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AN ANALYSIS OF A HUMAN MOBILITY TRAJECTORIES AND PROXIMITY ALGORITHM MANAGEMENT

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ABSTRACT
An Advancement into location-based trajectories has become focal point in research community and researchers who never saw the need before now have come to the reality of the enormous benefits associated with space technology. One aspect of Space technology that have changed goofy state of the society is the Global Positioning System (GPS) designed and launched by the United State Department of Defense in 1973. The idea behind the technology was basically reserved for the military use but as technology and computing power evolves, unprecedentedly, research area such as mobility trajectories prediction human proximity management etc. have now opened a new scope for research exploration. One of the key factors that has changed this aspect of research is the availability of the GPS function in most handheld devices or smart phones. The embedded features as seen in most smart phones today is use to collect human mobility trajectory data which researchers have now seen as ample opportunity to approximately calculate through different algorithm the most likely place to be visited. Human mobility trajectories and proximity algorithm management is indeed an interesting area in trajectory prediction. As the search by researchers on the best trajectory prediction-based location algorithm continues little attention is being given to the multi-factor synergy of the current prediction algorithms. This paper provides a crystalized classification of different algorithms used in the realization of proximity trajectories prediction and explained the conceptual sequence of the divergent approach to human mobility trajectory location.

KEYWORDS: *Trajectory, Location, Mobility, Proximity, prediction, Markov Chain*

INTRODUCTION
The trend as seen in communication, transportation, transmission, acquisition, networking, banking, marketing etc. is owned to the advancement in modern computing technology (Cisco Press 2009; Osagie *et al.,* 2018). This monumental change that has eroded the distressed period of human mobility has contributed largely to the societal development. Managing this complexity of change is one aspect that must be examined. One of the technologies that has formed part of

human life is the Personal Communication Systems (PCSs) (Guo *et al.,* 2004). The PCSs is a Mobile Computing Device (MCD) that can be accessed at any locations (Lyytinen and Yoo, 2002). As PCSs proliferation continue, owning to the advancement in technology, the quest to solve human mental state of position had in recent times gained interest in research community. It is believed that in the next future, problem such as census, population growth can well be managed by Personal Communication Systems and this is due to the fact that mobility of handheld devices (wireless devices) eliminates the cumbersomeness of manual effort

The flexibility to the Personal Communication Systems is seen as the catalyst for managing human mobility. No mobile device is designed to be stereotype. One of the aims for its design is to make it relocatable at all times, but in recent times, many researchers have found this area of PCSs interesting and are currently researching how different predictions can give exert location of human. The PCSs can manage several types of information. Aside the usual call functions, there are countless numbers of features within the handheld device that talk more about the user information. The control of these features is what is known as Proximity Management in Mobile Computing (PMMC) (Yavas *et al.,* 2005; Defersha and Chen, 2008). The management includes information such as area visited or location of the user, and others such as user's information storing and update. As discussed above, researchers are using this method to analyse movement of individual. The area most visited are examined with the view to predicting the movement of end users through the availability of the information provided by the proximity services.

Though, social services (social media) provide handful information on mobile mobility but of great interest to some researchers is the information provided by the GPS (Global Positioning System) in different brands of handheld devices. GPS is a satellite-based radio navigation tool owned by the United Sate (US) and provides human information like area positioning and timing. The tool is designed to move (orbiting) round the earth for possible information. A user of mobile devices allows the GPS to locate the whereabouts of end user. Since its introduction, it has gained wide patronage and has become one of the most reliable features in modern mobile devices. The feature as designed has ability to tell the whereabouts of user's navigation on earth and most researchers who have carried out research on mobility prediction focused on the GPS feature to determine where could be the next spot of visit by the user (Kaplan and Hegarty, 2005; Coutts and Duffield, 2010).

Trajectory mobility as it relates to computing is one aspect of information technology that has come and would constantly experience interest from research community. As the hope to get adequate information (data) on the whereabouts/trajectories of human at any given point in time through actualization of different algorithms that determines the sequential flow of human trajectories this paper aimed at providing that crystalized classification of algorithms used in the realization of proximity trajectories prediction by objectively looking at the conceptual sequence of the divergent approach to human mobility trajectory location.

LITERATURE REVIEW

Human mobility trajectories study is gaining interest in research community. Though, several aspects such as "Mobility Prediction in Wireless Network", "Deep Learning Based Traffic and Mobility Prediction using Machine Learning", "Handover Technics in Mobility" etc. have all been looked into. However, complexity in human activities has ignited continuous focus on this area of mobile activity (Hug *et al.,* 2020). It is quite difficult to predict how human navigate his/her surroundings. Notwithstanding, advancement in technology has increased the interest of researchers into mobility trajectories and this is with the view to provide answers to unquestionable trajectories of human movement. A report by Yavas *et al.,* (2005) showed thatthere is a considerable amount of research into mobility management but, they opined that most research had focused on location update that the PCS provide. In their work, they explained that little attention has been given to Mobility prediction and exerted some drawbacks such as lack of pattern matching, that prediction is based on speed probability of user etc. Aljadhai and Znati (2001) on predictive mobility support for Qos provisioning in mobile wireless networks, they integrate mobility model into the service model for efficient network and services utilization. In the model, probabilistic approach was used to determine the most likely cluster to be visited by the mobile unit. The research of Nanopoulos *et al.,* (2003) focused on predictive prefetching on web and this was achieved through identification of two key factors: The order of dependencies between pages access and the appearance frequencies of user access sequences calculation. These factors engineered the framework for describing prefetching. In a work title "A review on current work in mobility prediction for wireless network" Doss *et al.,* (2004) explained that the next generation of networks such as 4G and beyond would ensure the smooth and seamless heterogeneous support for real time multimedia service. The idea behind the postulation is based on the signal strength associated with 4G network and beyond. It is believed the idea will aid the timeless measurement accuracy of data synchronization. A survey by Zhang and Dai, (2018) on "mobility prediction: State-of-the-Art schemes and future applications" covers state-of-the-art approaches which includes Markov chain (MC), hidden Markov model, (HMM), artificial neural network (ANN), Bayesian network and data mining for the prediction of Mobility projection. A neural network prediction system that is able to capture some of the patterns demonstrated by users moving in a wireless domain and can thereafter predict the future behaviour of users was presented by (Capka and Boutaba, 2004). In a related work, Yap *et al.,* (2020) presented an enhanced handover mechanism using mobility prediction (eHMP) to assist mobile devices. The work showed that the network throughput of eHMP in homogenous performance increased by 106% with transmission rate of 85% while the network performance rate of eHMP was 55% with transmission rate decreased of 75%. The percentage rates as shown revealed that mobility prediction coupled with multipath protocol have ability to improve the Qos for mobile devices. In a work presented by Torkestani, (2012), it was shown that convergence properties of their proposed algorithm with a convergence theorem in simulated work estimated the motion of mobility prediction behaviour.

ATTRIBUTES OF DEVICE MOBILITY AS A TRADEMARK FOR HUMAN MOBILITY

The functionality of systems attributes are the embedded factors of the internal cell arrangements and every system designed work according to this internal rule. Mobile device aside the traditional function of call attributes has other internal attributes for evaluating mobility trajectories and these are attributes often called features, they are designed to help solve one predominant problem of human mobility but little or no attention had been given to this critical area of research in the time past. However, there are research into mobility trajectories but less effort has been given to it attribute. Human movement has been discovered to be of two distinct patterns within a network framework: (1) Regular movement (2) Irregular movement (Cisco Press, 2009).

a. **Regular Movement:** Several literatures have tried to examine this movement as a fixed movement within the mobility trajectory. It gives credence to the underlying design of a network substations that the device mobility resides on a given point. All mobile users have over the years created a steady pattern within the dataset of the network substation. These patterns, show a movement of a constant propagation of user most visited places. For example, a mobile users who antecedent for movement is well known to be between work place, church, school, market etc, would definitely have a regular pattern within the dataset of the network roaming base-station.
b. **Irregular movement:** This movement are occasioned by the network is inversely proportional to the regular movement. It is often called random movement. This pattern of movement is quite unique because the roaming pattern has a zigzag movement in nature thereby making it complex to ascertain the trajectory as captured by the substation of the service provider. Under mobility trajectory, these two movements are never the same because one has a definite assertion while the other has infinite trajectory as roamed.

Device mobility showed clearly the requirements for device mobility configuration. What this mechanism does is to reconfigure unified communication manger endpoint by capturing and determining the exert location using the internet protocol (IP) address. This aspect validates the state of the handheld device user as the device roam different substations of the service provider through clustering approach. Device mobility has some distinctive attributes and features that allows the determination of the user geolocation:

i. All internet-oriented phone has an embedded feature specified IP address based on geolocation
ii. The IP address create room for location of end user's location
iii. Device mobility as design make used of multisite substations
iv. The design crate easy to go roaming within sites of service provider

Mobility trajectory is not an isolated pattern within the network clustering analysis. The disconnecting idea on network roaming has indeed hindered the successful analysis of the mobility trajectory to give adequate result or projection on the likely sport such user can be located. To understand the dynamics of the mobility of the trajectory the following characteristic of device mobility as itemized above must be discussed and examined. The specified IP address feature which allows multisite settings environment along with a unique call centre makes handheld devices to navigate within substation with identification blueprint that further show the path or pattern movement of such user (Cisco Press, 2009).

THE MOBILITY PARAMETERS OF A DEVICE

There are several aspects of device mobility but of great importance is on the ability of a device to allocate (assigned) dynamically without manual configuration (Osagie *et al.,* 2018). As shown in fig 1, the parameter can be viewed from two angle and these are: (1) Roaming-Sensitive Settings and (2) Device Mobility-Related Settings. The configuration as shown in fig 1 gives credence to site-specification on phone usage location. The literal explanation means that device mobility as an entity had little or no power over the parameters of the user's phone specific geolocation and this is because the roaming-sensitivity settings cater for region, location, connection duration, data, time, media resources group list (MRGL), network location and SRST reference which are either configure as phone and device pool respectively. Cisco Press (2009) did a critical classification on the device mobility-related settings and the following such as device mobility calling setting, AAR calling search space and AAR group configuration are well catered for within the spectrum of network configuration. The device parameters as explained are corresponding that are to be assigned on both device pool and phones. The parameters have no restriction except the device mobility calling setting because it is known to be the calling search space in the phone configuration window. One aspect of the roaming-sensitivity strings which is very unique is the non-impact on the rout calls and this is because it modifies the device CSS, AAR.

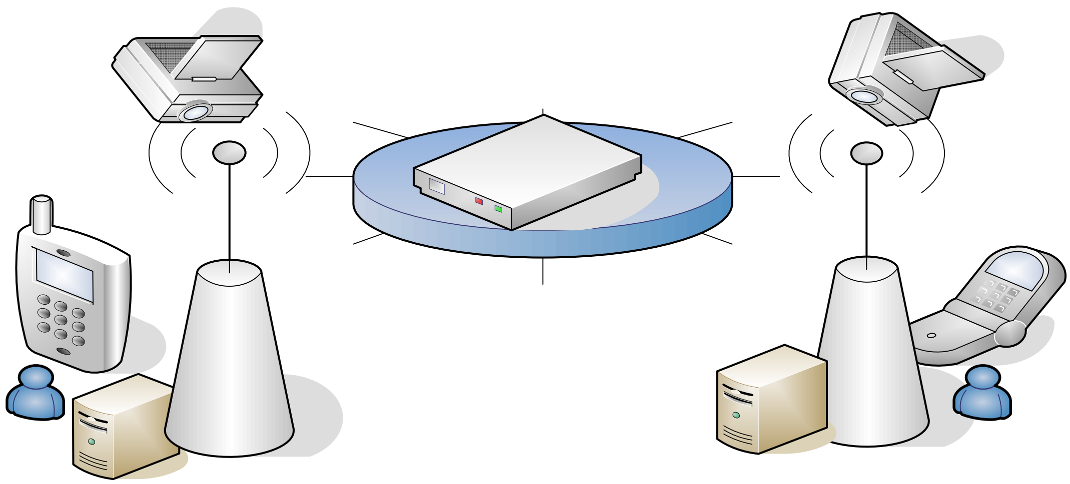

Fig 1: The Location-Dependent Device Configuration

The classification of the geolocation as seen in figure 1, is a direct simplification of the roaming-sensitivity setting as well as device mobility-related setting and the setting is achieved through the configuration of the device pools. The understanding of the device internal unique address such as the IP allocation of the subnet within the dataset and phone addresses gives distinct classification of the device pool for exert location of the user. The design structure is arranged to make CUCM application within the substation state precisely the geolocation using the IP subnet address of the required pool. CUCM is a software application that works on the principle of location validation and has ability to specify location based on the predefined centres as captured by the physical structure of the phone and device policy pool (Cisco Press, 2009).

THE PROXIMITY OF GPS IN HUMAN MOBILITY

Several works have been done in this regard but of interest is the proximity evaluation which hitherto give clear indication of the closeness of the trajectory of human movement. In a work published by Chaix *et al., 2019;* Chaix, (2018), a comparison was made between sensor tracking device and GPS based mobility and the end product of the survey was to understand the diversity in the movement structure of human so as to generate enough data that could influence human decision making. GPS play a critical role in modern society and its importance cannot be overemphasised. Its importance is due to the enormous benefits associated with it usage. GPS is a satellite-based radio navigation tool owned by the United Sate (US) and provides human information like area positioning and timing. The tool is designed to move (orbiting) round the earth for possible information (Kaplan and Hegarty, 2005; Coutts and Duffield, 2010).

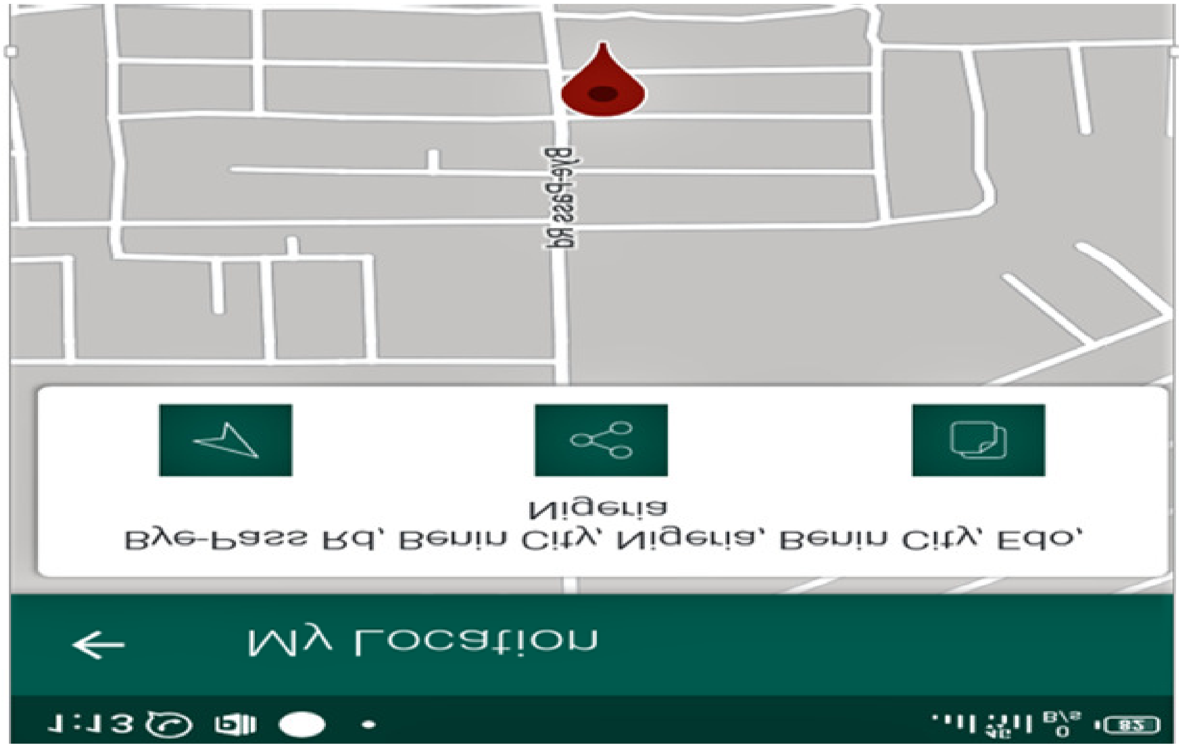

Fig 2: livestream of location by GPS

The illustration as showed in figure. 2 is a classical demonstration of the GPS location based. The system proximity can be ascertained through different models such as clustering and spatial identification within a dataset. The idea behind the proximity evaluation is to ensure the most visited places are adequately evaluated to make projection of the possible place such user intend to visit next. Human trajectory can be uncertain due to many reasons and adequate data collection through the help of monitoring device such as GPS would give clear indication of how often such user of the handheld device visits a place. The reason for the database for such movement which states the time, location, and proximity is to ensure that within a certain period the number of movements made are captured so as to aid the comparison evaluation. Data is one of the most important tools for determining the sustainability of a society, so, collecting such data into a pool of dataset gives clear picture of the intended value and its usage (Kaplan and Hegarty, 2005; Coutts and Duffield, 2010; Basile *et al., 2019*).

EVALUATING MOBILITY TRAJECTORIES MODELS AND ALGORITHMS

One vital aspect of human trajectory is the algorithm employed to predict the next spot or movement of human location. There are different models and algorithms in human trajectory. Thus far, no one has been classified as the best algorithm, because as discussed below, each of them solved the human trajectory based on applied principle.

The criteria for different models and algorithms operation say from Marcov model, T-pattern tree to Apriori-Traj Algorit algorithm is sole embedded principle of a frequently reoccurring frequency of human trajectory rout (Chen, 2008).

Markov Model

Markov model is an embodiment of stochastic model that predominantly function based on randomly evolves (changing) state. The model which is a probabilistic model applies an order of knowing the next state from the current state. Notwithstanding, the movement criteria is centred on assumption of certain random movement that have the next state determined by the present state. From figure 3, if the present state is X0, so the prediction (probability) of next spot or locations in view of beginning state in a given network trajectory using the first order would P, if X1 for the next trajectory from X0 the equation would be: P(X1 | X0, X1, X2, ...Xn) = P(X1 | X0(1)). Markov model is a forecasting tool that tell more about the next possible location. There are several Markov models but this paper itemized four: (i) Markov chain, (ii) Hidden Markov model (iii) Markov decision process, (iv) Partially observable Markov decision process (Krumm, 2008; Wikimedia, 2020).

Bayesian Network

The Bayesian network is one of the classifications of probabilistic graphical models with a technique to support the application of Bayes Theorem in resolving complex problems. Though, different types of graphical models exist but, the most discussed are the Hidden Markov Model (HMM) and the Bayesian Network. The HMM is also a graphical model with undirected (circle) edges. It has been observed that Bayesian Networks inherently preventive. On a directed acyclic graph trajectory is based on direction. ed to as a directed acyclic graph (DAG). The human trajectory such as location, time sequence can be modelled using the Bayesian network. A Bayesian system show through a graph (DAG) asymmetrical element by demonstrating a formidable factor. There are useful opportunities associated with Bayesian Network (Chen and Pollino, 2012; Stephenson, 2000). The network does not only provide a structural visualization of the design model but show relationship of both dependent and independent variables in the network as well as computation of the probabilistic system. From figure 3, if we assume that node A, B to C is a segment of the corresponding DAG, then the variable that can be considered on a conditional state would be:

A depends B, e.g. P(A|B)
C depends upon B, e.g. P(C|B)
It can easily be classified to say that there exist no direct relationship between A and C,
P(A|B, C)
P(C|B, A)

P(A|C, B) = P(A|B)
This can further be translated to: (B, P(A|B), P(C|B)) or P(B). = P(A, C | B) = P(A|B) * P(C|B)
The probability of P(A, B, C), would be P(A, B, C) = P(A|B) * P(C|B) * P(B)

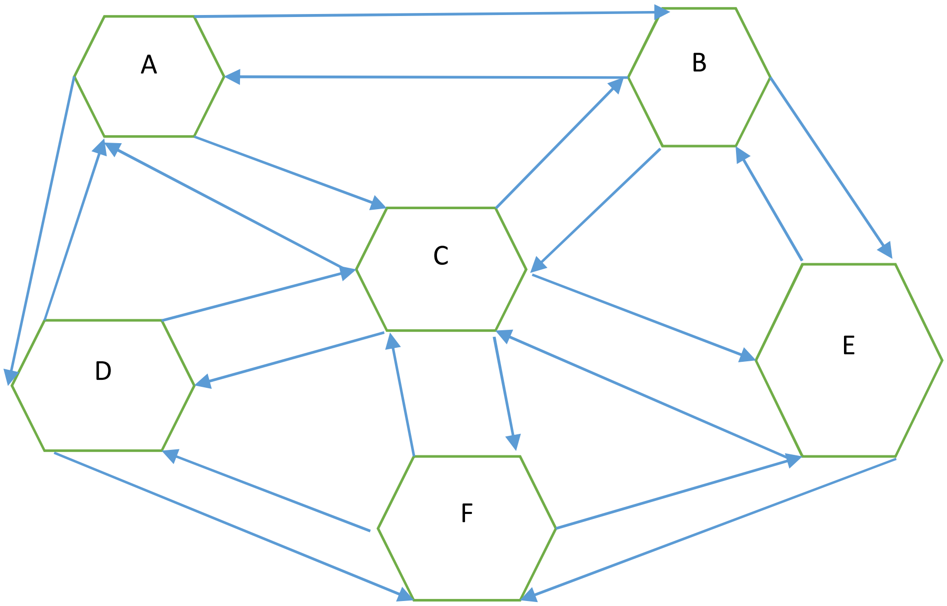

Figure 3: A Six node Directed Acyclic Graph (DAG)

Apriori-Traj Algorithm

Like other algorithms, the Apriori-Traj Algorithm is a projection-oriented algorithm of a trajectory. It is predominantly used in the prediction of a trajectory through the utilization of a reoccurring sequence of an object. The algorithm which uses movement rule by observing a moving object from a large pool of data set. The segmented trajectories form the larger pool by which the rule activates it working principle is a co-factor of balance movement. From the awareness of large pool of data, the algorithm has an overview position of a high level of acceptability in the trajectory prediction (Daud *et al.,* 2020; Monreale *et al.,* 2009).

T-pattern Tree

T-pattern Tree as it is popularly called is method that structurally extract pattern trajectories within a certain time (Daud *et al.,* 2020; Monreale *et al.,* 2009). From tree structure. Network theory and data structure emphasis network structure from both edges and node. Every network as seen from the figure 3 is known to have nodes which determines movement trajectories. Figure 3 has node A to F which represent the most visited location. The most concentrating platform of T-pattern Tree focus more on the proximity trajectory. The pattern movement gives credence to the futuristic prediction of the next steps or moves expected

Traj-Prefix-Span Algorithm

The Traj-prefix-span algorithm it is an enhanced multifactor algorithm that combined three working mechanisms in one. It activates the rout of the database trajectory through holistic parsing (scanning). The database trajectory scanning open up all trajectories to see the most possible recurring trajectory. The discovering of the most reoccurring rout gives a clear indication of the trajectory projection of the dataset. The algorithm repeat these procedures by way of recursion to actualize a dataset void of no trajectories. For classification purpose, the trajectory synchronization is achieved through a closer search of an object motion which give rise to certain principle or philosophy from which location can be predicted using probabilistic model (Daud *et al.,* 2020; Morzy, 2007)

Hybrid Genetic Algorithm (HGA)

The HGA as it sounds, work on the principle of Genetic Algorithm which is a search-based optimization techniques that utilises the philosophical doctrine of genetic and natural selection. The algorithm being an enhancement of Genetic Algorithm has ability to perform a whole form of search (Daud *et al.,* 2020; Xu and Wolfson, 2003). Human trajectories cut across vehicle utilization and HGA is basically a vehicle routing algorithm. Since HGA is an algorithm for crossover rate, population, number iteration, mutation and genetic tendency it then demonstrates wholesome awareness of human trajectory. HGA is of two branch HGA1 and HGA2 that are predominantly versatile in the selection process of chromosomes

Seman-Predict

Seman-predit is a prediction made on the Semantics associated with trajectory path (Daud *et al.,* 2020; Ying *et al.,*). In compiler, semantic is the meaning of the source code. The algorithm work by given meaning to the trajectory operation. Through the assigned meaning within the trajectory, a clarification is made on certain principle associated with locations. The ascertained meaning then gives the trajectory next sport based on the overall assessment as studied from the initial meaning as assigned

Hybrid Prediction Model (HPM)

The HPM demonstrate high level of accuracy in predicting which focusses on pattern movement of an object. The algorithm details on the futuristic tendency of an object. i.e. where the object intended to have it resting place at later time. The algorithm provides a handful information of the pattern mobility of an object trajectory by accurately predicting all round query on the location and distance-time of an object (Daud *et al.,* 2020; Jeung *et al.,* 2008). The classification of this model is on two phases. The first phase tells more of the querying of the near off time inquiries know to be Forward Query that Processes recent trajectory an important location prediction of the next spot locations. The Backward Query utilizes the pattern selection mechanism to validate the intended output of the next request as queried

Query Triggered Revision (QTR)

The QTR is a speed-oriented algorithm and works on the principle of update adaptation of speed as obtained from GPS sensor. In a trajectory dataset concept, there is an associated problem of an Unhealthy Speed Update Triggered Revision (USUTR) (Daud *et al.,* 2020; Xu and Wolfson, 2003). The update allows accurate speed prediction within a given period in the dataset trajectories. The updated version of trajectory dataset is carried out QTR which a mechanism used in classifying trajectory dataset update when queried.

CONCLUSION

As part of contribution to the development of sound based human trajectory prediction system through the utilization of substantive models and algorithm, this paper carried out a review into actualization of key result of the exert model or algorithm accurate enough to solve human complexity in trajectory prediction. From the review, no model/algorithm has been classified to be the best suited for human trajectory prediction or proximity management. However, it is believed that there are some of the models/algorithms that are predominately heterogeneous and homogenous in literatures and this, further raised some fundamental questions of the model/algorithm acceptability in research community. This is not to say that Markov model and others listed above solved trajectory prediction better. In this case, its simplicity as reviewed is one of the key factors of its usage amongst researchers. To solve the endless uncertainty of the best model/algorithm as well as complexity attached to the prediction accuracy, the author recommends a "Multi-factor" approach to the exiting mechanism and this will allow a combination of multiple models and algorithms through adaptation. Aside the analysis, this paper demonstrates the conceptual frame work of the working mechanism of human complexity trajectory prediction through the figure 3 DAG diagram of a three possible path spanning through point A to C with full classification of dependent and nondependent variables A, B, C.

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