Personalized Productivity Prediction Using Desktop Activity

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ABSTRACT: Productivity monitoring has become an essential feature of modern digital work environments. The traditional methods of measuring productivity involve manual monitoring and evaluation, which may not correctly reflect the real productivity of the users. This paper suggests a personalized system of productivity prediction based on desktop activity monitoring. The system monitors the activities of the users, such as the use of applications, typing, mouse movement, working hours, etc., and then uses machine learning algorithms to predict the level of productivity of the users. The proposed system can provide personalized insights about the patterns of users, which can be helpful for understanding their productivity. The main focus of the proposed system is to identify patterns in computer usage that determine how well one performs at work. The constant analysis of user interaction with the computer allows for trends in productivity to be identified, which would be extremely useful in improving how users utilize their computers. The integration of machine learning algorithms allows the system to be dynamic in accommodating different user patterns, providing personalized information rather than generalized levels of productivity. In addition, it would be useful in identifying time-wasting activities to prevent user distractions during working hours. The proposed system can also be utilized in a remote working environment, where the challenge of monitoring user productivity is significant. The experimental analysis proves that the proposed system can effectively utilize the available desktop activity to estimate the levels of user productivity with reasonable accuracy. The proposed system can offer a powerful solution to the intelligent assessment of user productivity in the modern digital working environment. There is a potential for such a model to be used for decision-making processes for individuals and organizations, considering that it has the potential to offer data-driven information on productivity. The model can be extended to include workplace analytics systems, which can be used to enhance the workflow and digital management of tasks in the workplace. The results indicate the potential benefits that can be obtained by incorporating behavioural data and intelligent algorithms in designing a more adaptive and efficient productivity monitoring system.

Keywords: Productivity Prediction, Desktop Activity Monitoring, Machine Learning, User Behaviour Analysis, Activity Log Analysis.

1. INTRODUCTION:

Productivity monitoring has been identified as a significant aspect of modern digital workplaces. The existing methods for measuring productivity involve the monitoring and assessment of data, which may not precisely indicate how a user is performing in his or her job role. In this paper, a personalized productivity prediction system based on desktop activity monitoring is presented. In this system, user interaction data is collected in terms of application usage, typing frequency, mouse movement, and active work periods. Machine learning is used for analysing the collected data and determining the productivity level of individual users. The proposed model can learn user behaviour patterns and provide personalized productivity predictions.

The focus of the proposed system is to recognize patterns in daily computer usage that affect productivity in work situations. Continuous analysis of user interaction behaviour can also enable the system to identify productivity trends and hence provide valuable feedback on how to improve user productivity. The integration of machine learning algorithms into the system can enable it to adjust to different user behaviours and offer personalized predictions instead of generalized productivity measures. Moreover, the system can enable the identification of time-consuming processes and eliminate distracting elements during work hours. The proposed model can also be implemented in a remote working environment where productivity is difficult to monitor. Analysis of the experiment shows that desktop activity can be used to estimate productivity levels in an effective manner. Therefore, this model offers an intelligent solution for the scalability of productivity assessment in the contemporary digital working environment.

The proposed model can assist in the decision-making process for personal as well as organizational productivity. The proposed system can also be integrated with workplace analytics tools for the efficient use of the workflow. The results of the proposed model have shown the possibility of using behavioral data with intelligent algorithms for an efficient productivity monitoring system.

2. LITERATURE REVIEW:

Digital tech has really changed how we work today. Nowadays, we mostly do all this for work or school using computers. Therefore, it is a big issue to understand how people use these systems. Recently, everyone is concerned with how people perform at tasks using these systems and how they can improve at it.

Some studies checked data from computers to get how people act and their work habits. Back in 2012, Huang, White, and Dumais looked at how people move their mouse and click around to understand what they were doing. They found out that how you move your mouse and what you browse can show what you're trying to do and how focused you are. So, watching how people interact with their computers can tell us a lot about their actions and how well they perform.

Then, in 2004, Fogarty and others came up with a system using sensors to guess when someone is okay to interrupt by watching what they're doing on the computer. They proved that keeping an eye on keyboard and mouse activity, plus what apps they're using, can help you know when it's a fair time to interrupt without screwing up their work. This meant that watching people's actions can really help make work easier and cut down on annoying interruptions. Also, in 2004, Horvitz, Koch, and Apacible created Busy Body. It uses machine learning to figure out how much interruptions mess with people when they're using computers. The system looked at what people were doing and guessed how interruptions would change how well they did their tasks. Their work showed that guessing what will happen can the productivity by cutting out distractions when using computers.

It is going with this in 2008 by building models of users using sampling ways. They mixed data about what people do with machine learning to understand habits and guess what they'll do next. The study showed that smart models can learn from past actions and change to fit different people's habits over time.

Another thing that's important is checking what people do on their computers to understand their work habits and how their productivity. Muller and others studied desktop activity in 2010 and saw how it connects to how well people work. They learned that steady habits, like typing a lot and using specific apps, are signs of a good work session. They also noticed that if people switch between apps all the time or don't do anything for a while, they don't get as much done.

Recent studies about productivity have started machine learning to check big sets of data from digital tools. In 2019, Tan and Netessine checked productivity and showed that data from computers can be used to see how well people work. The research asserted that the guessing process would reveal hidden patterns of productiveness.

Additionally, machine learning techniques such as Support Vector Machines, Random Forests, and Neural Networks are used in monitoring how people behave. These algorithms can find patterns in big data sets and create models that get better. In 2017, Mitchell said that machine learning is helpful when a lot of data about behaviour needs to be checked to see habits and guess what will happen.

But, a lot of systems that check productivity only give general ideas instead of giving work guesses for each person. Most systems just measure simple things like how long someone is active or what apps they use. They don't get that everyone acts differently. So, we need smarter systems that can change for each person and guess how productive they are.

This study will fix this by creating a model to make guesses on people’s productivity based on their computer activities and machine learning. The system will make guesses about individuals by trying to determine how fast they can type, the programs they use, and how long they have been idle. This will be useful for productivity work and smart systems that observe what happens at work.

3. CASE AND METHODOLOGY:

The proposed productivity prediction system will have the ability to examine the data related to desktop activities and predict productivity levels. The productivity prediction system consists of four stages: data collection, data pre-processing, model training, and productivity prediction. The first stage involves gathering user interaction data from desktop systems. A monitoring application records various activity indicator, such as application usage time, keyboard typing frequency, mouse movement patterns, and system idle duration. These parameters describe the behaviour of the users during their work sessions.

The data collected will be in the form of activity log files, which will have information about the time stamps for each activity performed. This will give a clear idea of how the users interact with their computer. The data collected will have noise, i.e., extra information, and some fields will be empty. Therefore, the pre-processing phase becomes important in order to clean the data and make it ready for processing.

In the feature extraction phase, various algorithms will be implemented on the activity data in order to obtain important features like the duration of work, switching of applications, intensity of typing, and idle time percentage. After the pre-processing phase, the machine learning algorithms will train the model for prediction. The methods that can be used for classifying the level of productivity on the basis of behavioural characteristics include Random Forest, SVM, and Logistic Regression.

The model will recognize the patterns from the history of activities and relate them to the level of productivity, which includes high, medium, and low. During training, the dataset is split into training and testing subsets to assess the model's predictive performance.

Productivity Prediction:

Once the model is trained, it can analyse new desktop activity data and forecast productivity levels in real time. The system generates productivity scores based on the learned behavioural patterns and gives feedback to users about their work efficiency. This predictive system helps users recognize unproductive habits, manage their time better, and enhance their work performance.

4. RESULTS & ANALYSIS:

Our productivity prediction system was tested by using information collected from people's computers during their regular workdays. This information included things such as how long they used certain apps, how many times they typed, how many times they moved their mouse, and how long they were idle on their computers. This information helped us train our model and determine how productive they were. When collecting data, logs were kept on what people were doing on their computers. Each log showed when they used something on the system. This gave us a good look at how people worked with apps, how much they typed or moved their mouse, and how much time they spent actually doing stuff. We used this to create a set of behaviours that showed how people work online. Once we cleaned our data, we divided it into two parts: one for training our machine learning model, and another for testing how well our model performed in making predictions. We got a glimpse of a few machine learning algorithms: Random Forest, Support Vector Machine, and Logistic Regression. Of all the algorithms, Random Forest performed better in making predictions on productivity. It performed better because it could handle a lot of data and figure out how behaviour correlated with productivity in a sneaky way. By analysing our test results, we found that there are a few key behaviours that impact productivity, such as what apps a person used. People who used apps related to their tasks, such as coding programs, document editors, and data analysis programs, tended to score higher in productivity.

Also, typing speed mattered. People who tended to type regularly tended to be working on things like writing or coding. If someone tended to type little and be idle a lot, it was a sign they weren't really working. How people interacted with their mouse was another way we could tell something about them. Constant mouse movement usually meant they were using apps, while little movement and long idle times suggested they were not doing much or were distracted. By putting mouse data together with typing and app use, the system could guess productivity better. Another big deal we noticed was idle time. Long idle periods really dragged down productivity scores. Individuals who often left their computer alone during work hours tended to have lower productivity predictions than individuals who stayed active. The system could also track how productive people had been over time. Examining this data at various times of the day could help us figure out when people tended to be the most productive. Many people tended to be more productive during certain times of the day, mostly when they were more focused.

This can be helpful for people to better organize their workdays. The system also offered a productivity score that categorized people into three categories: high, medium, and low productivity. This is based on their behaviour levels learned during our training data. The results showed that the model could tell the difference between productive and unproductive habits. The test results also pointed out that it is important to put different behaviours together to guess productivity better. Just knowing what apps someone used was not enough. However, with the inclusion of typing, mouse movement, and idle time, as well as the use of applications, the model was better at guessing things. In a nutshell, the findings from the study reveal that with the monitoring of computer use and the use of machine learning, it is possible to guess the level of productivity in online work areas. The system is very informative regarding how people are working or how they are performing by simply observing how they uses their computers. The study also suggests that customized models for predicting productivity can be beneficial to everyone. Individuals can utilize the information obtained by such a system to reduce distractions and work better. Organizations can utilize these systems to get a feel of how well individuals are doing and how to stay productive. To make it better, we could include things such as information obtained from task managers, calendars, and collaborative tools. This could make the productivity predictions more spot-on and give us a better understanding of how people work.

5. CONCLUSION

The investigation for modern work tracking begins by observing the daily computer usage patterns of people. The software determines peak work periods through its ability to identify patterns which users demonstrate through their mouse and keyboard activities. The system develops better decision-making capabilities through its continuous learning process which uses historical behaviour data. The system employs intelligent algorithms which learned from actual user behaviour to create its predictions. Focus periods become discernible through the visual material which users observe on their screens. The system starts to make accurate predictions about future events when it reaches a threshold level of collected information. People display their actual work patterns through their computer usage behaviour. The frequency of email checking indicates a person who engages in task switching. This tracking method identifies the times when people maintain their focus and when they lose it. People become aware of their existing habits which they had previously overlooked. Offices need to track employee activities throughout the day to establish better work patterns. The identification of patterns requires a timeframe which extends beyond one day. The work which appears to occupy time becomes actual productive use of time. Work progress displays differently in various team environments. Not everyone functions effectively during extended work periods. Some people perform better by working quickly between their scheduled meetings. The screen contains more information than our current understanding. People actually waste more time when they are required to use time. User stations track various activities which become visible through their click and window monitoring system. The system eliminates all the preconceptions which managers typically hold. The actual usage patterns that users exhibit will create improved operational workflows for future use. The prediction accuracy will improve through the integration of additional data which includes task application updates and calendar information and team chat records. The next step requires the integration of all existing system components to allow models to analyse aggregate data from various activity log files.

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