A Data-driven Approach to Agent Based Exploration of Customer Behaviour

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Abstract

Customer retention is a critical concern for most mobile network operators because of the increasing competition in the mobile services sector. This concern has driven companies to exploit data as an avenue to better understand customer needs. Data mining techniques such as clustering and classification have been adopted to understand customer retention in the mobile services industry. However, the effectiveness of these techniques is debatable due to the increasing complexity of the mobile market itself. This study proposes an application of Agent-Based Modeling and Simulation (ABMS) as a novel approach to understanding customer retention. A dataset provided by a mobile network operator is utilised to automate decision trees and agent based models. The most popular churn modeling techniques were adopted in order to automate the development of models, from decision trees, and subsequently explore customer churn scenarios. ABMS is used to understand the behavior of customers and detect possible reasons why customers churned or stayed with their respective mobile network operators. Data analysis is able to identify that location and choice of mobile devices were determinants for the decision to churn or stay with their mobile network operator - with word of mouth as an important factor. Importantly, agent based simulation is able to explore further the determinants in the wider marketplace.

Keywords

Agent Based Modelling; CADET Approach; Decision Trees

Introduction

Simulation models that describe agents have become a widely used tool for understanding phenomena. These models have been used across industries and often provide insights into complex problems. A popular simulation model is the Agent-based model (ABM). The agent-based model allows researchers and practitioners to study how system level properties emerge from the adaptive behaviour of individuals and on the other hand how systems affect individuals (1).

Agent-based models consist of a number of entities with individual rules of behaviours. Entities in such models interact with one another and with their surrounding environment. Such interaction may influence the behaviour of the agents. Harnessing this information and understanding the influence of agents interaction with other agents and agent interaction with the environment can provide some useful insights to business problems, in this case customer churn.

There are various ways of describing agent based models. Adopting the design science paradigm, this paper presents a novel approach to agent based modelling. The Customer Agent Decision Tree (CADET) approach is a data-driven approach that provides key drivers that collectively uncover the decision of individual agents in an environment. The CADET approach is not industry specific. Thus, it can be applied in different sectors. The CADET approach is validated by applying it to investigate customer retention in the mobile services industry (MSI). The next section presents a background on customer retention in the MSI

Background on Customer Retention

Over the last decade, the number of mobile phone users have increased reaching an overwhelming number of 7 billion (2). In developed countries, telecommunication companies have mobile penetration rates above 100% with no new customers (3). Therefore, customer retention receives a growing amount of attention from telecommunication companies. The high penetration rate of above 100% in the mobile services sector has motivated substantial research into customer retention. It has been shown in the literature that customer retention is profitable to a company because: (1) acquiring new customers cost five times more than retaining existing customers (4; 5). (2) Existing customers generate higher profits, become less costly to serve, and may provide new referrals through providing positive word-of-mouth while dissatisfied customers might spread negative word of mouth (6; 7; 8). (3) Loosing customers may lead to opportunity costs because of reduced sales (9; 10). However, a small improvement in customer retention can lead to a significant increase in profit (11). A number of studies in the area of customer retention have revealed that customer satisfaction is a strong predictor of customer retention (12). This is as a result of the relationship between both conceptual elements (13). Factors that drive customer satisfaction

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(such as service quality) can also drive customer retention. (14). Furthermore, customer satisfaction is often seen as a motivator for customer retention (15). While it seems that satisfied customers will remain with their mobile service provider, this is not always the case because satisfied customers can defect while dissatisfied customers can be retained (15).

Customer churn is a term that is widely used in the area of customer retention to describe customers who switch to a different mobile service provider or leave the market entirely.

There are two basic approaches that can be used to address customer churn namely, untargeted and targeted approaches (16). Untargeted approaches rely on outstanding product and mass advertising to increase brand loyalty and retain customers while targeted approaches rely on identifying customers who are likely to churn and then providing them with either a direct incentive or a customised plan for them to stay (16). Various types of information can also be used to predict customer churn, such as information on socio-demographic data (e.g. sex, age, or post code) and call behaviour statistics (e.g. the number of international calls, billing information, or the number of calls to the customer helpdesk).

The main factors that influence customer churn in the mobile services market are (1) customer satisfaction, (2) switching costs, (3) relationship quality and (4) price (17; 18; 19). Price is the most important factor for customer churn, followed by customer service, service quality and coverage quality (20). However, social influence is another key driver to customer churn in the mobile services industry (21; 22). This paper proposes an approach to ABM in order to explore social influence on customer churn behaviour. The next section presents approaches to modelling customer behaviour with respect to customer retention.

Customer Modelling Behaviour

Customers often interact with other customers about products and services they purchase. In addition to the advertisement campaigns carried out by MNOs, interaction among customers also influences customer purchase and repurchase decision. There are various theories in social science and marketing concerned with understanding and modelling customer behaviour (23). Customer behaviour may change as a result of an act of a consumer changing preference on a product or service (24). A number of approaches have been applied to understand the concept behind consumers changing preferences (24).

Customer retention can be achieved if a company is able to understand patterns in which customers behave and the likely triggers for such behaviour (25). Understanding customers, managing interactions and relationships with them is a vital part of customer relationship management (CRM). A company with a good CRM should be able to predict possible changes in customer behaviour (25). Predicting customer behaviour can be achieved through customer behaviour modelling (26), by applying tools and techniques to gain a better insight on customer behavioural patterns and in turn predict future behaviour (27). Neslin et. al., (28) characterised CRM models as either analytical or behavioural models. Analytical models involve large datasets that are stored in data warehouses. These datasets require models that can easily scale the dataset and provide results to increase company revenue (28). Behavioural models make use of surveys to analyse cognitive responses to services provided (28). Furness (29) classified customer behaviour modelling into (1) descriptive modelling, (2) predictive modelling and (3) a combination of descriptive and predictive modelling. Descriptive modelling describes models that attempt to answer why questions. An example of descriptive modelling is clustering. When a customer clustering exercise is conducted, customers belong to a certain cluster because they collectively possess similar attributes or behaviours. Predictive modelling describes models that answer the who questions. For example who will buy a product or service? In the context of customer churn, predictive models can give insight on who is likely to churn (30). Predictive models typically work by predicting future customer behaviour based on their past behaviour (30). Finally, the combination of descriptive and predictive modelling addresses problems by integrating both descriptive and predictive models to provide a more concise answer on who and why questions at the same time (3). Descriptive and predictive models are popularly carried out using data mining approaches. The next section presents an overview of applying data mining approaches to investigate customer churn.

Applying Data Mining Techniques for Modeling Churn

Data mining techniques are popularly used to build churn prediction models (31; 32). Data mining simply means extracting hidden knowledge from data, and it is a popular technique for understanding customer behaviour from raw data. Data mining methods are widely used in the literature for analysing and investigating customer churn for two main reasons: they have better prediction results (33) and they are more suitable for analysing large data sets (34).

Numerous studies have applied various data mining techniques to study customer churn. These studies include (35; 36; 37). The most popular data mining techniques for predicting churn include decision trees, logistic regression and support vector machines (SVM) (35). Furthermore, numerous industries have attempted to apply data mining techniques to study customer churn. These industries include banking (38; 39), insurance (40), retail (41; 42), and economics (28). Most studies that addressed customer churn using data mining techniques do not account for the social effect of customer retention (43). As a result, this area has been neglected and it is considered a major driver for customer retention (21; 22). The next section presents an overview of the social network analysis.

Social Network Analysis

Social network analysis (SNA) is an evolving scientific research area. SNA has developed to be a primary technique for describing the social structure and interaction between network representation (44). A social network is an inter-connection between nodes using various links (24). For the purpose of this study, nodes represent customers and the links represent the relationships between customers.

SNA typically focuses on static networks. Static networks are the mapping of relationships between discrete entities (45). These networks do not change their structure over time. Recently, researchers have focused on dynamic networks that are capable of representing the continuous transmission of information and influence (46). Dynamic networks are a vital aspect of ABMS. Using dynamic network analysis involves understanding the agent rules that govern network structure and growth, and how networks and their relationships convey information (47). SNA is an approach to anticipating and modelling society as different sets of people or groups linked to one another (24). SNA is a method of enquiry that focuses on the relationships between subjects. This approach seeks to understand subjects by collecting information from different sources, analysing the information and visualising the results. SNA has proved to be useful in explaining some important phenomena such as investigating the spread of disease, understanding the internet and explaining the small word effect to the spreading of information (48). Sociologists and market researchers believe that the life of an individual depends on how that individual engages with the web of social connections (45). The social networks term is loosely used to refer to social and professional networking sites including but not restricted to Facebook, LinkedIn and Twitter. Each networking site represents an online community. An online community is an example of a social structure. The people (also known as the nodes) who sign up on these online communities alongside the relationship between them represent social networks. A social network structure consists of nodes and the interrelationship between the nodes. Due to the growing interest of social network analysis, researchers have investigated the principles of the network approach. These principles include (24);

1. Actors and their actions should be viewed as autonomous and independent units rather than as interdependent units.
2. The links between actors should be viewed as channels for transfer of material and non-material resources.
3. Social network models focusing on individuals view the structural environment as a network imposing certain constraints on individual actions
4. Social network models conceptualise structure (social, economic, political, and so on) as long-lasting patterns of relations among actors.

Milgrim (48) is an empirical research study of social structure and it introduces 'six degrees of separation' phenomenon while addressing the 'small world problem'. In this study, some participants were chosen at random and asked to deliver a letter to a target person using only a chain of friends and acquaintances. There was a starting person and a target person in different states in America. The starting person was advised to send the letter across to his friend or acquaintance who is likely to know the target person. The procedure started in Nebraska and the destination of the letter was Boston, Massachusetts. The process will continue until the message gets to the target person. When the letters arrived in Boston, Milgram discovered that it took an average number of six steps for the letter to get to the destination. Hence, Milgram labelled the phenomena six degrees of separation. This study concludes by describing how people of a population are connected. Although (48) study was not subject to an evaluation process, his concept of the small world is widely adopted in social networks research to provide an explanation about how information spreads in the real world. The small-world network has become one of the most widely-used social network models (49). The next section provides a background on social impact of customer retention.

Social Impact on Customer Retention

More recently, the influence of social networks have been found to be a key contributing factor to customer retention (50; 51). Social networks' influence is typically carried out with the use of word of mouth (WOM) (52). WOM is the informal communication between private parties regarding evaluations of goods and services (53). 75% of defected customers spread a negative WOM to one or more customers (54). The following section presents some relevant studies on the impact of social influence on customer retention.

(21) developed a model that integrates social network analysis with traditional churn modelling concepts. The model was applied to a dataset of over half a million subscribers, provided by a large mobile network provider. The dataset contained customer call detail records (CDR). To compute social tie strength, the authors used three attributes namely: 1) the number of calls placed between two users, 2) the total duration of calls between two users and 3) neighbourhood overlap of the two connected users. This study found users that make phone calls to numbers on a different network are likely to churn in future to save costs.

Similarly, (22) conducted a study investigating the impact of social networks on customer retention. However, the latter differs from the former in that it uses both networked and non-networked (customer-related) information about millions of users. The key finding of this study was that churn not only had an impact on customers' friends, it also had an impact on friends of friends.

Although the studies mentioned above have contributed to the knowledge of customer retention, they do not capture the possible factors as to why customers made their decision to churn. ABMS is able to capture the dynamics of customer behaviour (55). The next section presents a background on ABMS.

Agent Based Modelling and Simulation

Over the years, researchers and industry practitioners have attempted to apply different techniques to understand customer behaviour in the market place. The ABMS approach is a typical example of one of these techniques (56). ABMS provides an understanding of how systems work under certain conditions. ABMS works by creating scenarios that imitate real life conditions, for example, carrying out an ABMS exercise with customers who walk into a retail store. ABMS can be used in this context to derive insights on customer behaviour in the retail store (57). This process provides an explanation of the relationship between elements in a complex system. ABMS is composed of two main activities: modelling and simulation. Modelling is the process of representing real life events into a model while simulation is the process of executing the represented models such that they imitate the proposed system. Agent based models are composed of agents and a structure for agent based interaction.

Agents can represent anything from a number of patients in a hospital to consumers of a product or service. ABMs are often characterised by rules and these rules define the behaviour of agents in the system (47). These behaviours are often influenced by agent interactions with other agents in the system, making the outcome difficult to predict. In such cases, a balance may be difficult to reach, making the ability to study the underlying system and the dynamics of the behaviour imperative. ABM is distinct from traditional modelling approaches where characteristics are often aggregated and manipulated (49). Traditional modelling techniques for modelling maybe suitable for their purposes but they may not be able to provide adequate level of details in regards to the independent behaviours of agents. Although the commonly used data mining techniques for modeling consumer markets are powerful with regard to their purposes, they are generally not able to provide sufficient levels of detail with regards to the modelling interdependent behaviors of consumers in a market place

In addition, ABM is able to sufficiently represent interdependent systems even on a large scale i.e. incorporating a high number of factors, with each factor's level of detail and the behavioral complexity of those factors (57). ABM is a relatively new approach for modelling complex systems that are composed of interacting independent elements (47). The ABM technique can be applied to any aspect of a phenomena (47). ABM has been applied in various areas including economics (58), health-care (59), management science (47) and geography (60). In business, ABM has been applied to help decision makers understand underlying market structures and anticipate dynamics in the market place (47). ABM has also been utilised in artificial life research, to explore life in order to uncover how it might be, rather than how it actually is (61). ABM is also used in consumer modelling to understand and to predict consumer modelling process (62). Consumers are represented as independent agents with individual characteristics and an independent decision making process (63). Sellers are represented as agents who present their products with different characteristics into the market (64). In the study of social behaviour and interactions, ABM starts with a set of assumptions derived from the real world (deductive), and produces simulation-based data that can be analysed (inductive) (65). ABM must create a clear representation of what happens in reality so that every agent performs a task of an individual as if it is happening in social reality (64).

ABM has a number of benefits such as the ability to model individual decision making while incorporating heterogeneity and interaction/feedback (66). In addition, ABM has the ability to incorporate social/ecological processes, structures, norms and institutional factors (67). These advantages make it possible to couple human and natural systems in an ABM. This paper applies the design science paradigm as an overarching methodology with the application of the CADET approach to capture the dynamics in customer behaviour in a simulated environment. The next section provides a background on design science research methodology.

Design Science Research Methodology

Design science research is a multidisciplinary approach that primarily uses design as a research method or technique to solve a problem and learn from the process of solving that problem (68). Apart from its popular adoption in information systems, it is also widely used in disciplines such as education, engineering computer science, and health-care (69). March and Smith (70) describe DSR as a research methodology that allows research to produce relevant and improved effectiveness by strategically combining research output (product) and research processing (activities) from both natural and design science in a two-dimensional framework. The design science output or artefacts includes constructs, models, methods and instantiations while the natural science activities include build, evaluate, theorise and justify (70). The DSR output classification defined by (70) can help establish appropriate measures to build, evaluate, theorise and justify a DSR. The four research outputs are described below:

Constructs: Constructs are a set of concepts that are used to describe problems within a domain and specify their solutions. Constructs also form the vocabulary of a discipline.

Models: Are a set of statements which express relationships among constructs and represent real-world design activities in a domain (70). Models can also be used to suggest solutions to problems in a solution space.

Methods: Are a sequence of steps used to execute a task. These steps provide guidelines on how to solve problems with the use of constructs and models. Furthermore, methods can be described as a set of methodological tools that are created by design science and applied by natural science (70).

Instantiations: Are the utilisation of constructs, models and methods to showcase an artefact in a domain. They demonstrate the effectiveness of constructs, models and methods (70). Newell and Simon (71) describe the importance of instantiations in computer science by explaining how they offer a better understanding of a problem domain, and as a result, provide improved solutions. Instantiations provide working artefacts that can drive significant advancement improvement in both design and natural sciences. A DSR methodology incorporates five stages of a design cycle to address design research problem. These phases are designed to aid sustainable development during the research and transfer knowledge from one iteration to the next iteration until a desired result is achieved. The next section explains the DSR processes.

The Design Science Research Process

The DSR process follows a stepwise approach structured as five phases.

Awareness of Problem : The DSR process begins by identifying the problem under study. The identified problem may arise from multiple sources such as the literature or current problems in the industry. The research problem needs to be clearly defined and articulated. The output of this phase is a formal or informal proposal for new research. In this study, the main problem is identifying an effective approach

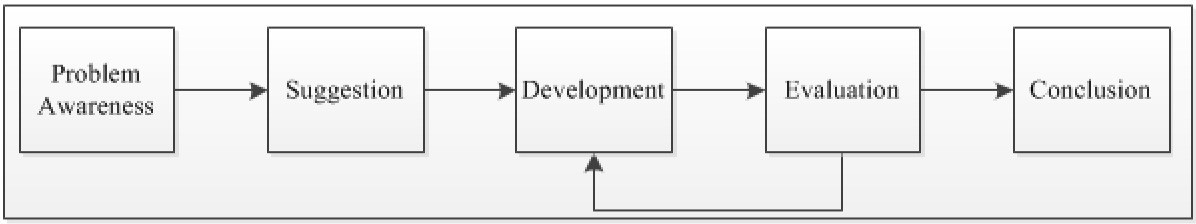

Figure 1. Design Science Research Process

to modelling customer behaviour as a means to improve customer retention.

Suggestion: This phase is explored when a research proposal has been presented. Possible solutions about the research problem are explored and evaluated, leading to the acquisition of further insights to the domain under study. The specifications of the appropriate solutions to the research problem are defined. The output of this phase is a conditional design or representation of proposed solutions. In this study, the CADET approach to ABMS is suggested in this phase.

Development: This phase involves further developing and implementing the DSR artefacts based on the suggestions from the previous phases. The outputs of this phase are the artefacts, which are core elements of the DSR process. (70) described DSR artefacts into four categories: Constructs, models, methods and instantiations. In this phase, the CADET approach to ABMS is developed using a selected machine learning algorithm.

Evaluation: The developed artefacts are analysed and evaluated according to the criteria set in phase 1 (awareness of problem phase). Deviations and expectations should be noted and explained in this phase. If the outcomes derived from the development or evaluation phase do not meet the objectives of the problem, the design cycle returns to the first phase, along with the knowledge gained from the process of the first round of work. These phase may be iterated until the evaluation of the artefacts meets the solution requirements. The outputs of this phase are performance management that should improve the efficiency and effectiveness of the artefact. In this phase, the CADET approach to ABMS is evaluated by its application to a telco dataset on an ABMS platform.

Conclusion: This is the last phase of the DSR cycle. The results of the research are written up and communicated to a wider audience in forms of professional publications and scholarly publications (72). Kuechler and Vaishnavi (73) categorise the knowledge gained in this phase as either firm or loose ends. Firm knowledge are facts that have been learned and can be repeatably applied or behaviour that can be repeatably invoked, while loose ends are anomalous behaviour that defies explanation and may well service as the subject of further research (73). The CADET approach to ABMS can be categorised as firm knowledge because it can be replicated on different datasets (both structured and unstructured) in various industries. The next section provides a summary of DSR evaluation.

Design Science Research Evaluation

Evaluation is an integral part of the DSR process. Usually, it is concerned with answering the question 'How well does the artefact work?' (70). The evaluation process provides an avenue to validate the performance of an artefact and measure progress according to the defined metrics (70). Artefacts are constructed to carryout specific problems, thereby, demonstrating their effectiveness in solving the problems. The process of developing an artefact may result in deviations from expectations. In this case, these deviations should be properly explained (73). Knowledge gained from the evaluation phase of one iteration can be applied into further iterations. Evaluation plays an essential role in DSR as it is iterative in manner. Hence, it is important to develop appropriate evaluation metrics to assess artefact performance and to measure the efficiency and effectiveness of the artefact developed (70). The criteria for evaluating the quality of an artefact depends on the artefact type (70).

Table 1 presents types of artefacts as described by (70) and their evaluation criteria. The main artefact derived in this study is the CADET approach and it is evaluated by applying it to a Telco dataset. The CADET approach was derived as a means to address the crucial problem of customer retention in the MSI. A number of studies in the literature have applied ABMS to address customer retention (74; 75), however, the CADET approach is different from other studies as it applies decision trees to model agent behaviour in an ABMS environment. The next section presents an overview of decision trees as a means to derive the CADET approach.

Decision Trees

A decision tree is an analytical decision tool that uses a tree-like graph and their possible consequences to arrive at a decision. The tree-like structure represents the relationships between events. Decision tree analysis is a method commonly used in data mining (76). The goal of decision trees is to create a model that predicts a target variable based on the input variables. Each leaf on a decision tree shows a connection to the target variable.

Decision trees are sequential models that logically combine a series of simple tests; every individual test compares a numeric attribute against a threshold value or a nominal attribute against a set of possible values (77). Decision trees consist of many nodes and branches in different stages and various conditions. (78). Decision tree analysis are popularly used for customer churn analysis in the MSI (35). In the case of this study, instances are classified into churn or no-churn. Decision tree models are usually represented in a top-down manner. The main aim of a decision tree is to derive a tree which solves a particular business problem and is easy to understand. To achieve such result, the decision tree undergoes two stages - tree building and tree pruning. Tree building is carried out using top-down

Name	Description	
Artefact	Brief Description	Evaluation Criteria
Construct	The conceptual vocabulary and symbols describing a problem within a domain	Completeness, clarity, elegance, ease of understanding and ease of use.
Model	A set of propositions or statements expressing relationships between constructs. Models represent situation as problem and solution statements.	Precision with real-world phenomena, completeness, level of detail, robustness, and internal consistency.
Method	A sequence of steps used to perform a task. A method can be tied to a particular model. A method may not be articulated explicitly but represents tasks and results.	Operationality (ability for the method to be reused), efficiency, generality and ease of use.
Instantiations	Application of constructs, models and methods to provide working artefacts.	Efficiency and effectiveness of an artefacts. Also, the influence of the artefact on its users and on the environment at large.

Table 1. DR Artefact Evaluation Criteria (69)

strategy (also known as a divide and conquer strategy). The process of tree building involves:

- Selecting the attribute for the root node.
- Splitting instances into subsets.
- Repeat recursively for each branch.
- Stop if all instances have achieved the same class.

A root node is selected by comparing the number of bits (splitting based on information gain) for possible root nodes and choosing the node that has the most bits of information. After selecting the root node, the next step is to look at the branches that emanate from the root node. The process of selecting the node with the most bits of information is repeated. This process continues until all instances have the same number of bits i.e. when there are no more classes to split on (accuracy is 100%). The tree pruning process involves eliminating error-prone branches. A pruned tree can improve a classifiers performance and can facilitate further analysis of the model for the purpose of knowledge acquisition. The pruning process should never remove predictive parts of the classifier. For better understanding of how decision trees work, the example below (Figure 2):

If (Contract length >=24 months, Location= midlands, priceplan <30 and data <4gb), then Churn = Yes.

A number of algorithms can be used to build decision trees. These algorithms include CART (Classification and Regression Trees), Chi-squared automatic interaction detector (CHAID), Iterative Dichotomiser (ID3) and C4.5 which is the successor of ID3. The CART algorithm is selected to build the CADET approach to ABM. The next section presents the CADET approach.

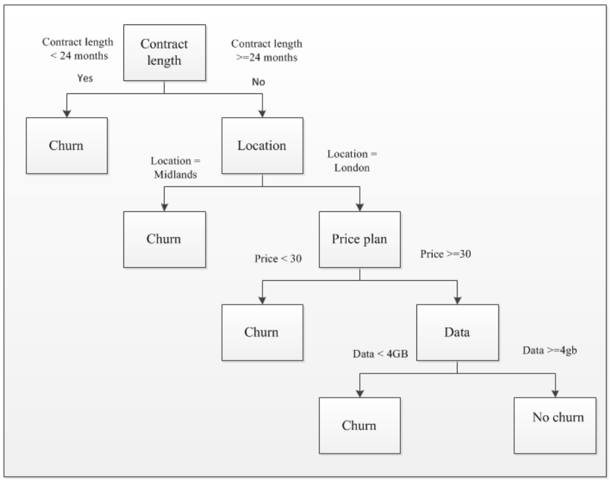

Figure 2. Decision Tree Classification Process

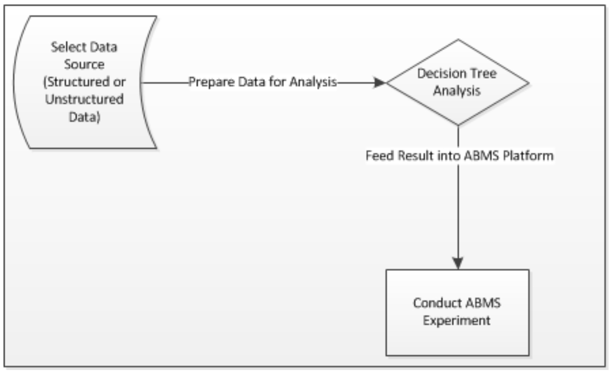

Figure 3. CADET Utilisation Process

The CADET Approach

A number of approaches techniques can be used to carryout ABMS. Researchers have extended agent oriented methodologies in two areas; object oriented (OO) methodologies and knowledge engineering methodologies(79). The three common views in OO technologies for describing ABMs are static for describing the structure of objects; dynamic for describing object interaction and functional for describing the data flow of the methods of the objects (79). The flow chat is another popular example for representing the process flow of an agent based model (1).

We present the CADET approach, a novel approach for agent based modelling using results derived from decision tree analysis. The CADET approach is derived by applying the CART algorithm to a dataset and visualising the tree-like structure derived from the analysis. The agent attributes are derived from the decision tree flow process. The CADET approach can be applied to various domains and industries.

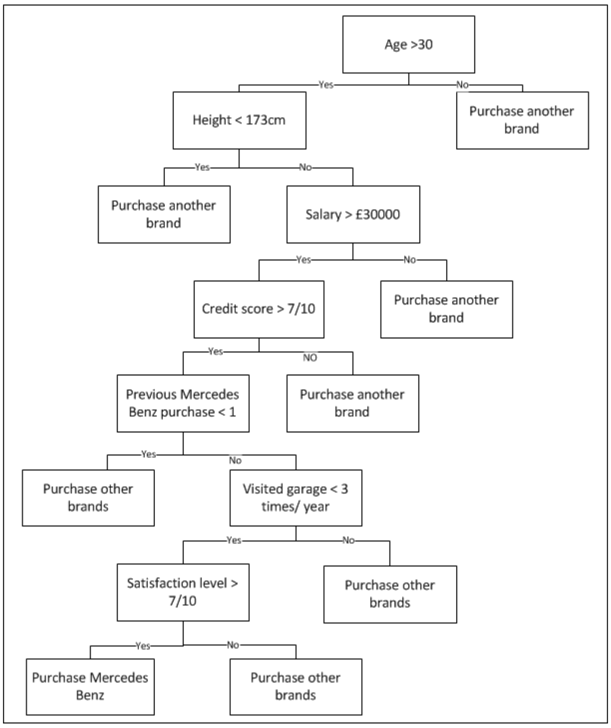

Figure 4. An example of describing an ABM using the CADET approach

To further explain the structure and functionality of the CADET approach, we present a scenario below;

A Mercedes Benz car dealership provides a number of products and services. In order to understand customer purchase behaviour, a decision tree analysis is conducted. The analysis is carried out to improve understanding on customer purchase behaviour. A decision tree approach is chosen to understand the trend and the pattern for the process of customer decision. The analysis shows that customers who have certain attributes purchase Mercedes Benz cars from the Mercedes Benz car dealership. The variables used for this analysis are age, height, salary, credit score, previous Mercedes Benz purchase, number of services/repairs and satisfaction level. The target variable is either to purchase a Mercedes Benz car or to go purchase another car brand.

The decision tree analysis shows that customers that are over 30 years old, are often interested in purchasing a Mercedes Benz while customers who are less than 30 years old often buy other car brands. The next variable on the decision tree is height. Customers with height less than 170cm often buy other brands while taller customers are often interested in purchasing Mercedes Benz. The next variable on the decision tree is salary. If salary is greater than 30,000, move to the next step, else consider purchasing other brands. The next step is credit score. If credit score is greater than 7, move to the next step otherwise, consider purchasing other brands. This process is followed until the end of the tree. Figure 3 displays a diagrammatic representation of the CADET framework and Figure 4 displays the decision tree analysis process described above. The TEA-SIM tool is used to validate the CADET approach. Hence, it is briefly described below.

TEA SIM Tool

Over the years, companies have spent a large amount of money on products and services that enable them manage and understand their customer behaviour more effectively.

Advertisement and word of mouth can be a powerful tools for customer retention. However, customers are often skeptical about advertisement and may turn to their family or friends within their network to seek advice before deciding whether to purchase or repurchase a product or service. Some companies have manipulated word of mouth by running schemes that offer customers benefits for expressing positivity about their product or service. As positive word of mouth is a great tool for marketing, negative word of mouth can also be a damaging tool for businesses. Dissatisfied customers of a product or service may share their experience about their dissatisfaction with members of their social network which can include family and friends.

The TEA-SIM tool is a data-driven agent based simulation platform (80) built by incorporating a cognitive process for understanding how the members of a small-world network (48) make decisions. In addition, the TEA-SIM tool is a decision support tool that can be adopted by various industries to model various entities such as customers, products and services. It also provides a medium for companies to see the interaction process between agents and how the interactions influence agent decisions. The result derived from this process can be used to provide information to organisations so that they can strengthen their customer relationship management (CRM) strategies by exploring the effect of word of mouth to improve customer retention.

The dynamic nature of the TEA-SIM tool provides a unique approach to understanding customer behaviour. It can be used to observe the pattern of customer interaction and perform further analytics to explore the possibilities of incorporating those patterns into the marketing strategies in order to increase revenues. The TEA-SIM tool also works as a generic model that captures the key drivers behind customer change of behaviour and it can also work well in a consultancy environment. It is a cross-industry tool that is not unique to any industry. Experimenting with the TEA-SIM tool proves that it can improve understanding on factors that can drive customer churn. The TEA-SIM tool is not a precise prediction tool. As a result, agent-based modelling is used to provide insight into the behaviour of a population of customers.

Applying the CADET Approach to a Real-World Dataset

Models are built for the purpose of mimicking real-world events. The CADET approach for conducting agent based modelling is a novel approach for building agent based models using decision trees. In this study, the decision tree analysis is used to describe customers that either remain with their mobile network operator (MNO) after their contract period and customers that leave their MNO after their contract period. The CADET approach shows that customers decision to stay or leave their MNO is driven by a set of subjective attributes.The attributes are the individual nodes on the decision tree. Mobile network customers may have attributes such as mobile phone type, customer location,

Name	Description
Contract length	Length of contract
Gender	Customer's gender
Sales channel	Company that delivered contract
Post code	Post code in which customer lives
County Name	The name of county where customer lives
Region	The region where customer lives
Devices	Name and model of device used by customer
Tenure	Number of months with the present mobile service provider
Life stage segment	Customer age
Number of complaints	Number of complaints throughout contact period
Q2_bytes	2nd Quarter Data Usage
Q3_bytes	Third Quarter Data Usage
Q2_Voice	2nd Quarter Voice Usage
Q3_Voice	3rd Quarter Voice Usage
No_of_Repairs	Number of times customer phone has been repaired
Prob_Handset	Number of Times Customer has reported problems with handset

Table 2. Dataset description

price plan and data usage. The decision to churn or stay is composed of a number of phases represented on the decision tree. The final node of the decision tree is customer final decision to stay with or leave a MNO. Decision trees consist of dependent and independent variables. The dependent variables are the nodes that make up the final node. These variables influence customers final decision. The primary purpose of applying the CADET approach for ABMS using the TEA-SIM application is to understand how much influence a customer's environment, family, and friends within their network have on customer retention. In addition, the CADET approach utilised with the TEA-SIM model provides information on the possible decisions a customer might make when they interact with other customers within their network or environment. We believe that if a customer meets another customer within the environment, and they share the same MNO, they may have a conversation on their overall customer experience and that conversation may influence a customers decision to renew their contract. The CADET approach to agent based modelling seeks to provide an understanding on how customer variables along with customer network can influence customer retention. The next section presents a description of the dataset used to conduct the experiment in this study.

Step 1	If tenure is $>$ or $<$ 24 consider the next node.
Step 2	If tenure is $\ngtr$ 24 and tenure $<$ 14, churn, else consider the next node.
Step 3	If tenure $\ngtr$ 24, and tenure $\nless$ 24, and device = samsung then churn, else renew contract.
Step 4	If tenure $>$ 24, and contract length $\ngtr$ 12, then churn else consider the next node.
Step 5	If tenure $>$ 24, and contract length $>$ 12, and region = midlands, then churn, else consider the next node.
Step 6	If tenure $>$ 24, and contract length $>$ 12, and region $\neq$ midlands, and region $\neq$ London, then churn else consider the next node.
Step 7	If tenure $>$ 24, and contract length $>$ 12, and region $\neq$ midlands, and region = London, and device = iphone 5, then churn, else move to the next node.
Step 8	If tenure $>$ 24, and contract length $>$ 12, and region $\neq$ midlands, and region = London, and device = iphone 5, and problem with handset $>$ 3, and gender = male, then churn else renew contract.
Step 9	If tenure $>$ 24, and contract length $>$ 12, and region $\neq$ midlands, and region = London, and device = iphone 5, and problem with handset $\ngtr$ 3, and number of complaints $>$2, then churn, else renew contract.

Table 3. Steps for Decision Tree Analysis

Dataset Description

To demonstrate the usability of the CADET approach, we collected a dataset from a UK telecommunications company. The dataset comprises of 19,919 observations and 16 variables. The dependent variable (output variable) for this dataset is whether the customer churned or stayed with their mobile Network operator after their contract. The predictor variables (input variables) are customers' data (such as type of device, price plan and region). The dataset contains 50% of customers who churned and 50% of customers who stayed with the MNO until the end of their contract. The dataset is based on a 24 month contract. Some customers stayed

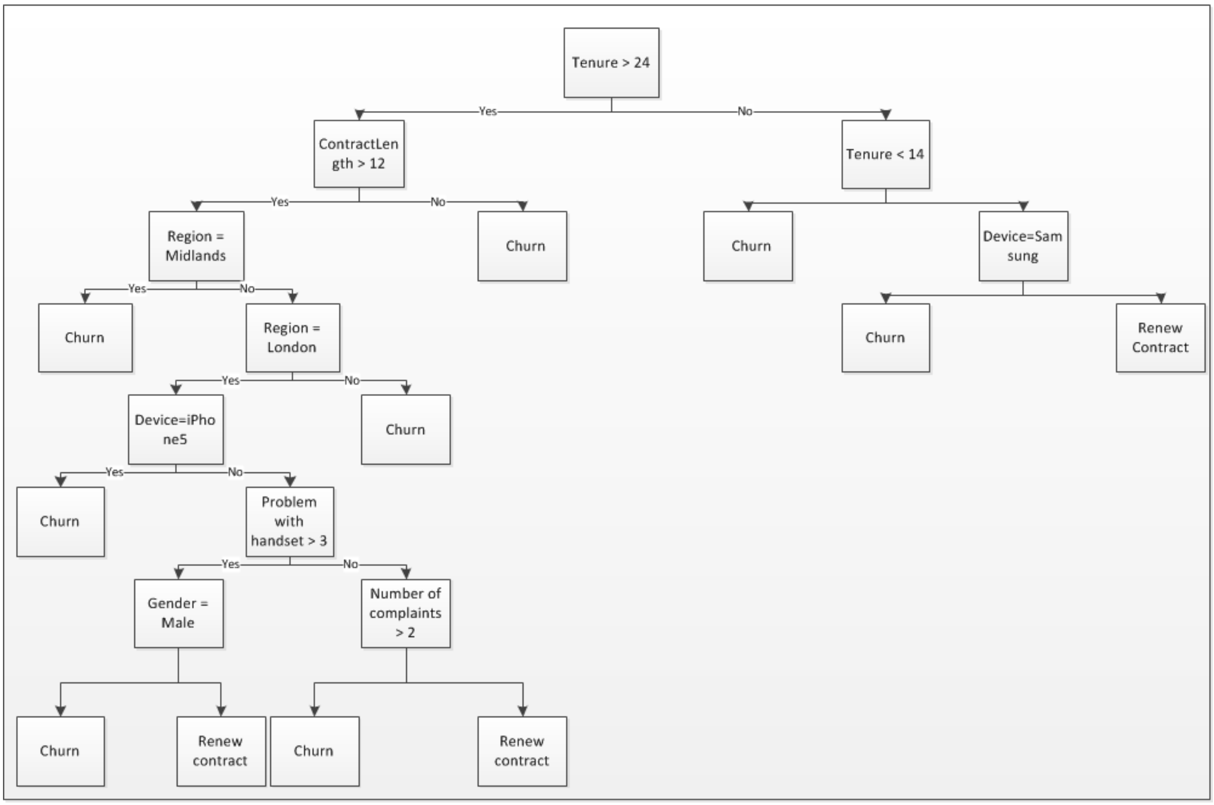

Figure 5. Decision tree analysis

with the MNO after the end of the 24 month period (i.e they renewed their contract) while other customers left the MNO after the 24 month contract. The dataset comprises of different data types as a means to represent the entire customer base. Table 2 presents a tabular description of the dataset. The next section presents details of experiment conducted.

Model Structure & Experiment

To apply the CADET approach with the TEA-SIM tool, the CART decision tree algorithm is run on the dataset described above and the result of the decision tree is visualised. From the decision tree (see figure 5), we can see the flow of the decision process for customers who have decided to stay with their MNO or move to a different MNO. Leaves of the decision tree instructs the required agent types (e.g. Churn or Renew Contract) and the earlier branching directs specific agent behaviour. The top of decision tree analysis shows that a customer's tenure is either greater than 24 or not. If tenure is greater than 24 then move to the next variable on the left. However, if tenure is not greater than 24, then move to the next variable on the right-side of the tree. This process continues until the end of the tree. The end of the tree displays the end result of the process i.e. either customer churned or renewed their contract at the end of the 24-month contract period. Figure 5 displays the decision tree analysis diagram.

To simulate this process, agents are fed into the Tea-Sim tool as json data definition. Agents behaviour within the ABMS environment is illustrated in figure 6. Agents typically communicate with other agents in the simulation environment and take actions after evaluating services provided by their MNO. To conduct the ABMS experiment, three files are created and run on the Tea-sim tool. The files are init.json, model.json and steps.php. The json files describe agent attributes and the ABMS environment. The php file describes the interaction process of the agents.

The init.json file (figure 7) is composed of the following attributes: grid, agent and simulation. n and m under "grid" represent the number of rows and columns required for the ABMS experiment. "Agents" is composed of agent type, instances and the position of the agents. The init.json files show that the instances are six in number and the position is random. "Simulation" on the init.json file represent the number of runs for the experiment. In this experiment, "start" is 0 and "end" is 25. This means that the agents in the grid should move 25 times.

The model.json file (figure 8) describes customer type and attributes. There are two types of customers with customer id 1 and customer id 2. Customer id 1 represent churn customers while customer id 2 represent stay customers. From the decision tree analysis carried out (figure 6.4), churn customers have the following attributes:

tenure $>$14, device = samsung, contract $>$12 months, region = midlands, region $\neq$ London, device = iPhone5, problem with handset $>$3, gender = male, number of complaints $>$2.

Furthermore, stay customers have the following attributes: tenure $>$24, contract length $>$ 12, region $\neq Midlands, region = London, device \neq$ iPhone5, problem with handset $<$ 3, gender = female, number of complaints $<$ 2.

The steps.php file (figure 9) describes agent interaction. To summarise the code, if a churn customer meets a stay

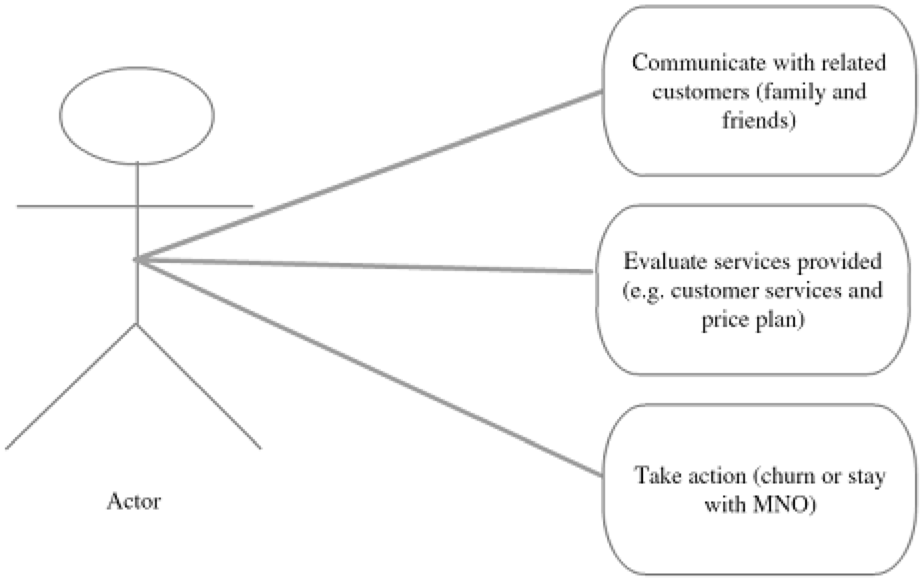

Figure 6. Conceptual Architecture of Customer Behaviour Modelling

```
{
"grid" :
        { "n" : 10, "m" : 10 }, "agents" :
        [ { "type" : "customers.1", "instances" : 6, "position" : "rnd"},
        { "type" : "customers.2", "instances" : 5, "position" : "rnd" } ],
        "simulation" : { "start" : 0, "end" : 25 } }
```

Figure 7. Init.json file

```
{
"customers" : [
{ "id" : 1, "name": "ChurnCustomers",
"attributes":[ {"name" : “tenure”, "value" : < 14 months} ,
{ "name" : “device”, "value" : samsung } ,
{"name" : “contract”, "value" : < 12 months} ,
{ "name" : “region”, "value" : midlands } ,
{"name" : “region”, "value" : !London} ,
{ "name" : “device”, "value" : iPhone5 } ,
{"name" : “problemsWithHandset”, "value" : > 3 } ,
{ "name" : “gender”, "value" : male } ,
{"name" : “number of complaints”, "value" : > 2} ,
{ "name" : "_img" , "value" : "img/ChurnCustomer.jpeg" } ] },


{"id": 2, "name": "RenewCustomers",
"attributes":[{ "name" : “tenure”, "value" : > 24},
{ "name" : "churn", "value" : false } ,
{ "name" : “contract length“, "value" : > 12},
{ "name" : "region", "value" = !Midlands} ,
{ "name" : “region”, "value" : London } ,
{ "name" : "device", "value" : !iphone5} ,
{ "name" : “problemsWithHandset” , "value" : < 3 } ,
{ "name": “gender”, “value” : female } ,
{"name" : “number of complaints”, “value”: < 2} ,
{ "name" : "_img" , "value" : "img/RenewCustomer.jpeg" } ] }]}
```

Figure 8. Model.json

customer, the stay morphs to a churn customer. The crying face in figure 10 represents churn customer and the smiley face represent stay customers. Overall, this experiment shows how customer behaviour can be influenced by the environment. Figure 10 shows the process in which the agents interact on the TEA-SIM model. The agents move from one grid to another and their decisions are based on the interaction with family/friends as represented in figure 10.

Conclusion

Customer retention is extremely important to mobile network operators because of the fierce competition in the MSI. Hence, companies in the MSI are increasingly strengthening the CRM strategies in order to retain customers. Numerous factors can influence the decision for customers to purchase or adopt a product or service. However, customers are likely to trust the word of mouth of someone in their network. This paper presents the CADET approach, a novel data-driven approach to ABMS, thereby developing artefacts in the process of study. March and Smith (70) describe artefacts as constructs, models, methods and instantiations. This paper presents a set or artefacts where each artefact contributes to the process of modelling and simulation. This study presents the CADET approach as a data-driven framework for ABMS. The CADET approach is utilised with a novel ABMS tool, the TEA-SIM tool. The application of the CADET approach on the TEA-SIM tool demonstrates the effectiveness of the data-driven process used to conduct the ABMS experiment. This effectiveness of this experiment demonstrates instantiation in the form, of a working artefact (70).

The TEA-SIM tool provides a generic approach for companies across industries to better understand their customers. In addition, the TEA-SIM tool can also help decision makers in organisations work on better strategies to understand customer behaviour, enhance customer retention, and subsequently improve CRM.

This paper also presents a real-life example of implementing the CADET approach using the TEA-SIM tool. The CADET approach was used to effectively provide an Agent-Based model using the results derived from decision trees. In this study, the CADET approach was applied to a dataset from a telecommunications company. However, the concept of the CADET approach can be extended and implemented in other industries such as health-care, manufacturing and financial services.

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```
<?php

class customers_ChurnCustomers extends Agent {
    function step($step) {
            if (!$this->churn && $this->anyNeighbour (1, 2, array("churn"=>false),
array("churn" => true, "_img" => "img/ChurnCustomer.jpeg"))) {
                    $this->churn = true;
                    $this->_img = "img/ChurnCustomer.jpeg";
            }
            $this->move(1);
            $this->morph(2);

    }
}

class customers_StayCustomers extends Agent {
    function step($step) {
        $this->move(1);
            }
        }
```

Figure 9. Stepper function for dataset

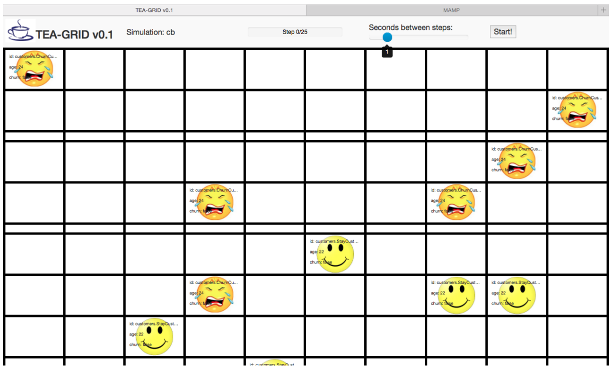

Figure 10. Agent interaction process

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