



General Online Research Conference GOR 19 6 to 8 March 2019, TH Köln – University of Applied Sciences, Cologne, Germany

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Methods and Tools for the Automatic Sampling and Analysis of YouTube Comments

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Agenda

- Relevance
- Automatic vs. Manual Sampling
- Automatic vs. Manual Analysis
- Emojis
- Outlook





Relevance of YouTube

- Largest / most important online video platform (Alexa Traffic Ranks, 2018; Konijn, Veldhuis, & Plaisier, 2013)
- Esp. popular among adolescents who use YouTube to watch movies & shows, listen to music, and retrieve information (Feierabend, Plankenhorn, & Rathgeb, 2016)
- For adolescents, YouTube partly replaces TV (Defy Media, 2016)





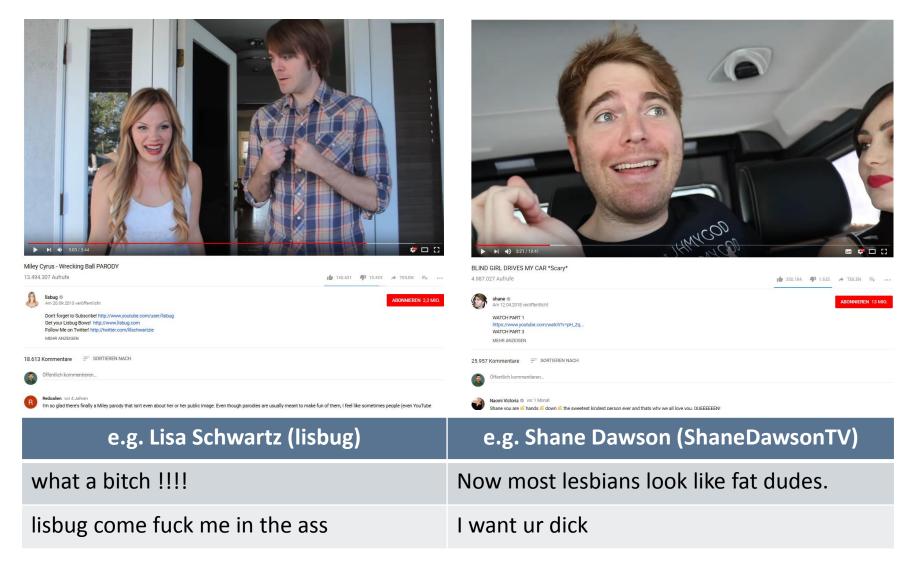
Comments on YouTube

- Useful for research on media content, communicators, and user interaction
- Data publicly available
- Relatively easy to retrieve via YouTube API





Research Example







Research Overview

- What do people write (content)?
 - Sexist Online Hate Speech (Döring & Mohseni, 2018, in press, under revision; Wotanis & McMillan, 2014)
 - Comment characteristics (Thelwall, Sud, & Vis, 2012)
 - ▶ Subtopics, sentiments, & gender differences (Thelwall, 2017)
- Who writes it (communicator)?
 - User experiences (Defy Media, 2016; Lange, 2007; Moor, Heuvelman, & Verleur, 2010; Oksanen, Hawdon, Holkeri, Näsi, & Räsänen, 2014; Szostak, 2013; Yang, Hsu, & Tan, 2010)





Understanding YouTube Comments

- Unusual spelling: ^v_e
 - Spaced
 - CAPITALISED
 - ▶ 13375p34k
- Neologism: Emoji = e (picture) + moji (character)
- Slang: Ur effin hot
- Irony: This is great! <= <= <=</p>
- Emojis: cultural, intraindividual, contextual, and platform differences





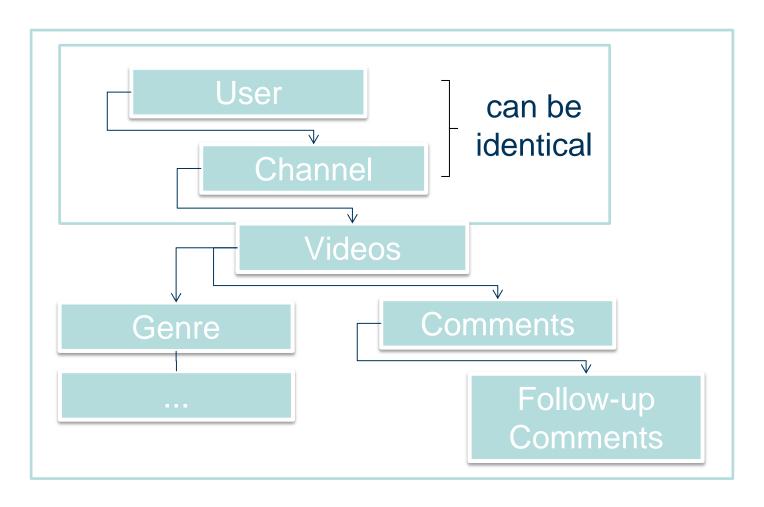
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YouTube data structure







Options for YouTube comment scraping

Method	Manual	Webometric Analyst	YouTube Data Tools	<u>Tuber</u>
Туре	n/a	Program	Web service	Package for R
Platforms	All	Win	All	Win, Mac, Linux, Unix
Collected Features	Depends on coding scheme	Channel Info, Video Info, Comments, Video Search	Channel Info, Video Info, Comments, Video List	Channel Info, Video Info, Comments, Subtitles, All searches
Scoping	Depends on coding scheme	100 most recent or all comments	All comments	20-100 most recent or all comments

Short tutorials on how to use the tools are available in our GitHub repo: https://github.com/JuKo007/YouTubeComments





Tool Comparison

Method	Manual	Webometric Analytics	YouTube Data Tools	Tuber	
Need API-Key	No	Yes	No	Yes	
Disadvantages	Time- consuming	Only first 5 follow-up comments; No error feedback; Undetectable Time-outs	Lacking flexibility; Less infos	Only first 5 follow-up comments (Issue on GitHub open)	
Ease of Use	High	Low	High	Low	
License	n/a	Free for n/c	Open Source	Open Source	
Example: Dayum Video (22.2.@2p.m.)	47.163	44.828	47.153	44.810	





Webometric Analytics

VideoID	Co						Comment Updated		CommentText Display	
DcJFdCmN	_	UgyPhXB5E7Fwip 6y_OF4AaABAg						19-02-22T 41:41.000Z	2019 Lets go	
Comment <i>i</i> Name	CommentAuthor CommentAuth Name			orl					CommentTotalReply Count	
kevork gan	nal	http://www.you I/UC6aYwoJeQA						true	0	
		omment Comment keCount VewerRati			IsReply	Comr	ner	ntPosterInf	0	
true	0 none			0						





YouTube Data Tools

	reply Count	like Count	publishedAt	authorl	Name ⁻	text	
UgyPhXB5E7Fwi p6y_OF4AaABAg	0	0	22.02.2019 08:41	kevork {	gamal	2019 Lets go)
authorChannel Id	autho	orChan	nelUrl		isRepl	y isReplyTo	isReplyTo Name
UC6aYwoJeQAIt_ Nmu3fjy9pg	•	_	.youtube.com JeQAIt_Nmu3		0		





Tuber

authorDisplay Name	authorProf	auth				authorChannelld. value				
2 kevork gamal	https://yt3.ggpht.com NjWx9Ys1hFE/AAAAAA AAI/AAAAAAAAAAAA/X 23CLC2w/s28-c-k-no-r rj-c0xffffff/photo.jpg			e.cor 6aYw	http://www.youtub e.com/channel/UC 6aYwoJeQAIt_Nmu 3fjy9pg			—		
videold te	xtDisplay	textOrig	ginal	canRa	te	viewer	Rating	likeCount		
DcJFdCmN98s 20)19 Lets go	19 Lets go 2019 Lets		TRUE	RUE			0		
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Interactive Jupyter Notebook & R script with examples for scraping and simple sentiment analysis of comment text and emojis can be found in our GitHub repo: https://github.com/JuKo007/YouTubeComments





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Automatic vs. Manual Analysis

- Manual Content Analysis
 - Two or more humans code text units
- Automatic Content Analysis
 - From frequencies of letters to meaning of text units (NLP)
 - Supervised vs. unsupervised
- Automatic Sentiment Analysis
 - Typically bag-of-words approach
 - Dictionaries or ML
- Automatic Topic Modelling
 - Frequencies & networks of topics





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Understanding Emojis

- Interpreting emojis
 - Emoji ≈ verbal descriptor
 - Multiple meanings: \mathbf{M} = clapping, praying, blessed
 - ▶ Context-dependent: **a** = eggplant or penis
 - Culture-dependent
 - Person-dependent
 - Platform-dependent: see next slide
- Interpreting emojis in (con-)text
 - Meaning of emoji can depend on text: â â
 - Emojis can stress meaning of text: Hot!
 - 🕨 Emojis can change meaning of text: Great! 📤 🛭

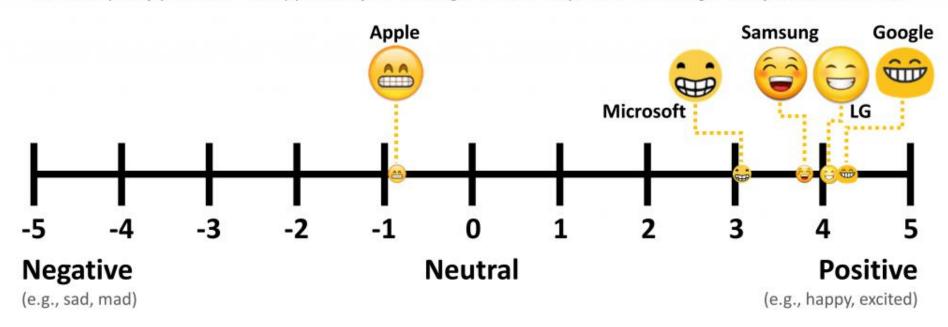




Platform Dependence: Emojis

Same Emoji + Different Smartphone Platform = Different Emotion

For example, if you send the Apple emoji to a Google Nexus, they'll see the Google emoji, and vice versa!



Miller et al., 2016



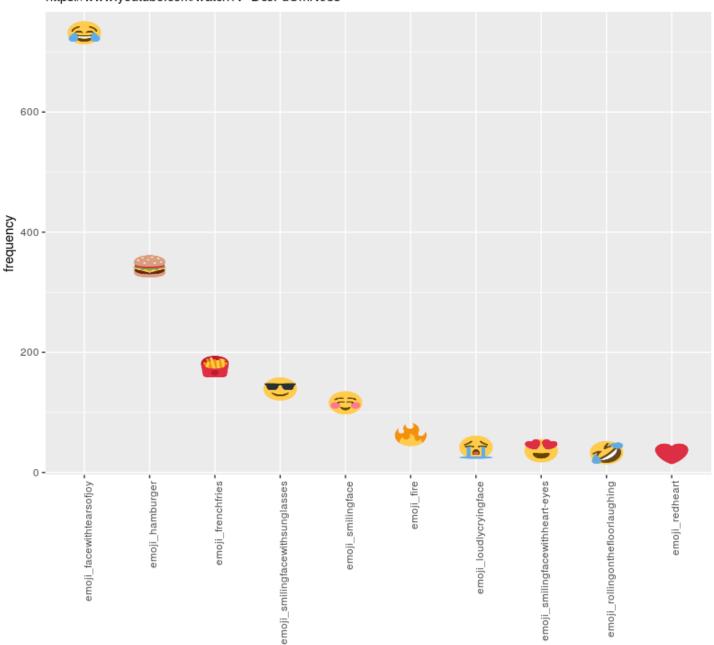


Parsing Emojis

- Parsing emojis
 - Manual emoticons ≠ emojis
 - Encoding can differ \(\begin{aligned}
 \equiv \text{ (a) } \\ \equiv \text{ (b) } \\ \equiv \text{ (c) } \\ \
 - Hex: <f0><U+009F><U+0098><U+0082>
 - Unicode: U+1F602
 - HTML: 😂
 - Constant dictionary updates needed for new emojis
 - 230 new emojis in 2019

10 most frequent emojis

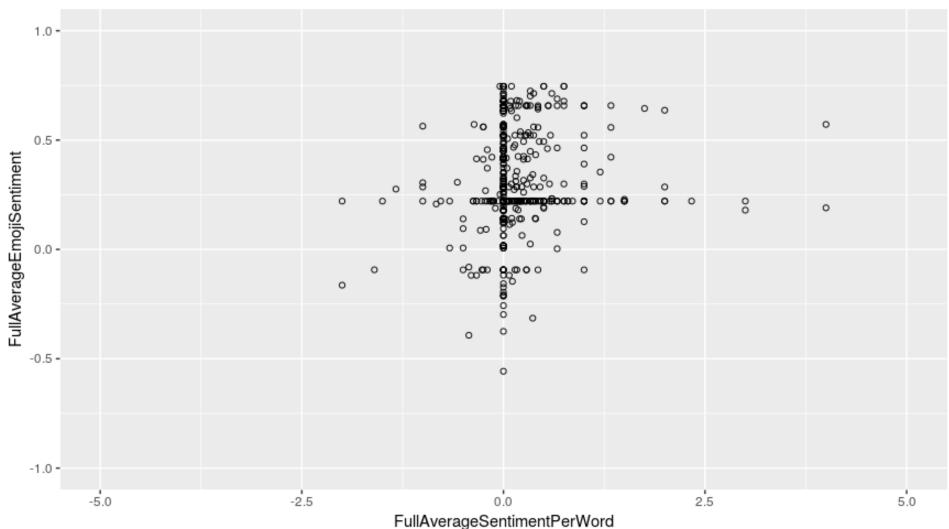
Schmoyoho - OH MY DAYUM ft. Daym Drops https://www.youtube.com/watch?v=DcJFdCmN98s



feature

Averaged sentiment scores for text and emojis

Schmoyoho - OH MY DAYUM ft. Daym Drops https://www.youtube.com/watch?v=DcJFdCmN98s







Limitations of Emoji Sentiment Analysis

- Dictionary does not include all emojis
- Many emojis with small/neutral valence ratings
- Differences in interpretation due to multiple meanings, (con-)text, culture, person, & platform





Limitations of Bag-Of-Word Sentiment

Senti- ment	Comment
>+10	Schmoyoho, we're not really entertained by you anymore. You're sort of like Dane Cook. At first we thought, " Wow ! Get a load of this channel! It's funny !" But then we realized after far too long, " Wow , these guys are just a one trick pony! There is absolutely nothing I like about these people!" You've run your course. The shenanigans, the "songifies" we get it. It's just not that funny man. We don't really like you.
<-10	Fucking hilarious! And that guy could either do commercials or be an actor, I've never, in my entire life, heard anyone express themselves that strongly about a fucking hamburger. And now all I know is I have never eaten one of those but damned if I won't have it on my list of shit to do tomorrow! Hell of a job by schmoyoho as well, whoever said this should be a commercial hit it on the head.





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Outlook

- Systematic sampling of videos
- Going beyond bag-of-words/-emojis
 - N-grams
 - Word/emoji embeddings
- Machine Learning
 - Instead of dictionary-based sentiment analysis
- Topic Models with emojis
 - Using textual description of emojis
- Automated text analysis using network techniques (see, e.g., https://github.com/cbail/textnets) + emojis





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