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SOCIAL NETWORK BASED HEALTH ANALYSIS USING USER TRUST BEHAVIOR MODEL

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ABSTRACT

The main objective of this project is to warn the people about their health concern from social network through user behavior model. Also to implement a trust based user behavior model in the social network. This project will saves more lives from various health issues. According to the study, depression is a global health concern. Depression is the leading cause of disability worldwide, a major contributor to the global burden of disease, and is affecting many people worldwide. Untreated depression has been linked to problems ranging from Stroke to coronary artery disease, two of the top ten leading causes of death in the world in according to the previous research. Forums and social media websites dedicated to depression have recently sprung up for patients and healthcare workers to share their experiences from managing depression in their daily lives to their reactions to antidepressants. This project is to analyze the user's activity in the social network to monitor their health conditions. This is because social network became part of a life now days. And also people like to post their emotion and feelings through social networks only; this makes people better and satisfied to share their feeling with their friends and relatives. Our project is to analyze the data from the user input. This analysis will be done using their profile information, post and comments. This information will change one user from another.

Keywords: Data training, Text categorization, Text recompilation, trust model creation, user recommendation

1. INTRODUCTION

A social structure made of nodes that are generally individuals or organizations. A social network represents relationships and flows between people, groups, organizations, animals, computers or other information/knowledge processing entities. Social networking has grown to be become one of the largest and most influential components of the web, but despite how prevalent it is in the Western World (especially among the younger crowd), not everyone uses it or understands it. Just think of the older people you might know or people who've live in locations where internet access isn't the norm. The open-ended nature of social networks may only add to the confusion. Once signed in to a social network, having answered a few basic profile questions, it's easy to sit back and wonder what you are supposed to do next. Social networking is a nice form of entertainment, great for meeting people with similar interests and useful for staying in touch with old friends/acquaintances. It can also be a very effective promotional tool for businesses, entrepreneurs, writers, actors, musicians or artists. Most of us have hobbies, or things that we are keenly interested in such as books, television, video games or movies. Social networks allow us to reach out to others that have the same interests

2. LITERATURE SURVEY

Depressive disorders were the second leading cause of YLDs in 2010. MDD accounted for 8.2% (5.9%–10.8%) of global YLDs and dysthymia for 1.4% (0.9%–2.0%). Depressive disorders were a leading cause of DALYs even though no mortality was attributed to them as the underlying cause. MDD accounted for 2.5% (1.9%–3.2%) of global DALYs and dysthymia for 0.5% (0.3%–0.6%).[1] There was more regional variation in burden for MDD than for dysthymia; with higher estimates in females, and adults of working age. Whilst burden increased by 37.5% between 1990 and 2010, this was due to population growth and ageing. MDD explained 16 million suicide DALYs and almost 4 million ischemic heart disease DALYs. This attributable burden would increase the overall burden of depressive disorders from 3.0% (2.2%–3.8%) to 3.8% (3.0%–4.7%) of global DALYs[1]. Text and structural data mining of web and social media (WSM) provides a novel disease surveillance resource and can identify online communities for targeted public health communications (PHC) to assure wide dissemination of pertinent information[2]. Most information retrieval systems use stop word lists and stemming algorithms. However, we have found that recognizing singular and plural nouns, verb forms, negation, and prepositions can produce dramatically different text classification results[3]. As part of the recent surge of research on large, complex networks and their properties, a considerable amount of attention has been devoted to the computational analysis of social networks structures whose nodes represent people or other entities embedded in a social context, and whose edges represent interaction, collaboration, or influence between entities. Natural examples of social networks include the set of all scientists in a particular discipline, with edges joining pairs who have co-authored papers; the set of all employees in a large company, with edges joining pairs working on a common project; or a collection of business leaders, with edges joining pairs who have served together on a corporate board of directors.[4]

3. METHODOLOGY

Text Categorization

The text categorization has been implemented for data analysis purpose. Basically text categorization is the feed and comparison based process. Text categorization needs a training data set for analysis. This makes the system more perfect and efficient data retrieval. The problem of classification has been widely studied in the database, data mining, and information retrieval communities. The problem of classification is defined as follows. We have a set of training records D={X1,...,XN}, such that each record is labeled with a class value drawn from a set of k different discrete values indexed by{1...k}.The training data is used in order to construct a classification model, which relates the features in the underlying record to one of the class labels. For a given test instance for which the class is unknown, the training model is used to predict a class label for this instance. In the hard version of the classification problem, a particular label is explicitly assigned to the instance, whereas in the soft version of the classification problem, a probability value is assigned to the test instance.

Feeling sad today	Negative	-
Had a good day	Positive	+
Am ok	Moderate	=

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The above mentioned table shows the sentiment of the user behavior in the social network.

4. PROPOSED METHODOLOGY

All the problems and requirements were overcome in the proposed architecture, through developing a dedicated application for this analysis model. This application will make a major impact among the market researchers like data analyst, data reporter, business analyst, business growth predictors and etc. This application is easy, simple and user friendly to use all types of sentimental analysis model. Here raw data will be given as the input and out the output will a tremendous data reporting model. Some marketers prefer leaving the analysis to dedicated methods, the methods behind sentiment analysis is nothing short from fascinating the various levels of analysis, the detail and the intricacy that make this analysis more accurate when performed by another human rather than a machine. Nowadays, sentiment analysis is an integral part of social listening, although it can also be performed on its own. Sentiment analysis is more than just a feature in a social analytics method. This is a field that is still being studied. While this comment is general, it can be broken down into sentences. This comment has a number of opinions around Simply Measured, both positive and negative. Sentiment refers to the emotion behind a social media mention. It's a way to measure the tone of the conversation is the person happy, annoyed, and angry or neutrals. Sentiment adds important context to social conversations. Without it, measurement of mentions alone could be misleading. If the requirement is to measuring mentions for a company's new product, user might assume a surge in mentions meant it was being well received. After all, more mentions more people talking about the product. Measuring sentiment will help you understand the overall feeling surrounding a particular subject, enabling you to create a broader and more complete picture of the social conversations that matter to you.

5. ALGORITHM

DECLARATION

DS = data set

V = Vocabulary (Extracted from dataset)

C = Categorization :sen count

N = Occurrence

A(Pj | Ni) = Array Deceleration: Pj denotes positive and Ni denoted negative

R = Result

- Let initiate the process : class index : System.Web.UI.Page, Open database access to receive the dataset: OleDbConnection con;
- Declare Array : ArrayList reccomment = new ArrayList(); Received data will be stored in an array;
- String.IsNullOrEmpty (GridView1.Rows[i].Cells[j].ToString())) Confirming the data grid is empty to receive the data;
- Now LET dataset will be DS;

- Updating positive word : posi.Add((string)red[0].ToString()); Positive word will be stored as the separate string collection : cmd1.ExecuteReader();
- Updating Negative word : nega.Add((string)red[0].ToString()); Negative word will be stored as the separate string collection : cmd2.ExecuteReader();
- Grid updating: GridView2.Rows[i].Cells[j].Text == posi and nega;
- Merging as a neural Networks = A(Pj | Ni) array deceleration for Pj and Ni;
- OleDbDataReader rd1 = cmd1.ExecuteReader();
- postedby = rd[0].ToString();

pdate = rd[1].ToString();

ptime = rd[2].ToString();

shareto = rd[3].ToString();

post = rd[4].ToString();

memname = rd[5].ToString();

comment = rd[6].ToString();

memdate = rd[7].ToString();

- Display the DS grid value in the data reader : GridView4.Visible = false; cmd1 = new OleDbCommand(query, con);
- Data analysis process: Let V = Vocabulary: toterr.Add(rd1[0].ToString()): Spliting word as vocabulary
- Also Split word will be stored as the C = Categorization : string[] a = toterr [i1] .ToString () .To Upper().Split(' ');
- Now Analysis will produce the result: Compare Srting[DS,V,C] with A(Pj | Ni)
- loadarr();

pcount = posi.Count; ncount = nega.Count; scount = sen.Count;

- (sen[i].ToString() == posi[j].ToString());
- (sen[i].ToString() == nega[j].ToString());
- Display Result R : input sen = r count
- rcount = rank.Count; for ranking: (sen[i].ToString() == rank[j].ToString())

stat = rd[8].ToString();

- Display ranking result : string[] a = toterr[i1].ToString().ToUpper().Split(' ');
- Retrieve data from the DB
- Display results in charts

CONCLUSION

Classification is very essential to organise data, retrieve information correctly and swiftly. Implementing machine learning to classify data is not easy given the huge amount of heterogeneous data that's present in the web. Text categorization algorithm depends entirely on the accuracy of the training data set for building its decision trees. The text categorization algorithm learns by supervision. It has to be shown what instances have what results. Due to this text categorization algorithm, it cannot be successfully classify documents in the web. The data in the web is unpredictable, volatile and most of it lacks Meta data. The way forward for information retrieval in the web, in the future opinion would be to advocate the creation of a semantic web where algorithms which are unsupervised and reinforcement learners are used to classify and retrieve data. Thus the thesis explains the trends, threads and process of the text categorization algorithm which was implemented for finding the sensitive data analysis

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