Challenges in Transition to m Commerce in Rural India

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ABSTRACT
With advent of m commerce the marketing and channel environment in rural India has changed drastically. India being a predominantly agricultural economy has lot of potential for m commerce marketing. With advent of legislative policy changes such as Digital India programme, m commerce is no option but is a necessity. With introduction of Payment banks, mobile applications and mobile commerce platforms rural India cannot remain in isolation. This *descriptive research paper* is aimed at studying the reasons for decreased mobile usage in rural India. This paper aims at providing a comprehensive literature review of relevant research work done in this field. Hidden Markov Model is an approach to study the temporal sequence of behavior in channel migration and channel choice. Various empirical models have been derived for different kinds of data distributions including univariate, bivariate and multivariate data distributions. An descriptive study to evaluate various kinds of models for different kinds of data distribution is aimed at identifying the best kind of Hidden Markov Model for studying the issue of channel migration in Rural India. The study concludes that Hidden Markov Model based on Multinomial Logit Regression approach is the best model to study the given problem.

Keywords
m Commerce, Hidden Markov Model, Literature Review

1. INTRODUCTION
With advent of m commerce, India is fast moving towards a multichannel environment. This multi channel environment will comprise of internet, m commerce besides brick – mortar and retail format. As per IAMAI the internet penetration is estimated to be 462 Million users in 2016 and 371 Million m commerce users. Despite all marketing efforts the reach of m commerce in rural area is abysmal. There is a huge digital divide between the urban and rural areas in terms of m commerce penetration .The rural population constitutes 78% of the total population in India. As per various studies hardly 24% of the rural population is digitally literate. The research study is aimed at identifying the role of training and other underlying behavior such as consumer experience in channel migration and the major challenges .(Deshmukh, Deshmukh, & Thampi, 2013)In their paper have highlighted the position of e – Commerce in India vis a vis M Commerce in India. They have calibrated that 72% of the young men contribute to the internet activity in India. (“M-commerce – The Next Generation Commerce,” 2016) by Confederation of Indian Industries has highlighted that the number of mobile users is slated to increase to 371 MN by 2016. As per the report the growth prospects of m commerce in India are far promising. The major policy changes by the Prime Minister Sh Narendra Modi have further laid emphasis on use of mobile for banking purposes. As per the survey conducted by Confederation of Indian Industries, the key reason for the increasing preference for m commerce is that 73% it saves time, 69% prefer m commerce since it leads to ongoing activity, 55% prefer it as it leads to reduction in waiting queues and 63% feel that it leads to multi-tasking. Various research studies have established the fact that m commerce has lot of potential in Tier II and Tier III cities in India. As per the various studies the major reason for increasing thrust on m commerce is the declining cost of smart phones and increasing user base. Indian is witnessing major disruption in field of m commerce with the advent of technology. India has an added advantage in form of lower bandwidth price and technology advancements such as VoIP (Voice over Internet Protocol). Despite the advantages, there is huge risk of digital frauds and data theft.

2. PROBLEM RECOGNITION
This research study is aimed at studying the various challenges in use of m commerce in Tier II and Tier III cities in India. In rural India comprising of Tier II and Tier III cities majority of population does not use mobile for commerce. Various studies have established that hardly 36% of the rural women are able to use mobile services for banking and commerce independently. They lack a mental model for setting up, configuring, navigating and transacting through the m commerce channel. The study is aimed at identifying the major issues in m commerce in a phased manner. And identifying a learning model to facilitate m commerce in rural India. A Questionnaire based study will be done to evaluate the problem and identify the barriers to use of mobile commerce.

The *Hidden Markov Model based on Multinomial Logit Regression* is proposed to capture the channel choice behavior of the customers in Tier II and Tier III cities in India, based on secondary and primary data to put in place a learning model. It aims at analyzing the impact of prior category experience and marketing promotions the latent factors on channel choice (observed factors).

Further a **Chi Square** nonparametric testing is proposed for testing the significance level.

3. RESEARCH METHODOLOGY
The first phase of the research is comprised of a comprehensive literature review of the published papers and research material on M- Commerce. The main objective is to identify the various factors that impact the implementation of M-Commerce in Tier II and Tier III cities. It aims at highlighting the various challenges to implementation of m Commerce. The major objective of literature review in this phase is to review the existing research material, to study the problem that has been studied by the researcher, study the methodology adopted and the type of research conducted.

The methodology adopted involved a two-pronged approach - (1) Review of Indexed Journals, Peer Review and Conference proceedings (2) Publications in non-review journal

4. PEER REVIEWED JOURNALS

In peer reviewed journals the research was done using the key words. The most relevant keywords were used to search for the research papers published in the relevant field and area. To search for the articles keywords such as mobile commerce, mobile banking, m commerce was being used to search for the research publications and articles. After defining the search criteria, the results were filtered on basis of their correlation to the main theme and scope of article.

5. DISTRIBUTION OF ARTICLES BY SUBJECT

The distribution of the article is shown in the table below. A majority of articles reviewed were in domain area i.e. Mobile Commerce, application, regulations and issues involved.

In the next phase sorting of the articles was done in order of their relevance to the research topic. The Literature Review comprises of most of the relevant research papers on Hidden Markov Model and m Commerce. The *Synthetic Matrix Table* containing the index of all the research papers along with the relevant details is compiled and is given below:

Table 1. Synthetic Matrix

Author	Year	Type of Study	Findings
Deshmukh, Deshmukh & Thampi	2013	Descriptive	Transition from e commerce to m commerce
Department of Information Technology	2015	Descriptive	Transformation to m Commerce policy
EWT Ngai	2007	Descriptive	ICT infrastructure & m Commerce
Strom R et.al		Descriptive	Theories of m Commerce
Tiwari et.al	2006	Descriptive	Convergence of Technologies
Priscila et.al		Descriptive	Advantages & disadvantages of m Commerce
Suryawanshi	2014	Descriptive	Evaluation of m Commerce
Muthu Kumar & Muthu	2015	Descriptive	Potential of m Commerce in India
Prasad et.al	2016	Descriptive	Role of m Commerce in India
Ratna n d		Descriptive	Study on Digital India
Author	**Year**	**Type of Study**	**Findings**
Jeanne Hogarth	2006	Descriptive	Role of digital literacy in increasing usage
Nirala Vishwadyalaya	2017	Descriptive	Role of digital media in Economic growth
Suryawanshi	2014	Descriptive	Technological Reforms & its impact
Jun Zhang and Zhang	2014	Descriptive	Hidden Markov Models
Ansari, Montoya & Netzer	2016	Descriptive	Hidden Markov Model
Chang & Chang	2012	Descriptive	Customer Relationship Management & Hidden Markov Model
Ascarza & Hardie	2009	Descriptive	Customer renewal & usage behavior
Rabiner & Gold	1975	Descriptive	Speech recognition theory
Zucchini & Macdonald	2009	Descriptive	Hidden Markov Models
Netzer et al	2008	Descriptive	Hidden Markov Model
Moon , Kamakura & Ledolter	2007	Descriptive	Promotion Response Models
Bansal & Taylor	1999	Descriptive	Multivariate Multinomial Model & Maximization Likelihood Estimation
Green & Frank	1999	Descriptive	Multinomial Logit Model & Marketing Model

6. M COMMERCE IN RURAL INDIA

(Care et al., 1992)**,** Department of Electronics and Information Technology, Government of India in their report have discussed the need to prepare India for the Digital India campaign. In the report use of mobile phone and bank accounts as the major reason for enabling participation in digital and financial space. The report highlights 4 major pillars namely broadband for rural India, Universal access to mobile phones, Mobile seva and information based services as the major area for research. The report has enumerated various mobile based information services and projects for rural India. It substantiates that Mobile Commerce in rural India not an option but a necessity.

(Ngai & Gunasekaran, 2007)in their descriptive paper have discussed the literature review done for mobile commerce. They have classified their research into five categories i.e. m commerce theory and application, wireless network infrastructure, mobile middleware, wireless user infrastructure and mobile application and cases. They have provided a distribution of the mobile commerce articles by subject matter. The authors in their article have emphasized the need to relate the impact of culture on m Commerce and lack of research in area of mobile banking and payment.

Matthew Zook et.al in their descriptive paper have discussed various contemporary trends in society including mobile phones and internet. The authors have highlighted various factors impacting the use of wireless technologies including market positioning, portability and user friendliness. The authors have emphasized the emergence of various patterns in changing patterns of mobility and communication. They purport as citizens' move toward a more interactive society, enormous amount of untethered information is generated leading to parallel globalization of the system. They further assert that untethered information has led to empowerment of people and accumulation of indelible tracks. They raise concern about the data privacy issues across the time and space. The recommend further research to harness the potential of the existing data storage in form of databanks.

Strom R et.al in their empirical paper have evaluated 64 qualitative papers to define and formulate a theory of m Commerce. The author has enumerated various mobile based applications and consumer based applications. The author has critically evaluated the works of various authors. They emphasize the classification of the market into various segment on basis of the level of usage as low, heavy and moderate usage. They have given a descriptive analysis of various models to highlight the value of mobile marketing for the consumers. They have discussed the TAM (Technology Acceptance Model) by Davis, TRA (Theory of Reasoned Action) by Fishbein and Azjen and theory of attribution model by Rogers. They highlight the interactive feature of the mobile phone advertising, push based advertising, increasing playfulness in increasing the mobile usage. They highlight various emotional, utilitarian and social values that affect the consumer preference as compared to the internet. The author enumerates the findings of various authors who emphasize the relevance of various emotional factors in adoption of mobile services and devices. Moreover, they highlight the importance of various social values in SMS advertising. They assert that in high involvement situation the mobile marketing will work complementary to the fixed internet Personal Computer. They assert the role of mobile advertising for frontline staff in increasing the efficiency and effectiveness of mobile internet. They have classified the mobile advertising into pull based and push based advertising. They emphasize the integration of pull based and push based advertising. They assert the usefulness of the mobile marketing in increasing the stickiness of the consumers. They criticize the importance of mobile marketing in reducing the competition in the market. They further substantiate the need for creating a body of knowledge about the mobile advertising.

(Tiwari, Buse, & Herstatt, 2006)in their paper have discussed the various synergies that originate from the convergence of technologies. They assert that m commerce originated from the convergence of information technology and technological telecommunications. They further highlight the wider contextual definition of m Commerce as encompassing broader features such as ubiquity, localization, immediacy, automatic connectivity and simple authentication procedure through SIM. They have emphasized the application of e Commerce for various purposes such as mobile banking, mobile banking, mobile entertainment, mobile information and mobile marketing. They have cited a case study to highlight the role of technology convergence in finding newer business opportunities. They highlight the importance of regulations and legal act and enactments for ensuring the compliance with the consumer protection act, 1986, maintaining confidentiality.

Priscillia et.al. in their descriptive paper have evaluated the concept of m Commerce and redefined m commerce. The author propagate that the thin line between mCommerce and eCommerce is blurring. They assert that m Commerce implies the use of multiple devices such as PDA (Personal Development Assistant) and mobile phones for transactional purposes. They have emphasized the various advantages of using m Commerce including convenience. They further elaborate the limitations in using m commerce including limited screen size of display, limited infrastructure in terms of power connectivity, They further describe the thin line of difference between the m Commerce and e Commerce. They argue that e Commerce is far wider in context and they have emphasized that m Commerce is relevant due to the feature of immediacy, ubiquity and mobility.

7. FACTORS AFFECTING CONSUMER BEHAVIOR

(Suryawanshi, 2014) in their analytical paper have discussed the potential of m commerce in India. They have highlighted the various factors that impact the use of m – Commerce including personalization, privacy, mobility, immediacy factor and localization. They have emphasized the major challenges to m commerce in India as data transmission state, wireless infrastructure, security and privacy.

(Muthukumar & Muthu, 2015) in their descriptive paper have highlighted the potential of mobile commerce in India. They cite the availability of budget smartphones availability at EMI plans as the major reason for increasing thrust on mobile commerce by various private players like ICICI Bank. They have emphasized the astonishing rate of growth of 200% in number of internet users in year 2014 to augur well for the mobile commerce in rural India. They have identified Entertainment as the major category spend segment in m commerce in India. They have asserted that the increasing disposable income of the rural families, easy access to credit, growth in modern format, rapid urbanization and trend towards nuclear family as the major driver of m commerce in rural India They have citied the findings of report by Internet & Mobile Association of India (IAMAI) to support the major urban and rural divide as the major area for future growth. However, they propagate that increasing penetration of smartphones in India is the major area of growth. They conclude that major reason for urban rural divide is illiteracy and lack of know how. They assert that increasing digital financial literacy has a far greater role to increase the usage of m commerce in rural India.

(Prasad, Gyani, & P.R.K.Murti, 2012) in their analytical paper have highlighted the increasing role of m commerce in India. They have provided astonishing facts regarding increased mobile usage from 7.94 Lakhs to 52.41 Crores in India. They recommend the use of mobile commerce particularly to address the issue of remote location. They have cited the case study of ICICI Bank, Airtel, Tata and Reliance which have been using this channel to cater to the needs of Rural India. They have highlighted the advantage of using m commerce as accessibility, connectivity, security and ease of use as the main reason for promoting the use of m commerce in India. They have cited the use of mobile commerce mainly for mobile financial services, user specific mobile advertising, inventory management, wireless business engineering, and interactive games. They propagate that the introduction of various m services like mobile wallet, social media such as Facebook as the major drivers of m commerce in India.

(Ratna n.d.) in their study on Digital India have discussed various mobile initiatives and their role in promoting development. They have discussed the role of interactive mobile applications, and mobile phone information dissemination.

8. ROLE OF DIGITAL FINANCIAL LITERACY

(Care et al., 1992) in their ethnographic study titled Accelerating digital literacy and empowering women have propounded a grounded theory of propagating use of m commerce in India . The report attributes the lack of digital and financial skills as the major reason for lack of usage of mobile phone by women in India. Their findings support the fact that lack of knowledge to set up internet, search and navigate, create content and configure content as the main reason for failing to use m commerce. The report argues that women face dilemma and are not aware about the phenomena of using a mobile phone for commerce. They further purport that women are not comfortable learning on their own and need a social environment. The cross nation study of Kenya and India has been done to establish the fact that women are not initiators in learning new skills. The report lauds the initiative taken by various players such as Airtel, ICICI Bank, Garmin Foundation in propagating the use of mobile phones in Tier II and Tier III cities in India. They emphasize the role of m commerce in empowering women through participation, inclusion and decision making. Technical literacy have been sighted as the major reason for increasing the mobile usage in rural India. The primary study done by GSMA establishes the fact that an average woman in rural India is not comfortable setting up, navigating, configuring and using m commerce. The analysis of the usage of mobile phone in rural India establishes the fact the rural people use mobile phone mainly to receive calls, send SMS and listen to music. The urban and rural divide was visible in lack of usage of mobile for social networking in rural India. The study

further emphasizes the use of vernacular language to propagate the use of m Commerce. They cited difficulty in understanding content as the major reason for lack of mobile usage. The report has put in place a four dimensional learning model – independent learning, social network, community resource person and formal training. Lack of social environment support and incentives besides knowledge and awareness were cited as the major reasons cited for non-usage. In the initial stages as per the report social learning and formal training are the best means to incentivize learning through formal training programmes.

(Hogarth, 2006) in their study have highlighted the role of financial literacy in increased usage of m commerce and better financial planning. They emphasize that increasing financial complexity and advent of financial products have increased the need for financial literacy. They create a contrast effect by comparing the decisions made in absence of financial literacy with informed decisions. They further substantiate the role of legislative policy changes such as m commerce in increasing the need of financial literacy.

(Nirala, Vishwavidyalaya, and Vishwavidyalaya 2017) in their paper have highlighted the role of Mobile, tablets as the major drivers of economic growth through m commerce. They have highlighted the role of various legislative policy measures such as Digital India campaign in driving m commerce in Rural India. Their exploratory study is aimed at identifying the major barriers to m commerce in India. They have recommended increasing technical literacy as the major barrier beside lack of mobile penetration and infrastructural issues. They emphasize that advent of mobile channels like payment banks and mobile-Pesa has made it imperative to transition to new technology.

9. HIDDEN MARKOV MODEL

Hidden Markov Model refers to the recognition of the temporal patterns. Temporal Patterns are the patterns that unfold with time. The major applications of temporal sequence are activity recognition, sign level recognition, natural phenomenon to name a few. The channel migration from brick mortar e commerce to m commerce is a temporal sequence and can be analyzed and classified using Hidden Markov Model. In any activity like channel migration, based on input the system will migrate from state Si in time interval t to Sn in time t+n. When it makes the transition in the next state it will emit an output. The output can be identified on basis of input and hence output is unobserved and input is observable. Based on this data state transition matrix can be generated which enumerates the finite set of state through which the system transitions. And similarly the output matrix can be generated from the finite set automata. Hence, Hidden Markov Models comprise of two states namely, ῳ which represents the invisible which cannot be observed and the visible state ϕ which can be observed. Hidden Markov Model has lot of applications in process identification. The starting point of the sequence is the

In model more than 1 invisible state can be classified as ῳ1, ῳ2, and ῳ3. In a hypothetical Markov Model $^{\theta}$ generated in a process, we can have number of invisible states ῳ1,ῳ2 and ῳ3…ῳn which cannot be observed by the perceiver. V is the visible state that are emitted by the Markov Model when the model is in a previous state and let the visible state can be ϕ1, ϕ2, ϕ3. The probability of transition from state ῳ i (t-1) to ῳj (t) can be expressed as aij. This can be expressed as transition matrix in each of the state. In each state the process can generate one of the visible states. Let's assume is state ῳ1 the process can generate visible symbol ϕ 1. The probability that the process generate symbol ϕk when the process is in state ῳj can be expressed as P (ϕk/ῳj) = bjk.

10. ASSUMPTIONS OF HIDDEN MARKOV MODEL

- The probability of particular state depends only on the previous state

$$P(\acute{\omega} i \mid \acute{\omega}1 \ldots \acute{\omega} i - 1) = P(\acute{\omega} i \mid \acute{\omega} i - 1) \quad \ldots\ldots.(1.1)$$

- The probability of an output observation oi depends only on the state that produced the observation qi and not on any other state or any other observations

$$P(vi \mid \dot{\omega}1 \ldots \dot{\omega}i, \ldots, vT, v1, \ldots, vi, \ldots, vT) = P(□^{□} \mid \dot{\omega}i) \quad \ldots\ldots\ldots(1.2)$$

- Each Hidden Markov Model has one accepting state and all the transitions take place in that accepting state.

11. MARGINAL DISTRIBUTIONS

The marginal distribution of Xt and higher order marginal distribution, such as (X, Xt+k). In this research paper derivation as per (Walter Zucchini, 2016) for state – dependent distributions are given below. For continuous distributions, the derivations can be done analogously.

12. UNIVARIATE DISTRIBUTION

For discrete valued observations □$^{□}$, probability of the unobserved observations P($^{\theta}$t=i) is defined as ώ(t) for t = 1,…….T. Further we derive:

P (□$^{□}$ = t) =∑P (ὠt =i). P(□$^{□}$=t/ὠ=i) = ∑u(t)p(x)……(1.3)

The expression can be further simplified as:

P(X) = (u1(t)…………..um(t)(Transition Matrix)*(1). In this expression p(x) denotes the diagonal matrix with its diagonal element being pi(x). This expression is true for a homogeneous and not for stationary Markov chain

13. STATIONARY MARKOV MODEL

In case of univariate stationary distribution $^{\delta}$, then result is $^{\delta}$P(X). Invariably for a stationary distribution the probability will be 1.

14. CENTRAL ISSUES IN HIDDEN MARKOV MODEL

Hidden Markov Model is characterized by three fundamental problems:

Problem (Likelihood): To determine the likelihood P (O) given an HMM λ = (A, B) and an observation sequence O

Problem (Decoding): To discover the best hidden state sequence Q given an observation sequence O and a Hidden Markov Model λ

Problem (Learning): To determine the parameters A and B of the Observation sequence O and the state of states in the Hidden Markov Model. This is the problem to train the Hidden Markov Model or the classifiers learning i.e. the ability to learn the patterns.

15. LIKELIHOOD COMPUTATION

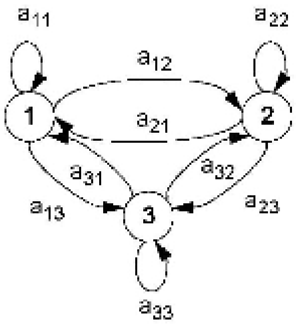
Likelihood Computation: Forward Algorithm

The Likelihood Problem is to determine the likelihood P (▯▯|ᶿ), (where ▯ is the visible states and ᶿ is the hidden state) given a Hidden Markov Model λ = (A, B) and an observation sequence O.

Ergodic Hidden Markov Model

Hidden Markov Model in which there is (non –zero) probability of transitioning between any two states. Such a Hidden Markov Model is fully connected is called Ergodic Hidden Markov Model. Sometimes in some of the Hidden Markov Model, in which transitions between the state have zero probabilities.

Figure Number 1: Transition Probabilities



In the Hidden Markov Modelᶿ there are 3 hidden states ῳ1, ῳ2 and ῳ3 and 3 visible states denoted by ▯▯. The probability of transition from ῳ1 to ῳ2 is *a12* and *a21* respectively. The probability of transition from 2 to 3 is *a23* and from 3 to 2 *a32.* The probability of transition from 3 to 1 is *a13* and from 3 to 1 is *a31* and from 1 to 3 *a13.* The probability of staying in state 1 *a11*, in state 2 is *a22* and state 3 is *a33.* In the state ῳ1 the emission will be made with probability *b11, b12* and *b13* , in the state ῳ2 the emission will be made with the probability *b21, b22 and b23* and in the state ῳ3 the emission is made with the probability *b31, b32* and *b33.*

For a Hidden Markov Model the likelihood problem is to determine the likelihood P (▯▯|ᶿ) or the probability of the visible state given the transition matrix. The visible states λ have probability function *b11, b12 and b23* and unobserved sequences has probability function *ῳ1, ῳ2 and ῳ3for* each of the observed state.

In case of Hidden Markov Model for recognition of temporal sequences there could be *n* number of model sequence. For every sequence there will be 1 hidden sequence and hence total of n number of hidden sequences denoted by ᶿ1…..ᶿn. An input sequence is to be classified to one of this sequence. Every sequence or class is to be represented by a separate Hidden Markov Model. Hence ᶿn will have its corresponding ώi, ώj and ώk. Applying Bayes Theorem the probability P (▯▯|ᶿ) can be calculated.

Bivariate Distribution

In such a model where there is N number of hidden states, we will have ▯▯number of hidden states. Then

- P(w_r^t) = $\prod_{r=1}^{t}$P(w(t)/ώ(t-1), is the product of probability of transition from time step t to t-1 for rth sequence of hidden state
- P ($v^t/w^{t)}$=$\prod_{t=1}^{T}$ P (V(t)/w(t)), is the probability of visible emission given a particular state.
- P($v^{t/\theta}$) =∑∏P(v(t)/w(t)).p(w(t)/Pw(t-1))……(1.4)

After having calculated the joint probability of the observations with a particular hidden state sequence, the total probability of the observations can be calculated by summing all possible hidden state sequence:

P(0)= ∑ $P(0,Q) = \sum_{T=1}^{n} P(\frac{0}{Q}).P(Q)$ ……..(1.5)

In case of a particular case the event sequences are summated. There will be NT possible hidden sequences for Hidden Markov Model with *N* hidden states and observed sequences of *T* observations. In case of very large number of hidden states and observed sequences, the total observation likelihood for each hidden state cannot be calculated. To resolve this issue the recursive **Backward and Forward** logarithm can be used given by **Baum Welch** can be used. The algorithm explains, that given a sequence of visible state what is the probability that the model will be in a particular state at step t-1.The first assumption is that the process begins in an absorbing state ώ0.

State t=0 t=1 t=2 t=3 ……..tn

ώ0
ώ1
ώ2
ώ3
….ώi

ώ0 is the only absorbing state and no transition can be made from this state. Let's consider the probability of making the transition from ώ2. The probability of being in a particular state ώ1at time (t-1) is α1 (t-1), ώ2 at time (t-2) is α2 (t-2) and ώi is αi (t-i). The probability of transition from ώ1 to ώ2 is a12; from ώ2 to ώ2 is a22 and so on. Hence the probability of making transition from ώ1 to ώ2 in time step t is sum of the product of α2 (t-2) x a12, and from ώ2 to ώ2 is α2 (t-2) x a22 and from ώ1 to ώi is αi (t-i).x aii and so on. The probability of emission of visible sequences is vt visible symbol in time step t in this state 2 is given b2t. The probability that the process is in state ώ2 in time step t after having emitted visible symbol vt is sum of all the transition probabilities multiplied by b2t. The probability can be expressed as:

αi (t) = 0 ; if t =0 and j is not initial state; if j is initial state then it will be 1

Otherwise $\alpha i(t) = \sum \quad \alpha i\big(t-1\big)aij)bjkvt$……(1.6)

Hence algorithm for probability that HMM ᶿ has generated the visible symbol v^t **(Forward Algorithm).** For t incremental t+1

$\alpha j(t) = bjkvt \sum_{k=0}^{n} \quad \alpha i\big(t-1\big)aij$………(1.7)

16. SCALING THE LIKELIHOOD OF COMPUTATION

In case of the discrete state dependent distribution, the elements of αt, being made up of product of probabilities, become progressively smaller as t increases, and eventually round up to zero. In fact with the probability 1 the likelihood approaches 0.

The likelihood is a product of the matrices, not of the scalars; it is not possible to circumvent numerical underflow by simply computing the log of likelihood as the sum of logs of its factors. In this respect the computation of the likelihood of an independent mixture model

17. MAXIMIZATION OF THE LIKELIHOOD OF CONSTRAINTS

Reparameterization to avoid the constraints

The elements of τ and those of , the vector of state defendant means in a Poisson Hidden Markov Chain are subject to the non-negatively and other constraints. In particularly the sum of the rows is equal to 1. Estimation of the parameters should satisfy such constraints. Thus when maximizing the likelihood we need to solve a constrained optimization problem, not an unconstrained one. The special software such as NAG are used for this purpose. In general there are two group of constraints: that apply to the parameters of the state defendant distributions and those that apply to the parameters of the Markov Chain. In case of the Poisson Hidden Markov Model relevant constraints are:

- The means λi of the state dependant distributions must for i = 1….m should be non-negative
- The rows of the transition probability matrix should add up to 1, and all the parameters Ύij must be non – negative

The constraints can be imposed by making transformations. The transformation of the parameters λi is easy. Define $\eta i = \log \lambda i$ for i = 1……m. Then $\eta \in R$. After we have maximize the likelihood with respect of the unconstrained parameters, the constrained parameters estimates can be obtained by transforming back $\lambda i = \exp \eta i$.

The Reparameterization of the matrix τ requires more work, but be accomplished quite elegantly.

Using the above t

rn $P(\frac{V^T}{\theta})$ ***is α0(T) the state ends there***.

(Blunsom 2004) has recommended Baum Welch – Forward backward algorithm to compute the likelihood of a particular observation sequence.

The Hidden Markov Model has two states, namely unobserved state or the latent state and the observed state. Given these 2 states, we can find out the transition probabilities as aij and bjk, where aij is the transition from state ϕ i at time t to ϕ j at time (t-1). Both ϕi and ϕj are the hidden states and the probability of emission is given by bjk. The problem is to generate the transition probability and emission probability. Different methods can be used to solve this. There always a transition to one of the state from another state, so the sum of probabilities is equal to 1. This will be true for all values of i

$$\sum \quad aij = 1 \ldots\ldots\ldots\ldots(1.8)$$

When machine is any state it emits a visible symbol with probability bjk. And the summation of the probability bjk is equal to 1 for all values of j

$$\sum \quad bij = 1 \ldots\ldots\ldots\ldots(1.9)$$

18. DECODING PROBLEM

We can have n number of temporal Hidden Markov Models from $^{0}1$, $^{0}2$…^{0}n, we can have corresponding visible states v1tovn. The problem is to find out the most likely sequence t of hidden state that has generated v^t

19. LEARNING PROBLEM

In a Hidden Markov Model, the observed state and hidden state are known. By using a large number of training sessions aij the probability of observed state and bij, probability of unobserved state is to be calculated.

20. LITERATURE REVIEW

(Suryawanshi, 2014) in their paper have highlighted the massive technology revolution in India leading to manifold increase in mobile subscribers. As per the paper the total number of mobile subscribers in India has jumped from 261 Million in 2007 -08 to 910 Million in 2013 – 14. The authors emphasize that the rate of growth in number of internet users is increasing at the rate of 58% annually. The number of smartphone subscribers is expected to grow at CAGR 91% from 2012 through 2016, jumping from 29 Million to 382 Million. The authors have tried to highlight the major gaps in research in terms of digital security and privacy issue.

(Zhang, Jun, & Zhang, 2014) have proposed the Hidden Markov Model for an infinite number of states. They argue that the Infinite Hidden Markov Models are the nonparametric Bayesian extension of the Hidden Markov Model. They argue that in order to make better prediction and inferences, the Infinite Hidden Markov Model was introduced. Hierarchical Dirichlet process of Hidden Markov Model was used as a non-parametric model to accommodate infinite number of Hidden Markov states.

(Ansari, Montoya, & Netzer, 2012)proposed the Hidden Markov Model to capture the donation behavior of the individuals. (Zucchini and Macdonald 2009) proposed the most comprehensive Hidden Markov Model theory for time series. The author proposed that HMM (Hidden Markov Models) is the models that generate observation based on underlying unobserved criteria. The authors assert that the players employ learning rules as Experience Weighted Attraction Model to determine what actions to choose. They have developed a hierarchical non-homogeneous Markov Model based on various kinds of learning rule. They have empirically derived the attraction strategy for individuals in different scenarios and under different learning rule. They have used inverse logit transformation to reparametrize and develop the parameter estimate.

(Chang, 2012) have contended that CRM (Customer Relationship Management) plays an increasingly important role in reducing the churn and increasing the retention in the multichannel environment. The authors assume that consumers are heterogeneous in both transition and channel choice. They have proposed a multinomial Hidden Markov Model (HMM) to address the change in preference of purchase incidence and channel choice across the time. In their study, the authors have emphasized the importance of customer segmentation through Latent Class Model (LCM). However, the authors purport the importance of multi segment HMM (Hidden Markov Model) to capture the dynamic changes over the time and cross-sectional heterogeneity. They argue that customer purchase experience and the underlying learning behaviour are the main latent factors that impact the channel choice in purchase decision. As per the authors category experience and the learning during the purchase experience are the most important factors that impact purchase decision. Their research further recommends examining the spill over impact of the learning in purchase behaviour.

(Ascarza & Hardie, 2013) have emphasized the increasing role of retention and churn rates in marketing of products. They emphasize that retention is not the only criteria but it is the usage that impacts the payoff business. They propose a dynamic latent trait model that incorporates usage and renewal behavior simultaneously. Their model forecasts the usage and renewal behavior in the settings where usage is not known in advance. In their model they assume that the renewal process is always binary and renewal process is absorbing. They assume that every consumer has a latent behavior which is called “commitment” which follows the dynamic stochastic process. The authors as opposed to other researchers pioneered the customer usage and renewal behavior in contractual setting.

(Rabiner & Juang, 1986) have developed a speech theory for speech recognition based on observed symbols by drawing an analogy between the linear or nonlinear, time varying or time variant, deterministic or stochastic Markov model. . (Rabiner and Gold 1975). Compared the **Baum Welch algorithm** and **Viterbi Algorithm** and concluded that Viterbi Algorithm optimizes the previous states instead of the observation probability. Whereas the Baum and Welch forward and backward algorithm is based on Expectation Maximization (EM). This algorithm is used to optimize the probability of the observation sequence, being in a certain state. In context of speech recognition theory the authors have emphasized the use of these algorithms in Hidden Markov Model training. The authors have highlighted the significance of these algorithms in parameter estimation for the hidden state sequences. They have discussed the method of Expectation Maximization method of calculation of hidden and observed probabilities in a Hidden Markov Model. They have defined the F (k, i) = Probability of being in state Si having seen O0, O2, O3, O4…..On with m as the length of observation. They have defined the probability of observed sequence as P (Observed sequence) = Sum of P (O0, O1, O2….Sp).

The authors have demonstrated that in a Hidden Markov Model there are mainly three problems namely – probability of observation sequence, probability of choosing the state sequence given its observation sequence and how to define the model parameters. They have discussed the main type of Hidden Markov Models as ergodic and non ergodic model. The authors have further highlighted the major issues in implementation of the Hidden Markov Model. They have criticized the Hidden Markov Model for computational issues concerning the implementation of forward backward algorithm, finite set of training for computing the parameters and need to design formulas to handle the multiple observations.

(Zucchini & Macdonald, 2009) have propounded that “Hidden Markov models (HMMs) are models in which the distribution that generates an observation depends on the state of an underlying and unobserved Markov process”. (Zucchini and Macdonald 2009) have applied marginalization to calculate the probability of occurrence of events. The authors have propounded the model to estimate the state sequence, given the observation sequence and transition matrix. The author have propounded the marginal distribution of hidden markov model and underlying the parameter process of the model. They have discussed the process of parameter estimation, point and interval forecasting, decoding and model estimation for various distributions including binomial and Poisson distribution. The authors have generalized the Hidden Markov Model for univariate, multivariate, bivariate, discrete and continuous mixture distributions. (Netzer, Lattin, and Srinivasan 2008) have used the Hidden Markov Model to study the dynamics of customer relationships. The authors have constructed the non-homogeneous Hidden Markov Model to model the latent relationship state and its impact on buying behavior. The authors have proposed the transition between the states as the function of time varying covariates such as customer firm encounters. They have used the hierarchical Bayes approach to capture unobserved relationship state. They have asserted the importance of dynamics of customer relationship and significance of various customer encounters in transitioning the customer from one state to another. The authors propound that various discrete encounters such as service encounters, customer initiated encounters, exposure and response to marketing actions initiated by the firm including building the relationships using the marketing databases. They have propounded various models to incorporate the unobserved part of the propensity for transition using the Ordered Logit Model.

(Netzer, Lattin, & Srinivasan, 2008) in their article have stressed the importance of customer relationship management. They argue that the set of customer encounter and customer interaction impact the set of customer relationships over time. They have put in place an empirical Hidden Markov Model to relate the latent behavior with purchase behavior. They emphasized the need for an integrated database to facilitate marketing. They have recommended the use of Markov Chain Monte Carlo hierarchical Bayes procedure to define the relationship state dependence on purchase behavior of the customers.

(Moon, Kamakura, & Ledolter, 2007) in their paper have critically evaluate the existing promotion response models have ignored competitive promotions. They have proposed a random coefficient hidden markov model in which competitor’s behavior as the latent behavior to be evaluated simultaneously with the promotion response model. They have put in place a model to forecast and estimate the response of clients to the marketing communications. From the time series data they have estimated the Hidden Markov Model. They have evaluated the promotion response in an empirical framework using SUR (System of Regression), Regression without competitor and Latent variable regression model.

(Bansal & Taylor, 1999) have developed a multivariate multinomial Logit markov framework and statistical procedure to evaluate the consumer switching behavior. They have used a Maximum Likelihood Estimation procedure with explanatory variables utilizing the general least square method to estimate the multi brand switching behavior of the customer. As part of the diagnostic approach the author has recommended the application of first order Markov Model for describing the consumer switching and customer loyalty measures. As an alternative approach the author has suggested the multivariate multinomial Logit Markov framework to study the consumer switching behavior. In the paper they have critically evaluated the work of various authors. They have drawn a crisp comparison between the zero order models, first order markov models and infinite state markov model. They have emphasized the need to consider the effect of the explanatory variables such as marketing mix, customer segmentation variables and its impact on brand choice probabilities. They have empirically validated the binomial logit based brand choice model, Poisson distribution based marketing mix model. They have propounded a Maximum Likelihood Estimation based Model for implementation.

(Green & Frank, 1966) in their paper have highlighted the need to include the behavior of the consumer to the changes in the Marketing Mix variables. They have propounded a Multinomial *Logit Model* to predict the response of the consumers to the changes in the marketing mix variables in the product characteristics. They have critically evaluated the Bayesian inference model by performing a cost benefit analysis. The author has tried to highlight the various limitations of the model in terms of formulation of the prior, requirement of a likelihood function and the computation of the integrals.

21. EXPERIMENTAL ANALYSIS

The purpose of this research is to capture the transition to M Commerce in Rural India. The data for this analysis was collected from the Primary survey conducted in Akodara village, Gujarat. The Markov model comprises of two states, using Branch Banking and using Mobile Banking. There are two possible state of emissions. The model uses :

Branch Banking having two states – ATM and Public Banking

- Mobile Banking having two states – Mobile Applications, Mobile internet
- Digital Literacy Workshop, for which probability of using Digital Media is 0.80 and other Media is 0.2
- Marketing programme for which probability of using digital media is 0.60 and other Media is 0.40

  The Model will create the sequence (ATM, Public Banking, Mobile Application and Mobile Internet) with the following rules:
- Captured the data of people using Branch Banking and noting down the channel that is being used, which is the emission
- Conducting a Digital Literacy workshop and observing the result over the next few days
  - If result is Branch Banking, do a Marketing promotion and note the result
  - If the result is Mobile Banking, continue with Digital Workshop and note the result

22. CONCLUSION

The Hidden Markov Model is one of the best techniques to understand the impact of the hidden factors such as marketing and promotion in case of consumer durables on Brand Equity or Brand behavior of the product. This model is being used frequently for speech recognition, labelling and tagging problems. It helps to identify the state of sequences at a given point of time, as a joint probability distribution of observations given the hidden state sequence. [16] has introduced the idea of Hidden Markov Model to identify three fundamental problems pertaining to likelihood, learning and decoding problem. Maximum Likelihood Estimation (MLE) technique could be used for estimating the probability of a particular sequence given the series of observation and latent state sequences. Baum Welch forward backward algorithm and the Viterbi algorithm are the most popular techniques for finding out the most likely state sequence and hidden state sequence given the path of events or observations. Hidden Markov Model is being used extensively for the studying the impact of marketing techniques on Consumer attitude and buying behavior of the consumers. The training of the Hidden Markov Model is a popular technique for estimating the probability of emitted sequence given the set of observation sequence. The training of the Hidden Markov Model is essential any kind of application. The training could be both supervised or unsupervised. The proposed model has lot of utility in estimating the probability of transition to m Commerce given the digital trainings and workshops. Many of the authors such as [12] have emphasized the importance of customer relationship management in form of customer interaction and customer encounters on customer relationships. The evolved response models as recommended by [10] have emphasized the role of competitors promotion on consumer behavior. Hidden Markov Model can be used for identifying the impact of various factors including catalog, promotions, digital advertisement on transition to m Commerce in rural areas. The impact of the marketing activities and digital literacy form the latent factors that cannot be observed. This model could be used to find out the probability of complete transition to m Commerce in the rural areas.

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