Semantically Interoperable Social Media Platforms

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Competitive intelligence in social media analytics has significantly influenced behavioral finance worldwide in recent years; it is continuously emerging with a high growth rate of unpredicted variables per week. Several surveys in this large field have proved how social media involvement has made a trackless network using machine learning techniques through web applications and Android modes using interoperability.

information system machine learning sentiment analysis social media analytics

1. Introduction

Machine learning not only influences the social media market but, simultaneously, it is highly capable of tracking the so-called unpredictable real-time matrices of growth, needs, results, and features. Machine learning is one of the most powerful tools to control the human mind′s transition through machine interpretation [1][2]. Individuals as well as sets of individuals using social media platforms are targeted by business media, multistoried companies, product sellers, and influencers. Facts and figures show that more than 56% of eighth-graders are additionally unhappy because their weekly social media involvement is over 10 h. Spending over 3 h per day on social media presents a high risk to the mental health of adolescents. According to the National Center for Health Research, 32% and 13% of children aged 12–17 suffer from depression and anxiety because of the inappropriate use of social media, respectively. Furthermore, 25% of 25-year-old adults have a mental illness, and they belong to the highest usage group [3]. Apart from individual consumption, teenagers are experiencing crimes related to online harassment and cyberbullying. However, the numbers are only based on reported and known occurrences. Tracking particular algorithms behind the consumer attraction strategies of each social media platform is inconceivable and unrealistic [4]. Still, in recent years, researchers have identified possible measurement factors to monitor the mental health of social media users using machine learning techniques [5][6]. Existing machine-learning-based solutions can predict a product value after studying historical sales-related data. For example, it can indicate the increase and decrease in the share market curve, and it can even measure the happiness index using behavioral analytics [7][8][9].

2. Sentiment Analysis and Social Media

Social media platforms have been working as marketing and interpreting platforms for the last few years. Social media could manipulate, amplify, and reinforce one′s personal and social rank. Individuals and organizations

mostly connect to a social media platform based on their choice of exposure [10]. Though very few platforms charge a certain subscription amount, most of them are free of cost if you have a connecting device like a smartphone, desktop, or laptop with internet connectivity. Hence, engagement in a specific social media platform is directly related to human interest. Feedback procedures vary from one platform to another in the form of like, comment, post, tag, send, share your feelings and moods, emoji, hashtag, and many more. Social media engagement and pleasure are directly influenced by human emotion, and the feedback through these platforms also affects human sentiment [10][11]. Most likely, the inventors of social media invented these platforms to reach out to specific communities in the shortest and fastest time. However, it can help product marketing through consequence penetration, consumer attractions, live promos, and easy money transaction in sales [11]. Additionally, positive ratings could be key growth factors in terms of customer support, bargaining, immediate response, and feedback. Similarly, these platforms help to monitor customer loyalty and public relation [12]. Besides this business growth, individual interests are also encouraged and entertained by millions of connected people worldwide through these social networks [13]. Whilst traders analyze customer feedback and sentiments using machine learning as their brand momentum drives, researchers intend to explore the distinct proposition of an individual social media handler through machine learning.

3. Information Systems and Machine Learning

In information systems, artificial intelligence applications and systems can perform their defined task without any human interaction. Furthermore, without being explicitly programmed, a computer could be equipped with machine learning with the capacity to comprehend real-time inputs [14]. Machine learning is a kind of artificial intelligence that can program a computer to adjust when exposed to exotic data. There are three types of machine learning: supervised, unsupervised, and reinforcement to make a computer intelligent. Additionally, supervised learning could be applied to two categories: regression problems and classification problems. In comparison, unsupervised learning deals with clustering and dimensionality reduction [15].

4. Machine Learning Models and Sentiment Analysis

Supervised ML holds two segments of attributes: independent features and dependent or derived features [16]. Whenever a continuous variable in supervised learning represents the output, it is a regression problem. On the other hand, if the ML model has a fixed number of categories as the output, it becomes a classification problem. If there are two categories as the output for a classification problem, then it is called a binomial classification problem. If the model has more than two categories as the output, it is called a multi-class classification problem. Similarly, a model could be learned even if the dependent variable is absent in the available dataset. This kind of machine learning procedure is known as unsupervised machine learning. The train dataset could be comprised in two ways into an unsupervised ML model: clustering and dimensionality reduction [17]. The clustering procedure makes a group concerning similar conditions or likenesses factors if there is no dependent variable in the available dataset. Dimensionality reduction converts higher dimensional data to its lower dimensions for an implemented ML model. Linear regression, logistic regression, decision tree, AdaBoost, random forest, xgboost, Naive Bayes, SVM,

and KNN are popular supervised algorithms in information systems. Similarly, K-Means, DB Scan, Hierercial clustering, K-nearest neighbor clustering, PCA, and LDA are a few unsupervised learning algorithms [18]. Based on some real-time situations, the parameter settings could be changed for a designed ML model to achieve a better performance [16][17][18].

5. Natural Language Processing

Several supervised and unsupervised models are available for natural language processing problems in data science [19]. Support vector machine (SVM), logistic regression (LR), gradient boosting (GB), and neural networks (NNs) are a few known machine learning (ML) algorithms used for both classification and regression challenges [20] [21]. An ML model′s accuracy and success rate determine the model selection based on the target dataset. Basic feature engineering reflects the basic modeling of tabular format data (basic features) for the training and validation datasets. Data extend further for logistic regression. The datasets can reach for extreme gradient boosting (XGB) in support of pushing the computational resource limit.

Researchers could conduct an approximate string matching operation to improve the accuracy of the discussed machine learning algorithm altogether [21][22]. The string matching operation in data science is known as Fuzzy features inclusion. Fuzzy features contribute a positive push to the comprehensive computational process and improve the accuracy of the absolute model. The most traditional way to handle text data has four pathways: hashing of words, count vectorization, term frequency–inverse document frequency (TF-IDF), and singular-value decomposition (SVD).

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