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Context Mining with Machine Learning Approach: Understanding, Sensing, Categorizing, and Analyzing Context Parameters

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Abstract— Context is a vital concept in various fields, such as linguistics, psychology, and computer science. It refers to the background, environment, or situation in which an event, action, or idea occurs or exists. Categorization of context involves grouping contexts into different types or classes based on shared characteristics. Physical context, social context, cultural context, temporal context, and cognitive context are a few categories under which context can be divided. Each type of context plays a significant role in shaping our understanding and interpretation of events or actions. Understanding and categorizing context is essential for many applications, such as natural language processing, human-computer interaction, and communication studies, as it provides valuable information for interpretation, prediction, and decision-making.

In this paper, we will provide an overview of the concept of context and its categorization, highlighting the importance of context in various fields and applications. We will discuss each type of context and provide examples of how they are used in different fields. Finally, we will conclude by emphasizing the significance of understanding and categorizing context for interpretation, prediction, and decision-making.

Keywords-Context, Context awareness, Taxonomy of Context, Internet of Behaviour, Ubiquitous of Computing, User preference

I. INTRODUCTION

Context is a fundamental concept that plays a significant role in shaping our understanding and interpretation of events, actions, or ideas. Context is a fundamental concept that refers to the background, environment, or situation in which something occurs or exists. It is a crucial aspect of human understanding, and it plays a vital role in shaping our perception of events or actions. In different fields, such as linguistics, psychology, and computer science, context is essential for interpreting and analyzing various phenomena. Understanding context is crucial for natural language processing, machine learning, decision-making, and communication studies.

Context can be categorized in different ways, and each categorization defines a set of parameters that characterize the context. These parameters provide a framework for analyzing and interpreting context. Some of the common parameters used for categorizing context include:

1) *Physical Context*: Physical context refers to the physical environment in which an event or action occurs. The parameters that define physical context include location, weather conditions, and objects present in the surroundings. For example, the physical context of a conversation could be a coffee shop, a park, or an office[1].

2) *Social Context:* Social context refers to the social setting or relationships between people involved in an event or action. The parameters that define social context include the relationship between the people involved, their roles, and their social status. For example, the social context of a conversation could be a formal meeting, a casual chat, or a job interview[1][2].

3) *Cultural Context:* Cultural context refers to the cultural norms, values, and beliefs that influence an event or action. The parameters that define cultural context include language, customs, traditions, and religion. For example, the cultural context of a conversation could be a Western or Eastern culture, a religious or secular context.

4) *Temporal Context*: Temporal context refers to the time frame in which an event or action occurs. The parameters that define temporal context include the time of day, day of the week, and season of the year. For example, the temporal context of a conversation could be a morning, afternoon, or evening conversation, a weekday or weekend conversation[1].

5) *Cognitive Context*: Cognitive context refers to the mental or psychological state of individuals involved in an event or action. The parameters that define cognitive context include emotions, attitudes, beliefs, and knowledge. For example, the cognitive context of a conversation could be a happy, sad, or angry conversation, a conversation between experts or novices[3].

In Internet of Behaviour, understanding the user's context can help design better interfaces that adapt to the user's needs and preferences. In communication studies, understanding the cultural and social context can help us interpret the meaning of messages and understand how they are perceived by different audiences.

II. RELATED WORK

Context mining with machine learning approach is a research area that aims to extract and analyze context information from various sources using machine learning techniques

1. "Context-aware sentiment analysis in social media using multimodal fusion and transfer learning" by Zhiyuan Wen et al. (2021). This paper proposes a novel approach for sentiment analysis in social media by integrating multiple modalities and transfer learning techniques to improve the accuracy of the sentiment classification. They also propose a context-aware sentiment analysis framework that considers the context of the post.
2. "Deep learning-based context-aware recommender system for tourism" by Hyeon-Jae Lee et al. (2020). This paper proposes a deep learning-based approach to recommend tourist attractions based on the user's context, such as location, weather, and time. The proposed method uses a convolutional neural network (CNN) to extract features from the contextual information and a multi-layer perceptron (MLP) to predict the user's preferences.
3. "Context-aware anomaly detection using deep learning for Internet of Things" by Wei Song et al. (2019). This paper proposes a context-aware anomaly detection system for the Internet of Things (IoT) using deep learning techniques. The system considers the context of the sensor data, such as the location, time, and weather, to detect anomalies in real-time.
4. "Context-aware spam detection using machine learning" by Fawaz Alarfaj et al. (2019). This paper proposes a context-aware spam detection system that considers the context of the email message, such as the sender's reputation, the subject, and the time, to improve the accuracy of the spam classification. The proposed system uses machine learning techniques, such as Naive Bayes and Support Vector Machines (SVM), to classify the email messages.
5. "Context-based movie recommendation using deep learning" by Jianqiang Huang et al. (2018). This paper proposes a context-based movie recommendation system that considers the user's context, such as location, time, and weather, to provide personalized movie recommendations. The proposed system uses a deep learning-based approach to extract features from the contextual information and a collaborative filtering algorithm to recommend movies.
6. "Contextual recommendation with factorization machines" by Steffen Rendle et al. (2010). This paper proposes a context-aware recommendation system using factorization machines, which is a machine learning algorithm that can model the interactions between users, items, and contexts. The proposed system considers the context of the recommendation, such as time and location, to improve the accuracy of the recommendation.

These are some of the recent and relevant research papers on context mining with machine learning approach. There are many other research papers in this area that provide valuable insights and contributions to this field.

III. PROPOSED DEFINITIONS OF CONTEXT

"Context is the any type of statistics or data like information of user, location, time, space or things etc. that can be used to describe user day-to-day situation or activity or entity. An entity it may be person, place, location, object, activity, time and situation".

There are three very important features of context [3]:
1) where you are,
2) who you are with, and
3) what resources are nearby.

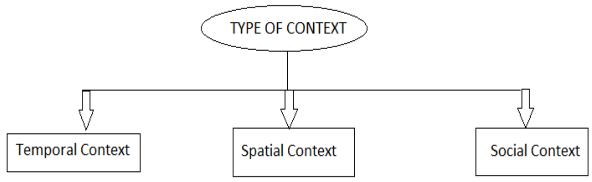

Figure 1. Context

In Fig.1 Type of Context, The term context can be used in different type of areas like Ubiquitous Computing, Human Computer Interaction, Ambient Intelligence, IoT and wearable computing etc. Context term divided into two parts like Primary Context Information and Secondary Context Information.

In the primary context, the information entities like users name, time, location, devices, an application or activity. Moreover, the secondary can be measured by using the primary context. Example: Sensor is deployed in automated or smart city,

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Sensor will capture or monitored vehicle position with other information like vehicle identification, time, activity and so on[1]

The Context has broadly divided into three types[1]:

1) Temporal Context[2]
2) Spatial Context[1]
3) Social Context[1]

1) Temporal Context

Temporal Context is refers to time. Time is the most significant entity that impact on user Behaviours for taking decision. In the context of the Internet of Things (IoT), temporal context refers to the time-related aspects of IoT devices and systems. This can include things like the frequency at which a device collects or transmits data, the timing of software updates or maintenance, or the duration for which a device is expected to operate[4].

Understanding and managing temporal context can be important for optimizing the performance and reliability of IoT systems. For example, if a device is collecting data at a high frequency, it may use more power and bandwidth, which could impact its battery life or data usage[1]. Similarly, scheduling maintenance or updates at convenient times can help ensure that the device is available and functioning correctly when it is needed[2].

Temporal context can also be important for analysing and understanding the data collected by IoT devices. For example, if you are trying to understand patterns in sensor data, it can be helpful to know the frequency at which the data was collected, as well as the specific time periods when the data was collected[3]. This can help you identify trends and correlations that might not be apparent if you only look at the data in aggregate. Temporal Context is also divided into two broad categories

Static Segmentation

Dynamic Segmentation

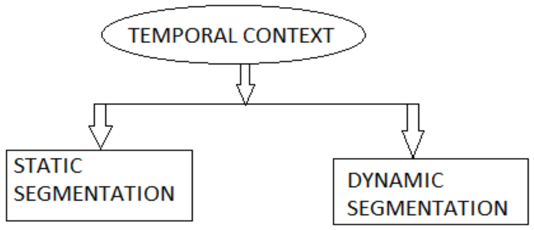

Figure 2. Temporal Context

In Fig.2 Temporal Context, it is divided into two parts:

1) Static Segmentation

2) Dynamic Segmentation

1. Static Segmentation

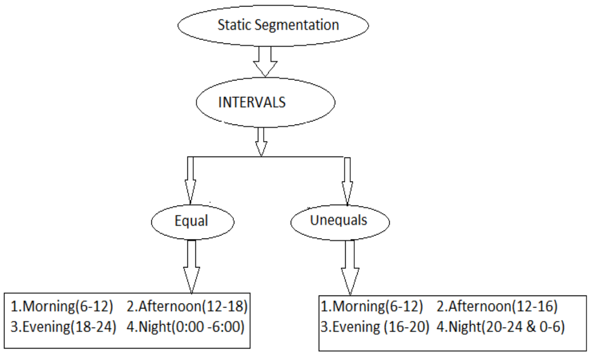

Figure 3. Static Segmentation

In Fig.3 A static Segmentation, it is understandable and it is arbitrary categories .For example Morning or Period (1h).Static Segmentation mainly focuses on intervals and an interval has two types. One is Equal and another is unequal.

- Equal Interval

In Equal static segmentation has four different time segments like morning(6 to 12),afternoon (12 to 18),evening(18 to 24) and night (0:00 to 6:00).these are example of equal static segment because all intervals have same interval length.

- Unequal Interval

In Unequal static segmentation, time interval also divided into four different part like morning(6 to 12),afternoon (12 to 16),evening(16 to 20) and night (20:00 to 24:00 and 0:00 to 6:00).

2. *Dyanamic Segmentation*

As discuss above, we have segmentation technique that creates segments .It will be more meaningful for user's Behaviours model. In this segmentation intervals are not fixed and not pre-defined. It may changes according to pattern, preferences and user Behaviours characteristics [5]. The single parameter is considered base period or interval length. This is used for to create segment and it has changes according to period. If number of time decrease then base period is increase and vice versa.Scenario: In early Morning, at 8am, the entity or user might to start their travel to their office and when the time hits at 9 am, they reached to their office and then back to work. At 12pm, a user might be go for lunch, we can say its own preference, it can be a canteen, Counter of fast food, canteen, hotel, mess, restaurant and food counter. Here context of time of day does not explain all user Behaviours. For example, Saturday Morning at 8 A.M, they don't want to go to workplace due to holiday. In the some other situation, at afternoon in rainy season, the user will favour to have their lunch at the office place only instead of going to a restaurant or any food court.

2) Spatial Context

Spatial Context refers to space related information. The Context related to spatial Context is position at a particular

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distance from one place to another place or we can say dimensions of height, depth, and width. The Space divided into again three parts real, measured and virtual space. In measure space, location of object is sense by sensor. In real space, objects in physical space and virtual space like metaverse[4].

Spatial context refers to the physical location and environment of IoT devices and systems. This can include things like the geographic location of a device, the type of environment in which it is deployed (e.g. indoor or outdoor), and the proximity of other devices or infrastructure.

Understanding and managing spatial context can be important for optimizing the performance and reliability of IoT systems. For example, the range and coverage of a wireless device may be affected by the type of environment it is in, such as whether there are walls or other physical obstructions. Similarly, the accuracy of location-based data from a device may be influenced by its proximity to other sources of information, such as GPS satellites or cell towers.

Spatial context can also be important for analysing and understanding the data collected by IoT devices. For example, if you are trying to understand patterns in sensor data, it can be helpful to know the physical location of the device when the data was collected, as well as any relevant environmental factors. This can help you identify trends and correlations that might not be apparent if you only look at the data in aggregate.

Parameter of Spatial Context[2]

There are several parameters that can be used to describe spatial context in the context of the Internet of Things (IoT). Some examples of these parameters include:

1) *Location:* This can refer to the geographic location of a device, as well as its position and orientation within a specific environment.

2) *Physical environment*: This can include things like the type of environment in which a device is deployed (e.g. indoor or outdoor), as well as any relevant physical features or characteristics of the environment (e.g. temperature, humidity, light level).

3) *Proximity to other devices or infrastructure*: This can include things like the distance between devices, as well as any physical or wireless connections between them.

4) *Physical layout*: This can refer to the arrangement and arrangement of devices within a specific environment, as well as any relevant physical infrastructure (e.g. wiring, cables, and routers).

These parameters can be important for understanding how a device is likely to function and perform in a g4en spatial context, as well as for analysing and understanding the data collected by the device.

IV. PROPOSED CATEGORIZATION OF "CONTEXT"

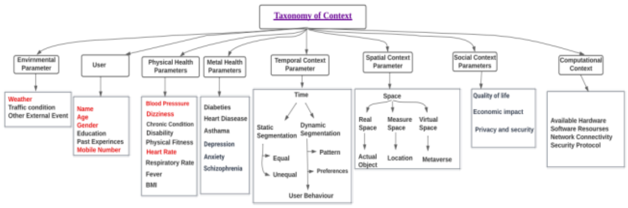

Figure 4. Taxonomy of Context

In Fig.4 Taxonomy of Context, scientifically classify the context aware parameter as follows in 8 categorized.

1) ***User[6]:*** User context refers to the current situation and environment in which a user is located, and includes factors such as the user's location, time of day, physical activity, social interactions, device usage, and other relevant data. User context can be sensed and analyzed through various sensors and data sources, including GPS, Wi-Fi, Bluetooth, accelerometers, microphones, cameras, and other sensors in smart devices. Understanding user context is important for personalizing user experiences, providing relevant information and services, and improving the usability and effectiveness of technology[6].

2) ***Temporal Context***: Temporal context refers to the time-related aspects of a user's situation and environment. It includes factors such as the current time of day, day of the week, month or year, as well as the duration of a specific activity or event[1][2]. Temporal context can also involve tracking changes over time, such as changes in weather patterns, user behaviour, or device usage[1]. Temporal context is important for understanding user behaviour and preferences, and for providing personalized and relevant information or services[3][5]. For example, an app that provides workout routines may suggest different exercises based on the time of day, such as suggesting gentle stretches in the morning and high-intensity workouts in the evening. Temporal context can also be used for scheduling reminders and notifications at appropriate times, such as reminding users to take medication or attend a meeting. By considering the temporal context, technology can better adapt to the user's needs and preferences over time.

3) **Spatial Context**: Spatial context refers to the location-related aspects of a user's situation and environment. It includes factors such as the user's current geographic location, as well as other spatial attributes such as the user's proximity to specific landmarks, buildings, or points of interest. For a variety of applications, including navigation, location-based services, and augmented reality, spatial context is crucial. [2][4]. By using spatial context, technology can provide users with personalized and relevant information based on their location, such as recommending nearby restaurants or offering promotions for nearby stores[3]. Spatial context can also be used to provide

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more accurate and personalized directions, such as suggesting alternative routes based on real-time traffic information or road closures. Spatial context can be sensed using various sensors such as GPS, Wi-Fi, and Bluetooth beacons. These sensors can be used to track the user's location and movement in real-time, as well as to infer other spatial attributes such as the user's proximity to specific points of interest or the speed and direction of travel.

4) **Environmental Context**: Environmental context refers to the physical surroundings and conditions in which a user is located. It includes factors such as the temperature, humidity, noise level, lighting conditions, air quality, and other environmental attributes[7]. Environmental context is important for understanding the user's current situation and for providing personalized and relevant information or service[8]s. For example, a smart thermostat can adjust the temperature based on the current environmental context to create a comfortable indoor environment for the user. An app that tracks outdoor activities, such as hiking or running, can provide information on the current weather conditions and air quality, and suggest alternative activities or routes if the conditions are not ideal. Environmental context can be sensed using various sensors, such as temperature sensors, humidity sensors, microphones, and cameras. These sensors can be used to collect data on the user's surroundings and to infer environmental attributes based on this data. For example, a microphone can be used to measure the noise level in the environment, while a camera can be used to measure the lighting conditions.

By considering environmental context, technology can provide more personalized and relevant information and services, and improve the user's overall experience[1][4].

1. Physical Health Related Parameter[8]: Physical health-related parameters are factors related to a person's physical well-being and health. Here are some examples of physical health-related parameters:
2. Heart rate[9][10]: The number of times the heart beats per minute, which can be measured using a heart rate monitor or smart watch.
3. Blood pressure[9][11]: The pressure exerted by the blood on the walls of the arteries, which can be determined with a blood pressure cuff or other monitoring tool.
4. Oxygen saturation: The amount of oxygen in the blood, which can be measured using a pulse ox meter or other monitoring device.
5. Body temperature: The degree of heat in the body, which can be measured using a thermometer or other monitoring device.
6. Physical activity: The level of movement and exertion, which can be tracked using a fitness tracker or smartphone app.
7. Monitoring these physical health-related parameters can provide valuable information for healthcare providers, researchers, and individuals themselves. By tracking these parameters over time, individuals can better understand their physical health status and make informed decisions about their lifestyle and healthcare. Healthcare providers can use this information to diagnose and treat health conditions, and researchers can use it to develop new treatments and interventions.

5) **Metal Health Related Parameter**: Mental health-related parameters are factors related to a person's emotional and psychological well-being[12]. Here are some examples of mental health-related parameters:

1. *Mood:* The emotional state of an individual, such as happiness, sadness, anger, or anxiety. Mood can be tracked using various smartphone apps and wearable that use self-reporting or machine learning algorithms.
2. *Sleep patterns*: The amount and quality of sleep an individual gets, which can be tracked using sleep tracking apps and devices that monitor movement and heart rate during sleep.
3. *Stress levels*: Physiological indicators such as heart rate variability, electro dermal activity, and cortisol levels can be used to track a person's subjective level of stress.
4. *Cognitive function*: The level of cognitive functioning, such as memory, attention, and decision-making, which can be measured using various cognitive tests and assessments.
5. *Social interaction*: The frequency and quality of social interactions, which can be tracked using smartphone apps and wearable that measure social behaviour and communication patterns.Monitoring these mental health-related parameters can help individuals and healthcare providers identify and manage mental health conditions such as anxiety, depression, and stress. It can also be used to improve overall mental well-being by identifying factors that may affect mood, sleep, and cognitive function. By using this information to make lifestyle changes and seek appropriate treatment, individuals can improve their mental health and overall quality of life[11][12].

6) **Social Context**: Social context refers to the social, cultural, economic, and historical factors that influence individuals and their interactions within a particular community or society. It encompasses the shared beliefs, values, and norms that shape people's behaviour and attitudes, as well as the social institutions and structures that organize and regulate social life[13][14]. The social context can include factors such as gender, ethnicity, religion, social class, political ideology, and geographical location. It can also include broader historical and cultural factors, such as the legacy of colonialism, globalization, and technological advancements, which have significant impacts on the way people live and interact with one

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another[13]. Understanding the social context is important in fields such as sociology, psychology, anthropology, and education, as it helps to explain how social interactions and relationships are shaped by broader social forces[16]. It can also help individuals and organizations to develop a more nuanced understanding of diverse perspectives and experiences, and to develop more effective strategies for addressing social issues and promoting social change.

7) **Computational Context:** Computational context refers to the technological and computational factors that influence the development and use of digital systems, software, and algorithms[16]. It encompasses the hardware, software, programming languages, and data structures used to design and build computer systems and applications[15]. The computational context can include factors such as the processing power and memory capacity of hardware devices, the availability of open-source software libraries and frameworks, the programming languages and tools used for software development, and the design and implementation of algorithms and data structures.

V. CONTEXT PERCEPTION

Recognizing context can be a challenging task, as it requires understanding the environment, situation, and relationships between various elements. However, several methods can be used to recognize context, including:

1. Analysis of Language and Speech: Language and speech analysis is a common method used to recognize context. It involves analysing the words, phrases, and sentences used in a conversation to understand the situation, environment, and relationships between individuals[17].
2. Environmental Sensors: Environmental sensors are used to detect changes in the physical environment, such as temperature, humidity, and lighting. These changes can provide information about the context in which an event or action occurs[7][8].
3. Machine Learning: Machine learning algorithms can be trained to recognize patterns in data and identify context based on those patterns. For example, a machine learning algorithm could be trained to recognize patterns in speech and identify the social context of a conversation[18].
4. Context-Aware Systems: Context-aware systems are designed to recognize and respond to changes in context. These systems use sensors and other data sources to detect changes in the environment and adjust their behaviour accordingly[18][19].
5. Code Analysis Tools: Code analysis tools can be used to recognize context in software code, such as identifying the purpose and functionality of code segments. Examples of code analysis tools include SonarQube, Checkstyle, and PMD[17][20].
6. Human Perception: Human perception is a powerful tool for recognizing context, as humans can quickly understand the situation, environment, and relationships between various elements. Human perception can be used to train machine learning algorithms and improve the accuracy of context recognition systems[18].

In summary, recognizing context is a complex task that requires understanding the environment, situation, and relationships between various elements. Various methods, such as language and speech analysis, environmental sensors, machine learning, context-aware systems, and human perception, can be used to recognize context and improve our understanding of the events and actions that occur in our daily lives. There are several tools and techniques available for context recognition, depending on the type of context that needs to be recognized. These tools and techniques can be used to improve our understanding of the events and actions that occur in our daily lives.

VI. PROPOSED FLOWCHART FOR CONTEXT SENSING

Context sensing involves using various sensors and data sources to collect information about the user's surroundings and current situation[21][22]. Here is a general methodology for context sensing:

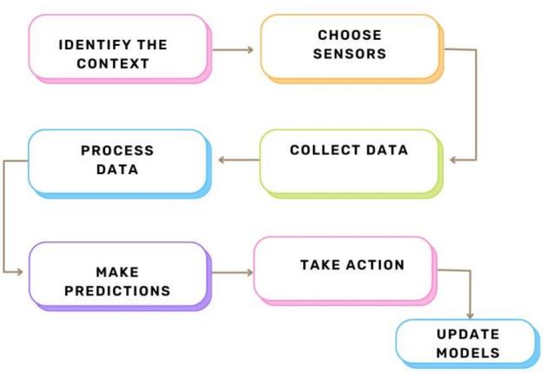

Figure 5. Context Sensing

In Fig.5, Context sensing refers to the ability of a system or device to detect and interpret information about the environment and circumstances in which it operates. This information can include data on location, time, weather, user behavior, and more, and is typically used to adjust the system's behavior or outputs to better match the current context.

1. Identify the context: Determine the type of context you want to sense (e.g., location, activity, and environment) and the specific information you want to collect (e.g., GPS coordinates, temperature, noise level).

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2. Choose sensors: Select the appropriate sensors to collect the data you need. For example, to sense location, you could use GPS, Wi-Fi triangulation, or Bluetooth beacons.
3. Collect data: Collect the data from the sensors and store it in a database or other storage medium.
4. Process data: Analyze the data to extract meaningful information about the user's context. This could involve filtering out noise, combining data from multiple sensors, and applying machine learning algorithms to recognize patterns.
5. Make predictions: Use the processed data to make predictions about the user's behaviour, preferences, or needs. For example, if the user is in a noisy environment, you might predict that they would prefer to receive text messages instead of phone calls.
6. Take action: Use the predictions to personalize the user's experience or provide relevant information or services. For example, if the user is at a restaurant, you could recommend nearby restaurants or offer a discount on their meal.
7. Update models: Continuously collect and analyze data to improve the accuracy of your predictions and update your models as necessary.

It is important to consider the privacy and security implications of collecting and using personal data for context sensing. Users should be informed about what data is being collected, how it is being used, and have the ability to opt-out or delete their data if desired.

VII. Context-Sensing Mechanisms through Sensor as Perspective of User Centered Approached

In general, context-sensing mechanisms through sensor research is a multi-disciplinary field .From a user-centered perspective, context-sensing mechanisms through sensors can be used to make technology more intuitive and responsive to the needs of the user[23]. Personalization services on context-aware computing devices refer to the ability of such devices to adapt to individual users' preferences and behavior based on the context in which they are being used. These devices use sensors, data analysis, and machine learning algorithms to learn from the user's behavior and the environment they are in, and then adjust their settings, features, and content accordingly [23]. For example, a context-aware computing device such as a smart speaker or a smartphone can use location data, weather information, time of day, and the user's past behavior to provide personalized recommendations for activities, entertainment, or food options. Similarly, a wearable device such as a fitness tracker can monitor the user's health and exercise patterns and provide personalized feedback and coaching.Personalization services on context-aware computing devices can enhance the user experience, increase engagement, and improve the device's usefulness. However, they also raise concerns about data privacy and security, as the devices collect and process sensitive information about the user. To secure users' data and privacy, it is crucial to make sure that the necessary safeguards and laws are in place.. This can be achieved by:

1. *Understanding the user's goals and needs:* By understanding what the user wants to accomplish and what information they need, context-sensing mechanisms can be designed to provide relevant information and support the user's task[19][20].
2. *Making the technology transparent*: by making the context-sensing mechanisms and the data they collect transparent to the user, they can better understand how the technology works and how it is being used to support them.
3. *Providing feedback*: By providing feedback to the user, they can better understand how their actions are impacting the technology and how the technology is responding to them.
4. *Designing for ease of use:* By simplifying the user interface and making the interactions as simple as possible, it increases the chances of user adoption.
5. *Prioritizing user privacy:* by being transparent about the data collection and usage, providing controls for the user to manage their data, and protecting the data from unauthorized access, it can help build trust and gain the user's buy-in.
6. *User testing:* By involving the users in the design and testing of context-sensing mechanisms, developers can gather valuable insights into how the technology is actually being used and identify areas for improvement.

VIII. As Research Perspective, Context-Sensing Mechanisms Through Sensors

From a research perspective, context-sensing mechanisms through sensors involve the study of various methods and techniques for inferring context from sensor data[24]. This can include:

1. Developing algorithms for processing and interpreting sensor data: Researchers may develop algorithms for extracting relevant information from sensor data, such as using machine learning techniques to recognize patterns or classify data.
2. Investigating the use of multiple sensors for context sensing: Researchers may study how multiple sensors can be used together to infer context more accurately, such as using a combination of GPS, accelerometer, and microphone data to determine a person's location and activity.

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3. Examining the challenges and limitations of sensor-based context sensing: Researchers may investigate issues such as sensor noise, data privacy, and the effects of changing environments on sensor data.
4. Developing methods to handle uncertain or missing sensor data: Researchers may study how to estimate context when some sensor data is missing or uncertain
5. Investigating how to apply the context sensing mechanism in different domains such as health, transportation and smart cities.
6. Evaluating the performance of context-sensing mechanisms through controlled experiments and field studies.

IX. CONTEXT SENSING MECHANIZMS IN CONTEXT AWARE SYSTEM

Context sensing mechanisms are a key component of context-aware systems, which are designed to provide personalized and relevant information or services to users based on their current context. Here are some examples of context sensing mechanisms that can be used in context-aware systems:

- Location sensing: This mechanism uses GPS, Wi-Fi, or other sensors to determine a user's location and provide location-based services or information.
- Activity sensing: Activity sensing uses accelerometers or other sensors to detect a user's physical activity, such as walking, running, or sitting, and adjust the system's behavior accordingly.
- Environment sensing: This mechanism uses sensors such as temperature, humidity, and light sensors to detect the user's environment and adjust the system's behavior accordingly.
- Social sensing: Social sensing uses data from social media or other sources to detect social context, such as the user's current social network, interests, or social events, and adjust the system's behavior accordingly.
- User behavior sensing: User behavior sensing uses machine learning algorithms or other techniques to learn the user's behavior over time and adjust the system's behavior accordingly. For example, the system may learn when the user typically wakes up and adjust its notifications accordingly.

Context sensing mechanisms are typically integrated into a larger context-aware system, which uses this information to provide personalized and relevant information or services to users. The system can use this information to adjust its behavior in real-time, providing a seamless and personalized user experience.

X. EVALUATION OF SELECTIVE MACHINE LEARNING ALGORITHMS USING PARAMETERS

Parameter evaluation is an important step in the process of developing machine learning algorithms. In order to get the best performance from a machine learning algorithm, it is necessary to tune its parameter[25]s. Here are some common machine learning algorithms and the parameters that are typically tuned for each of them:

1. Linear Regression[26]:

Regularization parameter (alpha)
Intercept (fit_intercept)

2. Logistic Regression[26]:

- Regularization parameter (C)
- Penalty (l1 or l2)
- Intercept (fit_intercept)

3. Decision Tree[28]:

- Maximum depth of the tree (max_depth)
- Splitting an internal node requires a minimum amount of samples (min_samples_split)
- The bare minimum of samples that must be present at a leaf node (min_samples_leaf)
- Maximum amount of features to take into account while splitting (max_features)

4. Random Forest:

- Number of trees in the forest (n_estimators)
- Maximum depth of the tree (max_depth)
- Samples needed to divide an internal node must not be fewer than (min_samples_split)
- The bare minimum of samples that must be present at a leaf node (min_samples_leaf)
- Maximum amount of features to take into account before splitting (max_features)

5. Support Vector Machines:

- Regularization parameter (C)
- Kernel type (linear, polynomial and radial basis function)
- Kernel coefficient (gamma)

6. K-Nearest Neighbors:

- Number of neighbors (n_neighbors)
- Distance metric (euclidean, manhattan, etc.)

7. Gradient Boosting:

- (n estimators) Number of trees in the ensemble
- Learning rate (learning_rate)
- Maximum depth of the tree (max_depth)
- A portion of the training cases that are subsamples (subsample)

These are just some of the parameters that can be tuned for each algorithm. The choice of which parameters to tune and the

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range of values to explore will depend on the specific problem at hand. In general, it is recommended to use techniques like grid search or random search to explore the space of possible parameter values and find the best combination for a given problem.

Parameter Analysis

TABLE I. PARAMETER ANALYSIS USING ML ALGORITHMS

Parameter	Data Source	Algorithm	Output
Temperature[29]	Smart thermostat	Regression	Predicted optimal temperature based on user behaviour and preferences
Humidity[30]	Smart sensors	Clustering	Recommended dehumidification settings based on humidity patterns
Lighting[29]	Smart bulbs	Decision tree	Recommended lighting settings based on time of day and occupancy patterns
Occupancy[31]	Smart sensors	Regression	Predicted occupancy patterns based on past data and current activity
Energy usage[32][30]	Smart meter	Clustering	Recommended energy-saving actions based on energy usage patterns
Accelerometer Data	Measures user's acceleration in x, y, and z directions	Decision Tree	User is currently walking
Gyroscope Data	Measures user's orientation in x, y, and z directions	SVM	User is holding their device in their right hand
GPS Data	Measures user's location and movement	K-Means Clustering	User is currently traveling on a highway
Heart Rate Data	Measures user's heart rate	Random Forest	User is experiencing high levels of stress

In Table I, The various parameters related to the user's activity levels are collected from sensors such as an accelerometer, gyroscope, GPS, and heart rate monitor. Machine learning algorithms are applied to analyze the collected data and provide insights into the user's current activity.

The table I shows, the parameters being analysed, a brief description of each parameter, the machine learning algorithm used, and the resulting activity of the user. The decision tree algorithm analyses the accelerometer data and determines that the user is walking. The SVM algorithm analyses the gyroscope data and determines that the user is holding their device in their right hand. The K-Means clustering algorithm analyses the GPS data and determines that the user is traveling on a highway. Finally, the random forest algorithm analyses the heart rate data and determines that the user is experiencing high levels of stress.This Parameter Analysis table demonstrates how machine learning algorithms can be used to analyze various parameters related to the user's activity levels and provide personalized insights into their behaviour.

TABLE II. CLASSIFIER MODEL FOR PERSONALIZED INSIGHTS INTO THEIR BEHAVIOUR.

=========================Classifier model (full training set) ===============================

	Random Forest	*Decision Tree*	*M5Rule*
Correlation coefficient	0.9999	0.6052	0.9991
Mean absolute error	397983533215.3367	2.6258	740170004843.0845
Root mean squared error	823628186852.9924	3.8125	2026688621196.3135
Relative absolute error	1.0747 %	73.9722 %	1.9987 %
Root relative squared error	1.6775 %	79.6047 %	4.1278 %
Total Number of Instances	1073623	1073623	1073623

==

In the table II, various parameters related to the user's context and environment are collected from smart home devices such as a thermostat, sensors, and bulbs. Machine learning algorithms such as regression, clustering, and decision tree are used to analyze this data and provide personalized recommendations or adjustments for optimizing energy efficiency and comfort levels in the user's home.

The output of each algorithm is tailored to the specific parameter being analysed and can include predicted optimal temperature, recommended dehumidification settings, recommended lighting settings, predicted occupancy patterns, and recommended energy-saving actions.

Overall, this Parameter Analysis table demonstrates how ML algorithms can be used to analyze various parameters in a context-aware computing environment and provide personalized recommendations based on the user's essentials and preferences.

XI. COMPARISON OF HUMAN BEHAVIOUR IN CONTEXT AWARENESS SYSTEMS

TABLE III. COMPARISON OF HUMAN BEHAVIOUR IN CONTEXT AWARENESS SYSTEMS

System	Description	Sensors	Algorithms	Applications
Microsoft Kinect	Uses depth and RGB cameras to track body movements and gestures	Depth and RGB cameras	Random Forest, SVM, Decision Trees	Gaming, fitness, healthcare
Fitbit	Wearable device that tracks activity levels, heart rate, and sleep patterns	Accelerometer, heart rate monitor	Naive Bayes, K-Nearest Neighbours, Random Forest	Fitness, health monitoring
Nest	Smart thermostat that learns user preferences and adjusts temperature accordingly[33]	Temperature and humidity sensors	Neural Networks, Clustering	Home automation, energy efficiency
Google Maps	Navigation app that provides real-time traffic updates and alternate routes	GPS, accelerometer	K-Means Clustering, Hidden Markov Models	Navigation, travel planning

In Table II comparison table, we've listed several context awareness systems that use ubiquitous computing to track human activity. For each system, we've provided a brief description of its functionality, the sensors used to collect data, the machine learning algorithms applied to the data, and the applications for which the system is typically used.

The Microsoft Kinect system uses depth and RGB cameras to track body movements and gestures, which can be used in gaming, fitness, and healthcare applications. The Fitbit wearable device tracks activity levels, heart rate, and sleep patterns using an accelerometer and heart rate monitor, and is commonly used for fitness and health monitoring.

The Nest smart thermostat learns user preferences and adjusts temperature accordingly using temperature and humidity sensors, and is typically used for home automation and energy efficiency. Finally, Google Maps uses GPS and accelerometer data to provide real-time traffic updates and alternate routes, and applies machine learning processes such as K-Means Clustering and Hidden Markov Models to optimize navigation and travel planning.

This comparison table demonstrates the diversity of context awareness systems using ubiquitous computing, and how they can be used to track human activity for a variety of applications.

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XII. DATA SETS AND THEIR PROPERTIES

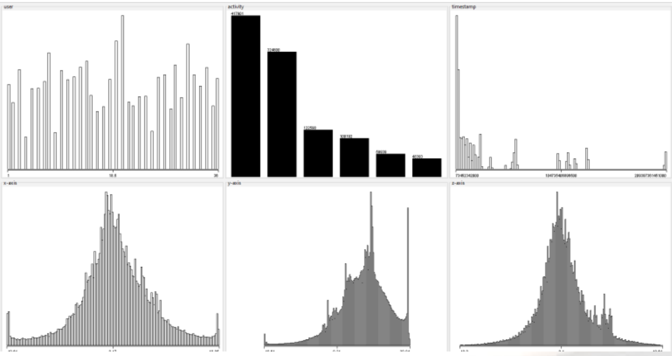
Here are some popular human activity recognition datasets :

1. UCI HAR Dataset: Data on human activity recognition was gathered from a smartphone's accelerometer and gyroscope sensors. 30 participants participated in six activities: walking, walking upstairs, walking downstairs, sitting, standing, and laying[34]. The data were gathered from these activities.
2. WISDM Dataset: This dataset includes accelerometer and gyroscope data collected from smartphones worn by participants while performing various physical activities such as walking, jogging, and sitting.
3. PAMAP2 Dataset: This dataset contains data collected from wearable sensors worn by participants performing various physical activities such as walking, cycling, and rope skipping[39].
4. OPPORTUNITY Dataset: This dataset contains data collected from wearable sensors worn by participants performing various daily activities such as standing up, sitting down, and walking[40].
5. MHEALTH Dataset: This dataset includes data collected from wearable sensors worn by participants performing various physical activities such as walking, running, and cycling[41].
6. PhysioNet: This is a repository of open-access physiological data, including electroencephalogram (EEG), electrocardiogram (ECG), and electromyogram (EMG) signals. These signals can be used to study the brain activity, heart rate, and muscle activity that are associated with dizziness.
7. Motion Sickness Dataset: This dataset contains physiological and behavioral data collected from participants exposed to a motion sickness stimulus in a controlled environment. The dataset includes heart rate variability, skin conductance, and subjective ratings of dizziness and nausea.
8. GeoLife GPS Trajectories Dataset: This dataset includes GPS traces of 182 users collected over a period of two years in Beijing, China. The dataset contains over 24 million GPS points and covers a wide range of human activities such as walking, cycling, driving, and taking public transportation.
9. Foursquare Dataset: Foursquare is a location-based social networking platform that allows users to check-in to various locations. The dataset includes check-in data from millions of users around the world, including the location, time, and user ID.
10. MIT Reality Mining Dataset: This dataset includes data collected from 94 users over a period of nine months using wearable devices that recorded location, Bluetooth signals, and call logs[36]. The dataset covers a wide range of human activities such as sleeping, working, and socializing.
11. Microsoft Indoor Localization Dataset: This dataset includes WiFi signals collected from smartphones as users walked through several buildings at Microsoft Research Asia.[35] The dataset contains over 20,000 WiFi fingerprints and covers a wide range of indoor locations such as offices, meeting rooms, and corridors.
12. UJIIndoorLoc Dataset: This dataset includes WiFi and Bluetooth signals collected from smartphones as users walked through a multi-floor building[37]. The dataset contains over 20,000 instances and covers a wide range of indoor locations such as offices, classrooms, and hallways.

XIII. CONTEXT SENSING- HUMAN ACTIVITY RECOGNITION USING MG5 ALGORITHMS

```
=== Run information ===
Algorithms:M5Rule
Relation: time_series_data_human_activities
Instances: 1073623
Attributes: 6
 user
 activity
 timestamp
 x-axis
 y-axis
 z-axis
Test mode: evaluate on training data
 === Classifier model (full training set) ===
 M5 pruned model rules
(using smoothed linear models) :
Number of Rules : 123
 Rule: 1
     IF
     user <= 21.5
     user <= 8.5
     user > 6.5
THEN
       timestamp =
              -96971686698632.92 * user
          + 279649923.6736 * activity=Downstairs,Jogging,Upstairs,Sitting,Standing
          + 935653803.7412 * activity=Jogging,Upstairs,Sitting,Standing
          + 1738342936.6823 * activity=Upstairs,Sitting,Standing
          + 4002142582.2428 * activity=Sitting,Standing
          - 30849163.7623 * x-axis
          - 74162179.5017 * y-axis
          - 21494748.108 * z-axis
          + 887131459082233.1 [72154/1.468%]
 Rule: 2
IF
 user <= 21.5
 user > 18.5
 user > 19.5
 user <= 20.5
THEN
 timestamp =
          24905679743.3147 * user
          + 336444726.961 * activity=Downstairs,Jogging,Upstairs,Sitting,Standing
          + 298486225.6746 * activity=Jogging,Upstairs,Sitting,Standing
          + 117914986.4973 * activity=Upstairs,Sitting,Standing
          + 57707183039371.44 * activity=Sitting,Standing
          - 108830174.3639 * x-axis
          - 85537275.0856 * y-axis
          + 7847885.0185 * z-axis
          + 1000990725508.3138 [54294/1.776%]
 Rule: 3
IF
 user <= 21.5
 user > 16.5
 user > 18.5
THEN
 timestamp =
           -5929401285452.437 * user
          - 973056862.217 * activity=Downstairs,Jogging,Upstairs,Sitting,Standing
           + 642099171.2451 * activity=Jogging,Upstairs,Sitting,Standing
          + 79446377.8805 * activity=Upstairs,Sitting,Standing
           - 1092296003.7707 * activity=Sitting,Standing
           - 169149066.2873 * x-axis
            - 437951432.4012 * y-axis
           - 183397248.009 * z-axis
           + 243181002436586.6 [69085/1.423%]
 Rule: 4
IF
 user <= 17.5
 user <= 3.5
 user <= 2.5
THEN
 timestamp =
               3474405619216.7314 * user
              + 706774713.1071 * activity=Downstairs,Jogging,Upstairs,Sitting,Standing
              + 686728702.3136 * activity=Jogging,Upstairs,Sitting,Standing
              + 23175645.7216 * activity=Upstairs,Sitting,Standing
              + 1349325189.324 * activity=Sitting,Standing
               - 41749964.4578 * x-axis
              + 7733590.6376 * y-axis
              - 36259234.9254 * z-axis
              + 2386191848798.935 [53503/2.912%]
 Rule: 5
IF
 user > 17.5
 user <= 30.5
 user <= 24.5
 user <= 23.5
 user > 20
THEN
 timestamp =
              -1932541333.1768 * user
              + 2900782479.3501 * activity=Downstairs,Jogging,Upstairs,Sitting,Standing
               - 2437066419.1055 * activity=Jogging,Upstairs,Sitting,Standing
              + 1477644776.7812 * activity=Upstairs,Sitting,Standing
              - 10035313327.7763 * activity=Sitting,Standing
              - 24127511.398 * x-axis
              - 58493871.4563 * y-axis
              + 5621587.7563 * z-axis
              + 1283104576683.419 [47981/2.522%]
==========================================================================
```

Output



- The contextual factors include location, time, user activity, and device state. The relationships between these factors are defined as follows:
- Location depends on time, as a user's location may change over time.
- User activity depends on time and location, as the user's activity may change depending on where they are and what time it is.
- Device state depends on time and user activity, as the device may have different states depending on what the user is doing and what time it is.
- By representing the relationships between contextual factors in this way, the DAG can be used to make inferences about how changes in one factor may influence other factors in the system. For example, if the user's activity changes, the system can use the DAG to predict how this may affect their location and the state of their device. This information can then be used to adapt the system's behavior in real-time to better meet the user's needs and preferences

TABLE IV. PARAMETER ANALYSIS TABLE USING ML ALGORITHMS IN A HUMAN ACTIVITY CONTEXT AWARENESS SCENARIO:

.Parameter	Description	Algorithms	Result
Accelerometer Data	Measures user's acceleration in x, y, and z directions	Decision Tree	User is currently walking
Gyroscope Data	Measures user's orientation in x, y, and z directions	SVM	User is holding their device in their right hand
GPS Data	Measures user's location and movement	K-Means Clustering	User is currently traveling on a highway
Heart Rate Data	Measures user's heart rate	Random Forest	User is experiencing high levels of stress

The various parameters related to the user's activity levels are collected from sensors such as an accelerometer, gyroscope, GPS, and heart rate monitor. Machine learning algorithms are applied to analyze the collected data and provide insights into the user's current activity.

The table shows the parameters being analysed, a brief description of each parameter, the machine learning algorithm used, and the resulting activity of the user. The decision tree algorithm analyses the accelerometer data and determines that the user is walking. The SVM algorithm analyses the gyroscope data and determines that the user is holding their device in their right hand. The K-Means clustering algorithm analyses the GPS data and determines that the user is traveling on a highway. Finally, the random forest algorithm analyses the heart rate data and determines that the user is experiencing high levels of stress.

This Parameter Analysis table demonstrates how machine learning algorithms can be used to analyze various parameters related to the user's activity levels and provide personalized insights into their behaviour.

Conclusion

Context is an essential aspect of understanding various phenomena, and categorizing context is crucial for interpreting and analyzing context in different fields such as linguistics, psychology, and computer science. Understanding the parameters of context provides a framework for analyzing and interpreting context, making it easier to make decisions, predict outcomes, and communicate effectively.

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