Big Data Analytics on Customer Behaviors with Kinect Sensor Network

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Abstract

In modern enterprises, customer data is valuable for identifying their behavioral patterns and developing marketing strategies that can align with the preferences of different customers. The objective of this research is to develop a framework that promotes the use of Kinect sensors for Big Data Analytics on customer behavior analysis. Kinect enables 3D motion capture, facial recognition and voice recognition capabilities which allow to analyze customer behaviors in various aspects. Information fusion on the network of multiple Kinect sensors can achieve enhanced insight of the customer emotion, habits and consuming tendencies. Big Data Analytic techniques such as clustering and visualization are applied on the data collected from the sensors to provide better comprehension on the customers. Prediction on how to improve the customer relationship can be made to stimulate the vendition. Finally, an experimental system is designed based on the proposed framework as an illustration of the framework implementation.

Keywords: Big Data, Kinect, Customer Behavior Analysis, Human Computer Interaction.

1. INTRODUCTION

With the increasingly market competition fierce, the core of competition has been shifting from the products to the customers. Customer Relationship Management (CRM) has become an emerging topic for enterprises, which encourage relationship enhancement, sales force automation and opportunity prediction that require the marketing to be of higher technology and systemization. Analysis of different consumer behaviors and clustering customers into different characteristic groups will contribute to the development of efficient marketing strategies to enhance customer satisfaction and loyalty [1]. Especially in the dealer stores of Toyota, customer-centric operations are highly valued. It is advocated that the behaviors and characteristics of visiting customers should be tracked, managed and analyzed. The results can then be utilized to provide better services and information to the customers.

As a recent evolution of sensing technology, Microsoft introduced Kinect as a cost-efficient device for RGB-D mapping, motion tracking, facial recognition and voice recognition. Kinect has been widely used in interactive gaming that allows the players to control the objects in the games by gestural or vocal commands. Because of its economical price and flexible functionality, enterprises also start to adopt Kinect as a production component in different environments, for example, in facial authentication systems and for robotic controls [2]. For its versatility, we propose to use Kinect to collect various aspects of customer behavior for analysis.

However there are some known limitations with Kinect. The racemization range of a Kinect device is approximately 0.7 to 6 meters, and it is capable of simultaneously tracking up to six people [3].

For enterprise scenarios such as in a retail store, one Kinect can hardly cover all monitor areas. We need to form a sensor network by connecting multiple Kinect devices to collect all the essential information within the specific scene and merging the multiple sources of data by utilizing Information Fusion techniques.

The data collected from the sensor network per day can be in a very large volume, which additionally needs to be combined with data from other sources for analysis. To process the data of various sources and multiple forms, the techniques of Big Data Analytics (BDA) are required to comprehend the large amount of data and extract indicative information to perform business estimation and support decision makings [4]. Through the analysis on the data related to customer behaviors, we expect to have better understand of them, so that we can serve them in a manner they feel more comfortable, or we can find a better way to persuade them to consume our goods.

2. PRELIMINARY METHODOLOGIES AND INSUFFICIENCIES

Various studies have been presented on Consumer Behavior Analysis (CBA) to create a more effective tool for understanding consumer behaviors. Through selection of appropriate techniques to collect, analyze and understand the data related to consumers, enterprises can improve their marketing strategies by utilization of affecting factors such as consumer psychology influenced by the environment, and consuming motivation and decision tendencies differing between products [5].

A fundamental aim of CBA is to develop a radical behaviorist framework that suits the interpretation and prediction of human economic behavior in common occasions. The framework is denoted as Summative Behavioral Perspective Model [6] (see Fig. 1). This model assumes consumer choice as a point where the experience of consumption meets a new opportunity to consume. Such point is the joint production of the learning history of the consumer meeting the current consumer behavior setting.
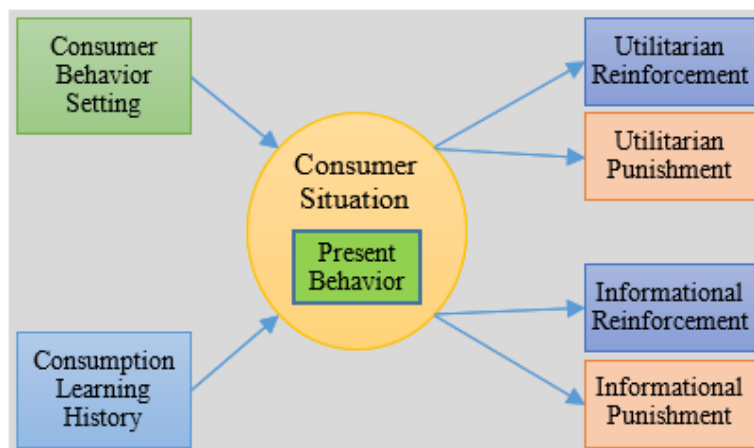

FIGURE 1: Summative Behavioral Perspective Model.

The Consumer Behavior Setting (CBS) comprises the antecedent stimulus conditions that certain setting elements encourage or inhibit the behavior predicted to occur in such contexts. The Consumption Learning History (CLH) is the past choices of the consumers that are believed to be influential on the present consumer behaviors. In addition, current choice is also affected by the reinforcing and punishing consequences. Utilitarian Reinforcement is the functional outcomes of behavior that consists of direct usable, economic and technical benefits of owning and consuming a product or service. Informational Reinforcement is the symbolic outcomes that stems from the prestige or status and the self-esteem generated by ownership and consumption such as performance feedbacks to the users. The corresponding punishing consequences are the

aversive costs of purchase and consumption. All these factors of the developed model can be used to analyze the consumer situation in terms of their demands, intention and psychological condition. Therefore, whenever we need to estimate the consumer situation, we need to combine the information of CBS, CLH and other influential factors to deduct a conclusion. This process can be presented as Consumer Behavior Analysis Flow [5] (see Fig. 2).
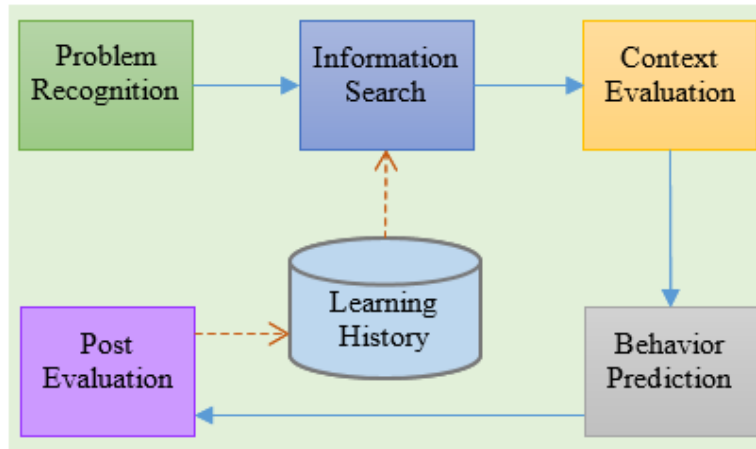

FIGURE 2: Consumer Behavior Analysis Flow.

The analysis flow starts from recognizing the problem. This is to set the main goal of the analysis. A problem can be to enhance customer relationship or to make a marketing strategy. Then we need to determine what information is relevant for solving the problem. Such relevant information is searched out from the databases of the historic records. In combination with the contextual information, the extracted data is analyzed. The analysis result leads to a perdition about the present or future situation of the consumer that are utilized for decision makings. After the execution of the decision, the subsequent effects should be observed and recorded to verify the prediction and for future analysis.
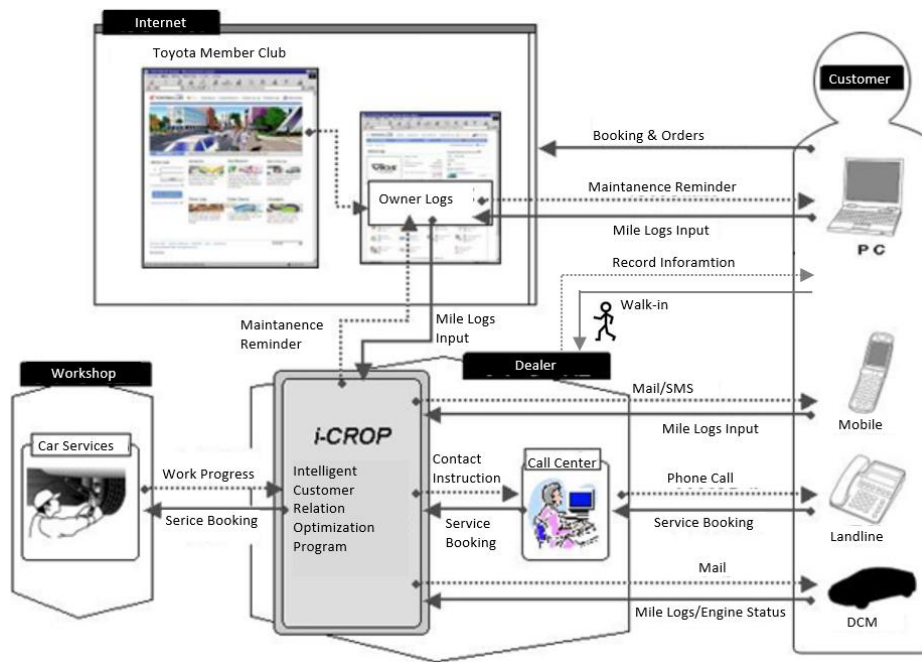

FIGURE 3: Toyota eCRB Project Overview.

Toyota has been implementing this flow in its eCRB (Evolutionary Customer Relationship Building) project (see Fig. 3). The project is attempting to integrate customers, dealers and distributors with multiple inter-related systems to keep track of the customer information. In addition, it keeps the customers informed about new products and the status of their vehicle that has been sent for services via multiple channels in terms of SMS and email etc.

A core task of eCRB is to mark down the information of customers who walk into the dealer store and the information will be utilized for follow-up and further analysis. Currently, sales consultants go and talk with the visiting customers and use an iPad app called i-CROP to record the valuable information acquired from the conversations (see Fig. 4), for example ages, interests and contacts are logged. However, many customers are impatient to be questioned by the consultants, especially when seeing the consultant taking notes during the conversations. Further, the notes taken by the consultants are inconsistent and unsuitable for systematic and comprehensive analysis.

FIGURE 4: Customer Records in i-CROP Client.

The growing demand of strategic planning entails a more automated and systematic approach to keep track of visiting customers. More aspects of their behaviors should be marked down for comprehensive and systematic analysis. Meanwhile, innovative measures can be introduced into sensing their behaviors so that the customers will not feel unhappy when they find themselves are being monitored.

Worcester Polytechnic Institute designed an automated system using Kinect devices for remote control and user identification in a smart home environment [7]. In the project, the vocal recognition function of Kinect enables the remote control of the appliances, by calling vocal commands, within a smart house. The facial recognition function is used to replace the traditional door keys to lock or unlock the house doors. Motion tracking function is used to monitor the walking activities of people in the house. However it lacks of details of analytic processes and algorithms that may apply to analyze the data collected from the Kinect sensors. Although the project arouses researchers' concern about using of Kinect for human motion tracking, it is illuminative for enhancing the flexibility and operation efficiency of Toyota's eCRB system.

3. THE PROPOSED FRAMEWORK

In order to achieve more comprehensive analysis, the analytic system should be implemented with several distinguished sensing approaches, so that the consumer behaviors can be observed with different aspects. The diversified data sources are believed to provide more accurate analytic

results overall. Kinect is capable of motion and voice capture, and Kinect v2 even has the ability to detect the pulse of human beings [8]. These can assist to measure both the external (e.g. facial expressions) and internal behaviors (e.g. emotions) of the consumers. In addition, to increase the accuracy, the analytic system should not only implement passive observations, but also actively trigger some interactions with the customers and watch the non-regulatory feedings.
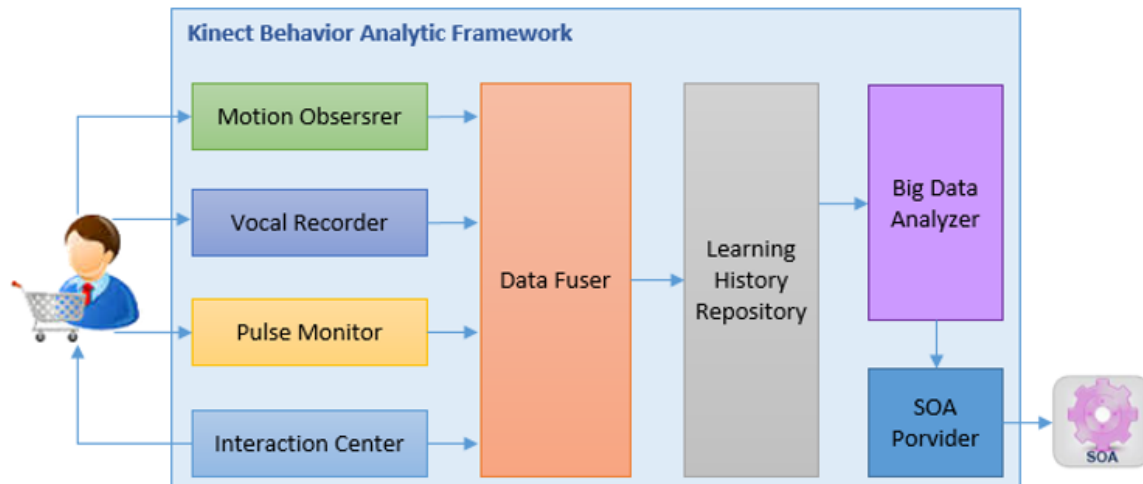

FIGURE 5: Kinect Behavior Analytic Framework.

Based on the above concerns, we propose a design namely Kinect Behavior Analytic Framework (KBAF, Fig. 5). It is consisted of eight core modules: Motion Observer, Vocal Recorder, Pulse Monitor, Interaction Center, Data Fuser, Learning History Repository, Big Data Analyzer, and SOA Provider. In small environments, a single Kinect sensor might be able to competent for all sensing tasks. In large environments, one Kinect device might not be able to cover all monitor areas, whereas a sensor network is required to connect multiple Kinect devices. The sensing modules can be implemented separately. Each Kinect sensor is in charge of monitoring certain locations or aspects of the customers.

Motion Observer is a sensing module that uses Kinect for body tracking and facial recognition. Body tracking enables to count the visitor numbers and monitor the reactions of the customers towards different products. Facial recognition can analyze the ages and genders of the customer, and allows to observe the facial expressions of customer under different contexts which can be used to infer the emotions and the interests of a customer. It can also recognize the revisits of customers. Higher revisit count might signals higher purchase tendency of the customers.

Vocal Recorder is a sensing module that uses Kinect for capturing voice. As facial recognition with Kinect has restricted precision, assistance of vocal recognition can increase the accuracy of customer recognition. On the other hand, the captured vocal data can be used to detect the emotion status of the customer by analyzing the vocal patterns [9], so that we can determine the communication strategy toward specific customers.

Pulse Monitor is a sensing module that detects the heartbeats of the customer. Pulse detection is a new function added to Kinect v2 [8]. According to past research, emotion can be recognized from the pulse waveform [10]. With the pulse information, we can trace the emotional change of customers. Based on this information, we may get a better understanding of which products are more interested to which customers, and apply corresponding sales strategies based on the differences of interests.

Interaction Center is a module that intentionally triggers events that allow the customers to participate and response. During the participation, the reactions and feedbacks of the customers

are observed. Customers evoke behaviors related with the established events. Through examining the influences on the customer behaviors related to the specific events, the reinforcing or punishing effects of the environmental conditions can be learned [6]. The reinforcing and punishing variables are used to enhance accuracy of the consumer behavior prediction.

Data Fuser is a data process module that transforms raw data into analyzable data for future archival or analytical purposes. The original data is in multiple forms in terms of video, image and voice data etc. The raw data is unsuitable for comparison and statistical analysis, and the computation is inefficient and inaccurate. Directly keeping the video and voice data also consumes huge storage space. In addition, in some environments multiple Kinect devices are used to enlarge the monitor areas or increase the capture quality. Multi-sensor integration is necessary to enhance the synergistic effect of the monitoring by better robustness and noise suppression. Therefore, normalizing the raw data into a consistent format and endowing with proper metadata is essential for successful analytics.

Learning History Repository is a database modeled for flexible storage and retrieval of data. It stores the monitor records and corresponding metadata about the visited customers and environmental information about the visits. Although the data sourced from different sensors have been refined by the Data Fuser, the contents and formats are not all textually similar or meaningful. NoSQL databases are encouraged to be implemented to support flexible and efficient processes on the unstructured data [11].

Big Data Analyzer is the module that performs analytic processes in terms of statistical analysis and visualization on the archived data in the repository. Some enterprises might select to implement this module with commercial analytic software (e.g. SPSS, SAS or Stata). Some others might consider to develop in-house analyzers with dedicated analytic algorithms and analytic frameworks including Python, R and Mahout. Especially R is favored by large enterprises as it comes with a sum of built-in statistical functions and powerful drawing facilities. Moreover, it can work together with a popular distributed computing framework called Hadoop. HDFS (Hadoop Distributed File Systems) and MapReduce are the most vital functionalities with the Hadoop. For larger storage space or redundant storage strategy, HDFS is usually used to share data between different modules. MapReduce is a data optimizing component that are helpful for abstracting large volume of data and providing efficient job control and task management to enhance analysis performance [4].

SOA Provider is the module that converts the past analytic results into web services that can be retrieved by other systems. SOA (Service-oriented Architecture) is a design style for system development based on loosely coupled, coarse-grained and autonomous components. In large information systems of enterprise, SOA encourages to encapsulate complex business logics into services that can be distributed as flexibly consumable components. Request/Reaction Pattern of SOA should be implemented to allow asynchronous communication when the results are being retrieved [12].

4. EXPERIMENT DESIGN AND EVALUATION
KBAF can be implemented in many different environments with different sensor fusion and analytic algorithms. Toyota is developing an experimental project called iDealer that has been designed based on the KBAF (see Fig. 6). The main aim of this project is to establish a serial of facilities to capture and analyze the behaviors of visiting customers and determine corresponding marketing strategies catering for different customers. iDealer project is mainly consisted of two sub-systems: Extroverted System and Analytic System.
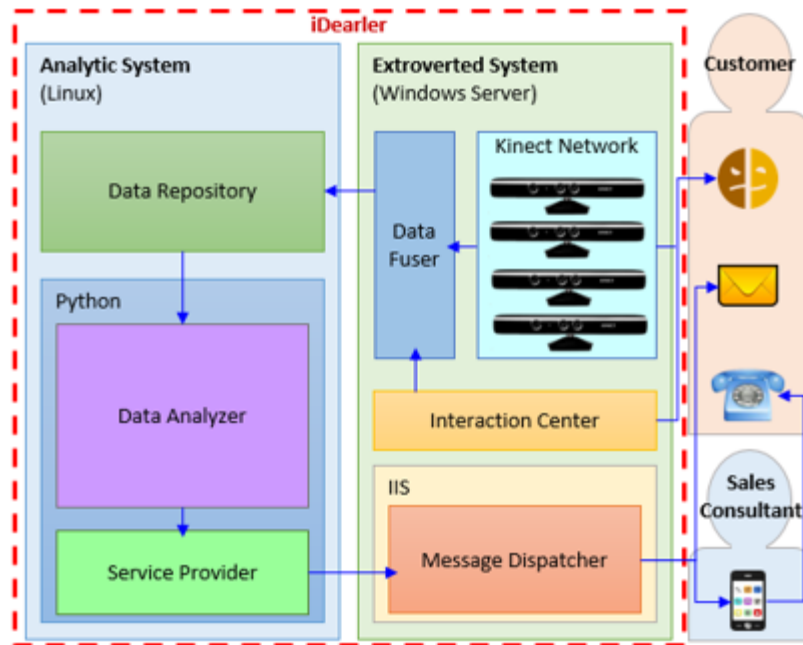
FIGURE 6: iDealer Project Overview.

Extroverted System works at the front end and directly interacts with the customers. It also uses Kinects sensors and touchable devices to capture the actions and reactions of the customers. As Kinect SDK is required to be installed on Windows platforms, we use Windows Server 2012 as the operating system for management of the sensor network. Analytic System works behind and in charge of the analytic processes. It is tasked to store and analyze the data collected from the Extroverted System. As Linux platforms have more powerful statistic tools and higher flexibility for analytic algorithm implementation, we choose Ubuntu as its operating system.

Interaction Center is the brain of the Extroverted System. It manages media and interactive components presented to the customers. In a Toyota dealer store, there are several large-screen displays playing various advertising video clips such as car introduction and car news (see Fig. 7). While the customers are watching such videos, their reactions are monitored by Kinect. From the sensed data collected, we could understand the emotional changes of customer when playing different video, so that we can adapt the marketing strategy accordingly. For example, if customers feel disappointed when watching the video of Highlander, we can offer more discounts on Highlander to stimulate its sales. More directly, Interaction Center can receive feedbacks from the interactive applications when the customers are playing with the applications. These applications include multi-media car type information panel and car racing games etc. The actions taken by customers on the applications provides many clues of personal information about the customers themselves such as their favored car and favored colors. For instance, a customer click Camry for many times, we might infer that he/she is thinking about buying a Camry.

FIGURE 7: Interactive Components and Behavior Recognition.

Kinect can be used on more aspects. For example, we can place a sensor facing the front gate, then the faces of most customers can be captured. As Kinect can be used for face recognition, we can use it to count the number of visitors or to identify the revisit customers. The facial captures are 3d models composed of polygonal meshes and texture images. They are exported as FBX files which can be stored in databases and used for identifying revisit customers. We compare both the meshes and images for face recognition to enhance the accuracy.

As the faces are captured in slightly varied distances and angles, the coordinates of mesh have to be normalized to be comparable with scaling and rotations. The vector normalizations can be expressed in the following equation:

$$P_N = [P_D - \overline{P_D}] \times R_{DM}^t + \overline{P_D}$$

where P_N denotes normalized deformed textured model, P_D the deformed 3D model coordinates, R_{DM}^t the rotation matrix, and $\overline{P_D}$ the mean coordinates of all the deformed models [13]. R_{DM}^t is calculated by applying the combination of necessary rotation of difference axes, which can be express as $R_{DM}^t = R_z R_x R_y$. The 3D decimal coordinates can then be projected into 2D integer coordinates for simpler comparison. The texture images of faces can be compared by using modified PCA (Principal Component Analysis) [14]. We project image A onto n-D unitary column vector by applying the transformation: $Y = AX$. Then we find out the image covariance matrix:

$$G = \frac{1}{n} \sum_{i=1}^{N} T(A_i - \bar{A})(A_i - \bar{A})$$

where i = (1,2,3, …N,) is the number of training samples and $\bar{A}$ denotes the average image matrix. If a given image A has optimal projection vectors X_1, X_2, …, X_d, we have $Y_k = AX_k$ $(k = 1,2,…,d)$. Suppose projection vectors $U = [X_1, X_2, …, X_d]$ and $V = [Y_1, Y_2, …, Y_d]$, the reconstructed depth map of the image can be obtained by:

$$\check{A} = VU^T$$

If d=N in the reconstructed image $\check{A}$, the image will be the same as the original image A, i.e. $A = \check{A}$.

However, Kinect has limited recognition distance. To achieve different monitor functions and cover more areas, multiple Kinect devices are required to work simultaneously. How to efficiently assembly the data from multiple sources of sensor arouses a problem of Information Fusion. One of the key tasks of Data Fuser is to resolve this problem.
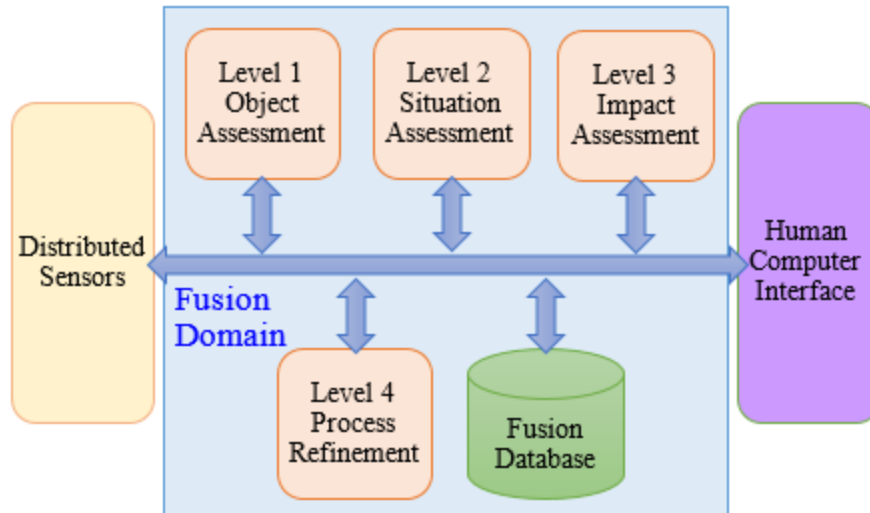
FIGURE 8: The Revised JDL Model.

According to JDL (Joint Directors of Laboratories) model (see Fig. 8), the activities of data fusion can be categorized into four levels in accordance with their functional sequences in an intelligent system, namely Object Assessment, Situation Assessment, Impact Assessment and Process Refinement [15]. Data Fuser sits at the level 1 and level 2 of the JDL model that it fuse the status information of customers and the underlying environments from multiple sources of sensor into normalized data suitable for query and analysis.

In the level 1 fusion, metrics are applied on various types of original data. For example, voice records of customer are categorized according to their sample shapes of sound waves. Emotional patterns of the voices can be identified and documented with ordinal notations. For instance, 0 stands for normal emotion, -2 stands for disappointment, and 3 stands for happiness etc. Similarly, facial images and pulse records can also be transformed into ordinal or numerical data. In addition, metadata is about attached with the transformed data such as the sensor number of the data source and capture dates of the data etc. The metadata provides contextual information related to the measurement results. Then the normalized data becomes ready for mathematically computation. In the level 2 fusion, based on the environmental and time relations of interest, the normalized data is aggregated into a representation that are suitable for further analysis.

After normalization and aggregation data is stored in a Fusion Database. Akin to Fusion Database, we create a Data Repository for efficient data storage and retrieval in the Analytic System of iDealer. It is implemented with CouchDB which is a NoSQL database relying on a different approach rather than relational data management structure, storage and retrieval methods. The motivation of using CouchDB is for the data storage of unstructured formats and availability for agile query with RESTful http requests which can enhance the efficiency of BDA processes. Data Fuser can append a new entry into the CouchDB by issuing PUT and POST requests (see Fig. 9), and such entry can be retrieved via http GET requests.
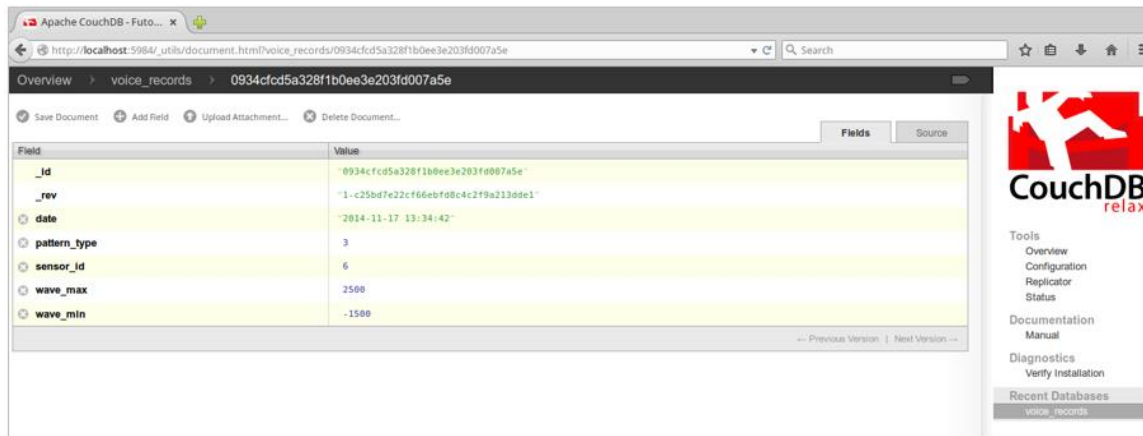
FIGURE 9: CouchDB Data Record.

Moreover, with CouchDB-Python library, we are able to perform database management and advanced mapping between JSON documents and Python objects. It simplifies processes for retrieving the data into Python environment and performing statistical analysis on the data objects. Besides the strong CouchDB support, various Python libraries for statistics and analytics are available. In addition, it is made with powerful data manipulation and algorithm implementation capacity, which renders Python to be an excellent choice for building data-centric applications.

The data analytic module in our project is called Data Analyzer, which is built on Python environment with several statistical frameworks, mainly including Pandas, Scikit and Matplotlib. Pandas provides rich data structures and handy functions to manipulate structured data such as to reshape, slice, aggregate and filter datasets. Scikit is a machine learning library which features various mathematical functions in terms of classification, regression and clustering analysis. It provides built-in API for applying large number of analytic tools such as Vector Machines, Logistic Regression, Naive Bayes, Random Forests, Gradient Boosting, K-means and DBSCAN. Matplotlib is a graph drawing framework that can be used to plot numeric data [16].

Data Analyzer provides level 3 and level 4 fusion of the JDL model. A number of data analytics are performed in accordance with business requirements of the dealer store. For example, customers are clustered into several categories (see Fig. 10), so that different marketing strategies are applied accordingly. We use Indicators of Collective Behavior (ICB) algorithm to identify maneuvering entities of akin actions [15]. Assuming totally N customers have been tracked, the edge weights (EW) graph of these entities can be represented as:

$$EW_{ij} = \left(\alpha \times \frac{d_{ij}}{\max_{i \neq j \in N}\{d_{ij}\}} \right) + \left(\beta \times \frac{\Delta s_{ij}}{\max_{i \neq j \in N}\{\Delta s_{ij}\}} \right) + \left(\gamma \times \frac{\Delta h_{ij}}{\max_{i \neq j \in N}\{\Delta h_{ij}\}} \right)$$

where d_{ij} denotes the distance between entities i and j, Δs_{ij} and Δh_{ij} are the differences in the speed and heading of the entities, and α, β and γ are the constant determinants of emphasis to separation, speed, and heading criteria. The nodes of EW graph is then allocated into candidate clusters by repeating application of Parzen window estimator [17]:

$$p_n(x;k) = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{d_{ik}} K(\frac{x - x_i}{d_{ik}})$$

where d_{ik} denotes the distance from x_i to its kth nearest neighbor, K is the kernel function to compute similarities, and the output probability dense $p_n(x)$ are used for searching clusters. Another example is to establish regression analysis on the customer counts. We use Gaussian Processes to solve this regression problem [18], in which the distribution can be expressed as:

$$P(x|\mu,\Sigma) = |2\pi\Sigma|^{-\frac{1}{2}}\exp\left(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right)$$

where μ and Σ are the mean and covariance of the distribution. We can apply promotion strategies on business downturn or reinforce sale consultants in peak seasons in accordance with the prediction based on the visiting customer distribution (e.g., Fig.10 shows a single month prediction of customer numbers).
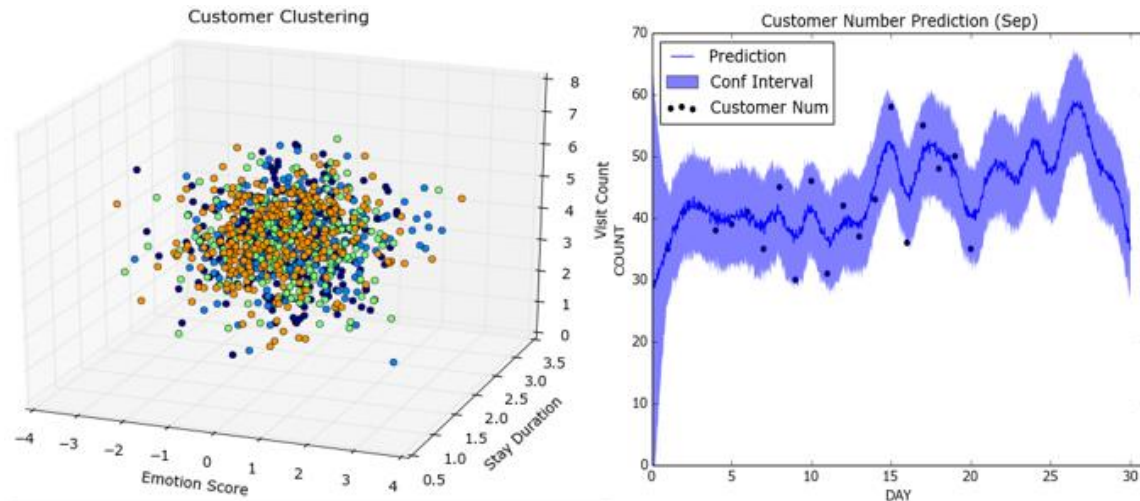

FIGURE 10: Analytics with Customer Data.

The analytic results are forwarded to the Service Provider, a web component that can convert the analytic results to web services available to other modules or other systems. It is implemented by two python toolkits, namely Webpy and Soaplib. Webpy is a simple and powerful web development framework that can easily interact with other python libraries. Soaplib is a python library that can publish SOAP web services using WSDL standard, and answering SOAP requests. Many enterprises implement well encapsulated web services to communicate between systems to reduce the complexity of information systems and increase the integration. For example, Toyota is constructing TSB (Toyota Service Bus) to enable the sharing of data and systems globally. The updated results are periodically retrieved by Message Dispatcher in the Extroverted System, and forwarded to sales consultants to follow-up. Many customers have left their contact methods in our databases. When the sales consultants receive the analytic reports on their smart phones, they might give phone calls to the high profile customers, give them more descriptions about their favored cars, or even offer the customers special discounts to persuade them. Additionally, based on the analytic results, Message Dispatcher can automatically send promotion email to the customers to inform them about the products or services they might be interested. For the customers whose contact information is not in the databases, they will be attended by the sales consultants next time when they visit the dealer store.

5. CONCLUSION AND FUTURE RESEARCH
This research explores the potential value for utilizing the concepts of big data analytics and information fusion with Kinect sensors for customer behavior analysis. Kinect sensors provide capacities of voice recognition, motion tracking and facial recognition that allows us monitor customer behaviors in multiple aspects. Information fusion is useful when multiple sensors are utilized simultaneously to enlarge the monitor area or enhance capture efficiency. It can assemble the information from multiple sources to a more analyzable form that enhances the accuracy of the analytic results and the efficiency of analysis process. In addition, the data repository also enables the Big Data Analytics to be performed on the sensor records to probe for deeper and more ensconced information about the customer values. The important incentive for customer

behavior analytics for enterprises is to use the analytic reports to develop marketing strategies that can effectively enhance customer relationship and promote their products.

For future research directions, we consider to use the developed system to make more complex predictions for product promotion in Toyota retail stores, e.g. the demand per vehicle model per season, and to develop approaches to evaluate and improve the prediction accuracy.

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