Abstract

With one billion monthly viewers, and millions of users discussing and sharing opinions, comments below YouTube videos are rich sources of data for opinion mining and sentiment analysis. We introduce the YouTube AV 50K dataset, a freely-available collection of more than 50,000 YouTube comments and metadata below autonomous vehicle (AV)-related videos. We describe its creation process, its content and data format, and discuss its possible usages. Especially, we do a case study of the first self-driving car fatality to evaluate the dataset, and show how we can use this dataset to better understand public attitudes toward self-driving cars and public reactions to the accident. Future developments of the dataset are also discussed.

1 Introduction

Social media has become prevalent and important for social networking and opinion sharing in recent years (Asur and Huberman, 2010). By changing the way we perceive and interact with the world, social media has changed our lives profoundly (Safko, 2010; He et al., 2013). With millions of posts and replies uploaded every day on social media such as Facebook, Twitters and YouTube, it is an abundant and informative data source of public opinions; thus, it has attracted lots of attention from both academia and industry to understand people and society (Perrin, 2015; Boulianne, 2015; Ceron et al., 2014). Most previous text mining-based social media analysis focused on Twitter and Facebook (Kulkarni and Rodd, 2018). YouTube, generally considered as a video platform, the values of its text comments below videos have long been underestimated. Being the second most popular website in the world (alexa.com) and having 1.9 billion active users (statista.com), YouTube is an attractive source of research in social media analysis with immense potentials.

Recent developments in autonomous vehicle technology have helped bring self-driving vehicles to the forefront of public interest (Schoettle and Sivak, 2014b). Autonomous vehicles, particularly after the first fatal crash of self-driving cars recently happened in Arizona (Wakabayashi, 2018), have become a popular topic in social media. In order to investigate users’ acceptance, safety concerns, and willingness to purchase of autonomous vehicles, extensive studies have been conducted (Howard and Dai, 2014; Kyriakidis et al., 2015; Schoettle and Sivak, 2014a). However, these research rely heavily on surveys, which have disadvantages that (i) securing a high response rate is hard; (ii) uncertainty over the validity of the data and sampling issues; and (iii) concerns surrounding the design, implementation, and evaluation of the survey (Wright, 2005; Kelley et al., 2003; Fowler Jr, 2013; Fricker and Schonlau, 2002).

Latest techniques in opinion mining and sentiment analysis from social media data (Pang et al., 2008; Pak and Paroubek, 2010; Esuli and Sebastiani, 2007; Baccianella et al., 2010; Liu, 2012) offer new possibilities to overcome disadvantages of traditional surveys, and the YouTube AV 50K dataset is introduced under this background.

This paper is organized as follows. In Section 2 we introduce our motivation of building this dataset as well as the data creation process, annotation methods, data formats, and basic statistics of the dataset. We propose possible usages of the dataset with examples in Section 3, including metadata analysis, text visualization, sentimental analysis, recommendation systems, and text regression. Related works are presented in Section
4. Finally, Section 5 describes our visions and future goals of this project.

2 The Dataset

2.1 Motivation

The YouTube Autonomous Vehicle (AV) 50K dataset is our attempt to help researchers in both natural language processing (NLP) community and autonomous vehicle community by providing a large-scale annotated corpus in the autonomous vehicle domain specifically. The dataset contains comments that are legally available to the public below a comprehensive list of autonomous vehicle-related videos on YouTube. Main purposes of the dataset includes: (i) encourage researchers on theories and algorithms to connect their works with real-world data; (ii) provide a reference dataset and benchmarks for evaluating research; and (iii) help new researchers quickly get started in natural language processing, data analysis, and autonomous vehicles.

2.2 Corpus

The core of the corpus is from the YouTube Data APIs. The APIs can be used to search for videos matching specific search terms, topics, locations, publication dates, and much more. Other helpful features for social media analysis include metadata of video, comment, playlist, author, and channel. For example, original text, like count, publish date, author name, and viewer rating can be found in each comment representation. Basically, any public available resources on YouTube can be downloaded using the APIs. Tutorials and more information can be found in the API document.

2.3 Annotation

Sentiment score is a numerical representation of the sentiment polarity, the degree of negative, neutral, or positive, for a piece of text. We used the Natural Language API for sentimental analysis. We consider the sentiment score given by the API as a benchmark and will discuss different models for sentimental analysis in our upcoming paper. Evaluation of the annotation will be shown in the following Section 3.

2.4 Content

The YouTube AV 50K contains comments and metadata for all public self-driving-related videos on YouTube. Basic statistics is shown in Table 1.

| Item                | #   |
|---------------------|-----|
| Channels            | 50  |
| Data size (MB)      | 119 |
| Videos              | 632 |
| Annotated comments  | 19,126 |
| Unique authors      | 21,005 |
| First level comments| 21,498 |
| Total comments      | 30,456 |
| Word count          | 796,371 |

Table 1: Basic statistics of YouTube 50K

The data is stored using JSON format (Crockford, 2006) described by YouTube Data API to efficiently handle the heterogeneous types of information such as text, user id, publish date, like count, etc. Each comment is described by a JSON object, whose structure is shown in Figure 1.

The YouTube AV 50K website is a core component of the corpus. It contains tutorials, code samples, API documents, an issue section, and the pointers to the actual data, hosted by Goodata Foundation.

3 Proposed Usages

A wide range of social media analysis tasks can be performed and measured on the YouTube AV 50K dataset. In this section, we propose some possible usages of the dataset, and illustrate and evaluate the power of the dataset.

3.1 Metadata Analysis

A basic usage of the dataset is to analyze the metadata. This task is already very interesting, because trending topics, geographic information, and even patterns of human behaviors can be discovered from the metadata of a large volume of comments and videos. Statistical descriptions and visualisations can also be done for related research. An example of analyzing human comment behaviors is given in Figure 2, which illustrates a clear pattern that YouTube users are most active at around 8pm and least active in the early morning. Surprisingly,
the figure shows that YouTube users leave more comments in average on every weekday rather than weekends. Another example usage is to provide channel rankings using the video metadata from the dataset. We provide a ranking of top 20 English news channels in YouTube by their monthly views from May 9, 2018 to June 9, 2018 in Table 2. The results are exactly the same compared to data from KEDOO\textsuperscript{7} downloaded by the YoutubeStat.py module (Li and Lin, 2018).

3.2 Text Visualization

Word cloud is a straightforward and appealing visualization method for text. It has served as a starting point for many studies in text mining and opinion mining (Heimerl et al., 2014). Our dataset, which has large amount of text data about people’s attitudes toward autonomous driving, is an ideal playground for word cloud generation as well as research in sentimental analysis and opinion mining. Figure 3 provides word clouds of the dataset generated by using a wordcloud library in Python\textsuperscript{8}. On March 19, 2018, a self-driving Uber vehicle killed a pedestrian in Arizona and this incident is believed to be the first fatality associated with self-driving technology (Wakabayashi, 2018). Figure 3a is generated from comments one month before the incident while Figure 3c shows a word cloud of comments one month after. We can see a clear divergence of topics in these two figures where the happening of the incident was the watershed.

3.3 Sentimental Analysis

Finding out what other people think has always been an important part of information collection and decision making. Gathering opinions of hot, and probably controversial topics in the social media has aroused tremendous attention in the research community. In recent years, autonomous driving technologies have achieved great progresses and gradually become such a topic - popular and controversial. Self-driving cars have been put through millions of miles of road tests, and some believe that the technology has the potential to be safer than human drivers (Koopman and Wagner, 2017). However, with the recent fatal incident, public concerns of safety are clearly increasing according to the time series boxplot in Figure 4, which also shows an interesting process of destroying and rebuilding public trusts over time, illustrated by the boxes that went up to the peak in February, then dropped dramatically in March because of the incident, and finally went up again recently.

Sentiment scores used in the boxplot are floating-point numbers representing sentiment polarities ranging from -1 to 1, where -1 is extreme negative, 0 is neutral, and 1 is extreme positive. The scores are already given in the dataset and were generated by the sentiment analysis feature of the Google Cloud Natural Language API\textsuperscript{9}. It is natural that some might argue the validity of the API. We admit that the API is not perfect according to our experiments, and will provide a detailed comparison of results from this API and other state-of-the-art models in our upcoming paper. For now, we just introduce a model and leave other concerns to our next paper. The model is

\[
\Phi(\Theta) = \phi(\Theta) + \epsilon_\phi
\]

where \(\Theta\) is an embedding of text, \(\phi(\cdot)\) is a prediction model, \(\Phi(\cdot)\) is the real model to be found, and \(\epsilon_\phi\) is independent to \(\Theta\) but dependent to \(\phi\). The \(\epsilon_\phi\) of the model given by the API is considered to be white noise.
3.4  Recommendation Systems

With the expectation of immense commercial values (Graham, 2007), recommendation systems for advertisement have been studied extensively, and two main paradigms have emerged: content-based recommendation and collaborative recommendation (Balabanović and Shoham, 1997). Traditional content-based recommendation systems are Information Filtering (IF) systems that need proper techniques for representing the items and producing the user profile, and some strategies for comparing the user profile with the item representation, including content analyzer, profile learner, and filtering component (Lops et al., 2011). The YouTube AV 50K dataset can be used either to generate sentimental scores mentioned in section 3.3 for user profile enrichments or to directly encode comment texts and metadata as inputs for deep neural networks to finally output ratings in recommendation systems.

3.5  Text Regression

Text regression is a method of predicting a real-world continuous quantity associated with the text’s meaning based on a piece of text and it was reported to significantly outperform past volatility in predicting financial indices (Kogan et al., 2009). Empirically, sales of products could be greatly influenced by online reviews. The case would be especially true for vehicle industry, because vehicles are generally more valuable than normal goods, and intuitively, people would be more careful in the selection processes and tend to look up more reviews. Considering these features, the YouTube AV 50K dataset is appealing for vehicle market as a source of sales prediction and risk measurement research. One of our upcoming papers would combine Bayesian deep learning with text regression to address this issue (Li, 2018; Lin et al., 2018).

4  Related Works

The YouTube AV 50K is the first dataset dedicated for social media analysis in autonomous vehicle-related fields. Other very large datasets for social media analysis includes:

- Amazon Fine Food Reviews\(^{10}\): 568,454 food reviews Amazon users left up to October 2012.
- Amazon Reviews\(^{11}\): Stanford collection of 35 million amazon reviews.
- Disasters on social media\(^{12}\): 10,000 tweets with annotations whether the tweet referred to a disaster event.
- Reddit Comments\(^{13}\): every publicly available reddit comment as of july 2015. 1.7 billion comments.

\(^{10}\)https://www.kaggle.com/snap/amazon-fine-food-reviews
\(^{11}\)https://snap.stanford.edu/data/web-Amazon.html
\(^{12}\)https://www.figure-eight.com/data-for-everyone/
\(^{13}\)https://www.reddit.com/r/datasets/comments/3bxlg7/i_have_every_publicly_available_reddit_comment/
| #  | Channel                  | Monthly Views  | Subscribers  |
|----|--------------------------|----------------|--------------|
| 1  | Inside Edition           | 395025524      | 3129845      |
| 2  | CNN                      | 155319328      | 3794747      |
| 3  | ABC News                 | 144872445      | 3850158      |
| 4  | Barcroft TV              | 129030102      | 4627820      |
| 5  | MSNBC                    | 74032667       | 963021       |
| 6  | Fox News                 | 60536948       | 1242054      |
| 7  | Crime Watch Daily        | 53485050       | 877800       |
| 8  | BBC News                 | 45344148       | 2619048      |
| 9  | The Young Turks          | 45159957       | 3899180      |
| 10 | Guardian News            | 42598679       | 136110       |
| 11 | RT                       | 40166881       | 2632872      |
| 12 | TODAY                    | 40073086       | 758845       |
| 13 | The Royal Family Channel | 38726120       | 314798       |
| 14 | USA TODAY                | 38444609       | 634366       |
| 15 | VICE News                | 36201734       | 3048964      |
| 16 | TomoNews US              | 34828513       | 2230927      |
| 17 | CBS News                 | 34513896       | 752014       |
| 18 | DramaAlert               | 34501164       | 3888026      |
| 19 | CBS This Morning         | 34236213       | 390538       |
| 20 | Vox                      | 32228568       | 4166051      |

Table 2: Top 20 YouTube English news channels ranked by monthly reviews (from May 9th, 2018 to June 9th, 2018)

- Twitter Cheng-Caverlee-Lee Scrape[^14]: Tweets from September 2009 - January 2010, geolocated.
- Classification of political social media[^15]: Social media messages from politicians classified by content.
- Corporate messaging[^16]: A data categorization job concerning what corporations actually talk about on social media.

Above is a selected list and not intended to be comprehensive. More related open datasets can be found in following Github repositories:

- [niderhoff/nlp-datasets][^17]
- [awesomedata/awesome-public-datasets][^18]

## 5 Future Works

We want to expand the impacts of our previous research in autonomous vehicles (Gong et al., 2018; Lin et al., 2015; Li, 2018; Lin et al., 2018) and have better understanding of what people think of self-driving cars. We are especially interested in people’s opinions toward the transitions from level 0: no automation to level 5: full automation (Blumberg and Galyean, 1995; Yan et al., 2007). Although YouTube AV 50K already provides rich sources of data annotated by state-of-the-art NLP techniques, we aware of the shortages of the techiques; for example, doing aspect-level sentimental analysis and detecting sarcasm are still challenging. We would keep an eye on latest progresses in the NLP community and be open and ready to apply such techniques to our dataset.

Another improvement we would like to perform is to keep expanding the dataset as the autonomous driving field is growing rapidly and many exciting achievements are expected, which might greatly change the self-driving landscape as well as public opinions. Hopefully, such changes would mitigate people’s security concerns and bring out safer, smoother, and smarter transportation.

[^14]: [https://archive.org/details/twitter_cikm_2010](https://archive.org/details/twitter_cikm_2010)
[^15]: [https://www.figure-eight.com/data-for-everyone/](https://www.figure-eight.com/data-for-everyone/)
[^16]: [https://registry.opendata.aws/commoncrawl/](https://registry.opendata.aws/commoncrawl/)
[^17]: [https://github.com/niderhoff/nlp-datasets](https://github.com/niderhoff/nlp-datasets)
[^18]: [https://github.com/awesomedata/awesome-public-datasets](https://github.com/awesomedata/awesome-public-datasets)
Figure 3: Word cloud generated from YouTube comments below self-driving related videos before and after the first self-driving car fatality on March 19, 2018 in Tempe, Arizona.

Acknowledgments

The authors are grateful to Jiarong Li, Hongjie Jiang, Shouyu Wang for helpful discussions, and to the anonymous reviewers for useful feedbacks. This work was supported by grants from the Goodata Foundation (GDF grant 52c-cc-14f-73) and from the NEXTRANS Center, Purdue University.

References

alexa.com. Alexa top 500 global sites.

Sitaram Asur and Bernardo A Huberman. 2010. Predicting the future with social media. In Proceedings of the 2010 IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology-Volume 01, pages 492–499. IEEE Computer Society.

Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. 2010. Sentiwordnet 3.0: an enhanced lexical resource for sentiment analysis and opinion mining. In Lrec, volume 10, pages 2200–2204.

Marko Balabanović and Yoav Shoham. 1997. Fab: content-based, collaborative recommendation. Communications of the ACM, 40(3):66–72.

Bruce M Blumberg and Tinsley A Galyean. 1995. Multi-level direction of autonomous creatures for real-time virtual environments. In Proceedings of the 22nd annual conference on Computer graphics and interactive techniques, pages 47–54. ACM.

Shelley Boulianne. 2015. Social media use and participation: A meta-analysis of current research. Information, Communication & Society, 18(5):524–538.

Andrea Ceron, Luigi Curini, Stefano M Iacus, and Giuseppe Porro. 2014. Every tweet counts? how sentiment analysis of social media can improve our knowledge of citizens political preferences with an application to italy and france. New Media & Society, 16(2):340–358.

Douglas Crockford. 2006. The application/json media type for javascript object notation (json). Technical report.

Andrea Esuli and Fabrizio Sebastiani. 2007. Sentiwordnet: a high-coverage lexical resource for opinion mining. Evaluation, 17:1–26.

Floyd J Fowler Jr. 2013. Survey research methods. Sage publications.

Ronald D Fricker and Matthias Schonlau. 2002. Advantages and disadvantages of internet research surveys: Evidence from the literature. Field methods, 14(4):347–367.
Siyuan Gong, Anye Zhou, Jian Wang, Tao Li, and Srinivas Peeta. 2018. Cooperative adaptive cruise control for a platoon of connected and autonomous vehicles considering dynamic information flow topology. arXiv preprint arXiv:1807.02224.

Brian Graham. 2007. Social network e-commerce and advertisement tracking system. US Patent App. 11/413,259.

Wu He, Shenghua Zha, and Ling Li. 2013. Social media competitive analysis and text mining: A case study in the pizza industry. International Journal of Information Management, 33(3):464–472.

Florian Heimerl, Steffen Lohmann, Simon Lange, and Thomas Ertl. 2014. Word cloud explorer: Text analytics based on word clouds. In System Sciences (HICSS), 2014 47th Hawaii International Conference on, pages 1833–1842. IEEE.

Daniel Howard and Danielle Dai. 2014. Public perceptions of self-driving cars: The case of berkeley, california. In Transportation Research Board 93rd Annual Meeting, volume 14.

Kate Kelley, Belinda Clark, Vivienne Brown, and John Sitzia. 2003. Good practice in the conduct and reporting of survey research. International Journal for Quality in health care, 15(3):261–266.

Shimon Kogan, Dimitry Levin, Bryan R Routledge, Jacob S Sagi, and Noah A Smith. 2009. Predicting risk from financial reports with regression. In Proceedings of Human Language Technologies: The 2009 Annual Conference of the North American Chapter of the Association for Computational Linguistics, pages 272–280. Association for Computational Linguistics.

Philip Koopman and Michael Wagner. 2017. Autonomous vehicle safety: An interdisciplinary challenge. IEEE Intelligent Transportation Systems Magazine, 9(1):90–96.

DS Kulkarni and SF Rodd. 2018. Extensive study of text based methods for opinion mining. In 2018 2nd International Conference on Inventive Systems and Control (ICISC), IEEE.

Miltos Kyriakidis, Riender Happee, and Joost CF de Winter. 2015. Public opinion on automated driving: Results of an international questionnaire among 5000 respondents. Transportation research part F: traffic psychology and behaviour, 32:127–140.

Tao Li. 2018. Modeling uncertainty in vehicle trajectory prediction in a mixed connected and autonomous vehicle environment using deep learning and kernel density estimation. The Fourth Annual Symposium on Transportation Informatics.

Tao Li and Lei Lin. 2018. Youtubestat.py: a python module to download youtube statistics and rankings.

Lei Lin, Siyuan Gong, and Tao Li. 2018. Deep learning-based human-driven vehicle trajectory prediction and its application for platoon control of connected and autonomous vehicles. The Autonomous Vehicles Symposium 2018.

Lei Lin, Ming Ni, Qing He, Jing Gao, and Adel W Sadek. 2015. Modeling the impacts of inclement weather on freeway traffic speed: exploratory study with social media data. Transportation Research Record: Journal of the Transportation Research Board, (2482):82–89.

Bing Liu. 2012. Sentiment analysis and opinion mining. Synthesis lectures on human language technologies, 5(1):1–167.

Pasquale Lops, Marco De Gemmis, and Giovanni Semeraro. 2011. Content-based recommender systems: State of the art and trends. In Recommender systems handbook, pages 73–105. Springer.

Alexander Pak and Patrick Paroubek. 2010. Twitter as a corpus for sentiment analysis and opinion mining. In LREC, volume 10, pages 1320–1326.

Bo Pang, Lillian Lee, et al. 2008. Opinion mining and sentiment analysis. Foundations and Trends® in Information Retrieval, 2(1–2):1–135.

Andrew Perrin. 2015. Social media usage. Pew research center, pages 52–68.

Lon Saeko. 2010. The social media bible: tactics, tools, and strategies for business success. John Wiley & Sons.

Brandon Schoettle and Michael Sivak. 2014a. Public opinion about self-driving vehicles in china, india, japan, the us, the uk, and australia.

Brandon Schoettle and Michael Sivak. 2014b. A survey of public opinion about autonomous and self-driving vehicles in the us, the uk, and australia.

statista.com. Youtube - statistics & facts.

Daisuke Wakabayashi. 2018. Self-driving uber car kills pedestrian in arizona, where robots roam. The New York Times.

Kevin B Wright. 2005. Researching internet-based populations: Advantages and disadvantages of online survey research, online questionnaire authoring software packages, and web survey services. Journal of computer-mediated communication, 10(3):JCMC1034.

Jun Yan, Ryszard Kowalczyk, Jian Lin, Mohan B Chhetri, Suk Keong Goh, and Jianying Zhang. 2007. Autonomous service level agreement negotiation for service composition provision. Future Generation Computer Systems, 23(6):748–759.