0.063095
5	comment_empath_party	0.035532
6	comment_empath_celebration	0.031779
7	comment_empath_childish	0.022779
8	comment_empath_family	0.015800
9	comment_empath_music	0.015739

	Metric	Value
0	video_negative_emotion	0.028876
1	video_friends	0.024049
2	video_children	0.020750
3	video_party	0.017348
4	video_death	0.017293
5	video_speaking	0.015425
6	video_family	0.014660
7	video_positive_emotion	0.014360
8	video_violence	0.013034
9	video_giving	0.012382

Limitations & Future Work

- Analysis conducted only on transcripts and comments
  - Not on videos, YouTuber's appearances or manners -> which might affect viewers' perception
  - Not include how well the YouTubers were performing in the game videos
    - Might be super non-toxic in transcripts but just terrible in playing
      - e.g., PewDiePie

- In the future, we can explore more on Topic Modelling for toxic youtuber:
  - What theams are more prone to toxic comment section (maybe strong opinions etc.,)?
  - Characterize most often used words, amount of profanity for each YouTuber

- Seperate the influence of game-brought toxicity (action / non-action) and YouTuber-brought toxicity

- Analyze profanity used in different context:
  - The use of certain language within the gaming community while playing games.
  - Such language does not necessarily imply malicious intent
  - Prompting us to explore methods for detecting the genuine intentions behind oral language use beyond the literal words in the gaming area.

Conclusion

To summarize, we are able to say with cautious confidence that action games video tends to include more toxicity when compared to non-action game videos. We were able to observe a mild positive relationship between game type and toxicity and channel and toxicity.

We were also surprised to find that the transcript's toxicity is that much higher than those of the comments sections. It is interesting to find that even though quite often profanity and offensive words are used in videos, comment sections don’t seem to react as strongly as we’d expected.

We assume this is due to the fact that words used in different contexts can have vastly different meanings and projected perceptions. This showed us the limitations of the NLP and sentiment analysis tools that we used but also provided us with an interesting, potential future research question.

References

Subscribed

[1] Deslauriers, P., St-Martin, L. I. L., & Bonenfant, M. (2020). Assessing Toxic Behaviour in Dead by Daylight : Perceptions and Factors of Toxicity According to the Game's Official Subreddit Contributors. *Game Studies*, 20(4).

[2] Milner, R. M. (2011). Discourses on text integrity: Information and interpretation in the contested fallout knowledge community. Convergence: The International Journal of Research into New Media Technologies, 17(2), 159–175. https://doi.org/10.1177/1354856510397096

[3] Perspective. (n.d.). Using machine learning to reduce toxicity online. https://perspectiveapi.com/

[4] SocialBook. (2020). Top 100 Gaming YouTubers. *Social Book*. https://socialbook.io/youtube-channel-rank/top-100-gaming-youtubers

THANK YOU!

https://github.com/IMT-547-Team-1/YouTube-Toxic-Comments

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PAUSE