

Social Media Analytics for YouTube Comments: Issues, Gender and Sentiment¹

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The need to elicit public opinion about predefined topics is widespread in the social sciences, government and business. Traditional survey-based methods are therefore being partly replaced by social media data mining but YouTube comments tend to be overlooked, despite the ongoing popularity of the site. This article introduces a systematic social media analytics strategy to gain insights about a topic from YouTube by searching for relevant videos, downloading their comments and analysing them with a term frequency approach. The results of a proof-of-concept investigation of sets of videos about dance styles show that it is possible to identify plausible patterns of subtopic difference, gender and sentiment. The analysis also points to the generic limitations of social media analytics that derive from their exploratory multi-method nature.

Keywords: social media analytics; YouTube comments; opinion mining

Introduction

Questionnaires, interviews and focus groups are standard social science and market research methods for eliciting opinions from the public, service users or other specific groups. In industry, mining social media for opinions expressed in public seems to be standard practice with commercial social media analytics software suites that include an eclectic mix of data mining tools (e.g., Fan & Gordon, 2014). Within academia, there is also a drive to generate effective methods to mine the social web (Stieglitz, Dang-Xuan, Bruns, & Neuberger, 2014).

Many existing social research techniques have been adapted for the web, such as content analysis (Henrich & Holmes, 2011), ethnography (Hine, 2000), surveys (Crick, 2012; Harrison, Wilding, Bowman, Fuller, Nicholls, et al. 2016; Tijdens & Steinmetz, 2016), or network analysis (Ackland & Gibson, 2013; Corley, Cook, Mikler, & Singh, 2010). Some quantitative methods focus on counting web activities, such as tweets, retweets hashtags, keywords, or YouTube video comments, and use these for analyses of the levels of interest in a topic or set of resources (Bruns & Stieglitz, 2012; Sugimoto & Thelwall, 2013), or for a time series analysis of trends in interest (Bruns & Stieglitz, 2013; Stieglitz & Krüger, 2011; Thelwall, 2007). In contrast, the computational approach uses algorithms to generate new insights (Giglietto, Rossi, & Bennato, 2012). Examples include community detection based upon connections between users or resources (Jürgens, 2012), and automatic categorisation (Bouman, Drossaert, & Pieterse, 2012), with sentiment polarity being the most common example (Thelwall, Buckley, & Paltoglou, 2011). Using natural language processing techniques, it may also be possible to extract highly specific information, such as the symptoms of illegal drug

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use at specific dosage levels (Chary, Park, McKenzie, Sun, Manini, & Genes, 2014). Theoretical analyses may also use an analytic approach (e.g., Dynel, 2014).

An alternative strategy, the social media analytics approach (Stieglitz, Dang-Xuan, Bruns, & Neuberger, 2014), is to combine a range of different methods in order to generate insights, such as, “sentiment analysis, topic modeling, social network analysis, trend analysis etc.” (Fan & Gordon, 2014). This extensive method triangulation and the ability to study a phenomenon dynamically (Edwards, Housley, Williams, Sloan, & Williams, 2013) partially offset the low sampling validity of social web data by merging different types of information (e.g., comments, likes, hit counts) to look for deeper insights. Although social media analytics software has been developed to enable the user to explore their data in multiple different ways (Burnap, Rana, Williams, Housley, Edwards, et al., 2015), combined methods or at least guiding frameworks are needed in order to help researchers to select and evaluate appropriate analysis strategies.

YouTube is a logical free source of social web data because it has been world’s second or third most popular website since October 2007 according to Alexa.com², and is already exploited by commercial organisations (Fan & Gordon, 2014). Although Twitter is analysed more in academic publications (e.g., Pak & Paroubek, 2010) it is limited by the presence of spam and bots, and restrictions on free data collection. The multiple purposes for YouTube and its international and inter-generational audiences make it a potentially valuable source of information about the act of watching videos, the issues depicted in them and the uses and gratifications gained from them.

YouTube has been investigated for the accuracy of videos about important topics (Briones, Nan, Madden, & Waks, 2012), its communication value (Lewis, Heath, Sornberger, & Arbuthnott, 2012), the content of a small themed set of videos (Jaspal, Turner, & Nerlich, 2014) and for the system itself (Thelwall, Sud, & Vis, 2012). There are also analyses of topics on YouTube that use a single primary method, such as content analysis (e.g., Desai, Shariff, Dhingra, Minhas, Eure, & Kats, 2013; Smith, Fischer, & Yongjian, 2012).

There are a few published general purpose social media analytics strategies as well as discussions of the advantages of combining methods (e.g., Lünich, Rössler, & Hautzer, 2012). The *Vista* method exploits time series visualisations to track changes in sentiment, username mentions and keyword frequency over time for an event on Twitter, allowing explorations of subtopics through deeper queries of the data (Hoerber, Hoerber, El Meseery, Odoh, & Gopi, 2016). A YouTube-specific general purpose method analysed the success of six anti-smoking videos through their manually filtered comments, various metrics (e.g., views, Likes), networks of interactions between commenters, automatically detected comment sentiment and a manual content analysis. These were combined to produce an evidence-based evaluation of the success of the campaign (Chung, 2015).

The current article extends ideas of the above paper (Chung, 2015) for research into *issues* within YouTube, rather than pre-defined small sets of videos, and extends the methods through word frequency and gender analyses, as widely used elsewhere but modified here. None of these contributions are individually novel, but their combination, elaboration and support with free software are intended to lower the

² http://web.archive.org/web/20090601000000*/http://www.alexa.com/topsites and http://web.archive.org/web/20050201000000*/http://www.alexa.com/site/ds/top_sites?ts_mode=global&lang=none

barrier against using YouTube audience analytics in research. This paper therefore proposes a method for gathering and analysing YouTube comments on a relatively large scale (larger than for any previous published academic analyses of a topic on YouTube) to gain quick free insights into an issue, with a focus on gender, sentiment and discussion themes. The paper also discusses the limitations of YouTube comment data and the contexts in which it might be useful, reports an illustrative analysis of dance-related videos and discusses the generic limitations of research methods based on social media analytics.

Research questions

The overall goal of this paper is to introduce the systematic Comment Term Frequency Comparison (CTFC) social media analytics method, supported by free software, to investigate YouTube culture around a specific topic.

- RQ1: Can the CTFC method identify plausible and/or insightful subtopic dimensions of discussions about a topic in YouTube comments?
- RQ2: Can the CTFC method identify plausible and/or insightful gender dimensions of discussions about a topic in YouTube comments?
- RQ3: Can the CTFC method identify plausible and/or insightful sentiment dimensions of discussions about a topic in YouTube comments?
- RQ4: Can the CTFC method identify plausible and/or insightful networks of relationships between topics?

The YouTube *CTFC* method comprises a technique for gathering relevant YouTube comments as well as a set of techniques for analysing them, both of which are supported by the free Webometric Analyst and Mozdeh software. Like grounded theory and similar qualitative approaches, the primary analysis method is exploratory and can be characterised a (sophisticated) fishing expedition because its goal is to gain insights into the topic rather than to test hypotheses. As a consequence, it is impossible to assess the efficacy of the method rigorously. Moreover, the method is a combination of multiple different approaches so that it would be difficult to perform, say, a more sophisticated evaluation based upon multiple topics. Nevertheless, there is a need for general purpose exploratory YouTube analysis methods, given the popularity of the site, and these limitations are probably generic to any such attempt.

The CTFC method

The CTFC method comprises both data gathering and analysis. Whilst the complete method involves many different types of analyses, a particular application can ignore irrelevant ones. This section gives an overview of the method. For an extended version with additional technical details and software instructions, see Appendix 3.

CTFC Step 1: Data gathering and filtering

The data gathering step involves creating a list of relevant videos and downloading their comments. Care is needed to ensure that relevant data is collected because any problems with the data will result in weaker analyses (i.e., *garbage in, garbage out*). The recommended data gathering stages are illustrated here with the dance videos topic.

- (1) *Topic definition and delineation*: The scope of the project must be defined at the outset. This should be designed to guide decisions about which videos are

relevant and should be guided by the goals of the research project. *Dance*: the scope of the project is videos with a primary focus on a single dance style, including instructional and performance videos but excluding those focusing on the music associated with the dance and videos that contrast different dance styles.

- (2) *Initial subtopic query set generation*: The topic must be split into a set of subtopics and a YouTube query generated to match each one. *Dance*: The subtopics are dance styles and the initial query set was generated from a Wikipedia page on Dance style categories (en.wikipedia.org/wiki/List_of_dance_style_categories) with dance style names recorded as phrase searches.
- (3) *Query testing and refinement*: Each query in the set generated in the previous step should be tested in YouTube.com to ensure that it generates a high percentage (90% as a guideline figure) of correct matches.
- (4) *Video list generation*: Free software can be used to download a list of videos matching the queries. *Dance*: The list of 36,702 videos with title matches was used.
- (5) *Video list checking*: The list of videos matching the queries should be checked and false matches removed.
- (6) *Comment downloading*: Free software can be used to download the comments on the matching videos.
- (7) *Duplicate commenter removal*: Users should be restricted to a maximum of one comment each to protect the word frequency analysis from the actions of prolific individuals.
- (8) *Comment pre-processing*: The comments should be loaded into the analytics software.
- (9) *Language filtering*: YouTube comments can be written in any language but the word frequency analysis relies upon the terms being in the same language. The next stage is therefore to filter out comments that may not be in the chosen language. A simple way to achieve this approximately is to exclude all comments that do not contain any terms that are common in the selected language and rare in others (Grefenstette, 1995).

The above steps produce dataset of YouTube comments in the chosen language, together with the identity of the video commented upon, the commenter and the query used to find the video. For the analysis to work well, a large collection of comments is needed.

CTFC Step 2: Time series graph

A time series graph should be produced to assess the typical dates of comments as background information to see the time period that the comments relate to.

CTFC Step 3: Subtopic word frequency analysis

The subtopic word frequency analysis seeks issues that are characteristic of each subtopic in the sense of being more discussed by people that comment on the subtopic than on other subtopics of the broad topic. It is important to keep the comparison within the broad topic so that the characteristic issues of subtopics are more fine-grained. A related approach has previously been used with Twitter (Bryden, Funk, & Jansen, 2013).

The word frequency analysis method is to compare the frequency of terms that match one subtopic with their frequency for the remaining subtopics in order to find terms that are unusually frequent for the chosen subtopic. The standard chi-squared statistic should be used for this by listing terms that are more frequent for the subproject in descending order of chi-square value. From this list, higher chi-square values associated with increased likelihood of a term being characteristic of the subtopic.

This method is imperfect for several reasons. It relies upon individual words whereas concepts may be expressed through phrases. First, if key concepts are expressed using phrases that only include common words (e.g., “to be or not to be”) then the method will not identify any of the words within the phrase and the concept will be missed. Second, the comments may contain substantial unrelated discussions, such as an off-topic argument between two commenters, and these can result in spurious issues being identified. This can be guarded against by reading a random sample of comments from the subtopic containing the identified keyword. Finally, the terms for each individual subtopic depends on the other subtopics in the set. For example, if there is only one subtopic about swing dancing then the term “swing” is likely to be near the top of its term list, but if there are several swing subtopics, then this would make the term less specific to the subtopic and reduce its chi-squared value.

The top terms (e.g., the 50 with the highest chi-square value) identified by the basic word frequency analysis should be manually examined for relevance and insights into the subtopic. A term’s importance should be interpreted using the fact that it is relatively frequent in subtopic comments compared to the other subtopics. The top terms are likely to include predictable nouns associated with the subtopic, including the subtopic name, but terms with a less obvious association are more interesting. The presence of irrelevant terms that need to be identified manually and removed is an expected characteristic of any word frequency comparison approach (Thelwall, Prabowo, & Fairclough, 2006).

CTFC Step 4: Gender analysis

The gender analysis seeks issues that disproportionately originate from male or female commenters. This can point to gender differences in opinions about the videos as well as the aspects of the videos that are discussed. Gender differences may give insights into a topic even if a study does not have a specific focus on gender. For this, terms in the female-authored comments should be compared to terms in the male-authored comments (a) overall for the project and (b) for each individual subproject. Although commenter gender information is (no longer) provided by YouTube, it can be inferred from commenters’ names. Commenters must be registered within YouTube and have a channel name (possibly with spaces) and a username (without spaces). Potential first names should be extracted from the first of these and from the second if it uses camel case (e.g., PardeepSingh) and then compared against a dictionary of common first names, organised by predominant gender.

In principle, it may also be interesting to conduct comparative word frequency analyses by age range, nationality, and other demographic variables but no information about these is available from YouTube. Thus, gender is the only practical commenter segmentation information.

CTFC Step 5: Sentiment analysis

The sentiment analysis seeks issues that elicit particularly strong positive or negative sentiment. These should be identified by a word frequency comparison of comments

with strong sentiment against the remainder. This can be achieved through automatic sentiment strength detection, such as with the program SentiStrength that is designed for the short informal text of social media posts, including YouTube comments (Thelwall, Buckley, & Paltoglou, 2012). For positive sentiment, the technique is the same as for the basic word frequency analysis except for splitting the comments into two sets, one of which has a positive sentiment strength score of at least 3 (moderate) out of 5, and the second set containing the remaining comments. For negative sentiment strength the procedure is the same except that the split is based on comments having a negative sentiment strength of at least 3 out of 5. Both analyses can be conducted across the whole project or within individual subprojects.

CTFC Step 6: Overview network

The overview network is a network diagram of strength of relationships between subtopics. Although subtopic similarity can be analysed by many different statistical methods, such as clustering, factor analysis or multi-dimensional scaling, the method recommended here is a simple network diagram, with subtopics represented by nodes in the network and lines occurring between nodes when their comments tend to use similar words. This network is therefore a comment term similarity network. A network is preferable to cluster analyses because subtopics on YouTube can be expected to relate to others in multiple different ways, rather than through a single dimension of difference. A network is preferable to multidimensional scaling because connections in networks are explicit whereas multidimensional scaling maps can place dissimilar objects close together to aid the overall coherence of a picture.

The logical metric to use to compare subtopic term similarity is the standard information retrieval metric of cosine similarity based upon Term Frequency and Inverse Document Frequency (TF-IDF). This measures the virtual angle between two subtopics, with wider angles occurring for pairs of subtopics that tend to use different terms. Here the term frequency is the number of comments within the subtopics that contain a term rather than the total number of terms in all comments within the subtopics (i.e., multiple occurrences of a term within a single comment are ignored). The TF-IDF weighting gives more importance to terms that are common for the two subtopics compared and rare in other subtopics.

CTFC Steps 0 and 7: Pilot testing and insight verification

The above analyses are likely to be influenced by spam, off-topic conversations in comments, and off-topic videos. The initial results may therefore not give substantial insights. Two strategies are recommended to maximise the value of the method: pilot testing and insight verification.

A small-scale initial pilot test should be run to identify any large scale obvious problems with the initial queries for subtopics. All the analyses should be attempted in the pilot study but the purpose is to quickly check for likely sources of off-topic information so that the subtopic queries can be adjusted to avoid them in the main test. The main analysis can follow this with the revised queries.

The second strategy is to trace and verify the causes of all insights during the main analysis. This means reading comments containing the relevant terms, except in the case of the network diagrams, where this is not possible. In cases where the cause of an apparent insight is spam or off-topic comments, the insight should be ignored. If there are too many problems at this stage then the analysis may need to be repeated with modified queries, if possible, to eliminate the problems. Thus, for a particularly serious

project, the method may need to be attempted several times until the insights reflect the topic rather than spurious factors.

Results

This section describes the result of applying the CTFC method to the topic of dance in YouTube videos, as described above. See Appendix 1 for background information about the issue.

Step 2: Time series graph

Comments on the videos matching the search spanned an 11-year period, with disproportionately many from recent years (Figure 1). The increase over time is likely to be partly due to older videos being deleted and older comments not being retrieved for videos with greater than the per video maximum from the YouTube API.

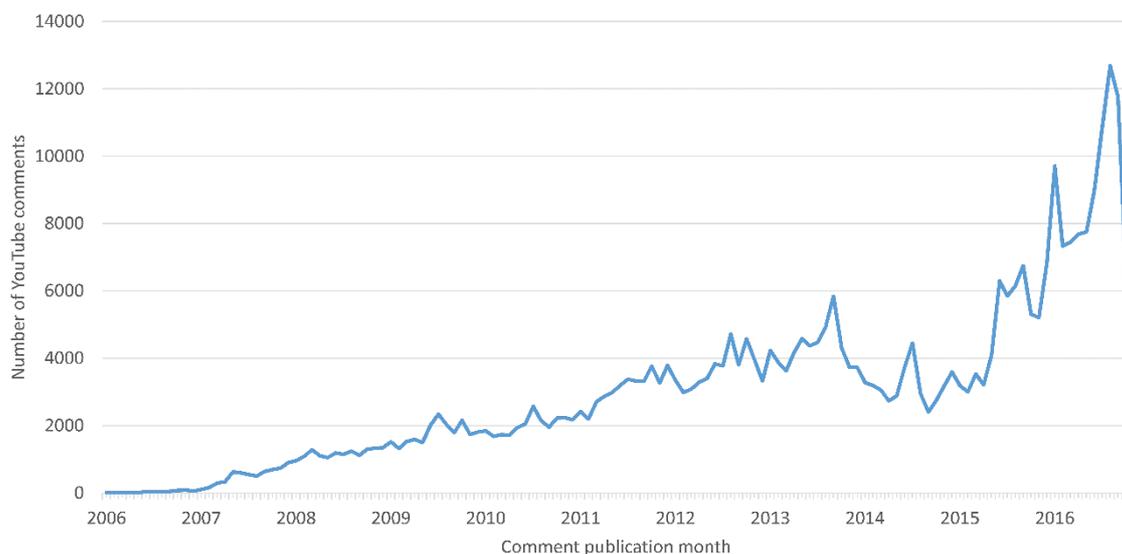


Figure 1. Overall comment frequency per month for the complete dataset.

Step 3: Subtopic word frequency analysis

For each of the 30 dances (i.e., subtopics), the five words most strongly associated with the videos matching the dance style searches were analysed (Table 1). These are terms that occur more frequently in comments for a given dance video set compared to the remaining dance video sets. Although a fuller analysis would cover more terms, analysing the top five for each dance may give insights into the aspects of the dance that are most comment-worthy on YouTube, and hence help to evaluate transparently whether CTFC Step 3 is likely to be useful.

Most of the top terms are dance genre names, dancer names, songs, or dance moves (Table 1), none of which seem likely to give deep insights into an individual dance genre. A partial exception is that in some cases the music-terms point to an above average degree of association between the dance and the music, or a subsumption of the dance within the music (hardcore dancing, electro dance). Terms that mention a country or nationality are not particularly insightful either, except in the case of Bollywood dance, where analysis of the comments containing the terms points to an

individual high profile example of the dance, given by a successful Miss America candidate as part of the contest.

Sentiment terms are rarer in Table 1. Contemporary dance is disproportionately seen as being *beautiful*, Hit Dem Folks as being *lit*, with the dancers *killing* it, whereas Zumba is *fun*. In the first two cases the positive reception of the dances are partly language-specific, however. The contrasting language styles of these two cases point to the importance not only of the sentiment expressed but also the term selected to express it. Thus, the other dance styles are either appreciated less or are appreciated with more commonly used terms. Thus, the key sentiment finding is that both dance genres are appreciated with unusual terms. For Zumba the term fun suggests enjoyment through participation, perhaps set against a context in which people expect not to enjoy exercise.

The context terms help to identify topics that are driven by a primarily non-dance issue, such as those associated with a video game (Ballroom, Disco dancing, Electric boogaloo). In addition, they point to ritual contexts in which a dance may be used (Bachata, Cheer dance, Hardcore dancing) or a dance's origins (Crip walk).

Overall, then, whilst most of the terms do not give deep insights into dance genres, some may and the terms can also point to data collection problems and individual important contexts for the dance.

Table 1. The top five terms for each dance. These are relatively common in comments for each dance compared to comments for other dances (English comments only, includes non-gender commenters). Terms associated with the dance name, moves, music, and origins are in bold. Pronouns and names of people are in italic. Sentiment terms are underlined. Terms associated with appearance are italic and underlined. Terms associated with lessons are bold and underlined.

Dance genre	Top 5 terms	Comment
Acro dance	acro <i>Chloe Abby Katrina</i> tuck	Back tuck: move
Bachata dance	bachata Dominican <i>chambelan quince</i> ven	Ven tu: song name
Ballet dance/dancing	ballet pointe ballerina <i>Kaylee</i> splits	On pointe, splits: positions
Ballroom dance	<i>Squall Rinoa</i> ff8 fantasy ballroom	ff8: Computer game
Belly dance	belly <i>Sadie Shakira Joven Ellen</i>	
Bollywood dance	Indian Bollywood India <i>Nina</i> America	Miss America, Nina Davuluri
Breakdancing	<i>Bridgette</i> breakdancing <i>Roger</i> bboy <i>Mr</i>	
Cheer dance	cheer team cheerleader tryout cheerleading	
Contemporary dance	contemporary <i>Travis Tate</i> <u>beautiful</u> <i>Robert</i>	
Crip Walk	crip walk blood gang <i>Gosu</i>	
Disco dance	<i>toby</i> disco <i>Jessica Sylvester Rayman</i>	
Disco dancing	map <i>muselk</i> server <i>Alfie</i> disco	Team Fortress 2: Computer game disco-themed custom map
Electric boogaloo	<i>Jesse</i> game boogaloo space <i>Karkat</i>	Dragon Age 2, FTL: Computer games
Electro Dance	electro mix <i>yarus</i> remix mixes	<i>Electro dance</i> is a music style name
Hard dance	<i>Monstercat</i> hardstyle <i>Stonebank Ravine</i> hard	<i>Hard dance</i> is a music style name
Hardcore dancing	hardcore pit mosh moshing metal	Moshing, mosh pit: dances; Metal: music style
Hip Hop dance	<i>Kenneth Matt</i> Jabbawockeez <i>bailey dana</i>	Jabbawockeez: Hip Hop dance crew.
Hit Dem Folks	<u>lit</u> folks hit <i>Meechie</i> <u>killed</u>	Lit, killed: excellent;
House dance	<i>momo</i> house mix <i>Junho Chaeyeon</i>	"House dance mix" a common phrase
Jazz dance	jazz flute turn pirouette jazz-funk	"Freedom jazz dance" piece for flute; Pirouette: dance move
Jumpstyle dance	jumpstyle <i>Klaas elan</i> hardjump tecktonik	Hardjump, tecktonik: dance styles
Kpop dance	kpop <i>Infinite BTS VIXX Miu</i>	
Line dance	line wobble cotton boots linedance	Wobble: dance move; Cotton eyed joe: song; Boots: clothing
Lyrical dance	<i>Jadine</i> lyrical <i>Nadine Gerald Ade</i>	
Melbourne Shuffle	shuffle shuffling melbourne shuffler <u>lmfao</u>	Lmfao: funny
Popping dance	popping <i>Dytto Hoan Nelson Gucchon</i>	
Reggaeton dance	reggaeton <i>Maga Yomo Inga</i> <i>calla</i>	Bella Calla: song
Robot dance	robot <i>Usher mj Michael Jackson</i>	
Salsa dance	salsa <i>Eugene Claudia</i> Cuban <i>quimbara</i>	Quimbara: song
Tap dance	tap tapping cover Irish <i>Tamera</i>	Just (Tap) Dance: Song (cover version); Mislabeled Irish dance video;
Zumba dance	zumba workout <i>Vijaya Madelle</i> <u>fun</u>	Zumba is a dance fitness program

Step 4: Gender analysis

The five words most strongly associated with females and males within the comments for each dance style were analysed for insights into gender differences. Again the purpose of analysing just the top five terms is to evaluate whether Step 4 is likely to be useful.

Females. In the entire corpus, the 10 most female-associated terms are: she, amazing, her, beautiful, cute, omg, belly, ballet, really, workout. These include female pronouns, dance styles, positive sentiment terms and a use of dance (workout).

Positive sentiment in individual dance genres: Positive sentiment terms are a female-associated characteristic, including cute (M:1 topic; F:6 topics), omg (M:0; F:8), amazing (M:0; F:8), liked (M:0; F:2), thanks (M:0; F:3), awesome (M:0; F:1), good (M:0; F:1), beautiful (M:1; F:3), but with some exceptions: great (M:1; F:0), sexy (M:1; F:0), hot (M:1; F:0).

Pronouns: Pronouns are a female-associated characteristic, including she (M:0 topic; F:8 topics), your/you're/u (M:0; F:4), her (M:0; F:3). Pronouns (and thanks: M: 0, F:3) suggest a more direct involvement in the people in the video (she/her) as well as exchanges with other commenters (your/you're/u).

Appearance: Comments on the appearance of the dancers are a female-associated characteristic, including cute (M:1 topic; F:6 topics), shoes (M:0; F:1), hair (M:0; F:1), makeup (M:0; F:2), outfit (M:0; F:1), with the exception of sexy (M:1; F:0), hot (M:1; F:0).

Learning or practicing: Terms associated with learning are female-associated, including learn/learned (M:0; F:1), class/classes/teach (M:0; F:2), workout (M:0; F:2), and perhaps also can/can't (M:1; F:3).

Table 2. Top words (highest chi-square) for **female** compared to male authored comments for the dance. Terms associated with the dance name, moves, music, and origins are in bold. Pronouns and names of people are in italic. Sentiment terms are underlined. Terms associated with appearance are italic and underlined. Terms associated with lessons or workouts are bold and underlined.

Dance subtopic	Top 5 terms
Acro dance	how acro year <i>Abby u</i>
Bachata dance	main <u>dress</u> <u>cute</u> <i>chambelan*</i> did
Ballet dance/dancing	<i>she her</i> pointe when year
Ballroom dance	<u>cute</u> <u>omg</u> <u>makeup</u> ballroom classes
Belly dance	move <u>skinny</u> <u>thanks</u> <i>she I'm</i>
Bollywood dance	<i>she</i> with else <i>you're</i> <u>loved</u>
Breakdancing	<i>Annie snow</i> house <i>Bratayley</i> <u>gymnastic</u>
Cheer dance	cheer trying out do team
Contemporary dance	<u>amazing</u> <u>beautiful</u> <i>Maddie</i> <i>you're</i> use
Crip Walk	<u>liked</u> <u>amazing</u> <u>good</u> <u>xx</u> <u>hell</u>
Disco dance	workout <i>Jessica</i> <u>fun</u> challenge day
Disco dancing	<i>she</i> <u>amazing</u> <i>her</i> <u>beautiful</u> <u>cute</u>
Electric boogaloo	<i>Karkat</i> hardy voice act too
Electro Dance	<u>shoes</u> <u>wonderful</u> kept watching walking
Hard dance	<u>cute</u> v <u>makeup</u> <u>hair</u> <u>beautiful</u>
Hardcore dancing	<i>she</i> girl hardcore <u>omg</u> shower
Hip Hop dance	<u>amazing</u> <i>Kenneth</i> <i>she Dana</i> <u>omg</u>
Hit Dem Folks	<u>killed</u> <u>cute</u> <i>her</i> <u>outfit</u> <u>liked</u>
House dance	<i>Junho Momo</i> ending <i>Taeyeon Wooyoung</i>
Jazz dance	turn <u>amazing</u> <i>she</i> really <u>loved</u>
Jumpstyle dance	can <u>amazing</u> jumpstyle <u>omg</u> <u>haha</u>
Kpop dance	really infinite them <u>best</u> <u>vixx</u>
Line dance	<u>fun</u> make class have teach
Lyrical dance	<i>your</i> well on did have
Melbourne Shuffle	<u>omg</u> <u>xx</u> <u>thanks</u> <u>meh</u> <u>awesome</u>
Popping dance	<u>omg</u> <i>Dytto</i> <i>she</i> cant <u>amazing</u>
Reggaeton dance	<u>cute</u> am can don't reggaeton
Robot dance	<i>Michael</i> <u>omg</u> <u>amazing</u> <u>wow</u> <i>usher</i>
Salsa dance	<i>Eugene Claudia</i> <i>judge</i> really couple
Tap dance	much <u>omg</u> been learn learned
Zumba dance	<u>fun</u> <u>thanks</u> much workout <i>Jessica</i>

* Chambelan (Spanish) escort

Males. The 10 most male-associated terms in the whole corpus are: shit, fuck, shuffle, man, fucking, crip, dude, bro, shuffling, hardstyle. These include male common nouns, dance styles and swear words.

Swearing: Strong and moderate swearwords are male-associated, including fuck/fucking (M:4 topics; F:0 topics), and shit (M:5; F:0). The term shit was usually associated with mildly negative sentiment, but also had a few positive uses, such as in the phrase,

“[pronoun or name] killed that shit”. Fucking was usually employed as a booster term in a negative context and fuck was used in varied negative ways.

Music: Name is a male gendered term (M: 4; F: 0) and typically associated with a comment requesting the song name. This aligns with the higher use of explicitly music-related terms by males, such as play/playing (M:2; F:0), mix/remix (M:3; F:0), and music (M:1; F:0).

Common nouns: Several generic terms for people, especially male(s), were male associated, including people (M:1; F:0), man (M:4; F:0), dude (M:1; F:0), bro (M:2; F:0), and bitch (M:2; F:0), but not girl (M:1; F:1). This suggests a more abstract perspective compared to the use of pronouns by females.

Table 3. Top words (highest chi-square) for **male** compared to female authored comments for the dance. Terms associated with the dance name, moves, music, and origins are in bold. Pronouns and names of people are in italic. Sentiment terms are underlined. Terms associated with appearance are italic and underlined. Terms associated with lessons are bold and underlined.

Dance subtopic	Top 5 terms
Acro dance	original watch must <u>spectacular</u> honest
Bachata dance	en <i>Edwin</i> salsa bachata style
Ballet dance/dancing	god art watched system culture
Ballroom dance	game <u>best</u> second already people
Belly dance	<i>Joven</i> <u>sexy</u> <i>he</i> instant <u>hot</u>
Bollywood dance	India <u>shit</u> at anti-white since
Breakdancing	<u>shit</u> game bboy <u>bitch</u> <i>Wolf</i>
Cheer dance	NU* sa ang na lang
Contemporary dance	<u>funny</u> <u>bitch</u> front film <u>bich</u>
Crip Walk	walk c clown gangsta real
Disco dance	mix lo does who la
Disco dancing	<u>shit</u> <u>fuck</u> shuffle man <u>fucking</u>
Electric boogaloo	<u>better</u> does ship lot <i>Jesse</i>
Electro Dance	don't keep <u>fuck</u> track DJ
Hard dance	on hardstyle dj remix <u>fucking</u>
Hardcore dancing	hardcore mosh <i>your</i> <u>fag</u> if
Hip Hop dance	crew <i>Jabbawockeez</i> <u>shit</u> name <u>best</u>
Hit Dem Folks	<u>shit</u> bro kid cop <i>tre</i>
House dance	mix man <u>fuck</u> music name
Jazz dance	<i>he</i> guy isn't play playing
Jumpstyle dance	can man jumpstyle hardjump <i>they</i>
Kpop dance	Asian girl porn <u>beautiful</u> sex
Line dance	de DJ left dude old
Lyrical dance	kc night similar took man
Melbourne Shuffle	smack alpha twin vid <u>nice</u>
Popping dance	name more <i>John</i> popping battle
Reggaeton dance	<u>cute</u> bro <u>hot</u> <u>ass</u> all
Robot dance	guy camera <u>judge</u> popping up
Salsa dance	video <u>great</u> name <i>Anthony</i> from
Tap dance	play deck guy bass band
Zumba dance	Google information <i>his</i> shed esta

*NU: National University (Philippines). Related terms are from bilingual comments.

Overall, the gender analysis seems to give much more substantial insights into gendered reactions to videos, both overall and for individual dance genres. The strongly gendered comments are unsurprising given the importance of gender for most types of dance.

Step 5: Sentiment analysis

The ten terms associating most strongly with positive sentiment overall were: **Please**; **nice**; **wow**; **beautiful**; **loved**; **job** (e.g., **nice/great/good job**); **pretty**; **hope**; **perfect**;

keep (going/up the good work/it up). For five dance genres the term dancer suggests positive comments about the dancers, and for others the terms hilarious/lmao (8 dances) suggest amusement. Other occasional sentiments are respect (4) and inspire/inspired/inspiration (4). Occasional topics include mix/mixes (4) and workouts (4).

For the Melbourne Shuffle, terms in commonly echoed track listings were excluded for sentiment classification of the titles (*Scantraxx Roots - Headhunterz Vs Abject Superstar DJ - Dark Oscillators Smack my derb - Alpha Twins Young Birds - Patrick Bunton*).

Table 3. Top five words (highest chi-square) for **positive sentiment strength** (positive 3-5; negative 1-2) compared to the remaining comments for the dance; terms in the top 10 overall list are excluded. Unusual terms are in bold.

Label	Top 5	Comment
Acro dance	pretty such an fantastic absolutely	
Bachata dance	sexy liked dancer fine both	
Ballet dance/dancing	wonderful adorable Kaylee such graceful	
Ballroom dance	wonderful liked these romantic beauty	The ballroom dance scene in Final Fantasy 8 is romantic for a videogame.
Belly dance	sexy wonderful excellent gorgeous smile	
Bollywood dance	proud wonderful liked smile fantastic	Indian Americans proud of Miss America's dance.
Breakdancing	hilarious lmao respect adorable liked	
Cheer dance	luck congrats cheering liked smile	"Good luck" trying out for a team.
Contemporary dance	hilarious absolutely inspiration inspired dancer	
Crip Walk	respect lmao liked vid check	Requests to check out other videos
Disco dance	mix workout job Jessica fantastic	
Disco dancing	liked xx game hilarious sexy	
Electric boogaloo	hilarious hug congrats enjoy work	
Electro Dance	mix work enjoy mixes liked	
Hard dance	work liked mix enjoy adorable	
Hardcore dancing	hilarious lmao hero rofl greatest	Song in <i>Guitar Hero</i> game.
Hip Hop dance	proud dancer workout liked work	National pride comments on competition video.
Hit Dem Folks	liked work lmao adorable vid	
House dance	mix enjoy sexy work Ryan	
Jazz dance	dancer technique fantastic omg excellent	
Jumpstyle dance	kiss liked sexy tutorial yellow	Song lyric, "suck my dick, kiss my ass"; dancer, "the girl in yellow"
Kpop dance	sexy cover dancer adorable omg	
Line dance	enjoyed enjoy sharing teach ladies	"Thanks for sharing!"
Lyrical dance	Jadine couple liked Kyla inspire	
Melbourne Shuffle	liked vid inspired work enjoy	
Popping dance	excellent inspiration fantastic respect	
Reggaeton dance	sexy workout work exercise fine hey	
Robot dance	proud greatest liked hilarious respect	
Salsa dance	excellent sexy work enjoy enjoyed	
Tap dance	wonderful fantastic absolutely smile brilliant	
Zumba dance	workout enjoyed party fantastic enjoy	<i>Dance Party (Zumba style) video.</i>

The ten terms associating most strongly with negative sentiment overall were: **Shit; fuck; killed; stupid; wtf; hate; idiot; dislike; die; dead**. For several dances terms associated with fear are evident (afraid/scared: 4 dances) suggesting performance worries (except for the Kpop comments). The negative sentiments in some comments were expressions of sadness elicited by a performance, which is implicit praise for it: crying/cry (4), sad (1 - 7 times used in other contexts). Another common term is annoying (7 dances), directed at dancers, commenters, minor parts of the video, and the video production.

The terms choreo/choreography/choreographer (5 dances) caused sentiment classification errors (matching the base negative term stem chore*) and were excluded from the results, as was the term holy, as found in the phrases “holy shit” and “holy crap”. The songs *I'll Hurt You - Busta Rhymes ft. Eminem* and *The Quick and the Dead - Rudebrat* caused incorrect sentiment results for Popping dance and their constituent terms were excluded.

Table 3. Top five words (highest chi-square) for **negative sentiment strength** (positive 1-2; negative 3-5) compared to the remaining comments for the dance; terms in the top 10 overall list are excluded. Unusual terms are in bold. Terms associated with song titles and off topic discussions are excluded.

Label	Top 20	Comment
Acro dance	cry hurt crying Abby rude	Criticising rude comments. Comment on dancer crying.
Bachata dance	horrible crap ugly fucked hating	Ugly dancing and dancers
Ballet dance/dancing	hurt sad worst horrible scared	Scared of learning or performing. Emotional responses to sad performance.
Ballroom dance	core worst said cry crisis	<i>Crisis Core</i> game off topic discussion. Emotional responses to dance.
Belly dance	shame disgusting ugly bullshit Joven	Fat shaming discussion
Bollywood dance	racist white American ignorant terrorist	Discussion of racism around an Indian Miss America Bollywood dance
Breakdancing	annoying hurt crap fucking fucked	
Cheer dance	nervous scared horrible ugly terrible	Nervous about trying out for team
Contemporary dance	cry crying tears sad awful	Emotional responses to sad dances.
Crip Walk	ass thug fucking fucked shut	Gang thug discussion
Disco dance	asshole annoying sad moron fail	
Disco dancing	worst hurt hated embarrassing annoying	
Electric Boogaloo	space fight piss evil clipboard	Comments on joke in irrelevant video.
Electro Dance	lied shitty ugly worst crap	<i>Lied</i> – German song in bilingual comments.
Hard dance	war crap shitty disliked worst	War-themed song lyrics
Hardcore dancing	hurt hardcore pit metal bullshit	Dancers might get hurt
Hip Hop dance	ugly horrible jealous disliked screaming	
Hit Dem Folks	ugly thug savage hater lame	
House dance	crap lied worst cunt sad	<i>Lied</i> – German song in bilingual comments.
Jazz dance	drop sad bob Latin dumbass	<i>Death drop</i> dance move.
Jumpstyle dance	war fail hurt lame cold	Russian soldiers dancing; Vicarious pain from moves
Kpop dance	sad hurt annoying worst scared	
Line dance	bullshit sad annoying afraid hating	
Lyrical dance	crying cry yeah IK horrible	Emotional responses to sad dance, “made me cry”. IK = “I know”
Melbourne Shuffle	LMFAO crap cunt fail ugly	LMFAO dance music duo.
Popping dance	annoying terrible fail hating why rude	
Reggaeton dance	worse shame kind fucking ugly	
Robot dance	worst annoying crap camera bitch	Poor video camera angles.
Salsa dance	fight sad punched shame fucked	Fight interrupting dance
Tap dance	wars fight jealous worst crap	Star Wars themed tap dance
Zumba dance	loss weight shame hurt losing	Dancing for weight loss

Overall, whilst the negative sentiment terms seem to point to individual incidents rather than general themes about the dance genres, the positive terms suggest different ways in which the videos are enjoyed (i.e., gratifications gained from them).

Step 6: Networks

The network (Figure 2; see also Appendix 2) show the existence of several clusters of dances with videos that have attracted similar comments.

Melbourne Shuffle/Hard dance/Jumpstyle dance connecting to *Electro dance/ House dance*: These all have more male than female commenters and are participatory rather than performance dances.

Acro/Ballet/Contemporary/Jazz: The first three of these are classical dance styles jazz dance and all four are theatre-based performance arts. These all have more female than male commenters.

Lyrical/Cheer/Zumba dance: These do not have a natural association except for having more female than male commenters. Lyrical dance was formed from ballet, jazz and contemporary dance and so fits better within a different cluster. They associate because all have some bilingual English/Filipino comments.

Salsa/Bachata/Regaeton: These are Latin dance styles. They have more female than male commenters.



Figure 2. A network of the (cosine) similarity between the terms used in comments posted to each dance topic videos. Only the strongest 25% of all connections are shown. Disconnected nodes are shaded in blue. Thicker lines indicate higher cosine similarity between topics. Node area indicates comment volume.

It is difficult to evaluate the usefulness of the networks since they point to patterns that seem reasonably obvious but also have unexpected gaps.

Discussion and limitations

RQ1: Can the CTFC method identify plausible and/or insightful subtopic dimensions of discussions about a topic in YouTube comments? Whilst the subtopic comparison results seem to be broadly plausible (the discussion around Table 1), none of the terms seem likely to surprise an expert on these dance styles and so it is difficult to agree that the method has been insightful.

RQ2: Can the CTFC method identify plausible and/or insightful gender dimensions of discussions about a topic in YouTube comments? The method was successfully able to identify a range of themes and attitudes that were predominantly from either females or males for individual dances and across the dance topic. For instance, there was a male focus on music for some dances and a female association with positive sentiment. Whilst these seem plausible, none seem obvious and so it seems reasonable to claim that they are insightful.

RQ3: Can the CTFC method identify plausible and/or insightful sentiment dimensions of discussions about a topic in YouTube comments? The sentiment terms gave some plausible insights into why dances were liked, such as for individual dancers or if they were considered to be humorous. This information seems plausible and may also be useful to a researcher of dance genres. It could therefore be claimed to be somewhat insightful.

RQ4: Can the CTFC method identify plausible and/or insightful networks of relationships between topics? The network diagrams were plausible in some of the clusters but with clear anomalies. Network diagrams are difficult to evaluate for accuracy but can be useful a starting point for interviews with experts to trigger discussions and as a starting point for their analysis of structure (Cross, Borgatti, & Parker, 2002). The network diagrams presented here seem to be adequate for this purpose. A limitation of the networks is that it is impossible to see the reason for the strength of the connections in the graphs and they could be due to similarity in language styles, sentiment or topics of discussion, and are partly due to coincidences.

Both the networks and the word frequency analyses point to some subtopics not being a good fit for the dance category. One problem is that the method used to select the dances for analysis apparently selected at least one rare dance (Electric Boogaloo) that attracted many videos and comments only because of its inclusion in a video game. The findings around this dance were therefore not insightful about dance in general or even about this dance itself. The Bollywood dance example is similar in the sense that discussions around the topic were arguably not relevant to dance as much as the wider social and cultural issues triggered by its performance by a Miss America winner. Issues such as these could be circumvented by an additional round of manual filtering to remove Electric Boogaloo and Miss America-related comments. In practice, a decision to conduct this extra round of filtering would depend on the underlying goals of any analysis.

A generic problem for any analysis of YouTube comments is that “the feedback from those who did not post comments is unknown” (Chung, 2015). Away from YouTube, the attitudes of people who do not watch relevant YouTube videos is similarly unknown.

An important limitation is that the results influenced by the mix of types of dance video for each genre. Some were instructional, others were professional or amateur performances, and others seemed to be more about the music than the dance. Whilst it would have been possible to manually filter the videos so that they would only have been about one aspect, such filtering is time consuming and reduces the total number of comments available for analysis.

A more generic limitation is that the value that can be extracted for a topic may vary considerably between topics, with some yielding nothing and others perhaps yielding more than dance. Thus, the current paper illustrates the potential and limitations of the method but does not prove its usefulness for any given other topic. Another generic limitation is that the word frequency methods include a degree of unpredictability because key concepts that do not have unique names may not be picked up. Thus, important subtopic, gender and sentiment issues may have been overlooked because they were typically described with common words and hence did not rank highly in the word lists. Thus, the CTFC method is intrinsically not comprehensive and prone to overlooking important issues. In addition, whilst some comments were about the dances themselves but others were about specific events in videos that might not be relevant to the dance. Discussions about a fight at a salsa dance are an example of this. Highly commented videos that mention the topic frequently in a peripheral way (e.g., Electric Boogaloo; perhaps Miss America for Bollywood dance) are also a problem for detailed insights and point the importance of manual filtering and keeping in mind clear goals for an analysis to aid this filtering.

Finally, the implementation and evaluation of the CTFC method are subjective to the author and it is a human trait so identify patterns where there are none, so the interpretation of the positive aspects of the data may be optimistic.

Conclusions

The CTFC method has described some aspects of the dances analysed and the context in which they are discussed on YouTube. The results highlight gender, sentiment and subtopic differences between the dances that could serve as a starting point for deeper analyses of the topic, such as through interviews or ethnographies. Although the method involves automation and is supported by flexible software to produce the main results, manual checking needed of the initial queries and the term frequency lists produced, and the results seem likely to be influenced by some irrelevant discussion for any topic.

Applications of the CTFC method are most likely to be successful for topics that are extensively discussed on YouTube, especially if the discussions tend to be narrowly focussed on the topic of interest rather than on other issues. The method would therefore be particularly useful for discussing large scale YouTube-specific phenomenon but might also be useful in other contexts to give an initial exploratory analysis of an issue that has not been researched before. In this context, some of the findings might be useful to confirm or deny the researcher's initial understanding of a topic that has not been researched much before and for which there is not a body of background evidence to rely upon.

This paper also highlights some of the limitations of social media analytics as a research method. In addition to the specific issues discussed above, social media analytics methods have the following generic problems.

- They are lengthy to describe, since they necessarily involve multiple methods. This makes them difficult to learn and fully evaluate. It also makes them an awkward object of academic research.
- Any generic social media analytics method is necessarily complex since it involves a combination of automatic processing and human judgements (e.g., to filter out spam) as well as analytical decisions that are specific to any given topic.
- Any method is difficult to effectively evaluate since it may work well for one topic but not another, it has multiple components that would need to be assessed

separately, and possibly in different ways, and it has visual components that would need human judgements to assess. For example, the current article is long despite analysing a single topic, omitting the background information about that topic necessary for the reader to evaluate the findings, and presenting a limited set of the results.

- Social media analytics methods are almost inevitably exploratory and hence, even though they are likely to involve quantitative methods, are unlikely to be assessable through traditional hypothesis testing because the null hypothesis would not exist before the analysis.

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Appendices

The appendices are online at <https://figshare.com/s/2024440df704ed615f62> or doi:10.6084/m9.figshare.5257939.