TASK SCHEDULING IN CLOUD COMPUTING TECHNOLOGY USING DEEP NEURAL NETWORKS ALGORITHMS ON HEALTHCARE SYSTEMS

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Abstract

Virtualization has received considerable attention from different fields since it was introduced in the last epoch. However, because of the present environment and the decentralized organization, it is more difficult to establish trust connections between users and cloud services. This provides a highly versatile virtualized IT platform. In the existing wireless communications (mobile) template, the Internet of Things (IoT) definition is used. The proposed Deep Neural Networks model collects information, and granulates and classifies it by DNN classification to provide the information to the users, patients, caretakers and physicians.

Keywords:

Cloud Computing, Reliability Assessment, Trust proof, Personal Opinion, Internet of Things

1. INTRODUCTION

As a mathematical formality of open environment, cloud computing offers broad prospects through its many key functions such as stability, flexibility and network autonomy [2]. Applications and resources are distributed and delivered using cloud computing service, which enables interactions between third parties and customers through an unreliable model platform. Service providers are not entitled to anticipate how they act, but are bound to face various kinds of customers [1]. The services users have no right to have the provision to know user data and programs that are often distributed in a dedicated hosting. Consumers, hence, cannot trust cloud infrastructure to these advantages.

As a first step towards optimizing user engagement, an overall engagement model is urgently needed which could provide insight into different network environments, in particular the current fog computing context [8]. Several studies of understanding and modeled commitment in past works have consistently been perceived to be fundamental elements related to commitment in quality of service (QoS), together with some objective context factors such as location, device and temporal attributes [3] – [6]. The relationship between user involvement and QoS was extensively explored in related works either at the application level (e.g. startup time, buffer frequency and bitrate) or at network level (e.g., signal strength throughout).

However, most of the works involved have ignored other important human factors, such as the personalized interest of users in a certain video. The new era of customization actually raises users' aesthetic and personal needs, particularly in mobile video services, where users typically present predictable features and demand for services [7]. Therefore, the user commitment cannot be met solely with high-quality delivery, as a reflection of "the degree of delight or annoyance of the applicant or service user." Sessions with the same buffer frequency therefore sometimes involve different users because of a difference in user interest in the video content. Nevertheless, many research papers have ignored or excluded the subjective factors' impact as their quantification is difficult. In some studies, video popularity in QoE models is considered a subjective human factor, but video popularity can only describe the average user preferences, but without personalization. Only a few macro-level pieces psychologically and cognitively assess the subjective human factors for each session [9]. In such projects, large experiments and surveys with a very large population of subjects provide the subjective factors; however, such experiments and surveys are costly to carry out and are not suitable for streaming applications on the VoD systems [10] – [12].

In addition to the accurate understanding and predicting of user involvement, a commitment model based on both QoS and user interest is needed to also optimize system resources allocation and deliver better personalized services. First, it could help designers deploy the appropriate bandwidth resources to optimize user involvement, to find out how this subjective factor affects user engaging. On the other hand, the Recommendation System (RS) might decide to recommend to users video items which are of interest and which have good quality of view and which could finally be enjoyed longer time between the QoS element and the human factors. It is therefore essential to understand the relationship between participation and human factors as well as the QoS to clarify how best resources can be allocated and services tailored.

A challenge before creating such a model is how the user's interest in a video can be quantified. User interest is measured in previous recommender systems either by explicit user evaluations or in general by implicit evaluations, for example, user involvement. The former measuring method is accurate but cannot be collected in applications that are time-sensitive. The latter is not exact, as sometimes user involvement is not the reaction to its pure video interest but is also affected by other factors like starting delay.

Another challenge is how the relationships between user participation and both factors can be characterized in a common model to provide insight into practical applications. Intuitive, but not independent, the two factors have an impact on user commitment beyond the scope of a model of linear regression. For example, user interest affects not only the user involvement but also the patience of users with QoS. The Machine Learning (ML) Algorithms, i.e. the Decision Trees and the Naive Bayes algorithms, can characterize such a relationship, but not in a concise format.

This paper is dedicated to addressing both these challenges. In order to estimate the user interests from user behaviours, we propose the Deep Neural Networks algorithm. We analyze the relationship between user engagement and both QoS and user interests via a measurement of a cloud system.

2. RELATED WORKS

As they may at least be controlled partially via the platform, QoS parameters are often examined as primary factors related to QoE. The specific QoS-metrics vary across different fields including application level metrics, e.g. startup time, buffer frequency, buffer ratio, bitrate, and also network-level metrics, e.g. flow rate, flow duration, transmission rate and signal strength. Due to uncertain network conditions, application-level QoS metrics capture the quality of users more closely than network-level users.

Sometimes QoS metrics compete with one another, or conflict with each other. Previous work indicates, for example, the competition between the start time and the buffer event. Moreover, in Bitrate Adaptation Schemes, the balance between bitrate and buffer event is often studied.

Several technologies are also suggested for adjusting the QoS parameters on the client, server and network. These include the adaptation of bitrate, prefetching, selection of transport protocol and deployment of a cache.

QoS factor alone cannot determine user satisfaction or the exploration of other potential “configuration” factors. The factors considered can be classified as context information, such as connectivity and time effects, content features, types and popularity, user features such as location, device, or gender.

User interests are frequently ignored, however. Some works dealt with human factors in the psychological and cognitive perspectives (similar to the user interest in the paper defined in essence) and attempted, including human factors, to integrate. The conduct of such work is, however, expensive and takes a long time and involves technical and psychological experts. It is still an open problem to identify subjective human factors suitable for real time streaming applications.

When it comes to understanding the effects of human factors on system design (e.g. user interest), one study takes advantage of the individual interest in optimizing the allocation of stocks in CDN. This study does not however take into account factors of quality and therefore does not contribute to making a decision on user interest and QoS.

The problem addressed in a customized recommendation system (RS) that is a hot topic because of the information overload in the past decade is the prediction of a user's interest in a certain item. Collaborative filtering (CF) algorithms such as K-Nearest Neighbor, Matrix Factorization and Bayesian beliefs nets have been extensively studied as a popular kind of recommendation algorithm. Since CF algorithms do not need item contents data, they can be used in video system applications where it is difficult to get explicit descriptions of content of items (i.e. videos).

Furthermore, how user interest can be achieved and quantified is also studied. Most works ask users after buying items, viewing video and surfing the website for explicit ratings. In time sensitive applications such as online VoD systems, this method is accurate but not practical. User compartments are instead used in some applications as implicit ratings, such as time spent on a page, scrolling and clicking on web sites, time spent on a video and past purchases. User behaviors are sometimes as reliable as they have been proven, but they are still noisy on VoD systems.

3. PROPOSED MULTI-FACTOR MODEL FOR DETERMINING QOS

Existing service trust research is based largely on the security framework in which the reputation of cloud-based computer ecosystems is enhanced by increasing the Internet security, stability and confidentiality that fosters customer relationships between users and cloud services. However, because confidence is a human idea, work in security is only a small contributor to trust and does not represent the subjective characteristics of confidence.

There are, however, independent studies in the business environment that measure the quality of cloud computing systems. Many scientists regard user rating and feedback as the only demonstration of trust that reflects the wishes of system users. But there are two clear disadvantages: the historical factor and the factor duration of the ties of trust are not represented. Therefore, customer rating and suggestion-driven approaches alone cannot give a detailed measure of the reputation of the service. In this paper, a new model for assessing cloud service legitimacy in a business environment is suggested, with the aim of assessing fact, history and time to ensure that the legitimacy of service users is properly, flexibly and dynamically evaluated.

In either cloud computing world, cloud application stack architecture was commonly used. In all of this architecture, cloud systems become the conceptual nucleus of cloud services. A database server can collect confidence-based data from cloud services. Cloud services can be evaluated on the basis of the information provided through the cloud platform. The effects of different evidence sources should be taken fully into account in such an assessment. The evaluation results, which combine different variables, represent the level of reliable service in its entirety and reliability.

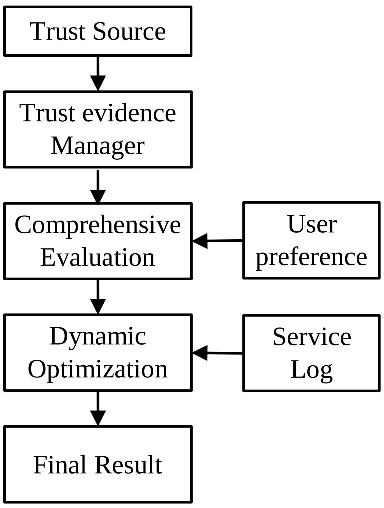

Fig.1. System for assessing the quality of operation

In this article, we take into account the QoS application level metrics that capture delivery impacts on the customer side. We focus in particular on the metrics listed below.

Startup Delay. It is time before a video begins to play, and right after the user starts an application, excluding the time spent on ads. It is measured in seconds.

Buffer Frequency. It is the ratio of the number of pamphlets to the total pamphlet and play time. The number of times per minute is measured.

Buffering Ratio. This is the proportion of time used to buffer or restart buffer in a session to the total buffer and playtime. The percentage is measured.

Average Buffer Length. Once a buffer occurs, the user has to spend average time buffering. The buffering ratio is calculated as the buffering ratio. It is a new metric to complement the frequency of the buffer.

We do not distinguish between buffering and restart buffering and we do not discuss a different quality metric, bitrate, because of a lack of information. This failure does not diminish the worth of our study, since it is not about investigating the relation between quality metrics, but about dealing with conflicting or competing links between quality and the interest of the users. The model can be extended if needed or once the data is available. Compared to QoS metrics at network level, metrics are more general in various network contexts at the application level.

- *Trust Evidence Management*: User rating is used in most trust-related research, as a kind of conventional trust proof. The customer rating is still a very crucial evidence of trust in cloud computing environments. User rating is a sort of subjective evidence which represents the user subjective feelings towards the service. Because it includes the desires of the service users, in most situations the customer rating often belongs to some sort of evidence of customization.
- *Trust Evidence of Cloud Services*: As already mentioned, cloud services are provided by service providers in the cloud industry, and the service is used by customers over the Internet. The marketing strategy is generally recognized by major manufacturers, and many potential applications are currently in place. In this mode there is a stronger cloud platform which is now the logical center of the higher cloud services.
- *User Rating Record*: User ratings are used as a kind of conventional evidence for most trust-related research. The rating of customers is still a very important proof of confidence in cloud computing. User rating is a kind of subjective proof that represents the subjective feelings of the user towards the service. Since it covers the wishes of the service users, customer ratings are often some sort of proof of customization in most situations.
- *Service Call Record*: Over a time period, the calling record unit is objective and acts as an important guidance on service integrity. Calling logs for services are qualitative proof of customer behavior. Without taking into account any factors, the customer is more likely to use the product with a large success or user satisfaction.
- *Services Certification*: Including cloud services, cloud infrastructure reviews baseline certification software. However, number of suppliers can go beyond the respective qualifications or have the standard. The cloud platform accredits this capacity and customer satisfaction. A company accredited has a better chance from the consumer's point of view of quality.

4. DEEP NEURAL NETWORK

Deep Neural networks (DNNs), also known as convolutional networks, consist of multiple levels of nonlinear operations, such as a number of hidden layer neural networks. Deep learning methods aim to teach feature hierarchies, which are formed by the use of features at lower levels at higher levels of hierarchy. Deeper architectures are pre-trained on each layer with an uncontrolled learning algorithm. Network is then trained in a monitored mode using background reproduction algorithm.

Based on the biological neural network, deep learning remains the best intelligence for the identification in a song of a person, in an image or melody. This is why deep learning is considered to be suitable over traditional algorithms for machine learning. Given the use of a domain-expert approach in most conventional machine learning concepts, how the machine learning will be based on man-made logic.

An AI aspect is a DNN which aims to emulate the approach of learning that people are taking to gather certain kinds of knowledge. DNN also contains a number of artificial neurons and uses them to identify and store information, just like bio-neurons in the brain. DNN is made up of input and output layers and (most often) of one or more hidden layers composed of units, transforming the input in something that can be used by the output layer.

Around 86 billion neurons are present in the human brain. These neurons are like a mesh connected. Entities known as dendrites accept stimuli from the outside environment or inputs from sensory bodies. These inputs generate electrical impulses that pass through the neural network rapidly. A neuron may then send or not send messages to other neurons to handle the problem. This is referred to as neuron activation. Thousands of other neurons are connected by axons to the neuron.

DNN consist of several artificial neuronal nodes imitating the neurons. There is only one kind of link between one neuron and others, in contrast to biologic neurons. The neurons receive input data and simple operations on those data are performed. These surgeries result in other neurons being transferred. The activation function determines whether the result is passed. Both function extraction and classification play an important role in the activation function. In DNN, weight and bias are used to achieve this.

5. PERFORMANCE EVALUATION

Service quality influences the consumer experience in the use of various types of services and is a key factor in establishing a relationship of satisfaction with consumers.

Table.1. Individual characteristics of patients

Personal Attributes	Description	Symptoms Attributes
RNO	Reference number of user	Headache
Name	Name of user	Forger places
Age	Age of user	Poor judgment
Gender	Gender of user	Forgetting recently learned info

This service quality can be categorized as configuration category and scientific evidence as different users have lower quality criteria for different quality attributes. Data related to health can be taken from various websites on the internet.

To anticipate the disease, a. DNN based inference method could be deployed for the identification of disease forms and k-means grouping in disease evaluation. Evaluating the illness is the key aspect of the current proposal. If this method is successful, then the position of the disease and the infection itself may be forecasted and therefore the damage that could be caused by the disease may be minimized. The proposed system for detecting and plotting the positions of the Disease on the map is defined as follows:

Table.2. Summary of 10-fold Cross Validation of Random Decision Tree

Attributes	Result
Correctly classified instances	44.4%
Incorrectly classified instances	55.6%
Kappa Statistics	0
Mean absolute error	0.4345
Root mean square error	0.5193
Relative absolute error	9.923%
Root relative square error	10.23%
Total number of instances	9
Unknown instances	1

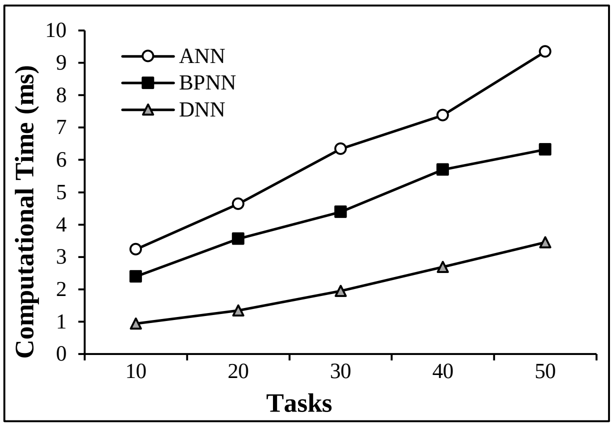

Fig.2. Analysis of Computational Time

The results of computational time shows that the proposed method achieves reduced computational time in Fig.2 using the proposed system than the existing ANN and BPNN.

6. CONCLUSION

This program is very easy to reach and gives better precision and precise results. We have used DNN classification technique for clustering various distributed data, which groups the data of the entire person and gives better performance. The findings we inferred in the classification technique of DNN are best suited for other clustering techniques such as ANN and BPNN. The data mining tool we have installed in all the cluster results maps various data attributes in a graphical way. The statement of clinician shows that the proposed application is an appropriate tool for helping and assisting doctors in tracking and engaging with their cancer patient.

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