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Sentiment Analysis on Ads Data

The advertainment industry impacts most, if not all, industries on the planet. From technology to healthcare to education, ads play an important role in not only selling products and services but also spreading information. Sentiment analysis is beginning to play an important role in how ads data is analyzed and how it can impact this wide spreading industry. Sentiment analysis, in the most basic sense, is the use of natural language processing to systematically identify and study subjective information. Ads are subjective by fault; its purpose is to inform and persuade a person. This allows for a gateway to use ads data and user-generated ads data, views, and interaction, with sentiment analysis allowing a better understanding of the ads and the impact it presents to the viewer. Even within the technology industry, different platforms have been used to experiment with this style of analysis; YouTube as an example platform for using sentiment analysis on user-generated ads data, and Facebook with semantic analysis with sentiment analysis to predict fraudulent ads. But research is also being done on understanding the kind of information displayed on ads and the ambiguity factor of ads.

Ads are YouTube's primary source of revenue. Without them, YouTube would not be where it is today. As the number of people watching YouTube videos increased, it also increased the data collected in viewer-generated and user-generated categories. And as the number of platform users increased, the number of ads shown and viewed increased along with it. The next step is determining user and viewer interaction with the ad to determine how an ad impacted the video-watching experience. This can be done by analyzing the sentiment from viewer- and user-generated data. Being able to gauge public reaction can affect how ad selection occurs over time as the ability to predict how someone will react to an ad becomes clear. This, in turn, could help YouTube in their ads selection. The journal article "YouTube Ad View Sentiment Analysis using Deep Learning and Machine Learning" by Mehta & Deshmukh discusses the application of different learning models to generate data to conduct sentiment analysis. The suggested models were from the category of Deep Learning and Machine Learning, including algorithms such as Linear Regression, Support Vector Machine, Decision Tree, Random Forest, and Artificial Neural Network. Though this study could not find the expected sentiment results, it did prove that it was feasible to conduct such analysis on this kind of ad data. With such an intricate platform, YouTube provides a variety of variables that can impact the results of the study. In addition, the collected data is impacted by events occurring outside the scope of the ads alone, such as who the viewer is and who the channel/video owner is. Regardless of the outcomes of the study, it did display that with further study and experimentation, sentiment analysis on such kind of user and viewer-generated data can be applied not only to YouTube ads but also to other social media platforms as well; to foresee reactions to impact how ads work.

Sometimes it is hard to tell if an ad is real or fake. Fraudulent ads have had a massive impact on the industry and have resulted in large amounts of misinformation being spread, and in the long run, impacting the many industries that rely on ads. The previous journal article studies the ability to apply machine learning to sentiment data collected from YouTube ad interaction data. But ads data itself can also be analyzed to gain a sentiment understanding. Facebook is another platform where its primary source of revenue comes from ads. And not only Facebook but many businesses, both large and small, rely on Facebook ads to gain and maintain traction. When we introduce fraudulent ads into this mix, it results in ads becoming unreliable and having, in some cases, catastrophic impacts on industries. In a research article, “Semantic Analysis Of Fraudulent Ads In Facebook,” Rais & Widodo conducted a semantic analysis of fraudulent Facebook ads to analyze the fraudulent ads. When breaking down the semantic analysis of ads, data can be split into two categories. The first is where ads are emphasized more on the affective and social meaning. This is where the seller is leading the customer's opinion; that the seller can be trusted. In cases like this, the terms used are conceptual and provide details. The second is where ads are more emphasized on the thematic meaning, focusing on singular words in the ad. When the terminology and the combination of how ads text is used are applied with sentiment analysis, ads data can be categorized, most of the time, into one of two categories. This study showed that this method of sentiment analysis has a lot of variables that can affect the outcome, and given that ads data is very diverse; determining if an ad is fraudulent or not can be determined by this analysis alone, but instead can help as a preventative measure taken to draw out fraudulent ads.

Ambiguity is an interesting way to describe an ad, though it is what many ads are based upon. A good advertisement is based on being concise, creative, and persuasive, while the idea of ambiguity expresses doubtfulness and uncertainty. When discussing ambiguity can be broken into two different types, lexical and structural. Lexical ambiguity is where there can be multiple interpretations of phase. Structural ambiguity is where a phrase can have more than one structure underneath it. Between these two types of ambiguity, it can describe many uses within the advertising industry. The paper “The Semantic Analysis of Ambiguity in Advertisements” by Dong and Shao, discusses the semantic analysis done on advertisements. Breaking it down, ambiguity can help make ads more concise, as sometimes the lack of information makes it simpler, with fewer words and different impacts. This can be shown by having a sentence as an ad compared to using a singular word or phrase instead to send the message. Ambiguity can also add different reactions to the ad; for example, reducing the complexity of the ad can add humor, which would leave a greater impact on the viewer. Conciseness can also result in increasing interest and attention-grabbing, as well as persuading. Sometimes the less that is said, the more believable it is to be a good product. When ambiguity is applied to ads data, it usually falls into one of these three goals. Sentiment analysis on ads has shown that ad data can be taken to determine the type and level of ambiguity a current ad has, and advertisers can take that information to further the impact of their ad. Furthermore, by combining sentiment analysis from ads data with ad interaction data, advertisers can gain an understanding of the impact of ads on users.

As research continues, sentiment analysis on ads and ads data has, and will continue to impact the ads business and methodology for search and result as well as ads display. Studies using YouTube and Facebook as a basis to learn more about user engagement with ads and predict which ads are fraudulent can be applied to platforms across technology. This can change the scope of how ads analysis is done. Not only for making ads reliable and trustworthy but also for understanding how ads impacts and draws users to interact with them. But this isn't the only type of analysis that can be done. Combining semantic and sentiment analysis, ad data can directly be taken to determine ambiguity, a concept, and a style that is very impactful when generating an ad. But these are only three examples of how sentiment analysis can be applied to ads and user-generated ads data, in addition to how sentiment analysis can be combined with different forms of study to get even greater findings. Sentiment analysis for ads is just at its start; as more research is conducted, it will lead to both a better understanding of how users interact with ads, but also impact the creation of them as well.

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