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Big data applicable for human health from mining activity pattern

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Abstract: Migration of the people from villages and rural areas to cities has been a common issue in the modern day life. The people get injured, affected, and diseased on the cities when they don't take precautions and doesn't have good life style. In this case the need of the health care systems plays an important role. The vast amount of people get addicted, take treatment every day and the data relevant to each of the user or patient has to be maintained, as the remote devices has taken place in every home like thermometer, blood tester etc by patients making a smart environment.

A Frequent pattern based patient data mining, data clustering, analysis and data prediction method has been proposed in this work. Analyze and to measure the change in the energy usage of the occupants' behavior. As user habits will decide their health , the proposed work will track on the routine of the people and manage the acquired data.

Keywords: Analyze, cluster, smart environment, prediction remote device

1. Introduction

The demand for health care resources will be greatly affected by this vast invasion of people to city centers. This unmatched demographic change places huge burden on cities to rethink the traditional approaches of providing health services to residents. In responding to the new needs and challenges, cities are currently embracing massive digital transformation in an effort to support sustainable urban communities, and provide healthier environment [1], [2]. Smart meter data provide real-time information on aggregate energy consumption in homes. Disaggregating smart meter data via intrusive or non-intrusive means [10] helps understand how appliances consume electricity in individual households. Recent studies of energy-related feedback have found that electricity consumption data, aggregated or disaggregated down to appliance level, is not often meaningful to households as it is not tied to their lived experience [11,12]. Social scientists have argued that domestic energy use is the largely invisible consequence of deeply embedded social practices occurring within the home [13,14]. Activities such as cooking, washing, listening to music or playing computer games are more consistent with households' own experiences of life at home. Activities are a simple descriptive term for these common ways in which households spend their time [15]. Activities are also used in time-use statistics collected by the national statistical agencies to characterize domestic life [16]. Providing information on energy use through the lens of activities should resonate more clearly with households. Moreover, activities are a more stable constituent of domestic life whereas appliances may be commonly replaced or retrofitted [17].

The organization of this paper is as follows: section (2) related work. in section (3), statement of the problem, (4) methodology ,the proposed system (5),implemantation(6) ,system architecture(7),results(8). finally, we conclude the paper and discuss future work in section (9).

2. Related Work

1) The potential of cloud-supported cyber-physical systems (CCPSs) has drawn a great deal of interest from academia and industry. CCPSs facilitate the seamless integration of devices in the physical world (e.g., sensors, cameras, microphones, speakers, and GPS devices) with cyberspace.
2) With the innovations and increasing popularity of smart cities, video analytics (e.g., from social media, entertainment, surveillance, smart health monitoring, and crowd management) are used in a range of application domains to provide safety, security, and well-being for residents.
3) The author has proposed the study which deals with the missing link prediction connection between the entities. Hence the author has proposed the concept of addressing the missing entities by using the matrices and array based structures called as *tensors*. link prediction problem has been addressed by the data fusion occurred where the tensors shares data simultaneously with each other.
4) Image classification speech learning and language processing are few of the application of the deep learning techniques. Big data is highly noon-linear in nature hence the deep learning can't handle it as it uses the vectors in space of data storage specially in case of the heterogeneous data. Author has proposed the deep

computation model in the case of the feature learning in the big data, using the tensor to model complex type of the data.

5) Mining the unprecedented and increasing the volume of the data has been challenging task. Among the many techniques the clustering is one of the general technique which has been used. DBSCAN (density based clustering method) which is used for spatial data. Time complexity, managing varied density datasets, setting the parameter are some of the problems associated with the method.
6) In this paper the author has proposed the algorithm of possibility on the concept of clustering to overcome the possible noise in the algorithm of the FCM (Fuzzy C-Means) based data clustering
7) In an age where there is a strong dependency on electrical appliances for domestic routines, this paper proposes an algorithm for identifying domestic activities from non-intrusive smart meter aggregate data. We distinguish two types of activities: Type I activities are those that can be recognized using only smart meter data and Type II activities are recognized by combining smart meter data with basic environmental sensing (temperature and humidity).
8) Aggregating fine-granular data measurements from smart meters presents an opportunity for utility companies to learn about consumers' power consumption patterns.
9) As many people are now taking advantages of on-line services, the value of the private data they own comes into sight as a problem of fundamental concern. This paper takes the position that, individuals are entitled to secure control over their personal information, disclosing it as part of a transaction only when they are fairly compensated.

3. Statement of the Problem

The peoples has changed the habits of their lifestyle which can be known by their everyday based routines, by which we can detect and trace the anomalous type of the activities of the people life which may indicate the possible problem associated in the taking self-care, like preparing the food, taking shower or bath in time.

The correlation between the digital home appliance use in the home of the peoples known as smart home, the routine of the activities which are used by the health care based centers application and to find out the possible health related problems of the people.

4. Methodology

In the implementation phase we will explain in brief regarding the procedures used in the development of the work.

The process of the proposed work can be explain in short as follows,

- Data collection form the users house by using the smart devices
- Recognition of the Pattern based on the data collected from the devices in the initial stages
- In this the Clustering of the collected data is performed by using the PCM method of data clustering
- Finally the people Activity is predicted based on the collected data and the clustering is performed and displayed to the user
- The user result is obtained by the Bayesian network, for human pattern analysis and also to store the error logs.

5. Proposed System:

To overcome the problems associated in above methods we have proposed the work of energy data from the smart home based meters which are installed to track the important activities. The assumption made that the devices will keep the privacy of the people life. Figure 1 shows proposed work System architecture, The proposed work will perform the clustering of the people behavior data by the tensor space optimization in Hadoop, which allows to manipulate the big data generated by the activities inside the home.

6. Implementation

In this we will explain in brief regarding the procedures used in the development of the work.

1. Data collection.
2. Data based Pattern Recognition.
3. Data Clustering.
4. Human Activity prediction.

6.1Data Preparation:

In this phase the real data from the form the users house by using the smart devices It includes the raw records at time tick of 6 seconds. Initially the noise present in the data is removed .after the de-noising the dataset size is reduced . synthetic dataset has been developed for the subsequent dataset management.

A high time resolution based time series data is transformed into 1 minute pulse and later into 30 min frequency data and so on, ie, 24 * 2 = 48 reading for each appliances is stored.

6.2Pattern Recognition:

The activities will generate the pattern based on the data type. Each of the devices data is generated by the system processing and the data is transmitted o the health monitoring system all the devices are set to check the data processed at 30 minute interval. Recognition of the Pattern based on the data collected from the devices in the initial stages. The data is processed into blocks and used for the later purpose in defined patterns.

6.3Clustering:

The data which is acquired from the appliances form the devices which run parallel and simultaneous. In this the Clustering of the collected data is performed by using the PCM method of data clustering size of each cluster indicate the number of users in the domain and real strength of the data the supervised classification of the data is performed by the data which is not similar inside group but similar from the other user of different group.

6.4Activity prediction:

The pattern based on the frequency of the occurrence based on the users habitat which is time- series based data. We have used the Bayesian network a type of the directed acyclic graph, where nodes- random data variables and the edges - probabilistic of the data dependencies.

7. System Architecture

A System architecture as shown in fig 7.1 is the systematical model that defines the structure of the system, behaviour of the system and more representation of a system. A description of a system, including a mapping of functionality onto hardware and software components. And also human interaction with these components.

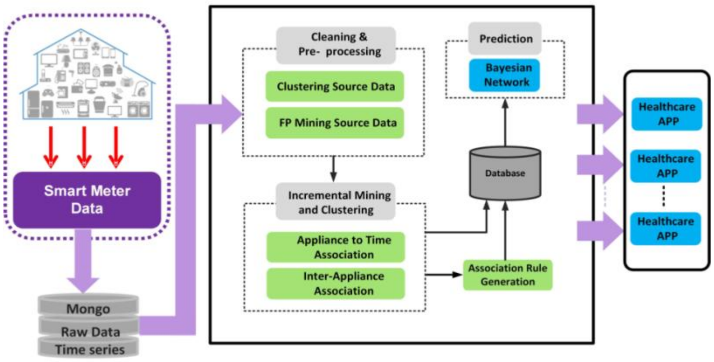

Fig 7.1 System architecture

8. Results

For the evaluation of proposed model we perform our experiments using the data set. Considering three home appliances, the dataset contains time series data for three houses with total 21 appliances for 30mins for per day using the appliances. Appliances like tv, computer, laptop, microwave, bread toast, washing machine, kitchen lights.

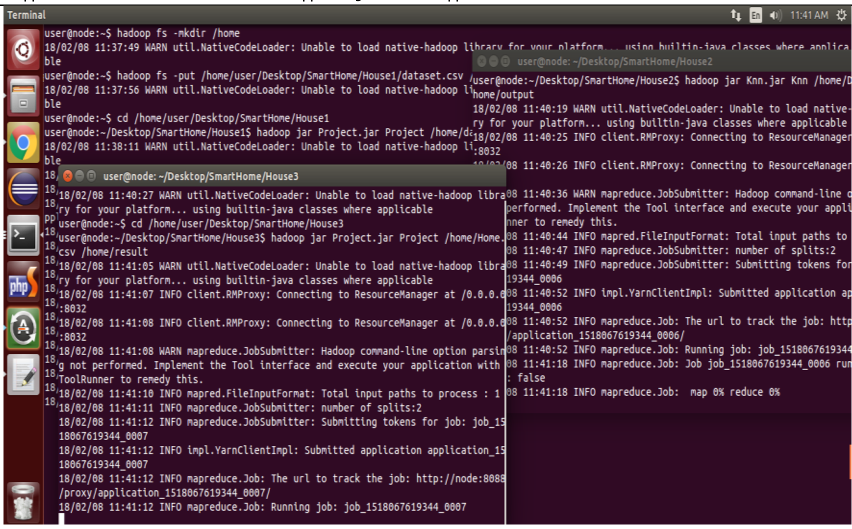

Fig8.1: To create a Directory and three type of user node creation

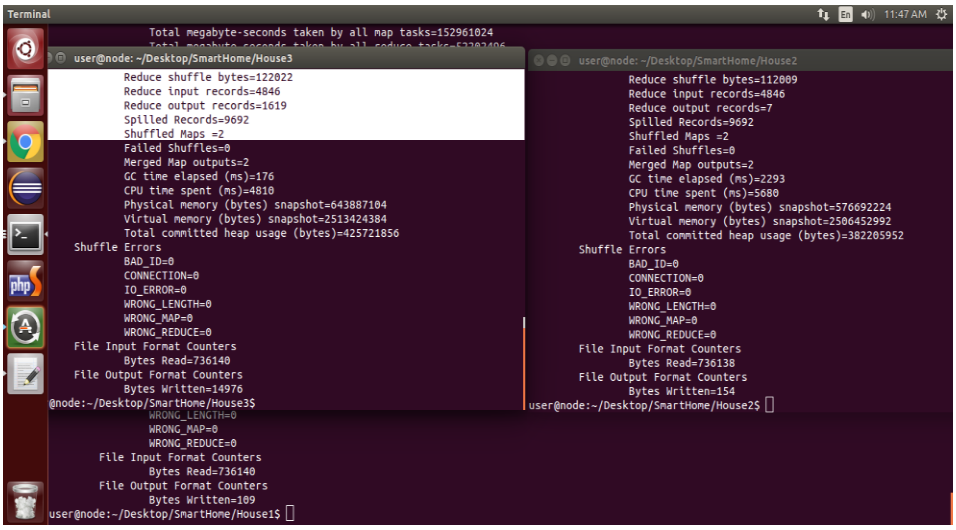

Fig 8.2: Mapping and reducing to the three nodes at a time

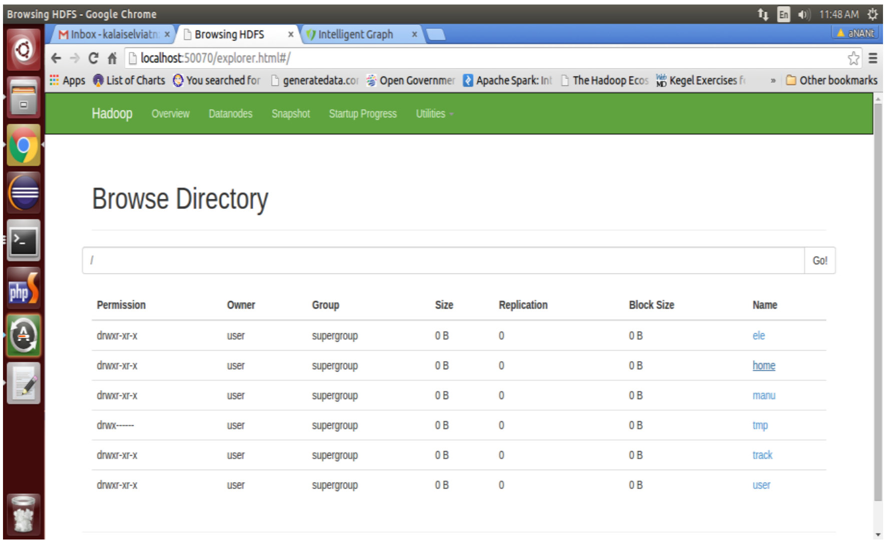

Fig 8.3: To view the Output directory from the browser

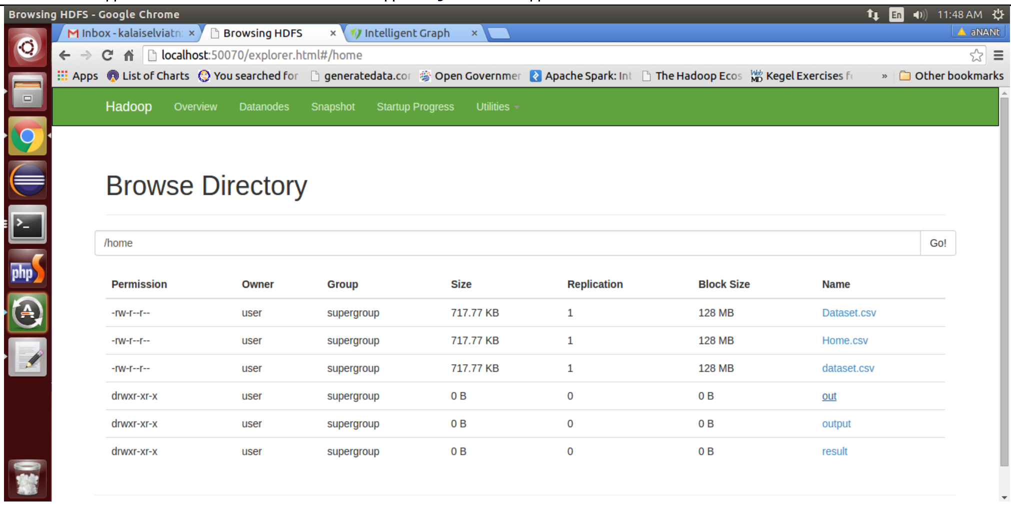

Fig 8.4: To view the 3 types of output from the cluster methods

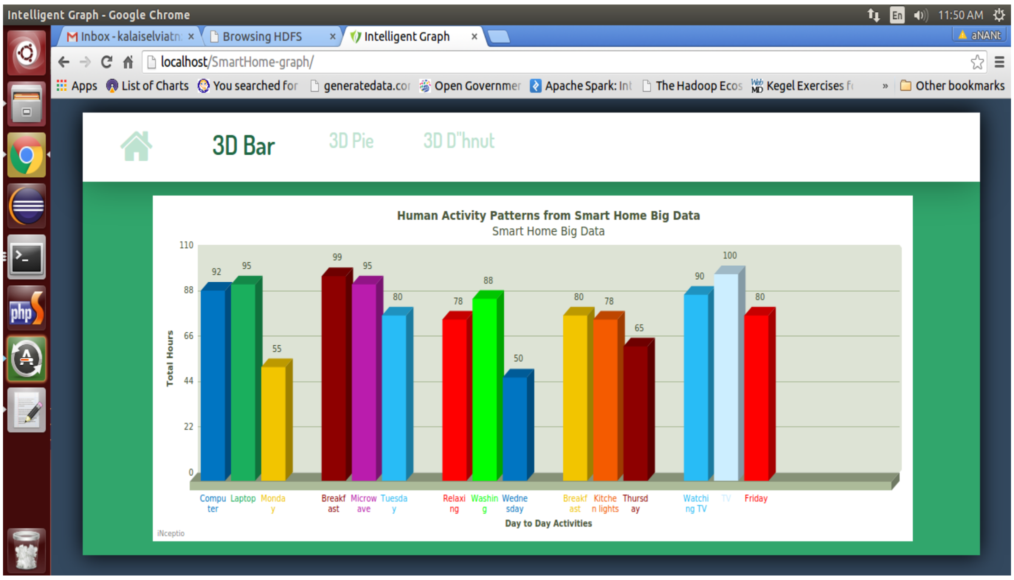

Fig 8.5: To view the output from the bar chart

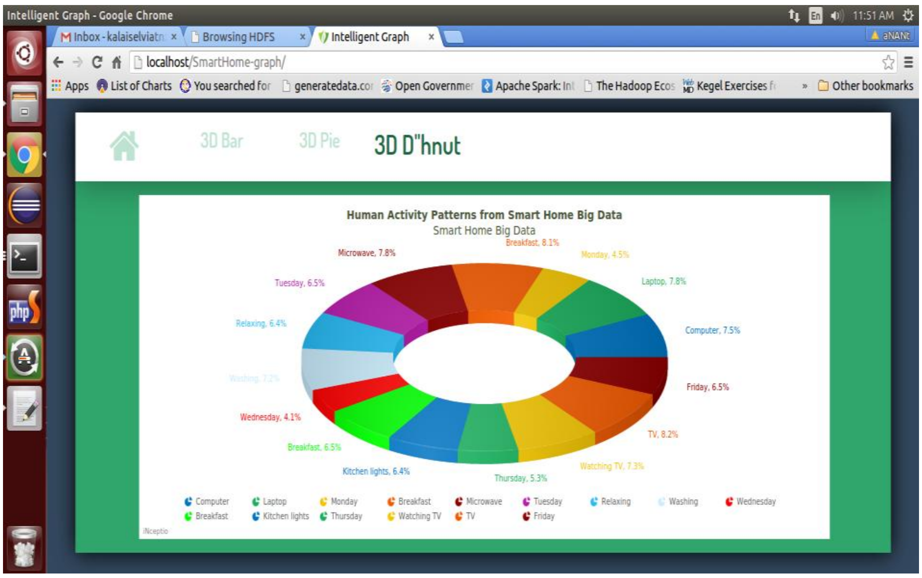

Fig 8.6: To view the output from the 3D D'hnut chart

9. Conclusion

By the proposed work of monitoring the energy data from the smart home based meters which are installed to track the important activities of human allow to manipulate the lifestyle of the people .the activities can be traced appliance to appliance by using the incremental based frequent mining and also based on the prediction model by using the Bayesian network. The use of the Hadoop has been aspiring as the distribution of the huge dataset has been performed easily. The data can be manipulated and secured by encryption at the core level by using the cloud computing.

Future Work

In this the proposed work has to be implemented to access the real time online data and also to communicate with the remote devices with alert messages ,sms or email. Which makes easy to the people responsible for the data maintainer.

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