**Lecture Notes on Data Engineering and Communications Technologies 225**

# Leonard Barolli Editor

# Advances in Intelligent Networking and **Collaborative** Systems

The 16th International Conference on Intelligent Networking and Collaborative Systems (INCoS-2024)



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# Advances in Intelligent Networking and Collaborative **Systems**

The 16th International Conference on Intelligent Networking and Collaborative Systems (INCoS-2024)



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# **Welcome Message from the INCoS-2024 Organizing Committee**

Welcome to the 16th International Conference on Intelligent Networking and Collaborative Systems (INCoS-2024), which is held from September 19–21, 2024, at Soonchunhyang (SCH) University, Asan, South Korea.

INCoS is a multidisciplinary conference that covers the latest advances in intelligent social networks and collaborative systems, intelligent networking systems, mobile collaborative systems, secure intelligent cloud systems, and so on. Additionally, the conference addresses security, authentication, privacy, data trust, and user trustworthiness behavior, which have become crosscutting features of intelligent collaborative systems.

With the fast development of the Internet, we are experiencing a shift from the traditional sharing of information and applications as the main purpose of the networking systems to an emergent paradigm, which locates people at the very center of networks and exploits the value of people's connections, relations and collaboration. Social networks are playing a major role as one of the drivers in the dynamics and structure of intelligent networking and collaborative systems.

Virtual campuses, virtual communities, and organizations strongly leverage intelligent networking and collaborative systems by a great variety of formal and informal electronic relations, such as business-to-business, peer-to-peer, and many types of online collaborative learning interactions, including the virtual campuses and e-learning systems. Altogether, this has resulted in entangled systems that need to be managed efficiently and in an autonomous way. In addition, the conjunction of the technologies based on IoT, cloud, mobile, and wireless infrastructures are bringing new dimensions of collaborative and networking applications a great deal by facing new issues and challenges.

The aim of this conference is to stimulate research that will lead to the creation of responsive environments for networking and the development of adaptive, secure, mobile, and intuitive intelligent systems for collaborative work and learning.

The successful organization of the conference is achieved thanks to the great collaboration and hard work of many people and conference supporters. First, we would like to thank all authors for their continued support to the conference by submitting their research work and for their presentations and discussions during the conference days. We would like to thank PC Co-chairs, Track Co-chairs, TPC members, and external reviewers for their work by carefully evaluating the submissions and providing constructive feedback to authors.

We would like to acknowledge the excellent work and support by the International Advisory Committee. Our gratitude and acknowledgment for the conference keynotes for their interesting and inspiring keynote speeches.

We greatly appreciate the support by Web Administrator Co-Chairs. We are very grateful to Springer as well as several academic institutions for their endorsement and assistance.

Finally, we hope that you will find these proceedings to be a valuable resource in your professional, research, and educational activities.

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# **INCoS-2024 Keynote Talks**

# **A Vector Database Approach for Natural Environment Monitoring and Analysis**

Prof. Kosuke Takano

Kanagawa Institute of Technology, Atsugi, Japan

**Abstract.** By using spatiotemporal data obtained from various sensor devices can be analyzed the changes in the natural environment. However, to semantically and spatiotemporally analyze the massive amount of sensor data accumulated daily, it is important to realize observation data management by balancing resource size, computational cost, and semantic quality. In this, keynote talk will be introduced a vector database approach that can be applied to data retrieval, analysis, and prediction during the observation of global and local changing natural and ecological environments. Our approach can increase the reusability of massive observation data by compressing them to the feature vectors as embedding matrices using appropriate neural networks, achieving fast semantic retrieval and spatiotemporal analysis. We will present some research results to evaluate the proposed approach.

# **Taxonomy Construction of Anti-Tampering Technology Schemes from System Programmer's View**

Prof Ki-Woong Park

Sejong University, Seoul, South Korea

**Abstract.** In this talk, we analyze the recent anti-tampering technologies from a "system programmer's" perspective. We have constructed a taxonomy matrix for these technologies and introduced a specialized classification framework. Using this framework, we assign identification numbers to the detailed technologies and operating principles embedded in existing anti-tampering solutions based on the "sensing & actions" perspective and their "stackable position". This approach enables the creation of a roadmap for anti-tampering technologies and facilitates anti-tampering orchestration to build secure systems. Finally, we introduce software-defined orchestration for anti-tampering, which allows selecting of the most suitable anti-tampering technology for a given system.

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# <span id="page-24-0"></span>**Depression Tendency Estimation Method Using AI Chatbot**

Riko Indo<sup>1</sup>, Fujino Tochishita<sup>1</sup>, Hiroyoshi Miwa<sup>1( $\boxtimes$ ), Daichi Nomiyama<sup>2</sup>,</sup> and Soichiro Kude<sup>2</sup>

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**Abstract.** Mood disorders, such as depression, manifest in various psychological and physical symptoms. Persistent feelings of sadness can disrupt daily functioning, while accompanying issues like insomnia and loss of appetite further exacerbate the condition. If left untreated, depression can lead to a range of complications, including severe illnesses and potentially life-threatening outcomes. In recent years, there has been a notable rise in psychiatric disorder cases, with a significant increase observed in mood disorders, particularly depression. Many individuals either fail to recognize their symptoms or are hesitant to seek professional help. As a result, only a fraction of affected individuals receive adequate treatment. This paper proposes a method for estimating depressive tendencies by analyzing observable data, such as conversational content between users and chatbots, as well as their usage patterns. By leveraging these insights, we aim to improve early detection and intervention strategies for individuals at risk of depression.

#### **1 Introduction**

Depression is a mood disorder that manifests as mental symptoms, such as persistent sadness interfering with work and daily life, and physical symptoms, including insomnia and loss of appetite. Early detection and treatment increase the probability of a complete cure, but delayed treatment may prolong symptoms and lead to various illnesses or, in the worst case, prove fatal.

In recent years, the total number of patients with psychiatric disorders has been increasing, with a significant rise observed in mood disorders, particularly depression [\[1](#page--1-4)[–3\]](#page--1-5). However, many individuals experiencing depression are either unaware of their condition or hesitant to seek medical care, even when experiencing subjective symptoms, resulting in few receiving treatment.

Research has shown a preference for interacting with chatbots over humans when sharing their situation [\[4\]](#page--1-6). In this paper, we examine a method for estimating depressive tendencies by analyzing observable data, such as conversational content and chatbot usage patterns, based on natural interactions between users and chatbots. We propose some algorithms for the method and evaluate the performance of the algorithms.

#### **2 Previous Research**

According to [\[5](#page--1-7)], people with depressive tendencies use more perfectionistic words such as "completely," "absolutely," etc., in addition to negative words. This indicates a desire to view things in black and white. [\[6](#page--1-8)[–8](#page--1-9)] also showed that people with depression tend to use negative words and the first person singular more frequently. People who frequently use the first person singular subconsciously distinguish between themselves and others, while those who frequently use the first person plural believe that they are part of society. These two types of thinking may be related to depressive tendencies.

[\[9](#page--1-10)] is the study on estimating depressive tendencies. In this study, we detected students with depression with an accuracy rate of 85.7 percent by collecting students' location information, smartphone usage, call history, and sleep information, and extracting features using machine learning. The system also detected students with changes in the severity of their depression symptoms with an accuracy rate of 85.4% and the degree of change with an accuracy rate of 82.9%. However, because this system requires the use of a wide variety of personal information, the burden of collecting such information is too great to be practically feasible.

According to  $[10-12]$  $[10-12]$ , the psychological tendencies of users can be determined from their social networking texts. [\[13](#page--1-13)[–19\]](#page--1-14) predicts the tendency to depression based on Twitter comments, usage, and other factors. [\[13\]](#page--1-13) uses commonly used words, usage patterns, and relationships with other users as features, and classifies them using decision trees, polynomial simple Bayesian classifiers, linear SVM, and radial basis function kernel SVM. The classification accuracy of the linear SVM was the best, achieving an accuracy of 82.5%. In addition, [\[14](#page--1-15)[,15](#page--1-16)] analyzed the tweets of depressed users in the year before they were diagnosed with depression and found that frequently used words, emotions, degree of interest in society, and changes in relationships with other users were effective in predicting the onset of depression. The classification accuracy was 70%.

[\[16](#page--1-17),[17\]](#page--1-18) analyzed the content of users' tweets and the emotions of frequently used emojis and emoticons, and by using these as features, classification could be performed with high accuracy using linear SVM. According to [\[18](#page--1-19)], which used tweets to estimate the mental changes of postpartum mothers, they analyzed the contents and emotions of 376 mothers' tweets before and after childbirth, and their relationships with other users. They predicted mothers at risk of postpartum depression by SVM with 71% accuracy. The accuracy was improved by using tweets from the first three weeks postpartum, and it was found that classification was possible with an accuracy of 83%. In addition, [\[19\]](#page--1-14) used frequently used words, emotions, usage status, and relationships with other users as features, and used radial basis function kernel SVM for classification, which resulted in 66% accuracy. The comparison of accuracy by changing the time period of tweets used showed that a time period of about two months is sufficient for predicting depression, and that tweets from earlier time periods may contain outdated information and may not represent the user's current state. In addition to the time and content of tweets, these studies used Twitter-specific information such as the number of followers, number of followings, number of retweets, and replies to other users, which may not be used in other SNSs.

[\[20](#page--1-20)] is a study to predict depressive tendencies from textual data, and it predicted these tendencies using blog entries over a long period of time. In this study, they estimated nine depressive symptoms based on the DSM-5 diagnostic criteria, which are often used to diagnose depression in practice. Using these symptoms as features, they estimated the depressive tendencies of blog authors. The results enabled estimation with an accuracy of approximately 80%. However, since blogs are often written in long sentences, it is difficult to encourage bloggers to continue posting regularly.

Furthermore, [\[21](#page--1-21)] is a study on the estimation of depressive tendencies using chatbots. This method estimates whether a user has a tendency to depression by having a one-question-and-one-answer conversation with a chatbot that asks questions such as "How have you been feeling since last week?" and "What do you think about the future?" It can estimate the user's current mental state but cannot track changes over time. It is difficult to repeat the process casually because 55% of the users felt that the questions were designed to estimate whether they are depressed, and because the conversation is in a question-andanswer format rather than a natural one. In addition, this system assumes that the individual correctly recognizes their own state, uses the diagnostic system at the appropriate time, and gives answers that enable accurate diagnosis by the algorithm. However, it is difficult to expect a person in a psychologically unstable state to always satisfy this assumption.

#### **3 Estimating Depressive Tendencies**

In this section, we describe the depression tendency estimation method (ses also Fig. [1\)](#page-27-0). The data used include the contents of conversations with chatbots and their usage status, which are analyzed to estimate depressive tendencies. For the analysis of conversational content, we estimate the psychological tendencies of users' statements by using generative AI and morphological analysis of these statements. For the analysis of usage, we estimate the time until the user responds to the chatbot's message, the time at which the user responds, and the number of times the user responds, analyzing the changes over time and the deviation from the average to predict users whose motivation is declining.



<span id="page-27-0"></span>**Fig. 1.** The depression tendency estimation method

In this paper, we implemented a chatbot based on IBM Watson, an AI-based question answering service, combined with ChatGPT. By using IBM Watson, the chatbot is able to accurately respond to expected questions, and by combining it with ChatGPT, the chatbot is able to provide natural responses to unexpected questions. This enables a natural conversation with the user, and we have built a chatbot that can be used continuously.

Next, we describes a method (algorithm) for analyzing conversational content. We use morphological analysis and generative AI to estimate the psychological tendencies of user utterances. The method using generative AI estimates the psychological tendency of each sentence, rather than dividing the user's utterance into words. The method using morphological analysis first analyzes the user's utterance and divides it into morphemes, which are the smallest units that have meaning in language. The number of perfectionist words, the number of negative words, the number of affirmative words, the number of first person singular pronouns, and the number of first person plural pronouns are then determined. For the extraction of perfectionist words, we use the perfectionist word dictionary found in the reference [\[5\]](#page--1-7). To extract negative and positive words, we use the Word Emotional Polarity Mapping Table [\[22\]](#page--1-22). The word polarity correspondence table is a table of words, readings, parts of speech, and emotional polarity. The emotional polarity of a word is a number indicating whether the word is positive or negative. The more positive the word is, the closer the emotional polarity approaches 1; the more negative the word is, the closer the emotional polarity approaches -1. This table can be used to extract negative and positive words from an utterance. The proportion of each word category is used to estimate the psychological tendency of the user's utterance. Since the goal of this paper is to extract users with depressive tendencies, we set a threshold value higher than the user average for the percentages of perfectionist words, negative words, and first person singular pronouns, and check whether the threshold value is exceeded or not. For the percentages of positive words and first person plural pronouns, we set the threshold value lower than the user average and check if it is below the threshold.

According to [\[14\]](#page--1-15), which estimated depressive tendencies based on the content of Twitter posts and conversations with other users, the depressed user group posted 38% fewer posts and 32% fewer responses than the non-depressed user group, and both numbers decreased over time. This can be said to indicate a decrease in motivation, which is one of the symptoms of depression. Therefore, in this paper, we will observe and analyze user activity over a long period of time. The data used includes the times when the chatbot sends a conversation request and when the user responds to the request.

From this data, we obtain the time until the user responds to the chatbot's conversational prompts, the time when the user responds, and the number of times the user responds. We then look at changes over time and deviations from the average. As an evaluation metric, we set a threshold for the response time that exceeds the user's average response time and check whether this threshold is exceeded. The average response time is calculated each week, and the increase from the previous week is determined. A threshold is set for the increase amount to be greater than the average increase of other users, and we check whether it exceeds this threshold. Thus, we can identify users whose response times tend to increase over time and whose motivation is gradually declining.

Then, the difference in the number of reactions during the day and at night is analyzed. To analyze the difference in the number of responses between day and night, we divide the day into two periods: daytime (from 6:00 am to 6:00 pm) and nighttime (the rest of the day). We then determine the difference between the number of responses during the night and during the day. For users who respond more frequently at night, a threshold is set for the difference that is larger than the user average. Users who respond more frequently at night than during the day are identified by checking if the difference exceeds the threshold. The average number of responses during the day and night is calculated for each week, along with the increase from the previous week. A threshold is set for the increase amount, which is greater than the average increase of other users, and we check if it exceeds this threshold. This allows us to determine if the difference in the number of responses between daytime and nighttime tends to increase over time, and if this trend is significant. Thus, we can identify users whose difference in the number of responses between day and night tends to increase over time, indicating they are more active at night and may have a disturbed life rhythm.

Furthermore, a threshold is set for the number of reactions to a value smaller than the user average, and it is checked whether it is below the threshold. The average number of responses per week is calculated, and the decrease from the previous week is determined. For the decrease amount, we set a threshold to a value smaller than the average decrease of other users and check whether it is below the threshold. This method identifies users whose number of responses tends to decrease over time and whose motivation is gradually decreasing.

Furthermore, a threshold is set for the number of reactions to a value smaller than the user average, and users with a low number of reactions are extracted by checking whether the number of reactions is below the threshold. The average number of responses in each week is calculated, and the amount of decrease from the previous week is determined. For the amount of decrease, we set a threshold to a value smaller than the average of other users, and check whether it is below the threshold. In this way, we extract users whose number of responses tends to decrease over time, and whose tendency is remarkable, i.e., users whose motivation is gradually decreasing.

#### **4 Performance Evaluation**

#### **4.1 Analysis Algorithm Using Conversation Contents**

The classifiers used in our analysis are linear SVM, SVM with radial basis function kernels, decision trees, and logistic regression, which were used in [\[13](#page--1-13)[–19](#page--1-14)] on estimating depressive tendencies and showed high accuracy. SVM is a classifier that can discriminate high-dimensional data with high accuracy and low risk of overfitting by maximizing the distance between the boundary for separating different classes and the nearest point to the boundary. In this paper, we use linear SVMs and SVMs with radial basis function kernels. The linear SVM also allows for the separation of intermediate layers by applying a soft margin to allow for misclassification. Decision trees are a method for analyzing data in a tree structure. The tree structure visualizes the classification process and facilitates interpretation of the results. Logistic regression is a classifier that categorizes classes by predicting the probability of the occurrence of the target variable from the explanatory variables. Since the probability of the occurrence of the target variable can be calculated, it has the advantage of showing the degree of influence of each explanatory variable. In our analysis, we compare the classification accuracy of these four classifiers.

To evaluate the performance of the algorithm for analyzing conversational content, we analyzed Twitter conversations. Using the Twitter API to collect two months of tweets from 59 depressed users and 104 nondepressed users, and predicted the results using a classifier, as shown in Table [1.](#page-29-0) When we focus on the recall, which indicates the percentage of users who are actually depressed and can be predicted to be depressed, the highest recall is 0.67 for linear SVM. The F value, the harmonic mean of the precision and recall, which is important for building a well-balanced model, was also highest for linear SVM, at 0.69.

				Accuracy   Precision   Recall   F-measure
Linear SVM	0.78	0.73	0.67	0.69
SVM with radial basis function kernels 0.77		0.71	0.62	0.66
Decision tree	0.67	0.55	0.53	0.54
Logistic regression	0.78	0.73	0.63	0.66

<span id="page-29-0"></span>**Table 1.** Evaluation of Analysis Algorithm Using Conversation Contents